



Planning, Learning and Acting

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Dyna-Q+

1. Adds a bonus $\kappa\sqrt{\tau(s,a)}$ to reward in planning

 $\tau(s,a)$ denotes the number of time steps (s,a) has not been tried

2. Actions that have not been tried from a previously visited state are allowed to be considered in planning Where would you put these steps in Dyna-Q to get Dyna-Q+?

Tabular Dyna-Q

Initialize Q(s, a) and Model(s, a) for all $s \in S$ and $a \in A(s)$ Loop forever:

- (a) $S \leftarrow \text{current (nonterminal) state}$
- (b) $A \leftarrow \varepsilon$ -greedy(S, Q)
- (c) Take action A; observe resultant reward, R, and state, S'
- (d) $Q(S,A) \leftarrow Q(S,A) + \alpha \left[R + \gamma \max_a Q(S',a) Q(S,A) \right]$
- (e) $Model(S, A) \leftarrow R, S'$ (assuming deterministic environment)
- (f) Loop repeat n times:

 $S \leftarrow \text{random previously observed state}$

 $A \leftarrow \text{random action previously taken in } S$

$$R, S' \leftarrow Model(S, A)$$

$$Q(S,A) \leftarrow Q(S,A) + \alpha \left[R + \gamma \max_{a} Q(S',a) - Q(S,A) \right]$$

Dyna-Q+: calculating visitation counts

Consider an MDP with one actions (L) and two states (x, y) with the following episode

$$S_0$$
 A_0 S_1 A_1 S_2 A_2 S_3 A_3 S_4 A_4 y L x L y L

Calculate $\tau(s, a)$ for all state-action pairs at each step

1. An agent observes the following two episodes from an MDP,

$$S_0 = 0, A_0 = 1, R_1 = 1, S_1 = 1, A_1 = 1, R_2 = 1$$

$$S_0 = 0, A_0 = 0, R_1 = 0, S_1 = 0, A_1 = 1, R_2 = 1, S_2 = 1, A_2 = 1, R_3 = 1$$

and updates its deterministic model accordingly. What would the model output for the following queries:

- (a) Model(S = 0, A = 0):
- (b) Model(S = 0, A = 1):
- (c) Model(S = 1, A = 0):
- (d) Model(S = 1, A = 1):

2. An agent is in a 4-state MDP, $S = \{1, 2, 3, 4\}$, where each state has two actions $A = \{1, 2\}$. Assume the agent saw the following trajectory,

$$S_0 = 1, A_0 = 2, R_1 = -1,$$

 $S_1 = 1, A_1 = 1, R_2 = 1,$
 $S_2 = 2, A_2 = 2, R_3 = -1,$
 $S_3 = 2, A_3 = 1, R_4 = 1,$
 $S_4 = 3, A_4 = 1, R_5 = 100,$
 $S_5 = 4$

and uses Tabular Dyna-Q with 5 planning steps for each interaction with the environment.

- (a) Once the agent sees S_5 , how many Q-learning updates has it done with **real experience**? How many updates has it done with **simulated experience**?
- (b) Which of the following are possible (or not possible) simulated transitions $\{S, A, R, S'\}$ given the above observed trajectory with a deterministic model and random search control?

i.
$$\{S=1, A=1, R=1, S'=2\}$$

ii.
$$\{S=2, A=1, R=-1, S'=3\}$$

iii.
$$\{S=2, A=2, R=-1, S'=2\}$$

3. Modify the Tabular Dyna-Q algorithm so that it uses Expected Sarsa instead of Q-learning. Assume that the target policy is ϵ -greedy. What should we call this algorithm?

Tabular Dyna-Q

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- (f) Loop repeat n times:

 $S \leftarrow \text{random previously observed state}$

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6. (Exercise 8.2 S&B) Why did the Dyna agent with exploration bonus, Dyna-Q+, perform better in the first phase as well as in the second phase of the blocking experiment in Figure 8.4?

