Sentiment-Aware Stock Market Prediction: A Deep Learning Method

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***Abstract*—Stock market prediction has attracted much attention from academia as well as business. However, it is a challenging research topic, in which many advanced computational methods have been proposed, but not yet attained a desirable and reliable performance. This study proposes a new method for stock market prediction, which adopts the Long Short-Term Memory (LSTM) neural network and incorporates investor sentiment and market factors to improve forecasting performance. By extracting investor sentiment from forum posts using Naïve Bayes, this paper makes it possible to analyze the irrational component of stock price. Our empirical study on CSI300 index proves that our prediction method provides better prediction performance . It gives a prediction accuracy of 87.86%, outperforming other benchmark models by at least 6%. Furthermore, our empirical study reveals evidence that helps to better understand investor sentiment and stock behaviors. Finally, this work shows the potential of deep learning financial time series in the presence of strong noises.**

Keywords—investor sentiment; deep learning; stock market prediction

I. INTRODUCTION

With the continuous expansion of Chinese stock market, more and more people have begun to carry out scientific and detailed research attempting to define the rules by which the stock market operates which are seemingly divergent. With emerging indicators to evaluate stock market, investors are trying to extract features as they can from all aspects so that they can predict the market changes. Early research on stock market prediction [1, 2, 3] was based on random walk theory and the Efficient Market Hypothesis (EMH) [4]. According to the EMH stock market prices are largely driven by new information, i.e. news, rather than present and past prices. Since news is unpredictable, stock market prices will follow a random walk pattern and cannot be predicted with more than 50% accuracy [5].

A growing body of research has, however, critically examined EMH [6], in particular form the perspective of the Socionomic Theory of Finance (STF) [7, 8], behavioral economics [9] and behavioral finance [10]. Numerous studies show that stock market prices do not follow a random walk and can indeed, to some degree, be predicted [5,11,12,13] thereby calling into question EMH's basic assumptions. For example, recent theoretical studies in behavioral finance have demonstrated that emotion influences investment decisions [14, 15]. It is therefore reasonable to assume that the public mood and sentiment can drive stock market values. Such an inference was further confirmed by the findings of Li [16] and Schumaker et al. [17]. The authors discovered that the sentiments contained in financial reports or news articles affect stock returns.

However, if it is our goal to study how investor sentiment influences the stock market, we need early assessments of the public mood that are both reliable and scalable at a time-scale and resolution appropriate for practical stock market prediction. Over the past years significant progress has been made in sentiment analysis techniques that extract indicators of public mood directly from social media content such as blog content and forum texts. Tetlock [18], Tetlock et al. [19], and Chen et al. [20] report that views (particularly negative views) expressed in news and social media forecast a firms' earnings and stock returns. Antweiler and Frank [21] downloaded text messages from Yahoo! Finance and RagingBull.com on some relatively large-sized firms in the calendar year 2000, and report that a positive shock to message board posting predicts negative returns on the next trading day and that investor sentiment from Internet posting messages has predictive power for volatility and trading volume.

Forecasting highly volatile financial time series, e.g. stock returns at an intermediate frequency, could be challenging task in the presence of strong noise. Artificial neural networks are good nonlinear function approximates [22], so they are a natural approach to consider with modeling time series which are suspected to have non-linear dependence on inputs. It is indeed not new to forecast financial time series using machine learning methods and recurrent neural networks are well-suited for this task. This early work [23] is among the first a few which use recurrent neural nets to predict stock prices, [24] instead reported a volatility forecasting model, [25] incorporated public mood data in the up and down direction prediction of market fund Dow Jones Industrial Average. Recently a particular type of recurrent neural network named Long Short-Term Memory (LSTM) [26] has shown remarkable results in tasks such as artificial handwriting generation [27], language forecasting [28] and speech recognition [29].

As a special type of Recurrent Neural Netorks (RNN), LSTM can learn long-term reliance on information, and in many cases, it has achieved considerable success and has been widely used. We consider it a very suitable model to describe the characteristics of the stock market. On the other hand, lots of

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research suggests that investor sentiment may cause prices to deviate from the underlying fundamentals. In this work, we attempt to predict the CSI300 prices using the LSTM which incorporate the investor sentiment extracted from forum texts together with market data. The rest of this paper is organized as follows. Section Ⅱ introduces previous related work in the area of predicting stock market with investor sentiment. The dataset and primary technical methods are detailed in section Ⅲ. Section Ⅳ and Section Ⅴ discusses the experimental results and review the limitations. Finally we briefly conclude the paper in Section Ⅵ.

