

Artificial Intelligence

CS 165A

Oct 27, 2020

Instructor: Prof. Yu-Xiang Wang

Today

→ Search algorithms

Student feedback

- “I am really enjoying the course so far, but I didn’t manage to solve all HW1 questions, will it affect my grade? Should I drop the course?”
 - Many people will make mistakes in HW questions, and that is perfectly fine!
 - I give at least 30% A and A- and that’s even before adding bonus points...
 - Even if you missed HW1 entirely, you can get partial credits via late submission.
 - So I encourage you to stay on.
- Will the coding part of HW2 – 4 as difficult as that of HW1?
 - Coding part of HW1 is a substantial project.
 - Coding parts of HW2, HW3 and HW4 will build towards a learning PACMAN
 - They will be of less work (more similar to HW2, but you still need similar conceptual understanding)

Kaiqi will discuss the HW1 this week.

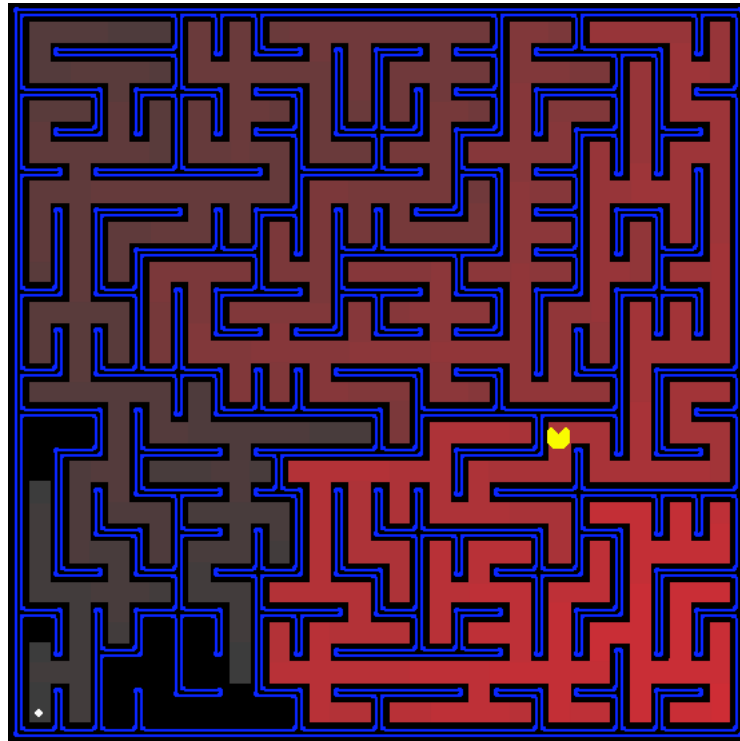
- Many of you have spent hours working on the coding part of HW1
- Now it's the time to get feedback.
- Please attend his discussion section
- Again: attending discussions / watching the TA's videos are very important parts of this course.
 - Feedback wanted on the asynchronous instruction in discussion classes.

Recap: Problem Formulation and Search

- Problem formulation
 - State-space description $\langle \{S\}, S_0, \{S_G\}, \{O\}, \{g\} \rangle$
 - **S**: Possible states
 - **S₀**: Initial state of the agent
 - **S_G**: Goal state(s)
 - Or equivalently, a goal test **G(S)**
 - **O**: Operators $O: \{S\} \Rightarrow \{S\}$
 - Describes the possible actions of the agent
 - **g**: Path cost function, assigns a cost to a path/action
- At any given time, which possible action **O_i** is best?
 - Depends on the goal, the path cost function, the future sequence of actions....
- Agent's strategy: Formulate, Search, and Execute
 - This is *offline* problem solving

Recap: PACMAN

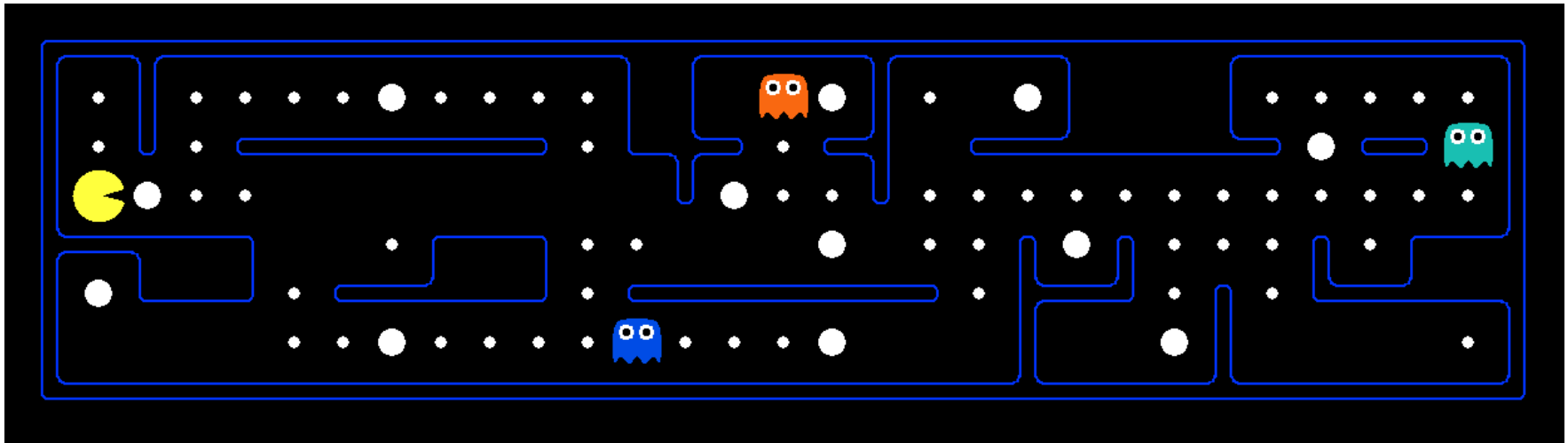
- The goal of a simplified PACMAN is to get to the pellet as quick as possible.
 - For a grid of size 30*30. Everything static.
 - What is a reasonable representation of the State, Operators, Goal test and Path cost?



30x30

Quiz: PACMAN with static ghosts

- The goal is to eat all pellets as quickly as possible while staying alive. Eating the “Power pellet” will allow the pacman to eat the ghost.



- State (how many?)
- Operators?
- Goal-Test?
- Path-Cost?

$$30 \times 30 \times 5$$

$$\textcircled{2} \quad \frac{30 \times 30 \times 5}{2}$$

$$\frac{4}{30 \times 30} + \frac{30 \times 30}{1}$$

Recap: General Tree Search Algorithm

- Uses a queue (a list) and a **queuing function** to implement a *search strategy*
 - **Queuing-Fn**(*queue*, *elements*) inserts a set of elements into the queue and determines the order of node expansion

function **GENERAL-SEARCH**(*problem*, QUEUING-FN) **returns** a solution or failure

nodes ← MAKE-QUEUE(MAKE-NODE(INITIAL-STATE[*problem*]))

loop do

if *nodes* is empty **then return** failure

node ← REMOVE-FRONT(*nodes*)

if GOAL-TEST[*problem*] applied to STATE(*node*) succeeds **then return** *node*

nodes ← QUEUING-FN(*nodes*, EXPAND(*node*, OPERATORS[*problem*]))

end

Recap: Breadth-First Search

- All nodes at depth d in the search tree are expanded before any nodes at depth $d+1$
 - First consider all paths of length N , then all paths of length $N+1$, etc.
- Doesn't consider path cost – finds the solution with the shortest path
- Uses FIFO queue

```
function BREADTH-FIRST-SEARCH(problem) returns a solution or failure  
return GENERAL-SEARCH(problem, ENQUEUE-AT-END)
```


Recap: Breadth-First Search

- Complete? **Yes**
- Optimal? **If shallowest goal is optimal**
- Time complexity? **Exponential: $O(b^{d+1})$**
- Space complexity? **Exponential: $O(b^{d+1})$**

In practice, the memory requirements are typically worse than the time requirements

b = branching factor (require finite b)
d = depth of shallowest solution

This lecture: Search algorithms

- Uninformed search
 - DFS
 - Depth-limited search
 - Iterative Deepening search
 - Bidirectional search
 - Uniform cost search
- Tree search vs Graph search
- Informed Search
 - A*-Search

Depth-First Search

Depth-First Search

- Always expands one of the nodes at the deepest level of the tree
 - Low memory requirements
 - Problem: depth could be infinite
- Uses a stack (LIFO)

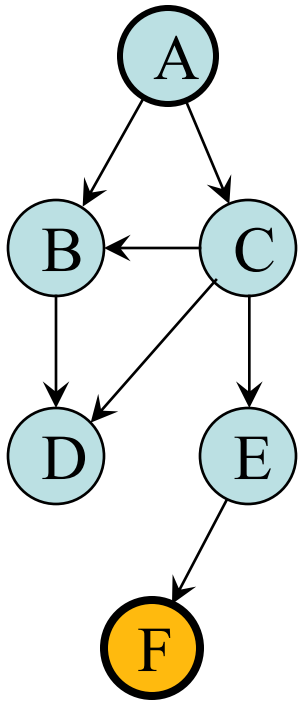
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```

Example

State space graph

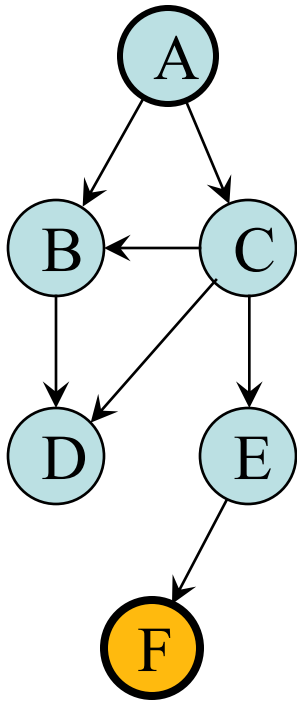


Search tree

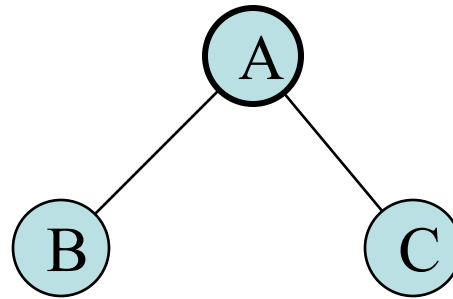


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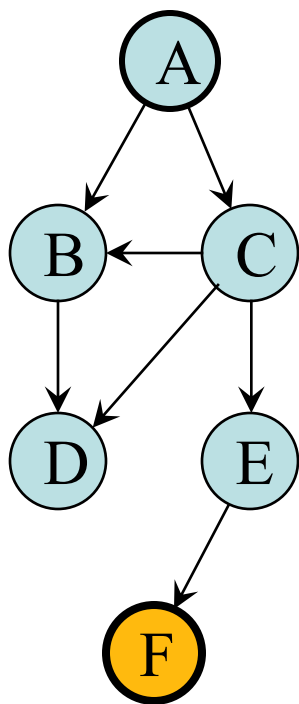


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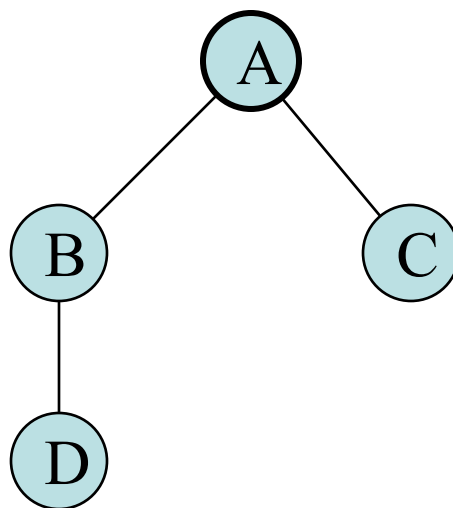


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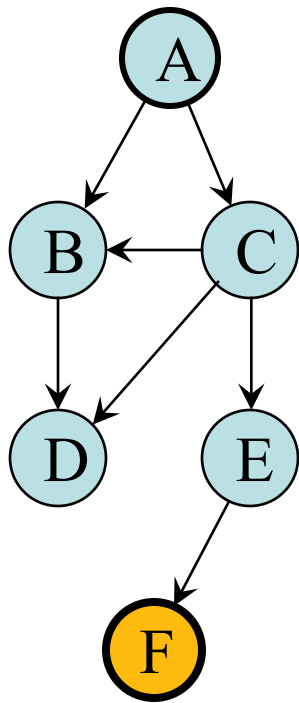


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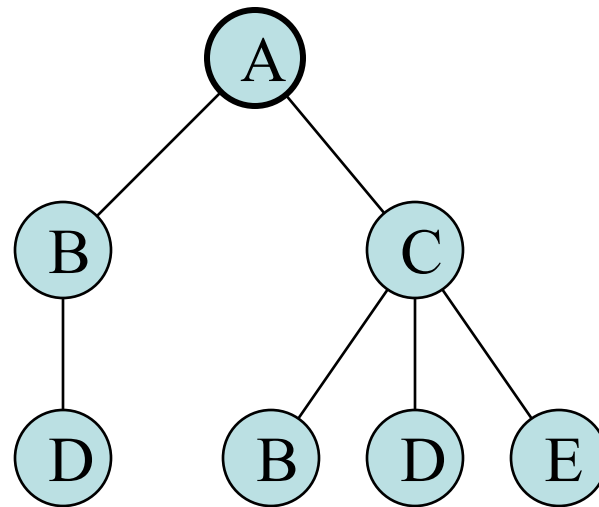


Example

State space graph

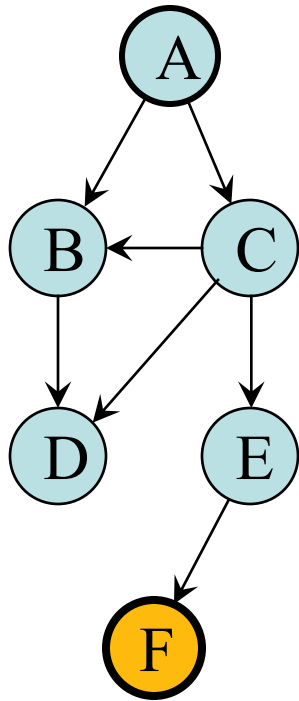


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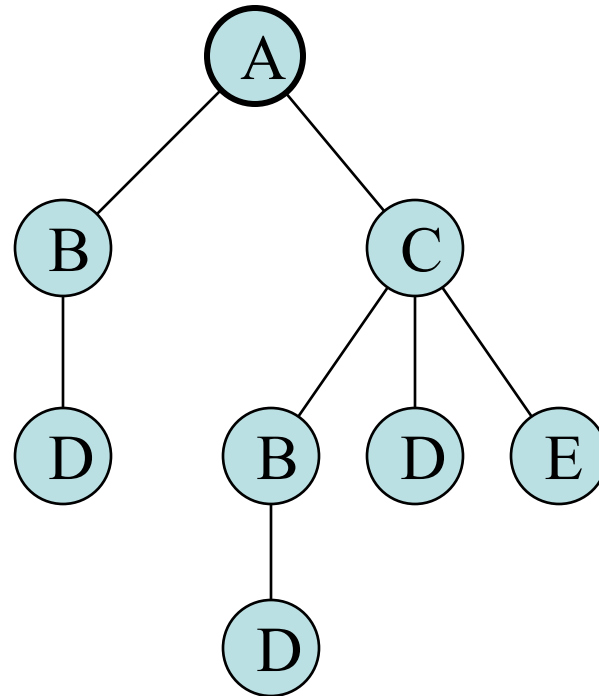


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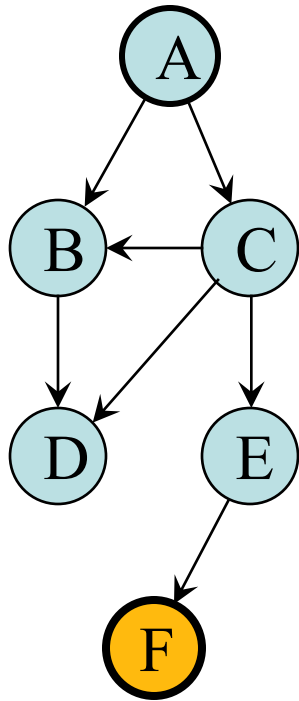


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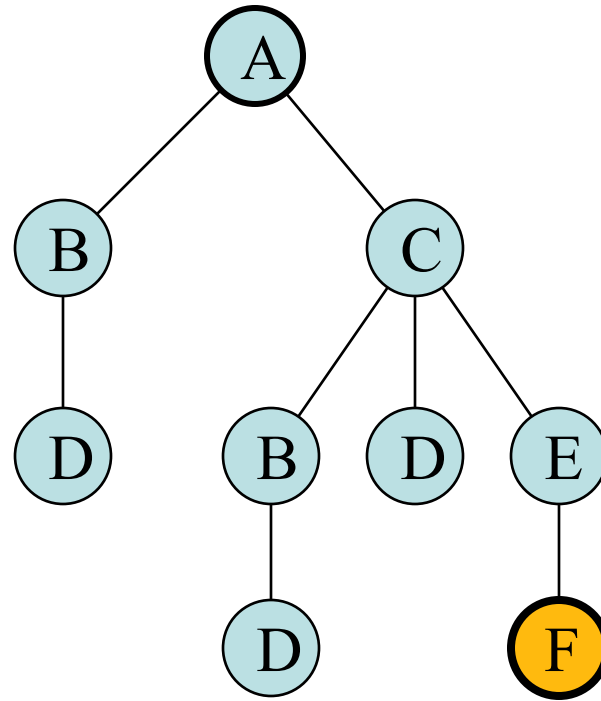


