

CS7IS2: Artificial Intelligence

Lecture 2: Informed search

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Uninformed search: summary

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

Informed search

- › Estimate “desirability” of each node in the frontier and expand the most desirable unexpanded node
- › Heuristic search – estimate of the path cost from each node
 - $n(n)$ – heuristic function
 - Vs uninformed search = blind/exhaustive exploration of the full search space
- › Same as with uninformed searches – informed search algorithms only differ by what node do they choose to expand next

Best-first search

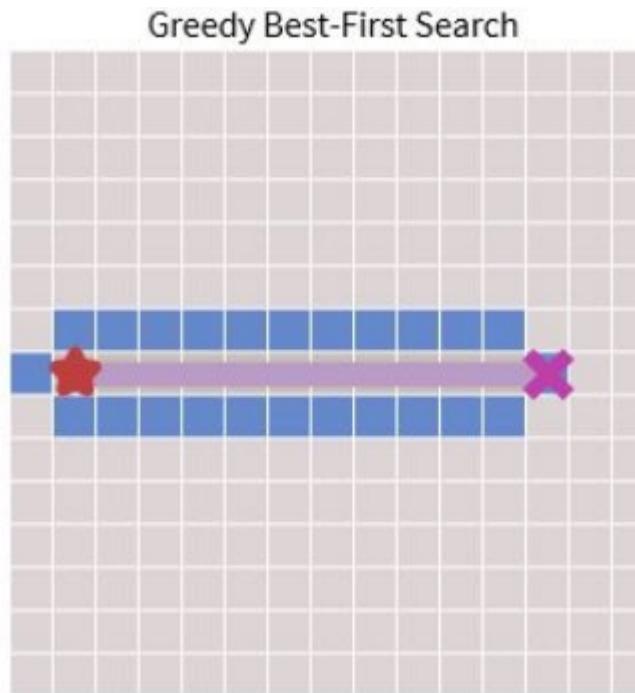
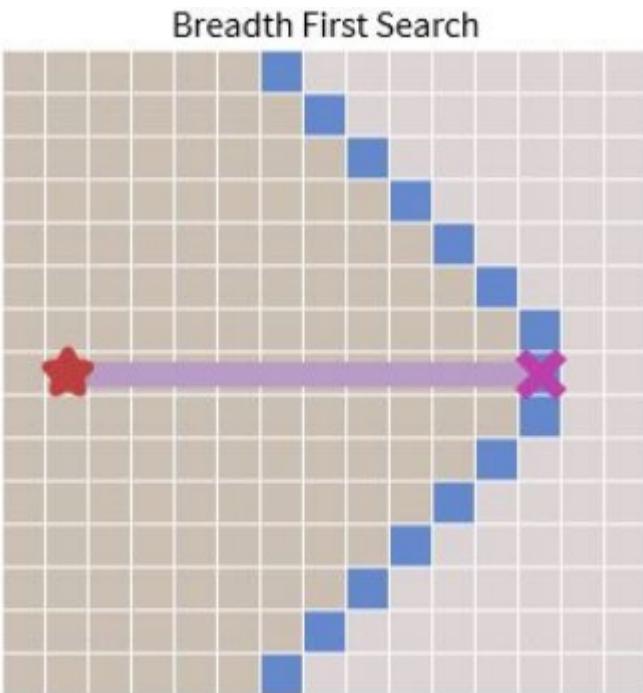
- › Node selected for expansion based on a function $f(n)$
- › $f(n)$ is a cost estimate, and the nodes with the lowest $f(n)$ are expanded first
- › Choice of $f(n)$ = search strategy
- › Special-cases: greedy search and A* search

Greedy best-first search (GBFS)

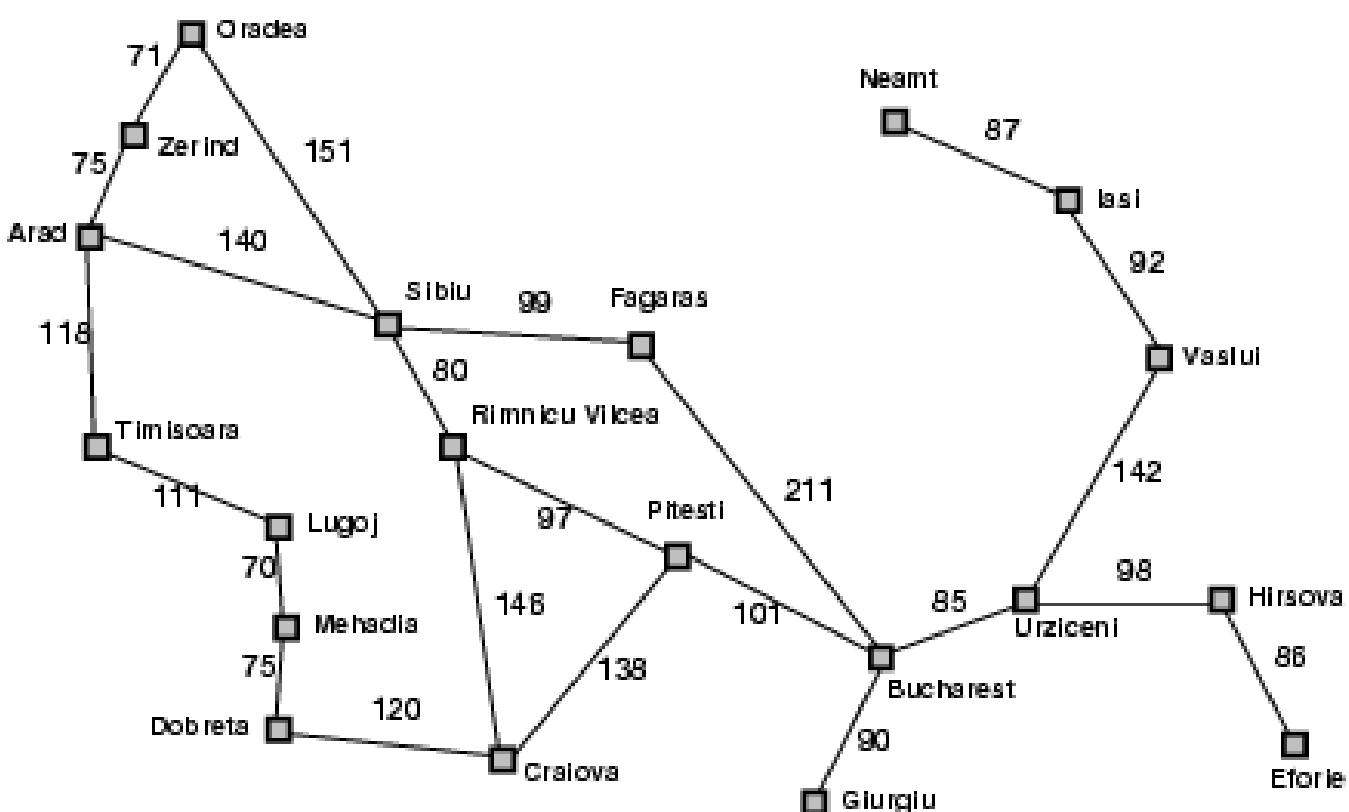
- › Expand the node **that appears to be closest** to the goal, under assumption that it is the closest to the goal
- › $f(n) = h(n)$

