

# Search

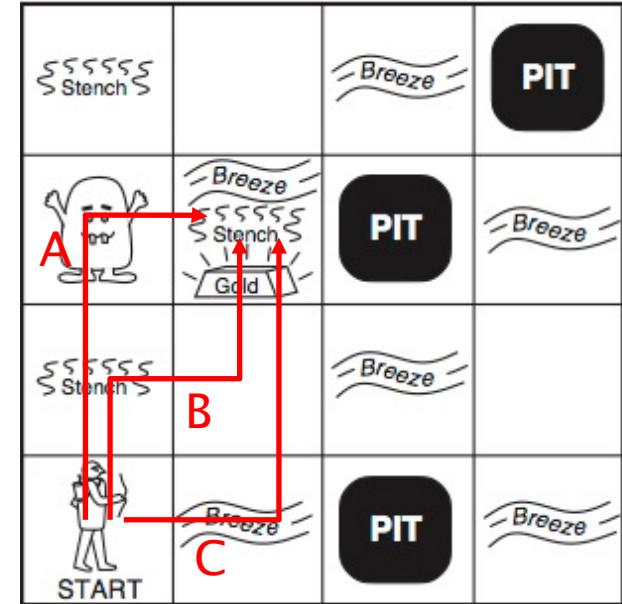
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# Overview

- ▶ Problem-solving agent
- ▶ Formulating problems
- ▶ Search
  - Uninformed search
  - Informed (heuristic) search
  - Heuristics
  - Admissibility

# Problem-Solving Agent

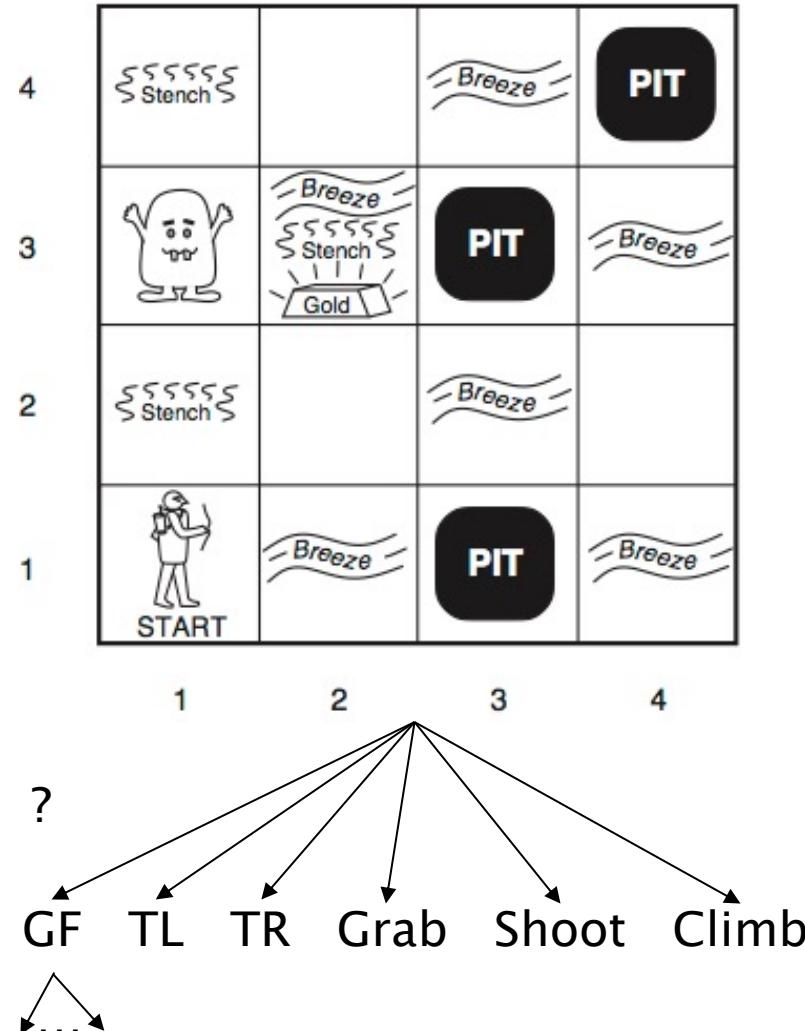
- ▶ Type: Goal-based
- ▶ Feature-based state representation
  - Agent location, orientation, ...
- ▶ Assume solution is a fixed sequence of actions
- ▶ Rationality: Achieve goal (minimize cost)
- ▶ Search for sequence of actions achieving goal



Which solution: A, B or C?

# Wumpus World Example

- ▶ Initial state →
- ▶ Goal state
  - Any state where agent has gold and not in cave
- ▶ Solution?



# Problem-Solving Agent

```
function SIMPLE-PROBLEM-SOLVING-AGENT (percept) returns an action
  persistent: seq, an action sequence initially empty
            state, some description of the current world state
            goal, a goal, initially null
            problem, a problem formulation
  state  $\leftarrow$  UPDATE-STATE (state, percept)
  if seq is empty then
    goal = FORMULATE-GOAL (state)
    problem = FORMULATE-PROBLEM (state, goal)
    seq = SEARCH (problem)
    if seq = failure then return a null action
    action = FIRST (seq)           // action = seq[0]
    seq = REST (seq)             // seq = seq[1...]
  return action
```

# Well-Defined Problems (5 parts)

## 1. Initial state

- State: relevant features of the problem

## 2. Actions

- Action: state → state
- ACTIONS( $s$ ) returns set of actions applicable to state  $s$

## 3. Transition model

- RESULT( $s, a$ ) returns state after taking action  $a$  in state  $s$

## 4. Goal test

- True for any state satisfying goal

## 5. Path cost

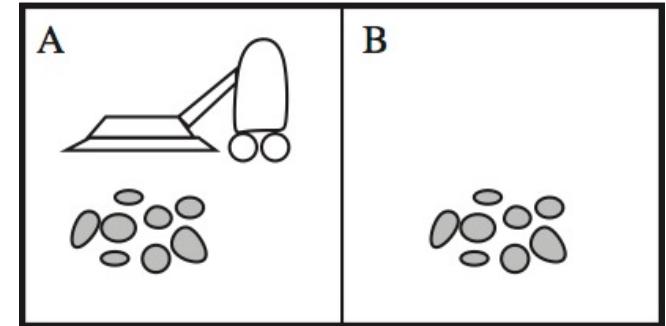
- Sum of costs of individual actions along a path
- Path: sequence of states connected by actions
- Step cost  $c(s, a, s')$ : cost of taking action  $a$  in state  $s$  to reach state  $s'$

# Well-Defined Problems: Terminology

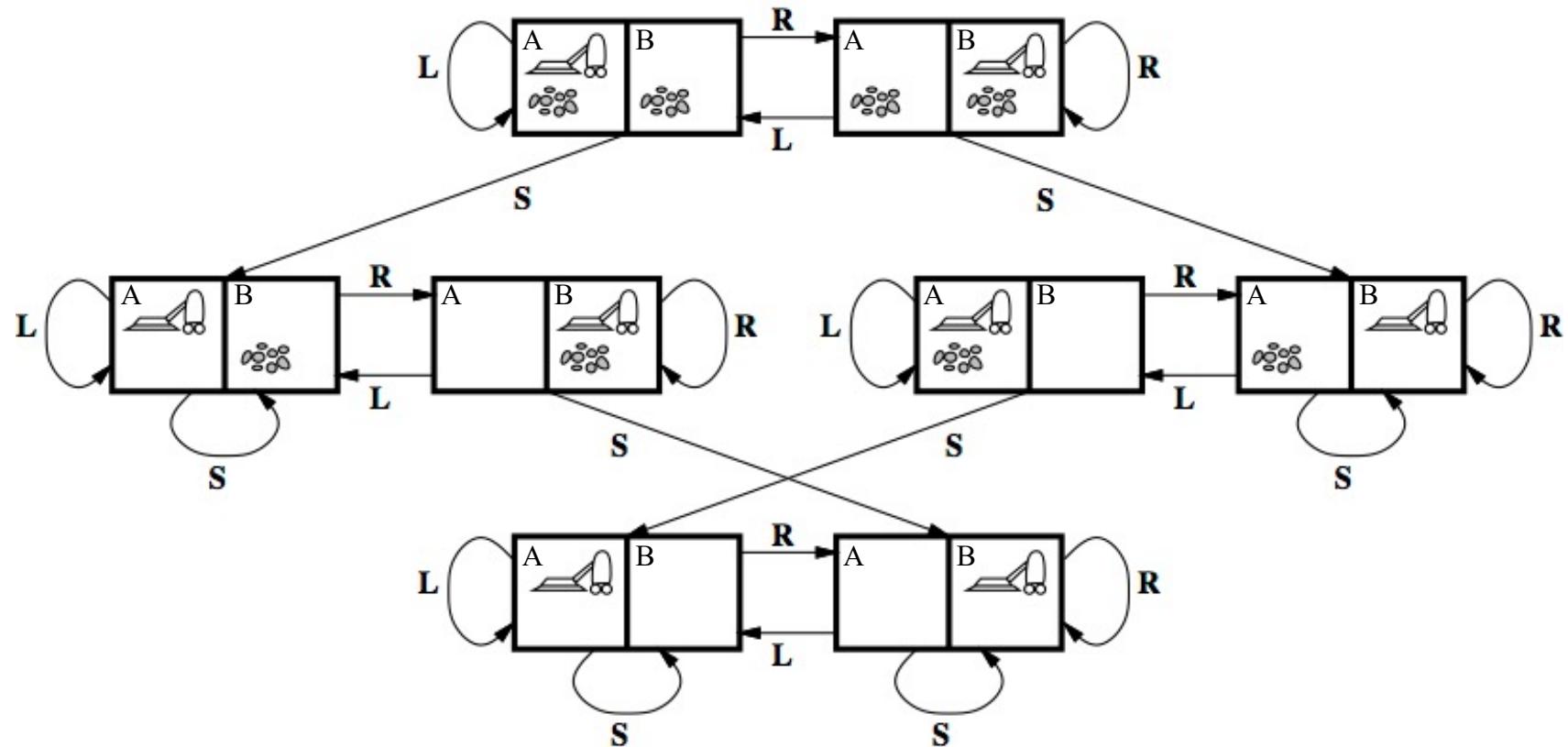
- **State space**: set of all states reachable from the initial state by any sequence of actions
  - State space forms a directed graph of nodes (states) and edges (actions)
- **Solution**: sequence of actions leading from the initial state to a goal state
- **Optimal solution**: solution with minimal path cost

