

Informed Search

Informed search strategies

- Use the problem-specific knowledge beyond the definition of the problem itself to find more efficient solutions than uninformed strategy
 - Best-first search
 - Greedy best-first search
 - A* search
 - Heuristics
 - Local search algorithms
 - Hill-climbing search
 - Simulated annealing search
 - Local beam search
 - Genetic algorithms

Best-first search

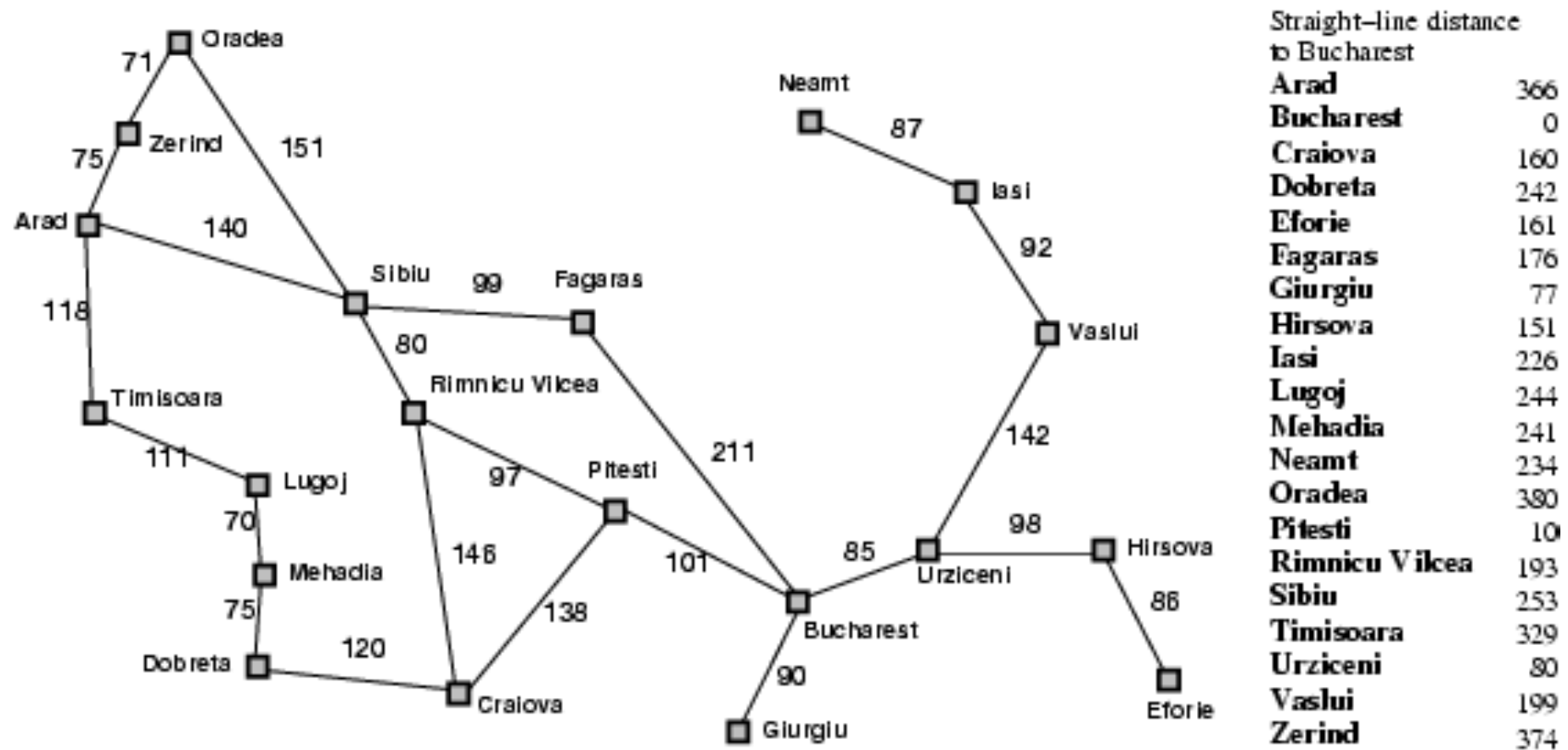
- Idea: use an **evaluation function** $f(n)$ for each node
 - estimate of "desirability"
 - Expand most desirable unexpanded node

- 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



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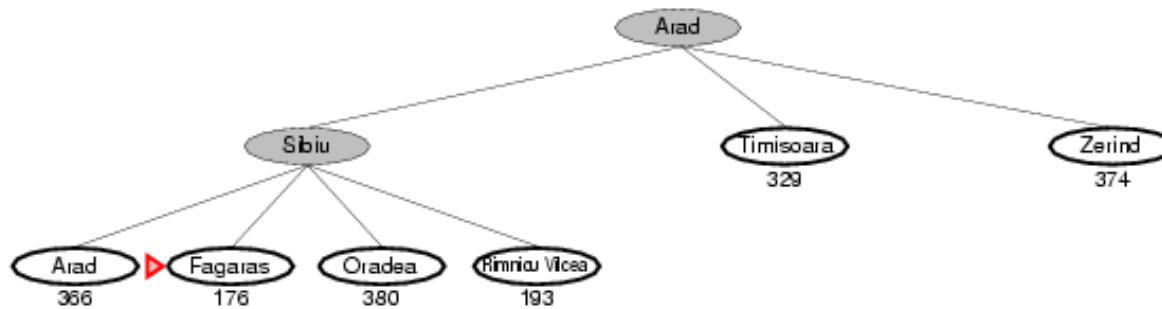
Greedy best-first search

