

**CS 480**

***Introduction to Artificial Intelligence***

**January 18, 2024**

# Announcements / Reminders

- **Contribute to the discussion on Blackboard, please**
- **Please follow the Week 02 To Do List instructions (if you haven't already):**
- **Next week I \*\*\*plan\*\*\* to start attendance taking (for my personal records of class participation)**

# Teaching Assistants

Name	e-mail	Office hours
Nagaraju, Ashish	anagaraju@hawk.iit.edu	Mondays 10:30 AM – 12:30 PM CST in SB 108
Vishwanath, Tejass	tvishwanath@hawk.iit.edu	Fridays 02:00 PM - 03:00 PM CST in SB 108

TAs will:

- assist you with your assignments,
- hold office hours to answer your questions,
- grade your lab work (**a specific TA will be assigned to you**).

**Take advantage of their time and knowledge!**

**DO NOT email them with questions unrelated to lab grading.**

**Make time to meet them during their office hours.**

**Add a [CS480 Spring 2024] prefix to your email subject when contacting TAs, please.**

# Plan for Today

- **Intelligent Agents**
- **Solving problems by Searching**

# Designing the Agent for the Task

**Analyze the  
Problem / Task  
(PEAS)**

**Select Agent  
Architecture**

**Select Internal  
Representations**

**Apply  
Corresponding  
Algorithms**

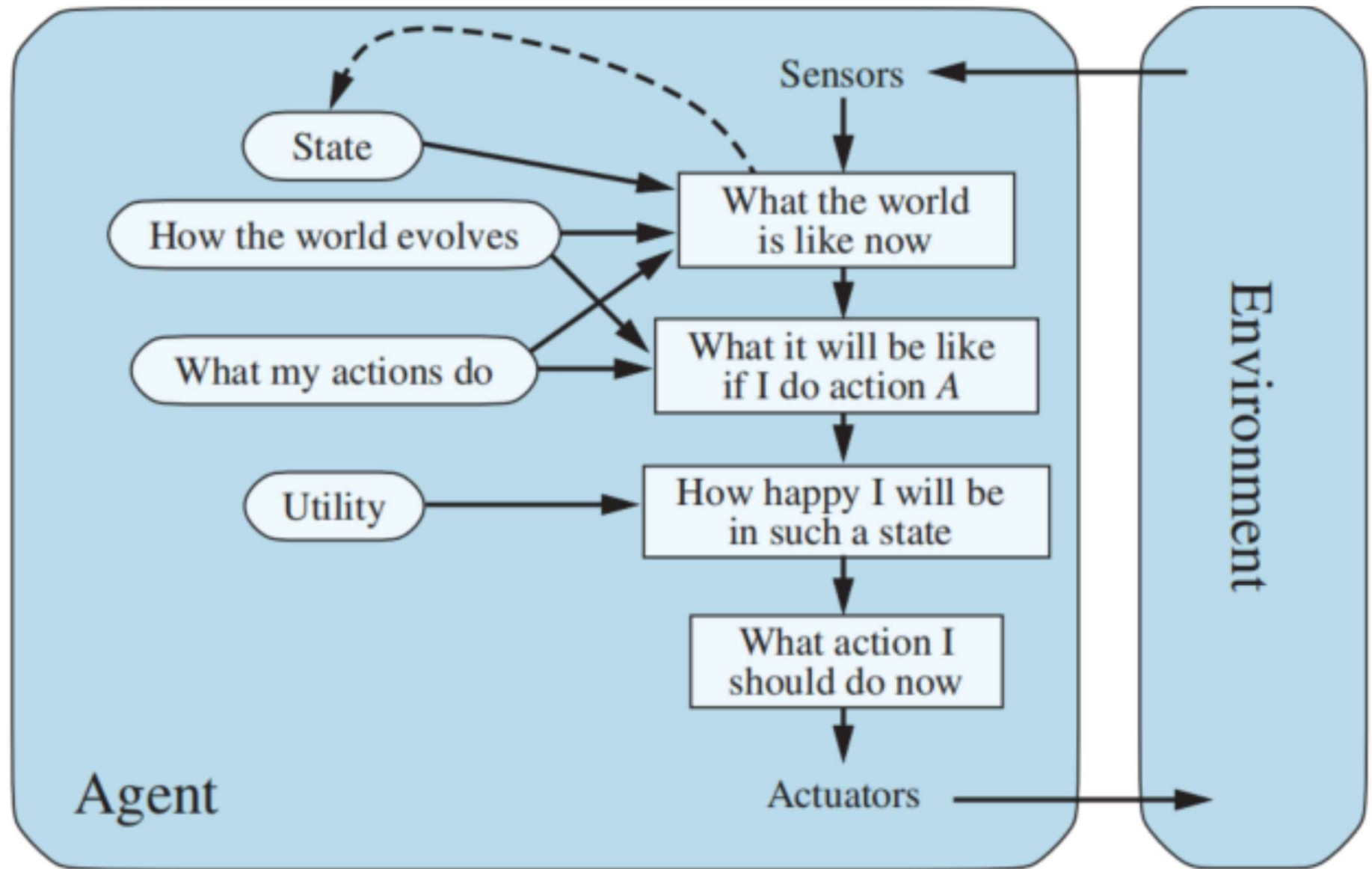
# **Agent Structure / Architecture**

**Agent = Architecture + Program**

# Typical Agent Architectures

- Simple reflex agent
- Model-based reflex agent:
- Goal-based reflex agent
- Utility-based reflex agent

# Model-based Agents: Challenges?

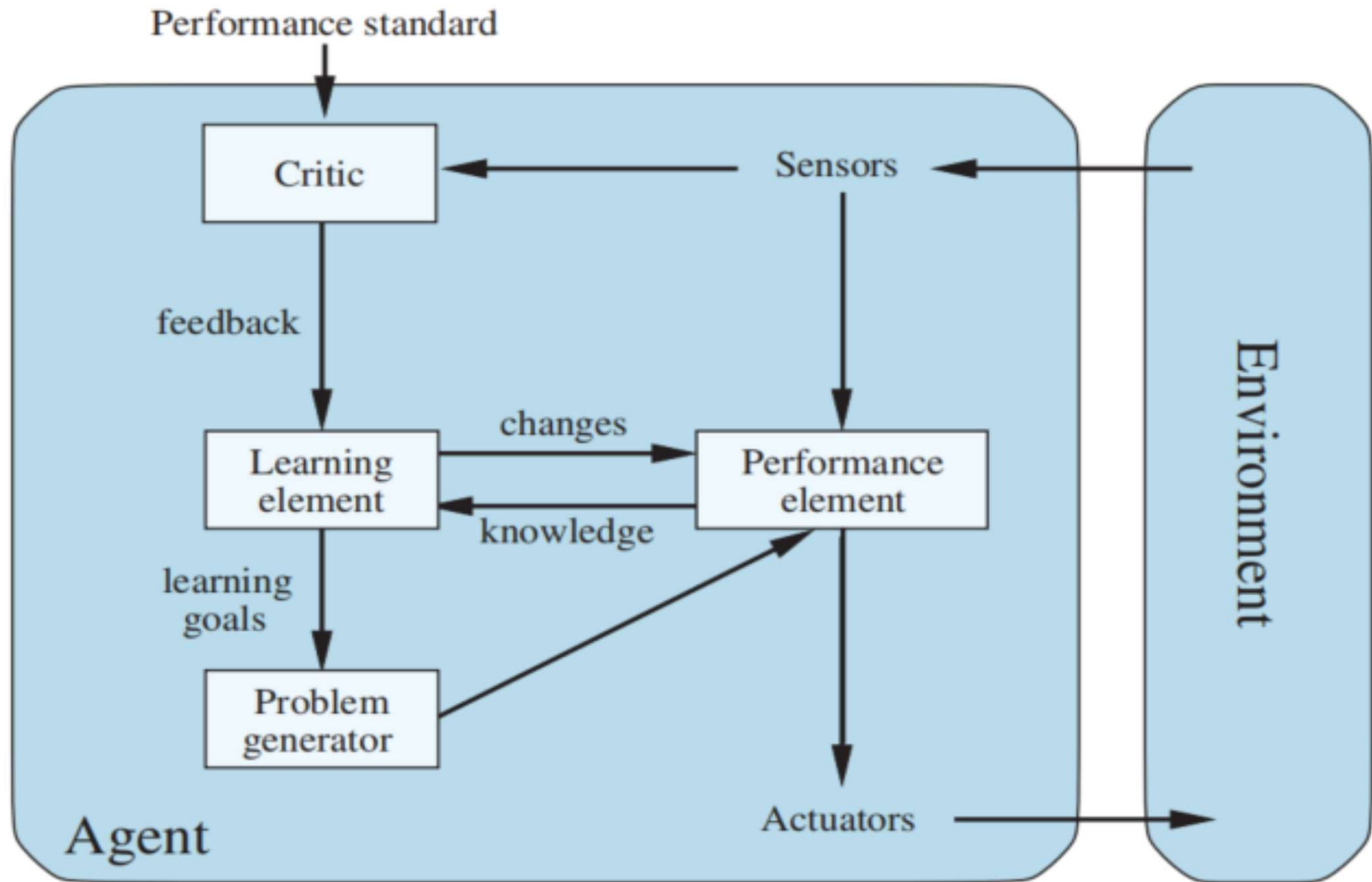




# Typical Agent Architectures

- Simple reflex agent: uses condition-action rules
- Model-based reflex agent: keeps track of the unobserved parts of the environment by maintaining internal state:
  - “how the world works”: state transition model
  - how percepts and environment is related: sensor model
- Goal-based reflex agent: maintains the model of the world and goals to select decisions (that lead to goal)
- Utility-based reflex agent: maintains the model of the world and utility function to select PREFERRED decisions (that lead to the best expected utility:  $\text{avg} (EU * p)$ )

