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*INF5390 – Kunstig intelligens*

# **Solving Problems by Searching**

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# Outline

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- Problem-solving agents
- Example problems
- Search programs
- Uninformed search
- Informed search
- Summary

AIMA Chapter 3: Solving Problems by Searching

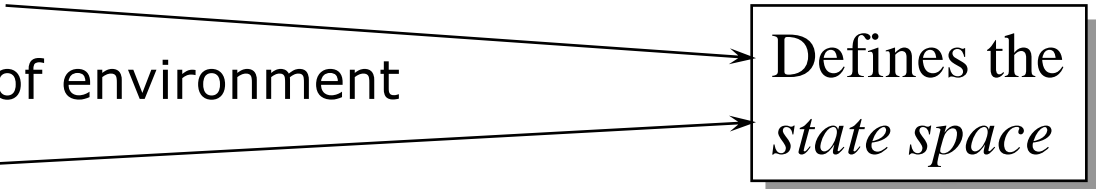
# Problem-solving agents

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- Goal-based agents know their goals and the effect of their actions
- How do such agents determine the sequence of actions that lead to the goal?
- *Problem-solving agents* are goal-based agents that use *search* to find action sequences
- The agent must formulate the search problem in terms of goals and actions before solving it

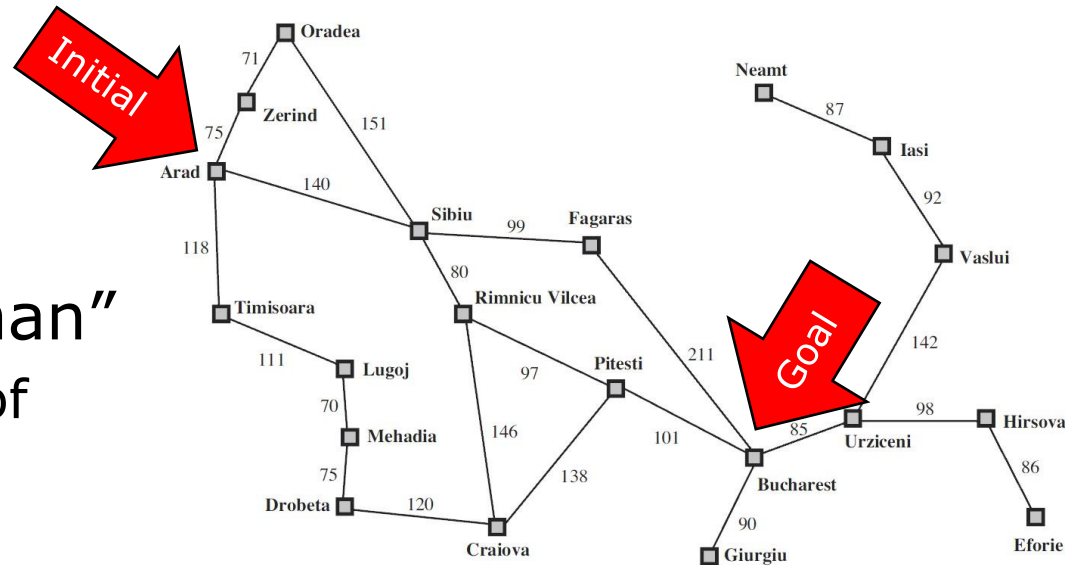
# Formulation of a search problem

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- Initial state
    - ✓ Initial state of environment
  - Actions
    - ✓ Set of actions available to agent
  - Path
    - ✓ Sequence of actions leading from one state to another
  - Goal test
    - ✓ Test to check if a state is a goal state
  - Path cost
    - ✓ Function that assigns cost to a path
  - Solution
    - ✓ Path from initial state to a state that satisfies goal test
- 
- The diagram shows two arrows originating from the 'Initial state' and 'Actions' bullet points, respectively, and pointing towards a rectangular box on the right. The box contains the text 'Defines the state space' in a serif font, with 'state space' in italics. The box has a thin black border and a light gray drop shadow.

# Some real-world problems

- Route finding
  - ✓ E.g. airline or car travel planning
- “Traveling salesman”
  - ✓ E.g. movements of circuit board drills
- Robot navigation
  - ✓ Route finding in continuous space
- Automatic assembly sequencing
  - ✓ Synthesizing assembly operation sequences



# Simple problem-solving agent

```
function SIMPLE-PROBLEM-SOLVING-AGENT(percept) returns an action
persistent: seq, an action sequence, initially empty; state, some description of the
  current world state; goal, a goal, initially null; problem, a problem formulation
state <= UPDATE-STATE(state, percept)
if seq is empty then
  goal <= FORMULATE-GOAL(state)
  problem <= FORMULATE-PROBLEM(state, goal)
  seq <= SEARCH(problem)
  if seq = failure then return a null action
action <= FIRST(seq)
seq <= REST(seq)
return action
```

