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SALES FORECASTING USING TIME SERIES AND NEURAL NETWORKS

Angela P. Ansuj, M. E.Camargo, R. Radharamanan and D. G. Petry

Center of Natural and Mathematical Sciences
Federal University of Santa Maria, Santa Maria (RS), 97119-900, Brazil

ABSTRACT

This paper presents the use of time series ARIMA model with interventions, and neural network back-propagation model in analyzing the behavior of sales in a medium size enterprise located in Santa Maria (RS), Brazil for the period January 1979 - December 1989. The forecasts obtained using the back-propagation model were found to be more accurate than those of ARIMA model with interventions.

KEY WORDS

Sales forecasting, ARIMA , neural networks, and back-propagation model.

INTRODUCTION

In various areas of research, the models obtained using neural networks are found to be better compared to other ways of modeling. Lapedes and Farber (1987), published an article where they trained the network to generate a time series using a specific equation. They obtained agreeable results which provided accurate forecasting. In this paper, the sales data collected from a medium size enterprise located in Santa Maria (RS), Brazil for the period January 1979 - December 1989 have been analyzed using the time series ARIMA model with interventions and the back-propagation neural network model. Initially, the exploratory analysis and partial autocorrelation functions have been used to analyze the time series sales data to verify the existence of seasonal components, non-stationarity, and the randomness in the data. The number of intermediate layers for the back-propagation model has been determined by trial and error approach. Error analysis of the time series has been carried out for accurate forecasting. The results obtained are presents and discussed.

METHODOLOGIES

ARIMA Model with Interventions

The intervention analysis is a transfer function stochastic model from which it is possible to interpret and incorporate its effects to the time series model (Box and Jenkins, 1970). The major effects of intervention can be noted observing the changes in inclination level of the time series. Based on these changes, the error variables can be altered and components that were not present in the model can be introduced. Let a time series for which you have verified and estimated an ARIMA model with which you were making forecasts for certain time. At a given instant, an independent phenomenon occurred that originated a time series, but whose effects can be manifested on the time series. This external event, whose effects will influence the time series being studied, should be incorporated in the model as an additional information to the time series. This addition of information is called intervention. The intervention model can be represented by:

$$f(k,x,t) = \sum_{j=1}^{k} v_j(B)\, x_{tj} + \eta_t \tag{1}$$

$$f(k,x,t) = \sum_{j=1}^{k} \frac{w_j(B)}{\sigma_j(B)}\, x_{tj} + \eta_t \tag{2}$$

where: x_{tj}, $j = 1, 2, \ldots, k$ are exogenous variables (interventions). Eventually, x_{t-b} can be used where b is the time space occurred between the input and the output series (discrepancy between the time series); k is a set of unknown parameters which appears in v_j (B) or in w_j (B) and σ_j (B); where: $v_j (B) = w_j (B)/\sigma_j (B)$, $j = 1, 2, \ldots, k$ is the transfer function of j-th exogenous variable, such that v_j (B), w_j (B) and σ_j (B) are polynomials in B and η_t is the noise that can be represented by an ARIMA model with seasonal components. Each series x_{tj} is an indicator that assumes the values 0 or 1, representing, respectively, the absence or the presence of j-th intervention, that is, the non-occurrence or the occurrence of j-th event. The time series indicators of the intervention can be represented by three types of binary variables: Impulse function (type 1); step function (type 2); and impulse seasonal function (type 3).

Neural Network Model

The back-propagation model is a paradigm commonly used in the areas of signal recognition, and principally in forecasting of time series (Beale and Jackson, 1991). The back-propagation model uses a topology of 3 or more layers. The connections between the units are interlayers that are directed from the input layer to the output layer. The neural network adjusts itself as a time series forecasting model in the following form:

1 - The input units are made up of information relevant to the forecasting;

2 - The weights are the model parameters and will be estimated through learning by the network that takes into account the pair of inputs to the respective output targets (real values of the time series).

