Artificial Intelligence

Hai Thi Tuyet Nguyen

Outline

CHAPTER 1: INTRODUCTION (CHAPTER 1)

CHAPTER 2: INTELLIGENT AGENTS (CHAPTER 2)

CHAPTER 3: SOLVING PROBLEMS BY SEARCHING (CHAPTER 3)

CHAPTER 4: INFORMED SEARCH (CHAPTER 3)

CHAPTER 5: LOGICAL AGENT (CHAPTER 7)

CHAPTER 6: FIRST-ORDER LOGIC (CHAPTER 8, 9)

CHAPTER 7: QUANTIFYING UNCERTAINTY(CHAPTER 13)

CHAPTER 8: PROBABILISTIC REASONING (CHAPTER 14)

CHAPTER 9: LEARNING FROM EXAMPLES (CHAPTER 18)

CHAPTER 4: INFORMED SEARCH AND EXPLORATION

4.1 Informed search algorithm

1. Best-first search
2. A* search
3. Heuristics

4.2 Local search algorithms

1. Hill-climbing
2. Annealing Simulated
3. Genetic algorithm

4.1 Informed search algorithm

1. Best-first search
2. A* search
3. Heuristics

4.1 Review: Tree search

A strategy is defined by picking **the order of node expansion**

function TREE-SEARCH(*problem, fringe*) **returns** a solution, or failure
    fringe ← INSERT(MAKE-NODE(INITIAL-STATE[*problem*]), *fringe*)
    loop do
        if *fringe* is empty **then return** failure
        node ← REMOVE-FRONT(*fringe*)
        if GOAL-TEST(*problem*, STATE(*node*)) **then return** *node*
        fringe ← INSERTALL(EXPAND(*node*, *problem*), *fringe*)

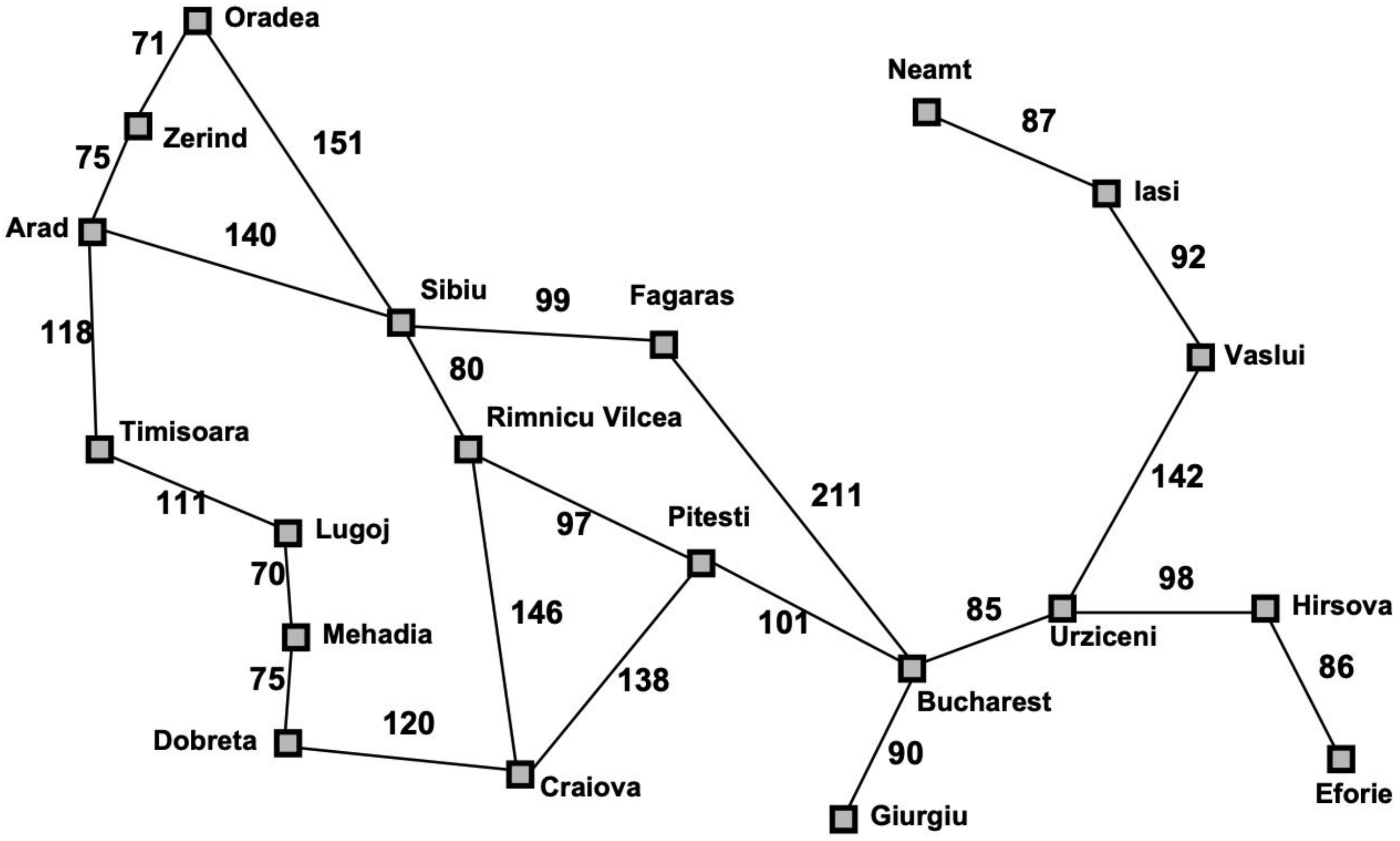
4.1 Best-first search

- **Idea:** use an evaluation function for each node – estimate of “desirability”
  $\Rightarrow$ Expand most desirable unexpanded node

- **Implementation:**
  fringe is a queue sorted in decreasing order of desirability

- **Special cases:**
  - greedy search
  - A* search

4.1 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

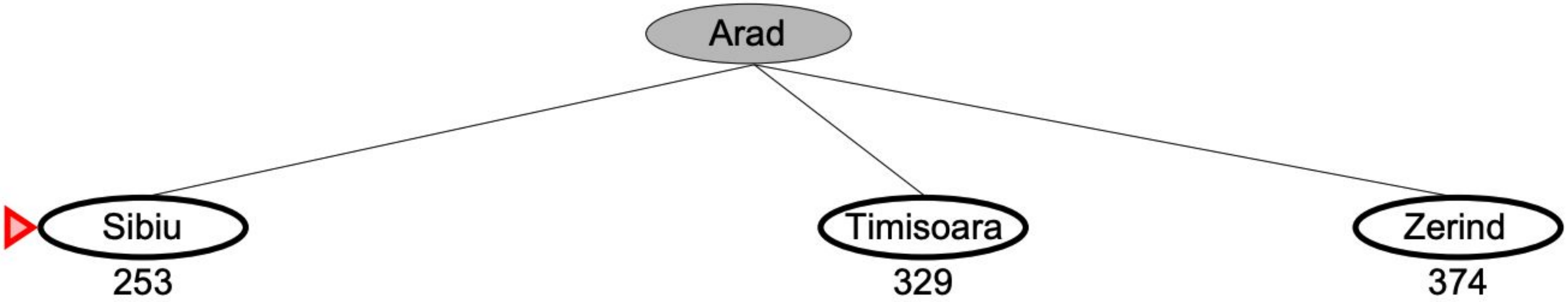
4.1 Greedy search

- Evaluation function **f(n)**, heuristic function **h(n)**
  $f(n) = h(n)$
  $h(n)$ = estimate of cost from n to the closest goal
  E.g., **$h_{SLD}(n)$** = straight-line distance from n to Bucharest

