

# Online and Reinforcement Learning (2025)

## Home Assignment 2

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# 1 Short Questions

Determine whether each statement below is True or False and provide a very brief justification.

1. **Statement:** “In a finite discounted MDP, every possible policy induces a Markov Reward Process.”

**Answer: False.** This statement assumes that the policy depends only on the current state. If we allow policies to depend on the *entire* past history (*history-dependent* policies), then the resulting transitions in the state space may no longer satisfy the Markov property, since the chosen action at each step might be a function of all previous states and actions. Hence not *every* (fully history-dependent) policy necessarily induces a Markov Reward Process in the *original* state space.

2. **Statement:** “Consider a finite discounted MDP, and assume that  $\pi$  is an optimal policy. Then, the action(s) output by  $\pi$  does not depend on history other than the current state (i.e.,  $\pi$  is necessarily stationary).”

**Answer: False.** While it is true that there *exists* an optimal policy which is stationary deterministic, it does not follow that *all* optimal policies must be so. In fact, multiple distinct policies (some stationary, others possibly history-dependent or randomized) can achieve exactly the same optimal value. Hence it is incorrect to say that *any* optimal policy  $\pi$  must be purely state-dependent (stationary).

3. **Statement:** “In a finite discounted MDP, a greedy policy with respect to optimal action-value function,  $Q^*$ , corresponds to an optimal policy.”

**Answer: True.** From the Bellman optimality equations for  $Q^*$ , a policy that selects

$$\arg \max_a Q^*(s, a)$$

at each state  $s$  is indeed an optimal policy. This policy attains the same value as  $Q^*$  itself, thus achieving the optimal value.

4. **Statement:** “Under the coverage assumption, the Weighted Importance Sampling Estimator  $\hat{V}_{\text{wIS}}$  converges to  $V^\pi$  with probability 1.”

**Answer: True.** The coverage assumption ensures that the target policy’s state-action probabilities are absolutely continuous w.r.t. the behavior policy. Under this assumption, Weighted Importance Sampling (though slightly biased) is a *consistent* estimator of  $V^\pi$ , meaning it converges almost surely to  $V^\pi$  as the sample size grows unbounded.

## 2 MDPs with Similar Parameters Have Similar Values

**Setup:** We have two discounted MDPs

$$M_1 = (S, A, P_1, R_1, \gamma) \quad \text{and} \quad M_2 = (S, A, P_2, R_2, \gamma),$$

sharing the same discount factor  $\gamma \in (0, 1)$ , the same finite state-action space, and rewards bounded in  $[0, R_{\max}]$ . For all state-action pairs  $(s, a)$ :

$$|R_1(s, a) - R_2(s, a)| \leq \alpha, \quad \|P_1(\cdot | s, a) - P_2(\cdot | s, a)\|_1 \leq \beta.$$

Consider a fixed stationary policy  $\pi$ , and let  $V_1^\pi$  and  $V_2^\pi$  be its value functions in  $M_1$  and  $M_2$ , respectively. The goal is to show that

$$|V_1^\pi(s) - V_2^\pi(s)| \leq \frac{\alpha + \gamma R_{\max} \beta}{(1 - \gamma)^2} \quad \text{for every state } s \in S.$$

**Step 1: Write down the Bellman equations for each MDP.**

By definition of  $\pi$ , the Bellman fixed-point form is:

$$V_1^\pi = r_1^\pi + \gamma P_1^\pi V_1^\pi, \quad V_2^\pi = r_2^\pi + \gamma P_2^\pi V_2^\pi,$$

where

$$r_m^\pi(s) = R_m(s, \pi(s)), \quad (P_m^\pi f)(s) = \sum_{s'} P_m(s' | s, \pi(s)) f(s'), \quad m = 1, 2.$$

Define  $\delta = V_1^\pi - V_2^\pi$ . Then

$$\delta = (r_1^\pi - r_2^\pi) + \gamma (P_1^\pi V_1^\pi - P_2^\pi V_2^\pi).$$

To facilitate the separation of terms, we introduce and subtract  $\gamma P_1^\pi V_2^\pi$ , which allows us to rewrite the second term as:

$$P_1^\pi V_1^\pi - P_2^\pi V_2^\pi = (P_1^\pi V_1^\pi - P_1^\pi V_2^\pi) + (P_1^\pi V_2^\pi - P_2^\pi V_2^\pi).$$

Substituting this back, we obtain:

$$\delta = (r_1^\pi - r_2^\pi) + \gamma P_1^\pi (V_1^\pi - V_2^\pi) + \gamma (P_1^\pi - P_2^\pi) V_2^\pi.$$

