Problem solving and search

Chapter 3

Artificial Intelligence





Slides from AIMA — http://aima.cs.berkeley.edu

Outline

- ► Problem-solving agents
- ► Problem types
- Problem formulation
- ► Example problems
- ► Basic search algorithms
- ► Informed search algorithms

Problem-solving agents

Restricted form of general agent:

```
function SIMPLE-PROBLEM-SOLVING-AGENT (percept) returns an action
   static: seq, an action sequence, initially empty
          state, some description of the current world state
          goal, a goal, initially null
          problem, a problem formulation
   state ← Update-State(state, percept)
   if seq is empty then
       goal ← Formulate-Goal(state)
       problem ← Formulate-Problem(state, goal)
       seg \leftarrow Search(problem)
   action ← Recommendation(seq, state)
   seq \leftarrow Remainder(seq, state)
   return action
```

Note: this is offline problem solving; solution executed "eyes closed." Online problem solving involves acting without complete knowledge.

Example: Romania

On holiday in Romania; currently in Arad. Flight leaves tomorrow from Bucharest

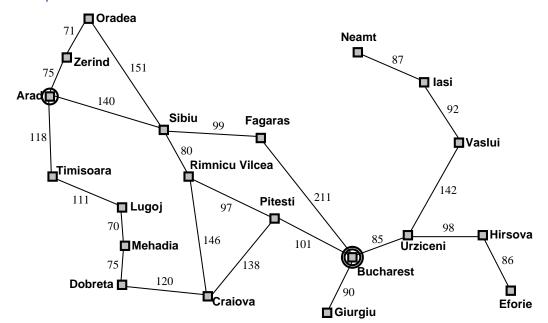
► Formulate goal: be in Bucharest

> states: various cities

actions: drive between cities

Find solution: sequence of cities, e.g., Arad, Sibiu, Fagaras, Bucharest

Example: Romania



Problem types

- ► Deterministic, fully observable ⇒ single-state problem
 - Agent knows exactly which state it will be in; solution is a sequence
- ► Non-observable ⇒ conformant problem
 - Agent may have no idea where it is; solution (if any) is a sequence
- ► Nondeterministic and/or partially observable ⇒ contingency problem
 - percepts provide new information about current state
 - solution is a contingent plan or a policy
 - often interleave search, execution
- ▶ Unknown state space ⇒ exploration problem ("online")

Single-state, start in #5. Solution??

```
Single-state, start in #5. Solution?? [Right, Suck] Conformant, start in \{1, 2, 3, 4, 5, 6, 7, 8\} e.g., Right goes to \{2, 4, 6, 8\}. Solution??
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Conformant, start in {1, 2, 3, 4, 5, 6, 7, 8}
e.g., Right goes to {2, 4, 6, 8}. Solution??
[Right, Suck, Left, Suck]
Contingency, start in #5
Murphy's Law: Suck can dirty a clean carpet
Local sensing: dirt, location only.
Solution??
```

