Graph-Based Learning for Stock Movement Prediction with Textual and Relational Data

Qinkai Chen^{†‡} Christian-Yann Robert[§]

†Ecole Polytechnique, Palaiseau, France ‡Exoduspoint Capital Management France, Paris, France §ENSAE Paris, Palaiseau, France qinkai.chen@polytechnique.edu christian-yann.robert@ensae.fr

Abstract

Predicting stock prices from textual information is a challenging task due to the uncertainty of the market and the difficulty in understanding the natural language from a machine's perspective. Previous researches mostly focused on sentiment extraction based on single news. However, the stocks on the financial market can be highly correlated, one news regarding one stock can quickly impact the prices of other stocks. To take this effect into account, we propose a new stock movement prediction framework: Multi-Graph Recurrent Network for Stock Forecasting (MGRN). This architecture allows to combine the textual sentiment from financial news and multiple relational information extracted from other types of financial data. Through an accuracy test and a trading simulation on the stocks of the STOXX Europe 600 index, we demonstrate a better performance from our model than other benchmarks.

1 Introduction

Fama (1965) and Malkiel (1989) show that the movement of stock price can be explained jointly by all known information, although it is volatile and non-stationary (Adam et al., 2016). The information can include all types of available information, such as historical prices (Kohara et al., 1997), macroeconomic indicators (Garcia and Liu, 1999), financial news (Ding et al., 2014), etc. Most of the research focuses on the time series analysis of the numerical indicators, i.e., using historical prices to predict future prices (Luo et al., 2017). Although simple and efficient, this method does not

consider the market sentiment and market moving events, based on which most rational human investors trade. With the development of the natural language processing, more recent research works start to use textual data for stock movement prediction (Ding et al., 2014, 2015; Hu et al., 2018). However, these researches assume that all the stocks are independent and predict the price movement of each stock independently, although Hou (2007) shows that the movement of one stock can significantly impact other correlated stocks.

To take stock correlation into consideration, Guo et al. (2018) and Ye et al. (2021) integrate the relationship information into traditional time series analysis without using textual data. Cheng et al. (2020) and Sawhney et al. (2020) design neural networks to take both textual data and one pre-defined relationship graph into consideration. However, the stock relationships can come from multiple aspects, such as price correlation (Campbell et al., 1993), sector of activity (Vardharaj and Fabozzi, 2007) and supply chain (Pandit et al., 2011). We will demonstrate that considering multiple relationships at the same time can benefit the prediction performance.

Hence, we want to design an improved model which has the following characteristics: (1) learn from both text data and relational data, (2) incorporate an unlimited number of relational graphs into the structure, (3) take temporal patterns of the news into account instead of learning from only one news at a time.

To address the above-mentioned challenges, we first discuss previous works (Sec. 2), we then propose a new stock price movement prediction framework: Multi-Graph Recurrent Network for Stock Forecasting (MGRN). MGRN combines textual information from a financial news provider and relationship data from different sources to predict the variation of stock prices (Sec. 3). MGRN

The authors would like to thank Mathieu Rosenbaum from Ecole Polytechnique for his valuable guidance and advice during this work. The authors also appreciate the insightful discussions with Jean-Sebastien Deharo and Alexandre Davroux.

jointly learns from texts and relationships through its graph-based structure, it can also learn from news' temporal patterns with its recurrent structure (Sec. 4). With various experiments, we show the performance of our MGRN model as well as other benchmark models (Sec. 5). We also perform trading simulations to show the profitability of our results in real-life scenario (Sec. 6).

2 Related Work

2.1 Stock Movement Prediction

There are various approaches to predict stock prices and the researches on this topic span on different domains. Econometricians use time-series analysis (Mills and Mills, 1990) to predict future prices based on historical prices and volumes data. Financial analysts rely on company fundamental data such as earnings and debt ratio (Ozlen, 2014; Wang and Xu, 2004), or macroeconomic data such as GDP and CPI index (Hoseinzade and Haratizadeh, 2019) to predict the trend of stock prices from a economic point of view. Computer scientists tend to use machine learning techniques to interpret the stock price movement. With the development of the natural language processing, more researches focus on predicting stocks prices based on financial news or social media texts.

Schumaker and Chen (2009) use a classical feature engineering method to extract features from text data, Ke et al. (2019) use a TF-IDF (Crnic, 2011) like method to identify positive and negative words in financial texts. Nowadays, more researches adopt deep learning methods to analyze financial news. Ding et al. (2014, 2015) use structured representations and convolutional networks to analyze news sentiments. Hu et al. (2018) apply attention mechanism to directly handle the raw text without using widely used recurrent neural network. Xu and Cohen (2018) propose a model which considers jointly text and price information. All these methods assume that all news are independent to simplify the problem. Although useful, this is contrary to the the common sense and some findings (Hou, 2007; Klößner and Wagner, 2014) which explain the price interactions among stocks.

