Basic Search

Philipp Koehn

19 February 2019

Outline

- Problem-solving agents
- Problem types
- Problem formulation
- Example problems
- Basic search algorithms

problem-solving agents

Problem Solving Agents

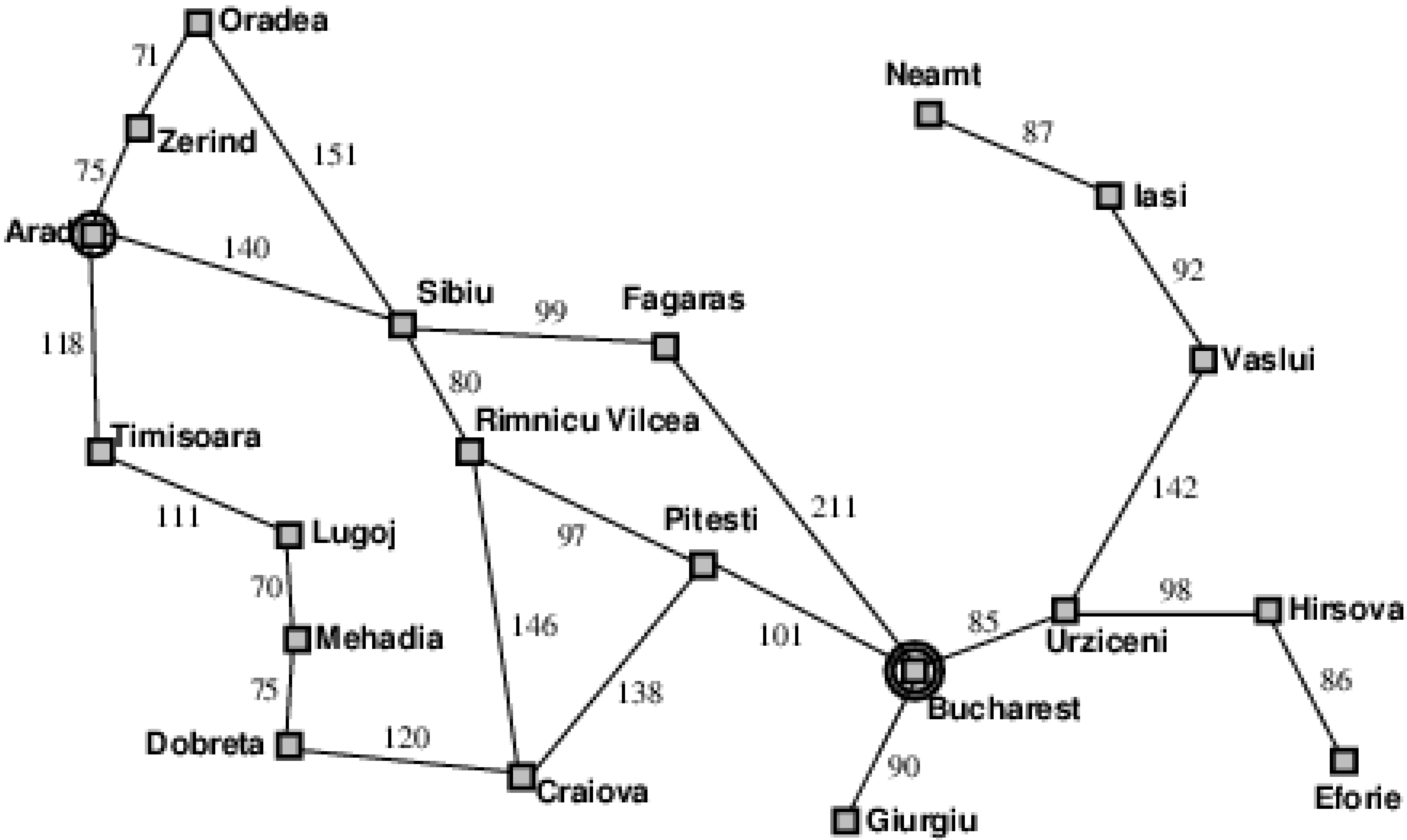
Restricted form of general agent:

```
function SIMPLE-PROBLEM-SOLVING-AGENT( percept) returns an action
    static: 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)
    action ← RECOMMENDATION(seq, state)
    seq ← REMAINDER(seq, state)
    return action
```

Note: this is **offline** problem solving; solution executed "eyes closed."
Online problem solving involves acting without complete knowledge.

Example: Romania



Example: Romania

- On holiday in Romania; currently in Arad
- Flight leaves tomorrow from Bucharest
- Formulate goal
  - be in Bucharest
- Formulate problem
  - **states**: various cities
  - **actions**: drive between cities
- Find solution
  - sequence of cities, e.g., Arad, Sibiu, Fagaras, Bucharest

problem types

Problem Types

- **Deterministic, fully observable** $\Longrightarrow$ **single-state problem**
  - agent knows exactly which state it will be in
  - solution is a sequence

- **Non-observable** $\Longrightarrow$ **conformant problem**
  - Agent may have no idea where it is
  - solution (if any) is a sequence

- **Nondeterministic** and/or **partially observable** $\Longrightarrow$ **contingency problem**
  - percepts provide **new** information about current state
  - solution is a **contingent plan** or a **policy**
  - often **interleave** search, execution

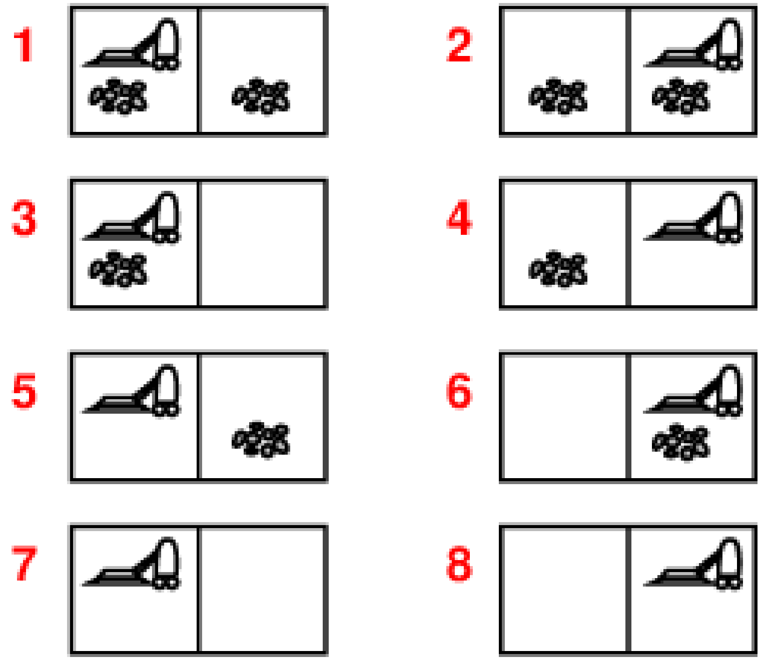
- **Unknown state space** $\Longrightarrow$ **exploration problem** ("online")

Example: Vacuum World

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

Conformant, start in $\{1, 2, 3, 4, 5, 6, 7, 8\}$
e.g., $Right$ goes to $\{2, 4, 6, 8\}$. Solution?
$[Right, Suck, Left, Suck]$

Contingency, start in #5
Murphy's Law: $Suck$ can dirty a clean carpet
Local sensing: dirt, location only.
Solution?
$[Right, \textbf{if } dirt \textbf{ then } Suck]$



problem formulation

Single-State Problem Formulation

- A **problem** is defined by four items:
  - **initial state** e.g., "at Arad"
  - **successor function** $S(x)$ = set of action–state pairs
    e.g., $S(Arad) = \{\langle Arad \rightarrow Zerind, Zerind\rangle, \ldots\}$
  - **goal test**, can be
    explicit, e.g., x = "at Bucharest"
    implicit, e.g., $NoDirt(x)$
  - **path cost** (additive)
    e.g., sum of distances, number of actions executed, etc.
    $c(x, a, y)$ is the **step cost**, assumed to be ≥ 0

