Cooperating with Unknown Teammates in Robot Soccer

Samuel Barrett Peter Stone

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

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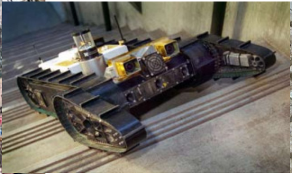
Disclaimer

- Added results from paper
- Different planning algorithm
- Still ongoing work

Example

Example

Example



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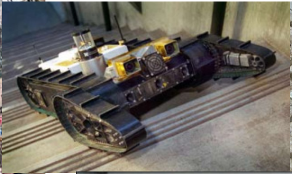
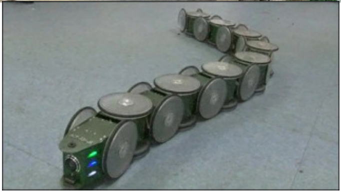
Example





Example

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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

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Motivation

- Agents are becoming more common and lasting longer
  - Both robots and software agents
- Pre-coordination may not be possible
- Agents should be robust to various teammates
- Need to adapt quickly!

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Research Question:

How can an agent cooperate with unknown teammates to play robot soccer?

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Ad Hoc Agent Evaluation

- Can the ad hoc agent replace any teammate on the team?
- Compare against other ad hoc agents
- Depends on possible tasks
- Depends on possible teammates

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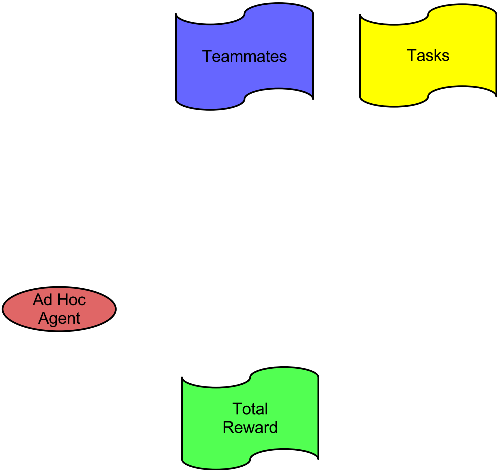
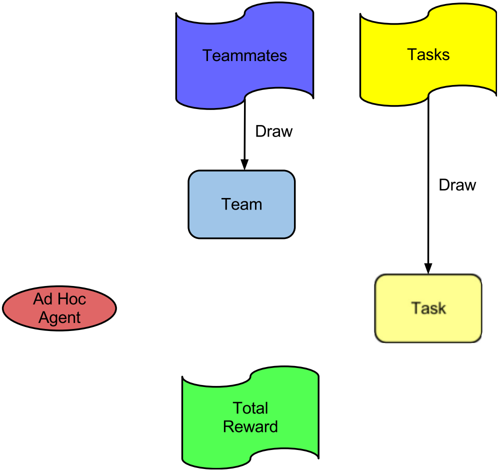
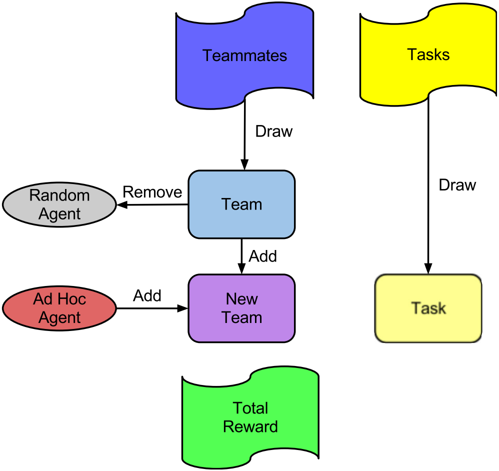
Ad Hoc Agent Evaluation



