CS378
Autonomous Multiagent Systems
Spring 2005

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Week 14b: Thursday, April 27th

Good Afternoon, Colleagues

Are there any questions?

– Competitive fitness sharing? (vs. opponent sampling?)
– How many games of TTT did it take to learn?
– Why do they compare vs. older methods?
– What's Nim?
– Why 2 populations (vs. self play)
– What's new with keepaway? Any coevolution?
– What learning updates when others have the ball?

The Tournament

1.	**Untitled**	Plaisance, Romer
2.	**HIVE**	Menzies, Ma
3.	**Team Voodoo**	Schneider, Guimbarda
4.	**YoHoHo**	Bland, Gray
5.	**Dynamic**	Rathmann, Marocha
6.	**Team America**	Huie, Hasan
7.	**Goal Rushers**	Kret, Massey
8.	**Listos**	Huerta, Nelson
9.	**Marigo**	Nimmagadda, Ristroph

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10.	**FOOBAR BAZ**	Knox, Edwards, Doyle

Machine Learning

Hypothesis space: set of possible functions

Training examples: the data

Learning method: training examples $\mapsto$ hypothesis

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Agent Learning

Policy: how to **act** (generate training examples)

neural network training, Q-learning, decision tree training, clustering, genetic algorithms, genetic programming, ...

3 vs. 2 Keepaway (joint with Rich Sutton)

- Play in a **small area** (20m $\times$ 20m)
- **Keepers** try to keep the ball
- **Takers** try to get the ball
- **Episode:**
  - Players and ball reset randomly
  - Ball starts near a keeper
  - Ends when taker gets the ball or ball goes out
- Performance measure: **average possession duration**
- Use **CMUnited-99 skills**:
  - HoldBall, PassBall(k), GoToBall, GetOpen

Available Skills (from CMUnited-99)

HoldBall(): Remain stationary while keeping possession of the ball.

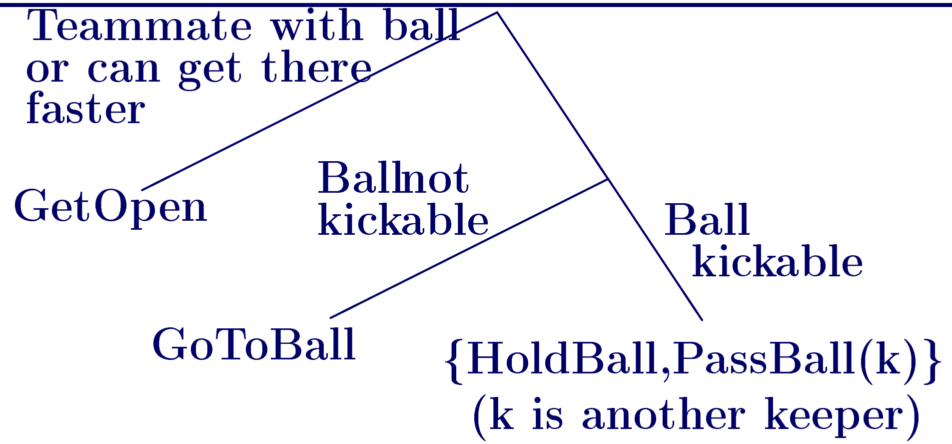
PassBall(k): Kick the ball directly to keeper k.

GoToBall(): Intercept a moving ball or move directly towards a stationary ball.

GetOpen(): Move to a position that is free from opponents and open for a pass from the ball's current position (using SPAR (Veloso et al., 1999))

BlockPass(k): Get in between the ball and keeper k

The Keepers' Policy Space



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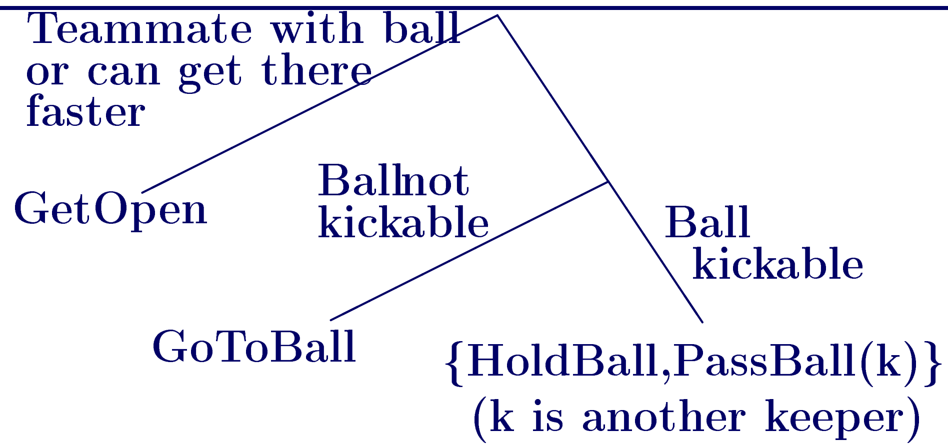


