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An intelligent fuzzy-based recommendation system for consumer electronic products

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Abstract

Developing an intelligent recommendation system is a good way to overcome the problem of overloaded products information provided by the e-commerce enterprises. As there are a great number of products on the Internet, it is impossible to recommend all kinds of products in one system. We believe that the personalized recommendation system should be built up according to the special features of a certain sort of product, and forming professional recommendation systems for different products. In this paper, based on the consumer's current needs obtained from the system-user interactions, we propose a fuzzy-based system for consumer electronics to retrieve optimal products. Experimental results show the system is feasible and effective.

Keywords: Fuzzy logic; Consumer electronics; Recommendation system; Personalization service

1. Introduction

In recent years, the on-going advances of Internet and Web technologies have promoted the development of electronic commerce, which has caused both companies and customers to face a new situation. In order to expand their markets and create more business opportunities, enterprises have been developing new business portals and providing large amounts of product information, as a result of which customers have more opportunities to choose various products that meet their needs.

Information from Internet marketing and electronic commerce is of uncertainty, but it really has potential and impact. It expands the opportunities for branding, innovating, pricing, and selling. However, the exponentially increasing information along with the rapid expansion of the business Web sites causes overload of information. So consumers have to spend more and more time browsing the net in order to find the information needed. One way to overcome the above problem is to develop intelligent recommendation system to provide personalized information services (Schafer, Konstan, & Riedi, 2001): retrieving the information a consumer desires and helping him determine which one to buy. The purpose of personalized information services is to adjust strategies of promotion and advertisement to fit customer interests.

New enterprises can deal with a particular customer's Web experiences by providing customer personalization service and communicating or interacting with customers. Such understandings of customers can be transformed customer information into quality services or products (Weng & Liu, 2004). To improve customer satisfaction, feedback rate, loyalty, Web sales, and reputation, one-to-one marketing is seen as the most effective approach for customer relationship management. However, with the great number of customers, how do enterprises identify their interests? The answer to this question is to build personalized Internet services. The purpose of personalization is to adjust strategies of promotion and advertisement to fit customer interests. First, it is necessary to understand customer interests and preferences and then provide suitable products or services at a right time. The mechanism of this

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research aims not only to promote visiting rate of Web stores, increase opportunities of selling, and advertisement revenue, but also to increase a website's profits.

Depending on the sort of product, various personalized recommender systems can be built up to guide the consumers in a large product feature space. For such frequently-purchased products as books, CDs, and DVD films, recommendation systems can be developed to reason his preferences by analyzing his personal information, browsing history, and the products he purchased. By contrast, a common consumer less frequently-purchased such commodities as notebook computers and digital cameras, what is more, enterprises lack enough information about the customer's past purchases and his specific requirements for a particular product, so it is difficult and impossible to reason a customer's previous preferences. In this situation, advises from domain experts are strongly demanded. Recommendation systems are thus expected to have specific domain knowledge and capability to interact with consumers. Consequently the systems can acquire and analyze a customer's current needs on some kinds of products he identified, and then evaluate the relevant products to help him choose the optimal ones.

With the personalized recommendation systems, consumers can immediately access the information they are interested in, and save their time for reading the electronic documents. On the other hand, enterprises can get to know customers' buying behaviors and then develop most appropriate marketing strategies to attract different customers and efficiently deliver the information they are interested in. The customer's satisfaction and loyalty can thus be increased, and the increase in the visiting frequency of the customers can further create more transaction opportunities and benefit the Internet enterprises.

In this approach, we present a fuzzy-based recommendation system for those less frequently-purchased products, especially for consumer electronics. When a common buyer is going shopping, some distinctive features of consumer electronics may get him into some trouble. First, compared with other products, the life of a new model consumer electronic is short, namely about 2 years. As the new models of a product come out at all times in the market, it makes a common consumer difficult to know all models of a product. Second, accompanied by newly-produced models, a great number of new techniques come forth to improve product functions. Eventhough knows the details of the techniques in a new model, he still does not know whether it is worth spending more money on it. Last, because of the widening price gap among the different models of the same product and the continuously dropping price of a new model within its life cycle, it is hard for a common consumer to know the prices of all product models. For new models, the price falls by half within several months since it comes into the market.

The proposed system aims to assist a consumer to navigate the product feature space in an interactive way in which the consumer has his own need in each feature dimension so that the customer can find the optimal products according to his personal preferences. We have also built up a system of this kind for laptop computer recommendations. The experimental results show that both systems can give sensible recommendations, and adapt to customers' up-to-date preferences. The remainder of the paper is organized as follows. In Section 2, research background is expatiated, including personalization and recommendation systems. Section 3 gives an overview of the recommendation system. The elementary theoretical background is provided in Section 4, followed by Section 5 explaining the implementation issues of the proposed method. Section 6 reports the experimental process and the results of the study. Finally, the conclusion is given in Section 7.

2. Research background

The purpose of this research is to build up a personalized recommendation system based on product features.

