Interest-Based Personalized Recommender System

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***Abstract* — The challenge in a recommendation system is to help users in dealing with the problem of information overload. Personalization, when applied to recommendation in e-market can transform a product into a dedicated solution for an individual. In this paper, we describe the method used for personalization of recommendations generated by an Interest-Based Recommender System (IBRS). This paper proposes a design framework for a personalized multi-agent IBRS. The IBRS is an agent- based recommender system that takes into account user's preferences to generate recommendations. The system is based on the agents having Belief-Desire-Intention (BDI) architecture. These BDI user agents are empowered with cognitive capabilities and interact with recommender and other user agents using argumentation. The explanation process uses argumentation so that the recommender can look deeper into the reasons behind user's likes and dislikes. The IBRS considers user's feedback for recommendation repair action. This results in improvement of the personalization process. The experimental study is conducted for Travel Recommender System to show that personalized interest-based recommendations improve quality.**

Keywords- Recommender system; personalization; BDI agents; argumentation

I. INTRODUCTION

Over the years, the affluence of electronic commerce has changed the traditional trading methods, therefore more and more people are tempted to conduct electronic shopping. However, the exponentially increasing information along with the rapid expansion of the business web sites is the major cause of the problem of information overload. This makes the consumer spend more and more time on the internet to separate the relevant information from the irrelevant one.

One way to overcome the above problem is to develop recommender systems [2, 10, 11] for filtering information and recommending items which are likely to be of interest to the user. The use of personalization techniques in e-commerce, for structuring suitable recommendations for users is common today. The classification of personalization techniques [19] is based on (1) content; (2) collaborative-filtering; (3) hybrid; (4) knowledge (5) model-based. Personalization in recommender systems can be empowered if the systems are provided with the ability to qualitatively exploit data and reason beyond user's personal interests. In the view of [5, 6], the optimal technology for recommender systems run by E-commerce sites will be persistent, and partially automatic. This requires some input from customers to increase interactivity. These requirements can be fulfilled by use of argumentation [3] and user modeling in the recommender systems.

In this direction of research, the **Interest-Based Recommendation (IBR)** [13] is a technique that uses interactive agent-based argumentation to generate interesting recommendations. Most existing literature [3, 4, 8] supports the claim that argumentation is useful in various kinds of user support systems like expert systems, systems for automated negotiation, recommender systems etc. The Interest-Based Recommender System (IBRS) is an agent-based recommender system using argumentation, which takes into account user's preferences and their requirements' feasibility to generate relevant recommendations. IBR (Interest-Based Recommendation) is structured on an argument-based framework [13] for generating recommendations for the users (and automated user agents). IBR rests on the idea that the agents can explicit the goals underlying the required recommendation and discuss alternative ways to achieve them. IBRS enables an autonomous multi-agent recommender with inference abilities, so that it can explore and reason about the deep underlying motives behind user's personal preferences. By doing so, it is able to resolve the conflicts between preferences and recommendations, and thereby give suggestions accompanied by convincing arguments [15]. This makes the system more transparent [18] to the user as it enables them to look at the reasons behind recommendations. During the extended interaction with the IBR agent, the user agent may acquire the information necessary to establish modified or new preferences. This helps in improving the user acceptability of the generated personalized recommendations. These agents work cooperatively for better qualitative and quantitative results even when the human user is not involved directly.

In this paper, we describe various methods used for the personalization of interest-based recommendations and

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propose a design framework for a personalized multi-agent IBRS. We extend the present day recommender systems by making them more effective, so that a higher number of suitable recommendations are generated and hence accepted by the users. In the following section, we discuss the various approaches along which personalization systems can be classified.

II. Personalization in Recommender Systems

A personalized recommender system can provide information in diverse ways [19]. It aims to provide users with what they need without requiring them to ask for it explicitly. This means that a personalization system must somehow infer what the user requires based on either previous or current interactions with the user. This can be done by recording and analyzing a customer's previous preferences. For such personalized recommender systems a customer's personal information is first collected, and then the system analyzes customer's preferences to build a user model. This approach is often referred to as *content-based filtering*. An alternative approach to recommendation [5] is to not only use the profile for the active user but also other users with similar preferences, when recommending items. This approach is referred to as *collaborative filtering*. As both the techniques have their own pros and cons, therefore a combined approach referred to as *hybrid recommender system* was found to be better [17].

