FORECASTING ITALIAN GDP GROWTH RATE AND ITALIAN INFLATION RATE USING TIME SERIES NEURAL NETWORK MODELS

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Abstract

Predicting the future evolution of GDP growth rate and inflation rate is a central concern in economics. Forecasts are typically produced either from economic theory based models or from simple linear time series models. The classical methods used for time series prediction, like ARIMA models or structural time series models, assume that there is a linear relationship between inputs and outputs. Artificial neural network modeling has recently attracted much attention as a new technique for estimation and forecasting in economics and finance. The chief advantages of this approach are that such models can usually find a solution for very complex problems, and that they are free from the assumption of linearity that is often adopted to make the traditional methods tractable. Neural networks have been successfully used for forecasting of financial and economics data series. In this article we predicted Italian GDP growth rate and Italian inflation rate using neural networks, and we compared the forecasting performance of such non-linear models using different estimation algorithms and different delays.

1 INTRODUCTION

The article conducted a detailed analysis of the forecasting performance of univariate and bivariate time series models for GDP growth rate and inflation rate, the two key variables for macroeconomic analysis. We considered a large variety of models and we compared the goodness of fit and forecasts of the competing models on the basis of MSE (mean squared error) and R (correlation coefficient between outputs and targets).

2 SURVEY OF THE EMPIRICAL LITERATURE

The use of neural networks was introduced in economics at the beginning of the nineties. There has been considerable interest in applications of neural networks in the economics literature, particularly in the areas of financial statistics and exchange rates. In contrast, relatively few studies have applied neural network methods to macroeconomic time series, such as GDP growth rate and inflation rate. The article by [33] is likely the definitive introduction of neural networks to the econometrics literature, the authors draw many of the parallels between econometrics and neural networks. [33]'s theoretical contribution has been followed with some applied work by [38]. These authors demonstrate that the 14 macroeconomic series analyzed can be nicely modelled using neural networks. [49] represents another major attempt at using neural nets to forecast macroeconomic variables. This paper compares the relative usefulness of different linear and nonlinear models using a wide array of out-of-sample forecasting performance indicators. The results were mixed, but [49] nevertheless concluded that artificial neural network models were promising even where there is no explicit non-linearity. [32] is a good introduction to neural networks and their uses in economics, with an application to the forecast of corn futures. Comparing a neural network to an ARIMA model, they find that the forecast error of the neural net model is between 18% and 40% lower than that of the ARIMA model, using different forecasting performance criteria. [3] develops a neural net model that has some success at forecasting the S&P 500 index. [45] compares the performance of Back-Propagation Artificial Neural Network (BPN) models with the traditional econometric approaches to forecasting the inflation rate. The results show the BPN models are able to forecast as well as all the traditional econometric methods, and to outperform them in some cases. [51] uses neural network forecasting for Canadian GDP growth rate. He finds that neural networks yield statistically lower forecast errors for the year-over-year growth rate of real GDP relative to linear and univariate models. However, such forecast improvements are less notable when forecasting quarterly real GDP growth. [46] evaluates the usefulness of neural networks for inflation forecasting, the paper showed a pseudo-out-of-sample forecasting experiment using recent U.S. data, neural networks outperform univariate autoregressive models on average for short horizons of one and two quarters. Finally, [47] examines the efficacy of neural networks application for inflation forecasting. In a simulated out-of-model forecasting investigation using recent Nigeria inflation rate data obtained from the appropriate authorities, [47] shows that the neural networks do better, in some cases, than univariate autoregressive models.

Table 1: Descriptive statistics for GDP growth rate for the period 1962:1 to 2017:4.

Variable	Mean	Median	Standard Deviation	Skewness	Kurtosis	IQR
Italy	0.561	0.433	0.997	0.612	3.974	1.107

Table 2: Descriptive statistics for inflation rate for the period 1962:1 to 2017:4.

