

## Artificial Neural Networks: State of the Art in Business Intelligence

## Sunil Sapra<sup>\*</sup>

Department of Economics and Statistics, California State University, Los Angeles, CA 90032, USA

\*Corresponding author: Sunil Sapra, Department of Economics and Statistics, California State University, Los Angeles, CA 90032, USA, Tel: 13233432531; E-mail: ssapra@exchange.calstatela.edu

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## Editorial

Business data is one of the most valuable assets, which an organization owns. Such data includes sales figures for the past few years, the loyalty of customers, and information about the impact of previous business strategies. Business data offers great potential for improving the business intelligence of an organization.

Most businesses today store huge volumes of data in data warehouses given the immense value of information contained in the data. Data mining techniques, such as neural networks are able to model the relationships that exist in data collections and consequently can be used for increasing business intelligence across a variety of business applications. The influential edited volume by Smith and Gupta [2] presents a series of case studies from different functional areas of business to elucidate neural network technology.

As these case studies illustrate, ANNs can be used for prediction, classification, and segmentation problems across a wide variety of business areas. In recent years, ANNs have been employed in fields as diverse as engineering, statistics, marketing, finance, economics, and pharmaceuticals.

The two main types of neural networks are multilayered feedforward neural network (MFNN) and self-organizing map (SOM). The MFNN is used for prediction problems, such as stock market prediction, and classification problems, such as classifying bank loan applicants as good or bad credit risks. The SOM is used for clustering data according to similarities, such as finding application in market segmentation. These two main neural network architectures have been used successfully for a wide range of business areas as described in Smith and Gupta [2], including retail sales, marketing, risk assessment, accounting, financial trading, business management, and manufacturing.

Artificial neural networks were originally developed to mimic the human brain. A biological brain consists of interconnected cells called neurons, each of which can be activated by other neurons, and which can then activate other neurons in turn. A simple ANN has an input layer of neurons where data can be passed into the network, an output layer where results come out, and a few hidden layers in the middle where information is processed. Each neuron within the network has a set of "weights" and an "activation function" that controls the firing of its output. Training a neural network involves adjusting the neurons' weights so that a given input produces the desired output. Backpropagation is the main algorithm used for training neural networks. By the early 1990s ANNs had proved to be useful for accomplishing simple tasks, such as recognizing handwritten numbers. However, accomplishing more complex tasks remained a challenge since the standard training technique of learning by example employed by ANNs did not work with larger or deeper networks with more

layers. Failure of ANNs to deliver on their promise led to declining enthusiasm for ANNs.

Given the close similarity between ANNs and regression models, it is important to understand the statistical perspective on ANNs. Faraway [1] describes ANNs as a controlled flexible class of nonlinear regression model. The complexity of the model can be controlled in a measured way from relatively simple models to models, which are more suitable for large datasets with complex structure. ANNs do not require nearly as much expertise as statistical models. However, the user cannot ignore statistical issues involving transformation and scaling of the data, outliers, and influential points.

ANNs are an excellent tool for forecasting, but their results are difficult to interpret since ANNs introduce complex interactions. In the absence of appropriate controls, the ANNs can over-fit the data producing overoptimistic predictions. Nevertheless, ANNs work very well for large complex datasets in comparison with statistical methods for which building the model can impede progress. A key weakness of the ANNs however is that they do not possess sound statistical theory for inference, diagnostics, and model selection. Nevertheless, ANNs used carefully, can outperform statistical methods for certain problems.

Time and again, artificial intelligence in general and ANNs in particular, have failed to live up to their promise. Why is it different this time? As a recent article in the Economist [1] points out, things have changed over the past few years due to the feasibility of deep networks made possible by new training techniques, availability of billions of documents, images and videos available for training purposes with the rise of internet, and the realization that graphical processing units (GPUs), the specialized chips used in PCs and videogame consoles to generate cool graphics, are also well suited to modelling neural networks. With deeper networks, more training data and powerful new hardware, deep neural networks have made rapid progress in the areas of speech recognition, image classification and language translation.

Deep learning systems have also become competitive with the rival regression models in making predictions. Deep neural networks have come a long way since 1990s when interest in ANNs nearly died and are now enjoying a kind of renaissance in business. The next few years are likely to witness a growing interest in putting neural networks to work in business, engineering, drug discovery, and more. The time for business community to embrace ANNs towards improving business intelligence has finally arrived.

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