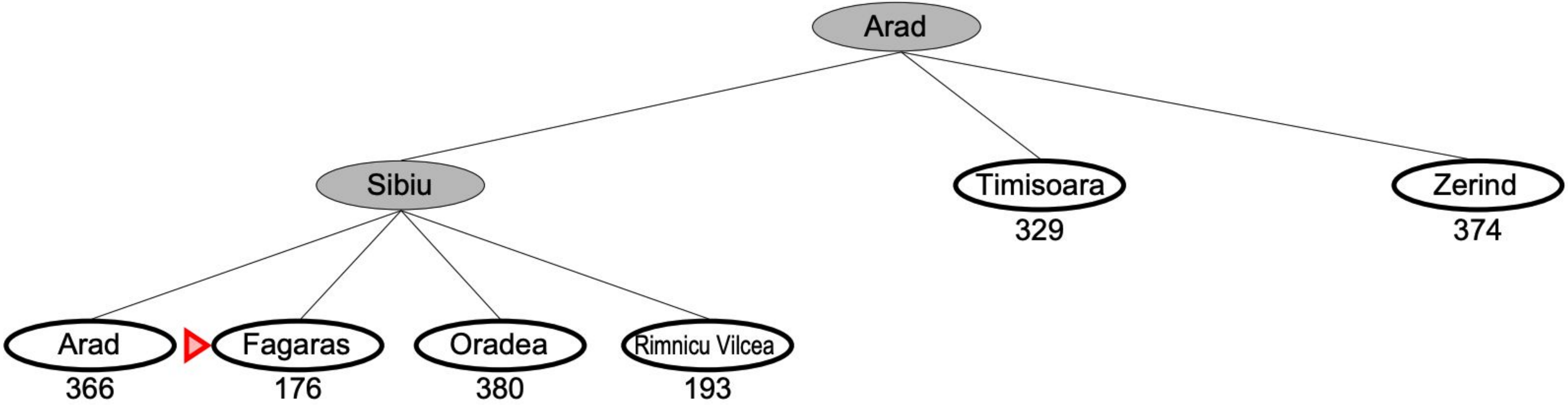
- Greedy search expands the node that appears to be closest to goal

4.1 Greedy search example

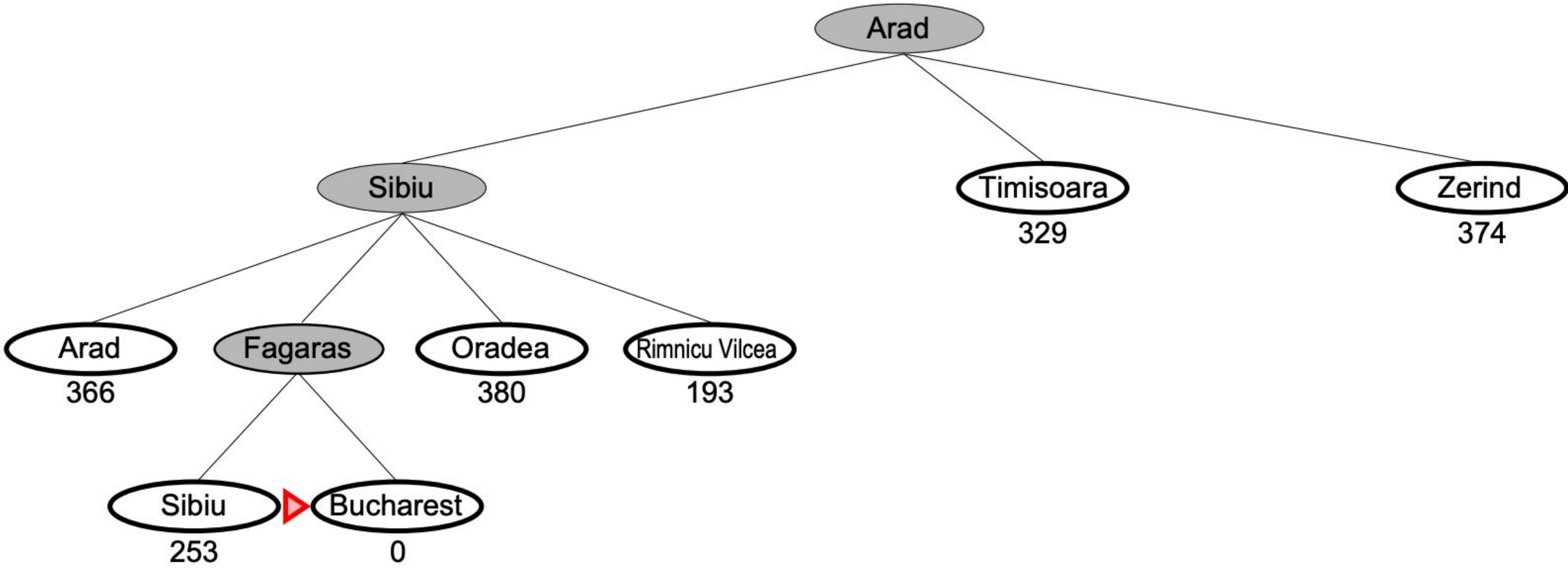
4.1 Greedy search example



4.1 Greedy search example



4.1 Greedy search example

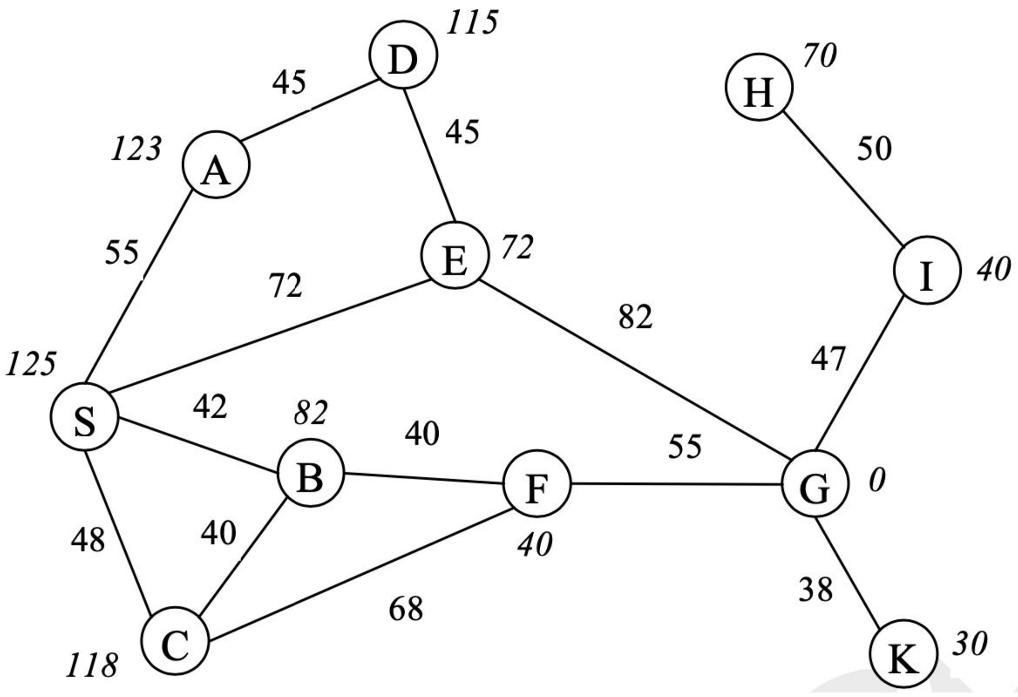


4.1 Properties of greedy search

- Complete: no, can get stuck in loops,
  E.g., 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