# Implied environment properties

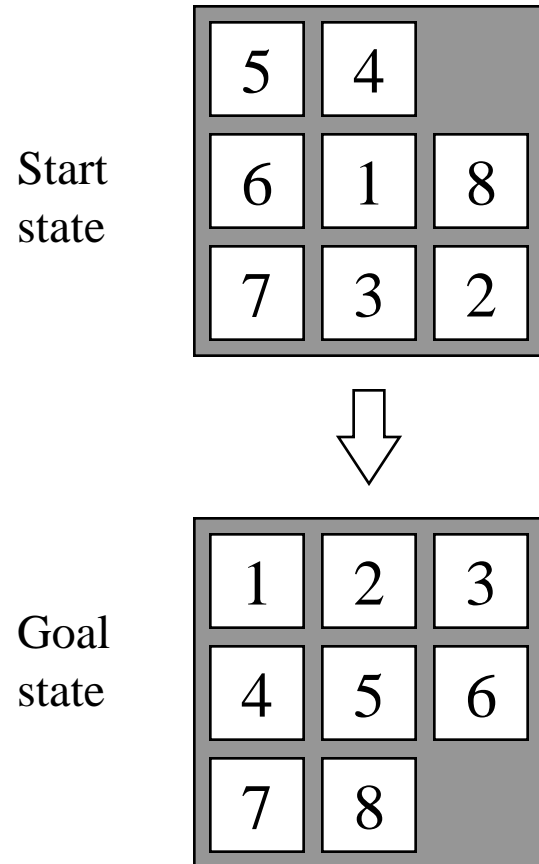
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- Fully observable
  - ✓ Agent has full knowledge
- Deterministic
  - ✓ No surprises
- Static
  - ✓ No changes under deliberation
- Discrete
  - ✓ Discrete alternative actions

Simplest  
possible  
environment  
type!

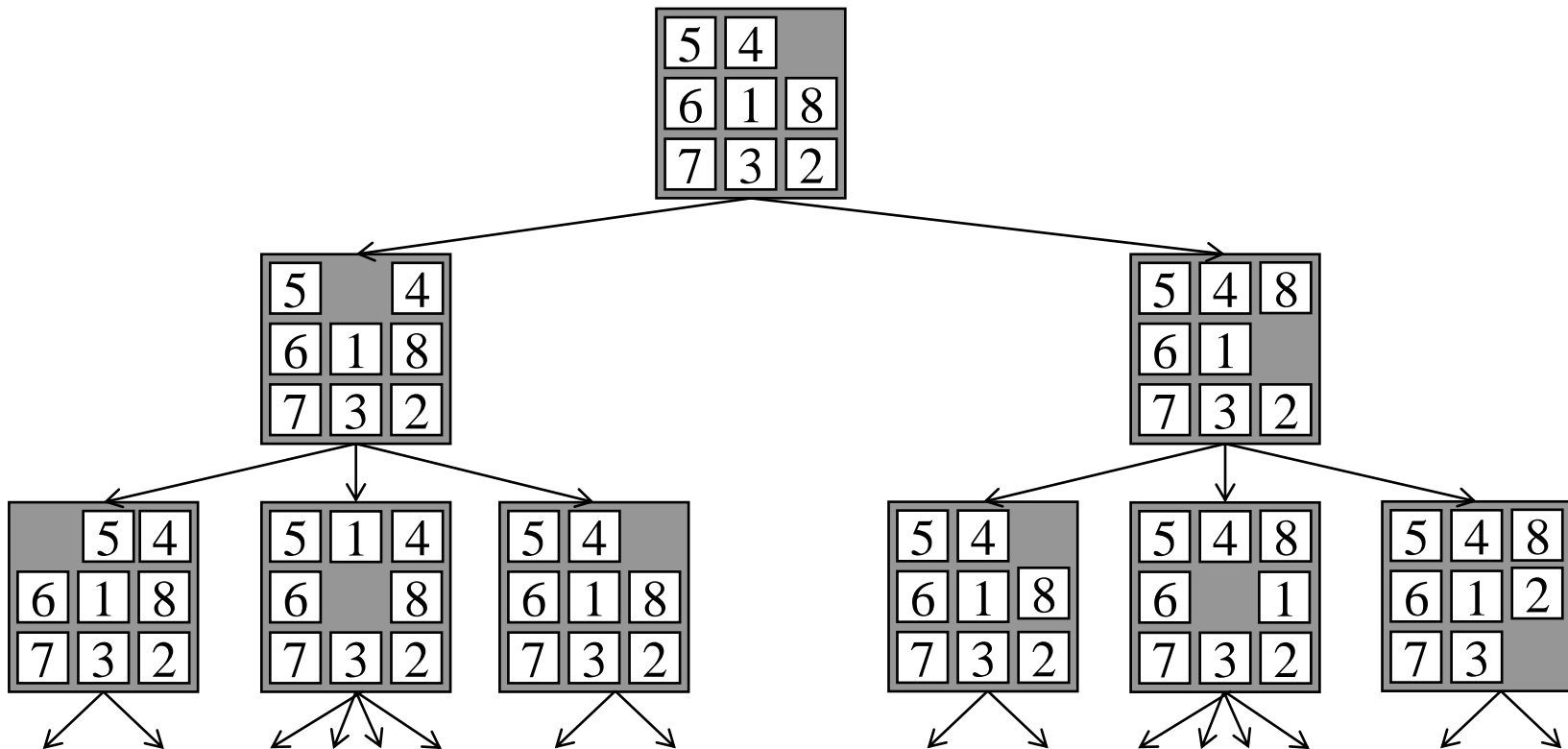
# Example toy problem: 8-puzzle

- States
  - ✓ Location of each tile
- Operators
  - ✓ Blank moves left, right, up, down
- Goal test
  - ✓ State matches goal configuration
- Path cost
  - ✓ Number of moves



