Keepaway Soccer:

From Machine Learning Testbed to Benchmark

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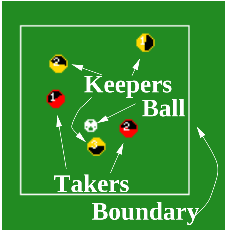
RoboCup Symposium, 2005

Keepaway: A Subtask of Simulated Soccer



- Play in a **small area**
- **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 **pre-defined skills**:
  - HoldBall, PassBall(k), GoToBall, GetOpen

Previous Studies

Keepaway as a Successful Machine Learning Testbed

- **Temporal-Difference Learning** [Stone and Sutton, 2001]
- **Evolutionary Algorithms** [DiPietro et al., 2002]
- **Genetic Programming** [Hsu and Gustafson, 2002]
- **Relational Reinforcement Learning** [Walker et al., 2005]
- **Transfer Learning** [Taylor and Stone, 2005]

Previous Studies

Problems as a Benchmark

- Results not directly comparable
  - Different simulators, low-level behaviors, experimental setups, and evaluation metrics.
- Prohibitively large startup cost
  - Must reimplement keepaway players
  - Requires domain expertise

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Outline

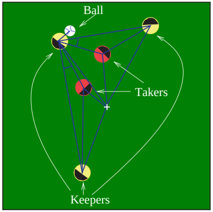
1. Benchmark Repository
   - Standardized Players
   - Online Resources
2. An Empirical Study
   - Fixed Policies
   - Function Approximators

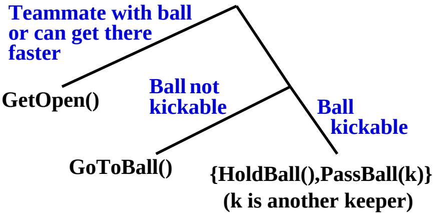
Outline

Player Framework

- **Open-source** player (C++)
  - built on UvA Trilearn base player
- Implements all but learning
  - high-level skills, world model, communication.
- Simple interface to learning algorithm

Standardized Learning Scenario





- **Keeper With Ball** can HoldBall(), PassBall(k)
- **Relational State Features:**
  - 11 distances among players, ball, and center
  - 2 angles to takers along passing lane
- **Takers** follows fixed policy

Learning Agent Interface

- Learner must implement three C++ functions
  - `int startEpisode(double state[])`
    called on first action opportunity
  - `int step(double reward, double state[])`
    called on each action opportunity after first
  - `void endEpisode(double reward)`
    called once at end of episode
- Presents domain as continuous state Semi-Markov Decision Process
- Allows for **TD-learning** or **policy search**

Online Resources

- Complete player **source code**
- Concrete **results** for comparison
- Graphical **tools** to evaluate performance
  - Generate learning curves
- Step-by-step **tutorials**
  - Walk through how to apply new learning algorithm
  - Students with **no prior keepaway experience** completed basic tutorial in **under an hour**

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Fixed Policies

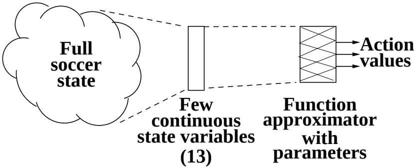
- Fixed policies included with benchmark players
  - **Always Hold:** always HoldBall
  - **Random:** HoldBall or PassBall(k) randomly
  - **Hand-coded:** simple heuristic policy

- Report **average performance** over 1000 episodes
  - sanity check for new installations

Policy	3 vs. 2	4 vs. 3	5 vs. 4
Always Hold	**3.4**±1.5	**4.1**±1.8	**4.8**±2.2
Random	**7.5**±3.7	**8.3**±4.4	**9.5**±5.1
Hand-coded	**8.3**±4.7	**9.2**±5.2	**10.8**±6.7

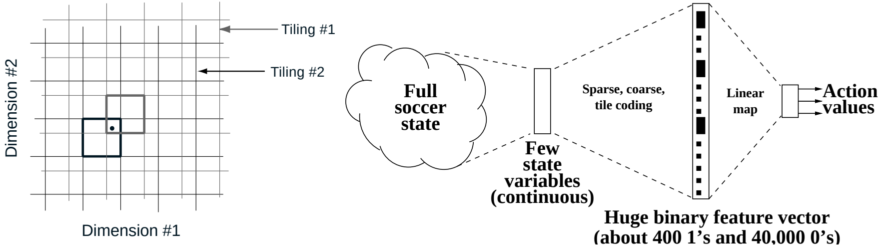
Experimental Setup

- Learn $Q^{\pi}(s, a)$: **Expected possession time**
- Sarsa(λ)
  - **On-policy method**: advantages over e.g. Q-learning
  - Not known to converge, but works (e.g. [Sutton, 1996])
- **3 Keepers** vs. **2 Takers**
  - Each keeper learns **separate value function**
- Compare different **function approximators**



CMAC tile-coding

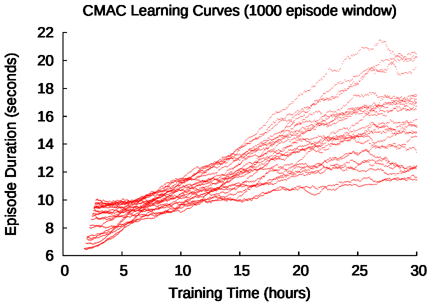
- Form of sparse, coarse coding based on **CMACs** [Albus, 1981]



- Tiled state variables **individually** (13)
- Linear FA on thousands of features

CMAC tile-coding

- 24 independent learning trials
- 1000 episode sliding window



- Reproduction of previous results

Radial Basis Functions

- Generalization of tile-coding to a **continuous function**
- **Gaussian:** $\phi(x) = \exp(-\frac{x^2}{2\sigma^2})$

- Better best-case performance than CMAC
  - between 5 and 25 hours
- Not significantly better on average

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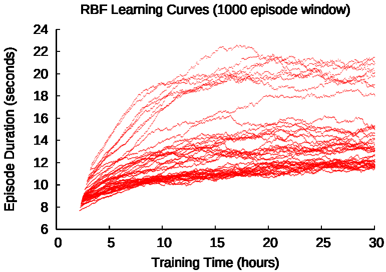

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Neural Network

- **3 separate feed-forward networks** (1 per action)
  - 20 (sigmoid) nodes in hidden layer
  - Linear output node
- Trained with standard **back-propagation**

- Learned policies **not as good** as with CMAC or RBF
  - But **more consistent** (lower variance)
- Room for **parameter optimization**

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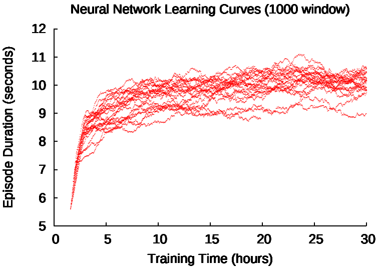

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Conclusion and Future Work

- Keepaway can now be used as an **RL benchmark**
- **Benchmark Repository** publicly available since December at:
  `http://www.cs.utexas.edu/~AustinVilla/sim/keepaway/`
  - **Mailing list** has 16 (11 non-UT) subscribers
  - At least one outside researcher with learning results
- Possible **future uses** and **extensions**
  - Compare policy search and TD methods
  - Explore **multi-agent learning** questions
  - Different state and action representations
  - Transfer learning