

# Artificial Intelligence Uninformed search

Peter Antal

[antal@mit.bme.hu](mailto:antal@mit.bme.hu)

# Outline

- ▶ The “symbols&search” hypothesis for AI
- ▶ Problem-solving agents
  - A kind of goal-based agent
- ▶ Problem types
  - Single state (fully observable)
  - Search with partial information
- ▶ Problem formulation
  - Example problems
- ▶ Basic search algorithms
  - Uninformed

(Contact hours: Friday 12h–14h?)

# AI as “symbol manipulation”?

- ▶ The Box and Banana problem
  - Human, monkey, pigeon(?)



(“That is either the worlds biggest pigeon, or the worlds smallest banana...” ;-)

# AI as “symbol manipulation”

- ▶ The Logic Theorist, 1955
  - → see lectures on logic
- ▶ The Dartmouth conference (“birth of AI”, 1956)
- ▶ List processing (Information Processing Language, IPL)
- ▶ Means–ends analysis (“reasoning as search”)
  - → see lectures on planning
- ▶ The General Problem Solver
- ▶ Heuristics to limit the search space
  - → see lecture on informed search
- ▶ The physical symbol systems hypothesis
  - intelligent behavior can be reduced to/emulated by symbol manipulation
- ▶ The unified theory of cognition (1990, cognitive architectures: Soar, ACT–R)
  
- ▶ Newel&Simon: Computer science as empirical inquiry: symbols and search, 1975

# Problem-solving agent

- ▶ Four general steps in problem solving:
  - Goal formulation
    - What are the successful world states
  - Problem formulation
    - What actions and states to consider give the goal
  - Search
    - Determine the possible sequence of actions that lead to the states of known values and then choosing the best sequence.
  - Execute
    - Give the solution perform the actions.

# Problem-solving agent

**function** SIMPLE-PROBLEM-SOLVING-AGENT(*percept*) **return** an action

**static:** *seq*, an action sequence

*state*, some description of the current world state

*goal*, a goal

*problem*, a problem formulation

*state* ← UPDATE-STATE(*state*, *percept*)

**if** *seq* is empty **then**

*goal* ← FORMULATE-GOAL(*state*)

*problem* ← FORMULATE-PROBLEM(*state*, *goal*)

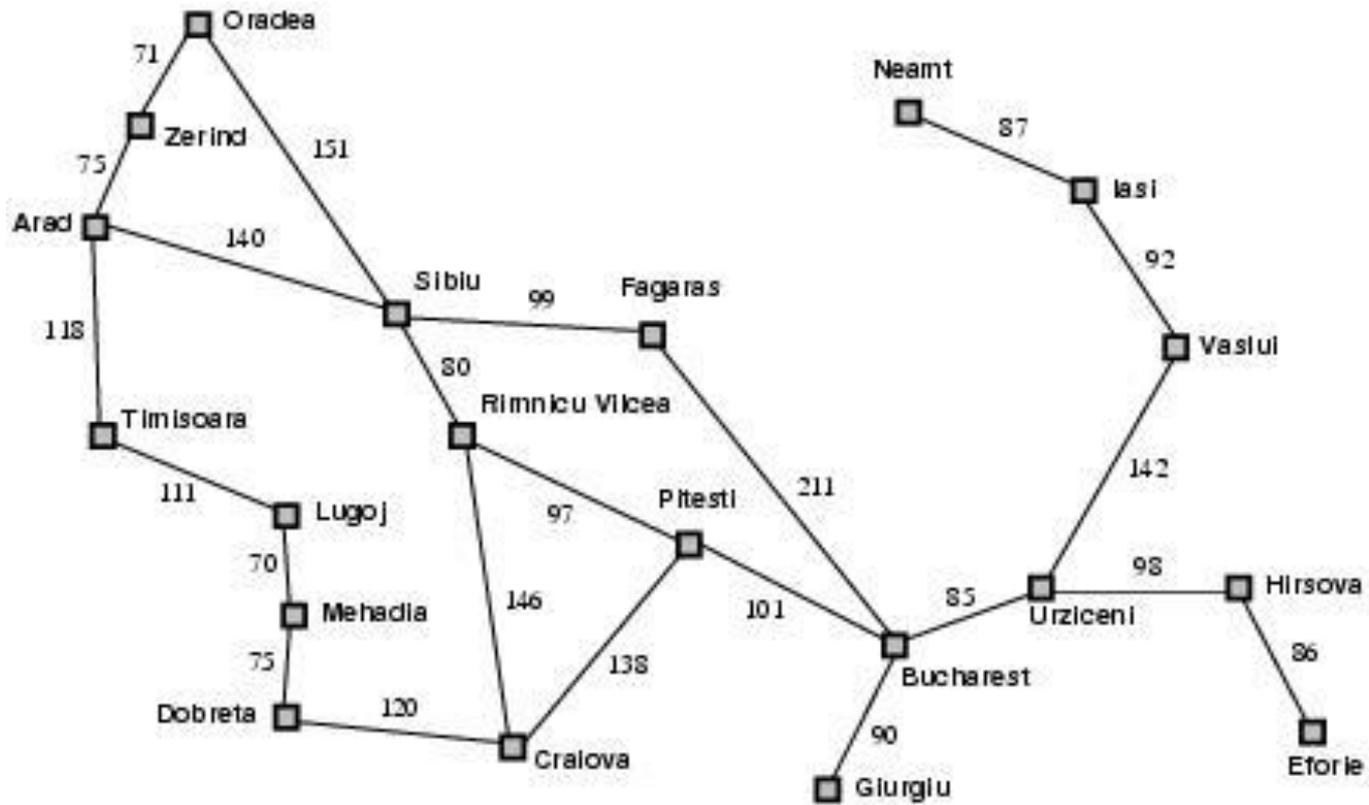
*seq* ← SEARCH(*problem*)

*action* ← FIRST(*seq*)

*seq* ← REST(*seq*)

**return** *action*

# Example: Romania



# Example: Romania

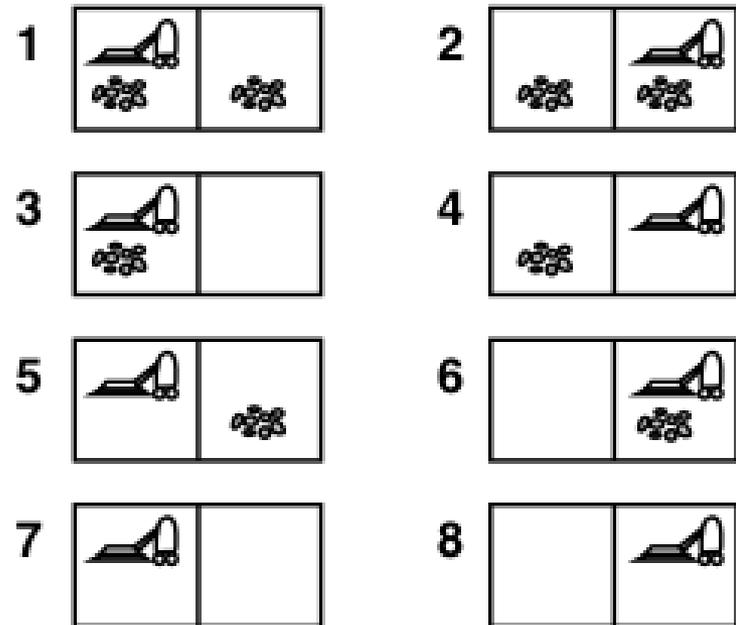
- ▶ On holiday in Romania; currently in Arad
  - Flight leaves tomorrow from Bucharest
- ▶ Formulate goal
  - Be in Bucharest
- ▶ Formulate problem
  - States: various cities
  - Actions: drive between cities
- ▶ Find solution
  - Sequence of cities; e.g. Arad, Sibiu, Fagaras, Bucharest, ...

# Problem types

- ▶ Deterministic, fully observable  $\Rightarrow$  *single state problem*
  - Agent knows exactly which state it will be in; solution is a sequence.
- ▶ Partial knowledge of states and actions:
  - Non-observable  $\Rightarrow$  *sensorless or conformant problem*
    - Agent may have no idea where it is; solution (if any) is a sequence.
  - Nondeterministic and/or partially observable  $\Rightarrow$  *contingency problem*
    - Percepts provide *new* information about current state; solution is a tree or policy; often interleave search and execution.
  - Unknown state space  $\Rightarrow$  *exploration problem* (“online”)
    - When states and actions of the environment are unknown.

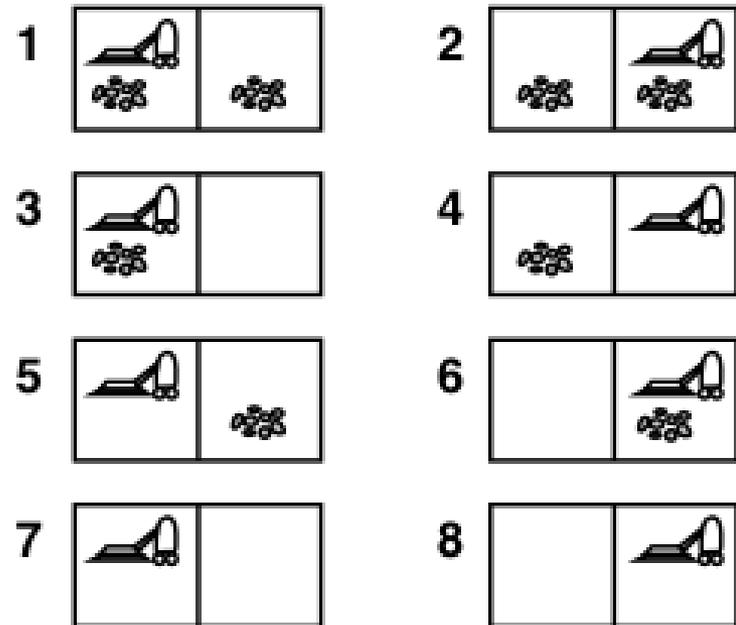
# Example: vacuum world

- ▶ Single state, start in #5. Solution??



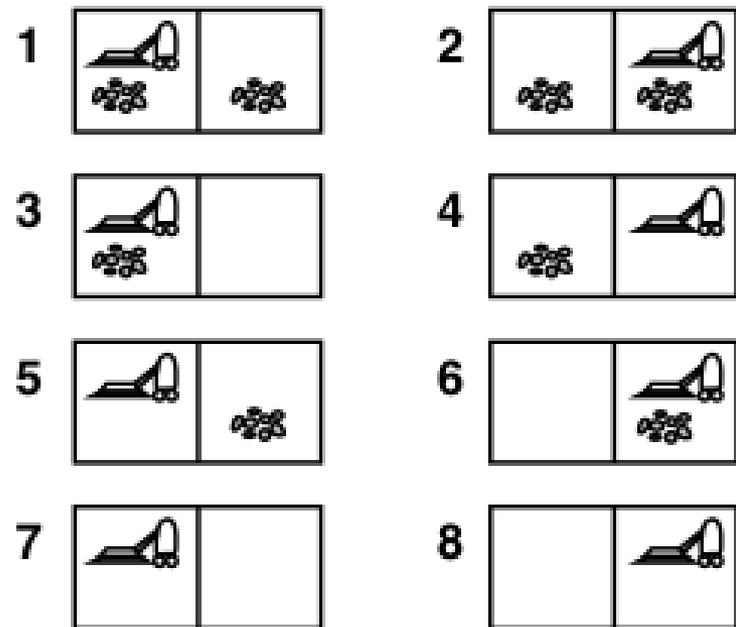
# Example: vacuum world

- ▶ Single state, start in #5. Solution??
  - *[Right, Suck]*



# Example: vacuum world

- ▶ Single state, start in #5.  
Solution??
  - *[Right, Suck]*
- ▶ **Sensorless**: start in {1,2,3,4,5,6,7,8} e.g. Right goes to {2,4,6,8}.  
Solution??
- ▶ **Contingency**: start in {1,3}. (assume Murphy's law, Suck can dirty a clean carpet and local sensing: [location,dirt] only. Solution??



