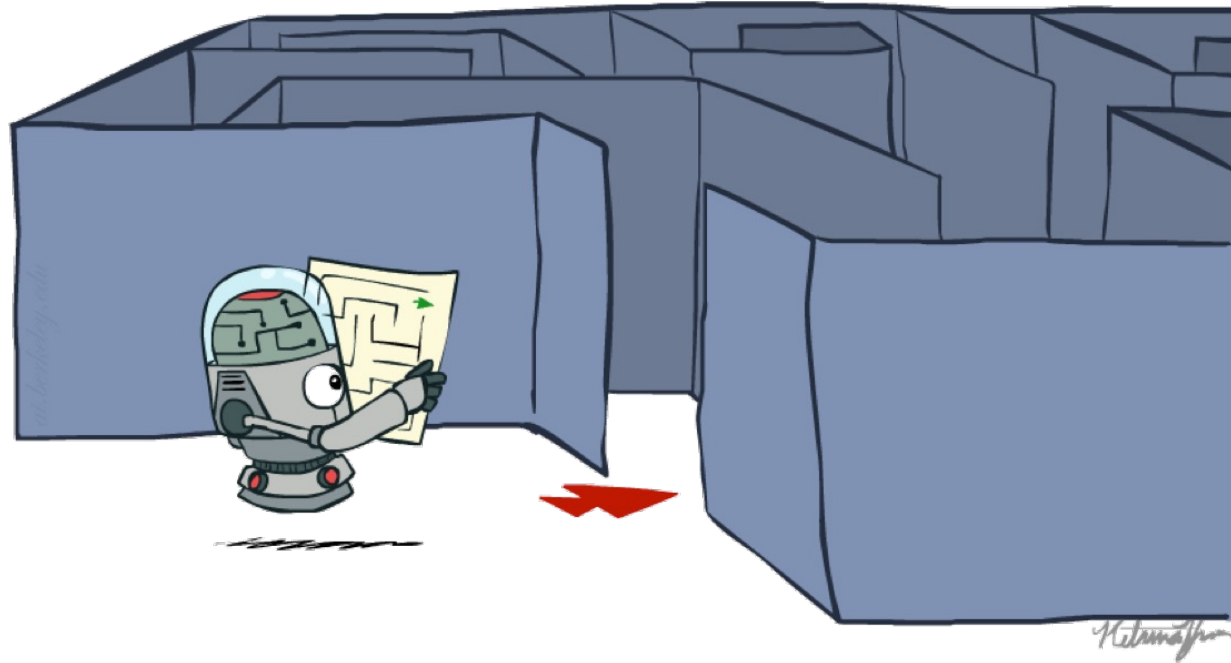


# Artificial Intelligence

## Search

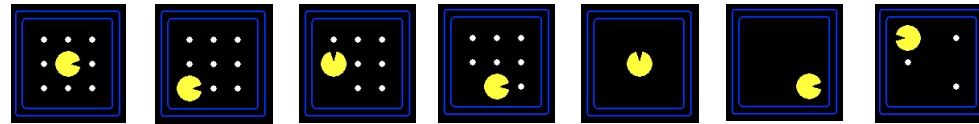


[These slides adapted from Dan Klein, Pieter Abbeel, and Nikita Kitaev]

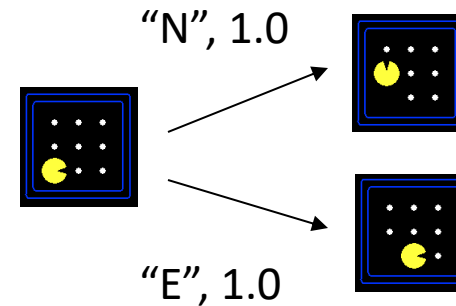
# Search Problems

- A **search problem** consists of:

- A state space

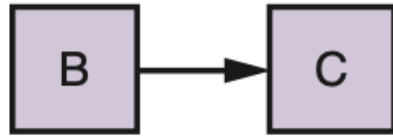


- A successor function  
(with actions, costs)

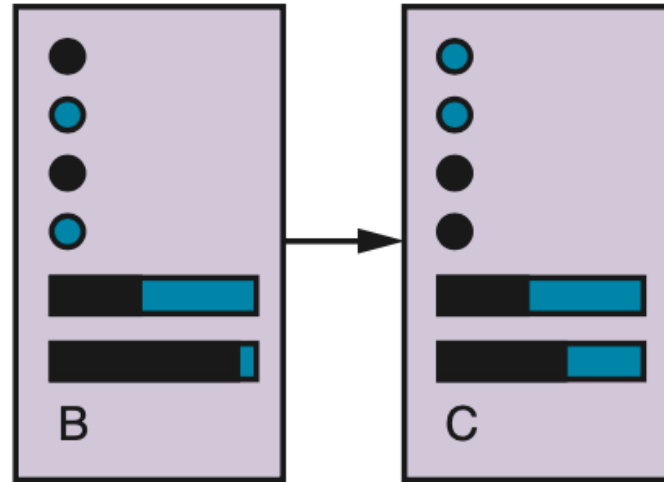


- A start state and a goal test
- A **solution** is a sequence of actions (a plan) which transforms the start state to a goal state

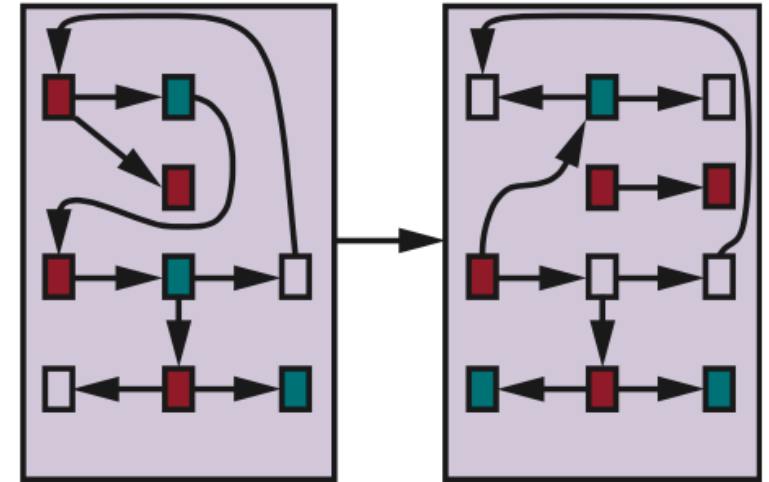
# Different state representation



(a) Atomic



(b) Factored



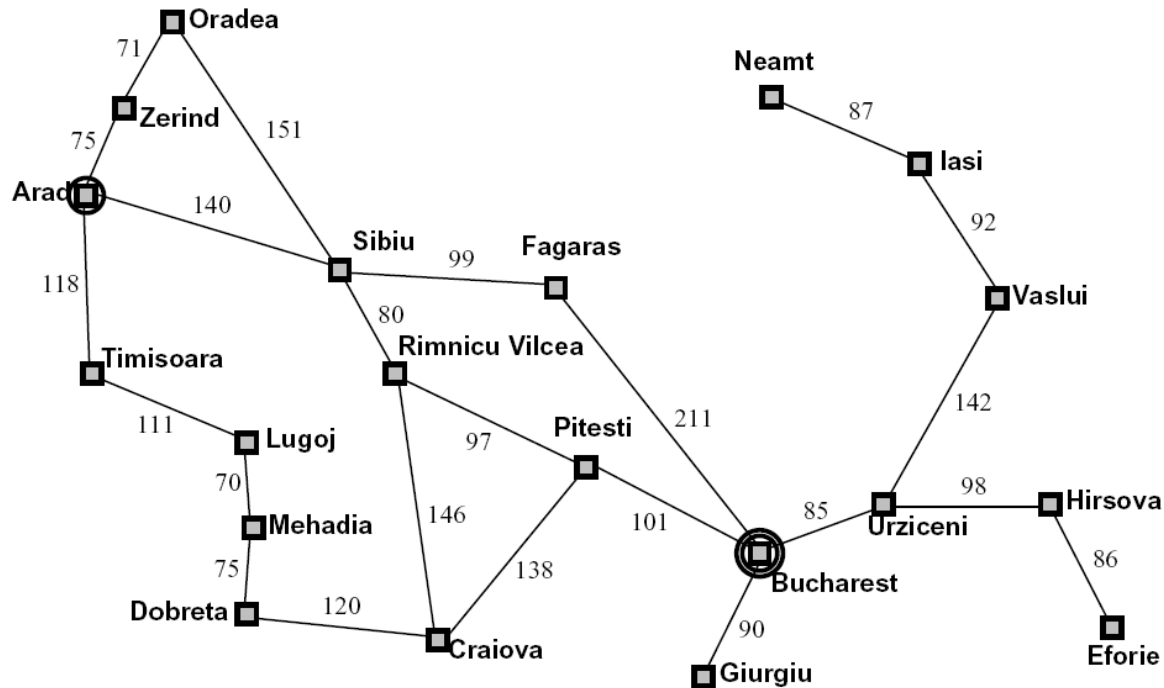
(c) Structured

# Search Problems Are Models

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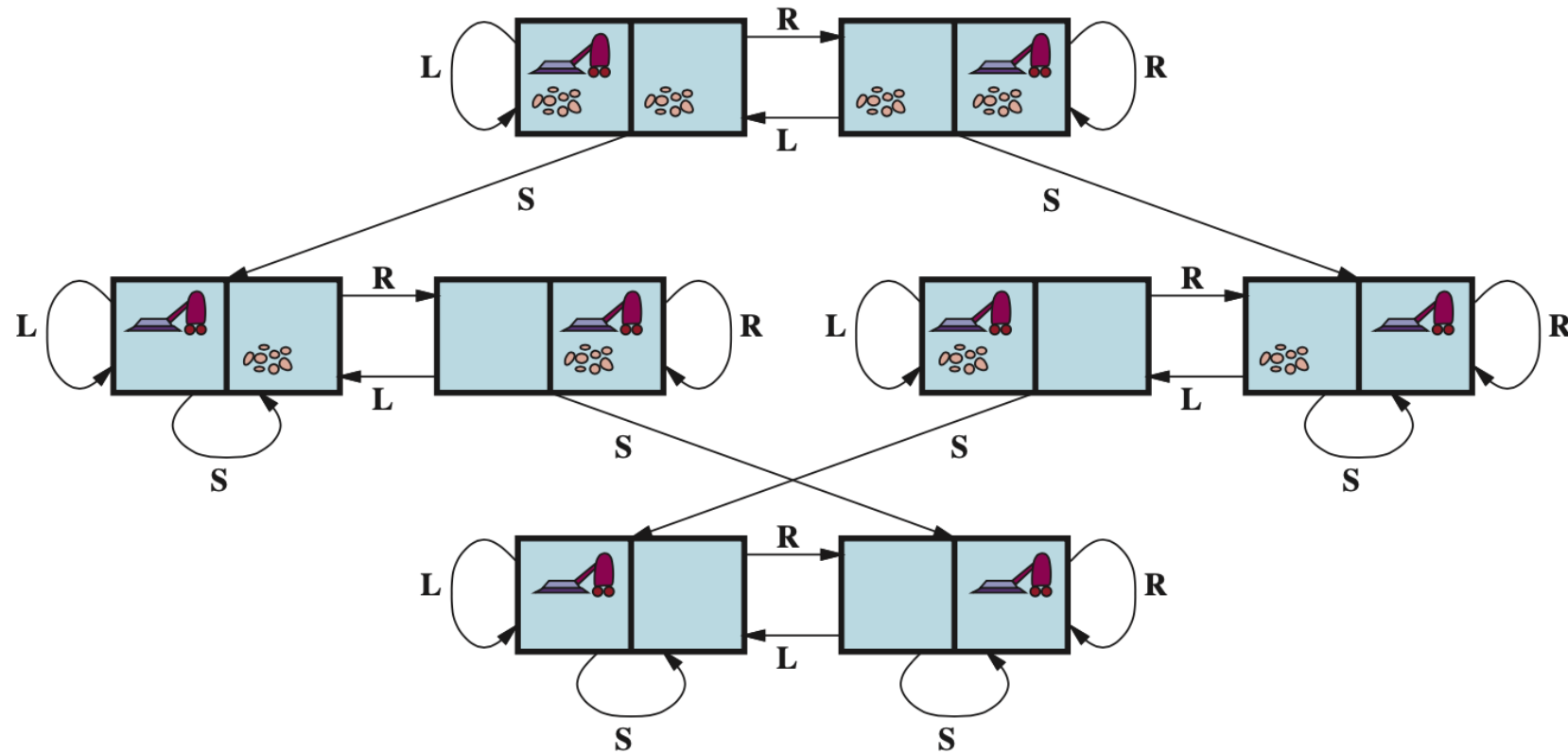


# Example: Traveling in Romania



- State space:
  - Cities
- Successor function:
  - Roads: Go to adjacent city with cost = distance
- Start state:
  - Arad
- Goal test:
  - Is state == Bucharest?
- Solution?

