CAP6671 Intelligent Systems

Lecture 13:

Multi-agent Reinforcement Learning

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Schedule: T & Th 9:00-10:15am

Location: HEC 302

Office Hours (in HEC 232):
T & Th 10:30am-12

Presentations on Related Work

- 30 minute presentation on one paper that you think is relevant to your project
- Presentation should include:
  - Strengths/weaknesses of paper
  - Detailed presentation of how the system described in the paper works
  - Discussion of how the paper relates to your project
- Email me about when you want to present your paper

Strengths/Problems of Paper

Strengths/Problems of Paper

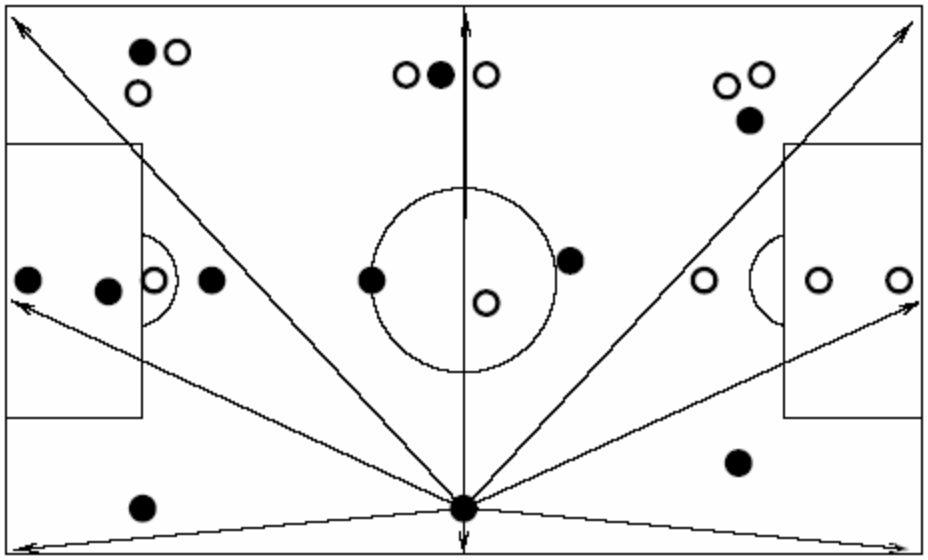
- Pros:
  - Works in a non-Markovian domain
  - Handles multi-agent teams
  - Large state space
  - Has been generalized to the network routing domain
- Cons:
  - Much of the work is done by the feature selection mechanism
  - No convergence guarantee
  - Relies on intermediate reinforcement

Characteristics

- Opaque-transition
  - No simple function which governs the transition from one state to another
- Chained agents
  - No single agent's actions can achieve the goal
- Team-partitioned
  - Each teammate learns and uses a separate part of the table based on its position in the team

What is the agent trying to learn?

Action Representation



Actions=possible kicks towards all the corners of the field

Agent is trying which of 8 possible kicks it should make when it has possession of the ball

How many Q-values are there?

- Number of states 22^{10^9}
- # Q-values is normally equal to SxA
- Q-table used in this system only has 88 values; each player only learns 8 Q-values per game
- How is this done?
  - Answer: by the use of a single feature (kick success)

Algorithm

- State generalization
  - Move from raw representation of state space through the outputs (f: S->V)
- Value function learning
  - Determine whether each possible action is likely to succeed (represented by Q-values)
- Action selection
  - Update Q-table based on action chosen and reward received

Value Function Learning

- Insight: use high level action-dependent features to describe the state space
- Only need to consider the features relevant to the action being performed

$e(s,a_0)$	$e(s,a_1)$	$Q(v,a_0)$	$Q(v,a_1)$
u_0	u_0	$q_{0,0}$	$q_{1,0}$
u_0	u_1	$q_{0,0}$	$q_{1,1}$
u_0	u_2	$q_{0,0}$	$q_{1,2}$
u_1	u_0	$q_{0,1}$	$q_{1,0}$
u_1	u_1	$q_{0,1}$	$q_{1,1}$
u_1	u_2	$q_{0,1}$	$q_{1,2}$
u_2	u_0	$q_{0,2}$	$q_{1,0}$
u_2	u_1	$q_{0,2}$	$q_{1,1}$
u_2	u_2	$q_{0,2}$	$q_{1,2}$

