CS 5/7320
Artificial Intelligence

Solving problems by searching
AIMA Chapter 3
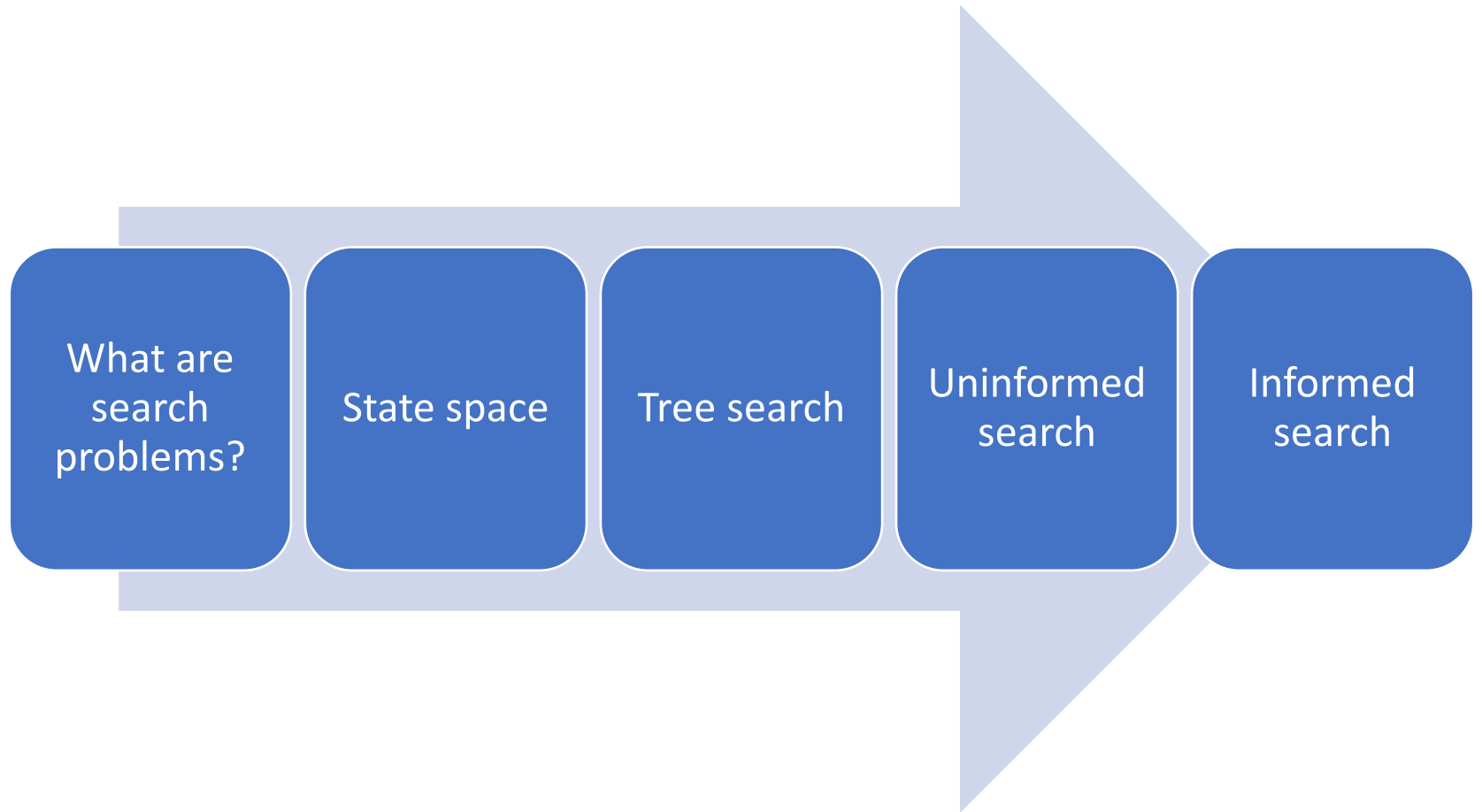
Slides by Michael Hahsler
based on slides by Svetlana Lazepnik
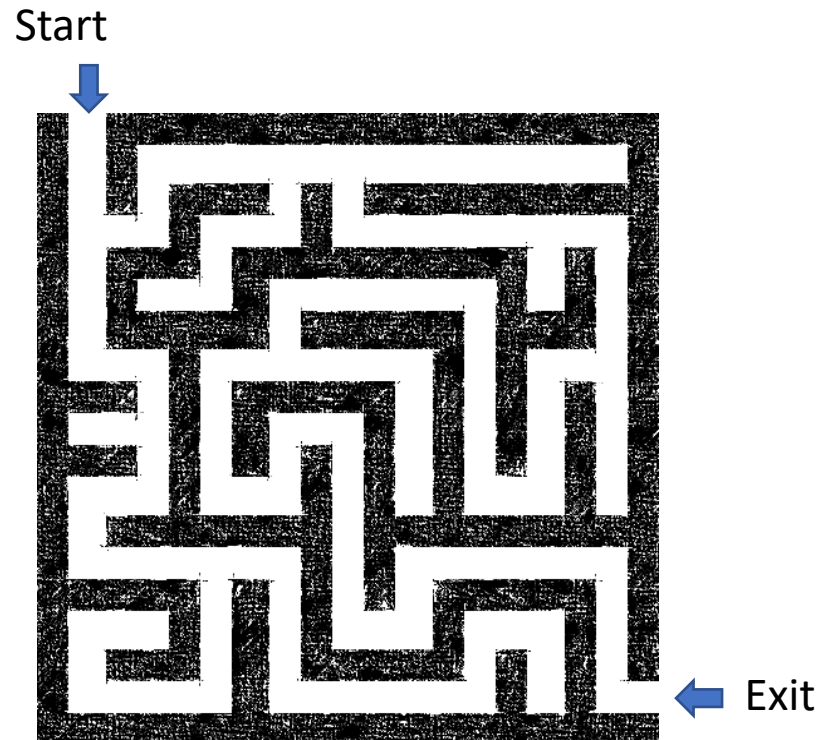with figures from the AIMA textbook.

Contents

What are search problems?

State space

Tree search

Uninformed search

Informed search

What are Search Problems?

- We will consider the problem of designing **goal-based agents** in **known**, **fully observable, and deterministic** environments.

- Example environment:

Start

Exit

Remember: Goal-based Agent

- The agent has the task to reach a defined **goal state**.
- The agent needs to move towards the goal. It can use **search algorithms** to plan actions that lead to the goal.
- The performance measure is typically the cost to reach the goal.
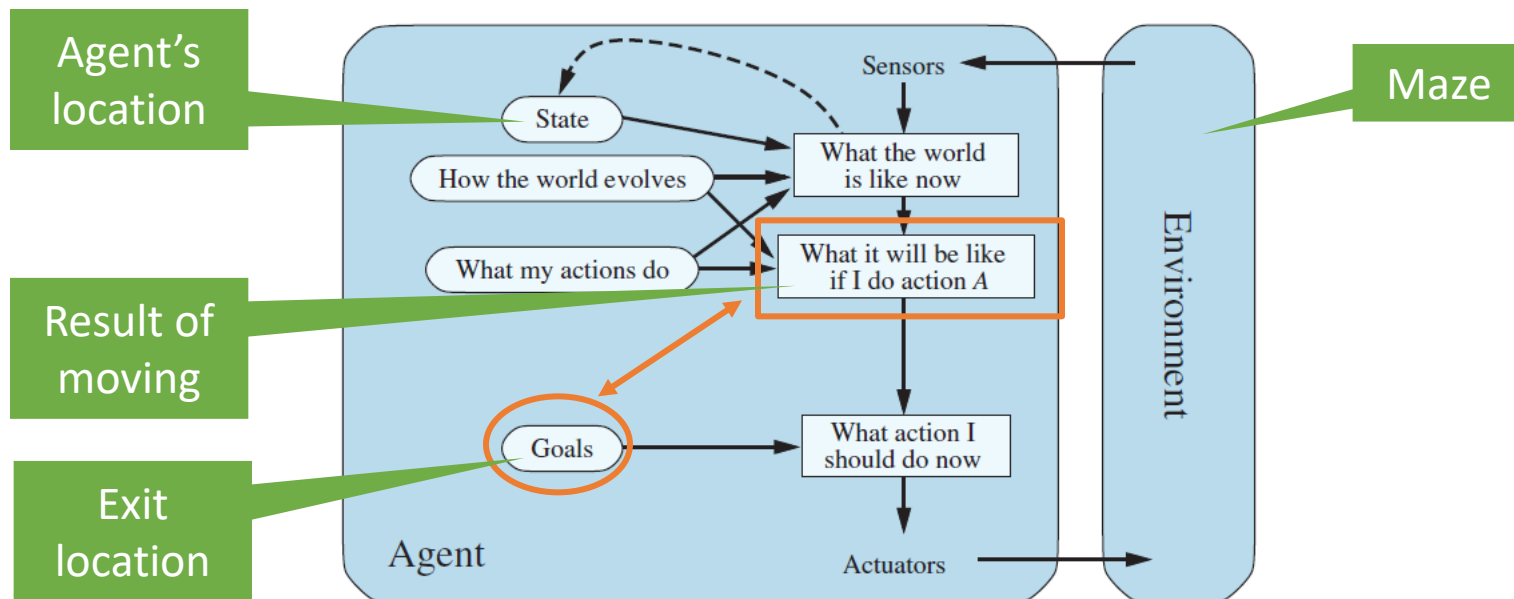
$$a_s = \text{argmin}_{a \in A}[cost(s, s_1, s_2, \ldots, s_n | s_n \in S^{goal})]$$

What are Search Problems?

- For now, we consider only a discrete environment using an **atomic state representation** (states are just labeled 1, 2, 3, ...).

- The **state space** is the set of all possible states of the environment and some states are marked as **goal states**.

- The **optimal solution** is the sequence of actions (or equivalently a sequence of states) that gives the lowest path cost for reaching the goal.
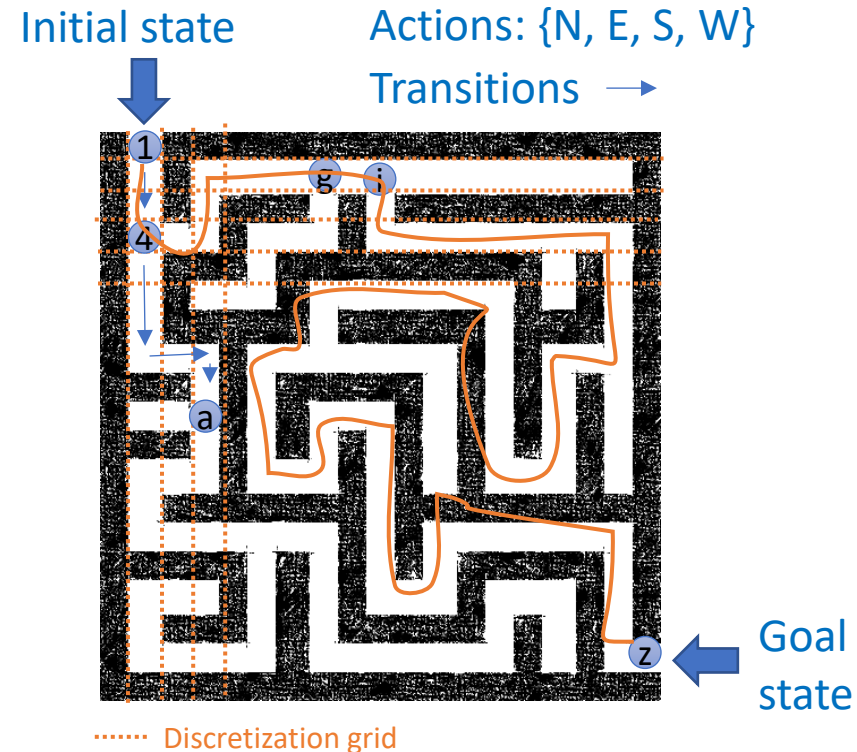
Initial state
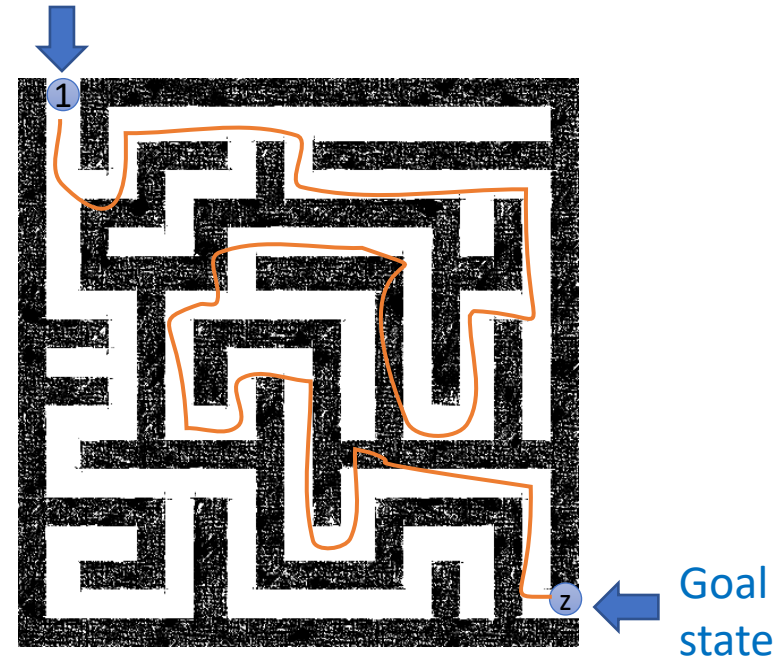
Goal state

Phases:

1) **Search/Planning**: the process of looking for the **sequence of actions** that reaches a goal state. Requires that the agent knows what happens when it moves!

2) **Execution**: Once the agent begins executing the search solution in a deterministic, known environment, it can ignore its percepts (**open-loop system**).

Definition of a Search problem

- **Initial state:** state description
- **Actions:** set of possible actions A
- **Transition model:** a function that defines the new state resulting from performing an action in the current state
- **Goal state:** state description
- **Path cost:** the sum of *step costs*

Initial state

Actions: {N, E, S, W}

Transitions →

Goal state

······ Discretization grid

Important: The **state space** is typically too large to be enumerated or it is continuous. Therefore, the problem is defined by initial state, actions and the transition model and not the set of all possible states.

Transition Function and Available Actions

Original Description

Initial state

Actions: {N, E, S, W}

Transitions →

•••••• Discretization grid

Goal state
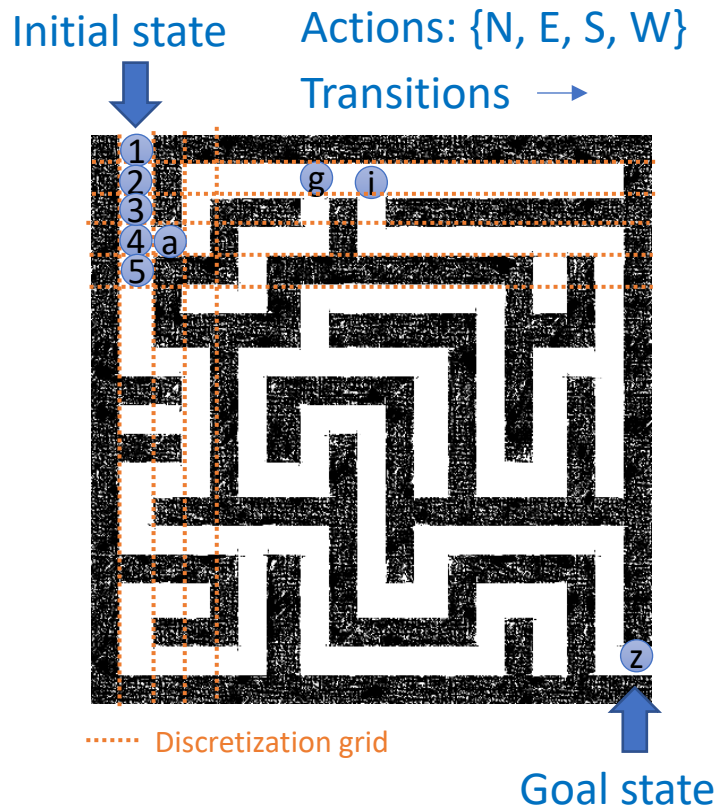
- As an action schema:
  $Action(go(dir))$

  PRECOND: no wall in direction dir
  EFFECT: change the agent's location according to dir

- As a function:
  $f: S \times A \rightarrow S$ or $s' = result(a, s)$

- Function implemented as a table representing the state space as a graph.

s	a	s'
1	S	2
2	N	1
2	S	3
...	...	...
4	E	a
4	S	5
4	N	3
...	...	...