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Single-state, start in #5. Solution?? [Right, Suck]
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[Right, Suck, Left, Suck]
Contingency, start in #5
Murphy's Law: Suck can dirty a clean carpet Local sensing: dirt, location only.
Solution??
[Right, if dirt then Suck]
```

Single-state problem formulation

A problem is defined by four items:

- ▶ initial state e.g., "at Arad"
- ▶ successor function S(x) = set of action–state pairs e.g., $S(Arad) = \{\langle Arad \rightarrow Zerind, Zerind \rangle, \ldots \}$
- goal test, can be
 - explicit, e.g., x = "at Bucharest"
 - ▶ implicit, e.g., NoDirt(x)
- ▶ path cost (additive) e.g., sum of distances, number of actions executed, etc. c(x, a, y) is the step cost, assumed to be ≥ 0

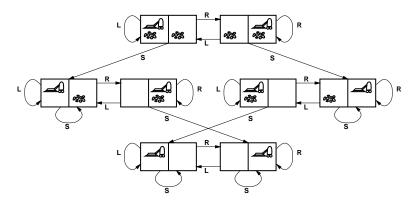
A solution is a sequence of actions leading from the initial state to a goal state

Selecting a state space

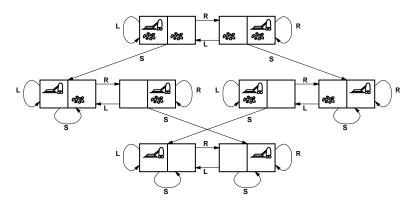
Real world is absurdly complex

- ⇒ state space must be **abstracted** for problem solving
 - ► (Abstract) state = set of real states
 - ► (Abstract) action = complex combination of real actions e.g., "Arad → Zerind" represents a complex set of possible routes, detours, rest stops, etc. For guaranteed realizability, any real state "in Arad" must get to some real state "in Zerind"
 - ► (Abstract) solution = set of real paths that are solutions in the real world

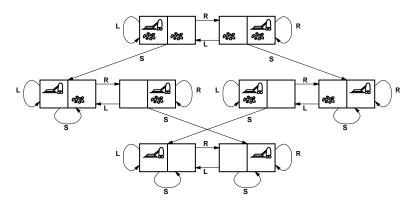
Each abstract action should be "easier" than the original problem!



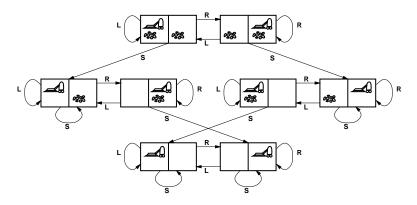
- ► states??:
- <u>actions</u>??:
- ▶ goal test??:
- path cost??:



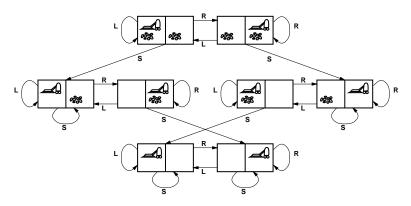
- <u>states??</u>: integer dirt and robot locations (ignore dirt amounts etc.)
- actions??:
- ▶ goal test??:
- path cost??:



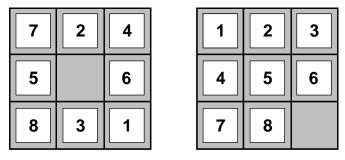
- ▶ <u>states</u>??: integer dirt and robot locations (ignore dirt amounts etc.)
- ▶ <u>actions</u>??: *Left*, *Right*, *Suck*, *NoOp*
- goal test??:
- path cost??:



- ▶ <u>states</u>??: integer dirt and robot locations (ignore dirt amounts etc.)
- ▶ <u>actions</u>??: *Left*, *Right*, *Suck*, *NoOp*
