Homework 4

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# Descriptions & Algorithms

## Problem 1:

Description: Create an evaluation function for Reflex Agent such that actions obtained from the agent will reliably win in a Pacman game on the testClassic layout.

Algorithms:

Our evaluation function is

minF = smallest distance to the next food

distSG = distance to scared ghosts that are reachable in time and are closer than minF

We would like to minimize the number of actions that Pacman remains still because it is typically unproductive so we set that value to negative infinity. Likewise, a state where the game has been lost is unfavorable, so the value is also set to negative infinity.

## Problem 2:

Description: Implement the minimax algorithm for MinimaxAgent such that actions obtained from the agent’s getAction() function will return the optimal action.

Algorithms: This problem utilizes the minimax algorithm. MinimaxAgent has a function named getAction() which should return Pacman’s next action in the game. To determine which action that Pacman should take, we apply the minimax algorithm and have Pacman take the move with the maximum heuristic integer value at the end.

The algorithm takes in several parameters including the gameState, depth, and player type.

The gameState is utilized to generate the successor states from taking various actions.

The depth determines how large the search tree will be.

If the playertype is Pacman, then the function will find the action with the maximum value and return them is a tuple.

If the playertype is a ghost, then the function will find the action that minimizes the overall score and return that as a tuple.

In order to find the maximum and minimum values, the algorithm will recursively find the max/min values further down the tree and return those values upwards.

The final score returned is the maximal/optimal move for the player assigned a maximum value.

## Problem 3:

Description: Implement the minimax algorithm for AlphaBetaAgent using alpha-beta pruning. The resulting runtime should be faster than the MinimaxAgent for the same test-case/map.

Algorithms: This problem utilizes the minimax algorithm with alpha-beta pruning. Once again, AlphaBetaAgent has function named getAction() which should return Pacman’s next action in the game, and minimax is utilized to determine that action. However, alpha-beta pruning shortens the search process by pruning off branches that are unnecessary to search through.

The algorithm takes in the same parameters as minimax, but also has additional parameters alpha and beta.

The parameters that are the same as minimax are utilized for the same reasons.

The alpha and beta are used to determine the global minimum and maximum for the entire tree.

We know that if the value of a successor state is greater than beta for a maximum run-through of the algorithm, then it means that the min state one recursion above it will never choose any of the successors, so we may prune off the search there.

If the value of a successor state is less than alpha from a minimum run-through of the algorithm, then it means that the closest max state above it will never choose a value from this subtree, so we may prune off the search there.

## Problem 4:

Description: Implement the expectimax algorithm for ExpectimaxAgent such that actions obtained from the agent’s getAction() function will be determined by the algorithm.

Algorithms: This problem utilizes the expectimax algorithm. This algorithm is similar to minimax except that it includes a state for random chance.

This algorithm takes in the same parameters as minimax and utilizes them for the same purpose.

For pacman specifically, we assume that all ghost agents will randomly choose their actions, so we propagate the expected value upwards in such a recursive call.

For pacman agent, we want pacman to yield the best results possible, so we do the same as we did in minimax – return the maximum value move.

## Problem 5:

Description: Implement a better evaluation than in problem 1!

Algorithms: For this problem, we create a new evaluation function.

Our evaluation function is

In the case that the move is STOP or the ghostPos = pacmanPos, we want to return the minimum value possible. This is because these are the moves we consider least optimal. We want to keep Pacman moving and if ghostPos = pacmanPos, then the game has been lost.

In the case that there are no nearby scared ghosts, we want the action that is closest to the nearest food. In order to achieve this we use 1/minFoodDist. Large distances will yield smaller results as we use the distance as a fraction, and the smallest food distance will yield the highest score in this case. In this case, we subtract the 1/minGhostDist because we wish to maximize the distance between Pacman and the ghost when the ghost is not edible.

In the case that there are nearby scared ghosts, we prioritize this state over other states. We add the distance of the first scared ghost that is closer than the minimum food distance. This places its priority over the actions that move toward the smallest food distance as there is an additional factor being added in.

# ANALYSIS

## RANGE OF OUTCOME VALUES

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | ReflexAgent | MinimaxAgent | AlphaBetaAgent | ExpectimaxAgent |
| testClassic d=2 | 560 - 564 | 170 - 554 | -86 - 538 | 254 - 552 |
| smallClassic d=2 | -410 – 1563 | -311- 840 | -524 – 962 | -332 – 1607 |
| mediumClassic d=2 | -347 – 429 | -2027 – 52 | 1452 – 312 | -1119 – 2094 |
| trappedClassic d=2 | -502 – 532 | -502 – 532 | -502 – 532 | -502 – 532 |
| minimaxClassic d=2 | -493 – 516 | -499 – 516 | -500 – 516 | -498 – 516 |
| minimaxClassic d=3 | -493 – 516 | -500 – 514 | -496 – 513 | -510 – 513 |
| minimaxClassic d=4 | -493 – 516 | -496 – 516 | -492 – 516 | -493 – 516 |

We sampled across multiple layouts and created a chart listing the range of values that resulted from each of the Agents. What we can see is that the range of values for every agent ranged a significant amount, and this range increases for more complex maps. i.e. MediumClassic is the most complex map sampled and its range is far larger than other maps. We can see even with increasing depth, the range of values for the same map will remain the same. The range of values varies for any type of agent.

## AVERAGE SCORE

We sampled the average score of multiple layouts and depths to compare differences and similarities. We can see from the results that the performance of all agents suffer increasingly as the complexity of the layout increases (seen from testClassic, smallClassic, and mediumClassic). ReflexAgent fares the best with increasing complexity.

We see that in the case that the pacman is trapped, agents other than ReflexAgent perform much better.

The other observation that we can conclude is that the higher the depth, the more accurate the result as can be seen in the last 3 tests performed.

# Contribution And Conclusion