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An expert system for perfume selection using artificial neural network

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ABSTRACT

The objective of this research is to help customers in purchasing perfumes, with the aid of the expert system program developed by using artificial neural networks. The expert system's role is in the preparation to capture the data from the customer's requirements and predict appropriate perfume. For this end, factors of perfume costumers' decision were recognized using Fuzzy Delphi method and a back propagation neural network classification model was developed and trained with 2303 data of customers. In addition, to validate the approach, the expert system program has been tested with 583 data of customers. The model demonstrates the usefulness of 70.33% classification rate in classifying consumers' styles that looks satisfying.

1. Introduction

Nowadays customers' loyalty and satisfaction is the source of competitive advantage and a key for survival and growth of business firms (Armstrong & Kotler, 2000; Frederick, 1996; Weitz & Jap, 1995). Matzler, Bailom, Hinterhuber, Renzl, and Pichler (2004) showed that customer satisfaction increases customer loyalty and decreases price sensitivity. Numerous studies have confirmed the positive correlation between customer satisfaction and profitability (Eklof, Hackl, & Westlund, 1999; Garbarino & Johnson, 1999; Grossman, 1998; Hallowell, 1996). Hence, increasing customer satisfaction is one of the critical sources for business managers in today's competitive market (Deng et al., 2008). With this goal in mind, several business managers are attempting to identify critical service attributes that improve customer satisfaction in order to compete in the marketplace. Wong, Zeng, Au, Mok, and Leung (2009) proposed a fashion mix-and-match expert system to provide customers with professional and systematic mix-and-match recommendations automatically and to enhance customer service and improve sales. So, focusing on customers and providing what they need is one of best ways to increase satisfaction. Generally, when any customer wants to purchase a perfume, there are numerous parameters affecting on this decision. However, it is a difficult and a complex task to identify the customer's needs such as the smell of a perfume. So it is difficult to develop a precise mathematical model for eliciting the decision and another approach is required to acquire the hidden pattern of the overall evaluation by perfume buyers. Since the customer's criteria for purchasing perfume can have a complex hidden pattern, the model should have an ability to perform pattern recognition, classification and forecast which make the artificial neural network (ANN) an appropriate technique to be applied in the expert system. The objective of this research, therefore, is to identify customer requirements and then develop and design the expert system in order to recommend best perfume product for their purchasing. Also validation of the expert system is done by the software used by the authors. 2303 subjects were used to train the model, and 583 subjects were used to evaluate the classification of the model. The paper is organized as follows:

Section 2 illustrates the background of the models used in this research and some relevant literatures. Section 3 describes the proposed research method in relation to the ANN. Section 4 describes implementing expert system and finally conclusion appears in Section 5.

2. Literature review

The three basic elements of this research are: the perfume, the expert system, and the ANN. These elements are described below in regard to the nearest relevant literatures.

2.1. The perfume

Perfume is a mixture of fragrant essential oils and aroma compounds, fixatives, and solvents used to give the human body, animals, objects, and living spaces a pleasant smell. Perfume and fragrance are actually synonyms in normal use. Perfume derives from the French word "per fumem" meaning through smoke, due to its first use for religious purposes like incense. Fragrance derives from the French word "fragrens" meaning pleasant smell. The

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perfumes date back more than 4000 years. Perfumery, or the art of making perfumes, began in ancient Mesopotamia and Egypt and was further refined by the Romans and Persians. One of the oldest uses of perfumes came from the burning of incense and aromatic herbs used in religious services. The Egyptians invented glass and perfume bottles were one of the first common uses for glass. Uses of perfumes or fragrances in general are described according to their strength, that is, the concentration of perfumed essence:

– perfumes or concentrates (15–40% concentration of essence);
– eau de parfum (EDP) or parfum de toilette (7–15%);
– eau de toilette (EDT) (3–8%);
– eau de cologne (EDC) (1.5–6%); and
– male fragrances which include aftershave lotions. (Monopolies & Mergers Commission, 1993)

In addition to the fragrance smell and their strength, there are some other factors for these products that are very critical to the purchasing decision of the customer in the first buying and the continual buying of the product.

2.2. The expert system

An expert system is the computer program that emulates the behavior of human experts in a well-specified manner, and narrowly defines the domain of knowledge (Giarratano & Riley, 1989). It captures the knowledge and heuristics that an expert employs in a specific task (Medsker & Liebowitz, 1994). In this research, the expert system roles have been designed to capture the data of perfumes and customer requirements. After that the system is able to use these data and make advice for customer's purchasing decision.

2.3. Artificial neural network

Recent research suggests that the relationships in variables such as customer satisfaction, loyalty, and profit models are in fact characterized by nonlinearity and asymmetry (Agustin & Singh, 2005; Anderson & Mittal, 2000; Anderson & Sullivan, 1993; Mittal, Ross, & Baldasare, 1998), implying that the frequently-used symmetric linear functional forms would result in model misspecification. Furthermore, several researchers (Anderson & Mittal, 2000; Mittal et al., 1998; Ngobo, 1999) proposed that asymmetric nonlinear satisfaction and loyalty models have superior predictive power. Moreover, speedy growth of the collected data by firms not only leads to a complicated and messy data structure but also results in a large number of data that makes the problems for traditional statistical methods too hard. Thus, hidden knowledge in this data volume cannot be used directly. This nature of customer behavior problem and the ability of ANN in eliciting the nonlinear relations among the variables are our main incentive in applying ANN in the problem.

