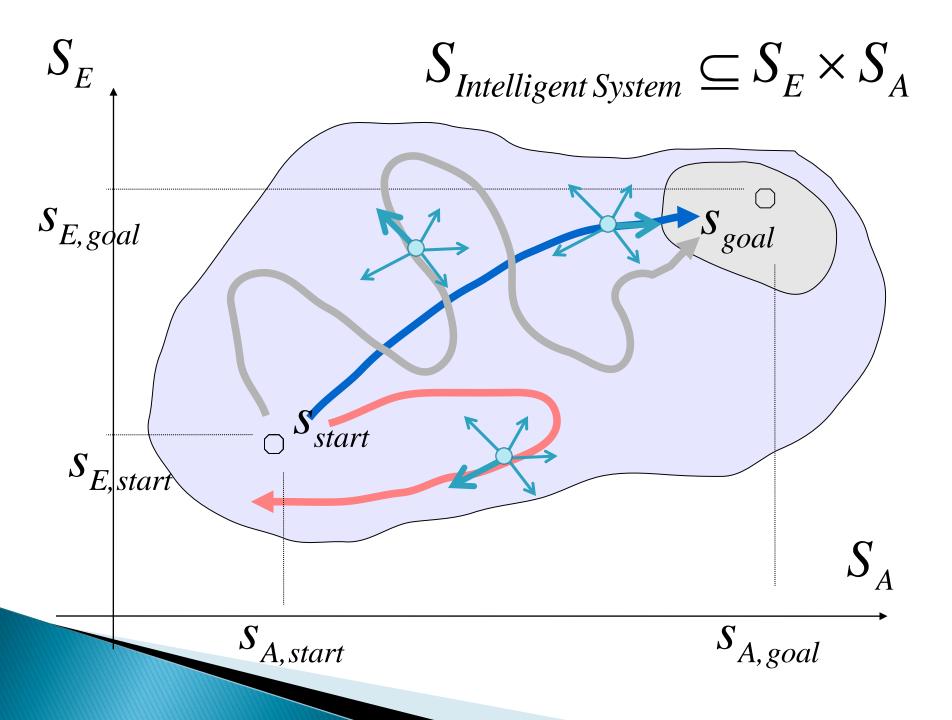
# Artificial Intelligence Uninformed search

More about Textbook, Chapter 3, Soving Problems by Searching

# Outline

- Problem-solving (goal-oriented) agents
- Solving
  - Single state (fully observable)
  - Multiple state (search with partial information)
     Problem Types
- How to define a problem?
  - Example problems
- What algorithm can solve it actually?
   Uninformed search algorithms



### Al as "symbol manipulation" - expressing the goal and its direction

- The Logic Theorist, 1955  $\rightarrow$  see lectures on logic
- The Dartmouth conference ("birth of AI", 1956)
- List processing (Information Processing Language, IPL)
- Means-ends analysis ("reasoning as search") → see lecture on planning
- The General Problem Solver
- Heuristics to limit the search space  $\rightarrow$  see lecture on informed search
- The Physical Symbol System Hypothesis
  - intelligent behavior can be reduced to/emulated by symbol manipulation (A. Newel, H. Simon: Computer science as empirical inquiry: symbols and search, 1975)
- The unified theory of cognition (1990, cognitive architectures)

➔ expressing (human) problem solving symbolically

Al as "symbol manipulation" - required? enough?

The Box and Banana problem
Human, monkey, pigeon, crow, ...







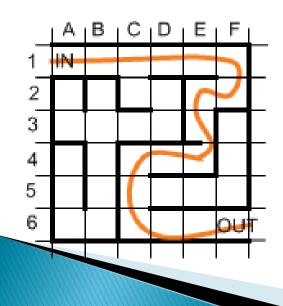
# Problem-solving agent

- Four general steps in problem solving:
  - (1) Goal formulation
    - What are the demanded, successful world states (state-space of the problem)
  - (2) Problem formulation
    - What actions and states are possible/legal to consider, given the goal
  - (3) Problem solving with search
    - Determine the possible sequence of actions that lead to the states of known values and then choose the best sequence.
  - (4) Executing the solution
    - Given the solution, perform its prescribed actions.