II. RELATED WORK

This section briefly surveys related work on stock market prediction using investor sentiment.

One area of research concentrates on predicting the stock market using econometrics models. Lee et al. used the investors intelligence (II) sentiment index and employed a generalized autoregressive conditional heteroscedasticity-in-mean (GARCH) specification to test the impact of noise trader risk on both the formation of conditional volatility and expected return [30]. Baker and Wurgler used the principal component analysis to construct an investor sentiment index, and predicted that a group of investor sentiment had larger effects on securities whose valuations were highly subjective and difficult to arbitrage [31]. Brown and Cliff investigated investor sentiment and its relation to near-term stock market returns, and found that although sentiment levels and changes were strongly correlated with contemporaneous market returns, the test showed that sentiment had little predictive power for near-term futures stock returns [32].

Another area of research is that of capturing media influence on stocks and bridging some connections based on artificial intelligence and natural language processing techniques. In particular, Schumaker and Chen experimented with several textual representative approaches, and found that representing news with proper nouns was most efficient [33]. Xiong et al. applied the Long Short-Term Memory neural network to model S&P 500 volatilities incorporating Google domestic trends as indicators of the public mood and macroeconomic factors, and developed a neural network model outperforming other linear and autoregressive benchmark models by at least 31%. Their work shows the potential of deep learning financial time series in the presence of strong noise [34].

Most research based on deep learning are only using stock history data and market trading indicators as input variables. In this paper, we integrate investor sentiment and related market data into a deep learning model to forecast a future stock price.

III. METHODOLOGY

A. Methods Overview

As shown in Fig. 1 we proceed in three phases. In the first phase, we employ a Naïve Bayes method to classify these posts into one of three categories: positive, negative, or neutral. In the second phase, we construct an investor sentiment index to measure the daily mood of stock market. In the third phase, we deploy a Long Short-Term Memory model to test the hypothesis that the prediction accuracy of stock market prediction models can be improved by including measurements of investor sentiment.

B. Naïve Bayes Classification

To implement the sentiment classification on our document data, we used the following standard bag-of-features framework. Let $\{f_1, \ldots, f_m\}$ be a predefined set of m features that can appear in a document. Let $n_i(d)$ be the number of times f_i occurs in document d. Then, each document d is represented by the document vector $\vec{d} = (n_1(\mathrm{d}), n_2(\mathrm{d}), \ldots, n_m(\mathrm{d}))$.

One approach to text classification is to assign to a given document d the class $c^* = argmax_c P(c|d)$. We derive the Naïve Bayes (NB) classifier by first observing through Bayes' rule,

