

# Informed search algorithms

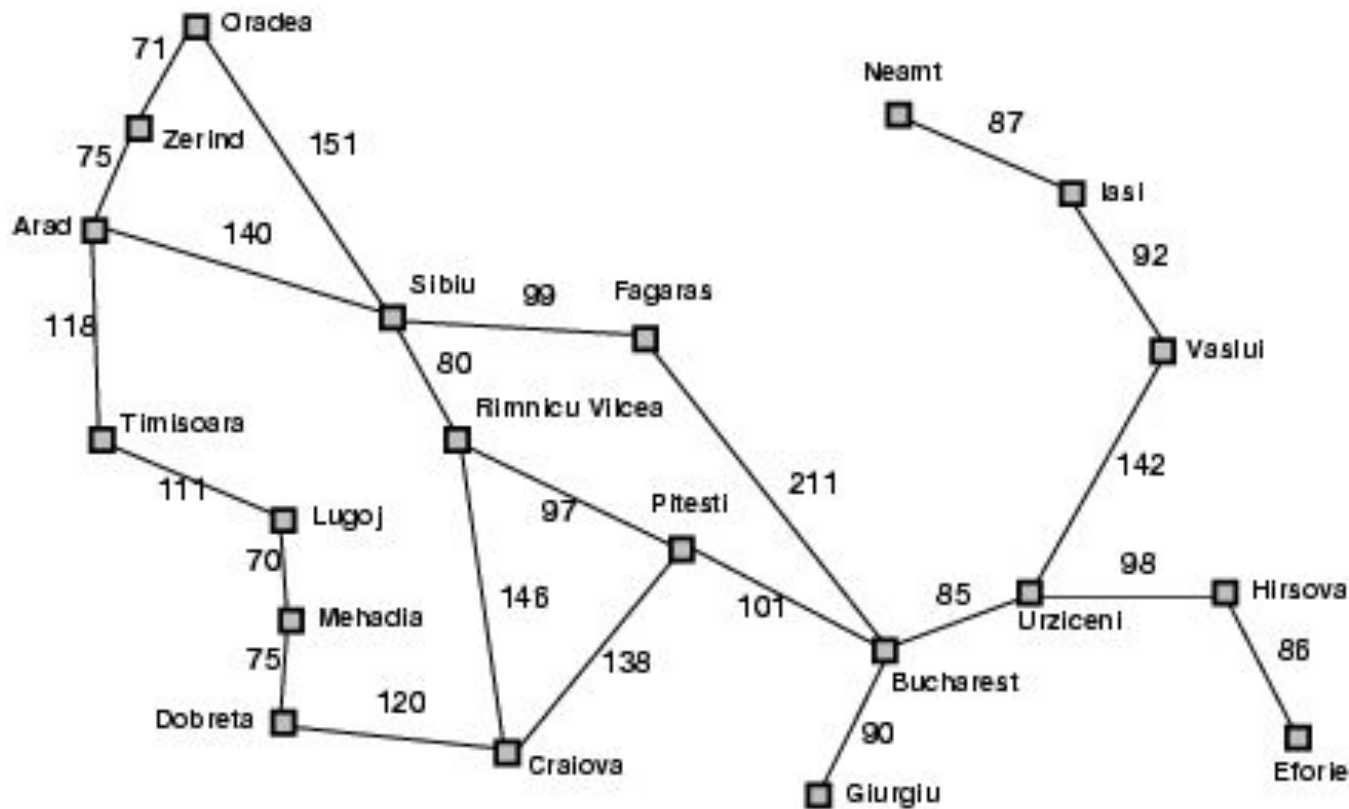
# Informed search

- Uses problem-specific knowledge beyond the definition of the problem itself.
- Can find solutions more efficiently than an uninformed strategy

# Best-first search

- Best-first search is an instance of the general TREE-SEARCH or GRAPH-SEARCH algorithm in which a node is selected for expansion based on an evaluation function,  $f(n)$ .
- The evaluation function construed as a cost estimate, so the node with the lowest evaluation is expanded first.
- Idea: use an **evaluation function**  $f(n)$  for each node
  - estimate of "desirability"
  - Expand most desirable unexpanded node
- Implementation:
  - Order the nodes in fringe in decreasing order of desirability
  - Special cases:
    - greedy best-first search
    - $A^*$  search