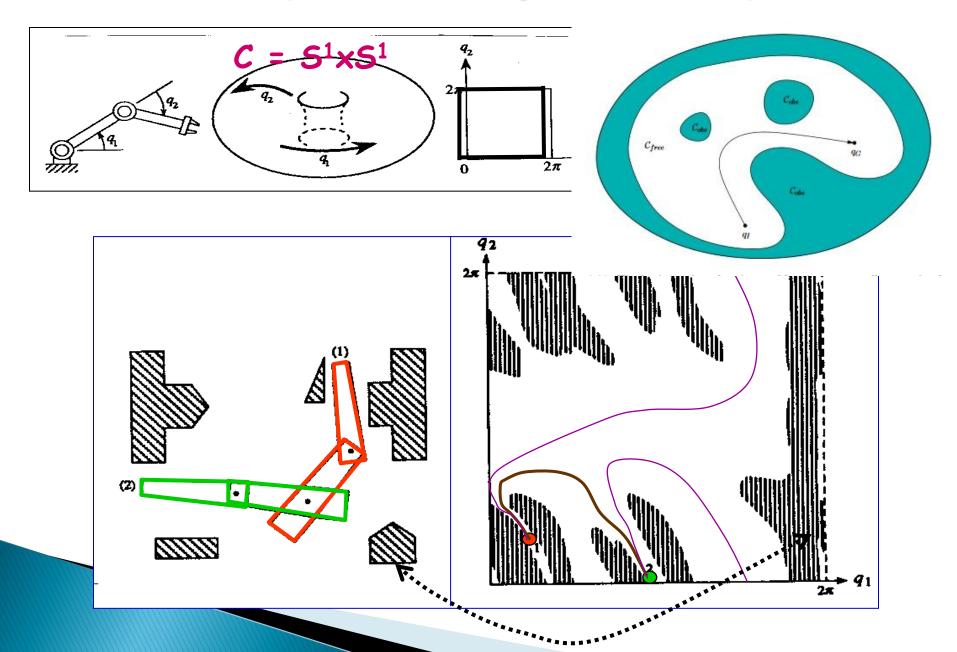
### Physical State-Spaces

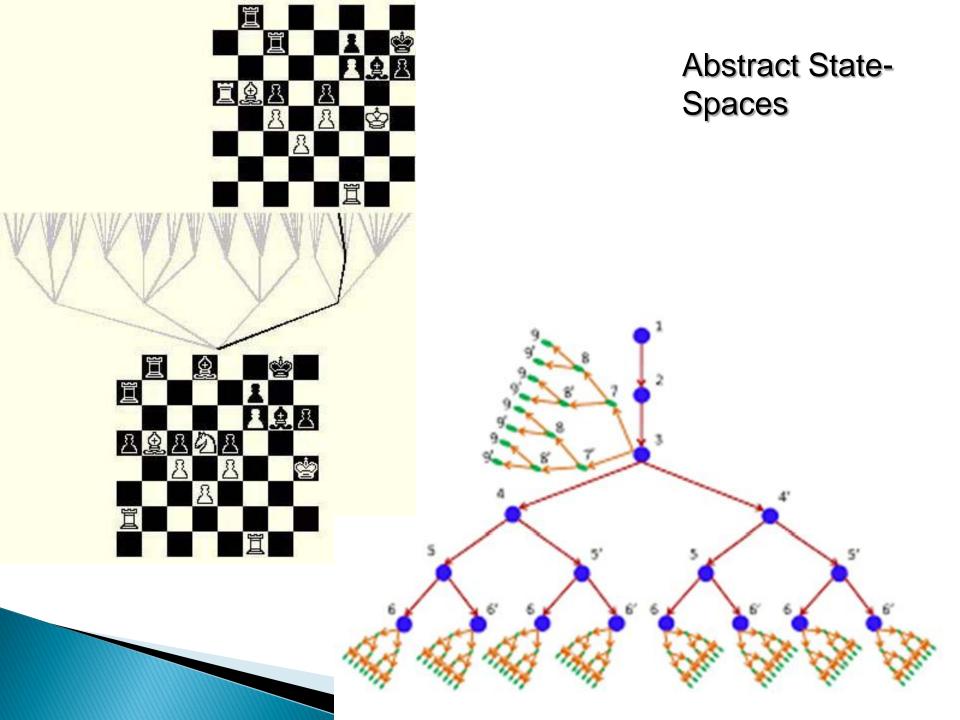






#### Reduce robot to a point $\rightarrow$ Configuration State-Spaces



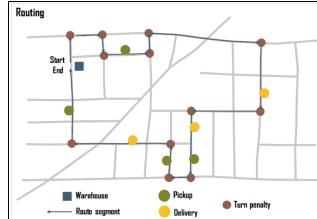


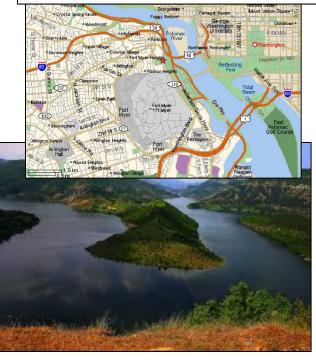
# Example: Romania

- On holidays in Romania; currently in town of Arad
   Flight leaves home tomorrow from Bucharest
- Formulating the goal
  - Be in (time at the airport in) Bucharest
- Formulating the problem
  - States: various cities (closer or further from the goal!)
  - Actions: driving from a city to a city
- Finding <u>solution</u>
  - Sequence of cities; e.g. Arad, Sibiu, Fagaras, ..., Bucharest (ending in the goal!)
- Executing the solution

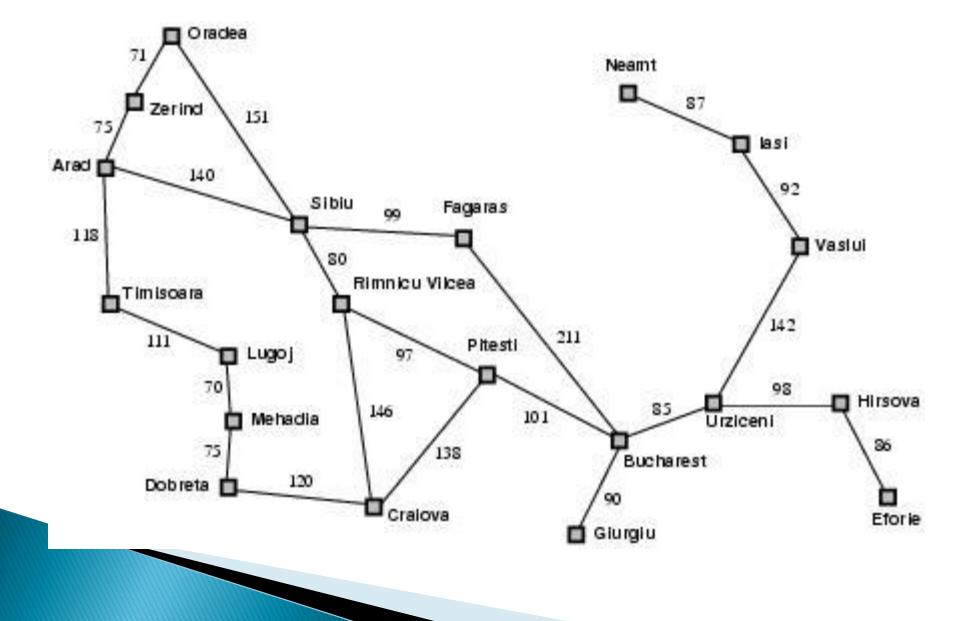
# Selecting a state space

- Real world is 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 action is a complex set of possible routes, detours, rest stops, etc.
  - The abstraction is valid if the path between two states is passable in the real world.
- (Abstract) solution = set of real paths that are real solutions in the real world.
  - Abstract problem should be "easier" than the real problem.