# Learning Agent



# Designing the Agent for the Task

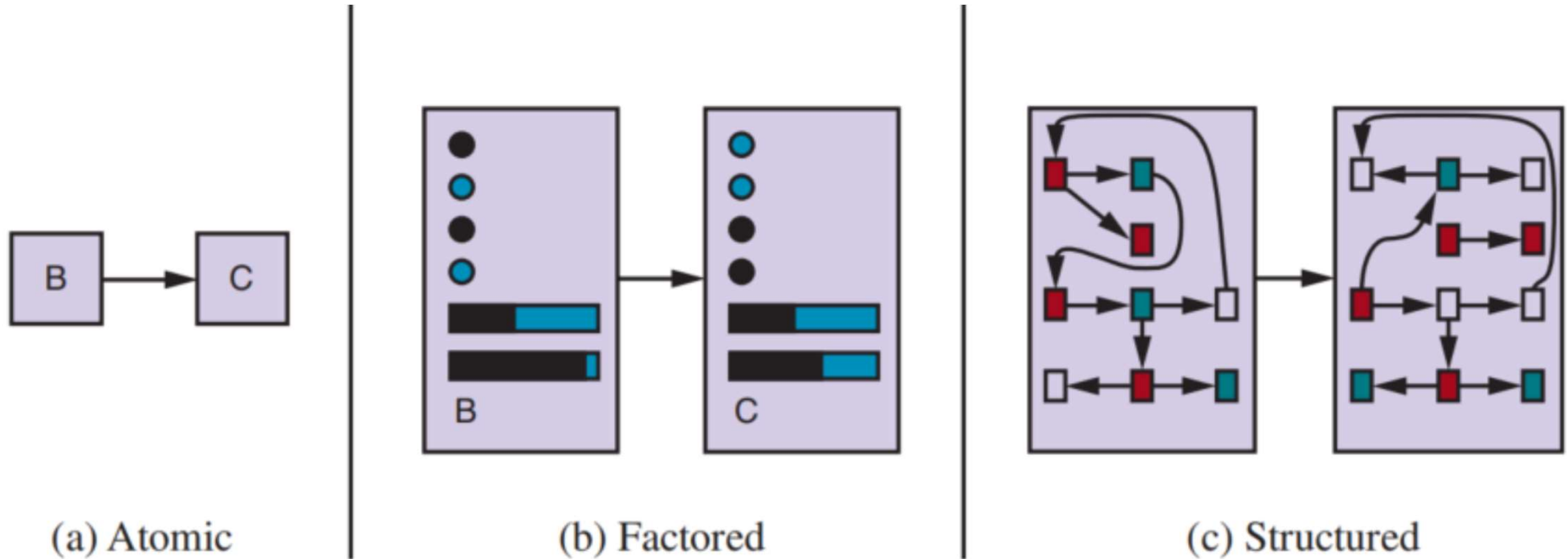
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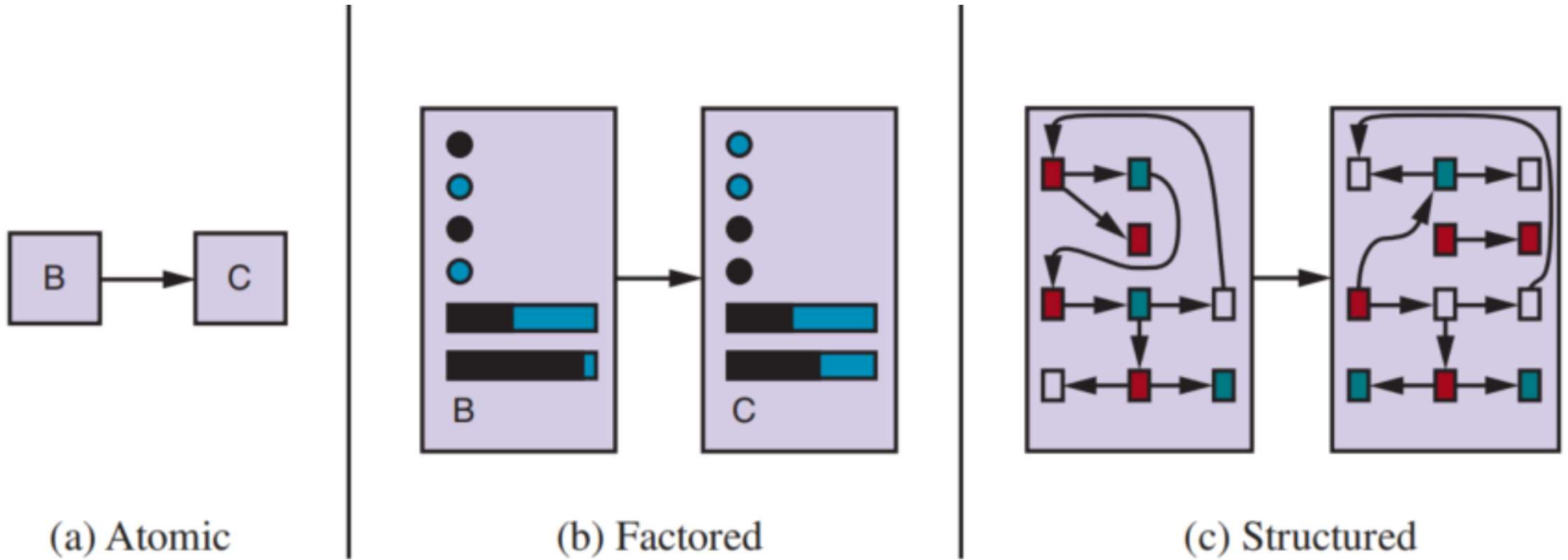
**Apply  
Corresponding  
Algorithms**

# State and Transition Representations



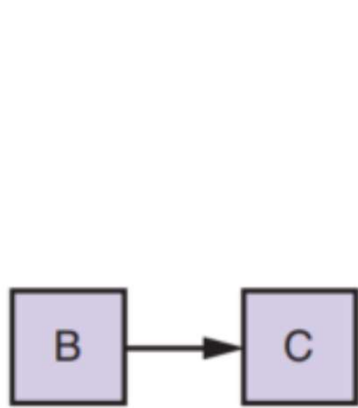
- **Atomic:** state representation has NO internal structure
- **Factored:** state representation includes fixed attributes (which can have values)
- **Structured:** state representation includes objects and their relationships

# State and Transition Representations

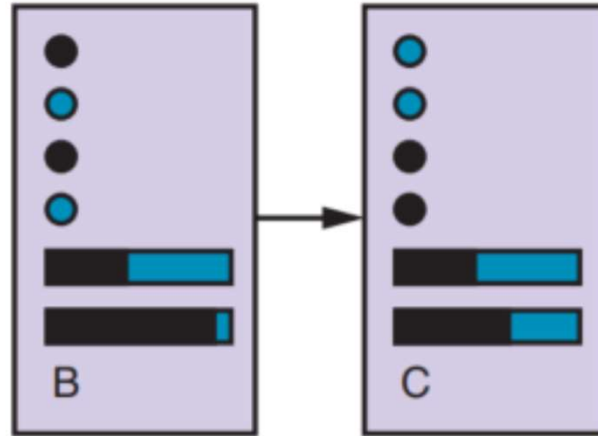


Complexity, level of detail, expresiveness, more difficult to process

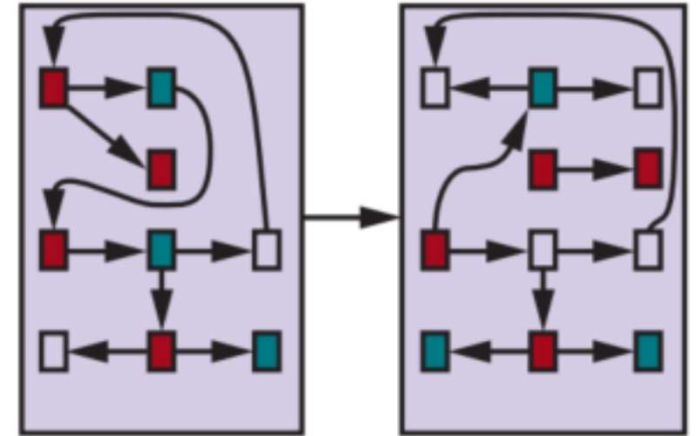
# Representations and Algorithms



(a) Atomic



(b) Factored



(c) Structured

- Searching
- Hidden Markov models
- Markov decision process
- Finite state machines

- Constraint satisfaction algorithms
- Propositional logic
- Planning
- Bayesian algorithms
- Some machine learning algorithms

- Relational database algorithms
- First-order logic
- First-order probability models
- Natural language understanding (some)

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# Finite State Machine: A Turnstile

