Predicting IPOs Performance Using Generalized Growing and Pruning Algorithm for Radial Basis Function (GGAP-RBF) Network

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Abstract

Finance and investing is the second most frequent business area of neural networks applications after production/operations. Although many research results show that neural networks can solve almost all problems more efficiently than traditional modeling and statistical methods, there are opposite research results showing that statistical methods in particular data samples outperform neural networks. Many papers on neural network applications on stock markets provide forecast only on existing stocks. However, many new stocks are being listed each year. Thus the aim of this study is to explore this relatively un-tapped region in the stock market and to investigate if neural networks can predict the returns of these IPOs. As for the prediction model, this study uses a proposed sequential learning Radial Basis Function (RBF) and this neural network aims to take advantage of the relationship between time series and firm specific information. Since IPOs have prior information of itself, the predicted values will be based on related time series and variables of the firm specific factors. Experimental results based on IPOs from the Singapore Stock Exchange are presented to evaluate the performance of the prediction.

1. Introduction

Forecasting time series is an important yet controversial problem in business and economics. There has been abundant work done on ways to predict stock prices in hope of providing investors with optimal decisions during trading. IPOs are a special part of the equity market, which in times is for the risk portion of an individual's portfolio. Investing in IPOs is a way to invest in the future. Many IPOs are young companies that offer new and cutting edge technology [1]. With as many as 40 new listing each year on the Singapore Stock Exchange, IPOs presents a lucrative option for many investors. Going public may also involve some hidden risks mostly in the form of share price volatility and decline in share value. More often than not, it is difficult for individual investors to be knowledgeable of these companies. In the absence of sound investment advices, investors often take a common-sense approach to investing in the companies that boast the latest and greatest technologies.

Neural networks have been applied to many financial prediction problems. However, most of these applications assumed predefined network architecture and use a training algorithm to learn the weights of the network. It is usually very difficult to fine-tune the balance between network complexity and learning accuracy for most real world problems. If too much emphasis is placed on network complexity, a compact network with a large bias will evolve. However, if emphasis was placed on learning accuracy, the end result could be a very large neural network with large variance [5]. Thus having a neural network that is able to grow and prune itself according to the application and with good generalization capabilities avoids such a trade-off. This is the reason the sequential learning algorithm for radial basis function (RBF) networks referred to as Generalized Growing and Pruning algorithm for RBF (GGAP-RBF) [10] was selected as the prediction model. Each time an observation is learnt; the network will grow as well as shrink accordingly. This paper investigates the use of this neural network model to forecast the performance of IPOs listed on the Singapore Exchange. The rest of this paper will discuss the architecture of the prediction model, results of the prediction application and a conclusion of this study.

2. Prediction Model

2.1Time Series Prediction

The time series prediction can be expressed succinctly as follows: Given a sequence of past time series values, $x(t)$, $x(t-\tau)$, $x(t-2\tau)$, … where t is the current time and τ is the sampling time step, a neural network model would be constructed to find the continuation series point $x(t+\tau)$, $x(t+2\tau)$, ... The time series can be implicitly written as:

$$x(t+\tau) = f\,[x(t), x(t-\tau), x(t-2\tau), \ldots]$$

for some function f. The neural network is then trained to approximate f so that it can predict the subsequent values of the time series.

2.2 Neural Network Model

Most of the statistical models cannot result in satisfactory predicted results in many forecasting applications due to over-fitting or under-fitting issues. This is because the traditionally mathematical model has to consider whether the system is the linear or nonlinear model, what the appropriate order of function for prediction is, and how to test the fitness of the forecasting model [2]. Thus, it is important to identify an intelligent method as a prediction tool. Besides that, selection of a learning algorithm is also crucially dependent on its accuracy and speed. As such, GGAP-RBF was selected as the prediction model. Simulation results for benchmark problems in the function approximation area show that GGAP-RBF outperforms several other sequential learning algorithms in terms of learning speed, network size and generalization performance regardless of the sampling density function [3].

