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A diversity-based method for infrequent purchase decision support in e-commerce

Rustam Vahidov *, Fei Ji

Department of Decision Sciences & MIS, John Molson School of Business, Concordia University, 1455 de Maisonneuve Blvd. W, Montreal, Que., Canada H3G 1M8

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Abstract

In this paper we propose a method for supporting consumer buying decisions in e-commerce. We are advocating the diversity-driven approach to generating alternatives for infrequently purchased products (i.e., computers, vehicles, etc.). Our method is based upon the well-known "divergence/convergence" principle of problem solving. The paper discusses the method based on fuzzy weighted-sum model and cluster analysis, the architecture and the operation of the decision support system for generating product alternatives. The preliminary experiments with the prototype for notebook selection provide some support in favor of our approach over the catalog-based systems.

Keywords: Decision support systems; Buyer support; Recommendation systems; Fuzzy sets; Alternative generation

1. Introduction

Electronic commerce offers unprecedented ways of empowering modern customers [1]. At the same time, the wealth of information threatens to cognitively overload the customers. Thus, it is essential to offer means of facilitating buyer's decision processes using computer-based tools. As Zwass notes: "the digital retailing practice has to embrace the broad approach to the opportunities offered by an interactive medium that attracts many millions of potential buyers" [2]. This "added-value" interactivity that goes beyond simple browsing, search, and order-taking to include progressive methods of search and advisory seems to be of considerable importance for the success of e-commerce websites and malls [3]. A recent study suggests that utilization of value-added search mechanisms in web stores promotes shopping enjoyment and, consequently their intention to return [4]. Another study suggests that advisory information from retailer to assist the buyer's decision-making process is

* Corresponding author. Tel.: +514 848 2424x2974; fax: +514 848 2428.
E-mail address: rvahidov@jmsb.concordia.ca (R. Vahidov).

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important for both browse- and search-oriented tasks [5].

This work is motivated by the customers' need for supporting tools that would effectively utilize available product information in the presence of multiple product alternatives. This is particularly the case when the customer is not sure exactly what kind of product and merchant characteristics and related services he or she is looking for. The customer will have to make effective trade-offs between the price and other important decision variables using his/her judgment. Such situations are likely to occur when the purchase of items under consideration is infrequent (e.g., computers, furniture, etc.) [6]. The type of problems, where the objectives (characteristics of the sought products) are not well-defined is considered to be essentially "ill-structured". One important principle of solving ill-structured problems is known as divergence/convergence principle that encourages the problem solvers (buyers) to consider multiple diverse alternative solutions (products) at the earlier phases of analysis, and to gradually move towards convergence at the later stages of decision making through systematic evaluation of alternatives. The category of information systems that traditionally targets ill-structured problems is known as decision support systems (DSSs).

The importance of decision support in e-commerce context has been emphasized in the past [7]. Some researchers believe that the use of DSS by the customers could lead to "caveat mercator" ("seller beware") phenomenon when the buyers will be able to effectively utilize powerful tools (e.g., optimization models) to improve their decision making [8]. In our approach to providing buying decision support we are primarily relying on: allowing the customers to imprecisely express their "vague" requirements for products/services; and the employment of the well-known "divergence/convergence" principle from problem solving in supporting buyers' decisions.

In the following we outline the existing approaches to buyer support in e-commerce, discuss the principles of problem solving as applied to improving buyer's decision making processes, propose a method for supporting buyers, discuss a prototype for notebook selection, and present the results of preliminary experiments. The paper finishes with the conclusions and discussion of the future research.

2. Background

Different versions of consumer buying behavior (CBB) model [9] have been used extensively in research on e-commerce buyer support [10,11]. Miles and Howes related CBB model to Simon's decision making model traditionally used in DSS literature [12]. The CBB activities of managing search criteria, search for products, and comparison of products corresponded to the intelligence, design, and choice phases of Simon's model respectively. Building on this work Nah and Davis [13] argued that searching capability is more appropriate for the customers who know what they are looking for, while browsing seems to fit customers who do not have such a clear objective. Detlor et al. [5] stressed that searching corresponds to the customer's goal-directed activities, while browsing relates to the experiential behavior. They suggested that commercial website design should fit both of these behaviors.

Internet presents new interesting opportunities for providing decision support capabilities [14]. Silverman et al. [7] emphasized the importance of incorporating DSS functions in the design of commercial websites. They have distinguished three levels of DSS in this regard: access focused, transaction focused, and relationship focused. The first category includes websites with basic search and browsing capabilities. The second one incorporates more advanced support including shopping focused tools and guided choices. The third one is more similar to CRM systems in targeting the maintenance of long-term relationship with the customers. Our focus in this paper is in the second level of DSS according to the above categorization.

The basic decision aids that a site could offer to potential customers include search and browsing capabilities. However, in this case the customer has to know what product characteristics he or she is looking for (in case of search) or have a relatively small set of offerings to browse through. A more advanced active type of support is offered by recommendation systems [15]. Lee et al. [6] distinguish between two types of shopping including frequently (regularly) vs. infrequently purchased items. For frequent shopping activities the focus is on eliciting customer preferences and suggesting products according to the customer profile. Different techniques have been utilized to this end.

One common model-based approach is to model customer's preferences using a vector of weights representing relevances of product attributes to a given customer. Lee et al. used this approach for recommending DVDs to customers. Their agent-based system used genetic algorithms to learn customer's preferences. Similar approach was used in [16] where the system learned user preferences for the source of document recommendation. Kim et al. [17] utilized web usage mining for decision tree induction in order to generate personalized recommendations in e-shopping support. One way to elicit customer preferences is through the use of conjoint analysis: a technique long used in marketing [18]. In this approach customer is presented with different products and feature combinations and asked to compare them in terms of desirability. The customer preferences are used by a model to rank the available products. For example, "Active Sales Assistant" (http://activebuyersguide.com/) from Active Decisions offers such service for choosing a product from a variety of categories.

