CMPT310 Winter2024

Project 3

Project 3: Reinforcement Learning

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Introduction

In this project, you will implement value iteration and Q-learning. You will test your agents on Gridworld. This project includes an autograder for you to grade your solutions on your machine. This can be run on all questions with the command:

```
python autograder.py
```

It can be run for one particular question, such as q2, by:

```
python autograder.py -q q2
```

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It can be run for one particular test by commands of the form:

```
python autograder.py -t test_cases/q2/1-bridge-grid
```

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The code for this project contains the following files, available as a zip archive.

Files you'll edit:	
`valueIterationAgents.py`	A value iteration agent for solving known MDPs.
`qlearningAgents.py`	Q-learning agents for Gridworld, Crawler and Pacman.
`analysis.py`	A file to put your answers to questions given in the project.
Files you might want to look at:	
`mdp.py`	Defines methods on general MDPs.
`learningAgents.py`	Defines the base classes `ValueEstimationAgent` and `QLearningAgent` , which your agents will extend.
`util.py`	Utilities, including `util.Counter` , which is particularly useful for Q-learners.
`gridworld.py`	The Gridworld implementation.
Supporting files you can ignore:	
`environment.py`	Abstract class for general reinforcement learning environments. Used by `gridworld.py` .
`graphicsGridworldDisplay.py`	Gridworld graphical display.
`graphicsUtils.py`	Graphics utilities.
`textGridworldDisplay.py`	Plug-in for the Gridworld text interface.

`autograder.py`	Project autograder
`testParser.py`	Parses autograder test and solution files
`testClasses.py`	General autograding test classes
`test_cases/`	Directory containing the test cases for each question
`reinforcementTestClasses.py`	Project 3 specific autograding test classes

Files to Edit and Submit: You will fill in portions of `valueIterationAgents.py`, `qlearningAgents.py`, and `analysis.py` during the assignment. Once you have completed the assignment, you will submit these files to Gradescope (for instance, you can upload all `.py` files in the folder). Please do not change the other files in this distribution.

Evaluation: Your code will be autograded for technical correctness. Please do not change the names of any provided functions or classes within the code, or you will wreak havoc on the autograder. However, the correctness of your implementation – not the autograder's judgements – will be the final judge of your score. If necessary, we will review and grade assignments individually to ensure that you receive due credit for your work.

Academic Dishonesty: We will be checking your code against other submissions in the class for logical redundancy. If you copy someone else's code and submit it with minor changes, we will know. These cheat detectors are quite hard to fool, so please don't try. We trust you all to submit your own work only; please don't let us down. If you do, we will pursue the strongest consequences available to us.

Getting Help: You are not alone! If you find yourself stuck on something, contact the course TAs for help. Office hours, section, and the discussion forum are there for your support; please use them. If you can't make our office hours, let us know and we will schedule more. We want these projects to be rewarding and instructional, not frustrating and demoralizing. But, we don't know when or how to help unless you ask.

Discussion: Please be careful not to post spoilers.

MDPs

To get started, run Gridworld in manual control mode, which uses the arrow keys:

```
python gridworld.py -m
```

You will see the two-exit layout from class. The blue dot is the agent. Note that when you press up, the agent only actually moves north 80% of the time. Such is the life of a Gridworld agent!

You can control many aspects of the simulation. A full list of options is available by running:

```
python gridworld.py -h
```

The default agent moves randomly

```
python gridworld.py -g MazeGrid
```

You should see the random agent bounce around the grid until it happens upon an exit. Not the finest hour for an AI agent.

Note: The Gridworld MDP is such that you first must enter a pre-terminal state (the double boxes shown in the GUI) and then take the special 'exit' action before the episode actually ends (in the true terminal state called `TERMINAL_STATE` , which is not shown in the GUI). If you run an episode manually, your total return may be less than you expected, due to the discount rate (`-d` to change; 0.9 by default).

Look at the console output that accompanies the graphical output (or use `-t` for all text). You will be told about each transition the agent experiences (to turn this off, use `-q`).

Positions are represented by `(x, y)` Cartesian coordinates and any arrays are indexed by `[x][y]` , with `'north'` being the direction of increasing `y` , etc. By default, most transitions will receive a reward of zero, though you can change this with the living reward option (`-r`).

