Reinforcement Learning Tutorial 3, Week 4

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Dynamic Programming / Monte Carlo

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Overview: The following tutorial questions relate to material taught in weeks 2 and 3 of the 2022-23 Reinforcement Learning course. They aim at encouraging engagement with the course material and facilitating a deeper understanding.

This week you are presented with a couple of exercises asking you to do some computations by hand for Dynamic Programming and Monte Carlo. For Dynamic Programming, don't feel the need to run these till convergence. The **Problem 1** solution will only give you enough to see how it works, and then give you the details on what it converged to and after how many steps. **Problem 1** requires 2 outer loops of the *Policy Iteration* algorithm, and the first *Policy Evaluation* converges after 15 updates (4 updates are enough to understand what is going on).

If you are so inclined, you could also write a quick script to tackle Problem 1. This can be a good exercise in understanding how the algorithm works and help prepare you for the coursework.

Generally, when considering Reinforcement Learning algorithms, note that most of them [1] can be understood as a specific instance of the *Generalised Policy Iteration* procedure: We, until the policy converges, iterate over 1 step of some form of *Policy Evaluation* (which needs to do at least improve the evaluation of the current policy by a little) and 1 step of some form of *Policy Improvement* (which we generally want to be at least somewhat greedy to get convergence guarantees). After the Policy Improvement step we get a new policy whose evaluation (via state-value or action-value function) we try to improve upon on the next Policy Evaluation step, and so forth until convergence. See Sutton and Barto [2018], section 4.6, page 86 for details.

The Monte Carlo policy evaluation methods in **Problem 2** could replace the

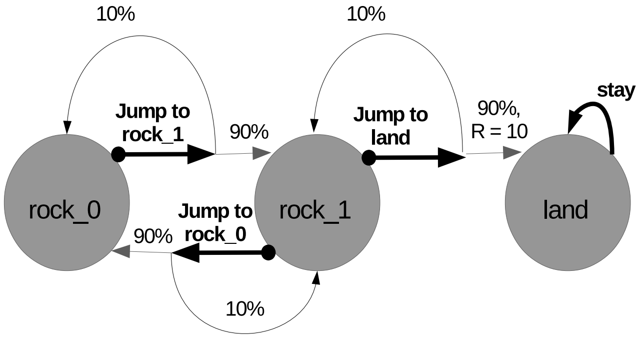
[1] policy gradient methods generally don't follow this template

Iterative Policy Evaluation step (a Dynamic Programming algorithm) of the Policy Iteration algorithm. *[Though we wouldn't usually do this while evaluating the state-value function. Why?]*

Problem 1 - Dynamic Programming

Consider the Hop-a-long MDP from tutorial 2 Andreadis [2022] below, with a discount factor of $\gamma = 0.9$ and assuming a reward of 10 for reaching land (and 0 otherwise). Apply two iterations of *Policy Iteration*, starting from a uniform initial policy.

Do the final values and policy agree with your intuition?



Problem 2 - Monte Carlo

Compute the state-value function for a given policy π and MDP without access to the MDP's model, using the following four episodes, in order:

$$\text{rock}_0, 0, \text{rock}_0, 0, \text{rock}_1, 10, \text{land} \tag{1}$$
$$\text{rock}_1, 0, \text{rock}_0, 0, \text{rock}_1, 10, \text{land} \tag{2}$$
$$\text{rock}_0, 0, \text{rock}_0, -100, \text{sea} \tag{3}$$
$$\text{rock}_1, 0, \text{rock}_0, -100, \text{sea} \tag{4}$$

Note: the solutions will use a discount factor of 1. *[Why is this acceptable?]*

Part 1

Use first-time visit Monte Carlo to evaluate the state-value function at each state. Show your calculation.

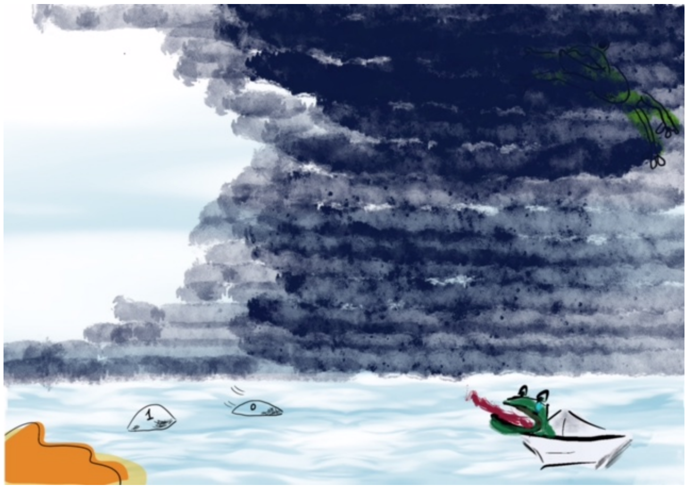


Figure 1: “Frog with More Problems”
Image and title used with permission from Yana Knight and Andreadis [2021]

Part 2

Use every-time visit Monte Carlo to evaluate the state-value function at each state. Show your calculation.

Part 3

How would you expect the state-values estimated by both first-time visit Monte Carlo and every-time visit Monte Carlo to change as the number of episodes considered goes to infinity?

(No mathematical proofs required, just a short description of the expected values).

Part 4

Which are the absorbing states?

References

P. Andreadis. Reinforcement Learning Tutorial 2, Week 3 — with solutions — MDPs. https://www.learn.ed.ac.uk/webapps/blackboard/execute/content/file?cmd=view&content_id=_6991543_1&course_id=_86409_1, 2022.

Yana Knight and Pavlos Andreadis. ”Story of Yana”. http://storyofyana.com/, 2021.

Richard S Sutton and Andrew G Barto. *Reinforcement learning: An introduction.* MIT press, 2018.