Application of Self-Organizing Mapping Neural Network for Discovery of Market Behavior of Equity Fund

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Abstract: - Maximizing the profit and minimizing the loss notwithstanding the trend of the market is always desirable in any investment strategy. The present research develops an investment strategy, which has been verified effective in the real world, by employing self-organizing map neural network for mutual funds and tracking the trends of stock market indices according to macro-economy indicators, weighted indices, and rankings of mutual funds. Our experiment shows if utilizing strategy 3 according to our model during a period from January 2002 to December 2008 the total returns could be at 122 percents even though the weighted index falls 22 percents and averaged investment returns for random transaction strategies stand at minus 25 percents during the same period. As such, we conclude that our model does efficiently increase the investment return.

Key Words: Equity Fund, Neural Network, Self-Organizing Mapping, Investment Strategy

1 Introduction
It is widely perceived that the general investing public may have hard time digesting all relevant information associated with a variety of financial products and derivatives. Though, investors may choose to invest in a single financial product or stock market doing so might only lead to substantial risk on the part of investors [1]. Investment in mutual funds provides an alternative with effectively reduced risks as the mutual fund pools the investment money together and may target distinct markets around the world for balancing the risks arising out of the investment [2]. Therefore, the present research chooses the mutual fund for the illustration of our proposed investment approach.

Traditional performance evaluation models, such as the early Treynor indicator [3], the Sharpe indicator [4] and the Jensen indicator [5], are derived from the capital asset pricing model (CAPM). However, these models merely evaluate the relationship between risks and investment returns, which is an important reference for the investors when it comes to selection of mutual fund, but what concerns them the most should be how to timely and properly respond to the turns of the markets so as to maximize their investment returns.

The macroeconomic indicators tend to represent the spatial and temporal context of the economy. There exists interdependence between the stock market and the macroeconomic. The performance of the stock-based mutual fund depends on the performances of the stocks in its portfolio.

As the current computing devices possess large amount of computing power, how to fully utilize the computing resource becomes more and more critical in the advancement of technology. A self-organizing mapping neural network, which mimics the human brain activities, could equip its output units with similar functions learned from inputs of the network. This characteristic is very suitable for research of behavior clustering in the context of different time and space between macro-economy and the mutual fund. Nobel Prize Laureate D. Kahneman proposed Prospect Theory [6] successfully explaining that a certain degree of difference exists between real environment and efficiency market and proving regular behaviors of human beings are associated with irrationalities. Since then, relevant studies utilizing artificial intelligence (AI) to predict stock markets have been gaining their popularity [7][8][9]. Therefore, this paper presents the use of self-organizing mapping neural network [10], making the appropriate grouping between the mutual fund and the macro-economy. Based on the results of the study, another reference for investment decisions could be provided to help investors at the time of navigating the ever-changing market.

1.1 Research scope and limitation
Sample period and data source
(1) Sample period: October 1998 to December 2008
(2) Sample data: Select 189 Taiwan-based mutual funds and 13 macro-economy indicators from Taiwan futures data from Taiwan Futures Exchange while the Taiwan-based mutual fund is categorized by Dr. Lee and Dr. Chiu as the type “1” domestic stock-based mutual funds provided in Taiwan mutual fund evaluation website
(3) Data source: Taiwan Economic Journal (TEJ) and Taiwan Futures Exchange
- Research Limitation
(1) As there are a variety of mutual funds on the market and for the purpose of ranking the Taiwan weighted index (as a hypothetical mutual fund) relative to our mutual fund selections, only domestic stock-based mutual funds are selected
(2) As the discrepancy in when the selected domestic stock-based mutual funds were launched, the mutual fund if not launched in a particular month such mutual fund would not be ranked for that particular month
(3) To simplify our model, only purchasing transactional fee (1.5 percents) is taken into account in our simulated mutual fund transactions with no discount (such as 50-percent off in the transactional fee), other fees (such as procedural fee associated with “short-term” transaction), and 5-point deduction from transaction cost in a single simulated future transaction (buy and sell) [11]
(4) To simplify our model, our simulated mutual fund transactions do not consider certain factors such as fluctuations in interest and commodity price.