$\Rightarrow$

$e(s,a_1)$	$Q(v,a_0)$	$Q(v,a_1)$
u_0	$q_{0,0}$	$q_{1,0}$
u_1	$q_{0,1}$	$q_{1,1}$
u_2	$q_{0,2}$	$q_{1,2}$

- Normally features are independent of actions

Learning Rule

- Modified version of the Q-learning which only takes into account immediate reward and not future transitions

$$Q(v,a) = Q(v,a) + \alpha(r - Q(v,a))$$

- Standard Q-learning

$$Q(s,a) := Q(s,a) + \alpha(r + \gamma \max_{a'} Q(s',a') - Q(s,a))$$

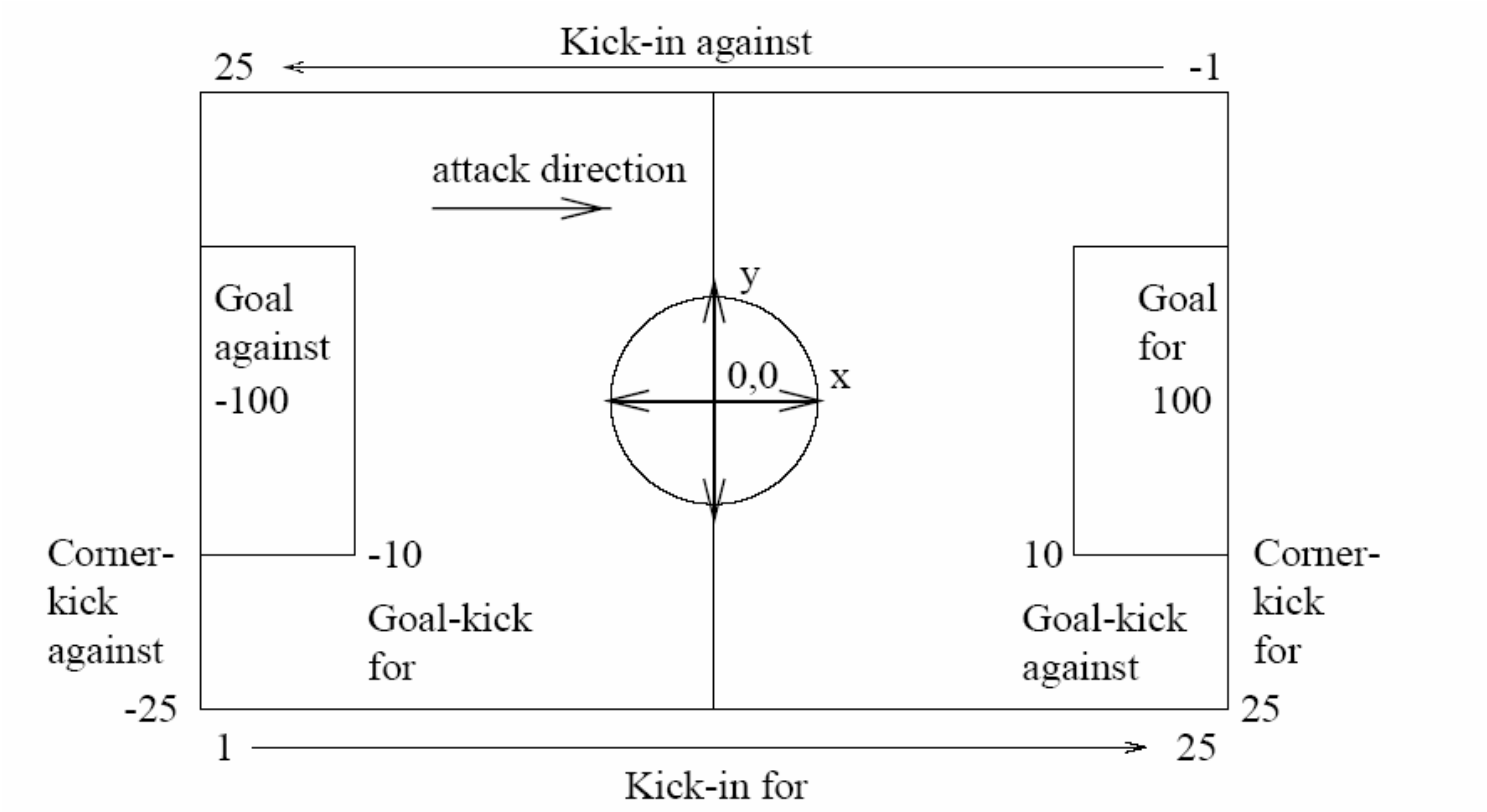
Action Selection

- Features themselves are discriminative of whether the action should be used
- Hence never consider actions when the feature lacks a certain value (filter based on W)
- If only successful kicks are considered then effectively there is only one state (SuccessfulKick) and 8 actions
- Number of Q-values learned by each agent is 8!
- During the game the actions can be selected using any standard exploration policy (e.g. Boltzmann, greedy)

