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**CHALLENGES FOR AIDED ONLINE SHOPPING AND PRODUCT  
SELECTION – A DECISION MAKING PERSPECTIVE.**

**Maciej Dabrowski**

Digital Enterprise Research Institute  
J.E. Cairnes School of Business & Economics  
National University of Ireland Galway, Ireland  
t: +353 (0)91 495 784  
f: +353 (0)91 495 541  
[maciej.dabrowski@deri.org](mailto:maciej.dabrowski@deri.org)

**Thomas Acton**

Business Information Systems Group  
J.E. Cairnes School of Business & Economics  
National University of Ireland Galway, Ireland  
t: +353 (0)91 493 806  
f: +353 (0)91 494 565  
[thomas.acton@nuigalway.ie](mailto:thomas.acton@nuigalway.ie)

**Willie Golden**

Business Information Systems Group  
J.E. Cairnes School of Business & Economics  
National University of Ireland Galway, Ireland  
[willie.golden.@nuigalway.ie](mailto:willie.golden.@nuigalway.ie)

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## ABSTRACT

Consumers often face a task to select a best option from a large set of alternatives, such as choosing a car to buy<sup>1</sup>, an apartment to rent<sup>2</sup>, or an unforgettable trip to book<sup>3</sup>. E-commerce sites frequently provide the possibility to search for structured items, usually by asking a user to fill in a form asking about the requirements that a desired product has to satisfy (preferences). This process is used, for example, when searching for a used car, or a flight on popular websites, and is also referred to as preference-based search or parametric search. Although such choice-based approaches are prevalent, both users and retailers can find them unsatisfying. One of the major reasons is that users are often not able to correctly transform their preferences into requirements using online forms, and thus they are rarely provided with the information they need.

On the other hand, consumers making purchase decisions in online shops are often unable to evaluate all available alternatives in great depth, and so seek to reduce the amount of information processing. Interactive decision aids that provide support to consumers are particularly valuable in helping to determine which alternatives are worth further, detailed consideration. Customers are being provided with a number of different decision aids that, ideally, should enable them to search, browse and compare vast numbers of available products. Retailers offer various recommender systems that attempt to provide customers with manageable and relevant set of products based on user profiles, history of interactions and product descriptions. Moreover, various techniques for preference elicitation (e.g. dialogs in conversational recommender systems) are used to enable better understanding of customers' needs. However, there are many factors (e.g. the number of available products but also by the precision of information preference elicited) that can impact the performance of decision aids in online shops. We discuss the most popular decision aids in the context of online shopping and decision-making.

We also introduce the concept of a soft-boundary pre-filtering decision aid. The decision aid modifies the pre-filtration criteria provided by the decision maker and thus, allows him to reconsider selected alternatives she initially eliminated. We propose a model of such a decision aid, give an overview of its different configurations, and provide the illustrative example of the scenario of use in the apartment selection decision problem. We also hypothesise about the impact of the proposed decision aid on decision quality and consideration set size and quality. We conclude the paper with an overview of potential directions for future research and a discussion of benefits of application of the soft-boundary pre-filtering decision aid.

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<sup>1</sup> <http://www.carzone.ie/>

<sup>2</sup> <http://daft.ie/>

<sup>3</sup> <http://orbitz.com/>

## INTRODUCTION

Consumers often face a task to select a best option from a large set of alternatives, such as choosing a car to buy, an apartment to rent, or an unforgettable trip to book (<http://expedia.com>). E-commerce sites frequently provide the possibility to search for structured items, usually by asking a user to fill in a form asking about the requirements that a desired product has to satisfy (preferences). This process is used, for example, when searching for a used car, or a flight on popular websites, and is also referred to as preference-based search or parametric search. Although such choice-based approaches are prevalent, both users and retailers can find them unsatisfying. One of the major reasons is that users are often not able to correctly transform their preferences into requirements using online forms, and thus they are rarely provided with the information they need.

