A Pattern Matching Tool for Time-Series Forecasting[1]

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ABSTRACT

In this paper we describe a pattern recognition based tool for forecasting. We compare the results of forecasting with this tool against the Exponential smoothing method on Santa Fe series data and US financial index. The results show that the pattern recognition based tool is highly accurate on standard error measures.

1. INTRODUCTION

In the 1970's the ARIMA model was defined for use in time series analysis and forecasting. Subsequently, other derivatives of this model have been defined such as ARARMA and more recently the delta NARMA model[1], a non-linear extension of ARIMA and ARARMA. Apart from statistical models, there are many different types of neural networks that can be applied to the problems of forecasting, such as multilayer perceptrons with backpropagation, recurrent neural networks[2] or even biologically inspired neural networks. However, statistical and connectionist approaches have their own limitations: statistical approaches have problems with handling non-linear data and connectionist approaches have the problem of obtaining good network generalization[3]. For this reason researchers have continued to explore other methods including neuro-fuzzy methods[4], evolutionary fuzzy network methods[5], fuzzy techniques[6] and pattern imitation methods[7,8]. In this paper we describe a pattern matching technique which is used for forecasting. This technique is tested using benchmark data from the Santa Fe Time Series Competition[9] and the U.S. financial index. This technique is compared with the established Exponential Smoothing method.

2. PATTERN MATCHING

A pattern matching approach is based on the premise that current structures may be matched with old structures to generate a future prediction. Consider a three point structure (Y(t-2), Y(t-1) and Y(t)) in a time series (Y_1, Y_2, … Y_t). We may define the change in time-series as of type (i) *increasing* Y(t-2) < Y(t-1) and Y(t-1) < Y(t), (ii) *decreasing* Y(t-2)>Y(t-1) and Y(t-1)>Y(t), or *alternating* Y(t-2) < Y(t-1) and Y(t-1) > Y(t). The change between a given Y(t-1) and Y(t) may be encoded as a 0 if Y(t-1) > Y(t) and as a 1 if Y(t-1) < Y(t), for position Y(t-1). Therefore, the original time-series may be represented with a binary series showing the direction of change, *high* or *low*. Now imagine that we wish to predict a point *y*(t+1) given past data. Using a three structure element for matching, the change at points *y*(t-3), *y*(t-2) and *y*(t-1) is determined. This change sequence (pattern) is searched in the past data for finding a match at *x*(t-3), *x*(t-2) and *x*(t-1). The aim is to observe *x*(t+1) in order to predict *y*(t+1): this obviously requires some scaling based on the size of past and recent time-series values. The scaling factor *s* depends on the ratios of [*x*(t) - *x*(t-1)]: [*y*(t) - *y*(t-1)], and [x(t-1) - x(t-2)] : [y(t-1) - y(t-2)]. A more rigorous approach on similar principles may be adopted for an *n* element structure, where the match between a current and past structure depends on a larger number of ratios. The scaling factor *s* is used for generating the new prediction which is given as:

$$y(t+1) = y(t) + s[x(t+1) - x(t)]$$

The approach is fuzzy in nature since there is only a partial match between a current and past structure. The structural match may be controlled in future studies with the help of fuzzy coefficients that control the spatial characteristics of the match.

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3. EXPERIMENTAL DETAILS

In our experiments we compare the pattern matching forecasting tool with the established statistical method of Exponential smoothing method for time-series prediction. The aim is to compare performances in terms of the root-mean-square error, mean absolute percentage error and correctly predicting direction of series change, *up* or *down* [10].

Our data includes *Series A* which is a univariate time series measured in a Physics laboratory experiment. *Series D* is a univariate time-series generated for the equation of motion of a dynamic particle. *Series E* is a univariate time-series for a set of astrophysical data (variation in light intensity of a star). These three series have been taken from the Santa Fe competition (see http://www.cs.colorado.edu/~andreas/ Time-Series/ SantaFe.html, for Santa Fe data). S*eries S&P s*eries is the US financial index over a period of eight years (up to August 1996) [Figures 1 to 4].

For the purposes of this study, we compare the pattern matching performance against the Exponential smoothing method for series A, D, E and S&P. The Exponential smoothing method (a special case of the ARIMA model) is based on the premise that a future prediction is a weighted sum of the past values in the series, i.e.

$$y(t+1) = \alpha(y(t) + (1-\alpha)y(t-1) + (1-\alpha)^2y(t-1) + ...)$$

where α is the smoothing constant set by the experimenter, $0 \leq \alpha \leq 1$.

4. RESULTS

We next derive the optimal exponential factor α for the Exponential model when applied to Series A, D and E (see equation 4). We first find the optimal α for time series A = .99, series D = .99, series E = .3, and series S&P = .4. We also derive the optimal size of patterns used for matching in the pattern matching algorithm. The optimal size (k) of the patterns used in the pattern matching algorithms (obtained by varying k, $2 \leq k \leq 5$ and noting the model producing least errors) for these different series are: series A (k=4), series D (k=3), series E (k=2) and series S&P (k=3).

The comparative performance of the forecasting methods is shown in Table 1. It should be noted that the error measures are not comparable across different series as they have different units of measurement. Table 1 shows the results on three error measures for predicting the last 10% (estimation period = 90%) and predicting the last 25% (estimation period = 75%) of series A, D, E and S&P. It should be observed that the pattern technique is highly successful in predicting the correct direction of forecast change for most series and is superior than the Exponential smoothing method on all measures. The highly successful performance of the pattern matching algorithm on predicting the financial index is especially encouraging. In most financial markets, this is often the single most important measure for the traders deciding on a buy-sell-hold strategy for their stocks. Figure 5 shows the S&P index predicted for the last 100 days of the series (summer of 1996). The graph shows that the pattern matching techniques follows the daily variations and the trend of the index very well.

