Search

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Objectives

Specific Objectives

- To understand the role of the search in AI
- Main search algorithms

Source

- Stuart Russell & Peter Norvig (2009). Artificial Intelligence: A Modern Approach. (3rd Edition). Ed. Pearsons.

Outline

- **Introduction**
- Problem formulation
- Problem types
- Basic search algorithms
- Conclusions

Introduction

- Early AI works were directed to:
  - Proof of theorems
  - Solving crosswords
  - Games

- All in AI is search
  - Not entirely true (obviously) but more than we can imagine
  - Finding a good/best solution to a problem among several possible solutions

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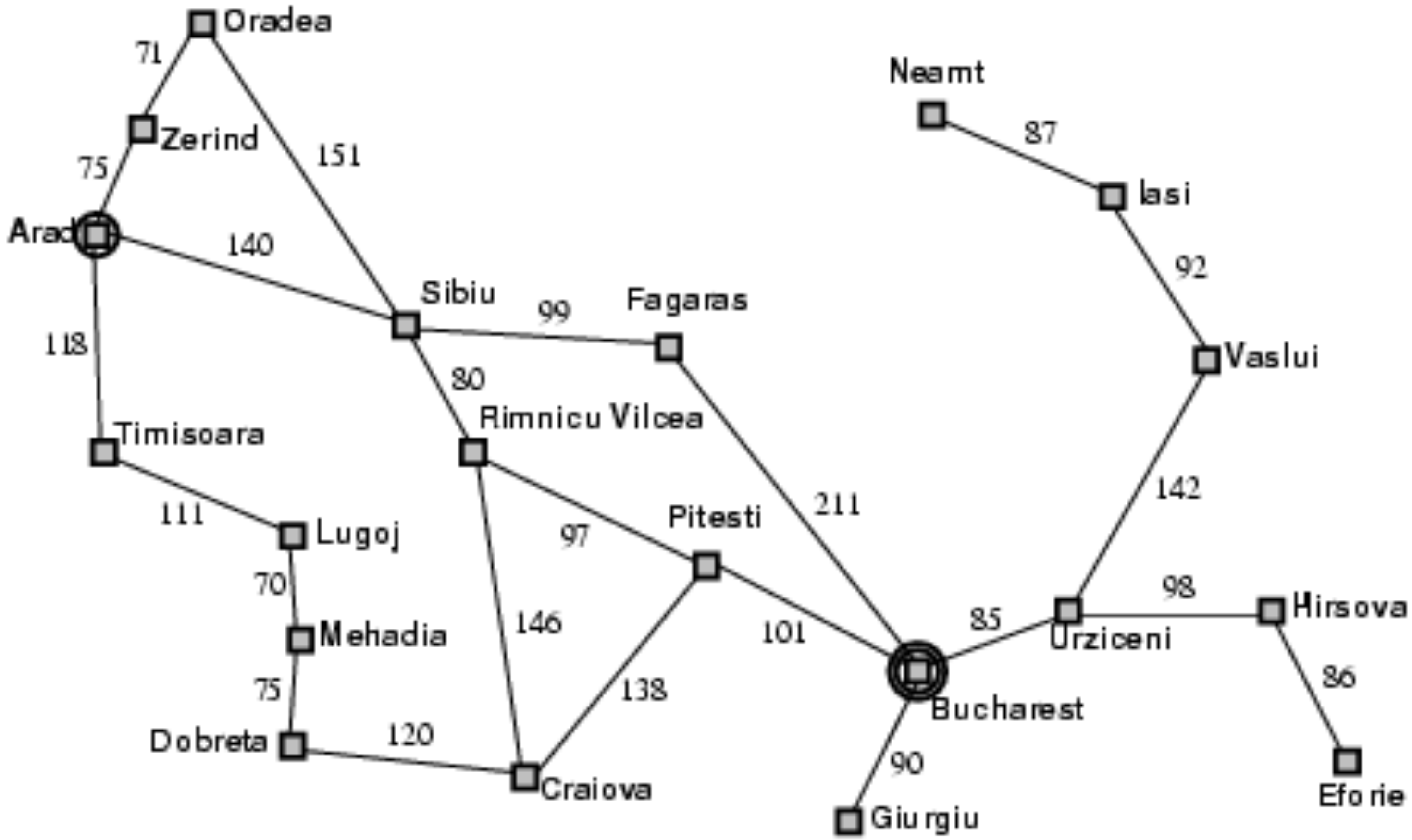
Problem formulation



Problem formulation (I)

- Agent must maximize its performance measure
- Example: On holiday in Romania; currently in Arad
  Flight leaves tomorrow from Bucharest
- Formulate goal:
  - be in Bucharest
- Formulating the problem:
  - states: multiple cities
  - actions: drive between cities
- Finding a solution:
  - Sequence cities, eg., Arad, Sibiu, Fagaras, Bucharest
- Process of finding such a solution: **Search**

Problem formulation (II)

- Assumptions of the environment:
  - Static: search and formulation is done without considering changes in the environment
  - Observable: the initial state is known
  - Discrete: the alternative locations are known
  - Deterministic: each state is determined by the current state and the action executed

- The solutions are simple sequences of actions, they are executed without considering perceptions

Problem formulation (III)

- A problem is defined by four items:
  1. initial state e.g., "at Arad”
  2. actions or successor function S(x) = set of action–state pairs

     e.g., S(Arad) = {<Arad → Zerind, Zerind>, … }
  3. goal test, can be
     - explicit, e.g., x = "at Bucharest"
     - implicit, e.g., Checkmate(x)
  4. path cost (additive)
     - e.g., sum of distances, number of actions executed, etc.
     - c(x,a,y) is the step cost, assumed to be ≥ 0

- A solution is a sequence of actions leading from the initial state to a goal state

Problem formulation (IV)

- Real world is absurdly complex
  → state space must be abstracted for problem solving
- (Abstract) state = set of real states
- (Abstract) action = complex combination of real actions
  - e.g., "Arad → Zerind" represents a complex set of possible routes, detours, rest stops, etc.
- For guaranteed realizability, any real state "in Arad" must get to some real state "in Zerind"
- (Abstract) solution =
  - set of real paths that are solutions in the real world
- Each abstract action should be "easier" than the original problem

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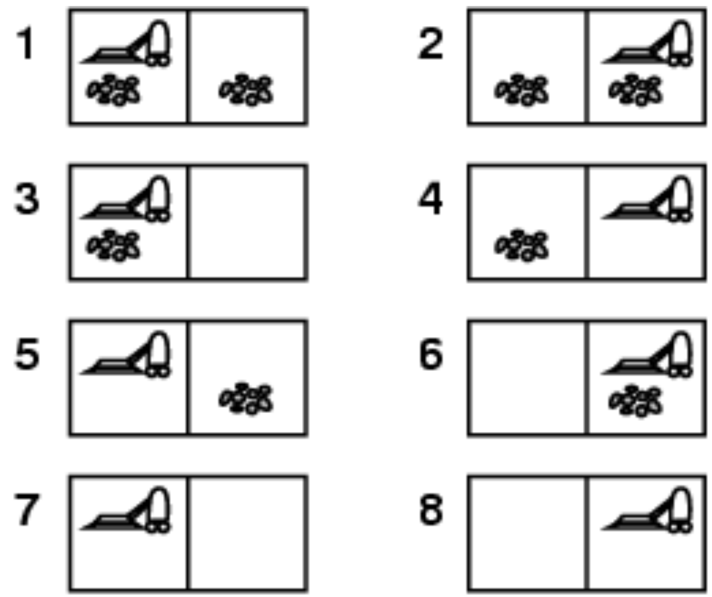
Problem types

- Deterministic, fully observable → **single-state problem**
  - Agent knows exactly which state it will be in; solution is a sequence
- Non-observable → **sensorless problem** (conformant problem)
  - Agent may have no idea where it is; solution is a sequence
- Nondeterministic and/or partially observable → **contingency problem**
  - percepts provide new information about current state
  - often interleave search with execution
- Unknown state space → **exploration problem**

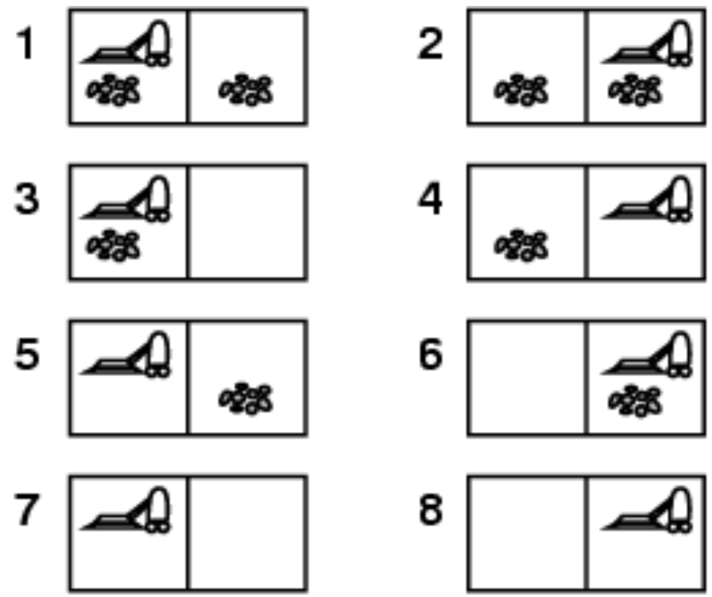
Problem types: example

- Single-state, start in #5.
  Solution?



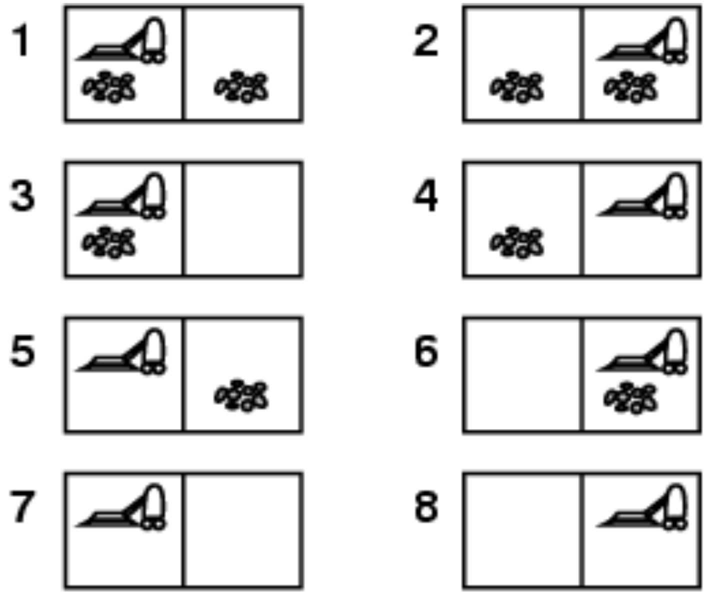
Problem types: example (I)

- Single-state, start in #5.
  Solution? *[Right, Suck]*



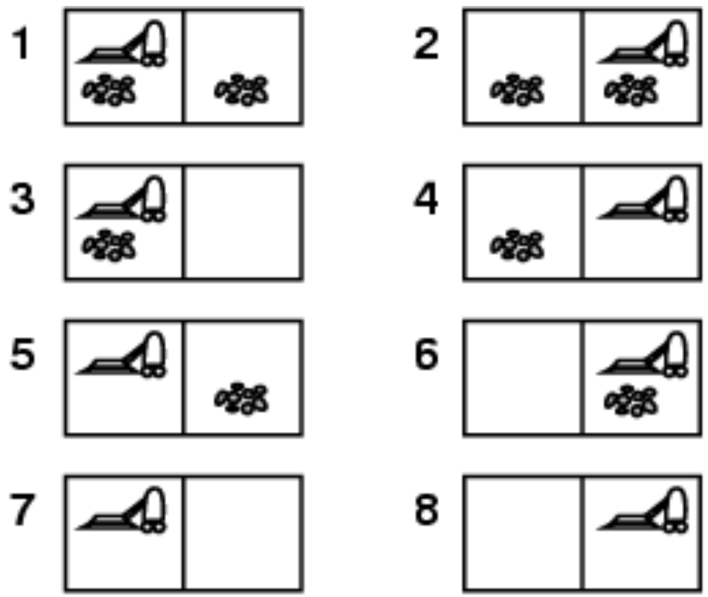
Problem types: example (II)

- Single-state, start in #5.
  Solution? *[Right, Suck]*
- Sensorless, start in {1,2,3,4,5,6,7,8} e.g., Right goes to {2,4,6,8}
  Solution?



