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10/15/25

### Assignment 3 Report

Purpose: To document results from the experiments of testing paths generated by Greedy and A\* algorithms, along with changing values of beta and/or alpha.

#### Part 1:

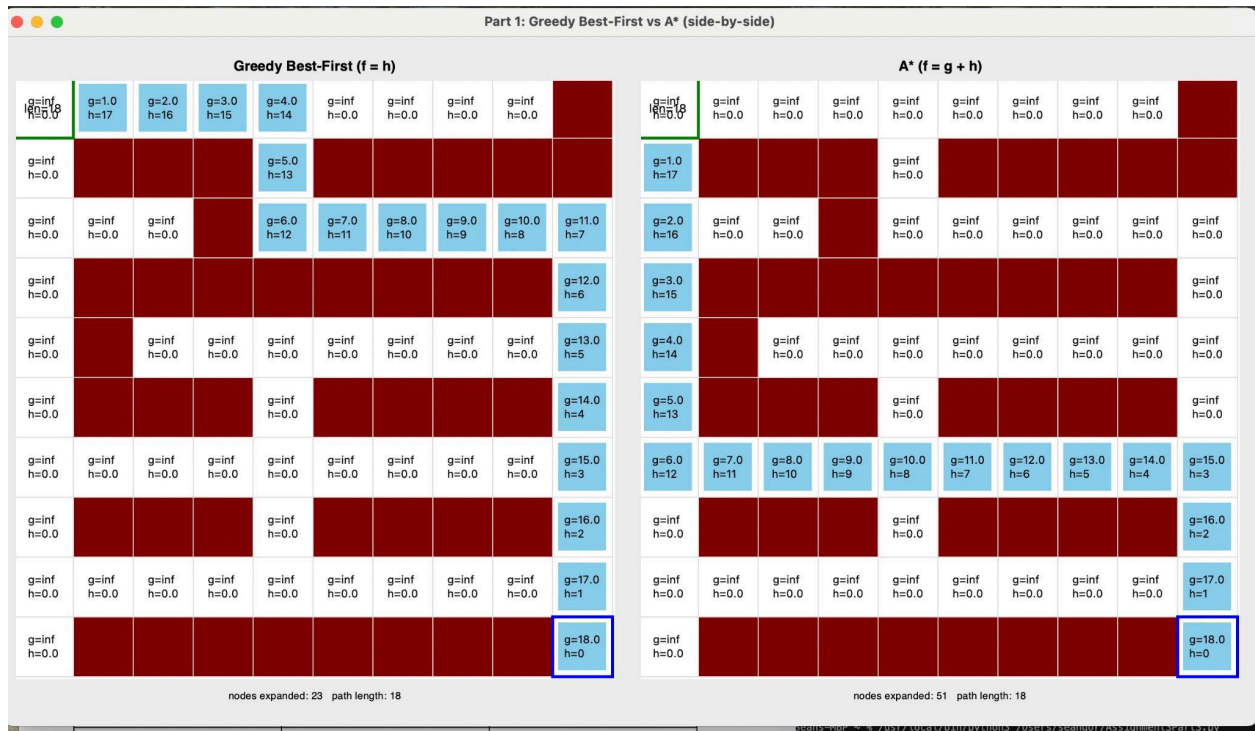
Code Used (Manhattan Distance heuristic):

```
67     def heuristic(self, pos):
68         # Manhattan (Part 1)
69         return abs(pos[0] - self.goal_pos[0]) + abs(pos[1] - self.goal_pos[1])
```

```
120     for dx, dy in ((0,1),(0,-1),(1,0),(-1,0)):
121         nx, ny = u.x + dx, u.y + dy
122         if not (0 <= nx < self.rows and 0 <= ny < self.cols): continue
123         v = self.cells[nx][ny]
124         if v.is_wall: continue
125
126         tentative_g = u.g + 1.0
127         h = self.heuristic((nx, ny))
128
129         if self.strategy == "ASTAR":
130             if tentative_g < v.g: # relax on g
131                 v.g = tentative_g
132                 v.h = h
133                 v.f = v.g + v.h
134                 v.parent = u
135                 if (nx, ny) not in in_open:
136                     pq.put((v.f, v)); in_open.add((nx, ny))
137             else: # GREEDY
138                 improved_g = False
139                 if tentative_g < v.g:
140                     v.g = tentative_g
141                     improved_g = True
142                 new_f = h # f = h
143                 if new_f < v.f or improved_g:
144                     v.h = h
145                     v.f = new_f
146                     v.parent = u
147                 if (nx, ny) not in in_open:
148                     pq.put((v.f, v)); in_open.add((nx, ny))
149
150     return expanded, 0 # no path
151
```

