A NEW AUTOMATIC FORECASTING METHOD BASED ON DEEP DENDRITIC ARTIFICIAL NEURAL NETWORK

Eren Bas – Erol Egrioglu

Abstract

The development of automated methods for time series forecasting provides practitioners with the ability to perform solutions without requiring expert knowledge. In this study, hypothesis testing methods are developed for the deep dendritic artificial neural network for the adaptation of the dendritic neuron model, and a new automatic forecasting method based on hypothesis testing is proposed. In the proposed method, basic time series tools such as unit root tests and partial autocorrelation coefficients are utilised. The method proposed in the article allows a researcher to obtain forecasts without making any hyperparameter selection and without the need for subjective decisions. The performance of the proposed automatic forecasting method is compared with the benchmark methods in the M4 competition and the winning methods of this competition over 500 different time series selected from the M4 competition. As a result of the applications, it has been observed that the proposed method provides more accurate prediction results than all other methods according to the criteria used in the competition.

Key words: Forecasting, Automatic Forecasting Method, Deep Learning, Explainable Artificial Intelligence

JEL Code: C45, C53

Introduction

In recent years, there have been many applications of deep artificial neural networks on the forecasting problem. Many different artificial neural network methods have been proposed in the literature. Many different artificial neural network methods have been proposed in the literature. Long short-term memory deep neural networks (LSTM) (Hocreiter and J. Schmidhuber, 1997), gated recurrent unit deep neural networks (GRU) (Cho et al., 2014) and convolutional neural networks (CNN) (Kunihiko F.,1980) are the most widely used types of deep artificial neural networks. While CNN is a feed-forward network, LSTM and GRU are feedback networks and are considered more suitable for the time series forecasting problem due to their time-dependent dynamic structure. There are many studies using LSTM and GRU in the literature. Some of them are given in this section. Jiang and Hu (2018), Chung and Shin (2018), Tian et al. (2018), Veeramsetty et al. (2021), Liu and Dong (2021) and Bilgili et al. (2022) used LSTM based models in their studies. Bendali et al. (2020), Inteha et al. (2021), Liu et al. (2022) and Lin et al. (2022) used GRU-based models for forecasting in different aims. Both LSTM and GRU are artificial neural networks that use the additive combining function within the cell structure. For the first time in the literature, Egrioglu and Bas (2024) proposed a deep artificial neural network "DeepDent" that works with the multiplicative combining function. In Egrioglu and Bas (2024), the "DeepDent" artificial neural network is proposed as well as a literature review for the problem of forecasting with artificial neural networks.

In this study, a new automatic prediction method is presented. The proposed method is based on input significance tests and various statistical tools developed for the "DeepDent" artificial neural network.

In the second part of the study, the algorithm of the proposed automatic forecasting method is presented, and in the third part, the results obtained by applying the proposed algorithm to the M4 competition time series are given. In the last section, the results obtained are discussed.

1 Proposed Automatic Forecasting Method

In the application of artificial neural networks to the forecasting problem, many subjective decisions need to be made. With the automatic solution of the forecasting problem, practitioners can solve forecasting problems without having technical details. In this study, an automatic forecasting method based on the "DeepDenT" deep artificial neural network developed by Egrioglu and Bas (2024) is proposed. The algorithm of the proposed method is given below.

Algorithm 2. Algorithm of Automatic “DeepDenT”

Step 1. Stationarity in the time series is checked. If the time series is not stationary, stationarity is ensured by differencing.

Firstly, it is investigated whether there is a non-stationarity due to seasonality. If the following condition is satisfied, the series is seasonally differenced by using (2).

$$|ACF_m| > 1.645\sqrt{\frac{1 + 2(ACF_1 + \sum_{i=2}^{m-1} ACF_i^2)}{n}} \tag{1}$$

$$z_t = (1 - B^s)^D x_t \tag{2}$$

In (2), s presents a seasonality period. After the non-stationarity due to seasonality is investigated, non-stationarity due to trend is investigated with unit root tests. Augmented Dickey-Fuller test is applied to time series. If the series has a unit root, the differencing operation is applied by using the (3) equation.

