An Analysis Framework for Ad Hoc Teamwork Tasks

Samuel Barrett Peter Stone

The University of Texas at Austin {sbarrett,pstone}@cs.utexas.edu

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Ad Hoc Teamwork

- Only in control of a single agent
- Unknown teammates
- Shared goals
- No pre-coordination
- Examples in humans:
 - Pick up soccer
 - Accident response





- Agents are becoming more common and lasting longer
- Pre-coordination may not be possible
- Previous work focuses on specific subsets of the ad hoc teamwork problem
- Unify research in ad hoc teamwork



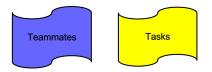
- Analyze ad hoc team problems in terms of 3 dimensions
- Analysis helps for reusing prior algorithms on new domains
- Better identify areas for future research





- Not whether they win, but how well they cooperate
- Compare against other ad hoc agents
- Depends on possible tasks
- Depends on possible teammates

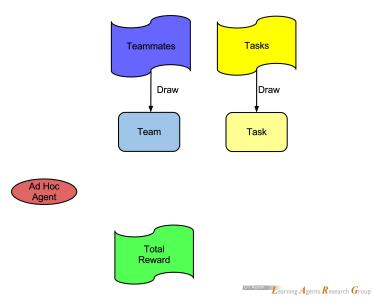


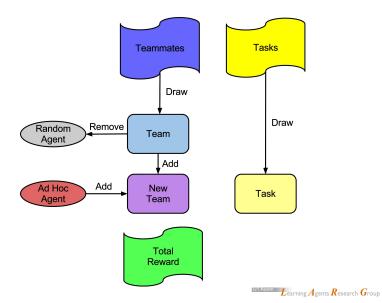




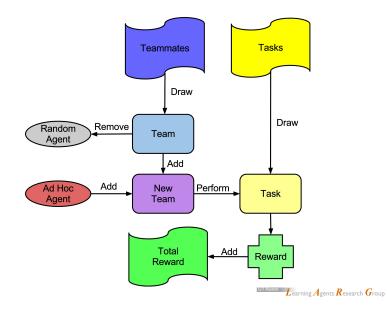


Learning A gents R esearch G roup





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- Analyze ad hoc team problems
- Identify informative dimensions
- Give explicit measures to compare problems



Does the ad hoc agent know what its teammates' actions will be for a given state, before interacting with them?



Does the ad hoc agent know what its teammates' actions will be for a given state, before interacting with them?

- What the ad hoc agent knows ahead of time, not what it can learn
- Compare expected distribution of teammates' actions to true distribution
- Averaged over all states and teammates
- Higher values \rightarrow more knowledge \rightarrow easier planning



Team Knowledge

$$K(T, P) = \begin{cases} 1 & \text{if } JS(T, P) = 0\\ 1 - \frac{JS(T, P)}{JS(T, U)} & \text{if } JS(T, P) < JS(T, U)\\ -\frac{JS(P, U)}{JS(U, \text{Point})} & \text{otherwise} \end{cases}$$

Team Knowledge =
$$\frac{\sum_{s=1}^{n} \sum_{t=1}^{k} K(T_t(s), P_t(s))}{nk}$$

- T True distribution
- P Predicted distribution
- JS Jensen-Shannon divergence, a symmetric variant of KL

Point - distribution with all weight on one point

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Does the ad hoc agent know the transition and reward distribution given a joint action and state before interacting with the environment?



Does the ad hoc agent know the transition and reward distribution given a joint action and state before interacting with the environment?

- 2 parts transition and reward are separate
- Compare expected next state/reward distribution to true distribution
- Given full information of joint action
- Averaged over all states
- Higher values \rightarrow more knowledge \rightarrow easier planning



How much does the ad hoc agent's actions affect those of its teammates?



How much does the ad hoc agent's actions affect those of its teammates?

