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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.

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 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 human–machine 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 1
The 4Es model by Holbrook (2000).

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