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P3-ReinforcementLearning

posted 48 minutes ago by Scott Alfeld

Project 3: Reinforcement Learning

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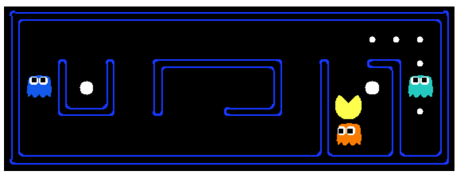


Pacman seeks reward.
Should he eat or should he run?
When in doubt, Q-learn.

Introduction

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.

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 staff 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`).

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 (6 points): Value Iteration

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, U_k. In addition to running value iteration, implement the following methods for `ValueIterationAgent` using U_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 U_k is computed from a fixed vector U_{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:

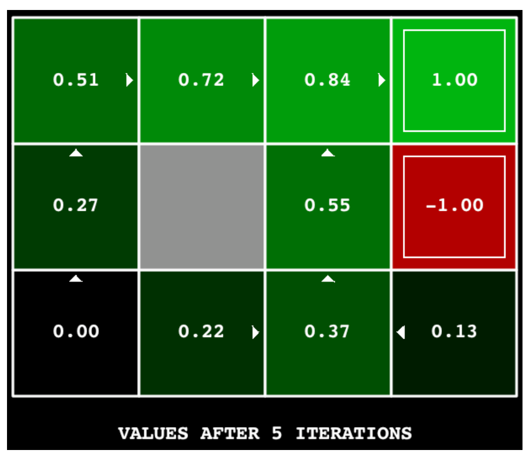
```
python autograder.py -q q1
```

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
```



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 (1 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:

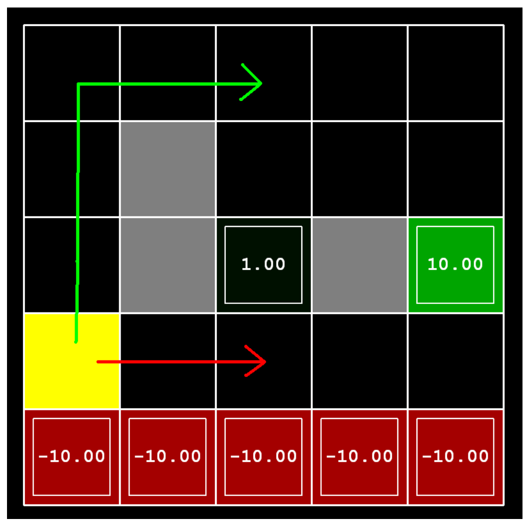
```
python gridworld.py -a value -i 100 -g BridgeGrid --discount 0.9 --noise 0.2
```

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
```

Question 3 (5 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 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): 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.

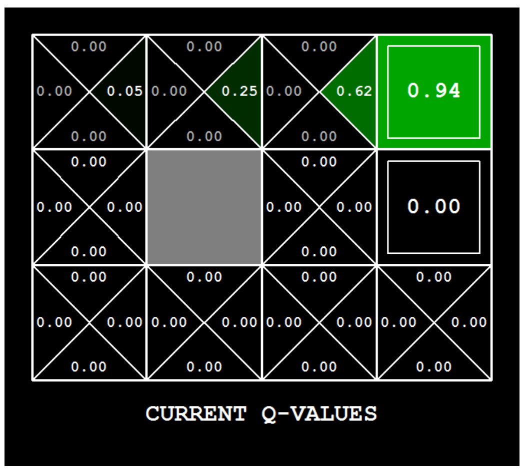
Note: For `computeActionFromQValues`, you should break ties randomly for better behavior. The `random.choice()` function will help. In a particular state, actions that your agent *hasn't* seen before still have a Q-value, specifically a Q-value of zero, and if all of the actions that your agent *has*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



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 q4
```

Question 5 (3 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.

```
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`.

To test your implementation, run the autograder:

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

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.

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.

Question 6 (1 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
```

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.

To grade your answer, run the autograder:

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

Question 7 (1 point): Q-Learning and Pacman

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.

Question 8 (3 points): Approximate Q-Learning

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:

$$w_i \leftarrow w_i + \alpha \cdot difference \cdot f_i(s,a)$$
$$difference = (r + \gamma \max_{a'} Q(s', a')) - Q(s,a)$$

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.

Grading: We will run your approximate Q-learning agent and check that it learns the same Q-values and feature weights 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 q8
```

Congratulations! You have a learning Pacman agent!

P2-GamePlaying

posted Feb 10, 2015, 3:48 PM by Scott Alfeld **[updated Feb 20, 2015, 8:47 AM]**

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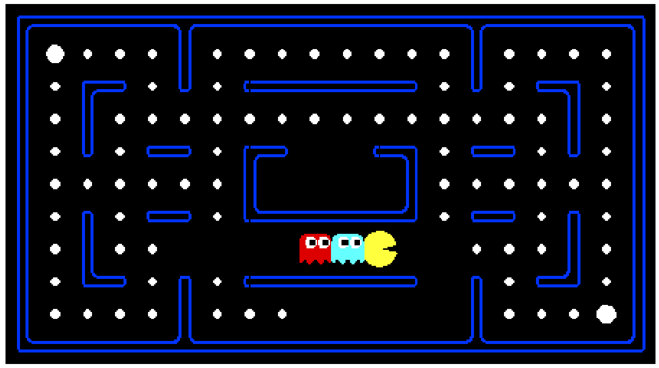

Pacman, now with ghosts.
Minimax, Expectimax,
Evaluation.

Introduction

In this project, you will design agents for the classic version of Pacman, including ghosts. Along the way, you will implement both minimax and expectimax search and try your hand at evaluation function design.

The code base has not changed much from the previous project, but please start with a fresh installation, rather than intermingling files from P1.

As in P1, this project includes an autograder for you to grade your answers on your machine. This can be run on all questions with the command:

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python autograder.py
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It can be run for one particular question, such as q2, by:

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python autograder.py -q q2
```

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

```
python autograder.py -t test_cases/q2/0-small-tree
```

By default, the autograder displays graphics with the `-t` option, but doesn't with the `-q` option. You can force graphics by using the `--graphics` flag, or force no graphics by using the `--no-graphics` flag.

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

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

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

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

Files you'll edit:

`multiAgents.py`	Where all of your multi-agent search agents will reside.

Files you should look at:

`pacman.py`	The main file that runs Pacman games. This file also describes a Pacman `GameState` type, which you will use extensively in this project
`game.py`	The logic behind how the Pacman world works. This file describes several supporting types like AgentState, Agent, Direction, and Grid.
`util.py`	Useful data structures for implementing search algorithms.

Files you can ignore:

`graphicsDisplay.py`	Graphics for Pacman
`graphicsUtils.py`	Support for Pacman graphics
`textDisplay.py`	ASCII graphics for Pacman
`ghostAgents.py`	Agents to control ghosts
`keyboardAgents.py`	Keyboard interfaces to control Pacman
`layout.py`	Code for reading layout files and storing their contents
`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
`multiagentTestClasses.py`	Project 2 specific autograding test classes

Files to Edit and Submit: You will fill in portions of `multiAgents.py` during the assignment. You should submit this file with your code and comments. Please *do not* change the other files in this distribution or submit any of our original files other than this file.

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 staff 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.

Multi-Agent Pacman

First, play a game of classic Pacman:

```
python pacman.py
```

Now, run the provided `ReflexAgent` in `multiAgents.py`:

```
python pacman.py -p ReflexAgent
```

Note that it plays quite poorly even on simple layouts:

```
python pacman.py -p ReflexAgent -l testClassic
```

Inspect its code (in `multiAgents.py`) and make sure you understand what it's doing.

Question 1 (4 points): Reflex Agent

Improve the `ReflexAgent` in `multiAgents.py` to play respectably. The provided reflex agent code provides some helpful examples of methods that query the `GameState` for information. A capable reflex agent will have to consider both food locations and ghost locations to perform well. Your agent should easily and reliably clear the `testClassic` layout:

```
python pacman.py -p ReflexAgent -l testClassic
```

Try out your reflex agent on the default `mediumClassic` layout with one ghost or two (and animation off to speed up the display):