# Example: (an abstract) Romania



# **Problem formulation**

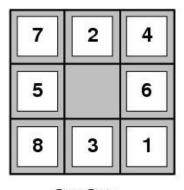
- A problem is defined by:
  - (1) An initial state, e.g. 'at Arad'
  - (2) Successor function (an operator to move in state-space)
     S(X)= set of action-state pairs
    - e.g.  $S(Arad) = \{ < Arad \rightarrow Zerind, Zerind >, ... \}$

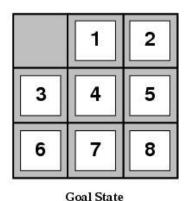
intial state + successor function = state space as a graph

- (3) Goal test, here can be:
  - x='at Bucharest'
- (4) Path cost (additive)
  - e.g. sum of distances, number of actions executed, ...
  - c(x,a,y) is the step cost (petrol?!), assumed to be >= 0

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

# Examples: 8-puzzle





- States
  - The location of the eight tiles, and the blank.
- Initial state
  - $\circ$  {(7.0),(2,1),(4,2), ..., (8,6),(3,7),(1,8)}
- Actions (operators)
  - 4 actions (blank moves Left, Right, Up, Down)
- Goal test
  - Is a given state a goal state =  $\{(\_,0),(1,1),...,(7,7),(8,8)\}$ ?
- Path cost
  - Each step costs 1



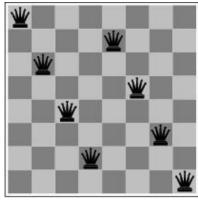
# Examples: 8-queens problem

### States

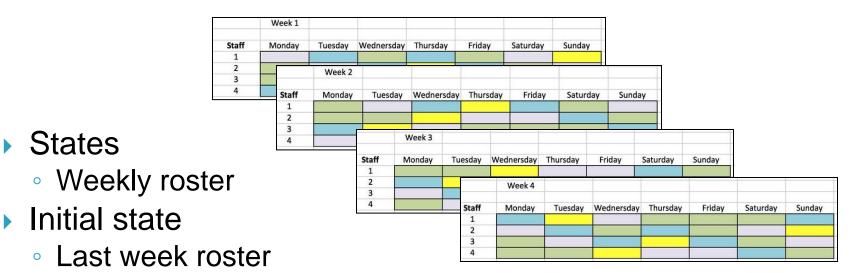
- Complete-state: Any arrangement of all 8 queens
- Incr/1-state: Any arrangement of 0 to 8 queens
- Incr/2-state: n (0≤ n≤ 8) queens on the board, one per column in the n leftmost columns with no queen attacking another.
- Initial state
  - Complete-state: Any arrangement of all 8 queens on the board
  - Incr/1, Incr/2: no queens on board
- Actions
  - Complete-state: move a queen to an empty square
  - Incr/1: Add a queen to an empty square
  - Incr/2: Add a queen in the leftmost empty column, not attacking others
  - From 3 x 10<sup>14</sup> to 2057 possible sequences to investigate, depending on problem formulation.
- Goal test

ALL8 queens on board and none attacked

Path cost None



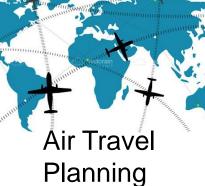
### Examples: Police precinct shift roster



- Action (operator)
  - Moving shifts, moving weekdays, scheduled holidays, participating in special events
- Goal test
  - Captain input
- Path cost
  - Complicated: paid overtime, burden of late shifts, personal incompatibility, paid skipped holidays, ...

# Examples: Route Finding Problems

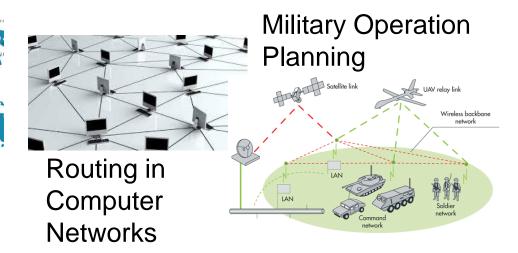




Car Navigation

- States
  - Locations
- Initial state
  - Starting point
- Action (operator)
  - Move from one location to another
- Goal test
  - Arriving at a certain location
  - Path cost

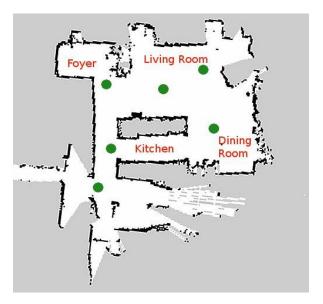
May be quite complex, money, time, travel comfort, scenery, ...



# Examples: Robot Navigation

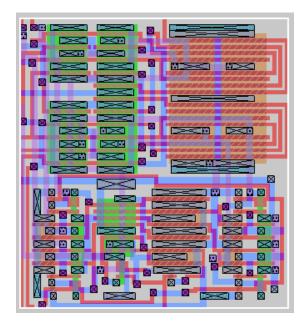
- States
  - Locations, Position of actuators
- Initial state
  - Starting poisition (task?)
- Action (operator)
  - Movement, actions of actuators
- Goal test
  - Task-dependent
- Path cost
  - May be quite complex distance, energy consumption, ...





# Examples: VLSI layout problem

- States
  - Positions of components, wires on chip
- Initial state
  - Incremental: no components placed
  - Complete-state: all components placed (e.g. randomly, manually)
- Action (operator)
  - Incremental: place components, route wire
  - Complete-state: move component, move wire
- Goal test
  - All coponents placed. Components connected as specified
- Path cost
  - May be quite complex, distance, capacity, number of connections per components, ...



# Basic search algorithms

How do we find the solutions of previous problems?

- Traversal of the search space (a tree or a graph)
- From the initial state to a goal state
- Legal sequence of actions as defined by successor function

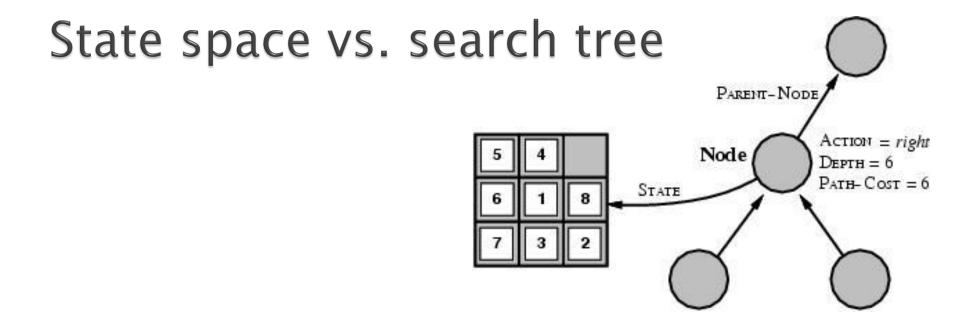
General procedure

- Check for goal state
- Expand the current state
- Determine the set of reachable states
- Return "failure" if the set is empty
- Select one from the set of reachable states
- Move to the selected state

