

CS 4700:
Foundations of Artificial Intelligence

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Problem Solving by Search
R&N: Chapter 3

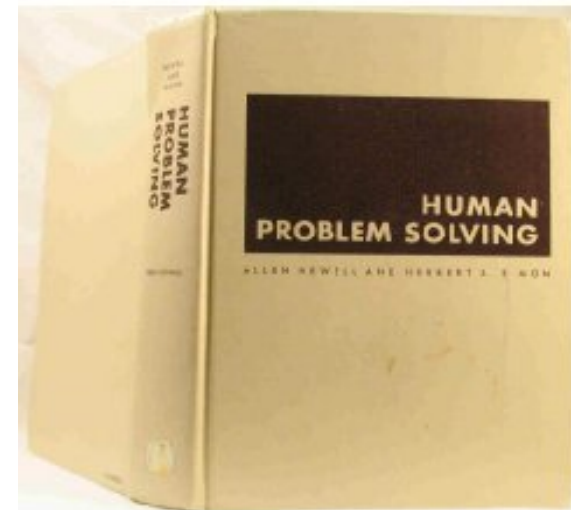
Introduction

Search is a central topic in AI.

**Originated with Newell and Simon's work on problem solving;
Human Problem Solving (1972).**

Automated reasoning is a natural search task.

**More recently: Given that almost all AI formalisms
(planning, learning, etc) are NP-Complete or worse,
some form of search (or optimization) is generally
unavoidable (i.e., no smarter algorithm available).**



Outline

Problem-solving agents

Problem types

Problem formulation

Example problems

Basic search algorithms

Problem-solving agents

More details on “states” soon.

Problem solving agents are goal-directed agents:

1. **Goal Formulation:** Set of one or more (desirable) world states (e.g. checkmate in chess).
2. **Problem formulation:** What actions and states to consider given a goal and an initial state.
3. **Search for solution:** Given the problem, search for a solution --- *a sequence of actions to achieve the goal starting from the initial state.*
4. **Execution of the solution**

Note: Formulation may feel somewhat “contrived,” but was meant to model very general (human) problem solving process.

Example: Path Finding problem

Formulate goal:

- be in Bucharest (Romania)

Formulate problem:

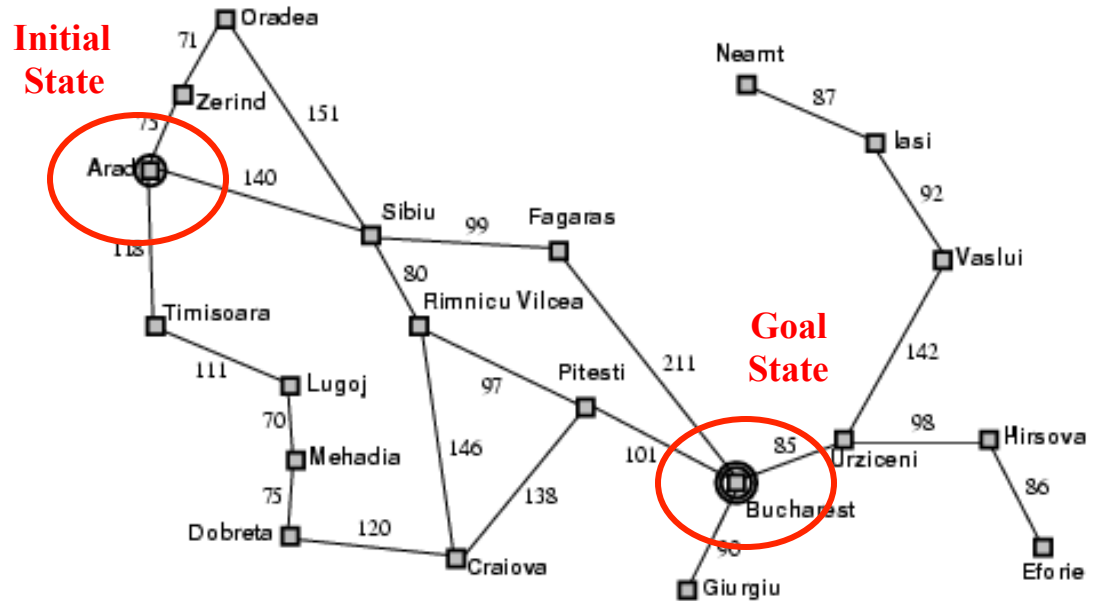
- **action**: drive between pair of connected cities (direct road)
- **state**: be in a city (20 world states)

Find solution:

- sequence of cities leading from start to goal state, e.g., Arad, Sibiu, Fagaras, Bucharest

Execution

- drive from Arad to Bucharest according to the solution

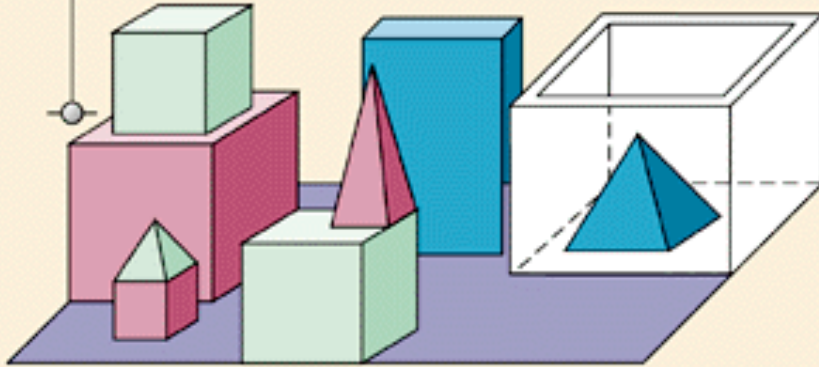


Environment: fully observable (map), deterministic, and the agent knows effects of each action. Is this really the case?

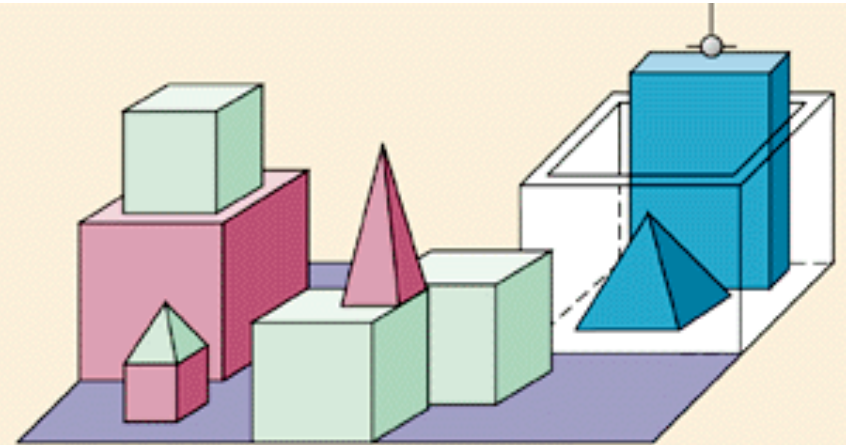
Note: Map is somewhat of a “toy” example. Our real interest: *Exponentially large spaces*, with e.g. 10^{100} or more states. Far beyond full search. Humans can often still handle those! (We need to define a distance measure.) One of the mysteries of cognition.

Micro-world: The Blocks World

gripper

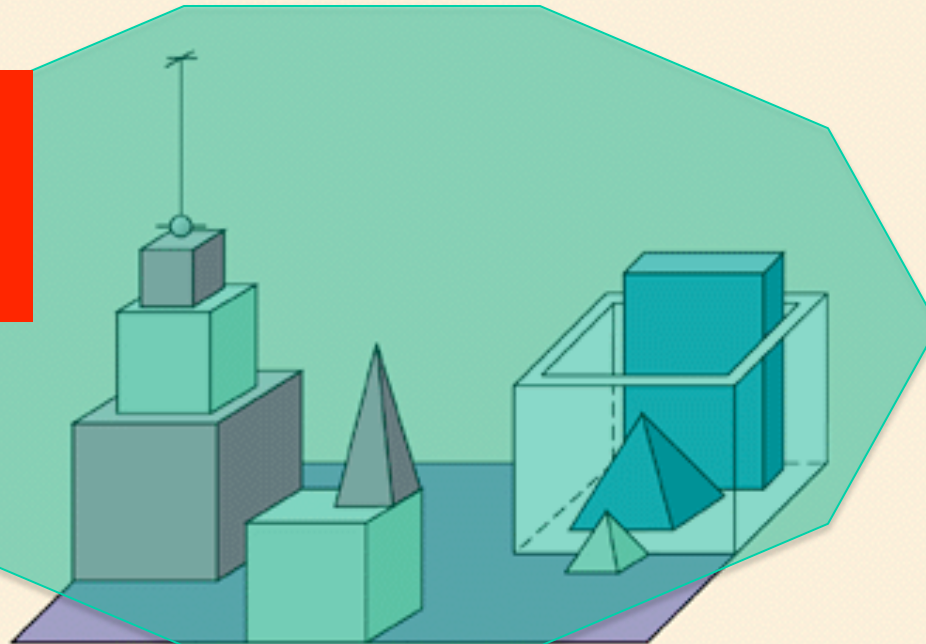


(a) "Pick up a big red block."



(b) "Find a block which is taller than the one you are holding and put it into the box."

How many
different possible
world states?



(c) "Will you please stack up both of the red blocks and either a green cube or a pyramid?"

- a) Tens?
- b) Hundreds?
- c) Thousands?
- d) Millions?
- e) Billions?**
- f) Trillions?

Size state space of blocks world example

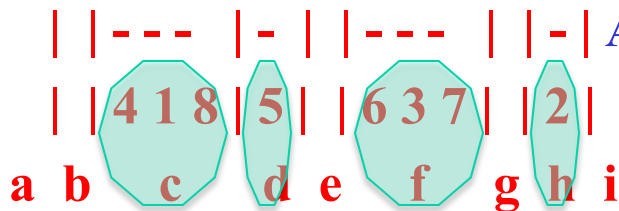
$n = 8$ objects, $k = 9$ locations to build towers, one gripper. (One location in box.)

All objects distinguishable, order matter in towers. (Assume stackable in any order.)

Blocks: Use r-combinations approach from Rosen (section 5.5; CS-2800).

----- consider $16 = (n + k - 1)$ “spots”

Select $k - 1 = 8$ “dividers” to create locations,
(16 choose 8) ways to do this, e.g.,



Allocate $n = 8$ objs to remaining spots, $8!$ ways, e.g.,
assigns 8 objects to the 9 locations
based on dividers

So, total number of states (ignoring gripper): $(16 \text{ choose } 8) * 8! = 518,918,400$
* 9 for location gripper: > 4.5 billion states even in this toy domain!

Search spaces grow exponentially with domain. *Still need to search them, e.g., to find a sequence of states (via gripper moves) leading to a desired goal state.*

How do we represent states?

[predicates / features]

Problem types

1) Deterministic, fully observable

Agent knows exactly which state it will be in; solution is a sequence of actions.

2) Non-observable --- sensorless problem

- Agent may have no idea where it is (no sensors); it reasons in terms of belief states; solution is a sequence actions (effects of actions certain).

3) Nondeterministic and/or partially observable: contingency problem

- Actions uncertain, percepts provide **new** information about current state (**adversarial problem if uncertainty comes from other agents**).
- Solution is a “strategy” to reach the goal.

