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RECOMMENDER SYSTEM FOR MARKETING OF CONSUMER ELECTRONICS IN INDIA

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Abstract: Green marketing has become an important and innovative method for companies to remain profitable and competitive as the public and governments are more concerned about environmental issues. However, most online shopping environments do not consider product greenness in their recommender systems or other shopping tools. This paper aims to propose the use of recommender systems to aid the green shopping process and to promote green consumerism basing upon the benefits of recommender systems and a compliance technique called foot-in-the-door (FITD). With the implementation of this concept, the Authors et al. are of the opinion that the marketing of Electronic Goods in India shall see an upsurge. In this study, the architecture of a recommender system for green consumer electronics is proposed. Customers' decision-making process is modelled with an adaptive fuzzy inference system in which the input variables are the degrees of price, feature, and greenness and output variables are the estimated rating data. The architecture has three types of recommendation: information filtering, candidate expansion, and crowd recommendation. Ad hoc customization can be applied to tune the recommendation results. The findings are reported in two parts. The first part describes the potentials of using recommender systems in green marketing and the promotion of green consumerism; the second part describes the proposed recommender system architecture using green consumer electronics as the context. Discussion of the proposed architecture and comparison with other systems are also included in this part. The proposed architecture provides a capable platform for personalized green marketing by offering customers shopping advices tailored to their preferences and for the promotion of green consumerism.

Index Terms **- Green Consumerism, Adaptive Fuzzy Inference System, Green Marketing.**

I. INTRODUCTION

Recommender systems have become an important technology for electronic commerce on many fronts (Bose, 2009; Kauffman & Walden, 2001). It can filter for online shoppers the vast amount of information, saving the customers from the information overload problem (Chen, Shang, & Kao, 2009). It can be a decision aid for customers who are challenged when they are in the market for unfamiliar products. It can be a strategic marketing platform on which online venders can personalize promotions and sales for each customer (Chen, 2008; Shih, Chiu, Hsu, & Lin, 2002). Recommender systems have been vigorously researched and developed in the fields of academia and business. Some notable examples include Apple Inc.'s Genius of iTunes that make music recommendations, University of Minnesota's MovieLens and Netflix's Cinematch that recommend movie titles, Amazon.com's recommender system that generates recommendations of an assortment of products, and Outbrain.com's blog rating widget that recommends blogs a rater might be interested in. The domain of recommender systems is not limited to the famous instances mentioned above. Recommender systems for news, web pages, jokes, academic articles, consumer electronics, restaurants, and a plethora of other subject matters, have been researched and implemented (Adomavicius & Tuzhilin, 2005; Iijima & Ho, 2007). However, to our knowledge, few researches have dealt with recommender system of green product. Green product is increasingly important in our global village as the general public is becoming more concerned of our impact on the planet. Driven by this trend, companies have been trying to design and manufacture greener products and have been trying to promote their products and brand images by communicating their greenness to the customers via a variety of channels. Yet, ecolabeling remains one of the fundamental ways to inform the customers how green their products are and in what respect their products are green. Eco-labels, usually issued by third-party organizations, are textual or graphical presentations of the environmental characteristics of a product, which can be found on the product itself, on the packaging, or in the manual. Examples of eco-labels include Green Seal, Energy Star, and WEEE (Waste Electrical and Electronic Equipment Directive). Studies have shown that public education campaign is one of the key determinants of successful eco-labeling programs (Malcohn, Paulos, Stoeckle, & Wang, 1994). Public education campaign of eco-labeling programs can be done via methods such as media coverage, regulation, promotion, school curriculum, and so on. This research proposes using recommender systems, in addition to these methods, as a means to educate and inform on-line customers. The justification of such proposal relies on two of the primary functions of a recommender system: information filtering and candidate expansion. When customers are confronted with a flood of products or with unfamiliar products, they may have difficulty in making a shopping decision. Based upon what they have purchased before, a recommender system can help the customers by filtering out items that are unlikely to be preferred. For example, Amazon.com's recommender system generates a personalized list of recommended products each time a customer visits their web site. As to candidate expansion, when a customer is evaluating the decision to buy a product, a recommender system can ensure that other good candidates are included in the consideration set by finding related products based upon the product under consideration. Take Amazon.com's recommender system for example again. When a customer is looking at the catalog page of a product, the recommender system recommends items similar to the current item. Tapping into the capabilities of information filtering and candidate expansion, recommender systems can be transformed into a green product advocate informing the customers of available choices that are greener. A recommender system of green products can also sieve through a set of products to retrieve only the items matching an implicitly or explicitly degree of greenness designated by a customer. Such system can also find other products whose greenness and other aspects are comparable based upon a product under consideration. The reduced effort in the decision-making process may enhance the quality and users' satisfaction of the decision (Häubl & Trifts, 2000), which in turn will make green shopping a more enjoyable experience.