```
python pacman.py --frameTime 0 -p ReflexAgent -k 1
```

```
python pacman.py --frameTime 0 -p ReflexAgent -k 2
```

How does your agent fare? It will likely often die with 2 ghosts on the default board, unless your evaluation function is quite good.

Note: As features, try the reciprocal of important values (such as distance to food) rather than just the values themselves.

Note: The evaluation function you're writing is evaluating state-action pairs; in later parts of the project, you'll be evaluating states.

Options: Default ghosts are random; you can also play for fun with slightly smarter directional ghosts using `-g DirectionalGhost`. If the randomness is preventing you from telling whether your agent is improving, you can use `-f` to run with a fixed random seed (same random choices every game). You can also play multiple games in a row with `-n`. Turn off graphics with `-q` to run lots of games quickly.

Grading: we will run your agent on the `openClassic` layout 10 times. You will receive 0 points if your agent times out, or never wins. You will receive 1 point if your agent wins at least 5 times, or 2 points if your agent wins all 10 games. You will receive an addition 1 point if your agent's average score is greater than 500, or 2 points if it is greater than 1000. You can try your agent out under these conditions with

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

To run it without graphics, use:

```
python autograder.py -q q1 --no-graphics
```

Don't spend too much time on this question, though, as the meat of the project lies ahead.

Question 2 (5 points): Minimax

Now you will write an adversarial search agent in the provided `MinimaxAgent` class stub in `multiAgents.py`. Your minimax agent should work with any number of ghosts, so you'll have to write an algorithm that is slightly more general than what you've previously seen in lecture. In particular, your minimax tree will have multiple min layers (one for each ghost) for every max layer.

Your code should also expand the game tree to an arbitrary depth. Score the leaves of your minimax tree with the supplied`self.evaluationFunction`, which defaults to `scoreEvaluationFunction`. `MinimaxAgent` extends `MultiAgentSearchAgent`, which gives access to `self.depth` and `self.evaluationFunction`. Make sure your minimax code makes reference to these two variables where appropriate as these variables are populated in response to command line options.

Important: A single search ply is considered to be one Pacman move and all the ghosts' responses, so depth 2 search will involve Pacman and each ghost moving two times.

Grading: We will be checking your code to determine whether it explores the correct number of game states. This is the only way reliable way to detect some very subtle bugs in implementations of minimax. As a result, the autograder will be *very* picky about how many times you call `GameState.generateSuccessor`. If you call it any more or less than necessary, the autograder will complain. To test and debug your code, run

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

This will show what your algorithm does on a number of small trees, as well as a pacman game. To run it without graphics, use:

```
python autograder.py -q q2 --no-graphics
```

Hints and Observations

- The correct implementation of minimax will lead to Pacman losing the game in some tests. This is not a problem: as it is correct behaviour, it will pass the tests.
- The evaluation function for the pacman test in this part is already written (`self.evaluationFunction`). You shouldn't change this function, but recognize that now we're evaluating *states* rather than actions, as we were for the reflex agent. Look-ahead agents evaluate future states whereas reflex agents evaluate actions from the current state.
- The minimax values of the initial state in the `minimaxClassic` layout are 9, 8, 7, -492 for depths 1, 2, 3 and 4 respectively. Note that your minimax agent will often win (665/1000 games for us) despite the dire prediction of depth 4 minimax.

```
python pacman.py -p MinimaxAgent -l minimaxClassic -a depth=4
```

- Pacman is always agent 0, and the agents move in order of increasing agent index.
- All states in minimax should be `GameStates`, either passed in to `getAction` or generated via `GameState.generateSuccessor`. In this project, you will not be abstracting to simplified states.
- On larger boards such as `openClassic` and `mediumClassic` (the default), you'll find Pacman to be good at not dying, but quite bad at winning. He'll often thrash around without making progress. He might even thrash around right next to a dot without eating it because he doesn't know where he'd go after eating that dot. Don't worry if you see this behavior, question 5 will clean up all of these issues.
- When Pacman believes that his death is unavoidable, he will try to end the game as soon as

possible because of the constant penalty for living. Sometimes, this is the wrong thing to do with random ghosts, but minimax agents always assume the worst:

```
python pacman.py -p MinimaxAgent -l trappedClassic -a depth=3
```

Make sure you understand why Pacman rushes the closest ghost in this case.

Question 3 (5 points): Alpha-Beta Pruning

Make a new agent that uses alpha-beta pruning to more efficiently explore the minimax tree, in `AlphaBetaAgent`. Again, your algorithm will be slightly more general than the pseudocode from lecture, so part of the challenge is to extend the alpha-beta pruning logic appropriately to multiple minimizer agents.

You should see a speed-up (perhaps depth 3 alpha-beta will run as fast as depth 2 minimax). Ideally, depth 3 on `smallClassic` should run in just a few seconds per move or faster.

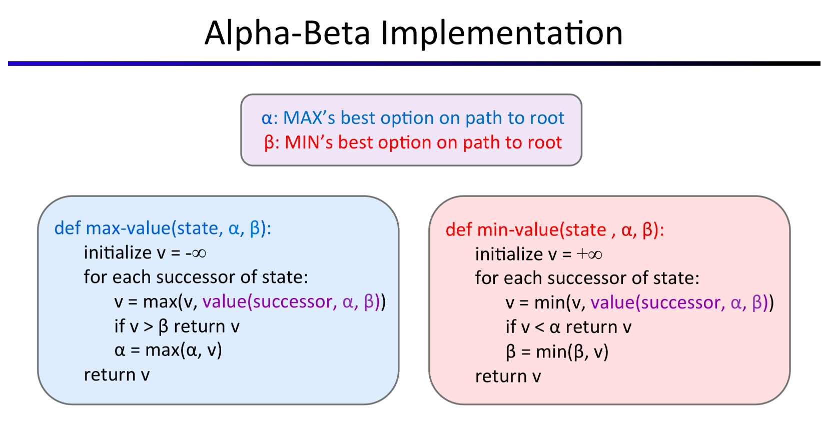
```
python pacman.py -p AlphaBetaAgent -a depth=3 -l smallClassic
```

The `AlphaBetaAgent` minimax values should be identical to the `MinimaxAgent` minimax values, although the actions it selects can vary because of different tie-breaking behavior. Again, the minimax values of the initial state in the `minimaxClassic` layout are 9, 8, 7 and -492 for depths 1, 2, 3 and 4 respectively.

Grading: Because we check your code to determine whether it explores the correct number of states, it is important that you perform alpha-beta pruning without reordering children. In other words, successor states should always be processed in the order returned by`GameState.getLegalActions`. Again, do not call `GameState.generateSuccessor` more than necessary.

You must *not* prune on equality in order to match the set of states explored by our autograder. (Indeed, alternatively, but incompatible with our autograder, would be to also allow for pruning on equality and invoke alpha-beta once on each child of the root node, but this will *not* match the autograder.)

The pseudo-code below represents the algorithm you should implement for this question.



To test and debug your code, run

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

This will show what your algorithm does on a number of small trees, as well as a pacman game. To run it without graphics, use:

```
python autograder.py -q q3 --no-graphics
```

The correct implementation of alpha-beta pruning will lead to Pacman losing some of the tests. This is not a problem: as it is correct behaviour, it will pass the tests.

Question 4 (5 points): Expectimax

Minimax and alpha-beta are great, but they both assume that you are playing against an adversary who makes optimal decisions. As anyone who has ever won tic-tac-toe can tell you, this is not always the case. In this question you will implement the `ExpectimaxAgent`, which is useful for modeling probabilistic behavior of agents who may make suboptimal choices.

As with the search and constraint satisfaction problems covered so far in this class, the beauty of these algorithms is their general applicability. To expedite your own development, we've supplied some test cases based on generic trees. You can debug your implementation on small the game trees using the command:

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

Debugging on these small and manageable test cases is recommended and will help you to find bugs quickly. **Make sure when you compute your averages that you use floats.** Integer division in Python truncates, so that `1/2 = 0`, unlike the case with floats where `1.0/2.0 = 0.5`.

Once your algorithm is working on small trees, you can observe its success in Pacman. Random ghosts are of course not optimal minimax agents, and so modeling them with minimax search may not be appropriate. `ExpectimaxAgent`, will no longer take the min over all ghost actions, but the expectation according to your agent's model of how the ghosts act. To simplify your code, assume you will only be running against an adversary which chooses amongst their `getLegalAction`s uniformly at random.

To see how the ExpectimaxAgent behaves in Pacman, run:

