Bond University
ePublications@bond

Information Technology papers | Faculty of Business

4-30-2010

Financial time series forecasting with machine learning techniques: A survey

Bjoern Krollner
Bond University, Bjoern_Krollner@bond.edu.au

Bruce Vanstone
Bond University, Bruce_Vanstone@bond.edu.au

Gavin Finnie
Bond University, Gavin_Finnie@bond.edu.au

Follow this and additional works at: http://epublications.bond.edu.au/infotech_pubs

Part of the Artificial Intelligence and Robotics Commons

Recommended Citation
Bjoern Krollner, Bruce Vanstone, and Gavin Finnie. (2010) "Financial time series forecasting with machine learning techniques: A survey" European Symposium on Artificial Neural Networks: Computational and Machine Learning. Bruges, Belgium.Apr. 2010.

http://epublications.bond.edu.au/infotech_pubs/110

This Conference Paper is brought to you by the Faculty of Business at ePublications@bond. It has been accepted for inclusion in Information Technology papers by an authorized administrator of ePublications@bond. For more information, please contact Bond University's Repository Coordinator.

ESANN 2010 proceedings, European Symposium on Artificial Neural Networks - Computational Intelligence and Machine Learning. Bruges (Belgium), 28-30 April 2010, d-side publi., ISBN 2-930307-10-2.

Financial Time Series Forecasting with Machine Learning Techniques: A Survey

Bjoern Krollner, Bruce Vanstone, Gavin Finnie

School of Information Technology, Bond University
Gold Coast, Queensland, Australia

Abstract. Stock index forecasting is vital for making informed investment decisions. This paper surveys recent literature in the domain of machine learning techniques and artificial intelligence used to forecast stock market movements. The publications are categorised according to the machine learning technique used, the forecasting timeframe, the input variables used, and the evaluation techniques employed. It is found that there is a consensus between researchers stressing the importance of stock index forecasting. Artificial Neural Networks (ANNs) are identified to be the dominant machine learning technique in this area. We conclude with possible future research directions.

1 Introduction

Stock index prediction is an important challenge in financial time series prediction. The stock market is subject to large price volatility which translates to high risks for holders of common shares. Portfolio diversification permits the reduction of company specific risk, but the 2007/2008 financial crises highlighted the enormous effects of systematic market risk on portfolio returns. Derivative trading vehicles based on stock indices provide an effective means to hedge against systematic risk. In addition, they offer profit making opportunities for speculators. Determining more effective ways of stock index prediction is important for market participants in order to make more informed and accurate investment decisions.

This paper surveys recent literature in the domain of machine learning techniques and artificial intelligence used to forecast stock market movements. The main contribution of this survey is to provide researchers with a cohesive overview of recent developments in stock index forecasting and to identify possible opportunities for future research.

2 Technologies Used

Machine learning techniques aim to automatically learn and recognise patterns in large amounts of data. There is a great variety of machine learning techniques within the literature which makes the classification difficult. This paper divides the literature into artificial neural network (ANN) based and evolutionary & optimisation based techniques.

Table 1 shows that variations of ANNs and hybrid systems are very popular in the recent literature. There is a clear trend to use established ANN models and enhance them with new training algorithms or combine ANNs with emerging technologies into hybrid systems.

Technology	Number	Publications
ANN based	21	[1], [4], [5], [8], [13], [15], [16], [20], [24], [25], [27], [31], [33], [35], [36], [37], [38], [39], [41], [43], [46]
Evolutionary & optimisation techniques	4	[23], [29], [30], [45]
Multiple / hybrid	15	[2], [3], [6], [7], [11], [14], [17], [18], [21], [22], [26], [32], [34], [40], [42]
Other	6	[9], [10], [12], [19], [28], [44]

Table 1: Reviewed papers classified by machine learning technique

3 Forecasting Time-frame

Table 2 gives an overview of the different forecasting intervals used in the literature. The prediction periods are categorised into one day, one week, and one month ahead predictions. Publications using multiple or different time-frame are listed under 'Multiple / Others'. Most papers make one day ahead predictions e.g. predicting the next day's closing price. However, being able to predict the stock index one day ahead does not necessarily mean that an investor can take advantage of this information in terms of trading profit, especially since the index itself cannot be traded. Surprisingly, only three publications [15, 22, 41] use data of actually tradable stock index futures for their studies.

Time-frame	Number	Publications
Day	31	[1], [2], [3], [4], [6], [7], [8], [9], [10], [13], [14], [17], [19], [20], [21], [22], [24], [27], [28], [31], [32], [33], [34], [35], [36], [37], [40], [41], [42], [44], [45]
Week	3	[18], [23], [43]
Month	3	[26], [38], [39]
Multiple / Other	9	[5], [11], [12], [15], [16], [25], [29], [30], [46]

Table 2: Reviewed papers classified by forecasting time-frame

4 Input Variables

Selecting the right input variables is very important for machine learning techniques. Even the best machine learning technique can only learn from an input if there is actually some kind of correlation between input and output variable.

