Stock Trend Prediction: an Effective Hybrid Deep Model Based on Lead and Lag Correlation Graphs

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***Abstract*—The recognition of the importance of incorporating relevant stock data in the prediction of stock trends has been acknowledged. Nevertheless, the challenge of effectively modeling the relation between stocks and utilizing this relation to enhance the quality of forecasts remains a significant hurdle. Considering this context, we propose a deep-learning architecture designed to predict stock trends. The proposed framework involves the construction and utilization of a lead graph and lag graph. First, the lead graph and lag graph are constructed using the Dynamic Time Warping (DTW) method in order to reflect the interrelation between stocks. Then, we apply the Graph Convolutional Network (GCN) to extract characteristics from the prices of each stock and the lead or lag stocks. Ultimately, the stock features obtained by GCN are utilized as input for the Gated Recurrent Unit (GRU) network in order to predict the future movement of the stock. We conducted experiments with real stock data, and the findings demonstrate that the method proposed in this article outperforms approaches that do not account for lead and lag stocks or only consider similar stocks. These results provide empirical evidence supporting the effectiveness of incorporating lead graphs and lag graphs in the stock prediction process.**

Keywords—lead and lag correlation graphs, GCN, GRU network, financial time series

I. INTRODUCTION

Accurately forecasting the trend of the stock market is a formidable task, however, it holds considerable importance in reducing investment risks and enhancing asset and portfolio returns. In recent times, there has been a significant focus on the development of models that effectively capture the relations between various types of data and the fluctuations in stock prices based on the application of machine learning techniques[1], [2] or deep learning approaches[3], [4]. However, it is worth noting that a significant portion of academic research tends to view stocks as independent entities, often overlooking the complex interdependencies that impact the stock prices of different companies. Multiple studies[5], [6],both statistical and empirical, have shown strong evidence supporting the existence of interdependencies among different enterprises within distinct relational contexts. Hence, the incorporation of stock dynamic relations into deep learning models for predictive purposes is a significant and unresolved issue. Nevertheless, there exist two significant challenges associated with the utilization of these cross effects: (1) the construction of a suitable representation for stock relations and (2) the extraction of the cross effects across stocks.

For the first challenge, a predominant approach in study is the utilization of the Pearson correlation coefficient to establish a graphical representation based on the synchrony of stock prices[7]. Nevertheless, this methodology is subject to many constraints. Firstly, it is important to note that the Pearson correlation coefficient only quantifies the degree of relation between stocks, without demonstrating any causal relation. Determining the causal relation between two stocks remains a problem, even in cases where a robust correlation is observed. Additionally, it is important to note that this technique fails to consider the widely recognized lead-lag relation observed in several empirical studies. Therefore, Dynamic Time Warping (DTW) is utilized in this paper to capture the lead-lag relation between stocks and construct lead correlation graphs and lag correlation graphs as a means of addressing the restriction of the Pearson correlation coefficient.

In order to overcome the second challenge in an efficient manner, we employ the Graph Convolutional Network (GCN) as a means to extract cross-correlations among stocks. When comparing the approach of directly combining the features of related stocks to that of GCN, it becomes evident that GCN offers more pronounced advantages in extracting cross effects across stocks. Additionally, we utilize separated lead graphs and lag graphs instead of a singular lead-lag graph in order to mitigate the coupling between the lead relation and the lag relation, as well as to simplify the graphical representation. By employing this approach, the model is able to adjust to various stock market scenarios, thereby assigning distinct weights to both lead and lag relations and enhancing the accuracy of predictions.

Based on the preceding discourse, we introduce a unique deep-learning framework referred to as GCGRU-LL. Considering the fact that the prediction of stock trends entails the study of time series data, hence, the Gated Recurrent Unit (GRU) model is employed to effectively capture the temporal dependencies that exist within historical market data[8]. Furthermore, lead correlation graphs and lag correlation graphs are employed to generate characteristics with the cross-effect by GCN to enhance the predictive capabilities of our approach. The performance of the GCGRU-LL model is evaluated using three China stock market index constituents. The experimental results demonstrate that the model outperforms baseline techniques in terms of performance. The contributions can be concisely summarized as follows:

(1) We design lead and lag graphs constructed based on the lead-lag theory and DTW. It represents the cross effects between different stocks. We incorporate the lead-lag relation inside prediction model of stock trends to enhance the accuracy.