Example Policies

Random: HoldBall or PassBall(k) randomly

Hold: Always HoldBall

Hand-coded:

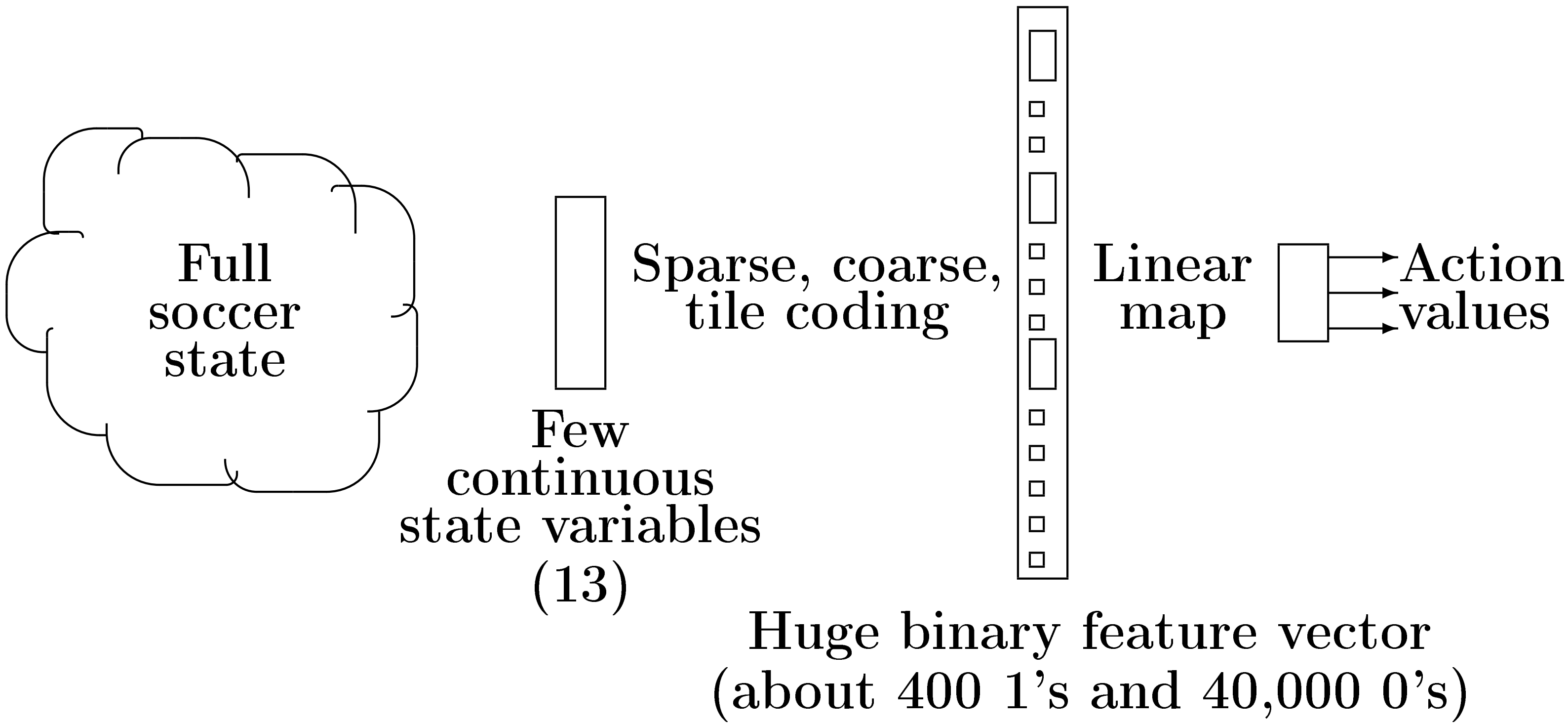
- **If** no taker within 10m: HoldBall
- **Else If** there's a good pass: PassBall(k)
- **Else** HoldBall

