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A TIME-DEPENDENT GROUP MATCHMAKING MECHANISM FOR CREATION OF AGENT-BASED COMMUNITIES

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1. Introduction

E-marketplaces that utilize agent technology to ease trading and automate negotiation for users have been popular for years. In many cases, these agent-mediated marketplaces exploit a facilitator to provide an infrastructure of trade. The facilitator conducts matchmaking to pair existing agents with the same interests. However, existing facilitator is inattentive to potential newcomers (agents yet to arrive) at matching. Favorable newcomers can bring preferable offers to the facilitator that generates finer matches for agents and hence maximizes agents' expected utilities. In this paper, we propose a facilitator that considers newcomers at matchmaking. We achieve this by studying a similar facilitator that also considers newcomers. We enhance the existing work by introducing new features such as group matchmaking and a lifetime for the offer. The facilitator's optimal matchmaking strategy can be computed by exploiting the Markov decision process.

2. Purpose

An example scenario explains the necessity of our research – An agent seeks three participants to play double's tennis at 4pm, has registered its offer (utility function and attributes) to the facilitator at 2pm. The utility function represents agent's opinion on others while examples of attributes (fixed and flexible) are the deadline and the location respectively. Based on agent's registration, the facilitator searches its dynamic database and, two agents waiting for tennis partners are found. At 3pm, an agent interested in tennis has registered. The facilitator now ponders whether to accept current participant as the best one or wait for potential newcomers before the deadline.

To realize the above scenario, following requirements are needed:

1) Consideration of potential newcomers.
2) Group matchmaking mechanism.
3) Individual utility function for agents.
4) Lifetime restriction on each offer.

3. Related Work

3.1 Markov Decision Process

A Markov decision process (MDP) [1] is a model for sequential decision making when outcomes are uncertain. At any decision epoch, choosing an action in a state generates a reward and determines the state at next decision epoch through a transition probability function. The MDP is referred as a finite-horizon model if the set of decision epochs is finite. Decision makers seek policies or strategies that are optimal for choosing an action.

3.2 MPD for Time-dependent Matchmaking

In the paper by Choi, et al [2], the adoption of MDP for time-dependent matchmaking that handles potential newcomers has been proposed. In the marketplace, all agents are associated with the same utility function and find a desire offer through the assistance of a mediator. For any offer, the utility function is inverse proportional to its duration where good offers with high utilities disappear faster while offers with low utilities remain. The mediator provides updated statistical information and an offer to the agent simultaneously. The agent decides whether to accept the current offer or wait for a better one. By exploiting the MDP model, the key to compute the optimal decision strategy depends on defining the expected utility for waiting $V_t(n)$, where t is the remaining time step.

$$V_t(n) = c(t) + \sum_{e_i} \sum_{n' \in N} \Pr(n'+e_i) \cdot V^*_{t-1}(n'+e_i) \quad (1)$$

$$\Pr(n'+e_i) = \Pr(e_i) \cdot \prod_{j=1}^{K} \binom{n_j}{n'_j} l_j^{(n_j - n'_j)} \cdot (1-l_j)^{n'_j} \quad (2)$$

$$\pi^*_t(n) = \begin{cases} accept & if \quad \max_j (u(j) \mid n_j > 0) > V_t(n) \\ wait & otherwise \end{cases} \quad (3)$$

(1) consists of the cost function $c(t)$ and the gained utility where n' is the next offer collection and e_i is the new offer entered. (2) defines the state transition probabilities where $\Pr(n')$ is the multiplication of the probabilities of all possible offers. The collection of offers in category j is denoted by n_j, where all offers in the same category have same utility value, and K is the total possible of categories. The l_j denotes the probability of losing of an offer. (3) represents the optimal strategy for agent's decision making where if the current utility is higher than the expected utility, then the optimal action is to accept.

Although Choi's paper considers potential newcomers, nevertheless, their work is inadequate for realizing our research. For requirement 2), the matchmaking pairs agents in sequential fashion where the mechanism suffers inconsistency of group members. In addition, the MDP model is adopted in a distributed manner. It is feasible when agents negotiate in pairs and the same utility function is employed. However, it becomes complicated when we consider matchmaking in groups and agents with different utility functions. For requirement 3), the sharing of the same utility function is impractical since the eagerness of each agent in fact varies. For requirement 4), the duration of an offer depends on the utility function alone. The notion of the lifetime for agents has been neglected.

In our work, we intend to overcome these problems.