Greedy best-first search

- › Each step moving closer to the target, e.g.,



Greedy best-first search – Romania example



Straight-line distance to Bucharest	
Arad	366
Bucharest	0
Craiova	160
Dobreta	242
Eforie	161
Fagaras	176
Giurgiu	77
Hirsova	151
Lasi	226
Lugoj	244
Mehadia	241
Neamt	234
Oradea	380
Pitesti	10
Rimnicu Vilcea	193
Sibiu	253
Timisoara	329
Urziceni	80
Vaslui	199
Zerind	374

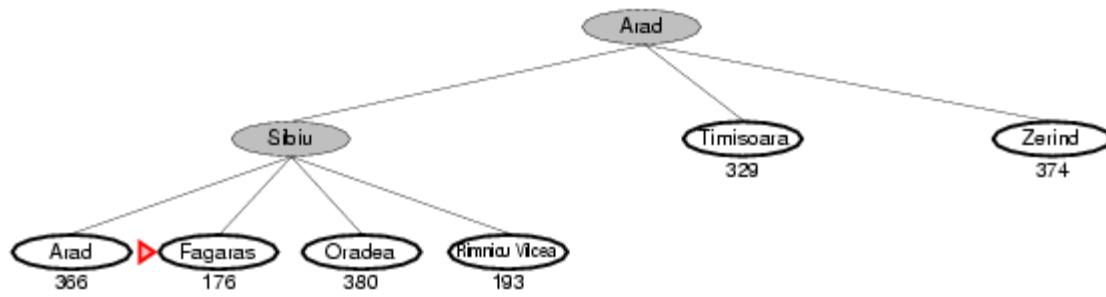
Greedy best-first search example



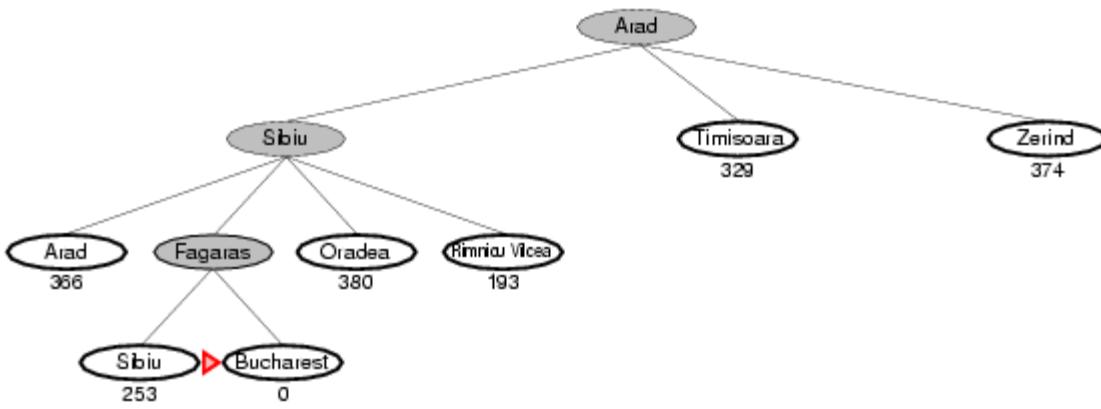
Greedy best-first search example



Greedy best-first search example



Greedy best-first search example



Properties of greedy best-first search

Complete?

- No, can get stuck in loops, e.g., Iasi -> Neamt -> Iasi ->

Complete in finite space with repeated-state checking

Time?

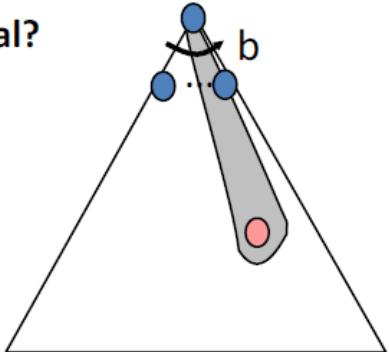
- $O(b^m)$, but a good heuristic can give dramatic improvement

Space?

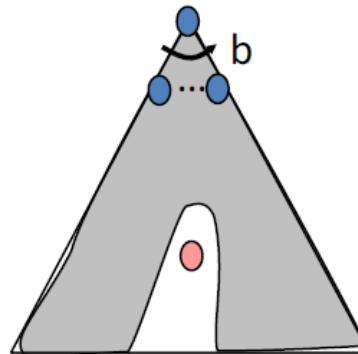
- $O(b^m)$, keeps all nodes in memory

Optimal?

