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ANFIS model for time series prediction

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Abstract. This paper describes an architecture of ANFIS (adaptive network based fuzzy inference system), to the prediction of chaotic time series, where the goal is to minimize the prediction error. We consider the stock data as the time series. This paper focuses on how the stock data affect the prediction performance. In the experiments we changed the number of data as input of the ANFIS model, the type of membership functions and the desired goal error, thereby increasing the complexity of the training.

Introduction

Stock market prediction is important and of great interest because successful prediction of stock prices may promise attractive benefits. These tasks are highly complicated and very difficult. A fuzzy inference system employing fuzzy if-then rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. This fuzzy modeling or fuzzy identification has found numerous practical applications in control, prediction and inference.

Utilizing intelligent systems such as neural networks, fuzzy systems and genetic algorithms for the purpose of prediction in the field of finance has extensive applications. Lately, Adaptive Network Based Fuzzy Inference Systems (ANFIS), artificial neural networks (ANNs) and support vector machines (SVMs) have been successfully applied to solve the problems of predicting financial time series, including financial stock market prediction. [1] uses ANFIS and neural network to forecast the annual excess returns of the three publicly traded companies. The results reveal that the ANFIS and neural network techniques are able to generate forecasts with significant predictive ability with an autoregressive moving average (ARMA) model. [2] develops a neuro-fuzzy adaptive control system to forecast the next day's stock price trends of the ASE and the NYSE index. The experimental results reveal that the proposed system performs very well in trading simulations, returning results superior to the buy and hold strategy. It also demonstrates solid and superior performance in terms of percentage of prediction accuracy of stock market trend. [3] investigates the predictability of stock market return with ANFIS to predict the return on stock price index of the Istanbul Stock Exchange (ISE). The experimental ANFIS can be a useful tool for economists and practitioners dealing with the forecasting of the stock price index return. [4] describes an architecture for ensembles of ANFIS with emphasis on its application to the prediction of chaotic time series, the Mackey–Glass, Dow Jones and Mexican stock exchange. The methods used for the integration of the ensembles of ANFIS are: integrator by average and the integrator by weighted average. The performance obtained with this architecture overcomes several standard statistical approaches and neural network models reported in the literature.

This paper continues the research works about the time series prediction with ANFIS and we will focuses on how the data affect the prediction performance.

Theory of ANFIS

In this section, we present the basic theory of ANFIS model. Both artificial neural network and fuzzy logic are used in ANFIS' architecture. ANFIS consists of if–then rules and couples of input–output.

Also for ANFIS training, learning algorithms of neural network are used. As we have already seen, fuzzy systems present particular problems to a developer:

- Rules. The if-then rules have to be determined somehow. This is usually done by 'knowledge acquisition' from an expert. It is a time consuming process that is fraught with problems.
- Membership functions. A fuzzy set is fully determined by its membership function. This has to be determined. If it's gaussian then we should set the parameters.

The ANFIS approach learns the rules and membership functions from data. ANFIS is an *adaptive network*. An adaptive network is network of nodes and directional links. Associated with the network is a learning rule - for example back propagation. It's called adaptive because some, or all, of the nodes have parameters which affect the output of the node. These networks are learning a relationship between inputs and outputs. Adaptive network covers a number of different approaches but for our purposes we will investigate in some detail the method proposed by Jang known as ANFIS. The ANFIS architecture is shown below. The circular nodes represent nodes that are fixed whereas the square nodes are nodes that have parameters to be learnt.

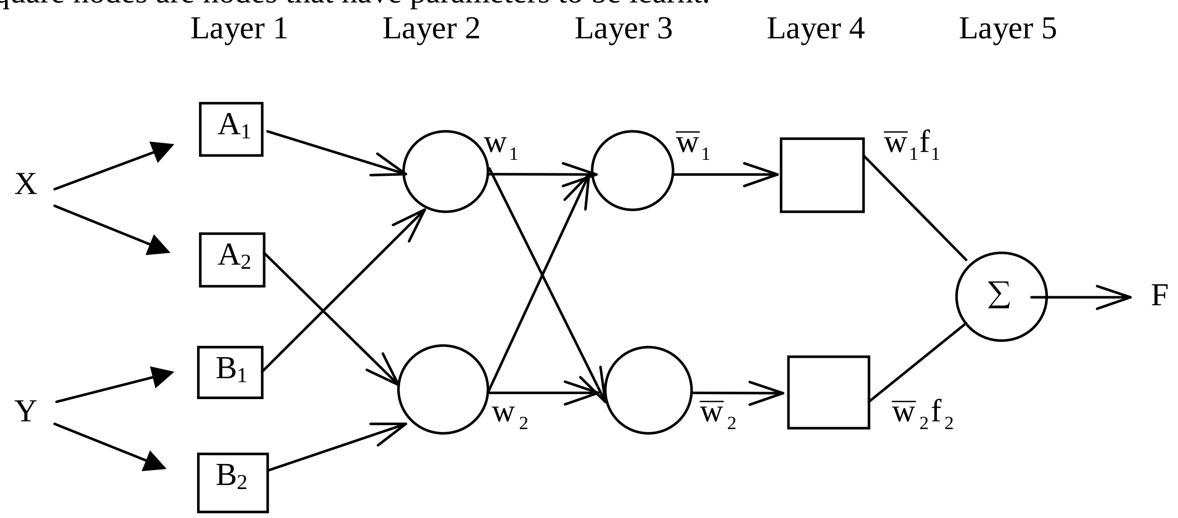

Fig 1. An ANFIS architecture for a two rule Sugeno system

A Two Rule Sugeno ANFIS has rules of the form:

$$\textit{If } x \textit{ is } A_1 \textit{ and } y \textit{ is } B_1 \quad \textit{THEN } f_1 = p_1 x + q_1 y + r_1 \tag{1}$$

$$\textit{If } x \textit{ is } A_2 \textit{ and } y \textit{ is } B_2 \quad \textit{THEN } f_2 = p_2 x + q_2 y + r_2 \tag{2}$$

For the training of the network, there is a forward pass and a backward pass. We now look at each layer in turn for the forward pass. The forward pass propagates the input vector through the network layer by layer. In the backward pass, the error is sent back through the network in a similar manner to backpropagation.