- Available actions in a state come from the transition function. E.g.,
  $actions(4) = \{E, S, N\}$

Note: Known and deterministic is a property of the transition function!

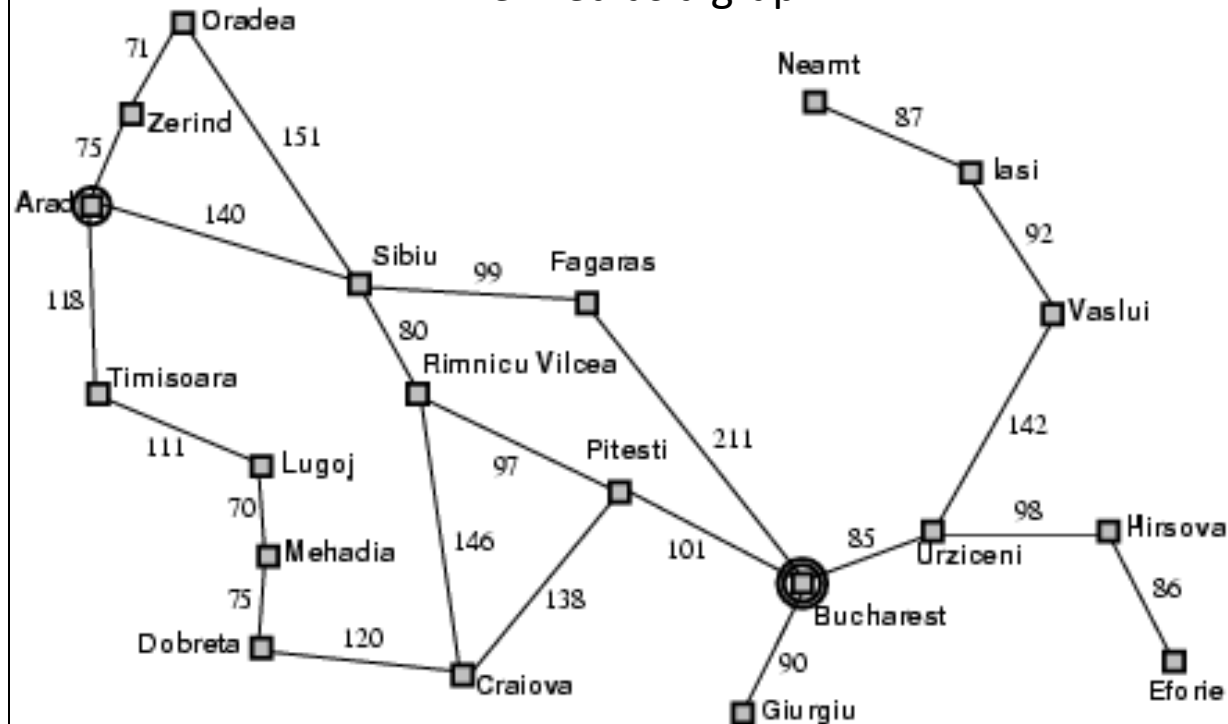# Example: Romania Vacation

- On vacation in Romania; currently in Arad
- Flight leaves tomorrow from Bucharest

- **Initial state:** Arad
- **Actions:** Drive from one city to another.
- **Transition model and states:** If you go from city A to city B, you end up in city B.
- **Goal state:** Bucharest
- **Path cost:** Sum of edge costs.

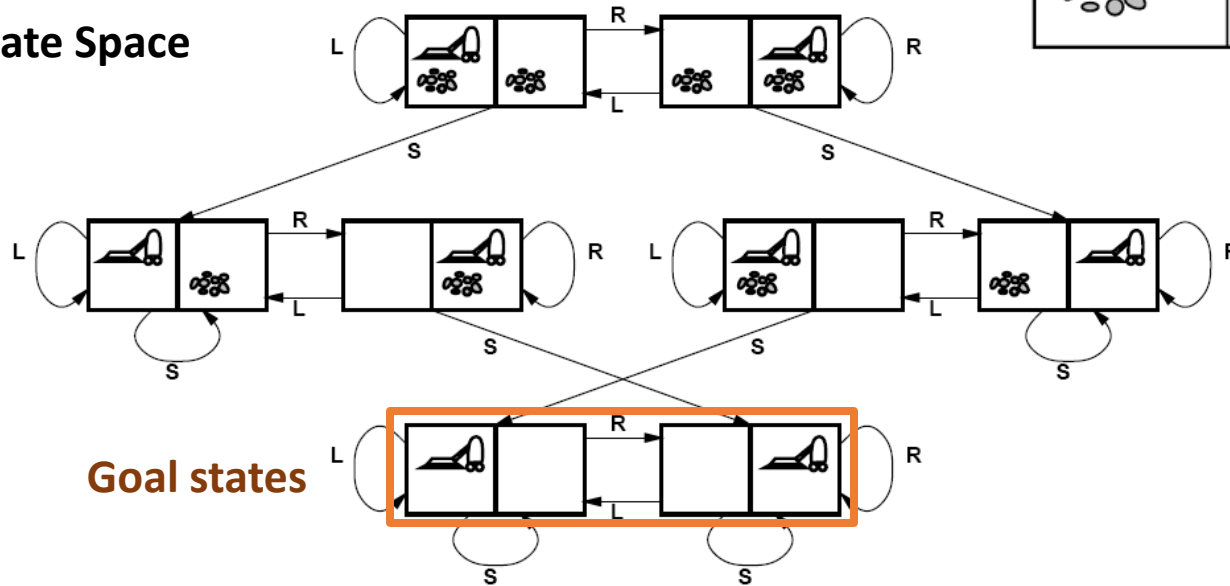**State Space/Transition model**
Defined as a graph

Distance in miles

Example: Vacuum world

State Space

Goal states

- **Initial State:** Defined by agent location and dirt location.

- **Actions:** Left, right, suck

- **Transition model:** Clean a location or move.

- **Goal state:** All locations are clean.

- **Path cost:** E.g., number if actions

There are 8 possible atomic states of the system.
Why is the number of states for n possible locations $n(2^n)$?

Example: Sliding-tile Puzzle

- **Initial State:** A given configuration.

- **Actions:** Move blank left, right, up, down

- **Transition model:** Move a tile

- **Goal state:** Tiles are arranged empty and 1-8 in order

- **Path cost:** 1 per tile move.

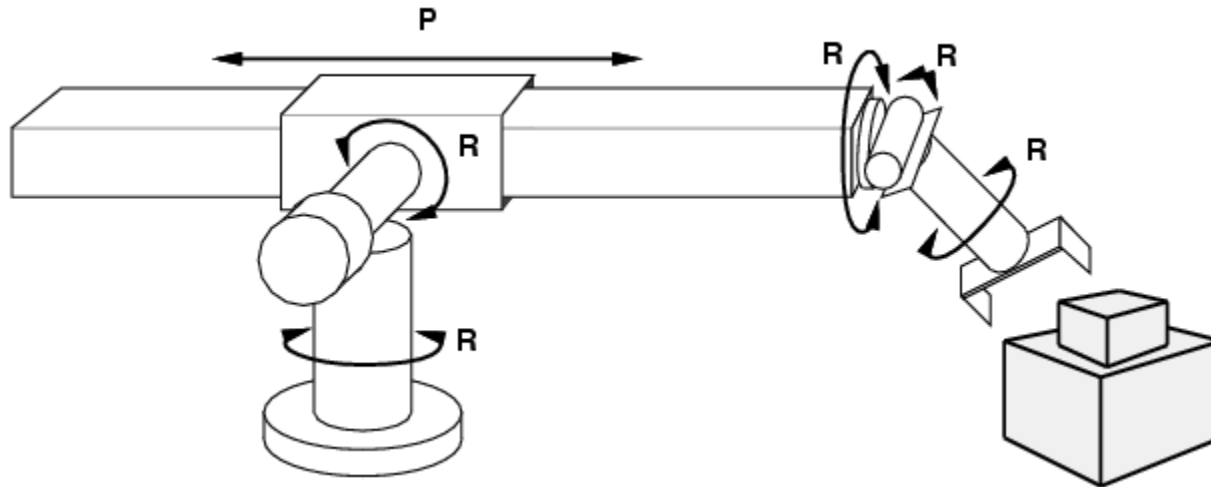**State space size**

Each state describes the location of each tile (including the empty one). ½ of the permutations are unreachable.

- 8-puzzle: $9!/2 = 181,440$ states
- 15-puzzle: $16!/2 \approx 10^{13}$ states
- 24-puzzle: $25!/2 \approx 10^{25}$ states

Example: Robot Motion Planning

- **Initial State:** Current arm position.

- **States:** Real-valued coordinates of robot joint angles.

- **Actions:** **Continuous** motions of robot joints.

- **Goal state:** Desired final configuration (e.g., object is grasped).

- **Path cost:** Time to execute, smoothness of path, etc.
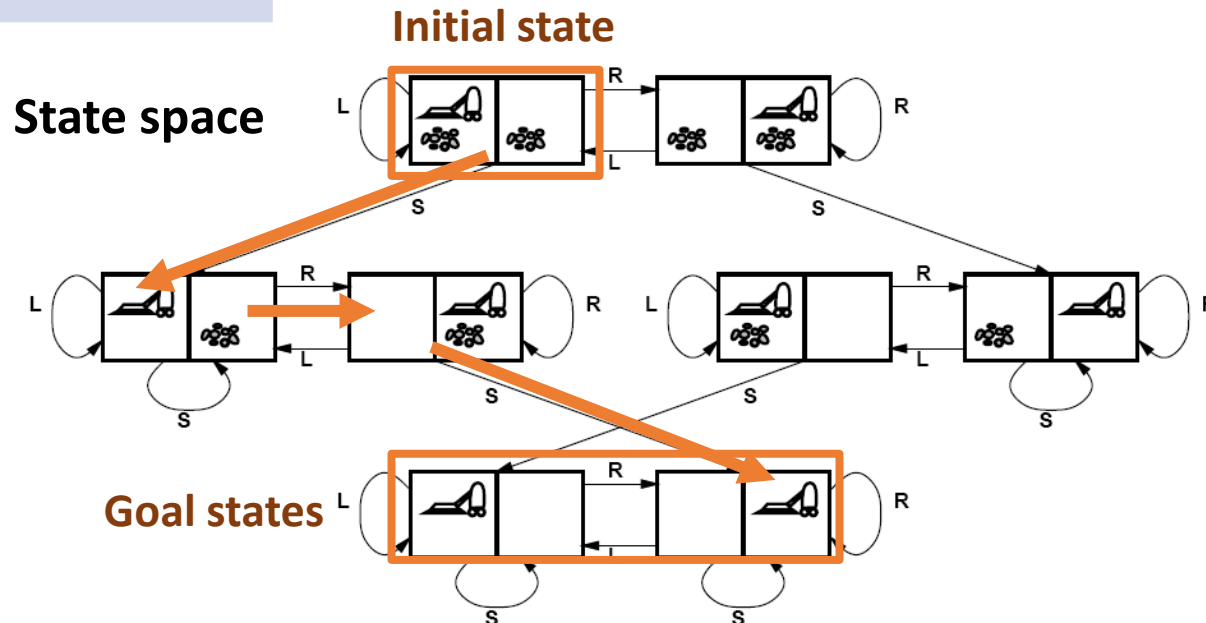
Solving Search Problems

Given a search problem definition

- Initial state
- Actions
- Transition model
- Goal state
- Path cost

How do we find the optimal solution (sequence of actions/states)?
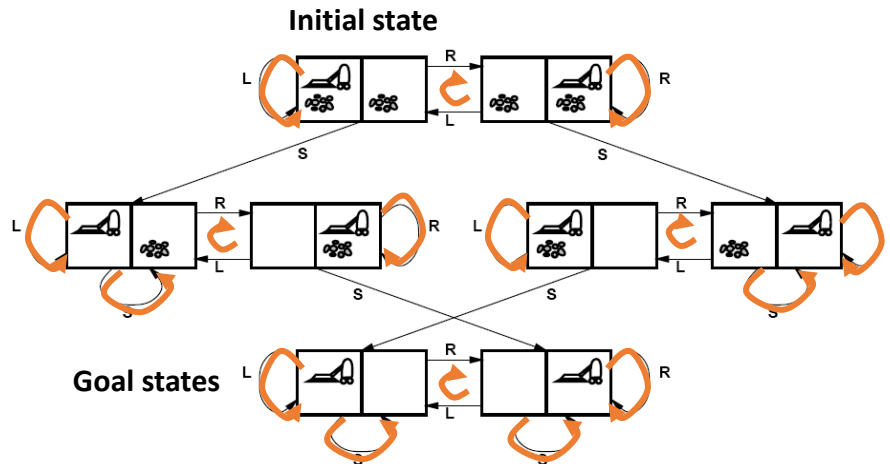
Construct a search tree for the state space graph!

State space

Initial state

Goal states

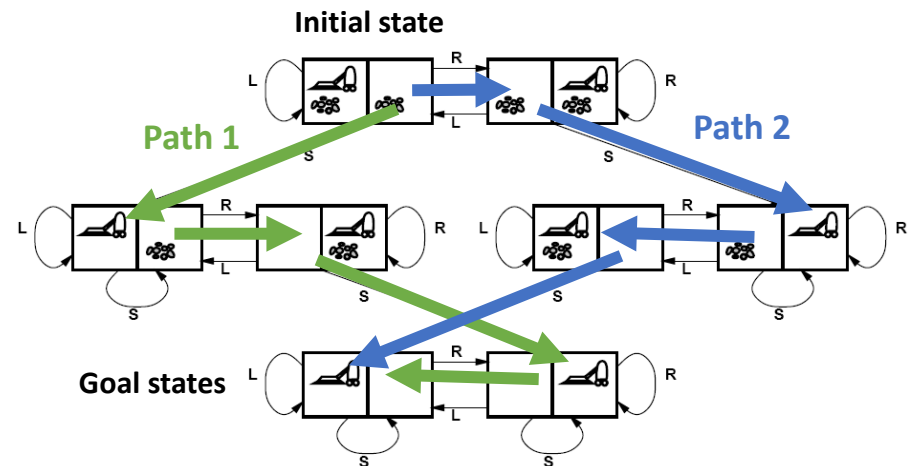# Issue: Transition Model is Not a Tree! It can have Redundant Paths

Cycles

Return to the same state. The search tree will create a new node!

