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Text based Deep Learning for Stock Prediction

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Abstract: We propose a deep learning method for event driven stock market prediction. First, events are extracted from news text, and represented as dense vectors, trained using a novel neural tensor network. Second,a deep convolutional neural network is used to model both short-term and long-term influences of events on stock price movements. For example, professional traders in their long-term careers have accumulated numerous trading rules, the myth of which they can understand quite well. On the other hand, deep learning models have been hardly interpretable. This paper presents DeepClue, a system built to bridge text-based deep learning models and end users through visually interpreting the key factors learned in the stock price prediction model. We make three contributions in DeepClue. First, by designing the deep neural network architecture for interpretation and applying an algorithm to extract relevant predictive factors, we provide a useful case on what can be interpreted out of the prediction model for end users. Second, by exploring hierarchies over the extracted factors and displaying these factors in an interactive, hierarchical visualization interface, we shed light on how to effectively communicate the interpreted model to end users. Third, we evaluate the integrated visualization system through two case studies in predicting the stock price with online financial news and company related tweets from social media. Quantitative experiments comparing the proposed neural network architecture with state-of-the-art models and the human baseline are conducted and reported. All the study results demonstrate the effectiveness of DeepClue in helping to complete stock market investment and analysis tasks.

Keywords: Deep learning, visualization, model interpretation, stock prediction, neural network.

1. INTRODUCTION

In this paper, we target the research problem of how to interpret text-based deep stock prediction model for end users, so that they can make up their stock trading decisions as well as improve the prediction model based on the interpretation. In particular, we investigate research questions including what kind of information can be effciently extracted from prediction model as interpretations, and how to communicate such information in an effective way to end users. Throughout this work, we depend on an interactive visualization interface to bridge the prediction model and end users, which turns out a natural and straightforward choice. DEEP learning techniques are reshaping the landscape of predictive analysis in the big data research area and have made major breakthroughs in image and speech recognition, question answering , machine translation and many other application domains. For example, fanancial news such as Amazon port beats forecasts was accompanied with a surge of Amazons stock price, while Oil price hits a record high triggered worries on the auto industry and weakened their performance in the stock market.

2. LITERATURE SURVEY

1. "DeepClue:Visual Interpretation of Text –based Deep Stock Prediction" This paper presents deep clue, a system build to bridge text based deep learning model and end user through visually interpreting the key factor learn in the stock price prediction model. All the study results demonstrate the effectiveness of DeepClue in helping to complete stock market investment and analysis tasks.

2. "Stock Prediction Using Twitter Sentiment Analysis" In order to test our results, we propose a new cross validation method for financial data and obtain 75.56% accuracy using Self Organizing Fuzzy Neural Networks (SOFNN) on the Twitter feeds and DJIA values from the period June 2009 to December 2009. We also implement a naive protfolio management strategy based on our predicted values. Our work is based on Bollen et als famous paper which predicted the same with 87% accuracy.

3. "Deep Learning for Event-Driven Stock Prediction" We propose a deep learning method for event driven stock market prediction. First, events are extracted from news text, and represented as dense vectors, trained using a novel neural tensor network. Second, a deep convolutional neural network is used to model both short-term and long-term influences of events on stock price movements.

4. "Exploiting Social Relations and Sentiment for Stock Prediction" we first exploit cash-tags (followed by stocks ticker symbols) in Twitter to build a stock network, where nodes are stocks connected by edges when two stocks co occur frequently in tweets. We then employ a labeled topic model to jointly model both the tweets and the network structure to assign each node and each edge a topic respectively. This Semantic Stock Network (SSN) summarizes discussion topics about stocks and stock relations. We further show that social sentiment about stock (node) topics and stock relationship (edge) topics are predictive of each stocks market.

5. "ImageNet Classification with Deep Convolutional Neural Networks" We trained a large, deep convolutional neural network to classify the 1.2 million high resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax.