2.2 Graph Neural Network

With the popularity of graph learning, more researchers start to use graph-based structure to capture complex non-linear interactions among the nodes. Graph Convolutional Network (GCN) is

one of the most used graph networks, and it has gained more popularity since it obtains outstanding result on node classification task (Kipf and Welling, 2016). Some recent researches apply this technique on stock movement prediction tasks.

Chen et al. (2018) and Kim et al. (2019) combine historical price and corporation relationship knowledge graph through graph-based models. However, they only take historical price data as input without considering the information from news or social media texts. Sawhney et al. (2020) design a Multipronged Attention Network (MAN-SF) to consider both textual data and relationship data at the same time. However, the study only considers one pre-built graph from Wikidata¹. In the real world, the relationships among companies come from multiple dimensions and it can change significantly over time.

To close the gap in the researches, we propose MGRN, which can ingest both textual data and an unlimited number of relationship graphs built from different sources, as opposed to the previous researches. In addition, MGRN contains a recurrent structure to model the temporal interactions of the news, instead of assuming the independence of the news.

3 Problem Formulation

Following Ding et al. (2015) and Xu and Cohen (2018), we formulate the stock movement prediction as a binary classification task. Given a universe of stocks S, for a stock $s \in S$, we define its market adjusted return r_s between t and $t + \Delta t$ as:

$$r_{s,t} = \frac{P_{s,t+\Delta t}}{P_{s,t}} - \frac{P_{m,t+\Delta t}}{P_{m,t}} \tag{1}$$

where $P_{s,t}$ denotes the price for stock s at time t, and $P_{m,t}$ denotes the market index value at time t.

We define the target of our stock movement prediction task for stock s between t and $t + \Delta t$ as:

$$Y_{s,t} = \begin{cases} 1, & r_{s,t} > 0 \\ 0, & r_{s,t} \le 0 \end{cases}$$
 (2)

For a traditional single stock movement prediction task, the goal is to predict $Y_{s,t}$ from all the news related to the stock s in a look-back window T, it can be written as:

$$\hat{Y}_{s,t} = f(E_{s,t}^T, \theta) \tag{3}$$

¹https://www.wikidata.org/

where $E_{s,t}^T$ denotes all the news for stock s between t-T and t and θ denotes the trainable parameters.

However, our goal is to consider both news and cross effects among stocks when predicting stock movement. Our prediction is hence written as:

$$\hat{Y}_{s,t} = f([E_{1,t}^T, ..., E_{n,t}^T], [G_1, ..., G_g], \theta)$$
 (4)

where n is the number of stocks in our universe S, G_i is the graph constructed from data source i and g is the number of graphs we construct from different data sources.

4 Multi-Graph Recurrent Network for Stock Forecasting

The architecture of our MGRN model is shown in Figure 1. It has three sub-components: Financial News Encoder, Multi-Graph Convolutional Network and Recurrent Neural Network. We introduce the details of each component in the following subsections.

4.1 Financial News Encoder

Single news embedding

For each news e, we need to represent it with an embedding $v_e \in \mathbb{R}^d$. Following the work of Sawhney et al. (2020), we simply use Universal Sentence Encoder (Cer et al., 2018) to convert a sentence into a fixed-length embedding.

Aggregated news embedding

Unlike stock movement prediction based on single news, graph-based network structure requires a valid node embedding for each node when we train and predict. Hence, we need to choose a reasonable time window to make sure that for most of the stocks, there is at least one piece of news in this window. This is to avoid too many zero vectors as node embeddings. We simply choose a period of one day when we aggregate the news, following Kim et al. (2019) and Li et al. (2020). It means that for stock s and on day d, we select all the news concerning s between the market close time on day d and the market close time on day d-1 to get its aggregated embedding.

Iyyer et al. (2015) and Wieting et al. (2015) show that a simple average aggregation can have similar and even better performance than more complicated recurrent models such as LSTM. For the sake of simplicity without sacrificing the accuracy, we use an average over all news embeddings

of a stock s as its aggregated news embedding on day d. We denote it by $v_{s,d}$. We have:

$$v_{s,d} = \frac{1}{n} \sum_{i=1}^{|E_{s,d}^1|} e_{s,t}^i$$
 (5)

where $e^i_{s,t} \in E^1_{s,d}$ is the embedding of the *i*-th news about s happening at time t between d and d-1.

4.2 Multi-GCN Attention Network

Graph Representation

We model the stock relationships with a graph G. We use the graph's adjacency matrix $A \in \mathbb{R}^{n \times n}$ to represent the relationships among n stocks. The element $A_{i,j}$ denotes the intensity of relationship between the stock i and the stock j. We set $A_{i,i} = 1$.

There are two types of relationships: (1) boolean relationship represented by a simple graph and (2) continuous relationship represented by a weighted graph.

For a boolean relationship, we have $A_{i,j} \in \{0,1\}$. If there is a connection between stock i and j, $A_{i,j}$ is set to 1. Otherwise, it is set to 0. For example, GICS sector 2 relationship is a boolean relationship. If two stocks are both in the same sector, we assert that they are connected. Supply chain relationship is also a boolean relationship. If one company is another company's supplier, we assert that they are connected.