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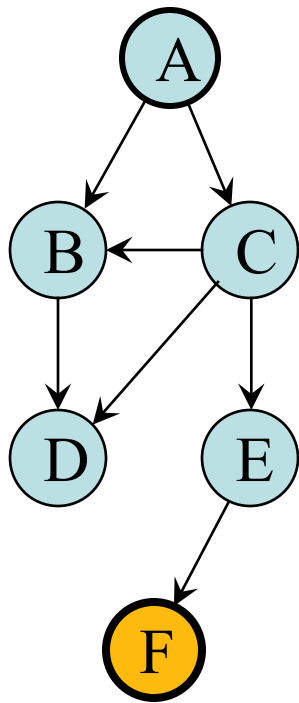


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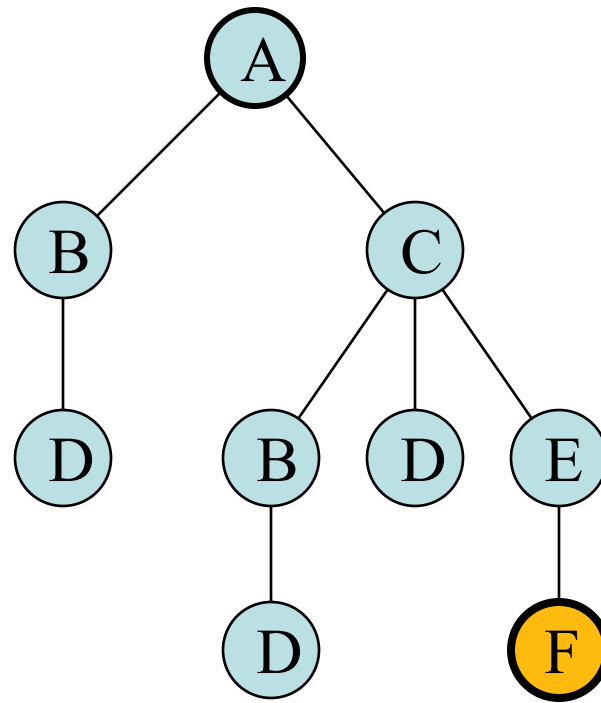


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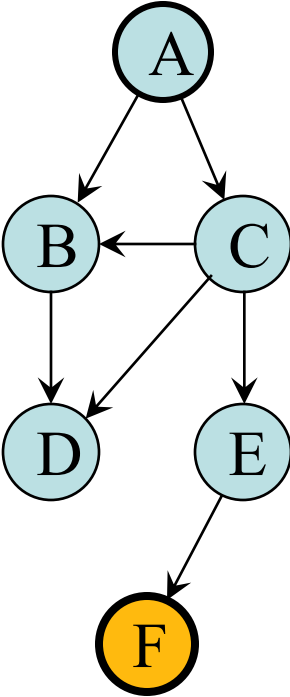
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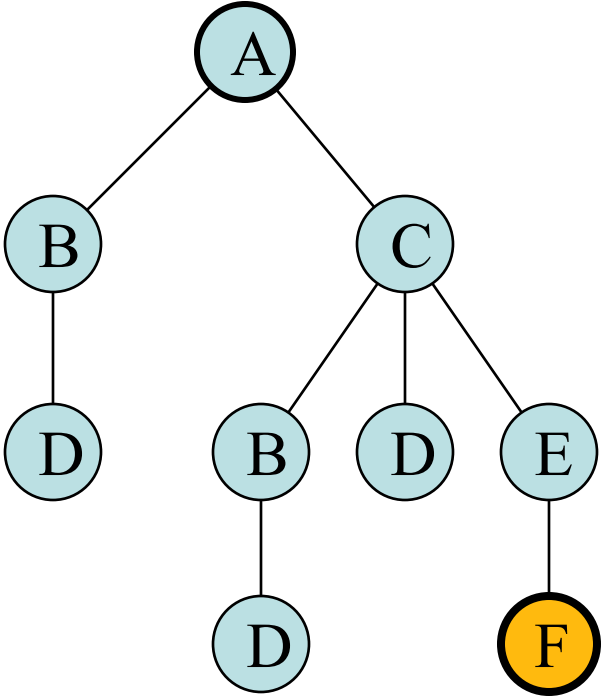
Queue

Example

State space graph



Search tree

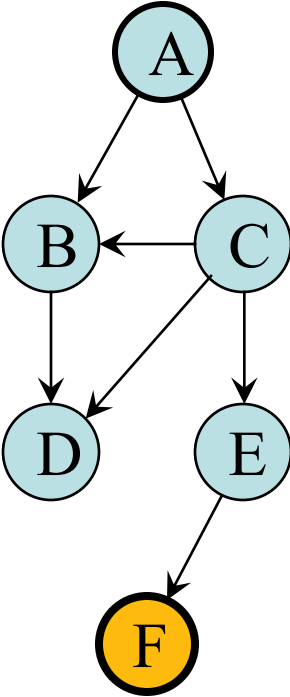


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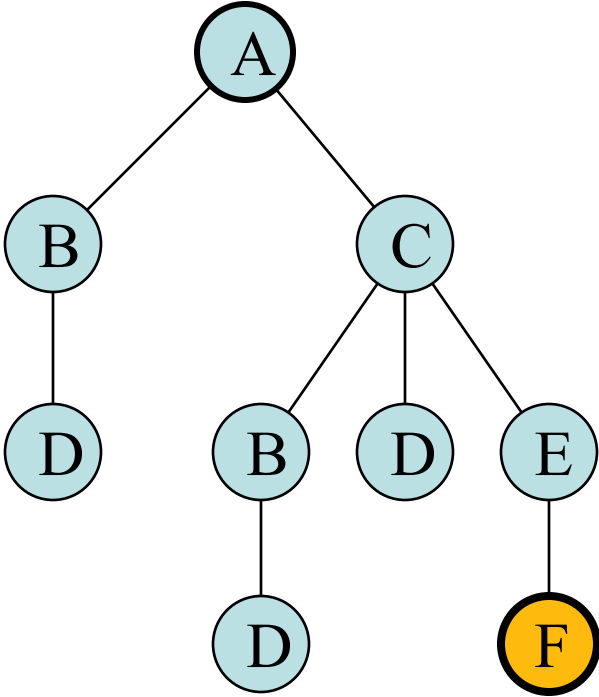
(A)

Example

State space graph



Search tree

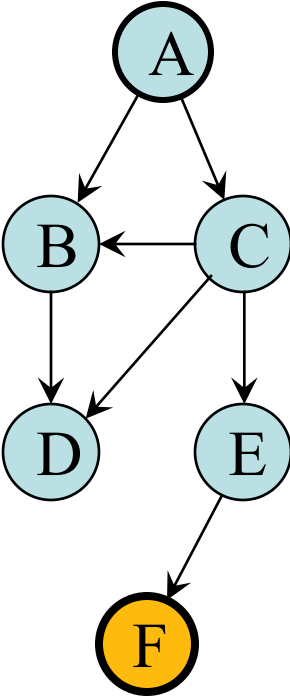


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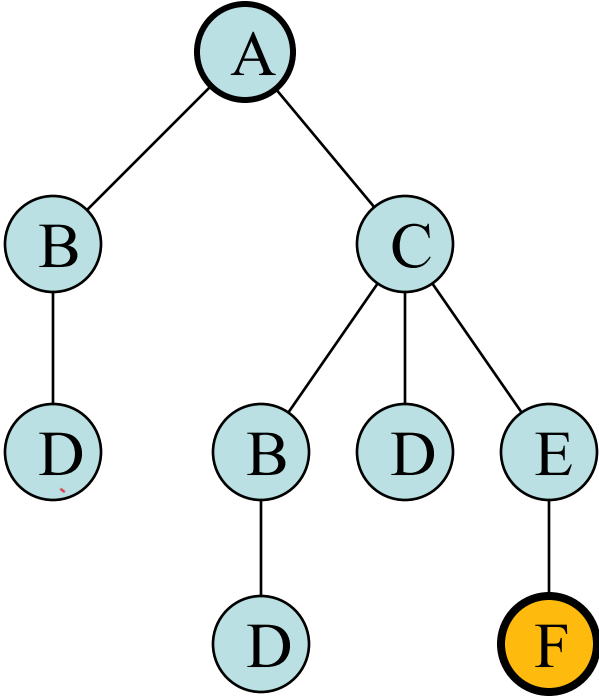
- (A)
- (B C)

Example

State space graph



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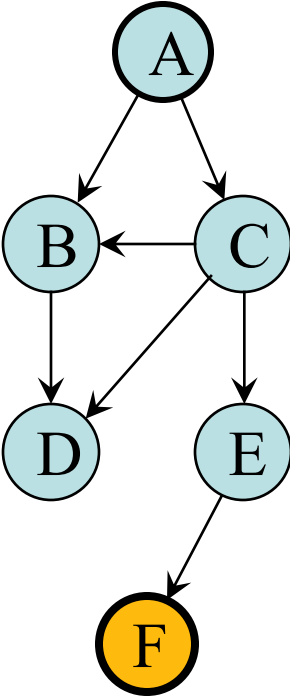


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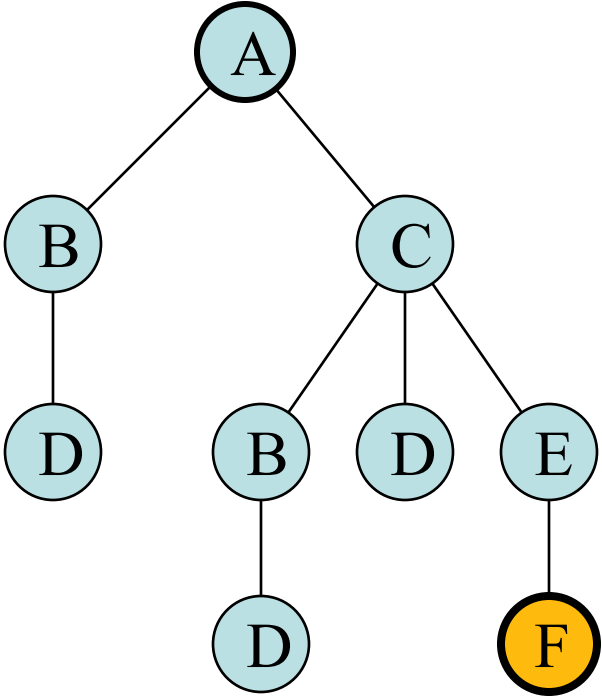
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- (D C)

Example

State space graph



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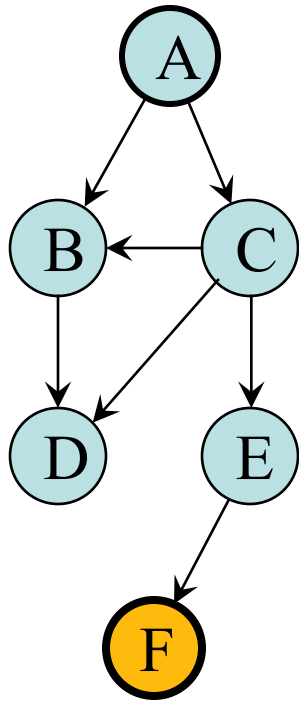


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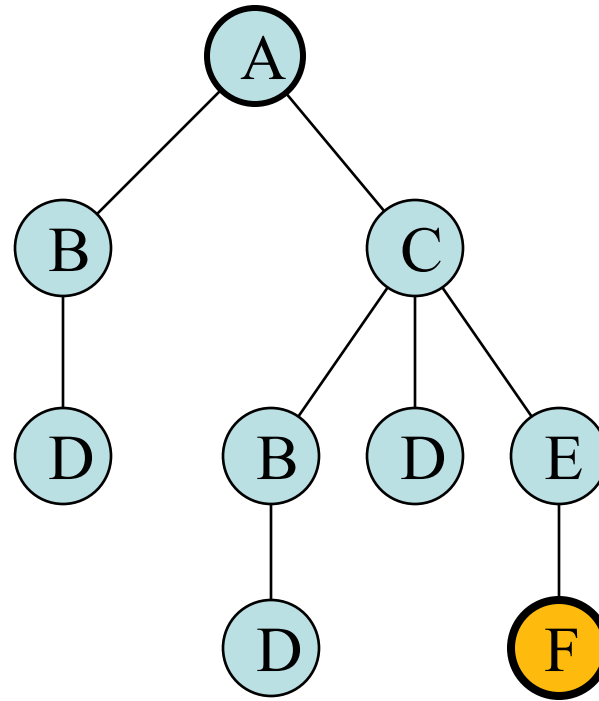
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Example

State space graph



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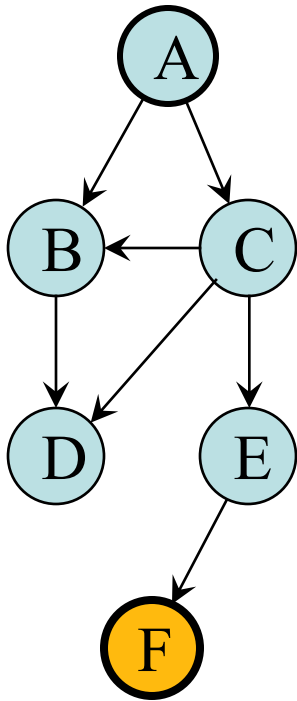


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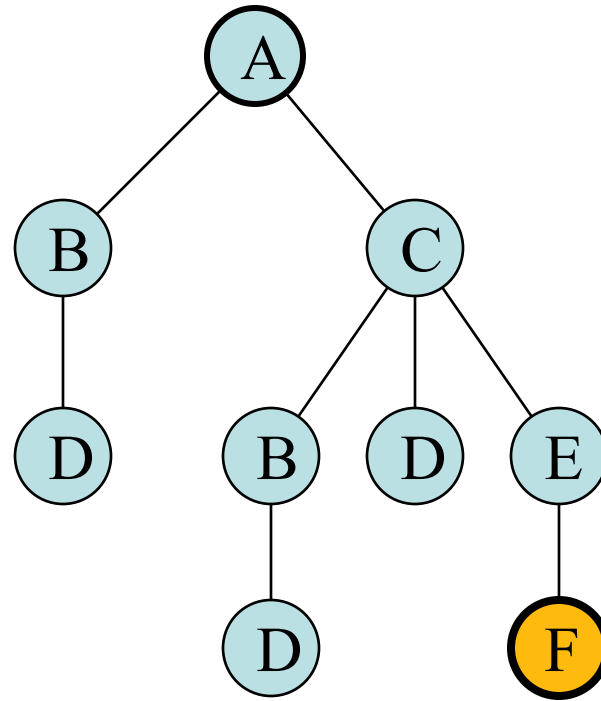
- (A)
- (B C)
- (D C)
- (C)
- (B D E)

Example

State space graph



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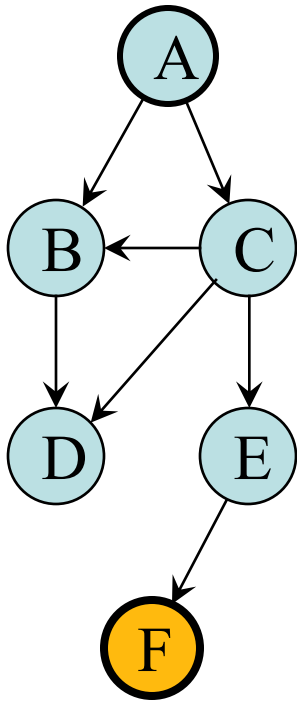


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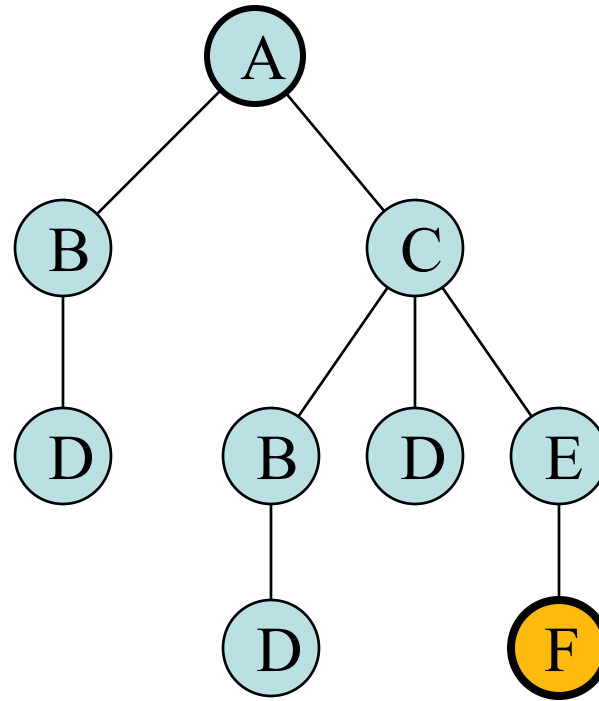
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State space graph