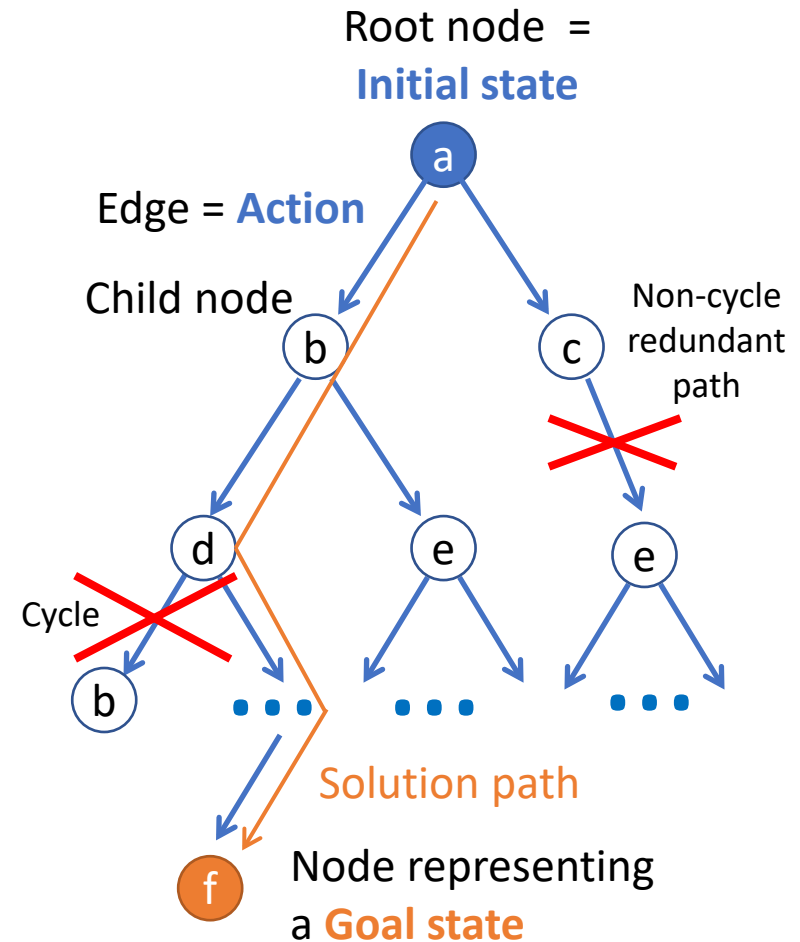**Non-cycle redundant paths**

Multiple paths to get to the same state

Search Tree

- Superimpose a "what if" tree of possible actions and outcomes (states) on the state space graph.

- The **Root node** represents the initial stare.

- An action child node is reached by an **edge** representing an action. The corresponding state is defined by the transition model.

- Trees cannot have **cycles (loops)** or **multiple paths to the same state.** These are called redundant paths. Cycles in the search space must be broken to prevent infinite loops. Removing other redundant paths improves search efficiency.

- A **path** through the tree corresponds to a sequence of actions (states).

- A **solution** is a path ending in a node representing a goal state.

- **Nodes vs. states:** Each tree node represents a state of the system. If redundant path cannot be prevented then state can be represented by multiple nodes.

Root node =
Initial state

Edge = **Action**

Child node

Non-cycle redundant path

Cycle

Solution path

Node representing a **Goal state**

Differences Between Typical Tree Search and AI Search

Typical tree search

- Assumes a given tree that fits in memory.

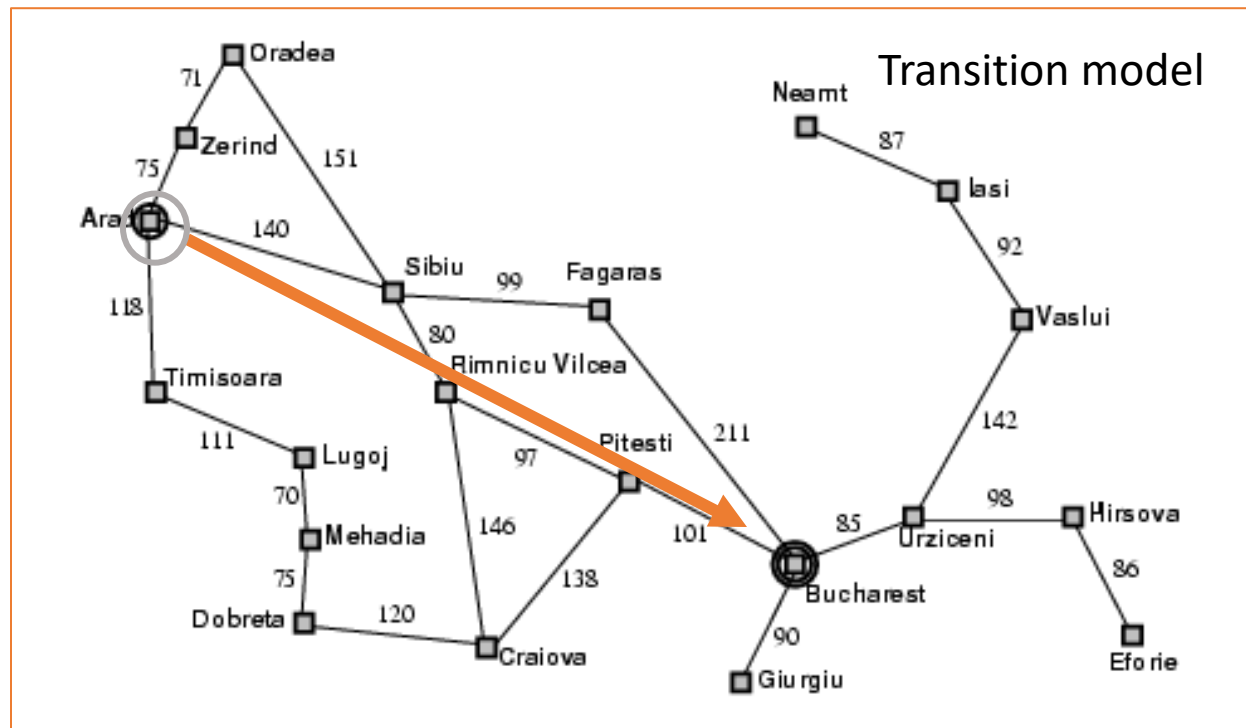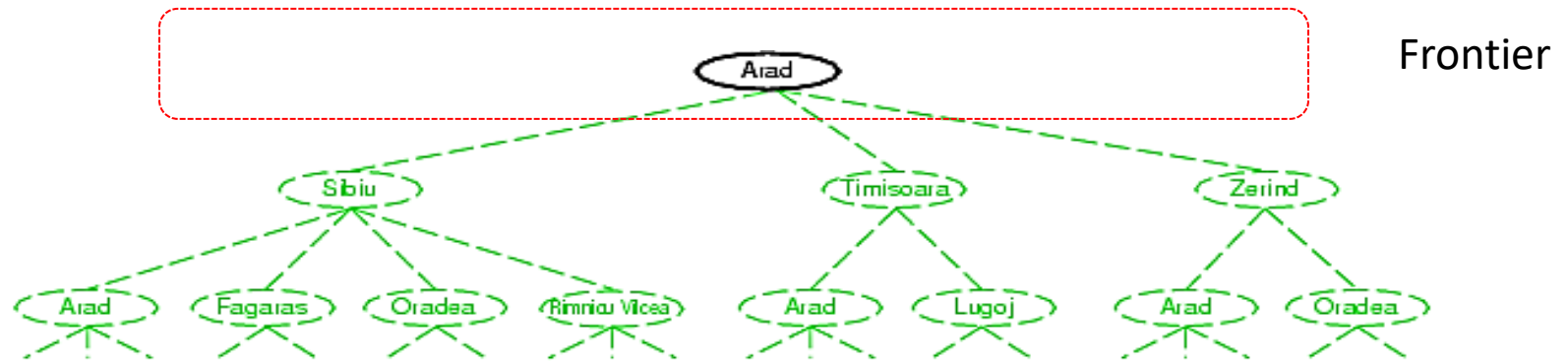- Trees have by construction no cycles or redundant paths.

AI tree/graph search

- The search tree is too large to fit into **memory**.
  a. **Builds parts of the tree** from the initial state using the transition function representing the graph.
  b. **Memory management** is very important.

- The search space is typically a very large and complicated graph. Memory-efficient **cycle checking** is very important to avoid infinite loops or minimize searching parts of the search space multiple times.

- Checking redundant paths often requires too much memory and we accept searching the same part multiple times.
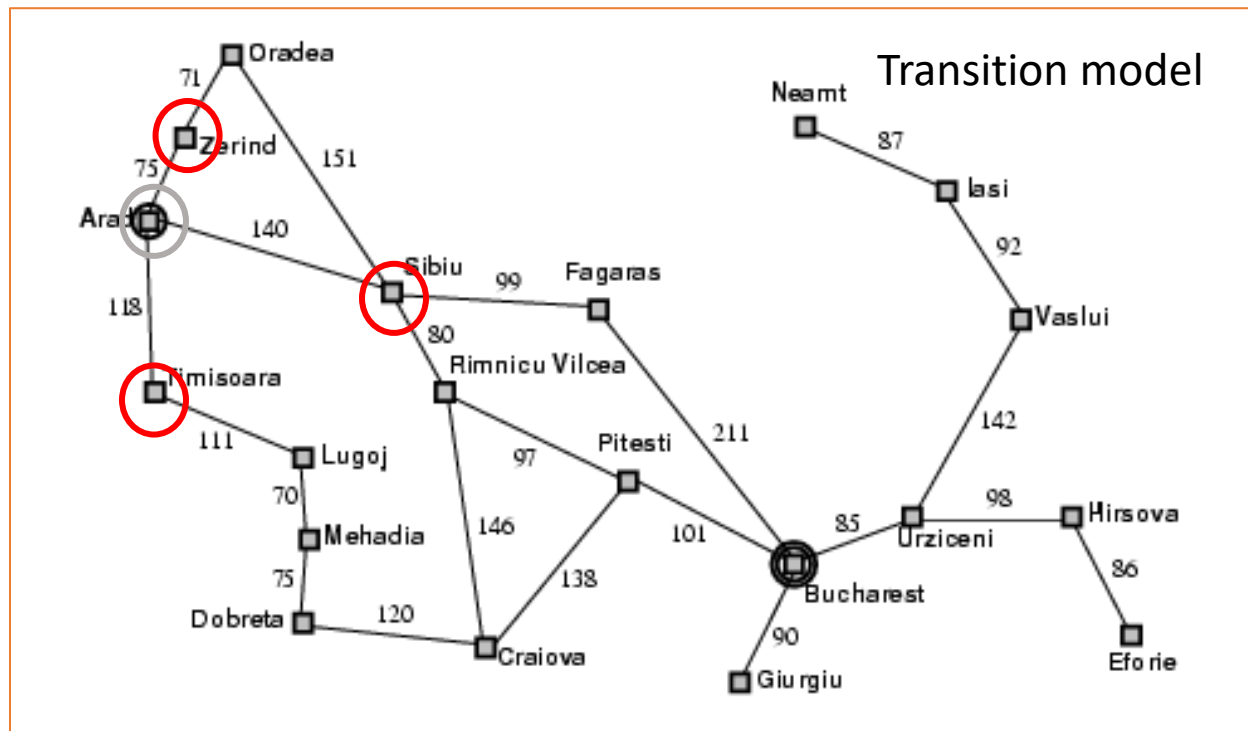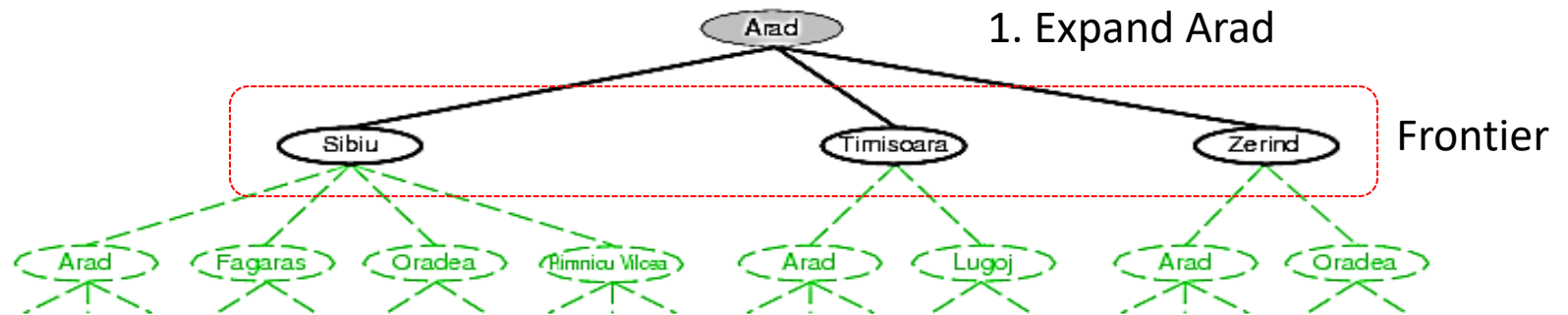
Tree Search Algorithm Outline

1. Initialize the **frontier** (set of unexplored know nodes) using the **starting state/root node.**

2. While the frontier is not empty:
   a) Choose next frontier node to expand according to **search strategy.**
   b) If the node represents a **goal state,** return it as the solution.
   c) Else **expand** the node (i.e., apply all possible actions to the transition model) and add its children nodes representing the newly reached states to the frontier.
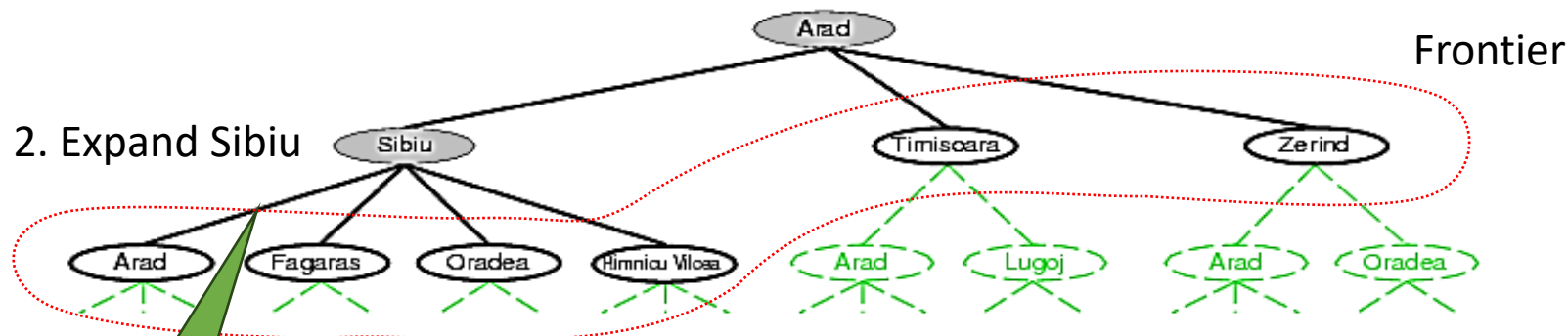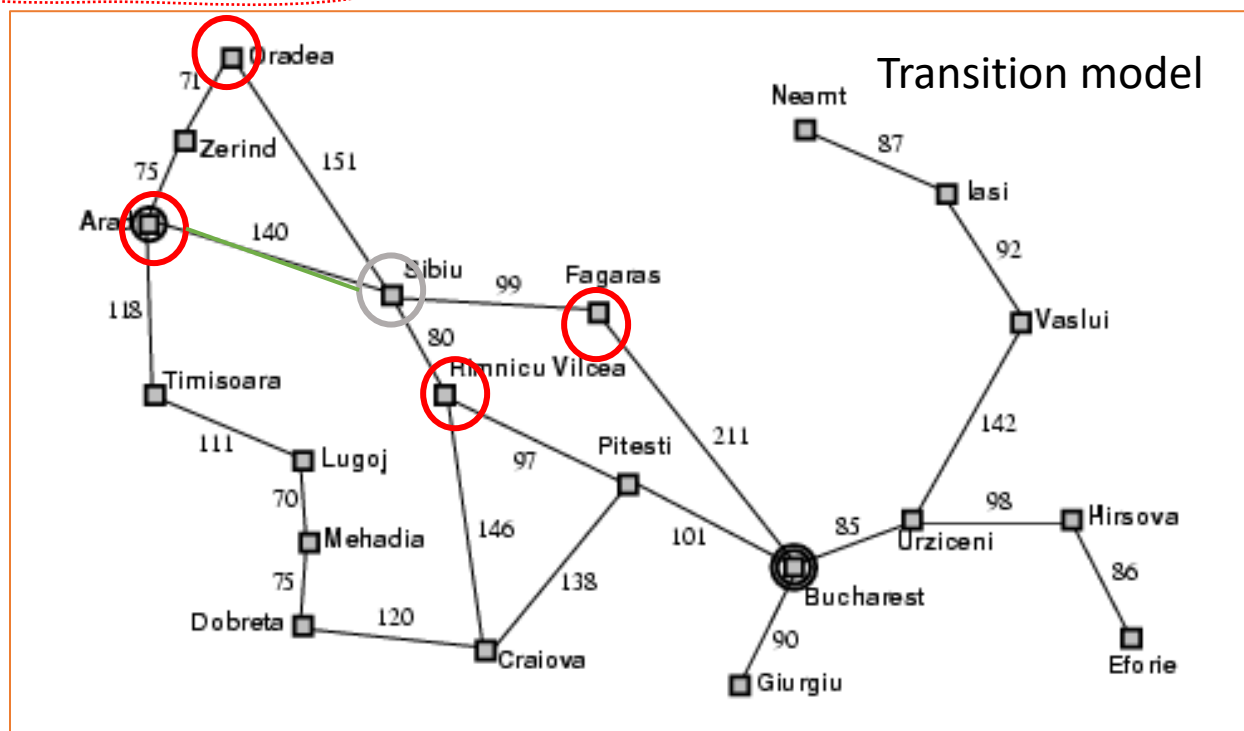
Tree Search Example

Frontier

Transition model

Tree Search Example

1. Expand Arad

Frontier

Transition model

Tree Search Example

Frontier

2. Expand Sibiu

Example of a cycle

Transition model

We could have also expanded Timisoara or Zerind!