# Cleaner



# Puzzles

---

7	2	4
5		6
8	3	1

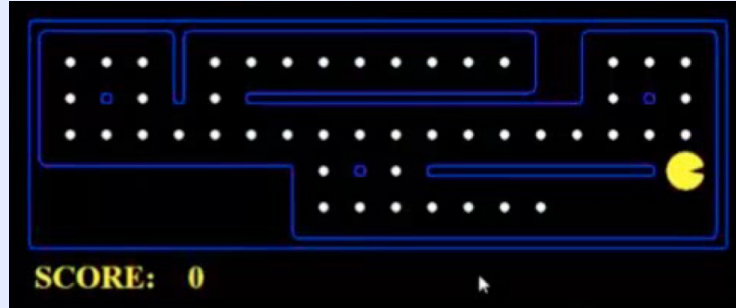
Start State

	1	2
3	4	5
6	7	8

Goal State

# What's in a State Space?

The **world state** includes every last detail of the environment



A **search state** keeps only the details needed for planning (abstraction)

## ■ Problem: Pathing

- States:  $(x,y)$  location
- Actions: NSEW
- Successor: update location only
- Goal test: is  $(x,y)=\text{END}$

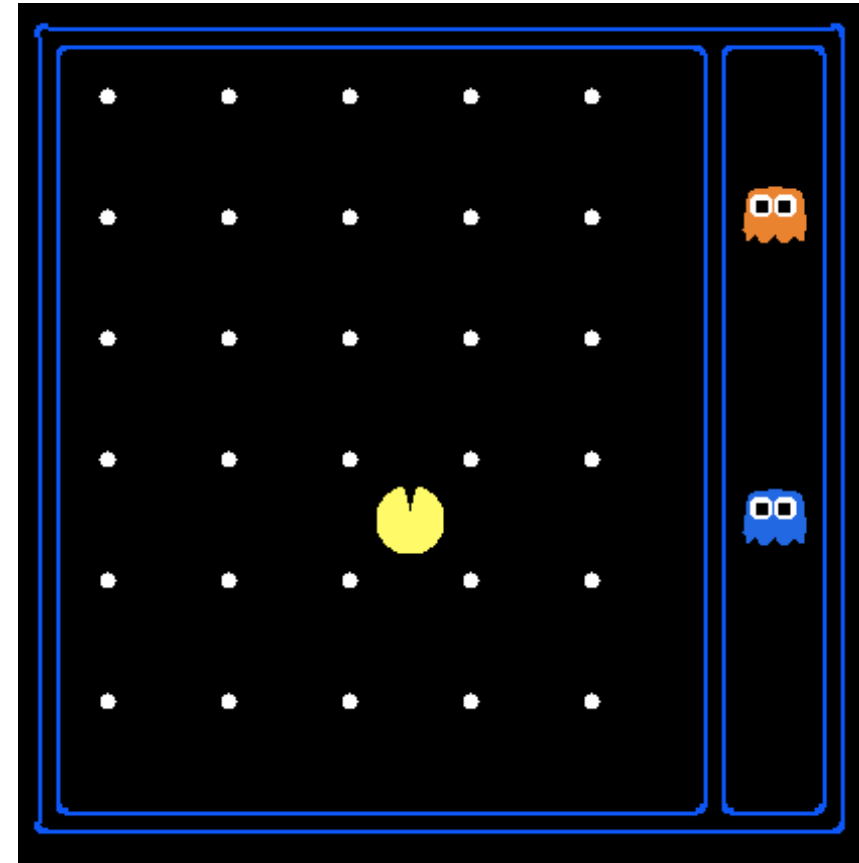
## ■ Problem: Eat-All-Dots

- States:  $\{(x,y), \text{dot booleans}\}$
- Actions: NSEW
- Successor: update location and possibly a dot boolean
- Goal test: dots all false

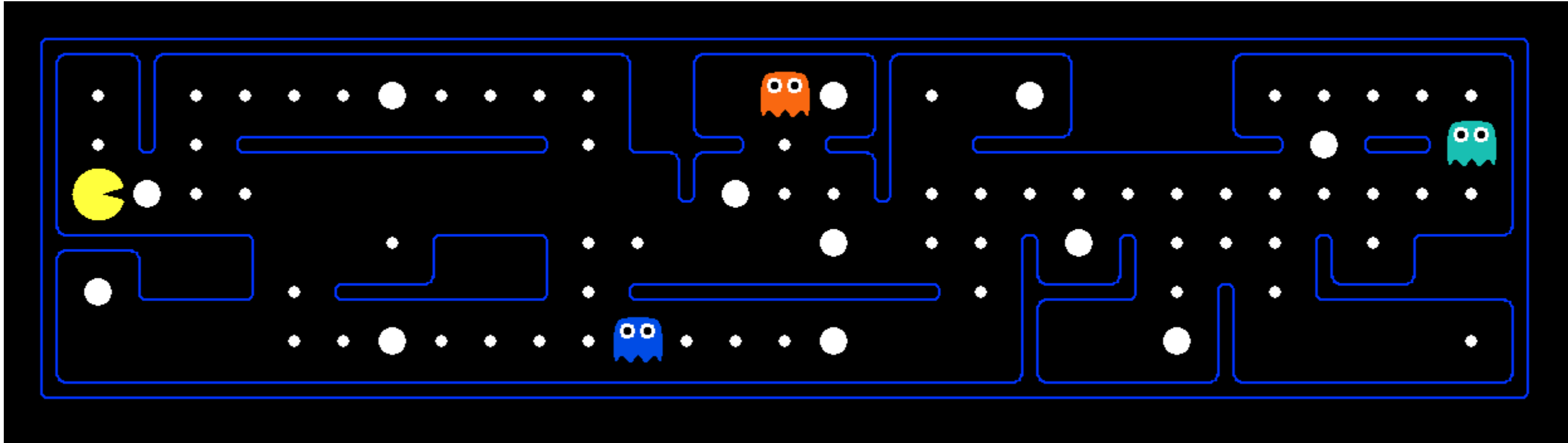


# State Space Sizes?

- World state:
  - Agent positions: 120
  - Food count: 30
  - Ghost positions: 12
  - Agent facing: NSEW
- How many
  - World states?  
 $120 \times (2^{30}) \times (12^2) \times 4$
  - States for pathing?  
120
  - States for eat-all-dots?  
 $120 \times (2^{30})$



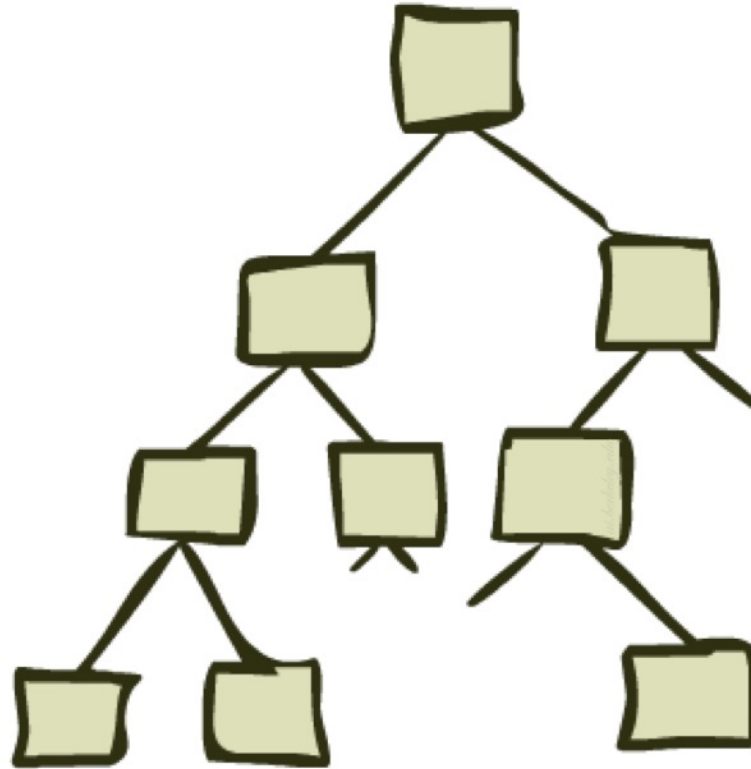
# Quiz: Safe Passage



- Problem: eat all dots while keeping the ghosts perma-scared
- What does the state space have to specify?
  - (agent position, dot booleans, power pellet booleans, remaining scared time)

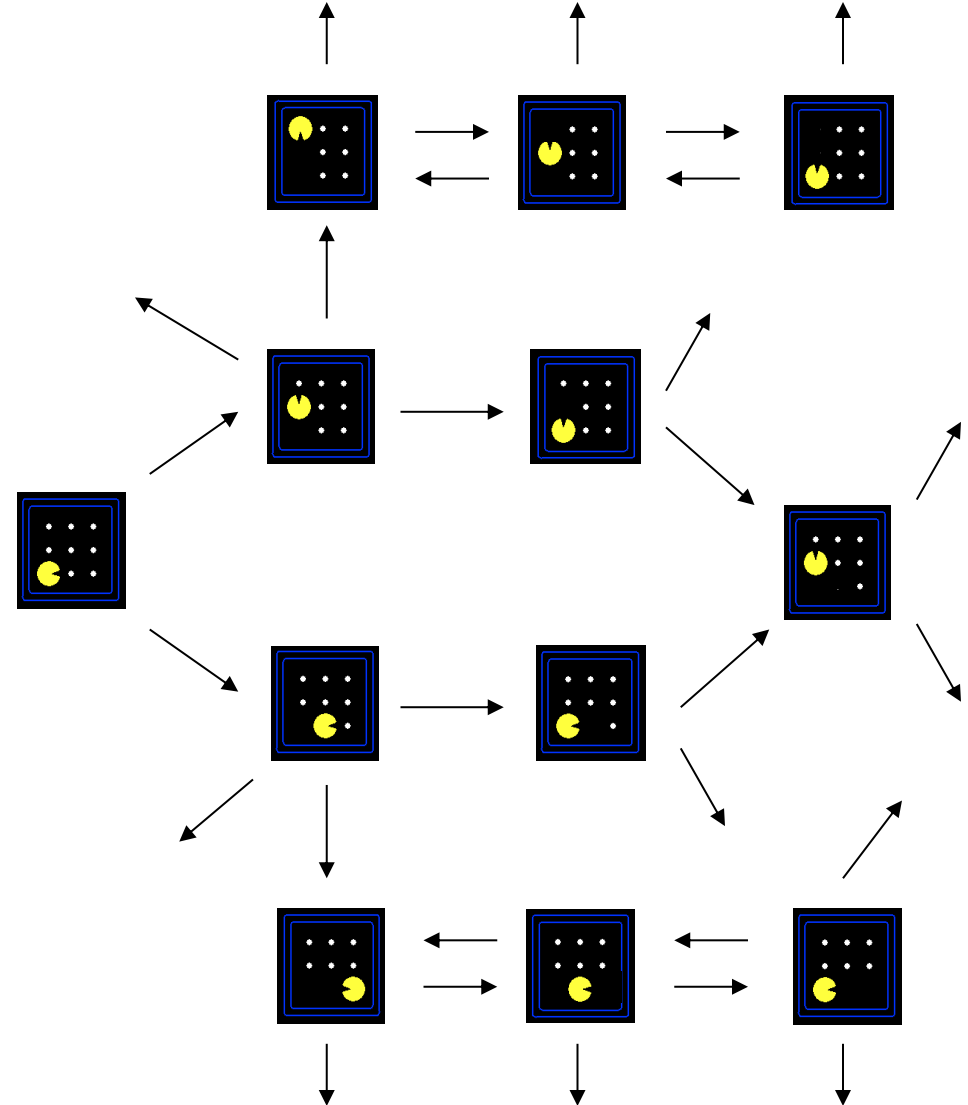
# State Space Graphs and Search Trees

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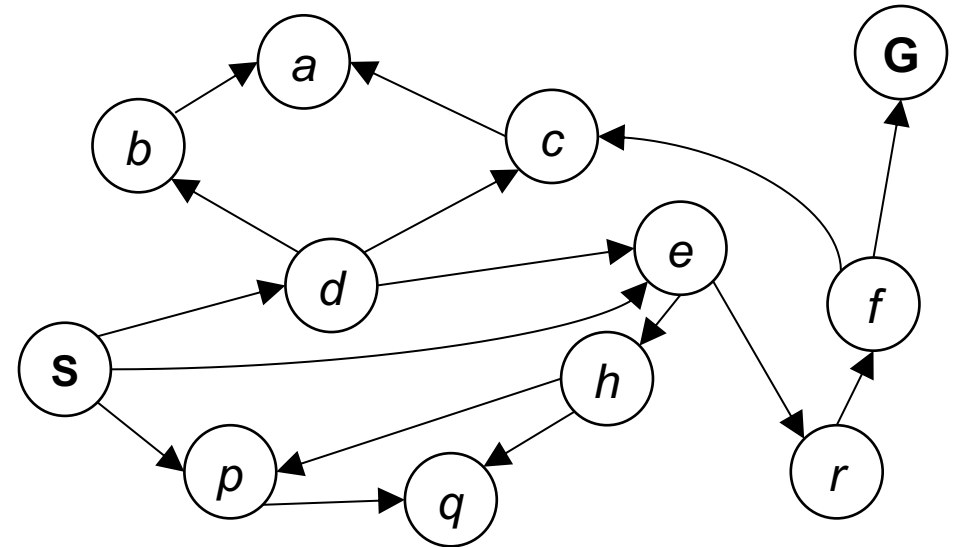
# State Space Graphs

