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A Comparative Study on Business Forecasting Accuracy among Neural Networks and Time Series

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Abstract

This study shows that neural networks have been advocated as an alternative to traditional statistical forecasting methods. Numerous articles comparing performances of statistical and Neural Networks (NNs) models are available in the literature. The need for increased accuracies in time series forecasting has motivated the researchers to develop innovative models. The results obtained in this study suggest that the approach of combining the strengths of the conventional and ANN techniques provides a robust modeling framework capable of capturing the non-linear nature of the complex time series and thus producing more accurate forecasts.

Keywords: forecasting; neural networks; time series.

1. Introduction

NN (neural networks) have gained enormous popularity in the recent years. Most applications, however, are in areas where data are abundant as NN are very data intensive. In macroeconomics, due to the scarcity of large data samples, there exist only a few studies involving the use of NN that can be used to gauge its usefulness in the field [2]. The author in [1] contrasts models of the UK economy constructed using NN and a variety of econometric models. The authors in [3] use NN to forecast Canadian inflation and compare the results to those from time series and econometric models. The results in these studies, based on out-of-sample forecasts, do not permit a demarcation between the linear models and NN as the latter is able to justify its theoretical superiority in only some of the cases. In fact, these observations reflect the results of quite a large number of such comparative studies across different fields. This has led to questions being raised on whether studies implement NN in such a way that it stands a reasonable chance of performing well.

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Indeed, the risks of making bad decisions are extremely high while building a NN as there are no established procedures available to decide on the choice of the parameters of the NN, which basically is problem dependent. Although there have been attempts in several studies to develop guidelines in making these choices , so far this matter, is still subject to trial and error. Thus, despite the many satisfactory characteristics of the NN, building a NN for forecasting a particular problem is a nontrivial task. Consequently, tedious experiments and time-consuming trial and error procedures are inevitable [1].

2. Forecasting

Forecasting is the process where predict the future value on a specific field with the help of past data records and concluded in the specific result. Forecasting start with the specific assumption based on the management's experience, knowledge and judgment. These estimates are predicted into the coming day, month, or year.The most important comparative study of forecasting methods in recent years was the M3-Competition, undertaken by authors in [6]. In that study 22 extrapolative forecasting methods, both commercial and academic, were compared on the basis of their accuracy in forecasting 3003 time series from a wide variety of settings. The methods included an automatic neural network, implemented the author in [9], his thesis makes reference to Hill , so we presume that the authors in [9] used lessons learned from Hill and others to implement the best possible general extrapolation network. That neural network’s performance was generally significantly worse than that of the other methods, regardless of forecast interval or horizon [4].

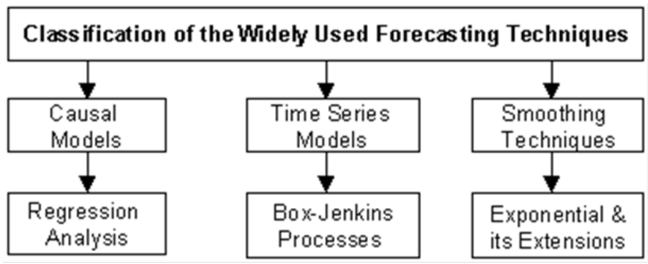

Figure 1: Forecasting

3. Business Forecasting

Experience, knowledge and judgement. These estimates are predicted into the coming day, month, or year. There are several fields where forecasting is used like exchange rate forecasting more specifically dollar rate forecasting with respect to Indian Rupee, or Pound forecasting in Indian Rupees, gold price forecasting, weather forecasting, tide forecasting. Exchange Rate Forecasting is very important in modern time for world economy because of market strategy, investor to invest in foreign projects. Foreign exchange rate are most important and largest financial markets in the world with trading taking place twenty-four hours a day around the world and a large amount of dollars of currencies transacted each day through the world each day. Transactions in foreign exchanges market determine the rate at which currencies are exchanged, which determine the cost of purchasing foreign goods and foreign assets. So An exchange rate between two countries is the rate at which one currency will be exchanged to another. It is regarded as the one country's currency in terms of another [5].