4.1 Properties of greedy search

- Greedy search found path 1 with path cost as 154: S -> E -> G
- Optimal path with path cost as 137: S -> B -> F -> G



4.1 A* search

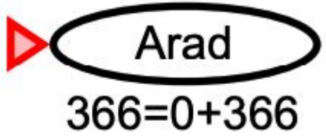
- Idea: avoid expanding paths that are already expensive
- Evaluation function $f(n) = g(n) + h(n)$

  $g(n)$ = cost to reach n

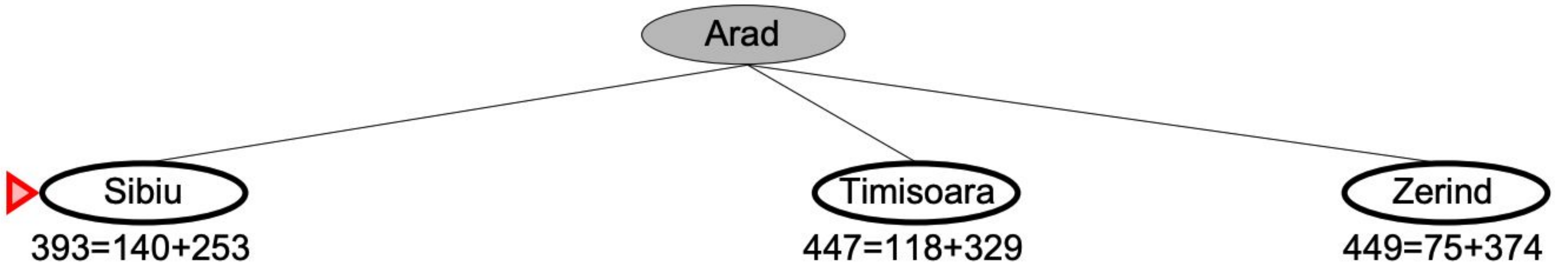
  $h(n)$ = estimated cost from n to goal