- No



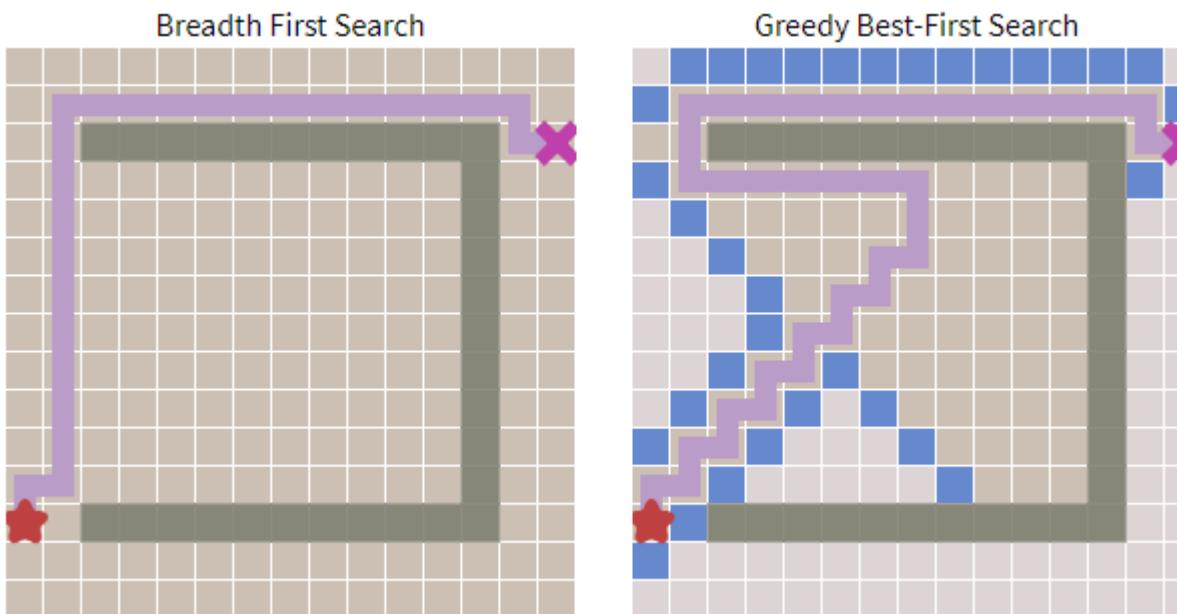
Common case: takes you straight to the (wrong) goal



Worst case: badly-guided DFS

Optimality

- › Demo of BFS vs Greedy best-first search
- › <https://cs.stanford.edu/people/abisee/tutorial/greedy.html>



Uniform-cost search (UCS): revise

Expand least-cost unexpanded node

- $g(n)$ cost function for a given path to the node n

Implementation:

- Fringe = priority queue ordered by path cost, lowest first

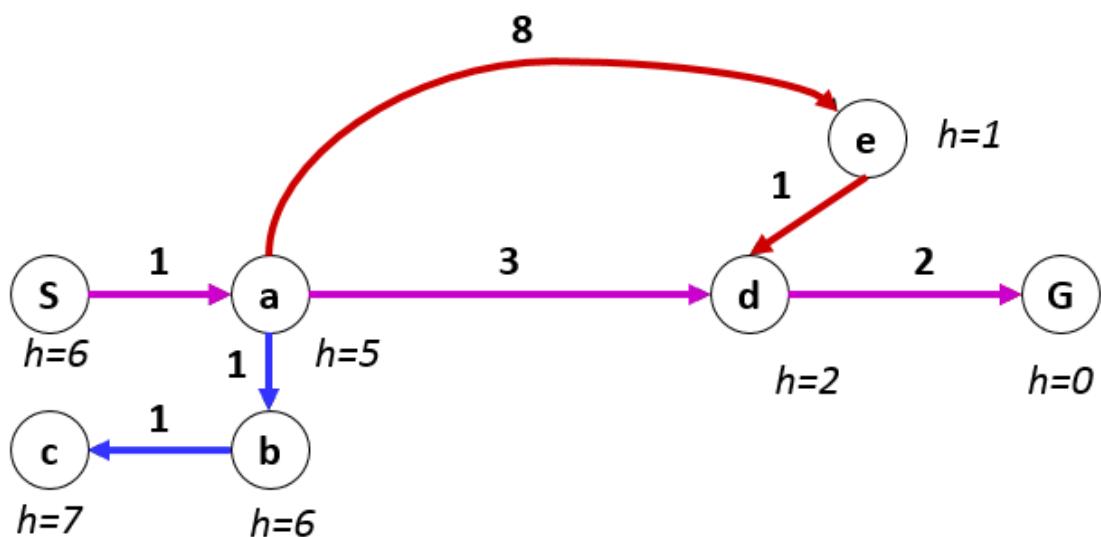
Goal test is applied to a node when it is selected for expansion

A test is added in case a better path is found to a node currently on the frontier

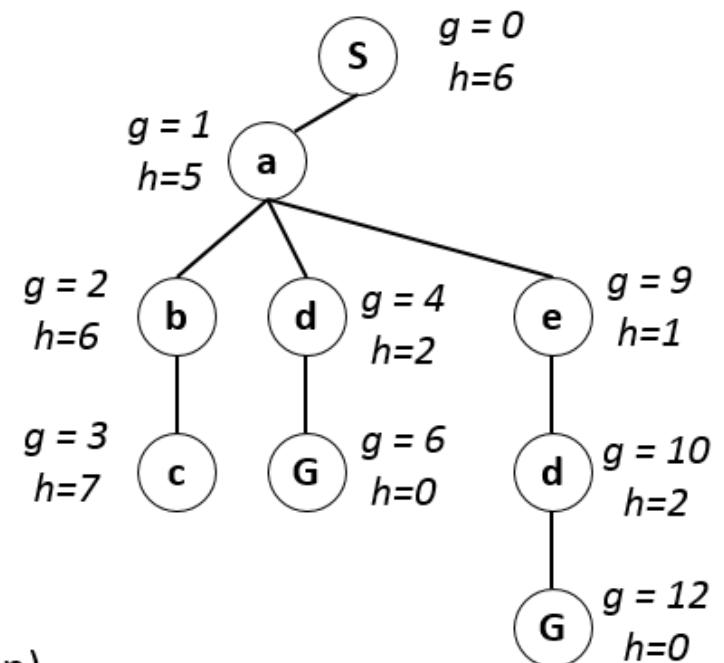
Equivalent to breadth-first if step costs all equal

A* - Combine UCS with GBFS

- Uniform-cost orders by path cost, or *backward cost* $g(n)$
- Greedy orders by goal proximity, or *forward cost* $h(n)$