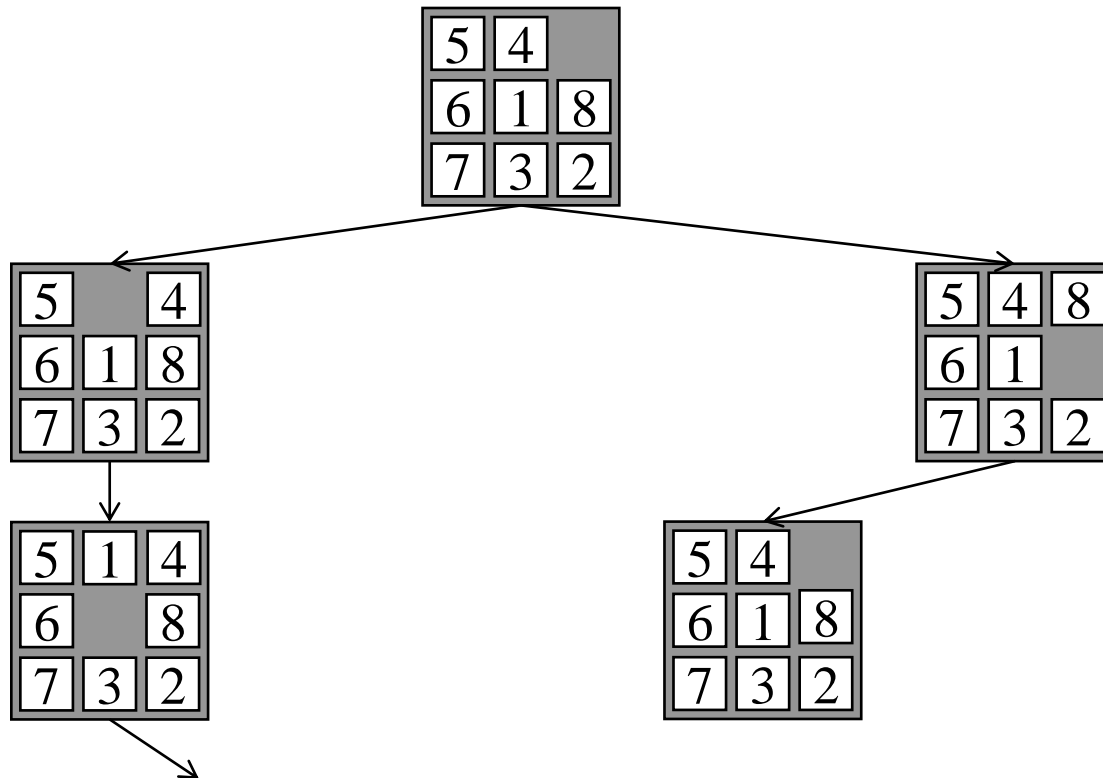


# Expanding a search tree fully ...



... or partially or in different order

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Search tree  $\neq$  State space!

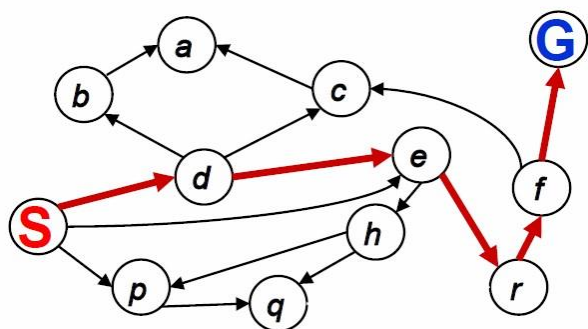
# Searching for solutions

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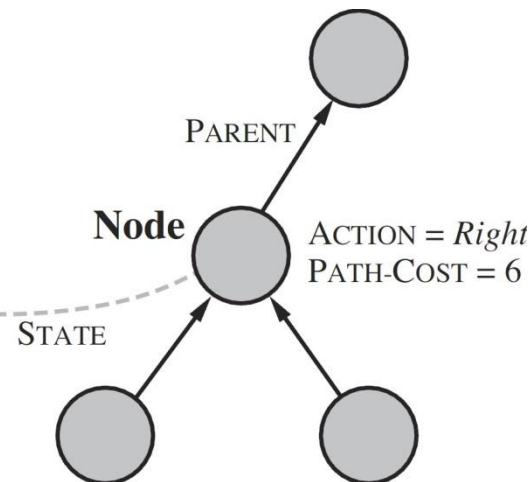
- The search starts in an *initial state*
- Thereafter, it iteratively explores the state space by selecting a state node and applying operators to generate *successor nodes*
- The choice of which node to expand at each level is determined by the *search strategy*
- The part of the state space that is explored is called the *search tree*