- Evaluation function $f(n) = h(n)$ (**h**euristic) = estimate of cost from n to *goal*
- Greedy best-first search expands the node that **appears** to be closest to the goal
- Implementation: as a priority queue to keep the fringe in ascending order of f -values
- e.g., $h_{SLD}(n)$ = straight-line distance from n to Bucharest

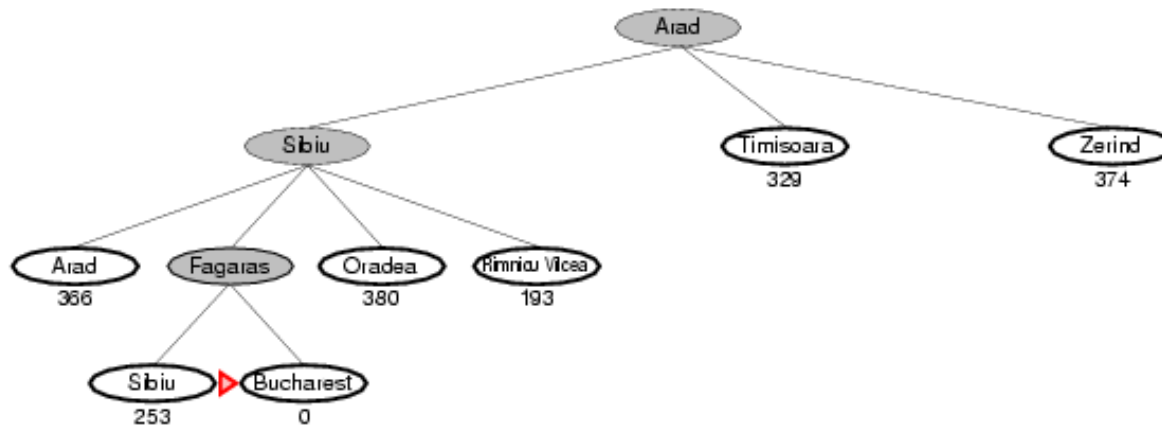
Greedy best-first search example



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., 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

Similar to depth-first search

Each state has b successors (branching factor)

d is the depth of the shallowest solution

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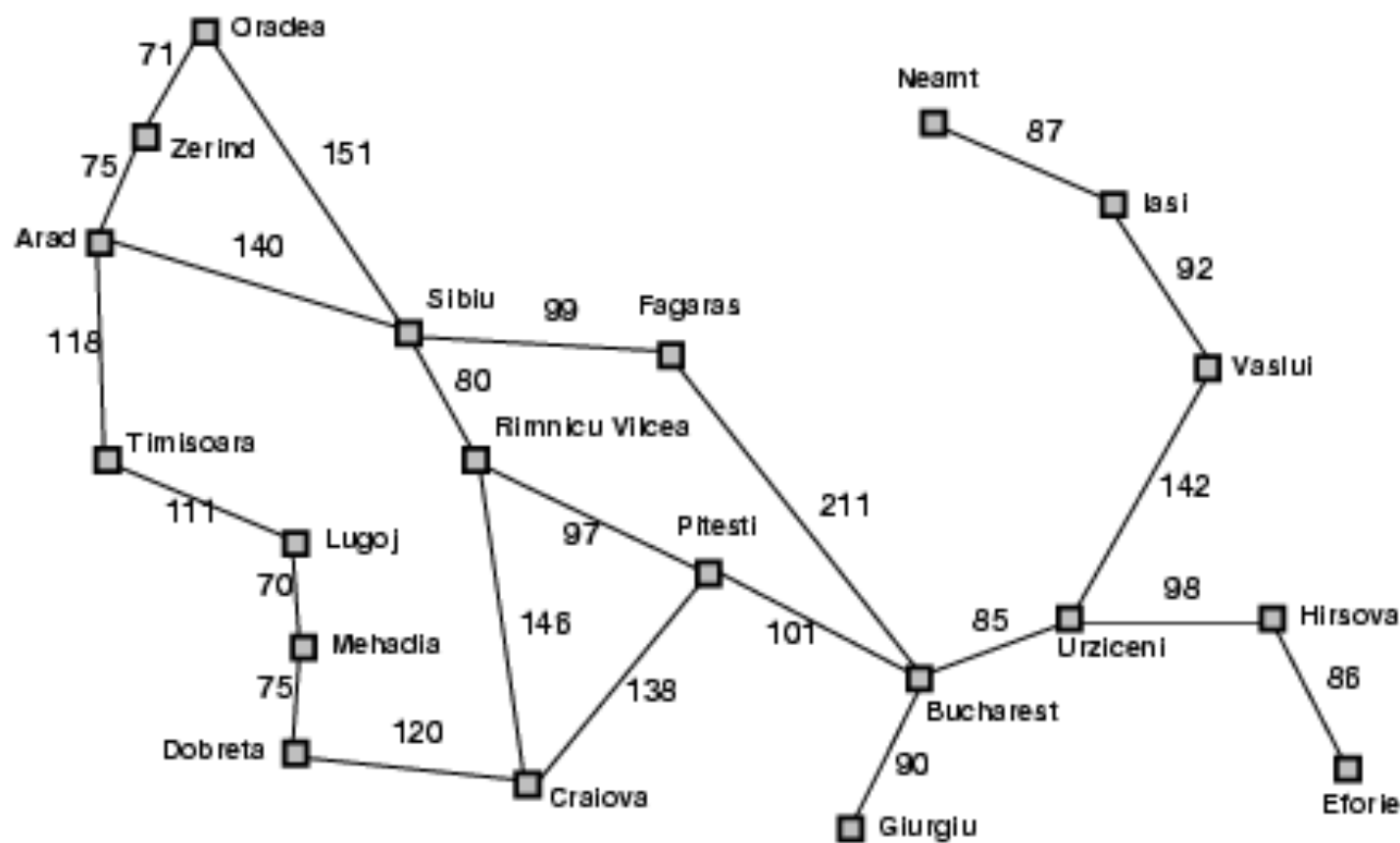
A* search

