Mutual Fund Performance Evaluation System Using Fast Adaptive Neural Network Classifier

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Abstract

Application of financial information systems requires instant and fast response for continually changing market conditions. The purpose of this paper is to construct a mutual fund performance evaluation model utilizing the fast adaptive neural network classifier (FANNC), and to compare our results with those from a backpropagation neural networks (BPN) model. In our experiment, the FANNC approach requires much less time than the BPN approach to evaluate mutual fund performance. RMS is also superior for FANNC. These results hold for both classification problems and for prediction problems, making FANNC ideal for financial applications which require massive volumes of data and routine updates.

1. Introduction

Mutual funds are popular investment vehicles in the modern world. To evaluate a fund's performance, numerous measures have been devised. For example, the Sharpe Index [17], Jenson Index [10] and Treynor Index [22] are all used widely in the market, and many investors place great importance on a fund's ranking in these measures. However, evaluations for mutual funds are mostly made periodically in weeks or even in months, making it useful only for comparing historical performance. To catch up with the fast changing market conditions, an evaluation system should be able to update new status constantly and whenever at request by the user.

Meanwhile, although these indices are frequently adopted for performance evaluations, they do not provide predictive variables, and so cannot be used directly in forecasting superior mutual funds. To address this problem, researchers have explored various approaches. In particular, evaluation methods based upon artificial neural networks (ANN) have been the focus of significant development, as the forecasting and calculating abilities of ANN are superior to traditional algorithms in many respects [5,20,15].

Backpropagation neural networks (BPN) is an ANN model widely used in finance with a supervised neural network which can analyze continuous data [19]. Udo [23] discusses a BPN model better in bankruptcy classification than statistical methods. Davalos, Gritta and Chow [6] utilize BPN to predict the bankruptcy risk of major US air carriers, while Surkan and Singleton [21] use BPN to improve bond rating. Multi-layer perceptrons (MLP) is applied to predict mutual fund performance by Indro, Jiang, Patuwo and Zhang [9] and they subsequently obtain better forecasting result in blended funds, but not for growth funds. Ahn, Cho and Kim [1] propose a hybrid intelligent system that predicts the failure of firms based on past financial performance data by combining a rough set approach with MLP. Lam [14] investigates the ability of backpropagation neural networks to integrate fundamental and technical analysis for financial performance prediction.

Although BPN is commonly applied in financial studies, it has some limitations—the training cost is frequently too high, local minima often mislead the result, and online learning is impossible. There are other types of ANN models designed for classification problems which eliminate the drawbacks of BPN, such as the Self Organization Map (SOM) [12,16] and Adaptive Resonance Theory (ART) [4] families. Unlike BPN, these types of neural models can be trained quickly and can classify a new unknown pattern without accurate information. However, most of them are unsupervised models, a characteristic which limits their applications in financial fields.

FANNC is a new approach to neural networks derived by Zhou, Chen and Chen [24]. Its algorithm seems particularly suitable for instant and fast response to the continually changing financial market conditions. The method is based on adaptive resonance theory and field theory. ART can perform online learning and work under a non-stationary world. The Coulomb potential model for electrostatic forces provides the basis for the field theory approach to artificial neural networks. It enables one-pass learning and can perform real-time supervised learning at high speed.

FANNC is a four-layer structured neural network with the architecture illustrated in Figure 1. The function of the feedback connections is to transfer an active signal to

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each successive layer in order to implement competition and resonance.

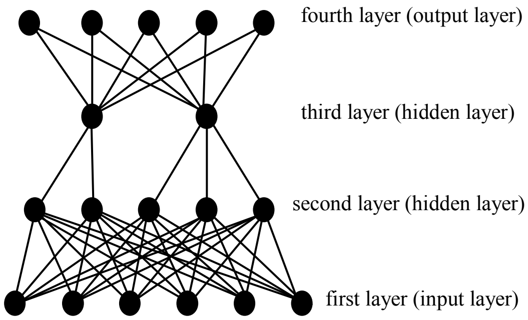

Figure 1 FANNC architecture

FANNC incorporates the concept of the attracting basin, represented in field theory as the electric field produced by the trained instance. Each second-layer unit defines an attracting basin by the responsive centers and the responsive characteristic widths of the Gaussian weights connected with them. These second-layer units are used to classify inputs internally, while the third-layer units are used to classify outputs internally.

In this study, we adopt FANNC to evaluate mutual fund performance and compare the results with those from BPN. Input and output instances are discussed in section 2. The training process and the results are provided in section 3. In section 4, we compare and analyze the results. Section 5 concludes.

