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# A neural network to predict civilian unemployment rates

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## ABSTRACT

*Forecasting national unemployment is one of the most important problems of modern economies, and most researchers have relied upon statistical techniques with their stringent data assumptions and low accuracy rates to predict changes in this macroeconomic data. This paper describes how a neural network using leading economic indicator data can help to predict civilian unemployment rates. Results show that the neural network provides superior estimates of rates one month into the future compared to multi-linear regression and two naive forecasting techniques.*

## INTRODUCTION

Securities traders, politicians, businessmen, and others are concerned with national unemployment, and some have argued that the monthly *U. S. Employment Report* may be the most important statistical release from the United States government (Plocek, 1991, p. 1). Many economic decisions depend on employment expectations, encouraging researchers to seek out new methods to forecast this measure of the nation's economic health. However, many unemployment and other macroeconomic data forecasting techniques are inaccurate because of their reliance on consensus estimates, linear models, or other less-robust statistical techniques.

One technique which may increase the accuracy of unemployment forecasts is neural network modeling. Neural networks have been applied to numerous financial applications that require prediction such as thrift failure (Salchenberger, Cinar, & Lash, 1992) and stock market forecasting (Kamijo & Tanagawa, 1990), and some research has shown how neural networks may be applied to macroeconomic forecasts (e.g., Aiken, Krosp, Govindarajulu, Vanjani, & Sexton, 1995). This paper shows how a neural network may be used to forecast unemployment rates in the United States.



 

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# BACKGROUND

## Unemployment

Employment and unemployment often are used as measures of the nation's economic health (*The Economist Guide to Global Economic Indicators,* 1994, p. 56). For example, a large rise in employment implies an increase in national economic growth, while a decrease in employment indicates a less robust economy. In theory, this arises because of the business cycle. As demand increases, companies take on more workers and unemployment decreases. When there is no more labor available, demand bubbles over into inflation or imports. When demand increases, companies first tend to increase overtime. They take on more employees only when higher demand is perceived to be strong and durable. When demand turns down, hours are cut before jobs (*The Economist Guide to Global Economic Indicators,* 1994, p. 63). Thus, according to this source, employment and unemployment tend to lag the overall state of the economy by about six months.

However, other sources have shown that unemployment may be used as a leading or lagging indicator. During the period from 1949 to 1983, the peak in unemployment rates tended to lag troughs in the business cycle an average of three months (a median of two months), and troughs in the unemployment rate tended to lead peaks in the business cycle an average of three months with a median of two months (Moore, 1990, p. 121).

In addition, the unemployment rate may be misleading as a measure of economic health. Unemployment may increase while overall employment is also rising if the labor force grows more rapidly than the economy (as when the employment of women grew by 30% during the early 1970s) (Valentine, 1987, p. 171). Nevertheless, many key economic decisions are based upon estimates of future unemployment.

## Forecasting Unemployment

There are many ways to forecast economic time series including econometric models, autocorrelation, multi-linear and related techniques, and consensus estimates from a panel of experts (Granger & Newbold, 1986). Perhaps most approaches rely at least in part on use of leading economic indicators developed by the federal government or other sources. For example, the three-month "rule-of-thumb" which states that a recession can be expected after three successive declines in the composite index of leading economic indicators often is cited in news reports. However, Table 1 shows that forecasts using the three-month rule-of-thumb are very inaccurate. There were five false signals of peaks using the 3/89 revision and seven false signals using the 12/93 revision. There were no false signals of troughs for either revision. In addition to false signals, there is a large variation in lead times using this technique.

