Chapter X

Credit Scoring Using Supervised and Unsupervised Neural Networks

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Some of the concerns that plague developers of neural network decision support systems include: (a) How do I understand the underlying structure of the problem domain; (b) How can I discover unknown imperfections in the data which might detract from the generalization accuracy of the neural network model; and (c) What variables should I include to obtain the best generalization properties in the neural network model? In this paper we explore the combined use of unsupervised and supervised neural networks to address these concerns. We develop and test a credit-scoring application using a self-organizing map and a multilayered feedforward neural network. The final product is a neural network decision support system that facilitates subprime lending and is flexible and adaptive to the needs of e-commerce applications.

INTRODUCTION TO CREDIT SCORING

Credit scoring is a technique to predict the creditworthiness of a candidate applying for a loan, credit card, or mortgage (Hancock, 1999). The ability to accurately predict the creditworthiness of an applicant is a significant
determinant of success in the financial lending industry (Mester, 1997; Brill, 1998; Henley, 1995; Reichert, Cho & Wagner, 1983). Refusing credit to creditworthy applicants results in lost opportunity, while heavy financial losses occur if credit is given indiscriminately to applicants who later default on their obligations.

There are two basic components of a credit granting decision. The scorecard allocates points in relation to an applicant’s suitability for credit. For example, Fair, Isaac & Co.’s FICO credit score system uses past payment history, amount of credit owed, length of time credit has been established, and types of credit as variables upon which points are scored (Engen, 2000). Linear discriminant analysis is most commonly used for credit scorecard analysis. Non-linear techniques such as decision trees, expert systems, and neural networks are being investigated to increase the accuracy of credit prediction (Rosenberg & Gleit, 1994). The second component of the credit-granting process is the underwriter, an expert credit analyst who concentrates on the qualitative aspects of the decision. The best results are obtained when the recommendations from the scorecard and the underwriter are jointly considered.

The growth of credit scoring is increasing the access to credit of low-income and minority applicants (Anonymous, 2000). Prior to the advent of credit scoring, creditworthiness was based primarily on the underwriter’s decision. The subjective nature of the underwriter’s evaluation process could result in discrimination and ethnic bias. By contrast, a transaction-based credit scoring recommendation is more objective (Reotsi, 2000). The decision support provided by credit scoring enables the underwriter to reallocate time from routine decisions and focus on the evaluation of borderline or uncertain applicants, a market segment referred to as subprime lending. The higher margins associated with subprime lending are attractive to companies that have developed expertise in this segment (Anonymous, 2000a).

Recent advances in e-commerce and Internet-based transactions require real-time automated credit decisions. One of the first organizations to provide this service is eCredit, through their Global Financing Network system. This organization automates the entire credit approval process in real time, from accessing credit-bureau information to credit scoring and notifying applicants about decisions. In e-commerce, static scorecards rapidly become obsolete, creating a need to develop real-time and adaptive solutions. As a result, traditional statistical techniques are now being combined with advanced technology such as neural networks to provide models capable of understanding the multifaceted, non-linear interactions that exist among credit variables (Desai, Conway, Crook & Overstreet, 1997; Desai, Crook & Overstreet, 1996; Ryman-Tubb, 2000).
Online Methods for Portfolio Selection
Tatsiana Levina (2006). Business Applications and Computational Intelligence (pp. 431-460).
www.igi-global.com/chapter/online-methods-portfolio-selection/6036?camid=4v1a