Predicting Price-Limit-Hitting Stocks with Hierarchical Graph Neural Network

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ABSTRACT

In most stock markets, stock prices are not allowed to rise above a daily limit (called price limit). In order to make overnight profits, some investors buy price-limit-hitting stocks with their price limits and sell them in the next trading day. But it is high risk because the price-limit-hitting stocks might close with a lower price than their price limits. Fortunately, we found that the price-limit-hitting stocks will rise in the next trading day with high ratio if they close with their price limits. Therefore, it is of meaningful to predict whether a price-limit-hitting stock will close with its price limit (Type I) or not (Type II). In this paper, we propose a Hierarchical Graph Neural Network (HGNN) for predicting price-limit-hitting stock classification once a stock touches its price limit. In HGNN framework, we construct stock relation graph, and fuse stock information hierarchically from different views including node view, relation view and graph view, which takes historical sequence feature and stock relation into consideration. Extensive experimental results show that our method achieves high classification accuracy, and high return ratio on two real datasets.

CCS CONCEPTS

• **Social and professional topics** → **Economic impact**; • **Information systems** → *Information extraction.*

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KEYWORDS

hierarchical graph neural network, stock prediction, price limit

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1 INTRODUCTION

Stock market plays an important role in the economic development of modern society [23]. Predicting the future trend of stock has always been of great interest to the stock investors [3, 4]. Previous works mainly focus on predicting the exact price [24] or price movement (up or down) [15]. However, these methods could suffer from weak generalization due to the highly stochastic property of stock market [5]. Therefore, some studies have suggested that it is more efficient by utilizing the rules in stock market for stock investment instead of predicting stock price directly [10].

The rule of price limit is widely adopted to restrain the surge and crash of stock price [1]. **Price limit** means that stock price is not allowed to exceed a daily limit [19]. For example, the Chinese stock markets impose a price limit of 10% on regular stocks based on the closing price of previous trading day. If the price of a stock hits its daily price limit, it is called **price-limit-hitting** stock. Moreover, the price-limit-hitting stocks can be divided into two types according to their closing prices. One type (called **Type I** in this paper) is the price-limit-hitting stocks whose closing prices stay at the price limits finally. Correspondingly, the price-limit-hitting stocks belong to the other type (called **Type II** in this paper) if their closing prices are lower than the daily price limits.

It is significant to predict whether a price-limit-hitting stock will close with price limit (Type I) or not (Type II) on a trading day.

According to the delayed price discovery hypothesis [8], stock price will keep rising in the subsequent period (usually the next trading day) after hitting the price limit. We have verified this hypothesis on Chinese stock market data from 01/01/2018 to 12/31/2019, including the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE). We compare the price limits of current trading day to the opening prices of the next trading day. The results show that 68.5% and 68.7% price-limit-hitting stocks of Type I will rise at the opening of the next day. Unfortunately, only about 3% price-limit-hitting stocks of Type II will rise at the opening of the next day.

In this work, we formulate the prediction of price-limit-hitting stock type as a binary classification task. Inspired by the investigation of stock market information at different views can improve the stock prediction performance [14], we propose a Hierarchical Graph Neural Network (HGNN) for the price-limit-hitting stock classification task to automatically learn the information of hierarchical view in stock data. Firstly, we extract *node-view* feature to strengthen the importance of price-limit-hitting stock itself, including the historical feature and limit feature from historical sequential data and limit-related indicators respectively. Secondly, we construct the stock relation graph based on the categories of stock industry, and a Graph Neural Network (GNN) layer is designed to obtain the *relation-view* feature to reflect relational information of neighboring stock nodes by the graph convolution operation. An attention encoder is then employed to aggregate the hidden information of all the nodes at *graph view*, and the *graph-view* feature indicates the movement trend of the whole market. Finally, the type classification layer is utilized to fuse information of different views for predicting the type of price-limit-hitting stock. We empirically show that the experimental results and return ratios of HGNN outperform that of baselines on two real market datasets.

2 RELATED WORKS

In recent years, stock prediction has been an interesting problem in the financial field and there are many methods for stock prediction that have been studied. These methods can be divided into two categories: historical sequence based methods and stock relation based methods.

