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Simple Ensemble-Averaging Model based on Generalized Regression Neural Network in Financial Forecasting Problems.

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Abstract

This study introduces an ensemble-averaging model based on GRNN (Generalized Regression Neural Network) for financial forecasting. The model trains all input individually using GRNNs and uses a simple ensemble-averaging committee machine to improve the accuracy performance. In financial problem, there are many different factors that can effect the asset price movement in different time. The experiment is implemented in two different datatsets, S&P 500 index and currency exchange rate. The predictive abilities of the model are evaluated on the basis of root mean squared error, standard deviation and percent direction correctness. The study shows a promising result of the model in both datasets.

1. Introduction

The traditional assumption of asset price movement is based on the theory of market efficiency, which simply implies that all public information on future price movement for a tradable asset has already been embraced in its current price [1]. In statistical terms, this implies the so-called "random walk" model, whereby the expectation for the next period is the current value. The empirical finance literature up to the 1970's universally reinforces this view for all actively traded capital markets, by testing and failing to refute the random walk hypothesis on daily, weekly, and monthly data. By the end of the 1980's financial theory had matured to provide a more comfortable fit with trading realities. The conventional tests of the random walk hypothesis were recognized to be rather weak, in the sense that the evidence would have to be very strong to reject this null hypothesis. Econometric tests introduced during the 1980's specify a more general model for the time series behavior of asset returns.

The novelty about neural networks lies in the ability to model nonlinear processes with few a priori assumptions about the specific functional form of the function. Recent research has documented the superiority of non-parametric forecasting methods, such as neural networks over traditional statistical methods for modeling time series data. In financial problem, there are many different factors that possibly effect the asset price movement in different time. Various factors input to the model has more possibility to better shape up the asset price movement behavior.

The purpose of this study is to introduce the simple ensemble-averaging model based on GRNN (Generalizd Regression Neural Network) to evaluate the predictive performance in forecasting S&P 500 Index and currency exchange rate. Our goal is to compare the performance of the simple ensemble-averaging model and the single GRNN.

2. Neural Network Architectures

2.1 Generalized Regression Neural Network (GRNN)

GRNN architecture subsumes the basis-function method. It approximates any arbitrary function between input and output vectors, drawing the function estimate directly from training data. It looks much like the common feed-forward topology used with backpropagation training; however, its operation is fundamentally different. GRNN is based on nonlinear regression theory for function estimation. The training set consists of values for x, each with a corresponding value for y. This regression method will produce the estimated value of y, which minimizes the mean-squared error. Based on Radial-Basis Function network architecture, GRNN trains rapidly without any training pathologies such as paralysis or local minima problems [2].

GRNN is based on the following formula from statistics

$$E[y \mid X] = \frac{\int_{-\infty}^{\infty} y f(x,y)\, dy}{\int_{-\infty}^{\infty} f(x,y)\, dy}$$

where

y = output of the estimator

x = the estimator input vector

$E[y|x]$ = the expected value of output, given the input vector x

$f(x,y)$ = the joint probability density function (pdf) of x and y.

The function value is estimated optimally as follows:

$$y_i = \frac{\sum_{i=1}^{n} h_i w_{ij}}{\sum_{i=1}^{n} h_i}$$

where

w_{ij} = the target output corresponding to input training vector x_i and output j.

$h_i = \exp[-D_i^2 / (2\sigma^2)]$, the output of a hidden layer neuron

$D_i^2 = (x-u_i)^T(x-u_i)$, the squared distance between the input vector x and the training vector u

x = the input vector.

u_i = training vector i, the center of neuron i.

σ = a constant controlling the size of the receptive region.

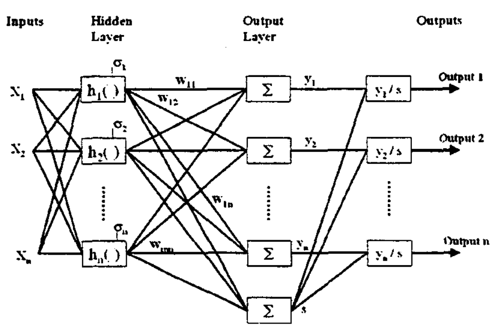

Figure 1: Generalized Regresstion Neural Network Architecture

From the above picture, a hidden layer neuron is created to hold the input vector. The weight between the newly created hidden neuron and the output neuron is assigned the target value.