ANNs are distributed and parallel information systems which simulate the human brain to process information. ANNs simulate human cognition by modeling the inherent parallelism of neural circuits in the brain using mathematical models of how the circuits function (Spangler, May, & Vargas, 1999). They could be used to learn complex patterns of information and generalize the learned information (Venugopal & Baets, 1994). ANNs are massively parallel interconnections of simple neurons as a collective system and consist of many nonlinear computational elements called nodes which are interconnected through direct links. One or more input values are taken and combined into a single value, and transform into an output value. It can be used in applications where a model of a system is required based on an input set of training data. ANNs are widely used to examine the complex relationship between input variables and output variables (Nelson & Illingworth, 1994). Since early 1980, there has been an explosive growth in pure and applied research related to neural networks. During this period, the multilayer feed-forward neural networks were introduced and immediately found wide application in many fields (Rumelhart & McClelland, 1986). The use of ANNs has gained popularity in business and marketing that have helped to solve many problems, including market segmentation, sales forecasting, direct marketing, new product development, and target marketing (Bishop, 1995; Callan, 1999; Curry & Moutinho, 1993; Fausett, 1994; Hassoum, 1995; Hu, Shanker, & Hung, 1999; Zahavi & Levin, 1997; Zhang, Hu, Patuwo, & Indro, 1999). The ANNs approach has been applied more recently to consumer satisfaction and loyalty analyses (e.g. Audrain, 2002; Hackl & Westlund, 2000; Willson & Wragg, 2001). Gronholdt and Martensen (2005) applied ANNs in customer satisfaction analysis to identify existing patterns in the data, and synergies between the drivers of satisfaction. Many researchers are devoted to the study of using of ANNs on marketing. de Ville (1996) applied ANNs to explore consumer behavior for market segmentation and advertising. Crooks (1995) utilized ANNs to train data of consumer behavior for predicting potential customers to avoid un-target advertisement (Lee, Shih, & Chung, 2008). The ANN has various structure types and the most widely used ANN is the multilayer perceptron architecture, in a supervised learning method that has the back propagation nature of the learning paradigm (Hagen, Demuth, & Beale, 1996).

2.4. Related work

The most relevant research in this issue has been done by Kengpol and Wangananon (2006) in which a software program developed by authors that has the capability of compiling customer behaviors and expert knowledge that advising appropriate fragrance note. The objective of the research is to develop and design the expert system in order to assess customer satisfaction on fragrance notes. This benefits greatly the perfume manufacturer in offering the right smell to the right customer group of its new product in order to achieve customer satisfaction. The assumption of the research is to believe in the principle that "in general, the same customer group will like the same fragrance notes". Customer groups, concerning to age, and gender, consisted of 8 varieties of customers (male/female of teen, young, adult, and old), so the input layer of neural network architecture, have eight nodes. Also fragrance notes were categorized into 52 main notes and therefore output layer has 52 nodes. The BPNN architecture with 1 hidden layer and 30 nodes in the layer has been used to classify main fragrance groups. The proposed expert system has been designed using Visual Basic 6.0. One of the principal traits of the work is on that a combination of expert knowledge and customer behavior on preferred fragrance notes, have been used for prediction of the fragrance notes. However, the main objective of the work was offering the right smell to the right customer group in order to achieve customer satisfaction and this, benefits greatly the perfume manufacturer. For producing an appropriate perfume for the target groups, the manufacture needs to know desired smells and select one from their variety of fragrance notes. Kengpol & Wangananon tried to delegate this task to expert system and watch the chosen smell/fragrance notes advised by the program, for each type of customer.

As mentioned before, the concentration of this work is on customer's age and gender in one side and the fragrance notes on the other side. However, in buying luxury goods such as perfumes, there are some other affecting factors, have been missed here. Extending Kengpol & Wangananon's work by adding more variables affecting on purchasing decisions of perfume buyers was our main objective in this research. In addition, the proposed expert system by Kengpol & Wangananon suggest the right fragrance note/smell for the right customer, benefiting manufactures, but proposed expert system in this research suggest the right perfume product for the right customer, benefiting sellers and buyers.

3. Research methodology

The research steps include Defining Variables, Data Collection, System Designing and Implementation, as shown in Fig. 1. These steps are described as below:

3.1. Defining variables

The first step in system modeling is the identification of input and output variables. This task is usually done by studying the problem domain and by negotiation with the domain experts. Of course there are an infinite number of possible candidates which should be restricted to certain numbers. In this research the primary variables were defined with reference to the interviews with experts. Five perfume sellers with a good knowledge and more than 10 years experience in this field have been interviewed. These experts have been selected from major perfume stores in Tehran, the capital city of Islamic Republic of Iran. In this way 11 primary variables have been recognized. Then the questionnaire was prepared using these 11 variables and a 1–10 point scale has been applied to denote the importance of each variable. A higher point indicated a higher importance. At last, a total of 50 questionnaires (one for each perfume seller) were distributed among perfume sellers in Tehran major perfume shops, and 30 returned were valid. The valid response rate was 60%.