2.1. Personalization

Personalization, a special form of differentiation, is that a website can respond to a customer's unique and particular needs. Mobasher et al. defined Web personalization as an act of response according to the individual user's interest and hobby on Internet usage (Mobashe, Dai, & Luo, 2002). Through personalization, businesses can get to know customers' buying behaviors and accordingly develop more appropriate marketing strategies to attract each customer of a specific type and efficiently deliver the suitable information and products/services to him/her. The customer's satisfaction and loyalty can thus be enhanced, and the increase in each customer's visiting frequency can further create more transaction opportunities and benefit the Internet businesses (Lee & Liu, 2002).

The term 'personalization' is often used in the context of recommendation systems that selectively promote products to end-users based on the analysis of earlier interactions (Schafer, Konstan, & Riedi, 1999). Adomavicius and Tuzhilin proposed 5 stages of personalization: (1) collect customer information, (2) profile customers, (3) compare similarity, (4) deliver and present personalized information, and (5) measure customer responses.

In this paper, personalization takes on a broader meaning for the purpose of this research project; it involves the storage and processing of a rich databank of information about each individual end-user with detailed preference and requirements information, and about every product with detailed features and descriptions. This research project's approach to increase the accessibility of systems relies on domain-based personalization of all interactions between an end-user and the system at a fine-grained level. Personalization of interactions with systems can potentially reduce complexities through the automatic filtering and translation of content and the elimination of features not directly related to the task at hand (Chiasson, Hawkey, McAllister, & Slonim, 2002). End-user access to computerized systems relies increasingly on personal electronic computing devices such as personal data assistants, organizers, cellular phones, and wearable computers.

2.2. Recommendation systems

E-commerce website can predict a customer's future purchasing behaviors through his past purchasing behaviors and demographic data. Therefore personalized products can be recommended to customers and achieve the effects of transforming browsing people into consumers, increasing customer loyalty and enhancing cross selling.

A recommendation system can provide personalized information services in different ways; it depends on whether the system has been recording and analyzing a customer's previous preferences. In the first type of personalized recommendation system, a customer's personal information is first collected, then the system reasons out the customer's preferences by analyzing and modeling the available personal information. Once the consumer's personal information is obtained, the recommendation system can then construct a computational model for him to predicate his preferences for other items of the same application domain. In fact, the work of recommendation can be regarded as classification: using the known information already to set up a model to predict the unknown events (Lee & Liu, 2002).

Unlike the above system which is concerned about a consumer's previous preferences, another type of personalized recommendation system is designed for the less frequently-purchased products and consumer specific needs in a single purchase. In addition, a consumer needs specific domain knowledge to evaluate the corresponding quality of this. Therefore instead of modeling a customer's past preferences, the recommendation system uses the ephemeral information a consumer provided when he is consulting the system for suggestions, and the built-in expert knowledge about the product to look for the optimal ones. Recommendation system of this type aim to assist a customer to find out what he really wants, when he can simply identify the type of products he needs and describe the features or specific functions of products.

Initially the recommendation system retrieves some products from the database, by measuring the similarity between the products in the database and the features of the target products. Then the consumer can adjust his needs on certain features of the recommended products, and accordingly ask the system to suggest new items. In this way the consumer can gradually find out the best product that meets his needs.

3. System architecture

In this section, an on-line intelligent recommendation system for personalized Internet shopping is proposed, which uses data mining techniques and fuzzy logic in accordance with the proposed marketing strategies to help the business prepare the highly potential and suitable promotion products for each individual customer. The recommendation system is demanded when a customer is going to buy such less frequently-purchased products as laptops. As analyzed in Section 1, the experiences of buying such products may not be helpful. What a consumer needs now is some expertise to recognize the ideal products based on his current preferences. Under such circumstances, an appropriate way to provide personalized information

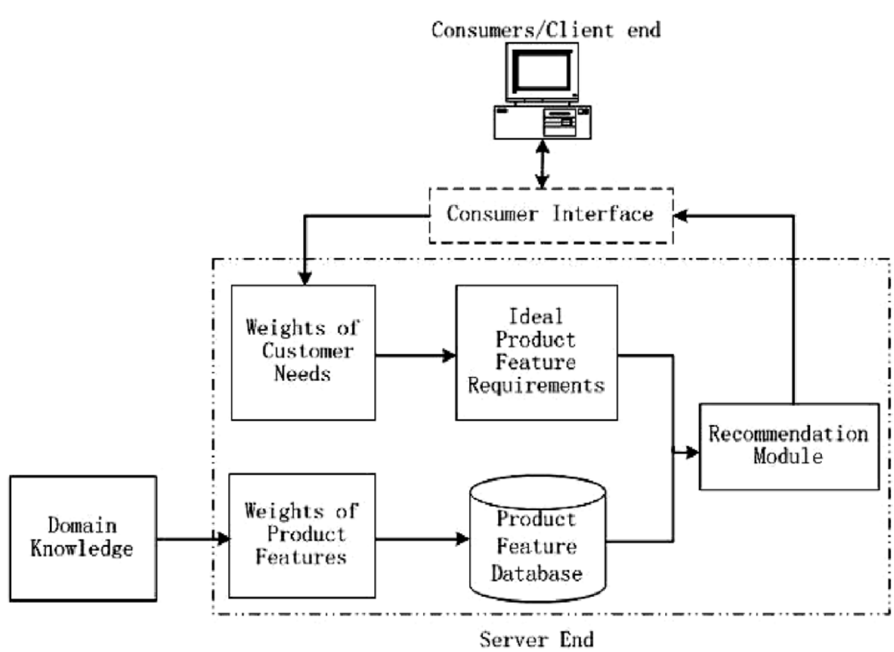

Fig. 1. The architecture of proposed system.

services is to create an interactive environment in which a consumer can iteratively express his preferences or needs to the recommendation system which can use the ephemeral information along with the built-in domain knowledge to find the ideal products.

