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# Informed Search

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# Heuristic

From Wikipedia:

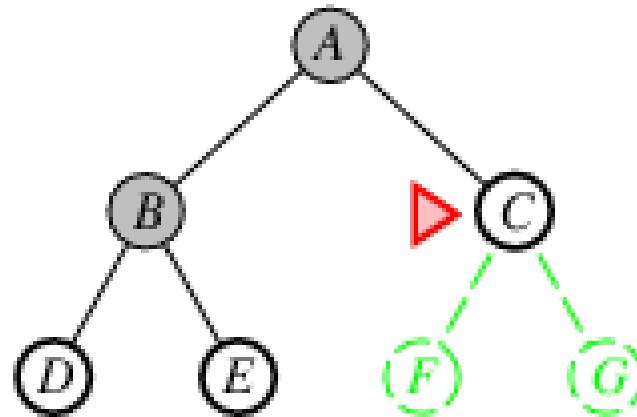
*any approach to problem solving, learning, or discovery  
that employs a practical method  
not guaranteed to be optimal or perfect  
but sufficient for the immediate goals*

# Outline

- Best-first search
- A\* search
- Iterative improvement algorithms
  - hill-climbing
  - simulated annealing
  - genetic algorithms

# best-first search

# Review: Tree Search



- Search space is in form of a tree
- Strategy is defined by picking the **order of node expansion**

# Best-First Search

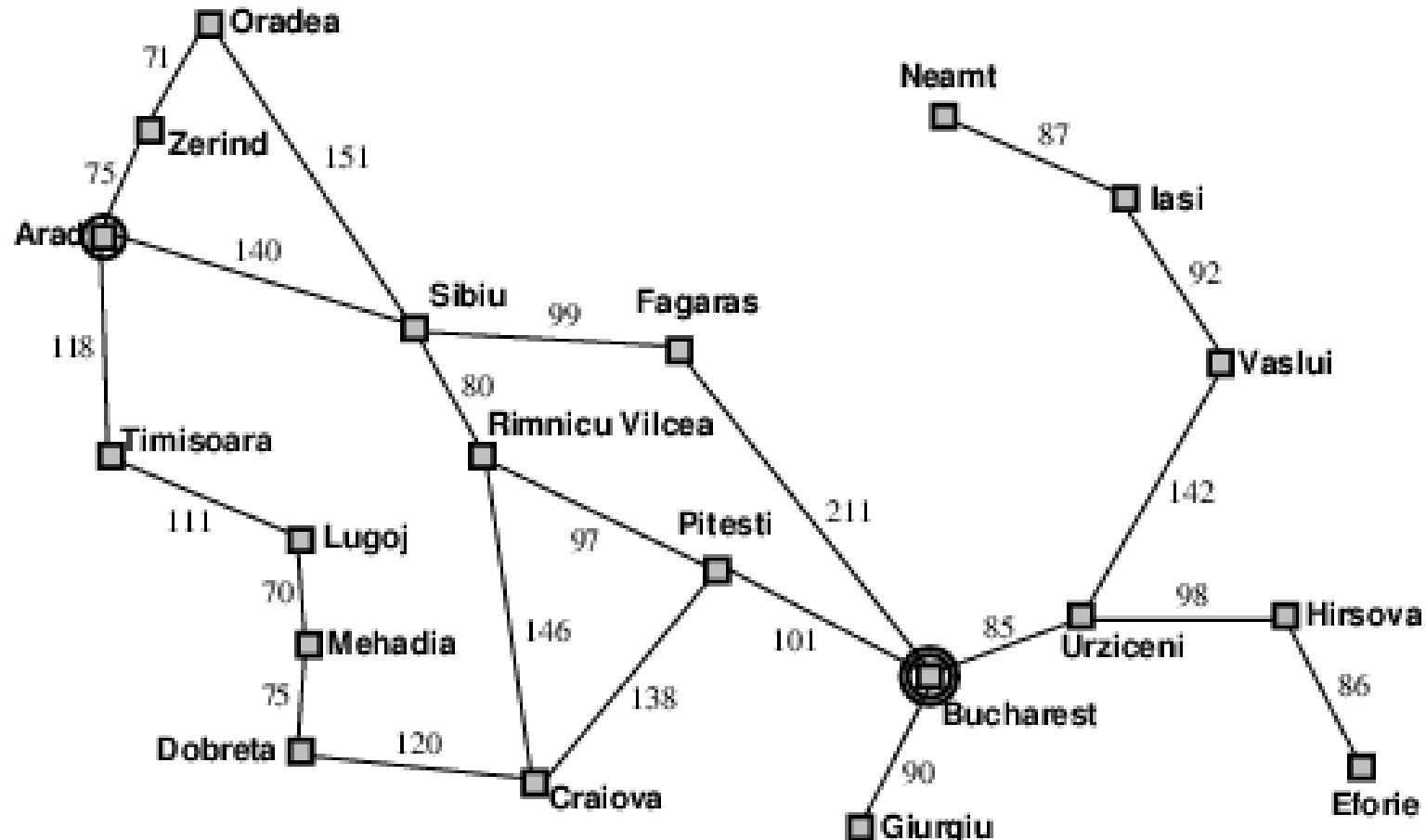
- **Idea:** use an **evaluation function** for each node
  - estimate of “desirability”
- ⇒ Expand most desirable unexpanded node
- **Implementation:**  
**fringe** is a queue sorted in decreasing order of desirability
- Special cases
  - greedy search
  - A\* search