This section first introduces the notion of significance for the hidden neurons based on their statistical average contribution over all inputs seen so far, although those inputs are discarded and not stored in the system after being learned. Suppose that the observations (x_i, y_i), $i = 1, 2, \ldots$, are drawn from a sampling range X with a sampling density function $p(x)$. Suppose that at an instant of time, n observations (x_i, y_i) have been learned by the sequential learning system. Let the sampling range X be divided in N small spaces Δ_j, $j = 1, \ldots, N$. The size of Δ_j is represented by $S(\Delta_j)$. Since the sampling density function is p(x) there are about $n.p(x_j).S(\Delta_j)$ samples in each Δ_j, where x_j is any point chosen in Δ_j. The statistical contribution of neuron k to the overall output of the RBF network is hence given by

$$E_q(k) = \| \alpha_k \|_q \left(\sum_{j=1}^{N} \phi_k^q (x_j) p(x_j) S(\Delta_j) \right)^{1/q} \tag{1}$$

And the significance of the a specified neuron k, E_{sig}(k) is defined as

$$E_{sig}(k) = \lim_{n \to +\infty} E_q(k) = \| \alpha_k \|_q \left(\int_x \exp\left(-\frac{q \| x - \mu_k \|^2}{\sigma_k^2} \right) p(x) dx \right) \tag{2}$$

For a more detailed discussion of the significance of neurons, please refer to [10]

2.2.1 Growing Criterion

The RBF network initially begins with no hidden neurons. For each iteration of the training phase, the inputs that are fed into the network may initiate new hidden neurons based on a growing criterion as follows:

$$\begin{cases} \| x_n - \mu_{nr} \| > \varepsilon_n \\ \| e_n \|_q \left(\int_x \exp\left(-\frac{q \|x - x_n\|^2}{k^2 \|x_n - \mu_{nr}\|^2} \right) p(x) dx \right)^{\frac{1}{q}} > e_{\min} \end{cases} \tag{3}$$

where x_n is the latest input received, μ_{nr} is the center of the hidden neuron nearest (in the Euclidean distance sense) to x_n. $e_{\min}$ is the expected approximation accuracy and ε_n is a threshold to be selected appropriately and   is an overlap factor that determines the overlap of the responses of the hidden neurons in the input space.

The first criterion ensures that a new neuron is only added if input data is sufficiently far from the existing neurons. The second criterion ensures that the significance of the newly added neuron obtained by substituting equation (4) in equation (2) is greater than the required approximation accuracy $e_{\min}$.

Whenever a new hidden neuron is added, the parameters associated with it are given by

$$\begin{cases} a_{K+1} = e_n \\ m_{K+1} = x_n \\ s_{K+1} = k \| x_n - m_{nr} \| \quad \text{where } e_n = y_n - \mathrm{f}(x_n) \end{cases} \tag{4}$$

2.2.2 Pruning Criterion

The significance of a neuron will determine whether that neuron will be removed. When the significance of neuron k is less than the approximation accuracy $e_{\min}$, neuron is considered insignificant and therefore should be removed. This, however, does not mean that neuron k does not affect the approximation result at all. It is removed only because the contribution of neuron k is not significant enough for the required approximation accuracy. Thus given the approximation accuracy $e_{\min}$, neuron k will be pruned if

$$\begin{aligned} E_{sig}(k) &= \lim_{n \to \infty} E_{avg}(k) \\ &= \| \alpha_k \|_q \left(\int_X \exp\left(-\frac{q \| x - \mu_k \|^2}{\sigma_k^2} \right) p(x)\, dx \right)^{1/q} < e_{\min} \end{aligned} \tag{5}$$

The above condition implies that after learning each observation, the significance for all neurons should be computed and checked for possible pruning. This will be a computationally intensive task. But it is shown in the next section that only the nearest neuron is possibly insignificant and needs to be checked for pruning and there is no need to compute the significance of all neurons in the network.

2.2.3 Adjustment and Pruning of Nearest Neuron

In order to increase the learning speed further, it can be shown that only the nearest neuron (in the Euclidean distance sense) is possibly insignificant and needs to be checked for pruning after receiving the most recent input and no new neuron was added. Hence there is no need to compute the significance of all neurons in the network. The reason is as follows: Suppose that after sequentially learning n observations, a RBF network with K neurons has been obtained. All these K neurons should be significant since insignificant neurons would have been pruned after learning the nth observation. When a new (n+1)th observation arrives and the growing criterion is satisfied, a new significant neuron K+1 will be added. The parameters of all other neurons will be unchanged and those neurons will remain significant after learning the (n+1)th observation. Thus every neuron including the newly added neuron will be significant. Hence pruning checking need not be done whenever a new neuron is added.