Problem types: example (III)

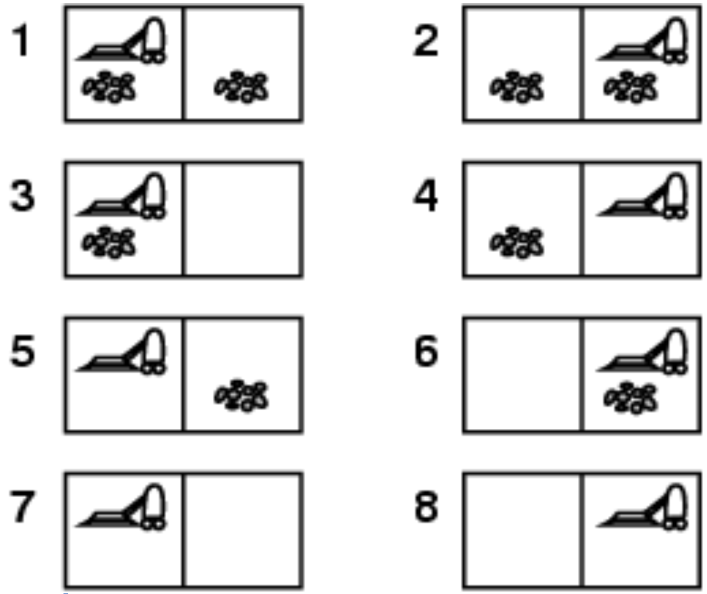
- Single-state, start in #5.
  Solution?*[Right, Suck]*
- Sensorless, start in {1,2,3,4,5,6,7,8} e.g., Right goes to {2,4,6,8}
  Solution? *[Right,Suck,Left,Suck]*



Problem types: example (IV)

- Single-state, start in #5.
  Solution? *[Right, Suck]*

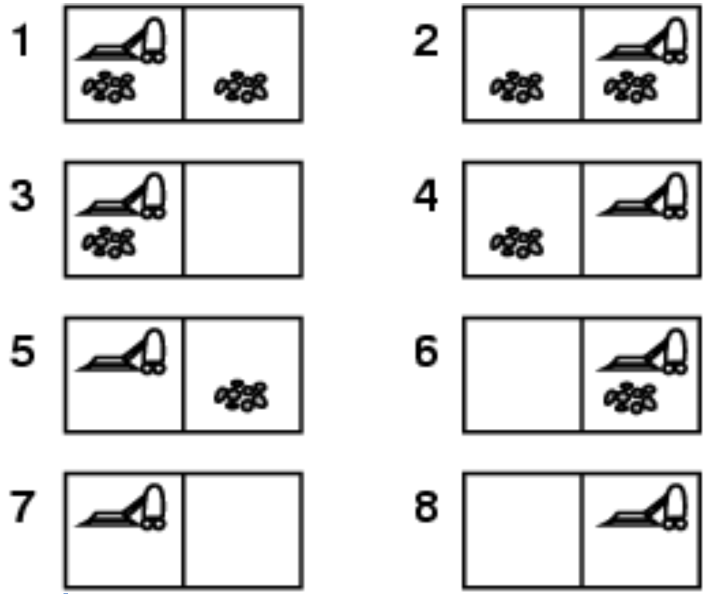
- Sensorless, start in {1,2,3,4,5,6,7,8} e.g., Right goes to {2,4,6,8}
  Solution? *[Right,Suck,Left,Suck]*
- Contingency
  - Nondeterministic: suck may dirt the carpet
  - Partially observable: location, dirt at current location
  - Percept: [L, Clean], i.e., start in #5 or #7
    Solution?



Problem types: example (V)

- Single-state, start in #5.
  Solution? *[Right, Suck]*

- Sensorless, start in {1,2,3,4,5,6,7,8} e.g., Right goes to {2,4,6,8}
  Solution? *[Right,Suck,Left,Suck]*
- Contingency
  - Nondeterministic: Suck may dirt the carpet
  - Partially observable: location, dirt at current location
  - Percept: [L, Clean], i.e., start in #5 or #7
    Solution? *[Right, **if** dirt **then** Suck]*



Type of environment

- **Fully observable** (vs. partially observable): an agent's sensors give it access to the complete state of the environment at each point in time
- **Deterministic** (vs. non-deterministic): the next state of the environment is completely determined by the current state and the action executed by the agent
- **Episodic** (vs. sequential): the agent's experience is divided into atomic "episodes" (each episode consists of the agent perceiving and then performing a single action), and the choice of action in each episode depends only on the episode itself
- **Discrete** (vs. continuous): A limited number of distinct, clearly defined percepts and actions
- **Static** (vs. dynamic): if the environment does not change when the agent is deliberating
  - Semidynamic: the environment does not change but the performance of the agent
- **Single agent** (vs. multiagent): an agent operating by itself in an environment

Environment	Observable	Deterministic	Episódic	Static	Discrete	Agents
Chess						
Chess with clock						
Poker						
Taxi						
Medical diagnosis						
Image analysis						
Clasifier *Robot*						
Refinery controller						
Interactive Tutor						

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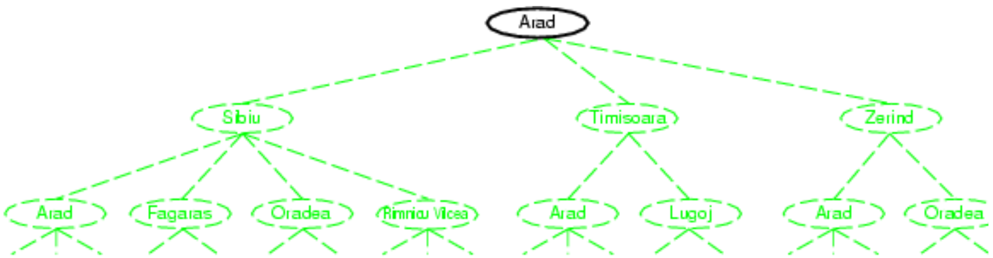
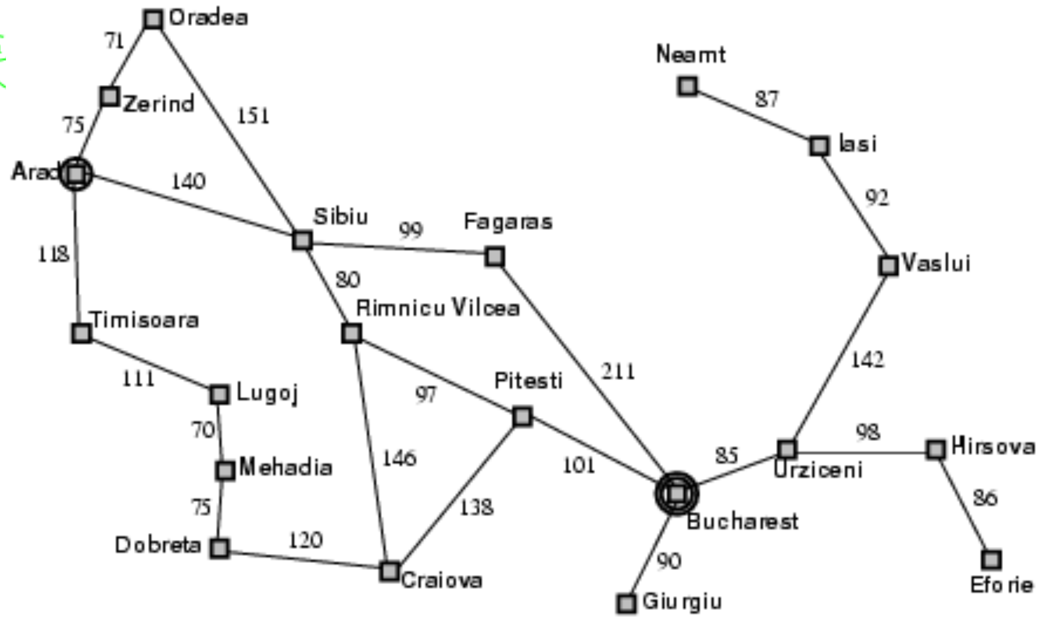
- Problem formulation
- Problem types
- **Search algorithms**
- Conclusions

Search algorithms

- We have formulated problems, we now need to solve them: search tree
- In general we can have a search graph rather than a tree when the state can be reached from multiple paths
- Basic idea:
  - offline, simulated exploration of state space by generating successors of already-explored states (i.e. expanding states)

Search algorithms: tree search example





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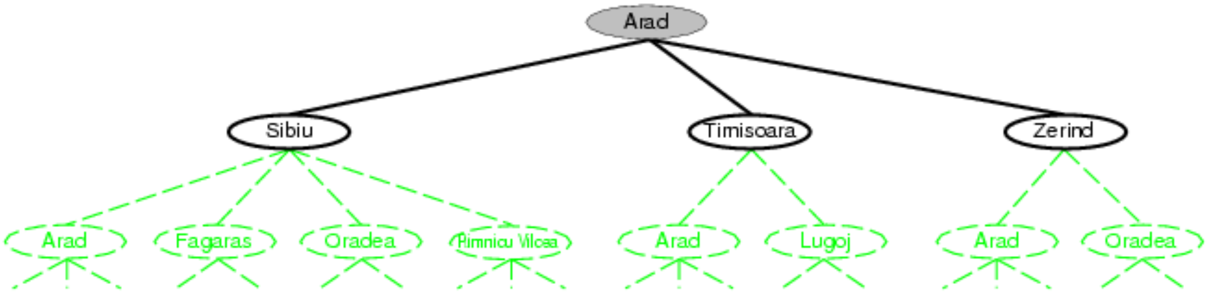
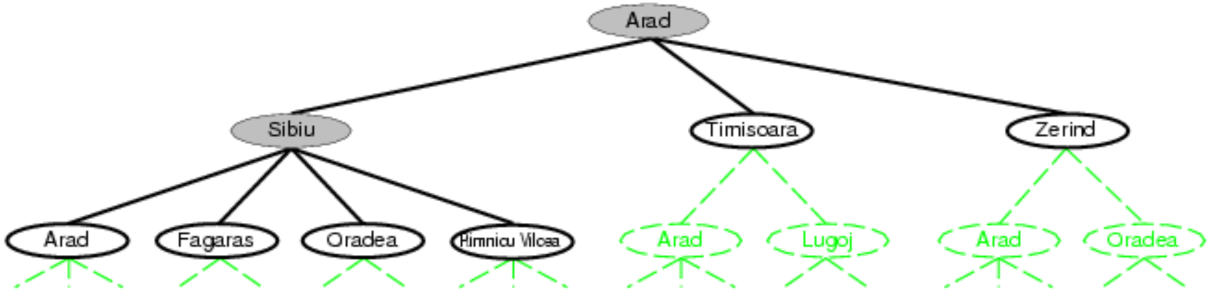
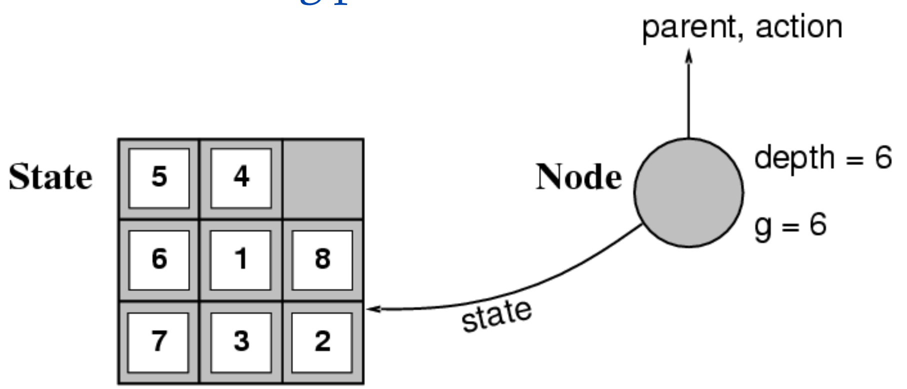