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

Selecting a State Space

- Real world is absurdly complex
  $\Rightarrow$ state space must be **abstracted** for problem solving

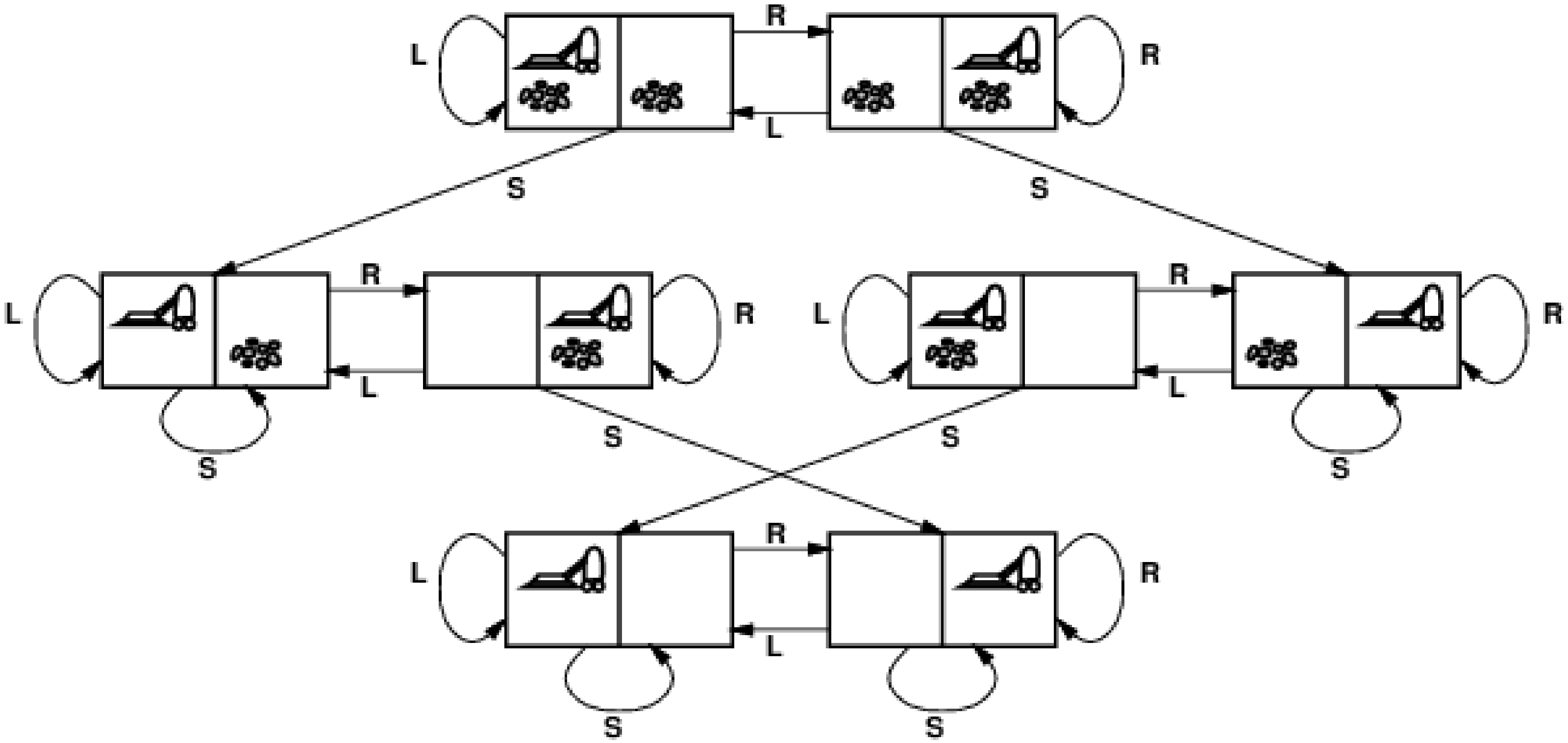
- (Abstract) state = set of real states

- (Abstract) action = complex combination of real actions
  e.g., "Arad $\rightarrow$ Zerind" represents a complex set
  of possible routes, detours, rest stops, etc.
  For guaranteed realizability, **any** real state "in Arad"
  must get to **some** real state "in Zerind"

- (Abstract) solution =
  set of real paths that are solutions in the real world

- Each abstract action should be "easier" than the original problem!

Example: Vacuum World State Space Graph



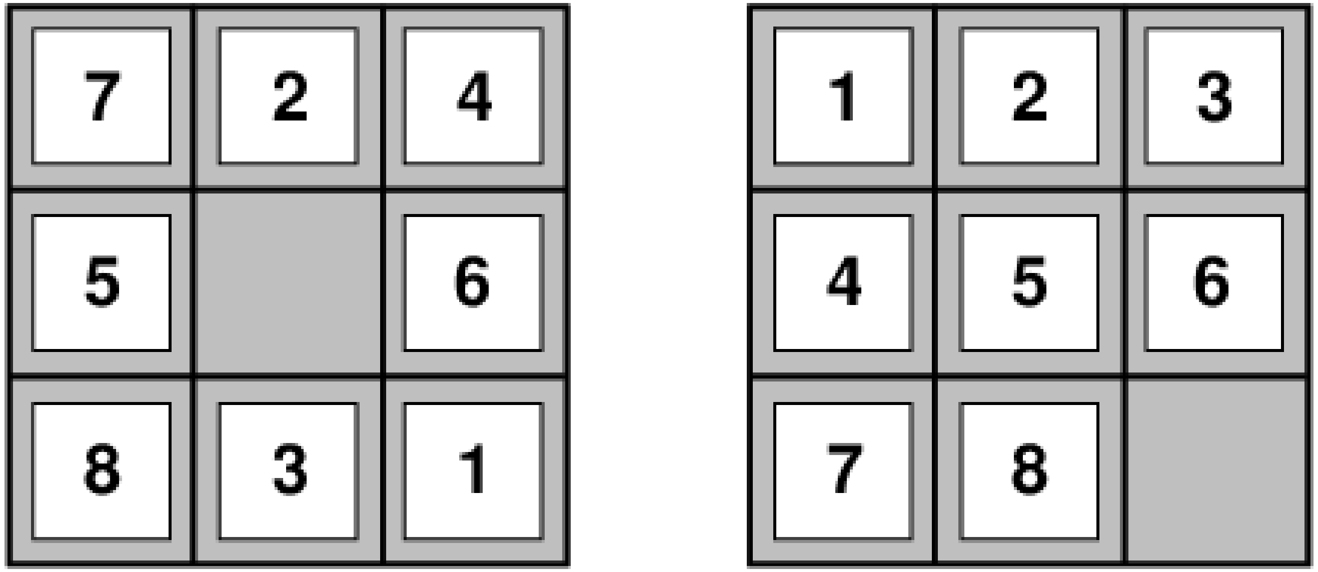
states?: integer dirt and robot locations (ignore dirt **amounts** etc.)

actions?: $Left$, $Right$, $Suck$, $NoOp$

goal test?: no dirt

path cost?: 1 per action (0 for $NoOp$)

