Progress in Learning 3 vs. 2 Keepaway

Gregory Kuhlmann
Department of Computer Sciences
University of Texas at Austin

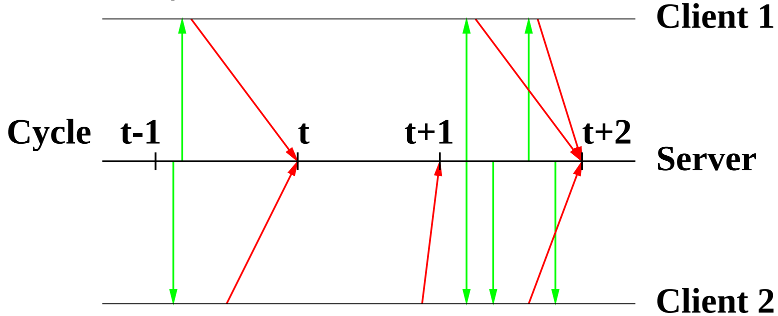
Joint work with
Peter Stone

RoboCup and Reinforcement Learning

- Reinforcement Learning — suited to soccer
  - Sequential decision making
  - Achieving delayed goals
  - Handling noise and stochasticity
  - Rapid decision-making
- Challenges
  - Multiple learning agents
  - Large state space
  - Not within realm of theoretical results

RoboCup Simulator

- Distributed: each player a separate client
- Server models dynamics and kinematics
- Clients receive sensations, send actions

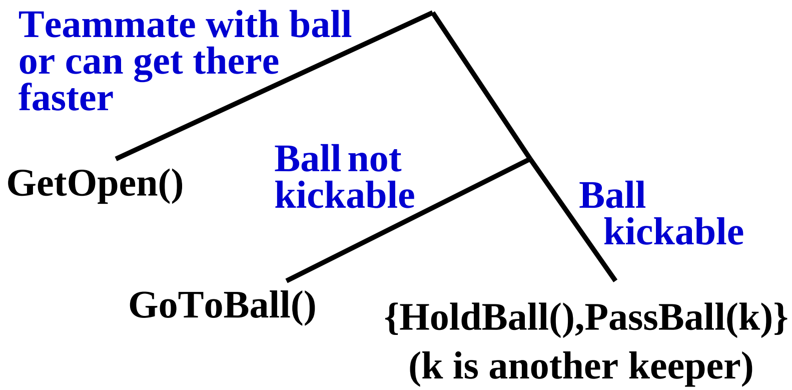


- Parametric actions: dash, turn, kick, say
- Abstract, noisy sensors, hidden state
  - Hear sounds from limited distance
  - See relative distance, angle to objects ahead
- $> 10^{9^{23}}$ states
- Limited resources : stamina
- Play occurs in real time ($\approx$ human parameters)

3 vs. 2 Keepaway

- 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 of bounds
- Performance measure: average episode duration

Keeper Policy Space



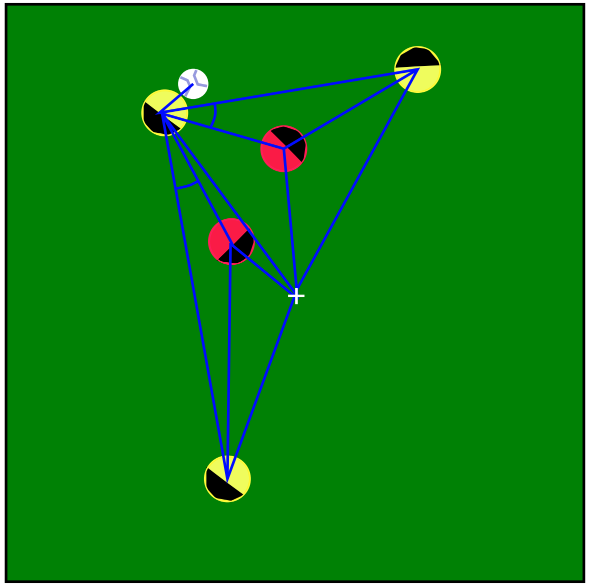
- Basic skills from CMUnited-99 team
- Example Policies
  - Random
  - Hold
  - Hand-coded

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: $s_0, a_0, r_1, s_1, \ldots, s_t, a_t, r_{t+1}, s_{t+1}, \ldots, r_T, s_T$
- $r_t = 1$
- $V^\pi(s) = E\{T \mid s_0 = s\}$
- Goal: Find π^* that maximizes V for all s

