CS 214: Artificial Intelligence Lab
Spring 2022-23, IIT Dharwad
Assignment-5
Artificial Intelligence Lab

Instructions

In this project, you will implement value iteration and Q-learning. You will test your agents first on Gridworld (from class), then apply them to a simulated robot controller (Crawler) and Pacman.

As in previous projects, 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

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

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

See the autograder tutorial in Project 0 for more information about using the autograder.

The code for this project contains the following files, which are available in 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 should read but NOT edit:

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.
featureExtractors.py	Classes for extracting features on (state,action) pairs. Used for the approximate Q-learning agent (in qlearningAgents.py).

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.
crawler.py	The crawler code and test harness. You will run this but not edit it.
graphicsCrawlerDisplay.py	GUI for the crawler robot.
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. You should submit these files with your code and comments. Please *do not* change the other files in this distribution or submit any of our original files other than these files.

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).

As in Pacman, 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: Value Iteration (15 Points)

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 running value iteration, 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 the 6th paragraph of chapter 4.1.

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: Use the util.Counter class in util.py, which is a dictionary with a default value of zero. Methods such as totalCount should simplify your code. 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:

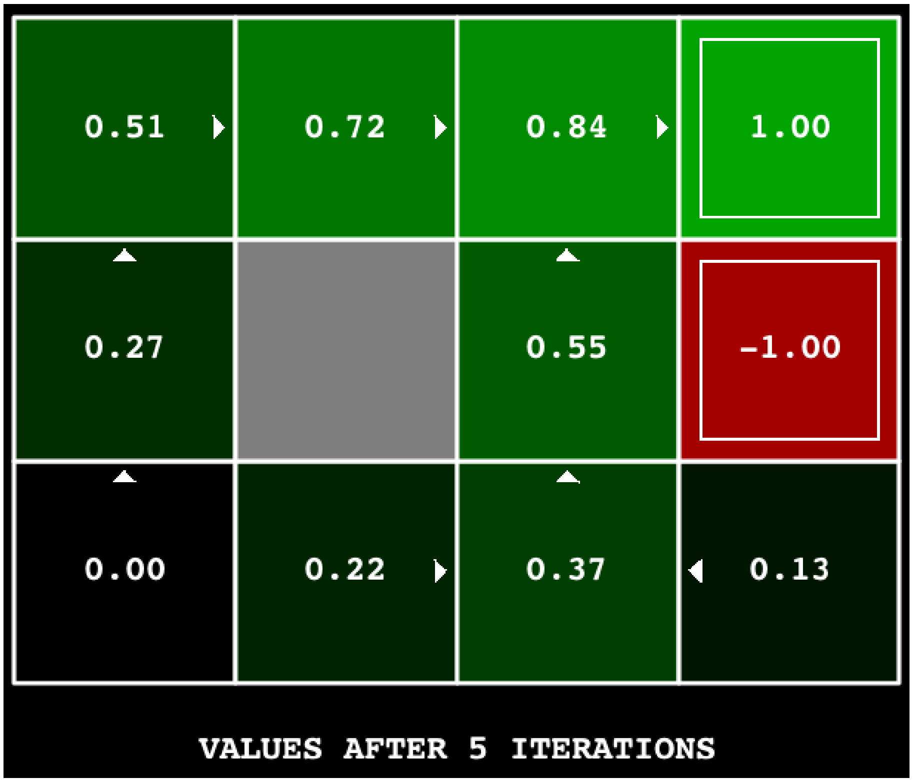
```
python autograder.py -q q1
```

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



Question 2: Q-Learning (15 Points)

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.

