Artificial Intelligence

Programming Project Part 2: Searchclient

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Group Declaration of Work Breakdown

IDEAS: Sejal and Angelo
PROGRAMMING: Sejal and Angelo
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Exercise 5: Heuristics

Part 1: choice of data structure for the frontier

The data structure we use for the frontier is a priority queue. For best first search, we want to always choose the state that has the lowest cost according to our heuristic. A priority queue in Java works perfectly for this task since we can pass it our custom heuristic comparator and it will order the states as they are placed into the priority queue. This means that we can just use the `poll()` method to grab the state with the lowest cost.

Parts 2 and 3: mathematically precise specification and reasoning of the heuristics

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FIRST HEURISTIC: Manhattan distance

Our first heuristic was quite simple. Our very first thought was that the most important information for our heuristic to use was each box's distance from the goal. Since every level is a grid of squares, Manhattan distance is a simple implementation that would work well. Let x_b, y_b be the x- and y-coordinates of the box respectively. Let x_g, y_g be the coordinates of the corresponding goal. Then,

$$\text{Manhattan distance} = |x_b - x_g| + |y_b - y_g|$$

Our heuristic was the sum of the Manhattan distances between every goal and a corresponding box. Let $numGoals$ be the amount of goals, g_n be the n^{th} goal of the level, and b_n be the goal's corresponding box. Then,

$$\mathsf{h}(n) = \sum_{i=1}^{numGoals} \mathsf{dist}(g_i, b_i)$$
$$\mathsf{h}(n) = \sum_{i=1}^{numGoals} |x_{b_i} - x_{g_i}| + |y_{b_i} - y_{g_i}|$$

It is important to note that in situations where there were multiple boxes of the same label, the heuristic would use the box that was furthest to the bottom-right of a level. In situations where there were multiple goals of the same label, the heuristic would only account for the most bottom-right goal, ignoring the rest. If the level had multiple boxes and multiple goals all of the same level, both problems would exist in parallel. Another notable limitation of this heuristic is not accounting for the position of the agent.

Table 3: Optimized Implementation #2 - Exercise 2					
Level	Frontier	Time (s)	Memory Used (MB)	Solution length	States Generated
SAD1	BFS	0.029	3.72	19	80
SAD1	DFS	0.025	3.59	27	75
SAD2	BFS	14.467	692.72	19	635190
SAD2	DFS	0.022	3.59	25	86
SAfriendofDFS	BFS	1.185	72.13	8	89112
SAfriendofDFS	DFS	0.031	3.72	60	305
SAfriendofBFS	BFS	0.048	5.12	3	1227
SAfriendofBFS	DFS	35.552	2015.72	981528	2953986
SAFirefly	BFS	18.261	2252.72	60	1961416
SAFirefly	DFS	24.539	4101.72	2517074	4089953
SACrunch	BFS	179.986	3840.72	N/A	6464388
SACrunch	DFS	9.218	4392.28	380992	1023377

Figure 1: Uninformed search implementation from part 1 of the project

Table 1: Heuristic Implementation #1 using best-first search client - Exercise 5					
Level	Evaluation	Time (s)	Memory Used (MB)	Solution length	States Generated
SAD1	A*	0.074	4.00	19	78
SAD1	Greedy	0.072	3.62	21	75
SAD2	A*	41.015	940.72	19	359928
SAD2	Greedy	0.092	4.56	53	284
SAfriendofDFS	A*	2.820	75.93	8	35432
SAfriendofDFS	Greedy	0.046	3.62	10	120
SAfriendofBFS	A*	0.038	3.34	3	50
SAfriendofBFS	Greedy	0.038	3.34	3	30
SAFirefly	A*	2.555	121.30	60	9209
SAFirefly	Greedy	0.195	15.68	99	787
SACrunch	A*	180.000	1317.82	N/A	1888924
SACrunch	Greedy	8.013	554.48	140	166347
SAsoko1_64.lvl	Greedy	0.085	4.84	62	123
SAsoko2_64.lvl	Greedy	0.550	10.84	62	309
SAsoko3_64.lvl	Greedy	172.183	8192.00	N/A	813831