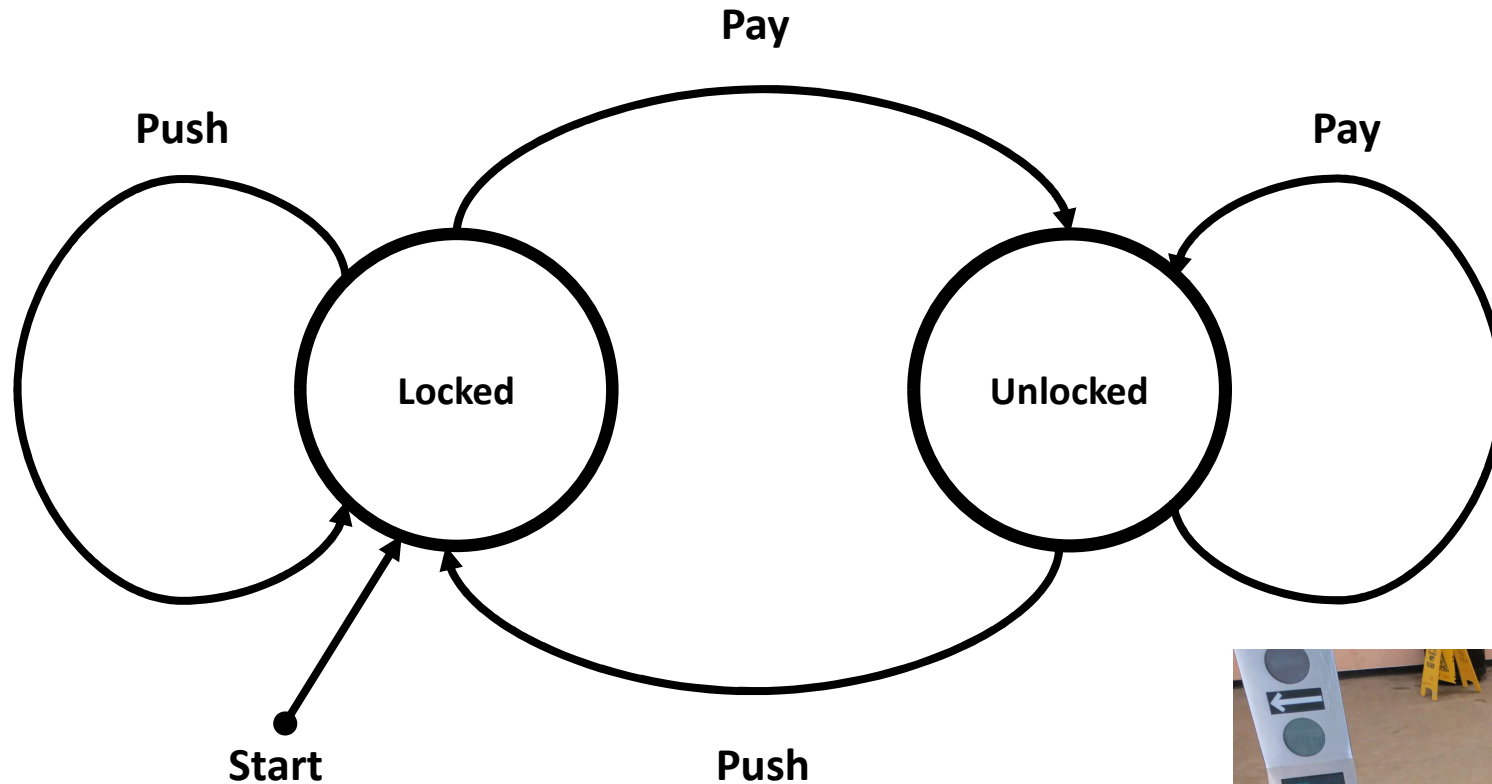
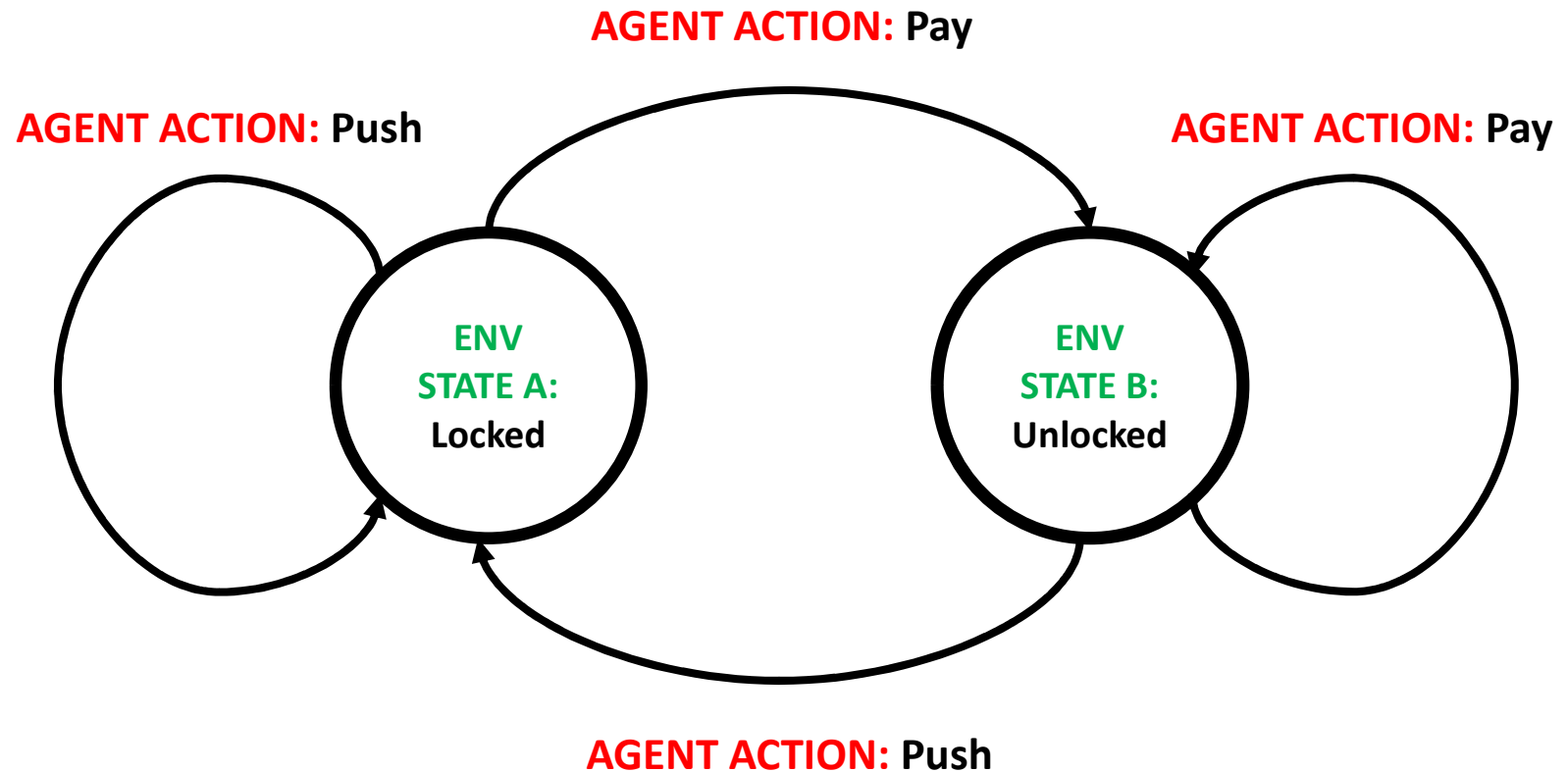


