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Review: Best-First and Uniform-Cost Search

Image source: [Russell & Norvig \(2021\)](#)

```
function BEST-FIRST-SEARCH(problem, f) returns a solution node or failure
  node ← NODE(STATE=problem.INITIAL)
  frontier ← a priority queue ordered by f, with node as an element
  reached ← a lookup table, with one entry with key problem.INITIAL and value node
  while not IS-EMPTY(frontier) do
    node ← POP(frontier)
    if problem.IS-GOAL(node.STATE) then return node
    for each child in EXPAND(problem, node) do
      s ← child.STATE
      if s is not in reached or child.PATH-COST < reached[s].PATH-COST then
        reached[s] ← child
        add child to frontier
  return failure
```

```
function UNIFORM-COST-SEARCH(problem) returns a solution node, or failure
  return BEST-FIRST-SEARCH(problem, PATH-COST)
```

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Improving on Uninformed Search

- ▶ Uniform-Cost Search always checks the node in the frontier with the least path-cost so far
- ▶ This is node **evaluation**: ranks each node, chooses *best*
 - ▶ We can create other forms of this sort of best-first search, by changing *how* we do the evaluation
- ▶ We can do better (sometimes) if we have a **heuristic**
 - ▶ An *estimate* $h(n)$ of remaining cost from node n to the goal
 - ▶ Node evaluation can now be based also upon *estimated cost after n* , instead of only *known cost before, $g(n)$*
 - ▶ These heuristic values affect how we order our priority queue, and therefore the order of expanding frontier

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Using Heuristics

- ▶ **Heuristic**: problem-specific knowledge, used to reduce *expected* search effort (*actual* performance may vary)
 - ▶ Evaluate relative desirability of expanding a node
 - ▶ Heuristics estimate the “distance” to a goal
- ▶ Examples depend on the domain:
 - ▶ Travel planning:
 - ▶ Euclidean (straight-line) distance
 - ▶ 8-puzzle
 - ▶ Manhattan distance
 - ▶ Number of misplaced tiles
 - ▶ Game-play:
 - ▶ Maximum possible amount won
 - ▶ Worst possible opponent play

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Greedy Search

- ▶ A simple form of heuristic search
 - ▶ Order fringe nodes in terms of heuristic value $h(n)$
 - ▶ Always expand node with least heuristic estimate
- ▶ For example: suppose we are searching for a path from point A to point B in a graph and:
 - ▶ We know size of graph, $|V| = N$
 - ▶ We know nothing else about it
 - ▶ Each edge-move has uniform cost = 1 unit per step
- ▶ What heuristics might we use? What is the result?

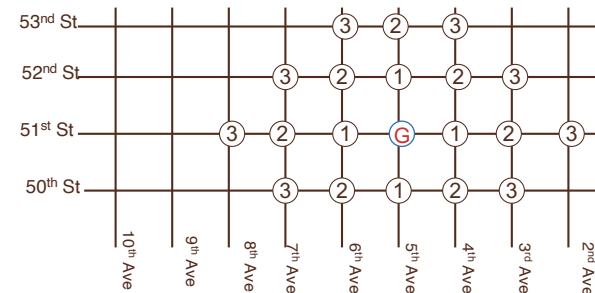
Performance of greedy search is dependent upon *how good* the heuristic is: in some cases, just the same as doing a simple (and exponential) breadth/depth-first search!

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The Manhattan Distance Heuristic



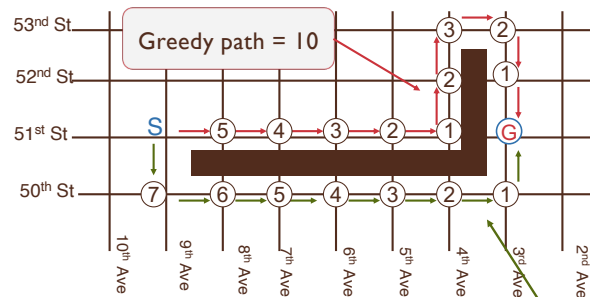
A common heuristic for grid-based search problems: how many moves do we need to make horizontally or vertically to get to the goal G ?