(2) We propose the GCGRU-LL a hybrid deep neural network model to improve the stock trend prediction in datasets.

(3) We conduct extensive experiments on three China stock market index constituents to showcase the superior performance of GCGRU-LL in comparison to baseline models.

The subsequent sections of this article are structured in the following manner: Section 2 provides a concise overview of the existing related literature. Section 3 provides a detailed explanation of the GCGRU-LL approach. The experimental findings and analysis are given in Section 4, while the conclusions and future works are provided in Section 5.

II. Related Works

A. Stock price prediction

The prediction of stock prices has garnered significant attention over the course of several decades due to its crucial role in mitigating investment risks and enhancing asset returns and portfolios. In recent times, there have been several proposals for machine learning and deep learning approaches aimed at predicting stock prices. For instance, convolutional neural networks (CNN), bidirectional long-term short-term memory (BiLSTM), and attention mechanism (AM) are used in combination to perform data mining on the input feature matrix and apply the model to the field of stock prediction[9]. Besides, the adversarial training approach is also used in stock price forecasts to improve the overall predictive capabilities of models[10].

However, the sole reliance on past price data becomes insufficient in providing a comprehensive understanding of stock price trends. In order to reveal underlying patterns in stock prices, it is imperative to incorporate additional sources of information. For example, news headlines are integrated as features in the prediction of stock prices by the encoding capability of LSTM to supply more information[11]. Furthermore, stock price charts can be regarded as images and inputted into Deep Learning Neural Networks (DLNN) for analyzing pictures, which aims to simulate the function of financial analysts in the prediction of short-term stock prices[12].

Despite extensive attempts to understand the underlying principles that drive movements in stock prices, the majority of the aforementioned studies have failed to consider cross effects across stocks.

B. Relation construction

With gradually realizing the importance of utilizing relevant stock in stock prediction, scholars have commenced a research endeavor to examine cross effects among stocks and their incorporation into the stock trend prediction process. One of the primary obstacles in this domain pertains to the representation of stock-to-stock relations. The existing correlations among stocks can be categorized into two distinct classifications: explicit and implicit. The former refers to relations that are marked by tangible significance, such as the interdependencies among businesses in the supply chain and collaborative or strategic alliances between companies[13], [14]. However, these kinds of relations have limited effect on the stock trend prediction because of the difficulties associated with obtaining data and the infrequent updates. The latter, which lacks a concrete explanation grounded in real-world contexts, must be artificially extracted from data. A frequently employed methodology involves the computation of the similarity between series of stock prices. Based on this, stocks exhibiting correlation coefficients beyond a specific threshold or ranking within the top k are chosen to establish the relations, resembling the process of clustering[15], [16].

C. Lead-lag relation with DTW

The lead-lag effects in the stock market are a helpful concept for market analysis. [17]. This represents that the price movement of one asset and the subsequent movement of another asset are correlated. Investors can be able to anticipate future stock trends with the use of the lead-lag relation across stocks. In this paper, we utilize DTW to extract lead-lag relation values between stocks[18]. DTW, known as an effective time series similarity measurement, has been widely utilized in the field of time series data mining [19],[20]. Through computing lead-lag relations by DTW, we can capture the causal relation across stocks, which is an abstract explanation for the lead-lag relations across stocks. This is not something that can be accomplished with the Pearson correlation.

