ARTIFICIAL NEURAL NETWORKS: AN INTRODUCTION AND APPLICATION IN A CONSUMER BEHAVIOR SETTING

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When investigating relationships between variables of interest in Consumer Behavior, researchers have used a myriad of statistical tools in order to uncover and understand the impact of important demographic, psychological, environmental, and situational relationships on attitudes and behaviors. In this paper, the authors discuss a relatively new tool in the marketer's tool box--the artificial neural network, also referred to as neural networks. Following the summary of the development and application of an neural networks in business and marketing, the authors present a neural network application for determining attitude toward a web site based on the color and congruency of advertisements placed on the site.

INTRODUCTION

Trying to determine how consumers behave has been extensively investigated in the fields of marketing and psychology. Researchers have sought to develop theories and models to assist managers in predicting how many and which consumers will behave in certain situations. For example, a sales manager of a grocery chain may want to know if the end-aisle display of a product influences a specific segment of their customers to purchase the product. Assuming the store uses a rewards type card, which is presented at time of purchase, the manager can then use statistical tools to see if the desired customer group was influenced by the display. The results can help the sales manager make decisions concerning the use of end-aisle displays; however, the decision guidance is only as useful as the statistical tool the manager used.

In order to predict how a customer will behave in a particular setting, most marketing researchers have chosen to use multivariate analysis and econometric tools. In forecasting brand shares, the multinomial logit model (MNL) has been found to be a robust tool for modeling consumer's probability of choice in a competitive setting; however, when the number of brands in the category are numerous, the tool may have problems with classification (Agrawal and Schorling 1996).

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In determining consumer preferences, attitudes, judgments, and decision making, marketers have relied on compensatory linear models using tools such as structural equation modeling, multiple regression, ordinary least squares regression, analysis of variance, logistic regression, and discriminant analysis based on their ability to mimic consumer judgment and choice processes (West, Brockett and Golden 1997). However, research has shown that preference is not linear (Coombs and Avrunin 1977) and that judgment and choice are not based on compensatory rules but noncompensatory rules (Payne, Bettman and Johnson 1993) that revolve around attribute thresholds that provide ease for the consumer to use in a buying situation.

Due to these problems, new methods have been investigated to accurately predict consumer decision making. Artificial neural networks (hereafter referred to as neural networks), primarily developed for science and medical applications, have recently emerged in the marketing literature as an alternative analysis tool. The purpose of this manuscript is to provide an overview of neural network applications in business and to use a neural network to investigate advertising effects, thus providing an illustration of the process. We first provide a brief overview of neural networks, followed by a summary of the use of neural networks in business applications. Finally, we provide a brief illustration of a neural network application.

NEURAL NETWORKS DEFINED

An artificial neural network is designed to mimic the human brain. The brain continuously receives information from stimuli through receptors, interprets the information, and then decides on a response through effectors. The process is reversed when sending feedback through the system (Figure 1). The brain is a complex information processing system with a structure composed of neurons. The structure builds its own rules through experiences over time. These experiences allow the brain to use knowledge to adapt to its surrounding environment (Haykin 1999).

Neural networks have been defined as "a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use" (Haykin 1999, p.2). A neural network is an information processing system that models the way the human brain gathers knowledge through learning and then stores that knowledge through interconnections. The neural network uses processing units like neurons of the human brain to build connection strengths between the units (synaptic weights) to store the learned knowledge. The learning process (learning algorithm) orders the network of synaptic weights to design the desired neural network; however, as the network learns, it can modify its own typology. The learned knowledge then allows for the neural network to make generalizations of the outputs based on certain inputs.

Neural networks provide many benefits to researchers (Haykin 1999). Neural networks are nonlinear and adaptive. Neural networks allow input-output mapping so that the researcher can supervise the network's learning with training samples, then provide output responses which provide contextual information. Neural networks can also be used to uncover theoretical relationships in large amounts of data (Flynn, Eastman and Newell 1995) as well as provide a richer interpretation of the interconnected relationship between variables of interest (Curry and Moutinho 1993). In addition, the output provided by neural networks has been shown to outperform other statistical tests when compared to a holdout sample (Jain and Nag 1997), thus increasing the validation of the research findings. These networks classify information (Kiang 2002) that can be used to test assumptions and build theory.