- goal test??: no dirt
- path cost??:



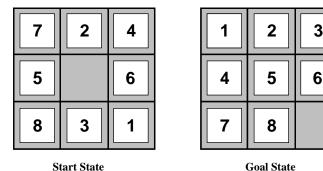
- <u>states??</u>: integer dirt and robot locations (ignore dirt amounts etc.)
- ▶ <u>actions</u>??: *Left*, *Right*, *Suck*, *NoOp*
- goal test??: no dirt
- ▶ path cost??: 1 per action (0 for NoOp)



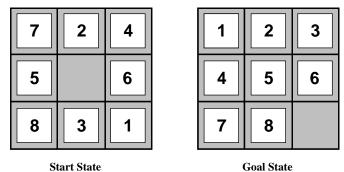
Goal State

Start State

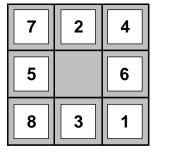
- ► <u>states</u>??:
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- ▶ path cost??:

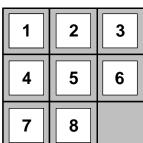


- ▶ <u>states</u>??: integer locations of tiles (ignore intermediate positions)
- ► actions??:
- ▶ goal test??:
- ▶ path cost??:



- **Goal State**
- states??: integer locations of tiles (ignore intermediate positions)
- <u>actions??</u>: move blank left, right, up, down (ignore unjamming etc.)
- ▶ goal test??:
- ▶ path cost??:

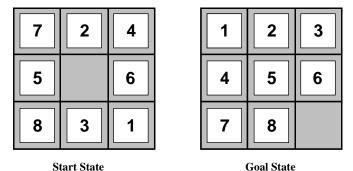




Start State

Goal State

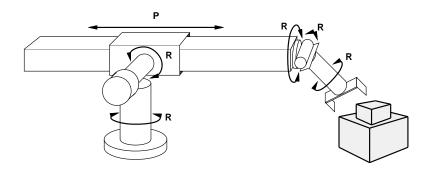
- <u>states??</u>: integer locations of tiles (ignore intermediate positions)
- ▶ <u>actions</u>??: move blank left, right, up, down (ignore unjamming etc.)
- ▶ goal test??: = goal state (given)
- path cost??:



- <u>states??</u>: integer locations of tiles (ignore intermediate positions)
- <u>actions??</u>: move blank left, right, up, down (ignore unjamming etc.)
- goal test??: = goal state (given)
- ▶ path cost??: 1 per move

[Note: optimal solution of *n*-Puzzle family is NP-hard]

Example: robotic assembly



- <u>states??</u>: real-valued coordinates of robot joint angles parts of the object to be assembled
- <u>actions</u>??: continuous motions of robot joints
- goal test??: complete assembly with no robot included!
- **path** cost??: time to execute

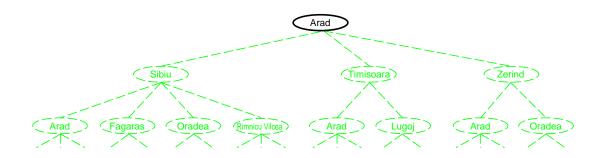
Tree search algorithms

Basic idea: offline, simulated exploration of state space by generating successors of already-explored states (a.k.a. expanding states)

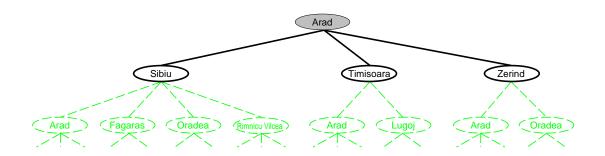
```
function TREE-SEARCH( problem, strategy) returns a solution, or failure initialize the search tree using the initial state of problem loop do

