Recommending Travel Packages Upon Distributed Knowledge

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Introduction

The internet is a rich source of information where the user can find almost everything s/he is looking for. In the last years, the internet has grown exponentially and the information overload problem has appeared. In order to deal with these issues, Recommender Systems have been developed (Resnick *et al.* 1994). The main characteristic of recommender system is the ability to aggregate information and to match the recommendations with the information people is looking for.

Despite recommender systems being efficient, for some recommender applications it is possible that a single information source does not contain the complete information needed for the recommendation. For example, in the tourism domain, the travel package recommendation is composed by several information components such as flights, hotels and entertainment, and specific knowledge to assemble all the components is necessary. Due for the distributed nature of the information, multiagent systems (MAS) are promising to retrieve, filter and use information relevant to the recommendation. MAS can be use to avoid unnecessary processing and can be built to deal with dynamic changes in the information source.

We propose a multiagent recommender approach where the agents work in a distributed and cooperative way, sharing and negotiating knowledge with the global objective of recommending the best travel package to the user. In order to achieve this goal, this approach uses a combination of a distributed truth maintenance system (TMS) as in (Huhns & Bridgeland 1991) and a distributed constraint optimization (DCOP) (Modi *et al.* 2003). The distributed TMS helps to keep the integrity of the knowledge base of each agent, while the distributed constraint optimization approach is used to help the coordination among the agents during the search processes. This novel combination is applied in the tourism domain to be validated in a real-world application.

The Proposed Approach

Planning a travel is not an easy task for the travel agent. He needs to know every detail about the destination chosen by the passenger and all details involving the whole trip such as the timetable of attractions, hotels or flights. Using this travel recommendation example, we have created a basic multiagent scenario with a group of agents in the community with a common global goal (the recommendation) and separate individual goals (the component that each one needs to search). A community *C* consists of *n* agents $a_1, a_2, ..., a_n$, each located inside a predefined range of action *R*. There are two different types of agents within the community: the Assembler - *Asm* and the Searcher - *Src*.

Asm agents are responsible for the communication with the user and to show the final recommendation. Each creates a list of tasks (flights, hotels and attractions) that is sent to the *Src* agents. The community may have several *Asm* agents and each one creates a different recommendation tailored to each user. *Scr* agents are responsible for choosing a task from a list. Each *Src* agent has its own local knowledge base (KB) and the reason maintenance system component (*TMS*), responsible for maintaining the integrity of the transferred information among the agents and their KBs.

We adopted the ATMS (de Kleer 1986), creating a rule base - *R*, consisting of causal and logical rules derived from prior experience of the travel agents, a premise set - *I* that are the user's preferences, and an assumption set - *A*, that contains the assumptions of the agents. Based on these model components, the agents derive propositions - *rec* that represent parts of the final recommendation that will be presented by the *Asm* agent.

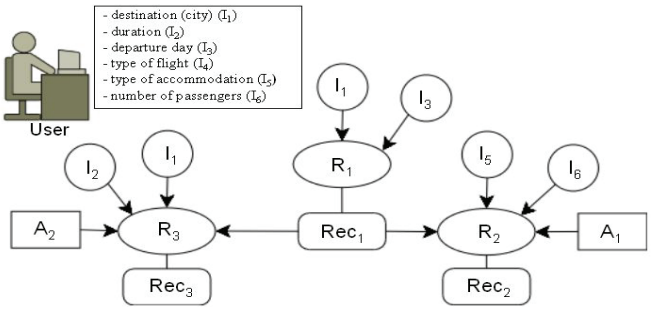

Figure 1: ATMS representation in the multiagent scenario

Figure 1 shows a piece of the ATMS representation. The first proposition (rec_1) depends on two preferences informed by the user: the city destination (I_1) and the depar-

ture day (I_3). The second proposition (rec_2) finds the best hotel for the user. The premises *day* and *time of arrival* come from the flight's information. If the user did not inform the type of accommodation then the agent uses the first assumption A_1 assuming that the type of accommodation is economic. The proposition rec_3 depends on the destination, the duration and the flight's information. In order to search for the best attractions, for example, the agent needs information about the flights (duration of the package for example). Trying not to delay the recommendation process, this agent assumes a standard duration and starts its process, looking for attractions in the destination that fit in the period the user wants to stay there. The fact of assuming some information is very common in the real travel recommendation process. In the most cases the passenger is not sure about what he wants to do exactly, he depends on the travel agent recommendation. Table 1 shows some examples of rules that have been defined to the travel package recommendation process. Each rule is used to derive a proposition.