Example: The 8-Puzzle

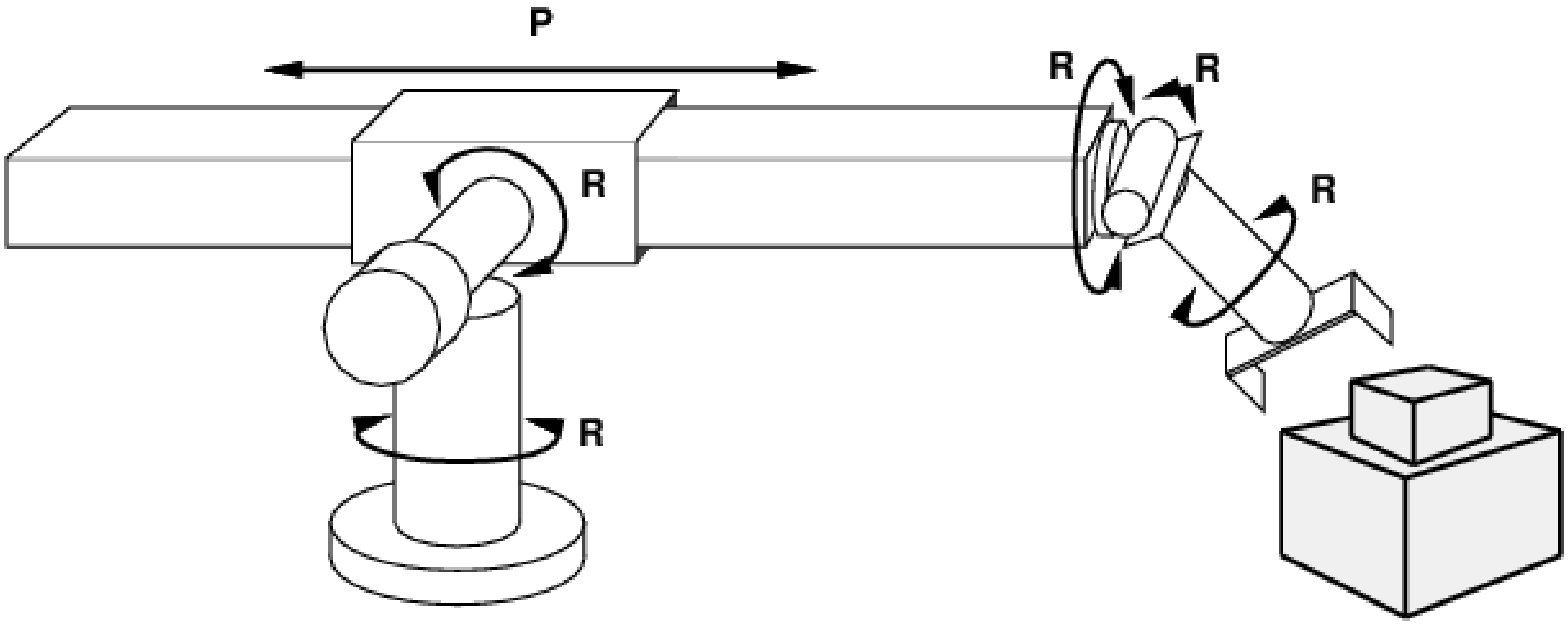


Start State Goal State

states?: integer locations of tiles (ignore intermediate positions)
actions?: move blank left, right, up, down (ignore unjamming etc.)
goal test?: = goal state (given)
path cost?: 1 per move

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

Example: Robotic Assembly



states?: real-valued coordinates of robot joint angles
parts of the object to be assembled
actions?: continuous motions of robot joints
goal test?: complete assembly
path cost?: time to execute

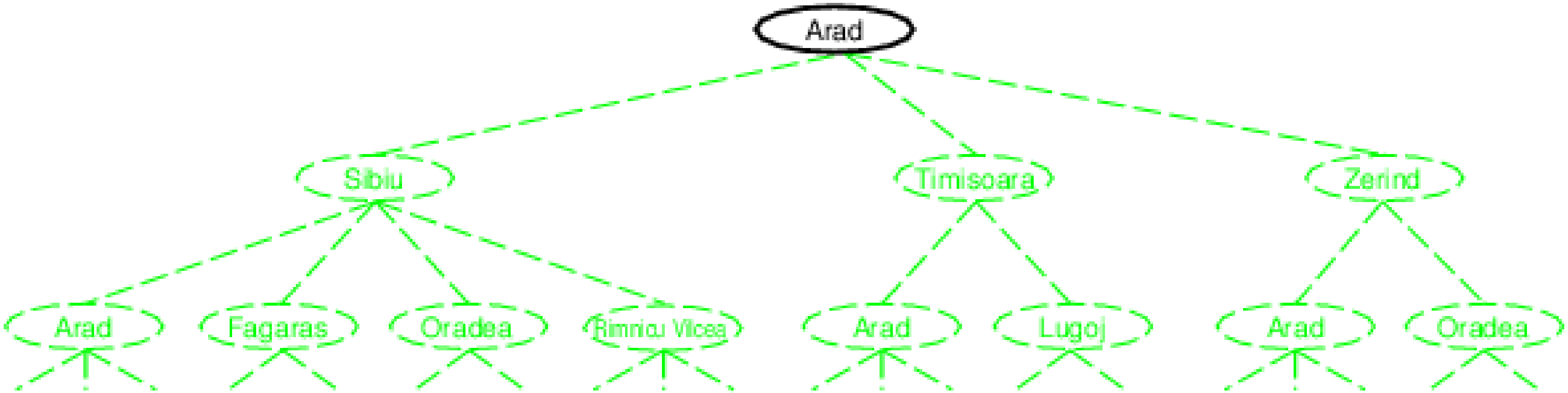
tree search

Tree Search Algorithms

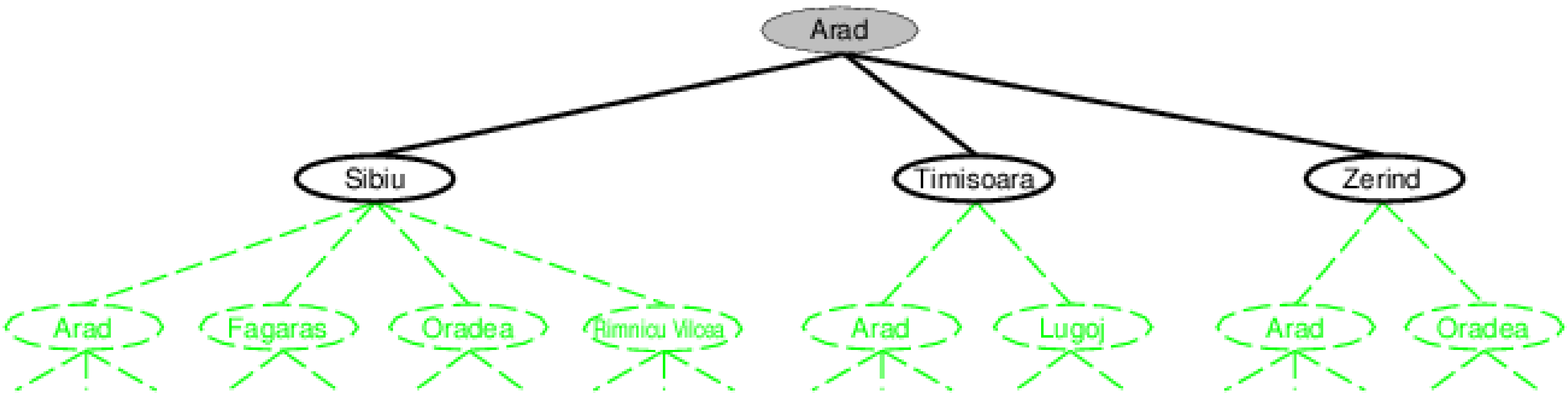
- Basic idea: offline, simulated exploration of state space
  by generating successors of already-explored states
  (a.k.a. **expanding** states)

function TREE-SEARCH(*problem, strategy*) **returns** a solution, or failure
  initialize the search tree using the initial state of *problem*
  loop do
    if there are no candidates for expansion **then return** failure
    choose a leaf node for expansion according to *strategy*
    if the node contains a goal state **then return** the corresponding solution
    else expand the node and add the resulting nodes to the search tree
  end