On the other hand, consumers making purchase decisions in online shops are often unable to evaluate all available alternatives in great depth, and so seek to reduce the amount of information processing involved (Payne, 1976). Häubl & Trifts (2000) discuss the stage process in the context of online shopping and argue that interactive decision aids that provide support to consumers are particularly valuable in helping to determine which alternatives are worth further, detailed consideration. The performance of decision aids in online shops (e.g. recommender systems) can be affected not only by the number of available products but also by the precision of information preference elicited (Scholz, 2008). Utility theory provides a solid mathematical foundation for recommendations of products. (Keeney and Raiffa, 1993). However, it assumes complex preference models that cannot be elicited in e-commerce scenarios because of lengthy and effortful preference elicitation procedures.

On the other hand, interactive decision aids that provide support to consumers are particularly valuable in helping to determine which alternatives are worth further, detailed consideration. Customers are being provided with a number of different tools that, ideally, should enable them to search, browse and compare vast numbers of available products. Retailers offer various recommender systems that attempt to provide customers with manageable and relevant set of products based on user profiles, history of interactions and product descriptions. Moreover, various techniques for preference elicitation (e.g. dialogs in conversational recommender systems) are used to enable better understanding of customers' needs. However, there are many factors (e.g. the number of available products but also by the precision of information preference elicited) that can impact the performance of decision aids in online shops. We discuss the most popular decision aids in the context of online shopping and decision-making.

In this paper, we introduce the concept of a soft-boundary pre-filtering decision aid. The decision aid modifies the pre-filtration criteria provided by the decision maker and thus, allows him to reconsider selected alternatives she initially eliminated. We propose a model of such a decision aid, give an overview of its different configurations, and provide the illustrative example of the scenario of use in the apartment selection decision problem. We also hypothesise about the impact of the proposed decision aid on decision quality and consideration set size and quality. We conclude the

paper with an overview of potential directions for future research and a discussion of benefits of application of the soft-boundary pre-filtering decision aid.

### **CUSTOMER PREFERENCES IN DECISION MAKING**

Discussion on different classifications of decision maker's preferences and decision-making processes has been widely disputed in IS research. Firstly, the information-processing approach to human decision-making indicates that information-processing capacity of decision-makers is limited. Thus, most decisions are influenced by the notion of bounded rationality in the way that accuracy-effort tradeoffs are assessed and decision-makers tend to show decision-context-specific behaviours (Bettman et al., 1998). Moreover, in domains where alternatives described with a number of decision attributes are available, individuals typically do not have specific pre-formed strategies on selection of attribute importance and tradeoffs they are prepared to make (Haubl and Murray, 2001). Decision makers tend to construct their preferences when they are prompted to express evaluative judgment or to make a decision (Payne et al., 1992). However, In Decision Making, existence of constructed and stable preferences is argued (Bettman et al., 2008). They comment on work of Simonson (2008) and argue "constructive processes can lead to stable preferences as the outcome". There is a growing consensus that preferences are typically constructed when decisions are made and are influenced by the method of preference elicitation, the description of the options, and the choice context. This problem has also been recognized in other domains (e.g. Recommender Systems). In particular Ricci et al. (2003) argued that both "short term preferences" (goal oriented, constructed preferences) and "long term" (stable) preferences should be taken into account in the process of computing recommendations. However, they note that short-term preferences are highly contextual, and thus, should be much more important in particular decision problem than the long-term preferences. Extensive summary of work showing that preferences can be influenced by various features of the task and decision context are available in (Lichtenstein and Slovic, 2006) and in (Bettman et al., 1998).

