Application of Half-Life Theory and Fuzzy Theory to a Selection And Recommendation System for Web Advertisement Delivery In Consideration of the Time Effect

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Abstract: - With the rapid development of the Internet, Web marketing has become more and more popular among businesses. However, excessive advertisement information is not only a burden to consumers but also a waste of marketing efforts. In this study, a personalized Web advertisement selection and recommendation system is proposed through a membership-based advertisement marketing website whose advertisement content is determined by consumer preference. As consumer preference declines with time, which is called the time effect, the proposed system applies the half-life theory and the fuzzy theory to members' browsing behaviors and automatically analyzes browsers' time-affected preference levels associated with the advertised products. Then, the target markets of the advertisement suppliers' products are matched with customer preference so as to filter out a portfolio of candidate advertisements for delivery. Finally, advertisement delivery is arranged via a commercial advertisement delivery scheduling and recommendation model so that browsers obtain exactly the advertisements they need, the benefits of target marketing are increased, and Web advertising service providers' market competitiveness is strengthened. Thus, a win-win-win scenario for the consumers, the advertisement suppliers, and the Web advertising service providers is realized.

Keywords: - Fuzzy theory, Half-life theory, Personalized service, Web advertisement selection, E-commerce

1 Introduction

The advent of the Internet has removed the limitation of "time" and "space" on human interaction. Now that interaction between individuals is not restricted by geographical boundaries, social exchange is no more confined to the "neighborhood" but extends to the "global village" [1]. On the other hand, with regards to Web marketing, e-commerce is playing a more and more important role in our daily life, and it is no wonder that significant attention is being focused on the evaluation of e-commerce websites in recent years [2]. Therefore, it has been a heated research subject in the academic community to find ways to increase the marketing effect of advertising websites. Although it is a low-cost approach with a perfect operation mode for commercial enterprises to place advertisements on the Internet, waste ensues and the advertising effect decreases with time. If target marketing is conducted according to the properties of ads and consumers' interests, not only will consumers' purchasing desire be stimulated, but also the consumers can save a lot of time and be spared from the annoyance of unwanted ads. Moreover, the enterprises are thus allowed to cut cost [3]. The most important feature that distinguishes the Internet from other media is the one-to-one communication between the Internet and its users. In order to make the most of this feature and provide consumers browsing the Internet with exclusive service that caters to their personal needs and habits, it is necessary to know the consumers' browsing habits and preferences [4]. However, lacking research tools for exploring consumers' preferences, Web advertising service providers nowadays tend to choose advertisements for consumers subjectively [5].

In recent years, e-commerce has been studied by many. For example, Langheinrich [4] implemented a dynamic advertisement selection system able to deliver customized advertisements to users of an online search service or Web directory, which is just focused on users' short-term interests in a non-intrusive way. Huang and Hung used an online shopping support system to improve the entire online shopping process of a shopping website [6], and yet the system does not automatically analyze consumers' preferences associated with products. As a result, the consumers still have to select their preferred product ads on their own so that the function of target marketing is not effectively achieved. In addition, some researchers applied the fuzzy theory to online marketing analysis because fuzzy models in this area are capable of making explicit the diverse forms of uncertainty [7] that are inherent to market analysis and the measure of highly abstract notions. To raise the effectiveness of Web advertisements, Sung [8] used fuzzy rules to express customer segments' surfing patterns on the basis of expert advice and recommend appropriate advertisements by fuzzy inference. In order to build and maintain relationships with customers (or suppliers), giving each of them personalized treatment, Sicilia and García [9] described a fuzzy model for characterizing vagueness in customer value segmentation, and a straightforward mathematical method for assessing value segments that allow for some degree of flexibility. Besides, Kong and Liu [10] used a fuzzy analytic hierarchy process to evaluate the success factors of e-commerce websites. It can be known from the literature cited above that the fuzzy theory has been applied by some researchers to the study of consumer behaviors, but the influence of such important factor as the time effect on consumer preference level has not been examined. Also, few studies have been done regarding enhancement of the overall benefits of website browsers, advertisement supplies, and Web advertising service providers.

In a membership-based single-website advertising environment, this study considers the impact of the time effect on consumer preference levels associated with products. More particularly, this study uses consumers' effective browsing and monetary purchase amounts as a basis and, by applying the half-life theory and the fuzzy theory to analyzing the time-affected consumer preference levels in relation to products, establishes a consumer preference level analysis system. Furthermore, based on the consumer preference levels obtained, comparison is made between the preferences of different consumers so as to filter out groups with similar shopping preferences and produce a suggested list of members having similar preferences. Moreover, in order to enhance interaction between other and self in the cyberspace and increase a closeness among consumers so that people who have common interests but are totally strange to one another can get together through the Internet [1], the website is equipped with a chat room and a friend-making function to promote exchange between online groups, thereby extending website browsing time and reinforcing consumers' loyalty to the website and products [11].

