Stock Trend Prediction using Financial Market News and BERT

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Abstract: Stock market trend prediction is an attractive research topic since successful predictions of the market's future movement could result in significant profits. Recent advances in language representation such as Generative Pre-trained Transformer (GPT) and Bidirectional Encoder Representations from Transformers (BERT) models have shown success in incorporating a pre-trained transformer language model and fine-tuning operations to improve downstream natural language processing (NLP) systems. In this paper, we apply the popular BERT model to leverage financial market news to predict stock price movements. Experimental results show that our proposed methods are simple but very effective, which can significantly improve the stock prediction accuracy on a standard financial database over the baseline system and existing work.

1 INTRODUCTION

Recently, a new language representation model named Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019) has achieved huge successes in many natural language processing tasks such as natural language inference, question answering, named entity recognition, etc. In this paper, we apply BERT to financial data modeling to predict stock price movements.

Traditionally neural networks have been used to model stock prices as time series for forecasting purposes, such as in (Kaastra and Boyd, 1996; Adya and Collopy, 1998; Zhu et al., 2008). In these earlier works, due to the limited training data and computing power available back then, shallow neural networks were used to model various types of features extracted from stock price data sets, such as historical prices and trading volumes to predict future stock yields and market returns.

Lately, in the community of natural language processing, many methods have been proposed to explore additional information (mainly online text data) for stock forecasting, such as financial news (Ding et al., 2016; Xie et al., 2013; Hu et al., 2018; Peng and Jiang, 2016), Twitter sentiments (Si et al., 2014; Nguyen and Shirai, 2015; Xu and Cohen, 2018) and financial reports (Lee et al., 2014). For example, (Hu et al., 2018) propose to mine news sequences directly from a text with hierarchical attention mechanisms for stock trend prediction, where they apply the self-paced learning mechanism to imitate effective and efficient learning. (Xu and Cohen, 2018) propose a new deep generative model jointly exploiting text and price signals. Their model introduces recurrent, continuous latent variables for better treatment of stochasticity, and uses neural variational inference to address the intractable posterior inference.

In this paper, we propose to use the recent BERT model to leverage on-line financial news to predict future stock movements. Figure 1 shows how events reported in the news in August 2018 affected the stock price movement of `Tesla Inc`. The proposed model combines historical price information with financial news for more accurate predictions. We conducted experiments on real-world data sets and experimental results show that representations of financial news using BERT are very effective. Its incorporated enhancing semantics representations can significantly improve the prediction accuracy over a model that relies only on historical price information. Our BERT-based model also provides more accurate predictions than previous works (Ding et al., 2016; Hu et al., 2018; Peng and Jiang, 2016).

The remainder of the paper is organized as follows. Section 2 presents existing work in the field of stock trend prediction. Section 3 describes our proposed neural model based on financial market news and BERT for the stock trend prediction task. Section 4 discusses experimental results and compares

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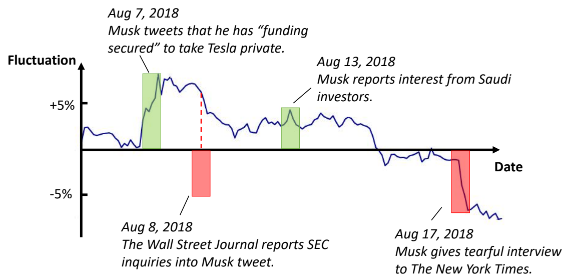


Figure 1: Example of news (`CNN.com`) influence of *Tesla Inc*. Rectangular highlight amplitude of stock price movements resulting from actual events.

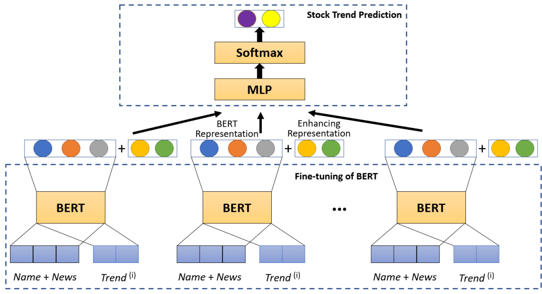


Figure 2: The Architecture of our proposed stock price prediction model.

the performance of our proposed model with that of existing state-of-the-art systems. Finally, Section 5 sums up the paper with concluding remarks.