On the other hand, one can differentiate between *hard*, and *soft* preferences (also called constraints). Typically, preferences provided by a decision-maker are treated as hard-constraints. In other words, if values of a given attribute of a product do not exactly match customer's criteria, a product won't be included for consideration. However, when a customer expresses his preference for a product with certain features, he also might consider products without such features (e.g. one would like to buy a car with leather upholstery, however, cars without such feature can be also considered). To address this drawback of hard-constraints systems (Stolze, 2000) the concept of soft-constraint was proposed. Based on the notion of soft and hard constraints the notion of Soft and Hard Navigation has been introduced (Stolze, 2009). When using Soft Navigation, instead of hard filtering constraints users express preferences of various strengths for product features. The stated preferences are the base to evaluate the alternatives so that the highest-scoring products have the highest probability of being selected by a customer (Stolze, 2000). This approach is typically based on the concept of similarity between values/items (Stahl, 2002) and is widely used in Recommender Systems domain (McSherry, 2002, Stahl, 2006, Bergmann et al., 2001).

Finally, (McSherry and Aha, 2007) propose a model for a recommender system where four types of preferences are identified:

Following the **assumed preferences** approach, customer preferences for particular attributes can be “assumed” to be consistent among all decision makers based on the characteristics of an attribute. For example, preference for Price attribute is typically to minimize the value (also referred to as *Lower-is-Better* (McSherry, 2003b) or *cost-type* (Xu, 2007) attribute). Thus, one can assume with high probability that price minimization will be a consistent goal of decision makers. According to (McSherry and Aha, 2007) assumed preferences are typically in form of soft constraints, meaning a decision maker is willing to compromise the target ideal values (e.g. in case initial preference is to buy a car in price range [€10000, €12000], cars cheaper than €10000 can be also considered).

In contrast, **explicit preferences** are defined as directly stated by a decision maker. Typically explicitly stated preferences are hard-constraints – a consumer is not willing to accept any compromise on the value. Lets consider an example in e-Commerce, where a customer with medium budget is looking to go skiing during winter holidays in Italian Alps. He may be willing to spend a bit more than he initially stated or buy a stay in French Alps resort (soft-preferences), however he is not willing to compromise on the purpose of the trip (“skiing”, not “sightseeing” or “fishing”) as it is a hard-constraint (example adopted from (Ricci et al., 2002)

Thirdly, **predicted preferences** appear when a history of previous decisions, or preference elicitation dialogs is available, some preferences may be predicted with reasonable accuracy. For example, in progressive critiquing recommender systems (Bridge et al., 2005) the preferred value of an attribute can be predicted as the nearest available value that satisfies the recent critique on the value of an attribute in the presented item (Ricci et al., 2002). For example, customer willing to buy a trip shorter than proposed (in the conversation) 14 days may be interested in 11 as well as 7-days trips.

Finally, **implicit preferences** are indirectly elicited from the available information about the consumer. For example, during a dialog in conversational recommenders, when a consumer is indicating his critique on the presented values, the attributes he is not critiquing can be assumed to be suitable. Thus, these values become consumer’s implicit preferences. For example, when all the trip proposals involve air transport (i.e. transport=”plane”) and customer does not critique it, one can assume that she is happy with this transport option and is not interested in other (e.g. ”bus” or “train”).

In this section we discussed four types of preferences that are typical for c-Commerce scenarios. Although the problem of customer preference elicitation is widely addressed in the literature, there are still many research problems open. In the next section we elaborate approaches from the Recommender Systems domain that propose methods for dealing with these problems and are relevant for online shopping scenarios.