Search Strategies: Properties

- 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?
  - **Optimality:** does it always find a least-cost solution?
  - **Time complexity:** how long does it take?
  - **Space complexity:** how much memory does it need?

Search Strategies: Time and Space Complexity

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

- Worst case time and space complexity are measured in terms of the **size of the state space *n*** (= number of nodes in the search tree).

$$O(n)$$

- Often used metrics if the state space is only implicitly defined by initial state, actions and a transition function are:
  - b: maximum branching factor of the search tree (number of available actions).
  - m: length of the longest path (loops need to be removed).
  - d: depth of the optimal solution.

$$n = f(d, m, b) \Rightarrow O(f(d, m, b))$$

Uninformed Search

Uninformed Search Strategies

The search algorithm/agent is **not** provided information about how close a state is to the goal state. It just has the labels of the atomic states and the transition function.

It blindly searches following a simple strategy until it finds the goal state by chance.

Search strategies we will discuss:
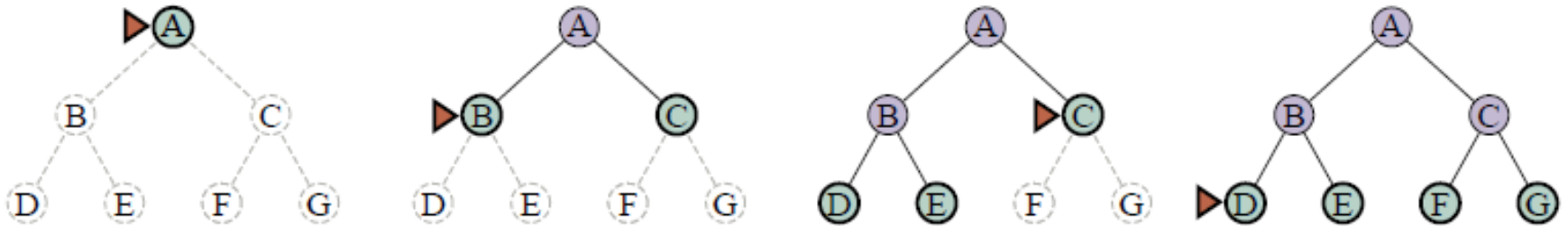
Breadth-first search
Uniform-cost search
Depth-first search
Iterative deepening search

Breadth-First Search (BFS)

Expansion rule: Expand shallowest unexpanded node in the frontier (=**FIFO**).

Figure 3.8 Breadth-first search on a simple binary tree. At each stage, the node to be expanded next is indicated by the triangular marker.

Data Structures
- **Frontier** data structure: holds references to the green nodes (green) and is implemented as a FIFO **queue**.
- **Reached** data structure: holds references to all visited nodes (gray and green) and is used to prevent visiting nodes more than once (redundant path checking).
- Builds a **tree** with links between parent and child.

Implementation: BFS

function BREADTH-FIRST-SEARCH($problem$) **returns** a solution node or $failure$
  $node \leftarrow$ NODE($problem$.INITIAL)
  if $problem$.IS-GOAL($node$.STATE) **then return** $node$
  $frontier \leftarrow$ a FIFO queue, with $node$ as an element
  $reached \leftarrow \{problem$.INITIAL$\}$
  while not IS-EMPTY($frontier$) **do**
    $node \leftarrow$ POP($frontier$)
    for each $child$ **in** EXPAND($problem, node$) **do**
      $s \leftarrow child$.STATE
      if $problem$.IS-GOAL(s) **then return** $child$
      if s is not in $reached$ **then**
        add s to $reached$
        add $child$ to $frontier$
  return $failure$

Expand adds the next level below node to the frontier.

reached makes sure we do not visit nodes twice (e.g., in a cycle or other redundant path). Fast lookup is important.

35

Implementation: Expanding the Search Tree

- AI tree search creates the search tree while searching.

- The EXPAND function tries all available actions in the current node using the transition function (RESULTS). It returns a list of new nodes for the frontier.

function EXPAND($problem$, $node$) **yields** nodes
  $s \leftarrow node$.STATE
  for each $action$ **in** $problem$.ACTIONS(s) **do**
    $s' \leftarrow problem$.RESULT(s, $action$)
    $cost \leftarrow node$.PATH-COST + $problem$.ACTION-COST(s, $action$, s')
    yield NODE(STATE=s', PARENT=$node$, ACTION=$action$, PATH-COST=$cost$)

Transition function

Node structure for the search tree. Yield can also be implemented by returning a list of Nodes.

Time and Space Complexity Breadth-First Search

d: depth of the optimal solution
m: max. depth of tree
b: maximum branching factor
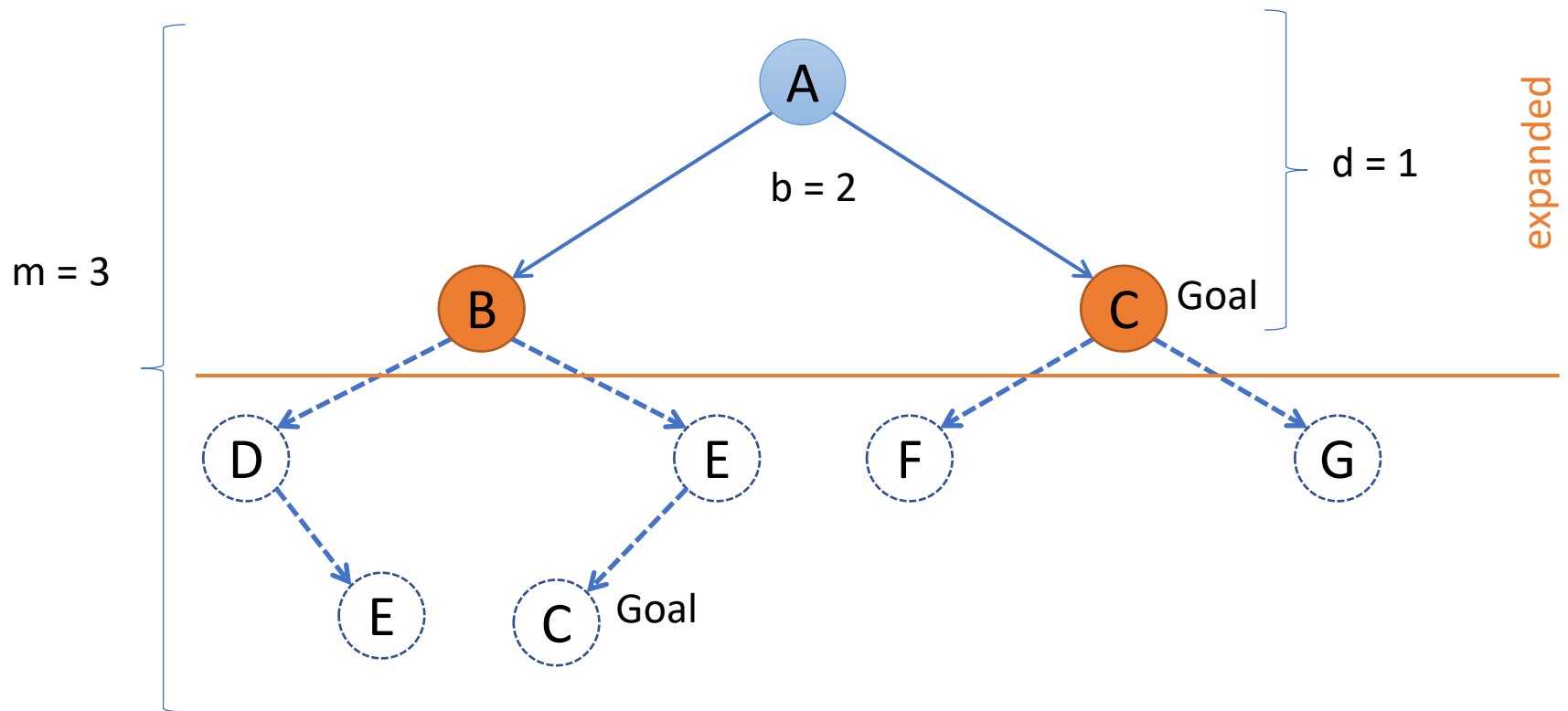
All paths to the depth of the goal are expanded:

$$1 + b + b^2 + \ldots + b^d \Rightarrow O(b^d)$$

Properties of Breadth-First Search

d: depth of the optimal solution
m: max. depth of tree
b: maximum branching factor

- **Complete?**
  Yes

- **Optimal?**
  Yes – if cost is the same per step (action). Otherwise: Use uniform-cost search.

- **Time?**
  Number of nodes created: $O(b^d)$

- **Space?**
  Stored nodes: $O(b^d)$

Note:
  - The large space complexity is usually a bigger problem than time!

Uniform-cost Search (= Dijkstra's Shortest Path Algorithm)

- **Expansion rule**: Expand node in the frontier with **the least path cost** from the initial state.

- Implementation: **best-first search** where the frontier is a **priority queue** ordered by lower $f(n)$ = **path cost** (cost of all actions starting from the initial state).

- Breadth-first search is a special case when all step costs being equal, i.e., each action costs the same!

- **Complete?**

    Yes, if all step cost is greater than some small positive constant $\varepsilon > 0$

- **Optimal?**

    Yes – nodes expanded in increasing order of path cost

- **Time?**

    Number of nodes with path cost ≤ cost of optimal solution (C^*) is $O(b^{1+C^*/\varepsilon})$.

    This can be greater than $O(b^d)$: the search can explore long paths consisting of small steps before exploring shorter paths consisting of larger steps

- **Space?**

    $O(b^{1+C^*/\varepsilon})$

See Dijkstra's algorithm on Wikipedia

> *d:* depth of the optimal solution
> *m:* max. depth of tree
> *b:* maximum branching factor

Implementation: Best-First Search Strategy

function UNIFORM-COST-SEARCH(*problem*) **returns** a solution node, or *failure*
   return BEST-FIRST-SEARCH(*problem*, PATH-COST)

function BEST-FIRST-SEARCH(*problem*, *f*) **returns** a solution node or *failure*
   node ← NODE(STATE=*problem*.INITIAL)
   frontier ← a priority queue ordered by *f*, with *node* as an element
   reached ← a lookup table, with one entry with key *problem*.INITIAL and value *node*
   while not IS-EMPTY(*frontier*) **do**
      node ← POP(*frontier*)
      if *problem*.IS-GOAL(*node*.STATE) **then return** *node*
      for each *child* **in** EXPAND(*problem*, *node*) **do**
         s ← *child*.STATE
         if *s* is not in *reached* **or** *child*.PATH-COST < *reached*[*s*].PATH-COST **then**
            reached[*s*] ← *child*
            add *child* to *frontier*
   return *failure*

See BFS for function EXPAND.

> The order for expanding the frontier is determined by $f(n)$ = path cost from the initial state to node n.

> This check is the difference to BFS! It visits a node again if it can be reached by a better (cheaper) path.

Depth-First Search (DFS)

- **Expansion rule**: Expand deepest unexpanded node in the frontier (last added).

- **Frontier**: **stack** (LIFO)

- **No reached data structure!**

  Cycle checking checks only the current path.

  Redundant paths can not be identified and lead to replicated work.
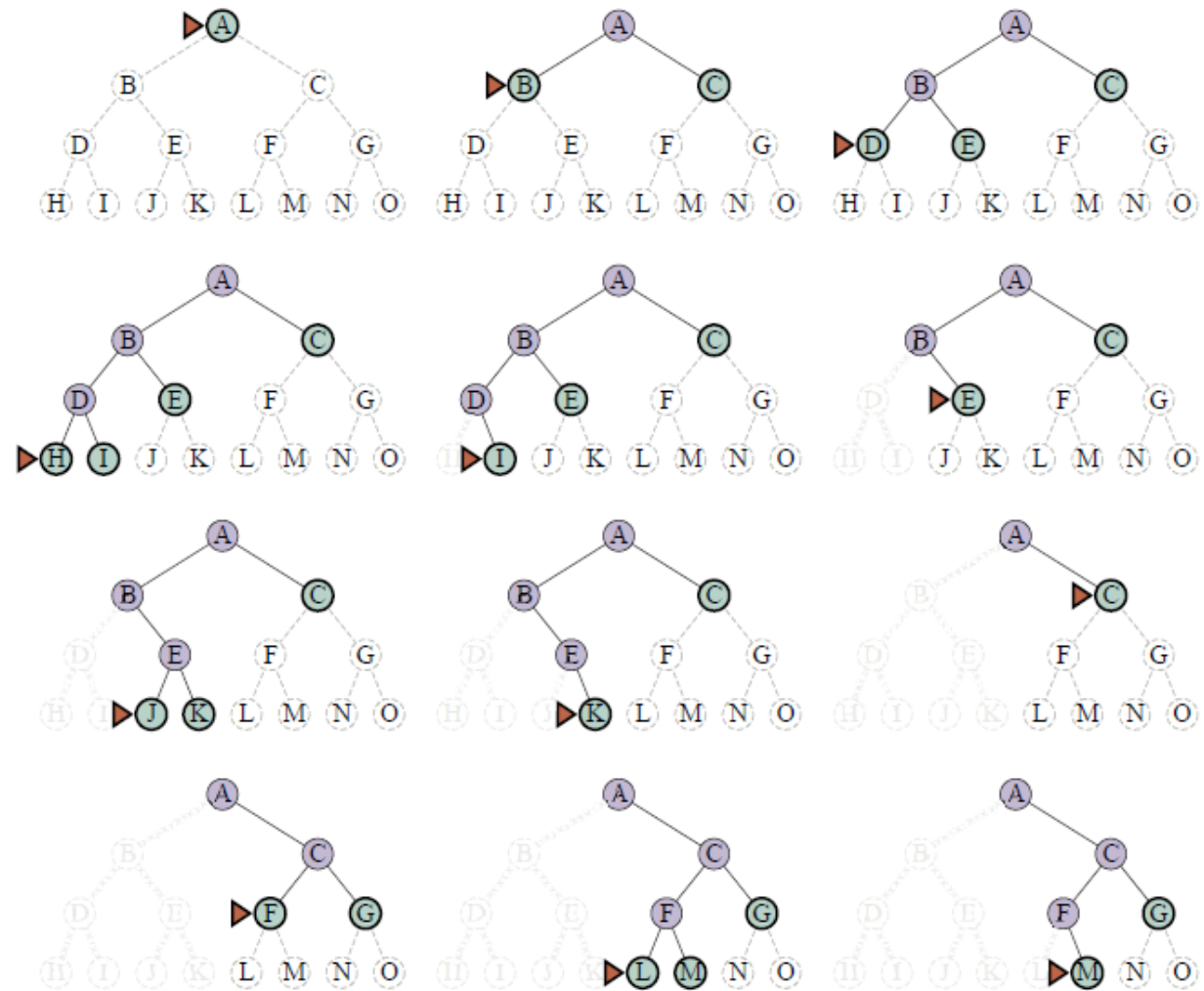
Figure 3.11 A dozen steps (left to right, top to bottom) in the progress of a depth-first search on a binary tree from start state A to goal M. The frontier is in green, with a triangle marking the node to be expanded next. Previously expanded nodes are lavender, and potential future nodes have faint dashed lines. Expanded nodes with no descendants in the frontier (very faint lines) can be discarded.