Layered Approach

- Divide and conquer the learning task
- Low level modules make a big difference to success
- Predicting kick success
  - Use 200 continuous value attributes describing teammate/opponent positions
  - C4.5 decision tree algorithm
- Intercepting ball
  - Trained a neural network specifically for the interception behavior

Reward Representation

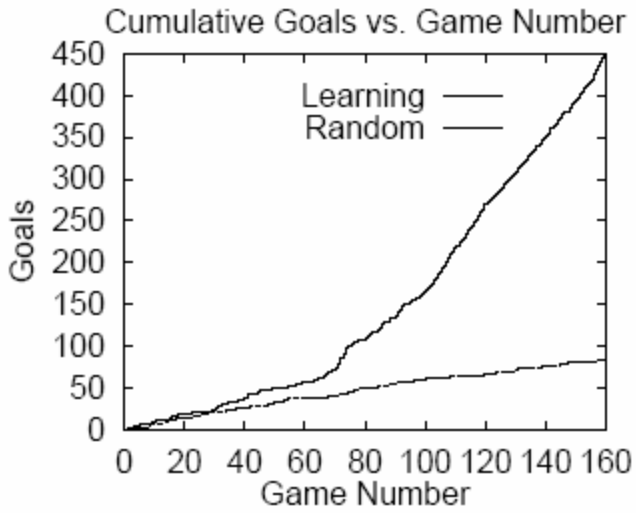


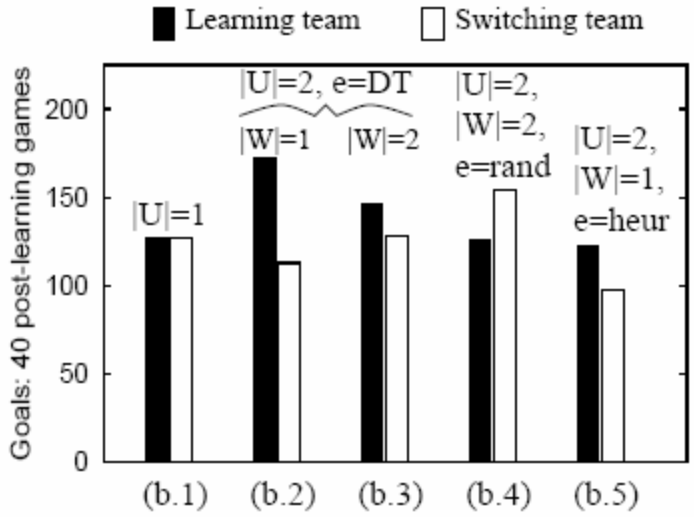
- Use intermediate rewards rather than just rewarding at goals
- Base reward functions are scaled by time events occur
- Must be observed by agent doing the learning

Results

- Evaluated vs. random team and switching team
- Random team just makes random passes
- Switching team uses hand-coded policy in which the agents all stay towards one half of field
- Interesting notes:
  - 11 players got an average of 1490 action reinforcement pairs per game
  - Each action is only tried on average 186 times over 160 games

Results


Cumulative Goals vs. Game Number
Goals
Game Number
Learning
Random
0
50
100
150
200
250
300
350
400
450
0 20 40 60 80 100 120 140 160


Learning team
Switching team
Goals: 40 post-learning games
|U|=1
|U|=2, e=DT
|W|=1
|W|=2
|U|=2,
|W|=2,
e=rand
|U|=2,
|W|=1,
e=heur
0
50
100
150
200
(b.1)
(b.2)
(b.3)
(b.4)
(b.5)

Conclusion

- Divide and conquer your problem
- Layering outputs of multiple classifiers is a very effective approach
- RL will be more effective if state space is small