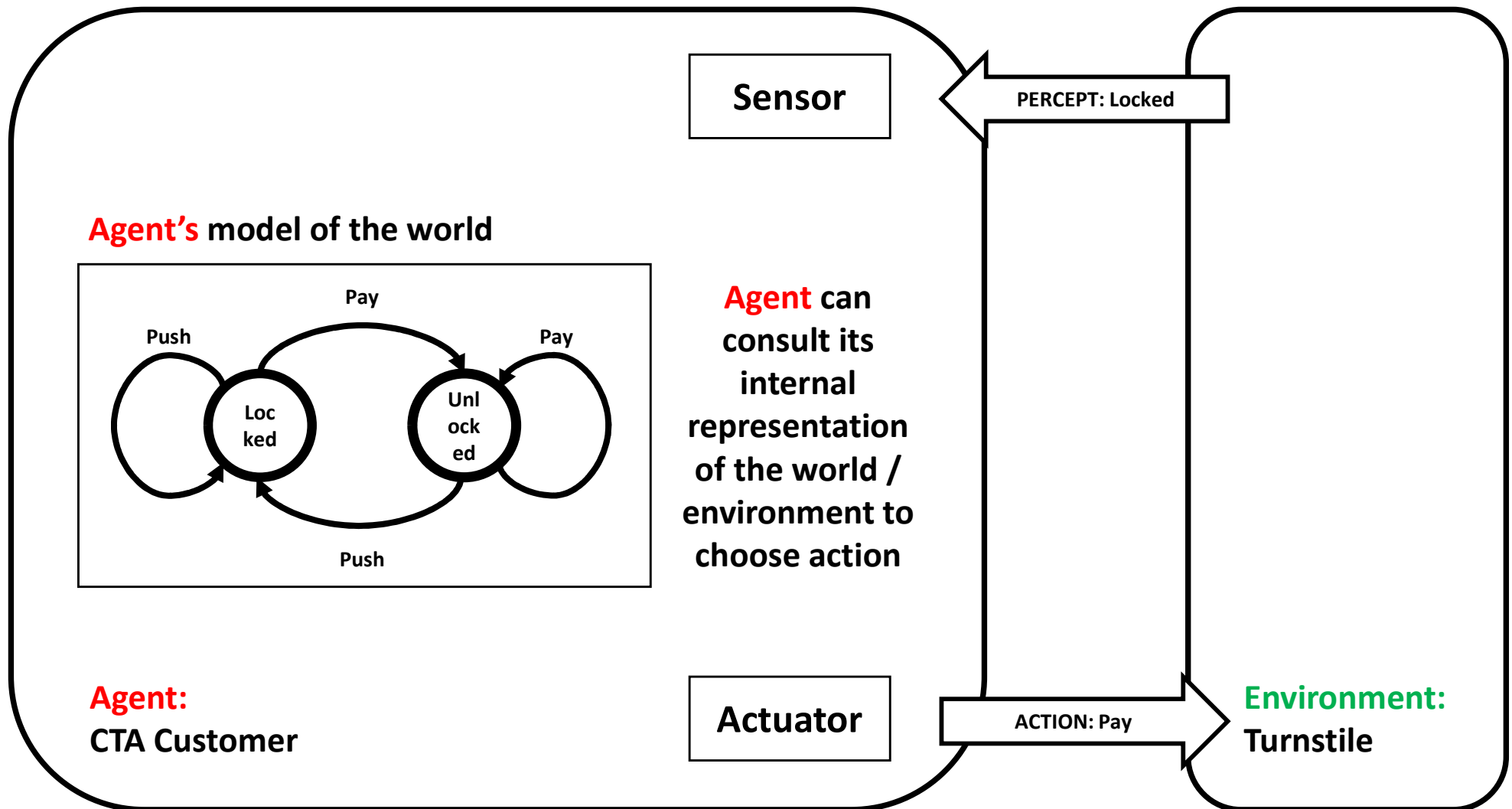
Image source: Wikipedia



# Finite State Machine: A Turnstile

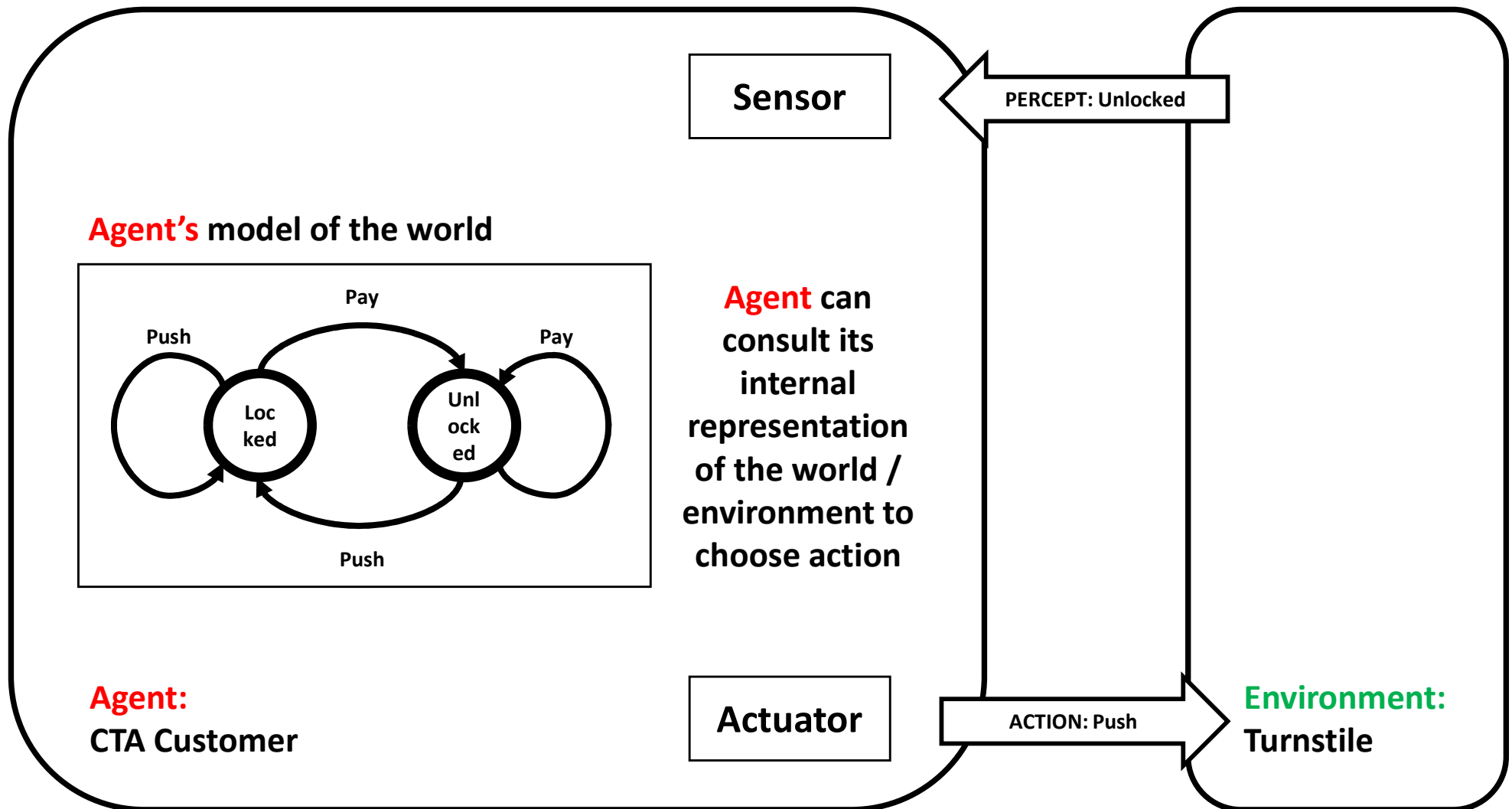


# Model-based Reflex Agent Example



**Note:** This problem could be easily solved with a simple (without internal model) reflex agent.

# Model-based Reflex Agent Example

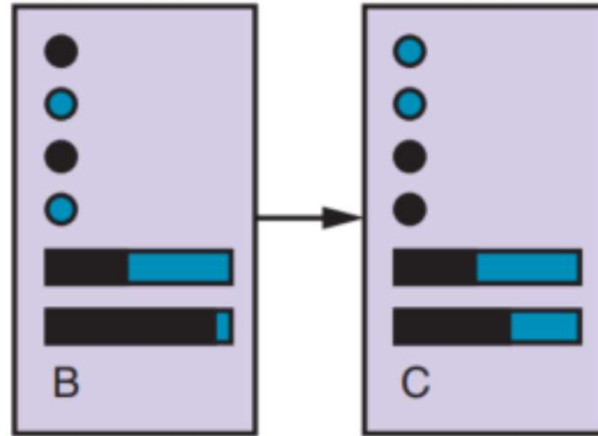


**Note:** This problem could be easily solved with a simple (without internal model) reflex agent.

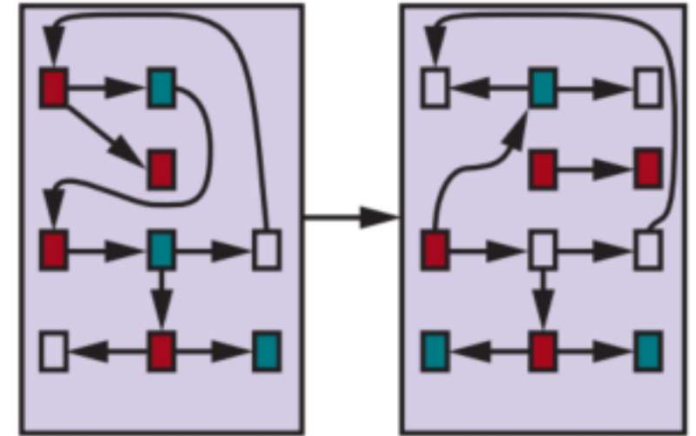
# Representations: Examples



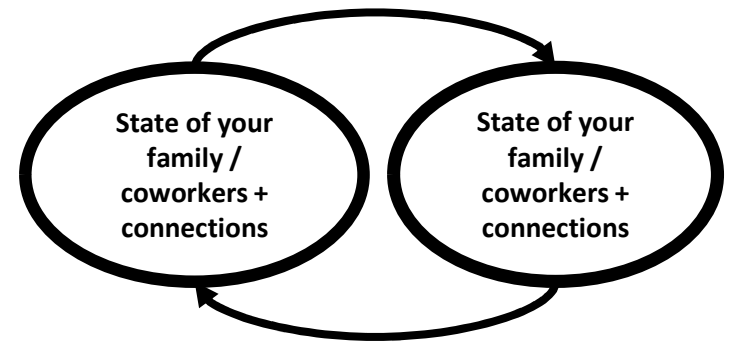
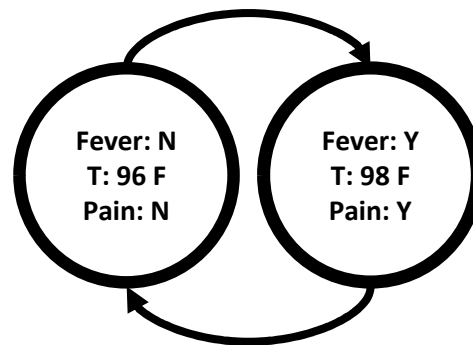
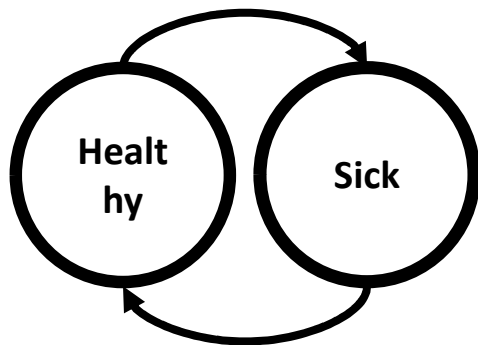
(a) Atomic



(b) Factored



(c) Structured



# Designing the Agent for the Task

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# BTW: How Would you Program it All?

