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Collaborators:

CMPUT 366Assignment 1: Step sizes & Bandits

Due: Tuesday Sept 18 by gradescope

Policy: Can be discussed in groups (acknowledge collaborators) but must be written up individually

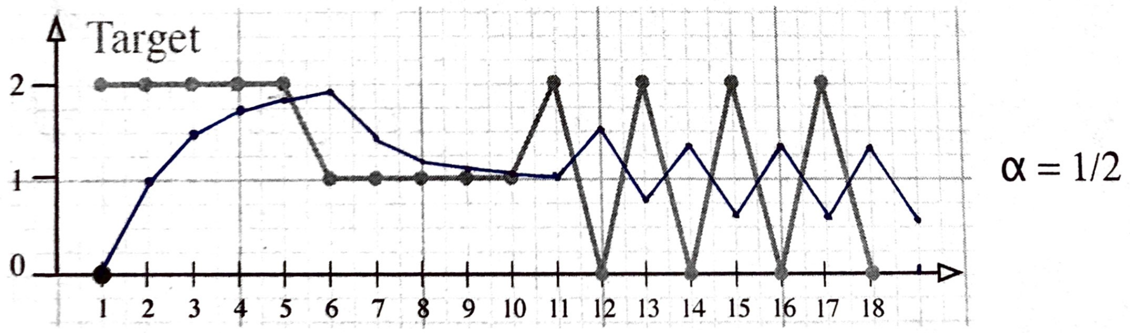
There are a total of 100 points on this assignment, plus 15 points available as extra credit!

Question 1 [50 points] Step-sizes. Plotting recency-weighted averages.

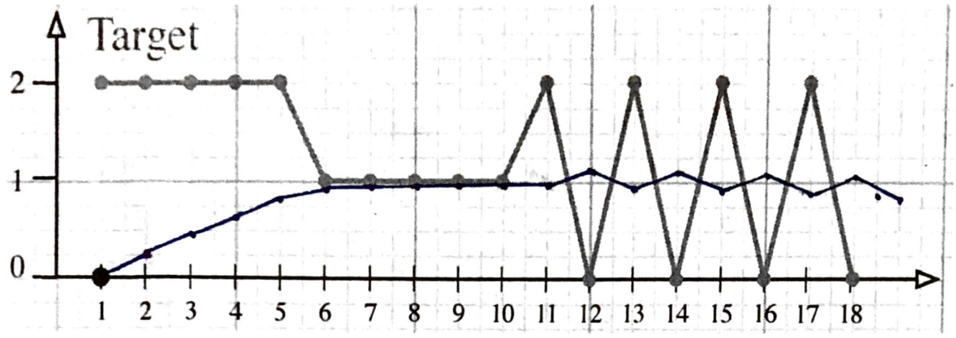
Equation 2.5 (from the SB textbook, 2nd edition) is a key update rule we will use throughout the course. This exercise will give you a better hands-on feel for how it works. This question has **five** parts.

Do all the plots in this question by hand. To make it easier for you, I'll include some graphing area and a start on the first plot here, so you should just be able to print these pages out and draw on them.

Part 1. [15 pts.]
Suppose the target is 2.0 for five steps, then 1 for five steps, and then alternates between 2.0 and 0 for 8 more steps, as shown by the grey line in the graph below. Suppose the initial estimate is 0, and that the step-size (in the equation) is 0.5. Your job is to apply Equation 2.5 iteratively to determine the estimates for time steps 1-19. Plot them on the graph below, using a blue pen, connecting the estimate points by a blue line. The first estimate Q_1 is already marked below:

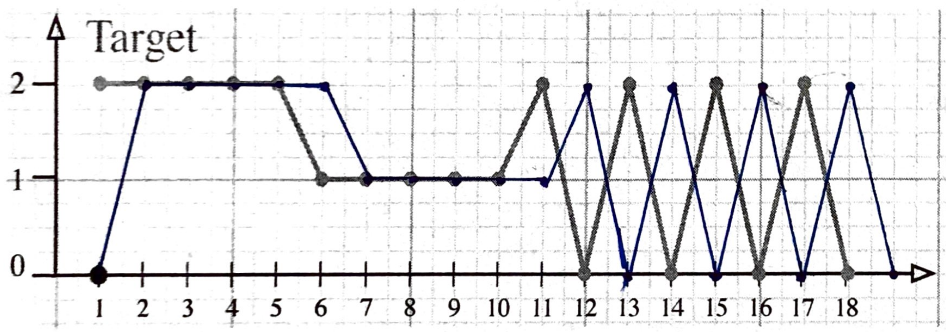


Part 2. [5 pts] Repeat the graphing/plotting portion of Part 1, this time with a step size of 1/8.



$\alpha = 1/8$

Part 3. [5 pts.] Repeat with a step size of 1.0.



$\alpha = 1$

Part 4. [10 pts.] Best step-size questions.

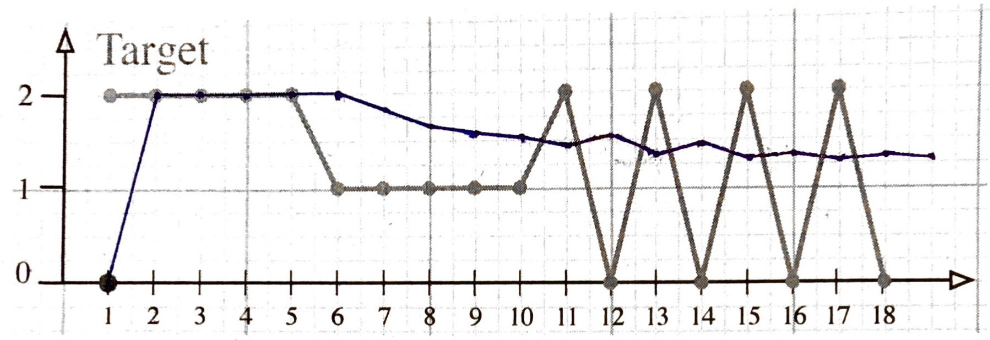
Which of these step sizes would produce estimates of smaller absolute error if the target continued alternating for a long time? Please explain your answer.