- A* Search orders by the sum: $f(n) = g(n) + h(n)$



Example: Teg Grenager

A*

$$f(n) = \text{Current path cost} + \text{estimated remaining path cost}$$

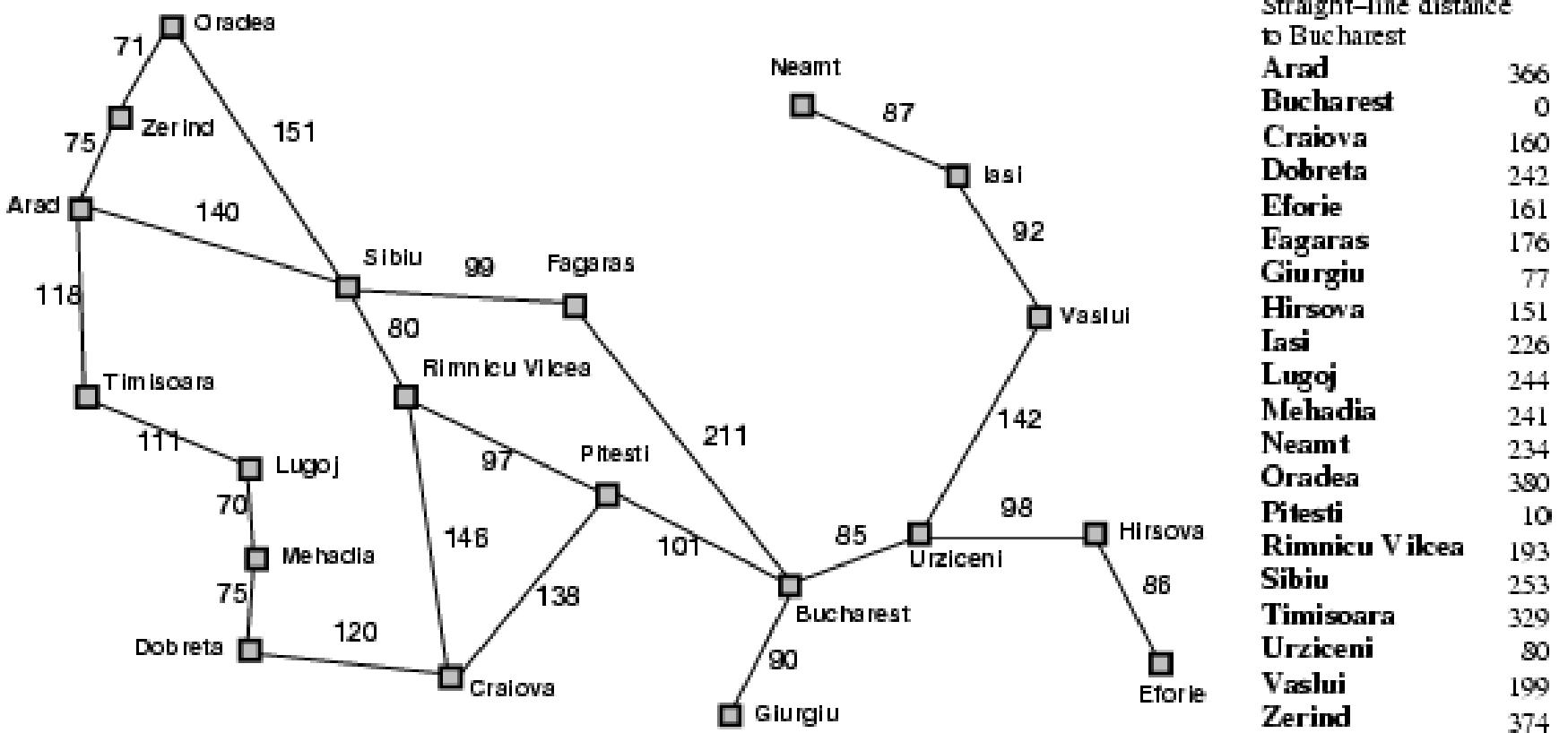
- › actual cost of path so far + estimated cost to goal

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

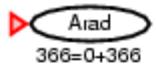


- › This helps avoid local maxima traps
 - › May be slower than Greedy Best-First
 - But guarantees shortest path
- * › Main idea: avoid paths that have already been expensive *