To boost user interactivity with the recommender system one can apply either reactive or proactive approaches to personalization [16]. The former approach involves a conversational process that requires explicit interactions with the user either in the form of queries or feedback. Proactive approaches on the other hand learn user preferences and provide recommendations based on the learned information, not necessarily requiring the user to provide explicit feedback to the system for recommendation. Personalization of recommender systems also vary in the kind of information they use to generate recommendations. Typically, the information utilized by these systems include: item-related and user-related information. Lastly, personalization of recommendation can also be classified depending on whether the approach to personalization is memory-based or model-based [19]. Memory based systems simply memorize all the data and generalize from it at the point of generating recommendations whereas model-based systems work in two phases for recommendation generation. The first phase is carried out offline, where user data is collected and a user-model is generated for use in future online interactions. The second phase is carried out in real-time as a new visitor begins an interaction with the Web-site. Data from the current user session is obtained and using the user-models, personalized recommendations are generated.

After looking at the different categories of classifications for personalization, we give an outline of the application of varying degrees of personalization to produce recommendations. The degree of personalization encompasses several issues including both the accuracy and the usefulness of recommendations. The work in [6] specifically identified three common levels as follows. First, when recommender applications provide identical recommendations to each customer, the application is classified as *non-personalized*. Second, recommenders that use current customer inputs to customize the recommendation according to the customer's current interests provide *ephemeral personalization.* Finally third, the most highly-personalized recommender applications use *persistent personalization* to create recommendations that differ for different customers, even when they are looking at the same items. Also, the work on persuasive recommendation [1] and visual interface for critiquing-based recommender systems [7] are examples of the ongoing research work in the field of persistent personalization in recommendation.

The personalized recommendation process can be automated to a required degree depending on the needs of the customer and the e-business. Schafer and Konstan in their work [6], present a taxonomy based on the features most important to customers of the e-commerce sites. The two key dimensions in the taxonomy are the degree of automation, and the degree of persistence in the recommendations. As per the taxonomy, the optimal technology for personalizing the e-commerce recommender systems will be persistent, and only partially automatic, requiring some input from customers and rewarding the customers with valuable recommendations based on their input.

Comparing with the state-of-the-art, IBRS is one such multi-agent recommender system that is based on cognitive agents capable of inferencing, interacting and sharing knowledge using argumentation. All this to provide and enhance the quality of personalized information services. The system requires minimum input from the user and can work even when the user is offline. As per the taxonomy mentioned above, personalization in the proposed Interest-Based Recommender Systems (IBRS) is persistent and partially automatic and hence suitable to be run by e-commerce sites. Since IBRS is partially automatic, therefore it supports user interactivity both reactively (it's reactive when the user gives an explicit online input to the personalized system) and proactively (when the automated user agent interacts implicitly on the consumer's behalf with the recommender agent). The personalization approach in IBRS is hybrid as the recommendation agent uses both content-based filtering and collaborative filtering. It's model-based since IBRS models the consumer profile to build a user agent based on the profile. IBRS being hybrid in nature utilizes both item-related and user-related information to generate recommendations. Section 3 outlines a design framework for the personalized multi-agent IBRS and present the system overview. Section 4 gives the experimental study.

III. Developing the Personalized IBRS

As described above, the major tasks of a personalized recommender system include collecting a customer's personal interests, building a model to describe the information collected, and managing a customer's information. Hence, an agent-based methodology is appropriate in developing such recommender systems [12]. We give a framework for the proposed personalized agent-based recommender system. It can solve problems in a distributed way. Under this arrangement each agent performs a specific work and different agents work simultaneously to achieve the overall task. Figure 1 illustrates the structure of our recommender system. Our proposed framework consists of two phases: *the Modeling phase* and the *Recommendation phase.* Different agents perform their functions in order to achieve the objective of the particular phase.