- Compare resulting joint action distribution for different ad hoc agent's actions
- One step effects
- Similar to empowerment
- Higher values \rightarrow more reactive \rightarrow harder planning, but more control



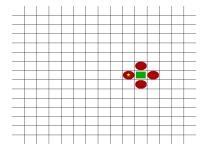
- Analyze variations on an example domain
- Identify how to reuse prior work
- Analyze more domains
- Identify areas for future research



- Grid world Torus
- N Predators and 1 Prey
- Predators' goal is to capture the prey as quickly as possible
- Act simultaneously
- Collisions randomly decided - loser stays still



4-Predator Known Behaviors



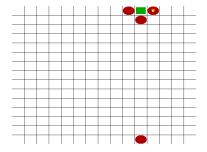
- 4 predators
- Teammates use 1 of 4 behaviors
- Teammate behavior is known



Domain	Team	Environment	Teammate
Domain	Knowledge	(Trans, Reward)	Reactivity
4 Known	1	(1,1)	0.00105-0.501



4-Predator Unknown Behaviors



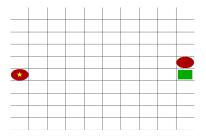
- 4 predators
- Teammates are drawn from set of 4 behaviors
- Teammate behavior is not known



Domain	Team	Environment	Teammate
Domain	Knowledge	(Trans, Reward)	Reactivity
4 Known	1	(1,1)	0.00105-0.501
4 Unknown	0.155–0.807	(1,1)	0.00105-0.501



- 2 predators
- Choose high level behavior to play for an episode
- Both know expected capture time for behaviors
- Teammate plays best response
- Capture by both predators neighboring the prey

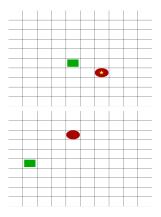




Domain	Team	Environment	Teammate
Domain	Knowledge	(Trans, Reward)	Reactivity
4 Known	1	(1,1)	0.00105-0.501
4 Unknown	0.155–0.807	(1,1)	0.00105-0.501
2 Simul	1	(1,1)	0.198



2-Predator Teaching



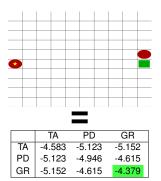
- 2 predators taking turns
- Choose high level behavior to play for an episode
- Ad hoc agent knows expected capture times for behaviors
- Teammate chooses greedily based on observed capture times



Domain	Team	Environment	Teammate
Domain	Knowledge	(Trans, Reward)	Reactivity
4 Known	1	(1,1)	0.00105-0.501
4 Unknown	0.155–0.807	(1,1)	0.00105-0.501
2 Simul	1	(1,1)	0.198
2 Teach	1	(1,1)	0.0342-0.118



- Repeated normal-form game
- Shared payoffs
- Choosing behaviors corresponds to choosing row/column
- Try to find lowest cost path to optimal cell





- Efficient algorithm when memory size of 1
- Exponential algorithm when memory size of >1
- Can handle non-deterministic teammates





- Flocking control controlling a flock with a "shill" agent
 - Han, Li, and Guo 2006
- Unknown teammates (UTM) cooperative box pushing, meeting in a 3x3 grid, and multi-channel broadcast
 - UTM-1 follow a fixed set of actions
 - UTM-2 attempt to play optimally, but have limited observations
 - Wu, Zilberstein, and Chen 2011
- Simulated pickup soccer ad hoc agent given a different playbook
 - Bowling and McCracken 2005



Domain	Team	Environment	Teammate
Domain	Knowledge	(Trans, Reward)	Reactivity
Flocking control	1	(1,1)	0.0732-0.880
Cooperating with	0	(1,1)	0
UTM-1 teammates	0	(1,1)	0
Cooperating with	0	(1,1)	>0
UTM-2 teammates	0	(1,1)	>0
Simulated pickup soccer	>0	(>0,1)	>0

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- Most prior work focused on planning to interact with teammates
- Low team knowledge must explore teammates' behaviors
- Low environment knowledge must explore environment
- Trade-off between exploiting current knowledge, exploring teammates, and exploring the environment
- More complex domains



• Can analyze ad hoc team problems in terms of:

- Team Knowledge
- Environmental Knowledge
- Teammate Reactivity
- Analysis helps for reusing prior algorithms on new domains
- Better identify areas for future research



 Analyzing domains can help ad hoc team agents cooperate with a variety of teammates

