Listening to Chaotic Whispers: A Deep Learning Framework for News-oriented Stock Trend Prediction

Ziniu Hu, Weiqing Liu, Jiang Bian, Tie-Yan Liu, Xuanzhe Liu

ABSTRACT

Stock trend prediction plays a critical role in seeking maximized profit from stock investment. However, precise trend prediction is very difficult since the highly volatile and non-stationary nature of stock market. Exploding information on Internet together with advancing development of natural language processing and text mining techniques have enable investors to unveil market trends and volatility from online content. Unfortunately, the quality, trustworthiness, and comprehensiveness of online content related to stock market varies drastically, and a large portion consists of the low-quality news, comments, or even rumors. To address this challenge, we imitate the learning process of human beings facing such chaotic online news, driven by three principles: *sequential content dependency*, *diverse influence*, and *effective and efficient learning*. In this paper, to capture the first two principles, we designed a Hybrid Attention Networks (HAN) to predict the stock trend based on the sequence of recent related news. Moreover, we apply the self-paced learning mechanism to imitate the third principle. Extensive experiments on real-world stock market data demonstrate the effectiveness of our approach. Further simulation illustrates a straightforward trading strategy based on our prediction model can significantly increase the annualized excess return.

ACM Reference format:
Ziniu Hu, Weiqing Liu, Jiang Bian, Tie-Yan Liu, Xuanzhe Liu. 2016. Listening to Chaotic Whispers: A Deep Learning Framework for News-oriented Stock Trend Prediction. In *Proceedings of ACM Conference, Los Angeles, CA, USA, Feb 2018 (WSDM'18),* 9 pages.
DOI: 10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

In order for seeking maximized profit, stock investors continuously attempt to predict the future trends of market [20], which, however, is quite challenging due to highly volatile and non-stationary nature of market [1]. Traditional efforts on predicting the stock trend have been carried out based on information from various fields. One of most basic ways relies on technical analysis upon recent prices and volumes on the market. Such methods yield the very limitations on unveiling the rules that govern the drastic dynamics of the market. Meanwhile, another basic method focuses on analyzing financial statements of each company, which is though incapable of catching the impact of recent trends.

With the rapid growth of Internet, content from online media has indeed become a gold mine for investors to understand market trends and volatility. Even more, the advancing development of Natural Language Processing techniques has inspired increasing efforts on stock trend prediction by automatically analyzing stock-related articles. For instance, Tetlock et al. [24] extracts and quantifies the optimism and pessimism of Wall Street Journal reports, and observes that trading volume tends to increase after pessimism reports and high pessimism scored reports tend to be followed by a down trend and a reversion of market prices.

Not surprisingly, the effectiveness of such textual analyses depends on the quality of target articles. For instance, comparing with reading a comprehensive report of a company from Wall Street, analyzing a simple declarative news about this company is less likely to produce an accurate prediction. Unfortunately, the quality, trustworthiness, and comprehensiveness of online content related to stock market varies drastically, and a large portion of the online content consists of the low-quality news, comments, or even rumors.

To address these challenge, we imitate the learning process of human beings facing such chaotic online news, which can be summarized into three principles:

- **Sequential Context Dependency**: Even if individual news is very likely to be of low-quality or not informative enough, human can comprehensively consider a sequence of related recent news as a unified context of the stock and consequently make more reliable prediction on the subsequent stock trend. More importantly, within the unified sequential context, human can pay different attention to various parts according to their respective importance and influence.
- **Diverse Influence**: While the influence of different online news can be diverse greatly, human beings can discriminate them based on the intrinsic content. For instance, some breaking news (e.g. air crash, military conflict) will profoundly affect the trend of related stocks, whilst some useless comments or vague rumors may cause little disturb on the stock trends. In real-world investment, people tend to consciously and comprehensively consider the estimated impact of each news at the time of predicting the subsequent stock trend.
- **Effective and Efficient Learning**: News cannot always provide obviously informative indication on stock trend, especially when the content of news contains vague information on stock trend or even there is very limited number of news of certain stocks in a period. In order for both effective and efficient learning, human beings tend to first gain knowledge by focusing on informative occasions, and then turn to disturbing evidences to obtain uneasy experience.

To capture the first two principles of humanfis learning process, we design a Hybrid Attention Networks (HAN) to predict the stock trend based on the sequence of recent related news. First, to imitate the humanfis cognition on sequential context with diverse attentions, we construct an attention-based recurrent neural networks (RNN) at the higher level. In particular, the RNN structure enables the processing of recent related news for a stock in a unified sequence, and the attention mechanism is capable of identifying more influential time periods of the sequence. Second, to further model

WSDM'18, Los Angeles, CA, USA
2016. 978-x-xxxx-xxxx-x/YY/MM...$15.00
DOI: 10.1145/nnnnnnn.nnnnnnn

diverse influence of news, we propose a news-level attention-based neural networks at the lower level, which aims at recognizing more important news from others within the same time point.

To imitate the effective and efficient learning of human, we employ the self-paced learning (SPL) [13] mechanism to make the training process more effective. Since the news-based stock trend prediction is more challenging in some situations, SPL enables us to automatically skip those training samples from some challenging periods in the early stage of model training, and progressively increase the complexity of training samples. Self-paced learning mechanism can automatically choose the suitable training samples for different training stage, which enhanced the final performance of our model.

To validate the effectiveness of our approach, in this paper, we will perform extensive experiments on real-world data. Comparing with traditional approaches, the experiment results show that our method can significantly improve the performance of stock trend prediction. Furthermore, we simulated the stock investment using a simple trading strategy based on our trend prediction model, and the results illustrate that our trading strategy can achieve much better annualized excess return than the baseline methods.

To sum up, the contributions of our work include:

- A summarization of principles for imitating the learning process of human beings, particularly for stock trend prediction from chaotic online news.
- A Hybrid Attention Networks with self-paced learning for stock trend prediction, driven by principles of humanfis learning process.
- Experimental studies on real-world data with simulated investment performance based on real stock market.

