CS W4701 Artificial Intelligence

Fall 2013 Chapter 3 Part 4: Informed Search

Jonathan Voris (based on slides by Sal Stolfo)

Announcements

- Midterm: Thursday October 24 2:40-3:55 PM in Pupin 301
- Final: Thursday December 5th 2:40-3:55 PM in Pupin 301

Summary of Uninformed Search Algorithms

Criterion	Breadth- First	Uniform- Cost	Depth- First	Depth- Limited	lterative Deepening
Complete?	Yes	$\operatorname{Yes}_{O(h[C^*/\epsilon])}$	No	No	Yes
Time	$O(0^{\omega+1})$	$O(0^{10^{-7}})$	$O(0^m)$	$O(0^{\circ})$	$O(b^{\omega})$
Space	$O(b^{d+1})$	$O(b^{\lceil C^*/\epsilon \rceil})$	O(bm)	O(bl)	O(bd)
Optimal?	Yes	Yes	No	No	Yes

Outline

- Best-first search
 - Greedy best-first search
 - A^* search
- Heuristics

Recap: Tree Search

- Core concept:
 - Exploration of state space by generating successors of already-explored states (a.k.a. **expanding** states)

function TREE-SEARCH(problem, strategy) returns a solution, or failure
initialize the search tree using the initial state of problem
loop do
if there are no candidates for expansion then return failure
choose a leaf node for expansion according to strategy
if the node contains a goal state then return the corresponding solution
else expand the node and add the resulting nodes to the search tree

Smarter Search

- Uninformed search parameter selection: crude application of domain knowledge
 - Node ordering
 - Search strategy
- But still limited to:
 - Expand successors
 - Reached goal?
- What if we had a way to assess relative state quality?

Goal-based Agents



Utility-based Agents



Best-first Search

- Recall uniform-cost search
 - Expand node with lowest path cost function value g(n)
- New idea: use an evaluation function f(n) for each node
 - Estimate of "desirability"
 - Expand most desirable unexpanded node
- Implementation: Order the nodes in fringe in decreasing order of desirability
- Special cases:
 - Greedy best-first search
 - A^{*} search

Heuristics

- f(n) presents a chicken and egg problem
 - Need to know which state is closest to goal
 - If we know that, what is the point of the agent?
- Instead, utilize domain specific knowledge to estimate preferable states
- Known as a heuristic
 - Greek word heuriskein: "To discover"
 - Learning aid
 - Feedback that facilitates self learning
- h(goal) = 0 always

Greedy Best-first Search

- Evaluation function f(n) = h(n) (heuristic)
 Estimate of cost from n to goal
- e.g., h_{SLD}(n) = straight-line distance from n to Bucharest
- Greedy best-first search expands the node that appears to be closest to goal

Romania with Step Costs in km











Properties of Greedy Best-first Search

- <u>Complete?</u>
 - No Can get stuck in loops, e.g., lasi → Neamt → lasi → Neamt →...
- <u>Time?</u>
 - O(b^m), but a good heuristic can give dramatic improvement
- <u>Space?</u>
 - $-O(b^m)$ keeps all nodes in memory
- Optimal?

-No

A* Search

- Idea: Avoid expanding paths that are already expensive
- Evaluation function
 - f(n) = estimated cost of cheapest path through n - f(n) = g(n) + h(n)
- g(n) = cost so far to reach n
- h(n) = estimated cost from n to goal
- f(n) = estimated total cost of path through n to goal

Romania with Step Costs in km















- A heuristic h(n) is admissible if for every node n,
 h(n) ≤ h^{*}(n), where h^{*}(n) is the true cost to reach the goal state from n.
- An admissible heuristic never overestimates the cost to reach the goal, i.e., it is optimistic

- f(n) won't overestimate then either

- Example: *h*_{SLD}(*n*)
 - Never overestimates the actual road distance
- <u>Theorem</u>: If *h(n)* is admissible, A^{*} using TREE-SEARCH is optimal

Proof: Optimality of A*

Suppose some suboptimal goal G₂ has been generated and is in the fringe. Let n be an unexpanded node in the fringe such that n is on a shortest path to an optimal goal G.



