Learning Cases to Resolve Conflicts and Improve Group Behavior

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Groups of agents following fixed behavioral rules can be limited in performance and efficiency. We propose a framework in which individual group members learn cases from problem-solving experiences to improve their model of other group members. We use the predator-prey, or pursuit, domain (Korf 1992) to show that simultaneous learning by group members can lead to significant improvement in group performance and efficiency over agent groups following static behavioral rules. The goal of four predators in the pursuit domain is to capture a prey by surrounding it. Agents are allowed only horizontal and vertical moves (no diagonal ones) on a grid world which wraps around. Agents cannot communicate with other agents in our work. In spite of its apparent simplicity, it has been shown that there is no evident effective hand-coded localized strategy (versus a centralized strategy that dictates move of every agent at each time step) (Haynes, Lau, & Sen 1996). The predator behavioral rules that we have used for learning is an enhanced version of the Manhattan Distance (MD) algorithm, called MD-EDR. Prey algorithms used include prey moving in a straight line (Linear) or not moving at all (Still).

We propose a multiagent case-based learning (MCBL) framework in which agents learn cases to override default behavioral rules. When the actual outcome of the action of an agent using its behavioral rules is not consistent with the expected outcome based on the model the agent has of other agents, the agent recognizes that a conflict has occurred and that its behavior is not appropriate in that situation. For those situations, the agent learns exceptions to its behavioral rules that are likely to prevent future conflicts. Agents follow their behavioral rules except when a learned case suggests alternative actions. Through this process, the agents dynamically evolve a behavior that is suited for the group in which it is placed.

Behavioral rules can be modeled as a function which maps the state (s) and the applicable action set (A) of an agent to a preference ordering of those actions: $BH(s, A) \Rightarrow A' = < a_{x_1} a_{x_2} \ldots a_{x_k} >$. The cases an agent learns allows it to modify this preference ordering: $CB(s, A') \Rightarrow A'' = < a'_{x_1} a'_{x_2} \ldots a'_{x_j} >, j \leq k$. The cases used in our system are negative in nature (they eliminate one or more of the most preferred actions as suggested by behavioral rules).

The ideal case representation for the predator–prey domain is to store the entire world and to have each case inform all predators where to move. But this representation leads to too many possible cases. We limit the case window to represent the potential conflicts that can occur "after" the agent selects a move based on the default rules or learned case (see Figure 1). Expected movement of other agents is implicitly modeled by storing the orientation of the prey's position with respect to the desired direction of movement of the agent (the 'X' in the case window). More details regarding the choice of the case window is presented in an extended paper (Haynes, Lau, & Sen 1996).

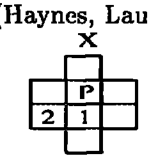

Figure 1: Case window for **predator 1**.

The predators are trained on 100 random scenarios (each lasting 100 time steps) and tested on a separate 100 problems. Capture rates with still prey are MD 3%, MD-EDR 46%, MD-CBL 97%. Capture rates with linear prey are MD 2%, MD-EDR 20%, MD-CBL 54%. Results show the remarkable contribution of concurrent individual learning to group performance. We plan to add forgetting to the learning scheme.

Acknowledgments : This work has been supported, in part, by an NSF grant IRI-9410180.

References

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