CS 3346A / CS 3121A Assignment 2

Due: Friday, Nov. 13th, 2020 (midnight)
Total Weight: 15%
Silent Policy: A silent policy will take effect 24 hours before this assignment is due, i.e. no question about this assignment will be answered, whether it is asked on the discussion board, via email or in person.

Part 1: **Pacman Project (7%)**

Search:

Question 7 (3 points): Eating All The Dots (a continued question from the A1**)**

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).

python3 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:

python3 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**

Multi-Agent Pacman

After downloading the code (A2-multiagent.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:

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 (2 points): Reflex Agent

Improve the ReflexAgent in multiAgents.py to play respectively. 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 (2 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.

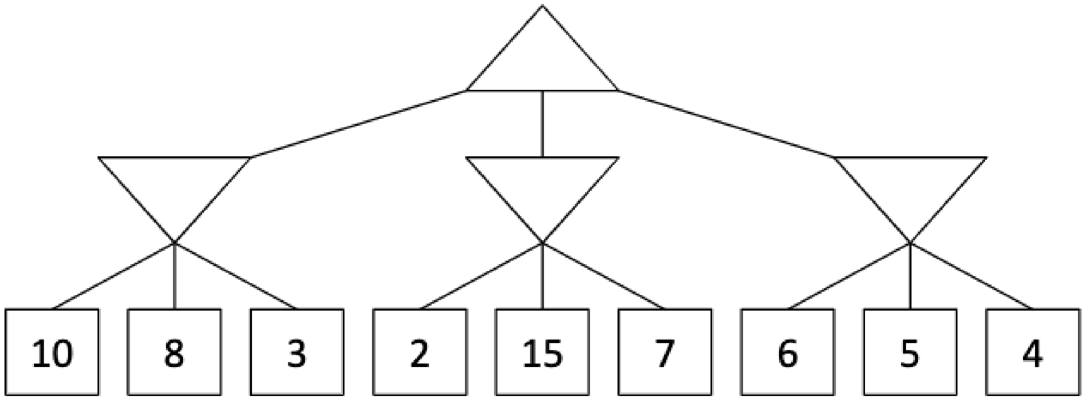
Submission

Please submit your final implementation python files:
`search.py` and `searchAgents.py` for **Search:Q7**
`multiAgents.py` **for Multi-Agent Q1 and Q2** through OWL.

Please *do not* change the other files in this distribution or submit any of our original files other than the expected files.

Part 2: **(8%)**

1. Games:



1. Consider the zero-sum game tree shown below. Triangles that point up, such as at the top node (root), represent choices for the maximizing player; triangles that point down represent choices for the minimizing player. Assuming both players act optimally, fill in the minimax value of each node.

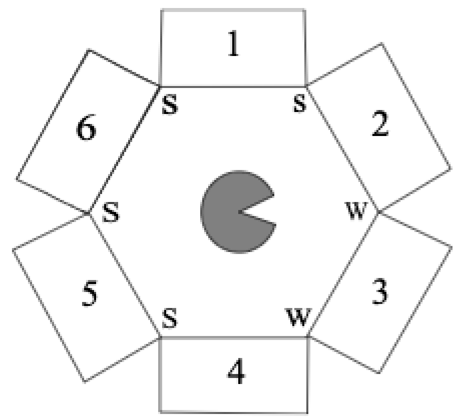
2. Which nodes can be pruned from the game tree above through alpha-beta pruning? If no nodes can be pruned, explain why not. Assume the search goes from left to right; when choosing which child to visit first, choose the left-most unvisited child.

3. Again, consider the same zero-sum game tree, except that now, instead of a minimizing player, we have a chance node that will select one of the three values uniformly at random. Fill in the expectimax value of each node. Redraw the game tree below to show your answer.

4. Which nodes can be pruned from the game tree above through alpha-beta pruning? If no nodes can be pruned, explain why not.

2. CSPs: Trapped Pacman

Pacman is trapped! He is surrounded by mysterious corridors, each of which leads to either a pit (P), a ghost (G), or an exit (E). In order to escape, he needs to figure out which corridors, if any, lead to an exit and freedom, rather than the certain doom of a pit or a ghost. The one sign of what lies behind the corridors is the wind: a pit produces a strong breeze (S) and an exit produces a weak breeze (W), while a ghost doesn't produce any breeze at all. Unfortunately, Pacman cannot measure the strength of the breeze at a specific corridor. Instead, he can stand between two adjacent corridors and feel the max of the two breezes. For example, if he stands between a pit and an exit he will sense a strong (S) breeze, while if he stands between an exit and a ghost, he will sense a weak (W) breeze. The measurements for all intersections are shown in the figure below. Also, while the total number of exits might be zero, one, or more, Pacman knows that two neighboring squares will not both be exits.



Pacman models this problem using variables X_i for each corridor *i* and domains P, G, and E.

1. State the binary and/or unary for this CSP (either implicitly or explicitly).
2. Cross out the values from the domains of the variables that will be deleted in enforcing arc consistency.

X_1	P	G	E
X_2	P	G	E
X_3	P	G	E
X_4	P	G	E
X_5	P	G	E
X_6	P	G	E

3. According to MRV, which variable or variables could the solver assign first?
4. Assume that Pacman knows that X_6 = G. List all the solutions of this CSP or write none if no solutions exist.

Submission

Please submit your final answers in a **PDF** file through the OWL. (**Please note you will not receive grades if TA can not recognize your handwriting, please finalize your solutions clearly and neatly and transform it to be a PDF version.)**