As to the selection and delivery of ads, in order to efficiently present the ads supplied by the advertisement suppliers to consumers and make the ads correspond to the consumers' preference, this study proposes Web ads whose contents are determined by consumer preference, as opposed to the conventional ones that are supplied in one direction only. Hence, the ads delivered are highly relevant to consumers and capable of arousing the consumers' interest in the advertised products [12]. Therefore, an advertisement matching system is created in this study to match members' personal preferences with the advertisement suppliers' expected target markets so as to filter out a portfolio of candidate ads for delivery. In addition, commercial recommendation rules are used to create a delivery scheduling system for determining the order of advertisement delivery and thus enhance the effects and fairness of advertisement delivery.

To ensure that the methodology proposed in this study effectively magnifies the effects of target marketing, a shopping website with Web advertisement based on the methodology of this study is developed so that the methodology is corrected with experience accumulated in practical operation, and a shopping environment capable of offering rapid and convenient service and satisfying consumer preference is provided.

2 System Design

2.1 System Architecture

In this study, a selection and recommendation system for Web advertisement delivery is created. The system is divided by function into three subsystems, namely consumer preference level analysis subsystem, advertisement matching subsystem, and delivery scheduling subsystem. The architecture of the system is shown in <figure 1>.

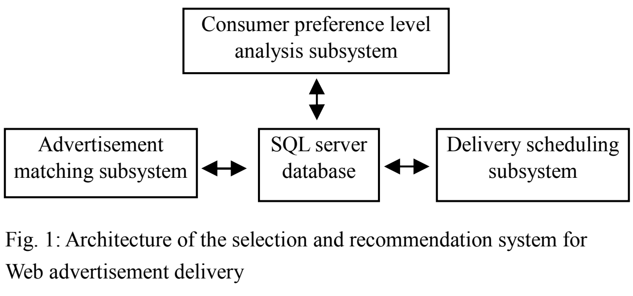

Fig. 1: Architecture of the selection and recommendation system for Web advertisement delivery

(1) Consumer preference level analysis subsystem

This subsystem uses the half-life theory and the fuzzy theory to analyze the time-affected consumer preference levels associated with products, so that consumers' preference levels in relation to different products can be known. Also, the market trends of various advertised products can be obtained and serve as a reference for advertisement suppliers regarding the arrangement of product advertisements, thereby increasing the marketing effects of Web advertisements. In addition, this subsystem analyzes the differences of preference levels among members so as to produce a list of members having similar shopping preferences. The list is provided to members as a suggested list for determining whether or not to exchange among the listed members.

(2) Advertisement matching subsystem

This subsystem segments the target markets of advertisements as set by the advertisement suppliers and uses the fuzzy theory to calculate the market condition values of products. The obtained values are matched with consumer preference levels so that the advertisements can be delivered precisely to the target markets and suit consumer preferences.

(3) Delivery scheduling subsystem

This subsystem effectively designs and arranges the advertisement delivery schedule. The sequence and frequency of advertisement delivery is controlled to enhance the effect of delivery. Meanwhile, commercial fairness in advertisement delivery is assured by preventing certain advertisements from being delivered at an excessively low frequency or not being delivered at all.

2.2 Consumer Preference Level Analysis Subsystem

This subsystem introduces the half-life theory and the fuzzy theory to the analysis of consumer preference levels in relation to products. The subsystem is further divided by function into a preference level analysis module and a similarity calculation module, as shown in <Figure 2>. The function and operating procedure of each module is explained in detail as follows:

(1) Preference level analysis module

Customers' behaviors on the website are collected and recorded. The behavior record is then fit into a fuzzy function for calculation, in which the fuzzy function transforms the behavior record into a value ranging from 0 to 1. Afterward, a time-related decay factor is introduced into the system to convert the value into a time-affected preference level, which is in turn normalized to produce a preference level value [13]. The preference level value is stored in a behavior database and transmitted to the similarity calculation module for calculating similarities.

This module utilizes the half-life theory to precisely estimate the intensities of consumer preference so that product market trends can be understood, thus enabling personalized website service and Web marketing. The calculated consumer preference level not only facilitates prediction of product market trends but also helps advertisement suppliers to adjust advertisement categories for dynamic marketing.

(2) Similarity calculation module

This module calculates the similarity of preferences among members. On a daily basis, the module calculates and cross-compares the members' preference levels associated with products in order to filter out member groups having similar preferences. Members of the same group are listed in a suggested list of fellow shoppers. The list is stored in a match database and will be sent to the members' browsers when they log in the next time for reference by the logged in members. Apart from that, the website provides a chat room and a friend-making function to solidify consumers' loyalty to the website.