# Romania





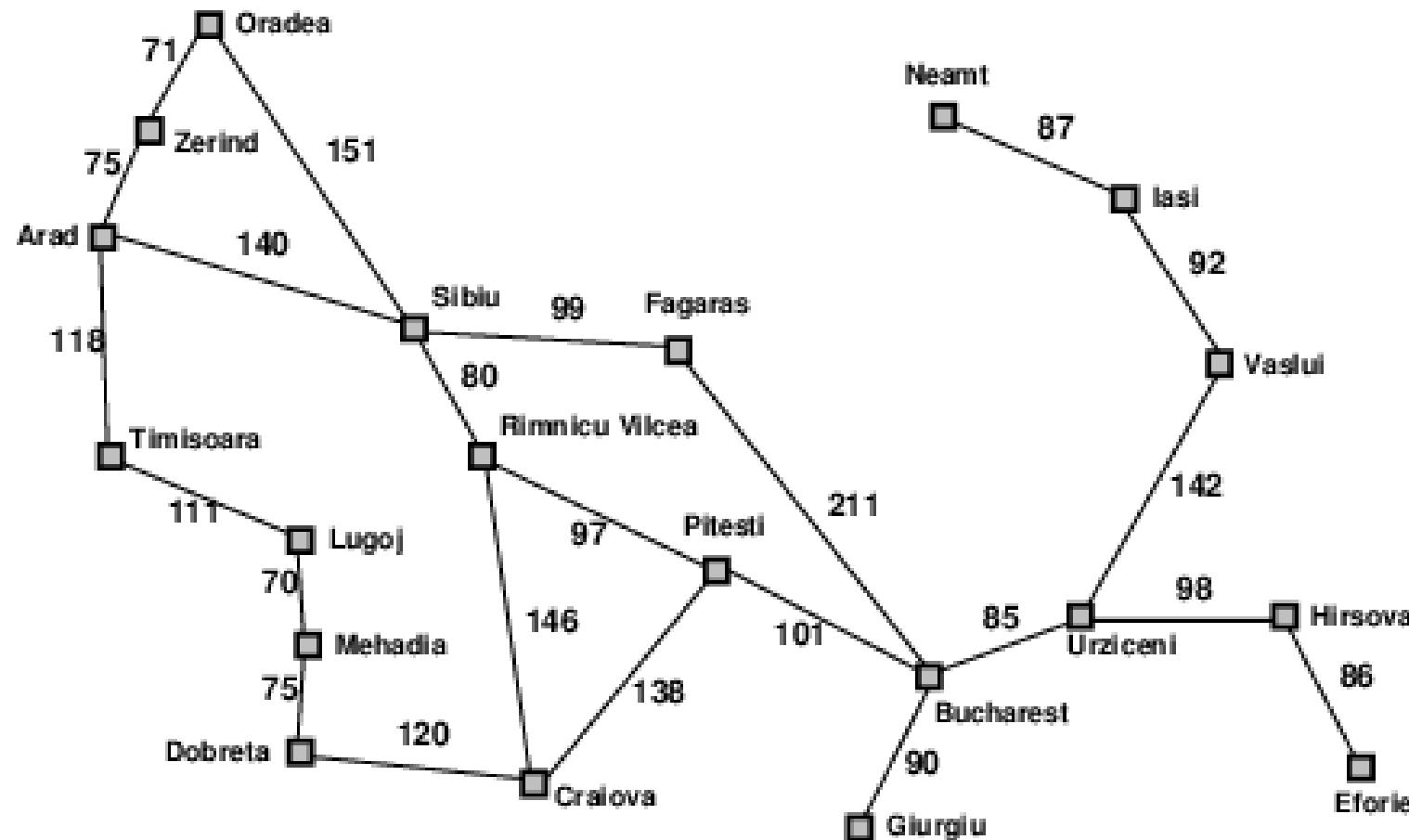
# Romania



# Greedy Search

- State 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

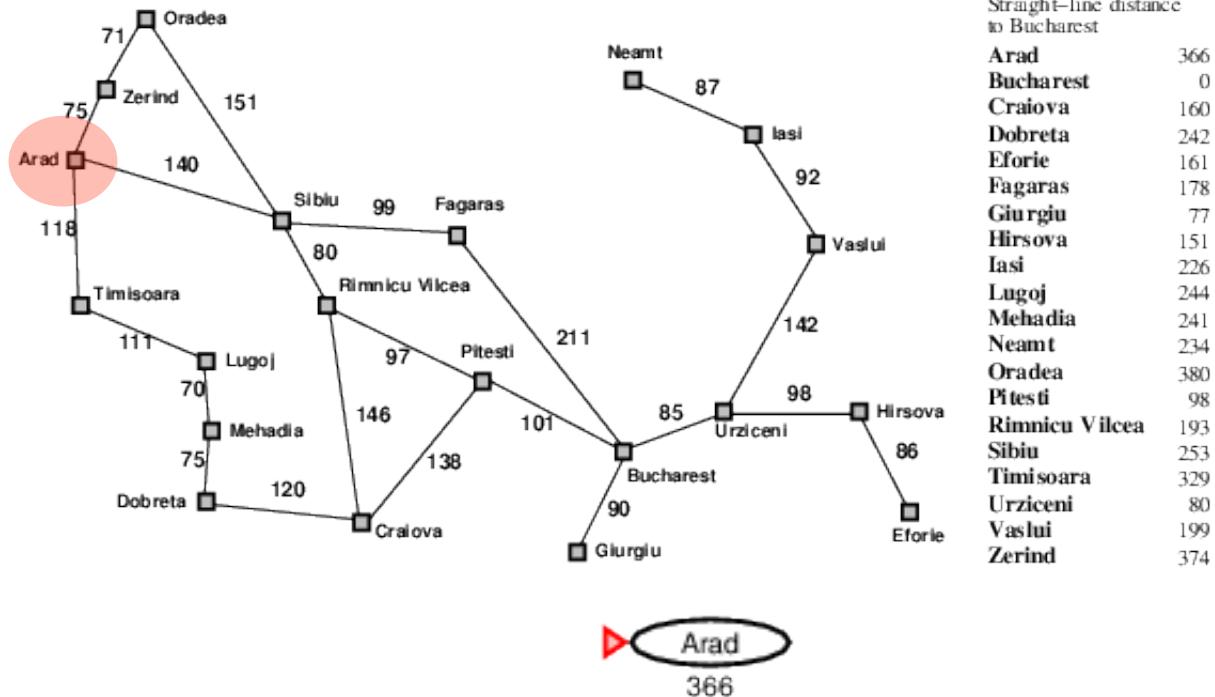
# Romania with Step Costs in km



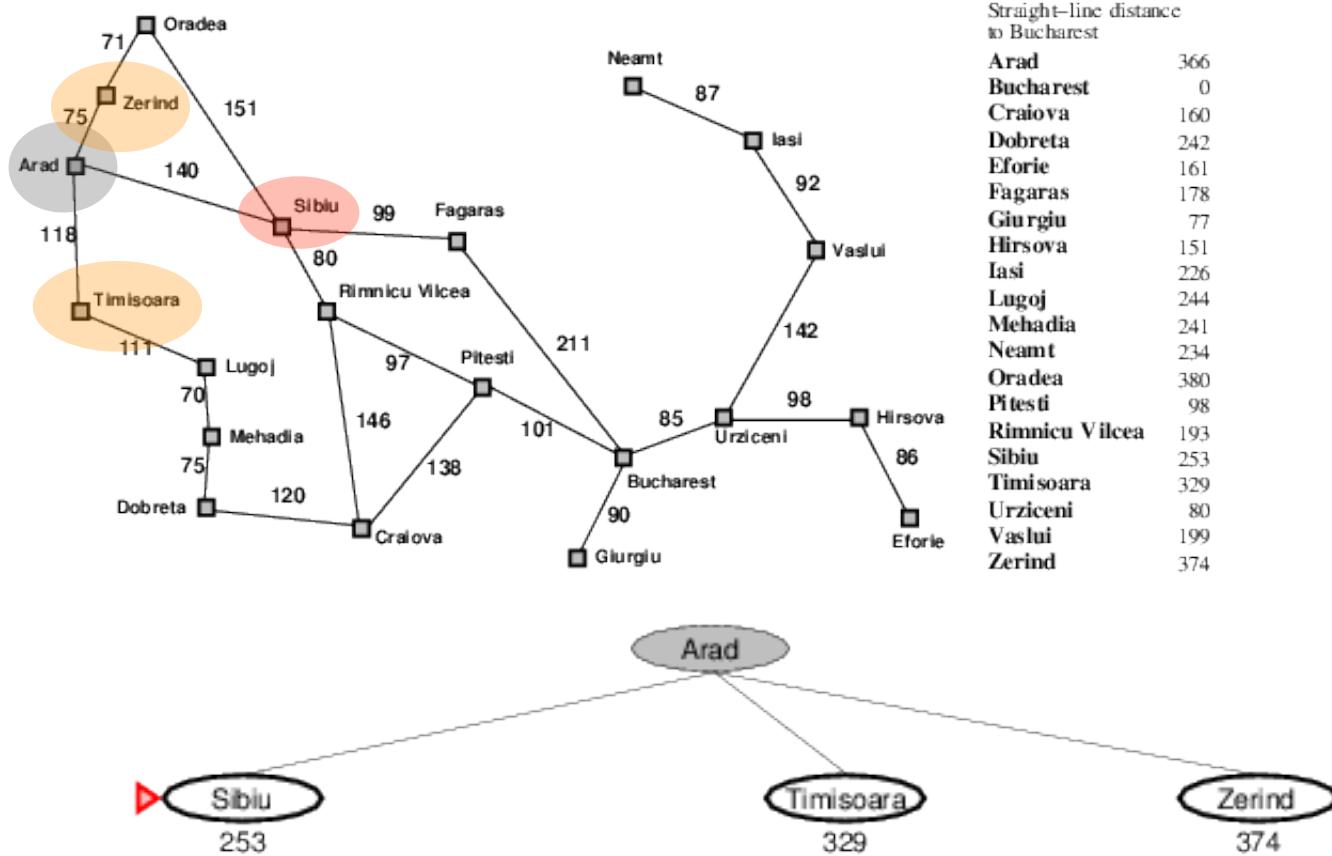
Straight-line distance to Bucharest

Arad	366
Bucharest	0
Craiova	160
Dobreta	242
Eforie	161
Fagaras	178
Giurgiu	77
Hirsova	151
Iasi	226
Lugoj	244
Mehadia	241
Neamt	234
Oradea	380
Pitesti	98
Rimnicu Vilcea	193
Sibiu	253
Timisoara	329
Urziceni	80
Vaslui	199
Zerind	374

