Exercise 0
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CS 7180 - Prof. Amato
Code Setup:

1. Unzipped the 'ex4.zip' file
2. 'cd' into the 'code' directory
3. run 'source ./init' to setup the pyenv

Questions:

1. (a)
   - Prior to the infinite loop, create a dictionary for storing the number of times state s has been reached:
     $N(s) = 0 \forall s \in S$
   - After the check for "first-visit", increment the number of times state s has been reached and use the updated $N(s)$ value to average the return at that state:
     $N(s) = N(s) + 1$
     $V(s) = V(s) + \frac{1}{N(s)}[G - V(s)]$

   (b)
   - Prior to the infinite loop, create a dictionary for storing the number of times action a has been taken at state s:
     $N(s, a) = 0 \forall s \in S \forall a \in A$
   - After the check for "first-visit", increment the number of times action a has been taken in state s and use the updated $N(s, a)$ value to average the return for that state-action pair:
     $N(s, a) = N(s, a) + 1$
     $Q(s, a) = Q(s, a) + \frac{1}{N(s,a)}[G - Q(s, a)]$

2. (a) I would expect the average return for a state to be the same. When using every-visit MC, we include returns which are computing later in the episode, in other words: smaller returns. This brings our average lower that had we used first-visit, as we would have a higher likelihood of encountering a state earlier in the episode, and thus having a higher return. However, in blackjack, episodes are incredibly brief with often fewer than five steps per episode. The probability of encountering the same state twice in a given episode is low, and even still, the brief nature of each episode means the expected return when a given state is first entered will be roughly equal, but slightly greater, than the expected return when that state is reached later in the episode.

   (b) i. First Visit:
   T - 1: $G = \gamma G + r = 1$
   $Q(T, a) = Q(T, a) + \frac{1}{N(T,a)=1}[G - Q(T, a)] = 1$
   T - 2 $\rightarrow$ 9 :G $= \gamma G + r$

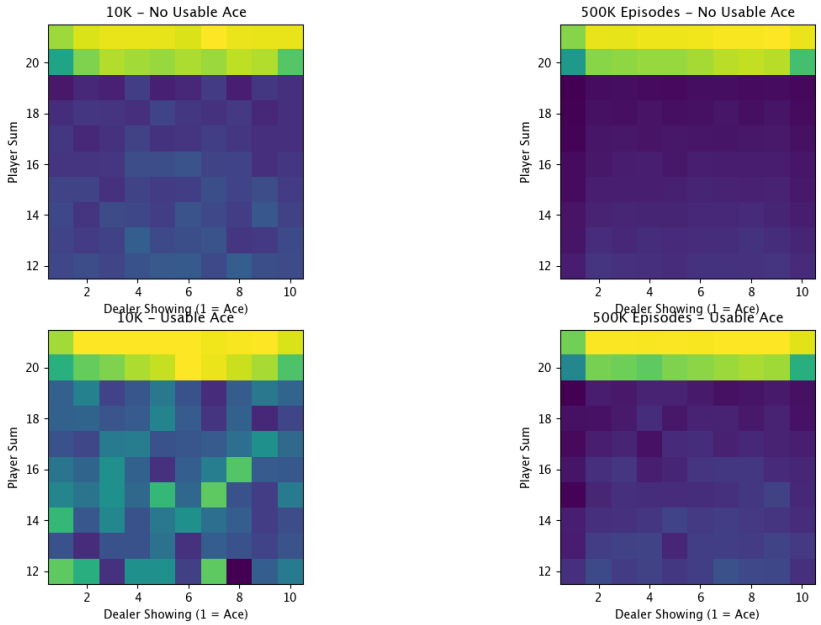
T - 10: $G = G + r = 9 + 1 = 10$ $Q(NT, a) = Q(NT, a) + \frac{1}{N(T,a)=1}[G - Q(NT, a)] = 10$
The estimate for $Q(NT, a) = \frac{1}{N(s,a)=1}[10 - Q(NT, a)] = 10$

ii. Every Visit:
$Q(T, a) = 1$
$Q(NT, a) = \frac{G_{T-2}+G_{T-3}...+G_{T-10}}{N(NT,a)} = \frac{2+3+4...+10}{9} = 6$

