Reinforcement Learning Beyond Small MDPs: Practical Generic Reinforcement Learning

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2014

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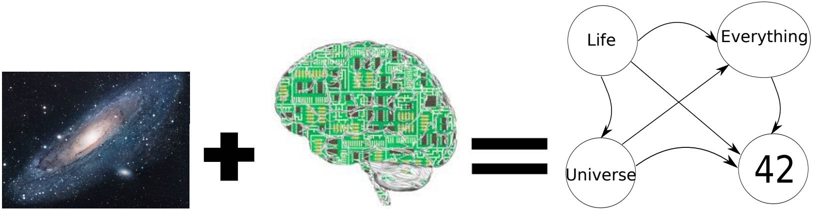
Feature Reinforcement Learning



Feature RL aims to automatically reduce a complex real-world non-Markovian problem to a useful (computationally tractable) representation (MDP).

Formally we create a map ϕ from an agent's history to a state representation. ϕ is then a function that produces a relevant summary of the history.

$$\phi(h_t) = s_t$$

Feature Markov Decision Process (ΦMDP)

To select the best ϕ, one defines a cost function.

$$\phi_{best} = \arg\min_{\phi}(Cost(\phi)).$$

- Feature RL is a recent framework.
- Original cost from Hutter 2009 is a model-based criterion.

$$Cost(\phi|h) = CL(s_{1:n}|a_{1:n}) + CL(r_{1:n}|s_{1:n}, a_{1:n}) + CL(\phi)$$

A practically useful modification adds a parameter α to control the balance between reward coding and state coding,

$$Cost_{\alpha}(\phi|h_n) := \alpha CL(s_{1:n}|a_{1:n}) + (1-\alpha) CL(r_{1:n}|s_{1:n}, a_{1:n}) + CL(\phi).$$

- A global stochastic search (e.g. simulated annealing) is used to find the ϕ with minimal cost.
- For fixed ϕ, MDP methods can be used to find a good policy

Model-free cost criterion

Daswani&Sunehag&Hutter 2013 introduced a fitted-Q cost

$$Cost_{QL}(\phi) = \min_Q \frac{1}{2} \sum_{t=1}^{n} (r_{t+1} + \gamma \max_a Q(\phi(h_{t+1}), a) - Q(\phi(h_t), a_t))^2 + Reg(\phi)$$

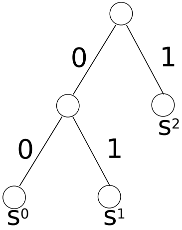
- $Cost_{QL}$ also extends easily to the linear function approximation setting by approximating $Q(h_t, a_t) \leftarrow \xi(h_t, a_t)^T w$ where $\xi : \mathcal{H} \times \mathcal{A} \to \mathbb{R}^k$ for some $k \in \mathbb{R}$.
- Connects feature rl to feature selection for TD methods, e.g. Lasso-TD or Dantzig-TD using ℓ_1 regularization while above *Reg* tends to be a more aggressive ℓ_0.
- For a fixed policy, a TD cost without $\max_a$ can be defined but one can also reduce the problem to feature selection for supervised learning using pairs (s_t, R_t) where R_t is the return achieved after state s_t.

Input : Environment $Env()$;
Initialise ϕ ;
Initialise history with observations and rewards from $t = init\_history$ random actions;
Initialise M to be the number of timesteps per epoch;
while *true* **do**
    $\phi = SimulAnneal(\phi, h_t)$;
    $s_{1:t} = (\phi(h_1), \phi(h_2), ..., \phi(h_t))$;
    $\pi = FindPolicy(s_{1:t}, r_{1:t}, a_{1:t-1})$;
    for $i = 1, 2, 3, ...M$ **do**
        $a_t \leftarrow \pi(s_t)$;
        $o_{t+1}, r_{t+1} \leftarrow Env(h_t, a_t)$;
        $h_{t+1} \leftarrow h_t a_t o_{t+1} r_{t+1}$;
        $t \leftarrow t + 1$;
    end
end

Algorithm 1: A high-level view of the generic ΦMDP algorithm.

Feature maps

- Tabular : use suffix trees to map histories to states (Nguyen&Sunehag&Hutter 2011,2012). Looping trees for long-term dependences (Daswani&Sunehag&Hutter 2012)
- Function approximation : define a new feature class of event selectors. A feature ξ_i checks the $n - m$ position in the history (h_n) for an observation-action pair (o, a).



If the history is $(0, 1), (0, 2), (3, 4), (1, 2)$ then a event-selector checking 3 steps in the past for the observation-action pair $(0, 2)$ will be turned on.