Intelligent solutions also exist for building knowledge based recommender systems, including "Exsys Corvid" (http://www.exsys.com/) and "DecisionScript" (http://www.vanguardsw.com/decisionscript/). For instance, Exsys website features demos on camcorder selection and restaurant recommendation. An alternative knowledge-based approach includes inductive techniques [19]. For example, Kim et al. [20] used decision-induction techniques for personalized advertisements in storefronts using data mining coupled with demographic data.

Another class of methods that has earned much popularity in generating recommendations is so-called collaborative filtering [21,22]. The core idea is very intuitive: to provide an advice to a customer based on the purchasing patterns of other similar-minded individuals. The similarity-based techniques, such as nearest-neighbor and cluster analysis are typically utilized by such recommendation systems. Firefly system, for example, used this "word-of-the-mouth" approach in making recommendations to like-minded people [11]. Similarly in [23] a collaborative method is proposed for generating movie recommendations.

Often shopping support technologies are incorporated in so-called software agents [11,24,25]. Agents are software components that possess the features of autonomy, reactivity, proactiveness, and social ability [26]. They can be used at different levels of consumer buying behavior model, including product and merchant brokering [11,27] and negotiations [28]. For example, Maamar [29] proposed a scheme for association of users with software agents in investigation, negotiation, and settlement phases of e-commerce-related activities. In our view the features of autonomy and proactiveness of agents are very appealing for e-commerce customer support as they promise to relieve the cognitive burden on the users.

3. A framework for decision support for infrequent purchases

We find it useful for our purposes to organize the past work along two dimensions: frequency of purchase and system proactiveness. The first dimension is important as it relates to the "structuredness" of the shopping task. In ill-structured tasks the objectives may be unclear, while in well structured ones these are relatively well-defined [30]. Since infrequent shoppers are likely to have less defined objectives and preferences, their tasks will tend to be ill-structured. Ill-structured tasks have traditionally been the realm of decision support systems [31,32].

The importance of the second dimension is related to the recent paradigmic shift in DSS research towards the design of active systems [33–36]. The proponents of active DSS criticize the traditional "toolbox"-oriented DSSs for its passive nature and argue in favor of the new type of the system that would take initiative in performing some of the decision-related tasks. In this connection Angehrn noted that an ideal type of human–DSS interaction would be the one where both parties are active [33].

Table 1 summarizes the available buying support approaches outlined in the previous section. The two aforementioned dimensions form four quadrants depending on the frequency of shopping and the degree of proactiveness of the decision support. The frequent shopping/passive support quadrant includes traditional e-commerce shopping support tools that provide searching and browsing capabilities. Here, no attempt is made to elicit customer requirements and provide advisory information.

Active support systems would try to elicit some information from the customer and to automatically generate a list of suggestions, possibly rank-ordered. Many established e-businesses have this capability (e.g., amazon). The recommendations could be generated using collaborative filtering, conjoint analysis or other approaches discussed in the earlier section. The reason we have placed these active technologies in the "frequent shopping" fragment is because only after some historical information is available an attempt at modeling persistent or semi-persistent preferences of the customers can be justified. Moreover, eliciting "precise" utilities and preferences may not make much sense in the case where the user simply does not have any such well-defined preferences and may actually lead to overlooking the alternatives that the user might have chosen otherwise.

The basic mechanisms for infrequent shopping are browsing product categories and searching. Probably, as noted in [13] browsing is more important here than in the case of frequent shopping as it is an experiential or discovery-oriented activity.

Table 1
Summary of buyer support methods

Shopping	Support	
	Passive	Active
Frequent	Electronic catalog, basic search and browse	Recommendation systems, software agents
Infrequent	Browse, basic and advanced search, comparison shopping	Active DSS for shopping support

Searching tools here should be more "value-added" than in the case with frequent shopping. For example, Lee et al. [6] proposed an approach where the functional features of a product are distinguished from its characteristics, as the user may not be able to assess the latter. For instance, the user may be able to better interpret the term "performance of CPU", rather than the frequency and type of CPU. The user can then define weights for these functional characteristics iteratively and for each such iteration the system would generate the list of top 10 matching products. Interestingly this approach is to a certain degree in accordance with the "means-end" model from marketing research (although the authors did not view it in this context). Subramony has recently applied the "means-end" model to human-computer interactions for web browsing behavior and found it to be an adequate fit [37]. The central concept in this theory is a "ladder" leading from product attributes to more abstract consequences of those attributes and to even more abstract values associated with those consequences. The consequences are related to "desirabilities", which are in turn determined by the personal values, such as "satisfaction" and "security". Subramony applied the model to investigate why people prefer some websites over others in general (not in e-shopping specifically).

The "infrequent/active" quadrant is most appealing one for our purposes. Ideally, the user and the system would work together to identify promising alternatives. In this respect, Pu et al. [38] have recognized that the customer preferences have to be elicited interactively and certain level of inconsistencies and "affordances" in user preferences have to be tolerated. They use constraint satisfaction problem solving in order to display the list of feasible candidates to the user and refine the user preference model. We agree with the idea of allowing the customers to have some level of "softness" in expressing their preferences. To this end, use of fuzzy modeling could be helpful as it allows imprecise specification of relevant information items. The resulting fuzzy model would then more fully reflect the degree of vagueness in customer preferences and allow determination of the set of alternatives that would be interesting to a customer. On the other hand, we think that any such method should also incorporate the principles of problem solving for ill-structured decisions.