# Romania with step costs in km



Straight-line distance  
to Bucharest

<b>Arad</b>	366
<b>Bucharest</b>	0
<b>Craiova</b>	160
<b>Dobreta</b>	242
<b>Eforie</b>	161
<b>Fagaras</b>	176
<b>Giurgiu</b>	77
<b>Hirsova</b>	151
<b>Iasi</b>	226
<b>Lugoj</b>	244
<b>Mehadia</b>	241
<b>Neamt</b>	234
<b>Oradea</b>	380
<b>Pitesti</b>	10
<b>Rimnicu Vilcea</b>	193
<b>Sibiu</b>	253
<b>Timisoara</b>	329
<b>Urziceni</b>	80
<b>Vaslui</b>	199
<b>Zerind</b>	374

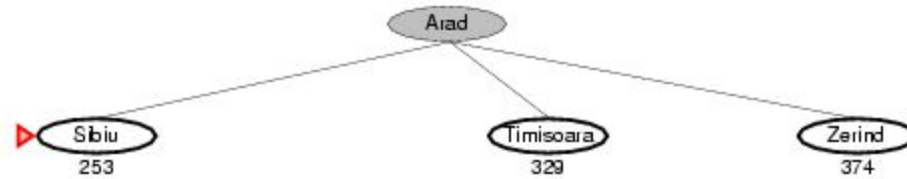
# Greedy best-first search

- Evaluation function  $f(n) = h(n)$  (**h**euristic)  
= estimate of cost from  $n$  to *goal*
- e.g.,  $h_{SLD}(n)$  = straight-line distance from  $n$  to Bucharest
- Greedy best-first search expands the node that **appears** to be closest to goal

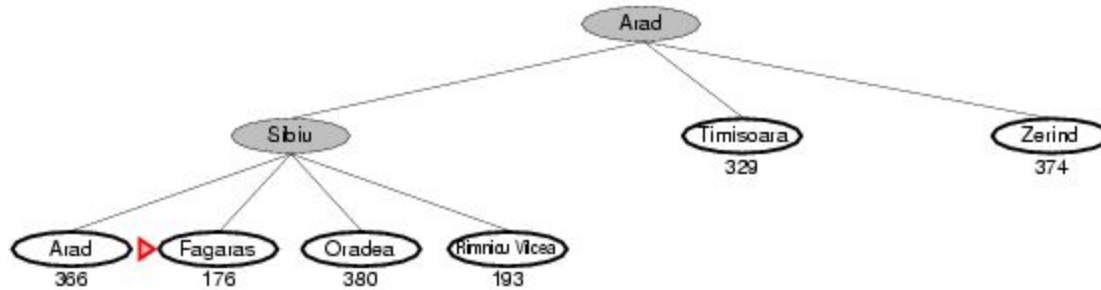
# Greedy best-first search example



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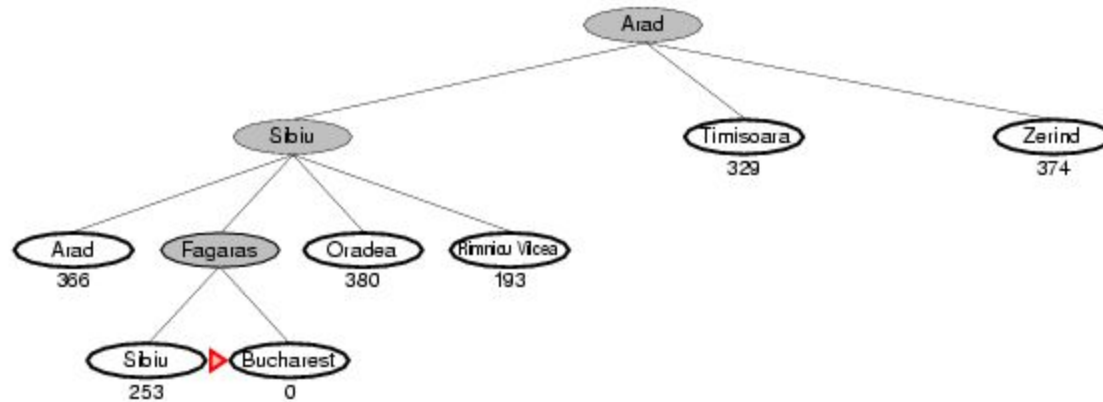


