Machine Learning

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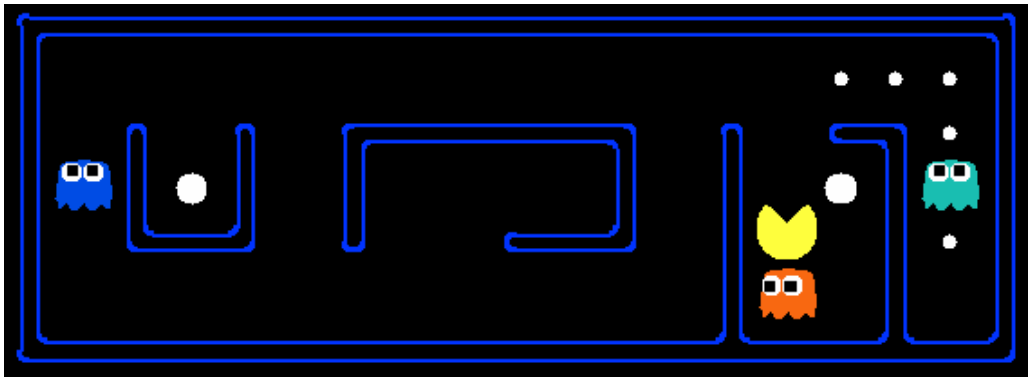


There are nine exercises in this lab (22 marks):

1 (3 marks): Value iteration
2 (1 mark): Bridge grid
3 (5 marks): Discount grid
4 (5 marks): Q-learning
5 (2 marks): Action selection
6 (1 mark): Testing Q-learning
7 (1 mark): Q-learning with PacMan
8 (3 marks): Approximate Q-learning
9 (1 mark): Testing approximate Q-learning

Introduction

In this lab, you will implement value iteration and q-learning, a reinforcement learning algorithm. You will test your agents first on Gridworld, then apply them to a simulated robot controller (Crawler) and PacMan.

Files you will 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 lab.

Files you should read:

`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).

Evaluation

Your code will be autograded for technical correctness. Please *do not* change the names of any provided functions or classes within the code as this will cause issues for the autograder.

Inside this lab directory there is a local autograder and a set of test cases for you to evaluate your code. The local autograder is a file called `autograder.py`. To run the autograder, run the command:

```
python autograder.py
```

You can also select individual exercises for the autograder to run. For example, if you wanted to just test exercise 2, you would run the command:

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

The test cases are within the `test_cases` directory. For each test case, both the test and solution are provided. If your code is failing one of the test cases you can go into this direcory to see all of the details for that particular test case.

This lab is worth a total of 22 points.

MDPs

Markov Decision Processes are a useful way to model sequential decision problems for fully observable, but stochastic environments.

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 the *up* arrow key, 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`).

Before starting the first exercise you should read through the file `mdp.py` which contains the MDP methods you will need to implement value iteration.

Exercise 1 (3 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 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.