# Vacuum World Problem

- ▶ State representation
  - Location: A, B
  - Cleanliness of rooms: Clean, Dirty
  - Example state: (A,Clean,Clean)
  - How many unique states?
- ▶ **Initial state:** Any state
- ▶ **Actions:** Left, Right, Suction
- ▶ **Transition model**
  - E.g.,  $\text{Result}((\text{A}, \text{Dirty}, \text{Clean}), \text{Suction}) = ?$
- ▶ **Goal test:** State = (?,Clean,Clean)
- ▶ **Path cost**
  - Number of actions in solution (step cost = 1)

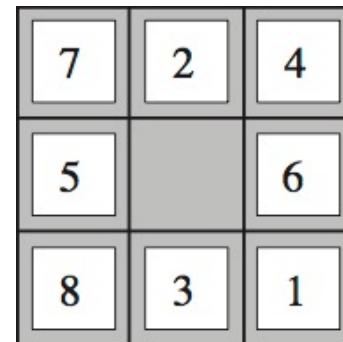


# Vacuum World State Space

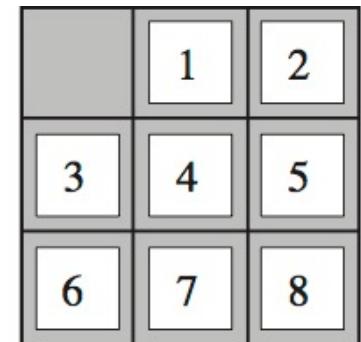


# 8-Puzzle

- ▶ State: Location of each tile (and blank)
  - E.g., (B,1,2,3,4,5,6,7,8)
  - How many states?
- ▶ **Initial state:** Any state
- ▶ **Actions:** Move blank tile Up, Down, Left or Right
- ▶ **Transition model**
- ▶ **Goal test:** State matches Goal State
- ▶ **Path cost:** Number of steps in path (step cost = 1)



Start State

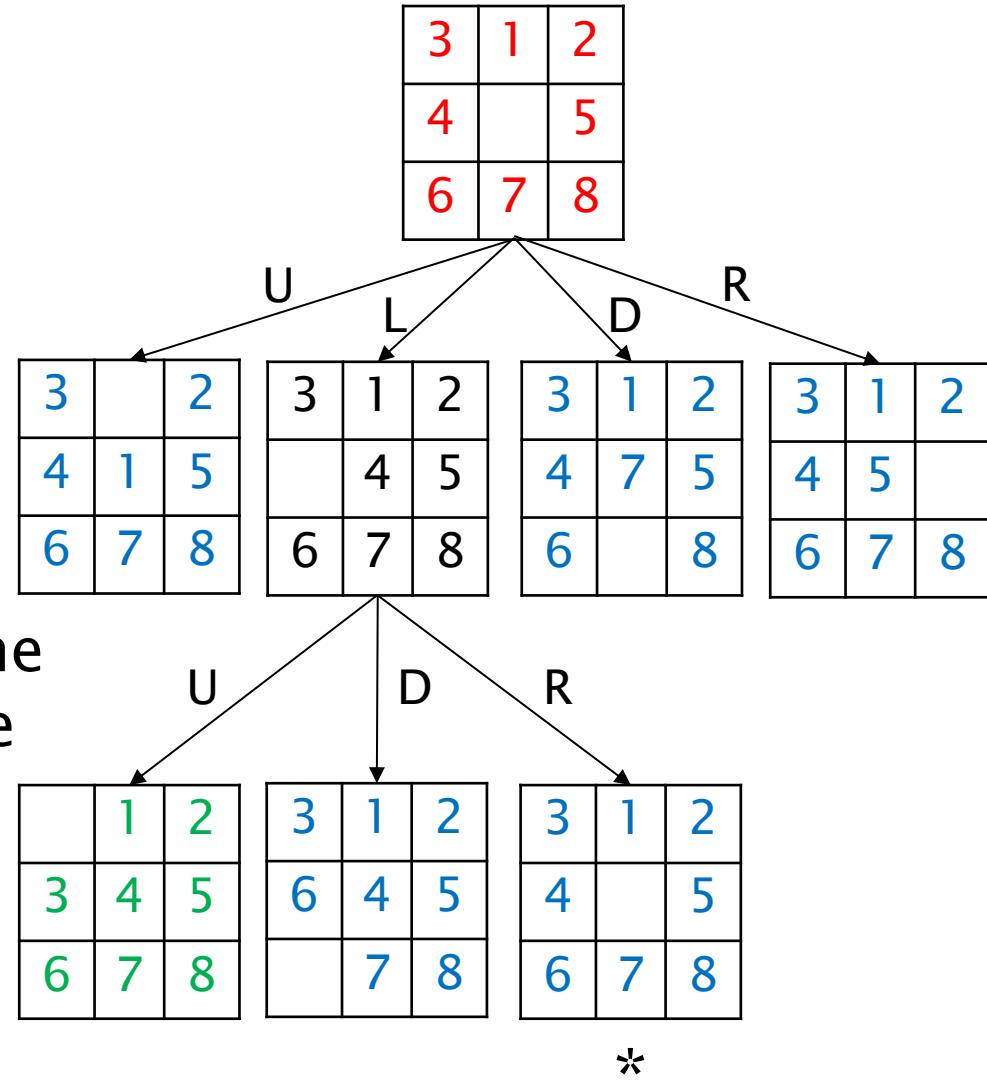


Goal State

# Search

## ▶ Search tree

- Root node is **initial state**
- Node branches for each applicable move from node's state
- **Frontier** consists of the leaf nodes that can be expanded
- Repeated states (\*)
- **Goal state**



# Search Demo

- ▶ Nice 8-puzzle search web app
  - <http://tristanpenman.com/demos/n-puzzle>

Caution: This app may not produce answers consistent with algorithms used in this class.

