Artificial Intelligence CS 165A Oct 22, 2020

Instructor: Prof. Yu-Xiang Wang

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- $\square \rightarrow \text{Problem Solving by Search}$
 - \rightarrow Search algorithms



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Student Feedback (from past two weeks)

- "Your handwriting is sometimes not legible."
 - Will do.
- "Sharing annotated lecture slides"
 - Will do.
- "computer engineering peers and I are struggling a lot with the gradient/multivariable concepts"
 - Don't be scared. The concept of gradient is natural. Try visualize in 2D, 3D and work with examples, such as $f(x,y) = x^2 + xy$ to build intuition.
- "I feel that I am not doing well in HW1. Am I gonna fail?"
 - Probably no. Evaluation is quite lenient this quarter (late days, partial credits). Everyone can keep up.

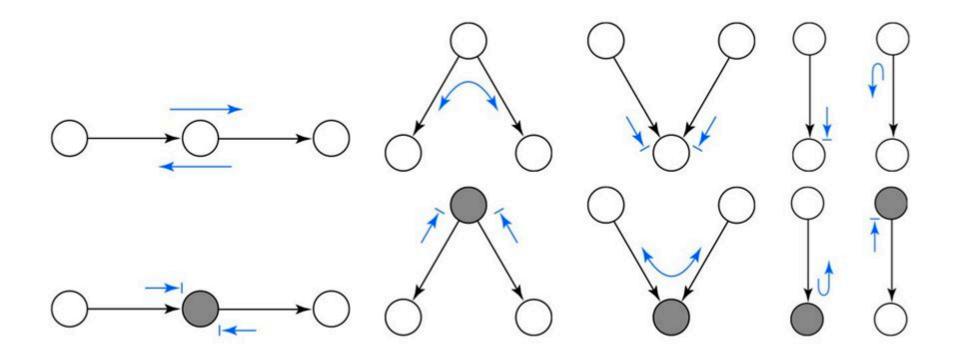
Recap of the last lecture

- Three steps in modelling with Bayesian networks
- Inference with Bayesian networks using only CPTs
- Three equivalent ways of describing structures of a joint distribution
 - Factorization \Leftrightarrow DAG \Leftrightarrow the set of conditional independences
- Prove conditional independence by definition.

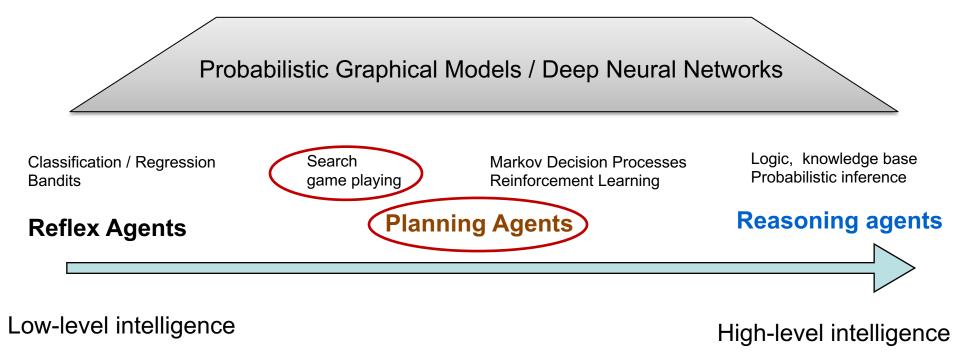
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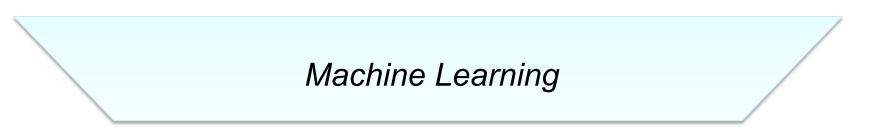
- Reading conditional independences from the DAG itself.
- d-separation
 - Three canonical graphs
- Bayes ball algorithm for determining whether $X \perp Z \mid Y$
 - Bounce the ball from any node in X by following the ten rules
 - If any ball reaches any node in Z, then return "False"
 - Otherwise, return "True"

The Ten Rules of Bayes Ball Algorithm



Structure of the course





(Again this idea is adapted from Percy Liang's teachings)

Reflex Agents vs. Planning agent

(illustration credit: Dan Klein)

- Reflex agents act based on immediate observation / memory; often optimizes immediate reward.
- Planning agent looks further into the future and "try out" different sequences of actions --- <u>in its mind</u> --- before taking an action; optimizes long-term reward.

Modeling-Learning-Inference Paradigm

	Modeling	Learning	Inference
Classifier agent (Spam filter)	Feature engineering Hypothesis class	Minimize Error rate	trivial
Probabilistic Inference agent (Sherlock)	Joint distribution Draw edges in BN Conditional independences	Fitting the CPTs with MLE	Marginalization (conceptually easy)
Search agents	State-Space- diagram	Environment given (learn edge weights)	Nontrivial search algorithms

Search sequence of lectures

- Today: Finish Graphical models. Start "Search"
- Oct 27: Search algorithms
- Oct 29: Minimax search and game playing
- Nov 3: Finish "search" + Midterm review. HW2 Due.
- Recommended readings on search:
 - AIMA Ch 3, Ch 5.1-5.3.

Remaining time today

• Formulating problems as search problems

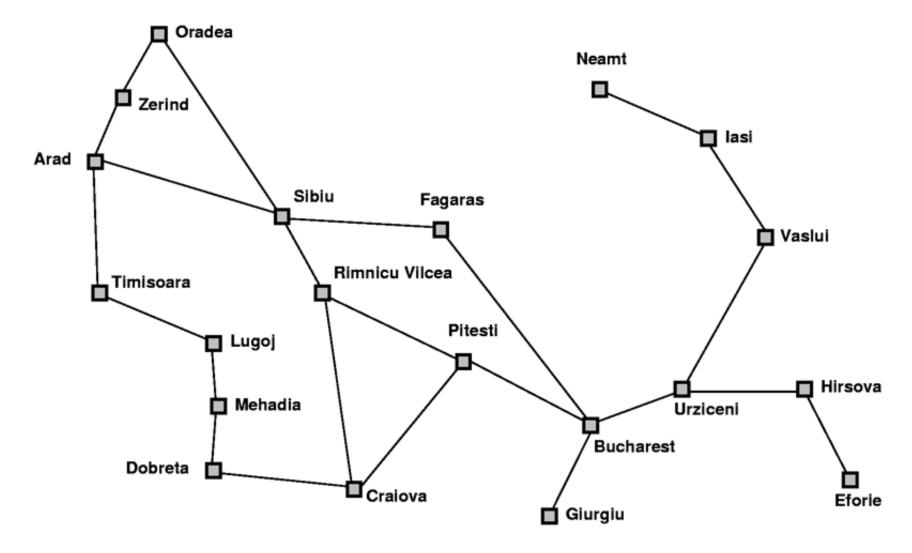
• Basic algorithms for search

Example: Romania

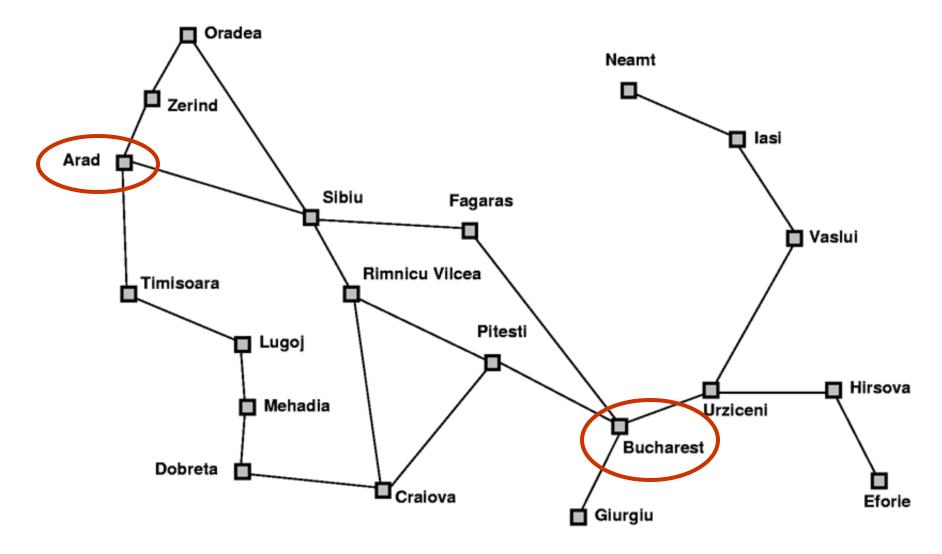
You're in Arad, Romania, and you need to get to Bucharest as quickly as possible to catch your flight.

- Formulate problem
 - States: Various cities
 - Operators: Drive between cities
- Formulate goal
 - Be in Bucharest before flight leaves
- Find solution
 - Actual sequence of cities from Arad to Bucharest
 - Minimize driving distance/time

Romania (cont.)



Romania (cont.)



Romania (cont.)

Problem description <{S}, S₀, {S_G}, {O}, {g}>

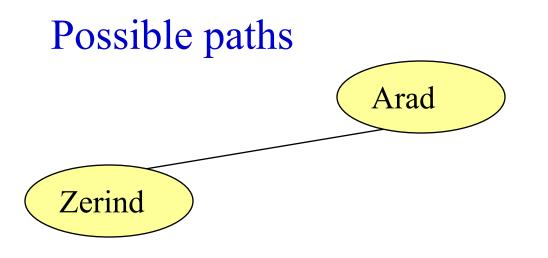
- $\{\mathbf{S}\}$ cities (\mathbf{c}_i)
- $S_0 Arad$ •
- S_G Bucharest 、

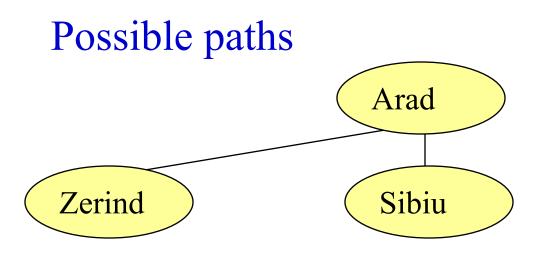
- G(S) – Is the current state (S) Bucharest?

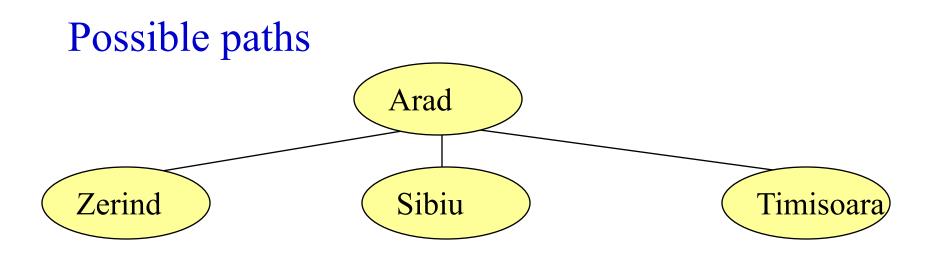
- $\{O\}$: $\{c_i \rightarrow c_j, \text{ for some } i \text{ and } j\}$
- g_{ij}
 - Driving distance between c_i and c_j ?
 - Time to drive from c_i to c_j ?
 - 1?

