# A Dynamic Attributes-driven Graph Attention Network Modeling on Behavioral Finance for Stock Prediction

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Stock prediction is a challenging task due to multiple influencing factors and complex market dependencies. Traditional solutions are based on a single type of information. With the success of multi-source information in different fields, the combination of different types of information such as numerical and textual information has become a promising option.

Although multi-source information provides rich multi-view information, how to mine and construct structured relationships from them is a difficult problem. Specifically, most existing methods usually extract features from commonly used multi-source information as predictive information sources, without further pre-constructing stock relationship graphs with dependencies using broader information. More importantly, they typically treat each stock as an isolated forecasting, or employ stock market correlations based on a fixed predefined graph structure, but current methods are not sensitive enough to aggregate the attribute features extracted from multi-source information and stock relationship graph, to obtain the dynamic update of market relations and relationship strength. The stock market is highly temporally, and the attributes of nodes are affected by the time perception of other attributes, which is not fully considered.

To address these problems, we propose a novel dynamic attributes-driven graph attention networks incorporating sentiment (DGATS) information, transaction data, and text data. Inspired by behavioral finance, we separately extract sentiment information as a factor of technical indicators, and further realize the early fusion of technical indicators and textual data through Kronecker product-based tensor fusion. In particular, by LSTM and temporal attention network, the short-term and long-term transition features are gradually grasped from the local composition of the fused stock trading sequence. Furthermore, real-time intra-market

The authors are thankful for the anonymous referee's constructive comments. This work was supported by the National Natural Science Foundation of China ( Grant Nos. 61972227 and 72171133), Natural Science Foundation of Shandong Province (ZR2022MF245), and in part by the Fostering Project of Dominant Discipline and Talent Team of Shandong Province Higher Education Institutions.
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1556-4681/2023/09-ART16 $15.00
https://doi.org/10.1145/3611311

dependencies and key attributes information are captured with graph networks, enabling dynamic updates of relationships and relationship strengths in predefined graphs. Experiments on the real datasets show that the architecture can outperform the previous methods in prediction performance.

CCS Concepts: • **Information systems** → **Data mining**; • **Computing methodologies** → **Knowledge representation and reasoning**; • **Applied computing** → *Economics;*

Additional Key Words and Phrases: Knowledge graph, behavioral finance, dynamic relationship, stock prediction

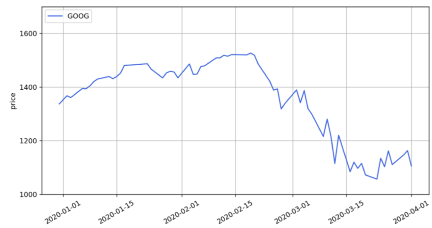
**ACM Reference format:**
Qiuyue Zhang, Yunfeng Zhang, Xunxiang Yao, Shilong Li, Caiming Zhang, and Peide Liu. 2023. A Dynamic Attributes-driven Graph Attention Network Modeling on Behavioral Finance for Stock Prediction. *ACM Trans. Knowl. Discov. Data.* 18, 1, Article 16 (September 2023), 29 pages.
https://doi.org/10.1145/3611311

## 1 INTRODUCTION

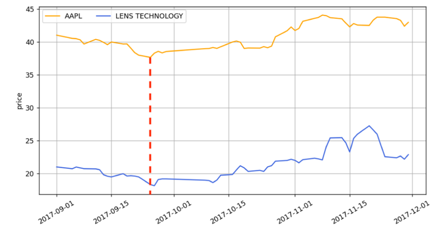
With the development of stock markets all around the world, stock trading has become an important investment channel and the total capitalization of the global stock markets has exceeded $93 trillion by 2020.[1] To maximize investment returns, stock investors and experts are constantly trying to predict the future state of the market, and there is some evidence that the stock market is predictable, which stimulates further research on key techniques of stock prediction [5, 10, 48]. With the wide application of artificial intelligence technology, a lot of work within this field has been focused on the research of stock automatic classification or regression to help investment institutions or investors make better decisions [41]. On this basis, behavioral finance is to attempt to interpret the systematic effects of the psychological decision-making process on financial markets, using cognitive psychology and social science to explain the irrational investor behavior that the model does not capture [26]. However, guided by behavioral finance, stock prediction is challenging because of the complex influencing factors and dynamic dependencies arising from the co-movement effect of involved stocks.

Traditional stock prediction approaches are based on time series analyses using Kalman Filters, Autoregressive Models, and their extensions [18, 21]. This kind of model usually uses a series of technical indicators as a prediction source and represents it as a continuous random process, and verifies the fitting effect of the model by historical trading data. However, the volatility of the stock market is determined by sophisticated factors, and the assumptions of traditional methods may not apply to changing realities, which means that these statistical models tend to be theoretical [12]. Recently, deep neural networks have shown a valuable ability to extract hidden features of stock data, thereby greatly improving prediction performance [6]. Later on, in addition to conventional trading data such as stock prices or trading volumes, text-based data was also included in the original market information source, and there is evidence that media information can monitor the popularity of a product or service and predict its future earnings, election results and even stock market prices [9]. Especially with the in-depth study of behavioral finance, the sentiment factor extracted from text information has received close attention from experts, and numerous studies have validated the importance of public sentiment in stock prediction [44, 47]. Most people know that emotion will affect investment decisions, and behavioral finance studies financial decision-making psychology, which mainly applies the insight of psychological research to financial decision-making, so it can explain why individuals make specific decisions. For example, as

[1] https://data.worldbank.org/indicator/CM.MKT.LCAP.CD?end=2020&start=1975&view=chart




(a) Google's stock price changes post-pandemic




(b) Stock price comparison of AAPL and LENS TECHNOLOGY

Fig. 1. Two examples of historical stock prices. (a) The movement of Google's stock after the outbreak of the epidemic at the end of 2019. (b) A comparison of the stock prices of AAPL and LENS TECHNOLOGY over the same trading period.

shown in Figure 1(a), since the outbreak of the new coronavirus at the end of 2019, investors in social media have shown a negative attitude towards the stock market, while Google's stock has indeed shown a downward trend for a long time, which directly confirms the close relationship between investor sentiment and the stock market. Therefore, based on technical indicators formed by transaction data and textual media data with sentiment information, guided by the research results of behavioral finance, which has strong theoretical and practical significance for stock prediction.

The **Efficient Market Hypothesis (EMH)** states that all valuable information has been timely, accurate, and fully reflected in the stock price, so that different sources of information can play their respective values and jointly affect the rise and fall of stock price [8]. In the field of economics, Hirschman put forward the concept of linkage effect in 1985, that is, all related industries or departments, whether forward or backward, can produce induced investment through expansion, and the realization of induced investment can eventually expand the whole industry chain [16]. If this concept is expanded from the industry, it can also be applied to the financial market. The linkage effect has affected all aspects of the financial market as an objective existence since the birth of the financial market. Based on the above linkage effect, King and Wadhwani put forward the theory of market contagion for the first time in 1990, mainly studying the inter-market linkage effect caused by investors' behavior factors, indicating that the stock price of the securities market changes with the stock price of other securities markets [19]. Specifically, the same or opposite movement of stock prices among markets, regions, industries, and sectors forms a stock co-movement effect [1]. Naturally, that the stock price changes of the target stocks are affected by related stocks in the real world, so the connections between stocks have recently been exploited for financial market forecasting [3, 14]. Given that correlation in financial markets form non-euclidean data, most researchers introduced graph embedding representation methods to learn distributed representations between stocks corresponding to the underlying stock changing trends [15, 34, 38]. However, these studies mostly treat each stock as a node in the graph, and the connection edges between different nodes determine the stock relationship by the extensive information collected in advance, i.e., a prior-fixed graph structure, which ignores that stock relationships are influenced by multiple factors and are likely to change with time and characteristic factors of stock network. Since the real stock market is dynamic in real-time, the state of the market relationships and the strength of the relationships are constantly changing, assuming that the relationship vector has only static weights will limit the fidelity of the modeling. Taking Figure 1(b) as an example, Apple Inc. and Lens Technology Co Ltd. are the *supplier_customer* relationship, when the new iPhone version was released in October 2017, the strength of the relationship between the two changed significantly, especially for the stock price of Lens Technology would have a stronger impact. With

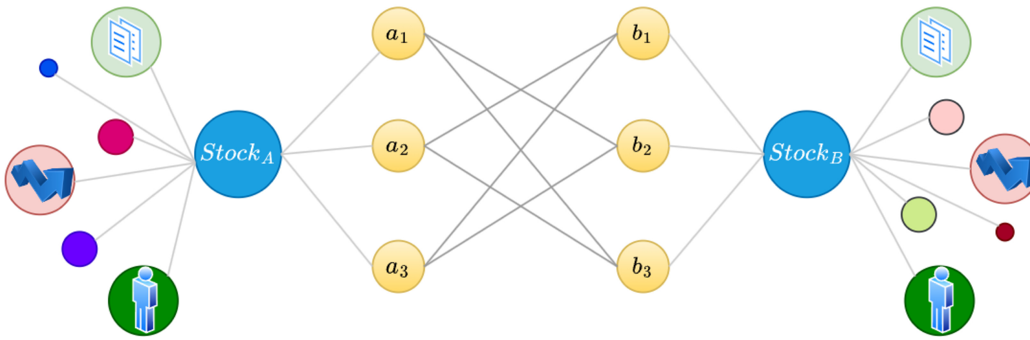



Fig. 2. A toy example of attributes-driven stock collecting multi-source information and node interaction. $a$ and $b$ represent the attributes of $Stock_A$ and $Stock_B$.

the application of **Graph Neural Networks** (**GNNs**), there are increasing numbers of deformed structures, and complex dynamic relationships and stock attributes in financial markets can be simultaneously characterized [12, 52], which makes it possible to make full use of stock relations constructed from real markets information as a supplement of valid knowledge. Attributes are widely used in the financial field, so different researchers give them different characteristics for specific tasks. In essence, it refers to the information describing the nature of things themselves or the nature of connections between things [27]. Based on the existing research results, the features related to the stock can be defined as attributes, some researchers try to condense the media information as the attributes of the stock, others regard the relational features between stocks as attributes, and they all divide the stock attributes into a single type of information [5, 37]. Therefore, the analysis task based on multi-source information can make stock nodes collect the features of different types of information and expand into richer attributes, which provides us with attributes-driven research ideas and expands the previous simple event-driven stock prediction analysis method [24]. For example, as shown in Figure 2, different types of data contain information on stock trends, and the features extracted from them form the attributes of corresponding stocks, which prompts us to establish an attribute-driven solution. However, the attributes of a stock network node are affected by other attributes of the associated nodes, which makes the GNNs in the stock market need to have attribute sensitivity, to accurately evaluate the influence between the network nodes. Therefore, the specially designed GNNs adapted to the financial market can aggregate the time-aware market signals of the stock network and characteristic factors to some extent, and it is especially suitable for capturing the domain knowledge inside the stock to establish the dynamic relationship and strength over time.