```
python pacman.py -p ExpectimaxAgent -l minimaxClassic -a depth=3
```

You should now observe a more cavalier approach in close quarters with ghosts. In particular, if Pacman perceives that he could be trapped but might escape to grab a few more pieces of food, he'll at least try. Investigate the results of these two scenarios:

```
python pacman.py -p AlphaBetaAgent -l trappedClassic -a depth=3 -q -n 10
```

```
python pacman.py -p ExpectimaxAgent -l trappedClassic -a depth=3 -q -n 10
```

You should find that your `ExpectimaxAgent` wins about half the time, while your `AlphaBetaAgent` always loses. Make sure you understand why the behavior here differs from the minimax case.

The correct implementation of expectimax will lead to Pacman losing some of the tests. This is not a problem: as it is correct behaviour, it will pass the tests.

Question 5 (6 points): Evaluation Function

Write a better evaluation function for pacman in the provided function `betterEvaluationFunction`. The evaluation function should evaluate states, rather than actions like your reflex agent evaluation function did. You may use any tools at your disposal for evaluation, including your search code from the last project. With depth 2 search, your evaluation function should clear the `smallClassic` layout with one random ghost more than half the time and still run at a reasonable rate (to get full credit, Pacman should be averaging around 1000 points when he's winning).

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

Grading: the autograder will run your agent on the `smallClassic` layout 10 times. We will assign points to your evaluation function in the following way:

- If you win at least once without timing out the autograder, you receive 1 points. Any agent not satisfying these criteria will receive 0 points.
- +1 for winning at least 5 times, +2 for winning all 10 times
- +1 for an average score of at least 500, +2 for an average score of at least 1000 (including scores on lost games)
- +1 if your games take on average less than 30 seconds on the autograder machine. The autograder is run on EC2, so this machine will have a fair amount of resources, but your personal computer could be far less performant (netbooks) or far more performant (gaming rigs).
- The additional points for average score and computation time will only be awarded if you win at least 5 times.

Hints and Observations

- As for your reflex agent evaluation function, you may want to use the reciprocal of important

values (such as distance to food) rather than the values themselves.
- One way you might want to write your evaluation function is to use a linear combination of features. That is, compute values for features about the state that you think are important, and then combine those features by multiplying them by different values and adding the results together. You might decide what to multiply each feature by based on how important you think it is.

P1: Search

posted Jan 26, 2015, 2:01 PM by Scott Alfeld **[updated Jan 27, 2015, 1:57 PM by dmbasavin]**

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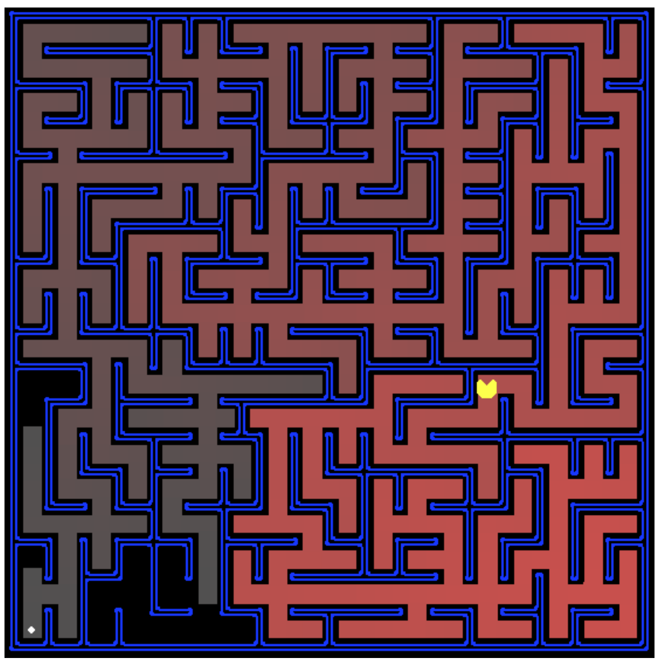

All those colored walls,
Mazes give Pacman the blues,
So teach him to search.

Introduction

In this project, your Pacman agent will find paths through his maze world, both to reach a particular location and to collect food efficiently. You will build general search algorithms and apply them to Pacman scenarios.

As in Project 0, this project includes an autograder for you to grade your answers on your machine. This can be run with the command:

```
python autograder.py
```

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

The code for this project consists of several Python files, some of which you will need to read and understand in order to complete the assignment, and some of which you can ignore. You can download all the code and supporting files as a zip archive.

Files you'll edit:	
`search.py`	Where all of your search algorithms will reside.
`searchAgents.py`	Where all of your search-based agents will reside.
Files you might want to look at:	
`pacman.py`	The main file that runs Pacman games. This file describes a Pacman GameState type, which you use in this project.
`game.py`	The logic behind how the Pacman world works. This file describes several supporting types like AgentState, Agent, Direction, and Grid.
`util.py`	Useful data structures for implementing search algorithms.
Supporting files you can ignore:	
`graphicsDisplay.py`	Graphics for Pacman
`graphicsUtils.py`	Support for Pacman graphics
`textDisplay.py`	ASCII graphics for Pacman
`ghostAgents.py`	Agents to control ghosts
`keyboardAgents.py`	Keyboard interfaces to control Pacman
`layout.py`	Code for reading layout files and storing their contents
`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
`searchTestClasses.py`	Project 1 specific autograding test classes

Files to Edit and Submit: You will fill in portions of `search.py` and `searchAgents.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.

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.

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Discussion: Please be careful not to post spoilers.

Welcome to Pacman

After downloading the code (P1_search.zip), unzipping it, and changing to the directory, you should be able to play a game of Pacman by typing the following at the command line:

```
python pacman.py
```

Pacman lives in a shiny blue world of twisting corridors and tasty round treats. Navigating this world efficiently will be Pacman's first step in mastering his domain.

The simplest agent in `searchAgents.py` is called the `GoWestAgent`, which always goes West (a trivial reflex agent). This agent can occasionally win:

```
python pacman.py --layout testMaze --pacman GoWestAgent
```

But, things get ugly for this agent when turning is required:

```
python pacman.py --layout tinyMaze --pacman GoWestAgent
```

If Pacman gets stuck, you can exit the game by typing CTRL-c into your terminal.

Soon, your agent will solve not only `tinyMaze`, but any maze you want.

Note that `pacman.py` supports a number of options that can each be expressed in a long way (e.g., `--layout`) or a short way (e.g., `-l`). You can see the list of all options and their default values via:

```
python pacman.py -h
```

Also, all of the commands that appear in this project also appear in `commands.txt`, for easy copying and pasting. In UNIX/Mac OS X, you can even run all these commands in order with `bash commands.txt`.

Note: if you get error messages regarding Tkinter, see this page.

Question 1 (3 points): Finding a Fixed Food Dot using Depth First Search

In `searchAgents.py`, you'll find a fully implemented `SearchAgent`, which plans out a path through Pacman's world and then executes that path step-by-step. The search algorithms for formulating a plan are not implemented -- that's your job. As you work through the following questions, you might find it useful to refer to the object glossary (the second to last tab in the navigation bar above).

First, test that the `SearchAgent` is working correctly by running:

```
python pacman.py -l tinyMaze -p SearchAgent -a fn=tinyMazeSearch
```

The command above tells the `SearchAgent` to use `tinyMazeSearch` as its search algorithm, which is implemented in `search.py`. Pacman should navigate the maze successfully.

Now it's time to write full-fledged generic search functions to help Pacman plan routes! Pseudocode for the search algorithms you'll write can be found in the lecture slides. Remember that a search node must contain not only a state but also the information necessary to reconstruct the path (plan) which gets to that state.

Important note: All of your search functions need to return a list of *actions* that will lead the agent from the start to the goal. These actions all have to be legal moves (valid directions, no moving through walls).

Important note: Make sure to **use** the `Stack`, `Queue` and `PriorityQueue` data structures provided to you in `util.py`! These data structure implementations have particular properties which are required for compatibility with the autograder.

Hint: Each algorithm is very similar. Algorithms for DFS, BFS, UCS, and A* differ only in the details of how the fringe is managed. So, concentrate on getting DFS right and the rest should be relatively straightforward. Indeed, one possible implementation requires only a single generic search method which is configured with an algorithm-specific queuing strategy. (Your implementation need *not* be of this form to receive full credit).

Implement the depth-first search (DFS) algorithm in the `depthFirstSearch` function in `search.py`. To make your algorithm *complete*, write the graph search version of DFS, which avoids expanding any already visited states.

Your code should quickly find a solution for:

```
python pacman.py -l tinyMaze -p SearchAgent
```

```
python pacman.py -l mediumMaze -p SearchAgent
```

```
python pacman.py -l bigMaze -z .5 -p SearchAgent
```

The Pacman board will show an overlay of the states explored, and the order in which they were explored (brighter red means earlier exploration). Is the exploration order what you would have expected? Does Pacman actually go to all the explored squares on his way to the goal?

Hint: If you use a `Stack` as your data structure, the solution found by your DFS algorithm for `mediumMaze` should have a length of 130 (provided you push successors onto the fringe in the order provided by getSuccessors; you might get 246 if you push them in the reverse order). Is this a least cost solution? If not, think about what depth-first search is doing wrong.

Question 2 (3 points): Breadth First Search

Implement the breadth-first search (BFS) algorithm in the `breadthFirstSearch` function in `search.py`. Again, write a graph search algorithm that avoids expanding any already visited states. Test your code the same way you did for depth-first search.

