

CS 440 MP1

Section Q4

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Abstract

Within this report, we investigate creating agents that use different path planning algorithms and do an analysis of how they compare for a set of sample problems. **Insert summary of results.** We later apply A^* algorithms to guide an agent to solving the Sokoban puzzle. **Insert summary of results.**

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1 Part 1 - Multi-Goal Search

Within this section, we investigate using search algorithms to tackle single-goal and multi-goal objectives. To handle this problem, the provided maze is processed into a graph, G_m , that can be used to figure out what actions a given agent can take and when they reach some goal node. To model the motion of some agent, we define the state, \mathbf{x} , as the following:

$$\mathbf{x} = (p, b_1, b_2, \dots, b_n)$$

where p is an index representing the graph node the agent is on and b_k represents a Boolean variable that is 1 (true) when the agent has passed through the k^{th} goal point at some point prior and 0 (false) otherwise. Note that this state is always implicitly dependent on the maze graph, G_m . We know an agent has completed a maze when it reaches a state that satisfies the following:

$$b_1 \wedge b_2 \wedge \dots \wedge b_n = 1$$

To model the step by step motion of an agent, the transition function is defined as the following:

Algorithm 1: Transition Function - Multi-goal

```

Data: State,  $\mathbf{x}$ 
Data: Action,  $a$ 
Data: Maze Graph,  $G_m$ 
Data: Goal Node Set,  $V_g = \{p_1, p_2, \dots, p_n\}$ 
Result: New State,  $\mathbf{x}_n$ 

// Set the new state with the
// current state's boolean configuration
for  $k \in \{1, 2, \dots, |V_g|\}$  do
    |  $\mathbf{x}_n(b_k) = \mathbf{x}(b_k)$ 
end

// Update position in maze given the action  $a$ 
 $\mathbf{x}_n(p) = \text{getNextPosition}(\mathbf{x}, a, G_m)$ 

// Check if new position is in goal node set
// If so, find index associated with goal node and
// set corresponding boolean to 1
if  $\mathbf{x}_n(p) \in V_g$  then
    | Get  $m \ni \mathbf{x}_n(p) = p_m$ 
    | Set  $\mathbf{x}_n(b_m) = 1$ 
end

return  $\mathbf{x}_n$ 

```

Given the state representation and transition function described above, we are now able to implement and test our search-based agents. That said, we are now able to dive into solving each challenge of Part 1.

1.1 Part 1.1 - Basic Pathfinding

In this first challenge for Part 1, the goal is to implement search algorithms for navigating through a maze environment to a single goal location. For this challenge, we have implemented the following search algorithms:

- Depth-First Search
- Breadth-First Search
- Greedy Best-First Search
- A* Search

For Greedy and A*, we have also set their Heuristic Function as the Manhattan Distance metric, defined as the following:

$$d_M(u, v) = |u - v|_1$$

where $u, v \in \mathbb{R}^2$ represent positions in the maze we want the distance between and $|\cdot|_1$ is the L_1 norm. Using this formula, the heuristic function will be:

$$h(n) = d_M(n, g)$$

where n is the 2-D position of the current agent's position and g is the 2-D position of the goal point. Given the above search strategies and heuristic, Table 1 and Table 2 show the stats between each method for each of the provided mazes:

	Medium Maze	Big Maze	Open Maze
Depth-First Search	124	474	59
Breadth-First Search	68	148	45
Greedy Best-First Search	68	222	77
A* Search	68	148	45

Table 1: Solution Path Cost

Note that Appendix A contains visuals for the solution paths for each case. Now as we can see in the tables, Depth-First Search (DFS) tended to arrive at a solution to a given maze quickly but at the expense of a sub-optimal path cost. We can note that Breadth First Search (BFS) and A* both, as expected, produced optimal path costs but it is interesting to note that for the Big Maze

	Medium Maze	Big Maze	Open Maze
Depth-First Search	198	1029	319
Breadth-First Search	345	1259	523
Greedy Best-First Search	77	311	27761
A* Search	202	1495	667

Table 2: Number of Nodes Expanded

and Open Maze, BFS actually reached the optimal solution faster. It seems feasible that the Manhattan distance heuristic would, at times, take A* in a path that would lead to dead ends, in turn requiring A* to expand more nodes than BFS would have to.

One other thing to note was the interesting characteristics of the Greedy Search. We can see that on one end, it reached an optimal result in a very low number of expanded nodes for the Medium Maze. On the other end, it reaches a sub-optimal path cost after expanding a huge number of states in the Open Maze. Greedy obviously lacks robustness and this can be suspected due to the fact it does not take into account how far it has come but only thinks about how far away it thinks it is. Given this one sided thinking, the agent can get too excited being "close" to the goal even though they may be winding through a lot of poor sub-paths.