When a new observation arrives and the growing criterion is not satisfied, no new neuron will be added and only the parameters of the nearest neuron will be adjusted. This means that the parameters all the other neurons remain unchanged, and consequently, those neurons except for the nearest one will remain significant after learning the (n+1)th observation. Hence one only needs to check whether the nearest neuron becomes insignificant after adjustment. If the nearest neuron becomes insignificant, it should be removed. The adjustment of the parameters of the nearest neuron will be done using the Extended Kalman Filter (EKF) algorithm. The effect of the EKF is to improve the accuracy and obtain a more compact network. In the EKF algorithm, the Kalman gain vector computation becomes dramatically simpler because only one neuron is adjusted. (Refer to Yingwei [1] for EKF equation details.)

2.2.4 The GGAP-RBF Algorithm

The network initially begins with no hidden neurons. Thus $K = 0$. For each observation (x_n, y_n) presented to the network, where $x_n \in X \subseteq \mathbf{R}^l$ and n = 1,2,…, do

1. Compute the overall network output:

$$f(x_n) = \sum_{k=1}^{K} \alpha_k \exp\left(-\frac{1}{\sigma_k^2} \| x_n - \mu_k \|^2\right)$$

   where K is the number of hidden neurons.

2. Calculate the parameters required in the growth criterion:

$$\varepsilon_n = \max\left\{\varepsilon_{\max}\gamma^n, \varepsilon_{\min}\right\}, (0 < \gamma < 1)$$

$$e_n = y_n - f(x_n)$$

3. Apply the criterion for adding neurons:

   If $\| x_n - \mu_{nr} \| > \varepsilon_n$ *and*

$$\| e_n \|_q \left(\int_X \exp\left(-\frac{q \| x - \mu_k \|^2}{\sigma_k^2}\right) p(x)dx\right)^{1/q} < e_{\min}$$

   allocate a new neuron $K + 1$ with

$$\alpha_{K+1} = e_n$$

$$\mu_{K+1} = x_n$$

$$\sigma_{K+1} = k \| x_n - \mu_{nr} \|$$

   Else

   adjust the network parameters $\alpha_{nr}, \mu_{nr}, \sigma_{nr}$ for the nearest neuron only.

   check the criterion for pruning the adjusted hidden neuron:

   If

$$E_{sig}(nr) = \| \alpha_{nr} \|_q \left(\int_X \exp\left(-\frac{q \| x - \mu_{nr} \|^2}{\sigma_{nr}^2}\right) p(x)dx\right)^{1/q} < e_{\min}$$

   remove the nr^{th} hidden neuron

   reduce the dimensionality of the EKF

   Endif

   Endif

3. Experimental Results

3.1 Data Selection

The basis of this study is the assumption that in the long term, some economic indicators such as long term interest rate affect the performance of IPOs after some delay. Hence the correlation tests will be used to determine the length of this delay. In turn, the indicator that returns an acceptably high coefficient will be used to input to the neural network for training and forecasting.

For the investigation of correlation between various economic indexes and IPO stock prices, stock data of all the IPOs listed on the Singapore Exchange in year 2002 were extracted to perform the correlation tests. Various time lengths were tested in order find the periods whereby the economic indexes had the highest correlation on the performance of IPOs after listing. These data, together with the stock performance of the IPOs, are used as training data for the neural network model.

Test results showed that economic indexes such as Singapore Interbank interest rate (1-year), Singapore Oil and Gas price index and certain market indexes reflected direct effects on the performance of IPOs within the first 3 months after listing. The prediction system uses a moving average of daily data of each index for minimizing the influence due to random walk. The following list shows the indexes used.