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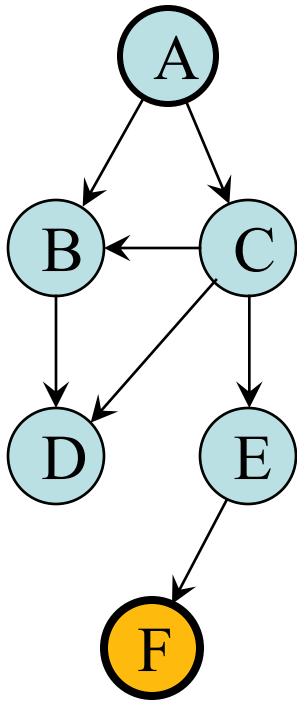


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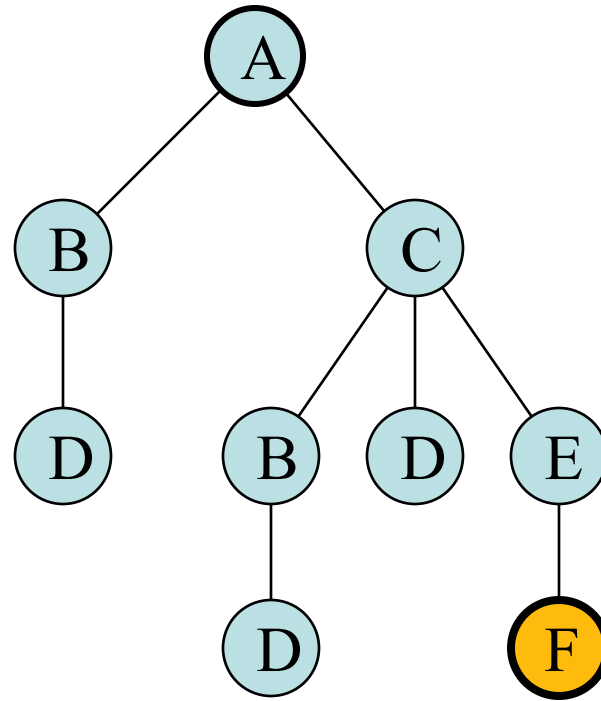
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Example

State space graph



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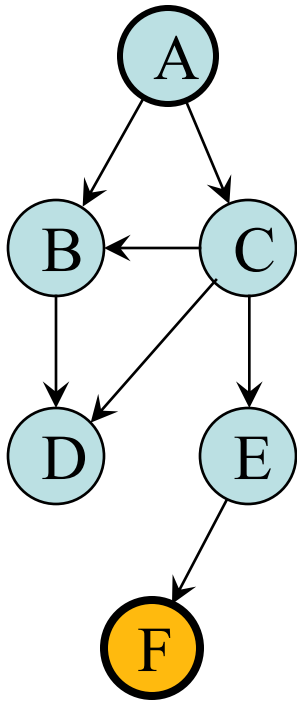


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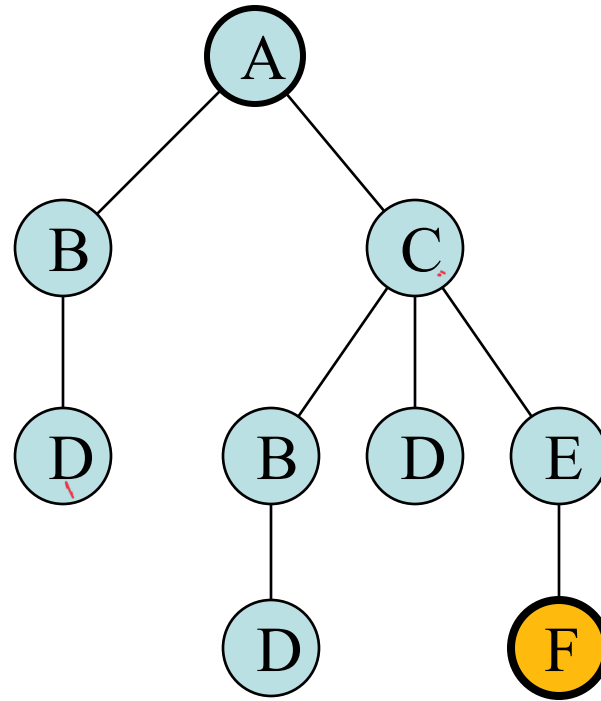
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- (D C)
- (C)
- (B D E)
- (D D E)
- (D E)
- (E)

Example

State space graph



Search tree



Queue

- (A)
- (B C)
- (D C)
- (C)
- (B D E)
- (D D E)
- (D E)
- (E)
- (F)

Depth-First Search

- Complete?
- Optimal?
- Time complexity?
- Space complexity?

m = maximum depth of the search tree
(may be infinite)

Depth-First Search

- Complete? **No**
- Optimal?
- Time complexity?
- Space complexity?

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Depth-First Search

- Complete? No
- Optimal? No
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Depth-First Search

- Complete? No
- Optimal? No
- Time complexity? Exponential: $O(b^m)$
- Space complexity?

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Depth-First Search


- Complete? No
- Optimal? No
- Time complexity? Exponential: $O(b^m)$
- Space complexity? Polynomial: $O(bm)$

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What is the difference between the BFS / DFS that you learned from the algorithm / data structure course?

- Nothing, except:
 - Now you are applying them to solve an AI problem
 - The graph can be infinitely large
 - The graph does not need to be known ahead of time (you only need local information: goal-state checker, successor function)

Space complexity of DFS

- Why is the *space* complexity (memory usage) of depth-first search $O(bm)$?
 - Remove expanded node when all descendents evaluated
 - At each of the m levels, you have to keep b nodes in memory 

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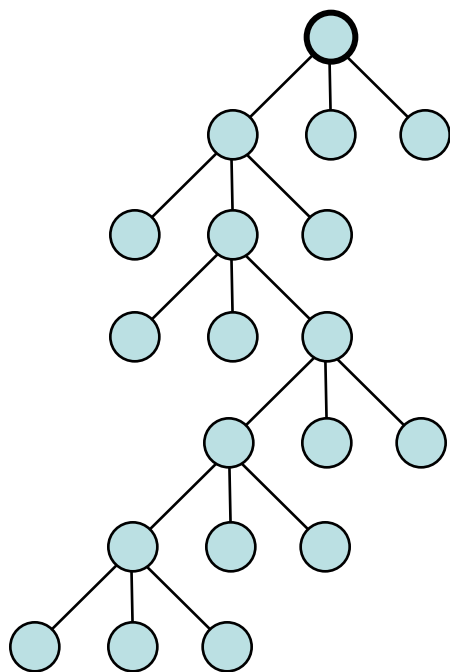
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$$\text{Nodes in memory: } bm+1 = 19$$

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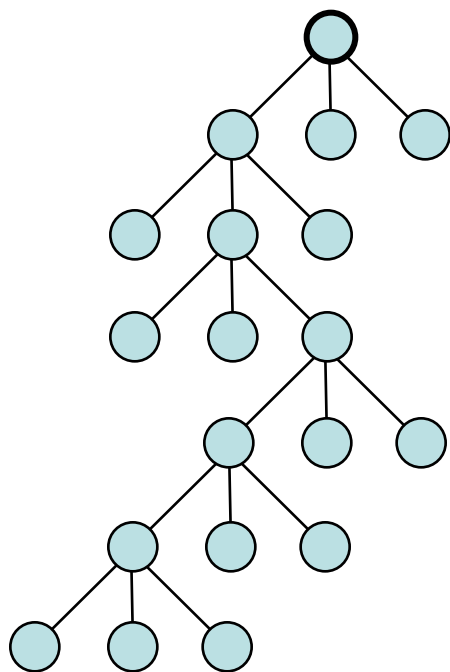
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Example:

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Actually, $(b-1)m + 1 = 13$ nodes, the way we have been keeping our node list

Space complexity of DFS

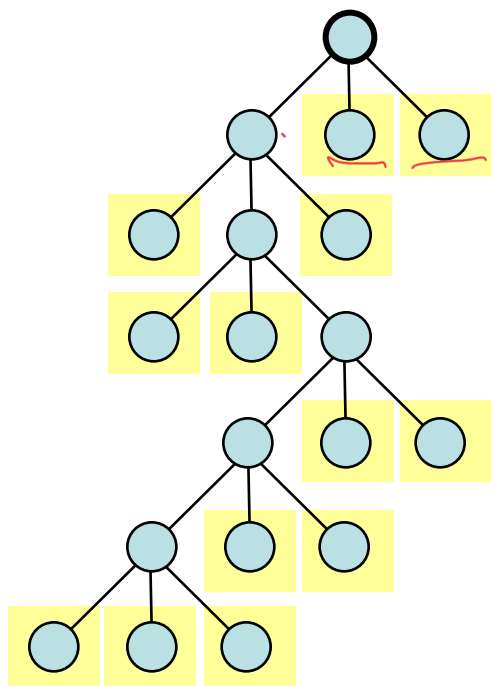
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Depth-Limited Search

- Like depth-first search, but uses a depth cutoff to avoid long (possibly infinite), unfruitful paths
 - Do depth-first search up to depth limit l
 - Depth-first is special case with limit = inf
- Problem: How to choose the depth limit l ?
 - Some problem statements make it obvious (e.g., TSP), but others don't (e.g., MU-puzzle, from the supplementary slide last time)