Question 1 (30 points): Value Iteration

Recall the value iteration state update equation:

$$V_{k+1}(s) \leftarrow \max_a \sum_{s'} T(s, a, s')\,[R(s, a, s') + \gamma V_k(s')]$$

Write a value iteration agent in `ValueIterationAgent`, which has been partially specified for you in `valueIterationAgents.py`. Your value iteration agent is an offline planner, not a reinforcement learning agent, and so the relevant training option is the number of iterations of value iteration it should run (option `-i`) in its initial planning phase. `ValueIterationAgent` takes an MDP on construction and runs value iteration for the specified number of iterations before the constructor returns.

Value iteration computes k-step estimates of the optimal values, V_k. In addition to `runValueIteration`, implement the following methods for `ValueIterationAgent` using V_k:

- `computeActionFromValues(state)` computes the best action according to the value function given by self.values.
- `computeQValueFromValues(state, action)` returns the Q-value of the (state, action) pair given by the value function given by `self.values`.

These quantities are all displayed in the GUI: values are numbers in squares, Q-values are numbers in square quarters, and policies are arrows out from each square.

Important: Use the “batch” version of value iteration where each vector V_k is computed from a fixed vector V_{k-1} (like in lecture), not the “online” version where one single weight vector is updated in place. This means that when a state’s value is updated in iteration k based on the values of its successor states, the successor state values used in the value update computation should be those from iteration $k-1$ (even if some of the successor states had already been updated in iteration k). The difference is discussed in Sutton & Barto in Chapter 4.1 on page 91.

Note: A policy synthesized from values of depth k (which reflect the next k rewards) will actually reflect the next $k+1$ rewards (i.e. you return π_{k+1}). Similarly, the Q-values will also reflect one more reward than the values (i.e. you return Q_{k+1}).

You should return the synthesized policy π_{k+1}.

Hint: You may optionally use the `util.Counter` class in `util.py`, which is a dictionary with a default value of zero. However, be careful with `argMax`: the actual argmax you want may be a key not in the counter!

Note: Make sure to handle the case when a state has no available actions in an MDP (think about what this means for future rewards).

To test your implementation, run the autograder:

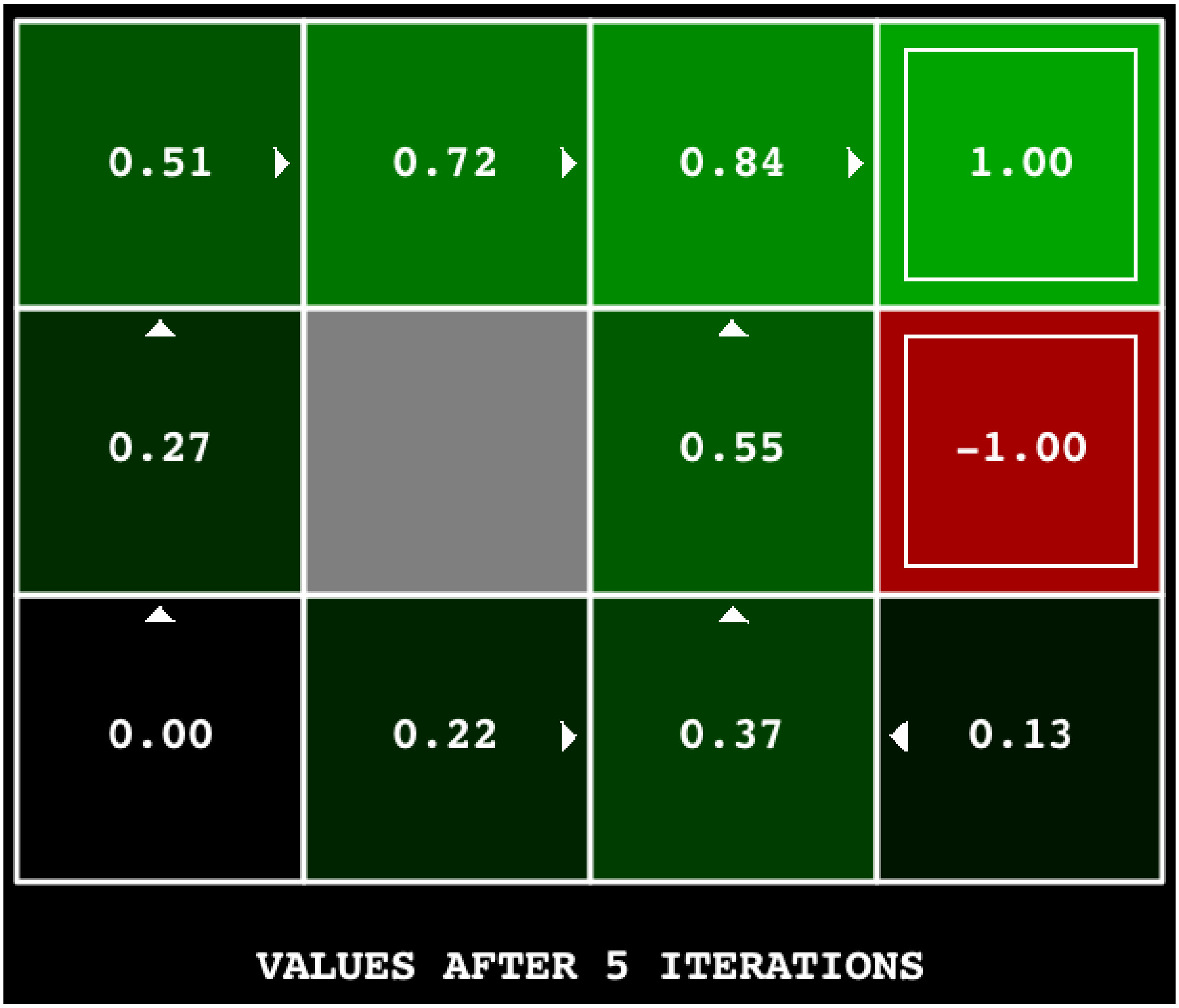
```
python autograder.py -q q1
```

The following command loads your `ValueIterationAgent`, which will compute a policy and execute it 10 times. Press a key to cycle through values, Q-values, and the simulation. You should find that the value of the start state (`V(start)`, which you can read off of the GUI) and the empirical resulting average reward (printed after the 10 rounds of execution finish) are quite close.

```
python gridworld.py -a value -i 100 -k 10
```

Hint: On the default `BookGrid`, running value iteration for 5 iterations should give you this output:

```
python gridworld.py -a value -i 5
```



0.51 ▶	0.72 ▶	0.84 ▶	1.00
▲ 0.27		▲ 0.55	-1.00
▲ 0.00	0.22 ▶	▲ 0.37	◀ 0.13

VALUES AFTER 5 ITERATIONS

Grading: Your value iteration agent will be graded on a new grid. We will check your values, Q-values, and policies after fixed numbers of iterations and at convergence (e.g. after 100 iterations).

Question 2 (5 point): Bridge Crossing Analysis

`BridgeGrid` is a grid world map with the a low-reward terminal state and a high-reward terminal state separated by a narrow “bridge”, on either side of which is a chasm of high negative reward. The agent starts near the low-reward state. With the default discount of 0.9 and the default noise of 0.2, the optimal policy does not cross the bridge. Change only ONE of the discount and noise parameters so that the optimal policy causes the agent to attempt to cross the bridge. Put your answer in `question2()` of `analysis.py`. (Noise refers to how often an agent ends up in an unintended successor state when they perform an action.) The default corresponds to:

```
python gridworld.py -a value -i 100 -g BridgeGrid --discount 0.9 --noise 0.2
```