The system analyzes a consumer's current requirements and finds out the most ideal products for him. The ideal solution here means the one which can best satisfy the consumer's requirements and provide optimal quality service at the same time. Based on the current system, the customer needs can be transferred into feasible alternative combinations of the desired product. Fig. 1 shows the architecture of the proposed system, which consists of four modules: (1) weights of customers' needs, (2) weights of product features, (3) ideal feature requirements module, and (4) recommendation module. In the following sections, each module of the proposed system is described in detail. Anyway the implementation procedures used in this study include the following steps:

(1) Establish the algorithms for ranking customer needs by their importance.
(2) Set up the fuzzy rules between customer needs and product features.
(3) Establish the algorithms for evaluating the requirement of each product feature according to an individual customer's needs and the fuzzy inference rules.
(4) Establish the algorithms to evaluate the alternatives and use fuzzy geometrical distance and fuzzy synthetic distance methods to search for the optimal combination.
(5) Investigate the customer needs and possible product alternatives; choose product according to consumer needs and recommend it.

4. Theoretical background

4.1. Linguistic definition and fuzzy numbers

Based on the proposed system, the consumer needs and the candidate product features can be expressed in an appropriate way. In the approach, we use triangular fuzzy numbers to characterize consumer needs and product features.

A triangular fuzzy number is a particular case of fuzzy sets. It has a triangle-shaped membership function, which can be viewed as possibility distribution. It is supposed that $\tilde{q}$ is a triangular fuzzy number with membership function $\mu_{\tilde{p}}(x)$, and is denoted as $\tilde{q} = (q_1, q_2, q_3)$, where q_1, q_2 and q_3 are real numbers with $q_1 \leqslant q_2 \leqslant q_3$. This membership function is shown in Fig. 2 and the related properties (Hsieh & Chen, 1999; Hu & Sheu, 2003; Sun & Kalenchuk, 2000; Tsai & Hsiao, 2004) are not elaborated here.

To help consumers easily express their judgments, and domain experts easily evaluate product features, the linguistic terms are used to linguistically evaluate the importance of customer needs and ratings of product features. Seven linguistic sets are allowable to describe the variables of one's subjective judgment: (1) very low, (2) low, (3) medium low, (4) medium, (5) medium high, (6) high, (7) very high. Moreover, these linguistic sets can be quantified with the corresponding triangular fuzzy numbers as shown in Table 1 and Fig. 3.

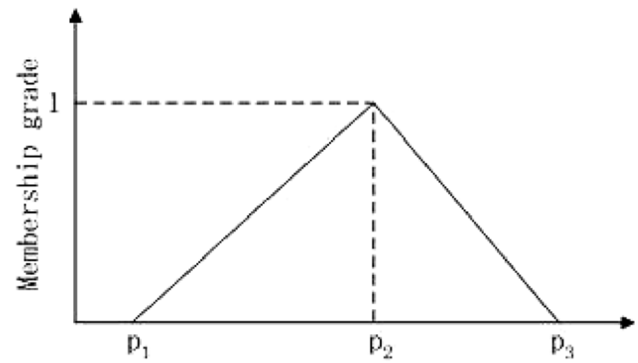

Fig. 2. Membership function of a triangular fuzzy number.

Table 1
Linguistic definition for the importance and the ratings

Linguistic terms	Triangular fuzzy numbers
Very low (VL)	(0, 1, 2)
Low (L)	(1, 2, 3)
Medium low (ML)	(2, 3, 4)
Medium (M)	(3, 4, 5)
Medium high (MH)	(4, 5, 6)
High (H)	(5, 6, 7)
Very high (VH)	(6, 7, 8)

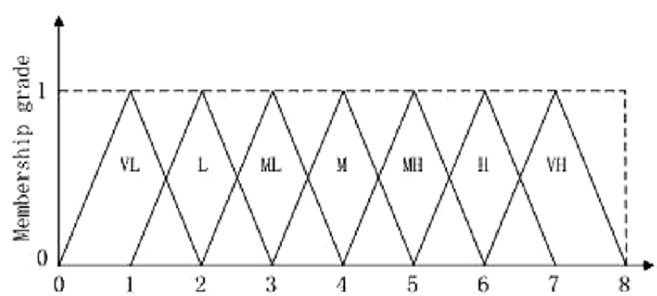

Fig. 3. Membership functions of triangular fuzzy numbers.

4.2. Similarity measure of triangular fuzzy numbers

In this study, we utilize Euclidean fuzzy near compactness between two fuzzy numbers to measure the similarity between consumer needs and product features.