2. Preparing Input and Output Instances

2.1 Raw data preparation

The mutual funds listed in Taiwan Economic Journal (TEJ) database are used as input instances for our experiment. In order to get some detailed information from the sample funds, we select three historical periods: 1995-1996, 1997-1998 and 1999-2000 so the concerns of confidentiality about the data will not arise. Raw data collected from these instances are then calculated to provide the input variables for our models. In the following sections these data are processed period by period.

2.2 Input Instances

Many factors that affect mutual fund performance such as the size of the mutual fund and some of the manager's characteristics have been studied in prior literature [2,3]. In this study, we focus on the manager's momentum strategies and herding behavior as the input variables applied in FANNC and BPN.

2.2.1 Momentum strategies

Momentum investors buy stocks that were past winners and sell stocks that were past losers [8]. On measuring the momentum, Grinblatt, Sheridan and Wermers [7] suggest the following equation:

$$M_k = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N}(\tilde{w}_{i,t} - \tilde{w}_{i,t-1})\tilde{R}_{i,t-k+1} \qquad (1)$$

where $\tilde{w}_{i,t}$ is the portfolio weight on security i at date t, $\tilde{R}_{i,t-k+1}$ is the return of security i(i=1,…,N) from date $t-k$ to date $t-k+1$, with k as the lag index.

The two most recent benchmark dates are represented by $k=1$ and $k=2$. They may be the major factors that affect the momentum of the fund. We refer M_1 as lag-1 momentum (L1M) and M_2 as lag-2 momentum (L2M).

Furthermore, we can decompose the L1M into 'buy' and 'sell' parts. The equations are:

$$M_{1B} = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{\tilde{w}_{i,t} > \tilde{w}_{i,t-1}}(\tilde{w}_{i,t} - \tilde{w}_{i,t-1})(\tilde{R}_{i,t} - \overline{R}_i) \qquad (2)$$

$$M_{1S} = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{\tilde{w}_{i,t} < \tilde{w}_{i,t-1}}(\tilde{w}_{i,t} - \tilde{w}_{i,t-1})(\tilde{R}_{i,t} - \overline{R}_i) \qquad (3)$$

We subtract the mean from the return in order to have measures that approach zero under no momentum investing. Similar to the lag-1 momentum measures, the 'buy' and 'sell' parts of the lag-2 momentum measure are:

$$M_{2B} = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{\tilde{w}_{i,t} > \tilde{w}_{i,t-1}}(\tilde{w}_{i,t} - \tilde{w}_{i,t-1})(\tilde{R}_{i,t} - \overline{R}_i) \qquad (4)$$

$$M_{2S} = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{N}\sum_{\tilde{w}_{i,t} > \tilde{w}_{i,t-1}}(\tilde{w}_{i,t} - \tilde{w}_{i,t-1})(\tilde{R}_{i,t} - \overline{R}_i) \qquad (5)$$

2.2.2 Herding behavior

Herding behavior is a trade tendency in which mutual fund managers buy and sell the same stocks in the same period. Recently institutional herding behavior attracts some interests in academics as well as in professionals [11,18]. There are three measurements of herding behavior. The first one is unsigned herding measure (UHM) presented by Lakonishok, Shleifer, and Vishny [13]. UHM measures the average tendency of all managers either to buy or to sell a particular stock at the same time. Namely,

$$UHM_{i,t} = \left|p_{i,t} - \overline{p}_t\right| - E\left|p_{i,t} - \overline{p}_t\right| \qquad (6)$$

where $p_{i,t}$ equals the proportion of the mutual funds that purchase stock i during quarter t, and $\overline{p}_t$, the expected value of $p_{i,t}$, is the mean of $p_{i,t}$ over all stocks during quarter t.

UHM can not differentiate a manager's herding between selling and buying the stocks. Grinblatt, Sheridan and Wemers [7] propose the signed herding measure (SHM) which provides an indication of whether a fund is "following the crowd" or "going against the crowd" for a particular stock during the specified period.

$$SHM_{i,t} = I_{i,t} \times UHM_{i,t} - E[I_{i,t} \times UHM_{i,t}] \qquad (7)$$

where $I_{i,t}$ is an indicator for 'buy' or 'sell' herding. $I_{i,t}$ is defined as follows:

$I_{i,t} = 0$ if $|p_{i,t} - \overline{p}_t| < E|p_{i,t} - \overline{p}_t|$

$I_{i,t} = 1$ if $p_{i,t} - \overline{p}_t > E|p_{i,t} - \overline{p}_t|$ and the mutual fund is a buyer of stock *i* during quarter *t*,

or if $-(p_{i,t} - \overline{p}_t) > E|p_{i,t} - \overline{p}_t|$ and the fund is a seller of stock *i*.

