Neural Network Solution to Economic Forecasting

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Abstract:
In recent years, neural networks have received an increasing amount of attention among macroeconomic forecasters because of their potential to detect and reproduce linear and nonlinear relationships among a set of variables. Many attempts to apply ANN as a forecasting tool has been successful. This paper highlighted the application of Neural Network in economic forecasting. Back propagation neural Network are used to forecast the approximated time in years for a specified input cost or benefits. Different types of benefits and coasts are used in the training and testing phase. A better understanding of neural networks will help economists decide on the relevance of using these models.

1- Introduction:
A forecast is a prediction concerning the future. Good forecasting will reduce, but not eliminate, the uncertainty that all managers feel. Both public and private enterprises operate under conditions of uncertainty. Management wishes to limit this uncertainty by predicting changes in cost, price, sales, and interest rates. Accurate forecasting can help develop strategies to promote profitable trends and to avoid unprofitable ones. Demand Forecasting is a critical managerial activity which comes in two forms:
- Quantitative Forecasting : Gives the precise amount or percentage.
- Qualitative Forecasting : Gives the expected direction Up, down, or about the same

The selection of forecasting techniques depends in part on the level of economic aggregation involved.
The hierarchy of forecasting is:
- National Economy (GDP, interest rates, inflation, etc.)
- sectors of the economy (durable goods)
- industry forecasts (all automobile manufacturers)
- firm forecasts (Ford Motor Company)
- Product forecasts (The Ford Focus)

The choice of a particular forecasting method depends on several criteria:
- costs of the forecasting method compared with its gains
- complexity of the relationships among variables
- time period involved
- accuracy needed in forecast
- lead time between receiving information and the decision to be made

Of great interest to forecasters of the economy is predicting the “business cycle”, or the overall level of economic activity. The business cycle affects society as a whole by its fluctuations in economic quantities such as the unemployment rate (the misery index), corporate profits (which affect stock market prices), the demand for manufactured goods and new housing units, bankruptcy rates, investment in research and development, investment in capital equipment, savings rates, and so on. The business cycle also affects important socio-political factors such as the general mood of the people and the outcomes of elections. Macroeconomic modeling and forecasting is challenging for several reasons:
- No a priori Models: A convincing and accurate scientific model of business cycle dynamics is not yet available due to the complexities of the economic system, the impossibility of doing controlled experiments on the economy, and non-quantifiable factors such as mass psychology and sociology that influence
economic activity. There are two main approaches that economists have used to model the macro economy, econometric models and linear time series models:

- **Econometric Models:** These models attempt to model the macro economy at a relatively fine scale and typically contain hundreds or thousands of equations and variables. The model structures are chosen by hand, but model parameters are estimated from the data. While econometric models are of some use in understanding the workings of the economy qualitatively, they are notoriously bad at making quantitative predictions.

- **Linear Time Series Models:** Given the poor forecasting performance of econometric models, many economists have resorted to analyzing and forecasting economic activity by using the empirical “black box” techniques of standard linear time series models. As we have found in our own work, however, neural networks can often outperform standard linear time series models. The lack of an *a priori* model of the economy makes input variable selection, the selection of lag structures, and network model selection critical issues.

- **Noise:** Macroeconomic time series are intrinsically very noisy and generally have poor signal to noise ratios. The noise is due both to the many unobserved variables in the economy and to the survey techniques used to collect data for those variables that are measured. The combination of short data series and significant noise levels makes controlling model variance, model complexity, and the *bias / variance tradeoff* important issues (Geman, Bienenstock and Doursat, 1992).

- **Nonstationarity:** Due to the evolution of the world’s economies over time, macroeconomic series are intrinsically nonstationary. The combination of noise and nonstationarity gives rise to a *noise / nonstationarity tradeoff* (Moody, 1994a), where using a short training window results in too much model variance or *estimation error* due to noise in limited training data, while using a long training window results in too much model bias or *approximation error* due to nonstationarity.

- **Nonlinearity:** Traditional macroeconomic time series models are linear (Granger and Newbold, 1986; Hamilton, 1994). However, recent work by several investigators have suggested that nonlinearities can improve macroeconomic forecasting models in some cases.