Suppose $\tilde{q}_A = (q_A^1, q_A^2, q_A^3)$ is a compared triangular fuzzy number, while $\tilde{q}_B = (q_B^1, q_B^2, q_B^3)$ is the target triangular fuzzy number. Then the Euclidean fuzzy near compactness between $\tilde{q}_A$ and $\tilde{q}_B$ is defined as follows:

$$N_E(\tilde{q}_A, \tilde{q}_B) = 1 - \frac{1}{\sqrt{3}}\left(\sum_{j=1}^{3} |q_A^j - q_B^j|^2\right)^{1/2} \tag{1}$$

The above equation denotes one kind of similarity degree by calculating the Euclidean fuzzy near compactness between two triangular fuzzy numbers. While the near compactness between $\tilde{q}_A$ and $\tilde{q}_B$ gets smaller, $\tilde{q}_A$ is more similar to $\tilde{q}_B$.

Furthermore, assume there are two sets of triangular fuzzy numbers, $\widetilde{X} = (\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_n)$ and $\widetilde{Y} = (\tilde{y}_1, \tilde{y}_2, \ldots, \tilde{y}_n)$. In fuzzy number set $\widetilde{X}$, each fuzzy number $\tilde{x}_i$ is individually compared with a target fuzzy number $\tilde{y}_i$ in fuzzy number set $\widetilde{Y}$. Because every fuzzy number in fuzzy number sets, $\widetilde{X}$ and $\widetilde{Y}$, represents a consumer's need or a product's feature actually, each fuzzy number in a fuzzy number set has a different importance for identifying the consumer needs or the product features. Hence, by assigning a different weight according to the importance of the fuzzy number in a set, we can achieve better results. In this approach, a location weight vector $(v_1, v_2, \ldots, v_n)$ is assigned to $\widetilde{X}$ and $\widetilde{Y}$, what is normalized as $\sum_{i=1}^{n} v_i = 1$. And the fuzzy near compactness between the fuzzy number set $\widetilde{X}$ and $\widetilde{Y}$ is described as following:

$$N_E(\widetilde{X}, \widetilde{Y}) = \sum_{i=1}^{n} (N_E(\tilde{x}_i, \tilde{y}_i) \times v_i), \tag{2}$$

where v_i is the corresponding weight for the ith triangular fuzzy numbers. From the above equation, the smaller value for $N_E(\widetilde{X}, \widetilde{Y})$ denotes the higher synthetic similarity to the target fuzzy number set while the individual values of $N_E(\tilde{x}_i, \tilde{y}_i)$ and v_i get larger.

5. Implementation methods

Since collecting and analyzing a consumer's personal needs are the basis of the system, our aim is to establish a transformation model for translating customer needs into optimal combination suggestions of applicable alternatives. To establish this model, the relationship between customer needs and product features needs to be constructed. Utilizing fuzzy operation, optimal alternative searching is performed based on the consumer's subjective needs. The procedure for establishing this system is described below.

5.1. Establishing and weighting customer needs

In the approach, a laptop computer is taken as the objective product to demonstrate the effectiveness of the recommendation method. The interface in Fig. 4 presents some specially designed questions about the products for consumers. Presumably the consumer does not have enough domain knowledge to answer quantitative questions that concern about the specifications of the product, the system has to inquire some qualitative ones instead. For example, it is relatively difficult for an on-line game player to indicate the speed and the type of processor he prefers, but it is easy to express his need on the features

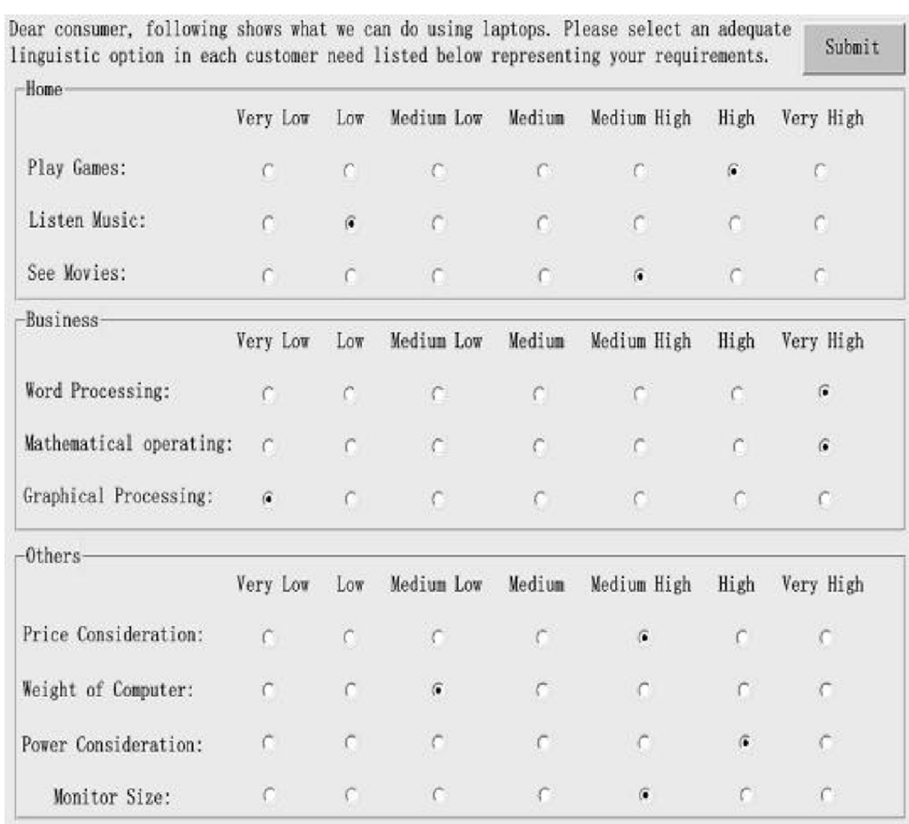

Fig. 4. The interface to obtain Customer needs.