The rest of the paper is organized as follows. We introduce related work in Section 2. We presents empirical analysis to reveal principles for designing news-oriented stock prediction framework in section 3, based on which we propose a new deep learning framework with details in Section 4. Experimental setup and results are demonstrated in Section 5. We conclude the paper and point out future directions in Section 6.

2 RELATED WORK

Stock trend prediction has attracted many research efforts due to its decisive role in stock investment. In general, traditional approaches can be categorized two primary approaches: technical and fundamental analysis, according to the various types of information they mainly relied on.

Technical analysis deal with the time-series historic market-data, such as trading price and volume, and make predictions based on that. The main gaol of this type of approach is to discover the trading patterns that can be leveraged for future prediction. One of the most widely used model in this direction is the Autoregressive (AR) model for linear and stationary time-series [15]. However, the non-linear and non-stationary nature of stock prices limits the applicality of AR models. Hence, previous studies attempted to applied non-linear learning methods [19] to catch the complex patterns underlying the market trend. With the developement of deep learning, more research efforts have been paid on exploiting deep neural networks for financial prediction [2, 8, 12, 14, 21, 25]. 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 in financial predition [3, 7, 22]. In most recent time, Zhang *et al.* [28] proposed a new RNN, called State Frequency Memory (SFM), to discover multi-frequency trading patterns for stock price prediction.

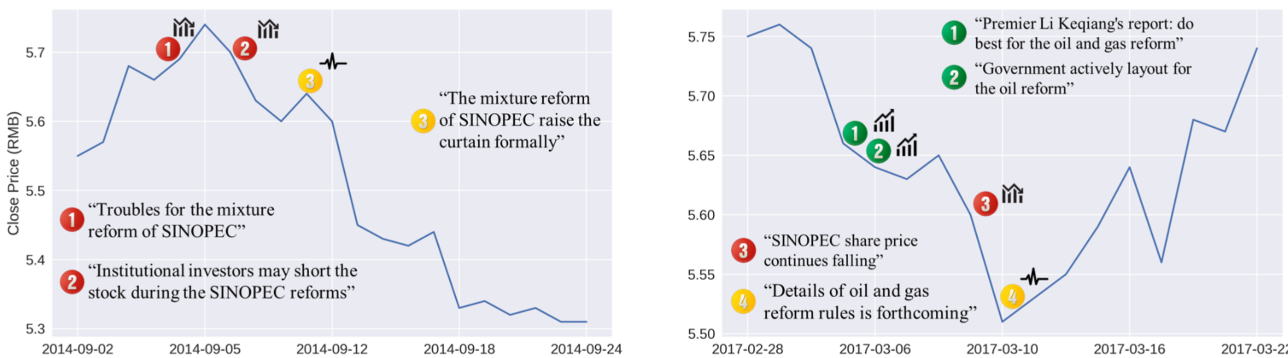
One major limitation of technical analysis is that it is incapable of unveiling the rules that govern the dynamics of the market beyond price data. Fundamental approaches, on the contrary, seek information from outside market-historic-data, such as geopolitics, financial environment and business principles. Information explosion on the Internet has promoted online content, especially news, as one of the most important sources for fundamental analysis. There have been many attempts to mine news data for better predicting market trends. Nassirtoussi *et al.* [18] proposed a multi-layer dimension reduction algorithm with semantics and sentiment to predict intraday directional-movements of a currency-pair in the foreign exchange market. Ding *et al.* [5] proposed a deep learning method for event-driven stock market prediction. They further augmented their approach [6] by incorporating a outside knowledge graph into the learning process for event embeddings. Wang *et al.* [26] performed a text regression task to predict the volatility of stock prices. Xie *et al.* [27] introduced a novel tree representation, and use it to train predictive models with tree kernels using support vector machines. Hagenau *et al.* [10] extract a large scale of expressive features to represent the unstructured text data and employs a robust feature selection to enhance the stock prediction.

Another major aspects for market news mining is to analyze sentiments from public news and social media, and then use it to predict market trends. Li *et al.* [16] implements a generic stock price prediction framework using sentiment analysis. Zhou*et al.* [29] studies particularly the Chinese stock market. They conduct a thorough study over 10 million stock-relevant tweets from Weibo, and find five attributes that stock market in China can be competently predicted by various online emotions. Nguyen *et al.*[23] explicitly consider the topics relating to the target stocks, and extracting topics and related sentiments from social media to make prediction.

While there have been many efforts in exploiting news for stock prediction, few of them paid enough attention to the quality, trustworthiness, and comprehensiveness of news, which highly affects the effectiveness of textual analysis. In this paper, we address the challenge of chaotic news by imitating the learning process of human beings, inspired by which we propose a Hybrid Attention Networks (HAN) to predict the stock trend based on the sequence of recent related news and employ self-paced learning for effective and efficient learning.

3 MOTIVATION & EMPIRICAL ANALYSIS

In this section, through empirical analysis, we will reveal three principles of human learning process with respect to stock trend prediction via chaotic news. These principles will consequently provide essential guidelines in designing our learning framework.



(a) Industry reform of SINOPEC on September, 2014 (b) Industry reform of SINOPEC on March, 2017

Figure 1: An example of two news sequences about the petrol industry reform, jointly shown with the stock price of SINOPEC that is one of the biggest petrol companies in China. In the figure, red, green and yellow circles represent negative, positive and neutral news respectively.

3.1 Sequential context dependency

Due to the diverse quality of online financial news, human investors usually prefer not to rely on individual news to make prediction due to its limited or even vague information. Instead, by broadly analyzing a sequence of news and combining them into a unified context, each news in which can yield complementary correlation and information to others, human can make more reliable prediction on the stock trend.