4. Decision support and problem solving

Problem solving is very closely related to decision making, and some authors make no distinction between them [30]. One fundamental principle of solving ill-structured problems is promoting divergent (idea generation) and convergent (systematic evaluation) activities during different phases of problem solving. Evans argues that a computer algorithm for supporting problem solving would generate diverse alternatives in preferably a single run [39]. While divergent and convergent activities should be used in all phases of problem solving, the divergence is stressed more during the earlier phases, while the convergence is emphasized more in later phases [40].

Divergent approaches to alternative generation in DSSs have been employed recently using agent technology [41] and genetic algorithms [35]. In our approach we follow the logic that is consistent with the above discussion: once we have identified the set of potentially attractive products, we look to provide more diverse product alternatives in the beginning and more convergent ones towards the end of the shopping process. In the beginning a buyer views the most diverse product offerings. When he or she chooses to explore more the neighborhood of one of these products, the system generates new alternatives of somewhat lesser diversity. The process is graphically depicted in Fig. 1. The symbols for divergence and convergence are borrowed from the creative problem solving literature [40]. One could see that at each step the user analyzes the diverse offers and then "converges" on one of them. This leads to a new set of (less) diverse offers. The process continues until there is the final convergence and choice of the final product. The process may not be as "linear" as described here. The buyer could select the desired product early, or could iteratively move to the earlier phases and back. Nevertheless, the figure gives a good overall view of alternative generation process.

5. Method for buyer decision support

As both browsing (experiential) and searching (goal-directed) behaviors are important in the buying process we incorporated them in our method for decision support. First, the customer imprecisely specifies his/her preferences and the system generates the set of interesting products for the customer to limit the size of promising products. Secondly, the system generates diverse offerings

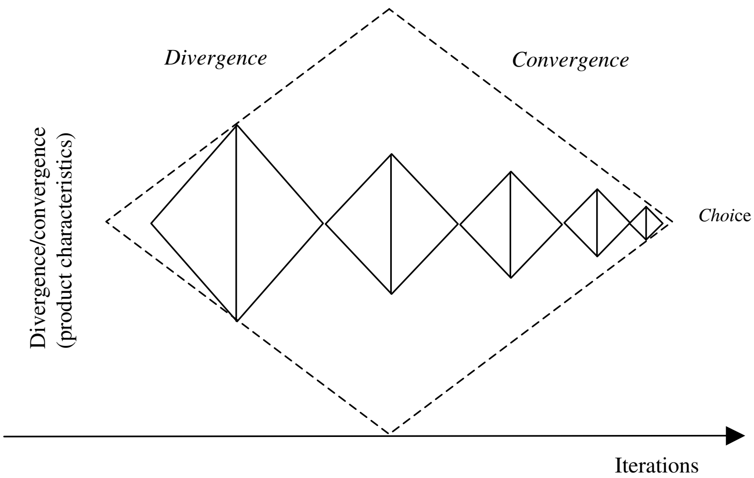

Fig. 1. Divergent and convergent processes in product selection decision.

to the customer, effectively implementing divergent browsing in a accordance with problem-solving principle outlined earlier.

5.1. Identifying promising alternative products

Fuzzy sets and fuzzy arithmetic offer a natural and intuitive means to capturing and modeling "vague" information, such as customer preferences [42,43]. In our approach we use fuzzy numbers to represent the importance placed by the customer on different product attributes (e.g., price, memory, etc.). Fuzzy sets are sets where a membership value is associated with elements indicating the degree of belonging of that element to a fuzzy set. The degree of membership of an element x to a fuzzy set a is denoted as $\mu_a(x)$. Support of a fuzzy set is an interval S such that

$$S_a = \{x \mid \mu_a(x) > 0\}.$$

Fuzzy numbers are fuzzy sets defined over real numbers that have bounded support and a single maximum value of 1 for the membership function. In this work we adopt triangular shape for fuzzy numbers for the sake of conceptual and computational simplicity. Fig. 2 gives some examples of triangular fuzzy numbers. It is easy to see that these numbers can be given by specifying three points on a real-number scale. For example, the fuzzy number a on the figure can be interpreted as "around 10". The value of "10" has a membership of 1. The further one goes from that "peak" value, the smaller the membership gets. Thus, the value of "7" can be barely regarded as "around 10". Support of fuzzy number a is (7,13), and its peak value is 10. An important notion associated with fuzzy numbers is α-cuts. These are defined as:

$$S_a^\alpha = \{x \mid \mu_a(x) \geqslant \alpha\}.$$

The use of "strictly larger than" sign would turn the above into a strong α-cut. A strong α-cut of level 0 is also a support of fuzzy set.

We can elicit the importance of the attributes using leftmost, peak, and rightmost values of the fuzzy weights. For example, the user might say that the brand name is at least moderately important, most likely very important, and at most extremely important. These terms will have associated numbers similar to Likert scale. Since we are not dealing with precise crisp numbers we can afford asking the user to specify imprecise weights directly. This information will be treated in a very liberal fashion to form a set of "promising" products for the customer without any strict ranking or ordering.

Our approach is related to the "fuzzy weighted averages" method that incorporates vagueness in the desirability of different attribute values of alternative solutions [44,45]. In particular, the application of this approach to engineering problems has been elaborated in [46]. The authors have stressed that at the early stages of the design process the description of the design solution is typically vague. This vagueness gradually reduces at later stages. We find this situation similar to that faced by those e-commerce shoppers who do not have well-defined objectives. We use a linear model in order to calculate the overall attractiveness of a candidate product:

$$\tilde{U}^a = \sum_{i=1}^{n} \tilde{u}_i^a \cdot \tilde{w}_i. \qquad (1)$$

Here $\tilde{U}^a$ represents the overall fuzzy utility, or attractiveness of product a; $\tilde{u}_i^a$ represents the utility of the ith attribute of that product; and $\tilde{w}_i$ denotes a fuzzy weight of that attribute. Similar models have been proposed for fuzzy multi-attribute decision-making [47]. Note that we regard the weights as fuzzy values to allow the flexibility in constructing the model. The utilities of individual attributes are in general also treated as fuzzy values. We expect that most of the product attributes will be