1	2	3
	4	5
7	8	6

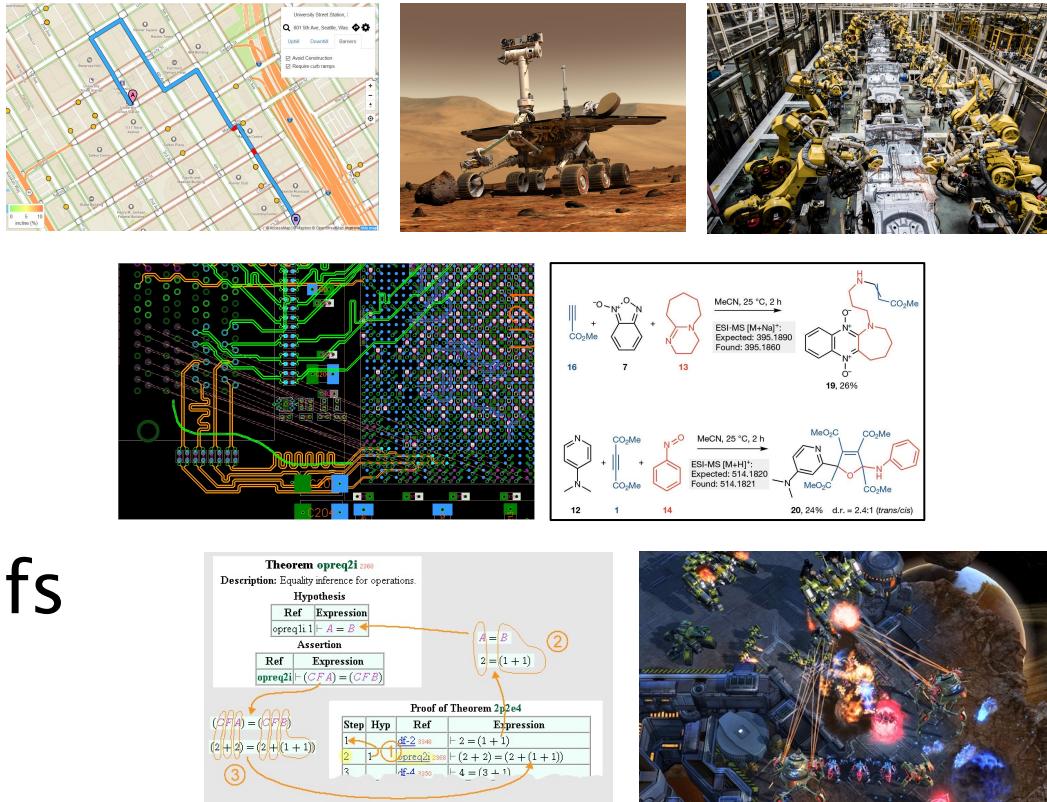
Initial State

1	2	3
4	5	6
7	8	

Goal State

# Real-World Search Problems

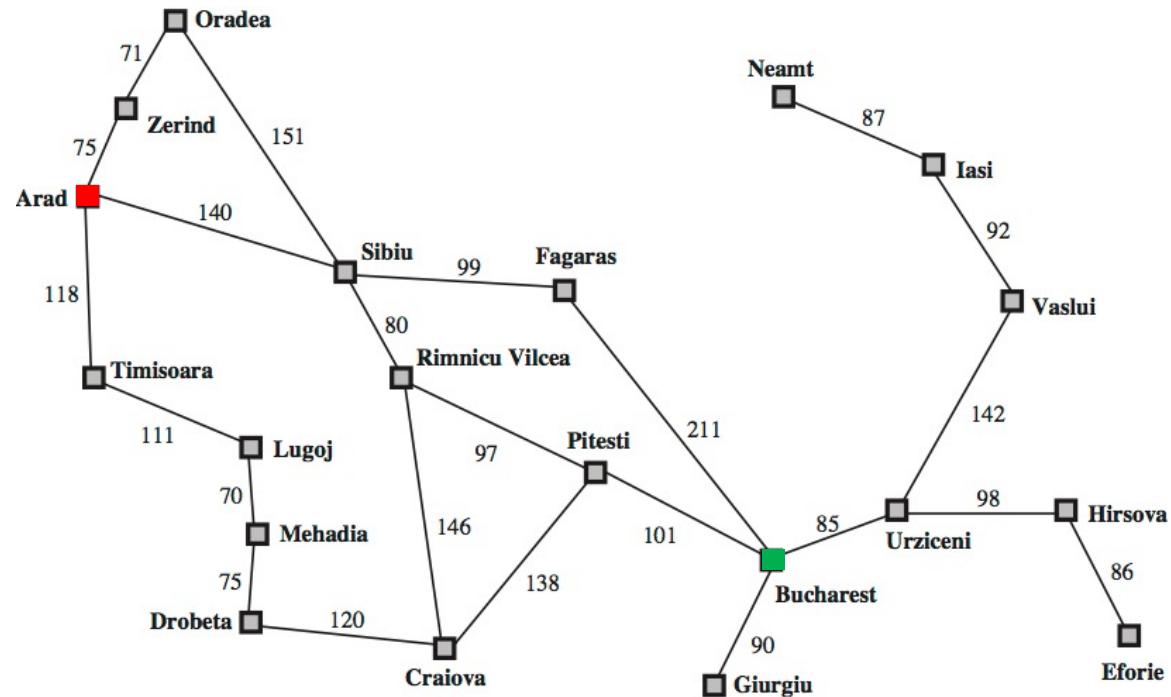
- ▶ Route finding
- ▶ Robot navigation
- ▶ Factory assembly
- ▶ Circuit layout
- ▶ Chemical design
- ▶ Mathematical proofs
- ▶ Game playing



- ▶ Most of AI can be cast as a search problem

# Route Finding Example

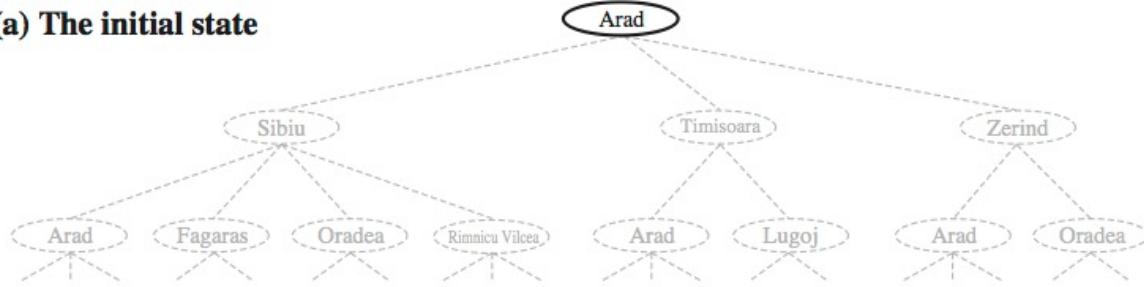
- ▶ Romania road map
- ▶ Initial state: **Arad**
- ▶ Goal state: **Bucharest**



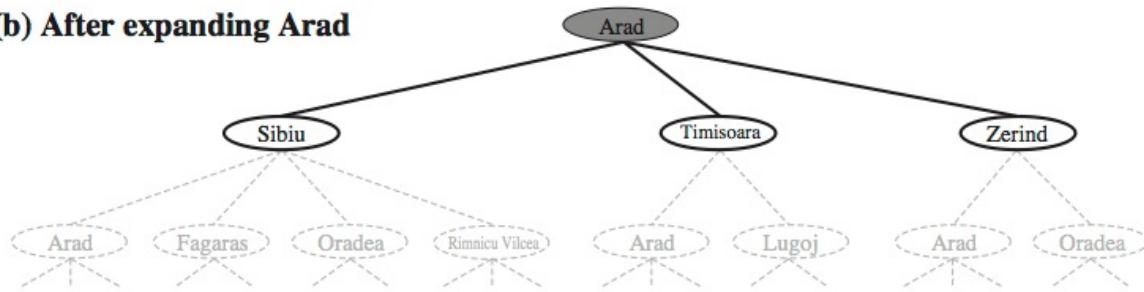
# Route Finding Example

## Search Tree

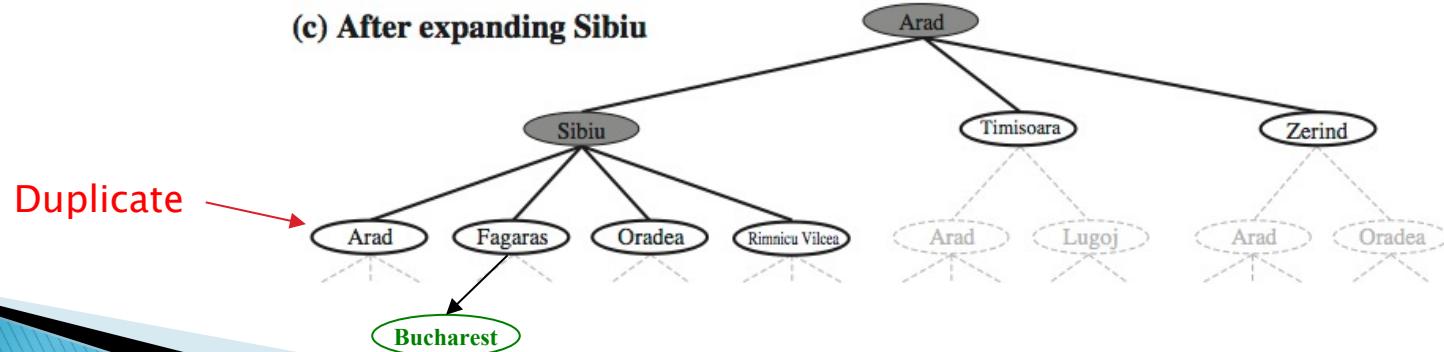
(a) The initial state



(b) After expanding Arad



(c) After expanding Sibiu



# Tree Search

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

  initialize the frontier using the initial state of *problem*

**loop do**

**if** the frontier is empty **then return** failure

choose a leaf node and remove it from the frontier

**if** the node contains a goal state **then return** the corresponding solution

  expand the node, adding the resulting nodes to the frontier

- ▶ Search strategy determines how nodes are chosen for expansion
- ▶ Suffers from repeated state generation

# Graph Search

**function** GRAPH-SEARCH (*problem*) **returns** a solution, or failure

  initialize the frontier using the initial state of *problem*

  initialize the explored set to be empty

**loop do**

**if** the frontier is empty **then return** failure

    choose a leaf node and remove it from the frontier

**if** the node contains a goal state **then return** the corresponding solution

    add the node to the explored set

    expand the node, adding the resulting nodes to the frontier

      only if not in the frontier or explored set

- ▶ Keep track of explored set to avoid repeated states
- ▶ Changes from TREE-SEARCH highlighted

# Measuring Performance

- ▶ Completeness
  - Is the search algorithm guaranteed to find a solution if one exists?
- ▶ Optimality
  - Does the search algorithm find the optimal solution?
- ▶ Time and space complexity
  - Branching factor  $b$  (maximum successors of a node)
  - Depth  $d$  of shallowest goal node
  - Maximum path length  $m$
  - Complexity  $O(b^d)$  to  $O(b^m)$

# Uninformed Search Strategies

- ▶ No preference over states based on “closeness” to goal
- ▶ Strategies
  - Breadth-first search
  - Depth-first search
  - Depth-limited search
  - Iterative deepening search

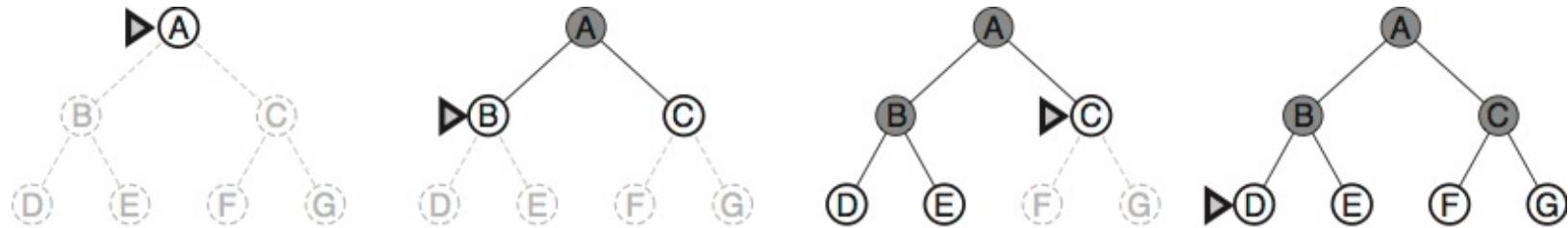
# Breadth–First Search

- ▶ Expand shallowest nodes in frontier
- ▶ Frontier is a simple queue
  - Dequeue nodes from front, enqueue nodes to back
  - First-In, First-Out (FIFO)