- ❑ 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* is optimal if $h(n)$ is an admissible heuristic such that $h(n)$ never overestimates the cost to reach the goal

A* search example

▶ Arad
366=0+366

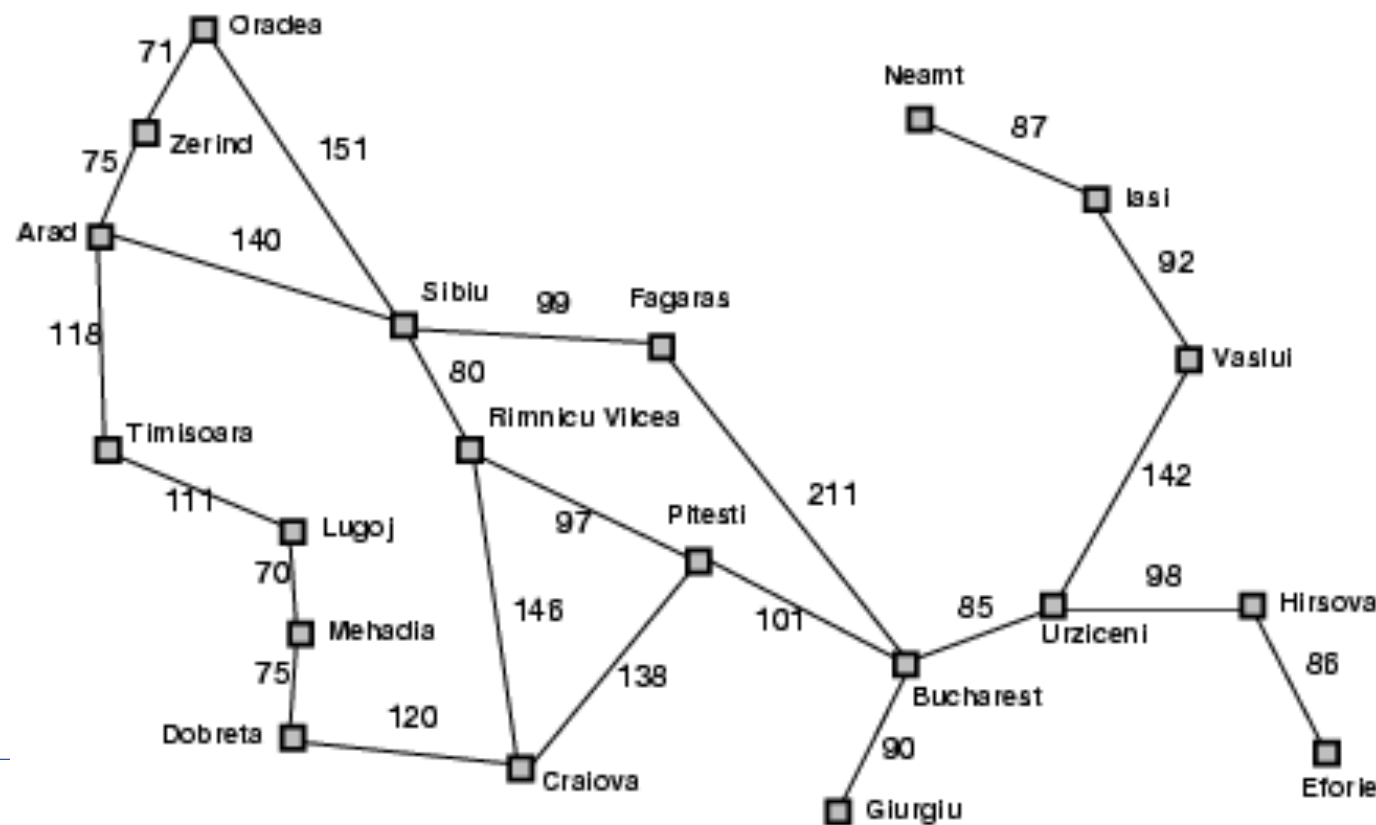
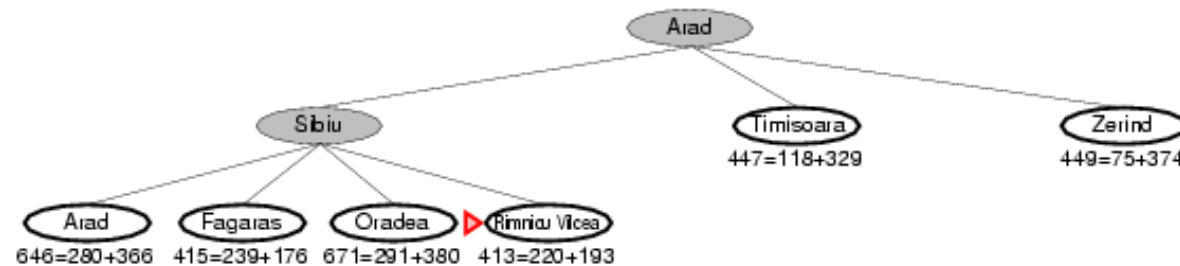
A* search example