# State space vs. search tree

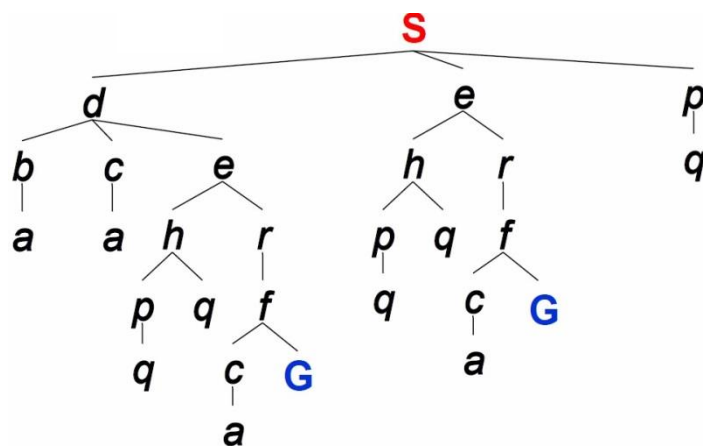
## State space



5	4	
6	1	8
7	3	2



## Search tree



Node in a search tree points to a state in state space

# Tree search vs. graph search

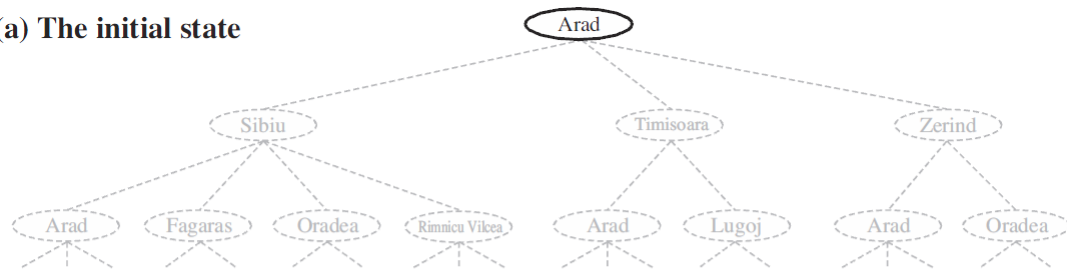
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- The state space may contain *loops* (path back to earlier state) or *redundant paths* (more than one path between two states)
- Simple tree expansion will run infinitely or “explode” in such search spaces
- To avoid the problem, tree search can be replaced by generalized *graph search*
- In graph search, the algorithm keeps track and avoids expanding *already visited nodes*
- In the lecture, we will only study tree search

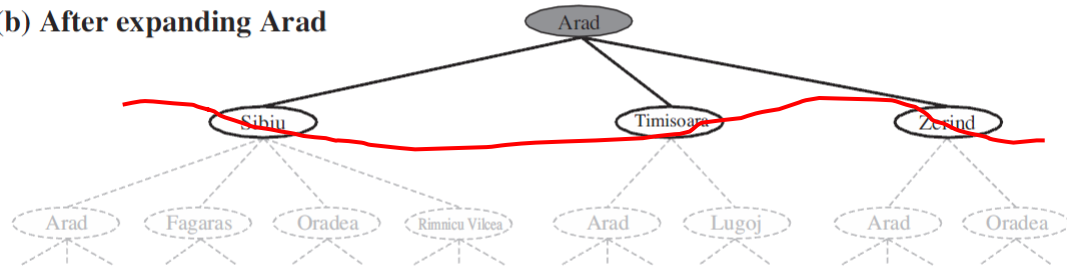
# Tree search – General idea

- Start in initial state
- Expand possible nodes
- Keep a **frontier** of unexpanded nodes
- Select next node to expand according to strategy
- Continue until goal (or give up)

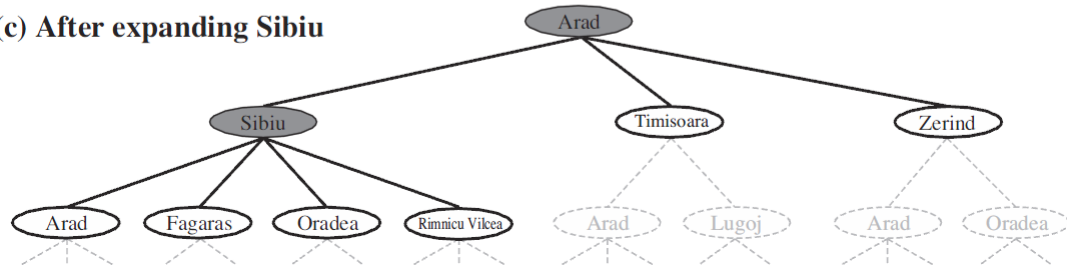
(a) The initial state



(b) After expanding Arad



(c) After expanding Sibiu



# Uninformed search strategies

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- Uninformed
  - ✓ No information on path cost from current to goal states
- Six uninformed strategies
  - ✓ Breadth-first
  - ✓ Uniform-cost
  - ✓ Depth-first
  - ✓ Depth-limited
  - ✓ Iterative deepening
  - ✓ Bidirectional
- Differ by *order* in which nodes are expanded

# Evaluation of search strategies

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- **Completeness**
  - ✓ Guaranteed to find a solution when there is one?
- **Optimality**
  - ✓ Finds the best solution when there are several different possible solutions?
- **Time complexity**
  - ✓ How long does it take to find a solution?
- **Space complexity**
  - ✓ How much memory is needed?



