INTRODUCTION TO ARTIFICIAL INTELLIGENCE LECTURE 3: INFORMED SEARCH

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Problem solving by searching

Problem solving is an essential part of intelligence.

Problem solving can be represented as a search strategy.

Uniformed searching is **blindly** following transitions from states to states.

Informed search uses extra information in making choices of transitions.

This information is given in the form of **heuristic function**.

RECAP: SEARCH PROBLEMS FORMALLY

Formally, a search problem consists of the following elements:

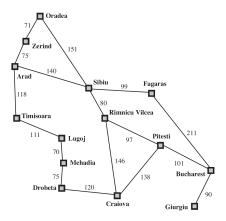
- \triangleright s_0 : Initial state
- ▶ ACTIONS(s): Returns the set of actions **applicable** in state s.
- ▶ RESULTS(s, a): Returns the state s' reached from s by executing action a.
- ▶ GOAL-TEST(s): Returns true if s is goal state, otherwise false.
- ▶ STEP-Cost(s, a): The cost of executing action a in s. Most often we will assume STEP-Cost(s, a) = 1 for all s and a.

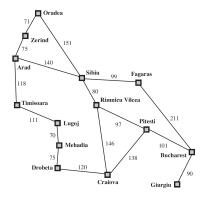
A state g is called a **goal state** if GOAL-TEST(g) = true.

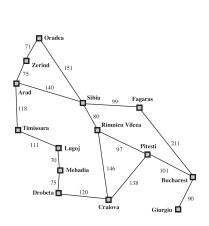
A **solution** to a search problem is a **sequence of actions** (a **path**) from s_0 to a goal state. It is **optimal** if it has minimum sum of step costs.

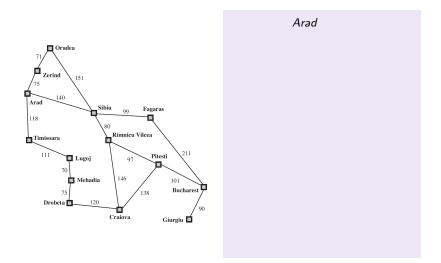
A REAL WORLD PROBLEM

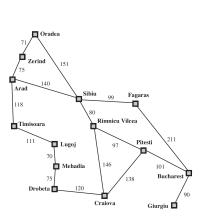
ROUTE-FINDING

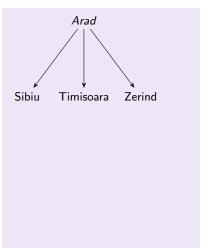


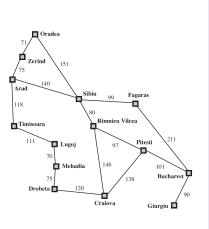


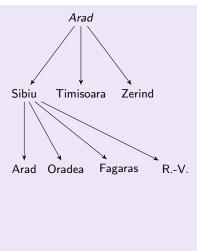


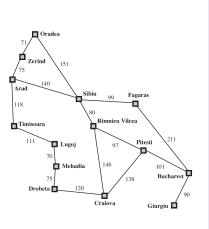


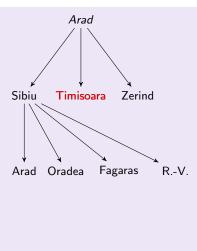


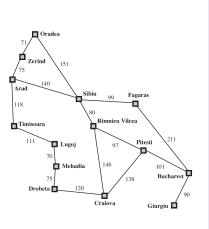


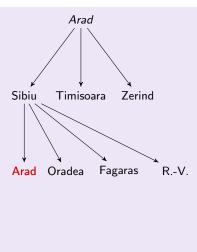


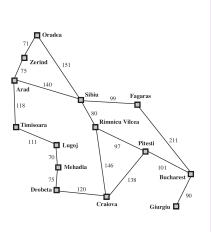


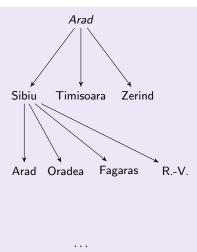












THE TREE-SEARCH ALGORITHM

```
function TREE-SEARCH (problem) returns a solution, or failure
  frontier := {s₀} (initial state) // we initialise the frontier
  loop do
  if frontier = ∅ then return failure
  choose a node n from frontier
  remove n from frontier
  if n is a goal state then return solution
  for each child m of n // we expand n
  add child m to frontier
```

SEARCH STRATEGIES OF TREE-SEARCH AND GRAPH-SEARCH

Different search strategies can be achieved by simply changing how choose node from frontier and add child to frontier work.