Mapping Keepaway to RL

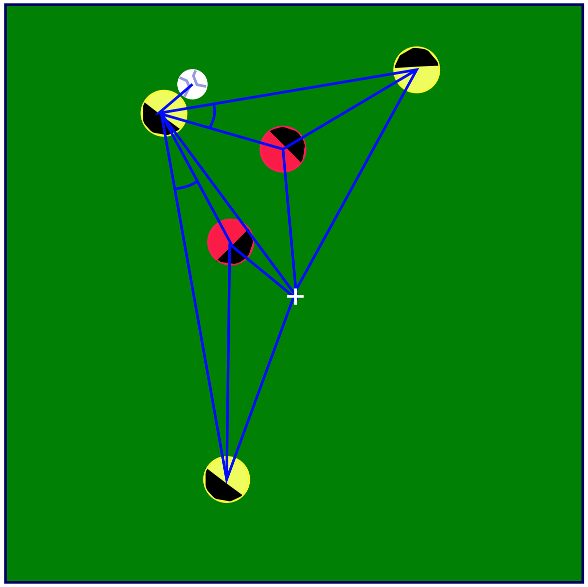
Discrete-time, episodic, distributed RL

- Simulator operates in discrete time steps, $t = 0, 1, 2, \ldots$, each representing 100 msec
- Episode: $s_0, a_0, r_1, s_1, \ldots, s_t, a_t, r_{t+1}, s_{t+1}, \ldots, r_T, s_T$
- $a_t \in$ {HoldBall, PassBall(k), GoToBall, GetOpen}
- $r_t = 1$
- $V^\pi(s) = E\{T \mid s_0 = s\}$
- Goal: Find π^* that maximizes V for all s

Representation



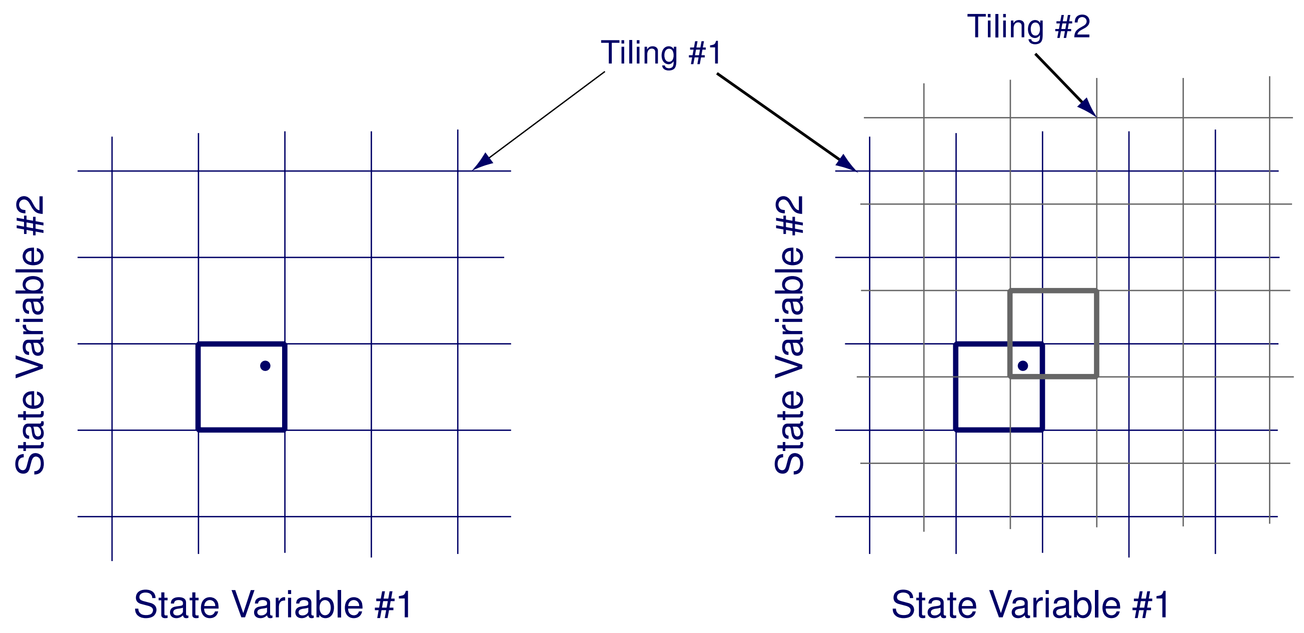
s: 13 Continuous State Variables



- 11 distances among players, ball, and center
- 2 angles to takers along passing lanes

