Planning and Learning For Decentralized MDPs With Event Driven Rewards

Tarun Gupta[1], Akshat Kumar[2]†, Praveen Paruchuri[1]†
[1]Machine Learning Lab, Kohli Centre on Intelligent Systems, IIIT Hyderabad
[2]School of Information Systems, Singapore Management University
tarun.gupta@research.iiit.ac.in, akshatkumar@smu.edu.sg, praveen.p@iiit.ac.in

Abstract

Decentralized (PO)MDPs provide a rigorous framework for sequential multiagent decision making under uncertainty. However, their high computational complexity limits the practical impact. To address scalability and real-world impact, we focus on settings where a large number of agents primarily interact through *complex* joint-rewards that depend on their entire histories of states and actions. Such history-based rewards encapsulate the notion of events or tasks such that the team reward is given only when the joint-task is completed. Algorithmically, we contribute — 1) A nonlinear programming (NLP) formulation for such event-based planning model; 2) A probabilistic inference based approach that scales much better than NLP solvers for a large number of agents; 3) A policy gradient based multiagent reinforcement learning approach that scales well even for exponential state-spaces.

1 Inference Model for TIDec-MDP

Figure 1 shows the mixture of BNs for TIDec-MDPs. In EM, optimizing the expected log-likelihood (or the M-step) becomes decoupled resulting in a separate optimization problem for each agent regardless of the number of joint rewards or the number of agents in a joint-reward. This is a significant scalability boost as NLP solvers directly optimize the monolithic program which quickly becomes unscalable due to a large number of variables/nonlinear terms, whereas EM's solves an independent *convex* program for each agent.

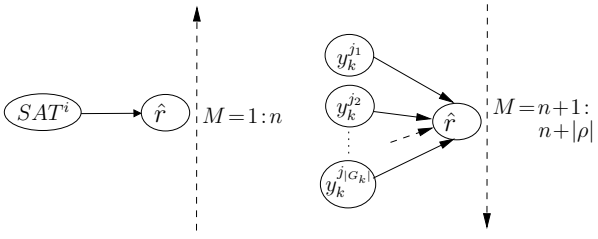


Figure 1: Mixture model for TIDec-MDP; M is mixture variable with discrete domain from 1 through $n+|\rho|$; there is one BN (left) for each agent $i=1:n$; one BN (right) for each joint-reward $k \in \rho$

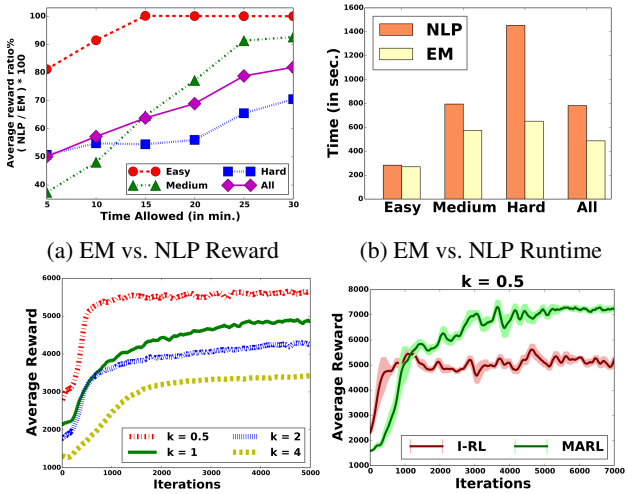
†Equal advising.

2 RL for Event-Based Rewards

The previous section presented a scalable EM approach for TIDec-MDPs. However, the scalability still suffers when the state-space of each agent i is exponential, which is often the case for several patrolling and coverage problems. To address such settings, we develop a reinforcement learning (RL) approach that uses function approximators such as deep neural nets (NN) to represent agent policies and optimizes them using the policy gradient approach.

3 Experimental Results

The y-axis of Figure 2a shows the ratio (in %) of total average rewards obtained by NLP w.r.t. the EM within the cutoff time on the x-axis. Figure 2b shows that EM has a much lower runtime on an average. Figure 2c shows the quality achieved by Multi-Agent RL (MARL) for different settings of the reset time k. Figure 2d shows quality improvements by MARL over independent policy optimization (I-RL) for reset time of $k = 0.5$ hours.



(a) EM vs. NLP Reward

(b) EM vs. NLP Runtime

(c) RL Hard Settings

(d) I-RL vs. MARL

Figure 2: Experimental Results

The longer version of the paper can be found at http://www.mysmu.edu/faculty/akshatkumar/pub.html