# Data structures for search trees

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- Datatype *node* with components:
  - ✓ STATE - search space state corresponding to the node
  - ✓ PARENT-NODE - node that generated this node
  - ✓ ACTION - action that was applied to generate this node
  - ✓ PATH-COST - cost of path from initial node (called  $g$ )
  - ✓ DEPTH - number of nodes on path from initial node
- Search tree nodes kept in a *queue* with operators:
  - ✓ MAKE-QUEUE(*Elements*) - create queue with given elements
  - ✓ EMPTY?(*Queue*) - true if no more elements in queue
  - ✓ FIRST(*Queue*) - returns first element of the queue
  - ✓ REMOVE-FIRST(*Queue*) - removes and returns first element
  - ✓ INSERT(*Element*, *Queue*) - inserts an element into queue
  - ✓ INSERT-ALL(*Elements*, *Queue*) - inserts set of elements into queue

# General tree-search algorithm

```
function TREE-SEARCH(problem, frontier) returns a solution, or failure
frontier <= INSERT(MAKE-NODE(problem.INITIAL-STATE), frontier)
loop do
  if EMPTY?(frontier) then return failure
  node <= REMOVE-FIRST(frontier)
  if problem.GOAL-TEST applied to node.STATE succeeds
  then return SOLUTION(node)
  frontier <= INSERT-ALL(EXPAND(node,problem), frontier)

function EXPAND(node, problem) returns a set of nodes
```

-*frontier* is an initially empty queue of a certain type (FIFO, etc.)

-SOLUTION returns sequence of actions back to root

-EXPAND generates all successors of a node

# Breadth-first search

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```
function BREADTH-FIRST-SEARCH(problem)
```

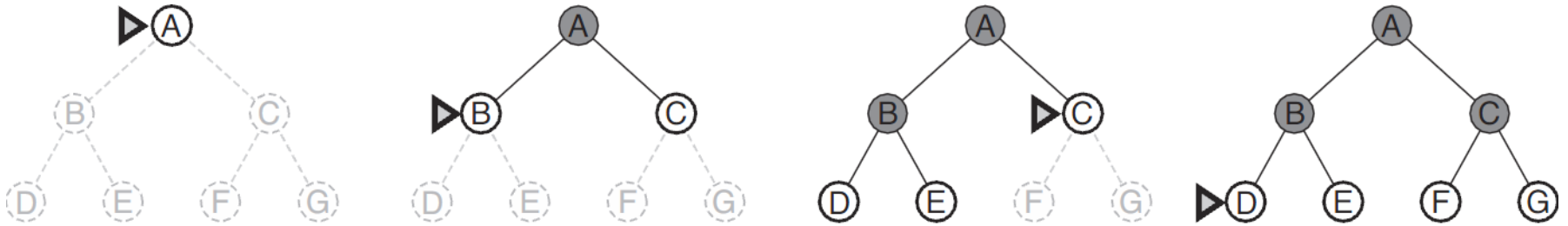
```
    returns a solution or failure
```

```
    return TREE-SEARCH(problem, FIFO-QUEUE())
```

- FIFO – First In First Out (add nodes as last)
- Expands all nodes at a certain depth of search tree before expanding any node at next depth
- Exhaustive method - if there is a solution, breadth-first will find it (completeness)
- Will find the shortest solution first (optimal)

# Breadth-first search illustrated

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- All nodes on one level are explored before moving to next level

# Complexity of breadth-first search

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- Branching factor ( $b$ ) - number of successors of each node (average)
- If solution is found at depth  $d$ , then max. number of nodes expanded is
$$1 + b + b^2 + b^3 + \dots + b^d$$
- Exponential complexity ( $O(b^d)$ )
  - ✓ For  $b=10$ , 1000 nodes/sec, 100 bytes/node problem, time/memory increases from 1ms/100 bytes at depth 0 to 35 years/10 petabytes at depth 12 ( $10^{13}$  nodes)
- In general, we wish to avoid exponential search

# Uniform-cost search

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- Breadth-first is optimal because it always expands the *shallowest* unexpanded node
- Uniform-cost search expands the node  $n$  with *lowest path cost*  $g(n)$
- This is done by storing the frontier as a priority queue ordered by  $g$
- Uniform-cost search is optimal since it always expands the node with the lowest cost so far
- Completeness is guaranteed if all path costs  $> 0$

# Depth-first search

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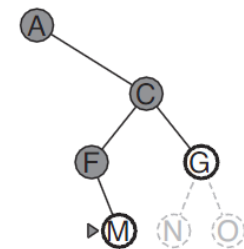
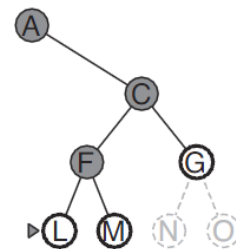
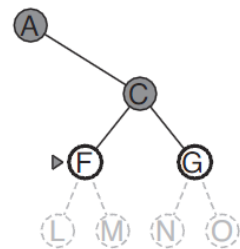
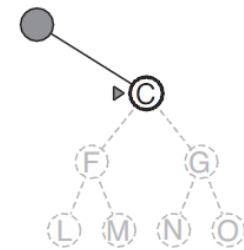
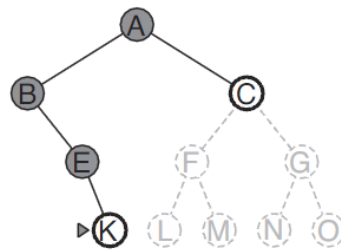
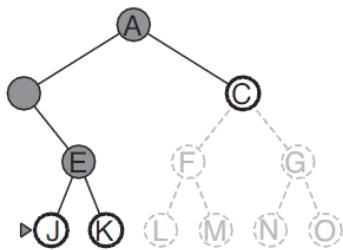
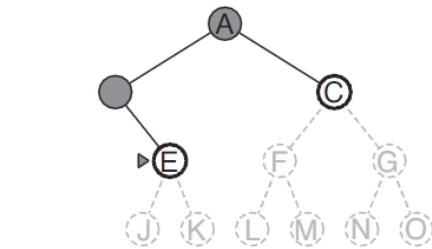
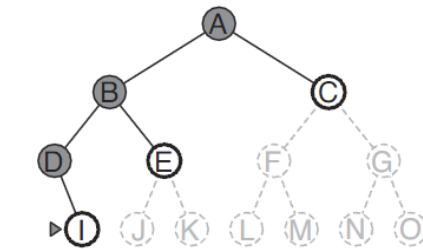
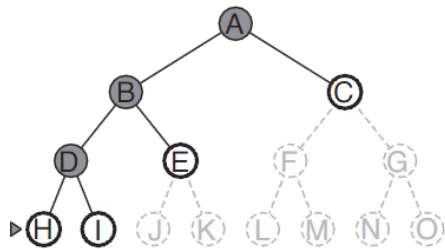
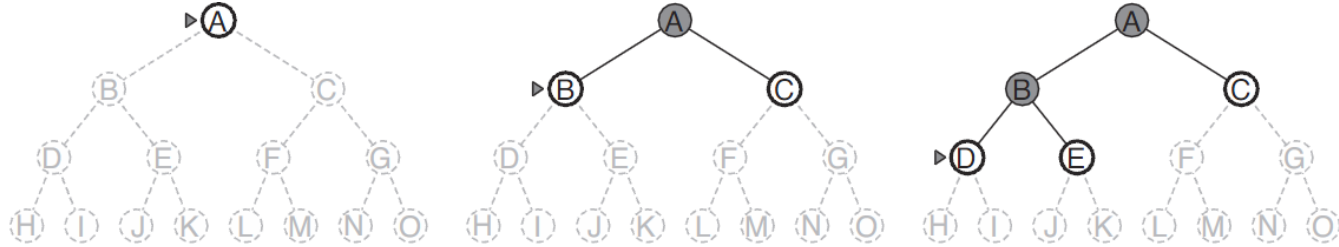
```
function DEPTH-FIRST-SEARCH(problem)
```