Layer 1: The output of each node is:

$$O_{1,i} = \mu_{A_i}(x) \qquad \textit{for } i = 1,2$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \qquad \textit{for } i = 3,4$$

So the $O_{1,i}(x)$ is essentially the membership grade for x and y.

The membership functions could be anything but for illustration purposes we will use the bell shaped function given by:

$$\mu_A(x) = \frac{1}{1 + \left| \frac{x - c_i}{a_i} \right|^{2b_i}} \tag{3}$$

where a_i, b_i, c_i are parameters to be learnt. These are the premise parameters.

Layer 2: Every node in this layer is fixed. This is where the t-norm is used to 'AND' the membership grades - for example the product:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2$$

Layer 3: Layer 3 contains fixed nodes which calculates the ratio of the firing strengths of the rules:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}$$

Layer 4: The nodes in this layer are adaptive and perform the consequent of the rules:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i)$$

The parameters in this layer (p_i, q_i, r_i) are to be determined and are referred to as the consequent parameters.

Layer 5: There is a single node here that computes the overall output:

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

This then is how, typically, the input vector is fed through the network layer by layer. We now consider how the ANFIS learns the premise and consequent parameters for the membership functions and the rules. There are a number of possible approaches but we will use the hybrid learning algorithm which uses a combination of Steepest Descent and Least Squares Estimation (LSE). It can be shown that for the network described if the premise parameters are fixed the output is linear in the consequent parameters. So, the hybrid learning algorithm uses a combination of steepest descent and least squares to adapt the parameters in the adaptive network.

Research design and experiments

The research data used in this study are daily closing price of the stock. We download real stock data from Yahoo Finance. The whole data set covers the period from March 1993 to March 2013, a total of 20 years stock data. Because the stock data is generally exceed the sensitive data area of ANFIS. This paper gives two method to change data space: one is using $r_{t1} = \ln\left(\frac{y_t}{y_{t-1}}\right)$ (Method I), where r_{t1} denotes the ANFIS input data at time *t*, y_t and y_{t-1} are the stock data for time *t* and $t-1$, respectively. The other is linearly compressing data space as $r_{t2} = \frac{y_t}{\max\limits_{t=1,2,3......}(y_t)}$ (Method II), where $\max\limits_{t=1,2,3......}(y_t)$ means the maximum value for all of the y_t. In this study, we use the daily closing price in input and output layer. The hybrid learning algorithm for ANFIS has been used. The variants of the algorithm used in the study are two input membership functions and three input membership functions for each of all the inputs, respectively. The statistical methods, such as the root mean squared (RMS) is used to compare predicted and actual values for model validation. The error can be estimated by the RMS and is defined as:

$$RMS = \sqrt{\frac{\sum_{m-1}^{n}(y_{pre,m} - t_m)^2}{n}} \tag{4}$$

where *n* is the number of data patterns in the independent data set, $y_{pre,m}$ indicates the predicted, t_m is the measured value of one data point *m*.

The related test results (RMS) are shown in Table 1 with 3 kinds of input data such as the two input data method (Method I and Method II) and the source data with the same number of training data. As shown in Table 1, the Method I is better than the other method. Next, we use the method I as the input data and study the appropriate amount of training data to o improve performance. In general, the training accuracy improves by decreasing the number of input membership functions, as indicated by the smaller RMS (Table 2). On the other hand, if the number of input membership functions is increased, the ANFIS has more complex network structure. So, the convergence to the target error rate takes more iteration. This situation is very time consuming.

We can conclude from Table 2 that in generally, the addition of the number of input can develop the prediction performance, but the addition of the groups of the training data almost has no effect on performance. We analyzed the reason is that the stock data contains a lot of disturbance and noise, so the more the number of groups, the more disturbances and noise is introduced, so instead cause poor training results.

Table 1 Prediction with different input data method (RMS)

	Method I	Method II	Prediction by the source data
RMS	590.6767	1.4872e+006	2.2965e+006

Table 2 the relationship between the prediction performance and the number of training data

		The groups of the training data					
		1	3	5	7	9	12
The number of input data	2	898.3435	902.8945	1570.2	670.3112	1992.1	3528.7
	3	202.8126	720.9982	590.6767	579.9741	731.6035	377.7904

Conclusions

Predicting the stock market are highly complicated and very difficult because there are too many factors that may influence stock prices. In this study, the adaptive neural fuzzy inference system (ANFIS) is adopted to predict stock market. The study shows that the performance of stock price prediction can be significantly enhanced by using ANFIS. The prediction performance of this method shows the advantages of ANFIS. It is rapid, easy to operate, and not expensive. The findings demonstrate the learning and predicting potential of the ANFIS model in financial applications.

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