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Toward Mitigating Tourists' Indifference in POI Recommendation Systems Using MAS

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***Abstract*— POI recommendation is one of the artificial intelligence techniques used to personalize a user's experience in the field of smart tourism. However, this technique suffers from the problem of sparse data due to the indifference of the ratings of the places visited by the user. To mitigate this problem, we propose in this work a Multi-agent System for Reconciling POI Recommendation Algorithms (MSRPRA) using three types of POI recommendation algorithm that exploit user ratings, check-ins during visits and explicitly declared trust relationships between users. Additionally, a voting system is employed to merge the results of these three algorithms.**

Keywords—Point of Interest recommendation; multi-agent system; collaboratif filtring;

I. INTRODUCTION

Nowadays, artificial intelligence (AI) is integrated in several fields such as e-tourism [1], e-commerce [2], etc. The recommendation is one of the techniques of AI that can be used by these fields to personalize and improve the user experience. This technique uses AI algorithms (deep learning [3], decision tree [4], etc.) to exploit the potential of the vast amounts of data collected during the use of systems to make them more intelligent.

These systems include smart tourism, which uses ubiquitous technologies and AI algorithms to enhance the tourist experience by assisting them on their trip to discover new tourism destinations [5]. Artificial Intelligence is currently supporting this field to make the tourist experience increasingly personalized according to the needs of each tourist [6]. Indeed, to recommend the most relevant places for tourists, AI recommends Points of Interest (POIs) using the tourist's profile, which can either be (1) declared by the tourist through their demographic data, preferred categories, etc., or (2) inferred from their evaluations, the check-ins he carried out during the tourist visit, etc [7]. In this work, we will focus on the implicit profile of the tourist, which can be formed using information gathered from the visit's history such as browsing duration, clicks, comments, etc. [8]. Our interest in this type of profile is justified by the fact that tourists do not tend to express their preferences or personal data when using smart tourism tools [7].

In the literature, Recommendation Systems (RS) [8] are divided into two main classes: (1) Collaborative Filtering Recommendation Systems (CFRS) and (2) Content-Based Recommendation Systems (CBRS). The CBRS [7] match the content description of the POIs with the tourist's profile, whereas the CFRS [9] [10] calculate the similarity between tourists to predict the POIs to visit. These systems rely on the explicit ratings of the POIs given by tourists to compute similarities used to initiate their recommendation processes. However, the majority of users tend to overlook rating the places they've visited, which can lead to cold-start problems due to data scarcity. To resolve this cold-start issue in RS due to the indifference of POI ratings, several studies combine the results of multiple recommendation algorithms [11]. This type of solution helps mitigate data scarcity problems in ratings by incorporating other types of data such as check-ins or the number of comments per POI. Nevertheless, reconciling the lists of POIs obtained by recommendation algorithms using these different types of data (rating, check-in, and comments) presents a real challenge. To address this challenge, several recent studies in the literature [13-17] have utilized multi-agent systems (MAS) as a solution to user indifference issues because they allow the merging of POI lists obtained through the simultaneous use of multiple recommendation algorithms.

For these reasons, in this article we propose a Multi-Agent System for Reconciling POI Recommendation Algorithms, which we will call MSRPRA. This system uses three types of agent: (1) context agents that collect the context of each user, (2) method agents that return ordered lists of POIs according to the algorithm used and the context adopted, and (3) a coordinator agent that selects the most relevant POIs by merging these lists of POIs.

The rest of the document is structured as follows. In section 2, we present the state of the art on SR development approaches using SMAs in order to explain our research motivations. In section 3, we present our proposed method for reconciling different recommendation algorithms using an SMA-based approach. Before concluding, in Section 4 we detail our analysis of the problem and discuss the advantages and limitations of our approach. Finally, in Section 5, we summarize the contributions of our article in order to propose some perspectives for our work.

II. RELATED WORK

In recent years, several research projects have focused more on intelligent Recommendation Systems (RS) that aim to satisfy users' preferences using Multi-Agent Systems (MAS) [12]. Multi-Agent Recommendation Systems (MARS) are

SRs that integrate autonomous and cooperative agents to improve the quality of recommendations.