# Greedy best-first search example





# Greedy best-first search example



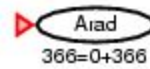
# Properties of greedy best-first search

- Complete? No – can get stuck in loops, e.g., lasi □ Neamt □ lasi □ Neamt □
- Time?  $O(b^m)$ , but a good heuristic can give dramatic improvement
- Space?  $O(b^m)$  -- keeps all nodes in memory
- Optimal? No

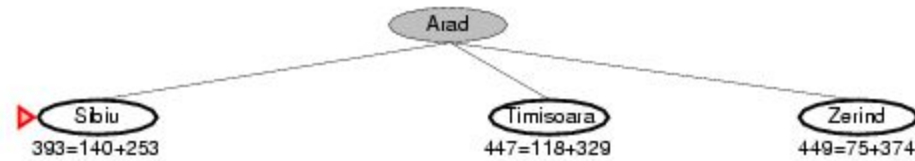
# A\* search

- 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 from  $n$  to goal
- $f(n)$  = estimated total cost of path through  $n$  to goal

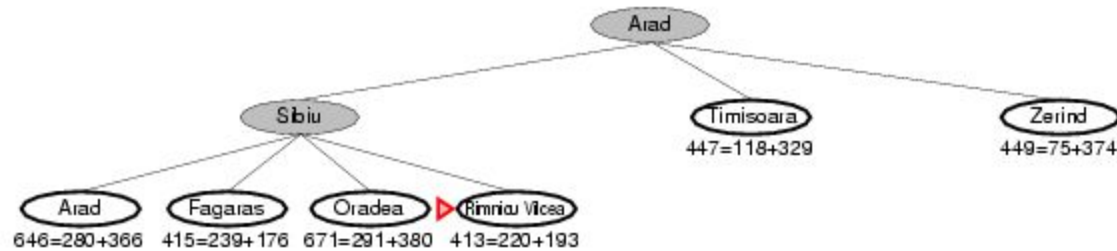
# A\* search example



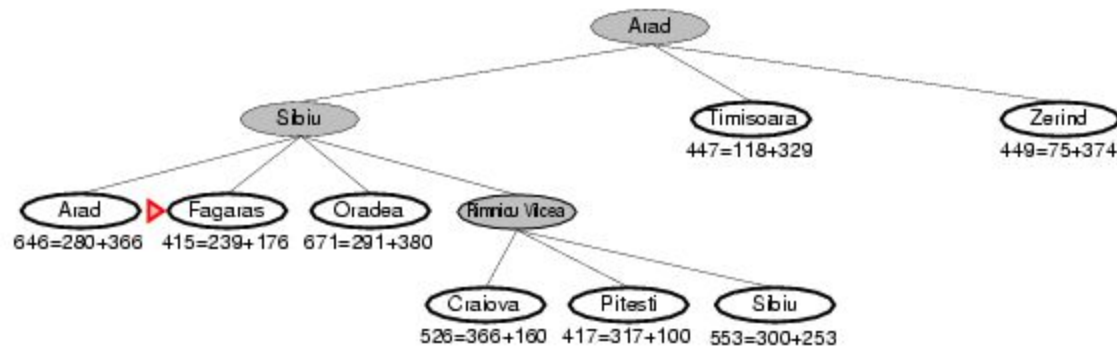
# A\* search example



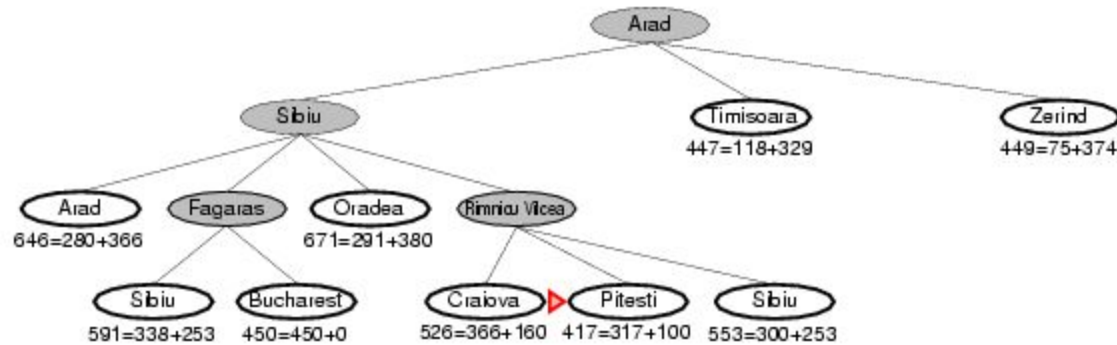