Afterwards, the Fuzzy Delphi Method proposed by Hsu and Yang (2000) was adopted to denote expert consensus with geometric means. The process is demonstrated as follows:

(1) Organize expert opinions collected from questionnaires into estimates, and create the triangular fuzzy number as follows:

$$\widetilde{T}_A = (L_A, M_A, U_A)$$
$$L_A = \min(X_{A_i})$$
$$M_A = \sqrt[n]{\prod_{i=1}^{n}(X_{A_i})} \quad i \text{ denotes the } i\text{th expert}, \quad i = 1, 2, \ldots, n$$
$$U_A = \max(X_{A_i})$$

where X_{A_i} indicates the appraisal value of the ith expert for criterion A; L_A indicates the bottom of all the experts' appraisal value for criterion A; M_A indicates the geometric mean of all the experts' appraisal value for criterion A and U_A indicates the ceiling of all the experts' appraisal value for criterion A.

(2) Selection of appraisal variables.
In this study, the geometric mean M_A of each indicator's triangular fuzzy number was used to denote the consensus of the expert group on the variable value, so that the impact of extreme values could be avoided. For the threshold value r, the 80/20 rule was adopted with r set as 8. This indicated that among the factors for selection, "20% of the factors account for an 80% degree of importance of all the factors". The selection criteria were as below:
If $M_A \geqslant r = 8$, this variable is accepted.
If $M_A < r = 8$, this variable is rejected. (Kuo & Chen, 2008)

After fuzzy estimation, the fuzzy number of each variable is shown in the Appendix B. The more influential variables are listed in Table 1 respectively. In this case, all of the 11 variables gain $M_A \geqslant 8$ and have been accepted as an influent variable in forecasting perfume customer's behavior.

3.2. Data collection

One of the most important stages in the design of a supervised ANN is the data collection and data preparation, thus the examples for training must be representative of all the possibilities concerning the application. Researches that have used ANNs with supervised learning support the previous statement (Yin, Rosendahl, & Luo, 2003). The data used for this work have been extracted from a number of questionnaires collected from 2886 of perfume customers in major perfume stores in Tehran from November 2008 to February 2009. The survey questionnaire was titled "your criteria on your perfume choice". The following instructions were provided at the beginning of the questionnaire. "The questionnaire seeks to gain a better understanding of your opinions on choosing perfumes. This survey is anonymous and your opinions are very important to us. Therefore, please be as truthful as possible". The questionnaire consists of two main type questions, including demographic questions and other personal information questions. Totally the questionnaire consists of 11 questions which were developed and reworded from perfume market experts. Some questions are formulated to 3, 5 or 7 point Likert scale items with one indicating "strongly low" and the other side number, indicating "strongly high". They were used to evaluate the criteria of choosing perfumes. The questionnaire is appended to the Appendix A.

3.3. System designing

System designing phase, mainly consisted of two steps, expert system designing step, and ANN designing step, described below:

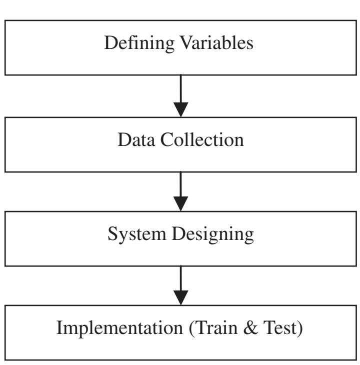

Fig. 1. The steps of the research.

Table 1
The appraisal consensuses of each variable.

Variable	M_A
Gender of customer (Male, Female)	9.88
Recommended age (Teen, College, Mature, Retired, Anyone)	9.76
Fragrance family (Floral, Fresh/Aquatic, Citrus/Fruity, Herbal, Oriental/Spicy, Powdery, Woody/Earthy)	9.74
Product brand prestige (Low, Medium, High)	9.37
Scent strength (Subtle, Moderate, Intense)	8.91
Scent life (Low, Medium, High)	8.73
Bottle or package design (Low, Medium, High)	8.58
Recommended use (Daily Use, Evening Use, Seasonal, Special Occasions, bedtime, Work, Everywhere)	8.44
Price of the product (Low, Medium, High)	8.33
Newness of product (Low, Medium, High)	8.28
Diversification need or the size of the product (Low, Medium, High)	8.06

3.3.1. Expert system designing

Based upon Medsker and Liebowitz (1994) concerning the theory of expert systems, which should have three main components that are:

(1) User interface.
(2) Inference engine (for making decision).
(3) Database (for storing the data, rules, and training the system).

Fig. 2 illustrates the system model that embraces the ANN in the expert system. The customer/user can interact with the interface of the expert system to ask and read the advice from the program. The Inference engine consists of the data of customers and data of perfumes that are classified by the ANN system.

