Introduction to
Artificial Intelligence and Machine Learning
Homework 4 - Reinforcement

2019/12/04

Question 1 – Value Iteration Agent

- An MDP is given
- *U(s)*: self.values = util.Counter() – a dictionary
- __init__(self, mdp, discount = 0.9, iterations =100):
  - For each iteration, for every state in the MDP, find the maximum value of $Q(s, a)$ for all possible actions of state s
  - Recall that $U(s) = \max_{a \in A(s)} Q(s,a)$

- getValue(self, state):
  - return self.values[state]

Question 1 – Value Iteration Agent

- getQValue(self, state, action):
  - Use getTransitionStatesAndProbs in mdp.py
  - $Q(s, a) = \sum_{s'} P(s'|s, a)[R(s'|s, a) + \gamma U(s')]$

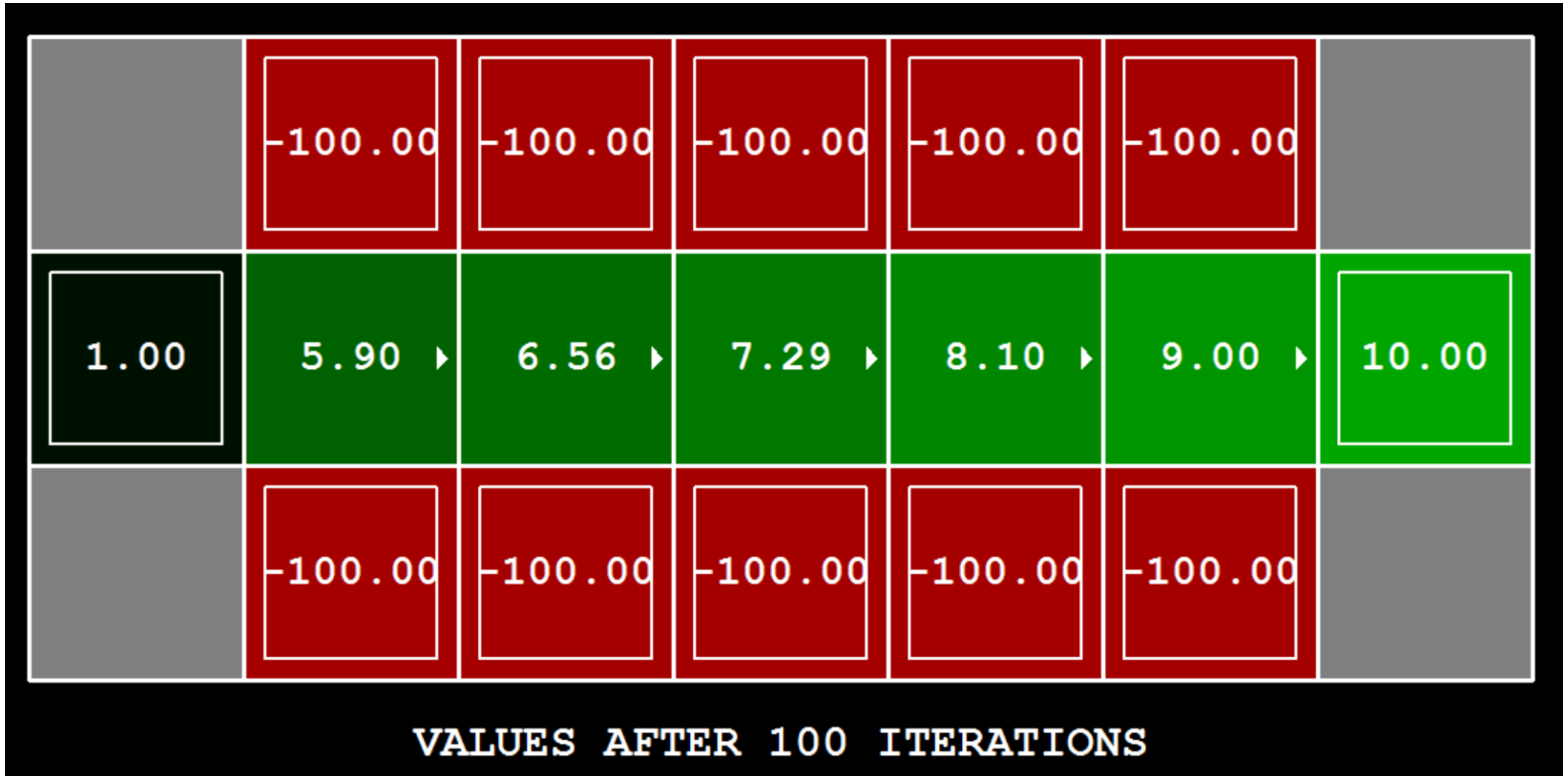
- getPolicy(self, state):
  - If terminal state, return none.
  - Else, return the action that results in the maximum value of $E[\text{utility of taking a}] = \sum_{s'} P(s'|s, a)\, U(s')$