A* – Romania example



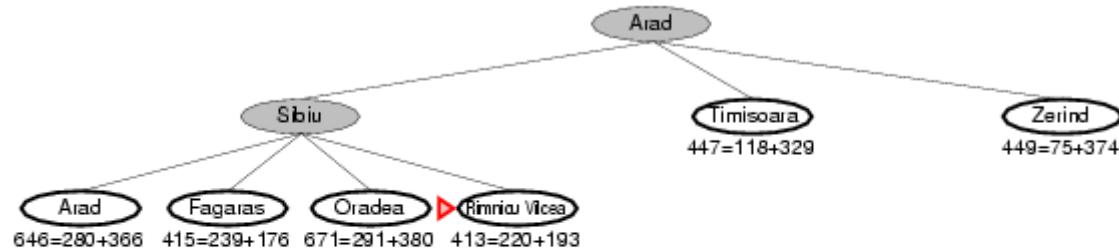
A* search example



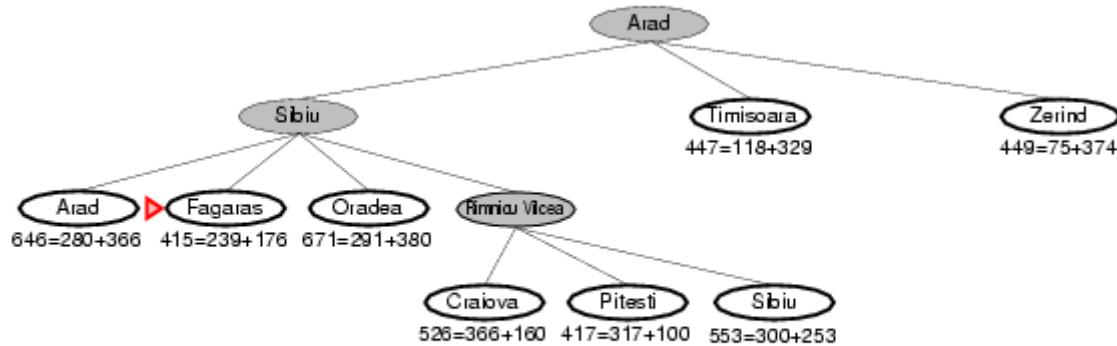
A* search example



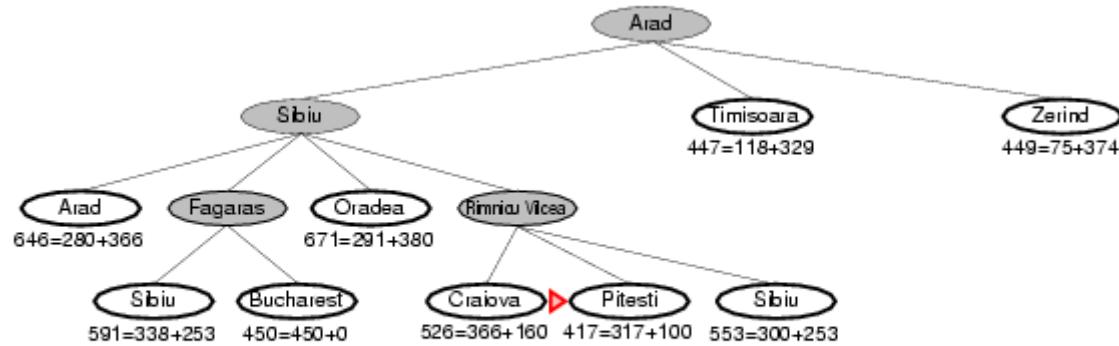
A* search example



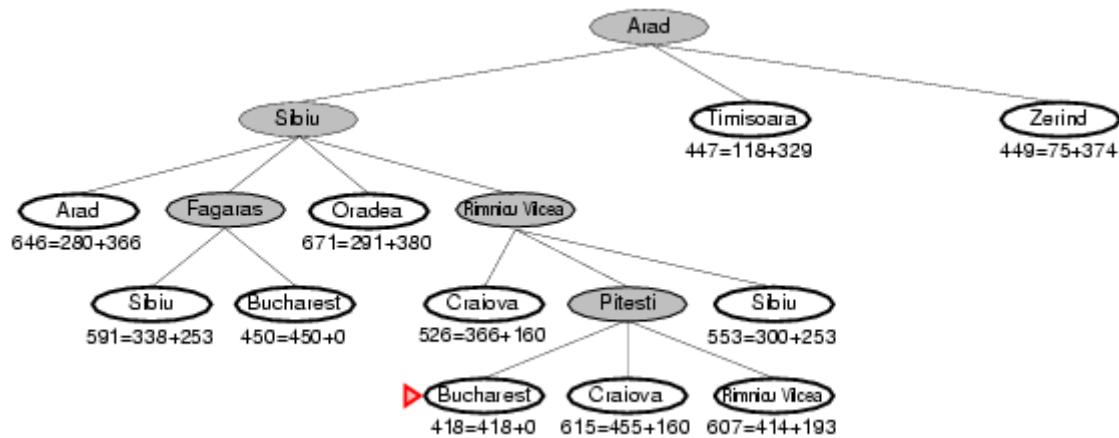
A* search example



A* search example

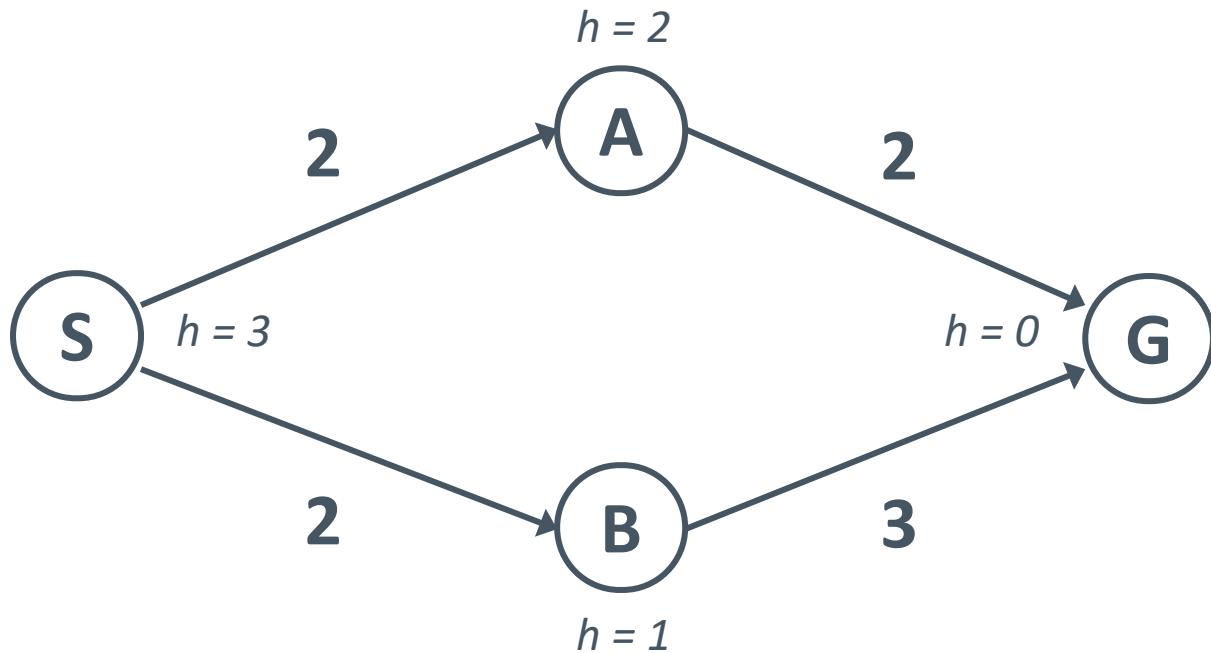


A* search example



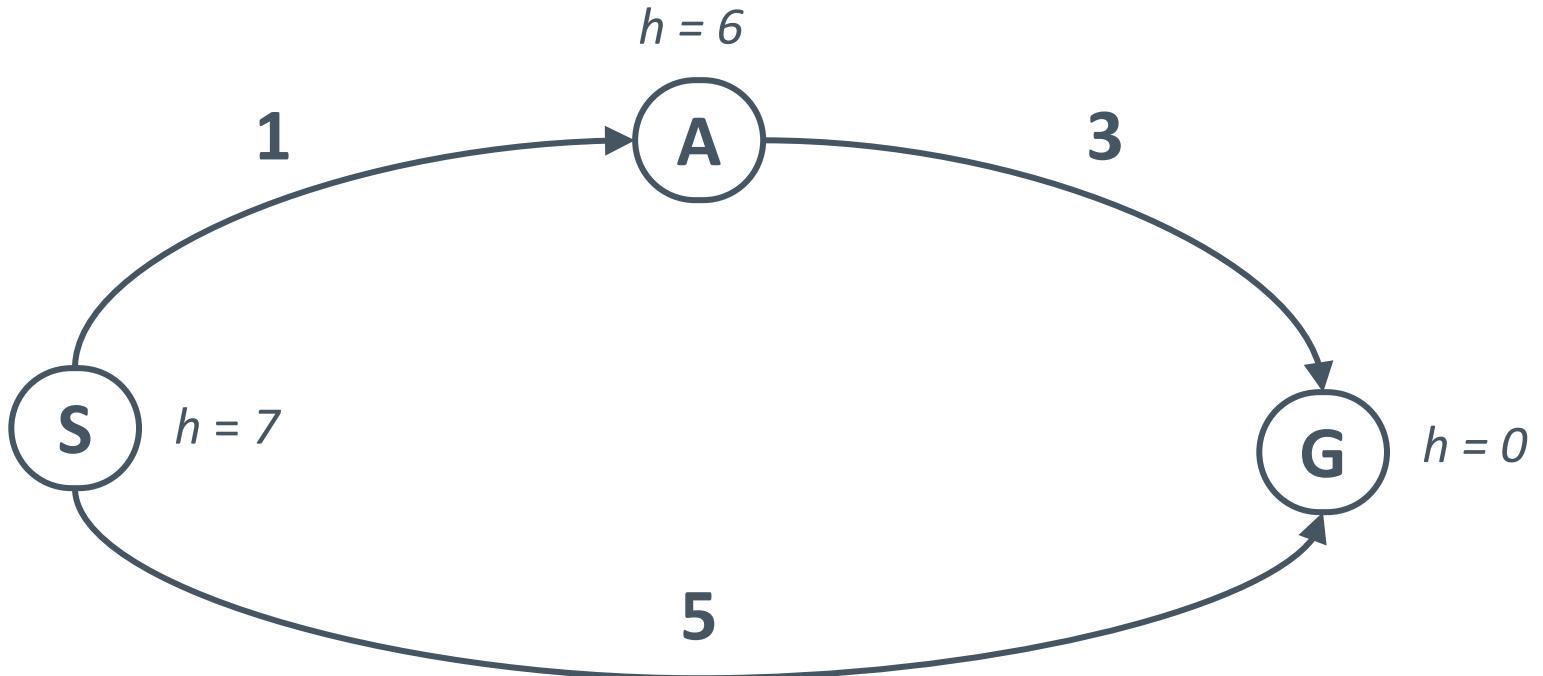
When should A* terminate?

- › Should we stop when we enqueue a goal?



- › No: only stop when we dequeue a goal

Is A* Optimal?



- › What went wrong?
- › Actual bad goal cost < estimated good goal cost
- › We need estimates to be less than actual costs in order for A* to be optimal