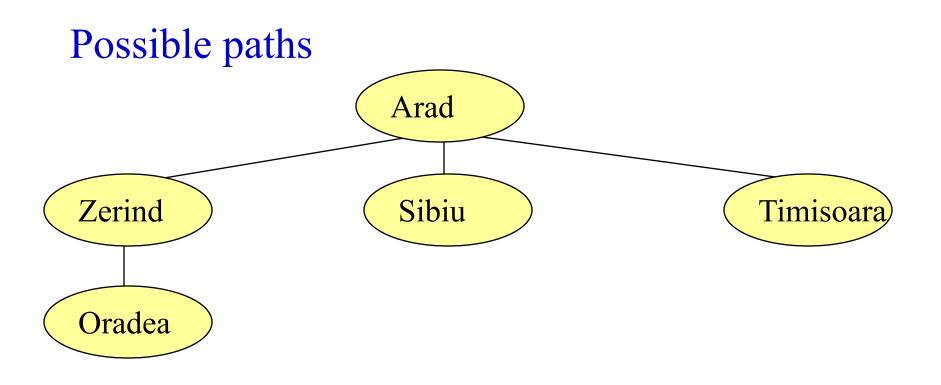
Possible paths

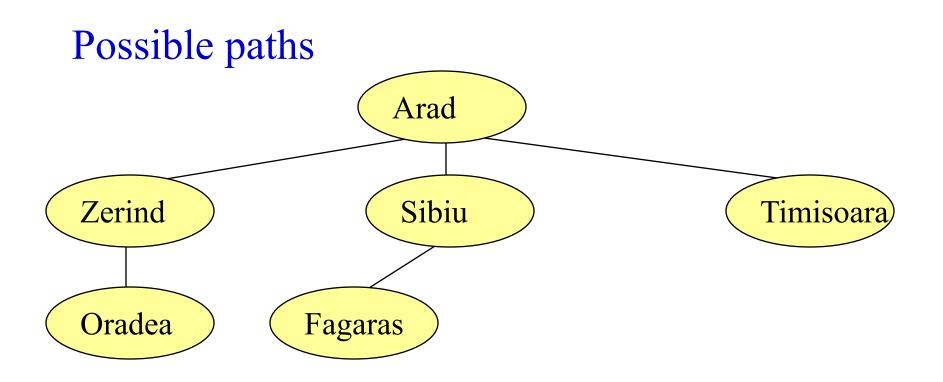


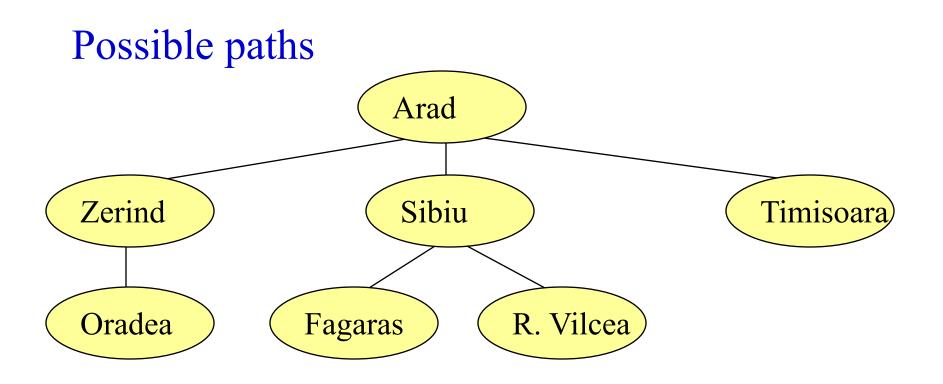


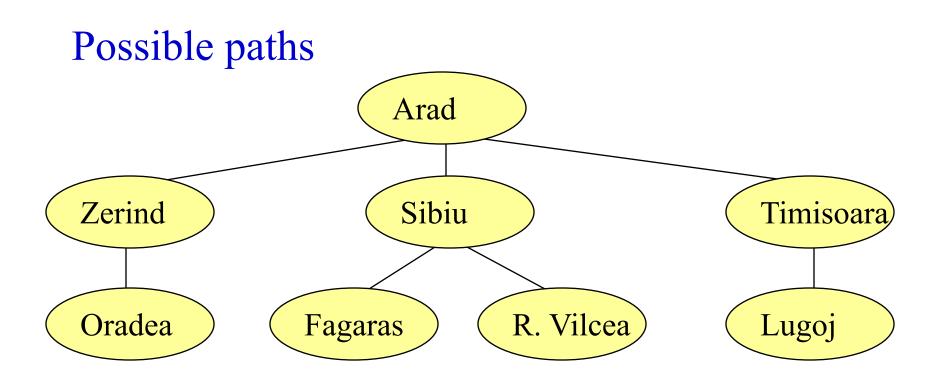


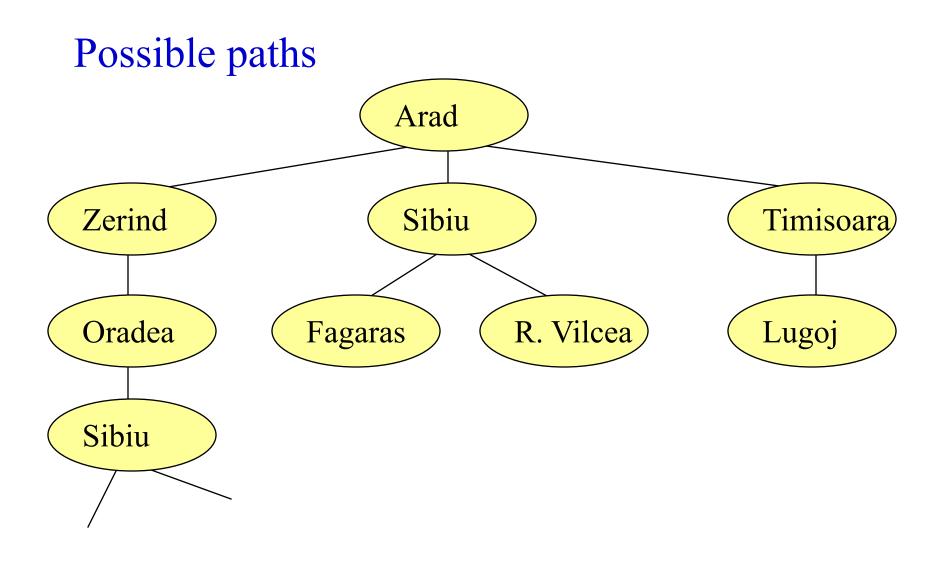


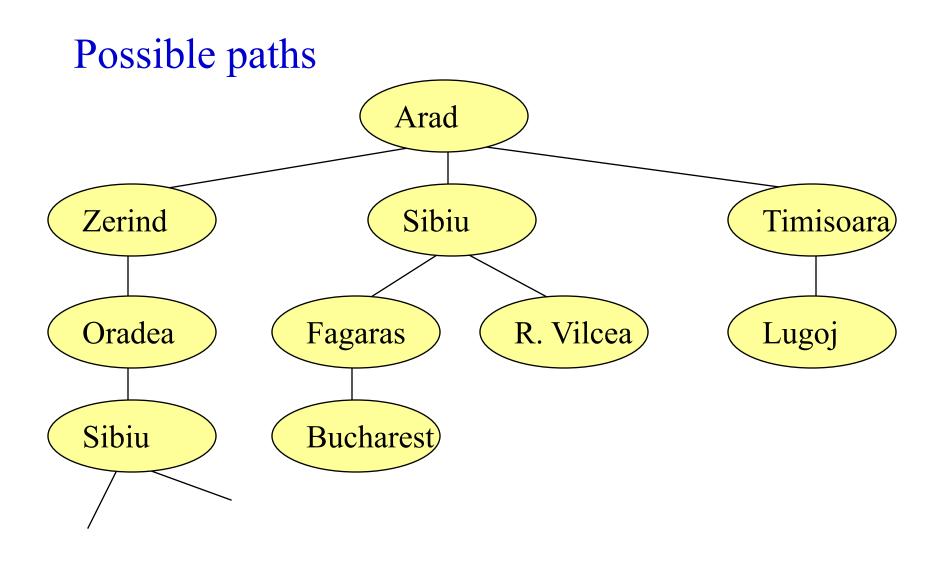


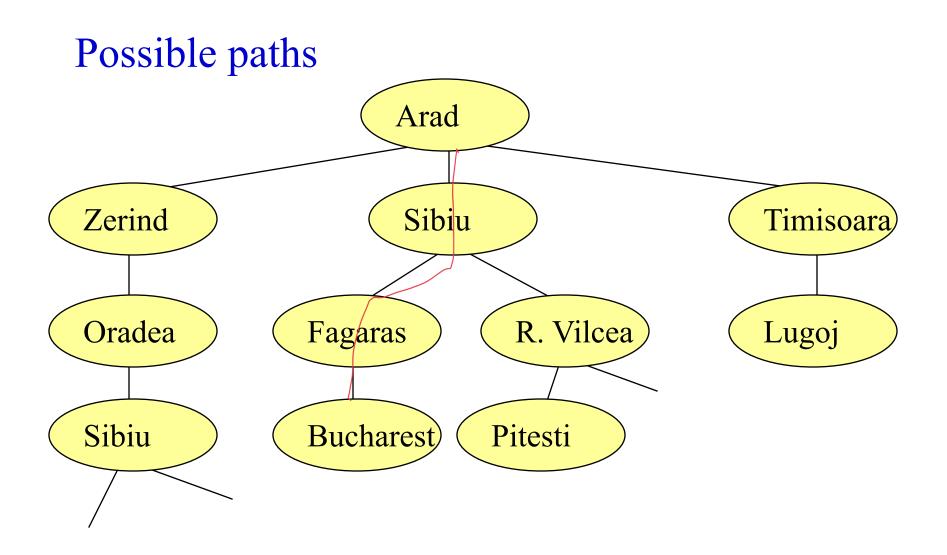


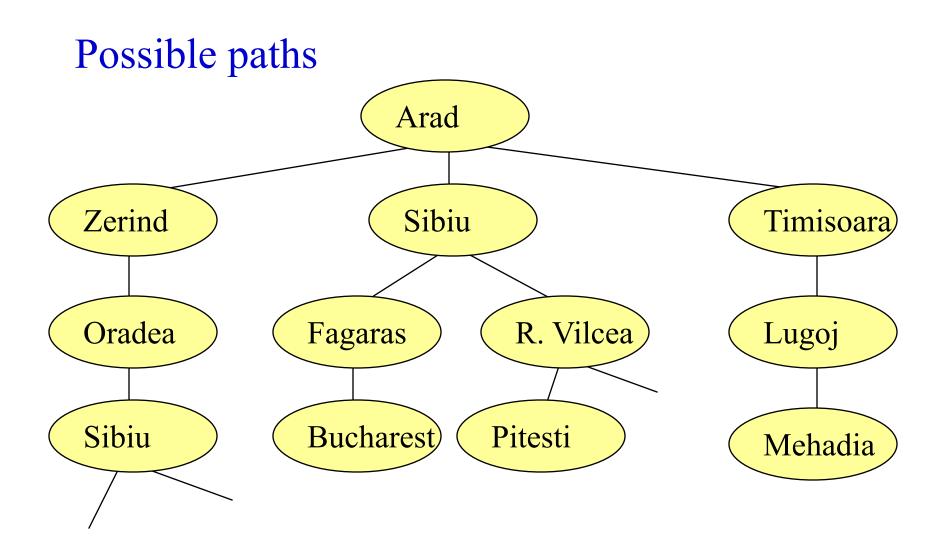


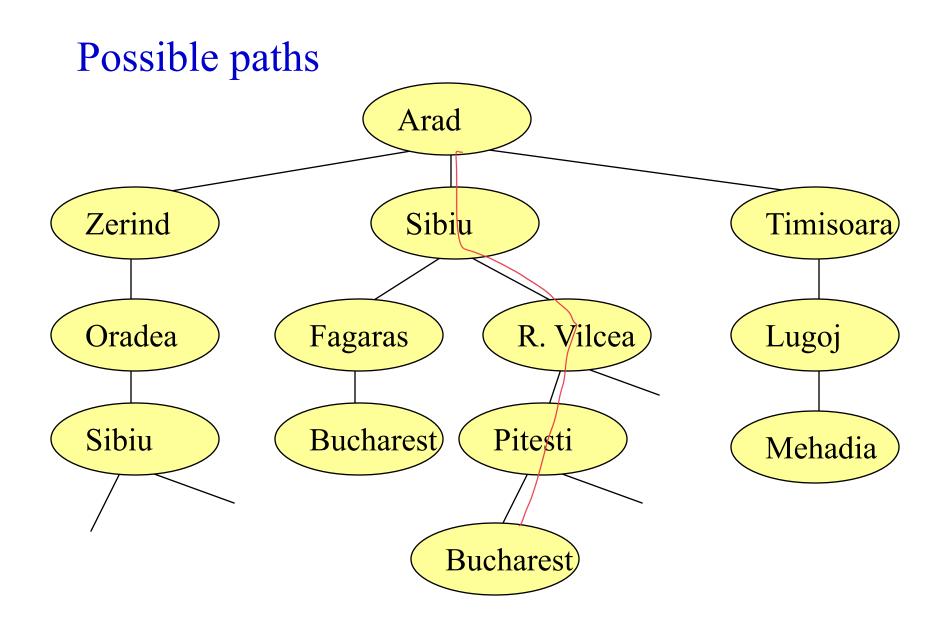