of multi-media. Therefore the qualitative questions are advanced according to the consumer's job, hobby and other aspects that a consumer is concerted about.

After gathering the consumer's qualitative needs, the interface can then deliver them to the weight consumer needs model that is capable of conducting certain mapping between the needs and the quantitative product features from the expert agent to find the ideal products.

In the weight consumer needs model, each consumer could be represented by a qualitative features vector $(\tilde{q}_1, \tilde{q}_2, \ldots, \tilde{q}_3)$. Here $\tilde{q}_i$ is a triangular fuzzy number representing ith consumer need. The values of $\tilde{q}_i$ are presented in Table 1.

5.2. Establishing and weighting product features

A product is specified by a set of critical components and different vendors have their own ways to categorize their products. For example, a laptop can be described by processor, memory, monitor, etc., and the processors could be named as Pentium 4 or AMD each with a special meaning.

In the approach, the technical data about products (i.e. laptops) are collected from the Internet by hand and stored in the product feature database. A product P_i is represented as a series of critical component names, and the majority of components have some technical features. The technical features here are selected by domain experts to consider the quality of the component from different views. For instance, the technical features of a processor include process frequency, process type, cache size, etc.

It should be noted that different components have different technical features. Therefore each component is represented as a vector of technical feature names $(c_i^1, c_i^2, \ldots, c_i^n)$. Then each component of a certain product is converted to a vector of feature functional values $\widetilde{F}_i = (\tilde{f}_i^1, \tilde{f}_i^2, \ldots, \tilde{f}_i^n)$, in which each $\tilde{f}_i^j = (f_i^{j1}, f_i^{j2}, f_i^{j3})$ is a triangular fuzzy number (shown in Table 1), representing the quantitative ability value of jth technical feature of ith component. Because different technical features have different influences on the capability of a component, a feature weight vector $(w_i^1, w_i^2, \ldots, w_i^n)$ is assigned to the technical features functional vector. Hence, we could calculate the component capability value of a component as the following equation, $\tilde{p}_i = (p_i^1, p_i^2, p_i^3)$, which is shown as a triangular fuzzy number too.

$$p_i^k = \sum_{j=1}^{n} (f_i^{jk} \times w_i^j) \tag{3}$$

where $f_i^{jk} \in \tilde{f}_i^j$, $p_i^k \in \tilde{p}_i$ and $k = 1, 2, 3$. The component capability vector $\widetilde{P} = (\tilde{p}_1, \tilde{p}_2, \ldots, \tilde{p}_n)$ is composed by the

Table 2
Technical features of critical component in a laptop

Component	Feature weight (w_i^j)	Technical feature	Candidates
CPU	0.45	Frequency	1.2 GHz, 2.0 GHz, 2.4 GHz , etc.
	0.25	L2 Cache	512 KB, 1 MKB, etc.
	0.1	Type	Power PC G4, Pentium 4, etc.
	0.15	FSB	400 MHz, 600 MHz, etc.
	0.05	Manufacturer	Intel, AMD, IBM, etc.
Motherboard	0.7	Chipset type	Intel 925, nVIDIA Force4, etc.
	0.3	Chipset manufacturer	Intel, nVIDIA, SiS, VIA, etc.
Memory	0.7	Size	256 MB, 512 MB, etc.
	0.3	Type	DDR, SDRAM
Graphics	0.6	Graphic Card	ATI Mobility Radeon 9200, ATI Mobility Radeon X600, etc.
	0.4	Graphic RAM	64 MB, 128 MB, etc.
Hard driver	0.1	Size	20 GB, 30 GB etc.
	0.45	Type	Ultra ATA, etc.
	0.3	REV	5400, 7200, etc.
	0.15	Manufacturer	Portable, Samsung, etc.
Sound	1	Speaker	Built-in stereo speakers, etc.
Connectivity	0.2	Modem	56 Kbps, etc.
	0.8	Network connection	10-/100-Mbps Ethernet, 54g 802.11b/g WLAN with 125HSM/SpeedBooster support, etc.
Display	0.8	Type	WXGA Display with XBRITE technology, etc.
	0.2	LCD native resolution	1024 × 768, etc.
Screen size	1	Screen size	12.1 in., 17.0 in., etc.
Weight	1	Weight	2 kg, 3 kg, etc.
Price	1	Price	800$, 1000$,1500$ etc.
Power	1	Time	4 h, 3 h, etc.

quantitative capability values of all components, that represent the quantitative ability of the critical components.