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```
function DEPTH-LIMITED-SEARCH(problem, depth-limit) returns a  
  solution or failure  
return GENERAL-SEARCH(problem, ENQUEUE-AT-FRONT-IF-UNDER-  
  DEPTH-LIMIT)
```

Must explicitly represent node depth

Depth-Limited Search

l = depth limit

- Complete? No, unless $d \leq l$
- Optimal? No
- Time complexity? Exponential: $O(b^l)$
- Space complexity? Exponential: $O(bl)$

Iterative-Deepening Search

- Since the depth limit is difficult to choose in depth-limited search, use depth limits of $l = 0, 1, 2, 3, \dots$
 - Do depth-limited search at each level

Iterative-Deepening Search

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 - Do depth-limited search at each level

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

Iterative-Deepening Search

- IDS has advantages of
 - Breadth-first search – similar optimality and completeness guarantees
 - Depth-first search – Modest memory requirements
- This is the preferred blind search method when the search space is *large* and the solution depth is *unknown*
- Many states are expanded multiple times
 - Is this terribly inefficient?
 - No... and it's great for memory (compared with breadth-first)

- Why is it not particularly inefficient?

$$b^0 + b^1 + b^2 + \dots + b^{l_{opt}} = \frac{1 - (b^{l_{opt}+1} - 1)}{b^{l_{opt}} - 1} \approx O(b^{l_{opt}})$$

Iterative-Deepening Search: Efficiency

- Complete? **Yes**
- Optimal? **Same as BFS**
- Time complexity? **Exponential: $O(b^d)$**
- Space complexity? **Polynomial: $O(bd)$**

Bidirectional Search

Bidirectional Search

Forward search only:



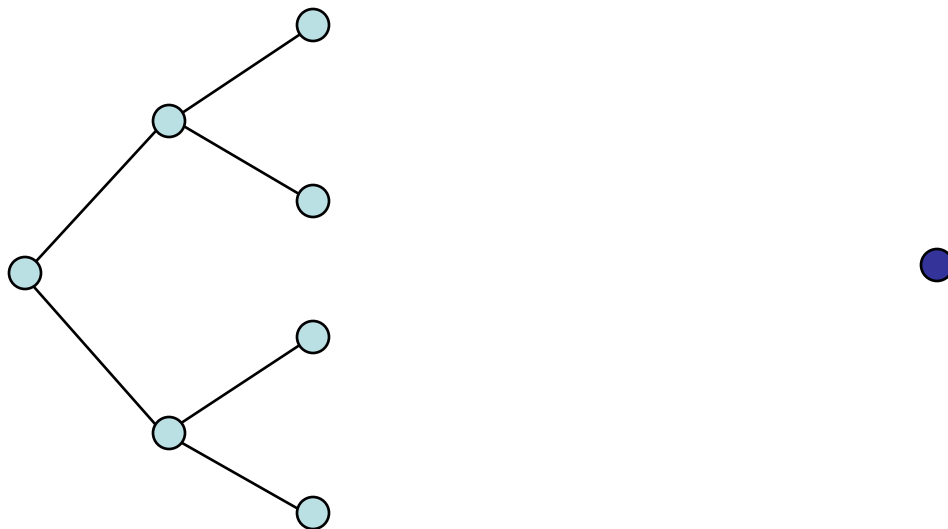
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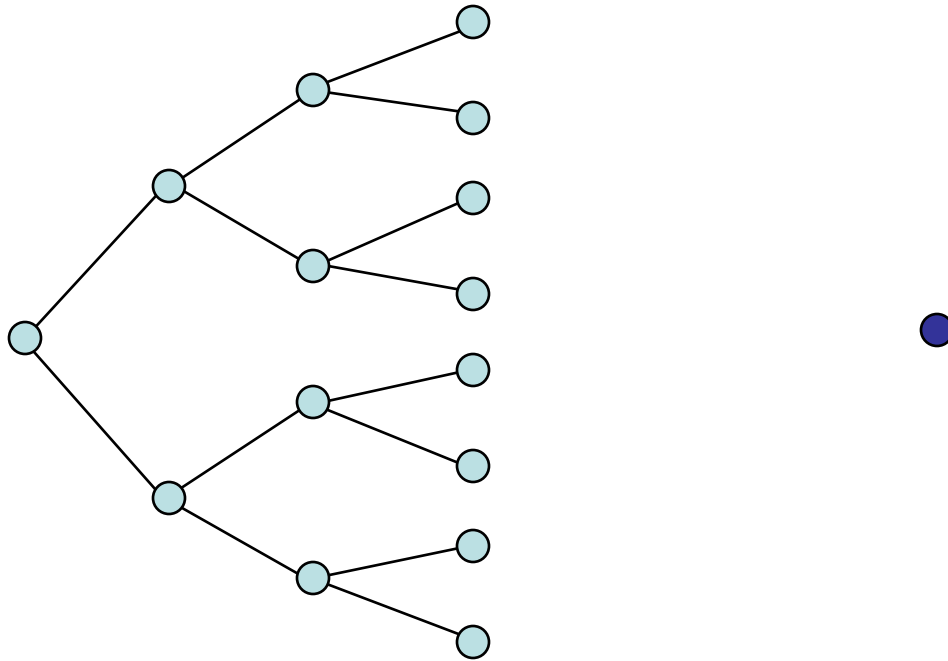
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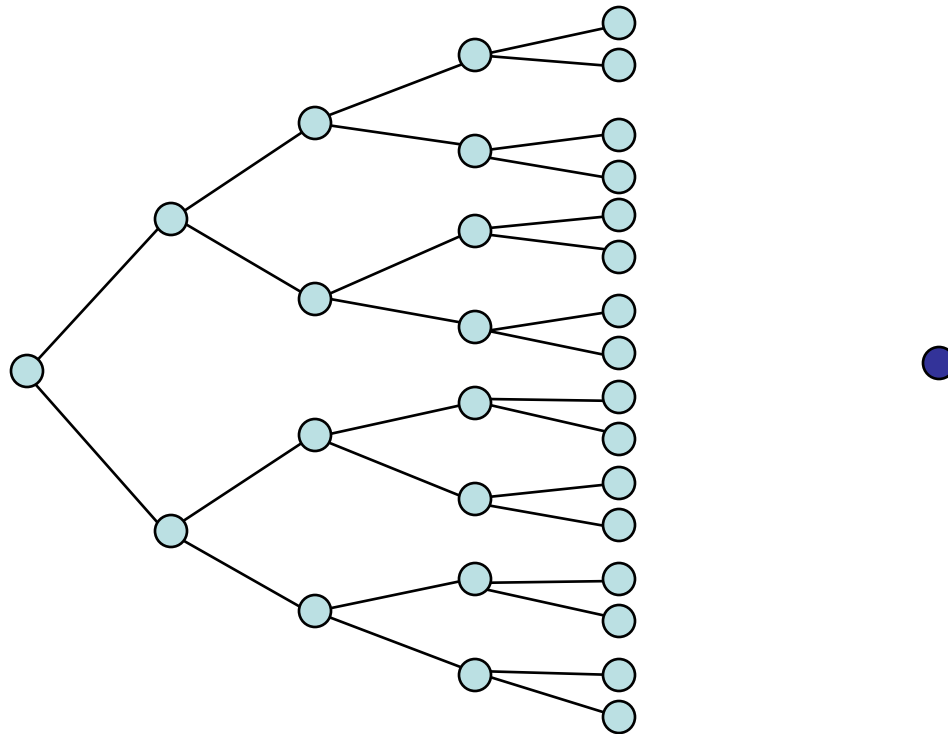
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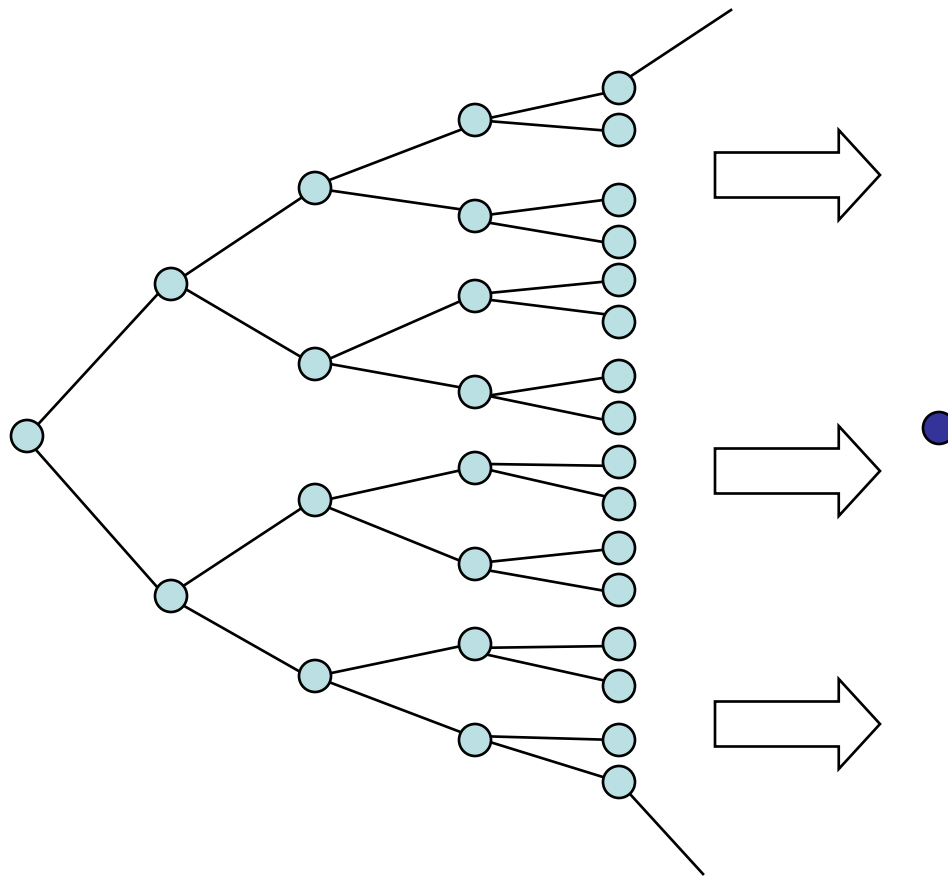
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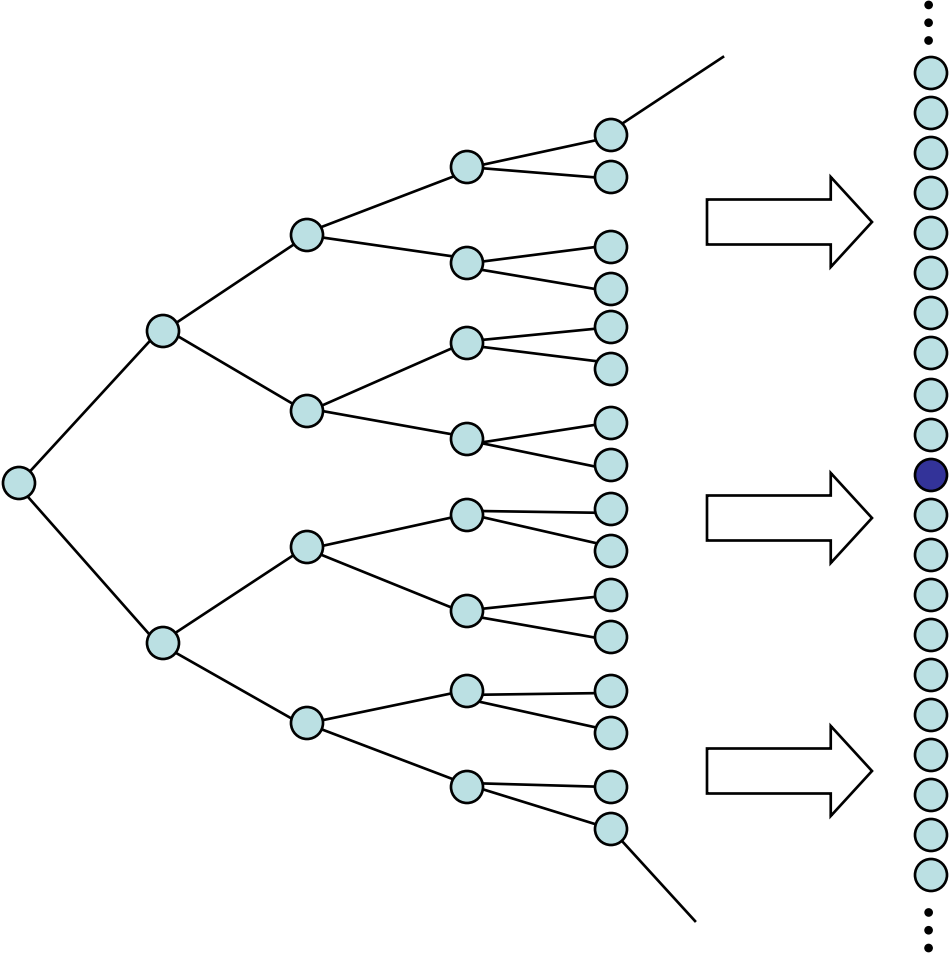
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Bidirectional Search

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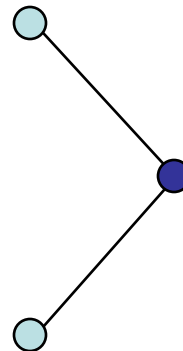
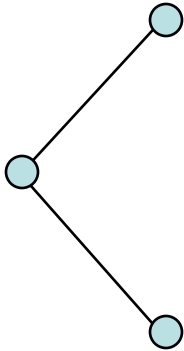
Bidirectional Search

Simultaneously search forward from the initial state and backward from the goal state



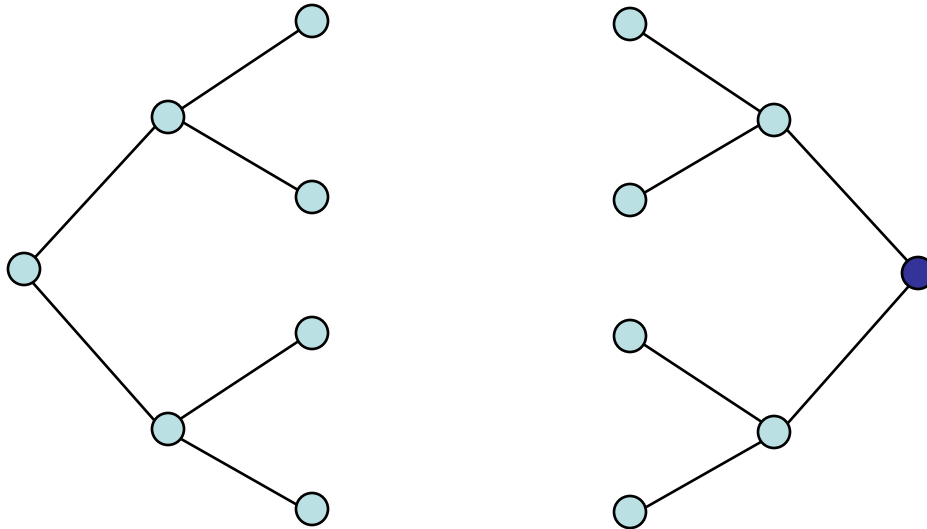
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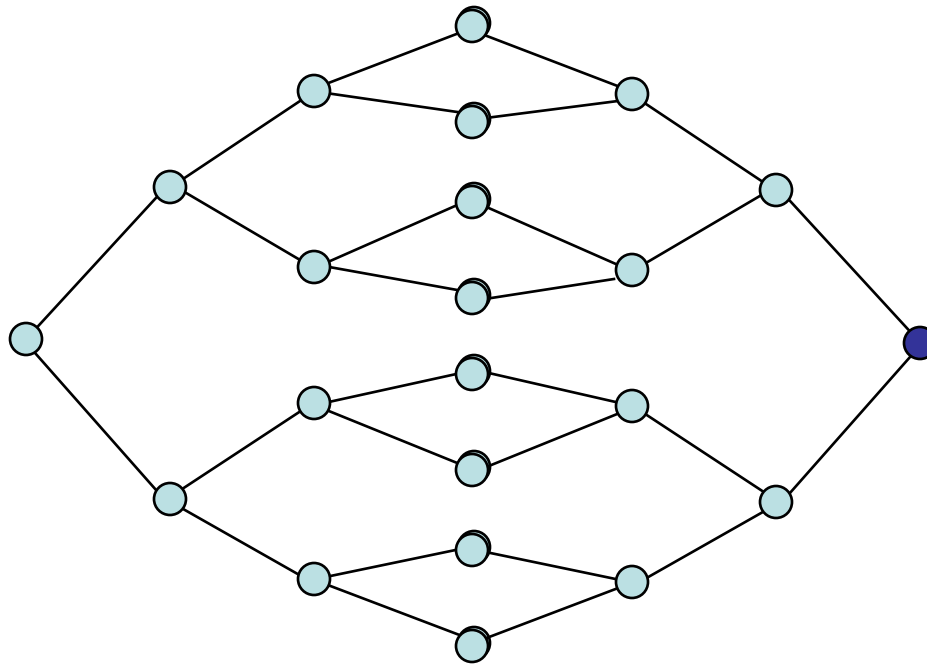
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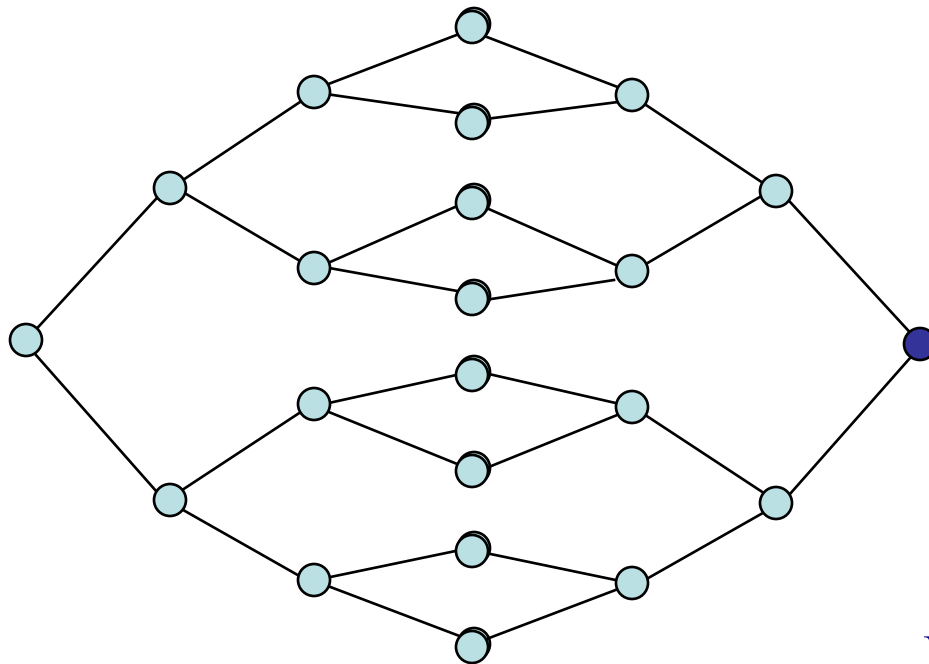
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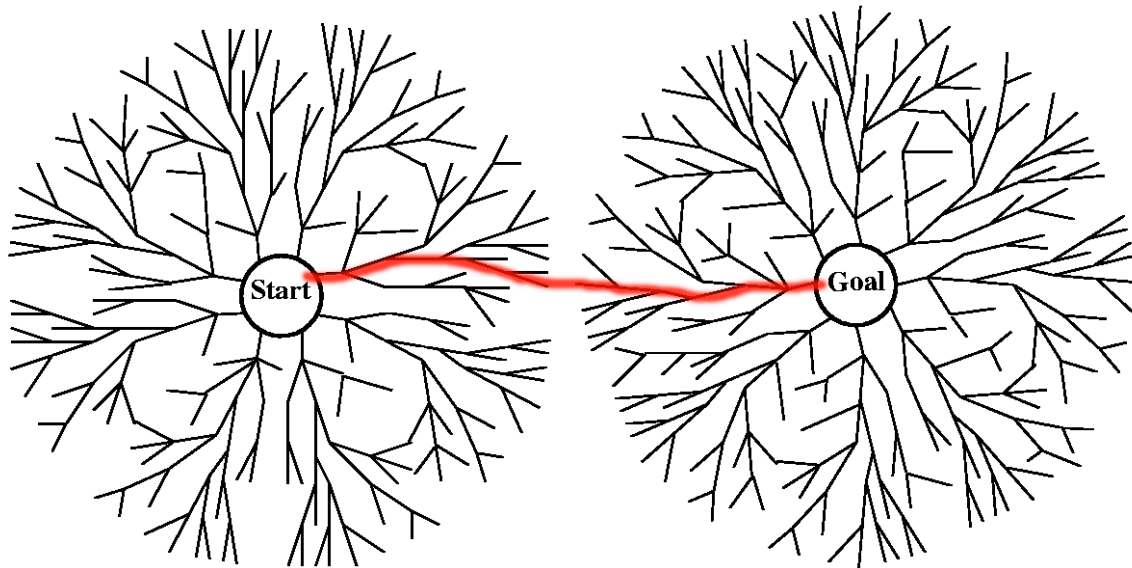
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Much more efficient!

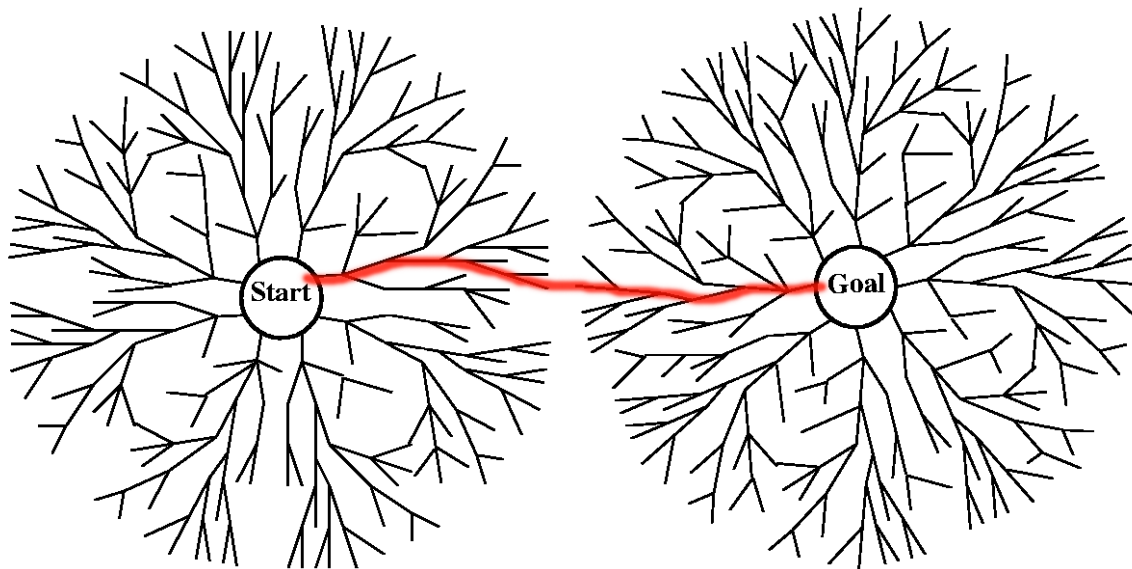
Bidirectional Search



Example:
 $4^{10} \approx 1,000,000$
 $2 \cdot 4^5 \approx 2,000$

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Bidirectional Search



Example:
 $4^{10} \approx 1,000,000$
 $2 * 4^5 \approx 2,000$

- $O(b^{d/2})$ rather than $O(b^d)$ – hopefully
- Both actions and predecessors (inverse actions) must be defined
- Must test for intersection between the two searches
 - Constant time for test?
- Really a search strategy, not a specific search method
 - Often not practical....

Bidirectional Search

- Complete? Yes
- Optimal? Same as BFS
- Time complexity? Exponential: $O(b^{d/2})$
- Space complexity? Exponential: $O(b^{d/2})$

* Assuming breadth-first search used from both ends

Uniform Cost Search

- Similar to breadth-first search, but always expands the lowest-cost node, as measured by the path cost function, $g(n)$
 - $g(n)$ is (actual) cost of getting to node n
 - Breadth-first search is actually a special case of uniform cost search, where $g(n) = \text{DEPTH}(n)$
 - If the path cost is **monotonically increasing**, uniform cost search will find the optimal solution

Uniform Cost Search

- Similar to breadth-first search, but always expands the lowest-cost node, as measured by the path cost function, $g(n)$
 - $g(n)$ is (actual) cost of getting to node n
 - Breadth-first search is actually a special case of uniform cost search, where $g(n) = \text{DEPTH}(n)$
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function **UNIFORM-COST-SEARCH**(*problem*) **returns** a solution or failure
return **GENERAL-SEARCH**(*problem*, **ENQUEUE-IN-COST-ORDER**)

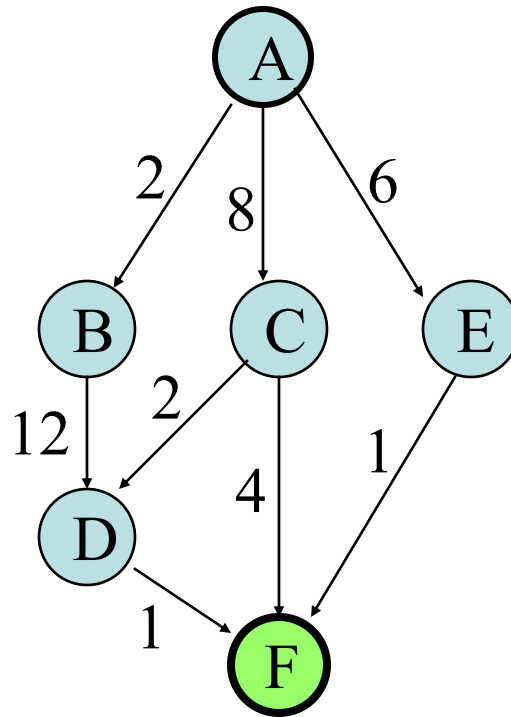
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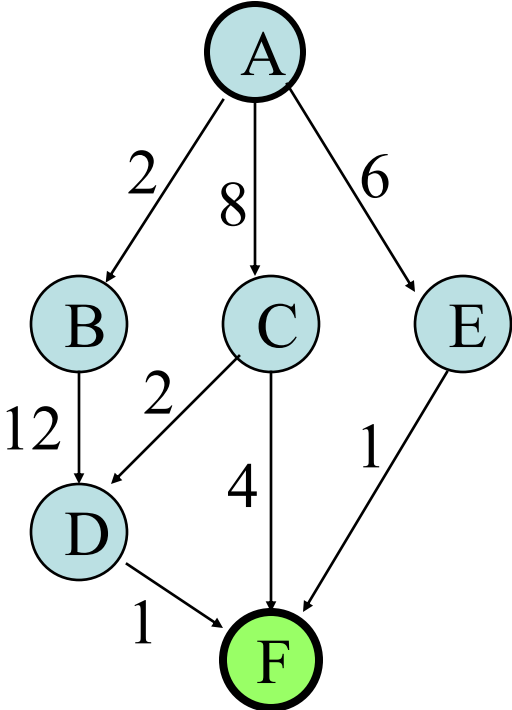
(Dijkstra's algorithm of an potentially infinite graph)

Example (3 min work)



Try breadth-first and uniform cost

Example (3 min work): Breath-First Search



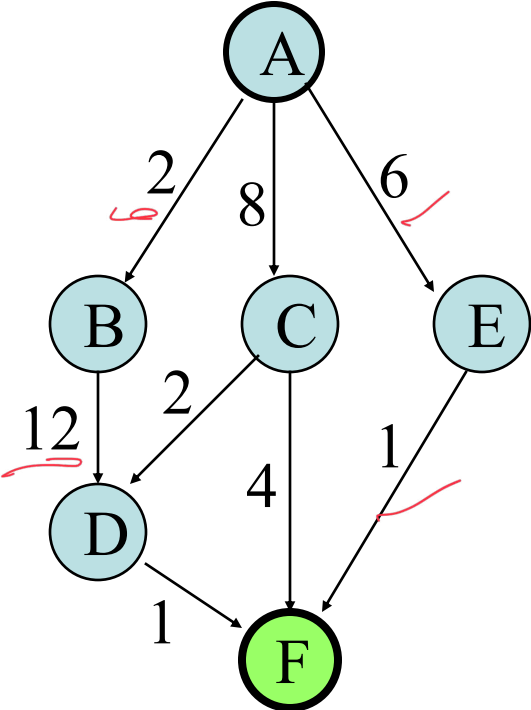