**Table 1. Lead Time (in months) Using the Three-month Rule-of-Thumb Forecast for Peaks and Troughs in the Economy (Rogers, 1994)**

| Peak | 3/89 Revision | 12/93 Revision | Trough | 3/89 Revision | 12/93 Revision |
|---|---|---|---|---|---|
| Nov. 1948 | +2 | +2 | Oct. 1949 | +1 | +1 |
| July 1953 | +2 | +2 | May 1954 | +1 | +1 |
| Aug. 1957 | +6 | +6 | Apr. 1958 | -1 | -1 |
| Apr. 1960 | +1 | +8 | Feb. 1961 | +5 | -1 |
| Dec. 1969 | +5 | +5 | Nov. 1970 | -2 | -2 |
| Nov. 1973 | +3 | +6 | Mar. 1975 | -2 | -2 |
| Jan. 1980 | +12 | +12 | Jul. 1980 | -1 | -1 |
| Jul. 1981 | -4 | +5 | Nov. 1982 | 0 | 0 |
| Jul. 1990 | +12 | +12 | May 1991 | -1 | -2 |
| Average: | +4.3 | +6.4 | Average: | 0.0 | -0.8 |

Techniques using leading economic indicators have other problems including (Shilling, 1991):

1. *Indices Revision.* Composite indices are often revised as researchers try to make them better predictors of the economy. For example, a revised index peaked in January 1973 well ahead of the November top in the economy, and bottomed in December 1974, before the March 1975 business trough, but the preliminary index didn't top out until August 1974, 21 months after the trough.

2. *Data Revisions and Timeliness.* Normal data revisions after an index's initial release are often large. In a ranking of ten industrial nations' government statistical agencies, the United States was ranked seventh in terms of data timeliness and tied for sixth in terms of data reliability (*The Economist Guide to Global Economic Indicators,* 1994, p. 37).

3. *Inflection Points.* Perhaps the most important problem is trying to decide whether a few months' change in direction of the composite indicator of leading economic indicators truly portends a turning point in the economy or is merely a false alarm. Increasing the number of months in the rule-of-thumb will reduce the occurrence of false alarms, but will also cause the technique to miss some true turning points.

Most techniques using leading economic indicators are unable to account for the many complex interrelationships among the data. Thus, new techniques such as neural network modelling may yield better results.

## NEURAL NETWORKS

Artificial neural networks are based upon the biological principles underlying the human brain. Much like the human brain, they learn new associations, new patterns and new functional dependencies inductively by observing the data supplied to them (Haykin, 1994).

Neural networks provide several advantages over alternate statistical modeling and prediction techniques. Neural networks are not programmed, like some software packages, but rather are "trained" by exposing the network to individual examples of the data to be used for predictions or classifications. The process is repeated until the neural network recognizes underlying patterns between inputs (independent variables) and outputs (dependent variables).

In addition, the neural network does not require any assumptions for the underlying data to be forecasted. For example, multi-linear regression requires that the data meet certain conditions of homoscedasticity (variance) and independence of variables and assumes that the underlying relationship of the data is linear rather than non-linear. Other forecasting techniques require other assumptions for the data. Therefore, using a neural network, no tests need to be conducted for these assumptions as other statistical techniques require.

