Online Value Function Improvement

Mitchell Keith Bloch

University of Michigan
2260 Hayward Street
Ann Arbor, MI. 48109-2121
bazald@umich.edu

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Reinforcement Learning

- Primary objective is to learn how to act, or to derive an optimal policy
- Prefer actions leading to positive rewards to actions leading to negative rewards
- Outcomes are are characterized as a discounted return, $\sum_{t=0}^{\infty} \gamma^t r_t$
- Deriving good estimates of these returns for different actions is essential for many RL algorithms

See [Sutton and Barto, 1998] for an excellent primer.

Temporal Difference Method: Q-Learning

Given

- a discount rate, γ
- a Q-function, $Q(s, a)$, to represent value estimates for state-action pairs, and
- an immediate reward, r,

the update rule is expressed:

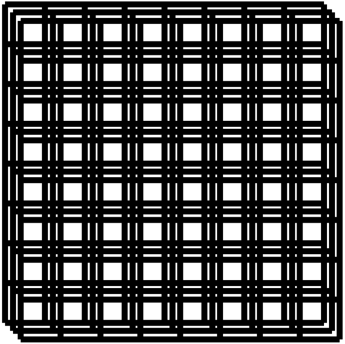
$$Q(s, a) \stackrel{\alpha}{\leftarrow} r + \gamma \max_{a^*} Q(s', a^*) \tag{1}$$

.

Without approximation, all $Q(s, a)$ values are independent.

- This uses $O(|s| \times |a|)$ memory.
- This doesn't support generalization.

Tile Coding: CMAC



- A tile coding partitions the state-space, providing a coarser representation.
- The CMAC (Cerebellar Model Articulation Controller) is the traditional approach to using multiple tile codings. [Sutton, 1996]

Soar-RL

- Soar-RL provides Q-learning and Sarsa [Nason and Laird, 2004]
- Conditions on RL-rules encode which features to test and how to discretize continuous state, defining the mapping $\mathcal{S} \times \mathcal{A} \Rightarrow \mathcal{Q}$
  - Can be one-to-one (if there no continuous features)
  - Can use coarse coding, effectively implementing tile coding
  - Potentially arbitrary, non-uniform abstraction
- Typical generalizations in Soar-RL rules effectively implement one or more tile codings

Motivation

We're concerned with the problem of generating a value function capable of supporting the computation of a near-optimal policy for a task with

- a large state-space
- composed of many features,
- some of which may be continous.

We're additionally concerned with problems of

- efficient learning,
- computational limitations,
- and memory limitations.

Overview of Our Work (In Progress)

We have broken down the problem into a number of subproblems:

1. Large, Sparse State-Spaces
2. Combining Values from Hierarchical/Overlapping Tilings
3. Credit Assignment for Hierarchical/Overlapping Tilings
4. Deciding When and Where to Refine the Value Function
5. Deciding How to Refine the Value Function
6. Complexities of These Approaches

Problem 1: Large, Sparse State-Spaces

Many agents developed using cognitive architectures operate in environments with

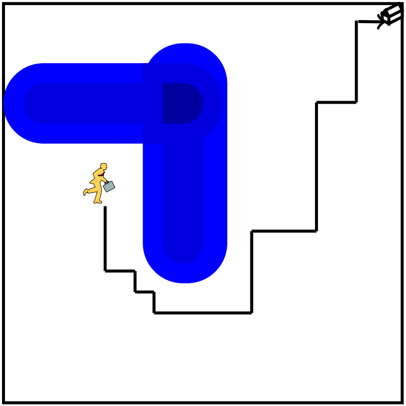
- large state-spaces,
- state-spaces described by large numbers of features, or
- continuous features which cannot be perfectly discretized.

Thankfully,

- the portion of the environment an agent must explore is often a relatively small subset of the state-space,
- features are not totally independent from one another,
- and satisfactory discretizations can usually be found.

Our strategy: hierarchical tile coding

Puddle World

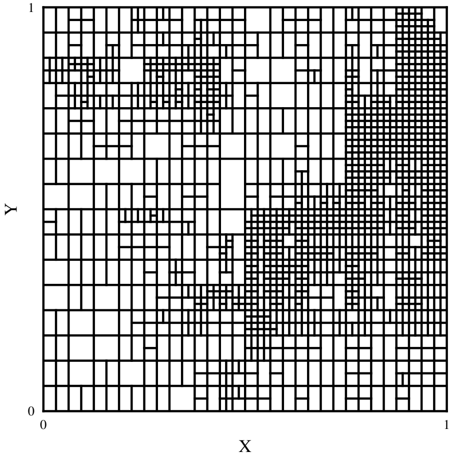


See [Sutton, 1996].

- **Goal:** Get to the upper-right corner, avoiding the puddles if possible.
- 2-dimensional state-space
- Continuous-valued features
- **Four actions:** North, South, East, and West
- Stochastic movement

What Does a Hierarchical Tile Coding Look Like?

A partial tiling for the "move North" action in Puddle World:



Problems 2 & 3: Hierarchical/Overlapping Tilings

Combining Values:

- Summation is typical (i.e. linear function approximation).
- This works for statically and dynamically generated tilings.

Credit Assignment:

- The standard approach has been even credit assignment between tiles.
- We consider alternatives which shift credit from more general tilings to more specific tilings over time.

