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# Structured Neural Network Techniques for Modeling Loyalty and Profitability

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## ABSTRACT
Customer satisfaction and customer loyalty are related to key measures of financial performance for firms. The ability to find key drivers for predicting loyalty and profitability is an important step in developing marketing strategies that lead to high quality, long-term relationship with customers. Traditional techniques for modeling the network of cause-and-effect relationships related to loyalty and profitability such as structural equation models and partial least squares lack the capability of fitting the nonlinear and asymmetric relationships naturally existing in the loyalty-profitability network. This article presents a new technique namely structured Neural Network (SNN) technique for modeling loyalty and profitability and demonstrates an application for a chemical company.

## 1. INTRODUCTION
The long-term success of any business depends on providing customers with value and satisfaction that will influence them to repurchase and grow together. Reichheld and Sasser (1990) identified numerous bottom line benefits of customer retention. Loyal customers, they found, not only purchase more, but will pay higher prices, are easier to service (thus reducing operating costs), and help to expand the customer base by giving positive referrals. Retention in the chemical industry manifests itself in maintaining high quality account share as well as tiding the storm in the everpresent price cycles that plague the industry.

Recent research findings have confirmed that customer satisfaction and customer loyalty are related to key measures of financial performance, including but not limited to retention. Building and enhancing long-term relationships with customers generates positive returns to a company (Garbarino and Johnson 1999; Grossman 1998); increased sales, lower costs, and more predictable profit streams are some of the tangible benefits to the company of having loyal customers (Bejou and Palmer 1998; Terrill et al. 2000). Customer loyalty has also been documented as a source of competitive advantage and a key to firm survival and growth (Bharadwaj et al. 1993; Reichheld 1993; Reichheld, 1996; Terrill, 2000 ).

The marketing literature also suggests that different customer segments may place different levels of importance on product and service attributes, and that for different segments attribute may have more or less impact on predicting satisfaction, loyalty, and retention. For example, Mittal and Katrichis (2000) argue that newly acquired and loyal customers should be treated as distinct segments. They present three case studies from the automotive, mutual fund, and credit card industry to show that attribute importance varies significantly between these two segments. As pointed out by Anderson and Mittal (2000) that failure to consider segment-specific differences may lead a firm to optimize performance on the wrong attribute for a given segment.

This article presents a case study for modeling loyalty and profitability for a company in the chemical industry, which will be named as Company A through out the article. The complete modeling process for this project included three stages which spanned several years of elapsed time and was conducted by three different research teams. The first stage was to establish the network of the cause-and-effect relationships in the individual business study specifically for the attitudinal or performance portion of the performance-satisfaction-loyalty-profitability chain. This stage was completed and the results were reported in Rey and Johnson (2002) and Rey (2002). The second stage was to model the same basic Loyalty construct as in the first stage, but used customer attitudinal performance data, perceived values, satisfaction, image and customers' characteristics across the accumulation of 40+ individual business studies spanning four years. This article focuses on this second stage. The third stage was to model profitability using the structure discussed in the stage two herein as well as a variety of internal data including employee satisfaction, market orientation, and other financial data. Stage three was conducted within Company A using a similar technique proposed in stage two.

The technique developed for the second stage modeling is a neural network technique, namely, structured neural network (SNN). Section two discusses the motivation behind the development of the SNN technique for modeling the loyalty-profitability chain. Section three discusses the SNN technique. Section four presents the strategies for building the SNN model to model the loyalty data for Company A. Section five summaries the results and gives a brief discussion. A brief conclusion and remarks about the SNN techniques is discussed in section six.

## 2. LOYALTY-PROFITABILITY FRAMEWORK

There is a long history of development of the loyalty and profitability framework in the marketing research literature (e.g., Dick and Basu, 1994; Oliver, 1994; Oliver, 1997; Gustafsson and Johnson, 2000; Gustafsson and Johnson, 2004). The loyalty framework developed by Company A in stage one is given in Figure 1. For the purpose of modeling the loyalty construct in stage two, the same model shown in Figure 1 was adopted. The complete loyalty-profitability framework adopted in stage three also includes loyalty pseudo-behavior and financial components, which is given in Figure 2.