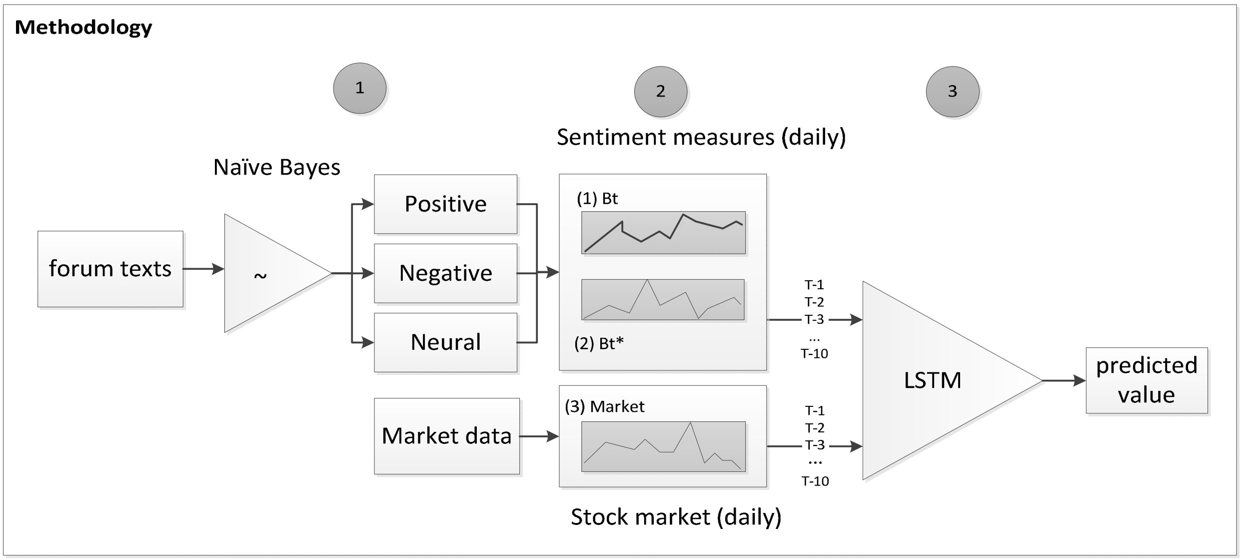

Figure 1. Methodology

$$P(c|d) = \frac{P(c)P(d|c)}{P(d)} \quad (1)$$

where P(d) plays no role in selecting c^*. To estimate the term P(d|c), Naïve Bayes decomposes it by assuming the f_i's are conditionally independent given d's class:

$$P_{NB}(c|d) = \frac{P(c)\prod_i^m P(f_i|c)^{n_i(d)}}{P(d)} \quad (2)$$

Our training method consists of relative-frequency estimation of P(c) and P(f_i|c), using add-one smoothing.

C. Measures of Investor Sentiment

Following Antweiler and Frank [21], as a proxy for investor sentiment, we construct measure of investor sentiment based on explicitly revealed sentiment. The first revealed sentiment measure is defined as

$$B_t = \frac{M_t^{pos} - M_t^{neg}}{M_t^{pos} + M_t^{neg}} \quad (3)$$

where $M_t^c = \sum_{i \in D(t)} w_i x_i^c$ denotes the weighted sum of posts of type c ∈ $\{pos, nue, neg\}$ in time interval D(t), where x_i^c is an indicator variable that is one when post I is of type c and zero otherwise, and w_i is the weight of the post. When the weights are all equal to one, M_t^c is simply the number of posts of type c in the given time interval. Furthermore, let $M_t = M_t^{pos} + M_t^{neg}$ be the total number of "revelant" posts. The second revealed sentiment measure is defined as

$$B_t^* = \ln\left[\frac{1+M_t^{pos}}{1+M_t^{neg}}\right] \approx B_t \ln(1 + M_t) \quad (4)$$

This measure considers the number of traders expressing a particular sentiment, and is mostly used in their research.

For our analysis, we sum up the messages from stock forums to measure the sentiment of stock market and focus on the case in which each post is weighted equally($w_i = 1$). Also, we select one day as the time period to ensure sufficient samples and prevent over-fitting. For a specific trading day, the corresponding sentiment measures are calculated using posts recorded from 15:00 of the last trade day to 15:00 of the current trade day.

D. Long Short-Term Memory Model for Stock Prediction

In our recurrent neural network modeling of stock prediction, a Long Short-Term Memory (LSTM) model is employed for each input time series. The structure of this neural network is shown in Fig. 2 [34]. It has a dynamic "gating" mechanism. Running through the center is the cell state I_i which we interpret as the information flow of the market sensitivity. I_i has a memory of past time information [26] and more importantly it learns to forget [35] through Equ. 5.

$$I_i = f_i \cdot I_{i-1} + c_i \cdot \tilde{I}_i \quad (5)$$

Here f_i is the fraction of past-time information passed over to the present, $\tilde{I}_i$ measures the information flowing in at the current time and c_i is the weight of how important this current information is. Equ. 5 answers the fundamental question of memory in time series forecasting. It is an equivalent as

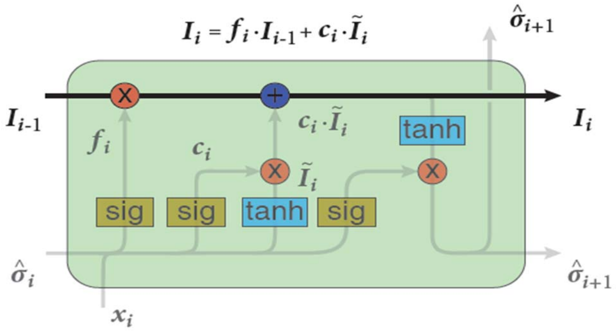

Figure 2. Structure of LSTM [34]

evaluating autocorrelation and partial autocorrelation functions to determine the p and q maximum lags in the autoregressive moving average model(ARMA(p,q)) [36].