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Bayesian general reinforcement learning: MC-AIXI-CTW

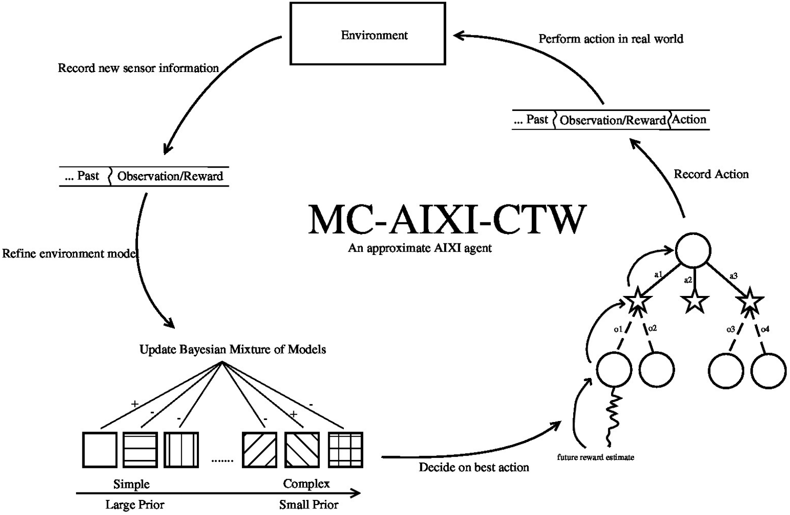
Unlike Feature RL, the Bayesian approach does not pick one map but uses a mixture of all instead. The problem is (again) split into two main areas:

- Learning - online sequence prediction / model building
- Planning/Control - search / sequential decision theory

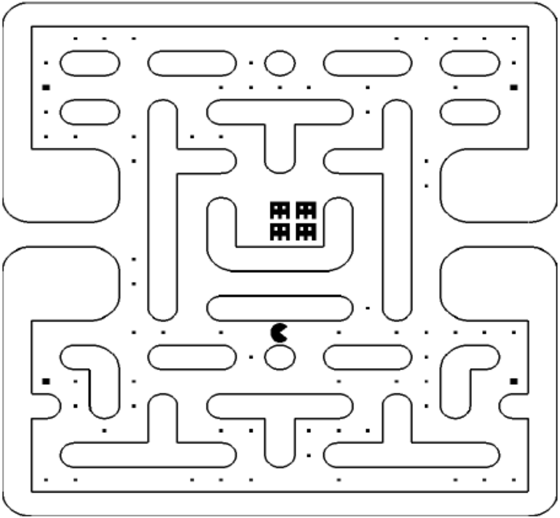
The hard parts:

- Large model class required for Bayesian mixture predictor to have *general* prediction capabilities.
- Fortunately, an efficient and general class exists: all Prediction Suffix Trees of maximum finite depth D. Class contains over $2^{2^{D-1}}$ models!
- The planning problem can be performed approximately with Monte-Carlo Tree Search (UCT)
- MC-AIXI-CTW (Veness et. al. 2010) combines the above

Overview of proposed agent architecture



Domain : POCMAN



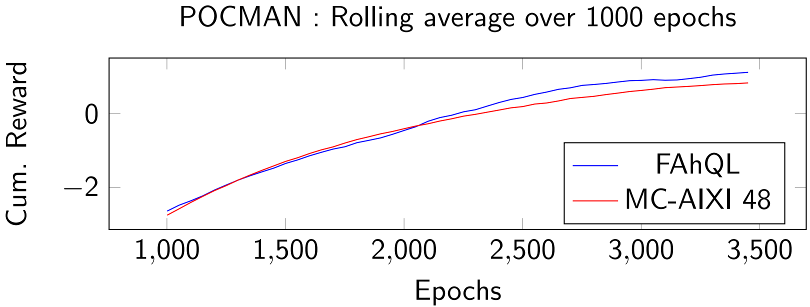


Figure : MC-AIXI vs hQL on Pocman

Agent	Cores	Memory(GB)	Time(hours)	Iterations
MC-AIXI 96 bits	8	32	60	$1 \cdot 10^5$
MC-AIXI 48 bits	8	14.5	49.5	$3.5 \cdot 10^5$
FAhQL	1	0.4	17.5	$3.5 \cdot 10^5$

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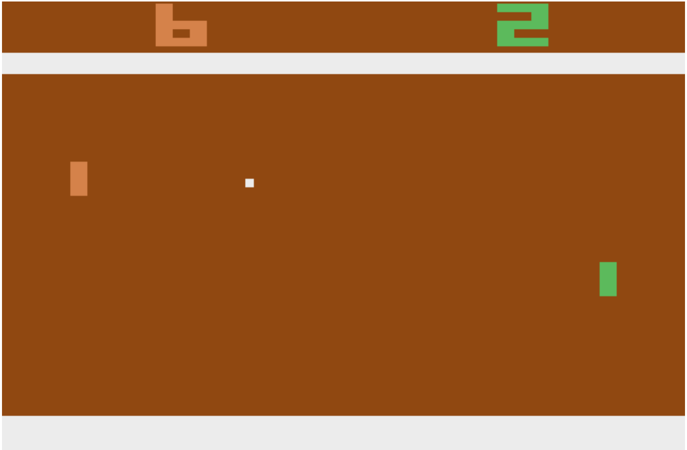
The Arcade Learning Environment (ALE)

ALE (Nadaf 2010, Bellamare et. al. 2012) is an interface built upon the open-source Atari 2600 emulator Stella. It provides a convenient interface to ATARI 2600 games.



