Intelligent Product Search with Soft-Boundary Preference Relaxation

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Abstract. This paper proposes a novel method for preference relaxation in online product search, which enables consumers to make quality choices without suffering from the commonly experienced information overload. In online shopping scenarios that involve multi-attribute choice tasks, it can be difficult for consumers to process the vast amounts of information available and to make satisfactory buying decisions. In such situations consumers are likely to eliminate potentially good choices early on, using hard-constraint filtering tools. Our approach uses edge sets to identify the alternatives on the soft boundary and the principle of alternative domination to suppress the alternatives on this boundary that are irrelevant. We demonstrate how our approach outperforms existing methods for product search in a set of simulations using two sets of 2650 car advertisements and 1813 digital cameras gathered from a popular online store.

Keywords: Decision Theory, Recommender Systems, Preference Relaxation, Electronic Commerce

Abbreviations: NR – No Relaxation, SR – Standard Relaxation, SBR – Soft-Boundary Preference Relaxation, SBR_{ADD} – Soft-Boundary Preference Relaxation with Addition, SBR_{REP} – Soft-Boundary Preference Relaxation with Replacement

1 Introduction

In this paper we present a novel approach to improve customer product search in online shopping scenarios. Drawing upon existing work in information filtration, recommender systems and decision theory, we detail a new method for preference relaxation, referred to as Soft Boundary Preference Relaxation, which improves customer choice quality. We present a detailed description of the method, and discuss its performance based on a set of simulations in two product domains using actual datasets: digital cameras and used cars. Our method explicitly addresses the potential for any increased information overload when additional, recommended alternatives are presented to customers.

Consumers seeking a suitable product online often face a choice from amongst a large set of options. Choosing a car to buy or a plane ticket to book using popular e-commerce websites often requires searching through a very large list of products that can be difficult to grasp or compare. To address this issue, many e-commerce sites offer product filtration tools, which assist customers typically by asking them to fill a form to gather preferences. The process of searching online product catalogues to locate the product(s) that best match consumer's product needs is often referred to as preference-based search (Viappiani, Pu, & Faltings, 2008) or parametric search (Burke, 2002). Considering the potential for a large number of products in contemporary online product catalogues, it may be necessary for consumers to iteratively refine their preferences to arrive to product lists of a manageable size: this requires effort and can be very frustrating (Hagen, Manning, & Paul, 2000). Further, consumers often construct or adjust their preferences whilst interacting with the product catalogue, and may need extra support, for example through suggestions of interesting products (Viappiani, et al., 2008). Thus, the main challenge for online product catalogues is in providing support to consumers to find the most valuable products that match their needs (Zhang & Jiao, 2007), typically through more effective product filtration, recommendation, and preference elicitation.

Typically, preference elicitation processes involve presenting a form-type interface where a user can input his or her preferences. Such an approach to product search, also referred to as Navigation-by-Asking (Shimazu, 2002), is widely used in e-commerce settings, but is often inefficient (Viappiani, Faltings, & Pu, 2006), especially when consumers are not fully aware of available products or no suitable offers are returned in a search result set. According to behavioural decision theory (Payne, Bettman, & Johnson, 1993; Slovic, 1995), an awareness of available products leads to the construction of personal preferences. Faced with a shopping decision, consumers tend to construct their preferences when they are prompted to express evaluative judgment (Payne, Bettman, & Johnson, 1992). However, form-filling approaches do not sufficiently guide consumers to find the most suitable products (Viappiani, et al., 2006). Further, such approaches work under the assumption that consumers can accurately state their requirements, or more formally, levels within a product attribute that are acceptable or not (Klenosky & Perkins, 1992). In addition, form-based product search tools tend to use a non-compensatory approach in the evaluation of available alternatives in which all products that possess at least one attribute with unacceptable values are rejected from further consideration (Oppewal & Klabbers, 2002). This approach is also referred to as logical product filtration with no relaxation (NR). When stated product requirements are over-specified, the search result presented in a response to such a failing query (Mirzadeh & Ricci, 2007) may be empty, causing confusion.

Indeed, previous research indicates that form-based approaches may lead to inaccurate product choices as consumers often fail to reject products with attribute levels, which they themselves had previously described as unacceptable (Klein, 1987). Therefore, there is a need for tools that can provide online consumers with lists of products that not necessarily fully match their stated preferences – so called suggestions or recommendations. Numerous studies propose the use of recommendations to improve consumer decision-making performance (Bridge & Ricci, 2007; Häubl & Murray, 2001; Kim, Kim, & Cho, 2008; Pu, Chen, & Kumar, 2008). Providing a consumer with a relevant yet diverse set of suggestions has become an important research problem (Smyth & McClave, 2001). The tools that implement various methods for nominating product suggestions to improve consumer's performance in online product search are referred to as recommendation agents (RAs) (Resnick & Varian, 1997; Xiao & Benbasat, 2007) representing content and/or collaborative recommender systems (Adomavicius & Tuzhilin, 2005), utility-based tools, and preference relaxation methods (Mirzadeh & Ricci, 2007).

This research argues that the use of preference relaxation is an effective approach for the identification of product recommendations. Classical approaches to preference relaxation (Mirzadeh & Ricci, 2007; Mirzadeh, Ricci, & Bansal, 2004), referred to here as Standard Preference Relaxation (see Section 3.1) may increase consumers' decision-making performance through positive effects on decision quality. Nevertheless, the major disadvantage of the Standard Preference Relaxation approach is an increase in decision effort (see section 4). Directly addressing this drawback, this paper proposes a novel Soft-Boundary Preference Relaxation method in two variants (see Section 3.3 for details) and examines its impact on consumers' decision-making performance in the context of preference-based search in online shops.