3. Experiment Descriptions and Dataset.

Each network is individually trained using one different input and applied the combination of networks outputs through a committee machine based on a simple ensemble averaging. Simple ensemble averaging, a static structure type of committee machine models, linearly combines the all output from different experts to produce an overall output [3].

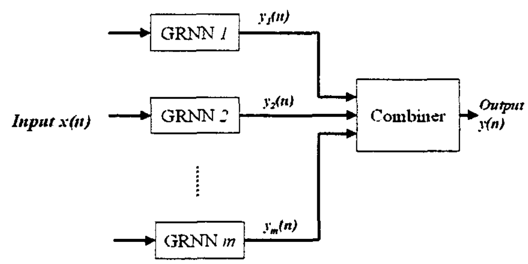

Figure 2: Block diagram of an ensemble-averaging model based on GRNN

The experiments are implemented through two different datasets. The first is to predict the S&P 500 Index. The attributes of the data included the last closed index, the last high index, the last low index, the last two-day index and the last week index. The training historical data is the daily closed index starting from 01/04/88-12/31/98 . And the test data is to forecast daily closed index during 01/04/99-09/20/99 period.

The second dataset is the currency exchange of Baht (Thai currency) and US Dollars. The data attributes consisted of the exchange rate between Baht and US Dollars, Canadian Dollars, UK Pound and Australian Dollars. The historical training data was gathered during 01/04/93-04/30/99. And the test data will forecast exchange rate (THB/USD) during 05/03/99-11/04/99.

4. Results and comparisons.

From the results in the following Table 1 and Table 2, the network with individual trained inputs has better overall results. The outcomes can be seen similarly in both datasets. To forecast the next-day S&P index using only last index trained to one GRNN network brings a small error size but poor direction correctness. On the other hand, using only the last week index into one GRNN network has larger error size but better direction forecasting. Using five inputs into one GRNN network gives the worst result in direction forecasting. The ensemble averaging model with five independently trained inputs yields good result in both error size and direction.

Attributes	Root Mean Squared Error	Standard Deviation	% Direction Correctness
Last Index (1 input, 1 GRNN Network)	1.4344	1.4383	45.00
High Index (1 input, 1 GRNN Network)	1.6122	1.6133	50.00
Low Index (1 input, 1 GRNN Network)	1.5557	1.5575	52.22
Last two-day Index (1 input, 1 GRNN Network)	1.8488	1.8475	48.33
Last week Index (1 input, 1 GRNN Network)	2.3642	2.3482	56.11
5 inputs, 1 GRNN Network	1.5014	1.4416	47.00
Ensemble-averaging Model (5 inputs, 5 GRNN Networks)	1.4400	1.4374	55.56

Table 1: Result of S&P 500 Composite Index forecasting

For currency exchange rate dataset, the results come up in similar pattern. The ensemble-averaging model with four independently trained inputs gives an above-averaged result in both error size and direction forecasting.

Attributes	Root Mean Squared Error	Standard Deviation	% Direction Correctness
THB / USD (1 input, 1 GRNN Network)	0.7677	0.7471	62
THB / CAD (1 input, 1 GRNN Network)	1.3720	1.2403	58
THB / GBP (1 input, 1 GRNN Network)	1.7485	1.2754	58
THB / AUD (1 input, 1 GRNN Network)	2.4554	2.4230	67
4 Inputs, 1 GRNN Network	1.0622	1.0251	41
Ensemble-averaging Model (4 Inputs, 4 GRNN Networks)	1.2653	1.2103	62

Table 2: Result of Currency Exchange Rate forecasting

5. Conclusion.

A short-term financial forecasting has been demonstrated using two different datasets to test the ensemble-averaging model based on GRNN. From the experiments, the simple ensemble-averaging model based on GRNN has proved to achieve higher prediction accuracy for the values and directions in both datasets. One advantage of using individual GRNN network to train only one input is the output responding speed owning to that input. The disadvantage, however, is the training time, which is proportional to the number of input factors. The most important criterion to measure the efficiency of the predicting tool in financial problem is the percent correctness of the movement direction. This experiment shows some improvement in the direction forecasting in both data sets. The possible further model improvement is to gather more input factors and add the adjustable weight to each GRNN output to make the model able to adjust the priority to each input factor in different time. Research is currently under way to improve performance of GRNN and the committee machine model for financial forecasting problems.

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