For example, Figure 1 illustrates two news sequences referring to petrol industry reforms happened in September, 2014 and March, 2017, respectively. The figure also displays the stock share price around the same two periods of SINOPEC, which is one of the biggest petrol companies in China. Undoubtedly, the stock trend of SINOPEC yield tight correlation to these two petrol industry reforms.

From the figure, we can see two yellow circles with the *fluctuation* sign representing two news declaring the launch of two reforms, respectively. By merely referring to these two news, we can hardly tell the future trend of SINOPEC after these two reforms, since they revealed quite limited details about the reforms. However, the difference between these two reforms lies in the respective sequences of previous news. In particular, previous news with the *down* sign in the period of September, 2014, provided strong indication that the reform may probably cause negative effects; while in the period of March, 2017, previous news with the *rise* sign demonstrate quite positive signals. In reality, human investors can naturally synthesize those context information and the news of reform and make more accurate predictions.

Therefore, to imitate such analysis process as a human, an ideal framework should interpret each news in a temporal sequential context, so that the prediction can be drawn by analyzing all the news within a certain time period integratively rather than assessing each of them separately.

3.2 Diverse Influence

Significant news have more intensive and durable influence on the market than those more trivial ones. For example, the third news with the *down* sign in Figure 1(b) summarizes that the stock price of SINOPEC has been continuously going down and offers a negative signal to its future trend. However, compared with the positive news reporting the reform on petrol industry in the same period, this negative one yields much weaker importance. As it turns out later, the stock price of SINOPEC starts to turn around and keeps a strong rising period shortly after one more day dropping down.

Based on this influence diversity phenomenon, we can conclude that when analyzing the news in the sequential context, an ideal framework should have the ability to distinguish those news with more intensive and durable influence from the others, so that the news with the greater influence will be valued more for the prediction.

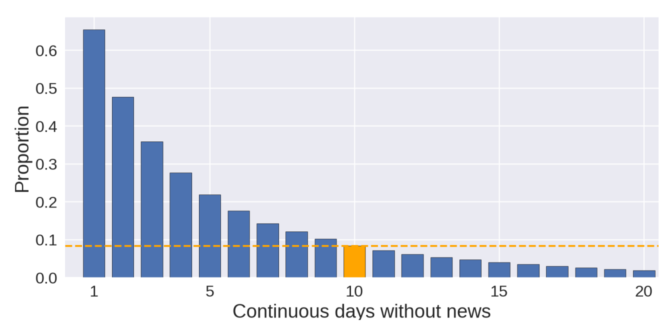


Figure 2: Proportion of the sequence of certain number of consecutive days without news.

3.3 Effective and Efficient Learning

News cannot always provide informative indication on stock trend, especially when there exist only a very limited number of news of certain stocks in a period. According to the online news we collected, Figure 2 shows the occurrence rates of the situation that there is no news about a neglected stock "Jiai Technology" for continuous l days or more. Within those 8.4% of time periods with no news for 10 days or more, it is quite tough to make any news-oriented prediction. Additionally, other situations, such as the aggregating of vague news, also introduce difficulties to the prediction.

Such diverse difficulties in news-oriented stock trend prediction at different time periods have motivated human investors to find a more effective and efficient learning process. In reality, human investors tend to first gain knowledge by focusing on informative occasions, and then turn to uneasy evidences to further optimize their prediction rules. Inspired by this, an ideal learning framework for stock prediction should follow a similar process, which in particular conduct learning on occasions with more informative news at earlier stage, followed by further optimization on hard situations.

4 DEEP LEARNING FRAMEWORK FOR NEWS-ORIENTED TREND PREDICTION

In this section, we first formalize the problem of the stock trend prediction. Then, we present our approach based on the three design principles discussed in Motivation (Section 3). We first proposes a Hybrid Attention Networks(HAN), which consists of two attention layers on the news level and temporal level. Also, we incorporate a self-paced learning mechanism that lets the model choose easier data to learn first so as to improve the model capacity.

4.1 Problem Statement

We regard the problem of stock trend prediction as a classification problem. For a given date t and a given stock s, we can calculate the rise percent for the subsequent date $t+1$ by:

$$Rise\_Percent(t+1) = \frac{Close\_Price(t+1) - Close\_Price(t)}{Close\_Price(t)}$$

Similar to many previous studies, we can divide rise percent into three classes: *DOWN*, *UP*, and *PRESERVE*, representing significant dropping, rising, and steady stock trend on next day, respectively.

The stock trend prediction task can be formulated as the following: given a time sequence length N, the stock s and date t, the goal is to use the news corpus sequence from time $t-N+1$ to t, denoted as $[C_{t-N+1}, C_{t-N+2}, ..., C_{t-1}, C_t]$, to predict the class of $Rise\_Percent(t+1)$, i.e. *DOWN*, *UP*, or *PRESERVE*. Note that, each news corpus C_i contains a set of news with the size of L, $C_i = [n_{i1}, n_{i2}, ..., n_{iL}]$, denoting L related news on day i. Intuitively, the influence of news on a price trend is similar among different stocks. Therefore, we simply build one single classifier to accomplish this task.

4.2 Hybrid Attention Networks

Based on the **Sequential Context Dependency** principle, our framework should analyze and interpret news in a temporal sequential context and pay more attention to the critical time periods based on the context information. In addition, based on the **Diverse Influence** principle, not all news are equally significant for stock trend prediction, our model should distinguish important ones from others. To capture these two principles, we design a hybrid attention network(HAN), which incorporates attention mechanisms at both the news level and the temporal level.