**Figure 1: Loyalty Intention Framework Adopted for the SNN Model in Stage Two**

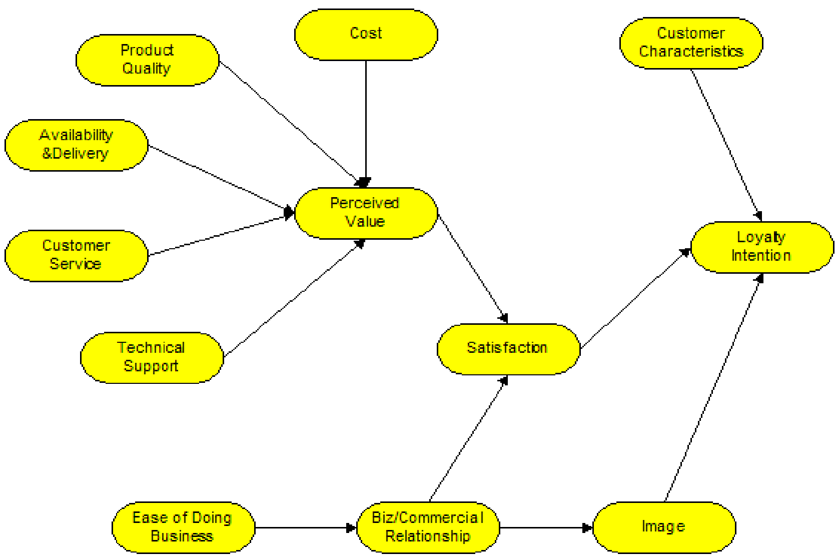
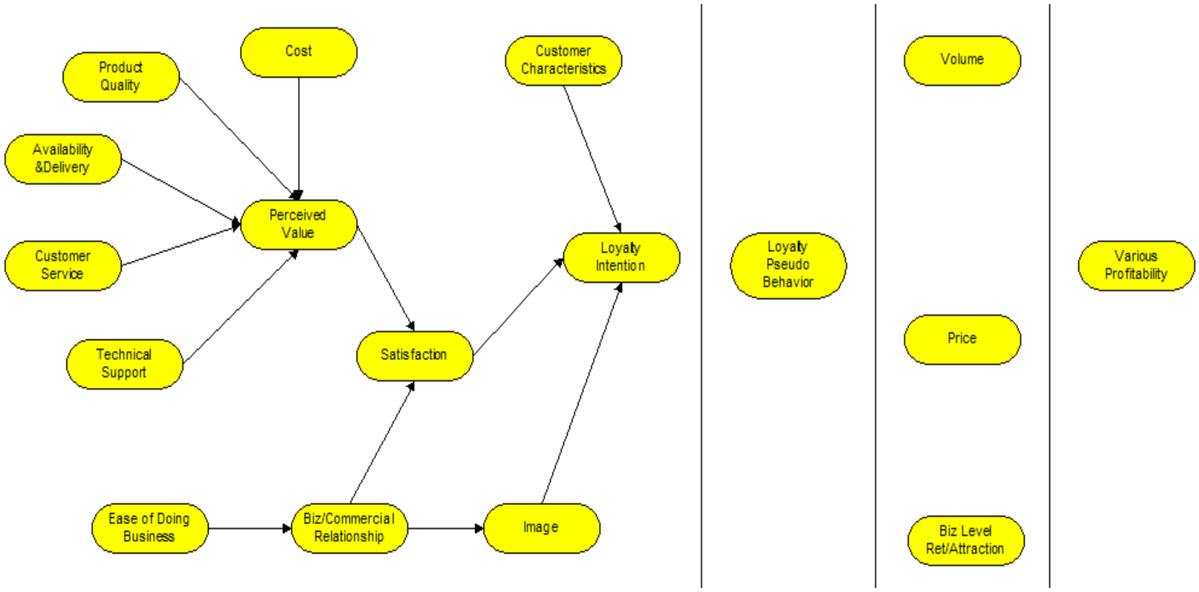



**Figure 2: The Complete Loyalty-Profitability Framework Used in Stage Three**




A brief description of the conceptual complete model shown in Figure 2 will now be presented. Consistent with the literature, customer perceptions of product and service attributes (technical support, customer service, availability and delivery, product quality, and cost) lead to customer perceptions of value. In turn, perceived value, ease of doing business, and the business relationship influence and predict customer satisfaction. Loyalty intentions (intentions to repurchase and recommend) are predicted by the firm's perceived image in the marketplace, customer characteristics (type of buyer, type of firm, etc.), and their current level of customer satisfaction. Loyalty intention predicts loyalty behaviors, which in turn affects the customer's purchase volume, level of price sensitivity, and retention. Various profitability measures are directly predicted by these variables.

### 2.1 THE DIMENSIONALITY OF LOYALTY CONSTRUCT

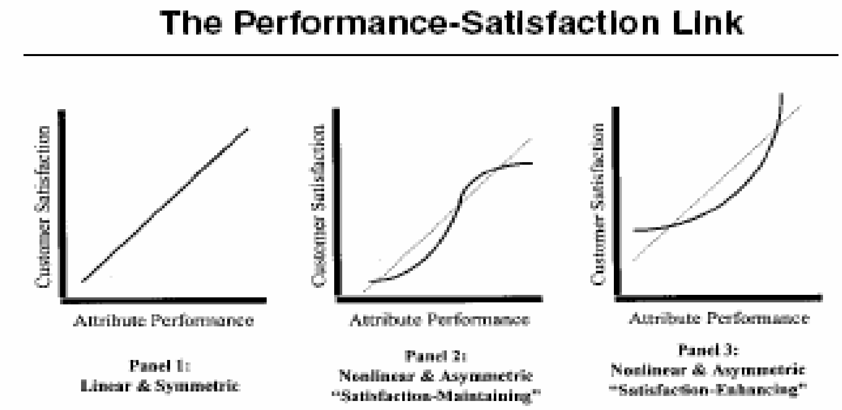
When attempting to model loyalty based on a theoretical framework, it is necessary to address the dimensionality of the loyalty construct and to efficiently apply the SNN. A number of research initiatives have focused on investigating the conceptual domain of the loyalty construct (e.g., Bloemer et al. 1999; Butcher et al. 2001; Gustafsson and Johnson, 2000). It has been conceptualized in a number of different ways including: as a behavioral outcome (e.g., Bansal and Taylor 1999; Sharma and Patterson 2000); as a two-dimensional construct that includes both repurchase behavior and a relative attitude towards the provider (e.g., Dick and Basu 1994; Pritchard et al. 1999); or as a three-dimensional construct that includes a behavioral, attitudinal, and a cognitive component, the latter reflecting consumers' brand beliefs and exclusive consideration of one service provider (e.g., Bloemer et al. 1999; de Ruyter et al. 1998). In Jones and Taylor's (2003) study, they found the two-dimensional construct: behavior dimension and the combined attitude/cognitive dimension is a better construct for describing loyalty for the service industry. In our study of a chemical industry customer base, a similar two-dimensional construct is also conceptualized for loyalty. The two-dimensional conceptualization is congruous with the predominance of literature in psychology that focuses on "pro-relationship maintenance acts" (e.g., Rusbult et al. 1999), suggesting that loyalty captures, in essence, what Oliver (1999) referred to as "what the person does" (behavioral loyalty) and the psychological meaning of the relationship (attitudinal/cognitive loyalty). In an industrial B2B setting, Company A has shown as well that the attitudinal aspect of loyalty is often a better predictor of financial impact. (Rey, 2004).