Node to expand:

A
B
C
E
D
D
D
F

Frontier:

A
BCE
CED
EDDF
DDFF
DFFF
RFFF

Example (3 min work): Uniform Cost Search



Node to expand:

- A
- B
- E
- F**

Frontier:

- A: 0
- B: 2, E: 6, C: 8
- E: 6, C: 8, D: 14
- F: 7, C: 8, D: 14

Uniform-Cost Search

C = optimal cost
 ϵ = minimum step cost

- Complete? **Yes, if $\epsilon > 0$**
- Optimal? **Yes**
- Time complexity?
- Space complexity?

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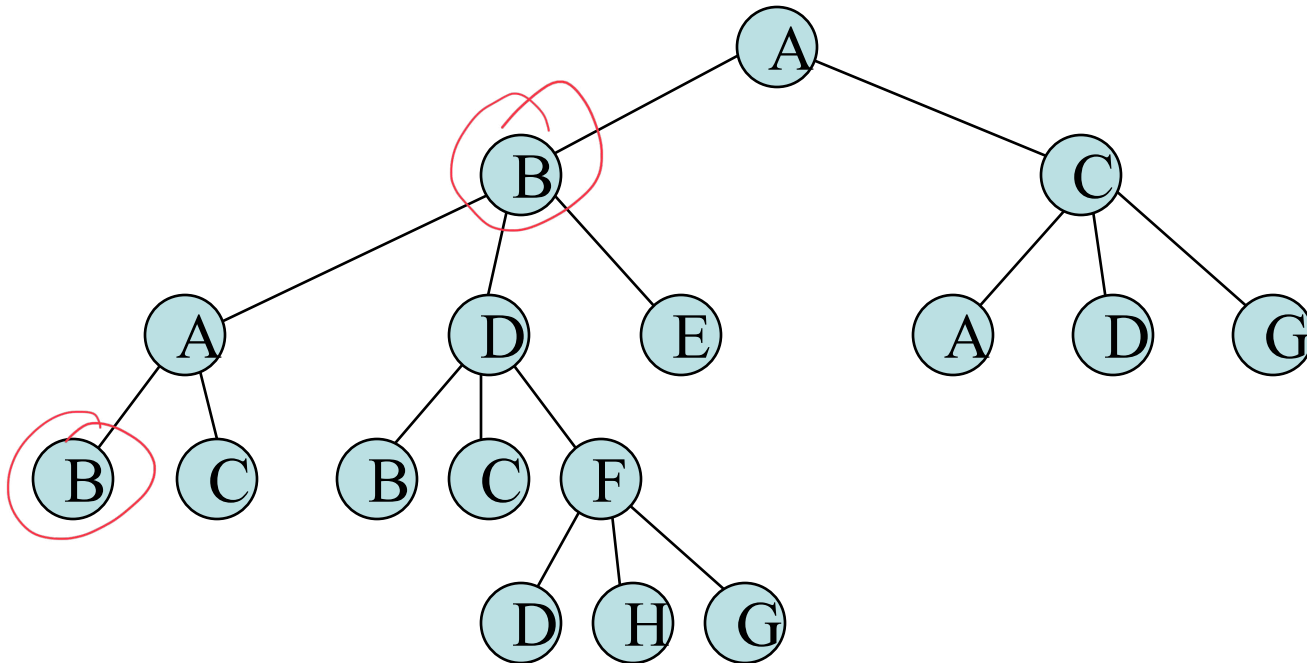
Same as breadth-first if all edge costs are equal

Can we do better than Tree Search?

- Sometimes.
- When the number of states are small
 - Dynamic programming (smart way of doing exhaustive search)

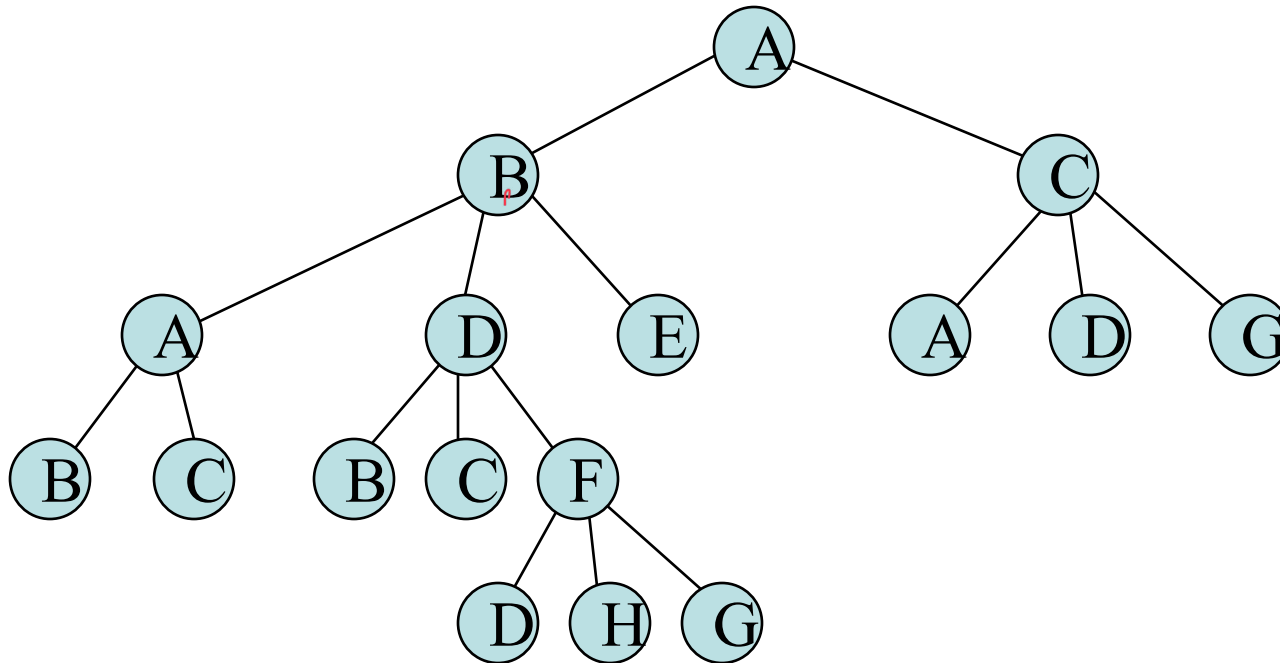
State Space vs. Search Tree (cont.)

Search tree (partially expanded)



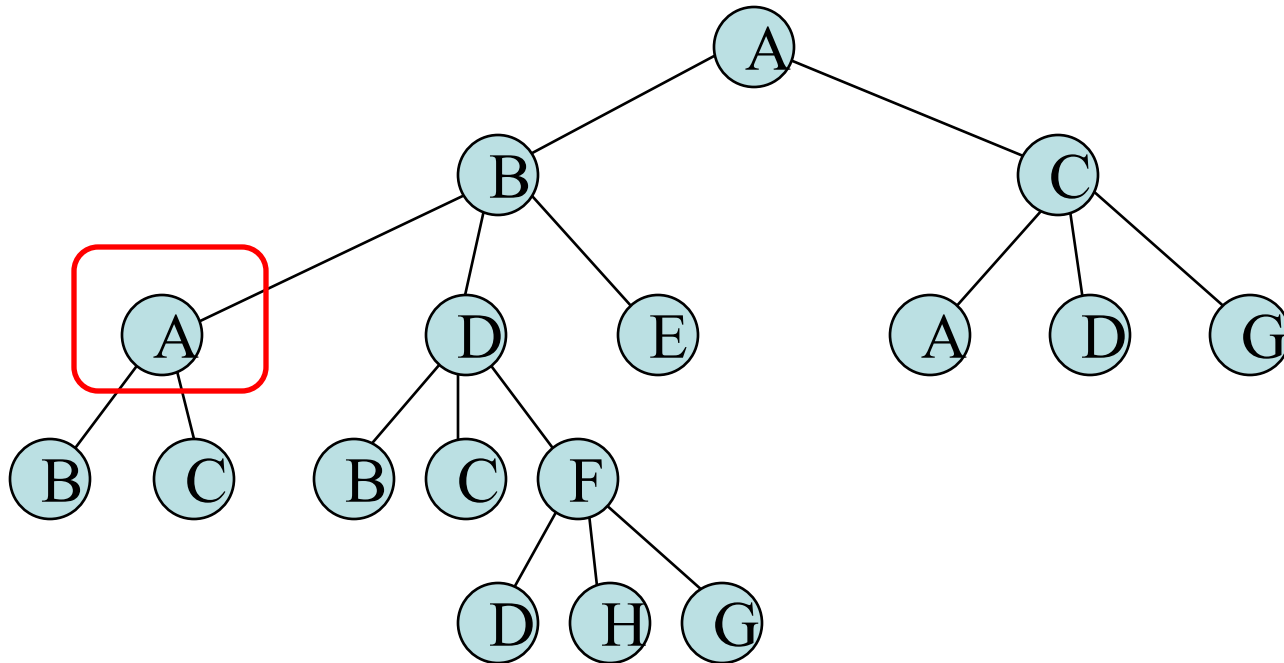
Search Tree => Search Graph

Dynamic programming (with book keeping)



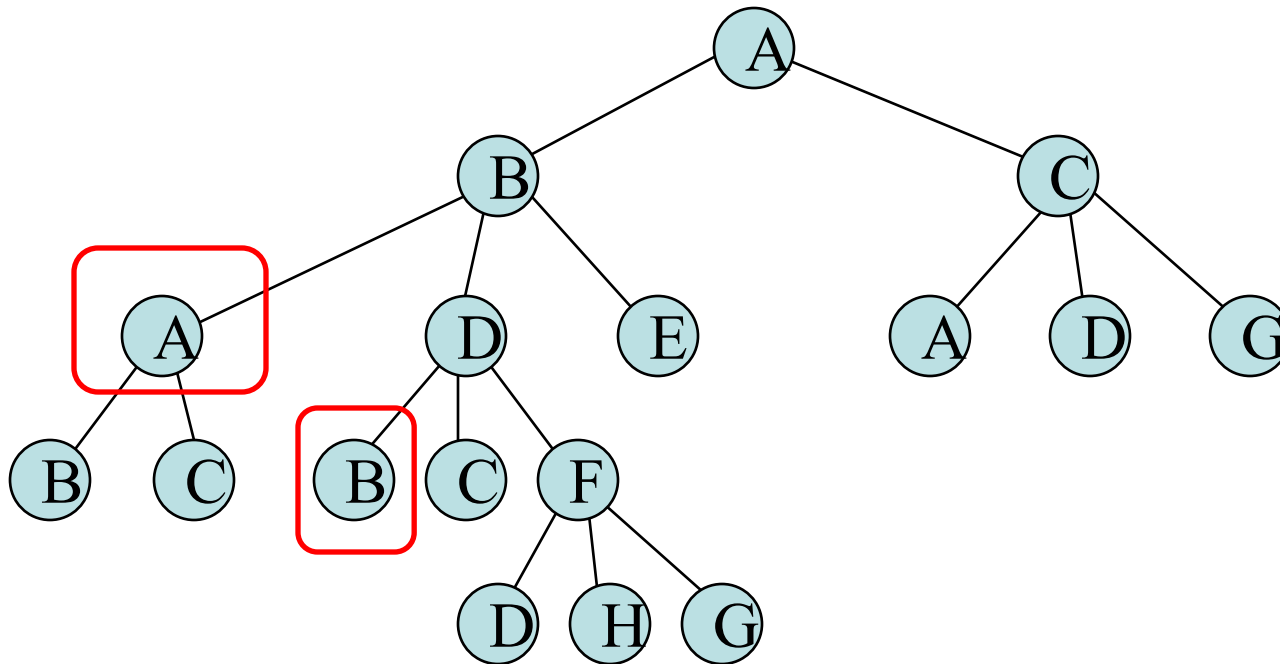
Search Tree => Search Graph

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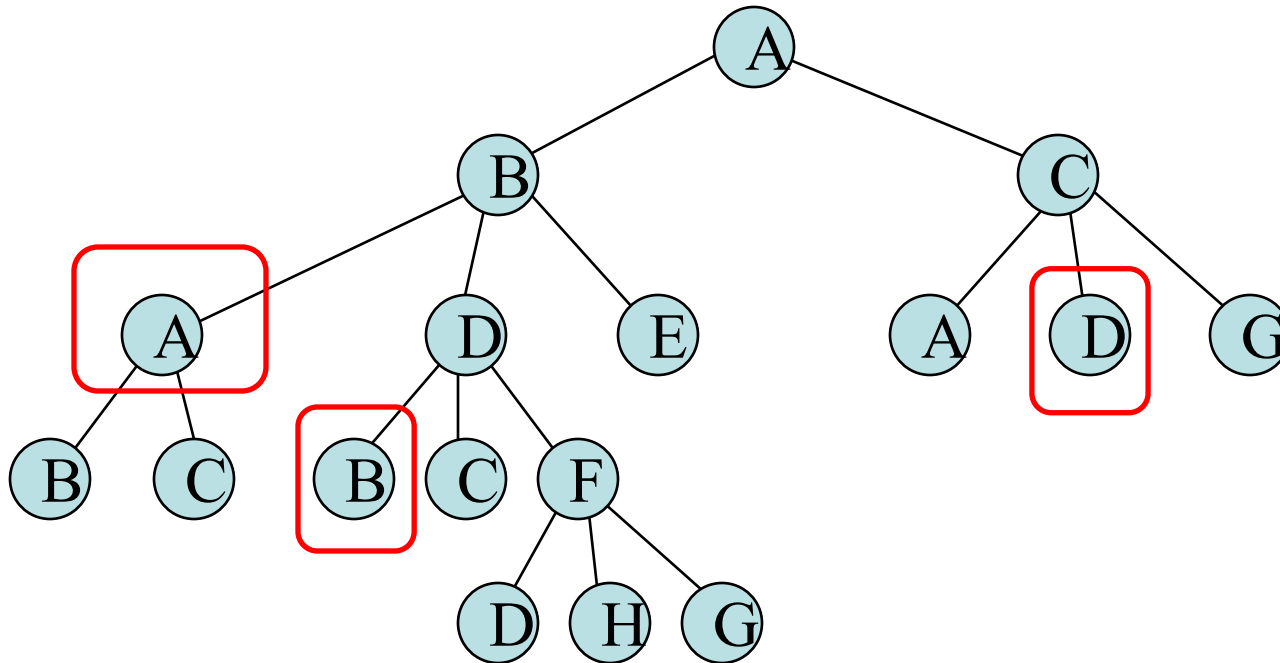
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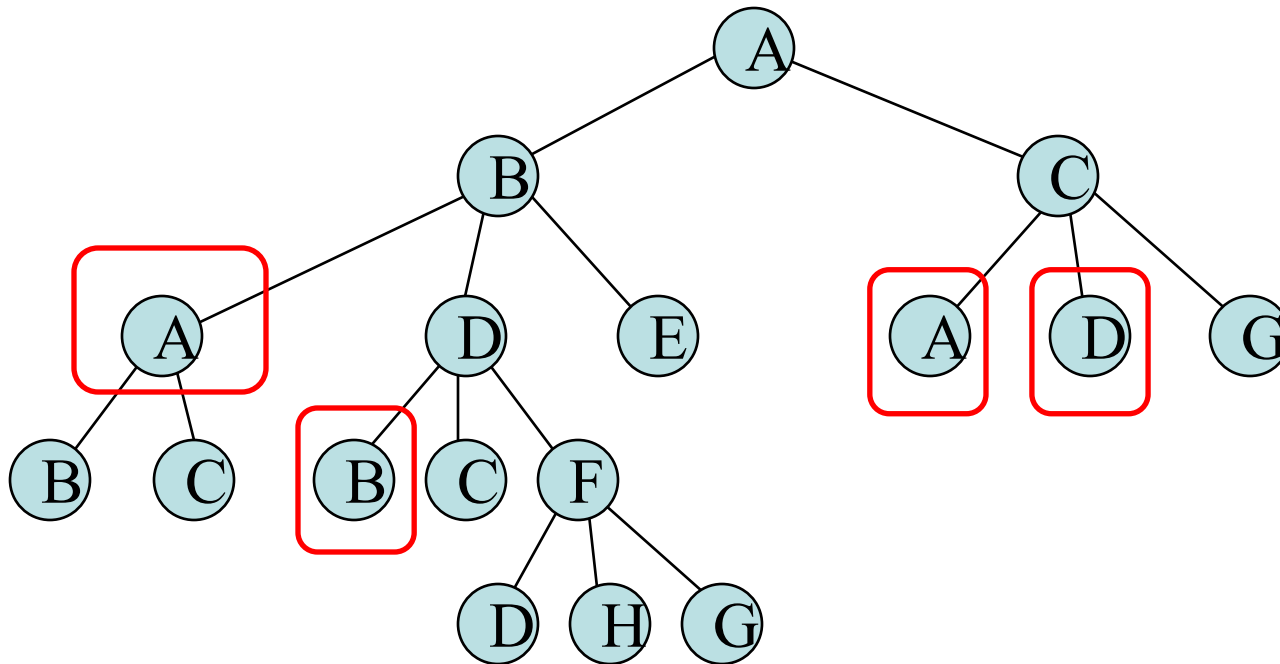
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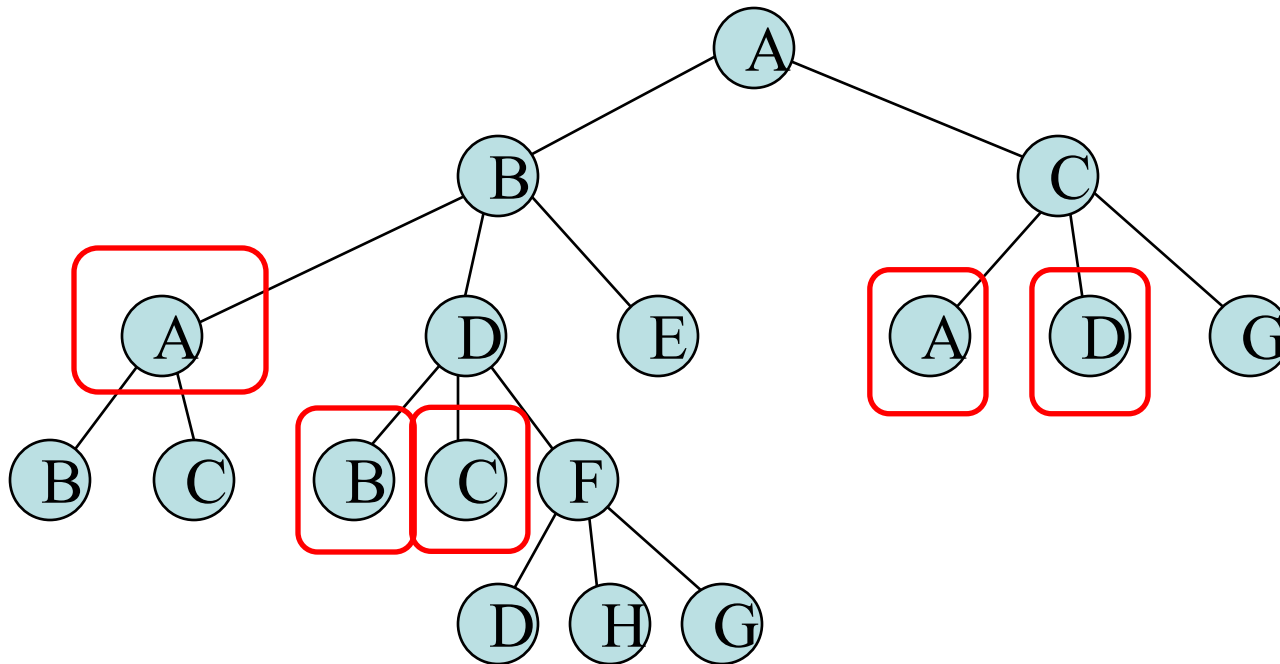
Search Tree => Search Graph

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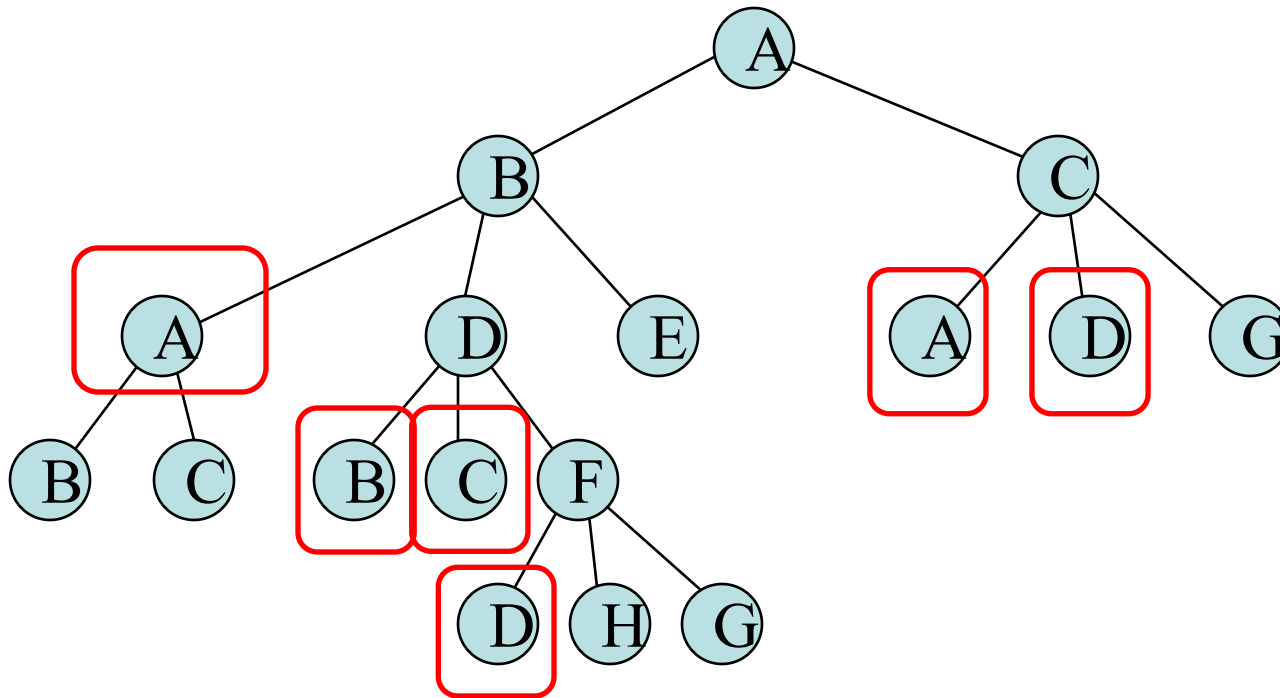
Search Tree => Search Graph

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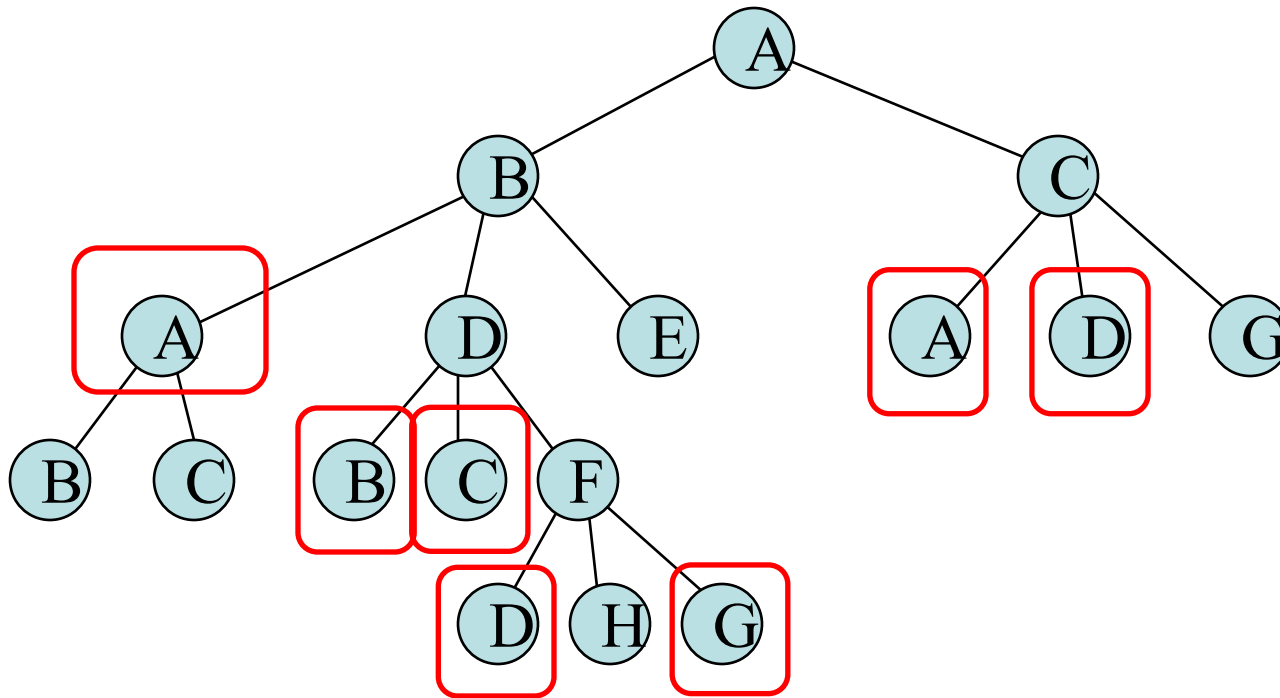
Search Tree => Search Graph

Dynamic programming (with book keeping)



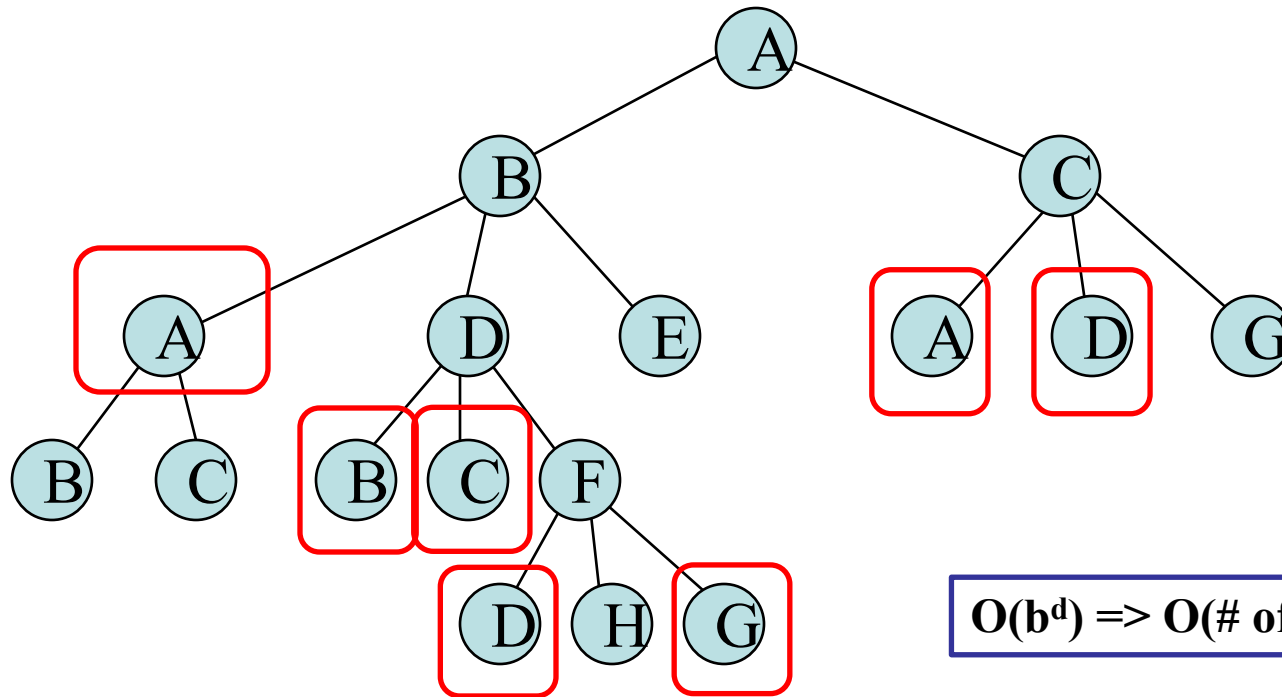
Search Tree => Search Graph

Dynamic programming (with book keeping)



Search Tree => Search Graph

Dynamic programming (with book keeping)



$$O(b^d) \Rightarrow O(\# \text{ of states})$$

Graph Search vs Tree Search

- Tree Search
 - We might repeat some states
 - But we do not need to remember states
- Graph Search
 - We remember all the states that have been explored
 - But we do not repeat some states

Summary table of uninformed search

Criteria	BFS	Uniform-cost	DFS	Depth-limited	IDS	Bidirectional
Complete?	Yes [#]	Yes ^{#&}	No	No	<u>Yes[#]</u>	Yes ^{#+}
Time	$O(b^d)$	$O(b^{1+[C^*/e]})$	$O(b^m)$	$O(b^l)$	$O(b^d)$	$O(b^{d/2})$
Space	$O(b^d)$	$O(b^{1+[C^*/e]})$	$O(bm)$	$O(bl)$	$O(bd)$	$O(b^{d/2})$
Optimal?	Yes ^{\$}	Yes	No	No	<u>Yes^{\$}</u>	Yes ^{\$+}

b : Branching factor

d : Depth of the shallowest goal

l : Depth limit

m : Maximum depth of search tree

e : The lower bound of the step cost

[#]: Complete if b is finite

[&]: Complete if step cost $\geq e$

^{\$}: Optimal if all step costs are identical

⁺: If both direction use BFS

(Section 3.4.7 in the AIMA book.)

Practical note about search algorithms

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- The computer can't "see" the search graph like we can
 - No "bird's eye view" – make relevant information explicit!



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Practical note about search algorithms

- The computer can't "see" the search graph like we can
 - No "bird's eye view" – make relevant information explicit!
- What information should you keep for a node in the search tree?
 - State
 - (1 2 0)
 - Parent node (or perhaps complete ancestry)
 - Node #3 (or, nodes 0, 2, 5, 11, 14)
 - Depth of the node
 - $d = 4$
 - Path cost up to (and including) the node
 - $g(\text{node}) = 12$
 - Operator that produced this node
 - Operator #1

Remainder of the lecture

- Informed search
- Some questions / desiderata
 1. Can we do better with some side information?
 2. We do not wish to make strong assumptions on the side information.
 3. If the side information is good, we hope to do better. 
 4. If the side information is useless, we perform as well as an uninformed search method. 

Best-First Search (with an Eval-Fn)

function **BEST-FIRST-SEARCH**(*problem*, EVAL-FN) **returns** a solution or failure

QUEUING-FN ← a function that orders nodes by EVAL-FN

return **GENERAL-SEARCH**(*problem*, QUEUING-FN)

- Uses a heuristic function, $h(n)$, as the EVAL-FN
- $h(n)$ estimates the cost of the best path from state n to a goal state
 - $h(goal) = 0$

Greedy Best-First Search

- Greedy search – always expand the node that appears to be the closest to the goal (i.e., with the smallest h)
 - Instant gratification, hence “greedy”

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function **GREEDY-SEARCH**(*problem*, h) **returns** a solution or failure
return **BEST-FIRST-SEARCH**(*problem*, h)

Greedy Best-First Search

- Greedy search – always expand the node that appears to be the closest to the goal (i.e., with the smallest h)
 - Instant gratification, hence “greedy”