The adaptability of a recommender system can also contribute to the promotion of green consumerism by using a technique called foot-in-the-door (FITD) technique (Freedman & Fraser, 1966). FITD is a compliance technique in which a person is more likely to accept a larger request if this request is preceded by a smaller request. The technique is also found to be effective in computer-mediated communication (CMC) in addition to face-to-face or telephone communications (Guéguen, 2002). In a recommender system of green products, items with higher degree of greenness and with comparable or equal degrees of price and feature can be first recommended to a user who is reluctant to buy green products. Appropriate feedback should be given to the user about the environmental contribution of the purchase one has made. The degree of greenness of the recommended items in the future can be adjusted accordingly if the users' purchasing transactions reflect acceptance or rejection of the items.

The goal of this paper is to develop a recommender system architecture for green consumer electronics. Instead of simply adding an additional green attribute to the conventional recommender systems, the architecture uses an adaptive behavioral agent to find the products of a certain degree of greenness according to users' behaviors. The agent uses an adaptive fuzzy inference system to learn users' behavior over time with a basic assumption that a bilateral relationship of either symbiosis or antibiosis exists between the pairs of price vs. feature, price vs. greenness, and feature vs. greenness.

The rest of this paper is organized as follows. The next section gives brief review of recommender systems and fuzzy inference systems. The proposed architecture is presented and discussed in Section 3. Conclusions and future research directions are presented in the final section.

II. Related work

Recommender system

Recommender systems have a variety of forms with different functions (Manouselis & Costopoulou, 2007; Wan, Menon, & Ramaprasad, 2007). Therefore, it warrants a clear definition of the kind of recommender systems this paper is dealing with. Schein, Popescul, Ungar, and Pennock (2005) define recommender systems as the following: ''Recommender systems suggest items of interest to users based on their explicit and implicit preferences, the preferences of other users, and user and item attributes''. This definition points out the fundamental parts and necessary input and output data of a recommender system. First, a recommender system needs data of preferences from single user or multiple users. The system can explicitly elicit preferences from users by asking them to rate some items, or implicitly by inferring their preferences from past transactions (Resnick & Varian, 1997). Second, a recommender system requires attributes of users and items.

Manouselis and Costopoulou (2007) refer to these two sets of attributes as ''user model'' and ''domain model'', respectively. Several representations can be used as user models, such as per user product ratings, demographic attributes, transaction histories, and so on. On the other hand, domain models can be represented as characteristics of products and as derived attributes such as taxonomies, hierarchies, and ontologies. Both models may utilize the acquired user preferences to derive their own data. The core of a recommender system is the mechanism of suggestion generation based upon the user model and domain model. The mechanism can be formulated as follows (Adomavicius & Tuzhilin, 2005): Let C be the set of all customers and P be the set of all products that a recommender knows of. In addition, let U(c, p) be the utility function that associates (c, p) pairs with utility values which can be ratings, profits, or some other measurements. The objective of a recommender system is to find a set of items p0 e P such that U(c, p) is maximized for a customer. The mathematical formulation is as follows:

$$\forall c \in C, \quad p' = \arg\max_{p \in P} U(c,p)$$

In the formulation, ''arg max'' means ''the argument of the maximum''. Recommender systems can be generally classified into three categories according to the mechanism of recommendation generation (Adomavicius & Tuzhilin, 2005; Schein et al., 2005): (1) Content- based systems recommend items that are similar to the ones a user preferred in the past. (2) Collaborative systems recommend items that other like-minded users preferred in the past. (3) Hybrid systems recommend items by combining content-based and collaborative methods in recommendation generation.