III. Methodology

A. Graph Construction

To gain a comprehensive understanding of the complex cross-effects across stocks, we rely on the lead-lag theory to extract the lead-lag relation. Besides, to demonstrate the efficacy of the lead-lag relation, we employ the Pearson correlation coefficient based on stock price synchrony as a comparison. Following this, we generate four distinct graphical representations as follows:

(1) Lead-lag Graph $\mathbf{G}_{\mathbf{LL}} = (\mathbf{V}; \mathbf{E}_{\mathbf{LL}}; \mathbf{A}_{\mathbf{LL}})$ containing lead relation and lag relation, (2) Lead Graph $\mathbf{G}_{\mathbf{Lead}} = (\mathbf{V}; \mathbf{E}_{\mathbf{Lead}}; \mathbf{A}_{\mathbf{Lead}})$ only containing lead relation, (3) Lag Graph $\mathbf{G}_{\mathbf{Lag}} = (\mathbf{V}; \mathbf{E}_{\mathbf{Lag}}; \mathbf{A}_{\mathbf{Lag}})$ only containing lag relation, (4) Similar Graph $\mathbf{G}_{\mathbf{p}} = (\mathbf{V}; \mathbf{E}_{\mathbf{p}}; \mathbf{A}_{\mathbf{p}})$ containing Pearson correlation relation, where $|V| = N$ refers N companies in the graph, $\mathbf{A} = (a_{ij})_{N*N}$ is the adjacency matrix which represents the specific stocks network. Different graphs

are used as model input to compare the effectiveness of different relationship graphs.

(1)Lead-lag relation: In this paper, we use DTW to compute the lead-lag relation among stocks. The specific calculation method is as follows: Given two stock price sequences $\mathbf{X}=\{\mathbf{x}_1,\mathbf{x}_2,\ldots\mathbf{x}_m\}$, $\mathbf{Y}=\{\mathbf{y}_1,\mathbf{y}_2,\ldots\mathbf{y}_n\}$, where m and n represent the lengths of the two sequences respectively. What's more, $\mathbf{X}$ and $\mathbf{Y}$ have already undergone Z-normalization. $\mathbf{X}$ and $\mathbf{Y}$ form a $m \times n$ matrix D as follows:

$$\mathbf{D}=\begin{bmatrix} \mathbf{d}(\mathbf{x}_m,\mathbf{y}_1) & \mathbf{d}(\mathbf{x}_m,\mathbf{y}_2) & \cdots & \mathbf{d}(\mathbf{x}_m,\mathbf{y}_n) \\ \vdots & \vdots & \iddots & \vdots \\ \mathbf{d}(\mathbf{x}_2,\mathbf{y}_1) & \mathbf{d}(\mathbf{x}_2,\mathbf{y}_2) & \cdots & \mathbf{d}(\mathbf{x}_2,\mathbf{y}_n) \\ \mathbf{d}(\mathbf{x}_1,\mathbf{y}_1) & \mathbf{d}(\mathbf{x}_1,\mathbf{y}_2) & \cdots & \mathbf{d}(\mathbf{x}_1,\mathbf{y}_n) \end{bmatrix} \tag{1}$$

$\mathbf{d}(\mathbf{x}_1,\mathbf{y}_1)$ in the matrix represents the euclidean distance between x_1 and y_1 which is calculated as follows:

$$d(x_1,y_1)=\sqrt{\sum_i (x_{1i}-y_{1i})^2} \tag{2}$$

x_{1i} and y_{1i} represent the value of the i-th dimension of x_1 and y_1. DTW finds an optimal path P from D(1,1) to D(n,m), to minimize the cumulative distance between the two time series. By calculating the area under the optimal path after Min-max normalized, the lead-lag value between stocks can be obtained, which is recorded as $CR\_DTW(\mathbf{X},\mathbf{Y})$. If $CR\_DTW(\mathbf{X},\mathbf{Y}) \geq 0.51$, it means that stock $\mathbf{X}$ leads stock $\mathbf{Y}$. When $0.51 > CR\_DTW(\mathbf{X},\mathbf{Y}) > 0.49$, $\mathbf{X}$ and $\mathbf{Y}$ have no leading lag relation; when $CR\_DTW(\mathbf{X},\mathbf{Y}) \leq 0.49$, stock $\mathbf{X}$ leads Stock $\mathbf{Y}$. In this paper, we use stock price data from the past 30 days to calculate the lead-lag values between two stocks every day, and then use the exponential weighted moving average method (EWMA) to smooth the leading lag value. The processed lead-lag value is used as the lead-lag relation between stocks.