Tree Search Example



Tree Search Example



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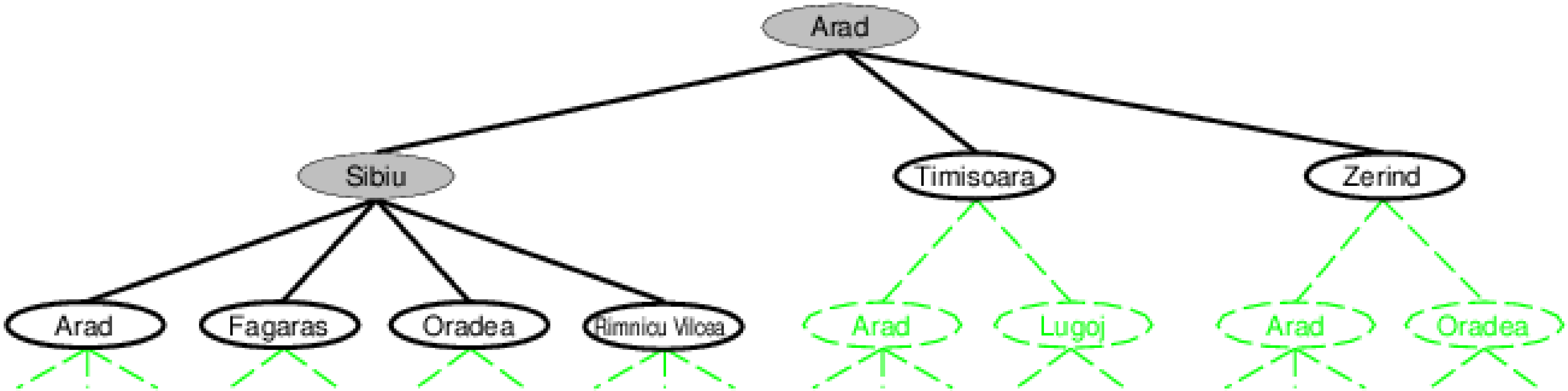
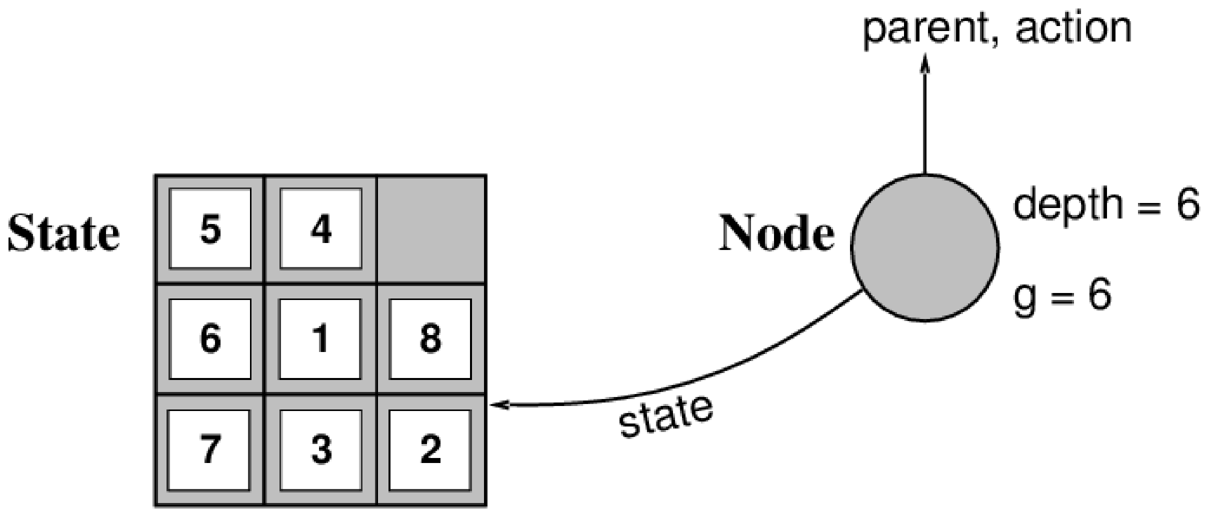


Implementation: States vs. Nodes

- A **state** is a (representation of) a physical configuration
- A **node** is a data structure constituting part of a search tree includes **parent**, **children**, **depth**, **path cost** $g(x)$
- States do not have parents, children, depth, or path cost!



- The EXPAND function creates new nodes, filling in the various fields and using the SUCCESSORFN of the problem to create the corresponding states.

Implementation: General Tree Search


```
function TREE-SEARCH( problem, fringe) returns a solution, or failure
   fringe ← INSERT(MAKE-NODE(INITIAL-STATE[problem]), fringe)
   loop do
       if fringe is empty then return failure
       node ← REMOVE-FRONT(fringe)
       if GOAL-TEST(problem, STATE(node)) then return node
       fringe ← INSERTALL(EXPAND(node, problem), fringe)
```

```
function EXPAND( node, problem) returns a set of nodes
   successors ← the empty set
   for each action, result in SUCCESSOR-FN(problem, STATE[node]) do
       s ← a new NODE
       PARENT-NODE[s] ← node;  ACTION[s] ← action;  STATE[s] ← result
         PATH-COST[s] ← PATH-COST[node] + STEP-COST(STATE[node], action,
result)
       DEPTH[s] ← DEPTH[node] + 1
       add s to successors
   return successors
```

Search Strategies

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

- Strategies are evaluated along the following dimensions
  - **completeness**—does it always find a solution if one exists?
  - **time complexity**—number of nodes generated/expanded
  - **space complexity**—maximum number of nodes in memory
  - **optimality**—does it always find a least-cost solution?

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

Uninformed Search Strategies

Uninformed strategies use only the information available in the problem definition

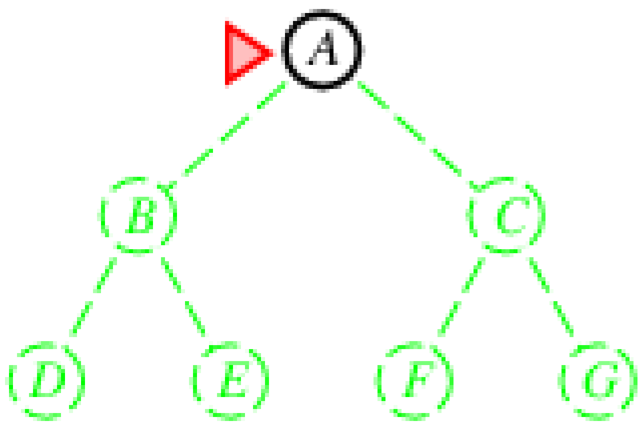
- Breadth-first search
- Uniform-cost search
- Depth-first search
- Depth-limited search
- Iterative deepening search

breadth-first search

Breadth-First Search

- Expand shallowest unexpanded node

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



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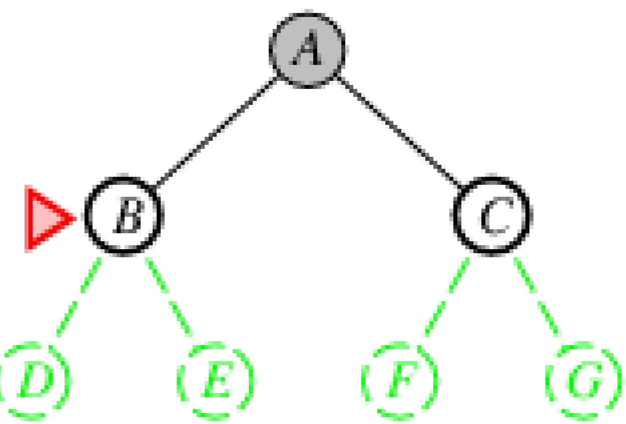