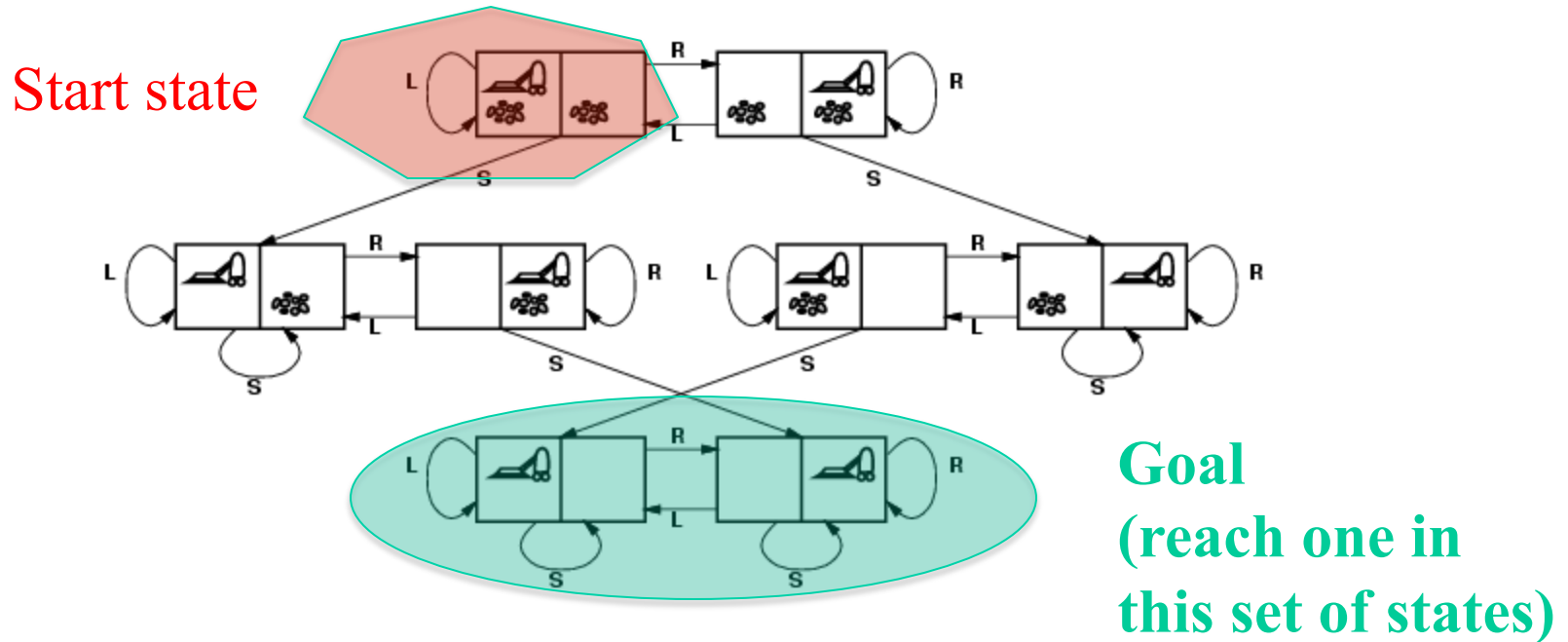
4) Unknown state space and uncertain action effects: exploration problem

- Solution is a “strategy” to reach the goal (end explore environment).

Increasing complexity



Example: Vacuum world state space graph



states?

The agent is in one of 8 possible world states.

actions?

Left, Right, Suck [simplified: left out No-op]

goal test?

No dirt at all locations (i.e., in one of bottom two states).

path cost?

1 per action

Minimum path from Start to Goal state: **3 actions**

Alternative, longer plan: **4 actions**

Note: path with thousands of steps before reaching goal also exists.

Example: The 8-puzzle “sliding tile puzzle”

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

Aside:
variations
on goal state.
eg empty square
bottom right or
in middle.

states? the boards, i.e., locations of tiles
actions? move blank left, right, up, down
goal test? goal state (given; tiles in order)
path cost? 1 per move

Note: finding **optimal** solution of n -puzzle family is NP-hard!

Also, from certain states you can't reach the goal.

Total number of states $9! = 362,880$ (more interesting space;
not all connected... only half can reach goal state)

Goal state

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

15-puzzle

Search space:

$16!/2 = 1.0461395 \text{ e}+13$,
about 10 trillion.

Too large to store in RAM
(≥ 100 TB). A challenge to search
for a path from a given board to goal.

Korf:
Disk errors
become a
problem.

Longest minimum path: **80 moves**. Just 17 boards, e.g.,

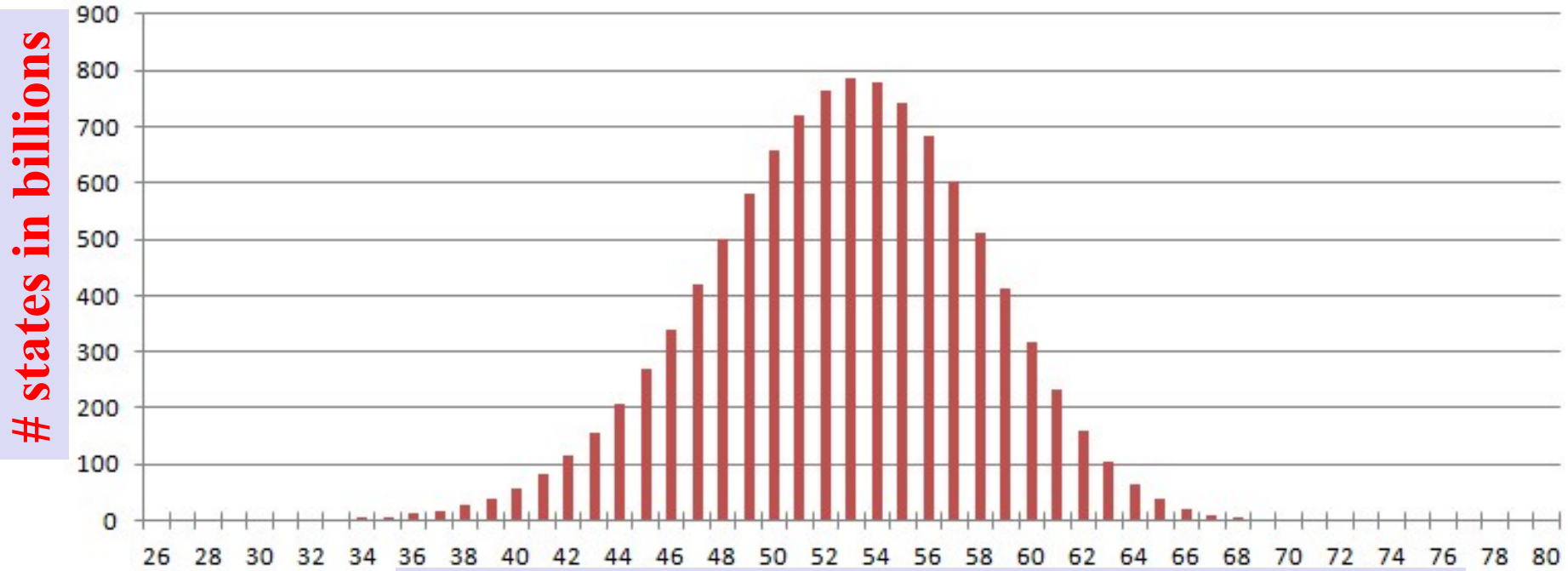
	12	9	13
15	11	10	14
3	7	2	5
4	8	6	1

Average minimum soln. length: 53.

People can find solns. But not necessarily
minimum length. See **solve it!** (Gives strategy.)

Korf, R., and Schultze, P. 2005. Large-scale *parallel breadth-first search*. In
Proceedings of the 20th National Conference on Artificial Intelligence (AAAI-05).
See **Fifteen Puzzle Optimal Solver**. **With effective search: opt. solutions in seconds!**
Average: milliseconds.

Where are the 10 trillion states?



minimum distance from goal state (# moves)

dist.	# states
0	1
1	2
2	4
3	10
4	24
5	54

etc.

dist.	# states
76	272,198
77	26,638
78	3,406
79	70
80	17

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

17 boards farthest away from goal state (80 moves)



*What is
it about
these 17
boards
out of
over 10
trillion?*

Each require 80 moves to reach:

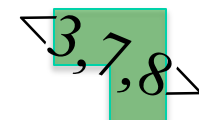
**Intriguing similarities. Each number
has its own few locations.**

Interesting machine learning task:

Learn to recognize the hardest boards!

(Extremal Combinatorics, e.g. LeBras, Gomes, and Selman AAAI-12)

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



17 boards farthest away from goal state (80 moves)

<div> <div>12 9 13</div> <div>15 11 10 14</div> <div>3 7 2 5</div> <div>4 8 6 1</div> </div>	<div> <div>12 10 13</div> <div>15 11 14 9</div> <div>3 7 2 5</div> <div>4 8 6 1</div> </div>	<div> <div>11 9 13</div> <div>12 15 10 14</div> <div>3 7 6 2</div> <div>4 8 5 1</div> </div>	<div> <div>15 9 13</div> <div>11 12 10 14</div> <div>3 7 6 2</div> <div>4 8 5 1</div> </div>	<div> <div>12 9 13</div> <div>15 11 10 14</div> <div>3 7 6 2</div> <div>4 8 5 1</div> </div>	<div> <div>12 14 13</div> <div>15 11 9 10</div> <div>3 7 6 2</div> <div>4 8 5 1</div> </div>
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Most regular extreme case:

Each quadrant
reflected along
diagonal. “move
tiles furthest away”

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

Goal state

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

Thanks to Jonathan GS

A few urls:

[Play the eight puzzle on-line](#)

[Play the fifteen puzzle on-line](#)

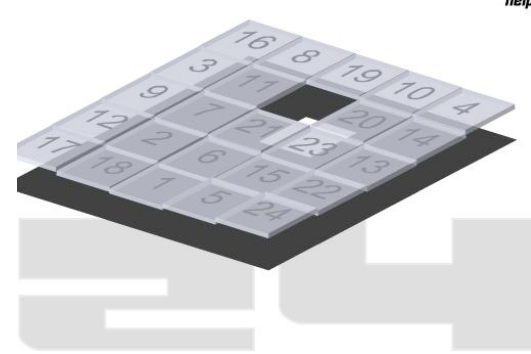
Let's consider the search for a solution.

Aside: in this tree, immediate duplicates are removed.



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Branching factor 1, 2, or 3 (max). So, approx. 2 --- # nodes roughly doubles at each level. *Number states of explored nodes grows exponentially with depth.*



For 15-puzzle, hard initial states: 80 levels deep, requires exploring approx. $2^{80} \approx 10^{24}$ states.

If we block all duplicates, we get closer to 10 trillion (the number of distinct states: still a lot!).

Really only barely feasible on compute cluster with lots of memory and compute time. (Raw numbers for 24 puzzle, truly infeasible.)

Can we avoid generating all these boards? Do with much less search?
(Key: bring average branching factor down.)