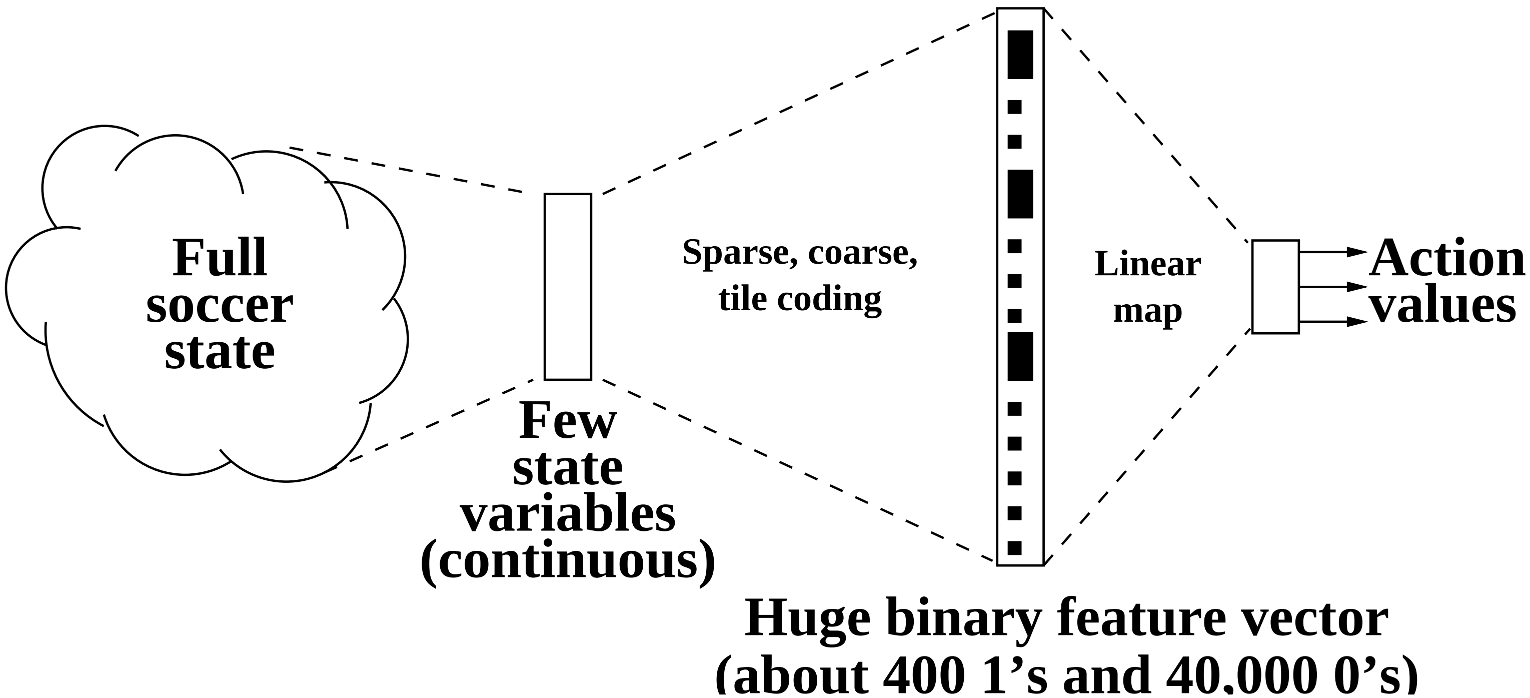
Keeper's State Variables



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

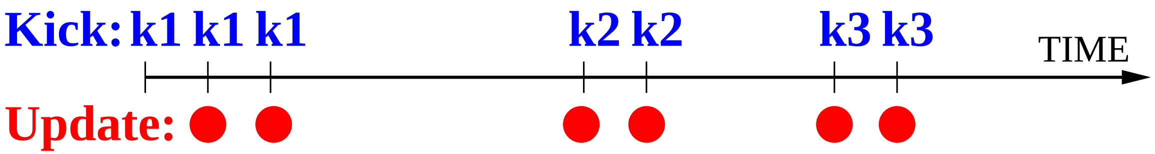
Function Approximation: Tile Coding

- Form of sparse, coarse coding based on CMACS [Albus, 1981]
- Tiled state variables individually (13)