The major disadvantages of neural networks are the following: 1) Their lack of a test statistic (Flynn, Eastman and Newell 1995); 2) Their lack of a theoretical background--neural networks are the ultimate black box, and 3) Their increased time to process due to learning and potential overfitting of the data (Vellido, Lisboa and Vaughan 1999). However, as the tool is utilized more and interpretations become more precise, these disadvantages may become insignificant.

NEURAL NETWORK DEVELOPMENT

Based on the human brain, a mathematical model is made on the foundation of the brain structure of neurons and pathways (West, Brockett and Golden 1997). Neural networks are fundamentally made up of a processing unit, which is the basic building block for the network (Figure 2). The units take multiple inputs that can be linear, nonlinear, and/or continuous (the input layer) through a learning algorithm that applies the optimal connection weights. These connection weights are then summed into a single value for the processing unit (Abu-Mostafa, Atiya, Magdon-Ismail and White 2001) while accounting for bias. The

FIGURE 1
Human Brain

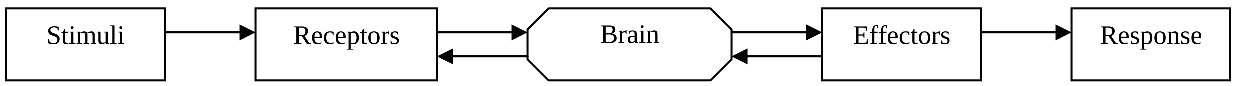
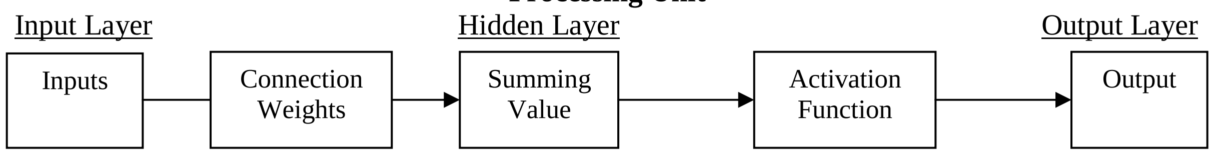


FIGURE 2
Processing Unit



summed value is then applied to the activation function (the hidden layer) and an output (output layer).

Neural networks are constructed by connecting processing units or neurons with interconnection weights. These interconnections create pathways between the processing units. As the pathway becomes useful, the weight of the interconnection increases and reinforces the connection. This reinforcement allows the network to judge success, increase knowledge, and train the neural network to make generalizations (West, Brockett and Golden 1997).

NEURAL NETWORK APPLICATIONS

Neural networks have been utilized in many different areas of research including document retrieval in search engines, decision making, construction disputes, natural gas consumption, and data mining. One study used a neural network to locate the correct keyword for document retrieval and found that it performed 50 percent better than other information retrieval systems in identifying underlying keywords (Chen and Kim 1995). Another study investigates how people make decisions based on multiple criteria (Chen and Lin 2003). A neural network was applied to find the most desirable solution by capturing the preference structure of the decision maker.

In Hong Kong, researchers examined the construction industry's dispute resolution problem which led to an increase in management resources to address such problems (Cheung, Tam and Harris 2000). A neural network was applied to find amicable resolutions as well as to identify sensitive variables most likely to have caused the disputes.

Gas utilities have also utilized the prediction power of combining two neural networks by modeling the relationship between weather variables (such as temperature and wind speed) and previous gas consumption with future consumption (Khotanzad, Elragal and Lu 2000) to determine the amount of natural gas needed. The results of the neural network can help ensure that gas utilities purchase enough gas from the pipeline companies to avoid financial penalties and shortages.

In looking for general patterns in real world data, researchers in the medical and business field use data mining to search for useful observations that can be patterned to help predict the future. Neural networks have been shown to produce the best overall results in large multiple classifications that can help in extracting knowledge from data (Spangeler, May and Vargas 1999).

