Machine Intelligence

2. Problem Solving as Search

Got a Problem? Gotta Solve It!

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Thanks to Thomas D. Nielsen and Jörg Hoffmann for slide sources

Agenda

A (Classical Search) Problem

→ Problem: Find a route to Madrid.

- Starting from an initial state . . . (Aalborg)
- . . . apply actions . . . (Using a road segment)
- . . . to reach a goal state. (Madrid)
- Performance measure:

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- Performance measure: Minimize summed-up action costs. (Road segment lengths)

Another (Classical Search) Problem (The "15-Puzzle")

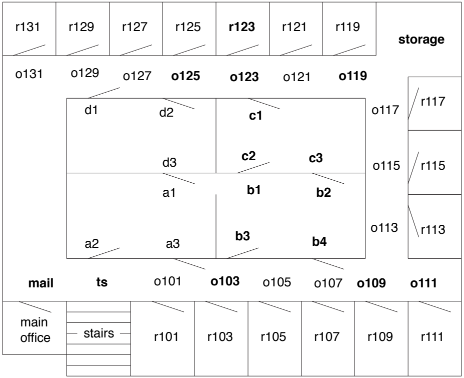
→ Problem: Move tiles to transform left state into right state.

9	2	12	6
5	7	14	13
3	4	1	11
15	10	8	

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	

- Starting from an initial state ... (Left)
- ... apply actions ... (Moving a tile)
- ... to reach a goal state. (Right)
- Performance measure: Minimize summed-up action costs. (Each move has cost 1, so we minimize the number of moves)

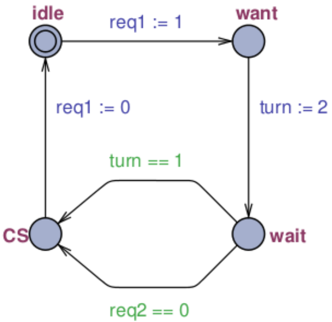
Another (Classical Search) Problem: Office Robot

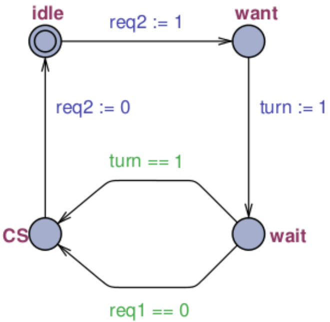


- States: locations, e.g. r131, storage, o117, c3,. . .
- Actions: move to neighboring locations, e.g. *move_r131_o131*, *move_o119_storage*, *move_b2_c3*,. . .
- Performance measure: Minimize summed-up action costs. (Each move has cost proportional to time, so we minimize the time to reach a location)

Yet Another (Classical Search) Problem

→ Problem: Finding bugs in software artifacts.





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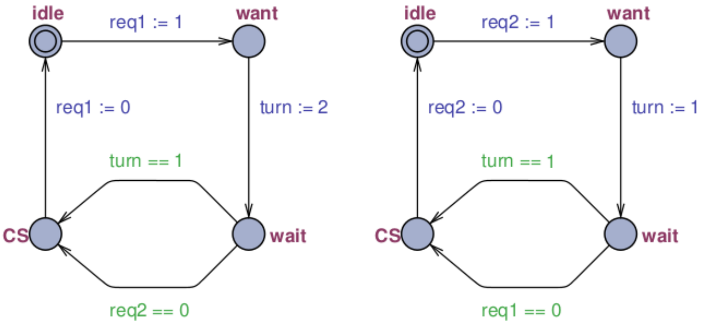

- Starting from an initial state . . . (Both idle)
- . . . apply actions . . . (Automaton transitions)
- . . . to reach a goal state. (Goal=error: both in critical section CS)
- Performance measure: Minimize summed-up action costs. (Each transition has cost 1, so we minimize the length of the error path)

Classical Search Problems

. . . restrict the agent's environment to a very simple setting:

- Finite numbers of states and actions (in particular: discrete).
- Single-agent (nobody else around).
- Fully observable (agent knows everything).
- Deterministic (each action has only one outcome).
- Static (if the agent does nothing, the world doesn't change).

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> → Classical search problems are one of the simplest classes of action choice problems an agent can be facing. Despite that simplicity, classical search problems are very important in practice (see also next slide).

→ And despite that "simplicity", these problems are computationally hard! Typically harder than **NP** . . .

Examples of Classical Search Problems

Just to name a few:

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- Puzzles (Rubik's Cube, 15-Puzzle, Towers of Hanoi . . .).
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- Query optimization in databases. Actions = rewriting operations.
- Sequence alignment in Bioinformatics. Actions = re-alignment operations.
- Natural language sentence generation. Actions = add another word to a partial sentence.

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- **Local Search:** Overview of methods foresaking completeness/optimality, taking decisions based only on the local surroundings.
  → How to exploit the knowledge in a greedy way?

→ Some implementation details, as well as plain breadth-first search and depth-first search, are moved to the "Background" and "Lookup Section" and won't be discussed.

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Before We Begin

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That definition really is quite simple:

- The underlying base concept are state spaces.
- State spaces are (annotated) directed graphs.
- Paths to goal states correspond to solutions.
- Cheapest such paths correspond to optimal solutions.

A **directed graph** consists of

- a set of **nodes**
- a set of **arcs** (ordered pairs of nodes)

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- $c : A \mapsto \mathbb{R}_0^+$ *is the cost function.*
- $T \subseteq S \times A \times S$ *is the transition relation. We require that* T *is deterministic, i.e., for all* $s \in S$ *and* $a \in A$*, there is at most one state* s' *such that* $(s, a, s') \in T$*. If such* (s, a, s') *exists, then* a *is applicable to* s*.*
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We say that Θ has the transition (s, a, s') if $(s, a, s') \in T$. We also write $s \xrightarrow{a} s'$, or $s \rightarrow s'$ when not interested in a.
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A **Solution** consists of

- For any given start state, a sequence of actions that lead to a goal state
- (optional) a sequence of actions with minimal cost
- (optional) a sequence of actions leading to a goal state with maximal value

State Spaces Terminology

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  - $n = 0$ possible; then $s = s'$.
  - $a_1, \ldots, a_n$ is called path from s to s'.
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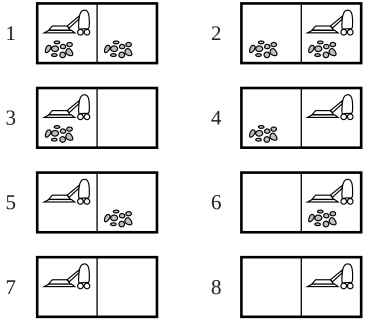
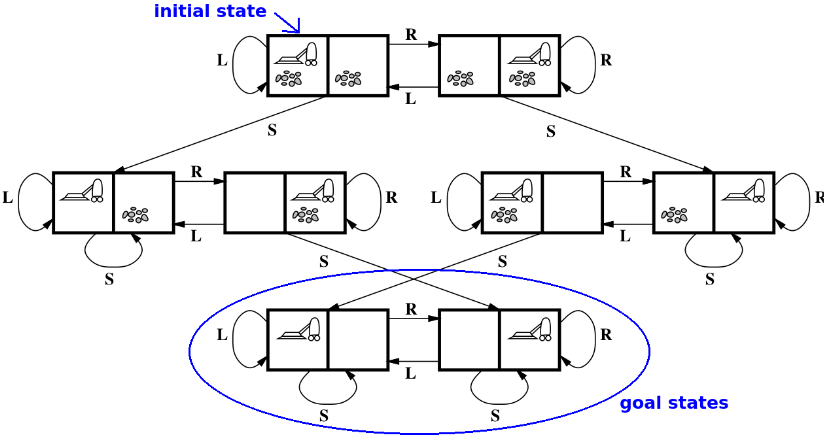
$\rightarrow$ Unsolvable Θ do occur naturally!

Example Vacuum Cleaner

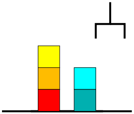


- Starting from state 1 (dirty!) . . .
- . . . go right(R), left (L), or suck (S) . . .
- . . . to clean the apartment.
- Performance measure: Minimize number of actions.

Example Vacuum Cleaner: State Space



So, Why All the Fuss? Example Blocksworld



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- A single action either takes a block with the hand or puts a block we're holding onto some other block/the table.

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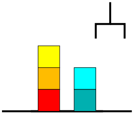

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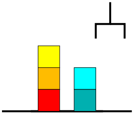

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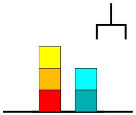

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→ In other words: Search problems typically are computationallly hard (e.g., optimal Blocksworld solving is **NP**-complete).

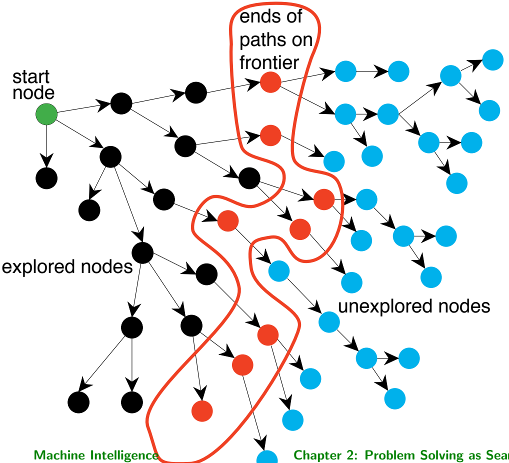
Agenda

Graph Search

A state-space problem can be solved by searching in the state-space graph for paths from start states to goal states.

How to "search"? Start at the initial state. Then, step-by-step, expand a state by generating its successors . . .

→ This does not require the whole graph at once. Only the Search space.



Generic Search Algorithm: Best-first search

Input: a graph API(*),
frontier := $\{\langle$InitialState()$\rangle\}$;
explored := $\{\}$;
while *frontier* is not empty:
  select and **remove** node $\langle s_0, \ldots, s_k \rangle$ from *frontier*;
  if $GoalTest(s_k)$
    return $\langle s_0, \ldots, s_k \rangle$;
  if $s_k \in$ *explored*
    continue
  add s_k to *explored*
  for every action a in Actions(s_k)
    add $\langle s_0, \ldots, s_k,$ ChildState$(s, a)\rangle$ to *frontier* ;
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→Some variants perform GoalTest and closed list operations at generation time

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(*) The algorithm does not require the complete graph as input. Only needed are:

- InitialState(): Returns the initial state of the problem.
- GoalTest(s): Returns a Boolean, "true" iff state s is a goal state.
- Actions(s): Returns the set of actions that are applicable to state s.
- ChildState(s, a): Requires that action a is applicable to state s, i.e., there is a transition $s \xrightarrow{a} s'$. Returns the outcome state s'.
- Cost(a): Returns the cost of action a.