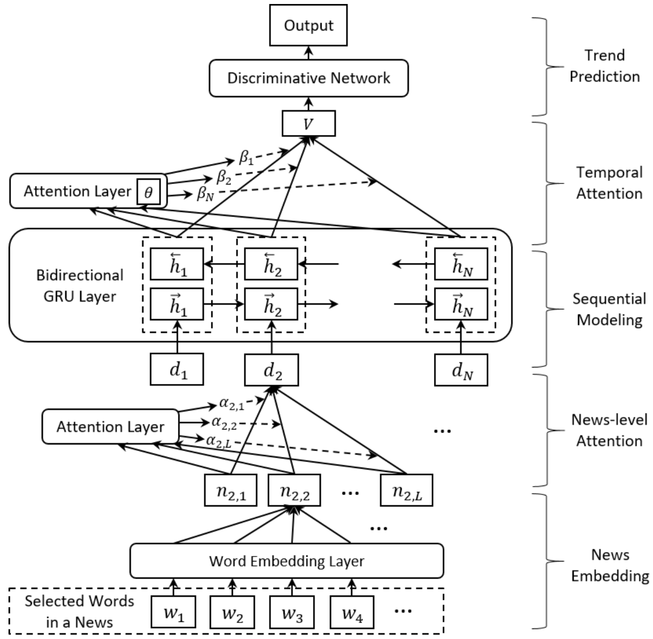


Figure 3: The overall framework of the Hybrid Attention Networks (HAN).

We summarize the overall framework in Figure 3. Given the input of a sequence of news corpus, a news embedding layer will encode each news into a vector n_{ti}. Next, a news-level attention layer first assigns an attention value to each news in a day, then calculate the weighted mean of these news vector as a corpus vector for this day. Afterwards, these corpus vectors are encoded by a bi-directional Gated Recurrent Units (GRU). The output of GRU module represents respective hidden vectors for each day. Next, another temporal attention layer will assign an attention value to each day, then calculate the weighted mean of these hidden values to construct a vector to represent the overall sequential context information for this date, and finally a classification will be made by a discriminative network. The details of the architecture are elaborated below.

News Embedding: For each i^{th} news in news corpus c_t, we use the word embedding to calculate the embedded vector for each word, and then average all the words' vectors to construct a news vector n_{ti}. To reduce the complexity of the framework, we pretrain an unsupervised Word2Vec as the embedding layer rather than tuning the embedded rules in the learning process.

News-level Attention: Since not all news contribute equally to predicting the stock trend, we introduce attention mechanism to aggregate the news weighted by an assigned attention value, in order to reward those news offering critical information. Specifically,

$$u_{ti} = sigmoid(W_n n_{ti} + b_n)$$
$$\alpha_{ti} = \frac{exp(u_{ti})}{\sum_j exp(u_{tj})}$$
$$d_t = \sum_i \alpha_{ti} n_{ti}$$

We first feed the news vector n_{ti} through a one-layer network to get u_{ti}, then calculate a normalized importance weight α_{ti} though a softmax layer. Finally, we calculate the overall corpus vector d_t as a weighted sum of each news vectors respectively, and use this vector to represent all news information for date t.

Thus, we get a corpus vector d_t for each date t, and form a temporal sequence $D = [d_i], i \in [1, L]$. Obviously, the attention layer can be trained end-to-end and gradually learn to assign more attention on those reliable and informative news.

Sequential Modeling: To encode the temporal sequence of corpus vectors, we adopt Gated Recurrent Units (GRU). GRU is a variant of recurrent neural networks that uses a gating mechanism to check the state of sequences without separate memory cells. At date t, the GRU computes the news state h_t by linearly interpolating the previous state $h_t - 1$ and the current updated state $\tilde{h_t}$, as:

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h_t}$$

The current updated state $\tilde{h_t}$ computed by non-linearly combining the corpus vector input for this time-stamp and the previous state, as:

$$\tilde{h_t} = tanh(W_h d_t + r_t * (U_h h_{t-1}) + b_h)$$

where the r_t denotes the reset gate which controls how much past state should be used for update the new state, and z_t is the update gate which decides how much past information is kept and how much new information is added. These two gates are calculated in each date t by:

$$r_t = \sigma(W_r d_t + U_r h_{t-1} + b_r)$$
$$z_t = \sigma(W_z d_t + U_z h_{t-1} + b_z)$$

Therefore, we can get the hidden vector for each date t through GRU, and concatenate the hidden vectors from both directions to construct a bi-directional encoded vector h_t as:

$$\overrightarrow{h_i} = \overrightarrow{GRU}(d_i), i \in [1, L]$$
$$\overleftarrow{h_i} = \overleftarrow{GRU}(d_i), i \in [L, 1]$$
$$h_i = [\overrightarrow{h_i}, \overleftarrow{h_i}]$$

The resulted h_i incorporates both the information of its surrounding context and itself. In this way, we encode the temporal sequence of corpus vector.

Temporal Attention: According to previous discussions, not all days contribute to the prediction equally. Therefore, we have to distinguish the importance difference between these days by introducing the temporal-level attention mechanism as:

$$o_i = sigmoid(W_h h_i + b_h)$$
$$\beta_i = \frac{exp(o_i \theta_i)}{\sum_j exp(o_j \theta_j)}$$
$$V = \sum_i \beta_i h_i$$

where θ is a parameter vector for each day in the softmax layer, indicating in general which day is more significant, and V is a weighted sum of each encoded corpus vectors respectively. By combining both o_i as the hidden representation of corpus content, and the parameter vector θ through the softmax layer, we can get an attention vector β and use it to calculate the weighted sum V. In this way, V can incorporate the sequential news context information with temporal attention, and we use this vector for the following classification task.

Trend Prediction: The top discriminative network is a standard two-layer Multi-layer Perceptron (MLP), which takes V as input and produce the three-class classification of the future stock trend via a softmax function.

4.3 Self-paced Learning Mechanism

As discussed in Section 3.3, there exist some natural challenges of news-oriented stock trend prediction, such as the scarceness of news and the aggregating of vague news, and these challenges cause the crucial learning difficulties for a portion of training samples. To conduct an effective and efficient learning, it is natural to skip those training samples from some challenging periods at the earlier training stage, and progressively increase the complexity of training samples.