Search algorithms: tree search example



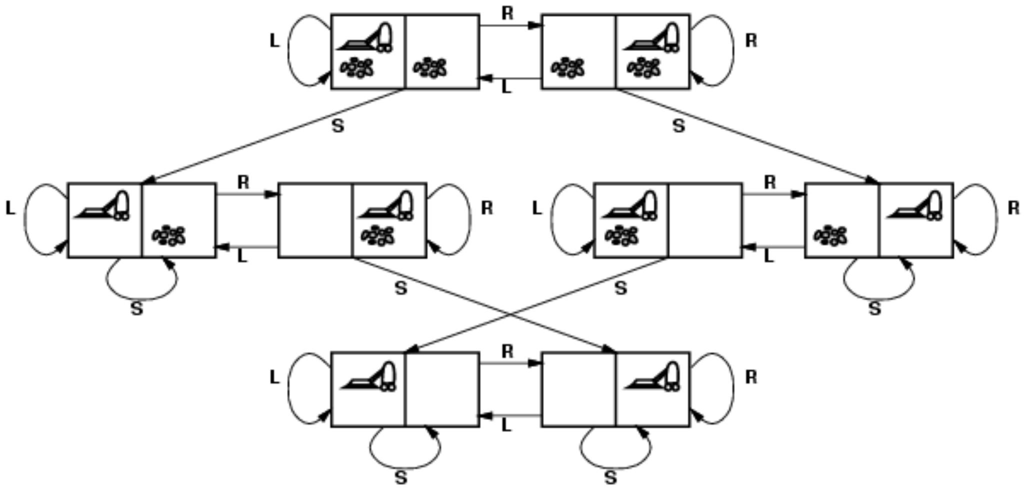
Search algorithms: states vs. nodes

- A state is a (representation of) a physical configuration
- A node is a data structure constituting part of a search tree includes state, parent node, action, path cost *g(x)*, depth



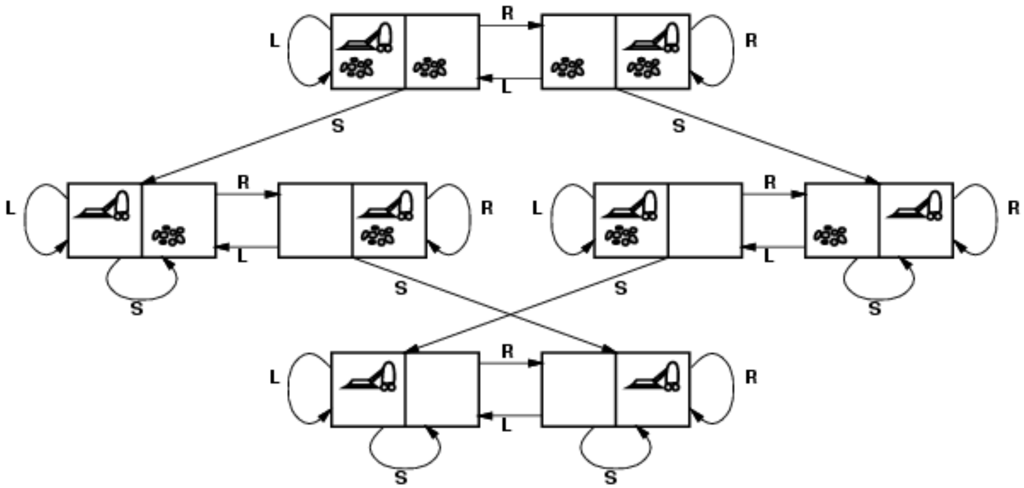
- The `Expand` function to create the corresponding states

Search algorithms: Vacuum world (I)



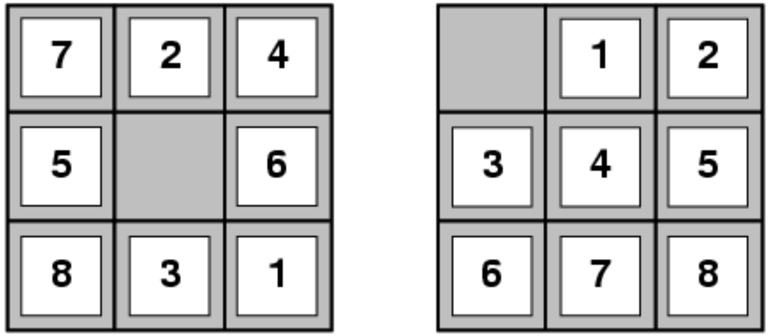
- states?
- actions?
- goal test?
- path cost?

Search algorithms: Vacuum world (II)



- <u>states?</u> integer dirt and robot location
- <u>actions?</u> *Left, Right, Suck*
- <u>goal test?</u> no dirt at all locations
- <u>path cost?</u> 1 per action

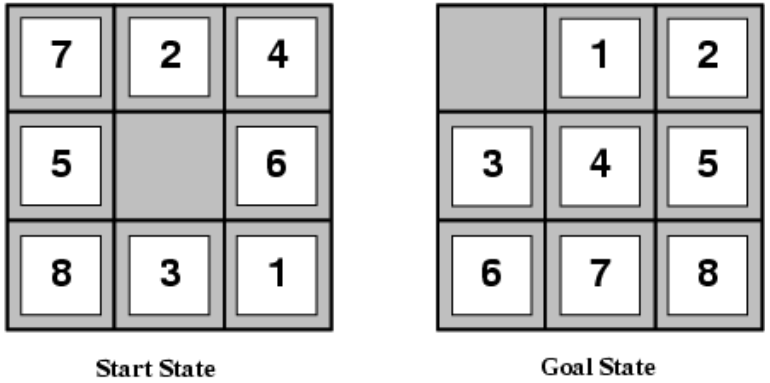
Search algorithms: The 8-puzzle (I)



Start State   Goal State

- states?
- actions?
- goal test?
- path cost?

Search algorithms: The 8-puzzle (II)



- states? locations of tiles
- actions? move blank left, right, up, down
- goal test? = goal state (given)
- path cost? 1 per move

[Note: optimal solution of *n*-Puzzle family is NP-hard]

Search strategies

- A search strategy is defined by picking the order of node expansion
- Strategies are evaluated along the following dimensions:
  - completeness: does it always find a solution if one exists?
  - time complexity: number of nodes generated
  - space complexity: maximum number of nodes in memory
  - optimality: does it always find a least-cost solution?

- Time and space complexity are measured in terms of
  - b: maximum branching factor of the search tree
  - d: depth of the least-cost solution
  - m: maximum depth of the state space (may be ∞)

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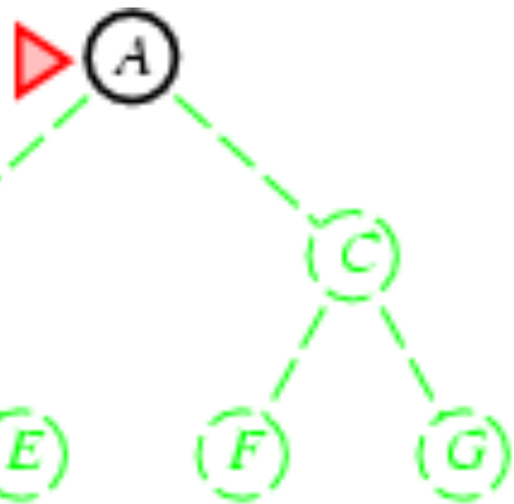
- Basic search algorithms
  - **Uninformed search**
  - Informed search
- Conclusions

Introduction

- Uninformed search strategies use only the information available in the problem definition
  - Breadth-first search/ Búsqueda en anchura
  - Uniform-cost search/ Búsqueda de coste uniforme
  - Depth-first search/ Búsqueda en profundidad
  - Depth-limited search/ Búsqueda en profundidad limitada
  - Iterative deepening search/Búsqueda de profundización iterativa

Breadth-first search

- Expand shallowest unexpanded node
- Implementation:
  - *fringe* is a FIFO queue, i.e., new successors go at end



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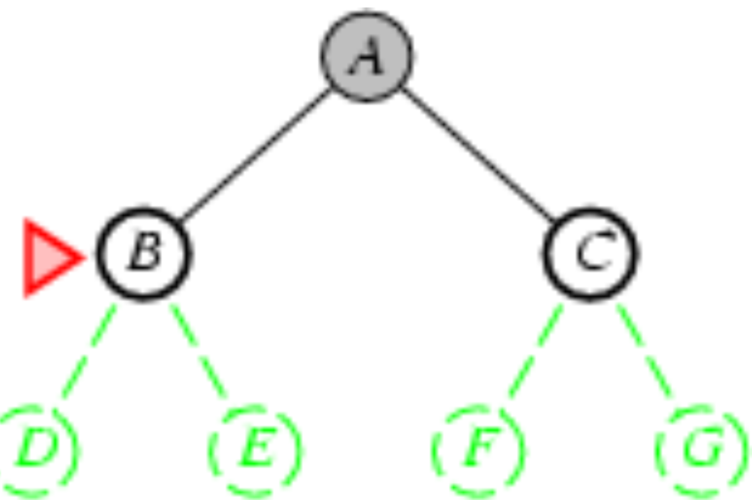

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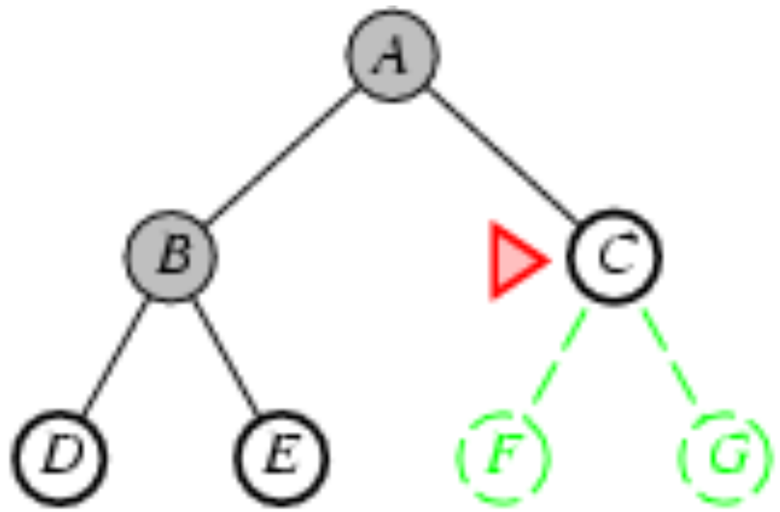

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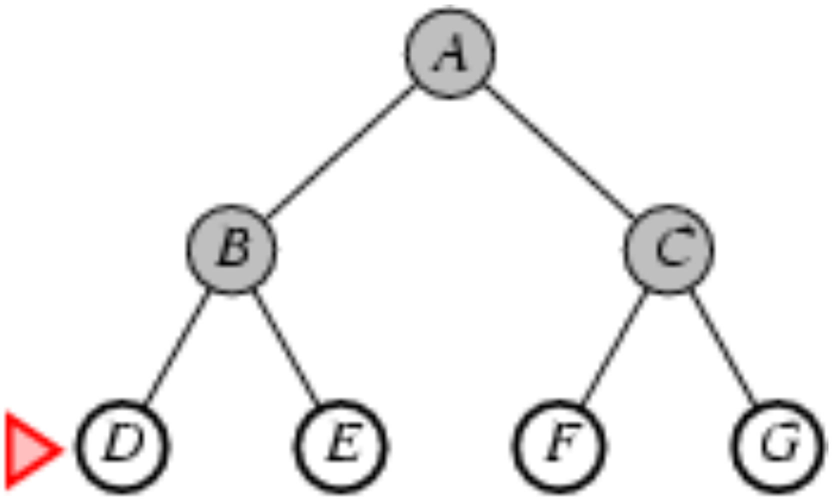


Properties of breadth-first search

- Complete? Yes (if b is finite)
- Time? $1+b+b^2+b^3+\ldots+b^d+b(b^d-1) = O(b^{d+1})$
- Space? $O(b^{d+1})$ (keeps every node in memory)
- Optimal? Yes (if cost = 1 per step)

