

Introduction to Artificial Intelligence A* Search

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Best-First Search Review

- Advantages
 - Takes advantage of domain information to guide search
 - Greedy advance to the goal
- Disadvantages
 - Considers cost to the goal from the current state
 - Some path can continue to look good according to the heuristic function





The A* Algorithm

• Consider the overall cost of the solution.

f(n) = g(n) + h(n) where g(n) is the path cost to node n

think of f(n) as an estimate of the cost of the best solution *going through the node n*





The A* Algorithm

A*-Search(initial-test) ;; functions cost, h, succ, and GoalTest are defined open <- MakePriorityQueue(initial-state, NIL, 0, h(initial-state), h(initial-state)) ;; (state, parent, g, h, f) while (not(empty(open))) node pop(open), state node-state(node) closed
push (closed, node) if GoalTest(state) succeeds return node for each child in succ(state) new-cost ode-g(node) + cost(state,child) if child in open if new-cost < g value of child update(open, child, node, new-cost, h(child), new-cost+h(child)) elseif child in closed if new-cost < q value of child insert(open, child, node, new-cost, h(child), new-cost+h(child)) delete(closed,child) else open push(child, node, new-cost, h(child), new-cost+h(child)) return failure



A* Search: Example





A* Search : Example



Figure 4.4 Stages in an A* search for Bucharest. Nodes are labelled with f = g + h. The *h* values are the straight-line distances to Bucharest taken from Figure 4.1.



Admissible Heuristics

- we also require h be *admissible*:
 - a heuristic h is admissible if $h(n) < h^*(n)$ for all nodes n,
 - where h* is the actual cost of the optimal path from n to the goal
- Examples:
 - travel distance straight line distance must be shorter than actual travel path
 - tiles out of place each move can reorder at most one tile distance of each out of place tile from the correct place each move moves a tile at most one place toward correct place



Optimality of A*

- · Let us assume that f is non-decreasing along each path
 - if not, simply use parent's value
 - if that's the case, we can think of A* as expanding f contours toward the goal; better heuristics make this contour more "eccentric"
- Let G be an optimal goal state with path cost f*
- Let G_2 be a suboptimal goal state with path cost $g(G_2) > f^*$.
 - suppose A* picks G_2 before G (A* is *not* optimal)
 - suppose n is a leaf node on the path to G when G_2 is chosen
 - if h is admissible, then $f^* \ge f(n)$
 - since n was not chosen, it must be the case that $f(n) \ge f(G_2)$
 - therefore $f^* \ge f(G_2)$, but since G_2 is a goal, $h(G_2)=0$, so $f^* \ge g(G_2)$
 - But this is a contradiction --- G_2 is a better goal node than G
 - Thus, our supposition is false and A* is optimal.



Completeness of A*

- Suppose there is a goal state G with path cost f*
 - Intuitively: since A* expands nodes in order of increasing f, it must eventually expand node G
- If A* stops and fails
 - Prove by contradiction that this is impossible.
 - There exists a path from the initial state to the node state
 - Let n be the last node expanded along the solution path
 - n has at least one child, that child should be in the open nodes
 - A* does not stop until there are open list is empty (unless it finds a goal state). Contradiction.
- A* is on an infinite path
 - Recall that $cost(s1,s2) > \delta$
 - Let n be the last node expanded along the solution path
 - After $f(n)/\delta$ the cumulative cost of the path becomes large enough that A* will expand n. Contradiction.



UCS, BFS, Best-First, and A*

- f = g + h => A* Search
- h = 0 => Uniform cost search
- g = 1, h = 0 => Breadth-First search
- *g* = 0 => Best-First search



Road Map Problem







State contains 8 queens on the board

Successor function returns all states generated by moving a single queen to another square in the same column (8*7 = 56 next states)

h(s) = number of queens that attack each other in state s.





H(s) = 1



Heuristics : 8 Puzzle







• Reachable state : 9!/2 = 181,440

- Use of heuristics
 - h1 : # of tiles that are in the wrong position
 - h2 : sum of Manhattan distance

1	2	3
8	5	6
7		4

1	2	3
8		4
7	6	5



Effect of Heuristic Accuracy on Performance

- Well-designed heuristic have its branch close to 1
- $h_2 \text{ dominates } h_1 \text{ iff}$ $h_2(n) \ge h_1(n), \forall n$
- It is always better to use a heuristic function with higher values, as long as it does not overestimate
- Inventing heuristic functions
 - Cost of an exact solution to a relaxed problem is a good heuristic for the original problem
 - collection of admissible heuristics
 h*(n) = max(h₁(n), h₂(n), ..., h_k(n))



	Search Cost			Effective Branching Factor		
d	IDS	A*(h_1)	$\mathbf{A}^*(h_2)$	IDS	$A^{*}(h_{1})$	$A^{*}(h_{2})$
2	10	6	6	2.45	1.79	1.79
4	112	13	12	2.87	1.48	1.45
6	680	20	18	2.73	1.34	1.30
8	6384	39	25	2.80	1.33	1.24
10	47127	93	39	2.79	1.38	1.22
12	364404	227	73	2.78	1.42	1.24
14	3473941	539	113	2.83	1.44	1.23
16		1301	211	-	1.45	1.25
18	_	3056	363	-	1.46	1.26
20	_	7276	676	_	1.47	1.27
22	-	18094	1219	-	1.48	1.28
24	_	39135	1641	_	1.48	1.26

Figure 4.8 Comparison of the search costs and effective branching factors for the ITERATIVE-DEEPENING-SEARCH and A* algorithms with h_1 , h_2 . Data are averaged over 100 instances of the 8-puzzle, for various solution lengths.





- Completeness
 - provided finite branching factor and finite cost per operator
- Optimality
 - provided we use an admissible heuristic
- Time complexity
 - worst case is still O(b^d) in some special cases we can do better for a given heuristic
- Space complexity
 - worst case is still O(b^d)



Relax Optimality

- Goals:
 - Minimizing search cost
 - Satisficing solution, i.e. bounded error in the solution

$$f(s) = (1-w) g(s) + w h(s)$$

- g can be thought of as the breadth first component
- w = 1 => Best-First search
- $w = .5 => A^*$ search
- w = 0 => Uniform search



Iterative Deepening A*

- Goals
 - A storage efficient algorithm that we can use in practice
 - Still complete and optimal
- Modification of A*
 - use f-cost limit as depth bound
 - increase threshold as minimum of f(.) of previous cycle
- Each iteration expands all nodes inside the contour for current f-cost
- same order of node expansion



IDA* Algorithm

IDA* (state,h) returns solution f-limit <- h(state) loop do solution, f-limit □ DFS-Contour(state, f-limit) if solution is non-null return solution if f-limit = ∞ return failure

end

```
DFS-Contour (node,f-limit) returns solution

if f (node) > f-limit return null, f(node)

if GoalTest(node) return node, f-limit

next-f □ ∞

for each node s in succ(node) do

solution, new-f □ DFS-Contour(s, f-limit)

if solution is non-null return solution, f-limit

next-f □ Min(next-f, new-f)

end

return null, next-f
```



IDA* Properties

• Complete:

- if shortest path fits into memory

- Optimal:
 - if shortest optimal path fits into memory
- Time Complexity: O(b^{2d})
- Space Complexity: O(bd)



Mapquest

<u>http://www.mapquest.com/</u>

- MapQuest uses a "double Dijkstra" algorithm for its driving directions, working backward from both the starting and ending points at once. MapQuest uses a "double Dijkstra" algorithm for its driving directions, working backward from both the starting and ending points at once.
- the algorithm uses heuristic tricks to minimize the size of the graph that must be searched.