To analyze the product features of a laptop computer, two domain experts are employed to select technical features for each critical component of a laptop according to the quality of the component from different views. Different products were analyzed to determine the more important features and these were laid out into a hierarchy structure, as shown in Table 2.

In the table, 10 critical components of a laptop, 25 technical features, its corresponding feature weight and the candidate value of those components are listed, where the feature weights are identified by the domain experts according of the importance to the capability of corresponding component.

5.3. Measure similarity between consumer needs and product features

To estimate the optimality of each product for a consumer, a quantitative way to represent customer qualitative needs could facilitate the following similarity measure. As shown in Fig. 4, there is an interface for a consumer, who is asked to express his needs on some qualitative questions. Three types of questions are listed in the interface, including job, hobby and other aspects a consumer might be concerted in. Through those questions, we could become aware of the purpose of a consumer buying a laptop. For instance, a consumer is a game player, so the laptop he needs should have higher capability on features concerning some critical components in a laptop, including memory, graphic card, screen and so on. Furthermore the candidate's answers of those questions are divided into seven levels, which could be converted to triangular fuzzy numbers as shown in Table 1, the qualitative needs of a consumer are expressed in a quantitative way. Owing to the capabilities of critical components in a laptop represented by triangular fuzzy numbers as mentioned before, it is convenient for the similarity measure between the product capabilities and the consumer's needs.

In the system, the qualitative needs of a certain consumer are converted to a vector of consumer's need values $\widetilde{R} = (\tilde{r}_1, \tilde{r}_2, \ldots, \tilde{r}_n)$, in which $\tilde{r}_i$ is a triangular fuzzy number, representing the answer of the ith qualitative question in Fig. 4, i.e. the quantitative denotation of ith qualitative customer need.

Since consumer's opinions on customer needs are quantified as fuzzy number vectors, there should be a manner to translate the vectors into product feature.

As the qualities of critical components are the key factors in the capability of a laptop, each qualitative need of a certain consumer is correlated to a number of critical components of a laptop. Therefore, assume that the corresponding components of ith customer need are represented by a component capability vector $\widetilde{P}_i = (\tilde{p}_i^1, \tilde{p}_i^2, \ldots, \tilde{p}_i^n)$, where $\tilde{p}_i^j$ is a triangular fuzzy number calculated by Eq. (3), representing the quality of jth component. Considering that different components have different influences on the capability of a laptop in a certain customer need, an ability weight vector $\widetilde{V} = (v_i^1, v_i^2, \ldots, v_i^n)$ is assigned to the component capability value vector. Hence we could measure the synthetical capability value of a laptop about a certain customer need. The ith synthetical capability is represented by a triangular fuzzy number $\tilde{q}_i = (q_i^1, q_i^2, q_i^3)$ and calculated by the following equation.

$$q_i^k = \sum_{j=1}^{n} (p_i^{jk} \times v_i^j) \tag{4}$$

where $p_i^{jk} \in \tilde{p}_i^j$, $q_i^k \in \tilde{q}_i$ and $k = 1, 2, 3$. Based on the previous method, a vector $\widetilde{Q} = (\tilde{q}_1, \tilde{q}_2, \ldots, \tilde{q}_n)$ is obtained, what denotes the synthetical capability values of a laptop. The ith fuzzy number $\tilde{q}_i$ in the vector represents the integrative ability of the product for the ith qualitative need $\tilde{r}_i$ of a consumer.

To evaluate the capability of laptops based on customer needs, relationships between consumer needs and product components have to be developed with the ability of product to measure customer needs. In the study, domain experts judge the relations between customer needs and product features. Table 3 lists the details of the relationship between the qualitative needs of a consumer and the critical components of a laptop.

Based on the previously obtained vectors $\widetilde{R}$ and $\widetilde{Q}$, respectively, representing the quantified consumer needs

Table 3
The relationship between the consumer qualitative need and the critical component

Consumer qualitative need	Ability weight (v_i^j)	Critical components
Play games	0.2	CPU
	0.1	Memory
	0.1	Motherboard
	0.25	Graphics
	0.05	Hard driver
	0.15	Sound
	0.15	Screen
Listen music	1	Sound
See movies	0.3	Graphics
	0.3	Sound
	0.3	Screen
	0.1	Hard driver
Word processing	1	CPU
Mathematical operating	0.5	CPU
	0.15	Motherboard
	0.35	Memory
Graphical processing	0.2	CPU
	0.2	Memory
	0.25	Graphics
	0.1	Hard driver
	0.25	Screen
Price consideration	1	Price
Weight consideration	1	Weight
Power consideration	1	Power
Screen size	1	Screen

Fig. 5. Typical recommendation results.

and the synthetical abilities of a product, we could calculate the fuzzy near compactness of the two fuzzy number vectors according to Eqs. (1) and (2). For each laptops in the product database, the synthetical capability vector and its fuzzy near compactness with the consumer need vector could be calculated based on the previous method. And the smaller near compactness denotes the higher synthetic similarity to the qualitative needs of a certain consumer, i.e. the laptops with smaller near compactness are the ideal alternatives for the customer.

The mechanism for the most ideal alternative combination to suit consumer's needs is summarized as follows, and Fig. 5 shows a result of the proposed system.