# A\* search example



# A\* search example

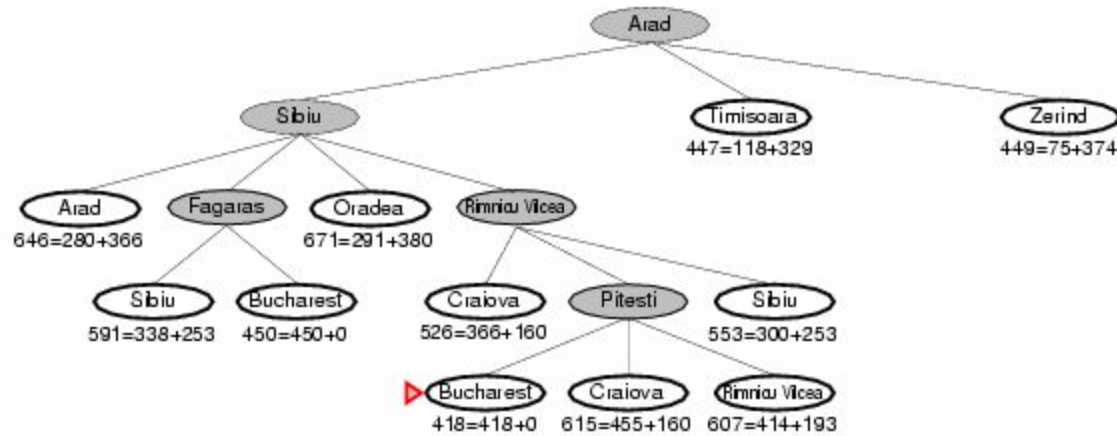


# A\* search example





# A\* search example



# Conditions for optimality:

## Admissibility and consistency

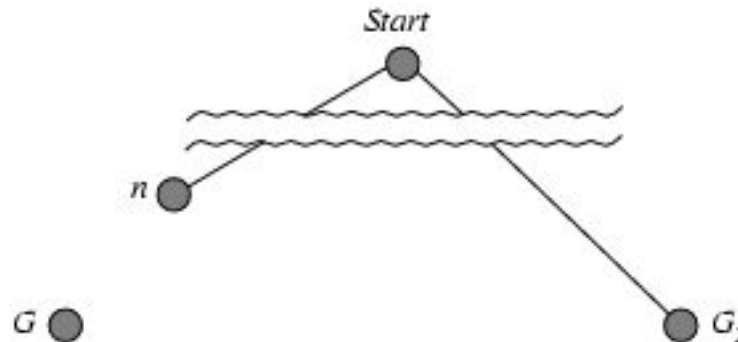
- An **ADMISSIBLE HEURISTIC** is one that never overestimates the cost to reach the goal.
- Because  $g(n)$  is the actual cost to reach  $n$  along the current path, and
- $f(n) = g(n) + h(n)$ , we have as an immediate consequence that  $f(n)$  never overestimates the true cost of a solution along the current path through  $n$ .
- Admissible heuristics are by nature **optimistic** because they think the cost of solving the problem is less than it actually is. Eg. straight line distance.