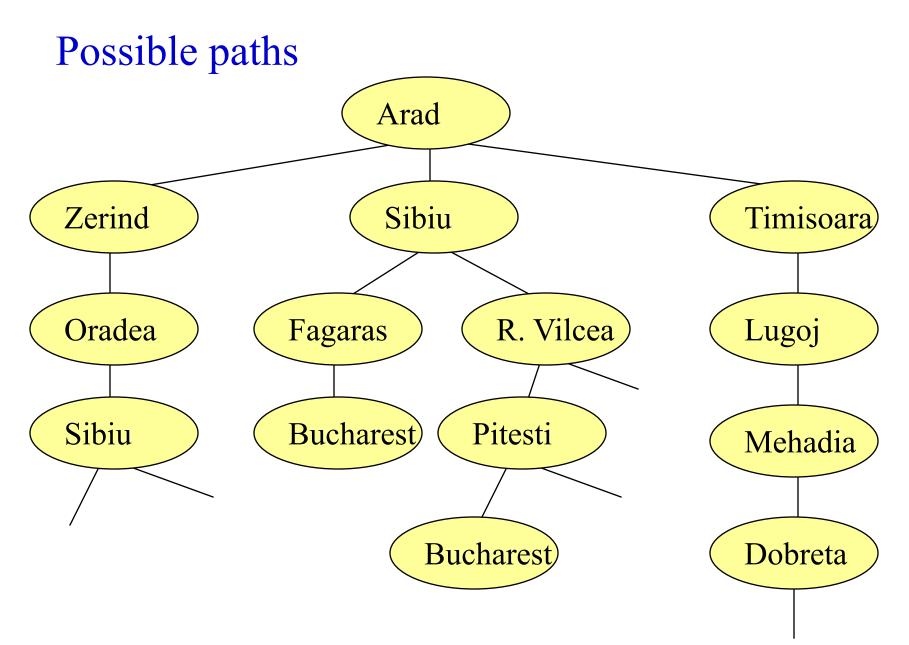


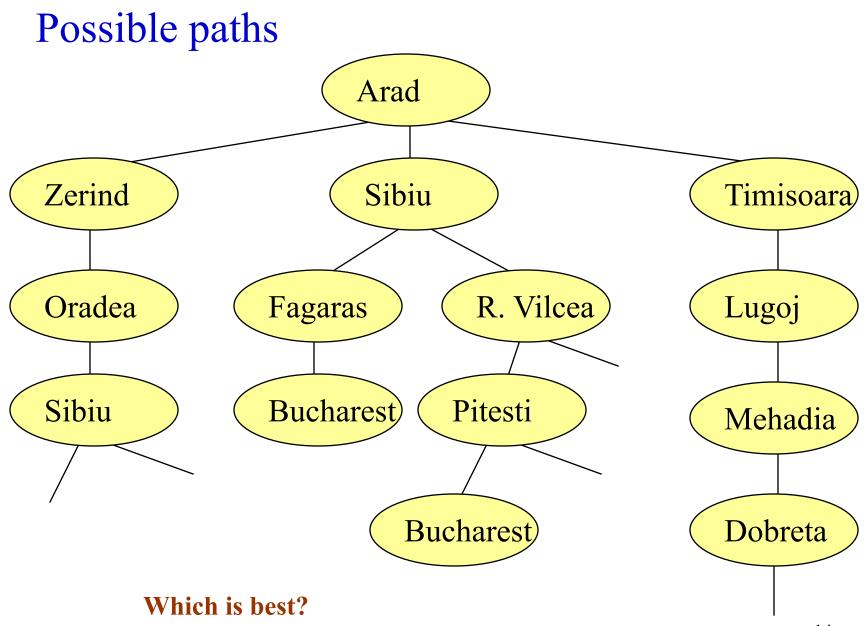


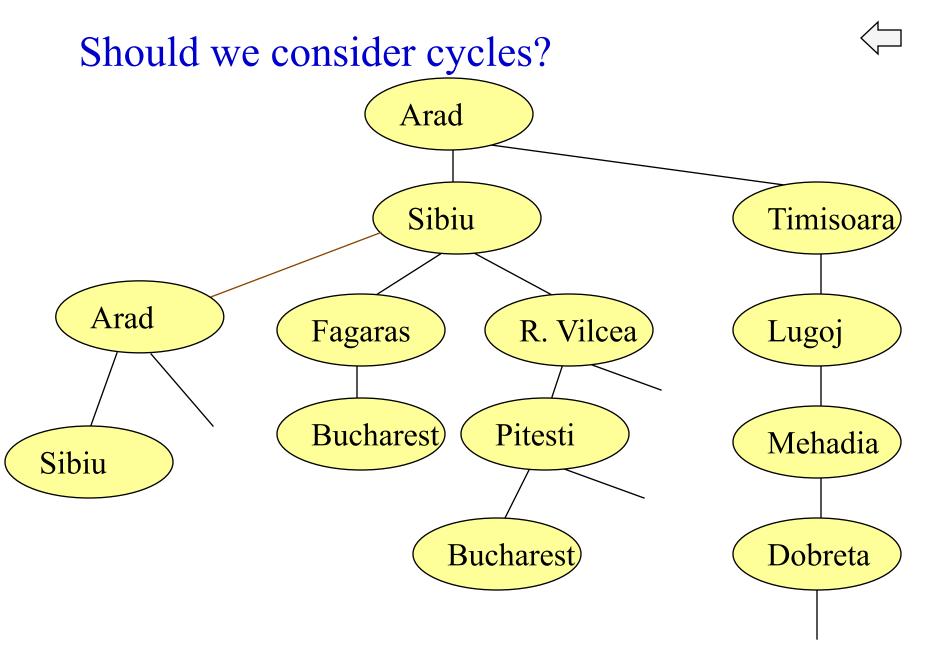


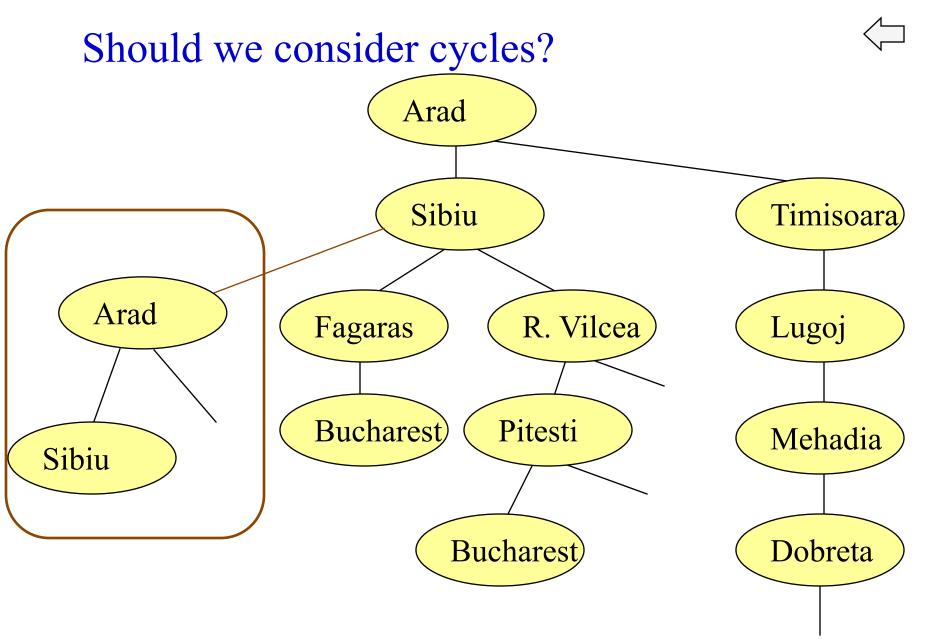


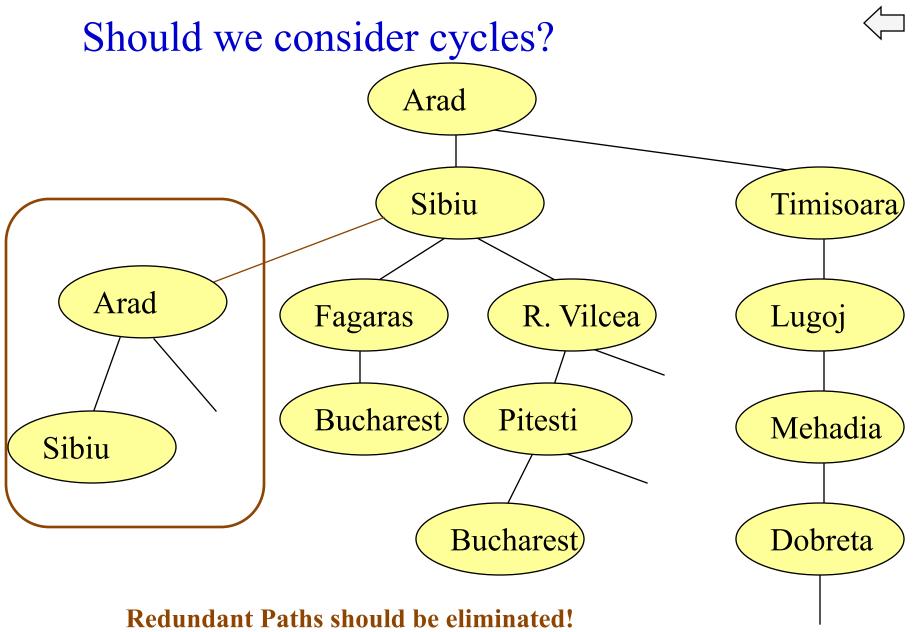












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- $b = 8, d = 15 → b^d = 35,184,372,088,832$
- Ouch.... Combinatorial explosion!