### 2.2 THE NEED FOR NEW TECHNIQUES FOR MODELING LOYALTY AND PROFITABILITY

Traditional techniques for modeling loyalty and profitability include multiple regression with interactions, principle component regression, structural equation modeling (SEM) and partial least square (PLS) techniques. Gustafsson and Johnson (2004) compared multiple regression, partial least square and principle component regression techniques for three different service industries. They suggested that one should not solely rely on one technique until they are carefully compared. This is mainly due to the fact that the modeling structure and the underlining assumptions are different and serve for different purposes. Strengths of these traditional techniques include (1) parameter/weight estimates are more easily interpreted, (2) easy to construct, and (3) in most cases, confidence level and hypothesis testing can be performed. The weakness of these techniques include (1) inability to model nonlinear relationship between inputs and targets, (2) inability to model higher order interactions effectively, (3) require distribution assumptions such as normality, and (4) inability to effectively model large amounts of messy data..

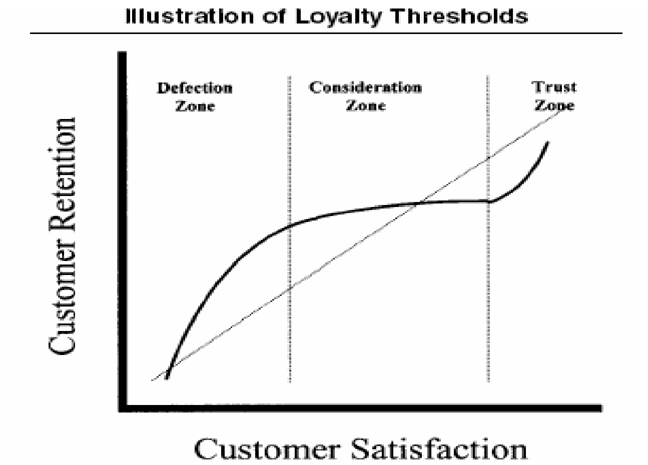
Anderson and Mittal (2000) gave a thorough discussion about the nature of nonlinearity and asymmetry in the chain relationship between attribute performance, satisfaction, loyalty and profit, and showed that the relation between each link often is nonlinear and asymmetric. For instance, the relationship between attribute performance and satisfaction can be one of the three relations as shown in Figure 3. The relation between satisfaction and retention is often nonlinear as shown in Figure 4. Increase of satisfaction for customers in the Trust Zone will significantly increase retention, while a small decrease of satisfaction for customers in the Defection zone tends to drive a significant reduction in retention.

**Figure* 3**




*: From Anderson and Mittal (2000)

**Figure * 4**




*: From Anderson and Mittal (2000)

Similar evidence is also found in a variety of industries such as health care ((Mittal and Baldasare 1996), airlines and telephone directory service (Danaher 1998), automotive (Mittal, Ross, and Baldasare 1998), and business-to-business marketing (Kumar 1998).

In the Chemical industry, similar nonlinear and asymmetric relationships also exist based on exploring the Company A's data. In particular, the non-linear relationship between attribute performance and loyalty as shown in Figure 4 is evident in Company A's data. Marketing literature has suggested that many marketing characteristics such as customer's satisfaction, retention rates, and profit measurements do not follow a normal distribution. In addition, the fast growth of data collected by firms not only results in a complex and messy data structure but also in a large amount of data. The traditional statistical inference and hypothesis testing may no longer be appropriate in these situations. In various data mining literature (e.g., see, Hand, et, al, 2001; Hastie, 2001; Riply, 1996) a variety of techniques have been developed for dealing with problems involving large amounts of non-normal, nonlinear, and messy data.

## 3. THE PROPOSED NEURAL NETWORK TECHNIQUES FOR MODELING LOYALTY AND PROFITABILITY

A key feature of the loyalty-profitability chain models (Figure 1 and 2) is that the attribute performance, satisfaction, loyalty and financial constructs in the models are inherently abstract or latent variables. Statistical techniques for modeling loyalty and/or profitability need to accommodate the fact that the model is a network of cause-and-effect relationships (as from quality, to satisfaction, to loyalty, to profitability) that contains latent variables. Traditional SEM and PLS techniques are natural choices for modeling such a network of cause-and-effect relationships. (e.g., see Johnson and Gustafsson, 2000; Hahn, et al, 2002; Gustafsson and Johnson, 2004) However, the weaknesses mentioned above have caught the attention of various researchers. Alternative modeling techniques have been developed to deal with these drawbacks. For instance, Hahn, et al (2002) proposed a mixture PLS model for taking into account the difference of business segments. Ansari, et, al. (2000) proposed a hierarchical Bayesian methodology for treating heterogeneity in structural equation models. Hruschka (2001) applied a one hidden layer neural network to model net attraction.

The following question was asked when attempting to model the loyalty and profitability for Company A:

> *"Is it possible to model the network of cause-and-effect relationships, pre-determined by a theoretical framework for loyalty and/or profitability by taking into account the nature of nonlinear and asymmetric relationships without the assumptions such as normality and homogenous variance for large and messy data?"*

A nonlinear SEM or PLS model would take care of the nonlinear and asymmetric relationships. However, it still leaves the assumptions and the issue of large and messy data unsolved. The technique proposed for this modeling problem is called a 'Structured Neural Network" (SNN) technique. The idea is to construct a neural network system that mimics the hypothetical network of cause-and-effect relationships for loyalty and profitability based on the existing theoretical framework. The major advantage of a neural network technique is that it is a universal approximator (Riply, 1996) for any type of function. However, since the weight estimates of the neural network model are not meaningful for interpreting the impact of the inputs (or independent variables), it has been criticized as a 'Black Box' approach. Therefore, in the development of the structured neural network system, some strategies are implemented to deal with the issue of validity of the technique.