Function Approximation: Tile Coding

- Form of sparse, coarse coding based on CMACS (Albus, 1981)



- Tiled state variables individually (13)

Policy Learning

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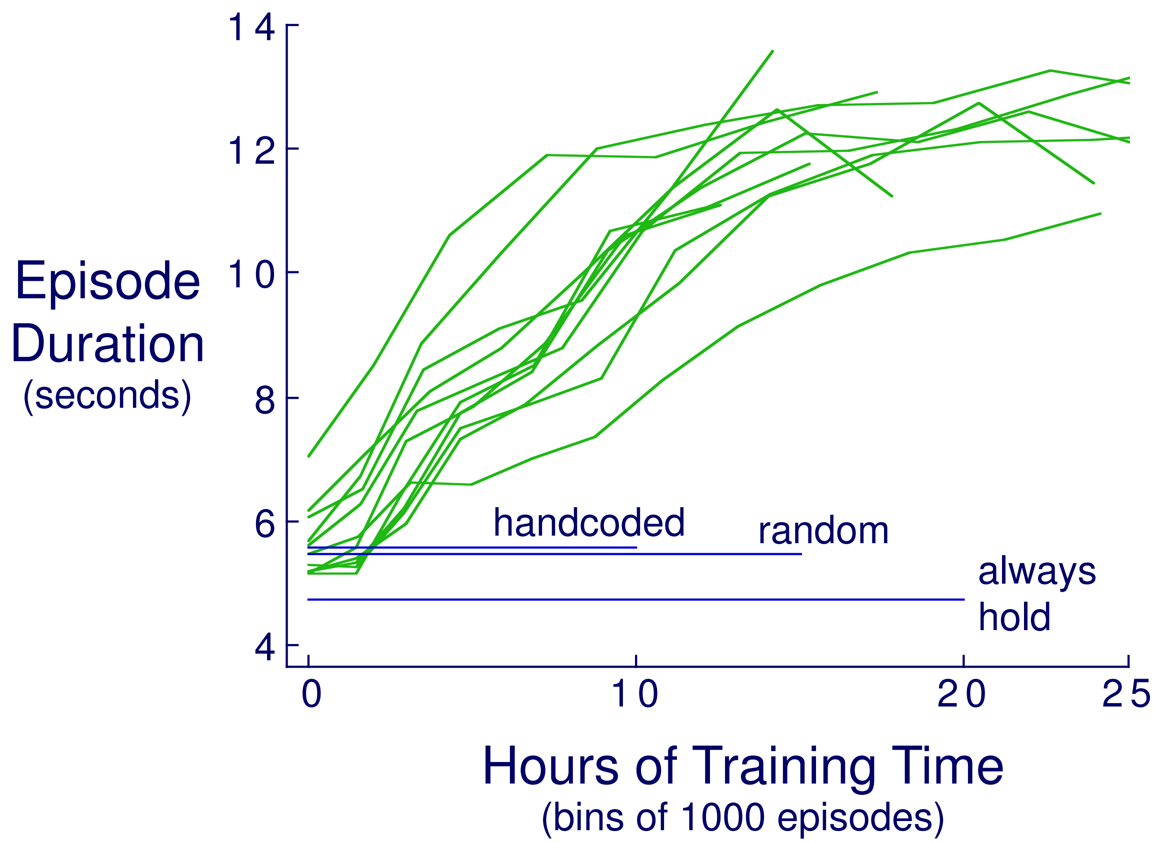
- Learn $Q^\pi(s,a)$: Expected possession time
- Linear Sarsa(λ) — each agent learns independently
  - On-policy method: advantages over e.g. Q-learning
  - Not known to converge, but works (e.g. (Sutton, 1996))