In [13], the authors propose a multi-agent recommendation application that can recommend tourist locations in the city of Valencia (Spain) and propose a plan of activities. However, this application requires the intervention of the tourist at each stage to specify their needs and note the places they have visited.

In the same context, in [14], the authors proposed a MARS for e-tourism using reputation-based collaborative filtering, enabling the recommendation of services such as hotels, places to visit, and restaurants. The system assigns an agent for each service, and each agent returns the list of that particular service. However, although this approach leverages the strengths of MAS in distributing and cooperating on recommendation tasks, this solution presents the issue of a sparse matrix.

In another context, to personalize websites, the authors in [15] integrated two recommendation techniques: association rules and collaborative filtering. They incorporated agents to reduce response time and to separate processing from model updates to enhance performance. Their approach is incremental; the system integrates additional information after each session. However, their system requires a lot of updates at the end of each session.

A centralized MAS architecture was proposed in [16], to recommend locations to users. The server agent collects the data from the client agents, and then calculates the predictions of the evaluations. The list of the most relevant places is sent to the client agent, which in turn selects those within 1 km of the user's current location and displays them to the tourist.

A video recommendation system based on MAS was proposed in [17]. The authors propose 7 agents (location, age, financial, identity, personality, needs, social) and an information centre agent (ICA) responsible for collecting and processing information. Each agent specifies whether the POI is interesting or not, then the ICA ranks the POIs. However, in this system, the history is not exploited, and each agent does not classify the films, he only expresses his interest or not towards the film.

Table 1 represents a synthesis of recommendation works based on MAS.

TABLE I. SYNTHESIS OF RECOMMENDATION WORKS BASED ON MAS

Works	**Application domain**	**Used Techniques**	**Recommended objects**
[13]	Tourism	Demographic data filtering, Content-based filtering	Location and plan of activities
[14]	Tourism	Collaborative filtering based on reputation	hotels, places to visit, restaurants
[15]	Web pages	Association rules and collaborative filtering	Next web page
[16]	Points of interest	Sentiment analysis	Next location
[17]	Movies	Content-based filtering	List of movies
Our approach	**Tourism**	**Collaborative filtering**	**List of POIs**

Previous works have used agents for their autonomies and their abilities to cooperate with each other in order to accomplish global tasks. However, these systems do not address the problem of indifference in the rating of places visited by users. This problem arises when users do not explicitly express their preferences (providing ratings for POIs or leaving comments). To mitigate this indifference problem, we will explore the possibility of using SMAs to exploit the temporal and geographical behavior of tourists and existing trust relationships with other users.

III. PROPOSED METHOD

The indifference of item/POI scoring is a real problem in the field of recommendation in general and tourism more specifically. Therefore, in this section, we propose a Multi-Agent System for Reconciling POI Recommendation Algorithms (MSRPRA) to alleviate this problem.

This system consists of five agents, which are intelligent, autonomous and cooperative. We propose three agent roles: (1) the context agent, which collects the context of each user, (2) the method agent, which returns ordered lists of POIs according to the algorithm used and the context adopted, and (3) the coordinator agent, which selects the most relevant POIs by merging these lists of POIs. The following figure illustrates the architecture of our system:

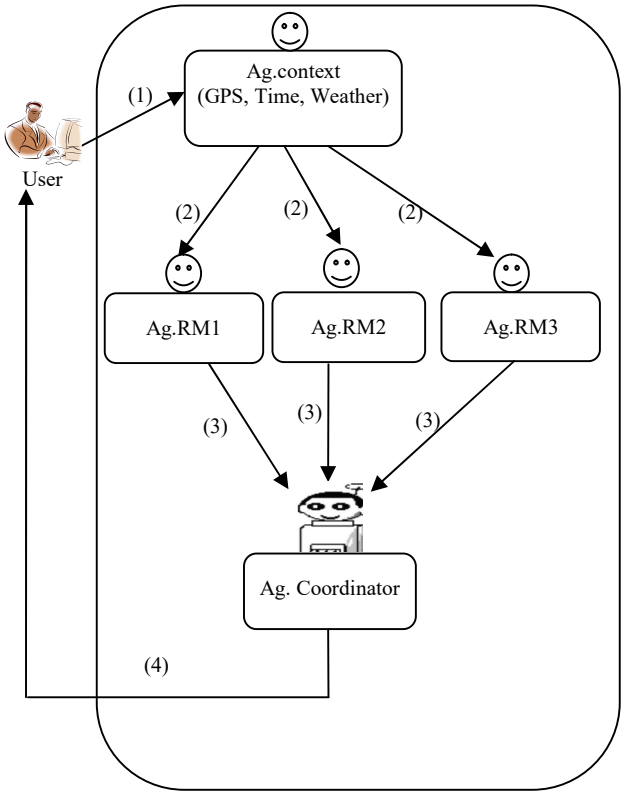

Fig.1. General Architecture of our system

As shown in fig1, in step (1) the context agent collect context data (location, weather, time) from user phone, and selects the unvisited POIs that are closest to the user's current location, are currently available and are appropriate to the

current weather situation. In step (2) the context agent sends the preliminary list to the recommendation agents (Ag.RM1, Ag.RM2 and Ag.RM3). On receipt of the preliminary list of POIs, each recommendation agent applies its own recommendation method to select only the most relevant top-k locations, and each agent , in step (3), sends a sorted list (list1, list2 and list3) to the coordinating agent. In the final step (4), the coordinating agent applies a negotiation technique to aggregate the three lists into a final list, which is returned to the user.

In the following, we explain the role of each agent in our system.

A. Context agent

This agent collects the user's contextual data, such as the location deduced from the Smartphone's GPS, the date and time of day and the weather, which can be retrieved using a weather API. This data is used to select preliminary list of POIs that are closest to the user's current location, are currently available and are appropriate to the current weather situation.

B. Recommendation Agents

These agents exploit the history of places visited (the number of visits, the ratings given to POIs already visited, etc.) as well as the trust relationships explicitly declared by the user. In our system, we propose three agents: Ag.RMethod1, Ag.RMethod2 and Ag.RMethod3 where each agent performs a recommendation method.

These three POI recommendation methods use three types of similarity: Pearson similarity [18], Jaccard similarity [19] and similarity based on trust [20].

Each agent uses a type of similarity to calculate predictions for unvisited POIs based on tourists' previous visit history. Next, each agent returns the top-k most relevant places ranked in descending order of prediction values. Finally, we obtain three lists of POIs, with each list associated with a single agent.

C. Coordinator Agent

In MAS, negotiation is a form of coordination among agents that allows them to communicate and manage conflicts [21]. There are several negotiation approaches, such as game theory, heuristics, and argumentation and voting. Game theory is based on mathematics, where agents are in a game and their goal is to maximize their gains [22]. However, an agent must anticipate the behavior of all the others and find the optimal solution, which requires high a computational cost. Heuristics were developed to solve the problem of game theory. In these negotiation models, agents rely on their reasoning and strategies for decision-making without pursuing the optimal solution [23]. However, this means they do not explore the entire space of solutions. In game theory and heuristics, agents only focus on proposals. These methods do not allow agents to explain the motivations behind their choices. Argumentation is an approach that allows agents, in addition to presenting proposals, to provide explanations for these proposals and their decisions, whether to accept or reject them [24]. Each agent has the possibility of accompanying its proposals with arguments to explain why the others should consider them favorably. However, this technique requires additional communication costs. The vote is a technique in the theory of collective decision-making or social choice that allows the selection of one alternative from various possible options. It provides participants with the opportunity to express their preferences among a set of solutions [21].

For our system, we have chosen the voting technique, because this technique seems to be adapted to our design, where the agents do not coordinate.

In our design, the recommendation agents do not communicate. Each agent is autonomous and its objective is to return a list of places which is calculated based on one of the three proposed recommendation methods. These agents communicate with the coordinator to send it the lists.

The coordinating agent's objective is to return the final sorted list of places to recommend to our user. After receiving the three lists: list1, list2 and list3 from the agents: Ag.RMethod1, Ag.RMethod2 and Ag.RMethod3 respectively, the agent applies the voting technique to aggregate the three lists into a final list.