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Open list: Set of all *nodes* that currently are candidates for expansion. Also called frontier.

Closed list: Set of all *states* that were already expanded. Used only in graph search, not in tree search (up next). Also called explored set.

Tree Search vs. Graph Search

Duplicate Elimination:

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Graph Search:

- ... is another word for "use duplicate elimination".
- Search space is "graph-like": We do consider said possibility.

Criteria for Evaluating Search Strategies

Guarantees:

Completeness: Is the strategy guaranteed to find a solution when there is one?

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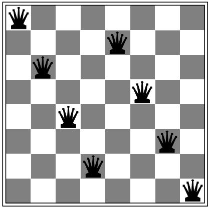
Typical state space features governing complexity:

Branching factor b: How many successors does each state have?

Goal depth d: The number of actions required to reach the shallowest goal state.

Questionnaire



- Chess board, numbering the 8 columns $C_1, \ldots, C_8$ from left to right.
- 8 queens $Q_1, \ldots, Q_8$, each Q_i to be placed "in its own" column C_i.
- We fill the columns left to right, i.e., the actions allow to place Q_i somewhere in C_i, provided all of $Q_1, \ldots, Q_{i-1}$ have already been placed.
- Goal: Placement where no queens attack each other.

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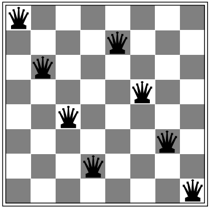

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Tree search always terminates in?

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(D): 8-Queens.

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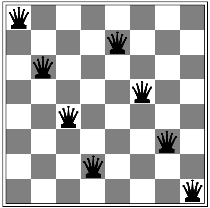

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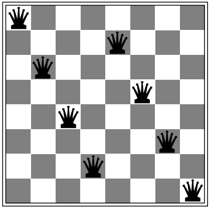

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→ (D): Yes, because after adding 8 queens to the board there are no more applicable actions. That is, the *maximum length of a path in the state space* is bounded by 8.

Agenda

Preliminaries

Blind search vs. informed search:

- Blind search does not require any input beyond the problem API.

  Pros and Cons: Pro: No additional work for the programmer. Con: It's not called "blind" for nothing . . . same expansion order regardless what the problem actually is. Rarely effective in practice.

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  $\rightarrow$ Note: In planning, h is generated automatically from the declarative problem description (**Chapters 11**).

Preliminaries, ctd.

Blind search strategies covered:

- Breadth-first search, depth-first search.
- Uniform-cost search. Optimal for non-unit costs.
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Content I will not talk about:

- Breadth-first search and depth-first search.
- The pseudo-code in what follows will use some basic functions.

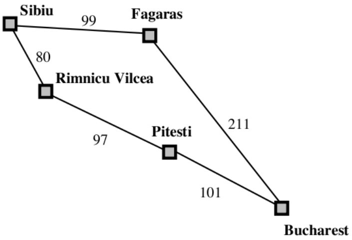
→ Both are in the "Background Section". I strongly recommend you read that section. Post any questions you may have in Moodle.

Uniform-Cost Search: Pseudo-Code

function Uniform-Cost Search(*problem*) **returns** a solution, or failure
  node ← a node n with n.*State*=*problem.InitialState*
  frontier ← a priority queue ordered by ascending g, only element n
  explored ← empty set of states
  loop do
    if *Empty?(frontier)* **then return** failure
    n ← *Pop(frontier)*
    if *problem.GoalTest*(n.*State*) **then return** *Solution*(n)
    explored ← *explored*∪n.State
    for each *action* a **in** *problem.Actions*(n.*State*) **do**
      n' ← *ChildNode*(*problem*,n,a)
      if n'.State$\notin$ [*explored* ∪ States(*frontier*)] **then** *Insert*(n', $g(n')$, *frontier*)
      else if ex. n'' ∈*frontier* s.t. n''.State= n'.State and $g(n') < g(n'')$ **then**
        replace n'' in *frontier* with n'

- Goal test at node-expansion time.
- Duplicates in frontier replaced in case of cheaper path.

Route Planning in Romania: Uniform-Cost Search



Search protocol:

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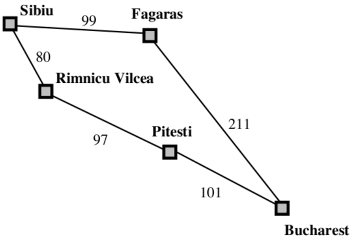
Route Planning in Romania: Uniform-Cost Search



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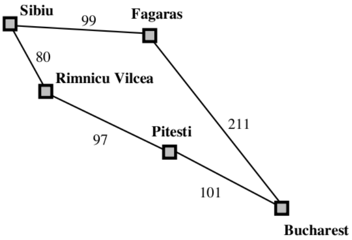

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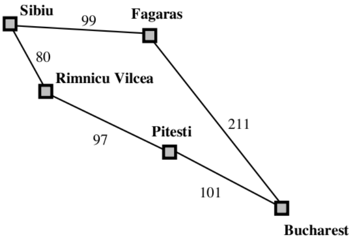

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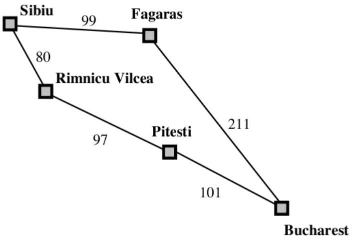

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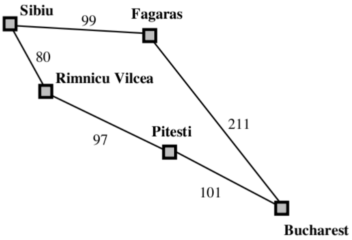

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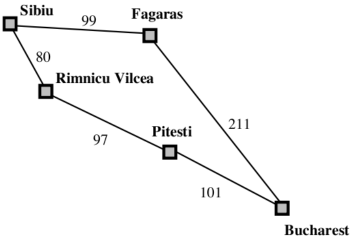

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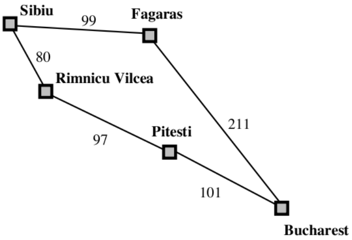
Route Planning in Romania: Uniform-Cost Search



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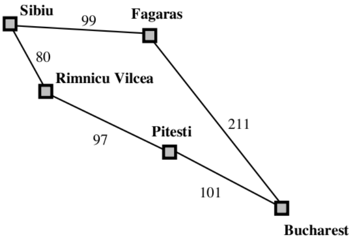

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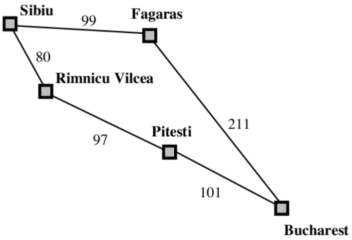

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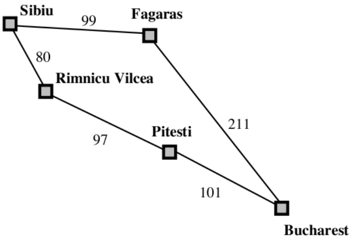

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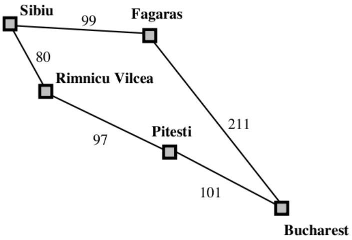
Route Planning in Romania: Uniform-Cost Search



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   Replace Bucharest $g = 310$ with Bucharest $g = 278$ in frontier!
5. Expand Bucharest $g = 278$.

Uniform-Cost Search: Guarantees and Complexity

Lemma. *Uniform-cost search is equivalent to Dijkstra's algorithm on the state space graph.* (Obvious from the definition of the two algorithms.)

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Theorem. *Uniform-cost search is optimal.* (Because Dijkstra's algorithm is optimal.)

- Completeness: Yes, thanks to duplicate elimination and our assumption that the state space is finite.
- Time complexity: $O(b^{1+\lfloor g^*/\epsilon \rfloor})$ where g^* denotes the cost of an optimal solution, and ϵ is the positive cost of the cheapest action.
- Space complexity: Same as time complexity.

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Iterative Deepening Search: Pseudo-Code

function ITERATIVE-DEEPENING-SEARCH($problem$) **returns** a solution, or failure
  for $depth = 0$ **to** ∞ **do**
    $result \leftarrow$ DEPTH-LIMITED-SEARCH($problem$, $depth$)
    if $result \neq$ cutoff **then return** $result$

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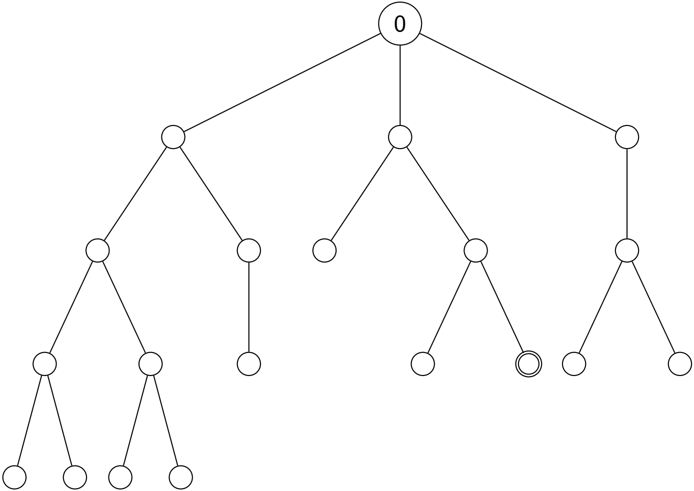
    if *result* ≠ cutoff **then return** *result*

function Depth-Limited Search*(problem, limit)* **returns** a solution, or failure/cutoff
  node ← a node n with n*.state*=*problem.InitialState*
  return Recursive-DLS*(node, problem, limit)*

function Recursive-DLS*(n, problem, limit)* **returns** a solution, or failure/cutoff
  if *problem.GoalTest(n.State)* **then return** the empty action sequence
  if *limit* $= 0$ **then return** *cutoff*
  cutoffOccured ← *false*
  for each *action* a **in** *problem.Actions(n.State)* **do**
    n' ← *ChildNode(problem,n,a)*
    result ← Recursive-DLS*(n', problem, limit*-1*)*
    if *result* = *cutoff* **then** *cutoffOccured* ← *true*
      else if *result* ≠ *failure* **then return** $a \circ$ *result*
  if cutoffOccured **then return** *cutoff* **else return** *failure*