# Breadth-First Search

```
function BREADTH-FIRST-SEARCH (problem) returns a solution, or failure
  node  $\leftarrow$  a node with STATE = problem.INITIAL-STATE, PATH-COST = 0
  if problem.GOAL-TEST(node.STATE) then return SOLUTION(node)
  frontier  $\leftarrow$  FIFO queue with node as only element
  explored  $\leftarrow$  empty set
  loop do
    if EMPTY(frontier) then return failure
    node  $\leftarrow$  DEQUEUE(frontier) // choose shallowest node in frontier
    add node.STATE to explored
    for each action in problem.ACTIONS(node.STATE) do
      child = CHILD-NODE(problem, node, action)
      if child.STATE is not in explored or frontier then
        if problem.GOAL-TEST(child.STATE) then return SOLUTION(child)
        frontier  $\leftarrow$  ENQUEUE(child, frontier)
```

# Breadth-First Search



- ▶ 8-puzzle demo

1	2	3
4	8	5
7		6

Initial State

1	2	3
4	5	6
7	8	

Goal State

# Breadth–First Search

- ▶ Complete?
- ▶ Optimal?
- ▶ Time complexity
  - Number of nodes generated (worst case)

$$\sum_{i=0}^d b^i = \frac{b^{d+1} - 1}{b - 1} = O(b^d)$$

- ▶ Space complexity
  - $O(b^{d-1})$  nodes in explored set
  - $O(b^d)$  nodes in frontier
  - Total  $O(b^d)$

# Breadth–First Search

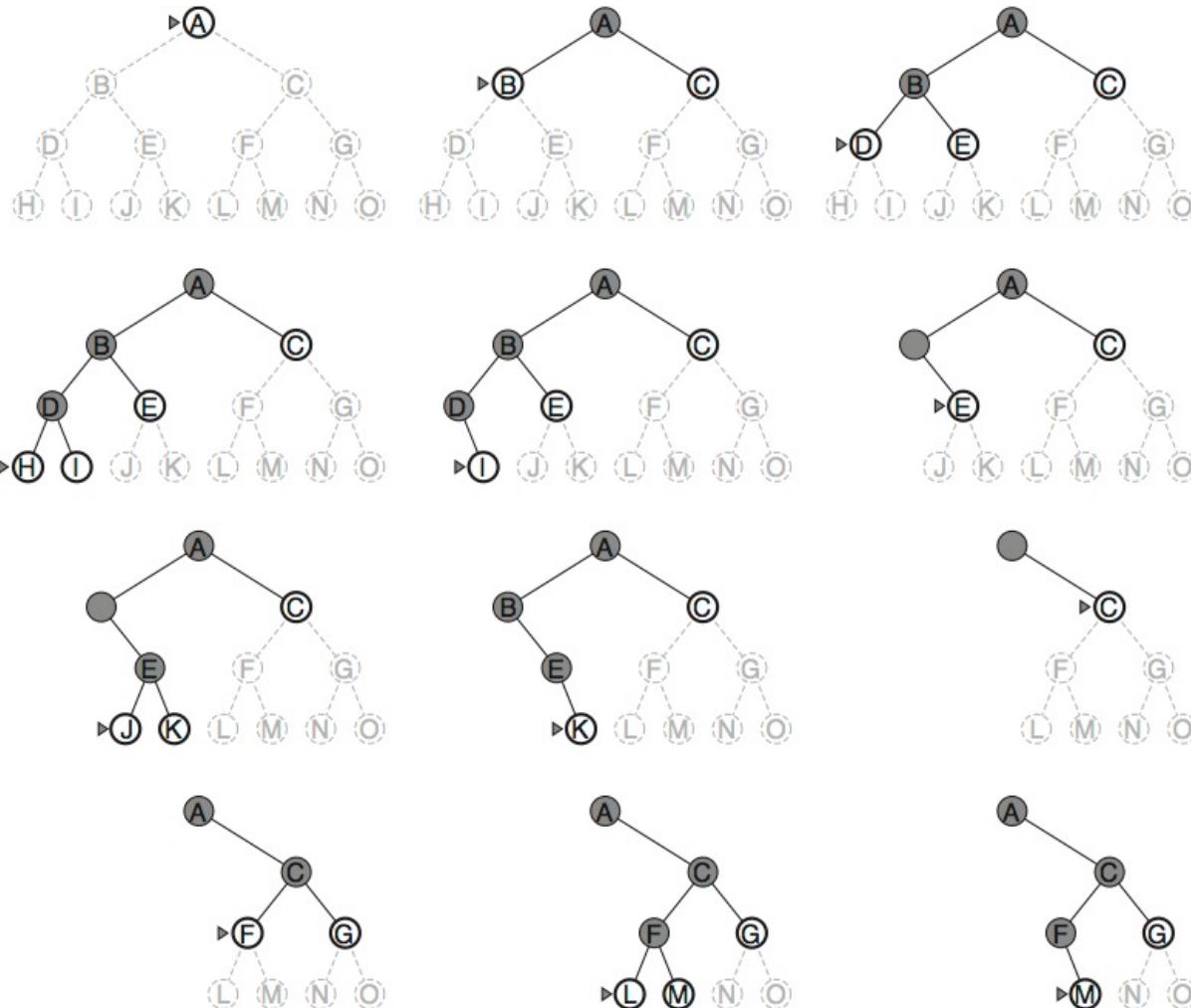
- ▶ Exponential complexity  $O(b^d)$
- ▶ For  $b=4$ , 1KB/node, 1M nodes/sec

Depth	Nodes	Time	Memory
2	16	0.02 ms	16 KB ( $10^3$ )
4	256	0.26 ms	256 KB ( $10^3$ )
8	65,536	0.07 sec	65 MB ( $10^6$ )
16	4.3B	71.6 min	4.3 TB ( $10^{12}$ )
20	$10^{12}$	12.7 days	1 PetaByte ( $10^{15}$ )
30	$10^{18}$	366 centuries	1 ZettaByte ( $10^{21}$ )

# Depth-First Search

- ▶ Always expand the deepest node
- ▶ Frontier is a simple stack
  - Push nodes to front, pop nodes from front
  - Last-In, First-Out (LIFO)
- ▶ Otherwise, same code as BFS
- ▶ Or, implement recursively

# Depth-First Search



DEMO

# Depth-First Search

- ▶ Tree-Search version
  - Not complete (infinite loops)
  - Not optimal
- ▶ Graph-Search version
  - Complete
  - Not optimal
- ▶ Time complexity ( $m = \max \text{ depth}$ ):  $O(b^m)$
- ▶ Space complexity
  - Tree-search:  $O(bm)$
  - Graph-search:  $O(b^m)$

# Depth-Limited Search

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

```
function RECURSIVE-DLS (node, problem, limit) returns a solution, or failure/cutoff
  if problem.GOAL-TEST(node.STATE) then return SOLUTION(node)
  else if limit = 0 then return cutoff
  else
    cutoff_occurred ← false
    for each action in problem.ACTIONS(node.STATE) do
      child = CHILD-NODE(problem, node, action)
      result ← RECURSIVE-DLS (child, problem, limit – 1)
      if result = cutoff then cutoff_occurred ← true
      else if result ≠ failure then return result
    if cutoff_occurred then return cutoff else return failure
```