Abstraction

- The real world is highly complex!
 - The state space must be *abstracted* for problem-solving
 - Simplify and aggregate
 - Can't represent all the details
- Choosing a good abstraction
 - Keep only those relevant for the problem
 - Remove as much detail as possible *while retaining validity*

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- Formulate, search, execute (action)

• Problem formulation

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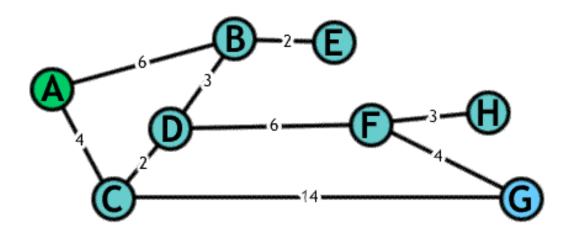
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 - This is *offline* problem solving

State-Space Diagrams

- State-space description can be represented by a statespace diagram, which shows
 - States (incl. initial and goal)
 - Operators/actions (state transitions)
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State-Space Diagrams

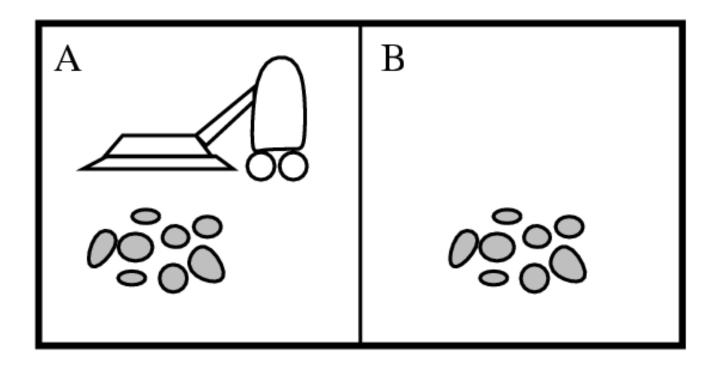
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Typical assumptions

- Environment is observable
- Environment is static
- Environment is discrete
- Environment is deterministic

Example: The Vacuum World



The Vacuum World

• Simplified world: 2 grids

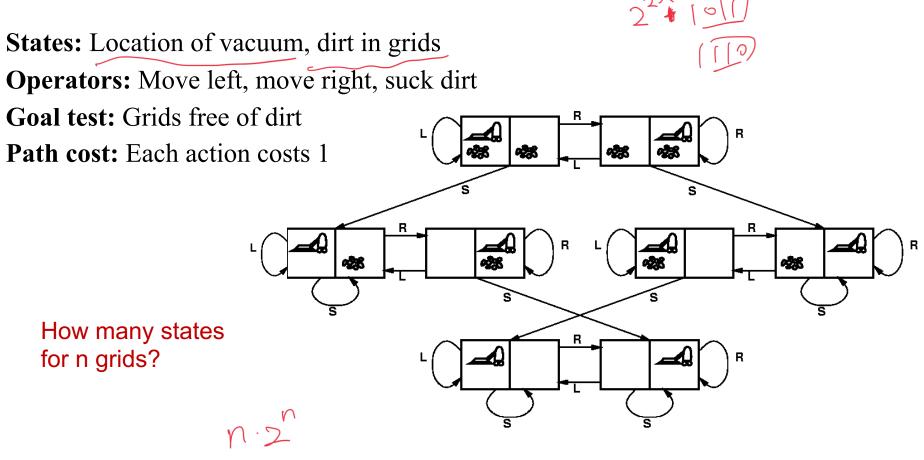
The Vacuum World

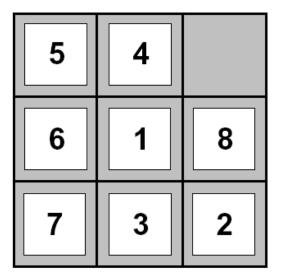
• Simplified world: 2 grids

States: Location of vacuum, dirt in grids **Operators:** Move left, move right, suck dirt, Goal test: Grids free of dirt R R Path cost: Each action costs 1 R R R R 028 28 必求 感觉 R R NON

The Vacuum World

• Simplified world: 2 grids

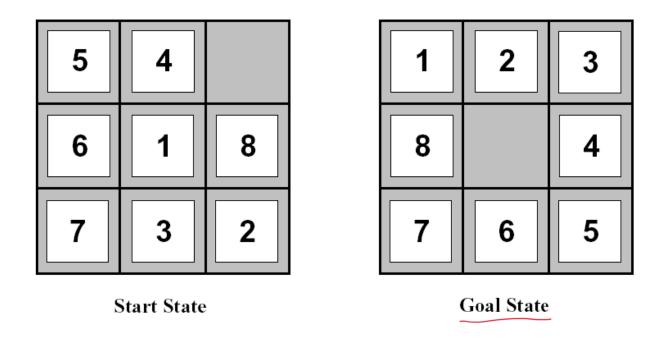




1	2	3
8	-	4
7	6	5

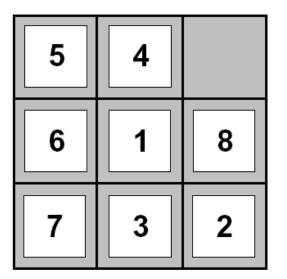


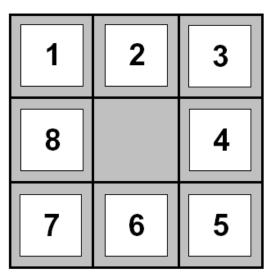
Goal State



States: Various configurations of the puzzle
Operators: Movements of the blank
Goal test: Goal configuration
Path cost: Each move costs 1

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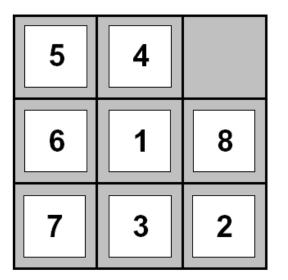


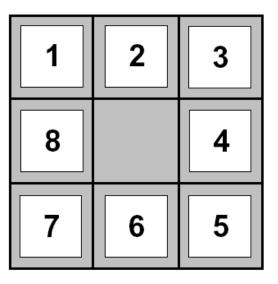
Start State

Goal State

States: Various configurations of the puzzleOperators: Movements of the blankGoal test: Goal configurationPath cost: Each move costs 1

How many states are there?





Start State

Goal State

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How many states are there?

9! = 362,880

8-Puzzle is hard (by definition)!

- Optimal solution of the N-puzzle family of problems is NP-complete
 - Likely exponential increase in computation with N
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 - Start and end in Bucharest, visit every city at least once
 - Find the shortest tour

8-Puzzle is hard (by definition)!

- Optimal solution of the N-puzzle family of problems is NP-complete
 - Likely exponential increase in computation with N
 - Uninformed search will do very poorly
- Ditto for the Traveling Salesman Problem (TSP)
 - Start and end in Bucharest, visit every city at least once
 - Find the shortest tour
- Ditto for lots of interesting problems!

Example: Missionaries and Cannibals (3 min discussion)

Problem: Three missionaries and three cannibals are on one side of a river, along with a boat that can hold one or two people. Find a way to get everyone to the other side, without ever leaving a group of missionaries in one place outnumbered by the cannibals in that place 4x4

• States, operators, goal test, path cost?

G, 0

MMM

CCC

Or

CIG



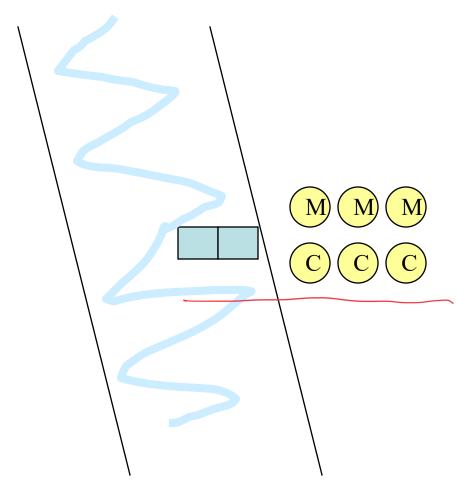
• Initial state

• Goal state

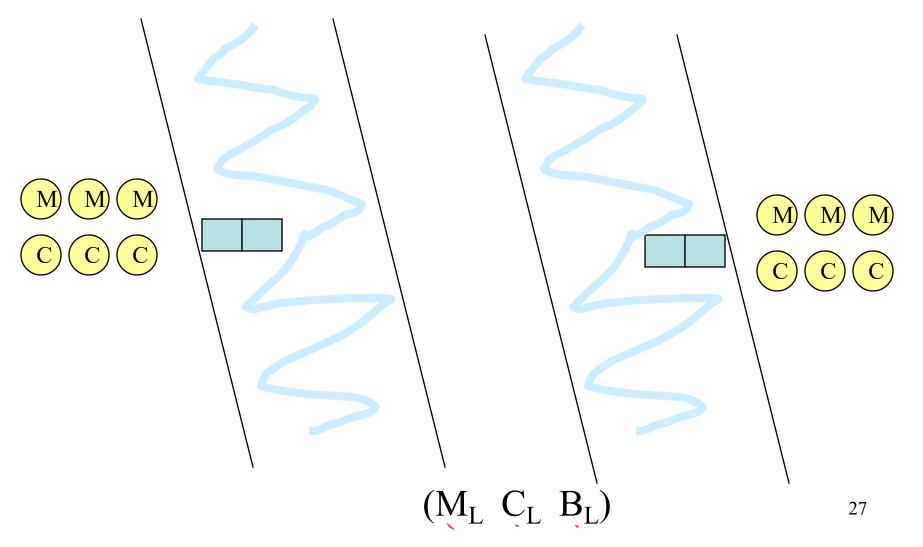
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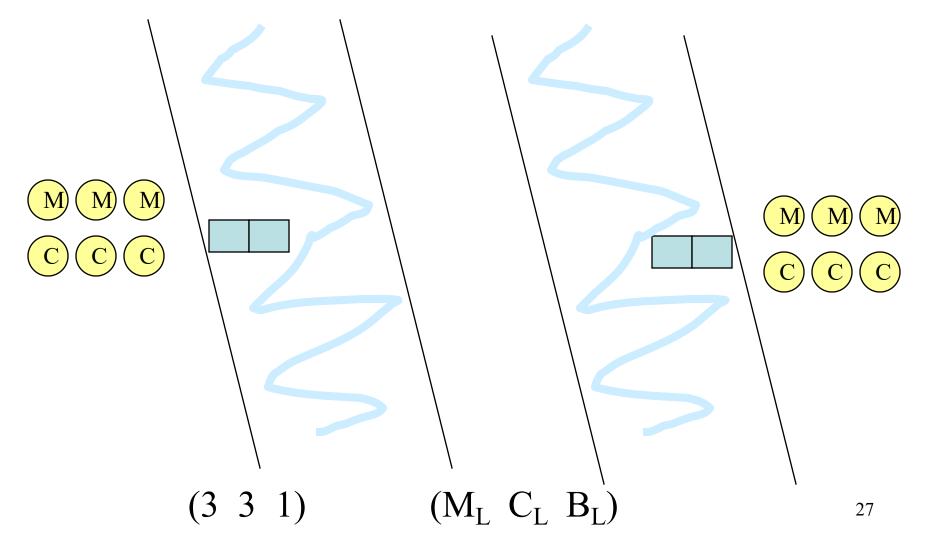
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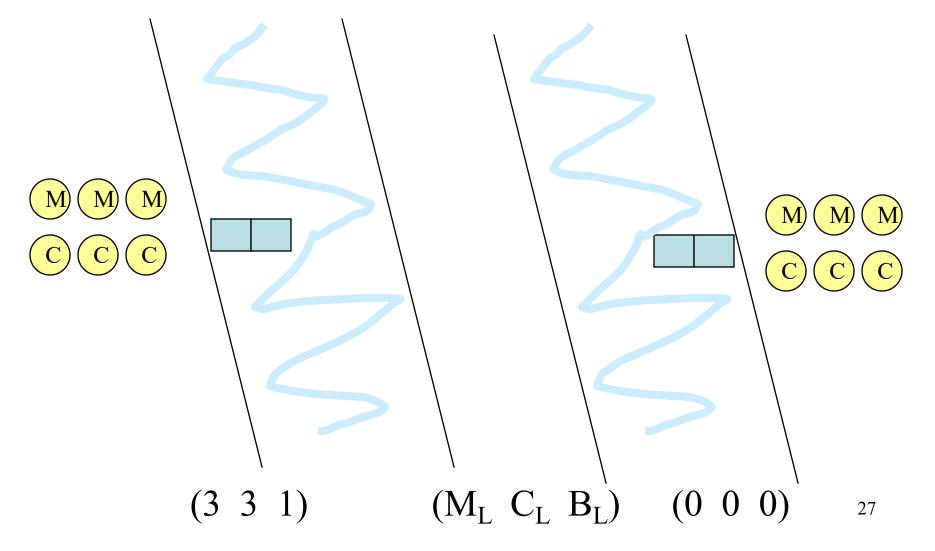
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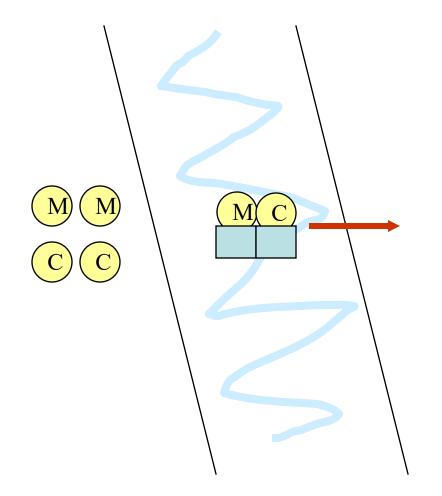
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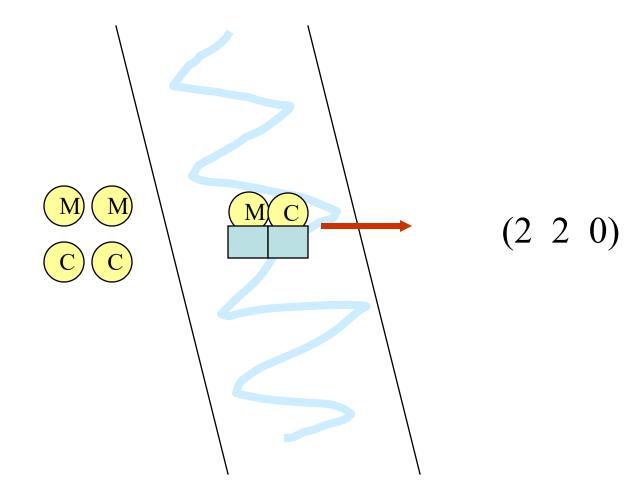
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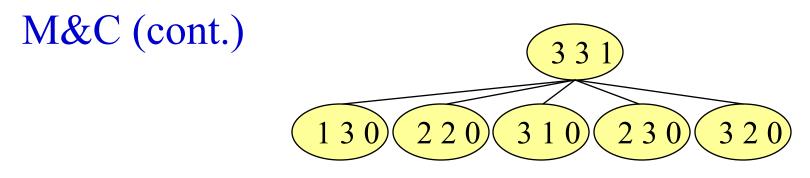