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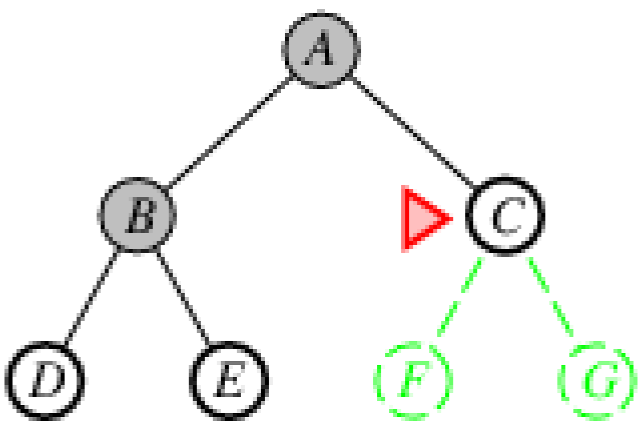

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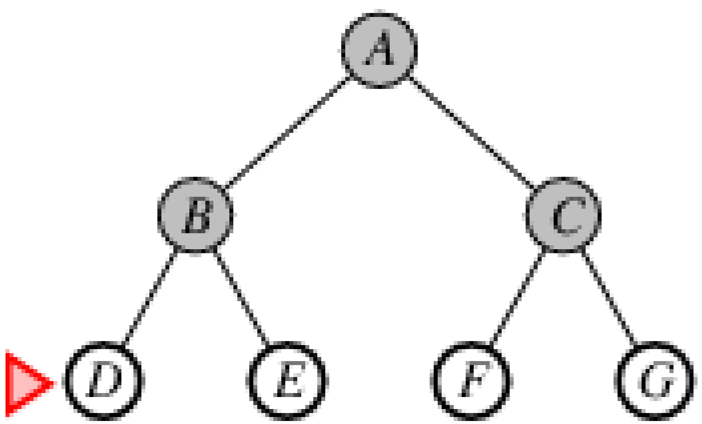


Properties of Breadth-First Search

- Complete? Yes (if b is finite)
- Time? $1 + b + b^2 + b^3 + \ldots + b^d + b(b^d - 1) = O(b^{d+1})$, i.e., exp. in d
- Space? $O(b^{d+1})$ (keeps every node in memory)
- Optimal? Yes (if cost = 1 per step); not optimal in general
- **Space** is the big problem; can easily generate nodes at 100MB/sec $\rightarrow$ 24hrs = 8640GB.

uniform cost search

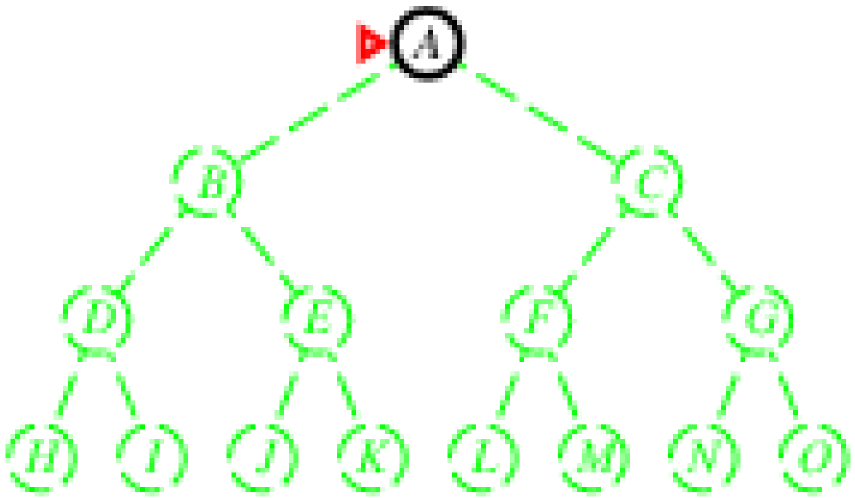
Uniform-Cost Search

- Expand least-cost unexpanded node
- **Implementation**:
  fringe = queue ordered by path cost, lowest first
- Equivalent to breadth-first if step costs all equal
- Properties
  - Complete? Yes, if step cost $\geq \epsilon$
  - Time? # of nodes with $g \leq$ cost of optimal solution, $O(b^{\lceil C^*/\epsilon \rceil})$
    where C^* is the cost of the optimal solution
  - Space? # of nodes with $g \leq$ cost of optimal solution, $O(b^{\lceil C^*/\epsilon \rceil})$
  - Optimal? Yes—nodes expanded in increasing order of $g(n)$

depth first search

Depth-First Search

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



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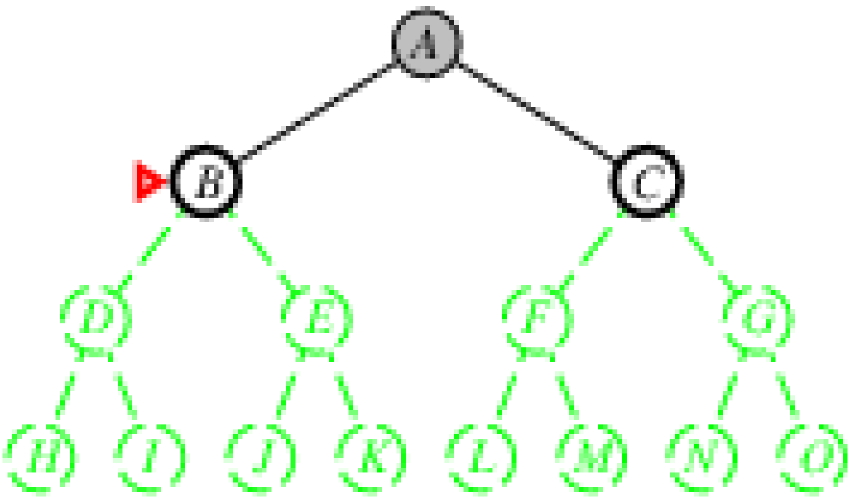

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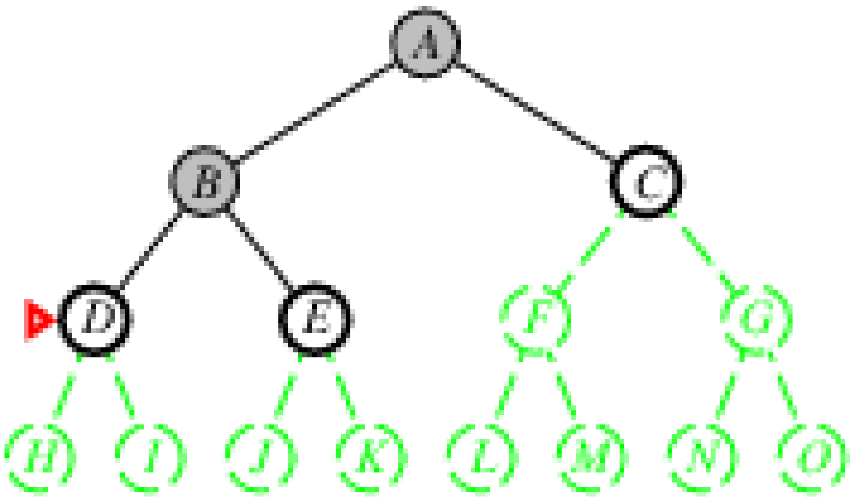