```
function GREEDY-SEARCH(problem, h) returns a solution or failure  
return BEST-FIRST-SEARCH(problem, h)
```

- Greedy search often performs well, but:
 - It doesn't always find the best solution / or any solution
 - It may get stuck
 - Its performance completely depends on the particular h function

A* Search (Pronounced “A-Star”)

- Uniform-cost search minimizes $g(n)$ (“past” cost)

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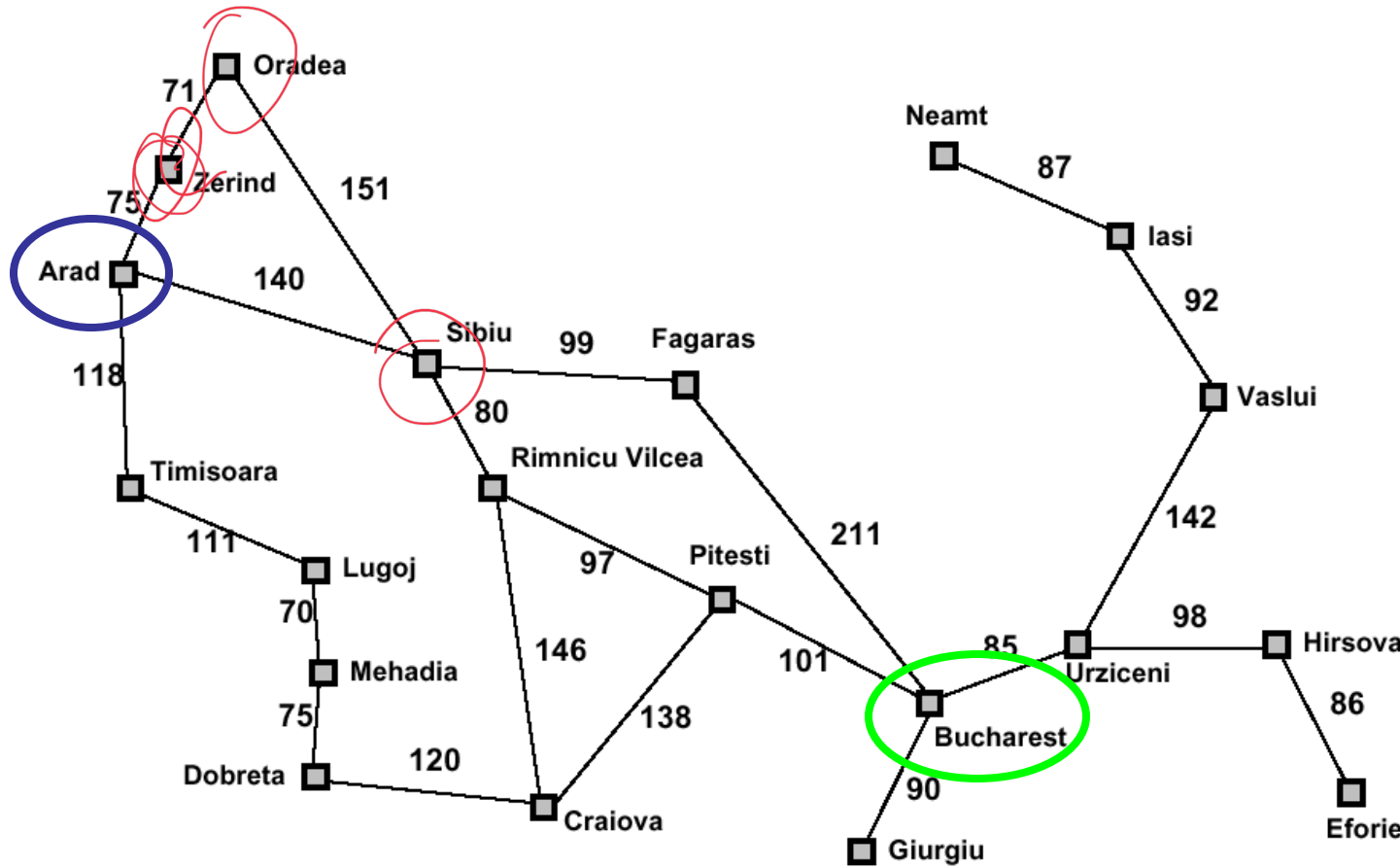
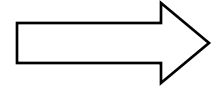
- Uniform-cost search minimizes $g(n)$ (“past” cost)
- Greedy search minimizes $h(n)$ (“expected” or “future” cost)
- “A* Search” combines the two:
 - Minimize $f(n) = g(n) + h(n)$
 - Accounts for the “past” and the “future”
 - Estimates the cheapest solution (complete path) through node n

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```
function A*-SEARCH(problem, h) returns a solution or failure  
return BEST-FIRST-SEARCH(problem, f)
```