Borda Method: The Borda voting system is frequently used in situations involving the selection of multiple winners; it relies on a weighted vote. This method involves each agent ranking alternatives in order of preference and assigning a positive number of points, 'n', to the top-ranked alternative, 'n-1' points to the second-ranked alternative, and 1 (or 0) point to the last alternative on the list. The number 'n' must be less than or equal to the number of alternatives [25].

Example: We assume we have a set L of 10 unvisited locations: L = {l1, l2, l3, l4, l5, l6, l7, l8, l9, l10}, and each agent must return the top-5 locations. N =4. We have chosen to present three scenarios in the following:

Scenario 1: the three agents return 3 lists with the same locations.

TABLE II. LISTS OF LOCATIONS TRIED BY EACH AGENT FOR SCENARIO 1

List_AgRM1	List_AgRM2	List_AgRM3	N
l_3	l_2	l_3	4
l_6	l_6	l_8	3
l_2	l_1	l_1	2
l_1	l_3	l_2	1
l_8	l_8	l_6	0

For each location, we calculate the score as follows:

l_3: 4+1+4= 9

l_6: 3+3+0= 6

l_2: 2+4+1= 7 → Final list is: List_F= {l_3, l_2, l_6, l_1, l_8}

l_1: 1+2+2= 5

l_8: 0+0+3= 3

Scenario 2: one of the agents returns a location that does not exist in the other lists.

TABLE III. LISTS OF LOCATIONS TRIED BY EACH AGENT FOR SCENARIO 2

List_AgRM1	List_AgRM2	List_AgRM3	N
l_1	l_2	l_3	4
l_5	l_4	l_2	3
l_2	l_6	l_1	2
l_4	l_1	l_4	1
l_6	l_5	l_5	0

For each location, we calculate the score as follows:

l_1: 4+1+2= 7

l_2: 2+4+3= 9

l_3: 0+0+4= 4 → Final list is: List_F= {l_2, l_1, l_4, l_3, l_5}

l_4: 1+3+1= 5

l_5: 3+0+0= 3

l_6: 0+2+0= 2

Scenario 3: the three lists are different.

In this scenario, we need to expand the lists. The coordinator agent must request recommendations from the agents to send sorted lists of all unvisited places. Subsequently, we follow a similar procedure as in the previous scenarios and return the final list of top places.

IV. DISCUSSION

To mitigate the problem of user indifference towards place ratings, we used three recommendation algorithms based on three distinct data sources: user ratings, check-ins during visits, and explicitly declared trust relationships among users. To reconcile these algorithms, we employed the Borda voting method. As illustrated in the example in the previous section, we observed that regardless of the scenario, our system can merge the three lists, and we noticed that the final list contain the most relevant places from each algorithm.

The use of these methods allowed us to mitigate the cold start problem because each agent returns a list of the top Points of Interest (POIs) to recommend by utilizing multiple data sources.

The Multi-Agent Systems enabled us to efficiently reconcile and merge the lists obtained from the three recommendation algorithms described earlier.

Unlike the work [13] [14], our approach is solely based on user behavior (history, trust relationships, and ratings). However, this is still inadequate as integrating demographic data and Point of Interest (POI) characteristics could bring more accuracy to our system.

V. CONCLUSION

In this research, we designed a Multi-Agent System for Reconciling POI Recommendation Algorithms (MSRPRA). This system uses three types of POI recommendation algorithm: the first algorithm is based on Pearson similarity, the second algorithm uses Jaccard similarity and the last algorithm relies on trust relationships between users to calculate their similarities. These algorithms exploit three types of data: (1) user ratings, (2) check-ins during visits and explicitly declared trust relationships between users. Initial simulation results indicate that our MSRPRA can be a valuable tool for efficiently gathering crucial data to alleviate the problem of indifferent ratings of places visited by users. This work contributes to the field of POI recommendation, particularly in the context of Smart tourism, where the problem of data scarcity prevents the cold start of SRs thus causing tourist dissatisfaction.

Future research could focus on enhancing this system by integrating other algorithms such as Deep Learning or other types of data, like tourists' comments. Overall, our research establishes a solid foundation for implementing an intelligent smart tourism application for the Oran province.

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