$$z_t = (1 - B)^d z_t \tag{3}$$

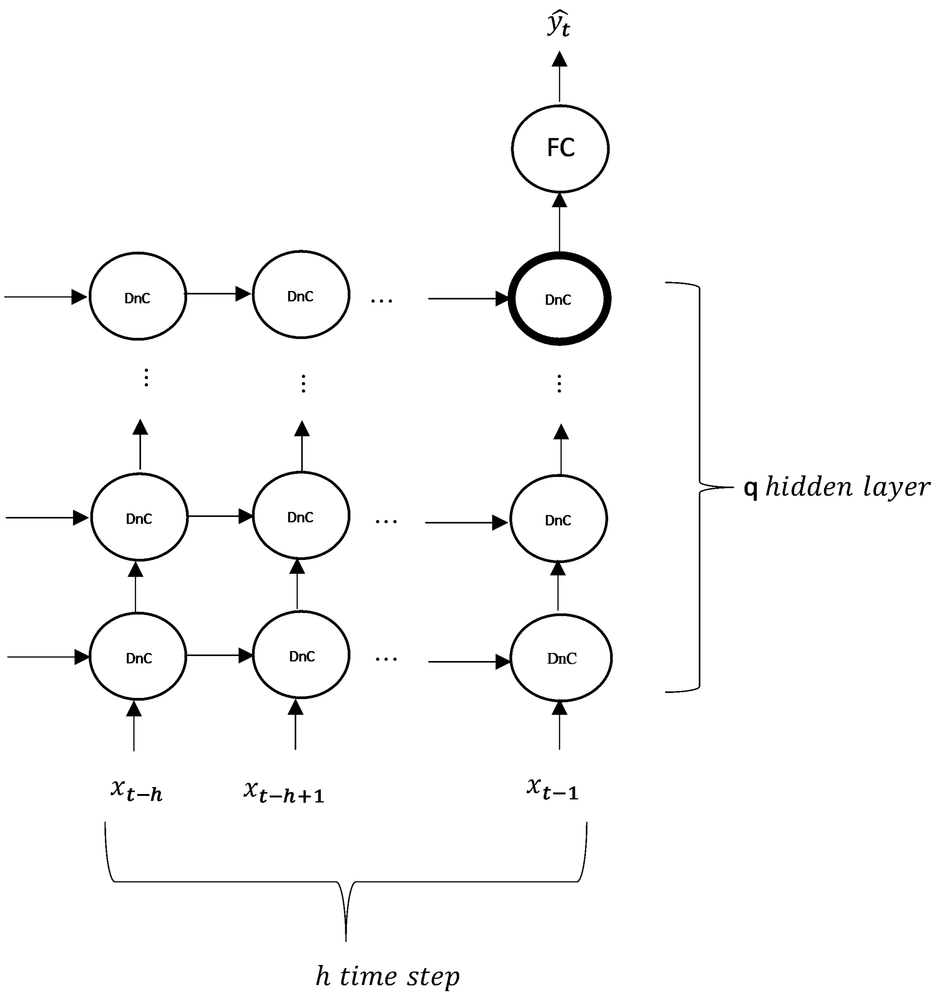
Step 2. The lagged variables to be used in the solution of the time series with DeepDenT are selected with the help of the partial autocorrelation coefficients calculated for the time series and the standard errors of these coefficients.

Step 3. The deep neural network given in Figure 1 is trained with the delayed variables determined in Step 2.

Step 4. Significant lagged variables are determined by applying an input significance test for the “DeepDenT” artificial neural network.

Fig. 1: The "DeepDenT" Architecture

"Source: Egrioglu and Bas (2024) "



Step 5. "DeepDenT" is applied with significant lagged variables in Step 4 and go to Step 3.

Step 6. Forecasts are computed by trained "DeepDenT" The forecasts are retransformed according to pre-processing operations.