A search tree is generated

Nodes are added as more states are visited

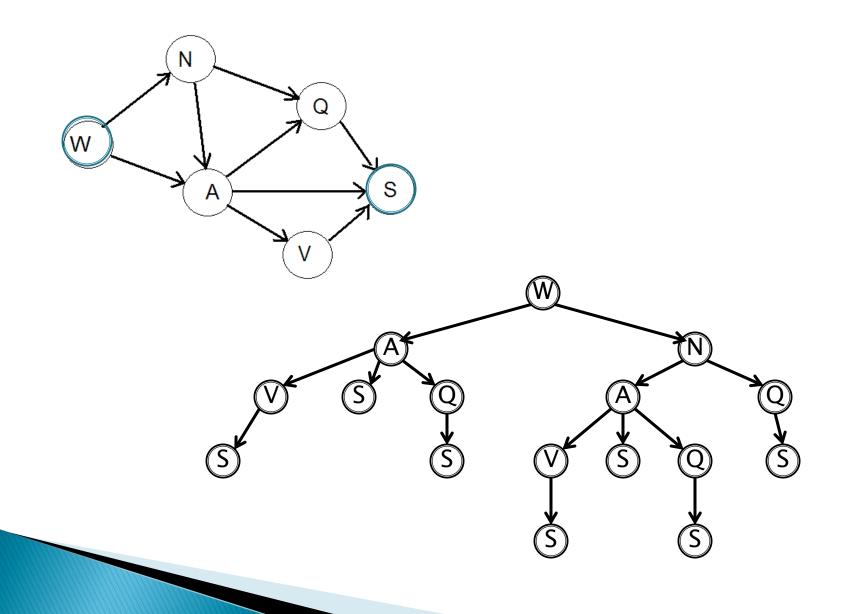
The tree specifies possible paths through the search space



A state is a (representation of) a physical configuration

- A node is a data structure belonging to a search tree
  - A node has a *parent*, *children*, ... and includes *path cost*, *depth*, ...
  - Here node= <state, parent-node, action, path-cost, depth>
    FRINGE= contains generated nodes which are not yet expanded.

### State space vs. search tree



# Tree search algorithm (1)

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)

# Tree search algorithm (2)

function EXPAND(*node,problem*) return a set of nodes

successors  $\leftarrow$  the empty set

for each <action, result> in SUCCESSOR[problem](STATE[node])
do

 $s \leftarrow a \text{ new NODE}$   $STATE[s] \leftarrow result$   $PARENT-NODE[s] \leftarrow node$   $ACTION[s] \leftarrow action$   $PATH-COST[s] \leftarrow PATH-COST[node] + STEP-COST(node, action, s)$   $DEPTH[s] \leftarrow DEPTH[node]+1$ add s to successors **return** successors

Graph-search – handling repeated states and loops, later ...

# 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 measure problem difficulty and are 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  $\infty$ )

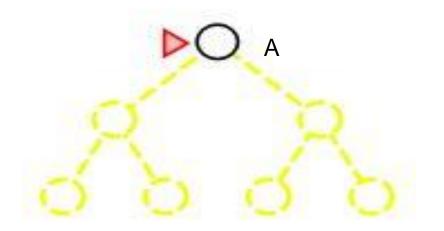
# Uninformed search strategies

- (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  $\rightarrow$  informed search.

We do not have this information here!

- Search methods defined by node expansion algorithm:
  - Breadth-first (BF) search
  - Uniform-cost search
  - Depth-first (DF) search
  - Depth-limited search
  - Iterative deepening (ID) search
  - Bidirectional search

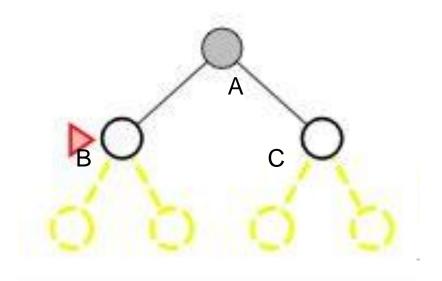
- Expand shallowest unexpanded node
- Implementation: *fringe* is a FIFO queue



o to be expanded yet

- $\bigcirc$  on fringe
- $\bigcirc$  expanded
- deleted from memory

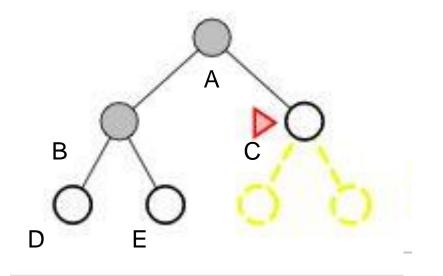
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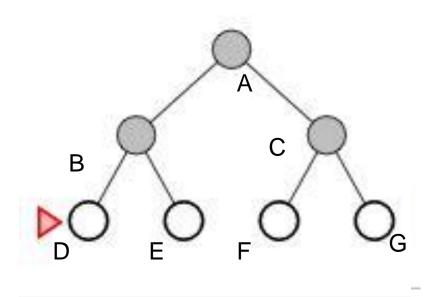
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- Expand shallowest unexpanded node
- Implementation: *fringe* is a FIFO queue



o to be expanded yet

- $\bigcirc$  on fringe
- expanded
- deleted from memory

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

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

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

- Completeness:
  - YES (if *b* is finite)
- Time complexity:
  - Total number of nodes generated:
- Space complexity:
  - Idem, because each node is retained in the memory

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

- Completeness:
  - YES (if *b* is finite)
- Time complexity:
  - Total number of nodes generated:

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

- Space complexity:
  - Idem, because each node is retained in the memory
- Optimality:
  - Does it always find the least-cost solution?
  - In general YES
    - unless actions have different cost.

- Two lessons:
  - Maintaining large memory is a bigger problem than the execution time.
  - Exponential complexity search problems cannot be solved by uninformed search methods for any but the smallest instances.



*b* = 10 **branching factor** (Chess app. 35 !)

