

# Artificial Neural Networks Used in Automobile Insurance Underwriting

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## INTRODUCTION

As the heart of the insurance business, the underwriting function has remained mostly unchanged for nearly 400 years when Lloyd's of London was a place where ship owners would seek out men of wealth. The two would contractually agree to share the financial risk, in the unlucky event that the ship would be lost at sea (Gibb, 1972; Golding & King-Page, 1952).

Today, insurance underwriters perform a similar function on behalf of their respective insurance companies. Underwriters gathering pertinent information and analyze their potential clients to determine whether or not they should underwrite the risk; and if so, what premium they would require for the insurance policy. Insurance companies employ actuaries to help the underwriter in this process by studying past insurance losses and making predictive models for future risks. Using traditional statistical methods, insurance actuaries look for loss-contributing characteristics within the risk (Webb, Harrison et al., 1992). When the actuaries find positive relationships between the policy characteristics and subsequent losses, they create "underwriting guidelines" for the underwriters to follow, when analyzing potential clients (Malecki & Underwriters, 1986).

For hundreds of years, actuaries used pencil and paper to perform their statistical analysis; it was a long time before they had the help of a mechanical adding machine, still longer before they had computers. As recently as 1981, computers were not considered important to the underwriting process. Leading experts in insurance underwriting believed that the human-judgment factor involved in the insurance underwriting process was too complex for any computer to handle as effectively as a human underwriter (Holtom, 1981).

Recent research in the application of technology to the underwriting process has shown that Holtom's statement may no longer hold true (Kitchens, 2000; Lemaire, 1985; Rose, 1986). The time for computers to take-on an important role in the insurance underwriting judgment process may be here. The author intends to illustrate the applicability of artificial neural networks to the insurance underwriting process.

## BACKGROUND

The American Institute for Chartered Property Casualty Underwriters reports that the most common considerations found in automobile underwriting guidelines are: age of operators, age and type of automobile, use of the automobile, driving record, territory, gender, marital status, occupation, personal characteristics of the operator, and physical condition of the vehicle. Traditionally, these comprise the basic variables used in determining the acceptability, classifying, and rating of private passenger automobile insurance policies (Malecki & Underwriters, 1986).

Private passenger automobile insurance is well suited for artificial intelligence applications applied to the underwriting function. There are three primary reasons for this: there is a fixed set of finite data used to make the underwriting decision; policies are highly standardized; and deviations from the standard insurance contract are rare.

In recent years, researchers have considered the application of computers to the process of automobile insurance underwriting. Two studies attempted to predict the acceptability of a given policy from a broad underwriting standpoint (Gaunt, 1972; Rose, 1986). Two other studies considered the possibility of predicting a loss on an individual-policy basis (Lemaire, 1985; Retzlaff-Roberts & Puelz, 1966). Another study focused the relationship between premium and customer retention from year-to-year. One study was designed to predict losses on individual policies using artificial neural networks (Kitchens, 2000).

The recent use of artificial neural networks represents what may result in the most accurate application of computers in the underwriting process. Originally developed in the 1940's, artificial neural networks were designed to replicate and study the thought process of the human brain (Cowan & Sharp, 1988). Early research showed that all processes that can be described with a finite number of symbolic expressions could be represented with a finite number of interconnected neurons (Whitley, Starkweather et al., 1990). Thus, artificial neural networks also provide a means of economic problem solving.

The author believes that for a number of reasons discussed in the following section, artificial neural networks can be successfully applied to the insurance underwriting process in order to reduce the ratio of insurance losses to insurance premiums.

### NEURAL NETWORKS FOR INSURANCE UNDERWRITING

Artificial neural networks were first developed in the 1940's as a mathematical model used to study the human thought process (Cowan & Sharp, 1988). McCulloch and Pitts in 1943 proved that all processes which can be described with a finite number of symbolic expressions can be represented in a network of interconnected neurons (Whitley, Starkweather, & Bogart, 1990). This makes the artificial neural network a mathematical modeling tool in addition to a representation of the human brain.

Using a data set consisting of dependent and independent variables, an artificial neural network can be trained until it converges on an optimal solution for the dependent variable(s). If properly developed, the resulting model will be at least as accurate as traditional statistical models (White, 1989).

The insurance business, as practiced in the United States, has certain characteristics that produce less than optimal financial results. There are five basic reasons that the unique abilities of artificial neural networks can improve the underwriting process:

First, an artificial neural network model will be successful because the inequity of the current rate classification system will allow neural networks the opportunity to more accurately assess the risk level of each and every individual policy holder, rather than a class of policy holders (Wood, Lilly et al., 1984).

Second, an artificial neural network model will produce improved results because current actuarial methods of study will benefit from the broad range of available tools "such as more recent developments in the field of artificial intelligence (Cummins & Derrig, 1993; Kitchens, 2000).

Third, an artificial neural network model will improve the current state of actuarial research. Traditionally, the primary method of research in this field has been to predict the *pure premium* (the amount of premium required to pay all of the losses in a given class of insured accounts, a.k.a. "relative rates"). In comparison, *actual premiums* include the pure premium along with other important factors such as profit margin and operating expenses. The traditionally used pure premium models follow an actuarial approach, but not necessarily an underwriting approach. While it is intended to reduce corporate loss ratios, current actuarial

research does not take an underwriting approach to the process. A fresh perspective on the problem could produce improved results.

Fourth, an artificial neural network will produce improved results because historically, statistical models used in predicting insurance losses have been able to produce only marginal incremental improvements. Given the current state of technology, the time has come for new insurance actuarial models to take advantage of the available speed and flexibility of artificial neural networks to solve what is clearly a complex problem, which will require extensive training and is likely to involve a complex architecture (Kitchens, 2000).

Fifth, even if the actuarial models are "perfect" (which the author contends they are not), the neural network should be capable of at least matching the current statistical results, if not improving upon them. This is because artificial neural networks comprise a class of nonlinear statistical models whose processing methods are designed to simulate the functioning of the human brain (Hawley, Johnson et al., 1990). The advantage of neural network models over other modeling methods grows with the complexity of the relationship between input and output variables; however, greater complexity of the underlying relationships between variables requires a more complex design (Lee, White et al., 1993). Provided the appropriate network architecture, a neural network output function can accurately approximate any mathematical function (White, 1989). Further, a model can achieve any degree of desired accuracy if the neural network is properly designed (Funahashi, 1989).

### NEURAL NETWORK MODELS: DESIGN ISSUES

Automobile accidents occur with a certain degree of randomness, and it is expected that they will be very difficult to predict on an individual-policy basis. Previous research has shown that an underwriter's ability to predict the actual value of a paid claim is exceedingly difficult, if possible at all (Kitchens, Johnson et al., 2001). However, a successful system needs only to predict the incident (occurrence) of a loss, not the dollar value. In addition, a successful model would not have to predict each and every accident, as long as the predictions that the model makes are accurate. In fact, a new model needs only to outperform any current models, in order to prove its self worthwhile. As an industry rule-of-thumb, the average loss-to-gross-premium ratio is approximately 60%. The rest of the collected premium is used to pay operating expenses and a small profit of approximately 3%. Thus, if a new model could reduce losses by 1%, it would represent

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