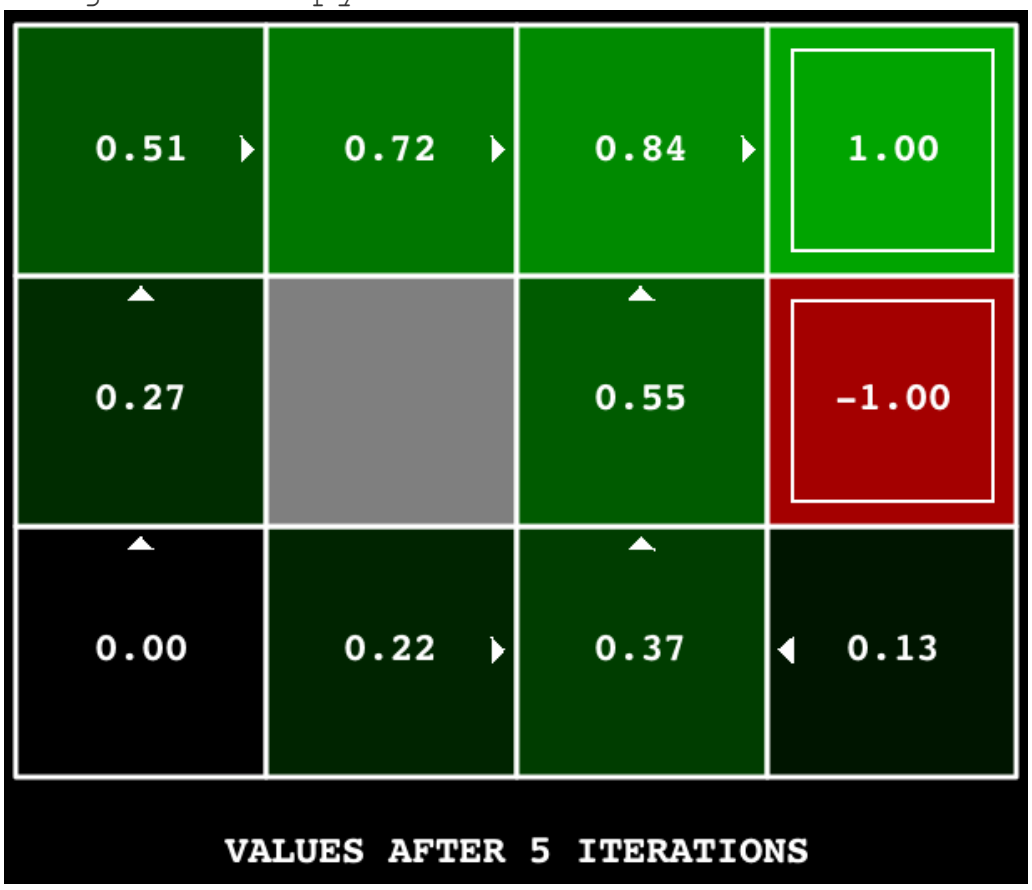
The `ValueIterationAgent` takes an MDP on construction and runs value iteration for the specified number of iterations before the constructor returns. We will perform value iteration where each set of values is computed from the fixed previous set of values. You will store the values in a dictionary. To make a copy of a dictionary `d` in python, simply do: `mycopy = d.copy()`. You will also write the method `getPolicy` that uses the utility values to generate a policy.

The following command loads your `ValueIterationAgent`, which will compute a policy and execute it 10 times. After value iteration is complete, press a key to start the simulation. You should find that the value of the start state (`V(start)`) and the empirical resulting average reward 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
```



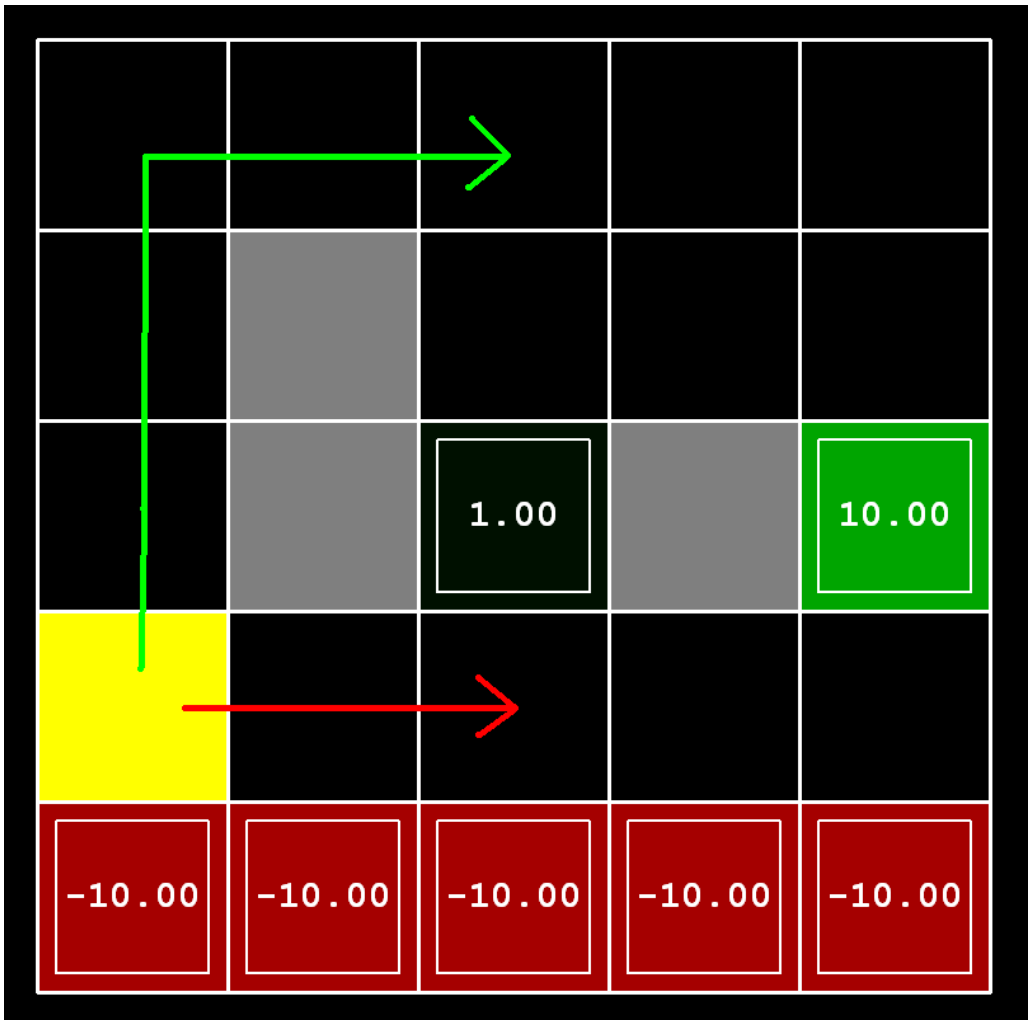
Your value iteration agent will be graded on a new grid. We will check your values and policies after fixed numbers of iterations and at convergence (e.g. after 100 iterations).

Hint: Use the `util.Counter` class in `util.py`, which is a dictionary with a default value of zero.

Exercise 2 (1 point) On `BridgeGrid` 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
```