However, for a continuous relationship, we have $A_{i,j} \in [0,1]$. The more important the relation between two stocks, the larger this value. For example, the historical price relationship is a continuous relationship. The intensity of the relationship between two stocks is calculated as the correlation coefficient of two stocks' daily return time series.

Following Duvenaud et al. (2015) and Kipf and Welling (2016), we normalize our adjacency matrix with a symmetric normalization:

$$\hat{A} = D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \tag{6}$$

where $D \in \mathbb{R}^{n \times n}$ is a generalized diagonal node degree matrix for both simple graphs and weighted graphs, defined as:

$$D_{i,j} = \begin{cases} \sum_{k} A_{i,k}, & i = j \\ 0, & i \neq j \end{cases}$$
 (7)

²https://www.msci.com/gics

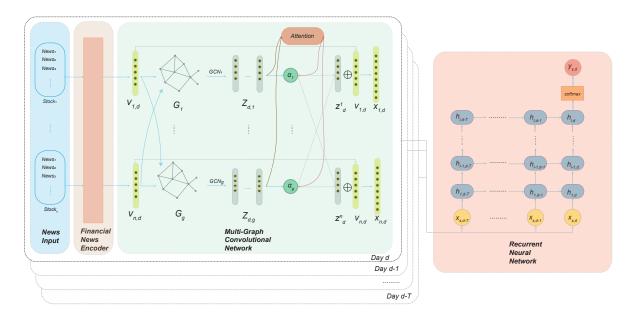


Figure 1: An overview of the architecture of the MGRN model. Our MGRN model includes three sub-components: (1) Financial News Encoder, which encodes textual news into a fixed length vector for each stock and each day $(v_{s,d})$. (2) Multi-Graph Convolutional Network, which takes the encoded daily news vectors and the graphs as input. Through this multi-graph structure, we get multiple node embeddings for each stock. We then combine these node embeddings into a single embedding $(\hat{x}_{s,d})$ through an attention mechanism. (3) Recurrent Neural Network, which takes the combined embeddings during a look-back window T as input and extracts temporal patterns among the news. $h_{i,j}$ denotes the j-th LSTM cell on the i-th layer. Finally, through a fully-connected layer, we predict whether the stock price increases or decreases $(\hat{y}_{s,d})$.

Such normalization guarantees that the operations involving A do not change the scale of the result on both simple graphs and weighted graphs.

Single Graph Convolutional Network

We use the same GCN structure as proposed by Kipf and Welling (2016). For day d, we construct our daily news matrix with $X_d = [v_{1,d}, ..., v_{n,d}]^T$. We also have one graph G and its adjacency matrix is A.

Our GCN with L layers can be written as the following function:

$$H^{(l+1)} = \sigma(\hat{A}H^{(l)}W^{(l)}) \tag{8}$$

with $H^{(0)}=X_d$ and $H^{(L)}=Z_d$ as the final graph output. We have $H^{(l)}\in\mathbb{R}^{n\times f_l}$ where f_l denotes the number of output features for layer l. In Equation (8), σ denotes the activation function and $W^{(l)}$ represents the weight matrix for the layer l.

With such an operation, we obtain a new node representation of dimension f_L for each stock from $H^{(L)}$.

Attention Aggregation Layer

Given g graphs $G_1, ..., G_g$ with their adjacency matrix $A_1, ..., A_g$, we attribute each graph an independent GCN. For day d, we have g graph outputs $Z_{d,1}, ..., Z_{d,g}$. We combine these graph outputs to get an aggregated graph output with an attention mechanism (Vaswani et al., 2017).

We define $W_a \in \mathbb{R}^{f_L \times w}$ and $q \in \mathbb{R}^{w \times 1}$, both of which are trainable parameters. We then calculate the attention coefficients $\alpha_i \in \mathbb{R}^{n \times 1}$ for graph i using the following formula:

$$\alpha_i = \frac{exp(Z_{d,i}W_aq)}{\sum_j exp(Z_{d,j}W_aq)}$$
 (9)

We then aggregate all the $Z_{d,i}$ using:

$$Z_d = \sum_i \alpha_i \otimes Z_{d,i} \tag{10}$$

where \otimes denotes element-wise multiplication.

Finally, we concatenate the graph output Z_d with the original daily news embeddings. Our final output after the graph layer for the day d becomes:

$$\hat{X}_d = X_d \oplus Z_d \tag{11}$$

where \oplus denotes concatenation. This is to ensure that we can capture the information from both graphs and the orignal text embeddings.

4.3 Recurrent Neural Network

We then build a recurrent network to capture the temporal patterns in the news.

We first repeat the same process described in Section 4.2 from day d to day d-T. We have the outputs from the graph layer denoted by $\hat{X}_d, ..., \hat{X}_{d-T}$ as the input of our recurrent network.

We use a straightforward multi-layer recurrent neural network with LSTM cells (Hochreiter and Schmidhuber, 1997) shown on the right-hand side of Figure 1. At the final layer, we use a fully connected layer followed by a softmax to make the final prediction.

We input the concatenated outputs from the graph layer and financial news encoder layer sequentially into the first layer of the RNN model. For each stock at each day, we get its $P_{s,d}^+$ denoting the probability that the stock price will increase the next day and $P_{s,d}^- = 1 - P_{s,d}^+$ representing the price drop probability.

We train our MGRN network with an Adam optimizer (Kingma and Ba, 2014) by minimizing the binary cross entropy loss, given as:

$$l = \sum_{s} \sum_{d} Y_{s,d} ln(P_{s,d}^{+}) + (1 - Y_{s,d}) ln(1 - P_{s,d}^{+})$$
(12)

where $Y_{s,d}$ is the true stock price movement defined in Equation 2.

5 Experiments

5.1 Datasets and Graph Building

Financial News Dataset

The dataset that we use is Bloomberg News³. In this dataset, each entry contains a *timestamp* denoting when this news happened, a *ticker* which signifies the stock related to this news and the *headline* of this news. In addition to the necessary information above, we can also find a *score* which is among -1, 0 and +1, and a *confidence* between 0 and 100 associated with the *score*. These two fields are given by Bloomberg's proprietary classification algorithm, it will serve as one of the benchmarks for our prediction model. We present a sample dataset in Table 1.

It is worth noting that we remove the stocks which do not have enough news. This is to ensure that we do not have too many zero vectors as our daily news vector (Equation 5). We only select the stocks which have more than 2 news per day in average. With a such filter, we have 168 stocks in the stock universe, and we observe that there are only 15% (Table 2: Zero vector rate) zero vectors among all daily news vectors, meaning that given a stock and a date, there is a 85% chance there is at least one piece of news.

Stock Price Dataset

We extract all the market close prices for all the stocks in the universe, we also extract the Europe STOXX 600 index value at the market close time⁴ for our market adjusted return calculation. We use the stock prices for both labelling and building a correlation graph from stock returns.

For labelling, we follow the procedure described in Section 3. However, we observe that there are some delisted stocks which no longer have prices after a certain date, preventing us from correctly calculating their returns. Hence, we remove the stocks which are delisted during our training period. There are three such stocks, leaving us 165 stocks in total in our experiments.

We also use the stocks prices to build a weighted graph G_c . For all stocks, we first calculate its market adjusted returns with Equation 1, we have a vector $v_s = [r_{s,1},...,r_{s,T_c}]$ containing all the returns from the first day until the last day in our training dataset. We calculate the Pearson Correlation Coefficient (Freedman et al., 2007) between stock i and stock j, such that its adjacency matrix A_c is given by:

$$A_{c,i,j} = \frac{cov(v_i, v_j)}{std(v_i)std(v_j)}$$
(13)

where cov represents the covariance and std denotes the standard deviation.

Stock Sector Data

In finance, each company is classified into a specific sector with Global Industry Classification Standard (GICS). We use this data to construct a sector graph G_s . Its adjacency matrix A_s is defined as:

$$A_{s,i,j} = \begin{cases} 1, & sector(i) = sector(j) \\ 0, & otherwise \end{cases}$$
 (14)

There are four granularities in GICS sector data: Sector, Industry Group, Industry, Sub-Industry.

³https://www.bloomberg.com/professional/product/event-driven-feeds/

⁴17:30 Central European Time

Headline	TimeStamp	Ticker	Score	Confidence
1st Source Corp: 06/20/2015 - 1st Source announces the promotion of Kim Richardson in St. Joseph	2015-06- 20T05:02:04.063	SRCE	-1	39
Siasat Daily: Microsoft continues rebranding of Nokia Priority stores in India opens one in Chennai	2015-06- 20T05:14:01.096	MSFT	1	98
Rosneft, Eurochem to cooperate on monetization at east urengoy	2015-06- 20T08:01:53.625	ROSN RM	0	98

Table 1: A sample dataset from Bloomberg News dataset that we use as our financial news data.

We can therefore construct four graphs with this dataset. In our experiments, we use the Industry granularity as it gives the best performance. The performances with different sector graphs are discussed in Section 5.4

Supply Chain Data

We use the supply chain data from Factset⁵ to construct a supply chain graph. This dataset describes the supplier-customer relationship (SCR) among different companies. We construct a supply chain graph G_{sc} such that

$$A_{sc,i,j} = \begin{cases} 1, & i \text{ and } j \text{ have } SCR \\ 0, & otherwise \end{cases}$$
 (15)

We show the heatmaps of three graphs in Figure 2.

Dataset Split

Following the standard in deep learning researches, we split our dataset into three subdatasets: train, dev and test. The details are shown in Table 2.

Parameter Settings

We use a look-back window T=20 days and we use a look-forward window $\Delta t=1$ day to label our data.

The GCN model we use has two hidden layers, with 128 and 64 dimensions respectively. Our RNN model also has two layers, with 128 and 64 LSTM cells respectively. We train our model with an Adam optimizer for 10 epochs. We set the batch size to 32.

	Train	Dev	Test
Total news	1,199,367	316,944	439,949
Start	01/2016	07/2018	01/2019
End	06/2018	12/2018	12/2019
Nb. Stocks	165	165	165
Trading days	652	118	256
Data points ⁶	107,580	19,470	42,240
Zero vector rate	15%	17%	19%

Table 2: Statistics of the news dataset. Zero vector rate means the ratio of zero vector among all embedded daily news vectors $v_{s,t}$. We only select the 165 stocks which have relatively more news to make this value as small as possible in order not to impact our GCN model.

5.2 Evaluation Metrics

Accuracy

Following previous researches on the stock movement prediction task (Ding et al., 2015; Hu et al., 2018; Sawhney et al., 2020), we use accuracy to evaluate the performance of our model.

However, this simple metric does not reflect the need of a real-life investor, since he does not need to make trades on all prediction results. The investor only trades when he is more confident about the prediction. In other words, the accuracy on the predictions with higher probability is more important than those with a mediocre probability. Hence, we also include "percentile accuracy" in our evaluation metrics.

We note that the score $S_{s,d} \in [-1,1]$ for a stock s on day d as:

$$S_{s,d} = (P_{s,d}^+ - 0.5) \times 2$$
 (16)

For **each day**, we choose the top $\frac{q}{2}$ -percentile scores and the bottom $\frac{q}{2}$ -percentile scores of that day, where q is a value between 0 and 100. We

⁵https://www.factset.com/marketplace/catalog/product/factsetsupply-chain-relationships

⁶Number of stocks multiplied by number of trading days, this equals the total predictions we make in each dataset.

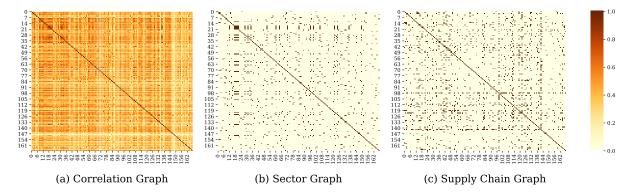


Figure 2: The heatmaps of our three graphs G_c , G_s and G_{sc} . We can see some common characteristics in these heatmaps, for example, the top-left corner of the correlation graph and the sector graph. However, the graphs are rather uncorrelated, we prove this with the experiment results in Section 5.4.

denote the accuracy calculated based on such selection as Acc_q . The accuracy on the whole test set is therefore Acc_{100} .

Trading Simulation

We use a simple long/short trading strategy similar to Ke et al. (2019). For each day, we attribute equally weighted long positions for the stocks whose scores are in the top $\frac{q}{2}$ -percentile. For the stocks whose scores are in the bottom $\frac{q}{2}$ -percentile, we give each stock the same short position. In this case, our long position equals to our short position, leaving no market exposure for our strategy.

We use annualized return and Sharpe ratio (Sharpe, 1994) to evaluate the performance of our strategies. The annualized Sharpe ratio is defined as the ratio of the expected return R to its standard deviation multiplied by square root of the number of trading days D_y in one year:

$$Sharpe = \frac{\mathbf{E}(R)}{\sigma(R)} \times \sqrt{D_y}$$
 (17)

5.3 Baseline Models

We compare the performance of our MGRN model with other baseline models to demonstrate its performance.

We include the following baseline models:

- RAND: Random guess of $Y_{s,t}$.
- ARIMA: Auto-Regressive Integrated Moving Average model (Ho and Xie, 1998) based on historical prices.
- BBG: The prediction given by Bloomberg which comes along with Bloomberg News dataset (Table 1).

- Mean-BERT: We fine-tune the Bidirectional Encoder Representations from Transformers (BERT) model proposed by Devlin et al. (2018) as a classification model. We use the average score of all the news for stock s on day t as its $S_{s,d}$.
- MAN-SF⁸: A stock movement prediction framework proposed by Sawhney et al. (2020). The model combines price data, news data and relational data to predict stock return.
- RNN: The model introduced in Sec. 4.3 without adding any graph. This is the same as a MGRN model with an identity matrix as graph adjacency matrix.

To make a detailed analysis of the improvement brought by different graphs, we train our MGRN model with different graphs:

- MGRN-Corr: MGRN model with return correlation graph G_c (Eq. 13).
- MGRN-Sector: MGRN model with sector graph G_s (Eq. 14).
- MGRN-Supply: MGRN model with supply chain graph G_{sc} (Eq. 15).
- MGRN: the full MGRN model using three graphs G_c , G_s and G_{sc} at the same time.

5.4 Experiment Results

Table 4 shows the accuracy of different models on the test set with different q-percentiles. We

⁸MAN-SF only allows to have one relationship, we use the correlation for this model.

\overline{q}	1	.00		50		20		10		2
metric	Ret. ⁷	Sharpe	Ret.	Sharpe	Ret.	Sharpe	Ret.	Sharpe	Ret.	Sharpe
RAND	0.53	0.25	0.29	0.05	-0.5	-0.12	-0.6	0.11	3.59	0.33
ARIMA	0.3	0.09	0.79	0.16	2.26	0.9	1.5	0.13	2.24	0.36
BBG	2.78	0.66	3.72	0.57	3.89	0.56	2.56	0.35	18.48	1.54
Mean-BERT	0.21	0.05	0.98	0.41	4.25	0.66	7.21	0.98	8.08	1.11
MAN-SF	0.17	0.58	0.41	0.13	1.06	0.32	3.77	0.57	4.02	0.37
RNN	0.74	0.31	1.01	0.3	3.09	0.57	4.36	0.67	5.32	0.9
MGRN-Corr	1.27	0.4	2.04	0.51	3.45	0.57	5.06	0.61	15.19	1.19
MGRN-Sector	1.22	0.39	2.47	0.51	3.67	0.62	5.26	0.79	8.42	0.57
MGRN-Supply	1.05	0.42	1.92	0.58	3.11	0.72	10.86	1.31	10.55	0.7
MGRN	2.18	0.94	2.07	0.62	8.71	1.7	12.03	1.33	26.22	1.51

Table 3: The trading simulation result of all models with different q-percentiles.

find that our MGRN model shows the best performance, outperforming other baseline models.

We compare the single graph models (MGRN-Corr, MGRN-Sector and MGRN-Supply) and the vanilla model without graph (RNN). We find that all the graphs can help improve the performance, especially for the most extreme scores (a smaller qvalue). However, it is difficult to say which graph has the best performance, since each graph has different optimal performances on different percentiles. For example, the supply chain graph has the most added value on the most extreme scores (highest with q = 2), while the return correlation graph is more powerful on less extreme scores (highest with q = 10 and q = 20). This also signifies that the information in each graph is rather independent, making it more reasonable to combine different graphs.

We validate our hypothesis that combining different graph can help improve model performance by comparing the full model (MGRN) with the single graph models. We find that when using all three graphs together, we have a significant improvement in accuracy (5% with q=10 and 3.5% with q=20). It proves that our model can absorb necessary information from multiple independent graphs at the same time, validating the effectiveness of combining relationship information from different sources.

We also notice that adding a graph can lead to a worse result compared with the no-graph RNN in some scenario, for example, MGRN-Supply is worse than RNN when q=10 and q=20. However, when combining with other graphs, the result is better than using any graph individually. This is

because the errors usually come from several particular stocks, especially when we only have only one source of information. If the source is incorrect, it can lead to significant error. The benefit of using multiple graphs is to reduce the impact of these cases by making decisions based on more than one source of information.

Table 3 shows the trading simulation result using the strategy described in Sec. 5.2. We can also confirm that our MGRN model outperforms other models and that combining the graphs together is beneficial. Although sometimes Bloomberg Sentiment Score shows better stability (Sharpe Ratio), MGRN model is still the model that consistently gives the best performance. This validates the usage of MGRN model in real-world scenario.

\overline{q}	100	50	20	10	2
RAND	0.471	0.471	0.472	0.473	0.488
ARIMA	0.479	0.509	0.521	0.512	0.519
BBG^9	0.501	0.500	0.487	0.488	0.551
Mean-BERT	0.518	0.528	0.561	0.593	0.665
MAN-SF	0.504	0.499	0.516	0.530	0.599
RNN	0.515	0.521	0.545	0.580	0.690
MGRN-Corr	0.516	0.531	0.576	0.623	0.696
MGRN-Sector	0.515	0.524	0.550	0.580	0.709
MGRN-Supply	0.515	0.522	0.534	0.557	0.720
MGRN	0.522	0.537	0.580	0.633	0.740

Table 4: The accuracy of baseline models and MGRN models with different q-percentiles.

Sector Graphs

⁸The annualized return is shown in %

⁹As the Bloomberg Sentiment Score is a three class classification, we remove all the neutral predictions to be comparable with our two class classification result

As we mentioned in Section 5.1, there are four granularities in our GICS sector data. We compare the performances from all four granularities, and we find that the Industry level (the third granularity) shows the best performance, especially on more extreme scores. Hence, we choose to use Industry level to build G_s . The detailed result is shown in Table 5.

level	name	q=100	q=20	q=10
1	Sector	0.519	0.521	0.542
2	Industry Group	0.514	0.529	0.569
3	Industry	0.515	0.550	0.580
4	Sub-Industry	0.509	0.542	0.556

Table 5: The accuracy of MGRN-Sector model but with the sector graphs built from different GICS sector granularities.

5.5 Qualitative Analysis: An Example

We give a detailed study on one specific case to show how our MGRN model helps improve stock movement prediction.

We focus on the stock **TLW LN**¹⁰ on the Dec. 6, 2018. We notice a news in the evening of that day: *Tullow Oil Chairman Thompson Acquires Shares*. This is a positive signal since the executive of Tullow Oil buys its shares, showing confidence as an insider. Based on this piece of news among others, our vanilla MGRN (RNN) without any relational input gives a slightly positive score for this stock at 0.025. However, we observe a return of -7.7% on the next trading day which is contrary to our prediction result.