3 - The hidden layers are the links between the input and the output layers. Its role is important for the selection of better sets of weights, since the non-linearity of the model can be located in the activating function of the hidden units.

4 - The output layer is made up of only one unit and carries the needed information for forecasting.

5 - The network is trained for estimating the model parameters. After training, forecasting for the periods 1, 2, ..., etc., in the future can be generated on the output layer.

6- The hyper parameters are the values provided by the user that in general are constants. They are: rate of learning, momentum term, and the varying interval size of weights.

EXPERIMENTAL RESULTS

ARIMA Model with Intervention

The adjusted model is with interventions - ARIMA $(1, 1, 6)(0, 1, 0)_{12}$. The estimated parameters and statistics of the model are presented in Table 1.

Table 1 - Estimated parameters and statistics "t" for the univariate model with interventions for the time series sales data

Parameter	Estimated Value	Statistic "t"
ϕ_1	-0.37774	-4.05
θ_6	-0.56638	-6.45
ξ_1	-0.14228	-4.93
ξ_2	-0.22293	-.5.06
ξ_3	0.17447	4.21
ξ_4	0.11857	3.37
ξ_5	0.99164	2.99

The adjusted statistic and noise statistics for the model are:

$R^2 = 0.98015$; Mean $= -0.00708 \cong 0.00$; and Variance $= 0.00227$

The identified interventions for the sales data during the period analyzed are presented in Table 2 considering a level of significance of 5%.

Table 2 - Types of detected interventions

Type of intervention	Instant	Period
$X_{1t} \rightarrow 1$	99	MAR/87
$X_{2t} \rightarrow 1$	131	NOV/89
$X_{3t} \rightarrow 2$	123	MAR/89
$X_{4t} \rightarrow 3$	115, 127	JUN/88
$X_{5t} \rightarrow 2$	108	DEC/87

The types of interventions occurred are: impulse, step, and seasonal impulse. It is observed that the estimated coefficients of the intervention variables "ξ_i" have their expected signals. That is, ξ_1 and ξ_2 have negative signals, when ξ_3, ξ_4 and ξ_5 have positive signals.

The inclusion of these variables in the model can be justified in the following form:

1 - The first intervention represents the reflections due to Cruzado Plan that imposed freezing of prices, which was in vigor from March to November of 1986;

2 - The intervention of November 1989, is the reflection of heterodox shock of Summer Plan;

3 - The intervention occurred in March 1989 is due to the price increase in consequence to inflationary memory;

4 - The increase in sales in June 1988 is characterized by the seasonal effect, since every year starting from 1988 there has been increase in sales (more emphasize in the year 1988); and a harmonic observed with reference to the month June is highly significant;

5 - Finally, X_{5t} represents the intervention due to Bresser Plan, a new tentative of freezing the prices, this time for a very short period of time, from July to October 1987.

<u>Neural Network</u>

<u>Architecture</u> : The chosen architecture (after testing various architectures by evaluating forecast values) is given by:

i) 14 units in the input layer, in the following form:
- 2 past lags: x_t and x_{t-1};
- 12 seasonal units.

ii) two units in the hidden layer;
iii) one unit in the output layer x_{t+1}.

Training: The sales series was trained 1950 times, updating the weight for every 20 repetitions. The learning constant was maintained at 0.14 and in the last 400 repetitions, a memory loss term of 0.5 was used. This term was used to provide more weight for the most recent observations. The momentum term used was 0.8. The varying interval size of the weight was 4.

CONCLUSIONS

The ARIMA model with intervention presented a residual variation of 0.00227, where as the neural network model presented a residual variation of 0.00104. The chosen neural network presented, for the last 12 months, better forecasts than that of ARIMA model with interventions. The mean absolute error of the forecast was 7.6486 and that of the ARIMA model with interventions was 9.8642. The sales time series presented a marked seasonality for which it was necessary to use 12 binary units (0 or 1) for determining the relative weight for each month. The model obtained by the neural network was superior to ARIMA model, in adjustment as well as in forecasting for the data analyzed.

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