Neural Networks for Macroeconomic Forecasting:
A Complementary Approach to Linear Regression Models

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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. This paper provides a highly accessible introduction to neural networks and establishes several parallels with standard econometric techniques. To facilitate the presentation, an empirical example is developed to forecast Canada's real GDP growth. For both the in-sample and out-of-sample periods, the forecasting accuracy of the neural network is found to be superior to a well-established linear regression model developed in the Department, with the error reduction ranging from 13 to 40 per cent. However, various tests indicate that there is little evidence that the improvement in forecasting accuracy is statistically significant.

A thorough review of the literature suggests that neural networks are generally more accurate than linear models for out-of-sample forecasting of economic output and various financial variables such as stock prices. However, the literature should still be considered inconclusive due to the relatively small number of reliable studies on the topic. Despite these encouraging results, neural networks should not be viewed as a panacea, as this method also presents various weaknesses. Contrary to many researchers in the field, who tend to adopt an all-or-nothing approach to this issue, we argue that neural networks should be considered as a powerful complement to standard econometric methods, rather than a substitute. The full potential of neural networks can probably be exploited by using them in conjunction with linear regression models. Hence, neural networks should be viewed as an additional tool to be included in the toolbox of macroeconomic forecasters.

INTRODUCTION

The human brain constitutes the most complex computer known to mankind. In order to better understand the brain, many researchers have attempted to duplicate its various abilities through the development of artificial intelligence. Part of this research, led by cognitive scientists over the last half-century, focused on artificial neural networks. Simply put, a neural network is a mathematical model that is structured like a brain and that attempts to identify patterns among a group of variables. The scientists that pioneered the research in this field were attempting to develop a system that could learn through experience in order to further their understanding of the brain's learning abilities. However, the surprising "learning" capacity displayed by neural networks subsequently led to their application in a wide variety of tasks such as translating printed English text into speech (Sejnowski and Rosenberg, 1986), playing backgammon (Tesauro, 1989), recognizing hand-written characters (LeCun et al., 1990), playing music (Brecht and Aiken, 1995) and diagnosing automobile engine misfires (Armstrong and Gross, 1998).

Recent research also suggests that neural networks may prove useful to forecast volatile financial variables that are difficult to forecast with conventional statistical methods, such as exchange rates (Verkooijen, 1996) and stock performance (Refenes, Zapranis and Francis, 1994). Neural networks have also been successfully applied to macroeconomic variables such as economic growth (Tkacz, 1999), industrial production (Moody, Levin and Rehfuss, 1993) and aggregate electricity consumption (McMenamin, 1997). Applications to macroeconomics are quite novel and are still considered to be at the frontier of empirical economic methods.

As it will be shown, the simplest types of neural networks are closely linked to standard econometric techniques. Throughout this paper, parallels will be established between neural networks and econometric methods in order to facilitate the comprehension of readers versed in econometrics. A better understanding of neural networks will help economists decide on the relevance of using these models for macroeconomic and financial forecasting.

The paper also provides a thorough review of the empirical literature applying neural networks to macroeconomic forecasting. However, this literature should still be viewed as inconclusive due to the relatively limited number of reliable studies available. To enhance the discussion, this paper then examines the relative advantages and disadvantages of these models from a more theoretical point of view, in order to help identify the areas where their application may be potentially fruitful. Several myths about neural networks are also dispelled.

The paper is organized as follows. Section 1 presents some basic characteristics of the brain that inspired the design of the first neural networks. Section 2 presents a very accessible introduction to neural networks that establishes parallels with standard econometric techniques. Section 3 explains how the network is estimated from the data. Section 4 presents an empirical example of a neural network forecasting real GDP growth and compares its forecasting accuracy to a linear regression model. Section 5 reviews the

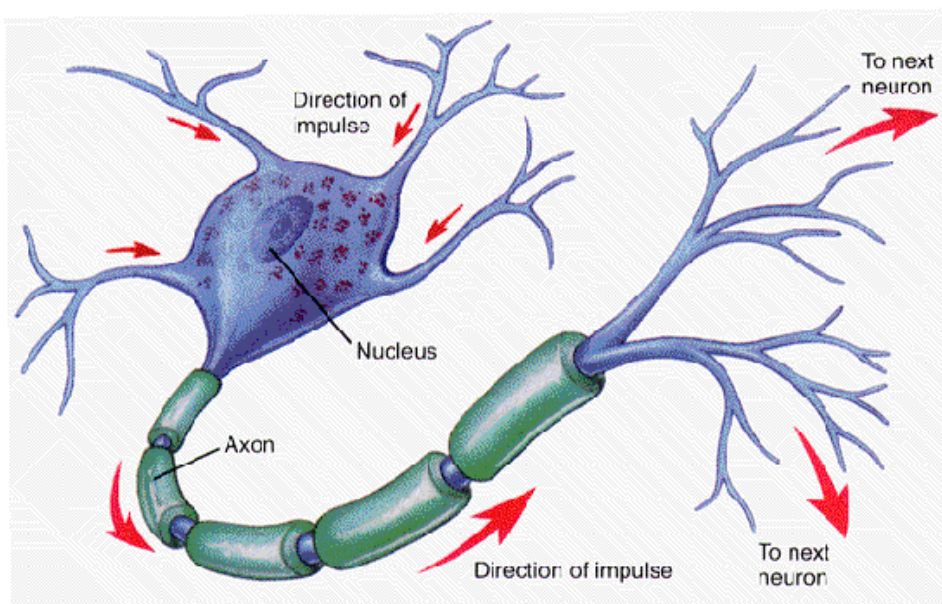
empirical literature comparing these models to econometric techniques. Section 6 reviews the relative strengths and weaknesses of neural networks from a more theoretical point of view and Section 7 concludes.

1. 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 the relatively simple task of selectively transmitting electrical impulses among each other. When a neuron receives impulses from neighbouring 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.

Figure 1
Basic illustration of a neuron



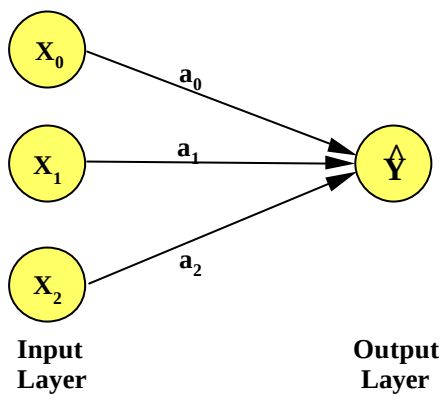
Source: Brown & Benchmark Introductory Psychology Electronic Image Bank, 1995. Times Mirror Higher Education Group, Inc.

The power of the brain seems to stem from this complex network of connections between neurons and the manner in which the activity of millions of neurons can be synchronised and combined in a fraction of a second. Keeping in mind these stylized facts, let us now move on to a basic description of a neural network.

2. THE SIMPLEST FORM OF NEURAL NETWORK[1]

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 X_0, X_1 and X_2 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 *feedforward* network.

Figure 2
A basic feedforward neural network



Each connection between an input and the output is characterised 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. These products are then summed, yielding the following value:

$$a_0X_{0t} + a_1X_{1t} + a_2X_{2t} \qquad (1)$$

The output neuron then processes this value using an *activation function*, noted *f(x)*. In the simplest form of feedforward neural network, the activation function is the identity,

[1] This Section draws considerably on Kuan and White (1994).

i.e. $f(x) = x$. In this case, the value given in (1) would constitute the final output of the network for observation t:

$$Y_t = a_0X_{0t} + a_1X_{1t} + a_2X_{2t} \quad (2)$$

Typically, one of the inputs, called the *bias*, is equal to 1 for all observations. Assuming that X_0 is the *bias*, the output of the network is given by:

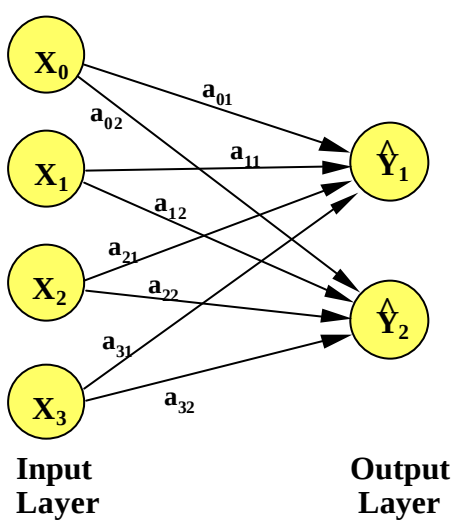
$$Y_t = a_0 + a_1X_{1t} + a_2X_{2t} \quad (3)$$

In general, the researcher also provides the network with the *target output value* (noted Y_t) that the network should try to reproduce through its computations, given the value of the inputs. A forecasting error for each observation is then computed as the difference between Y_t and Y_t. Using various iterative algorithms (the most common of which is called the *backpropagation algorithm*), the weights of the network will be modified until the forecasting errors across the entire sample are minimized, as measured by the sum of squared errors or the mean absolute error. As the weights are changed with each iteration, the network is said to be *learning*.

From the above discussion, it is obvious that a two-layer feedforward neural network with an identity activation function is identical to a **linear regression model**. The input neurons are equivalent to independent variables or regressors, 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).

Figure 3
A simple feedforward neural network with two outputs



In this figure, a_{ij} denotes the weight that links input *i* to output *j*. Assuming again that X_0 is a bias term, the network output is given by:

$$Y_1 = a_{01} + a_{11}X_1 + a_{21}X_2 + a_{31}X_3$$
$$Y_2 = a_{02} + a_{12}X_1 + a_{22}X_2 + a_{32}X_3 \quad (4)$$

We obtain a system of linear equations very similar to a system of **seemingly unrelated regression equations** (*à la* Zellner). In the presence of time-series data, we can construct a neural network equivalent to a **vector autoregressive model** by simply adding lagged values of the dependent and independent variables to the group of inputs. By introducing a link between Y_1 and Y_2, we would obtain a neural network equivalent to a **system of simultaneous equations**.