4. Proposal

4.1 Basic Ideas

We propose a mechanism that considers potential newcomers at matchmaking by exploiting MDP at the facilitator level (shown in Figure 1). First, all agents register offers to the facilitator with a utility function and attributes. The facilitator filters and classifies agents according to the given information. The facilitator performs MDP matchmaking to create optimal communities.

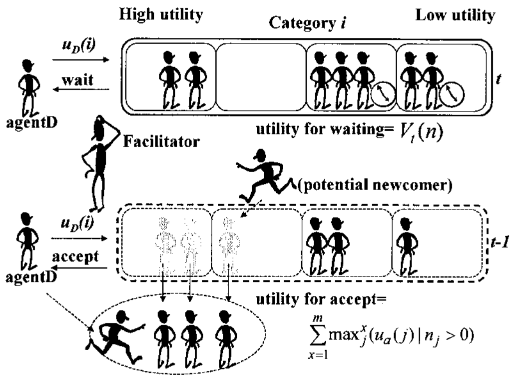

Figure1 Matchmaking at facilitator level

For formulating the MDP, we assume the collection of offers remain unchanged for every time step. When agents come and leave the system frequently, the collection of utility functions changes at each time step. However, if we regard these agents as the minority, then the changes have no affect when the collection is large.

For the group matchmaking in the requirement 2), the facilitator evaluates all agents sequentially within a time step t. At each evaluation, the facilitator decides whether to accept the offer or wait for the next one by utilizing the MDP. If the facilitator decides to accept the offer, a community is formed with other requested agents, where these agents are deleted from the facilitator's list. The facilitator moves on to the next time step, t-1, after all agents have been evaluated.

For the utility function in requirement 3), we assume the utility function of each agent is independent of the time. The facilitator has a collection of utility functions of each agent and is denoted by $U = \sum_{agent} u_a$

We put the lifetime mentioned in requirement 4), to an offer that mimics the deadline of trading in the real world. We assume the lifetime and the probability of the community formation of an offer are independent of one another.

4.2 Problem Formulation

Now we formulate the matchmaking mechanism into an MDP. We define all elements of an MDP for calculating the optimal strategy. The state space consists all possible collections of offers n where n_j is the collection of offers for category j; *accept* and *wait* are possible actions; the state transition probabilities are defined by the changes of offer collections; we have the current utility and the expected utility for accept and wait respectively. In another word, if the facilitator decides to accept the current offer, an accumulated utility of m top offers $\sum_{x=1}^{m}\max_j^x(u_a(j)\,|\,n_j>0)$ is received, where m is the number of offers required to create a community and $\max_j^x$ denotes the *xth* highest offer selected from the category j. If the facilitator decides to wait, the expected utility for waiting is equivalent to (1), except for $\Pr(n'+e_i)$.

We now clarify the difference between our state transition probabilities to (2). Here, the h_j is the probability of losing due to the lifetime. The probability of community formation f_j is proportional to U while inverse proportional to m. Now the formula becomes

$$\Pr(n'+e_i) = \Pr(e_i)\cdot\prod_{j=1}^{K}\binom{n_j}{n'_j}\cdot(h_j+f_j)^{(n_j-n'_j)}\cdot\left(1-(h_j+f_j)\right)^{n'_j}$$

4.3 Optimal Value Function and Policy

Based on 4.2, we can specify the optimal value function as

$$V_t^*(n) = \max\left(\sum_{x=1}^{m}\max_j^x(u_a(j)\,|\,n_j>0),\ \ V_t(n)\right)$$

where the initial value function is

$$V_0^*(n) = \sum_{x=1}^{m}\max_j^x(u_a(j)\,|\,n_j>0)$$

Finally, the optimal matchmaking strategy can be extended from (3) and formulated into

$$\pi_t^*(n) = \begin{cases} accept & if \quad \sum_{x=1}^{m}\max_j^x(u_a(j)\,|\,n_j>0) > V_t(n) \\ wait & \qquad otherwise \end{cases}$$

5. Conclusions and Future Works

In this paper, a facilitator that considers newcomers at matchmaking has been proposed. The Markov decision process model has been adopted to compute the optimal group matchmaking strategy at the facilitator level. We will discuss on how to derive the global optima for the facilitator.

6. References

[1] Puterman, M. L. *Markov Decision Processes: Discrete Stochastic Dynamic Programming*. John Wiley and Sons, 1994.

[2] Choi, S.P.M. and Liu, J. "A Dynamic Mechanism for Time-Constrained Trading". In *Proc. of Agents 2001*, May.