As Adomavicius and Tuzhilin (2005) point out, content-based and collaborative systems have some challenges to be dealt with. For content-based systems, the first problem is ''limited content analysis'', in which case the recommendation is limited by the features associated with the items. However, some features are harder to extract than others are. For example, extracting features from textual information is easier than from multimedia data. Also, items that are identical in terms of features are indistinguishable.

The second problem is overspecialization, in which case the system can only recommend items that are similar to items a user liked in the past. In other words, the lack of diversity may jeopardize the practicality of a recommender system. The third problem is ''new user problem'', in which case a user is unable to get reliable recommendations until a sufficient number of transactions are present for the recommender system to learn about the users' preferences. Collaborative systems also have the ''new user problem'' which is similar to that of content-based systems. Another two problems of collaborative systems are ''new item problem'' and sparsity. New item problem refers to situations in which the system is unable to recommend newly added items because these items have yet to be included in the user preference data. Sparsity problem refers to situations in which there are few like-minded users, or in which there are items that are preferred by few people.

Fuzzy set theory and recommender systems

Fuzzy set theory and its extensions have been used to model various aspects of recommender systems. For example, it has been used to model users' knowledge of a subject matter to select an appropriate navigation technique (Kavcic, 2004). Fuzzy set theory can be used to bridge the gap between linguistic user inputs and precise attributes of products. In a consumer electronics shopping aid system (Cao & Li, 2007), customers' needs are elicited by answering some questions about their needs and concerns. Based on these answers and some predefined fuzzy sets, the system then computes the weight of each specification to get the suitability scores of products. Fuzzy sets have been applied to model similarities between item vs. item, user vs. item, and user vs. user in movie recommendation (Perny & Zucker, 2001). Fuzzy sets also have been used to represent the characteristics of items and users (Wang, 2004).

III. The Architecture

Definitions and assumptions

The core of the proposed recommender system architecture for green consumer electronics is an adaptive behavioral agent that learns users' preferences in terms of price, feature, and greenness. Feature is defined as the functional and non-functional characteristics of a product. Functional characteristics are directly related to the utilization of a product. Take digital camera for example, functional characteristics may include lens magnifying power, sensor pixel count, battery stamina, and so on. On the other hand, non-functional characteristics are not directly related to the use of a product, such as brand, industrial design, emotion invoked by the use of the product, and so on. Greenness is the degree of how green a product is, and price is the degree of the retail monetary value of a product. The representations of the degrees will be described later.

The adaptive behavioral agent has two assumptions. First, there is a bilateral relationship between the pairs of price vs. feature, price vs. greenness, and feature vs. greenness. The relationships are either symbiosis or antibiosis. For example, a product whose feature set is rich and innovative may have a relatively high price. However, a product in a competitive market may have an aggressively low pricing and still have a rich feature set. Likewise, greenness may drive the price higher or lower. For example, green products are usually the result of vigorous research and development or the use of new material or manufacturing process, which mean extra costs. Yet, in some cases, the new design, material, or manufacturing process actually saves money. Relationships between the three pairs are mutually enhancing or decreasing. So, feature can drive greenness higher or lower, and vice versa. Fig. 1 illustrates the idea.

The second assumption is that in India customers make their shopping decisions according to the criteria of price, feature, and greenness. The inclusion of greenness makes this assumption an unusual one. However, as the green consumerism is becoming a trend, such assumption is rational. The exclusion of other criteria is a practical simplification of the architecture.

Domain model

The domain model defines the representation of products and the generation of the representations in our recommender architecture. Each product is represented by three cardinal numbers that stand for the degree of price, feature, and greenness, respectively.