All coefficients here are learned through training with the python deep learning library Keras [37]. Specifically, we set up the maximum lag to include 10 continual observations. The model is trained by the "rmsprop" method with 64 examples in a batch, with categorical cross entropy as the objective loss function and validation fraction as 5%. Moreover, data points are shuffled during training, and the learning rate has been set at 0.02 in our work [38] and all initial weights are set to be small positive constant terms, similar to the normalized initialization given in [39]. To prevent overfitting, the dropout has been set at 20% and we add a L2 regularization constraint with parameter 0.01.

IV. Empirical Results

A. Datasets

In this study, we capture the investor sentiment from messages in discussion boards. Specifically, we apply our focused Web crawler to download postings from guba.eastmoney.com, a popular stock discussion forum. We collect more than 18 million posts from constituent stocks of CSI300 index that had been recorded between January 1, 2009 and October 31, 2014. In addition, we extract open-values, closing-values and volume of daily CSI300 index from Wind database to generate time series.

B. Sentiment Classification and Measurement

We start by manually classifying a training data set of 5,000 posts. We invite ten financial practitioners to carry out emotional annotations, each marked 1000, to ensure that each post has two staves marked. For the post with different marks, we have a third expert mark it and take the majority of the label as the final label of the post. Finally, we have 1586 positive posts, 1765 negative posts and 1649 neutral posts.

To test the classification model, we carry out a 5-hold cross-validation. As shown in Table. 1, we can see that the positive and neutral classes have higher precision than that of the negative class, while negative class has a much higher recall than the other two classes, especially than the neutral class. This shows that many samples from the neutral class are assigned to

TABLE I. NAÏVE BAYES CLASSIFICATION PERFORMANCE

Id	Negative			Positive			Neutral		
	p	***r***	***f***	***p***	***r***	***f***	***p***	***r***	***f***
1	53.35%	83.8%	65.2%	74.73%	70.47%	72.54%	73.05%	38.87%	50.74%
2	55.31%	82.51%	66.23%	68.65%	63.6%	66.03%	67.36%	35.53%	46.52%
3	55.74%	86.62%	67.83%	72.59%	67.38%	69.89%	71.43%	36.26%	48.1%
4	53.93%	85.41%	66.12%	68.98%	62.83%	65.76%	67.9%	36.42%	47.41%
5	54.07%	86.59%	66.57%	72.49%	64.34%	68.17%	75.18%	37.59%	50.12%

a. p-precision r-recall f-2*p*r/(p+r)

the negative class, which means the negative samples and the neutral samples are difficult to distinguish.

We then aggregate the classification results into indices that measure investor sentiment during each period. In our analysis, we take one day as the time period. As shown in Fig. 3, it is easy to see that the majority of the time we studied was in a stock market downturn, and that the corresponding investor sentiment measure was generally negative during the entire sample period, indicating that investors were generally bearish in the market during the sample period.

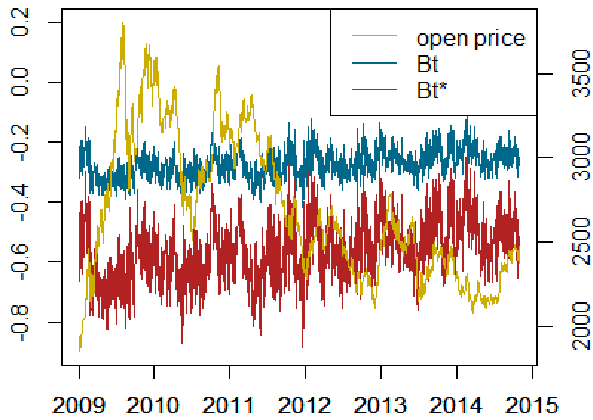

Figure 3. CSI300 index and sentiment measures

C. Sentiment-aware Stock Market Prediction-Open Price

To address the effects and assess the contribution that investor sentiment can make in predictive models of CSI300 index, we compare the performance of a Long Short-Term Memory model that predicts CSI300 open-values on the basis of two sets of inputs: (1) the past 10 days of CSI300 data including open-values, closing-values and volumes, and (2) the same combined with the measure of investor sentiment. We also normalize the input to reduce prediction error by dividing each input value by the last input value, in this case it is divided by the 10th value.