(2)Similar relation: Similar to the calculation of the lead-lag value, Firstly, use the stock price series from the past 30 days to calculate the Pearson correlation coefficient between two stocks every day and then use EWMA to smooth Pearson correlation coefficient.

(3) Graphs constructed by four different methods: For the lead-lag graph, the element in A_{LL} is the monthly lead-lag value between stocks. For the lead graph, the element in $\mathbf{A}_{\mathbf{Lead}}$ is the monthly lead-lag value between stocks if $\text{value} \geq 0.51$, otherwise 0. For the lag graph, the element in $\mathbf{A}_{\mathbf{Lag}}$ is the monthly lead-lag value between stocks if $\text{value} \leq 0.49$, otherwise 0. For the similar graph, the element in A_P is the absolute value of the monthly Pearson correlation coefficient between stocks. All non-zero elements in adjacent matrices are Min-max normalized. An example of the lead graph is shown in Fig. 1.

B. GCN

GCN is an exceptionally effective deep learning technique that processes the complexities of graph data with ease. The efficacy of this method in extracting interdependencies among nodes in a graph has been demonstrated, and it has demonstrated exceptional performance across various applications[21], [22]. The basic principle of GCN is message passing and information aggregation. By encoding both global graph structures and node attributes, node representations get updated by a layer-propagation rule as below:

$$H^{l+1}=\sigma(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H^l W^l) \tag{3}$$

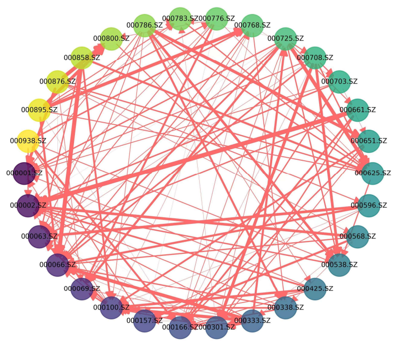

Fig. 1. An example of the lead graph of a group of stocks

in which the adjacency matrix $\tilde{\mathbf{A}}=\mathbf{A}+\mathbf{I}$, the degree matrix $\tilde{\mathbf{D}}=\mathbf{diag}(\sum_j \tilde{\mathbf{A}}_{ij})$, and the $\mathbf{H}^{l+1}$, $\mathbf{H}^l$ are middle layers output. $\sigma(\cdot)$ is the activation function, while $\mathbf{W}^{(l)}$ is the weight of the lth layer. In this study, a two-layer GCN is used and ReLU is utilized as the activation function.

C. GRU

The task of predicting stock trends is commonly categorized as a time-series problem. RNNs have demonstrated notable efficacy in properly addressing time-series challenges through their capacity to effectively capture time dependencies. Within the variations of RNNs, LSTM and GRU have gained significant recognition for effectively tackling the issues associated with gradient disappearing or exploding. In addition, the GRU model has shorter training times in comparison to the LSTM model because of its decreased parameter count. Empirical data has been presented to support the notion that the effectiveness of GRU is equivalent to that of LSTM across a range of applications [8]. Hence, considering this context above, the GRU model has been chosen as the predictive tool for forecasting stock trends in this research. The network design of GRU is seen in Fig. 2.

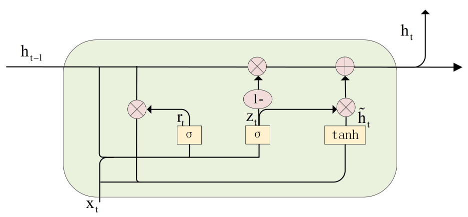

Fig. 2. GRU Network Structure

D. Proposed Model

The schematic representation of our model, GCGRU-LL, is illustrated in Fig. 3. The architectural framework consists of three discrete phases. In the initial stage, the lead-lag relation, which elucidates the cross effects among stocks, is represented through the use of graphs. By representing the cross effects