Screenshot of

output chart:



Both algorithms get to the path in the same number of steps (since the path length is the same for both); however, the paths are different. In addition, the A\* algorithm opens more nodes than the greedy algorithm does (according to the screenshot above). This may be because A\* checks all possible paths to the goal, in order to figure out the lowest overall value of the evaluation function (both  $f$  and  $g$ ). So it will consider all the nodes and their path costs so far, not just the current one. On the flip side, the Greedy Best First search algorithm (shown on the left) expands less nodes. This could be due to the fact that it minimizes the distance to the goal ( $h(n)$ ), without regard to the cost ( $g(n)$ ). Therefore, if it sees a short-term low cost, it will automatically go to that node without considering others (in a cumulative manner). This satisfies the overall behavior of Greedy Best First Search.

## Part 2:

Code Used (shows Euclidean distance heuristic)

```

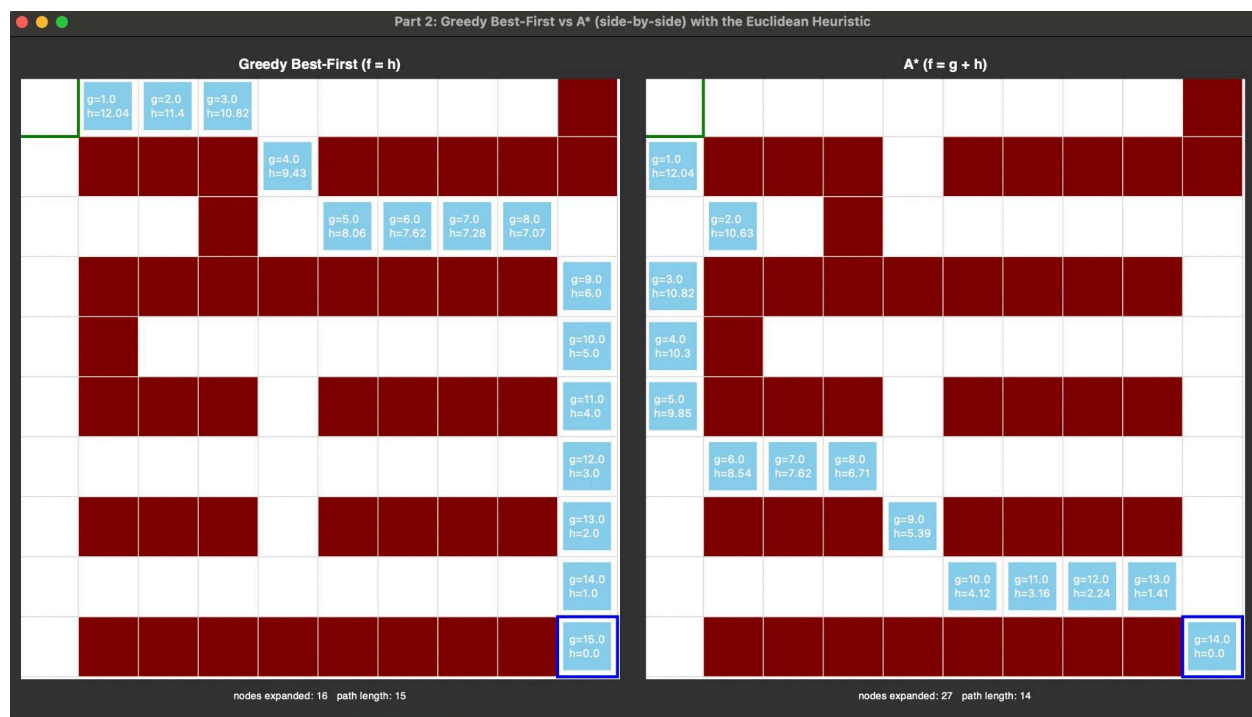
64 def heuristic(self, pos):
65     # Using Euclidean Distance for this part
66     return math.sqrt(math.pow(self.goal_pos[0] - pos[0], 2) + math.pow(self.goal_pos[1] - pos[1], 2))