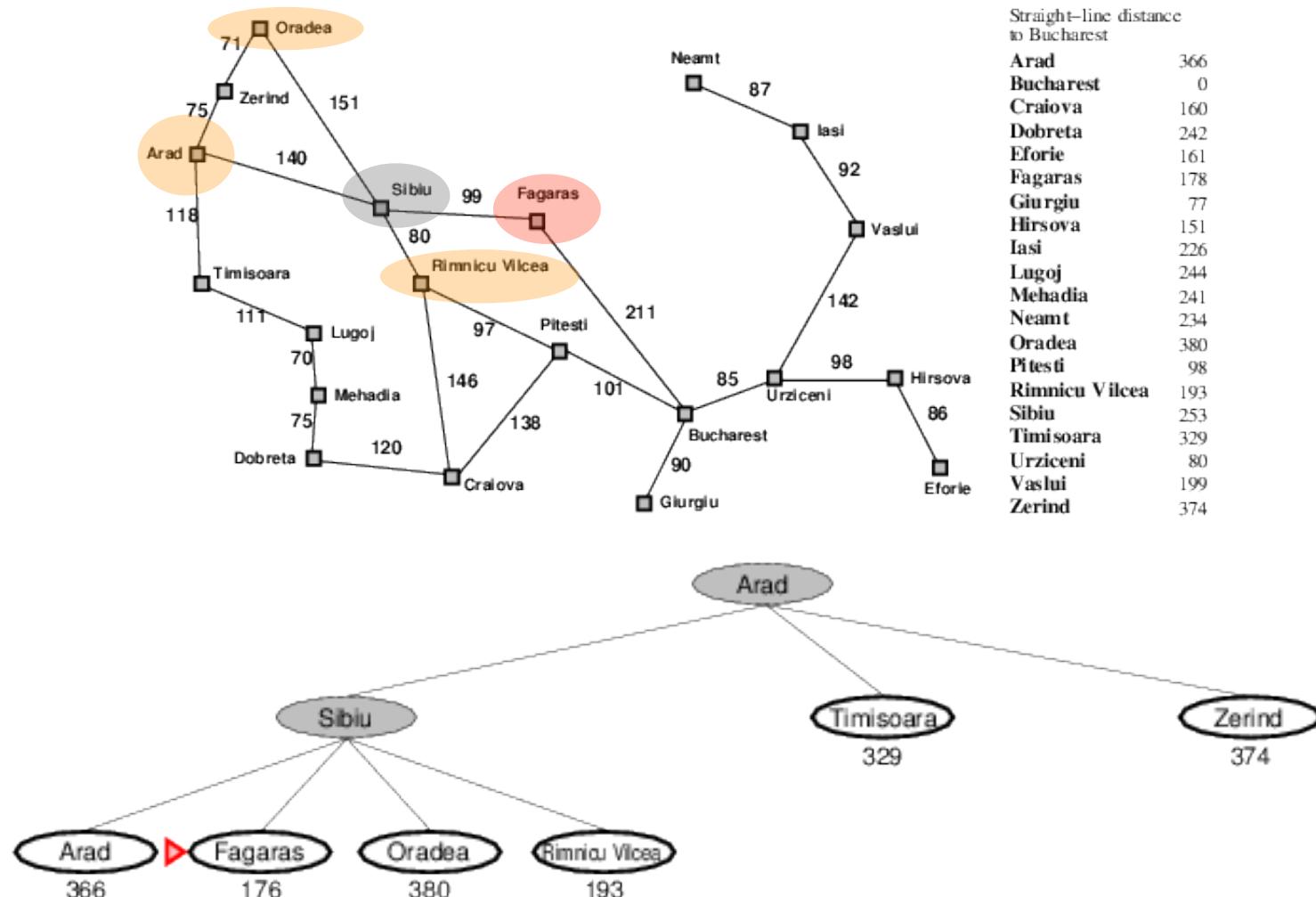
# Greedy Search Example



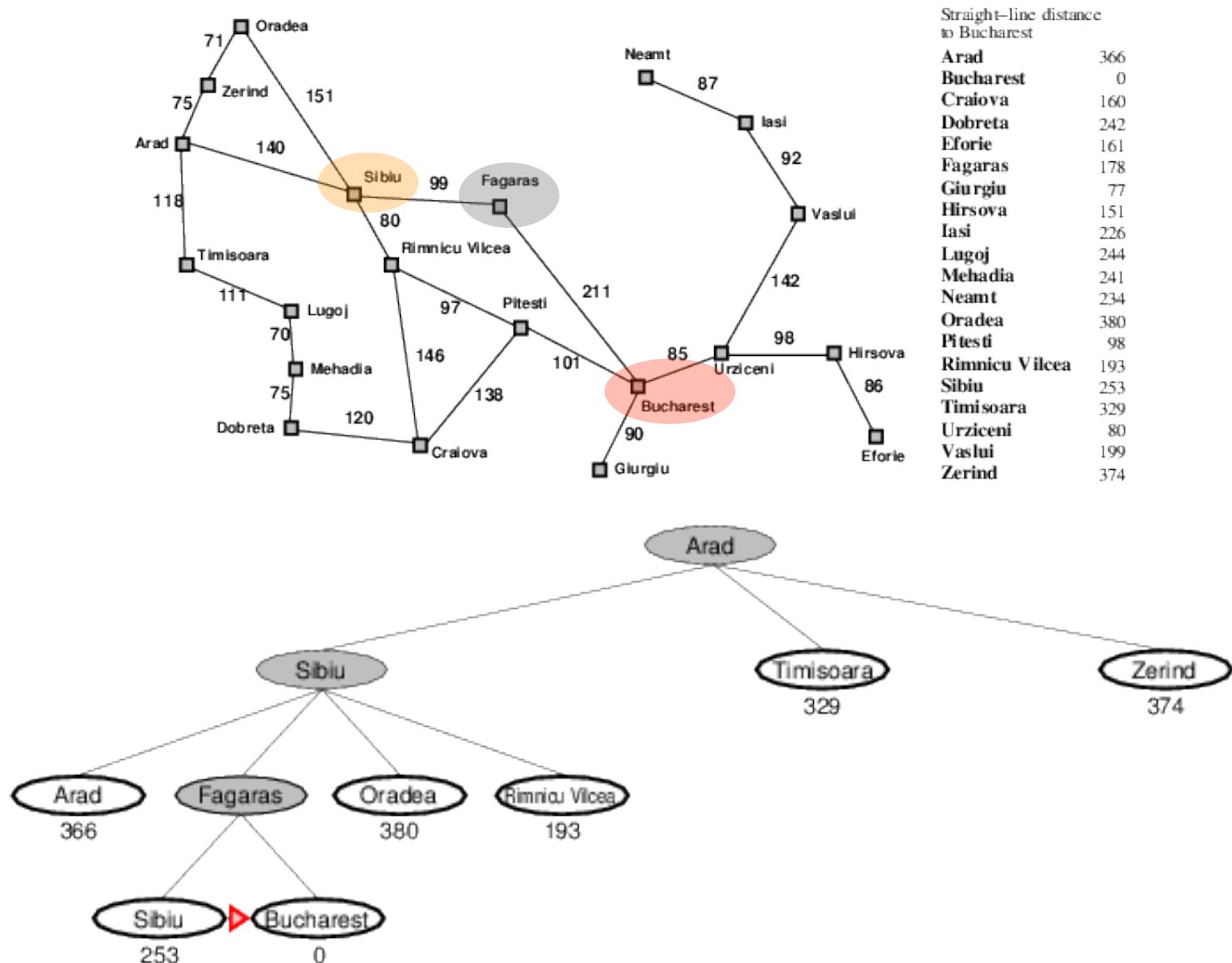
# Greedy Search Example



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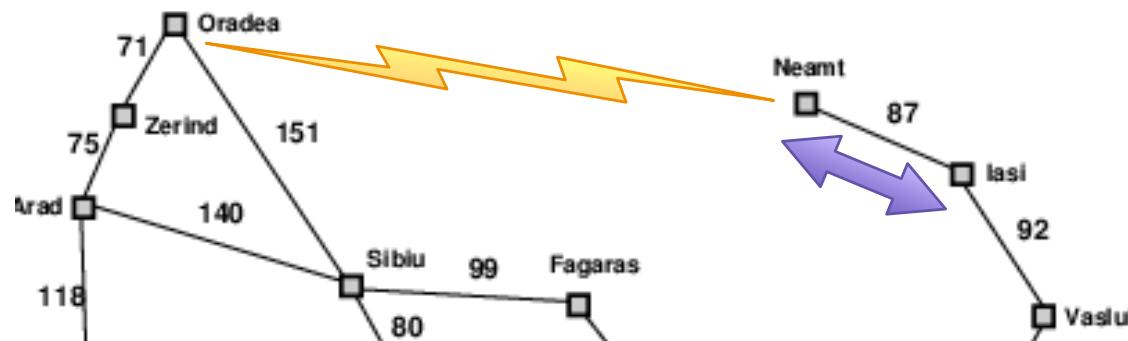


# Greedy Search Example



# Properties of Greedy Search

- **Complete?** No, can get stuck in loops, e.g., with Oradea as goal,  
Iasi → Neamt → Iasi → Neamt →



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

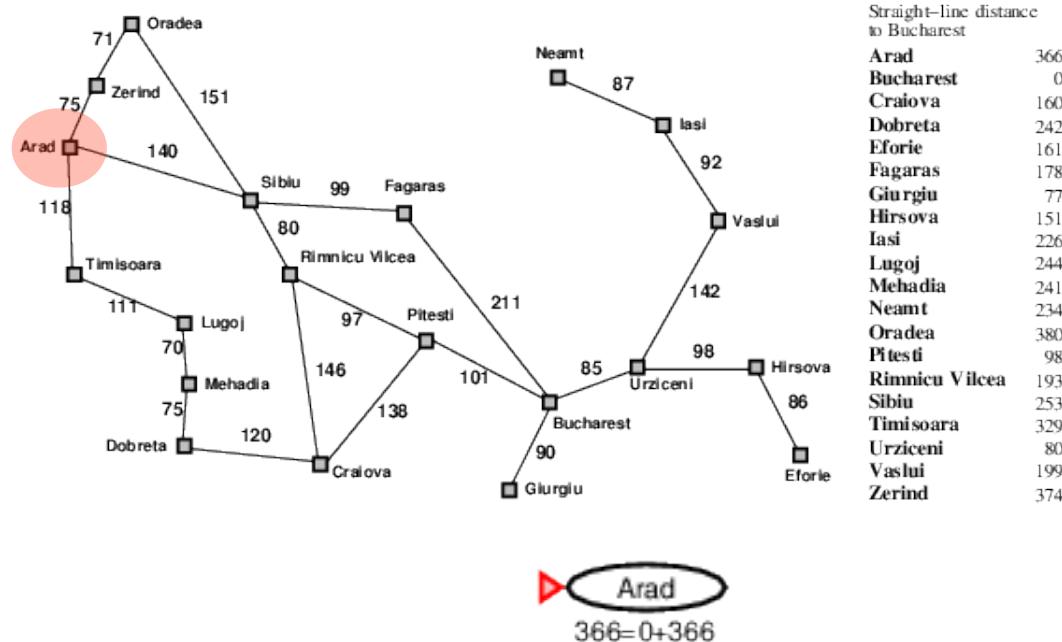


# a\* search

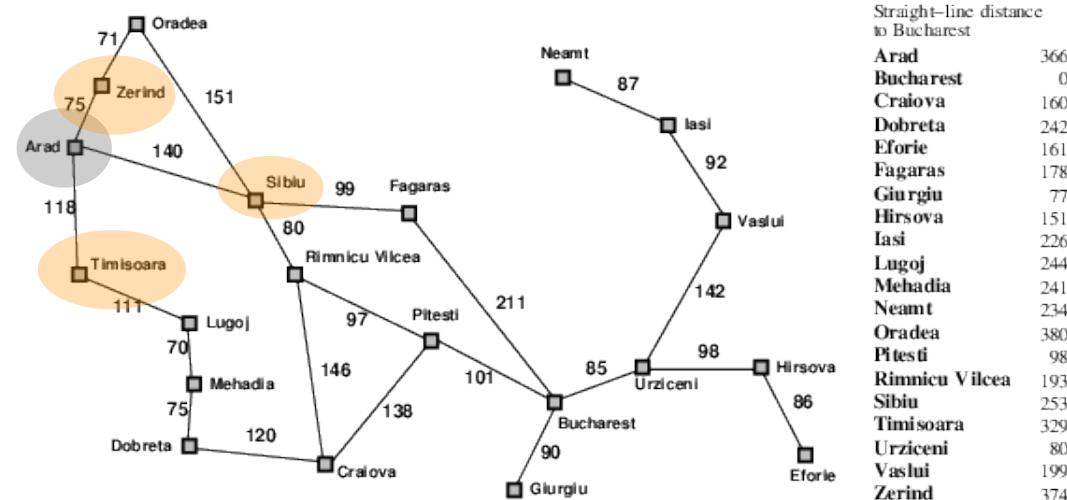
# A\* Search

- Idea: avoid expanding paths that are already expensive
- State 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.,  $h(n) \leq h^*(n)$  where  $h^*(n)$  is the **true** cost from  $n$
  - also require  $h(n) \geq 0$ , so  $h(G) = 0$  for any goal  $G$
- E.g.,  $h_{SLD}(n)$  **never overestimates** the actual road distance
- **Theorem:** A\* search is optimal

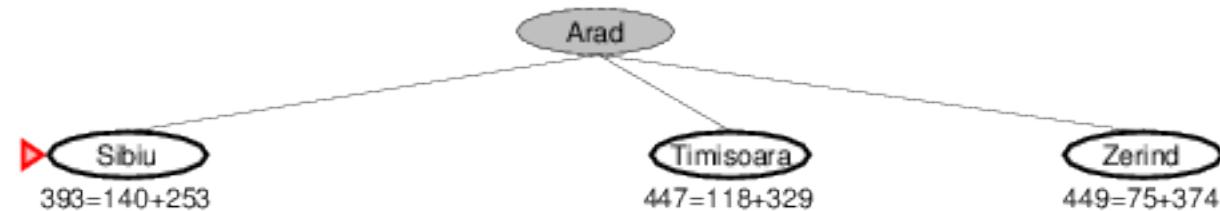
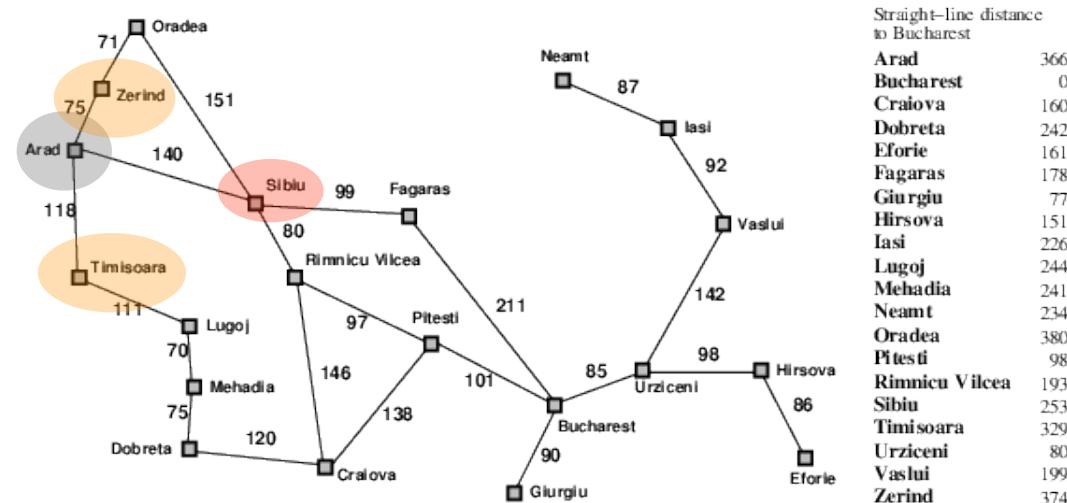
# A\* Search Example



