Warning: this assignment is out of date. It may still need to be updated for this year's class. Check with your instructor before you start working on this assignment.

This assignment is due on Tuesday, October 29, 2019 before 11:59PM.

You can download the materials for this assignment here:

- skeleton files (/homeworks/hw6/skeleton.zip)

Homework 6: Reinforcement learning [100 points]

Instructions

In the last homework, you have implemented value iteration agent, which 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.

In this homework, You will 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. The code for this homework can be found here (/homeworks/hw6/skeleton.zip).

- **Files you will edit and submit:**
  - **qlearningAgents.py**: A q-learning agent for reinforcement learning.
  - **analysis.py**: A file to put your answers to questions given in the project.

Your code will be autograded for technical correctness. Please ***do not*** change the names of any provided functions or classes within the code, ***do not*** change any file that is not one of the two files for submission explained in 1 above. Once you have completed the assignment, you should submit your file on Gradescope (https://www.gradescope.com/courses/59562). You may submit as many times as you would like before the deadline, but only the last submission will be saved.

1. Q-Learning [35 Points]

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 homework, you need to 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.

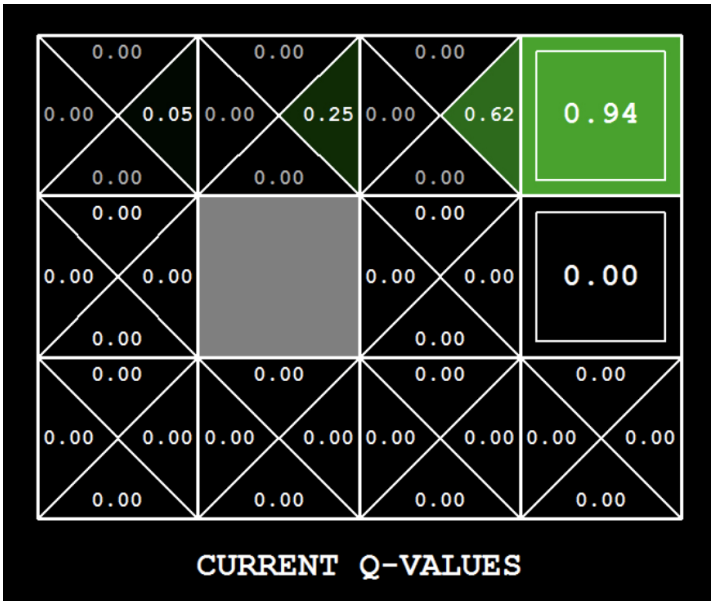
Important: Make sure that in your `computeValueFromQValues` and `computeActionFromQValues` functions, you only access Q values by calling `getQValue`. This abstraction will be useful for approximate Q-learning you will implement later when you override `getQValue` to use features of state-action pairs 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 north and then east along the optimal path for four episodes, you should see the following Q-values:



2. Epsilon Greedy [20 points]

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.

```
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 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.

3. Bridge Crossing Revisited [10 points]

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
```

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? `question6()` 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.

4. Q-Learning and Pacman [10 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: 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.

5. Approximate Q-Learning [20 points]

Implement an approximate Q-learning agent that learns weights for features of states, where many states might share the same features. Write your implementation in `ApproximateQAgent` class in **qlearningAgents.py**, which is a subclass of `PacmanQAgent`.

Note: Approximate Q-learning assumes the existence of a feature function $f(s, a)$ over state and action pairs, which yields a vector $f_1(s, a). .f_i(s, a). .f_n(s, a)$ of feature values. We provide feature functions for you in featureExtractors.py. Feature vectors are util.Counter (like a dictionary) objects containing the non-zero pairs of features and values; all omitted features have value zero.

The approximate Q-function takes the following form

$$Q(s, a) = \sum_{i=1}^{n} f_i(s, a) w_i$$

where each weight w_i is associated with a particular feature $f_i(s, a)$. In your code, you should implement the weight vector as a dictionary mapping features (which the feature extractors will return) to weight values. You will update your weight vectors similarly to how you updated Q-values:

$$w_i \leftarrow w_i + \alpha * difference * f_i(s, a)$$

$$difference = (r + \gamma \max_{a'} Q(s', a')) - Q(s, a)$$

Note that the *difference* term is the same as in normal Q-learning, and *r* is the experienced reward.

By default, `ApproximateQAgent` uses the IdentityExtractor, which assigns a single feature to every (state,action) pair. With this feature extractor, your approximate Q-learning agent should work identically to `PacmanQAgent`. You can test this with the following command:

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

Important: `ApproximateQAgent` is a subclass of `QLearningAgent`, and it therefore shares several methods like getAction. Make sure that your methods in `QLearningAgent` call getQValue instead of accessing Q-values directly, so that when you override getQValue in your approximate agent, the new approximate q-values are used to compute actions.

Once you're confident that your approximate learner works correctly with the identity features, run your approximate Q-learning agent with our custom feature extractor, which can learn to win with ease:

```
python pacman.py -p ApproximateQAgent -a extractor=SimpleExtractor -x 50
-n 60 -l mediumGrid
```

Even much larger layouts should be no problem for your `ApproximateQAgent`. (warning: this may take a few minutes to train)

```
python pacman.py -p ApproximateQAgent -a extractor=SimpleExtractor -x 50
-n 60 -l mediumClassic
```

If you have no errors, your approximate Q-learning agent should win almost every time with these simple features, even with only 50 training games.

6. Feedback [5 points]

1. **[1 point]** Approximately how many hours did you spend on this assignment?
2. **[2 point]** Which aspects of this assignment did you find most challenging? Were there any significant stumbling blocks?
3. **[2 point]** Which aspects of this assignment did you like? Is there anything you would have changed?

This assignment adapted from the Reinforcement Learning assignment (http://ai.berkeley.edu/reinforcement.html) from UC Berkeley's AI course (http://ai.berkeley.edu/home.html).