Variable	Mean	Median	Standard Deviation	Skewness	Kurtosis	IQR
Italy	6.111	4.400	5.654	1.347	0.863	5.268

3 DATA

The dataset come from OECD (http://www.oecd.org) and the time series are quarterly for GDP growth and for inflation. There are 2 series in the data set (one for Italian GDP growth and one for Italian inflation rate) and the sample is from 1962:1 to 2017:4 (224 observations in each series). Neural networks, more than linear models, need larger samples in order to be estimated properly, this is due to the large number of parameters introduced in such models. The two series are right skewed and leptokurtic, so they have fat tails and high peak (see Table 1 and Table 2). In Table 3 and Table 4 are shown the test statistics (and p-values) for normality, autocorrelation and randomness regarding the mentioned two time series. The two series are non normal, autocorrelated and non random. In Figure 1 are shown the time series plots of the 2 series.

4 NEURAL NETWORKS FOR TIME SERIES FORECASTING

We considered two types of neural network models for time series forecasting, the NARX model and the NAR model (see [6] and [5]). In the first type of neural network model, you can predict future values of a time series $y(t)$ from past values of that time series and past values of a second time series $x(t)$. You can add also same more series $x(t)$. This form of prediction is called nonlinear autoregressive with exogenous (external) input, or NARX (see Figure 2), and can be written as follows:

$$y(t) = f(y(t-1), ..., y(t-d), x(t-1), ..., (t-d)) \quad (1)$$

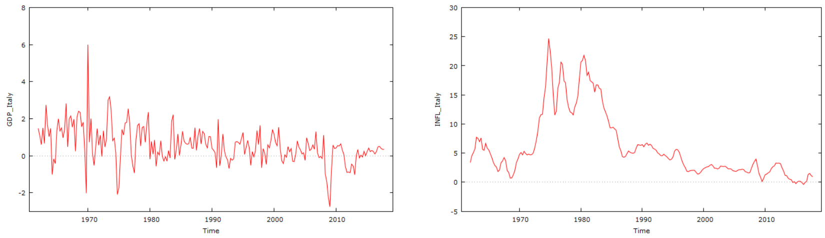
Where d is the number of delays. This model could be used to predict future values of a stock or bond, based on such economic variables as unemployment rates, GDP, etc. In the second type of neural network model, there is only one series involved. The future values of a time series $y(t)$ are predicted only from past values of that series. This form of prediction is

Table 3: Tests for GDP growth rate for the period 1962:1 to 2017:4.

Variable	Jarque-Bera Normality Test	Shapiro-Wilk Normality Test	Ljung-Box (2) Autocorrelation Test	Ljung-Box (4) Autocorrelation Test	White Noise Test
Italy	161.390 (0.000)	0.952 (0.000)	52.958 (0.000)	60.082 (0.000)	-4.168 (0.037)

Table 4: Tests for inflation rate for the period 1962:1 to 2017:4.

Variable	Jarque-Bera Normality Test	Shapiro-Wilk Normality Test	Ljung-Box (2) Autocorrelation Test	Ljung-Box (4) Autocorrelation Test	White Noise Test
Italy	74.703 (0.000)	0.828 (0.000)	415.130 (0.000)	763.620 (0.000)	144.938 (0.000)



(a) GDP growth rate of Italy. **(b)** Inflation rate of Italy.

Figure 1: Time series plots of GDP growth rate and inflation rate for Italy from the first quarter of 1962 till the forth quarter of 2017.

called nonlinear autoregressive, or NAR (see Figure 3), and can be written as follows:

$$y(t) = f(y(t-1), ..., y(t-d)) \quad (2)$$

Where d is the number of delays. This model could also be used to predict financial instruments, but without the use of one or more companion series.

To train the NARX and NAR neural network models we divided each time series into three sets as follows:

- The first 60% of the data has been used for training, these are presented to the network during training, and the network is adjusted according to its error.
- From 60% to 80% of the data has been used to validate that the network is generalizing and to stop training before overfitting, these are used to measure network generalization, and to halt training when generalization stops improving.
- The last 20% of the data has been used as a completely independent test of network generalization, these have no effect on training and so provide an independent measure of network performance during and after training.