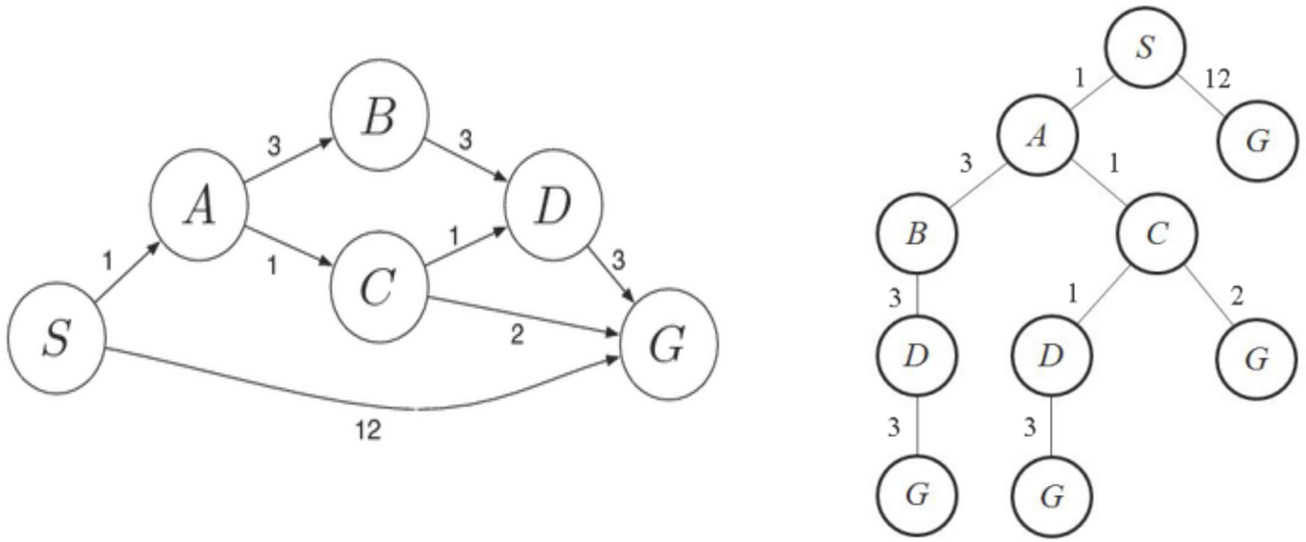
Space is the bigger problem (more than time)

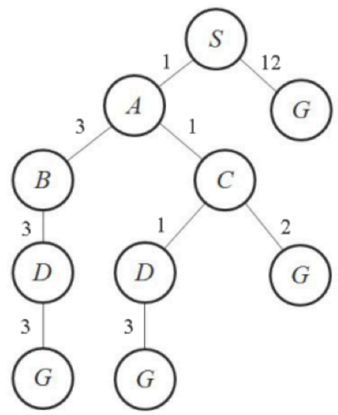
Each state has b successors (branching factor)

d is the shallower depth

Uniform-cost search

- Expand least-cost unexpanded node
- Implementation:
  - *fringe* = queue ordered by path cost
- Find the solution with minimum cumulative cost, i.e. an optimal solution





Uniform-cost search (Solution)

Initialization: { [**S , 0**] } V = S

Iteration1: { [**S->A , 1**] , [S->G , 12] } V= S, A

Iteration2: { [**S->A->C , 2**] , [S->A->B , 4] , [S->G , 12] } V= S, A, C

Iteration3: { [**S->A->C->D , 3**] , [S->A->C->G , 4] , [S->A->B , 4] , [S->G , 12] } V= S, A, C, D

Iteration 4: [S->A->C->D->G , 6], [S->A->C->G , 4] , **{[S->A->B, 4]** , [S->G , 12] } V= S, A, C, D, B

Iteration 5: {[S->A->B->D->G, 10] , [**S->A->C->G , 4**], [S->A->C->D->G , 6], [S->G , 12]}

Solution: S->A->C->G.

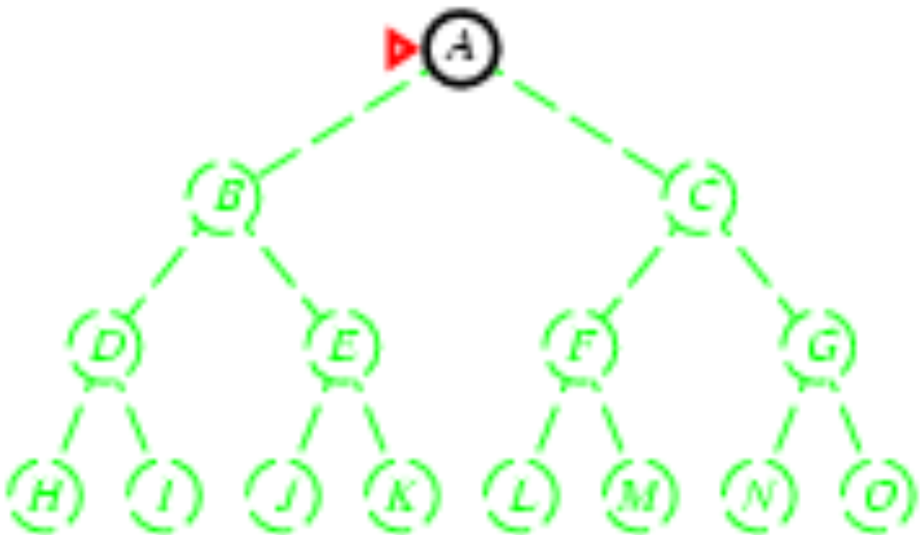
Uniform-cost search

- Complete? Yes, if step cost $\geq \varepsilon$
- Time? # of nodes with $g \leq$ cost of optimal solution, $O(b^{ceiling(C^*/\varepsilon)})$ where C^* is the cost of the optimal solution
- Space? # of nodes with $g \leq$ cost of optimal solution, $O(b^{ceiling(C^*/\varepsilon)})$
- Optimal? Yes – nodes expanded in increasing order of $g(n)$

If all costs are equal → $O(b^d)$

Depth-first search

- Expand deepest unexpanded node
- Implementation:
  - *fringe* = LIFO queue, i.e., put successors at front



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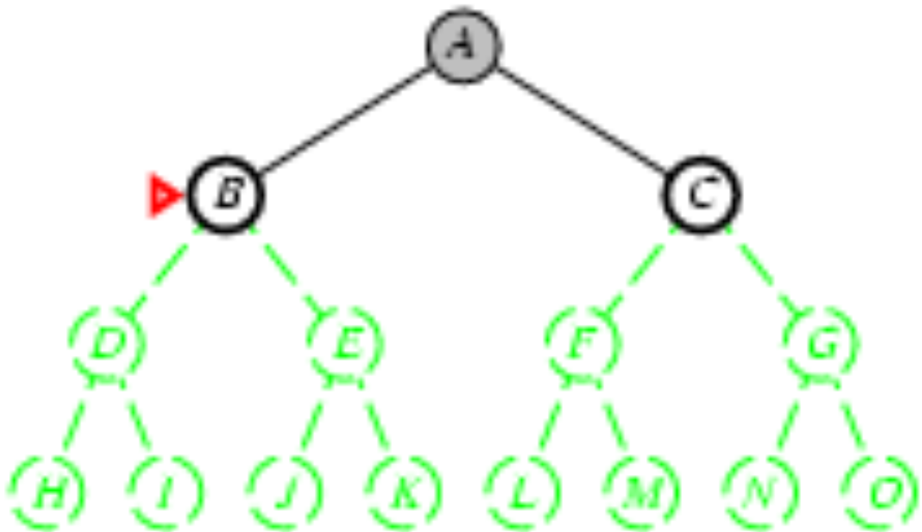

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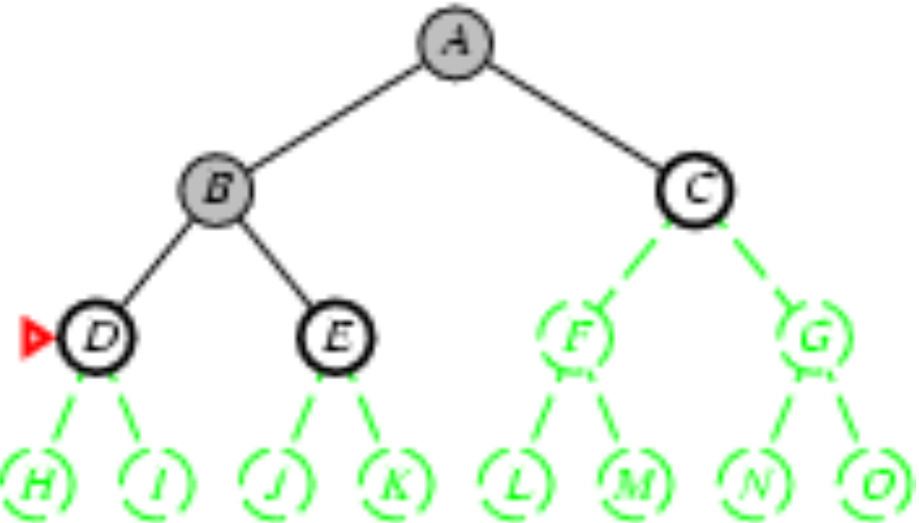

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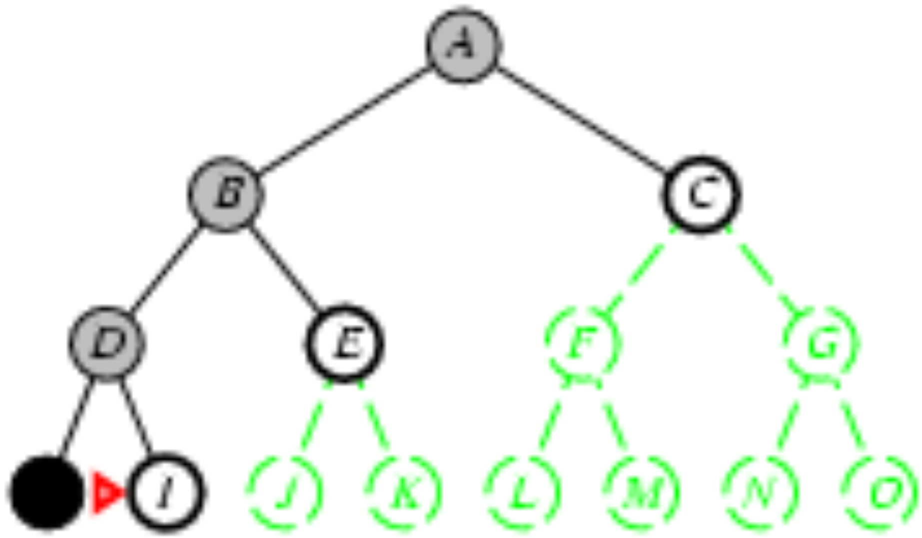

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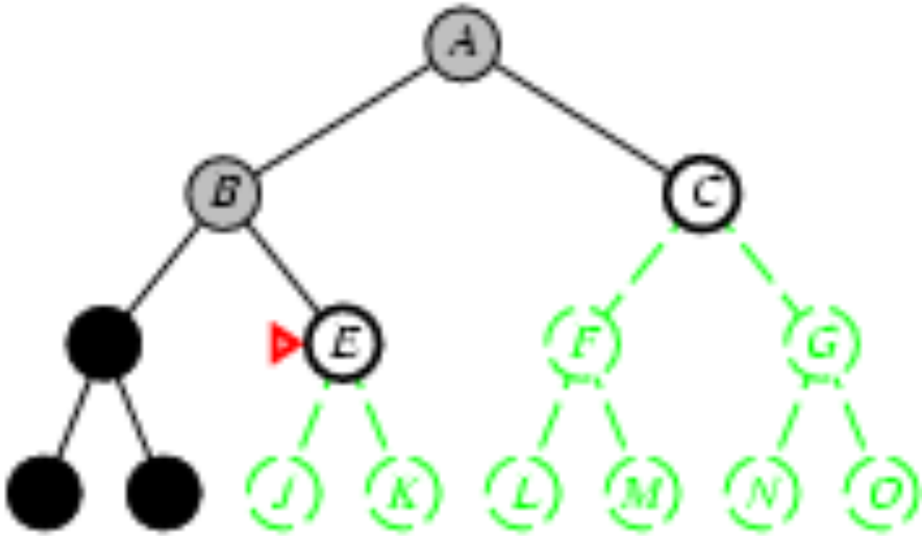

