

Intel·ligència Artificial

Pràctica 1

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Contents

1	Algorithms descriptions and decisions on implementation	2
1.1	BFS	2
1.2	DFS	3
1.3	UCS	4
1.4	A*	5
2	Decision taken on Heuristics	6
2.1	Food Heuristic	6
2.2	Corners Heuristic	7
3	Performance Analysis	8
3.1	Search Algorithms	8
3.2	Corners	10
3.3	Food	11

1 Algorithms descriptions and decisions on implementation

1.1 BFS

Breadth First Search is a search algorithm characterised by level search, in other words, by exploring a whole level before going to the next one.

To do so in our implementation we decided to use a FIFO queue as a fringe. In order to make it easy for us to use the FIFO queue we used the "Util.Queue" python library so that we can pop and push elements in and out of the fringe. in Figure1 you can see our implementation of the algorithm.

```
def breadthFirstSearch(problem):  
    """Search the shallowest nodes in the search tree first."""  
  
    n = node.Node(problem.getStartState())  
    expanded = set()  
    expanded.add(n.state)  
  
    fringe = util.Queue()  
    fringe.push(n)  
  
    while not fringe.isEmpty():  
        current = fringe.pop()  
        expanded.add(current.state)  
        if problem.isGoalState(current.state): return current.total_path()  
        for state, action, cost in problem.getSuccessors(current.state):  
            new_node = node.Node(state, current, action, cost)  
            if new_node.state not in expanded and new_node not in fringe.list:  
                fringe.push(new_node)  
                expanded.add(new_node.state)
```

Figure 1: BFS implementation code snippet

Our implementation (Figure1) is a graph implementation, meaning that we keep track of the nodes we've explored (using the expanded set).

This implementations for each node puts all of their successors in the fringe and process them in FIFO order, this way we make sure the exploration goes level by level, because when the successors of the next node are pushed into the fringe, these will go to the bottom of the queue.

1.2 DFS

The implementation of the Depth First Search algorithm is practically identical to the BFS¹ one, changing only the data structure used for the fringe for a stack or a LIFO queue. To do so we used the "Util.Stack" library provided by python. In Figure 2 you can see our implementation of the DFS algorithm.

```
fringe = util.Stack()
n = node.Node(problem.getStartState())

if problem.isGoalState(n.state): return n.total_path()
fringe.push(n)

expanded = set()

while not fringe.isEmpty():
    n = fringe.pop()
    expanded.add(n.state)
    for state, action, cost in problem.getSuccessors(n.state):
        new_node = node.Node(state, n, action, cost)
        if new_node.state not in expanded and new_node not in fringe.list:
            if problem.isGoalState(state): return new_node.total_path()
            fringe.push(new_node)
```

Figure 2: DFS implementation code snippet

By changing the data structure of the fringe, now when the node successors enter the fringe, these go to the top of the queue instead of the bottom. By doing so the algorithm will explore one branch until the end (if there is an end) before exploring another.

1.3 UCS

For the implementation of the Unified Cost Algorithm we used a Priority Queue using the "util.PriorityQueue" library provided by python.

In our implementation we get the successors of a given node, if we haven't explored it yet we update the fringe with the given successor. Then when we pop the next node from the fringe, this will be the node with the least cost. By doing that when we eventually find a solution, we can guarantee that it is the best one.

```
def uniformCostSearch(problem):
    """Search the node of least total cost first."""
    """ YOUR CODE HERE """

    fringe = util.PriorityQueue()
    n = node.Node(problem.getStartState())
    fringe.push(n, 0)
    expanded = dict()

    while not fringe.isEmpty():
        current = fringe.pop()
        if problem.isGoalState(current.state): return current.total_path()
        expanded[current.state] = current
        for state, action, cost in problem.getSuccessors(current.state):
            new_node = node.Node(state, current, action, cost+current.cost)
            if state not in expanded:
                fringe.update(new_node, current.cost)
```