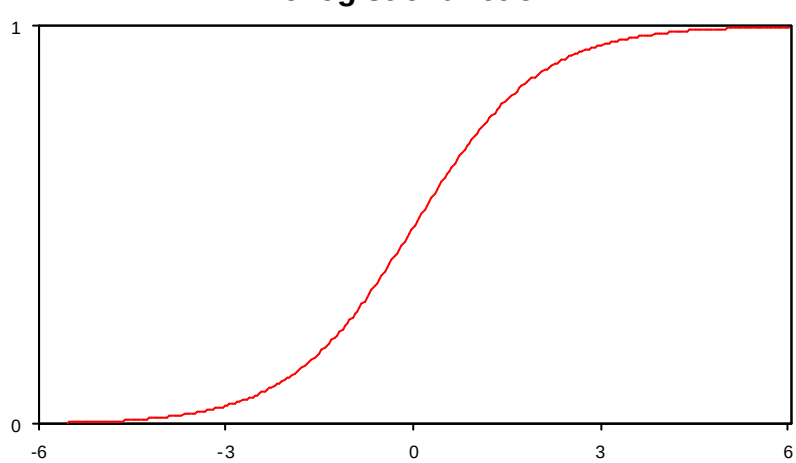
2.1 Nonlinear activation functions

All of the above examples assumed an identity activation function in the output neuron(s). To truly exploit the potential of neural networks, a nonlinear activation function must be used. Virtually all neural networks use nonlinear activation functions at some point within the network. This permits the network to reproduce nonlinear patterns in complex data sets. Ideally, the activation function should be continuous, differentiable and monotonic, as this will facilitate the optimization algorithm's task of finding the appropriate weights. The most frequently used activation function in the neural network community is the logistic cumulative distribution function:

$$f(x) = \frac{1}{1+e^{-x}} \quad (5)$$

The logistic function is bounded between 0 and 1, as illustrated in Figure 4. By using a bounded function, neural network researchers were attempting to reproduce the activation state of a real neuron. When the function is close to 1, this implies that the signals received by the neuron have led to a high level of activation. When the function is near 0, the neuron is barely responding to the impulse received.

Figure 4
The logistic function



If we are forecasting a variable that may take negative values, it is better to use the hyperbolic tangent as an activation function:

$$f(x) = \frac{(e^{x} - e^{-x})}{(e^{x} + e^{-x})} \tag{6}$$

The hyperbolic tangent function has the same profile as the logistic function, but is bounded between -1 and 1.

Returning to the simple feedforward network of Figure 2, a logistic activation function in the output neuron would lead to the following output for observation *t*:

$$Y_t = f(a_0 + a_1 X_{1t} + a_2 X_{2t}) = \frac{1}{1 + e^{-(a_0 + a_1 X_{1t} + a_2 X_{2t})}} \tag{7}$$

The resulting network is the same as a **binary logit probability model**. If the activation function were a normal cumulative distribution function, we would obtain a **binary probit model**. The use of other bounded functions would yield many other networks capable of dealing with nonlinear problems where the dependent variable is bounded.

When dealing with a dependent variable that is not bounded, we could choose an unbounded nonlinear activation function such as $f(x) = x^3$. However, neural network researchers have preferred to maintain bounded activation functions, and to allow for an unbounded dependent variable by adding *hidden layers* to the structure of the network.

2.2 Neural networks with hidden layers

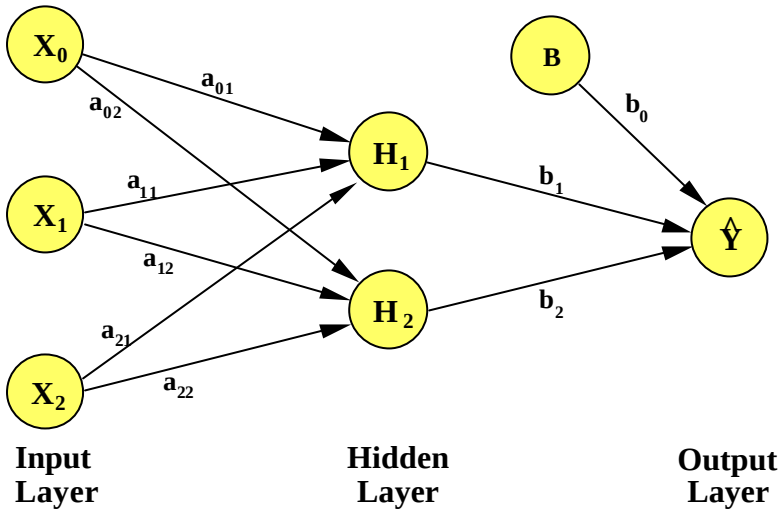
The networks described thus far had a very simple two-layer structure linking inputs to outputs. In real world applications, the network structure is generally more complex. Researchers almost always design a structure that includes one or more *hidden layers*, as in Figure 5. In this figure, a_{ij} 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.

Contrary to the input and output units, the hidden units do not represent any real concept. They have no interpretation or meaning. They are merely an intermediate result in the process of calculating the output value. Hence, they have no parallel in econometrics. Hidden units behave like output units, i.e. they compute the weighted sum of the input variables and then process the result using an activation function, almost always a logistic function. In the network illustrated in Figure 5, the result produced by the hidden units would be:

$$H_1 = f(a_{01} + a_{11} X_1 + a_{21} X_2) = \frac{1}{1 + e^{-(a_{01} + a_{11} X_1 + a_{21} X_2)}} \tag{8}$$

$$H_2 = f(a_{02} + a_{12} X_1 + a_{22} X_2) = \frac{1}{1 + e^{-(a_{02} + a_{12} X_1 + a_{22} X_2)}} \tag{9}$$

Figure 5
A feedforward neural network with one hidden layer



By placing the logistic activation function in the hidden units rather than in the output unit, the network is no longer limited to producing estimates of bounded variables. If the dependent variable is unbounded, the output unit will generally use an identity activation function, i.e. the output will be equal to the weighted sum of the hidden unit values, weighted by the b_j coefficients. This will yield a continuous, nonlinear, unbounded output as expressed in equation (10):

$$Y = b_0 + b_1H_1 + b_2H_2$$

$$Y = b_0 + \frac{b_1}{1+e^{-(a_{01}+a_{11}X_1+a_{21}X_2)}} + \frac{b_2}{1+e^{-(a_{02}+a_{12}X_1+a_{22}X_2)}} \qquad (10)$$

If the dependent variable is bounded, the output unit will generally use a logistic activation function, thus generating a bounded output, as in equation (11):

$$Y = f(b_0 + b_1H_1 + b_2H_2)$$

$$Y = \frac{1}{1+e^{-(b_0 + b_1H_1 + b_2H_2)}}$$

$$Y = \frac{1}{1+e^{-\left(b_0 + \frac{b_1}{1+e^{-(a_{01}+a_{11}X_1+a_{21}X_2)}} + \frac{b_2}{1+e^{-(a_{02}+a_{12}X_1+a_{22}X_2)}}\right)}} \qquad (11)$$

The network can therefore produce a bounded or unbounded output while maintaining its nonlinear characteristics[2].

The inclusion of hidden units in the network has another important virtue. Many authors have rigorously demonstrated that a three-layer neural network with a logistic activation function in the hidden units, such as equation (10), is a *universal approximator*[3]. That means that if a sufficient number of hidden units are included, the network can approximate almost any linear or nonlinear function to a desired level of precision. This suggests that neural networks could be used as a powerful tool to identify and reproduce complex nonlinear data generating processes in time-series data. Whether studying growth of real GDP, inflation, employment growth or exchange rates, the neural network should, in theory, be able to detect and duplicate any complex nonlinear pattern in the data. Furthermore, no *a priori* knowledge of the data generating process is necessary, as would be the case with standard nonlinear regression. It is sufficient to use a general functional form, such as equation (10), but with a greater number of hidden units[4].

There is no theoretical basis to determine the appropriate number of hidden units or layers in a network. Based on the universal approximator property described above, it seems logical to use a large number of hidden units. However, if too many hidden units are added, the network becomes prone to overfit the data. This implies that the network might achieve a superior forecasting accuracy over the estimation period, but will generate poor out-of-sample forecasts. In addition, the number of weights in the network increases rapidly as more hidden units are added, thus lengthening the time necessary to estimate the model.

In practice, the design of the network architecture is a tedious process of trial and error. Researchers will generally estimate a large number of different networks and select the one that leads to the smallest forecasting errors. Section 3 provides more details on this procedure and the error criteria used[5].

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[2] Another method to deal with an unbounded dependant variable is to rescale it so that all values lie between 0 and 1. This method is frequently used in the neural network literature.

[3] See, among others, Cybenko (1989), Funahashi (1989), Hornik, Stinchcombe and White (1989, 1990), Stinchcombe and White (1989) and White (1992).

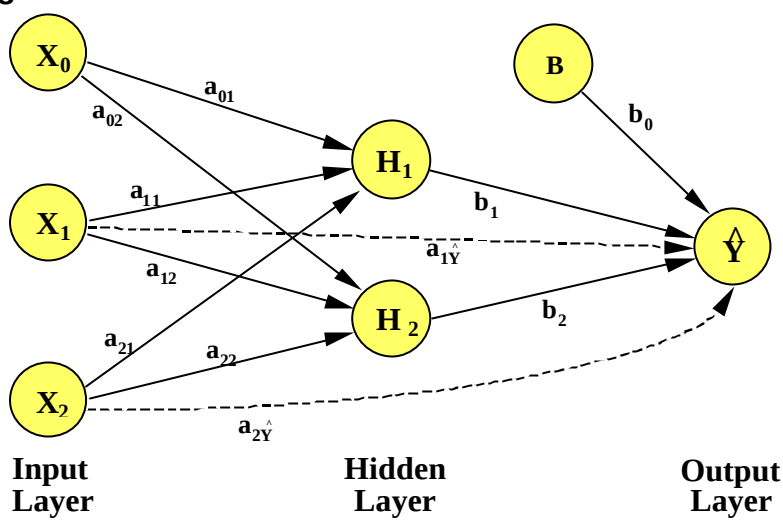
[4] Since a "generic" neural network is used to approximate an unknown functional form, we should acknowledge that our model is misspecified (Kuan and White, 1994). Hence, a researcher interested in performing hypothesis tests on the estimated weights would need to apply the theory of least squares for misspecified nonlinear regression models (White, 1981; 1992; Domowitz and White, 1982; Gallant and White, 1988).

[5] Some researchers, such as McMenamin (1997), have applied various information criteria to guide the choice of the architecture. However, results from Swanson and White (1995, 1997) and Sarle (1995) indicate that the use of information criteria does not always lead to the best architecture. In practice, trial and error remains the most reliable approach.

2.3 Augmented neural networks

Another model can be created if we add direct connections from the inputs to the output (Figure 6). In this structure, called an *augmented* neural network, the inputs are directly connected to the output by the weights a_{1Y} and a_{2Y}. It is not necessary that the bias term X_0 be connected to the output given that the output already has a bias term B.

Figure 6
An augmented feedforward neural network with one hidden layer



Assuming an identity activation function for the output neuron, the augmented neural network is very interesting because it encompasses the linear regression model. It is therefore the most frequently encountered architecture in the neural network literature on macroeconomic forecasting. Using equation (10), we can directly derive the output for the augmented network:

$$Y = b_0 + a_{1Y}X_1 + a_{2Y}X_2 + \frac{b_1}{1+e^{-(a_{01}+a_{11}X_1+a_{21}X_2)}} + \frac{b_2}{1+e^{-(a_{02}+a_{12}X_1+a_{22}X_2)}} \qquad (12)$$

The augmented network can therefore be viewed as a standard linear regression model augmented with nonlinear terms. If the dependent variable under examination does not exhibit any nonlinear traits, the coefficients b_1 and b_2 will be equal to zero, thus yielding a standard linear model.