- State space graph: A mathematical representation of a search problem
  - Nodes are (abstracted) world configurations
  - Arcs represent successors (action results)
  - The goal test is a set of goal nodes (maybe only one)
- In a state space graph, each state occurs only once!
- We can rarely build this full graph in memory (it's too big), but it's a useful idea



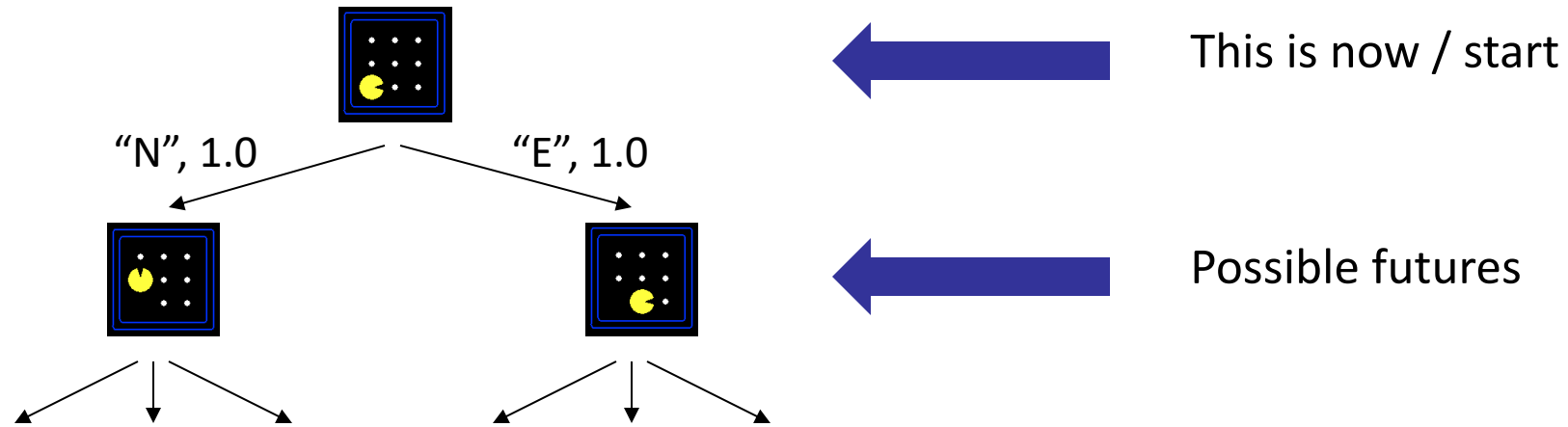
# State Space Graphs

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  - Arcs represent successors (action results)
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- We can rarely build this full graph in memory (it's too big), but it's a useful idea



*Tiny state space graph for a tiny search problem*

# Search Trees

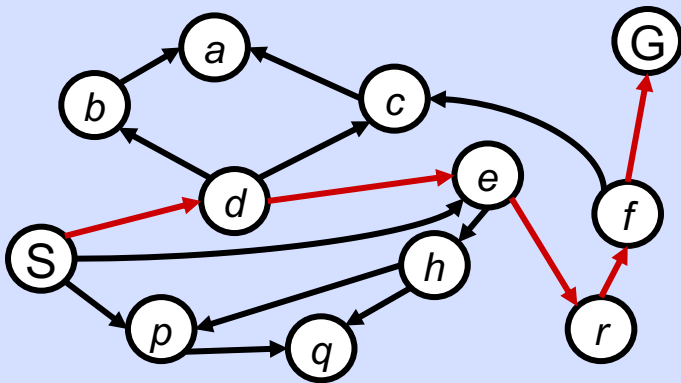


- A search tree:

- A “what if” tree of plans and their outcomes
- The start state is the root node
- Children correspond to successors
- Nodes show states, but correspond to PLANS that achieve those states
- For most problems, we can never actually build the whole tree

# State Space Graphs vs. Search Trees

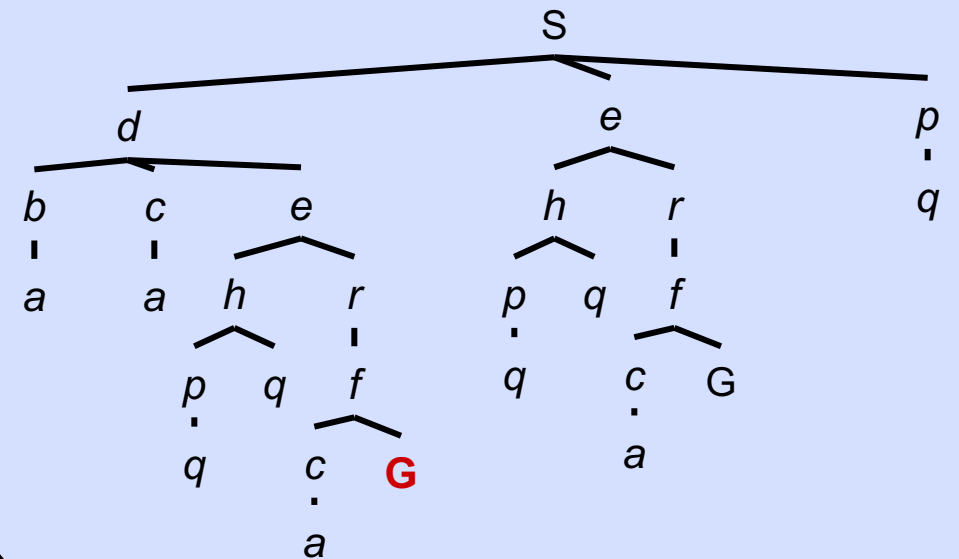
## State Space Graph



*Each NODE in the search tree is an entire PATH in the state space graph.*

*We construct both on demand – and we construct as little as possible.*

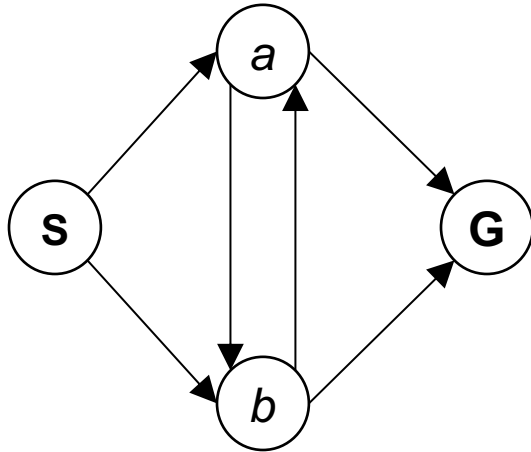
## Search Tree



# Quiz: State Space Graphs vs. Search Trees

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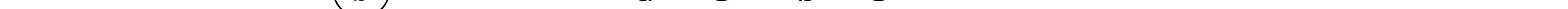
Consider this 4-state graph:

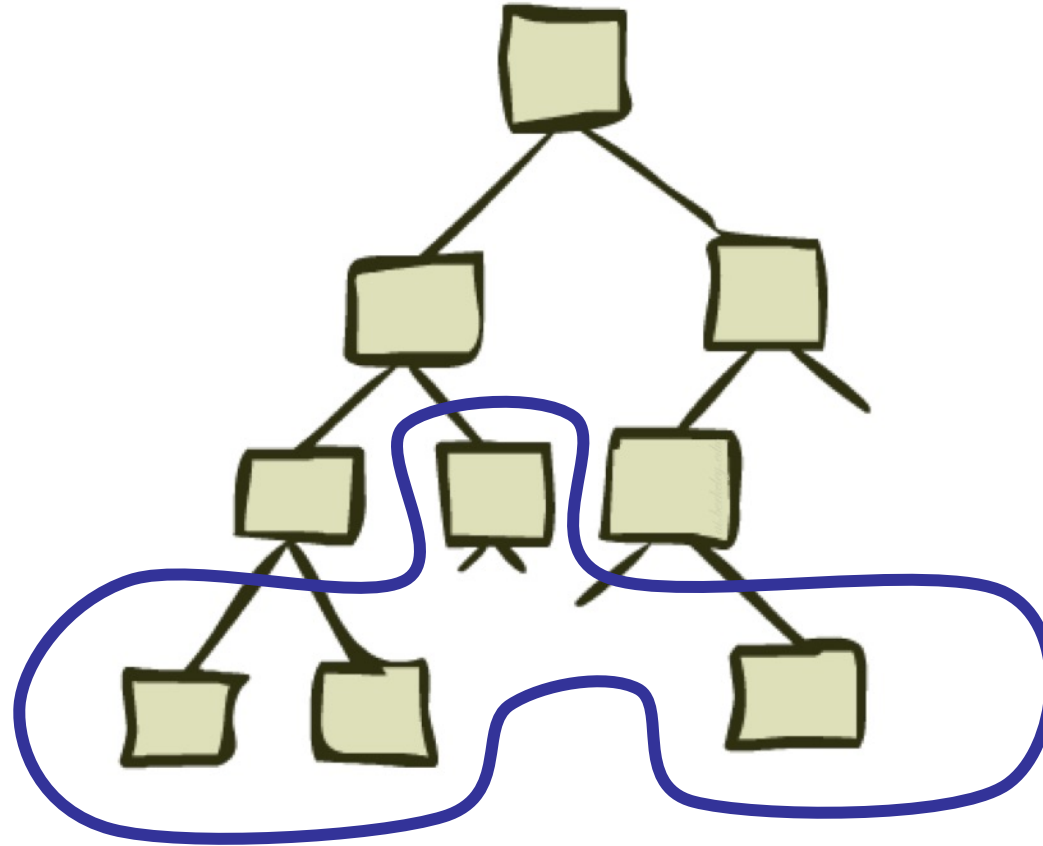


How big is its search tree (from S)?