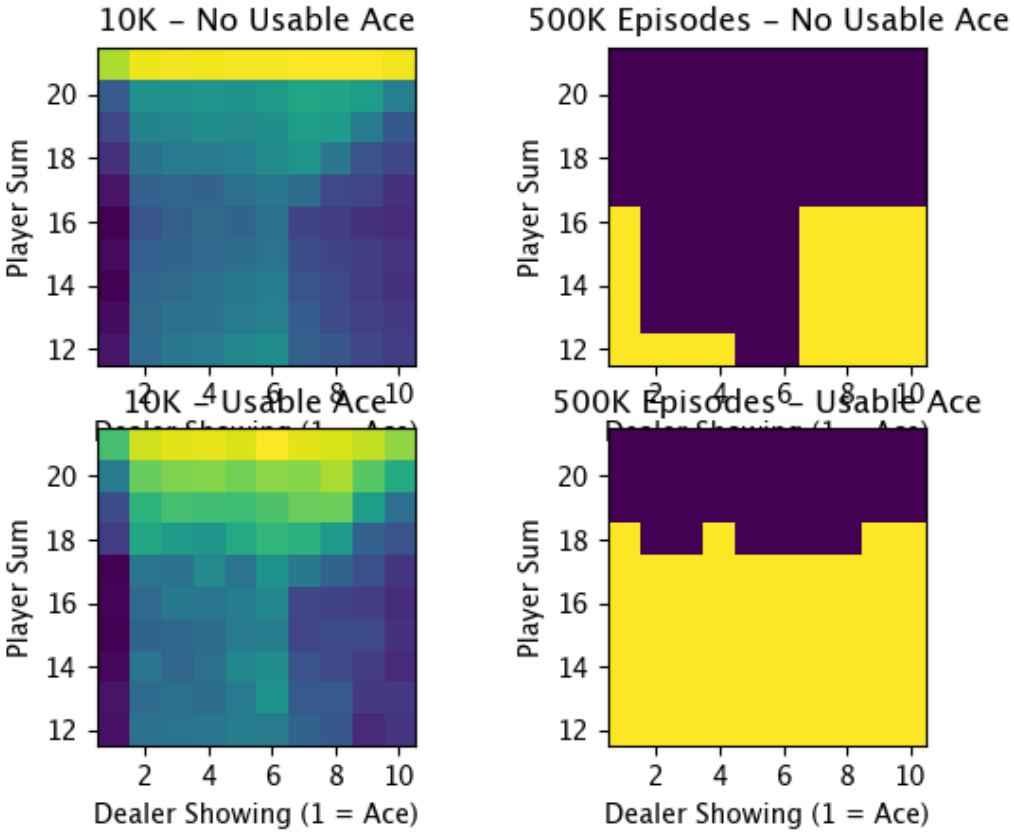
3. Blackjack:
The algorithms for MC control live in ‘blackjack.py‘

(a) To run Blackjack without exploring starts run: ‘python src/monte_carlo/run_blackjack.py‘

(b) To run Blackjack with exploring starts run: ‘python src/monte_carlo/run_blackjack_es.py‘