2.4 More complex networks

The feedforward networks discussed thus far are among the simplest that exist in the neural network literature. In more complex networks, neurons in the same layer may be connected to each other and outputs may be connected to inputs or to hidden units, yielding a wide range of models characterized by simultaneity. Some advanced neural network techniques are related to more complex statistical methods such as kernel discriminant analysis, k-means cluster analysis or principal component analysis (Sarle,

1998). Some neural networks do not have any close parallel in statistics, such as Kohonen's self-organizing maps and reinforcement learning. These advanced methods exceed the scope of this paper and will not be addressed here. It is also uncertain whether these techniques could be useful for the type of forecasting performed in economics.

3. ESTIMATION OF NETWORK WEIGHTS

The network weights are estimated using a variety of iterative algorithms, the most popular being the backpropagation algorithm. Sarle (1994) argues that these algorithms are generally inefficient because they are very slow. Results can be obtained much faster by using a standard numerical optimization algorithm such as those used in nonlinear regression. Sarle (1994) concludes by stating: "Hence, for most practical data analysis applications, the usual neural network algorithms are not useful. You do not need to know anything about neural network training methods such as backpropagation to use neural networks." In accordance with this view, we will not expand further on neural network training algorithms[6].

Neural networkers usually divide their sample into two separate data sets. The *training set* is used by the algorithm to estimate the network weights, while the *test set* is used to evaluate the forecasting accuracy of the network. Since the test set is not used during the estimation of the network weights, the forecasts made from the test set amount to an *ex post* out-of-sample forecast. The neural networker aims at minimizing the forecasting error in the training set using a criterion such as the mean squared error (MSE).

3.1 Early stopping

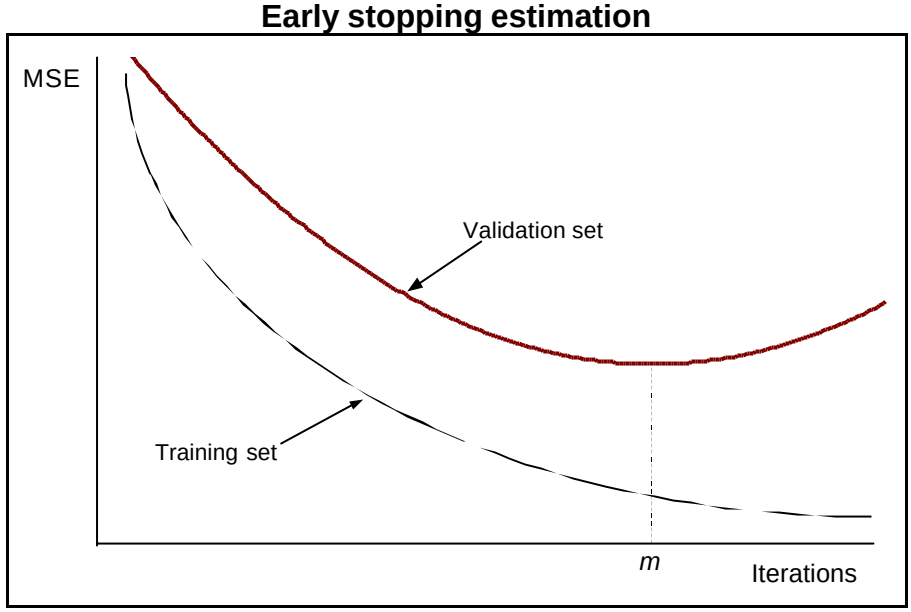
Experience has shown that neural networks are prone to overfit the data in the training set, thus yielding poor out-of-sample forecasts. To minimize this problem, several procedures have been developed. One of the most frequently used procedures is called *early stopping*[7], which involves the division of the data set into three parts: a training set, a test set and a validation set. As discussed above, the training set is used by the algorithm to estimate the network weights, while the test set is set aside for out-of-sample forecasting. The validation set is a portion of the data that is not used during the training (i.e. the algorithm never "sees" the validation set), but which serves as an indicator of the out-of-sample forecasting accuracy of the network. After each iteration in the estimation process, an out-of-sample forecast is generated using the observations in the validation set and the MSE is calculated. Figure 7 shows the typical evolution of the MSE in the training and validation sets throughout the estimation process. As the number of iterations increases, the MSE in both the training and validation sets will generally decline. Experience suggests that after a certain number of iterations, the MSE in the

[6] The interested reader is referred to Gibb (1996) for a discussion on training algorithms.

[7] Sarle (1998) discusses other commonly used methods to minimize the overfitting problem, such as "weight decay" and adding "noise" to the inputs.

validation set will start increasing because the network is "specializing" in the observations of the training set and is therefore losing its ability to generalize for other data. The estimation procedure stops when the forecasting error is minimized in the validation set rather than in the training set (after *m* iterations in Figure 7). This method ensures that the network is not specializing in the data of the training set, but that it is also able to generalize for out-of-sample data. This is a novel approach because econometricians do not use out-of-sample information to estimate the coefficients. Out-of-sample forecasts are typically dealt with in a separate stage, after the coefficients have been estimated. By focusing on the forecasting errors in the validation set, neural networkers are adopting a results-oriented approach to the estimation process, which is a major reason for the forecasting success of these models.

Figure 7
Early stopping estimation



Since the early stopping procedure leads the researcher to select the network with the lowest MSE in the validation set, the forecasting errors from the validation set will be optimistically biased, i.e. they cannot be considered as an unbiased estimate of the forecasting accuracy of the model in the entire population. To obtain an unbiased estimate of the generalization capacity of the network, out-of-sample forecasts must be performed using the *test set*. In particular, to compare the out-of-sample forecasting accuracy of a neural network with that of a linear regression model, the sample used for the comparison must not be part of the training or validation sets of the network.

Despite its appeal, the early stopping procedure is considered somewhat inefficient by statisticians because it does not use all the information contained in the sample to estimate the weights. Only the data from the training set have a direct bearing on the value of the weights. Moreover, when dealing with small samples, the decomposition of the sample into training, validation and test sets can leave too few observations in each set to obtain reliable results. Finally, the results of the estimation could be sensitive to the arbitrary choice of observations that will compose each set. In

spite of these shortcomings, the early stopping procedure is frequently used in the literature and has enabled researchers to develop accurate networks.

3.2 Designing the model

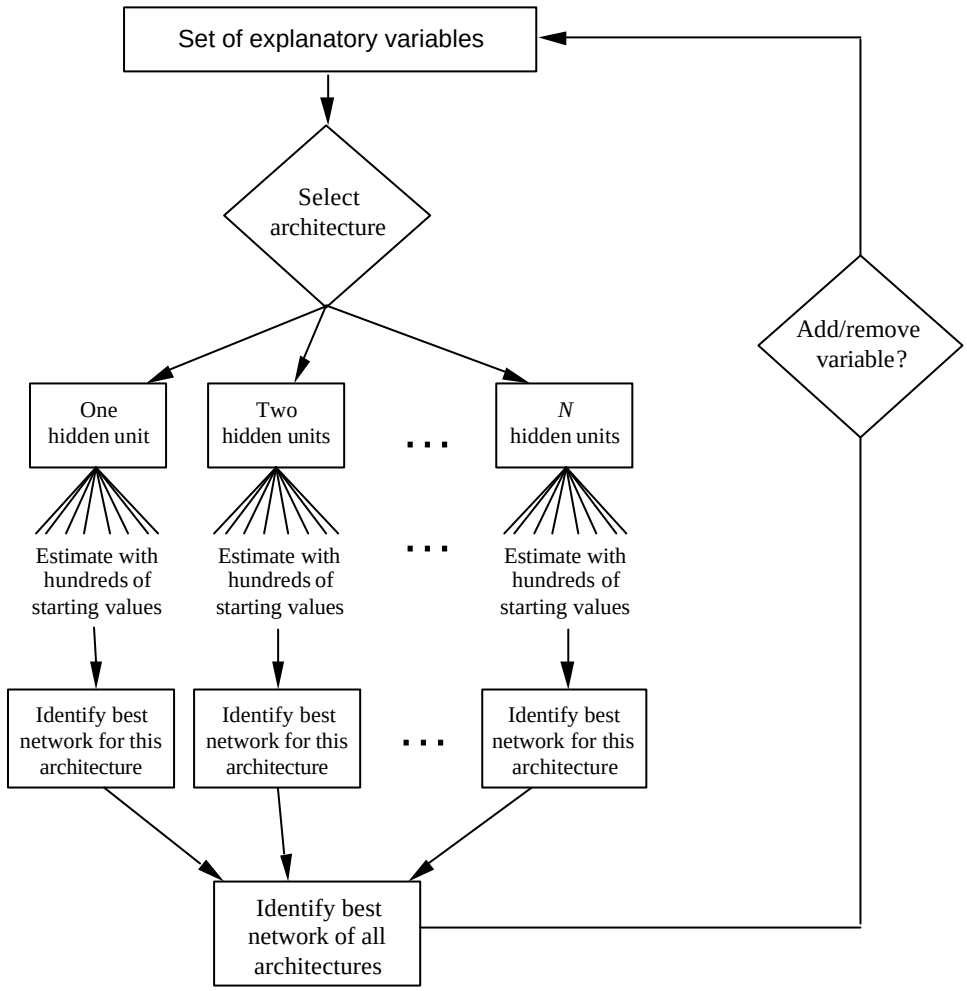
When an econometrician is building a linear regression model for forecasting purposes, a significant part of the work consists in identifying the explanatory variables and the number of lags that will allow the most accurate forecasts. This will generally require many hours of experimentation with alternative 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 8.

As with any nonlinear estimation technique, one can never be sure that the global minimum has been attained. In practice, this implies that the results of the estimation procedure are sensitive to the initial values of the weights. Thus, for a given set of inputs and a given network architecture, the early stopping procedure described above must be repeated hundreds or thousands of times using different starting values for the weights. The estimated weights that lead to the lowest MSE in the validation set will be considered as the best possible outcome for that specific network architecture and for the specific set of inputs that was used in the network.

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. The two architectures may then be evaluated by comparing the minimum of the MSE attained in each architecture.

Figure 8
Designing a neural network



After having evaluated many different architectures, the one that minimizes the MSE will be retained[8]. This will yield the neural network with the lowest forecasting errors for a given set of inputs. Each time the researcher wishes to experiment with a different set of inputs, by adding or removing a variable, the network must be re-estimated under several different architectures, each one requiring several hundreds or thousands of starting values. Hence, the researcher must perform three levels of minimization:

- For a given network architecture, find the starting values that minimize the MSE in the validation set;
- Find the architecture with the lowest minimum MSE;
- Find the set of inputs that lead to the most accurate network.

[8] Alternatively, the researcher could retain several networks and generate a forecast by averaging the forecasts of the various models.