In the next section we provide a brief overview of the literature on preference-based search and recommender systems in so far as necessary to document our new method of soft boundary searching. We then present an overview of the research design and results of an application of the method across two choice scenarios using real-world data sets. We conclude with a discussion of our findings, and implications for future research.

2 Background

Information Filtering techniques typically perform a progressive removal of non-relevant content based on the information in a user profile acquired either in an implicit (e.g. studying user behaviour) or an explicit (e.g. asking user to state his preferences) manner. These techniques provide a theoretical foundation for building Recommender Systems (Resnick & Varian, 1997) that enable content personalization - an important stream of research in e-commerce (Lee, Liu, & Lu, 2002).

Numerous studies (Bridge & Ricci, 2007; Viappiani, et al., 2008) use recommendations to improve consumer decision-making (Bridge & Ricci, 2007; McGinty & Smyth, 2003; Viappiani, et al., 2008). Nevertheless, it is crucial (Gretzel & Fesenmaier, 2006; Smyth & McClave, 2001) that the product suggestions provided to consumers are relevant (similar to their stated preferences) yet diverse (so that they can discover new opportunities and adjust their preference model) 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". Further, dynamism in user preferences (Cao, Chen, Yang, & Xiong, 2009) is a problem recognized in Recommender Systems research.

Assumptions that the decision maker can accurately state (and indeed bound) which levels within an attribute are acceptable versus unacceptable is fundamental to a self-explicated approach (Klenosky & Perkins, 1992). Decision makers often use a conjunctive evaluation of available alternatives in which all the alternatives that possess at least one attribute with unacceptable values are rejected from further consideration. Product search and filtering mechanism offered online adhere to that approach, and filter out all products that do not fully conform to the stated requirements. However, previous research indicates that decision makers tend to fail to fully adhere to self-explication. Klein (1987) found that decision makers often fail to reject alternatives with attribute levels which they themselves had previously described as unacceptable, and showed that significant numbers of participants can choose an alternative described with at least one attribute level they initially indicated as "completely unacceptable". Preference relaxation mechanisms may assist in alleviating this problem. A decision aid implementing preference relaxation can potentially improve consumer decisions in online shopping websites, in a similar way as other recommendation systems such as the one proposed by Julià, Sappa, Lumbreras, Serrat, & López (2009) or Wang and Benbasat (2007).

The rigidity of typical preference elicitation (filtering) mechanisms is a well-established problem (Chaudhuri, 1990) that can potentially lead to the elimination of all available products from consideration. Indeed, over-specification of consumer requirements leading to an empty result sets motivated research on similarity-based retrieval (McSherry, 2004) and query relaxation methodologies (Mirzadeh & Ricci, 2007). Similarity based recommenders (Bridge, Goker, McGinty, & Smyth, 2005; Stahl, 2006), although a very popular approach in e-commerce, suffer from a number of disadvantages. First, products that are most similar to the preferences stated by a customer, are not always optimal suggestions, as a slightly less similar product may be objectively much more attractive to a consumer (for example, a PC notebook with a new type of battery that is much lighter and provides more up-time than expected by a consumer while stating the preferences). Second, many similarity-based recommender systems often suggest a predefined number of top recommendations, leading only to a limited increase in consumer awareness.

On the other hand, the process of filtering involves the application of filtering rules (or restrictions on attributes) to the items in the set to be filtered (Chaudhuri, 1990; Mirzadeh & Ricci, 2007). Consumer preferences are the key input for alternative pre-filtration, as only alternatives that fully satisfy all provided preferences are presented to the user as a result to his or her query. To address this, Mirzadeh and Ricci proposed a mechanism for preference relaxation for queries producing an empty result set (Mirzadeh & Ricci, 2007). However, they do not investigate the impact of the extent of relaxation on decision maker behaviour, and their method is applicable primarily to failing queries.

Our research differs from these approaches. First, we primarily focus on reduction of the number of erroneously filtered-out products by intelligent relaxation of the preferences provided by a consumer. Second, many of the existing methods for computation of product suggestions require prior knowledge or history of user interactions and preference models, which are not required in our approach. Therefore, the preference relaxation approach proposed in this paper is easily applicable to any ecommerce platform that utilizes form-based product filtration mechanism. Our approach increases the average quality of result sets presented to a user after product filtration, leads to increased product knowledge, more accurate preference models, and better decision-making.

3 Preference Relaxation methods

Presume you intend to buy a car priced between \$7000 and \$8000 with reasonable mileage (25000 to 75000 km). Would you be willing to pay slightly more (\$8100) for a car with mileage lower than you expected (11000 km)? The ability to locate cars with such attribute values which, albeit out of the boundary ranges specified, may provide consumers with a better awareness of possible choices.

The method proposed here enables consumers to consider products that would ordinarily be eliminated early in the selection process by falling outside "rigid" preferences. In the subsections below we discuss our approach in more detail and contrast it with common simple preference relaxation methods.

3.1 Standard Preference Relaxation

Typically, preferences on numerical attributes are expressed using value ranges. As such, we allow the decision maker to specify his or her attribute value range preference for an i^{th} attribute as $d_i = [d_L, d_U]$ where d_L d_U indicates the lowest (highest) acceptable value for a given attribute.

We now introduce "softening" variables e_U (upper) and e_L (lower), and a relaxation factor δ (where $e_i = \delta * d_i$), which enhance the filtering rule (value range) built based on attribute value preference p causing the filtering rule to be less restrictive. The alternatives that satisfy the less strict preference $d^* = [d_L - e_L, d_U + e_U]$ remain in the set and can be considered by the consumer.