- Problem description <{S}, S₀, {S_{Gi}}, {O_i}, {g_i}>
- {**S**} : { ({0,1,2,3} {0,1,2,3} {0,1}) }
- $S_0: (3 \ 3 \ 1)$
- $S_G : (0 \ 0 \ 0)$
- **g** = 1
- $\{\mathbf{O}\}$: $\{(x \ y \ b) \rightarrow (x' \ y' \ b')\}$
- Safe state: $(x \ y \ b)$ is safe iff -x > 0 implies $x \ge y$ and x < 3 implies $y \ge x$
 - Can be restated as

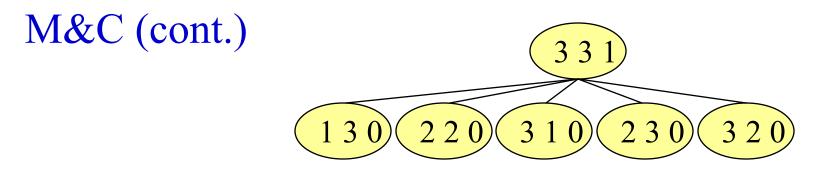
$$(x = 1 \text{ or } x = 2) \text{ implies } (x = y)$$

Operators:

 $(x y 1) \rightarrow (x-2 y 0)$ $(x y 1) \rightarrow (x-1 y-1 0)$ $(x y 1) \rightarrow (x y-2 0)$ $(x y 1) \rightarrow (x y-1 y 0)$ $(x y 1) \rightarrow (x y-1 0)$ $(x y 0) \rightarrow (x+2 y 1)$ $(x y 0) \rightarrow (x+1 y+1 1)$ $(x y 0) \rightarrow (x y+2 1)$ $(x y 0) \rightarrow (x +1 y 1)$ $(x y 0) \rightarrow (x y+1 1)$



- 11 steps
- $5^{11} = 48$ million states to explore



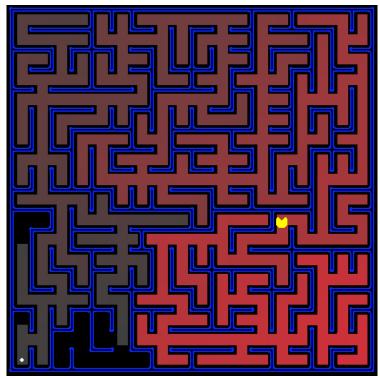
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One solution path:

- (3 3 1)
- (2 2 0)
- (3 2 1)
- (3 0 0)
- (3 1 1)
- $(1\ 1\ 0)$
- (2 2 1)
- (0 2 0)
- (0 3 1)
- (0 1 0)
- (0 2 1)
- $(0\ 0\ 0)$

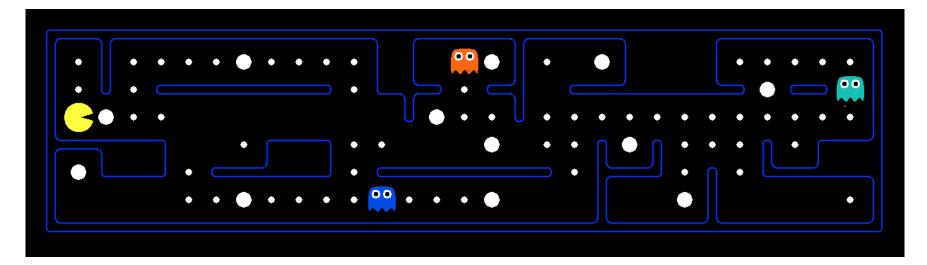
More quizzes: PACMAN

- 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?



More quizzes: 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.



• Think about how to formulate this problem. We will revisit it in the next lecture.

Quick summary on problem formulation

- Formulate problems as a search problem
 - Decide your level of abstraction. State, Action, Goal, Cost.
 - Represented by a state-diagram
 - Required solution: A sequence of actions
 - Optimal solution: A sequence of actions with minimum cost.
- Caveats:
 - Might not be a finite graph
 - Might not have a solution
 - Often takes exponential time to find the optimal solution

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Let's try solving it anyways!

- Do we need an exact optimal solution?
- Are problems in practice worst case?

Searching for Solutions

- Finding a solution is done by searching through the state space
 - While maintaining a set of partial solution sequences
- The *search strategy* determines which states should be expanded first

Searching for Solutions

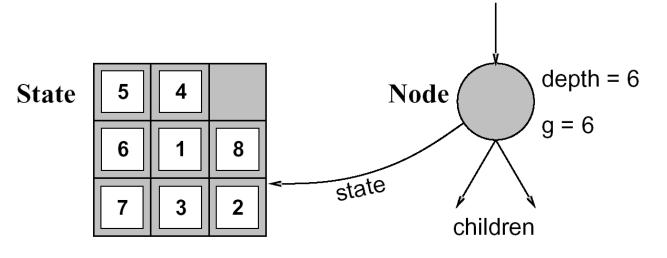
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 - Expand a state = Applying the operators to the current state and thereby generating a new set of successor states
- Conceptually, the search process builds up a *search tree* that is superimposed over the state space
 - Root node of the tree \leftrightarrow Initial state
 - Leaves of the tree \leftrightarrow States to be expanded (or expanded to null)
 - At each step, the search algorithm chooses a leaf to expand

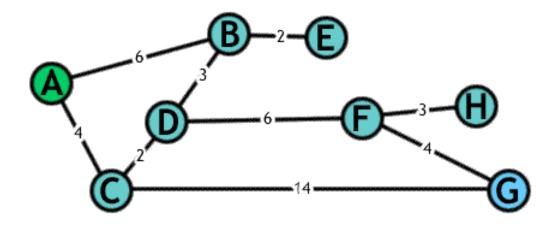
State Space vs. Search Tree

- The state space and the search tree are not the same thing!
 - A *state* represents a (possibly physical) configuration
 - A *search tree node* is a <u>data structure</u> which includes:
 - { parent, children, depth, path cost }
 - States do not have parents, children, depths, path costs
 - Number of states ≠ number of nodes in the search tree parent



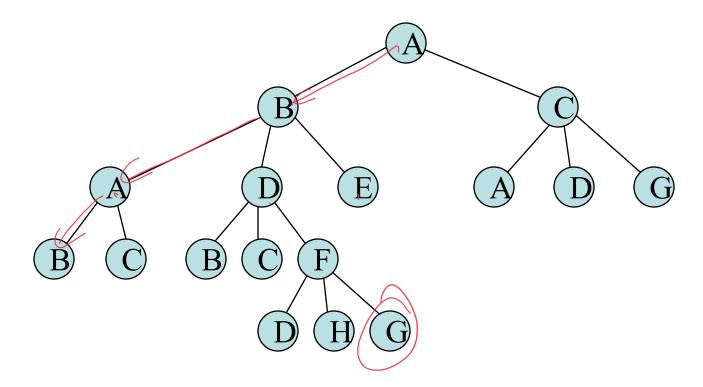
State Space vs. Search Tree (cont.)

State space: 8 states



State Space vs. Search Tree (cont.)

Search tree (partially expanded)



Search Strategies

- Uninformed (blind) search
 - Can only distinguish goal state from non-goal state
- Informed (heuristic) search
 - Can evaluate states

Uninformed ("Blind") Search Strategies

- No information is available other than
 - The current state
 - Its parent (perhaps complete path from initial state)
 - Its operators (to produce successors)
 - The goal test
 - The current path cost (cost from start state to current state)

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- Blind search strategies
 - Breadth-first search
 - Uniform cost search
 - Depth-first search
 - Depth-limited search
 - Iterative deepening search
 - Bidirectional search

General Search Algorithm (Version 1)

• Various strategies are merely variations of the following function:

General Search Algorithm (Version 1)

• Various strategies are merely variations of the following function:

function GENERAL-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

(Called "Tree-Search" in the textbook)

General Search Algorithm (Version 2)

