3806ICT - Maze Solving

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1 Abstract

This reported aimed to analyze the differing ability between Q-learning (a form of reinforcement learning) and CSP model checking using the depth-first search (DFS) engine. Testing was conducted on mazes ranging in size from 5x5 to 505x505, and the produced path length of each method, along with the time taken for them to run, and their memory usage, were evaluated. It was found that while CSP took a significantly longer time to run and used more memory (exceeding the memory limit of the test system by 355x355), it always found a path to the goal, which Q-learning was unable to do. It was seen that Q-learning tended to get 'stuck' while searching for the goal in a local optimum position, where it no longer has the ability to move randomly enough to escape the local optimum, and so expends the rest of its steps (up to maximum) in the same 1 or 2 states. It was concluded that, despite finding the same results while trying to manually calibrate the Q-learning values, it is worth exploring different reward functions/algorithms to allow it to escape these local optima.

2 Introduction

Searching through a maze is a very complex task, because as the size of the maze increases, the number of possible states increases drastically. This makes it very difficult to find the optimal solution in a reasonable amount of time.

Q-learning and CSP model checking using DFS are two very different solutions to this maze search problem. Q-learning aims to search for a path from start to goal using a reward function that guides the algorithm, whereas CSP model checking using DFS is an exhaustive search of possible paths to the goal.

One of the key differences between Q-learning and model checking is that Q-learning is not guaranteed to find a path at all, whereas CSP is able to find a path every single time. The downside of this is that its runtime and memory usage can balloon quickly, and as maze size increases it quickly becomes impractical to use.

3 Test Design

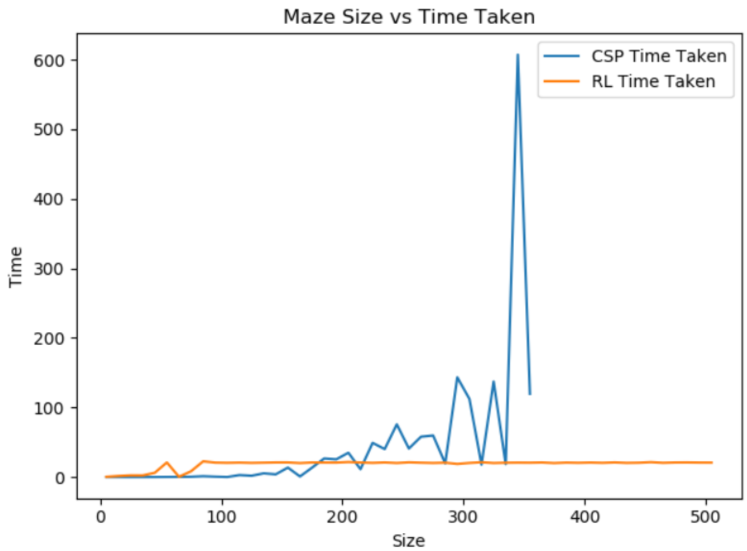
For this report, the designed test was to randomly generate mazes of size 5x5 to size 505x505 and profile the running of both PAT analyzing it with CSP in DFS mode and Q-learning. This allowed comparison of the time taken for it to run, the length of the path it found, and the memory it used to do so.

As for the implementation of these, the maze generator utilised a backtracking algorithm in $C++$, the CSP had an adjustment that marked its previous moves, and the reinforcement learning was the lab's version split into scripts. The reason for the maze using backtracking and being so optimised is because we want to be able to speed up generating samples. Furthermore, backtracking gives us a good time, memory, produced minimal dead ends, is bias free and not uniform [Pullen, 2015].

In terms of the hardware and software configuration, it was ran on WSL2 inside of Windows 10 on a Ryzen 5900 with 32GB of RAM. Due to it being in WSL2, mono was used to run PAT 3 which means that the times are likely around three times slower than they would be on just Windows. The reason for using WSL2 is because we have access to the time command, which makes recording the memory of the reinforcement learning script easier.

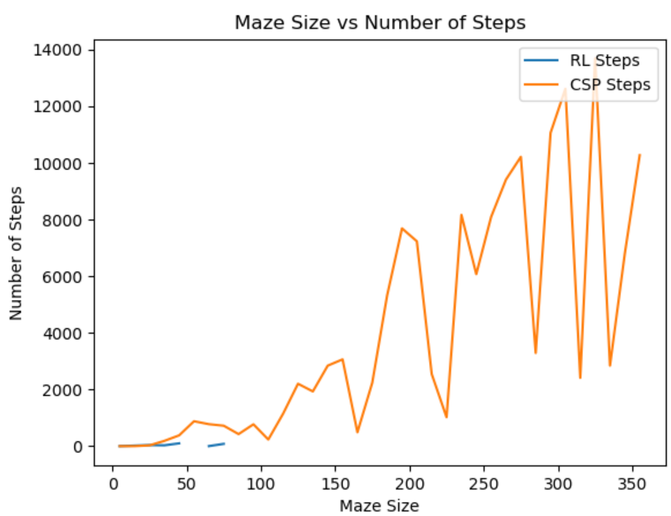
4 Results

Size	CSP Path Length	CSP Time Taken (sec)	CSP Memory Usage (KB)	RL Path Length	RL Time Taken (sec)	RL Memory Usage (KB)
5	3	0.0125483	8691.928	5	0.42	52476
15	5	0.0149705	12324.304	23	1.56	52692
25	31	0.0264754	13624.272	41	2.41	52732
35	189	0.0504123	13854.6	33	2.36	52772
45	385	0.1140375	23686.088	103	6.18	52924
55	883	0.2224756	47826.784	N/A	21.05	53228
65	779	0.3070878	66045.064	5	0.4	52364
75	725	0.4824123	64616.464	85	8.41	53272
85	429	1.2390332	206209.072	N/A	22.65	53208
95	775	0.6181151	95940.288	385	20.8	53048
105	237	0.1414343	44906.904	N/A	20.51	53268
115	1153	2.8849482	571280.384	N/A	20.82	52880
125	2207	1.9307304	446417.984	N/A	20.41	53692
135	1935	5.3970906	467968.992	N/A	20.73	53652
145	2845	3.9961035	777228.416	N/A	21.06	53560
155	3067	13.6618017	2025940.864	N/A	21.08	53708
165	493	0.8841495	269999.168	N/A	20.11	54148
175	2245	13.6013149	1097147.648	N/A	21.01	54100
185	5325	26.767407	2554897.152	N/A	20.92	54132
195	7691	25.5085239	5052180.992	N/A	20.85	54504
205	7235	34.9948211	4563559.424	N/A	21.65	54196
215	2549	11.3362358	4005557.76	N/A	20.96	54712
225	1023	49.2342707	12712168.448	N/A	20.43	54900
235	8167	40.2563064	6696100.352	N/A	21.05	54856
245	6075	75.8756731	12245105.664	N/A	20.22	55404
255	8097	41.0211563	14666722.304	N/A	21.23	55688
265	9415	58.0503016	15315657.728	N/A	20.69	55872
275	10217	59.8128569	15368540.16	N/A	20.28	56248
285	3293	19.6668813	4052617.728	N/A	20.68	56504
295	11063	143.4064528	17374568.448	357	18.88	56752
305	12619	112.3534874	17285484.544	N/A	20.33	57380
315	2415	17.9483529	4523416.576	N/A	21.37	57380
325	13693	137.4000611	24939696.128	N/A	20.2	57716
335	2847	18.7191763	4038628.352	N/A	20.64	57848
345	6807	607.3551285	28047468.544	N/A	20.79	58004
355	10275	119.7228921	21051107.328	N/A	20.69	58088
365	N/A	N/A	N/A	N/A	21.01	58772
375	N/A	N/A	N/A	N/A	20.14	58944
385	N/A	N/A	N/A	N/A	20.83	59756
395	N/A	N/A	N/A	N/A	20.52	59384
405	N/A	N/A	N/A	N/A	20.9	59716
415	N/A	N/A	N/A	N/A	20.49	60272
425	N/A	N/A	N/A	N/A	21.09	60512
435	N/A	N/A	N/A	N/A	20.39	60264
445	N/A	N/A	N/A	N/A	20.65	60724
455	N/A	N/A	N/A	N/A	21.46	61720
465	N/A	N/A	N/A	N/A	20.5	61328
475	N/A	N/A	N/A	N/A	21.0	63628
485	N/A	N/A	N/A	N/A	21.07	63248
495	N/A	N/A	N/A	N/A	20.87	62624
505	N/A	N/A	N/A	N/A	20.81	62940



It can be seen from this figure that, when it successfully found a path, reinforcement learning was much quicker than CSP, following a time trend closer to $O(n)$. This is likely because the number of iterations is a constant, and actually if we look at the table we can see that the time spent trying to solve something is constant.

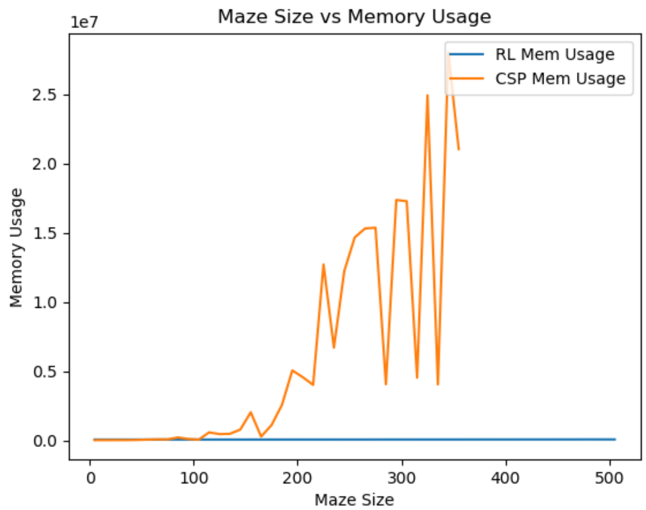
CSP, on the other hand, followed a polynomial curve, somewhat following a trend of $O(n^2)$. This makes sense because CSP uses DFS, which would be $O(|V|+|E|)$ where V is vertices (number of cells in the graph, which is n^2) and E is edges (which is more or less constant).



When the number of steps in the found path is shown on its own, however, it paints a much worse picture for the Q-learning algorithm. It was able to find a path from the start point to the goal in only a few of the maze sizes, whereas CSP (while eventually running out of memory) was able to find a path in every maze it was able to search.

It is suspected here that Q-learning often failed to find the goal in larger maze sizes due to its reward algorithm. As it proceeded through the maze and its step count for each iteration increased, it became less and less likely to perform the required 'random' movements that were not greedy to escape local optima. This lead to it getting stuck in long dead-end paths, where there is a much higher incentive for the algorithm to remain in the current state than move back out.

Different configurations of starting values were tested to try overcoming this problem, such as increasing alpha, gamma, epsilon, the maximum number of steps and the maximum number of iterations. However, none of these were capable of avoiding the issue faced. More max steps meant just more steps where the agent did not move, more iterations were ineffective as it behaved the same way each iteration, gamma was already at 0.99 so further increases were un-noticeable, and alpha and epsilon increases did nothing, likely because by the time the algorithm had reached a dead end the chance of backtracking was so low that it was effectively impossible to fix.



This graph shows the difference in memory usage between RL and CSP. This is to be expected, as DFS is an exhaustive search, which holds all of the current nodes for the path currently being checked in memory. While more memory efficient than BFS, it is still very memory hungry, but well-worth the results considering the performance of RL.

5 Conclusion

In testing for this report, it is clear that Q-learning does not perform as well as CSP for this task at such high maze sizes. It was consistently faster, less memory intensive and more accurate than CSP at smaller maze sizes, however the algorithm could not perform at higher maze sizes, failing to find paths at all.

It is advised that the reinforcement learning algorithm be adjusted to be dynamic (scaling the variables based on the maze size), and introducing a random restart algorithm to it. An alternative to random restart would be to just introduce a penalty for repeatedly entering the same states, or rewarding it for finding new ones. With these, it is potentially possible to keep an $O(n)$ time complexity solving the maze at larger mazes as well.

If a solution were to be required for deployment using identical configurations to those used in this report, it is recommended that Q-learning be used for smaller maze sizes (for example, below 50) and CSP be used for maze sizes that are larger.

References

[Pullen, 2015] Pullen, W. D. (2015). Maze classification. `http://www.astrolog.org/labyrnth/algrithm.htm`.