When designing a linear regression model, only the last stage of minimization needs to be done, i.e. the selection of the most relevant set of explanatory variables. Thus, it is clear that the design of a neural network is much more time consuming than the design of a linear model. Fortunately, this process can be somewhat shortened with a little programming. As will be explained later, the use of a linear regression model to assist in the selection of the inputs can also greatly reduce the length of this process.

4. AN APPLICATION TO REAL GDP FORECASTING

An empirical example is perhaps the best way to illustrate the differences between a neural network and a linear regression model. A neural network has therefore been constructed to forecast quarterly growth of Canada's real GDP. This model is compared to a linear regression model developed in the Department of Finance by Lamy (1999). To facilitate the comparison, the neural network uses exactly the same explanatory variables and the same sample period as the linear regression model. Any differences in the results can therefore be attributed solely to the estimation procedure.

4.1 The linear regression model

Lamy (1999) has developed an accurate model for one-quarter ahead forecasts of quarterly growth of Canada's real GDP. The model has performed very well, both in-sample and out-of-sample. Over the period from 1978Q1 to 1998Q2, his model explains 82 per cent of the variance of real GDP growth. The estimated coefficients are also very stable when the model is estimated over different sample periods. In addition, the model is quite parsimonious, as it contains only the following six explanatory variables (with their abbreviation in parenthesis):

- The quarterly growth rate of Finance Canada's index of leading indicators of economic activity (one-quarter lag) (L_{t-1})
- Employment growth (contemporaneous) (E_t)
- Employment growth (one-quarter lag) (E_{t-1})
- The Conference Board's index of consumer confidence (contemporaneous) (C_t)
- The first difference of the real long term interest rate (nine-quarter lag) (R_{t-9})
- The first difference of the federal government budgetary balance as a share of GDP (three-quarter lag) (F_{t-3})

Four dummy variables were added to control for four quarters considered as outliers[9]. For the purposes of the present illustration and in order to leave some data for out-of-sample forecasts, the linear regression model was estimated using data from 1978Q1 to 1993Q2 (62 observations). The estimation results are given in equation (13):

$$GDP_t = -1.695 + 0.075 \cdot L_{t-1} + 0.304 \cdot E_t + 0.251 \cdot E_{t-1} + 0.019 \cdot C_t - 0.175 \cdot R_{t-9} - 0.320 \cdot F_{t-3} - 1.155 \cdot D1 + 1.168 \cdot D2 - 0.906 \cdot D3 - 0.843 \cdot D4 + e_t \qquad (13)$$

[9] The four quarters in question are 1980Q3, 1981Q1, 1986Q4 and 1991Q3.

where *D1*, *D2*, *D3* and *D4* are the dummy variables and e_t is the residual term. All coefficients are significantly different from zero at a confidence level of 95 per cent.

4.2 The neural network equivalent

Determining the number of inputs and outputs of the network is a straightforward process. The linear regression model above has six regressors and four dummy variables. Our neural network will therefore contain ten inputs. Since we have only one dependent variable, the network will have a single output. As explained in Section 2.2, the number of hidden units to include in the network is largely the result of trial and error. For the present illustration, an architecture with only two hidden units was selected. Although this architecture is probably too simplistic to capture the complexity of the problem at hand, its simplicity will facilitate the comprehension of the dynamics of the model. The purpose of this section is thus to present a concrete example of a network, not to develop a high-performance forecasting tool. Hence, the network presented here should not be considered as the best possible model that neural networks could offer.

Figure 9 illustrates the architecture of the network. This is a fully connected network, i.e. all inputs are connected to all hidden units. Bias terms have been included for both the hidden units ($Bias_H$) and the output unit ($Bias_O$). In addition, direct connections have been added between the inputs and outputs (dashed arrows), thus yielding an *augmented* neural network (cf. Figure 6). As explained above, the augmented neural network nests the linear regression model. The hidden units have a hyperbolic tangent activation function while the output unit has an identity activation function.

The early stopping procedure was used to estimate the 35 weights of the network[10]. In order to implement this procedure, the sample was divided into three separate parts: a training set (1978Q1 to 1993Q2), a validation set (1993Q3 to 1995Q4) and a test set (1996Q1 to 1998Q2). The training set, which correspond to the in-sample period of the linear regression model in equation (13), is the only portion of the data that the training algorithm used to estimate the network weights.

[10] The neural network literature suggests that rescaling the data is often beneficial to improve forecasting accuracy because the estimation algorithms tend to perform better when the input values are small and centred around zero. In the network presented here, only the Conference Board index of consumer confidence was modified by dividing all values by 100. Therefore, the base value of the index is 1 instead of 100.

Figure 9
An augmented neural network to forecast real GDP growth

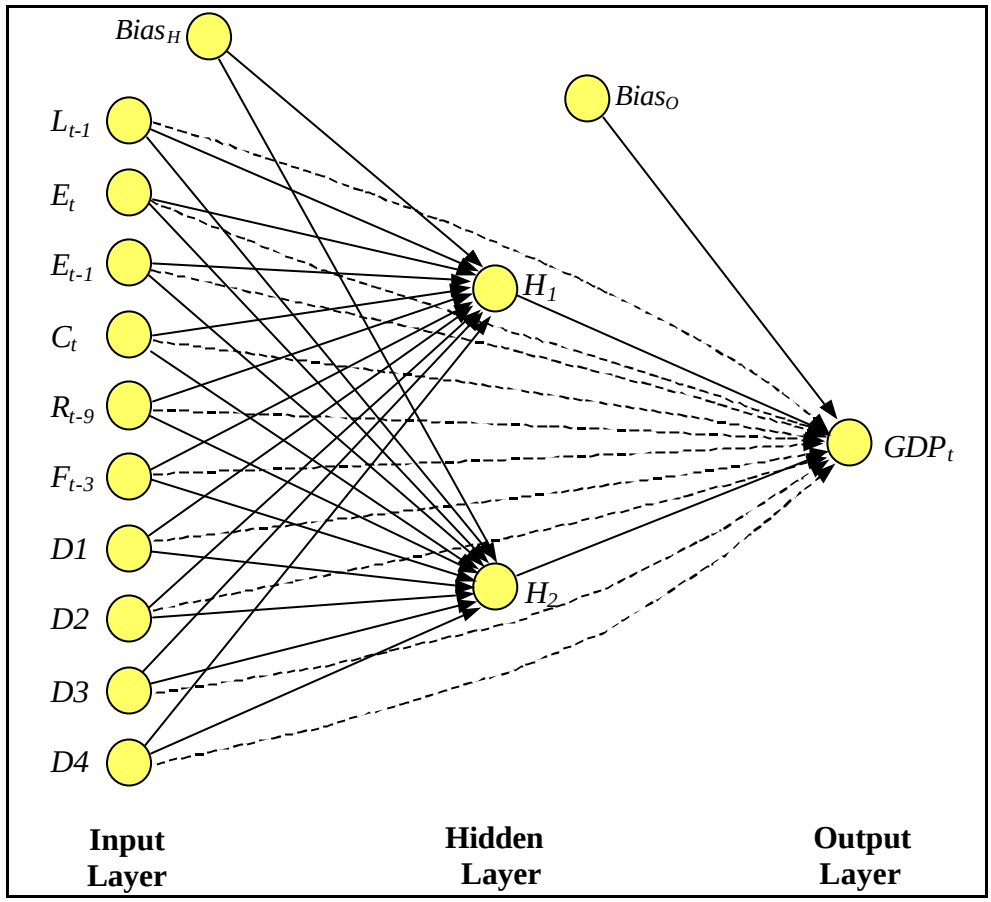
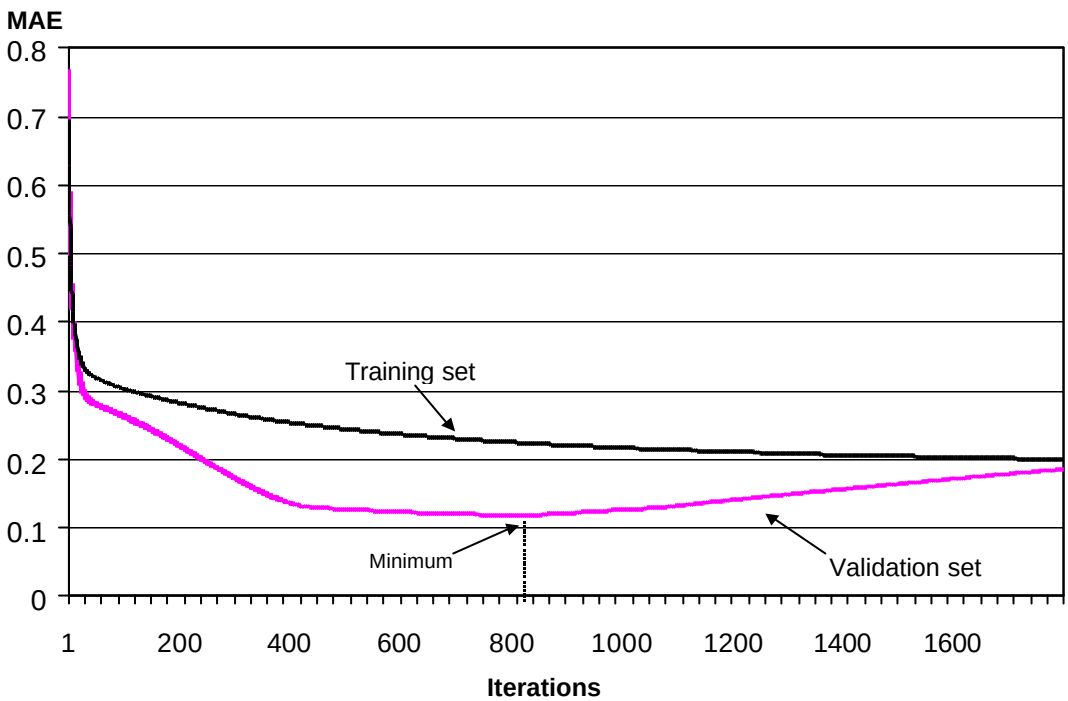


Figure 10 illustrates the evolution of the mean absolute error (MAE)[11] in the training and validation sets throughout the iteration process. The MAE in the validation set reaches a minimum after 819 iterations, while the MAE in the training set continues to decline continuously. To reduce the risk of overfitting the network, the procedure was therefore stopped after 819 iterations, with a MAE of 0.118 in the validation set.

