

Problem Solving and Search

Chapter 3

Outline

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

Problem-Solving Agents

In the *simplest* case, an agent will:

- formulate (or be given) a goal and a problem;
- search for a sequence of actions that solves the problem;
- then execute the actions.

When done it may formulate another goal and start over.

- In this case the performance measure is simply whether or not the goal is attained.

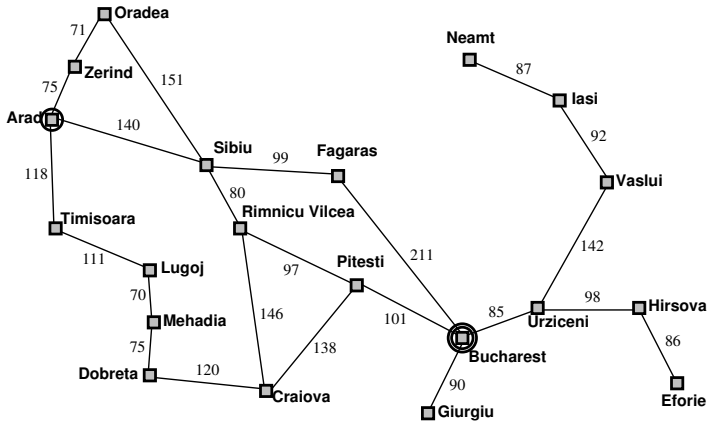
This is *offline* problem solving, executed “eyes closed.”

- Requires complete knowledge about the domain
- *Online* problem solving involves acting without necessarily having complete knowledge.

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

Example: Romania



Problem Formulation: State-Space Search

A *problem* is defined by five items:

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 2. *Actions* available to the agent E.g. Vacuum: Suck, Left, ...
 3. *Transition model*: What actions do; defines a graph.
 - I.e. $RESULT(s, a)$ = state resulting from doing a in s .
e.g. $RESULT(In(Arad), Go(Zerind)) = In(Zerind)$
- 1.–3. define the *state space*

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4. *Goal test*. Can be *explicit*, e.g. $x = \text{“at Bucharest”}$
implicit, e.g. $NoDirt(x)$

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 5. *Path cost* (additive)
e.g. sum of distances, number of actions , etc.
 $c(x, a, y)$ is the *step cost*, assumed to be ≥ 0

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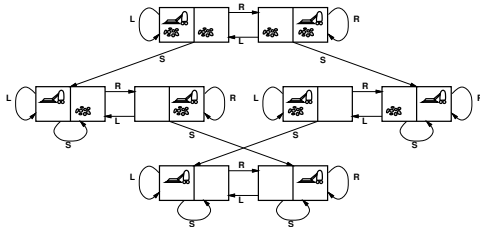
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A *solution* is a sequence of actions from initial state to a goal state.

Selecting a State Space

- The real world is highly complex and contains lots of irrelevant information.
 - ⇒ state space must be *abstracted* for problem solving
- (Abstract) state will have irrelevant detail removed.
- Similarly, actions must be at the right level of abstraction
 - e.g., “Go(Zerind)” omits things like starting the car, steering, etc.
- (Abstract) solution =
set of paths that are solutions in the real world

Example: Vacuum World State Space Graph



states:

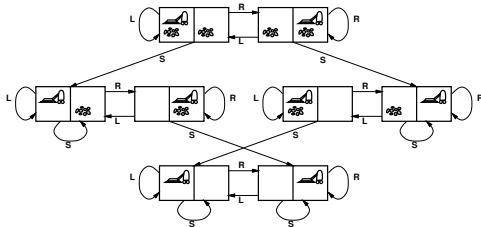
actions:

transition model:

goal test:

path cost:

Example: Vacuum World State Space Graph



states: dirt and robot locations (so 2×2^2 possible states)