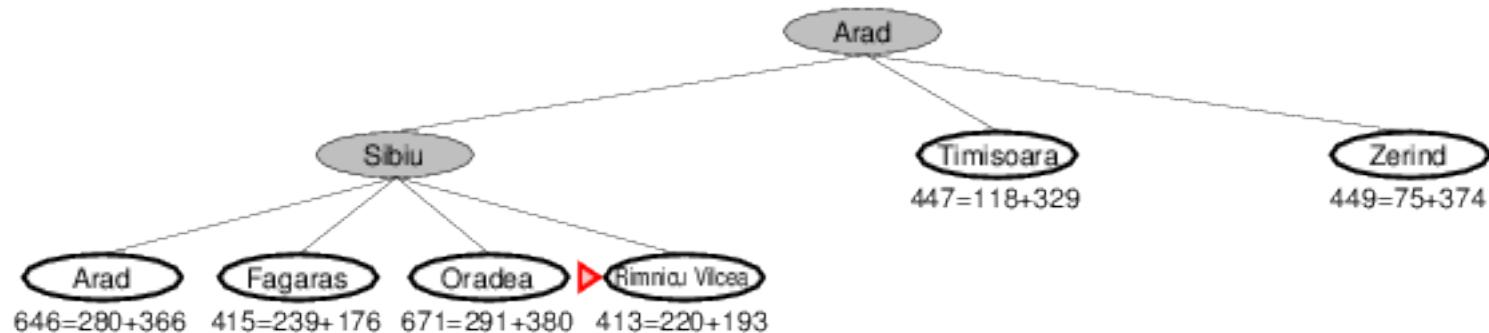
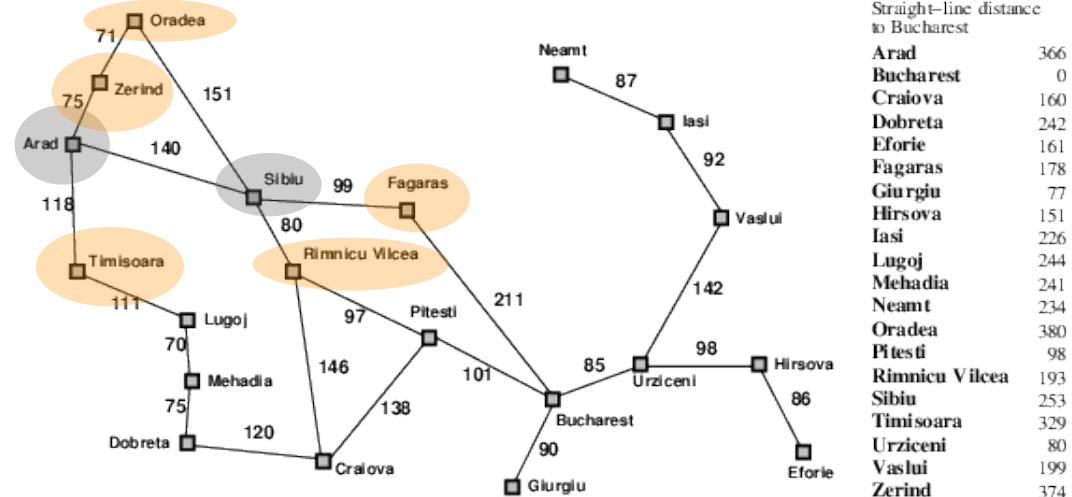
# A\* Search Example