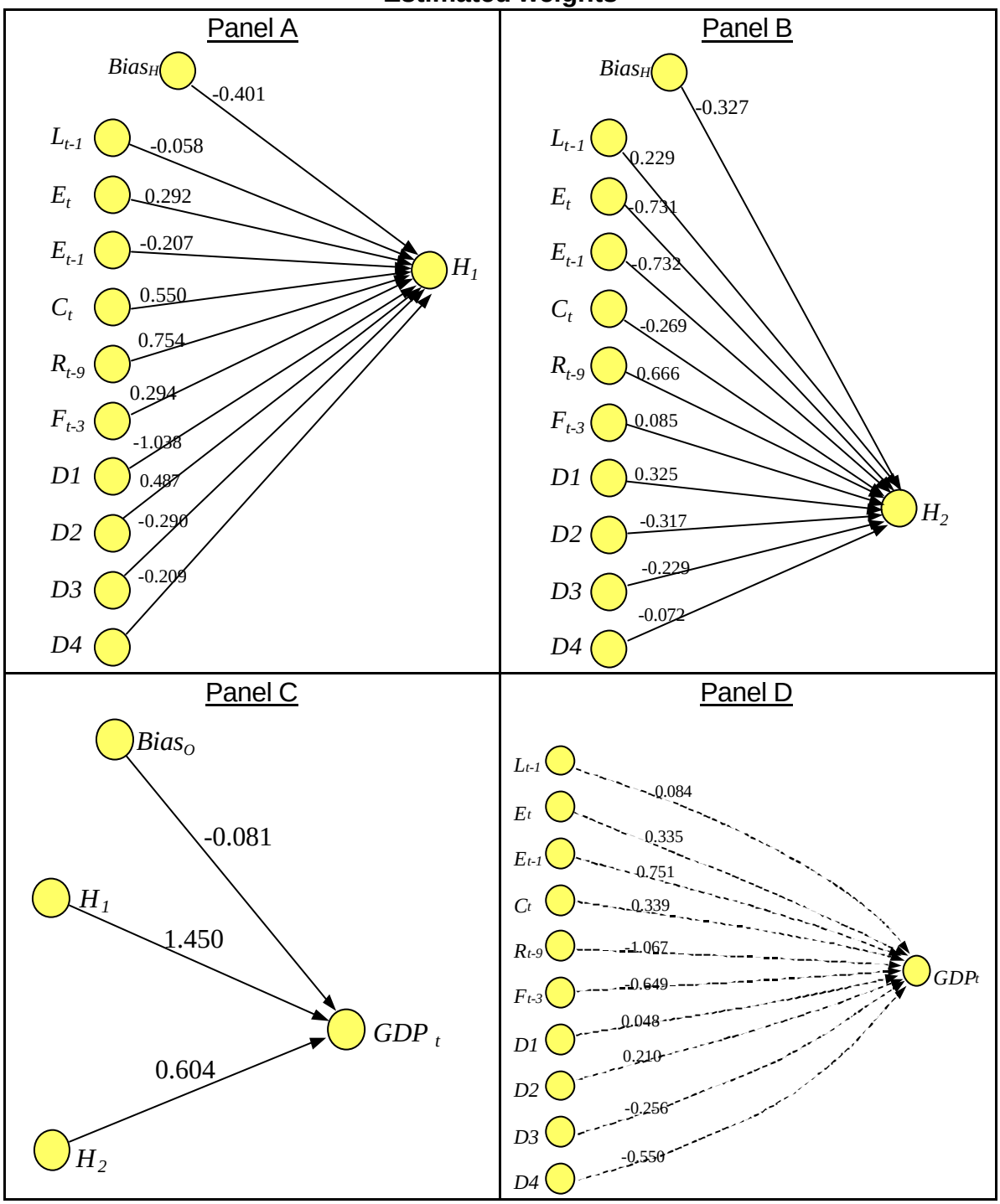
Figure 10
Results of the early stopping estimation procedure



[11] The software used to estimate the network weights (MATLAB with the Netlab toolbox) was programmed to provide the mean absolute forecasting error, rather than the mean squared error as discussed in Section 3. This does not have a significant effect on the results. The Netlab toolbox can be downloaded free of charge from http://www.ncrg.aston.ac.uk/netlab/index.html.

In Figure 11, the estimated weights are presented for various sections of the network. The connections from the inputs and $Bias_H$ to the hidden unit H_1 are presented in Panel A. Panel B presents a similar diagram for the connections between the inputs and H_2. Panel C displays the estimated weights between the hidden units and the output unit and Panel D illustrated the direct connections from the inputs to the output.

Figure 11
Estimated weights



4.3 Producing forecasts

Suppose we want to produce a forecast of real GDP growth for 1998Q2. The values of the regressors/inputs for 1998Q2 are given below:

L_{t-1} =	0.66	R_{t-9} =	1.13
E_t =	0.67	F_{t-3} =	0.84
E_{t-1} =	0.75	D1 = D2 = D3 = D4 = 0	
C_t =	1.1497		

In the case of the linear regression model, the forecast for 1998Q2 is straightforward:

$$\begin{aligned} GDP_t = & -1.695 + 0.075\cdot(0.66) + 0.304\cdot(0.67) + 0.251\cdot(0.75) + 1.9\cdot(1.1497) \\ & - 0.175\cdot(1.13) - 0.320\cdot(0.84) - 1.155\cdot(0) + 1.168\cdot(0) - 0.906\cdot(0) \\ & - 0.843\cdot(0) \end{aligned} \quad (14)$$

$$= \mathbf{0.46}$$

The linear regression model forecasts real GDP growth of 0.46 per cent in 1998Q2. Actual real GDP growth in 1998Q2 was 0.44 per cent.

In the neural network, the first step consists in calculating the value of the hidden units. To obtain a value for H_1, the network must first multiply the value of each input by the corresponding weight, as depicted in Panel A of Figure 11. This value is denoted Z_1.

$$\begin{aligned} Z_1 = & -0.401 - 0.058\cdot(0.66) + 0.292\cdot(0.67) - 0.207\cdot(0.75) + 0.550\cdot(1.1497) \\ & + 0.754\cdot(1.13) + 0.294\cdot(0.84) - 1.038\cdot(0) + 0.487\cdot(0) - 0.29\cdot(0) - 0.209\cdot(0) \end{aligned} \quad (15)$$

$$= 1.332$$

The value of H_1 is obtained by inserting Z_1 into the hyperbolic tangent activation function:

$$H_1 = TANH(1.332) = \frac{(e^{z_1} - e^{-z_1})}{(e^{z_1} + e^{-z_1})} = \frac{(e^{1.332} - e^{-1.332})}{(e^{1.332} + e^{-1.332})} = 0.8697 \quad (16)$$

In a similar fashion, using the weights in Panel B of Figure 11, H_2 can be shown to equal:

$$H_2 = TANH(-0.6999) = \frac{(e^{-0.6999} - e^{-(-0.6999)})}{(e^{-0.6999} + e^{-(-0.6999)})} = -0.6043 \quad (17)$$

Using the analogy of the human brain and remembering that the values produced by the hyperbolic tangent function are bounded between –1 and 1, it could be said that the

neuron H_1 is being strongly stimulated by the specific stimuli provided by the input values, while H_2 is moderately stimulated.

The output unit GDP_t has an identity activation function, meaning that the hyperbolic tangent function will not be used to process the linear combination of the "stimuli" reaching the output unit. The network's forecast will simply be equal to the linear combination of the hidden units (panel C of Figure 11) and the inputs (panel D):

$$\begin{aligned} GDP_t = & -0.081 + 1.45 \cdot H_1 + 0.604 \cdot H_2 + 0.084 \cdot L_{t-1} + 0.335 \cdot E_t \\ & + 0.751 \cdot E_{t-1} + 0.339 \cdot C_t - 1.067 \cdot R_{t-9} - 0.649 \cdot F_{t-3} + 0.048 \cdot D1 \\ & + 0.21 \cdot D2 - 0.256 \cdot D3 - 0.55 \cdot D4 \end{aligned} \quad (18)$$

Evaluating this equation with the values for 1998Q2 yields:

$$\begin{aligned} GDP_t = & -0.081 + 1.45 \cdot (0.8697) + 0.604 \cdot (-0.6043) + 0.084 \cdot (0.66) + 0.335 \cdot (0.67) \\ & + 0.751 \cdot (0.75) + 0.339 \cdot (1.1497) - 1.067 \cdot (1.13) - 0.649 \cdot (0.84) \\ & + 0.048 \cdot (0) + 0.21 \cdot (0) - 0.256 \cdot (0) - 0.55 \cdot (0) \end{aligned} \quad (19)$$

$$= \mathbf{0.30}$$

The network therefore forecasts real GDP growth of 0.30 per cent for 1998Q2, which is considerably less accurate than the linear model's forecast. Obviously, the calculations required to make a forecast using a neural network are significantly more complex than in the case of a linear regression model. Fortunately, these calculations can be executed instantaneously by the same software that estimated the network weights.

Equation (18) clearly illustrates how the *augmented* neural network encompasses the linear regression model. If the second and third terms of the right-hand side of this equation are removed, equation (18) becomes a simple linear combination of the inputs. These two terms, which are nonlinear transformations of the inputs, help the network to capture nonlinear relationships among the variables. If the network had not detected any nonlinearities in the data generating process, the estimated weights for H_1 and H_2 would have been zero and the network would have become a standard linear regression model. In the current example, the non-zero values of the weights for H_1 and H_2 suggest the presence of some nonlinearities.

4.4 Relative forecasting performance

Is all this computational effort worthwhile? A comparison of the forecasting accuracy of both methods provides some insight into this question. Table 1 compares the forecasting performance of this neural network and the linear regression model for one-quarter ahead forecasts. Three common criteria were used to compare the two models: the mean absolute error, the mean squared error and the Theil inequality coefficient. The table suggests that the network was more accurate than the linear regression model, both in-sample and out-of-sample. The network reduced the forecasting errors by between

13 and 25 per cent for the in-sample period and by 20 to 40 per cent for out-of-sample forecasts.

Table 1: Comparative forecasting accuracy of both models

	In-sample 1978Q1 to 1993Q2			Out-of-sample 1996Q1 to 1998Q2		
	Linear regression model	Neural network	Difference (in %)	Linear regression model	Neural network	Difference (in %)
Mean absolute error	0.2604	0.2241	-14.0	0.2914	0.2240	-23.1
Mean squared error	0.1092	0.0823	-24.6	0.1295	0.0774	-40.2
Theil inequality coefficient[1]	0.1553	0.1348	-13.2	0.2161	0.1721	-20.4

1. The Theil inequality coefficient is bounded between 0 and 1. The value of the coefficient approaches zero as forecasting accuracy increases.

From a theoretical point of view, this result is not too surprising. Given that an augmented neural network encompasses the linear regression model, the network should not, in theory, perform worse than a linear model. Two factors could nonetheless have led the network to perform worse than the linear model. First, the optimizing algorithm could have remained trapped in a local minimum that was far from the global minimum. To avoid this problem, the network weights were re-estimated using 800 sets of random starting values. The network with the greatest accuracy in the validation set was retained. Second, the network could have overfit the data despite the use of the early stopping procedure. When the number of observations in the training and validation sets is small, overfitting might still occur when using the early stopping procedure. This does not seem to have occurred in the current example, given the relatively good out-of-sample forecasting performance of the network.