Iterative deepening: an example



Perform depth-bounded search to level $k =$. (number indicates the order in which nodes are visited within this iteration)

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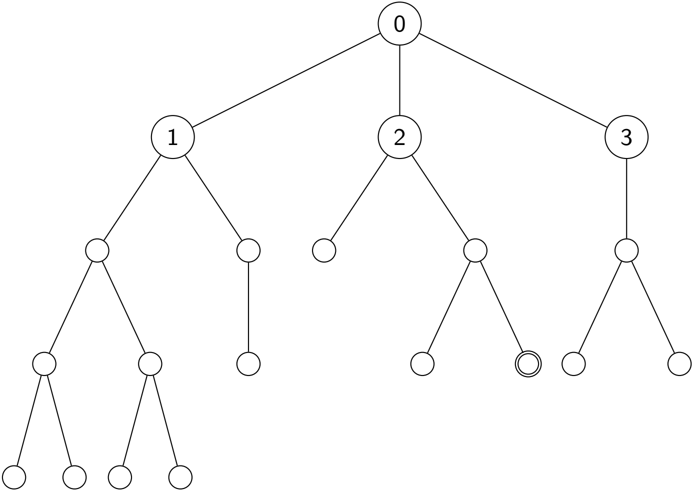

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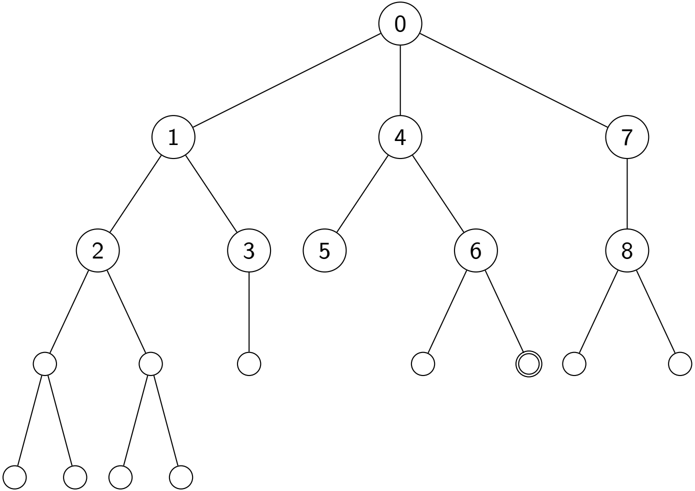

Perform depth-bounded search to level $k = 2$. (number indicates the order in which nodes are visited within this iteration)

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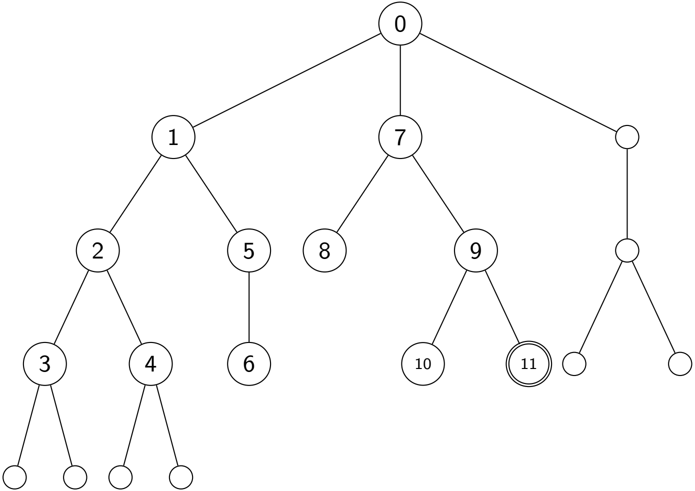
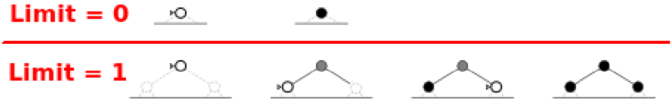


Perform depth-bounded search to level $k = 3$. (number indicates the order in which nodes are visited within this iteration)

Iterative Deepening Search: Illustration

Limit = 0

Iterative Deepening Search: Illustration



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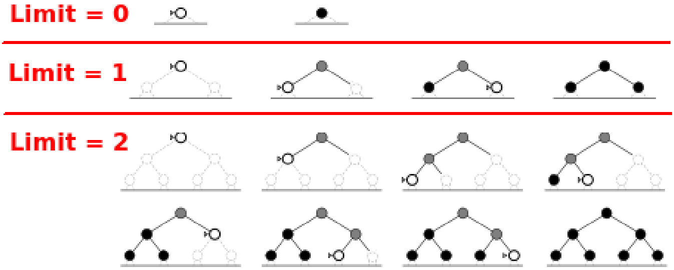

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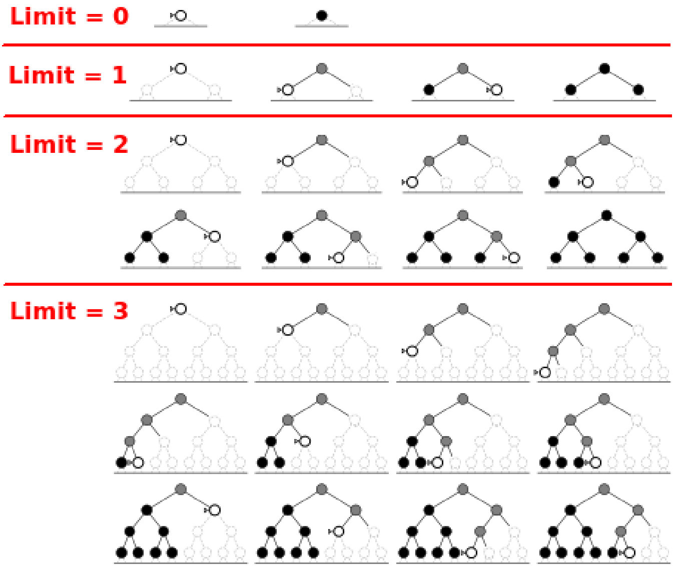

Iterative Deepening Search: Guarantees and Complexity

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Keep doing the same work over again until you find a solution."

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BUT: Optimality? Yes![2] Completeness? Yes! Space complexity? $O(b\,d)$.
Repeated computation: depth-bounded search k repeats computations of depth-bounded search $k-1$. **How bad is it?**

Question!

Assume branching factor $b = 10$, and goal depth $d = 5$. By which factor we increase the amount of explored states with respect to breadth-first search?

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Not as problematic as it looks!: constant overhead of $(b/(b-1))$.

Time complexity:

Breadth-First-Search	$b + b^2 + \cdots + b^{d-1} + b^d \in O(b^d)$
Iterative Deepening Search	$(d)b + (d-1)b^2 + \cdots + 3b^{d-2} + 2b^{d-1} + 1b^d \in O(b^d)$

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Assume branching factor $b = 10$, and goal depth $d = 5$. By which factor we increase the amount of explored states with respect to breadth-first search?

(A): $\approx 10\%$ (B): $\approx 50\%$ (C): $\approx 100\%$ (D): $\approx 1000\%$

Not as problematic as it looks!: constant overhead of $(b/(b-1))$.

Time complexity:

Breadth-First-Search	$b + b^2 + \cdots + b^{d-1} + b^d \in O(b^d)$
Iterative Deepening Search	$(d)b + (d-1)b^2 + \cdots + 3b^{d-2} + 2b^{d-1} + 1b^d \in O(b^d)$

Example: $b = 10, d = 5$

Breadth-First Search	$10 + 100 + 1,000 + 10,000 + 100,000 = 111,110$
Iterative Deepening Search	$50 + 400 + 3,000 + 20,000 + 100,000 = 123,450$

Iterative Deepening Search: Guarantees and Complexity

"Iterative Deepening Search=
Keep doing the same work over again until you find a solution."

BUT: Optimality? Yes![2] Completeness? Yes! Space complexity? $O(b\,d)$.
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→ IDS combines the advantages of breadth-first and depth-first search. It may be the preferred blind search method in large state spaces with unknown solution depth.

→ Videos illustrating vs. depth-first search: `http://movingai.com/dfid.html`

Blind Search Strategies: Overview

Criterion	Breadth-First	Uniform-Cost	Depth-First	Depth-Limited	Iterative Deepening	Bidirectional (if applicable)
Complete?	Yes[a]	Yes[a,b]	No	No	Yes[a]	Yes[a,d]
Optimal?	Yes[c]	Yes	No	No	Yes[c]	Yes[c,d]
Time	$O(b^d)$	$O(b^{1+\lfloor g^*/\epsilon \rfloor})$	$O(b^m)$	$O(b^l)$	$O(b^d)$	$O(b^{d/2})$
Space	$O(b^d)$	$O(b^{1+\lfloor g^*/\epsilon \rfloor})$	$O(bm)$	$O(bl)$	$O(bd)$	$O(b^{d/2})$

b	finite branching factor
d	goal depth
m	maximum depth of the search tree
l	depth limit
g^*	optimal solution cost
$\epsilon > 0$	minimal action cost

Footnotes:

[a] if b is finite

[b] if action costs $\geq \epsilon > 0$

[c] if action costs are unit

[d] if both directions use breadth-first search

Agenda

(Not) Playing Stupid

→ Problem: Find a route to Madrid.