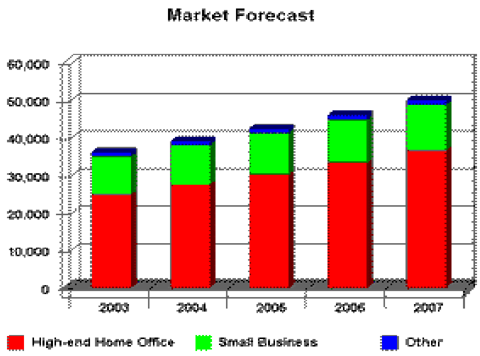

Figure 2: Business Forecasting

4. Neural Networks

Neural networks have been compared with other methods in smaller studies as well. In a comparison of neural networks with Box-Jenkins and Holt-Winters exponential smoothing, the authors in [14] found that neural networks often gave poorer out-of-sample forecasts. They also concluded that they were difficult to interpret. They used a well-known airline data to fit several NNs [14]. Although the fit measures (the Akaike information criterion and the Bayesian information criterion) were comparable for various NN structures, ex ante forecasting performance varied greatly. They concluded therefore that NN models were hard to interpret and that little guidance could be given on how many parameters to use [11]. The accuracy of the predictive system which is made by ANN can be tuned with help of different network architectures. Network is consists of input layer ,hidden layer & output layer of neuron, no of neurons per layer can be configured according to the needed result accuracy & throughput, there is no cut & bound rule for that. The network can be trained by using sample training data set, this neural network model is very much useful for mapping unknown functional dependencies between different input & output tuples [19]. ANN is a powerful tool widely used in soft-computing techniques for forecasting stock price. The first stock forecasting approach was taken by White, he used IBM daily stock price to predict the future stock value. When developing predictive model for forecasting Tokyo stock market , Kimoto, Asakawa, Yoda, and Takeoka have reported on the effectiveness of alternative learning algorithms and prediction methods using ANN. Chiang, Urban, and Baldridge have used ANN to forecast the end-of-year net asset value of mutual funds. Trafalis used feed-forward ANN to forecast the change in the S&P (500) index. In that model, the input values were the univariate data consisting of weekly changes in 14 indicators.Forecasting of daily direction of change in the S&P (500) index is made by Choi, Lee, and Rhee 1995. Despite the wide spread use of ANN in this domain, there are significant problems to be addressed. ANNs are data-driven, and consequently, the underlying rules in the data are not always apparent. Also, the buried noise and complex dimensionality of the stock market data makes it difficult to learn or re-estimate the ANN parameters . It is also difficult to come with an ANN architecture that can be used for all domains. In addition, ANN occasionally suffers from the overfitting problem 12**]**]. NNs seems to outperform traditional forecasting methods for monthly and quarterly time series. The author in [29] found using world observations of monthly flour prices in three cities, NNs outperformed ARMA in multivariate time-series forecasting. Caire also found that the forecasting quality of NNs is equivalent, but not superior to the result with using the ARIMA approach for daily data [34].

Refenes compared NNs to multiple linear regression using monthly stock rankings. He found that both the in-sample and out-of-sample performance of the network gave a better fit than linear regression. Nam found that NNs were superior to the linear regression and Winters' exponential models for monthly airline passenger traffic [23]. Kohzadi compared NNs and ARIMA models to forecast US monthly live cattle and wheat prices. his results showed that NNs were considerably more accurate than traditional ARIMA models [24]. Hann found that NNs outperformed linear regression in weekly data, and could produce similar predictions in monthly data with regard to the criteria of Theil's U, the annualized return and the Sharpe Ratio. Later, Remus designed a comprehensive comparison published in Management Science. He used a sample of 111 time series from the M-competition in their research. He compared NNs with six traditional forecasting models, including deseasonalized exponential smoothing, Box-Jenkins, deseasonalized Holt's, graphical (human judgment), a combination of six methods and a naïve model. His study showed that NNs did significantly better than traditional statistical and human judgment methods based on the absolute percentage error (APE), when forecasting quarterly and monthly data [16]. However, with annual data, NNs did not outperform traditional models but were comparable. Subsequently, Goh compared the accuracy of demand models and found that NNs outperformed the univariate Box-Jenkins approach and multiple loglinear regression on quarterly data, using relative errors. In Leung's study, NNs had better forecasting accuracy than multivariate transfer function models and random walk models for currency exchange rate forecasting of monthly data. Moreover, this difference was statistically significant[9].

