Neural Network Based Stock Market Forecasting

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Summary
We develop a useful prediction system in forecasting stock price for Egypt stock market (Egypt stock exchange weighted stock index, Commercial International Bank as CIB). The system is based on a recurrent neural network trained by using ARIMA analyses by differencing the raw data of the CIB series and then examining the ACF and PACF plots. The series can be identified as a nonlinear version of ARIMA (1, 1, 2). Neural networks trained by using first differentiation of data. The networks trained by using history data for 6-years ago to predict 12 weeks market trend.

Key words:
Neural Network, Time Series, Forecast, ARIMA, Egypt Stock Market.

1. Introduction

In Egypt, many people have tried to model the behavior of the stock market. Although the Random Walk Theory claims that the change of stock price are independent of its history, and we cannot obtain any indication to predict future price trends from stock price history data. The stock price change is so complex that researchers have not been able to discover a suitable model to handle behavior of stock market efficiently. In this paper, using ARIMA-based recurrent networks [1,2] in association with feature data pre-processing, we intend to forecast the trends of Egypt stock market.

Autoregressive Integrated Moving Average (ARIMA) model is a linear nonstationary model [3], it uses difference operator to convert nonstationary series to stationary. Due to the availability of computer softwares of **ARIMA** model and high performance computers, more and more forecasting problems can now be modeled easier than before. But in modeling nonlinear series, we need to turn to other approaches. Considering neural networks capable of learning nonlinear information from appropriate trainings [4,5]**,** we develop a ARIMA-based prediction system that uses the recurrent neural network [2] and make training on history data for the network. We also compare prediction performances for the ARIMA-based recurrent neural network, using raw data and first difference data respectively.

2. Data analysis

Many time series (e.g., stock price) behave as though they have no fixed mean. Such nonstationary behavior can be removed by performing suitable differences on the raw data of the series [3].

The autocorrelation function (ACF) is used to determine whether a series stationary or nonstationary. After certain times of differencing, one can always obtain nearly stationary series. Based on this consideration, we will apply difference operator to the series of Egypt stock exchange weighted stock index (CIB) for years 2002 - 2007. The resulting difference data are used for training the recurrent network to function as a nonlinear ARIMA (p,d,q) model. But to do this, we need to first identify the orders of p,d,q.

The **p** parameter is the order of autoregression. In any autoregression process, each value is a linear function of the preceding value or value. In a first-order autoregressive time-series model, only the single preceding value is used in model building; in a second-order process the two preceding values are used in building a model; and so on. The coefficient for the autoregressive parameter usually is greater than a-1 and less than a+1. Indicating that the influence of earlier observation dies out exponentially. In a first order autoregressive process, the current value is a function of the preceding value, which is in turn a function of its preceding value. Thus, each shock or disturbance to the system has a diminishing effect on all subsequent time periods.

The **d** parameter is the differencing parameter, providing adjustments needed to make the time series data stationary. Time series data are stationary when two consecutive values in the series depend only on the time interval between them and not on time itself. A time-series with a constant mean value over time is consistent with this notion. However, real-world time-series are most often nonstationary; that is the mean value of the time-series changes over time, usually because there is some trend in the series data prior to an attempt at specifying the model.

The third ARIMA parameter is **q**, the order of the moving average, in a moving average process, each value is

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determined by the average of the current disturbance (i.e., error term) and one or more previous disturbances. The order of the moving average process specifies how many previous disturbances are averaged into the new value.

It is important to differentiate between the autoregressive parameter and the moving average one. Each value in a moving-average series is a weighted average of the most recent random disturbances (i.e. error terms), while each value in an autoregression is weighted average of the recent values of the series.

As can be seen in Fig. 1, the series is obviously nonstationary, because the ACF values do not die out after a certain length of time. We then try to first difference the series and the plot of its ACF is shown in Fig. 2**,** and the plot of PACF (i.e., partial ACF) is shown in Fig.3. As indicated in Fig. 2 and Fig. 3, we have identified the CIB series as ARIMA (1, 1, 2).

