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```

search - single unit

Test 1

```
python pacman.py -1 bigMaze -z .5 -p SearchAgent -a
fn=astar,heuristic=manhattanHeuristic
```

Implementation

```
def aStarSearch(problem, heuristic=nullHeuristic):
   # Use Priority Queue to implement non-recursive A*:
    # 1. Push the start node into the queue.
    # 2. Do while-loop until the queue is empty:
    # - Get the top node.
      - IF the node is the GOAL
          * break the while-loop and return
    # - ELSE IF the top node has been visited or has no successor:
           * continue
    # - ELSE
           * Go through its successors.
           * Push those unvisited successors into the queue with their cost.
    # Return:
    # actions: a list of actions that approach the GOAL.
    from util import PriorityQueue
    actions = [] # Store the result
    tmp_actions = [] # Store the temp result in the while-loop
    visited = [] # Store the nodes that have been visited
    pQueue = PriorityQueue()
    # The priority queue
    # element type : [current state, actions so far]
    pQueue.push([problem.getStartState(), actions], 0) # Initialization
```

```
# While-Loop
while not pQueue.isEmpty():
    # Get the top node
    cur_node, actions = pQueue.pop()
    # GOAL, which means the cur_node is the target state,
    # and is also the last element of the actions list.
    if problem.isGoalState(cur_node):
        break
    # Check visited
    if cur node in visited:
        continue
    visited.append(cur_node)
    succs = problem.getSuccessors(cur_node)
    # As declare above, getSuccessors() return a generator contains
    # elements in the form: (succ[list], Direction[n, s, e, w], cost[int])
    for succ, dir, cost in succs:
        # Also, Check visited
        if succ in visited:
            continue
        tmp_actions = actions + [dir]
        next_cost = problem.getCostOfActions(actions)
                    + heuristic(succ, problem)
        pQueue.push([succ, tmp_actions], next_cost)
# Return the Goal actions
return actions
```

Test Result

```
(python27) λ python pacman.py -l bigMaze -z .5 -p SearchAgent -a fn=astar,heu
ristic=manhattanHeuristic
[SearchAgent] using function astar and heuristic manhattanHeuristic
[SearchAgent] using problem type PositionSearchProblem
Path found with total cost of 210 in 0.1 seconds
Search nodes expanded: 549
Pacman emerges victorious! Score: 300
Average Score: 300.0
Scores: 300.0
Win Rate: 1/1 (1.00)
Record: Win
```

Test 2

```
python pacman.py -1 mediumCorners -p AStarCornersAgent -z 0.5
```

Grading

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

```
def cornersHeuristic(state, problem):
   # Develop this Heuristic using manhattan distance.
   corners = problem.corners # These are the corner coordinates
   walls = problem.walls # These are the walls of the maze,
                         # as a Grid (game.py)
   x, y = state[0]
   step = (x, y)
   cur_corners = state[1]
   corners_to_approch = []
   h_n = 0
   # This Part seems to be a little tricky, I'd like to briefly
   # explain as follow:
   # 1. Go through the list 'corner'(which stores the state of
        each corner, 0 to be not-visited), to find those not-visited
        corners and add them to the list 'corners_to_approach'.
   # 2. The sentence 'while len(corners_to_approch) > 0:' means
        to loop until each corner is visted, during this process,
        the codes below will calculate what the h(n) is,
        in terms of heuristic function.
   # 3. Every time in the while-loop, find the mahattan distance from
        current position to each not-visited corner, choose the smallest
        one(this step actually means that the pacman go to the closest
        corner first). Then, add the distance to h_n, remove this corner
        from 'corners_to_approach'. Keep doing so until 'corners_to_approach'
        is empty(all corners have been visited, you win).
   for pos in range(len(corners)):
        if not cur_corners[pos]:
            corners_to_approch.append(corners[pos])
   while len(corners_to_approch) > 0:
       tmp_dist = []
        for corner in corners_to_approch:
            dist = util.manhattanDistance(step, corner)
            tmp_dist.append(dist)
       minidist = min(tmp_dist)
        h_n += minidist
        step = corners_to_approch[tmp_dist.index(minidist)]
        corners_to_approch.remove(step)
   return h_n # Default to trivial solution
```

Test Result

```
(python27) λ python pacman.py -1 mediumCorners -p AStarCornersAgent -z 0.5
Path found with total cost of 106 in 0.1 seconds
Search nodes expanded: 692
Pacman emerges victorious! Score: 434
Average Score: 434.0
Scores: 434.0
Win Rate: 1/1 (1.00)
Record: Win
```

Grading

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)	