Implementation: DFS

- DFS could be implemented like BFS/Best-first search and just taking the last element from the frontier (LIFO).

- However, to reduce the space complexity to $O(bm)$, the reached data structure needs to be removed! Options:
  - ~~Recursive implementation~~ (cycle checking is a problem leading to infinite loops)
  - Iterative implementation: Build tree and abandoned branches are removed from memory. Cycle checking is only done against the current path. This is similar to Backtracking search.

DFS uses $\ell = \infty$

function DEPTH-LIMITED-SEARCH($problem$, ℓ) **returns** a node or $failure$ or $cutoff$
    $frontier \leftarrow$ a LIFO queue (stack) with NODE($problem$.INITIAL) as an element
    $result \leftarrow failure$
    while not IS-EMPTY($frontier$) **do**
        $node \leftarrow$ POP($frontier$)
        if $problem$.IS-GOAL($node$.STATE) **then return** $node$
        if DEPTH($node$) $> \ell$ **then**
            $result \leftarrow cutoff$
        else if not IS-CYCLE($node$) **do**
            for each $child$ **in** EXPAND($problem$, $node$) **do**
                add $child$ to $frontier$
    return $result$

If we only keep the current path from the root to the current node in memory, then we can only check against that path to prevent cycles, but we cannot prevent other redundant paths. We also need to make sure the frontier does not contain the same state more then once!

See BFS for function EXPAND.

Time and Space Complexity
Depth-First Search
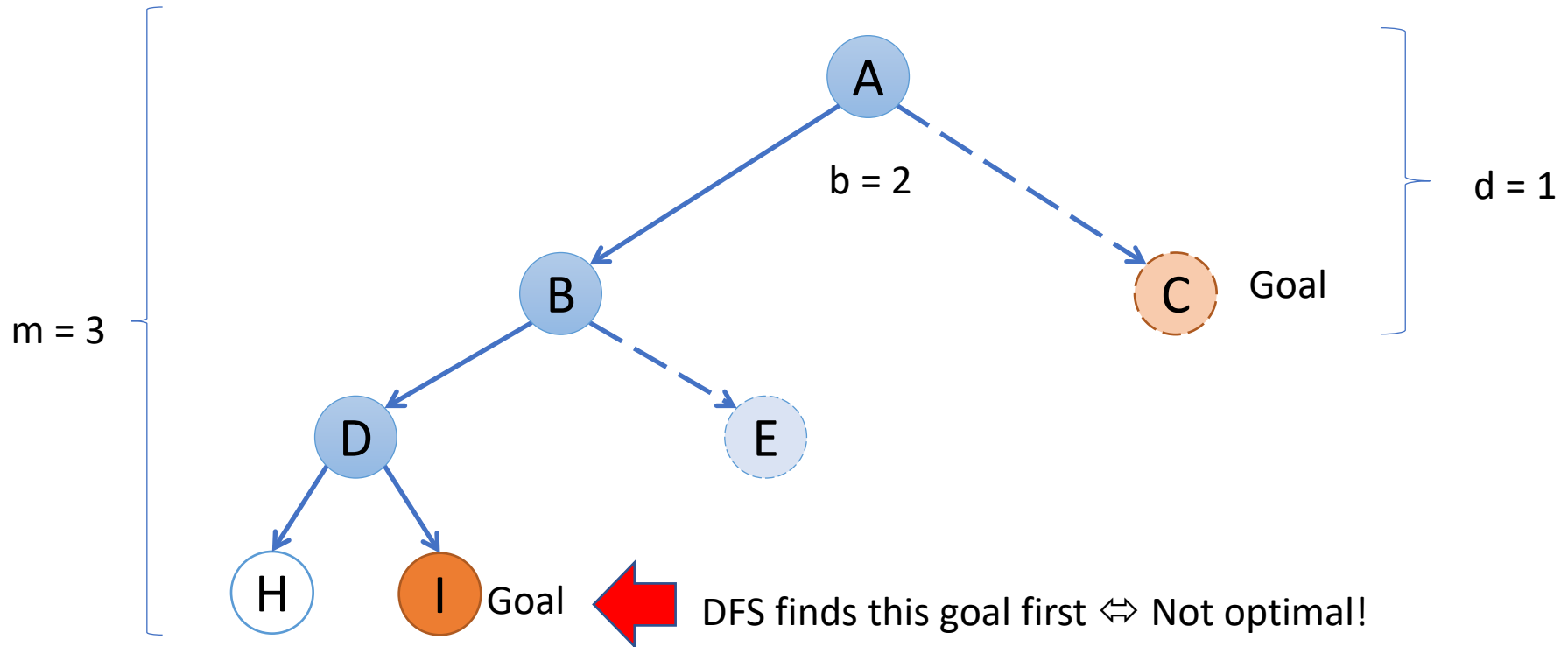
- Time: $O(b^m)$ – worst case is expanding all paths.
- Space: $O(bm)$ - if it only stores the frontier nodes and the current path.

Properties of Depth-First Search

- **Complete?**
  - Only in finite search spaces. Cycles can be avoided by checking for repeated states along the path.
  - **Incomplete in infinite search spaces** (e.g., with cycles).

- **Optimal?**
  No – returns the first solution it finds.

> *d:* depth of the optimal solution
> *m:* max. depth of tree
> *b:* maximum branching factor

- **Time?**
  The worst case is to reach a solution at maximum depth m in the last path: $O(b^m)$
  Terrible compared to BFS if $m \gg d$.

- **Space?**
  $O(bm)$ is **linear in max. tree depth m** which is very good but only achieved if **no reached data structure and memory management** (forget old branches) is used! Cycles can be broken but redundant paths cannot be checked.

Iterative Deepening Search (IDS)

Can we
    a) **get DFS's good memory footprint,**
    b) **avoid infinite cycles, and**
    c) **preserve BFS's optimality guaranty?**

Use depth-restricted DFS and gradually increase the depth.

1. Check if the root node is the goal.
2. Do a DFS searching for a path of length 1
3. If goal not found, do a DFS searching for a path of length 2
4. If goal not found, do a DFS searching for a path of length 3
5. …

Iterative Deepening Search (IDS)
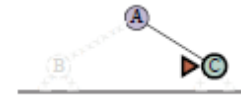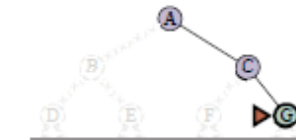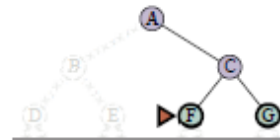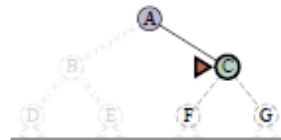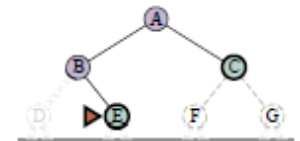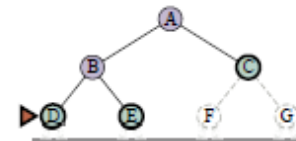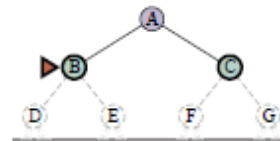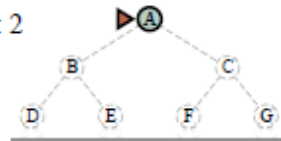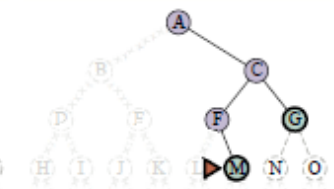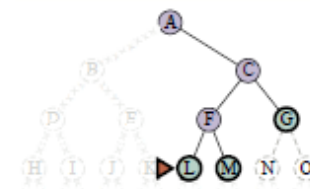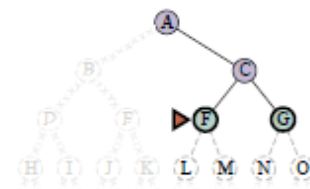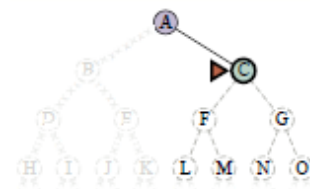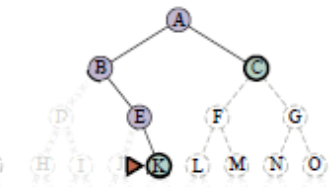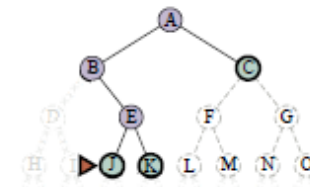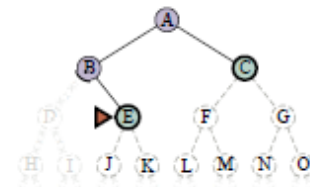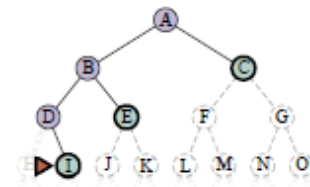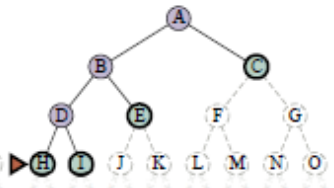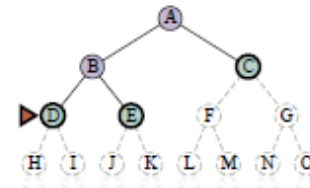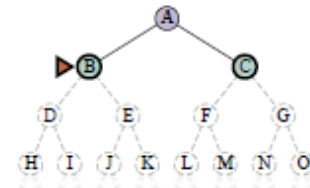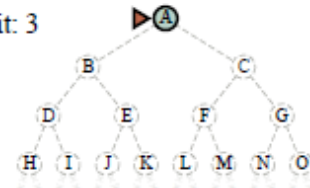
Implementation: IDS

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

function DEPTH-LIMITED-SEARCH($problem, \ell$) **returns** a node or $failure$ or $cutoff$
  $frontier \leftarrow$ a LIFO queue (stack) with NODE($problem$.INITIAL) as an element
  $result \leftarrow failure$
  while not IS-EMPTY($frontier$) **do**
    $node \leftarrow$ POP($frontier$)
    if $problem$.IS-GOAL($node$.STATE) **then return** $node$
    if DEPTH($node$) $> \ell$ **then**
      $result \leftarrow cutoff$
    else if not IS-CYCLE($node$) **do**
      for each $child$ **in** EXPAND($problem, node$) **do**
        add $child$ to $frontier$
  return $result$

See BFS for function EXPAND.

Properties of Iterative Deepening Search

- **Complete?**
  Yes

- **Optimal?**
  Yes, if step cost = 1 (like BFS)

- **Time?**
  Consists of rebuilding trees up to d times
  $db + (d-1)b^2 + \ldots + 1b^d = O(b^d)$ ⇔ Slower than BFS, but the same complexity class!

- **Space?**
  $O(bd)$ ⇔ linear space. Even less than DFS since $m \leq d$. Cycles need to be handled by the depth-limited DFS implementation.

Note: IDS produces the same result as BFS but trades **better space complexity** for worse run time.

This makes IDS/DFS the workhorse of AI.

Informed Search

Informed Search

- AI search problems typically have a very large search space. We would like to improve efficiency by **expanding as few nodes as possible.**

- The agent can use **additional information** in the form of "hints" about what promising states are to explore first. These hints are derived from
  - information the agent has (e.g., a map with the goal location marked) or
  - percepts coming from a sensor (e.g., a GPS sensor and coordinates of the goal).

- The agent uses a **heuristic function $h(n)$** to rank nodes in the frontier and always select the most promising node in the frontier for expansion using the **best-first search** strategy.

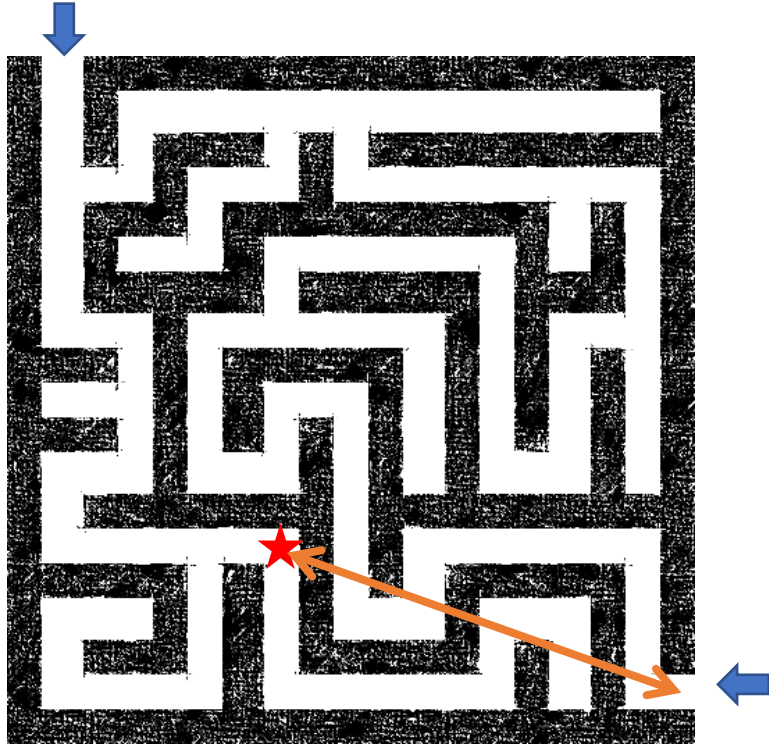- Algorithms:
  - Greedy best-first search
  - A* search

Heuristic Function

- **Heuristic function** $h(n)$ estimates the cost of reaching a node representing the goal state from the current node n.
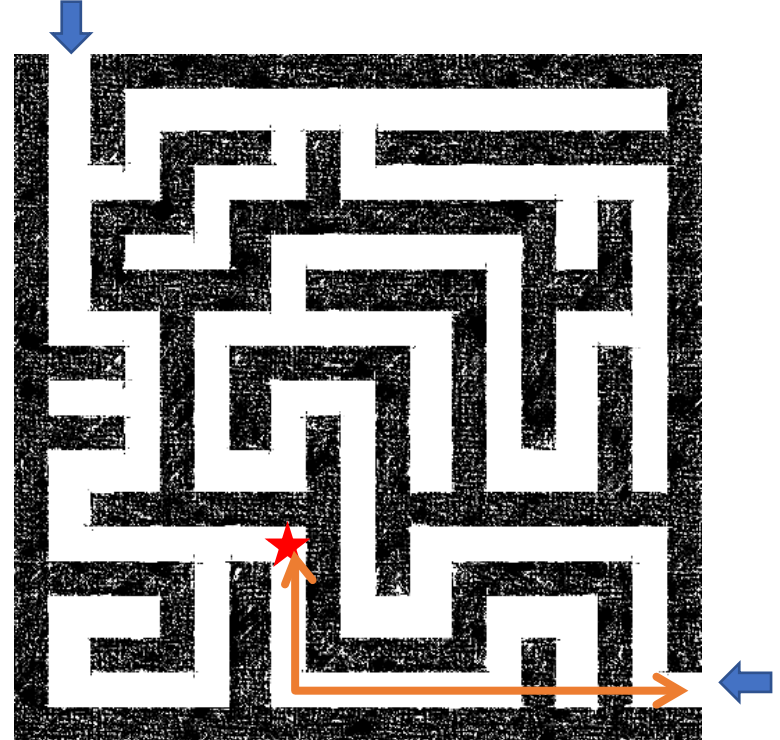
- Examples:

Euclidean distance
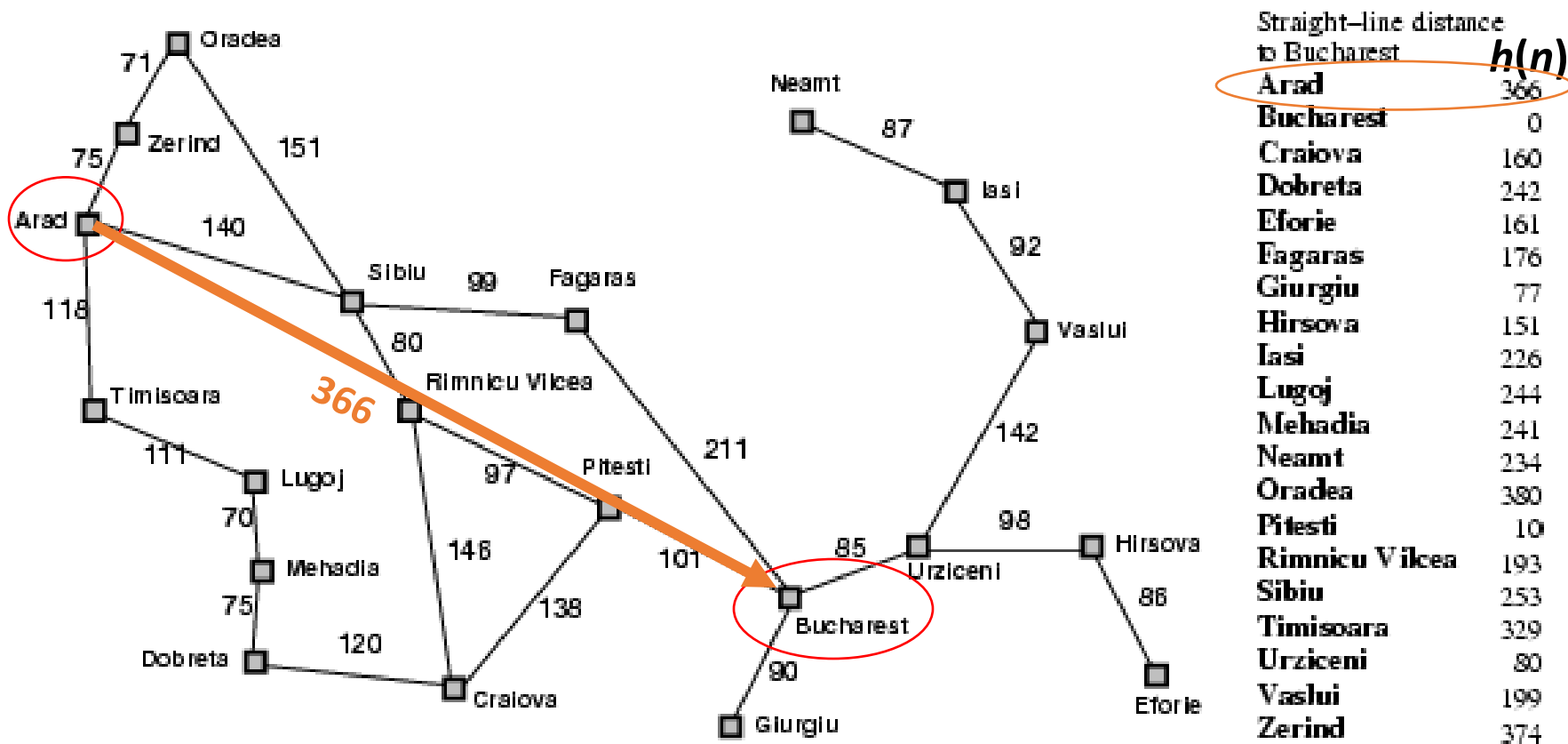
Start state

Manhattan distance

Start state

Goal state

Goal state

Heuristic for the Romania Problem

Estimate the driving distance from Arad to Bucharest using a straight-line distance.

Straight–line distance to Bucharest	$h(n)$
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

Greedy Best-First Search Example
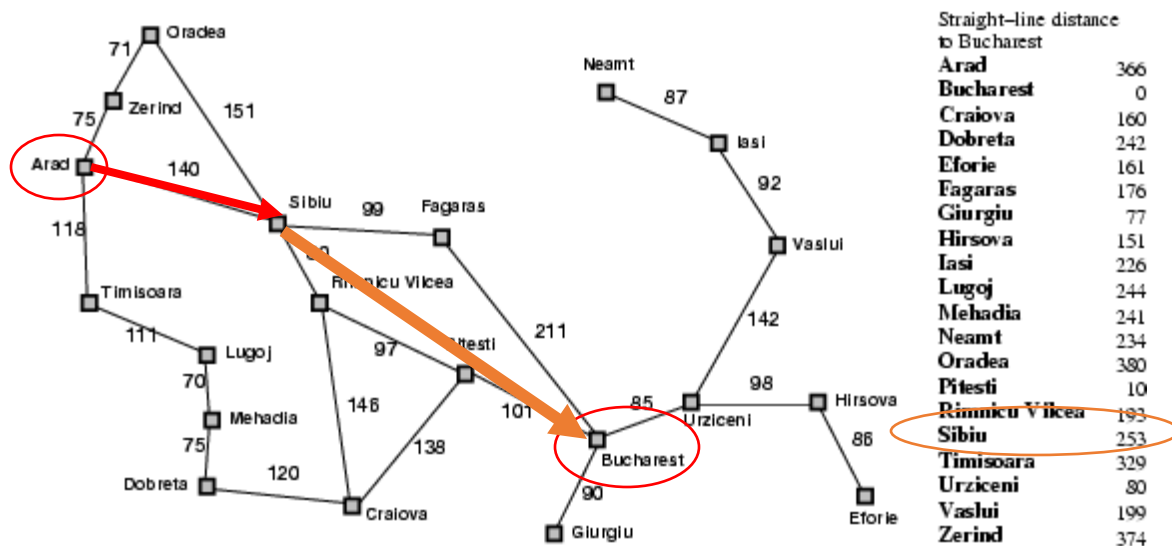
Expansion rule: Expand the node that has the lowest value of the heuristic function *h*(*n*)

$h(n)= 366$
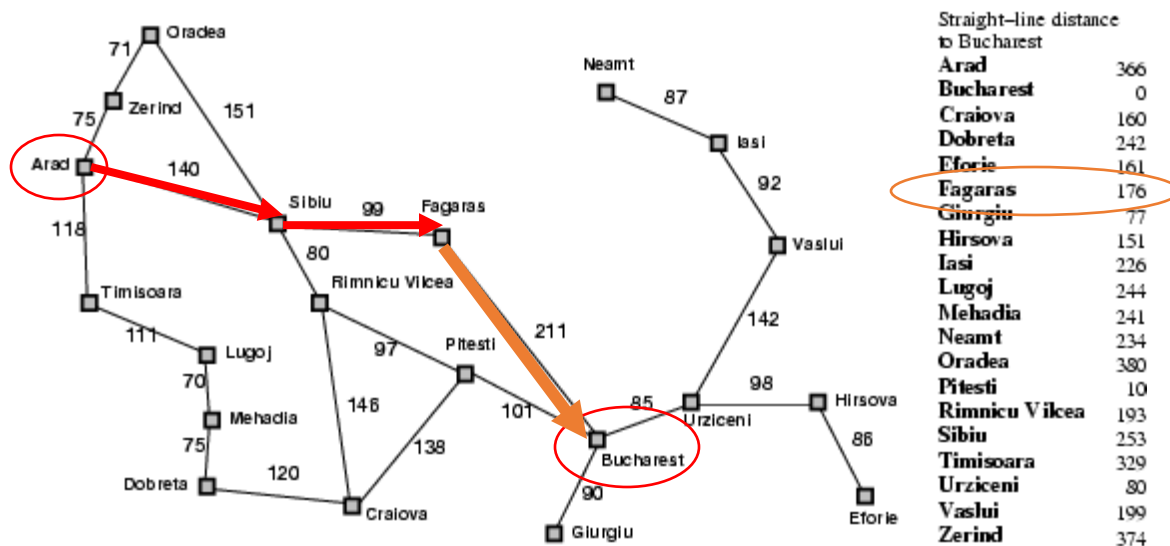

Straight–line distance to Bucharest	
Arad	366
Bucharest	0
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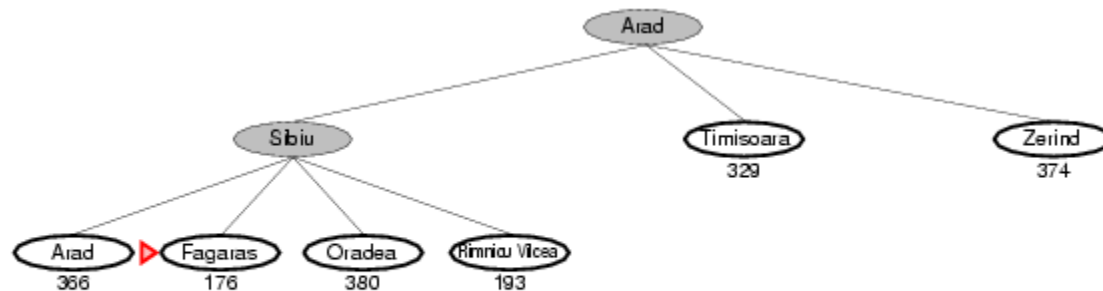
Greedy Best-First Search Example

Greedy Best-First Search Example

Greedy Best-First Search Example
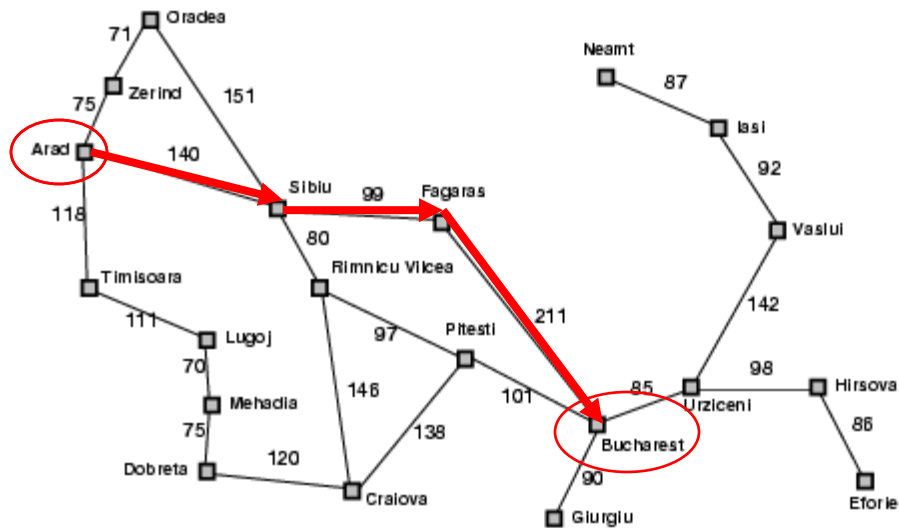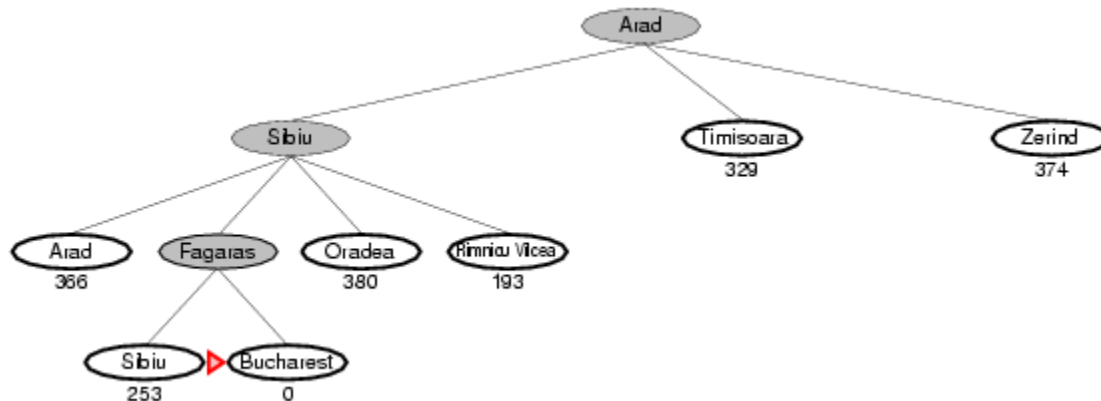
Total:
140 + 99 + 211 = 450 miles

Properties of Greedy Best-First Search

- **Complete?**
  Yes – Best-first search if complete in finite spaces.

- **Optimal?**
  No

Total:
  140 + 99 + 211 = 450 miles

Alternative through Rimnicu Vilcea:
  140 + 80 + 97 + 101 = 418 miles

Straight–line distance to Bucharest	
Arad	366
Bucharest	0
Craiova	160
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Fagaras	176
Giurgiu	77
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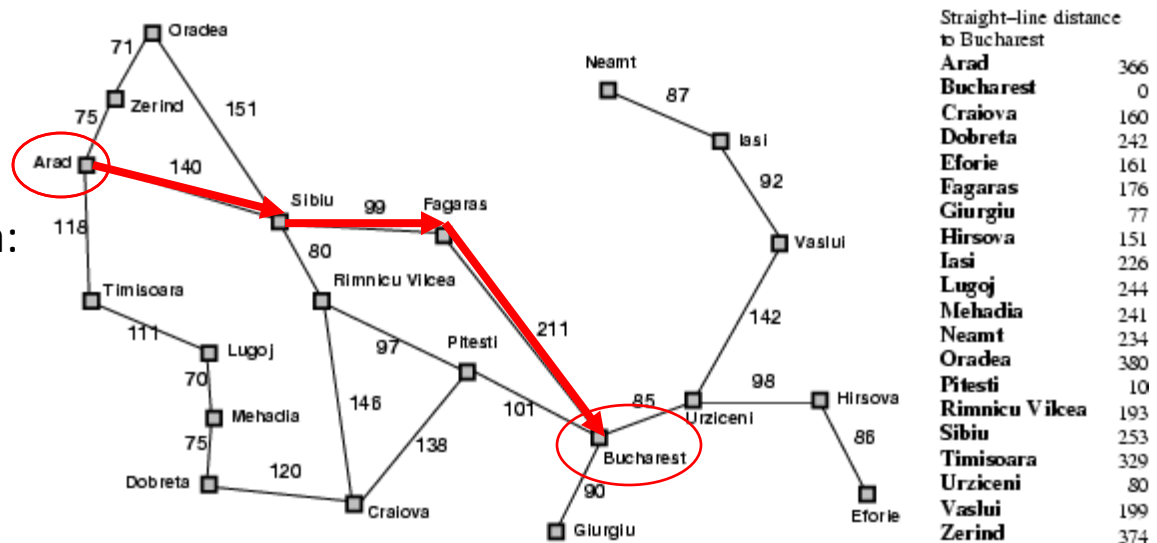
Implementation of Greedy Best-First search
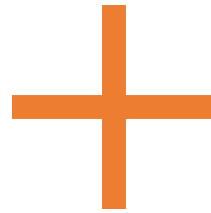
Best-First Search $+$ Expand the frontier using $f(n) = h(n)$

Implementation of Greedy Best-First Search

Heuristic $h(n)$ so we expand the node with the lowest estimated cost

function BEST-FIRST-SEARCH(*problem*, *f*) **returns** a solution node or *failure*
    node ← NODE(STATE=*problem*.INITIAL)
    frontier ← a priority queue ordered by *f*, with *node* as an element
    reached ← a lookup table, with one entry with key *problem*.INITIAL and value *node*
    while not IS-EMPTY(*frontier*) **do**
        node ← POP(*frontier*)
        if *problem*.IS-GOAL(*node*.STATE) **then return** *node*
        for each *child* **in** EXPAND(*problem*, *node*) **do**
            s ← *child*.STATE
            if *s* is not in *reached* **or** *child*.PATH-COST < *reached*[*s*].PATH-COST **then**
                reached[*s*] ← *child*
                add *child* to *frontier*
    return *failure*

The order for expanding the frontier is determined by *f(n)*

This check is the different to BFS! It visits a node again if it can be reached by a better (cheaper) path.