Straight-line distance
to Bucharest

Arad	366
Bucharest	0
Craiova	160
Dobreta	242
Eforie	161
Fagaras	176
Giurgiu	77
Hirsova	151
Iasi	226
Lugoj	244
Mehadia	241
Neamt	234
Oradea	380
Pitesti	100
Rimnicu Vilcea	193
Sibiu	253
Timisoara	329
Urziceni	80
Vaslui	199
Zerind	374

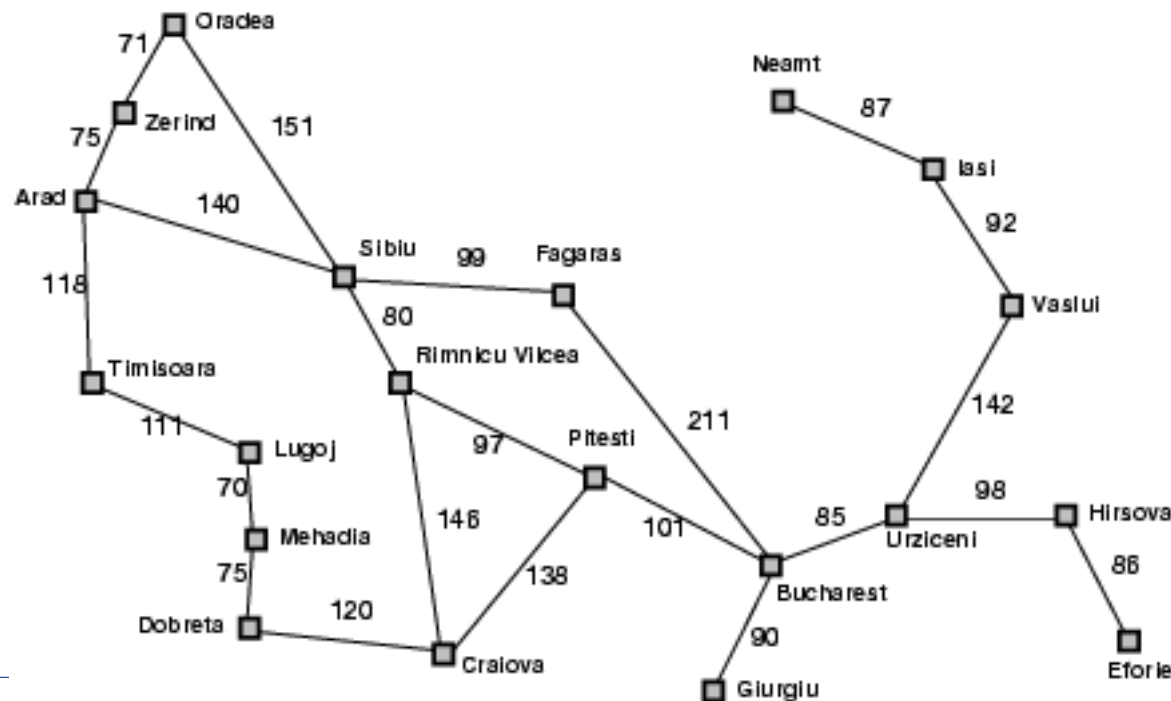