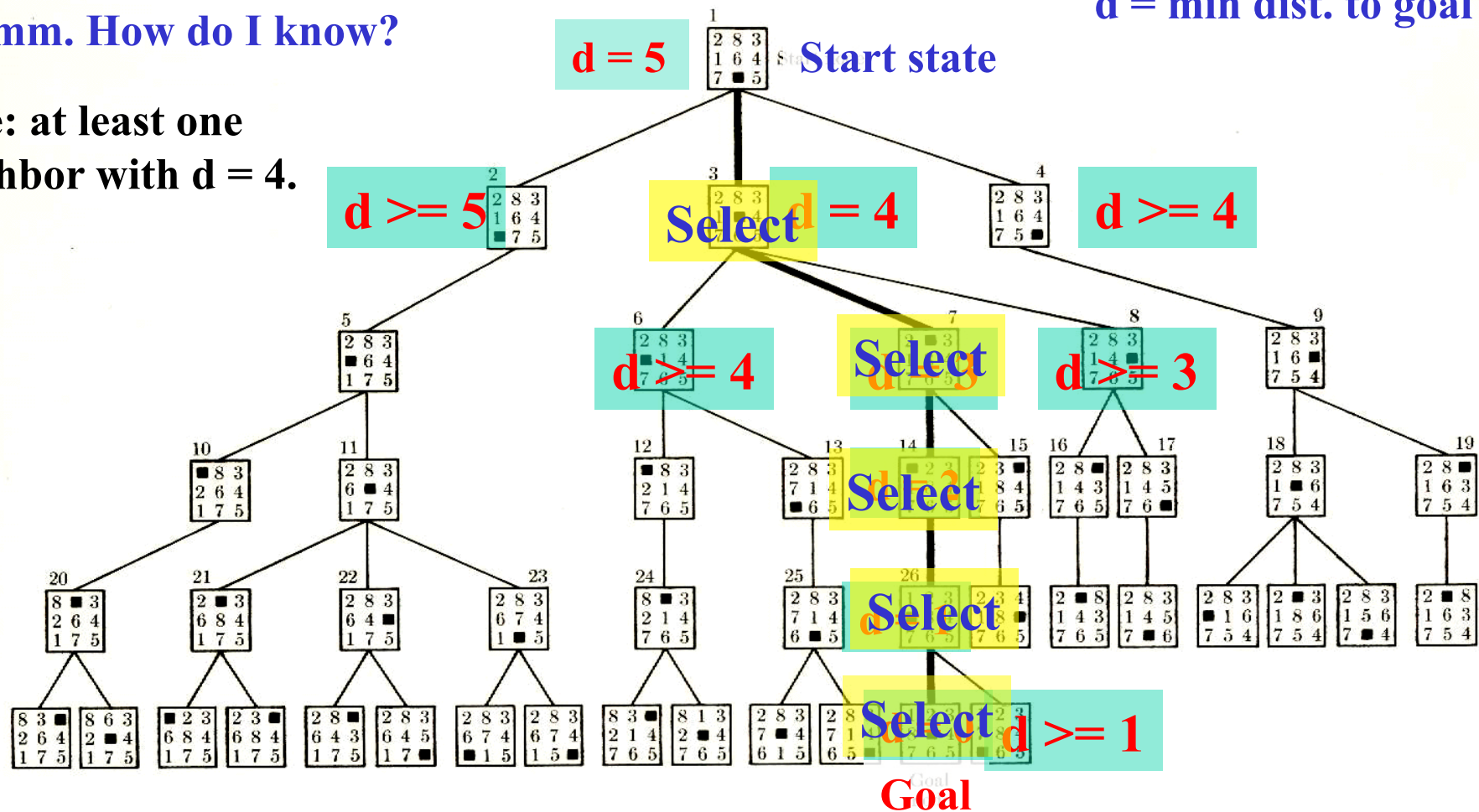
Gedanken experiment: Assume that you knew for each state, the minimum number of moves to the final goal state. (Table too big, but assume there is some formula/algorithm based on the board pattern that gives this number for each board and quickly.)

Using the minimum distance information, is there a clever way to find a minimum length sequence of moves leading from the start state to the goal state? What is the algorithmic strategy?

Hmm. How do I know?

$d = \text{min dist. to goal}$

Note: at least one neighbor with $d = 4$.



A breadth-first search tree. (More detail soon.)

Branching factor approx. 2. So, with “distance oracle” we only need to explore approx. $2 * (\text{min. solution length})$. (Why 2 times?)

For 15-puzzle, hard initial states: 80 levels deep, requires exploring approx. $2^{80} \approx 10^{24}$ states.

But, with distance oracle, we only need to explore roughly $80 * 2 = 160$ states! (only linear in size of solution length)

We may not have the exact distance function (“perfect heuristics”), but we can still “guide” the search using an approximate distance function.

This is the key idea behind “heuristic search” or “knowledge-based search.” We use knowledge / heuristic information *about the distance to the goal* to guide our search process. We can go from exponential to polynomial or even linear complexity. More common: brings exponent down significantly. E.g. from 2^L to $2^{(L/100)}$.

The measure we considered would be the “perfect” heuristic. Eliminates tree search! Find the right “path” to goal state immediately.

State evaluation functions or “heuristics”

Provide guidance in terms of what action to take next.

General principle: Consider all neighboring states, reachable via some action. Then select the action that leads to the state with the highest utility (evaluation value). This is a fully **greedy** approach.

Aside: “Highest utility” was “shortest distance to the goal” in previous example.

Because eval function is often only an estimate of the true state value, greedy search may not find the optimum path to the goal.

By *adding some search* with certain guarantees on the approximation, we can still get optimal behavior (A* search) (i.e. finding the optimal path to the solution). **Overall result: generally exponentially less search required.**

N-puzzle heuristics (“State evaluation function” wrt the goal to be reached):

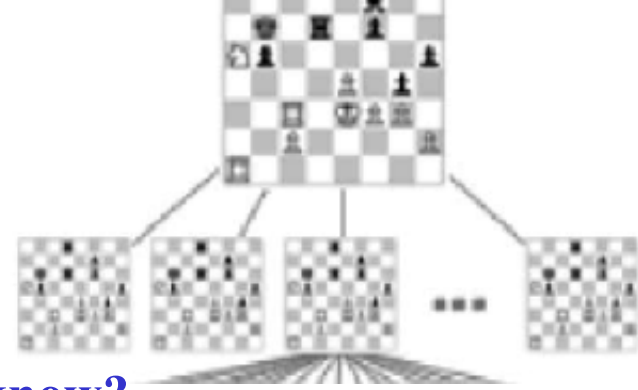
- 1) Manhattan Distance:** For each tile the number of grid units between its current location and its goal location are counted and the values for all tiles are summed up. (underestimate; too “loose”; not very powerful)
- 2) Felner, Ariel, Korf, Richard E., Hanan, Sarit, Additive Pattern Database Heuristics, Journal of Artificial Intelligence Research 22 (2004) 279-318.** The 78 Pattern Database heuristic takes a lot of memory but solves a random instance of the 15-puzzle within a few milliseconds on average. An optimal solution for the 80 moves cases takes a few seconds each. So, thousands of nodes considered instead of many billions.

Note: many approx. heuristics (“conservative” / underestimates to goal) combined with search can still find **optimal** solutions.

State evaluation function (or utility value) is a very general and useful idea.

Example:

- In chess, given a board, what would be the perfect evaluation value that you would want to know?
(Assume the perspective of White player.)



A: $f(\text{board}) \rightarrow \{+1, 0, -1\}$, with +1 for guaranteed win for White,
0 draw under perfect play, and
-1 loss under perfect play.

Perfect play: all powerful opponent.

Given f , how would you play then?

In practice, we only know (so far) of an approximation of f .

$f(\text{board}) \rightarrow [-1, +1]$ (interval from -1 to +1)

based on “values” of chess pieces, e.g., pawn 1 point, rook 5 points.

Informally, board value gives “probability (?) of winning.”

State evaluation function (or utility value) is a very general and useful idea.

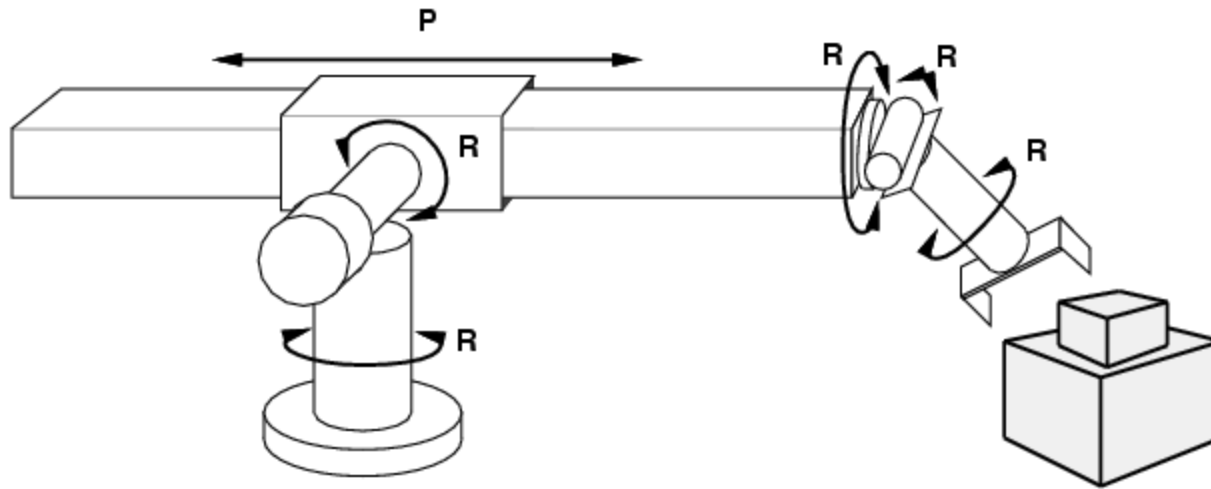
Examples:

- **TD-Gammon backgammon player. Neural net was trained to find approximately optimal state (board) evaluation values (range $[-1, +1]$). (Tesauro 1995)**
- **“Robocopter” --- automated helicopter control; trained state evaluation function. State given by features, such as, position, orientation, speed, and rotors position and speed. Possible actions change rotors speed and position. Evaluation assigns value in $[-1, +1]$ to capture stability.**



(Abbeel, Coates, and Ng 2008)

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

Other example search tasks

VLSI layout: positioning millions of components and connections on a chip to minimize area, circuit delays, etc.

Robot navigation / planning

Automatic assembly of complex objects

Protein design: sequence of amino acids that will fold into the 3-dimensional protein with the right properties.

Literally thousands of combinatorial search / reasoning / parsing / matching problems can be formulated as search problems in exponential size state spaces.

Search Techniques

Searching for a (shortest / least cost) path to goal state(s).

Search through the state space.

We will consider search techniques that use an explicit **search tree** that is generated by the **initial state + successor function**.

initialize (initial node)

Loop

choose a node for expansion
according to strategy

goal node? → done

expand node with successor function

Tree-search algorithms

Basic idea:

- 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
```

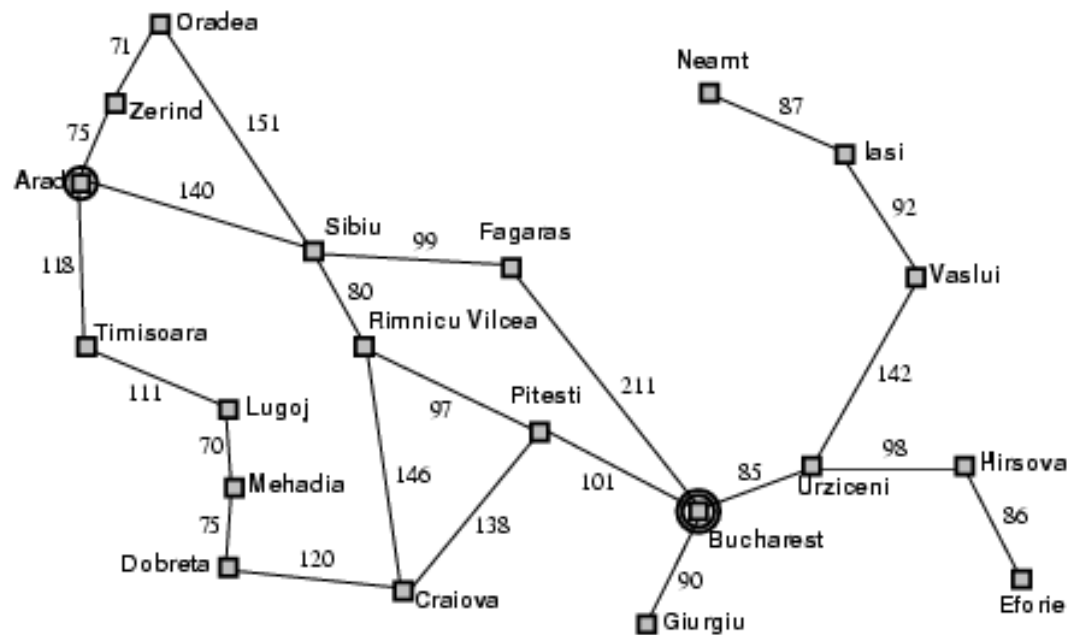
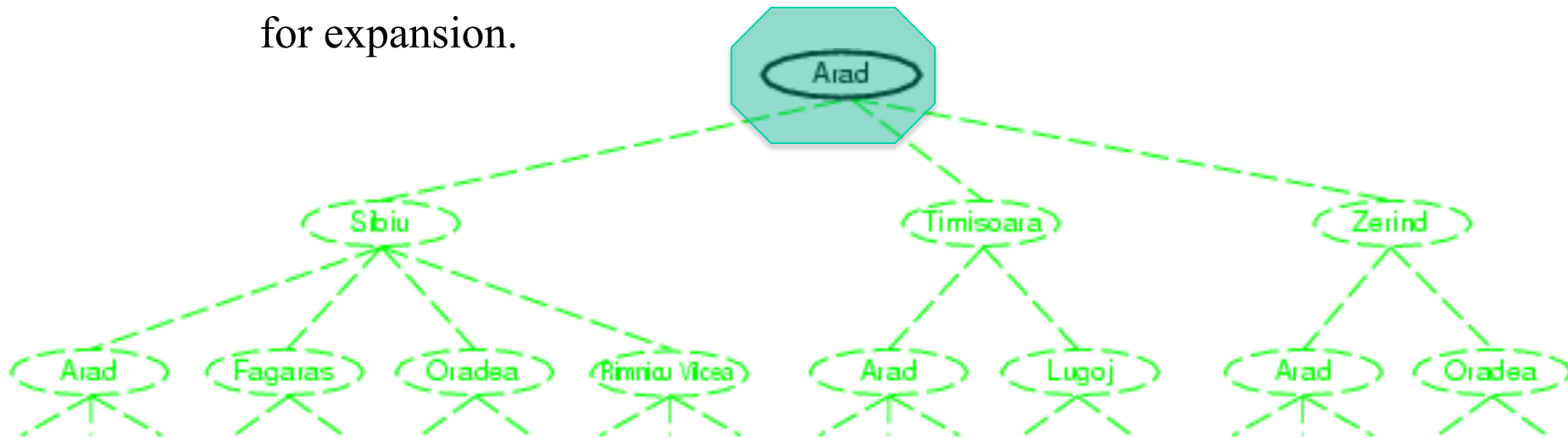
Fig. 3.7 R&N, p. 77

Note: 1) Here we only check a node for possibly being a goal state, *after* we select the node for expansion.

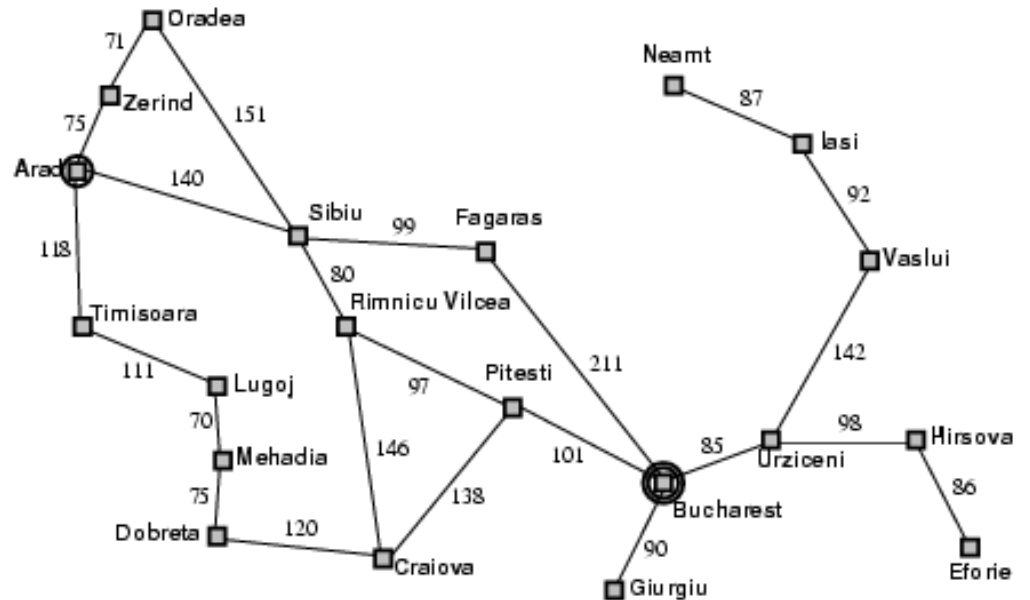
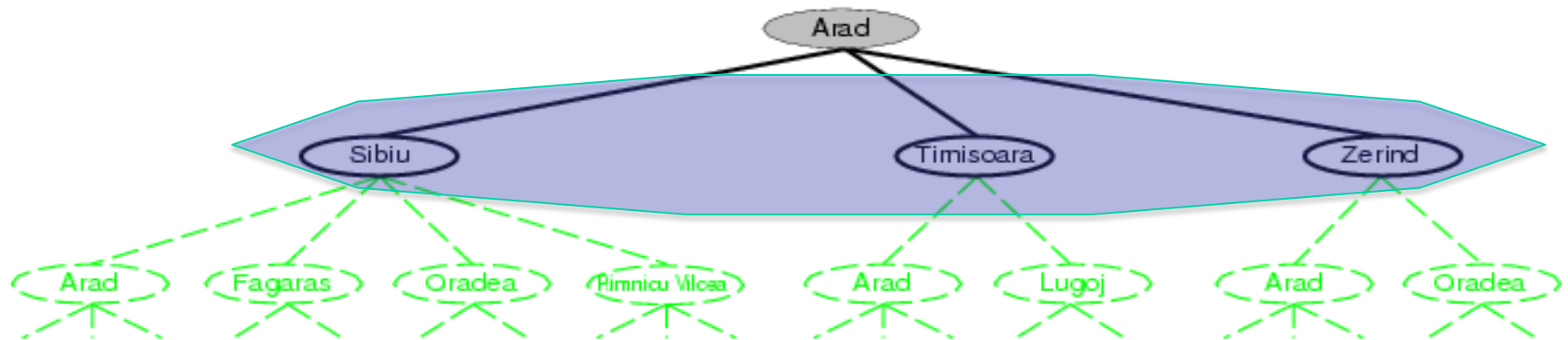
2) A “node” is a data structure containing state + additional info (parent node, etc).

Tree search example

Node selected
for expansion.

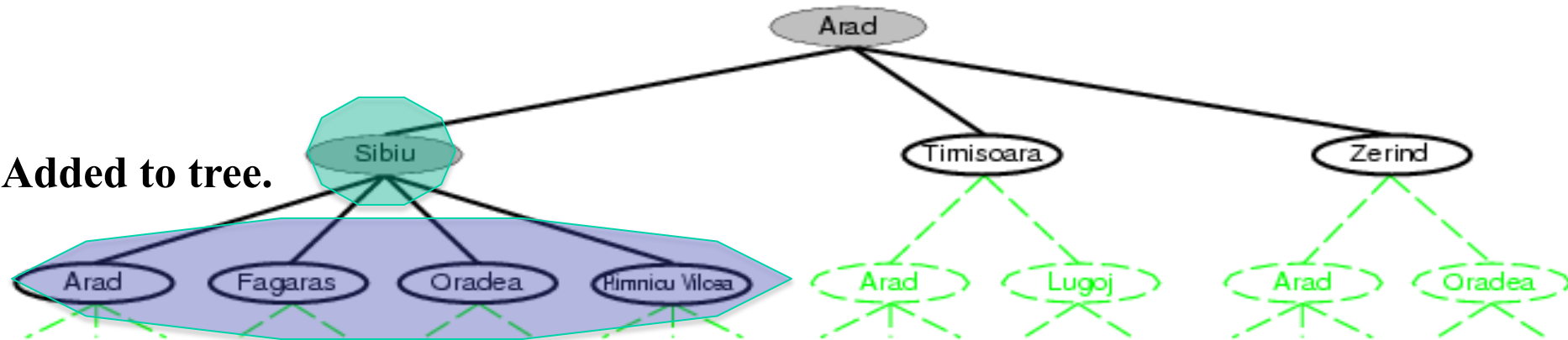


Nodes added to tree.



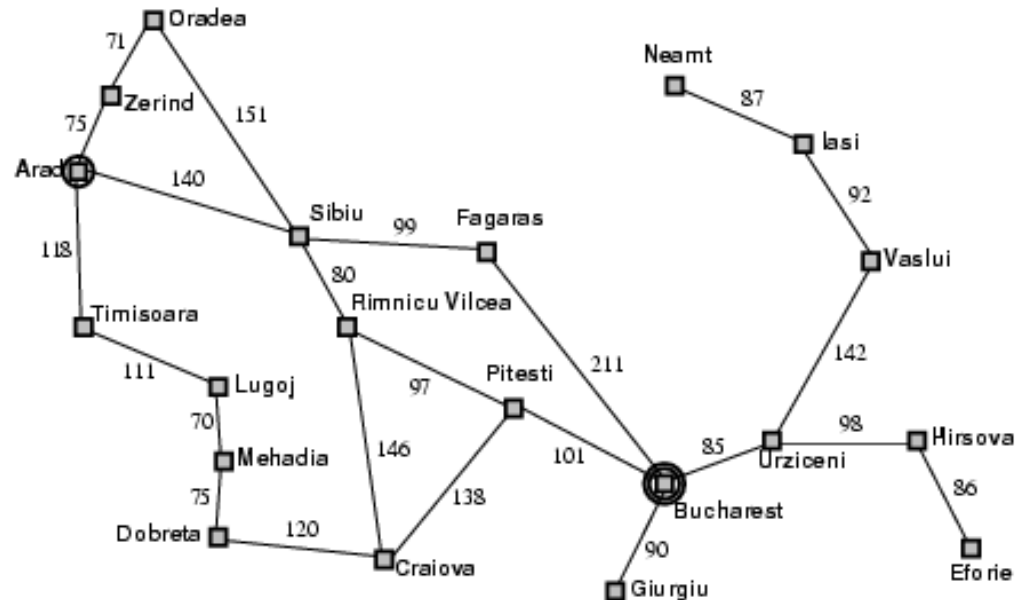
Selected for expansion.

Added to tree.



Note: Arad added (again) to tree!
(reachable from Sibiu)

Not necessarily a problem, but
in **Graph-Search**, we will avoid
this by maintaining an
“explored” list.



Graph-search