```
    returns a solution or failure
```

```
    return TREE-SEARCH(problem, LIFO-QUEUE())
```

- LIFO – Last In First Out (add nodes as first)
- Always expands a node at deepest level of the tree, backtracks if it finds node with no successor
- May never terminate if it goes down an infinite branch, even if there is a solution (not complete)
- May return an early found solution even if a better one exists (not optimal)

# Depth-first search illustrated





# Complexity of depth-first search

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- Depth-first has very low memory requirements, only needs to store one path from the root
- With branching factor  $b$  and depth  $m$ , space requirement is only  $bm$ .
  - ✓ For  $b=10$ , 100 bytes/node problem, memory increases from 100 bytes at depth 0 to 12 Kilobytes at depth 12
- Worst case time complexity is  $O(b^m)$ , but depth-first may find solution much quicker if there are many solutions ( $m$  may be much larger than  $d$  – the depth of the shallowest solution)

# Depth-limited search

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- Modifies depth-first search by imposing a cutoff on the maximum depth of a path
- Avoids risk of non-terminating search down an infinite path
- Finds a solution if it exists within cutoff limit (not generally complete)
- Not guaranteed to find shortest solution (not optimal)
- Time and space complexity as for depth-first

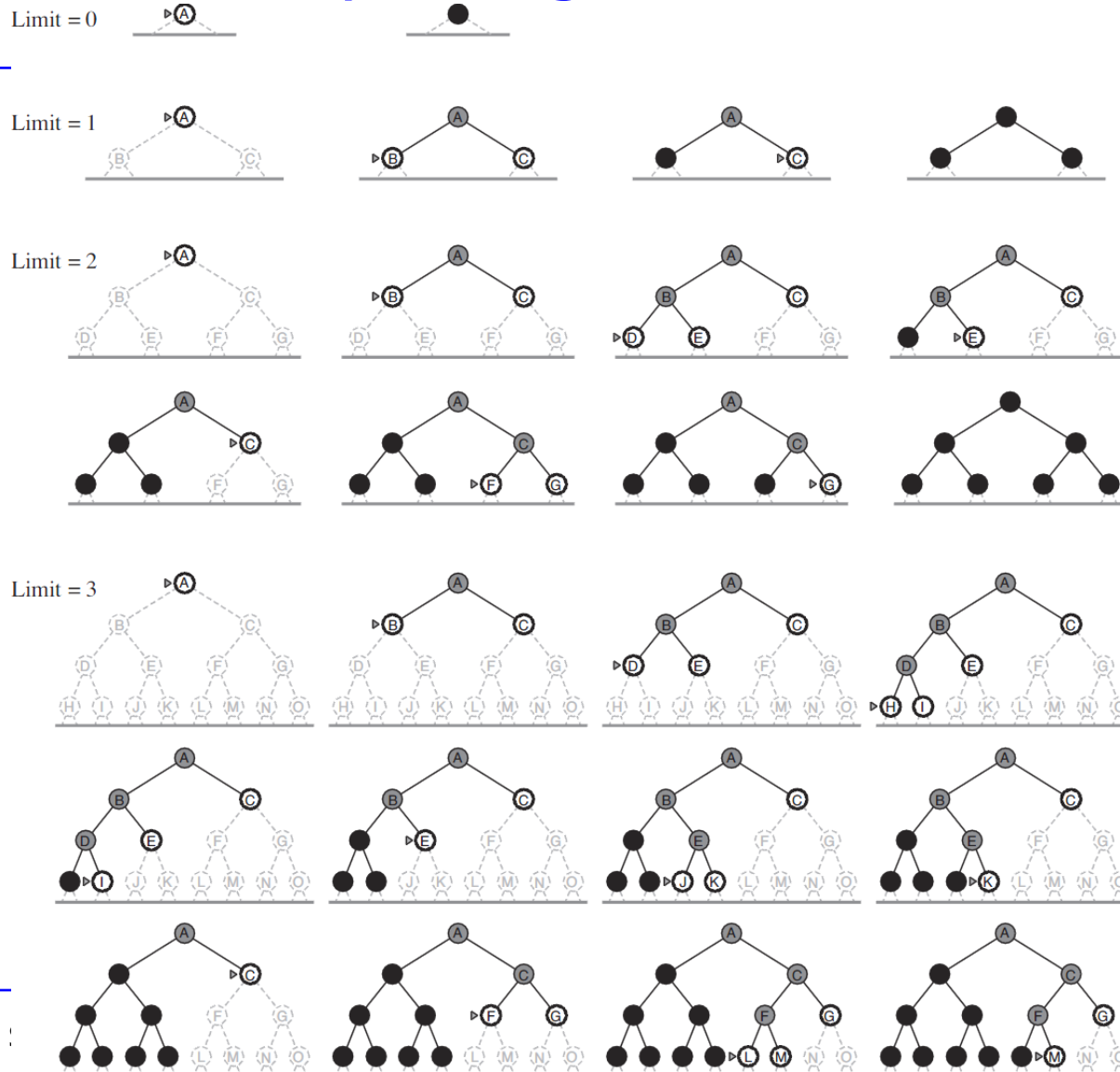
# Iterative deepening search

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

- Modifies depth-limited search by iteratively trying all possible depths as the cutoff limit
- Combines benefits of depth-first and breadth-first

# Iterative deepening search illustrated



# Complexity of iterative deepening search

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- May seem wasteful, since many states are expanded multiple times (for each cutoff limit)
- In exponential search trees most nodes are at lowest level, so multiple expansions at shallow depths do not matter much
- Time complexity is  $O(b^d)$ , space complexity  $O(bd)$