Exercise 3 (5 points) Consider the `DiscountGrid` layout, shown below. This grid has two terminal states with positive payoff (shown in green), 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.



Give an assignment of parameter values for discount, noise, and livingReward which produce the following optimal policy types or state that the policy is impossible by returning the string `'NOT POSSIBLE'`. The default corresponds to:

```
python gridworld.py -a value -i 100 -g DiscountGrid
--discount 0.9 --noise 0.2 --livingReward 0.0
```

a. Prefer the close exit (+1), risking the cliff (-10)
b. Prefer the close exit (+1), but avoiding the cliff (-10)
c. Prefer the distant exit (+10), risking the cliff (-10)
d. Prefer the distant exit (+10), avoiding the cliff (-10)
e. Avoid both exits (also avoiding the cliff)

`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.

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.

Exercise 4 (5 points) 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 constructor, `getQValue`, `computeValueFromQValues`, `computeActionFromQValues`, and `update` 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, then an unseen action may be optimal.

Important: Make sure that you only access Q values by calling `getQValue` in your methods. This abstraction will be useful for question 9 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."

Exercise 5 (2 points) Complete your q-learning agent by implementing epsilon-greedy action selection in `getAction`, meaning it chooses random actions epsilon of the time, and follows its current best q-values otherwise.

```
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 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`.

Exercise 6 (1 point) 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()` 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`.

With no additional code, you should now be able to run a q-learning crawler robot:

```
python crawler.py
```

If this doesn't work, you've probably written some code too specific to the `GridWorld` problem and you should make it more general to all MDPs. You will receive full credit if the command above works without exceptions.

This will invoke the crawling robot from class using your q-learner. Play around with the various learning parameters to see how they affect the agent's policies and actions. Note that the step delay is a parameter of the simulation, whereas the learning rate and epsilon are parameters of your learning algorithm, and the discount factor is a property of the environment.

Exercise 7 (1 point) 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 last 10 runs.

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 `getPolicy` 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.

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 about 1,000 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'll find that training the same agent on the seemingly simple `mediumGrid` may 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.

Approximate Q-learning and State Abstraction

Exercise 8 (3 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

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

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:

$$\begin{aligned} w_i &\leftarrow w_i + \alpha[correction] f_i(s,a) \\ correction &= (R(s,a) + \gamma V(s')) - Q(s,a) \end{aligned}$$

Note that the correction term is the same as in normal Q-Learning.

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
```

Exercise 9 (1 point) 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.

Submitting your code

To submit your code, you need to add, commit, and push the files you modified. You should only have changed `valueIterationAgents.py`, `qlearningAgents.py`, and `analysis.py`.