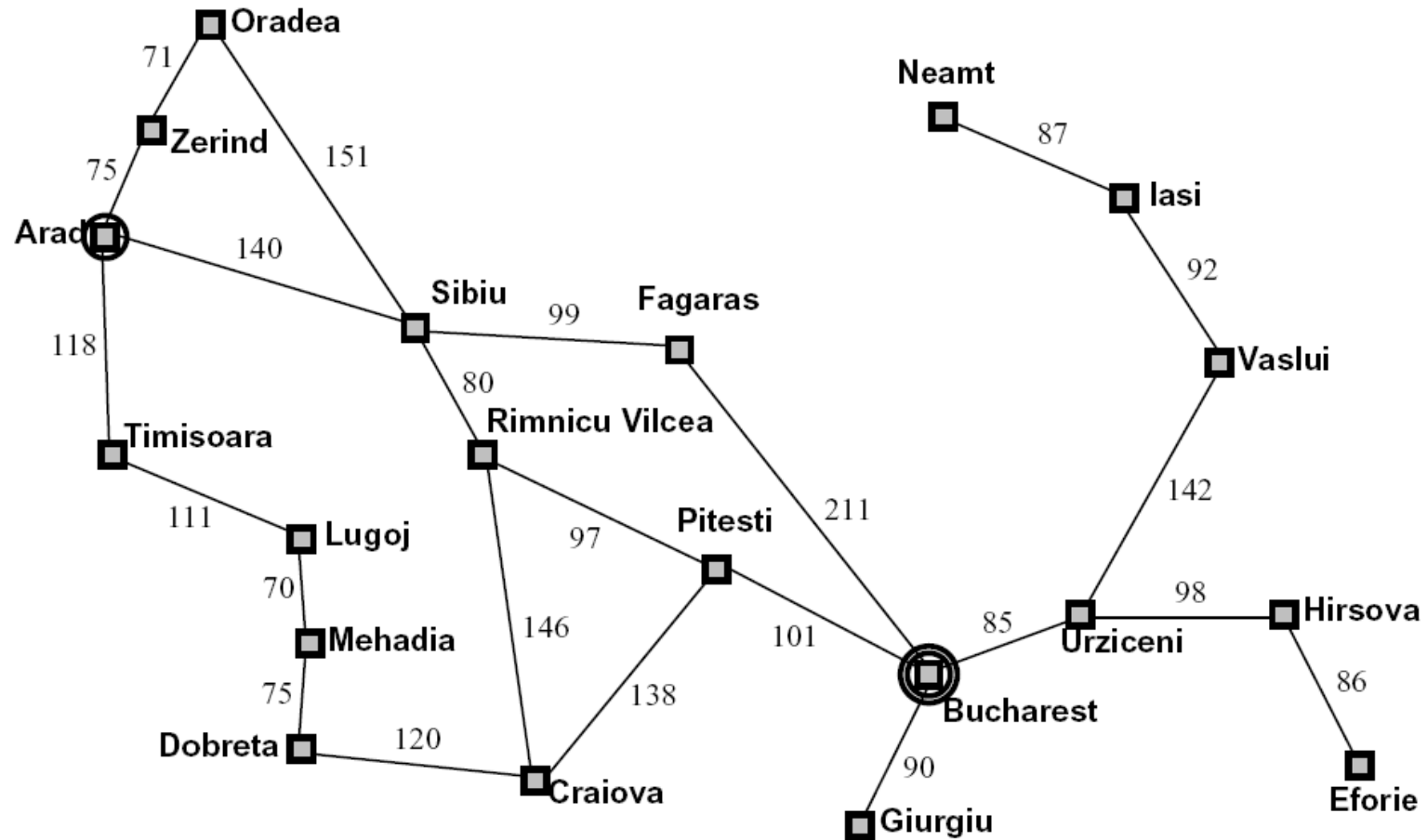




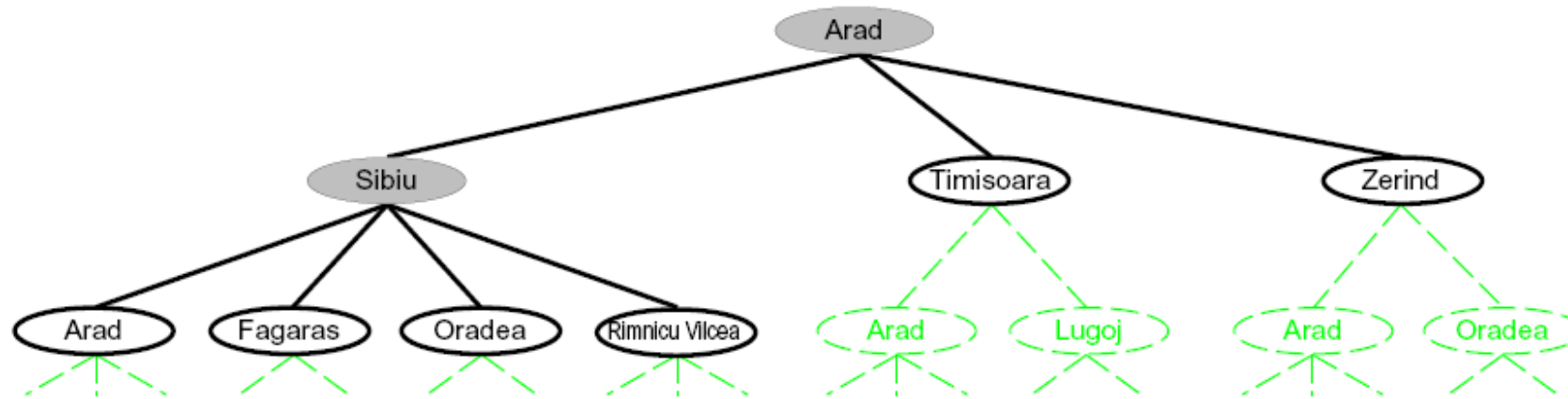




# Search Example: Romania



# Searching with a Search Tree



## ■ Search:

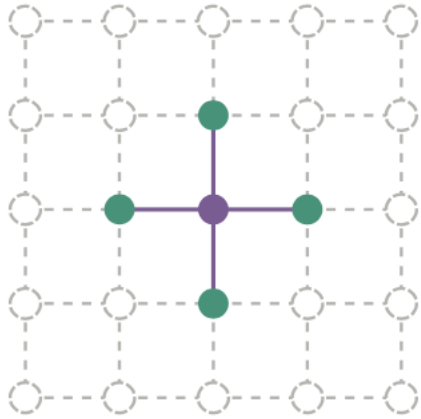
- Expand out potential plans (tree nodes)
- Maintain a **fringe** of partial plans under consideration
- Try to expand as few tree nodes as possible