Other studies of neural networks work to find the best type of algorithm to be used in the training of the network. In looking at many different types of data sets (medical, financial, criminal, and agricultural) and their classifications based on the neural network, the genetic algorithm (instead of the back-propagation algorithm) has been shown to be the best training tool in real world problems to aid in decision making (Sexton and Dorsey 2000).

Business Applications of Neural Networks

Neural networks have been applied in finance (finance, accounting, and auditing), management (management and production), and marketing literature (consumer behavior, logistics, and marketing management). In most of the research conducted using neural networks in business, the technique yielded similar to better results than other statistical tests (Vellido, Lisboa and Vaughan 1999).

First, in finance, neural networks have helped improve the field of research by revisiting traditional problems (Abu-Mostafa et al. 2001) such as bankruptcy, financial risk management, pricing and hedging derivative securities, forecasting future currency exchange rates, and trading in emerging capital markets. With the help of traditional financial ratio indicators as inputs, neural networks have helped increase bankruptcy prediction accuracy, providing a four percent improvement (Atiya 2001). The increase in prediction accuracy will help banks control their outstanding debts and calculate a fair interest rate of a loan. Also, financial risk management systems (information systems that monitor and measure risk associated with holding financial instruments) can be crafted from neural networks to predict prepayments and future interest rates, thus lowering losses to a financial institution (Bansal, Kauffman and Weitz 1993).

In the modeling of securities, neural networks that include Bayesian regularization produce significantly smaller pricing option and hedging performance errors (Gencay and Qi 2001). This allows financial firms to more accurately assess potential gains. Also, in the investigation of emerging capital markets, neural networks help researchers understand how external signals affect trading. When forecasting with neural networks and including external market signals, the researchers found a prediction accuracy of 63 percent by finding and exploiting inefficiencies in the market (Walczak 1999). Furthermore, in forecasting future currency exchange rates, neural networks have been shown to predict rates with 60 percent accuracy when smaller quantities of training data are used with back-propagation algorithms (Walczak 2001). The smaller amount of data allows for a decrease in cost and time (Walczak 2001).

Second, in management, neural networks have helped in understanding employee behavior, successful new ventures, organizational structure, and voluntary employee turnover. In looking at nonwork-related web surfing behavior, neural networks have been used to profile employee web usage behavior. By looking at the classification of employee web usage, high nonwork users and low nonwork users of the network, managers can develop a better web management strategy to lower costs to the organization and increase productivity at work (Anandarajan 2002). Voluntary turnover behavior has also been studied using neural networks. Managers use the networks to predict turnover behavior as well as to classify those employees who are “leavers” and to help with theory building and understanding the psychological process of employee withdrawal behavior (Somers 1999).

When management is faced with new ventures, neural networks can assist in determining the success or failure of the opportunity (Jain and Nag 1997). Managers can help save losses in profits, jobs, and productivity by utilizing neural networks as a resource. Neural networks have also been applied in organizational structure (Randolph and Miller 1999). When an organization’s policy body changes, so does the structure of the organization. This change can cause failure within the organization as well as product or service failure. Neural networks are used to estimate general organizational effectiveness that can ensure success once the change is made.

Finally, in marketing, neural networks have been used to help understand inventory control, advertising, new product development, and consumer behavior. In looking at forecasting brand shares, Agrawal and Schorling (1996) found that when compared with other statistical methods, neural networks deal better with non-linearities in the data, large numbers of categorical variables, and complex relationships regarding inputs and provided superior prediction rates. However, they also noted that results were harder to interpret than other statistical tools.