3. EXISTING SYSTEM

Tweets in Relation to the Stock Market :

Micro-blogging activities are well correlated with the stock market. Figure 3 shows us how the Twitter activities response to a report announcement of $aapl (Jan. 23 2013). The report was made public soon after the market closed at 4:00pm, while the tweets volume rose about two hours earlier and reached the peak at the time of announcement, then it arrived the second peak at the time near the market's next opening (9:30am). By further accumulating all days' tweet volume in our dataset as hourly based statistics, we plot the volume distribution in Figure 4. Again, we note that trading activities are well reflected by tweet activities. The volume starts to rise drastically two or three hours before the market opens, and then reaches a peak at 9:00pm. It drops during the lunch time and reaches the second peak around 2:00pm (after lunch). Above observations clearly show that market dynamics are discussed in tweets and the content in tweets' discussion very well reflects the fine-grained aspects of stock market trading, opening and closing.

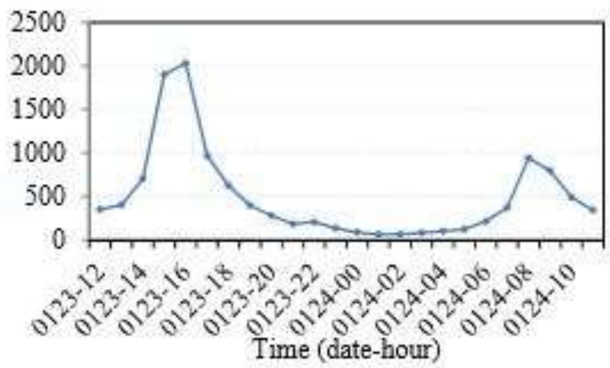

Figure 1 . Tweet activity around $aapl's earnings report date on Jan 23 2013.

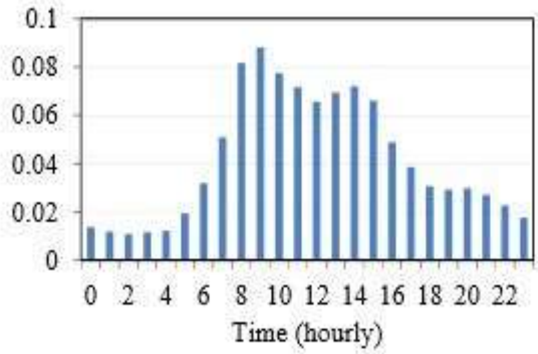

Figure 2 . Tweet volume distribution in our data over hours averaged across each day.

4. PROPOSED SYSTEM

We take news data as an example to introduce the architecture of the neural network model adopted in this work. The model is built for each particular S& P 500 rm. The goal of the model is to predict a stock price y that is close to the real stock price y of the rm. The raw input of each model is the set of financial news titles collected on the target rm. Intuitively, news content can be useful for further enhancing the sprediction accuracy.

Fig Shows the System architecture:

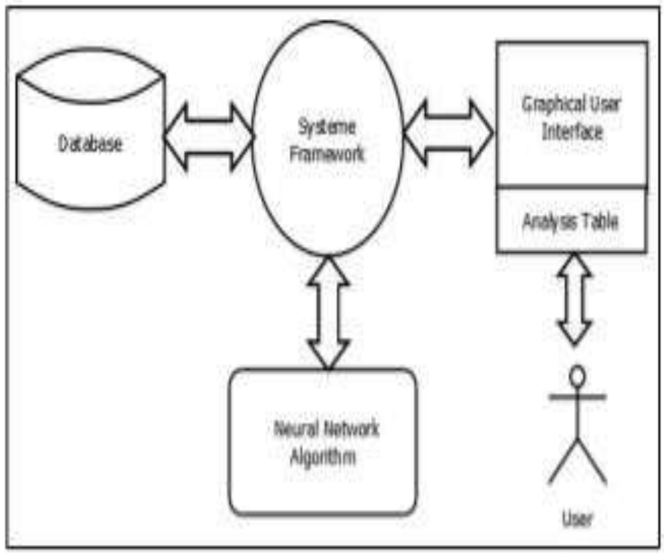

Fig 3 .proposed system architecture

- Registration - Register user with First name, last name, email, password, confirm password, and contact no. etc.