However, this approach, referred to as Simple Preference Relaxation (SR), often leads to a very large number of alternatives presented to the user, resulting in information overload and increasing decision effort (Turetken & Sharda, 2004). In order to prevent these negative effects we use an approach based on the concept of an Edge Set (ES). Below, we show how such an approach can be used to create a subset of potentially interesting items for suggestion to the consumer.

3.2 Soft Boundary Preference Relaxation

An *Edge Set* is a set of alternatives that fall into a value range based on an initial consumer value preference for a given attribute (see Figure 1). For every preference value range, two edge sets can be constructed (lower and upper): $ES_{LOWER} = [d_L - e_L, d_L + e_L]$ and $ES_{UPPER} = [d_U - e_U, d_U + e_U]$. We explain this concept using price range preference p_{PRICE} = [\$6000, \$7000]. For example, assuming variables $e_U = 350$ and $e_L = 300$ (for $\delta = 0.05$) an *edge set* can be constructed: ES = [\$5700, \$6300] $\cup$ [\$6650, \$7350]. Thus the ES will contain items that fall into the [$5700, $6300] or [$6650, $7350] price range. More specifically, our approach involves three steps. First, we create *edge set* based on provided interval boundaries.

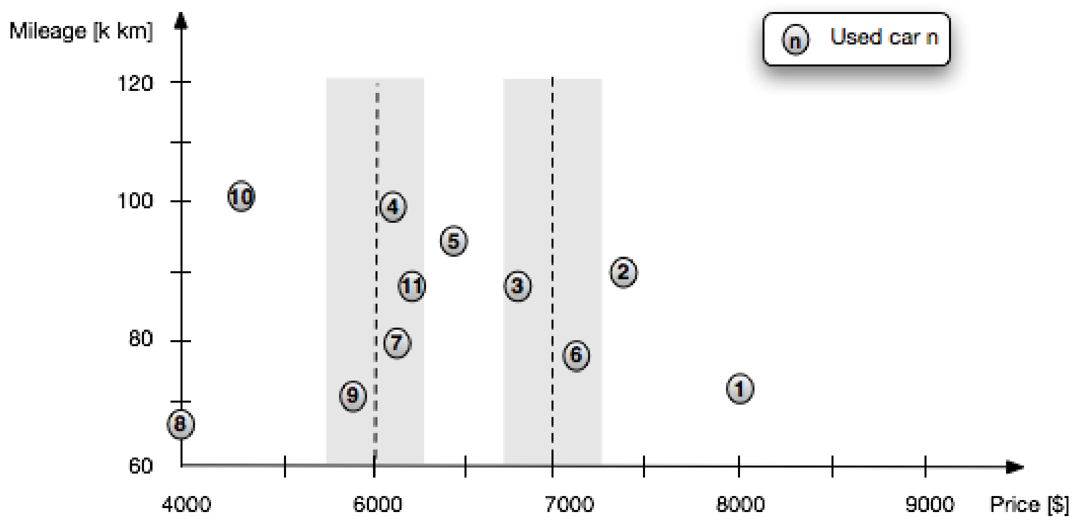

Figure 1 An example of Edge Set for a [$6000, $7000] price preference.

The inclusion of all alternatives satisfying the relaxed criteria would ordinarily increase the number of items presented to the user, contributing to information overload. To address this issue we incorporate a selection mechanism into our relaxation method that includes only some of those cases (see Algorithm 1). Following the creation of the edge set based on relaxed preferences using a selected δ (e.g. 0.05) the algorithm identifies the subset of all non-dominated alternatives (also referred to as the skyline (Borzsonyi, Kossmann, & Stocker, 2001)) that are part of this set. An item is non-dominated if no other item is better for any preference on attribute without being worse for at least one preference on other attributes (Häubl & Trifts, 2000). If a non-dominated item is a member of an edge set and it does not satisfy the non-relaxed initial DM preferences (is not a member of $\text{ResultSet}_{\text{NR}}$) it is added to the set of *suggestions*, as it may be considered valuable. We define two methods for inclusion of *suggestions* in the result set presented to a consumer. First, we propose to add suggestions to an initial result set constructed using a non-relaxed (NR) query. This method, further referred to as SBR_{ADD} (Soft Boundary Preference Relaxation with addition), may lead to increases in the size of result sets.

To address this drawback for the Soft Boundary Preference Relaxation with Addition approach, and to prevent an increase in cognitive load, we propose an alternative method. Instead of simple addition to the set, the method would replace dominated, low-utility items from a non-relaxed result set ($\text{ResultSet}_{\text{NR}}$) that belong to the EdgeSet, with high-utility alternatives. We refer to this method as SBR_{REP} (Soft Boundary Preference Relaxation with Replacement). With this approach, the total size of the set is kept constant, and the alternatives with lowest utility according to current preference model (in this study we use the WADD model) are substituted with items from the skyline. Collectively, we refer to these two mechanisms as SBR (Soft Boundary Preference Relaxation).

```
Input: Products, Preferences, δ, Method
Output: ResultSet_SBR
SKYLINE ⟵ findSkyline(Products);
ResultSet_NR ⟵ filter(Products, Preferences);
PREF_RELAXED ⟵ relaxPreferences(Preferences, δ);
SUGGESTIONS ⟵ ∅;
EdgeSet ⟵ filter(Products,PREF_RELAXED) ;
foreach Product p ∈ EdgeSet do
    if p ∈ SKYLINE and p ∉ ResultSet_NR then
        SUGGESTIONS ⟵ SUGGESTIONS ⊕ p;
    end
end
if Method = ADD then
    ResultSet_SBR ⟵ ResultSet_NR ⊕ SUGGESTIONS ;
end
if Method = REPLACE then
    LowUtilSet ⟵ findLowUtil(ResultSet_NR ∩ EdgeSet, |SUGGESTIONS|);
    ResultSet_SBR ⟵ ResultSet_NR ⊖ LowUtilSet;
    ResultSet_SBR ⟵ ResultSet_SBR ⊕ SUGGESTIONS ;
end
```