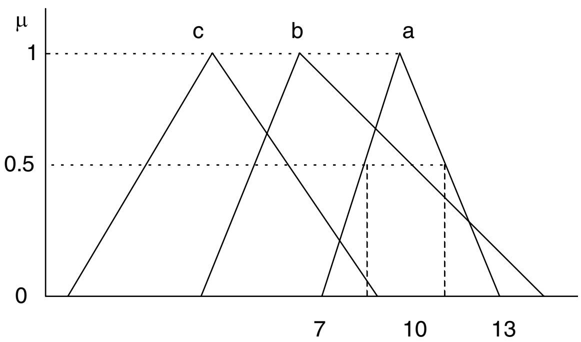

Fig. 2. Fuzzy numbers.

mapped into crisp utilities (e.g., memory, screen size, etc.). However, there may be some qualitative aspects of the products that could be represented by fuzzy utilities (e.g., reputation of the manufacturer). In such cases expert or user judgment could be used to specify imprecise utilities. In case of quantitative attributes the most straightforward approach to calculating utilities is to simply scale the value of an attribute on some pre-determined scale (e.g., 0 to 100) if the increase in the attribute's value also implies the increase in it's utility (e.g., the larger the memory size the better). When lower attribute values are desirable (e.g., for price) the direction of scaling should simply be changed. Nonlinear transformations could also be employed without affecting the overall generality of the method. The details of performing fuzzy arithmetic operations in order to calculate (1) are fairly well-defined and are not discussed here. One could be referred to the corresponding literature for an in-depth coverage (e.g. [42]).

The purpose of using the fuzzy-linear model (1) is to partition the set of all alternatives into few sets representing different "grades" or "desirabilities" for the customer. For example, first-grade products would constitute the set of all interesting products (an "A" class), second-grade products would be less desirable ("B" choices), and so on ("C", "D", etc.). Ordinarily, the product attribute (content) – based recommendation systems would try to fine-tune the crisp weights and utility values in order to provide the ranked list ordered by the degree of desirability. These systems assume that users are capable of making accurate judgments regarding comparison of alternatives. For example, they can compare different brands of products and assign a number representing their degree of willingness to buy one rather than the other. This may well be the case for more frequent purchasers. In less structured tasks the users may not be able to make such judgments. This is why we let the customers express their feeling of relevance of different factors using imprecise terms.

Fuzzy scores representing the utility of the alternatives could be ordered using a method for ordering fuzzy numbers [47]. However, our purpose is not ordering, but rather determining the set of "good" alternatives to focus on further. We partition the set of all alternatives into different grades as follows. We introduce the parameter called certainty level, c. It is simply the level at which the α-cut is specified. The higher the c the less vagueness is tolerated and vice versa. When c equals one the method converges to ordinary ordering task with overall utilities being crisp numbers and the "A" set contains one or several utility-equivalent candidates. At the level of zero maximum vagueness is introduced. The lower the certainty level the more candidates would be considered promising. By setting α level to equal c we derive a set of closed intervals representing all of the candidates:

$$\begin{aligned} &\Omega^{\alpha} = \{S_j^{\alpha}\}, \quad j = 1, \ldots, m, \\ &S_j^{\alpha} = \{x \mid \mu_j(x) \geqslant \alpha\}, \quad \alpha = c. \end{aligned} \tag{2}$$

Here $\mu_j(x)$ represents a membership function for the utility of jth alternative. Simply put, the expression (2) defines the set of intervals derived by taking α-cuts of all candidate utilities. For further discussion we will also represent S_j^{α} as closed intervals using their left and right boundaries for convenience purposes:

$$S_j^{\alpha} = (l_j^{\alpha}, r_j^{\alpha}). \tag{3}$$

We then determine a number of reference sets that are intervals corresponding to different grades of alternatives. The first-grade reference set (also referred to as "A"-class reference set) is defined so that:

$$S_r^{\alpha,1} = \{S_j^{\alpha} \mid \max_{l_j^{\alpha}} \max_{r_j^{\alpha}} (l_j^{\alpha}, r_j^{\alpha})\}. \tag{4}$$

In other words it is the interval that has the largest right boundary. If there are several such intervals then the interval with the largest left boundary is chosen. We can also denote the first-grade reference interval similar to (3) as

$$S_r^{\alpha,1} = (l^{\alpha,1}, r^{\alpha,1}). \tag{5}$$

The subsequent reference intervals are determined similar to (4), but with one extra condition as:

$$S_r^{\alpha,k} = \{S_j^{\alpha} \mid \max_{l_j^{\alpha}} \max_{r_j^{\alpha}} (l_j^{\alpha}, r_j^{\alpha}), r_{ji}^{\alpha} \leqslant l^{\alpha,k-1}\} \; k = 1, \ldots, p. \tag{6}$$

Here p is the number of reference sets (intervals). As a result the set

$$\Omega_r^\alpha = \{S_r^{\alpha,k}\} \quad (7)$$

will consist of a number of non-overlapping intervals used for further partitioning of the product alternatives. Intuitively, the intervals in (7) represent the representative "A"-class, "B"-class and so on of the product alternatives for a given customer. All of the candidates are then assigned to one of these grades as follows:

$$\Omega_*^\alpha = \{S^{\alpha,k}\},$$
$$S^{\alpha,k} = \{S_j^\alpha \mid r_j^\alpha > l^{\alpha,k}, S_j^\alpha \notin S^{\alpha,k-1}\} \quad (8)$$

In other words, the interval belongs to a certain grade if it has an overlap with the reference interval for that grade and it does not belong to a higher grade ("higher" in this case refers to the lower value of k). Intuitively if there is some uncertainty regarding the preference of a product as compared to the representative product of a certain grade, then that product is assigned to that grade. The superset Ω_*^α thus represents the final partitioning of the product alternatives into first, second, and further grades. We will be using the first-grade ("A"-class) alternatives to guide the customer decision-making. If the customer wants to explore more suggestions he/she will be able to switch to lower-grade sets as well.

