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The Graph Convolutional Networks Framework for Predicting Pandemic Impact on Stock Prices

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Abstract—**Covid-19 has dealt an unprecedented hit to the global economy and all industries, with varying degrees of decline from retail to real estate. This volatility is most evident in stock prices. Previous stock price forecasting methods typically used historical data for each stock as a separate input into the system. This paper proposes an attention-based parallel graph convolutional network framework, which consists of two parallel GCNs. The first GCN takes stock features as input, and the second GCN takes other industry features as input, and sets an attention model to reflect the pairwise interactions between networks. Experimental results on selected stock data show that the model outperforms both the LSTM model and the GCN model in accuracy and F1 score.**

Keywords-GCN; parallel GCNs; stock prices; forecasting methods

I. Introduction

Covid-19 has a globally socioeconomic impact on each economic sector and industry. The toll of the COVID-19 pandemic on the global economy is unprecedented. According to estimates by the International Monetary Fund (IMF), the median global GDP fell by 3.9% during the pandemic [1]. From the stock market, to commodities, healthcare, real estate, retail, education, all industries are suffering from operating difficulties caused by the pandemic, resulting in lower profits or zero; labour costs are getting higher and higher for employers; for those who are employed, income is more difficult to retain than it was before the pandemic. Nicola et al. gave an in-depth summary on the socio-economic effects that Covid-19 cause on each sector and industry, by the categories of primary sectors, secondary sectors, and tertiary sectors [2].

Kuk explored the effects of the first few months of the COVID-19 crisis (March 2020~ June 2020) on the market for rental housing in 49 metropolitan areas in the United States [3]. The authors assembled a data set on rental housing in the 49 metropolitan areas gathered continuously throughout the crisis from Craigslist. The study in the paper [4] explored the impact of 'stay at home' restriction in pandemic on the price of foods in European countries. To find the correlation between the two factors, the author analysed on the European Union's Harmonised Index of Consumer Prices (HICP) and the Stay-at-Home Restriction Index (SHRI) from the Oxford COVID-19 Government Response Tracker (OxCGRT) dataset for January to May 2020. The effects of the COVID-19 pandemic on property development, the construction industry, and Malaysia's national economy were also researched [5]. It mainly employed the systematic review methodology, summarized based on 39 relating studies. Studies found that COVID-19 exacerbated existing issues in property development, the housing market, and the construction industry. While the economy has improved in the year of 2021, it remains below pre-pandemic levels. On the other hand, vaccines and their coverage also greatly affect the ability of economic recovery. Other researchers believe that, depending on the duration of the crisis, Africa's GDP will be permanently 1% to 4% lower than it was before COVID [6].

Traditional stock price forecasting methods usually use the historical data of each stock individually as system input, and this forecasting method ignores the correlation between multiple stock data and the influence of other industries on stock prices. This paper proposes a Graph Convolutional Networks framework for predicting pandemic impact on the stock prices. This structure contains two parallel GCN structure. The first GCN structure sets each stock as a node in the GCN, and the relationship between each other becomes the node's edge; the second GCN network sets other industries as nodes in the GCN, and the relationship with each other becomes the edge of the node. An attention model is set between two parallel GCN structure, and the pairwise interaction relationship between the two networks is explicit to further improve the accuracy of predicting stock trends. The experimental results on market-based stock datasets show that the model outperforms LSTM model and GCN model.

II. Related Work

An important factor to consider when forecasting stock movements is the interconnections between the firms, because stocks of related companies tend to move together. To achieve this, the researchers [7] proposed a novel pipeline involving variational autoencoder (VAE), graph convolutional network, and long-short term memory network (LSTM), which is shown in Fig.1. The input given to VAE is a feature matrix of the firm. VAE reduces the dimension of the input and identifies the latent

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features, therefore producing more meaningful distances between stocks, which are demonstrated as nodes on the graph. The GCN layer uses this graph and processes time-series feature matrix, which then is given to LSTM to make predictions as the final output.