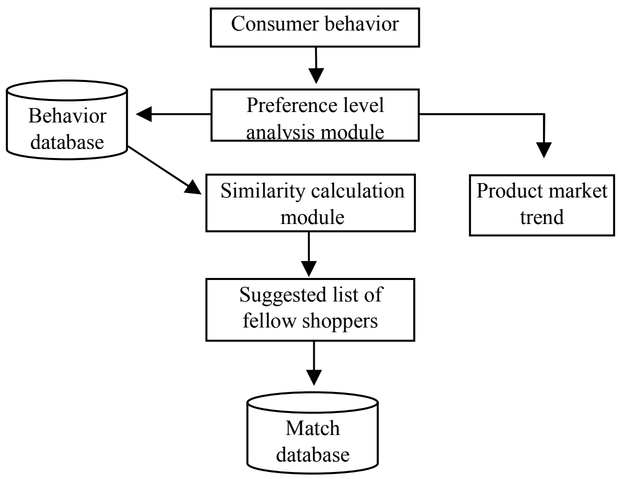

Fig. 2: Architecture of consumer preference level analysis subsystem

2.2.1 Preference Level Analysis Module

In this study, the main variable in the preference level analysis module is the record of consumers' behaviors (including effective browsing and monetary purchase amounts) on the e-commerce website. An equation is established for estimating the consumer preference level, in which the influence of purchase behavior on preference level is enhanced by a purchase weight. Then, the half-life theory and the fuzzy theory are applied in order to create a module operation model. The design and operation steps of the module are described in detail below.

Step 1 Establishment of preference level equation

As mentioned above, consumer preference is cumulated by two factors, monetary purchase amount and browsing time. However, the monetary purchase amount is the more important of the two factors. Therefore, the following equation uses a purchase weight to intensify the influence of monetary purchase amount on preference level. An equation is established for calculating consumers' preference levels associated with products:

$$L=ES+W \tag{1}$$

where L is consumer preference level, E is purchase weight, S is a monetary amount coefficient, and W is a browsing coefficient. These variables are defined as follows:

(1) Browsing coefficient W:

The browsing coefficient W is determined by the browsing advertisements time t of a particular type of products. Based on the S- function in fuzzy functions, the browsing coefficient W is defined as follows and plotted in <Figure 3>.

$$W=\begin{cases} 0 & 0 \le t < t_0 \\ 2\left(\dfrac{t-t_0}{t_1-t_0}\right)^2 & t_0 \le t < \dfrac{t_0+t_1}{2} \\ 1-2\left(\dfrac{t-t_1}{t_1-t_0}\right)^2 & \dfrac{t_0+t_1}{2} \le t < t_1 \\ 1 & t_1 \le t \end{cases} \tag{2}$$

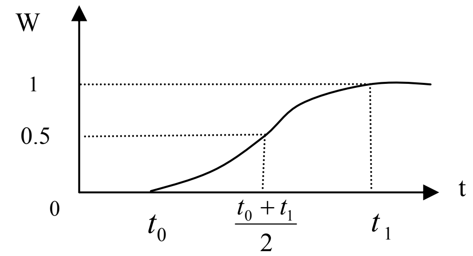

Fig. 3: Graph of browsing coefficient function

In the above function, t_0 is the shortest browsing time, and t_1 is the longest browsing time. Although W is an increasing S-function, it is found in practical application that consumers may leave their computers temporarily while browsing advertisements, which leads to overestimation of t but does not necessarily mean the consumers are interested in the type of products in the advertisements. According to function (2), the above-mentioned scenario will be interpreted as the consumers preferring that particular type of products and causing a miscalculation in the preference level. Therefore, the function of the browsing coefficient W is modified as follows. The graph of the modified function is plotted in <Figure 4>.

$$W=\begin{cases} 0 & 0 \le t < t_0 \\ 2\left(\dfrac{t-t_0}{t_u-t_0}\right)^2 & t_0 \le t < \dfrac{t_0+t_u}{2} \\ 1-2\left(\dfrac{t-t_u}{t_u-t_0}\right)^2 & \dfrac{t_0+t_u}{2} \le t < t_u \\ 1-2\left(\dfrac{t-t_u}{t_1-t_u}\right)^2 & t_u \le t < \dfrac{t_u+t_1}{2} \\ 2\left(\dfrac{t-t_1}{t_1-t_u}\right)^2 & \dfrac{t_1+t_u}{2} \le t < t_1 \\ 0 & t_1 \le t \end{cases} \tag{3}$$

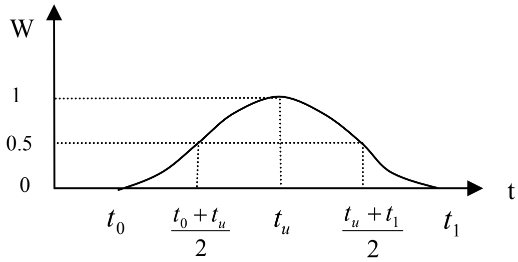

Fig. 4: Graph of modified browsing coefficient function

Regarding the estimation of browsing time, it is required in this study that each member fill out a preset questionnaire upon registration, and the time each member takes to read the questionnaire (RT, read time) is recorded along with the total word count (TW, total word) of the questionnaire. Therefore, the time each member i takes to read a single word ($AvgT_i$, average time) can be calculated by the following equation:

$$AvgT_i=\frac{RT}{TW} \tag{4}$$

The $AvgT_i$ thus obtained is multiplied by the word count ($word_j$) of the introduction to an advertised product j to produce the population mean (t_μ) of the member i's reading time associated with the advertised product j, as expressed by the following equation:

$$t_\mu=AvgT_i * word_j \tag{5}$$

Calculation of t_μ is intended mainly to make more objective the reading time computed from each member's browsing different advertisements, thus enabling delivery of advertisements that better suits user preference. With t_μ being set as the browsing time corresponding to the curve apex, and the extreme values t_0 and t_1 being set outside the