## **RECOMMENDER SYSTEMS**

Decision aids based on recommendations and suggestions have recently become an important stream of research in e-commerce. Recommender systems combine ideas from a number of research domains including information retrieval (IR), user model-

ling, machine learning, and human computer interaction (HCI). Typically, recommenders are classified into one of the general categories (Adomavicius and Tuzhilin, 2005). In *content-based approaches* a user is recommended with the items similar to his preference. This approach requires information on product features in order to assess similarities, which can be seen as domain specific, but a priori unknown utility functions (Stahl, 2004). Moreover, items need to be in a form that can be parsed automatically using information retrieval techniques (e.g. customer reviews (Otterbacher, 2008, Otterbacher, 2009, Aciar et al., 2007, Miao et al., 2009, Aciar et al., 2006)). *Collaborative recommendations* methods, unlike content-based recommenders attempt to predict utility of items for a particular user based on the previous interaction with similar users (Adomavicius and Tuzhilin, 2005). As the recommendations are computed based on item ratings provided by “recommendation partners” (users with similar profiles) (Bridge et al., 2005) item descriptions (properties) are not required. Instead, user profiles need to be constructed. Thus, main drawbacks of this approach mentioned in the literature include problems learning new users’ preferences, acquiring item ranking for new items, and necessity of acquiring a critical mass of users (Adomavicius and Tuzhilin, 2005). Thirdly, *hybrid approaches* involve various combinations of both aforementioned methods in order to avoid certain of their limitations. Different efforts for combining collaborative and content-based methods into a hybrid recommender system can be classified as (Adomavicius and Tuzhilin, 2005):

- Combination predictions of separate implementations of collaborative and content-based methods.
- Incorporating some content-based characteristics into collaborative approach
- Incorporating some collaborative characteristics into content-based approach
- Constructing a general unified model that incorporates both approaches

There are numerous studies that propose the use of recommendations to improve consumer decision-making (Bridge and Ricci, 2007, Burke, 2002, Hostler et al., 2005, Pu and Faltings, 2000, Pu et al., 2006, Viappiani et al., 2007, Viappiani et al., 2008, Shimazu, 2002). Providing a consumer with a relevant (similar to his stated preferences) yet diverse (so that he can discover new opportunities and adjust his preference model) set of suggestions has become an important research problem (Smyth and McClave, 2001, Bridge and Ferguson, 2002). In particular, Smyth and McClave (2001) argue that not only similarity of cases to the user query but also diversity of the cases (relative to each other) is important. On the other hand, McSherry (2003b) discussed the compromise-driven approach to retrieval (CDR) being a special of a more general approach called coverage-optimized retrieval, which aims to ensure that for any case that is acceptable to the user, the retrieval set contains a case that is as good or better in some objective sense and is also likely to be acceptable – Coverage Optimized Retrieval (CORE). He defines compromises as a set of attributes with respect to which an item fails to satisfy user preference. It is important to note that compromises that a user is prepared to make are often unrelated to the importance of the attributes in her query, and thus, cannot be predicted a priori. (McSherry, 2003a) in his work defines three compromise criteria explaining when a given product  $p1$  is better than product  $p2$ : the weak compromise criterion (CORE-1) -  $p1$  is at least as similar to the user’s query as  $p2$  and involves fewer (or exactly the same) number of compromises than  $p2$ ; the strong compromise criterion (CORE-2) -  $p1$  is at least as similar to the user’s query as  $p2$  and the compromises in  $p1$  are a subset of compro-

mises in  $p_2$ ; the dominance criterion –  $p_1$  is more similar to user's query than  $p_2$  on all attributes in the query. CORE is based on the assumption that a result set should cover the whole product space according to one of the given compromise. McSherry showed that for CORE-1 and CORE-2 the size of the result set is dependant on the number of attributes in the query and tends to be very small (e.g.  $|AQ|+1$  for CORE-1 and  $2|AQ|$  for CORE-2 where  $|AQ|$  is the number of attributes in the user's query. However, according to McSherry's experiments, the average result set size tends to be much smaller than the maximum (e.g. 7.5 items for a travel database with 1000 products). The small size of the result set makes this approach applicable in cases where the presentation space is limited (e.g. mobile devices). However, a potential problem with this approach is that in many domains a decision maker is not seeking for a single item that closely matches her query, but would like to be informed of all items that are likely to be of interest (McSherry, 2003b). Moreover, the cases most similar to the user's query may not necessarily be the ones most acceptable by the user (under dynamic preference assumption). Finally, the CORE approach utilizes user query mostly for assessing number of preferences on attributes that are not satisfied as the utility for cost-type and benefit-type attributes is computed over the whole spectrum of values available in the case base.