```
function GRAPH-SEARCH(problem) returns a solution, or failure
  initialize the frontier using the initial state of problem
  initialize the explored set to be empty
  loop do
    if the frontier is empty then return failure
    choose a leaf node and remove it from the frontier
    if the node contains a goal state then return the corresponding solution
    add the node to the explored set
    expand the chosen node, adding the resulting nodes to the frontier
      only if not in the frontier or explored set
```

Fig. 3.7 R&N, p. 77. See also exercise 3.13.

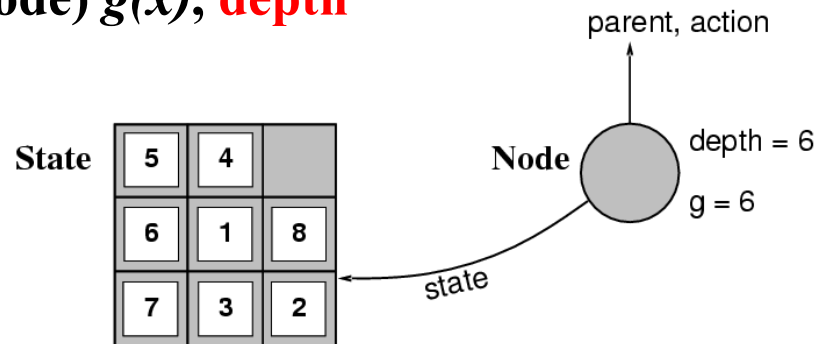
Note:

- 1) Uses “explored” set to avoid visiting already explored states.
- 2) Uses “frontier” set to store states that remain to be explored and expanded.
- 3) *However, with eg uniform cost search, we need to make a special check when node (i.e. state) is on frontier. Details later.*

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 **state**, tree **parent node**, **action** (applied to parent), **path cost** (initial state to node) $g(x)$, **depth**



The **Expand** function creates new nodes, filling in the various fields and using the **SuccessorFn** of the problem to create the corresponding states.

Fringe is the collection of nodes that have been generated but not (yet) expanded. Each node of the fringe is a **leaf node**.

Implementation: general tree search

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

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

Search strategies

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

Strategies are evaluated along the following dimensions:

- **completeness**: does it always find a solution if one exists?
- **time complexity**: number of nodes generated
- **space complexity**: maximum number of nodes in memory
- **optimality**: does it always find a least-cost solution?

Time and space complexity are measured in terms of

- ***b***: maximum branching factor of the search tree
- ***d***: depth of the least-cost solution
- ***m***: maximum depth of the state space (may be ∞)

Uninformed search strategies

Uninformed (blind) search 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**
- **Bidirectional search**

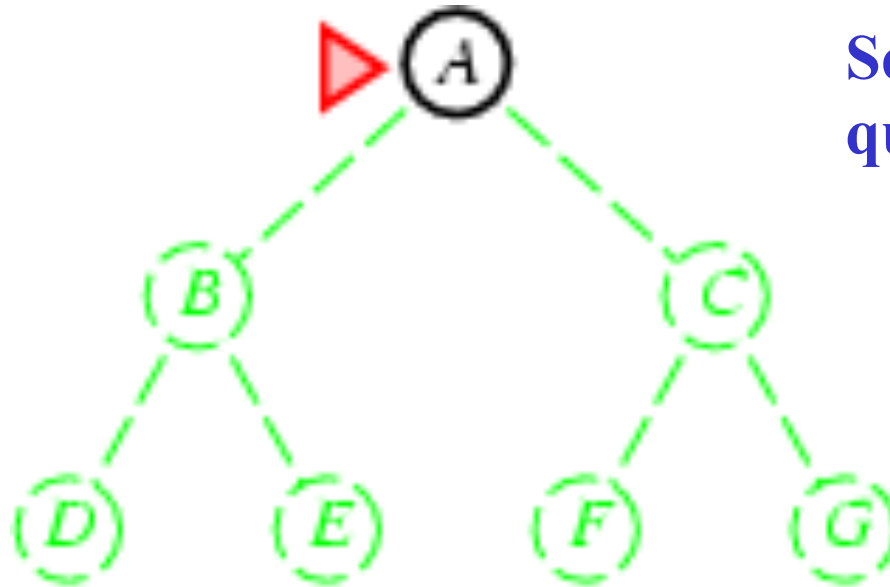
Key issue: type of queue used for the **fringe of the search tree** (collection of tree nodes that have been generated but not yet expanded)

Breadth-first search

Expand shallowest unexpanded node.

Implementation:

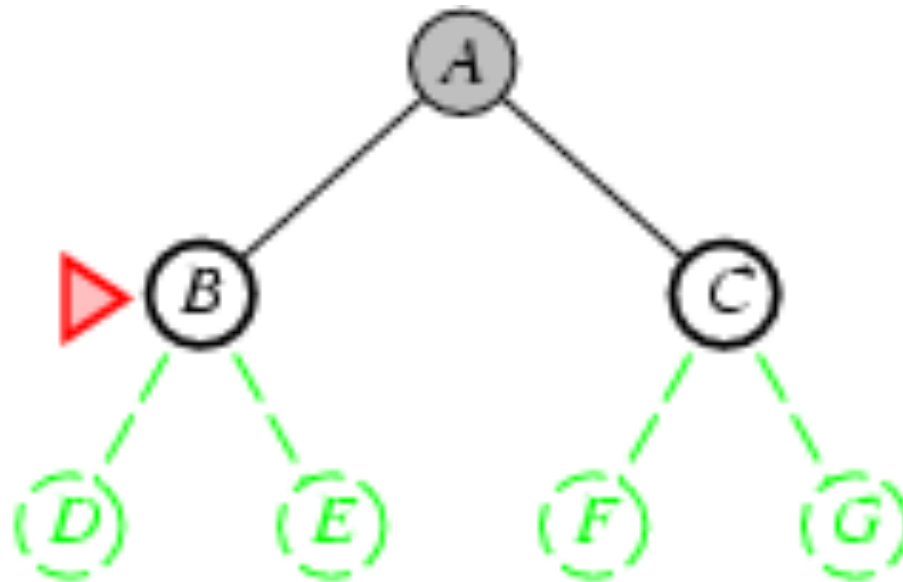
- *fringe* is a FIFO queue, i.e., new nodes go at end **Fringe queue: <A>**