We used a log-sigmoid transfer function for the Hidden part of the network and a linear transfer function for the Output part of the network (see Figure 2 and Figure 3). Moreover to train the neural network we used different number of delays and ten hidden neurons. There are plenty of the training

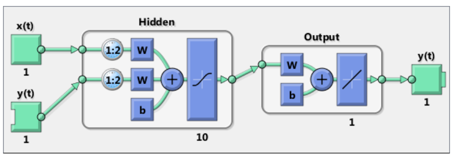


Figure 2: The NARX network with 1 input series, 2 number of delays and 10 hidden neurons (source http://www.mathworks.com).

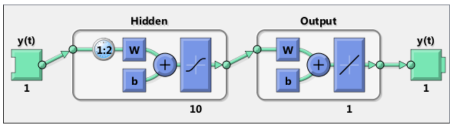


Figure 3: The NAR network with 2 number of delays and 10 hidden neurons (source http://www.mathworks.com).

algorithms available in neural network. In this article three algorithms have been used to train the NARX and NAR network: Levenberg-Marquardt (see [35] and [40]), Scaled Conjugate Gradient (see [44]), and Bayesian Regularization (see [39] and [17]). Levenberg-Marquardt is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization, this is a simple method for approximating a function. One of the main drawbacks of the Levenberg-Marquardt algorithm is that, for certain problems it needs the large storage of some matrices. Scaled Conjugate Gradient algorithm can train any network as long as its weight, net input, and transfer functions that have derivative functions. Bayesian regularization algorithm, a suitable method for estimation when a large number of inputs is used for best output, minimizes a grouping of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well.

5 EMPIRICAL RESULTS

In Table 5 and Table 6 are reported the MSE and R, for different training algorithms and different delays, for estimated NAR models, in Table 7 and Table 8 those for NARX models. As we can see for those tables, on the basis of MSE, the best models for GDP are NAR with 9 delays and NARX with 10 delays, both estimated with Bayesian regularization. The best models for inflation are NAR with 9 delays and NARX with 8 delays both estimated with Bayesian regularization. In Table 9 are presented the test statistics for forecasting errors of the mentioned models. All the series exhibit randomness. Moreover the forecasting errors of NAR and NARX for inflation are uncorrelated. In Figure 4 and Figure 5 we reported the plots of MSE for estimated NAR and NARX models.

6 CONCLUDING REMARKS

Research in economics using artificial neural networks has future possibilities and applications especially in order to find new types of artificial neural networks, new training algorithms and new perspectives of use in economics and finance.

