Collaborative Human Task Assignment for Open Systems (Extended Abstract)

Bin Chen, Adam Eck, and Leen-Kiat Soh
Department of Computer Science and Engineering
University of Nebraska, Lincoln, NE
{bchen, aeck, lksoh}@cse.unl.edu

ABSTRACT
Through gathering information, acting autonomously, learning, and behaving socially, intelligent agents provide useful interfaces between complex systems and human users. For example, agents can interact with people to discover their preferences, skills, and expertise, then find suitable tasks that exploit the users' abilities. We describe modeling environmental openness and human learning in a multiagent system for a human collaborative task assignment problem.

Categories and Subject Descriptors
I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence – *intelligent agents, multiagent systems*

General Terms
Performance, Design, Experimentation, Human Factors.

Keywords
Collaborative Task Assignment; Openness; Human Learning; Emergent Behavior

1. INTRODUCTION
Human collaborative task assignment occurs in environments where there exist human users and tasks that require multiple people to combine their individual skills and expertise to work together towards a common (possibly temporary) goal. As motivation, each participant earns a share of a joint reward if the task is accomplished successfully. For example, the assignment could be used to (1) form temporary teams of freelance workers (e.g., independent software developers or artists) to satisfy contracts from companies lacking the internal expertise to accomplish tasks (e.g., developing particular pieces of software or graphic design), (2) combine the expertise and skills of office workers across divisions within large companies to accomplish tasks needed by the company, or (3) match students to peer-based learning tasks in computer-aided education.

In such a problem, software agents are valuable in assisting human users in identifying appropriate tasks (or subtasks) to complete, as well as in securing such tasks (or subtasks) for their human users. Such agents can first model the abilities of their assigned users, then find and acquire tasks that best benefit their users, with the emergent behavior that the overall system benefits from the task assignment. When modeling a human user, an agent should take into account the impacts of human learning on its human user's expertise and skills, especially so when deciding on which tasks to pursue. This consideration is non-trivial, as the task providing the most immediate reward might not simultaneously provide the greatest opportunity for learning that would improve a human user's expertise and skills and ultimately lead to greater future rewards. Therefore, an agent faces a difficult tradeoff when selecting tasks for its learning-capable human user.

Furthermore, when the environment is open where existing human users may leave while new human users may enter, or existing tasks may disappear and new tasks may appear, modeling human learning and leveraging that in an agent's reasoning become more complicated. In this paper, we focus on modeling openness and human learning in human collaborative task assignment as a first key step towards a solution approach to address this human collaborative task assignment problem.

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2. MODELING OPENNESS
We consider two types of openness: (1) agent openness and (2) task openness. Our definition of task openness follows from Chen *et al*. [3] while that of agent openness is a slight variant from [3].

Agent openness represents the phenomenon that human users (who are also intelligent, non-artificial agents) join and leave the environment over time. For example, in a freelance software development environment, individual developers might leave software companies to do independent freelance work instead, whereas others might switch from being freelance workers to working solely for a software company. Likewise, in an office worker environment, the company might hire new employees and let others go over time. As a result of agent openness, various agents (with the number of agents determined by the degree of agent openness) will leave and/or join the environment over time. Thus, the set of human users H (and their corresponding software agents A) is non-stationary and changes over time. To closely model many real-world scenarios, we assume that agents do not necessarily know their peers around them at any point in time, nor how many peers they have. Note that new expertise entering the environment would be helpful for completing collaborative tasks. However, as existing agents leave the environment, they will take their expertise with them, potentially creating a void in important skills or expertise, making it more difficult for collaborative tasks to be completed. This exodus could especially hurt the system since human users' capabilities do improve due to learning over time, so the amount of overall expertise leaving the system due to openness could exceed the amount of expertise joining the system.

Task openness represents the phenomenon that the set of tasks that require collaboration to solve could also change. For example, in a freelance software development environment, changes in programming paradigms and the types of software needed by clients would cause different collaborative tasks to exist over time. Moreover, in an office worker environment, different seasonal activities of the company could require different tasks over time. As a result of task openness, a number of tasks will disappear from the environment, while new batches of tasks might be introduced for human users to work on (again, with the numbers of changing tasks being determined by the degree of task openness). Given that different expertise and capabilities are required of users to solve their tasks, task openness will affect the ability of agents to acquire tasks for their users. That is, as easier tasks become available, more users would be qualified to complete tasks, increasing the competition among them. On the other hand, as tasks become more difficult, it would be more difficult for an agent to find a suitable task for its assigned user. Furthermore, new tasks requiring different skills could bring previously unmet opportunities for users to leverage their capabilities.