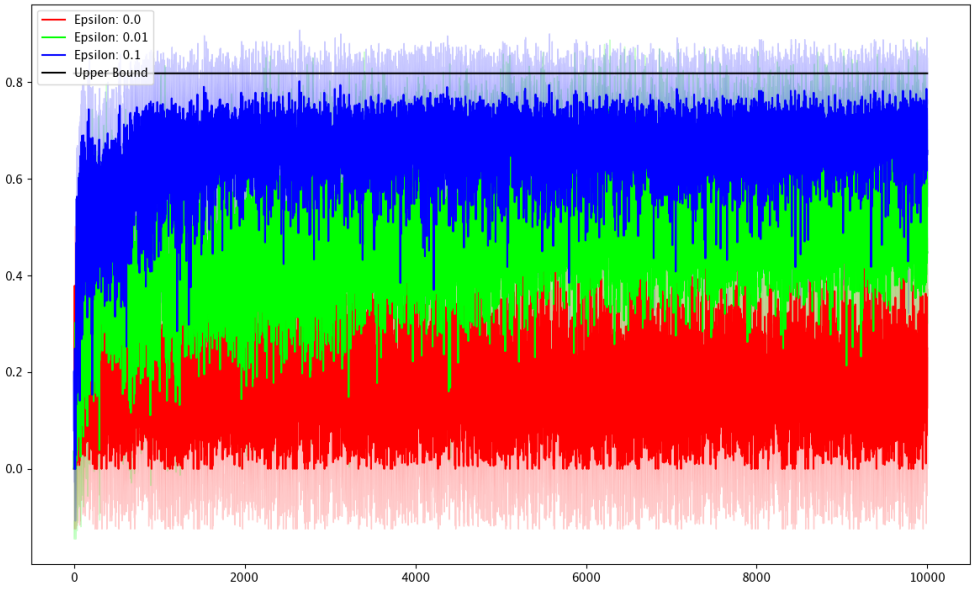
Blackjack First-Visit MC



Blackjack First-Visit MC w/ Exploring Starts

4. Four Rooms:
   The algorithms for MC Control live in ‘algorithms.py‘. The environment for the Four Rooms problem lives in ‘env.py‘.

   (a) To run the four rooms problem: ‘python src/monte_carlo/run_four_rooms.py‘



Four Rooms MC with Epsilon Soft Policy

5. (a)

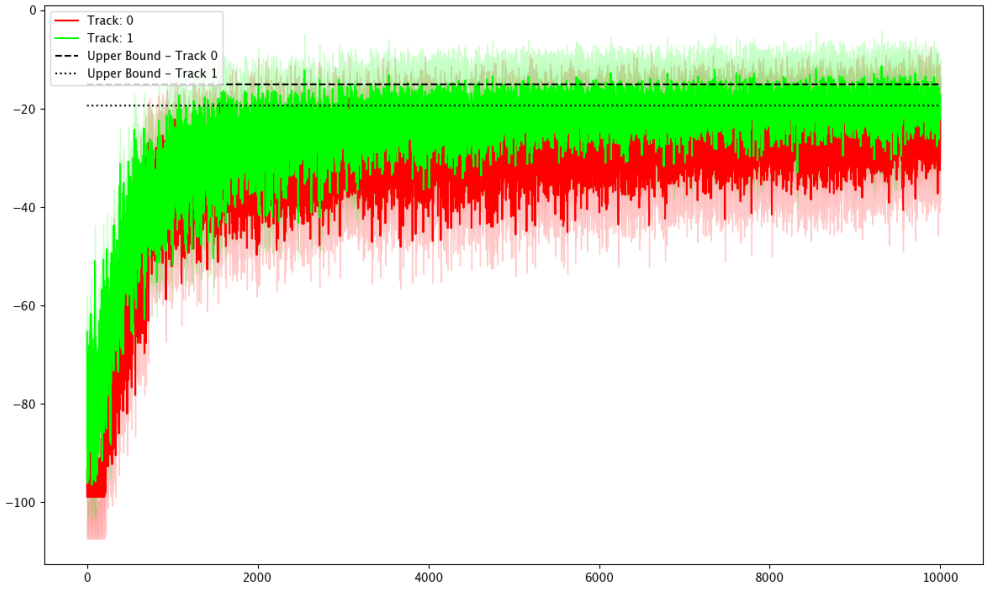
   (b) Because if $A_t \neq \pi(S_t)$, we exit and do not update the weight. It is therefore redundant to check $\pi(A_t|S_t)$ as we know it is 1 (since π is a greedy policy), else we would have exited.

6. Racetracks:
   The algorithms for on-policy and off-policy MC Control live in 'algorithms.py'. The environment lives in 'racetracks.py'

   (a) To run the racetracks problem using On-Policy MC Control: 'python src/monte_carlo/run_on_policy_racetrack.py'

   (b) To run the racetracks problem using Off-Policy MC Control: 'python src/monte_carlo/run_off_policy_racetrack.py'

   - Note: This will not converge and learning will be very slow (effectively does not happen). This is because the inner-loop (evaluating an episode) terminates after the first timestep always, as $A_t \neq \pi(s)$ each time. Since we are updating $Q(s, a)$ in that loop, it makes sense that this condition occurs at each step. I am not sure how to properly implement off-policy importance sampling as a result. My main confusion is:
     - For off-policy MC control, If π is a greedy policy, then whenever the action chosen by the behavior policy is not the argmax of $Q(s)$, then we will stop the learning process for that episode, as $W\frac{\pi(a|s)}{b(a|s)} = W\frac{0}{\epsilon} = 0$. However, if $\epsilon = 0.1$, then $1/10$ steps will be random and probably not the greedy action. So in training, we will only ever go back 10 steps from the end of the episode. How can we learn about earlier steps in the episode if we always terminate so quickly?



On-Policy MC Control for Racetrack Problem