Algorithm 1 The Soft Boundary Preference Relaxation Mechanism

As indicated earlier, our method assumes variables e_U (upper) and e_L (lower), and a relaxation factor δ, which relax the value preference *p*. Selecting an appropriate value of δ is not trivial, as it resembles *closeness* (similarity of values) and can differ among consumers (Motro, 1990). However, some studies (Bosc, Hadjali, & Pivert, 2009; A. Hadjali, D. Dubois, & H. Prade, 2003) report that the maximum relaxation value δ_{max} should not be greater than $(3-\sqrt{5})/2$, that is, ~0.382. Thus, the relaxation factor δ should be selected from the interval [0, 0.382] to satisfy the concept of closeness (Allel Hadjali, Didier Dubois, & Henri Prade, 2003). Although Mirzadeh and Ricci (2007) report that relaxation parameters are attribute-dependent and should be tuned according to consumer sensitivity to changes in that feature, in our study we implemented the former simpler relaxation approach to explore potential effects in the first instance, with a view towards possible expansion of parameters in future work. Although our approach is applicable to all types of attributes (continuous, categorical, or binary), in this study we investigate the methods that use continuous numerical attributes as, commensurate with the literature (Mirzadeh & Ricci, 2007), relaxation of binary and nominal constraints is trivial, as they are typically discarded during the relaxation process. Indeed, relaxation of categorical attributes can be performed based on learned similarity measures, as demonstrated by Stahl (2002, 2006).

4 Hypotheses

The simulations explored the effect of preference relaxation on decision performance in the context of multi-attribute preferential choice problems. Four methods were investigated: logical filtering with no relaxation (NR), Standard Preference Relaxation (SR), Soft-Boundary Preference Relaxation with Addition (SBR_{ADD}) and with Replacement (SBR_{REP}). Effects of these methods on consumer decision-making performance were assessed through their impact on a number of indicators.

Many dependent variables have been proposed as good indicators of the impact of a recommendation agent on consumer decision performance (Hostler, Yoon, & Guimaraes, 2005; Parra & Ruiz, 2009; Payne, et al., 1993; Xiao & Benbasat, 2007). This study concentrates on three common performance indicators: decision quality, decision effort and product awareness. Decision quality and effort are common indicators of objective decision performance in the information systems literature (Acton, 2007; Häubl & Trifts, 2000; Parra & Ruiz, 2009), and product awareness is a widely used indicator of recommender method performance that facilitates higher quality decisions (Chen & Pu, 2007; McGinty & Smyth, 2003; Smyth & McClave, 2001).

The impact of recommendation agents on decision quality has been investigated in many studies. For example, Pereira (2001) observed that query-based RAs improved both objective and subjective indicators of decision quality. Other studies (Häubl & Trifts, 2000; Hostler, et al., 2005) demonstrated an assessment of decision quality through non-dominance (Pareto optimality) of the selected alternative(s), also referred to as an "ideal selection" (Häubl & Trifts, 2000). Indeed, such conceptualization of decision quality has been used as a measure of decision performance (Hostler, et al., 2005). Häubl and colleagues (Häubl & Murray, 2005; Häubl & Trifts, 2000) showed that the use of RA increases decision quality by reducing the likelihood of selecting a non-dominated alternative. Similar results were obtained by (van der Heijden, 2006) , who showed that the use of RA leads to a higher number of non-dominated alternatives in the consideration set. It follows that the use of preference relaxation methods should lead to increased decision quality in comparison to logical filtering, and so we hypothesize:

[H1]: Standard Preference Relaxation has a positive effect on decision quality.

Similarly, Soft-Boundary Preference Relaxation methods should lead to higher quality decisions by facilitating the consideration of a larger number of non-dominated alternatives. Consequently, compared to non-relaxing methods, Soft-Boundary Preference Relaxation should positively impact decision quality, and we hypothesize:

[H2]: Soft Boundary Preference Relaxation has a positive effect on decision quality.

The level of effort required to make a decision is another common decision performance indicator (Payne, et al., 1993). Effort is directly related to the amount of information that needs to be considered by a user (Eppler & Mengis, 2004; Turetken & Sharda, 2004). Cognitive load imposed on the customer to find the best offer among the list of products presented to him is considered an effort-related evaluation criterion for product selection tasks (Branting, 2002). Intuitively, preference relaxation mechanisms increase effort by relaxing rigid requirements, and therefore incorporating more alternatives for consideration by a user. Therefore, in contrast to logical filtering, the SR method should lead to significantly larger result sets, leading to higher choice effort:

[H3]: Standard Preference Relaxation has a negative effect on decision-making effort.

On the other hand, Soft-Boundary Preference Relaxation methods select only a small subset of products that satisfy relaxed preferences that are non-dominated. Therefore, no impact on decision effort in comparison to No Relaxation method should be observed:

[H4]: Soft Boundary Preference Relaxation has no effect on decision-making effort.

