Informed search algorithms

CHAPTER 4, SECTIONS 1–2, 4

Outline

◇ Best-first search

◇ A* search

◇ Heuristics

◇ Hill-climbing

◇ Simulated annealing

Review: General search

```
function GENERAL-SEARCH( problem, QUEUING-FN) returns a solution, or failure
   nodes ← MAKE-QUEUE(MAKE-NODE(INITIAL-STATE[problem]))
   loop do
      if nodes is empty then return failure
      node ← REMOVE-FRONT(nodes)
      if GOAL-TEST[problem] applied to STATE(node) succeeds then return node
      nodes ← QUEUING-FN(nodes, EXPAND(node, OPERATORS[problem]))
   end
```

A strategy is defined by picking the *order of node expansion*

Best-first search

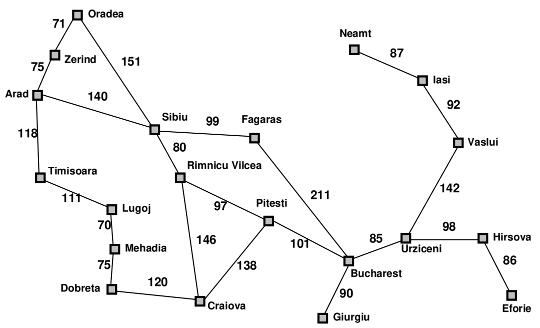
Idea: use an *evaluation function* for each node
– estimate of "desirability"

⇒ Expand most desirable unexpanded node

Implementation:
QUEUEINGFN = insert successors in decreasing order of desirability

Special cases:
greedy search
A* search

Romania with step costs in km



Straight–line distance to Bucharest	
Arad	366
Bucharest	0
Craiova	160
Dobreta	242
Eforie	161
Fagaras	178
Giurgiu	77
Hirsova	151
Iasi	226
Lugoj	244
Mehadia	241
Neamt	234
Oradea	380
Pitesti	98
Rimnicu Vilcea	193
Sibiu	253
Timisoara	329
Urziceni	80
Vaslui	199
Zerind	374

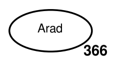
Greedy search

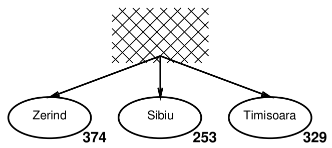
Evaluation function $h(n)$ (heuristic)
= estimate of cost from n to *goal*

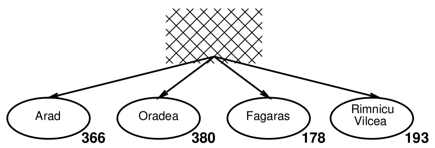
E.g., $h_{\mathrm{SLD}}(n)$ = straight-line distance from n to Bucharest

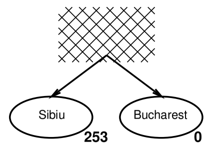
Greedy search expands the node that *appears* to be closest to goal

Greedy search example









Properties of greedy search

Complete??

Time??

Space??

Optimal??

Properties of greedy search

Complete?? No–can get stuck in loops, e.g.,
Iasi $\rightarrow$ Neamt $\rightarrow$ Iasi $\rightarrow$ Neamt $\rightarrow$
Complete in finite space with repeated-state checking

Time?? $O(b^m)$, but a good heuristic can give dramatic improvement

Space?? $O(b^m)$—keeps all nodes in memory

Optimal?? No

A* search

Idea: avoid expanding paths that are already expensive

Evaluation function $f(n) = g(n) + h(n)$

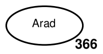
$g(n)$ = cost so far to reach n
$h(n)$ = estimated cost to goal from n
$f(n)$ = estimated total cost of path through n to goal

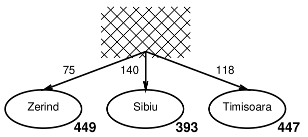
A* search uses an *admissible* heuristic
i.e., $h(n) \leq h^*(n)$ where $h^*(n)$ is the *true* cost from n.