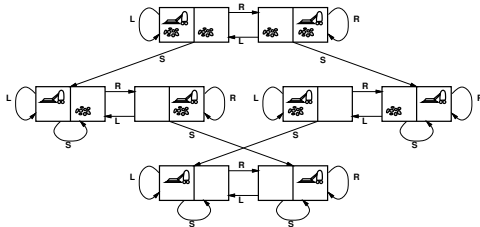
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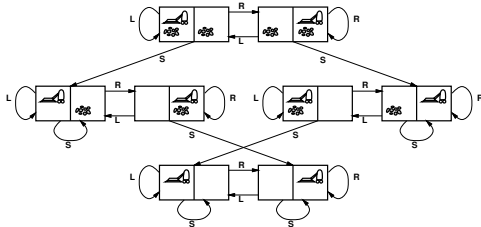
actions: *Left, Right, Suck, NoOp*

transition model:

goal test:

path cost:

Example: Vacuum World State Space Graph



states: dirt and robot locations

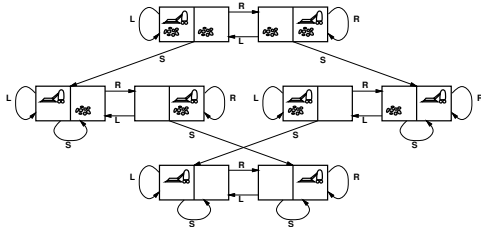
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transition model: actions as expected, except moving left (right) in the right (left) square is a *NoOp*

goal test:

path cost:

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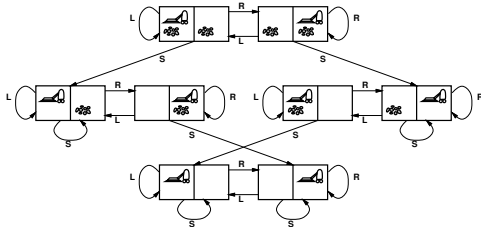
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actions: *Left*, *Right*, *Suck*, *NoOp*

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goal test: no dirt

path cost: 1 per action (0 for *NoOp*)

Example: The 8-puzzle

7	2	4
5		6
8	3	1

Start State

1	2	3
4	5	6
7	8	

Goal State

states:

actions:

transition model:

goal test:

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7	2	4
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Goal State

states: (integer) locations of tiles.



Ignore intermediate positions

actions:

transition model:

goal test:

path cost:

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states: locations of tiles

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path cost: 1 per move

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

Example: Airline Travel

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- Also perhaps fares, domestic/international, and other “historical aspects”.

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goal test: At the final destination?

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goal test: At the final destination?

path cost: Depends on total cost, time, waiting time, seat type, type of plane, etc.

Others Examples

How about:

- Crosswords?
- n-Queens?
- Propositional Satisfiability?
- Coffee and Mail Delivering Robot?
- Others?

Tree Search Algorithms

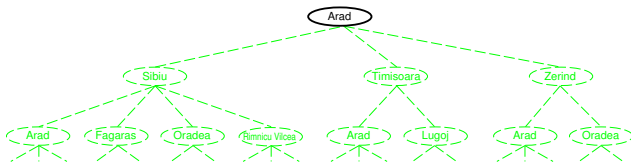
Basic idea:

- Offline exploration of the state space
 - So, exploring a *directed graph*
 - Result of exploration is a *tree*
- Generate successors of already-explored states (a.k.a. *expanding* states)

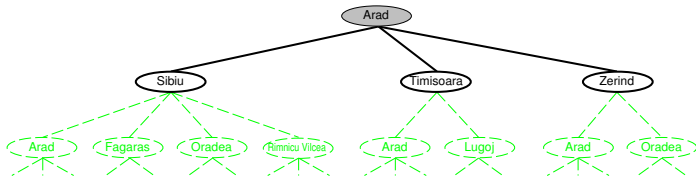
⇒ The set of nodes available for expansion is the *fringe* or *frontier*.

- Key issue: Which node should be expanded next?

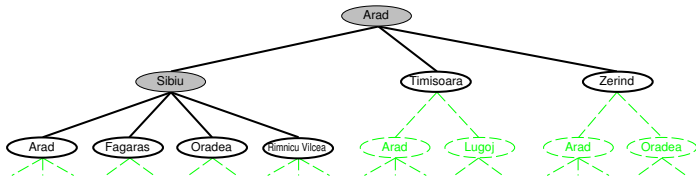
Tree search example



Tree search example



Tree search example



Implementation: General Tree Search

In outline:

Function **Tree-Search**(**problem**) **returns** a solution or failure

Initialize the search tree by 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 some **strategy**)

 - remove the leaf node from the frontier

if the node satisfies the goal state **then return** the solution

 expand the node and add the resulting nodes to the search tree

}

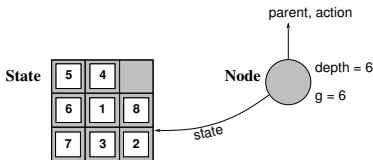
Aside: **Strategy** will most often be implicit in the resulting function.