```

```

116 #include diagonal directions for this part since the Euclidean Distance is being used
117 for dx, dy in ((0,1),(0,-1),(1,0),(-1,0), (1, -1), (-1, 1), (1, 1), (-1, -1)):
118     nx, ny = u.x + dx, u.y + dy
119     if not (0 <= nx < self.rows and 0 <= ny < self.cols): continue
120     v = self.cells[nx][ny]
121     if v.is_wall: continue
122
123     tentative_g = u.g + 1.0
124     h = self.heuristic((nx, ny))
125
126     if self.strategy == "ASTAR":
127         if tentative_g < v.g: # relax on g
128             v.g = tentative_g
129             v.h = h
130             v.f = v.g + v.h
131             v.parent = u
132             if (nx, ny) not in in_open:
133                 pq.put((v.f, v)); in_open.add((nx, ny))
134     else: # GREEDY
135         improved_g = False
136         if tentative_g < v.g:
137             v.g = tentative_g
138             improved_g = True
139         new_f = h # f = h
140         if new_f < v.f or improved_g:
141             v.h = h
142             v.f = new_f
143             v.parent = u
144             if (nx, ny) not in in_open:
145                 pq.put((v.f, v)); in_open.add((nx, ny))
146
147     return expanded, 0 # no path

```



As noticed in the screenshots above, both algorithms get to the goal; however, they both take separate routes, and, as predicted, the A\* version reaches the goal slightly faster than the Greedy

Best-First version. Even though the heuristic changed (Euclidean distance instead of the Manhattan distance), the overall results remained the same, because the approaches of each algorithm still remain the same. The greedy algorithm opened fewer nodes because it focuses on nodes closer to the goal, disregarding cost. The only difference is that the paths can go diagonally sometimes if it fits the strategy.

### Part 3:

In this experiment, I tested certain values of Alpha (prioritizing  $g(n)$ , the path cost accumulated so far and to other nodes) and Beta (prioritizing  $h(n)$ , nodes that are closer to the goal without regard to cost). The results are shown below:

#### Section a

**Table:**

Alpha	Beta:	Observed Behavior
1	25	Graph turns downward later, initially stays on the horizontal path because it thinks it will reach the goal sooner.
5	16	Similar to the first one, the graph turns downward later, due to the relatively low alpha value and higher beta value. It acts more greedy (also more $h(n)$ ).
12	5	Contrary to the first two, the graph turns downward earlier, probably due to the prioritization of $g(n)$ because the Alpha value is larger than the Beta value). It considers cost of going to nodes over ones that are solely closer to the goal.
20	1	Similar to the one above, since the alpha value is much higher than the beta value, the

		algorithm prioritizes $g(n)$ over $h(n)$ the graph expands more nodes and notices that staying on that horizontal track will not find the best path.
--	--	--

**Code snippet incorporating the values of Alpha and Beta in the algorithm:**

```

#### Agent goes E, W, N, and S, whenever possible
for dx, dy in [(0, 1), (0, -1), (1, 0), (-1, 0)]:
    new_pos = (current_pos[0] + dx, current_pos[1] + dy)

    if 0 <= new_pos[0] < self.rows and 0 <= new_pos[1] < self.cols and not self.cells[new_pos[0]][new_pos[1]].is_wall:

        #### The cost of moving to a new position is 1 unit
        new_g = current_cell.g + 1

        if new_g < self.cells[new_pos[0]][new_pos[1]].g:
            #### Update the path cost g()
            self.cells[new_pos[0]][new_pos[1]].g = new_g

            #### Update the heuristic h()
            self.cells[new_pos[0]][new_pos[1]].h = self.heuristic(new_pos)

            #### Update the evaluation function for the cell n: f(n) = g(n) + h(n)
            self.cells[new_pos[0]][new_pos[1]].f = (ALPHA * new_g) + (BETA * self.cells[new_pos[0]][new_pos[1]].h)
            self.cells[new_pos[0]][new_pos[1]].parent = current_cell

            #### Add the new cell to the priority queue
            open_set.put((self.cells[new_pos[0]][new_pos[1]].f, new_pos))

