Stock price prediction with LSTM network
Project Progress Report for COMP 562

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Abstract

The time series of stock prices are non-stationary and nonlinear, making the prediction of future price trends much challenging. To learn long-term dependencies of stock prices, we first perform unsupervised learning to extract and construct useful features, then build a deep Long Short-Term Memory (LSTM) network to generate the prediction. The experiments on real market dataset demonstrate that the proposed model outperforms other four baseline models in the mean square error.

1. Introduction

In the financial industry, stock price prediction has constantly been a popular field of research. According to many widely accepted studies, stock markets have been proved to be predictable in some scenarios. While different features are available for prediction, it's interesting to focus solely on past trading patterns. In the last decade, there has been a huge increase in the application of deep neural network. As a result, applying deep learning on stock market prediction has become a field of interest.

1.1. Literature Review

Our research assumes minute-level price fluctuation pattern is independent of corporate fundamentals and macro economy. Thus, unlike the studies of (Chiang et al., 2016), (Chourmouziadis & Chatzoglou, 2016), and (Zhong & Enke, 2017) in which daily price data are used as input, we seek to develop a predictive model based on minute-level price data. The prediction of future stock price had also been understood as both classification and regression problems in previous studies. (liang Chen & yu Chen, 2016) and (Zhong & Enke, 2017) provided prediction of market direction as either up or down. In more complicated cases, (Chourmouziadis & Chatzoglou, 2016) specified cash and stock within the optimal portfolio composition. Our study intends to give a prediction of the stock return of the next minute.

There have been linear and nonlinear models to predict stock price movement with varying degrees of success. (Chong et al., 2017) noted a multilayer artificial neural network might be particularly suitable with such time-series data, due to its higher computational power and sophistication of algorithm. Such model selects features based on raw input price data automatically and does not require understanding or providing data from the side of fundamentals or macro economy, which fits our assumption about minute-level price fluctuation pattern. For performance measurement, previous studies have used trade simulation or various MSE methods (Chiang et al., 2016); (Chourmouziadis & Chatzoglou, 2016); (Zhong & Enke, 2017); (Chong et al., 2017).

1.2. Data

Due to certain limitation and just for preliminary testing of our strategy, we are currently using 10 days of minute-level price data of 50 stocks, in total of 3900 time steps. Our aim is to obtain data of 10 years for model training. Each stock, at each time step, has 5 features, open/high/low/close price and volume. Therefore, in total, each time step contains 250 features. The input will contain 60 lagged time step, and we aim to predict the close prices of the 50 stocks at next time step. We may adjust the number of lagged periods for better performance later. We use the first 9 days as training, and the last day as test.

2. Method

Our model will be composed of two parts, with the first part being unsupervised learning with traditional ML techniques like RBM, PCA, etc. The second part takes advan-

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tage of recurrent neural network (RNN) model, especially its variant LSTM.

2.1. Model

Following the practice in the research of Chong et al.(Chong et al., 2017), our model takes the form of

$$r_{t+1} = f \circ \phi(R_t) + \gamma, \, \gamma \sim \mathcal{N}(0, \beta).$$

We assume the return of one hour prior to the current time point has influence on the return of the stock in the next minute, so t is in unit of minutes. As mentioned above, R_t is the 250×60 dimensional raw level input vector. ϕ transforms the data to features, or representations. It hasn't been implemented. f is the predictor function, and is learned using RNN, which seems to be the state of the art method (Abe & Nakayama, 2018). Specifically, we use a network with 10 layer, each with 1000 LSTM units.

2.2. Loss Function and Training

We can formulate the problem in two ways.

1. Explicitly make the output dependent on the previous 60 time steps. We unroll the network for 60 time steps, and only calculate the MSE loss between the final output and the truth. This way, when we perform prediction, we should probably first run the model for 60 time steps and then only take the last output.

2. Make the training sequence to sequence, unroll the network for arbitrary time steps, and optimize against the MSE loss between the output sequence and the truth sequence.

3. Preliminary Results

We first transform the price data to returns, i.e.

$$r_{t+1} = \frac{x_{t+1} - x_t}{x_t}.$$

We then normalize the volume data by

$$v_{n,t+1} = \frac{v_{n,t+1} - m_n}{\sigma_n},$$

where m_n and σ_n are the mean and standard deviation of the volumes of all time steps of stock n.

