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A Logistic Neural Network Approach to Extended Warranty Claims

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Abstract

An extended warranty, sometimes called a service agreement, a service contract, or a maintenance agreement, is a prolonged warranty offered to consumers. Studying the extended warranty is extremely important for business investors and policymakers for effective warranty planning. However, measuring, forecasting and tracking the global diffusion of extended warranty have not been researched. This study uses model based on the knowledge of traditional diffusion theory as well as artificial neural networks. Additionally, it integrates the two into a hybrid model in order to study extended warranty growth. A count of greenery warranty can be used as a reliable measure of extended warranty growth in all the models. Our study demonstrates that a logistic Neural Network model, if properly calibrated, can create a very flexible response function to forecast the extended warranty claims. The logistic neural network successfully modeled both the usual and environmental influences in the warranty data, while the traditional formulation could only model the usual warranty claims. Logistic, artificial neural network and logistic neural network analysis are carried out on the green warranty presenting to a warranty repair department.

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

1. Introduction

An extended warranty is coverage for electrical or mechanical breakdown. It usually does not cover peripheral items, wear and tear, and damage by computer viruses, re-gassing, normal maintenance, accidental damage, or any consequential loss [2][3]. Also the extended warranties cost extra and for a percentage of the item's retail price. In retail consumer electronics, extended warranties cost 20% to 30% of the price, and give sales associates up to 15% commission at some retailers [1]. When considering the usual warranty system, it is often important to consider both the age of the system (that is, the time since it was introduced into service) and its cumulative usage, measured according to some specified variable. Notable in this context are North American automobile warranties, which have age and distance limits for specific systems on the vehicle, for example 3 years and 36,000 miles.Oh and Bai present a method for augmenting parametric warranty data models with selected observations from products whose lifetime exceeded the warranty period [9]. To make inference on product features or design changes, the authors suggest stratifying data or making model parameters a

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function of covariates. Unfortunately, none of these models differentiate between failure types or provide feedback or assessment of supporting business processes. Majeske suggests a general mixture model framework for automobile warranty data that includes parameters for product field performance, the manufacturing and assembly process, and dealer preparation process [7]. The warranty modeling techniques cited above fit warranty data using the parametric techniques. Parametric methods of warranty analysis require specification of a probability density function for estimating the warranty related functions. The vast amount of warranty claims recorded by the product dealers makes the statistical process of analyzing this data hardly feasible. Researchers have recently applied new nonparametric models for the warranty analysis, such as neural networks and fuzzy logic [5, 6]. 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 [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. Extended Warranty Processing

When considering the usual warranty issues, an important concept to keep in mind is the warranty chain. In figure 1, Supplier recovery is the recuperation from suppliers of costs for warranty claims when covered supplier parts cause the malfunction.Quality improvement with the warranty process consists of analyzing warranty problems to eliminate future costs through changes in design and manufacturing. If an operation doesn't have a system in place that measures the impact of quality improvements on costs, this is the hardest area of warranty activity to measure cost savings. Dealers and repair centers refer to the entry and submission of claims as well as logging of all repair work covered under warranty.

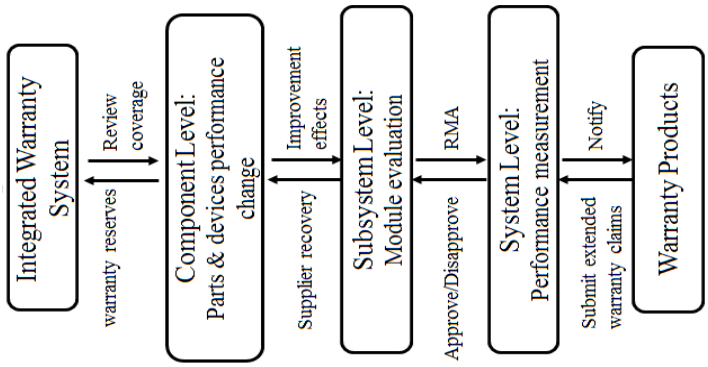

Figure 1. Extended Warranty Processing

Next step is composed of the repair work or replacement in the component level, and reserved the warranty data such as age and usage in the warranty database. Some replacement or repaired parts are again tested in the sub-system levels. These warranty works are corresponding to the Parts Return or RMA (Return Merchandise Authorizations). Since the results of RMA work give effect to the overall system, many

tests are needed as a whole. In the sub-system and component levels, the warranty data analysis is corresponding to a knowledge base system. The reason is that many uncertainties are existed and some qualitative evaluations are required by the expertise.