3.3.2. The artificial neural network designing

As mentioned before, ANNs are inherently nonlinear models that recognize patterns and make classifications accordingly. Therefore, they are widely used in classification problems because of their capability of approximating unknown functional relationships and hence are not constrained to predefined functional forms (Sharda, 1994; Zhang, 2004). Dasgupta, Dispensa, and Ghose (1994) found that the back propagation (BP) model of ANNs performs better than other model in classification. The ANNs models have the most success in classification problems are feed-forward multilayer networks (Haykin, 1999).Therefore, a feed-forward BP model is used in the research. The flow chart for perfume selection in Fig. 3 has been used while developing BP model.

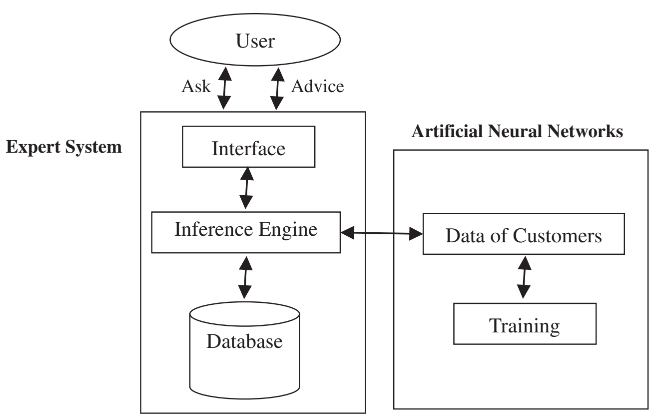

Fig. 2. The expert system model (Kengpol & Wangananon, 2006).

3.3.2.1. Neural network topology. Concerning to 11 variables for choosing perfumes, we recommended that first layer should have 11 nodes. In most cases, 1 hidden layer is sufficient for computing arbitrary decision boundaries for outputs (Khaw, Lim, & Lim, 1995). Kaastra and Boyd (1996) indicated that a neural network with 1 hidden layer with a sufficient number of neurons can approximate any continuous function. Therefore, the number of hidden layers is usually set at 1. For the number of neurons, BPNN practitioners can refer the selection principle of neuron number introduced in Haykin's book (1999) to determine the number of neurons in the hidden layer. This number is crucial to BPNN model performance. No precise formula exists for determining the number of neurons in the hidden layer. Maren, Harston, and Pap (1990) demonstrated that the bound of neurons in first hidden layer was between $2N + 1$ and $OP(N + 1)$, where N is the number of input variables and OP is the number of output variables. Since N is 11 and OP is 49 in this case, the bound of neurons in the hidden layer is [23,588]. So, by performing some trials in the range, the final number of neurons in the hidden layer can be determined. In this way, hidden layer neurons have been set at 50. The third layer (called the output layer) should have 49 nodes, which means 49 perfumes (these perfumes selected among numerous products, so that cover as possible as all range of Price, Size, Fragrance Family, and other variables recognized). So the final architecture of our research is a multilayer perceptron that has 11 input nodes, 50 hidden nodes, and 49 output nodes. The MSE, correlation coefficient (r) results, and calculation speed indicate that this structure outperforms others. According to this, we can simulate the structure of the ANNs in Fig. 4. The hyperbolic tangent activation function is adopted for the links between input layer and hidden layer, and so is adopted for the links between hidden layer and output layer. Other types of

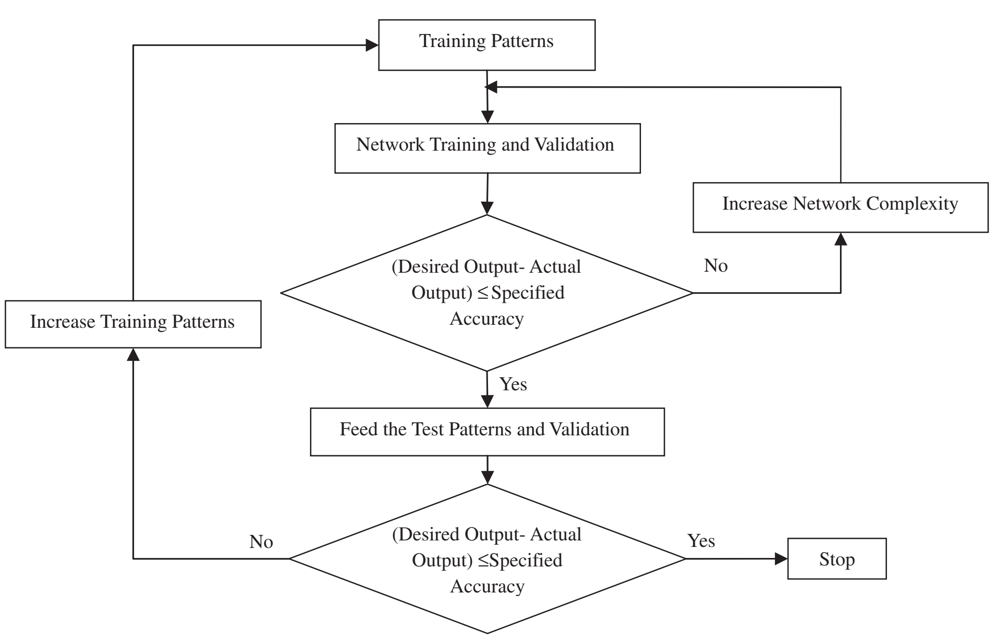

Fig. 3. Flow chart for perfume selection using BPANN (Chowdary, 2007).