Stocks are characterized by the property that they are affected by various time-series market signals, deep learning models such as **recurrent neural networks** (**RNNs**) and variants are used to generate sequence embeddings that capture temporal dependencies in historical market information. Then, the common strategy for mixing different kinds of market indicators from different sources is to concatenate or weighted summation into a hybrid vector [23, 33], which treats stocks as independent and inevitably ignores their intrinsic correlations. Some researchers further integrate different market factors and explore their interactions, they generally use deep learning models to extract features, and then use **support vector machines** (**SVM**), bilinear pooling, and attention mechanisms to construct correlation matrices [51], which requires multiple operations to achieve the fusion of feature information. However, such assumptions lose some information during data transfer and lack the interaction of different market factors, so they cannot be fully applied to the real stock market and should be modeled in conjunction with downstream tasks.

Therefore, it is necessary to consider that the information can be fully integrated while maintaining the interactions of the information after the feature vectors are input at the beginning.

In view of the above research results and existing problems, guided by behavioral finance and the co-movement effect, the sufficient conditions for the current exploration of the stock market can be considered in the modeling of two types of source data, including the integration of technical indicators converted from real market data and the textual media with investor sentiment information. In this article, we propose a **dynamic attributes-driven graph attention networks incorporating sentiment (DGATS)** information with market trading data and textual information, for which the target is to directly predict stock movement. First, a Kronecker product-based tensor fusion method is used to interact with historical market features and text features to prevent information loss and provide a solid factual basis for robust inference of stock states and relationships. Then, the technical indicators and text fusion vectors are fed into the **LSTM and temporal attention (LSTM-Att)** modules to generate sequence embeddings that preserve the temporal dependencies of their fused market information. After that, we construct a dynamic stock relationship graph to depict the real relationship in the stock market, synthesize the theoretical and practical guiding significance of modern behavioral finance and the co-movement effect on investment, and aggregate historical technical indicators and sentiment information with stock features extracted from historical sequences and text information. On this basis, a DGATS is designed to capture dynamic stock relations by masked self-attention mechanism and deal with the attributes problems with improved GCN based on a gated mechanism, which can describe the actual market relations and comprehensive collection of multiple factors affecting the market. Finally, the dynamic relationship graph and the salient features of the corresponding stocks are concatenated to predict the movements of stocks. In summary, the main contributions of this article are as follows:

— Guided by behavioral finance and co-movement effect, an attributes-driven framework combining dynamic relationships of the stock network, technical indicators, and textual media with sentiment information as source data is proposed, which fully considers multiple types of information that affect stock market volatility.
— To comprehensively capture stock network relationships and aggregate attributes in a dynamic manner, the attributes-driven GAT introduces a masked self-attention mechanism into a spatial domain-based graph neural network, in cooperation with a non-linear transformed GCN, which could infer general dynamics relationships from observed market signals and aggregate attribute states sensitively.
— A pre-emptive Kronecker product-based tensor fusion modeling is proposed to capture multi-modal market signals with feature interactions, thereby reducing information loss and providing reliable ground truth for inferring stock states and relationships.

## 2 RELATED WORK

The work of this article is directly related to stock prediction based on multi-source information such as text and technical indicators, stock prediction with external market relation modeling, and multi-modal information fusion.

### 2.1 Stock Prediction with Multi-Source Information

The EMH pointed out that the transmission of information in the market is high-speed and effective, any public information that can affect the price of financial assets will make a timely and rational response to asset prices. With the continuous development and improvement of the theoretical system of economics and finance, some interdisciplinary scholars put forward effective processing of historical data to analyze and predict financial markets from different perspectives. Considering that the volatility of the real stock market is affected by multiple factors, the stock prediction method has gradually evolved from a real historical sequence to a path based on multi-source information.

The traditional financial model focuses on technical analysis, construct technical indicators from historical transaction data, and uses typical machine learning algorithms such as Naive Bayes, Adaboosting, SVM, and random forest to simulate real-time stock trends [30, 32]. However, constructing effective technical signatures often requires a great deal of specialized knowledge, and the assumed stochastic processes may not be the best choice for simulating the highly non-linear and non-stationary volatility of the stock market [41]. Recently, deep models, led by RNNs, have gradually replaced primitive mathematical and machine learning models as promising solutions to capture the sequential dependencies [35, 36, 50]. For instance, Qin et al. proposed an enhanced **long short-term memory** (**LSTM**) with an attention mechanism to realize the stock prediction, and believed that the traditional attention mechanism plus encoder-decoder is not suitable for time series prediction problems [35]. In addition, Zhang et al. proposed a state-frequency memory recurrent network to simultaneously model time-domain and frequency-domain information of time series for price prediction based on past market series [50]. Although the above models extract some valuable temporal information by virtue of memory cells, the stored information is still limited.

In addition to the above historical sequences, stock prediction also takes into account valuable textual information such as Weibo, Twitter opinions, forum posts, and so on, especially hidden investor sentiment. Behavioral finance regards investors' investment behavior as a psychological process, and believes that in addition to the basic value of the stock, the behavioral characteristics and psychological factors of investors in the investment process will also have an important impact on the stock price [26]. Some research results have proved that investor sentiment has an important influence on stock prediction and is an important reason for the predictability of financial markets [25, 31]. For example, Nguyen et al. applied the text sentiment analysis model for the stock market prediction, which uses the latent Dirichlet allocation model to obtain the topic content and sentiment information contained in social media opinions [31]. Li et al. constructed a special LSTM to learn information from technical indicators and text sentiment, using a traditional fully connected network for predicting stock price trend [25]. It can be seen that the sentiment factors contained in the media information can reflect the subjective attitude of investors towards the financial market, thereby enhancing the forecasting effect.

### 2.2 Stock Prediction with Market Relation Modeling

The rapid development of modern information technology and the change in research paradigm make some scholars have realized the limitations of local sample analysis and started to analyze the correlation between stocks from the perspective of complexity, so the co-movement effect-driven network modeling method has been applied. A new idea explores the construction of data as a graph structure to capture the interdependence between stock markets, which is then integrated into the learning process to obtain better performance on target tasks. Therefore, some works no longer treat stocks as independent of each other, but use graph-based learning methods on top of traditional forecasting methods to obtain correlations between stocks [3, 10]. Chen et al. constructed a graph containing all related companies based on the investment facts of the real market, and incorporate the target company's related information into the prediction, mainly using **Graph Convolutional Networks** (**GCN**) [20] to transform stock prediction into a node classification problem [3]. Moreover, Feng et al. used LSTM cells to transform the original GCN structure to update the stock market graph in a time-sensitive manner to enrich sequence embedding, for which the goal is directly predicting a list of stocks ordered by desired criteria such as returns [10]. Although graph-based stock predictions have made progress, they are mainly based on simple graph structures to detect stock relationships, relying heavily on fixed prior knowledge. Therefore, the proportion of attributes to be transported cannot be dynamically adjusted according to the attribute state of the associated node, as explained by the previous example of Google's stock price decline.

Most GNNs, including the above structure, generate relational embedding by analyzing attribute features and market relational structures. Specifically, the attributes of stock nodes in the network are converted by the weight matrix and transferred to the related node, and further use the attention mechanism to dynamically infer the market relationship to form an attributes-driven graph network. Obviously, the weights for each attribute are kept dynamically updated and shared with all nodes based on the above operation, which stimulates the emergence of attribute-based aggregators and GNNs [4, 12]. For example, Cheng et al. proposed an attribute-mattered **graph attention network (GAT)**, which is realized by capturing the momentum spillover of listed companies, each node is represented by its relationship embedding, that is, the aggregation of its neighbor attributes in the graph [4]. Feng et al. also put forward a relationship-aware dynamic attributed GAT for stock recommendation task, which not only uses time series modules to encode temporal features, but also constructs a new GNN structure to obtain global information [12]. In addition to the deformed GNNs structure, there are some sensitive nonlinear aggregators that handle attribute states, which typically determine the number of attributes to be transmitted based on the full states of the attribute across all connected nodes. For instance, Wang et al. proposed to use the maximum pool aggregator in GCN to aggregate dynamic relationships, so that only adjacent nodes maintain the maximum value in some attributes [13]. Although the above graph structures are sensitive to attribute states and dynamically update market relations, they usually only consider neighbor nodes without allowing all nodes to participate in operations, making the predefined market relations generate noise in the long run. Consequently, the attribute-sensitive dynamic GAT seems to be able to capture the relations and relationship strength of time perception over time, and truly simulate the stock market changes.

### 2.3 Multi-modal Information Fusion

More recently, a large number of empirical studies have provided strong evidence to support that fusing different types of information has a significant impact on predicting asset prices. For example, Xu et al. adopted the concatenation method to fuse the text and stock price using the preprocessed features as the input of the prediction model [47]. Xu et al. developed a stock movement prediction network using Twitter opinion and stock price data as source information by means of an incorporative attention mechanism that combines multiple attention mechanisms to clean up context embedding using local semantics [46]. In addition, popular fusion techniques in the **computer vision (CV)** field, such as bilinear pooling, attention-based fusion methods, and others have attracted our attention [49]. It can be seen that the above-mentioned fusion methods, especially the commonly used concatenation methods, assume that each information pattern has no intersection, and contextual co-occurrence relationships decrease or may be eliminated as information is transmitted [23]. Therefore, in the fields of video and image processing, tensor-based fusion methods have begun to appear and have been recognized by researchers [43, 53]. Wang et al. proposed a collaborative learning algorithm based on the spatio-temporal tensor fusion model, which takes into account the interaction between vehicles by introducing LSTM to encode trajectories and constructing a novel circular social mechanism to create information between multiple vehicles [43]. To this end, a general and extensible tensor-based early fusion idea to predict stock movements based on multimodal data provides a powerful tool for us.

Consequently, we propose a model for stock prediction utilizing technical indicators, textual media with sentiment information, and dynamic stock market relationships, where the fusion of technical indicators and textual information is inspired by multimodal fusion, employing an early Kronecker product-based tensor fusion operation. Our proposed DGATS is able to describe the dynamic relationship between stocks accurately, and aggregate key attributes to capture the time-aware relationship and relationship strength to better characterize the volatility. In terms of the performance of stock prediction, DGATS can more accurately and effectively predict stock movements, helping investors avoid risks and reduce losses.