- $g(G_2) > g(G)$
- $f(G_2) = g(G_2)$
- f(G) = g(G)
- $f(G_2) > f(G)$

since G_2 is suboptimal since $h(G_2) = 0$ since h(G) = 0from above

Proof: Optimality of A*

• Suppose some suboptimal goal G_2 has been generated and is in the fringe. Let *n* be an unexpanded node in the fringe such that *n* is on a shortest path to an optimal goal *G*.



Consistent Heuristics

- A heuristic is consistent if, for every node *n*, every successor *n*' of *n* generated by any action *a*:
 h(*n*) ≤ *c*(*n*,*a*,*n*') + *h*(*n*')
- Consistency means f(n) should not decrease along path



Consistent Heuristics

- **Theorem:** If *h(n)* is consistent, A*using GRAPH-SEARCH is optimal
- Assume h(n) is consistent
- f(n) along path is non-decreasing
- Mathematically speaking:
 - f(n') = g(n') + h(n')
 - = g(n) + c(n,a,n') + h(n')
 - \geq g(n) + h(n)
 - $\geq f(n)$
- Whenever n is expanded, we've found the best path to n
 - Otherwise we would've followed the better path first
- Thus all nodes expanded in non-decreasing order of f(n)
- f(goal) = g(goal)
 - Because f(goal) = g(goal) + h(goal) and h(goal) = 0
- First goal node expanded must be therefore be least expensive goal

Admissibility and Consistency

- Consistency is stricter than admissibility
 - All consistent heuristics are admissible
 - Not all admissible heuristics are consistent



Optimality of A*

- A^{*} expands nodes in order of increasing *f* value
- Gradually adds "f-contours" of nodes
- Contour *i* has all nodes with $f=f_i$, where $f_i < f_{i+1}$



Properties of A*

- <u>Complete?</u>
 - Yes (unless there are infinitely many nodes with f(n) ≤ optimal solution cost C*)
- <u>Time?</u>
 - Exponential
 - $O(b^{(h^*-h)})$
- <u>Space?</u>
 - Keeps all nodes in memory
- Optimal?
 - Yes
 - Also optimally efficient
 - Expanding fewer nodes may miss optimal solution

E.g., for the 8-puzzle:

- $h_1(n)$ = number of misplaced tiles
- $h_2(n)$ = total Manhattan distance

(i.e., no. of squares from desired location of each tile)



Start State





• $h_2(S) = ?$

Goal State

E.g., for the 8-puzzle:

- $h_1(n)$ = number of misplaced tiles
- $h_2(n)$ = total Manhattan distance

(i.e., no. of squares from desired location of each tile)



Start State





• $h_2(S) = ?$

Goal State

E.g., for the 8-puzzle:

- $h_1(n)$ = number of misplaced tiles
- $h_2(n)$ = total Manhattan distance

(i.e., no. of squares from desired location of each tile)





- $h_1(S) = 8$ Start State
- $h_2(S) = 3+1+2+2+3+3+2 = 18$

Dominance

- If $h_2(n) \ge h_1(n)$ for all *n* (both admissible)
- then h_2 dominates h_1
- h_2 is better for search
- Typical search costs (average number of nodes expanded) over 100 8-puzzle instances:
- d=12
 - IDS = 364,404 nodes
 - $A^{*}(h_{1}) = 227 \text{ nodes}$
 - $A^*(h_2) = 73$ nodes
- d=24
 - IDS = too many nodes
 - $A^{*}(h_{1}) = 39,135 \text{ nodes}$
 - $A^*(h_2) = 1,641 \text{ nodes}$

Relaxed Problems

- A problem with fewer restrictions on the actions is called a **relaxed problem**
- The cost of an optimal solution to a relaxed problem is an admissible heuristic for the original problem
- If the rules of the 8-puzzle are relaxed so that a tile can move anywhere, then h₁(n) gives the shortest solution
- If the rules are relaxed so that a tile can move to any adjacent square, then h₂(n) gives the shortest solution

Summary

- Heuristic functions estimate costs of shortest paths
- Good heuristics can dramatically reduce search cost
- Greedy best-first search expands lowest h
 - incomplete and not always optimal
- A* search expands lowest *g* + *h*
 - Complete
 - Optimal
 - Also optimally efficient (up to tie-breaks, for forward search)
 - Can't explore fewer nodes due to risk of missing optimal solution
- Admissible heuristics can be derived from exact solution of relaxed problems