The selection of a product is context dependent, as the relative value of an option depends not only on the characteristics of that option, but also upon characteristics of other options in the choice set (Payne, Bettman, & Schkade, 1999). According to behavioral decision theory (Payne, et al., 1993; Tversky, 1996) the existence of such context impacts the perceived quality of available products and also leads to construction of new preferences. Tversky (1996) pointed out that increased awareness of product options causes users to adjust their initial preferences based on available choices, in contrast to maximizing fit to pre-computed preferences. This belief has support in the recommender systems literature, where the diversity of the set of recommended products is a sought after characteristic (Bridge & Ferguson, 2002). Indeed, Bodapati (2008) showed that product awareness is a necessary condition for actual purchase. Further, according to Fleder and Hosanger (2007), recommendation agents impact sales diversity. Intuitively, preference relaxation allows for the consideration of products that are filtered out when using logical filtering approaches. Consequently, we argue that preference relaxation mechanisms will increase consumers' awareness of existing products, in contrast to the non-relaxed approach, indicated by result set diversity:

[H5]: Standard Preference Relaxation has a positive effect on product awareness.

[H6]: Soft Boundary Preference Relaxation has a positive effect on product awareness.

These research hypotheses were investigated using software simulations (see Section 5.2) using two datasets, described in the next section.

5 Evaluation

5.1 Datasets

In order to evaluate the proposed decision aid and compare it with the standard preference relaxation mechanism we performed a set of simulations using two real-world datasets. We collected a set of 2650 used car advertisements from Autotrader, and extracted 1813 digital cameras offered by Amazon῾s e-Commerce website.

5.1.1 Used cars

The first dataset comprised 2650 used car advertisements collected from an online car website, run and managed by the Autotrader media group. Additional attributes for used cars in the set that were not present in advertisements, such as reliability (see Section 5.2), were automatically generated using standard information retrieval methods based on product reviews collected from car review websites (e.g. whatcar.com). Generated attributes were classified as benefit-type and given scores ranging from 0 to 5 to resemble star ratings (e.g. 5 points for *maintenanceCost* describes the relatively lowest maintenance cost).

5.1.2 Digital Cameras

The second dataset consisted of 1813 digital cameras extracted from the "Point & Shoot Digital Cameras" category on Amazon.com. The products were extracted using Java software and Web Services API provided by Amazon. Information on a number of attributes was collected for each product: brand, model, price, zoom, screen size, resolution, and weight. Further, customer ratings on each product were extracted. These attributes were manually classified into cost-type (e.g. price) and benefit-type (e.g. resolution) categories.

5.2 Method

The simulation design was based on a *leave-one-out* (LOV) (McSherry, 2004) approach in which each alternative was temporarily removed from the dataset and its description was used as a user preference. The leave-one-out method, also known as n-fold cross validation (Kohavi, 1995), is a method commonly used in evaluation of recommender systems. In LOV approach each of available alternatives is temporarily removed from the list of offers and is treated as a consumer's product preferences/requirements.

Consistent with bounded rationality (Lipman, 1995), and based on previous studies in relevant product domains: used cars (Dabrowski, Jarzebowski, Acton, & O'Riain, 2010) and digital cameras (Aciar, Zhang, Simoff, & Debenham, 2007; Pu, et al., 2008), 6 most popular attributes were chosen for this experiment. To best resemble user behaviour, the preferences in the simulations were constructed similarly to filtering interfaces of popular websites, where value preference intervals were selected to simulate possible user entries. For example, the price intervals for used cars (in $) were: [1000, 2000] ... [5000, 6000], [6000, 8000] … [12000, 14000], [14000, 18000], and [18000, 30000] following the values available for price filtration in a popular used car search engine. Using the LOV approach, every used car advert in the set was temporarily removed from the set and its values were used to create preference values (based on available preference intervals).

For example, a car at $5900 would be represented as a user search query with price preference [$5000, $6000], following the intervals defined based on existing product search engines available. Simulations were run for combinations of 1 to 6 stated preferences and for relaxation factors 0.05, 0.1, 0.2, 0.3 and 0.382 (δ_{max}). Thus, for every set of parameters a maximum number of 2650 non-failing relaxed queries were issued and relevant result sets were constructed for all four methods investigated: logical filtering with no relaxation (NR), Standard Preference Relaxation (SR), Soft Boundary Preference Relaxation with Addition (SBR_{ADD}), and with Replacement (SBR_{REP}). Particular characteristics of these constructed result sets (see the next section) were assessed and compared to evaluate the methods under investigation.

5.3 Measures

In this experiment a number of measures were used to evaluate the four methods. This section discusses the rationale for these measures.

In the evaluation of customer choice-based decision outcomes this study investigated quality-related aspects of decision-making performance as suggested by Xiao and Benbasat (2007). Two measures of objective decision quality are prevalent in the literature: non-dominance of the selected alternative(s) (Grether & Plott, 1979; Häubl & Trifts, 2000; Johnson & Payne, 1985), and product fit to customer preferences (Pereira, 2001), also conceptualized as *utility* (Johnson & Payne, 1985).

Share of non-dominated alternatives. Häubl et al (2000) showed that the share of considered products that are non-dominated indicates the quality of a set of products considered by a consumer, which positively impacts decision quality. Such conceptualization of decision quality has been used as a measure of decision performance (Hostler, et al., 2005). For example, Swamnathan (2003) in the study of web-based RA utilized the purchase of non-dominated alternative as a direct indicator of decision quality. Similar conceptualization was used in the studies performed by Olson and Widing (2002). Finally, van der Heijden {, 2006 #463} suggested the use of the share on non-dominated alternatives in the consideration set in this context. Therefore, this study utilizes share of non-dominated alternatives in the result set as a measure of decision quality.