**3.1 A BRIEF REVIEW OF THE BASIC NEURAL NETWORK TECHNIQUE**

A neural network (NN) can be considered as a two-stage nonlinear or classification model, usually represented by a network diagram. Multiple linear regression, logistic regression and generalized linear models are some commonly used special cases. The two-stage process is, first, to derive a hidden layer of variables through a nonlinear function acting upon the linear combination of the inputs: $H_{i.} = g\left(Z'X_{i.}'\right),\ i = 1,2,\ldots,N$ , where g is the activation function and $Z$ is the weight matrix of the inputs. Additional layers can be derived using $H_{i.}$ as inputs to create two or more hidden layers. Commonly used activation functions are: Hyperbolic tangent: $\tanh a = \left(e^{a} - e^{-a}\right)/\left(e^{a} + e^{-a}\right)$ , Logistic function: $1/\left(1+e^{-a}\right)$ , Arctangent function: $\left(2/\pi\right)\tan^{-1}\left(a\right)$ and Elliott function: $a/\left(1+|a|\right)$ . The target $Y_{i.}$ is modeled as the function of the linear combination of $H_{i.}$ defined as $Y_{i.} = f\left(W'H_{i.}'\right)+\varepsilon$ , where $f$ is the activation function connecting hidden layers with the targets. The function $f$ can be taken the same as $g$ or as an identity function. If f is taken as an identity function, Y is a linear combination of H.

In modeling with a NN model, one usually normalizes both targets and inputs to eliminate the problem of different units and magnitudes among the variables. The Backpropagation algorithm is one of the earlier techniques developed to estimate the weights. Many alterative algorithms have been developed (Ripley,1996). Most algorithms for estimating the weight matrices $Z$ and $W$ minimize certain objective functions, which are defined as the functions of the difference between the observed values $Y$ and predicted values $\hat{Y}$ . For detailed description of algorithms, one may refer to Fausett (1994) or Ripley (1996).

**3.2 THE STRATEGIES FOR BUILDING AN SNN MODEL FOR MODELING THE LOYALTY FRAMEWORK**

The following strategy is applied to build a structured neural network model for fitting the theoretical framework of cause-effect relationship.

(1) Network Identification: The framework in Figure 1 is used as the underlying network for building the SNN model in the stage Two modeling. Each node in the SNN model represents a latent variable in the framework. The layout and the number of hidden layers are determined by the framework itself. For example, the Product Quality, Cost, Customer service, Availability/Delivery and Technical Support are the nodes for the first hidden layer, which are the inputs for the second hidden layer “Perceived Value”. The “Ease of Doing Business” is also a first Hidden Layer, which is the input for “Biz/ Commercial Relation. The “Perceived Value” and ” Biz/Commercial Relationship” are the inputs for the third hidden layer, “Satisfaction”. The “Customer Characteristics”, “Satisfaction” and “Image” latent variables are at the third Hidden Layer, which are the direct inputs for the “Loyalty Intent” Target. Thus, based on the loyalty framework, the SNN model for modeling the target Loyalty (Purchasing Intent Dimension) has three hidden layers. The links are directional as shown in Figure 1.

(2) Loyalty Dimensionality Determination: For most NN modeling, the Target variable is usually clearly pre-determined as the dependent variable. In the loyalty modeling, since there is more than one dimension for the loyalty construct, one needs to determine the dimensionality. This is accomplished by using the questions from the survey conducted by Company A. Factor analysis was performed on the questions related to loyalty in the survey. A two dimensional construct was obtained. The first dimension is labeled “Purchase Intent” and the second dimension is labeled “Purchase Behavior”. This finding is consistent with the result in Jones and Tayler (2003).

(3) Determination of Target Responses: Factor analysis using vari-max rotation gives two loyalty dimensions as attitudinal (Purchase Intent) and behavior (Purchase Behavior). Factor scores were obtained using standardize regression for each dimension as the target responses for modeling.

(4) Determination of the number of neurons for each hidden node (latent variable): For each hidden node, the number of neurons decides the degree of approximation of the inputs to the node. The more the neurons, the better the approximation supposes to be, but the risk of over fitting also increases. Therefore, it is important to determine an adequate number of neurons for each node. Principle Component Analysis is applied to determine the number of the principle components of the input variables for each hidden node as the number of neurons for the hidden node. The percent of variation explained for choosing the number of neurons is 80% or higher. Hence, the eigenvalues may be less than one in some cases.

The following Figures (Figures 5 and 6) are examples of a traditional NN and a Structured Model

**Figure 5: Traditional NN model**

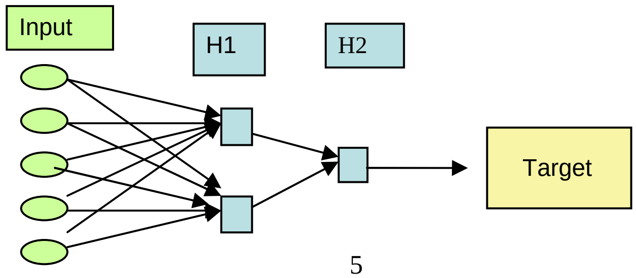
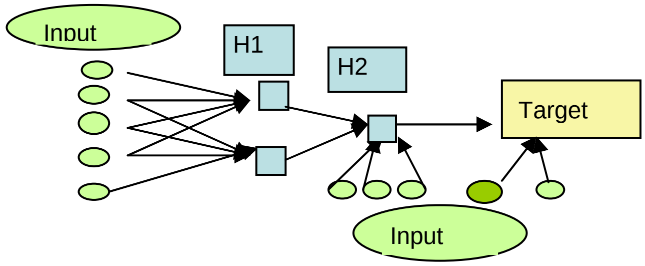


**Figure 6: Structured NN Model**




## 4. THE CONSTRUCTION OF SNN MODEL FOR LOYALTY USING ENTERPRISE MINER

In this section, we discuss applying the SNN technique to model the loyalty link using SAS Enterprise Miner®. The SAS® data mining framework, SEMMA® is applied for building the model.

The perceptual data was collected from a series of Customer Loyalty studies conducted by the Company A for their various businesses. The total number of cases, after data cleansing, was 11,275. The survey consisted of items related to each latent variable shown in Figure 1. A total of 48 questions are identified as input variables for the model. Two target variables are considered. They measure the two loyalty dimensions: Target 1 is the attitudinal intent dimension and Target 2 is the Behavior dimension. The final SNN model for the Loyalty Intent dimension is given in Figure 7. The complete Enterprise Miner diagram for this model and other competing models is given in Figure 8.