## 3 PRELIMINARIES

For all $S$ stocks, we get a set of transaction data to construct technical indicators, collect textual media of the stock to obtain media sentiment information, and construct a popular market relationship graph. For a stock $s$, $m_i^t \epsilon R^L$ is the $L$-dimensional feature vector corresponding to the technical indicators on day $t$, and $n_i^t \epsilon R^{L'}$ corresponds to the text article $t$. Five technical indicators are selected and each has been proven to apply to stock market analysis tasks [24]. In particular, six sentiment features are defined to represent the media factor from textual media. To build an easily generalizable stock relationship graph based on rich historical information, we collected five popular relationships for this study. Next, we introduce the variables commonly used in the article, where $x$ (lower-case letter) denotes index, $X$ (upper-case letter) denotes a scalar, $\mathbf{x}$ (bold lower-case letter) denotes a vector, $\mathcal{X}$ (script letter) denotes a matrix, and $\theta$ denotes parameter learned by the model during training.

### 3.1 Behavioral Finance

After Lewellen et al. proposed behavioral finance theory, related researchers began to explore the impact of investors' emotional states on financial markets, and extracted emotional feature values from multi-channel information to further improve the prediction accuracy of financial indicators [22]. Behavioral finance, which is derived from the combination of finance, psychology, and behavior, believes that stock prices are not only determined by the intrinsic value of enterprises but are largely affected by investors' psychology and behavior. Based on historical theoretical research results [26], investor sentiment is one of the psychological factors that affect investors' trading behavior. Emotions are people's emotional tendencies, and for different investors, emotions deviate from rationality to varying degrees. There is a wealth of evidence that people are overconfident in their judgments, which in turn stems from the self-attribution bias, where people tend to attribute success to their talents and failures to bad luck rather than their own incompetence. In most cases, there is an inertia in people's minds and more reliance on previous information. In an uncertain information environment, investors are prone to herd mentality and are influenced by the collective choice behavior of external investors to make similar decisions. As shown in Figure 3, investors browse objective or subjective texts on news platforms or social media platforms, such as financial news, micro-blog, forum posts, and Twitter, that is, financial text data. When this information affects a stock company, their emotions will deviate. Therefore, mining investor sentiment information from these financial text data has guiding significance for stock forecasting research.

The sentiment resources commonly used at this stage are mainly from the following two aspects: one is the online news, the negative sentence of financial news and the relationship between the market and the New York Times and 40 world financial index linkage studies strongly support the new economic paradigm of behavioral finance; second, social media resources, investors often post subjective comments on social platforms, and the hidden emotional characteristics can easily affect the financial market [2, 17]. In this study, we use textual media and extract six sentiment information to represent the media factor into technical indicators.

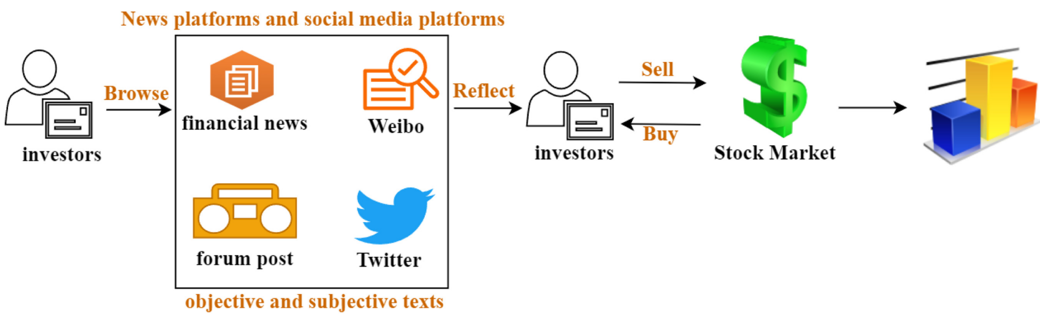



Fig. 3. Investor sentiment affects trading fluctuation in the stock market.

### 3.2 Graph Neural Network

Although traditional deep learning methods have made great progress in deeply extracting the features of Euclidean spatial data, the data in many practical application scenarios are based on non-European space, and the performance of traditional deep learning methods in processing is still unsatisfactory. Therefore, researchers have defined and designed a novel neural network for processing graph data by drawing on the ideas of **convolutional neural network** (**CNN**), RNN, and deep autoencoder, thus a new research hotspot-GNN came into being [11, 45]. Especially for financial-related tasks, to analyze the graph-based relationships and internal characteristics of stock market generated data in non-European space, there are some GNN-based models to mine the relations behind the financial market. At present, the conventional network models dealing with graph relations are divided into two categories. The first one is GCN, which is used to aggregate the feature information of different stocks; the second one is GAT, the internal self-attention mechanism that infers the latent relation of the stocks with observed features and integrates content information.

*3.2.1 Graph Convolutional Network.* GCN is a special graph-based learning method that extends from traditional data ( such as images ) to graph data, which is combined with the advanced CNN whose core idea is to use convolution to capture local patterns in the input data, aiming at capturing local relationships on the graph. However, it is not feasible to manipulate the adjacency matrix of a graph directly using CNN, because when we switch row data of matrices, the filtering output of the convolution may change, and the switched matrix still represents the original graph relation structure. Therefore, more and more experts have made improvements based on traditional GCN, which provides us with ideas. One possible approach is to use the Laplacian matrix to capture local connections in the space, which use the theory of graph to implement convolution operations on topological graphs. But the stock market is a special domain, and the attributes in all nodes have a great impact on the analysis task, which makes us need to speculate on the importance of attributes before further analysis of nodes and edges.

A large number of methods now regard the weight of each attribute as fixed and share parameter values on all stock nodes. Thus, it cannot adjust the proportion of attributes to be transferred based on the attribute state of the connected nodes over time and requires additional information. In addition, for traditional GCN, abnormal "price" declines of stocks usually affect neighboring firms according to the stock graph relationship. But in some special cases of the actual market, an unusual "price" drop in stock should not affect the price of a neighbor's stock, as the price drop may be accompanied by only a small amount of trading volume, indicating that its trading price has been underestimated. Therefore, to address the problems that may be encountered in real markets, we employ a linear gated mechanism in GCN to comprehensively consider the influence degree of node attributes, which will be described in detail below.

*3.2.2 Graph Attention Network.* The GAT is a combination of GNNs and an attention layer, which assigns different weights to different nodes that only exist in their neighbors. Compared with GCN, the GAT has a new dimension that can be learned, which is the weight coefficient on the edge. In the previous model, this weight coefficient matrix is the Laplacian matrix of the graph, and the graph attention model can learn it adaptive and avoid introducing too many learning parameters by using the attention mechanism, which makes the graph attention model very expressive. From the spatial perspective, the mechanism introduces an adaptive graph shift operator, which guides the learning of the operator by means of learning, to complete the targeted transformation operation of the input graph signal. In many sequence-based tasks, the attention mechanism has almost become an essential operation. One of the strengths of the attention mechanism is that it can handle variable-size inputs and then make decisions by focusing on the most relevant parts.

The key of GAT is the graph attention layer, and its processing object is each node of the whole graph, while the main idea is to use the self-attention mechanism to calculate the feature representation of each node by paying attention to its neighborhood. Considering that there are many nodes in the graph structure, complex background noise will have a negative impact on GNNs performance. Under the action of self-Attention, the GAT model will focus on the most important node or node information in the graph to improve the **signal-to-noise ratio** (**SNR**). Self-Attention makes use of the connection between graph nodes more ingeniously, distinguishes the level of connection, and enhances the effective information needed in the task, which updates the internal features of all nodes to infer the relationships. Furthermore, a multi-head attention mechanism as a long-term strategy has been widely proposed in attention network-based methods [40]. Considering that the long-term strategy includes feature correlations of different dimensions and is suitable for analyzing complex stock networks, some researchers try to use it to mine the relationships within the network to improve the performance of the results.

## 4 METHODOLOGY

In this section, we will model the temporal and spatial data in the stock market, and focus on the new GNNs structure based on the spatial concept. Specifically, we integrate the idea that stock trends change dynamically with time, capturing valuable information guided by behavioral finance and the co-movement effect. As we know, the data from each source can provide certain information for the target task, and the purpose of multi-source information fusion is to maximize the comprehensive analysis and judgment of the data from multiple sources in order to better complete the target task. Apart from the conventional text and transaction data, behavioral finance is based on the capital asset pricing model and the EMH framework to integrate the human perspective to explain the development of the market. Therefore, the sentiment factors extracted from the text and the real market trading data constitute the preliminary technical indicators. In general, some irrational investment behaviors will affect the movement of stocks to assist in obtaining excess returns, as shown in Formula 1, the excess expected return value is greater than 0.

$$E(r_{t+1}|\phi_t) = F([x_1, x_2, \dots, x_7]), \tag{1}$$

where $F$ represents the calculation process of neural network, $r_{t+1}$ denotes the excess returns and $\phi_t$ includes all information sets. In addition, $x_1, x_2, \dots, x_7$ correspond to the highest price, lowest price, opening price, closing price, volume, sentiment, and text. On this basis, we establish an attributes-driven GAT model to predict the movement of stocks. Next, we introduce the details, and Figure 4 illustrates its overall framework.

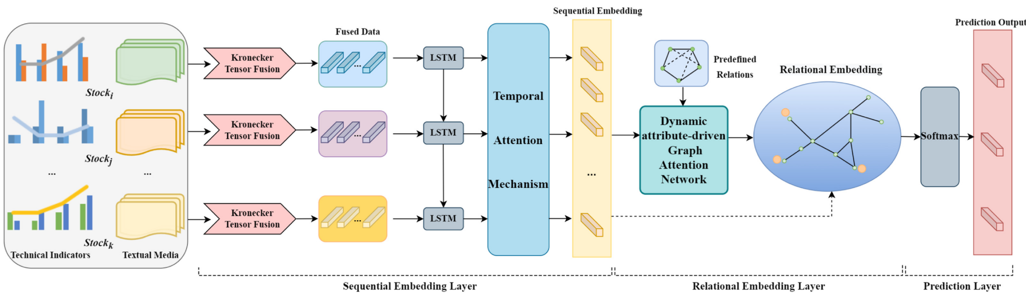



Fig. 4. The overall framework of the stock movement prediction model, including four parts: historical market information (technical indicators, textual media, and predefined stock relations), the generation process of sequential embeddings (sequential embedding layer), the generation process of relational embeddings (relational embedding layer) and final prediction outputs (prediction layer).