Figure 3: UCS implementation code snippet

1.4 A*

The implementation of the A* algorithm is practically the same as the UCS but adding heuristics when calculating the cost. The heuristic cost is added to the actual cost of a node. Doing that makes a path that the heuristic predicts to have a high cost not to be popped immediately despite having low actual cost, and could make pop from the fringe the node with the higher actual cost if the Heuristic thought that it was the best path. In other words, A* is like the UCS algorithm but Heuristics help to narrow down which path to follow.

```
def aStarSearch(problem, heuristic=nullHeuristic):
    fringe = util.PriorityQueue()
    n = node.Node(problem.getStartState())
    fringe.push(n, heuristic(n.state, problem))
    expanded = dict()

    while not fringe.isEmpty():
        current = fringe.pop()
        if problem.isGoalState(current.state): return current.total_path()
        expanded[current.state] = current
        for state, action, cost in problem.getSuccessors(current.state):
            new_node = node.Node([state, current, action, cost+current.cost])
            if state not in expanded:
                fringe.update(new_node, current.cost+heuristic(new_node.state, problem))
```

Figure 4: A* implementation code snippet

2 Decision taken on Heuristics

2.1 Food Heuristic

This heuristic gets the Manhattan distance to all the food and stores them in an array, the lower the distance, the better the cost that the heuristic will predict.

```
def get_manhattan_distance(p, q):  
    """  
    Return the manhattan distance between points p and q  
    assuming both to have the same number of dimensions  
    """  
    # sum of absolute difference between coordinates  
    distance = 0  
    for a,b in zip(p,q):  
        distance += abs(a - b)  
  
    return distance  
  
position, foodGrid = state  
unvisited_foods = foodGrid.asList()  
  
if not unvisited_foods:  
    return 0  
  
closest_food = min([get_manhattan_distance(position, food) for food in unvisited_foods])  
return closest_food
```

Figure 5: Food Heuristic

2.2 Corners Heuristic

This heuristic gets the Manhattan distance to all 4 corners and stores them in an array, the lower the distance, the better the cost that the heuristic will predict.

```
corners = problem.corners # These are the corner coordinates
walls = problem.walls # These are the walls of the maze, as a Grid (game.py)

""" YOUR CODE HERE """
coordinates = state[0]
visited_corners = state[1]
unvisited_corners = []

for one_corner in corners:
    if not one_corner in visited_corners:
        unvisited_corners.append(one_corner)

heuristic_number = 0

while len(unvisited_corners) != 0: # While not empty
    manhattan_distances = []
    # Get manhattan distance to every corner
    for each_corner in unvisited_corners:
        get_manhattan = util.manhattanDistance(coordinates, each_corner)
        manhattan_corner = (get_manhattan, each_corner)
        manhattan_distances.append(manhattan_corner)
    minimum, the_corner = min(manhattan_distances)
    coordinates = the_corner
    heuristic_number += minimum
    unvisited_corners.remove(the_corner)

return heuristic_number
```

Figure 6: A* implementation code snippet

We know that both these heuristics will be consistent because the path will always be equal or greater than the Manhattan distance, this is because Manhattan distance traces a straight line between Pac-Man and the food, but in real life Pac-man has to follow the grid and sort obstacles in order to get to the destination.

3 Performance Analysis

3.1 Search Algorithms

	DFS	A*(Euclidean)	BFS	A* (Manhattan)	UCS
<i>bigMaze</i>	0.1	0.0	0.1	0.0	0.1
<i>contoursMaze</i>	0.0	0.0	0.0	0.0	0.0
<i>mediumMaze</i>	0.0	0.0	0.0	0.0	0.0
<i>openMaze</i>	0.1	0.1	0.1	0.0	0.1
<i>smallMaze</i>	0.0	0.0	0.0	0.0	0.0
<i>testMaze</i>	0.0	0.0	0.0	0.0	0.0
<i>tinyMaze</i>	0.0	0.0	0.0	0.0	0.0

Table 1: Time taken for each algorithm

	DFS	A*(Euclidean)	BFS	A* (Manhattan)	UCS
<i>bigMaze</i>	210	210	210	210	210
<i>contoursMaze</i>	13	13	13	13	49
<i>mediumMaze</i>	68	68	68	68	130
<i>openMaze</i>	54	54	54	54	158
<i>smallMaze</i>	19	19	19	19	49
<i>testMaze</i>	7	7	7	7	7
<i>tinyMaze</i>	8	8	8	8	10

Table 2: Path cost for each algorithm

	DFS	A*(Euclidean)	BFS	A* (Manhattan)	UCS
<i>bigMaze</i>	620	557	620	549	390
<i>contoursMaze</i>	170	60	170	49	49
<i>mediumMaze</i>	269	226	269	221	144
<i>openMaze</i>	682	550	682	535	315
<i>smallMaze</i>	92	56	92	53	59
<i>testMaze</i>	7	7	7	7	7
<i>tinyMaze</i>	15	13	15	14	14