Implementation: States vs. Nodes

It is important to distinguish the *state space* and the *search tree*.

- A *state* represents a configuration in the problem space.
- A *node* is part of a search tree.
 - has attributes *parent*, *children*, *depth*, *path cost* $g(x)$.

States do not have parents, children, depth, or path cost (though one state may be reachable from another).



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

Search strategies

- A *strategy* is defined by picking the *order of node expansion*
- The *fringe* (also *frontier*) is a list of nodes that have been generated but not yet expanded.

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 - 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
- I.e. except for the goal state, there is no notion of one state being “better” than another.
- Examples:

Uninformed search strategies

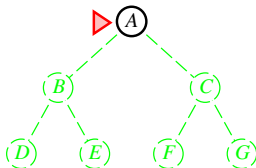
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- Examples:
 - Breadth-first search
 - Uniform-cost search
 - Depth-first search
 - Depth-limited search
 - Iterative deepening search

Breadth-first search

Expand the shallowest unexpanded node

Implementation

fringe is a FIFO queue, i.e., new successors go at end

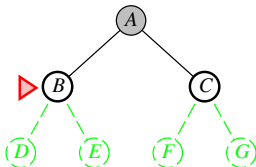


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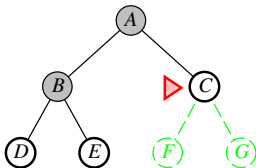


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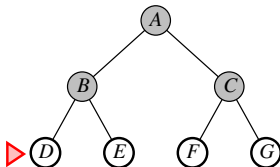


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Properties of breadth-first search

Complete: ??

Properties of breadth-first search

Complete: Yes (if b is finite)

Time: ??

Properties of breadth-first search

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Time: $1 + b + b^2 + b^3 + \dots + b^d = O(b^d)$
I.e., exponential in d

Space: ??

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Space: $O(b^d)$ (keeps every node in memory)

Optimal: ??

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Space: $O(b^d)$ (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.
So 24hrs = 8640GB.

Uniform-Cost Search

- Expand the least-cost unexpanded node
- *Implementation*
fringe = queue ordered by path cost, lowest first
- Equivalent to breadth-first if step costs all equal
- For the travel-in-Romania example, expand the node on the fringe for that city closest in distance to the city at the root (Arad).

Uniform-Cost Search

Complete: Yes, if step cost $\geq \epsilon$, for ϵ some small positive constant.

- So *NoOps* of cost 0 can be a problem.

Time: $O(b^{\lceil C^*/\epsilon \rceil})$, where C^* is the cost of the optimal solution

Space: $O(b^{\lceil C^*/\epsilon \rceil})$

- Time and space complexity can be worse than b^d .

Optimal: Yes

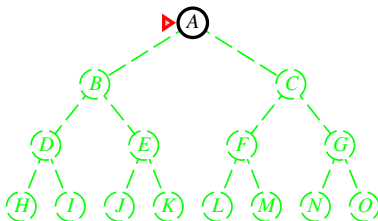
- Nodes expanded in increasing order of $g(n)$ where $g(n)$ is the cost to get to node n .

Depth-First Search

Expand the deepest unexpanded node

Implementation

fringe = LIFO queue, i.e., put successors at front

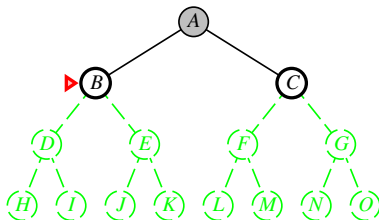


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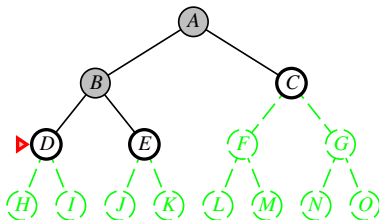