1000 decision / sec  $\simeq$  1kflop

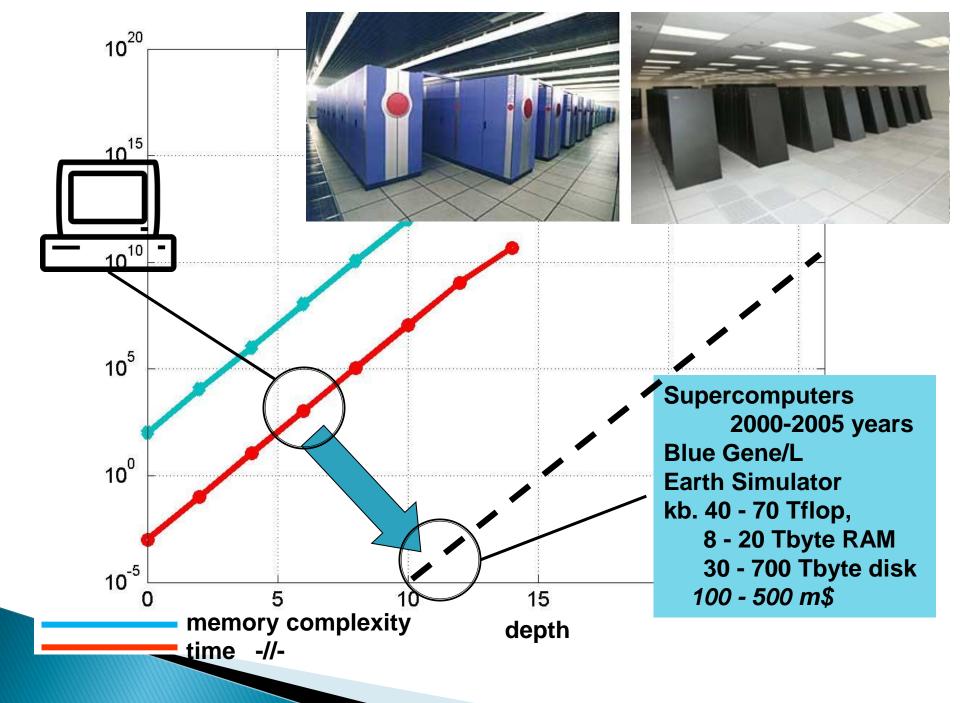
1 decision information: 100 byte

1 byte  $\cong$  1 letter

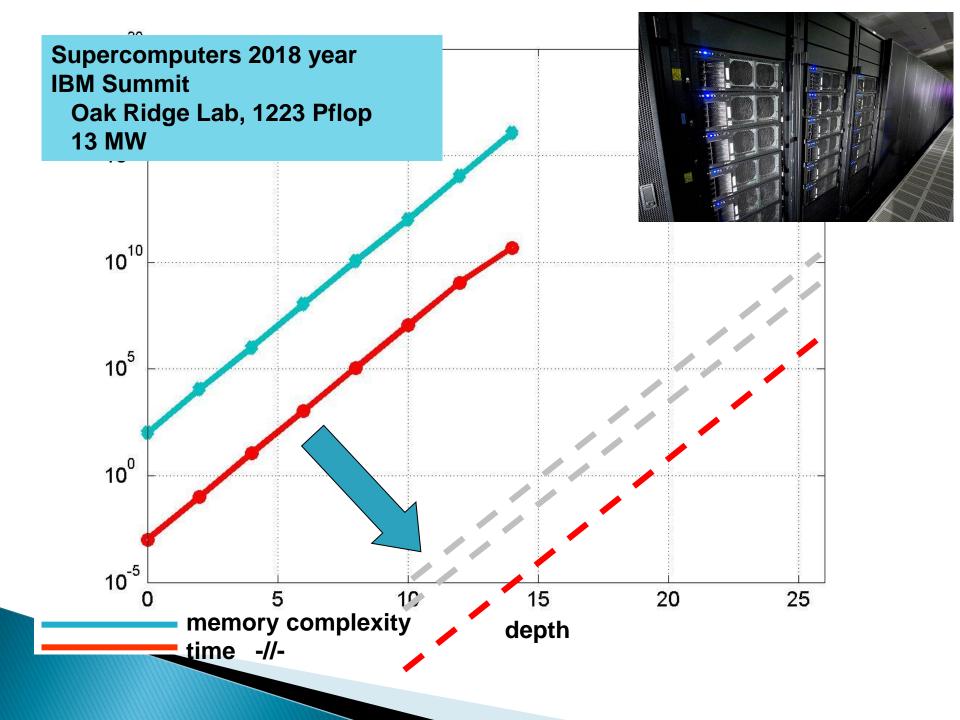
Depth	Decisions	Time Demand	Memory Demand
0	1	0.001 sec	100 byte
2	111	0.1 sec	11 kbyte
4	11111	11 sec	1 Mbyte
6	10 <sup>6</sup>	18 minutes	111 Mbyte
8	10 <sup>8</sup>	31 hours	11 Gbyte (PC)
10	10 <sup>10</sup>	128 days	1 Tbyte
12	10 <sup>12</sup>	35 years	111 Tbyte
14	10 <sup>14</sup>	1500 years	11111 Tbyte

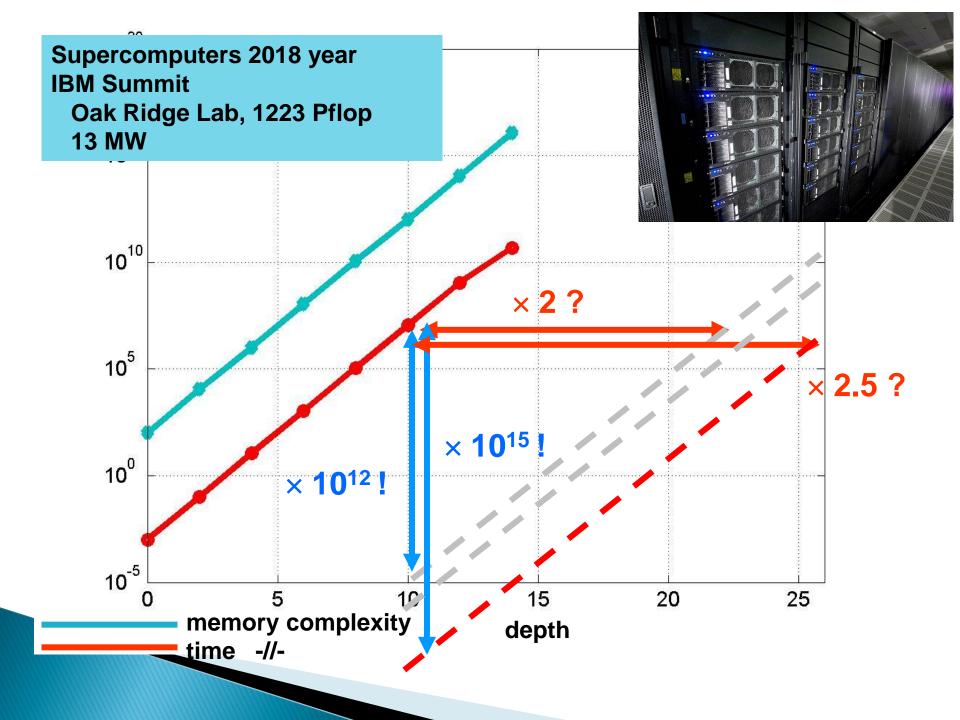
 $k = 10^3$ , M = 10<sup>6</sup>, G = 10<sup>9</sup>, T = 10<sup>12</sup>, P = 10<sup>15</sup>