The light blue blocks in Figure 7 represent the input variables from the survey, and the dark blue squares are the hidden layers representing the latent variables. The Loyalty Purchasing Intent dimension is the target (yellow block). The number inside each hidden layer is the number of neurons applied to the hidden node. Notice that the structure in Figure 7 mimics the loyalty perception portion of the framework shown in Figure 1.

**Figure 7: The SNN Model using Enterprise Miner**

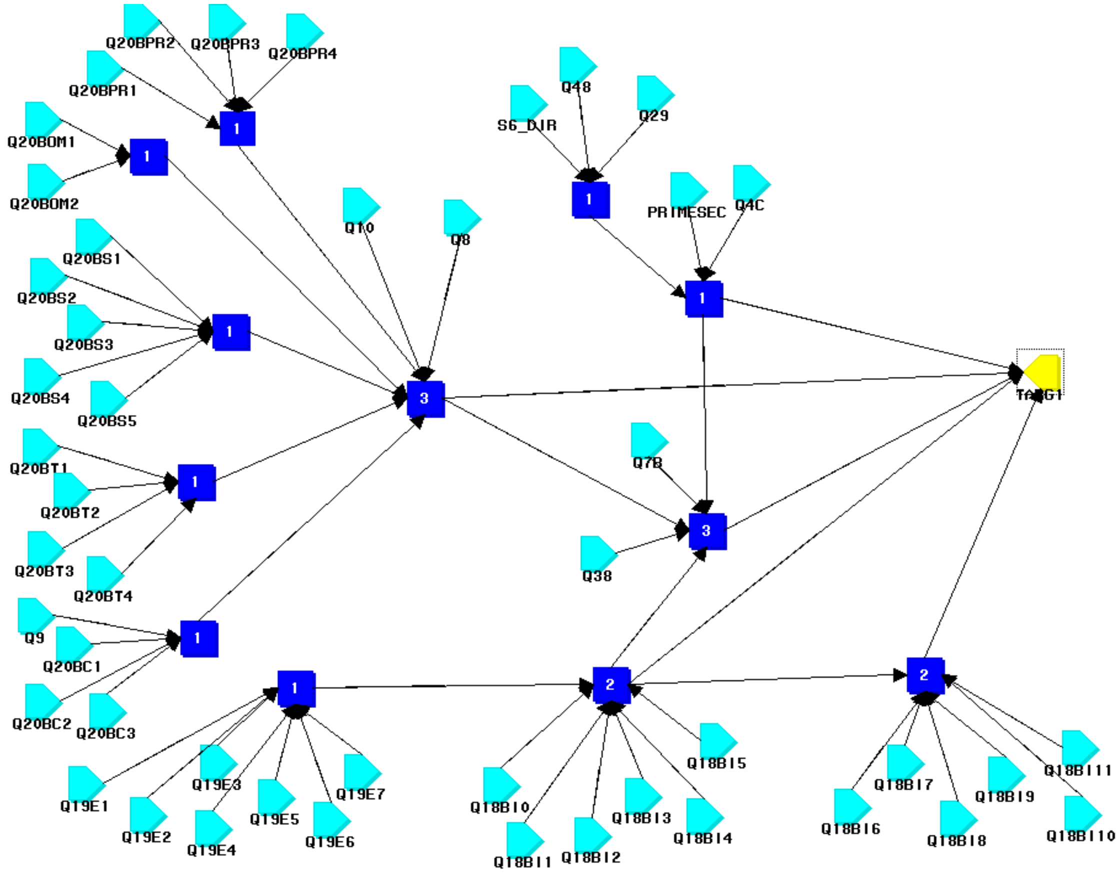
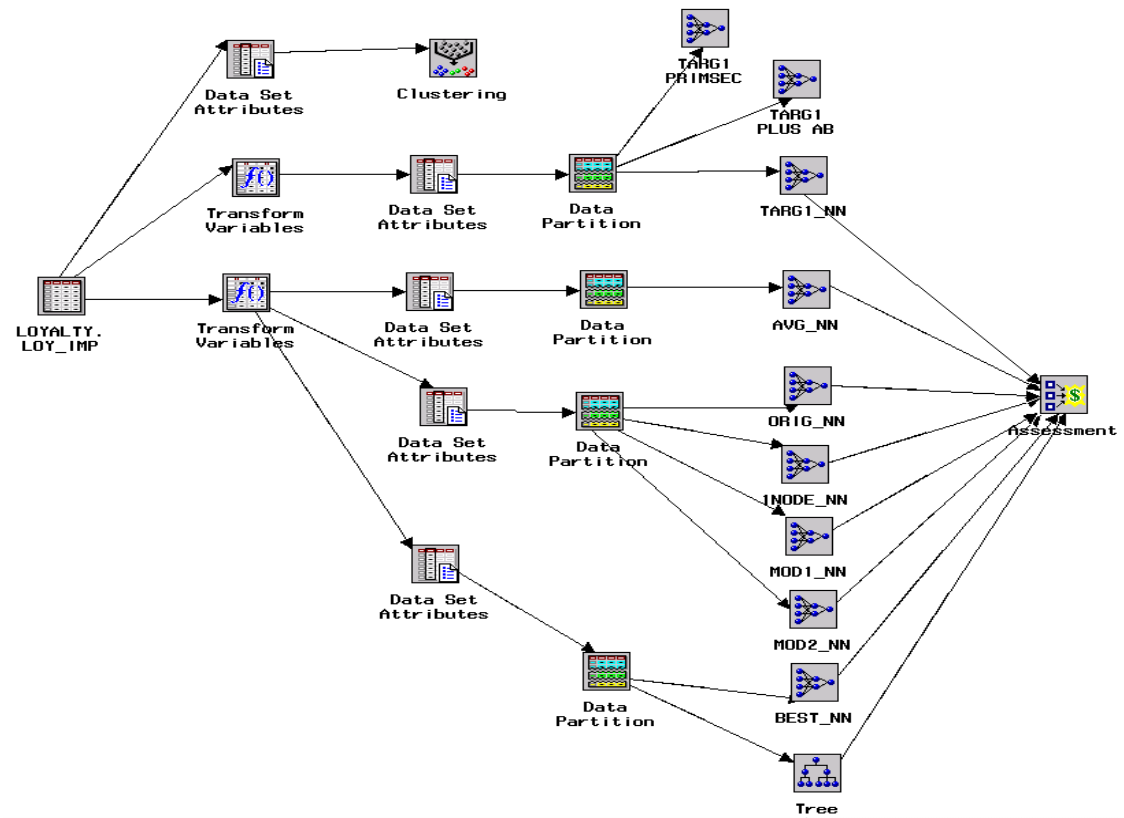