$I_{i,t} = -1$ if $p_{i,t} - \overline{p}_t > E|p_{i,t} - \overline{p}_t|$ and the mutual fund is a seller of stock *i* during quarter *t*,

or if $-(p_{i,t} - \overline{p}_t) > E|p_{i,t} - \overline{p}_t|$ and the fund is a buyer.

$SHM_{i,t}$ is set to be zero if fewer than 10 funds trade stock *i* during period *t*. If the number of funds trading stock *i* is small, no meaningful way can indicate whether the fund is herding or not.

Finally, the herding measure of a mutual fund (FHM) is then calculated by substituting the signed herding measure in place of the stock return in equation (1).

$$FHM = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{n}(\tilde{w}_{i,t} - \tilde{w}_{i,t-1})SHM_{i,t} \qquad (8)$$

where $\tilde{w}_{i,t}$ is the proportion of the funds trading stock *i* during quarter *t*.

2.3 Output instances

We use two sets of output instances in our performance evaluation models to study the classification capability and the predictive power of FANNC. In the former case, the output is the Sharpe index calculated for the same period in which the momentum and herding measures are determined. We denote this as the "classification case". In the latter case, we use as the output instance the Sharpe index calculated for the next month right after the period for momentum and herding measures. It is labeled the "prediction case". The output instances are calculated as follows:

Classification Sharpe Index:

$$Sharpe\ \ Index = \frac{\overline{R}_i - \overline{R}_f}{\sigma_i} \qquad (9)$$

Prediction Sharpe Index,

$$Sharpe\ \ Index = \frac{R_i^+ - \overline{R}_f}{\sigma_i} \qquad (10)$$

where

$\overline{R}_i$: the average monthly return for fund *i* in the calculation period.

R_i^+ : the return of fund *i* for the month after the calculation period.

$\overline{R}_f$: the average monthly risk-free rate represented by the 1-year CD rate of commercial bank.

σ_i : the standard deviation of the return of the fund *i* over the calculation period.

3. Training and Testing Process

All the input and output instance pairs discussed in the last section are divided into two parts. 80% of them are used for training and 20% are for testing.

3.1 Backpropagation neural networks

We apply Neural Connection by SPSS to implement the backpropagation neural networks (BPN) algorithm. Before training the network, we first set the stop criterion, learning coefficient and momentum coefficient. For stop criterion, we limit the maximum epochs to 3000 times as our experiment indicates that the root mean square (RMS) stabilizes by this time. To determine the learning and momentum coefficients, the software tests several pairs and chooses the most effective one automatically after training. In this study, this optimization process results in a value of 0.1 for the learning coefficient and a value of 0.9 for the momentum coefficient.

Next, we decide the activation function. The software offers us two choices: sigmoid function or hyperbolic tangent function. After training and testing, we find no remarkable differences between the two and we choose the sigmoid function as it is widely used in the literature of BPN.

To enhance the accuracy of BPN, we normalize the input and output instances by the standard normalization method.

$$f(x_i) = \frac{x_i - \mu}{\sigma} \qquad (11)$$

where x_i is the normalized variable, μ is the mean of *x*, and σ is the standard deviation of *x*. In a manner similar to the identification of the learning and momentum coefficients, the software determines the number of layers and nodes automatically. It also adjusts the network structure according to the input and output nodes. In this study, the architecture we obtain is a 7-4-1 network. When we input the instances into network, the feeding sequence and the selection of testing instances are arranged randomly. After the training, the software reports the RMS which is calculated from instances.

3.2 FANNC

As there is no commercial package readily available to implement FANNC, we use C++ to program the algorithm. There are seven variables to be determined in FANNC: responsive center θ_{ij}, responsive characteristic width α_{ij}, responsive center adjustment step δ, bias, the leakage competition threshold in the second layer, the outer layer similarity control coefficient Err, and the inner layer similarity control coefficient $Errc_u$.

When a new node in the second layer is generated, its related responsive center is set to the value of input component in current instance under training, and the responsive characteristic width is set to be the default value, 0.25. When this value increases slightly, the predictive ability of the network will increase; however, excessive increase in the responsive characteristic widths will decrease the predictive ability. The value for responsive center adjustment step, δ, affects the learning speed of the network and usually adopts a value between 0 and 1.0. In this paper, we choose the value to be 0.01.