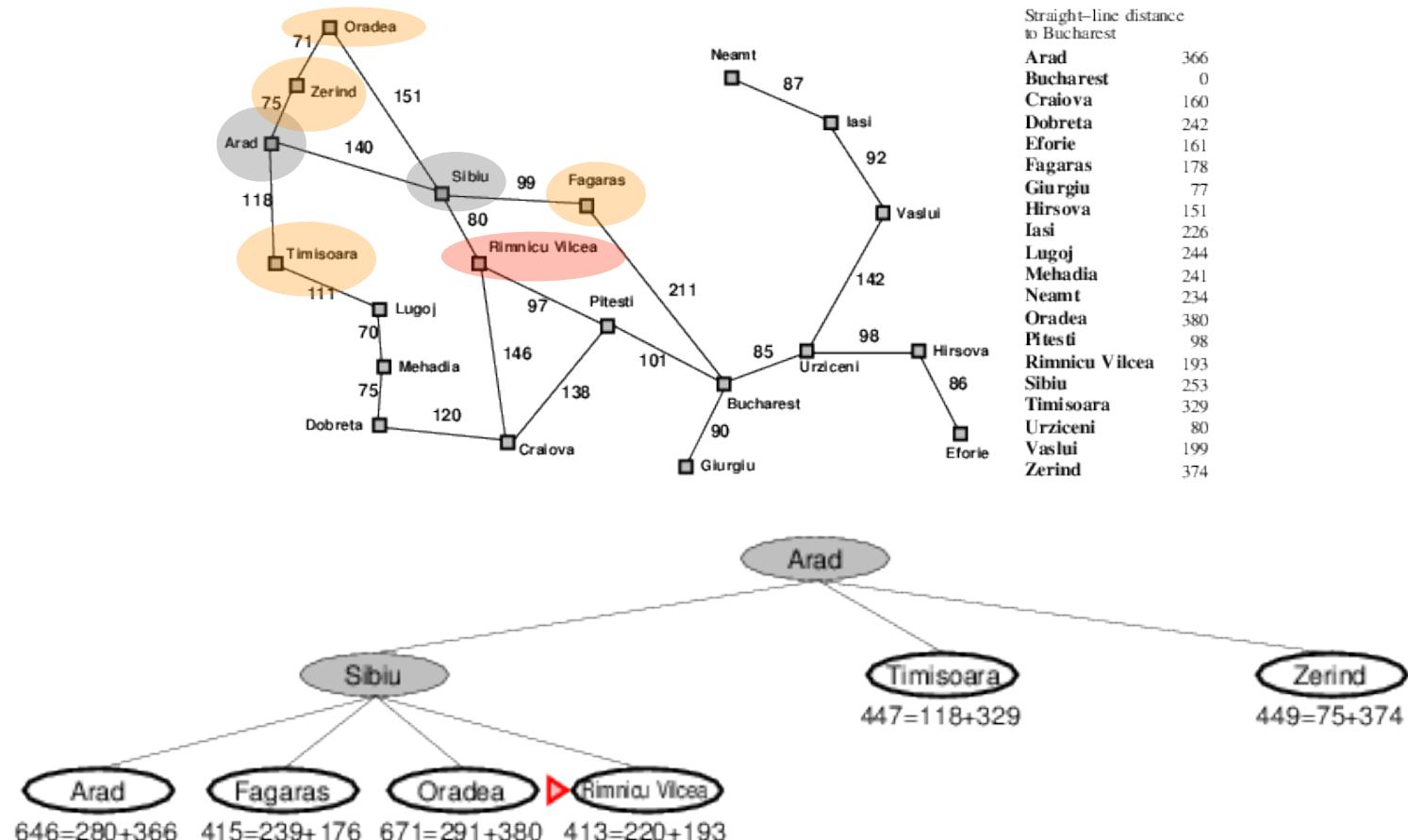
# A\* Search Example



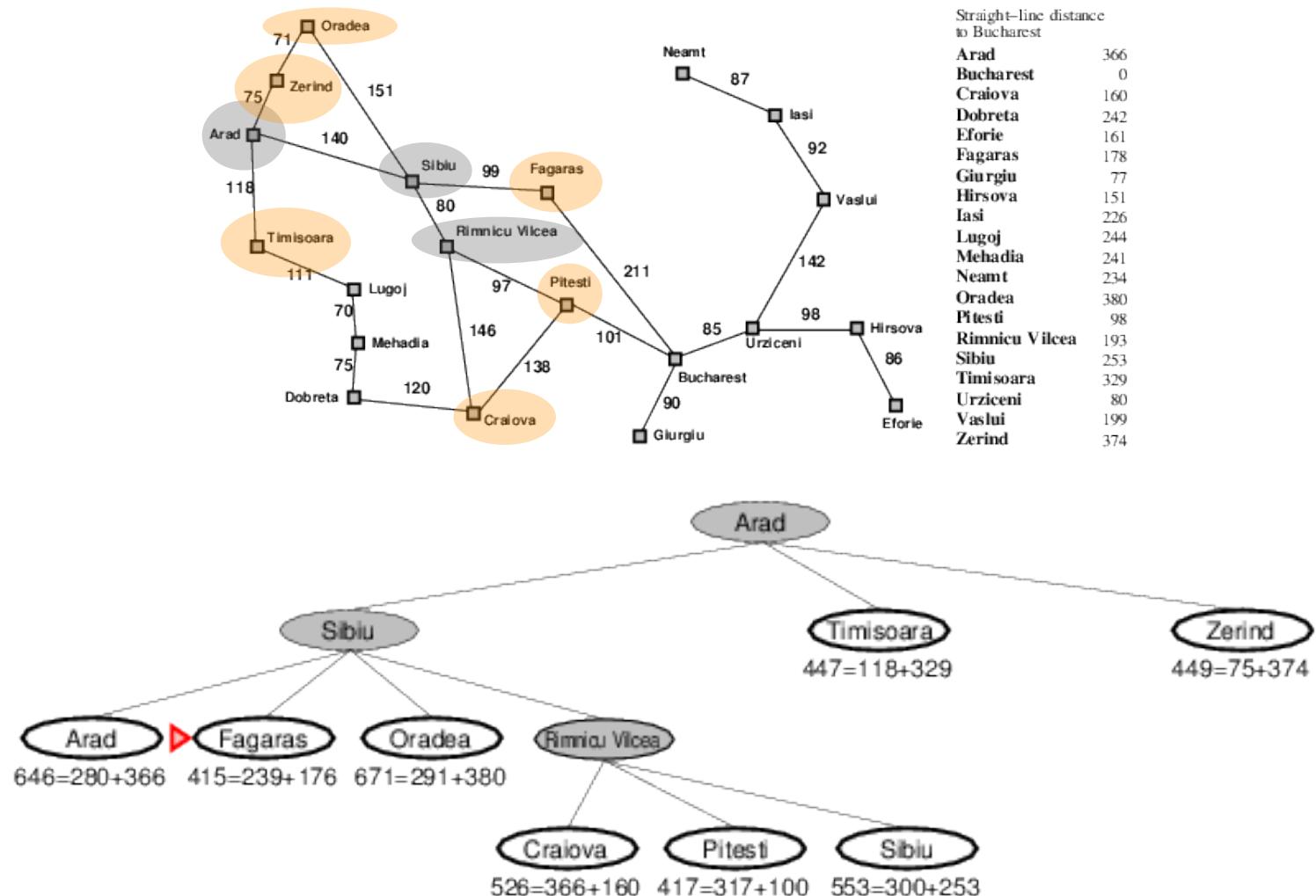
# A\* Search Example



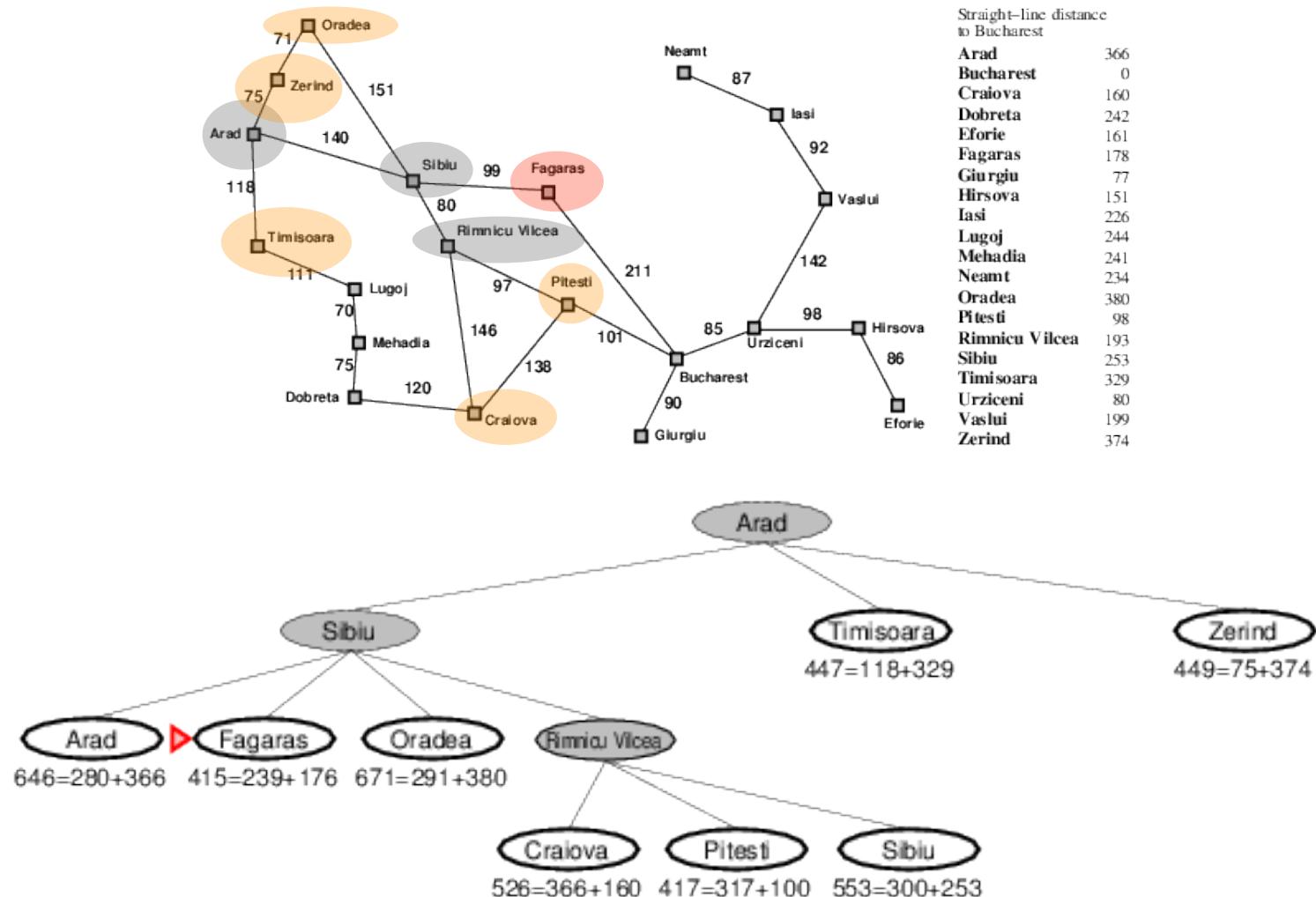
# A\* Search Example



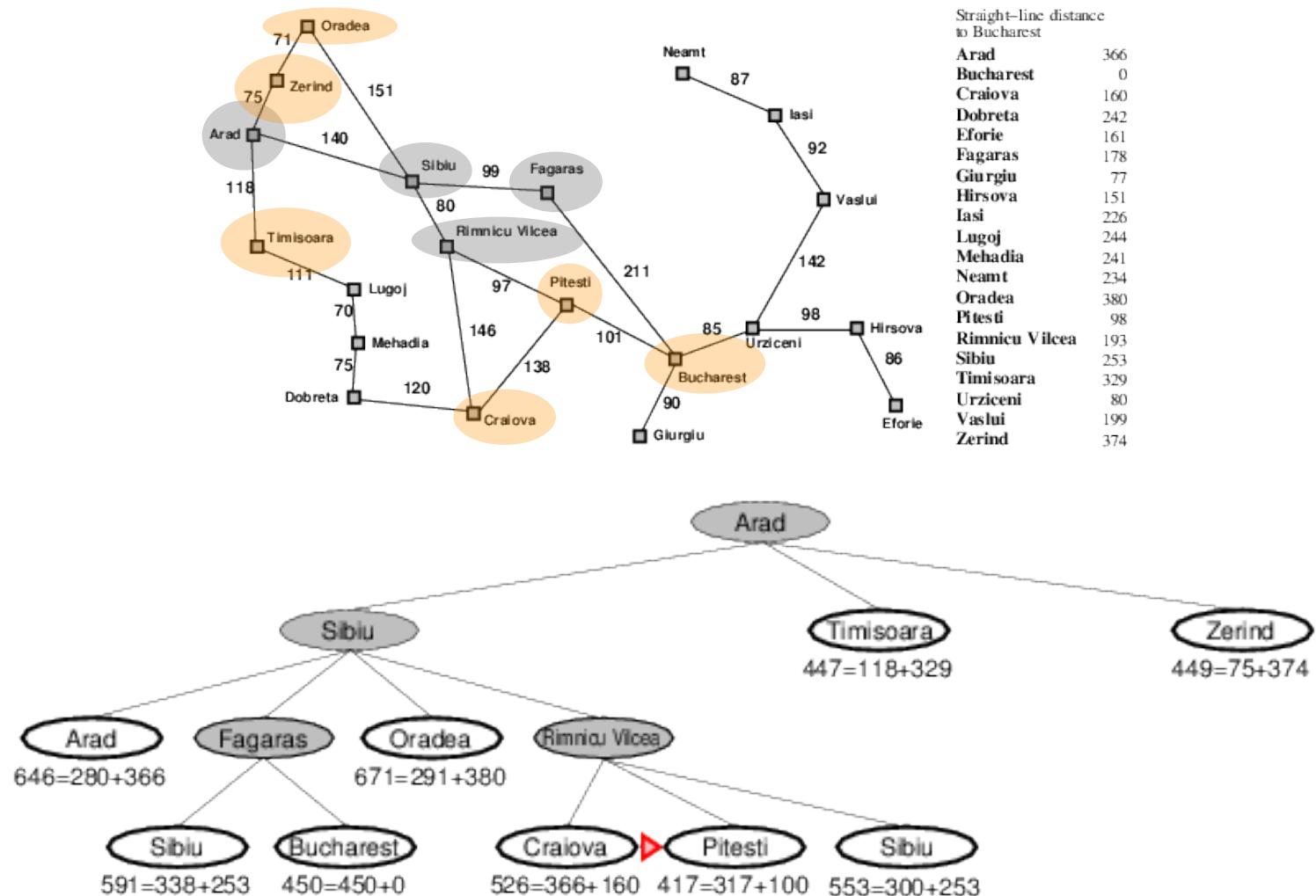
# A\* Search Example



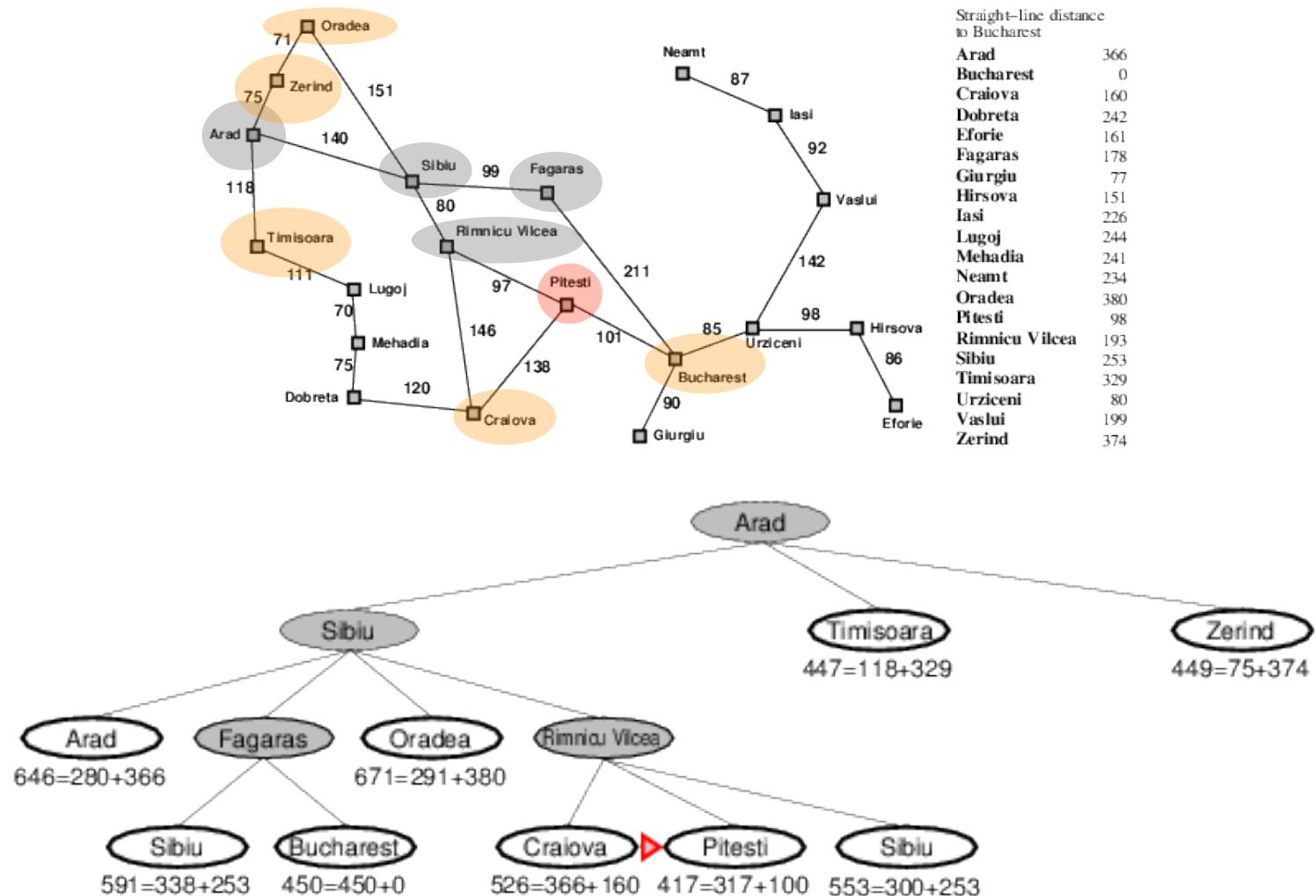
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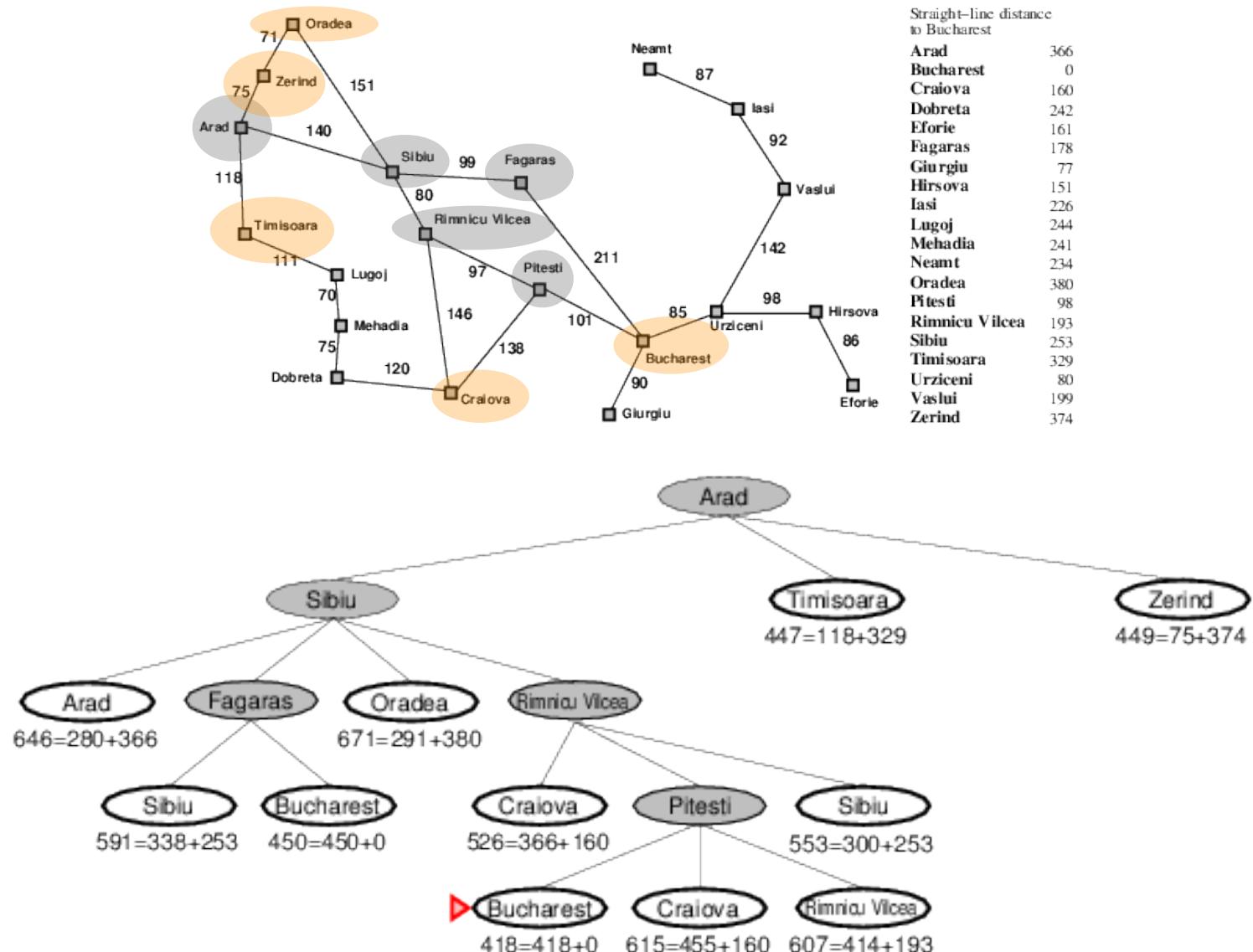
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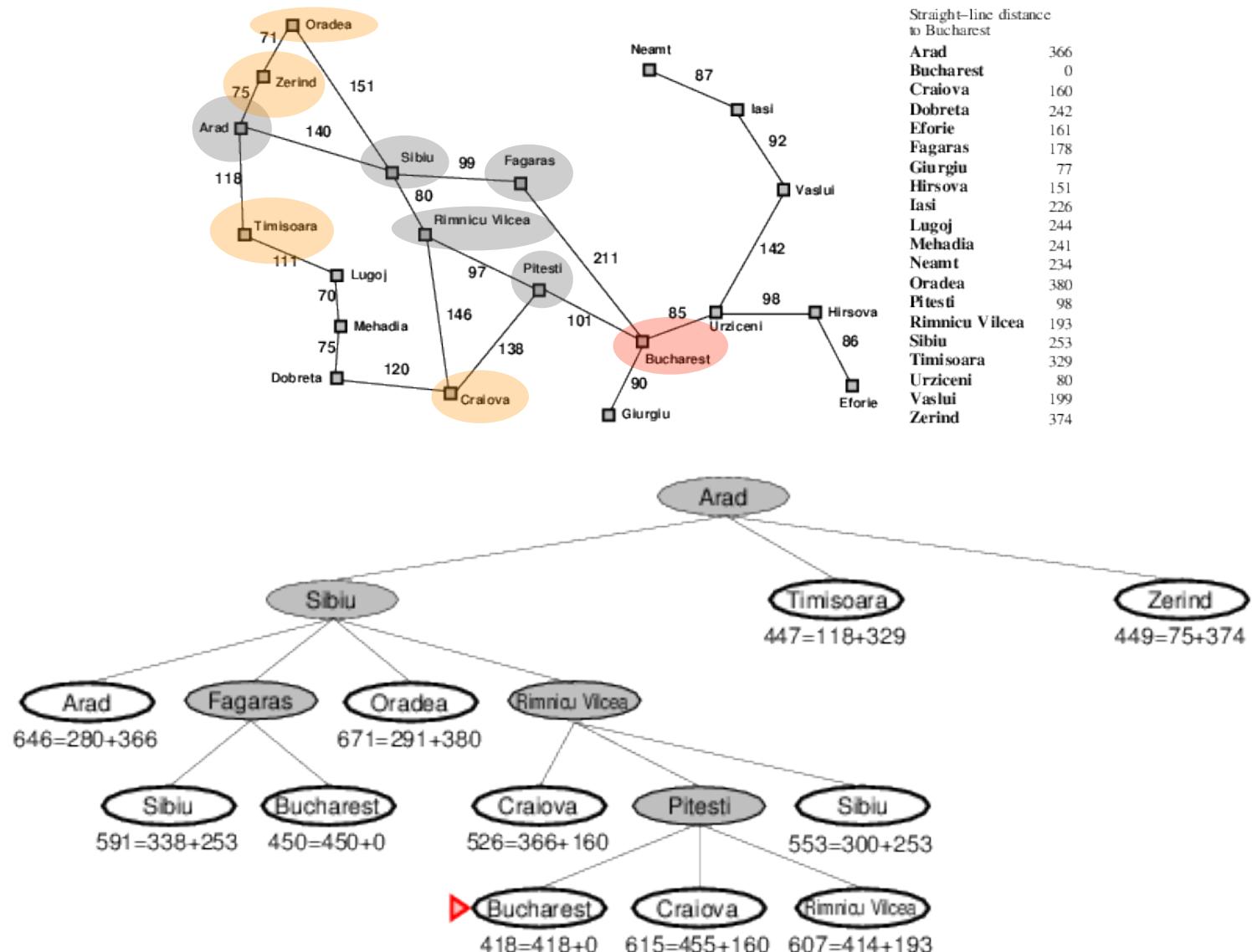
# A\* Search Example



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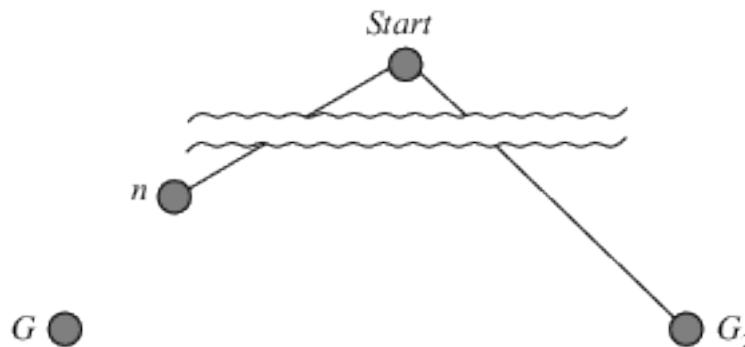
# A\* Search Example





# Optimality of A\*

- 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  $G$