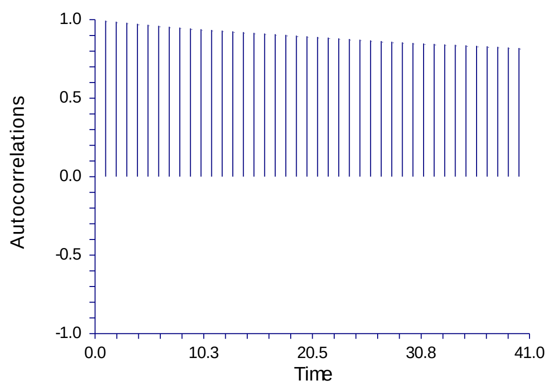

Fig.1. ACF of CIB Raw Data

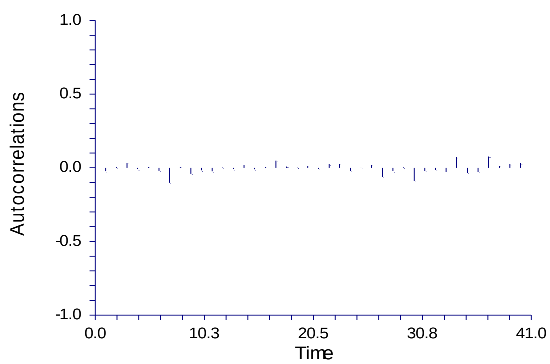

Fig.2. ACF of CIB 1st difference Data

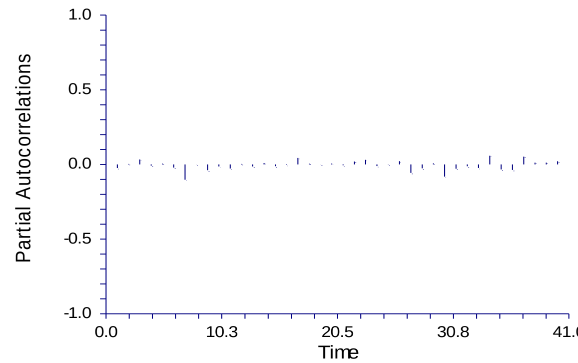

Fig.3. PACF of CIB 1st difference Data

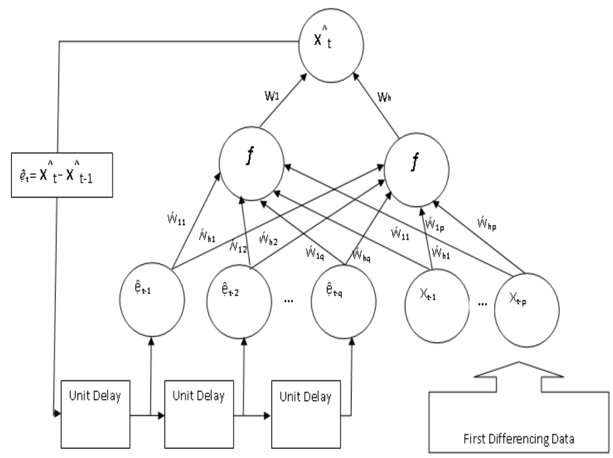

Fig.4 the ARIMA Base Recurrent Neural Network

3. Implementation

We develop an ARIMA-based recurrent network for prediction purpose, the stucture of the network is shown in Fig.4. The basic architecture originates from [1], but the feature data used and the way of error feedback are different. The number of the input nodes of the recurrent network equals p+q, and number of hidden nodes is selected by a trial and error.

Note that in Fig. 4, the input training data (after first difference) are stationary. Instead of using $x_t - \hat{x}_t$ as in [2], we use the feedback equation $\hat{e}_t = \hat{x}_t - \hat{x}_{t-1}$ as the next new input data for an unit-delay node. The reason we do this is that any two successive data must have largest correlation, according to ACF plots shown in Fig.2. We will use $\hat{e}_t = \hat{x}_t - \hat{x}_{t-1}$ not only during backpropagation training, but also during testing process. We believe that the network could suffer decrease in prediction accuracy if without referring to any error data $\hat{e}_t$ during the testing phase.