3.1. Evaluation

To evaluate our model performance on the test set, we employ the most popular and probably the standard validation strategy in time series analysis, the Walk Forward Validation strategy, where we do not retrain our model on each time step, but we make the last tested data point available to the model. In the case of our RNN, we do not reset the initial state, and simply let the model run forward to make prediction at each time step.

Table 1. Comparison between different methods with various metrics.

METHOD	MSE (10^{-7})	RE (%)	TE (%)
PROPOSED	8.5	9.5	0.05
ARIMA	73.2	25.8	0.23
GARCH	85.6	38.1	0.25
CHONG 2017	40.7	19.7	0.21
DEEP FNN	30.5	17.5	0.12

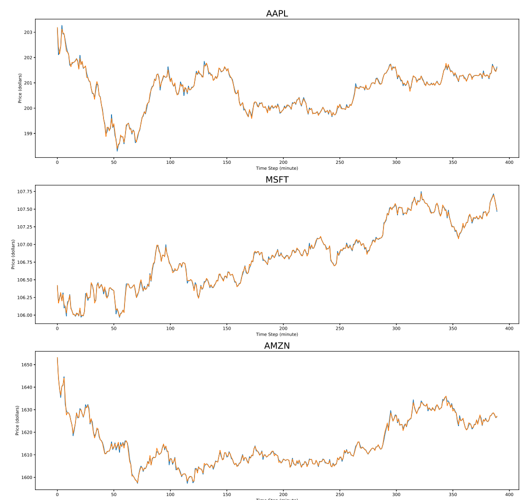

Figure 1. Comparison between true and predicted price.

In terms of evaluation metrics, we use mean squared error (MSE), mean relative absolute error (RE), and trend error rate (TE), which is the rate of predicting the wrong trend (e.g. positive return predicted as negative return).

3.2. Results

We compare our method with two popular statistical methods ARIMA and GARCH, the method from (Chong et al., 2017), and a simple feed forward network of 10 layers, each with 250 neurons to make the total number parameters roughly equal to that of our LSTM network. Table-1 shows the results.

Figure-1 plots the true price curve and the predicted price curve for 3 stocks.

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References

Abe, M. and Nakayama, H. Deep Learning for Forecasting Stock Returns in the Cross-Section. *ArXiv e-prints*, January 2018.

Chiang, Wen-Chyuan, Enke, David, Wu, Tong, and Wang, Renzhong. An adaptive stock index trading decision support system. *Expert Systems with Applications*, 59:195 – 207, 2016. ISSN 0957-4174. doi: https://doi.org/10.1016/j.eswa.2016.04.025. URL http://www.sciencedirect.com/science/article/pii/S0957417416301919.

Chong, Eunsuk, Han, Chulwoo, and Park, Frank C. Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies. *Expert Systems with Applications*, 83:187 – 205, 2017. ISSN 0957-4174. doi: https://doi.org/10.1016/j.eswa.2017.04.030. URL http://www.sciencedirect.com/science/article/pii/S0957417417302750.

Chourmouziadis, Konstandinos and Chatzoglou, Prodromos D. An intelligent short term stock trading fuzzy system for assisting investors in portfolio management. *Expert Systems with Applications*, 43:298 – 311, 2016. ISSN 0957-4174. doi: https://doi.org/10.1016/j.eswa.2015.07.063. URL http://www.sciencedirect.com/science/article/pii/S0957417415005230.

liang Chen, Tai and yu Chen, Feng. An intelligent pattern recognition model for supporting investment decisions in stock market. *Information Sciences*, 346-347:261 – 274, 2016. ISSN 0020-0255. doi: https://doi.org/10.1016/j.ins.2016.01.079. URL http://www.sciencedirect.com/science/article/pii/S0020025516300159.

Zhong, Xiao and Enke, David. Forecasting daily stock market return using dimensionality reduction. *Expert Systems with Applications*, 67:126 – 139, 2017. ISSN 0957-4174. doi: https://doi.org/10.1016/j.eswa.2016.09.027. URL http://www.sciencedirect.com/science/article/pii/S0957417416305115.