Artificial Neural Network (ANN) is able to microeconomic forecast. In recent years, neural networks have received an increasing amount of attention among macroeconomic forecasters because of their potential to detect and reproduce linear and nonlinear relationships among a set of variables. Many attempts to apply ANN as a forecasting tool has been successful. Steven Gonzalez (2007),

**2- BASIC CHARACTERISTICS OF THE BRAIN**

As cognitive scientists studied the brain and its ability to learn, they identified some key characteristics that seemed particularly important to the brain's success. These attributes were then used as a basis to construct neural networks. To achieve a better understanding of these networks, it is therefore useful to examine briefly these key features of the brain. The brain is composed of billions of simple units called *neurons* (Figure 1) that are grouped into a vast network. Biological research suggests that neurons perform there datively simple task of selectively transmitting electrical
impulses among each other. When a neuron receives impulses from neighboring neurons, its reaction will vary depending on the intensity of the impulses received and on its own particular "sensitivity" towards the neurons that sent them. Some neurons will not react at all to certain impulses. When a neuron does react (or is activated), it will send impulses to other neurons. The intensity of the impulses emitted will be proportional to the intensity of the impulses received. As impulses are transmitted among neurons, eventually a "cloud" of neurons becomes simultaneously activated, thus giving rise to thoughts or emotions (Nielsen 2007).

**Figure 1**
Basic illustration of a neuron

![Basic illustration of a neuron](source)

Like the brain, a neural network is essentially a collection of interconnected neurons, grouped in layers that send information to each other. The simplest form of network has only two layers: an input layer and an output layer. The network operates like an input-output system, using the values of the input neurons to compute a value for the output neuron. Figure 2 illustrates the standard graphical representation of a neural network. Each neuron is represented by a circle, while the connections between neurons are depicted by arrows. The output Y and the inputs X0, X1 and X2 are n x 1 vectors, where n is the number of observations. In this example, information runs exclusively from inputs to outputs, hence the term feed forward network (Davalo 2009).

**Figure 2**
A basic feed forward neural network

![A basic feed forward neural network](source)
Each connection between an input and the output is characterized by a weight $a_i$ which expresses the relative importance of a particular input in the calculation of the output. To calculate the output value for observation $t$, the output neuron starts by collecting the values of each input neuron for observation $t$ and multiplies each of them by the weight associated with the relevant connection.

A two-layer feed forward neural network with an identity activation function is identical to a linear regression model. The input neurons are equivalent to independent variables or repressor, while the output neuron is the dependent variable. The various weights of the network are equivalent to the estimated coefficients of a regression model and the bias is simply the intercept term. Note that in equations (2) and (3), the error term $e_t$ is omitted as only the mathematical expression of the computed output value, i.e. the "fit", is being provided. Some models may have more than one output if a researcher is interested in more than one dependent variable (Figure 3).

Researchers almost always design a structure that includes one or more hidden layers, as in Figure 5. In this figure, $a_{ij}$ denotes the weight for the connection linking input $i$ to the hidden unit $j$. We assume that $X_0$ is a bias term (i.e. an intercept term) for the hidden units while $B$ is a bias term for the output unit.
2.1 Designing the model:
When an econometrician is building a linear regression model for forecasting purposes, a significant part of the work consists in identifying the explanatory variables and the number of lags that will allow the most accurate forecasts. This will generally require many hours of experimentation with alternative specifications. Fortunately, the estimation of each alternative specification is instantaneous and the out-of-sample forecasts can be rapidly generated and assessed. Once the researcher has found the specification that minimizes the forecasting errors, a substantial portion of the work is completed and the researcher can then focus his/her efforts on diagnostic tests. When constructing a neural network, the overall task is much longer. The neural networker must not only choose a set of inputs, but must also identify the network architecture that leads to the best forecasts. Changes to the architecture can fundamentally alter the forecasts produced by the network, even when no changes are made to the inputs, outputs or sample size. To find the best architecture, the neural networker must proceed by trial and error. This process is summarized in Figure 5. To assess the performance of other architectures, the researcher must modify the architecture of the network by changing the number of hidden units or by adding or removing certain network connections. The whole early stopping procedure must again be repeated hundreds of times in the new architecture, by varying the starting values, in the hope of finding the global minimum.