In advertising, neural networks can be used to predict purchase intentions based on exposure to the advertisement, prior learning response, media type, and product category (Curry and Moutinho 1993). The neural network, based on the MOA framework (i.e., motivation, opportunity, and ability), helped not only to predict purchase intentions but also understand the cognitive process behind the intentions. Similarly, Thieme, Song and Calantone (2000) used neural networks to predict the success or failure of new products based on financial and technical capabilities. Most recently, Bose and Pal (2006), used a neural network to uncover the key financial ratios necessary that predicted online retailer success

In consumer decision making, neural networks have been used to predict consumer shopping behavior with great accuracy (Flynn, Eastman and Newell 1995). Neural networks have also been used to accurately predict outcomes when the decision rule is known or unknown, as well as when it is compensatory or noncompensatory (West, Brockett and Golden 1997). Neural networks also allow for nonlinear and linear inputs (West, Brockett and Golden 1997) based on the nature of the neural network. Furthermore, a neural network is based on *learning* the complex relationships between variables such as attributes and consumer choice (West, Brockett and Golden 1997) and therefore provides a better prediction of the decision made by the consumer. Neural Networks have been shown to be the most robust statistical tool available today, based on overfitting and worst-case model performance (West, Brockett and Golden 1997).

AN ILLUSTRATIVE APPLICATION OF NEURAL NETWORKS

This study examines overall attitude toward a web site based on the subject's involvement with the advertising content, the advertisement's dominant color, and the web site's content congruency with the ad. We followed a procedure similar to Moore, Stammerjohan and Coulter (2005) and used their stimuli and measures. Respondents were students enrolled in marketing classes at a Southeastern USA university. Respondents completed a pre-experiment questionnaire measuring their involvement with veterinary services and apartments using a nine-item involvement scale (Lichetenstein, Bloch and Black 1988). After completing the pre-experiment questionnaire, the respondents were asked to examine a particular web site containing information about how to find and evaluate apartments. The web site featured either a predominantly red or a predominantly blue colored advertisement. The advertisement appearing on the website was either a congruent ad or an incongruent ad. After exploring the website, respondents were asked to complete a post-experiment questionnaire measuring their overall attitude toward the web site (Chen and Wells 1999).

Depending on what experimental group they were assigned to, the respondents examined the apartment website and were exposed to banner ads. This particular study examines the effect of the color of the banner ad (i.e., red or blue) and the congruency of the ad (i.e., is the advertised product or service congruent or incongruent with the website topic). In the congruent ad condition the web site contained an ad relating to apartments. In the incongruent condition, the web site contained an ad unrelated to apartments (in this case, the ads were for veterinary services).

The Data

The total sample size for this study is 212. The sample is comprised of 53.3 percent female respondents (n=113) and 46.7 percent male respondents (n=99). The average age of respondents is 21.8 years with a minimum age of 17 and a maximum age of 30. To prepare the data for analysis, several steps were taken to re-code and enter the data into a format conducive to the neural network software (EasyNN version 8.01). The first step was to further classify the variables into input variables and output variables. The following variables are characteristics of the website advertising stimuli:

(1) Red banner advertisements (entered as a dummy variable--1=red, 0=not red)
(2) Blue banner advertisements (entered as a dummy variable--1=blue, 0=not blue)
(3) Congruency of the advertisement (entered as a dummy variable--1=congruent, 0=not congruent)
(4) Involvement with the advertised content (entered as a dummy variable--1=high involvement, 0=low involvement).

All four of these variables were entered into the software as input variables.

To determine whether the respondent has high involvement or low involvement with the advertised content, a mean scale value was computed using the responses of all 212 respondents. For "involvement with veterinary services," the computed mean was 4.18. For "involvement with apartments," the computed mean was 3.0. Respondents with scores above the computed mean were assigned a value of 1 indicating high involvement with the website topic; whereas, respondents with scores below the computed mean were assigned a value of 0 indicating low involvement with the website topic.

The four input variables indicated above were used to predict one output variable--attitude toward the website. Values associated with this output variable were entered into the Neural Network software as real numbers and represent the values of the summated ratings scale. The sample was partitioned into two different sets: a training sample and a validation sample. We used 70 percent of the full sample for training and 30 percent for validation.

The Model

The model was built using EasyNN version 8.01. The model-building procedure used a supervised learning scheme in which both input and output variables were presented to the Neural Network. The resulting model contains one hidden layer composed of five neurons. A back-propagation algorithm was used to adjust the weights between nodes.