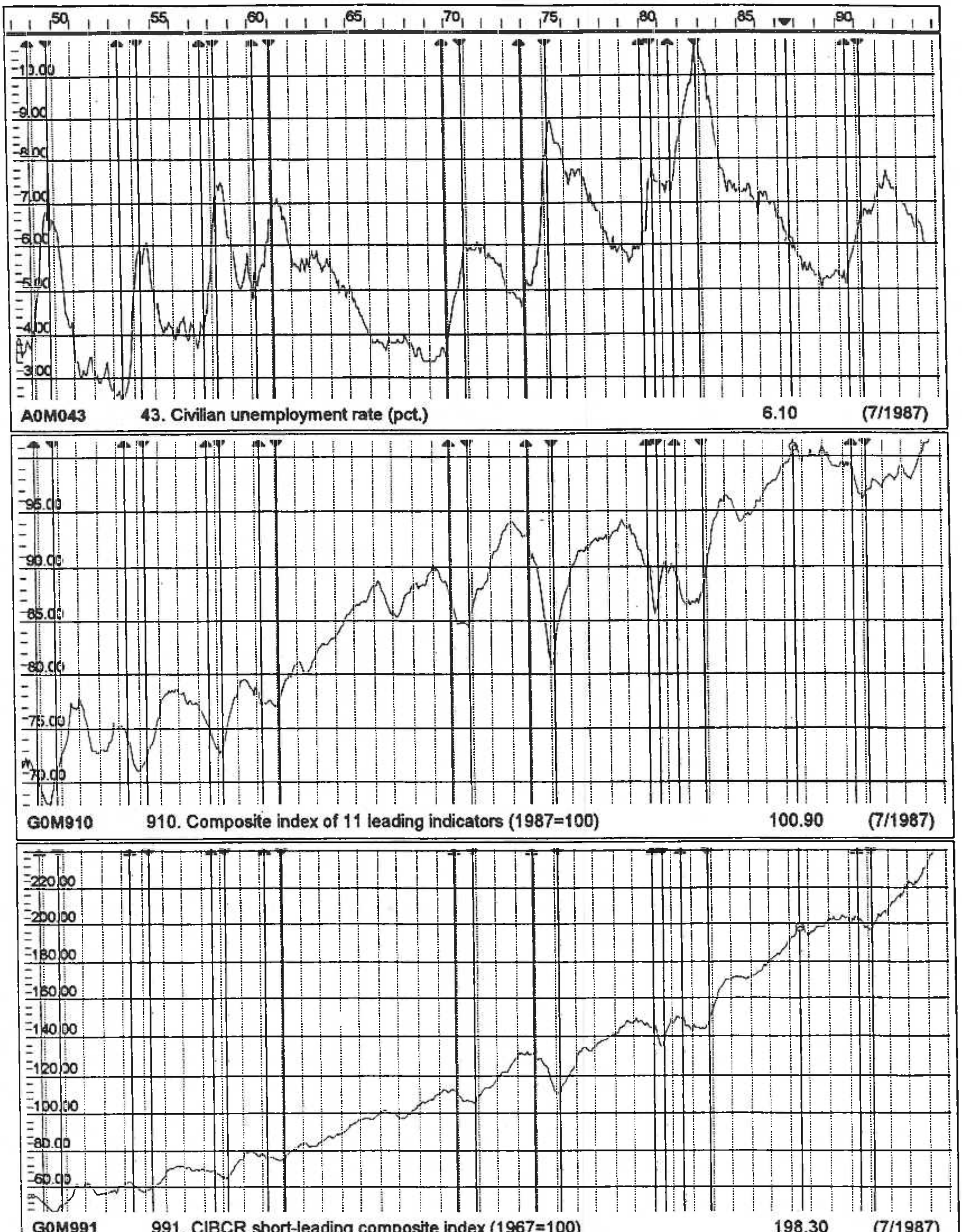
Finally, neural networks can develop models from incomplete or imperfect data. In other modelling techniques, missing data is a serious problem. Neural networks are able to develop an accurate model with a measure of acceptable fault tolerance despite the absence of some of the data.

A neural network is developed in a three-stage process (Klimasauskas, 1993; Marquez, Hill, Worthley, & Remus, 1993). First, decisions must be made about what the input variables will be, how many layers and nodes in each layer the network will have, the transfer function, and other training (or learning) parameters. Next, the network is trained using a subset of the data until the average error between the forecast and the actual values is reduced to a minimum (typically as close to zero as possible). Finally, the trained neural network is used to forecast with the remainder of the data to test whether or not the decisions made in the first stage were appropriate. For example, if the forecasts are poor, new variables may need to be added, the numbers of layers and nodes in the network may need to be changed, or a different transfer function may need to be used. The development of a neural network may take several iterations until a sufficiently accurate network model is generated.

## A NEURAL NETWORK MODEL

A neural network was developed to predict civilian unemployment rates using *NeuroForecaster/GA 3.1,* a product of NewWave Intelligent Business Systems (*NeuroForecaster User's Guide,* 1993) and following the process described above.