Historical sequence data have been the most exploited for stock prediction methods. Most historical sequence based methods learn historical patterns to predict stock movements [14, 16, 21]. Recently, machine learning approaches have become the valuable solution with the capability in a highly volatile market. Zhang et al. propose a State Frequency Memory (SFM) recurrent network to make long and short term predictions over time by capturing the multi-frequency trading patterns from past market data [24]. Qin et al. propose an Attentive-LSTM model with an attention mechanism to predict stock price movement [17]. Wang et al. propose a Convolutional LSTM based Variational Sequence-to-Sequence model with Attention (CLVSA) to extract the underlying features of the trend from raw financial sequence data [21]. Liu et al. design a Multi-scale Two-way Deep Neural Network to capture the multi-scale information in stock data [14]. Ding et al. propose a Gaussian Transformer based approach to tackle the stock prediction task [4]. External information is also considered in stock prediction. Sawhney et al. apply an architecture that achieves a potent blend of chaotic temporal signals from financial data and social media [18]. Li et al. propose a tensor-based event-driven LSTM model to focus on media-aware stock movements [11].

The relation between stocks is also important for stock prediction indicated by recent research [3]. In order to capture the relational information of stocks in the graph, Graph Neural Network (GNN) is adopted to obtain better performance by utilizing stock relation. Recently, some works have begun to apply GNN to describe information between related stocks. Chen et al. utilize Graph Convolutional Network (GCN) [9] to aggregate related corporation information of a target company by constructing the graph of investment fact [3]. Feng et al. consider that the stocks in the same sector or industry may affect each other to exhibit similar price trends [6]. Ye et al. model the influence of related stock based on three different graphs including relationships of shareholder, industry, and concept. Then, they take multiple relationships into concern to improve the prediction accuracy [22]. Furthermore, Li et al. propose a more practical objective to predict the overnight stock movement by using GCN based method, which models the connection among stocks with their correlation matrix [11].

Different from those methods, we aim to predict the type of price-limit-hitting stock and propose Hierarchical Graph Neural Network (HGNN) to fuse stock information hierarchically from different levels, which takes the historical feature, limit feature and stock relation into consideration, and achieves better performance in the SSE and SZSE.

3 PROBLEM DEFINITION

In this section, we begin with notations definitions. For day t, a stock set containing S_t stocks is defined as $\mathcal{S} = \{s^1, s^2, \cdots, s^{M_t}\} \cup \{s^{M_t+1}, s^{M_t+2}, \cdots, s^{S_t}\}$. Especially, M_t price-limit-hitting stocks is $\mathcal{M} = \{s^1, s^2, \cdots, s^{M_t}\} \in \mathcal{S}$, and others are non-price-limit-hitting stocks. We get a set of stock historical sequence data for past T time-steps before day t, $\mathcal{X}_t = \{X_t^1, X_t^2, \cdots, X_t^{S_t}\} \in \mathbb{R}^{S_t \times T \times K}$, where K is the dimension of features (e.g., opening price, low price, high price, closing price). For M_t price-limit-hitting stocks, we calculate the limit-related indicators (Moving Average, K Length, Rate of Change, Turnover Ratio, Amplitude, Bias Ratio) [12] $D_t = \{d_t^1, d_t^2, \cdots, d_t^{M_t}\}$ to capture the suddenness of the price limit, through the minutely historical trade data before the price limit occurs. In particular, each stock has its inherent industry categories. For example, 600199.SH (Golden Seed Winery Co.,Ltd.) belongs to the liquor-making industry. Subsequently, we define the stock relation graph and formulate the price-limit-hitting stock classification problem.

Definition 1. **Stock Relation Graph.** *An undirected graph $G_t = \{V_t, E_t, \mathcal{T}\}$, where V_t is a set of S_t nodes representing stocks on day t; E_t is a set of edges, indicating the industry relations between stock nodes; $\mathcal{T}$ is the type of stock node, including price-limit-hitting stock and non-price-limit-hitting stock.*

Problem 1. **Price-Limit-Hitting Stock Classification.** *The price-limit-hitting stock classification is a binary classification task. Given the stock relation graph G_t, stock historical sequences $\mathcal{X}_t$ and limit-related indicators D_t, the task is to learn a function f which is able to get the type label of price-limit-hitting stock $\hat{\mathbf{y}}_\mathbf{t}$ =*

$\{\hat{y}_t^1, \hat{y}_t^2, \cdots, \hat{y}_t^{M_t}\} \in \mathbb{R}^{M_t}$, where $\hat{y}_t^{m_t}$ is the predicted label of Type I (1) or Type II (0).