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- "Look at all locations 10km distant from Aalborg, look at all locations 20km distant from Aalborg, ..." = **Breadth-first search/Uniform-cost search.**

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- "Just keep choosing arbitrary roads, following through until you hit an ocean, then back up . . ." = **Depth-first search.**
- "Focus on roads that go the right direction." = **Informed search!**

Informed Search: Basic Idea

Recall: Search strategy=how to choose the next node to expand?

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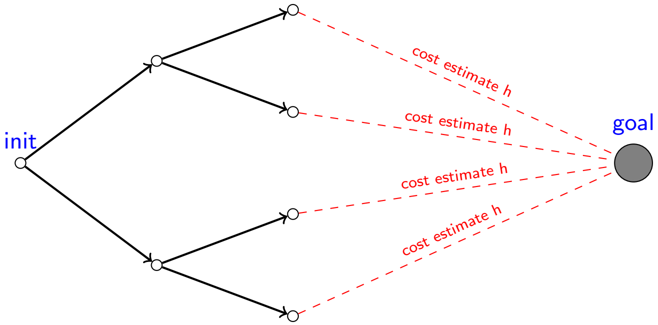
→ Informed search is a way of giving the computer knowledge about the problem it is solving, thereby stopping it from doing stupid things.

Informed Search: Basic Idea, ctd.



→ Heuristic function h estimates the cost of an optimal path from a state s to the goal; search prefers to expand states s with small $h(s)$.

Heuristic Functions

Definition (Heuristic Function). *Let Π be a problem with states S. A heuristic function, short heuristic, for Π is a function $h : S \mapsto \mathbb{R}_0^+ \cup \{\infty\}$ so that, for every goal state s, we have $h(s) = 0$.*

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- Return value ∞: To indicate dead ends, from which the goal can't be reached anymore.
- The value of h depends only on the *state* s, not on the *search node* (i.e., the path we took to reach s). I'll sometimes abuse notation writing "$h(n)$" instead of "$h(n.\text{State})$".

Heuristic Functions: The Eternal Trade-Off

Distance "estimate"? (h is an arbitrary function in principle!)

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  $\rightarrow$ Extreme cases?

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→ We need to trade off the accuracy of h against the overhead for computing $h(s)$ on every search state s.

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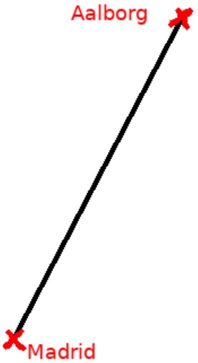
So, how to? $\rightarrow$ Given a problem Π, a heuristic function h for Π can be obtained as goal distance within a simplified (relaxed) problem Π'.

Heuristic Functions from Relaxed Problems: Example 1

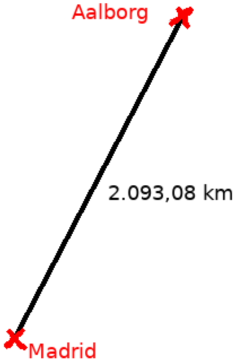
Problem II: Find a route from Aalborg to Madrid.

Heuristic Functions from Relaxed Problems: Example 1



Relaxed Problem Π': Throw away the map.

Heuristic Functions from Relaxed Problems: Example 1



Heuristic function h: Straight line distance.

Heuristic Functions from Relaxed Problems: Example 2

9	2	12	6
5	7	14	13
3	4	1	11
15	10	8	

—

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	

- Problem II: Move tiles to transform left state into right state.

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9	2	12	6
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- Problem Π: Move tiles to transform left state into right state.
- Relaxed Problem Π': Allow to move each tile to *any cell* in a single move, regardless of the situation.
- Heuristic function h: Number of misplaced tiles. Here: 13.

Heuristic Functions from Relaxed Problems: Example 3

9	2	12	6
5	7	14	13
3	4	1	11
15	10	8	

—

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	

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9	2	12	6
5	7	14	13
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—

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- Problem Π: Move tiles to transform left state into right state.
- Relaxed Problem Π': Allow to move each tile to any neighbor cell, regardless of the situation.
- Heuristic function h: Manhattan distance. Here: 36.

Heuristic Functions from Relaxed Problems: Example 4

9	2	12	6
5	7	14	13
3	4	1	11
15	10	8	

—

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	

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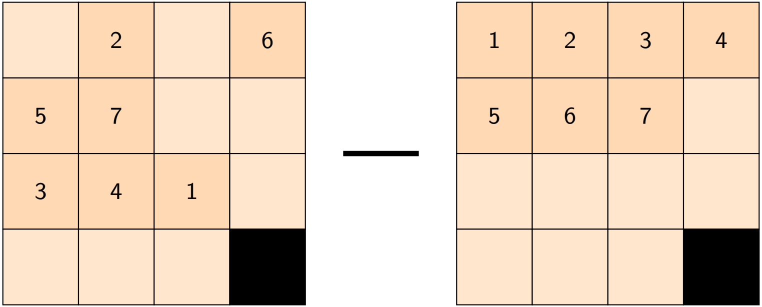
Heuristic Functions from Relaxed Problems: Example 4



Relaxed Problem Π': Don't distinguish tiles 8–15.

Heuristic Functions from Relaxed Problems: Example 4

	2		6
5	7		
3	4	1	

1	2	3	4
5	6	7	

Heuristic function h: Length of solution to reduced puzzle.

Heuristic Function Pitfalls: Example Path Planning

h^*:

I

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	24		18	17	16	15	14		12	13	14	15	16	17	18
2	23		19	18	17		13	12	11	12	13	14	15	16	17
3	22	21	20		16		12	11	10						
4	23	22	21		15	14	13		9	8		4	3	2	1
5	24	23	22		16	15		9	8	7	6	5		1	0

G

Heuristic Function Pitfalls: Example Path Planning

Manhattan Distance, “accurate h”:

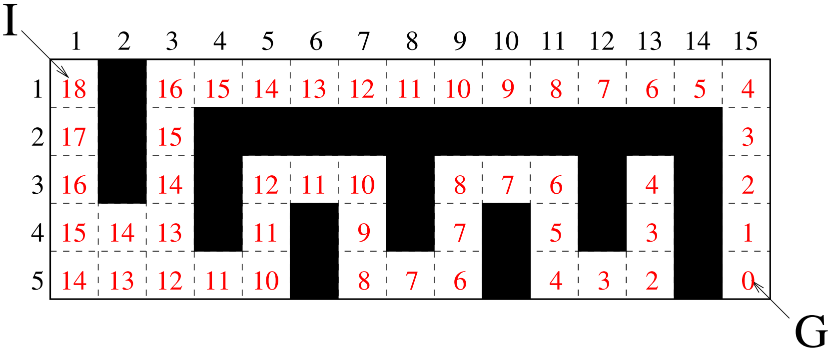
I

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	18		16	15	14	13	12		10	9	8	7	6	5	4
2	17		15	14	13		11	10	9	8	7	6	5	4	3
3	16	15	14		12		10	9	8						
4	15	14	13		11	10	9		7	6		4	3	2	1
5	14	13	12		10	9		7	6	5	4	3		1	0

G

Heuristic Function Pitfalls: Example Path Planning

Manhattan Distance, “inaccurate h”:



Properties of Heuristic Functions

Definition (Admissibility, Consistency). *Let Π be a problem with state space Θ and states S, and let h be a heuristic function for Π. We say that h is admissible if, for all $s \in S$, we have $h(s) \leq h^*(s)$. We say that h is consistent if, for all transitions $s \xrightarrow{a} s'$ in Θ, we have $h(s) - h(s') \leq c(a)$.*

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In other words . . .

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In other words . . .

- Admissibility: lower bound on goal distance.
- Consistency: when applying an action a, the heuristic value cannot decrease by more than the cost of a.

Properties of Heuristic Functions, ctd.

Proposition (Consistency $\Longrightarrow$ Admissibility). *Let Π be a problem, and let h be a heuristic function for Π. If h is consistent, then h is admissible.*

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Proof. We need to show that $h(s) \leq h^*(s)$ for all s. For states s where $h^*(s) = \infty$, this is trivial. For all other states, we show the claim by induction over the length of the cheapest path to a goal state.

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Properties of Heuristic Functions: Examples

Admissibility and consistency:

- Is straight line distance admissible/consistent? Yes. Consistency: If you drive 100km, then the straight line distance to Madrid can't decrease by more than 100km.
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- Can somebody come up with an admissible but inconsistent heuristic?

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- Is goal distance of the "reduced puzzle" (slide 15) admissible/consistent? Yes. Consistency: Moving a tile can't decrease goal distance in the reduced puzzle by more than 1. Same for misplaced tiles/Manhattan distance.
- Can somebody come up with an admissible but inconsistent heuristic? To-Madrid with $h(Aalborg) = 1000$, $h(Aarhus) = 100$.

→ In practice, admissible heuristics are typically consistent.

Properties of Heuristic Functions: Examples

Admissibility and consistency:

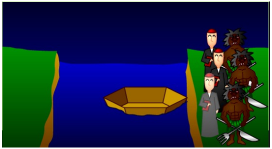
- Is straight line distance admissible/consistent? Yes. Consistency: If you drive 100km, then the straight line distance to Madrid can't decrease by more than 100km.
- Is goal distance of the "reduced puzzle" (slide 15) admissible/consistent? Yes. Consistency: Moving a tile can't decrease goal distance in the reduced puzzle by more than 1. Same for misplaced tiles/Manhattan distance.
- Can somebody come up with an admissible but inconsistent heuristic? To-Madrid with $h(Aalborg) = 1000$, $h(Aarhus) = 100$.

$\rightarrow$ In practice, admissible heuristics are typically consistent.

Inadmissible heuristics:

- Inadmissible heuristics typically arise as approximations of admissible heuristics that are too costly to compute. (We'll meet some examples of this in Chapter 11.)

Questionnaire



- 3 missionaries, 3 cannibals.
- Boat that holds ≤ 2.
- Never leave k missionaries alone with $> k$ cannibals.

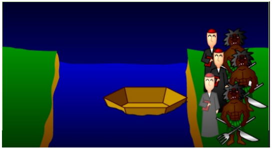
Question!

Is $h :=$ number of persons at right bank consistent/admissible?

(A): Only consistent. (B): Only admissible.

(C): None. (D): Both.

Questionnaire



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Question!

Is $h :=$ number of persons at right bank consistent/admissible?

(A): Only consistent. (B): Only admissible.

(C): None. (D): Both.