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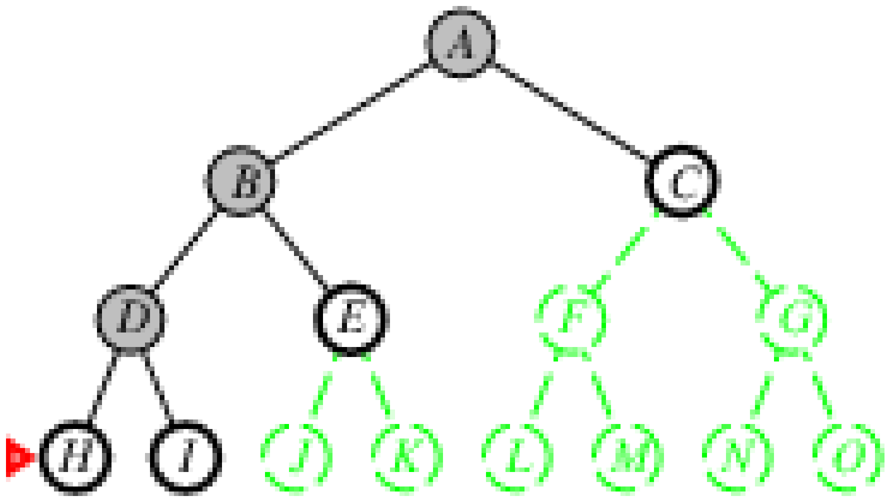

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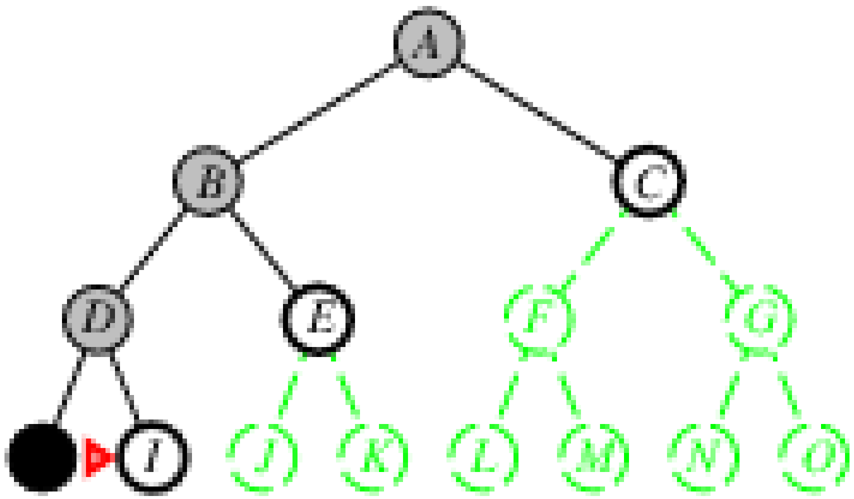

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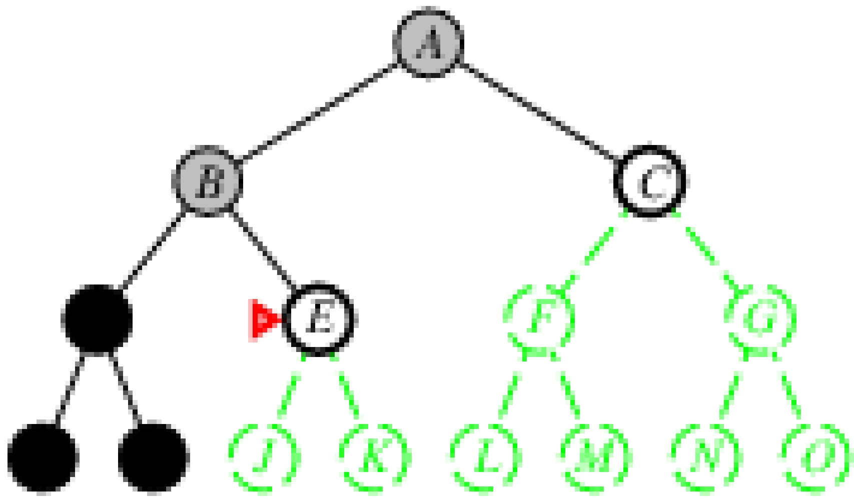

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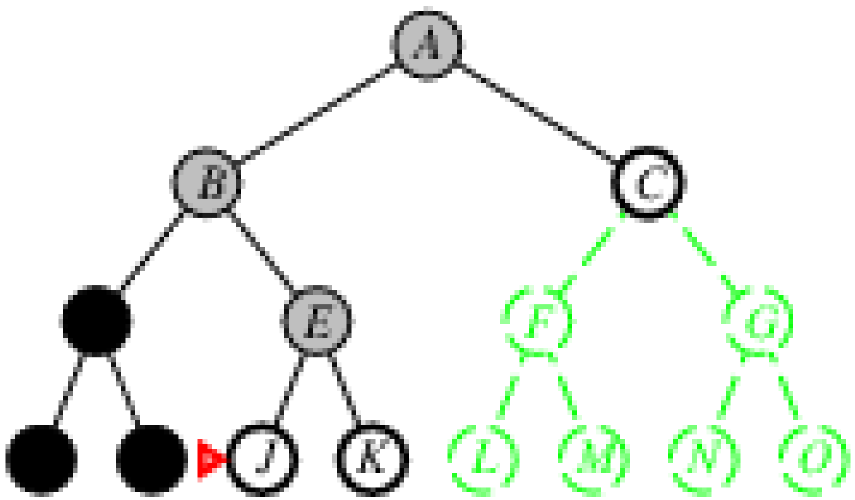

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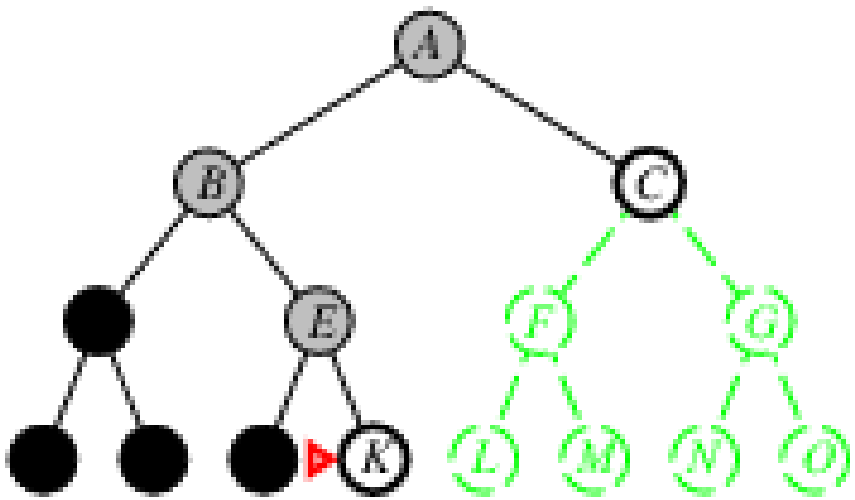

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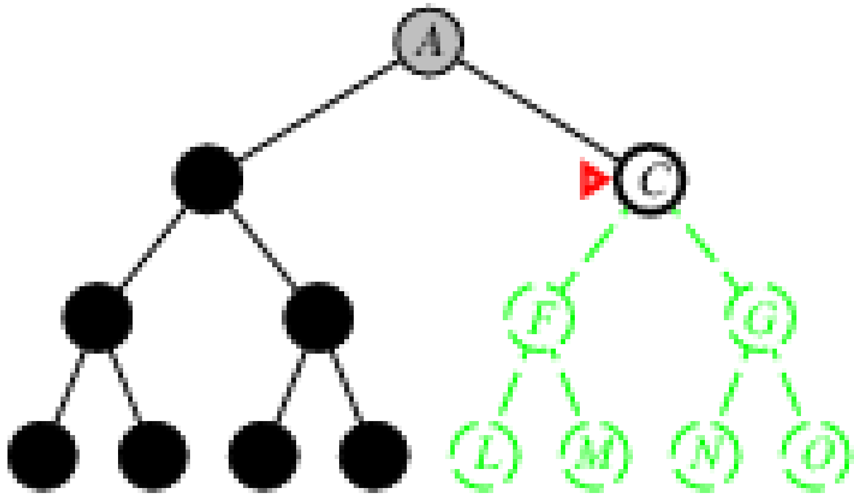