Fig 4. Registration

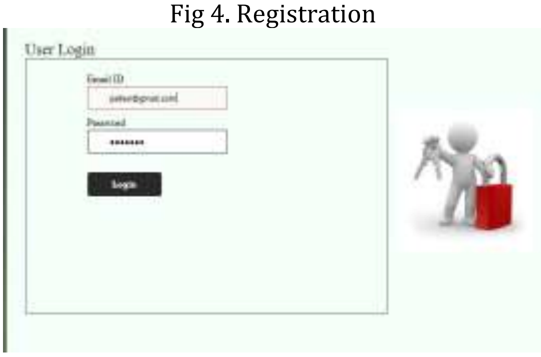

Fig 5 . login

4.1 Stock Prediction

This section demonstrates the effectiveness of our SSN based approach for stock prediction. We leverage the sentiment time-series on two kinds of topics from SSN: 1). Node topic from the target stock itself, 2). Neighbor node/edge topics. We note that the price correlation stock network (CSN) also defines neighbor relationships based on the Pearson's correlation coefficient between pair of past price series.

We build a two variables VAR model to predict the movement of a stock's daily closing price. One variable is the price time series of the target stock another is the covariate sentiment/price time series We setup two baselines according to the sources of the covariate time series as follows:

1. Covariate price time series from CSN, we try the price time series from the target stock's closest neighbor which takes the maximum historical price correlation in CSN.
2. With no covariate time series, we try the target stock's price only based on the univariate autoregression (AR) model. To summarize, we try different covariate sentiment ($S(.)$) or price ($P(.)$) time series from SSN or CSN together with the target stock's

Figure 6 . Expected output for Prediction (x-axis is the training window size, y-axis is the prediction accuracy) with different covariate sources.

Sr.No.	Err	Expected	Predited
1	3.5600397647795035	2019.42	2015.8599602352206
2	21.075580978927974	2019.42	1998.344419021072
3	22.318033764966685	2019.42	1997.1019662350334
4	21.704497159053517	2019.42	1997.7155028409466
5	21.853872894553888	2019.42	1997.5661271054462
6	18.925502667774026	2019.42	2000.494497332226
7	21.951102748055064	2019.42	1997.468897251945
8	20.58077208360214	2019.42	1998.839227916398
9	16.955833297575282	2019.42	2002.4641667024248
10	14.686436126558192	2019.42	2004.7335638734419

Table 1. Performance comparison of the average and best (in parentheses) prediction accuracies over all training window sizes.

5. MATHEMATICAL MODEL

Neural Network

1) Import all necessary libraries (NumPy, skicit-learn, pandas) and the dataset, and define

x and y.

2)Initialize the weights as between 0 and 1

3)while Optimal Weight not get

4) Propagating forward through NN

5)Get result for Comparing the real values

6) Then Backward Propagation for update weight

7)if Optimal weight not get repeat from step 3

8)Stop

6. ADVANTAGES

- Biases, gone forever.
- Cross-checking results become important.
- Scheduling tasks.
- Convenience galore.
- No Advisors required.

7. APPLICATIONS

- Market simulation
- Stock Market Analysis

- Stock Market Exchange

8. CONCLUSION

This paper proposed to build a stock network from co-occurrences of ticker symbols in tweets. The properties of SSN reveal some close relationships between involved stocks, which provide good information for predicting stocks based on social sentiment. Experimental results showed that event embeddings-based document representations are better than discrete events-based methods, and deep convolutional neural network can capture longer-term influence of news event than standard feedforward neural network.

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