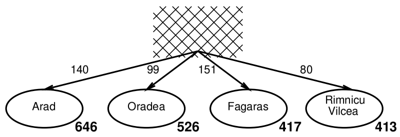
E.g., $h_{\mathrm{SLD}}(n)$ never overestimates the actual road distance

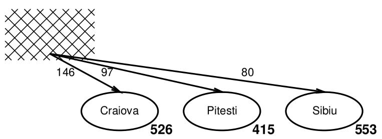
Theorem: A* search is optimal

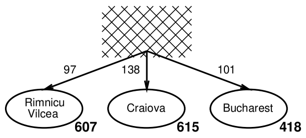
A* search example

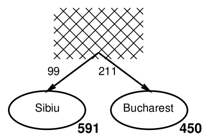






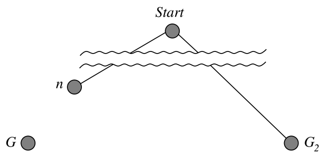






Optimality of A* (standard proof)

Suppose some suboptimal goal G_2 has been generated and is in the queue. Let n be an unexpanded node on a shortest path to an optimal goal G_1.



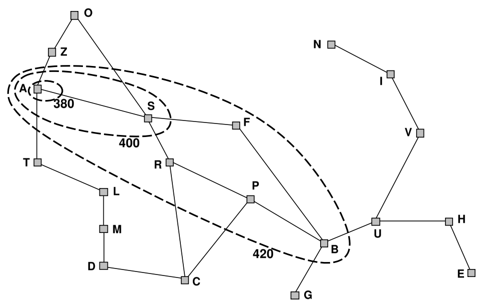
$$\begin{aligned} f(G_2) &= g(G_2) && \text{since } h(G_2)=0 \\ &> g(G_1) && \text{since } G_2 \text{ is suboptimal} \\ &\geq f(n) && \text{since } h \text{ is admissible} \end{aligned}$$

Since $f(G_2) > f(n)$, A* will never select G_2 for expansion

Optimality of A* (more useful)

Lemma: A* expands nodes in order of increasing f value

Gradually adds "f-contours" of nodes (cf. breadth-first adds layers)
Contour i has all nodes with $f = f_i$, where $f_i < f_{i+1}$



Properties of A*

Complete?? Yes, unless there are infinitely many nodes with $f \leq f(G)$

Time?? Exponential in [relative error in h × length of soln.]

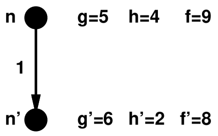
Space?? Keeps all nodes in memory

Optimal?? Yes—cannot expand f_{i+1} until f_i is finished

Proof of lemma: Pathmax

For some admissible heuristics, f may *decrease* along a path

E.g., suppose n' is a successor of n



But this throws away information!
$f(n) = 9 \Rightarrow$ true cost of a path through n is ≥ 9
Hence true cost of a path through n' is ≥ 9 also

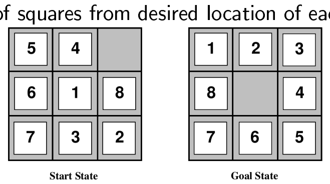
Pathmax modification to A*:
Instead of $f(n') = g(n') + h(n')$, use $f(n') = max(g(n') + h(n'), f(n))$

With pathmax, f is always nondecreasing along any path

Admissible heuristics

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)



$h_1(S) =$??
$h_2(S) =$??