Features for ALE

- Basic Abstraction of Screen Shots (BASS, from Nadaf 2010) first stores a background of the game it's playing. Then for every frame it subtracts away the background and divides the screen into 16x14 tiles. For each colour (8-bit SECAM) it creates a feature. It then takes the pairwise interaction of all these resulting features resulting in 1,606,528 features.
- Color provides object recognition.
- We study linear function approximation with BASS. We want to see how well one can do with that if one finds the right parameters
- Improved results has been achieved with non-linear neural/deep approaches.

The gap

Table : The gap between score (more is better) achieved by (linear) learning and (uct) planning

Game	UCT	BestLearner
Beam Rider	6,624.6	929.4
Seaquest	5,132.4	288
Space Invaders	2,718	250.1
Pong	21	-19

Out of 55 games, UCT has the best performance on 45 of them. The remaining games require a terribly long horizon.

Learning from an oracle

- Reinforcement learning is made much more difficult than supervised learning due to the need to explore.
- Therefore, many authors has in recent years been developing ways of teaching an rl agent through e.g. demonstration or advice with reduction to supervised learning.
- I will here discuss this idea in the context of Atari games through the Arcade Learning Environment (ALE) framework

Learning from UCT

A common scenario when applying reinforcement learning algorithms in real-world situations, learn in a simulator, apply in the real-world.

- UCT in the "real-world" still requires the simulator.
- UCT does not provide a policy representation, merely a trajectory.
- How do you extract a complete explicit policy from UCT?
- We will treat the value estimates from UCT as advice provided to the agent and we can then learn to play Pong with just a few episodes of data.
- Learning the value function is now a regression problem we solve using LibLinear (also exploring kernels, brings us back to feature selection/sparsification)
- Similar to the Dataset Aggregation algorithm for imitation learning (Ross and Bagnell 2010)

DAgger for reinforcement learning with advice Initialise $D \leftarrow \emptyset$
Initialise $\pi_1 (= \pi^*)$ t = 0 **for** *i = 1 to N* **do**

  while *not end of episode* **do**

    for *each action a* **do**

      Obtain feature $\phi(s_t, a)$ and oracle's $Q^*(s_t, a)$

      Add training sample $\{(\phi(s_t, a), Q^*(s_t, a))\}$ to D_a.

    end

    Act according to π_i

  end

  for *each action a* **do**

    Learn new model $\hat{Q}_i^a := {w_i^a}^\top \phi$ from D_a using regression

  end

  $\pi_i(\phi) = \arg\max_a \hat{Q}_i^a(\phi)$

end

Preliminary results

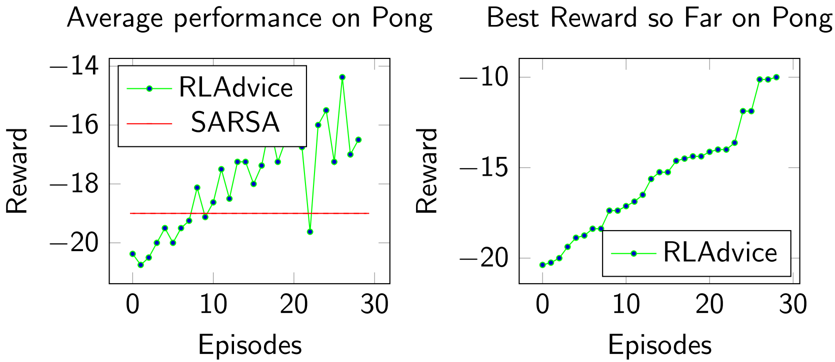


Figure : Pong Results: RLadvice with different amount of aggregated data (1-30 games) vs SARSA (linear function approximation) after 5000 games played. Results averaged over 8 runs

Conclusions/Outlook

- Reinforcement Learning is a powerful paradigm within which (basically) all AI problems can be formulated
- Many practical successes using MDPs by engineering problem reductions/reprentations
- Practically increasing the versatility of agents by learning reductions automatically.
- Recently introduced arcade gaming environment (from Alberta) for RL containing all ATARI games. Aim, have one generic RL agent solve all!
- Use data on how valuable states are from either simulations or experience to reduce complexity