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Statistical fuzzy interval neural networks for currency exchange rate time series prediction

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Abstract

In this paper, the statistical fuzzy interval neural network with statistical interval input and output values is proposed to perform statistical fuzzy knowledge discovery and the currency exchange rate prediction. Time series data sets are grouped into time series data granules with statistical intervals. The statistical interval data sets including week-based averages, maximum errors of estimate and standard deviations are used to train the fuzzy interval neural network to discover fuzzy IF-THEN rules. The output of the fuzzy interval neural network is an interval value with certain percent confidence. Simulations are completed in terms of the exchange rates between US Dollar and other three currencies (Japanese Yen, British Pound and Hong Kong Dollar). The simulation results show that the fuzzy interval neural network can provide more tolerant prediction results.

Keywords: Fuzzy data mining; Fuzzy neural networks; Granular computing; Interval computing; Time series prediction; Currency exchange rates; Statistical computing

1. Introduction

Vast amounts of capital are traded daily through the currency exchange market all around the world. Foreign exchange rates are affected by many highly correlated factors. Economic, political and psychological factors are strongly related to the performance of currency exchange markets. Therefore, the currency exchange rates prediction is a difficult problem. The most important motivation for predicting currency exchange rates is getting financial benefits. Furthermore there is the challenging job to prove whether the markets are predictable or not.

One research group believes that financial prediction mechanisms can be discovered to forecast the markets, and another research group considers that the financial markets may find all new information by correcting themselves. The characteristic that all currency exchange markets have in common is the uncertainty. The efficient market hypothesis (EMH) is formulated [1]. According this hypothesis, there is no way to make profit by predicting markets' behaviors and the markets are followed by random walks. However, some researchers have done a lot of research on if the financial markets are predictable. Heieh (1991) [3], Tsibouris and Zeidenberg (1996) [4] found evidences against EMH.

Till now, many different prediction methods have been developed to explain methods of currency exchange rates. These methods can be grouped into four categories: (i) technical analysis method, (ii) fundamental analysis methods, (iii) traditional time series forecasting, and (iv) machine learning methods. Technical analysts predict the market by tracing patterns that come from the study of charts that describe historic data of markets. Fundamental analysts study the intrinsic values of currencies and see if its current value is lower than the intrinsic value. Traditionally time series forecasting [7] dominates the financial market prediction, which tried to create linear prediction models to trace patterns in historic data. Box-Jenkins used statistical models to forecast the financial market in 1976 [5]. However, time series methods have their limitations for multidimensional time series with mutual non-linear dependencies.

Neural networks, with its ability of adaptively exploring a class of linear and nonlinear models [2], have an advantage over other systems for highly chaotic environments, such as currency exchange markets [11–13]. Granular neural networks (GNN) based on both soft computing and granular computing deals with granular data (i.e., granules) for granular data mining

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Table 1
Raw data (JPY/USD)

Period	Day 1	Day 2	Day 3	Day 4	Day 5
1/5,6,7,8,9/1998	133.99	133.88	131.7	132.49	131.52
1/12,13,14,15,16/1998	132.83	131.72	131.43	130.41	128.88
1/20,21,22,23,26/1998	128.8	127.5	127.22	125.78	126.64
1/27,28,29,30/1998, 2/2/1998	126.02	125.26	125.38	127.1	126.65
2/3,4,5,6,9/1998	126.02	123.78	123.31	124.26	124.28
2/10,11,12,13,17/1998	123.47	123.53	123.78	125.37	126.87
2/18,19,20,23,24/1998	126.35	126.25	127.73	128.92	128.15
2/25,26,27/1998, 3/2,3/1998	128.62	127.72	126.12	125.38	126.05
3/4,5,5,9,10/1998	126.79	127.61	128.42	127.78	127.63
3/11,12,13,16,17/1998	129.3	129.25	128.23	129.4	129.41
3/18,19,20,23,24/1998	130.17	130.43	130.34	130.28	130.25
3/25,26,27,30,31/1998	128.76	128.71	130.17	132.16	133.29
4/1,2,3,6,7/1998	133.76	133.5	135.05	134.71	133.68
4/8,9,10,13,14/1998	132.64	130.21	128.96	129.52	129.35
4/15,16,17,20,21/1998	129.45	131.78	131.85	132.23	131.33
4/22,23,24,27,28/1998	130.77	130.19	130.9	132.09	132.19
4/29,30/1998, 5/1,4,5/1998	132.05	132.37	133.01	132.98	131.74
5/6,.7,8,11,12/1998	132.73	133.09	132.88	132.84	134