## 4.1 Overview

Our proposed DGATS model aims at predicting the movement of stocks, which can realize accurate prediction by using historical information as source data. It relies on prior knowledge of the history of the stock market to build a stock relationship graph that represents the relationship between various stocks and applies specially designed GNNs to judge important attributes between any two connected stocks and capture time-aware relation strengths to infer latent relationships and aggregate attributes information.

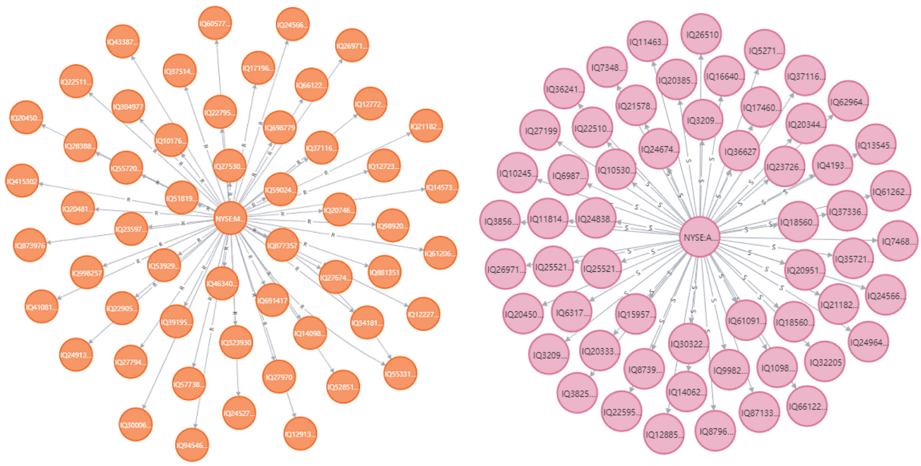
The complete framework of the DGATS model is shown in Figure 4, which includes the following four parts:

— **Market Information**: The model takes the technical indicators converted from historical data and textual media with sentiments extracted from the stock description as part of the input, and the pre-built market relationship graph is input as another part of the post-processing relationship embedding.
— **Sequential Embedding Layer**: The acquisition of sequence embedding needs to fully integrate technical indicators and textual information through tensor fusion based on Kronecker product in advance, and then adopt LSTM-Att for further processing.
— **Relational Embedding Layer**: The generation of relational embeddings mainly relies on the DGATS component proposed in this article, historical sequence embeddings, and predefined stock relational graphs as input to achieve dynamic time-aware relational strength changes to obtain the updated relational embedding.
— **Prediction Layer**: The output model mainly relies on the softmax function mapping to determine the movement of the target stock.

## 4.2 Market Information

Based on historical financial research, three types of market information are often used as source data to solve problems encountered in financial markets, namely technical indicators, textual data, and graphs based on stock relationships. Therefore, we adopted the above three types of data as market information.

*4.2.1 Technical Indicators.* Several technical indicators have been demonstrated to be the basis of theoretical and practical financial market prediction. As we know, transaction data can more realistically reflect the intrinsic value of corporations and investors' expectations, and thus be regarded as an important source for analyzing financial markets. This article selects 5 typical



(a) (b)

Fig. 5. a, b represent the complex stock market network relationship graph.

technical indicators, namely highest/lowest price, opening/closing price, and trade volume, which have been proven to have actual predictive value [14]. To facilitate the comparison of all related stocks and prevent the confusion caused by excessive data differences, we convert stock prices $P^t$ into return ratios $R^t$ at day $t$, as shown in Equation (2).

$$R^t = (P^t - P^{t-1})/P^{t-1}, \tag{2}$$

where $P^{t-1}$ denotes the stock price of the previous day. Likewise, the trade volume is normalized to the turnover ratio for downstream task analysis.

*4.2.2 Textual Media.* Behavioral finance theory reveals that investors are easily influenced by external information in the media and make irrational behaviors. Therefore, we adopt financial text released on the day $t$ as another vital source of information. A large number of studies have confirmed that the text data from the media contains a lot of valuable information, especially hidden sentiment information is an important signal affecting the stock market volatility. In this study, six typical sentiment features are extracted from text based on Loughran and McDonald's dictionary for stock prediction. These are positive, negative, uncertain, litigious, constrain, strong, moderate and weak, which are built into the media factors of technical indicators.

*4.2.3 Stock Relations.* In addition to the above input information, the predefined market relationship graph as input in the later stage, Figure 5 visualizes a partial real-world stock market relationship graph. The graph structure establishes relationships through a wide range of historical information and uses the structure proposed in the article to infer dynamic relationships with market signals. The predefined relationship graph includes a total of five types of commonly used relationships, namely, industry category, supply chain, competition, customer, and strategic alliance, which is represented by the corresponding adjacency matrix. If there is a relationship between two stock nodes, the corresponding value is 1, otherwise is 0.

### 4.3 Sequential Embeddings Layer

The stock market is highly affected by various time-series market signals, which makes a large number of researchers use neural networks to mine hidden features in multi-source information, and then use concatenation to fuse vectors as the input for the next step. However, this approach inevitably ignores internal relationships, which are vital for financial time series analysis [23]. Accordingly, we propose the Kronecker product-based tensor fusion to fuse technical indicators and media information to capture the interaction of different market signals while preventing the loss of important information during transmission. To generate favorable sequential embeddings for further updating the relational graph, the LSTM and temporal attention modules are constructed to capture the sequential dependencies and analyze the importance of the hidden features.

*4.3.1 Kronecker Tensor Fusion.* The sub-model aims at fusing technical indicators and textual data while preserving their interactions. For a given stock $i$, $\mathbf{m}_i^t \in R^D$ is the $D$-dimensional feature vector of technical indicators and $\mathbf{n}_i^t \in R^B$ is the $B$-dimensional feature vector of media articles on the day $t$. Besides traditional methods such as concatenation or weighted summation, the simple approach is to redefine the tensor fusion feature as shown in Equation (3), thereby modeling the weights of the numerical and textual feature vectors. In order to facilitate downstream tasks, we introduce a third-order tensor C to adjust the parameters, whose dimension is $C$.

$$\mathbf{x}_i^t = \mathcal{W} \times \mathbf{m}_i^t \times \mathbf{n}_i^t, \tag{3}$$

where $\mathcal{W}$ is the parameters in the form of a third-order tensor of size $D \times C \times B$; notation $\times$ denotes the tensor dot product. The proposed tensor $\mathcal{W}$ provides a fusion model that fully extracts rich information from multi-source information. However, due to the additional introduction of attribute vectors, the computational model is multiplied. To address this problem, inspired by multi-modal attributes feature fusion, we apply the tensor decomposition technique and Kronecker product to mingle multi-source information features and achieve optimization. First, to reduce the number of parameters, we adopt the Tucker Decomposition technique proposed by Tucker [39], which decomposes $\mathcal{W}$ into multiple components, as shown in Equation (4).

$$\mathcal{W} = \mathcal{S} \times U_D \times U_C \times U_B, \tag{4}$$

where $\mathcal{S}$ is a third order tensor of size $K_D \times K_C \times K_B$, $U_D$ is a matrix of size $K_D \times D$, $U_C$ is a matrix of size $K_C \times C$ and $U_B$ is a matrix of size $K_B \times B$. Furthermore, we can rewritten the Equation (4) as,

$$\mathbf{x}_i^t = \left(\left(U_D m_i^t\right) \otimes U_B n_i^t\right) \mathcal{S}^T U_C, \tag{5}$$

where $\otimes$ is Kronecker product. Using the introduced Kronecker product layer and other operations to fuse the features deeply and capture feature interactions. To facilitate comparison, we use the *sig* function to process the fusion features. From Equation (5), the fused representation of textual information $\mathbf{m}_i^t$ and numerical features $\mathbf{n}_i^t$ can be achieved. The fused feature $((U_D m_i^t) \otimes U_B n_i^t) \mathcal{S}^T U_C$ is a vector of the dimensionality $K_C$.

*4.3.2 LSTM and Temporal Attention Mechanism.* It is well known that financial data has correlation to the temporal information, so an LSTM model with temporal attention mechanism is introduced to mine valuable information at different times. Considering the characteristics of the high temporal and high volatility of financial data, LSTM cannot directly obtain accurate feature vectors at a certain moment when dealing with too long input data, so it cannot distinguish the criticality of information, which makes the utilization rate of downstream processes low. However, the temporal attention mechanism can solve the above problems well, even in the face of long-period data, by assigning attention scores to identify key information and avoid information noise affecting downstream tasks.

Before detailing the specific implementation process of LSTM, we first describe the terminology related to it. In each calculation process, $x$ represents the input vector, and three gates are introduced, namely, the input gate, forget gate, and the output gate, and the same shape as the hidden

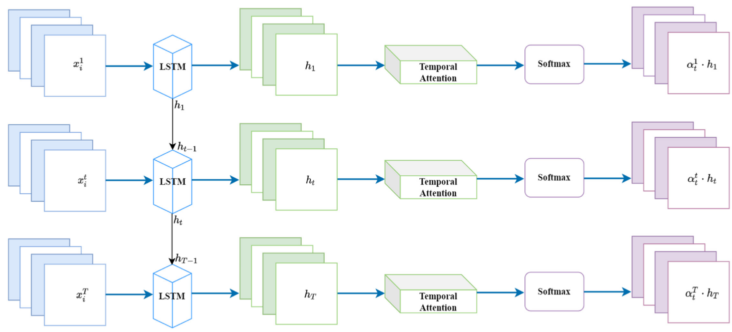



Fig. 6. LSTM and temporal attention network structure. The temporal attention mechanism calculates the attention score based on the hidden states from LSTM and obtains the updated state by attention coefficient.

state, the vectors $i_t$, $f_t$, $O_t$, and $h_t$ denote the above gates or state. Memory cells $C_t$ are used to record additional information, $\tilde{C}_t$ represents the cell state update value. Formally, the transition model, state vector, and control gate are defined via the following equations:

$$C_t = f_t \times +i_t \times \tilde{C}_t, \tag{6}$$

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f), \tag{7}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \tag{8}$$

$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C), \tag{9}$$

$$O_t = \sigma(W_O \cdot [h_{t-1}, x_t] + b_O), \tag{10}$$

$$h_t = O_t * tanh(C_t). \tag{11}$$

Based on the complete operational flow described above, we obtain important information about temporal. In recent years, attention mechanism has played an important role in solving problems in the fields of stock prediction, image processing, **natural language processing** (**NLP**), and other fields. From the perspective of the role of the attention mechanism, it includes spatial attention and temporal attention. Among them, temporal attention is widely used in time series data analysis, which can extract valuable information to generate sequential embeddings that benefit downstream tasks. The detailed implementation process is shown in Figure 6. For stock $i$, to generate the sequential embedding $\mathbf{v}_i^t$ on the target $t$ using market signal representations in the past $T$ days, $\mathcal{X}_1^t = [x_i^{t-T}, \dots, x_i^t]$. The attention mechanism calculation process at day $t$ are as follows:

$$h^T = \delta\left(W\left[h_{T-1}; x_i^t\right] + b\right), \tag{12}$$

$$h_t^{'} = \sum_{t=T-s}^{T} \alpha_t h_t, \tag{13}$$

$$\alpha_t = \frac{exp(h_T t)}{\sum_{k=T-s}^{T} exp(h_T k)}, \tag{14}$$

where $W$ and $b$ are learnable parameters, $s$ and $k$ denote time period. Since the attention-based mechanism can obtain the weight according to the importance of information, and there is a strong dependence between different stocks, which allows the attention mechanism to better map the acquired feature information to the space for the convenience of later use.