2 RELATED WORK

Stock market prediction has attracted a great deal of attention across the fields of finance, computer science, and other research communities. The literature on stock market prediction was initiated by economists (Keynes, 1937). Subsequently, the influential theory of Efficient Market Hypothesis (EMH) (Fama, 1965) was established, which states that the price of a security reflects all of the information available and that everyone has a certain degree of access to the information. EMH had a significant impact on security investment and can serve as the theoretical basis of event-based stock price movement prediction.

Various studies have found that financial news can dramatically affect the share price of a security. (Cutler et al., 1988) was one of the first to investigate the relationship between news coverage and stock prices, since empirical text analysis technology has been widely used across numerous disciplines. These studies primarily use bags-of-words to represent financial news documents. However, as (Xie et al., 2013) point out, bag-of-words features are not the best choice for predicting stock prices, and they explore a rich feature space that relies on frame semantic parsing. (Wang and Hua, 2014) use the same features as (Xie et al., 2013), but they perform non-parametric kernel density estimation to smooth out the distribution of features. These can be regarded as extensions to the bag-of-word method. The drawback of these approaches is that they do not directly model events, which have structured information.

There have been efforts to model events more directly (Fung et al., 2002; Feldman et al., 2011). Apart from events, to further model the long-term dependency in time series, recurrent neural networks (RNN), especially Long Short-Term Memory (LSTM) network, have also been employed for stock price movement prediction (Akita et al., 2016; Gao, 2016).

(Peng and Jiang, 2016) proposed a system to leverage financial news to predict stock movements based on word embedding and deep learning techniques. Our proposed model incorporates the representation of financial news using BERT, yielding higher accuracy than their model.

3 THE PROPOSED MODEL

The network architecture of our model is shown in Figure 2. The input of BERT is comprised of two parts as `sentence A` and `sentence B`, as shown in Figure 3. In this work, `sentence A` is the concatenation of the stock name with the related news in which it appears, while `sentence B` is the stock trend based on its next day's closing price consulted from the Center for Research in Security Prices (CRSP) financial database (crs, 2018). We feed the inputs into BERT and obtain the BERT representation, the fine-tuned embedding of stock with related news and trends as the BERT features. Specifically, the BERT representation is learned via BERT to indicate the relation of `sentence A` and `sentence B`. In addition, we incorporate enhancing semantics (i.e., bag-of-keywords, polarity score, and category presentation) from online financial news that have been proved to be effective. Finally, we train a discriminative network to predict the referred future trend (either up or down) for stocks.

3.1 BERT Representation

Language model pre-training has shown to be very effective for learning universal language representations by leveraging large amounts of unlabeled data.

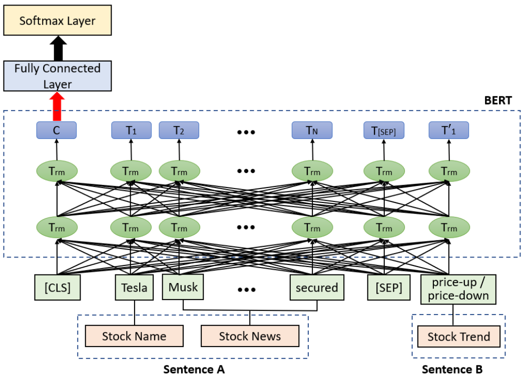


Figure 3: The network of fine-tuning BERT, based on news-trend pairs from our financial news corpus.

Some of the most prominent models are ELMo (Peters et al., 2018), GPT (Radford et al., 2018), and BERT (Devlin et al., 2019). Among these, ELMo uses a bidirectional LSTM architecture, GPT exploits a left-to-right transformer architecture, while BERT uses the bidirectional transformer architecture.

There are two existing strategies for applying pre-trained language models to downstream tasks: feature-based and fine-tuning. The feature-based approach, such as ELMo, uses task-specific architectures that include the pre-trained representations as input features. The fine-tuning approaches, such as GPT and BERT, introduce minimal task-specific parameters and train on the downstream tasks by jointly fine-tuning the pre-trained parameters and task-specific parameters. This two-stage framework has been demonstrated to be very effective in various natural language processing tasks, such as reading comprehension (Radford et al., 2018) and NLI (Devlin et al., 2019).