# Problem formulation

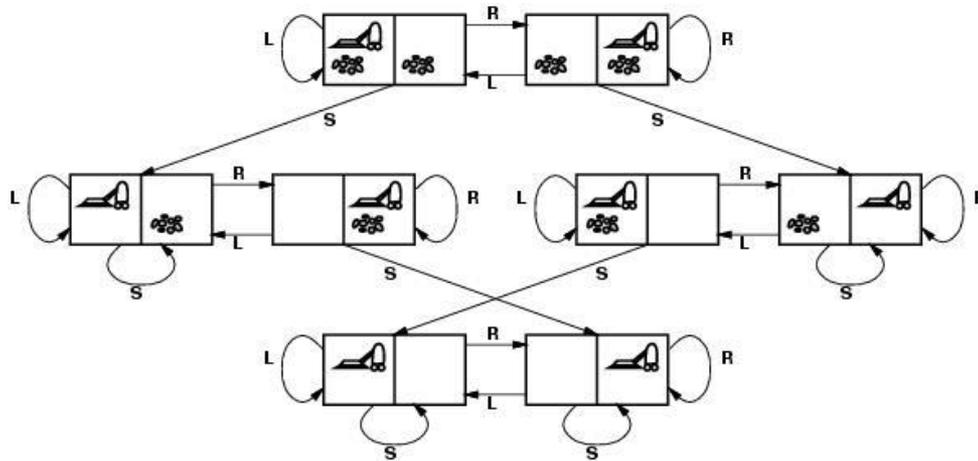
- ▶ A problem is defined by:
  - An **initial state**, e.g. *Arad*
  - **Successor function**  $S(X)$  = set of action–state pairs
    - e.g.  $S(\text{Arad}) = \{ \langle \text{Arad} \rightarrow \text{Zerind}, \text{Zerind} \rangle, \dots \}$initial state + successor function = state space
- **Goal test**, can be
  - Explicit, e.g.  $x = \text{'at bucharest'}$
  - Implicit, e.g.  $\text{checkmate}(x)$
- **Path cost** (additive)
  - e.g. sum of distances, number of actions executed, ...
  - $c(x, a, y)$  is the step cost, assumed to be  $\geq 0$

A **solution** is a sequence of actions from initial to goal state.  
**Optimal solution** has the lowest path cost.

# Selecting a state space

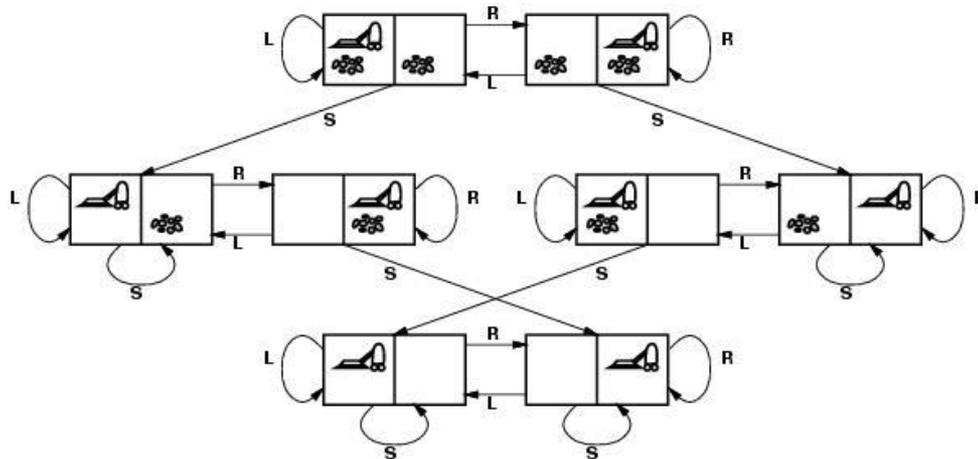
- ▶ Real world is absurdly complex.
  - State space must be *abstracted* for problem solving.
- ▶ (Abstract) state = set of real states.
- ▶ (Abstract) action = complex combination of real actions.
  - e.g. Arad → Zerind represents a complex set of possible routes, detours, rest stops, etc.
  - The abstraction is valid if the path between two states is reflected in the real world.
- ▶ (Abstract) solution = set of real paths that are solutions in the real world.
- ▶ Each abstract action should be “easier” than the real problem.

# Example: vacuum world



- ▶ States??
- ▶ Initial state??
- ▶ Actions??
- ▶ Goal test??
- ▶ Path cost??

# Example: vacuum world



- ▶ States?? two locations with or without dirt:  $2 \times 2^2 = 8$  states.
- ▶ Initial state?? Any state can be initial
- ▶ Actions??  $\{Left, Right, Suck\}$
- ▶ Goal test?? Check whether squares are clean.
- ▶ Path cost?? Number of actions to reach goal.

# Example: 8-puzzle

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

- ▶ States??
- ▶ Initial state??
- ▶ Actions??
- ▶ Goal test??
- ▶ Path cost??

# Example: 8-puzzle

7	2	4
5		6
8	3	1

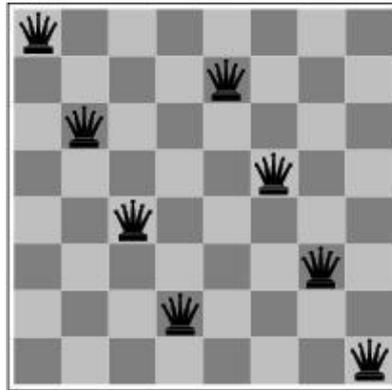
Start State

	1	2
3	4	5
6	7	8

Goal State

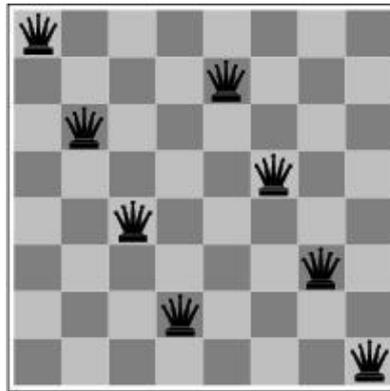
- ▶ States?? Integer location of each tile
- ▶ Initial state?? Any state can be initial
- ▶ Actions?? {*Left*, *Right*, *Up*, *Down*}
- ▶ Goal test?? Check whether goal configuration is reached
- ▶ Path cost?? Number of actions to reach goal

# Example: 8-queens problem



- ▶ States??
- ▶ Initial state??
- ▶ Actions??
- ▶ Goal test??
- ▶ Path cost??

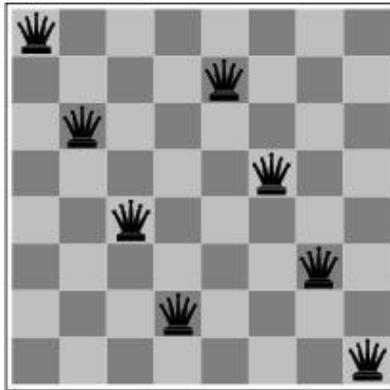
# Example: 8-queens problem



**Incremental** formulation vs. **complete-state** formulation

- ▶ States??
- ▶ Initial state??
- ▶ Actions??
- ▶ Goal test??
- ▶ Path cost??

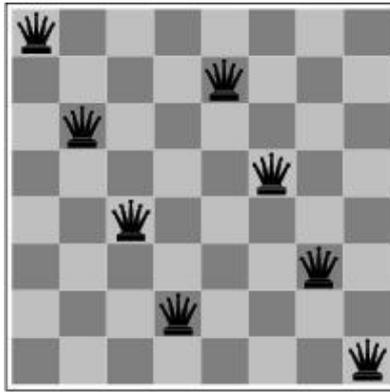
# Example: 8-queens problem



## Incremental formulation

- ▶ States?? Any arrangement of 0 to 8 queens on the board
  - ▶ Initial state?? No queens
  - ▶ Actions?? Add queen in empty square
  - ▶ Goal test?? 8 queens on board and none attacked
  - ▶ Path cost?? None
- $3 \times 10^{14}$  possible sequences to investigate

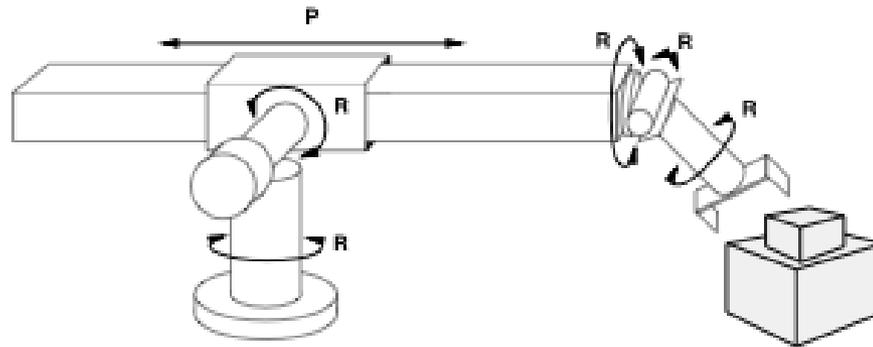
# Example: 8-queens problem



## Incremental formulation (alternative)

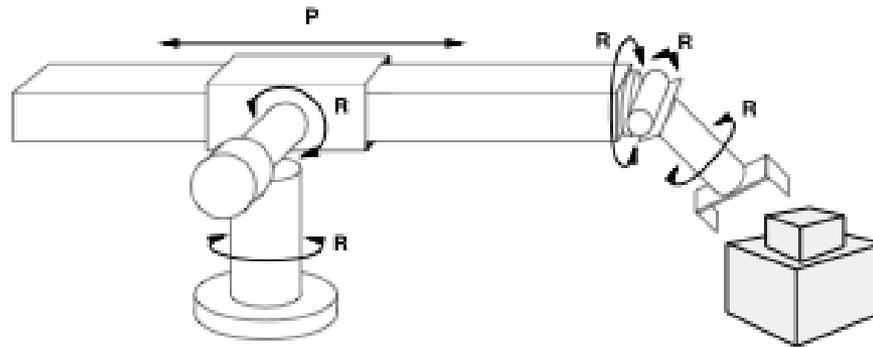
- ▶ States??  $n$  ( $0 \leq n \leq 8$ ) queens on the board, one per column in the  $n$  leftmost columns with no queen attacking another.
  - ▶ Actions?? Add queen in leftmost empty column such that is not attacking other queens
- 2057 possible sequences to investigate; Yet makes no difference when  $n=100$

# Example: robot assembly



- ▶ States??
- ▶ Initial state??
- ▶ Actions??
- ▶ Goal test??
- ▶ Path cost??

