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An Up-Trend Detection Using an Auto-Associative Neural Network : KOSPI 200 Futures

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Abstract — We propose a neural network based up-trend detector. An auto-associative neural network was trained with "up-trend" data obtained from the KOSPI 200 future price. It was then used to predict an up-trend. Simple investment strategies based on the detector achieved a two year return of 19.8 % with no leverage.

1. Introduction

Technical analysis uses certain stock chart patterns and shapes as signals for profitable trading opportunities [12]. The general goal of technical analysis is to identify regularities in the time series of prices by extracting nonlinear patterns from noisy data. They concentrate on the formation of a specific pattern. The human eyes can perform this signal extraction.

Recent breakthroughs in computer technology and numerical algorithms give rise to many methods in financial engineering. Nevertheless, technical analysis has survived through the years, because pattern recognition is one of the few repetitive activities for which computer do not have an absolute advantage yet[7].

Efforts to automate the pattern recognition process have been reported but their monetary performance left a lot to be desired [3]. We report yet another effort in that direction.

In this paper, we propose a neural network based up-trend detector using an auto-associative neural network. An auto-associative neural network (AANN) is basically a neural network whose input and target vectors are the same. The proposed detection process is as follow. First, the up-trend data is identified in historical database. Second, they are used to train AANN. Third, the trained AANN is used as an up-trend detector. A positive signal recommends to take a long position (see Figure 1).

In section 2, our definition of "up-trend" is given. In section 3, it is shown how to detect up-trend using auto-associative neural network. Experimental methods and results are given in sections 4 and 5. Concluding remarks are given in section 6.

2. Definition of Up-Trend

The definition of an up-trend in financial market is ambiguous and subjective. In order to obtain a training data set, we have to define an up-trend pattern. Before defining an up-trend, we introduce FK and FD variables which reveal the trend of the price movement.

The value of traditional $\%K_n^k$ of the stochastic process invented by Lane[10] reveals where the closing price of the current trading day stands relative to the retrospective fluctuation range of prices in the last k trading days. To represent where the closing price of the current trading day will stand in relation to the fluctuation range of price for the consecutive k trading days, FK_n^k, the forward version of $\%K_n^k$, is defined by the following equation [9]:

$$FK_n^k = 2 \times \frac{Max_{i=n}^{n+k}(H_i) - C_n}{Max_{i=n}^{n+k}(H_i) - Min_{i=n}^{n+k}(L_i)} - 1.$$

And its moving average FD_n^j is defined as follows:

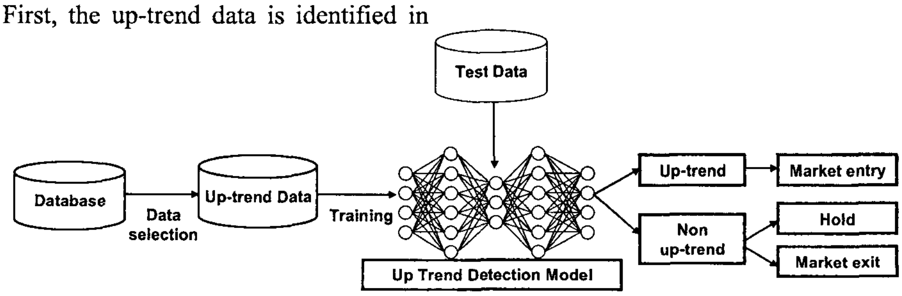

Figure 1. Detection Process framework

$$FD_n^j = \sum_{i=n}^{n+j-1} FK_i^k .$$

Now, the up-trend is defined as follows:

1. Identify up-trend beginning day(i_{begin}) or ending day(i_{end}) as follows.

If (FD_{i-1}^j < Upper Threshold)&(FD_i^j >Upper Threshold)

then $i_{begin} = i$;

else {if (FD_{n-1}^j > Lower Threshold) & (FD_n^j <Lower Threshold)

then $i_{end} = i$;}

2. Choose a larger i_{begin} and a smaller i_{end} .
3. Select the subinterval [i_{begin} , i_{end}].

3. Auto-Associative Neural Network as an Up-Trend Detector

A pattern classification method such as a neural network is an ideal candidate in an up-trend detection problem. The detection problem can now be formulated as a 2-class problem. A neural network is trained with up-trend data and non-up-trend data. Then given a new input data, or a current situation, the network tries to classify it as an up-trend or a non-up-trend. A problem with this approach is the inability to collect a sufficient case of non-up-trend data. This is a well known problem of partially-exposed environments in pattern classification where training data from on class are very few or non-existent. Related Problems include counterfeit bank note detection and typing pattern identity verification [1].