**Figure 8: The Complete Diagram for the SNN Model in SAS/EM®**




#### 4.1 THE PROCESS OF DATA PREPARATION, MODIFICATION, MODELING AND ASSESSMENT

Figure 8 shows the complete diagram of the process for building various types of models in SAS/EM®. It starts with data input node, followed by data transformation, data partition and modeling nodes. The diagram ends with an assessment node to compare the models. The following processes are considered during modeling:

(a) Scaling of the inputs and targets: The data transformation node is applied to identify outliers and to standardize the input variables. Each input variable is standardized using (x-mean)/s.d.. The target variable is standardized using the range normalization: (y-minimum)/range so that the target is between 0 and 1.

(b) Starting Weights and Stopping Rule: Five preliminary networks are conducted using random samples based on different seeds. The weight estimates that give the smallest error is chosen to be the initial values. This is done using the neural network options in the SAS/EM.

(c) Control over fitting: A simple cross validation approach is applied to guide against over fitting. The data are split into Training (60%), Validation (20%) and Testing (20%). Other partitions are also conducted. No noticeable differences are noticed.

(d) The objective function for model comparison: Three objective functions are used for model comparison. The primary objective function is the Average Error, which is also used by EM as the default for determining the final model, is defined as:

$$AE = SUM(y_i - y_{i(Pred)})^2/n$$ , where n is the total number of cases

The other two are Root Mean Square Error (RMSE) and Max Absolute Error (MAE):

$$MSE = SUM(y_i - y_{i(Pred)})^2/(n-p)$$, where p is total number of estimated weights.

$$MAE = MAX( |y_i - y_{i(Pred)}|$$

Model selection criteria such as AIC and SBC are checked, but not applied in our model building since the inputs are determined based on the domain knowledge about loyalty in this study. Variable selection is not a concern for the SNN modeling in this case.

(e) Dummy Variable Handling: For nominal input, deviation coding is used. For ordinal input, bathtub coding is used. For each case in the *i*th category, the *j*th dummy variable is set to $\sqrt{1.5C/(C^2-1)}$ for i >*j*,

Or otherwise to $-\sqrt{1.5C/(C^2-1)}$ otherwise (see SAS Enterprise Miner Reference Manual for details).

(f) Activation Functions: The hyperbolic tangent is used to connect the inputs and hidden nodes. Logistic activation function is used to link hidden layers and the target variable.

(g) The competing models considered include (1) Linear Model, (2) Traditional NN, that is, all of the input variables are feeding into the first hidden layer. To make a proper comparison, three hidden layers, similar to the SNN, are also used. The number of neurons for each hidden layer is three, which is the SAS® neural network default, (3) SNN having one neuron per node, and (4) SNN having multiple neurons per node, where the number of neurons are determined using Principle Component Analysis.

## 5. RESULTS AND DISCUSSION

Using the 60%/20%/20% data partition, the fit statistics for the SNN model with multiple neurons reported by SAS/EM® for Target 1 and Target 2 are given in Table 1 and Table 2. The objective function is the Average Error. The best model is the model that gives the smallest average error for the validation data. Figure 9 gives the average errors for different iterations in the modeling process. The best is obtained near the 90th iteration. The test data is not included in the modeling process. It is used as an independent evaluation of the model.

Both targets are range normalized. Values are between 0 and 1. The root mean square error for Target 1, the attitudinal purchasing intent, is about 15.5%. The root mean square error for the behavior target is about 32%. The maximum absolute errors are as high as .95 for the attitudinal target and .77 for the behavior target.