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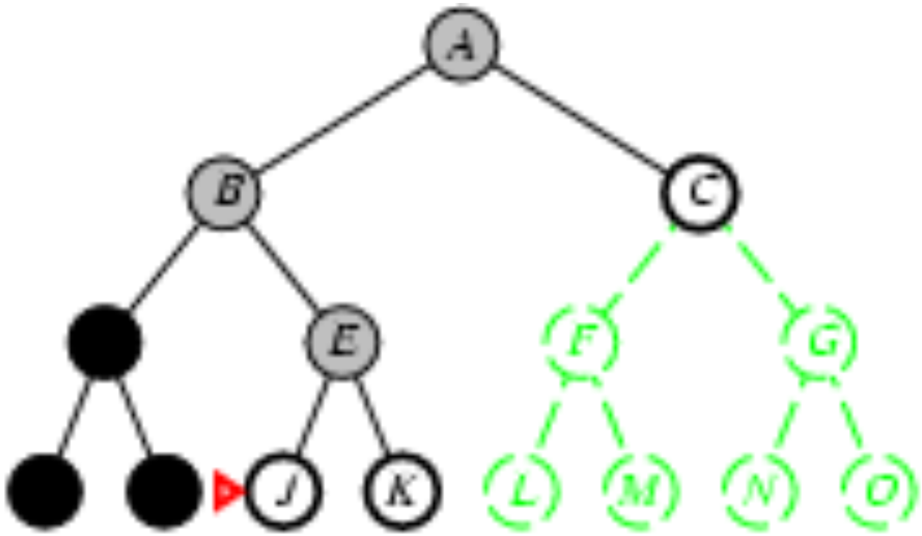

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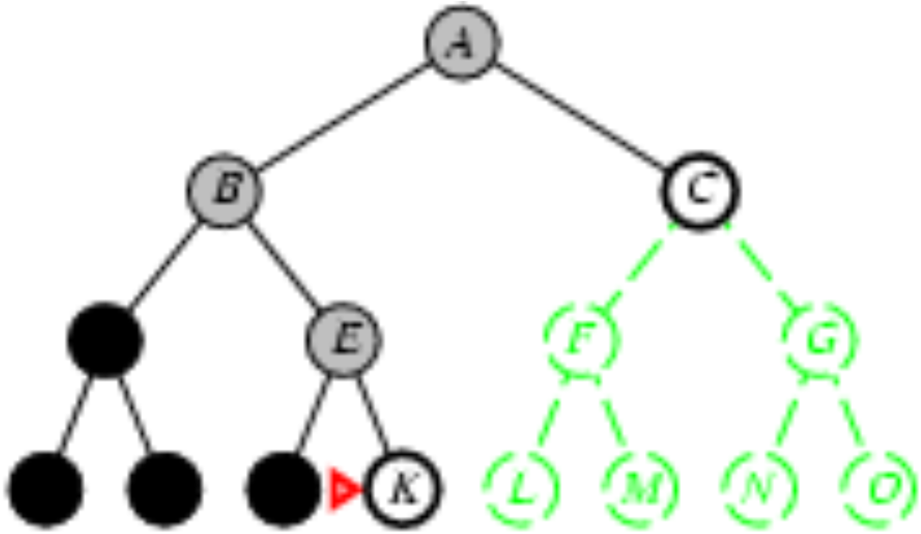

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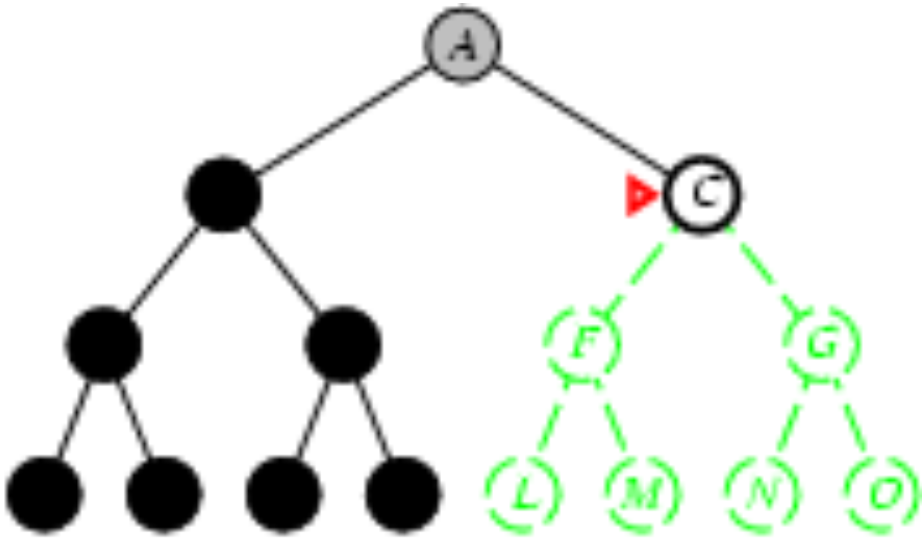

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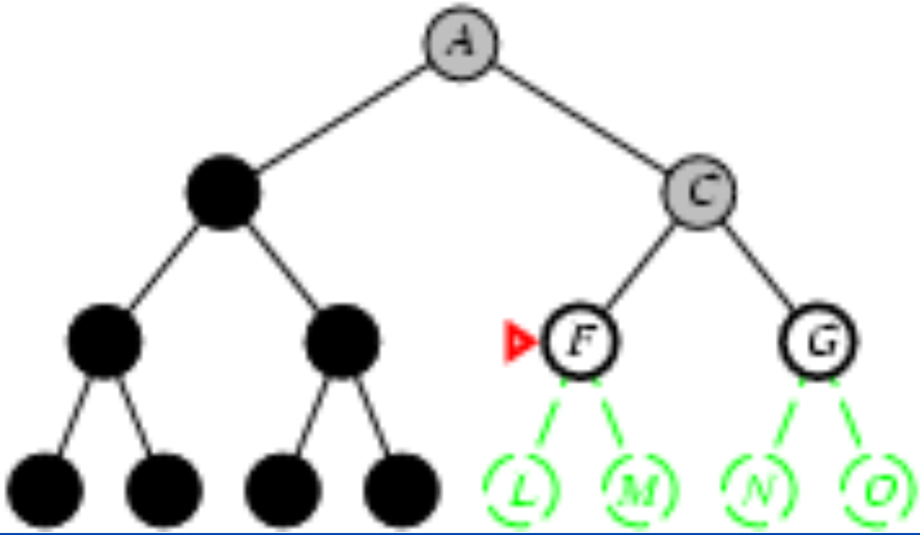

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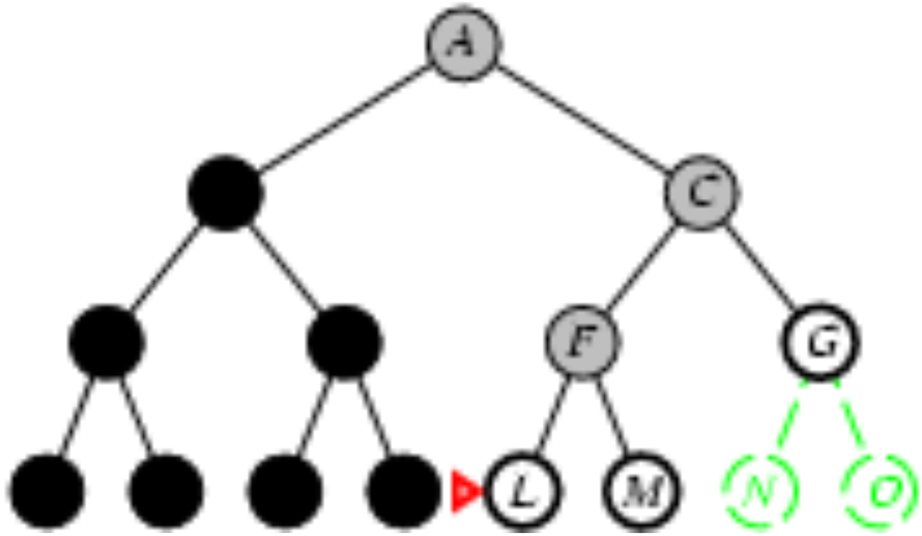

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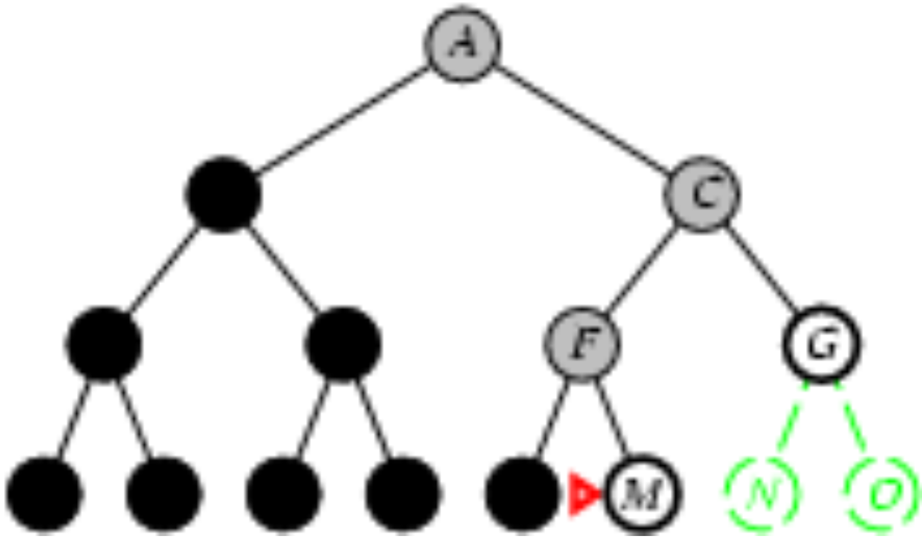


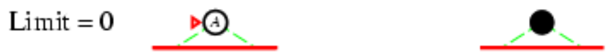
Properties of depth-first search

- Complete? No: fails in infinite-depth spaces, spaces with loops
  - Modify to avoid repeated states along path
    → complete in finite spaces
- Time? $O(b^m)$: terrible if m is much larger than d
  - but if solutions are dense, may be much faster than breadth-first
- Space? $O(bm)$
- Optimal? No

Depth-limited search

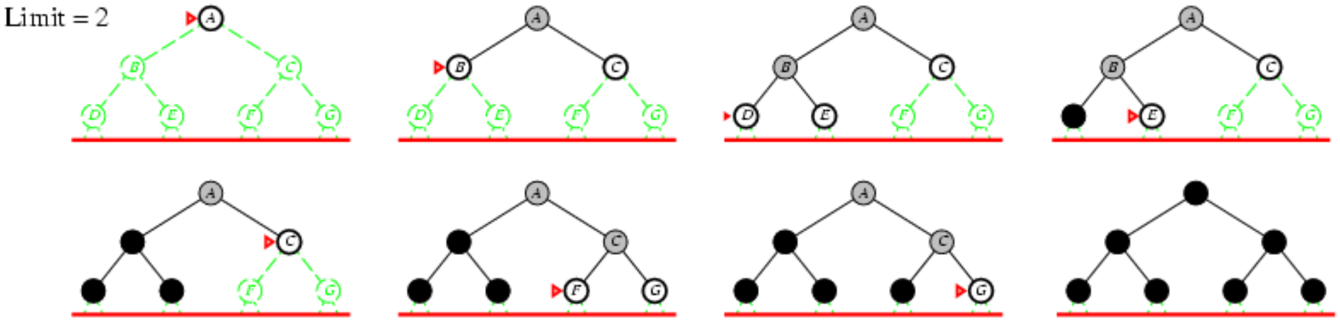
- = depth-first search with depth limit L
- i.e., nodes at depth L have no successor