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

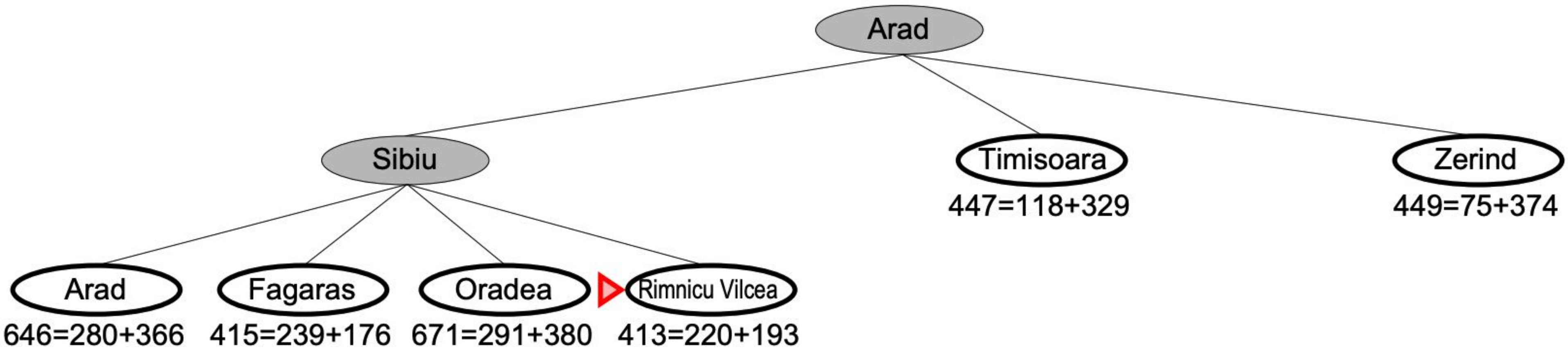
4.1 A∗ search example



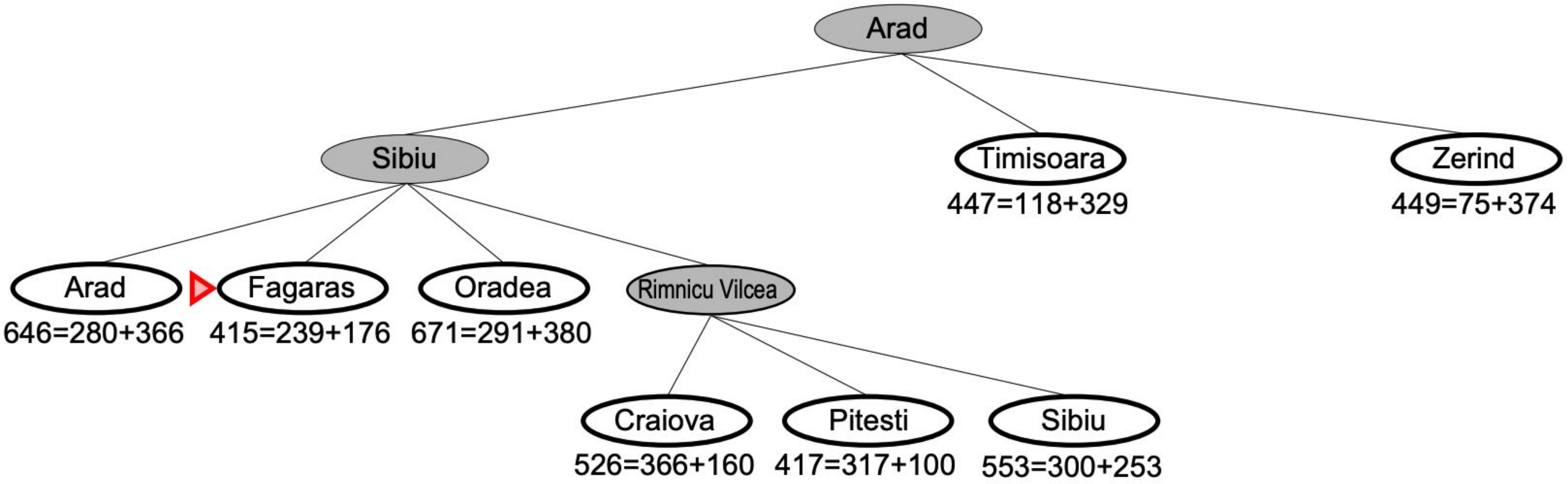
4.1 A∗ search example



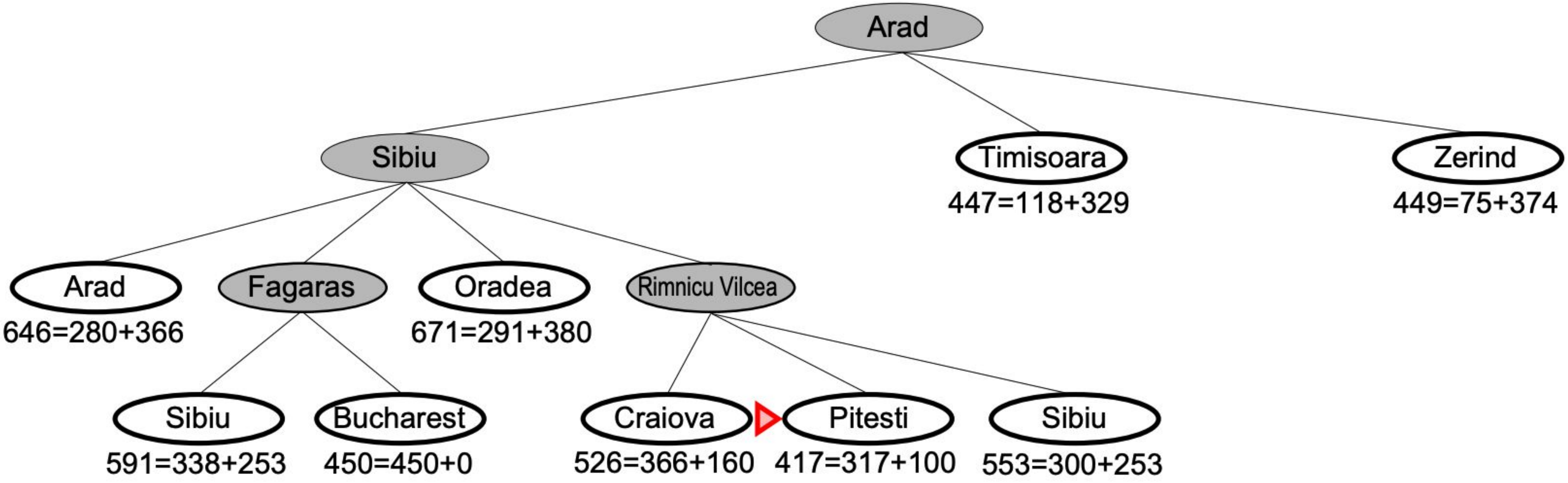
4.1 A∗ search example



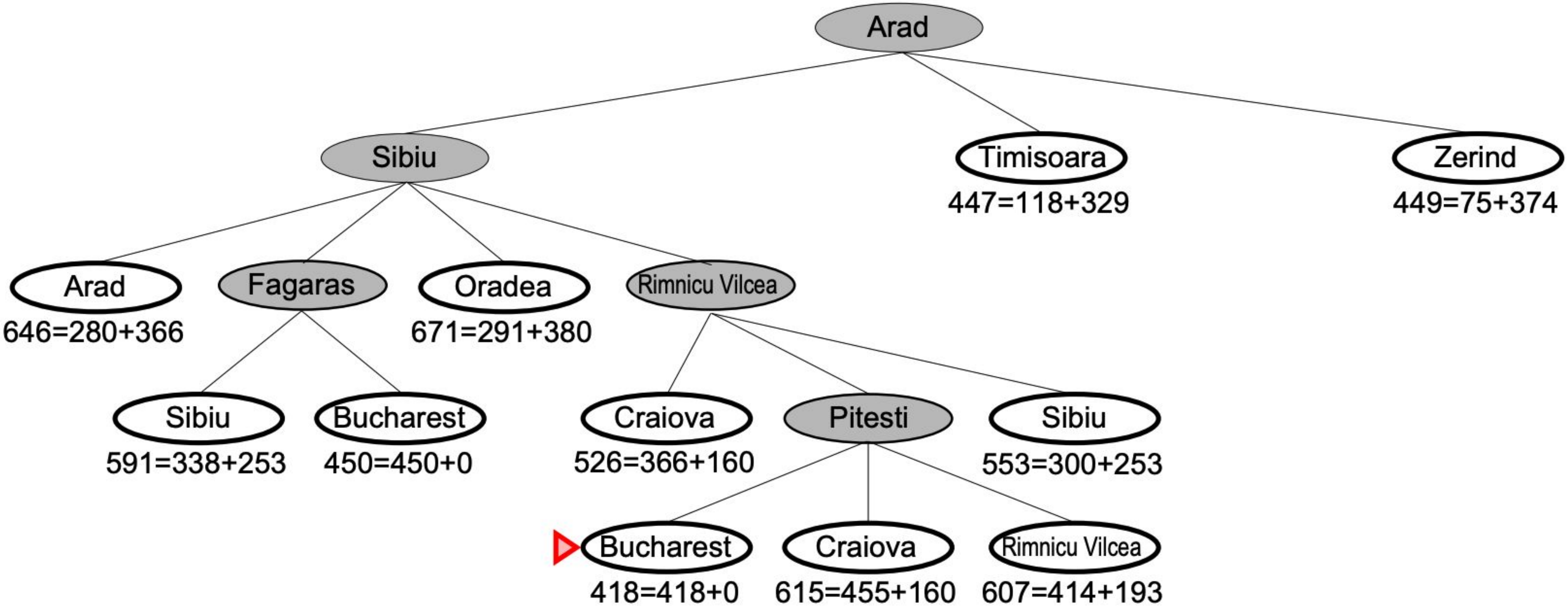
4.1 A* search example



4.1 A∗ search example



4.1 A∗ search example



4.1 Properties of A*

- Complete: yes, if there are not infinitely many nodes with $f \leq f(G)$
- Time: $O(b^m)$
- Space: $O(b^m)$, keeps all nodes in memory
- Optimal: optimal if $h(n)$ is admissible

4.1 Heuristic functions

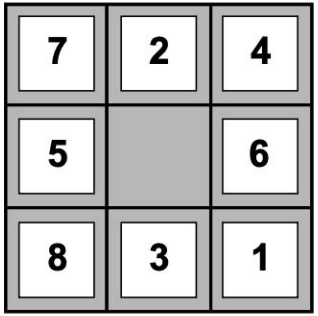
- The performance of heuristic search algorithms depends on the quality of the heuristic function.

- Good heuristics can sometimes be constructed:
  - relaxing the problem definition
  - precomputing solution costs for subproblems in a pattern database
  - learning from experience with the problem class

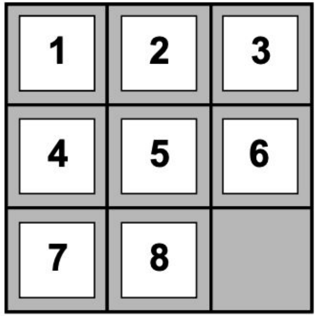
4.1 Heuristic functions

Look at heuristics for the 8-puzzle:

- *h1(n)* = the number of misplaced tiles.
- *h2(n)* = the sum of the distances of the tiles from their goal positions, i.e., Manhattan distances



Start State



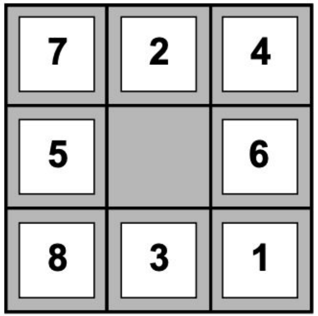
Goal State

4.1 Heuristic functions

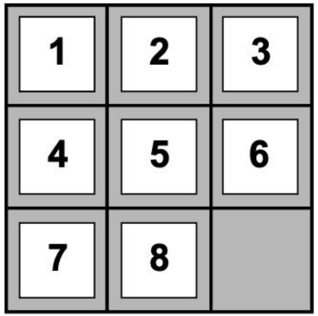
	Search Cost (nodes generated)			Effective Branching Factor		
d	IDS	$A^*(h_1)$	$A^*(h_2)$	IDS	$A^*(h_1)$	$A^*(h_2)$
2	10	6	6	2.45	1.79	1.79
4	112	13	12	2.87	1.48	1.45
6	680	20	18	2.73	1.34	1.30
8	6384	39	25	2.80	1.33	1.24
10	47127	93	39	2.79	1.38	1.22
12	3644035	227	73	2.78	1.42	1.24
14	–	539	113	–	1.44	1.23
16	–	1301	211	–	1.45	1.25
18	–	3056	363	–	1.46	1.26
20	–	7276	676	–	1.47	1.27
22	–	18094	1219	–	1.48	1.28
24	–	39135	1641	–	1.48	1.26

Figure 3.29 Comparison of the search costs and effective branching factors for the ITERATIVE-DEEPENING-SEARCH and A* algorithms with h_1, h_2. Data are averaged over 100 instances of the 8-puzzle for each of various solution lengths d.