Average utility of products. As noted above, decision quality is directly related to fulfilling particular user's criteria for product selection (preferences) that can be measured by the utility of selected alternatives (Bridge & Ricci, 2007). Some studies indicate that the goal of a recommendation agent is to locate products that closely match a user's preferences (Hostler, et al., 2005; Lee, et al., 2002). Indeed Johnson and Payne (1985) suggest the maximization of product utility value as a measure of decision quality. Similarly, Stahl (2004) pointed out the importance of product utility in recommendation systems. The higher the average utility of alternatives presented for choice ($AvgUtil \in [0,1]$), the more suitable options can be considered. Thus, this study measures decision quality with the average utility of products in a search result set constructed using the methods described in Section **Error! Reference source not found.**.

Size of a result set. In terms of the decision process, information overload is an important factor that increases decision-making effort and leads to changes in strategies employed by decision makers in selection tasks (Eppler & Mengis, 2004). Some studies measure decision effort by examining the number of products about which detailed information are obtained (Häubl & Trifts, 2000). Following the approach by Payne et al. (1999), our study measures the level of decision-making effort by the number of alternatives presented for consideration by a user, that is, the size of a result set.

Diversity of a result set. Vahidov and Ji (2005) indicated the importance of result set diversity in decision making. Tversky (1996) demonstrated that increased awareness of product options causes consumers to adjust their initial preferences based on available choices, in contrast to maximizing fit to pre-computed preferences. Recommender Systems research supports this claim through design of methods that suggest diverse sets of recommended products to consumers (Bridge & Ferguson, 2002). Indeed, Bodapati (2008) showed that product awareness is a necessary condition for actual purchase. To assess diversity of result sets our study uses a common conceptualization of normalized diversity ($diversity(ResultSet) \in [0,1]$) that is inversely proportional to similarity following the relation presented by Smyth and McClave (2001). The computation of similarity is performed using a law proposed by Shepard (1987), which suggests that perceived similarity of items is related to their distance via an exponential function:

$$sim(a_1,a_2) = e^{-dist(a_1,a_2)}$$

where $dist(a_1,a_2)$ is a normalised distance measure:

$$\forall_{a_1,a_2 \in A} \quad 0 \le dist(a_1,a_2) \le 1$$

Measures were assessed for the results sets generated using the four methods under study. The share of the non-dominated alternatives in the result set and average utility of products in the result set were used as decision quality indicators. Further, the number of alternatives in the result set indicated the decision effort necessary to make a decision, and the diversity of products in the result set indicated product awareness. The next section describes the results of the simulation.

5.4 Results – used cars

Related samples non-parametric tests were used to investigate the average share of non-dominated alternatives in the result sets for queries using the preference relaxing mechanisms discussed above, compared with the share for the non-relaxed method. Results show that on average, result sets constructed using relaxation contained similar share of non-dominated alternatives to the result sets constructed using no relaxation. In particular, on average 19.66% of non-dominated alternatives were observed when no relaxation was used, in contrast to only 19.55% in case of non-relaxing methods (NR) (see Table 1), representing a 0.6% increase. A larger increase was observed for the average utility of alternatives in a result set, with a 13.6% improvement ($AvgUtil_{NR}$ = 0.5161 and $AvgUtil_{SR}$ = 0.4543). These differences were statistically significant ($p < 0.001$), thus providing partial support for hypothesis H1.

Similarly, results indicate that the use of the Soft Boundary Preference Relaxation mechanism improves the share of non-dominated alternatives in a result set in contrast to both non-relaxing (NR) and Standard Relaxation (SR) methods. 28.95% (SBR_{ADD}), and 34.46% (SBR_{REP}) of non-dominated alternatives were observed for SBR methods in contrast to 19.66% (SR) and 19.55% (NR). These improvements (48.08% for SBR_{ADD} and 76.27% for SBR_{REP} in contrasts to NR) were statistically significant ($p < 0.001$). Similarly, the average utility of alternatives in a search result set was higher for all preference-relaxing methods, with 0.5161 (SR), 0.5228 (SBR_{ADD}), and 0.5311 (SBR_{REP}) in contrast to 0.4543 for the non-relaxed case. These values represent 13.6%, 15.08%, and 16.9% improvements respectively. The level of improvement in the average share of non-dominated alternatives and in the average utility of the alternatives in a search result set leads us to accept H2.

The second group of hypotheses (H3 and H4) examined the decision-making effort measured by a number of items from which customers had to choose. For the methods investigated, median values of 631 (SR), 440 (SBR_{ADD}), and 420 (SBR_{REP}) items in the result set were observed, in contrast to 420 items on average in a result set for non-relaxed queries (NR). These differences were statistically significant ($p < 0.001$), confirming H3 and indicating conditional acceptance of H4, as although SBR_{REP} does not increase the decision-making effort, the SBR_{ADD} method forces making the decision based on 4.8% larger result sets.

	δ	0.05	0.1	0.2	0.3	0.382	Overall
AvgUtil	NR	0.4543	0.4543	0.4543	0.4543	0.4543	0.4543
	SR	0.4875	0.5009	0.5175	0.5304	0.5443	0.5161
	SBR_{ADD}	0.4849	0.5033	0.5290	0.5431	0.5538	0.5228
	SBR_{REP}	0.4942	0.5129	0.5384	0.5501	0.5600	0.5311
%ND	NR	19.55%	19.55%	19.55%	19.55%	19.55%	19.55%
	SR	19.22%	19.68%	19.72%	19.87%	19.79%	19.66%
	SBR_{ADD}	24.82%	26.48%	28.83%	31.94%	32.65%	28.95%
	SBR_{REP}	27.42%	29.96%	33.89%	39.78%	41.24%	34.46%
|ResultSet|	NR	420	420	420	420	420	420
	SR	534	581	639	760	795	631
	SBR_{ADD}	432	435	440	464	469	440
	SBR_{REP}	420	420	420	420	420	420
Diversity	NR	0.0539	0.0539	0.0539	0.0539	0.0539	0.0539
	SR	0.0559	0.0563	0.0577	0.0591	0.0597	0.0576
	SBR_{ADD}	0.0550	0.0551	0.0563	0.0571	0.0574	0.0560
	SBR_{REP}	0.0541	0.0541	0.0550	0.0569	0.0569	0.0551

Table 1 Average utility (AvgUtil), share of non-dominated alternatives in the result set (%ND), median of the result set size (|RS|), and average diversity for relaxed (SR), non-relaxed (NR), SBR with addition (SBR_{ADD}) and replacement (SBR_{REP}) for different values of δ (used cars dataset).