Admissible heuristics

- › A heuristic $h(n)$ is **admissible** if for every node n ,
 $h(n) \leq h^*(n)$, 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**
- › Example: *Romania example straight line distance* - never overestimates the actual road distance
- › **Theorem:** If $h(n)$ is admissible, A* using TREE-SEARCH is optimal

Admissible heuristics

- › Inadmissible (pessimistic) heuristics break optimality by trapping good plans on the fringe

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?

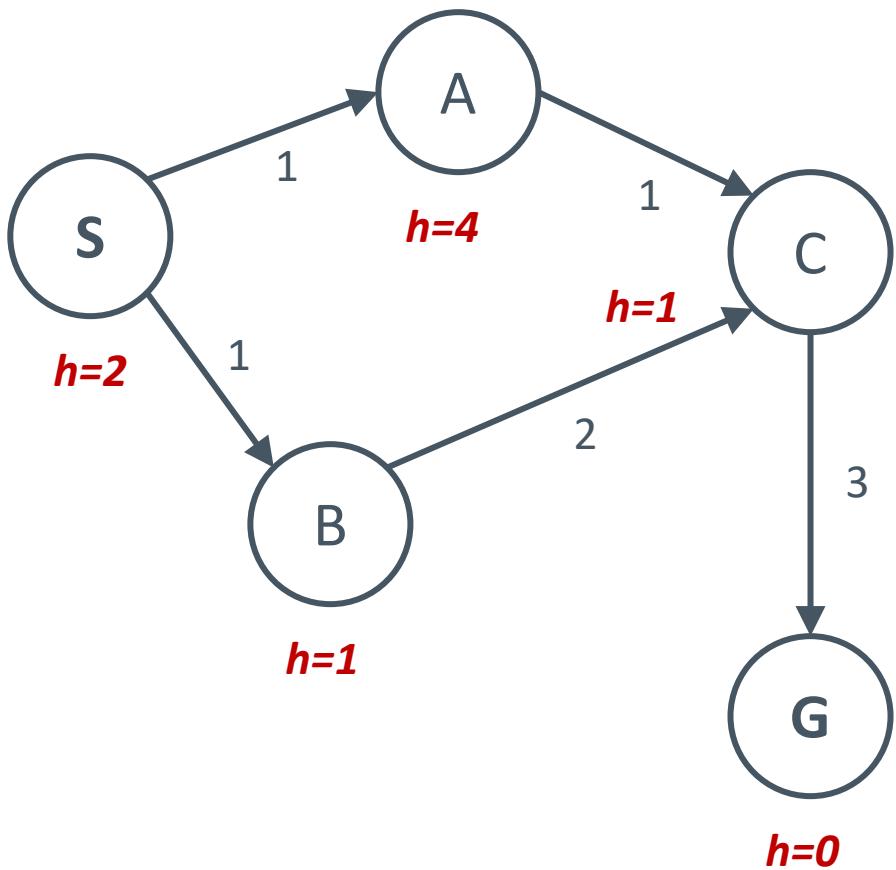
- Yes, cannot expand f_{i+1} until f_i is finished