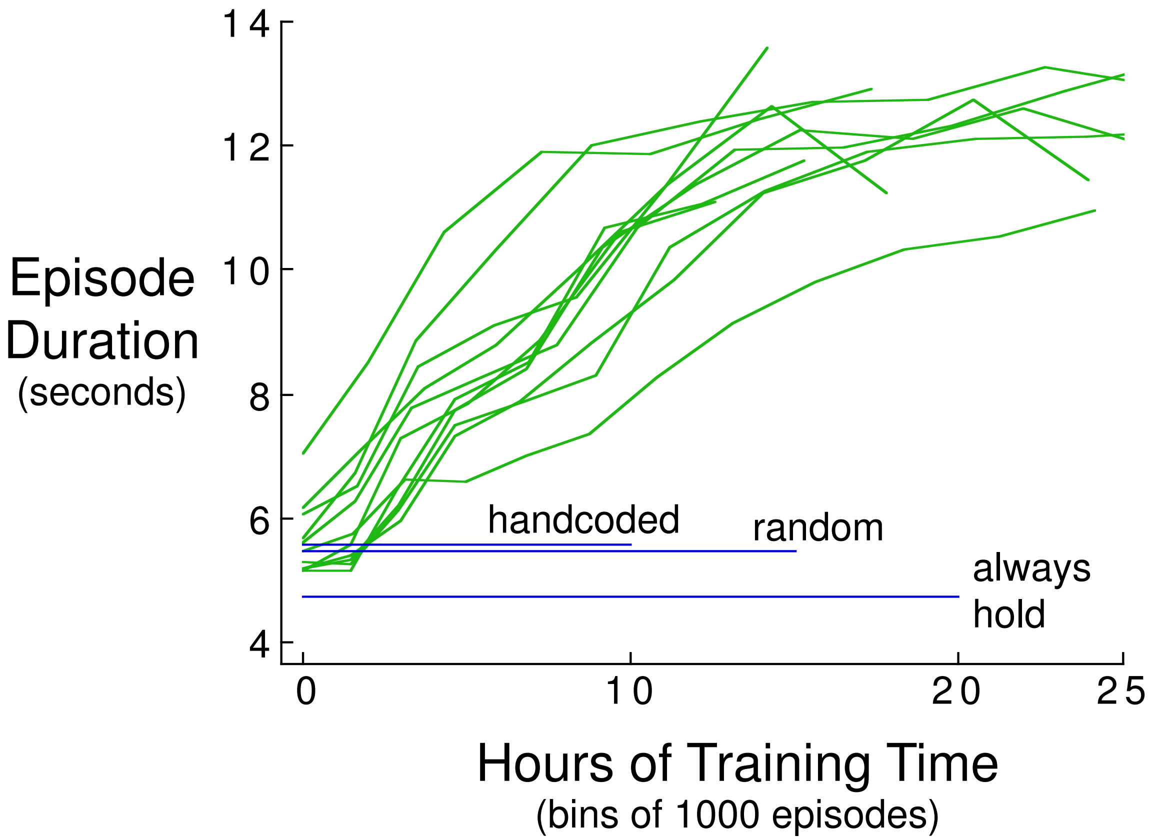


SMDP Sarsa(λ)

- Linear Sarsa(λ)
  - On-policy method: advantages over e.g. Q-learning
  - Not known to converge, but works (e.g. [Sutton, 1996])
- Only update when ball is kickable for **someone**:
  Semi-Markov Decision Process