A. System Overview

In the modeling phase, a ***user agent*** is activated when a customer logs into the system. The agent collects customer's current requirements, interests and preferences to include them into the user model. It can also communicate with other user agents to gather information. The agent maintains its mental attitudes in a persistent belief base. Argumentation is used for the revision of belief base [9] by keeping the belief base consistent whenever information is included or discarded. We use two main user modeling approaches: manual explicit modeling and automatic implicit modeling. The former approach requires users to provide explicit information about their preferences and needs. In the latter approach, gathering information is done rather automatically based on the online user behavior, agent dialogues, interactions and feedback based on recommendation utility. The originality of our approach is that, we use agents' behavior and their argumentation dialogues in order to revise the users' model. In the framework depicted in Figure 1, the ***user agent*** is accountable for creating and maintaining the user model. The user agent collects information both in implicit and explicit ways. Therefore, the user agent play the role of information collector, and a customer can activate it to gather his personal preferences about the products.

In the recommendation phase, the ***recommender agent*** employs a group of agents who perform their individual tasks and work collectively to generate interest-based recommendations for the user. There is an ***information management agent*** that takes the responsibility of analyzing and transferring a product item into a set of attributes defined by the system and provides a utility assessment for the product [13]. For example, we can use some features, such as destination, schedule, air-fare and hotel-stay, to represent a travel package. This agent maintains information about product items with values quantitatively indicating how much a customer likes them. Whenever a customer's personal profile is updated (by the user agent) while his preferences change, the same is communicated to the information management agent and updated in its information base. Since the customers' profiles are maintained by the user agent, the only way for other agents to access the information recorded in the consumers' profiles is thus through the approval of this agent. This maintains privacy and at the same time allows controlled knowledge sharing with the other agents.

There is another agent known as ***recommendation agent***. It keeps acting whenever a customer enters the system. With the learnt customer model from user agent and product preferences from information management agent, this agent can decide whether to recommend a specific product item to the corresponding customer or not. These recommended objects are obtained by using a range of interest-based recommendation strategies [14] based mainly on utility assessment [13, 15], content based filtering (CBF) and collaborative filtering (CF), where each is applied separately or in combination.

The recommendation agent is also responsible for evaluating the recommending performance. It does so by finding out the number of correct recommendations and their user acceptance rate. This evaluation is used to determine whether or not to trigger a recommendation repair activity. Repair helps in improving current recommendations by making them suitable according to user's preferences. It can also reveal previously unknown personal interests of the users. Repair can be manual (where inputs can be given by a human through a visual and interactive interface) or automated agent-based (where user agent and recommendation agent interact using argumentation dialogue to share knowledge and discover alternate options). Repair helps in improving the recommendation qualitatively and quantitatively [14] and hence increases the persuasive power of the system. This is because it provides the user with explanations and attempts to further explore user's goals to uncover the underlying sub-goals. Therefore, our argumentation-based IBRS enables agents with improved decision making [8] as well. The recommending performance result is also reported to the information management agent. Based on this result, the information management agent can then determine user's likes and dislikes. To determine how a customer likes a certain product, we calculate the weighted utility of the product based on the product's worth and user's preference [13].

B. Distinctive Features of an IBRS

Following the comparison of IBRS with state-of-the-art in previous section and the system description as given above, we state that in the proposed system, recommendation is not just about putting forward suitable suggestions to a user. Novelty of IBRS is that, while

