

<u>Unit 5 Reinforcement Learning (2</u>

Course > weeks)

> <u>Project 5: Text-Based Game</u> > 5. Parameter Tuning

## 5. Parameter Tuning

Extension Note: Project 5 due date has been extended by 1 more day to September 6 23:59UTC.

# Effects of adjusting epsilon

0 points possible (ungraded)

**Ungrading Note:** The problem is now ungraded because there has been a lot of confusion.

In this question, you will investigate the impact of  $\varepsilon$  on the convergence of Q-learning algorithm. Which of the below do you observe from running the algorithm?

 $lap{8}$  For very large arepsilon (say arepsilon=1), the algorithm converges slower compared to arepsilon=0.5

lacksquare For very large arepsilon (say arepsilon=1), the algorithm converges faster compared to arepsilon=0.5

lacksquare For very small arepsilon (say arepsilon=0.00001), the algorithm converges slower compared to arepsilon=0.5

For very small arepsilon (say arepsilon=0.00001), the algorithm converges faster compared to arepsilon=0.5 🗸

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#### **Solution:**

A large value of  $\varepsilon$  means exploring more (randomly), not using much of what we have learned. A small  $\varepsilon$ , on the other hand, will generate experience consistent with the current estimates of Q-values, but will explore less. For this toy task, however, the state space is small enough that random initalization is enough to induce diversity in the experience collected.

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You have used 0 of 3 attempts

Answers are displayed within the problem

### Effects of alpha

0 points possible (ungraded)

In this question, you will investigate the impact of lpha on the convergence of Q-learning algorithm. Fix the exploration parameter  $\varepsilon=0.5$  and do the experiments with different values of the training  $lpha\in[10^{-6},1]$ . What you have observed?

The algorithm converges for all values of lpha in less than 200 epochs

ightharpoonup The algorithm does not converge for all values of lpha in less than 200 epochs

The smaller  $\alpha$ , the slower the convergence

The smaller  $\alpha$ , the faster the convergence



#### Solution:

For large values of  $\alpha$ , learning is too instable. For small values of  $\alpha$ , learning is too slow.

**1** Answers are displayed within the problem

#### Discussion

Topic: Unit 5 Reinforcement Learning (2 weeks): Project 5: Text-Based Game / 5. Parameter Tuning

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# **≺** All Posts [staff, please look again] Effects of adjusting epsilon: what I see on the plots is not + accepted by the grader question posted 27 days ago by anonymous Tried to mark also the opposite choice to what I see, and this answer also got rejected. This post is visible to everyone. Soumya Ram (Staff) + 14 days ago - marked as answer 14 days ago by **Soumya\_Ram** (Staff) Sorry, this is an error on our behalf. We updated the problem one too many times. (now the solutions don't match the edited problem description). The problem is ungraded now. Show Comment (1) ▼ 15 other responses Add a Response **Cool7** (Community TA) + 27 days ago I think normally a very small $\epsilon$ will also lead to slower convergence. Agent will most likely stick to first action will yield positive reward even it's not the optimal action. But in our case, all most all Q values are negative, first positive Q value discovered is most likely within optimal policy. Maybe this is just a bad example for this question, but we really need to put in something we didn't observe? I also believe this example does not work well for the question asked. To get my answer accepted, I ended up selecting one option that was contradicting the plot. posted 27 days ago by OlgaSkv ••• Anonymous author, please mark this topic with [Staff] tag. Dear staff, please take a look, as results we obtain by looking at the plots are not accepted by grader. posted 26 days ago by <u>disguiser</u> Yes... Same here... posted 26 days ago by LiWeic1c9 Same here posted 24 days ago by **Tantrum83** Same