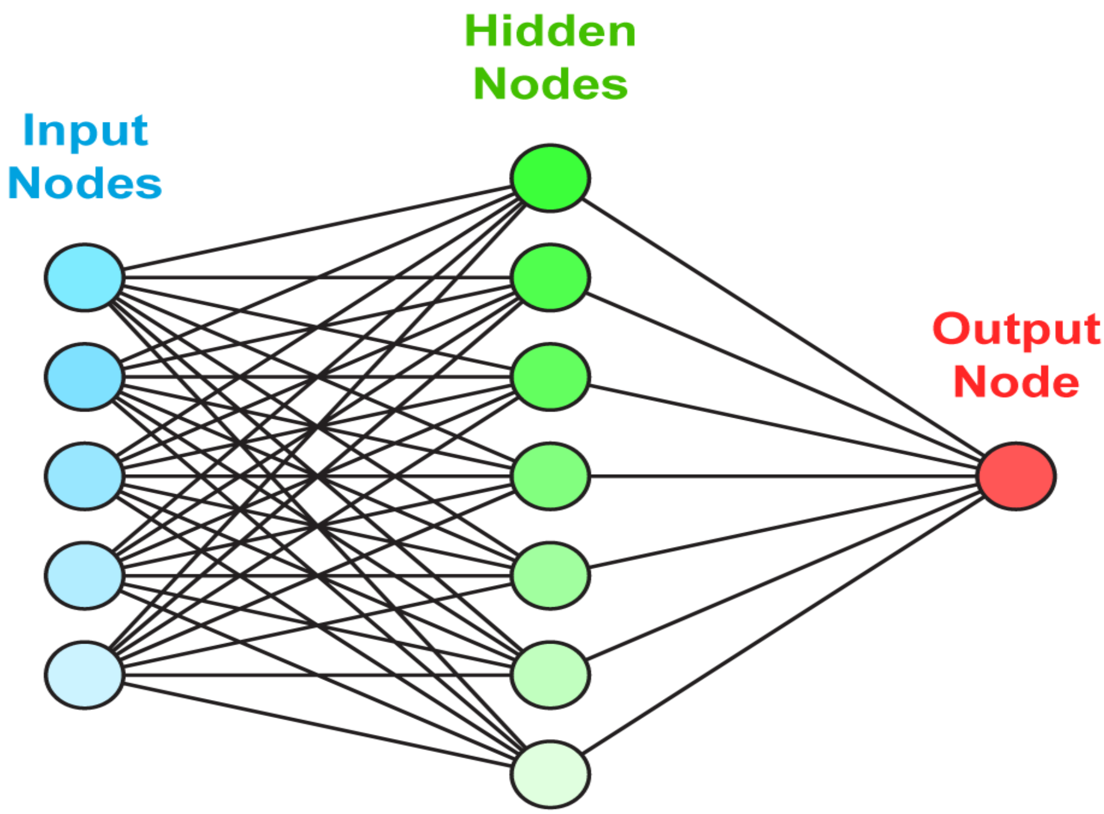

Figure 3: Neural Network

5. Time series

Time series analysis and its applications have become increasingly important in various fields of research, such as business, economics, engineering, medicine, environment, social sciences, politics, and others. Since Box and Jenkins published the seminal book (Time Series Analysis: Forecasting and Control), a number of books and a vast number of research papers have been published in this area [4]. Time series are any univariate or multivariate quantitative data collected over time either by private or government agencies. Common uses of time series data include: (1) modeling the relationships between various time series; (2) forecasting the underlying behavior of the data; and (3) forecasting what effect changes in one variable may have on the future behavior of another variable. There are two major categories of forecasting approaches: Qualitative and Quantitative. Qualitative Techniques: Qualitative techniques refer to a number of forecasting approaches based on subjective estimates from informed experts. Usually, no statistical data analysis is involved. Rather, estimates are based on a deliberative process of a group of experts, based on their past knowledge and experience. Examples are the Delphi technique and scenario writing, where a panel of experts are asked a series of questions on future trends, the answers are recorded and shared back to the panel, and the process is repeated so that the panel builds a shared scenario. The key to these approaches is a recognition that forecasting is subjective, but if we involve knowledgeable people in a process we may get good insights into future scenarios. This approach is useful when good data are not available, or we wish to gain general insights through the opinions of experts. Quantitative Techniques: refers to forecasting based on the analysis of historical data using statistical principles and concepts. The quantitative forecasting approach is further sub-divided into two parts: causal techniques and time series techniques. Causal techniques are based on regression analysis that examines the relationship between the variable to be forecasted and other explanatory variables. In contrast, Time Series techniques usually use historical data for only the variable of interest to forecast its future values [19]. The ability to model and perform decision modeling and analysis is an essential feature of many real-world applications ranging from emergency medical treatment in intensive care units to military command and control systems. Existing formalisms and methods of inference have not been effective in real-time applications where tradeoffs between decision quality and computational tractability are essential. In practice, an effective approach to time-critical dynamic decision modeling should provide explicit support for the modeling of temporal processes and for dealing with time-critical situations [24]. One of the most essential elements of being a high-performing manager is the ability to lead effectively one's own life, then to model those leadership skills for employees in the organization. This site comprehensively covers theory and practice of most topics in forecasting and economics. I believe such a comprehensive approach is necessary to fully understand the subject. A central objective of the site is to unify the various forms of business topics to link them closely to each other and to the supporting fields of statistics and economics. Nevertheless, the topics and coverage do reflect choices about what is important to understand for business decision making [29]. Almost all managerial decisions are based on forecasts. Every decision becomes operational at some point in the future, so it should be based on forecasts of future conditions [31]. Forecasts are needed throughout an organization -- and they should certainly not be produced by an isolated group of forecasters. Neither is forecasting ever "finished". Forecasts are needed continually, and as time moves on, the impact of the forecasts on actual performance is measured; original forecasts are updated; and decisions are modified, and so on [34]. For example, many inventory systems cater for uncertain demand. The inventory parameters in these systems require estimates of the demand and forecast error distributions. The two stages of these systems, forecasting and inventory control, are often examined independently. Most studies tend to look at demand forecasting as if this were an end in itself, or at stock control models as if there were no preceding stages of computation. Nevertheless, it is important to understand the interaction between demand forecasting and inventory control since this influences the performance of the inventory system [36].

