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Improving the effectiveness of experiential decisions by recommendation systems

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ABSTRACT

Providing experience-oriented offerings through e-commerce is an issue increasing critical in the growing commoditization of e-commercial services. The high accuracy of predictions rendered by Recommendation System (RS) technologies has strengthened the opportunities for experience-oriented offerings, making RS application an effective way of assisting consumers in online decision-making. This study proposes a RS for movie lovers using neural networks in collaborative filtering systems for consumers' experiential decisions. The experimental results reveal that it not only improves the accuracy of predicting movie ratings but also increases data transfer rates and provides richer user experiences. © 2014 Elsevier Ltd. All rights reserved.

1. Introduction

In the e-commerce context, the role of recommendation systems is similar to that of sales persons in retail stores (Komiak & Benbasat, 2006). For example, Amazon has a recommendation system (RS) that offers customers purchasing advice about books or music that may be of interest to them based on their product choices. This is a proven successful example, in which the RS acts like a personal in-store assistant, providing rich user experiences. Such experiences invoke positive emotional responses from customers. Previous studies have shown that customer decisions are much more influenced by emotions rather than rationally derived thought. RSs can help online stores invoke emotions important to customers and not only improve their satisfaction with purchases but also increase the average amount of purchases.

Most of the RSs are content-based, demographics-based, or utility-based, which all require high domain knowledge. An alternative collaborative approach independent of domain knowledge is needed, especially for new applications in the movie and music industries. The most critical problem of conventional approaches lies in their use of a single algorithm, such as the Self-Organizing Map (SOM) or nearest neighbor, which cannot consistently maintain the accuracy of prediction with numerical and non-numerical data. Moreover, few have taken experiential behavior into account

http://dx.doi.org/10.1016/j.eswa.2014.01.035 0957-4174/© 2014 Elsevier Ltd. All rights reserved. because the application of psychological analysis, like experiential flow, requires transforming non-numerical behavior data into numerical data in order to input into an RS. More specifically, the existing recommendation systems overlook psychological data for analyzing the flow state of experiential perception. This study proposes a multi-layer perception model integrating SOM with Neural Network Systems (NNS) based on experiential perspectives to improve the efficiency and accuracy of an RS.

2. Literature review

2.1. Consumer's purchasing behavior based on experiential perspectives

E-marketing with RSs, instead of human staff, may improve the efficiency of touch points to create customers' individual experiences, but it is difficult to create and manage these unique experiences. How to create the right online experiences has been addressed by a number of scholars who offered several distinct perspectives. Some recommended being extraordinary while others urged to pursue a previously unseen amalgamation of alternate approaches. In the context of e-shopping, the role of RSs is similar to that of sales persons in retail stores (Komiak & Benbasat, 2006). The difference between traditional commerce and e-commerce lies in the user experience that invokes emotions. This is a humanmachine interaction, so the emotional context is different than human-human interaction. User experiences may affect what customers expect in the future and what they expect from other





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Table 1The 4Es model by Holbrook (2000).

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Experience	Entertainment ^a	Exhibitionism	Evangelizing
Escapism ^a Emotions Enjoyment	Esthetics ^a Excitement Ecstasy	Enthuse Express Expose	Educate ^a Evince Endorse

^a This is one of the 4 realms of experience identified by Pine and Gilmore (1998).

service providers. According to a longitudinal study, predictive expectations were higher after having positive experiences and remained relatively stable after having negative experiences. It has been proven that these experiences are affected by emotions which significantly increase the average customer spending. Rinallo, Borghini and Golfetto (2010) were the first academic proponents of this experiential perspective. They argued that, at least in certain contexts (e.g., hedonic products such as novels, plays and sports), consumer actions may be motivated by the 3Fs (Fantasy, Feeling and Fun) concept (Holbrook & Hirschman, 1982) and the 4Es (Experience, Entertainment, Exhibitionism, Evangelizing) model (Holbrook, 2000). The latter model is illustrated in Table 1. In this paper, we propose a 3Is (Interesting, Individual, Interactive) experiential model for the contact points of e-service. The model emphasizes not only how to attract prospective customers but also to produce individual recommendations according to the customer's experience, by implementing the 4Es principles as four input neurons of a NNS. Such personalized services have shown that customers are searching for the emotional, sensory, and relational aspects of consumption goods and services. These aspects are intrinsically gratifying and contribute to establishing customers' individual and collective identities (Arnould & Thompson, 2005). Such identities enable service providers to recommend the next product to buy.

2.2. Recommendation system with collaborative filtering method

During the past decade, much research has been reported on RSs that are linked with learning mechanisms, knowledge-based perspectives, personalization, data mining systems, and other advanced methodologies, such as query language, fuzzy linguistics, etc. Many different entities were involved in the research, such as voting systems providers, film and television production companies, e-commerce providers, among others. Various methods have been applied to RSs such as dynamic personalization, robust classification (Symeonidis, Nanopoulos, Papadopoulos, & Manolopoulos, 2008), consumer-product graph analysis, etc. One prominent method takes consumers' experiences into account and applies collaborative filtering methods (CFM) to NNS. The RSs using this method apply CFM's nearest neighbor formation processes to derive explicit ratings for input neurons of NNS and compare the results with traditional NNS against user rating and prediction accuracy. Such a gathering, processing, transmission process improves the prediction effectiveness of the marketing RS (Mocean & Pop, 2012).

According to Resnick, Iacovou, Suchak, Bergstrom, and Riedl (1994), RSs had originally been identified as systematic processes that use one-to-one suggestions as input data. After a system developed a sufficient data set, integration and more elaborate applications were implemented to deliver individualized suggestions to new users, and to identify how experienced users choose product/service items in order to personalize their desired online services. All these were made possible by collecting and using personal interest/preference data from the customers. Schafer, Konstan, and Riedl (1999), categorized the recommendation methods into four types:

- (1) Non-personalized recommendation,
- (2) Attribute-based recommendation,
- (3) Item-to-item correlation,
- (4) People-to-people correlation.