$\rightarrow$ (A): No: If h is consistent then it is admissible, so "only consistent" can't happen (for any heuristic).

$\rightarrow$ (B): No: h is not admissible because a single move of the boat may get more than 1 person to the desired bank (example: 1 missionary and 1 cannibal at the wrong bank, with the boat).

$\rightarrow$ (C): Yes: h is not admissible so it can't be consistent either.

$\rightarrow$ (D): No, see above.

Agenda

Before We Begin

Systematic search vs. local search:

- Systematic search strategies: No limit on the number of search nodes kept in memory at any point in time.

  $\rightarrow$ Guarantee to consider all options at some point, thus complete.
- Local search strategies: Keep only one (or a few) search nodes at a time.

  $\rightarrow$ No systematic exploration of all options, thus incomplete.

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Tree search vs. graph search:

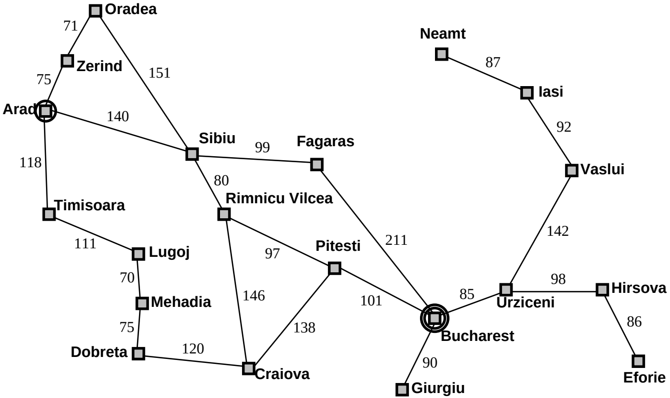
- For the systematic search strategies, we consider graph search algorithms exclusively, i.e., we use duplicate pruning.
- There also are tree search versions of these algorithms. These are easier to understand, but aren't used in practice. (Maintaining a complete open list, the search is memory-intensive anyway.)

Greedy Best-First Search

function Greedy Best-First Search*(problem)* **returns** a solution, or failure
  node ← a node n with n.*state*=*problem.InitialState*
  frontier ← a priority queue ordered by ascending h, only element n
  explored ← empty set of states
  loop do
    if *Empty?(frontier)* **then return** failure
    n ← *Pop(frontier)*
    if *problem.GoalTest*(n.*State*) **then return** *Solution*(n)
    explored ← *explored* ∪n.State
    for each *action* a **in** *problem.Actions*(n.*State*) **do**
      n' ← *ChildNode*(*problem*,n,a)
      if n'.State∉*explored* ∪ States(*frontier*) **then** *Insert*(n', $h(n')$, *frontier*)

- Frontier ordered by ascending h.
- Duplicates checked at successor generation, against both the frontier and the explored set.

Greedy Best-First Search: Route to Bucharest



Arad	366
Bucharest	0
Craiova	160
Drobeta	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
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Zerind	374

Greedy Best-First Search: Route to Bucharest

Subscripts: h. Red nodes: removed by duplicate pruning.

Arad
366

Greedy Best-First Search: Route to Bucharest

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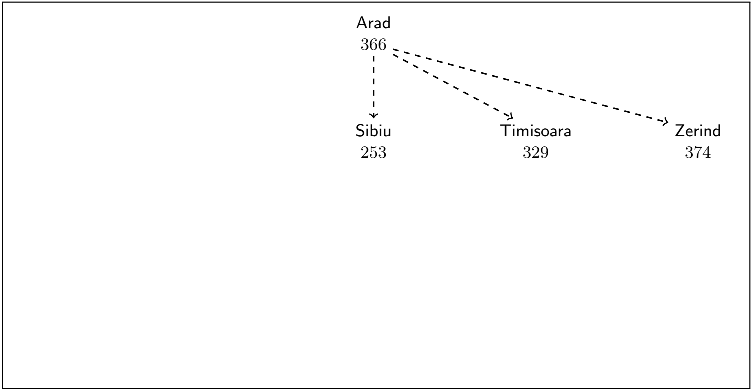

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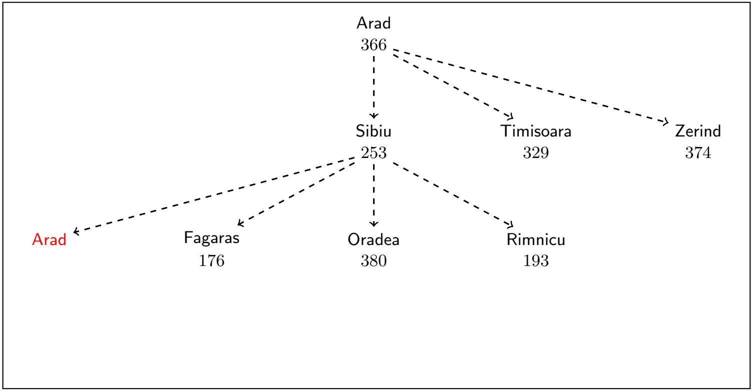

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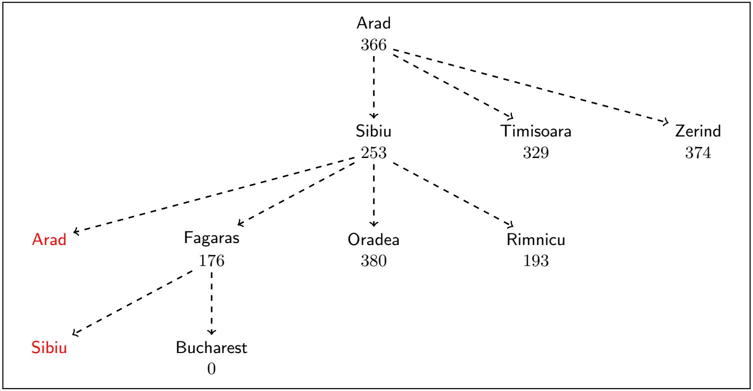

Greedy Best-First Search: Guarantees

- Completeness: Yes, thanks to duplicate elimination and our assumption that the state space is finite.
- Optimality?

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Can we do better than this?

Greedy Best-First Search: Guarantees

- Completeness: Yes, thanks to duplicate elimination and our assumption that the state space is finite.
- Optimality? No (h might lead us to Madrid via Amsterdam).

Can we do better than this?

$\rightarrow$ Yes: A^* is complete *and* optimal.

A^*

function A^**(problem)* **returns** a solution, or failure
  node ← a node n with n.*State*=*problem.InitialState*
  frontier ← a priority queue ordered by ascending $g + h$, only element n
  explored ← empty set of states
  loop do
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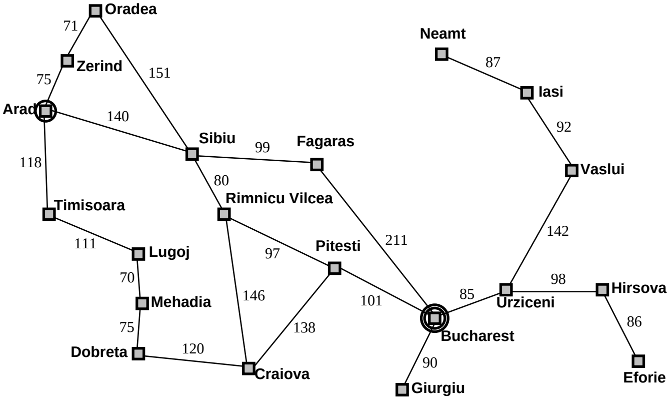
    n ← *Pop(frontier)*
    if *problem.GoalTest*(n.*State*) **then return** *Solution*(n)
    explored ← *explored*∪n.State
    for each *action* a **in** *problem.Actions*(n.*State*) **do**
      n' ← *ChildNode(problem,*n,a*)*
      if n'.State∉*explored* ∪ States(*frontier*) **then**
        Insert(n', $g(n') + h(n')$, *frontier*)
      else if ex. n'' ∈*frontier* s.t. n''.State= n'.State and $g(n') < g(n'')$ **then**
        replace n'' in *frontier* with n'

- Frontier ordered by ascending $g + h$.
- Duplicates handled exactly as in uniform-cost search.

A*: Route to Bucharest



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Subscripts: $g + h$. Red nodes: removed by duplicate pruning (without subscript), or because of better path (with subscript g).

Arad
$0 + 366 = 366$

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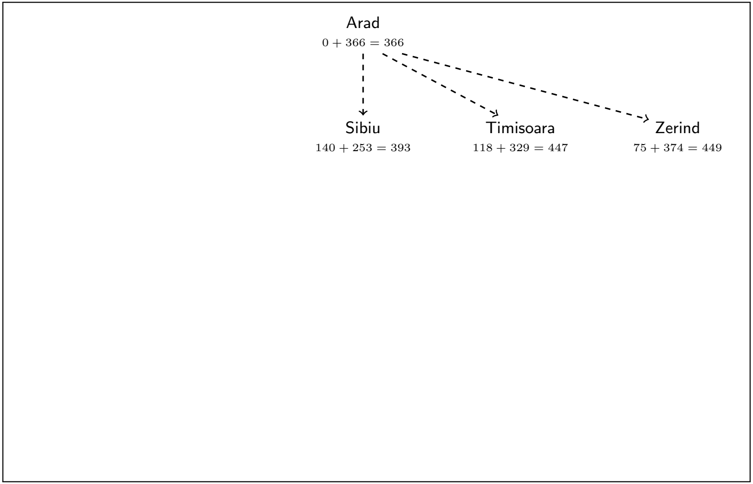

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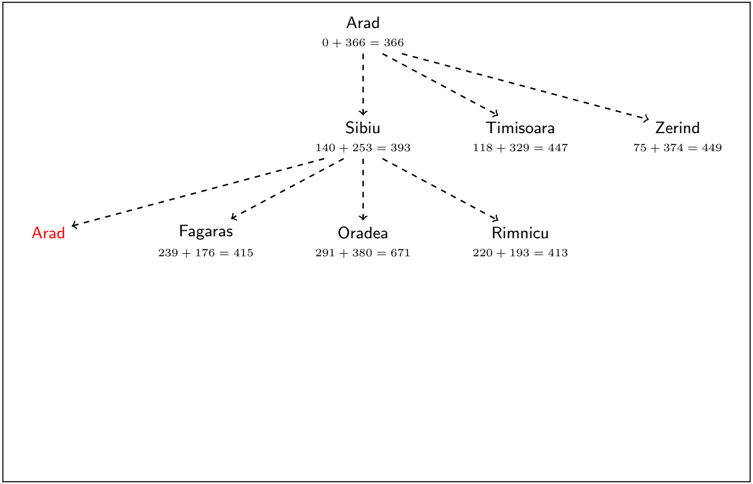