Finally, results indicated that the diversity of alternatives generated using preference relaxation methods are more diverse than when no relaxation is used. In particular, an average diversity of 0.1254 (SBR_{ADD}), 0.1248 (SBR_{REP}, and 0.1319 (SR) was observed for preference relaxation methods, in contrast to 0.1131 for the non-relaxing method (NR) (see Table 2). These values represent 10.9%, 10.34%, and 16.6% respective improvements. These differences were statistically significant ($p < 0.001$), confirming both H5 and H6.

	N	1	2	3	4	5	6	Overall
AvgUtil	NR	0.4386	0.4483	0.4550	0.4606	0.4649	0.4677	0.4543
	SR	0.4907	0.5050	0.5164	0.5270	0.5366	0.5451	0.5161
	SBR_{ADD}	0.5130	0.5195	0.5231	0.5265	0.5294	0.5317	0.5228
	SBR_{REP}	0.5283	0.5279	0.5321	0.5352	0.5374	0.5387	0.5311
%ND	NR	16.60%	17.91%	19.33%	20.97%	22.91%	25.26%	19.55%
	SR	16.46%	17.82%	19.41%	21.26%	23.32%	25.66%	19.66%
	SBR_{ADD}	19.96%	24.41%	28.76%	33.07%	37.42%	41.87%	28.95%
	SBR_{REP}	21.34%	27.58%	34.03%	40.65%	47.43%	54.33%	34.46%
|ResultSet|	NR	2623	692	420	260	147	116	420
	SR	2623	1212	639	477	345	238	631
	SBR_{ADD}	2623	770	450	308	175	139	440
	SBR_{REP}	2623	692	420	260	147	116	420
Diversity	NR	0.0000	0.0143	0.0352	0.0660	0.0751	0.0774	0.0539
	SR	0.0000	0.0194	0.0401	0.0772	0.0864	0.0900	0.0576
	SBR_{ADD}	0.0000	0.0163	0.0366	0.0737	0.0828	0.0872	0.0560
	SBR_{REP}	0.0000	0.0162	0.0737	0.0722	0.0819	0.0867	0.0551

Table 2 Average utility (AvgUtil), share of non-dominated alternatives in the result set (%ND), median of the result set size (|RS|), and average diversity for relaxed (SR), non-relaxed (NR), SBR with addition (SBR_{ADD}) and replacement (SBR_{REP}) for number of stated preferences N (used cars dataset).

5.5 Results – digital cameras

We compared the average share of non-dominated alternatives in result sets generated using the preference relaxation mechanisms outlined above with the non-relaxed method using related samples non-parametric tests. The results showed a positive effect of the preference relaxation methods on the share of non-dominated products in the list considered by a consumer. In particular, a 20.55% increase in the share of non-dominated products was observed in case of the Standard Relaxation method when compared with non-relaxed (10.05% and 8.33% respectively). Similar findings were obtained for the average utility of alternatives in result sets constructed using both methods ($AvgUtil_{NR}$ = 0.5454 and $AvgUtil_{SR}$ = 0.5620). Although the improvement is relatively small (3.03%), both results are statistically significant ($p < 0.001$), and therefore support H1.

The results related to the use of the Soft Boundary Preference Relaxation mechanisms show improvements in the share of non-dominated alternatives in a result set in contrast to both non-relaxing (NR) and Standard relaxation (SR) methods. In particular, 77.92% (SBR_{ADD}), and 90.77% (SBR_{REP}) improvement in the share of non-dominated alternatives was observed for SBR methods, in contrast to no relaxation (see Table 3). These differences were statistically significant with $p < 0.001$. The average utility of alternatives in a result set was similar to all preference-relaxing methods with 0.5620 (SR), 0.5443 (SBR_{ADD}), and 0.5506 (SBR_{REP}), the extent of improvement in the average share of non-dominated alternatives in a result set provides evidence for supporting H2.

	δ	0.05	0.1	0.2	0.3	0.382	W. A.
AvgUtil	NR	0.5501	0.5484	0.5454	0.5420	0.5407	0.5454
	SR	0.5599	0.5554	0.5605	0.5651	0.5689	0.5620
	SBR_{ADD}	0.5359	0.5379	0.5454	0.5494	0.5527	0.5443
	SBR_{REP}	0.5424	0.5447	0.5519	0.5556	0.5583	0.5506
%ND	NR	8.79%	8.62%	8.33%	8.33%	8.15%	8.33%
	SR	9.64%	10.00%	10.45%	10.20%	10.20%	10.05%
	SBR_{ADD}	13.33%	13.75%	14.82%	16.67%	17.58%	14.82%
	SBR_{REP}	13.54%	14.24%	15.91%	18.69%	19.32%	15.90%
|ResultSet|	NR	40	40	39	39	39	39
	SR	61	65	72	89	92	74
	SBR_{ADD}	43	43	44	46	46	44
	SBR_{REP}	41	40	40	40	40	40
Diversity	NR	0.0112	0.0110	0.0109	0.0104	0.0102	0.0109
	SR	0.0152	0.0161	0.0168	0.0183	0.0185	0.0172
	SBR_{ADD}	0.0125	0.0126	0.0129	0.0136	0.0136	0.0131
	SBR_{REP}	0.0120	0.0121	0.0122	0.0129	0.0130	0.0125

Table 3 Average utility (AvgUtil), median of the share of non-dominated alternatives in the result set (%ND), the result set size (|RS|), and diversity for relaxed (SR), non-relaxed (NR), SBR with addition (SBR_{ADD}) and replacement (SBR_{REP}) for different values of δ (digital cameras dataset).