Table 3 shows that over 75% of the reviewed papers rely in some form on lagged index data. The most commonly used parameters are daily opening, high, low and close prices. Also used often are technical indicators which are mathematical transformations of lagged index data. The most common technical indicators found in the surveyed literature are the simple moving average (SMA), exponential moving average (EMA), relative strength index (RSI), rate of change (ROC), moving average convergence / divergence (MACD), William's oscillator and average true range (ATR).

Input	Number	Publications
Lagged Index Data	35	[1], [2], [3], [4], [5], [6], [7], [8], [9], [11], [13], [14], [15], [16], [17], [19], [21], [24], [25], [26], [27], [28], [31], [33], [34], [35], [36], [37], [38], [39], [41], [42], [44], [45], [46]
Trading Volume	4	[11], [25], [28], [46]
Technical Indicators	13	[3], [4], [10], [20], [22], [23], [28], [29], [30], [32], [40], [41], [43]
Oil Price	4	[12], [15], [33], [38]
S&P 500 / NASDAQ / Dow Jones (non US studies)	4	[18], [20], [33], [41]
Unemployment Rate	1	[38]
Money Supply	3	[12], [38], [39]
Exchange Rates	3	[15], [18], [41]
Gold Price	3	[12], [15], [33]
Short & Long Term Interest Rates	6	[5], [15], [25], [26], [35], [39]
Others	10	[4], [5], [15], [17], [20], [26], [35], [38], [39], [41]

Table 3: Reviewed papers classified by input variables

5 Evaluation Methods

In order to determine the effectiveness of a machine learning technique, a benchmark model is needed. A variety of evaluation methods is used in the literature. This survey categorises the evaluation models into the categories buy & hold, random walk, statistical techniques, other machines learning techniques, and no benchmark model.

Table 4 shows that the majority of authors use other machine learning techniques as a benchmark. This category consists of publications which perform a comparative analysis between two different models or use an established model and propose an improvement to that model. The proposed improved version is then compared to the original version.

Over 80% of the papers report that their model outperformed the benchmark model. However, most analysed studies do not consider real world constraints like trading costs and slippage. 31 out of 46 studies use the forecast error as an evaluation metric. This is a surprising finding since a smaller forecast error does not necessarily translate into increased trading profits.

Eval. Model	Number	Publications
Buy & Hold	9	[3], [4], [5], [18], [25], [38], [39], [41], [43]
Random Walk	6	[5], [11], [18], [22], [28], [39]
Statistical Techniques	18	[5], [6], [9], [10], [11], [13], [15], [17], [18], [19], [24], [26], [28], [34], [35], [37], [39], [41]
Other Machine Learning Techniques	28	[2], [3], [4], [6], [7], [8], [11], [13], [14], [17], [18], [21], [22], [23], [24], [26], [29], [30], [31], [32], [34], [35], [39], [40], [42], [44], [45], [46]
No Benchmark Model	7	[1], [12], [16], [20], [27], [33], [36]

Table 4: Reviewed papers classified by evaluation models

6 Conclusion

This paper has examined recent literature in the domain of machine learning techniques and artificial intelligence used to forecast stock market movements. The reviewed papers have been categorised according to the machine learning technique used, the forecasting time-frame, the input variables used, and the evaluation techniques employed.

In regards to the employed machine learning technique, there seems to be a trend to use existing artificial neural network models which are enhanced with new training algorithms or combined with emerging technologies into hybrid systems. This finding indicates that neural network based technologies are accepted and suitable in the domain of stock index forecasting.

The surveyed forecasting time-frames revealed that the majority of publications tries to make one day ahead predictions using stock index data. It has been pointed out that for an investor it will be difficult to take advantage of this information, especially since the analysed literature does hardly examine any data of actually tradable derivatives.

Lagged index data and derived technical indicators have been identified as the most popular input parameters in the literature.

In summary, there seems to be a consensus between researchers stressing the importance of stock index forecasting and that the reported results are predominantly positive. Artificial Neural Networks (ANNs) have been identified as the dominant machine learning technique in this area.

The main finding of this survey is that there is a lack of literature examining if machine learning techniques can improve an investors' risk-return tradeoff under real world constraints.

References

[1] Abraham, A., Nath, B. & Mahanti, P. K. (2001), Hybrid intelligent systems for stock market analysis, *in* 'Proceedings of the International Conference on Computational Science-Part II', Springer-Verlag, London, UK, pp. 337–345.

