AIND - Planning Project

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Part 1 Result Documentation

Problem 1

Search Type	Node	Goal Tests	Time Elapsed	Solution
	Expansions		(s)	Length
breadth-first-search	43	56	0.043644952	6
breadth-first-tree-search	1458	1459	1.0484	6
depth-first-graph-search	21	22	0.02199	20
depth-limited-search	101	271	0.1110259	50
uniform-cost-search	55	57	0.053333	6
recursive-best-first-search with h-1	4229	4230	3.380909	6
greedy-best-first-graph-search with h-1	7	9	0.008354	6
astar-search with h-1	55	57	0.067594	6
astar-search with h-ignore- preconditions	41	43	0.040059	6
Astar-search-with h-pg- levelsum	11	13	0.6371	6

Depth-first-graph-search and depth-limited-search were the only two search types that resulted in a non-optimal solution length. As for the others, greedy-best-first-graph-search-with-h-1 was able to find the optimal solution with the least node expansions and goal tests it did followed by Astar-search-with-h-pg-levelsum which had a longer computing time. it was also the fastest search method. Greedy-best-first-graph-search was also the fastest search type that ended in an optimal solution.

Problem 2

Search Type	Node	Goal Tests	Time Elapsed	Solution	
	Expansions		(s)	Length	
breadth-first-search	3343	4609	11.1005	9	
breadth-first-tree-search	Stopped after 120s				
depth-first-graph-search	624	625	4.52146	619	
depth-limited-search	Stopped after 120s				
uniform-cost-search	4852	4854	15.51258	9	
recursive-best-first-search with h-1	Stopped after 120s				
greedy-best-first-graph-search with h-1	990	992	3.07647	21	
astar-search with h-1	4852	4854	15.05205	9	
astar-search with h-ignore- preconditions	1450	1452	5.316719	9	
Astar-search-with h-pg- levelsum	86	88	58.0178	9	

Breadth-first-tree-search, depth-limited-search and recursive-best-first-search-with-h-1 were all stopped after 2 minutes of run time after seeing that a solution could be reached in a much shorter time. The optimal solution length was 9 moves, and was reached by all except the depth-first-graph-search and greedy-best-first-graph-search-with-h-1 which found solutions with non-optimal lengths. The fastest search methods with optimal solution lengths were astar-search with h-ignore-preconditions, breadth-first-search, astar-search-with-h-1 and uniform-cost-search in that order. Astar-search-with h-pg-levelsum expanded the least nodes and goal tests to find an optimal solution, the next best being h-ignore-preconditions.

Problem 3

Search Type	Node	Goal Tests	Time Elapsed	Solution	
	Expansions		(s)	Length	
breadth-first-search	8602	3602 11196		12	
breadth-first-tree-search	Stopped after 360s				
depth-first-graph-search	1292	1293	3.4746	875	
depth-limited-search	Stopped after 360s				
uniform-cost-search	11483	11485	32.6559	12	
recursive-best-first-search with h-1	Stopped after 360s				
greedy-best-first-graph-search with h-1	907	909	2.28907	19	
astar-search with h-1	11483	11485	33.0492	12	
astar-search with h-ignore- preconditions	4117	4119	13.9255	13	
Astar-search-with h-pg-levelsum	279	281	126.4737	12	

Breadth-first-tree-search, depth-limited-search and recursive-best-first-search-with-h-1 were all once again stopped early (after 6 minutes each) as it was taking too long to find a solution. The optimal solution length was found to be 12 moves, and the only functions able to reach this optimal solution length were breadth-first-search, uniform-cost-search, astar-search-with-h-1 and Astar-search-with-h-pg-levelsum. The fastest of which was breadth-first-search, once again Astar-search-with-h-pg-levelsum expanded significantly less nodes than the others, but did however sacrifice computing time to do so. Uniform-cost-search, and astar-search-with-h-1 both expanded 11483 nodes with 11485 goal tests, they too 32.65 and 33.04 seconds respectively.

Top Performing Searches to reach optimal solution:

The main factor considered in this evaluation was the time in which the search types took to find a solution.