Eqs. (2)–(8) form the basis for a procedure for initial filtering of all products. For example, if in Fig. 2 we set the certainty level parameter at one then the partitioning becomes trivial as we're dealing with crisp numbers. The alternatives a, b and c will be assigned to first, second, and third grade, respectively. At the level 0.5 there would be two non-overlapping intervals, corresponding to reference sets formed by alpha cuts of a and c. The alternatives a and b would be assigned to first grade and treated as equivalent ones, while the alternative c would be second-grade. At the level of zero, there would be only one grade and all three alternatives would be considered equivalent from the point of view of their fuzzy utility.

5.2. Generating divergent product alternatives

Once the set of promising candidates have been identified, the next task is to present customer with candidates from that set without cognitively overloading him or her, as there still could be a large number of promising alternatives. We approach this problem of alternative generation based on the divergence-convergence principle outlined earlier.

Cluster analysis (CA) is a well-developed statistical method for grouping observations based on the chosen similarity measure [48]. Our approach is in employing cluster analysis in order to provide the most dissimilar clusters first, and then, based on the user's choice select the new dissimilar clusters from the selected cluster and so on until the individual products are selected. It is curious to note that while other recommendation algorithms are using CA to explore similarities between people, products, and behaviors for providing recommendations [22]; our approach proceeds in the opposite direction as we are interested in choosing the most dissimilar alternatives. In our view this reflects the essential difference between recommendation generation for frequent vs. infrequent shoppers. Our clustering algorithm uses a Euclidian distance metric for measuring distance between products X and Y calculated as

$$d(X, Y) = \sqrt{\sum_{i=1}^{n} w_i^2 (x_i - y_i)^2}.$$

Here the subscript i refers to different product features, e.g., RAM size, CPU type, etc, and w_i represents the weight, or importance of the given attribute. This weight is a crisp number derived from the fuzzy weights discussed earlier by defuzzification operation [43]. The clustering algorithm will then partition a set of products (from the class "A" set) into clusters. We chose hierarchical clustering method for its speed.

The method tracks at what point in the decision process the user is and produces a small number of alternatives at each step. Initially, the most diverse recommendations are produced. The centroids of the different clusters serve as the basis for alternative product offerings. Since the cluster centroids may not have the actual products corresponding to a particular combination of product features the closest matching product (the representative of the cluster) will be selected. When the user chooses to explore similar products in some cluster (in the vicinity of one of the alternatives) the new (sub-) cluster centroids within that cluster will serve as the basis for generating new alternatives. This process will continue until the user makes a final choice. The user may move back (''zoom out'') to explore a different cluster of products at any time.

6. E-commerce buyer decision support

6.1. System architecture

The architecture for e-commerce buying decision support system is shown on Fig. 3.

The user indicates preferences using the criteria management module. In particular, the user indicates relative importance of product attributes using fuzzy terms. This information is used to partition the products into different classes and calculate the distance metric between the product alternatives (e.g., if the importance for the price is high then the alternatives would differ most on the price dimension).

Fuzzy filtering module uses the information entered by the user and products from the database in order to assign grades to the products. The certainty level is set by the system initially to 0.5 and can be automatically increased or decreased to manipulate the number of alternatives generated. An important aspect of this manipulation is that a single parameter is used to specify the minimum ''quality'' bar for the alternatives.

Clustering module generates dissimilar suggestions as described earlier. The ''A''-class (or lower grades if asked by the user) alternatives are clustered using hierarchical method and *N* diverse alternatives are presented to the user. The maximum number of alternatives presented could be specified beforehand (we have set *N* equal to 3).

The ''recommender profiles'' are used to label the alternative offers generated by the system in terms of key types of ''values'' that a customer could relate with. This is in accordance with the aforementioned application of ''means-ends'' theory for web browsing which specifies that consumer choices relate to the abstract values held [37]. We believe that incorporation of different ''values'' in our system would promote more comfortable decision making at a cognitive level. For example, the value profiles may include ''cheap'' and ''luxury'' types. Then the alternatives generated by the system are labeled by the profile (e.g., ''luxury alternative'') along with the degree of match between the alternatives and the profile.

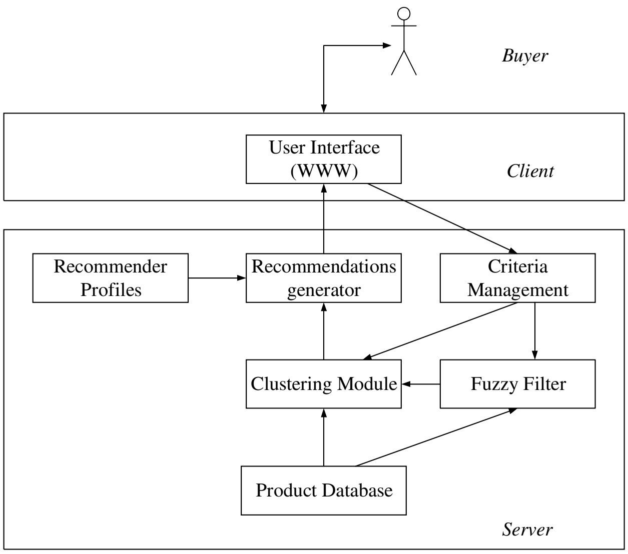

Fig. 3. Architecture of buyer DSS.