The remaining levels above the sub-system are connected to some warranty degree determination. An approximate reasoning method can be used for such warranty degree determination since the exact warranty degree determination is difficult. The reason is that there are many qualitative factors such as seasonality and assembly skills. Further, it is required the multidimensional analysis considered both the age and usage variables.The extended warranty generally does not progress in a smooth linear fashion. 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, $dC_t / dt = (p + qC_t)(k - C_t)$, where k is the potential number of warranty claims, C_t 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, $C_t = 1/(k+ab^t)$. For $a>0$ and $0<b<1$, C_t is an increasing S-curve which reaches the upper bound or the saturation point of $1/k$ as time t approaches its theoretical limit of infinity. This curve reaches its inflection point at $C_t=k/2$. That is, the inflection point occurs when C_t reaches 50% of its saturation level.

Even though these approaches cover the situation in which in the same decision table some missing attribute values are considered to be lost and other are "do not care" conditions, there exist many other possibilities to interpret missing attribute values. For example, for the attribute A2from the above example, we may introduce a special value 3, for case 2 and we may consider that the missing attribute value for case 5 should be 2.

3. Missing Treatment by Variation Relations

A neural network is a configuration of multiple layers of linear and non-linear functions which each feed into one another in a chosen order [4]. There are weights at each layer of the network which are all updated via a feedback process during a training phase. In this paper, only one “hidden” layer is defined along with one output layer.

The hidden layer in this case utilizes the hyperbolic tangent function while the output layer is linear. This is how neural networks can be using for regression of a continuous output. In this study, the neural network is modified to do the warranty identification using the logistic function. A logistic layer is added at the end of the process. In other words, the outputs from the linear layer are fed into a logistic layer to identify the warranty claims. Thus, the probability p_{nj} for class j is determined by the following formula for the outputs w_{nj} of the linear layer for a particular sample n.

$$p_{nj} = \exp(w_{nj}) / \sum_k \exp(w_{nk}) \tag{1}$$

Predictions of the actual warranty amounts of a specified input set are simple matrix operations. To perform the feedback during training of the network, two functions are required; one which is the function to be minimized - the negation of the likelihood of the warranty data - and two, the gradient of the negative likelihood to assist an optimization algorithm in determining which direction to descend next. We're

descending the negative likelihood which results in maximizing the likelihood. In order to develop and use the logistic neural network, two functions are needed. One is to create a logistic neural network, and the other is to use the logistic neural network, which are described below. In order to develop a logistic neural network, there are a number of steps that must be accomplished. It accepts several inputs which are needed to perform the process of developing the logistic neural network: Input warranty data, Actual warranty claims, Number of hidden nodes, Decay weight parameter, Number of iterations to be performed in minimum error search, Two precision values used by the function performing minimum error search, Logical value to determine which function is used to perform minimum error search. The input warranty data regularly standardized in all experiments which means to subtract the mean of the data and divide by the standard deviation. Once the warranty data is standardized, the initial values of the weight matrices, V and W, which are set to random uniformly distributed values between -0.01 and 0.01.

One is to compute the difference between the actual and predicted warranty based on the current iteration of the model. The current weight values are provided and unpacked. The output of the hidden nodes are computed based on the V weights and standardized inputs (plus bias) using the hyperbolic tangent function, $z_j = h(vx)$, where j is the number of hidden nodes and the activation function is $h(a) = tanh(a)$. The output of the hidden nodes are fed into the output nodes, multiplied by the output node weights, W, to yield the predicted targets, $w_i = z_j w$, 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, $g_i = exp(w_i)/\Sigma exp(w_k)$, 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, $d = \Sigma t_k(\ln g_k)$.When building a neural network, one area of concern is appropriately sizing the hidden node layer. How many hidden units are needed? Should too few hidden nodes be used, the model will not be able to deal with complicated problems. Should too many hidden nodes be used, the model will over fit the training data and actually produce a larger error for the test and validation data sets. A counterbalance to the model over fitting the data is a technique called weight decay. It decays the computed weights towards 0. When the difference between the predicted and actual classifications is computed, the sum of the squares of the weight is included, thereby biasing the squared error to be larger. This will have the effect, hopefully, of tamping the weights towards 0. The decay term is also included in the gradient functions computed for the weights in each layer. Another benefit of weight decay is that it aides in weeding out noise from the data to be modeled. The weight decay is computed as $\lambda*(\text{weights})^2$. 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. In a similar fashion to the above function, it is provided with the weights. The weights are unpacked into the hidden weights, V, and output weights, W. The weights are used along with the standardized inputs to compute the predicted target classifications as well as the difference between these and the actual target indicator values. This difference is then fed into the gradient computations. The variables with tildes are that parameter with the bias column added and the weights, v and w are all the weights including the bias weights while the variables with the hat indicate that the bias has been removed (one less value than the un-hat variable).