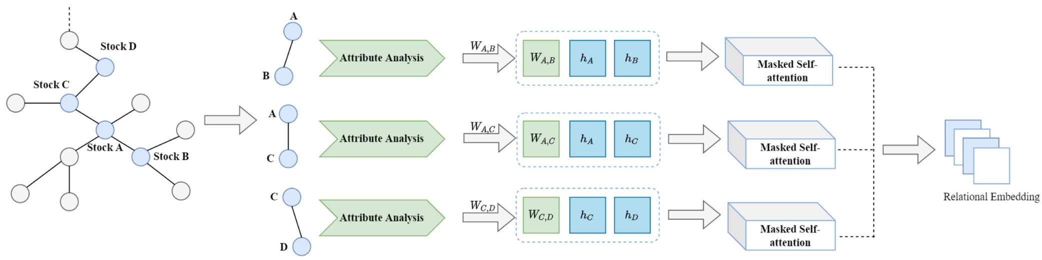



Fig. 7. Illustration of the attributes-driven GAT model, the "masked self-attention" is represented as the attention mechanism in the GAT.

### 4.4 Relational Embeddings Layer

We introduce dynamic attributes-driven GAT to deal with stock relations, which contains two units: GCN and attributes-driven GAT. The GCN is used to analyze the important attributes from sequential embeddings, the self-attention network captures dynamic time-aware market relations and updates the relation strength. The acquisition process of the complete relational embedding is shown in Figure 7.

**Graph Convolutional Network.** The fundamental challenge in GCN is considering the interferences of connected stocks' attributes. In the real world, changes in the target stock's market price are affected by related stocks and are easily disturbed by multiple attributes. Therefore, it is natural to think that the more accurate the analysis of key attributes among multiple stocks, the better the performance of a stock prediction model. To obtain more detailed relationships and analyze the attributes that affect the stock market, we propose an improved GCN mechanism.

To model the relationships of listed stocks, constructing them into a graph, in which $\mathcal{V} = [\mathbf{h}_1^t, \ldots, \mathbf{h}_N^t]$ is the representations of $N$ stocks, and $\varepsilon$ reflects the predefined relation graph of listed stocks, whose indexes are the name of listed stocks and values are their connection strengths. First, we use $\mathcal{S} = [\mathbf{s}_1^t, \ldots, \mathbf{s}_N^t]$ to represent the relational embeddings, which is calculated as Equation (15). A gate mechanism is introduced into the GCN that is a non-linear transformation of the related attributes, and the gate is multiplied by the elements of the attributes connecting the stock and the attributes of the source stock.

$$\mathbf{s}_i^t = \sigma\left(\sum_j^N E_{i,j} W_s \mathbf{h}_j^t \otimes sig\left(W_c \left[\mathbf{h}_i^t || \mathbf{h}_j^t\right] + \mathbf{b}\right)\right), \tag{15}$$

where $E_{i,j}$ denotes the relation between stock $i$ and $j$; $\sigma$ is an activation function; $sig$ is used to get the information gate; $W_s$, $W_c$, and $b$ are parameters to be learned. In the above process, GCN can analyze the importance of attributes and reduce the influence of some irrelevant attributes on neighbor stocks.

**Attributes-driven Graph Attention Network.** For a more comprehensive analysis of each stock node, the attributes and structure information of the node itself is required. Therefore, we specifically use a graph-based learning method to aggregate neighbor stock node features with time-aware relationships. Different from the traditional static stock relationship graph, we adopt a dynamic time-aware relationship mechanism. Specifically, the relationship and strength of the graph network nodes change dynamically with the information acquired over time, the relationship function that defines the stock nodes $i$ and $j$ is shown in Equation (16) at time $t$.

$$R_{i,j}^t = r\left(\mathbf{h}_i^t, \mathbf{h}_j^t\right). \tag{16}$$

However, some GAT-based methods cannot guarantee that stocks including the target node itself participate in the calculation and always use predefined network relationships. Therefore, we adopt a masked self-attention mechanism to solve the above problems, thereby reducing the noise generated by the predefined market relations. In this way, we define a market relationship using the attention mechanism to dynamically obtain market information and update time-aware market relations.

$$R^t_{i,j} = \phi\left(\mathbf{a}_r^T \left[W_i \mathbf{h}^t_i || W_j \mathbf{h}^t_j\right]\right), \tag{17}$$

$$E^t_{i,j} = \frac{exp(R^t_{i,j})}{\sum exp(R^t_{i,k})}, \tag{18}$$

where $||$ denotes concatenation operation; $\phi$ is an activation function [29]; $\mathbf{a}_r$ is a vector to convert connection strength to scalar. The $E^t_{i,j}$ denotes the normalized strength of the connection from $j$ to $i$ at time $t$. In addition, the relational embedding is dynamically updated on the basis of the aggregated feature attributes, and Equation (15) is redefined with the above-mentioned normalized connection strength. Given that we exploit the improved GCN and GAT models as the main structure to dynamically update the node information, the resulting relationship graph contains a weighted summation of different attributes and more comprehensive stock network relationships. To realize information interaction in different feature spaces, the multi-head attention strategy is widely added. The self-attention model can be seen as establishing the interaction between different forms of input vectors in linear projection space, and the multi-head attention is to establish different projection information in multiple different projection spaces, project the input matrix differently, obtain multiple output matrices, and then concatenate them together. The essence of the multi-head attention mechanism is multiple independent attention parallel computing processes, which can play an integrated role in preventing overfitting. Due to the correlation and interaction of different feature spaces contained in the multi-head strategy being suitable for the complex multi-dimensional correlation characteristics in the stock network, we utilize it to improve the performance of GAT. The calculation process of introducing a multi-head strategy is shown below.

$$\mathbf{s}^t_i =^M_{m=1} \sigma\left(\sum_j^N E^t_{i,j} W_s^m \mathbf{h}^t_j \otimes sig\left(W_c^m \left[\mathbf{h}^t_i || \mathbf{h}^t_j\right] + \mathbf{b}\right)\right), \tag{19}$$

where $m, E_{i,j^m}, W_s^m, W_c^m$ denote the number of head, the dynamic relations and learned parameters. The above three consecutive steps obtain the updated market relational embedding under the premise of fusing historical attributes and predefined relationships, which acts as the information source of the prediction layer.

### 4.5 Prediction Layer

To meet the practical needs of stock forecasting, more comprehensive stock information should be considered to help investors and institutions obtain higher returns. Therefore, we concatenate the sequential embeddings and revised relational embeddings generated above and then pass them to a fully connected layer to predict the movement of the stocks. Firstly, we concatenate the sequential embeddings and the market relations to form a complete relational embedding that not only incorporates key market information but also considers time-aware attributes-driven market relations. Then, the softmax function is applied to predict the probability of future stock movements, which is written by

$$\hat{y}^t_i = softmax\left(W_i \left[h^t_i || s^t_i\right] + \mathbf{b}_i\right), \tag{20}$$

where $W_i$ is the weight matrix, $\mathbf{b}_i$ is the bias vector. In addition, we adopt an objective function combined with cross-entropy loss to learn the parameters to optimize the model.

$$Loss = -\left[y_i^t log\hat{y}_i^t + \left(1 - y_i^t\right) log\left(1 - \hat{y}_i^t\right)\right], \tag{21}$$

where $y_i^t$ and $\hat{y}_i^t$ denote the ground truth and prediction results. Minimizing the loss of our proposed portfolio will force forecast results to be close to the true stock trend, thereby benefiting investors to make better investment decisions.

## 5 EXPERIMENT

### 5.1 Datasets

Stock historical technical indicators, textual media information, and predefined stock relation graph are used in our experiments. Next, we introduce the specific information of these three data.

**Historical technical indicators.** All stocks used in the datasets are from the NASDAQ and **New York Stock Exchange** (**NYSE**) and we select historical trading data for the period from 01/02/2013 to 12/08/2017, including 1026 and 1737 stocks, which can be obtained from Yahoo Finance.[2] In detail, following Zhang et al. [50], we split the entire stock historical dataset into training set (2013–2015), validation set (2016), and evaluation set (2017), and their lengths are 756, 252, and 237, respectively.

**Textual media.** We collect the financial text during the same period from Gao et al.[3] The transaction data corresponds to the date of the text data, ensuring that each stock has at least one text per day. Totally, 5,130 and 5,955 text are collected. The text was processed using traditional operations in the NLP, which means the collected text needs to be cleaned to remove useless information, such as HTML tags, special characters, stop words, and so on, for subsequent analysis and mining. We use the **Natural Language Toolkit** (**NLTK**), which is commonly used in NLP, to complete word segmentation and labeling, so as to reduce information noise and avoid affecting the experimental results. To make the text information understood by the deep learning model, we use the glove pre-training model to generate word embedding vectors.

**Stock relation graph.** There are five types of stock relations collected from the Capital IQ database to build a predefined relation graph. The node relationships and strengths of a graph structure would change in time-aware with the aggregation of attributes.