[2] Abraham, A., Philip, N. S. & Saratchandran, P. (2003), 'Modeling chaotic behavior of stock indices using intelligent paradigms', *Neural, Parallel Sci. Comput.* 11(1 & 2), 143–160.

[3] Armano, G., Marchesi, M. & Murru, A. (2005), 'A hybrid genetic-neural architecture for stock indexes forecasting', *Information Sciences* 170(1), 3–33.

[4] Bekiros, S. D. & Georgoutsos, D. A. (2008), 'Direction-of-change forecasting using a volatility-based recurrent neural network', *Journal of Forecasting* 27(5), 407–417.

[5] Chen, A.-S., Leung, M. T. & Daouk, H. (2003), 'Application of neural networks to an emerging financial market: forecasting and trading the taiwan stock index', *Comput. Oper. Res.* 30(6), 901–923.

[6] Chen, Q.-A. & Li, C.-D. (2006), 'Comparison of forecasting performance of ar, star and ann models on the chinese stock market index', *Advances in Neural Networks* 3973, 464–470.

[7] Chen, Y., Abraham, A., Yang, J. & Yang, B. (2005), Hybrid methods for stock index modeling, *in* 'International Conference on Fuzzy Systems and Knowledge Discovery', Springer Verlag, pp. 1067–1070.

[8] Chen, Y., Dong, X. & Zhao, Y. (2005), 'Stock index modeling using eda based local linear wavelet neural network', *International Conference on Neural Networks and Brain* 3, 1646–1650.

[9] Cheng, C.-H., Chen, T.-L. & Chiang, C.-H. (2006), 'Trend-weighted fuzzy time-series model for taiex forecasting', *Neural Information Processing* 4234, 469–477.

[10] Chu, H.-H., Chen, T.-L., Cheng, C.-H. & Huang, C.-C. (2009), 'Fuzzy dual-factor time-series for stock index forecasting', *Expert Systems with Applications* 36(1), 165–171.

[11] Chun, S.-H. & Kim, S. H. (2004), 'Automated generation of new knowledge to support managerial decision-making: case study in forecasting a stock market', *Expert Systems* 21(4), 192–207.

[12] Collard, L. B. & Ades, M. J. (2008), Sensitivity of stock market indices to commodity prices, *in* 'Proceedings of the 2008 Spring simulation multiconference', The Society for Computer Simulation, International, San Diego, CA, USA, pp. 301–306.

[13] de Faria, E., Albuquerque, M. P., Gonzalez, J., Cavalcante, J. & Albuquerque, M. P. (2009), 'Predicting the brazilian stock market through neural networks and adaptive exponential smoothing methods', *Expert Systems with Applications*

[14] Fu, J., Lum, K. S., Nguyen, M. N. & Shi, J. (2007), 'Stock prediction using fcmac-byy', *Advances in Neural Networks* 4492, 346–351.

[15] Hamid, S. A. & Iqbal, Z. (2004), 'Using neural networks for forecasting volatility of s&p 500 index futures prices', *Journal of Business Research* 57(10), 1116–1125.

[16] Hanias, M., Curtis, P. & Thalassinos, J. (2007), 'Prediction with neural networks: The Athens stock exchange price indicator', *European Journal of Economics, Finance and Administrative Sciences* 9, 21–27.

[17] Huang, S.-C. & Wu, T.-K. (2008), 'Integrating ga based time-scale feature extractions with svms for stock index forecasting', *Expert Systems with Applications* 35(4), 2080–2088.

[18] Huang, W., Nakamori, Y. & Wang, S.-Y. (2005), 'Forecasting stock market movement direction with support vector machine', *Computers & Operations Research* 32(10), 2513–2522.

[19] Huarng, K. & Yu, H.-K. (2005), 'A type 2 fuzzy time series model for stock index forecasting', *Physica A: Statistical Mechanics and its Applications* 353, 445–462.

[20] Jaruszewicz, M. & Mandziuk, J. (2004), 'One day prediction of nikkei index considering information from other stock markets', *International Conference on Artificial Intelligence and Soft Computing* 3070, 1130–1135.

[21] Jia, G., Chen, Y. & Wu, P. (2008), 'Menn method applications for stock market forecasting', *Advances in Neural Networks* 5263, 30–39.

[22] Kim, K.-J. (2004), 'Artificial neural networks with feature transformation based on domain knowledge for the prediction of stock index futures', *Intelligent Systems in Accounting, Finance & Management* 12(3), 167–176.

[23] Kim, M.-J., Min, S.-H. & Han, I. (2006), 'An evolutionary approach to the combination of multiple classifiers to predict a stock price index', *Expert Systems with Applications* 31(2), 241–247.