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Greedy Search Using the MD



Greedy search is **complete**, but it is *not* always optimal

Optimal path = 8

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A*: Optimal Heuristic Search

- ▶ Similar to Best-First search except that the evaluation is based on *total estimated path* (solution) cost, and we order our priority queue fringe by combined measure:

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

where we have:

$g(n)$ = cost of actual path so far from start state to n

$h(n)$ = heuristic estimate of remaining cost from n to goal

(By convention, for any **goal-state** G , $h(G) = 0$)

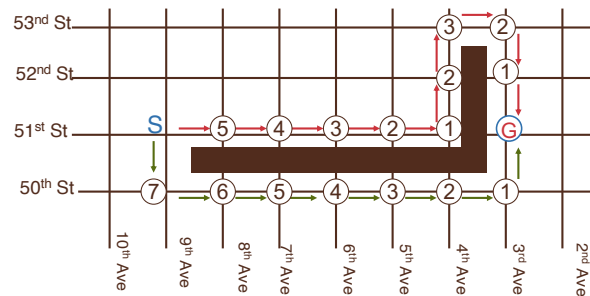
- ▶ Combines the greedy approach with the knowledge about actual path-costs that we have gained during search process

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Heuristic (h) Values

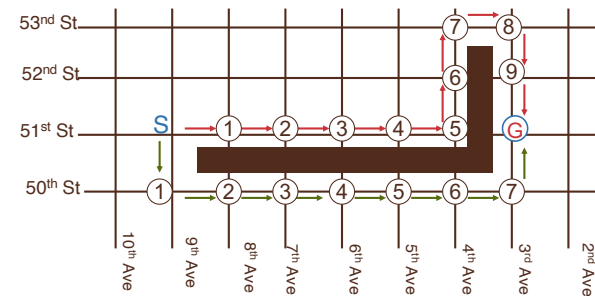


We can use the *same* heuristic as the Greedy search method

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Actual Cost (g) Values

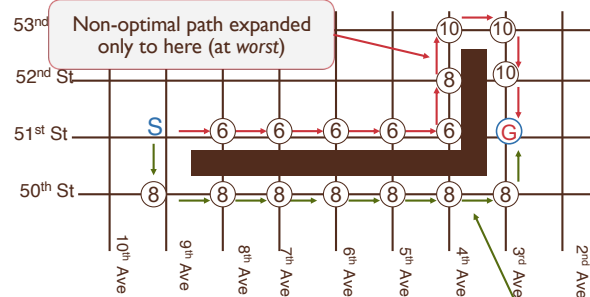


If each action has same cost (1), $g(n)$ is just path-length

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Final A* values: $f = g + h$



When heuristic is correct $f(n)$ is also correct

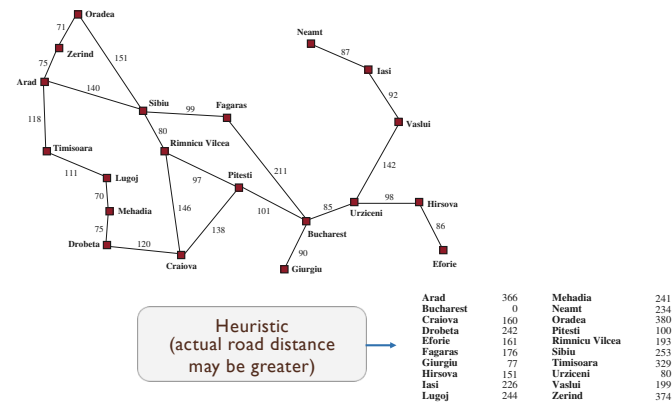
Optimal path will be expanded after that point, all the way to the goal

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Getting to Bucharest Using A*

