Expert Systems With Applications 83 (2017) 187–205

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies

Eunsuk Chong[a], Chulwoo Han[b], Frank C. Park[a,*]

[a] Robotics Laboratory, Seoul National University, Seoul 08826, Korea
[b] Durham University Business School, Mill Hill Lane, Durham DH1 3LB, UK

ARTICLE INFO

Article history:
Received 15 November 2016
Revised 15 April 2017
Accepted 16 April 2017
Available online 22 April 2017

Keywords:
Stock market prediction
Deep learning
Multilayer neural network
Covariance estimation

ABSTRACT

We offer a systematic analysis of the use of deep learning networks for stock market analysis and prediction. Its ability to extract features from a large set of raw data without relying on prior knowledge of predictors makes deep learning potentially attractive for stock market prediction at high frequencies. Deep learning algorithms vary considerably in the choice of network structure, activation function, and other model parameters, and their performance is known to depend heavily on the method of data representation. Our study attempts to provides a comprehensive and objective assessment of both the advantages and drawbacks of deep learning algorithms for stock market analysis and prediction. Using high-frequency intraday stock returns as input data, we examine the effects of three unsupervised feature extraction methods—principal component analysis, autoencoder, and the restricted Boltzmann machine—on the network's overall ability to predict future market behavior. Empirical results suggest that deep neural networks can extract additional information from the residuals of the autoregressive model and improve prediction performance; the same cannot be said when the autoregressive model is applied to the residuals of the network. Covariance estimation is also noticeably improved when the predictive network is applied to covariance-based market structure analysis. Our study offers practical insights and potentially useful directions for further investigation into how deep learning networks can be effectively used for stock market analysis and prediction.

1. Introduction

Research on the predictability of stock markets has a long history in financial economics (*e.g.*, Ang & Bekaert, 2007; Bacchetta, Mertens, & Van Wincoop, 2009; Bondt & Thaler, 1985; Bradley, 1950; Campbell & Hamao, 1992; Campbell & Thompson, 2008; Campbell, 2012; Granger & Morgenstern, 1970). While opinions differ on the efficiency of markets, many widely accepted empirical studies show that financial markets are to some extent predictable (Bollerslev, Marrone, Xu, & Zhou, 2014; Ferreira & Santa-Clara, 2011; Kim, Shamsuddin, & Lim, 2011; Phan, Sharma, & Narayan, 2015). Among methods for stock return prediction, econometric or statistical methods based on the analysis of past market movements have been the most widely adopted (Agrawal, Chourasia, & Mittra, 2013). These approaches employ various linear and nonlinear methods to predict stock returns, *e.g.*, autoregressive models and artificial neural networks (ANN) (Adebiyi, Adewumi, & Ayo, 2014; Armano, Marchesi, & Murru, 2005; Atsalakis & Valavanis, 2009; Bogullu, Dagli, & Enke, 2002; Cao, Leggio, & Schniederjans, 2005; Chen, Leung, & Daouk, 2003; Enke & Mehdiyev, 2014; Guresen, Kayakutlu, & Daim, 2011a; Kara, Boyacioglu, & Baykan, 2011; Kazem, Sharifi, Hussain, Saberi, & Hussain, 2013; Khashei & Bijari, 2011; Kim & Enke, 2016a; 2016b; Monfared & Enke, 2014; Rather, Agarwal, & Sastry, 2015; Thawornwong & Enke, 2004; Ticknor, 2013; Tsai & Hsiao, 2010; Wang, Wang, Zhang, & Guo, 2011; Yeh, Huang, & Lee, 2011; Zhu, Wang, Xu, & Li, 2008). While there is uniform agreement that stock returns behave nonlinearly, many empirical studies show that for the most part nonlinear models do not necessarily outperform linear models: *e.g.*, Lee, Sehwan, and Jongdae (2007), Lee, Chi, Yoo, and Jin (2008), Agrawal et al. (2013), and Adebiyi et al. (2014) propose linear models that outperform or perform as well as nonlinear models, whereas Thawornwong and Enke (2004), Cao et al. (2005), Enke and Mehdiyev (2013), and Rather et al. (2015) find nonliner models outperfrom linear models. Table 1 provides a summary of recent works relevant to our research. For more exhaustive and detailed reviews, we refer

* Corresponding author.
E-mail addresses: bear3498@snu.ac.kr (E. Chong), chulwoo.han@durham.ac.uk (C. Han), fcp@snu.ac.kr (F.C. Park).

http://dx.doi.org/10.1016/j.eswa.2017.04.030
0957-4174/