

# Stock Price Prediction with Deep Learning and Feature Engineering

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October 2, 2018

**Problem and its relevance to investments** Stock price predictability is one of the most important concerns for investors. As machine learning technique evolve in the area of economy, there has been growing interest in high frequency algorithmic trading. Previous studies have mostly focused on stock price prediction at a low frequency, and high frequency prediction studies haven been uncommon [1]. With the increasing availability of high-frequency trading data, better understanding of trading pattern will likely to lead to better prediction of stock price.

**The data** Quantopian([www.quantopian.com](http://www.quantopian.com)) has ongoing minute-level US equity pricing and volume data since January 1, 2002. We plan to use the data of 50 largest stocks as ranked by market capitalization. We conjecture that, due to correlation, past stock returns affect not only its own future returns but also the future returns of other stocks, and use 500 dimensional lagged stock returns (50 stocks and 10 lagged returns) as raw level input data. This large input dataset makes deep learning a particularly suitable choice for our research. The data from 2002 to 2017 will be used in the training set and the data from 2017 will be used in the testing set.

**The model** Following the practice in the research of Chong et al. [2], 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,  $R_t = [r_{1,t}, \dots, r_{1,t-60}, \dots, r_{50,t}, \dots, r_{50,t-60}]^T$  is the 500-dimensional raw level input vector.  $\phi$  transforms the data to features, or representations, and will be learned by principal component analysis (PCA), autoencoder (AE), restricted Boltzmann machine (RBM), and other unsupervised learning techniques.  $f$  is the predictor function, and will be learned using recurrent neural network (RNN), which seems to be the state of the art deep learning method for financial time series data analysis [3].

**Secret sauce, if any** We will also try to combine other statistical techniques such as univariate autoregressive model with ten lagged variables (AR(10)) with our proposed model. In addition, online learning techniques, model retraining, and data assimilation will be added to incorporate the latest data to improve the performance.

**How the model will be evaluated**

**Anticipated challenges** One of our key assumption is that

**The promise** With increasing amount of investors entering into the market, satisfactory stock price prediction will bring higher return for investors and further improve in capital scale.

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## References

- [1] M. Kearns and Y. Nevmyvaka, “Machine learning for market microstructure and high frequency trading,” 2013.
- [2] E. Chong, C. Han, and F. C. Park, “Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies,” *Expert Systems with Applications*, vol. 83, pp. 187 – 205, 2017.
- [3] M. Abe and H. Nakayama, “Deep Learning for Forecasting Stock Returns in the Cross-Section,” *ArXiv e-prints*, Jan. 2018.