Admissible heuristics

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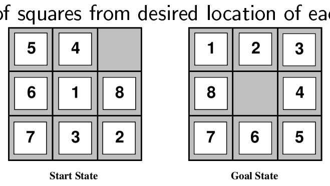


$h_1(S) =$?? 7
$h_2(S) =$?? 2+3+3+2+4+2+0+2 = 18

Dominance

If $h_2(n) \geq h_1(n)$ for all n (both admissible)
then h_2 *dominates* h_1 and is better for search

Typical search costs:

$d = 14$ IDS = 3,473,941 nodes
A$^*(h_1)$ = 539 nodes
A$^*(h_2)$ = 113 nodes
$d = 14$ IDS = too many nodes
A$^*(h_1)$ = 39,135 nodes
A$^*(h_2)$ = 1,641 nodes

Relaxed problems

Admissible heuristics can be derived from the *exact* solution cost of a *relaxed* version of the problem

If the rules of the 8-puzzle are relaxed so that a tile can move *anywhere*, then $h_1(n)$ gives the shortest solution

If the rules are relaxed so that a tile can move to *any adjacent square*, then $h_2(n)$ gives the shortest solution

For TSP: let path be *any* structure that connects all cities
$\Longrightarrow$ minimum spanning tree heuristic

Iterative improvement algorithms

In many optimization problems, *path* is irrelevant;
the goal state itself is the solution

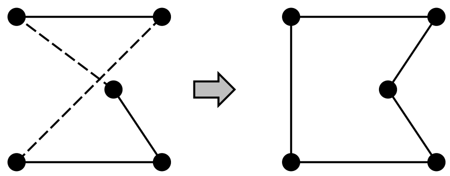
Then state space = set of "complete" configurations;
find *optimal* configuration, e.g., TSP
or, find configuration satisfying constraints, e.g., n-queens

In such cases, can use *iterative improvement* algorithms;
keep a single "current" state, try to improve it

Constant space, suitable for online as well as offline search

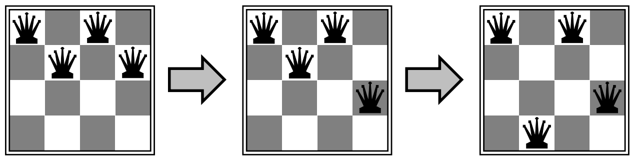
Example: Travelling Salesperson Problem

Find the shortest tour that visits each city exactly once



Example: n-queens

Put n queens on an $n \times n$ board with no two queens on the same row, column, or diagonal



Hill-climbing (or gradient ascent/descent)

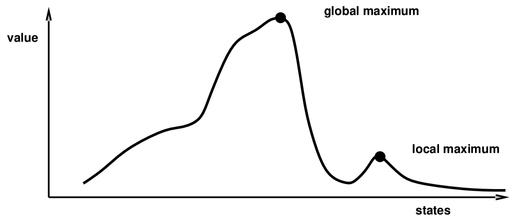
"Like climbing Everest in thick fog with amnesia"

```
function Hill-Climbing( problem) returns a solution state
   inputs: problem, a problem
   local variables: current, a node
                    next, a node

   current ← Make-Node(Initial-State[problem])
   loop do
      next ← a highest-valued successor of current
      if Value[next] < Value[current] then return current
      current ← next
   end
```


Hill-climbing contd.

Problem: depending on initial state, can get stuck on local maxima



Simulated annealing

Idea: escape local maxima by allowing some "bad" moves
but gradually decrease their size and frequency

```
function Simulated-Annealing( problem, schedule) returns a solution state
   inputs: problem, a problem
        schedule, a mapping from time to "temperature"
   local variables: current, a node
                    next, a node
                    T, a "temperature" controlling the probability of downward steps

   current ← Make-Node(Initial-State[problem])
   for t ← 1 to ∞ do
      T ← schedule[t]
      if T=0 then return current
      next ← a randomly selected successor of current
      ΔE ← Value[next] – Value[current]
      if ΔE > 0 then current ← next
      else current ← next only with probability e^(ΔE/T)
```


Properties of simulated annealing

At fixed "temperature" T, state occupation probability reaches Boltzman distribution

$$p(x) = \alpha e^{\frac{E(x)}{kT}}$$

T decreased slowly enough $\Longrightarrow$ always reach best state

Is this necessarily an interesting guarantee??

Devised by Metropolis et al., 1953, for physical process modelling

Widely used in VLSI layout, airline scheduling, etc.