See BFS for function EXPAND.

Properties of Greedy Best-First Search

- **Complete?**
  Yes – Best-first search if complete in finite spaces.

- **Optimal?**
  No

- **Time?**
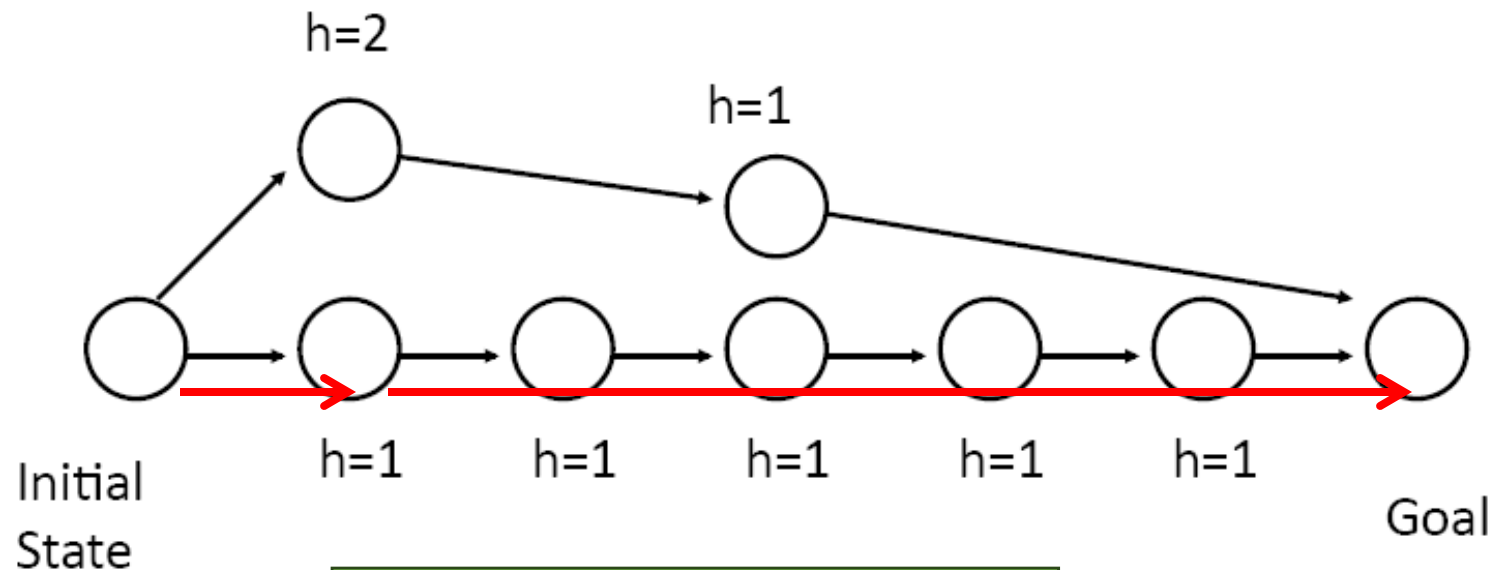 Worst case: $O(b^m) \Leftrightarrow$ like DFS
  Best case: $O(bm)$ – If $h(n)$ is 100% accurate we only expand a single path.

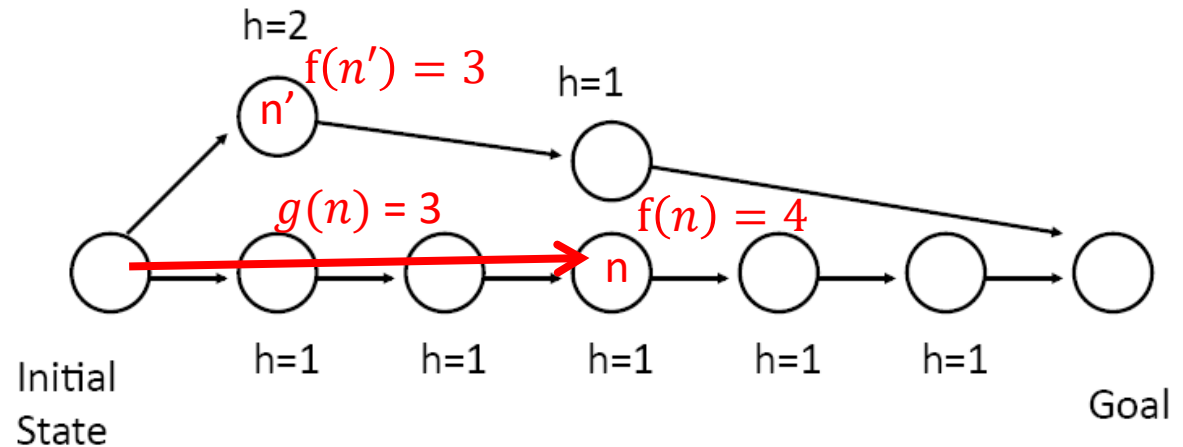- **Space?**
  Same as time complexity.

The Optimality Problem of Greedy Best-First search

Greedy best-first search only considers the estimated cost to the goal.

$h = 1$ is always better than $h = 2$. Greedy best-first will go this way and never reconsider!

A* Search

- **Idea**: Take the cost of the path to n called $g(n)$ into account to avoid expanding paths that are already very expensive.

- The evaluation function $f(n)$ is the estimated total cost of the path through node n to the goal:

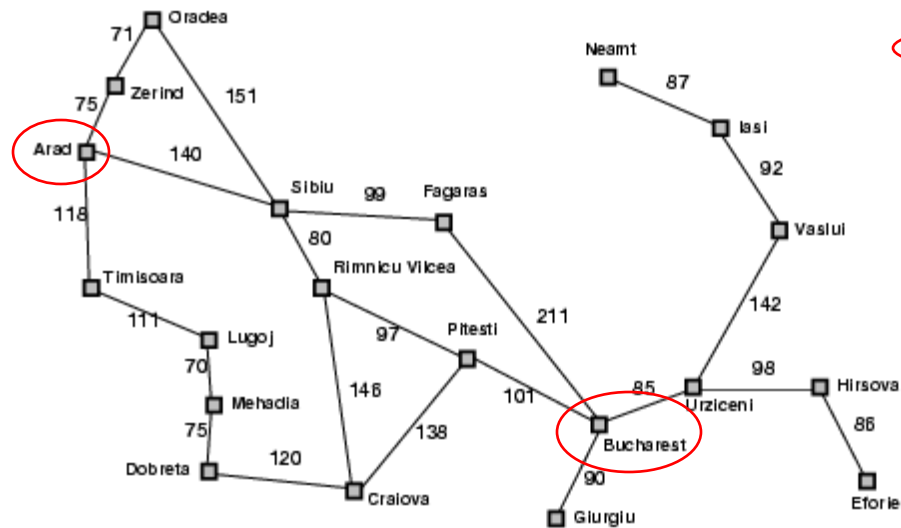$$f(n) = g(n) + h(n)$$

$g(n)$: cost so far to reach n (path cost)

$h(n)$: estimated cost from n to goal (heuristic)

- The agent in the example above will stop at n with $f(n) = 3 + 1 = 4$ and chose the path up with a better $f(n') = 1 + 2 = 3$.

Note: For greedy best-first search we just used $f(n) = h(n)$.

A* Search Example

Expansion rule: $f(n) = g(n) + h(n) =$

Arad
366=0+366

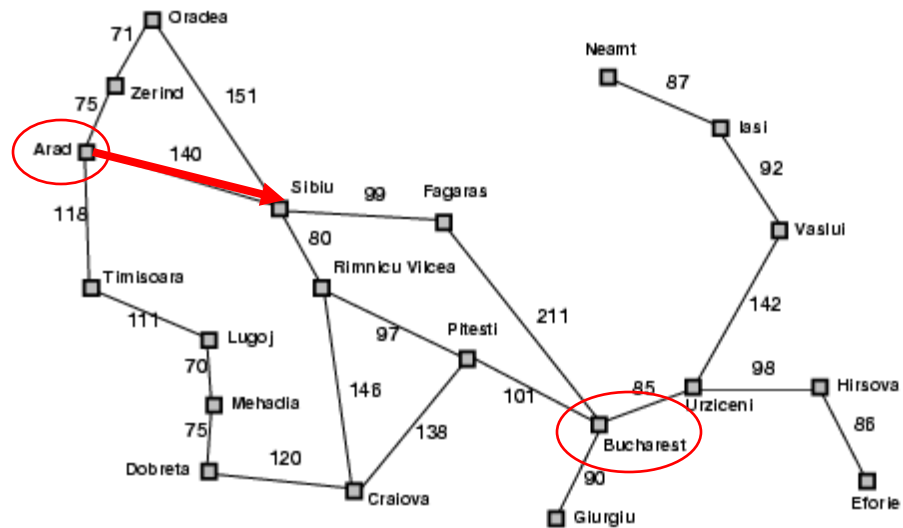**Expand the node with the smallest f(n)**

$h(n)$

Straight–line distance to Bucharest	
Arad	366
Bucharest	0
Craiova	160
Dobreta	242
Eforie	161
Fagaras	176
Giurgiu	77
Hirsova	151
Iasi	226
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Timisoara	329
Urziceni	80
Vaslui	199
Zerind	374

A* Search Example

$$f(n) = g(n) + h(n)$$

$h(n)$

A* Search Example

$$f(n) = g(n) + h(n)$$

$h(n)$

Straight-line distance to Bucharest

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A* Search Example

$$f(n) = g(n) + h(n)$$

$h(n)$

Straight–line distance to Bucharest

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A* Search Example

$$f(n) = g(n) + h(n)$$

$h(n)$

Straight-line distance to Bucharest

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A* Search Example

$$f(n) = g(n) + h(n)$$

BFS vs. A* Search

BFS

A*

A*

Source: Wikipedia

Implementation of A* Search

Path cost to n + heuristic from n to goal = estimate of the total cost
$$g(n) + h(n)$$

function BEST-FIRST-SEARCH(*problem*, *f*) **returns** a solution node or *failure*
   node ← NODE(STATE=*problem*.INITIAL)
   frontier ← a priority queue ordered by *f*, with *node* as an element
   reached ← a lookup table, with one entry with key *problem*.INITIAL and value *node*
   while not IS-EMPTY(*frontier*) **do**
      node ← POP(*frontier*)
      if *problem*.IS-GOAL(*node*.STATE) **then return** *node*
      for each *child* **in** EXPAND(*problem*, *node*) **do**
         s ← *child*.STATE
         if *s* is not in *reached* **or** *child*.PATH-COST < *reached*[*s*].PATH-COST **then**
            reached[*s*] ← *child*
            add *child* to *frontier*
   return *failure*

See BFS for function EXPAND.

> The order for expanding the frontier is determined by $f(n)$

> This check is different to BFS! It visits a node again if it can be reached by a better (cheaper) redundant path.

Optimality: Admissible Heuristics

Definition: A heuristic h is **admissible** if for every node n, $h(n) \leq h^*(n)$, where $h^*(n)$ is the true cost to reach the goal state from n.

I.e., an admissible heuristic is a **lower bound** and never overestimates the true cost to reach the goal.

Example: straight line distance never overestimates the actual road distance.

Theorem: If h is admissible, A* is optimal.

Proof of Optimality of A*

$$f(n) = g(n) + h(n)$$

For goal states: $f(n^*) = g(n) + 0$

n^* (goal)

$$C^* = f(n^*) = g(n^*) + 0$$

n

Any unexplored node n has:

$$f(n) \geq f(n^*)$$

n' (other goal)

$$g(n') \geq f(n) \Leftrightarrow g(n') \geq C^*$$
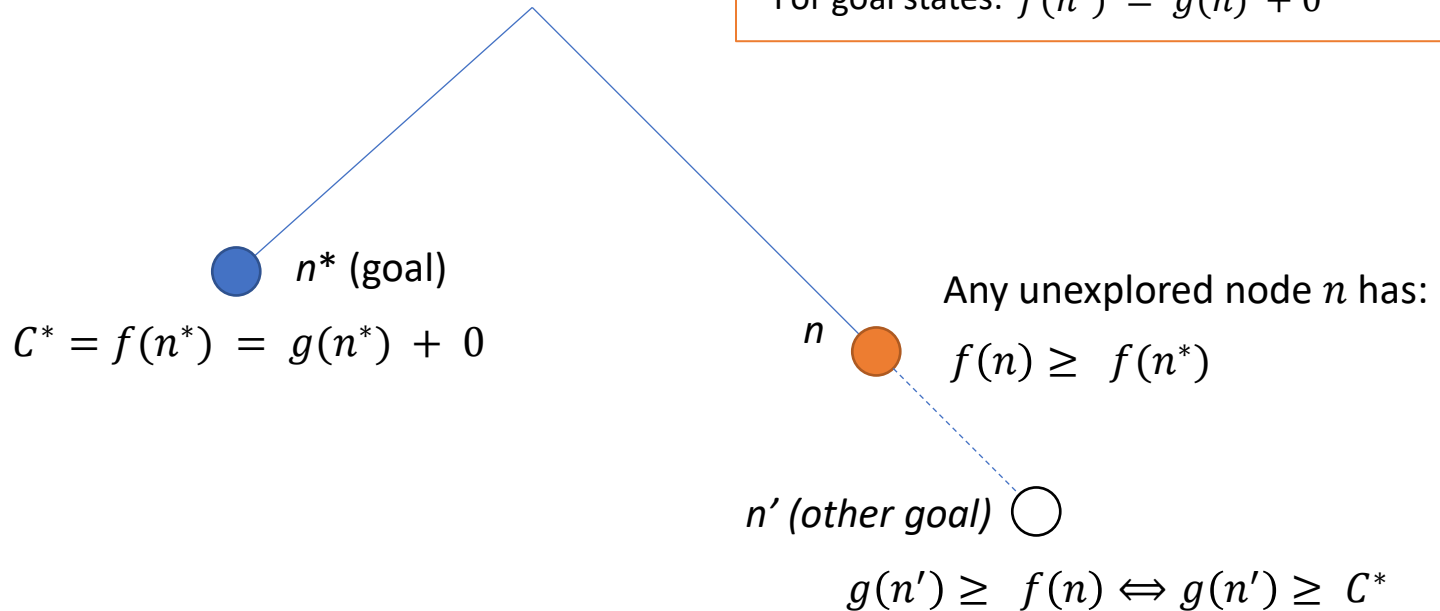
- Suppose A* terminates its search at goal n^* at a cost of $C^* = f(n^*)$.

- All unexplored nodes n have $f(n) \geq f(n^*)$ or they would have been explored before n^*.

- Since $f(n)$ is an *optimistic* estimate, it is impossible for n to have a successor goal state n' with $C' < C^*$.

- This proofs that n^* must be an optimal solution.

Guarantees of A*

A* is **optimally efficient**

    a.   No other tree-based search algorithm that uses the same heuristic can expand fewer nodes and still be guaranteed to find the optimal solution.

    b.   Any algorithm that does not expand all nodes with $f(n) < C^*$ (the lowest cost of going to a goal node) cannot be optimal. It risks missing the optimal solution.