- 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

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```
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
```

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```

"Nodes" is also known as a "frontier" --- the set of states we haven't yet explored/expanded. "EXPAND" is known as the "successor function" --- the set of all states that you could expand on.

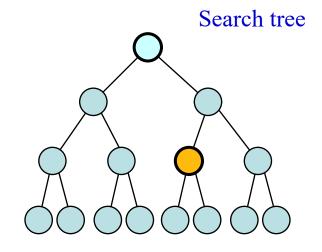
- Primary criteria to evaluate search strategies
 - Completeness
 - Is it guaranteed to find a solution (if one exists)?
 - Optimality
 - Does it find the "best" solution (if there are more than one)?
 - Time complexity
 - Number of nodes generated/expanded
 - (How long does it take to find a solution?)
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- Some performance measures
 - Best case
 - Worst case
 - Average case
 - Real-world case

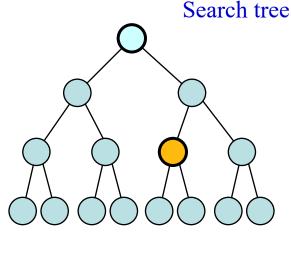
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- Complexity analysis and O() notation (see Appendix A)
 - -b = Maximum branching factor of the search tree
 - d = Depth of an optimal solution (may be more than one)
 - -m = maximum depth of the search tree (may be infinite)
- Examples
 - $O(b^3 d^2) polynomial time$
 - $O(b^d) exponential time$

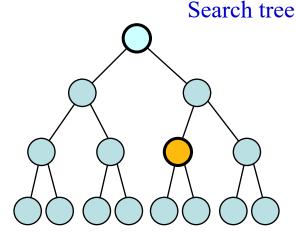


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For chess, $b_{ave} = 35$

b = 2, d = 2, m = 3

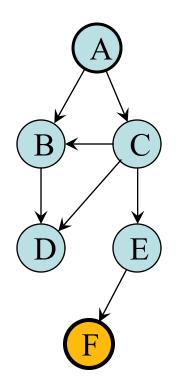
- All nodes at depth d in the search tree are expanded before any nodes at depth d+1
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- Doesn't consider path cost finds the solution with the shortest path
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function BREADTH-FIRST-SEARCH(*problem*) **returns** a solution or failure **return GENERAL-SEARCH**(*problem*, ENQUEUE-AT-END)



