

ICRA 2012 Tutorial on Reinforcement Learning

6. Exploration



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Exploration

- Key idea: to learn about unknown things, need to explore
- Challenge: how to explore efficiently?
- Model-based Exploration Methods
- Model-free Exploration Methods

Random Exploration

- ϵ greedy
 - Every time step, flip a coin
 - With probability ϵ , act randomly
 - With probability $1-\epsilon$, act according to current policy

Problems with Random Exploration

1. Keep thrashing around once learning is done
2. Exploration is by no means targeting underexplored states

Solutions:

- Lower ϵ over time (addresses 1, not 2)
- A better solution: exploration functions

Exploration Functions

- Modify rewards: place high bonus reward for state-action pairs that are not well-known

→ The optimal policy in the modified MDP performs targeted exploration

Model-based Exploration: Rmax

[Brafman and Tenenbholz, 2002] Rmax sketch:

Initialize all (x,u) as unknown, and $R(x,u) = R_{\max}$

Initialize T uniformly

Repeat until no more unknown states:

- Find optimal policy for current T, R

- Execute this policy

- Update T and R based on samples – if a pair (x,u) has been seen sufficiently often, make it “known” and give it its estimated reward

Model-free Exploration

- Insert exploration function into Q-learning:
 - Takes a value estimate and a count, and returns an optimistic utility, e.g. $b(q, n) = q + k/n$ (exact form not too important)

$$Q_{i+1}(s, a) \leftarrow (1 - \alpha)Q_i(s, a) + \alpha \left(R(s, a, s') + \gamma \max_{a'} Q_i(s', a') \right)$$

now becomes:

$$Q_{i+1}(s, a) \leftarrow (1 - \alpha)Q_i(s, a) + \alpha \left(R(s, a, s') + \gamma \max_{a'} f(Q_i(s', a'), N(s', a')) \right)$$

Exercise X (a)

Which of the following properties are true for Rmax?

- (1) Rmax will exploit its knowledge of T of known states to more efficiently reach unknown states
- (2) Everything else being equal, Rmax will favor passing through (x,u) with high reward
- (3) Rmax can get stuck in a bad part of the state space
- (4) The expected number of time steps for Rmax to have all states become known is optimal

Exercise X (b)

Which of the following is a natural generalization of the previous slides exploration function, $b(q, n) = q + k/n$, to Q-learning with linear function approximation, where

$$Q(x, u) = \sum_{i=1}^n w_i f_i(x, u)$$

(1) $b(x, u) = q(x, u) + k / (\text{number times } (x, u) \text{ was visited})$

(2) $b(x, u) = q(x, u) + \max_u \max_i f_i(x, u)$

(3) $b(x, u) = q(x, u) + \sum_i f_i(x, u)$

(4) $b(x, u) = q(x, u) + f(x, u)^T \Sigma f(x, u),$

with $\Sigma = (\sum_j f(x^{(j)}, u^{(j)}) f(x^{(j)}, u^{(j)})^T)^{-1}$

Bayesian Exploration

- Exploration thus far:
 - Considered as a goal in and of itself
- In practice often trade-off between exploration and exploitation
 - Bayesian exploration methods try to address this problem in a Bayesian setting
 - Computationally expensive, but
 - Bandits --- Gittins indeices provide exact solution efficiently
 - General – some approximations
 - e.g. Near-Bayesian Exploration (Kolter and Ng, 2009)