3- Neural Network Solutions:
In Cost-benefit analysis: identify all the financial benefits and costs associated with a project, there are different type of benefits and cost. Benefits types are: Tangible that
can be measured in dollars and with certainty and Intangible that cannot easily be measured in dollars or with certainty. While cost type are: Tangible: can be measured in dollars and with certainty, Intangible: cannot easily be measured in dollars or with certainty. One-time: a cost associated with project start-up and development or systems start-up and Recurring: a cost associated with ongoing evolution and use of a system. For example the possible IS Project Costs (Hoffer 2005):

- Procurement: Consulting, equipment, site preparation, capital, management time
- Start-up: Operating systems, communications installation, personnel hiring, organizational disruption
- Project-related: Application software, software modification, personnel overhead, training, data analysis, documentation
- Operating: System maintenance, rental, asset depreciation, operation and planning
- There are many financial measurements for economic feasibility like Net Present Value (NPV), Return on Investment (ROI), and Break-Even Analysis (BEA). Figure 8 show BEA for an information system example.

In our proposed system we use different type of benefits and cost versus the time to train BP Neural Network. Figure 5-8 specify the relationship between cost/benefit and the time. training set composed from the subsets of {Cost/benefit, value, time}. For example the subset {1, 2000, 2} means that cost value 2000$ at second year. While the subset {0, 1000, 3} means that benefit value 1000$ at third year. Training set contains many subsets like these. This subset must be taken intelligently from the history information of similar systems. After training, BP Neural Network must be able to forecast the year of the given cost or benefit. The number of neuron in the input layer are two (cost/benefit and value), and the number of neurons in the output layer is one (time). The number of hidden layers and the number of neurons in each hidden layer are selected by experiences work in the Math Lap software.

![Figure 5-8](source-handout-ig.png) **Figure 5-8** Break-even analysis for Customer Tracking System (Pine Valley Furniture)

After several series of trial and error using five different cases of data distribution, the result of training for Case 4 with twenty five hidden nodes depicting the lowest Root Means Square Error (RMSE) and the best Mean Absolute Percentage Error (MAPE), was chosen for forecasting. Based on the results (Table 2), Case 5 was
chosen for model forecasting because of the lowest RMSE (0.1) and the best value of MAPE (2.6%) in the training set. After the training and testing processes, Case 5 was taken as the best trained model that was presented to testing in another further steps. A set of data was introduced to the model for validation purposes.

<table>
<thead>
<tr>
<th>Hidden nodes</th>
<th>Case</th>
<th>Training RMSE</th>
<th>Testing RMSE</th>
<th>Approximated Error(0.0)</th>
<th>Approximated MAPE</th>
<th>Error(0.0)</th>
</tr>
</thead>
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<tr>
<td>10</td>
<td>1</td>
<td>0.323</td>
<td>0.665</td>
<td>0.3</td>
<td>4.7</td>
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<tr>
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<td>0.456</td>
<td>0.2</td>
<td>3.7</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>3</td>
<td>0.554</td>
<td>0.412</td>
<td>0.3</td>
<td>5.6</td>
<td></td>
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<tr>
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<td>4</td>
<td>0.345</td>
<td>0.567</td>
<td>0.1</td>
<td>2.6</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>5</td>
<td>0.210</td>
<td>0.421</td>
<td>0.2</td>
<td>4.0</td>
<td></td>
</tr>
</tbody>
</table>

4- CONCLUSION:
Results of this study indicate that Artificial Neural Network (ANN) is able to microeconomic forecast. The results also show that the suitability of distribution and sizes of data used can affect the accuracy of the forecasting. The model can be further improved by increasing the size of data used in the ANN modeling and using other types of neural network such as recurrent network. It has been shown that neural network has a potential to be used as a meaningful tool for the purpose of forecasting demand. The results also illustrates that the future values of economic are influenced by past and current housing demand data.

References:
2. Davalo E., Naim P. (2009), Neural Networks, Machllan.
12. Steven Gonzalez (2007), "Neural Networks for Macroeconomic Forecasting: A Complementary Approach to Linear Regression Models".