# Depth-Limited Search

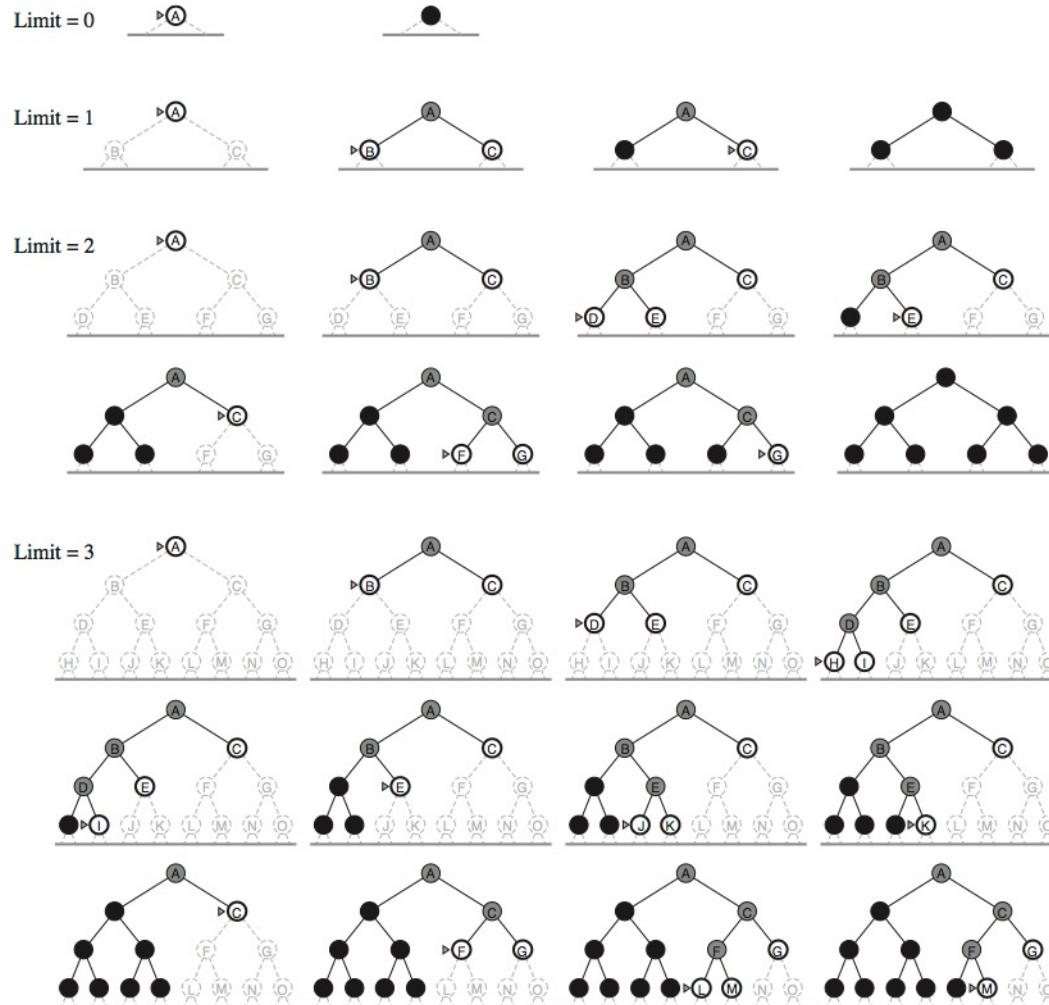
- ▶ Limit DFS depth to  $\ell$
- ▶ Still incomplete, if  $\ell < d$
- ▶ Non-optimal if  $\ell > d$
- ▶ Time complexity:  $O(b^\ell)$
- ▶ Space complexity:  $O(b\ell)$

# Iterative-Deepening Search

- ▶ Run DEPTH-LIMITED-SEARCH iteratively with increasing depth limit

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

# Iterative-Deepening Search



DEMO

# Iterative-Deepening Search

- ▶ Complete?
- ▶ Optimal?
- ▶ Space complexity:  $O(bd)$
- ▶ Time complexity

$$\sum_{i=0}^{d-1} (d-i)b^{i+1} = (d)b + (d-1)b^2 + \dots + (1)b^d = O(b^d)$$

- #Nodes at depth  $d$  = #Nodes at depths 1 to  $(d-1)$
- ▶ Iterative deepening best uninformed search when solution depth unknown

# Uninformed Search Strategies

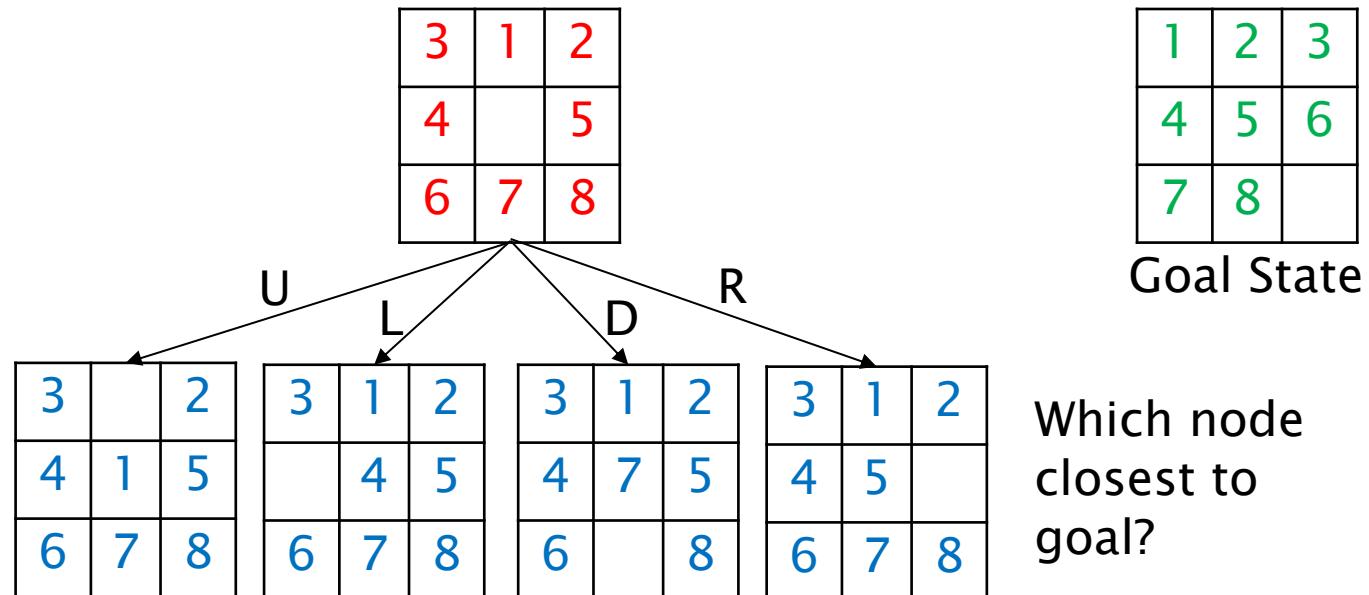
Criterion	Breadth-First	Depth-First	Depth-Limited	Iterative Deepening
Complete	Yes*	No	No	Yes*
Time	$O(b^d)$	$O(b^m)$	$O(b^\ell)$	$O(b^d)$
Space	$O(b^d)$	$O(bm)$	$O(b\ell)$	$O(bd)$
Optimal	Yes**	No	No	Yes**

\* Complete if  $b$  is finite

\*\* Optimal if step costs all the same

# Informed (Heuristic) Search

- ▶ Guided by problem-specific knowledge other than the problem formulation
- ▶ Problem-specific knowledge usually expressed as heuristics



# Heuristic Function

- ▶ Heuristic function  $h(n)$  estimates cost of the path from state  $n$  to a goal state
  - E.g., 8-puzzle
    - Number of tiles out?
    - Euclidean distance of each tile?
    - City-block (Manhattan) distance of each tile?
  - Non-negative function
  - For goal node  $h(n)=0$
- ▶ Recall path cost  $g(n)$  is the cost so far from the initial state to state  $n$
- ▶ Evaluation function  $f(n)$  =  $g(n) + h(n)$  estimates the total cost of a solution going through state  $n$

1	5	2
4	3	
7	8	6

1	2	3
4	5	6
7	8	

Goal State

# Heuristic Search Strategies

- ▶ Greedy best-first search
  - Choose node on frontier with smallest  $h(n)$
- ▶ A\* search
  - Choose node on frontier with smallest  $f(n)$
- ▶ Hill-climbing
  - Choose node with smallest  $h(n)$
  - Discard other nodes on frontier

# Greedy Best-First Graph Search

```
function BEST-FIRST-SEARCH (problem) returns a solution, or failure
  node  $\leftarrow$  a node with STATE = problem.INITIAL-STATE, COST = h(node)
  frontier  $\leftarrow$  priority queue ordered by COST, with node as only element
  explored  $\leftarrow$  empty set
  loop do
    if EMPTY(frontier) then return failure
    node  $\leftarrow$  DEQUEUE(frontier) // choose lowest cost node in frontier
    if problem.GOAL-TEST(node.STATE) then return SOLUTION(node)
    add node.STATE to explored
    for each action in problem.ACTIONS(node.STATE) do
      child = CHILD-NODE(problem, node, action)
      if child.STATE is not in explored or frontier then
        frontier  $\leftarrow$  ENQUEUE(child, frontier)
      else if child.STATE is in frontier with higher COST then
        replace that frontier node with child
```

Why not check  
Goal-Test here?

Why is this test  
necessary?

# Greedy Best-First Search

- ▶ Best-first search with  $f(n) = h(n)$
- ▶ Example: Route-finding problem
  - $h(n)$  = straight-line distance from city  $n$  to goal city

Straight-line distances to Bucharest:

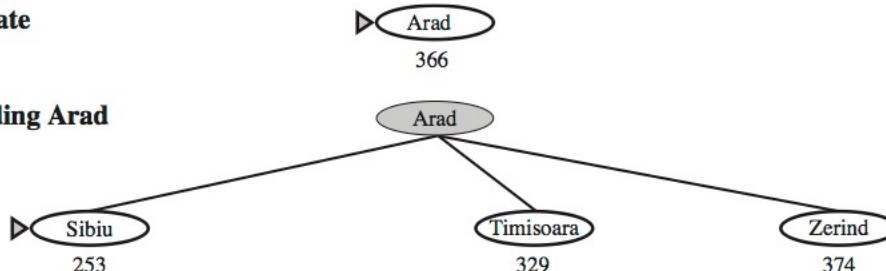
<b>Arad</b>	366	<b>Mehadia</b>	241
<b>Bucharest</b>	0	<b>Neamt</b>	234
<b>Craiova</b>	160	<b>Oradea</b>	380
<b>Drobeta</b>	242	<b>Pitesti</b>	100
<b>Eforie</b>	161	<b>Rimnicu Vilcea</b>	193
<b>Fagaras</b>	176	<b>Sibiu</b>	253
<b>Giurgiu</b>	77	<b>Timisoara</b>	329
<b>Hirsova</b>	151	<b>Urziceni</b>	80
<b>Iasi</b>	226	<b>Vaslui</b>	199
<b>Lugoj</b>	244	<b>Zerind</b>	374