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 end
```

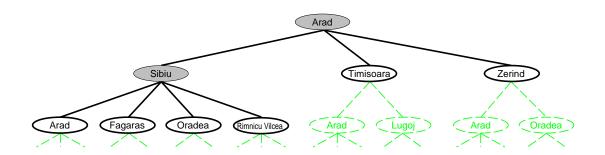
Tree search example



Tree search example



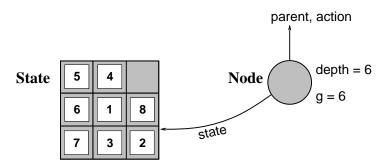
Tree search example



Implementation: states vs. nodes

- ▶ A state is a (representation of) a physical configuration
- A node is a data structure constituting part of a search tree includes parent, children, depth, path cost g(x)

States do not have parents, children, depth, or path cost!



The Expand function creates new nodes, filling in the various fields and using the SuccessorFn of the problem to create the corresponding states

Implementation: general tree search

loop do

function Tree-Search(problem, fringe) returns a solution, or failure
fringe ← Insert(Make-Node(Initial-State[problem]), fringe)

```
if fringe is empty then return failure
    node ← Remove-Front(fringe)
if Goal-Test(problem, State(node)) then return node
    fringe ← InsertAll(Expand(node, problem), fringe)

function Expand(node, problem) returns a set of nodes
    successors ← the empty set
    for each action, result in Successor-Fn(problem, State[node]) do
        s ← a new Node
    Parent-Node[s] ← node; Action[s] ← action; State[s] ← result
    Path-Cost[s] ← Path-Cost[node] + Step-Cost(State[node], action, result)
    Depth[s] ← Depth[node] + 1
        add s to successors
    return successors
```

Search strategies

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

Strategies are evaluated along the following dimensions:

completeness: does it always find a solution if one exists? time complexity: number of nodes generated/expanded space complexity: maximum number of nodes in memory optimality: does it always find a least-cost solution?

Time and space complexity are measured in terms of

 \emph{b} : maximum branching factor of the search tree

d: depth of the least-cost solution

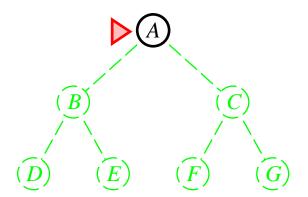
m: maximum depth of the state space (may be ∞)

Uninformed search strategies

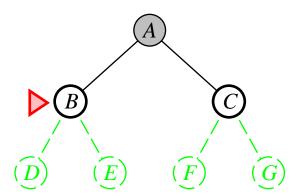
Uninformed strategies use only the information available in the problem definition

- ▶ Breadth-first search
- Uniform-cost search
- ► Depth-first search
- ► Depth-limited search
- ► Iterative deepening search

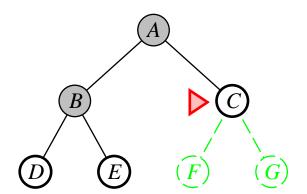
Expand shallowest unexpanded node



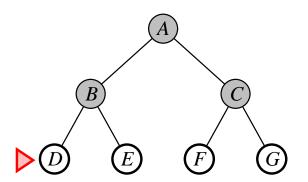
Expand shallowest unexpanded node



Expand shallowest unexpanded node



Expand shallowest unexpanded node



Properties of breadth-first search

► Complete??

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- ► <u>Time</u>??