```
python pacman.py -l mediumMaze -p SearchAgent -a fn=bfs
```

```
python pacman.py -l bigMaze -p SearchAgent -a fn=bfs -z .5
```

Does BFS find a least cost solution? If not, check your implementation.

Hint: If Pacman moves too slowly for you, try the option `--frameTime 0`.

Note: If you've written your search code generically, your code should work equally well for the eight-puzzle search problem without any changes.

```
python eightpuzzle.py
```

Question 3 (3 points): Varying the Cost Function

While BFS will find a fewest-actions path to the goal, we might want to find paths that are "best" in other senses. Consider`mediumDottedMaze` and `mediumScaryMaze`.

By changing the cost function, we can encourage Pacman to find different paths. For example, we can charge more for dangerous steps in ghost-ridden areas or less for steps in food-rich areas, and a rational Pacman agent should adjust its behavior in response.

Implement the uniform-cost graph search algorithm in the `uniformCostSearch` function in `search.py`. We encourage you to look through`util.py` for some data structures that may be useful in your implementation. You should now observe successful behavior in all three of the following layouts, where the agents below are all UCS agents that differ only in the cost function they use (the agents and cost functions are written for you):

```
python pacman.py -l mediumMaze -p SearchAgent -a fn=ucs
```

```
python pacman.py -l mediumDottedMaze -p StayEastSearchAgent
```

```
python pacman.py -l mediumScaryMaze -p StayWestSearchAgent
```

Note: You should get very low and very high path costs for the `StayEastSearchAgent` and `StayWestSearchAgent` respectively, due to their exponential cost functions (see `searchAgents.py` for details).

Question 4 (3 points): A* search

Implement A* graph search in the empty function `aStarSearch` in `search.py`. A* takes a heuristic function as an argument. Heuristics take two arguments: a state in the search problem (the main argument), and the problem itself (for reference information). The `nullHeuristic`heuristic function in `search.py` is a trivial example.

You can test your A* implementation on the original problem of finding a path through a maze to a fixed position using the Manhattan distance heuristic (implemented already as `manhattanHeuristic` in `searchAgents.py`).

```
python pacman.py -l bigMaze -z .5 -p SearchAgent -a
fn=astar,heuristic=manhattanHeuristic
```

You should see that A* finds the optimal solution slightly faster than uniform cost search (about 549 vs. 620 search nodes expanded in our implementation, but ties in priority may make your numbers differ slightly). What happens on `openMaze` for the various search strategies?

Question 5 (3 points): Finding All the Corners

The real power of A* will only be apparent with a more challenging search problem. Now, it's time to formulate a new problem and design a heuristic for it.

In *corner mazes*, there are four dots, one in each corner. Our new search problem is to find the shortest path through the maze that touches all four corners (whether the maze actually has food there or not). Note that for some mazes like `tinyCorners`, the shortest path does not always go to the closest food first! *Hint*: the shortest path through `tinyCorners` takes 28 steps.

Note: Make sure to complete Question 2 before working on Question 5, because Question 5 builds upon your answer for Question 2.

Implement the `CornersProblem` search problem in `searchAgents.py`. You will need to choose a state representation that encodes all the information necessary to detect whether all four corners have been reached. Now, your search agent should solve:

```
python pacman.py -l tinyCorners -p SearchAgent -a fn=bfs,prob=CornersProblem
```

```
python pacman.py -l mediumCorners -p SearchAgent -a fn=bfs,prob=CornersProblem
```

To receive full credit, you need to define an abstract state representation that *does not* encode irrelevant information (like the position of ghosts, where extra food is, etc.). In particular, do not use a Pacman `GameState` as a search state. Your code will be very, very slow if you do (and also wrong).

Hint: The only parts of the game state you need to reference in your implementation are the starting Pacman position and the location of the four corners.

Our implementation of `breadthFirstSearch` expands just under 2000 search nodes on `mediumCorners`. However, heuristics (used with A* search) can reduce the amount of searching required.

Question 6 (3 points): Corners Problem: Heuristic

Note: Make sure to complete Question 4 before working on Question 6, because Question 6 builds *upon your answer for Question 4.*

Implement a non-trivial, consistent heuristic for the `CornersProblem` in `cornersHeuristic`.

```
python pacman.py -l mediumCorners -p AStarCornersAgent -z 0.5
```

Note: `AStarCornersAgent` is a shortcut for

`-p SearchAgent -a fn=aStarSearch,prob=CornersProblem,heuristic=cornersHeuristic`.

Admissibility vs. Consistency: Remember, heuristics are just functions that take search states and return numbers that estimate the cost to a nearest goal. More effective heuristics will return values closer to the actual goal costs. To be *admissible*, the heuristic values must be lower bounds on the actual shortest path cost to the nearest goal (and non-negative). To be *consistent*, it must additionally hold that if an action has cost *c*, then taking that action can only cause a drop in heuristic of at most *c*.

Remember that admissibility isn't enough to guarantee correctness in graph search -- you need the stronger condition of consistency. However, admissible heuristics are usually also consistent, especially if they are derived from problem relaxations. Therefore it is usually easiest to start out by brainstorming admissible heuristics. Once you have an admissible heuristic that works well, you can check whether it is indeed consistent, too. The only way to guarantee consistency is with a proof. However, inconsistency can often be detected by verifying that for each node you expand, its successor nodes are equal or higher in in f-value. Moreover, if UCS and A* ever return paths of different lengths, your heuristic is inconsistent. This stuff is tricky!

Non-Trivial Heuristics: The trivial heuristics are the ones that return zero everywhere (UCS) and the heuristic which computes the true completion cost. The former won't save you any time, while the latter will timeout the autograder. You want a heuristic which reduces total compute time, though for this assignment the autograder will only check node counts (aside from enforcing a reasonable time limit).

Grading: Your heuristic must be a non-trivial non-negative consistent heuristic to receive any points. Make sure that your heuristic returns 0 at every goal state and never returns a negative value. Depending on how few nodes your heuristic expands, you'll be graded:

Number of nodes expanded	Grade
more than 2000	0/3
at most 2000	1/3
at most 1600	2/3
at most 1200	3/3

Remember: If your heuristic is inconsistent, you will receive *no* credit, so be careful!

Question 7 (4 points): Eating All The Dots

Now we'll solve a hard search problem: eating all the Pacman food in as few steps as possible. For this, we'll need a new search problem definition which formalizes the food-clearing problem: `FoodSearchProblem` in `searchAgents.py` (implemented for you). A solution is defined to be a path that collects all of the food in the Pacman world. For the present project, solutions do not take into account any ghosts or power pellets; solutions only depend on the placement of walls, regular food and Pacman. (Of course ghosts can ruin the execution of a solution! We'll get to that in the next project.) If you have written your general search methods correctly, `A*` with a null heuristic (equivalent to uniform-cost search) should quickly find an optimal solution to `testSearch` with no code change on your part (total cost of 7).