# Problem-Solving / Planning Agent

- **Context / Problem:**
  - correct action is NOT immediately obvious
  - a plan (a sequence of actions leading to a goal) may be necessary
- **Solution / Agent:**
  - come up with a computational process that will search for that plan
- **Planning Agent:**
  - uses factored or structured representations of states
  - uses searching algorithms

# Planning: Environment Assumptions

## Works with a “Simple Environment”:

- Fully observable
- Single agent (for now -> it can be multiagent)
- Deterministic
- Static
- Episodic
- Discrete
- Known to the agent



# Problem-Solving Process

- **Goal formulation:**
  - adopt a goal (think: desirable state)
  - a concrete goal should help you reduce the amount of searching
- **Problem formulation:**
  - an **abstract** representation of states and actions
- **Search:**
  - search for solutions within the **abstract** world model
- **Execute actions in the solution**

# Planning: Environment Assumptions

## Works with a “Simple Environment”:

- Fully observable
- Single agent (for now -> it can be multiagent)
- Deterministic
- Static
- Episodic
- Discrete
- Known to the agent

Important and helpful:

Such assumptions **GUARANTEE** a **FIXED** sequence of actions as a solution

What does it mean?

You can execute the “plan” without worrying about incoming percepts (open-loop control)

# Designing the Searching Problem

**Analyze and  
define the  
Problem / Task**

**Model and build  
the State Space**

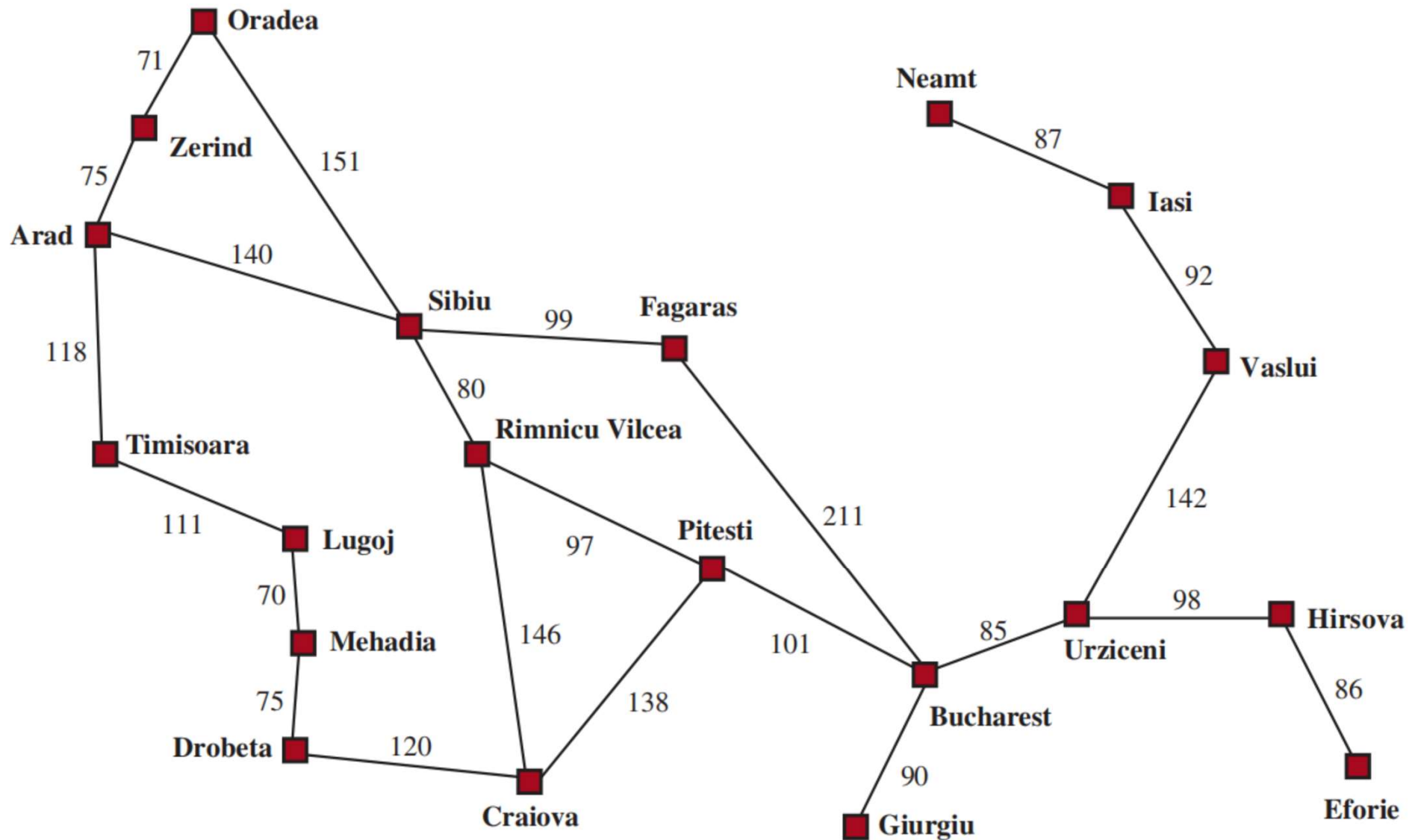
**Select searching  
algorithm**

**Search**

# Defining Search Problem

- Define a set of possible states: **State Space**
- Specify **Initial State**
- Specify **Goal State(s)** (there can be multiple)
- Define a FINITE set of possible **Actions** for EACH state in the State Space
- Come up with a **Transition Model** which describes what each action does
- Specify the **Action Cost Function**: a function that gives the cost of applying action  $a$  in state  $s$