95% limits of the entire value range, respectively, the Chebyshev's theorem is employed to define the shortest browsing time t_0 and the longest browsing time t_1 as:

$$t_0 = t_\mu - 4\sigma^2 \quad (6)$$

$$t_1 = t_\mu + 4\sigma^2 \qquad (\sigma^2 \text{ is variance}) \quad (7)$$

(2) Monetary amount coefficient S:

The monetary amount coefficient S is determined by the monetary purchase amount m of a particular type of products. Based on the S-function in fuzzy functions, once the lowest monetary purchase amount m_o and the highest monetary purchase amount m_1 are known, the monetary amount coefficient S is defined by the following function, whose graph is plotted in <Figure 5>.

$$S = \begin{cases} 0 & 0 \le m < m_0 \\ 2\left(\dfrac{m-m_0}{m_1-m_0}\right)^2 & m_0 \le m < \dfrac{m_0+m_1}{2} \\ 1-2\left(\dfrac{m-m_1}{m_1-m_0}\right)^2 & \dfrac{m_0+m_1}{2} \le m < m_1 \\ 1 & m_1 \le m \end{cases} \quad (8)$$

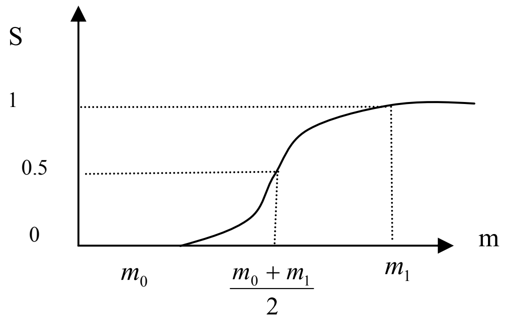

Fig. 5: Graph of monetary amount coefficient function

In this study, members' monetary purchase amounts are recorded when products are purchased. Then, the total monetary purchase amount of a particular type of products j by all members is divided by the total purchase quantity of that particular type of products j to find the average monetary purchase amount m_μ. After setting the average monetary purchase amount m_μ at the apex of the monetary amount coefficient, and the extreme values m_0 and m_1 outside the 95% limits of the entire value range, respectively, the lowest monetary purchase amount m_0 and the highest monetary purchase amount m_1 are defined by the Chebyshev's theorem and expressed as follows:

$$m_0 = m_\mu - 4\sigma^2 \quad (9)$$

$$m_1 = m_\mu + 4\sigma^2 \quad (\sigma \text{ is variance}) \quad (10)$$

(3) Purchase weight E:

Although consumer preference is the cumulative result of two factors, namely monetary purchase amount and browsing time, the monetary purchase amount is the more important of the two factors. Therefore, the present model uses a purchase weight E to intensify the influence of monetary purchase amount on preference level. The purchase weight E is defined as:

$$E = \frac{H+1}{B+1} \quad (11)$$

In equation (11), H is the total number of times a product has been viewed, and B is the total number of times the product has been purchased, so that E is the average number of times the product has been viewed per unit purchase. Whenever a consumer purchases a certain product, the total recorded number of times the same type of products has been viewed is divided by the total number of times consumers have bought that particular type of products. Thus, the purchase weight changes as the number of times viewed and the number of times purchased increase. It is objectively demonstrated by the product of the purchase weight E and the monetary amount coefficient S that the higher the price a consumer paid for a certain product, the higher the consumer's preference level. The "+ 1" part in equation (11) is intended to prevent system abnormality caused by H or B being zero. For example, when B is zero, the purchase weight E will approach infinity. This problem is solved by adding "1" to the numerator and the denominator of equation (11), respectively. As the numbers of times viewed and the numbers of times purchased gradually increase, the significance of the additional "1" is lowered accordingly.

Step 2 Introduction of the half-life theory

As mentioned earlier, the influence of the time effect on consumer preference level should be taken into account. The half-life theory is utilized in this study to derive a time-affected preference level value.