# General Tree Search

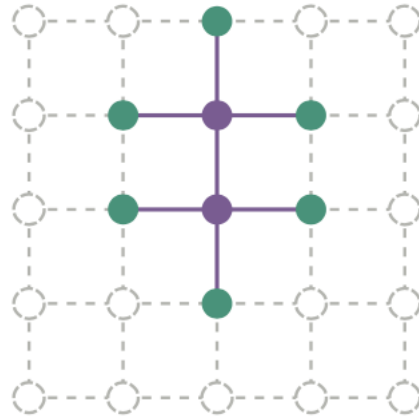
```
function TREE-SEARCH(problem, strategy) returns a solution, or failure
  initialize the search tree using the initial state of problem
  loop do
    if there are no candidates for expansion then return failure
    choose a leaf node for expansion according to strategy
    if the node contains a goal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

- Important ideas:
  - Fringe
  - Expansion
  - Exploration strategy
- Main question: which fringe nodes to explore?

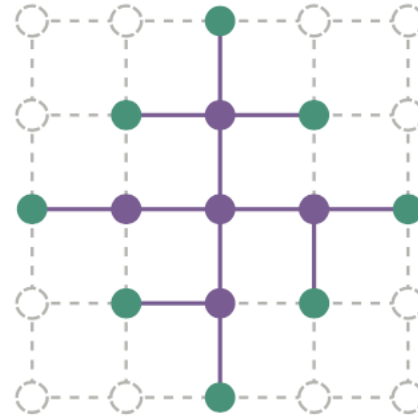
# Fringes and expansions



(a)

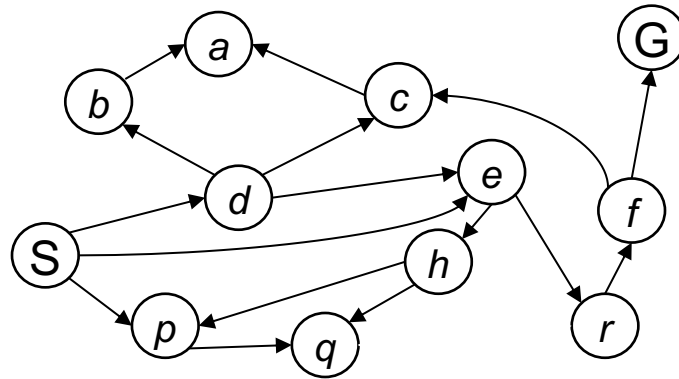


(b)

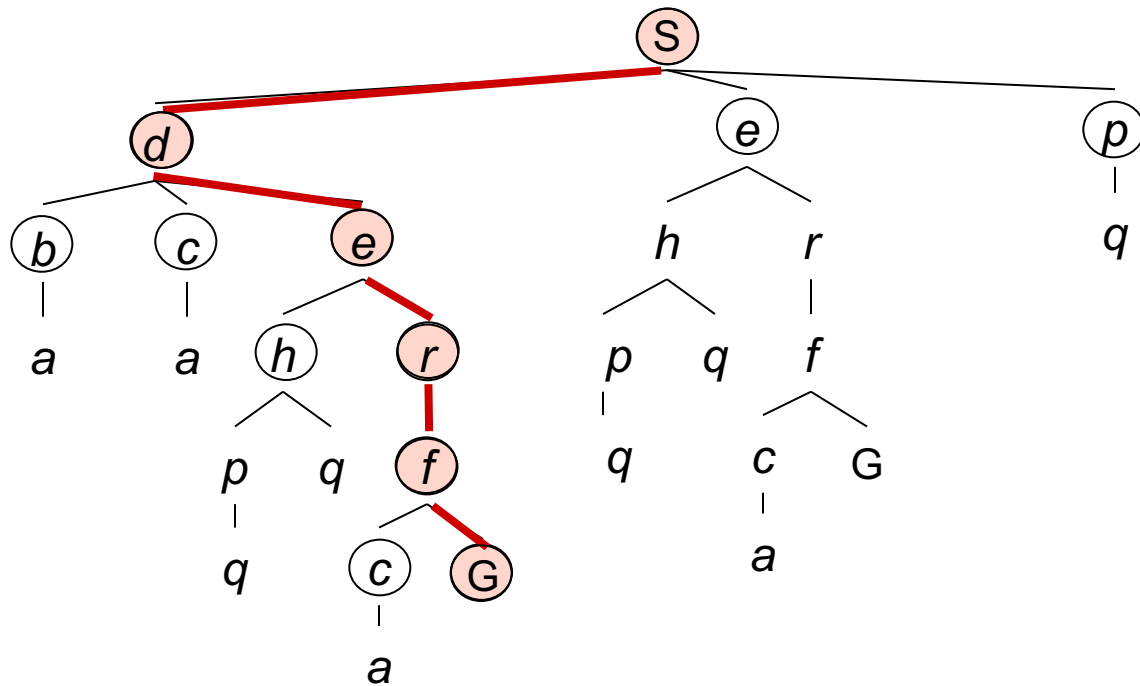
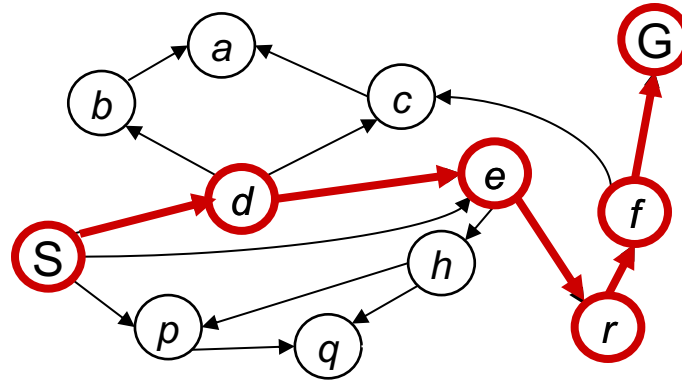


(c)

# Example: Tree Search



# Example: Tree Search



~~s~~  
~~s → d~~  
s → e  
s → p  
s → d → b  
s → d → c  
~~s → d → e~~  
s → d → e → h  
~~s → d → e → r~~  
~~s → d → e → r → f~~  
s → d → e → r → f → c  
~~s → d → e → r → f → G~~



# Depth-First Search

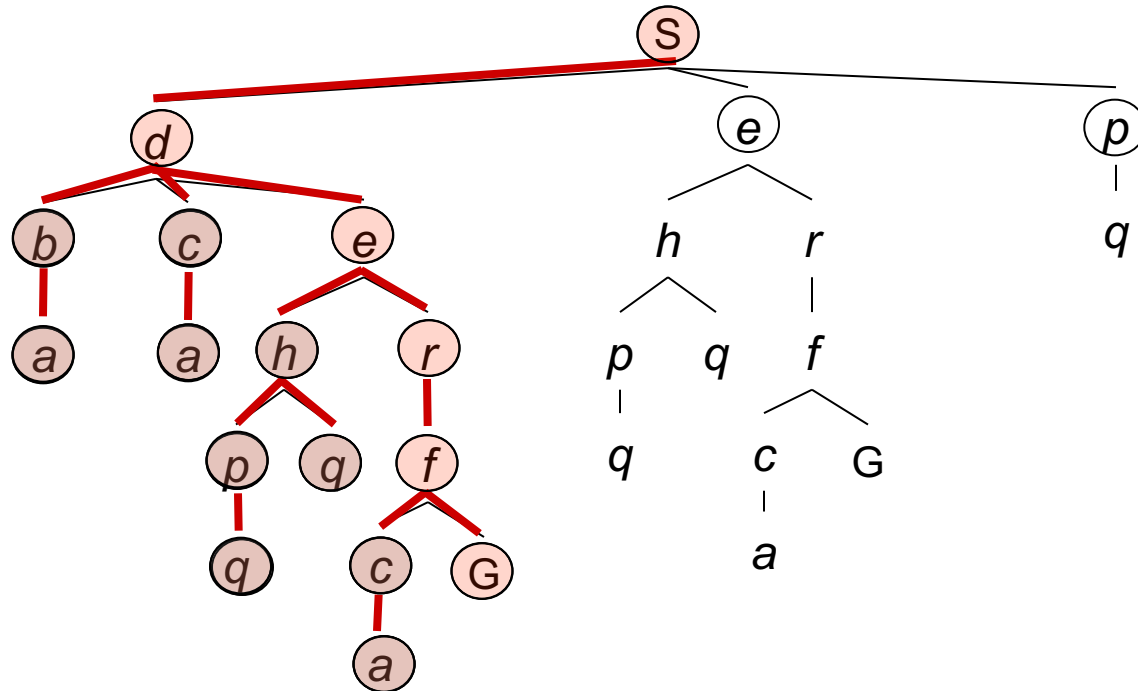
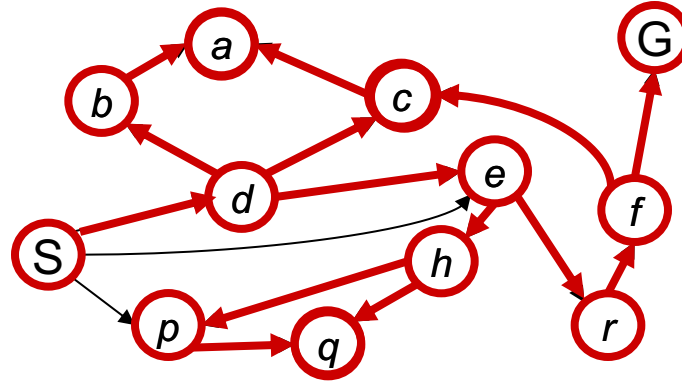
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# Depth-First Search

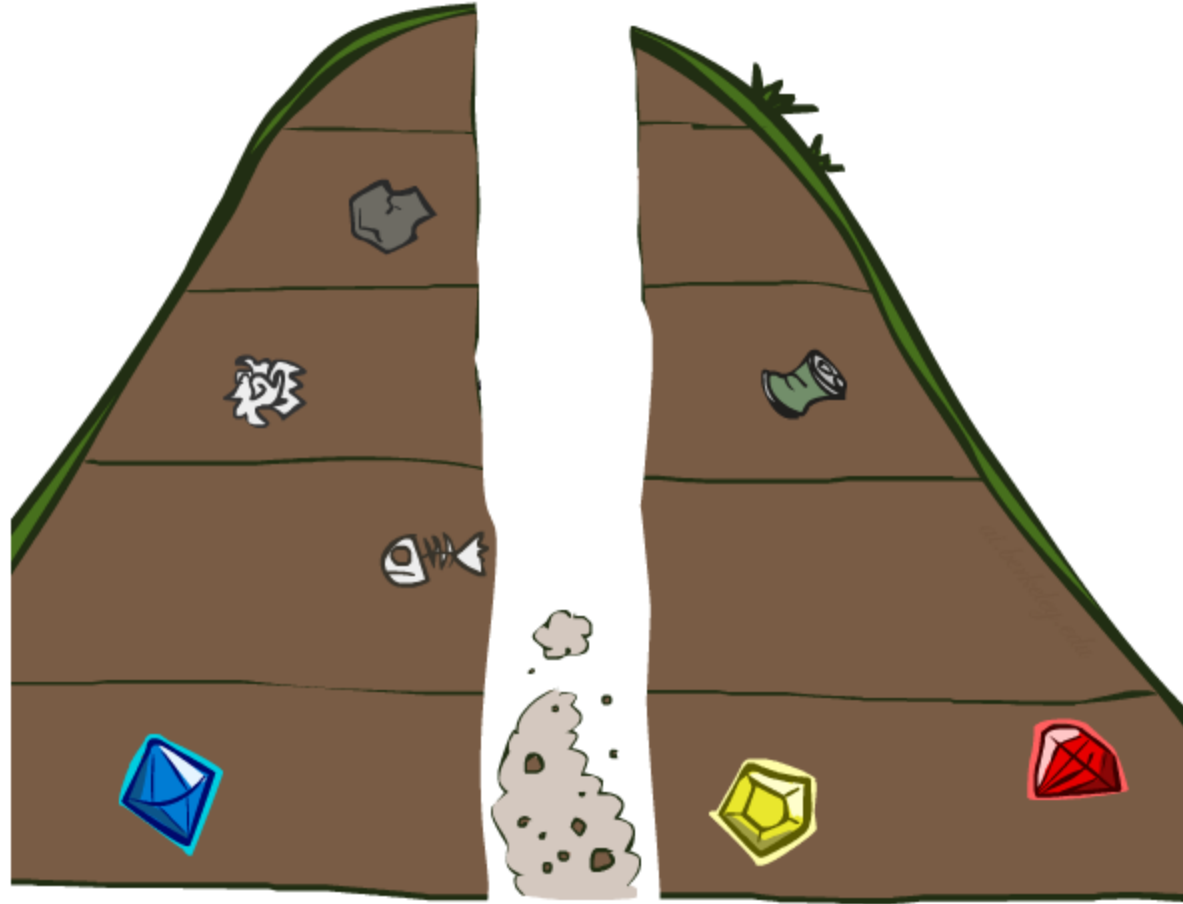
*Strategy: expand a  
deepest node first*

*Implementation:  
Fringe is a LIFO stack*



# Search Algorithm Properties

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# Search Algorithm Properties

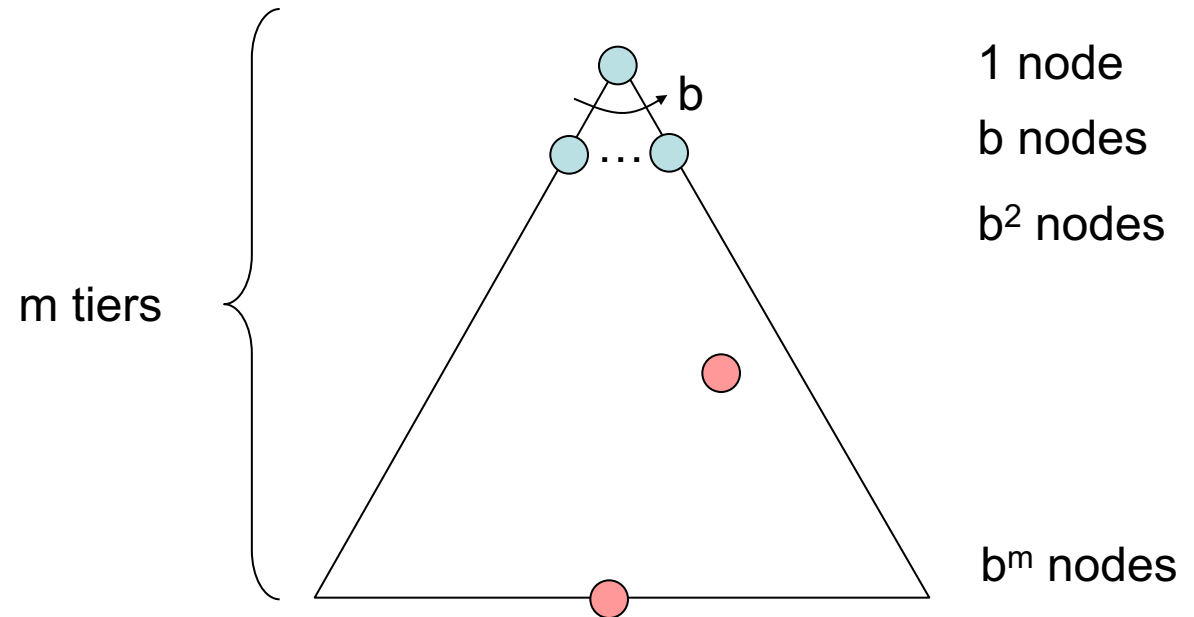
- Complete: Guaranteed to find a solution if one exists?
- Optimal: Guaranteed to find the least cost path?
- Time complexity?
- Space complexity?

- Cartoon of search tree:

- $b$  is the branching factor
- $m$  is the maximum depth
- solutions at various depths

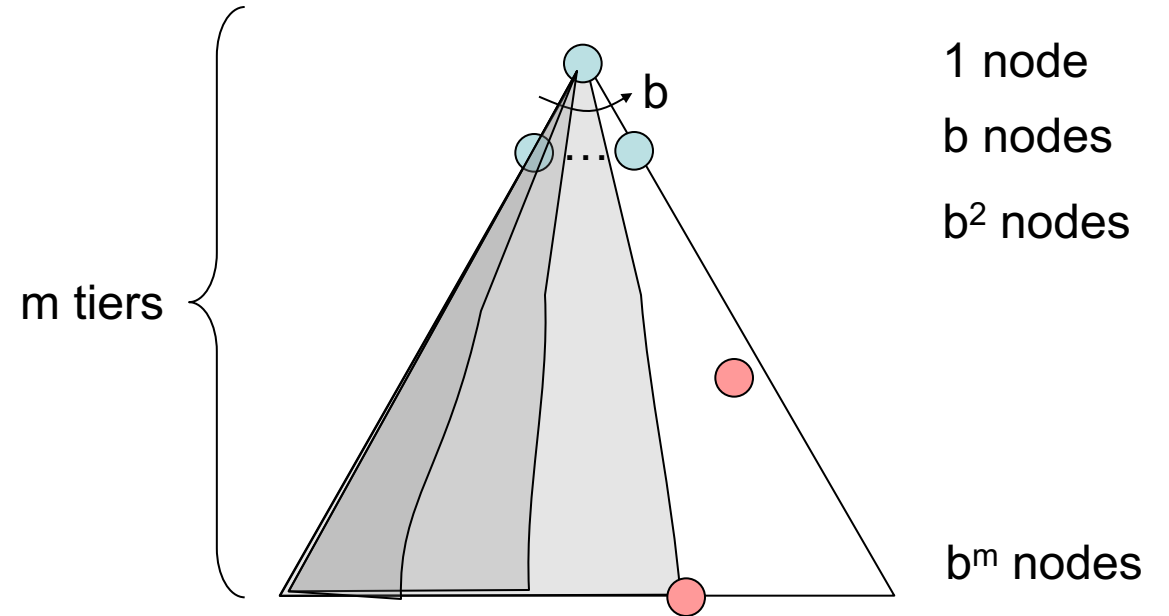
- Number of nodes in entire tree?