(First In First Out queue.)



Select A from
queue and expand.

Gives
<B, C>

Queue: $\langle B, C \rangle$

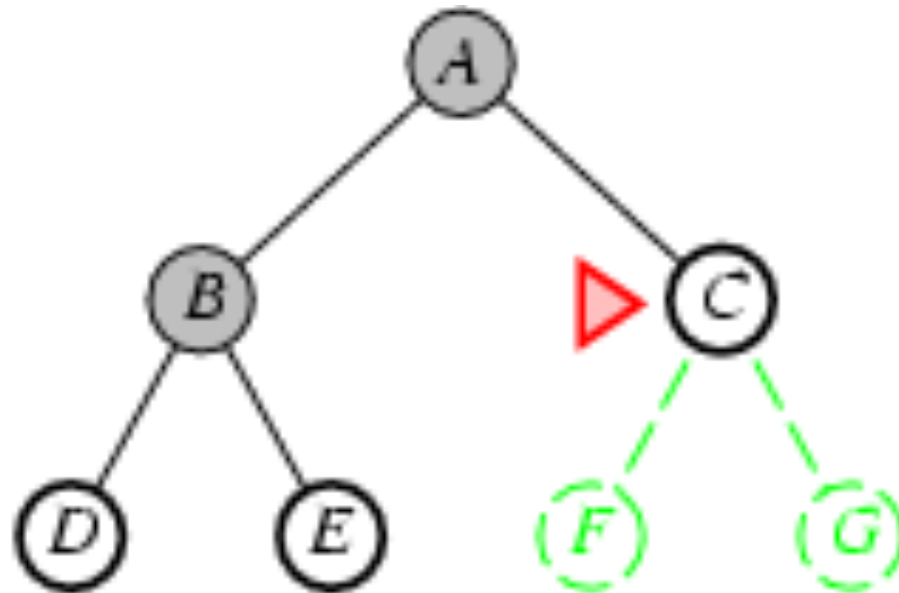


**Select B from
front, and expand.**

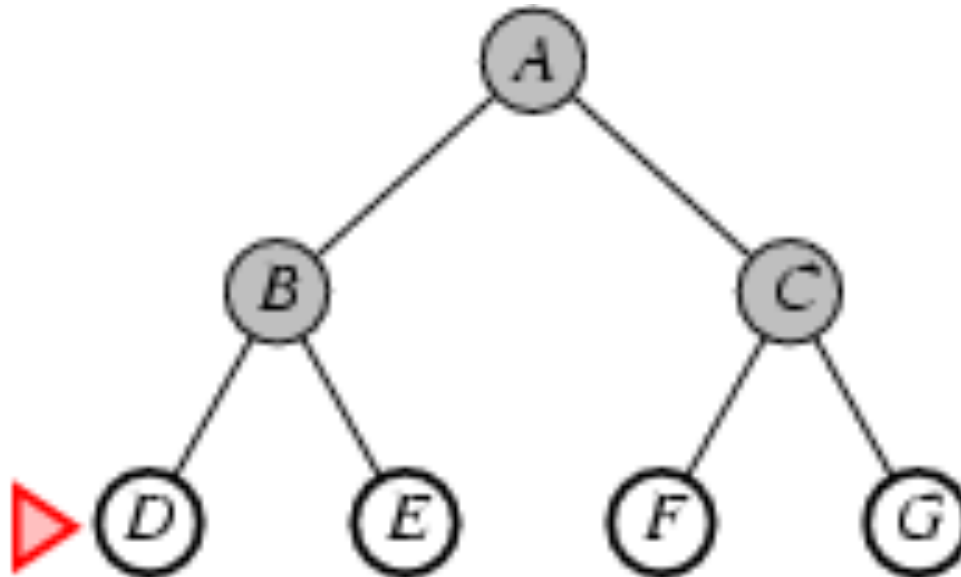
**Put children at the
end.**

**Gives
 $\langle C, D, E \rangle$**

Fringe queue: $\langle C, D, E \rangle$



Fringe queue: $\langle D, E, F, G \rangle$



Assuming no further children, queue becomes $\langle E, F, G \rangle$, $\langle F, G \rangle$, $\langle G \rangle$, $\langle \rangle$. Each time node checked for goal state.

Properties of breadth-first search

Note: check for goal only when node is expanded.

Complete? Yes (if b is finite)

Time? $1 + b + b^2 + b^3 + \dots + b^d + b(b^d - 1) = O(b^{d+1})$ Depth d , goal may be last node (only checked when expanded.).
Why?

Space? $O(b^{d+1})$ (keeps every node in memory; needed also to reconstruct soln. path)

Optimal soln. found?

Yes (if all step costs are identical)

Space is the bigger problem (more than time)

b : maximum branching factor of the search tree

d : depth of the least-cost solution

Uniform-cost search

Expand **least-cost** (of path to) unexpanded node
(e.g. useful for finding shortest path on map)

Implementation:

– *fringe* = queue **ordered by path cost**

g – cost of reaching a node

Complete? Yes, if step cost $\geq \epsilon$ (>0)

Time? # of nodes with $g \leq$ cost of optimal solution (C^*),
 $O(b^{(1+\lceil C^*/\epsilon \rceil)})$

Space? # of nodes with $g \leq$ cost of optimal solution,
 $O(b^{(1+\lceil C^*/\epsilon \rceil)})$

Optimal? Yes – nodes expanded in increasing order of $g(n)$

Note: Some subtleties (e.g. checking for goal state).

See p 84 R&N. Also, next slide.

Uniform-cost search

Two subtleties: (bottom p. 83 Norvig)

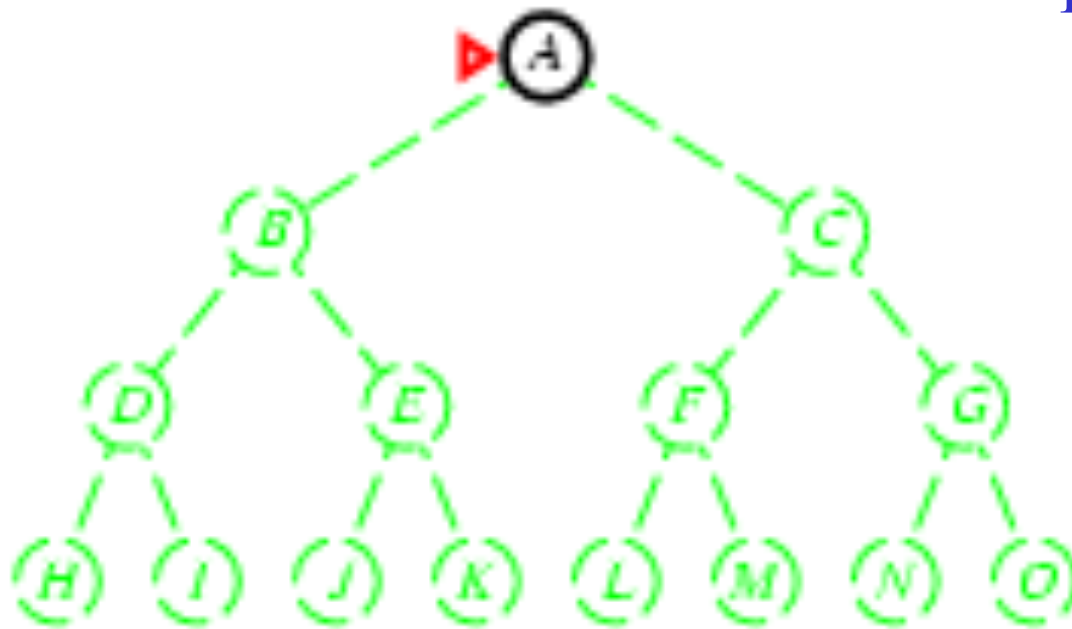
- 1) Do goal state test, only when a node is selected for expansion.
(Reason: Bucharest may occur on frontier with a longer than optimal path. It won't be selected for expansion yet. Other nodes will be expanded first, leading us to uncover a shorter path to Bucharest. See also point 2).
- 2) Graph-search alg. says “don't add child node to frontier if already on explored list **or already on frontier.**” BUT, child may give a shorter path to a state already on frontier. Then, we need to modify the existing node on frontier with the shorter path. See fig. 3.14 (else-if part).

Depth-first search

“Expand deepest unexpanded node”

Implementation:

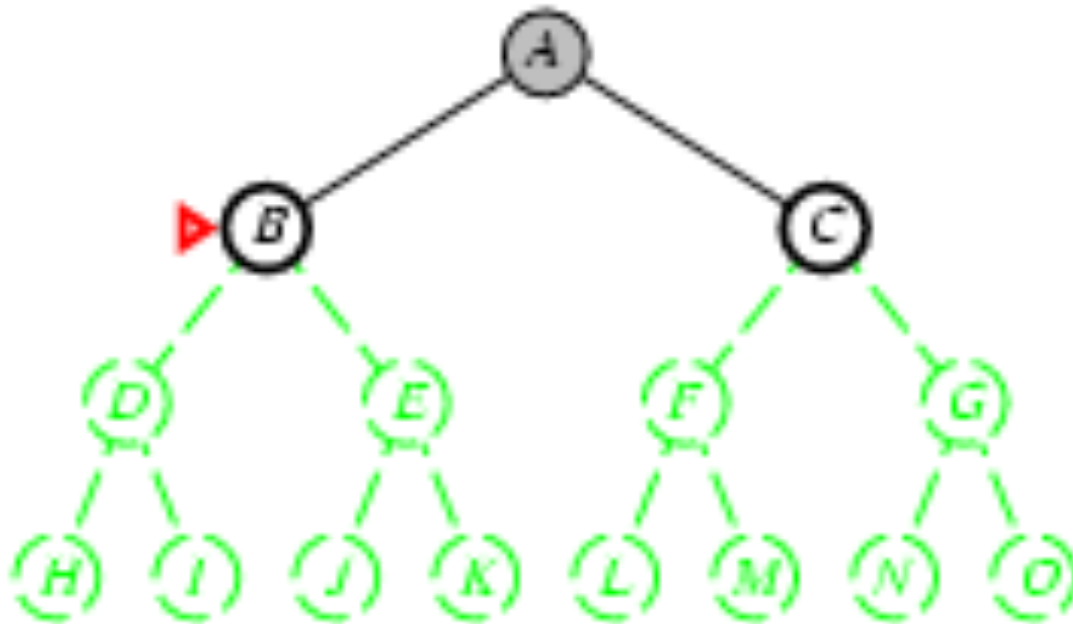
- *fringe* = LIFO queue, i.e., put successors at front (“push on stack”)