(1) The half-life theory

The so-call half-life refers to the time it takes a radioactive substance to decay to half its original amount. Each radioactive substance has a specific half-life. Although the radioactive substance does not vanish in the end, after decaying for a period of time (about several half-lives), its radioactivity becomes so low that the existence of the substance can be ignored [14]. When it comes to consumer preference, its decay due to the time effect should be considered. According to the half-life theory, it is assumed that consumer preference in relation to a particular type of product decays by half every d_0 days, wherein the value of d_0 depends on the property and popularity of products. In other words, after d_0 days, the preference level drops to:

$$\mathrm{L}_{\mathrm{d}_0} = \frac{L_0}{2} \tag{12}$$

(L_0 is the preference level on a particular day)

(2) Preference level L_d after d days

Considering the half-life of d_0 days, the preference level value after d days is defined as L_d and expressed by the following preference level equation:

$$\mathrm{L_d} = \mathrm{L_0} \times \frac{1}{2^{\frac{d}{d_0}}} \tag{13}$$

By defining a daily decay coefficient α as $\alpha = \frac{1}{2^{\frac{1}{d_0}}}$, equation (13) is rewritten as:

$$\mathrm{L_d} = \mathrm{L_0}\, \alpha^{\mathrm{d}} \tag{14}$$

(3) Preference level V accumulated till today

Given that the daily preference level value decays due to the time effect, a sum of preference level values accumulated till today is defined as V and represented by the following equation:

$$V = L_0 + L_1\alpha + L_2\alpha^2 + \ldots\ldots\ldots\ldots + L_n\alpha^n \tag{15}$$

where L_0 is preference level value calculated from the behavior record of today, L_1 is the preference level value of yesterday, L_n is preference level vale of the n^{th} day preceding today, and α is the daily decay coefficient. However, it is extremely time-consuming if the calculation must start each time from the very first browsing record. Therefore, equation (15) is revised as:

$$\begin{aligned} V &= L_0 + L_1\alpha + L_2\alpha^2 + \ldots\ldots\ldots\ldots + L_n\alpha^n \\ &= L_0 + \alpha\,(L_1 + L_2\alpha + \ldots\ldots + L_n\alpha^{n-1}) \\ &= L_0 + \alpha V_y \end{aligned} \tag{16}$$

It means that the preference level value accumulated till today can be obtained simply by calculating the sum of preference level values accumulated till yesterday V_y, multiplying the sum by the daily decay coefficient α, and then adding the preference level value calculated from the behavior record of today.

Step 3 Normalization of preference level value

The preference level value V is normalized so that its effect ranges from 0 to 1. The exponential function $f(x) = 2^x$ is been used here because of the characteristics of $f(0) = 1$ and increasing when x≧0. Therefore, the normalized function F(V) of the preference level value V is defined as:

$$\mathrm{F(V)} = \frac{2^{X_0 V} - 1}{1 + 2^{X_0 V}} \tag{17}$$

where X_0 is a coefficient of the normalized function, and the value of X_0 is adjustable and variable with the condition defining the preference level of each type of products. For instance, in order to find the value of the coefficient X_0 of a particular type of products, we can define that consumers are interested in this type of product if the consumers' accumulated preference level value V is 10. The value of 10 is further defined as the condition for the membership value to reach its midpoint, i.e., 0.5. Under this condition, the coefficient X_0 of the normalized function is derived as follows:

$$\mathrm{F(10)} = \frac{2^{10X_0} - 1}{1 + 2^{10X_0}} = 0.5$$

From the above equation we get X_0□0.159. Thus, the normalized equation in this example is:

$$\mathrm{F(V)} = \frac{2^{0.159V} - 1}{1 + 2^{0.159V}} \tag{18}$$

According to equation (18), if the preference level value V is 0, the preference level value normalized by the normalized function is also 0. if V is ∞, the normalized preference level value is 1. Finally, if the V value satisfies the predetermined definition of this type of products being preferred by consumers (V=10), the normalized preference level value is 0.5. It can be known from the above that the values of the normalized function are distributed within a reasonable range of [0,1]. The normalized preference level value is further defined as the preference coefficient (LF) and expressed as:

$$\mathrm{LF} = \mathrm{F(V)} = \frac{2^{X_0 V} - 1}{1 + 2^{X_0 V}} \tag{19}$$

2.2.2 Similarity Calculation Module

This module serves to calculate the similarity of product preferences among members. The design and operation steps of this module are described below:

Step 1 Calculation of preference similarity

The preference similarity between each two members can be determined by the following equation:

$$\text{D} = \sqrt{\sum_{i=1}^{m} (F(V)_{pi} - F(V)_{qi})^2} \quad (20)$$

where D (Distance) represents a difference of preference between two members p and q, and $F(V)_{pi}$ is the member p's normalized preference level associated with an i^{th} type of products. Assuming there are m types of products for example, by squaring the differences of preference levels between the two members from the first type to the m type of products, respectively, then summing up the squared differences, and taking square root of the sum, one obtains a value representing the average difference of preference between the two members. The distance D has a range of $0 \sim \sqrt{m}$, which is the range of average difference of preference between the two members.

However, it is found in practical application that ineffective comparison sometimes occurs when cross-comparing the calculated preference similarity between members. For example, if a member logging into the system has a very low preference level associated with products, it is not necessary to include this member in the list for cross-comparison. In consequence, system resources can be saved while the accuracy of effective samples is increased. As mentioned earlier, if members are interested in a particular type of products, the normalized preference level value F(V) must at least exceed 0.5. Therefore, a "non-characteristic member" is defined herein as a member whose preference level in relation to products is spaced from the origin by a distance not greater than 0.5, and non-characteristic members are not further analyzed and compared. The criterion for identifying a non-characteristic member is the consumer preference characteristic value (Idistance), which is calculated by the following equation:

$$\text{Idistance} = \sqrt{\sum_{i=1}^{m} (F(V)_{pi} - 0)^2} \quad (21)$$

Therefore, comparison is worthwhile only when the value of Idistance is greater than or equal to 0.5. Members who never browse the website are excluded from comparison for obvious reasons.