The leakage competition thresholds in the second layer, Err and $Errc_u$ play similar roles, as both determine how many new nodes will be generated in a trained network. When Err increases, the network tends to adjust its θ_{ij} and α_{ij} instead of generating new nodes in the second and the third layers. Increasing $Errc_u$ will increase the probability that only one new node is appended to the second layer and decrease the probability that two new nodes are appended to the second and the third layers simultaneously. The number of the nodes in the second and the third layers determines the predictability of the model and its ability to memorize the trained instances. In general, the predictability will decrease and the error from memorizing will increase when the node number increases. Zhou, et. al. [24] suggest that the leakage competition threshold be 0.8 and the maximum permissible error 0.11.

The architecture of FANNC is composed of seven input units and one output unit. The hidden layer units are generated dynamically. In this research, we utilize the regression function of FANNC to evaluate the mutual fund performance.

Like in BPN, input and output instances are normalized by the standard procedure. Meanwhile, feeding sequence and the selection of testing instances are arranged randomly.

4. Result Comparison

Table 1 and Table 2 provide the comparison of RMS and the processing time between the FANNC approach and the BPN approach. For both the classification case and the prediction case, FANNC is clearly superior to BPN.

Table 1 The results of Classification test

	Sample number		FANNC		BPN	
Period	Training	Testing	RMS	Time*	RMS	Time*
95-96	24	6	0.089896	< 1	0.186776	16
97-98	37	9	0.101789	< 1	0.221166	19
99-00	54	12	0.086623	< 1	0.222502	21

*Including training time and testing time. Units are in seconds.

Table 2 The results of prediction test

	Sample number		FANNC		BPN	
Period	Training	Testing	RMS	Time*	RMS	Time*
95-96	24	6	0.005062	< 1	0.008232	16
97-98	37	9	0.005199	< 1	0.011251	19
99-00	54	12	0.005305	< 1	0.010156	21

*Including training time and testing time. Units are in seconds.

RMS from FANNC is significantly lower than those from BPN, typically by a factor of two or three. As for processing time, FANNC consumes less than one second, while BPN requires at least 16 seconds. This difference in process time will only become more significant as the number of samples increases.

Figure 2 depicts the scatter diagram of classification RMS. Most of the points are distributed around the 45 degree line. However, we see that the points from FANNC are more concentrated and closer to 45 degree line when compared with the results generated by BPN. This implies that the FANNC approach has higher accuracy in Sharpe Index classification than the BPN approach.

These results are similar in the prediction case, as shown in figure 3. Like before, FANNC points are more concentrated and closer to 45 degree line.

In addition to the advantages in time consumption and RMS accuracy, FANNC is superior to BPN for financial applications in other aspects as well. First, FANNC is equipped with a real-time learning capability. When we obtain a new instance, re-training is not necessary, so in practice, we can use the algorithm to monitor a dynamic database. When the database is changed, the network will check whether the new instance can be classified by any existing attraction basin. If not, it will create a new one. Meanwhile, if the trained network fails to classify a new input, it can memorize and reclassify it later after more instances are available.

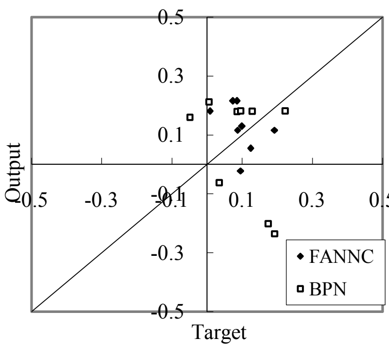

Figure 2 RMS in classification case, 1999-2000

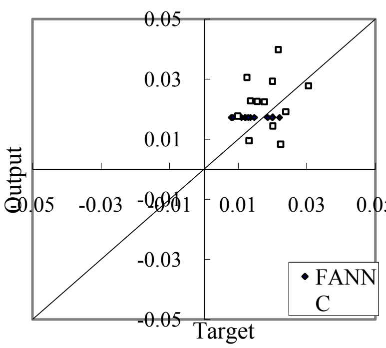

Figure 3 RMS in prediction case, 1999-2000

5. Conclusion

The purpose of this paper is to construct a flexible and responsive mutual fund performance evaluation system utilizing FANNC, and compare the results with those from BPN based model. FANNC is a newly developed neural network which combines the features of ART and field theory. In our experiment, FANNC not only requires significantly less time to evaluate mutual fund performance than the BPN approach but also has a superior RMS record. These results hold for both classification problems and prediction problems. Furthermore, the algorithm in FANNC assures fast processing time and easy on-line learning, thus making FANNC ideal for financial applications involving massive volumes of data and routine updates.

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