4 METHODOLOGY

In this section, we introduce the detailed design of the Hierarchical Graph Neural Network (HGNN), which includes *Feature Extraction Layer*, *Hierarchical GNN Layer* and *Hierarchical Fusion Classification Layer*.

4.1 Feature Extraction Layer

This layer aims to extract the historical features and limit features from historical sequences and limit-related indicators, respectively.

Historical Feature Extraction. The LSTM networks have been shown effective in capturing and characterizing the long term dependencies in stock sequence data [21]. Therefore, we utilize the LSTM networks to extract the historical features of stocks over time. For the stock s_t with historical sequence $X_t^{s_t} = \{x_1^{s_t}, x_2^{s_t}, \cdots, x_T^{s_t}\}$, we feed it into the LSTM and obtain the last hidden state $h_t^s \in \mathbb{R}^U$.

Limit Feature Extraction. Limit-related indicators for the price-limit-hitting stocks are combined value vectors by calculating the minutely trade sequential data before the occurrence of the price limit. We apply a Multiple-Layer Perceptron (MLP) to extract limit features from limit-related indicators [7]. Given the limit-related indicators $d_t^{m_t}$ of stock m_t, we obtain the corresponding limit feature $l_t^{m_t} \in \mathbb{R}^U$ from the MLP. The limit feature $l_t^{m_t} \in \mathbb{R}^U$ calculated from high frequency data can capture the suddenness of price limit.

4.2 Hierarchical GNN Layer

This layer aims to learn the **node-view**, **relation-view** and **graph-view** representations of stock node in stock relation graph by interacting the historical feature and limit feature.

Graph Convolution. The stock relation graph has two types of stock nodes, including price-limit-hitting node m_t and non-price-limit-hitting node z_t. For stock node z_t, we utilize the LSTM networks to get its historical feature as node representation $e_t^{z_t} = h_t^{z_t}$. For price-limit-hitting stock node m_t, we interact the historical feature and limit feature to obtain the **node-view** feature:

$$e_t^{m_t} = \psi(W_f^T[h_t^{m_t} \oplus l_t^{m_t}] + b_f), \tag{1}$$

where ψ is an activation function; $\oplus$ represents a concatenate operation; $W_f \in \mathbb{R}^{2U \times U}$ and b_f are the learnable parameters. We obtain all S_t stock node representations $E_t^{S_t} = \{e_t^1, e_t^2, \cdots, e_t^{S_t}\} \in \mathbb{R}^{S_t \times U}$.

To learn the stock node representation more comprehensively, we employ graph convolution operation to capture the relational information for updating the node representation in stock relation graph. For stock node s_t, we aggregate the features of its neighbor stock nodes to get the **relation-view** feature $a_t^{s_t} \in \mathbb{R}^U$ on each day t. The graph convolution operation is formulated as follows:

$$a_t^{s_t} = \sum_{j_t \in \mathcal{N}_{s_t} \cup \{s_t\}} \frac{1}{\sqrt{degree\,(j_t) \cdot degree\,(s_t)}} (\Theta \cdot e_t^{j_t}), \tag{2}$$

where $degree\,(s_t)$ denotes the degree of stock node s_t; $j_t \in \mathcal{N}_{s_t} \cup \{s_t\}$ and $\mathcal{N}_{s_t}$ is the neighborhood of stock node s_t. The neighboring node features are first transformed by a weight matrix Θ. In particular, one of all M_t price-limit-hitting stocks m_t's relation-view feature is $a_t^{m_t} \in \{a_t^1, a_t^2, \cdots, a_t^{M_t}\}$.