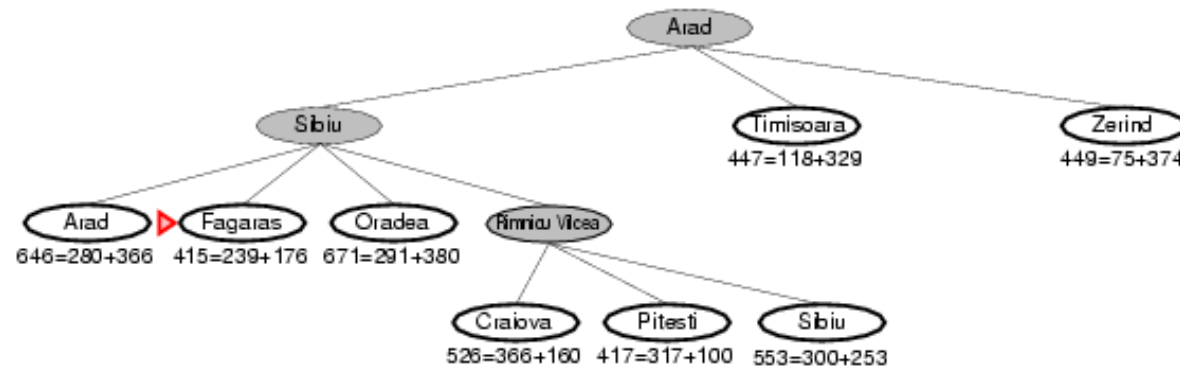
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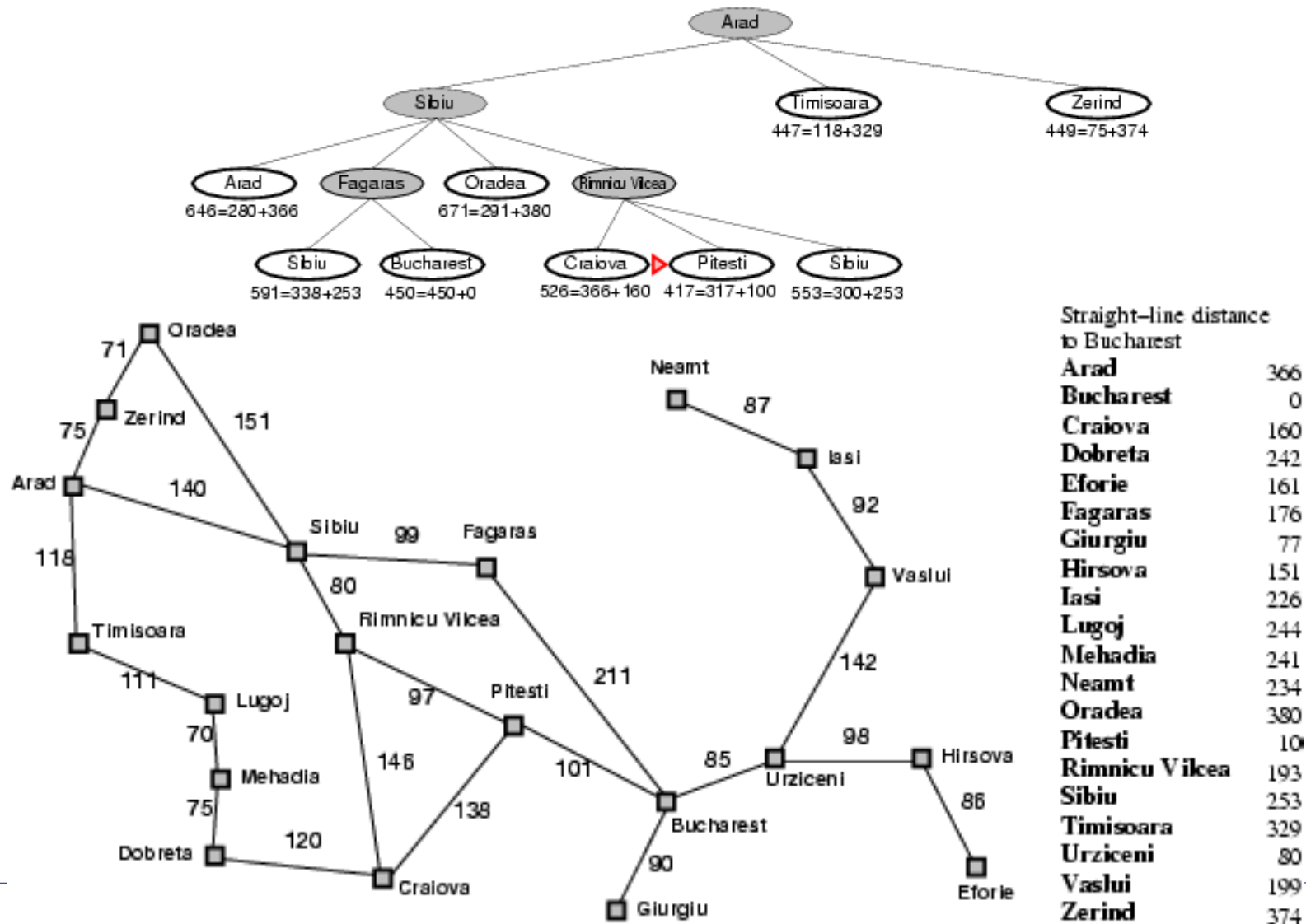
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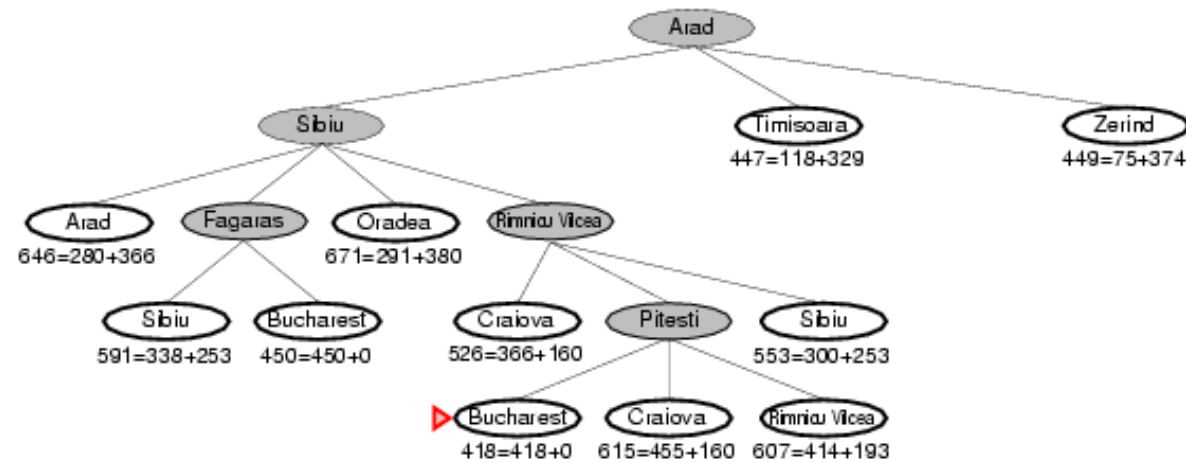
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A* search example