Step 2 Normalization of preference similarity

The preference similarity value D between consumers is normalized so that its effect ranges from 0 to 1. The normalized function F(D) is defined as:

$$\text{F(D)} = \frac{D_{\max} - D}{D_{\max} - D_{\min}} \quad (22)$$

where D_{mix} is the smallest difference, whose value is 0; and D_{max} is the greatest difference, whose value is $\sqrt{m}$.

For instance, assuming there are ten types of products (m=10), the greatest difference (i.e., $D = \sqrt{10}$) is normalized by the normalized function to produce a normalized similarity of 0. If D is 0, its normalized value is 1, meaning that shopping behaviors are identical. If D is $\sqrt{10}/2$, its normalized value is 0.5.

2.3 Advertisement Matching Subsystem

In order to match advertisement delivery with the expected target markets of advertisement suppliers, an advertisement matching subsystem is constructed in this study to ensure that all advertisements delivered provide personalized services. This subsystem performs market segmentation on the advertisement suppliers' ads, uses the fuzzy theory to quantify the target market conditions of products, and then matches the quantified results with consumer preference, so that consumers receive product advertisements they are interested in, and target marketing is thus accomplished. A detailed description of the architecture and matching procedure of the subsystem is given below by reference to <Figure 6>:

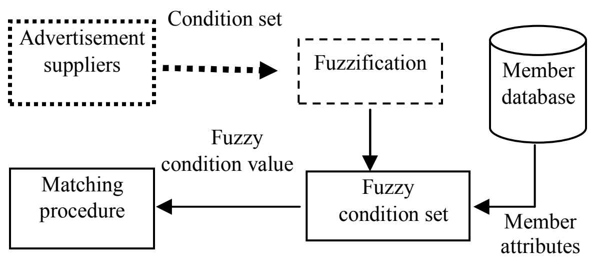

Fig. 6: Architecture of advertisement matching subsystem

Step 1 Obtaining condition factor (CF)

(1) After an advertisement supplier makes a deal with a Web advertising service provider, the advertisement supplier must select a number of member attributes and set limiting conditions (Cond) corresponding to the selected attributes, respectively. The n limiting conditions of an advertisement j

constitute a condition set of the advertisement j: $\left\{ Cond_k^j \middle| \ 1 \le k \le n, \ \ k \in N \right\}$.

(2) To enable better match with the advertisement supplier's market segmentation, the limiting conditions in the condition set may include two types of conditions: absolute conditions and fuzzy condition. For example, an absolute condition k corresponding to the age attribute is specified for an advertisement j and expressed as function (23), whose value is 1 if a member i's attributes satisfy the limiting condition, and is 0 if otherwise.

$$\mathrm{Cond}_{\mathrm{k}}^{\mathrm{i,j}} = \begin{cases} 1 & x \ge 20 \\ 0 & x < 20 \end{cases} \tag{23}$$

On the other hand, fuzzy conditions are generated by fuzzy transformation using the commonly used membership functions of the positive triangular fuzzy numbers or trapezoidal fuzzy members in the fuzzy theory [15]. For instance, a trapezoidal fuzzy condition k corresponding to the age attribute is specified for an advertisement j and expressed as function (24). By fitting member attributes into the function, one obtains a transformed value $Cond_k^{i,j}$ of this condition corresponding to a member i.

$$\mathrm{Cond}_{\mathrm{k}}^{\mathrm{i,j}}(\mathrm{x}:20,30,35,40) = \begin{cases} 0 & 0 \le x < 20 \\ \dfrac{x-20}{30-20} & 20 \le x < 30 \\ 1 & 30 \le x < 35 \\ \dfrac{x-40}{35-40} & 35 \le x < 40 \\ 0 & 40 \le x \end{cases} \tag{24}$$

(3) A condition transformed value set $\left\{ Cond_k^{i,j} \middle| \ 1 \le k \le n, \ \ k \in N \right\}$ is a set of n transformed values of n absolute or fuzzy conditions associated with an advertisement j and corresponding to n attributes of a member i in the member database, wherein the transformed value of each condition has a range of [0, 1]. In order to accurately determine a matching degree between members and advertisement conditions and thus achieve precise segmentation of advertisement conditions, a condition factor for a member i in relation to an advertisement j is defined in this study as:

$$\mathrm{CF}_{\mathrm{i,j}} = \min\left\{ Cond_1^{i,j}, Cond_2^{i,j}, ..., Cond_n^{i,j} \right\} \tag{25}$$

Step 2 Calculating advertisement chance (AC)