Of note, our work on agent and task openness within a problem model is similar to and builds upon prior research by Jumadinova *et al*. [5]. In particular, their research explored the impacts of agent and task openness when agents work together in ad hoc teams under the assumption of simple rules for forming teams based on agent capabilities. Here we add principled computational models of human learning based on an extensive literature review to improve how agents reason about the benefits of task accomplishment for human users.

3. MODELING HUMAN LEARNING

Human learning is especially important in the presence of agent and task openness within the collaborative task assignment problem because learning enables human users to gain expertise and skills needed both (1) to replace expertise leaving the environment due to agent openness, as well as (2) to perform a wider range of tasks encountered due to task openness. In particular, we model learning as increases in user capabilities $cap_{h,k} \in [0,1]$ (where h references a particular human user and k represents a particular skill or knowledge). We focus on two particular learning paradigms: (1) learning by doing and (2) learning by observation.

Learning by Doing. One way that humans learn is through experience gained by directly performing tasks. Here, a user h gains capability $cap_{h,k}$ in the skill or knowledge k it uses while participating in a task. To model *learning by doing*, we propose considering *experience curve effects* [4] to derive the learning gain function for a human user performing learning by doing. Different task types may have different learning curves (e.g., power law, exponential, sigmoidal) [6, 7]. For example, Leibowitz *et al.* [6] outline an exponential learning equation for success-based learning:

$$p_n = p_\infty - (p_\infty - p_0) \cdot e^{-\alpha \cdot S_n} \quad (1)$$

where p measures a user's performance, n counts the learning episode such that p_∞ is the maximum infinite-horizon performance achievable, p_0 is the initial performance, S_n is the accumulated sum of all previous performances preceding the n-th episode, and α is a constant rate coefficient. The change in performance, or learning gain, according to Leibowitz *et al*. [6], is:

$$\dot{p} = \alpha p \cdot (p_\infty - p) \quad (2)$$

The constant rate coefficient α caps the amount of learning gain at each episode. The general shape of this curve is a (concave downward) parabola: when a user's expertise is low, it learns a little; as its expertise grows, it starts to learn faster up to a peak rate; after it peaks, its learning slows back down. Thus, for a user's gain via learning by doing with a learning curve capped by α_{do}, using its capability $cap_{h,k}$, we have:

$$\Delta_{do} cap_{h,k} = \dot{cap}_{h,k} = \alpha_{do} \cdot cap_{h,k} \cdot (1 - cap_{h,k}) \quad (3)$$

Learning By Observation. To model learning by observation, we look to Bandura's social cognitive learning theory [1, 2] containing four stages involved in observational learning: attention, retention or memory, initiation or reproduction, and motivation. In human collaborative task assignment, *attention* implies that a user h learns about $cap_{h,k}$ from observing other users using skill or knowledge k only when they are in the same team collaboratively solving a task. To ensure *retention* (or memory), each user updates its capability after task execution, using Eqs. 4-5 as described later. *Initiation* (or reproduction) requires that "observers must be physically and intellectually capable of producing the act." [2]. That is, when a user h observes another user performing k, h can only learn if its skill is relatively close to what it is observing in order to improve h's capability. As a result, we model the learning gain function of user h observing a teammate performing skill or knowledge k as follows:

$$\Delta_{obs} cap_{h,k} = \begin{cases} \dot{p} & 0 \le obs_k - cap_{i,k} < \beta \\ 0 & otherwise \end{cases} \quad (4)$$

where obs_k is the observed production of k by the teammate, β is the threshold under which $cap_{h,k}$ is close enough to obs_k for learning by observation to take place, and $\dot{p}$ for observational learning is modeled similarly from Eqs. 1-2 above:

$$\dot{p} = \alpha_{obs} \cdot (obs_k - cap_{h,k}) \cdot \left(\beta - (obs_k - cap_{h,k})\right) \quad (5)$$

where α_{obs} refers to the cap for the corresponding learning curve for observational learning for that capability. In summary, gain from learning by observation is zero if a user observes a k being performed that is either (1) too much greater than her current capability ($\ge \beta$), or (2) if the user is more capable that the performance it observes. Finally, we assume that learning-aware human users are always *motivated* to learn, and thus we assume learning by observation to be of no cost to human users.

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