Four statistical tests were used to assess whether the improvement in forecasting accuracy was statistically significant: Wilcoxon's signed-rank test, a non-parametric sign test, the Diebold and Mariano (1995) test and the Ashley, Granger and Schmalensee (1980) test. In each of these tests, the null hypothesis postulates that the forecasting accuracy of both models is the same. All tests were two-tailed and were applied to the mean squared error and the mean absolute error. The results, which are summarized in Table 2, suggest that there is only limited evidence that the improvement in forecasting accuracy was statistically significant. At a 90-per-cent level of confidence, the null hypothesis could only be rejected in four or five of the fourteen possibilities presented in the table. Although the point estimates in Table 1 suggest that the neural network outperformed the linear model, the standard deviations of the test statistics were too large to conclude that the improvement was statistically significant.

Table 2: Significance levels[1] for four tests assessing the statistical significance of the improvement in forecasting accuracy

	Mean squared error		Mean absolute error	
	In-sample	**Out-of-sample**	**In-sample**	**Out-of-sample**
Wilcoxon's signed-rank test	0.065	0.203	0.060	0.333
Non-parametric sign test	0.374	0.754	0.374	0.754
Diebold and Mariano (1995) test	0.095[2]	0.244	0.072	0.277
Ashley, Granger and Schmalensee (1980) test	0.038	0.250	NA[3]	NA[3]

1. The significance level (p-value) provides the probability of observing a given difference in forecasting accuracy between the two models, if the null hypothesis is true (i.e. both models have the same accuracy).
2. The Diebold and Mariano test might not be accurate for the in-sample mean squared error because this test requires that the difference in the MSE between both models have a normal distribution. A Jarque-Bera test on the in-sample MSE differential led us to strongly reject a normal distribution.
3. The Ashley, Granger and Schmalensee test only applies to the mean squared error.

Additionally, forecast encompassing tests (cf. Chong and Hendry, 1986) were conducted for both the in-sample and out-of-sample periods. The results did not allow us to reject the null that neither model encompassed the other. Hence, based on all our tests, we cannot conclude that the improvement in forecasting accuracy is statistically significant.

The neural network developed in this section should be viewed as a **complement** to the linear regression model, rather than a substitute, because it used the explanatory variables of the linear model as a starting point. Although this may seem like a trivial point, it is in fact very important. The computational effort required to design a neural network makes it virtually impossible to build the model from scratch, without the help of a linear regression model. As explained in Section 3.2 (cf. Figure 8), the design of a neural network is a lengthy process of trial and error. For a given set of explanatory variables and a given network architecture, a neural network must be re-estimated hundreds or thousands of times with different sets of starting values in order to avoid a local minimum[12]. This entire process of re-estimation must be repeated for each different network architecture under consideration before a conclusion can be made as to the out-of-sample forecasting accuracy associated with a *given set of explanatory variables*. Thus, each time a change is made to the set of explanatory variables, the network must be re-estimated under several different architectures, each one requiring several hundreds or thousands of starting values. This process would be much too long if it were followed to the letter.

[12] In the current example, a Pentium 350 MHz took about 25 hours to re-estimate the network with 800 sets of starting values.

It is far more efficient to start by using a linear regression model to experiment with different sets of explanatory variables. Once a satisfactory set of variables has been identified, the researcher can proceed to evaluate different architectures. Thus, one of the three levels of minimization identified in Section 3.2 can be greatly shortened using a linear regression model. The linear model is thus an essential tool to facilitate the implementation of a neural network.

5. OTHER EXAMPLES OF NEURAL NETWORK APPLICATIONS

Obviously, one empirical example cannot serve as a basis to assess the effectiveness of neural networks. The empirical literature on the subject provides additional information in this respect. This section presents only a sample of the work that has been done. Much of the research performed in the fields of economics and finance has focused on forecasting the behaviour of various financial instruments, such as exchange rates or the prices of stocks, options and commodities. In this section, we will emphasize studies that forecast macroeconomic variables of interest to economists.

5.1 Encouraging results

The literature on neural networks contains numerous articles that proclaim the usefulness of these models for various forecasting exercices. However, as stressed by Chatfield (1993), many of these papers are unreliable because they lack methodological rigour. One frequently encountered deficiency occurs when researchers use the observations of their test set to guide the training process. Tal and Nazareth (1995) and Andersson and Falksund (1994) seem to have fallen into this trap. As explained in Section 3.2, the resulting forecasting errors are biased in favour of the neural network. Other authors provide their neural network with many more explanatory variables than the competing models (e.g. Bramson and Hoptroff, 1990), thus making the comparison somewhat unfair. Some authors do not even attempt to compare the accuracy of their networks with that of competing models. The authors simply calculate the average forecasting errors of their networks and conclude that the errors are “small” (e.g. Aiken, 1999 and Aiken and Bsat, 1999).

This kind of result cannot be used to judge the relative merits of neural networks. Thus, in the following discussion, we will only mention the articles that seem to have applied a more rigorous methodology. As will be shown, the literature suggests that neural networks perform well for forecasting economic output and various financial variables.

Hill et al. (1994) surveyed the literature comparing the forecasting performance of neural networks and statistical models. In the studies surveyed, neural networks performed as well as or better than standard statistical techniques for the forecasting of macroeconomic variables, measured in terms of the mean absolute percentage error. In time-series applications, results from some papers suggested that neural networks were more accurate in the later periods of the forecast horizon. They also seemed to perform

better for higher frequency data (i.e. with monthly and quarterly data), leading the authors to speculate that higher frequency data contained more nonlinearities. However, the authors concluded that the literature on the subject was still inconclusive.

This relatively positive outlook for neural networks is confirmed by three studies attempting to forecast economic output. Tkacz (1999) compared the accuracy of linear models and neural networks in forecasting Canada's real GDP growth using a series of financial indicators. At the 1-quarter and 4-quarter horizons, neural networks produced more accurate out-of-sample forecasts than the linear models. Using various tests, the improvement in forecasting accuracy obtained by the networks was generally found to be statistically significant. The author concluded that the networks may have been capturing some nonlinearities in the relationship between real GDP growth and financial indicators. Similarly, Fu (1998) found that neural networks outperformed linear regression models for out-of-sample forecasts of US real GDP growth. The neural networks were able to reduce the out-of-sample sum of squared residuals by between 10 and 20 per cent. Moody, Levin and Rehfuss (1993) obtained analogous results when forecasting the growth rate of the U.S. Index of Industrial Production. For all forecast horizons considered (which ranged from 1 to 12 months ahead), their two neural networks were found to be more accurate than a univariate autoregressive model and a multivariate linear regression model.

In the field of financial markets, several studies have reported favourable results regarding neural networks. We will only discuss two studies that focus on variables of interest to macroeconomists. Verkooijen (1996) compared the accuracy of various models in forecasting the monthly US dollar–Deutsche Mark exchange rate at horizons varying between 1 and 36 months ahead. For out-of-sample forecasts, the neural network models were found to be slightly more accurate than linear regression models and random walk forecasts, particularly at longer forecast horizons. The relative performance of the networks was even better when forecasting the direction of change of the exchange rate. In another study, Refenes, Zapranis and Francis (1994) compared the accuracy of a feedforward neural network and a multivariate linear regression model in forecasting stock performance within the framework of the arbitrage pricing theory. Their results showed that the neural network was more precise for both in-sample and out-of-sample forecasting.

Donaldson and Kamstra (1996) produced perhaps the only study examining the advantages of using neural networks to combine the forecasts of various models. The individual forecasts in their combining exercise were forecasts of the volatility of daily returns of four major stock market indices, as produced by a moving-average variance model (MAV) and a GARCH(1,1) model. When these individual forecasts were combined with neural networks, the resulting forecast generally had a lower out-of-sample mean squared error than when they were combined with linear techniques, such as the simple average of individual forecasts or a weighted sum of individual forecasts. Furthermore, encompassing tests revealed that the neural network pooled forecast encompassed several of the other pooled forecasts, but it was the only model that was

never encompassed by any other. Thus, they concluded that neural network combining produced better forecasts than the more traditional combining methods.

5.2 Less promising results

Church and Curram (1996) seems to be the only reliable study that has not found neural networks to be more accurate than linear models for macroeconomic forecasting. These authors compared the accuracy of neural networks with some linear models in forecasting aggregate consumption in the U.K. in the late 1980s. The linear models were taken from the literature that has sought to explain the significant decline in the growth rate of consumer spending in the late 1980s. Using the same explanatory variables as in the linear models, the networks produced forecasts that were equivalent to but no better than the linear forecasts. They conclude that, regardless of which type of model is estimated, the choice of explanatory variables is the main determinant of forecasting accuracy.

Although three other studies have concluded that neural networks are no better than linear models, these papers contain methodological deficiencies that make their results less reliable. These three studies will be discussed below, since they have received some attention in the economic literature on neural networks.

To our knowledge, Stock and Watson (1998) is the largest forecasting competition for macroeconomic time series that includes neural networks. A total of 49 univariate forecasting methods – including 15 feedforward neural networks – and various forecast pooling procedures were used to forecast 215 U.S. monthly macroeconomic time series at three forecasting horizons. The various pooling procedures provided the most accurate out-of-sample forecasts, suggesting that neural networks may help improve forecasting accuracy when combined with other forecasts[13]. However, when comparing the out-of-sample forecasting accuracy of individual models, the neural networks performed poorly relative to a "naïve" AR(4) forecast and relative to most other methods in the competition. The networks were also worse than the only other nonlinear method included in the competition, the logistic smooth transition autoregression model. Unfortunately, it does not appear that the authors applied the early stopping procedure or any other method to minimize the overfitting problem. This would explain the poor out-of-sample forecasting performance of their networks. In addition, it seems that a relatively small number of parameter vectors were used as initial values for the Gauss-Newton minimizing algorithm, thus reducing the likelihood of finding a solution close to the global minimum. These two factors, combined with the fact that the paper only examined univariate models, limit the scope of their results.

In another forecasting competition, Swanson and White (1997) compared various methodologies for forecasting nine U.S. macroeconomic variables. The methods studied included autoregressive models, vector autoregressive systems, feedforward neural

[13] The literature contains very little research on the merits of combining neural network forecasts with those of other models. Further research in this area would be very useful.

networks, professional "consensus" forecasts and a "no change" rule. A similar methodology was used in Swanson and White (1995) to compare various models for out-of-sample forecasting of spot interest rates. In both papers, the neural networks posted a rather ordinary performance. However, two factors tend to reduce the scope of these results. First, as in the case of Stock and Watson (1998), it seems that the authors did not apply any procedure to minimize the overfitting problem. Furthermore, the architectures for all the networks in Swanson and White (1995 and 1997) were selected using the Schwarz Information Criterion (SIC). After discussing the results in their 1997 paper, the authors acknowledged that this criterion "*cannot reliably be used as a shortcut to identifying models that will perform optimally out of sample.*" A little further, they concluded that "*in-sample SIC does not appear to offer a convenient shortcut to true out-of-sample performance measures for selecting models, or for configuring ANN* [Artificial Neural Network] *models when forecasting macroeconomic variables.*" The wording of the conclusion in the 1995 paper is almost identical to the above quotes. Hence, their conclusions suggest that the framework of their papers and the use of the SIC did not do justice to the true potential of the neural network methodology.