The last type, people-to-people correlation, uses the shoppers' past purchasing experiences, reads through information to find similar shoppers, and makes a mutual recommendation using those products between similar shoppers. In this situation, the way of judging the similarity between consumers most often used the "collaborative filtering method" which is explained in the following section, followed by the "neural network system".

2.2.1. Collaborative filtering method

To reduce the problem of information overload, both information retrieval and information filtering were applied to achieving the goal. In information retrieval, the system has to provoke the target customer's inputs, by displaying a keyword, a series of keywords, or even a sentence. It leads to more dynamic searching technology which meets with those changing demands from the customer's past purchasing experiences. In contrast, information filtering, which compares user profiles with sorted documents, leads to more stable information offerings by removing information noise according to individual or collective identities. In addition, information filtering was categorized into three types: content-based recommendation, collaborative filtering, and, economic filtering.

- (1) Content-Based Recommendation (CBR) uses the information retrieval method in which selected keywords match the "semantic concept" by the logic of "and," "or," or "not." Creating such a model of "attribute list" requires no need of ratings to avoid any cold-start problem, but the user is restricted to seeing items similar to those already experienced. The system then builds the "representation" of each user's preference and target content, compares the similarity between users and suggests a similar consumer's choice as a recommendation for the next product to buy. Such kind of recommendation system is called "item-to-item correlation," using the content of information for selection. It is totally different from a collaborative filtering system; the collaborative filtering system uses the majorities' points of view and has nothing to do with the content.
- (2) Collaborative Filtering (CF), also called "Active Collaborative Filtering", uses the word-of-mouth effect, automating the idea of "like people, like tastes." Input a purchasing list or evaluation command from any user, find the similar taste groups (i.e., "neighbors") in systematic language, and mutually recommend a "preference list" to each other.
- (3) Economic Filtering (EF) is based on the cost and effectiveness of the information produced. If a message is mailed to a great number of receivers, then the production cost per addressee is low and should be given lower reading priority.

Barragans-Martinez et al. (2010) proposed "Hybrid Recommendation System" that mixes more than two types of the above systems to avoid the disadvantages and optimize the advantages of each different method. Burke (2002) identified five types of RSs: demographic, utility-based, and knowledge-based, besides the aforesaid collaborative-filtering and content-based systems. "Demographic" uses the people-to-people RS, categorized by demographic information leading to various suggestions. The system collects customers' personal information through an interactive dialog and recommends products based on such information. The benefit of using this method is that it does not need historical data records, but may not get sufficient information for discovering related recommendations. "Utility-Based" involves counting users' usage of each purchase item. Both the trustworthiness and creditability of the seller and the products' delivery time for emergency purchases were also taken into account. "Knowledge-Based" combines knowledge base and collaborative filtering system in an attempt to manage the relationship between customer demand and RS suggestions.

2.2.2. Neural networking system (NNS)

Neural Networking System (NNS) is a useful tool in pattern recognition (Moschou, Ververidis, & Kotropoulos, 2007). It has been an active research area for the past few decades because of the variety of its applications. The NNSs have been widely used in machine learning, pattern recognition, image analysis, and data mining. Kim, Street, Russell, and Menczer (2005) demonstrated how NNS achieved the principal goals of customer targeting by improving the accuracy of prediction.

The flow and architecture of NNS is shown in Fig. 1. The three basic structures of a neural network are: (1) Input Layer, (2) Hidden Layers, and (3) Output Layer. Neural Networking Systems are composed of processing units, which are linked into nerve tree frameworks. The processing units have different processing weights (such as the linkage strength), to justify the output result. Each layer consists of one or more nodes, represented in this diagram by small cycles. The lines between the nodes indicate the flow of information from one node to the next.

2.3. Experiential recommendation system with 4Es as the neurons of NNS

A recommendation system is a system with one-on-one interaction and individualized communication patterns. Schafer, Konstan, and Riedl (2001), pointed out that these features could help build customer loyalty and increase profits, as it puts the experiential marketing perspective into a systematic view. The basic formation logic uses the collaborative filtering system to increase the customers' value by following two steps:

- (1) Apply the Self-Organizing-Map (SOM) in a Neural Networking System (NNS) to cluster users into groups.
- (2) Utilize the Nearest Neighborhood method to evaluate the similarities in the same experiential group through experimentation with Pearson correlation coefficient test.

Fig. 2 shows system success values created by RSs with experiential perspectives. The RS suggests items of interest to users based on their preferences, the preferences of other users, as well as user and item attributes. The system adapts the participative interactivity from Terveen and Hill (2001), and the categorization criteria and three values of the Weblog Success Model described by Du and Wagner (2006). The value-based concept of the Weblog Success Model is primarily associated with the system's content, technology, and social values for exploring customers' experiences. Using 3Is RSs can obtain content value, technology value, and social value for achieving system success. Barragans-Martinez et al. (2010), further combined the content-based collaborative filtering approach with an item-based collaborative filtering approach to recommend TV programming. Thus, basing on how recommendations are made, RSs can be classified into two categories: collaborative filtering RSs and content-based RSs (Adomavicius, Sankaranarayanan, Sen, & Tuzhilin, 2005). Algorithms for collaborative RSs can be grouped into two approaches: memory-based and model-based algorithms. In this study, we adopted the model-based approach. Our approach extends previous work by Goldberg, Roeder, Gupta, and Perkins (2001), which uses a collection of ratings to build a model, then uses the model to predict ratings. Through the improvement in the accuracy of prediction of model-based algorithms, the features of the Internet and RS technologies allow us to apply the experiential recommendation to not only the digital TV systems but also e-movies.