The first step in building a neural networks model is to train the neural networks. The neural networks was trained and resulted in a learning rate of 0.60 with a momentum of 0.60. When training a neural networks, guidelines for when to stop the training process should be followed. West, Brockett and Golden (1997) provide three different guidelines for stopping the training process. The first guideline follows that training should stop when the "error on the validation sample begins to increase" (West, Brockett and Golden 1997, p. 377). At this point, the model has been overfit; therefore, the researcher should stop training and revert back to the earlier weights that produced less error. A second guideline to follow is to stop training when the percentage misclassified in the training sample ceases to improve (West, Brockett and Golden 1997). The third guideline is to continue to train until improvement in the average error reaches some target or becomes stationary. This third guideline was used in the analysis of our dataset. The average error associated with our particular dataset stabilized at 0.162 before reaching the specified target error of 0.05. Training was stopped after 9449 cycles.

Training Session

The training session was conducted using 70 percent of the total dataset (n=147). The model resulting from the training session is presented in Figure 3. Values for the paths between each of the nodes are presented in Table 1. As is shown in Table 1, the input variable "involvement" is characterized by higher weights than any of the other input variables. The involvement input variable has the greatest amount of influence on each of the hidden nodes. Hidden node 3 has the greatest influence on the output variable attitude toward the website (-2.033). Table 2 contains additional information about the order of importance for each of the input variables. Overall, the most important input variable influencing attitude toward the website is involvement (with an importance rating of 44.272). Following the involvement variable, congruency is the next most important variable influencing attitude toward the website (with an importance rating of 32.871). Advertising colors blue and red follow with less influence on attitude toward the website (with importance ratings of 17.586 and 5.814 respectively).

Validation

The dataset used for validating the model is comprised of 30 percent of the total dataset (n=65). The validation model is structurally similar to the training session model; therefore, Table 3 contains the values for the paths between the nodes in the model.

Table 3 indicates that involvement is characterized again as having the greatest weights to hidden nodes 1 through 5. Hidden node 2 has the greatest influence on attitude toward the website (with a weight of -2.425). Table 4 contains additional information about the importance of each of the input variables to "attitude toward the website." Consistent with the training results, involvement again carries the greatest amount of relative importance with an importance rating of 40.844. With this set of data, the other input variables (red, blue and congruence) follow more closely in level of importance with ratings of 32.894, 31.886 and 28.161 respectively.