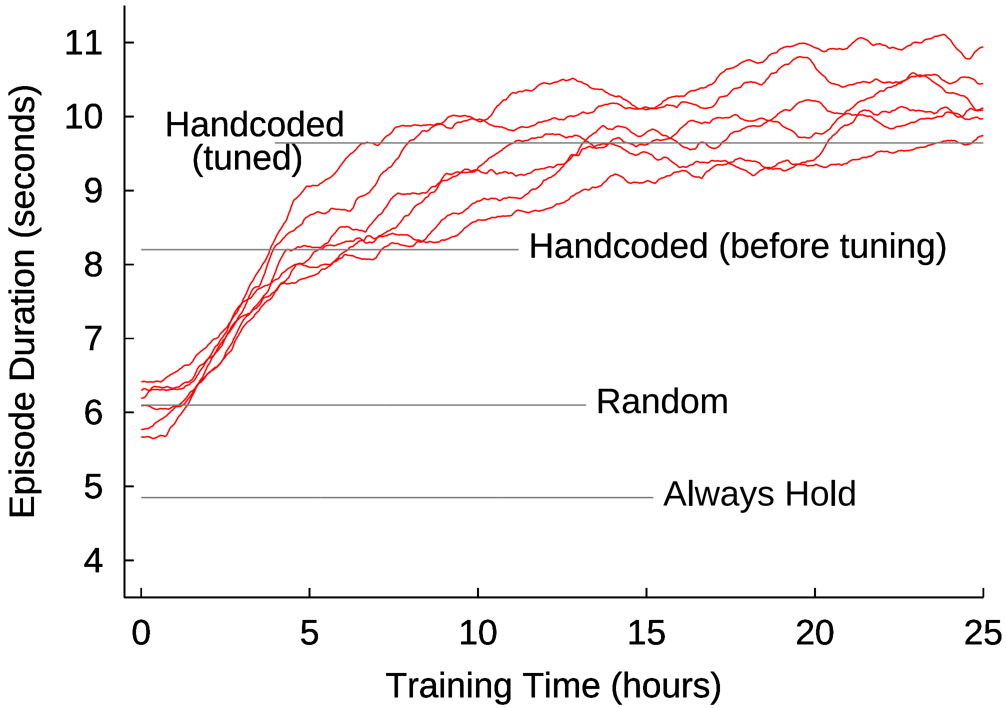


Previous Results



- Results scaled up to 4 vs. 3
- **360^o view angle. No perceptual noise**

Limited Vision



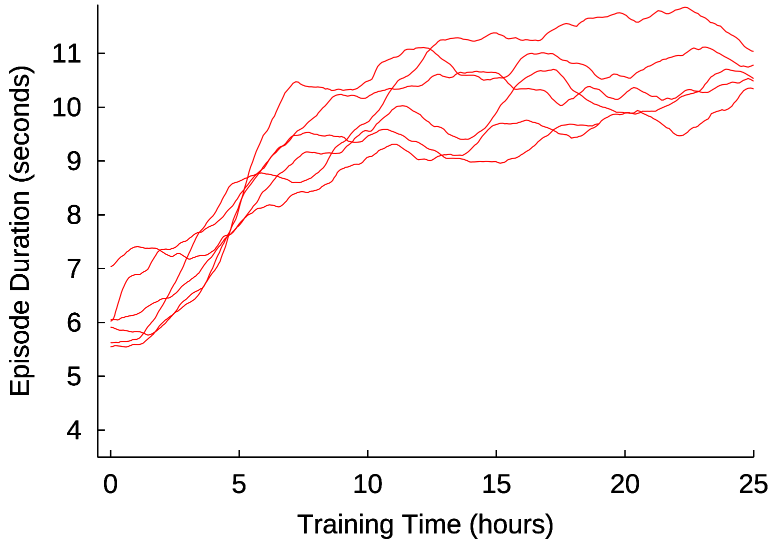
- With noise. Limited (90^o) vision
- As good as tuned handcoded policy

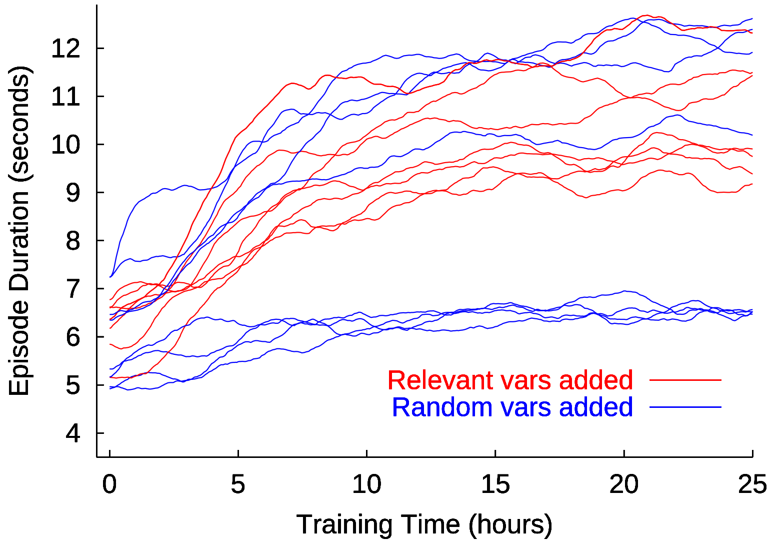
Varying Field Sizes

	Keeper Policy	
Field Size	Hand-coded	Learned ($\pm 1\sigma$)
30×30	**19.8**	18.2 $\pm$ 1.1
25×25	**15.4**	14.8 $\pm$ 0.3
20×20	9.6	**10.4 $\pm$ 0.4**
15×15	6.1	**7.4 $\pm$ 0.9**
10×10	2.7	**3.7 $\pm$ 0.4**