2 Research model development
The present research is conducted accounting to the flow chart shown in Fig. 1.

![Flow Chart](image)

Fig. 1 Research flow chart

2.1 Data collection
(1) Taiwan weighted index data, mutual fund information, and macro-economy indicators (13 in total) from TEJ
(2) Taiwan futures index data from Taiwan Futures Exchange
(3) Sample period: October 1998 to December 2008
Sample data: 189 Taiwan-based mutual funds from Taiwan mutual fund evaluation website and categorized by Dr. Lee and Dr. Chiu as the type “1” domestic stock-based mutual funds

2.2 Macro economy indicator and Rank ratio

2.2.1 Macro economy indicator
Macro-economy indicators may possess certain capability in predicting trend of finance market behaviors. Based on past researches, we use 13 macro-economy indicators, which are listed in table 1, as one set of inputs to the presently proposed research model.

Table 1 Macro-economy indicators as inputted variables

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Money supply (M1b) annual increase rate
Taiwan wholesale price index
business cycle signal score
Taiwan coincident indicator composite index
Taiwan leading indicator composite index
export
import
Taiwan discount rate
Dow Jones industrial index
NTD v. USD
one-month fixed term interest rate
one-year fixed term interest rate
money supply account M2 annual increase rate

2.2.2 Rank ratio between weighted index and mutual fund
To prepare a monthly rank ratio between weighted index and mutual funds, following steps are taken:
(1) Consider weighted index as a hypothetical mutual fund, and add it to our selected 189 stock-based domestic mutual funds to form a group of 190 mutual funds.

(2) Rank the weighted index relative to our selected mutual funds by computing net value variation percentages for the weighted index and selected mutual funds.

(3) Divide the rank of the weighted index and the number of the mutual funds in a particular month to come up with a percentage for the weighted index. For example, if the rank for the weighted index in October 2008 is 152 and the number of all mutual funds stands at 190 the percentage for the weighted index in that particular month is 80 percents.

(4) The percentage obtained from step (3) is rank ratio between the weighted index and mutual fund.

### 2.3 Normalization

Consider macro-economy indicators and ranking ratio between weighted index and mutual funds may be different in value range definition, and the input could be so concentrated or widespread that the grouping is affected, before any data is inputted into self-organizing mapping neural network, min-max normalization is employed to normalize values between 0 and 1. The normalization is as follows:

\[
X_i = \frac{X_i - \text{min}_i}{\text{max}_i - \text{min}_i}
\]

where X-i is the original value of ith indicator, min-i is the smallest original value for ith indicator and max-i is the biggest original value of ith indicator

### 2.4 Discover mutual fund market trend

According to Fig.1, input macro-economy indicators and rank ratio between the weighted index and mutual fund to self-organizing mapping neural network for learning. Network algorithm and parameter configuration are as follows:

**Network initial weight**

To render each location in a coordinate plane to represent the same, instead of selecting a random value our research configure the initial weight according to “Same weight increment method” proposed by Dr. Huang with same increment on basis of coordinate location from output module. Such method is as follows:

\[
W_{ijm} = \frac{m + n}{M \times N}
\]

Wijmn: weight of ith element of character vector corresponding to jth output unit on a two-dimension plane as (m, n)

M: length of network output matrix X

N: length of network output matrix Y

m: length of output unit matrix X

n: length of output unit matrix Y

Network input layer: 13 macro-economy indicators and one rank ratio between weighted index and mutual fund

Network output layer: 10 by 10 network topology matrix (100 output units)

Neighbor function: Gaussian function

Neighbor diameter: 2

Learning rate: 0.2

Learning times over 10,000 or averaged errors associated with output neural unit less than 0.0000001

**Step 1:** Mutual fund trend discovery model selects macro-economy indicators and rank ratios between weighted index and mutual funds when the weighted index in bull and bear markets respectively and inputs them to self-organizing mapping neural network to be grouped by learning. Thereafter, our approach obtains centers of the distribution of the data in terms of the 2-dimention plane. Figure 2 provide the details

**Step 2:** Select macro-economy indicators and rank ratios between the weighted index and mutual fund for our selected months respectively and input them into the self-organizing mapping neural network to be grouped by learning. Each result of the group by learning is represented in terms of a location in the 2-dimension plane. Compute distance between the results and the centers in the bull and bear markets obtained in step 1. When the result is closer to the center of bull market, “bull” signal is generated and thus mutual funds are to be purchased in the following month. While the result is closer to the center of bear market, a “bear” signal is generated and thus mutual funds are to be sold or futures are to be shorted in the following month. Fig.2 also provides the details.
2.5 Random walk model
Traditional finance engineering generally admits unpredictability of stock market and thus the trend of the market is consistent with Random Walk theory. As such, the stock price generally reflects all possible information in the market. Since the occurrence of the information is random, the change in stock price is random as well. Fama [12] proposed efficiency market theory based on an assumption that price moving trend in the past has nothing to do with that in the future. Therefore, a random trading strategy refers to each buy and sell of stock in the market should be randomly generated without any prediction on the trend of price moving.