```

**Screenshots:**

Test 1:

```

ALPHA = 1
BETA = 25

```

Test 2:

```

16 ALPHA = 5
17 BETA = 16

```

Test 3:

```

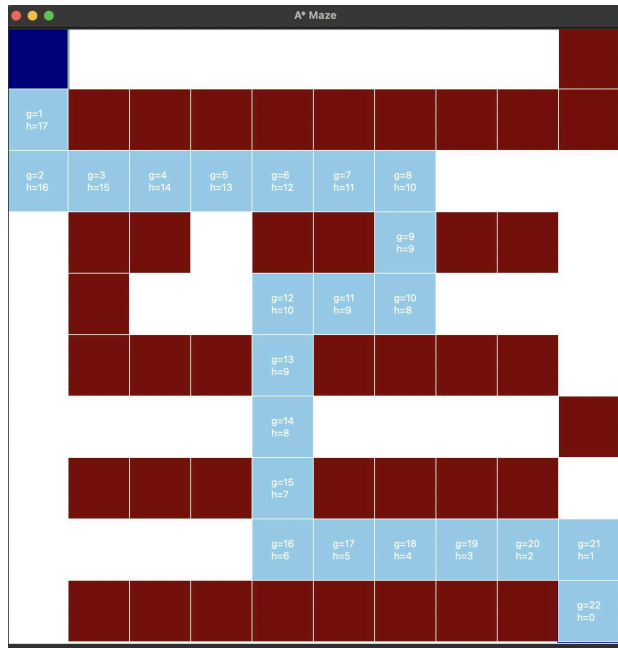
16 ALPHA = 12
17 BETA = 5

```

Test 4:

```
16  ALPHA = 25
17  BETA = 1
```

Maze for Test 1 and 2:



Maze for test 3 and 4:

Section b: (only beta values):

Code Used (showing how the value of Beta is incorporated in the pathfinding function):

```
133     ### Update the evaluation function for the cell n: f(n) = g(n) + h(n)
134     self.cells[new_pos[0]][new_pos[1]].f = (ALPHA * new_g) + (BETA * self.cells[new_pos[0]][new_pos[1]].h)
```

Test 1:

```
19  ALPHA = 1
20  BETA = 50
```

Test 2:

```
17  #initializing values of Alpha and Beta
18  ALPHA = 1
19  BETA = 25
```