Problem 1	Problem 2	Problem 3
greedy-best-first-graph-search with	astar-search with h-ignore-	breadth-first-search
h-1	preconditions	
astar-search with h-ignore-	breadth-first-search	uniform-cost-search
preconditions		
breadth-first-search	astar-search with h-1	astar-search with h-1
uniform-cost-search	uniform-cost-search	Astar-search-with h-pg-levelsum
astar-search with h-1	Astar-search-with h-pg-levelsum	
Astar-search-with h-pg-levelsum		
breadth-first-tree-search		
recursive-best-first-search with h-1		

So the only search types to reach an optimal solution for each problem were breadth-first-search, uniform-cost-search, astar-search-with-h-1 and Astar-search-with-h-pg-levelsum. And the overall best performer of these three

was breadth-first-search, followed by uniform-cost-search. This was based on time, for least node expansions, Astar-search-with-h-pg-levelsum expanded significantly less nodes in the more complex problem, this came at a cost however, and its heuristic function took much longer to compute and end up with a solution.

The reasons for the different uninformed search functions performing the way they do are justified with the comparison that is shown in the following Figure from AIMA Section, this shows what their expected/theoretical performance is in relation to some of their properties:

Criterion	Breadth- First	Uniform- Cost	Depth- First	Depth- Limited	Iterative Deepening	Bidirectional (if applicable)
Complete? Time Space Optimal?	$egin{aligned} \operatorname{Yes}^a \ O(b^d) \ O(b^d) \ \operatorname{Yes}^c \end{aligned}$	$\operatorname{Yes}^{a,b} O(b^{1+\lfloor C^*/\epsilon \rfloor}) \ O(b^{1+\lfloor C^*/\epsilon \rfloor}) \ \operatorname{Yes}$	No $O(b^m)$ $O(bm)$ No	No $O(b^\ell)$ $O(b\ell)$ No	$\operatorname{Yes}^a O(b^d) \ O(bd) \ \operatorname{Yes}^c$	$egin{array}{l} \operatorname{Yes}^{a,d} & O(b^{d/2}) & O(b^{d/2}) & \operatorname{Yes}^{c,d} & \end{array}$

Figure 3.21 Evaluation of tree-search strategies. b is the branching factor; d is the depth of the shallowest solution; m is the maximum depth of the search tree; l is the depth limit. Superscript caveats are as follows: a complete if b is finite; b complete if step costs b for positive b optimal if step costs are all identical; b if both directions use breadth-first search.

It is evident that the depth-first and depth-limited search types are not expected to complete the search and also not able to find the optimal solution, as was proven in the results that were obtained. All the remaining search functions shown in the image that were used, were able to find optimal solutions, as they were expected to do.

To summarize, this was a thoroughly enjoyable project with many challenges, it did however feel good to overcome them as I learnt a lot about logical statements and the use of them in planning problems. It was also very helpful to be able to compare the different search types against each other to see how they fared in problems of different complexity.

Optimal Solutions for the Problems:

Problem 1:

Using greed-best-first-graph-search with h-1:

Expansions = 7

Goal tests = 9

Time Elapsed: 0.0084166s

Plan Length = 6

Plan: Load(C1, P1, SFO)

Load(C2, P2, JFK)

Fly(P1, SFO, JFK)

Fly(P2, JFK, SFO)

Unload(C1, P1, JFK)

Unload(C2, P2, SFO)

Problem 2:

Using astar-search with h-ignore-preconditions:

Expansions = 1450

Goal tests = 1452

Time Elapsed: 4.51015s

Plan Length = 9

Plan: Load(C3, P3, ATL)

Fly(P3, ATL, SFO)

Unload(C3, P3, SFO)

Load(C2, P2, JFK)

Fly(P2, JFK, SFO)

Unload(C2, P2, SFO)

Load(C1, P1, SFO)

Fly(P1, SFO, JFK)

Unload(C1, P1, JFK)

Problem 3:

Using breadth-first-search:

Expansions = 8602

Goal tests = 11196

Time Elapsed: 24.5647s

Plan Length = 12

Plan: Load(C1, P1, SFO)

Fly(P1, SFO, ATL)

Load(C3, P1, ATL)

Fly(P1, ATL, JFK)

Load(C2, P1, JFK)

Unload(C1, P1, JFK)

Unload(C3, P1, JFK)

Fly(P1, JFK, ORD)

Load(C4, P1, ORD)

Fly(P1, ORD, SFO)

Unload(C2, P1, SFO)

Unload(C4, P1, SFO)