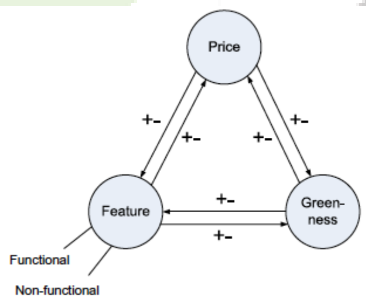

Fig. 1. The bilateral relationship between the pairs of prices vs. feature, price vs. greenness, and feature vs. greenness. Plus, sign means enhancing and minus sign decreasing.

The degree of price is a representation of how expensive a product is relative to other products under the same category, and the z-score normalization of the products' prices is used to obtain this degree. Let Pi be the set of all products under category i.

For a product p Pi, the degree of price DP of p is defined as the following:

$$DP= X p-M P i / S p i$$

M P i and S p I are the means and the standard deviations of the prices of products under category i, and Xp is the price of a particular product p. Products with higher DP values are more expensive than those with lower DP values. In the same way, the degree of feature represents the powerfulness of a product relatively to other products under the same category. The average of the z-scores of the quantifiable specifications of a product category is used to represent this degree.

User model

While the domain model described above is a set of attributes, the user model is represented by an FIS-based adaptive behavioural agent whose input variables are the attributes of the domain model and the output variable is the estimated rating of a product. As described in Section 2, an FIS contains fuzzy if-then rules that are derived from human experts' knowledge of a system. One method to determine the membership functions of an FIS is by observing the input and output variables and choosing the membership functions that fit the variables. The resultant system is a static FIS whose membership functions and parameters of the functions are predetermined. Another method of constructing the fuzzy ifthen rules is through a soft computing method called Adaptive Neuro-Fuzzy Inference Systems (ANFIS), in which the rules are obtained by training the system with the input and output variables (Jang, 1993).

The proposed architecture uses ANFIS and the rating data of products to obtain a FIS that represents a users' preference in terms of price, feature, and greenness. The architecture trains the ANFIS by feeding it with training data set {p, DP, DF, DG, r | p □ Pi}, where p is a product and r is the rating of a product supplied by the user. The resultant FIS of Pi for a user takes the input of {DP, DF, DG} and outputs r0 , the estimation of r, of product p.

To minimize the amount of user interaction, the architecture uses Asynchronous JavaScript and XML (AJAX) to elicit the rating data via one click from the user. In addition, the architecture uses the ANFIS module of the Fuzzy Logic Toolbox of MATLAB as the core of the adaptive behavioral agent representing users' preference.

The ANFIS used in the proposed architecture is a five-layer network with three input variables (i.e. DP, DF, and DG) and one output variable (estimated r, or r0).

IV.Recommendation generation

Recommendation generation is the process that takes account of the input variables (i.e. DP, DF, and DG) and produces an estimation of the output variables (i.e. r0). The proposed architecture has three types of recommendation: information filtering, candidate expansion, and crowd recommendation.

The aim of information filtering is to prevent a customer from being overwhelmed by the amount of information, such as unfamiliar products or a long list of products to choose from. In the proposed architecture, information filtering is very straightforward in that the customers' FIS acts like a filter. When a customer c is browsing products in Pi, the DP, DF, and DG of each product p in Pi is passed to the FIS of the customer FISc, and the one with maximal r0 is recommended to the customer, i.e.

$$\forall c \in C, \quad p' = \arg\max_{p \in P_i} FIS_c(p, DP_p, DF_p, DG_p)$$

The recommendation can generate one item (maximal r i) or a number of items (e.g. top five ris). The process of recommendation generation is illustrated in Fig below:

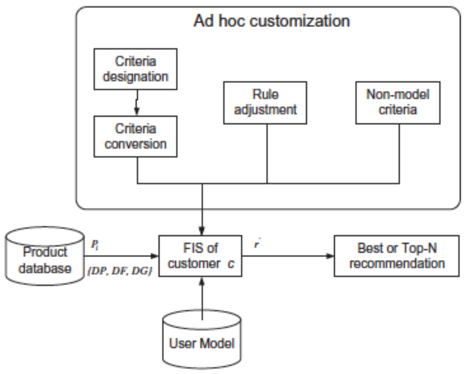

Fig.2. The process of the first type of recommendation: information filtering

Although the user model inferred from the rating data is used to represent the users' preference, there are situations when certain needs cannot be reflected in the user model, for example, when a user wants to use the search facility of an online shop to find products of a certain brand or price range. Such situations are handled in the ad hoc customization (the upper block of Fig. 2) in the architecture. There are three types of ad hoc customizations. The first type is criteria designation in which any of the three criteria considered in the user model is designated by the user in the form of search criteria. The designated criterion or criteria are then converted to non-fuzzy rule or rules to replace the corresponding fuzzy ones in the user model. This type of customization is suitable for users who are looking for products of specific specifications. The second type is rule adjustment in which any of the rules in the user model can be adjusted. For example, one may be searching for green product (mid-level greenness) with reasonable price tag (low price). Such linguistic values are then defuzzified and used, in tandem with the non-adjusted FIS rule in the user model, to filter the products. The third type is non-model criteria in which criteria not included in the user model are used to filter the products.

The non-model criteria are used as-is in the filtering of the recommendation result based on the user model. The second type of recommendation, candidate expansion, serves a different function from the first type. While the first type reduces the amount of information, the second type increases the amount of information. The process of candidate expansion is described as the following: When a customer is currently investigating a product that is satisfactory in terms of the criteria considered, the system can recommend other products that are similar in terms of the criteria. Let pn be the product that is currently viewed by a customer. The DP, DF, and

DG of pn first go through fuzzification that transforms the values into membership degrees and linguistic values. For example, {DP = - 2.3, DF = - 2.2, DG = - 2.2} is transformed into {cheap, feature poor, not green}. Then, the system queries the product database for products whose fuzzified DP, DF, and DG are the same as those of pn.
The third type of recommendation, crowd recommendation, makes use of the transactions of other customers to generate recommendations. The architecture first clusters the user into different groups according to the FIS rules of each customer so that customers in the same group have similar rules. Next, the architecture queries the transaction database to find out what products a group of like-minded customers have bought. The recommendation is then presented to a customer in that group based upon the result of the query. When a products' rating data is not enough or when a new customer has just begun to use the system, a quasi-conventional wisdom FIS is used. The rationale is as follows: When price (DP) is low and feature (DF) or greenness (DG) is high, it is a great bargain (hence favorable). When you pay more for more or less for less, it is a neutral condition (DP is high and DF or DG is high; DP is low and DF or DG is low). When you pay more for less, it is undesirable (DP is high and DF or DG is low). It is favorable when feature and greenness are mutually enhancing (DF is high and DG is high), undesirable when feature is poor and greenness is low (DF is poor and DG is low). It is neutral when the relationship between feature and greenness is antibiosis (DF is poor and DG is high; DF is rich and DG is low).

Conclusions
In this paper, we proposed using recommender systems to aid the green shopping process and to promote green consumerism based upon the benefits of recommender systems and the FITD compliance technique. A proposed recommender system architecture in the context of green consumer electronics was then described and discussed. Previous research on this type of recommender system used weights of certain green indices as inputs.

The architecture proposed in this paper accepts implicit and explicit criteria by modeling user preference and by considering ad hoc modification. The domain model is defined by the normalized scores of features, price, and greenness, and the user model by an adaptive FIS.

The architecture generates recommendations of consumer electronics to online customers by modeling their decision making with high-level decision variables. The distinctive part of the architecture is the mutual bilateral relationship of either symbiosis or antibiosis between the pairs of price vs. feature, price vs. greenness, and feature vs. greenness. User intervention is kept minimal, and on a par with commercially available recommender systems. The architecture has three types of recommendation. Information filtering recommendation uses the FIS of a customer to sieve through the product database to find the products that are likely to be preferable. Candidate expansion takes the fuzzified variables of a reference product to find other comparable products. Crowd recommendation tells a customer what other customers have bought by tapping into the wisdom of like-minded crowd. In addition, the architecture uses a quasi-conventional wisdom FIS to represent new users whose rating data are non-existent.

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