# Greedy Best-First Search Example: Arad to Bucharest

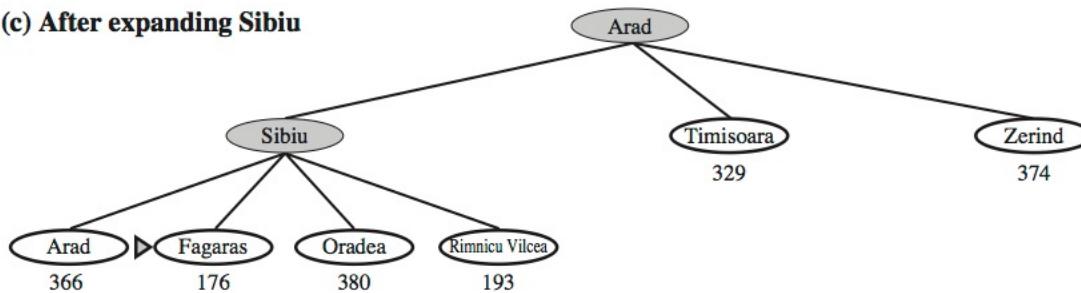
(a) The initial state



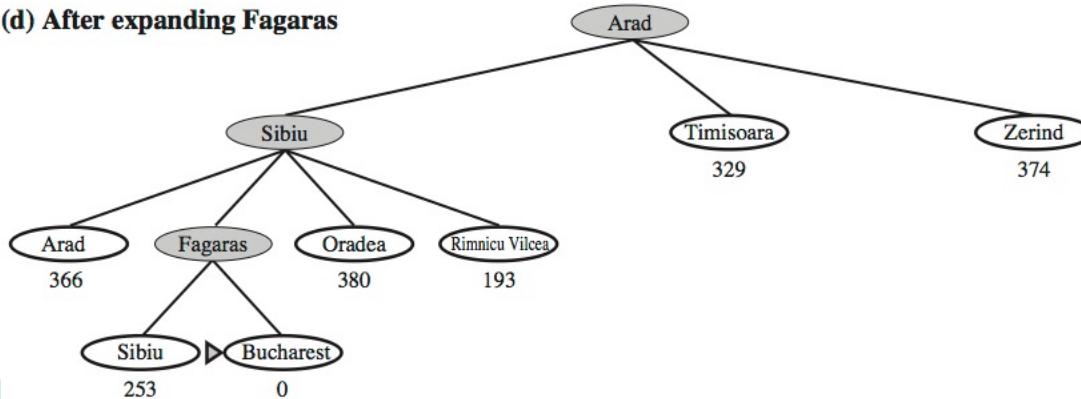
(b) After expanding Arad



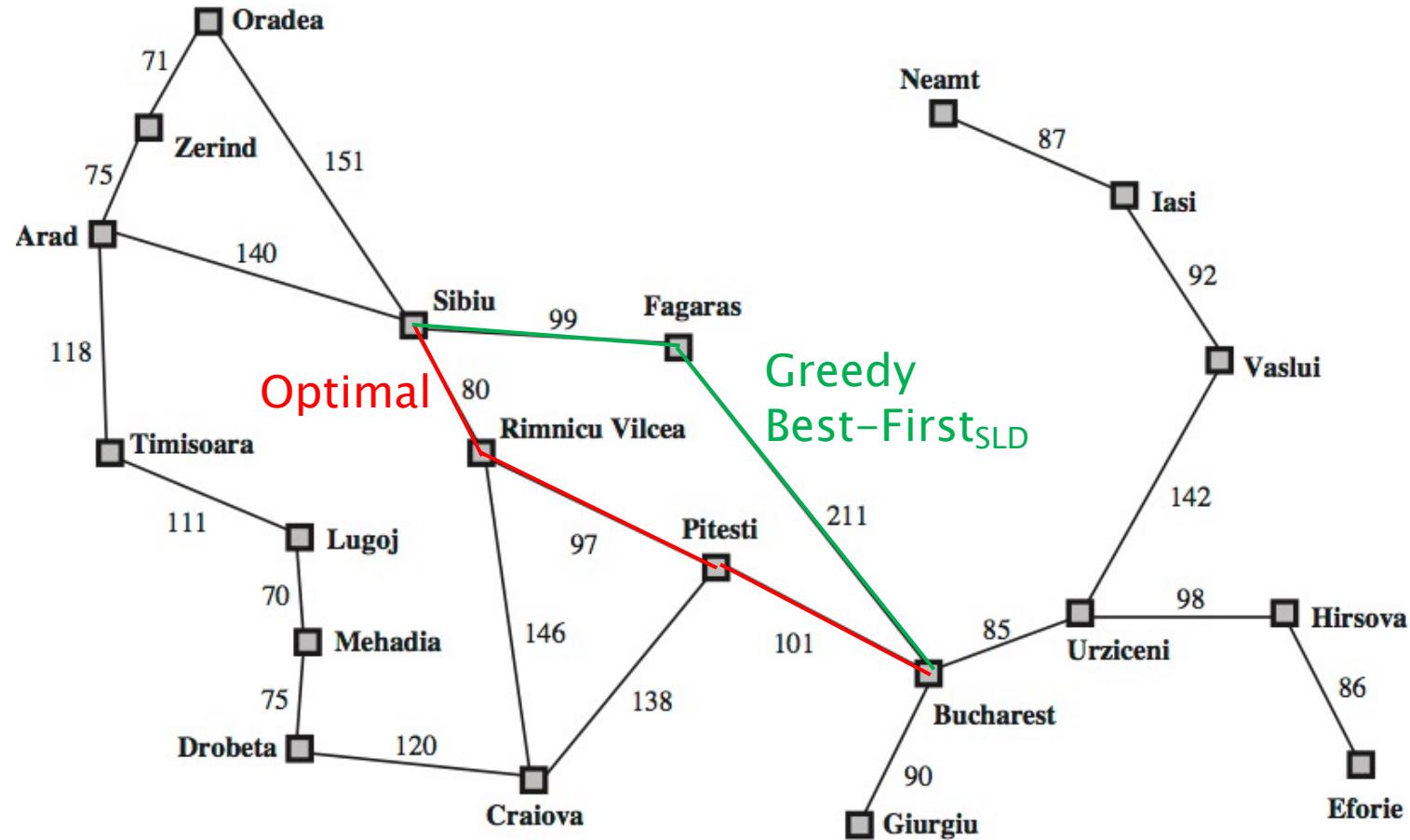
(c) After expanding Sibiu



(d) After expanding Fagaras

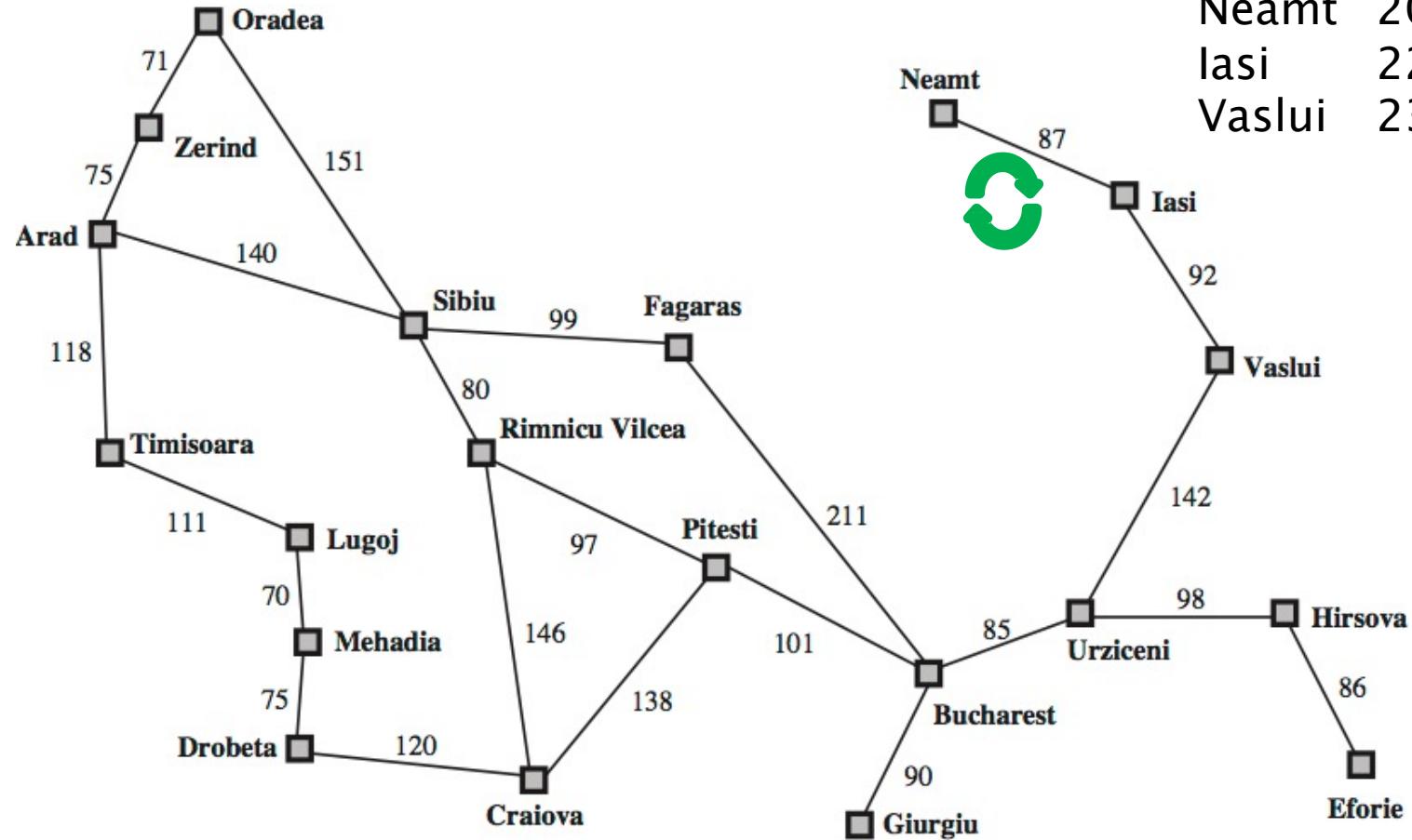


# Greedy Best-First Search Example: Arad to Bucharest



# Greedy Best-First Tree Search

## Example: Iasi to Fagaras



# Greedy Best–First Search

- ▶ Complete?
- ▶ Optimal?
- ▶ Time and space complexity:  $O(b^m)$ 
  - $b$  = branching factor
  - $m$  = maximum depth of search space
  - Worst case
    - Good heuristic can substantially improve