Heuristic Func.

```
def foodHeuristic(state, problem):
    position, foodGrid = state
    food_list = foodGrid.asList()
    h_n = 0
    if not food_list:
        return 0
    maxdist = [(0, 0), (0, 0), 0]
    for i in food_list:
        for j in food_list:
            if i == j:
                continue
            dist = mazeDistance(i, j, problem.startingGameState)
            if maxdist[2] < dist:</pre>
                maxdist = [i, j, dist]
    if maxdist[0] == maxdist[1] == (0, 0):
        h_n = util.manhattanDistance(position, food_list[0])
    else:
        dist1 = util.manhattanDistance(position, maxdist[0])
        dist2 = util.manhattanDistance(position, maxdist[1])
        h_n = min(dist1, dist2) + maxdist[2]
    return h_n
```

Test Result

```
(python27) λ python pacman.py -1 trickySearch -p AStarFoodSearchAgent
Path found with total cost of 60 in 16.9 seconds
Search nodes expanded: 423
Pacman emerges victorious! Score: 570
Average Score: 570.0
Scores: 570.0
Win Rate: 1/1 (1.00)
Record: Win
```

Multi-Agent - multiple agent

Preview

```
python pacman.py

python pacman.py -p ReflexAgent

python pacman.py -p ReflexAgent -l testClassic

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

Evaluation Func.

```
def evaluationFunction(self, currentGameState, action):
    # Useful information you can extract from a GameState (pacman.py)
    successorGameState = currentGameState.generatePacmanSuccessor(action)
    newPos = successorGameState.getPacmanPosition()
    newFood = successorGameState.getFood()
    curFood = currentGameState.getFood()
    newGhostStates = successorGameState.getGhostStates()
    newScaredTimes = [ghostState.scaredTimer for ghostState in newGhostStates]
    if action == 'Stop':
        return -1
    score = 0
    # score will be made up with:
    # 1. System score >> score += successorGameState.getScore()
    # 2. Super Food at new pos >> score += scared time of all ghosts
    # 3. Closest Food and closest ghost >>
        dist(Food) > dist(Ghost) >> score += dist(Ghost)/dist(Food)^2 * 0.7
         dist(Food) <= dist(Ghost) >> score += dist(Ghost)/dist(Food)^2 * 1.1
    # 4. Food at new pos >> score * 1.2
    # 1
    score += successorGameState.getScore()
    # 2
    for scaredTime in newScaredTimes:
        score += scaredTime
    # 3
    foodList = newFood.asList()
    ghostDist = []
    foodDist = []
    for ghost in newGhostStates:
        ghostDist.append(manhattanDistance(ghost.getPosition(), newPos))
    for pos in foodList:
        foodDist.append(manhattanDistance(pos, newPos))
    if len(foodDist):
        if min(foodDist) > min(ghostDist):
            score += (min(ghostDist) * (1.0/min(foodDist))**2) * 0.8
        else:
            score += (min(ghostDist) * (1.0/min(foodDist))**2) * 1.1
    # 4
    curFoodList = curFood.asList()
    if newPos in curFoodList:
        score = score * 1.1
```

Test Result

```
(python27) λ python autograder.py -q q1 --no-graphics
Starting on 10-6 at 10:20:04
Question q1
Pacman emerges victorious! Score: 1228
Pacman emerges victorious! Score: 1253
Pacman emerges victorious! Score: 1246
Pacman emerges victorious! Score: 1255
Pacman emerges victorious! Score: 1247
Pacman emerges victorious! Score: 1257
Pacman emerges victorious! Score: 1244
Pacman emerges victorious! Score: 1260
Pacman emerges victorious! Score: 1261
Pacman emerges victorious! Score: 1258
Average Score: 1250.9
Scores:
             1228.0, 1253.0, 1246.0, 1255.0, 1247.0, 1257.0, 1244.0, 1260.0,
1261.0, 1258.0
```

Test 1 - minimax

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
```

Test Result

```
(python27) λ python pacman.py -p MinimaxAgent -l minimaxClassic -a depth=4
Pacman emerges victorious! Score: 516
Average Score: 516.0
Scores: 516.0
Win Rate: 1/1 (1.00)
Record: Win
```

Test 2 - minimax

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
```

Test Result

```
(python27) λ python pacman.py -p MinimaxAgent -l trappedClassic -a depth=3
Pacman died! Score: -501
Average Score: -501.0
Scores: -501.0
Win Rate: 0/1 (0.00)
Record: Loss
```

Test 3 - minimax

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

Test Result