Attention Encoder. In the real stock market, the movement of one stock is related to the movement trend of the whole market, so we propose to obtain the **graph-view** feature of the stock relation graph by reshaping the relation-view features. In order to consider the importance of different nodes in the stock relation graph, we apply the attention encoder to learn the graph-view feature from all the stock nodes with attention scores. Formally, the graph-view feature of whole graph is computed by:

$$\begin{gathered} \eta_t^{s_t} = u_a^T \phi(W_a a_t^{s_t} + b_a), score_t^{s_t} = \frac{\exp(\eta_t^{s_t})}{\sum_{j_t} \exp(\eta_t^{j_t})}, \\ g_t = \sum_{j_t} score_t^{j_t} a_t^{j_t}, \end{gathered} \tag{3}$$

where $\eta_t^{s_t}$ indicates the importance of stock node s_t in the stock relation graph; ϕ is an activation function; $u_a \in \mathbb{R}^{M'}$, $W_a \in \mathbb{R}^{M' \times U}$, and b_a are parameters to be learned.

4.3 Hierarchical Fusion Classification Layer

This layer aims to fuse the information of different views including node-view, relation-view and graph-view features into stock representation and predict the type of price-limit-hitting stock.

Hierarchical Fusion. The node-view feature $e_t^{m_t}$ is conducive to strengthening the importance of price-limit-hitting stock itself. Moreover, the relation-view feature a^{m_t} and graph-view feature g_t reflect the relational feature of different graph structures in the stock relation graph, where relation-view feature contains the relational information among the neighborhood, and graph-view feature indicates the movement trend of the whole market. In order to incorporate the features of different views, we concatenate $e_t^{m_t}$, a^{m_t}, and g_t as the final representation of stock m_t.

Type Classification. We deploy a fully connected layer to predict the type label $\hat{y}_t^{m_t}$ of pirce-limit-hitting stock m_t:

$$\hat{y}_t^{m_t} = softmax(W_p^T[e_t^{m_t} \oplus a_t^{m_t} \oplus g_t]^T + b_p), \tag{4}$$

where $W_p \in \mathbb{R}^{3U}$ and b_p are the learnable parameters.

Loss Function. The task is formulated as a binary classification problem. We utilize the focal loss [13] as the loss function, which acts as a more effective alternative to cross entropy loss for dealing with hard classified examples.

5 EXPERIMENTS

5.1 Datasets

Stock Historical Sequence. We firstly collect the daily historical sequence data in SSE and SZSE market from 01/01/2018 to 12/31/2019, which have 10080 and 12556 valid price-limit-hitting stock samples, respectively. All datasets are split into training sets and testing sets. Moreover, to better reflect and capture the suddenness of the price limit, we extract the limit-related indicators from minutely historical trade data.

Stock Relation Graph. We get the 110 kinds of industry categories in the SSE and SZSE markets from China Securities Regulatory Commission Industry Classification, which are used to construct the stock relation graph with 1392 and 1312 stock nodes, 15559 and 16880 edges, respectively.

Table 1: Experimental results of the compared methods.

Model	SSE			SZSE		
	Acc(%)	F1(%)	ARR(%)	Acc(%)	F1(%)	ARR(%)
Navie Bayes	46.21±1.31	44.37±1.60	0.21	47.80±1.19	45.76±0.99	0.26
LR	58.59±1.03	59.43±0.95	0.16	57.42±0.34	58.27±0.32	0.19
SVM	58.04±2.11	58.90±2.05	0.08	58.16±1.06	59.01±1.05	0.02
XGBoost	60.59±0.80	61.11±0.69	0.38	59.10±1.73	59.87±1.67	0.55
LSTM	59.74±2.43	58.70±1.62	0.33	58.52±1.97	57.43±1.34	0.29
GCN	60.54±1.91	59.54±1.43	0.40	60.57±1.75	58.94±1.74	0.44
HGNN	**63.33±1.15**	**63.36±1.11**	**0.70**	**63.29±1.48**	**62.96±1.13**	**0.80**

5.2 Baselines

The classification task of price-limit-hitting stock in stock market is first proposed in this paper. We implement not only classical models but also the advanced neural network methods for comparison. For classical models, including Naive Bayes[11], LR [3], SVM [20], XGBoost [2], these methods takes the limit-related indicators as the input. For advanced neural network methods, including LSTM[16] and GCN [9], LSTM only utilizes the historical sequence as input, and GCN utilize the stock historical sequence and the stock relation graph as input in our experiment.