- $1 + b + b^2 + \dots + b^m = O(b^m)$



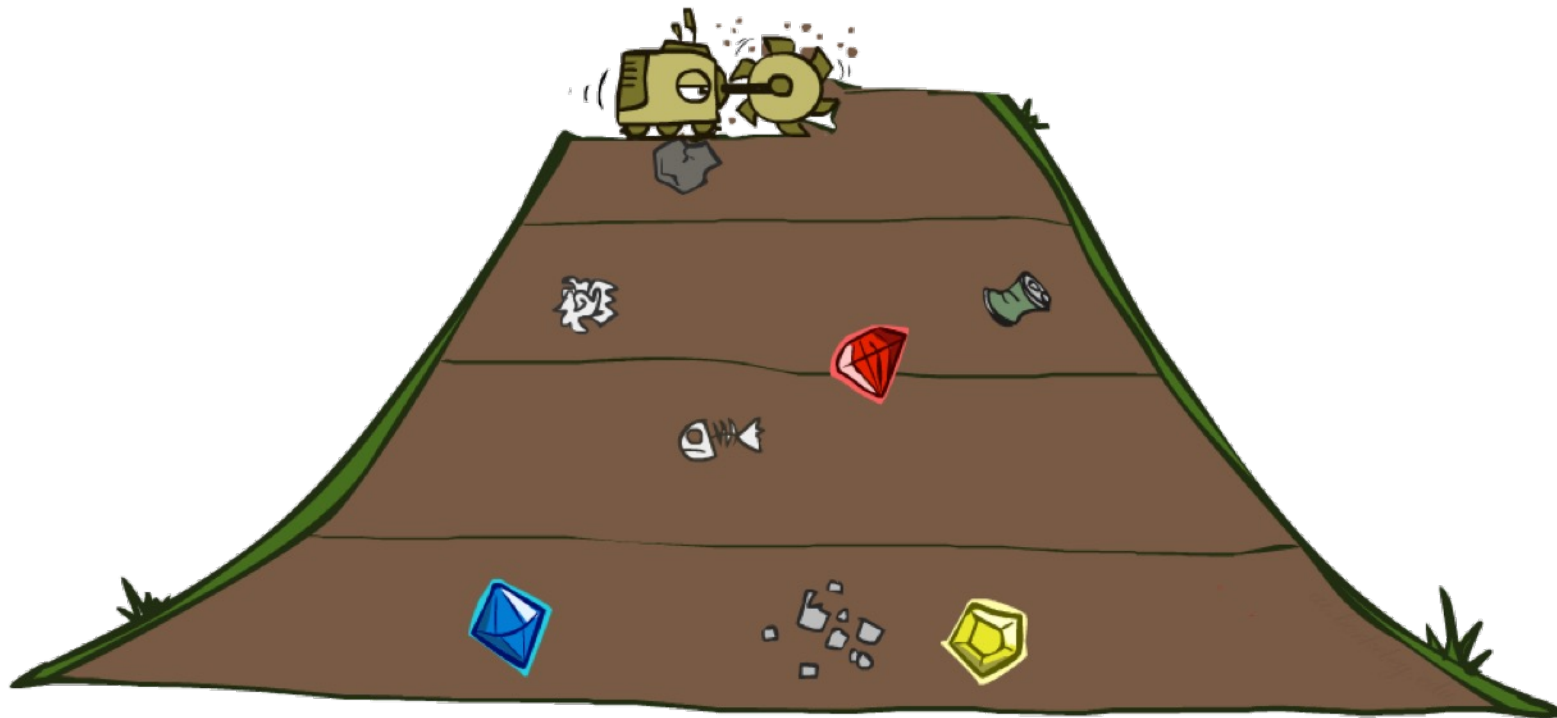
# Depth-First Search (DFS) Properties

- What nodes DFS expand?
  - Some left prefix of the tree.
  - Could process the whole tree!
  - If  $m$  is finite, takes time  $O(b^m)$
- How much space does the fringe take?
  - Only has siblings on path to root, so  $O(bm)$
- Is it complete?
  - $m$  could be infinite, so only if we prevent cycles (more later)
- Is it optimal?
  - No, it finds the “leftmost” solution, regardless of depth or cost



# Breadth-First Search

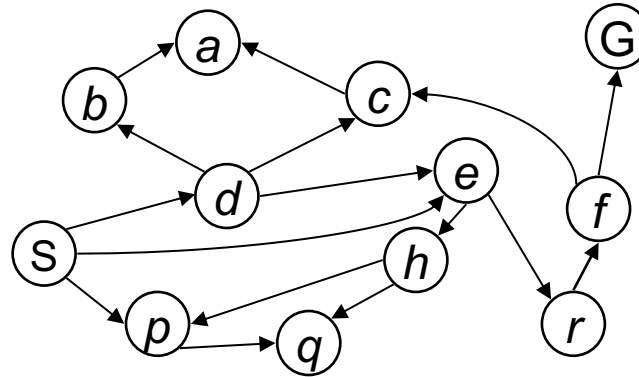
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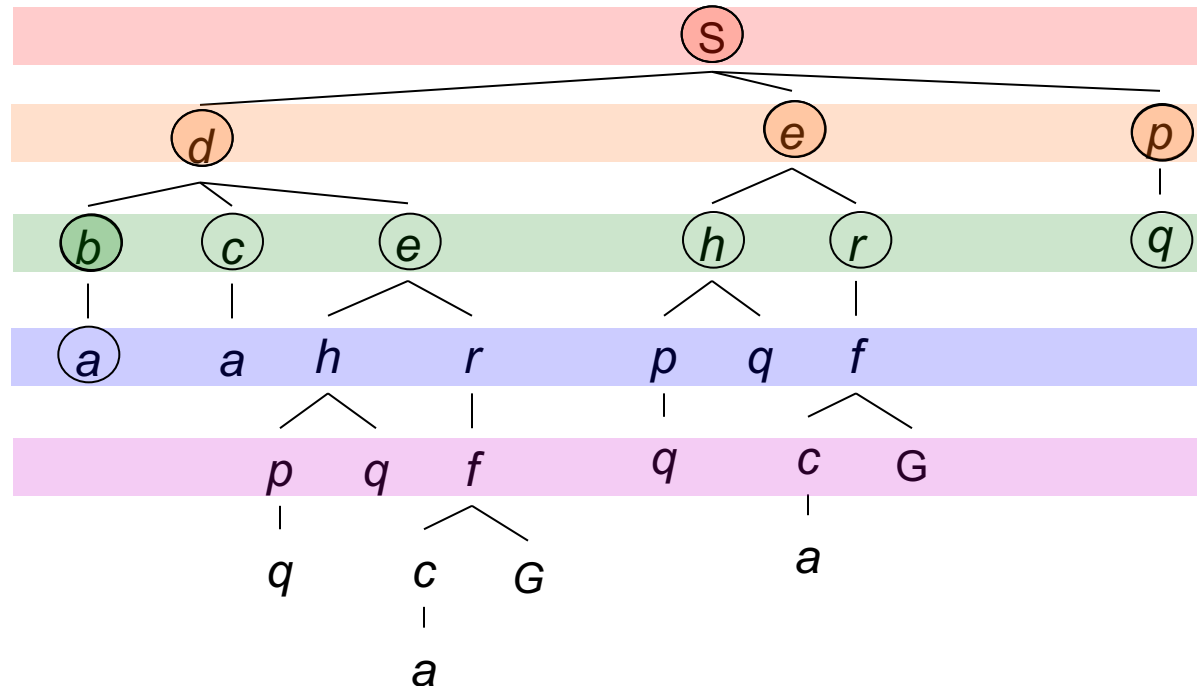
# Breadth-First Search

*Strategy: expand a shallowest node first*

*Implementation: Fringe is a FIFO queue*

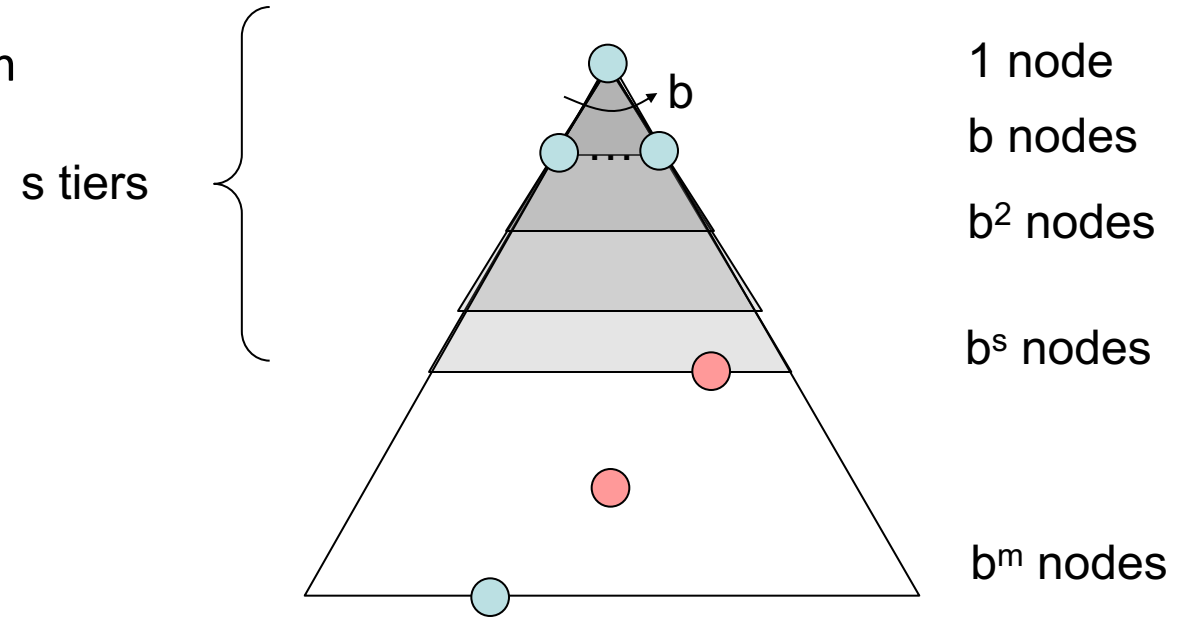


Search  
Tiers



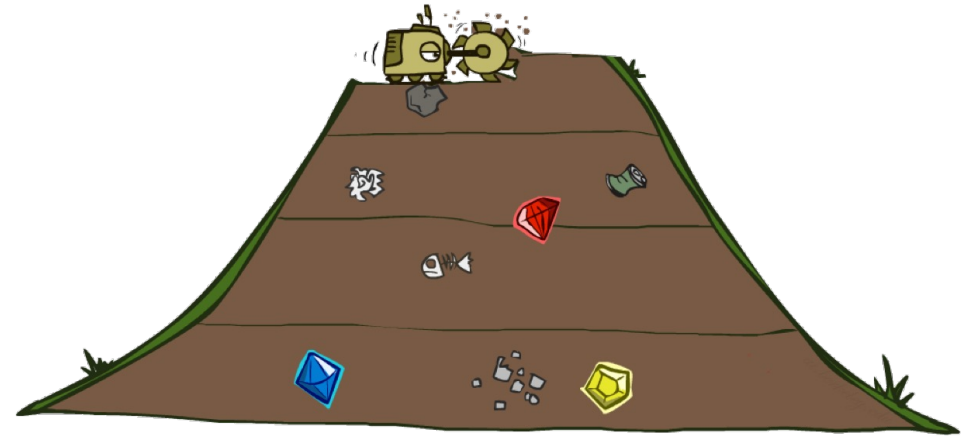
# Breadth-First Search (BFS) Properties

- What nodes does BFS expand?
  - Processes all nodes above shallowest solution
  - Let depth of shallowest solution be  $s$
  - Search takes time  $O(b^s)$
- How much space does the fringe take?
  - Has roughly the last tier, so  $O(b^s)$
- Is it complete?
  - $s$  must be finite if a solution exists, so yes!
- Is it optimal?
  - Only if costs are all 1 (more on costs later)





# Quiz: DFS vs BFS



# Video of Demo Maze Water DFS/BFS (part 1)

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# Video of Demo Maze Water DFS/BFS (part 2)

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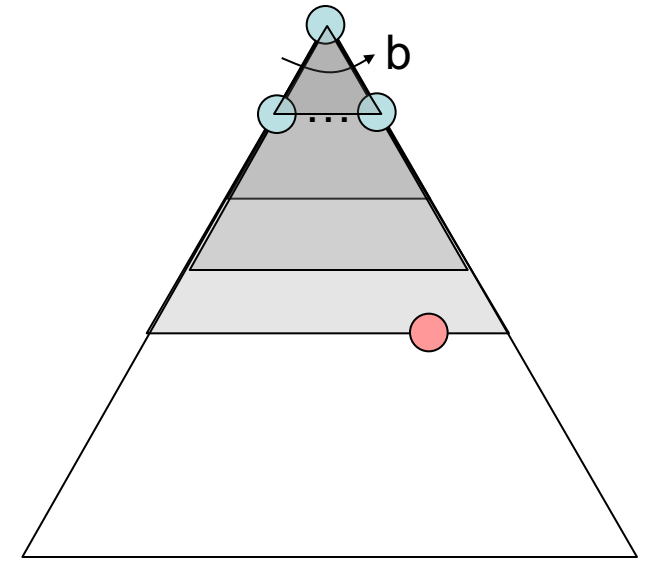
# Quiz: DFS vs BFS

---

- When will BFS outperform DFS?
- When will DFS outperform BFS?

# Iterative Deepening

- Idea: get DFS's space advantage with BFS's time / shallow-solution advantages
  - Run a DFS with depth limit 1. If no solution...