The second group of hypotheses related to decision-making effort (H3 and H4), in this case measured by a number of items from which an online consumer has to choose. For the methods investigated, a median of 74 (SR), 44 (SBR_{ADD}), and 40 (SBR_{REP}) items in the result set were observed, in contrast to only 39 items on average in a result set for non-relaxed queries (NR). These differences are statistically significant ($p < 0.001$), confirming H3. However, it is worth noting that the extent of increase in case of the SBR_{REP} method was extremely low (less than 0.3% when comparing the mean values) indicating only partial support for H4.

Finally, results indicated that the alternatives generated using preference relaxation methods were more diverse than those for the non-relaxed method. In particular, an average diversity of 0.0131 (SBR_{ADD}), 0.0125 (SBR_{REP}), and 0.0172 (SR) was observed, compared to 0.0109 for the non-relaxing method (NR) (see Table 3). These differences were statistically significant ($p < 0.001$), confirming H5 and H6. The results of the study are summarized in Table 4.

6 Discussion

Our study highlights the benefits of the application of intelligent preference relaxation methods in online product search scenarios. Furthermore, we propose a novel Soft Boundary Preference Relaxation method in two variants (with Addition and with Replacement) that not only possesses the advantages of classical preference relaxation methods but also minimizes additional information processing effort and maximizes product choice quality. First, we showed that preference relaxation methods lead to the construction of product choice sets that make a quality decision much more likely (e.g. with a greater share of non-dominated alternatives). Further, we demonstrated the positive impact of the Soft Boundary Preference Relaxation approach proposed here on product awareness evidenced by the diversity of items in result sets which, according to Vahidov and Ji (2005), leads to higher user satisfaction. In addition, we showed that standard Preference Relaxation (SR) induces a very significant increase in the size of a result set, leading to an unacceptable increase in decision-making effort. We propose two variants of a new method (SBR) that addresses this issue. Finally, we demonstrate that these proposed methods outperform the Simple Relaxation (SR) method and minimize additional decision-making effort. The summary of findings and research hypotheses is presented in Table 4.

	Hypotheses	Used Cars	Cameras	Overall
H1	Standard Preference Relaxation has a positive effect on decision quality.	Partially Supported	Supported	Partially Supported
H2	Soft Boundary Preference Relaxation has a positive effect on decision quality.	Supported	Partially Supported	Supported
H3	Standard Preference Relaxation has a negative effect on decision-making effort	Supported	Supported	Supported
H4	Soft-Boundary Preference Relaxation has no effect on decision-making effort	Partially Supported	Partially supported	Partially Supported
H5	Standard Preference Relaxation has a positive effect on product awareness.	Supported	Supported	Supported
H6	Soft Boundary Preference Relaxation has a positive effect on product awareness.	Supported	Supported	Supported

Table 4 Summary of hypotheses

The results show that in a large majority of cases the difference in the size of a result set for SBR_{REP} and non-relaxing method (NR) is not statistically significant (see Table 2). Further, when comparing SBR_{REP} and NR methods using the digital cameras dataset, we observed a minimal or close to none increase in the average size of a result set (the average size increased only by 0.3%). However we found a significant (20.55%) increase in the share of non-dominated alternatives. Another performance indicator related to the percentage of result sets that did not contain any non-dominated products. Using the digital camera dataset, we showed a significant improvement in this regard. In particular, out of 562,918 cases as many as 178,243 result sets do not contain non-dominated alternatives (31.66%). Preference relaxation methods decrease this negative effect by reducing the number of product sets without a non-dominated alternative to 129,486 (23.00%), representing a 37.65% improvement. Finally, although the initial impact of relaxation on diversity of the results sets seems low, this is due to the selected diversity measure, which favours small results sets. Indeed, the impact of relaxation on diversity is significantly higher for cases with 3 or more specified preferences (see Table 2), for which significantly smaller result sets are reported. As such, the study highlights the strong positive impact of SBR_{REP} on our decision-making indicators, with minimum negative impact on effort compared with other relaxation methods. Indeed overall, we showed that our method outperforms standard preference relaxation mechanisms.

In conclusion, the introduction of intelligent preference relaxation has an impact on many aspects of consumer decision performance. It ensures that valuable product offers are not erroneously filtered out based on inaccurate preference models provided by consumers using form-based filtering tools. During the process of filtering of initial, very large sets of products, consumers eliminate alternatives that might be valuable later, by providing inaccurate preferences for attributes and attribute values. The paper introduces and validates a new model for a decision aid based on preference relaxation that can limit the potentially negative effects of dynamic consumer preferences, whilst addressing limitations of existing methods. The results of the simulation experiment demonstrate the positive effects of preference relaxation on consumer decisions.

The e-commerce application of our method are particularly beneficial to providers of online shopping services: diverse result sets may lead to more consumer satisfaction and potentially higher customer retention (Vahidov & Ji, 2005). Moreover, increased average quality of the alternatives considered by a decision maker would reduce decision-making effort. This would have direct relevance to online consumers, as well as having value to e-commerce providers.

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