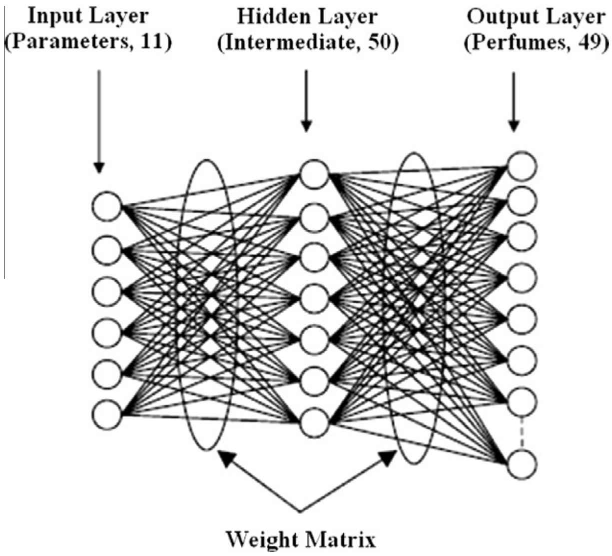

Fig. 4. ANN model structure.

activation functions have been tried, but no better performance on calculated MSE has been found.

Hush and Horne (1993) demonstrated there are 3 conditions for terminating network learning: (1) when the Root Mean Square Error (RMSE) between the expected value and network output value has reduced to a preset value; (2) when the preset number of learning iterations has been reached; or, (3) when the RMSE of a validation sample has begun to increase. The first 2 conditions are based on the preset values. In this research case 2 has been selected for terminating network learning and iteration epochs has been set at 5000.

3.3.2.2. Neural network computation. In ANNs the propagation and the activation rules specify how the inputs to the processing elements are combined to produce its activation level (Kronsjo & Shumsheruddin, 1992). The activation of a node is the sum of the products of its inputs and the weight of their links, which is given as in Eq. (1).

$$A_i(t+1) = \sum A_j w_{ij} \tag{1}$$

Where A_i is the activity function of the ith node and w_{ij} is the weight of the link from node j to node i. During training the learning rule specifies how the weights of the connections in the network are to be adjusted. The weights are usually adjusted in a large number of small steps. This can be done through the following equation:

$$\Delta w_{ij} = \eta(T_i - A_i)A_j \tag{2}$$

Where Δw_{ij} is the change to be made to w_{ij} during 1 learning step and η is a learning rate constant and $T_i$is the target or desired value for the activity of the ith node. The nodes of an ANN can be arranged in 3 or more layers. There may be an arbitrary number of nodes in each layer. The first/ input layer could receive data normalized between 0 and 1. There are also connections from each node in the second/ hidden layer to all nodes in the third/ output layer. The nodes in the second and third layers have internal threshold associated with them. During normal operation, the input patterns are used to set the activation level of the input nodes. Activity is then propagated from the input nodes to the hidden nodes. Finally activity is propagated from the hidden nodes to the output nodes. Propagation takes place according to the Eqs. (3) and (4).

$$net_i = a_j w_{ij} \tag{3}$$

$$a_i = \sigma(net_i - \theta_i) \tag{4}$$

where net_i is the net input to the ith node in the current layer, w_{ij} is the strength of the connection from the jth node, $a_i$is the activity of the ith node, θ_i is its threshold and σ is activation function. One of the most used activation functions is sigmoid function:

$$\sigma(a) = \frac{1}{(1+e^{-a})} \tag{5}$$

Another popular activation function is hyperbolic tangent function whose shape is rather similar to that of the S-shaped sigmoid function of Eq. (5). Tanh function is as Eq. (6) (Graupe, 2007):

$$\sigma(a) = \frac{1}{(1-e^{-2a})} \tag{6}$$

To train the network, the thresholds of the nodes and the strengths of the links are initially set to small random values. Then the network is trained with a set of training cases. Each case contains an input pattern and the corresponding desired output pattern.

The training for the complete set of training cases is continued to achieve good performance. Then activity is propagated from the hidden layer to the output layer. The actual activities of the output nodes are then compared with the target activities in the training case and error will be computed. Then the weights of the links from the hidden layer to the output layer are adjusted according to the following rule:

$$\Delta w_{ij}(n) = \eta \delta_i a_j + a \Delta w_{ij}(n-1) \tag{7}$$

where $\Delta w_{ij}(n)$ is the change to be made in the weight of the link from the jth node to the ith node in iteration (n), α usually called the momentum constant, is a positive number in the range $0 \leqslant \alpha < 1$. It controls the feedback loop acting around $\Delta w_{ij}(n)$ (haykin, 1997), η is a learning rate constant between 0 and 1, a_j is the activity of the jth node and σ_i is the error in node "i " in the output layer and can be obtained from Eq. (8).

$$\delta_i = a_i(1-a_i)(t_i - a_i) \tag{8}$$

where a_i is the actual activity of the ith node and t_i is the target activity for it. Also the weights of the links from the input layer to the hidden layer are adjusted according to the rule as given in Eq. (7). For the hidden layer the values of σ_i are calculated by propagating the error signals backwards from the output layer according to Eq. (9).

$$\delta_i = a(1-a_i)\sum_k \delta_k w_{ik} \tag{9}$$

where σ_k is the value of σ_i for the kth output node. Properly trained BPNNs tend to give reasonable answers when presented with inputs that they have never seen.