$$\begin{aligned} f(G_2) &= g(G_2) && \text{since } h(G_2) = 0 \\ &> g(G) && \text{since } G_2 \text{ is suboptimal} \\ &\geq f(n) && \text{since } h \text{ is admissible} \end{aligned}$$

- Since  $f(G_2) > f(n)$ , A\* will never terminate at  $G_2$



# Properties of A\*

- Complete? Yes, unless there are infinitely many nodes with  $f \leq f(G)$
- Time? Exponential in [relative error in  $h \times$  length of solution]
- Space? Keeps all nodes in memory
- Optimal? Yes—cannot expand  $f_{i+1}$  until  $f_i$  is finished

A\* expands all nodes with  $f(n) < C^*$

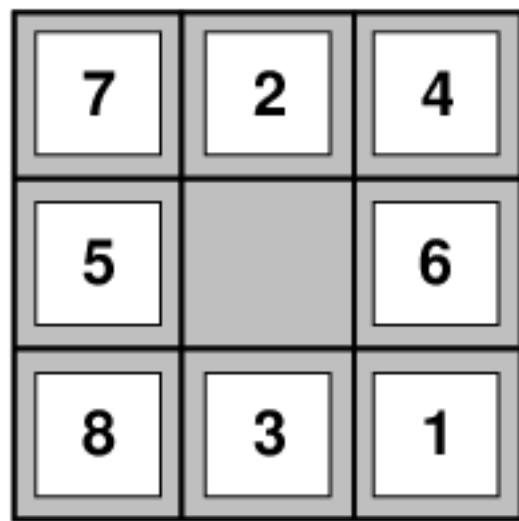
A\* expands some nodes with  $f(n) = C^*$