1. Singapore Interbank Interest Rate (1-year)
2. Singapore Oil and Gas Price Index
3. NASDAQ Index
4. FTSE 100 Index
5. Nikkei Index

These time series, coupled with the relevant firm specific factors, will be fed as inputs into the neural network. The firm specific factors are adjusted and fed as off-set coefficient to the neural network. This is to capture the relevant company details so as to produce a more accurate prediction. The relevant factors to be used as inputs were methodically identified from the list of available data. Each of the available firm specific information was fed into the neural network one after another and the output produced was observed. A particular factor is selected when it noticeably reduces the output error of the neural network. The list of factors chosen is as follows:

1. IPO Subscription Level
2. IPO Offer Price
3. 1st Day IPO Closing Price against Offer Price

3.2 Data Preprocessing

The input data is transformed before the actual modeling takes place. The standardizing of inputs is crucial because the contribution of an input will depend heavily on its variability relative to other inputs. If one input has a range of 0 to 1, while another input has a range of 0 to 1,000,000, then the contribution of the first input to the distance will be swamped by the second input. So it is essential to rescale the inputs so that their variability reflects their importance, or at least is not in inverse relation to their importance. This prevents the situation whereby a variable with a larger mathematical value overwhelms other variables used in the neural network.

3.3 Prediction Result

The neural network model was tested on several recent IPOs listed on the Singapore Exchange in the year 2003. The model was made to predict the closing price of the IPOs for the first 6 months of their listing. Some of the prediction results are shown in the following figures.

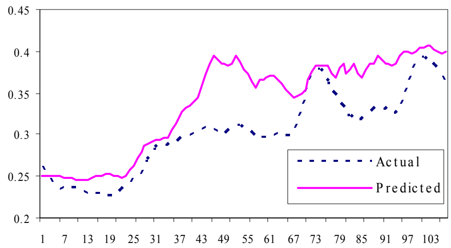

Figure 1: Prediction for Ocean Sky International Ltd

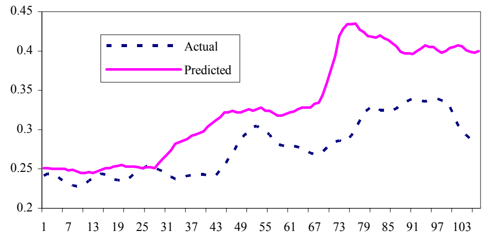

Figure 2: Prediction for Hongguo International Holdings Ltd

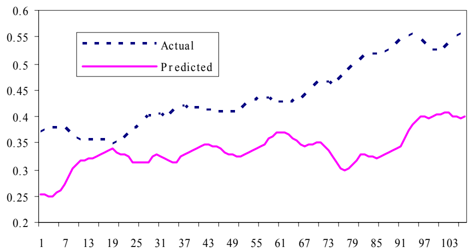

Figure 3: Prediction for Accord Customer Care Soln Ltd

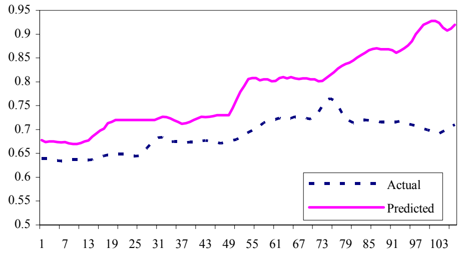

Figure 4: Prediction for Singapore Post Ltd

It can be seen from the above figures that the network was able to predict quite accurately the performance for a short term after the listing of the stock (i.e. the first 30 days). The accuracy, however, becomes lesser as the prediction period becomes longer. The first prediction performance for Accord Customer Care Solutions Ltd may seem worse than the other predictions. This may be the result of the amount of free float made available by the company. At the time of listing, only 10.7% of the company's capital was made available to the public. This could result in heavy manipulations by shareholders and hence the irregularity in the prediction.

4. Discussion

	1 Week	2 Weeks	3 Weeks	1 Month	2 Months	3 Months	6 Months
Ocean Sky International Ltd	0.010929	0.027628	0.042058	0.05668	0.093299	0.106536	0.09669
% Error	1.3%	1.0%	2.1%	2.4%	3.7%	7.1%	3.6%
Hongguo International Holdings Ltd	0.006912	0.025188	0.041941	0.052393	0.068201	0.102257	0.107505
% Error	1.3%	1.7%	0.5%	2.0%	5.5%	4.1%	11.2%
Accord Customer Care Soln Ltd	0.010929	0.027628	0.042058	0.05668	0.093299	0.106536	0.09669
% Error	12.2%	5.0%	3.1%	1.7%	7.7%	6.1%	15.8%
Singapore Post Ltd	0.010929	0.027628	0.042058	0.05668	0.093299	0.106536	0.09669
% Error	3.9%	3.3%	5.2%	7.1%	4.6%	8.0%	21.0%

Table 1. RMS Error of Predicted Output

The performance of the neural network can be further evaluated by RMS error of the predicted output at various time lengths of the prediction output. It can be seen from

Table 1 above that the predictions for the IPOs are most accurate in the 1st week. The error gradually increases as the prediction period becomes longer. This could be the effect of certain aftermarket factors that are beginning to influencing the IPO shares after the initial listing. After the first week, the prediction system discussed here only produced fair results, where errors could amount up to 25% on a particular trading day. However, even though the graphs deviated after the first week, it is evident that the model is still able to track the trend in the actual pricing.