Inspired by (Devlin et al., 2019), it is essential to embed stock news and trends into the same semantic space constraining similar stock news and trends being close to each other, while dissimilar ones being far away. In this work, as shown in Figure 3, we learn the embeddings by fine-tuning the BERT model with a large number of news-trend pairs from our financial news corpus. We train our model by iterating over the texts and mining the news-trend pairs in the corpus. In the original BERT model, it utilizes the next sequence prediction strategy where two sentences A and B are fed into the model to predict whether B comes following A or not. This strategy drives the model to learn better embeddings of both tokens and sentences by mining their semantic information.

In this work, strategies are developed in constructing the training data of our model to make the training process more reasonable. For example, we are given a sentence, "Musk, co-founder and chief executive officer of Tesla Motors, tweeted he had funding secured". Firstly, as shown in Figure 3, we retain the sentence containing the stock name as the news information to form part of `sentence A`. Secondly, when there are multiple stock names in a sentence, the model will be confused at which stock name we are interested in. To address this problem, we set the `sentence A` as the union of the *stock name* and the *stock news* sentence it lies in, which both include the news information and emphasizes the stock name. Generally speaking, we fine-tune the model by treating the stock name and its news as `sentence A` while the trend as `sentence B`, and they are separated with a special token [SEP]. The label of name-trend pair is based on its next day's closing price consulted from the Center for Research in CRSP database. As for this example, price-up is 1 while the price-down is 0, respectively. Similar to pre-trained BERT, we predict the relation of stock name and trend by adding a fully-connected layer and softmax on top of the BERT representation BERT_{FT}, which is formulated as a classification task.

3.2 Enhancing Data from Historical Prices

Given a stock s, let t and p_x denote a target date and the closing price of s on date x, respectively. Using the CRSP database (crs, 2018), we retrieve the closing prices of s on the five days before t to form a vector $\mathbf{p} = (p_{t-5}, p_{t-4}, p_{t-3}, p_{t-2}, p_{t-1})$. To further enhance the data, we compute the first and second order differences $\Delta\mathbf{p}$ and $\Delta\Delta\mathbf{p}$ as follows:

$$\Delta\mathbf{p} = (p_{t-4}, p_{t-3}, p_{t-2}, p_{t-1}) - (p_{t-5}, p_{t-4}, p_{t-3}, p_{t-2})$$

$$\Delta\Delta\mathbf{p} = (\Delta p_{t-3}, \Delta p_{t-2}, \Delta p_{t-1}) - (\Delta p_{t-4}, \Delta p_{t-3}, \Delta p_{t-2})$$

The enhancing data representation for each stock on a particular date is given by $\mathcal{R}^D = [\mathbf{p}; \Delta\mathbf{p}; \Delta\Delta\mathbf{p}]$.

3.3 Enhancing Semantics from Financial News

We follow (Peng and Jiang, 2016) to preprocess the text data from financial market news corpora. The articles are first divided into sentences, and only the sentences that contain at least a stock symbol, stock name or company name are kept. Each of these sentences is then labeled using the publication date of the original article and the stock name. Such a sentence may mention more than one stock, in which case the sentence is labeled multiple times, once for each mentioned stock.

The sentences are then grouped based on the publication dates and the stock names to form the samples. A sample is defined as a list of sentences in articles published on the same date and mentioning the same stock/company. Using the closing price difference between the published date and its following day (computed from the CRSP database), we label each sample as "positive" (price going up the next day) or "negative" (price going down the next day).

To retrieve enhancing semantics from financial news for the samples, we apply the following methods (Peng and Jiang, 2016): constructing bag-of-keywords, computing polarity scores, and category representation.

Constructing Bags-of-Keywords. We first initialized the vector representations for all words occurring in the training set. Following [19], we manually selected a small set of nine seed words, namely, 'jump', 'gain', 'slump', 'drop', 'surge', 'rise', 'shrink', 'fall', 'plunge', which are considered to be strong indications of stock price movements. We then performed an iterative searching process to collect other useful keywords. In each iteration, we compute the cosine distance between each seed word and other words occurring in the training set. The cosine distance represents the similarity between two words in the word vector space. For example, based on the pre-calculated word vectors, we have found other words, such as 'tumble', 'slowdown', 'rebound', 'decline', and 'climb', which have similar meaning or closely related to one or more seed words listed earlier. The top ten most similar words were chosen and added to the set of seed words at the end of each iteration. The newly added seed words were used to repeat the searching process to find another top ten most similar words, increasing the size of the seed word set with each iteration. The search process stopped when the seed word set reached 1,000 words, including the nine initial seed words. We found that the derived keywords in the final set are very similar in meaning as long as the seed words in the starting set are strong indications of stock price movements. In the last step, we generated a bag-of-keywords, a 1000-dimension feature vector, for each sample after weighting a list of selected keywords with term frequency–inverse document frequency (tf-idf): $\mathcal{R}^K \in \mathbb{R}^{1000}$.