Last In First Out



Fringe stack:
A

Expanding A,
gives stack:
B
C

So, B next.



**Expanding B,
gives stack:**

**D
E
C**

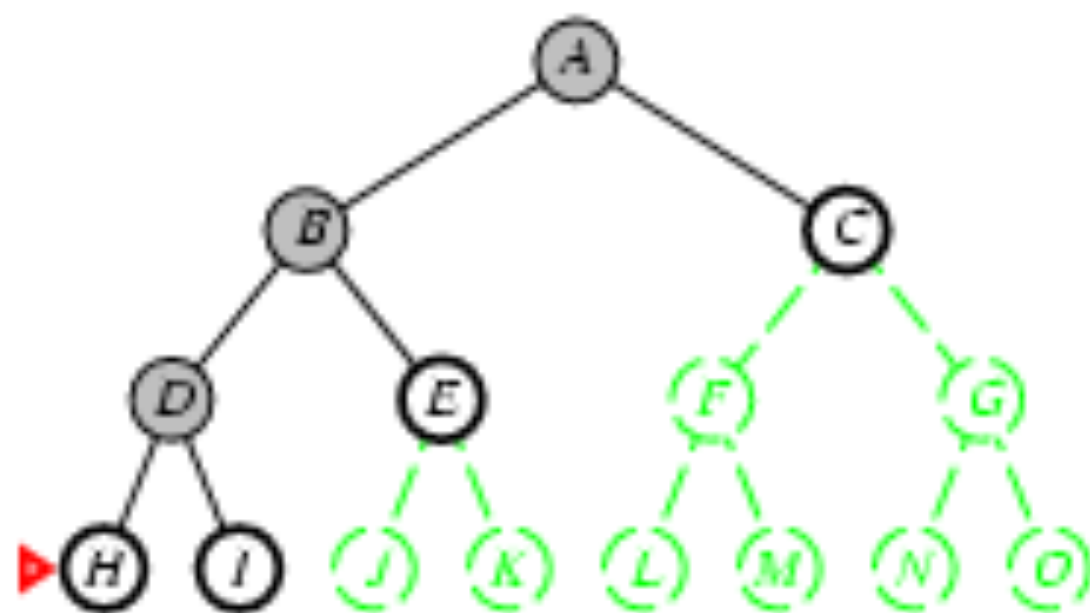
So, D next.

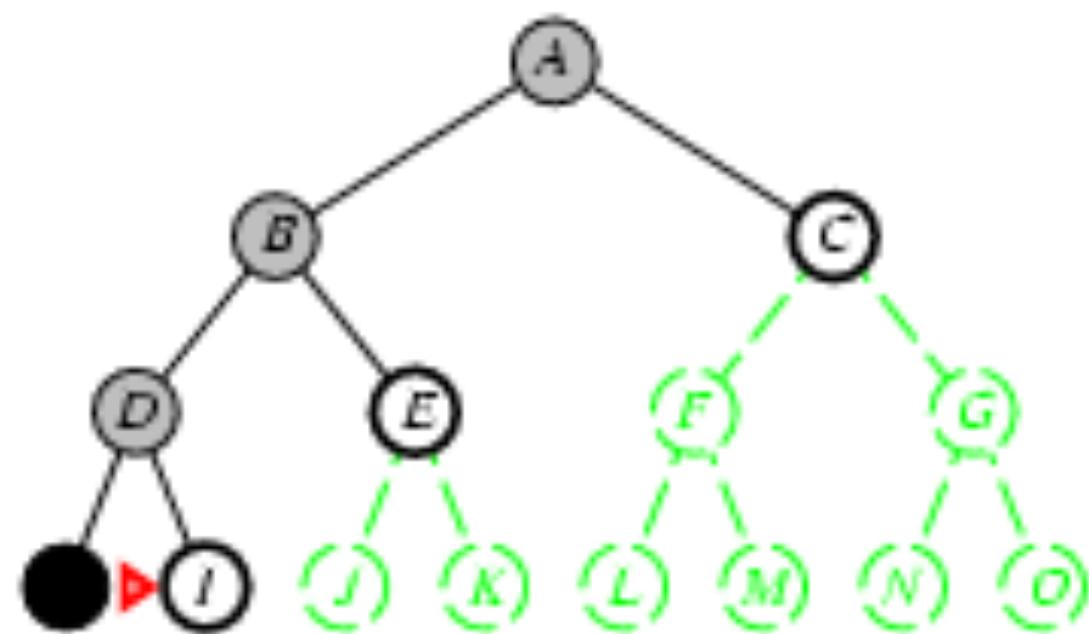
**Expanding D,
gives stack:**

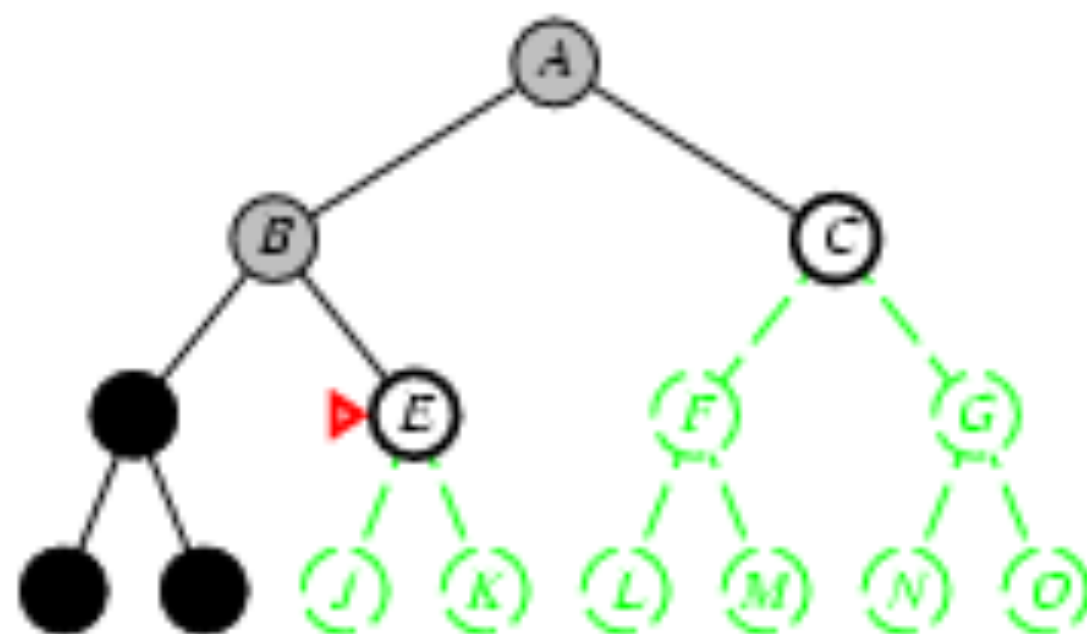
**H
I
E
C**

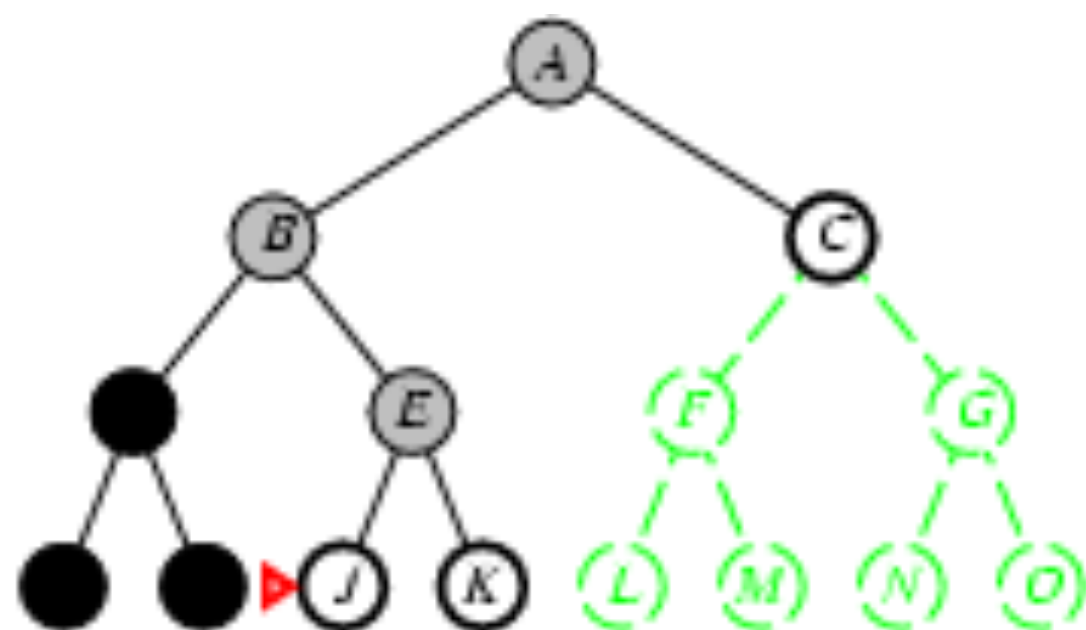
**So, H next.
etc.**

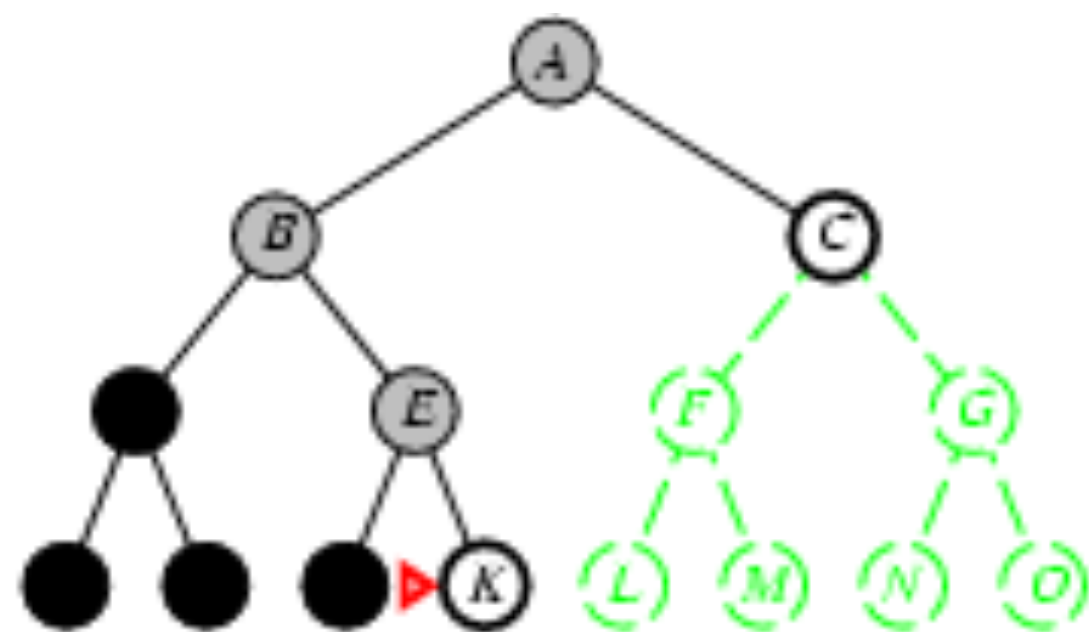


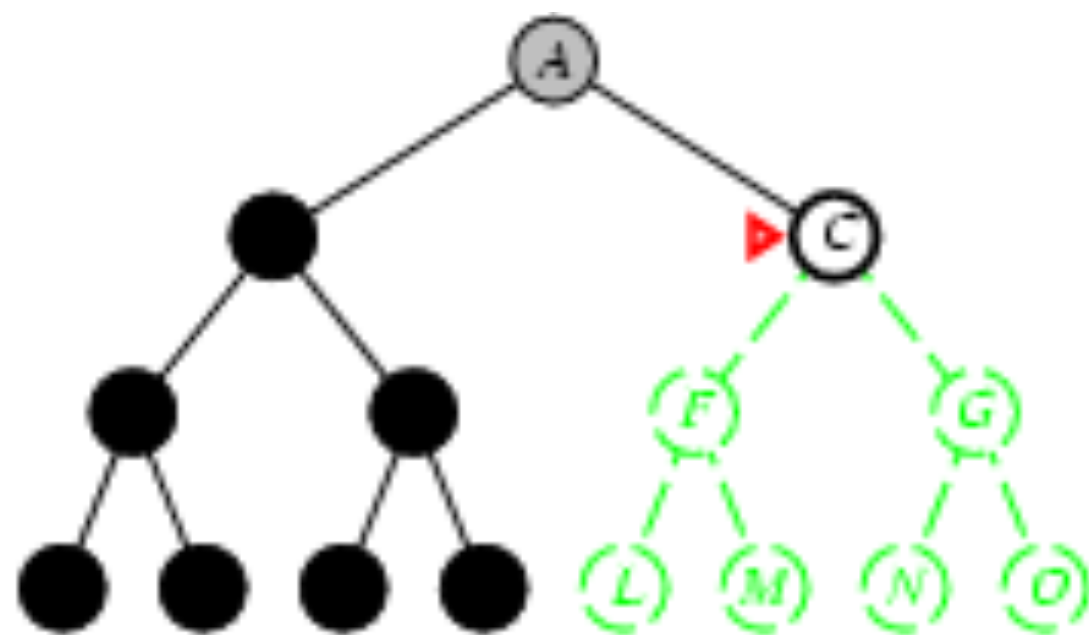


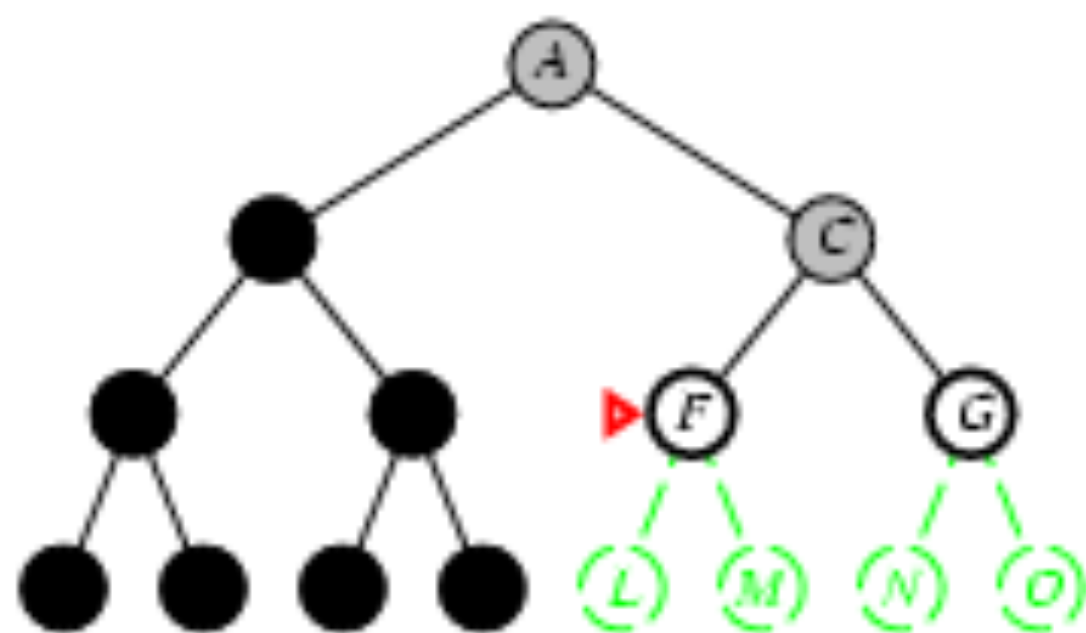


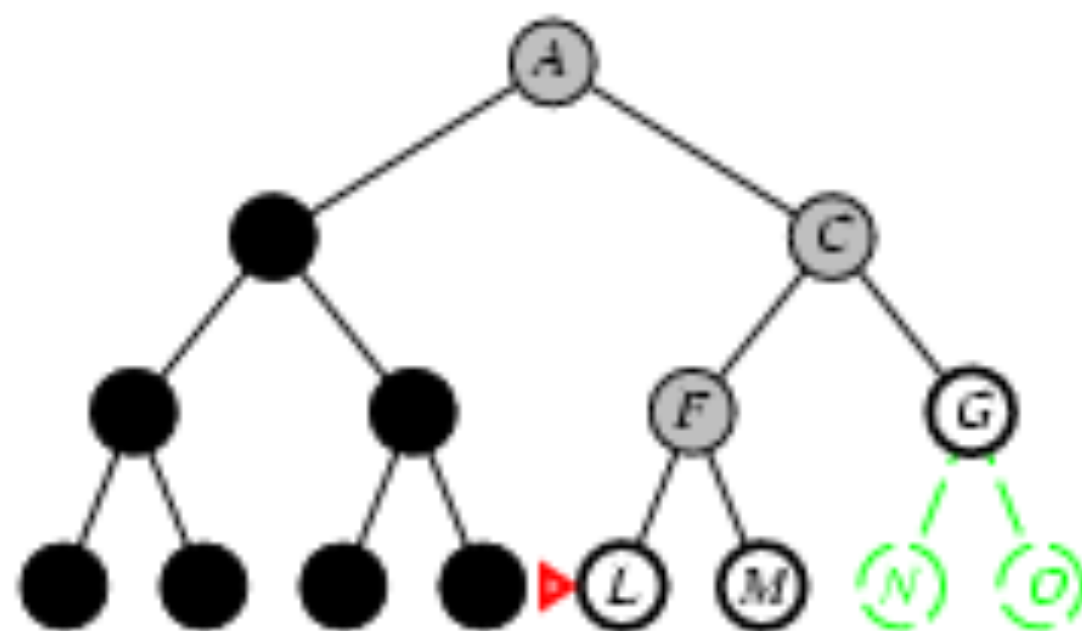


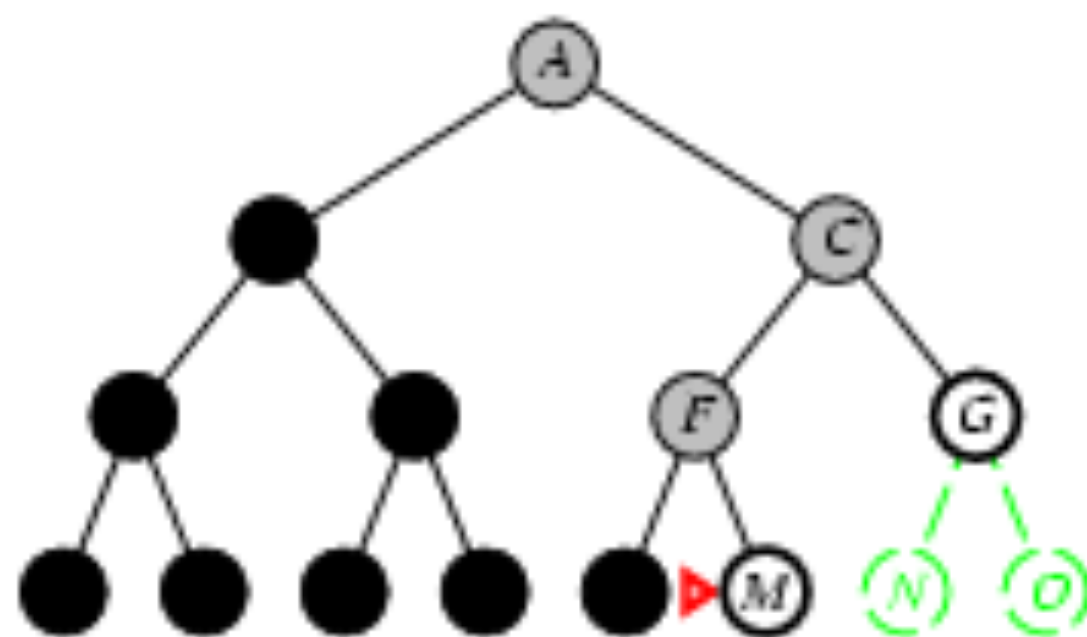












What is main advantage over breadth first search?

What information is stored? How much storage required?

The stack. $O(\text{depth} \times \text{branching})$.

Properties of depth-first search

Complete? No: fails in infinite-depth spaces, spaces with loops
Modify to avoid repeated states along path
→ complete in finite spaces

Time? $O(b^m)$: bad 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!

Note: Can also
reconstruct soln. path
from single stored
branch.

**Guarantee that
opt. soln. is found?** No

b : max. branching factor of the search tree
 d : depth of the shallowest (least-cost) soln.
 m : maximum depth of state space

Note: In “backtrack search” only one successor is generated
→ only $O(m)$ memory is needed; also successor is modification of
the current state, but we have to be able to undo each modification.
More when we talk about Constraint Satisfaction Problems (CSP).

[here]

Iterative deepening search

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

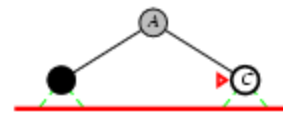
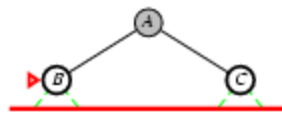
Iterative deepening search $l = 0$

Limit = 0



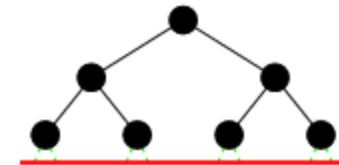
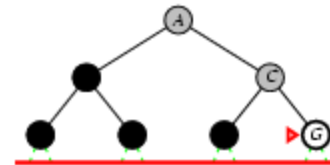
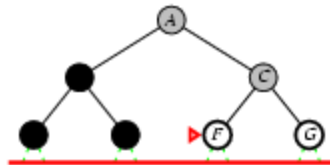
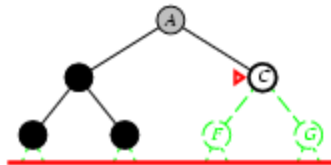
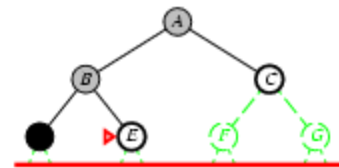
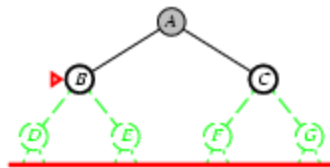
Iterative deepening search $l = 1$

Limit = 1



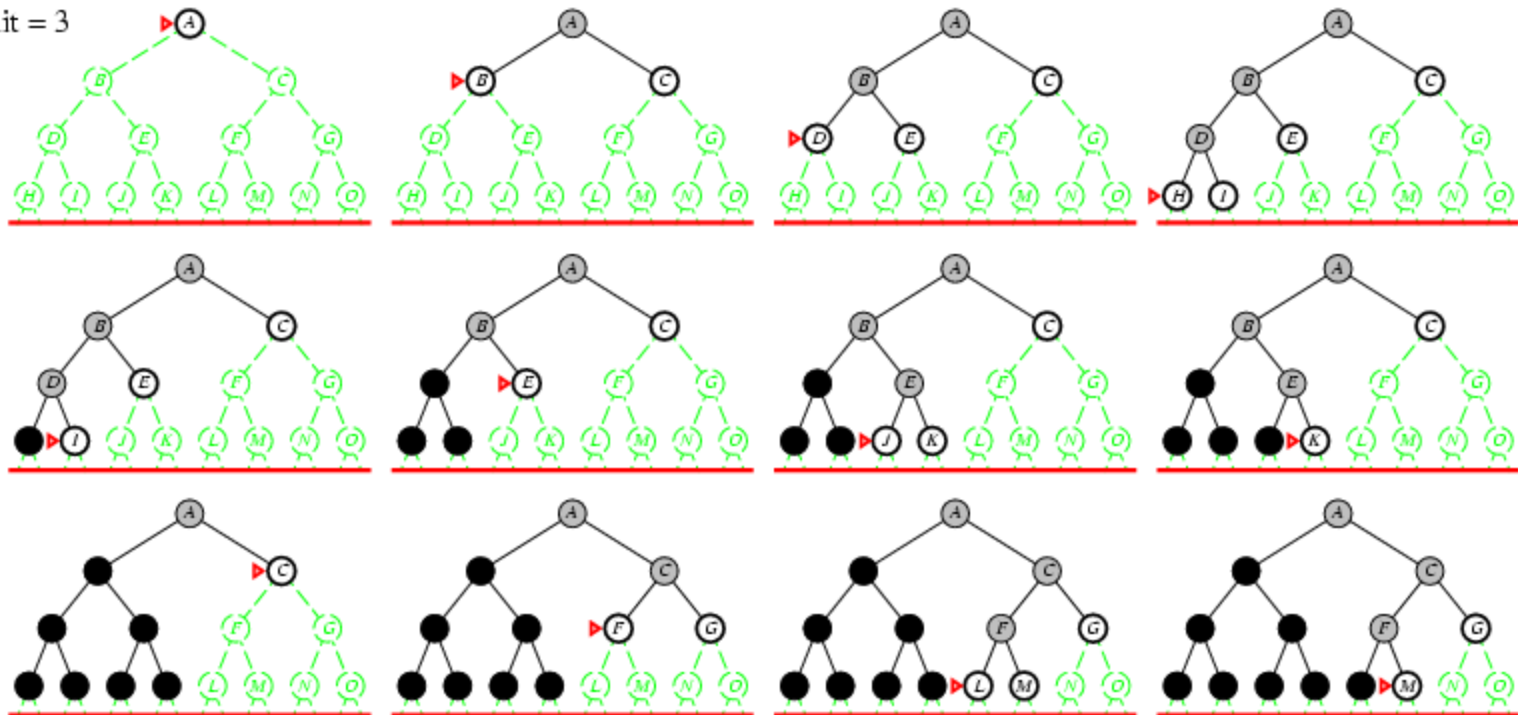
Iterative deepening search $l=2$

Limit = 2



Iterative deepening search $l=3$

Limit = 3



Why would one do that?

Combine **good memory requirements** of depth-first with the **completeness** of breadth-first when branching factor is finite and is **optimal** when the path cost is a non-decreasing function of the depth of the node.

Idea was a breakthrough in game playing. All game tree search uses iterative deepening nowadays. What's the added advantage in games?

“Anytime” nature.