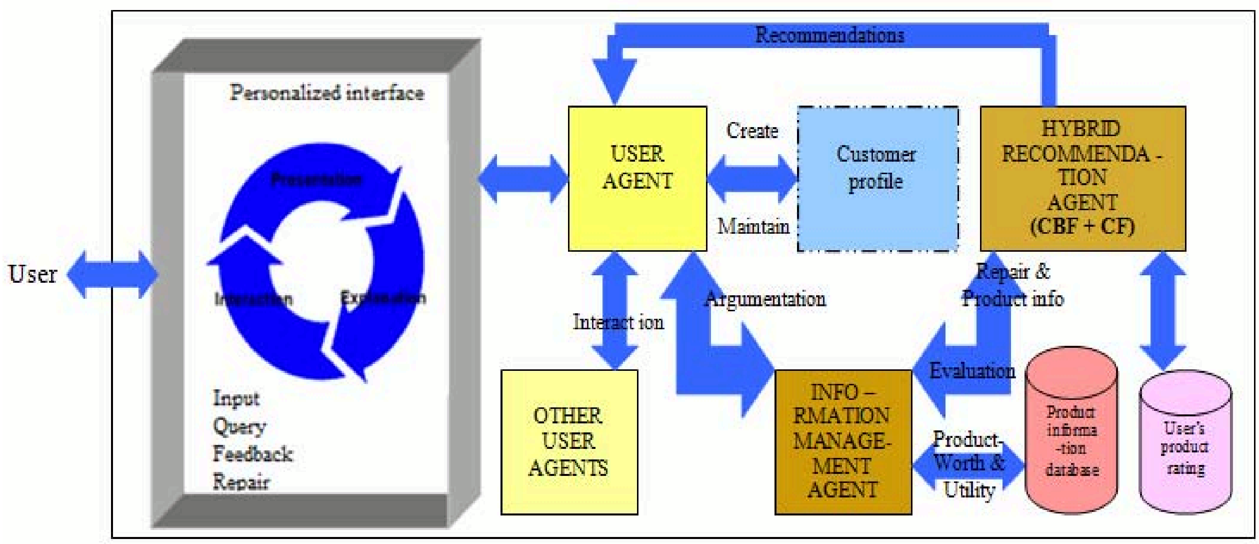

Figure 1. The framework for the proposed agent-based personalized IBRS

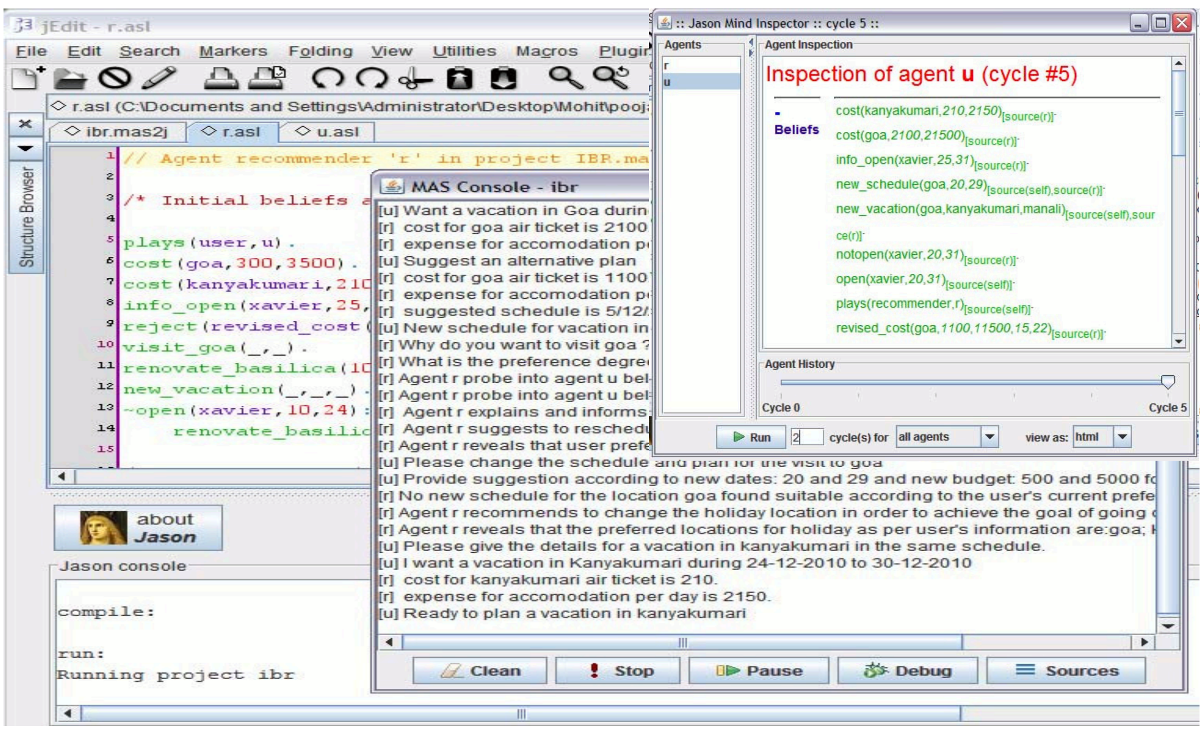

Figure 2. A snapshot to show agent interaction in the system and agents' beliefs getting updated as more information flows into the system