Figure 2: Informed search implementation starting point using a naive heuristic

Analyzing the improvements provided by A* and greedy best-first search over BFS and DFS

Figure 1 at the top of the previous page shows the benchmarks after we implemented the second optimization in part 1 of the programming project. It is worth taking a second to draw a comparison between the BFS and DFS search client implementation versus the best-first search client that takes a heuristic-based approach (Figure 2). For levels SAD1 and SAD2, we notice that the time and memory usage is slightly increased due to the pre-processing of the heuristic, but the optimal solution is found and using a minimal number of states. Moving onto SAfriendofDFS and SAfriendofBFS, we notice that the greedy evaluation blows DFS and BFS out of the water. The performance of A* for these levels is comparable to that of BFS. Significantly less states are generated. For SAFirefly, we see tremendous improvements across the board. SACrunch still proves to be troublesome for the searchclient, but the A* evaluation burns though memory less quickly and generates less states. The greedy implementation actually solves the level faster than DFS could and using about 1/8 of the memory to find a solution in only 150 moves! SAsoko1_64 and SAsoko2_64 don't prove to be an issue for the greedy informed search implementation, but SAsoko3_64 is a demanding one.

We can conclude that an informed search strategy is looking much more promising than the already optimized uninformed search approach. We must bear in mind that using Manhattan distance is only a starting point for our informed search implementation. Despite it being pretty naive, the optimizations and pre-processing are going to lead to huge performance improvements.

SECOND HEURISTIC: linking goals to boxes

The second heuristic we implemented attempted to address the obvious issues with the first attempt. It still uses the sum of Manhattan distances for box-goal pairs. However, the manner in which box-goal pairs are created is very different. Starting in the upper left, each goal links with the closest box of the same label. Boxes cannot be linked with more than one goal. Additionally, the heuristic also attempts to account for the position of the agent. The distance from the agent to the first box-pair link is added to the heuristic. The final change was to preprocess all of goal positions, since this is standard across every state of a level. Recall the variables used for the first heuristic. Let x_a and x_y be the coordinates of the agent and x_{b_c} and y_{b_c} be the coordinates of the first box linked to a goal. Then,

$$\mathsf{h}(n) = (\sum_{i=1}^{numGoals} \mathsf{dist}(g_i, b_i)) + \mathsf{dist}(a, b_c)$$

$$\mathsf{h}(n) = (\sum_{i=1}^{numGoals} |x_{b_i} - x_{g_i}| + |y_{b_i} - y_{g_i}|) + |x_a - x_{b_c}| + |y_a - y_{b_c}|$$

A big issue with this heuristic is that the distance of the agent to the first box-goal pair, which would typically be the 'A' goal, is usually not optimal.

Table 2: Heuristic Implementation #2 using best-first search client - Exercise 5

Level	Evaluation	Time (s)	Memory Used (MB)	Solution length	States Generated
SAD1	A*	0.055	3.65	19	75
SAD1	Greedy	0.058	3.65	21	52
SAD2	A*	0.119	8.56	19	861
SAD2	Greedy	0.088	3.65	21	78
SAfriendofDFS	A*	1.350	37.27	8	4579
SAfriendofDFS	Greedy	0.066	3.72	8	106
SAfriendofBFS	A*	0.053	3.37	3	40
SAfriendofBFS	Greedy	0.047	3.37	3	56
SAFirefly	A*	5.127	162.50	62	49106
SAFirefly	Greedy	3.192	62.35	240	19353
SACrunch	A*	180.000	1942.99	N/A	2484912
SACrunch	Greedy	25.474	1546.53	334	510164
SAsoko1_64.lvl	Greedy	0.071	4.00	62	123
SAsoko2_64.lvl	Greedy	0.272	9.40	62	309
SAsoko3_64.lvl	Greedy	180.000	668.72	N/A	59024

From the first heuristic to the second, we can see that assigning box-goal pairs may not necessarily always save time due to pre-processing costs, but it does result in generating less states, on average. It also occasionally helps the greedy evaluation find the most optimal solution (take a look at SAD2_greedy from Table 1 to Table 2: solution length decreases from 53 to 21). On the other hand, it also results in a less optimal solution (take a look at SACrunch_greedy from Table 1 to Table 2: solution length increases from 140 to 334. The best-first search client also struggles with Firefly. We see way less memory usage on the SAsoko levels, though.