As it can be seen from the above discussion, the empirical literature on neural networks does not offer a unanimous verdict, as empirical evidence on macroeconomic forecasting remains sparse. This problem is compounded by the fact that many studies seem to have methodological deficiencies. As suggested by Chatfield (1993), a greater effort must be made to establish fair comparisons between both approaches before any firm conclusions can be reached.

Overall, there seem to be more studies that conclude in favour of neural networks than against them. However, since the literature is not entirely conclusive, it may be preferable to examine the relative advantages and disadvantages of neural networks from a more theoretical point of view. This may help us isolate the areas where their application may be potentially fruitful.

6. RELATIVE STRENGTHS AND WEAKNESSES OF NEURAL NETWORKS VERSUS OTHER STATISTICAL TECHNIQUES

Despite progress made in nonlinear regression theory, the vast majority of applications in econometrics continue to assume a linear relationship between the dependent variable and the regressors. The simplicity of the linear model and the possibility of linearizing certain nonlinear relationships make the linear regression model a very attractive and powerful tool. The largest part of our discussion will therefore focus on comparing neural networks to linear regression models. Table 3 summarizes the relative strengths and weaknesses of neural networks that will be discussed in the following sections.

Table 3: Relative strengths and weaknesses of neural networks

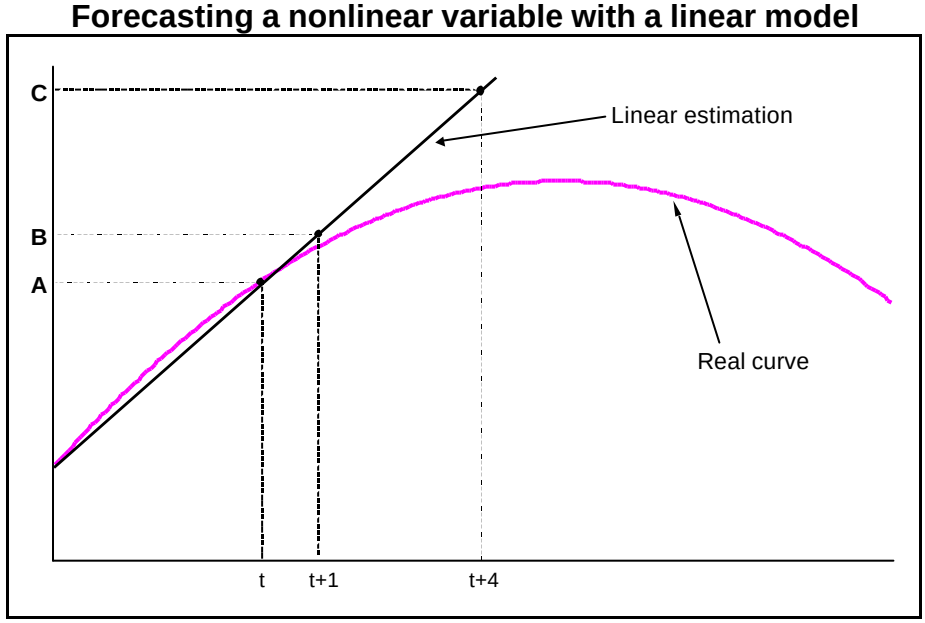
Strengths
Can successfully model nonlinear relationships
Do not require *a priori* information on the functional form of a relationship
The same architecture is very flexible
Weaknesses
It is difficult to interpret the estimated network weights ("black box" problem)
Unlikely to find the global minimum
Usually require large samples
The construction of the network architecture can be time consuming.

6.1 Relative strengths of neural networks

Can successfully model nonlinear relationships

First, neural networks with nonlinear activation functions should be more effective than linear regression models in dealing with nonlinear relationships. Figure 12 illustrates the classic problem that arises when estimating a nonlinear relationship with a linear model. If data from 0 to *t* are used to estimate a linear model, the one-period-ahead forecast (B) will be quite close to the actual value of the variable studied, since a linear function can give a reasonable approximation of the local behaviour of a nonlinear function. However, if one attempts to make forecasts several periods into the future, the estimated value of the linear model (C) can potentially get further and further from the true value of the variable. This might explain why some studies surveyed by Hill et al. (1994) and the results from Tkacz (1999) suggest that neural networks are more precise than other models in the later periods of the forecast horizon.

Figure 12
Forecasting a nonlinear variable with a linear model



Do not require *a priori* information on the functional form of a relationship

Although many nonlinear functions can be linearized using relatively simple mathematical transformations, this supposes that the researcher has some *a priori* knowledge of the nature of the nonlinearity that enables him to identify the appropriate transformation to apply to the data. Needless to say, such information is rarely available in the field of macroeconomic forecasting.

One could argue that nonlinear regression techniques would perform as well as neural networks when dealing with a nonlinear phenomenon. In theory, this is absolutely true. However, in practice, the estimation of a nonlinear regression model requires the econometrician to assume an *a priori* functional form for the relationship studied. Selecting the wrong functional form will lead to imprecise coefficient estimates and bad forecasts. On the other hand, when estimating a neural network, the researcher does not really need to worry about the functional form of the phenomenon studied because the "universal approximator" property of networks will allow it to mimic almost any functional form. No *a priori* knowledge is necessary to obtain precise forecasts.

The same architecture is very flexible

A third advantage of neural networks stems from the relative flexibility of network architectures. As illustrated at the beginning of this paper, a wide spectrum of statistical techniques (e.g. linear regression, a binary probit model, autoregressive models, etc.) can be specified by simply making minor modifications to the activation functions and the network structure (such as changing the number of units in each layer). The same basic architecture is therefore very flexible and can accommodate both discrete and continuous dependent variables.

6.2 Weaknesses and limitations of neural networks

It is difficult to interpret the estimated network weights ("black box" problem)

The complex nonlinear functional form of the network makes it very difficult to interpret the estimated network weights. In linear regression models, the values of the estimated coefficients provide a direct measure of the contribution of each variable to the model's output. In the case of neural networks, it is very complicated to analytically identify the impact of an input on the estimated output value. Even in the simplest of networks, such as in Figure 5, each input is fed through a nonlinear activation function and is also affected by two different weights (a_{ij} and b_j). Looking at equation (10), it is very difficult to trace the impact of either X_1 or X_2 on Y. Because of these difficulties, neural networks are sometimes called "a black box": the network uses the inputs to calculate the output, but the researcher does not clearly understand why a given value is forecasted. It must be noted that this problem can be greatly alleviated by applying the sensitivity analysis proposed by Refenes, Zapranis and Francis (1994). This procedure will be discussed in Section 6.3.

Unlikely to find the global minimum

As with all nonlinear estimation methods, it is difficult to find the global minimum of the error function. According to Goffe, Ferrier and Rogers (1994), an estimation problem with 35 weights (such as the network developed in Section 4) could yield several quintillion local minima. Nonetheless, some local minima could produce very accurate forecasts if they are reasonably close to the global minimum.

Usually require large samples

A relatively simple neural network can contain a large number of weights. In small samples, this leaves a limited number of degrees of freedom, which will often lead to an overfitting of the training set, even when the early stopping procedure is used. In fact, the early stopping procedure can exacerbate this problem because it requires that the sample be split into three data sets, thus limiting the number of observations available for estimation and out-of-sample forecasting. For researchers interested in forecasting the daily price of gold, data availability is not a problem because of the high frequency nature of the data. However, as shown in Section 4, an economist might encounter data constraints when attempting to forecast quarterly macroeconomic variables. Some of the studies mentioned earlier were nonetheless able to successfully forecast macroeconomic variables using relatively small samples. Our example from Section 4 also achieved a certain degree of success despite a modest sample size. Hence, the large-sample requirement of neural networks does not seem to constitute an insurmountable problem.

The construction of the network architecture can be time consuming

As explained above, the network architecture must be designed by trial and error. Even though this process can be greatly shortened by programming the software package to evaluate several architectures and by using a linear regression model to accelerate the choice of network inputs (cf. Section 4.4), the designing and estimation of a network is still considerably longer than in the case of a linear model.

6.3 A possible cure for the black box problem

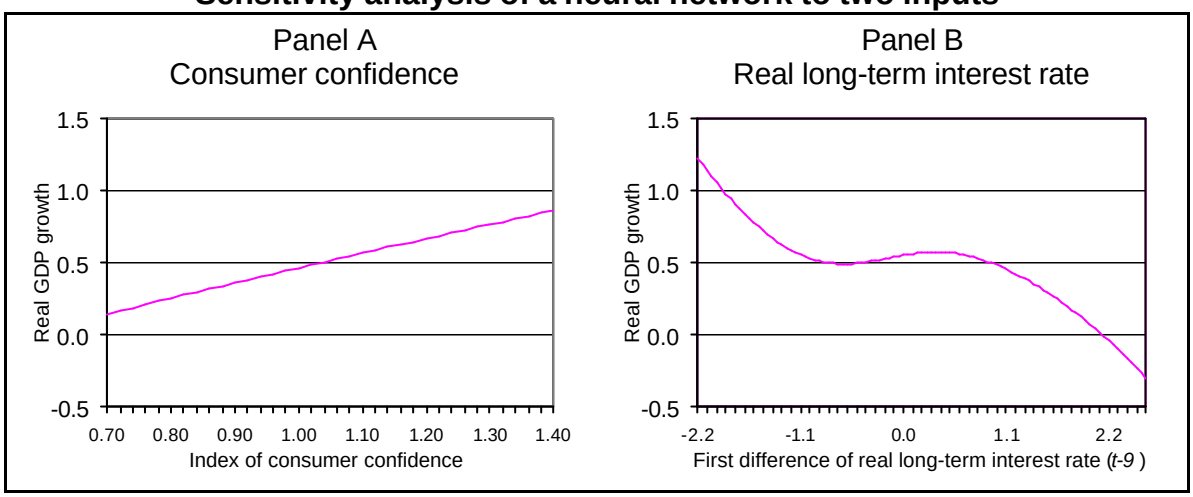
As mentioned previously, neural networks are often called a "black box" because of the difficulty in establishing the direct relationship between a given input and the output. To address this issue, Refenes, Zapranis and Francis (1994) designed a simple but effective way of assessing the sensitivity of the output to each input. Their method consists in charting the value of the output for a range of values of a given input[14], while all other inputs are fixed at their sample mean. If the value of the output remains relatively stable for different values of the input in question (within a reasonable range), we can assume that this input does not contribute significantly to the predictive power of the network. By applying this process to all inputs, the researcher can better understand the dynamics within the network and evaluate the contribution of each input to the

[14] This procedure requires that each input be roughly bounded within a certain range. This is the case for virtually all macroeconomic variables that are expressed as a growth rate.

estimated output value. The network can then be "pruned" through the elimination of irrelevant inputs.

