

CS 440 MP1

Section Q4

Christian Howard Luke Pitstick
howard28@illinois.edu pitstck2@illinois.edu

Liuyi Shi
liuyis2@illinois.edu

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 creating an agent based on search algorithms to tackle single-goal and multi-goal objectives. To handle this problem, the provided maze is processed into a graph 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 in the past, 0 (false) otherwise. We know an agent has completed a maze when it reaches a state that satisfies the following:

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

This check will be what is performed in the software implementation of the search algorithms to know we have found a goal state. The transition function for this agent is also the following:

Algorithm 1: Transition Function

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

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 and $|\cdot|_1$ is the L_1 norm. 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	0	0	0
Breadth-First Search	0	0	0
Greedy Best-First Search	0	0	0
A* Search	0	0	0

Table 1: Solution Path Cost

	Medium Maze	Big Maze	Open Maze
Depth-First Search	0	0	0
Breadth-First Search	0	0	0
Greedy Best-First Search	0	0	0
A* Search	0	0	0

Table 2: Number of Nodes Expanded

- 1.2 Part 1.2 - Search with Multiple Dots
- 1.3 Part 1 Extra Credit - Suboptimal Search
- 2 Part 2 - Sokoban