Computing Polarity Scores. Polarity scores (Turney and Pantel, 2010) can be used to measure how accurate each keyword indicates stock movements and the extent of the accuracy. To compute the polarity score, we first compute the point-wise mutual information for each keyword w as follows (Turney and Pantel, 2010):

$$\mathrm{PMI}(w, pos) = \log \frac{\mathrm{freq}(w, pos) \times N}{\mathrm{freq}(w) \times \mathrm{freq}(pos)}, \qquad (1)$$

where $\mathrm{freq}(w, pos)$ denotes the frequency of the keyword w occurring in all positive samples, N denotes the total number of samples in the training set, $\mathrm{freq}(w)$ denotes the total number of keyword w occurring in the whole training set and $\mathrm{freq}(pos)$ denotes the total number of positive samples in the training set. The polarity score for each keyword w can the be calculated as follows:

$$\mathrm{PS}(w) = \mathrm{PMI}(w, pos) - \mathrm{PMI}(w, neg). \qquad (2)$$

It should be noted that when a stock s is mentioned in a sentence, the keyword w in the sentence may not indicate the price movement of s. For example, given the sentence "Google lost half its market share and slipped into third place behind Amazon and Baidu in the second quarter of 2019", which contains the keyword 'slip'. In this sentence, Google is associated with keyword 'slip' while Amazon and Baidu are not. If the sentence is used as a sample for Google, the polarity score of 'slip' is computed as in Eq. (2). On the other hand, if this sentence is used as a sample for Amazon or Baidu, the polarity score of 'slip' is flipped by multiplying by -1. To determine whether a polarity score should be flipped or not, we used the Stanford parser (Manning et al., 2014) to determine whether the target stock is a/the subject of the keyword. If it is, the polarity score stays as is. Otherwise, the sign of the polarity score is flipped. Finally, after being weighted with tf-idf, the polarity score representation $\mathcal{R}^P \in \mathbb{R}^{1000}$ is obtained for each sample.

Category Representation. Certain types of market events are frequently reported in the news such as a company coming out with a new product, acquiring or merging another company, etc. The stock price of the company usually changes accordingly after the publication of such news. To take into account this factor in our model, we use a list of categories (Peng and Jiang, 2016) that indicate such events or activities of publicly listed companies, namely, new products, acquisition, price rise, price drop, law suits, fiscal reports, investment, bankrupt, government, analyst highlights. For each category, we manually assigned a set of words that are closely related to the category. For example, 'accumulated', 'allocate', 'funds', 'loaned' can be seed words of the category *investment* to describe an investment. We used BERT WordPiece embedding and an iterative search process as describe above to expand the list of keywords associated with each category. Words that have the cosine distances closest to those in the current seed word sets are selected until each category reaches 100 words.

After the above process is completed, we counted the total number of occurrences of each word in each category. We then obtained a category representation as $\mathcal{R}^C = (\log N_1, \log N_2, \ldots, \log N_c)$, where N_c is the total number of times the words in category c appear in the sample. In the case where N_c is zero, it is replaced by a large negative number (e.g., -999.9) in this paper.

3.4 Predicting Price Movements of Unmentioned Stocks

The prediction system described above are applicable to only stocks that are reported in the media. However, there are many stocks that are rarely or never mentioned in the news. (The New Stock Exchange has 2,800 companies listed.) In this section we extend the above system to predict price movements of stocks that are not mentioned in the news (unmentioned stocks).