### 5.2 Experimental Setups

The implementation of the DGATS model proposed in this article adopts the Pytorch framework and is optimized by the Adam optimizer, and the learning rate is set to 0.0005. For the time window size $T$ and the number of attention heads $M$, we select the best value by grid search within [3, 5, 10, 20, 30, 40, 50] and [4, 5, 6, 7,8,9,10]. In addition, based on the research experience of deep learning and stock prediction, the dimensions involved in this study are all set to [30, 60, 120, 150, 240, 300, 360]. For all the methods compared in experiments, we trained 10 times with multiple initializations and selected the best-performing parameter settings based on their performance during validation. To eliminate fluctuations from random initialization, we calculate the average test results of the proposed model.

### 5.3 Evaluation Metrics

The stock prediction solved by the method proposed in this article can be regarded as a binary classification problem, where the output is a judgment on the binary movement direction. When

[2] https://finance.yahoo.com
[3] https://github.com/xiaoting135/TRAN

the closing price of a stock on the same day is higher than the opening price, it indicates that the stock price rises, and vice versa, it indicates a decline, the 1 denotes rise and 0 denotes fall. In order to evaluate the real effect of the model, we used four metrics to observe their performance more intuitively, **accuracy** (**ACC**), **Matthews Correlation Coefficient** (**MCC**), F1 score, and **area under the precision-recall curve** (**AUC**) score, which is widely used in previous studies. The confusion matrix containing the number of samples is classified as **true positive** (**tp**), **false positive** (**fp**), **true negative** (**tn**), and **false negative** (**fn**), MCC is calculated as Equation (22). The calculation process of F1 can be derived from Equation (23).

$$MCC = \frac{tp \times tn - fp \times fn}{\sqrt{(tp + fp)(tp + fn)(tn + fp)(tn + fn)}}, \tag{22}$$

$$\begin{aligned} Precision &= \frac{TP}{TP + FP} \\ Recall &= \frac{TP}{TP + FN} \\ F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}&. \end{aligned} \tag{23}$$

While the AUC is derived from Duan et al. [7], which set threshold *beta* in the model, so that when the stock movement prediction is $p(y = 1) > \beta$ are recommended. AUC is an evaluation metric to measure the advantages and disadvantages of the binary classification model, and can well describe the overall performance of the model. To a certain extent, it can describe the probability that the positive examples are in front of the negative ones in the prediction results. As a result, the performance of the model can be evaluated with AUC. Moreover, the accuracy truly reflects the probability that the model prediction is accurate.

### 5.4 Experimental Results

We conduct multiple experiments and in-depth analysis of different types of experimental results to verify the advantages of the proposed method compared to other models, including the overall prediction performance compared with seven baseline models, the information fusion methods effect, the ablation study, and sensitivity analysis. In order to significantly demonstrate the practicality and real effects of our model in real-world trading, we compare the model proposed in this article with a method that has performed well in the financial domain in recent years, and apply it to the real trading market, comparing their recommendation results and returns.

*5.4.1 Comparison with Baseline Methods.* Considering the components and information sources of our framework, we compare DGATS with the following stock prediction baselines.

- **StockNet** [47]: It incorporates opinions from Twitter and stock price to achieve stock movement prediction, which is motivated by variational auto-encoders to generate stock movements from multiple factors modeled by latent variables.
- **LSTM+PS** [25]: Based on LSTM, this article combines technical indicators with news emotions, and additionally connects fully connected neural networks for stock prediction, thus constructing a corresponding stock prediction system.
- **LSTM+GCN** [3]: This method proposes a stock prediction model with GCN and LSTM as the main architecture, with technical indicators and corporation relationship graphs as source information. It takes GCN to aggravate information of the stock relationship graph and then feeds the fusion features to the LSTM encoder layer, which are input into a classifier for prediction.

Table 1. Evaluation Results ($\times 10^{-2}$) on the Datasets

| Models | NASDAQ | | | | NYSE | | | |
|---|---|---|---|---|---|---|---|---|
| | ACC | MCC | AUC | F1 | ACC | MCC | AUC | F1 |
| StockNet | 57.49 | 24.87 | 56.06 | 55.68 | 57.66 | 23.51 | 56.07 | 55.39 |
| LSTM+PS | 58.89 | 23.50 | 57.16 | 55.27 | 58.11 | 24.71 | 57.29 | 56.58 |
| LSTM+GCN | 55.70 | 23.49 | 54.02 | 53.88 | 55.48 | 21.43 | 54.19 | 53.44 |
| RSR | 57.14 | 22.46 | 56.72 | 56.03 | 56.98 | 23.33 | 55.17 | 54.62 |
| AD-GAT | 59.30 | 24.61 | 57.49 | 58.34 | 60.07 | 25.25 | 56.61 | 58.46 |
| TRAN | 59.67 | 25.71 | 57.49 | 58.94 | 61.48 | 26.79 | **60.51** | 60.09 |
| RA-AGAT | 57.26 | 21.28 | 56.49 | 56.56 | 58.41 | 22.38 | 57.18 | 56.69 |
| MAC | 60.01 | **27.82** | 57.43 | 59.24 | 61.55 | 24.32 | 58.93 | 59.45 |
| TRPCA | 58.11 | 24.74 | 55.02 | 57.59 | 59.22 | 23.63 | 57.29 | 57.33 |
| **DGATS** | **60.49** | 25.58 | **58.19** | **60.11** | **62.19** | **27.85** | 59.73 | **61.55** |

We examine each model in experiments and report the optimal performance.

- **RSR** [10]: This article tailors a deep learning model for stock rankings with historical transaction data as sequence embedding, and proposes an innovative temporal graph convolution component to capture time-aware stock relations.
- **AD-GAT** [4]: The framework is proposed to model momentum spillover effects, which dynamically captures the company associations used to spread momentum spillover effects from recent text data and market transaction signals by combining tensors, time series models, and attention mechanisms.
- **TRAN** [48]: It also uses text data and transaction data as source information to construct a time-aware model, aiming at updating the stocks relationship strength through the interaction between information. The features of the nodes and the neighboring nodes are aggregated by means of a graph convolution operation.
- **RA-AGAT** [12]: Sticking to the idea of automatically recommending systems, it proposes an attributed GAT model based on association information, whose encoded time series features are derived from the module, and using stacked GNNs models to obtain global information.
- **MAC** [28]: This method combines the numerical features of stocks and market-driven news sentiment, as well as the news sentiment of related stocks. In addition, a GCN is introduced to capture the news effect of related companies on target stocks, and the stock movement on the trading day is predicted based on the above multi-source features.
- **TRPCA** [42]: This study proposes a tensor representation and fusion method using text and transaction data as source information, taking into account the invariant correlation between stocks in a short time to obtain the intrinsic interaction of multimodal and multi-temporal stock market information.

Table 1 summarizes the performance of prominent models and DGATS on stock movement prediction concerning ACC, MCC, AUC, and F1 from which we have the following observations: first, compared with AD-GAT, TRAN, and MAC, which perform best in all baseline models, our proposed DGATS achieves better results. In fact, they are similar in structure and information sources, using text, transaction data, and market relations as prediction information sources, and fully considering the dynamic changes of the stock market. The MCC value of MAC is even higher than that of DGATS, which shows the advantages of the MAC model in the two classification problems of stock movement prediction. The main difference between MAC and DGATS is that DGATS uses tensor fusion operation and fusion of emotional information in advance, which also indirectly proves the superiority of our proposed model in structure and source information. In addition, compared with AD-GAT, our experimental results are increased by $1\% - 5\%$ on the whole, mainly due to the fact that we adopt the popular tensor fusion in multimodal fusion and the processing method suitable for temporal feature fusion, which makes the source information fully fused and maintained independence at the initial input stage, the above operations play a vital role in the overall prediction. Second, StockNet, LSTM + PS and TRPCA models belong to the traditional stock market forecasting model, they use the conventional neural network to process text and transaction data while ignoring the dependence on the stock market. Among them, StockNet used text and transaction data as information sources and used concatenation to fuse information, which makes different types of information have been processed in an independent state, thus ignoring the interaction between the market. LSTM + PS also made use of the technical indicators converted from text and transaction data as the information source, but on this basis, it extracted the emotional information of investors, which makes the original source information more comprehensive. For TRPCA, it adopted the method of tensor fusion to realize the fusion of multi-modal information, which provides ideas for the fusion of heterogeneous information in other fields, but its effect is general, which may be due to the loss of some information in the fusion process. Although the prediction effects of these two traditional prediction methods are not satisfactory, they lay a solid foundation for the later exploration of the stock market relationship. Third, LSTM + GCN and RSR belong to the field of stock forecasting earlier using knowledge graph, they are based on real market transaction data as an information source, with LSTM and GNNs as the main architecture. It can be seen that LSTM, as a model for processing time series, is often used in financial market analysis tasks, which is also one of the factors that this article uses LSTM to process fusion data. However, LSTM + GCN can only deal with static stock network market relations, which cannot adapt to the dynamic changes of financial markets, so its experimental effect is slightly lower than RSR. Although RSR uses only real stock prices as a source of information, it treats the original transaction data as sequential data, keeping the temporal of stock data and digging out more valuable information from continuous data. The main reason why the experimental results of the two models are lower than those of DGATS is that the source information is single, so it cannot provide sufficient auxiliary information for the prediction task, which makes the model lack basic supply data. Therefore, sufficient source information plays a full role in the overall prediction results. Finally, RA-AGAT is the latest research method of stock market forecasting this year. It adopts an innovative research idea with GNNs as the main body, so as to obtain more accurate dynamic market relations and the relationship strength between stock companies. On the basis of acquiring dynamic market relationship and relationship strength, DGATS uses multiple market information as prediction information sources, which improves the overall experimental results by $4\% - 6\%$ compared with RA-AGAT.

On the whole, the DGATS has greatly improved the experimental results compared with the current baseline model, which not only benefits from abundant information sources but also depends on the complete framework adapted to the processing of financial data. Thus, the source information plays their respective roles and assists each other, modeling a more realistic simulation of the dynamic changes of the stock market and achieving satisfactory experimental results.

*5.4.2 Ablation Studies.* Next, we conducted further ablation experiments to demonstrate the role of different components and information sources and how they affect the performance of the proposed DGATS from different perspectives.

— ***w/o* text**: It denotes that we don't introduce text into DGATS.
— ***w/o* sentiment**: It denotes that we don't introduce sentiment into technical indicators.
— ***w/o* technical indicators**: It denotes that we don't introduce transaction data into DGATS.
— ***w/o* graph embedding**: It denotes that we don't introduce a predefined stock relation graph into DGATS.