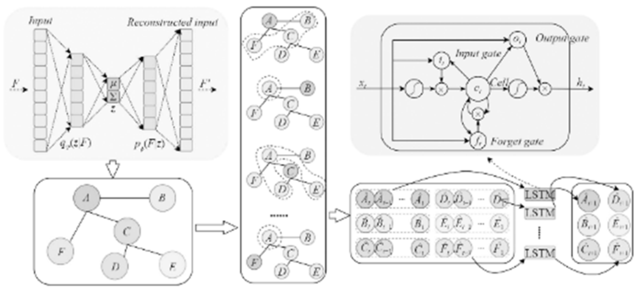

Figure 1. The spatial-temporal model using GCN-LSTM..

Building on Efficient Market Hypothesis, which states that the stock market reflects all the known information, Sawhney et al. proposed a stock movement prediction model that is not only based on financial information but also social media information (SMI) and the interconnections among the firms [8].

Graph neural networks (GNN) have become powerful and practical tools for machine learning tasks in graph domain. The paper [9] had a thorough review over different graph neutral network models following the general pipeline and discussed the variants of each model. Research on theoretical and empirical analyses of GNN models are also introduced. The authors listed some applications of GNN in structural scenarios and non-structural scenarios. For the structural scenarios, GNN allows researchers to capture the structure of graphs using neural networks for better graph matching; GNNs let us perform GNN-based reasoning about objects, relations, and physics in a simplified but effective way by modeling the objects as nodes and pair-wise interactions as edges; By applying GNNs to molecular graphs, better fingerprints can be obtained. The mechanisms of GNN can be applied into fields of graph mining, physics, chemistry and biology, knowledge graph, generative models, combinatorial optimization, traffic networks and recommendation system. For non-structural scenarios, the authors gave detailed introduction in the image and text field. Finally, four open problems indicating the major challenges and future research directions are suggested, including robustness, interpretability, pre-training and complex structure modeling.

The paper [10] introduced a novel Hierarchical Adaptive Temporal-Relational Network (HATR) to characterize and predict stock evolutions. The authors discussed the two traditional approaches for stock trend prediction (RUNs, CNNs) and suggested possible drawbacks. The HATR model resolved the imperfection of the existing model and further developed a dual attention mechanism with Hawkes process and target-specific query to detect significant temporal points and scales to customize stock representations. A multi-graph interaction module to learn correlations among stocks is developed, using the tensor derived from temporal module as inputs of graph notes. In addition, the authors applied HATR to three real-world datasets to examine and evaluate the HATR module. For each sample, they looked back 60 consecutive days and predicted the price on the next week using HATR. Then, the authors came up with several observation and results: 1) Neural- based methods (e.g., DA-RNN, HMG-TF, TGC) generally outperform traditional machine learning models. 2) HATR model achieves conspicuous improvements in terms of most metrics on all datasets. 3) Exploiting stock interrelations could usually impose positive effect on individual trend predictions. The experiments with the datasets validated the effectiveness of the HATR module. The authors also stated that models fed with the adaptive-learned relationship achieve better performance based on their investigation on the ablation effects on the relational modules.

Acknowledging that professional investors use their knowledge on inter-company relations to better predict stock movement, Matsunaga applied graph neural networks to mimic this effort. They based their research on graph convolutional network, which maps the firms as nodes and relationships as edges connecting the nodes in a diagram [11]. The problem with using GCN directly, however, is that it only applies static adjacency matrix, while the relationships among companies are often dynamic. They incorporated time-sensitivity into their model by adding a weighing factor for how strong the relationship is at each time step. They empirically tested this model using data from 4632 time steps in Nikkei 225 Market, which spreads about 20 years. They implemented a rolling window analysis to split this large dataset into training and testing sets. This long time span is to test if GNN model can be generalized through time. This model turned out to be outperforming both the benchmark Buy-Hold strategy and LSTM. This shows that GNNs are indeed a practical method for stock market predictions.