**Step 3: Take norms and use triangle/inequality bounds.**

Taking the supremum norm ( $\|\cdot\|_\infty$ ) on both sides we obtain

$$\|\delta\|_\infty = \|(r_1^\pi - r_2^\pi) + \gamma P_1^\pi \delta + \gamma (P_1^\pi - P_2^\pi) V_2^\pi\|_\infty.$$

By the *triangle inequality*, the norm of a sum is at most the sum of the norms, so we can split the right-hand side as:

$$\|\delta\|_\infty \leq \|r_1^\pi - r_2^\pi\|_\infty + \gamma \|P_1^\pi \delta\|_\infty + \gamma \|(P_1^\pi - P_2^\pi) V_2^\pi\|_\infty.$$

Now we can proceed with:

- *Reward difference:*

Since  $|R_1(s, a) - R_2(s, a)| \leq \alpha$ , it follows that  $\|r_1^\pi - r_2^\pi\|_\infty \leq \alpha$ .

- *Term with  $P_1^\pi \delta$ :*

We have

$$\|P_1^\pi \delta\|_\infty \leq \|\delta\|_\infty,$$

since  $P_1^\pi$  is a probability kernel and thus a contraction in sup norm.

- *Term with  $(P_1^\pi - P_2^\pi) V_2^\pi$ :*

For each  $s$ ,

$$|(P_1^\pi - P_2^\pi) V_2^\pi(s)| \leq \sum_{s'} |P_1(s' | s, \pi(s)) - P_2(s' | s, \pi(s))| |V_2^\pi(s')|.$$

By assumption,  $\|P_1(\cdot | s, a) - P_2(\cdot | s, a)\|_1 \leq \beta$ , and  $\|V_2^\pi\|_\infty \leq \frac{R_{\max}}{1-\gamma}$ . Hence,

$$\|(P_1^\pi - P_2^\pi) V_2^\pi\|_\infty \leq \beta \frac{R_{\max}}{1-\gamma}.$$

Putting these bounds together,

$$\|\delta\|_\infty \leq \alpha + \gamma \|\delta\|_\infty + \gamma \beta \frac{R_{\max}}{1-\gamma}.$$

#### Step 4: Solve for $\|\delta\|_\infty$ .

We isolate  $\|\delta\|_\infty$  on one side:

$$(1 - \gamma) \|\delta\|_\infty \leq \alpha + \gamma \beta \frac{R_{\max}}{1-\gamma}.$$

Thus

$$\|\delta\|_\infty \leq \frac{\alpha}{1-\gamma} + \frac{\gamma \beta R_{\max}}{(1-\gamma)^2}.$$

Since  $\alpha/(1-\gamma) \leq \alpha/(1-\gamma)^2$  whenever  $0 < \gamma < 1$ , we can write

$$\|\delta\|_\infty \leq \frac{\alpha + \gamma \beta R_{\max}}{(1-\gamma)^2}.$$

Hence, for every state  $s \in S$ ,

$$|V_1^\pi(s) - V_2^\pi(s)| \leq \|\delta\|_\infty \leq \frac{\alpha + \gamma R_{\max} \beta}{(1-\gamma)^2}.$$

This is the desired result.

### 3 Policy Evaluation in RiverSwim

We provide here a short report on the Monte Carlo simulation and exact computation of  $V^\pi$  for the RiverSwim MDP, where the policy  $\pi$  takes *right* action with probability 0.65 in states  $\{1, 2, 3\}$  and always takes *right* in states  $\{4, 5\}$ . The code used to run the experiments is contained in `HA2_RiverSwim.py`.

#### i) Monte Carlo Estimation of $V^\pi$ .

We generated  $n = 50$  trajectories of length  $T = 300$  each, for each possible start state, accumulating returns

$$G = \sum_{t=0}^{T-1} \gamma^t r_t,$$

and then averaged over the simulated trajectories to obtain an approximate value  $V^\pi(s)$ . We used the discount factor  $\gamma = 0.96$ . Below are the resulting Monte Carlo estimates (in a few seconds of execution time):

State	MC Estimate	Exact Value
1	4.01793	4.12090
2	4.61536	4.71119
3	5.96556	6.33460
4	9.47802	9.73803
5	11.21253	11.17784

#### ii) Exact Computation using the Bellman Equation.

We also computed the exact value function

$$V^\pi = (I - \gamma P^\pi)^{-1} r^\pi$$

by constructing the transition matrix  $P^\pi$  and reward vector  $r^\pi$  under policy  $\pi$ , and then numerically solving the linear system  $(I - \gamma P^\pi) v = r^\pi$  in Python with `numpy.linalg.solve`. The table above (right column) presents the resulting exact values of  $V^\pi(s)$  for  $s = 1, \dots, 5$ .