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- ► Optimal??

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- ▶ Space?? $O(b^{d+1})$ (keeps every node in memory)
- ▶ Optimal?? Yes (if cost = 1 per step); not optimal in general

Space is the big problem; can easily generate nodes at 100MB/sec so 24hrs = 8640GB.

Uniform-cost search

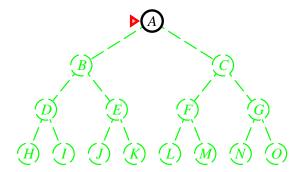
Expand least-cost unexpanded node

Implementation: fringe = queue ordered by path cost, lowest first

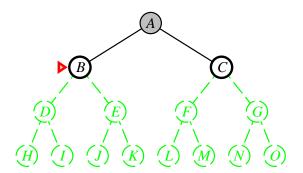
Equivalent to breadth-first if step costs all equal

- ▶ Complete?? Yes, if step cost $\geq \epsilon$
- ▶ <u>Time</u>?? # of nodes with $g \le \text{cost}$ of optimal solution, $O(b^{\lceil C^*/\epsilon \rceil})$ where C^* is the cost of the optimal solution
- ▶ Space?? # of nodes with $g \leq \text{cost of optimal solution, } O(b^{\lceil C^*/\epsilon \rceil})$
- ▶ Optimal?? Yes—nodes expanded in increasing order of g(n)

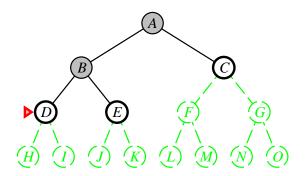
Expand deepest unexpanded node



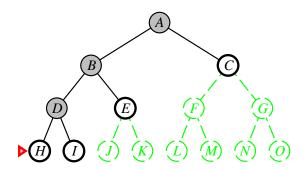
Expand deepest unexpanded node



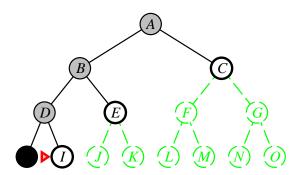
Expand deepest unexpanded node



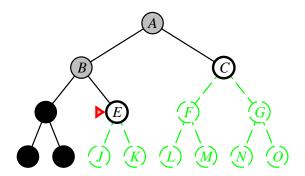
Expand deepest unexpanded node



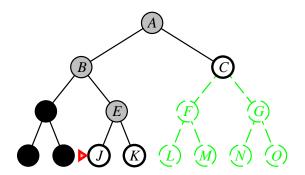
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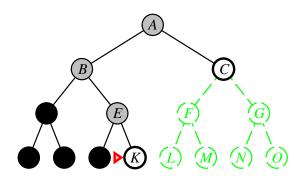
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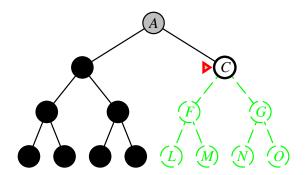
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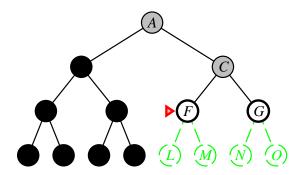
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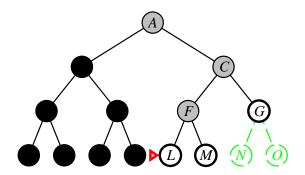
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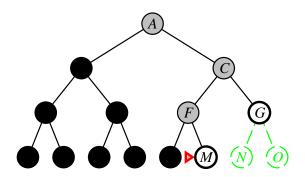
Expand deepest unexpanded node



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► Complete??

 Complete?? No: fails in infinite-depth spaces, spaces with loops Modify to avoid repeated states along path
 ⇒ complete in finite spaces

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- ► Time??

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- ▶ Time?? $O(b^m)$: terrible if m is much larger than d but if solutions are dense, may be much faster than breadth-first
- ▶ Space?? O(bm), i.e., linear space!

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- ▶ $\underline{\mathsf{Space}}$?? O(bm), i.e., linear space!
- ► Optimal?? No

Depth-limited search

= depth-first search with depth limit /, i.e., nodes at depth / have no successors

Recursive implementation:

```
function Depth-Limited-Search (problem, limit) returns soln/fail/cutoff Recursive-DLS (Make-Node (Initial-State [problem]), problem, limit) function Recursive-DLS (node, problem, limit) returns soln/fail/cutoff cutoff-occurred? ← false if Goal-Test (problem, State [node]) then return node else if Depth[node] = limit then return cutoff else for each successor in Expand (node, problem) do result ← Recursive-DLS (successor, problem, limit) if result = cutoff then cutoff-occurred? ← true else if result ≠ failure then return result if cutoff-occurred? then return cutoff else return failure
```

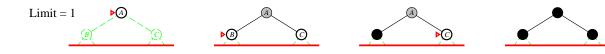
Iterative deepening search

```
function Iterative-Deepening-Search (problem) returns a solution inputs: problem, a problem  \begin{aligned} &\text{for } \textit{depth} \leftarrow \text{ 0 to } \infty \text{ do} \\ &\textit{result} \leftarrow \text{Depth-Limited-Search} (\textit{problem, depth}) \\ &\text{if } \textit{result} \neq \text{cutoff then return } \textit{result} \\ &\text{end} \end{aligned}
```

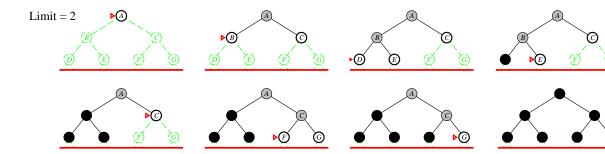
Iterative deepening search l = 0

Limit = 0

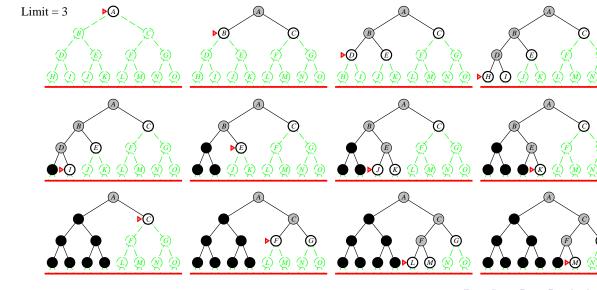
Iterative deepening search l = 1



Iterative deepening search l=2



Iterative deepening search l = 3



Properties of iterative deepening search

► Complete??

Properties of iterative deepening search

► Complete?? Yes

- ► Complete?? Yes
- ► <u>Time</u>??

- ► Complete?? Yes
- ► <u>Time</u>?? $(d+1)b^0 + db^1 + (d-1)b^2 + ... + b^d = O(b^d)$

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- ► Space??

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- ► <u>Time</u>?? $(d+1)b^0 + db^1 + (d-1)b^2 + ... + b^d = O(b^d)$
- ► <u>Space</u>?? *O*(*bd*)

- ► Complete?? Yes
- ► <u>Time</u>?? $(d+1)b^0 + db^1 + (d-1)b^2 + ... + b^d = O(b^d)$
- ► Space?? O(bd)
- ► Optimal??

- ► Complete?? Yes
- ► <u>Time</u>?? $(d+1)b^0 + db^1 + (d-1)b^2 + ... + b^d = O(b^d)$
- ► Space?? O(bd)
- Optimal?? Yes, if step cost = 1Can be modified to explore uniform-cost tree

Numerical comparison for b = 10 and d = 5, solution at far right leaf:

$$N(IDS) = 50 + 400 + 3,000 + 20,000 + 100,000 = 123,450$$

 $N(BFS) = 10 + 100 + 1,000 + 10,000 + 100,000 + 999,990 = 1,111,100$

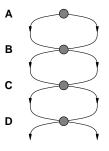
- \triangleright IDS does better because other nodes at depth d are not expanded
- ▶ BFS can be modified to apply goal test when a node is **generated**

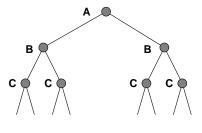
Summary of algorithms

Criterion	Breadth-	Uniform-	Depth-	Depth-	Iterative
	First	Cost	First	Limited	Deepening
Complete? Time Space Optimal?	Yes* b^{d+1} b^{d+1} Yes*	Yes* $b^{\lceil C^*/\epsilon \rceil}$ $b^{\lceil C^*/\epsilon \rceil}$ Yes	No b ^m bm No	Yes, if $l \ge d$ b^l No	Yes b ^d bd Yes*

Repeated states

Failure to detect repeated states can turn a linear problem into an exponential one!





Graph search