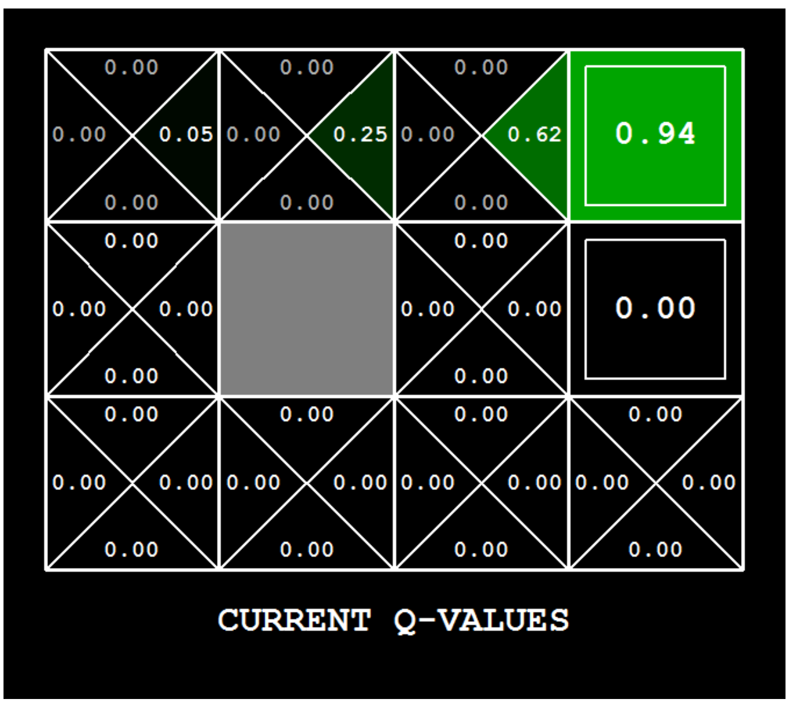
Note: For computeActionFromQValues, you should break ties randomly for better behavior. The random.choice() function will help. In a particular state, actions that your agent *hasn't* seen before still have a Q-value, specifically a Q-value of zero, and if all of the actions that your agent *has* seen 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 8 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
```

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:



python autograder.py -q q4

Question 3: Q-Learning and Pacman (20 Points)

Time to play some Pacman! Pacman will play games in two phases. In the first phase, *training*, Pacman will begin to learn about the values of positions and actions. Because it takes a very long time to learn accurate Q-values even for tiny grids, Pacman's training games run in quiet mode by default, with no GUI (or console) display. Once Pacman's training is complete, he will enter *testing* mode. When testing, Pacman's self.epsilon and self.alpha will be set to 0.0, effectively stopping Q-learning and disabling exploration, in order to allow Pacman to exploit his learned policy. Test games are shown in the GUI by default. Without any code changes you should be able to run Q-learning Pacman for very tiny grids as follows:

```
python pacman.py -p PacmanQAgent -x 2000 -n 2010 -l smallGrid
```

Note that PacmanQAgent is already defined for you in terms of the QLearningAgent you've already written. PacmanQAgent is only different in that it has default learning parameters that are more effective for the Pacman problem (epsilon=0.05, alpha=0.2, gamma=0.8). You will receive full credit for this question if the command above works without exceptions and your agent wins at least 80% of the time. The autograder will run 100 test games after the 2000 training games.

Hint: If your QLearningAgent works for gridworld.py and crawler.py but does not seem to be learning a good policy for Pacman on smallGrid, it may be because your getAction and/or computeActionFromQValues methods do not in some cases properly consider unseen actions. In particular, because unseen actions have by definition a Q-value of zero, if all of the actions that *have* been seen have negative Q-values, an unseen action may be optimal. Beware of the argmax function from util.Counter!

Note: To grade your answer, run:

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

Note: If you want to experiment with learning parameters, you can use the option -a, for example -a epsilon=0.1,alpha=0.3,gamma=0.7. These values will then be accessible as self.epsilon, self.gamma and self.alpha inside the agent.

Note: While a total of 2010 games will be played, the first 2000 games will not be displayed because of the option -x 2000, which designates the first 2000 games for training (no output). Thus, you will only see Pacman play the last 10 of these games. The number of training games is also passed to your agent as the option numTraining.

Note: If you want to watch 10 training games to see what's going on, use the command:

```
python pacman.py -p PacmanQAgent -n 10 -l smallGrid -a numTraining=10
```

During training, you will see output every 100 games with statistics about how Pacman is faring. Epsilon is positive during training, so Pacman will play poorly even after having learned a good policy: this is because he occasionally makes a random exploratory move into a ghost. As a benchmark, it should take between 1,000 and 1400 games before Pacman's rewards for a 100 episode segment becomes positive, reflecting that he's started winning more than losing. By the end of training, it should remain positive and be fairly high (between 100 and 350).

Make sure you understand what is happening here: the MDP state is the *exact* board configuration facing Pacman, with the now complex transitions describing an entire ply of change to that state. The intermediate game configurations in which Pacman has moved but the ghosts have not replied are *not* MDP states, but are bundled in to the transitions.

Once Pacman is done training, he should win very reliably in test games (at least 90% of the time), since now he is exploiting his learned policy.

However, you will find that training the same agent on the seemingly simple mediumGrid does not work well. In our implementation, Pacman's average training rewards remain negative throughout training. At test time, he plays badly, probably losing all of his test games. Training will also take a long time, despite its ineffectiveness.

Pacman fails to win on larger layouts because each board configuration is a separate state with separate Q-values. He has no way to generalize that running into a ghost is bad for all positions. Obviously, this approach will not scale.

NOTE:

- Download *reinforcement.zip*, unzip and rename it with your *group number*.
- Write your code in respective files.
- Test your code and submit it on moodle.
- Due date for the Assignment is *7th March 2023 (11:59PM)*
- Penalty for late submission is *10%* of secured marks.
- We will run a plagiarism check for all the submissions, if found copied *100%* penalty will be applied.
- Viva and demonstration of your submitted code is mandatory and we will share the time slots and date for the same..