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Probabilistic neural networks for the identification of qualified audit opinions

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Abstract

Prior studies that examine the application of neural networks in auditing investigate the efficiency of artificial neural networks (ANNs). In the present study, considering the well known disadvantages of artificial neural network, we propose the application of probabilistic neural networks (PNNs) that combine the computational power and flexibility of ANNs, while managing to retain simplicity and transparency. The sample consists of 264 financial statements that received a qualified audit opinion over the period 1997–2004 and 3069 unqualified ones, from 881 firms listed on the London Stock Exchange. The results demonstrate the high explanatory power of the PNN model in explaining qualifications in audit reports. The model is also found to outperform traditional ANN models, as well as logistic regression. Sensitivity analysis is used to assess the relative importance of the input variables and to analyze their role in the auditing process.

Keywords: Probabilistic neural networks; Auditing; Qualified audit reports

1. Introduction

In recent years neural networks (NNs) have received a lot of attention, and have been applied in various financial/accounting applications such as bankruptcy prediction (Charitou, Neophytou, & Charalambous, 2004; Luther, 1998; Pendharkar, 2005; Zhang, Hu, Patuwo, & Indro, 1999), bond trading (Huang, Chen, Hsu, Chen, & Wu, 2004), volatility forecasts (Hamid & Iqbal, 2004), portfolio management (Hung, Liang, & Liu, 1996), country risk rating (Yim & Mitchell, 2005) and auditing (Fanning & Cogger, 1998; Hansen, McDonald, & Stice, 1992). Calderon and Cheh (2002), Wong, Lai, and Lam (2000) and Wong and Selvi (1998) provide overviews of the research on NNs with applications in business and finance conducted over the last years. The vast majority of the studies has used multilayer feed-forward artificial neural networks (ANNs) trained with the back-propagation learning algorithm. However, numerous researchers document the disadvantages of this approach. For example, Calderon and Cheh (2002) mention that standard back-propagation networks are subject to problems of local minima, and can be tedious and extremely time-consuming to build. Results can also be very sensitive to specification of learning rates, momentum and other processing elements, and there is no clear guidance on the selection of those parameters. Salchenberger, Cinar, and Lash (1992) also point out the inability to explain conclusions or how they are reached, and the lack of formal theory which imposes a need for expertise on the user.

An alternative NN architecture, the probabilistic neural networks (PNNs; Specht, 1990) constitute a classification methodology that combines the computational power and flexibility of ANNs, while managing to retain simplicity and transparency. The main advantages of PNNs over ANNs include their simplified architecture which overcomes the difficulty of specifying an appropriate ANN

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model, as well as their easy implementation during training and testing. Calderon and Cheh (2002) point out that these advantages make PNNs a potentially attractive alternative in auditing.

So far PNNs have been applied in only a few studies in finance such as bankruptcy prediction (Etheridge & Sriram, 1997; Yang, Platt, & Platt, 1999), short-term liquidity modeling (Li, Shue, & Shiue, 2000) and stock index forecasting (Chen, Leung, & Daouk, 2003; Kim & Chun, 1998).

This study uses PNNs for the development of a model that explains qualifications in audit reports. Laitinen and Laitinen (1998) classify prior studies on qualified audit report information relevant to the present study into three categories. Studies from the first category use audit report information for the construction of bankruptcy prediction models (Keasey & Watson, 1987). Studies falling in the second category mainly deal with the construction of bankruptcy models for making audit opinions, relative to going concern (Koh, 1991). Studies from the third category develop models to explain (or predict) qualifications in audit reports (Dopuch, Holthausen, & Leftwich, 1987; Keasey, Watson, & Wynarzcyk, 1988; Laitinen & Laitinen, 1998).