Table 2. Ablation Studies

| Models | NASDAQ | | | | NYSE | | | |
|---|---|---|---|---|---|---|---|---|
| | ACC | MCC | AUC | F1 | ACC | MCC | AUC | F1 |
| *w/o* text | 56.49 | 21.35 | 55.79 | 55.20 | 56.72 | 20.38 | 55.91 | 55.88 |
| *w/o* technical indicators | 57.15 | 22.49 | 56.81 | 57.04 | 57.89 | 23.24 | 56.09 | 56.11 |
| *w/o* sentiment | 58.76 | 23.97 | 58.11 | 57.33 | 60.27 | 22.18 | 59.54 | 59.13 |
| *w/o* graph embedding | 54.87 | 21.42 | 54.35 | 54.01 | 55.43 | 21.08 | 54.39 | 54.11 |
| *w/o* attribute aggregator | 59.44 | 22.13 | 56.84 | 57.66 | 60.07 | 23.82 | 58.56 | 59.26 |
| DGATS (C) | 58.90 | 23.51 | 57.38 | 57.22 | 59.81 | 24.80 | 56.99 | 57.32 |
| **DGATS** | **60.49** | **25.58** | **58.19** | **60.11** | **62.19** | **27.85** | **59.73** | **61.55** |

We test each ablation model in the experiment to verify their effect.

— ***w/o* attribute aggregator**: It denotes that we don't introduce an attribute aggregator into DGATS.
— **DGATS (C)**: It denotes that we replace the Kronecker product-based tensor fusion with concatenation.

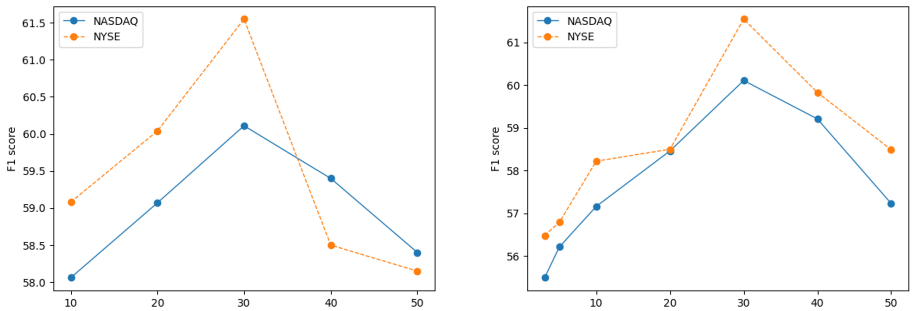
**Effect of text.** To test the effect of textual media, we remove the text from multi-source information and leave only technical indicators and stock relationship graph as the prediction information source. The experimental results show that the performance degradation of DGATS on three metrics is direct when text data is removed, but the performance degradation on MCC is not significant. This confirms that text information contains a lot of valuable information and can provide great help for stock prediction, which is of great significance for detecting stock market movements. As we know, the text contains a lot of valuable information, which can more directly reflect the attitude of investors and experts towards the development trend of financial markets.

**Effect of technical indicators.** We further verify the role of technical indicators in the overall framework. As shown in Table 2, the experimental results after removing technical indicators are significantly reduced. In the framework proposed in this article, we can find that the experimental results of removing technical indicators are slightly higher than those of removing text models. Therefore, the text plays a greater role than the technical indicators, which may be because it is difficult for us to extract real valuable information from numerical data, which is completely different from the text directly expressing emotional information.

**Effect of sentiment.** Sentiment information represents the subjective attitude of investors and can more directly reflect the development trend of the current market. Therefore, we remove emotional information to study its role. The experimental results show that the role of emotional factors is lower than the text and other technical indicators, which can better predict the stock market. It also indirectly proves the application of behavioral finance theory in the field of artificial intelligence, assisting deep learning models to achieve accurate prediction.

**Effect of stock relation graph.** In the proposed DGATS, stock relation graph is constructed with a large amount of real information and is used to describe the relationship between multiple stocks. Fusion stock market relationship data is more beneficial for NYSE stock forecasting than NASDAQ because it reflects long-term correlations between stocks, which are considered a more volatile market and dominated by short-term factors. In addition, the overall performance of the experimental results on both datasets without considering market relations is poor, which also verifies the importance of the relationship graph in stock prediction. As we all know, the stock market is dependent, which makes stock relational embeddings gather more factors and become an important information source for financial market prediction.

**Effect of attribute aggregator.** To validate the importance of the attribute aggregator module, we remove the component to observe its experimental results. Attribute analysis is very important




(a) Embedding dimension (b) Time window

Fig. 8. Influence of hyper-parameter settings.

for stock relation graph, which plays a decisive role in the change of node and node relation strength in the graph network. From the results, we can see that the attributes-driven model has an impact on the dynamic relationship graph, which confirms the significance of the research based on node attributes proposed in this article. This phenomenon also confirms that the simple attention mechanism to judge the market signal is insufficient.

**Effect of tensor fusion.** The tensor fusion module based on the Kronecker product aims at promoting LSTM-Att to generate deep features for representing the state of stocks and mining their internal relationships. Unlike previous methods that simply ignore or think that the market signal interaction of all stocks is the same, the tensor fusion module learns the interaction of market signals within the stock directly from the fluctuation of the input trading data. To judge whether different types of market information sources achieve deep integration, we use traditional concatenation operation to fuse the text and technical indicators, which does not take into account their interactions. Experimental results show that the results are not good after changing the fusion method, which shows the importance of feature interaction for financial market prediction.

Based on the above experimental results and analysis, we infer that source information and modules play different key roles in the overall framework. Comparing the four source information, we find that the graph relationship plays a more important role than the text and technical indicators through the evaluation index, followed by the role of the text, which further confirms the dependence of the stock market. Besides, the replacement of the fusion method illustrates the advantages of tensor fusion.

## 5.5 Sensitivity Analysis

We analyze the sensitivity of our model within reasonable parameters, including the dimension of the sequential embedding and the size of the time window, Figure 8 shows the results on the two datasets with different parameter settings. Obviously, when the parameter values are different, the prediction performance of the model is different, and as the parameter value increases, the experimental results show a downward trend after rising to the optimal value. Next, we analyze the effect of two key parameters in detail.

As we all know, embedding is an important means of complex network analysis, and the choice of embedding dimension has a crucial impact on the overall algorithm. Embedding algorithms based on neural networks use real-valued vectors to represent nodes, and generally use the embedding dimension of the network as a hyperparameter, or select the optimal dimension based on the real effect of downstream specific machine learning tasks. Few studies have explored the impact of deep learning structures on the embedding dimension, and networks vary in size and structure, making it difficult to find a common empirical value. The choice of dimensions varies with the network structure and learning task, and embedding dimensions that are too small or too large can lead to dimensional underfitting or overfitting. From Figure 8(a), the performance first increases as the dimension increases, because the attributes of the stock can be more fully processed, and then begins to decline when the dimension is greater than 30 probably due to overfitting. In stock prediction tasks, the size of the embedding dimension is often set to 30, which is quite different from traditional deep learning tasks, where they are usually set between 100 and 300. Based on previous research experience and the specific task of this article, we collected F1 scores under different dimensions within 10 to 60, and thus determined the optimal parameter value. Overall, the effect of the parameter on the experimental results is in line with our expectations, so the dimension of sequence embedding is set to 30, expecting satisfactory profits.

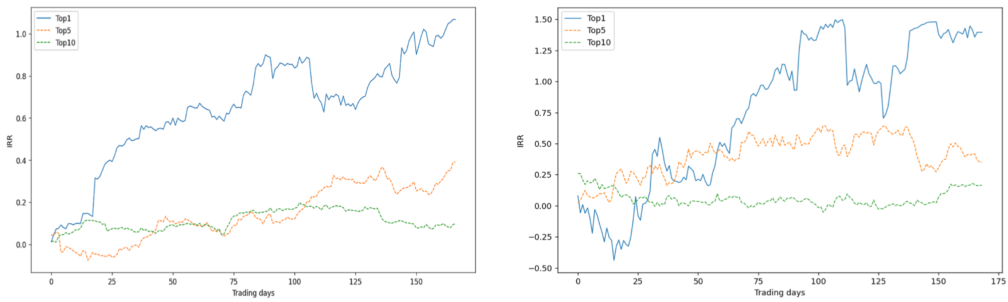
To explore how our model performs under different time window $T$, we set $T$ is 3, 5, 10, 20, 30, 40, 50, respectively. Some studies have shown that the time window is a key parameter in time series analysis tasks, and its size directly determines the information sources used in our analysis tasks. Figure 8(b) shows the comparison of the F1 score for the input period $T$ determined by different time window. The overall change trend of F1 is similar to the results in Figure 8(a), showing a pattern of first rising and then falling, and reaching the highest value when the time window is 30. It can be seen that the size of the time window will significantly affect the performance of DGATS on two datasets, which makes the time window long or short not suitable for the framework of this article. The above results are mainly caused by the characteristics of the stock market itself, when the time window is less than 30, the model obtains more sufficient source information as much as possible, thus providing enough data for prediction. However, when the time window continues to increase, we may obtain some outdated redundant information, which will affect the analysis effect and mislead the prediction results. Therefore, after quantitative analysis of the experimental results, we set the time window to 30 to ensure that DGATS achieves the best performance on the datasets.

### 5.6 Study on Different Market Simulation Strategies

*5.6.1 Market Recommendation Simulation.* In the real transaction process, investors always choose different stocks to avoid risks to the greatest extent and hope to get more returns based on a favorable investment strategy. Accordingly, we conduct a trading simulation to verify the practical value of the proposed DGATS model. To verify the performance of DGATS, we modified the prediction task into a regression task, that is, using a fully connected layer to replace the softmax function, we rank stocks according to the scores to obtain a ranking list for all stocks [14]. The **Investment Return Ratio** (**IRR**) denotes the score and as our main metric, the calculation method of the one-day return ratio is shown in Equation (2), and the IRR of multiple test days is shown below.

$$IRR = \sum_{t=1}^{T} R^t, \tag{24}$$

where $R^t$ is the actual return ratio of the highest predicted stock on the $t$th testing day. Based on the above theoretical analysis, we examine the performance of our method under Top1, Top5, and Top10 three different test strategies, respectively, to buy the Top 1, 5, and 10 stocks with the highest expected return. For example, using the Top5 strategy, we trade the top five stocks on each test day with an average budget. Accordingly, we calculate IRR by summing the average returns of the 5 stocks selected on each test day. The IRR results predicted by DGATS on these strategies are shown in Figure 9. As we expected, the top-ranked stock should earn higher returns.




(a) NASDAQ (b) NYSE

Fig. 9. Comparison of market simulation strategies (Top1, Top 5, and Top10) about IRR based on the prediction of DGATS.