Iterative deepening is the preferred (uninformed) search strategy when there is a large search space and the solution depth is unknown

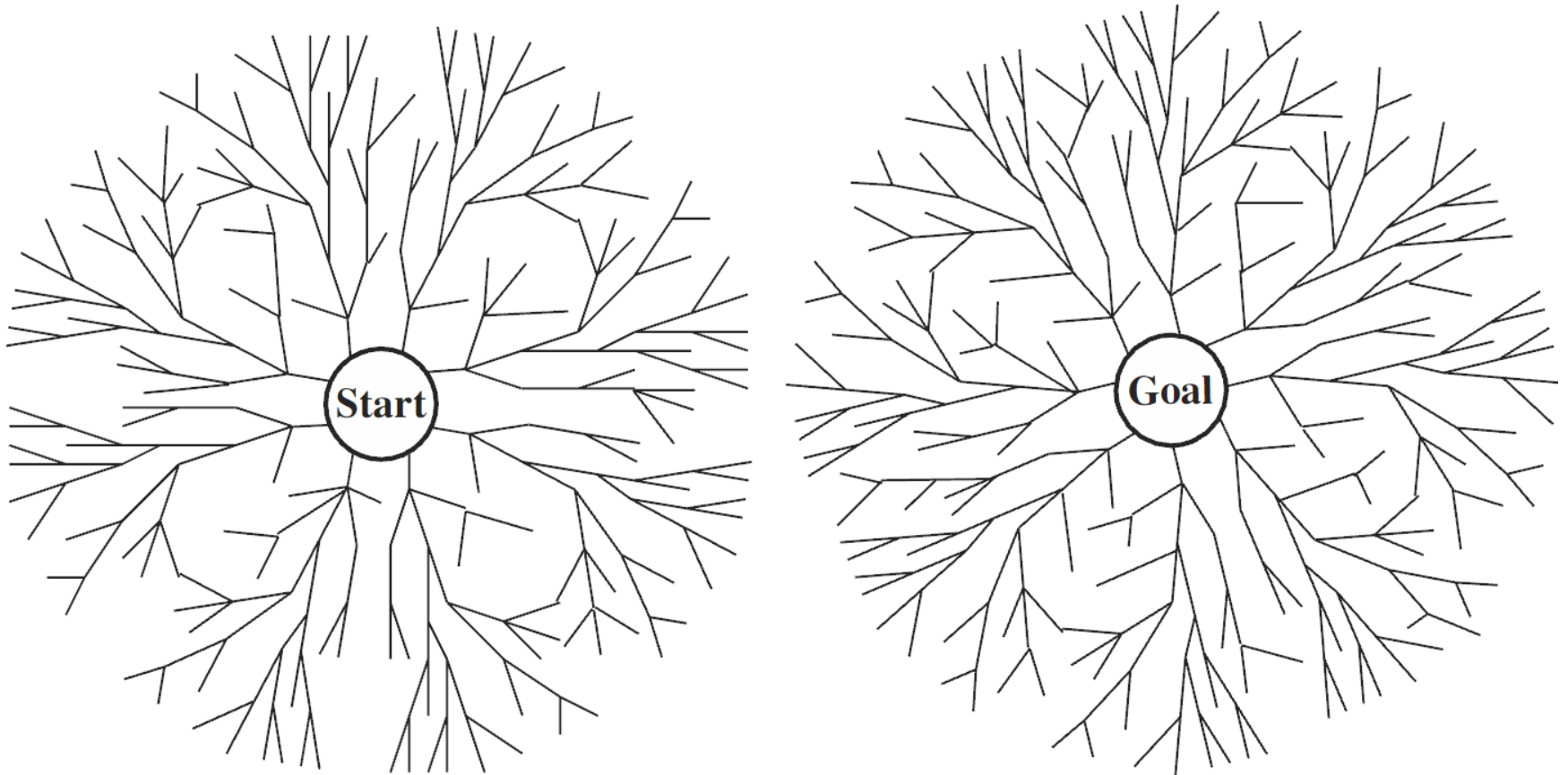
# Bidirectional search

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- Searches simultaneously both forward from initial state and backward from goal state
- Time complexity reduced from  $O(b^d)$  to  $O(b^{d/2})$ 
  - ✓ E.g. for  $b=10$ ,  $d=6$ , reduction from 1.1 mill nodes to 2.200
- But ...
  - ✓ Does the node *predecessor* function exist?
  - ✓ What if there are many possible goals?
  - ✓ Must check a new node if it exists in other tree
- Must keep at least one tree, space complexity  $O(b^{d/2})$

# Bidirectional search illustrated

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# Comparing uninformed search strategies

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Criterion	Breadth-first	Uniform-cost	Depth-first	Depth-limited	Iterative deepening	Bi-directional
Complete	Yes	Yes	No	No	Yes	Yes
Time	$b^d$	$b^{l+c/e}$	$b^m$	$b^l$	$b^d$	$b^{d/2}$
Space	$b^d$	$b^{l+c/e}$	$bm$	$bl$	$bd$	$b^{d/2}$
Optimal	Yes	Yes	No	No	Yes	Yes

b - branching factor  
d - depth of solution  
c – cost of solution

m - maximum depth of tree  
l - depth limit  
e – cost of action



# Informed search methods

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- Search can be improved by applying *knowledge* to better select which node to expand (*best-first*)
- An function to estimate the cost to reach a solution is called a *search heuristic* ( $h$ )
- *Greedy search*: Minimizes  $h(n)$  - the estimated cost of the cheapest path from  $n$  to the goal
- Greedy search reduces search time compared to uninformed search, but is neither optimal nor complete

# A\* search

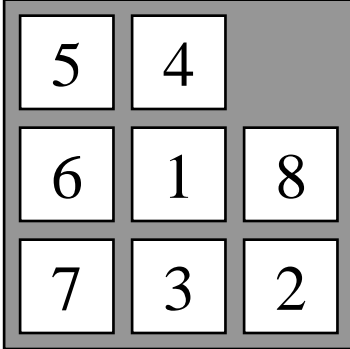
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- A\* - most widely known informed search method
  - Identical to Uniform-Cost except that it minimizes  $f(n)$  instead of  $g(n)$ :
    - ✓  $g(n)$  - the cost of the path so far
    - ✓  $h(n)$  - the estimated cost of the remaining path to goal
    - ✓  $f(n) = g(n) + h(n)$
  - Restriction:  $h$  must *never overestimate* the actual cost – i.e.  $h$  is “optimistic” (*admissible*)