[24] Lee, T.-S. & Chen, N.-J. (2002), 'Investigating the information content of non-cash-trading index futures using neural networks', *Expert Systems with Applications* 22(3), 225–234.

[25] Leigh, W., Hightower, R. & Modani, N. (2005), 'Forecasting the new york stock exchange composite index with past price and interest rate on condition of volume spike', *Expert Systems with Applications* 28(1), 1–8.

[26] Leung, M. T., Daouk, H. & Chen, A.-S. (2000), 'Forecasting stock indices: a comparison of classification and level estimation models', *International Journal of Forecasting* 16(2), 173–190.

[27] Liao, Z. & Wang, J. (2009), 'Forecasting model of global stock index by stochastic time effective neural network', *Expert Systems with Applications*

[28] Lu, C.-J., Lee, T.-S. & Chiu, C.-C. (2009), 'Financial time series forecasting using independent component analysis and support vector regression', *Decision Support Systems* 47(2), 115–125.

[29] Majhi, R., Panda, G., Majhi, B. & Sahoo, G. (2009), 'Efficient prediction of stock market indices using adaptive bacterial foraging optimization (abfo) and bfo based techniques', *Expert Systems with Applications* 36(6), 10097–10104.

[30] Majhi, R., Panda, G., Sahoo, G. & Panda, A. (2008), 'On the development of improved adaptive models for efficient prediction of stock indices using clonal-pso (cpso) and pso techniques', *International Journal of Business Forecasting and Marketing Intelligence* 1(1), 50–67.

[31] Ning, B., Wu, J., Peng, H. & Zhao, J. (2009), 'Using chaotic neural network to forecast stock index', *Advances in Neural Networks* 5551, 870–876.

[32] Niu, F., Nie, S. & Wang, W. (2008), 'The forecasts performance of gray theory, bp network, svm for stock index', *International Symposium on Knowledge Acquisition and Modeling* pp. 708–712.

[33] Pan, H., Tilakaratne, C. & Yearwood, J. (2005), 'Predicting the australian stock market index using neural networks exploiting dynamical swings and intermarket influences', *Journal of research and practice in information technology* 37(1), 43–55.

[34] Perez-Rodriguez, J. V., Torra, S. & Andrada-Felix, J. (2005), 'Star and ann models: forecasting performance on the spanish ibex-35 stock index', *Journal of Empirical Finance* 12(3), 490–509.

[35] Roh, T. H. (2007), 'Forecasting the volatility of stock price index', *Expert Systems with Applications* 33(4), 916–922.

[36] Shen, J., Fan, H. & Chang, S. (2007), 'Stock index prediction based on adaptive training and pruning algorithm', *Advances in Neural Networks* 4492, 457–464.

[37] Slim, C. (2004), 'Forecasting the volatility of stock index returns: A stochastic neural network approach', *Computational Science and Its Applications* 3045, 935–944.

[38] Stansell, S. R. & Eakins, S. G. (2004), 'Forecasting the direction of change in sector stock indexes: An application of neural networks.', *Journal of Asset Management* 5(1), 37–48.

[39] Thawornwong, S. & Enke, D. (2004), 'The adaptive selection of financial and economic variables for use with artificial neural networks', *Neurocomputing* 56, 205–232.

[40] Wang, W. & Nie, S. (2008), 'The performance of several combining forecasts for stock index', *International Seminar on Future Information Technology and Management Engineering* 0, 450–455.

[41] Witkowska, D. & Marcinkiewicz, E. (2005), 'Construction and evaluation of trading systems: Warsaw index futures', *International Advances in Economic Research* 11(1), 83–92.

[42] Wu, Q., Chen, Y. & Liu, Z. (2008), Ensemble model of intelligent paradigms for stock market forecasting, *in* 'Proceedings of the First International Workshop on Knowledge Discovery and Data Mining', IEEE Computer Society, Washington, DC, USA, pp. 205–208.

[43] Zapranis, A. (2006), 'Testing the random walk hypothesis with neural networks', *Artificial Neural Networks* 4132, 664–671.

[44] Zeng, F. & Zhang, Y. (2006), 'Stock index prediction based on the analytical center of version space', *Advances in Neural Networks* 3973, 458–463.

[45] Zhang, X., Chen, Y. & Yang, J. Y. (2007), Stock index forecasting using pso based selective neural network ensemble, *in* 'International Conference on Artificial Intelligence', pp. 260–264.

[46] Zhu, X.,Wang, H., Xu, L. & Li, H. (2008), 'Predicting stock index increments by neural networks: The role of trading volume under different horizons', *Expert Syst. Appl.* 34(4), 3043–3054.