A* search example



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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)
- **Theorem**: If $h(n)$ is admissible, A^* using TREE-SEARCH is optimal

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

Admissible heuristics for 8-puzzle

- ❑ Heuristic: produce a solution in a reasonable time frame, good enough to solve the problem
- ❑ The average cost for the 8-puzzle are approx. 22 steps. Here are 26 steps.
- ❑ Branching factor is approx. 3
 - Empty in the middle, 4 mov
 - Empty in the corner, 2 mov
 - Rest cases, 3 mov
- ❑ Depth-first search will look 3^{22} states
- ❑ If we keep track of repeated states, we could reduce to 170.000
- ❑ In the 15-puzzle = 10^{13}

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

Admissible heuristics for 8-puzzle

E.g., for the 8-puzzle:

- $h_1(n)$ = number of misplaced tiles
- $h_2(n)$ = total Manhattan distance
(i.e., + horizontal and vertical distance 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 location of each tile)

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

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

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

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

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Local search algorithms

- In many optimization problems, the **path** to the goal is irrelevant; the goal state itself is the solution
- State space = set of "complete" configurations. Find configuration satisfying constraints, e.g., n-queens
- In such cases, we can use **local search algorithms**
- Keep a single "current" state, try to improve it
- Work with one current state and generally moves to the neighboring state
- The paths followed by the search are not retained
 - They use little memory
 - You can find reasonable solutions in large state spaces or infinite

Example: n -queens

- Put n queens on an $n \times n$ board with no two queens on the same row, column, or diagonal



Informed search strategies

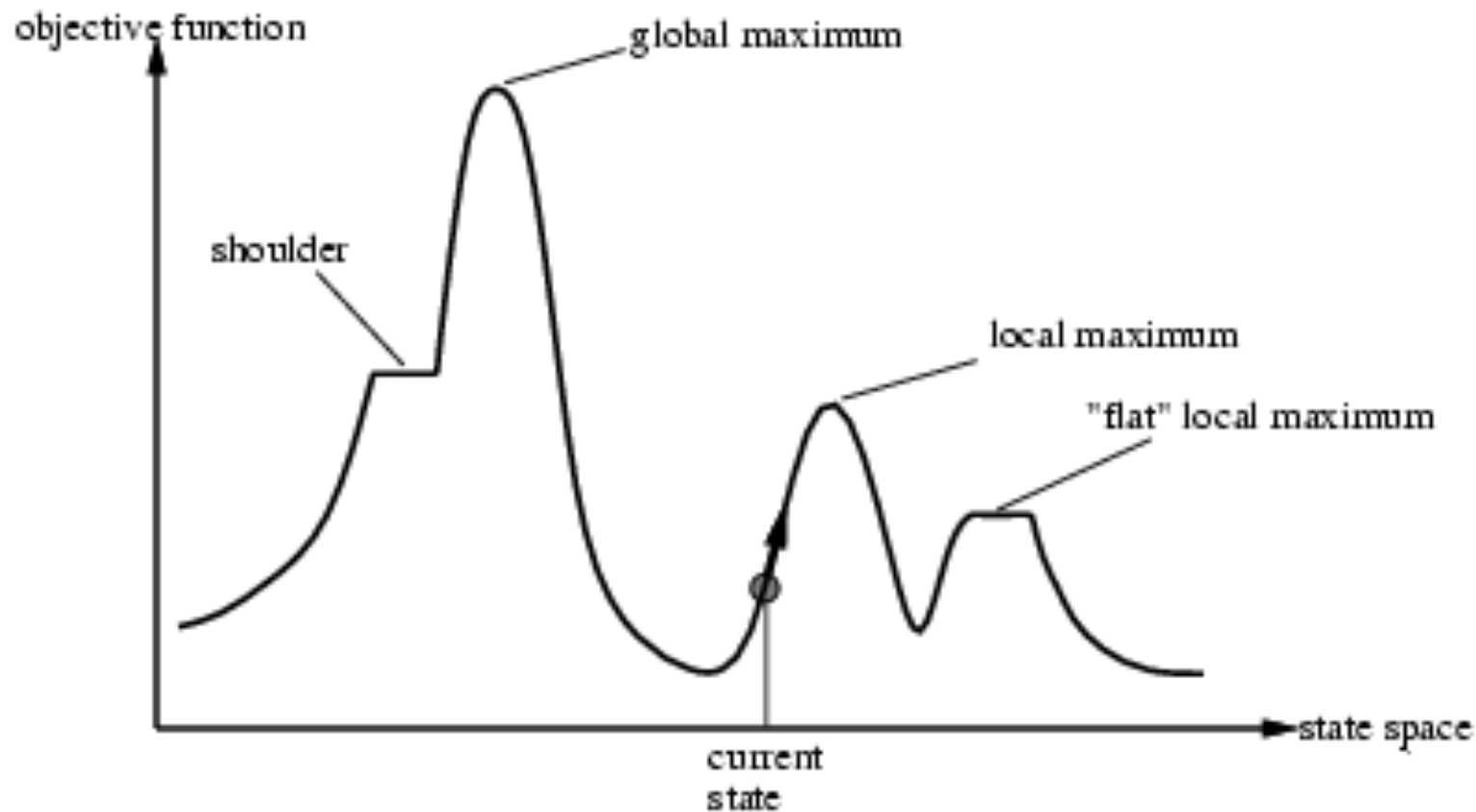
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Hill-climbing search