Breadth-first search (BFS):

- ► Frontier is queue (FIFO).
- choose node from frontier: dequeue node from frontier.
- ▶ add child to frontier: enqueue node to frontier.

EVALUATION OF SEARCH ALGORITHMS

FOR TREE-SEARCH

Criterion	Breadth- First	Uniform- Cost	Depth- First	Depth- Limited	Iterative Deepening	Bidirectional
Complete?	Yesa	$Yes^{a,b}$	No	No	Yesa	$\mathrm{Yes}^{a,d}$
Time	$O(b^d)$	$O(b^{1+\lfloor C^*/\epsilon \rfloor})$	$O(b^m)$	$O(b^\ell)$	$O(b^d)$	$O(b^{d/2})$
Space	$O(b^d)$	$O(b^{1+\lfloor C^*/\epsilon\rfloor})$	O(bm)	$O(b\ell)$	O(bd)	$O(b^{d/2})$
Optimal?	Yes^c	Yes	No	No	Yes^c	$\mathrm{Yes}^{c,d}$

Figure 3.21 Evaluation of tree-search strategies. b is the branching factor; d is the depth of the shallowest solution; m is the maximum depth of the search tree; l is the depth limit. Superscript caveats are as follows: a complete if b is finite; b complete if step costs b for positive b optimal if step costs are all identical; b if both directions use breadth-first search.

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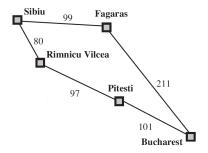
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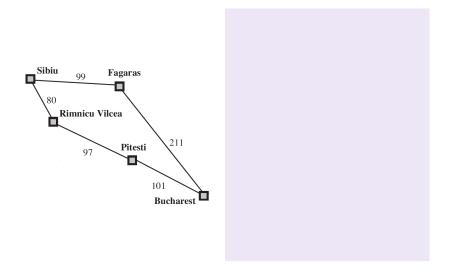
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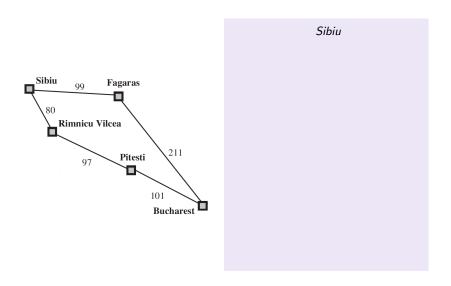
Differences with BFS:

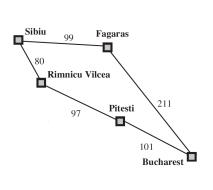
- ► GOAL-TEST is applied when a node is selected for expansion (rather than when it is first generated)

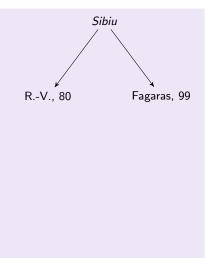
 (the first goal node that is generated may be on a suboptimal path)
- ▶ a test is added for a better path to a node currently on the frontier

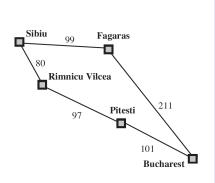


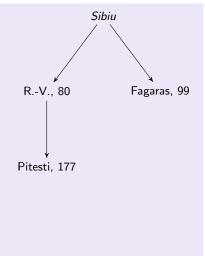


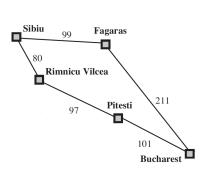


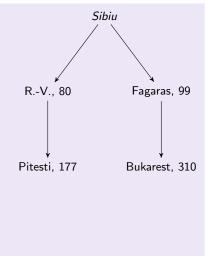


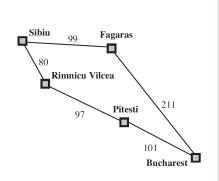


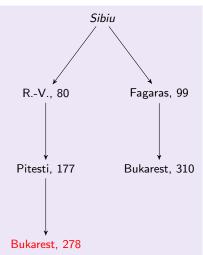












Best-first search

Best-first search is an instance of the general TREE- or GRAPH-SEARCH where node selection for expansion is based on an **evaluation function**, f.