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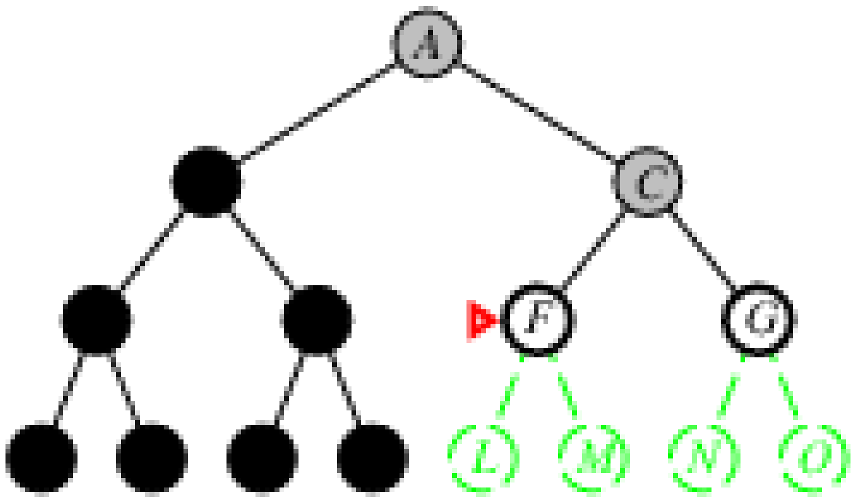

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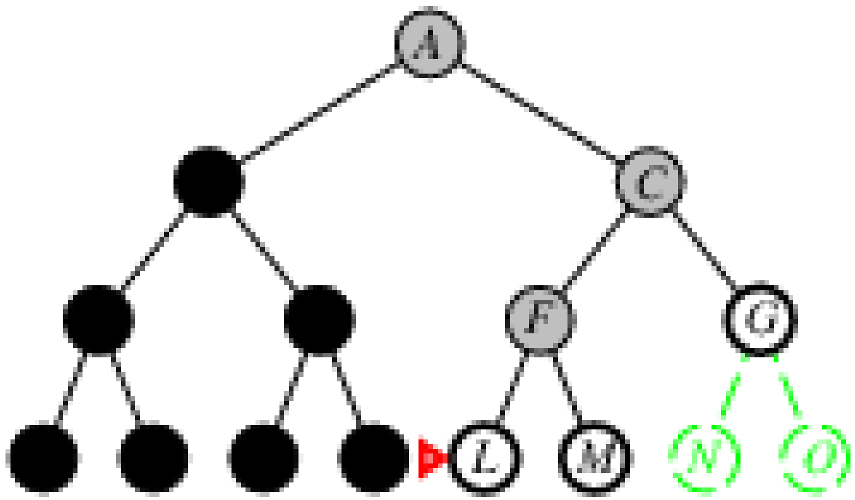

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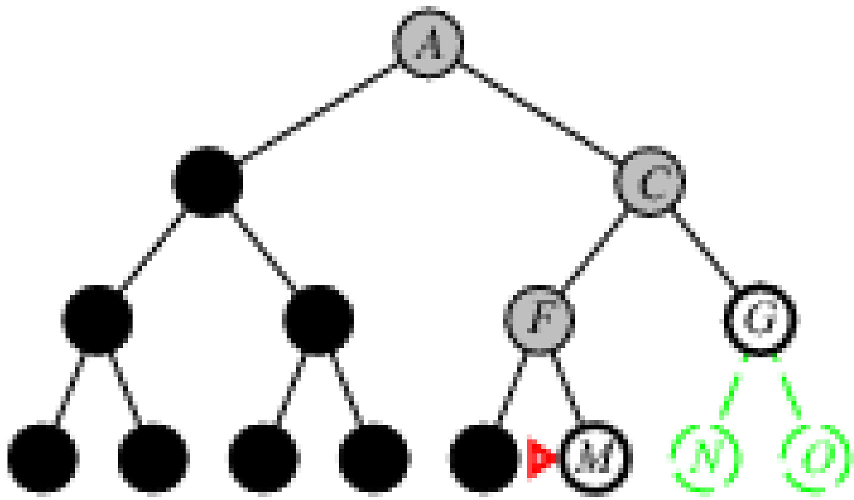


Properties of Depth-First Search

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

iterative deepening

Depth-Limited Search

- Depth-first search with depth limit l, i.e., nodes at depth l have no successors
- **Recursive implementation**:

```
function DEPTH-LIMITED-SEARCH( problem, limit) returns soln/fail/cutoff
   RECURSIVE-DLS(MAKE-NODE(INITIAL-STATE[problem]), problem, limit)

function RECURSIVE-DLS(node, problem, limit) returns soln/fail/cutoff
   cutoff-occurred? ← false
   if GOAL-TEST(problem, STATE[node]) then return node
   else if DEPTH[node] = limit then return cutoff
   else for each successor in EXPAND(node, problem) do
       result ← RECURSIVE-DLS(successor, problem, limit)
       if result = cutoff then cutoff-occurred? ← true
       else if result ≠ failure then return result
   if cutoff-occurred? then return cutoff else return failure
```

Iterative Deepening Search

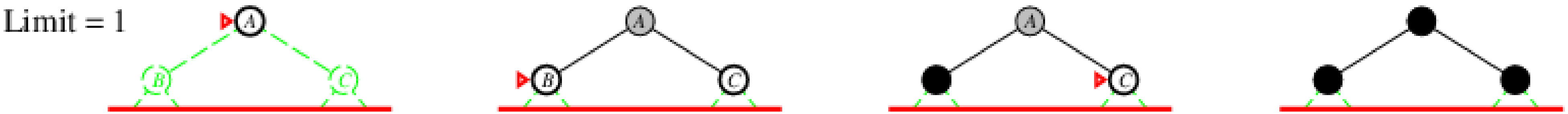

```
function ITERATIVE-DEEPENING-SEARCH( problem) returns a solution
    inputs: problem, a problem

    for depth ← 0 to ∞ do
        result ← DEPTH-LIMITED-SEARCH( problem, depth)
        if result ≠ cutoff then return result
    end
```