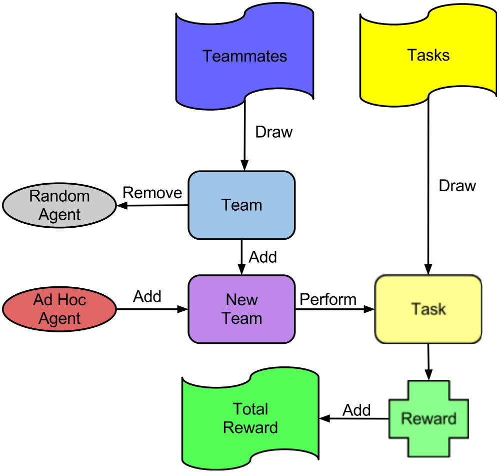
Ad Hoc Agent Evaluation



Ad Hoc Agent Evaluation



Ad Hoc Agent Evaluation



Half Field Offense

- 4 offensive players
- 5 defensive players
- Noisy observations and actuators
- Offense tries to score
- Defense are Helios agents
- Episode ends when:
  - Score
  - Ball leaves half field
  - Ball captured by defense

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Overview

- Build on Helios code release (*agent2d*)
- Model as Markov Decision Process (MDP)
- Learn to cooperate with past teammates
- Select policies online

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MDP Formulation

$$\text{MDP} = \langle S, A, P, R \rangle$$

- S = State
- A = Actions
- P = transition function
- R = reward function

MDP Formulation

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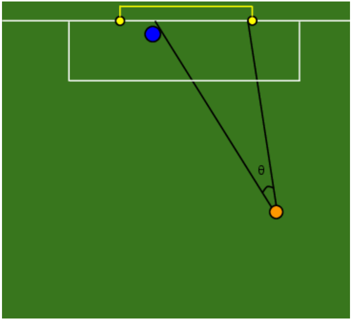
State:

- Agent's x,y position and orientation
- Agent's goal opening angle
- Teammate's goal opening angle
- Distance to opponent
- Distance from teammate to opponent
- Pass opening angle
- Distance to teammate



MDP Formulation

$$\text{MDP} = \langle S, A, P, R \rangle$$

Actions with ball:

- High level
- Select from a many options using hand-coded evaluation
- 6 actions:
    - Shoot
    - Short dribble
    - Long dribble
    - Pass x3

MDP Formulation

$$\text{MDP} = \langle S, A, P, R \rangle$$

Actions away from ball:

- 7 actions:
  - Stay still
  - Towards ball
  - Towards goal
  - Towards teammate
  - Away from teammate
  - Towards opponent
  - Away from opponent

MDP Formulation

$$\text{MDP} = \langle S, A, P, R \rangle$$

Transition function:

- Gives resulting state after taking an action
- Given by the 2D RoboCup simulator
- Not explicitly modeled

MDP Formulation

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Reward function:

- Describes the value of a state
- 1,000 on win
- -1,000 on loss
- -1 per step

Collect Data

- Collect $\langle s, a, r, s' \rangle$
  - s – original state
  - a – action
  - r – reward
  - s' – next state
- In parallel

Q-Learning

- Iterate through stored experiences
- Estimates values of state-actions
- Update rule:
  $Q(s, a) = Q(s, a) + \alpha[r + \gamma \max'_a Q(s', a') - Q(s, a)]$

Q-Learning

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- Update rule:
  $Q(s, a) = Q(s, a) + \alpha[r + \gamma \max'_a Q(s', a') - Q(s, a)]$
- Use Q(λ)
  - Incorporates elligibility traces
  - Aids in credit assignment

Function Approximation

- Generalize known values to neighbors
- Handles continuous space

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- Generalize known values to neighbors
- Handles continuous space
- CMAC Tile coding
  - $\hat{Q}(s, a) = \sum_i w_i f_i$
  - Perform parameter search over parameters

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Different Teammates

- Learning a single policy does not work well for all teammates
- Instead, learn policy for each teammate

Different Teammates

- Learning a single policy does not work well for all teammates
- Instead, learn policy for each teammate
- Question: how do we know which policy to use for an unknown teammate?

How to select?

- Can treat as a multi-armed bandit problem
  - Slow to learn
  - One pull = 1 game of HFO

How to select?