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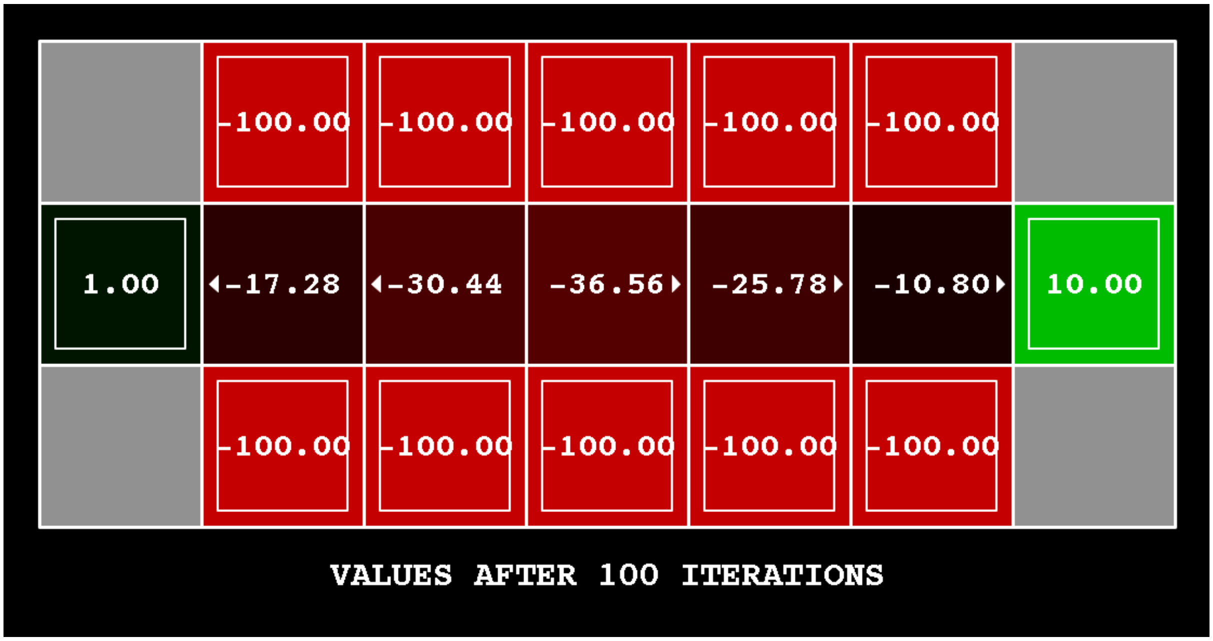

	-100.00	-100.00	-100.00	-100.00	-100.00	
1.00	◂-17.28	◂-30.44	-36.56▸	-25.78▸	-10.80▸	10.00
	-100.00	-100.00	-100.00	-100.00	-100.00	

VALUES AFTER 100 ITERATIONS

Grading: We will check that you only changed one of the given parameters, and that with this change, a correct value iteration agent should cross the bridge. To check your answer, run the autograder:

```
python autograder.py -q q2
```

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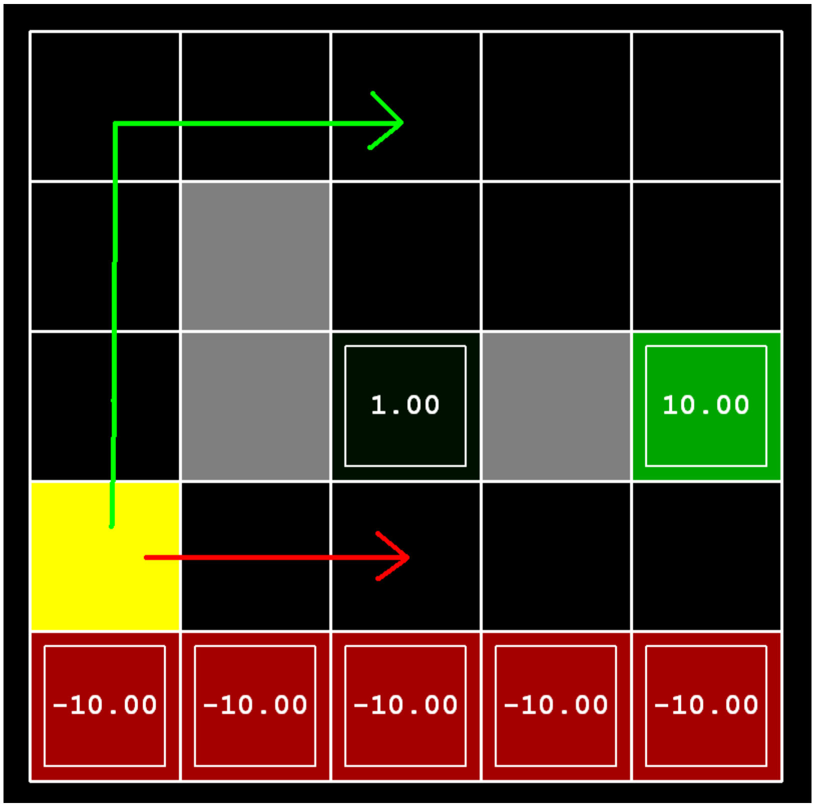
Question 3 (20 points): Policies

Consider the `DiscountGrid` layout, shown below. This grid has two terminal states with positive payoff (in the middle row), a close exit with payoff +1 and a distant exit with payoff +10. The bottom row of the grid consists of terminal states with negative payoff (shown in red); each state in this “cliff” region has payoff -10. The starting state is the yellow square. We distinguish between two types of paths: (1) paths that “risk the cliff” and travel near the bottom row of the grid; these paths are shorter but risk earning a large negative payoff, and are represented by the red arrow in the figure below. (2) paths that “avoid the cliff” and travel along the top edge of the grid. These paths are longer but are less likely to incur huge negative payoffs. These paths are represented by the green arrow in the figure below.