2.6 Model verification
To compare investment returns of different strategies from models proposed by the current research, explanations for those strategies for transaction simulations are as follows:
(1) Simulated transaction strategy 1: sample data includes information of stock-based domestic mutual funds at the beginning and end of months from January 2002 to December 2008. Buy if any “bull” signal was indicated in the preceding month or sell if any “bear” signal was generated in the preceding month. When compared with strategy 1, no mandatory “buy/sell” period (e.g., every three month) is set. Any buy and sell is dependent on buy and sell signals in the previous months.
(2) Simulated strategy 2: sample data includes information of stock-based domestic mutual funds at the beginning and end of months from January 2002 to December 2008, and Taiwan futures index data at the beginning and end of the months during the same period. Buy if any “bull” signal was indicated in the preceding month or short futures if any “bear” signal was generated in the preceding month, no mandatory “buy/sell” period (e.g., every three month) is set in this strategy. Any buy and sell is dependent on buy and sell signals in the previous months.

3 The transaction experiment flow
The goal of the experiment of the present research is to establish a stock-based mutual fund transaction system according to self-organizing mapping neural network with inputs from rank ratios between the weighted index and mutual funds and macro-economy indicators. In doing so, the trend of Taiwan weighted index could be predicted in a more accurate manner. The model invests the capital according to the generated “bull” or “bear” signal for simulated transactions. The experiment flow shown in Fig.3 includes data collection, data processing, and model verification.

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**Fig. 2 Mutual Fund Market Discovery Flow Chart**

**Fig. 3 Experiment flow chart**
Exchange, stock-based domestic mutual funds, and Taiwan index futures of Taiwan Futures Exchange from October 1st 1998 to December 31st 2008 (without considering October 1st 2001 to December 31st 2001). The detail is shown in Fig.4.

The data includes a group of 120 end-of-month Taiwan weighted indices, 120 start-of-month and end-of-month selected mutual fund data, and 120 start-of-month and end-of-month Taiwan index futures data. The present research utilizes data from October 1st 1998 to March 31st 2000 as training data for “center of bull market” while using the data from April 1st 2000 to September 30th 2001 as training data for “center of bear market.”

36 months (training period) 84 months (simulation period)

1998/10/01 2002/1/1
2001/09/30 2008/12/31

Fig. 4 Sampling period for present research

Signal determination: Compute distance to center of “bull market” (3.06, 2.67) and to center of “bear market” (7.83, 5.67). When the location closer to center of “bull market” a “bull” signal is prepared; otherwise, (when closer to center of “bear market” a “bear” signal is generated.

4 Result of experiment

4.1 Training result for center of “Bull Market” and center of “Bear Market”
The distribution of locations in 2-dimension plane during October 1998 to March 2000 so as to conclude the center of “bull market” is (3.06, 2.67). End of term total amount during bull market is shown in Fig.5.

4.2 Experiment result analysis and comparison
Invest hypothetical 10 millions according to three strategies developed by the present research and Random Walk strategy, the end-of-year investment return is shown in Table 2 and Table 3.

<table>
<thead>
<tr>
<th>Year</th>
<th>Rnd. Walk</th>
<th>Strategy 1</th>
<th>Strategy 2</th>
<th>Strategy 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>7,507,130</td>
<td>7,984,410</td>
<td>8,916,745</td>
<td>9,611,353</td>
</tr>
<tr>
<td>2003</td>
<td>11,341,446</td>
<td>11,409,613</td>
<td>11,137,585</td>
<td>10,468,139</td>
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<tr>
<td>2004</td>
<td>9,034,728</td>
<td>10,687,036</td>
<td>10,754,867</td>
<td>11,629,824</td>
</tr>
<tr>
<td>2005</td>
<td>12,923,707</td>
<td>12,278,177</td>
<td>15,011,452</td>
<td>16,136,171</td>
</tr>
<tr>
<td>2006</td>
<td>11,098,198</td>
<td>11,537,225</td>
<td>10,580,551</td>
<td>9,358,935</td>
</tr>
<tr>
<td>2007</td>
<td>10,393,863</td>
<td>9,821,865</td>
<td>11,790,144</td>
<td>11,112,584</td>
</tr>
<tr>
<td>2008</td>
<td>5,198,642</td>
<td>8,625,725</td>
<td>9,542,658</td>
<td>13,852,124</td>
</tr>
</tbody>
</table>