As described in Section III, we employ a LSTM model for each input time series, and combine them to a merge layer, followed by an ReLU linear layer and a SoftMax linear layer, to generate 2 outputs, corresponding to the possibility of the price rising or falling.

To properly evaluate the LSTM model's ability to predict daily CSI300 open prices, January 1, 2009 to March 21, 2014 (1263 trade days) is chosen as the training period while March 24, 2014 to October 31, 2014 (140 trade days) is chosen as the test period. We investigate three permutations of input variables to the LSTM model, the first of which, denoted I_0, represents a naïve, baseline model that has been trained to predict CSI300 open-prices at time t from the historical values at time $\{t-1, t-2, \ \dots, t-10\}$:

$$I_0 = \{CLOSE_{t-10,9,\dots,1}, OPEN_{t-10,9,\dots,1}, VOLUME_{t-10,9,\dots,1}\}$$

$$I_1 = \left\{\begin{matrix} CLOSE_{t-10,9,\dots,1}, OPEN_{t-10,9,\dots,1}, VOLUME_{t-10,9,\dots,1}, \\ B_{t-10,9,\dots,1} \end{matrix}\right\}$$

$$I_2 = \left\{\begin{matrix} CLOSE_{t-10,9,\dots,1}, OPEN_{t-10,9,\dots,1}, VOLUME_{t-10,9,\dots,1}, \\ B^*_{t-10,9,\dots,1} \end{matrix}\right\}$$

$CLOSE_{t-10,9,\dots,1}, OPEN_{t-10,9,\dots,1}, VOLUME_{t-10,9,\dots,1}$ represents respectively the CSI300 closing-prices, open-prices, and volume at time t-10, t-9, …, t-1, while $B_{t-10,9,\dots,1}$ and $B^*_{t-10,9,\dots,1}$ represents the sentiment measures (described above) at time t-10, t-9, …, t-1. LSTM model requires the tuning of a number of parameters that can influence the performance of the model. We maintain the same parameter values across our various input combinations to allow an unbiased comparison of model performance. In addition, to evaluate the performance of the LSTM model, we have developed a SVM as the benchmark model.

Forecasting accuracy is measured in terms of the direction accuracy (up or down), as well as the precision, recall, and F-measure during the test period (March 24, 2014 to October 31, 2014). The prediction results are shown in Table. 2. We can draw several conclusions from these results. First, the LSTM model shows much better performance than SVM, despite different inputs.

Second, among three LSTM model experiments, we find adding B_t, i.e. the input I_1, can get highest prediction accuracy. Compared to I_0 and I_2 , adding I_1 leads to significant improvements in accuracy (87.86% compared to 78.57% for I_0 and 81.43% for I_2). Thirdly, the LSTM model with B_t as input receives almost every indicator better than the LSTM model with B_t^* as input, except the recall of the down class (both 86.76%), indicating that we should use B_t as a predictive message for the next day's open price. However, in the SVM

TABLE II. CSI300 OPEN PRICE PREDICTION

Input & Method	Up			Down			*Accuracy*
	Precision	***Recall***	***F***	***Precision***	***Recall***	***F***	
I_0 + SVM	60%	37.5%	46.15%	52.63%	73.53%	61.35%	55%
I_1 + SVM	62.5%	41.67%	50%	54.35%	73.53%	62.5%	57.14%
I_2 + SVM	63.83%	41.67%	50.42%	54.84%	75%	63.35%	57.86%
I_0 + LSTM	**90.38%**	65.28%	75.81%	71.59%	**92.65%**	80.77%	78.57%
I_1 + LSTM	87.67%	**88.89%**	**88.28%**	**88.06%**	86.76%	**87.41%**	**87.86%**
I_2 + LSTM	85.94%	76.39%	80.88%	77.63%	86.76%	81.94%	81.43%

TABLE III. CSI300 CLOSE PRICE PREDICTION

Input & Method	Up			Down			*Accuracy*
	Precision	***Recall***	***F***	***Precision***	***Recall***	***F***	
I_0 + SVM	**51.4%**	76.39%	61.45%	**48.48%**	23.53%	31.68%	**50.71%**
I_1 + SVM	51.35%	**79.17%**	**62.3%**	48.28%	20.59%	28.87%	**50.71%**
I_2 + SVM	50.89%	**79.17%**	61.96%	46.43%	19.12%	27.08%	50%
I_0 + LSTM	46.81%	30.56%	36.97%	46.24%	63.24%	53.42%	46.43%
I_1 + LSTM	44.74%	23.61%	30.91%	46.08%	**69.12%**	**55.29%**	45.71%
I_2 + LSTM	50%	55.56%	52.63%	46.67%	41.18%	43.75%	48.57%

model with B_t as input produces almost every indicator worse than the SVM model with B_t^* as input, indicating the information contained in these two sentiment measures is slightly different. It is notable that the LSTM model with I_0 as input ppedicts the highes with precision in the up class (90.38%) and the highest recall in down class (92.65%). This is surprising since there is less information entering the model than the other two experiments.

Our LSTM model is fair in the sense that the Area Under Curve (AUC) in the training set converges to roughly the same value (92.31%) as the AUC evaluated in the test set (94.69%). Also, we have the dropout set at 0.2 and L2 regularization with 0.01 to prevent serious over-fitting.

D. Sentiment-aware Stock Market Prediction-Close Price

Similar to the experiments above, we also carry on a group of experiments to predict CSI300 close prices with the same experimental settings as we did in the CSI300 open prices prediction, and the prediction results are shown in Table 3.

We can see the prediction of close prices is much poorer than the prediction of open prices, both SVM and LSTM models. One possible reason is that the open price on the next day is closer to the close price in the input series than the close price on the next day, therefore when we predict the open price, we have the newer information than we do when predicting the close price. We can also see from the results that the SVM model is more stable in a way that no matter which value we predict, open or close, the accuracy is always more than 50%.

V. DISCUSSION

In this paper, we investigate whether investor sentiment as measured from large-scale collection of data collected from posts posted on stock forums is predictive of CSI300 index values. A Long Short-Term Memory model trained on the basis of past CSI300 index values and our investor sentiment time series demonstrated the ability of the latter to significantly improve the accuracy of other models to predict CSI300 open price. Given the performance increase for the LSTM model with only 4 layers and 30 nodes at most, we are hopeful to find equal or better improvements for more sophisticated market models that may, in fact, include other information derived from news sources, and a variety of relevant economic indicators.

Our analysis does not acknowledge a number of important factors that will however be examined in future research. First, the performance of sentiment classification is not satisfying. In this paper, we only applied Naïve Bayes for classification, thus we do not know if other classification methods, such as Support Vector Machine or Random Forest will help improve the performance. Second, these results are strongly indicative of a predictive correlation between measurements of the investor sentiment and CSI300 values, but offer no information on the causative mechanisms that may connect investor sentiment measures with CSI300 index values. The latter remains a crucial area for future research and may need to be examined more closely.

VI. CONCLUSION

In this paper, we develop a LSTM model which combined market information and investor sentiment to predict CSI300 index values in Chinese stock market. First, we deploy a Naïve Bayes sentiment classifier to assign all posts on stock forums to three classes: positive, negative, and neutral. And then we generate sentiment time series for subsequent work. Finally, we develop a deep neural network model which consists of a Long Short-Term Memory layer, a merge layer, a ReLU linear layer and a SoftMax layer. Trained on 90% of the entire data set, this model gives a prediction accuracy of 87.86% in the rest 10% of testing data, outperforming other input permutations and SVM method by at least 6%. This work shows the potential of deep learning financial time series in the presence of strong noises. This method has demonstrated in this work can be directly applicable for other financial market prediction using different variables and at completely different time-scales.

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