Table 3. Performance of DGATS and Ideal Investment Strategies in Two Datasets

| Method | NASDAQ | | | NYSE | | |
|---|---|---|---|---|---|---|
| | Top1 | Top5 | Top10 | Top1 | Top5 | Top10 |
| **Market** | 3.51 | 2.40 | 1.53 | 2.51 | 1.85 | 1.62 |
| **Selected** | 1.55 | 0.92 | 0.31 | 2.34 | 1.67 | 1.54 |
| **DGATS** | 1.12 | 0.45 | 0.20 | 1.29 | 0.22 | 0.34 |

From Figure 9(a) and (b), the return ratio of the Top1 simulation strategy is higher than Top5, and Top5 is higher than Top10, which reflects the stability of our model on two different datasets. This may be due to the ability of ranking algorithms to accurately rank stocks relative to future returns, which is of great reference for investors and investment institutions. If the prediction is accurate, stocks with higher expected profits will result in higher cumulative returns. In addition, we can find that the volatility of DGATS on the NYSE dataset is significantly stronger than that of NASDAQ, although their changing trends are roughly the same, which means that investors may face greater risk. The reason for this phenomenon may be caused by the volatility of the real market, and its changes will fundamentally affect the forecast of the return value. As mentioned before, the NYSE is significantly more volatile than the NASDAQ.

In addition, in order to further judge the actual role of DGATS, we compared two ideal investment strategies, one is to select the stocks with the highest yield during the test period from the real market; the other is among the trading stocks used in this article, the stocks with the highest profit during the test period are selected. Table 3 shows the performance of the compared investment strategies, we can observe that in the real trading market, the returns of NASDAQ and NYSE are different, but our model achieves similar returns, indicating that the performance of DGATS tends to be stable and achieves satisfactory recommendation performance. Nowadays, more and more researchers treat the stock prediction task as a stock recommendation task, dedicated to more investment advice for investors, in which the return ratio has become a key evaluation indicator. Therefore, we can speculate on the profits of the model proposed in this article, which can both avoid risks and provide stock buying recommendations. Moreover, our method adopts the Top1 strategy, specifically buying the top 1 stocks on each trading day, and achieving an IRR comparable to the investment strategy selected under Top10, which further proves the competitiveness of our proposed method. Through our investigation, the three strategies of DGATS achieve IRR values that outperform the experimental results of other excellent methods in the field of stock

Table 4. Profits Comparison between DGATS and TRAN

| Stock | DGATS | TRAN | Stock | DGATS | TRAN |
|---|---|---|---|---|---|
| AAPL | $1, 208 | $1, 184 | BAC | $947 | $903 |
| ABBV | $875 | $867 | CELG | $1, 484 | $1, 390 |
| CVX | $986 | $962 | DIS | $875 | $739 |
| INTC | $1, 796 | $1, 458 | GOOG | $927 | $868 |
| ORCL | $943 | $868 | PFE | $1, 094 | $993 |
| WMT | $1, 438 | $1, 322 | XOM | $1, 138 | $1, 029 |

recommendation. In total, our model is still far from the real return, which provides a research direction for us to further improve the method.

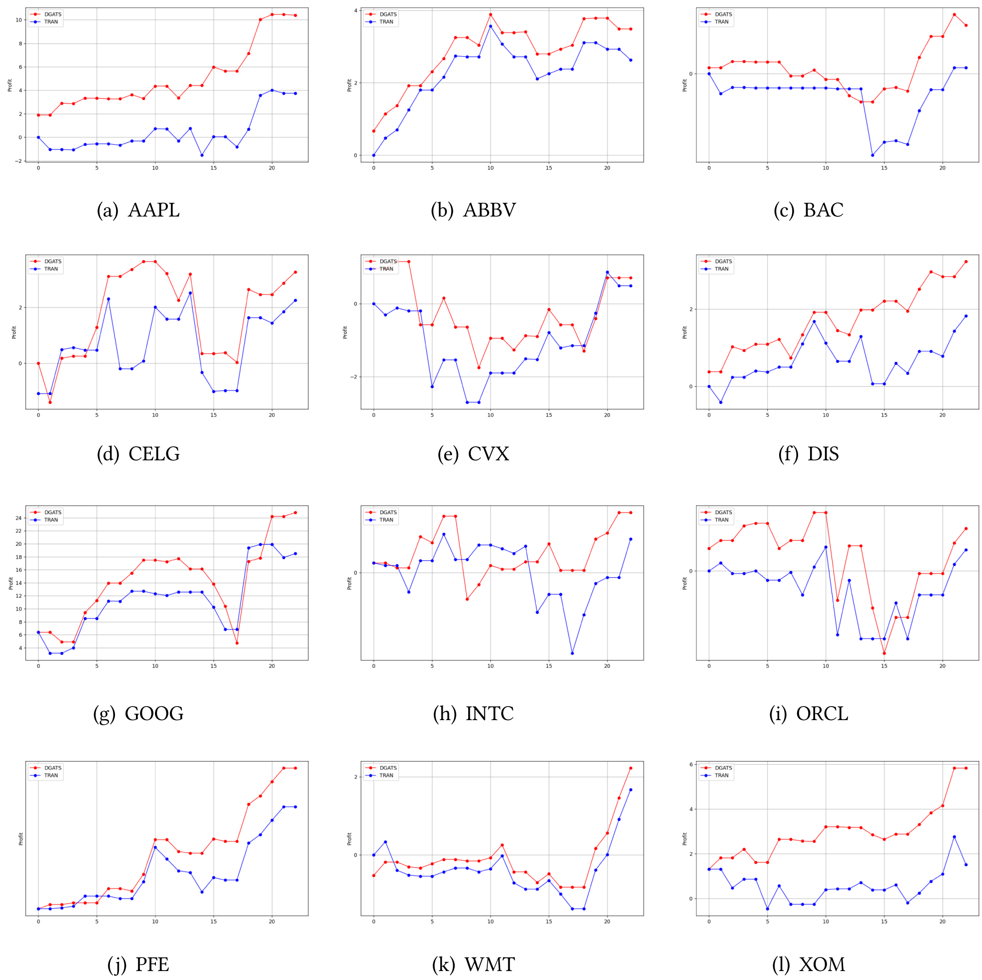
*5.6.2 Market Trading Simulation.* For investment institutions and individual investors, investment profit is the most concerning issue. Therefore, we use a stock trading simulation strategy to further demonstrate the practical value of DGATS, which simulates the behavior of everyday traders using our model in a near-realistic manner. DGATS is compared with the best-performing TRAN to illustrate the potential value of our approach. The specific simulation strategy is as follows: If the model predicts that a stock will rise the next day, traders will invest $ 10,000 in the stock. After buying, the length of time traders holds stocks is determined by the actual market changes. If the stock earns 2% or more over the next period of time, the traders sell it immediately; otherwise, traders sell their stocks at the closing price before the end of the day's trading. In addition, if the prediction results show that the price of a single stock will fall, the same strategy can be used to short the stock. If the current trader can buy the stock at a short selling price below 1%, the trader will cover the position; otherwise, traders buy corresponding stocks at the closing price.

Table 4 shows the overall profits on 12 stocks achieved by DGATS and TRAN over the selected 30 calendar days. We can see that the DGATS can obtain higher profits than TRAN and is practical. As we know, real profit is one of the key criteria to measure whether a model has application value. In the above experiments, we have analyzed the main reasons why TRAN is slightly lower than DGATS on four evaluation metrics, and they are also applicable to the profit gap caused when simulating real trading. To be honest, the main reason for the gap between the two models is their applicability in real financial markets. In addition, by comparing the real profits of the stock market during the same period, we found that both models outperformed the profits without the addition of analytical methods.

To investigate how much the profits of DGATS and TRAN can increase, Figure 10 shows the comparison of daily profits for 12 stocks. The daily profit of DGATS is generally higher than that of TRAN, which indicates that our proposed method largely avoids market risk and improves returns. Therefore, the obtained profit advantage matches the overall quantitative analysis results, and our framework achieves higher returns than TRAN, suggesting that there is great utility in trading strategies. Overall, the method proposed in this article is of great value in predicting stock movements and helping investors make the right decisions to improve profitability.

## 6 CONCLUSION

We study a popular research topic in the current financial market, that is, how to construct stock market relationships with time-aware dynamic attributes aggregation under the guidance of behavioral finance and co-movement effect, so that the prediction model can deeply integrate multi-source information to simulate the real stock market. To solve these problems, we proposed dynamic attributes aggregated GAT model to perform stock movement prediction using text,




(a) AAPL (b) ABBV (c) BAC

(d) CELG (e) CVX (f) DIS

(g) GOOG (h) INTC (i) ORCL

(j) PFE (k) WMT (l) XOM

Fig. 10. Comparison of daily profit changes of DGATS and TRAN models.

technical indicators, and stock relationships. The proposed method is inspired by the stock market dependencies and considers the impact of behavioral finance and the co-movement effect on financial markets. The overall framework involves not only pre-fusion of text and technical indicators, but also a time-series attention mechanism to analyze fused features for the accurate prediction, and to dynamically update stock market relationships and relationship strengths using GNNs.

In this study, a large number of experiments were conducted for quantitative and visual analysis to verify the effectiveness of DGATS and the role of multi-source information. First, we compared the prediction performance with a variety of baseline models to verify the overall performance of the model. Second, six different variants of the DGATS model were constructed and tested to analyze the impact of different components and parameters. In addition, to illustrate the parameters in the method used in this article, we conducted a sensitivity analysis to illustrate the effect of the parameters changes on the experimental results. Finally, different trading simulation strategies were performed as a profitability test. The results show that the proposed model achieves satisfactory performance on the stock movement prediction task. Compared to those state-of-the-art methods with the same research objective, DGATS has a better modeling effect on multi-source information guided by behavioral finance. According to the quantitative analysis results from the above experiments, the dynamic stock market relationships play a key role in the overall framework and are essential to improving experimental accuracy. Therefore, advanced GNNs technology must be used to process complex stock market relations.

The method proposed in this article has great practical significance. It can predict the fluctuation of stocks in advance for investors to avoid risks, which is of great value to the whole financial market. Obviously, the framework of this article provides ideas for classification problems in text, image, and other fields. However, although our model constructed a graph to reveal the interaction between stocks, it did not successfully capture the interaction between stocks. Therefore, in the future, we will try to add the multi-agent-based reasoning function to the graph structure to further improve the prediction performance.

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Received 8 September 2022; revised 1 June 2023; accepted 23 July 2023