# Example: robot assembly



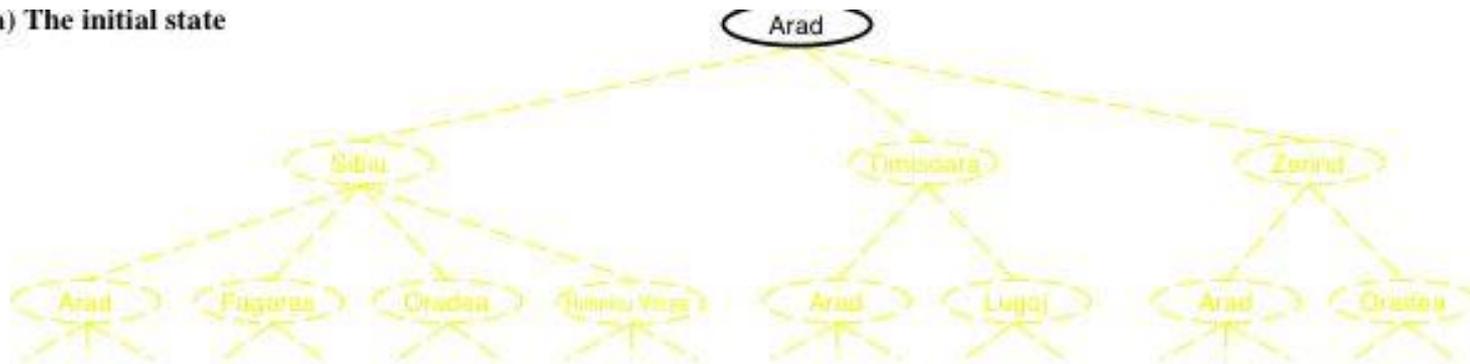
- ▶ States?? Real-valued coordinates of robot joint angles; parts of the object to be assembled.
- ▶ Initial state?? Any arm position and object configuration.
- ▶ Actions?? Continuous motion of robot joints
- ▶ Goal test?? Complete assembly (without robot)
- ▶ Path cost?? Time to execute

# Basic search algorithms

- ▶ How do we find the solutions of previous problems?
  - Search the state space (remember complexity of space depends on state representation)
  - Here: search through *explicit tree generation*
    - ROOT= initial state.
    - Nodes and leafs generated through successor function.
  - In general search generates a graph (same state through multiple paths)

# Simple tree search example

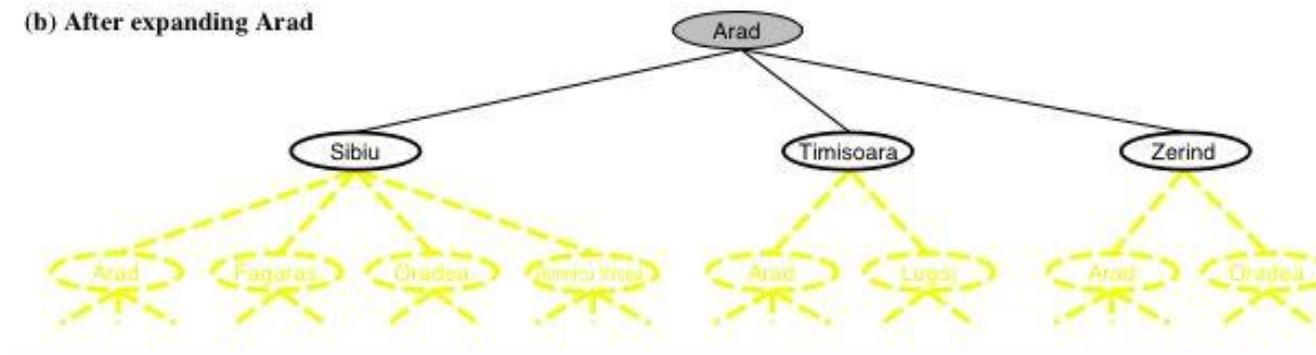
(a) The initial state



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

# Simple tree search example

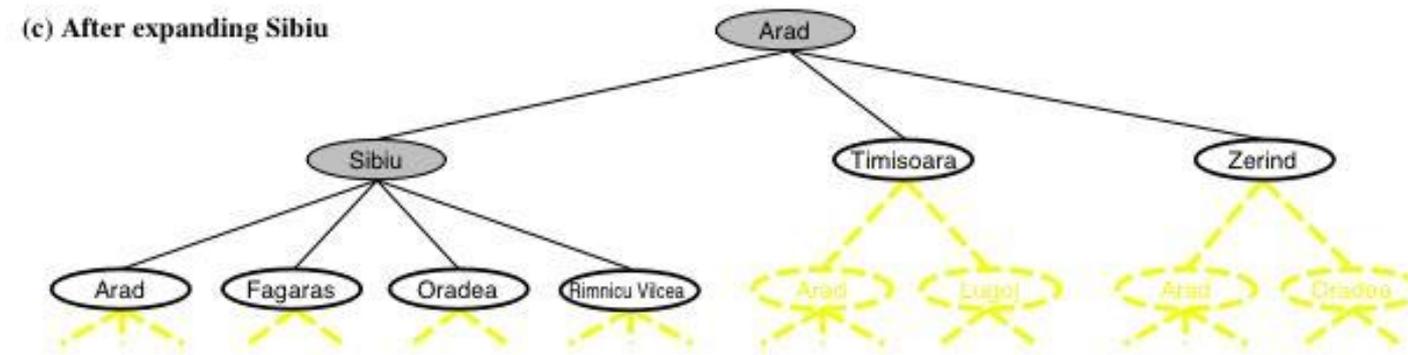
(b) After expanding Arad



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

# Simple tree search example

(c) After expanding Sibiu



**function** TREE-SEARCH(*problem, strategy*) **return** a solution or failure

Initialize search tree to the *initial state* of the *problem*

**do**

if no candidates for expansion **then return** *failure*

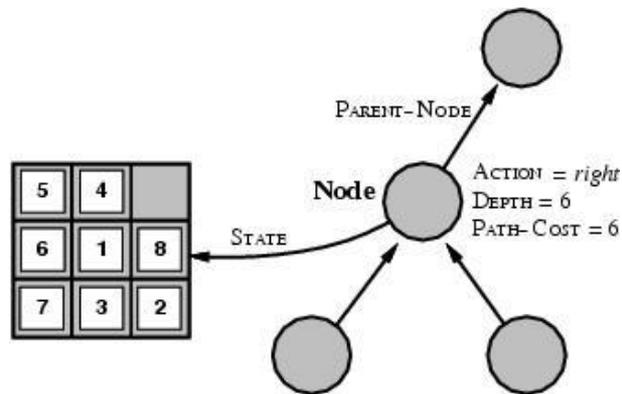
**choose leaf node for expansion according to** *strategy* ← **Determines search process!!**

if node contains goal state **then return** *solution*

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

**enddo**

# State space vs. search tree



- ▶ A *state* is a (representation of) a physical configuration
- ▶ A *node* is a data structure belong to a search tree
  - A node has a parent, children, ... and ncludes path cost, depth, ...
  - Here  $node = \langle state, parent\text{-}node, action, path\text{-}cost, depth \rangle$
  - *FRINGE* = contains generated nodes which are not yet expanded.
    - White nodes with black outline

# Tree search algorithm

```
function TREE-SEARCH(problem, fringe) return a solution or failure
  fringe ← INSERT(MAKE-NODE(INITIAL-STATE[problem]), fringe)
  loop do
    if EMPTY?(fringe) then return failure
    node ← REMOVE-FIRST(fringe)
    if GOAL-TEST[problem] applied to STATE[node] succeeds
      then return SOLUTION(node)
    fringe ← INSERT-ALL(EXPAND(node, problem), fringe)
```

# Tree search algorithm (2)

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

# Search strategies

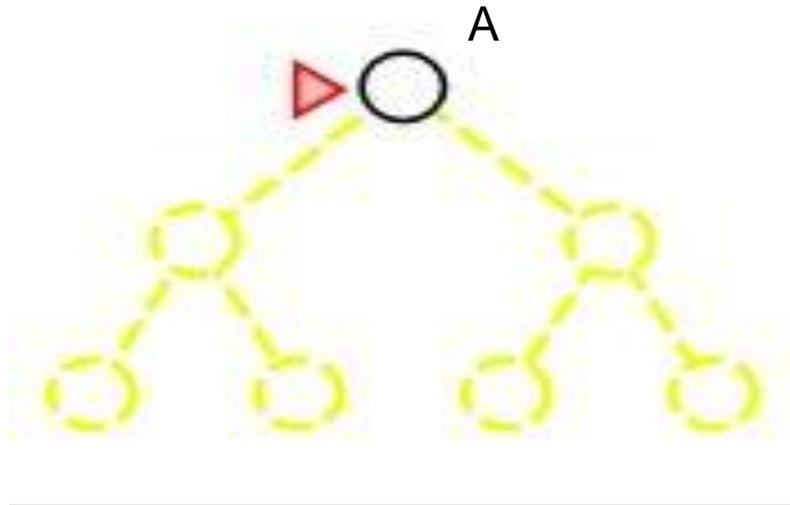
- ▶ A strategy is defined by picking the order of node expansion.
- ▶ Problem-solving performance is measured in four ways:
  - Completeness; *Does it always find a solution if one exists?*
  - Optimality; *Does it always find the least-cost solution?*
  - Space Complexity; *Number of nodes stored in memory during search?*
  - Time Complexity; *Number of nodes generated/expanded?*
- ▶ Time and space complexity are measured in terms of problem difficulty defined by:
  - $b$  – maximum branching factor of the search tree
  - $d$  – depth of the least-cost solution
  - $m$  – maximum depth of the state space (may be  $\infty$ )

# Uninformed search strategies

- ▶ (a.k.a. blind search) = use only information available in problem definition.
  - When strategies can determine whether one non-goal state is better than another → informed search.
- ▶ Categories defined by expansion algorithm:
  - Breadth-first search
  - Uniform-cost search
  - Depth-first search
  - Depth-limited search
  - Iterative deepening search.
  - Bidirectional search