**Comment:** Although the Monte Carlo estimates are not the finest approximation and slightly deviate from the exact values (particularly in states 3 and 4) due to limited sample size, they were obtained in just a few seconds of execution. Increasing the number of trajectories (or their length) would make the approximation even closer in practice.

### 4 Solving a Discounted Grid-World

*All of the Python code used to run these experiments (i.e. PI, VI, and Anchored VI, plus the 4-room environment and the visualizations) can be found in the file `HA2_gridworld.py`.*

#### Environment Setup:

We have a  $7 \times 7$  grid with walls, yielding 20 accessible states labeled 0 to 19. State 19

(bottom-right corner) has reward 1 and is effectively absorbing once reached. The agent chooses from 4 compass actions (0 = Up, 1 = Right, 2 = Down, 3 = Left), but transitions are *slippery*: probability 0.7 for the chosen direction, 0.1 each for perpendicular directions, and 0.1 for staying in place. We set  $\gamma = 0.97$  by default, except in part (iii) where  $\gamma = 0.998$ .

### (i) Solve the grid-world task using PI (Policy Iteration).

We implemented *Policy Iteration*, which alternates:

$$\text{Policy Iteration: } \begin{cases} \text{(a) Evaluate current policy } \pi : & V^\pi = (I - \gamma P^\pi)^{-1} r^\pi, \\ \text{(b) Improve } \pi : & \pi \leftarrow \arg \max_a \left[ r(s, a) + \gamma \sum_{s'} P(s' | s, a) V^\pi(s') \right]. \end{cases}$$

It converged in 5 iterations. The resulting *optimal policy* (array of size 20) is

$$\pi_{\text{PI}} = [1, 1, 1, 2, 2, 2, 0, 2, 3, 2, 2, 1, 1, 1, 1, 2, 1, 0, 1, 0].$$

The *optimal value function*  $V^*(s)$ , rounded to 2 decimals, is

$$V^* = [23.07, 23.97, 25.15, 26.26, 25.40, 23.97, 23.07, 27.71, 26.40, 25.15, 29.12, 26.26, 27.71, 29.12, 30.40, 31.74, 25.40, 26.40, 31.74, 33.33].$$

We can visualize  $\pi$  on the  $7 \times 7$  grid as:

```
[ [Wall, Wall, Wall, Wall, Wall, Wall, Wall],
  [Wall, Right, Right, Right, Down, Down, Wall],
  [Wall, Down, Up, Wall, Down, Left, Wall],
  [Wall, Down, Wall, Wall, Down, Wall, Wall],
  [Wall, Right, Right, Right, Right, Down, Wall],
  [Wall, Right, Up, Wall, Right, Up, Wall],
  [Wall, Wall, Wall, Wall, Wall, Wall, Wall] ].
```

### (ii) Implement VI and use it to solve the grid-world task.

We then implemented *Value Iteration*, repeatedly applying

$$V_{n+1}(s) = \max_a \left[ r(s, a) + \gamma \sum_{s'} P(s' | s, a) V_n(s') \right].$$

With  $\gamma = 0.97$ , VI converged in 48 iterations and recovered *the same* optimal policy and value function as in part (i). The same map display applies.

### (iii) Repeat (ii) with $\gamma = 0.998$ .

Now we let  $\gamma = 0.998$ . VI converged more slowly (56 iterations). The *value function* is larger (about 487–500 in some states), and the policy is slightly modified in some early states. We still see a path leading to state 19. Overall, it remains optimal, just at a bigger scale of values.

#### (iv) Anchored Value Iteration (Anc-VI) with different initial points.

We added an anchoring approach with:

$$V_{n+1} = \beta_{n+1} V_0 + (1 - \beta_{n+1}) \max_a \{\dots\}.$$

Using three different anchors:

- (a)  $V_0 = 0$     **(614 iterations to converge)**,
- (b)  $V_0 = 1$     **(613 iterations to converge)**,
- (c) random  $V_0$  in  $[0, 1/(1 - \gamma)]^{nS}$     **(606 iterations to converge)**,

they all converged to an *optimal policy* as well, matching the same final  $V^*$  observed before.

#### (v) Compare the convergence speed of VI vs. Anc-VI (with the same anchor).

Finally, we compared standard VI (`anc=False`) and the anchored variant (`anc=True`) for each available initialization of the values of  $V$  at time 0:

	$V_0 = 0$	$V_0 = 1$	$V_0 = \text{Random}$
<b>Standard VI</b>	592iters	591iters	583iters
<b>Anchored VI</b>	614iters	613iters	606iters

In this experiment, the *anchored* method needed slightly *more* iterations than the standard VI. However, they still converged to optimal policies. With different discount factors or parameters, anchored VI can sometimes speed up or slow down convergence.

## 5 Off-Policy Evaluation in Episode-Based River-Swim