A* Example

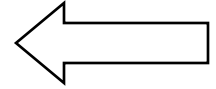


Straight-line distance to Bucharest

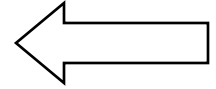
Arad	366
Bucharest	0
Craiova	160
Dobreta	242
Eforie	161
Fagaras	178
Giurgiu	77
Hirsova	151
Iasi	226
Lugoj	244
Mehadia	241
Neamt	234
Oradea	380
Pitesti	98
Rimnicu Vilcea	193
Sibiu	253
Timisoara	329
Urziceni	80
Vaslui	199
Zerind	374

$$f(n) = g(n) + h(n)$$

A* Example

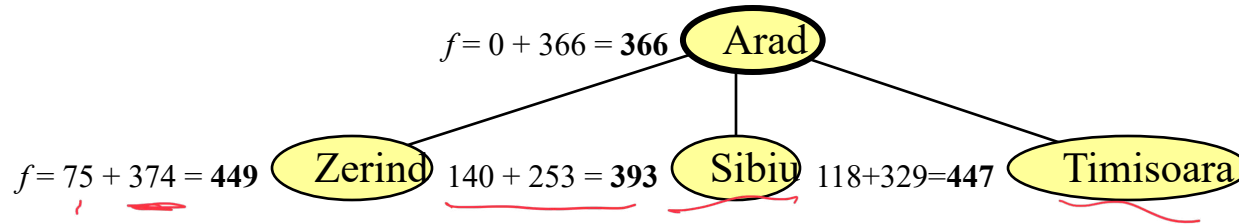
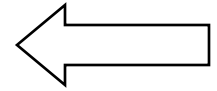


A* Example

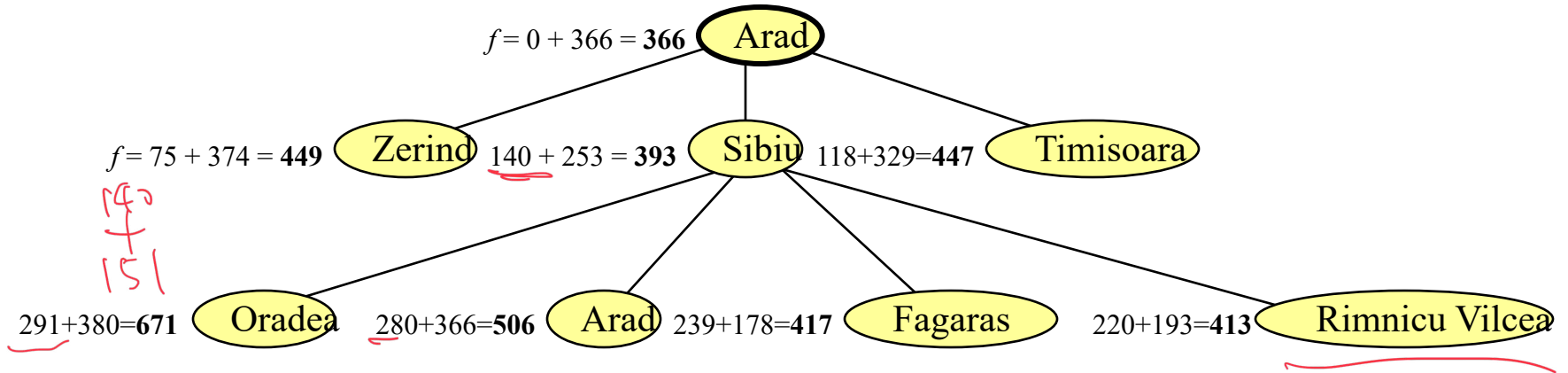
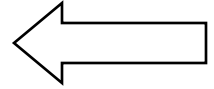


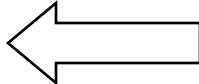
$$f = 0 + 366 = 366 \text{ Arad}$$

A* Example

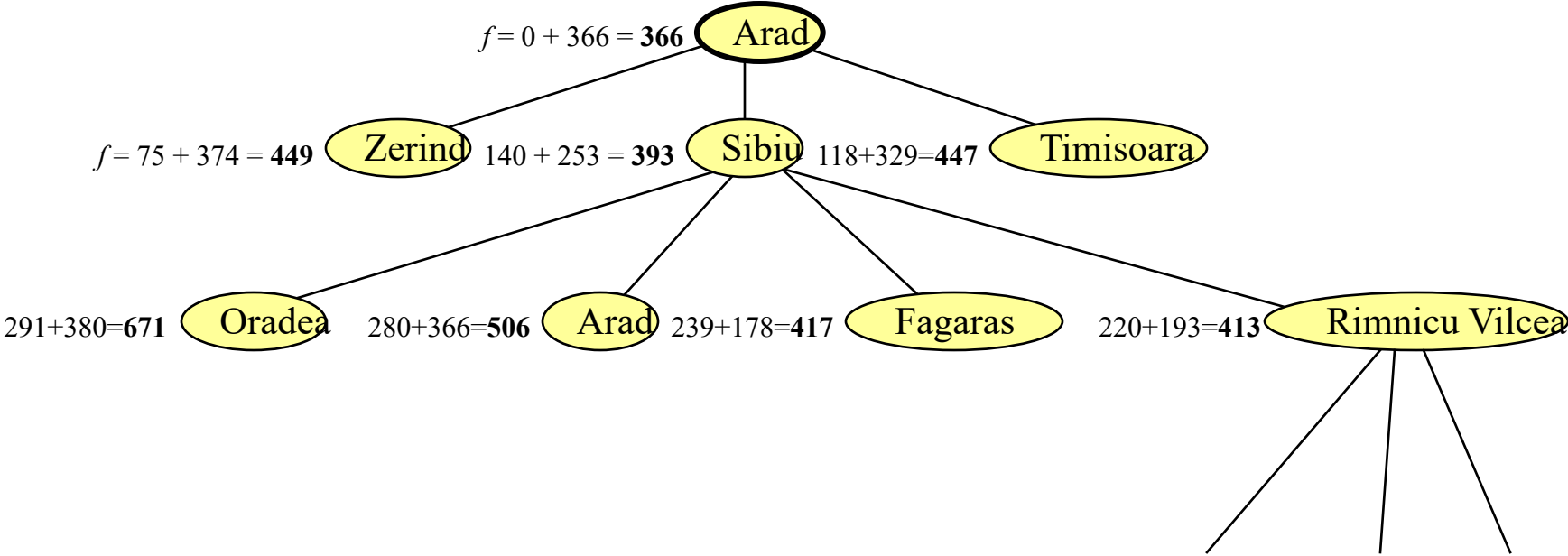


A* Example





A* Example



When does A* search “work”?

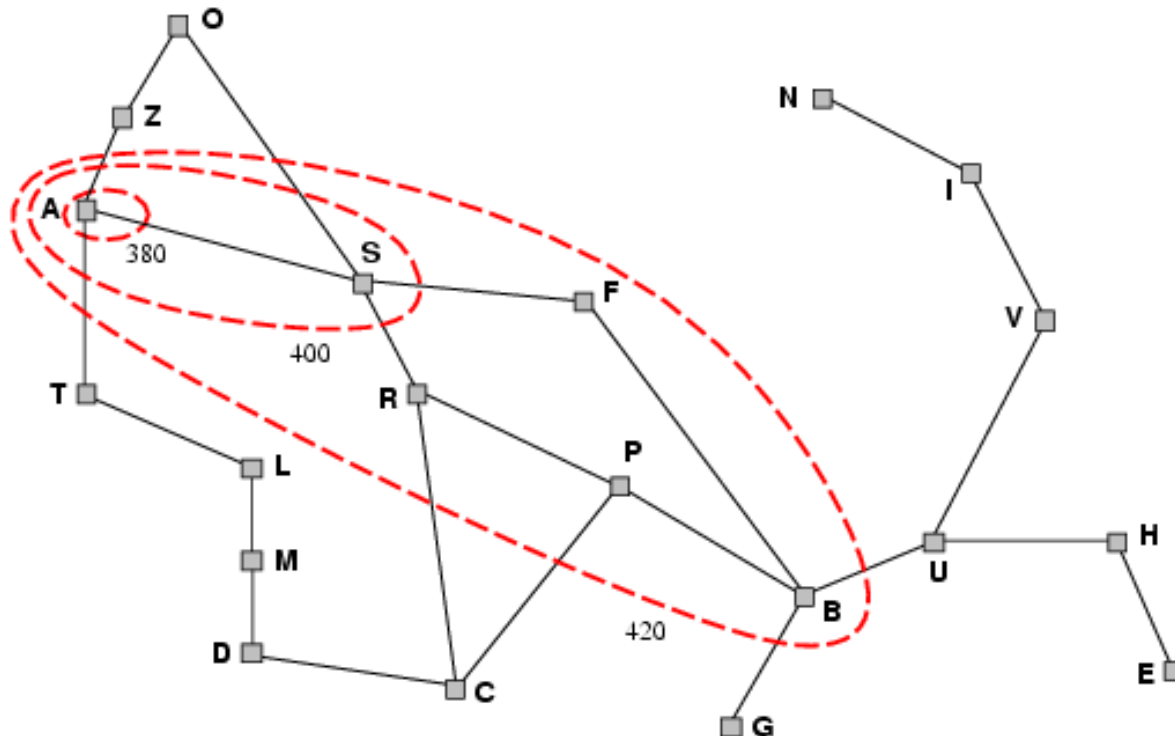
- Focus on optimality (finding the optimal solution)
- “A* Search” is optimal if h is **admissible**

When does A* search “work”?

- Focus on optimality (finding the optimal solution)
- “A* Search” is optimal if h is **admissible**
 - h is optimistic – it never overestimates the cost to the goal
 - $h(n) \leq$ true cost to reach the goal
 - So $f(n)$ never overestimates the actual cost of the best solution passing through node n

Visualizing A* search

- A* expands nodes in order of increasing f value
- Gradually adds " f -contours" of nodes
- Contour i has all nodes with $f=f_i$, where $f_i < f_{i+1}$
-



Optimality of A^* with an Admissible h

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- Let OPT be the optimal path cost.
 - All non-goal nodes on this path have $f \leq \text{OPT}$.
 - Positive costs on edges
 - The goal node on this path has $f = \text{OPT}$.