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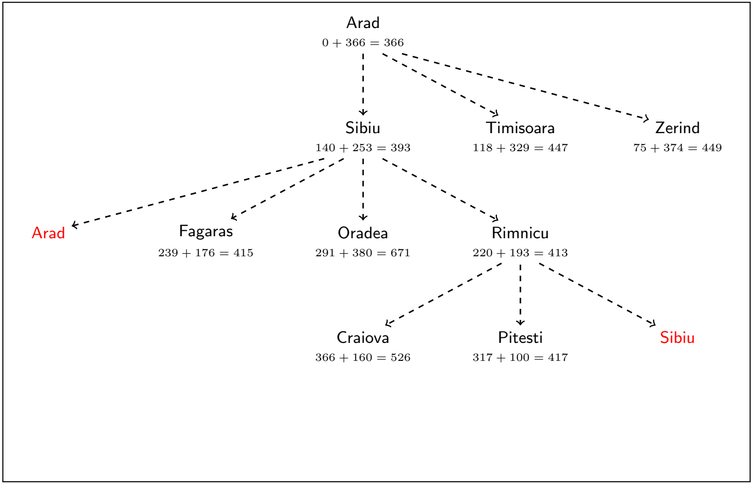

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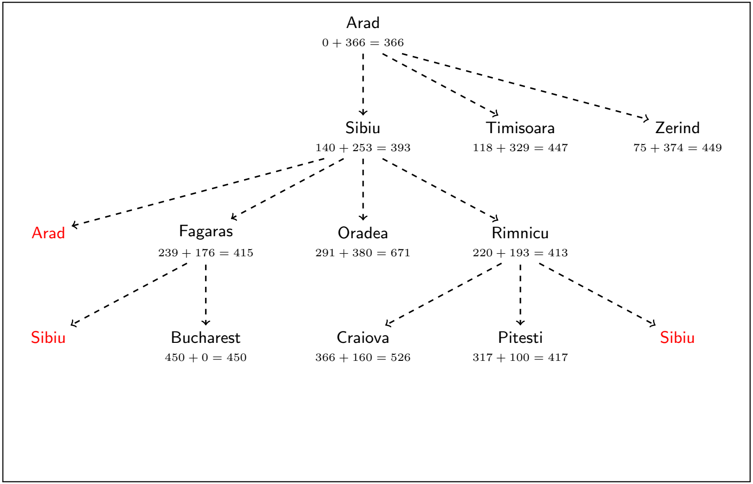

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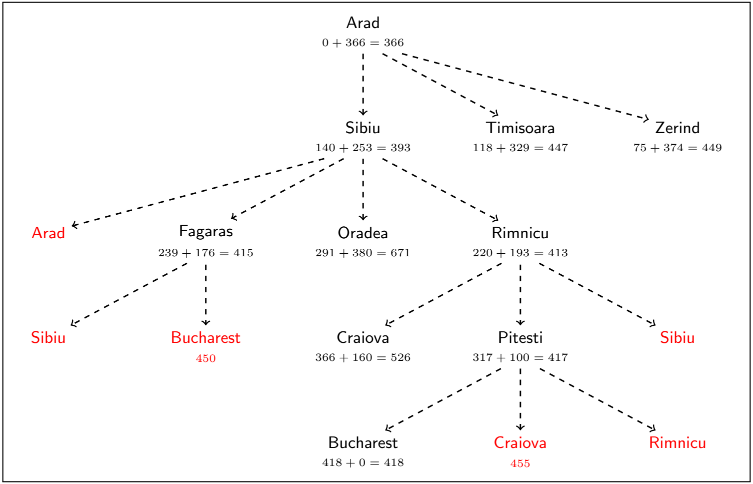

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If we set $h(s) := 0$ for all states s, what does greedy best-first search become?

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→ (C): The *only* difference between A^* and uniform-cost search is the use of $g + h$ instead of g to order the open list.

Optimality of A^*: Different Variants

- Our variant of A^* does duplicate elimination but not re-opening.
- Re-opening: check, when generating a node n containing state s that is already in the explored set, whether *(*) the new path to s is cheaper*. If so, remove s from the explored set and insert n into the frontier.

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  $\rightarrow$ But for our variant (as per slide 55), being admissible is NOT enough for optimality! Frequent implementation bug!

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  → But for our variant (as per slide 55), being admissible is NOT enough for optimality! Frequent implementation bug!

→ Recall: In practice, admissible heuristics are typically consistent. That's why I chose to present this variant.

Provable Performance Bounds: Extreme Case

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$\mathbf{A}^*$:

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$\mathbf{A}^*$:

- If all action costs are strictly positive, *and* we break ties $(g(n) + h(n) = g(n') + h(n'))$ by smaller h, then the search space is linear in the length of the solution.
- Otherwise, the search space may still be exponentially big.

Provable Performance Bounds: More Interesting Cases?

"Almost perfect" heuristics:

$$|h^*(n) - h(n)| \leq c \text{ for a constant } c$$

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- Basically the only thing that lead to some interesting results.
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→ Systematically analyzing the practical behavior of heuristic search remains one of the biggest research challenges.

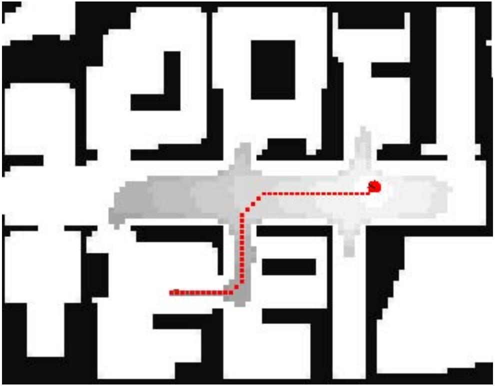
→ There is little hope to prove practical sub-exponential-search bounds. (But there are some interesting insights one *can* gain).

Empirical Performance: A^* in the 8-Puzzle

Without Duplicate Elimination; d = length of solution:

	Number of search nodes generated		
	Iterative	A^* with	
d	Deepening Search	misplaced tiles h	Manhattan distance h
2	10	6	6
4	112	13	12
6	680	20	18
8	6384	39	25
10	47127	93	39
12	3644035	227	73
14	-	539	113
16	-	1301	211
18	-	3056	363
20	-	7276	676
22	-	18094	1219
24	-	39135	1641

Empirical Performance: A^* in Path Planning



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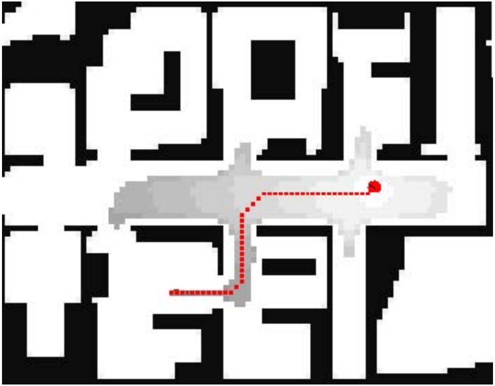

Live Demo vs. Breadth-First Search:

http://qiao.github.io/PathFinding.js/visual/

Greedy Best-First vs. A^*: Illustration Path Planning

Greedy best-first search, “accurate h”:

I

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	18		16	15	14	13	12		10	9	8	7	6	5	4
2	17		15	14	13		11	10	9	8	7	6	5	4	3
3	16	15	14		12		10	9	8						
4	15	14	13		11	10	9		7	6		4	3	2	1
5	14	13	12		10	9		7	6	5	4	3		1	0

G

$\rightarrow$ We will find a solution with little search.

Greedy Best-First vs. A^*: Illustration Path Planning

$A^*(g + h)$, "accurate h":

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	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	18		22	22	22	22	22		24	24	24	24	24	24	24
2	18		20	20	20		22	22	22	22	22	22	22	22	22
3	18	18	18		20		22	22	22						
4	18	18	18		20	20	20		22	22		24	24	24	24
5	18	18	18		20	20		24	22	22	22	22		24	24

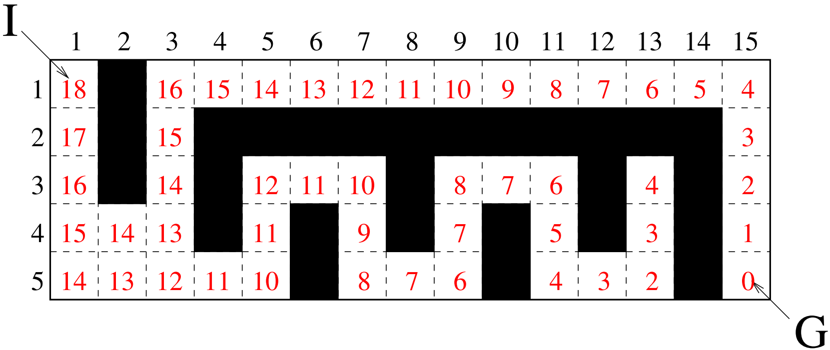
G

→ In A^* with a consistent heuristic, $g + h$ always increases monotonically (h cannot *de*crease by more than g *in*creases).

→ We need more search, in the "right upper half". This is typical: Greedy best-first search tends to be faster than A^*.

Greedy Best-First vs. A^*: Illustration Path Planning

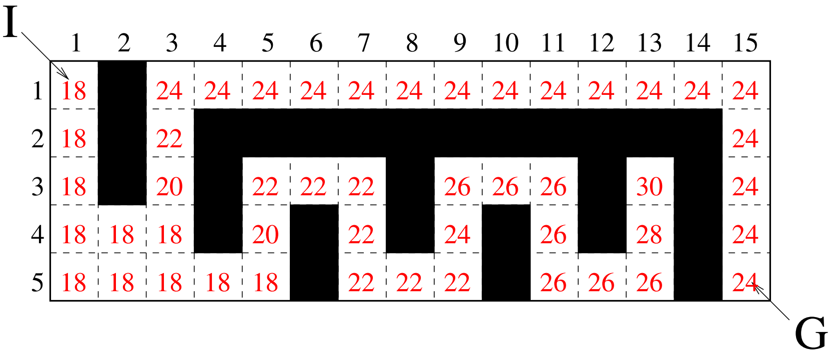
Greedy best-first search, “inaccurate h”:



→ Search will be mis-guided into the “dead-end street”.