The function f is a cost estimate: node n with lowest f(n) is expanded first.

Best-first graph search the same as UCS but with f for priority queue.

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Heuristic functions are the most common form in which additional knowledge of the problem is imparted to the search algorithm.

Heuristics are arbitrary, nonnegative, problem-specific functions, with one constraint: if n is a goal node, then h(n) = 0.

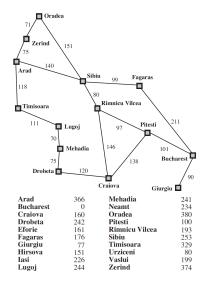
Greedy best-first search

Greedy best-first search tries to expand the node that is closest to the goal, on the grounds that this is likely to lead to a solution quickly.

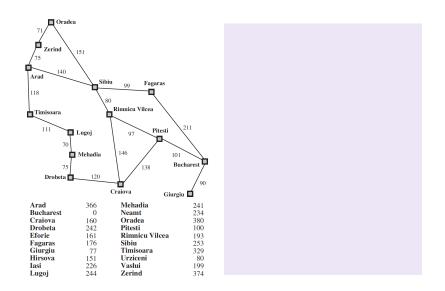
Greedy best-first search evaluates nodes by using just the heuristic function:

$$f(n)=h(n).$$

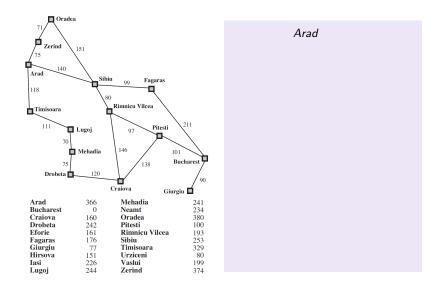
Greedy best-first search: Arad to Bucharest



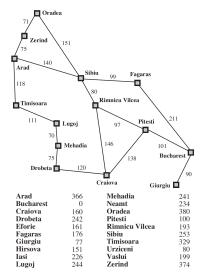
GREEDY BEST-FIRST SEARCH: ARAD TO BUCHAREST

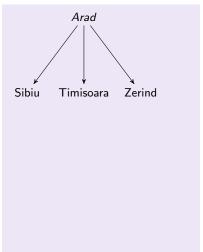


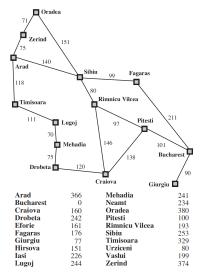
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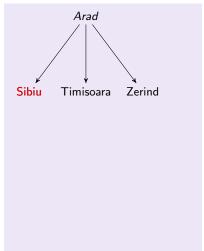


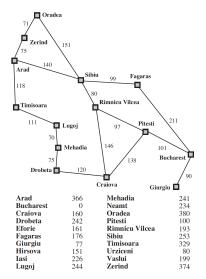
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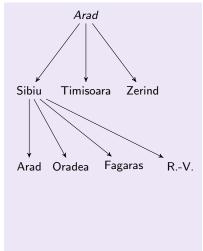


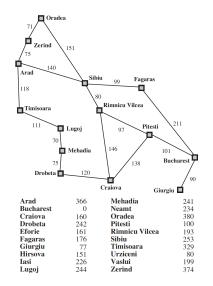


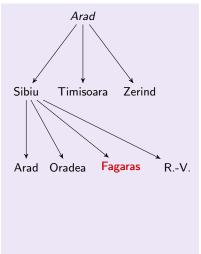


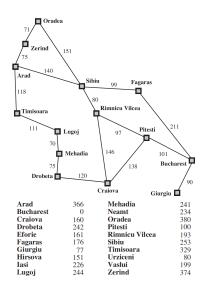


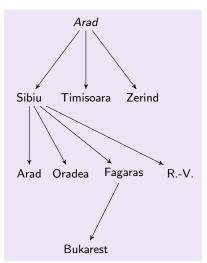












PROPERTIES OF GREEDY BEST-FIRST SEARCH

- ► It's greedy.
- ► It's incomplete.
- \blacktriangleright The complexity (for tree version) is as DFS.