As advertisements may be supplied by different advertisement suppliers, the advertisement chance, i.e., the probability of an advertisement's being delivered, should be determined by the money paid by each advertisement supplier for delivering his/her own advertisements. In this study, the advertisement chance (AC) of an advertisement supplier's advertisements is calculated by dividing the amount of money paid by this particular advertisement supplier (customer money; CM) by the total amount of money paid by all advertisement suppliers (sum money; SM), as expressed by the following equation:

$$\mathrm{AC} = \frac{CM}{SM} \tag{26}$$

The main purpose of this step is to ensure fairness of advertisement delivery. Now that the money paid by each advertisement supplier for delivering advertisements is variable, the advertisement chance is determined by the money each advertisement supplier pays so as to allow advertisement suppliers who pay more money to have greater chances of advertisement delivery.

Step 3 Calculating a match value of advertisement supplier's conditions (match advertisement; MA)

The matching degree (CF) of the limiting conditions as segmented by the advertisement suppliers is computed according to function (25) and then matched with the advertisement chance by means of the following function:

$$\mathrm{MA} = \min\{\mathrm{CF}, \mathrm{AC}\} \tag{27}$$

As each advertisement supplier pays a different amount of money, function (27) takes the minimum value to make the segmentation of advertisement conditions more precise.

Step 4 Calculating match degree (MD)

The match value of advertisement supplier's conditions MA is matched with the preference coefficient LF previously calculated according to equation (19), so as to determine a match degree between a member and a particular advertisement, wherein the match degree ranges from 0 to 1 and is computed as follows:

$$\mathrm{MD} = \min\{LF, MA\} \tag{28}$$

The minimum value is taken from the range of the preference coefficient LF and the match value of advertisement supplier's conditions MA for the purpose of simultaneous satisfaction of the preference coefficient LF and the match value of advertisement supplier's conditions MA, thus allowing the advertisements delivered to better suit consumers' preference.

2.4 Delivery Scheduling Subsystem

If the same advertisement is delivered at an excessively high frequency during a short period of time, it will bore the consumers and make advertisement delivery inefficient. On the other hand, it is equally inefficient and unfair to have some advertisements delivered at an excessively low frequency or not delivered at all. Therefore, a delivery scheduling subsystem is established in this study to prevent the aforesaid situations and enhance the efficiency and commercial fairness of advertisement delivery. The architecture of the subsystem is illustrated in <Figure 7> while its operation process is explained in detail below:

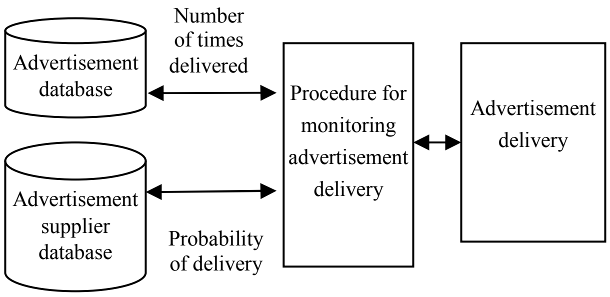

Fig. 7: Architecture of delivery scheduling subsystem

Step 1 Setting delivery threshold value

While delivering advertisements, those with higher match degree (MD) values should be delivered first so as to maximize the benefits of advertisement delivery. According to system design, the MD values of a particular member in relation to all the advertisements are retrieved and then sieved with a threshold value β. The results are stored in a match set (MS), as shown by the following function:

$$MS = \{MD \mid MD \geq \beta\} \tag{29}$$

Step 2 Delivery schedule design

The MS is stored, one after another, in a two-dimensional array (array A). The initial value of the number of times delivered is set at zero. The advertisements in the array are delivered randomly. When an advertisement has been delivered the predetermined number of times, it is put into another two-dimensional array (array B). Thereafter, each time an advertisement in the array A is delivered, the number of times delivered of each advertisement in array B is reduced by one. When an advertisement in array B has its number of times delivered reduced to zero, it is put back into array A and ready for future delivery. Thus, repetitive delivery of advertisements can be minimized lest excessively high exposure causes adverse effects on the advertisements. In addition, since an advertisement reaching its predetermined number of times delivered will be moved out for a while and then return to the array A for further delivery, the advertisements are delivered in an evenly random fashion. However, when few advertisements are available, the number of times delivered must not be set too high; otherwise, there may be no advertisements in array A to be delivered.

Step 3 Design for fairness of delivery

When advertisements are sieved with the threshold value β, those with low MD values tend to be eliminated. As a result, some advertisements will never be delivered. To avoid this and make advertisement delivery truly fair, upon delivery of a particular advertisement, the system counts the total number of times that a particular advertisement has been delivered and divides it by the total number of times delivered of all the advertisements, thereby obtaining a delivery percentage of that particular advertisement. This percentage is compared with the advertisement supplier's advertisement chance (AC). If the delivery percentage is higher than the AC value, future delivery of the advertisement is temporarily halted while those whose MD values have not reached the threshold value β are delivered instead. Hence, all the advertisements that should be delivered are effectively and impartially entered into the delivery schedule.