Curriculum Leaning [4] is a learning mode that can imitate such learning process. However, the sequence of training samples in curriculum learning is fixed by predetermined heuristics (curriculum), which cannot be adjusted to the feedback from the dynamic learned models. To alleviate this issue, Kuma *et al.* [13] designed Self-Paced Learning (SPL) to embed curriculum design into the learning objective, so it can jointly optimizes the curriculum and the learned model consistently.

Therefore, we take advantage of SPL in our framework to learn the stock patterns iteratively, from first using more reliable samples, then incorporating more samples with noisy labels. More formally, given a training set $D = (x_i, y_i)_{i=1}^n$, where $x_i \in R^m$ denotes all the inputs for the i^{th} observed sample, and y_i represents the corresponding stock trend label. Let $L(y_i, HAN(x_i, w))$ denotes the loss function between label y_i and the output of the whole model $HAN(x_i, w)$, and w represents the model parameter to be learned. Since we want to assign each sample an importance value v_i. The goal of SPL is to jointly learn the model parameter w and the latent weight variable $v = [v1, ..., v_n]$ by:

$$\min_{w, v \in [0,1]^n} E(w, v, \lambda) = \sum_{i=1}^{n} v_i L(y_i, HAN(x_i, w)) + f(v; \lambda) \quad (1)$$

where f denotes a self-paced regularizer which controls the learning scheme for penalizing the latent weight variables, and λ is a hyper-parameter that controls the pace at which the model learns new samples. In this paper, we choose the linear regularizer proposed in [11], which linearly discriminate samples with respect to their loss, as:

$$f(v;\lambda) = \frac{1}{2}\lambda \sum_{i=1}^{n}(v_i^2 - 2v_i) \tag{2}$$

Similar to [13] [11], we adopt Alternative Convex Search(ACS)[9] to solve Equation (1). ACS divides the variables into two disjoint blocks. In each iteration, a block of variables are optimized while fixing the other block. With the fixed w, the unconstrained close-formed solution for the linear regularizer (2) can be calculated by:

$$v_i^* = argmin_v E(w^*, v, \lambda) = \begin{cases} -\frac{1}{\lambda} l_i + 1 & l_i < \lambda \\ 0 & l_i \geq \lambda \end{cases}$$

where v_i^* denotes the i^{th} element in the iterated optimal solution, and l_i denotes loss for each element $L(y_i, ARN(x_i, w))$. In this way, the latent weight for samples that are different to what model has already learned will receive linear penalty.

Algorithm 1 Self-paced Learning.

Require: Input dataset, D; linear regularizer, f; self-paced step size, μ;
Ensure: Model Parameter, w;
1: Initialize v^*, λ in the curriculum region ψ;
2: **while** not converged **do**
3: Update $w^* = argmin_w E(w, v^*, \lambda)$;
4: Update $v^* = argmin_v E(w^*, v, \lambda)$;
5: **if** λ is small **then**
6: increase λ by the stepsize μ;
7: **end if**
8: **end while**
9: **return** w^*;

Based on the optimization equation, the overall learning process can be abstracted as Algorithm1. First, it initializes the latent weight variables in the feasible curriculum region. Then it alternates between two optimization steps described in ACS until it finally converges: Step 3 learns the optimal model parameter with the fixed and most recent v^* by standard back-propagation mechanism; Step 4 learns the optimal weight variables with the fixed w^*. Note that a small initial λ let only samples with small loss affect the learning at the beginning. As the training progresses and λ increases, more samples with larger loss will be gradually appended.

5 EXPERIMENTS

In this section, we first present our experimental setup. Then, we introduce extensive experiments to evaluate the performance of our proposed deep learning framework, followed by a systematic trading simulation to examine the effectiveness of our framework on real-world market.

5.1 Experimental Setup

5.1.1 Data Collection. We obtained the Chinese stock data, including time series in terms of price and trading volume from 2014 to 2017 in daily frequency. There are totally 2527 stocks, covering the vast majority of Chinese stocks.

In the meantime, we collected 1, 271, 442 economic news between 2014 and 2017[1]. For each news, we extracted the publication timestamp, title, and its content.

Then, we correlate each of collected news to individual stocks if the news mentioned the certain stock in its title or content. After that, we filter out those news with no correlation to any stock. After such processing, the total news amount is 425, 250. For each stock, we then aggregate all the news in a certain date to construct the news corpus for this day.

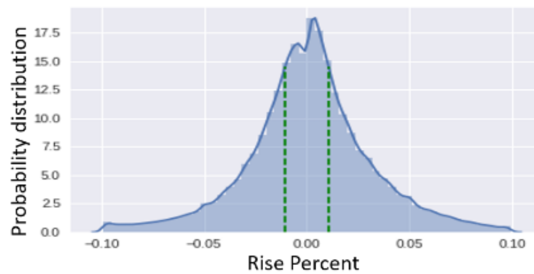


Figure 4: Probability distribution of the rise percent.

5.1.2 Learning Settings. To specify the label of the classification problem, we set up two particular thresholds to bin the rise percents, i.e., *DOWN* ($Rise\_Percent(t+1) < -1\%$), *UP* ($Rise\_Percent(t+1) > 1\%$), *PRESERVE* ($|Rise\_Percent(t+1)| \leq 1\%$). We define the thresholds so that the three categories are approximately even, as is shown in Figure 4.

For the following experiments, we split the dataset into a training set (60%) from Sep 2014 to April 2016, and a test set (40%) from April 2016 to Mar 2017. In all the following experiments, we tokenize each news and remove the stop words and the words appearing less than 5 times to build the vocabulary. We then obtain the word-level embedding by training an un-supervised CBOW Word2Vec[17] model with the dimension of 500 through the whole dataset. We neglect the difference between words in a news, and simply average the word embedding as the raw news vector.