A\* expands no nodes with  $f(n) > C^*$

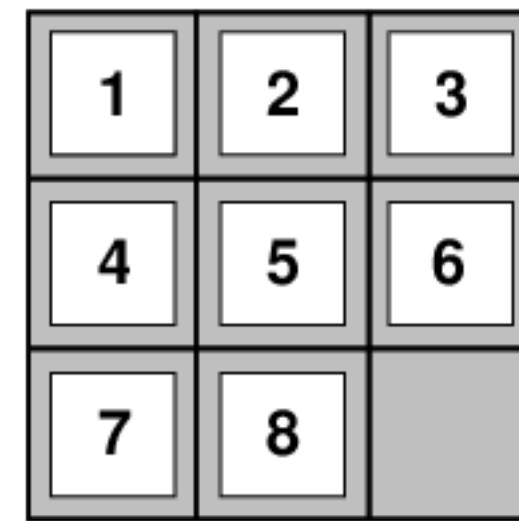


# Admissible Heuristics

- E.g., for the 8-puzzle



Start State

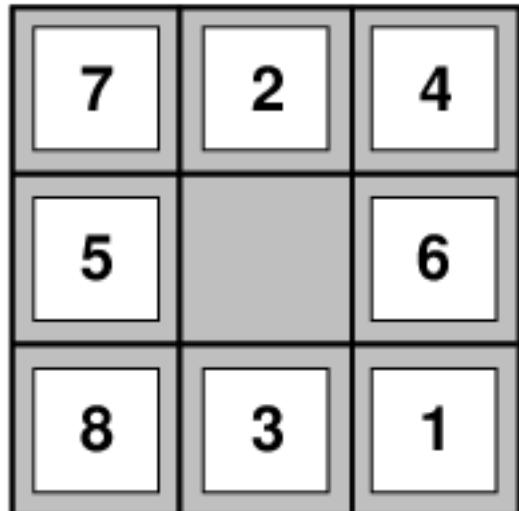


Goal State

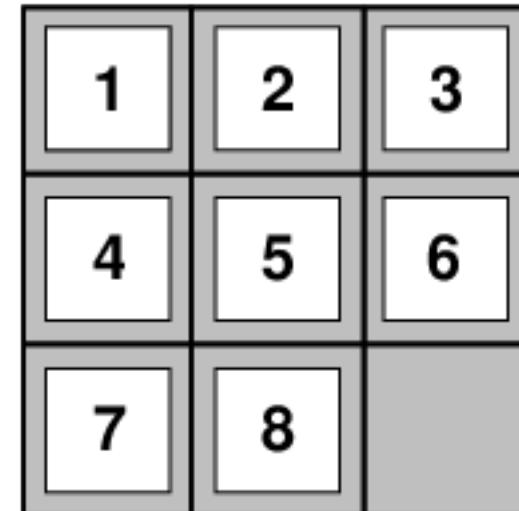


# Admissible Heuristics

- 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



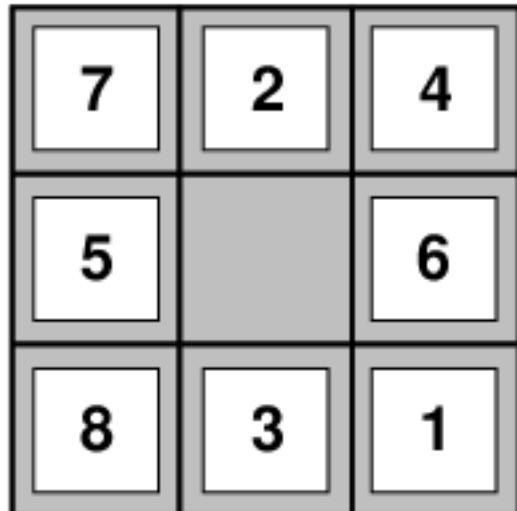
Goal State

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

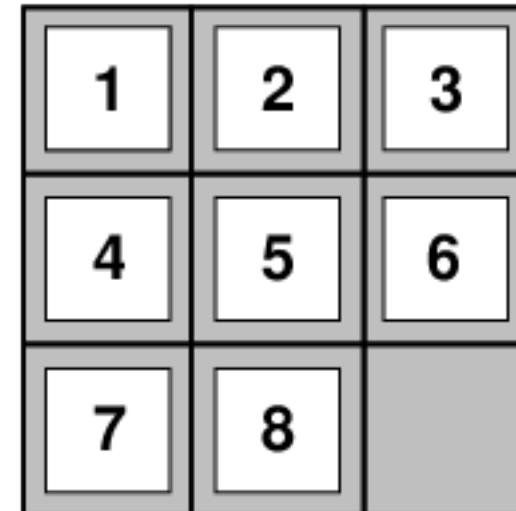


# Admissible Heuristics

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



Start State



Goal State

- $h_1(S) = ?$  6
- $h_2(S) = ?$   $4+0+3+3+1+0+2+1 = 14$

# Dominance

- If  $h_2(n) \geq h_1(n)$  for all  $n$  (both admissible)  
→  $h_2$  dominates  $h_1$  and is better for search
- Typical search costs ( $d$  = depth of solution for 8-puzzle)

$d = 14 \quad \text{IDS} = 3,473,941 \text{ nodes}$

$\text{A}^*(h_1) = 539 \text{ nodes}$

$\text{A}^*(h_2) = 113 \text{ nodes}$

$d = 24 \quad \text{IDS} \approx 54,000,000,000 \text{ nodes}$

$\text{A}^*(h_1) = 39,135 \text{ nodes}$

$\text{A}^*(h_2) = 1,641 \text{ nodes}$

- Given any admissible heuristics  $h_a, h_b$ ,

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

is also admissible and dominates  $h_a, h_b$



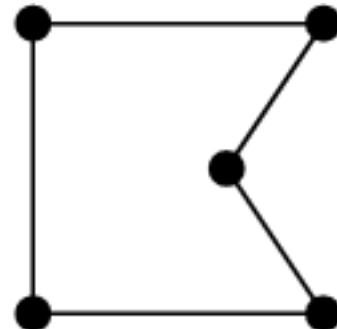
# Relaxed Problems

- 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**  
   $\Rightarrow h_1(n)$  gives the shortest solution
- If the rules are relaxed so that a tile can move to **any adjacent square**  
   $\Rightarrow h_2(n)$  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

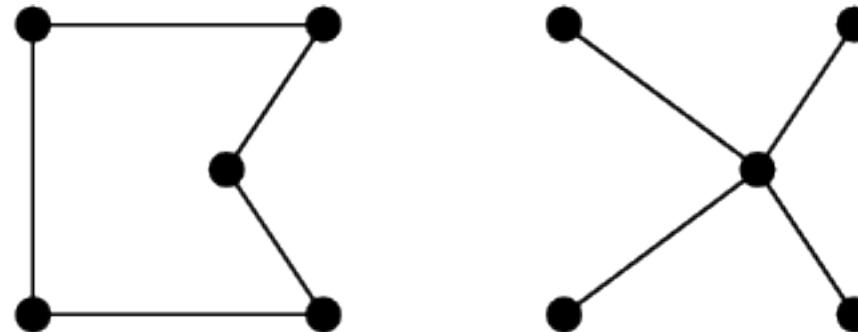
- Well-known example: travelling salesperson problem (TSP)
- Find the shortest tour visiting all cities exactly once





# Relaxed Problems

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



- Minimum spanning tree
  - connects all vertices without cycles, with the minimum total edge weight
  - can be computed in  $O(n^2)$
  - is a lower bound on the shortest (open) tour



# Summary: A\*

- 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 ■
- A\* search expands lowest  $g + h$ 
  - $h$  is never an over-estimate
  - complete and optimal
  - also optimally efficient (up to tie-breaks, for forward search) ■
- Admissible heuristics can be derived from exact solution of relaxed problems



# iterative improvement algorithms

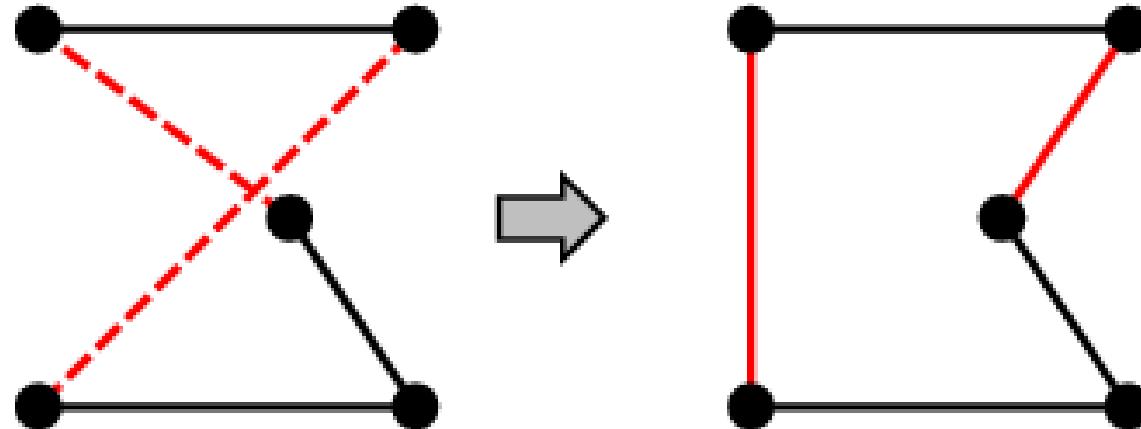
# Iterative Improvement Algorithms

- In many optimization problems, **path** is irrelevant; the goal state itself is the solution
- Then state space = set of “complete” configurations
  - find **optimal** configuration, e.g., TSP
  - find configuration satisfying constraints, e.g., timetable
- In such cases, can use **iterative improvement** algorithms  
→ keep a single “current” state, try to improve it
- Constant space, suitable for online as well as offline search



# Example: Travelling Salesperson Problem

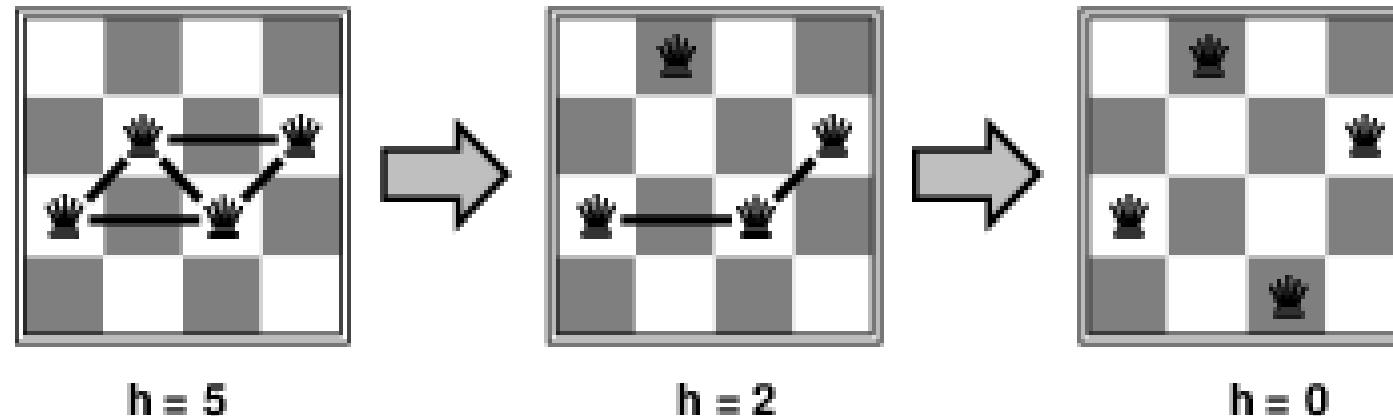
- Start with any complete tour, perform pairwise exchanges