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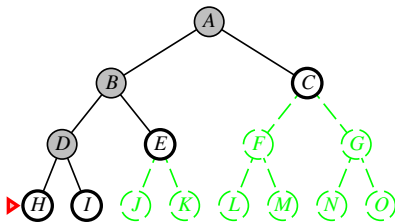


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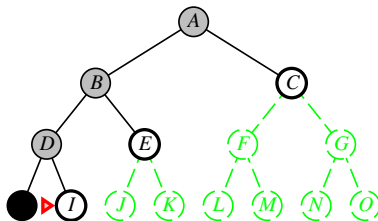


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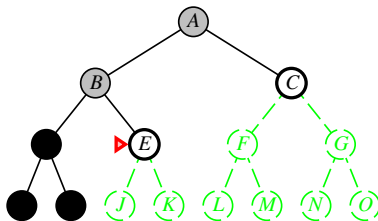


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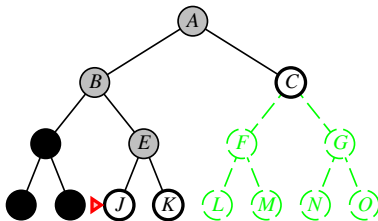


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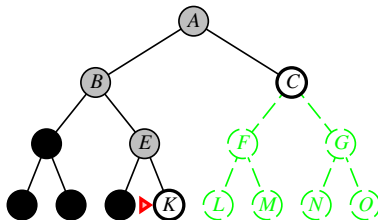


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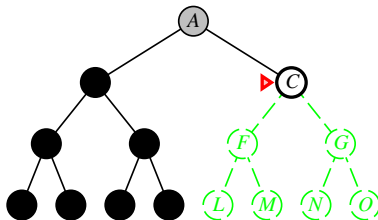


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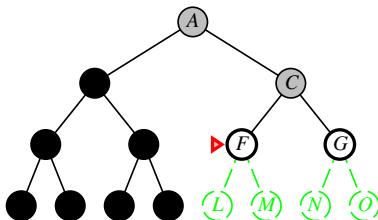


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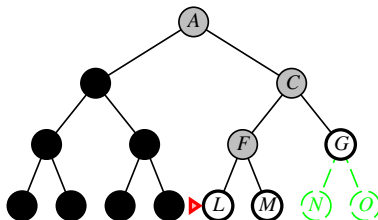


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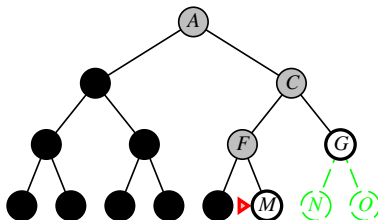


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Properties of depth-first search

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

Time: ??

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Time: $O(b^m)$: terrible if m is much larger than d

- But if solutions are dense, may be much faster than breadth-first

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Optimal: No

Depth-Limited Search

Depth-limited search = depth-first search with depth limit l ,

- i.e., nodes at depth l have no successors

Recursive implementation:

The implementation simply calls a “helper” function (described on the next slide):

Function **Depth-Limited-Search**(**problem**, **limit**)

returns soln/fail/cutoff

 Recursive-DLS(Make-Node(Initial-State[**problem**]),
 problem, **limit**)

Depth-Limited Search

Recursive implementation:

```
Function Recursive-DLS(node,problem,limit) returns soln/fail/cutoff
  cutoff-occurred?  $\leftarrow$  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  $\leftarrow$  Recursive-DLS(successor,problem,limit-1)
    if result = cutoff then cutoff-occurred?  $\leftarrow$  true
    else if result  $\neq$  failure then return result
  if cutoff-occurred? then return cutoff else return failure
```

- Note: second edition has a bug in the recursive call!