2 Applications

The performance of the proposed automatic forecasting method is investigated over 500 time series used in the M4 time series competition. In each category of the time series used in the M4 time series competition, the automatic forecasting method was applied for 500 time series in total, the first 100 series in each category of the time series with Yearly, Quarterly, Monthly, Daliy and Hourly time frequency. End of M4 time series competition

Tab. 1: M4 Competiton Data Results for Yearly, Quarterly and Monthly Time Series

"Source: Own research"

	Yearly		Quarterly		Monthly	
Method	**Median (SMAPE)**	**Median (MASE)**	**Median (SMAPE)**	**Median (MASE)**	**Median (SMAPE)**	**Median (MASE)**
ARIMA	15,1681	5,9229	2,0812	0,9695	8,0762	0,7844
Com	15,2521	6,0105	2,6991	1,1049	7,9118	0,7499
Damped	16,9141	5,8440	2,7590	1,0935	6,9371	0,8553
ETS	13,2248	4,6602	2,2443	0,8323	6,8364	0,8475
Holt	16,2951	6,0096	2,5333	1,0335	9,1865	0,8360
MLP	9,1902	4,4044	5,1100	1,9226	11,2919	1,2932
Naive	10,5544	4,4336	4,6780	1,9154	9,0108	1,3649
Naive2	10,5544	4,4336	4,6780	1,9154	7,2440	0,9998
RNN	7,8646	3,5238	5,1406	1,8390	11,1869	1,2892
SES	10,5545	4,4220	4,7493	1,9188	7,4153	0,9321
sNaive	10,5544	4,4336	4,678	1,9154	8,0416	0,8607
Teta	9,1132	3,9294	3,4664	1,3583	8,1777	0,8217
Winner Method	10,1114	4,431	2,5658	0,9316	7,0586	0,7156
AFM-DeepDent	1,6861	3,1714	0,5845	0,8434	2,1127	0,8190

Tab. 2: M4 Competiton Data Results for Daily and Hourly Time Series

"Source: Own research"

	Daily		Hourly	
Method	**Median (SMAPE)**	**Median (MASE)**	**Median (SMAPE)**	**Median (MASE)**
ARIMA	3,0986	4,0191	7,5048	1,2718
Com	2,6704	3,1697	5,9667	1,1948
Damped	2,9466	3,1620	5,3378	1,1075
ETS	2,9823	3,2142	5,6935	1,1981
Holt	3,2005	3,4203	13,6426	2,1852
MLP	5,9629	9,4773	10,2267	1,7159
Naive	2,7893	3,1084	6,0655	1,2317
Naive2	2,7893	3,1084	6,0655	1,2317
RNN	3,5514	5,0533	11,0844	1,7144
SES	2,7929	3,1058	6,1696	1,2820
sNaive	2,7893	3,1084	6,0655	1,2317
Teta	2,6604	3,1663	6,5219	1,3034

Winner Method	2,2911	3,2913	6,6429	1,121
AFM-DeepDent	0,4459	2,7110	1,4489	0,9788

In Tables 1 and 2, the medians of the SMAPE and MASE values calculated for the data at each time series frequency are given. Since the results obtained do not have a symmetrical distribution, median statistics were preferred instead of average. SMAPE and MASE values are calculated from the formulas given below.

$$SMAPE = 200 \times \frac{1}{ntest} \sum_{t=1}^{ntest} \frac{|x_t - \hat{x}_t|}{|x_t| + |\hat{x}_t|} \tag{4}$$

$$MASE = \frac{(\frac{1}{n}) \sum_{t=1}^{n} |x_t - \hat{x}_t|}{(\frac{1}{n-1}) \sum_{t=2}^{n} |x_t - x_{t-1}|} \tag{5}$$

Conclusion

In this study, a new automatic prediction method was introduced. The proposed method uses the "DeepDenT" deep artificial neural network. In addition to automatic stabilization of the time series, the method also provides automatic selection of model inputs based on partial autocorrelation and input significance tests. The proposed automatic forecasting method was applied to 500 time series that were fairly selected from the M4 time series. The results obtained show that both benchmark methods and M4 time series competition can achieve more successful forecasting results against the win method. In future studies, automatic prediction methods based on the hybrid approach of "DeepDenT" and classical prediction methods will be studied.

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