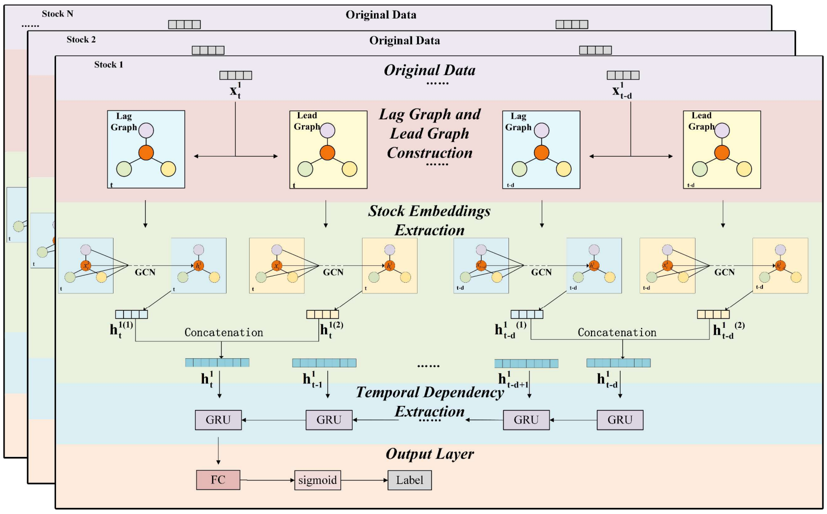

Fig. 3. The main framework of GCGRU-LL

across stocks in this approach, the model can enhance its comprehension of the cross-effects and their influence on stock prices. In this particular phase, the lead graph and the lag graph are employed as substitutes for the lead-lag graph, with the aim of mitigating the potential for causality confounding and reducing the overall complexity of the graphical representation.

The second phase involves utilizing GCN to acquire information about the intricate cross-effects among the stocks. For each graph, we could get features with graph information produced by GCN. Then, we integrate the two kinds of features from the lead graph and the lag graph by concatenation, merging two relations to create a cross-effect embedding for each stock at a specific point in time. Each stock shares the parameters of the GCN.

During the third phase, the GRU model is employed to gather information pertaining to temporal dependence through the analysis of historical data. Through the integration of historical information and cross-effect features, it becomes possible to capture the temporal patterns and cross effects that exert an influence on stock trends. Last, the model incorporates a fully connected layer with a sigmoid activation function, which takes into account the acquired features and relations from the preceding stages and generates an output in the form of a probability. What's more, the loss function of the model is the binary cross-entropy loss function, the formula is as follows:

$$\text{Loss}=-\frac{1}{N}\sum_{i=1}^{N}(y_i\cdot\log(\text{p}(y_i))+(1-y_i)\cdot\log(\text{p}((1-y_i)))) \qquad (4)$$

y_i is a binary label 0 or 1, $p(y_i)$ is the probability that the output belongs to y_i.

IV. Experiments and Results

A. Data Preparation

In order to establish the effectiveness of our model, we obtained daily datasets of the constituent stocks belonging to the CSI (China Securities Index) 100, CSI 300, and CSI 500 from the Wind financial database. The experiment involves selecting the previous volume, turnover, open price, close price, highest price, and lowest price of stocks within the preceding 30-days period to forecast the future stock trend within the subsequent day. The task of prediction is commonly recognized as a binary classification issue, where the dataset's label is specified subsequently:

$$y_t=\begin{cases}1, & p_t > p_{t-1}\\ 0, & p_t \le p_{t-1}\end{cases} \qquad (5)$$

Besides, these input features undergo z-score normalization before inputted into the model. For our analysis, we specifically retrieve the historical data from 2013/06/30 to 2023/6/30. Besides The dataset has been partitioned into three separate segments. The allocation of data is as follows: 70% is designated for training purposes, 10% is reserved for validation, and the remaining 20% is exclusively allotted for testing.

B. Baselines

The baseline models included in this research have been classified into three distinct categories. The initial group solely utilizes historical data of the target stock as input for its trend prediction. This group employs various models, namely (1) Logistic Regression (LR), (2) Autoregressive Integrated Moving Average (ARIMA), (3) Support Vector Machine (SVM), (4) Random Forest (RF), (5) Multilayer Perceptron (MLP), (6) AdaBoost, and (7) GRU.

The Second group simply concatenates features of the target stock and related stocks as input for stock trend prediction, which includes the following models (1) GRU-P : The GRU model with a target stock and two similar stocks, (2) GRU-L : The GRU model with a target stock and two lead stocks. This group takes both historical data and related stocks into account.