THIRD HEURISTIC: optimizing agent to boxes

The third heuristic improves upon the previous by using the distance of the agent to the **closest** box-goal pair. The formula for the heuristic is the same as above, except now x_{b_c} and y_{b_c} are the coordinates of the box with the shortest distance to its linked goal.

$$\text{h}(n) = (\sum_{i=1}^{numGoals} \text{dist}(g_i, b_i)) + \text{dist}(a, b_c)$$

$$\text{h}(n) = (\sum_{i=1}^{numGoals} |x_{b_i} - x_{g_i}| + |y_{b_i} - y_{g_i}|) + |x_a - x_{b_c}| + |y_a - y_{b_c}|$$

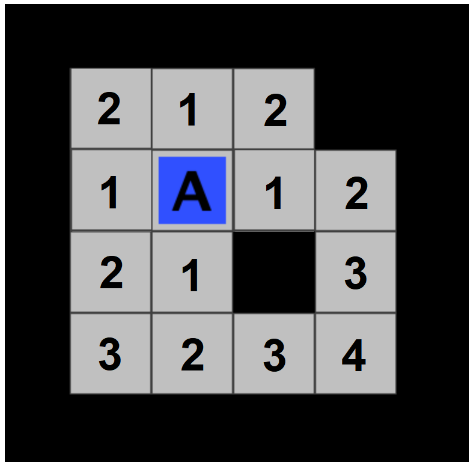
The largest issue facing our heuristic now is from how Manhattan distance is calculated. Our implementation of Manhattan distance completely ignores any walls that are blocking the path between two objects.

Table 3: Heuristic Implementation #3 using best-first search client - Exercise 5					
Level	Evaluation	Time (s)	Memory Used (MB)	Solution length	States Generated
SAD1	A*	0.128	3.65	19	75
SAD1	Greedy	0.117	3.65	21	52
SAD2	A*	1.705	57.85	19	19413
SAD2	Greedy	0.755	53.25	21	4437
SAfriendofDFS	A*	0.702	20.35	8	3401
SAfriendofDFS	Greedy	0.065	4.00	10	145
SAfriendofBFS	A*	0.037	3.37	3	40
SAfriendofBFS	Greedy	0.034	3.37	3	56
SAFirefly	A*	3.126	73.23	72	39157
SAFirefly	Greedy	0.783	31.36	140	2224
SACrunch	A*	180.000	1403.99	N/A	2285375
SACrunch	Greedy	14.836	169.72	190	202358
SAsoko1_64.lvl	Greedy	0.126	4.00	62	123
SAsoko2_64.lvl	Greedy	0.363	9.40	62	309
SAsoko3_64.lvl	Greedy	180.000	758.72	N/A	59024

The changes from the last heuristic to this one affect the performance in variable ways. In some cases we see a decrease in runtime (check out SAsoko1_64 and SAsoko2_64). But most notably is the SIGNIFICANT decrease in states generated when evaluating the level using A*. The amount of states generated decreases by almost an entire order of magnitude for most levels of A*. We also observe overall reductions in memory usage.

FOURTH HEURISTIC: pre-processing and more advanced calculations

The fourth heuristic has two major differences from the past iterations. The first change is that now the Manhattan distance calculations account for walls. For every square in the level, a distance map is generated. The distance map is a 2D array containing the distance of every other square to the selected square. See the below graphic for an example of a distance map. These distance maps are generated by running a breadth-first search. States are generated in waves that propagate from the starting tile outwards, with each wave of being one block further away.



The second large change is the amount of pre-processing. With this heuristic, not only are the goal positions pre-processed like with the previous two heuristics, but now the distance map for every square is generated before the algorithm to search is even initialized. Once again, the heuristic formula is the same as above, except the distance formula has been improved.

$$\mathrm{h}(n) = \left(\sum_{i=1}^{numGoals} \mathrm{dist}(g_i, b_i)\right) + \mathrm{dist}(a, b_c)$$

$$\mathrm{h}(n) = \left(\sum_{i=1}^{numGoals} |x_{b_i} - x_{g_i}| + |y_{b_i} - y_{g_i}|\right) + |x_a - x_{b_c}| + |y_a - y_{b_c}|$$

Table 4: Heuristic Implementation #4 using best-first search client - Exercise 5

Level	Evaluation	Time (s)	Memory Used (MB)	Solution length	States Generated
SAD1	A*	0.146	4.19	19	60
SAD1	Greedy	0.124	4.19	19	47
SAD2	A*	0.146	4.19	19	60
SAD2	Greedy	0.110	4.18	19	75
SAfriendofDFS	A*	0.282	13.15	8	1950
SAfriendofDFS	Greedy	0.060	4.56	8	130
SAfriendofBFS	A*	0.067	8.00	3	40
SAfriendofBFS	Greedy	0.074	8.28	3	56
SAFirefly	A*	1.959	193.39	62	29629
SAFirefly	Greedy	1.361	80.13	206	15218
SACrunch	A*	180.000	1929.75	N/A	2916068
SACrunch	Greedy	1.891	201.10	147	37380
SAsoko1_64.lvl	Greedy	0.084	5.37	62	123
SAsoko2_64.lvl	Greedy	N/A	N/A	N/A	N/A
SAsoko3_64.lvl	Greedy	N/A	N/A	N/A	N/A

This implementation really helped slash our benchmarks in every category. SAD1 and SAD2 have the lowest benchmarks we have ever seen for them, so that is a really good indicator that this heuristic is helping the search client become more and more informed so that it can be maximally efficient. The most significant improvement can be seen in SAfriendofDFS and SAfriendofBFS. Where before the search client was generating 3401 states for SAfriendof DFS A*, it now generates a little over half of that amount with 1950 states generated instead. The client performs better on SAFirefly A* but compromises performance on SAFirefly greedy, so there are always trade-offs to be aware of. We never were able to get SACrunch A* to be solvable by the best-firt search client. That is most likely due to the fact that the level is set up in such a way that the boxes are not perceived to be too far away from the goals, but there is a long pathway to get from the "island" where the boxes are to the "island" where the goals are. The walls are deceiving in this level because of where they are and how they separate the game board. We have thought about how to optimize for this if we had more time (see Discussion and Extensions section). Regarding SAsoko2_64 and SAsoko3_64, we struggled with them for this heuristic because we got a Java heap space error as the levels got more difficult. We know that our search client can solve some of the smaller levels like SAsoko2_16 and SAsoko3_08 but the fact that the state space grows so much in between each size of the level explains why our heap usage multiplies and we need to still figure out a way to reduce the amount of tedious algorithmic processing we do.

Discussion and Extensions

It looks like our best benchmark performance can be seen with heuristic implementation #4. With heuristics, you never really know if "the mess gets worse before it gets better" or if you are just digging yourself deeper and deeper into a ditch. In our case, it doesn't look like we quite cracked how to optimally handle all of the levels; most of our improvements optimized how the best-first search client solved one level but then compromised how it handled different levels. Overall, though, we were moving in the right direction, it seems, given the little time we had to work on the project.

If we had more time we would obviously have allocated that into figuring out what was going wrong with Heuristic 4 SAsoko2_64 and SAsoko3_64. Hopefully solving that bug would have led to performance improvements. But if we had more time AND more energy, our next heuristic would have been a super programmatically complex but conceptually simple implementation of Dijkstra's algorithm combined with Manhattan distance. We would have used Dijkstra's to map the location of the goals to boxes in an intuitive, algorithmic order, and we would have used Manhattan distance to tell the agent which box to work on moving first. But that is for next time.