Also, for investigating the accuracy of the model, four criteria: Mean Squared Error (MSE), Correlation Coefficient (r), Mean Absolute Error (MAE), and Correctness Rate are computed. MSE is evaluated using Eq. (10). The ANNs model achieves a better performance when MSE is small.

$$\mathrm{MSE} = \frac{\sum_{j=0}^{P}\sum_{i=0}^{N}(t_{ij} - y_i j)^2}{NP} \tag{10}$$

where P is the number of output possessing elements and N is the number of exemplars in the dataset. t_{ij} and y_{ij} are desired output and network output, respectively.

The size of the MSE can be used to determine how well the network output fits the desired output, but it does not necessarily reflect whether the two sets of data move in the same direction. For instance, by simply scaling the network output, we can change the MSE without changing the directionality of the data. The correlation coefficient solves this problem. By definition, the correlation coefficient between a network output x and a desired output t is evaluated by the Eq. (11):

$$r = \frac{\frac{\sum_i (x_i - \bar{x})(t_i - \bar{t})}{N}}{\sqrt{\frac{\sum_i (t_i - \bar{t})^2}{N}} \sqrt{\frac{\sum_i (x_i - \bar{x})^2}{N}}} \quad (11)$$

The correlation coefficient is confined to the range $[-1,1]$. When $r = 1$ there is a perfect positive linear correlation between x and t, that is, they covary, which means that they vary by the same amount. When $r = -1$, there is a perfectly linear negative correlation between x and t, that is, they vary in opposite ways (when x increases, t decreases by the same amount). When $r = 0$ there is no correlation between x and t, i.e. the variables are called uncorrelated. Intermediate values describe partial correlations.

MAE computes the average absolute difference between the actual and predicted numeric output and maintains the dimensionality of the errors without them being affected by large deviations between the actual and predicted numeric output. The MAE E_i of an individual hypothesis model i is evaluated by the Eq. (12):

$$E_i = \frac{1}{n} \sum_{j=1}^{N} |A_{ij} - T_j| \quad (12)$$

where A_{ij} is the value predicted by the individual hypothesis model i for the cluster j (where j is one of n clusters pre discovered in the dataset); and T_j is the actual value for cluster j of the test dataset. For a perfect fit, $A_{ij} = T_j$ and $E_i = 0$. So, the E_i index ranges from 0 to infinity, with 0 corresponding to the ideal.

And finally the correctness rate is defined as the proportion of correctly predicted parties or cases in which the predicted degrees of liabilities are exactly the same as the real ones.

4. Implementation

In this study authors used NeuroSolutions 5.07 software to build the BPNN model for perfume selection. As mentioned before, the BPNN model is modeled as 1 input layer, 1 hidden layer, and 1 output layer. The 11 attributes are the neurons in input layer and perfumes are 49 neurons in the output layer. The values for learning rate and momentum are respectively set at constant 0.02 and 0.7. The learning terminative rule is the preset 5000 iteration. Subjects were divided into an 80%/20% training/testing subjects. This is well in line with most studies in the neural network literature (Zhang, 2004). 2886 subjects were used to train and test the classification model. A total of 2303 subjects used for model training and 583 subjects for a testing subject used to measure the predictive accuracy of the ANNs models. As mentioned before for investigating the accuracy of different models, four criteria: MSE, MAE, Correlation Coefficient, and Correctness Rate are computed. For verifying and validating the ANN, Hagen et al. (1996) suggest investigating the reaction of the MSE in each epoch. As shown in Fig. 5, MSE value is decreased when the iterations of training is increased. This confirms that the neural networks computing are working correctly, because, when the iterations of training are increased, the MSE value should be decreased (Hagen et al., 1996). Training MSE starts at 0.25500 in the first epoch and ends at 0.01417 in the final epoch.

After training network by training data, we evaluate the program performance by doing the 583 data based upon similar customers. As mentioned earlier, the aim of the second survey is to evaluate the accuracy between the result advised by the program and the chosen perfume from each type of any customer. Hence, the higher number of right perfume choice advised by the program means higher accuracy of the expert system program.