In this question, you will choose settings of the discount, noise, and living reward parameters for this MDP to produce optimal policies of several different types. **Your setting of the parameter values for each part should have the property that, if your agent followed its optimal policy without being subject to any noise, it would exhibit the given behavior.** If a particular behavior is not achieved for any setting of the parameters, assert that the policy is impossible by returning the string `'NOT POSSIBLE'`.

Here are the optimal policy types you should attempt to produce:

1. Prefer the close exit (+1), risking the cliff (-10)
2. Prefer the close exit (+1), but avoiding the cliff (-10)
3. Prefer the distant exit (+10), risking the cliff (-10)
4. Prefer the distant exit (+10), avoiding the cliff (-10)
5. Avoid both exits and the cliff (so an episode should never terminate)

To see what behavior a set of numbers ends up in, run the following command to see a GUI:

```
python gridworld.py -g DiscountGrid -a value --discount [YOUR_DISCOUNT] --noise [Your_Noise]
    --livingReward [Your_living_Reward]
```

To check your answers, run the autograder:

```
python autograder.py -q q3
```

`question3a()` through `question3e()` should each return a 3-item tuple of `(discount, noise, living reward)` in `analysis.py`.

Note: You can check your policies in the GUI. For example, using a correct answer to 3(a), the arrow in (0,1) should point east, the arrow in (1,1) should also point east, and the arrow in (2,1) should point north.

Note: On some machines you may not see an arrow. In this case, press a button on the keyboard to switch to qValue display, and mentally calculate the policy by taking the arg max of the available qValues for each state.

Grading: We will check that the desired policy is returned in each case.

Question 4 (5 points): Prioritized Sweeping Value Iteration(extra point)

You will now implement `PrioritizedSweepingValueIterationAgent`, which has been partially specified for you in `valueIterationAgents.py`.

Prioritized sweeping attempts to focus updates of state values in ways that are likely to change the policy.

For this project, you will implement a simplified version of the standard prioritized sweeping algorithm, which is described in this paper. We've adapted this algorithm for our setting. First, we define the *predecessors* of a state `s` as all states that have a nonzero probability of reaching `s` by taking some action `a`. Also, `theta`, which is passed in as a parameter, will represent our tolerance for error when deciding whether to update the value of a state. Here's the algorithm you should follow in your implementation.

- Compute predecessors of all states.
- Initialize an empty priority queue.
- For each non-terminal state `s`, do: (note: to make the autograder work for this question, you must iterate over states in the order returned by `self.mdp.getStates()`)

  - Find the absolute value of the difference between the current value of `s` in `self.values` and the highest Q-value across all possible actions from `s` (this represents what the value should be); call this number `diff`. Do NOT update `self.values[s]` in this step.
  - Push `s` into the priority queue with priority `-diff` (note that this is negative). We use a negative because the priority queue is a min heap, but we want to prioritize updating states that have a higher error.
- For `iteration` in `0, 1, 2, ..., self.iterations - 1`, do:
  - If the priority queue is empty, then terminate.
  - Pop a state `s` off the priority queue.
  - Update the value of `s` (if it is not a terminal state) in `self.values`.
  - For each predecessor `p` of `s`, do:
    - Find the absolute value of the difference between the current value of `p` in `self.values` and the highest Q-value across all possible actions from `p` (this represents what the value should be); call this number `diff`. Do NOT update `self.values[p]` in this step.
    - If `diff > theta`, push `p` into the priority queue with priority `-diff` (note that this is negative), as long as it does not already exist in the priority queue with equal or lower priority. As before, we use a negative because the priority queue is a min heap, but we want to prioritize updating states that have a higher error.

A couple of important notes on implementation:

- When you compute predecessors of a state, make sure to store them in a set, not a list, to avoid duplicates.
- Please use `util.PriorityQueue` in your implementation. The `update` method in this class will likely be useful; look at its documentation.