1.2 Part 1.2 - Search with Multiple Dots

The goal of this part was to build heuristics for the A* algorithm that would allow an agent to tackle a set of multi-goal problems in a reasonable time frame. The heuristic being used for this section is one based on the Convex Hull.

Let us first define the distance metric, $d_{ch}(\cdot, \cdot, \cdot)$, as the following:

$$d_{ch}(x, y, \beta) = \beta |x - y|_2 + (1 - \beta) |x - y|_1$$

where $|\cdot|_1$ is the L_1 norm, $|\cdot|_2$ is the L_2 norm, and $\beta \in [0, 1]$ is a tuning parameter. Let us define p as the current location of the agent and define $V_u = \{\hat{g}_1, \hat{g}_2, \dots, \hat{g}_m\}$ as the set of m unvisited goal points. Let us then compute the convex hull of $\{p\} \cup V_u$, defined as:

$$(V_{ch}, E_{ch}) = \text{ConvexHull}\left(\{p\} \cup V_u\right)$$

where V_{ch} are the vertices on the convex hull of the input set and E_{ch} is the edge set of 2-tuples such that $E_{ch} = \{(x, y) : x, y \text{ are ordered vertices of some edge}\}$. For this heuristic, we will remove an edge from E_{ch} to ensure we only touch each point on the convex hull once. We will call the resulting edge set as \hat{E}_{ch} and will define it in the following way.

If $p \notin V_{ch}$, \hat{E}_{ch} will be equivalent to E_{ch} with the largest edge from E_{ch} removed and then an edge of minimal distance between p and some $v \in V_{ch}$ added. If $p \in V_{ch}$, \hat{E}_{ch} will be equivalent to E_{ch} with the largest edge that has the vertex p on it being removed. Given we have produced this new edge set \hat{E}_{ch} , the heuristic is then computed as:

$$h_{ch}(p) = \sum_{(x,y) \in \hat{E}_{ch}} d_{ch}(x, y, \beta) + \mu |V_I|$$

where V_I represents the set of goal points on the interior of the convex hull and $\mu = \min\{1, d\}$ where d is the smallest distance between any interior goal point and any other goal point within V_u . This heuristic is admissible because, looking at the first term, the convex hull based distance using the edge set \hat{E}_{ch} represents the shortest distance possible between points on the convex hull.

The secondary term is then just multiplying the number of goal points within the convex hull by the minimum distance μ to get to any neighboring goal point. This second term is a lower bound on the distance it will take to touch each of the interior goal points from any point along the convex hull. These two terms together in turn under estimate the minimal distance the agent will need to travel to touch each goal point, making the heuristic admissible.

1.3 Part 1 Extra Credit - Sub-optimal Heuristics

2 Part 2 - Sokoban

2.1 State and Transition Model Definitions

Within this section, the goal is to develop an agent that is capable of solving the Sokoban puzzle problem for a set of input puzzles. To handle this problem, the state representation has been defined as the following:

$$\mathbf{x} = (p, b_1, b_2, \dots, b_n)$$

where in this case p is the position of the agent, represented as a graph node index, and b_k represents the position of the k^{th} box's position, represented as a graph node index, within the puzzle environment. Note that, as before, the input puzzle is processed to construct a graph representation which is in turn an implicit part of the state and environment representation for this problem. To know when the agent has found a Goal State, the following condition must be met:

$$(b_1 \in V_g) \wedge (b_2 \in V_g) \wedge \dots \wedge (b_n \in V_g) = 1$$

where $V_g = \{g_1, g_2, \dots, g_n\}$ is the set of goal points within the puzzle we can place a box. The next step in formulating this problem is describing the Transition Model for the agent and what actions an agent can take based on its state. Algorithm 2 describes the Transition Model for Sokoban given our state representation, while Algorithm 3 refers to how we get the feasible action set for an agent given its current state. With these pieces described, we can readily approach solving Sokoban using the search methods discussed earlier.

Algorithm 2: Sokoban Transition Model Algorithm

```
Data: State,  $\mathbf{x}$ 
Data: Action,  $a$ , assumed to be valid
Data: Maze Graph,  $G_m$ 
Result: New State,  $\mathbf{x}_n$ 

// Set the new state with the
// current state's box configuration
for  $k \in \{1, 2, \dots, |V_g|\}$  do
|    $\mathbf{x}_n(b_k) = \mathbf{x}(b_k)$ 
end

// Update position in maze given the action  $a$ 
 $\mathbf{x}_n(p) = \text{getNextPosition}(\mathbf{x}, a, G_m)$ 

// Check if new position is in equivalent to
// the position of one of the boxes. If so update
// the location of the box using the same action
if  $\mathbf{x}_n(p) \in \{\mathbf{x}_n(b_1), \mathbf{x}_n(b_2), \dots, \mathbf{x}_n(b_n)\}$  then
|   Get  $i \ni \mathbf{x}_n(p) = \mathbf{x}_n(b_i)$ 
|   Set  $\mathbf{x}_n(b_i) = \text{getNextPosition}(\mathbf{x}_n(b_i), a, G_m)$ 
end

return  $\mathbf{x}_n$ 
```