In the paper [12], the authors comprehensively reviewed the GNN model in recent financial context. The authors categorized the commonly used graphs based on the construction methods and graph type. Based on construction method, financial graphs can be classified as Data-based construction, Knowledge-based construction, and Similarity-based construction. Meanwhile, based on graph type, the five categories are homogeneous graph, directed graph, bipartite graph, multi-relation graph, and dynamic graph. The explanation, examples, and visualization are presented in the paper. A table listing each graph, the category it fits in, and the application is clearly presented in the paper. In addition, the authors summarized the feature processing technique. The commonly used GNN models and the convolution process for the five types of graphs explained separately with details and visualizations. Three applications of GNN models in financial field are listed: 1) stock movement prediction. Predicting multiple stock movements could be formed as a node classification task and graph neural network models could be utilized to make the prediction. The authors listed great literature review over how GNN is applied into different situations when predicting stock prices.2) loan default risk prediction, With a binary outcome, loan default prediction could be seen as a classification problem and is commonly addressed utilizing user-related features with classifiers including neural network. To predict the default probability for guarantee loans, e-commerce loans, and other loans, graph-based models can be applied.3) recommender system of e-commerce. 4) Fraud detection.

Many researches predicted the movement trend of stocks based on news or historic market information. It was proposed in [13] to predict the overnight stock movement based on overnight financial news. They also took into account the connection between companies their stock prices. This paper proposed a Long Short Term Memory Relational Graph Convolution Networks model (LSTM-RGCN), applying graph neural network (GNN) to represent the correlation between stocks. This model first encodes news headline with a text encoder. Then they merge the news vector and the node embedding as the node vector. The node vectors are fed to the LSTM-RGCN to get the final representation of the node. Finally, stock movement can be predicted based on the node representation in the graph. The authors did an experiment with stocks within the TPX500, TPX100 index to verify the effectiveness of the model. Results shown that LSTM-RGCN outperforms all other baseline models. By introducing the information of relevant companies, the model can figure out the trend of the stock from the neighboring nodes. It is also shown that adding the graph structure can improve the accuracy of the model by a big margin. Moreover, LSTM-RGCN can infer the price movement of stocks that are not attached with any news as well as the whole market.

The authors proposed a novel method long short-term memory (LSTM-kNN) for predicting stock prices [14]. Stocks have a close relationship. The change in price of one stock might largely affect another stock, making it important to consider combined stocks price for the prediction model. Thus, the authors calculated the similarity among the nearest neighbors and exploited information from historical prices of stocks to enrich the input data for the model. Four active stocks in the US and three in Vietnam are used to evaluate the LSTM-kNN model. Results suggested that this model outperforms the vanilla LSTM and CNN model in terms of all metrics. LSTM-kNN is proved to be capable of capturing the relationship among stocks to make predictions. Optimizing the number of neighbors is a method to avoid overfitting and extend the ability of the model. Besides, combining deep neural networks is also a potential method that can improve the quality of prediction.

III. The Parallel Graph Convolutional Networks with Attention Model

The Multi-Graph Recurrent Network for Stock Forecasting (MGRN) incorporates textual and relational data for stock market predictions [10]. The first module is a financial text encoder, where the daily financial news is the input. The encoded textual information and relational data together form the input of the second module, which is Multi-Graph Convolutional Network. It is called a "multi-graph" network because this module will generate many embedding for each stock, and they are combined into one embedding by an attention mechanism. Finally, this is passed to the Recurrent Neural Network (RNN), which makes predictions about whether the stock price will increase or decrease.

As some researchers have pointed out, one company's stock price is correlated, although sometimes in an extremely complicated manner, to that of other related companies. This interconnection between the firms and the given company's history financial data should be considered to predict its future stock price [11]. It puts forth a deep learning model called Multi-GCGRU, which essentially contains two modules: one Graph Convolution Network and one Gated Recurrent Unit (GRU). Their model would first encode the predefined stock relationships into multiple graphs. The multi-layer Graph Convolutional Network was defined as the following propagation [12]:

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

Where $\tilde{A}$ is the adjacency matrix, $\tilde{D}$ and W are the weight layer matrix. σ is the activity function.

Here we give a parallel Graph Convolutional Networks with attention model, which is shown in Fig.2. By using two graph convolution layers, a topology graph with relational edges is formed between different stocks and between different industries, and the attention mechanism is used to train the two GCN models jointly. The propagation equation is:

$$H^{(l+1)} = \mathrm{softmax}\left(\mathrm{ReLU}\left(\sum_{k=0}^{\mathbf{K}} A_k \alpha_k\right) H^{(l)} W^{(l)}\right) \tag{3}$$

Where K=2, $\alpha = \mathrm{I} - \mathbf{D}^{-\frac{1}{2}}\mathbf{A}\mathbf{D}^{-\frac{1}{2}}$, A_k is the coefficient of the attention graph module corresponding to the two GCNs.