The third group takes historical data and stock cross effects into account with GCN. This group includes four models: (1) GCN-P: GCN with a similar Graph, (2) GCGRU-P: GCGRU with a similar Graph constructed by the Pearson correlation coefficient, (3) GCGRU-L: GCGRU with a lead-lag Graph constructed by DTW, (4) GCGRU-LL : GCGRU with a lead

Graph and a lag Graph representing for separating lead-lag relation into lead and lag relation.

C. The Effectiveness of Cross-Effects across Stocks

Table Ⅰ demonstrates that LR exhibits the poorest performance due to linear and stationarity assumptions, which are unsuitable for capturing the non-linear relation of stocks. Furthermore, GRU has exhibited a higher level of accuracy in forecasting compared to the remaining five machine learning models. This can be ascribed to the inherent temporal dependence present in stock prices, as well as the beneficial capabilities of GRU in effectively processing time-series data. Additionally, GCN-P, incorporating the Pearson correlation relation, slightly outperforms GRU in accuracy of prediction, indicating that the cross effect is similarly significant as temporal dependency. Remarkably, the incorporation of both cross effects, as reflected by the Pearson correlation relation, and temporal dependency in our GCGRU-P model leads to a significant enhancement in accuracy, with an approximate gain of 2.5%. Notably, all models that incorporate relational features exhibit superior performance compared to those that do not, illustrating the effectiveness of cross effects. Furthermore, the comparison between the performance of GCGRU-P (GCGRU-L) and GRU-P (GRU-L) demonstrates the significant superiority of GCN in extracting valid information about relevant stocks. This is because GCN can consider both node and edge weight in graphs.

TABLE I. PERFORMANCE COMPARISON OF GCGRU-LL WITH BASELINE METHODS ON THREE DATASETS

group	Model	CSI100		CSI300		CSI500	
		Acc	F1	Acc	F1	Acc	F1
1	LR	50.03	42.76	50.15	43.72	50.23	43.77
	SVM	50.68	45.28	51.09	44.77	51.9	47.49
	RF	50.94	44.14	51.54	46.06	52.01	46.05
	AdaBoost	51.03	44.88	52.41	49.24	51.45	45.44
	MLP	50.07	43.45	51.08	46.41	50.47	45.79
	GRU	**52.21**	**51.55**	**53.02**	**52.59**	**52.56**	**54.42**
2	GRU-P	52.36	52.53	54.14	54.74	53.42	55.66
	GRU-L	**53.13**	**53.31**	**54.89**	**55.3**	**54.41**	**55.75**
3	GCN-P	52.77	51.2	53.53	52.79	53.19	54.38
	GCGRU-P	54.83	53.77	56.58	55.67	56.25	57.01
	GCGRU-L	56.49	55.06	57.76	57.67	57.55	58.79
	GCGRU-LL	**57.74**	**56.34**	**58.87**	**60.02**	**58.57**	**60.65**

D. Relations Comparison

Based on the results presented in Table Ⅰ, it can be observed that the model utilizing the lead-lag relation demonstrates higher levels of Accuracy and F1 score performance compared to the model utilizing the Pearson correlation relation in three distinct datasets. The results indicate that the impact of the lead-lag relation across stock is more prominent in comparison to the influence of the Pearson correlation. There are three causes that can be ascribed to this phenomenon. (1) Causal relation: The DTW algorithm possesses the ability to detect both lead and lag causal relations, in contrast to the Pearson correlation coefficient which mostly emphasizes the degree of correlation. The lead-lag relation in stock analysis offers more relevant and significant information. (2) Non-linear relations: The DTW technique lays greater attention on the structure and alignment of the series, allowing it to capture non-linear relationships. In contrast, the Pearson correlation coefficient primarily emphasizes linear relations and may fail to consider important information when analyzing intricate stock relations. (3) Noise Robustness: The DTW method demonstrates superior resilience to noise compared to the Pearson correlation coefficient. In practical stock market scenarios, stock price data frequently exhibits substantial levels of noise, which might potentially impact the accuracy of Pearson correlation coefficients due to their susceptibility to extreme values and noise.