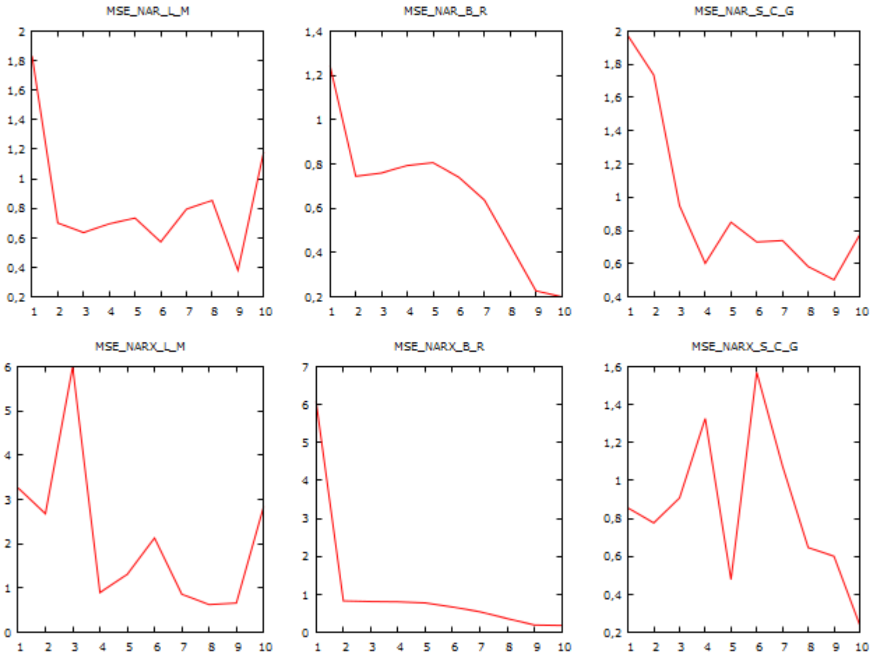


Figure 4: Plots of MSE for estimated NAR and NARX models for GDP growth rate.

7 APPENDIX

Table 5: NAR model for Italian GDP.

	Levenberg-Marquardt		Bayesian Regularization		Scaled Conjugate Gradient	
	MSE	R	MSE	R	MSE	R
NAR delay 1	1.830	0.412	1.242	0.350	1.970	0.200
NAR delay 2	0.700	0.325	0.744	0.417	1.735	0.162
NAR delay 3	0.635	0.489	0.759	0.417	0.948	0.152
NAR delay 4	0.695	0.471	0.793	0.422	0.602	0.369
NAR delay 5	0.733	0.586	0.806	0.426	0.849	0.376
NAR delay 6	0.572	0.582	0.740	0.427	0.730	0.322
NAR delay 7	0.794	0.454	0.636	0.427	0.739	0.227
NAR delay 8	0.853	0.461	0.433	0.431	0.582	0.332
NAR delay 9	0.380	0.650	0.190	0.430	0.502	0.306
NAR delay 10	1.181	0.417	0.200	0.449	0.773	0.360

Table 6: NAR model for Italian inflation.

	Levenberg-Marquardt		Bayesian Regularization		Scaled Conjugate Gradient	
	MSE	R	MSE	R	MSE	R
NAR delay 1	1.564	0.980	0.330	0.986	2.209	0.958
NAR delay 2	0.260	0.990	0.272	0.989	6.609	0.953
NAR delay 3	0.247	0.991	0.504	0.994	3.666	0.845
NAR delay 4	0.551	0.986	0.993	0.995	0.553	0.985
NAR delay 5	0.636	0.994	0.471	0.997	2.506	0.824
NAR delay 6	0.382	0.996	0.660	0.997	0.969	0.989
NAR delay 7	0.285	0.998	0.252	0.998	0.256	0.989
NAR delay 8	0.785	0.995	0.199	0.999	0.511	0.985
NAR delay 9	0.422	0.997	0.177	0.999	1.178	0.960
NAR delay 10	0.256	0.998	0.369	0.999	1.693	0.945

Table 7: NARX model for Italian GDP using the inflation as input series.

	Levenberg-Marquardt		Bayesian Regularization		Scaled Conjugate Gradient	
	MSE	R	MSE	R	MSE	R
NARX delay 1	3.257	0.226	6.077	0.124	0.855	0.270
NARX delay 2	2.677	0.378	0.828	0.411	0.776	0.312
NARX delay 3	5.986	0.248	0.811	0.418	0.907	0.222
NARX delay 4	0.898	0.377	0.804	0.434	1.326	0.210
NARX delay 5	1.307	0.474	0.775	0.453	0.478	0.235
NARX delay 6	2.128	0.306	0.668	0.467	1.569	0.204
NARX delay 7	0.859	0.426	0.542	0.474	1.076	0.287
NARX delay 8	0.627	0.202	0.362	0.475	0.646	0.352
NARX delay 9	0.661	0.233	0.195	0.474	0.601	0.166
NARX delay 10	2.840	0.633	0.183	0.490	0.240	0.145

Table 8: NARX model for Italian inflation using the GDP as input series.