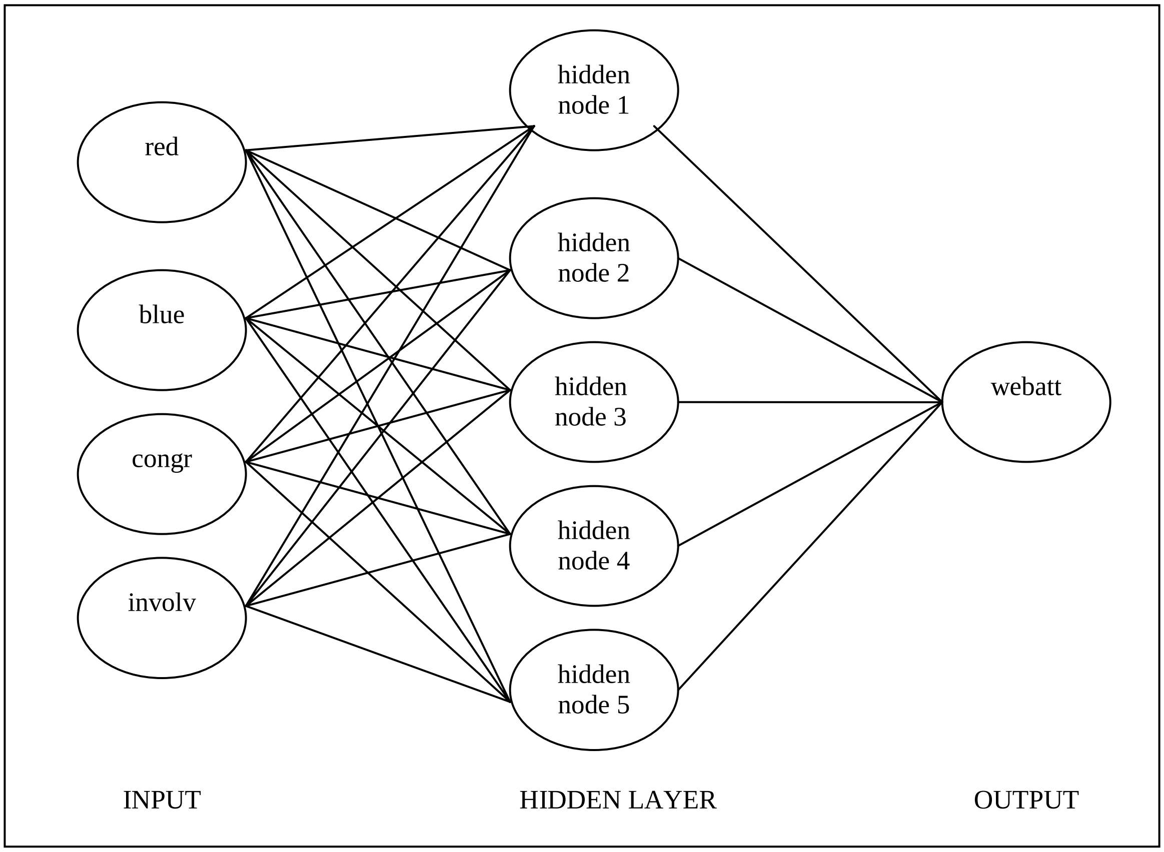
In the interpretation of the hidden nodes for the training set, the influence of hidden node 3 shows that individuals viewing a web site containing an ad using an attention-getting color and with incongruent content will have a lower overall evaluation of the web site as long as they are highly involved with the ad content. This suggests that an individual who is involved with veterinary services and is exposed to a categorically similar ad on an incongruent web site will have his/her attention pulled from the content of the web site. Future research should examine this relationship as it appears that this may assist the development of behavioral marketing campaigns which track consumers across websites.

Additionally, the most significant factors contributing to a positive evaluation of the web site were hidden nodes 1 and 2. These nodes are associated with individuals who were exposed to a web site with a congruent and soothing-colored ad (i.e., blue) and who were less involved with the ad's content, thus paying attention to the web site's content. Overall, between the two data sets we see that involvement with the content of the ad is very important in the overall linkages between attitude toward the web site and ads on a web site.

General Discussion

In consumer behavior, neural networks can help researchers understand the decision process based on different attributes of the product or service and the different environmental and personal influences on the consumer such as opinion leadership, demographics, etc. Researchers can use the information on how the attribute(s) is/are evaluated while accounting for the competition. Researchers can also see how the product is chosen by the consumer to understand and predict consumer purchase decisions on products (healthy and unhealthy) and services (credence and experiential) as well as discover how the decision making process is different based on the decision being made. Therefore, marketing researchers have the opportunity to use Neural Networks to build new theory in consumer behavior. Two aspects of caution are the lack of a test statistic (Flynn, Eastman and Newell 1995) and the lack of

FIGURE 3
Model Using Ad Color, Congruency, Involvement to Predict Attitude Toward the Website



interpretability of the results (Agrawal and Schorling 1996), which can both hinder theory building.

In retailing, neural networks can provide forecasting information to better assist with inventories, merchandising, and negotiations with manufactures (Agrawal and Schorling 1996), especially with the help of scanner data. By using neural networks, a store manager can order the correct amount of product, saving the store inventory costs and building a loyal customer base through reliability. Also, managers have more bargaining power over manufacturers concerning merchandising support and shelf space placement.

In building internet marketing strategies, neural networks can assist consumers in searching information on a firm's website, predict future purchases made based on present purchases, and classify customers based on their behavior patterns (Kiang 2002). Companies can even customize an entire customer experience through a company website by allowing the customer to opt in, track purchases and preferences in a customer database, and allowing the neural network to predict shopping behavior. The information provided could give the company an opportunity to anticipate items the customer might want and help build loyalty to the store and online shopping.