```
*** PASS: test cases\q2\6-tied-root.test
*** PASS: test_cases\q2\7-1a-check-depth-one-ghost.test
*** PASS: test_cases\q2\7-1b-check-depth-one-ghost.test
*** PASS: test_cases\q2\7-1c-check-depth-one-ghost.test
*** PASS: test_cases\q2\7-2a-check-depth-two-ghosts.test
*** PASS: test_cases\q2\7-2b-check-depth-two-ghosts.test
*** PASS: test_cases\q2\7-2c-check-depth-two-ghosts.test
*** Running MinimaxAgent on smallClassic 1 time(s).
Pacman died! Score: 84
Average Score: 84.0
Scores: 84.0
Win Rate: 0/1 (0.00)
Record:
              Loss
*** Finished running MinimaxAgent on smallClassic after 1 seconds.
*** Won 0 out of 1 games. Average score: 84.000000 ***
*** PASS: test_cases\q2\8-pacman-game.test
### Question q2: 5/5 ###
Finished at 13:13:42
Provisional grades
Question q2: 5/5
Total: 5/5
*** PASS: test_cases\q2\6-tied-root.test
*** PASS: test_cases\q2\7-1a-check-depth-one-ghost.test()
*** PASS: test_cases\q2\7-1b-check-depth-one-ghost.test
*** PASS: test_cases\q2\7-1c-check-depth-one-ghost.test
*** PASS: test_cases\q2\7-2a-check-depth-two-ghosts.test
*** PASS: test_cases\q2\7-2b-check-depth-two-ghosts.test
*** PASS: test_cases\q2\7-2c-check-depth-two-ghosts.test
*** Running MinimaxAgent on smallClassic 1 time(s).
Pacman died! Score: 84
Average Score: 84.0
Scores: 84.0
Win Rate: 0/1 (0.00)
Record: Loss
Record:
              Loss
*** Finished running MinimaxAgent on smallClassic after 1 seconds.
*** Won 0 out of 1 games. Average score: 84.000000 ***
*** PASS: test_cases\q2\8-pacman-game.test
### Question q2: 5/5 ###
Finished at 13:13:42
Provisional grades
Question q2: 5/5
Total: 5/5
```

Test 4 - alpha-beta pruning

Make a new agent that uses α - β pruning to more efficiently explore the minimax tree, in Alpha-Beta Agent. Again, your algorithm will be slightly more general than the pseudo-code from lecture, so part of the challenge is to extend the α - β pruning logic appropriately to multiple minimizer agents.

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

Test Result

Test 5 - alpha-beta pruning with deeper depth

```
python pacman.py -p AlphaBetaAgent -k 2 -a depth=4
```

Test Result

```
(python27) λ python pacman.py -p AlphaBetaAgent -k 2 -a depth=4
Pacman emerges victorious! Score: 1431
Average Score: 1431.0
Scores: 1431.0
Win Rate: 1/1 (1.00)
Record: Win
```

Further Study

scoreEvaluationFunction

```
def scoreEvaluationFunction(currentGameState):
    curPos = currentGameState.getPacmanPosition()
    curFood = currentGameState.getFood()
    curGhostStates = currentGameState.getGhostStates()
    curScaredTimes = [ghostState.scaredTimer for ghostState in curGhostStates]

score = 0
# score will be made up with:
# 1. System score >> score += currentGameState.getScore()
# 2. Super Food >> score += scared time of all ghosts
# 3. Closest Food and closest (not scared) ghost >>
# dist(Food) > dist(Ghost) >> score += dist(Ghost)/dist(Food)^2 * 0.8
# dist(Food) <= dist(Ghost) >> score += dist(Ghost)/dist(Food)^2 * 1.1
# 4. Closest Food and closest (not scared) ghost >>
# score += (max(ghostDist) * (1.0/min(ghostDist))
```

```
* (1.0/min(foodDist))) * 1.5
# 1
score += currentGameState.getScore()
# 2
scared_flag = True
for scaredTime in curScaredTimes:
    if not scaredTime:
        scared_flag = False
       break
    else:
       score += scaredTime
foodList = curFood.asList()
ghostDist = []
foodDist = []
for ghost in curGhostStates:
    ghostDist.append(manhattanDistance(ghost.getPosition(), curPos))
for pos in foodList:
    foodDist.append(manhattanDistance(pos, curPos))
if not scared_flag and len(foodDist):
    if min(foodDist) > min(ghostDist):
        score += (min(ghostDist) * (1.0/min(foodDist))**2) * 0.8
    else:
        score += (min(ghostDist) * (1.0/min(foodDist))**2) * 1.1
elif scared_flag and len(foodDist):
    score += (max(ghostDist) * (1.0/min(ghostDist))
              * (1.0/min(foodDist))) * 1.5
return score
```

In the evaluation, I especially focus on the 'capsules' which can make ghosts scared, in other words, my Pacman was designed to be more attracted by 'scared ghost'. That's because when testing my function with <code>python pacman.py -p AlphaBetaAgent -a depth=3 -l smallclassic</code>, I found that there's a big bonus when the Pacman ate the scared ghost.

However, when the ghosts are far away from the Pacman, the capsules might be a waste(Sure it means my function would not work well...) because it prefers taking close food rather than traveling far to chase the scared ghosts, and the scared time might run out as well.

As further study, the parameters in the function may play important roles, but I didn't pay much attention to this research.