**Figure 9: The Average Error Plot for the Validation and Training Data**

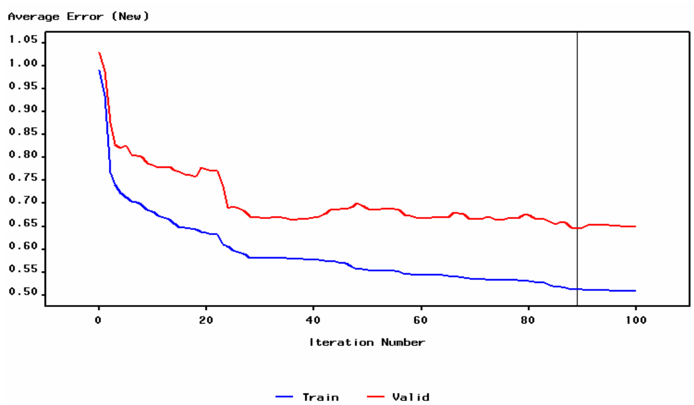



**Table 1 Fitted Statistics for the SNN Model for Modeling the Loyalty Dimension: Purchase Intent**

| | Fit Statistic | Training | Validation | Test |
|---|---|---|---|---|
| 1 | [ TARGET=STD_T1 ] | . | . | . |
| 2 | Average Error | 0.0233621716 | 0.0246701491 | 0.0226950612 |
| 3 | Average Squared Error | 0.0233621716 | 0.0246701491 | 0.0226950612 |
| 4 | Sum of Squared Errors | 155.3584414 | 54.175647395 | 50.110695144 |
| 5 | Root Average Squared Error | 0.1528468895 | 0.1570673393 | 0.1506488009 |
| 6 | Root Final Prediction Error | 0.1580137451 | . | . |
| 7 | Root Mean Squared Error | 0.1554517856 | 0.1570673393 | 0.1506488009 |
| 8 | Error Function | 155.3584414 | 54.175647395 | 50.110695144 |
| 9 | Mean Squared Error | 0.0241652576 | 0.0246701491 | 0.0226950612 |
| 10 | Maximum Absolute Error | 0.9551052684 | 0.9001932632 | 0.6579174158 |
| 11 | Final Prediction Error | 0.0249683437 | . | . |
| 12 | Divisor for ASE | 6650 | 2196 | 2208 |
| 13 | Model Degrees of Freedom | 221 | . | . |
| 14 | Degrees of Freedom for Error | 6429 | . | . |
| 15 | Total Degrees of Freedom | 6650 | . | . |
| 16 | Sum of Frequencies | 6650 | 2196 | 2208 |
| 17 | Sum Case Weights * Frequencies | 6650 | 2196 | 2208 |
| 18 | Akaike's Information Criterion | -24539.63712 | . | . |
| 19 | Schwarz's Baysian Criterion | -23036.31288 | . | . |

**Table 2 Fitted Statistics for the SNN Model for Modeling the Loyalty Dimension: the Purchasing Behavior**

| | Fit Statistic | Training | Validation | Test |
|---|---|---|---|---|
| 1 | [ TARGET=STD_T2 ] | . | . | . |
| 2 | Average Error | 0.0970664164 | 0.0993144416 | 0.0984742395 |
| 3 | Average Squared Error | 0.0970664164 | 0.0993144416 | 0.0984742395 |
| 4 | Sum of Squared Errors | 440.9727295 | 153.14286899 | 157.16488625 |
| 5 | Root Average Squared Error | 0.3115548368 | 0.3151419389 | 0.313806054 |
| 6 | Root Final Prediction Error | 0.3270980787 | . | . |
| 7 | Root Mean Squared Error | 0.3194210148 | 0.3151419389 | 0.313806054 |
| 8 | Error Function | 440.9727295 | 153.14286899 | 157.16488625 |
| 9 | Mean Squared Error | 0.1020297847 | 0.0993144416 | 0.0984742395 |
| 10 | Maximum Absolute Error | 0.7354742548 | 0.7742574805 | 0.6964007217 |
| 11 | Final Prediction Error | 0.1069931531 | . | . |
| 12 | Divisor for ASE | 4543 | 1542 | 1596 |
| 13 | Model Degrees of Freedom | 221 | . | . |
| 14 | Degrees of Freedom for Error | 4322 | . | . |
| 15 | Total Degrees of Freedom | 4543 | . | . |
| 16 | Sum of Frequencies | 4543 | 1542 | 1596 |
| 17 | Sum Case Weights * Frequencies | 4543 | 1542 | 1596 |
| 18 | Akaike's Information Criterion | -10153.91071 | . | . |
| 19 | Schwarz's Baysian Criterion | -8734.793935 | . | . |

Table 3 gives the root mean square errors for the Test data for the competing models. The linear model is the traditional linear regression model. The SNN with a single neuron is similar to a SNN model considering only one principle component from each set of inputs for the latent variable. The SNN with multiple neurons is the SNN model that takes into account an adequate number of principle components from each set of inputs for the latent variable. The Traditional NN model does not fit the network of the cause-and-effect relationships. Instead, it fits all of the input variables to a hidden layer with three neurons in each hidden layer. The number of estimated weights differs dramatically. For the linear model and the SNN model with one neuron, the models have 98 weight estimates. The SNN with multiple neurons has 221 weight estimates, while the traditional NN model has 419 weight estimates. This unto itself helps with issues surrounding parsimony.

**Table 3: The Comparison among Competing Models Based on the Root Mean Square Error for the Test Data**

| Target | Fit Statistics | Linear | SNN with Single Neuron | SNN with Multiple Neurons | Traditional NN |
|---|---|---|---|---|---|
| One: Purchase Intent | Root Mean Squared Error | .16401 | .2190 | .1506 | .1597 |
| One: Purchase Intent | Degrees of Freedom | 98 | 98 | 221 | 419 |
| Two: Purchase Behavior | Root Mean Squared Error | .4385 | .4212 | .3138 | .3177 |
| Two: Purchase Behavior | Degrees of Freedom | 98 | 98 | 221 | 419 |

#### 5.1 SOME IMPLICATIONS OF THE LOYALTY CONSTRUCTS – INTENT DIMENSION VS. BEHAVIOR DIMENSION

The comparison indicates that the SNN model with multiple neurons fits the best in every model; however, the linear model for the attitudinal intent dimension is comparable with the best SNN model with less than half of the weight estimates. A linear regression model maybe be adequate for the attitudinal dimension of the loyalty. This seems to indicate that the relationship between performance and satisfaction link can be described well using the linear relationship as given in the Panel 1 of Figure 1. This also suggests that a linear relationship is adequate between satisfaction and retention link for the attitudinal purchase intent dimension.

The behavior dimension of the loyalty construct is different from the intent dimension. The fact that the root mean square errors for the SNN and traditional NN, which fit the model with nonlinear relationship, is much smaller than the linear models using regression or one neuron NN seems to suggest that a nonlinear and asymmetric relationship exists between the performance-satisfaction-loyalty (behavior dimension) links. Literature has suggested that intent is different from actual purchasing behavior (e.g., Johnson and A. Gustafsson, 2000). The results from the chemical industry also suggest that there is a clear distinction between intention and behavior. Thus, one should not combine these two loyalty dimensions together in the modeling of profitability without a careful analysis of investigating if the difference exists.