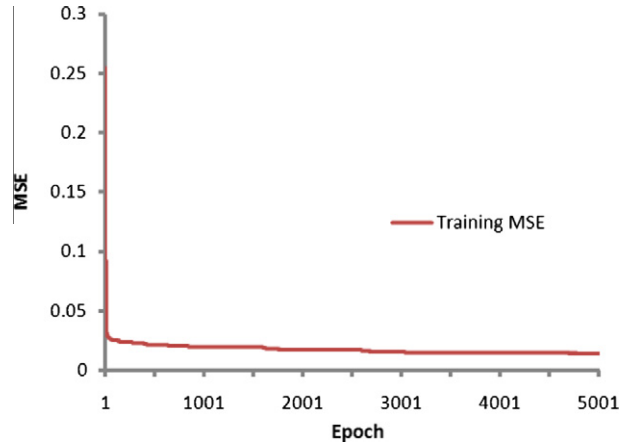

Fig. 5. MSE (vertical) versus epochs (horizontal).

The program performance evaluation is illustrated in Table 2, for example, 19 out of 49 perfumes which have been selected by customers were exactly similar to the result advised from the program, which means it can predict precisely at exactly 100%. In other words, for 38.8% of perfumes, the prediction accuracy is 100%. These 19 perfumes include 197 of 583 testing data (33.8%). For 5 out of all 49 perfumes (10.2%), percentage of the correctness is reached 0%. Just 6.5% of all the testing data has been placed on this part. The reason for this low accuracy may be that for example at perfume 44, there are only a few data (5 in total) and no customer prefers the recommended perfume from the program which produces a percent correctness of 0%. Totally, 75.5% of the correctness percentages are all equal or greater than 50%. In other words, for 37 out of 49 perfumes, the prediction accuracy is above 50%. Also, 76.3% of all testing data placed in this part. However, based upon the prediction target, the average percentage of the correctness by 70.34% advised from the program can be satisfying.

Besides, we calculated the correlation coefficients between the actual outputs, and the network outputs, for the test data sets. If the network performance is high, the correlation coefficients between the actual outputs and the network outputs should take the values that are very close to one. The correlation coefficient (r) between the actual output and the network output is relatively high with the average value of 0.68.

5. Conclusion

Across fashion or luxury goods market, there is a vast variety of requirements in different customers that makes it a difficult and complicated task to identify the best product. Therefore, the objective of this research is to develop and design the neural network based expert system using historical purchasing data in order to help customers on perfume choice. For this end, a panel discussion has been held and five perfume sellers from major perfume stores in Tehran, Iran with a good experience in the field have been interviewed. 11 primary variables, including demographic and other personal information recognized. Then a questionnaire was prepared using these 11 variables and fuzzy Delphi method has been applied to denote the importance of each variable. In this way, all the 11 variables identified as influent variable. A questionnaire survey using these variables was conducted to collect required data among consumers of perfumes in Tehran and 2886 customer data has been collected. Finally a feed-forward BPNN classification model was successfully developed to classify customers' data into different type perfumes and make help to customers. The correct classification rate of the model is 70.33%. The results recommended from the developed expert system that the prediction accuracy is

Table 2
Implementation results on testing data.

Perfume	*P1*	*P2*	*P3*	*P4*	*P5*	*P6*	*P7*	*P8*	*P9*	*P10*
Sum	9	8	7	10	5	11	6	8	8	9
MAE	0.04	0.04	0.04	0.04	0.03	0.04	0.03	0.05	0.04	0.06
MSE	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.01
r	0.98	0.83	0.93	0.96	0.95	0.98	0.92	−0.09	0.97	0.76
Percent Correct	100.00	75.00	100.00	100.00	100.00	100.00	100.00	0.00	100.00	77.78
	P11	*P12*	*P13*	*P14*	*P15*	*P16*	*P17*	*P18*	*P19*	*P20*
Sum	8	9	3	10	14	24	18	21	17	10
MAE	0.06	0.03	0.04	0.07	0.05	0.08	0.07	0.04	0.04	0.04
MSE	0.01	0.00	0.01	0.02	0.01	0.02	0.02	0.00	0.01	0.00
r	0.82	0.96	0.35	−0.04	0.74	0.63	0.69	0.97	0.87	0.89
Percent Correct	87.50	100.00	33.33	0.00	42.86	50.00	77.78	100.00	88.24	100.00
	P21	*P22*	*P23*	*P24*	*P25*	*P26*	*P27*	*P28*	*P29*	*P30*
Sum	10	13	21	22	16	27	36	35	18	12
MAE	0.07	0.06	0.08	0.08	0.04	0.03	0.10	0.10	0.04	0.04
MSE	0.02	0.02	0.02	0.02	0.00	0.00	0.03	0.04	0.00	0.01
r	0.47	0.58	0.64	0.67	0.98	0.99	0.66	0.64	0.98	0.88
Percent Correct	80.00	61.54	52.38	50.00	100.00	100.00	66.67	48.57	100.00	91.67
	P31	*P32*	*P33*	*P34*	*P35*	*P36*	*P37*	*P38*	*P39*	*P40*
Sum	8	4	6	7	10	12	15	14	4	7
MAE	0.06	0.07	0.05	0.05	0.05	0.07	0.07	0.07	0.06	0.04
MSE	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.00
r	−0.05	0.47	0.50	0.06	0.66	0.39	0.47	0.55	0.55	0.92
Percent Correct	0.00	100.00	50.00	0.00	70.00	33.33	33.33	35.71	50.00	100.00
	P41	*P42*	*P43*	*P44*	*P45*	*P46*	*P47*	*P48*	*P49*	*Total*
Sum	4	7	15	5	4	6	14	9	7	583
MAE	0.05	0.04	0.04	0.07	0.06	0.04	0.05	0.06	0.06	0.05
MSE	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.01	0.01
r	0.72	0.92	0.92	−0.01	0.68	0.83	0.98	0.77	0.64	0.68
Percent Correct	100.00	100.00	86.67	0.00	100.00	83.33	100.00	77.78	42.86	70.33