Algorithm 3: Sokoban Action Set Retrieval Algorithm

```
Data: State,  $x$ 
Data: Maze Graph,  $G_m$ 
Data: Goal Node Set,  $V_g = \{g_1, g_2, \dots, g_n\}$ 
Result: Action Set,  $A$ 

// Get set of box positions
 $B_p = \text{getBoxPositions}(x)$ 

// Initialize Action Set as the one based on the Connectivity
 $A = \text{getActionsFromConnectivity}(x(p), G_m)$ 

// Loop through possible actions and check they are valid
// given the rules of Sokoban
for  $a \in A$  do
    // Get the next node in the graph the
    // agent would be going to
     $p_n = \text{getNextPosition}(x, a, G_m)$ 

    // Check if  $p_n$  is the position of a box
    if  $p_n \in B_p$  then
        // Update position of matching box using action  $a$ 
        // and check if it is a valid position
         $u = \text{getNextPosition}(p_n, a, G_m)$ 

        // If new box position interferes with another box
        // or the wall, remove  $a$  from the action set  $A$ 
        if  $u \in B_p$  or  $\text{isWall}(u, G_m)$  then
            |  $A \leftarrow A \setminus \{a\}$ 
        end
    end
end

// Return the desired Action Set
return  $A$ 
```

2.2 Solving Sokoban with Breadth First Search

Using our state representation and the transition model for the agent, it becomes simple to apply BFS to tackling Sokoban problems. With this, the results of this BFS against the set of Sokoban puzzles provided can be found in Table 3. Animations of their solution, in the form of GIFs, can be found in the project zip with their identifiers as **bfs_sokoban*.gif**. As expected, BFS solved the Sokoban problems using how we modeled the state and environment, though Sokoban 4 did expand a considerable number of states.

	Sokoban 1	Sokoban 2	Sokoban 3	Sokoban 4
Number of Moves	8	144	34	72
Nodes Expanded	46	2,038,936	2,076,600	176,495,868
Run Time	0.13 s	3.47 s	4.70 s	207.12 s

Table 3: Sokoban solved by BFS

2.3 Solving Sokoban with A*

To tackle Sokoban, we go over a heuristic for A* and the results we achieve solving Sokoban. To keep things simple, the heuristic is defined as the following:

$$h_{\text{nearest}}(p) = \min_{b \in B_p} d_M(p, b) + \sum_{b \in B_p} \min_{g \in V_g} d_M(b, g)$$

where $B_p = \text{getBoxPositions}(\mathbf{x})$ and V_g represents the set of goal point locations for the boxes. This heuristic is admissible. The first term, representing the distance the agent has left to move to reach the boxes, is underestimating the distance the agent has to go since it is only looking at the distance to the nearest box. The second term also acts as a sum of the lower bounds to the distance the agent would have to push a given box b to some goal g . This is a lower bound in the second term, as formulated, because the nearest goal point to some box b is not necessarily a goal point the box can reach, nor is that goal point necessarily one that can be used to solve the overall puzzle. The sum of these components together in turn produces an underestimate of the distance the agent has left to travel before completion of the puzzle, making the heuristic admissible.

With this, the results of this A* formulation against the set of Sokoban puzzles provided can be found in Table 4. Animations of their solution, in the form of GIFs, can be found in the project zip with their identifiers as **as-tar_nearest_sokoban*.gif**. Watching the animations, it is interesting to see how the agent tackled trickier puzzles like Sokoban 2 and Sokoban 4 where the solution requires more seemingly long term thinking, i.e. making sure moves you make now allow for you to make moves later on boxes that are more constrained. Fortunately, the heuristic managed to solve all these puzzles in a reasonable time

frame, though we expect there are superior heuristics for managing Sokoban 2 and Sokoban 4.

	Sokoban 1	Sokoban 2	Sokoban 3	Sokoban 4
Number of Moves	10	148	36	72
Nodes Expanded	36	517,584	146,259	11,404,258
Run Time	0.14 s	2.49 s	0.95 s	40.16 s

Table 4: Sokoban solved by A* using $h_{\text{nearest}}(p)$

2.4 Comparison of Results

By checking Table 3 and Table 4, we can draw some obvious comparisons. First, BFS always achieved an optimal result and A* was right near it, though it might have missed the absolute optimal solution due to the repeated state detection. Additionally, A* performed much faster than BFS in terms of number of nodes expanded. The run-time comparison between BFS and A* also followed that trend generally, though A* did not run as many multiples faster than BFS with respect to run-time as it did number of nodes expanded. This makes sense because the heuristic computation of A* is going to cost CPU time that BFS does not have to worry about.

2.5 Part 2 Extra Credit - Sub-optimal Heuristics

Appendices

A Maze Solutions for Part 1.1

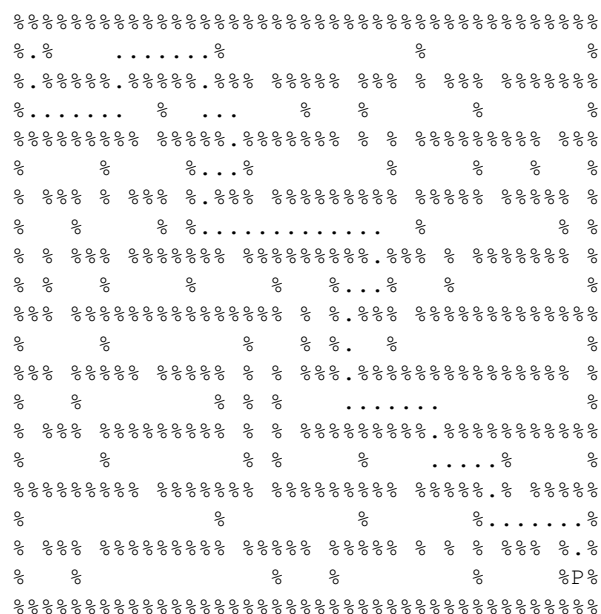


Figure 1: Solution to Medium Maze using BFS



Figure 5: Solution to Big Maze using DFS

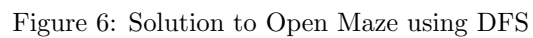




Figure 8: Solution to Big Maze using Greedy

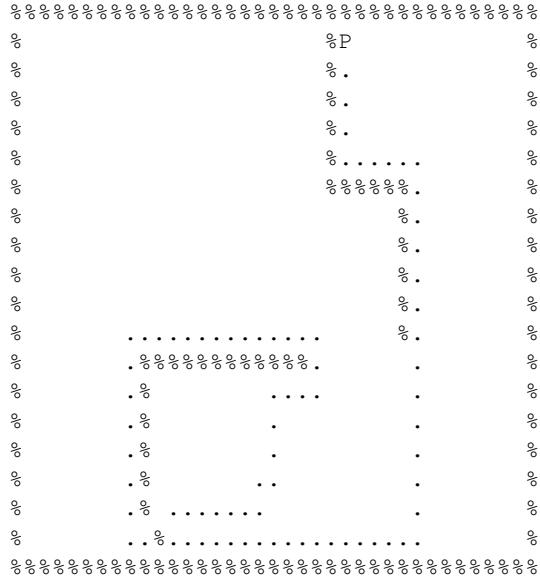


Figure 9: Solution to Open Maze using Greedy

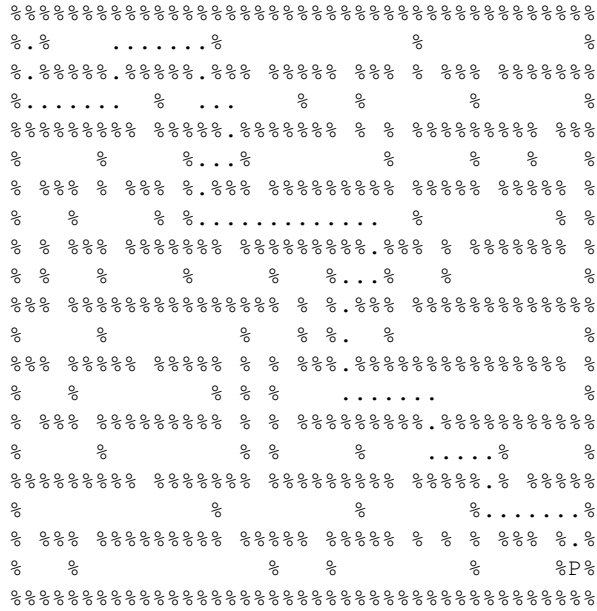
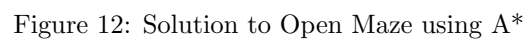


Figure 10: Solution to Medium Maze using A*



Figure 11: Solution to Big Maze using A*



B Maze Solutions for Part 1.2

C Open Source Software Used

The following list of Open Source software was used to help with this project:

- **gif-h**
 - A single header in C that allows for basic GIF processing
 - <https://github.com/ginsweater/gif-h>