Iterative deepening search $L = 0$

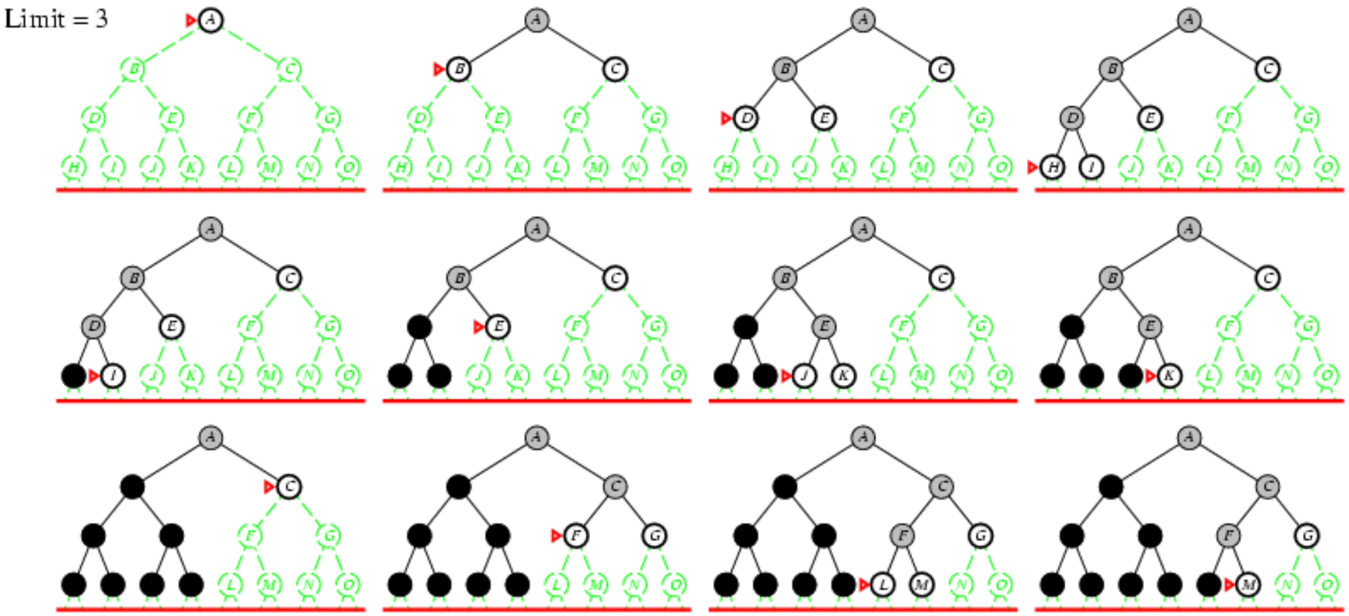


Iterative deepening search $L = 1$

Iterative deepening search L =2



Iterative deepening search $L=3$

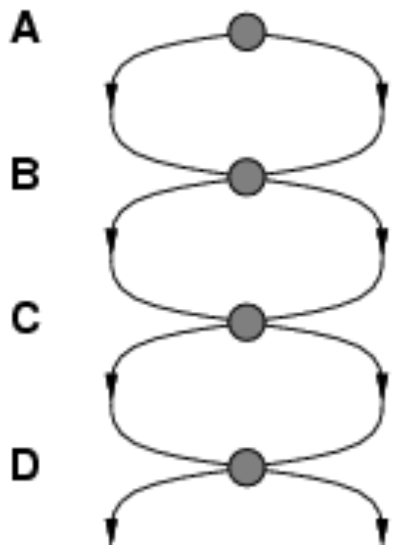


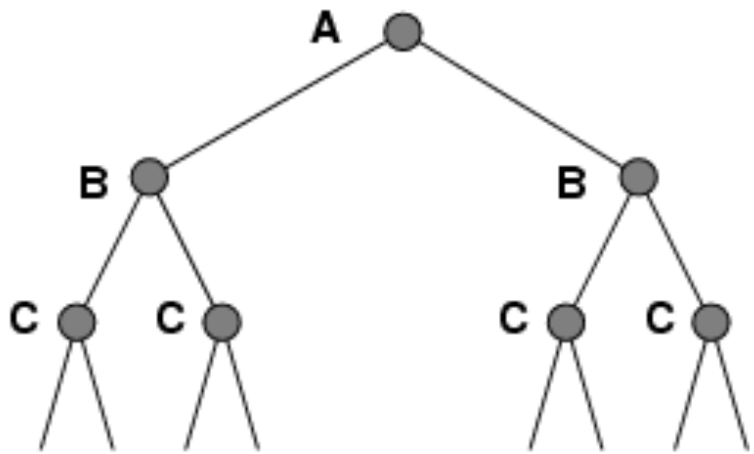
Properties of iterative deepening search

- <u>Complete?</u> Yes
- <u>Time?</u> $(d+1)b^0 + d\, b^1 + (d-1)b^2 + \ldots + b^d = O(b^d)$
- <u>Space?</u> $O(bd)$
- <u>Optimal?</u> Yes, if step cost = 1

Repeated states

- Failure to detect repeated states can turn a linear problem into an exponential one!





Summary of algorithms

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

Outline

- Introduction
- Problem formulation
- Problem types
- Basic search algorithms
  - Uninformed search
  - **Informed search**
- Conclusions

Informed search strategies

- Use the problem-specific knowledge beyond the definition of the problem itself to find more efficient solutions that uninformed strategies
  - Best-first search
    - Greedy best-first search/Búsqueda voraz primero el mejor
    - A*
  - Heuristics
  - Local search algorithms
    - Hill-climbing search/Búsqueda de escalada
    - Simulated annealing search/Búsqueda de temple simulado
    - Local beam search/Búsqueda de haz local
    - Genetic algorithms/Algoritmos genéticos

Best-first search

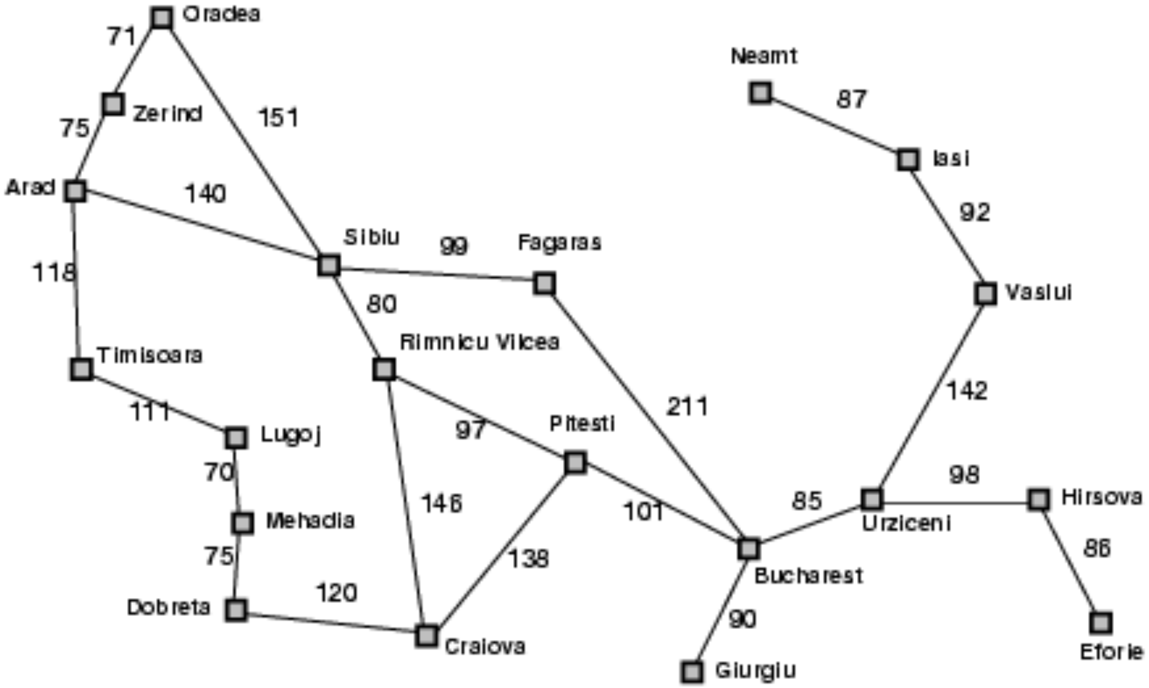
- Idea: use an evaluation function $f(n)$ for each node
  - estimate of "desirability"
  - Expand most desirable unexpanded node

- 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



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	10
Rimnicu Vilcea	193
Sibiu	253
Timisoara	329
Urziceni	80
Vaslui	199
Zerind	374

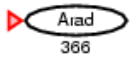
Informed search strategies

- Best-first search
  - **Greedy best-first search**
  - A* search
- Heuristics
- Local search algorithms
  - Hill-climbing search
  - Simulated annealing search
  - Local beam search
  - Genetic algorithms

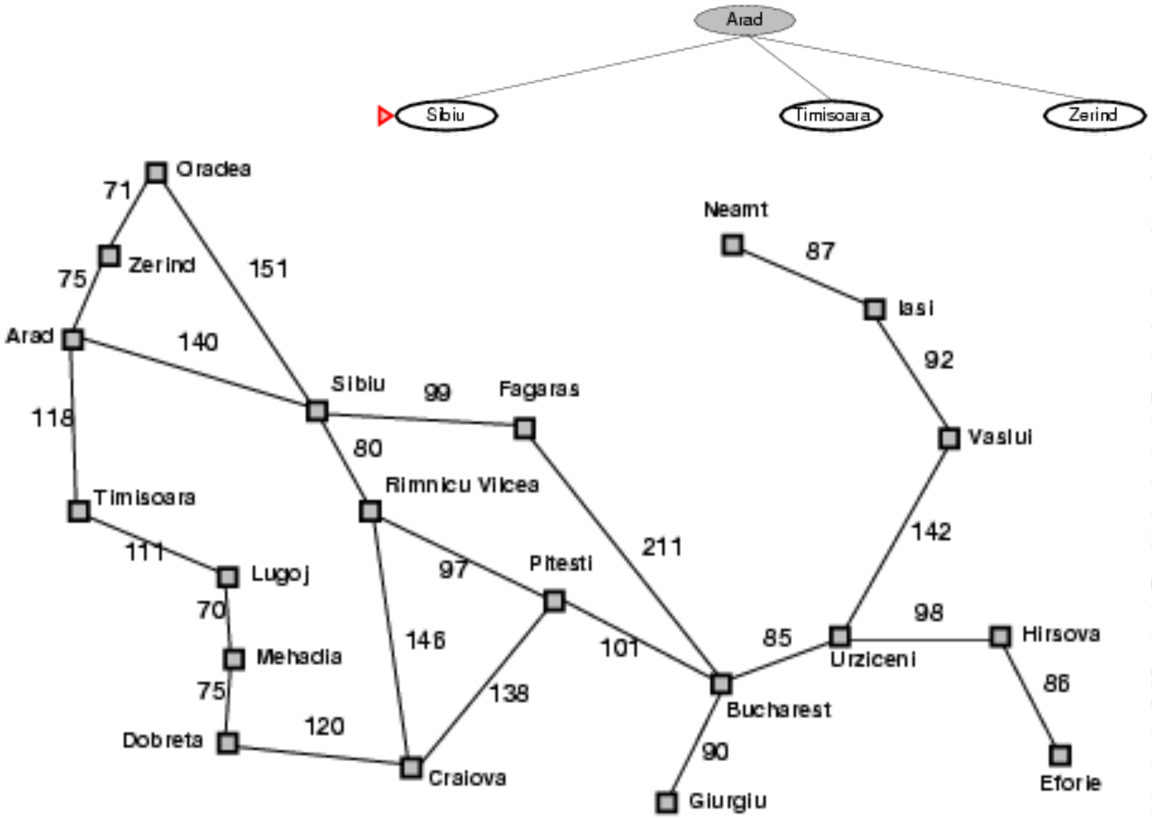
Greedy best-first search

- Evaluation function $f(n) = h(n)$ (heuristic) = 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