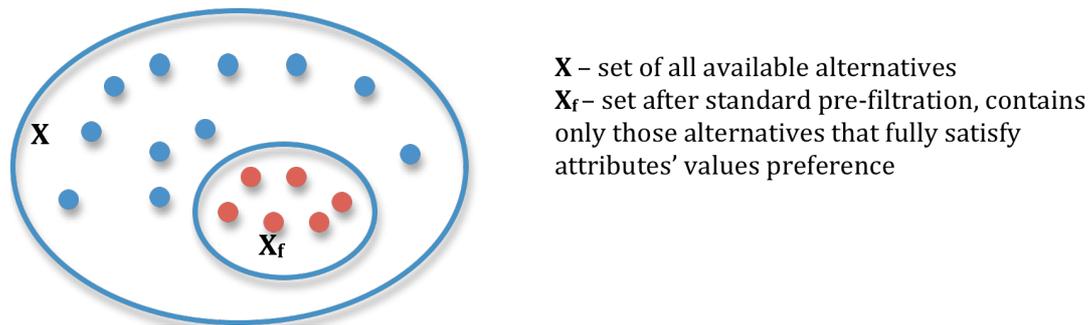
In contrast to basic, single-shot systems, more interactive approaches for recommendation have been proposed. Conversational recommenders with adaptive suggestions (Viappiani et al., 2007) emphasize the need for iterative preference construction enabling gradual improvements to the accuracy of suggestions. Pu et al. (2006) propose to use critiquing as a methodology for mixed-initiative recommender systems. In this technique users volunteer their preferences as critiques on examples, thus proper examples (suggestions) have to be selected to stimulate their preference expression by selecting. According to the Look-ahead principle (Viappiani et al., 2008), "Suggestions should not be optimal under the current preference model, but should provide high likelihood of optimality when an additional preference is stated".

In summary, Recommender Systems provide a rich set of methods for improving user experience in online shopping scenarios. More importantly they enable a user to more efficiently browse large sets of items. More importantly, the concept of recommendations often facilitates discovery of items initially not considered by a user due to the item characteristics. Thus, recommendation methods help to deal with dynamic customer preferences, for example, by increasing diversity of the result set. However, they never allow users to view all the items that satisfy their criteria, thus their use may be problematic in some domains (e.g. house domain). In the next section we propose a method that is designed to address the mentioned drawbacks of recommendation systems.

## **THE DECISION AID**

When the set of alternatives to consider is large, a decision maker suffers from information overload. High cognitive load influences strategy selection and thus negatively impacts the decision quality (Diehl, 2005, Todd and Benbasat, 2000). Filtering is one of the techniques used to limit the number of information items in the set presented to the user, thus allowing reduction of the effect of experienced information overload. The process of filtering involves application of filtering rules (or restriction on attrib-

utes) to the items in the set to be filtered (Hanani et al., 2001) so that only a subset of items is selected and presented to a user (see Figure 1).