# 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:  $h_{SLD}(n)$  (never overestimates the actual road distance)  
If  $h(n)$  is admissible,  $A^*$  using TREE-SEARCH is optimal

# Optimality of $A^*$ (proof)

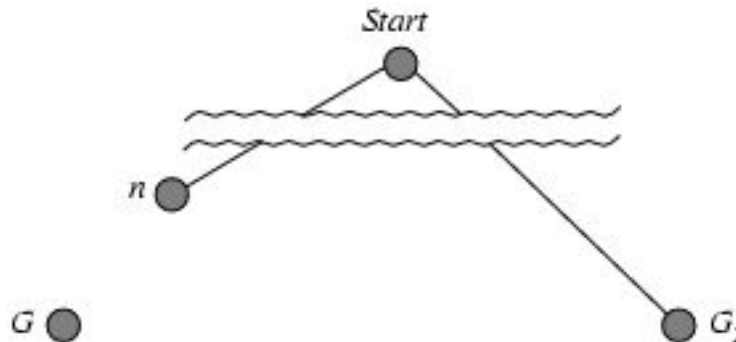
- Suppose some suboptimal goal  $G_2$  has been generated and is in the fringe. Let  $n$  be an unexpanded node in the fringe such that  $n$  is on a shortest path to an optimal goal  $G$ .



- $f(G_2) = g(G_2)$  since  $h(G_2) = 0$
- $g(G_2) > g(G)$  since  $G_2$  is suboptimal
- $f(G) = g(G)$  since  $h(G) = 0$
- $f(G_2) > f(G)$  from above

# Optimality of $A^*$ (proof)

- Suppose some suboptimal goal  $G_2$  has been generated and is in the fringe. Let  $n$  be an unexpanded node in the fringe such that  $n$  is on a shortest path to an optimal goal  $G$ .



- $f(G_2) > f(G)$  from above
- $h(n) \leq h^*(n)$  since  $h$  is admissible
- $g(n) + h(n) \leq g(n) + h^*(n)$
- $f(n) \leq f(G)$

Hence  $f(G_2) > f(n)$ , and  $A^*$  will never select  $G_2$  for expansion

# Consistency

- A second, slightly stronger condition called **CONSISTENCY** (or sometimes monotonicity) which is required only for applications of  $A^*$  to graph search.
- A heuristic  $h(n)$  is consistent if, for every node  $n$  and every successor  $n'$  of  $n$  generated by any action  $a$ , the estimated cost of reaching the goal from  $n$  is no greater than the step cost of getting to  $n'$  plus the estimated cost of reaching the goal from  $n'$ .

# Consistent heuristics

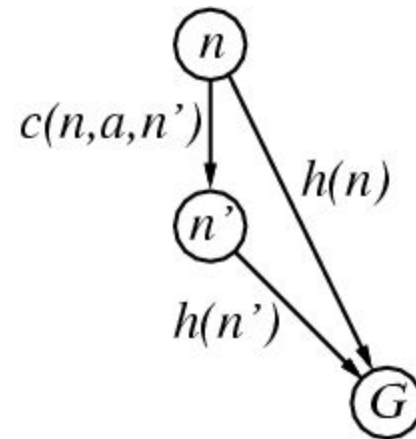
- A heuristic is **consistent** if for every node  $n$ , every successor  $n'$  of  $n$  generated by any action  $a$ ,