The extension includes the use of a stock correlation graph illustrated in Figure 4. A stock correlation graph is an undirected graph in which each vertex represents a stock and the edge between two vertices represents the correlation between the two stocks. The edge is assigned a weight indicating the correlation coefficient (ranging from -1 and 1) between the two stocks. The higher the correlation coefficient, the more impact one stock has on the other (and vice versa) in terms of price movement. For example, very often prices of stocks in the same sector, e.g., energy, move in tandem with each other due to an event, e.g., an oil crash, resulting in a positive coefficient between two stocks in the sector. To predict price movements of unmentioned stocks on a particular day, the above system is used to predict price movements of stocks mentioned in the news. The obtained results are then propagated in the graph using the correlation coefficients to predict price movements of unmentioned stocks.

To build the correlation graph, we selected the top 5,000 stocks from the CRSP database (crs, 2018) based on their market capitals and retrieved their closing prices for the seven years between January 1, 2012 and December 31, 2018. For every pair of stocks in the set, we kept only the stock pairs that have an overlapped trading period of at least 252 days, the number of trading days in one year. (Stocks can be added to or removed from the stock market.) The minimum duration of one year ensures the reliability of the derived correlation coefficient. During the process of constructing the graph, we discarded the edges whose absolute correlation values are smaller than 0.8 as they were deemed unreliable. In future work, we will assess how this threshold of correlation coefficient affects the prediction performance.

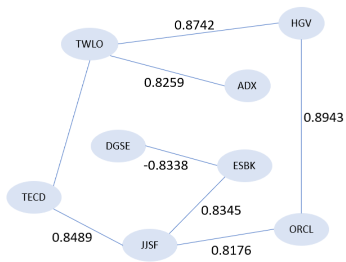


Figure 4: Illustration of a part of correlation graph which contains eight stocks. The symbol in the circle are the ticker name of the stock. The value along the edges are the correlation score of the two stocks connected by that edge.

To predict price movements of the unmentioned stocks, we first run our BERT model to obtain prediction results from the mentioned stocks. The results are then used to construct a vector $\mathbf{x} \in \mathbb{R}^{5000}$. Each of the 5,000 dimensions is associated with a stock and has two values output by our BERT model indicating the probability of price going up and down respectively. If a sample is identified as 'price-down', its probability is multiplied by -1 to be distinguished from a 'price-up' probability. For the unmentioned stocks, the two probability values are set to zero. Let $A \in \mathbb{R}^{5000\times5000}$ be a symmetric matrix that represents the correlation graph. The propagation process through the graph can be implemented as a matrix multiplication as follows: $\mathbf{x}' = A\mathbf{x}$.

The graph propagation is repeated multiple time until $\mathbf{x}'$ converges, which contains predicted price movements of the unmentioned stocks.

4 EXPERIMENTS AND ANALYSIS

4.1 Data Collection

The financial news data used in this paper, which contains 212,347 articles from CNN and 238,265 from CNBC, was collected. The news articles were published in the period from January 2012 to December 2018. For each news article, the publication timestamp, title, and content were extracted. Then, each of the collected news to a specific stock was correlated, if the news mentioned the name of the stock in the title or content. Finally, the news without any correlation to stocks was filtered out.

The historical stock security data are obtained from the CRSP database, which is published by the Chicago Business School and is widely used in financial modeling. The CRSP database is properly adjusted for all special price events such as stock splits as well as dividend yields. We only use the security data from 2012 to 2018 to match the period of financial news. For the following experiments, we split the dataset into a training set (85%) from January 2012 to May 2016, and a test set (15%) from June 2016 to December 2018. Then we further randomly sample a validation set from the training set with 10% size of it, to optimize the hyper-parameters and choose the best epoch.

4.2 Stock Trend Prediction using BERT and Enhancing Semantics

The model in this work has two networks to train, including the fine-tuning of BERT and the stock trend prediction module, we will detail the parameter setting as follows.

In the first set of experiments, we use our BERT model to predict stock trends based on a variety of enhancing semantics, namely bag-of-keywords ($\mathcal{R}^K$), polarity score ($\mathcal{R}^P$) and category presentation ($\mathcal{R}^C$). Considering the memory consumption of GPU, we exploit the uncased $\text{BERT}_{\text{BASE}}$ model for fine-tuning, where the model consists of 12 layers, with 768 hidden units and 12 heads. Therefore, the BERT representation, BERT_{FT}, we obtained is of length 768. As for fine-tuning over our financial news corpus, all hyper-parameters are tuned on the development set. The maximum length, dropout probability and batch size we used are 50, 0.1 and 128, respectively. AdamW (Loshchilov and Hutter, 2018) is applied for optimization with an initial learning rate of 5e-5. The maximum number of epochs is selected from [20, 30, 40].