satisfactory. The inference engine of the ANN can deliver even better results if the amount of data captured from the customer can be larger. There is a dearth of programs that can predict and deliver a satisfactory result to the customer in general and luxury goods, in particular. This program, therefore, can provide benefits to the both buyers and sellers. In addition, there is a new trend nowadays on buying since everything you want is available online, through online shopping. New lifestyle has dictated this change. Some people that they are very busy with their work and do not have time to visit the malls, prefer this kind of shopping.

According to new report by Global Industry Analysts, global fragrances & perfumes market will reach $33.6 Billion in 2012. Concerning to perfume products nature, traditional perfume stores survived and it seems that will continue to survive comparing to web stores and gain the majority of this market share for themselves. Although web stores empower consumers with the ability to buy anytime/anywhere, the advantages of web stores may be dampened by their inherent limitations and consumers' fear of the web. Concerning to complex pattern exist in perfume selection, such as smell of perfume, a little customers prefer electronic buying unless for pre-used perfumes. Such an expert system in web stores can help customers to choice the appropriate perfume based on historical customer's data. Advising right perfume for right customer will increase customer satisfaction, loyalty, and also profitability for the seller. Other benefits include time and money savings for customers. Be concern that, this research initially aims to help customers on perfume choice, therefore, it could be appropriate to the perfume sellers and buyers, although the model itself is feasible and applicable to any type of business, for example, food and beverages, fashion market, cars, all type of personal care or cosmetics, and even stock market. It can also be used by perfume manufactures for discovering customer's hidden pattern in their own minds or even market trends and produce the requested product by the customer's elegance. Also it could be interesting to the researchers to compare the performance of ANN approach with other meta-heuristics (e.g. Genetic Algorithm, Fuzzy Neural Networks) or traditional statistical methods (Linear/Nonlinear Regression) especially to examine whether ANN approach has any superiority in solving such a selection problems.

Appendix A. Customers' Questionnaire Structure

Your criteria on your perfume choice

The questionnaire seeks to gain a better understanding of your opinions on choosing perfumes. This survey is anonymous and your opinions are very important to us. Therefore, please be as truthful as possible.

1. What is your gender?
   (a) Male
   (b) Female
2. Who should wear this perfume?
   (a) Teen – 12–17
   (b) College – 18–24
   (c) Mature – 25–54
   (d) Retired – 55+
   (e) Perfect for Anyone
3. How would you rate brand prestige for this perfume?
   (a) Low
   (b) Medium
   (c) High
4. How important is price of the product for you?
   (a) Low
   (b) Medium
   (c) High

5. How important is newness of the product for you?
   (a) Low
   (b) Medium
   (c) High
6. How would you rate bottle or package design of the product?
   (a) Low
   (b) Medium
   (c) High
7. How strong is this fragrance?
   (a) Subtle
   (b) Moderate
   (c) Intense
8. How long does this scent last?
   (a) Low (1–5 h)
   (b) Medium (6–10 h)
   (c) High (11+ h)
9. When/Where do you recommend the perfume be worn?
   (a) Daily Use
   (b) Evening Use
   (c) Seasonal
   (d) Special Occasions
   (e) Bedtime
   (f) Work
   (g) Everywhere
10. How would you classify this fragrance?
   (a) Floral
   (b) Fresh/Aquatic
   (c) Citrus/Fruity
   (d) Herbal
   (e) Oriental/Spicy
   (f) Powdery
   (g) Woody/Earthy
11. How important is your diversification need on perfumes?
   (a) Low
   (b) Medium
   (c) High

Appendix B

The fuzzy number of each variable.

Variable	Fuzzy number
Gender of customer (male, female)	(9,9.88,10)
Recommended age (teen, college, mature, retired, anyone)	(9,9.76,10)
Fragrance family (floral, fresh/ aquatic, citrus/ fruity, herbal, oriental/ spicy, powdery, woody/ earthy)	(8,9.74,10)
Product brand prestige (low, medium, high)	(8,9.37,10)
Scent strength (subtle, moderate, intense)	(8,8.91,10)
Scent life (low, medium, high)	(8,8.73,10)
Bottle or package design (low, medium, high)	(7,8.58,10)
Recommended use (daily use, evening use, seasonal, special occasions, bedtime, work, everywhere)	(7,8.44,10)
Price of the product (low, medium, high)	(7,8.33,10)
Newness of product (low, medium, high)	(6,8.28,9)
Diversification need or the size of the product (low, medium, high)	(6,8.06,9)

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