Building an expert travel agent as a software agent

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Abstract

In this article, we present an expert software agent, named *Traveller*, that assists users in the tourism and travel domain. This agent combines collaborative filtering with content-based recommendations and demographic information about customers to suggest package holidays and tours. The combination of techniques in this hybrid approach takes advantage of the positive aspects of each technique and overcomes the difficulties shown by each of them when used in isolation. The results obtained when evaluating the agent demonstrate the benefits of using a combined technique to specify experts' knowledge.
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1. Introduction

A software agent acts as an assistant for users in a certain domain, for instance travel and tourism, and aims at providing these users useful help by, for example, recommending them potentially interesting tours or holidays. To assist users, a software agent needs knowledge not only about the application domain (resorts, hotels, airlines) but also about customers' preferences and interests. If the agent does not have rules that tell it what to do or what to recommend, it has to obtain the necessary knowledge from the observation of customers and their actions in order to become an expert in the domain we are considering.

Expert agents have been used to make recommendations of interesting items in a wide variety of application domains, such as Web page recommendation (Lieberman, Fry, & Weitzman, 2001), digital news (Resnick, Iacoyou, Suchak, Bergstrom, & Riedl, 1994), e-commerce (Schafer, Konstan, & Riedl, 2000), movie recommendation (Salter & Antonopoulus, 2006), restaurant recommendation

(Burke, 2000), among others. A variety of approaches have been used to perform recommendations in these domains, including content-based, collaborative, demographic, knowledge-based and others (Montaner, Lopez, & de la Rosa, 2003). In collaborative filtering approaches, recommendations are made by matching a user to other users that have similar interests and preferences, and suggesting items these others like. One of the disadvantages of this approach used in isolation is that the recommender system or agent cannot recommend an item until several users have rated it. This is known as the cold-start problem. In content-based approaches, recommendations are made considering content characteristics of the items the user has previously enjoyed. The problem with this approach is that the recommender system only recommends items closely related to those the user has liked in the past; no novel items are suggested. Demographic recommenders aim at categorizing users based on their personal attributes as belonging to stereotypical classes.

To overcome the difficulties of the most widely used approaches for making recommendations and to exploit their positive aspects, some authors have combined them into hybrid recommenders (Balabanovic & Shoham, 1997; Billsus & Pazzani, 2000; Burke, 2000; Salter & Antonopoulus, 2006). Hybrid recommenders generally combine

collaborative and content-based methods. For example, in Salter and Antonopoulus (2006) the authors combine collaborative and content-based filtering to recommend movies. The agent, named *CinemaScreen*, executes content-based filtering on a results set generated through collaborative filtering.

In this work, we present *Traveller*, an expert agent in the tourism and travel domain, which combines content-based user profiles, collaborative filtering, and also demographic user profiles to make recommendations. The agent assists users by suggesting them package holidays that are presumably interesting for the user according to his/her profile. The results obtained with our hybrid approach are promising with respect to the approaches used separately.

The article is organized as follows. In Section 2 we briefly describe the main characteristics of the most common recommendation approaches. In Section 3 we describe *Traveller*'s functionality. Then, in Section 4 we present our hybrid approach for recommending tours and holidays. In Section 5 we present some experimental results. Section 6 describes some related works in the domain of tourism recommendation. Finally, in Section 7 we present our conclusions and future work.

2. Recommendation approaches

A variety of approaches have been used to make recommendations. We briefly describe them below.

The content-based approach is based on the intuition that each user exhibits a particular behavior under a given set of circumstances, and that this behavior is repeated under similar situations. A content-based recommender learns a model of the user interests based on the features present in items the user rated as interesting either by implicit or explicit feedback. Thus, a user profile contains those features that characterize a user interests, enabling agents to categorize items for recommendation based on the features they exhibit. The user profiles derived by content-based recommenders depend on the learning methods employed. For example, text recommendations in agents like *NewsDude* (Billsus & Pazzani, 1999) or *NewsAgent* (Godoy, Schiaffino, & Amandi, 2004) use the words appearing in documents as features.

In contrast to the content-based approach, in which the behavior of users is predicted from their past behavior, collaborative filtering (CF) is based on the idea that people within a particular group tend to behave alike under similar circumstances. In the collaborative filtering approach the behavior of a user is predicted from the behavior of other like-minded people. A user profile in this approach comprises a vector of item ratings, with the ratings being binary or real-valued. The aim of collaborative filtering for the active user u_r is to predict the score for an item i_j, which has not been rated yet by u_r, in order to recommend this item. By comparing the ratings of the active user to those of other users using some similarity measure, the system or agent determines users who are most similar to the active one, and makes predictions or recommendations based on items that similar users have previously rated highly.

It is possible to identify two major classes of collaborative filtering, memory-based and model-based. Memory-based collaborative filtering uses nearest neighbor algorithms that determine a set of neighboring users who have rated items similarly, and combines the neighbors' preferences to obtain a prediction for the active user. Model-based collaborative recommenders generalize a model of user ratings using some machine learning approach and use this model to make predictions. Memory-based is the most popular prediction technique in CF applications since it is more efficient in medium-size matrices (Resnick et al., 1994). However, if the user-item matrix is large, the nearest neighbor computation becomes expensive. Then, model-based recommenders like (Zhang & Iyengar, 2002) are a suitable alternative.

In contrast, demographic recommenders aim at categorizing users based on their personal attributes as belonging to stereotypical classes. In this case, a user profile is a list of demographic features that represent a class of users. This representation of demographic information in a user profile can vary greatly. For example, Pazzani (1999) extract features from home pages to predict the preferences for certain restaurants, and Krulwich (1997) use demographic groups from marketing research to suggest a range of products and services.

Finally, in knowledge-based approaches recommendation is based on inferences about a user's needs and preferences, which are performed using some functional knowledge, that is, there is knowledge about how a particular item meets a particular user need and one can therefore reason about the relationship between a need and a possible recommendation. The user profiles in knowledge-based recommenders can also take different forms, since they can consist in any knowledge structure that supports inference. The restaurant recommender *Entrée* (Burke, 2000) makes recommendations by finding restaurants in a new city similar to restaurants the user knows and likes based on the knowledge of cuisines to infer similarity between restaurants. Ontology-based user profiling is also an example of knowledge-based recommendation. For example, *Quickstep* (Middleton, Shadbolt, & De Roure, 2004) is a recommender system that recommends on-line research papers to researchers by modeling user interests with an ontology of research paper topics.

The next section describes how CF, demographic information and the content-based approach can be combined to make recommendations in the tourism domain, taking advantage of the benefits of each technique.

3. *Traveller*'s overview

The expert agent *Traveller* suggests users package holidays. Fig. 1 shows an overview of *Traveller*'s functionality. The tour packages available are defined in a Travel Agency