Specifically, we use the enhancing data representation ($\mathcal{R}^D$) and BERT_{FT} to create the baseline and various enhancing semantics derived from the financial news are added on top of it. We measure the final performance by calculating the accuracy and Matthews Correlation Coefficient (MCC) on the test set. As shown in Table 1, the enhancing semantics derived from financial news can significantly improve the prediction accuracy and MCC score. According to the results in the table, baseline model incorporating $\mathcal{R}^P$ yields higher accuracy than $\mathcal{R}^K$ and $\mathcal{R}^C$. Moreover, baseline model incorporating $\mathcal{R}^P$ and $\mathcal{R}^P$ yields higher accuracy than the other two combinations. Additionally, we have obtained the best performance, i.e., an accuracy score of 58.4% and an MCC score of 0.33, by using all the enhancing representations discussed in Sections 3.2 and 3.3. We have also applied the event embeddings (Ding et al., 2016) and news embeddings (Hu et al., 2018) to the baseline

Table 1: Performance comparison of stock trend prediction on the test set.

System	Accuracy (%)	MCC
(Peng and Jiang, 2016) (word embedding)	55.5	0.25
(Ding et al., 2016) (event embedding)	56.0	0.28
(Hu et al., 2018) (news embedding)	55.8	0.26
$\mathcal{R}^D$	52.3	0.18
Baseline = $\mathcal{R}^D$ + BERT_{FT}	54.9	0.22
Baseline + $\mathcal{R}^K$	55.2	0.24
Baseline + $\mathcal{R}^C$	55.1	0.23
Baseline + $\mathcal{R}^P$	55.8	0.24
Baseline + $\mathcal{R}^K$ + $\mathcal{R}^C$	56.0	0.26
Baseline + $\mathcal{R}^K$ + $\mathcal{R}^P$	57.7	0.28
Baseline + $\mathcal{R}^C$ + $\mathcal{R}^P$	55.9	0.25
Baseline + $\mathcal{R}^K$ + $\mathcal{R}^C$ + $\mathcal{R}^P$	**58.4**	**0.33**

Table 2: The results of 2-by-2 contingency table from a random classifier and our baseline model ($\mathcal{R}^D$ + BERT_{FT}).

		Baseline	
		Correct	**Incorrect**
Random Guess	**Correct**	1501	942
	Incorrect	1114	1443

Table 3: Results of the McNemar test of our BERT models.

System	Accuracy (%)	χ^2	p-value
Random Guess	49.8	n/a	n/a
(Ding et al., 2016) (event embedding)	56.0	69.05	9.60×10^{-17}
(Hu et al., 2018) (news embedding)	55.8	50.49	1.20×10^{-12}
$\mathcal{R}^D$	52.3	14.39	0.00015
Baseline = $\mathcal{R}^D$ + BERT_{FT}	54.9	23.48	1.26×10^{-6}
Baseline + $\mathcal{R}^K$	55.2	28.67	8.58×10^{-8}
Baseline + $\mathcal{R}^C$	55.1	26.52	2.61×10^{-7}
Baseline + $\mathcal{R}^P$	55.8	34.53	4.20×10^{-9}
Baseline + $\mathcal{R}^K$ + $\mathcal{R}^C$	56.0	42.55	6.89×10^{-11}
Baseline + $\mathcal{R}^K$ + $\mathcal{R}^P$	57.7	66.31	3.85×10^{-16}
Baseline + $\mathcal{R}^C$ + $\mathcal{R}^P$	55.9	36.72	1.36×10^{-9}
Baseline + $\mathcal{R}^K$ + $\mathcal{R}^C$ + $\mathcal{R}^P$	**58.4**	**74.42**	6.32×10^{-18}

and the results are also listed in Table 1, which shows that our enhancing semantic representations produce better performance in predicting a pool of individual stock price trends.