Step 1: The domain experts rate the technical features of ith laptop in the product database and give the ith feature functional vector $\widetilde{F}_i$ for the technical features of the critical components.

Step 2: The corresponding component capability value and the component capability vector $\widetilde{P}_i$ are calculated according to Eq. (3) and Table 2.

Step 3: Through answering the qualitative question shown in Fig. 1, the consumer could obtain the consumer need vector $\widetilde{R}$, that quantifies the qualitative needs.

Step 4: The product synthetical capability vector $\widetilde{Q}$ is calculated according to Eq. (4) and Table 3, in which each fuzzy number denotes the compositive ability of a laptop on a certain consumer need.

Step 5: The fuzzy near compactness value s between $\widetilde{R}$ and $\widetilde{Q}$ is calculated according to Eqs. (1) and (2). If s is smaller than the predetermined threshold, then the laptop should be recommended to the customer.

Once the currently available products have been ranked by the above equations, the products with the smallest 10 ranks are then recommended to the customer. If the customer is not satisfied with the items recommended by the system, he can increase or decrease his requirements in different need feature dimensions. The modified specifications are used to calculate the optimality for each product again, and those products with smallest ranks are thus recommended to the customer.

6. Experiment and results

The proposed system could also be applied to recommend the products that a consumer generally does not often buy in a short period of time and has his specific needs in each single purchase. And because of the reasons mentioned in Section 1, it is especially suitable to recommend consumer electronic products, such as cell telephones, digital cameras, PDA and so on. Therefore the experiments concentrate on evaluating the system behaviors; that is, we shall observe whether the overall system can respond to the modifications made by the consumer. In the experiment, the recommendation system proposed in the approach is utilized to recommend laptops that best satisfy the consumer's current needs and with the optimal quality.

6.1. Evaluation measures of experiment

Precision and recall are used in this research as measures to evaluate the effects of the recommendation system; F1 is

Table 4
Parameter definitions of precision, recall and F1

Value	Meaning
x	The system and expert agree with the assigned category
y	The system disagrees with the assigned category but the expert did
z	The expert disagrees with the assigned category but the system did

also used to represent the effects of combining precision and recall.

$$\text{Recall } (r) = \frac{x}{x+z}, \quad \text{Precision } (p) = \frac{x}{x+y},$$
$$\text{F1} = \frac{2rp}{r+p} \tag{5}$$

where the values of x, y and z are defined in Table 4.

6.2. Experiment data set

The purpose of the experiment is to test the effects of the recommendation system in this research. We collect a data set of laptops from Amazon.com, which contains 128 laptops of different brands, including Sony, Apple, IBM, Compaq, and so on. Table 6 lists the technical features and their feature functional value of Sony VAIO VGN-FS680.

To compare the products or components of different vendors, domain expert knowledge is required to define the common criteria. For example, we can set the performance value of the 13.3 in. screen to *medium* and the 10.6 in. screen to *low*, where *medium* and *low* are two triangular fuzzy numbers defined in Table 1. For the recommendation system presented here, as an example, four technical feature criteria of CPU are listed in Table 5, that includes the technical parameters of the familiar notebook CPU in market.

In addition, the data sets collected in the experiments aim at notebook. Since there are some differences between the technical features of the components used in laptop and in desktop, the common technical criteria for laptop are different from the ones for desktop. For example, the CPU FSB value of laptop is universally lower than the value of desktop. Hence 533 MHz FSB of laptop CPU could be considered as high, but for desktop, the same value only could be considered as medium low.

6.3. Experiment performance

In the experiments, there are two levels of calculation and one time comparison. The first level calculation is to compute the component capability based on material values, which is a common criteria of technical features and feature weight between technical feature and components. The second level calculation is to compute the laptop synthetical capability based on the components capability calculated before and ability weight between components and consumer needs. The one comparison is to compare the laptop synthetical capability and the qualitative needs of a certain customer to find the appropriate products and recommend to the consumer.

For example, according to the information listed in Tables 2, 5, 6, we could calculate the CPU component capability of Sony VAIO VGN-FS680 as in Eq. (3). The capability value of the CPU used in the notebook is computed as following:

$$\begin{aligned}\text{Capability-Value}_{\text{CPU}} &= (4,5,6)\times 0.45 + (5,6,7)\times 0.25 \\ &\quad + (4,5,6)\times 0.1 + (5,6,7)\times 0.15 \\ &\quad + (5,6,7)\times 0.05 \\ &= (4.45, 5.45, 6.45)\end{aligned}$$

We could use the same method to calculate the capability values of other components, and obtain the component capability vector. Then we utilize the capability values of *CPU*, *memory*, *motherboard*, *graphics*, *hard driver*, *sound*, *screen* to calculate the laptop synthetical capability in the perspective of playing games.