Iterative deepening search

Number of nodes generated in an **iterative deepening search** to depth d with branching factor b :

Looks quite wasteful, is it?

$$N_{IDS} = d b^1 + (d-1)b^2 + \dots + 3b^{d-2} + 2b^{d-1} + 1b^d$$

Nodes generated in a **breadth-first search** with branching factor b :

$$N_{BFS} = b^1 + b^2 + \dots + b^{d-2} + b^{d-1} + b^d$$

For $b = 10$, $d = 5$,

$$- N_{BFS} = 10 + 100 + 1,000 + 10,000 + 100,000 = 111,110$$

$$- N_{IDS} = 50 + 400 + 3,000 + 20,000 + 100,000 = 123,456$$



Iterative deepening is the preferred uninformed search method when there is a large search space and the depth of the solution is not known.

Properties of iterative deepening search

Complete? Yes

(b finite)

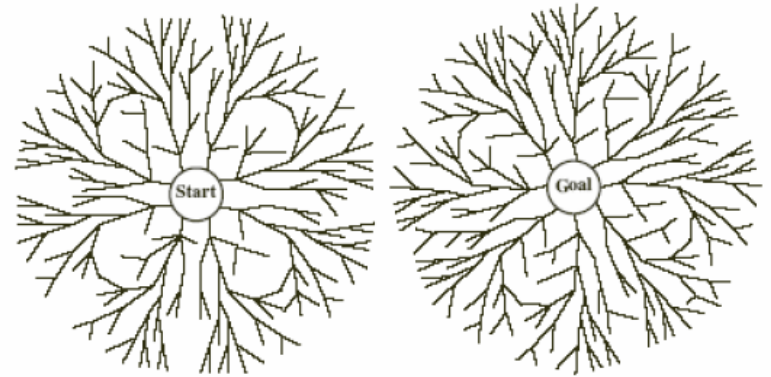
Time? $d b^1 + (d-1)b^2 + \dots + b^d = O(b^d)$

Space? $O(bd)$

Optimal? Yes, if step costs identical

Bidirectional Search

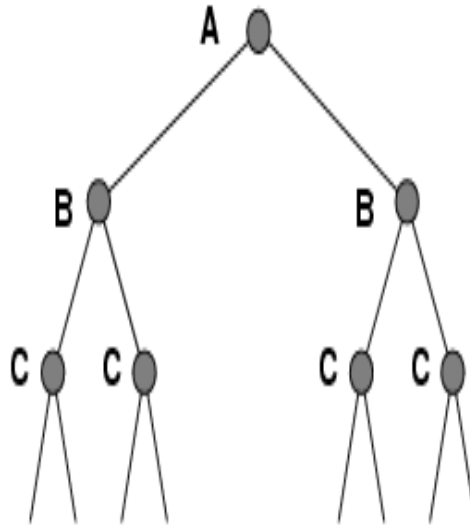
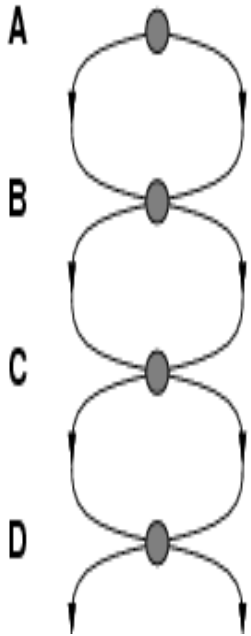
- Simultaneously:
 - Search forward from start
 - Search backward from the goalStop when the two searches meet.
- If branching factor = b in each direction, with solution at depth d
→ **only $O(2 b^{d/2}) = O(2 b^{d/2})$**
- Checking a node for membership in the other search tree can be done in constant time (hash table)
- Key limitations:
Space $O(b^{d/2})$
Also, how to search backwards can be an issue (e.g., in Chess)? What's tricky?
Problem: lots of states satisfy the goal; don't know which one is relevant.



Aside: The predecessor of a node should be easily computable (i.e., actions are easily reversible).

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

Repeated states



Don't return to parent node

Don't generate successor = node's parent

Don't allow cycles

Don't revisit state

Keep every visited state in memory!
 $O(b^d)$ (can be expensive)

Problems in which actions are reversible (e.g., routing problems or sliding-blocks puzzle). Also, in eg Chess; uses hash tables to check for repeated states. Huge tables 100M+ size but very useful.

See Tree-Search vs. Graph-Search in Fig. 3.7 R&N. But need to be careful to maintain (path) optimality and completeness.

Summary: General, uninformed search

Original search ideas in AI were inspired by studies of human problem solving in, eg, puzzles, math, and games, but a great many AI tasks now require some form of search (e.g. find optimal agent strategy; active learning; constraint reasoning; NP-complete problems require search).

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.

Avoid repeating states / cycles.