- Variants of this approach get within 1% of optimal quickly with 1000s of cities

# Example: $n$ -Queens

- Put  $n$  queens on an  $n \times n$  board with no two queens on the same row, column, or diagonal
- Move a queen to reduce number of conflicts ( $h$ )



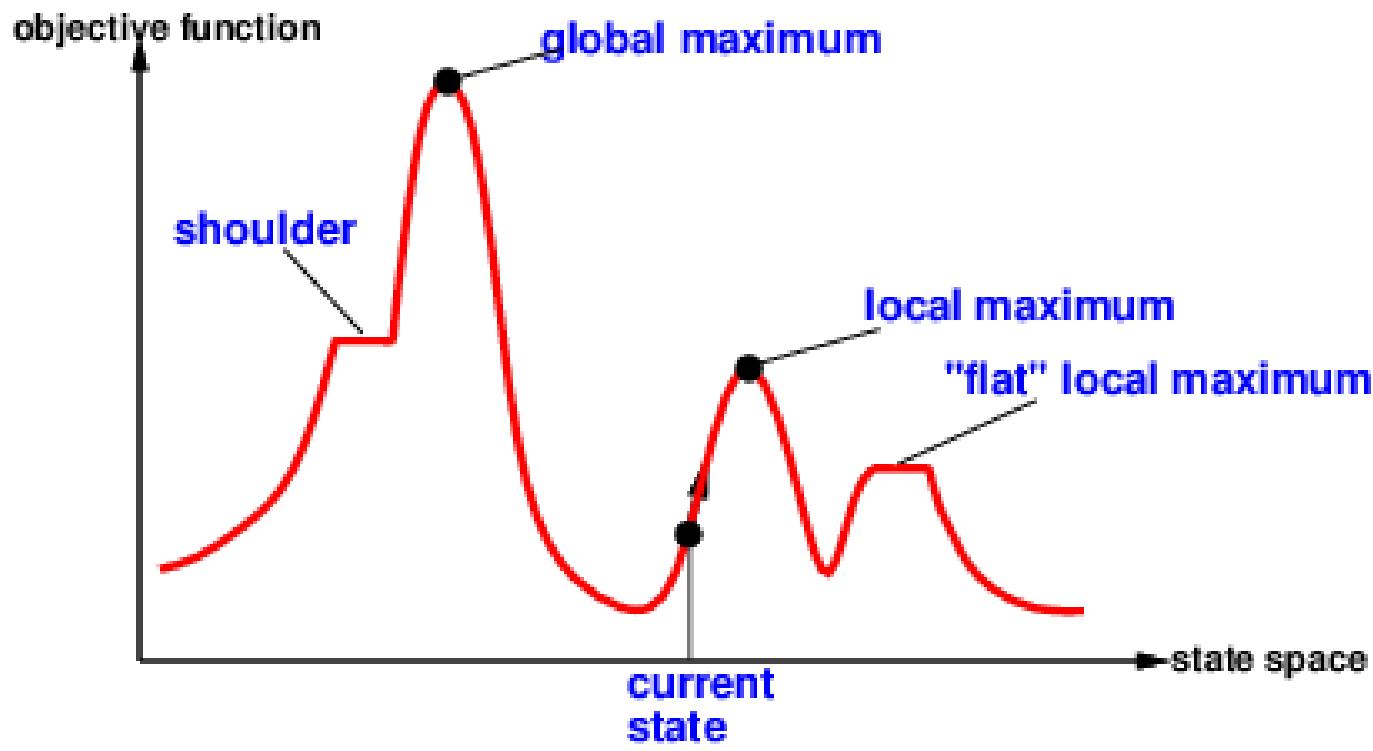
- Almost always solves  $n$ -queens problems almost instantaneously for very large  $n$ , e.g.,  $n = 1$  million

# Hill-Climbing

- For instance: Gradient Ascent (or Descent)
  - “Like climbing Everest in thick fog with amnesia”
1. Start state = a solution (maybe randomly generated)
  2. Consider neighboring states, e.g.,
    - move a queen
    - pairwise exchange in traveling salesman problem
  3. No better neighbors? Done.
  4. Adopt best neighbor state
  5. Go to step 2

# Hill-Climbing

- Useful to consider state space landscape



- **Random-restart hill climbing** overcomes local maxima—trivially complete
- **Random sideways moves** ☺ escape from shoulders ☺ loop on flat maxima



# Local Beam Search

- **Idea:** keep  $k$  states instead of 1; choose top  $k$  of all their successors!
- Not the same as  $k$  searches run in parallel!
- **Problem:** quite often, all  $k$  states end up on same local hill!
- **Idea:** choose  $k$  successors randomly, biased towards good ones

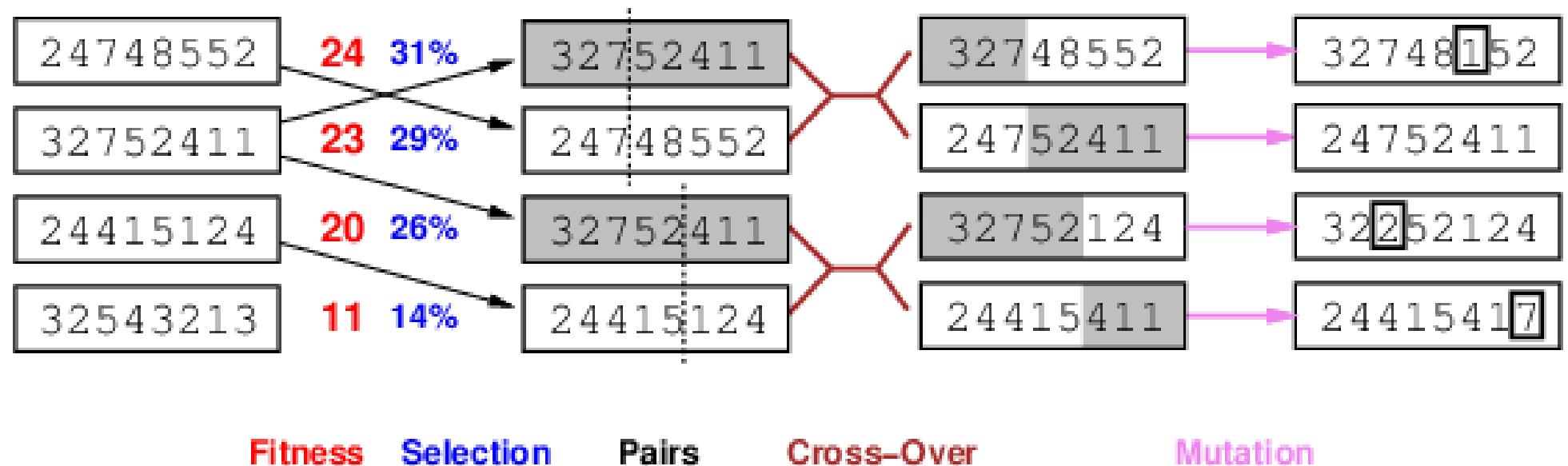


# Simulated Annealing

- Idea: escape local maxima by allowing some “bad” moves
- **But gradually decrease their size and frequency!**
- Iterate, reduce temperature T over time
  - compute **best** greedy move
  - draw **random** move
  - compute difference in value  $\Delta E = \text{value}(\text{random}) - \text{value}(\text{best})$
  - with probability  $e^{\frac{\Delta E}{T}}$ : return **random**
  - else: return **best**

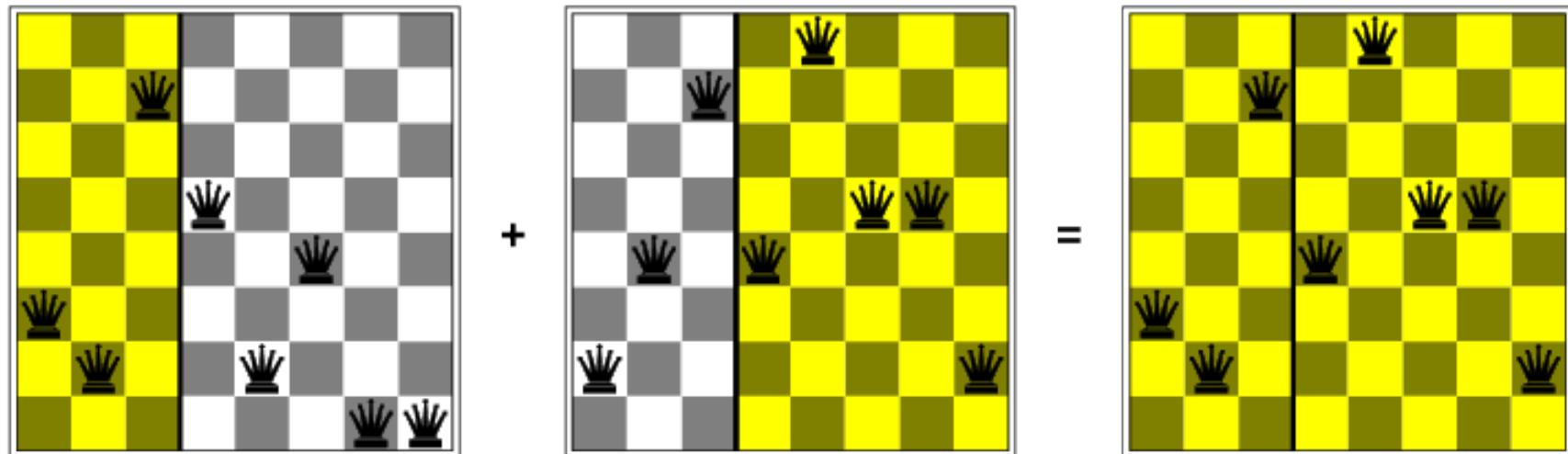
# Genetic Algorithms

- Stochastic local beam search + generate successors from **pairs** of states



# Genetic Algorithms

- GAs require states encoded as strings (GPs use programs)
- Crossover helps **iff substrings are meaningful components**



# Summary

- Exact search
  - exhaustive exploration of the search space
  - search with heuristics: A\*
- Approximate search
  - hill-climbing
  - simulated annealing
  - genetic algorithms