Auto-Associative Neural Network (AANN) has been used in many partially-exposed environments [1]. AANN is basically a neural network whose input and target vectors are the same [6]. AANN should reproduce an input vector at the output with a least error [4]. Let F denote an auto-associative mapping function, x_i an input vector and y_i an output vector. Then network F is usually trained to minimize the mean square error given by the equation:

$$E = \sum_{i=1}^{N} \left\| x_i - y_i \right\|^2 = \sum_{i=1}^{N} \left\| x_i - F(x_i) \right\|^2$$

Historical financial data have particular trends and characteristics. They tend to repeat themselves. The financial situations that correspond to up-trend are assumed to have unique characteristics. If the core information can be incorporated into the network input variables, the unique characteristics can be captured by the subspace of AANN embodied by the transformation at the hidden layers. Once AANN is trained with up-trend data, any up-trend data that shares common characteristic will result in a small error at the output layer while non-up-trend data will result in a large error at the output layer. With an appropriate threshold, the AANN can be used to detect the occurrence of the up-trend.

4. Data Collection and Neural Network Training

We used Korea Composite Stock Price Index 200 (KOSPI 200) future price data from Jan 1997 to Dec 2001 for the experiment. The KOSPI 200 is a kind of a market-value weighted index, similar to S&P 500 future [13]. The base date is May 1, 1996 with the base index of 100. And KOSPI 200 future is based on KOSPI 200.

Figure 3. KOSPI 200 future price from Jan 1997 to Dec 1999

For neural network training, such technical indicators as VR, RSI and MACD were used as input variables (for more details about technical indicators, see reference [11]). Using technical indicators can reduce the number of input variables effectively, while maintaining historical information. Reducing the number of input variables helps to prevent overfitting [8].
Figure 3 displays KOSPI 200 future data used in the training of this experiment. Only 208 days were found to fit the definition of the "up-trend" out of 883 days. The AANN used has a 4-layer structure whose hidden layers have a nonlinear transfer function (tangent sigmoid used). To reduce the variation, bagging approach was used [5]. The Levenberg-Marquardt algorithm was employed to minimize the sum of square error function. The experiment was performed on Matlab 5.3.

5. Results

Table 1 shows the mean and the standard deviation of distances between input vectors and output vectors. The distance of up-trend is generally smaller than that of non-up-trend.

Table 1. The means and standard deviations of the distance between input and output

Measurements	Up-trend	Non Up-trend
Mean	1.67	2.73
Standard Deviation	0.35	0.73

Figure 4 shows the KOSPI200 Future price during the test period 2000-2001 as well as the network's detection results of up-trend. Up-trend score is a reciprocal of the distance between input and output.

Two thresholds were employed. Up-trend score threshold 0.5 (distance threshold θ_{EER}=2.0) is a reciprocal of the distance that makes False Acceptance Rate(FAR) and False Rejection Rate(FRR) equal, namely Equal Error Rate(EER), in training set. Up-trend score threshold 0.54 (distance threshold $\theta_{FAR10\%}$ = 1.85) is a reciprocal of the distance that makes FAR about 10%.
The classification performance of AANN in test set (Jan 2000-Dec 2000) is given in Table 2. There is a trade-off between FRR and FAR. If the threshold of up-trend score increases, FAR becomes smaller and FRR becomes lager. Otherwise, vice versa.

Table 2. Classification performance of AANN in test set

Measurement		Training	Test
EER Threshold (θ_{EER})	FRR	16.4%	87.8%
	FAR	17.4%	8.0%
FAR 10 % Threshold ($\theta_{FAR10\%}$)	FRR	**28.8%**	93.9%
	FAR	**10.1%**	5.1%

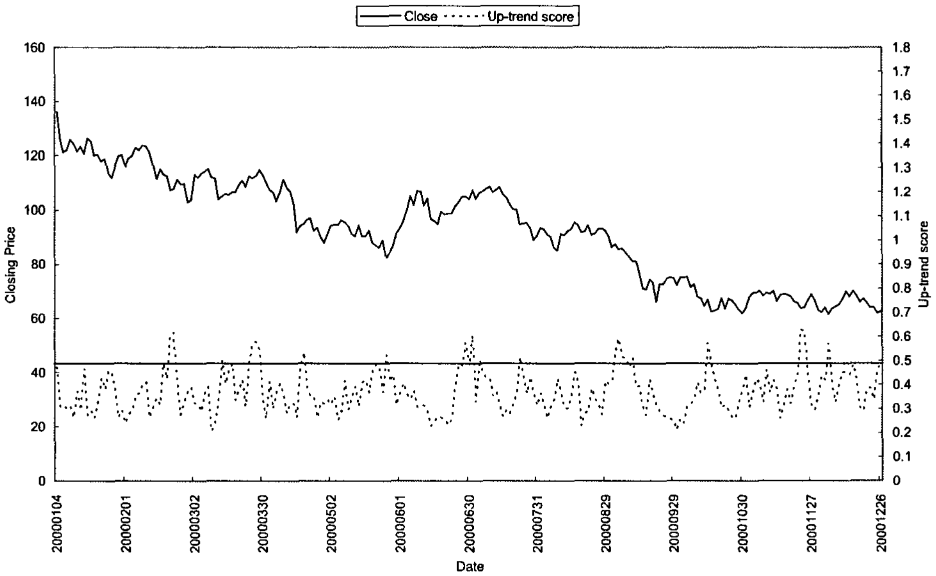

Figure 4. The results of test set

The large FRR in test set did not result in poor trading performance since one correct signal in the early stage of up-trend in sufficient to generate profit (see the strategy later).The proposed approach is also evaluated based on a financial measure of return rate. $S(i)$, based on hypothetical investment strategy based on up-trend signals, can be used as trading signals. $S(i)$ is as follows :

$$S(i) = \begin{cases} 1 \text{ if the distance between input and output is} \\ \quad \text{below entry threshold}(\theta_{\text{entry}}) \text{ at i - th day} \\ -1 \text{ if the distance between input and output is} \\ \quad \text{above exit threshold}(\theta_{\text{exit}}) \text{ at i - th day} \\ 0 \quad \text{otherwise} \end{cases}$$

For example, when $S(i)$ changes from 0 to 1, we can take a long position (see Table 3).