## Figure 1. Business Cycle Indicators Sample Screen



## Data

Data were obtained from Media Logic Incorporated's *Business Cycle Indicators* software which contains monthly and quarterly observations for approximately 250 macroeconomic time series over a period of about 50 years. The specific variables for the neural net model were selected through a combination of theory and subjective inspection of the time series shown by the software. For example, Figure 1 (a sample screen) shows that two time series (series #910: composite index of 11 leading indicators and series #991: CIBCR short-leading composite index) tend to lead changes in the civilian unemployment rate. (The darker vertical lines in this figure indicate the beginning and ending dates for recessionary periods.)

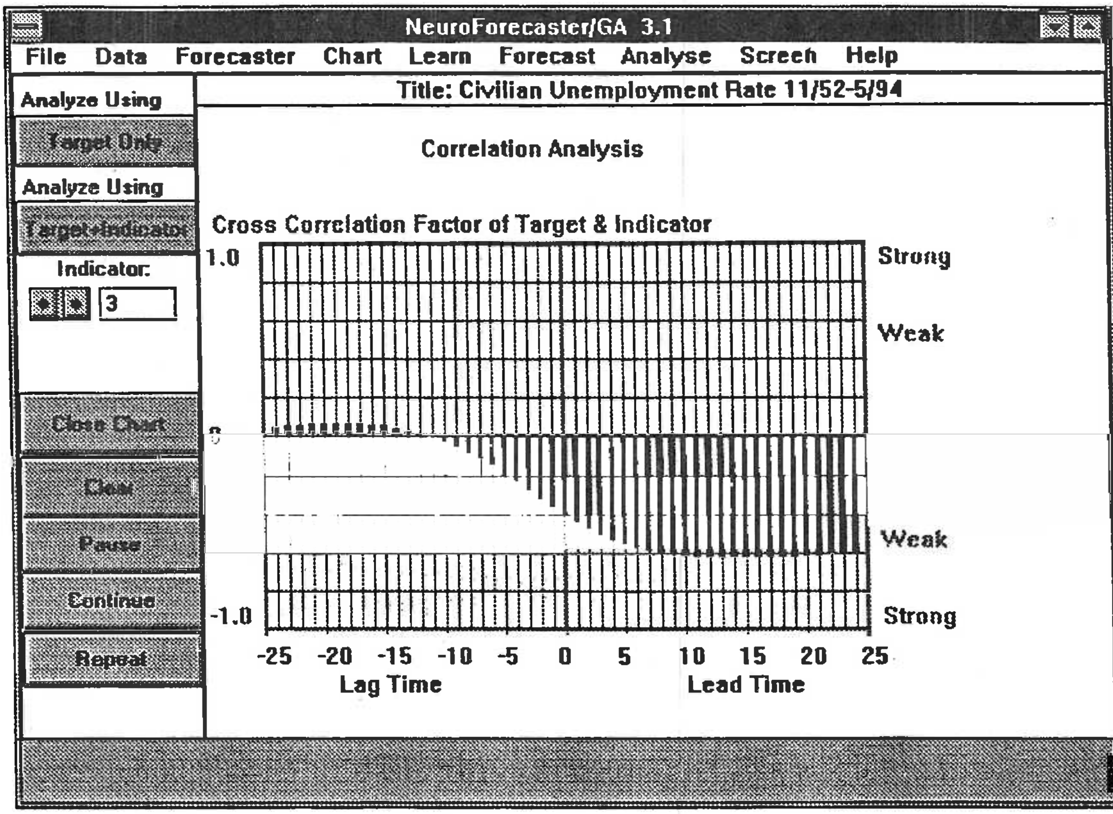
Other time series provided by the software also were inspected based upon theory. For example, some researchers have suggested that money growth, interest rates, and exports may affect the unemployment rate (Mills, Pelloni, & Zervoyianni, 1995), and forecasts of the German unemployment rate have used indicators of total industrial production and volume of total new orders (Funke, 1992). In addition, common wisdom suggests that the various leading economic indicator series and indicators such as consumer expectations should be investigated. After subjective visual inspection of the time series charts, correlation analyses were performed to confirm the variables' usefulness to the model.