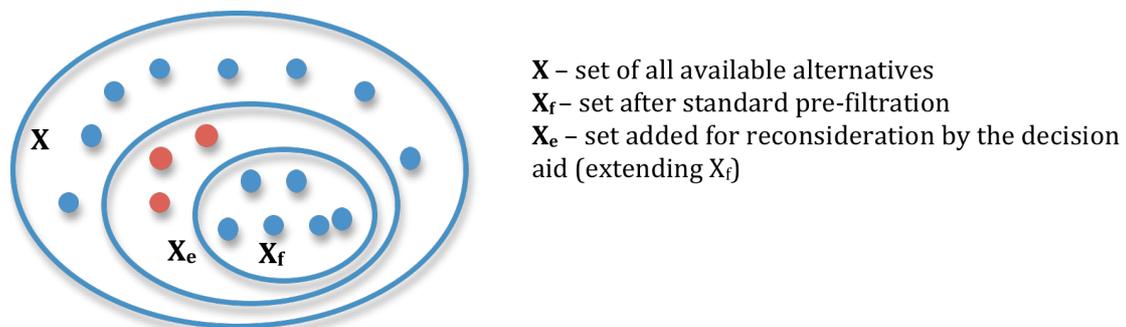


**Figure 1:** Initial pre-filtration of alternatives

User preferences are the key input for alternative pre-filtration. If an alternative does not satisfy all specified criteria, it is excluded. Thus, a new set is constructed, that contains only the alternatives that fully satisfy users attributes' values preference. As such, users are able to significantly limit the number of alternatives they will examine in more detail with preference-based constructed filtering rules.

### The Method

We propose a decision aid that would limit potential negative consequent of dynamics in the decision makers' preferences on attributes' weights and values. Such a decision aid applied in online shopping choice scenarios may increase consumer confidence and be of value to service providers. We propose a modification to the pre-filtration process by introducing "soft-boundaries" of value preference intervals specified by a customer during the pre-filtration process causing a filtering rule to be less restrictive.



**Figure 2:** Example of the decision aid usage

Thus the products, which satisfy the less strict filtration criteria, remain in the consideration set and can be further considered by the consumer (see Figure 2). The set of alternatives available for consideration is constructed based on the decision maker's preferences extended with the set of alternatives suggested by the soft-boundary decision aid. One can define a number of approaches for calculation of the set of products suggested for further consideration by the decision aid, for example:

- Fixed in relation to size of the attribute values preference interval – the size of the value preference interval is multiplied by softening factor  $k$ . In order to

limit the number of alternatives presented to a user it is advised that  $1 < k < 2$ . However, higher values are also possible.

- Proportional to boundary preference values – both lower and upper limit of the value interval are multiplied by  $k$ . Thus the upper limit of the interval is extended more than the lower limit. This approach is applicable for the benefit-type attributes as maximization of the benefit-type attribute value is in the interest of a decision maker. For the cost-type attributes the approach should be preceded with an appropriate transformation (e.g. preference values could be inverted) in order to favour lower values more.
- Based on the distribution of the attribute values – new interval boundaries are calculated based on the total number of alternatives required for reconsideration and based on the distribution of values of the particular attribute.

It is important to note that the values of  $k$  should be selected based on the customer sensitivity in changes to a given feature. The method proposed improved the diversity in the result set, thus is expected to deliver better quality customer decisions. Moreover, appropriate selection of the softening factor  $k$  enables user to discover potentially interesting alternatives and consider them during his decision making process keeping the increase in information overflow as low as possible.

## CONCLUSIONS

This research-in-progress paper introduced a new soft-boundary pre-filtering decision aid. We argued that during the process of pre-filtering of the initial, very large set of products, customers eliminate alternatives they could consider by providing preference on attributes and attributes' values. In this paper we introduce a model for a decision aid that can limit the potentially negative effects of dynamic preferences of customers. We also presented propositions about the impact of such a decision aid on decision quality and consideration sets.

If our decision aid increases the overall quality of the consideration set, and enables alternatives to be retained in that set that would otherwise be lost in an early elimination stage, decision quality may be increased. If it positively impacts decision quality, the decision aid might result in higher decision confidence and lead to higher satisfaction. As such, it is worthy of study. We believe that e-commerce application of such a decision aid can be highly beneficial to providers of online shopping services: increased satisfaction and confidence of consumers leads to higher customer retention and, typically, higher profits (HennigThurau and Klee, 1997). Moreover, increased average quality of the alternatives considered by a decision maker would reduce decision-making effort. This would have a direct relevance for online consumers, as well as having value to e-commerce providers.

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