$$\nabla v = -\frac{1}{NK}(\tilde{x}_s)^t \sum_k (t_k - g_k)(\hat{w})^t (1 - z^2) + \lambda v^2 \quad \textbf{(2)}$$

$$\nabla w = -\frac{1}{NK}(\tilde{z}_s)^t \sum_k (t_k - g_k) + \lambda v^2 \quad \textbf{(3)}$$

Here, N and K are the number of warranty claims and the number of warranty attributes, respectively. Notice that the computation of the v gradient removes the bias weight. This is necessary since the output node weights, w, has one more row (due to the bias weight) than output nodes. 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.

Once this function is called, it will start by standardizing the input warranty claims using the standardize function developed for the warranty data during the creation of the model. After this, the bias column will be bound to the input data. Then a forward pass through the model will be executed, first through the activation function of the hidden layer, then through the output layer and finally through the logistic layer. This processing will result in a set of indicator values which are the predicted class probability for each input sample. Once this processing is complete, the predicted probabilities, and the output of both the hidden and output nodes are returned. The hidden and output layer outputs are returned to facilitate debugging as needed. This function must be invoked multiple times once the model is developed.

4. Results and Analysis

Most often automotive warranty is specified in terms of {*Tmax, Mmax*} with *Tmax*being a specified maximum time period and *Mmax*a specified maximum mileage. All new cars come with a warranty that cover repairs for a certain period of time and a certain number of miles, such as 3 years and 36,000 miles. Table 1 provides a summary table for the warranty amounts analyzed in the exhaust system. This table is based on actual warranty claims reported about total type cars during recent years in automotive company, South Korea. The exhaust system is composed of automobile parts in connection with emission controls, yet most motorists do not even know they have one or more of these devices on their vehicle - let alone what it does. For instance, the only time most people even become aware of exhaust an oxygen sensor's existence is if they get a check engine light and there is a code that indicates an O_2 sensor problem their vehicle fails an emissions test because of a sluggish or dead O_2 sensors. The logistic model is an example of a generalized linear model. Therefore, the iteratively-reweighted least squares (IRLS) algorithm can be used to fit the logistic model. The IRLS algorithm is Newton's method applied to the problem of maximizing the likelihood of some outputs y given corresponding inputs x. It is an iterative algorithm; it starts with a guess at the parameter vector w, and on each iteration it solves a weighted least squares problem to find a new parameter vector.The logistic model is an example of a generalized linear model. Therefore, the iteratively-reweighted least squares (IRLS) algorithm can be used to fit the logistic model. The IRLS algorithm is Newton's method applied to the problem of maximizing the likelihood of some outputs y given corresponding inputs x. It is an iterative algorithm; it starts with a guess at the parameter vector w, and on each iteration it solves a weighted least squares problem to find a new parameter vector.The parameter estimates for the logistic model with two independent variables are -1.9591, 0.0144, and -0.0349. Thus, the logistic model of fitting two-attribute warranty data is

$p_{ij}/(1-p_{ij})) = \exp(-1.9591 + 0.0144*\text{Months} - 0.0349*\text{mileage})$, where p_{ij} is the cell ratio in two-way warranty table.