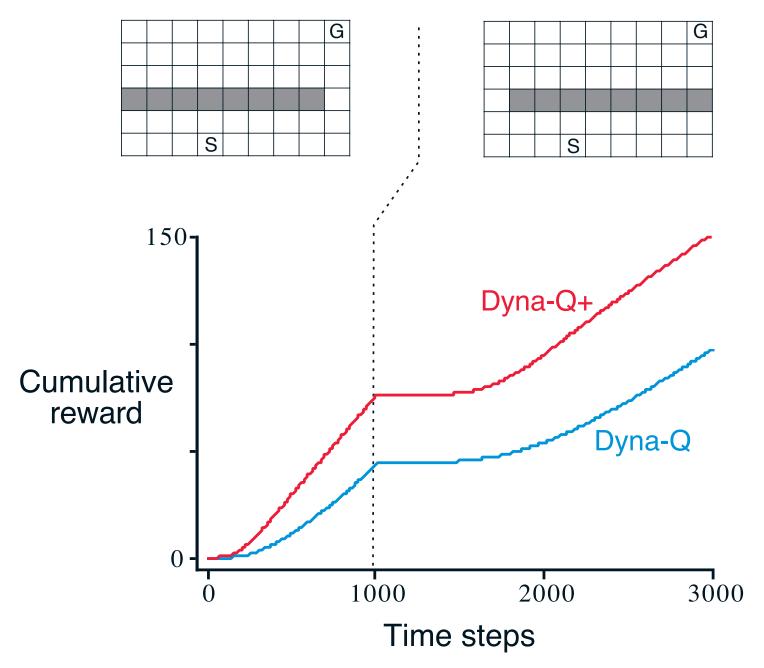


Figure 8.4: Average performance of Dyna agents on a blocking task. The left environment was used for the first 1000 steps, the right environment for the rest. Dyna-Q+ is Dyna-Q with an exploration bonus that encourages exploration.

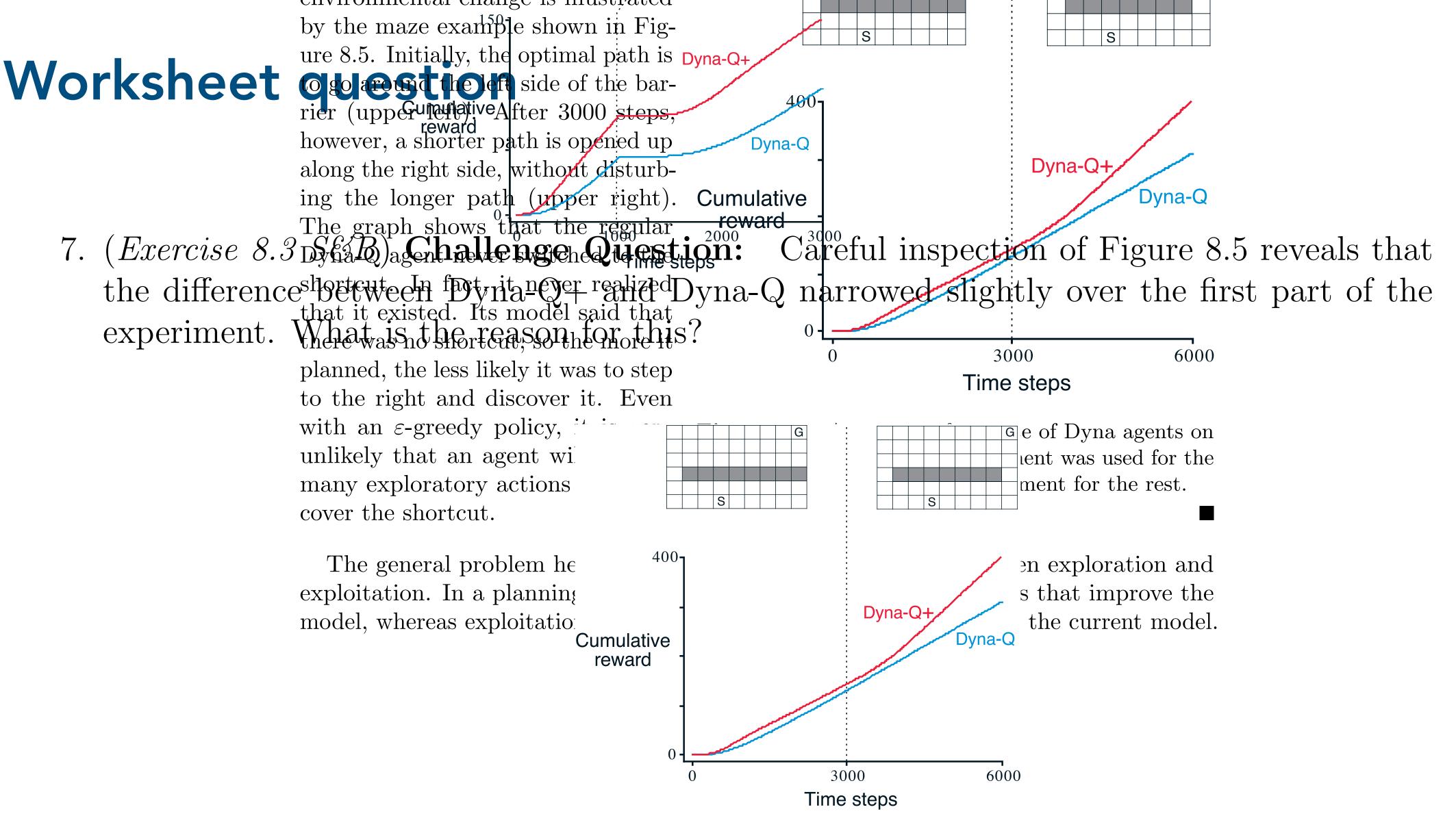


Figure 8.5: Average performance of Dyna agents on a shortcut task. The left environment was used for the first 3000 steps, the right environment for the rest.