5.3 Experimental Setup

Market Simulation. Inspired by previous market strategy [6], we design a more practical market simulation strategy to evaluate the performance through conducting back-testing on the test datasets of two markets. We assume that investor buy the price-limit-hitting stock m that is predicted to be Type I at price limit $Limit_t^m$ of the day t and sells it at the opening price $Open_{t+1}^m$ of the next day $t+1$. For buying a set of M price-limit-hitting stocks, we formulate the *Average Return Ratio* (ARR) as follows:

$$ARR = \sum_{m=1}^{M} \frac{Open_{t+1}^m - Limit_t^m}{Limit_t^m} / M, \tag{5}$$

Evaluation Metrics. To evaluate the performance of the type classification of price-limit-hitting stock, we select two metrics as evaluation metrics: Accuracy (Acc) and F1-score (F1) [14]. However, stock investors are most concerned about the return ratio on investment. Therefore, *Average Return Ratio* (ARR) also needs to be considered in experiment.

Parameter Settings. Our proposed model is implemented with Pytorch and optimized by Adam with learning rate of 0.001. In MLP module, we set the number of hidden layers as 2. For the window size of historical sequential input and the number of hidden units in LSTM, we select them via grid-search within the ranges of [4, 6, 8, 12, 16] and [8, 16, 32, 64]. And we also tune α and γ in loss function within the ranges of [0, 0.2, 0.4, 0.6, 0.8] and [0.1, 1, 2, 3]. We report the mean testing performance over ten different runs.

6 RESULTS AND ANALYSIS

We conduct a series of experiments to evaluate the performance of our proposed HGNN. We implement not only classical models but also the advanced models for comparison, and analyze the effectiveness of our proposal model from different aspects including the overall performance and the effect of hierarchical information.

Overall Performance. We first analyze the overall performance on two real market datasets. The experimental results of different models are presented in Table 1. HGNN achieves best results in both SSE and SZSE markets compared to other models. For example, the values of accuracy are 63.33% and 63.29% for our model in SSE and SZSE markets, respectively; the values of F1 score are 63.36% and 62.96% for our model in SSE and SZSE markets, respectively. Additionally, the stability of our model is also verified by the standard deviations of the evaluation metrics. Most investors chase the price continuation phenomenon to buy the stock when the price limit occurs. ARR can represent the average return when investors buy the stocks that hit their price limits in real stock market. Table 1 also shows the ARR values of all methods. It can be observed that our proposed HGNN can obtain return ratio much better than other models in both SSE and SZSE markets. This result proves the effectiveness and practicality of our proposed HGNN. Moreover, it further proves the necessity of the price-limit-hitting stock classification task.

The Effect of Hierarchical Information. Encoding stock relations effectively in stock markets can lead to more significant improvement in prediction. Compared with the historical sequence based method (LSTM), GCN obtain better performance of stock classification by introducing stock relation into stock prediction based on historical sequence. Compared to GCN method, HGNN has increased by an obvious improvement in both markets, which proves the advantage and practicability of our proposal in the classification task of price-limit-hitting stock type. By extracting and fusing different levels of stock information, especially the relation-view and graph-view information in the stock relation graph, our proposal HGNN can effectively utilize the information of related stocks and the whole market, so as to obtain more the clues of price limit and deal with the lack of information in the price-limit-hitting stock classification.

7 CONCLUSION

In this paper, we propose a novel classification objective that aims to predict the type of price-limit-hitting stocks. It is significant that predicting the type of price-limit-hitting stock, due to the different types of price-limit-hitting stocks will lead to extremely different profits for stock investments. Moreover, investigating the information of a stock market at different levels can improve the stock prediction performance. To automatically learn the information of hierarchical view in stock data, we propose a Hierarchical Graph Neural Network (HGNN) for price-limit-hitting stock type classification. Experimental results show that HGNN can achieve high return ratio for classifying the type of price-limit-hitting stock on two real stock markets.

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