Correlation analyses showed that many of the candidate series had no correlation at all or were coincident or even lagging. The two strongest correlations were obtained with the consumer sentiment and consumer expectations indicators (the other selected variables had weaker correlations but were still deemed to contribute to the model). Figure 2 shows that consumer sentiment has a fairly strong leading negative correlation of about -.6 about eight months before the current period. Thus, at least eight months of prior observations for this variable should be included in the forecasting model.

The final variables selected for the model consisted of: civilian unemployment rate (the target), consumer sentiment, consumer expectations, money supply M1, money supply M2, the composite index of 11 leading indicators, and the Center for International Business Cycle Research long-leading composite index and short-leading composite index.

(Figure 2 is on next page)

**Figure 2. NeuroForecaster Sample Screen Showing Consumer Sentiment's Leading Correlation with Civilian Unemployment Rates**




## Development

About 382 observations of monthly data were obtained for civilian unemployment rates (the target variable) and seven input variables. Next the data were separated into training and testing sets, shown in Table 2.

**Table 2. Neural Network Training and Testing Results**

| Training Period | Testing Period | Cumulative Iterations | Training Mean Error | Testing Mean Error | Std. Dev. | Testing Mean Absolute Error |
|---|---|---|---|---|---|---|
| 11/52-7/62 | 8/62-11/67 | 5.3 million | .10 | .02 | .13 | .10 |
| 3/58-11/67 | 12/67-4/74 | 5.5 million | .10 | -.01 | .14 | .10 |
| 8/63-4/74 | 5/74-10/77 | 5.6 million | .12 | .03 | .20 | .16 |
| 2/68-10/77 | 11/77-3/83 | 6.4 million | .12 | .04 | .19 | .15 |
| 7/73-3/83 | 4/83-8/88 | 6.6 million | .13 | .02 | .16 | .12 |
| 12/78-8/88 | 9/88-5/94 | 12.1 million | .11 | .00 | .14 | .11 |
| Average: | | | | .02 | .16 | .12 |

All of *NeuroForecaster's* default training parameters (e.g., learn rate, momentum, output processing, normalization, etc.) were used with the exception that "serial presentation" was chosen instead of "random presentation" and the network was configured to include data from the past eight months (in accordance with the correlation analysis described above). In addition, the network used the genetic algorithm which is often more accurate (but slower) than the other back propagation techniques also offered as choices. Training was continued for several million iterations until the training error was reduced to approximately 3%.

## Testing

Table 2 shows the testing (out-of-sample) errors for the neural net. On average, the mean testing error was .02 with a standard deviation of .16, and the mean absolute error was 0.12 for the period from August 1962 to May 1994.

Figure 3 shows a sample screen from *NeuroForecaster* during the testing phase. In this figure, the in-sample observations are to the left of the vertical line and the out-of-sample observations are to the right. The "Peek Window" shows that for June 1987 (the point just to the right of the vertical line), the forecasted unemployment rate was 5.919% versus an actual value of 5.917%.

(Figure 3 is on next page)