# Sample Problem: Romanian Roadtrip

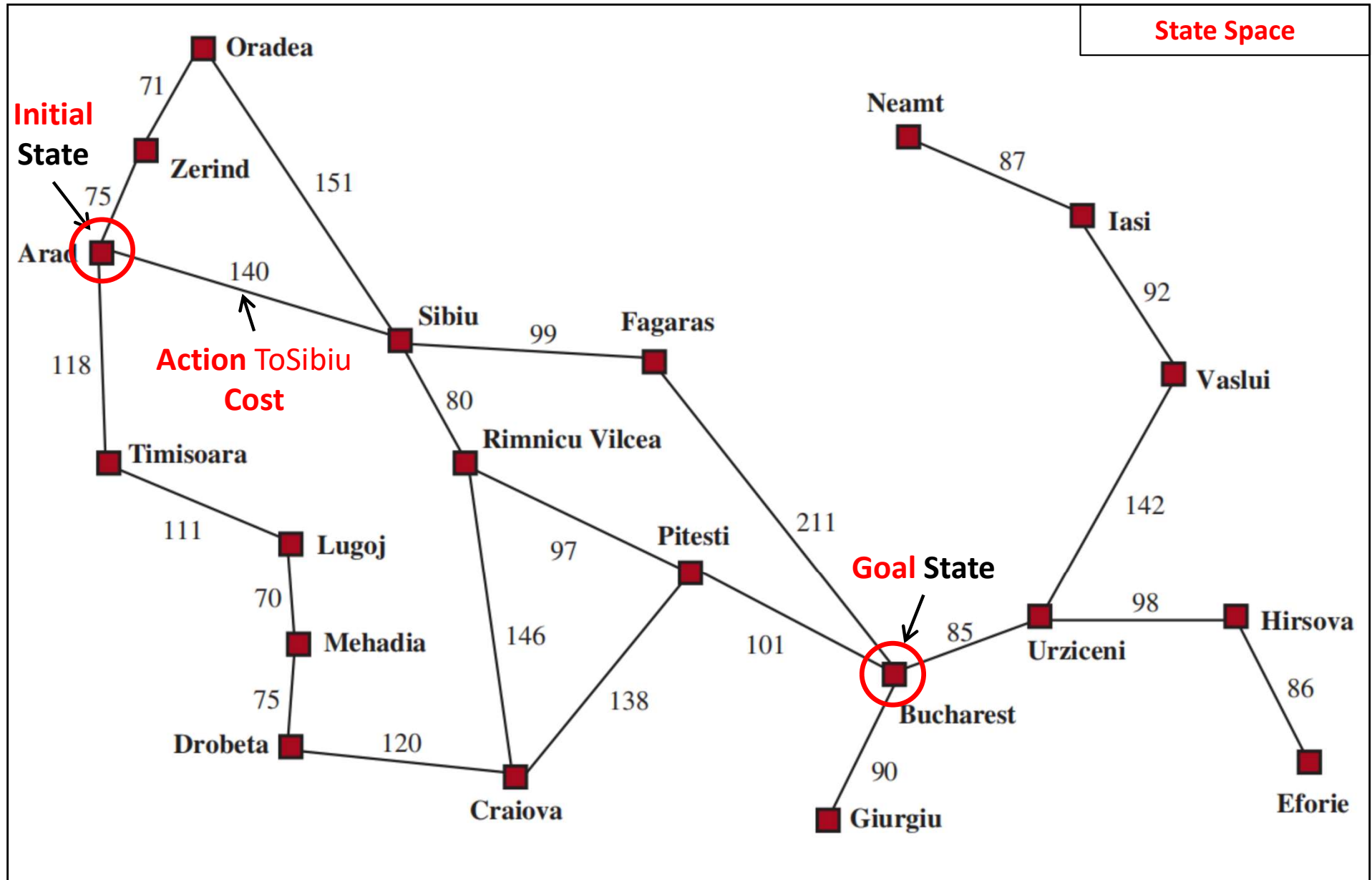


**Problem:** Get from Arad to Bucharest efficiently (for example: quickly or cheaply).

# Search Problem: Romanian Roadtrip

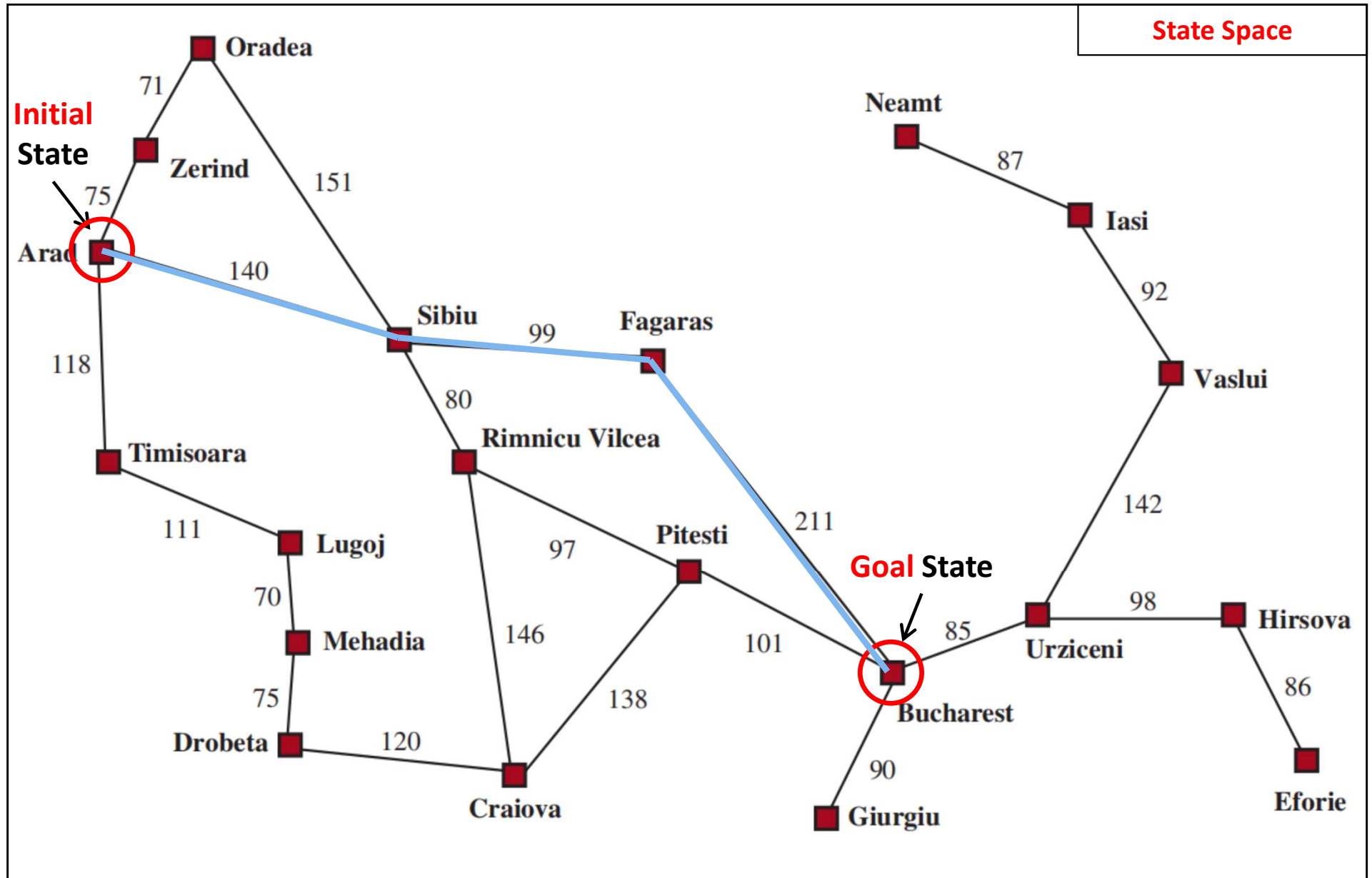
- State Space: **a map of Romania**
- Initial State: **Arad**
- Goal State: **Bucharest**
- Actions:
  - for example:  **$ACTIONS(Arad) = \{ToSibiu, ToTimisoara, ToZerind\}$**
- Transition Model:
  - for example:  **$RESULT(Arad, ToZerind) = Zerind$**
- Action Cost Function [ **$ActionCost(S_{current}, a, S_{next})$** ]
  - for example:  **$ActionCost(Arad, ToSibiu, Sibiu) = 140$**