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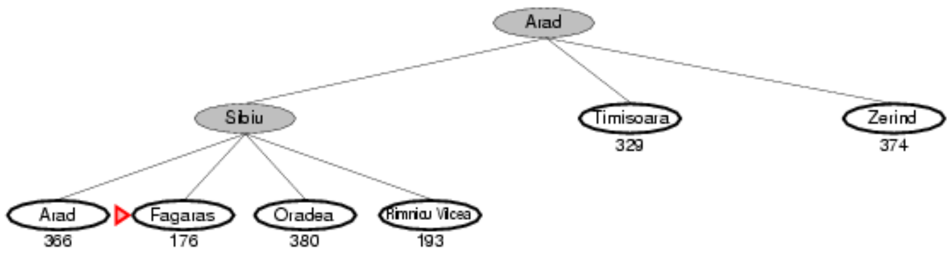
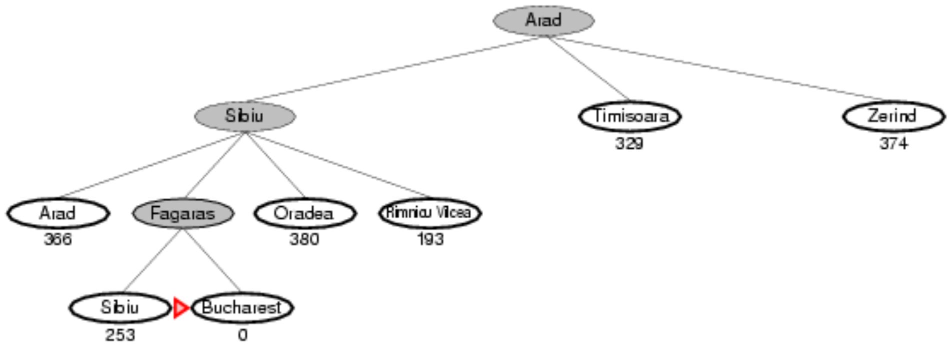
Greedy best-first search example



Greedy best-first search example



Properties of greedy best-first search

- Complete? No – can get stuck in loops, e.g., Iasi → Neamt → Iasi → 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

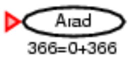
Informed search strategies

- Best-first search
  - Greedy best-first search
  - **A* search**
- Heuristics
- Local search algorithms
  - Hill-climbing search
  - Simulated annealing search
  - Local beam search
  - Genetic algorithms

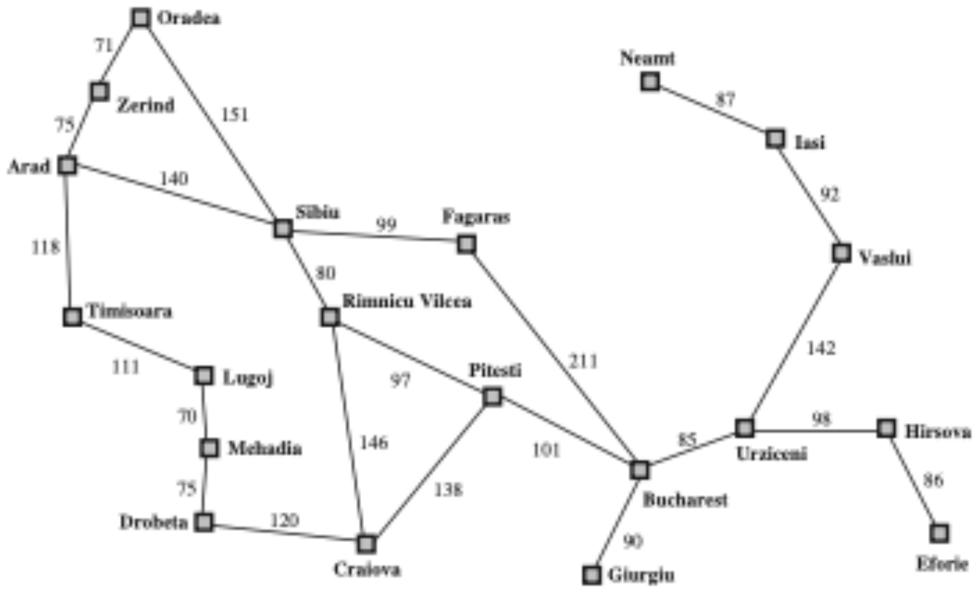
A^* search

- 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



A* search example



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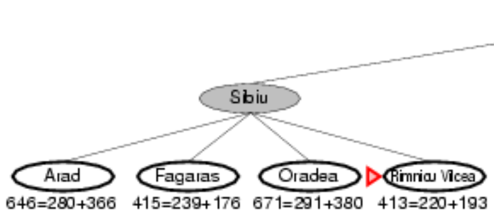
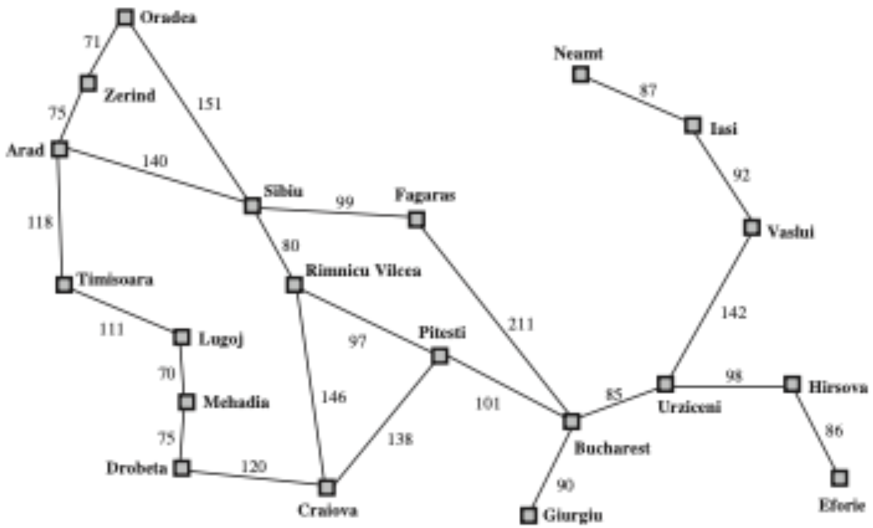
A* search example





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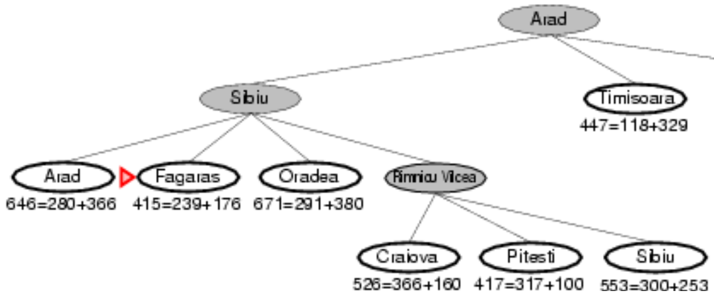
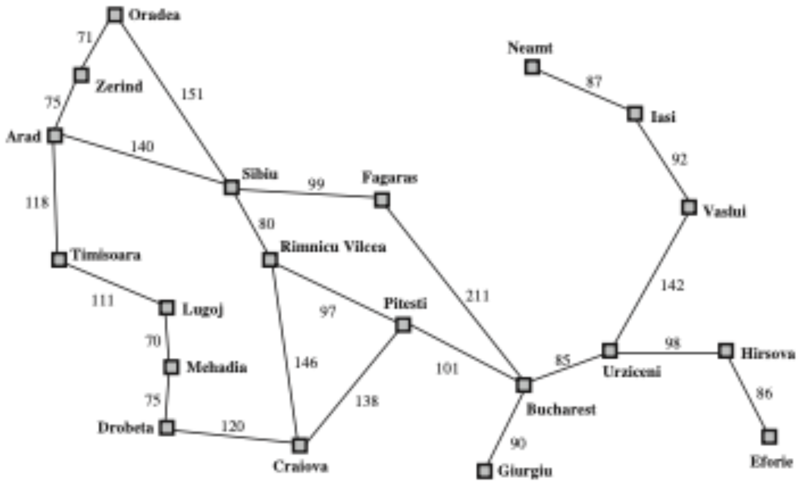
A* search example





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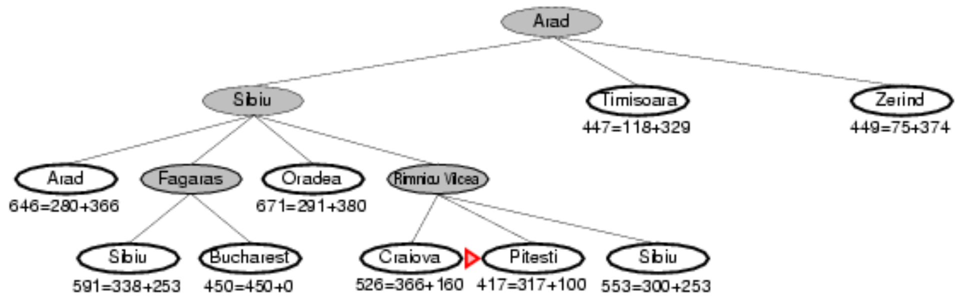
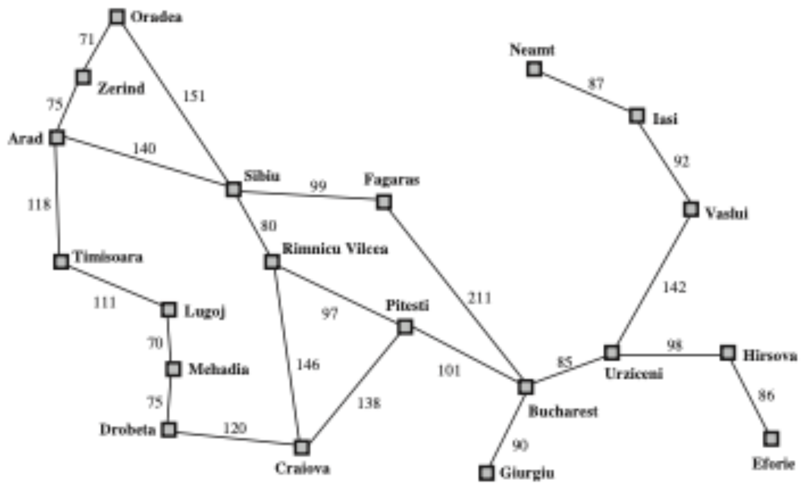
A* search example





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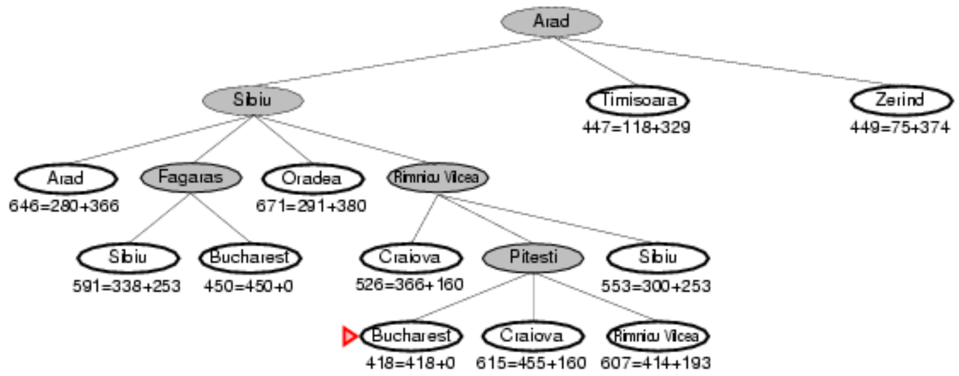
A* search example



Properties of A*

- <u>Complete?</u> Yes (unless there are infinitely many nodes with f $\leq f(G)$)
- <u>Time?</u> Exponential
- <u>Space?</u> Keeps all nodes in memory
- <u>Optimal?</u> Yes

Informed search strategies

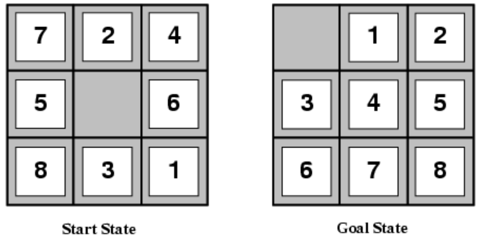
- Best-first search
- Greedy best-first search
- A^* search
- **Heuristics**
- Local search algorithms
  - Hill-climbing search
  - Simulated annealing search
  - Local beam search
  - Genetic algorithms