  - Run a DFS with depth limit 2. If no solution...
  - Run a DFS with depth limit 3. ....
- Isn't that wastefully redundant?
  - Generally most work happens in the lowest level searched, so not so bad!

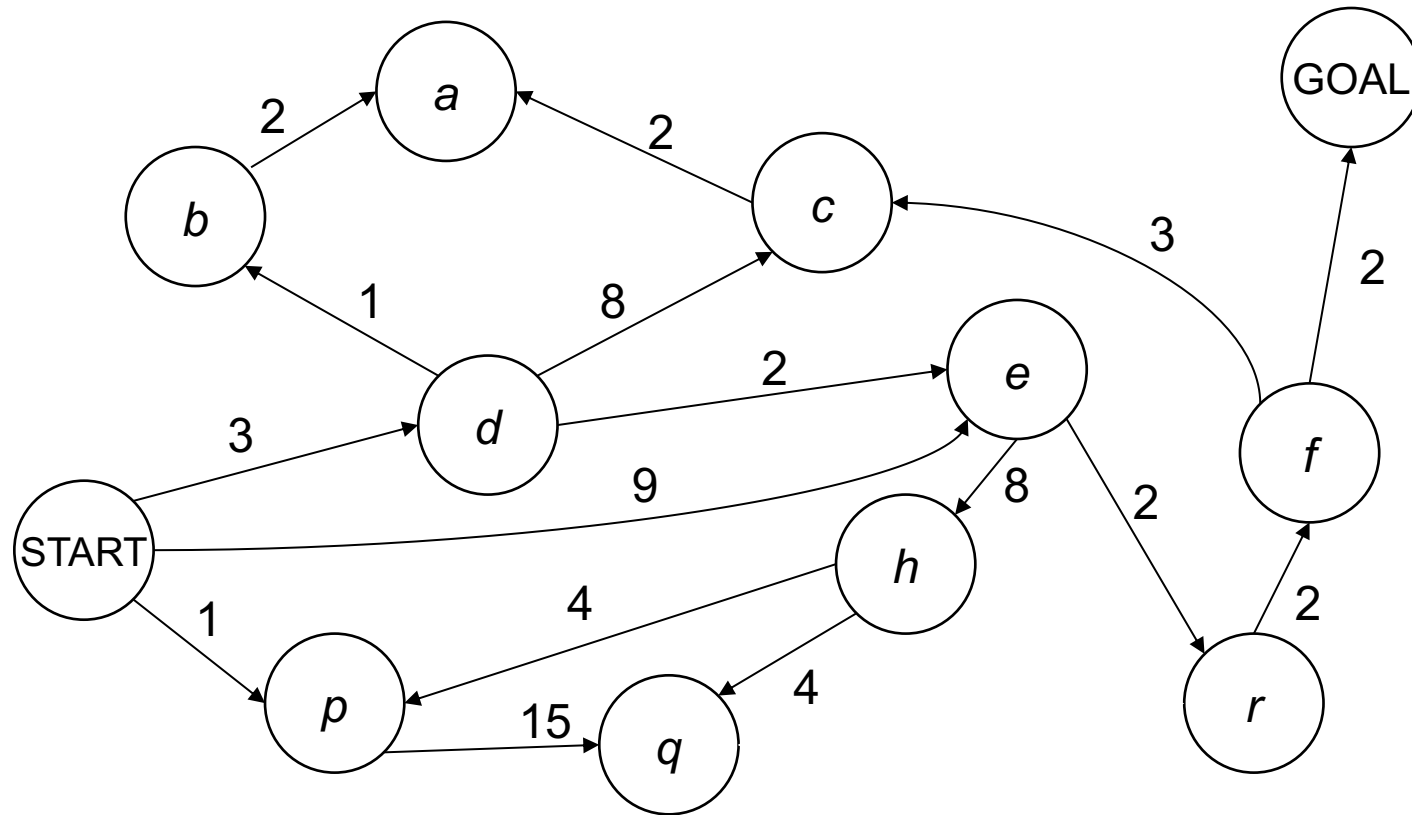


# Iterative Deepening Search (naive)

**function** ITERATIVE-DEEPENING-SEARCH(*problem*) **returns** a solution node or *failure*  
  **for** *depth* = 0 **to**  $\infty$  **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*

# Cost-Sensitive Search



BFS finds the shortest path in terms of number of actions.  
It does not find the least-cost path. We will now cover  
a similar algorithm which does find the least-cost path.

# Bi-directional Best-first

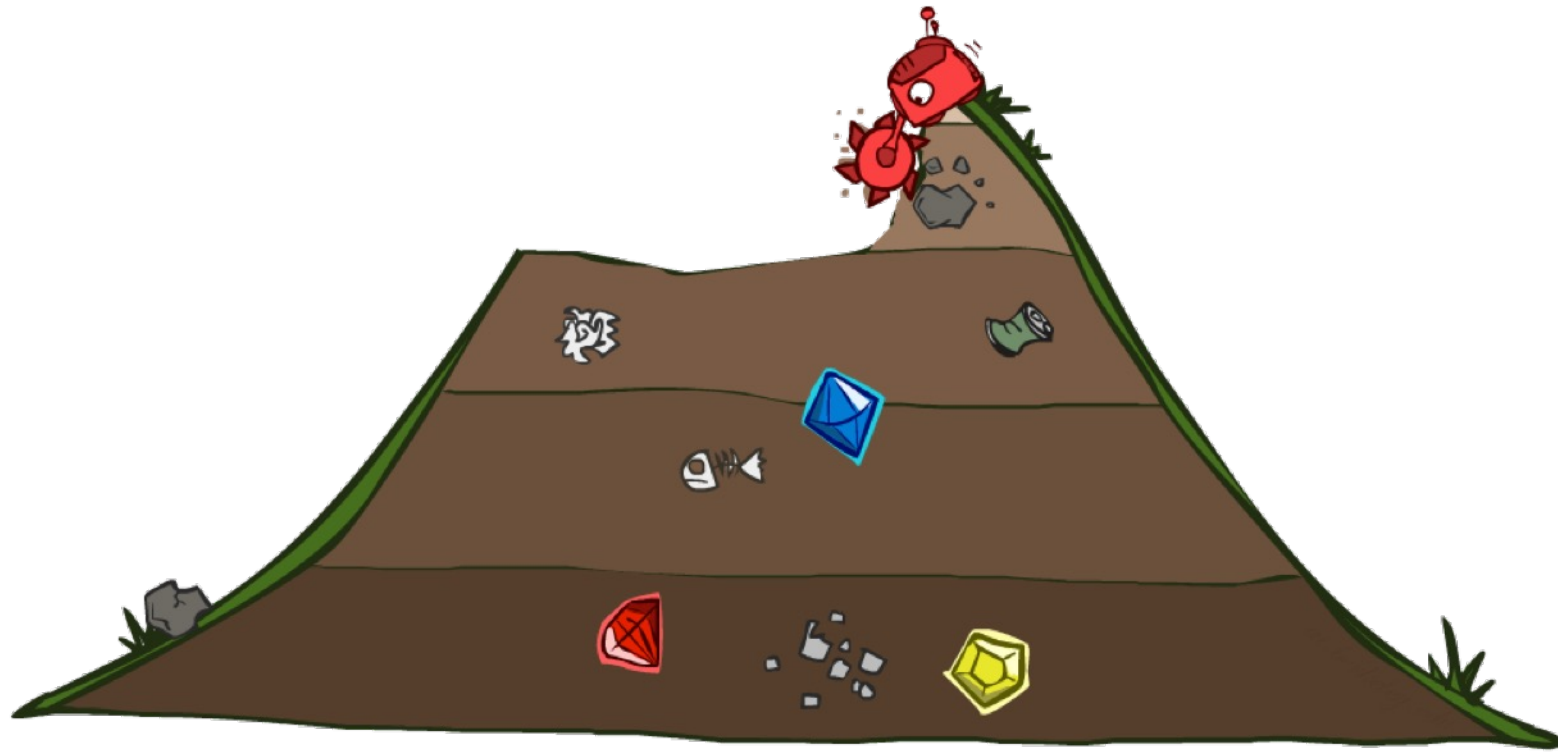
```
function BIBF-SEARCH( $problem_F, f_F, problem_B, f_B$ ) returns a solution node, or failure
   $node_F \leftarrow \text{NODE}(problem_F.INITIAL)$  // Node for a start state
   $node_B \leftarrow \text{NODE}(problem_B.INITIAL)$  // Node for a goal state
   $frontier_F \leftarrow$  a priority queue ordered by  $f_F$ , with  $node_F$  as an element
   $frontier_B \leftarrow$  a priority queue ordered by  $f_B$ , with  $node_B$  as an element
   $reached_F \leftarrow$  a lookup table, with one key  $node_F.STATE$  and value  $node_F$ 
   $reached_B \leftarrow$  a lookup table, with one key  $node_B.STATE$  and value  $node_B$ 
   $solution \leftarrow failure$ 
  while not TERMINATED( $solution, frontier_F, frontier_B$ ) do
    if  $f_F(\text{TOP}(frontier_F)) < f_B(\text{TOP}(frontier_B))$  then
       $solution \leftarrow \text{PROCEED}(F, problem_F, frontier_F, reached_F, reached_B, solution)$ 
    else  $solution \leftarrow \text{PROCEED}(B, problem_B, frontier_B, reached_B, reached_F, solution)$ 
  return  $solution$ 