A* SEARCH

 A^* evaluates a node n by combining:

- ightharpoonup g(n), the cost to reach the node, and
- ▶ h(n), the estimated cost to get from the node to the goal:
- $\qquad \qquad \blacktriangleright \ \ f(n) = g(n) + h(n).$

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 A^{\star} search is both complete and optimal.

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The A* algorithm is UCS except that it uses g + h instead of g.

 A^{\star} for Super Mario

Video of A^\star playing Super Mario

DESIGNING HEURISTICS

Designing good heuristic function h(n) is in many cases a great art form.

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Q: What properties should a good heuristic function have?

Designing heuristics

Designing good heuristic function h(n) is in many cases a great art form.

Q: What properties should a good heuristic function have?

A: Estimate cost to goal as precisely as possible; be as cheap as possible to compute (cheaper than computing the actual cost).

Admissibility and optimality

Recall: STEP-COST(s, a) is the **cost** of executing a in s.

Optimal cost of a node n:

The minimal cost to achieve a goal from n, denoted $h^*(n)$.

Admissible heuristics: cost of reaching the goal is never overestimated: the heuristics is **always optimistic**. Formally: $h(n) \le h^*(n)$ for all nodes n.

Optimal search algorithm: The algorithm always returns an **optimal solution**: a solution of minimal cost.

Theorem.

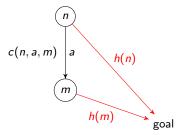
 A^* TREE-SEARCH is optimal when h is admissible.

Consistency

Let c(n, a, m) denote the STEP-Cost of executing action a to go from n to m.

Consistent heuristics: If m is reached by executing a in n then

$$h(n) \leq c(n,a,m) + h(m)$$

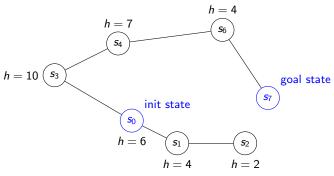


Theorem. Consistency ⇒ admissibility.

Theorem. A^* GRAPH-SEARCH is optimal when h is consistent. (See R&N, Chapter 3, for the discussion and proof outlines.)

Best-first tree-search vs graph-search

Consider the state space below. All step costs are 1.



- Q1 How does greedy best-first tree search behave on the problem?
- $\mathrm{Q}2\,$ How about greedy best-first graph-search?
- Q3 And A* tree-search?

Dominating heuristics

A heuristics h_2 is said to **dominate** a heuristics h_1 if

$$h_2(s) \geq h_1(s)$$
 for all s .

If h_2 dominates h_1 and both are admissible, A^* will never expand more nodes using h_2 than using h_1 . So h_2 is better in that sense.

If h_1, \ldots, h_n are admissible heuristics, then so is $h(s) = \max\{h_1(s), \ldots, h_n(s)\}$.

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It is always better to use h as heuristics than either of the h_i , unless the penalty in computation time of h is too high.

Relaxed problems

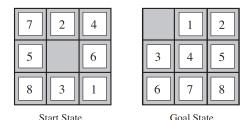
Often heuristics are generated via relaxed problems.

Relaxed problem:

A simplified version of a problem with fewer restrictions.

A solution to the original problem is also a solution to the relaxed problem.

Example



Relaxing the 8-puzzle:

- 1. A tile can move to any adjacent square.
- 2. A tile can move to any square.

GENERATING HEURISTICS VIA RELAXED PROBLEMS

Take a problem P and let $h_P^*(n)$ be the optimal cost to get to goal from n in P.

Given any problem P and relaxation P', a heuristics h for P can be defined by:

$$h(n)=h_{P'}^*(n).$$

In words: The **estimated cost** of a solution to the **real problem** is taken to be the **actual cost** of a solution to the **relaxed problem**.

- Q1 Why is h defined above admissible?
- Q2 Why is h defined above consistent?
- Q3 Which heuristics do we get from the sliding puzzle relaxations of the previous slide (1. Move to any adjacent square; 2. Move to any square)?
- Q4 Does one of the heuristics from the previous question dominate the other?
- Q5 Given P', how do we calculate $h_{P'}^*$?

THE END OF LECTURE 3