A* applications

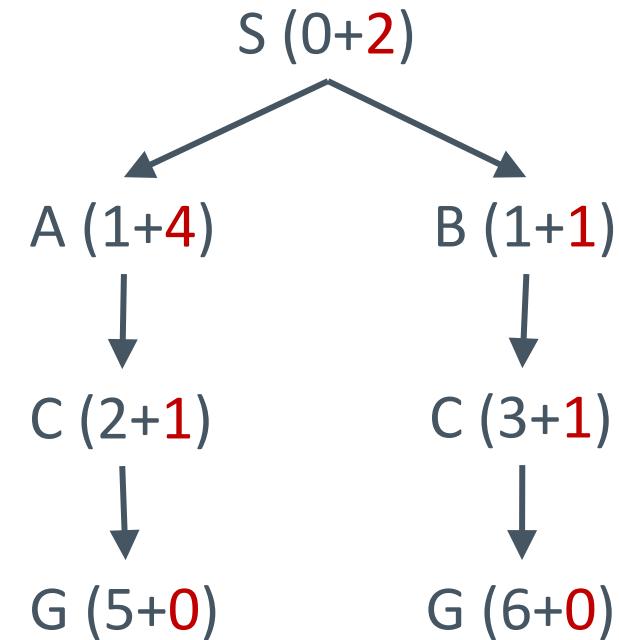
- › Video games
- › Pathing / routing problems
- › Resource planning problems
- › Robot motion planning
- › Language analysis
- › Machine translation
- › Speech recognition

A* Graph Search Gone Wrong?

State space graph

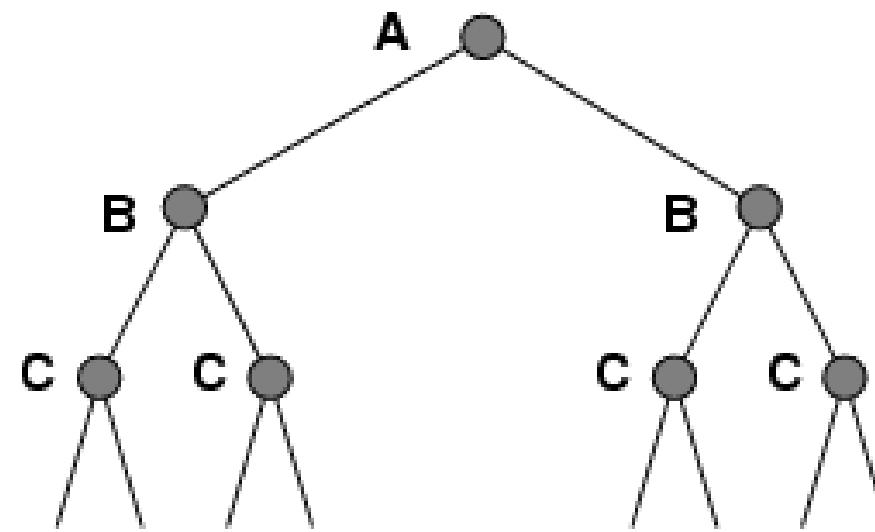
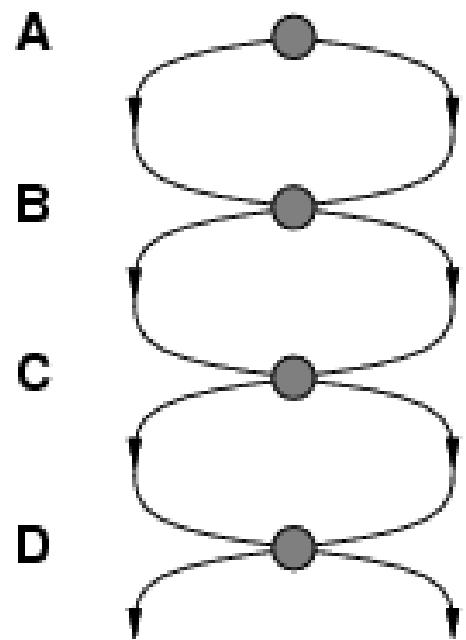


Search tree

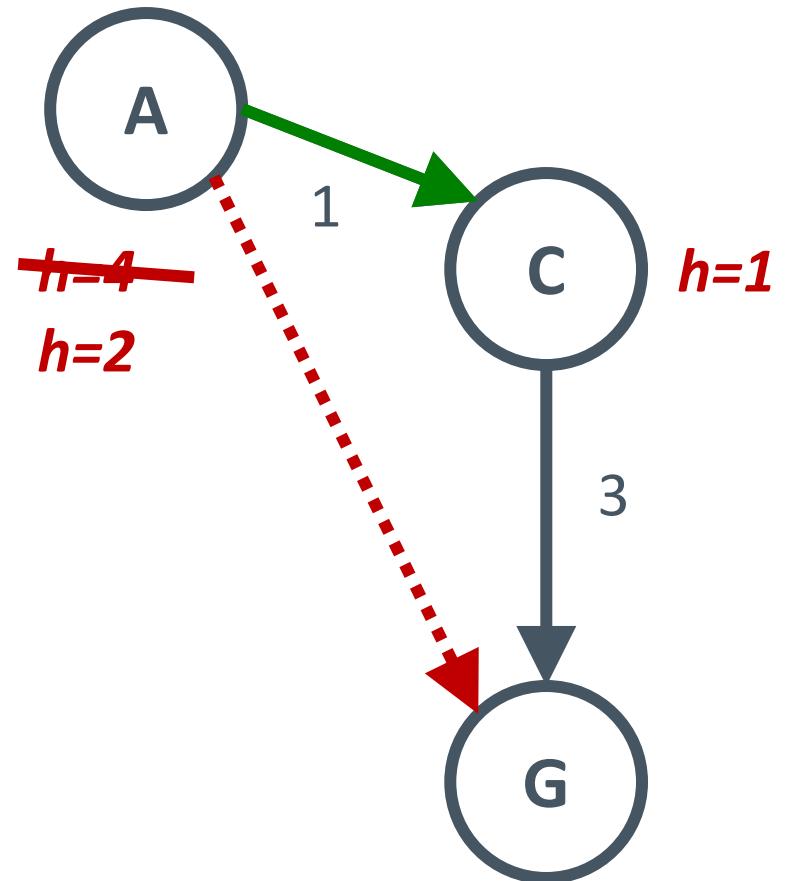


Repeated states

- › Reminder: graph search keeps track of closed/repeated states



Consistency of Heuristics



- › Main idea: estimated heuristic costs \leq actual costs
 - Admissibility: heuristic cost \leq actual cost to goal
$$h(A) \leq \text{actual cost from } A \text{ to } G$$
 - Consistency: heuristic “arc” cost \leq actual cost for each arc
$$h(A) - h(C) \leq \text{cost}(A \text{ to } C)$$
- › Consequences of consistency:
 - The f value along a path never decreases
$$h(A) \leq \text{cost}(A \text{ to } C) + h(C)$$
 - A* graph search is optimal