**Figure 3. NeuroForecaster Sample Screen Showing Forecasted and Actual Monthly Civilian Unemployment Rates**

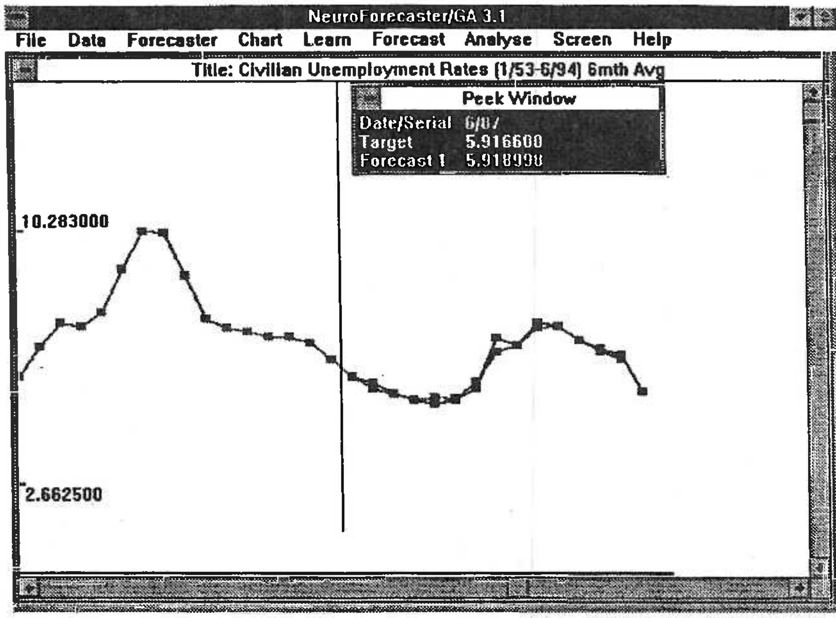



**Table 3. Multi-linear Regression In-sample and Testing Mean Absolute Errors**

| In-Sample Period | Testing Period | In-Sample Error | Testing Error |
|---|---|---|---|
| 11/52-7/62 | 8/62-11/67 | .54 | 3.73 |
| 3/58-11/67 | 12/67-4/74 | .28 | 3.05 |
| 8/63-4/74 | 5/74-10/77 | .26 | 0.65 |
| 2/68-10/77 | 11/77-3/83 | .36 | 1.49 |
| 7/73-3/83 | 4/83-8/88 | .30 | 2.03 |
| 12/78-8/88 | 9/88-5/94 | .56 | 1.68 |
| Mean: | | .38 | 2.11 |

For comparison, three other techniques (multi-linear regression, a "no-change," and a three-month average forecast) were used. Table 3 shows the results of multi-linear regression applied to the same training and testing periods. The in-sample and out-of-sample (or testing) mean absolute errors were much higher than the neural net's. In fact, the in-sample errors for the regression were over three times the neural net's out-of-sample errors. The regression's out-of-sample errors were about 18 times the neural net's out-of-sample errors.

## Table 4. Mean Absolute Errors for Forecasting Techniques

| Test Period | Neural Network | Regression | No Change | Three-Month Average |
|---|---|---|---|---|
| 8/62-11/67 | .10 | 3.73 | .12 | .12 |
| 12/67-4/74 | .10 | 3.05 | .11 | .15 |
| 5/74-10/77 | .16 | .65 | .20 | .31 |
| 11/77--3/83 | .17 | 1.49 | .17 | .25 |
| 4/83-8/88 | .14 | 2.03 | .14 | .19 |
| 9/88-5/94 | .12 | 1.68 | .12 | .15 |
| Mean: | .12 | 2.11 | .14 | .19 |

Table 4 shows mean absolute errors for the neural network, multi-linear regression, and two additional simple forecasting techniques. The "No Change" technique simply estimates next month's unemployment rate to be the same as the current month's unemployment rate. The "Three-Month Average" technique estimates next month's unemployment rate to be the same as the last three month's simple moving average of rates and is a variation of the smoothed-average forecasting technique (Valentine, 1987, p. 499).

The neural network and the "no change" estimates were closest to the actual rates. The mean absolute error for the neural network during the 32-year testing period was 0.1231 with a standard deviation of 0.1069. The mean absolute error for the "no change" technique during the same period was 0.1359 with a standard deviation of 0.1288. A difference-of-means T test was performed on the 382 monthly observations. Results showed a significant difference between the neural net's estimates and the actual rates (T=22.5, p=0.0001), and a significant difference between the "no change" estimates and the actual rates (T=20.6, p=0.0001). However, there was also a significant difference between the neural net's estimates and the "no change" estimates (T=21.9, p=0.0001), indicating superior performance for the neural net.

## CONCLUSION

Neural networks are powerful tools for forecasting many types of time series. A neural network developed using *NeuroForecaster* and macroeconomic data from *Business Cycle Indicators* software outperformed multi-linear regression and two relatively simple approaches. Similar results using other time series such as those for economic output, inflation, and stock prices, may be achieved with further research.

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