6.4. Simulation results

The recommendation system described above is to recommend products that best satisfy the consumer's current needs and with optimal quality. Therefore the experiments

Table 5
Common criteria of CPU technical features

Frequency	Type	L2 Cache	FSB	Manufacturer	Feature functional value
Upwards of 3.0 GHz (include 3.0 GHz)	Intel Pentium 4 M (Dothan), AMD Athlon 64-M	–	–	–	Very high
2.4 GHz–3.0 GHz (include 2.4 GHz)	Intel Mobile Pentium 4 Supporting HT, PowerPC G5	2 MB	533 MHz	Intel	High
1.8 GHz–2.4 GHz (include 1.8 GHz)	Intel Pentium 4 M (Centrino), AMD Athlon XP-M, Power PC G4	1 MB	–	AMD	Medium high
1.5 GHz–1.8 GHz (include 1.5 GHz)	Intel Mobile P4	512 KB	400 MHz	IBM	Medium
1.2 GHz–1.5 GHz (include 1.2 GHz)	Intel Mobile Pentium 4 M	256 KB	–	–	Medium low
1.0 GHz–1.2 GHz (include 1.0 GHz)	Intel Celeron-M	128 KB	133 MHz	–	Low
Downward of 1.0 GHz (Not include 1.0 GHz)	Intel Mobile Celeron	–	100 MHz	–	Very low

Table 6
The technical features of Sony VAIO VGN-FS680

Component	Technical feature	Feature value	Feature functional value
CPU	Frequency	1.86 GHz	Medium high
	L2 Cache	2 MB	High
	FSB	533 MHz	High
	Type	Intel Mobile Pentium 4	Medium high
	Manufacturer	Intel	High
Motherboard	Chipset type	Intel 915PM + ICH6-M	Medium
	Chipset manufacturer	Intel	Medium high
Memory	Size	1 GB	Very high
	Type	DDR SRDM	Medium high
	Frequency	400 MHz	High
Graphics	Chipset Type	nVIDIA GeForce Go 6200 with TurboCache	Medium high
	Graphic RAM	128MB	Medium high
	Chipset manufacturer	nVIDIA	Medium high
Hard driver	Size	100 GB	Medium high
	Type	Ultra ATA-100	Medium high
	REV	5400 rpm	High
	Manufacturer	Portable	Medium high
Sound	Speaker	Windows AC97 Integrated	Medium
Connectivity	Modem	56 Kbps V.92	High
	Network connection	Intel PRO/WIRELESS 2200BG Network Connection (802.11 b/g), 10Base-T/100Base-TX Fast Ethernet	High
Display	Type	WXGA Display with XBRITE technology	Medium high
	LCD Native Resolution	1280-by-800	Medium
Screen size	Screen size	15.4 in.	High
Weight	Weight	2.9 hundredths-pounds	Medium
Price	Price	$2,149.88	High
Power	Time	5 h	High

Table 7
The evaluation of seven consumers

	User 1	User 2	User 3	User 4	User 5	User 6	User 7
The number of products what satisfy a certain user in the 15 recommended products	12	13	13	12	11	14	13
The number of products what satisfy a certain user in the other 123 products	2	3	2	1	1	3	1
The number of products what do not satisfy a certain user in the ten recommended products	3	2	2	3	4	1	2

concentrate on evaluating the system behaviors. Fig. 5 shows the typical recommendation results corresponding to the consumer's needs listed in Fig. 4, in which fifteen laptops in all 138 laptops are recommended to the customer, according to the fuzzy near compactness value between the consumer qualitative need and the product synthetical capability. Furthermore, seven consumers use our experimental system and give their opinion about it, which is illustrated in Table 7. And the corresponding *recall*, *precision* and *F1* values are listed in Table 8. The average of *precision*, *recall* and *F1* measures are 83.82%, 87.57%, 85.39%, respectively.

Table 8
The experiment result

	Recall (%)	Precision (%)	F1 (%)
User 1	80	85.7	82.75
User 2	86.7	81.25	83.89
User 3	86.7	86.7	86.7
User 4	80	92.3	85.71
User 5	73.3	91.7	81.47
User 6	93.3	82.4	87.51
User 7	86.7	92.9	89.69
Average	83.82	87.57	85.39

7. Conclusions

In this paper, we first state that, in addition to developing or improving the software and hardware equipment directly related to the Internet infrastructure, Internet enterprises need to provide personalized information services to make a successful Internet business. Then we suggested that developing personalized recommendation system is a promising way to achieve this goal. Finally, we build up a personalized recommendation system for the consumer electronic products.

Because the consumer electronic products (such as laptops, digital cameras, etc.) are more expensive than those frequently-purchased commodities, we cannot reason out a common customer's personal preferences from his purchasing history and provide appropriate information services to meet his needs. Consumers' preference-based recommendation system is not sufficient to recommend the kind of products. So, it is required to construct a new recommendation system for the consumer electronic products, according to its special features mentioned in Section 1. The proposed system concentrates on finding optimal products by using the domain expert knowledge and the ephemeral information consumer offered. In the system, different interfaces are developed to interact with the consumer, transfer external domain knowledge to internal use, and calculate the optimality of each product. Here a multi-attribute decision making method is used to recommend optimal laptop computer for a customer, according to his needs and the quality of the product. Experimental results have shown the promise of our system. And the system is not only applied to e-commerce as an assistant system, but to the real-life business as an independent system.

Our present work is still wide open for future exploration. One is to consummate the fuzzy logical algorithm proposed in the paper, the other is to explore an easier way to obtain product knowledge from experts.

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