

Underwriting Automobile Insurance Using Artificial Neural Networks

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INTRODUCTION

As the heart of the insurance business, the underwriting function has remained basically unchanged for the past 400 years, since Lloyd's of London was a place where ship owners would seek out financial supporters. 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 and King-Page, 1952).

In the modern insurance market, insurance underwriters perform a similar financial function on behalf of their respective insurance companies. Underwriters gather 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 assist 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 and setting premiums (Malecki and 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. Only recently have they had the benefit of computers. As recently as 1981, computers were not considered important to the process of insurance underwriting. Leading experts in insurance underwriting believed that the judgment factor involved in the 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 (Gaunt, 1972; Kitchens, 2000; Rose, 1986). The time for computers to take on an important role in the insurance underwriting process may be upon us. 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 (CPCU) reports that the most common considerations found in automobile underwriting guidelines are:

- age of operators;
- age and type of automobile;
- use of the automobile;
- operator's driving record;
- territory;
- gender;
- marital status;
- operator's occupation;
- operator's personal characteristics; and
- physical condition of the vehicle.

Traditionally, these comprise the core variables used in determining the acceptability, classifying, and rating of private passenger automobile insurance policies (Malecki and 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 and 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 to the underwriting process. Originally developed in the 1940s, artificial neural networks were designed to replicate and study the thought process of the human brain (Cowan and 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 (Wilson, 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 1940s as a mathematical model used to study the human thought process (Cowan and Sharp, 1988). In 1943, McCulloch and Pitts proved that all processes which can be described with a finite number of symbolic expressions can be represented in a network of interconnected neurons (Wilson, Starkweather, et al., 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 policyholder, rather than a class of policyholders (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 and 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 (Kitchens, Booker, et al., 2002).

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, 2004; Kitchens, Johnson, et al., 2001).

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 (Kitchens, Booker, et al., 2002). 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

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