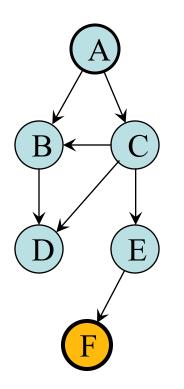


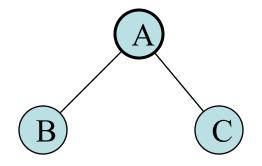




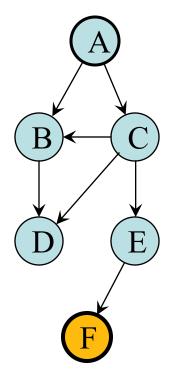


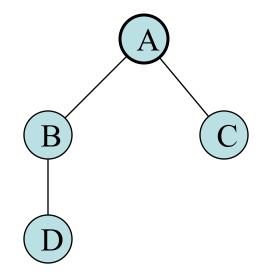




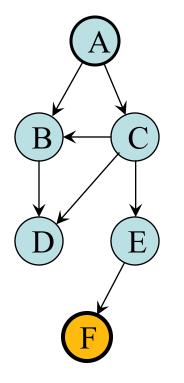


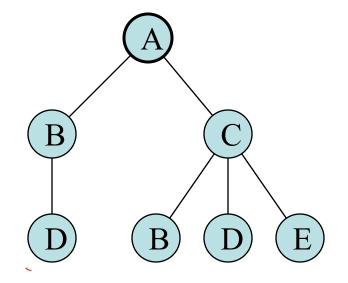




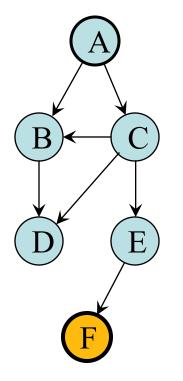


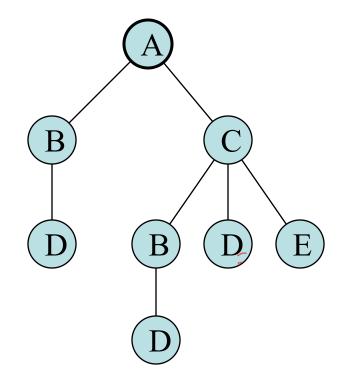




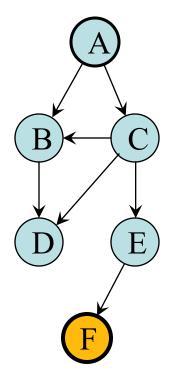


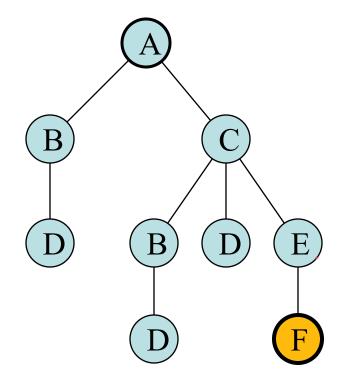




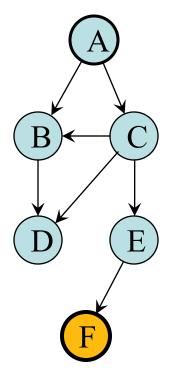






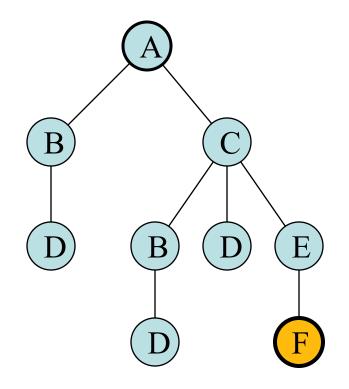




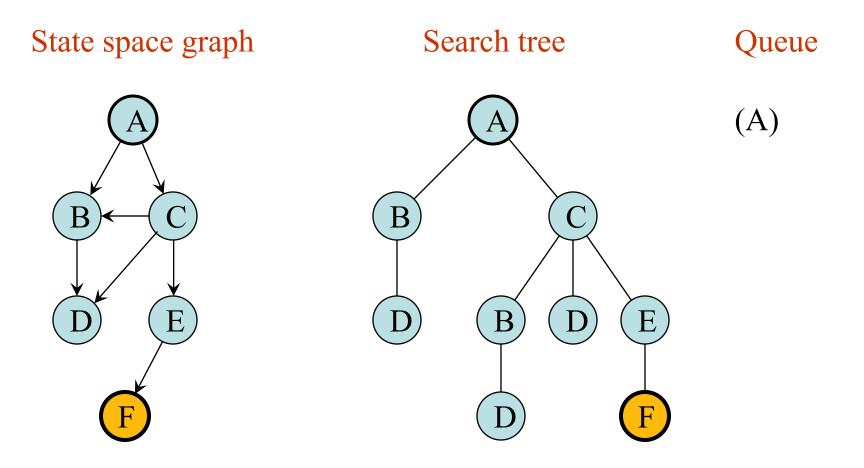




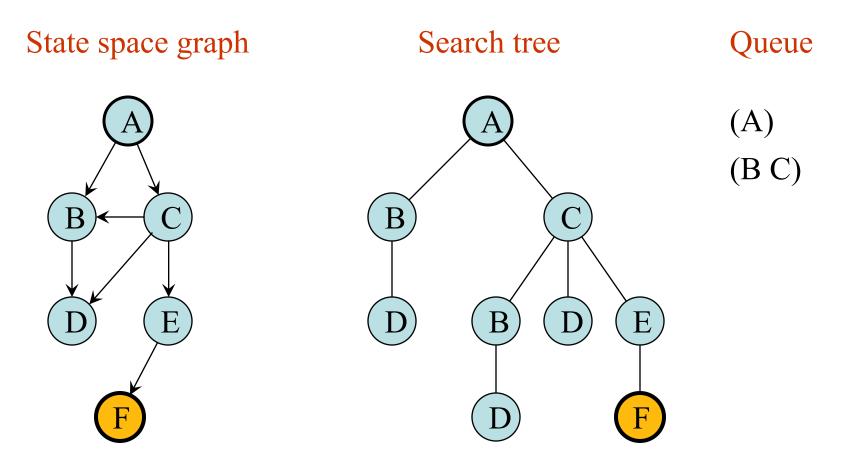




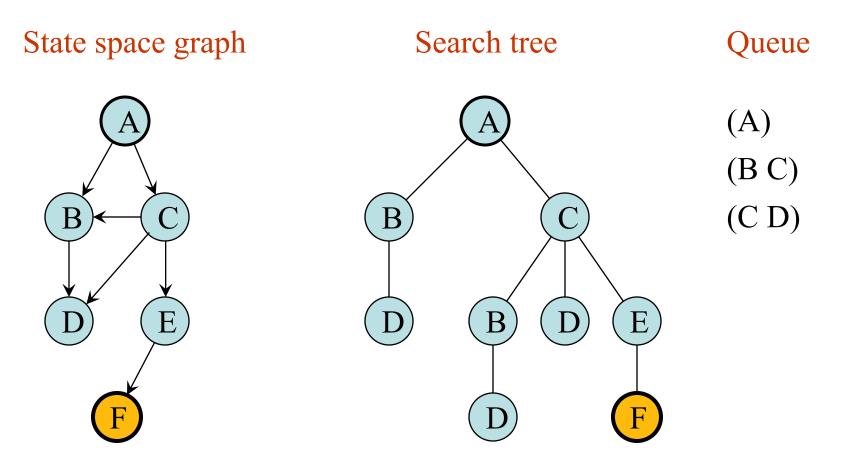




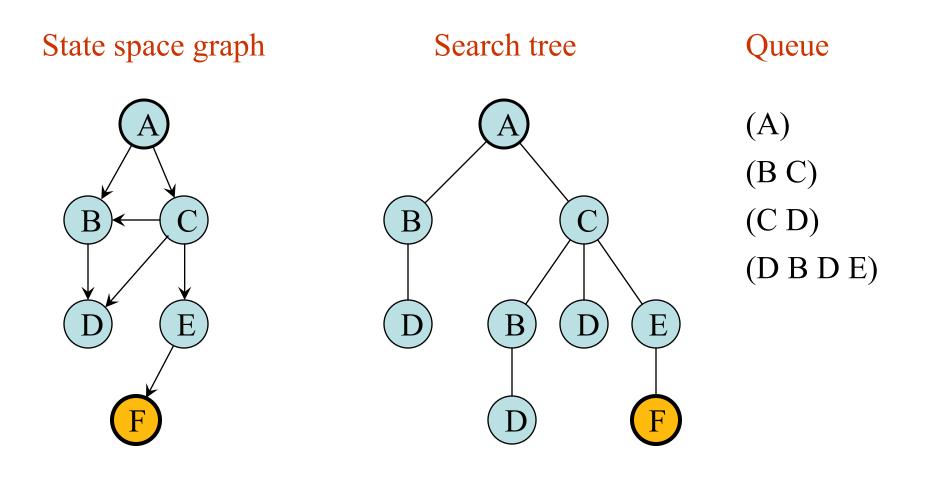




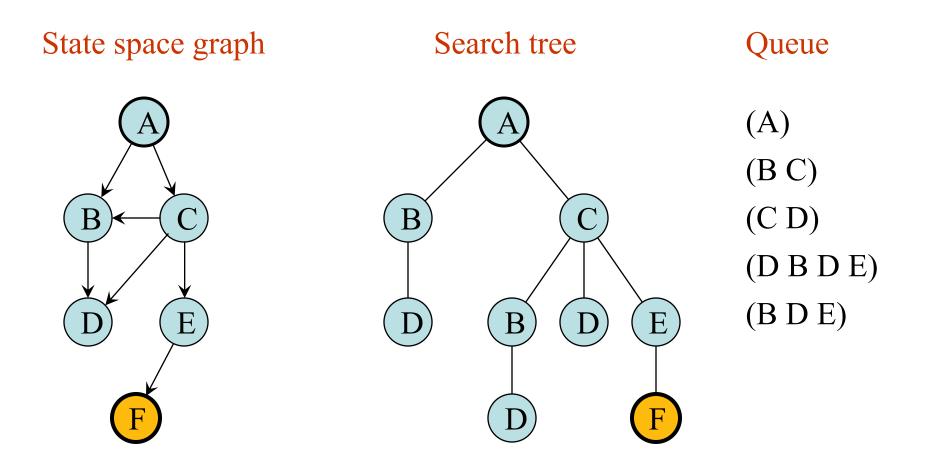




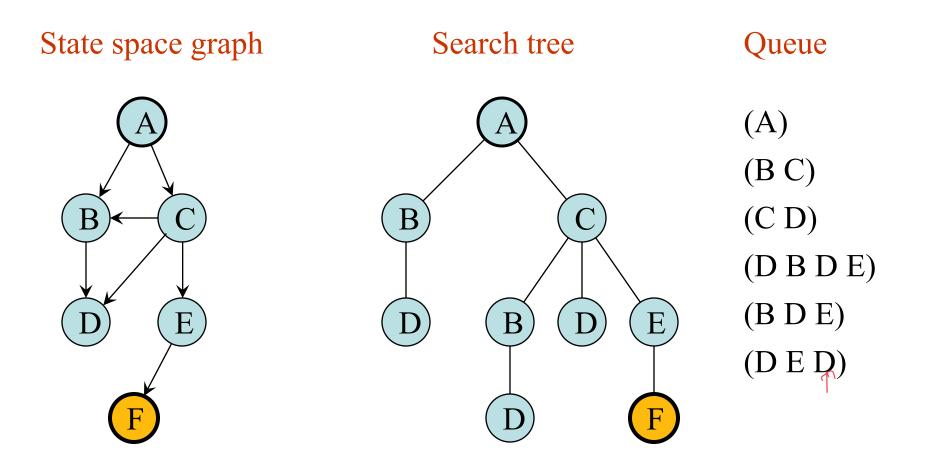




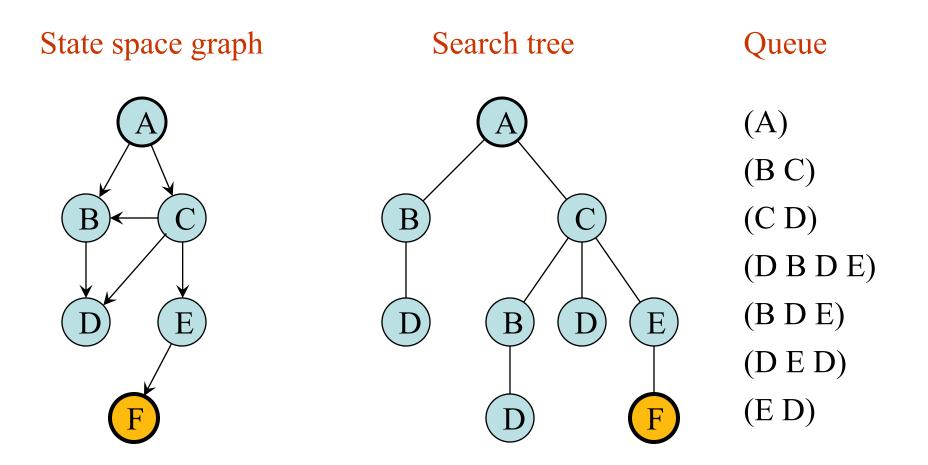




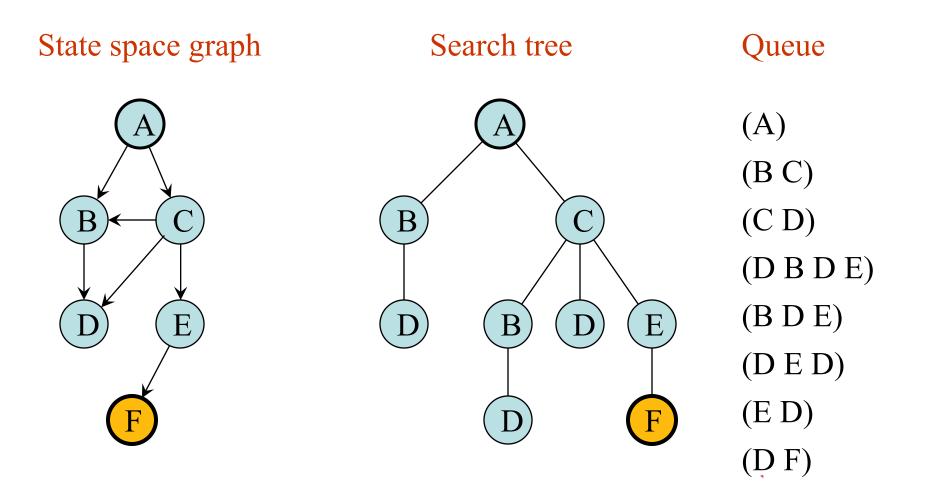




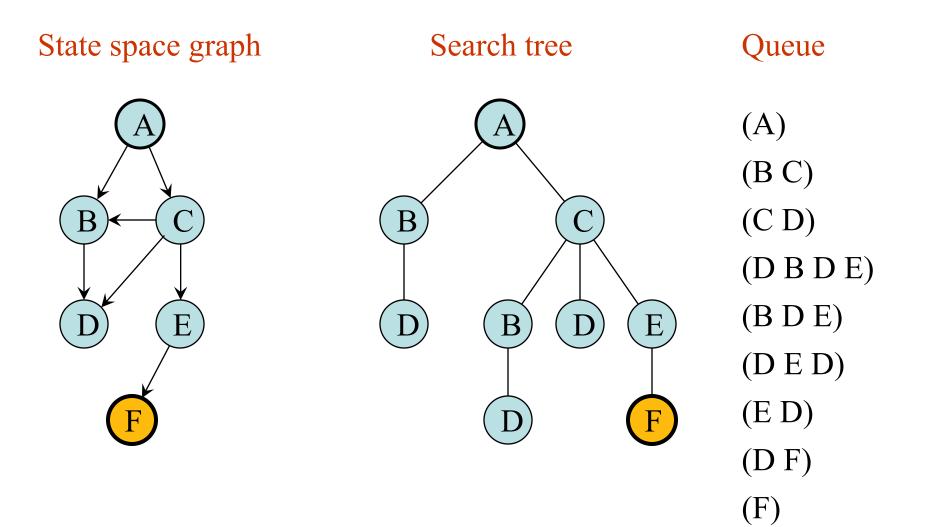




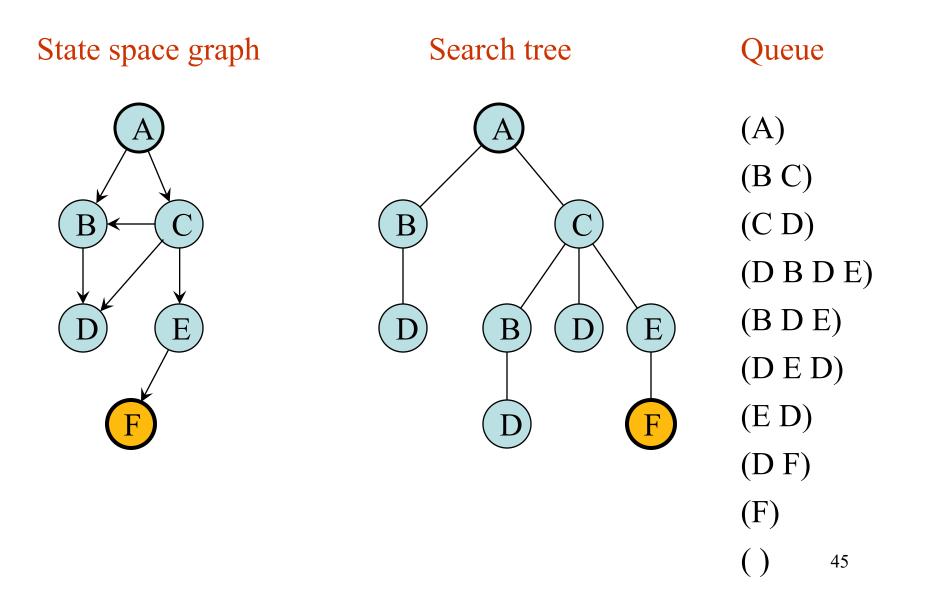












- Complete?
- Optimal?
- Time complexity?
- Space complexity?

- Complete? Yes
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In practice, the memory requirements are typically worse than the time requirements

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

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)

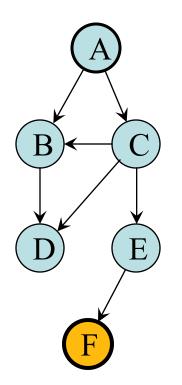
Depth-First Search

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function DEPTH-FIRST-SEARCH(*problem*) **returns** a solution or failure **return GENERAL-SEARCH**(*problem*, ENQUEUE-AT-FRONT)



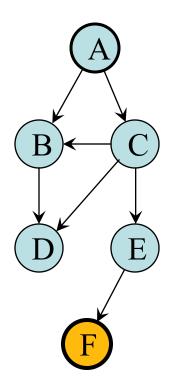


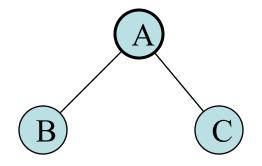




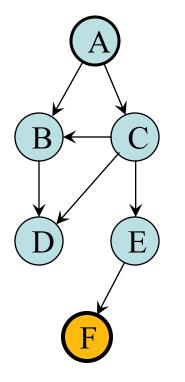


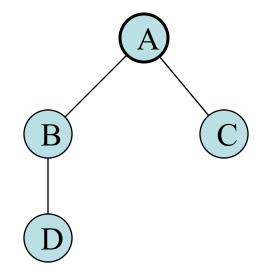