Stop loss is employed with threshold θ_{stop} to manage the risk of investment. Threshold θ_{entry}, θ_{exit} and θ_{stop} were determined in training set. In this paper, threshold θ_{EER} and $\theta_{FAR10\%}$ were used as θ_{entry}. Threshold θ_{exit} was set such that the FFR equals to 1 % in training data set.

For comparison, the buy and hold strategy was also evaluated. We assumed that one buys or sells at the opening price and that the market is perfectly liquid with no transaction cost.

The trading performance of AANN in test set 2000-2001 is given in Table 4. For 2001 test, the AANN was retrained with additional 241 data from year 2000. We assumed that only 1 contract was bought and sold no matter how the system performs. The total point earned(TPE) is the total point that was accrued following the proposed system. The maximum equity drawdown is the biggest drop in terms of TPE during the course of 2 year simulation trading. The TPE of detection with EER threshold 0.5 is better than that of detection with FAR 10% threshold 0.54.

Table 3. Simple trading strategy based on an up-trend signal

$S(i)$	Long position	No position
1	Hold long position	Take a long position
0	Hold long position	Hold no position
-1	Close long Position	Hold no position

Table 4. The trading performance of tested strategies (Jan 2000 ~ Dec 2001)

Strategy	Total point earned (A)	Number of trades	Maximum Drawdown (B)	Stirling Ratio (A/B)
EER Threshold	25.75	33	14.1	1.82
FAR 10% Threshold	21.5	21	12.2	1.76
Buy and Hold	-47.3	1	68.45	-0.69

6. Conclusions

In this paper, we proposed a neural network based up-trend detector. For the experiment, a definition of "up-trend" is given and the up-trend data were selected from the Korea Composite Stock Price Index 200 future price of 36 months (Jan 1997 – Dec 1999). The auto associative neural network was trained with the obtained data. It was then tested on out-of-sample period of Jan 2000 – Dec 2001 with a retraining. A simple investment strategy based on the detector achieved a two year profits of 25.75 points or 19.8 % in return (no leverage) in comparison with -47.3 points or -36.4% in return from a buy and hold strategy.

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References

[1] S. Cho, C. Han, D. Han, & H. Kim, Web Based Keystroke Dynamics Identity Verification using Neural Network. Journal of Organizational Computing and Electronic Commerce. Vol. 10, No. 4, December, 2000.
[2] J. Baek & S. Cho, Time to Jump in?: Long Rising Pattern Detection in KOSPI 200 Future Using an Auto-Associative Neural Network , ICONIP, pp. 160~165, Shanghai, China, Nov. 14-17, 2001.
[3] M. A. H. Dempster & C. M. Jones, Can technical pattern trading be profitably automated? 1. The channel & 2. Head and shoulders, Working Paper, Judge Institute of Management, University of Cambridge, 1999 (revised as: 2001 Can channel pattern trading be automated? Euro. J. Finance at press)
[4] C. Bishop, Neural Networks for Pattern Recognition. Oxford: Clarendon press,1994.
[5] L. Breiman, Bagging Predictors, Machine Learning, Vol. 24, No. 2, pp. 123-140, 1994.
[6] M. A. Kramer, Nonlinear Principal Components Analysis Using Auto Associative Neural Networks, AIChe J., Vol 37, No. 2, pp. 233-243, 1991
[7] A. W. Lo, H. Mamaysky, & J. Wang, Foundation of Technical Analysis: Computational Algorithms, Statistical Inference and Empirical Implementation. Journal of Finance, Vol LV, NO4, pp1705-1765, 2000
[8] G. S. Deboeck & M. Cader, Pre- and Postprocessing of Financial Data, Trading on The Edge, John Wiley & Sons, Inc, pp 27- 44, 1994
[9] G. S. Jang & F. Lai, Intelligent Trading of an Emerging Market, Trading on The Edge, John Wiley & Sons, Inc, pp 80-101, 1994
[10] G. C. Lane, Trading Strategies, Future Symposium International, 1984
[11] J. J. Murphy, Technical Analysis of The Financial Markets: A Comprehension Guide to Trading Methods and Applications, New York Institute of Finance. 1999
[12] Borsanaliz.com company, Tools for technical analysis stock exchange, http://www.geocities.com/ wallstreet/floor/ 1035/formations.htm, 2000
[13] Korea Stock Exchange, KOSPI & KOSPI 200, http://www.kse.or.kr, 2000