5. CONCLUSION

In this paper we have developed a simple time-series prediction methodology based on structural matching of time-series elements. We find that the pattern matching method performs very well when compared with other established statistical methods used frequently in practice. In the future, further studies adopting this strategy should also address the issues of noise management in such a matching process and its generalisation capabilities.

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Figure 1. Plot of Series A

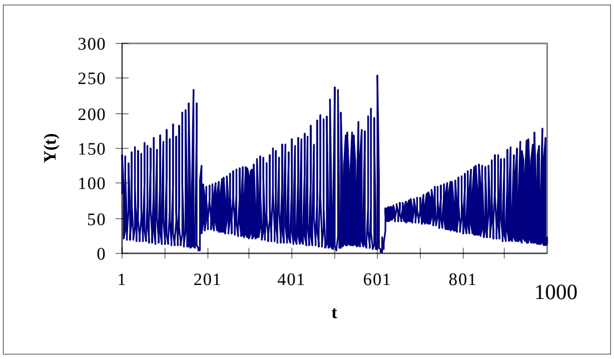

Figure 2. Plot of Series D

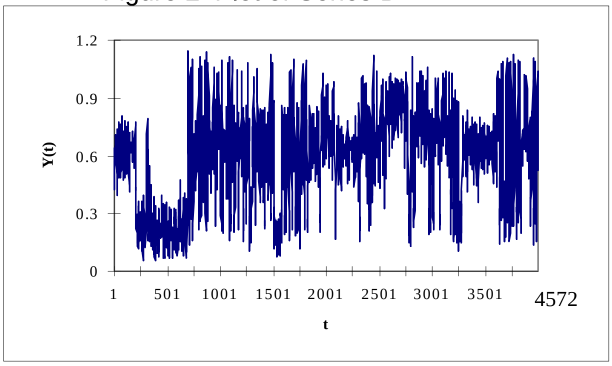

Figure 3. Plot of Series E

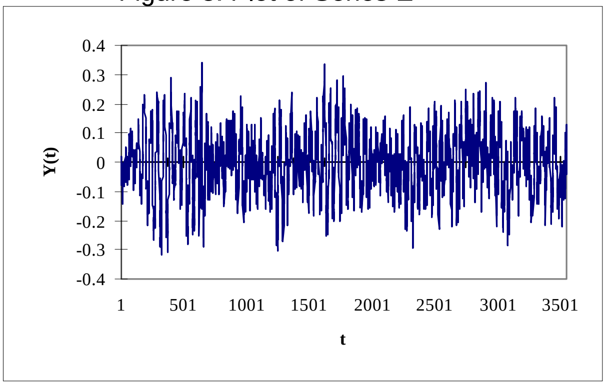

Figure 4. Plot of Series S&P

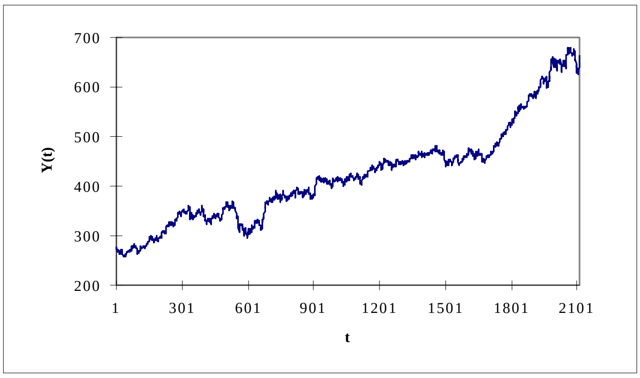

Figure 5. Forecasting the last 100 data points of the S&P series using the Pattern Matching Method

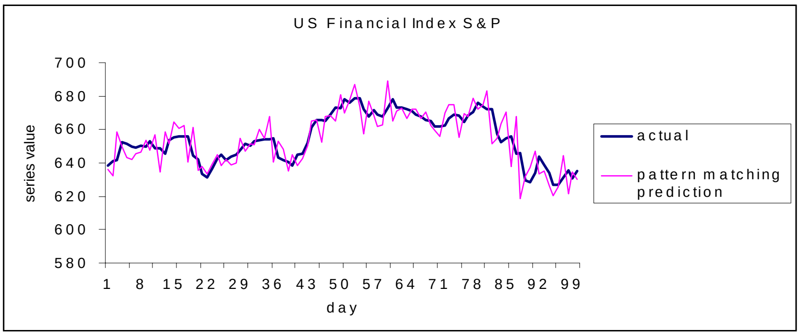

Table 1. The comparative performance pattern matching and exponential smoothing methods

Forecast series	**Forecast period %**	**ES RMSE**	**ES MAPE**	**Direction Success**	**PM RMSE**	**PM MAPE**	**Direction Success**
A	10	5.6	84.0	70	1.4	11.8	95
A	25	2.7	61.7	70	.7	8.7	94
D	10	.003	9.4	80	.002	8.6	84
D	25	.002	8.9	79	.002	8.8	81
E	10	.009	17.6	56	.006	8.6	66
E	25	.006	17.4	57	.004	8.9	68
SP	10	4.5	9.6	48	.6	1.1	76
SP	25	2.5	8.2	49	.4	0.9	72