# Sample Problem: Romanian Roadtrip



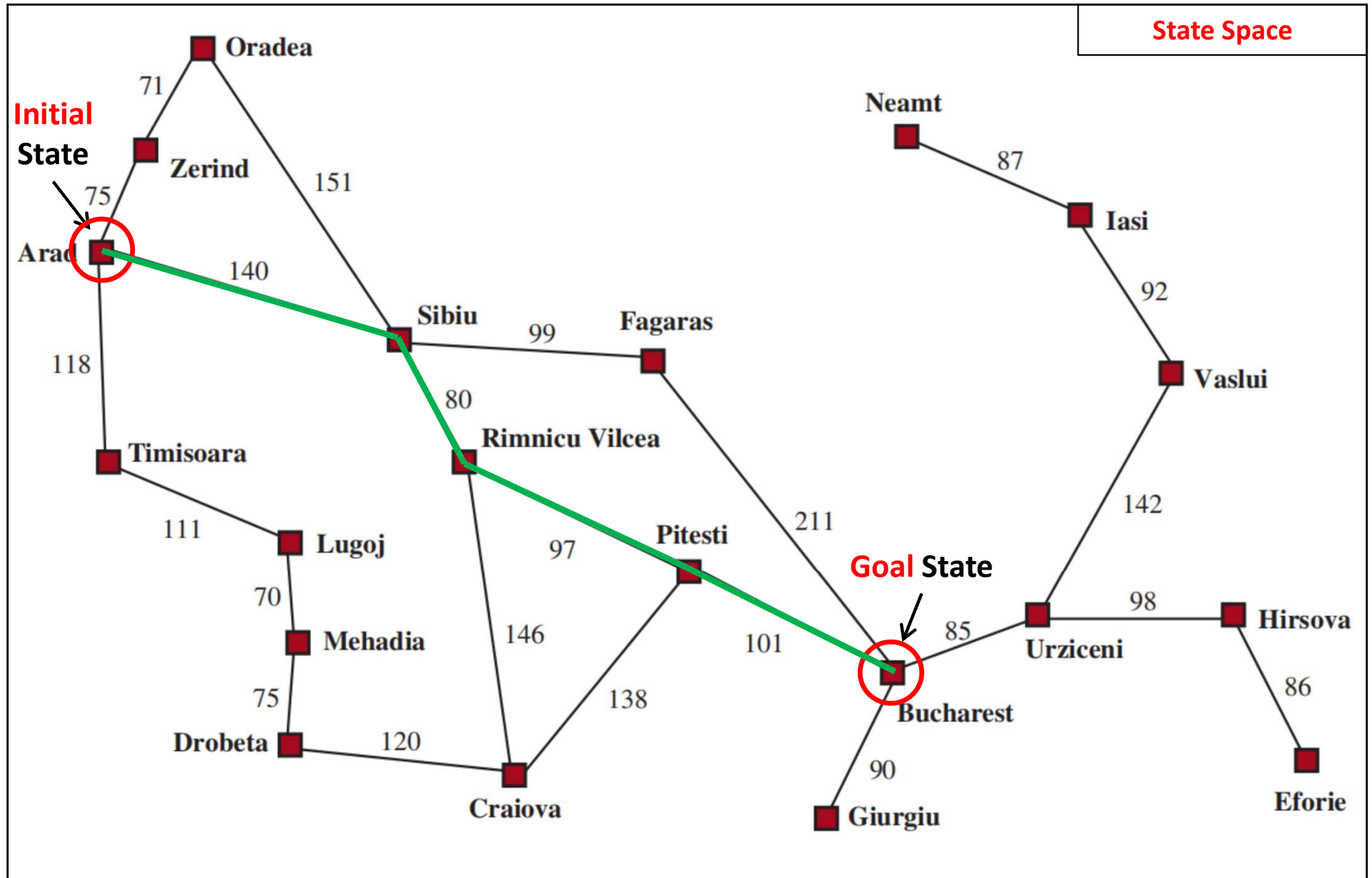


# Romanian Roadtrip: Potential Solution

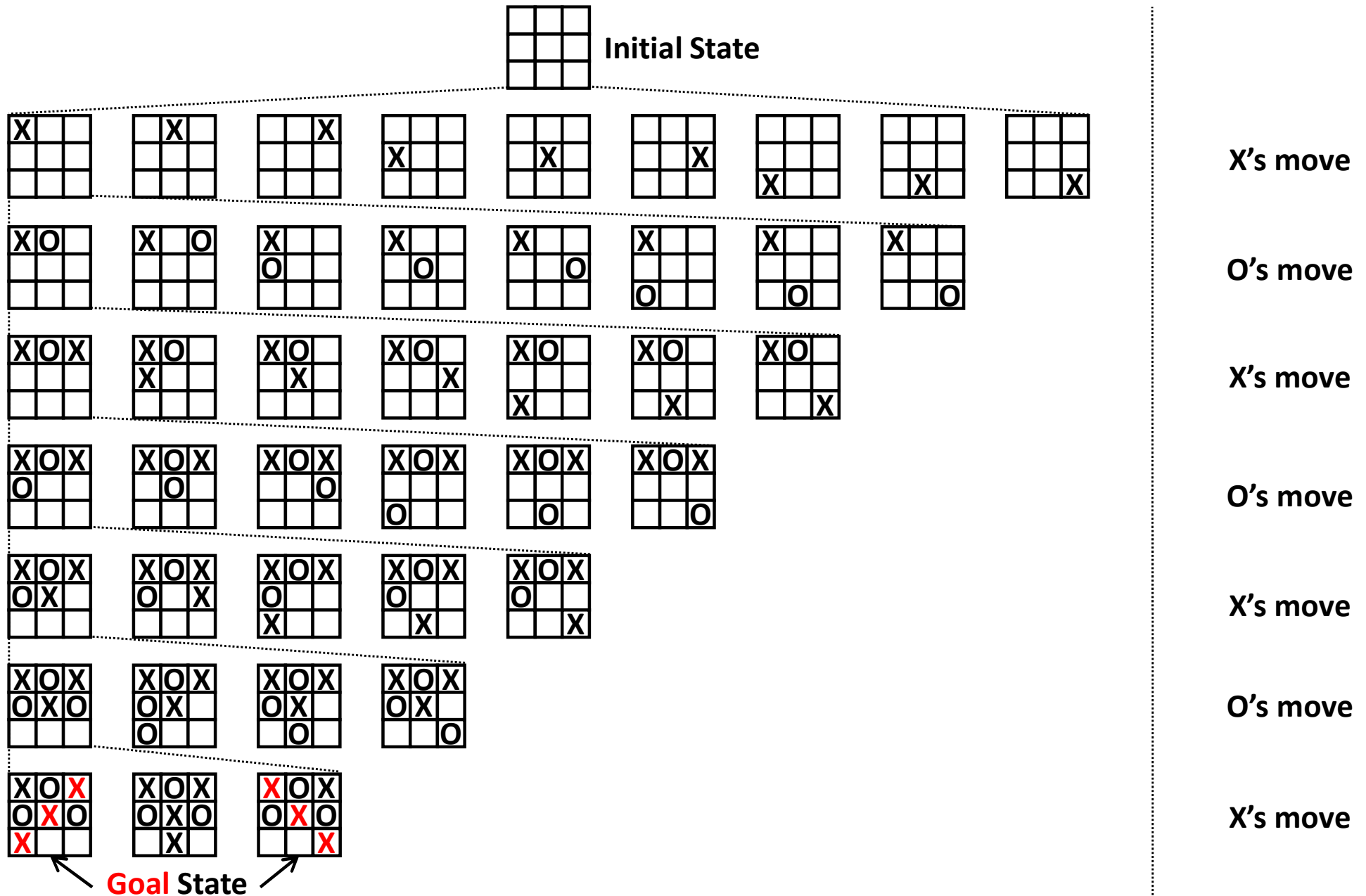




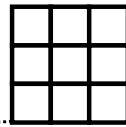
# Romanian Roadtrip: Potential Solution



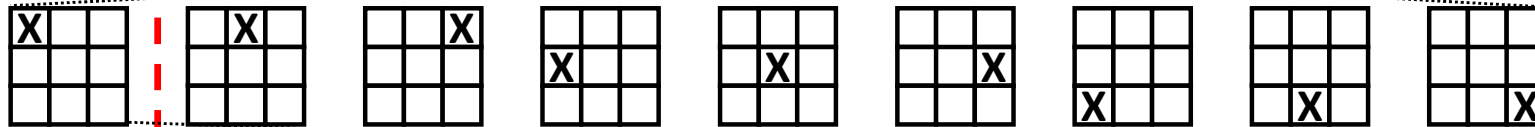
# Tic Tac Toe: (Partial) State Space



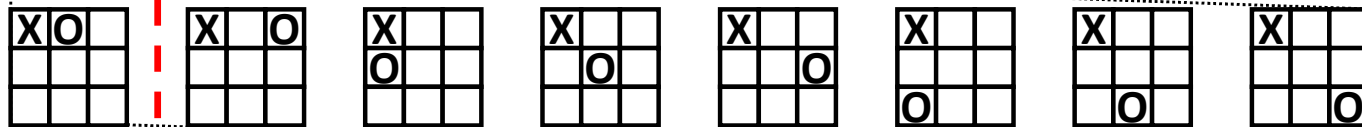
# Tic Tac Toe: Solution



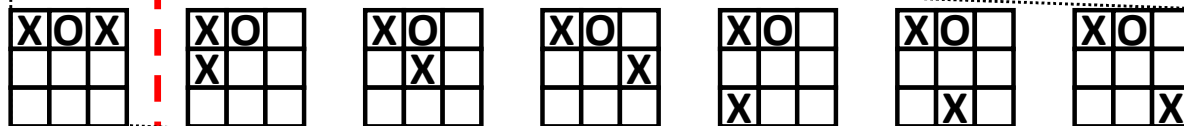
Initial State



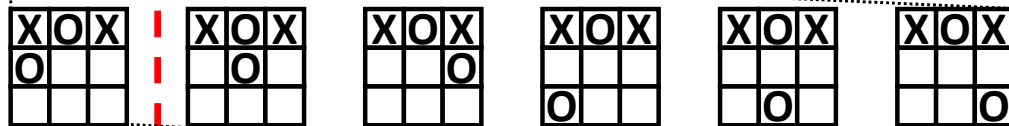
X's move



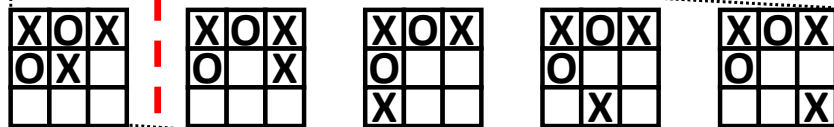
O's move



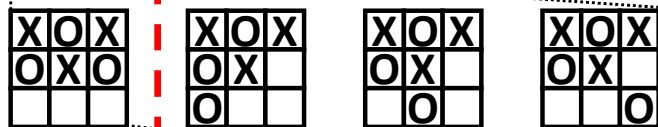
X's move



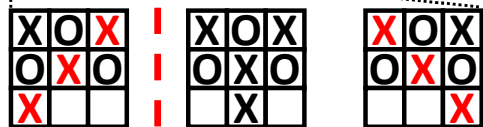
O's move



X's move



O's move



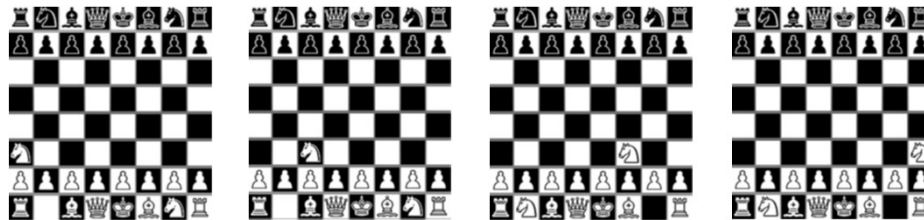
X's move

Solution

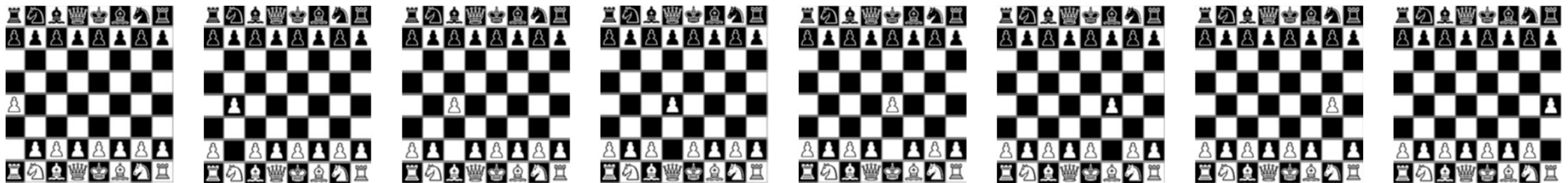
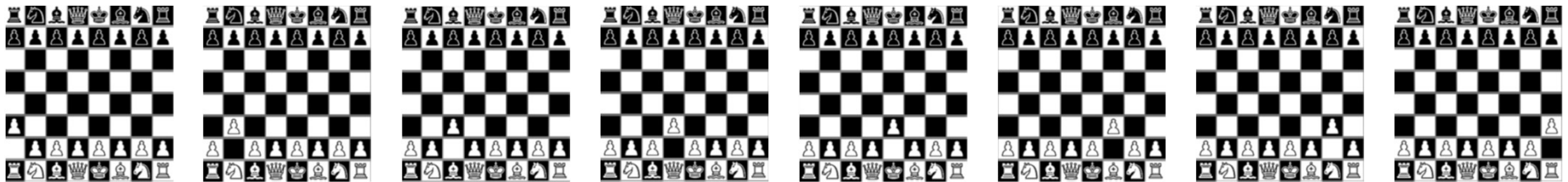
A **Solution** is a sequence of actions (a path) between the initial state and the goal state