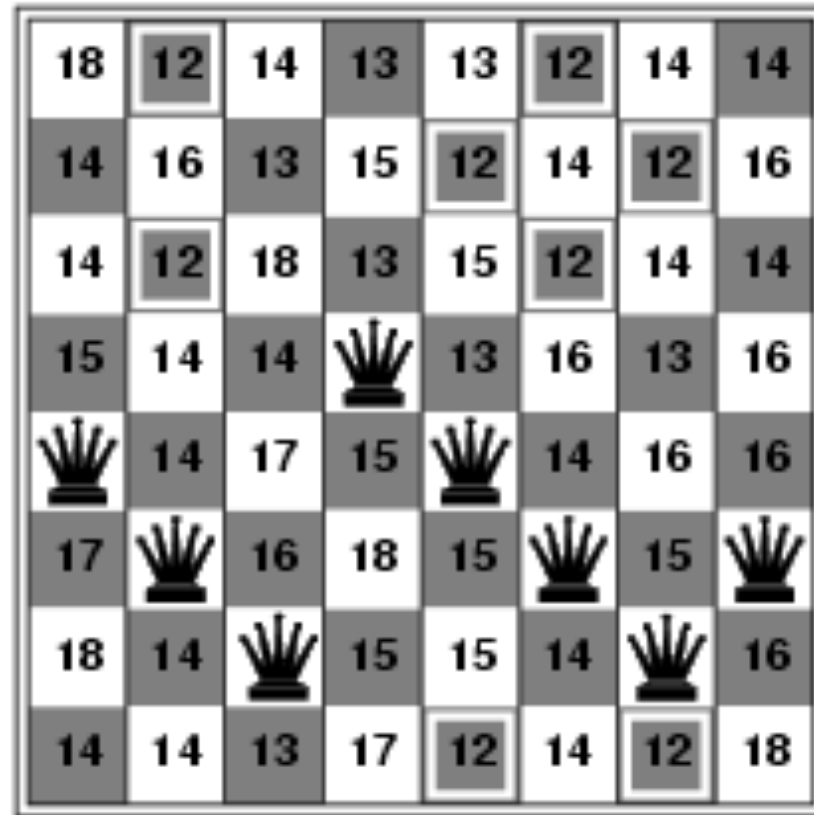
- It's just a loop that moves in the direction of increasing value
 - Ends when it reaches a peak where no neighbor has a higher value
 - The search tree is not kept, just a data structure of the current node to check the goal condition and its objective function value
- "Like climbing Everest in thick fog with amnesia"

Hill-climbing search

- Problem: depending on initial state, can get stuck in local maxima

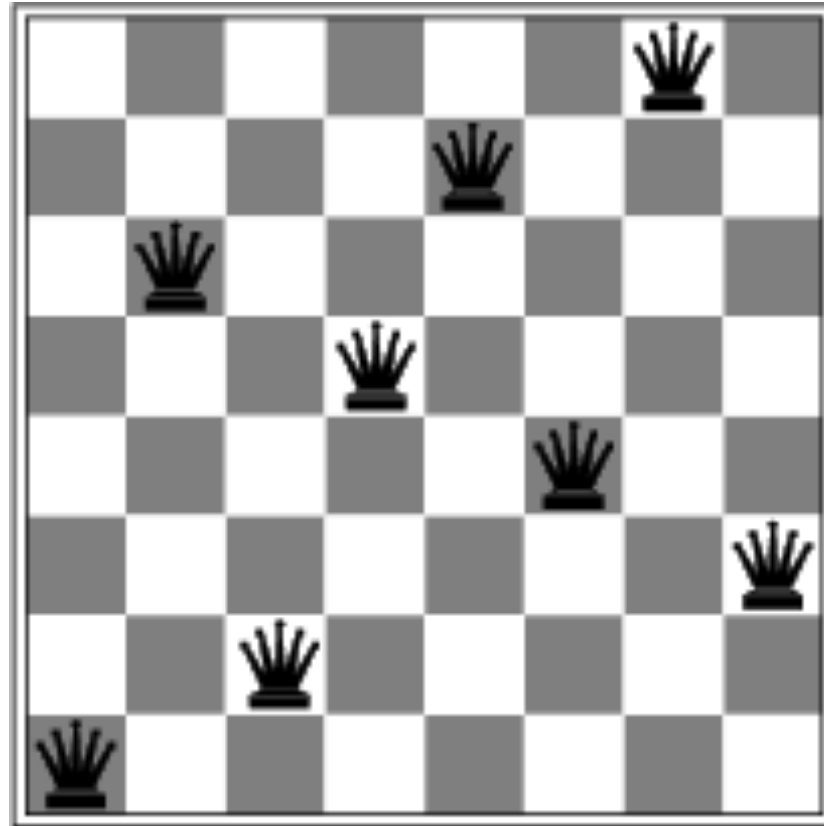


Hill-climbing search: 8-queens problem



- h = number of pairs of queens that are attacking each other, either directly or indirectly
- $h = 17$ for the above state
- The figure also shows the values of all successors, top successors have $h = 12$

Hill-climbing search: 8-queens problem



- A local minimum with $h = 1$ (obtained in 5 steps)

Hill-climbing search

- The algorithm gets stuck for several reasons:
 - Local Maximum: it is a peak that is higher than each of its neighbours, but lower than the maximum overall
 - Ridges: cause a sequence of local maxima that make navigation difficult
 - Plateau (flat): can lead to a local maximum where there is no ascendant exit or a terrace to advance
- In the 8-queens, it gets stuck in 86% and solve 14% cases
- If we allow lateral movements with the hope that we find a terrace (limiting them if reach a local maximum, e.g.100):→ 94% success
- Variants:
 - Stochastically (randomly chooses upward movements)
 - Random restart (the initial states are generated randomly)

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Simulated annealing search

- ❑ Simulated annealing is the process of tempering or hardening metals by heating and then cooling them gradually
- ❑ Idea: escape local maxima by allowing some "bad" moves but **gradually decrease** their frequency
- ❑ It combines hill-climbing with random generation successor
- ❑ One can prove: If T decreases slowly enough, then simulated annealing search will find a global optimum with probability approaching 1
- ❑ Widely used in VLSI layout, airline scheduling, etc

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Local beam search

- Idea: Keep track of k states rather than just one
 - Start with k randomly generated states
 - At each iteration, all the successors of all k states are generated
 - If any one is a goal state, stop; else select the k best successors from the complete list and repeat
 - Alternatively stochastic LBS randomly choose k successors, with the probability of choosing a successor as an increasing function of its value