4.1 Heuristic functions



Start State



Goal State

Look at heuristics for the 8-puzzle:

- $h1(n)$ = the number of misplaced tiles.
- $h2(n)$ = the sum of the distances of the tiles from their goal positions, i.e., Manhattan distances

$h1(S) = 6$

$h2(S) = 4+0+3+3+1+0+2+1 = 14$

If $h2(n) \geq h1(n)$ for all n (both admissible) then $h2$ ***dominates*** $h1$ and is better for search

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

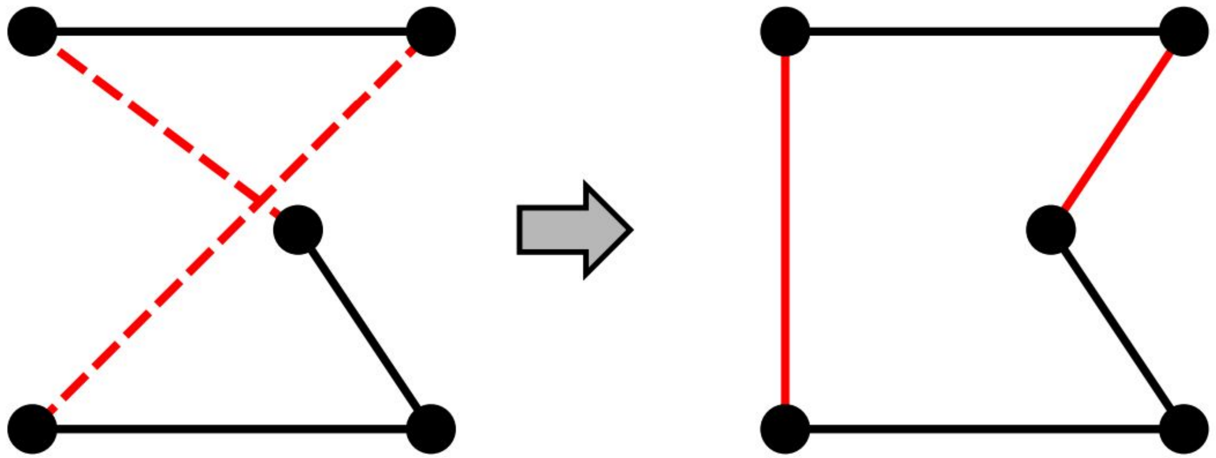
4.1 Local search algorithms

- In many optimization problems, the solution is the goal state, not the path
- Then the state space = set of complete configurations,
    - find the optimal configuration, e.g., Travelling Salesperson Problem (TSP)
    - find the configuration satisfying constraints, e.g., timetable
- In these cases, we can use the local search algorithms:

  keep a single "current state", try to improve it

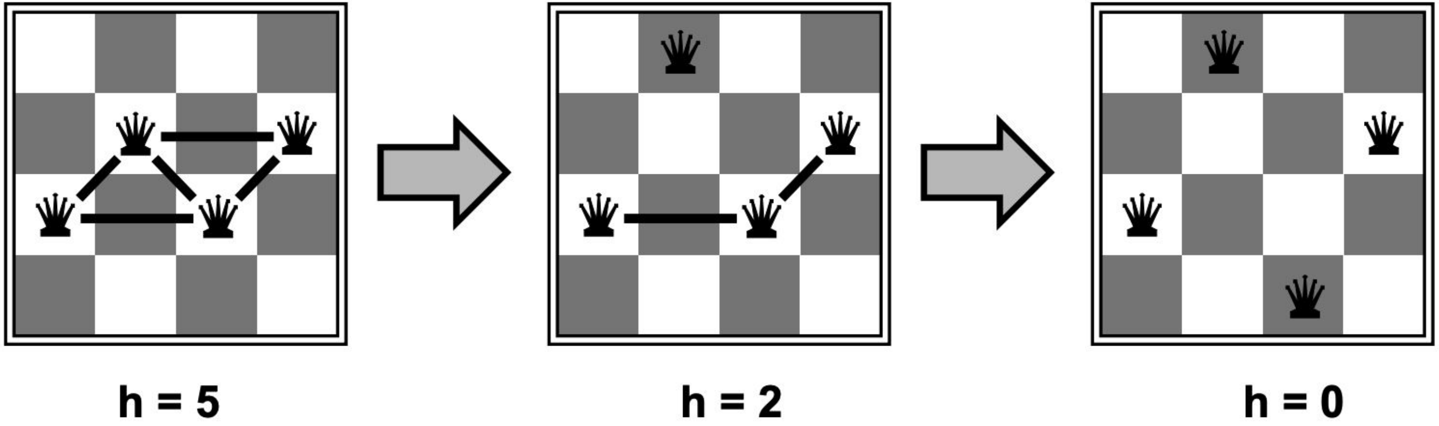
4.1 Example: Travelling Salesperson Problem (TSP)

- Start with the complete tour, perform pairwise exchanges
- Variants of this approach get within 1% of optimal very quickly with thousands of cities.



4.1 Example: n-queens

- Put n queens on an n x n board with no two queens on the same row, column, or diagonal.
- Move a queen to reduce a number of conflicts



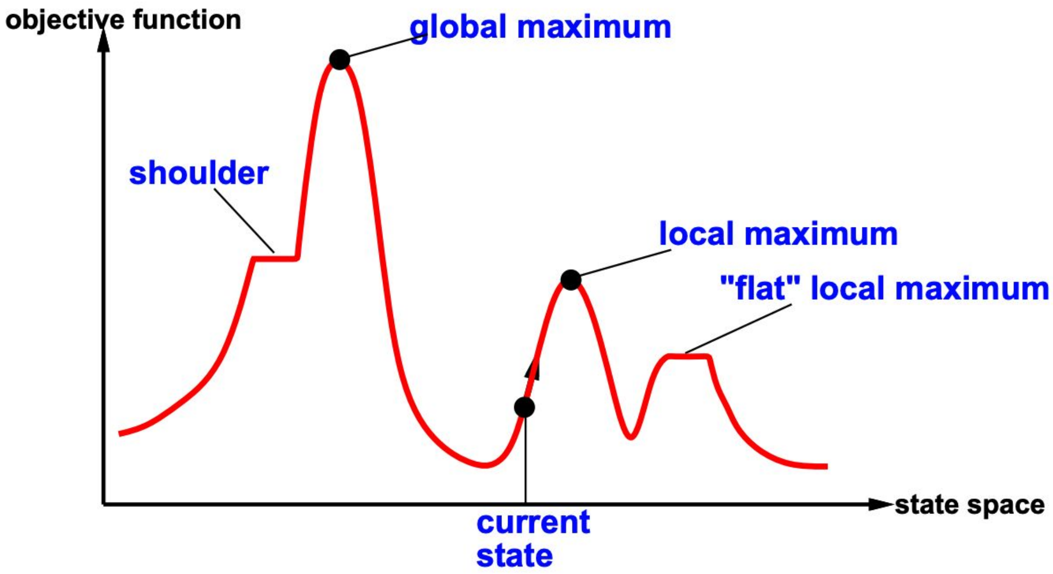
4.2 Local search algorithms

State space landscape:

- "location": state
- "elevation": the value of objective function; find the highest peak - a global maximum