### 5.2 THE ISSUE OF HOSTAGE AND MERCENARY CUSTOMERS

Figure 10 is the scatter plot between predicted and actual target for Target 1, the Purchase Intent. The plot indicates that there is a lot of variation in the data. This suggests that there is a need to further investigate causes that may be associated with loyalty.. The literature (e.g., Anderson and Mittal, 2000) suggests that satisfied customers may not be loyal customers (Mercenaries) and, on the contrary, dissatisfied customers may continue to purchase the product because of no other relevant vendor choices (Hostages). Figure 11 shows the types of customers for different degrees of satisfied customers. The data from the company A seems to indicate that there are a certain percentage of hostage or mercenaries customers. A better model will require a closer investigation to analyze these two groups of customers separately. This was investigated by Company A in stage three, where hostages were identified and adjusted before modeling the profitability.

**Figure 10: Scatter Plot between Actual (X) And Predicted Loyalty-Intent**

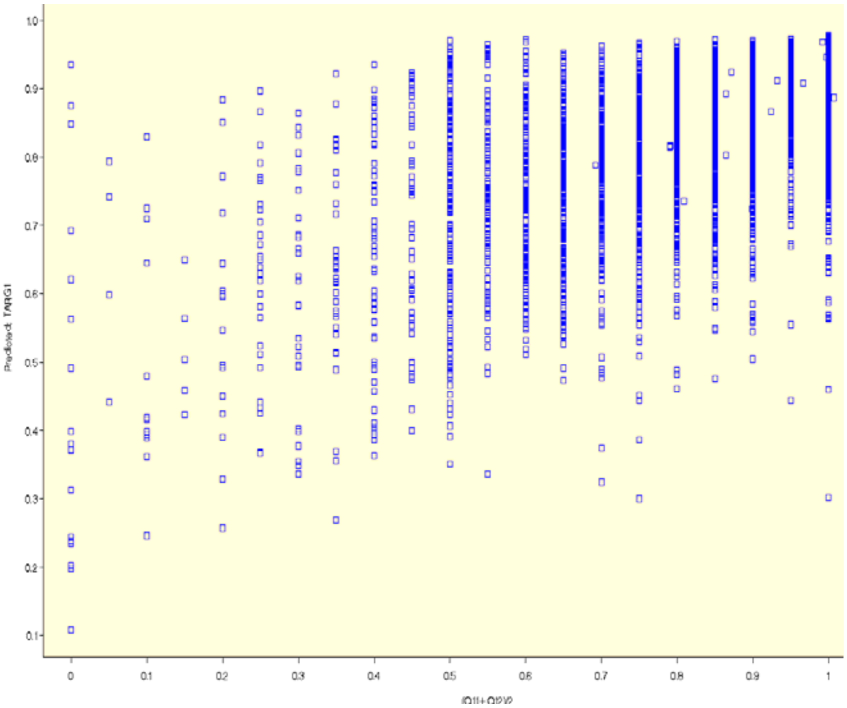
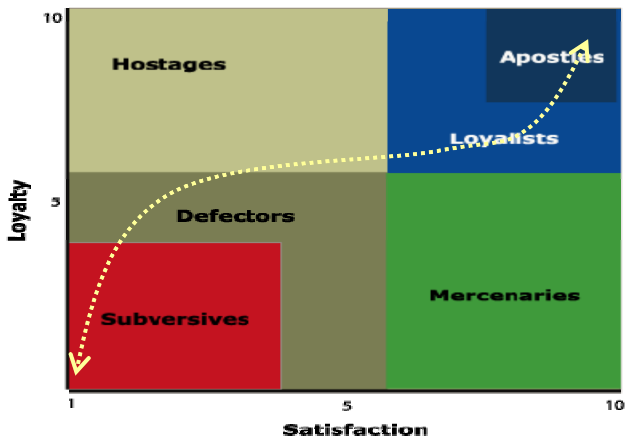


**Figure 11: The Types of Loyal Customers for Different Degrees of Satisfaction**



## 6. CONCLUSION

This article presents a data mining modeling technique, structured neural network, to model customer loyalty. The technique mimics the theoretical framework that describes the cause-and-effect relationships in the attitudinal portion of the satisfaction-loyalty-profit chain. The SNN technique takes into account the potential nonlinear and asymmetric relationships that can not be handled using the traditional SEM and PLS modeling techniques. If the relationship is nonlinear and asymmetric, then, the SNN model is shown that it performs better than others. Otherwise, a simpler model such as linear regression may be sufficient.

The loyalty study for Company A in the chemical industry indicates that the intent dimension of loyalty construct in the attitudinal portion of attribute performance- satisfaction-loyalty is more linear than the chain involving the behavior dimension. It is important to distinguish these two dimensions in the second stage of modeling profitability. In addition, the issue of handling hostages and mercenaries requires a separate study. Different marketing strategies should be developed for these groups of customers. The nonlinear and asymmetric relationships may be different for different segments of the company. If the size of the data is large enough to analyze specific segments, then, modeling the loyalty construct via each segment is worthy of further investigation.

The traditional NN model is an empirical modeling technique. In general, the underlying theoretical framework is not taken into consideration. Instead, the traditional NN model attempts to allow the data to speak for itself. The failure of the traditional NN model sends an important message that when applying the ‘black box’ neural network modeling, it is essential to take into account the contextual and theoretical knowledge. For the loyalty modeling case, it is clear that the theoretical framework provides a great deal of insight about the cause-and-effect relationships among the latent variables and input data and the targets. Structured neural network techniques should be considered for any predictive modeling problems when the contextual and theoretical knowledge is available to assist in the designing the structure.

A similar SNN technique that mimics the complete framework of satisfaction-loyalty-profitability shown in Figure 3 has in fact been applied to model the profitability by Company A internally. This article only focuses on stage two, the attitudinal part of the satisfaction-loyalty-profit chain, to demonstrate how the SNN model is built and the considerations needed in the process of building such a model based on a theoretical framework. This technique is applicable to other modeling problems where frameworks are well defined.

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