The present paper falls into the third category of the studies mentioned above. The purpose of the study is to explore the potential of PNNs for the development of models that explain qualifications in audit reports. Bell and Tabor (1991) as well as Chen and Church (1992) note that auditors can use the output of such models to plan specific auditing procedures that can be applied to achieve an acceptable level of audit risk. These models can also be used as a quality control tool in the final or review stage of an engagement and for contingency analyses on how changes in specific variables could add or detract from the probability of obtaining a qualified opinion (Kleinman & Anandarajan, 1999).

The analysis is based on a large sample of firms listed in the London Stock Exchange. Both financial and non-financial variables are introduced in the models and principal components analysis is employed to build a compact set of independent variables which have a clear interpretation for the auditing domain. Special emphasis is given on the specification of the smoothing parameter of the PNN model, as well as on the interpretability of the model. The latter issue is often overlooked in the application of non-parametric techniques such as network models, to financial and auditing problems. Actually, most past studies have been mainly focused on the predictive power of the developed models. However, a good model, expect for its predictive power, should also be able to provide meaningful information to the decision maker. To address this issue we perform sensitivity analysis which provides useful insight on the model's outputs, thus designating that a complex non-linear network model is not a simple "black-box" prediction tool, but it can also be used to highlight the important factors that describe qualifications in audit reports. Furthermore, the results of a comparative analysis with ANNs and logistic regression support the superiority of the PNN modeling framework in explaining qualifications in audit reports.

The remaining of the paper is structured as follows: Section 2 briefly outlines the PNN methodology. Section 3 describes the data and the variables used in the analysis, whereas Section 4 presents the empirical results. Finally Section 5 concludes the paper and discusses some possible future research directions.

2. Probabilistic neural networks

Probabilistic neural networks possess the simplicity, speed and transparency of traditional statistical classification models along with much of the computational power and flexibility of back-propagated neural networks (Specht, 1990).

A PNN can be realized as a network of four layers (Fig. 1). The input layer includes N nodes, each corresponding to one input attribute (independent variable). The inputs of the network are fully connected with the M nodes of the pattern layer. Each node of the pattern layer corresponds to one training object. The $1 \times N$ input vector $\mathbf{x}_i$ is processed by pattern node j through an activation function that produces the output of the pattern node. The most usual form of the activation function is the exponential one:

$$o_{ij} = \exp\left(-\frac{\|\mathbf{x}_j - \mathbf{x}_i\|^2}{\sigma^2}\right)$$

where σ is a smoothing parameter. The result of this activation function ranges between 0 and 1. As the distance $\|\mathbf{x}_j - \mathbf{x}_i\|$ between the input vector $\mathbf{x}_i$ and the vector $\mathbf{x}_j$ of the pattern node j increases, the output of node j will approach zero, thus designating the small similarity between the two data vectors. On the other hand, as the distance $\|\mathbf{x}_j - \mathbf{x}_i\|$ decreases, the output of node j will approach unity, thus designating the significant similarity between the two data vectors. If $\mathbf{x}_i$ is identical to $\mathbf{x}_j$, then the output

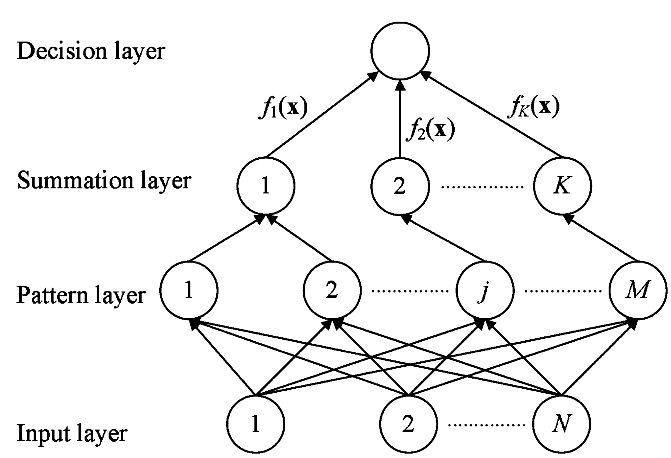

Fig. 1. Architecture of a probabilistic neural network.