11111 Tbyte  $\cong$  3 milliard human libraries



Supercomputers 2007-2008 years **IBM Blue Gene/L, upgrade** Lawrence Livermore Nat Lab, 478 Tflop **IBM Roadrunner, Los Alamos Nat Lab** 1.026 Pflop 10<sup>10</sup>1 10<sup>5</sup> 10<sup>0</sup> 10<sup>-5</sup> 5 10 15 20 25 memory complexity depth time -//-





# 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.

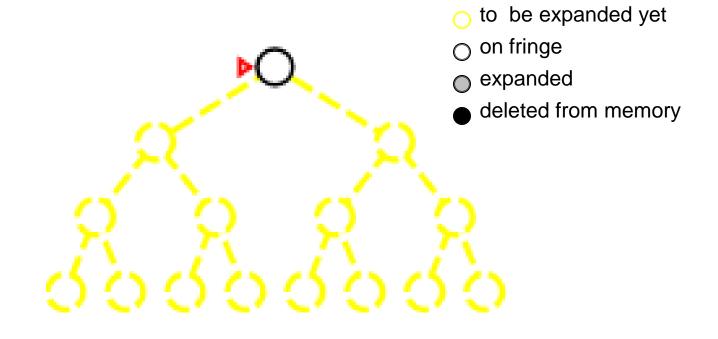
# Uniform-cost search

- Completeness:
  - YES, if step-cost >  $\epsilon$  (smal positive constant)
- Time complexity:
  - Assume C\* the cost of the optimal solution.
  - $\circ$  Assume that every action costs at least  $\epsilon$
  - Worst-case:

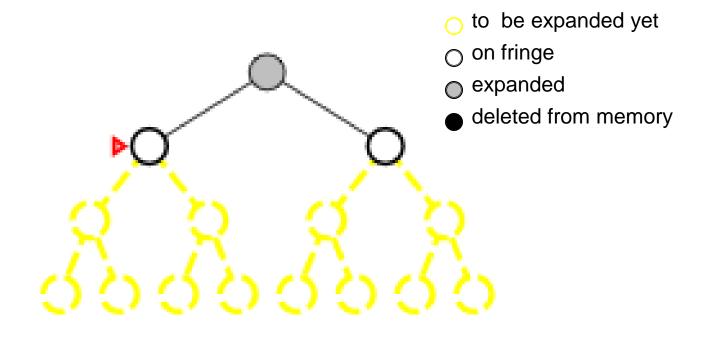
$$O(b^{C^{*/\varepsilon}})$$

- Space complexity:
  - Idem to time complexity
- Optimality:
  - nodes expanded in order of increasing path cost.
  - YES, if complete.

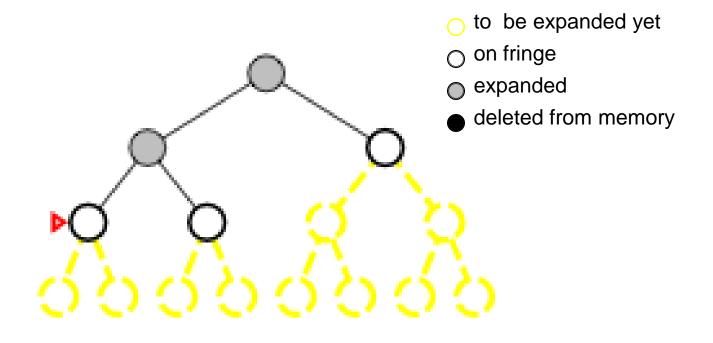
- Expand deepest unexpanded node
- Implementation: fringe is a LIFO queue (=stack)