```
python pacman.py -l testSearch -p AStarFoodSearchAgent
```

Note: `AStarFoodSearchAgent` is a shortcut for `-p SearchAgent -a fn=astar,prob=FoodSearchProblem,heuristic=foodHeuristic`.

You should find that UCS starts to slow down even for the seemingly simple `tinySearch`. As a reference, our implementation takes 2.5 seconds to find a path of length 27 after expanding 5057 search nodes.

Note: Make sure to complete Question 4 before working on Question 7, because Question 7 builds upon your answer for Question 4.

Fill in `foodHeuristic` in `searchAgents.py` with a consistent heuristic for the `FoodSearchProblem`. Try your agent on the `trickySearch`board:

```
python pacman.py -l trickySearch -p AStarFoodSearchAgent
```

Our UCS agent finds the optimal solution in about 13 seconds, exploring over 16,000 nodes.

Any non-trivial non-negative consistent heuristic will receive 1 point. Make sure that your heuristic returns 0 at every goal state and never returns a negative value. Depending on how few nodes your heuristic expands, you'll get additional points:

Number of nodes expanded	Grade
more than 15000	1/4
at most 15000	2/4
at most 12000	3/4
at most 9000	4/4 (full credit; medium)
at most 7000	5/4 (optional extra credit; hard)

Remember: If your heuristic is inconsistent, you will receive *no* credit, so be careful! Can you solve `mediumSearch` in a short time? If so, we're either very, very impressed, or your heuristic is inconsistent.

Question 8 (3 points): Suboptimal Search

Sometimes, even with A* and a good heuristic, finding the optimal path through all the dots is hard. In these cases, we'd still like to find a reasonably good path, quickly. In this section, you'll write an agent that always greedily eats the closest dot. `ClosestDotSearchAgent` is implemented for you in `searchAgents.py`, but it's missing a key function that finds a path to the closest dot.

Implement the function `findPathToClosestDot` in `searchAgents.py`. Our agent solves this maze (suboptimally!) in under a second with a path cost of 350:

```
python pacman.py -l bigSearch -p ClosestDotSearchAgent -z .5
```

Hint: The quickest way to complete `findPathToClosestDot` is to fill in the `AnyFoodSearchProblem`, which is missing its goal test. Then, solve that problem with an appropriate search function. The solution should be very short!

Your `ClosestDotSearchAgent` won't always find the shortest possible path through the maze. Make sure you understand why and try to come up with a small example where repeatedly going to the closest dot does not result in finding the shortest path for eating all the dots.

Teams for P1

posted Jan 26, 2015, 8:38 AM by Scott Alfeld **[updated Jan 26, 2015, 8:38 AM]**

There is an "assignment" (worth no points, but you're required to turn it in) on Moodle to select teams for P1. Due Wednesday Jan 28th at 3:00PM.
See instructions on Moodle page.

Project 0: Python Tutorial

posted Jan 20, 2015, 11:12 AM by Scott Alfeld **[updated Jan 20, 2015, 6:28 PM]**

Project 0: Unix/Python/Autograder Tutorial

Version 1.001. Last Updated: 08/26/2014.

Table of Contents

Introduction

The projects for this class assume you use Python 2.7.

Project 0 will cover the following:

- A mini-Python tutorial,
- Project grading: Every project's release includes its autograder for you to run yourself.

Files to Edit and Submit: You will fill in portions of `addition.py`, `buyLotsOfFruit.py`, and `shopSmart.py` in `tutorial.zip` 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.

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 staff 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.

Python Basics

Required Files

You can download all of the files associated with the Python mini-tutorial as a zip archive: python_basics.zip.

Table of Contents

The programming assignments in this course will be written in Python, an interpreted, object-oriented language that shares some features with both Java and Scheme. This tutorial will walk through the primary syntactic constructions in Python, using short examples.

We encourage you to type all python shown in the tutorial onto your own machine. Make sure it responds the same way.

Invoking the Interpreter

Python can be run in one of two modes. It can either be used *interactively*, via an interpeter, or it can be called from the command line to execute a *script*. We will first use the Python interpreter interactively.

You invoke the interpreter by entering `python` at the Unix command prompt.

```
[<your username> ~]$ python
Python 2.7.3 (r265:79063, Jan 14 2015, 14:20:15)
[GCC 4.4.7] on sunos5
Type "help", "copyright", "credits" or "license" for more information.
>>>
```

Note that your python may not be 2.7.3. If you see a different version when you run '`python`', you should set up an alias.
To do so:

1. Open the terminal (Applications -> System Tools -> Terminal) and type

   gedit ~/.bashrc

   or use your favorite text editor to edit the file ~/.bashrc

2. In the opened gedit window go all the way to the bottom of the .bashrc file.

3. Add the following line to the end of the .bashrc file

   alias python=/s/python-2.7.3/bin/python2.7

4. Restart the terminal.

Alternatively, you can define a separate alias for Python 2.7 and keep the old version intact:

alias python2.7=/s/python-2.7.3/bin/python2.7

In that case, you will have to type "python2.7" whenever you want to invoke the Python interpreter while doing your
homeworks, e.g., the following command

python2.7 listcomp.py

will run listcomp.py file using Python 2.7.

Operators

The Python interpreter can be used to evaluate expressions, for example simple arithmetic expressions. If you enter such expressions at the prompt (`>>>`) they will be evaluated and the result will be returned on the next line.

```
>>> 1 + 1
2
```

```
>>> 2 * 3
6
```

Boolean operators also exist in Python to manipulate the primitive `True` and `False` values.

```
>>> 1==0
False
>>> not (1==0)
True
>>> (2==2) and (2==3)
False
>>> (2==2) or (2==3)
True
```

Strings

Like Java, Python has a built in string type. The `+` operator is overloaded to do string concatenation on string values.

```
>>> 'artificial' + "intelligence"
'artificialintelligence'
```

There are many built-in methods which allow you to manipulate strings.

```
>>> 'artificial'.upper()
'ARTIFICIAL'
>>> 'HELP'.lower()
'help'
>>> len('Help')
4
```

Notice that we can use either single quotes `' '` or double quotes `" "` to surround string. This allows for easy nesting of strings.

We can also store expressions into variables.

```
>>> s = 'hello world'
>>> print s
hello world
>>> s.upper()
'HELLO WORLD'
>>> len(s.upper())
11
>>> num = 8.0
>>> num += 2.5
>>> print num
10.5
```

In Python, you do not have declare variables before you assign to them.

Exercise: Dir and Help

Learn about the methods Python provides for strings. To see what methods Python provides for a datatype, use the `dir` and `help` commands:

```
>>> s = 'abc'

>>> dir(s)
['__add__', '__class__', '__contains__', '__delattr__', '__doc__', '__eq__',
'__ge__', '__getattribute__', '__getitem__', '__getnewargs__',
'__getslice__', '__gt__', '__hash__', '__init__','__le__', '__len__',
'__lt__', '__mod__', '__mul__', '__ne__', '__new__', '__reduce__',
'__reduce_ex__','__repr__', '__rmod__', '__rmul__', '__setattr__', '__str__',
'capitalize', 'center', 'count', 'decode', 'encode', 'endswith',
'expandtabs', 'find', 'index', 'isalnum', 'isalpha', 'isdigit', 'islower',
'isspace', 'istitle', 'isupper', 'join', 'ljust', 'lower', 'lstrip',
'replace', 'rfind','rindex', 'rjust', 'rsplit', 'rstrip', 'split',
'splitlines', 'startswith', 'strip', 'swapcase', 'title', 'translate',
'upper', 'zfill']

>>> help(s.find)
```

```
Help on built-in function find:

find(...)
    S.find(sub [,start [,end]]) -> int

    Return the lowest index in S where substring sub is found,
    such that sub is contained within s[start,end].  Optional
    arguments start and end are interpreted as in slice notation.

    Return -1 on failure.