Furthermore, it can be observed from Table Ⅰ that the performance of the GCGRU-LL with separated lead graphs and lag graphs surpasses that of any model with a single graph. This phenomenon can be attributed to two reasons. On the one hand, the reason is that in graph representation, the weight of edges is usually used to signify the degree of correlation or the strength of influence between different stocks. However, due to the calculation method shown previously, the lead-lag relation graph has a bias towards the lead relation. Specifically, the weight assigned to the lead relation exceeds 0.5, surpassing the weight assigned to the lag relation, which makes the model tend to attach importance to the information of the lead relation and disregard the importance of the lag relation. On the other hand, the fact that this approach reduces the coupling between the lead relation and the lag relation and complexity of graphs, and this approach can adjust the structure and parameters of the lead and lag graphs according to actual needs, to adapt to different stock market situations and forecasts requirements, making the model more flexible and interpretable.

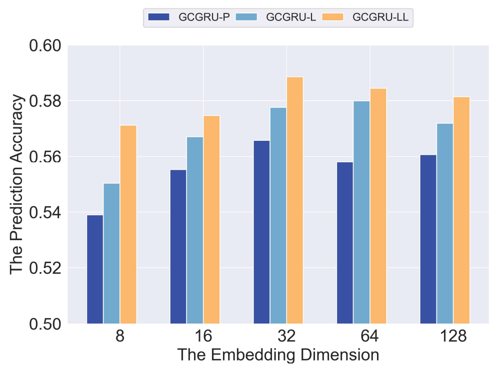

Fig. 4. The results of different embedding dimension on CSI300

E. Robustness Tests

To assess the effects of hyperparameters, we do comprehensive experiments and acquire empirical evidence.

Effect of the embedding dimension The evaluation findings are shown in Fig. 4. For the CSI300 dataset, GCGRU-LL achieves the best performance in dimension 32 which strikes an optimal balance between capturing relevant information and avoiding overfitting. Moreover, regardless of the embedding dimension, the GCGRU-LL model consistently achieves the best results, thereby confirming the validity of the lead-lag relation.

Effect of the length of historical information Evaluation results is shown in Fig. 5. To examine the impact of historical information length, a series of studies were done with different historical windows of 10, 15, 30, 45, and 60 days. The model demonstrates the optimal performance while considering a history window of 30 days. It is evident that the utilization of a historical window that is either too lengthy or excessively brief will result in a reduction in the accuracy of the model. Furthermore, the findings with different historical windows clearly highlight the reliability of the GCGRU-LL model.

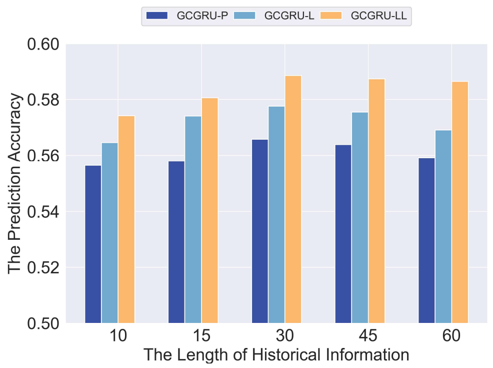

Fig. 5. The results of different lengths of historical information on CSI300

V. CONCLUSIONS AND FUTURE WORK

This research presents an effective methodology for integrating cross-effects among stocks, aiming to significantly enhance the accuracy of stock trend forecasts. The contribution of this research lies in modeling the cross-effects by representing lead-lag relations through graphs. Building upon this, we present a novel framework, namely GCGRU-LL, which presents a comprehensive methodology for efficiently capturing the cross-effects across stocks and temporal patterns in stock prices. This framework enhances the predictive accuracy of stock trend forecasting. The experimental findings conducted in the Chinese market provide evidence supporting the improved performance of our model in comparison to other baseline models.

In future work, we can incorporate additional types of stock relations, such as industry relations and geographical relations, among others, into the existing model. Moreover, this study only utilizes basic stock factors, through incorporating other additional information, such as technical indicators and investor sentiments to further enhance the model's performance.

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