6.2. Prototype for notebook selection

We have developed a prototype system using ASP.NET for notebook selection. In terms of the key criteria we chose to use price, brand name, producer, supplier, CPU, and memory, hard drive, and screen sizes. The values for different attribute utilities were represented as crisp numbers in the range from zero to one. For the qualitative variables expert ratings were used.

Fig. 4 represents the initial screen for eliciting judgmental information about the importance of the attributes, while tolerating some level of vagueness. For example, the brand name is allowed to be at least somewhat important (numeric value of 4); most likely fairly important (numeric value of 5) and at most quite important (numeric value of 6). This defines a symmetric fuzzy weight with the support (4, 6) and peak value of 5.

We will now present a scenario for selecting class "A" products. Table 2(a) shows a portion of the product database containing information on twelve different notebooks. Table 2(b) has the same information expressed in terms of utilities of individual product attributes. Note, that the lower the price, the higher is its utility.

Assume Table 3 represents fuzzy weights specified by the user. As one can see in this case all weights are identical with the widest possible support.

Fig. 5 shows fuzzy utilities of all the alternatives from the database calculated using the weights from Table 3. The corresponding numeric values are given in Table 4. As one can see from the figure, if certainty level is set to one, every product will have it's own grade set. At a zero level all products will be in the same grade (utility-equivalent).

When the certainty level is set to 0.5, there will be two reference sets: alternative #8 will be a representative of class "A", while alternative #1 will be a reference set for (and a sole member of) the "B" class (second grade). Setting fuzzy weights narrower will result in a more interesting situation (Table 5). Fig. 6 shows fuzzy utilities for the twelve

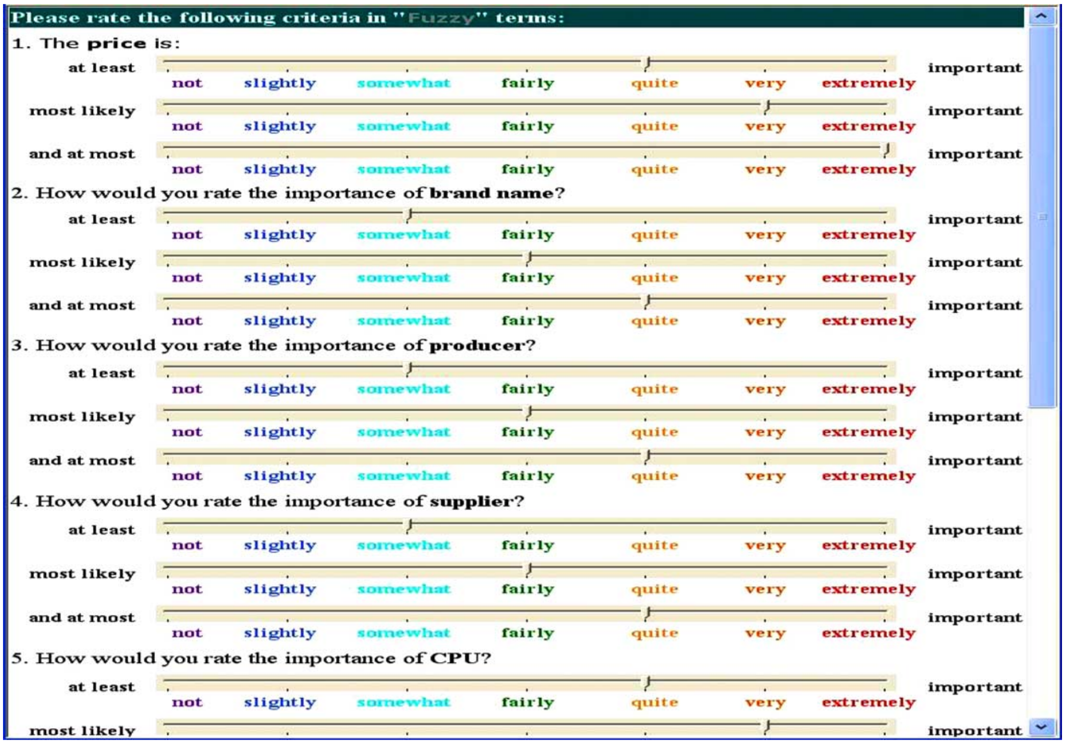

Fig. 4. Screenshot of the interface for defining fuzzy weights.

Table 2

ID	CPU ranking	CPU frequency	Memory	Hard drive	Screen size	Producer ranking	Brand series ranking	Supplier ranking	Price
(a) Portion of product database									
1	35	300	64	4.3	14.10	85	50.10	50	$538.50
2	65	1800	256	30	15.00	95	20.50	50	$1,744.49
3	65	1800	256	30	15.00	95	20.40	50	$1,828.49
4	65	1800	256	30	15.00	95	20.40	50	$1,944.53
5	45	1200	256	30	12.10	95	390.40	50	$2,136.00
6	45	1200	256	30	12.10	95	390.40	50	$2,309.93
7	75	1800	256	40	14.10	90	220.10	50	$2,518.43
8	75	2400	512	30	15.00	95	390.30	50	$2,698.50
9	75	1700	256	40	12.10	95	30.50	50	$2,849.93
10	75	2000	256	40	14.10	90	220.10	50	$2,994.21
11	75	2000	512	40	15.00	80	330.10	80	$3,399.99
12	70	2000	256	60	15.00	90	230.10	50	$4,522.50
(b) Portion of product database expressed as utilities									
1	0.000	0.000	0.000	0.000	0.690	0.333	0.080	0.000	1.000
2	0.750	0.714	0.429	0.461	1.000	1.000	0.000	0.000	0.697
3	0.750	0.714	0.429	0.461	1.000	1.000	0.000	0.000	0.676
4	0.750	0.714	0.429	0.461	1.000	1.000	0.000	0.000	0.647
5	0.250	0.429	0.429	0.461	0.000	1.000	1.000	0.000	0.599
6	0.250	0.429	0.429	0.461	0.000	1.000	1.000	0.000	0.555
7	1.000	0.714	0.429	0.641	0.690	0.667	0.540	0.000	0.503
8	1.000	1.000	1.000	0.461	1.000	1.000	1.000	0.000	0.458
9	1.000	0.667	0.429	0.641	0.000	1.000	1.000	0.000	0.420
10	1.000	0.810	0.429	0.641	0.690	0.667	0.540	0.000	0.384
11	1.000	0.810	1.000	0.641	1.000	0.000	0.837	1.000	0.282
12	0.875	0.810	0.429	1.000	1.000	0.667	0.567	0.000	0.000