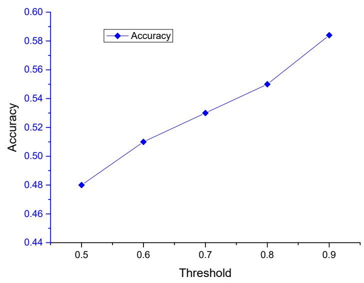
Furthermore, the accuracy of our best model (Baseline + $\mathcal{R}^K$ + $\mathcal{R}^C$ + $\mathcal{R}^P$) is much higher than (Peng and Jiang, 2016) (i.e., 2.9%, 58.4% vs 55.5%). It confirms the effectiveness of representations of financial news using BERT.

To verify the significance of different models by comparing the result of different enhancing representation combinations with the result of random classifier (the results are generated by random guess), we applied the McNemar test (McNemar, 1947), which is a statistical experiment used on paired nominal data. McNemar's test is applied on a 2-by-2 contingency table, which tabulates the outcomes of two tests on a sample of n subjects. In a McNemar test, a *null hypothesis* is defined such that the marginal probabilities in the contingency table are the same, whereas an *alternative hypothesis* is defined such that the marginal probabilities are not the same.

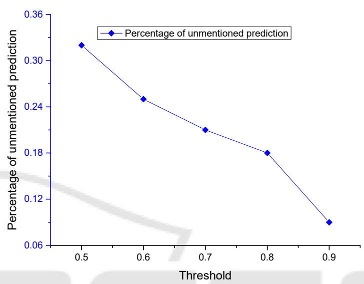
In particular, we define the null hypothesis as follows: *the predictive performances of our BERT models with different enhancing representation combinations would be the same as the random classifier*. For the results of each enhancing representation combination listed in Table 1, we created a 2-by-2 contingency table with the results generated by the random classifier and our baseline model with solely enhancing data representation ($\mathcal{R}^D$), as shown in Table 2. Each cell in Table 2 shows the matched result counts of these two classifiers. For instance, the top-left cell shows the number of results predicted correctly by both of the random classifier and our baseline model with solely enhancing data representation ($\mathcal{R}^D$). The McNemar test statistic χ^2 value computed using this table is 14.39 which has a p-value 0.00015. After constructing such a 2-by-2 contingency table for each of our BERT models with different enhancing representation combinations, we compute their χ^2 and p-value, results are shown in Table 3. The p-values are shown in Table 3 are significantly lower than the typical α value of 0.001, which provides strong evidence to reject the null hypothesis of a random guess.

4.3 Prediction Results for Unmentioned Stocks

We use our best model (Baseline + $\mathcal{R}^K + \mathcal{R}^C + \mathcal{R}^P$) to conduct the experiment in this section. We group all outputs from that model based on the dates of all samples on the test set. For each date, we create a vector x based on the model prediction results for all observed stocks and zeros for all unmentioned stocks, as described in section 3.4. Then, the vector is propagated through the correlation graph to generate another set of stock movement prediction. During the propagation, we compute the results by multiplying the vector with the correlation matrix. After the propagation converges, we may apply a threshold ($\tau \in [0,1]$) on the propagated vector to prune all low-confidence predictions. For example, as shown in Figure 4, we only keep correlation connections when correlation score above τ. The prediction of all unmentioned stocks is compared with the actual stock movement on the next day. Experimental results are shown in Figure 5, where the left curve shows the prediction accuracy and the right curve shows the percentage of unmentioned stocks predicted out of the 5000 stocks per day under various pruning thresholds. For example, using a large threshold 0.9, we can predict with an accuracy of 58.4% the price movements of 441 unmentioned stocks per day, in addition to 112 reported stocks per day on the test set.



(a) Accuracy



(b) Percentage of unmentioned stocks predicted

Figure 5: Predicting unmentioned stocks via correlation.

5 CONCLUSION

In this paper, we propose a model using the most recent state-of-the-art language model BERT to predict moving directions of future stock prices. Moreover, we incorporate a correlation matrix which makes use of the underlying relationships among stocks to expand our predictive results. Experimental results show that our proposed methods are simple but very effective, which can significantly improve the stock prediction accuracy on a standard financial database over the baseline system and existing work.

It should be noted that being able to predict the moving direction of stock prices does not necessarily lead to beating the market consistently. First, a certain type of trading strategy is required to be combined with the predictive results to make meaningful profit. Second, the amount of price change is another factor that should be used to compute the return on investment before making trade decisions. Therefore, the developments of a set of trading strategies and a system that predicts the return on investment are potential future research topics.

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