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Genetic algorithms

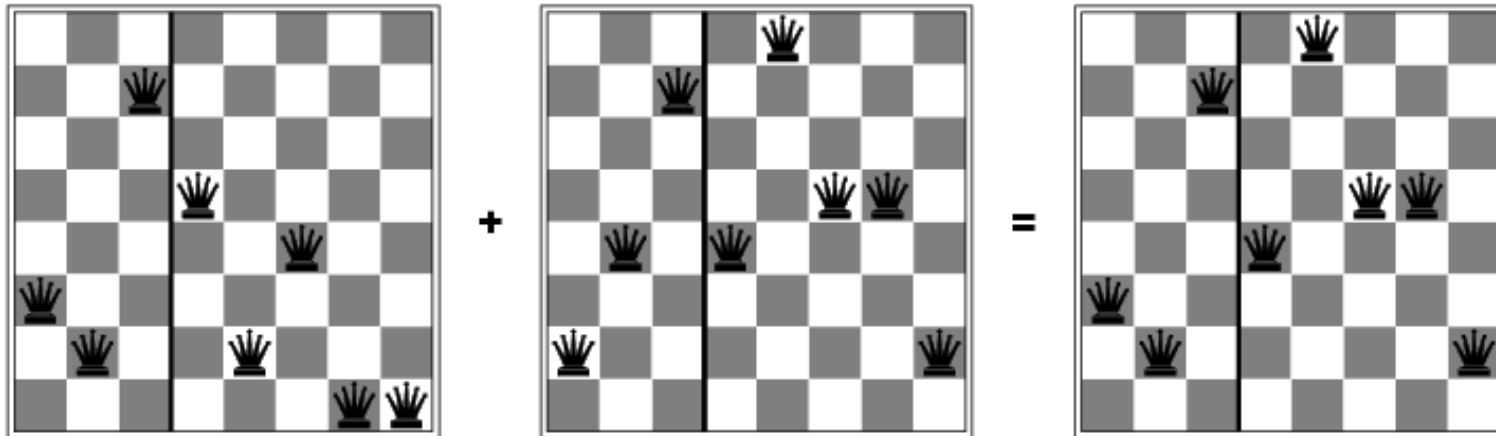
- A successor state is generated by combining two parent states
- Start with k randomly generated states (**population**)
- A state is represented as a string over a finite alphabet (often a string of 0s and 1s)
- Evaluation function (**fitness function**). Higher values for better states
- Produce the next generation of states by selection, crossover, and mutation

Genetic algorithms



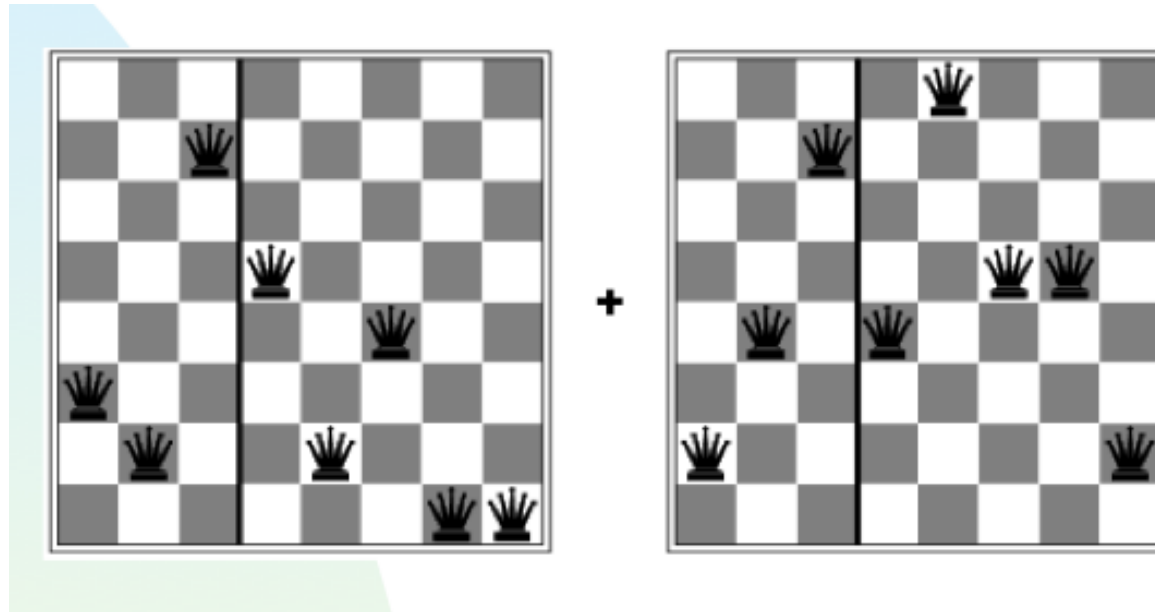
- The initial population is represented by chains of 8 digits representing states of 8 queens

Genetic algorithms



- It corresponds to the 2 parents of figure (c)
327 52411 (5 attacked queens)
247 48552 (4 attacked queens)

Genetic algorithms



- Fitness function: number of NON-attacking pairs of queens (min = 0, max = $8 \times 7/2 = 28$)
- Right: 247 48552 (4 attacked queens) = $28 - 4 = 24$
 $24/(24+23+20+11) = 31\%$
- Left: 327 52411 (5 attacked queens) = $28 - 5 = 23$
 $23/(24+23+20+11) = 29\%$

Genetic algorithms



probabilities

- ❑ Crossing points are chosen and d) the offspring are created crossing the chain parental crosspoint
- ❑ In e) each position is subject to random mutation with a small probability