Table 3
Fuzzy weights

Weight	CPU ranking	CPU frequency	Memory	Hard drive	Screen size	Producer ranking	Brand series ranking	Supplier ranking	Price
Min	1	1	1	1	1	1	1	1	1
Peak	4	4	4	4	4	4	4	4	4
Max	7	7	7	7	7	7	7	7	7

alternatives using these new weights (with the same attribute values).

Now if the certainty level is set to zero, there will be three reference intervals, and, accordingly three classes or grades. When the level is set to 0.5, there will be four classes of products. The reference sets for this case are shown with the dashed lines. The number of products in each class organized by certainty values is shown in Table 6.

The "A"-class alternatives are passed to the clustering module. As we have mentioned, the number of alternatives simultaneously generated is set to three. Thus, if the most important criterion (according to the weights) is price the three alternatives would greatly vary on price. For other combinations of weights the alternatives divergence depend on the particular combination used.

We have used three recommender "profiles" including "budget", "value", and "luxury" profiles. The budget profile seeks to minimize the price while compromising on other features of the product. The "luxury" profile, on the contrary, looks to maximize the quality while accepting high price. The "value" lies in between the two extremes. In

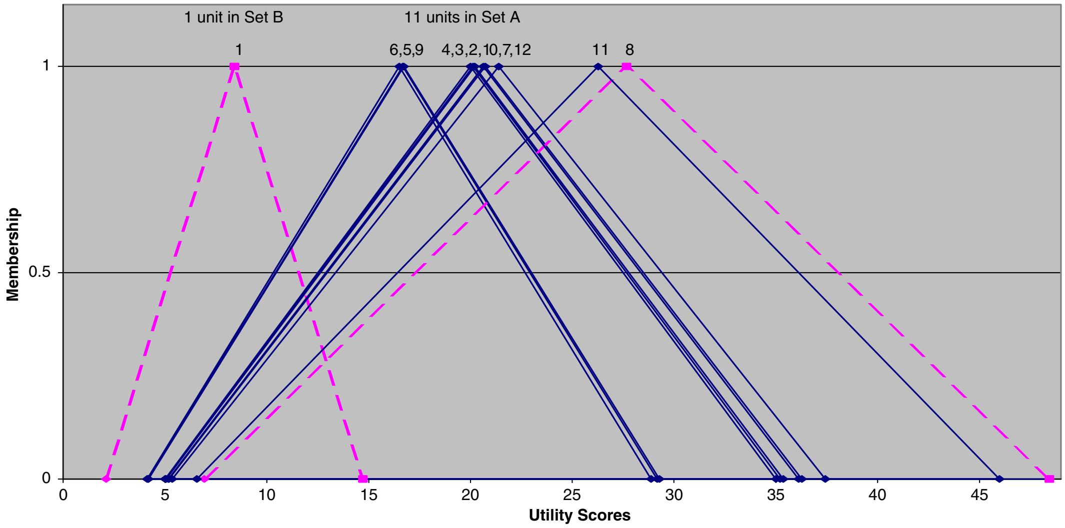

Fig. 5. Fuzzy utilities of alternatives.

Table 4
Fuzzy utilities of alternatives

Alternative	Fuzzy utilities		
	L	*P*	*R*
1	2.10	8.41	14.72
2	5.05	20.21	35.36
3	5.03	20.12	35.21
4	5.00	20.01	35.01
5	4.17	16.67	29.17
6	4.12	16.50	28.87
7	5.18	20.73	36.28
8	6.92	27.68	48.43
9	4.18	16.73	29.28
10	5.16	20.63	36.11
11	6.57	26.28	45.98
12	5.35	21.39	37.43

the prototype we used a simple method for calculating the support of different alternatives by the profiles. A simple additive formula for the criteria was used to obtain a score which is compared against profiles. Thus, the item that has best features and possibly the highest price would be an ideal choice for the luxury profile. Fig. 7 shows different profiles as they are mapped against the additive score.

Fig. 8 shows the screenshot of the prototype offering diverse notebooks (prices are in Canadian dollars). In this case the price was chosen as an important criterion. The products shown are the representatives of three diverse clusters. By clicking on "Search similar" the user is able to zoom into a particular cluster.

7. Preliminary experiments and results

We conducted preliminary experiments with our prototype. We restricted our product database

Table 5
Fuzzy weights: second scenario

Weight	CPU ranking	CPU frequency	Memory	Hard drive	Screen size	Producer ranking	Brand series ranking	Supplier ranking	Price
Min	5	5	3	3	3	3	3	3	5
Peak	6	6	4	4	4	4	4	4	6
Max	7	7	5	5	5	5	5	5	7