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

- If  $h$  is consistent, we have

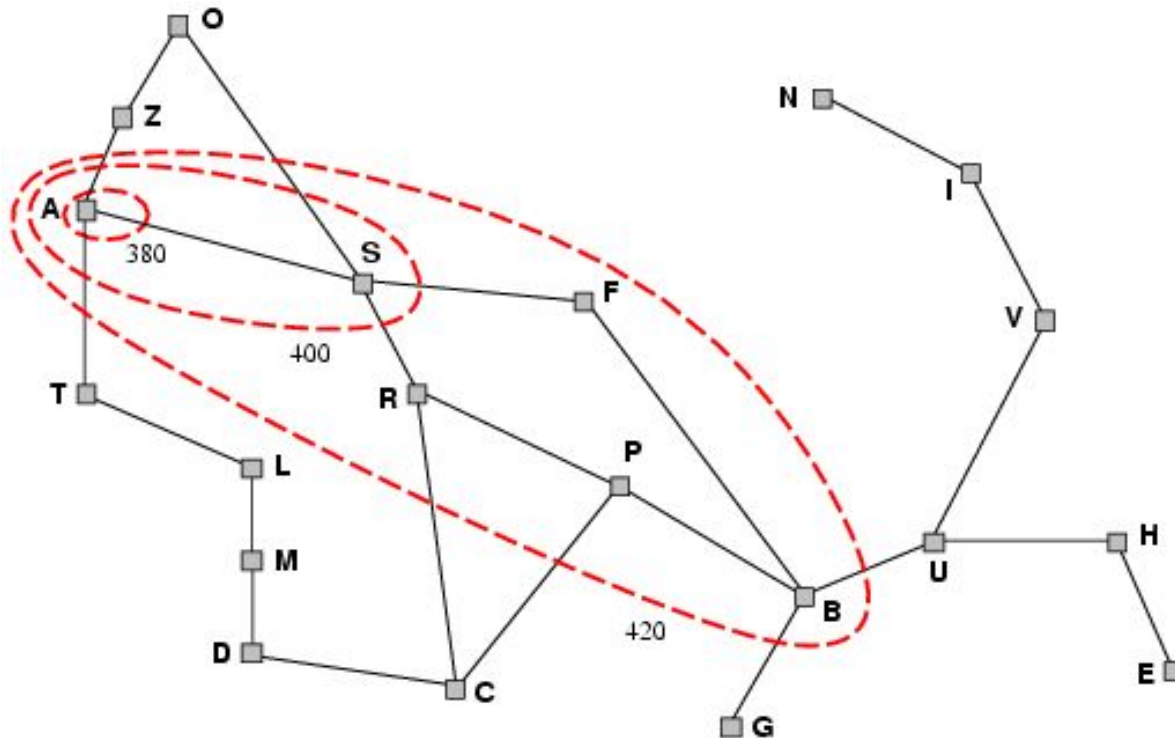
$$\begin{aligned} f(n') &= g(n') + h(n') \\ &= g(n) + c(n,a,n') + h(n') \\ &\geq g(n) + h(n) \\ &= f(n) \end{aligned}$$

- i.e.,  $f(n)$  is non-decreasing along any path.
- If  $h(n)$  is consistent, A\* using GRAPH-SEARCH is optimal



# Optimality of $A^*$

- $A^*$  expands nodes in order of increasing  $f$  value
- Gradually adds " $f$ -contours" of nodes
- 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
- Space? Keeps all nodes in memory
- Optimal? Yes

# Heuristic Functions

- The 8-puzzle is one of the earliest heuristic search problems.
- The objective of the puzzle is to slide the tiles horizontally or vertically into empty space until the configuration matches the goal state.
- Average solution cost is about 22 steps and average branching factor is 3 results in  $3^{22}$  states.

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

# Heuristic Functions

Heuristic Functions 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)

Both  $h_1$  and  $h_2$  are *admissible heuristics*.

# 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)

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

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

# 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)

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

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

# Effect of Heuristic Accuracy on Performance

- The effective branching factor generated by any heuristic search gives the quality of 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
- Typical search costs (average number of nodes expanded):
  - $d=12$  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

# Generating admissible heuristics from Relaxed problems

- A problem with fewer restrictions on the actions is called a **relaxed problem**
- The cost of an optimal solution to a relaxed problem is an admissible heuristic for the original 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



# Generating admissible heuristics from Subproblems

- Admissible heuristics can also be derived from solution cost of a subproblem of a given solution.