Linear Function Approximation

Using

- n weights, and
- a Boolean function, $\phi_i(s, a)$, to determine whether to include any given weight

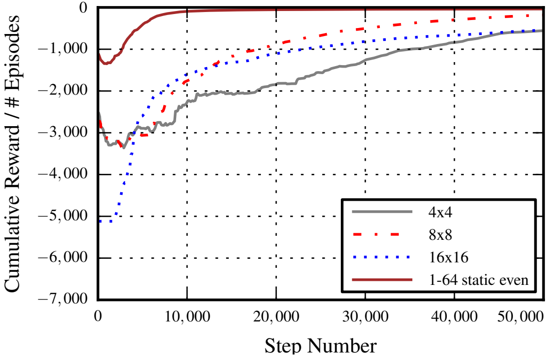
$Q(s, a)$ can be calculated:

$$Q(s, a) = \sum_{i=1}^{n} \phi_i(s, a) w_i, \tag{2}$$

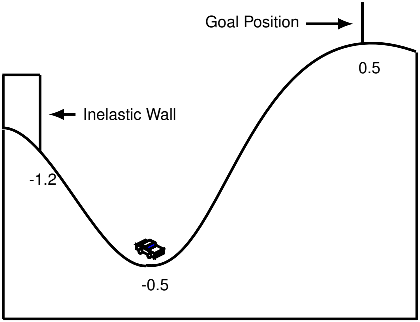
- This can reduce memory usage substantially.
- Done well, this may also support efficient generalization from experience.

Single Tilings vs Hierarchical: Puddle World

Performance for several agents using single tilings, and one using a static hierarchical tiling, in Puddle World:



Mountain Car

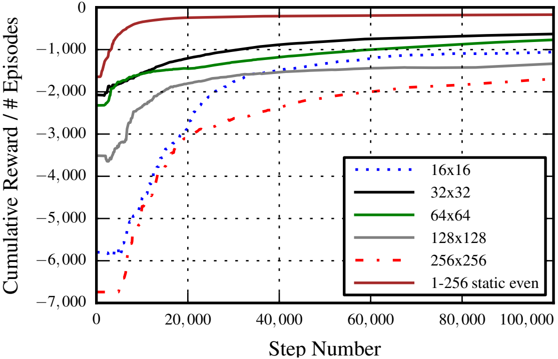


See [Moore, 1991].

- **Goal:** Get to the top of the hill.
- 2-dimensional state-space
- Continuous-valued features
- **Three actions:** Accelerate left, idle, and accelerate right
- Some dynamics

Single Tilings vs Hierarchical: Mountain Car

Performance for several agents using single tilings, and one using a static hierarchical tiling, in Mountain Car:



Problems 4 & 5: Refining the Value Function

When and Where:

- Must determine when and where the value function is not sufficiently specific to represent a near-optimal policy
- Must do this online, in an incremental fashion
- Must cope with error due to environmental stochasticity

Our criterion: **Cumulative Absolute Bellman Error**

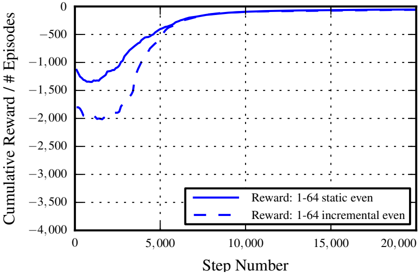
How:

- Must determine which features would be most beneficial to consider
- Must increase refinement of discretizations
- Must do this online, in an incremental fashion, without using a great deal of memory storing a model or instances

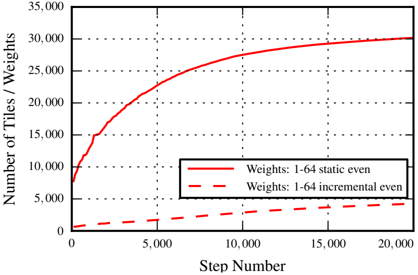
Static vs Dynamic (Hierarchical): Puddle World

Results for one agent using a static hierarchical tiling and another agent using an incremental hierarchical tiling in Puddle World:

Performance:



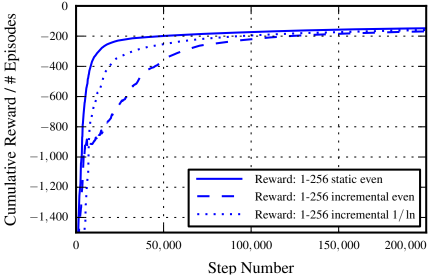
The number of weights:



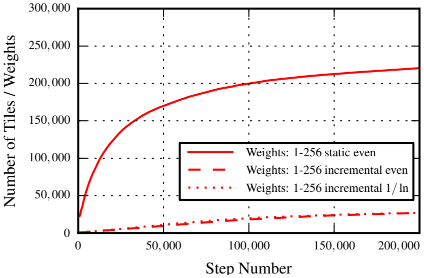
Static vs Dynamic (Hierarchical): Mountain Car

Results for one agent using a static hierarchical tiling and two agents using incremental hierarchical tilings (one with even credit assignment, and one with $1/\ln(\text{update count})$ credit assignment) in Mountain Car:

Performance:



The number of weights:



Problem 6: Complexities

Environmental:

- Environmental stochasticity
- Propagation delays / Mixing time
- Partial observability
- State aliasing

Keeping the value function small for

- savings in computation time and
- memory usage.

Other Environments

We wish to work more with additional environments:

- **Equilibrium Tasks:** 2 and 4-dimensional versions of Cart Pole
- **Relational Domains:** Blocks World
- **Future Work:** The above, and additionally Liar's Dice

We plan to

- improve our refinement criterion,
- add support for automatic feature selection, and
- focus more on the tradeoffs between computational and memory costs and learning efficiency.

Nuggets and Coal

Nuggets:

- We have an efficient codebase to experiment with.
- We have demonstrated the efficacy of deep hierarchical tile codings.
- We have shown that altenative credit assignment strategies have promise.
- Work so far is consistent with the implementation of Soar-RL.

Coal:

- Our current refinement/splitting criterion doesn't work very well in certain domains.
- The most recent experiments are not being done in Soar.

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