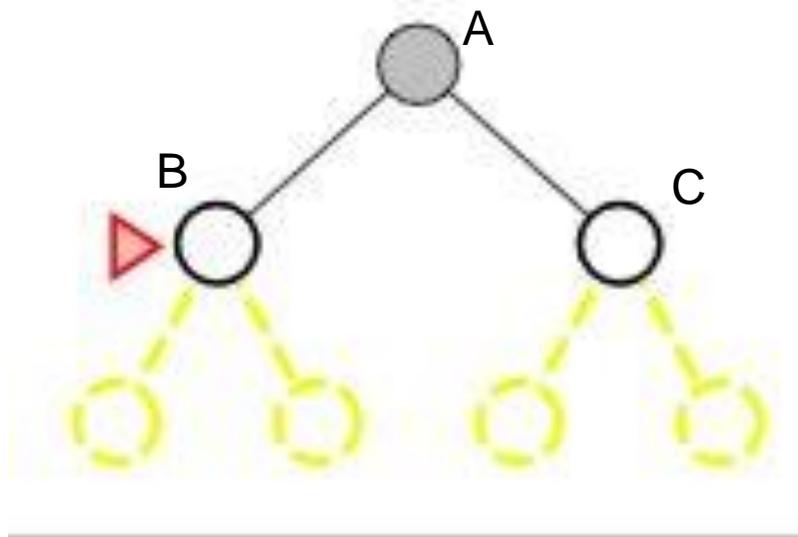
# BF-search, an example

- ▶ Expand *shallowest* unexpanded node
- ▶ Implementation: *fringe* is a FIFO queue



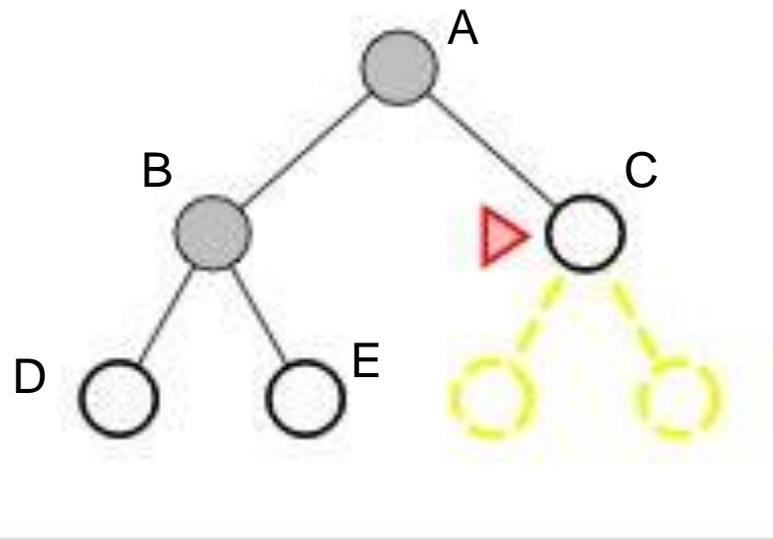
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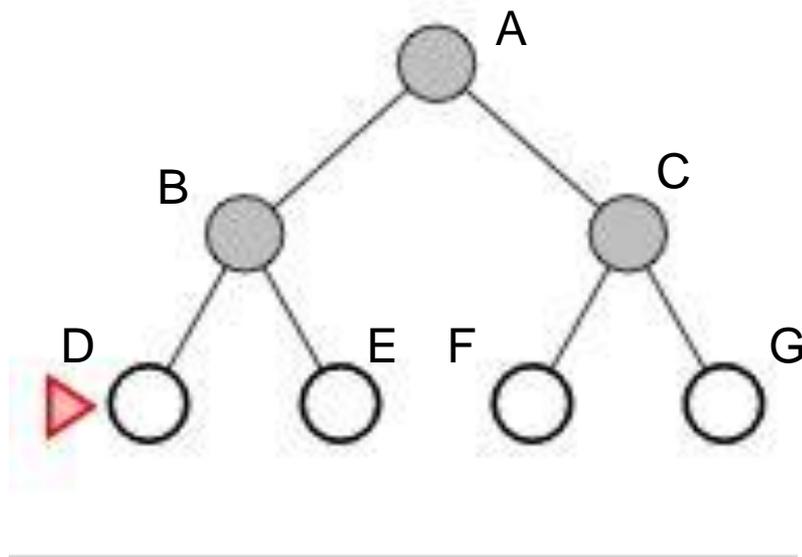
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# BF-search; evaluation

## ▶ Completeness:

- *Does it always find a solution if one exists?*
- YES
  - If shallowest goal node is at some finite depth  $d$
  - Condition: If  $b$  is finite
    - (maximum num. Of succ. nodes is finite)

# BF-search; evaluation

- ▶ **Completeness:**
  - YES (if  $b$  is finite)
- ▶ **Time complexity:**
  - Assume a state space where every state has  $b$  successors.
    - root has  $b$  successors, each node at the next level has again  $b$  successors (total  $b^2$ ), ...
    - Assume solution is at depth  $d$
    - Worst case; expand all but the last node at depth  $d$
    - Total numb. of nodes generated:

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

# BF-search; evaluation

- ▶ **Completeness:**

- YES (if  $b$  is finite)

- ▶ **Time complexity:**

- Total numb. of nodes generated:

- ▶ **Space complexity:**

- Idem if each node is retained in memory

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

# BF-search; evaluation

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- ▶ **Optimality:**

- *Does it always find the least-cost solution?*
- In general YES
  - unless actions have different cost.

# BF-search; evaluation

- ▶ Two lessons:
  - Memory requirements are a bigger problem than its execution time.
  - Exponential complexity search problems cannot be solved by uninformed search methods for any but the smallest instances.

DEPTH2	NODES	TIME	MEMORY
2	1100	0.11 seconds	1 megabyte
4	111100	11 seconds	106 megabytes
6	$10^7$	19 minutes	10 gigabytes
8	$10^9$	31 hours	1 terabyte
10	$10^{11}$	129 days	101 terabytes
12	$10^{13}$	35 years	10 petabytes
14	$10^{15}$	3523 years	1 exabyte

# Uniform-cost search

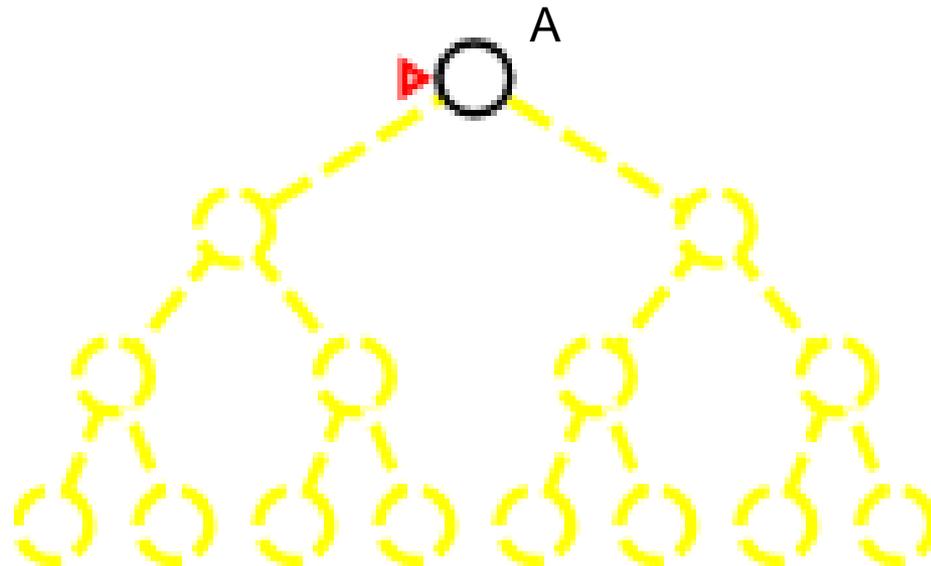
- ▶ Extension of BF-search:
  - Expand node with *lowest path cost*
- ▶ Implementation: *fringe* = queue ordered by path cost.
  
- ▶ UC-search is the same as BF-search when all step-costs are equal.

# Uniform-cost search

- ▶ **Completeness:**
  - YES, if step-cost  $> \epsilon$  (small positive constant)
- ▶ **Time complexity:**
  - Assume  $C^*$  the cost of the optimal solution.
  - Assume that every action costs at least  $\epsilon$
  - Worst-case:
- ▶ **Space complexity:**
  - Idem to time complexity  $O(b^{C^*/\epsilon})$
- ▶ **Optimality:**
  - nodes expanded in order of increasing path cost.
  - YES, if complete.

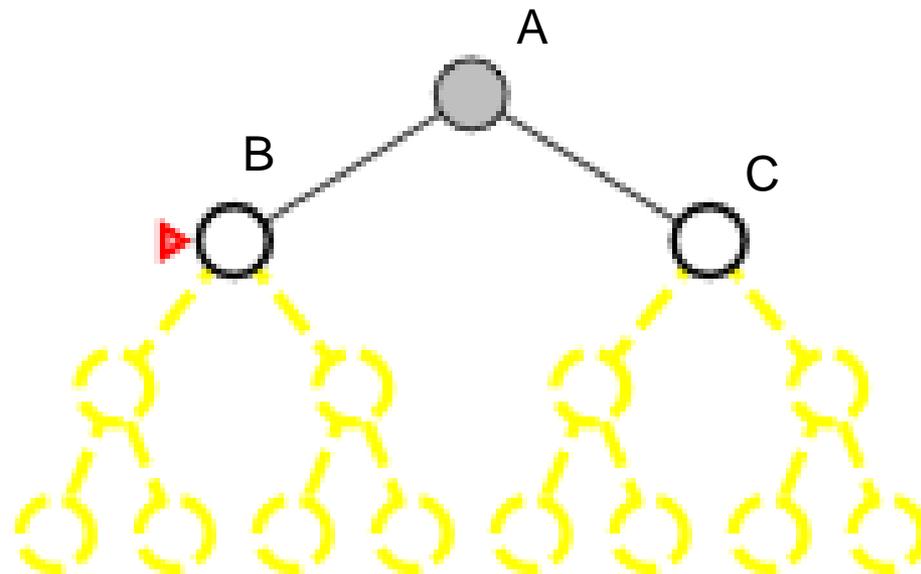
# DF-search, an example

- ▶ Expand *deepest* unexpanded node
- ▶ Implementation: *fringe* is a LIFO queue (=stack)