This procedure can be illustrated using the network estimated in Section 4. Figure 13 shows the sensitivity analysis of two of the inputs: the Conference Board's index of consumer confidence (C_t) and the first difference of the real long-term interest rate lagged by nine quarters (R_{t-9}). Each chart shows the network's forecast of real GDP growth for various values of the specified input, with all other inputs fixed at their sample mean. In these charts, the selected range for each input corresponds to the approximate range observed with the training set (1978Q1 to 1993Q2).

Figure 13
Sensitivity analysis of a neural network to two inputs



Panel A shows that the contribution of the index of consumer confidence is almost linear, with a 0.1-percentage-point increase in the index leading to about a 0.1-percentage-point rise in the network's forecast of real GDP growth.

Panel B suggests an interesting nonlinear relationship between the first difference of the real long-term interest rate and the network's forecast of economic growth. As expected, the relationship is generally negative. However, the flat portion of the curve – corresponding roughly to an increase or decrease in the real long-term interest rate of less than one percentage point – indicates that small variations in the interest rate have virtually no impact on the network's forecast of GDP growth. This is consistent with some economic theories that suggest that interest rates must move by a significant amount before consumers and businesses decide to modify their behaviour in a notable way.

The vertical amplitude of both curves in Figure 13 also shows that when each input fluctuates within a reasonable range, the variations in the value of the index of consumer confidence have less of an impact on the network's forecast of real GDP growth. Thus, the network's forecast seems more sensitive to the real long-term interest rate than to the index of consumer confidence.

Given the nonlinear nature of the network forecasts, the sensitivity of the output to each input will change when the values of the other inputs are modified. Fixing the other inputs at their sample mean is somewhat arbitrary. The researcher can therefore experiment by fixing the other inputs at different values. In particular, the researcher can fix all other inputs at their current value (i.e. their value at the end of the sample) in order to evaluate the imminent impact of a given scenario (e.g. if interest rates were to increase in the upcoming quarter).

In addition to this sensitivity analysis, a researcher may apply the *optimal brain surgeon* (OBS) test, developed by Hassibi and Stork (1993), to prune the network. The OBS test is essentially a Wald test that allows the researcher to assess if a given weight is significantly different from zero. Hence, the researcher may gain even more insight into the internal dynamics of the model and eliminate superfluous connections from the network.

6.4 A few myths about neural networks

The growth in popularity of neural networks in recent years has led some researchers to make partial judgements in favour or against these models. In this section, we will review a few of these claims (Table 4).

Table 4: Pseudo-strengths and pseudo-weaknesses of neural networks

Pseudo-strengths
Networks do not require the type of distributional assumptions used in econometrics
Networks are intelligent systems that learn
Pseudo-weaknesses
The architecture of a neural network is totally unrelated to economic theory
The early stopping procedure requires arbitrary decisions by the researcher

6.4.1 Pseudo-strengths of neural networks

Networks do not require the type of distributional assumptions used in econometrics

Some researchers, such as Aiken and Bsat (1999), claim that neural networks are not constrained by the distributional assumptions used in other statistical methods. However, as demonstrated by Sarle (1998), neural networks involve *exactly* the same type of distributional assumptions as other statistical methods. For more than a century, statisticians have studied the properties of various estimators and have identified the conditions under which these estimators are optimal, i.e. when they yield consistent unbiased estimates with a minimal variance. They discovered, for example, that optimal results are obtained when the errors have a zero mean, are uncorrelated with each other, and have a constant variance throughout the sample. By rigorously identifying these optimality conditions, statisticians have been able to assess the consequences of the violation of these conditions. Since many neural networks are equivalent to statistical

methods, they require the exact same conditions to attain an optimal performance. This implies, among others, that the residuals of a neural network should be subjected to the same diagnostic tests that are applied to the residuals of a linear regression model. Researchers who ignore these optimality conditions and proceed to estimate their network weights will obtain sub-optimal estimates. Most empirical studies involving neural networks do not pay attention to these optimality conditions.

Unfortunately, the literature does not contain any thorough investigation of the statistical properties of the neural network estimators. In particular, it would be worthwhile to develop a greater understanding of the variance of the network weights, which could be used to assess the variance of the network forecasts.

Moreover, researchers also tend to ignore issues of stationarity when building their network. A prudent researcher should verify that all variables in the network are stationary before experimenting with different architectures. In fact, level variables that are trend stationary but that are not bounded could also pose problems for the network. Since a hidden unit produces a value that is bounded, the use of input variables that grow continuously over time could eventually lead the hidden units to reach their maximal or minimal value. The contribution of each hidden unit to the network's output (which is given by the value of the hidden unit multiplied by the weight connecting it to the output unit) would then remain constant, even if the boundless input continues to grow over time. This would result in a deterioration of forecasting accuracy for subsequent periods[15]. Similar problems would arise when attempting to forecast a level variable that grows continuously over time. Hence, even trend stationary level variables should be transformed so that they do not grow continuously over time (e.g. by using the first difference, the growth rate, the ratio to GDP, etc.)

Networks are intelligent systems that learn

Many researchers place great emphasis on the ability of feedforward neural networks to "learn" relationships from a set of variables. They are therefore credited as being "intelligent" systems. In reality, the so-called "learning" ability of feedforward neural networks is simply the result of applying an algorithm to minimize an error function in order to fit the network output to a given data series. As such, these networks do not have any additional "learning" capabilities than say, a linear regression model. Both methods simply extract correlations from the data to approximate the behaviour of a given variable. The terms "learning" and "intelligent", probably borrowed from the researchers in the field of artificial intelligence that invented neural networks, tend to create confusion as to the true capabilities of these models.

[15] It is important to note that an augmented network's output is not bounded. The linear terms included in the network would still allow its forecast to grow continuously over time, but the network would loose its nonlinear properties once all hidden units reach their boundary.

6.4.2 Pseudo-weaknesses of neural networks

The architecture of a neural network is totally unrelated to economic theory

In econometrics, it is standard practice to choose a functional form that is based on a theoretical model. However, when working with neural networks, the same basic functional form (e.g. equation [10]) will be used for a variety of heterogeneous applications, from forecasting quarterly real GDP growth to predicting the daily price of IBM ordinary shares. The "atheoretical" nature of the neural network functional form could thus be viewed as a weakness to this approach.

However, one must remember that the functional forms used in theoretical economic models are chosen quite arbitrarily. Economic theory only provides information on the *explanatory variables* to be considered and not on the *functional form* of a relationship. Although the actual functional form used in a theoretical model is chosen based on certain characteristics that are consistent with economic theory – such as being concave or convex, bounded or unbounded, etc. – economic theory itself does not specify any functional form. The lack of theoretical underpinnings in the selection of the functional form is a problem inherent to all empirical analyses in economics, not just neural networks.

The early stopping procedure requires arbitrary decisions by the researcher

When implementing the early stopping procedure, the researcher must make a certain number of arbitrary decisions that can have a significant bearing on the estimation results. First, the researcher must divide the sample into training, validation and test sets. A commonly used "rule of thumb" consists in retaining 25 per cent of the sample for the validation set and an equal proportion for the test set, with the remainder being allocated to the training set. However, this guideline does not have any theoretical or empirical foundations. In addition, the researcher must decide which observations to include in each set. Some researchers assemble their validation set from the most recent observations in their time series, while others randomly select observations from the entire sample. Once again, there is no objective rule to this effect.

These criticisms should not be overemphasized since a researcher can estimate the network using different allotments of the data into the various sets and thus assess the sensitivity of the results to this allotment. Moreover, it is important to remember that econometricians make similar arbitrary decisions when they withhold observations from their sample in order to make out-of-sample forecasts. Econometricians using time-series data typically withhold an arbitrary number of observations from the end of their sample, since they are interested in assessing the model's capacity to forecast the future. To the extent that researchers in the neural network field assemble their validation and test sets from the last observations of the sample, they will be consistent with standard econometric practice.

7. CONCLUSION: ARE NEURAL NETWORKS RELEVANT FOR MACROECONOMIC FORECASTING?

The success of some of the studies described above and of the example developed in Section 4 suggest that some macroeconomic variables lend themselves to accurate forecasting with neural networks. These results also suggest that the four weaknesses discussed above do not seem to pose insurmountable obstacles to the effective use of neural networks.

Ultimately, neural networks will be able to improve on linear models if the relationships studied present significant nonlinearities. Although some of the studies surveyed by Hill et al. (1994) concluded that neural networks were more accurate for high frequency data, we would argue that these results were obtained only because the specific time series used in those studies exhibited more nonlinearities in their high frequency format and because the large samples available with high frequency data reduced the problem of overfitting[16]. Thus, those results may have had less to do with the data frequency than with the fundamental characteristics of the data set.

Neural networks should be viewed as a natural complement to the linear regression model. Researchers interested in constructing a neural network would benefit from using their best linear model as a starting point. As explained in Section 4.4, a linear regression model should be used to help choose the network inputs. Additionally, a researcher can use the estimated coefficients from the linear model as starting values for the augmented terms in the network (with the other weights being randomized at very small values). By proceeding in this way, we can maximize the probability of finding a network that will perform better than the linear model.

It is only after this avenue has been explored that the researcher should consider making more substantial departures from the linear model, such as using inputs that were not significant in the linear estimations. In the case of variables that can be accurately forecasted with linear models, the gains from departing from the linear model are likely to be small, as the data generating process probably contains few nonlinearities. In the case of variables that are not easily modelled with a linear equation, the researcher might have to experiment with networks that depart significantly from the linear model.

Overall, neural networks seem to have some potential to assist economists in their macroeconomic forecasting. At the very least, they deserve to be studied further, perhaps through forecasting competitions with other methods. It is only by implementing neural networks in a specific context that economists will be able to evaluate their true potential.

Obviously, acquiring the expertise to implement a high-quality neural network would involve a substantial investment in time and effort. This investment could be

[16] We see no reason to believe that *all* time series will necessarily exhibit more nonlinearities when they are measured in higher frequencies. However, at high frequencies, some financial series have a non-gaussian conditional distribution and some also exhibit an asymmetric behaviour that could be better captured by neural networks. This remains an empirical issue.

justified only if the potential gains from improved forecasting accuracy outweigh the investment required to implement the network. This will generally be true in the case of macroeconomic variables for which there is a lot of room for improved forecasting, i.e. variables that give rise to substantial forecasting errors with existing techniques (commodity prices might represent a good candidate in that respect). This would also be true for variables that are of such great importance that even a marginal improvement in forecasting accuracy would be desirable. This could be the case for nominal GDP growth or interest rates, which have far-reaching implications for the design of fiscal and monetary policies.

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