Question 2 – Value Iteration Agent

- Change only one of the parameters, the discount factor γ or the noise level, so that the agent will cross the bridge in the optimal policy
  - Noise level: the uncertainty of taking an action
    - Ex: When noise=0, for any given state s and action a in A(s), there will be one s' such that $P(s'|s,a)=1$; for any other state $s'' \neq s'$, it holds that $P(s''|s,a)=0$.
  - Discount factor: the level of importance of the future rewards

Question 2 – Value Iteration Agent

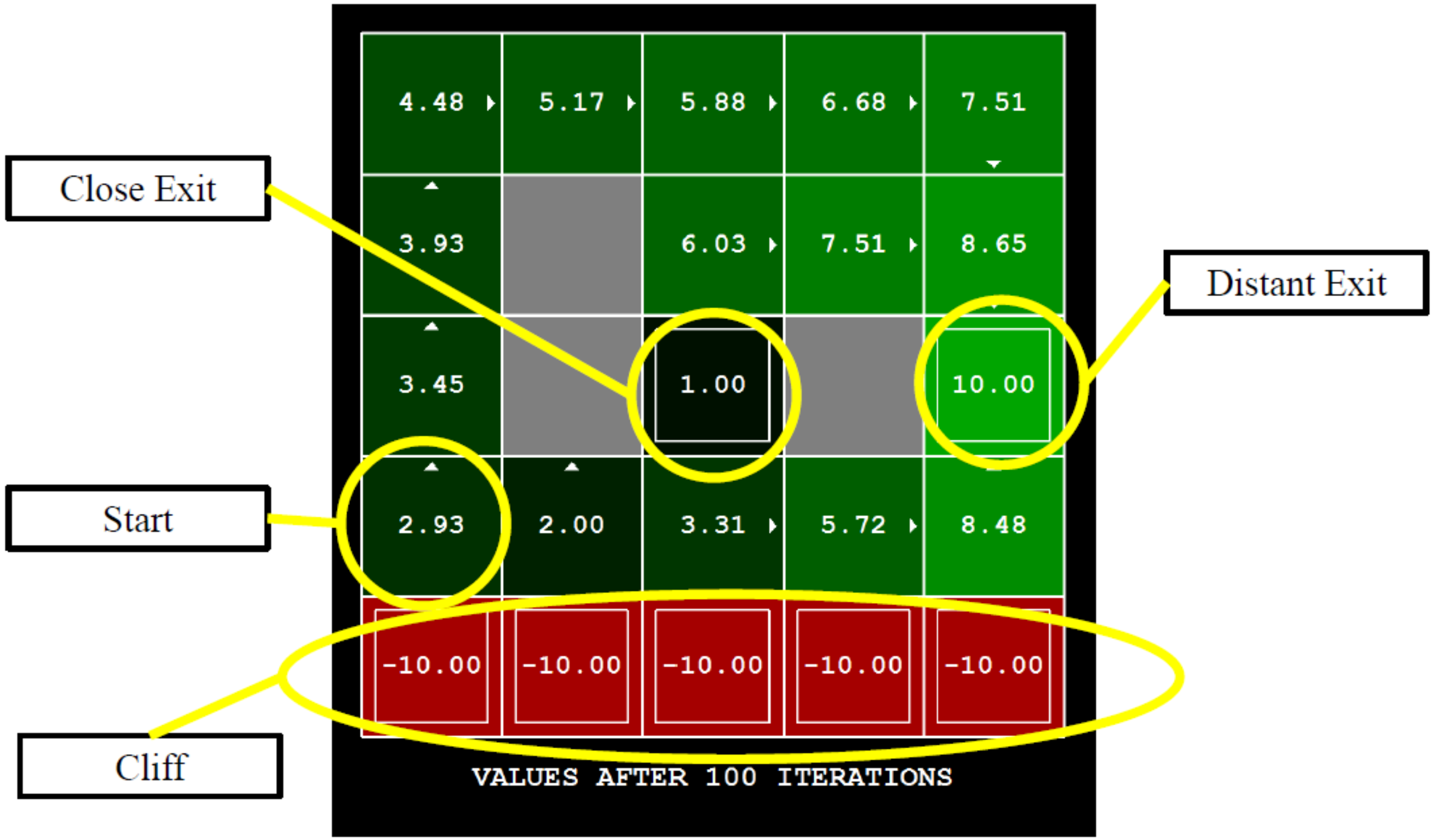
- The result should be something like this:



Question 3 – Value Iteration Agent

- Adjust the parameters, including the discount factor γ, the noise level, and the living reward, so that the agent acts as the descriptions
  - Living reward: The amount of reward given when the agent is still alive (i.e. doesn’t fall over the cliff)

Question 3 – Value Iteration Agent



Question 4~6 – Q Learning Agent

- Motivation: the transition probability and the reward of any given state are not known in advance.
- Construct a two dimensional (for states and actions) table to learn the utility of all states and the optimal policy.
  - One viable way to do this is to construct a “dictionary of dictionary” in python.
  - Another way is to create a dictionary with a tuple (state, action).

Question 4~6 – Q Learning Agent

- __init__(self, **args):
  - Construct your Q table here.
- getQValue(self, state, action):
  - If the state is already seen, return Qtable(state, action)
  - Otherwise, you should initialize the elements to 0 for these keys in Qtable
  - util.Counter may be helpful

Question 4~6 – Q Learning Agent

- getValue(self, state):
  - If there are no legal actions, return 0
  - Otherwise, return $\max_{\textit{action} \text{ belongs to } A(\textit{state})}$ Qtable(state, action)
  - Note: Please be advised to use the function "getQValue" instead of directly accessing the data in the Qtable here.
- getPolicy(self, state):
- getAction(self, state):
- update(self, state, action, nextState, reward):
  - Too simple to allow any hints…

Question 7 – Q Learning in Pacman

- Train a policy of Pacman by PacmanQAgent !

Question 8 – Approximate Q Learning Agent

- Motivation: the original Q learning method is not scalable.
- Extract the features of the state-action pair and learn the “weights” of the features instead.
- You only have to initialize the weights (you can use util.Counter) and override two functions “getQValue” and “update” according to the equations in the html file.
- You might need to call the function “getFeatures” defined in “featureExtractors.py”.

Submission

- Please use .zip or .gz file (no .rar or anything else) to package the files you need to submit (i.e. valueIterationAgents.py, qlearningAgents.py, analysis.py) directly (don’t create any folder).
- Verify your uploaded file by downloading it on ceiba
- Check the deadline carefully

Deadline

- 2019/12/18 27:00
- Allow late submission until 2019/12/25 27:00