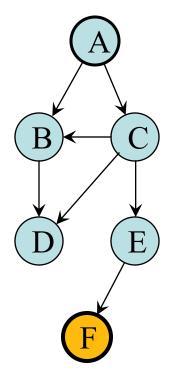


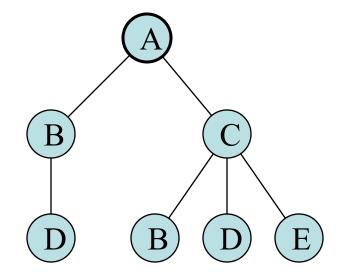




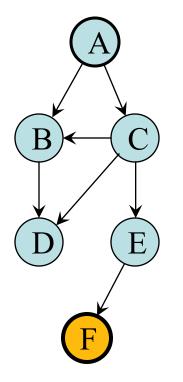


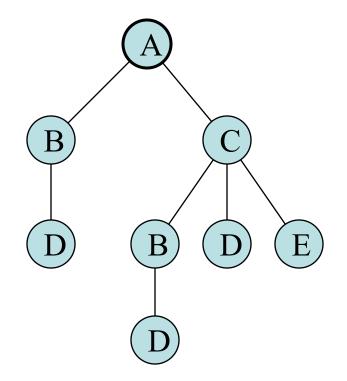




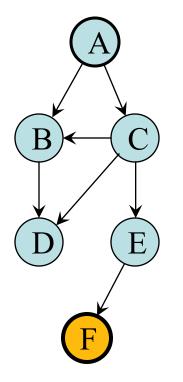


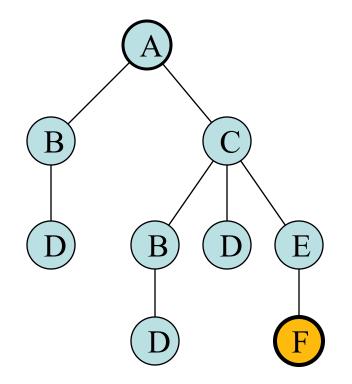




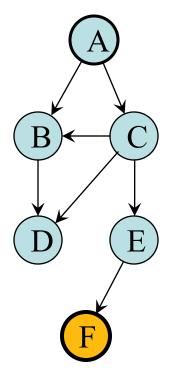






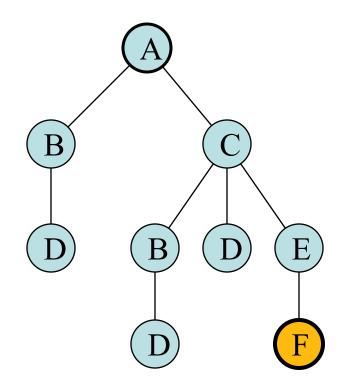




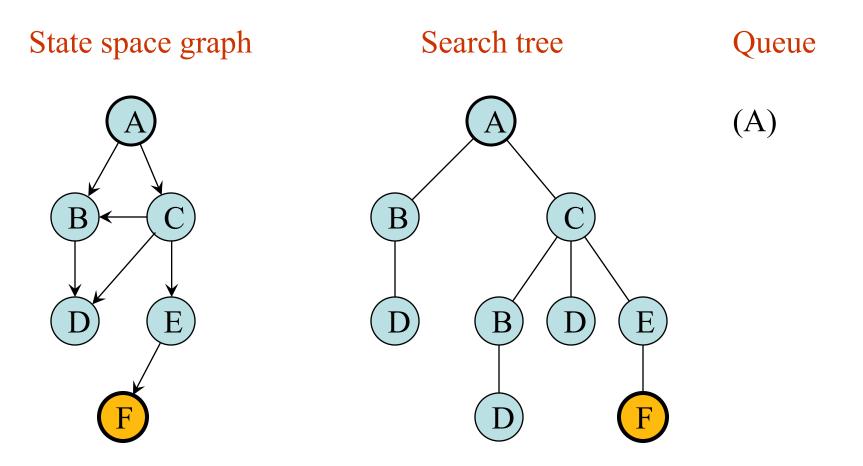




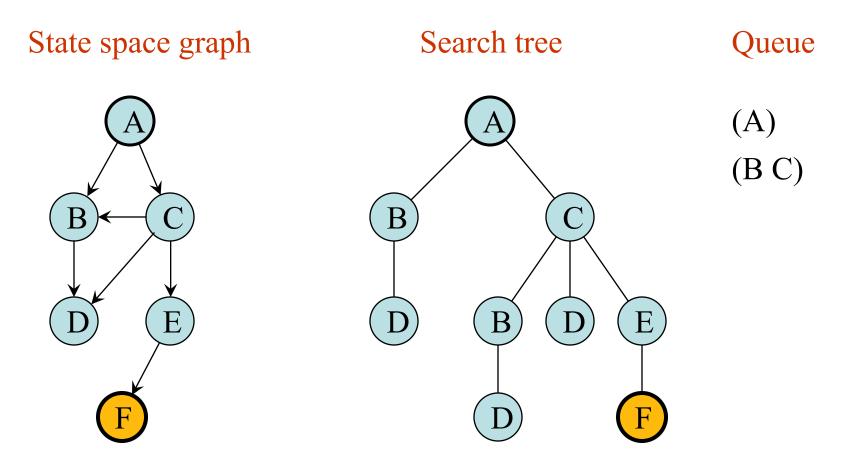




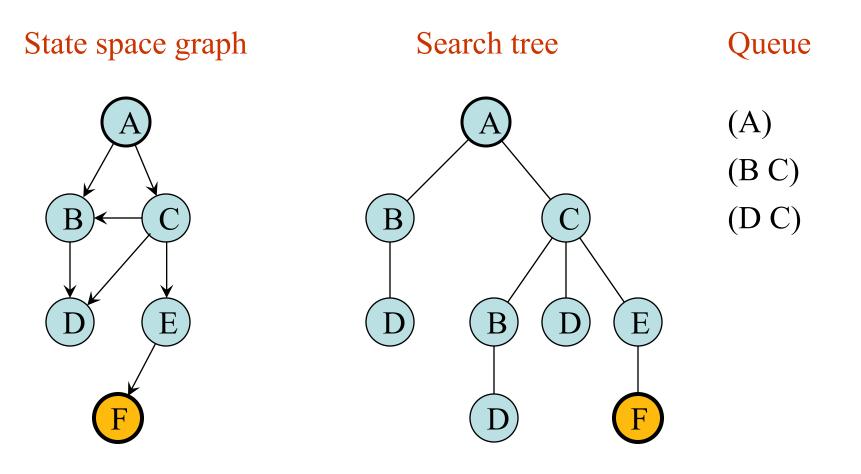




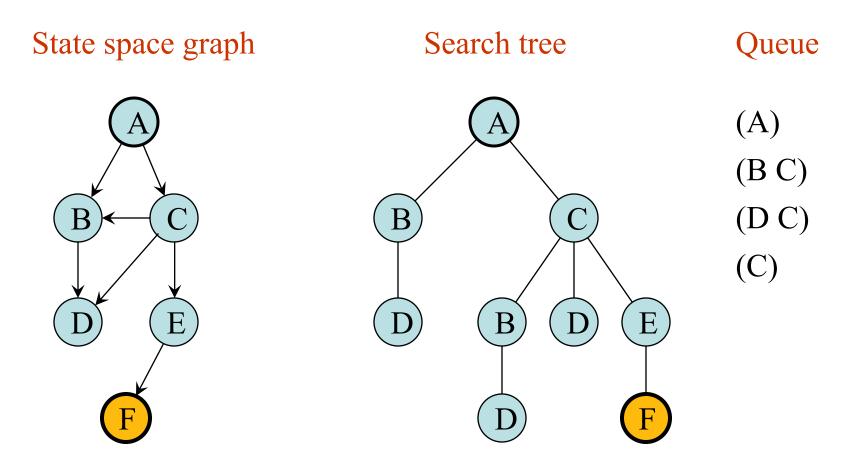




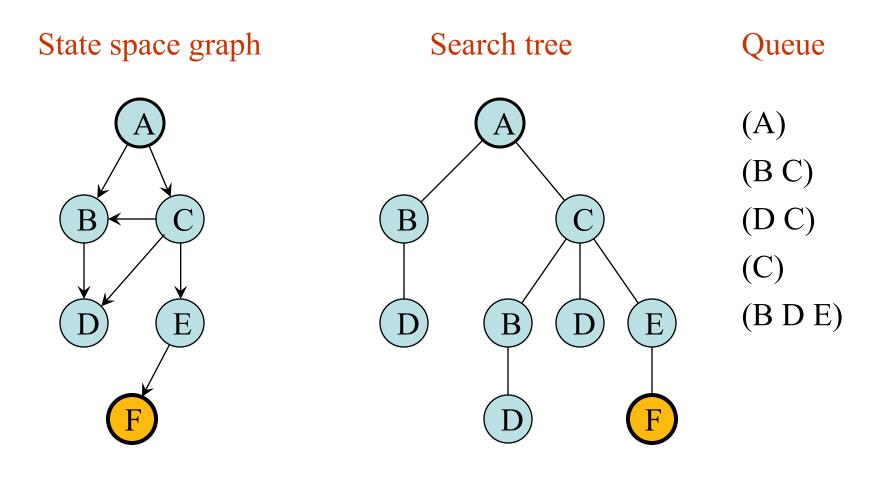




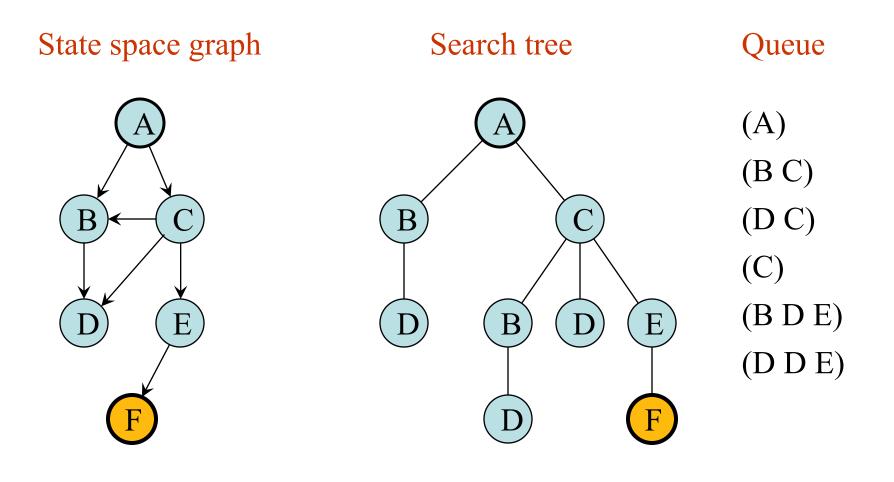




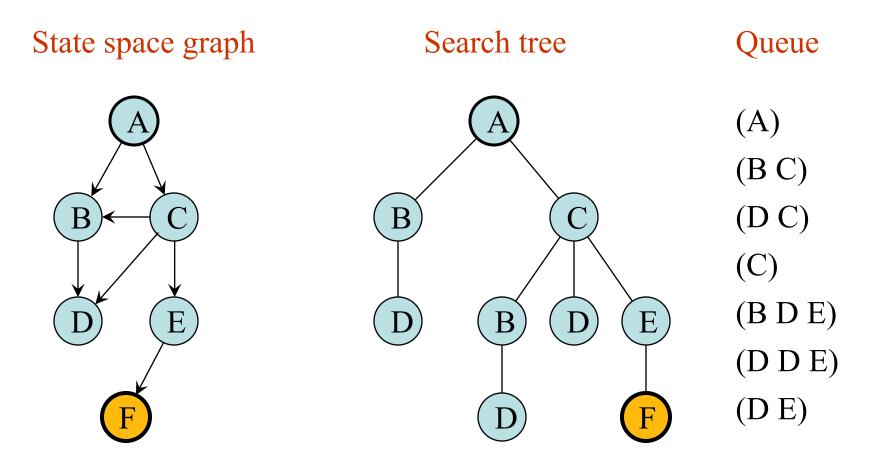




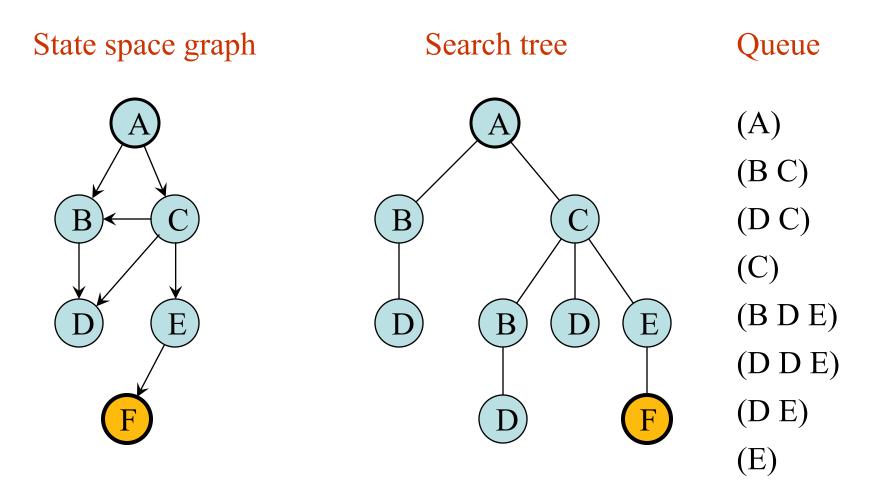




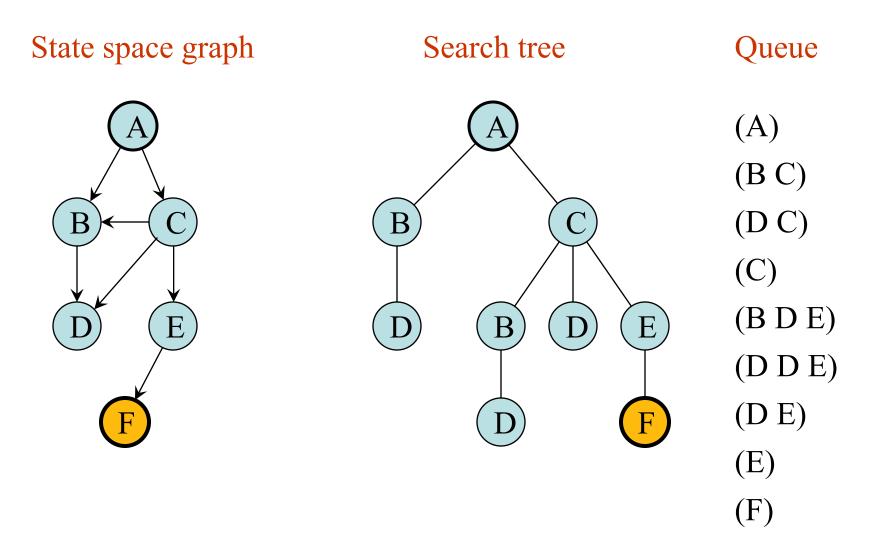












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- Space complexity? Polynomial: **O(***bm***)**

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)

Next lecture

- Informed search
- Start game solving / minimax search
- You should:
 - Read Chapter 3 of AIMA textbook
 - Start working on HW2

-----Supplementary slide------

- More examples
- More quiz questions

Example: MU-Puzzle

- States: Strings comprising the letters M, I, and U
- Initial state: MI
- Goal state: MU
- Operators: (where *x* stands for any string, *including the null string*)
 - 1. $x \ I \rightarrow x \ IU$ "Append U"2. $M x \rightarrow M x x$ "Replicate x"
 - 3. $xI I Iy \rightarrow xUy$ "Replace III with U"
 - 4. $xUUy \rightarrow xy$ "Drop UU"
- "Replace III with
- Path cost: one per step
- Try it
 - Can you draw the state-space diagram?
 - Are you guaranteed a solution?

U U	_	_	U	I	U	U	Ι	U

ΜI

 \rightarrow M I I

 \rightarrow M I I I I

 \rightarrow M U I U

 \rightarrow M U I U

 \rightarrow M U I U

 $\rightarrow \dots$

 \rightarrow M U I