Greedy Best-First vs. A^*: Illustration Path Planning

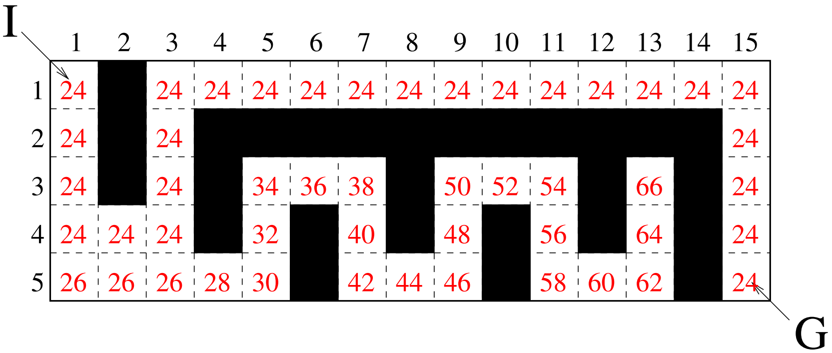
$\mathrm{A}^*(g+h)$, "inaccurate h":



$\rightarrow$ We will search less of the "dead-end street". For very "bad heuristics", $g+h$ gives better search guidance than h, and A^* is faster.

Greedy Best-First vs. A^*: Illustration Path Planning

$A^*(g+h)$ using h^*:



$\rightarrow$ With $h = h^*$, $g + h$ remains constant on optimal paths.

Questionnaire

Question!

1. Is A^* always at least as fast as uniform-cost search? 2. Does it always expand at most as many states?

(A): No and no.

(B): Yes and no.

(C): No and Yes.

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→ Regarding 2.: "Yes, but". Setting $h(s) := 0$ for uniform-cost search, both algorithms expand *only* states s where $g^*(s) + h(s) \leq g^*$, and *must* expand all states where $g^*(s) + h(s) < g^*$.

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Non-zero h can only reduce the latter. Which s with $g^*(s) + h(s) = g^*$ are explored depends on the tie-breaking used (which state to expand if there is more than one state with minimal $g + h$ in the open list). So the answer is "yes but only if the tie-breaking in both algorithms is the same".

Best-First Search Algorithms: Overview

Algorithm	Uniform-Cost	GBFS	A^*	WA^*
Criteria	$g(n)$	$h(n)$	$g(n) + h(n)$	$g(n) + wh(n)$
Complete?	Yes	Yes	Yes[a]	Yes[a]
Optimal?	Yes	No	Yes[b]	No[c]

Note: we assume that b is finite, action costs are ≥ 0, and the state space is finite.

Footnotes:

[a] if h is safe (only returns ∞ for dead-end states)

[b] if h is consistent or if h is admissible and we re-open nodes when a better path has been found

[c] No, but if guarantees that solution cost is only sub-optimal by a factor of w (assuming [b])

Agenda

Local Search

Do *you* “think through all possible options” before choosing your path to the canteen?

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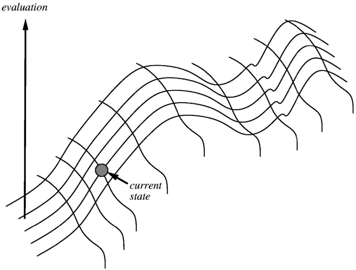
What is the computer's "nose"?



→ Local search takes decisions based on the h values of immediate neighbor states.

Hill Climbing

function Hill-Climbing*(problem)*
  $n \leftarrow$ a node n with n.*state*=*problem.InitialState*
  loop do
    $n' \leftarrow$ among child nodes n' of n with minimal $h(n')$,
      randomly pick one
    if $h(n') \geq h(n)$ **then return** *the path to* n
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$\rightarrow$ Hill-Climbing keeps choosing actions leading to a direct successor state with best heuristic value. It stops when no more immediate improvements can be made.

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- Alternative name (more fitting, here): Gradient-Descent.
- Often used in optimization problems where all "states" are feasible solutions, and we can choose the search neighborhood ("child nodes") freely. (Return just n.State, rather than the path to n)

Local Search: Guarantees and Complexity

Guarantees:

- Completeness: No. Search ends when no more immediate improvements can be made (= local minimum, up next). This is not guaranteed to be a solution.
- Optimality: No, for the same reason.

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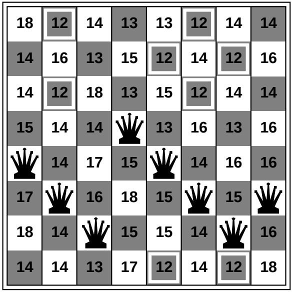
- Memory: Basically no consumption: $O(b)$ states at any moment in time.

Hill Climbing: Example 8-Queens Problem



Problem: Place the queens so that they don't attack each other.

Heuristic: Number of pairs attacking each other.

Neighborhood: Move any queen within its column.

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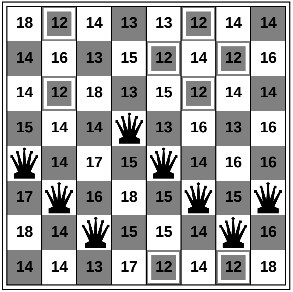

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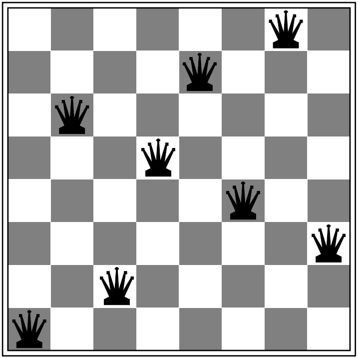
→ Starting from random initialization, solves only 14% of cases.

A Local Minimum in the 8-Queens Problem



→ Current h value is?

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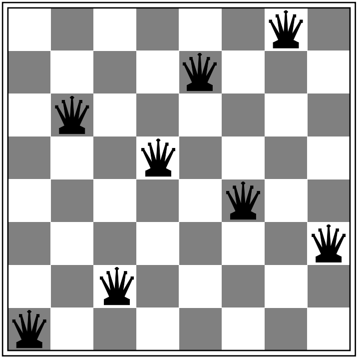

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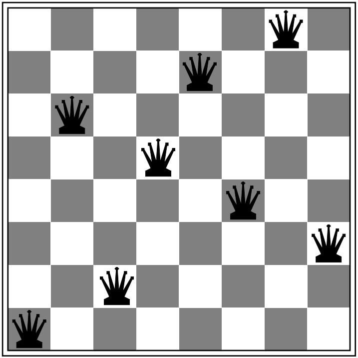

→ Current h value is? 1. To get $h = 0$, we must move either of the 2 queens involved in the conflict. But every such move results in at least 2 new conflicts, so this is a local minimum.

Local Search: Difficulties

Difficulties:

- Local minima: All neighbors look worse (have a worse h value) than the current state (e.g.: previous slide).

  $\rightarrow$ If we stop, the solution may be sub-optimal (or not even feasible). If we don't stop, where to go next?

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$\rightarrow$ Configuring these strategies requires lots of algorithm parameters. Selecting good values is a big issue in practice. (Cross your fingers . . .)

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Can local minima occur in route planning with h :=straight line distance?

(A): Yes. (B): No.

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Question!

What is the maximum size of plateaus in the 15-puzzle with h :=Manhattan distance?

(A): 0

(B): 1

(C): 2

(D): ∞

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What is the maximum size of plateaus in the 15-puzzle with h :=Manhattan distance?

(A): 0 (B): 1

(C): 2 (D): ∞

$\rightarrow$ 0: Any move in the 15-puzzle changes the position of exactly one tile x. So the Manhattan distance changes for x and remains the same for all other tiles, thus the overall Manhattan distance changes. So the h value of every neighbor is different from the current one, and there aren't any plateaus.

Agenda

Summary

- Classical search problems require to find a path of actions leading from an initial state to a goal state.
- They assume a single-agent, fully-observable, deterministic, static environment. Despite this, they are ubiquitous in practice.
- Search strategies differ (amongst others) in the order in which they expand search nodes, and in the way they use duplicate elimination. Criteria for evaluating them are completeness, optimality, time complexity, and space complexity.
- Uniform-cost search is optimal and works like Dijkstra, but building the graph incrementally. Iterative deepening search uses linear space only and is often the preferred blind search algorithm.
- Heuristic functions h map each state to an estimate of its goal distance. This provides the search with knowledge about the problem at hand, thus making it more focussed.
- h is admissible if it lower-bounds goal distance. h is consistent if applying an action cannot reduce its value by more than the action's cost. Consistency implies admissibility. In practice, admissible heuristics are typically consistent.
- Greedy best-first search explores states by increasing h. It is complete but not optimal.
- A^* explores states by increasing $g + h$. It is complete. If h is consistent, then A^* is optimal. (If h is admissible but not consistent, then we need to use re-opening to guarantee optimality.)
- Local search takes decisions based on its direct neighborhood. It is neither complete nor optimal, and suffers from local minima and plateaus. Nevertheless, it is often successful in practice.

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- Non-Deterministic Actions: What if there are several possible outcomes?
- Partial Observability: What if parts of the world state are unknown?
- Reinforcement Learning Problems: What if, a priori, the solver does not know anything about the world it is acting in?

Reading

- Chapter 3 Searching for Solutions
  We covered from 3.1 to 3.6, Section 3.8 explains Branch and Bound, which is another important search algorithm that we are not covering here.
- The Moving AI website (`https://www.movingai.com`) has a lot of resources.
  - Here, we have covered only a few basic algorithms, we could spend the whole course on this topic (`https://www.movingai.com/SAS/class.html`).
  - Of special interest are the interactive demos (`https://www.movingai.com/SAS/index.html`):
  - You can execute Dijkstra/$\mathrm{A}^*$and $W\mathrm{A}^*$ step by step in a graph (`https://www.movingai.com/SAS/ASG/`) and in a grid (https://www.movingai.com/SAS/ASM/).

