A Logistic Diffusion Model of Extended Warranty Data

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Abstract. The extended warranty is very important for business investors for effective warranty planning. This study develops a mixed model based on logistic diffusion function and artificial neural networks. A logistic function or logistic curve is the most common sigmoid curve. It models the S-curve of growth of some set. The initial stage of growth is approximately exponential; then, as saturation begins, the growth slows, and at maturity, growth stops. A popular neural net element computes a linear combination of its input signals, and applies a bounded logistic function to the result; this model can be seen as a "smoothed" variant of the classical threshold neuron. A count of greenery warranty can be used as a reliable measure of extended warranty diffusion. Our study demonstrates that a mixed model, if properly calibrated, can create a very flexible response function to forecast the extended warranty claims.

Keywords: Extended warranty, Green warranty, Logistic model, Neural Network

1 Introduction

A Poisson model can be used to predict claims for a two attribute warranty by fitting the cumulative Poisson parameter with various functions of age and usage. It suggest a technique for modeling warranty claims as truncated data that assumes warranty claims follow a Poisson process [3]. Another method is to augment parametric warranty data models with selected observations from products whose lifetime exceeded the warranty period [6]. The model fits warranty claims as a mixture of manufacturing or assembly defects and usage related failures. This research suggests that manufacturers can develop richer statistical models for warranty data that provide better fits and additional feedback.

Logistic model is the most common statistical model for processing multivariate warranty data. Artificial intelligence model like an artificial neural network (ANN) may also be useful to interpret the warranty data [4, 5]. The purpose of this study is to perform an artificial intelligence model on the warranty data and compare to the logistic model. Data mining techniques such as ANN are used for predicting the extended warranty diffusion and to constitute the extended warranty decision rules. They may be an alternative to conventional multivariate warranty analysis.
2 Background

When considering the usual warranty issues, an important concept to keep in mind is the warranty chain. Like the supply chain for purchasing and manufacturing, the warranty chain extends the scope of warranty activities beyond the walls of a single company to encompass suppliers, manufacturers, OEMs, distributors, dealers, repair centers, policy carriers, and customers. Parts return or Return Merchandise Authorization (RMA) covers the request, receipt, diagnosis, and repair of broken parts removed as part of repair work or replacement covered under warranty [1].

Warranty diffusions make two key assumptions regarding the phenomenon. First, the existing number of warranty claims positively drives the rate of warranty growth. Second, the difference between the potential number of warranty claims at the saturation level and the number of existing warranty also influences the rate of growth. Traditionally, diffusion has been specified by three basic models: internal-influence, external-influence, and mixed-influence. Mixed influence model represents both internal and external influences in the growth process, \[ \frac{dC}{dt} = (p + qC)(k - C), \]
where \( k \) is the potential number of warranty claims, \( C \) is the cumulative number of warranty claims at time period \( t \), \( p \) is the coefficient of external influence, and \( q \) is the coefficient of internal influence. Logistic model leads to the form, \( C_t = \frac{1}{k+ab^t} \). For \( a>0 \) and \( 0<b<1 \), \( C_t \) is an increasing S-curve which reaches the upper bound or the saturation point of \( \frac{1}{k} \) as time \( t \) approaches its theoretical limit of infinity. This curve reaches its inflection point at \( C_t = \frac{k}{2} \). That is, the inflection point occurs when \( C_t \) reaches 50% of its saturation level [2].

3 Development of Logistic Neural Network

In this study, the neural network is modified to do the warranty identification using the logistic function. One is to create a logistic neural network, and the other is to use the logistic neural network, which are described below. The output of the hidden nodes are fed into the output nodes, multiplied by the output node weights, \( W \), to yield the predicted targets, \( w_i = z_iw \), where \( i \) is the number of output units. Once this function is performed, it is necessary to add in the logistic phase which produces a normalized value used to perform the identification process, \( g_i = \frac{\exp(w_i)}{\sum \exp(w_k)} \), where \( k \) is the number of classes. Next the differences between the predicted and actual class indicator values are computed. These differences are then summed, that is, \( d = \sum t_k \ln g_k \). When building a neural network, one area of concern is appropriately sizing the hidden node layer. The decay term is also included in the gradient functions computed for the weights in each layer. Weight decay is computed as \( \lambda \cdot (\text{weights})^2 \). Once \( d \) is computed and the weight decay is subtracted, the negative of this difference is returned since we are trying to minimize the difference. Another function is to compute the gradient for the weights in the current iteration of the model.

\[
\nabla v = -\frac{1}{NK} (\bar{e} \sum (t_k - g_k) (\bar{w}) (1 - z^2) + \lambda \cdot \bar{w})^2 (1)
\]
Here $N$ and $K$ are the number of warranty claims and the number of warranty attributes, respectively. Once the scaled conjugate gradient descent algorithm has converged it returns the hidden and output weights. These weights are unpacked and, together with the standardize function and the results of the scaled conjugate gradient descent algorithm are returned to the calling routine.

4 Results and analysis

Results of the data used in the analysis of the components of the vehicle exhaust system fault data set was used. It is an iterative algorithm; it starts with a guess at the parameter vector $w$, and it solves a weighted least squares problem to find a new parameter vector. The root mean square error (RMSE) of fitting the logistic model with the IRLS algorithm was 250.9067. An inspection of the two-way warranty count data (Figure 1) showed that the logistic model indicates the inferior generalization power. Applying a multi-layered perceptron neural network model to predict the actual warranty amounts on the same calibration sample, the RMSE was 69.9357. Three layers of MLP neural network were used; one input layer for input variables (months and mileage), one hidden unit layer, and one output layer. Five units were used in the hidden layer. The NN model has the much smaller RMSE (69.9357) than that of the logistic model (250.9067) in the calibration data. It was evident that the NN forecasts are superior to logistic forecasts. However, the logistic NN model was the best (RMSE: 59.6052). The logistic NN model converged after 21 epochs with the objective function (sum of the absolute deviations among sample points) value of approximately 0.008 (see Figure 2).

5 Conclusion and Future Work

This paper makes a contribution to the extended warranty research by suggesting a
novel approach to model its diffusion. Our approach will be useful for most other extended warranty modeling studies in the future as long as there is some theoretically informed argument that external influence is suspected. The model development can be further enhanced by the simulation-theoretic approach. The theory of neural networks provided the architectural reason why NN models are more apt to capture non-linear complexities. Neural networks performed better in this case, enabling us to argue that any warranty diffusion that has significant external effects such as green warranty will be expected to benefit from this approach. The finding that extended warranty, influenced by environmental issues, should be modeled as a logistic neural network model is an important and new step in warranty research.

References