5.1.3 Compared Methods. To evaluate the effectiveness of our proposed deep learning approach, we compare the performance of the following methods:
SVM: we use the SVM with RBF kernel as one baseline. And, we define a corpus embedding for one day by averaging all embedding of news on that day. Then, we concatenate 10 corpus embedding w.r.t. each of previous 10 days as the input to SVM.
RandomForest: we use the RandomForest classifier as one baseline, with the number of trees in the forest as 40. The input format is the same as that of SVM.
MLP: we use the multilayer perceptron classifier as one baseline, with three layers of sizes as 256, 128, and 64, respectively. The input format is the same as that of SVM.
RNN: we use a GRU-based RNN as another baseline. The RNN takes a corpus sequence as the input, each corpus embedding is constructed the same as that of SVM.

[1]The news data are collected from two famous economic websites in China, which are http://www.eastmoney.com/ and http://finance.sina.com.cn/. We plan to release the dataset in the future.

AVG-RNN: we design a special baseline with a hybrid structure similar to our approach, but use a global average pooling as the vector aggregation to replace the two attention layers. This baseline is used to evaluate the effectiveness of the attention mechanism.
HAN: our proposed hybrid attention networks with normal learning process.
HAN-SPL: our proposed hybrid attention networks with self-paced learning process.

Note that all hyper parameters for these models are tuned using grid search via 10-fold cross-validation on the training data.

5.2 Effects of Two Attention Mechanisms

5.2.1 Studies on News Attention. Since the news attention is constructed by a single perception with the embedded news vector as input, we can calculate the attention score for every news pieces. To validate whether our model can select significant news and filter out those less informative ones, Figure 6 shows some detailed case results of the news attention. In this figure, the number in front of the news is the attention value, and it shows example news within three classes that have the lowest, middle, and highest attention scores respectively. From the figure, we can find that the sentences with the lowest attention score merely display the price and the code of the corresponding stock, which obviously have no implication to the future trend; the news with the middle attention score record the previous market performance of the corresponding stock, which provide some information about the stock; and, those with the highest score describes some prediction from official analyst or some significant events, which explicitly contain the predictive information to the market trend. These cases clearly illustrate that our news attention mechanism can indeed distinguish important news from uninformative ones, explaining why it can boost the performance.

5.2.2 Visualization of Temporal Attention. To further illustrate the effect of temporal attention, we calculate all the temporal attention vectors on the testing dataset, and employ the spectral method to generate eight clusters representing various patterns inside attentions, as shown in Figure 5. From this figure, we can find that the attention pattern on the temporal dimension is diverse as well as dynamic, and important news in few days ago can also express their influences.

5.3 Effects of Self-paced learning

To evaluate the effectiveness of self-paced curriculum learning (SPL) on our problem, we compare the result using the SPL and the standard training process. Both the convergence speed and the final result is considered as the comparison metric. As is shown in Figure 7, although the learning speed for SPL is slower than the one without using it, probably because that SPL will neglect the difficult examples first. As the round of epochs increase, the testing accuracy of the model using SPL gradually outperforms the one without using it, and at last converge to a better result.

5.4 Overall Performance

In the experiment setting of a tri-label classification problem, as the three label is approximately evenly split, we choose accuracy, which means the proportion of true results among the total number of testing samples. The final results is shown in Figure 8, in which we evaluate on each stock to calculate the accuracy on each stock in the test dataset, and draw the average accuracy with an error bar indicating the standard variance of the accuracy.

As illustrated in Figure 8, our proposed HAN approaches outperform the other baselines. Specifically, HAN outperform the AVG-RNN with the increase of approximately 2.5% accuracy, indicating the effectiveness of the two attention layers; and HAN-SPL outperforms the HAN with approximately 2% accuracy, indicating the effectiveness of the self-paced learning.

5.5 Market Trading Simulation

To further evaluate the effectiveness of our proposed framework, we take a back-testing by simulating a stock trading for one year, from April, 2016 to March, 2017.

5.5.1 Portfolio Strategy. Our estimation strategy conducts the trading in the daily frequency. At the end of each trading day, the model will give each stock a score based on the probability to have a rise trend. Based on the score ranking, a portfolio strategy will calculate a holding ratio for each stock, and then trade the stocks to fit the new ratio. We adopt a straightforward portfolio strategy called top-K. At the end of each trading day, the strategy will predict the next periods' stock trend, and evenly buy the top K stocks in its ranked list, holding them until the next trading day, at which time the strategy will sell all these stocks and make the next prediction and trading. To approximate the real-world trading, we also consider a transaction cost of 0.3% for each trading. We also calculate the average return of stock market by evenly buy and sell every stock as the baseline.

5.5.2 Simulated Back-Testing Results. To evaluate the performance of each prediction method, we use the annualized excess return as the metric, which is the annualized return compared to the average annualized return of stock market for each method. In reality, investors always choose multiple stocks to avoid risks. Therefore, we evenly invest on top K stocks, where k is set as 20, 40, 60, 80 respectively, to compare the results. As illustrated in Figure 9, the proposed HAN-SPL framework outperforms dramatically to the other baseline methods. With the annualized excess return of 0.662 while invest on top 20 stocks.

We also plot a cumulative profit curve for each methods with K as 40, as is illustrated in Figure 10. As shown in the profit curve, our method not only gains the best profit among all the baseline methods, but also maintains a relatively smooth profit record, without any dramatic fluctuation, indicating that most of the trading instructed by our proposed method do not make excessive loss. This reflects the relatively low-risk of our proposed method.