Why "Heuristic"?

What's the meaning of "heuristic"?

- Heuristik: Ancient Greek $\varepsilon\upsilon\rho\iota\sigma\kappa\varepsilon\iota\nu$ (= "I find"); aka: $\varepsilon\upsilon\rho\eta\kappa\alpha$!

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- Popularized in modern science by George Polya: "How to Solve It" (published 1945).
- Same word often used for: "rule of thumb", "imprecise solution method".
- In classical search (and many other problems studied in AI), it's the mathematical term just explained.

Optimality of A^*: Proof, Step 1

Idea: The proof is via a correspondence to uniform-cost search.

Optimality of A*: Proof, Step 1

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→ Step 1: Capture the heuristic function in terms of action costs.

Definition. *Let* Π *be a problem with state space* $\Theta = (S, A, c, T, I, S^G)$, *and let* h *be a consistent heuristic function for* Π. *We define the h-weighted state space as* $\Theta^h = (S, A^h, c^h, T^h, I, S^G)$ *where:*

- $A^h := \{a[s, s'] \mid a \in A, s \in S, s' \in S, (s, a, s') \in T\}$.
- $c^h : A^h \mapsto \mathbb{R}_0^+$ *is defined by* $c^h(a[s, s']) := c(a) - [h(s) - h(s')]$.
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→ Subtract, from each action cost, the "gain in heuristic value".

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Lemma. Θ^h *is well-defined, i.e.,* $c(a) - [h(s) - h(s')] \geq 0$.

Proof. By consistency, $h(s) - h(s') \leq c(a)$. This implies the claim.

Optimality of A^*: Proof – Illustration

Example: Finding a route from Saarbruecken to Moscow

- States: P (Paris), SB, DD (Dresden), M (Moscow).
- Actions: $c(\text{SBtoP}) = 400$, $c(\text{SBtoDD}) = 650$, $c(\text{DDtoM}) = 1950$.
- Heuristic (straight line distance): $h(\text{Paris}) = 2500$, $h(\text{SB}) = 2200$, $h(\text{DD}) = 1700$.

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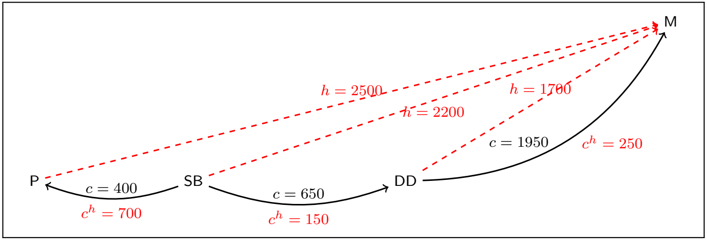
Θ and Θ^h: (Proof Step 1, Definition on previous slide)



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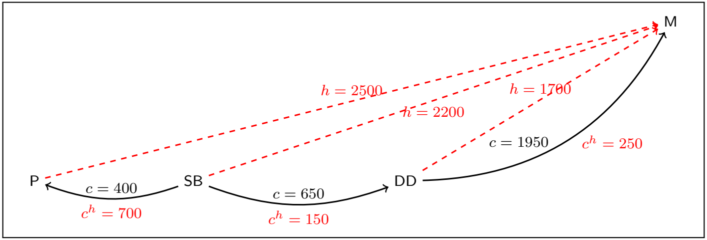

Optimal solution: (Proof Step 2, Lemma (A) on next slide)

- $g^* = 2600$ in Θ and $g^* = 400 = 2600 - h(\text{SB})$ in Θ^h.

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→ Step 2: Identify the correspondence.

Lemma (A). Θ *and* Θ^h *have the same optimal solutions.*

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Proof. Let $I = s_0 \xrightarrow{a_1} s_1, \ldots, s_{n-1} \xrightarrow{a_n} s_n$ be a solution in Θ, $s_n \in S^G$.

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Lemma (B). *The search space of A^* on Θ is isomorphic to that of uniform-cost search on Θ^h.*

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Lemma (A). *Θ and Θ^h have the same optimal solutions.*

Proof. Let $I = s_0 \xrightarrow{a_1} s_1, \dots, s_{n-1} \xrightarrow{a_n} s_n$ be a solution in Θ, $s_n \in S^G$. The cost of the same path in Θ^h is $[-h(s_0) + c(a_1) + h(s_1)] + [-h(s_1) + c(a_2) + h(s_2)] + \dots + [-h(s_{n-1}) + c(a_n) + h(s_n)] = \sum_{i=1}^{n} c(a_i) - h(I) + h(s_n) = [\sum_{i=1}^{n} c(a_i)] - h(I)$. Thus the costs of solution paths in Θ^h are those of Θ, minus a constant. The claim follows.

Lemma (B). *The search space of A^* on Θ is isomorphic to that of uniform-cost search on Θ^h.*

Proof. Let $I = s_0 \xrightarrow{a_1} s_1, \dots, s_{n-1} \xrightarrow{a_n} s_n$ be any path in Θ. The $g + h$ value, used by A^*, is $[\sum_{i=1}^{n} c(a_i)] + h(s_n)$.

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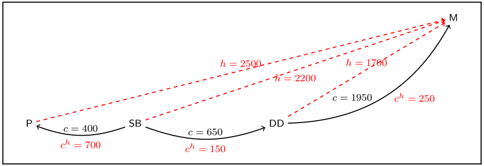
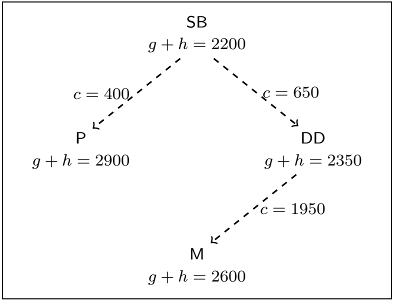
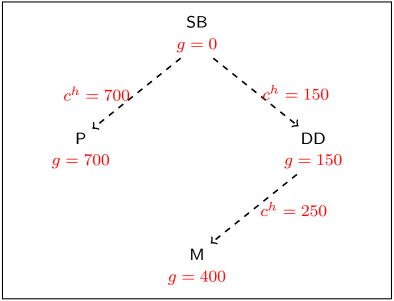
Optimality of A*: Proof – Illustration

Θ and Θ^h:



A* on Θ (left) and uniform-cost search on Θ^h (right): (Proof Step 2, Lemma (B) on previous slide)





Optimality of A^*: Proof, Step 3

→ Step 3: Put the pieces together.

Theorem (Optimality of A^*). *Let Π be a problem, and let h be a heuristic function for Π. If h is consistent, then the solution returned by A^* (if any) is optimal.*

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Theorem (Optimality of $\mathbf{A}^*$). *Let* Π *be a problem, and let* h *be a heuristic function for* Π*. If* h *is consistent, then the solution returned by* A^* *(if any) is optimal.*

Proof. Denote by Θ the state space of Π. Let $\vec{s}(A^*, \Theta)$ be the solution returned by A^* run on Θ. Denote by $\vec{S}(UCS, \Theta^h)$ the set of solutions that could in principle be returned by uniform-cost search run on Θ^h.

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By Lemma (B), $\vec{s}(A^*, \Theta) \in \vec{S}(UCS, \Theta^h)$: With appropriate tie-breaking between nodes with identical g value, uniform cost search will return $\vec{s}(A^*, \Theta)$.

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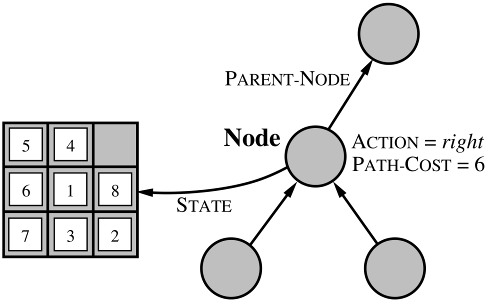
By Lemma (B), $\vec{s}(A^*, \Theta) \in \vec{S}(UCS, \Theta^h)$: With appropriate tie-breaking between nodes with identical g value, uniform cost search will return $\vec{s}(A^*, \Theta)$. By optimality of uniform-cost search, every element of $\vec{S}(UCS, \Theta^h)$ is an optimal solution for Θ^h. Thus $\vec{s}(A^*, \Theta)$ is an optimal solution for Θ^h. With Lemma (A), this implies that $\vec{s}(A^*, \Theta)$ is an optimal solution for Θ, which is what we needed to prove.

Implementation: What Is a Search Node?

Data Structure for Every Search Node n

- n.State: The state (from the state space) which the node contains.
- n.Parent: The node in the search tree that generated this node.
- n.Action: The action that was applied to the parent to generate the node.
- n.PathCost: $g(n)$, the cost of the path from the initial state to the node (as indicated by the parent pointers).



Implementation, ctd: Operations on Search Nodes

Operations on Search Nodes

Solution(n): Returns the path to node n. (By backchaining over the n.Parent pointers and collecting n.Action in each step.)

ChildNode(problem,n,a): Generates the node n' corresponding to the application of action a in state n.State. That is: n'.State:=problem.ChildState(n.State, a); n'.Parent:= n; n'.Action:= a; n'.PathCost:= n.PathCost+problem.Cost(a).

Implementation, ctd: Operations for the Open List

Operations for the Open List

Empty?(frontier): Returns true iff there are no more elements in the open list.

Pop(frontier): Returns the first element of the open list, and removes that element from the list.

Insert(element, frontier): Inserts an element into the open list.

→ Crucial point: *Where* "Insert(element, frontier)" inserts the new element. Different implementations yield different search strategies.

Direction of search

- The definition of searching is symmetric: find path from start nodes to goal node or from goal node to start nodes.
- Search complexity is b^n. Should use forward search if forward branching factor is less than backward branching factor, and vice versa.
- Note: sometimes when graph is dynamically constructed, you may not be able to construct the backwards graph.

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Bi-directional search

- You can search backward from the goal and forward from the start simultaneously.
- This wins as $2b^{k/2} \ll b^k$. This can result in an exponential saving in time and space.
- The main problem is making sure the frontiers meet.
- This is often used with one breadth-first method that builds a set of locations that can lead to the goal. In the other direction another method can be used to find a path to these interesting locations.

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