```
function GRAPH-SEARCH (problem, fringe) returns a solution, or failure
   closed ← an empty set
   fringe \leftarrow Insert(Make-Node(Initial-State[problem]), fringe)
   loop do
       if fringe is empty then return failure
       node \leftarrow Remove-Front(fringe)
       if Goal-Test(problem, State[node]) then return node
       if State[node] is not in closed then
            add STATE[node] to closed
            fringe \leftarrow InsertAll(Expand(node, problem), fringe)
   end
```

Summary

- ▶ Problem formulation usually requires abstracting away real-world details to define a state space that can feasibly be explored
- Variety of uninformed search strategies
- Iterative deepening search uses only linear space and not much more time than other uninformed algorithms
- Graph search can be exponentially more efficient than tree search

Informed Search Algorithms

- ► Best-first search
- ► A* search
- ► Heuristics

Review: Tree search

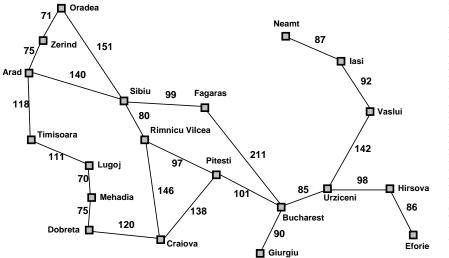
```
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  fringe ← Insert(Make-Node(Initial-State[problem]), fringe)
  loop do
    if fringe is empty then return failure
        node ← Remove-Front(fringe)
    if Goal-Test[problem] applied to State(node) succeeds return node
        fringe ← InsertAll(Expand(node, problem), fringe)
```

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: *fringe* is a queue sorted in decreasing order of desirability
- Special cases:
 - greedy search
 - ► A* search

Romania with step costs in km



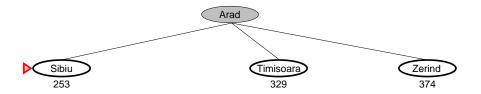
Straight-line distance to Bucharest

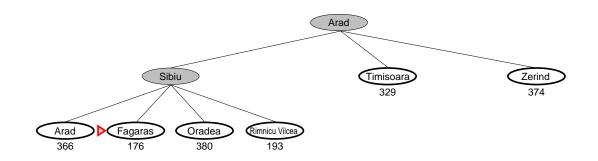
366
0
160
242
161
178
77
151
226
244
241
234
380
98
193
253
329
80
199
374

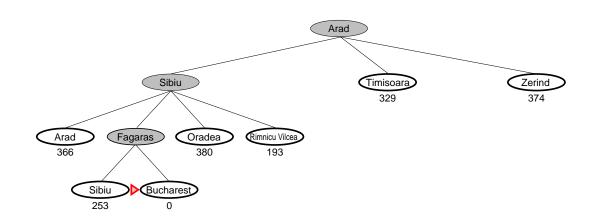
Greedy search

- ▶ Evaluation function h(n) (heuristic)
 - = estimate of cost from n to the closest goal
 - ▶ E.g., $h_{SLD}(n)$ = straight-line distance from n to Bucharest
- Greedy search expands the node that appears to be closest to goal









► Complete??

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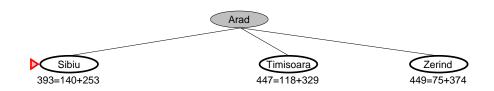
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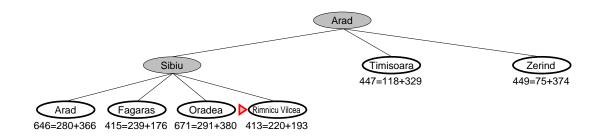
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- ► Optimal?? No

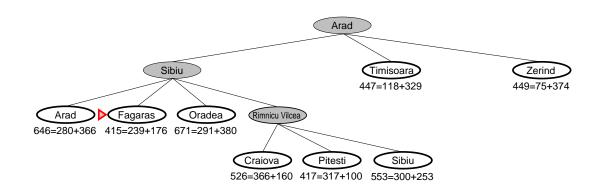
A* search

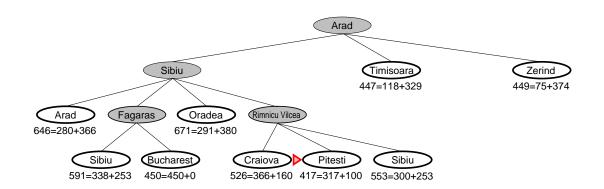
- Idea: avoid expanding paths that are already expensive
- ▶ Evaluation function f(n) = g(n) + h(n)
 - g(n) = cost so far to reach n h(n) = estimated cost to goal from n f(n) = estimated total cost of path through n to goal
- A* search uses an admissible heuristic i.e., $h(n) \le h^*(n)$ where $h^*(n)$ is the **true** cost from n. (Also require $h(n) \ge 0$, so h(G) = 0 for any goal G.)