Admissible heuristics

- Objective:
  - produce a solution that is good enough for solving the problem at hand
  - This solution may not be the best but approximate the exact solution
- $h(n)$ is admissible if for 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

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



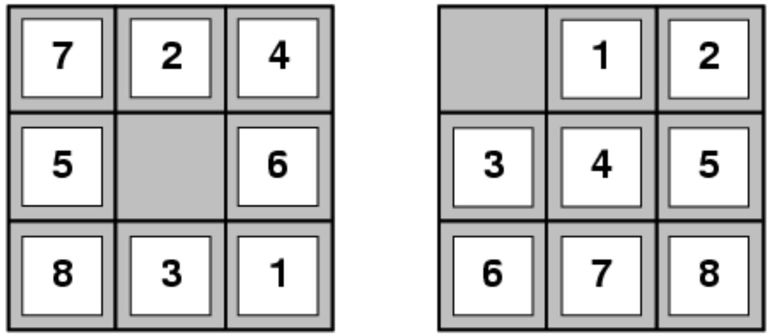
- Depth-first search will look 3^{22} states
- If we keep track of repeated states, we could reduce to 170.000
- In the15-puzle = 10^{13}

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)



Start State Goal State

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

Admissible heuristics for 8-puzzle

E.g., for the 8-puzzle:

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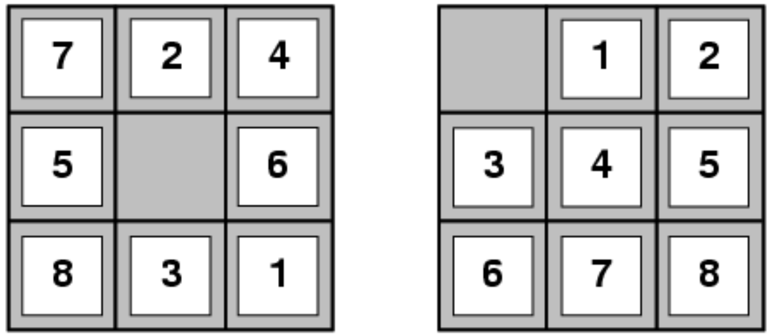
(i.e., + horizontal and vertical distance from desired location of each tile)



Start State   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

Informed search strategies

- Best-first search
  - Greedy best-first search
  - A^* search
- Heuristics
- **Local search algorithms**
  - Hill-climbing search
  - Simulated annealing search
  - Local beam search

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

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- Best-first search
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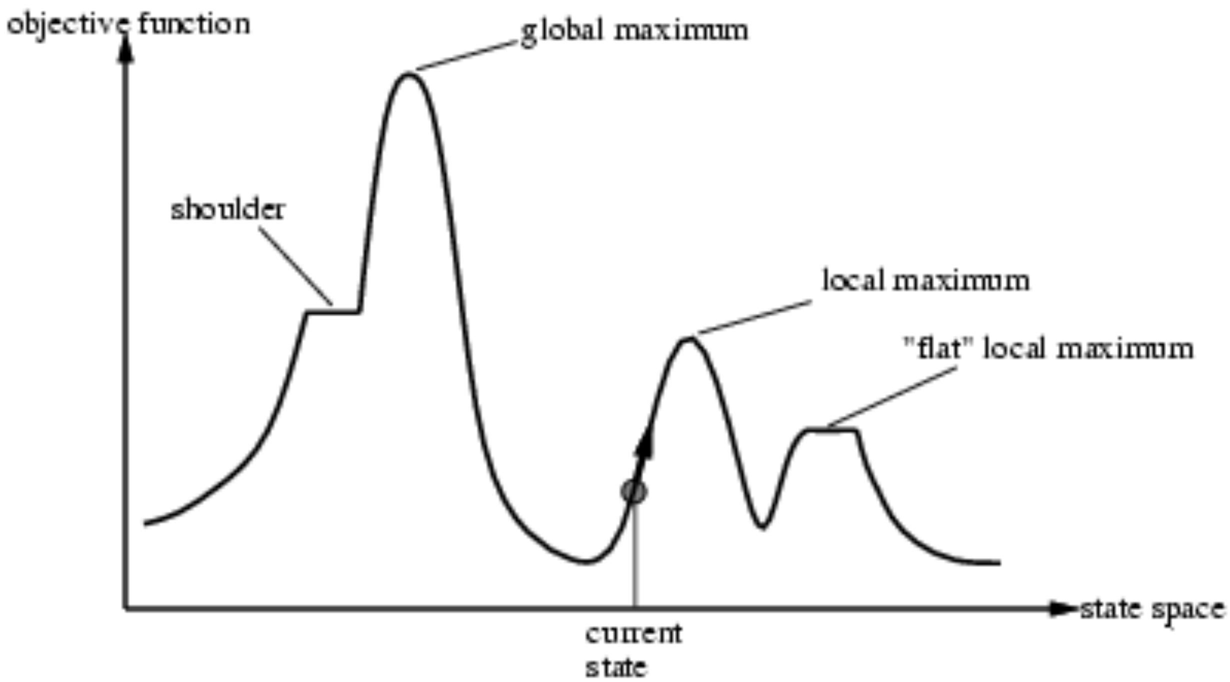
Hill-climbing search

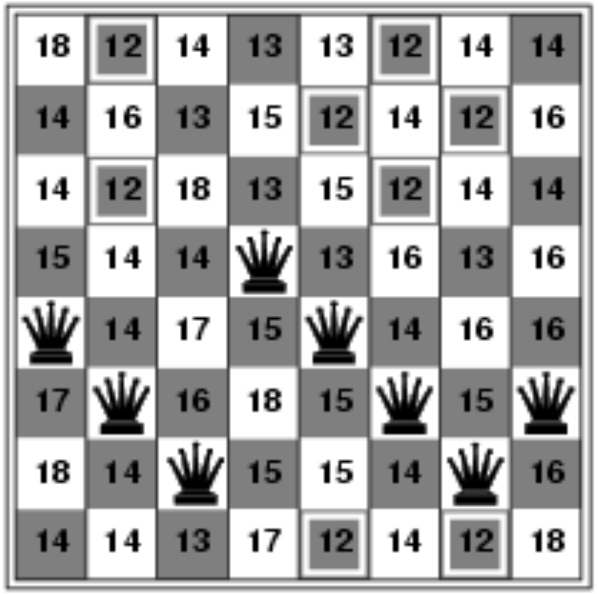
- It's just a loop that moves in the direction of increasing value
  - Ends when it reaches a peak where no neighbor has a higher value
  - The search tree is not kept, just a data structure of the current node to check the goal condition and its objective function value
- "Like climbing Everest in thick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

Hill-climbing search

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

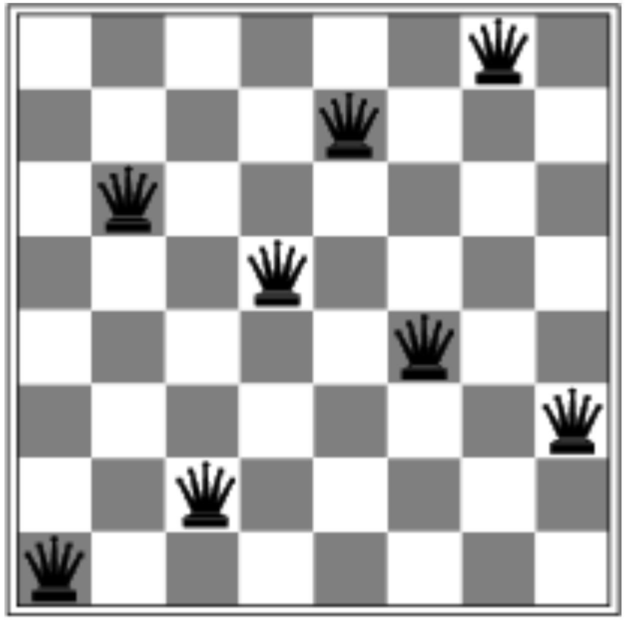


Hill-climbing search: 8-queens problem



- *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 stack 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)

Informed search strategies

- Best-first search
- Greedy best-first search
- A* search
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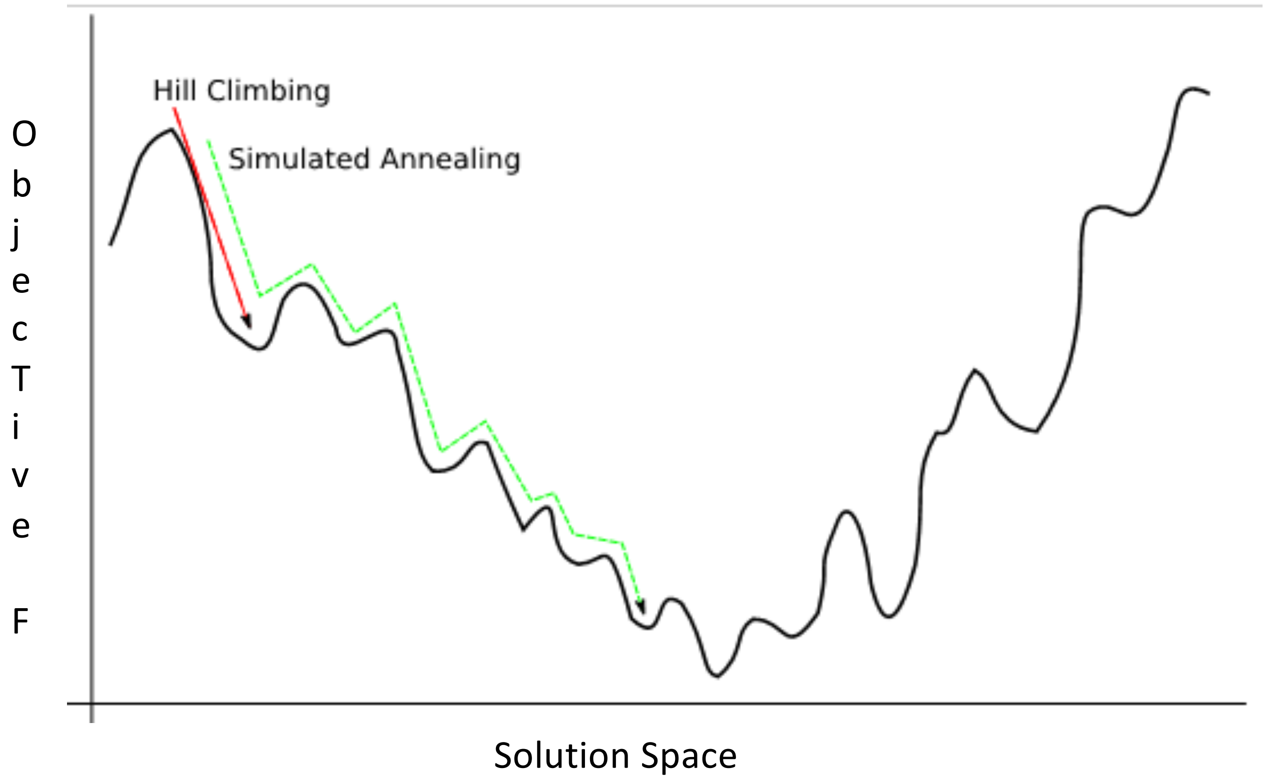
  - **Simulated annealing search**
  - Local beam search

Simulated annealing search

- 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
- Good for problems with a large search space, optimum is surrounded by many local optima
- Problem: determine the values of the parameters, and requires an important work of experimentation that depends on each problem
- Widely used in VLSI layout, airline scheduling, etc

Simulated annealing search



Informed search strategies

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- Local search algorithms
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  - Simulated annealing search
  - **Local beam search**

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

Outline

- Introduction
- Problem formulation
- Problem types
- Basic search algorithms
- **Conclusions**

Conclusions

- Problem formulation usually requires abstracting away real-world details to define a state space that can feasibly be explored

- Variety of uninformed and informed search strategies