Local search algorithms

1. Hill-climbing
2. Annealing Simulated
3. Genetic algorithm



4.2 Hill-Climbing

- Hill climbing known as greedy local search because it grabs a good neighbor state without thinking ahead about where to go next.
- How it works:
  - continually moves in the direction of increasing value, i.e., uphill.
  - terminates when it reaches a "peak" where no neighbor has a higher value

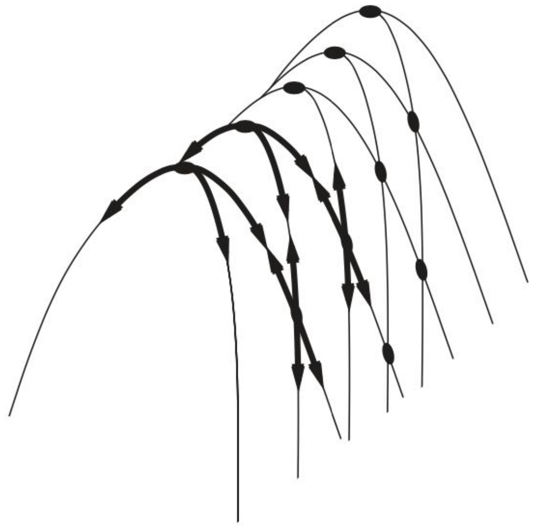
```
function HILL-CLIMBING(problem) returns a state that is a local maximum
   inputs: problem, a problem
   local variables: current, a node
                    neighbor, a node

   current ← MAKE-NODE(INITIAL-STATE[problem])
   loop do
       neighbor ← a highest-valued successor of current
       if VALUE[neighbor] ≤ VALUE[current] then return STATE[current]
       current ← neighbor
   end
```

4.2 Hill-Climbing

Hill climbing often gets stuck for the following reasons:

- Local maxima: a peak that is higher than each of its neighboring states, but lower than the global maximum.
- Ridges: they result in a sequence of local maxima
  => very difficult for greedy algorithms to navigate.
- Plateaux: an area of the state space landscape where the evaluation function is flat



4.2 Hill-Climbing

Variants of hill-climbing:

- Stochastic hill climbing: chooses at random from among the uphill moves
- First-choice hill climbing: generates successors randomly until one is generated that is better than the current state.
- Random-restart hill climbing:
  - it conducts a series of hill-climbing searches from randomly generated initial state, stopping when a goal is found
- The success of hill climbing depends on the shape of the state-space landscape:
  - if it has few local maxima and plateaux -> random-restart hill climbing will find a good solution very quickly

4.2 Simulated annealing search

- Idea: escape local maxima by allowing some bad moves, but gradually decrease their size and frequency
  - Simulated annealing search picks a random move.
  - If the move improves the situation, it is accepted.
  - Otherwise, the algorithm accepts the move with some probability.
    - The probability decreases with the "badness" of the move, ΔE by which the evaluation is worsened.
    - The probability decreases as the "temperature" T goes down

4.2 Simulated annealing search

function SIMULATED-ANNEALING(*problem, schedule*) **returns** a solution state
  inputs: *problem*, a problem
    schedule, a mapping from time to "temperature"
  local variables: *current*, a node
    next, a node
    T, a "temperature" controlling prob. of downward steps

  current ← MAKE-NODE(INITIAL-STATE[*problem*])
  for $t \leftarrow 1$ **to** ∞ **do**
    $T \leftarrow$ *schedule*[t]
    if $T = 0$ **then return** *current*
    next ← a randomly selected successor of *current*
    $\Delta E \leftarrow$ VALUE[*next*] – VALUE[*current*]
    if $\Delta E > 0$ **then** *current* ← *next*
    else *current* ← *next* only with probability $e^{\Delta E/T}$

4.2 Local beam search

- Idea: keeps track of k states rather than just one
  - It begins with k randomly generated states.
  - At each step, all the successors of all k states are generated.
  - If any one is a goal, the algorithm halts.
  - Otherwise, it selects the k best successors from the complete list and repeats.

- Problem: quite often, all k states end up on same local hill
- Idea: choose k successors randomly, biased towards good ones ~ stochastic beam search

4.2 Genetic algorithms

- A genetic algorithm (or GA) is a variant of stochastic beam search in which successor states are generated by combining two parent states

4.2 Genetic algorithms (GAs)

(a) GAs begin with a set of ***k*** randomly generated ***states***, called the ***population***

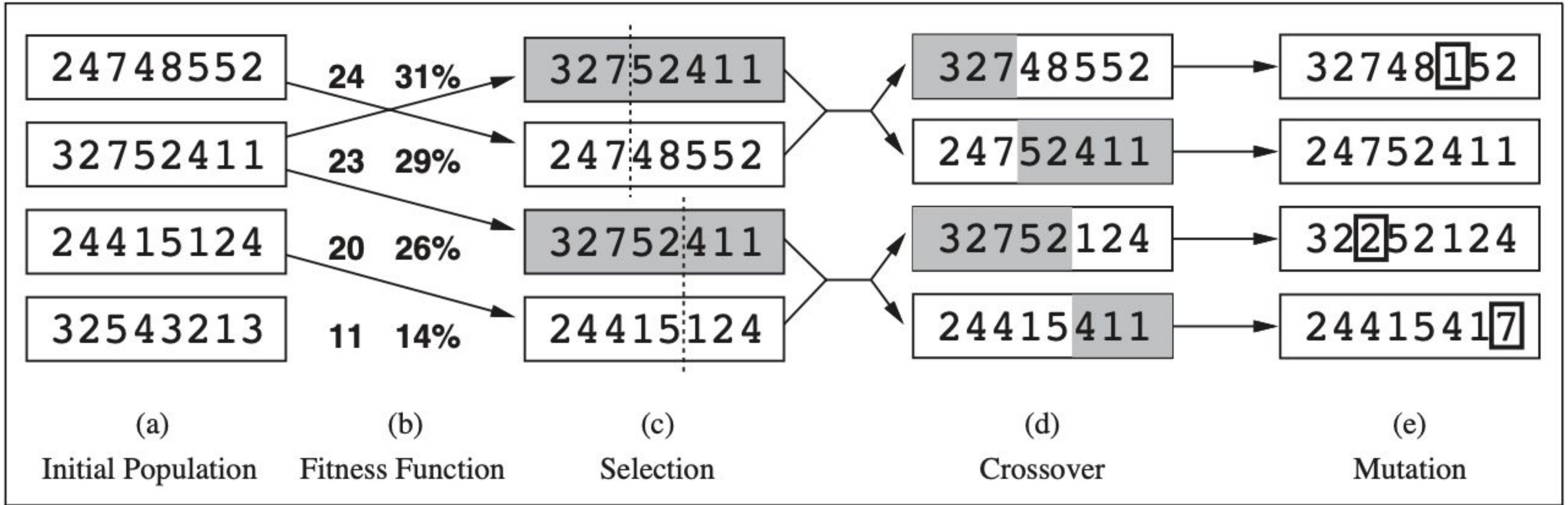


Figure 4.6 The genetic algorithm, illustrated for digit strings representing 8-queens states. The initial population in (a) is ranked by the fitness function in (b), resulting in pairs for mating in (c). They produce offspring in (d), which are subject to mutation in (e).

4.2 Genetic algorithms (GAs)

(b) Each state is rated by the **objective function**, i.e., the **fitness function**.