designing an effective personalized recommendation it takes the multiple facets of recommendation into consideration. These are: *interaction, explanation and presentation*. IBRS not only focus on how and what to present and explain to the user but it also takes a deeper look at the user's interactive participation in the recommendation process. To enhance *interactivity* and *autonomy* in the recommendation process, our system is based on BDI agents. These agents are empowered with cognitive capabilities and can interact to transfer knowledge and negotiate using argumentation with the recommender agent on behalf of the human user. This helps in automation of the recommendation process and enhances both offline and online consumer interactivity with the system and the other users. In turn, the *explanation* process also improves as by using argumentation, the recommender can look deeper into the reasons behind user's likes and dislikes. It can explore the hierarchical goal structure of the BDI user agents to uncover any hidden conflicts and thus resolve them. Also, the system becomes more transparent for the user as they can look beyond the suggestions presented to them by the recommender. The users then accept a recommendation, only if a convincing case is presented to them by the recommender. Finally, the recommendations are *presented* to the user keeping in view their personal requirements. This means that the same set of recommendations may have different visual presentations for different type of users. The kind of visual appearance is associated with user's preferences. This is persistent personalization and it enhances the persuasive power of the recommender system. Hence, with improvement in the recommendation quality, a higher number of personalized recommendations by IBRS get accepted by the users.

IV. RESULTS

To evaluate the presented system and the performance of our personalization approach for generating recommendations according to customer's interests, we developed an agent-based recommender system using argumentation for a case study on travel recommendations. This system was developed using Jason for building BDI agents enabled with inferencing and interaction capabilities. For simplicity, in our system we focused more on the explanation and interaction aspects of the interface, rather than the presentation and visualization of the results. We have conducted several random simulation runs between an automated user agent and interest-based recommender agent based on travel recommender system case study. The simulations were conducted using randomly generated input domains and several iterations of recommendation were performed. We studied how the preferences of consumers evolved and changed during knowledge transfer using argumentation and recommendation repair in IBRS. This resulted in a higher number of interest-based recommendations getting accepted. IBR also provided quantitative cost benefits to the user. As the users gain experience, a gradual decrease in knowledge transfer shows that lesser argumentation is required. This was because the user and the agents become more aware steadily. The snapshot in figure 2 shows agent communication and changes made in the beliefs of a user agent after new information is communicated by recommender using argumentation.

We observed qualitative and quantitative performance of IBRS based on the following parameters: number of correct and acceptable recommendations generated that reflects the qualitative benefit in terms of the number of user goals reached; number of knowledge transfers or updates reflects interaction between the agents and; the quantitative benefit is calculated in terms of cost saved. The first two parameters reflect qualitative benefits whereas the last one represents quantitative benefits of personalized IBR. These are measured against the increasing experience of the users with rise in the number of recommendation iterations. The increase in the experience of users is represented as the increase in the number of interactions between user agent and multi-agent recommender. A recommendation is accepted if it has a utility value higher than or equal to the expected utility calculated by the user agent. During our experimental study (refer graphs in figure 3 - 5) we observed that there was higher uncertainty amongst user agents with lesser experience in interaction with recommender. Therefore, the disparity between the expectation of a new user and system's recommendation was more. As a result there were lower chances of successful outcomes and user satisfaction whenever the recommender agent encountered a less experienced user agent. But the major qualitative interest of the agents (achieving their goals successfully) was satisfied anyway. The reason is that an IBR agent tends to probe into sub-goals routinely (with user's consent) if a user agent is not satisfied with the recommendations concerning its goals. By exploring the default hierarchical goal structure of BDI user agents, the recommender is able to locate actual cause of conflict between preferences and recommendations. Hence personalized recommendations can be improved further by resolving such conflicts related to user's preferences. We also observed that, with increase in the number of recommendation iterations between automated user and personalized multi-agent recommender, the benefits kept on increasing substantially.