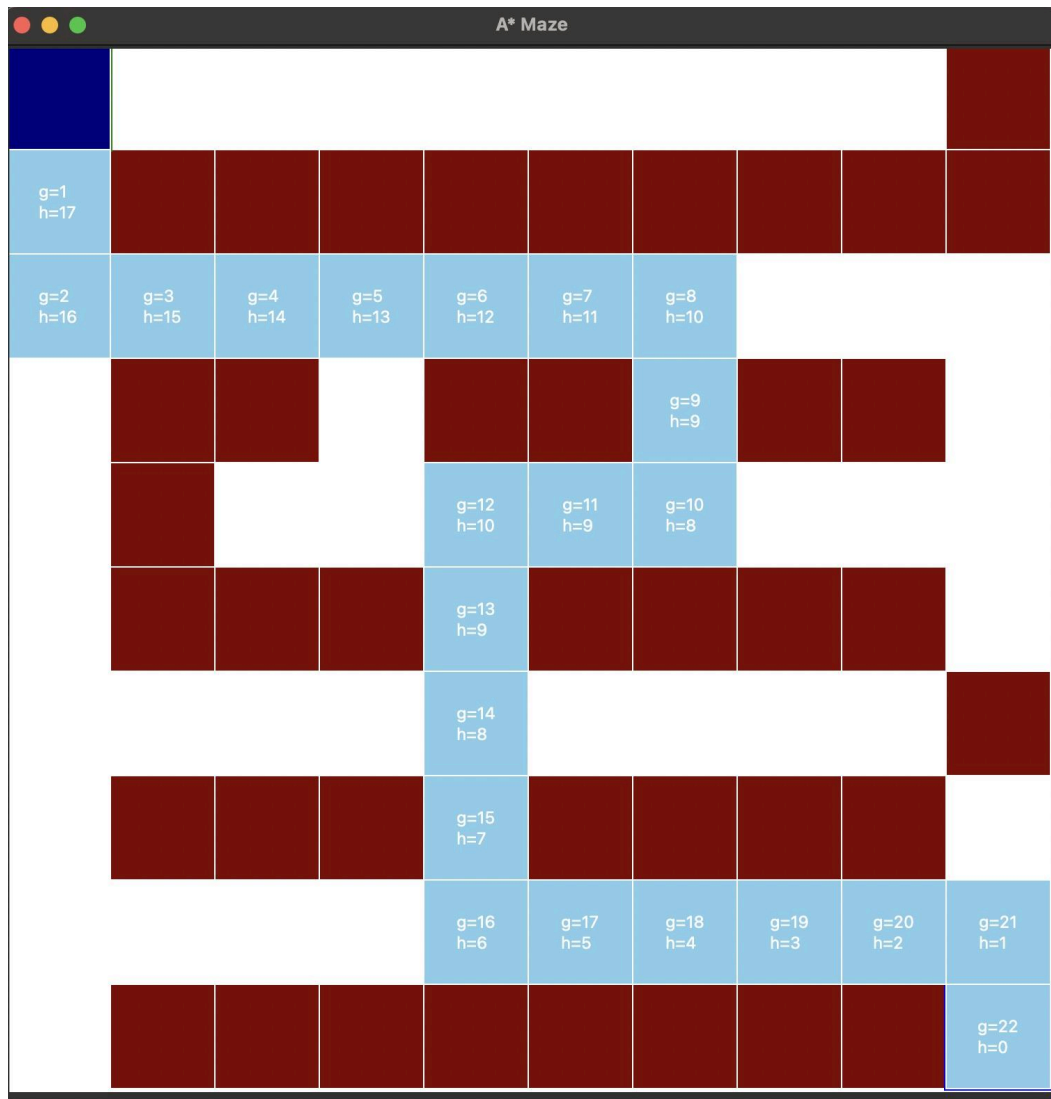
Test 3:

```
18  #initializing values of Alpha and Beta
19  ALPHA = 1
20  BETA = 10
```

Test 4:

```
19  ALPHA = 1
20  BETA = 1
```

Picture of maze when Beta was 50 and 25:



Picture of maze generated when Beta is 10 and 1:

A* Maze									
g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0
g=1 h=17	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0
g=2 h=16	g=3 h=15	g=4 h=14	g=5 h=13	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0
g=inf h=0	g=inf h=0	g=inf h=0	g=6 h=12	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0
g=inf h=0	g=inf h=0	g=inf h=0	g=7 h=11	g=8 h=10	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0
g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=9 h=9	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0
g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=10 h=8	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0
g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=11 h=7	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0
g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=12 h=6	g=13 h=5	g=14 h=4	g=15 h=3	g=16 h=2	g=17 h=1
g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=inf h=0	g=18 h=0

Alpha has the same value: For this experiment, the beta values varied, and the value of alpha was fixed at 1. As the beta was higher (like at 50 or 25), I saw that the path generated by the algorithm moved to the right more than the paths generated at lower beta values, which makes sense because as beta increases, the algorithm gets more greedy, and hence will open and follow nodes that it thinks are closer to the goal, without regard to other factors like obstacles or cost. It was hard to generate multiple paths for the beta values due to the nature of the maze; however, I did notice that when beta was 1, the algorithm turned earlier, which also makes sense because in that scenario, the algorithm would be less greedy and instead look at nodes with consideration to both cost AND distance to the goal. Since alpha and beta are the same in that scenario, the evaluation function would turn out to be  $f(n) = g(n) + h(n)$ .

## Conclusion:

Overall, this experiment proved that paths can be different based on various values of Alpha and Beta. I saw that as Alpha was high and Beta was low, that the path finding was based on prioritizing costs (like Dijkstra's or Uniform Cost search), while when Alpha was low and Beta was high, the path finding was based on algorithms prioritizing the locally best choice (without consider to cost, much like the hill climbing or greedy algorithms). This shows that there is a difference between algorithms with a high  $g(n)$  value but low  $h(n)$  value, and vice versa.