Past NNSs commonly used transfer functions with rational perspective as the neuron of a hidden layer. Contrary to this common practice, this study introduces transfer functions with experiential perspective into the first hidden layer of neurons before the traditional (rational) hidden layer. That is, the proposed NNS has experiential neurons in the first hidden layer and rational neurons in the second hidden layer. There are two plausible implementations of experiential neurons. One is through Holbrook and Hirschman's 3Fs (Fantasy, Feeling and Fun) and the other is Holbrook's 4Es (Experience, Entertainment, Exhibitionism, Evangelizing). This study adopted 4Es as the neurons because of the growing practice of employing on-line collaborative-filtering-systems for improving effectiveness of RSs in accurately extracting and recommending the similarity of users' 4Es experiences. In addition, we apply 3Is experiential RS to design contact points of services with Interesting, Individual, and Interactive interfaces which improve customer cognitional satisfaction and lead to customer online word of mouth (evangelizing), attitudinal loyalty and re-purchase intentions (Urban, 2010). From the RS survey of Bobadilla, Ortega, Hernando, and Gutiérrez (2013), there is an obvious trend to integrate various categories of data. Using our method, one could obtain the experiential data explicitly and implicitly and feed these data into RSs.



Fig. 1. The mechanism of a neural network system.



Fig. 2. A recommendation system adapted from Du and Wagner (2006) and Bobadilla et al. (2013) with the experiential perspectives.

3. Method

The experimental process and calculation are described in two parts as follows.

3.1. Data sets of experiment

This study used the MovieLens 100 k database from the "Group-Lens Research Project" of The University of Minnesota (http:// www.grouplens.org/node/12). The database gave us data from October 1997 to April 1998 which included 943 users and 1682 movies. Each user (i.e., audience) had to rate at least 20 movies, and the rating ranged from 1 to 5 points. Within the database, we collected two profiles that related to our study:

- (1) Movie: The profile of movie included coding of the movie, the title, the published date, DVD published date, and the attributes. There were 19 attribute categories according to the databases of University of Minnesota: Action, Adventure, Animation, Children's, Comedy, Crime, Documentary, Drama, Fantasy, Film-Noir, Horror, Musical, Mystery, Romance, Sci-Fi, Thriller, War, Western, and Unknown. Every movie had at least one attribute; for example, "Star Wars" had five: action, adventure, romance, sci-fi, and war.
- (2) User Rating: The profile of user rating included more than 100,000 scores measured by 5-point scales (1 and 2 being negative ratings, 3 being no comment, and 4 and 5 being positive ratings) created by 943 users rating 1,682 movies.

In order to have enough rating information, we selected the top 50 popular movies, and the top 100 users for these 50 movies. In total, there were 3808 units of rating information for this experiment to use, and 10% of the rating values were randomly selected for prediction purposes.

Using the SOM in the NNS to do the clustering, we assumed the different ratings from users towards films were due to the uses' experiential preferences towards the different attributes of the movies. In order to find out the preferences of user's experiences, we transformed the users' rating credits from those films with the users' preference points related those films' attributes. Each audience's preference towards the attributes of 1682 movies was calculated by the "mean" value of 50 films' rating points. Finally, the data selection with the top 50 popular movies were based on 7 input factors (i.e., "movie attributes") of Action, Adventure, Comedy, Drama, Sci-Fi, Thriller, and War.

This research used MATLAB 6.5: "Neural Network Toolbox" as the SOM model cluster tool. We used the mean value of the front 100 users' evaluations towards 7 movie attributes as the input data profile; then, using the parameters of SOM to train the network patent, we applied a networking learning mechanism to gather similar preference audiences. Under this rule, there were 4 neighboring clusters, creating 4 groups of audiences. The network training process is outlined in Appendix.

3.2. Mathematic calculation of algorithm

3.2.1. Self-organizing map (SOM) and nearest neighborhood

The self-organizing map (SOM) has been applied to exploratory analysis of high dimensional data, human posture classification and clustering, to mention a few (Moschou et al., 2007). The novel contribution of pattern clustering is in the assessment of SOM training algorithms in clustering with respect to the accuracy. Besides SOM establishes a mapping from the input data space onto a low dimensional lattice of nodes so that a number of topologically ordered and well defined prototypes are created using artificial intelligence to simulate the organized nodes on a map, as they apply to judgment, decision making, controlling, and production. Instead of decreasing the effectiveness of RS by calculating all data from the audiences, here we utilized SOM to cluster the neighbor grouping, and then used the nearest neighbor to calculate the Pearson coefficient within the same group. We compared the SOM variants under this experiment to the redistribution of emotional movie patterns (from the databases of the "GroupLens Research Project," originally classified as neutral) into the emotional states of anger, happiness, sadness, and surprise. The SOM produced 4 clusters of audience with high similarity and these clusters became the four nodes of the hidden layer in NNS.

We concerned ourselves with two major concepts: (1) network topology, and (2) neighborhood area. The first, "network topology," used a symmetric matrix (one, two or three axes) to identify the proper position for the output layer. The second, "neighborhood area," used the neighborhood center as the core and restrained the neighborhood distance (as in Eq. (3.2)) in each cycle of network learning process.