function PROCEED( $dir, problem, frontier, reached, reached_2, solution$ ) returns a solution
  // Expand node on frontier; check against the other frontier in  $reached_2$ .
  // The variable “dir” is the direction: either F for forward or B for backward.
   $node \leftarrow \text{POP}(frontier)$ 
  for each  $child$  in EXPAND( $problem, node$ ) do
     $s \leftarrow child.STATE$ 
    if  $s$  not in  $reached$  or  $\text{PATH-COST}(child) < \text{PATH-COST}(reached[s])$  then
       $reached[s] \leftarrow child$ 
      add  $child$  to  $frontier$ 
    if  $s$  is in  $reached_2$  then
       $solution_2 \leftarrow \text{JOIN-NODES}(dir, child, reached_2[s])$ 
      if  $\text{PATH-COST}(solution_2) < \text{PATH-COST}(solution)$  then
         $solution \leftarrow solution_2$ 
  return  $solution$ 
```



# Uniform Cost Search

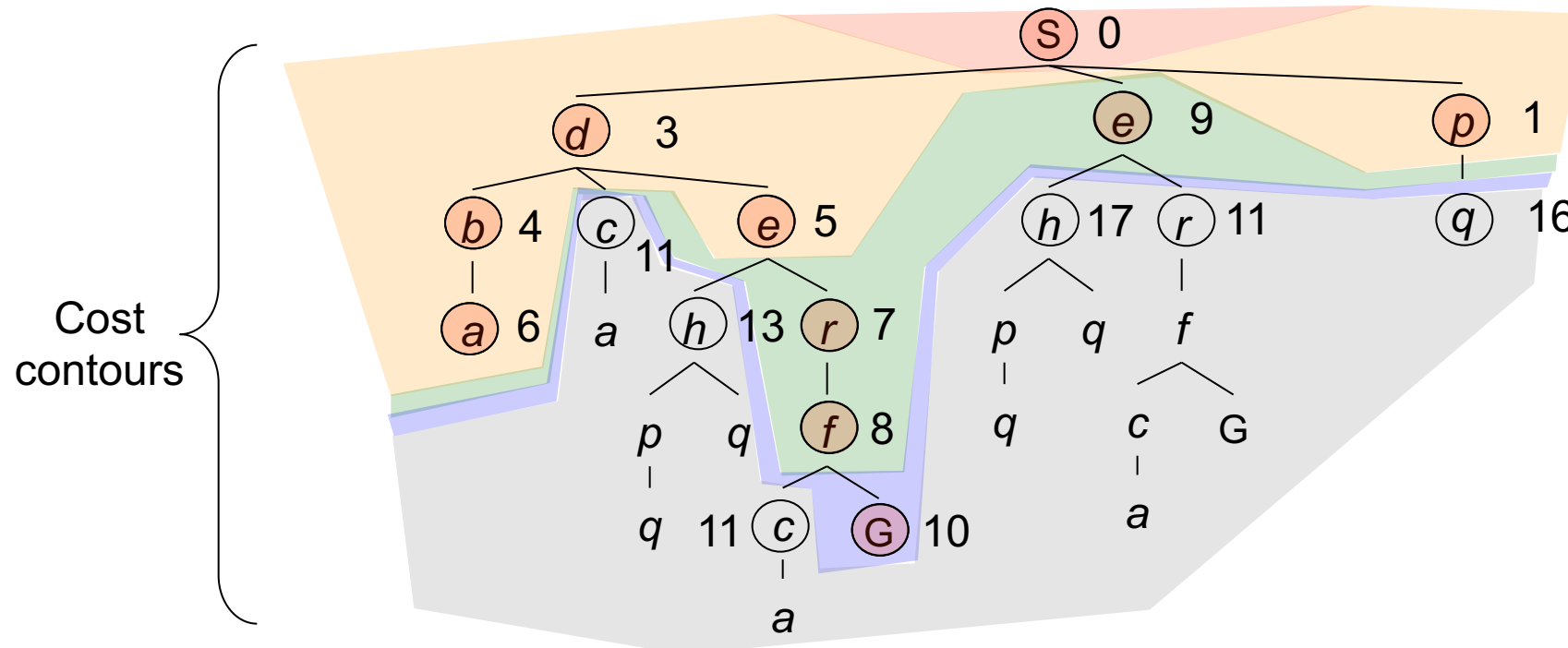
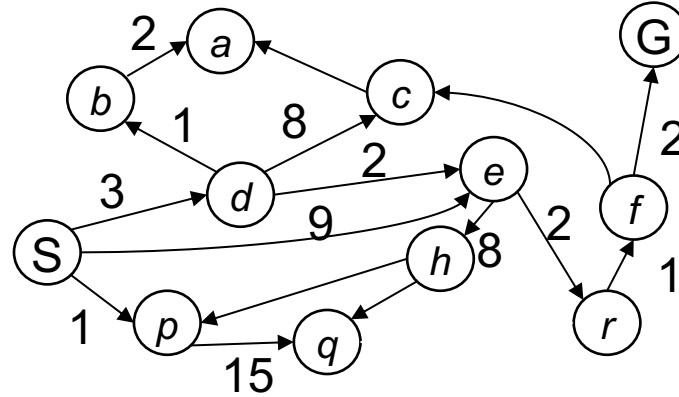
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# Uniform Cost Search

Strategy: expand a  
cheapest node first:

Fringe is a priority queue  
(priority: cumulative cost)



# Uniform Cost Search (UCS) Properties

## ■ What nodes does UCS expand?

- Processes all nodes with cost less than cheapest solution!
- If that solution costs  $C^*$  and arcs cost at least  $\varepsilon$ , then the “effective depth” is roughly  $C^*/\varepsilon$
- Takes time  $O(b^{C^*/\varepsilon})$  (exponential in effective depth)

## ■ How much space does the fringe take?

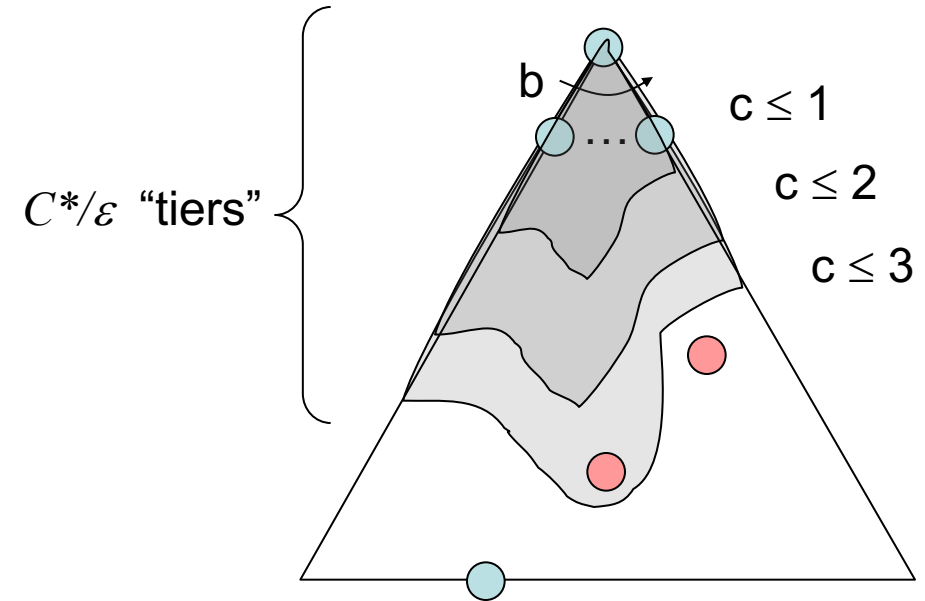
- Has roughly the last tier, so  $O(b^{C^*/\varepsilon})$

## ■ Is it complete?

- Assuming best solution has a finite cost and minimum arc cost is positive, yes!

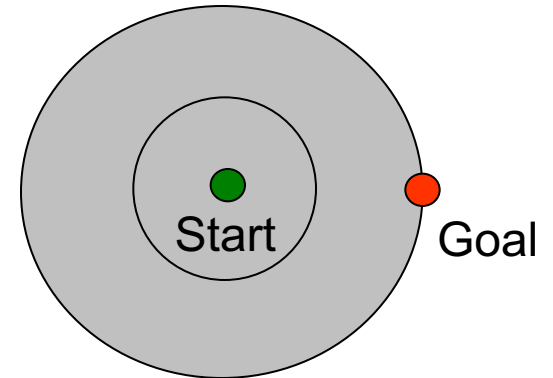
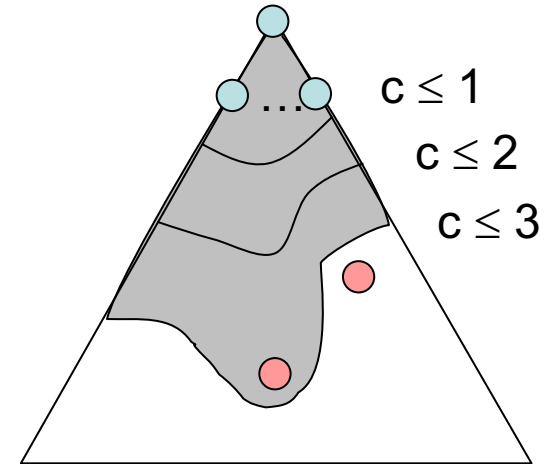
## ■ Is it optimal?

- Yes! (Proof next lecture via  $A^*$ )



# Uniform Cost Issues

- Remember: UCS explores increasing cost contours
- The good: UCS is complete and optimal!
- The bad:
  - Explores options in every “direction”
  - No information about goal location
- We’ll fix that soon!



# Video of Demo Empty UCS

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## Video of Demo Maze with Deep/Shallow Water --- DFS, BFS, or UCS? (part 1)

---



## Video of Demo Maze with Deep/Shallow Water --- DFS, BFS, or UCS? (part 2)

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## Video of Demo Maze with Deep/Shallow Water --- DFS, BFS, or UCS? (part 3)

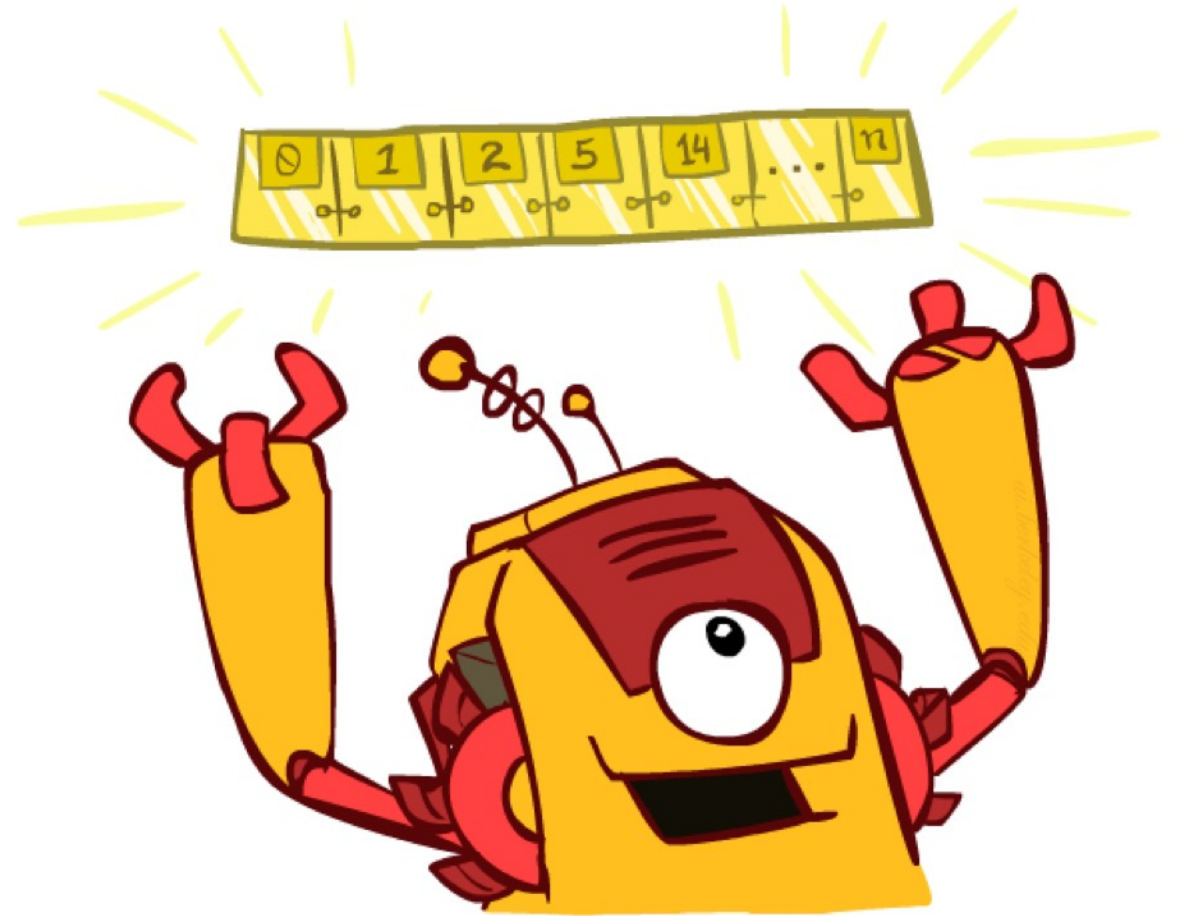
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# The One Queue

- All these search algorithms are the same except for fringe strategies
  - Conceptually, all fringes are priority queues (i.e. collections of nodes with attached priorities)
  - Practically, for DFS and BFS, you can avoid the  $\log(n)$  overhead from an actual priority queue, by using stacks and queues
  - Can even code one implementation that takes a variable queuing object



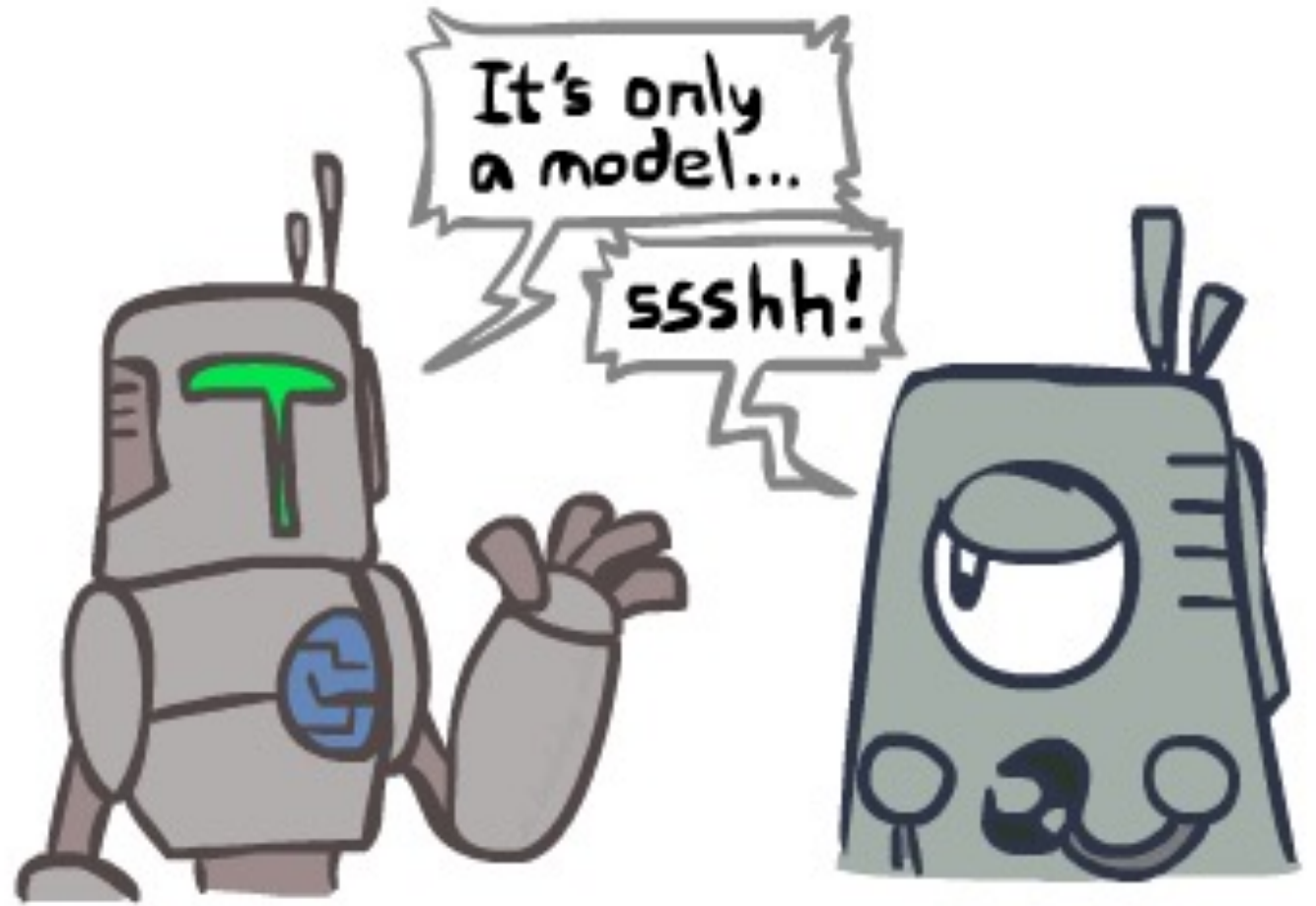
# Comparison

Criterion	Breadth-First	Uniform-Cost	Depth-First	Depth-Limited	Iterative Deepening	Bidirectional (if applicable)
Complete?	Yes <sup>1</sup>	Yes <sup>1,2</sup>	No	No	Yes <sup>1</sup>	Yes <sup>1,4</sup>
Optimal cost?	Yes <sup>3</sup>	Yes	No	No	Yes <sup>3</sup>	Yes <sup>3,4</sup>
Time	$O(b^d)$	$O(b^{1+\lceil C^*/\epsilon \rceil})$	$O(b^m)$	$O(b^\ell)$	$O(b^d)$	$O(b^{d/2})$
Space	$O(b^d)$	$O(b^{1+\lceil C^*/\epsilon \rceil})$	$O(bm)$	$O(b\ell)$	$O(bd)$	$O(b^{d/2})$

- $b$  branching factor;
  - $m$  maximum depth of the search tree;
  - $d$  depth of the shallowest solution, or is  $m$  when there is no solution;
  - $\ell$  depth limit
- Superscripts:
    1. complete if  $b$  is finite, and the state space either has a solution or is finite.
    2. complete if all action costs are  $\geq \epsilon > 0$ ;
    3. cost-optimal if action costs are all identical;
    4. if both directions are breadth-first or uniform-cost.

# Search and Models

- Search operates over models of the world
  - The agent doesn't actually try all the plans out in the real world!
  - Planning is all “in simulation”
  - Your search is only as good as your models...



# Search Gone Wrong?