One explanation given for this is that if patterns do exist in financial time-series data, perhaps they do not exist at every time period or simply the fact that the influences of factors used in the prediction are overwhelmed by the influences of factors not included in this study. A neural network that recognizes these patterns might be able to perform well when they occur, but poorly when they do not.

Another possible explanation could be that the scope of the variables captured for this study is not wide enough. Thus not all the information needed to correctly predict the performance is taken into account and hence possibly explains the discrepancy between the prediction and the actual performance.

5. Future Work

There are virtually an unlimited number of things that could influence a how an IPO performs in the market. Identifying the most influential inputs and trying to find correlations between them will be a way to improve prediction performance. The following present some areas of consideration to possibly improve the performance of the current model.

Underpricing - Ideally, stock prices should match the per share present value of the company. However, for IPOs to attract sufficient interest, the issuer must leave enough “money on the table” to compensate investors for the uncertainty about the security’s value. Thus if underpricing is present, attempts should be made to compensate for the difference.

IPO Anomalies - A number of other papers also attempt to document and explain IPO anomalies. Loughran and Ritter [11] report that IPOs completed in the 1970-1990 period have generated average annual returns of only five percent over the five year period subsequent to the offering. They argue that firms take advantage of windows of opportunity to issue stock publicly; these are periods when investors are willing to pay high prices, relative to some historical benchmarks, for corporate assets in certain industries. Rajan and Servaes [12] presented evidence consistent with this notion: more firms conduct IPOs when seasoned firms in their industries are trading at high multiples relative to the stock market and relative to historical levels. They also find that firms coming to market during these periods have poor aftermarket stock price performance.

New Business versus Current Business - Technology sector companies are geared towards future. This is reflected by numerous new business opportunities that these companies have. Stock market attaches a higher valuation multiple on these companies. Studies have shown that companies with higher future expectations in their IPO performed better.

Another perspective to possibly improve on the prediction capability will be to include intangible factors such as the optimism of the general public on IPOs, political factors such war, terrorism, local market news and more of other company related factors such as free float, PE ratio etc.

6. Conclusions

Initial public offering (IPO) offers a company liquidity and easy access to capital, but brings also risks of share price volatility and decline in share value. Predicting the performance of IPOs is important for both investors and companies to be listed. The search for a reliable way to predict the stock market has been evading the investors and researchers alike for many years. This study introduced the use of a sequential learning Radial Basis Function, combining with the technique of automatically adjusting the number of hidden neurons, to predict the performance of IPOs upon listing.

Finding the factors contributing to the performance of IPOs in the stock market is largely an unexplored field. This study also investigated the use of economic indexes and firm specific factors as inputs to the prediction model. The birth of neural network has aroused interests in their applications in various areas, and one of them is the stock market prediction. Prototypes and systems have been developed around the world by enthusiastic, one of which is used in this dissertation. But up to this point none have reported full success in predicting the stock market.

7. References

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Biography

Dr. Tong-Seng Quah is currently a professor with the School of Electrical and Electronic Engineering, Nanyang Technological University. An entrepreneur turned academician, Dr. Quah had been a faculty member of the Department of Information Systems & Computer Science as well as Institute of Systems Science, both within the National University of Singapore campus. Dr. Quah has undertaken joint projects with major companies in banking and airline industries, as well as statutory boards of the government body. Dr. Quah published widely in international conferences and journals. His research interests include A.I. applications utilizing neural networks, expert systems, data mining etc., such as financial markets modeling; Internet applications (such as e-commerce and e-learning) and software engineering (such as software reliability, fault prediction etc.) Dr Quah lectures in both undergrad as well as graduate courses such as Software Development Methodology, Software Quality Assurance and Project Management, Object-oriented System Analysis and Design, and Software Engineering.

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