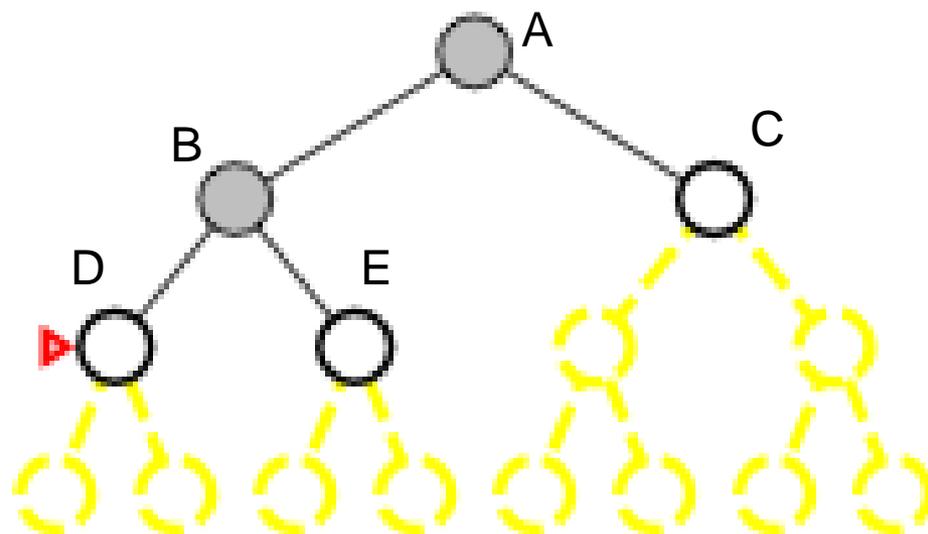
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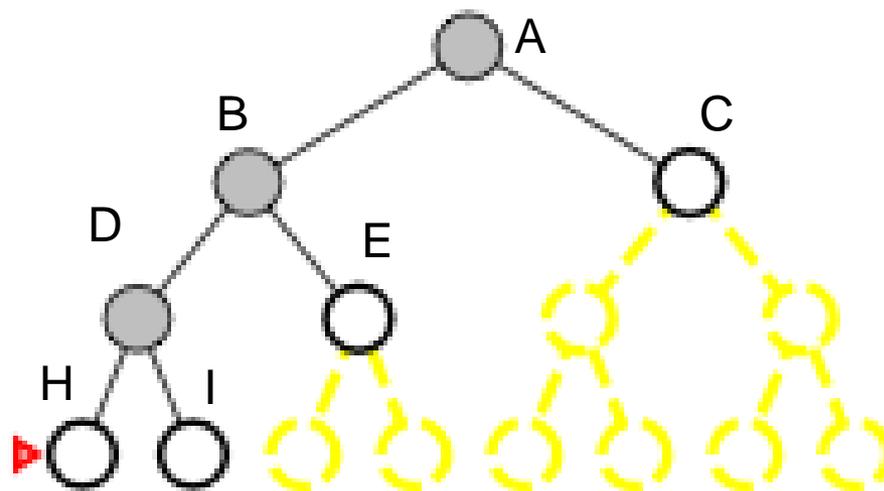
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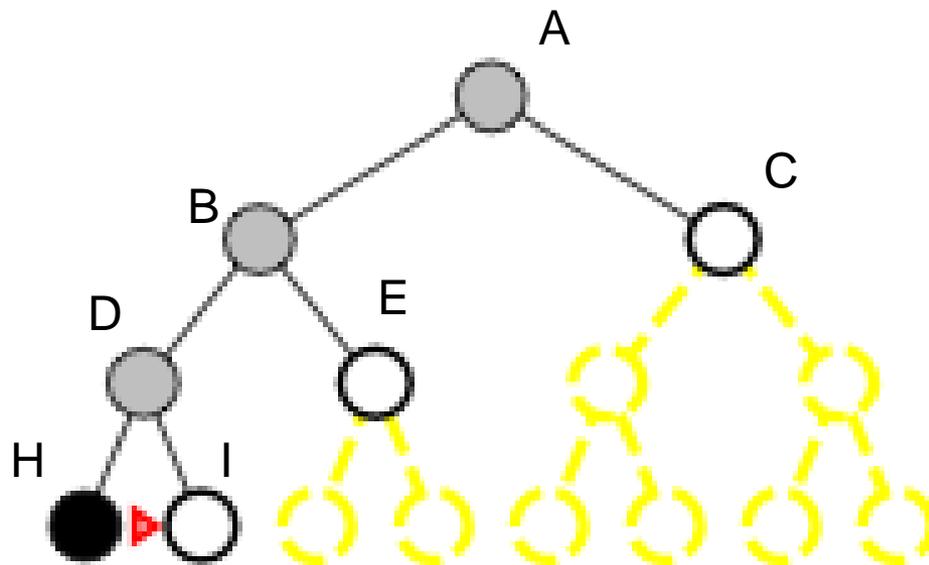
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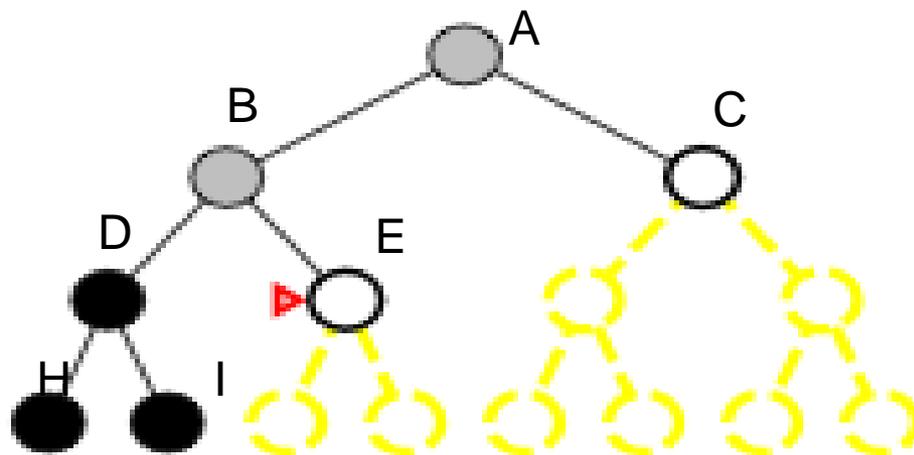
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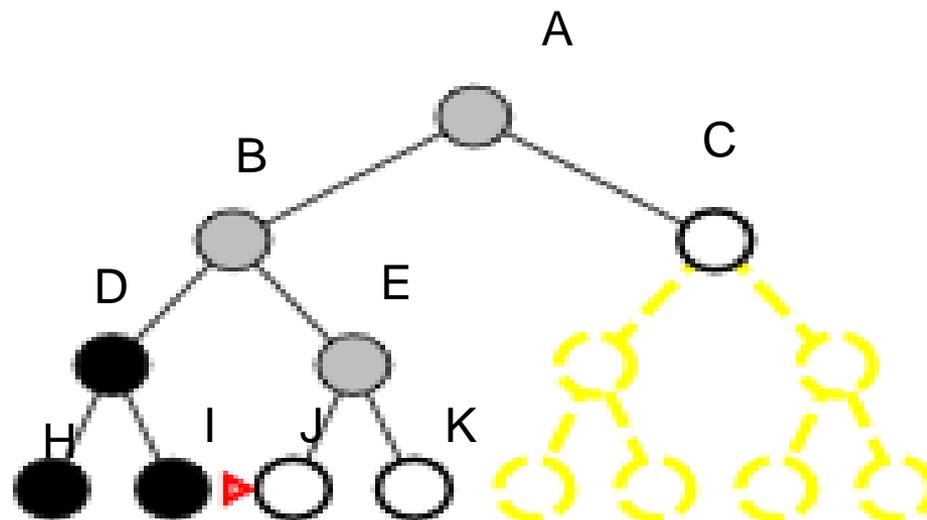
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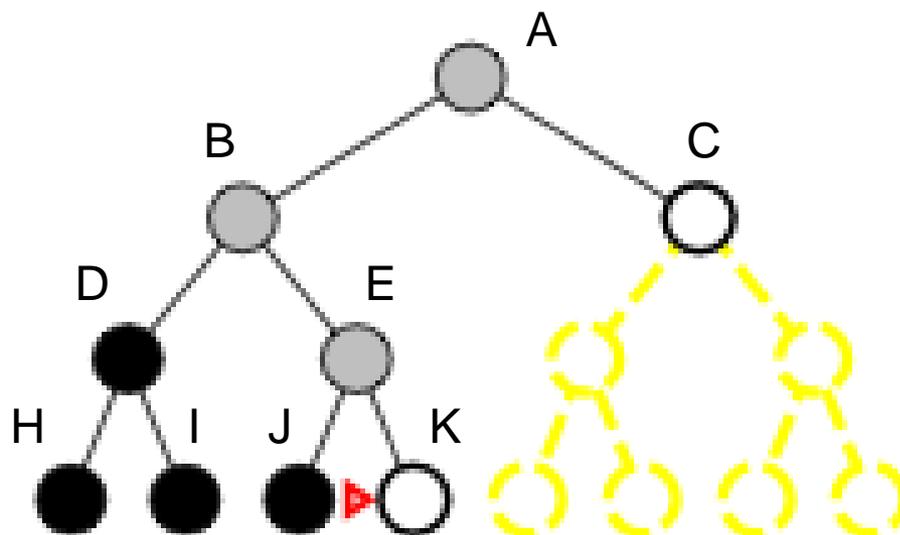
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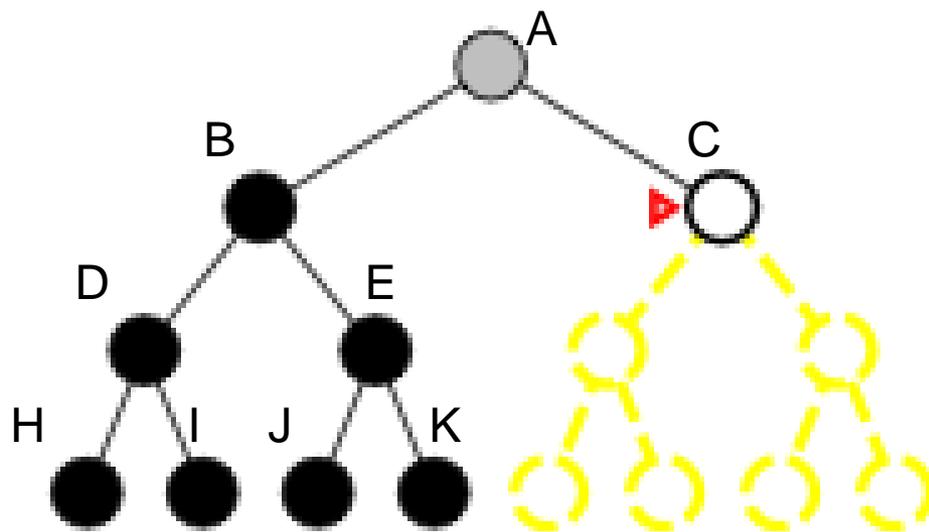
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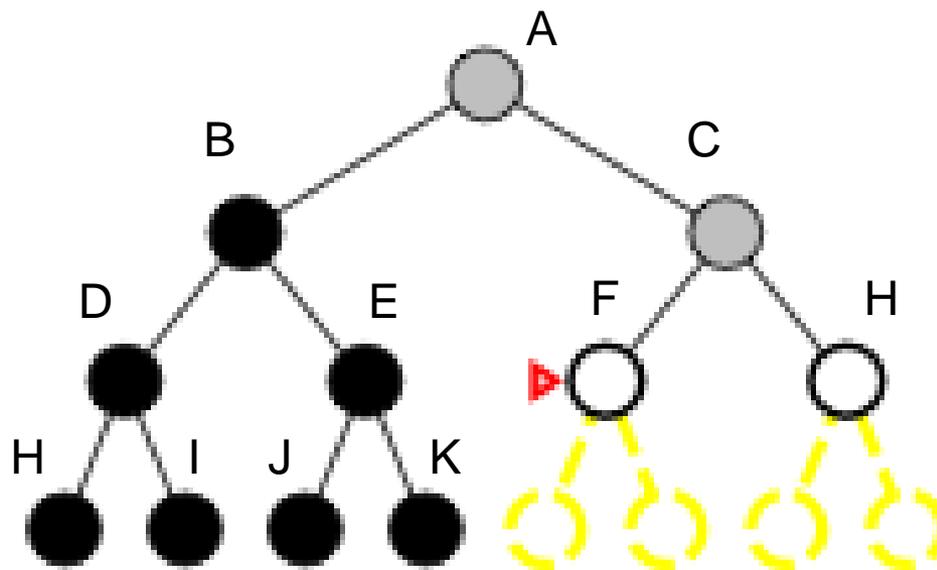
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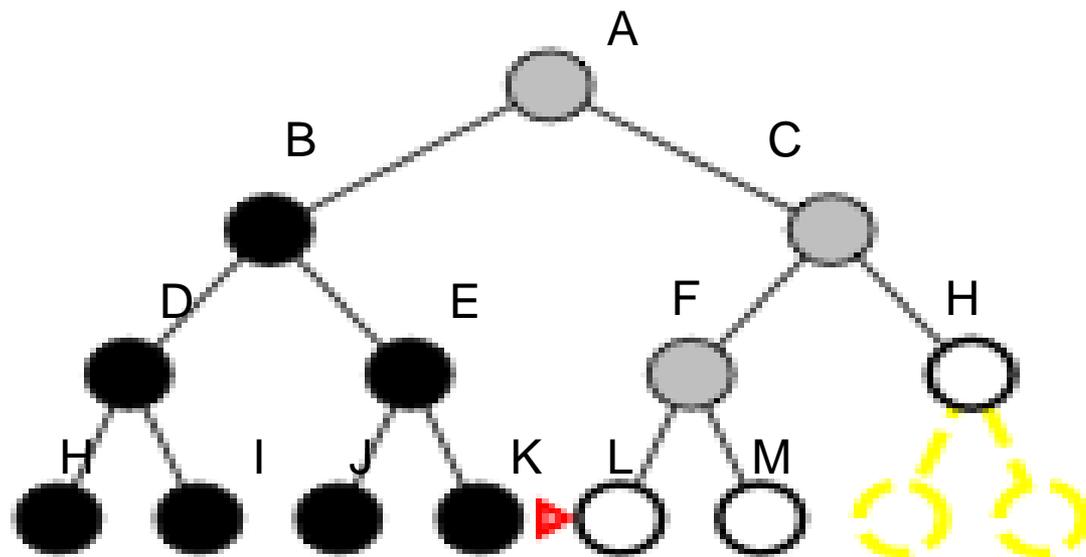
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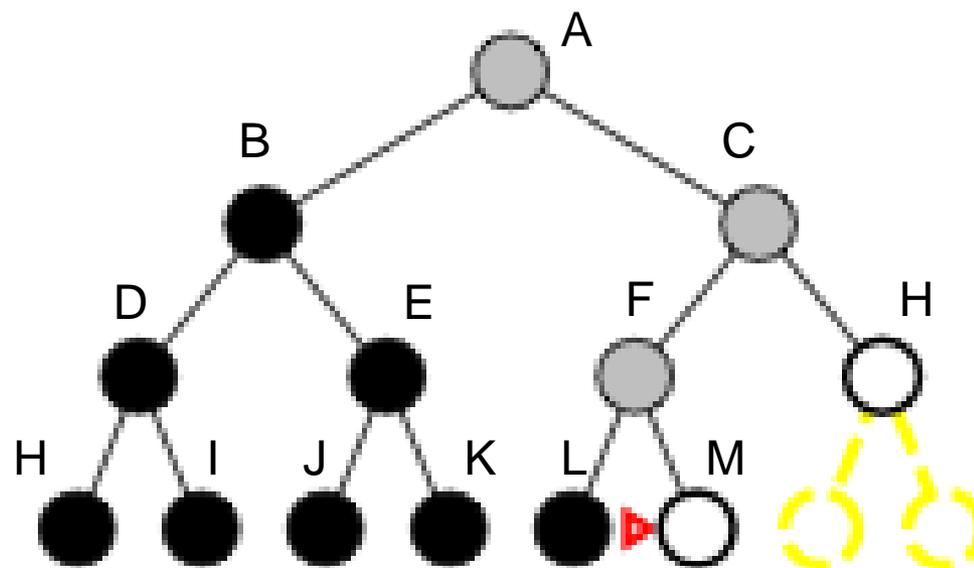
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# DF-search; evaluation