Properties of A*

- **Complete?**
  Yes

- **Optimal?**
  Yes

- **Time?**
  Number of nodes for which $f(n) \leq C^*$ (exponential)

- **Space?**
  Same as time complexity. This is often too much unless a very good heuristic is know.

Designing Heuristic Functions

Heuristics for the 8-puzzle

$h_1(n)$ = number of misplaced tiles

$h_2(n)$ = total Manhattan distance (number of squares from desired location of each tile)

Start State   **Goal State**

$$h_1(start) = 8$$
$$h_2(start) = 3 + 1 + 2 + 2 + 2 + 3 + 3 + 2 = 18$$

Are h_1 and h_2 admissible?

1 needs to move 3 positions

Heuristics from 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. I.e., the true cost is never smaller.**

- What relaxation is used by h_1 and h_2?
  - h_1: If the rules of the 8-puzzle are relaxed so that a tile can move anywhere, then $h_1(n)$ gives the shortest solution.
  - h_2: If the rules are relaxed so that a tile can move to any adjacent square, then $h_2(n)$ gives the shortest solution.

Start State

Goal State

$h_1(start) = 8$

$h_2(start)$
$= 3 + 1 + 2 + 2 + 2 + 3 + 3 + 2$
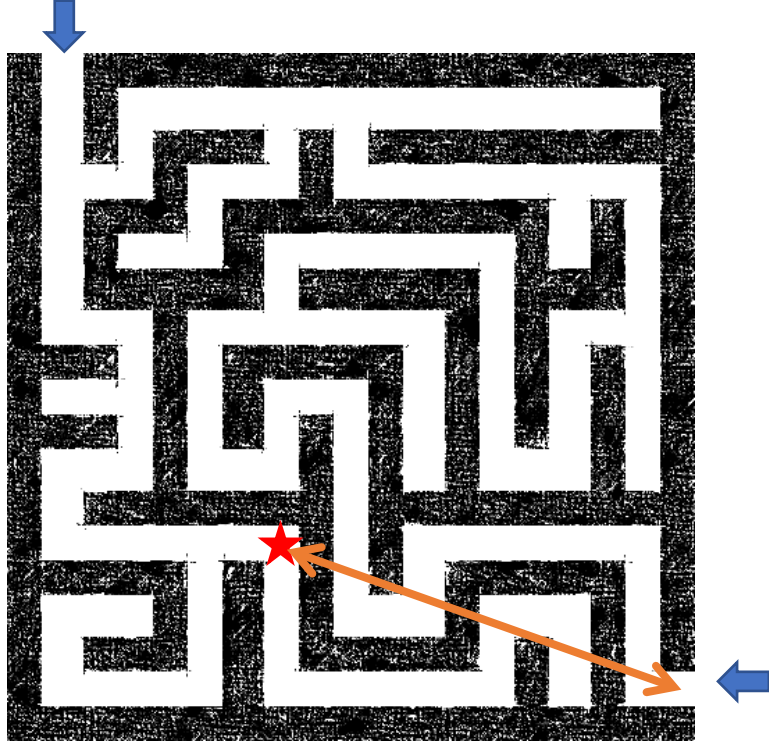$= 18$

Heuristics from Relaxed Problems

What relaxations are used in these two cases?

Euclidean distance

Start state

Manhattan distance

Start state
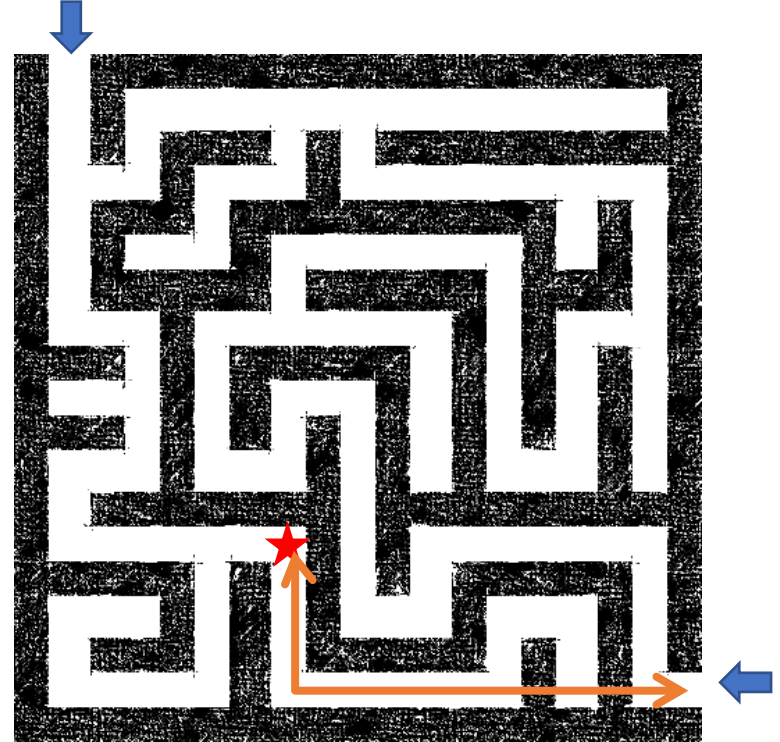
Goal state

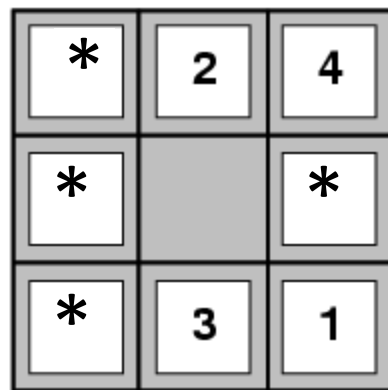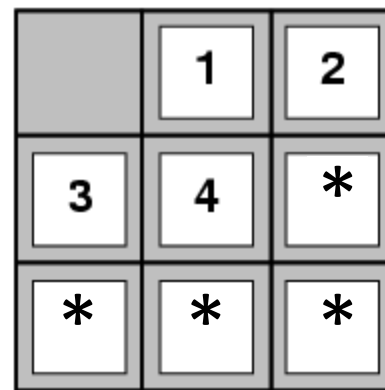Goal state

Heuristics from Subproblems

- Let $h_3(n)$ be the cost of getting a subset of tiles (say, 1,2,3,4) into their correct positions. The final order of the * tiles does not matter.

- Small subproblems are often easy to solve.

- Can precompute and save the exact solution cost for every or many possible subproblem instances – ***pattern database***.

Start State   Goal State

Dominance: What Heuristic is Better?

Definition: If h_1 and h_2 are both admissible heuristics and $h_2(n) \geq h_1(n)$ for all n, then h_2 dominates h_1

Is h_1 or h_2 better for A* search?
- A* search expands every node with
  $$f(n) < C^* \Leftrightarrow h(n) < C^* - g(n)$$
- h_2 is never smaller than h_1. A* search with h_2 will expand less nodes and is therefore better.

Example: Effect of Information in Search

Typical search costs for the 8-puzzle

- Solution at depth $d = 12$
  - IDS   = 3,644,035 nodes
  - A*(h_1) = 227 nodes
  - A*(h_2) = 73 nodes

- Solution at depth $d = 24$
  - IDS   ≈ 54,000,000,000 nodes
  - A*(h_1) = 39,135 nodes
  - A*(h_2) = 1,641 nodes

Combining Heuristics

- Suppose we have a collection of admissible heuristics $h_1, h_2, \ldots, h_m$, but none of them dominates the others.

- Combining them is easy:

$$h(n) \;=\; \max\{h_1(n), h_2(n), \ldots, h_m(n)\}$$

- That is, always pick for each node the heuristic that is closest to the real cost to the goal $h^*(n)$.

Satisficing Search: Weighted A* Search

- Often it is sufficient to find a **"good enough" solution** if it can be found very quickly or with way less computational resources. I.e., expanding fewer nodes.

- We could use inadmissible heuristics in A* search (e.g., by multiplying $h(n)$ with a factor W) that sometimes overestimate the optimal cost to the goal slightly.
    1. It potentially reduces the number of expanded nodes significantly.
    2. **This will break the algorithm's optimality guaranty!**

$$\mathrm{f}(n) = g(n) + W \times h(n)$$

Weighted A* search: $\quad g(n) + W \times h(n) \quad\quad (1 < W < \infty)$

The presented algorithms are special cases:

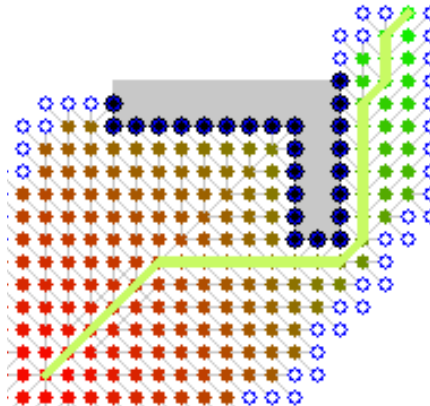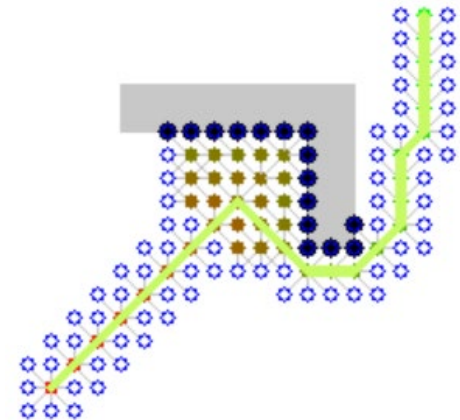|		
A* search:	$g(n) + h(n)$	$(W = 1)$
Uniform cost search/BFS:	$g(n)$	$(W = 0)$
Greedy best-first search:	$h(n)$	$(W = \infty)$

Example of Weighted A* Search

Reduction in the number of expanded nodes
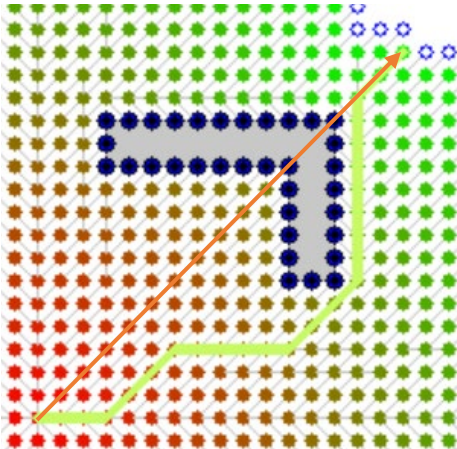
Breadth-first Search (BFS)
$f(n) = \#$ actions to reach n

Exact A* Search
$f(n) = g(n) + h_{Eucl}(n)$

Weighted A* Search
$f(n) = g(n) + 5\, h_{Eucl}(n)$

Source and Animation: Wikipedia

Implementation as Best-First Search

- All discussed search strategies can be implemented using Best-first search.
- Best-first search expands always the **node with the minimum value of an evaluation function $f(n)$.**

Search Strategy	Evaluation function $f(n)$
BFS (Breadth-first search)	$g(n)$ (=uniform path cost)
Uniform-cost Search	$g(n)$ (=path cost)
DFS/IDS (see note below!)	$-g(n)$
Greedy Best-first Search	$h(n)$
(weighted) A* Search	$g(n) + W \times h(n)$

- **Important note:** Do not implement DFS/IDS using Best-first Search! You will get the poor space complexity and the disadvantages of DFS (not optimal and worse time complexity)

Summary: Uninformed Search Strategies

Algorithm	Complete?	Optimal?	Time complexity	Space complexity
BFS (Breadth-first search)	Yes	If all step costs are equal	$O(b^d)$	$O(b^d)$
Uniform-cost Search	Yes	Yes	Number of nodes with $g(n) \leq C^*$	
DFS	In finite spaces (cycle checking)	No	$O(b^m)$	$O(bm)$
IDS	Yes	If all step costs are equal	$O(b^d)$	$O(bd)$

b: maximum branching factor of the search tree
d: depth of the optimal solution
m: maximum length of any path in the state space
C*: cost of optimal solution

Summary: All Search Strategies

| Algorithm	Complete?	Optimal?	Time complexity	Space complexity
BFS (Breadth-first search)	Yes	If all step costs are equal	$O(b^d)$	$O(b^d)$
Uniform-cost Search	Yes	Yes	Number of nodes with $g(n) \leq C^*$	
DFS	In finite spaces (cycles checking)	No	$O(b^m)$	$O(bm)$
IDS	Yes	If all step costs are equal	$O(b^d)$	$O(bd)$
Greedy best-first Search	In finite spaces (cycles checking)	No	Depends on heuristic	Worst case: $O(b^m)$ Best case: $O(bd)$
A* Search	Yes	Yes	Number of nodes with $g(n) + h(n) \leq C^*$	

Planning vs. Execution Phase

1. Planning is done by **a goal-based agent** using search. The result is a **plan**.
2. The plan can be executed by a **model-based reflex agent**.

Planning Agent
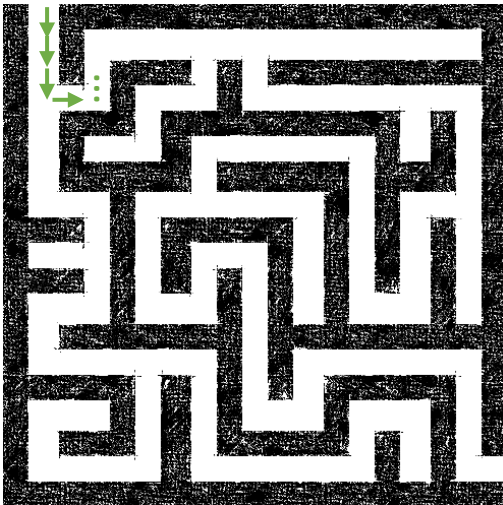
Execution Agent at step 2 in the plan
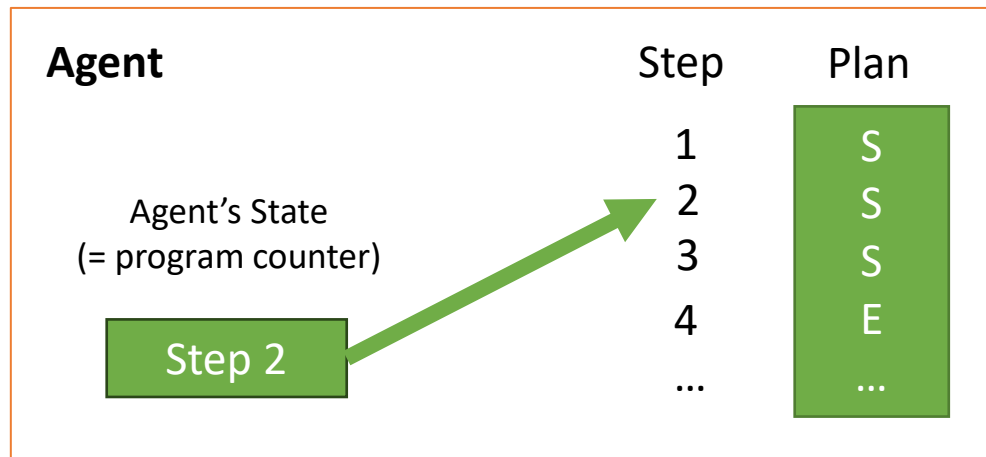
Note: The agent does not use percepts or the transition function. It blindly follows the plan.
Caution: This only works in an environment with **deterministic transitions**.

Conclusion

- Tree search can be used for planning actions for **goal-based agents** in known, fully observable and deterministic environments.

- Issues are:
  - The large search space typically does not fit into memory. We use a transition function as a compact description of the **transition model.**
  - The search tree is built on the fly, and we have to deal with **cycles, redundant paths, and memory management**.

- IDS is a memory efficient method used often in AI for **uninformed search**.

- **Informed search** uses heuristics based on knowledge or percepts to improve search performance (i.e., A* expand fewer nodes than BFS).