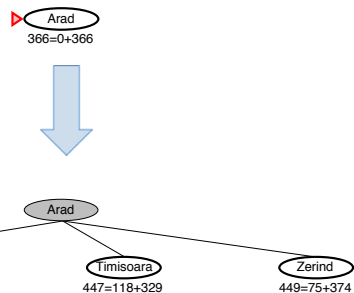
Image source: [Russell & Norvig \(2021\)](#)



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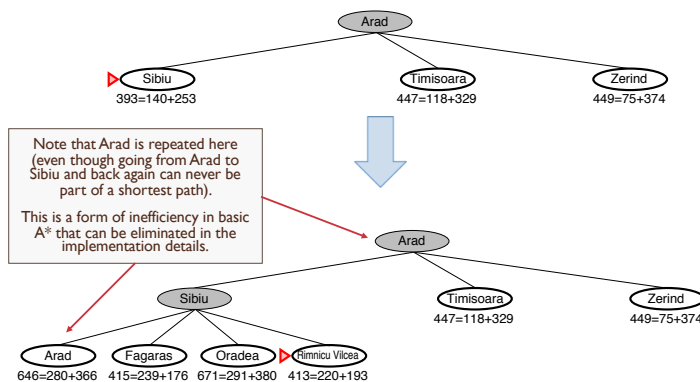
Getting to Bucharest Using A*



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Getting to Bucharest Using A*

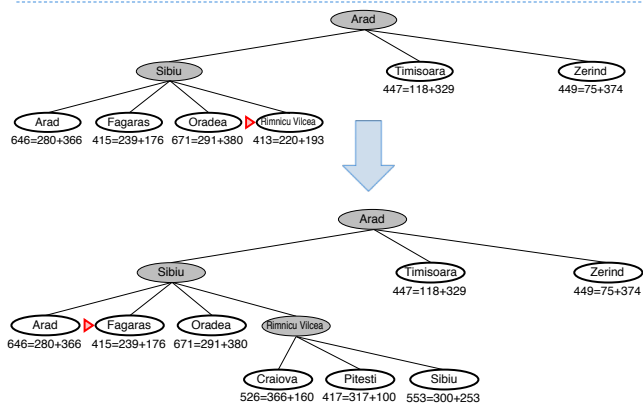


Note that Arad is repeated here (even though going from Arad to Sibiu and back again can never be part of a shortest path). This is a form of inefficiency in basic A* that can be eliminated in the implementation details.

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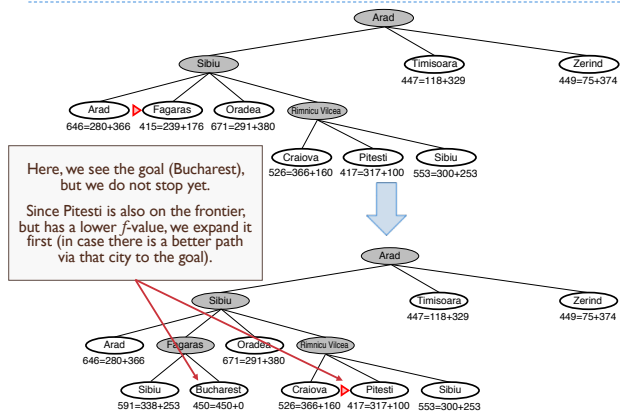
Getting to Bucharest Using A*



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Getting to Bucharest Using A*

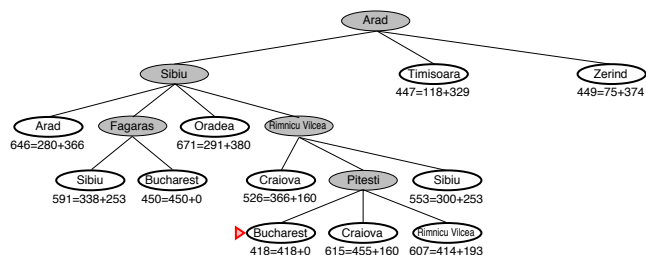


Here, we see the goal (Bucharest), but we do not stop yet. Since Pitesti is also on the frontier, but has a lower f -value, we expand it first (in case there is a better path via that city to the goal).