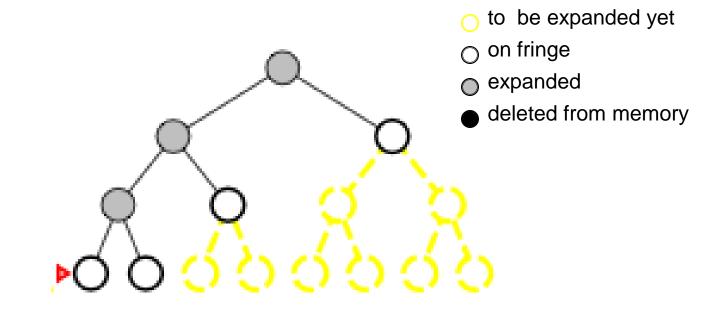
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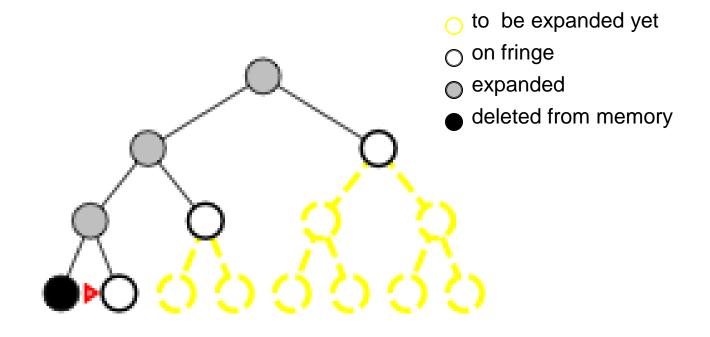
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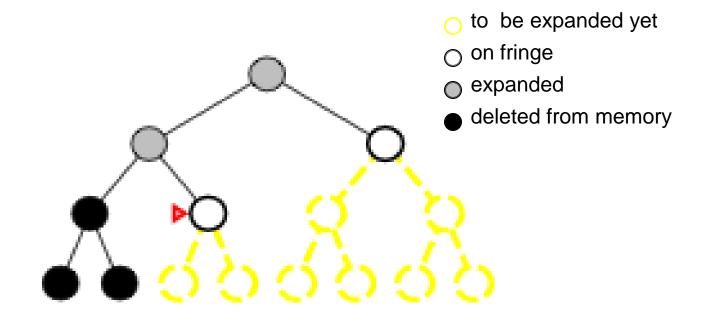
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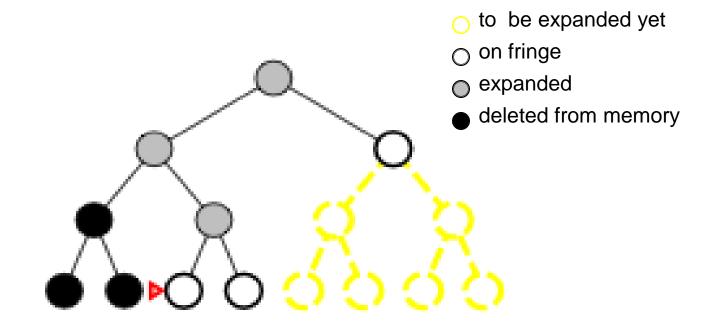
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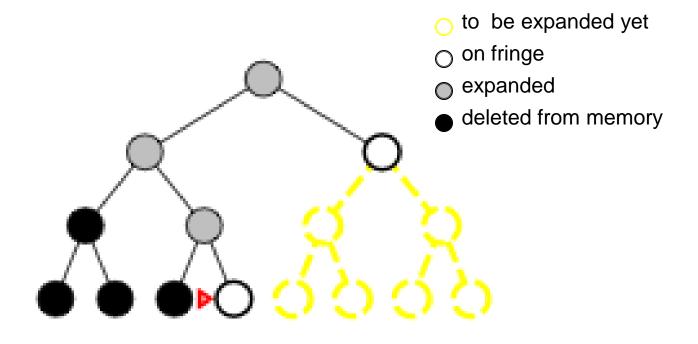
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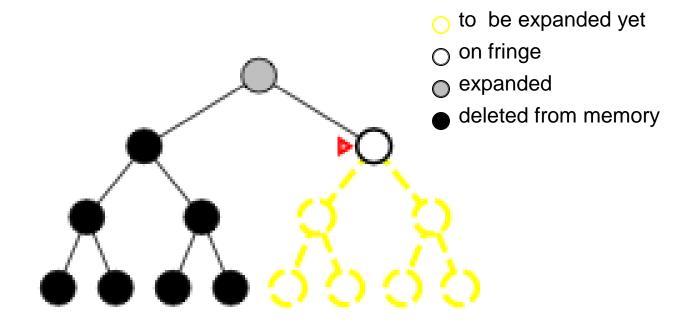
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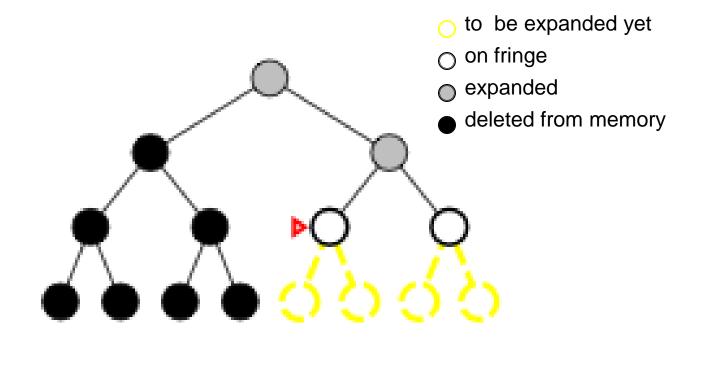
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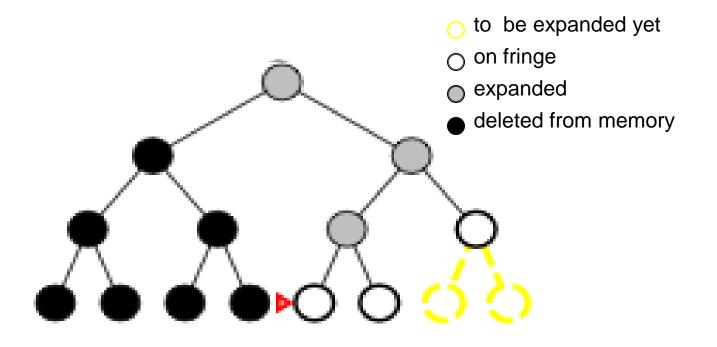
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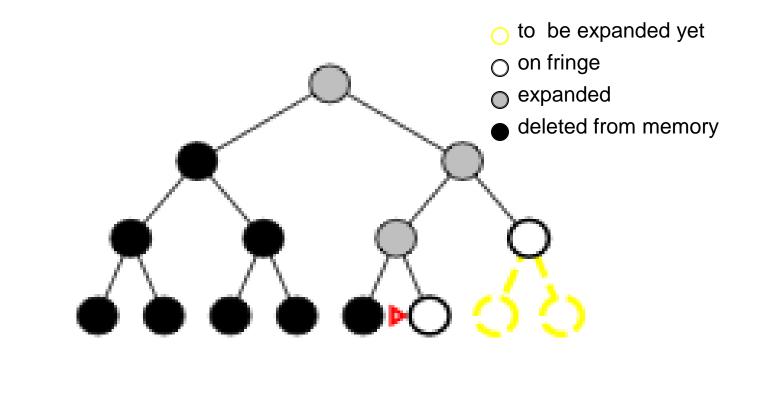
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- Expand deepest unexpanded node
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- Expand deepest unexpanded node
- Implementation: fringe is a LIFO queue (=stack)



- Completeness;
  - Does it always find a solution if one exists?
  - NO
    - unless search space is finite and no loops are possible.

- Completeness;
  - NO unless search space is finite.
- $O(b^m)$

- Time complexity;
  - May be terrible if *m* is much larger than *d* (depth of optimal solution)
  - But if many solutions, then faster than BF-search

- 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*.

- Completeness;
  - NO unless search space is finite.
- Time complexity;  $O(b^m)$
- Space complexity;
- Optimality; No

$$O(bm+1)$$

Same issues as completeness

# Depth-limited search

• DF-search with a depth limit *I*.