- ▶ Completeness;

- *Does it always find a solution if one exists?*

- NO

- *unless* search space is finite and no loops are possible.

# DF-search; evaluation

- ▶ Completeness;
  - NO unless search space is finite.
- ▶ Time complexity;
  - Terrible if  $m$  is much larger than  $d$  (depth of optimal solution)  $O(b^m)$
  - But if many solutions, then faster than BF-search

# DF-search; evaluation

- ▶ Completeness;
  - NO unless search space is finite.
- ▶ Time complexity;  $O(b^m)$
- ▶ Space complexity;  $O(bm + 1)$ 
  - Backtracking search uses even less memory
    - One successor instead of all  $b$ .

# DF-search; evaluation

- ▶ Completeness;
  - NO unless search space is finite.
- ▶ Time complexity;  $O(b^m)$
- ▶ Space complexity;  $O(bm + 1)$
- ▶ Optimality; No
  - Same issues as completeness
  - Assume node J and C contain goal states

# Depth-limited search

- ▶ Is DF-search with depth limit  $l$ .
  - i.e. nodes at depth  $l$  have no successors.
  - Problem knowledge can be used
- ▶ Solves the infinite-path problem.
- ▶ If  $l < d$  then incompleteness results.
- ▶ If  $l > d$  then not optimal.
- ▶ Time complexity:  $O(b^l)$
- ▶ Space complexity:  $O(bl)$

# Depth-limited algorithm

```
function DEPTH-LIMITED-SEARCH(problem, limit) return a solution or  
failure/cutoff  
return RECURSIVE-DLS(MAKE-NODE(INITIAL-STATE[problem]), problem, limit)
```

```
function RECURSIVE-DLS(node, problem, limit) return a solution or  
failure/cutoff  
cutoff_occurred? ← false  
if GOAL-TEST[problem](STATE[node]) then return SOLUTION(node)  
else if DEPTH[node] == limit then return cutoff  
else for each successor in EXPAND(node, problem) do  
    result ← RECURSIVE-DLS(successor, problem, limit)  
    if result == cutoff then cutoff_occurred? ← true  
    else if result ≠ failure then return result  
if cutoff_occurred? then return cutoff else return failure
```

# Iterative deepening search

- ▶ What?
  - A general strategy to find best depth limit  $l$ .
    - Goals is found at depth  $d$ , the depth of the shallowest goal-node.
  - Often used in combination with DF-search
- ▶ Combines benefits of DF- en BF-search

# Iterative deepening search

**function** ITERATIVE\_DEEPENING\_SEARCH(*problem*) **return** a solution or failure

**inputs:** *problem*

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

*result*  $\leftarrow$  DEPTH-LIMITED\_SEARCH(*problem*, *depth*)

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

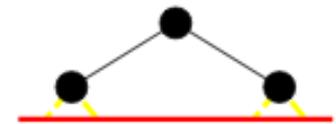
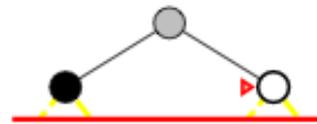
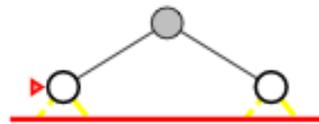
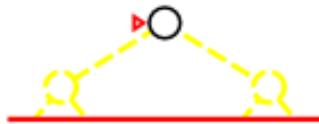
# ID-search, example