Iterative Deepening Search

Function **Iterative-Deepening-Search**(**problem**) **returns** a solution

inputs: **problem** a problem

for **depth** $\leftarrow 0$ **to** ∞ **do**

result \leftarrow Depth-Limited-Search(**problem**,**depth**)

if **result** \neq cutoff **then return** **result**

end

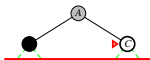
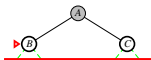
Iterative deepening search $l = 0$

Limit = 0



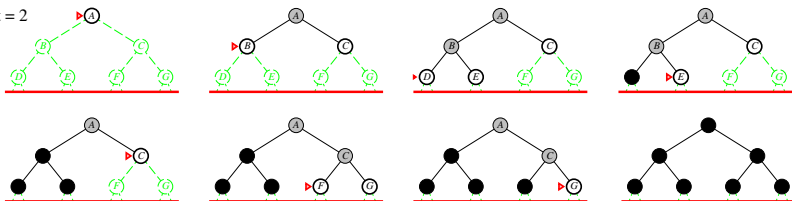
Iterative deepening search / = 1

Limit = 1



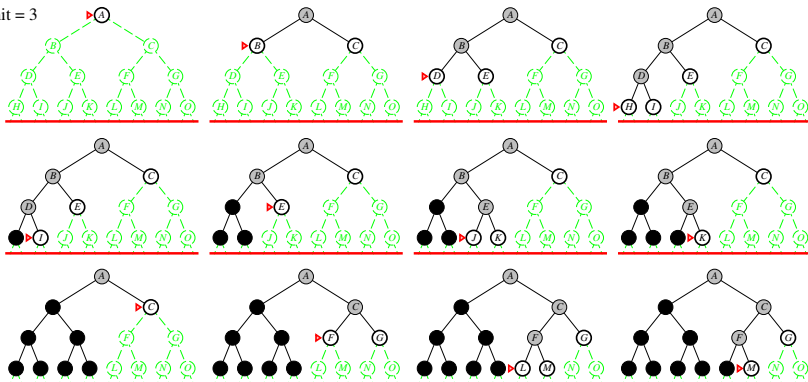
Iterative deepening search $l = 2$

Limit = 2



Iterative deepening search $l = 3$

Limit = 3



Properties of iterative deepening search

Complete: ??

Properties of iterative deepening search

Complete: Yes

Time: ??

Properties of iterative deepening search

Complete: Yes

Time: $(d + 1)b^0 + db^1 + (d - 1)b^2 + \dots + b^d = O(b^d)$

Space: ??

Properties of iterative deepening search

Complete: Yes

Time: $(d + 1)b^0 + db^1 + (d - 1)b^2 + \dots + b^d = O(b^d)$

Space: $O(bd)$

Optimal:

Properties of iterative deepening search

Complete: Yes

Time: $(d + 1)b^0 + db^1 + (d - 1)b^2 + \dots + b^d = O(b^d)$

Space: $O(bd)$

Optimal: Yes, if step cost = 1

Properties of iterative deepening search

- Comparison for $b = 10$ and $d = 5$, solution at far right leaf:

$$N(\text{IDS}) = 50 + 400 + 3,000 + 20,000 + 100,000 = 123,450$$

$$\begin{aligned} N(\text{BFS}) &= 10 + 100 + 1,000 + 10,000 + 100,000 \\ &\quad + 999,990 = 111,100 \end{aligned}$$

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- For BFS, we have the following ratio of IDS to BFS:

b	Ratio
2	3
3	2
5	1.5
10	1.2

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- Can be modified to explore uniform-cost tree

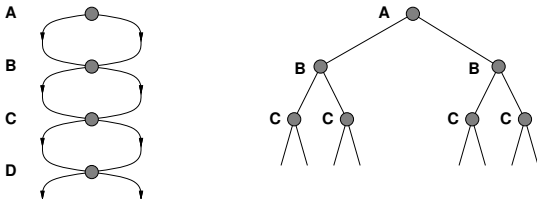
Summary of algorithms

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*

*: If b is finite.

Repeated states

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



- If we detect repeated states, then our search algorithm amounts to searching a graph rather than a tree.
 - Keep a list of encountered nodes, called the *closed* list.

Graph search

Function **Graph-Search**(**problem**, **fringe**) **returns** a solution, or failure

- closed** \leftarrow an empty set
- 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** **node**
 - if** **State**[**node**] is not in **closed** **then**
 - add **State**[**node**] to **closed**
 - fringe** \leftarrow *InsertAll*(Expand(**node**, **problem**), **fringe**)
- end**

Summary

- Problem formulation usually requires abstracting from 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