Table 3: Expanded nodes for each algorithm

	DFS	A*(Euclidean)	BFS	A* (Manhattan)	UCS
<i>bigMaze</i>	300	300	300	300	300
<i>contoursMaze</i>	497	497	497	497	461
<i>mediumMaze</i>	442	442	442	442	380
<i>openMaze</i>	456	456	456	456	352
<i>smallMaze</i>	491	491	491	491	461
<i>testMaze</i>	503	503	503	503	503
<i>tinyMaze</i>	502	502	502	502	500

Table 4: Score for each algorithm

3.2 Corners

	UCS corners	A* corners)
<i>bigMaze</i>	0.4	0.3
<i>contoursMaze</i>	0.1	0.0
<i>mediumMaze</i>	0.0	0.0

Table 5: Time for each algorithm

	UCS corners	A* corners)
<i>bigMaze</i>	162	162
<i>contoursMaze</i>	106	106
<i>mediumMaze</i>	28	28

Table 6: Path cost for each algorithm

	UCS corners	A* corners)
<i>bigMaze</i>	7949	6490
<i>contoursMaze</i>	1966	1653
<i>mediumMaze</i>	252	239

Table 7: Expanded nodes for each algorithm

	UCS corners	A* corners)
<i>bigMaze</i>	378	378
<i>contoursMaze</i>	434	434
<i>mediumMaze</i>	512	512

Table 8: Score for each algorithm

3.3 Food

	DFS	A*(Euclidean)
<i>bigSearch</i>	NAN	NAN
<i>greedySearch</i>	0.7	0.4
<i>mediumSearch</i>	NAN	NAN
<i>oddSearch</i>	NAN	NAN
<i>openSearch</i>	NAN	NAN
<i>smallSearch</i>	NAN	NAN
<i>testSearch</i>	0.0	0.0
<i>tinySearch</i>	NAN	NAN
<i>trickySearch</i>	NAN	NAN
<i>mediumDottedMaze</i>	NAN	NAN
<i>bigCorners</i>	NAN	NAN
<i>mediumCorners</i>	3.5	NAN
<i>tinyCorners</i>	0.1	0.1

Table 9: Time for each algorithm

	DFS	A*(Euclidean)
<i>bigSearch</i>	NAN	NAN
<i>greedySearch</i>	16.0	16.0
<i>mediumSearch</i>	NAN	NAN
<i>oddSearch</i>	NAN	NAN
<i>openSearch</i>	NAN	NAN
<i>smallSearch</i>	NAN	NAN
<i>testSearch</i>	7.0	7.0
<i>tinySearch</i>	NAN	NAN
<i>trickySearch</i>	NAN	NAN
<i>mediumDottedMaze</i>	NAN	NAN
<i>bigCorners</i>	NAN	NAN
<i>mediumCorners</i>	106.0	NAN
<i>tinyCorners</i>	28.0	28.0

Table 10: Path cost for each algorithm

	DFS	A*(Euclidean)
<i>bigSearch</i>	NAN	NAN
<i>greedySearch</i>	538.0	692.0
<i>mediumSearch</i>	NAN	NAN
<i>oddSearch</i>	NAN	NAN
<i>openSearch</i>	NAN	NAN
<i>smallSearch</i>	NAN	NAN
<i>testSearch</i>	12.0	14.0
<i>tinySearch</i>	NAN	NAN
<i>trickySearch</i>	NAN	NAN
<i>mediumDottedMaze</i>	NAN	NAN
<i>bigCorners</i>	NAN	NAN
<i>mediumCorners</i>	1475.0	NAN
<i>tinyCorners</i>	231.0	252.0

Table 11: Expanded nodes for each algorithm

	DFS	A*(Euclidean)
<i>bigSearch</i>	NAN	NAN
<i>greedySearch</i>	614.0	614.0
<i>mediumSearch</i>	NAN	NAN
<i>oddSearch</i>	NAN	NAN
<i>openSearch</i>	NAN	NAN
<i>smallSearch</i>	NAN	NAN
<i>testSearch</i>	513.0	513.0
<i>tinySearch</i>	NAN	NAN
<i>trickySearch</i>	NAN	NAN
<i>mediumDottedMaze</i>	NAN	NAN
<i>bigCorners</i>	NAN	NAN
<i>mediumCorners</i>	434.0	NAN
<i>tinyCorners</i>	512.0	512.0

Table 12: Score for each algorithm