3 System Implementation

After designing the aforesaid three subsystems, namely the consumer preference level analysis subsystem, the advertisement matching subsystem, and the delivery scheduling subsystem, practical operation of the system is evaluated by first creating a selection and recommendation system for Web advertisement delivery as shown in <Figure 8>, and then designing a shopping website with Web advertisement based on the system, as shown in <Figures 9, 10, 11, 12>, whose operation process is summarized as follows:

(1) The website is membership-based. A visitor registering for membership will be given a questionnaire for initializing personal parameters.

(2) When a member logs in, corresponding parameters such as member preference are retrieved from the member database.

(3) The member's behaviors on the website are monitored, including the advertisements browsed, the browsing time, and so on.
(4) The member's behaviors on the website are recorded, analyzed, and then stored in the database.
(5) Advertisements are retrieved from the advertisement database along with such parameters as identities of the corresponding advertisements suppliers, the amount of money paid by each advertisement supplier, condition segmentation, and so on.
(6) The member's preference coefficient is matched with the advertisement suppliers' conditions and the amounts of money paid by the advertisement suppliers.
(7) The calculated match degree is compared with the threshold value. Advertisements with match degree values higher than the threshold value are entered into the delivery schedule.
(8) The scheduled advertisements are sent to and delivered by an advertisement server. Steps 3 to 8 are repeated.

In addition, this study uses Microsoft SQL Server as the backend database, and the subsystem modules are connected to one another. Whenever external data are changed, the system will modify the backend behavior database in real time [16].

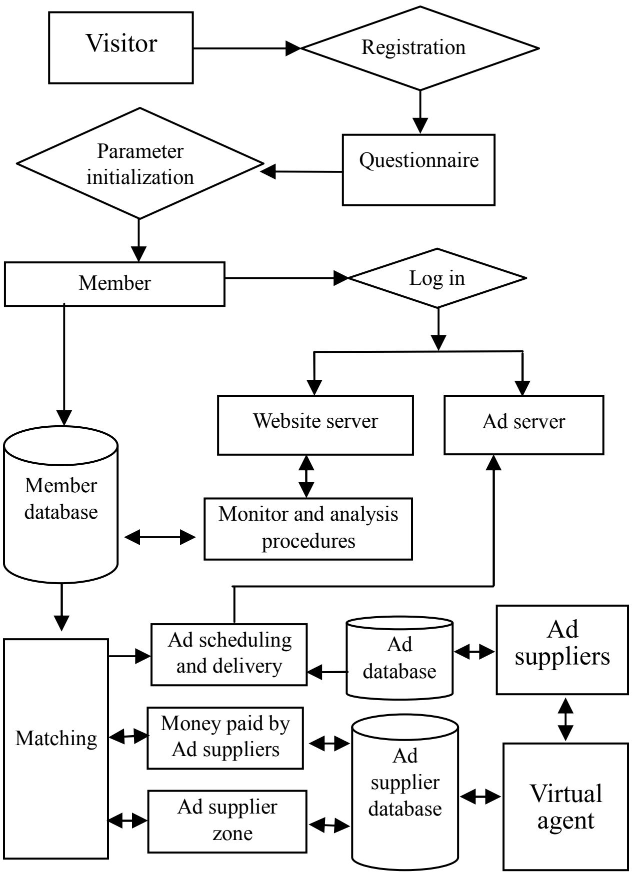

Fig. 8: Architecture of selection and recommendation system for Web ad delivery

Fig. 9: Screen image for visitor entry

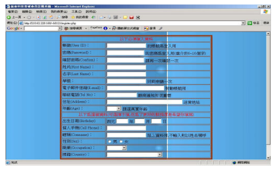

Fig. 10: Screen image for member registration

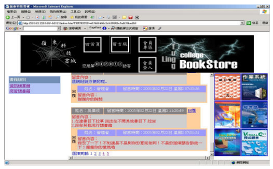

Fig. 11: Screen image of message board

Fig. 12: Screen image for ad management

4 Conclusion

In a membership-based single-website advertising environment, this study constructs a consumer preference analysis system based on the half-life theory and the fuzzy theory so as to know consumers' preference levels in relation to products and the products' market trends. It is hoped that the purpose of marketing is effectively achieved through an improved interface for providing personalized service to website browsers. Additionally, this study proposes a selection and recommendation model for product advertisements. The model considers members' personal preferences and matches them with the advertisement suppliers' expected target markets. Thus, a portfolio of candidate advertisements for delivery is filtered out, and the sequence of advertisement delivery is determined by commercial recommendation rules. The objective of this study is to ensure that all the advertisements delivered provide personalized service to members, and the delivery of advertisements produces enhanced positive effects, such as increasing the market competitiveness of Web advertising service providers and promoting a win-win-win situation for consumers, advertisement suppliers, and Web advertising service providers. Furthermore, in practice, a shopping website with Web advertisement based on the methodology proposed in this study is developed to proactively provide consumers with an environment for shopping preferred products and thereby maximize the effects of target marketing.

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