- Can treat as a multi-armed bandit problem
  - Slow to learn
  - One pull = 1 game of HFO
- Compare observed teammate actions to past experiences
  - Normally distributed
  - Update using Bayes rule
  - Bound loss

Teammates

- Externally-created teammates
- Total of 7 teammate types

Teammates

- Externally-created teammates
- Total of 7 teammate types
- 6 of top 8 teams from the 2013 competition
  - aut
  - axiom
  - cyrus
  - gliders
  - helios
  - yushan
- Plus the agent2d code release

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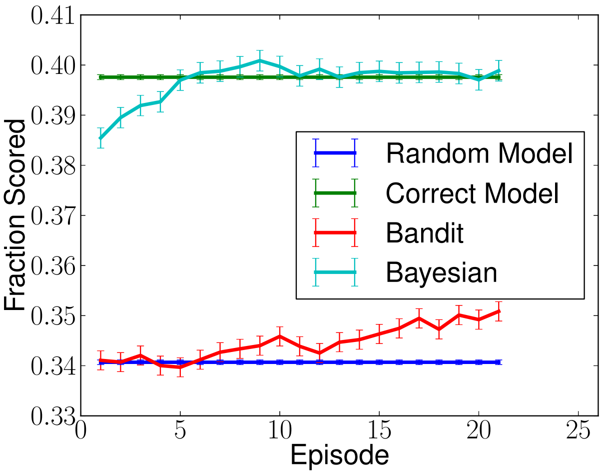
Setup

- 10,000 trials
- Randomly selected teammate
- Teammate is unknown to agent
- Baselines:
  - Randomly select a policy to use
  - Select the policy learned for that teammate

Problem Description

- Limited version of the game
- 2 offensive players
  - 1 teammate
- 2 defensive players

Results for 2v2



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- Knowing your teammate's behavior helps
- Bandit algorithm is slow for this setting
  - 7 arms
  - Only 25 pulls

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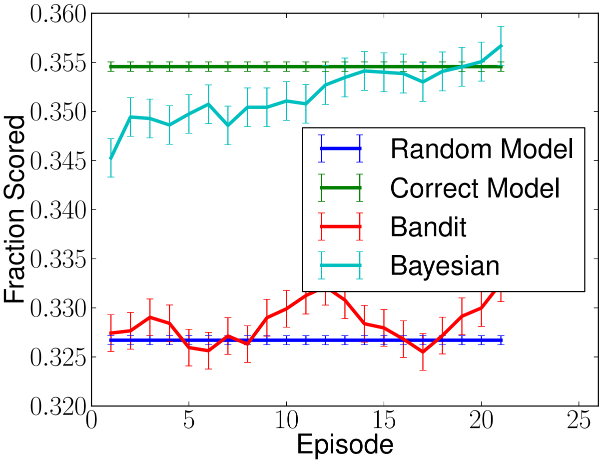
- Bandit algorithm is slow for this setting
  - 7 arms
  - Only 25 pulls
- Bayesian approach learns quickly
  - Outperforms bandit significantly

Problem Description

- 4 offensive players
  - 3 teammates
- 5 defensive players
- Harder task

Results for 4v5



Results for 4v5

- Less improvement by learning policy
  - Only 1 of 9 agents in play
- Slower to learn than 2v2 case
  - More noise from more agents

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- Can learn which policy to use
- Bayesian approach outperforms bandit significantly

Conclusions

- Handle a complex domain
- Can learn policy to cooperate with teammates

Conclusions

- Handle a complex domain
- Can learn policy to cooperate with teammates
- Can figure out how to cooperate with unknown teammates on the fly

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Related Work

- P. Stone and S. Kraus. To teach or not to teach? Decision making under uncertainty in ad hoc teams. In *AAMAS '10*, May 2010
- P. Stone, G. A. Kaminka, and J. S. Rosenschein. Leading a best-response teammate in an ad hoc team. In *AMEC*. November 2010
- F. Wu, S. Zilberstein, and X. Chen. Online planning for ad hoc autonomous agent teams. In *IJCAI*, 2011

Related Work

- S. Liemhetcharat and M. Veloso. Modeling mutual capabilities in heterogeneous teams for role assignment. In *IROS '11*, pages 3638 –3644, 2011
- M. Bowling and P. McCracken. Coordination and adaptation in impromptu teams. In *AAAI*, pages 53–58, 2005
- J. Han, M. Li, and L. Guo. Soft control on collective behavior of a group of autonomous agents by a shill agent. *Journal of Systems Science and Complexity*, 19:54–62, 2006

Thank You!

- Can learn to cooperate with different teammates in the 2D RoboCup domain