To test your implementation, run the autograder. It should take about 1 second to run. If it takes much longer, you may run into issues later in the project, so make your implementation more efficient now.

```
python autograder.py -q q4
```

You can run the `PrioritizedSweepingValueIterationAgent` in the Gridworld using the following command.

```
python gridworld.py -a priosweepvalue -i 1000
```

Grading: Your prioritized sweeping value iteration agent will be graded on a new grid. We will check your values, Q-values, and policies after fixed numbers of iterations and at convergence (e.g., after 1000 iterations).

Question 5 (30 points): Q-Learning

Note that your value iteration agent does not actually learn from experience. Rather, it ponders its MDP model to arrive at a complete policy before ever interacting with a real environment. When it does interact with the environment, it simply follows the precomputed policy (e.g. it becomes a reflex agent). This distinction may be subtle in a simulated environment like a Gridword, but it’s very important in the real world, where the real MDP is not available.

You will now write a Q-learning agent, which does very little on construction, but instead learns by trial and error from interactions with the environment through its `update(state, action, nextState, reward)` method. A stub of a Q-learner is specified in `QLearningAgent` in `qlearningAgents.py`, and you can select it with the option `'-a q'`. For this question, you must implement the `update`, `computeValueFromQValues`, `getQValue`, and `computeActionFromQValues` methods.

Note: For `computeActionFromQValues`, you should break ties randomly for better behavior. The `random.choice()` function will help. In a particular state, actions that your agent hasn’t seen before still have a Q-value, specifically a Q-value of zero, and if all of the actions that your agent has seen before have a negative Q-value, an unseen action may be optimal.

Important: Make sure that in your `computeValueFromQValues` and `computeActionFromQValues` functions, you only access Q values by calling `getQValue`. This abstraction will be useful for question 10 when you override `getQValue` to use features of state-action pairs rather than state-action pairs directly.

With the Q-learning update in place, you can watch your Q-learner learn under manual control, using the keyboard:

```
python gridworld.py -a q -k 5 -m
```

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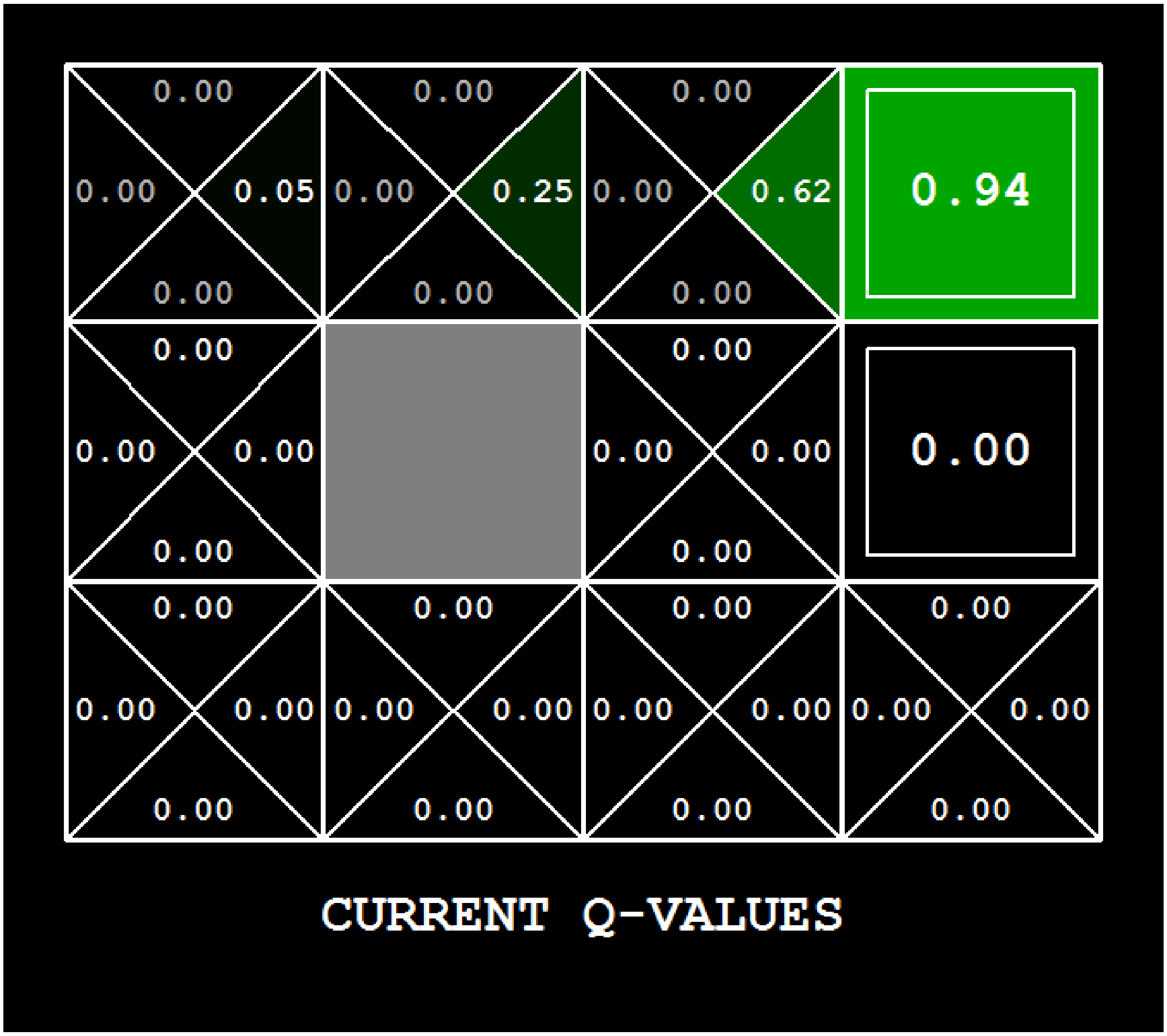
Recall that `-k` will control the number of episodes your agent gets to learn. Watch how the agent learns about the state it was just in, not the one it moves to, and “leaves learning in its wake.” Hint: to help with debugging, you can turn off noise by using the `--noise 0.0` parameter (though this obviously makes Q-learning less interesting). If you manually steer Pacman north and then east along the optimal path for four episodes, you should see the following Q-values:



Grading: We will run your Q-learning agent and check that it learns the same Q-values and policy as our reference implementation when each is presented with the same set of examples. To grade your implementation, run the autograder:

```
python autograder.py -q q5
```

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Question 6 (10 points): Epsilon Greedy

Complete your Q-learning agent by implementing epsilon-greedy action selection in `getAction`, meaning it chooses random actions an epsilon fraction of the time, and follows its current best Q-values otherwise. Note that choosing a random action may result in choosing the best action - that is, you should not choose a random sub-optimal action, but rather any random legal action.

You can choose an element from a list uniformly at random by calling the `random.choice` function. You can simulate a binary variable with probability `p` of success by using `util.flipCoin(p)`, which returns `True` with probability `p` and `False` with probability `1-p`.

After implementing the `getAction` method, observe the following behavior of the agent in `GridWorld` (with epsilon = 0.3).

```
python gridworld.py -a q -k 100
```

Your final Q-values should resemble those of your value iteration agent, especially along well-traveled paths. However, your average returns will be lower than the Q-values predict because of the random actions and the initial learning phase.

You can also observe the following simulations for different epsilon values. Does that behavior of the agent match what you expect?

```
python gridworld.py -a q -k 100 --noise 0.0 -e 0.1
```

```
python gridworld.py -a q -k 100 --noise 0.0 -e 0.9
```

To test your implementation, run the autograder:

```
python autograder.py -q q6
```

Question 7 (5 point): Bridge Crossing Revisited

First, train a completely random Q-learner with the default learning rate on the noiseless BridgeGrid for 50 episodes and observe whether it finds the optimal policy.

```
python gridworld.py -a q -k 50 -n 0 -g BridgeGrid -e 1
```

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Now try the same experiment with an epsilon of 0. Is there an epsilon and a learning rate for which it is highly likely (greater than 99%) that the optimal policy will be learned after 50 iterations? `question8()` in `analysis.py` should return EITHER a 2-item tuple of `(epsilon, learning rate)` OR the string `'NOT POSSIBLE'` if there is none. Epsilon is controlled by `-e`, learning rate by `-l`.

Note: Your response should be not depend on the exact tie-breaking mechanism used to choose actions. This means your answer should be correct even if for instance we rotated the entire bridge grid world 90 degrees.

To grade your answer, run the autograder:

```
python autograder.py -q q7
```

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Congradulation! Completed the assignment.

Submission

To submit, zib ONLY the python files you have edited and upload to Canvas.