Eq. (3.1) denotes the Neighborhood Radius (R) which is the parameter to control the distance of Neighborhood Area.

$$R = \left[1 - \frac{t}{T}\right] \tag{3.1}$$

T: The total frequency of learning

t: The current frequency of learning Eq. (3.2) below is the Neighborhood Distance.

$$r_{j} = \sqrt{(X_{j} - C_{x})^{2} + (Y_{j} - C_{y})^{2}}$$
(3.2)

- *r_j*: The distance between output processing unit *j* with its neighborhood center C.
- X_{j_i} , Y_j : The two zone topology location of output process unit *j*. C_{x_i} , C_{y_i} : The two zone topology location of the neighborhood center C

Other parameters include Neighborhood Factor, Neighborhood Function, and Neighborhood Restraint. The description of each parameter is as follows:

- Neighborhood Factor: This factor is to control the mutual-influence level of the same neighborhood output processing units, and the distance of the neighborhood. This factor is a function of Neighborhood Radius and Neighborhood Distance.
- Neighborhood Function: $R_factor_i = f(r_i, R)$ is function that determines the Neighborhood Factor based on Neighborhood Radius and Neighborhood Distance. In this study we used Gaussian function.
- Neighborhood Restraint: $R^t = R_rate \cdot R^{t-1}$ iteratively reduces the Neighborhood Radius during the learning process. R_rate is the neighborhood restraint radius factor (<1.0)

The SOM networking mechanism is quite simple and intuitive. First, set the network factor, and, input the users' preference as the training pattern. Then, calculate the distance between the input factor and output unit. The nearer they are (shorter distance), the higher the similarity is. After calculating all distances between output units and training patterns, and selecting the shortest distance as the victory unit (and as the neighborhood center), SOM self-adjusts the connecting weights between the input layer and output layer by the distance calculated from the neighborhood center, and forms the neighborhood factor (the longer the distance, the smaller the neighborhood factor, so the adjusted weight would be smaller also). After all users' information and training patterns were sequentially processed once, it completes one learning cycle. Each time the learning cycle finished, the neighborhood radius was restrained once, and the learning speed was reduced once, so by continuously repeated learning, all weights were adjusted statistically.

After training SOM to cluster and group users, the second step was to measure the similarities within the same group. In this research, we used the Pearson coefficient (Eq. (3.4)) to measure the similarities between the nearest neighbors. Resnick et al. (1994), were the pioneers in using the Pearson coefficient to judge the similarity between two items. Herlocker, Konstan, and Riedl (2002), compared couples of frequently-used evaluation criteria, suggesting that the Pearson coefficient remains the proper measurement of recommendation quality. So, in this research we followed the suggestion to adopt the Pearson coefficient as the weighting for predicting the similarity of audiences' preferences towards certain items. In the equations below, $P_{a,i}$ in Eq. (3.3) represents the prediction for the active user for item *i*. *n* is the number of co-rating users in the same cluster, *m* is the number of co-rated items, r_u , *i* is user *u*'s rating of item *i*, $\overline{r_a}$ is the active user's average rating, and $w_{a,u}$ is the similarity weight between the active user a and neighbor u—as defined by the Pearson correlation coefficient, which is shown in Eq. (3.4).

$$p_{a,i} = \overline{r_a} + \frac{\sum_{u=1}^{n} (r_{u,i} - \overline{r_u}) \times w_{a,u}}{\sum_{u=1}^{n} w_{a,u}}$$
(3.3)

$$\mathbf{v}_{a,u} = \frac{\sum_{i=1}^{m} \left[(\mathbf{r}_{a,i} - \overline{\mathbf{r}_{a}}) \times (\mathbf{r}_{u,i} - \overline{\mathbf{r}_{u}}) \right]}{\sqrt{\sum_{i=1}^{m} (\mathbf{r}_{a,i} - \overline{\mathbf{r}_{a}})^{2} \sum_{i=1}^{m} (\mathbf{r}_{u,i} - \overline{\mathbf{r}_{u}})^{2}}}$$
(3.4)

Given the mathematic calculation, the revised SOM algorithm for this system is summarized as follows:

Step 1: Initialize:

- Set weights *w_{ii}* to small random values.
 - Set neighborhood size $N_c(0)$ to a large value. The neighborhood size decreases slowly when time increases.
- Set learning speed $\alpha(t)$ and Neighborhood Radius $\sigma(t)$ to be between 0 and 1, in this case, $\alpha(0) = 0.5$ and $\sigma(0)$ = 1. In our experiments, we also attempted to test the composition of $\alpha(0) = 0.1$ and $\sigma(0) = 0.9$. $\alpha(t) = A/$ (B + t), where A and B are constants; the inverse time function is justified theoretically by the so-called stochastic approximation theory (Robbins & Monro, 1951).

Step 2: Calculate the minimum distance d_i (similarity) of this input, compute the weights w_i of each node j after presenting an input pattern y through the input layer, $d_j =$ $||y - w_j|| = \sqrt{\sum_{i=1}^n (y_i - w_{ij})^2}$. Meanwhile, select the node with the minimum distance as the winner *c*.

 w_i = the vector of weights for the output node *j*.

 w_{ii} = the *i* element of the vector w_{i} .

$$y_i$$
 = the *i* element of vector *y*.

 $i = 1, 2, \dots, n; j = 1, 2, \dots, m; n$ is the total number of elements in vector *y*; *m* is the total number of output nodes.

Step 3: Update the weights, connect the input layer to the winning node and its neighboring nodes, according to the learning rule.

$$w_{ij}(t+1) = w_{ij}(t) + c[y_i - w_{ij}(t)],$$
 where $c = \alpha(t)$
exp $\left(-\frac{\|r_c - r_j\|^2}{2 \cdot \sigma^2(t)}\right)$ for all nodes j in $N_c(t)$; where $[r_c - r_j]$
(according to the Eq. (3.2)) is the physical distance
between node i and the winning node c .

Step 4: Repeat above-mentioned steps until the weights have stabilized. For example: In this experiment, we continued from Step 2 to Step 3 for 40 epochs ($\Omega = 1, 10, 20, 30,$ and 50 were also tested).

3.2.2. Collaborative filtering system

Based on the Miller, Konstan, and Riedl (2004) theory of calculating the distance between the two nearest neighborhoods as a measurement of similarity, we performed three steps detailed as follows: (1) collecting users' rating records, (2) clustering groups by different interests, and (3) recommending suggestions to the group with the most similar taste.