DEMO

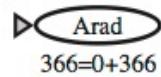
# A\* Search

- ▶  $f(n) = g(n) + h(n)$ 
  - Estimated cost of solution through  $n$
- ▶ Best-First-Search using Cost =  $f(n)$
- ▶ Complete and optimal assuming some constraints on  $h(n)$

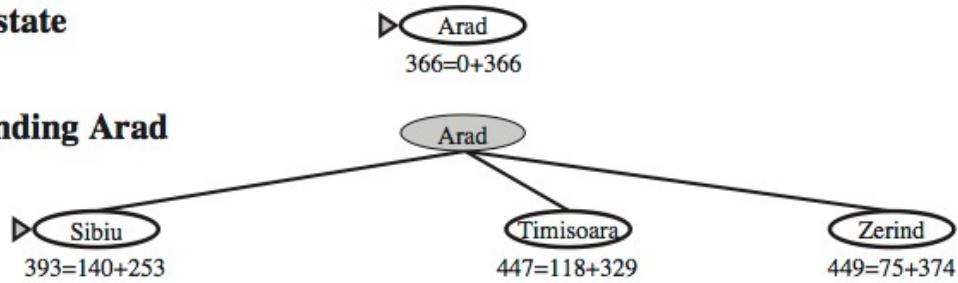
History: A\* generalizes over algorithms A1 and A2, which were heuristic extensions to Dijkstra's shortest path algorithm.

# A\* Search Example: Arad to Bucharest

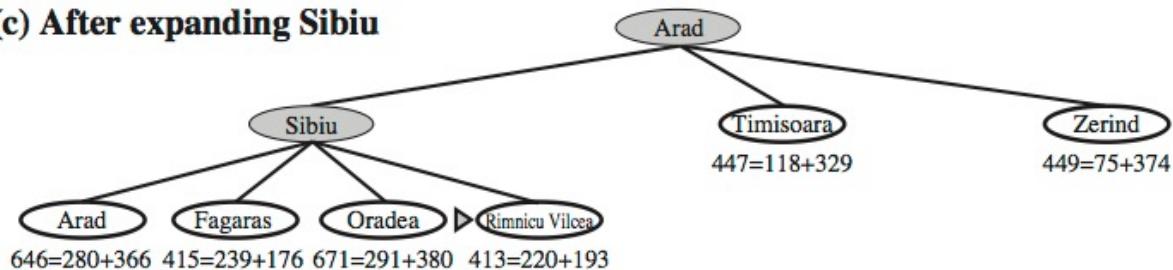
(a) The initial state



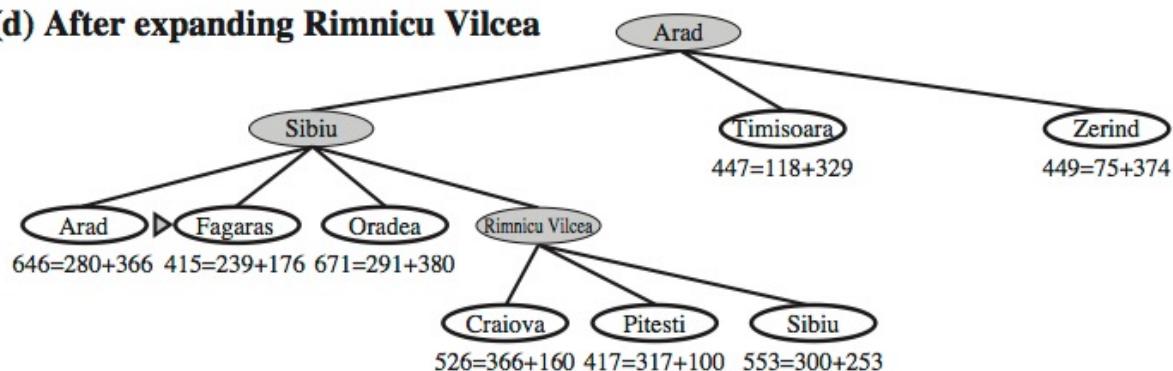
(b) After expanding Arad



(c) After expanding Sibiu

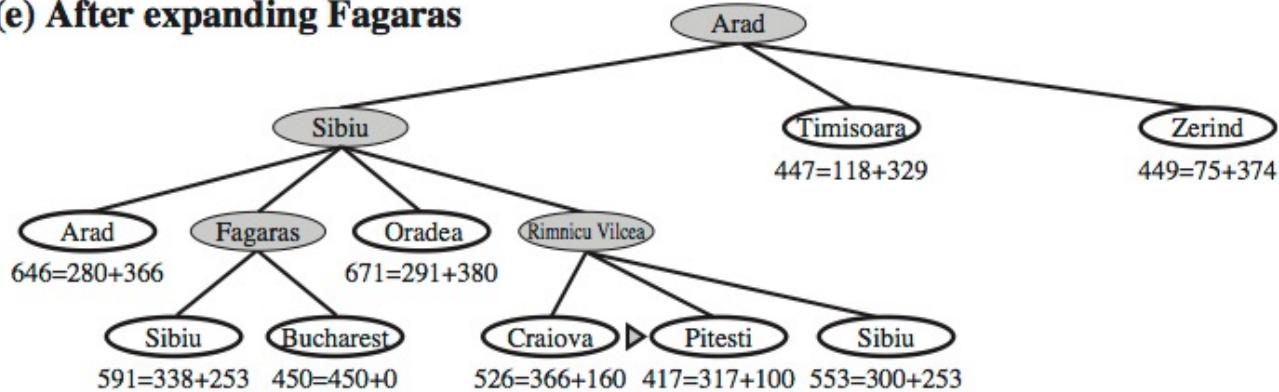


(d) After expanding Rimnicu Vilcea

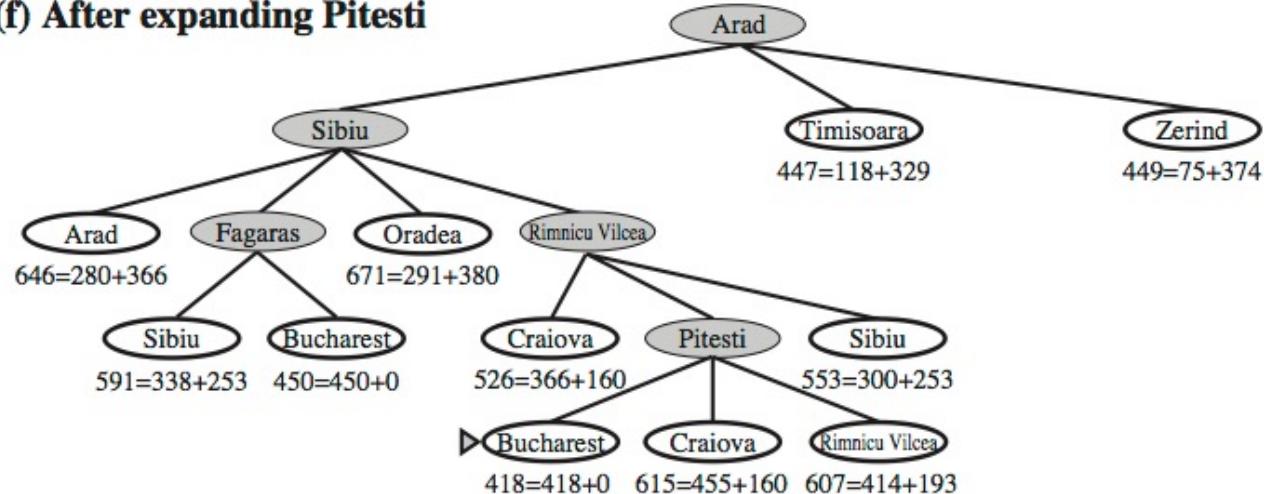


# A\* Search Example: Arad to Bucharest (cont.)

(e) After expanding Fagaras



(f) After expanding Pitesti



# Optimality of A\*

- ▶ For A\* **tree** search to be optimal,  $h(n)$  must be admissible
  - A heuristic function  $h(n)$  is admissible if it never over-estimates the cost of reaching the goal from  $n$
  - E.g., Straight-line distance for route finding
  - E.g., Tiles out of place in 8-puzzle
- ▶ For A\* **graph** search to be optimal, heuristic must further satisfy triangle inequality (also called consistent or monotonic)
  - A heuristic function  $h(n)$  satisfies the triangle inequality if  $h(n) \leq \text{cost}(n,a,n') + h(n')$