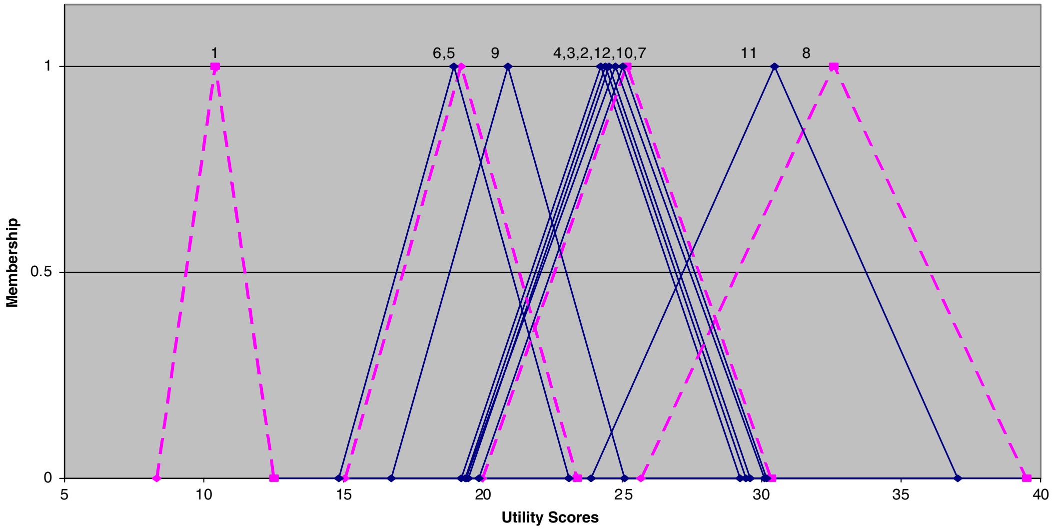

Fig. 6. Fuzzy utilities of alternatives: second scenario.

Table 6
Summary of fuzzy filtering with 12 alternatives

Certainty level	Set A	Set B	Set C	Set D
0	8	3	1	0
0.5	2	7	2	1
1	1	1	1	1 ...

size to twenty products and only included divergent alternative generation (without fuzzy filtering) for the experiments. Since this type of alternative generation could be also viewed as a kind of "divergent" browsing, we chose a simple catalog-based browsing as our benchmark. This allowed us to see the impact of diversity in alternative presentation on the effectiveness of support. Subjects included graduate business students at a major Canadian university. Two systems: one catalog based (CB) and one based on DSS were made available online and the subjects were assigned randomly to one of the systems. The subjects were then asked to fill out questionnaire measuring the user satisfaction and the intention of return. The measure of satisfaction was adapted from [49] and [50] while the intention of return, an important factor employed in usability assessment and online buyer behavior [12] was adapted from [51]. For example, the items pertaining to measuring user satisfaction included:

- The system helped me find the product I am interested in.
- The system provided an adequate support in performing information searching.

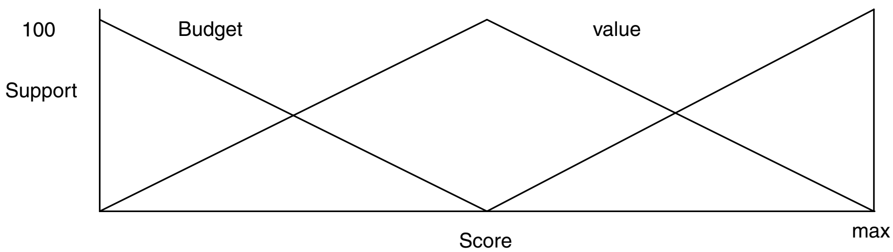

Fig. 7. Recommender profiles.

Fig. 8. Screenshot of the prototype.

Table 7
Experimental results

	Satisfaction		Intention to return		Perceived diversity	
	Mean/variance	*t* value significance	Mean/variance	*t* value significance	Mean/variance	*t* value significance
CB	3.25/3.52	2.9	3.45/4.16	3.13	3.00/2.33	3.67
DSS	5.06/0.78	0.0056	5.52/0.71	0.0039	5.33/2.33	0.0007

- I am satisfied with the help provided by the system.
- The way the product information is presented is useful.

Since we had a small sample size (the study was preliminary) we were not able to assess the reliability of our measures. However, these measures have been used in past studies.

Table 7 summarizes the findings. Overall, 23 usable responses were collected. These included twelve DSS and eleven CB user responses. As one can see, the variance of the satisfaction and intention to return scores was much higher in the CB system. The t-test assuming unequal variances indicated significantly higher satisfaction and intention to return scores for the DSS users. This result is encouraging for us as it provides some preliminary support in favor of our method compared to catalog-based shopping. We have further included two questions asking the users if they perceived the alternatives as being diverse. The results indicate that DSS users thought that the alternatives offered were indeed more diverse than did the CB users.

8. Conclusions

In this work we have argued in favor of facilitating imprecise preference elicitation and stressing divergent processes in providing decision support for infrequent shopping in e-commerce. We proposed a fuzzy model to allow customers some level of latitude in describing their preferences. We further relied on the divergence–convergence principle of problem solving to suggest alternatives to the user with the use of cluster analysis. The preliminary experiments with the prototype system for notebook selection have provided some support in favor of the divergence-based approach over the catalog-based browsing in terms of user satisfaction and intention to return. The major limitation of the study is the preliminary nature of the experiments. This topic requires a thorough treatment and will be the subject of future research. In this regard the effectiveness of the method needs to be tested through statistical hypotheses.

While trust is of crucial importance in e-commerce customer relationships, it has multiple meanings [52]. We do not address the security-related aspects of trust, but rather those that deal with the advice and information provided by the seller. Sultan et al. pointed that information and advice could positively affect customer's trust level [53]. They argued that a customer would tend to trust a sales person who reflects customer's level of knowledge. We believe that our design based on imprecise searching and divergent browsing could have a positive impact on customer's trust level. Our expectation is based on the fact that the ability to define preferences in a soft manner would reflect the customer's level of knowledge. Furthermore, diverse product recommendations would increase the customer's perception that the seller is genuinely interested in finding the right product for the customer.

The preliminary results of our work are encouraging. We believe that our method has a good potential to be effectively employed by the commercial websites.

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