>> s.find('b')
1
```

Try out some of the string functions listed in `dir` (ignore those with underscores '_' around the method name).

Built-in Data Structures

Python comes equipped with some useful built-in data structures, broadly similar to Java's collections package.

Lists

Lists store a sequence of mutable items:

```
>>> fruits = ['apple','orange','pear','banana']
>>> fruits[0]
'apple'
```

We can use the `+` operator to do list concatenation:

```
>>> otherFruits = ['kiwi','strawberry']
>>> fruits + otherFruits
>>> ['apple', 'orange', 'pear', 'banana', 'kiwi', 'strawberry']
```

Python also allows negative-indexing from the back of the list. For instance, `fruits[-1]` will access the last element `'banana'`:

```
>>> fruits[-2]
'pear'
>>> fruits.pop()
'banana'
>>> fruits
['apple', 'orange', 'pear']
>>> fruits.append('grapefruit')
>>> fruits
['apple', 'orange', 'pear', 'grapefruit']
>>> fruits[-1] = 'pineapple'
>>> fruits
['apple', 'orange', 'pear', 'pineapple']
```

We can also index multiple adjacent elements using the slice operator. For instance, `fruits[1:3]`, returns a list containing the elements at position 1 and 2. In general `fruits[start:stop]` will get the elements in `start, start+1, ..., stop-1`. We can also do `fruits[start:]` which returns all elements starting from the `start` index. Also `fruits[:end]` will return all elements before the element at position `end`:

```
>>> fruits[0:2]
['apple', 'orange']
>>> fruits[:3]
['apple', 'orange', 'pear']
>>> fruits[2:]
['pear', 'pineapple']
>>> len(fruits)
4
```

The items stored in lists can be any Python data type. So for instance we can have lists of lists:

```
>>> lstOfLsts = [['a','b','c'],[1,2,3],['one','two','three']]
>>> lstOfLsts[1][2]
3
```

```
>>> lstOfLsts[0].pop()
'c'
>>> lstOfLsts
[['a', 'b'],[1, 2, 3],['one', 'two', 'three']]
```

Exercise: Lists

Play with some of the list functions. You can find the methods you can call on an object via the `dir` and get information about them via the `help` command:

```
>>> dir(list)
['__add__', '__class__', '__contains__', '__delattr__', '__delitem__',
'__delslice__', '__doc__', '__eq__', '__ge__', '__getattribute__',
'__getitem__', '__getslice__', '__gt__', '__hash__', '__iadd__', '__imul__',
'__init__', '__iter__', '__le__', '__len__', '__lt__', '__mul__', '__ne__',
'__new__', '__reduce__', '__reduce_ex__', '__repr__', '__reversed__',
'__rmul__', '__setattr__', '__setitem__', '__setslice__', '__str__',
'append', 'count', 'extend', 'index', 'insert', 'pop', 'remove', 'reverse',
'sort']
```

```
>>> help(list.reverse)
Help on built-in function reverse:

reverse(...)
    L.reverse() -- reverse *IN PLACE*
```

```
>>> lst = ['a','b','c']
>>> lst.reverse()
>>> ['c','b','a']
```

Note: Ignore functions with underscores "_" around the names; these are private helper methods. Press 'q' to back out of a help screen.

Tuples

A data structure similar to the list is the *tuple*, which is like a list except that it is immutable once it is created (i.e. you cannot change its content once created). Note that tuples are surrounded with parentheses while lists have square brackets.

```
>>> pair = (3,5)
>>> pair[0]
3
>>> x,y = pair
>>> x
3
>>> y
5
>>> pair[1] = 6
TypeError: object does not support item assignment
```

The attempt to modify an immutable structure raised an exception. Exceptions indicate errors: index out of bounds errors, type errors, and so on will all report exceptions in this way.

Sets

A *set* is another data structure that serves as an unordered list with no duplicate items. Below, we show how to create a set, add things to the set, test if an item is in the set, and perform common set operations (difference, intersection, union):

```
>>> shapes = ['circle','square','triangle','circle']
>>> setOfShapes = set(shapes)
>>> setOfShapes
set(['circle','square','triangle'])
>>> setOfShapes.add('polygon')
>>> setOfShapes
set(['circle','square','triangle','polygon'])
>>> 'circle' in setOfShapes
True
>>> 'rhombus' in setOfShapes
False
>>> favoriteShapes = ['circle','triangle','hexagon']
>>> setOfFavoriteShapes = set(favoriteShapes)
>>> setOfShapes - setOfFavoriteShapes
```

```
set(['square','polyon'])
>>> setOfShapes & setOfFavoriteShapes
set(['circle','triangle'])
>>> setOfShapes | setOfFavoriteShapes
set(['circle','square','triangle','polygon','hexagon'])
```

Note that the objects in the set are unordered; you cannot assume that their traversal or print order will be the same across machines!

Dictionaries

The last built-in data structure is the *dictionary* which stores a map from one type of object (the key) to another (the value). The key must be an immutable type (string, number, or tuple). The value can be any Python data type.

Note: In the example below, the printed order of the keys returned by Python could be different than shown below. The reason is that unlike lists which have a fixed ordering, a dictionary is simply a hash table for which there is no fixed ordering of the keys (like HashMaps in Java). The order of the keys depends on how exactly the hashing algorithm maps keys to buckets, and will usually seem arbitrary. Your code should not rely on key ordering, and you should not be surprised if even a small modification to how your code uses a dictionary results in a new key ordering.

```
>>> studentIds = {'knuth': 42.0, 'turing': 56.0, 'nash': 92.0 }
>>> studentIds['turing']
56.0
>>> studentIds['nash'] = 'ninety-two'
>>> studentIds
{'knuth': 42.0, 'turing': 56.0, 'nash': 'ninety-two'}
>>> del studentIds['knuth']
>>> studentIds
{'turing': 56.0, 'nash': 'ninety-two'}
>>> studentIds['knuth'] = [42.0,'forty-two']
>>> studentIds
{'knuth': [42.0, 'forty-two'], 'turing': 56.0, 'nash': 'ninety-two'}
>>> studentIds.keys()
['knuth', 'turing', 'nash']
>>> studentIds.values()
[[42.0, 'forty-two'], 56.0, 'ninety-two']
>>> studentIds.items()
[('knuth',[42.0, 'forty-two']), ('turing',56.0), ('nash','ninety-two')]
>>> len(studentIds)
3
```

As with nested lists, you can also create dictionaries of dictionaries.

Exercise: Dictionaries

Use `dir` and `help` to learn about the functions you can call on dictionaries.

Writing Scripts

Now that you've got a handle on using Python interactively, let's write a simple Python script that demonstrates Python's `for` loop. Open the file called `foreach.py` and update it with the following code:

```
# This is what a comment looks like
fruits = ['apples','oranges','pears','bananas']
for fruit in fruits:
    print fruit + ' for sale'

fruitPrices = {'apples': 2.00, 'oranges': 1.50, 'pears': 1.75}
for fruit, price in fruitPrices.items():
    if price < 2.00:
        print '%s cost %f a pound' % (fruit, price)
    else:
        print fruit + ' are too expensive!'
```

At the command line, use the following command in the directory containing `foreach.py`:

```
[<your username> ~/tutorial]$ python foreach.py
apples for sale
oranges for sale
pears for sale
```

```
bananas for sale
oranges cost 1.500000 a pound
pears cost 1.750000 a pound
apples are too expensive!
```

Remember that the print statements listing the costs may be in a different order on your screen than in this tutorial; that's due to the fact that we're looping over dictionary keys, which are unordered. To learn more about control structures (e.g., `if` and `else`) in Python, check out the official Python tutorial section on this topic.

If you like functional programming you might also like `map` and `filter`:

```
>>> map(lambda x: x * x, [1,2,3])
[1, 4, 9]
>>> filter(lambda x: x > 3, [1,2,3,4,5,4,3,2,1])
[4, 5, 4]
```

You can learn more about `lambda` if you're interested.

The next snippet of code demonstrates Python's *list comprehension* construction:

```
nums = [1,2,3,4,5,6]
plusOneNums = [x+1 for x in nums]
oddNums = [x for x in nums if x % 2 == 1]
print oddNums
oddNumsPlusOne = [x+1 for x in nums if x % 2 ==1]
print oddNumsPlusOne
```

This code is in a file called `listcomp.py`, which you can run:

```
[<your username> ~]$ python listcomp.py
[1,3,5]
[2,4,6]
```

Exercise: List Comprehensions

Write a list comprehension which, from a list, generates a lowercased version of each string that has length greater than five. You can find the solution in`listcomp2.py`.

Beware of Indendation!

Unlike many other languages, Python uses the indentation in the source code for interpretation. So for instance, for the following script:

```
if 0 == 1:
    print 'We are in a world of arithmetic pain'
print 'Thank you for playing'
```

will output