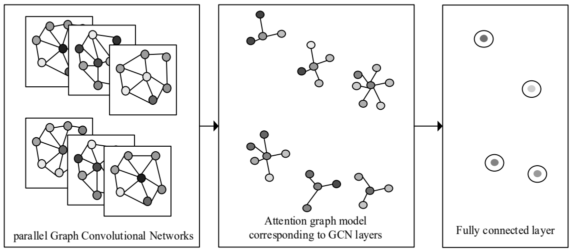

Figure 2. The parallel Graph Convolutional Networks with attention model.

The framework as shown in the Fig.2 includes two parallel Graph Convolutional Networks, in which the nodes of the first group of GCN are stock price features. In this paper, 20 stocks that are related to each other are selected to represent market trends, and the price fluctuation relationship between them is set as the node Pearson correlation coefficient is used to calculate the edge of the second group of GCN. The nodes of the second group of GCN are features of other industries. This paper selects the profitability of 10 different companies in different industries as features. The relationship between these companies becomes the edge of the node, using Pearson correlation coefficient to calculate. After two parallel GCN networks, an attention model is used to change the association of the two sets of GCN to describe the potential pairwise interactions between two networks to further improve the accuracy of predicting stock trends.

IV. Experiments and Results

To demonstrate the effect of the model, we obtained the prices of 20 stocks from 2016 to 2021 from a public dataset, including 10 large companies such as Netflix and Apple and 10 relatively small companies. Stock features include Open/High/Low/Close/Adj-Close, and the relationship between stocks includes total capital, number of employees, industry, etc., and the Pearson correlation coefficient is used to calculate the edge score. In addition, it also includes the characteristics of 10 enterprises in different industries, such as the real estate Zillow's house value index and the sales of Wal-Mart's designated stores, etc. The relationship between enterprises includes whether it is an upstream and downstream relationship and whether it is in the same area, etc. The Pearson correlation coefficient is used to calculate the edge Fraction.

These datasets are first cleaned and invalid data are removed, and then the datasets are randomly divided into training, validation and testing in a ratio of 5:4:1. The stock price predictors we use in this paper are accuracy and F1 score. The F1 score is defined as follows:

$$F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}} \tag{3}$$

We use SGD as an optimizer during training with an initial learning rate of 0.001, momentum=0.9 and weight decay set to 0.001.

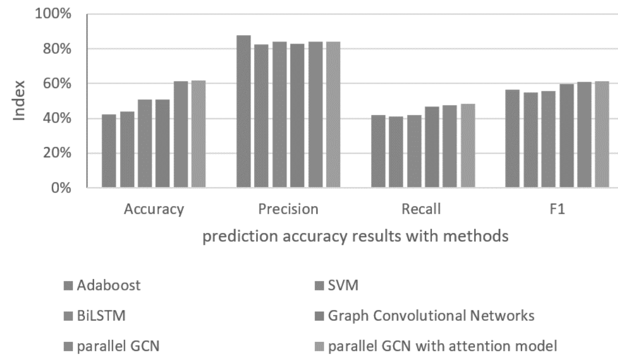

Figure 3. The Accuracy and F1 score results under different str uctures.

Fig.3 shows the Accuracy and F1-score results under Adaboost/SVM/BiLSTM/GCNs/parallel GCN/parallel GCN with attention model. Due to the temporal nonlinearity of stock prices, Adaboost and SVM have lower scores than subsequent neural network methods; while BiLSTM and Graph Convolutional Networks have the ability to build long-distance dependencies and describe irregular data structures, respectively. Advantages; parallel GCN and parallel GCN with attention model perform slightly better than the first two because of the introduction of more relational features and multiple industry features.

V. Conclusion

Stock prices are affected by various unexpected events and fluctuate, especially COVID19 has a huge impact on stock prices. Traditional stock price forecasting algorithms ignore correlations between multiple stock data and do not take into account the impact of other industry trends. This paper proposes a parallel graph convolutional network framework with an attention model to analyze the impact of the pandemic on stock prices. Experimental results compared with baseline systems show that the parallel graph convolutional network with attention model performs better on most metrics. In the next step, we will continue to study how to reduce the computational complexity of this framework.

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