R_1	I_1 (destination) $\wedge I_3$ (departure) $\rightarrow rec_1$
R_2	I_5 (accommodation) $\wedge I_6$ (passengers) $\wedge A_1 \rightarrow rec_2$
R_3	I_2 (duration) $\wedge I_1$ (destination) $\wedge A_2 \rightarrow rec_3$

Table 1: Example of Rules

Contradictions between the derived propositions in the recommendation process and what is demanded during the communication between the agents are viewed as signals that the set of assumptions should be modified. For example, if a proposition was derived with the information that the Louvre museum opens from Tuesday to Sunday but the agents are looking for a museum that opens on Monday, there is a contradiction and new assumptions that are compatible with the information needed should be generated using the ATMS. Assumptions are important because they affect the travel package recommendation and retracting these assumptions may change the recommendation. In the previous example, the agent has assumed that the user wants to stay in economic accommodation but if this hypothesis is not right and the user wants a first class hotel, there is a contradiction and the assumption should be retracted and a new hotel should be recommended.

In a multiagent scenario like this, it is necessary that agents coordinate their actions, especially when they need to communicate to each other and exchange information. The *Src* agents do not have a global view, goals and knowledge are local, making it difficult to cooperate. For this reason, we propose the combination of the TMS with the DCOP. This combination ensures that agents will coordinate their decision-making in this domain. A DCOP consists of *n* variables $V = x_1; x_2; ...; x_n$, each assigned to an agent, where the values of the variables are taken from a discrete domain $D_1; D_2; ...; D_n$, respectively. Agents choose values for the variables trying to optimize a global objective function. Two agents are considered neighbors if they have a constraint between them. In our scenario, two agents only have a constraint between them if they are inside the same community. The constraint between agents corresponds to the information the *Src* agent needs and the information it gets from other agent.

The special feature here is the cost function defined that works as a local similarity between the neighbor agents. In the point of view of an agent, getting the lower cost means finding a neighbor with the information it needs. It means that the higher the difference between the agents, the higher the cost. The agent communicates to its neighbors and to find a perfect match or at least the most similar information, it calculates the distance between the information the agent (a_u) is looking for, represented by i_{a_u} and the information the other agent (a_s) has, represented by (i_{a_s}) :

$$d(a_u, a_s) = sim(i_{a_u}, i_{a_s})$$

where $sim(i_{a_u}, i_{a_s})$ represents the local similarity between the features. In numeric features, this value is given by the Euclidean distance between the values. In symbolic features the local similarity is $\{1 : i_{a_u} = i_{a_s}; 0\}$. This cost function ensures that the agent will always return some information to the *Asm* agent.

Concluding Remarks

This abstract is a preliminary report that proposes and analyzes the utilization of distributed TMS and DCOP applied in a recommender system in the tourism domain. This combination can yield good recommendations, considering this as a complex domain that needs specific knowledge distributed over different sources. The travel package recommendation is an interesting process and there are few multiagent approaches exploring it. Another interested point is that the ideas presented here are being validated in a real scenario. A knowledge acquisition was done and the agents' knowledge bases were created with information from a real travel agency.

References

de Kleer, J. 1986. An assumption-based tms, extending the atms, and problem solving with the atms. *Artificial Intelligence* 28(2):127–224.

Huhns, M. N., and Bridgeland, D. M. 1991. Multiagent truth maintenance. *IEEE Transactions on Systems, Man, and Cybernetics* 21(6):1437–1445.

Modi, P. J.; Shen, W.-M.; Tambe, M.; and Yokoo, M. 2003. An asynchronous complete method for distributed constraint optimization. In *Second international joint conference on Autonomous agents and multiagent systems*, 161–168. New York, NY, USA: ACM Press.

Resnick, P.; Iacovou, N.; Suchak, M.; Bergstrom, P.; and Riedl, J. 1994. Grouplens: An open architecture for collaborative filtering of netnews. In *Proceedings ACM Conference on Computer-Supported Cooperative Work*, 175–186.