In sales management, neural networks can help profile the behavior of sales employees. Neural networks can help management understand such behavior. Doing so will assist in building sales management strategies concerning on-the-job policies to increase productivity, sales strategies that support increased performance,

TABLE 1
Values from Training Session

FROM NODE:	TO:	WEIGHT
Red	Hidden node 1	-0.840
	Hidden node 2	-0.770
	Hidden node 3	1.990
	Hidden node 4	-0.808
	Hidden node 5	1.407
Blue	Hidden node 1	0.849
	Hidden node 2	0.929
	Hidden node 3	5.588
	Hidden node 4	-8.263
	Hidden node 5	1.939
Congruent	Hidden node 1	3.685
	Hidden node 2	4.049
	Hidden node 3	-7.970
	Hidden node 4	-3.948
	Hidden node 5	13.219
Involvement	Hidden node 1	-8.204
	Hidden node 2	-9.561
	Hidden node 3	4.230
	Hidden node 4	4.238
	Hidden node 5	-18.040
Hidden node 1	Web Attitude	2.071
Hidden node 2	Web Attitude	2.001
Hidden node 3	Web Attitude	-2.033
Hidden node 4	Web Attitude	-1.092
Hidden node 5	Web Attitude	-1.281

TABLE 2:
Order of Importance for Training Model

INPUT VARIABLE:	IMPORTANCE
Involvement	44.272
Congruent	32.871
Blue	17.568
Red	5.814

TABLE 3
Values from Validation

FROM NODE:	TO:	WEIGHT
Red	Hidden node 1	-1.868
	Hidden node 2	-0.781
	Hidden node 3	16.158
	Hidden node 4	-3.771
	Hidden node 5	10.315
Blue	Hidden node 1	-7.398
	Hidden node 2	-1.459
	Hidden node 3	-3.450
	Hidden node 4	13.124
	Hidden node 5	-6.455
Congruent	Hidden node 1	-7.983
	Hidden node 2	-0.989
	Hidden node 3	-2.395
	Hidden node 4	-9.305
	Hidden node 5	7.490
Involvement	Hidden node 1	2.572
	Hidden node 2	-6.961
	Hidden node 3	-12.077
	Hidden node 4	10.366
	Hidden node 5	-8.869
Hidden node 1	Web Attitude	-1.543
Hidden node 2	Web Attitude	-2.425
Hidden node 3	Web Attitude	2.019
Hidden node 4	Web Attitude	-0.710
Hidden node 5	Web Attitude	-1.418

TABLE 4
Order of Importance for Validation

INPUT VARIABLE:	IMPORTANCE
Involvement	40.8443
Red	32.894
Blue	31.886
Congruent	28.161

and hiring/training strategies that lower turnover costs to the organization. Also, sales employees can provide data that can profile their customer base to forecast customer order amounts, frequency of customer orders and their overall choice behavior for new products, trials, etc.

In marketing management, neural networks can assist in multiple criteria--decision making, new product teams, and pricing. Marketing managers can use these networks to look at marketing strategies used in the past and to forecast new marketing strategies or new sales as well as pricing of new products. Managers can use neural networks to find an optimal organizational structure for new product teams and new product development decisions to ensure the success of new products. Also, neural networks can be utilized to predict the risk of joint ventures and alliances between firms. Technology, talent, knowledge, and capital (Smilor and Feeser 1991) can be inputs into the network to determine a successful venture. Furthermore, advertising campaigns can be chosen based on criteria chosen by management regardless of the criteria imposed on the project. These advertisements can then be analyzed to predict the effect of the advertisement on the consumer in pre-testing the market and post-testing marketing research.

CONCLUSION

Neural networks have emerged in the marketing research literature as an alternative tool to analyze data. These networks can help researchers understand complex consumer decision-making behavior. There is a tremendous opportunity for neural networks to be used in many areas of future marketing research based on its brain-like structure and its prediction capabilities.

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