# A\* Search

- ▶ Complete and optimal?
  - Yes, if heuristic is admissible
- ▶ Time and space complexity?
  - Still  $O(b^d)$  worst case
  - Space is typically the bottleneck
- ▶ A\* is optimally efficient
  - No other algorithm using the same consistent heuristic is guaranteed to expand fewer nodes

DEMO

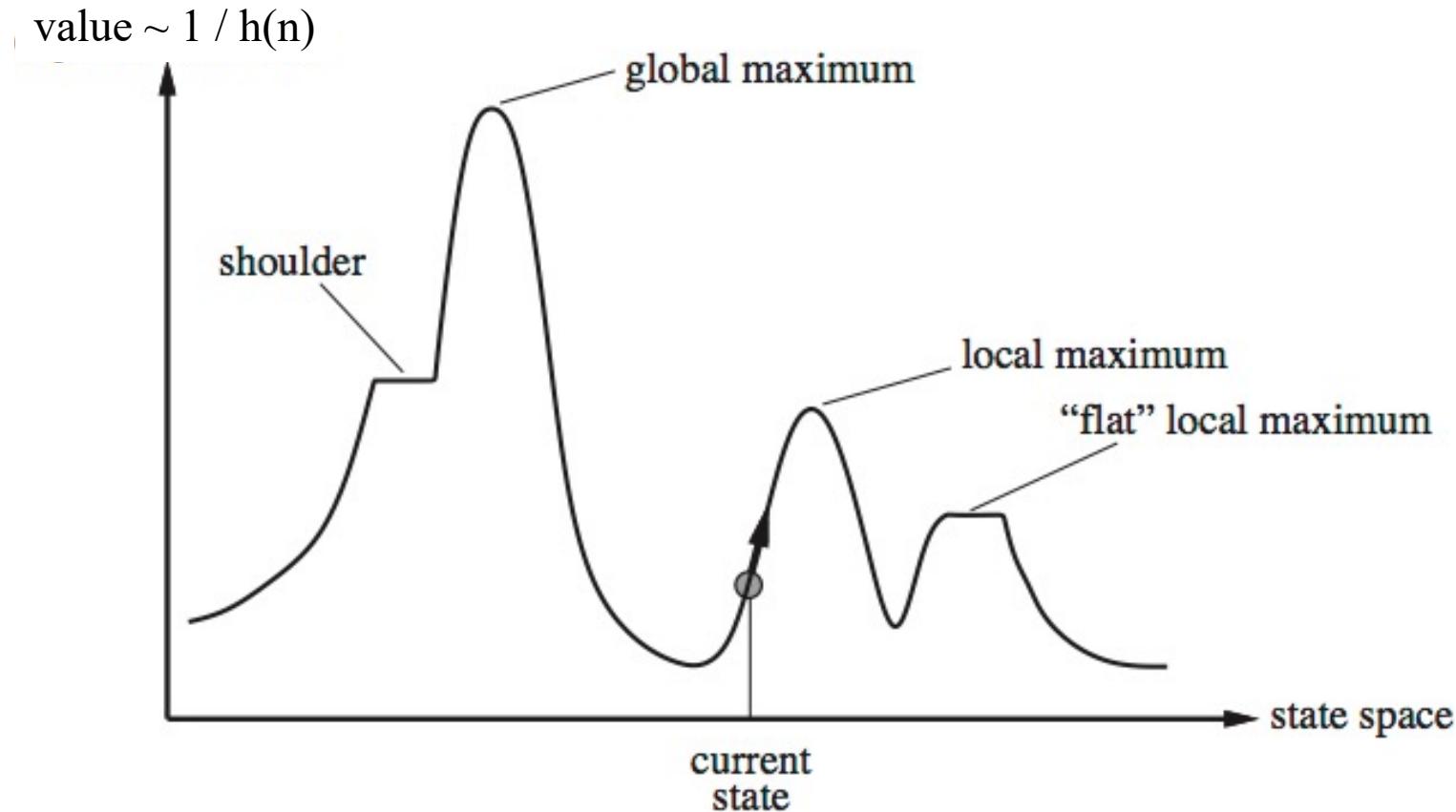
# Water Jug Problem

- ▶ **States:** Water jugs of various sizes with some amount of water in them
  - Jug  $j$  has capacity  $c(j)$  and contains  $w(j)$  gallons of water
- ▶ **Initial state:** Water jugs all empty:  $w(j) = 0$
- ▶ **Actions:**
  - Fill a jug to the top with water from water source
  - Pour water from one jug into another until second jug is full or first jug is empty
  - Empty all water from a jug
- ▶ **Transition model:**
  - $\text{Fill}(j)$ :  $w(j) = c(j)$
  - $\text{Pour}(j_1, j_2)$ :
    - $w(j_1) = \max(0, w(j_1) - c(j_2) + w(j_2))$
    - $w(j_2) = \min(c(j_2), w(j_1) + w(j_2))$
  - $\text{Empty}(j)$ :  $w(j) = 0$
- ▶ **Goal test:** Some  $w(j) = X$
- ▶ **Path cost:** Number of actions



Die Hard with a Vengeance (1995)  
 $c(1)=3$ ,  $c(2)=5$ , Goal:  $w(2)=4$

# State-Space Landscape



# Hill-Climbing Search

```
function HILL-CLIMBING (problem) returns a state which is a local maximum
  current  $\leftarrow$  MAKE-NODE(problem.INITIAL-STATE)
  loop do
    next  $\leftarrow$  current
    for each action in problem.ACTIONS(node.STATE) do
      child  $\leftarrow$  CHILD-NODE(problem, node, action)
      if child.VALUE > next.VALUE then next  $\leftarrow$  child          // VALUE ~ 1 / h(n)
    if next.VALUE  $\leq$  current.VALUE then return current.STATE      // Goal test?
    current  $\leftarrow$  next
```

- ▶ Also called “steepest ascent” or “greedy local search”
- ▶ Gets stuck on local maxima and plateaus
- ▶ Stochastic hill climbing
  - Random selection of *next* node

# Hill-Climbing

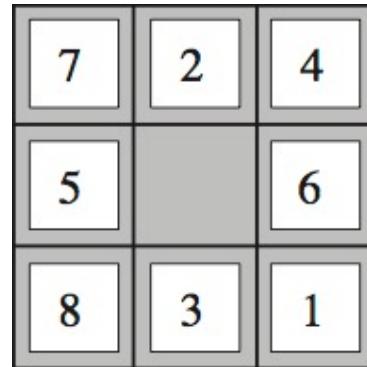
- ▶ Complete?
- ▶ Optimal?
- ▶ Time complexity?
- ▶ Space complexity?

# Designing Heuristics

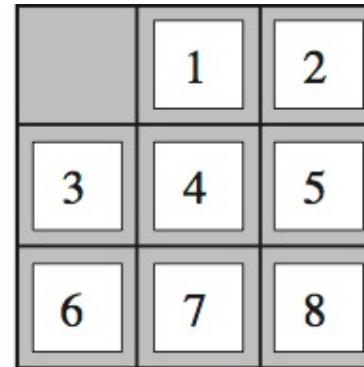
- ▶ Why not use  $h(n) = 1$ ?
- ▶ Why not use  $h(n) = \text{actual optimal cost to goal from } n$ ?
- ▶ How to measure quality of heuristic?

# Designing Heuristics

- ▶ E.g., 8-puzzle
  - $h_1$  = tiles out of place
  - $h_2$  = sum of tiles' city block distances



Start State



Goal State

$$h_1 = 8$$

$$h_2 = 3 + 1 + 2 + 2 + 3 + 2 + 2 + 3 = 18$$

Solution cost = 26

# Designing Heuristics

- ▶ Values averaged over 100 8-puzzle problems for each  $d$
- ▶ Note:  $A^*(h_2) \leq A^*(h_1)$

d	Search Cost (nodes generated)		
	IDS	$A^*(h_1)$	$A^*(h_2)$
2	10	6	6
4	112	13	12
6	680	20	18
8	6384	39	25
10	47127	93	39
12	3644035	227	73
14	-	539	113
16	-	1301	211
18	-	3056	363
20	-	7276	676
22	-	18094	1219
24	-	39135	1641

# Designing Heuristics

- ▶ Heuristic  $h_2$  dominates  $h_1$  if, for all nodes  $n$ ,  
 $h_2(n) \geq h_1(n)$ 
  - Implies A\* using  $h_2$  will typically generate fewer nodes than A\* using  $h_1$
  - “City block distance” dominates “tiles out of place”
- ▶ In general, want  $h(n)$  to be:
  - Admissible and consistent
  - Close to actual solution cost from node  $n$
  - But still fast to compute

# Designing Heuristics

- ▶ Relaxed problems
  - $h(n)$  = cost of solution to relaxed problem
  - E.g., 8-puzzle where you can swap tiles
- ▶ Subproblems
  - $h(n)$  = cost of solution to subproblem
  - E.g., get half the tiles in correct position
- ▶ Learning from experience
  - Collect experience as (state, solution cost) pairs
  - Learn  $h(n)$ : state → solution cost

# Summary

- ▶ Problem-solving agent
- ▶ Formulating problems
- ▶ Search
- ▶ Uninformed search (Iterative-Deepening)
- ▶ Informed (heuristic) search ( $A^*$ )
- ▶ Admissible heuristics