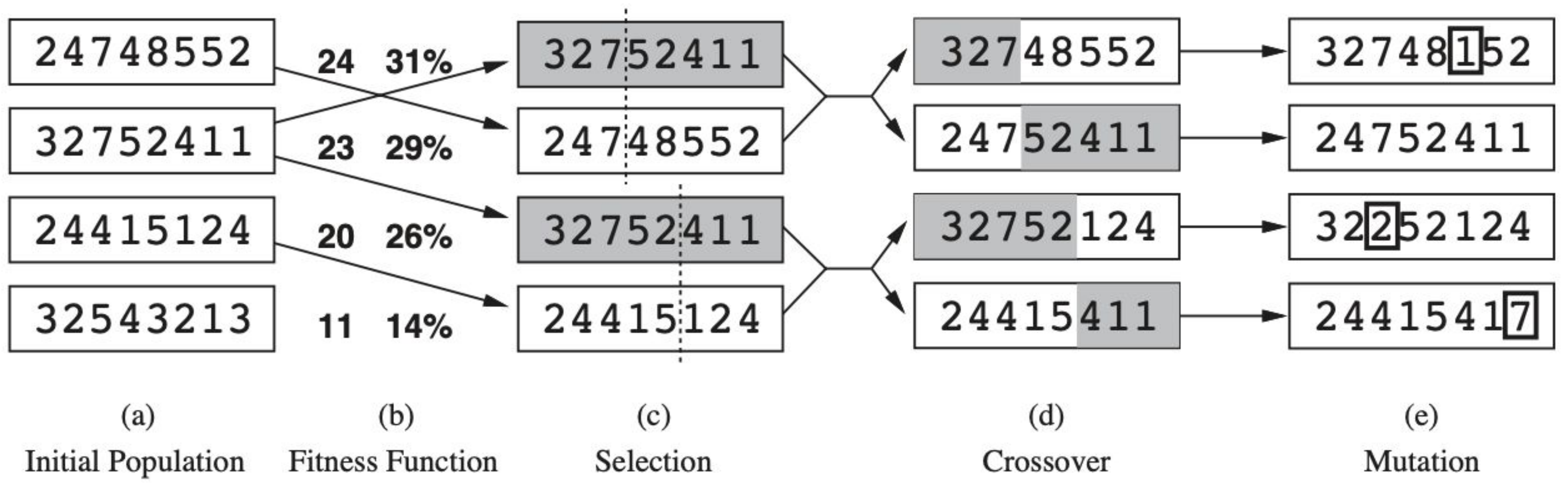


Figure 4.6 The genetic algorithm, illustrated for digit strings representing 8-queens states. The initial population in (a) is ranked by the fitness function in (b), resulting in pairs for mating in (c). They produce offspring in (d), which are subject to mutation in (e).

4.2 Genetic algorithms (GAs)

(c) 2 pairs are selected at random for ***reproduction***, in accordance with the probabilities in (b) Each pair to be mated, a ***crossover point*** is chosen randomly from the positions in the string.

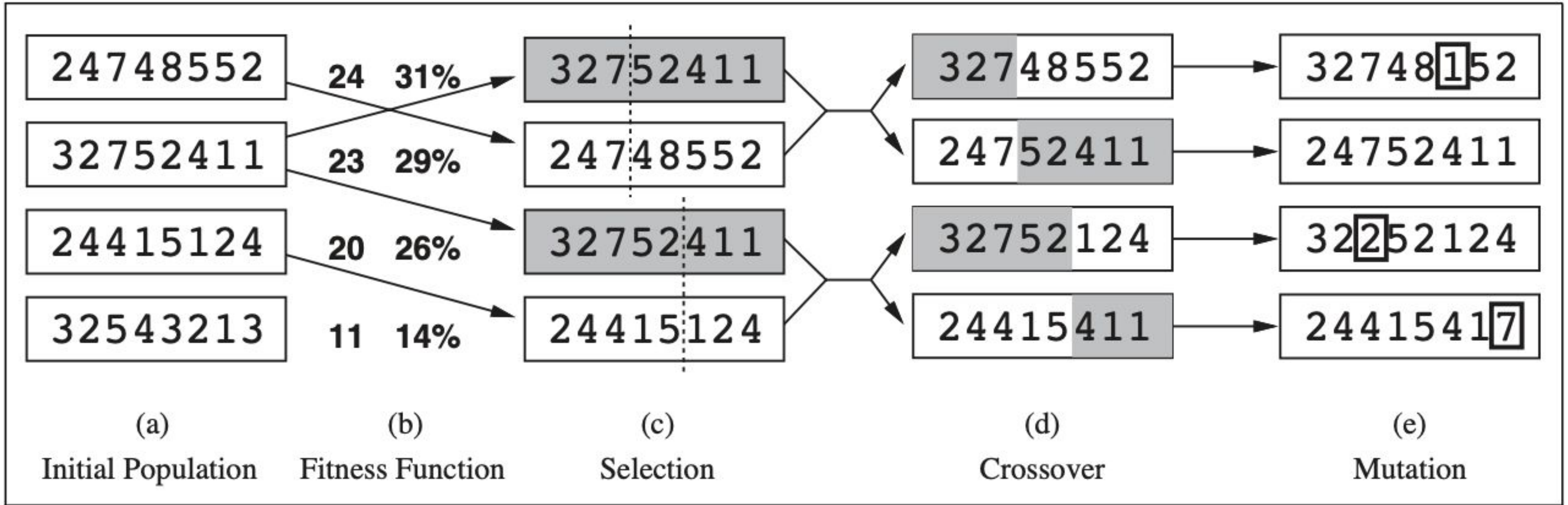


Figure 4.6 The genetic algorithm, illustrated for digit strings representing 8-queens states. The initial population in (a) is ranked by the fitness function in (b), resulting in pairs for mating in (c). They produce offspring in (d), which are subject to mutation in (e).

4.2 Genetic algorithms (GAs)

(d) the offspring themselves are created by crossing over the parent strings at the crossover point

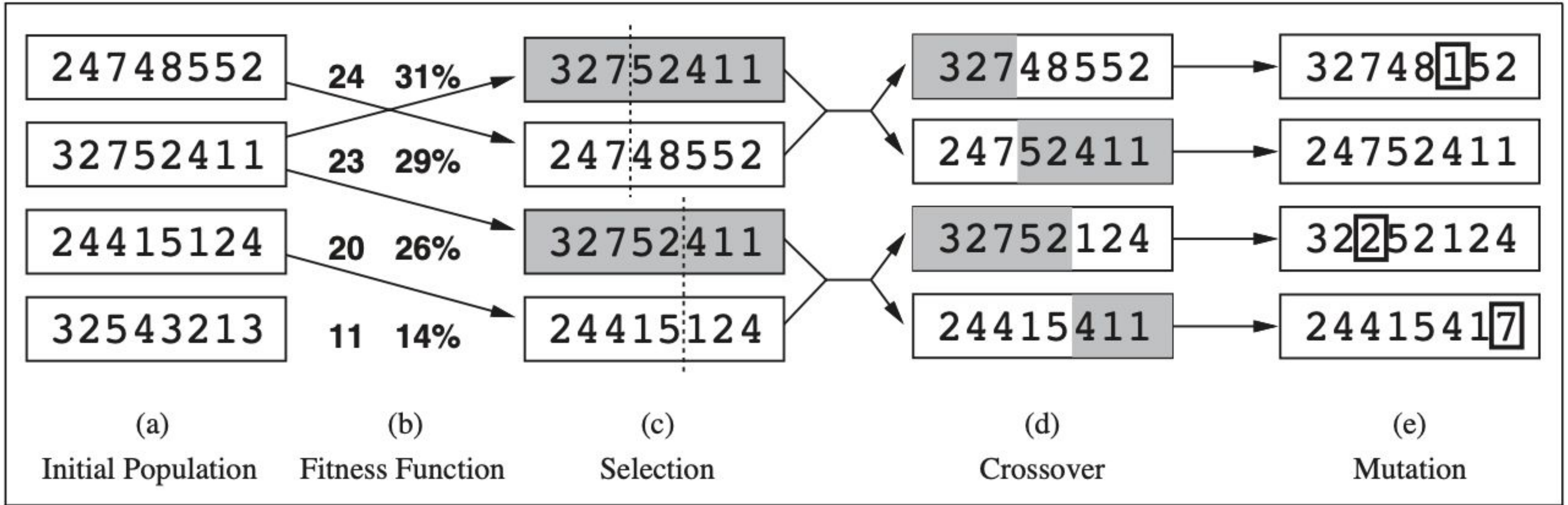


Figure 4.6 The genetic algorithm, illustrated for digit strings representing 8-queens states. The initial population in (a) is ranked by the fitness function in (b), resulting in pairs for mating in (c). They produce offspring in (d), which are subject to mutation in (e).