V. CONCLUSION AND FUTURE WORK

In this paper, we have indicated the importance of providing personalized information services in improving the quality of the recommendations in e-commerce. To realize this, we develop a personalized recommender system based on cognitive agents using argumentation. This system also enhances *interactivity* and *autonomy* in the recommendation process, empowering the recommendation technologies. The design framework for personalizing a new recommendation technique known as IBR (Interest-Based Recommendation) is presented in this paper. We give a system overview for the personalized IBRS, which works in the multi-agent settings and aims at providing the customers with best products based on their personal preferences. In this recommender system each agent is responsible for a certain sub-task, such as information gathering, user modeling, information managing, and recommendation generation. To assess our personalization approach in IBRS, we experimented with a travel recommender case study. Based on user profile, the recommendation agents prioritize the products according to their total utilities. Any conflict between the preferences and product recommendations is resolved using argumentation and repair process. Therefore, in this system, a preference and utility-based method is employed to generate recommendations. The experiment showed that the users were satisfied with the quality of recommendations and hence the acceptance rate of the interest-based recommendations also improved in the system.

Our work presented here points to some prospects of future research. We are currently exploring several techniques and strategies in the user modeling and recommendation generation in more detail, and performing more evaluations. We are also focusing on the presentation and visualization of the recommendation results and the role it plays in improving an Interest Based Recommendation.

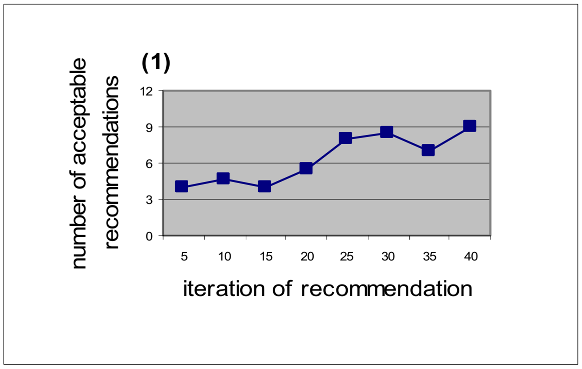

Figure 3. A higher number of recommendation acceptability indicates the improved quality

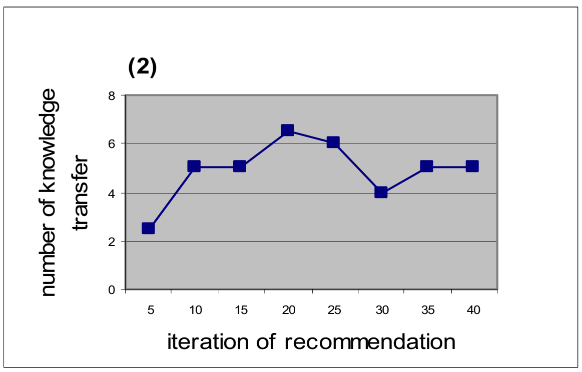

Figure 4. An initial increase in the information flow also stabilizes gradually

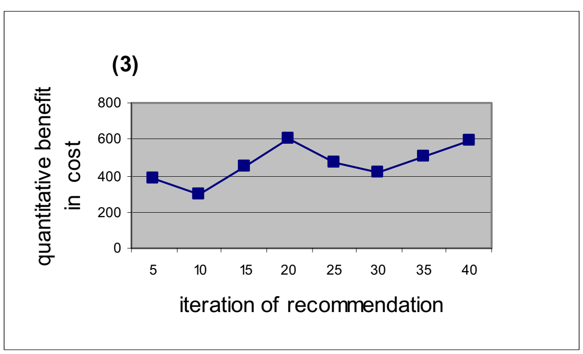

Figure 5. Personalized recommendation using argumentation also provides users with cost benefits

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