- Learning does better on harder problems

Changing the State Representation



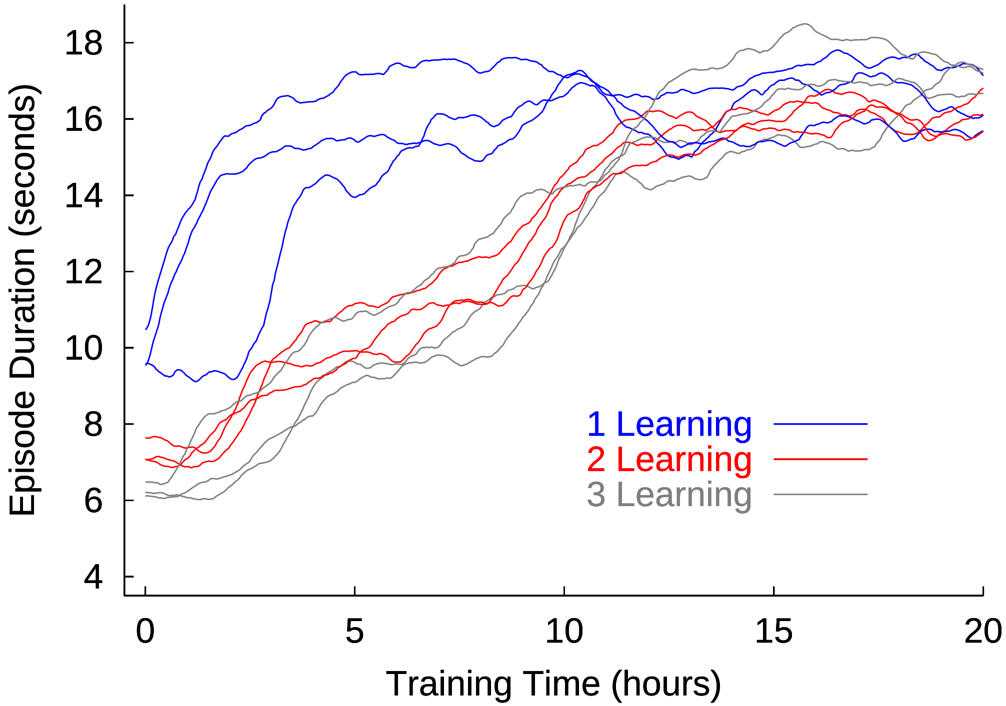


5 variables from the handcoded policy

13 original variable plus an additional 2

- Robust to redundant variables
- Sometimes confused by irrelevant variables

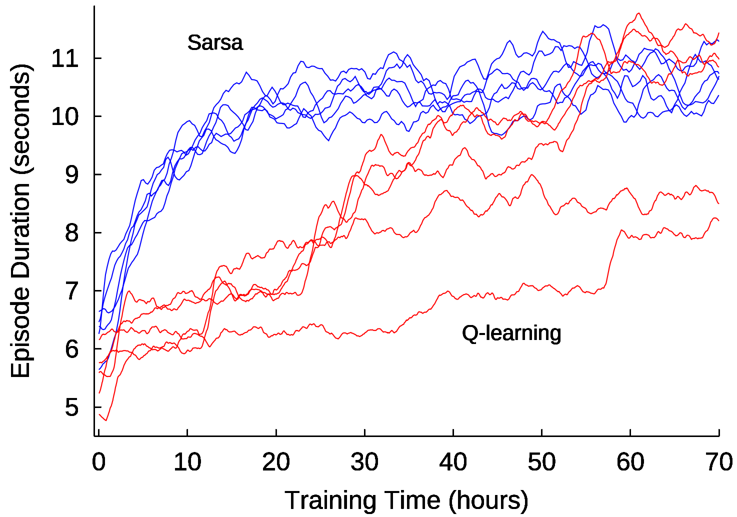
Difficulty of Multiagent Learning



- Multiagent learning is harder!

More Results

- Learns faster than on-policy method: Q-learning



Scaling up:

- Solution scales to: 4 vs. 3, 5 vs. 4, 6 vs. 5
- Learning time doubles each step

Conclusion

- SMDP Sarsa(λ) with tile-coding provides a robust multiagent learning solution despite lack of theoretical guarantees.
- Performs as well as a handcoded solution and is more robust.

- Keepaway domain part of official Soccer Server: `http://sserver.sourceforge.net/`

- Acknowledgement: Richard S. Sutton