	Levenberg-Marquardt		Bayesian Regularization		Scaled Conjugate Gradient	
	MSE	R	MSE	R	MSE	R
NARX delay 1	0.989	0.984	0.327	0.985	6.969	0.957
NARX delay 2	0.851	0.991	0.981	0.994	0.542	0.985
NARX delay 3	2.243	0.912	0.302	0.997	3.683	0.956
NARX delay 4	1.045	0.992	0.516	0.996	2.055	0.954
NARX delay 5	1.131	0.989	0.375	0.998	7.595	0.962
NARX delay 6	0.659	0.991	1.013	0.997	0.456	0.977
NARX delay 7	5.218	0.986	0.589	0.998	1.717	0.964
NARX delay 8	0.888	0.996	0.243	0.999	1.361	0.972
NARX delay 9	2.437	0.990	0.966	0.998	8.105	0.919
NARX delay 10	0.542	0.998	1.210	0.998	0.488	0.977

Table 9: Test statistics for forecasting errors of best NAR models and NARX models for Italy (p-values in parentheses).

Model	Jarque-Bera Normality Test	Shapiro-Wilk Normality Test	Ljung-Box (2) Autocorrelation Test	Ljung-Box (4) Autocorrelation Test	White Noise Test
NAR for GDP	12.348 (0.002)	0.899 (0.001)	14.099 (0.001)	15.398 (0.004)	0.350 (0.861)
NAR for inflation	0.764 (0.683)	0.969 (0.280)	0.587 (0.746)	0.671 (0.955)	-0.911 (0.649)
NARX for GDP	12.997 (0.002)	0.906 (0.002)	17.140 (0.000)	17.914 (0.001)	1.576 (0.430)
NARX for inflation	15.813 (0.000)	0.929 (0.009)	0.112 (0.946)	0.202 (0.995)	-2.942 (0.141)

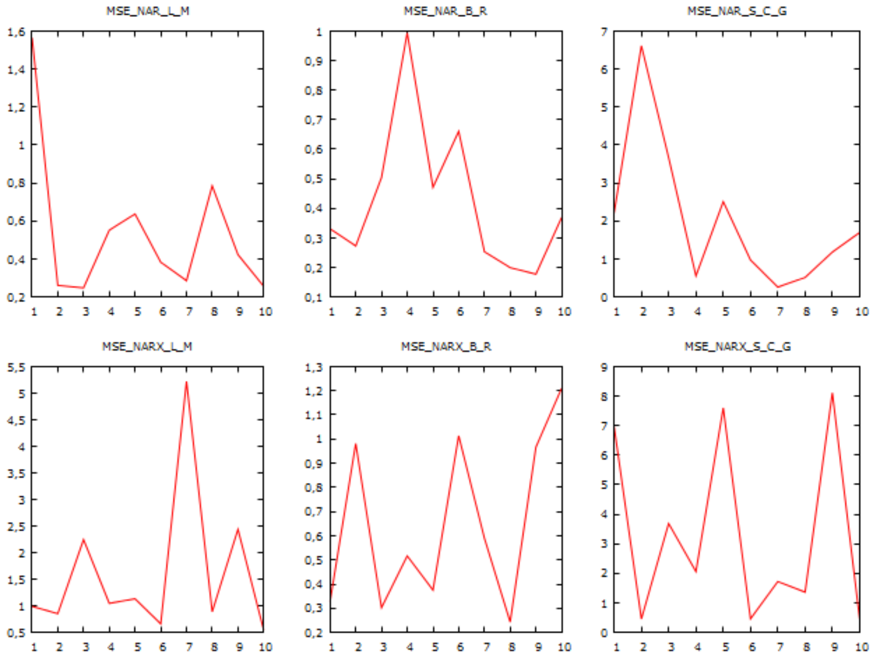


Figure 5: Plots of MSE for estimated NAR and NARX models for inflation rate.

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