Figure 3: Time series

5. Conclusion

Time-series methods make forecasts based solely on historical patterns in the data. Time-series methods use time as independent variable to produce demand. In a time series, measurements are taken at successive points or over successive periods. The measurements may be taken every hour, day, week, month, or year, or at any other regular (or irregular) interval. A first step in using time-series approach is to gather historical data. The historical data is representative of the conditions expected in the future. Time-series models are adequate forecasting tools if demand has shown a consistent pattern in the past that is expected to recur in the future. For example, new homebuilders in US may see variation in sales from month to month. But analysis of past years of data may reveal that sales of new homes are increased gradually over period of time. In this case trend is increase in new home sales. Time series models are characterized of four components: trend component, cyclical component, seasonal component, and irregular component. Trend is important characteristics of time series models. Although times series may display trend, there might be data points lying above or below trend line. Any recurring sequence of points above and below the trend line that last for more than a year is considered to constitute the cyclical component of the time series—that is, these observations in the time series deviate from the trend due to fluctuations. The real Gross Domestics Product (GDP) provides good examples of a time series that displays cyclical behavior. The component of the time series that captures the variability in the data due to seasonal fluctuations is called the seasonal component. The seasonal component is similar to the cyclical component in that they both refer to some regular fluctuations in a time series. Seasonal components capture the regular pattern of variability in the time series within one-year periods. Seasonal commodities are best examples for seasonal components. Random variations in times series is represented by the irregular component. The irregular component of the time series cannot be predicted in advance. The random variations in the time series are caused by short-term, unanticipated and nonrecurring factors that affect the time series. Time series models are used in Finance to forecast stock's performance or interest rate forecast, used in forecasting weather. Time-series methods are probably the simplest methods to deploy and can be quite accurate, particularly over the short term. Various computer software programs are available to find solution using time-series methods.

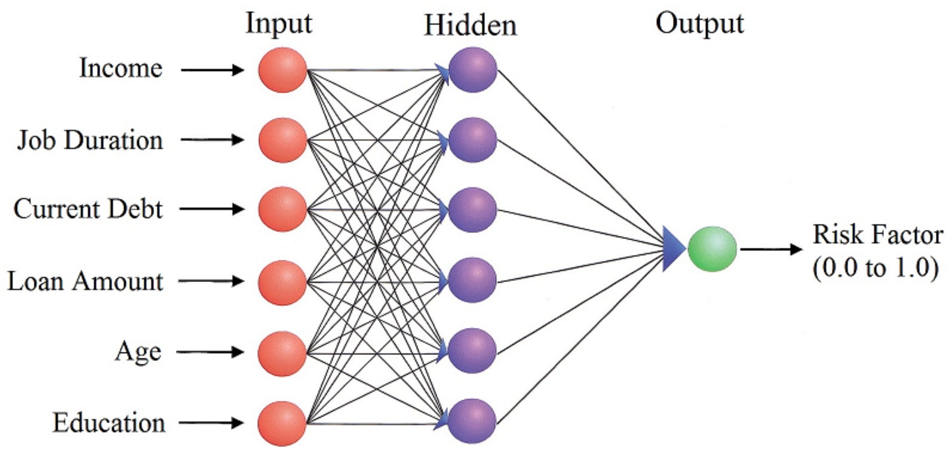

Figure 4: Machine Learning

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