- ▶ Limit=0



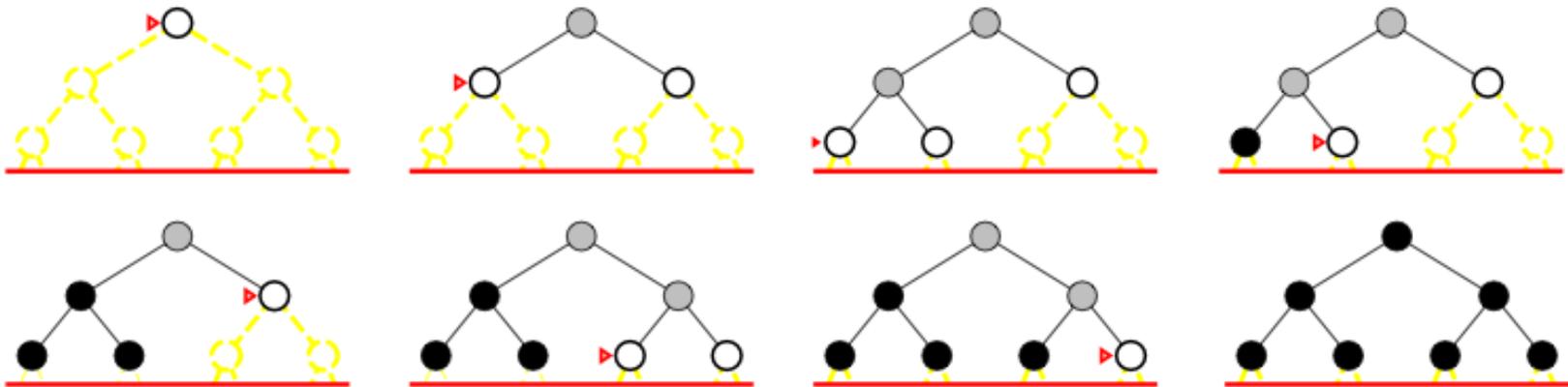
# ID-search, example

- ▶ Limit=1



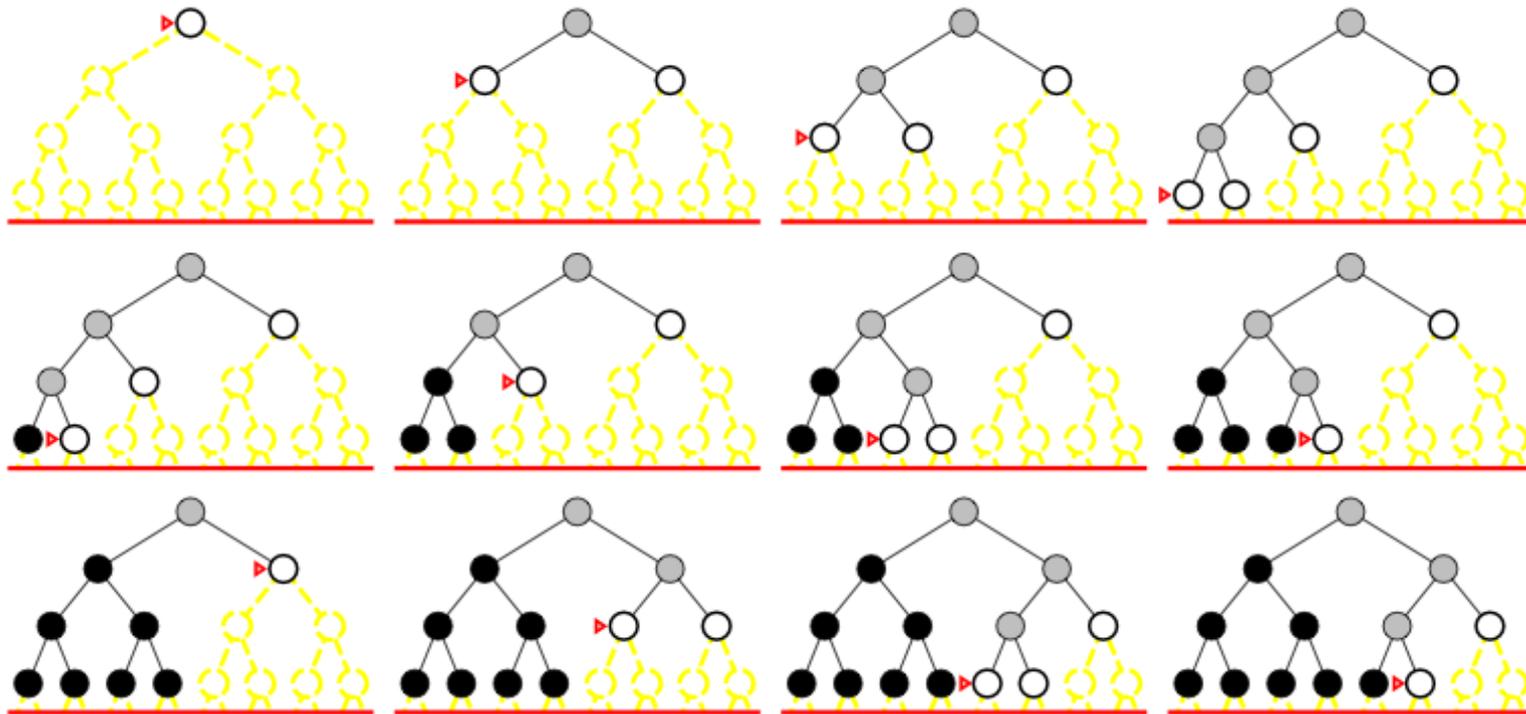
# ID-search, example

- ▶ Limit=2



# ID-search, example

▶ Limit=3



# ID search, evaluation

- ▶ Completeness:
  - YES (no infinite paths)

# ID search, evaluation

- ▶ **Completeness:**

- YES (no infinite paths)

- ▶ **Time complexity:**

- Algorithm seems costly due to repeated generation of certain states.

- Node generation:

- level d: once
- level d-1: 2
- level d-2: 3
- ...
- level 2: d-1
- level 1: d

$$O(b^d)$$

$$N(IDS) = (d)b + (d-1)b^2 + \dots + (1)b^d$$

$$N(BFS) = b + b^2 + \dots + b^d + (b^{d+1} - b)$$

Num. Comparison for b=10 and d=5 solution at far right

$$N(IDS) = 50 + 400 + 3000 + 20000 + 100000 = 123450$$

$$N(BFS) = 10 + 100 + 1000 + 10000 + 100000 + 999990 = 1111100$$

# ID search, evaluation

- ▶ **Completeness:**
  - YES (no infinite paths)
- ▶ **Time complexity:**  $O(b^d)$
- ▶ **Space complexity:**  $O(bd)$ 
  - Cfr. depth-first search

# ID search, evaluation

- ▶ **Completeness:**
  - YES (no infinite paths)
- ▶ **Time complexity:**  $O(b^d)$
- ▶ **Space complexity:**  $O(bd)$
- ▶ **Optimality:**
  - YES if step cost is 1.
  - Can be extended to iterative lengthening search
    - Same idea as uniform-cost search
    - Increases overhead.

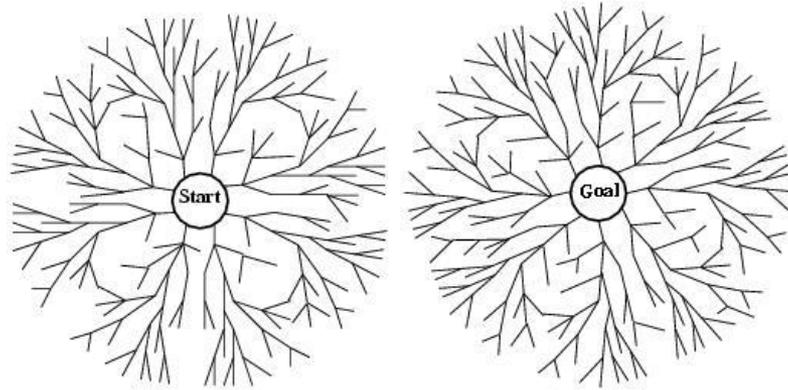
# Summary of algorithms

Criterion	Breadth-First	Uniform-cost	Depth-First	Depth-limited	Iterative deepening	Bidirectional search
Complete?	YES*	YES*	NO	YES, if $l \geq d$	YES	YES*
Time	$b^{d+1}$	$b^{C*/e}$	$b^m$	$b^l$	$b^d$	$b^{d/2}$
Space	$b^{d+1}$	$b^{C*/e}$	$bm$	$bl$	$bd$	$b^{d/2}$
Optimal?	YES*	YES*	NO	NO	YES	YES

# Summary

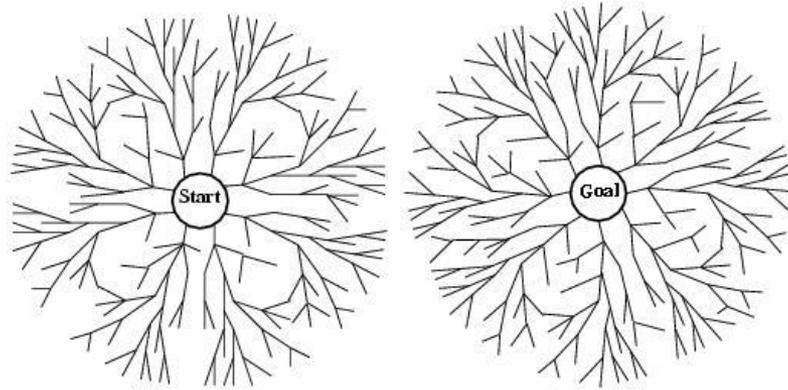
- ▶ The symbols&search paradigm in AI
- ▶ Uninformed search
  - Space complexity: OK!
  - Time complexity: exp. → the knowledge paradigm in AI
- ▶ Suggested reading
  - Newel&Simon: Computer science as empirical inquiry: symbols and search, 1975
  - Cognitive architectures: ACT-R
    - <http://act-r.psy.cmu.edu/>
    - <http://act-r.psy.cmu.edu/about/>
    - Allen Newell describes cognitive architectures as the way to answer one of the ultimate scientific questions: "How can the human mind occur in the physical universe?"
      - <http://act-r.psy.cmu.edu/misc/newellclip.mpg>

# Bidirectional search



- ▶ Two simultaneous searches from start and goal.
  - Motivation:  $b^{d/2} + b^{d/2} \neq b^d$
- ▶ Check whether the node belongs to the other fringe before expansion.
- ▶ Space complexity is the most significant weakness.
- ▶ Complete and optimal if both searches are BF.

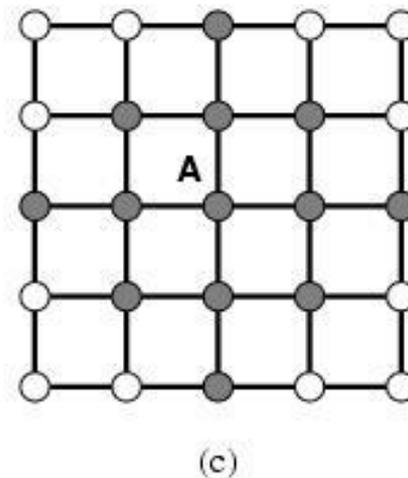
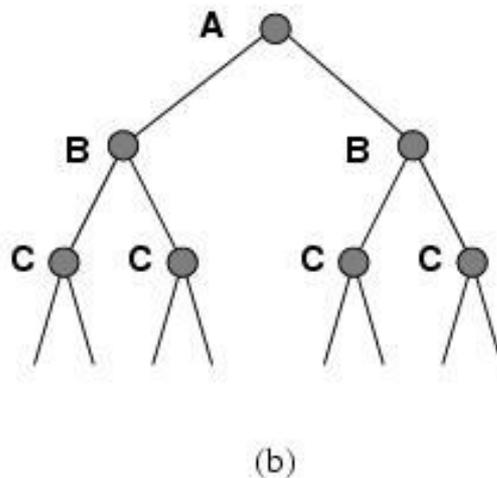
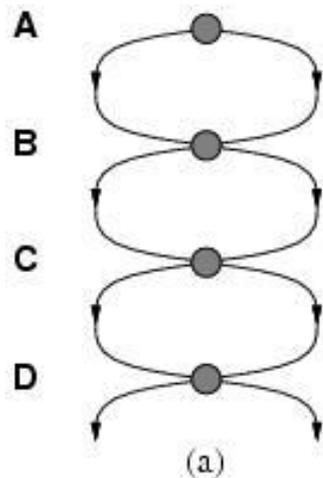
# How to search backwards?



- ▶ The predecessor of each node should be efficiently computable.
  - When actions are easily reversible.

# Repeated states

- ▶ Failure to detect repeated states can turn a solvable problems into unsolvable ones.



# Graph search algorithm

- ▶ Closed list stores all expanded nodes

```
function GRAPH-SEARCH(problem, fringe) return a solution or failure
  closed ← an empty set
  fringe ← INSERT(MAKE-NODE(INITIAL-STATE[problem]), fringe)
  loop do
    if EMPTY?(fringe) then return failure
    node ← REMOVE-FIRST(fringe)
    if GOAL-TEST[problem] applied to STATE[node] succeeds
      then return SOLUTION(node)
    if STATE[node] is not in closed then
      add STATE[node] to closed
      fringe ← INSERT-ALL(EXPAND(node, problem), fringe)
```

# Graph search, evaluation

- ▶ **Optimality:**
  - GRAPH-SEARCH discard newly discovered paths.
    - This may result in a sub-optimal solution
    - YET: when uniform-cost search or BF-search with constant step cost
- ▶ **Time and space complexity,**
  - proportional to the size of the state space (may be much smaller than  $O(b^d)$ ).
  - DF- and ID-search with closed list no longer has linear space requirements since all nodes are stored in closed list!!