Firstly, collected records of audiences' preferences will form the basis of categorization by rating records of sense. Audiences were asked to evaluate items directly by giving points as "explicit navigation of rating, ranking the level or sequence, or by giving text comments." This method is direct, accurate, and generally uses lower overall data transfer rates, but the disadvantages are that user responsibility increases and rating scarcity problems occur.

Secondly, each group clustered by interests should also be categorized as memory-based or model-based (Breese, Heckernman, & Kadie, 1998). To calculate the similarity, Breese et al. used correlation, vector similarities, default vote, inverse user frequencies, and case amplification.

To avoid scarcity and scalability problems, we used a mix of model based calculations. This also avoided having to deal with all kinds of data, focusing instead on selected data types directly related to the model and the purposes of the research. Note that Latent Semantic Indexing (LSI) used Singular Value Decomposition (SVD), Content analysis (Balabanovic and Shoham, 1997); the

Bayesian Network Model (Breese et al., 1998); and the Cluster Model (Schafer et al., 2001; Mobasher, Dai, Luo, & Nakagawa, 2002), all of whom attempted to reduce system loading and increase accuracy.

The third and last step is to recommend similar suggestions to the nearest interest group. After clustering different neighbor groups by similarity of rating, we regarded the preferences of the target audience within the same group as the priority of suggestion lists.

3.2.3. Neural networking system (NNS)

Although several NNSs have been used for recommendation research, this study follows the Multilayer Perception Model with the Back-Propagation Algorithm (MPM-BPA). The model has been mathematically proven to be universally approximate for any continuous function. MPM-BPA can handle a very high degree of nonlinear problem space very efficiently.

The Multilayer Perception Model (MPM) has the following mathematic calculation in order to input/output information and the system can also be adapted by different weights and training algorithms.

Eq. (3.5): Multilayer Perception Model (MPM)

$$y = w_0 + \sum_{j=1}^{q} w_j \cdot f\left(w_{0j} + \sum_{i=1}^{p} w_{ij} \cdot x_i\right) + \varepsilon$$
(3.5)

$$f(x) = \begin{cases} 1 & \text{If } x \ge 0\\ 0 & \text{if } x < 0 \end{cases}$$
(3.6)

where $w_{ij}(i = 0, 1, 2, ..., p; j = 1, 2, ..., q)$ and $w_j(j = 0, 1, 2, ..., q)$ are connection weights; p is the number of input nodes; q is the number of hidden nodes; and w_{0j} , w_0 are the weights for bias units connected to hidden nodes and output node.

f(.) = transfer function

 η : Learning speed with the modified weights

- *{T}*: Target value
- {*Y*}: Predict value

For an output layer node,

- δ_k : the deviation of node k in output layer, $\delta_k = (T_k - Y_k) \cdot Y_k (1 - Y_k)$
- the change of the weights $\Rightarrow \Delta W_j = \eta \cdot \delta_k \cdot f(w_{0j} + \sum_{i=1}^p w_{ij} \cdot x_i)$

• the change of the bias value per unit $\Rightarrow \Delta \theta_k = -\eta \cdot \delta_k$

For a hidden layer node,

• δ_j : the deviation of node j in hidden layer, $\delta_j = f(w_{0j} + \sum_{i=1}^p w_{ij} \cdot x_i) \cdot (1 - f(w_{0j} + \sum_{i=1}^p w_{ij} \cdot x_i) \cdot \sum_k \delta_k w_j$

• the change of the weights,
$$\Delta W_{ij} = \eta \cdot \delta_j \cdot X_i$$

• the change of the bias value per unit, $\Delta \theta_i = -\eta \cdot \delta_i$

For this study, we used the MPM to predict the audience's preference. The MPM networking system is comprised of seven inputs (Action, Adventure, Comedy, Drama, Sci-Fi, Thriller, War), one hidden layer had four experiential groups as four neurons. The four groups were adopted from the 4Es model (Entertainment, Educate, Escapist, Esthetic) of Pine and Gilmore (1998), and one output layer with a single neuron, as illustrated in Fig. 3.

Based on Box, Jenkins, and Reinsel (1970) methodology, our proposed model is a nonlinear function of several past observations and random errors as below:

$$Y_t = f(X_{t-1}, X_{t-2}, \dots, X_{t-p}, w) + \varepsilon_t$$

= $F[(Z_{t-1}, Z_{t-2}, Z_{t-3}, \dots, Z_{t-m}), (\mathbf{e}_{t-1}, \mathbf{e}_{t-2}, \mathbf{e}_{t-3}, \dots, \mathbf{e}_{t-n})]$

where *F* is a nonlinear function determined by the neural network, X_t is the original input data. $Z_t = (1 - B)^d (y_t - \mu)$, e_t is the residual at time *t* and *m* and *n* are integers.

A neural network is then used to integrate the nonlinear and linear relationships in residuals and original data. In Fig. 3, w_{ij} ($i = 0, 1, 2, \dots, p; j = 1, 2, \dots, q$ and $w_i(j = 0, 1, 2, \dots, q)$ are connection weights where *p* is the number (7) of input nodes; *q* is the number (4) of hidden nodes. Both w_{ij} and w_j are integers which are determined in the design process of the final neural network. To assess the forecasting performance of the proposed model, two steps are used in order to evaluate the performance of the established model as follows. The first step uses the Eviews Package Software, the best-fitted model used by many scholars (Khashei & Bijari, 2010). The auto-regressive model of order eight, AR(9-1), was chosen. In the second step, we used the pruning algorithms in MATLAB 7 packaged software to select the best-fitted network by comparing the ANN performance. The architecture of the best-fitted network is composed of seven inputs, four neurons in a hidden layer and one output neuron (in abbreviated form, N⁷⁻⁴⁻¹). The performance evaluation is discussed in the following section.

4. Results

After 500 learning cycles, the various changes of the weights converge into smaller and more stable as illustrated in Fig. 4. This optimized pattern is evidenced by the data in Appendix which indicate the changes of weights are mostly nil after 500 learning



Fig. 3. The structure of the best-fitted network of Multilayer Perception Model, N⁷⁻⁴⁻¹.