 - ▶ E.g., $h_{SLD}(n)$ never overestimates the actual road distance
- ► Theorem: A* search is optimal

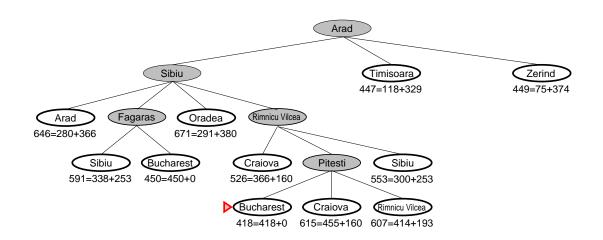






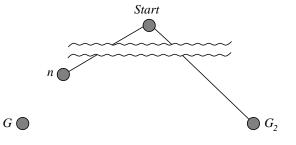






Optimality of A* (standard proof)

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 .



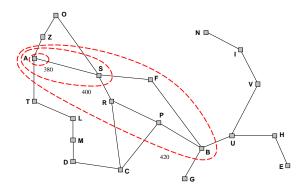
$$f(G_2) = g(G_2)$$
 since $h(G_2) = 0$
> $g(G_1)$ since G_2 is suboptimal
 $\geq f(n)$ since h is admissible

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 $f_i < f_{i+1}$



- ► Complete??
- ► <u>Time</u>??
- ► Space??
- ► Optimal??

- ▶ Complete?? Yes, unless there are infinitely many nodes with $f \leq f(G)$
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 - A* expands all nodes with $f(n) < C^*$
 - A* expands some nodes with $f(n) = C^*$
 - A* expands no nodes with $f(n) > C^*$

Proof of lemma: Consistency

A heuristic is consistent if

$$h(n) \le c(n, a, n') + h(n')$$

If *h* is consistent, we have

$$f(n') = g(n') + h(n')$$

$$= g(n) + c(n, a, n') + h(n')$$

$$\geq g(n) + h(n)$$

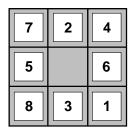
$$= f(n)$$

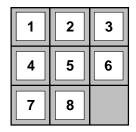
I.e., f(n) is nondecreasing along any path.

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)





Start State

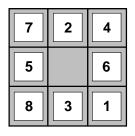
Goal State

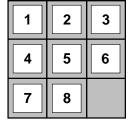
$$\frac{h_1(S)}{h_2(S)} = ??$$

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Start State

Goal State

$$\frac{h_1(S)}{h_2(S)} = ??$$
 6
 $\frac{h_1(S)}{h_2(S)} = ??$ 4+0+3+3+1+0+2+1 = 14

Dominance

If $h_2(n) \ge h_1(n)$ 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
 $d = 24$ IDS $\approx 54,000,000,000$ nodes
 $A^*(h_1) = 39,135$ nodes
 $A^*(h_2) = 1,641$ nodes

Given any admissible heuristics h_a , h_b ,

$$h(n) = \max(h_a(n), h_b(n))$$

is also admissible and dominates h_a , h_b

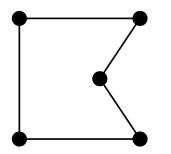


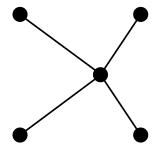
Relaxed problems

- ► 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
- Key point: the optimal solution cost of a relaxed problem is no greater than the optimal solution cost of the real problem

Relaxed problems contd.

Well-known example: travelling salesperson problem (TSP) Find the shortest tour visiting all cities exactly once





Minimum spanning tree can be computed in $O(n^2)$ and is a lower bound on the shortest (open) tour

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
- ightharpoonup A* search expands lowest g + h
 - complete and optimal
 - also optimally efficient (up to tie-breaks, for forward search)
- ▶ Admissible heuristics can be derived from exact solution of relaxed problems