Table 1.Two-way Warranty Data

Time (Months)	Usage (Mileage: 100km) 100~105	105~110	110~115	115~120	120~125	125~130	130~135	135~140	140~145	145~150	150~	Total
3	2	2	0	1	0	0	0	0	0	0	0	5
6	3	0	1	1	1	0	0	1	0	0	0	7
9	1	1	0	1	0	0	0	0	0	0	0	3
12	4	0	1	0	1	0	0	0	0	1	1	8
15	0	3	0	3	1	0	0	2	1	1	0	11
18	2	1	0	1	0	0	0	1	0	0	1	6
21	1	1	2	0	1	0	0	1	0	0	0	6
24	1	0	1	0	0	2	0	0	0	0	0	4
27	1	0	2	0	2	0	0	0	0	0	0	5
30	5	2	2	0	0	1	0	1	0	0	0	11
33	3	3	0	1	1	1	2	1	0	0	0	12
36	16	11	12	5	7	4	5	1	0	2	1	64
39	46	26	29	21	20	11	5	14	6	9	6	193
42	45	40	31	23	23	14	21	7	10	9	7	230
45	77	54	47	39	28	33	17	13	16	12	7	343
48	84	72	58	73	55	37	42	31	19	19	15	505
51	134	99	83	73	65	41	39	30	27	20	21	632
54	110	78	76	65	40	35	34	35	20	20	22	535
57	55	36	38	22	31	24	19	27	14	23	10	299
60	33	26	25	17	20	23	17	15	11	10	10	207
63	29	21	21	16	10	10	7	14	5	6	8	147
66	13	11	13	6	6	4	4	2	6	6	2	73
69	7	5	11	5	4	3	4	5	4	1	3	52
72	3	2	5	6	3	3	1	3	1	4	0	31
75	1	3	7	2	3	3	3	3	2	2	1	30
Total	676	497	465	381	322	249	220	207	142	145	115	3419

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 2) 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. One output unit was used in the output layer. The input node was connected to all the hidden nodes to represent the values of the target variables. The hidden nodes were in turn connected to the output node. The NN model converged after 32 epochs with the objective function (sum of the absolute deviations among sample points) value of approximately 0.01. The NN model has the much smaller RMSE (69.9357) than that of the logistic model (250.9067) in the calibration data (see Figure 3). It was evident that the NN forecasts are superior to logistic forecasts. However, the logistic NN model was the best (RMSE: 59.6052).

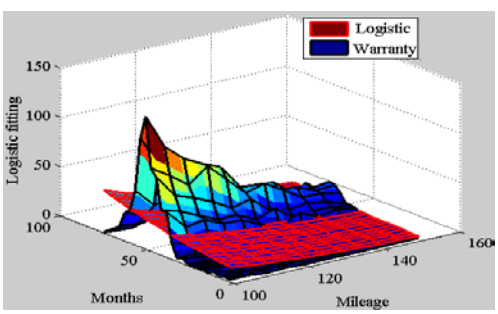

Figure 2. M Inferior Generalization Power of Logistic Model

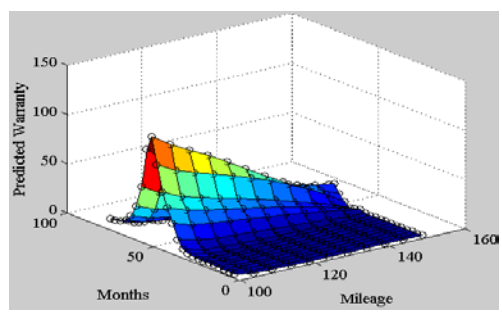

Figure 3. NN Model Fitting

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.

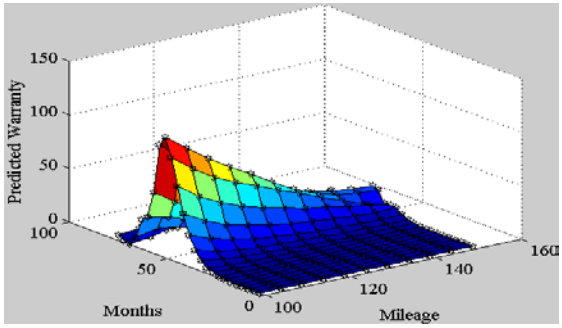

Figure 4. Logistic NN Fitting

In summary, the results indicate that the NN model is superior to the logistic model in forecasting the two-way warranty problem. The logistic NN model performed the best of all. The results seem to support the argument that the more flexible approach of a neural network model is better than the conventional models for forecasting the warranty amounts, especially when there is cause to believe that external factor such as green warranty perturb the pure warranty claims. However, this represents the results from one actual dataset. The validation of the current study must be further strengthened by conducting a simulated experiment that compares the models across various warranty datasets that are created to systematically examine the effects of different types of disturbances in the warranty data.

5. Conclusion and Future Work

This paper makes a contribution to the extended warranty research by suggesting a novel approach to model its diffusion. The mathematical models that fit S-curves to the extended warranty data thus essentially treat external perturbations as random error. These random errors reduce the accuracy of the forecasts of these models. 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. Similar contributions helped guide future research in other fields. For future research in extended warranty, this means setting up experiments that are designed to separate the influence categories, identify the specific factors within each, and study their relative contributions to the growth phenomenon.

Acknowledgements

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