Optimality

- › Tree search:
 - A* is optimal if heuristic is admissible
 - UCS is a special case ($h = 0$)
- › Graph search:
 - A* optimal if heuristic is consistent
 - UCS optimal ($h = 0$ is consistent)
- › Consistency implies admissibility
- › In general, most natural admissible heuristics tend to be consistent, especially if from relaxed problems

Generating heuristics?

- › Effect of heuristic accuracy on performance
- › How to generate admissible heuristics?
 - From relaxed problems
 - From sub-problems
 - From experience

Heuristic accuracy vs performance

- › Effective branching factor b^* - if a total number of nodes generated by A* is N, and the solution depth is d, then b^* is the branching factor that a uniform tree of depth d would have to have in order to contain $N+1$ nodes
- › $N+1 = 1 + b^* + (b^*)^2 + \dots + (b^*)^d$
- › Well-designed heuristic would have b^* closer to 1 -> allows large problems to be solved at a reasonable computational cost
- › Evaluate usefulness of a heuristic experimentally on a small set of problems

Heuristic dominance

- › Ideas for heuristics?

How to tell the difference
between two states, in terms of
which is closer to the goal?

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

Heuristic dominance

- › How to compare 2 heuristics?

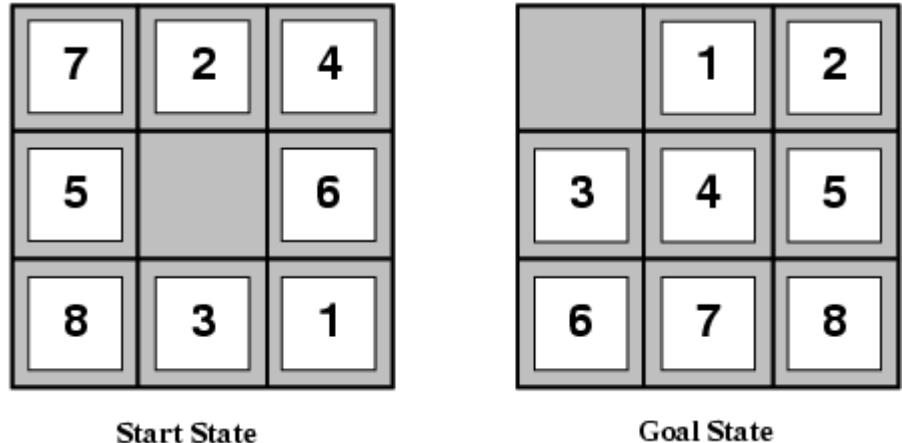
- E.g., for the 8-puzzle:

$h_1(n)$ = number of misplaced tiles

$h_2(n)$ = total Manhattan distance

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

Takes into account every "wrong" tile, and how "wrong" it is.
Higher "wrong" score = worse state to reach goal



Heuristic dominance

- › How to compare 2 heuristics?

Calculate h_1 and h_2 given the start state in the picture?

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

7	2	4
5		6
8	3	1

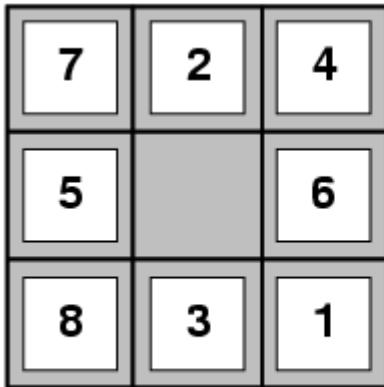
Start State

	1	2
3	4	5
6	7	8

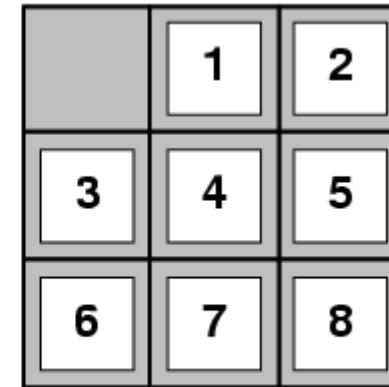
Goal State

Heuristic dominance

- › Which heuristic to choose?



Start State



Goal State

	Average nodes expanded when the optimal path has...		
	...4 steps	...8 steps	...12 steps
TILES	13	39	227
MANHATTAN	12	25	73

Heuristic dominance

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

- › $d=12$ IDS = 3,644,035 nodes
 $A^*(h_1) = 227$ nodes
 $A^*(h_2) = 73$ nodes
- › $d=24$ IDS = too many nodes
 $A^*(h_1) = 39,135$ nodes
 $A^*(h_2) = 1,641$ nodes

Heuristic dominance

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

Generating heuristics from 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

Generating heuristic

- › From sub-problems:
 - Eg 8-puzzle problem
 - Subproblem: getting tiles 1-4 into correct position (instead of all 8)
 - The cost of optimal solution is clearly a lower bound on the cost of the complete problem
- › Learning from experience:
 - Solving a lot of 8-puzzle problems – given experience of a number of states and costs to the path, predict the cost from remaining states

Summary of search strategies

Strategy	What to select from frontier	complete/ halts?	space
DFS	First node added	No	Linear
BFS	Last node added	Yes	Exponential
Best first	Globally minimal $h(p)$	No	Exponential
Lowest Cost first	Minimal cost (p)	Yes	Exponential
A*	Minimal cost (p) + $h(p)$	Yes	Exponential

Heuristics

- › Ideas for a heuristic to find a solution in:
 - a maze
 - Connect 4 game
 - Chess

Manhattan distance to more exit ignoring walls \Rightarrow not perfect but better than nothing.