6 CONCLUSION AND FUTURE WORK

In this paper, we pointed out three principles for news-oriented stock trend prediction, including *sequential context dependency*, *diverse influence* and *effective and efficient learning*, by imitating the learning process of human. Based on these principles, we proposed a new learning framework, particularly a Hybrid Attention Network (HAN) with self-paced learning mechanism, for stock trend prediction from online news. Extensive experiments on real stock

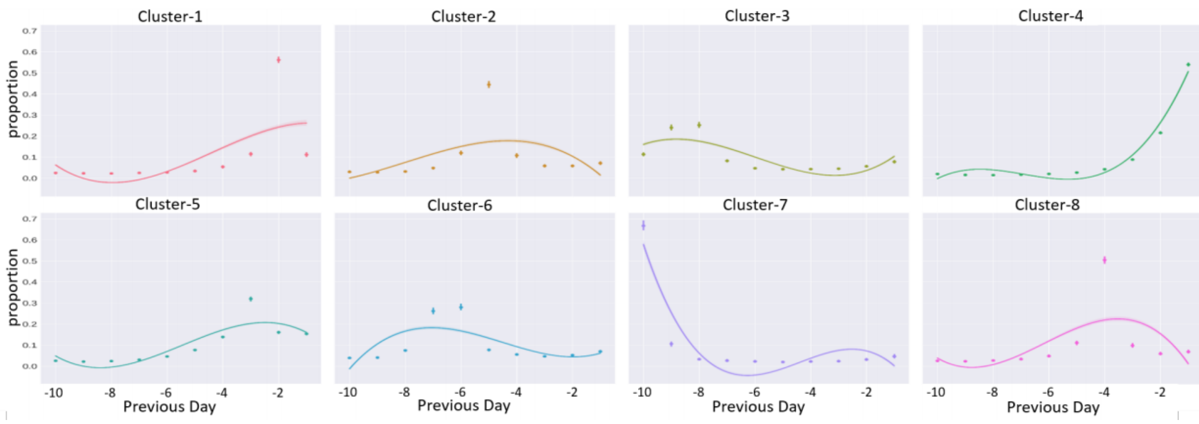


Figure 5: The eight attention weight clusters for temporal attention in different context.

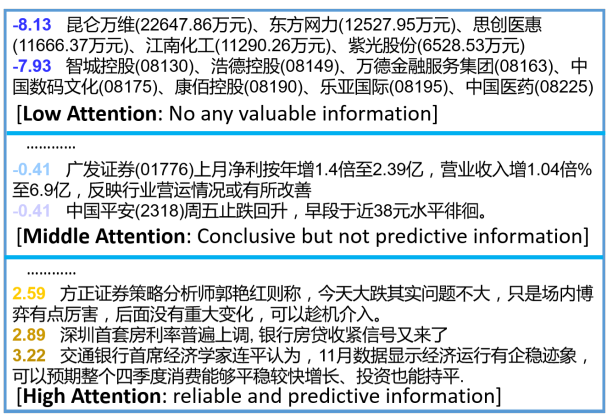


Figure 6: Example news in different levels of news attention.

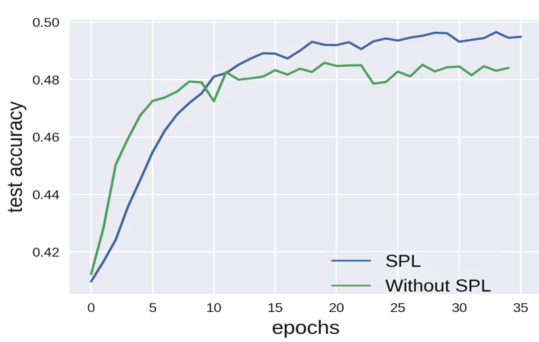


Figure 7: The learning curves of the model using self-paced learning and that without using SPL.

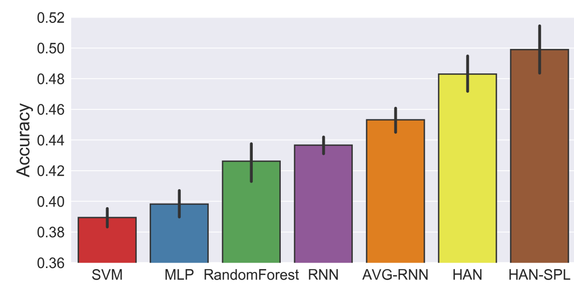


Figure 8: The accuracy result for compared methods, with a confidence intervals illustrating the standard variance.

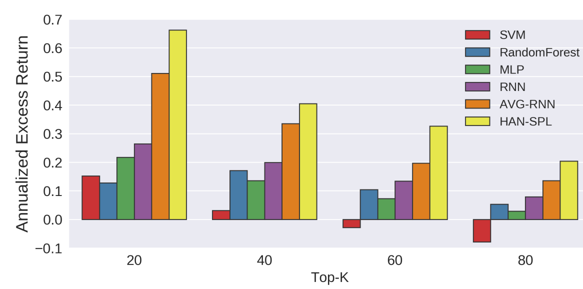


Figure 9: The annualized excess return for compared methods.

market data demonstrated that our proposed framework can result in significant improvement in terms of the accuracy of stock trend prediction. Meanwhile, through back-testing, our framework can produce appreciable profits, with highly increased annualized excess return, in a one-year round trading simulation.

In the future, beyond modeling the sequence of news related to one stock, we plan to further leverage the relationship between news related to different individual stocks, according to their industrial connections in real world. Moreover, we will investigate how to integrate the news-oriented approach with technical analysis for more accurate stock trend prediction.

REFERENCES

[1] K. Adam, A. Marcet, and J. P. Nicolini. Stock market volatility and learning. *The Journal of Finance*, 71(1):33–82, 2016.