4.2 Genetic algorithms (GAs)

(e) each location is subject to random mutation with a small independent probability.

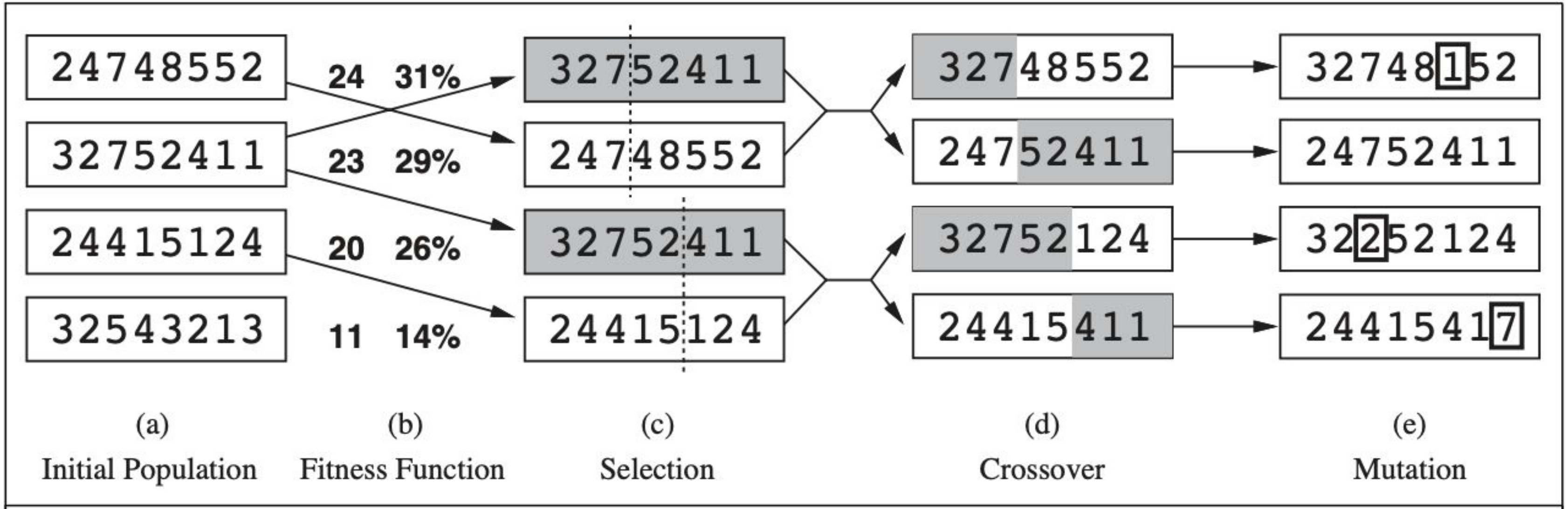


Figure 4.6 The genetic algorithm, illustrated for digit strings representing 8-queens states. The initial population in (a) is ranked by the fitness function in (b), resulting in pairs for mating in (c). They produce offspring in (d), which are subject to mutation in (e).

4.2 Genetic algorithms (GAs)

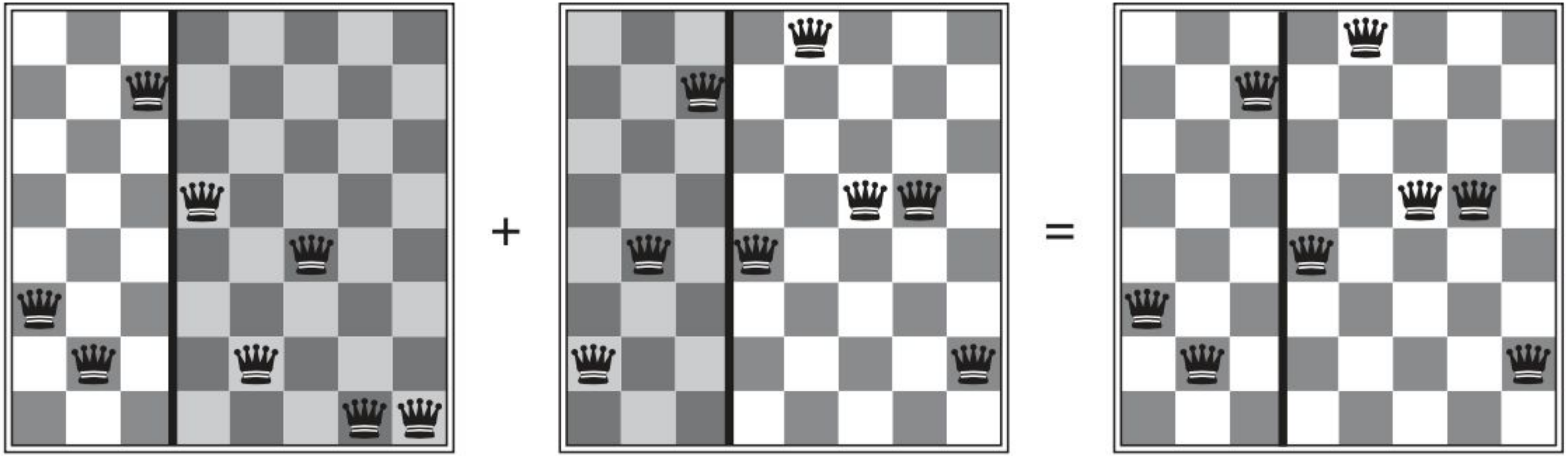


Figure 4.7 The 8-queens states corresponding to the first two parents in Figure 4.6(c) and the first offspring in Figure 4.6(d). The shaded columns are lost in the crossover step and the unshaded columns are retained.

4.2 Genetic algorithms (GAs)

```
function GENETIC-ALGORITHM(population, FITNESS-FN) returns an individual
  inputs: population, a set of individuals
          FITNESS-FN, a function that measures the fitness of an individual

  repeat
     new_population ← empty set
     for i = 1 to SIZE(population) do
        x ← RANDOM-SELECTION(population, FITNESS-FN)
        y ← RANDOM-SELECTION(population, FITNESS-FN)
        child ← REPRODUCE(x, y)
        if (small random probability) then child ← MUTATE(child)
        add child to new_population
     population ← new_population
  until some individual is fit enough, or enough time has elapsed
  return the best individual in population, according to FITNESS-FN
```

```
function REPRODUCE(x, y) returns an individual
  inputs: x, y, parent individuals

  n ← LENGTH(x); c ← random number from 1 to n
  return APPEND(SUBSTRING(x, 1, c), SUBSTRING(y, c + 1, n))
```

Figure 4.8 A genetic algorithm. The algorithm is the same as the one diagrammed in Figure 4.6, with one variation: in this more popular version, each mating of two parents produces only one offspring, not two.