Fig. 4. The convergence of the training process for the weight value after 500 learning cycles in RS.

Table 2

The change of the weights after 500 learning cycles.



Fig. 5. The prediction accuracy (MAE) of RS against Movie Rating Percentage (MRP).

cycles as shown in Table 2. When the learning cycles are between 100 to 500, the changes decrease continuously. When the cycles become 600, the changes are larger as shown in the part 2 of Appendix. This means we could determine the clustering rule by those input factors, and at the end, the SOM networking model with 500 learning cycles would be able to judge which group each user belongs to by different audiences' movie ratings.

In the literature of collaborative filtering systems, Herlocker et al. (2002) pointed out that the calculations of accuracy are diverse. Instead of Kuhn-Munkres' algorithm (Moschou et al., 2007), this experiment adopted the measurement of performance (Ghauth & Abdullah, 2011) by calculating the Mean Absolute Error (MAE) which determines the difference between the predicted rating and the actual rating from the audience. This measurement is important since it determines the relative accuracy of the rating prediction based on the user-given rating (del Olmo & Gaudioso, 2008). The formula is given as follows:

$$\mathsf{MAE} = \frac{\sum_{i=1}^{N} (P_i - R_i)}{N}$$

Where P_i is the predicted rating for item *i*; R_i is the audience-given rating for item *i*; and *N* is the total number of pair rating P_i and R_i .

If the MAE was smaller, the distance between the predicted values and actual values was smaller, leading to higher prediction accuracy. Contrarily, if the distance was larger, the predictions were less accurate. In other words, the MAE could reflect prediction quality, and a smaller MAE led to better prediction quality.



Fig. 6. The prediction accuracy (MAE) of RS against Audience Rating Percentage (ARP).

- (1) Using the MAE for the whole system: based on the above research methodology, we saved 10% of the rating values before the experiment for evaluating prediction accuracy, using their MAE. The total number of inputs for MAE was 100, the average was 0.7484, and the standard error was 0.3497.
- (2) The relationship between each movie's audience rating and the accuracy of the prediction (single movie): to avoid the scarcity problem of the CF, the system was designed by selecting the top 50 popular movies and top 100 audiences. We wanted to distinguish whether the size of the audience for each movie would affect the accuracy of the prediction. The movie rating percentage which was represented by the audience size divided by 100 and ranged from 0.87 to 0.35, was compared with the MAE to evaluate the prediction accuracy.Fig. 5 shows that as audience size increased, the MAE became smaller, which means the larger the audience that watched a certain movie, the more accurate our predictions. Using the Pearson Coefficient to analyze the relation between the Movie Rating Percentages (MRP) and the MAE, the Pearson Coefficient "r" equals to -0.318 (*p* = 0.03, N = 34) which is significant at p < 0.05 level. The result provided the evidence that when more people had watched a certain movie, richer information resources were available, leading to a more accurate prediction.

In the nearest neighbor method, we predict the users' preferences towards the attributes based on users' ratings of the same item to judge similarities within a group. The accuracy of the RS performed by the SOM is measured by MAE. If the users offer less rating information, level of prediction accuracy would be less. In this study, we use the Audience's Rating Percentages (ARP) to represent the proportion of movies being rated by the users out of 50 popular movies, and measured the accuracy by the MAE.

We observed Audience Rating Percentages (ARP) ranging from a high of 0.88 to the low of 0.4. The MAE ranged from 0.2732 to 1.1104; two of them reflected -0.105 negative related (but not obviously) by the Person Coefficient testimony, as shown in Fig. 6. This means the more an audience contributed rating information, the more understanding that audience might have. Therefore, the prediction accuracy was higher, and since the negative relative figure was not high, the above evidence shows that the audiences' rating amount had no effect on prediction accuracy.

5. Conclusions and future research

Schafer et al., (2001) pointed out that recommendation systems would build customer loyalties and increased profits. Du and Wagner (2006) demonstrated that web-Blog success would have

three characteristics: experiential content value, technology value, and social value (see Fig. 2). The findings of our study support the success of these characteristics: (1) experiential content value was improved by the accuracy of RS prediction (MAE as illustrated in Fig. 5), (2) technology value offered by the increased speed achieved by decreasing the number of learning cycles (down to 500 cycles as illustrated in Fig. 4), and (3) social value was improved by RS through identifying the nearest neighbors that shared the similar interest/preference within the social community.

Additionally, we improved the processing speed which is a key element in shaping expectations and experiential preferences for the RS (the training process takes only 500 learning cycles). The knowledge bases and interactive capabilities for encouraging e-transactions and generating loyalty to websites will continue to develop according to online experiences. The problem with collecting explicit customer information is usually that users experience system lag because of the heavy data loading. However, according to the results of this research, increased rating data volume from one single user would not affect the prediction accuracy of our recommendation system. For all practical purposes, web managers could use more or less information from users to reactively provide precise, satisfying recommendations, leading to improved customer satisfaction and loyalty towards their particular websites, and increased opportunities for immediate or future shopping. In the long run, this increases income and profit, and provides comparative advantages for web service providers.

Another contribution from this study was increasing prediction accuracy by using the Neural Networking System with the collaborative filtering recommendation system. Online shopping community is abundant with RSs. For the most part, online shopping websites have been using collaborative filtering systems to generate systematic recommendations. For instance, when eBay.com created an online exchange community, the recommendation system provided customers' credit evaluations, e.g., "My Favorites." CDNOW is a web-based service for CDs which is strategically allied with Amazon.com, and uses their recommendation system's "See Related Items," "Browse Style," and "Top Sellers" functionality. In this research, we present a modified collaborative filtering system, which: (1) collects explicit records to formulate users' experiential preferences, and uses a self-organizing map in a neural networking system to cluster users in a grouping process; and, (2) uses the nearest neighbor method to evaluate similarities within the same group and make a recommendation. This new RS could be a candidate system for online shopping websites to use.