  - Properties of A\*
    - ✓ Optimal (and optimally efficient)
    - ✓ Complete
    - ✓ Time/space exponential (space most severe problem)
-

# Heuristic functions

- Some admissible  $h$  for 8-puzzle

- ✓  $h1$  – number of misplaced tiles
- ✓  $h2$  – sum of distances of tiles from their goal positions
- ✓ Neither overestimate true cost



5	4	
6	1	8
7	3	2

- Branching factor  $b$  of 8-puzzle approx. 3
- *Effective* branching factor  $b^*$  using  $A^*$  depends on chosen heuristic function  $h$ 
  - ✓  $h1$  – effective  $b^*$  1.79-1.48 (depending on  $d$ )
  - ✓  $h2$  – effective  $b^*$  1.79-1.26 (always better than  $h1$ )
- Dramatic reduction of search time/space compared to uninformed search

# Summary

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- An agent can use *search* when it is not clear which action to take
- The problem environment is represented by a *state space*
- A search problem consists of an *initial state*, a set of *actions*, a *goal test*, and a *path cost*
- A *path* from the initial to the goal state is a *solution*
- Search algorithms treat states and actions as *atomic* – do not consider internal structure
- General *tree search* considers all possible paths, while *graph search* avoids redundant paths

# Summary (cont.)

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- Properties of search algorithms
    - ✓ *completeness* – finds a solution if there is one
    - ✓ *optimality* – finds the best solution
    - ✓ *time complexity*
    - ✓ *space complexity*
  - *Uninformed* search strategies have no information on cost to reach goal and include
    - ✓ *breadth-first* search
    - ✓ *uniform-cost* search
    - ✓ *depth-first* search
    - ✓ *depth-limited* search
    - ✓ *iterative-deepening* search
    - ✓ *bidirectional* search
-

## Summary (cont.)

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- *Informed search* uses knowledge on remaining cost to goal (*search heuristics*) to improve performance
- A\* is a complete and optimal informed search algorithm that uses search heuristics
- Heuristic function  $h$  in A\* must be *admissible*, and can greatly improve search performance