I

Intelligent Personalization Agent for Product Brokering

Sheng-Uei Guan
Brunel University, UK

INTRODUCTION

A good business to consumer environment can be developed through the creation of intelligent software agents (Guan, Zhi, & Maung, 2004; Soltysiak & Crabtree, 1998) to fulfill the needs of consumers patronizing online e-commerce stores (Guan, 2006). This includes intelligent filtering services (Chanan, 2001) and product brokering services (Guan, Ngoo, & Zhu, 2002) to understand a user's needs before alerting the user of suitable products according to his needs and preference.

We present an approach to capture user response toward product attributes, including nonquantifiable ones. The proposed solution does not generalize or stereotype user preference but captures the user's unique taste and recommends a list of products to the user. Under the proposed approach, the system is able to handle the inclusion of any unaccounted attribute that is not predefined in the system, without reprogramming the system. The system is able to cater to any unaccounted attribute through a general description field found in most product databases. This is useful, as hundreds of new attributes of products emerge each day, making any complex analysis impossible. In addition, the system is selfadjusting in nature and can adapt to changes in user preference.

BACKGROUND

Although there is a tremendous increase in e-commerce activities, technology in enhancing consumers' shopping experience remains primitive. Unlike real life department stores, there are no sales assistants to aid consumers in selecting the most appropriate product for users. Consumers are further confused by the large options and varieties of goods available. Thus, there is a need to provide on top of the provided filtering and search services (Bierwirth, 2000) an effective piece of software in the form of a product brokering agent to understand their needs and assist them in selecting suitable products.

A user's interest in a particular product is often influenced by the product attributes that range from price to brand name. This research classifies attributes as accounted, unaccounted, and detected. The same attributes may also be classified as quantifiable or nonquantifiable attributes.

Accounted attributes are predefined attributes that the system is specially customised to handle. A system may be designed to capture the user's choice in terms of price and brand name, making them accounted attributes. *Unaccounted attributes* have the opposite definition, and such attributes are not predefined in the ontology of the system (Guan & Zhu, 2004). The system does not understand whether an unaccounted attribute represents a model or a brand name. Such attributes merely appear in the product description field of the database. The system will attempt to detect the unaccounted attributes that affect the user's preference and consider them as *detected attributes*. Thus, detected attributes are unaccounted attributes that are detected to be vital in affecting the user's preference.

Quantifiable attributes contain specific numeric values (e.g., hard disk size) and thus their values are well defined. Nonquantifiable attributes, on the other hand, do not have any numeric values and their valuation may differ from user to user (e.g., brand name).

Related Work

User preference is an important concept in predicting customer behaviors and recommending products in personalised systems. Preference is the concept that relates a person to a target item that contains several kinds of attributes. Formalised preference models include positive and negative preference (Jung, Hong,

& Kim, 2002). Preferred items are known as positive preference, and nonpreferred items are known as negative preference.

A lot of research has targeted tracking customer preference in order to provide more customised recommendations. In the article by Guo, Miller, and Weinhardt (2003), agents operate on behalf of customers in e-commerce negotiations. The agents retrieve the required information about their customer's preference structures. In other research, Shibata, Hoshiai, Kubota, and Teramoto (2002) proposed an approach in which autonomous agents can learn customer-preference by observing the customer's reaction to contents recommended by agents. An intelligent preference tracking research done by Guan et al. (2002) made use of genetic algorithm-/ontology-based product brokering agents targeting m-commerce applications. The GA was used to tune parameters for tracking customer preference.

One of the main approaches to handle quantifiable attributes is to compile these attributes and assign weights representing their relative importance to the user (Guan et al., 2002; Zhu & Guan, 2001). The weights are adjusted to reflect the user's preference.

Much research aimed at creating an interface to understand user preference in terms of nonquantifiable attributes. This represents a more complex problem, as attributes are highly subjective with no discrete quantity to measure their values. Different users will give different values to a particular attribute. "MARI" (multi-attribute resource intermediary) (MARI) proposed a "word of mouth approach" to solve this problem. The project split users into general groups and estimated their preference to a specific set of attributes through the group the user belongs to. Another approach in handling nonquantifiable attributes involves requesting the user specifically for the preferred attributes. Shearin and Liberman (2001) provided a learning tool for the user to explore his preference before requesting him to suggest desirable attributes.

Most related approaches mentioned above can only identify specific tangible product attributes of interest to customers. In fact, many recommendation systems are not dynamic and flexible enough to adapt to the customer's unrecorded preference or preference changes. The attributes they are able to handle are hard-coded into the system and the consequence is that they are not able to handle attributes that lie beyond the predefined list. However, the list of product attributes is often large, possibly infinite. The approach used in related research may not be able to cover all the attributes, as they need to classify them into the ontology.

INTELLIGENT USER PREFERENCE DETECTION

The proposed approach attempts to capture user preference on the basis of two quantifiable accounted attributes, Price and Quality. It incrementally learns and detects any unaccounted attribute that affects the user's preference. If any unaccounted attribute is suspected, the system attempts to come up with a list of highly suspicious attributes and verify their importance through a genetic algorithm (Haupt & Haupt, 1998). Thus vital attributes that are unaccounted for previously will be considered. The unaccounted attributes are derived from the general description field of a product. The approach is therefore generic in nature, as the system is not restricted by the attributes it is designed to cater to.

Overall Procedure

As the system is able to incrementally detect the attributes that affect user preference, it first retrieves any information captured regarding the user from some previous feedback and generates a feedback in the form of a list of products for the user to rank and attempts to investigate the presence of any unaccounted attribute affecting the user's preference. The system will compile a list of possible attributes that are unaccounted for by analyzing the user feedback and ranking them according to their suspicion levels. The most suspicious attributes and any information captured from previous feedback are then verified through a genetic algorithm. If two cycles of feedback are completed, the system attempts to detect any quantifiable attributes that are able to form a generic group of attributes. The system finally optimizes all information accumulated by a genetic algorithm and recommends a list of products for the user according to the preference captured.

Tangible Score

In our application, we consider two quantifiable attributes, price and quality, as the basis in deriving the tangible score. The effect of these two attributes

Related Content