Optimality of A^* with an Admissible h

- Let OPT be the optimal path cost.
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Optimality of A^* with an Admissible h

- Let OPT be the optimal path cost.
 - All non-goal nodes on this path have $f \leq \text{OPT}$.
 - Positive costs on edges
 - The goal node on this path has $f = \text{OPT}$.
- A^* search does not stop until an f -value of OPT is reached.
 - All other goal nodes have an f cost higher than OPT.
- All non-goal nodes on the optimal path are eventually expanded.
 - The optimal goal node is eventually placed on the priority queue, and reaches the front of the queue.

Optimal Efficiency of A*

A* is optimally efficient for any particular $h(n)$

That is, no other optimal algorithm is guaranteed to expand fewer nodes with the same $h(n)$.

Optimal Efficiency of A*

A* is **optimally efficient** for any particular $h(n)$

That is, no other optimal algorithm is guaranteed to expand fewer nodes with the same $h(n)$.

- Need to find a good and efficiently evaluable $h(n)$.

A* Search with an Admissible h

- Optimal?
- Complete?
- Time complexity?
- Space complexity?

A* Search with an Admissible h

- Optimal? **Yes**
- Complete?
- Time complexity?
- Space complexity?

A* Search with an Admissible h

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A* Search with an Admissible h

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- Complete? Yes
- Time complexity? Exponential; better under some conditions
- Space complexity?

A* Search with an Admissible h

- Optimal? Yes
- Complete? Yes
- Time complexity? Exponential; better under some conditions
- Space complexity? Exponential; keeps all nodes in memory

b^d

b^d

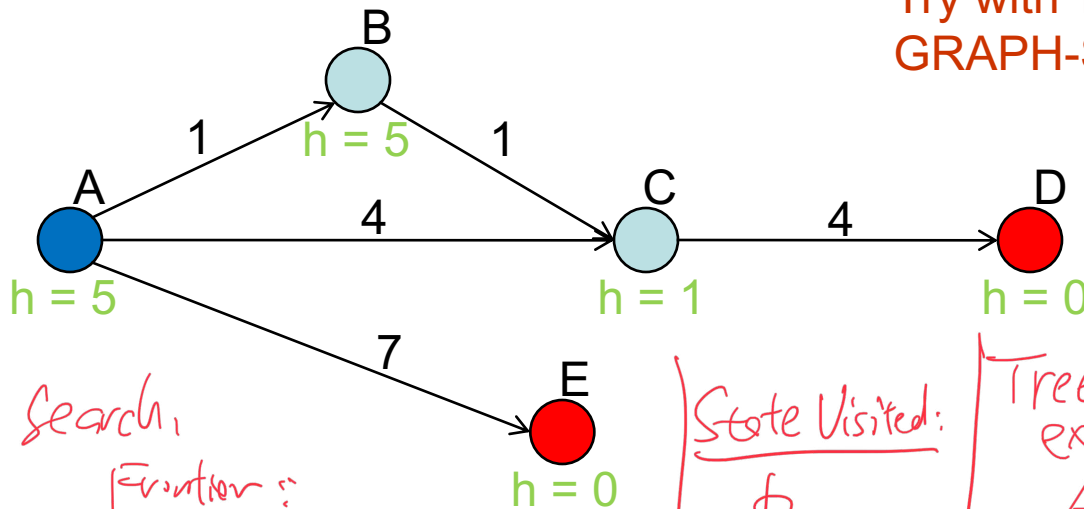
Recall: Graph Search vs Tree Search

- Tree Search
 - We might repeat some states
 - But we do not need to remember states
- Graph Search
 - We remember all the states that have been explored
 - But we do not repeat some states

Avoiding Repeated States using A* Search

- Is GRAPH-SEARCH optimal with A*?

Try with TREE-SEARCH and GRAPH-SEARCH



Graph Search:

Expand:

- A
- C
- B
- (E)**

Frontier:

- A: 0+5
- B: 1+5, C: 4+1, E: 7+0
- B: 1+5, E: 7+0, D: 8+0
- E: 7+0, D: 8+0

*: C cannot be added again because expanded before

E is suboptimal!

State Visited:

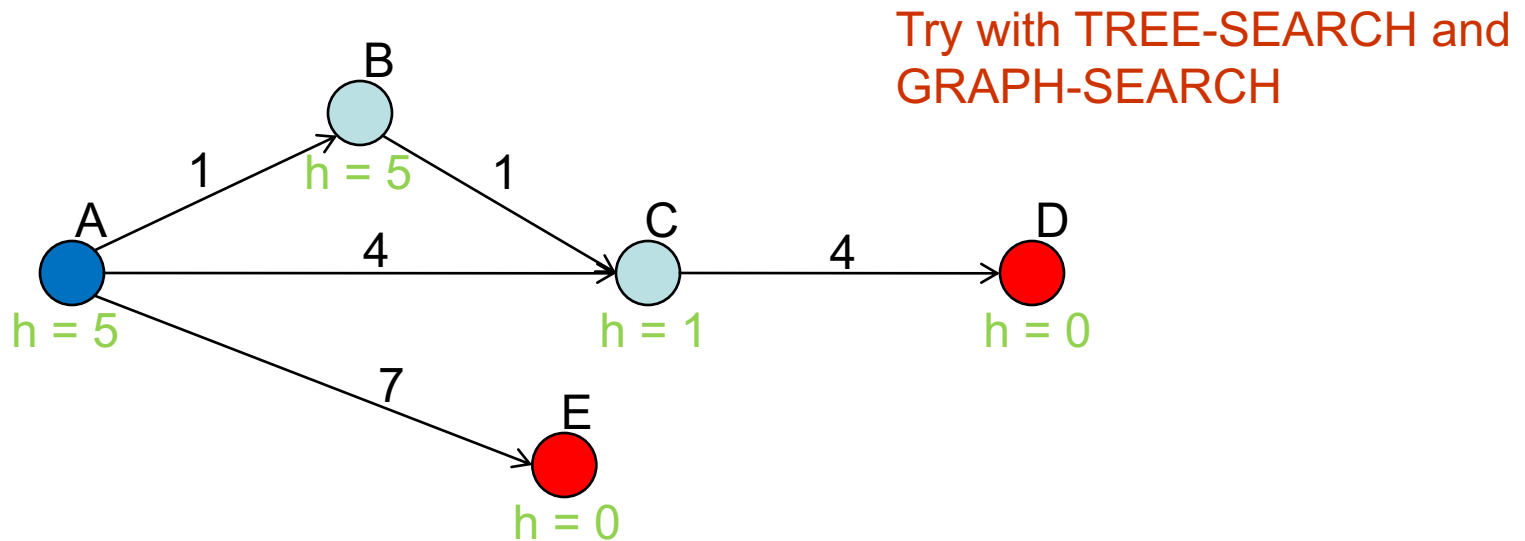
- ϕ
- A
- A, C
- A, C, B

Tree Search:

expand	Frontier
A:	A: 0+5
C:	B: 1+5, C: 4+1 E: 7+0
B:	B: 1+5, E: 7+0, D: 8+0
C:	C: 2+1, E: 7+0, D: 8+0
(D)	D: 6+0, ⁴⁸ E: 7+0, D: 8+0

Avoiding Repeated States using A* Search

- Is GRAPH-SEARCH optimal with A*?



Graph Search

Step 1: Among B, C, E, Choose C

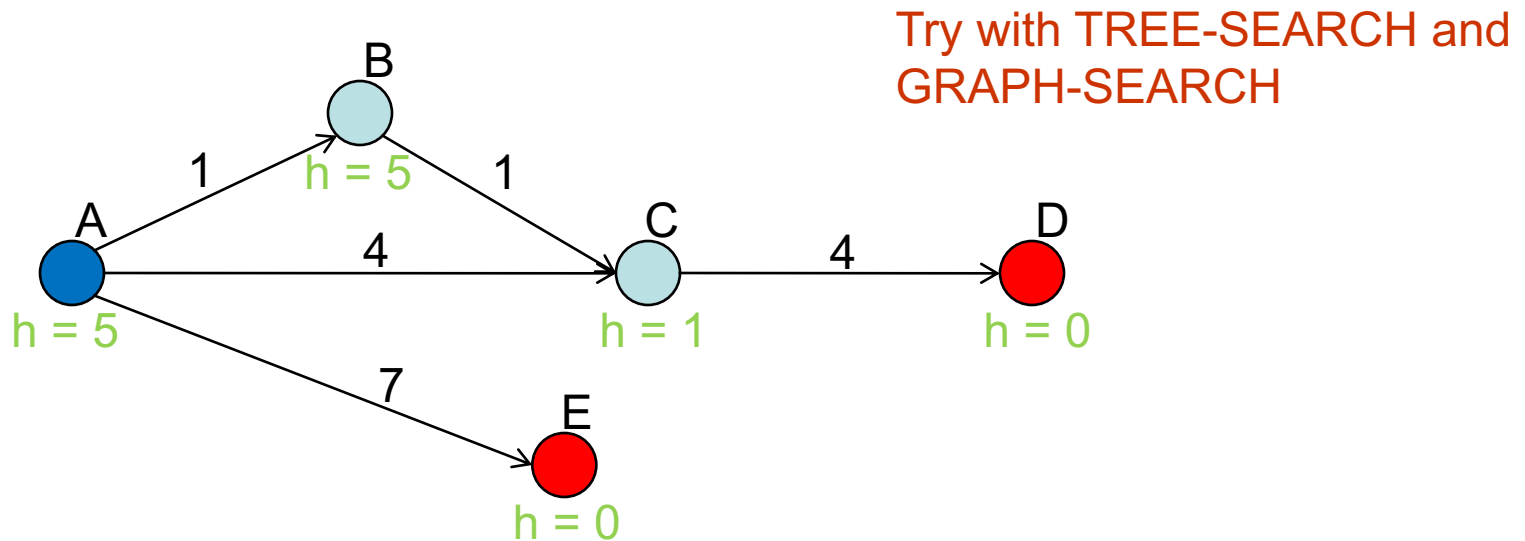
Step 2: Among B, E, D, Choose B

Step 3: Among D, E, Choose E. (you are not going to select C again)



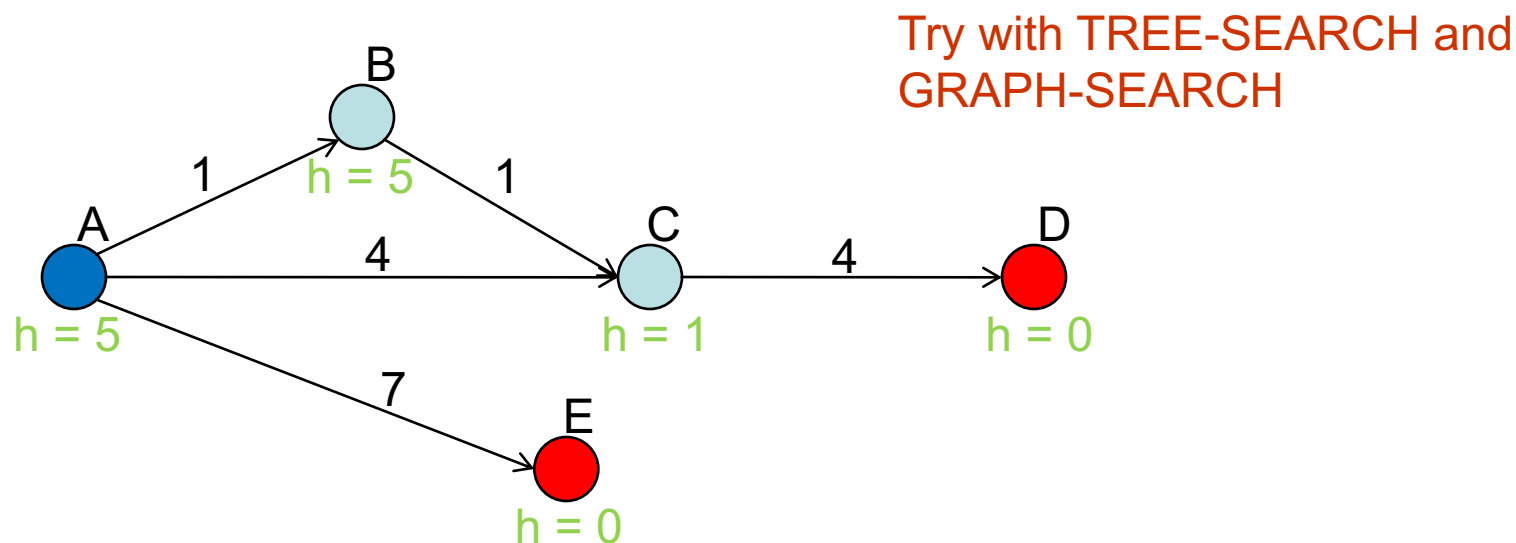
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Avoiding Repeated States using A* Search

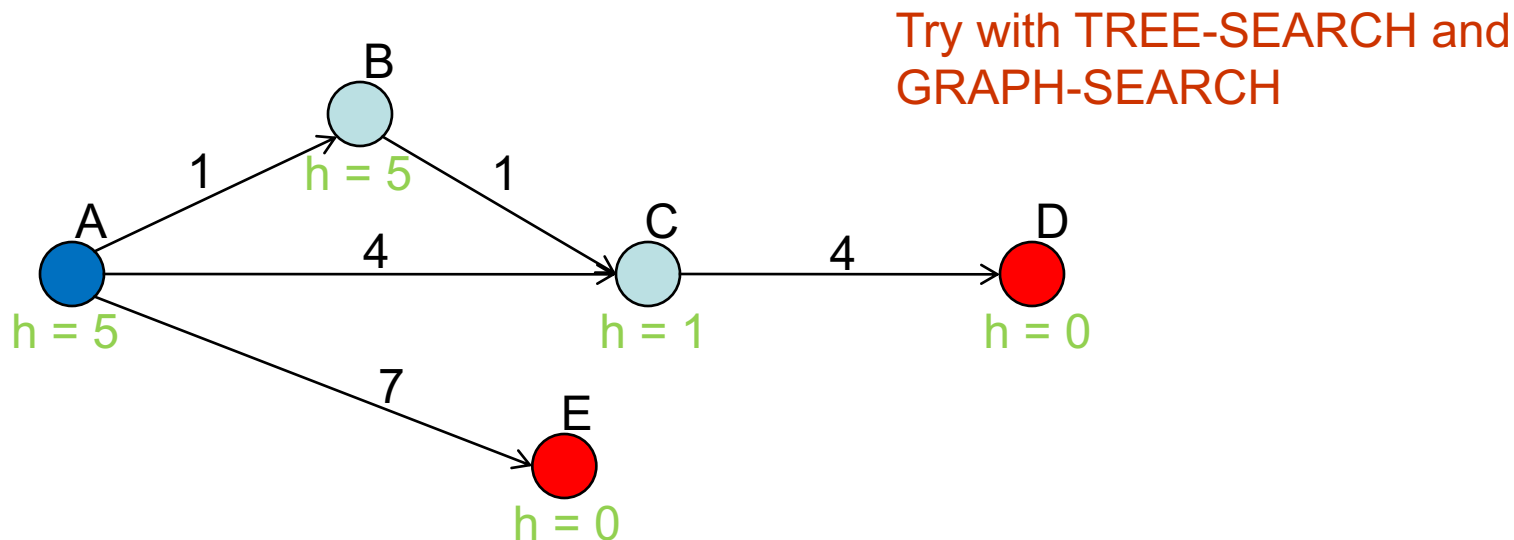
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Solution 1: Remember all paths: Need extra bookkeeping

Avoiding Repeated States using A* Search

- Is GRAPH-SEARCH optimal with A*?

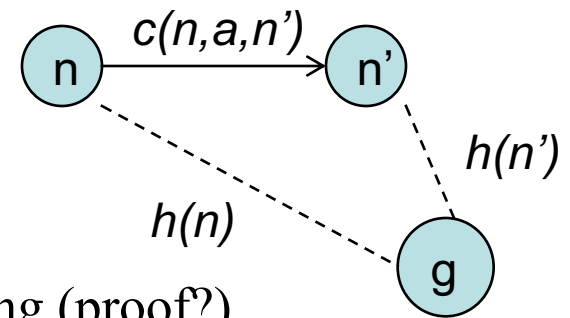


Solution 1: Remember all paths: Need extra bookkeeping

Solution 2: Ensure that the first path to a node is the best!

Consistency (Monotonicity) of heuristic h

- A heuristic is consistent (or monotonic) provided
 - for any node n , for any successor n' generated by action a with cost $c(n,a,n')$
 - $h(n) \leq c(n,a,n') + h(n')$
 - akin to triangle inequality.
 - guarantees admissibility (proof?).
 - values of $f(n)$ along any path are non-decreasing (proof?).
 - Contours of constant f in the state space
- GRAPH-SEARCH using consistent $f(n)$ is optimal.
- Note that $h(n) = 0$ is consistent and admissible.



Next lecture

- Examples
- Choosing heuristics
- Games and Minimax Search