If we look at the same prediction from MGRN-Sector model, we find that its $S_{s,d}$ equals -0.107, which is a correctly predicted negative value among the bottom 10-percentile. The only reason this new prediction is very different from that of vanilla MGRN is the impact from other related stocks. We find that GLEN LN¹¹ has the most negative score from vanilla MGRN in the same sector. When we look at the news, we can find plenty of negative news about this company on the same day, such as *Rosen Law Firm Announces Investigation of Securities Claims Against Glencore plc*. These negative news caused the price drop of GLEN LN by 3.4%, which potentially caused the

negative return (-2.6%) in the same sector since we do not observe many negative news about other companies.

We can also see the same phenomenon with MGRN-Corr since the correlation between two stocks are relatively high (0.56), but the prediction from MGRN-Supply is still false because there is no supplier-customer relationship between these two stocks. We show the detail of this analysis in Table 6.

Model	$A_{i,j}$	Ticker	Score	Result
RNN	0	TLW LN GLEN LN	0.025 -0.055	False True
MGRN-Corr	0.56	TLW LN GLEN LN	-0.036 -0.031	True True
MGRN-Sector	1	TLW LN GLEN LN	-0.107 -0.031	True True
MGRN-Supply	0	TLW LN GLEN LN	0.013 -0.055	False True

Table 6: Detailed results of the case study for TLW LN on the Dec. 6, 2018. MGRN-Corr and MGRN-Sector both give correct results because the negative signal from GLEN LN can reach TLW LN through the graphs, but MGRN-Supply still gives the wrong prediction since these two stocks do not have connection on this graph.

This example shows clearly how our MGRN model helps improve prediction result compared with a traditional recurrent model without relational modelling: the related stocks can transmit their information through the meaningful graph. The model can then make decision based on both its own information and the transmitted information.

6 Conclusion

We predict the stock movement by jointly considering financial news, multiple graph-based features and temporal patterns of the news. We introduce Multi-Graph Recurrent Network (MGRN) for this task. Through extensive experiments and trading simulations, we demonstrate the effectiveness of the model structure. The result also proves that adding relationship information, especially different relationship information from multiple sources, can help better predict stock movement. We plan to incorporate more types of data (such as time series) in our model to further improve the prediction accuracy.

 $^{^{10}}$ Tullow Oil plc is a multinational oil and gas exploration company.

¹¹Glencore plc is an Anglo-Swiss multinational commodity trading and mining company.

Acknowledgments

The authors gratefully acknowledge the financial support of the Chaire *Machine Learning & Systematic Methods* and the Chaire *Analytics and Models for Regulation* of Ecole Polytechnique.

References

- Klaus Adam, Albert Marcet, and Juan Pablo Nicolini. 2016. Stock market volatility and learning. *The Journal of Finance* 71(1):33–82.
- John Y Campbell, Sanford J Grossman, and Jiang Wang. 1993. Trading volume and serial correlation in stock returns. *The Quarterly Journal of Economics* 108(4):905–939.
- Daniel Cer, Yinfei Yang, Sheng-yi Kong, Nan Hua, Nicole Limtiaco, Rhomni St John, Noah Constant, Mario Guajardo-Céspedes, Steve Yuan, Chris Tar, et al. 2018. Universal sentence encoder. *arXiv* preprint arXiv:1803.11175.
- Yingmei Chen, Zhongyu Wei, and Xuanjing Huang. 2018. Incorporating corporation relationship via graph convolutional neural networks for stock price prediction. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*. pages 1655–1658.
- Dawei Cheng, Fangzhou Yang, Xiaoyang Wang, Ying Zhang, and Liqing Zhang. 2020. Knowledge graph-based event embedding framework for financial quantitative investments. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*. pages 2221–2230.
- Josipa Crnic. 2011. Introduction to modern information retrieval. *Library Management*.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. BERT: pre-training of deep bidirectional transformers for language understanding. *CoRR* abs/1810.04805. http://arxiv.org/abs/1810.04805.
- Xiao Ding, Yue Zhang, Ting Liu, and Junwen Duan. 2014. Using structured events to predict stock price movement: An empirical investigation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. pages 1415–1425.
- Xiao Ding, Yue Zhang, Ting Liu, and Junwen Duan. 2015. Deep learning for event-driven stock prediction. In *Twenty-Fourth International Joint Conference on Artificial Intelligence*.
- David Duvenaud, Dougal Maclaurin, Jorge Aguilera-Iparraguirre, Rafael Gómez-Bombarelli, Timothy Hirzel, Alán Aspuru-Guzik, and Ryan P Adams. 2015. Convolutional networks on graphs for