- i.e. nodes at depth / are not expaneded for successors.
- Problem knowledge can be used
- Solves the infinite-path problem, but
- If I < 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 it is?
  - A general strategy to find best depth limit *I*.
    - Goal is found at depth d, the depth of the shallowest goal-node.
  - Then use Depth-limited 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 ← 0 to ∞ do
 result ← DEPTH-LIMITED\_SEARCH(problem, depth)
 if result ≠ cuttoff
 then return result

Limit=0

o to be expanded yet

 $\ensuremath{\bigcirc}$  on fringe

 $\bigcirc$  expanded

deleted from memory





Limit=1

O to be expanded yet

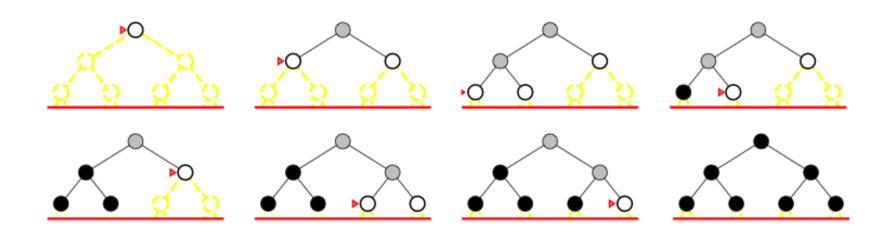
- $\bigcirc$  on fringe
- $\bigcirc$  expanded
- deleted from memory



Limit=2

O to be expanded yet

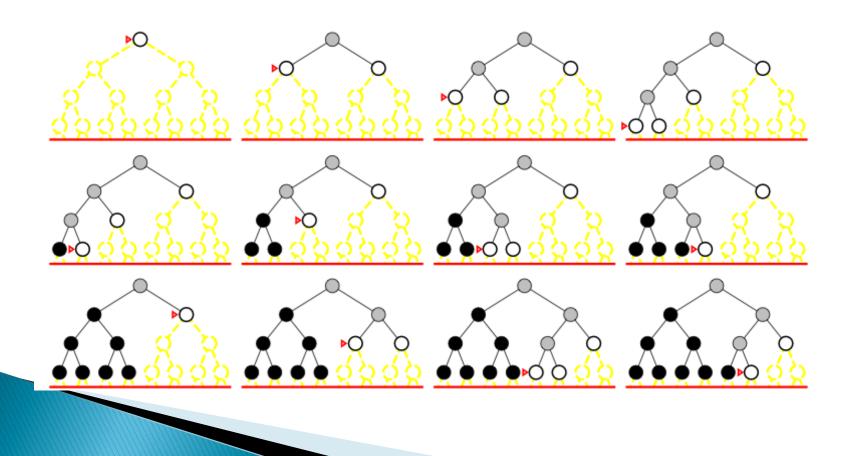
- $\ensuremath{\bigcirc}$  on fringe
- $\bigcirc$  expanded
- deleted from memory



Limit=3

O to be expanded yet

- $\bigcirc$  on fringe
- $\bigcirc$  expanded
- deleted from memory



- Completeness:
  - YES (no infinite paths)

- Completeness:
  - YES (no infinite paths)
- Time complexity:
  - Algorithm seems costly due to repeated generation of certain states.
  - Node generation:  $O(b^d)$ 
    - level d: once
    - level d-1: x 2
    - level d-2: x 3
- $N(IDS) = (d)b + (d-1)b^{2} + \dots + (1)b^{d}$  $N(BFS) = b + b^{2} + \dots + b^{d} + (b^{d+1} b)$
- level 2: x (d-1)
- level 1: x d
- N(IDS) = 50 + 400 + 3000 + 20000 + 100000 = 123450N(BFS) = 10 + 100 + 10000 + 100000 + 9999900= 1111100

Compare for b=10 and d=5 (solution at far right)

- Completeness:
  - YES (no infinite paths)
- Time complexity:
- Space complexity:
  - Cfr. depth-first search O(bd)

 $O(b^d)$ 

- Completeness:
  - YES (no infinite paths)
- Time complexity:
- Space complexity:
- Optimality:
  - YES if step cost is 1.
  - Can be extended to iterative lengthening search

 $O(b^d)$ 

- Same idea as uniform-cost search
- Increases overhead.

O(bd)

# **Bidirectional search**

- Completeness:
  - YES, if at least one direction BF-like
- Time complexity:  $O(b^{d/2})$
- Space complexity:  $O(b^{d/2})$

- Optimality:
  - F ...
  - Complexity of checking for a node in the other search tree
  - Doing search "backwards" from the goal
  - 0 . . .

# Summary of algorithms

Breadth- First	Uniform- cost	Depth-First	Depth- limited	Iterative deepening	Bidirectional search
YES*	YES*	NO	YES,	YES	YES*
			ifl≥d		
$b^{d+1}$	$b^{C^{*/e}}$	$b^m$	$b^l$	$b^d$	<i>b</i> <sup><i>d</i>/2</sup>
$b^{d+1}$	$b^{C^{*/e}}$	bm	bl	bd	$b^{d/2}$
YES*	YES*	NO	NO	YES	YES
	First YES* $b^{d+1}$	FirstcostYES*YES* $b^{d+1}$ $b^{C*/e}$ $b^{d+1}$ $b^{C*/e}$	FirstcostYES*YES*NO $b^{d+1}$ $b^{C*/e}$ $b^m$ $b^{d+1}$ $b^{C*/e}$ $bm$	FirstcostlimitedYES*YES*NOYES, $III \ge d$ III \ge d $b^{d+1}$ $b^{C*/e}$ $b^m$ $b^l$ $b^{d+1}$ $b^{C*/e}$ $bm$ $bl$	FirstcostlimiteddeepeningYES*YES*NOYES,YES $b^{d+1}$ $b^{C^*/e}$ $b^m$ $b^l$ $b^d$ $b^{d+1}$ $b^{C^*/e}$ $bm$ $bl$ $bd$ $b^{d+1}$ $b^{C^*/e}$ $bm$ $bl$ $bd$

# Summary

- The symbols & search paradigm in AI
- Uninformed search
  - Space complexity: OK!
  - Time complexity: exp.  $\rightarrow$  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/
    - <u>http://act-r.psy.cmu.edu/about/</u>
    - 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