# Search with partial information

- ▶ Previous assumption:
  - Environment is fully observable
  - Environment is deterministic
  - Agent knows the effects of its actions

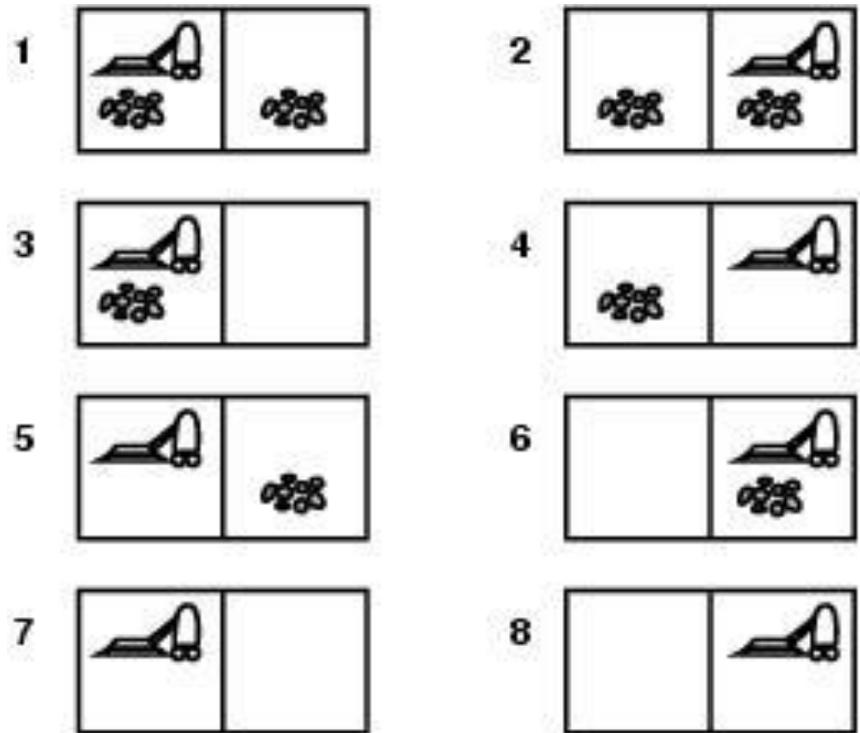
*What if knowledge of states or actions is incomplete?*

# Search with partial information

- ▶ (SLIDE 7) Partial knowledge of states and actions:
  - *sensorless or conformant problem*
    - Agent may have no idea where it is; solution (if any) is a sequence.
  - *contingency problem*
    - Percepts provide *new* information about current state; solution is a tree or policy; often interleave search and execution.
    - If uncertainty is caused by actions of another agent:  
*adversarial problem*
  - *exploration problem*
    - When states and actions of the environment are unknown.

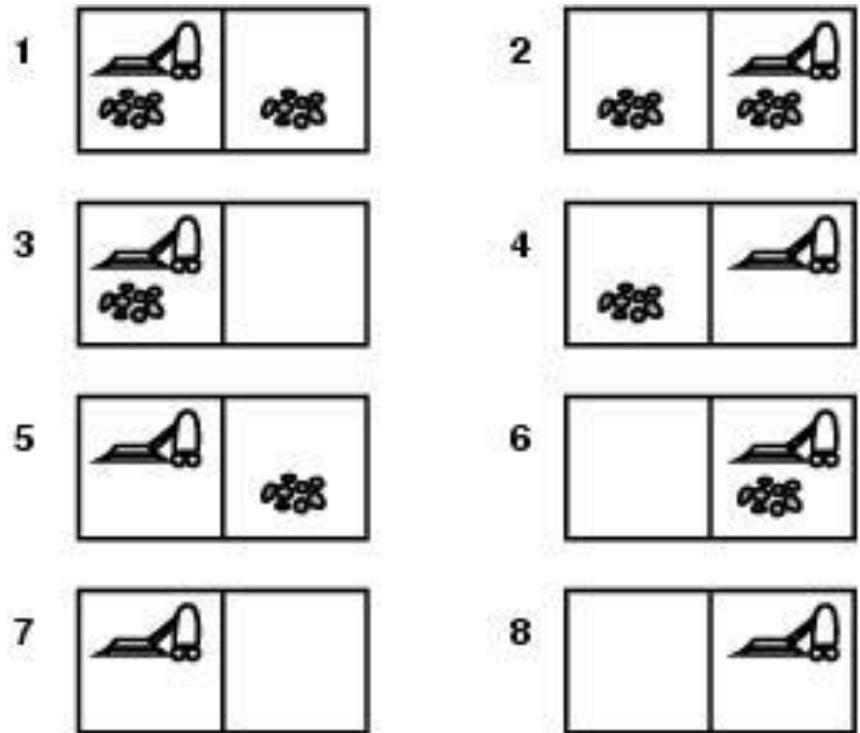
# Conformant problems

- ▶ start in {1,2,3,4,5,6,7,8} e.g. Right goes to {2,4,6,8}.  
Solution??
  - *[Right, Suck, Left, Suck]*
- ▶ *When the world is not fully observable:*  
*reason about a set of states that might be reached*  
=belief state

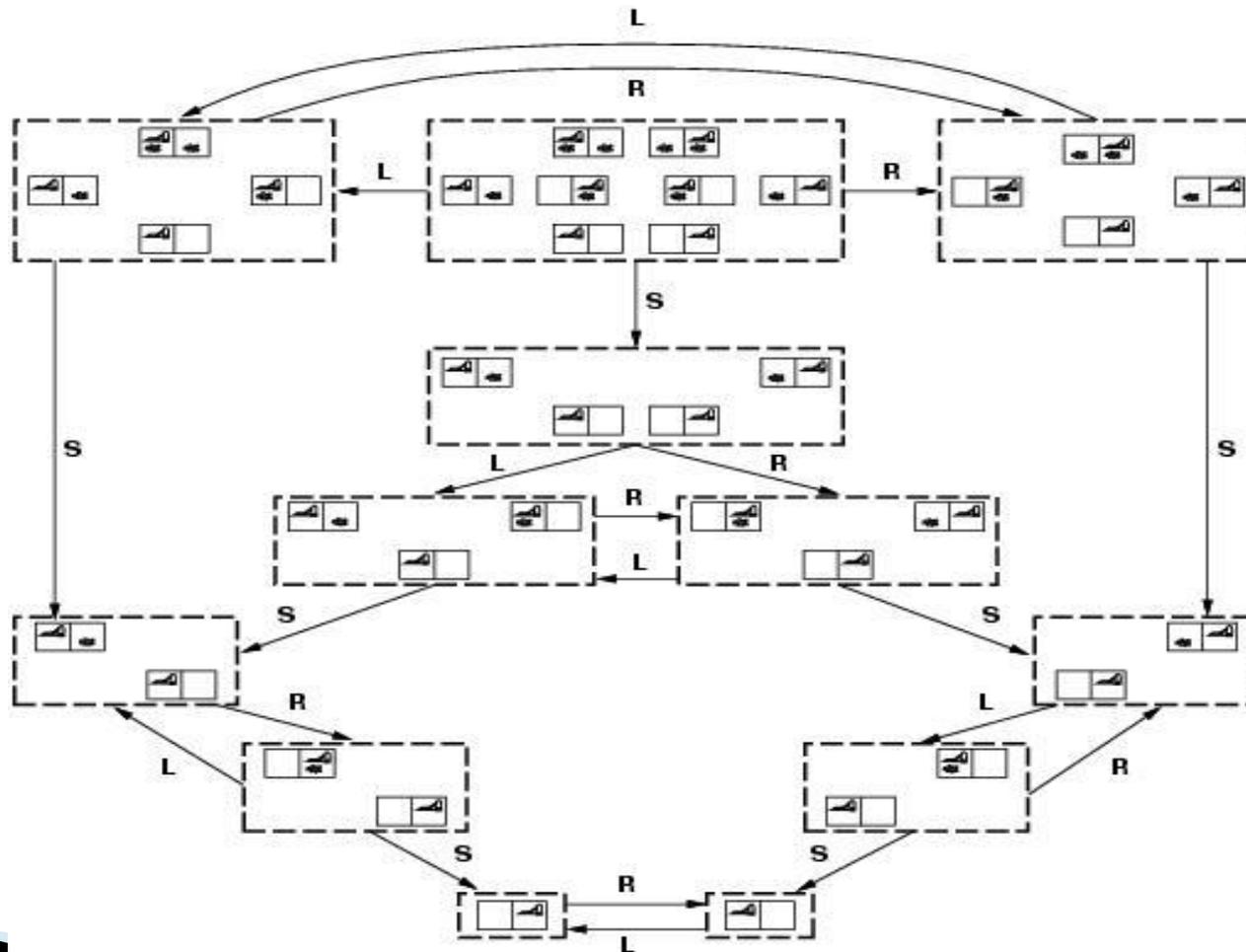


# Conformant problems

- ▶ Search space of belief states
- ▶ Solution = belief state with all members goal states.
- ▶ If  $S$  states then  $2^S$  belief states.
- ▶ Murphy's law:
  - *Suck can dirty a clear square.*

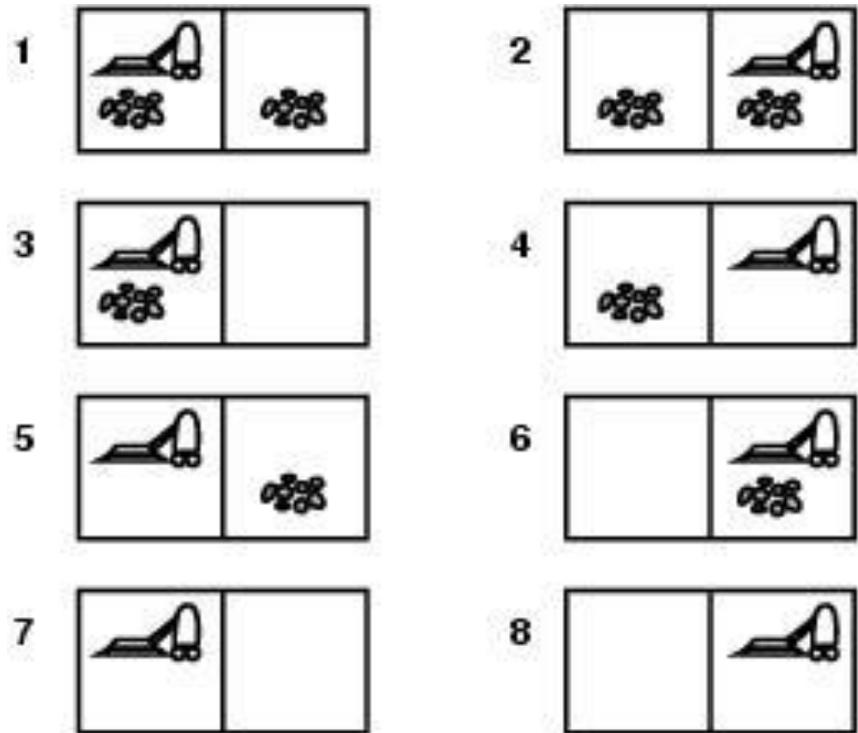


# Belief state of vacuum-world



# Contingency problems

- ▶ Contingency, start in {1,3}.
- ▶ Murphy's law, Suck *can* dirty a clean carpet.
- ▶ Local sensing: dirt, location only.
  - Percept = [L,Dirty] = {1,3}
  - [Suck] = {5,7}
  - [Right] = {6,8}
  - [Suck] in {6}={8} (Success)
  - BUT [Suck] in {8} = failure
- ▶ Solution??
  - Belief-state: no fixed action sequence guarantees solution
- ▶ Relax requirement:
  - [Suck, Right, if [R,dirty] then Suck]
  - Select actions based on contingencies arising during execution.



# Summary

- ▶ The symbols&search paradigm in AI
- ▶ Uninformed search
  - Space complexity: OK!
  - Time complexity: exp. → the knowledge paradigm in AI
- ▶ Suggested reading
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