and granular knowledge discovery [10,14]. The granular-data-based GNN are more useful to process granules with uncertain information than conventional numerical-data-based neural networks because real data have a lot of noise (i.e., not 100% accurate). Fast granular knowledge discovery methods are useful for large amounts of data in complex applications [15].

This paper describes a new granular neural network called the statistical fuzzy interval neural network (SFINN) using statistical interval input and output data. An application in currency exchange rates prediction between US Dollar and three other major currencies (Japanese Yen, British Pound and Hong Kong Dollar) is discussed. Input information, which is prepared from historic data, is used to train the FINN to discover statistical fuzzy interval knowledge. The output of the system will give the range of exchange rates with statistic information such as confidence, mean, and R.S.D.

The paper is organized as follows. Section 2 describes the methodology used in statistical data preparation. Section 3 discusses the SFINN. Section 4 presents experimental results of the SFINN. Section 5 summarizes major results and shows future research works.

2. Statistical interval data

An estimation problem occurs in science, business and in everyday life. Assume that we have sequences of exchange rates (US Dollar base) between US Dollar and Japanese Yen for a week (5 trade days): 100, 101, 102, 102 and 100.

The mean is $\bar{x} = 101$, and in the absence of any other information, the mean can be used as an estimate of μ, the “true” average exchange rate for the week. This kind of estimate is called a point estimate, since it consists of a single number, or a single point on the real number scale. Although this is the most common way in which estimates are expressed, it leaves room for many questions. For instance, it does not tell us anything about the possible size of error. And, of course, we must expect an error. Now we introduce a different way of presenting a sample mean together with an assessment of the error we might make if we use it to estimate the mean of the population from which the sample came [6].

$$\bar{x} - t_{\alpha/2} \times \frac{s}{\sqrt{n}} < \mu < \bar{x} + t_{\alpha/2} \times \frac{s}{\sqrt{n}} \quad (1)$$

$t_{\alpha/2} \times s/\sqrt{n}$ is the maximum error of estimate (E) with (1-α) × 100% confidence. The interval from $\bar{x} - t_{\alpha/2} \times s/\sqrt{n}$ to $\bar{x} + t_{\alpha/2} \times s/\sqrt{n}$ is called a confidence interval and (1-α) × 100% is called the degree of confidence. n is the sample size. The value of $t_{\alpha/2}$ is related to both the degree of confidence and n can be retrieved from [8].

All raw data are gathered from the Federal Reserve Bank of New York, representing the 12 noon buying rates. The data were recorded from January 5, 1998 to August 24, 2001 (184 weeks). Amongst the 184 weeks' data, the first 168 weeks' data were used for training and the remaining are used as validation. The partial time series data is shown in Table 1. The statistics summary is shown in Tables 2 and 3.

3. Statistical fuzzy interval neural networks

3.1. Architecture of the statistical fuzzy interval neural networks

A traditional neural network interprets information and knowledge by distributed crisp numerical weights. Two major disadvantages of the traditional neural network are:

(1) a learning algorithm is very slow because crisp weights in a neural network have no explicit physical meanings and therefore it is very difficult to effectively initialize weights at the very beginning, and
(2) it is very hard to extract linguistic knowledge such as IF-THEN rules from both numerical and linguistic data.