```
Thank you for playing
```

But if we had written the script as

```
if 0 == 1:
    print 'We are in a world of arithmetic pain'
    print 'Thank you for playing'
```

there would be no output. The moral of the story: be careful how you indent! It's best to use four spaces for indentation -- that's what the course code uses.

Tabs vs Spaces

Because Python uses indentation for code evaluation, it needs to keep track of the level of indentation across code blocks. This means that if your Python file switches from using tabs as indentation to spaces as indentation, the Python interpreter will not be able to resolve the ambiguity of the indentation level and throw an exception. Even though the code can be lined up visually in your text editor, Python "sees" a change in indentation and most likely will throw an exception (or rarely, produce unexpected behavior).

This most commonly happens when opening up a Python file that uses an indentation scheme that is opposite from what your text editor uses (aka, your text editor uses spaces and the file uses tabs). When you write new lines in a code block, there will be a mix of tabs and spaces, even though the whitespace is aligned. For a longer discussion on tabs vs spaces, see this discussion on StackOverflow.

Writing Functions

As in Java, in Python you can define your own functions:

```
fruitPrices = {'apples':2.00, 'oranges': 1.50, 'pears': 1.75}

def buyFruit(fruit, numPounds):
    if fruit not in fruitPrices:
        print "Sorry we don't have %s" % (fruit)
    else:
        cost = fruitPrices[fruit] * numPounds
        print "That'll be %f please" % (cost)

# Main Function
if __name__ == '__main__':
    buyFruit('apples',2.4)
    buyFruit('coconuts',2)
```

Rather than having a `main` function as in Java, the `__name__ == '__main__'` check is used to delimit expressions which are executed when the file is called as a script from the command line. The code after the main check is thus the same sort of code you would put in a `main` function in Java.

Save this script as *fruit.py* and run it:

```
[<your username> ~]$ python fruit.py
That'll be 4.800000 please
Sorry we don't have coconuts
```

Advanced Exercise

Write a `quickSort` function in Python using list comprehensions. Use the first element as the pivot. You can find the solution in `quickSort.py`.

Object Basics

Although this isn't a class in object-oriented programming, you'll have to use some objects in the programming projects, and so it's worth covering the basics of objects in Python. An object encapsulates data and provides functions for interacting with that data.

Defining Classes

Here's an example of defining a class named `FruitShop`:

```
class FruitShop:

    def __init__(self, name, fruitPrices):
        """
            name: Name of the fruit shop

            fruitPrices: Dictionary with keys as fruit
            strings and prices for values e.g.
            {'apples':2.00, 'oranges': 1.50, 'pears': 1.75}
        """
        self.fruitPrices = fruitPrices
        self.name = name
        print 'Welcome to the %s fruit shop' % (name)

    def getCostPerPound(self, fruit):
        """
            fruit: Fruit string
        Returns cost of 'fruit', assuming 'fruit'
        is in our inventory or None otherwise
        """
        if fruit not in self.fruitPrices:
            print "Sorry we don't have %s" % (fruit)
            return None
        return self.fruitPrices[fruit]

    def getPriceOfOrder(self, orderList):
        """
            orderList: List of (fruit, numPounds) tuples

        Returns cost of orderList. If any of the fruit are
        """
        totalCost = 0.0
        for fruit, numPounds in orderList:
            costPerPound = self.getCostPerPound(fruit)
            if costPerPound != None:
```

```
                totalCost += numPounds * costPerPound
        return totalCost

    def getName(self):
        return self.name
```

The `FruitShop` class has some data, the name of the shop and the prices per pound of some fruit, and it provides functions, or methods, on this data. What advantage is there to wrapping this data in a class?

1. Encapsulating the data prevents it from being altered or used inappropriately,
2. The abstraction that objects provide make it easier to write general-purpose code.

Using Objects

So how do we make an object and use it? Make sure you have the `FruitShop` implementation in `shop.py`. We then import the code from this file (making it accessible to other scripts) using `import shop`, since `shop.py` is the name of the file. Then, we can create `FruitShop` objects as follows:

```
import shop

shopName = 'the Berkeley Bowl'
fruitPrices = {'apples': 1.00, 'oranges': 1.50, 'pears': 1.75}
berkeleyShop = shop.FruitShop(shopName, fruitPrices)
applePrice = berkeleyShop.getCostPerPound('apples')
print applePrice
print('Apples cost $%.2f at %s.' % (applePrice, shopName))

otherName = 'the Stanford Mall'
otherFruitPrices = {'kiwis':6.00, 'apples': 4.50, 'peaches': 8.75}
otherFruitShop = shop.FruitShop(otherName, otherFruitPrices)
otherPrice = otherFruitShop.getCostPerPound('apples')
print otherPrice
print('Apples cost $%.2f at %s.' % (otherPrice, otherName))
print("My, that's expensive!")
```

This code is in `shopTest.py`; you can run it like this:

```
[<your username> ~]$ python shopTest.py
Welcome to the Berkeley Bowl fruit shop
1.0
Apples cost $1.00 at the Berkeley Bowl.
Welcome to the Stanford Mall fruit shop
4.5
Apples cost $4.50 at the Stanford Mall.
My, that's expensive!
```

So what just happended? The `import shop` statement told Python to load all of the functions and classes in `shop.py`. The line `berkeleyShop = shop.FruitShop(shopName, fruitPrices)` constructs an *instance* of the `FruitShop` class defined in *shop.py*, by calling the `__init__` function in that class. Note that we only passed two arguments in, while `__init__` seems to take three arguments: `(self, name, fruitPrices)`. The reason for this is that all methods in a class have `self` as the first argument. The `self` variable's value is automatically set to the object itself; when calling a method, you only supply the remaining arguments. The `self` variable contains all the data (`name` and `fruitPrices`) for the current specific instance (similar to `this` in Java). The print statements use the substitution operator (described in the Python docs if you're curious).

Static vs Instance Variables

The following example illustrates how to use static and instance variables in Python.

Create the `person_class.py` containing the following code:

```
class Person:
    population = 0
    def __init__(self, myAge):
        self.age = myAge
        Person.population += 1
    def get_population(self):
        return Person.population
    def get_age(self):
        return self.age
```

We first compile the script:

```
[<your username> ~]$ python person_class.py
```

Now use the class as follows:

```
>>> import person_class
>>> p1 = person_class.Person(12)
>>> p1.get_population()
1
>>> p2 = person_class.Person(63)
>>> p1.get_population()
2
>>> p2.get_population()
2
>>> p1.get_age()
12
>>> p2.get_age()
63
```

In the code above, `age` is an instance variable and `population` is a static variable. `population` is shared by all instances of the `Person` class whereas each instance has its own `age` variable.

More Python Tips and Tricks

This tutorial has briefly touched on some major aspects of Python that will be relevant to the course. Here are some more useful tidbits:

- Use `range` to generate a sequence of integers, useful for generating traditional indexed `for` loops:

```
for index in range(3):
    print lst[index]
```

- After importing a file, if you edit a source file, the changes will not be immediately propagated in the interpreter. For this, use the `reload` command:

```
>>> reload(shop)
```

Troubleshooting

These are some problems (and their solutions) that new Python learners commonly encounter.

- **Problem:**
  ImportError: No module named py
  Solution:
  When using `import`, do not include the ".py" from the filename.
  For example, you should say: `import shop`
  NOT: `import shop`**`.py`**
- **Problem:**
  NameError: name 'MY VARIABLE' is not defined
  Even after importing you may see this.
  Solution:
  To access a member of a module, you have to type `MODULE NAME.MEMBER NAME`, where `MODULE NAME` is the name of the `.py` file, and `MEMBER NAME` is the name of the variable (or function) you are trying to access.
- **Problem:**
  TypeError: 'dict' object is not callable
  Solution:
  Dictionary looks up are done using square brackets: [and]. NOT parenthesis: (and).
- **Problem:**
  ValueError: too many values to unpack
  Solution:
  Make sure the number of variables you are assigning in a `for` loop matches the number of elements in each item of the list. Similarly for working with tuples.
  For example, if `pair` is a tuple of two elements (e.g. `pair =('apple', 2.0)`) then the following code would cause the "too many values to unpack error":

```
(a,b,c) = pair
```

  Here is a problematic scenario involving a `for` loop:

```
pairList = [('apples', 2.00), ('oranges', 1.50), ('pears', 1.75)]
for fruit, price, color in pairList:
    print '%s fruit costs %f and is the color %s' % (fruit, price,
color)
```

- **Problem:**
  AttributeError: 'list' object has no attribute 'length' (or something similar)
  Solution:
  Finding length of lists is done using `len(NAME OF LIST)`.
- **Problem:**
  Changes to a file are not taking effect.
  Solution:
  1. Make sure you are saving all your files after any changes.
  2. If you are editing a file in a window different from the one you are using to execute python, make sure you `reload(YOUR_MODULE)` to guarantee your changes are being reflected. `reload` works similarly to `import`.

More References

- The place to go for more Python information: www.python.org
- A good reference book: Learning Python (From the UCB campus, you can read the whole book online)

Autograding

To get you familiarized with the autograder, we will ask you to code, test, and submit solutions for three questions.

You can download all of the files associated the autograder tutorial as a zip archive: tutorial.zip (note this is **different** from the zip file used in the UNIX and Python mini-tutorials, python_basics.zip). Unzip this file and examine its contents:

```
[<your username> ~]$ unzip tutorial.zip
[<your username> ~]$ cd tutorial
[<your username> ~/tutorial]$ ls
addition.py
autograder.py
buyLotsOfFruit.py
grading.py
projectParams.py
shop.py
shopSmart.py
testClasses.py
testParser.py
test_cases
tutorialTestClasses.py
```

This contains a number of files you'll edit or run:

- `addition.py`: source file for question 1
- `buyLotsOfFruit.py`: source file for question 2
- `shop.py`: source file for question 3
- `shopSmart.py`: source file for question 3
- `autograder.py`: autograding script (see below)

and others you can ignore:

- `test_cases`: directory contains the test cases for each question
- `grading.py`: autograder code
- `testClasses.py`: autograder code
- `tutorialTestClasses.py`: test classes for this particular project
- `projectParams.py`: project parameters

The command `python autograder.py` grades your solution to all three problems. If we run it before editing any files we get a page or two of output:

```
[<your username> ~/tutorial]$ python autograder.py
Starting on 1-21 at 23:39:51

Question q1
===========
*** FAIL: test_cases/q1/addition1.test
***     add(a,b) must return the sum of a and b
***     student result: "0"
***     correct result: "2"
*** FAIL: test_cases/q1/addition2.test
***     add(a,b) must return the sum of a and b
***     student result: "0"
***     correct result: "5"
*** FAIL: test_cases/q1/addition3.test
***     add(a,b) must return the sum of a and b
***     student result: "0"
***     correct result: "7.9"
*** Tests failed.

### Question q1: 0/1 ###
```

```
Question q2
===========
*** FAIL: test_cases/q2/food_price1.test
***     buyLotsOfFruit must compute the correct cost of the order
***     student result: "0.0"
***     correct result: "12.25"
*** FAIL: test_cases/q2/food_price2.test
***     buyLotsOfFruit must compute the correct cost of the order
***     student result: "0.0"
***     correct result: "14.75"
*** FAIL: test_cases/q2/food_price3.test
***     buyLotsOfFruit must compute the correct cost of the order
***     student result: "0.0"
***     correct result: "6.4375"
*** Tests failed.

### Question q2: 0/1 ###


Question q3
===========
Welcome to shop1 fruit shop
Welcome to shop2 fruit shop
*** FAIL: test_cases/q3/select_shop1.test
***     shopSmart(order, shops) must select the cheapest shop
***     student result: "None"
***     correct result: "<FruitShop: shop1>"
Welcome to shop1 fruit shop
Welcome to shop2 fruit shop
*** FAIL: test_cases/q3/select_shop2.test
***     shopSmart(order, shops) must select the cheapest shop
***     student result: "None"
***     correct result: "<FruitShop: shop2>"
Welcome to shop1 fruit shop
Welcome to shop2 fruit shop
Welcome to shop3 fruit shop
*** FAIL: test_cases/q3/select_shop3.test
***     shopSmart(order, shops) must select the cheapest shop
***     student result: "None"
***     correct result: "<FruitShop: shop3>"
*** Tests failed.

### Question q3: 0/1 ###


Finished at 23:39:51

Provisional grades
==================
Question q1: 0/1
Question q2: 0/1
Question q3: 0/1
------------------
Total: 0/3

Your grades are NOT yet registered.  To register your grades, make sure
to follow your instructor's guidelines to receive credit on your project.
```

For each of the three questions, this shows the results of that question's tests, the questions grade, and a final summary at the end. Because you haven't yet solved the questions, all the tests fail. As you solve each question you may find some tests pass while other fail. When all tests pass for a question, you get full marks.

Looking at the results for question 1, you can see that it has failed three tests with the error message "add(a,b) must return the sum of a and b". The answer your code gives is always 0, but the correct answer is different. We'll fix that in the next tab.

Question 1: Addition

Open `addition.py` and look at the definition of `add`:

```
def add(a, b):
    "Return the sum of a and b"
    "*** YOUR CODE HERE ***"
    return 0
```

The tests called this with `a` and `b` set to different values, but the code always returned zero. Modify this definition to read:

```
def add(a, b):
    "Return the sum of a and b"
    print "Passed a=%s and b=%s, returning a+b=%s" % (a,b,a+b)
    return a+b
```

Now rerun the autograder (omitting the results for questions 2 and 3):

```
[<your username> ~/tutorial]$ python autograder.py -q q1
Starting on 1-21 at 23:52:05

Question q1
===========
Passed a=1 and b=1, returning a+b=2
*** PASS: test_cases/q1/addition1.test
***     add(a,b) returns the sum of a and b
Passed a=2 and b=3, returning a+b=5
*** PASS: test_cases/q1/addition2.test
***     add(a,b) returns the sum of a and b
Passed a=10 and b=-2.1, returning a+b=7.9
*** PASS: test_cases/q1/addition3.test
***     add(a,b) returns the sum of a and b

### Question q1: 1/1 ###

Finished at 23:41:01

Provisional grades
==================
Question q1: 1/1
Question q2: 0/1
Question q3: 0/1
------------------
Total: 1/3
```

You now pass all tests, getting full marks for question 1. Notice the new lines "Passed a=..." which appear before "*** PASS: ...". These are produced by the print statement in `add`. You can use print statements like that to output information useful for debugging. You can also run the autograder with the option `--mute` to temporarily hide such lines, as follows:

```
[<your username> ~/tutorial]$ python autograder.py -q q1 --mute
Starting on 1-22 at 14:15:33

Question q1
===========
*** PASS: test_cases/q1/addition1.test
***     add(a,b) returns the sum of a and b
*** PASS: test_cases/q1/addition2.test
***     add(a,b) returns the sum of a and b
*** PASS: test_cases/q1/addition3.test
***     add(a,b) returns the sum of a and b

### Question q1: 1/1 ###
```

Question 2: buyLotsOfFruit function

Add a `buyLotsOfFruit(orderList)` function to `buyLotsOfFruit.py` which takes a list of `(fruit,pound)` tuples and returns the cost of your list. If there is some `fruit` in the list which doesn't appear in `fruitPrices` it should print an error message and return `None`. Please do not change the`fruitPrices` variable.

Run `python autograder.py` until question 2 passes all tests and you get full marks. Each test will confirm that `buyLotsOfFruit(orderList)` returns the correct answer given various possible inputs. For example, `test_cases/q2/food_price1.test` tests whether:

```
Cost of [('apples', 2.0), ('pears', 3.0), ('limes', 4.0)] is 12.25
```

Question 3: shopSmart function

Fill in the function `shopSmart(orders,shops)` in `shopSmart.py`, which takes an `orderList` (like the kind passed in to`FruitShop.getPriceOfOrder`) and a list of `FruitShop` and returns the `FruitShop` where your order costs the least amount in total. Don't change the file name or variable names, please. Note that we will provide the `shop.py` implementation as a "support" file, so you don't need to submit yours.

Run `python autograder.py` until question 3 passes all tests and you get full marks. Each test will confirm that `shopSmart(orders,shops)` returns the correct answer given various possible inputs. For example, with the following variable definitions:

```
orders1 = [('apples',1.0), ('oranges',3.0)]
orders2 = [('apples',3.0)]
dir1 = {'apples': 2.0, 'oranges':1.0}
shop1 =  shop.FruitShop('shop1',dir1)
dir2 = {'apples': 1.0, 'oranges': 5.0}
shop2 = shop.FruitShop('shop2',dir2)
shops = [shop1, shop2]
```

`test_cases/q3/select_shop1.test` tests whether:

```
shopSmart.shopSmart(orders1, shops) == shop1
```

and `test_cases/q3/select_shop2.test` tests whether:

```
shopSmart.shopSmart(orders2, shops) == shop2
```

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