$\alpha = \frac{1}{8}$, from step 10 to step 18 where target continued alternating, the error = target - estimates is smaller when $\alpha = \frac{1}{8}$ than $\alpha = \frac{1}{2}$ and $\alpha = 1$

Which of these step sizes would produce estimates of smaller absolute error if the target remained constant for a long time? Please explain your answer.

$\alpha = 1$, When target remained constant, the error is approximate to zero. And if the target change in a short time then remains constant for a long time, the Q line will follow the trend of the target at the same time, then quickly produce a zero error.

Part 5. [15 pts.] Repeat with a step size of $1/(t-1)$ for $t \geq 2$. (i.e., the first step size you will use is 1, the second is 1/2, the third is 1/3, etc.).



$\alpha = 1/(t-1)$

Based on all of these graphs, why is the 1/(t-1) step size appealing?

From step 1 to 5, the estimate is equal to target because the stepsize is 1 in step 1 and target stay constant. Then target's value changes and alternates, because of α is the sample-average step size, it produces smaller error in the long run.

Why is the 1/(t-1) step size not always the right choice?

when target alternates first, there would be producing big errors when α is not small, but when α is small in the long run, if target keeps constant and makes changes not so frequently, small step size cannot adapt the changes efficiently.

Question 2 [10 points] Bandit Example. Consider a multi-arm bandit problem with $k = 5$ actions, denoted 1, 2, 3, 4, and 5. Consider applying to this problem a bandit algorithm using ε-greedy action selection, sample-average action-value estimates, and initial estimates of $Q_1(a) = 0$ for all a. Suppose the initial sequence of actions and rewards is $A_1 = 2, R_1 = -2, A_2 = 1, R_2 = 5, A_3 = 3, R_3 = 3, A_4 = 1, R_4 = 4, A_5 = 4, R_5 = 3, A_6 = 2, R_6 = -1$. On some of these time steps the ε case may have occurred causing an action to be selected at random. On which time steps did this definitely occur? On which time steps could this possibly have occurred?

updated estimation

[0, −2, 0, 0, 0] step 1: A_1 might be randomly selected

[2.5, −2, 0, 0, 0] step 2: A_2 might be randomly selected

[2.5, −2, 1, 0, 0] step 3: A_3 must be randomly selected

[2.875, −2, 1, 0, 0] step 4: A_4 might be randomly selected

[2.875, −2, 1, 0.6, 0] step 5: A_5 must be randomly selected

[2.875, −1.83, 1, 0.6, 0] step 6: A_6 must be randomly selected.

Question 3. Bandit task Programming. [40 pts.]

This programing exercise will give you hands-on feel for how bandit problems are implemented, and how incremental learning algorithms select actions based on observed rewards. In addition, this exercise will be your first experience with RL-glue, the interface we will use for all programing questions in this course.

Recreate the learning curves for the optimistic bandit agent, and the epsilon-greedy agent in Figure 2.3 of Sutton and Barto. This requires you to implement **three** main components: $Q_{n+1} = Q_n + \frac{1}{n}[R_n - Q_n]$

1) A RL-Glue Environment program implementing the 10-armed bandit problem
2) A RL-Glue Agent program implementing an epsilon-greedy bandit learning algorithm. Use the incremental update rule (Equation 2.5), with two different parameter settings:
   - alpha = 0.1, epsilon = 0, and $Q_1 = 5$
   - alpha = 0.1, epsilon = 0.1, and $Q_1 = 0$

   $Q_{n+1} = Q_n + \alpha [R_n - Q_n]$
3) A RL-Glue Experiment program implementing the experiment to generate the data for your plot. Compute the % Optimal action per time-step, averaged over 2000 runs

All code must be written in **Python3** to be compatible with the RL-Glue interface provided to the class. It is not acceptable to implement your own interface.

Please submit:
1) your plot [10 pts.]
2) all your code (including any graphing code used to generate your plot) [30 pts.]

Bonus Programing Question. [5 pts.]
Implement the UCB agent described in chapter two and evaluate it on the bandit environment from Question 3. Can you get the UCB agent to outperform the epsilon-greedy agent? Feel free to modify the parameters of the epsilon-greedy agent (alpha, epsilon, and the initial Q estimates) in order to better understand the relative strengths of both algorithms. Describe how we would go about determining and reporting on which agent is better for this task.

As is shown in the plot produced by programing, when $c=2$ the UCB performs better than ε-greedy.

Bonus Question. [5 points extra credit]
Exercise 2.4 from Sutton and Barto (*Reward weighting for general step sizes*)

Bonus Question. [5 pts.]
Exercise 2.6 from Sutton and Barto (*Mysterious Spikes.* Use your implementation from Question 3 to better understand what is happening in Figure 2.3)

when $\varepsilon = 0$, the agent make the greedy choice from the whole steps. Because of the value of $Q_1 = 5$, so the estimates will be better by greedy selection in a short run. So there is a spikes show on the plot when in early steps