Table 2 End of Year Investment Return

<table>
<thead>
<tr>
<th>Year</th>
<th>Rnd. Walk (%)</th>
<th>Strategy 1 (%)</th>
<th>Strategy 2 (%)</th>
<th>Strategy 3 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2003</td>
<td>13.41</td>
<td>14.09</td>
<td>11.37</td>
<td>4.68</td>
</tr>
<tr>
<td>2004</td>
<td>-9.65</td>
<td>6.87</td>
<td>7.54</td>
<td>16.29</td>
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<tr>
<td>2005</td>
<td>29.23</td>
<td>22.78</td>
<td>50.11</td>
<td>61.36</td>
</tr>
<tr>
<td>2006</td>
<td>10.98</td>
<td>15.37</td>
<td>5.80</td>
<td>-6.41</td>
</tr>
<tr>
<td>2007</td>
<td>3.93</td>
<td>-1.78</td>
<td>17.90</td>
<td>11.12</td>
</tr>
<tr>
<td>2008</td>
<td>-48.01</td>
<td>-13.74</td>
<td>-4.57</td>
<td>38.52</td>
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<tr>
<td>Max*</td>
<td>29.23</td>
<td>22.78</td>
<td>50.11</td>
<td>61.36</td>
</tr>
<tr>
<td>Min*</td>
<td>-48.01</td>
<td>-20.15</td>
<td>-10.83</td>
<td>-3.88</td>
</tr>
<tr>
<td>Sum*</td>
<td>-25.02</td>
<td>23.44</td>
<td>77.34</td>
<td>121.69</td>
</tr>
</tbody>
</table>

Max: maximum annual averaged investment return
Min: minimum annual averaged investment return
Sum: Accumulative investment return from 2002 to 2008

From our experiment, Strategy 3 outperforms Strategy 2, Strategy 1, and Random Walk in terms of annual investment return during 2002 to 2008. Further, Strategies 1, 2, and 3 defeat the weighted index and Random Walk strategy. Result of experiment is summarized in Table 4.
Table 4 Simulated Transaction Comparison

<table>
<thead>
<tr>
<th>Description</th>
<th>Rtn %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weighted Index: Investment return on basis of 5872.14 in 2002/01 and 4591.22 in 2008/12</td>
<td>-21.8</td>
</tr>
<tr>
<td>Random Walk: Randomly purchase 10 mutual funds, buy/sell every three months, average 30 simulated transactions</td>
<td>-25.0</td>
</tr>
<tr>
<td>Strategy 1: Purchase top 10 mutual funds, buy when “bull,” wait when “bear,” and “buy/sell every three months</td>
<td>23.4</td>
</tr>
<tr>
<td>Strategy 2: Purchase top 10 mutual funds, buy when “bull,” wait when “bear” without any mandatory buy/sell period</td>
<td>77.3</td>
</tr>
<tr>
<td>Strategy 3: Purchase top 10 mutual funds, short futures, buy when “bull,” short futures when “bear” without any mandatory “buy/sell” period</td>
<td>121.7</td>
</tr>
</tbody>
</table>

5 Conclusion

The current research selects 189 stock-based mutual funds and a variety of macro-economy indicators as inputs to self-organizing mapping neural network. The present research also proposes an approach of determining the trend of the market so as to develop an investment model accordingly. While investing on basis of the proposed model, the investment return is far greater than Random Walk strategy and outperforms weighted index.

According to our experiment, the present model is:
(1) With superior market trend discovery capability
(2) A superior decision-making aiding tool helping the investor in analyzing potential market trends in the future
(3) With higher investment return than that from fixed term interest return or adoption of Random Walk transaction strategy

Though our model outperforms the weighted index and Random Walk trading strategy, it might not predict the future trend in price moving with 100 percents of accuracy. Therefore, the accuracy rate and investment return of the current model could be further improved. Couple of potential improvements could be:
(1) Selection of centers of “bull” and “bear” markets could be through artificial intelligence and adjusted dynamically at different points of time to render our model to be more accurate
(2) Assignment of different weights to the data according to the dates associated with the data to render our model to be more in line with what actually takes place.

References: