

Obtaining Approximately Admissible Heuristic Functions through Deep Reinforcement Learning and A* Search Forest Agostinelli, Stephen McAleer, Alexander Shmakov, Roy Fox, Marco Valtorta, Biplav Srivastava, Pierre Baldi



1	Abstract	3	Experiments	6	Effect of Subset Size
•	Deep reinforcement learning methods have been used to learn heuristic functions for A* search. These heuristic functions are not guaranteed to be admissible. We develop a domain agnostic method that corrects an inadmissible heuristic called approximately admissible conversion. On the 15-puzzle and 24-puzzle, our method produces a heuristic function that is empirically admissible in over	•	Using approximate value iteration, we train a deep neural network to be a heuristic function for the 15- puzzle and 24-puzzle. We find the cost of a shortest path for 1 million states from the 15-puzzle and compare it to the output of the adjusted heuristic function. We solve 500 test states for both the 15-puzzle and 24-puzzle and compare to the cost of a shortest path.	•	(a) Max overestimation (b) Percent inadmissible (c) Average heuristic value A larger subset decreases inadmissiblity while maintaining an informative heuristic.
	99.99% of cases and finds a shortest path for 100% of test cases.	4	Admissibility Results	7	Discussion
Ap inc on	Approximately Admissible Conversion proximately admissible conversion uses the fact that omplete runs of A* can be used to estimate a lower bound the cost of a shortest path (see paper for proof). The thod is as follows:	admis • •	X-axis: cost of a shortest path. Y-axis: Output of heuristic function. All points above the green line are inadmissible Before: 71.37% inadmissible After: 0.0019% inadmissible Heuristic is still highly correlated with the cost of a shortest path and thus informative.	•	Deep neural networks have the ability to learn informative heuristic functions in a domain-independent fashion. This can greatly increase the ease with which search methods such as A* search can be applied. Many real-world problems in fields such, as chemical synthesis, robotics, and quantum computing have connections to deep reinforcement learning and can benefit from shortest path solutions to increase efficiency and reduce resource consumption.
2. 3. 4.	a lower bound on the cost of a shortest path is initialized to zero for each state The inadmissible heuristic function is adjusted so that it does not overestimate the lower bound of any state in the subset A* search is then performed. A solution does not need to be found as the costs of expanded nodes are used to update the lower bound. This procedure then goes back to step 2 until the lower bounds stop increasing.	•	Shortest Path Results We use a batched version of A* search to take advantage of parallelism provided by GPUs. With approximate admissible conversion, a shortest path is found 100% of the time for both the 15- puzzle and 24-puzzle. Without it, the percentage of the time a shortest path is found can decrease by up to 31.5%.	8	References Agostinelli, F.; McAleer, S.; Shmakov, A.; and Baldi, P. 2019. Solving the Rubik's cube with deep reinforcement learning and search. Nature Machine Intelligence 1(8): 356–363. Bertsekas, D. P.; and Tsitsiklis, J. N. 1996. Neuro-dynamic programming. Athena Scientific. ISBN 1-886529-10-8. Harris, L. R. 1974. The heuristic search under conditions of error. Artificial Intelligence 5(3): 217–234. Hart, P. E.; Nilsson, N. J.; and Raphael, B. 1968. A formal basis for the heuristic determination of minimum cost paths. IEEE transactions on Systems Science and Cybernetics 4(2): 100–107. Zhang, YH.; Zheng, PL.; Zhang, Y.; and Deng, DL. 2020. Topological Quantum Compiling with Reinforcement Learning. Physical Review Letters 125(17): 170501.