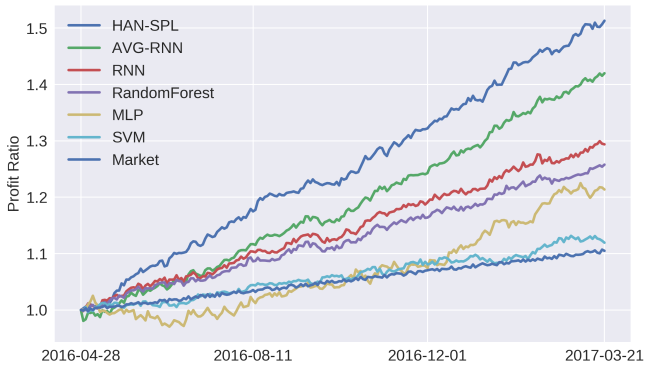


Figure 10: The cumulative profit curve of different methods with the portfolio of choosing top 40 stocks.

[2] A. A. Adebiyi, A. O. Adewumi, and C. K. Ayo. Comparison of arima and artificial neural networks models for stock price prediction. *Journal of Applied Mathematics*, 2014.

[3] R. Akita, A. Yoshihara, T. Matsubara, and K. Uehara. Deep learning for stock prediction using numerical and textual information. In *Computer and Information Science (ICIS), 2016 IEEE/ACIS 15th International Conference on*, pages 1–6, 2016.

[4] Y. Bengio, J. Louradour, R. Collobert, and J. Weston. Curriculum learning. *Journal of the American Podiatry Association*, 60(60):6, 2009.

[5] X. Ding, Y. Zhang, T. Liu, and J. Duan. Deep learning for event-driven stock prediction. In *International Conference on Artificial Intelligence*, pages 2327–2333, 2015.

[6] X. Ding, Y. Zhang, T. Liu, and J. Duan. Knowledge-driven event embedding for stock prediction. In *COLING*, pages 2133–2142, 2016.

[7] Q. Gao. *Stock market forecasting using recurrent neural network*. PhD thesis, University of Missouri–Columbia, 2016.

[8] M. Göçken, M. Özçalıcı, A. Boru, and A. T. Dosdoğru. Integrating metaheuristics and artificial neural networks for improved stock price prediction. *Expert Systems with Applications*, 44:320–331, 2016.

[9] J. Gorski, F. Pfeuffer, and K. Klamroth. Biconvex sets and optimization with biconvex functions: a survey and extensions. *Mathematical Methods of Operations Research*, 66(3):373–407, 2007.

[10] M. Hagenau, M. Liebmann, and D. Neumann. Automated news reading: Stock price prediction based on financial news using context-capturing features. *Decision Support Systems*, 55(3):685–697, 2013.

[11] L. Jiang, D. Meng, Q. Zhao, S. Shan, and A. Hauptmann. Self-paced curriculum learning. In *AAAI Conference on Artificial Intelligence*, 2015.

[12] K.-J. Kim and H. Ahn. Simultaneous optimization of artificial neural networks for financial forecasting. *Applied Intelligence*, pages 887–898, 2012.

[13] M. P. Kumar, B. Packer, and D. Koller. Self-paced learning for latent variable models. 2011.

[14] L. A. Laboissiere, R. A. Fernandes, and G. G. Lage. Maximum and minimum stock price forecasting of brazilian power distribution companies based on artificial neural networks. *Applied Soft Computing*, 35:66–74, 2015.

[15] L. Li, S. Leng, J. Yang, and M. Yu. Stock market autoregressive dynamics: A multinational comparative study with quatile regression. In *Mathematical Problems in Engineering*, 2016.

[16] X. Li, H. Xie, L. Chen, J. Wang, and X. Deng. News impact on stock price return via sentiment analysis. *Knowledge-Based Systems*, 69(1):14–23, 2014.

[17] T. Mikolov, K. Chen, G. Corrado, and J. Dean. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*, 2013.

[18] A. K. Nassirtoussi, S. Aghabozorgi, T. Y. Wah, and D. C. L. Ngo. Text mining of news-headlines for forex market prediction: A multi-layer dimension reduction algorithm with semantics and sentiment. *Expert Systems with Applications*, 42(1):306–324, 2015.

[19] R. K. Nayak, D. Mishra, and A. K. Rath. A naive svm-knn based stock market trend reversal analysis for indian benchmark indices. In *Applied Soft Computing*, 2015.

[20] W. Nuij, V. Milea, F. Hogenboom, F. Frasincar, and U. Kaymak. An automated framework for incorporating news into stock trading strategies. *IEEE Transactions on Knowledge and Data Engineering*, 2(11):823–835, 2014.

[21] J. Patel, S. Shah, P. Thakkar, and K. Kotecha. Predicting stock market index using fusion of machine learning techniques. *Expert Systems with Applications*, 42(4):2162–2172, 2015.

[22] A. M. Rather, A. Agarwal, and V. Sastry. Recurrent neural network and a hybrid model for prediction of stock returns. *Expert Systems with Applications*, 42(6):3234–3241, 2015.

[23] J. Si, A. Mukherjee, B. Liu, Q. Li, H. Li, and X. Deng. Exploiting topic based twitter sentiment for stock prediction. *ACL (2)*, 2013:24–29, 2013.

[24] P. C. Tetlock. Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance*, 62(3):1139fi?!1168, 2007.

[25] J. L. Ticknor. A bayesian regularized artificial neural network for stock market forecasting. *Expert Systems with Applications*, 40(14):5501–5506, 2013.

[26] W. Y. Wang and Z. Hua. A semiparametric gaussian copula regression model for predicting financial risks from earnings calls. In *Meeting of the Association for Computational Linguistics*, pages 1155–1165, 2014.

[27] B. Xie, R. J. Passonneau, L. Wu, and G. G. Creamer. Semantic frames to predict stock price movement. In *Meeting of the Association for Computational Linguistics*, pages 873–883, 2013.

[28] L. Zhang, C. Aggarwal, and G.-J. Qi. Stock price prediction via discovering multi-frequency trading patterns. In *Proc. of KDD*, 2017.

[29] Z. Zhou, J. Zhao, and K. Xu. Can online emotions predict the stock market in china? In *International Conference on Web Information Systems Engineering*, pages 328–342. Springer, 2016.