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Getting to Bucharest Using A*



Finally, when the goal is found on the frontier and **expanded**, since it now has the lowest f -value, we are done, and have found the best possible path to that goal.

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Admissibility and Consistency

- ▶ **Admissible** heuristic: *never overestimates* actual cost to reach the goal (so it never “discourages” us from expanding a node during search)
- ▶ For any node n , let $C^*(n)$ be the **optimal cost** from n to goal

$$\forall n, h(n) \leq C^*(n)$$

- ▶ For any nodes n and n' , let $a^*(n, n')$ be the **optimal action** that leads from n to n' , which is to say:

$$\forall a, c(n, a^*(n, n'), n') \leq c(n, a, n')$$

- ▶ This implies that optimal costs respect optimal paths/actions, i.e., if we have some optimal path ($Start, \dots, n_k, n_{k+1}, \dots, Goal$):

$$C^*(n_k) = c(n_k, a^*(n_k, n_{k+1}), n_{k+1}) + C^*(n_{k+1})$$

- ▶ Which in turn means that admissible heuristics respect optimal costs:

$$\forall n, n', h(n) \leq c(n, a^*(n, n'), n') + C^*(n')$$

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Admissibility and Consistency

$$\forall n, \forall a, \forall n', h(n) \leq c(n, a, n') + h(n')$$

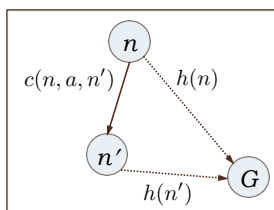
Heuristic estimate
for node n

Actual cost to get
from n to n'

Heuristic estimate
for next node n'

- ▶ **Consistent** heuristic: a form of “triangle inequality”
- ▶ Consistent heuristics do not overestimate *total costs* and do not overestimate costs of *single actions*

Theorem: If heuristic h is consistent, then h is admissible



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Consistency Implies Admissibility

- ▶ **Theorem:** If heuristic h is consistent, then h is admissible
 - ▶ Proven by induction on number of actions along path from some node to goal
- ▶ **Base case:** suppose node n is 1 step from the goal, G ; by the definition of consistency:

$$h(n) \leq c(n, a^*(n, G), G) + h(G)$$

- ▶ Since G is a goal-state, we have that $h(G) = 0$, and so:

$$h(n) \leq c(n, a^*(n, G), G) = C^*(n)$$

- ▶ **Inductive hypothesis:** Assume result holds for any nodes at distances $1, \dots, k$ steps from the goal
- ▶ **Inductive step:** Show result holds nodes $(k + 1)$ steps from the goal

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Consistency Implies Admissibility

- ▶ **Theorem:** If heuristic h is consistent, then h is admissible
- ▶ **Inductive hypothesis:** Assume result holds for any nodes at distances 1, ..., k steps from the goal
- ▶ **Inductive step:** Show result holds for nodes $(k + 1)$ steps from the goal
- ▶ Suppose we have nodes n, n' such that n is $(k + 1)$ steps from the goal on a path: $(Start, \dots, n, n', \dots, Goal)$
- ▶ By the definition of consistency:

$$h(n) \leq c(n, a^*(n, n'), n') + h(n')$$

- ▶ But since n' is only k steps from the goal, the inductive hypothesis tells us that $h(n')$ doesn't over-estimate, i.e., $h(n') \leq C^*(n')$
- ▶ Therefore, we have our result:

$$h(n) \leq c(n, a^*(n, n'), n') + C^*(n') = C^*(n) \quad \blacksquare$$

▶

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Other Important Results about Consistent and/or Admissible Heuristics

- ▶ **Theorem:** If heuristic h is consistent, then path costs are **monotonic** (never decrease)
- ▶ **Theorem:** If heuristic h is *admissible*, then A* search is **optimal**, and always finds best path to a goal
- ▶ **Theorem:** If heuristic h is *consistent* and *admissible*, then A* is **maximally efficient**; that is, no algorithm will *always* expand fewer nodes than A*

▶

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