The final contribution is that this study is the first to use SOM for identifying 4 clusters of audiences whose attributes correspond to Holbrook (2000) 4Es (Experience, Entertainment, Exhibitionism, Evangelizing). We are able to use these 4Es as 4 hidden neurons in a neural network analysis and generate more accurate recommendations for the audience.

According to Bobadilla et al. (2013), the evolution of existing RSs follows 4 levels of RSs: (1) Memory-based level (2) Content-based level (3) Social-based level (4) Context-based level. This study incorporates experiential data into a content-based RS. Namely, in addition to the traditional information, our RS may collect and use experiential database to enhance the accurate of prediction, such as the psychological factors from friends or emotional factors from relative music photos and videos. Future studies could integrate more and various categories of experiential data at these 4 levels of RSs. The experiential data can be obtained explicitly and implicitly by using our method or with a mixture of mixed methods, such as neural networks, tag analysis, similarity measures, fuzzy systems, genetic algorithm etc., along with collaborative filtering algorithm.

Another future study may be the application of data fusion technology to pre-process non-numerical data, such as, images, photos, music, video, or movie, into numerical data to be the input of an RS. This allows us to make multiple-criteria experiential decisions under uncertain information. Data fusion technology addresses the difficulty and restriction of fuzzy sets theory (Zimmermann, 2010), and uses a quantitative measure of the similarity searching method with an experiential database structure that has experiential detection or visualization of non-numerical data. This study provided a feasibility of adopting the data fusion method as the pre-processor of input in the algorithm of RS. Meanwhile, further adoption of time-varying experiential knowledge with data storage, retrieval, and fusion capabilities, such as photos in Facebook, could enhance temporal reasoning process, overcoming the limited availability of interval data and making real-time decision support feasible (Milea, Frasincar, & Kaymak, 2013).

6. Managerial implications

Regarding the managerial implications, there are six that worth noting. First, screen interfaces are not limited to online selling; in an off-line store, kiosks are being used to assisted selling off-theshelf products and become "an online channel within an off-line channel" in many industries. For example, *Drugstore.com* is an online pharmaceutical service network that not only selling products, but also making individual suggestions for the user's health care situation, using "Dr. Weil Recommendation" and "Customer Reviews" as the tools. A drugstore could provide a kiosk having the functions similar to Drugstore.com in the store, it does not need to display too many products on the shelf and improve consumers' experiential purchasing process.

Second, the RS proposed in this study can be used in the context of promotion for Internet TV (iTV) or Media On Demand (MOD). For example, customers' preferences could be pre-categorized according to their online movies and trailers viewing history. When a customer procrastinates buying a movie in his/her preferred category, the provider could draw his/her attention by sending stimuli, such as e-DMs or e-coupons (Shu & Gneezy, 2010), with special offers on the movies in the preferred category.

Third, the preferences and search style of even the most infrequent customer can be learned without much effort from our recommendation system's database. Our RS can be used to promote "last minute" market-penetration for the tourism services (just like airline seats or hotel rooms) with bundled packages (such as supplementary tour packages, shuttle bus services, free Internet access, etc.).

Fourth, the information gained from the historical experiential data allows provider to prepare marketing scenarios and determine marketing tactics, such as the experiential visual content and the communication style of direct e-mailings, or customer-service cues available to salespersons in point-of-sales systems.

Fifth, Moviefinder.com has provided members information of the newest movies, using "User Grade/Our Grade" and "Top 20" from a recommendation system. Amazon.com has used the complicity type of recommendation system to generate "Top Sellers," "Friend and Favorites," "Wish List," "Your Favorite Store," and "Your Recommendations". Moreover, Real.com is using the similarities between movies to connect the dots for movies matches. Our experiential recommendation system can be used in these websites to create ideal matches between the target audiences and the criteria, resulting in both higher profits and satisfied customers.

Finally, Nanou, Lekakos, and Fouskas (2010) suggest that an impressive system should allow customers to not only recommend items to each other, but also to choose particular referrers with whom they would like to socialize. They also conclude that RSs will proliferate in various sectors (e.g., e-commerce, news, movies, TV shows, music, entertainment, restaurants, and travel), especially in Internet-based applications, mobile devices, and other specialized appliances (e.g., personal video recorders or GPS) by

offering a personalized service and proposing only those items the customer will likely find interesting. Without accurate predictions, such an impressive proliferation of RSs will not be possible in the future. Our proposed RS is designed and implemented with efficient algorithms that could provide fast and accurate recommendations to help in this course.

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Appendix A. Experimental results of the proposed model:

Initial weight v	alue						
PE 1	3.2662	3.5	3.5429	3.9167	3.2708	3.7857	3.4167
PE 2	3.2662	3.5	3.5429	3.9167	3.2708	3.7857	3.4167
PE 3	3.2662	3.5	3.5429	3.9167	3.2708	3.7857	3.4167
PE 4	3.2662	3.5	3.5429	3.9167	3.2708	3.7857	3.4167
Weight value a	fter 100 learning cy	vcles					
PE 1	4.1565	4.1615	4.0324	4.31	4.2255	4.0611	4.3924
PE 2	3.8116	3.7381	3.7404	4.1781	3.8394	3.8151	4.0415
PE 3	3.8673	3.847	3.7385	3.9791	3.9331	3.8402	4.0055
PE 4	3.438	3.3264	3.3674	3.7803	3.4575	3.5317	3.554
Weight value a	fter 200 learning cy	vcles					
PE 1	3.4383	3.3268	3.367	3.7799	3.4575	3.5322	3.5542
PE 2	3.8101	3.7835	3.8199	4.1381	3.822	3.8088	3.9852
PE 3	3.8645	3.8022	3.6737	4.0259	3.9407	3.8436	4.0544
PE 4	4.1557	4.1608	4.0323	4.3093	4.225	4.0603	4.3919
Weight value a	fter 300 learning cy	vcles					
PE 1	3.8102	3.7836	3.8199	4.1382	3.8221	3.8089	3.9853
PE 2	4.1559	4.1608	4.0323	4.3095	4.2251	4.0606	4.392
PE 3	3.4383	3.3268	3.367	3.7799	3.4575	3.5321	3.5542
PE 4	3.8646	3.8022	3.6738	4.026	3.9407	3.8437	4.0545
Weight value a	fter 400 learning cy	vcles					
PE 1	4.1559	4.1608	4.0324	4.3095	4.2252	4.0606	4.392
PE 2	3.863	3.846	3.7326	3.9794	3.9329	3.8366	4.0082
PE 3	3.8153	3.7373	3.7471	4.1816	3.8381	3.8187	4.0397
PE 4	3.4382	3.3268	3.3669	3.7798	3.4575	3.532	3.5541
Weight value a	fter 500 learning cy	vcles					
PE 1	4.1559	4.1608	4.0324	4.3094	4.2251	4.0605	4.392
PE 2	3.863	3.846	3.7326	3.9793	3.9328	3.8366	4.0082
PE 3	3.8153	3.7373	3.7471	4.1816	3.8381	3.8187	4.0397
PE 4	3.4383	3.268	3.367	3.7798	3.4576	3.321	3.5541
Weight value a	fter 600 learning cy	vcles					
PE 1	4.1672	4.03	4.3073	4.2305	4.0701	4.3985	4.1672
PE 2	3.7255	3.7008	4.1569	3.8901	3.8244	4.0646	3.7255
PE 3	3.8582	3.776	4.0006	3.8848	3.8314	3.9844	3.8582
PE 4	3.3282	3.3773	3.7885	3.4595	3.5262	3.5554	3.3282
Weight value a	fter 700 learning cy	vcles					
PE 1	3.8153	3.7373	3.7471	4.1816	3.8382	3.8187	4.0397
PE 2	4.1559	4.1608	4.0324	4.3095	4.2252	4.0606	4.392
PE 3	3.4383	3.3268	3.3669	3.7798	3.4576	3.5321	3.5541
PE 4	3.8631	3.846	3.7326	3.9794	3.9329	3.8367	4.0082

Part 2.	The	change	of the	weights	after	learning	cycle
I alt 2.	IIIC	Change	or the	weights	anci	Icarining	Cycic

The change of the weights after 0–100 learning cycles								
PE 1	-0.8903	-0.6615	-0.4895	-0.3933	-0.9547	-0.2754	-0.9757	
PE 2	-0.5454	0.2381	-0.1975	-0.2614	-0.5686	-0.0294	-0.6248	
PE 3	0.6011	0.347	-0.1956	-0.0624	-0.6623	-0.0545	-0.5888	
PE 4	0.1718	-0.1736	0.1755	0.1364	-0.1867	0.254	-0.1373	

Experimental Results results of the Proposed Model:proposed model: (continued)

Part 2: The change of the weights after learning cycles							
The change of the weights after 200 learning cycles							
PE 1	0.7182	0.8347	0.6654	0.5301	0.768	0.5289	0.8382
PE 2	0.0015	-0.0454	-0.0795	0.04	0.0174	0.0063	0.0563
PE 3	0.0028	0.0448	0.0648	-0.0468	-0.0076	-0.0034	-0.0489
PE 4	-0.7177	-0.8344	-0.6649	-0.529	-0.7675	-0.5286	-0.8379
The chan	ge of the weights	after 300 learning	cycles				
PE 1	-0.3719	-0.4568	-0.4529	-0.3583	-0.3646	-0.2767	-0.4311
PE 2	-0.3458	-0.3773	-0.2124	-0.1714	-0.4031	-0.2518	-0.4068
PE 3	0.4262	0.4754	0.3067	0.246	0.4832	0.3115	0.5002
PE 4	0.2911	0.3586	0.3586	0.2833	0.2843	0.2166	0.3374
The chan	ge of the weights	after 400 learning	cycles				
PE 1	-0.3457	-0.3772	-0.2125	-0.1713	-0.4031	-0.2517	-0.4067
PE 2	0.2929	0.3148	0.2997	0.3301	0.2922	0.224	0.3838
PE 3	-0.377	-0.4105	-0.3801	-0.4017	-0.3806	-0.2886	-0.4855
PE 4	0.4264	0.4754	0.3069	0.2462	0.4832	0.3117	0.5004
The chan	ge of the weights	after 500 learning	cycles				
PE 1	0	0	0	0.0001	0.0001	0.0001	0
PE 2	0	0	0	0.0001	0.0001	0	0
PE 3	0	0	0	0	0	0	0
PE 4	-0.0001	0	-0.0001	0	-0.0001	-0.0001	0
The chan	ge of the weights	after 600 learning	cycles				
PE 1	-0.0089	-0.0064	0.0024	0.0021	-0.0054	-0.0096	-0.0065
PE 2	0.438	0.1205	0.0318	-0.1776	0.0427	0.0122	-0.0564
PE 3	-0.0445	-0.1209	-0.0289	0.181	-0.0467	-0.0127	-0.0553
PE 4	0.0031	-0.0014	-0.0103	-0.0078	-0.0019	0.0059	-0.0013
The change of the weights after 700 learning cycles							
PE 1	0.3495	0.4299	0.2829	0.1257	0.3923	0.2514	0.3588
PE 2	-0.3367	-0.4353	-0.3316	-0.1526	-0.3351	-0.2362	-0.3274
PE 3	0.4215	0.5314	0.4091	0.2208	0.4272	0.2993	0.4303
PE 4	-0.4279	-0.5178	-0.3553	-0.1909	-0.4734	-0.3105	-0.4528

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