4. Results

In this work, The series contain 2002-2007 training data and 2008 Jan-Mar testing data. To compare, we use ARIMA(1,0,1) (i.e., without differencing) and ARIMA(1,1,2) for the series. After training, we test these two networks performance for both training and testing data. The performance difference in Fig.5 and Fig. 6 is easily seen. The predictions follow the observations nicely in ARIMA(1,1,2),but poorly in ARIMA (1 ,0, 1). These results justify our previous arguments that the difference operations is necessary.

The predictions for 2008 Jan-Mar is shown in Fig 7.The prediction accuracy is quite good for the first six weeks. The effect of the nonlinear learning of neural networks is clear in the error residuals of the testing set. Fig 8.and Fig 9. are plots of the residuals against the prediction prices for the training and testing set.

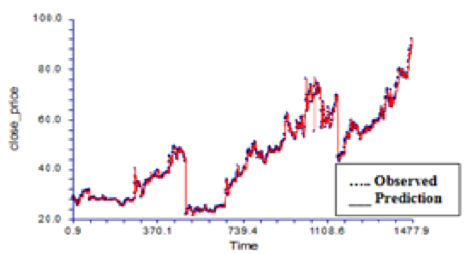

Fig.5. Prediction Performance of the network using CIB raw data

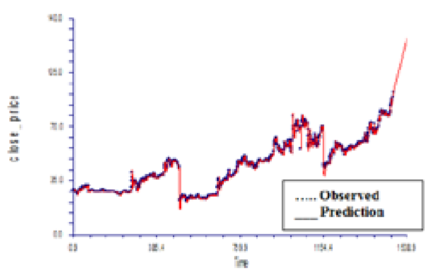

Fig.6. Prediction Performance of the network using CIB 1st difference data

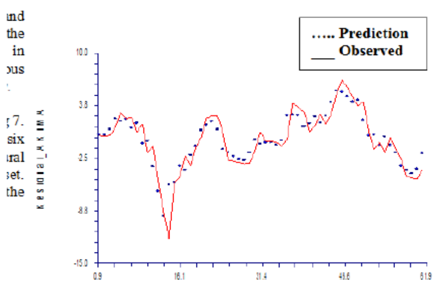

Fig.7. ARIMA based recurrent networks using CIB 1st difference data for predicting trend during Jan /2008 - Mar/2008.

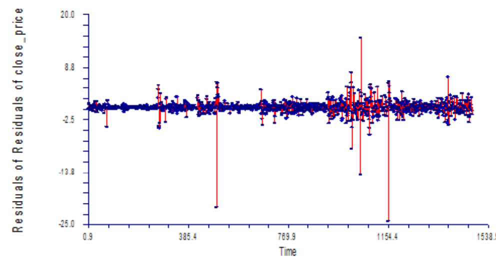

Fig.8. Residual vs. predictions for years 2002-2007.

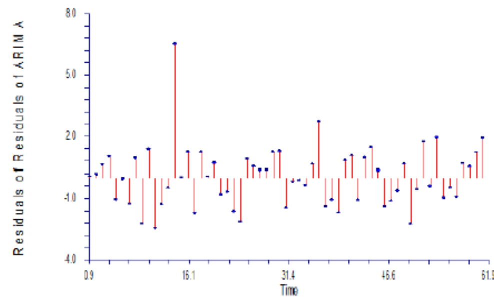

Fig.9. Residual vs. predictions for Jan-Mar 2008.

5. Conclusions

Our experimental results have shown that the ARIMA-based recurrent neural network is capable of predicting the market trend with acceptable accuracy. We also have identified the series of CIB as ARIMA(1,1,2), and shown that it can be stationary after first difference operation.

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