Main Result



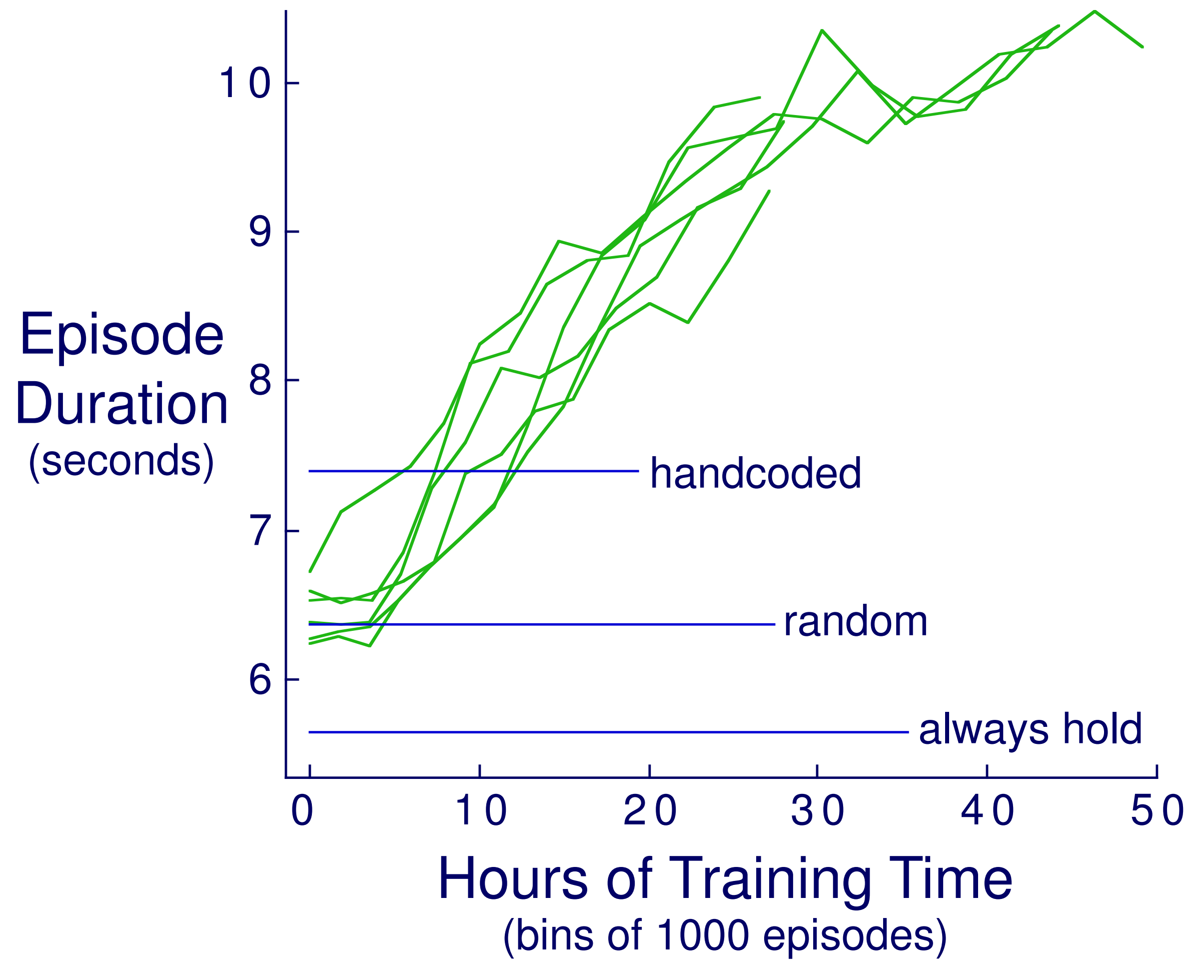
1 hour = 720 5-second episodes

Varied Field Size

Keepers		Testing Field Size 15x15	20x20	25x25
Trained on field of size	15x15	**11.0**	9.8	7.2
	20x20	10.7	**15.0**	12.2
	25x25	6.3	10.4	**15.0**
Benchmarks	Hand	4.3	5.6	8.0
	Hold	3.9	4.8	5.2
	Random	4.2	5.5	6.4

- Single runs
- learning specific to fields
  - mechanism generalizes better than policies

4 vs. 3 Keeper Learning



- Preliminary: taker learning successful as well

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- Keep a population of individuals
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  - Evaluate their fitness
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The fitness function matters

- Playing against top-notch competition → no info
- Playing against a single foe → too brittle

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  - Why compare against old methods?

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- Simultaneous learning by teammates could be thought of in this way as well.