- learning molecular fingerprints. arXiv preprint arXiv:1509.09292.
- Eugene F Fama. 1965. The behavior of stock-market prices. *The journal of Business* 38(1):34–105.
- David Freedman, Robert Pisani, and Roger Purves. 2007. Statistics (international student edition). *Pisani, R. Purves, 4th edn. WW Norton & Company, New York*.
- Valeriano F Garcia and Lin Liu. 1999. Macroeconomic determinants of stock market development. *Journal of applied Economics* 2(1):29–59.
- Li Guo, Lin Peng, Yubo Tao, and Jun Tu. 2018. News co-occurrence, attention spillover, and return predictability. *Attention Spillover, and Return Predictability (November 18, 2018)*.
- Siu Lau Ho and Min Xie. 1998. The use of arima models for reliability forecasting and analysis. *Computers & industrial engineering* 35(1-2):213–216.
- Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation* 9(8):1735–1780.
- Ehsan Hoseinzade and Saman Haratizadeh. 2019. Cnnpred: Cnn-based stock market prediction using a diverse set of variables. *Expert Systems with Applications* 129:273–285.
- Kewei Hou. 2007. Industry information diffusion and the lead-lag effect in stock returns. *The Review of Financial Studies* 20(4):1113–1138.
- Ziniu Hu, Weiqing Liu, Jiang Bian, Xuanzhe Liu, and Tie-Yan Liu. 2018. Listening to chaotic whispers: A deep learning framework for news-oriented stock trend prediction. In *Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining*. ACM, pages 261–269.
- Mohit Iyyer, Varun Manjunatha, Jordan Boyd-Graber, and Hal Daumé III. 2015. Deep unordered composition rivals syntactic methods for text classification. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. Association for Computational Linguistics, Beijing, China, pages 1681–1691. https://doi.org/10.3115/v1/P15-1162.
- Zheng Tracy Ke, Bryan T Kelly, and Dacheng Xiu. 2019. Predicting returns with text data. Technical report, National Bureau of Economic Research.
- Raehyun Kim, Chan Ho So, Minbyul Jeong, Sanghoon Lee, Jinkyu Kim, and Jaewoo Kang. 2019. Hats: A hierarchical graph attention network for stock movement prediction. *arXiv* preprint arXiv:1908.07999.
- Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

- Thomas N Kipf and Max Welling. 2016. Semisupervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907*.
- Stefan Klößner and Sven Wagner. 2014. Exploring all var orderings for calculating spillovers? yes, we can!—a note on diebold and yilmaz (2009). *Journal of Applied Econometrics* 29(1):172–179.
- Kazuhiro Kohara, Tsutomu Ishikawa, Yoshimi Fukuhara, and Yukihiro Nakamura. 1997. Stock price prediction using prior knowledge and neural networks. *Intelligent Systems in Accounting, Finance & Management* 6(1):11–22.
- Wei Li, Ruihan Bao, Keiko Harimoto, Deli Chen, Jingjing Xu, and Qi Su. 2020. Modeling the stock relation with graph network for overnight stock movement prediction. In *no. CONF*. pages 4541–4547.
- Linkai Luo, Shiyang You, Yanru Xu, and Hong Peng. 2017. Improving the integration of piece wise linear representation and weighted support vector machine for stock trading signal prediction. *Applied Soft Computing* 56:199–216.
- Burton G Malkiel. 1989. Efficient market hypothesis. In *Finance*, Springer, pages 127–134.
- Terence C Mills and Terence C Mills. 1990. *Time series techniques for economists*. Cambridge University Press.
- Serife Ozlen. 2014. The effect of company fundamentals on stock values. *European Researcher* 71(3-2):595–602.
- Shail Pandit, Charles E Wasley, and Tzachi Zach. 2011. Information externalities along the supply chain: The economic determinants of suppliers' stock price reaction to their customers' earnings announcements. *Contemporary Accounting Research* 28(4):1304–1343.
- Ramit Sawhney, Shivam Agarwal, Arnav Wadhwa, and Rajiv Shah. 2020. Deep attentive learning for stock movement prediction from social media text and company correlations. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. pages 8415–8426.
- Robert P Schumaker and Hsinchun Chen. 2009. Textual analysis of stock market prediction using breaking financial news: The azfin text system. *ACM Transactions on Information Systems (TOIS)* 27(2):12.
- William F Sharpe. 1994. The sharpe ratio. *Journal of portfolio management* 21(1):49–58.
- Raman Vardharaj and Frank J Fabozzi. 2007. Sector, style, region: Explaining stock allocation performance. *Financial Analysts Journal* 63(3):59–70.

- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *arXiv preprint arXiv:1706.03762*.
- Fenghua Wang and Yexiao Xu. 2004. What determines chinese stock returns? *Financial Analysts Journal* 60(6):65–77.
- John Wieting, Mohit Bansal, Kevin Gimpel, and Karen Livescu. 2015. Towards universal paraphrastic sentence embeddings. arXiv preprint arXiv:1511.08198.
- Yumo Xu and Shay B Cohen. 2018. Stock movement prediction from tweets and historical prices. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. pages 1970–1979.
- Jiexia Ye, Juanjuan Zhao, Kejiang Ye, and Chengzhong Xu. 2021. Multi-graph convolutional network for relationship-driven stock movement prediction. In 2020 25th International Conference on Pattern Recognition (ICPR). IEEE, pages 6702–6709.