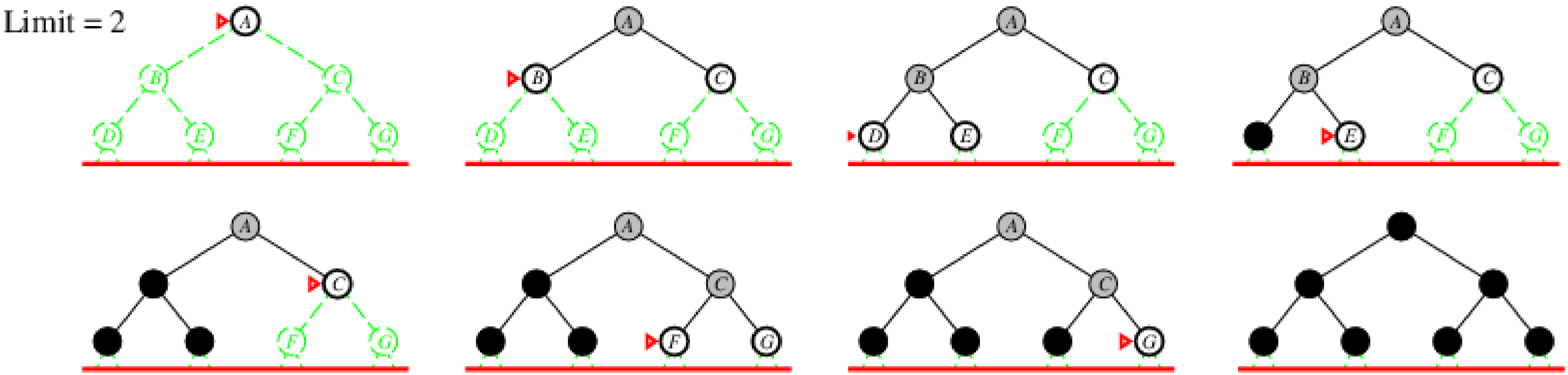
Iterative Deepening Search $l = 0$

Limit = 0

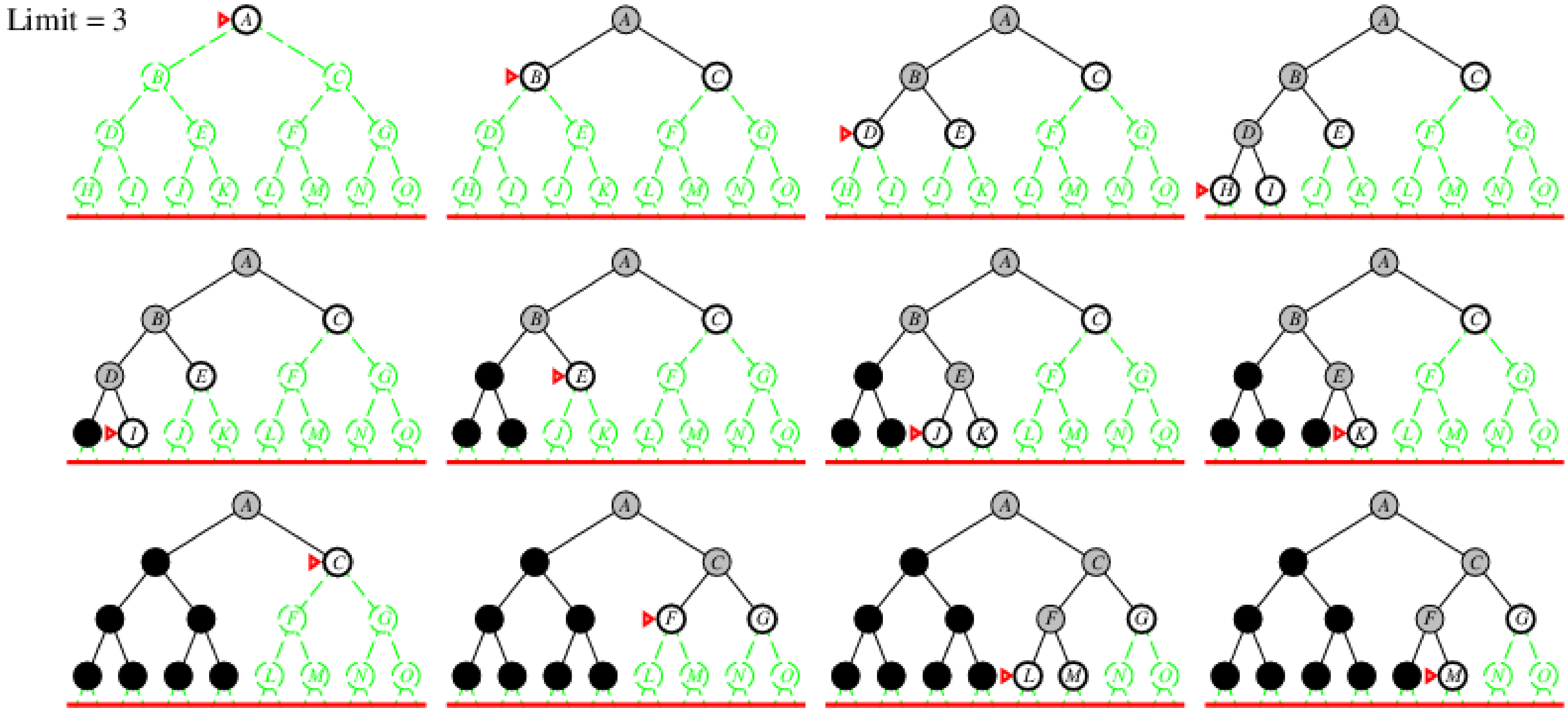
Iterative Deepening Search $l = 1$



Iterative Deepening Search $l = 2$



Iterative Deepening Search $l = 3$



Properties of Iterative Deepening Search

- Complete? Yes
- Time? $(d+1)b^0 + db^1 + (d-1)b^2 + \ldots + b^d = O(b^d)$
- Space? $O(bd)$
- Optimal? Yes, if step cost = 1
  Can be modified to explore uniform-cost tree
- Numerical comparison for $b = 10$ and $d = 5$, solution at far right leaf:

$$N(\mathsf{IDS}) = 50 + 400 + 3,000 + 20,000 + 100,000 = 123,450$$
$$N(\mathsf{BFS}) = 10 + 100 + 1,000 + 10,000 + 100,000 + 999,990 = 1,111,100$$

- IDS does better because other nodes at depth d are not expanded
- BFS can be modified to apply goal test when a node is **generated**

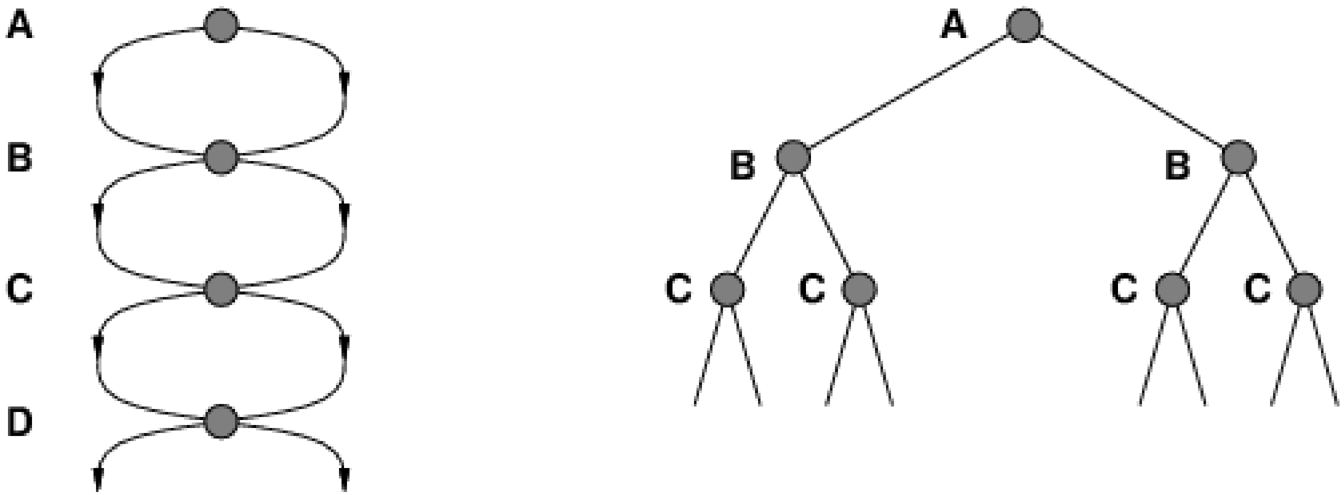
summary

Summary of Algorithms

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

Repeated States

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



Graph Search


```
function GRAPH-SEARCH( problem, fringe) returns a solution, or failure
    closed ← an empty set
    fringe ← INSERT(MAKE-NODE(INITIAL-STATE[problem]), fringe)
    loop do
        if fringe is empty then return failure
        node ← REMOVE-FRONT(fringe)
        if GOAL-TEST(problem, STATE[node]) then return node
        if STATE[node] is not in closed then
            add STATE[node] to closed
            fringe ← INSERTALL(EXPAND(node, problem), fringe)
    end
```

Summary

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

- Variety of uninformed search strategies

- Iterative deepening search uses only linear space
  and not much more time than other uninformed algorithms

- Graph search can be exponentially more efficient than tree search