# Chess: (First Move) State Space

Initial  
State



20 Possible **legal** first moves:  
16 pawn moves  
4 knight moves



# Designing the Searching Problem

**Analyze and  
define the  
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**Model and build  
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**Select searching  
algorithm**

**Search**

# State Space Model: A Graph

$ACTIONS(A) = \{toB, toC\}$

$ACTIONS(B) = \{toF\}$

$ACTIONS(F) = \{toE\}$

Action: toB

$RESULT(A, toB) = B$

$C(A, toB, B) = 1$

INITIAL  
STATE  
A

STATE  
B

STATE  
F

Action: toE

$C(F, toE, E) = 1$

Action: toF

$C(B, toF, F) = 1$

Action: toE

$C(D, toE, E) = 1$

Action: toB

$C(C, toB, B) = 1$

$C(A, toC, C) = 1$

Action: toC

STATE  
C

STATE  
D

GOAL  
STATE  
E

$RESULT(A, toC) = C$

Action: toD

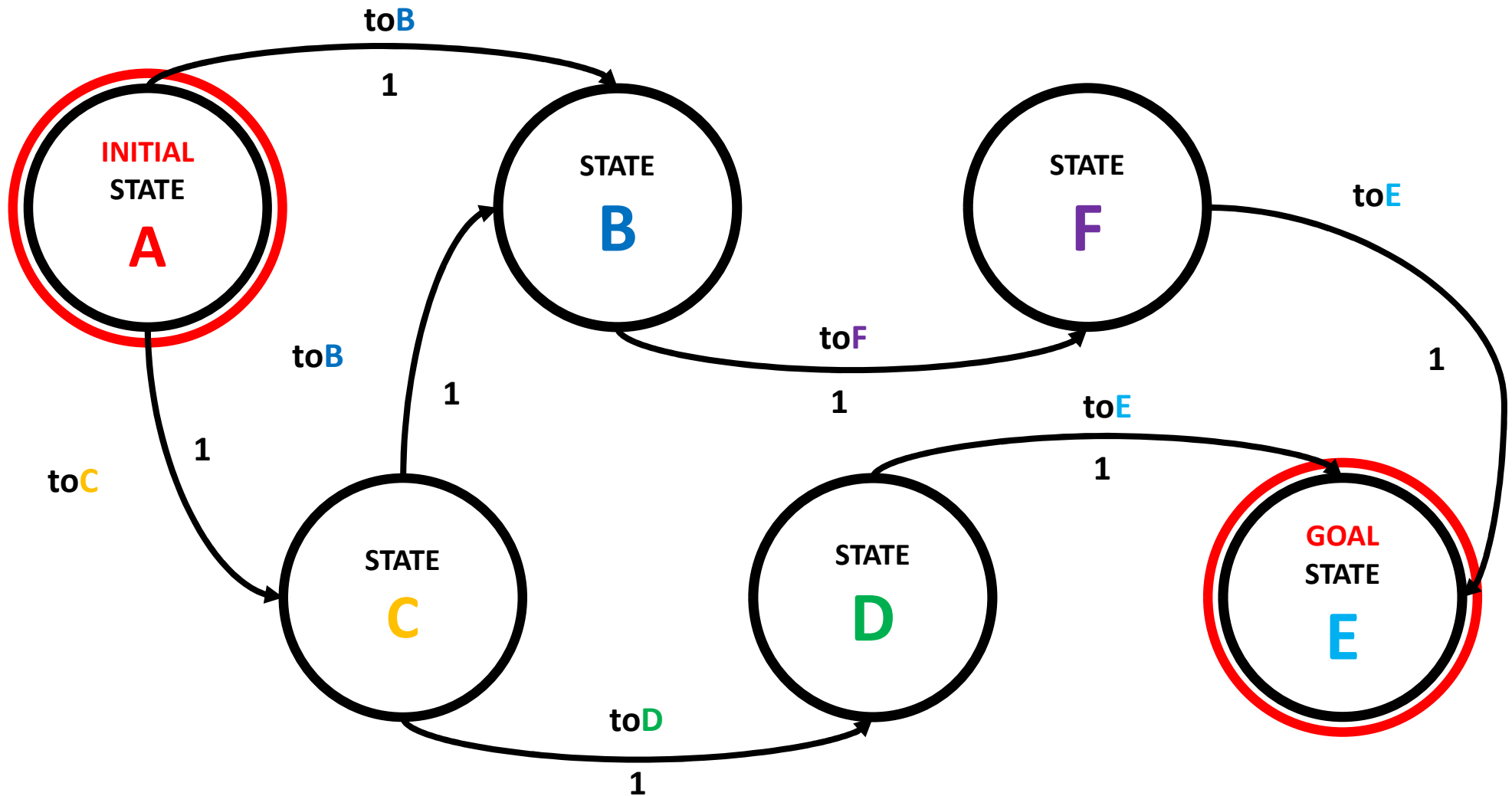
$C(C, toD, D) = 1$

$ACTIONS(C) = \{toB, toD\}$

$ACTIONS(D) = \{toE\}$

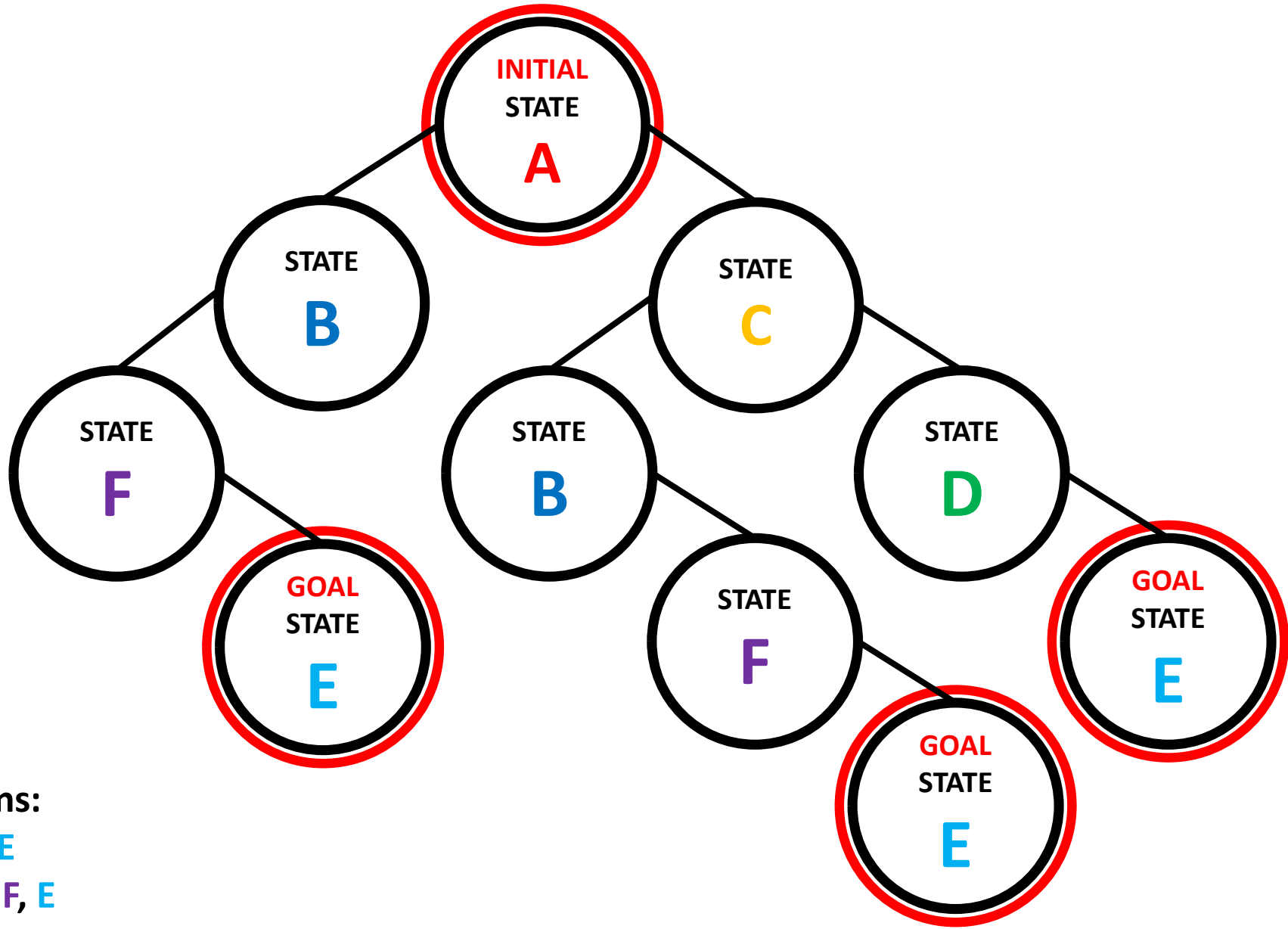
$ACTIONS(E) = \emptyset$

# State Space Model: A Graph





# Searching State Space: Search Tree



Solutions:

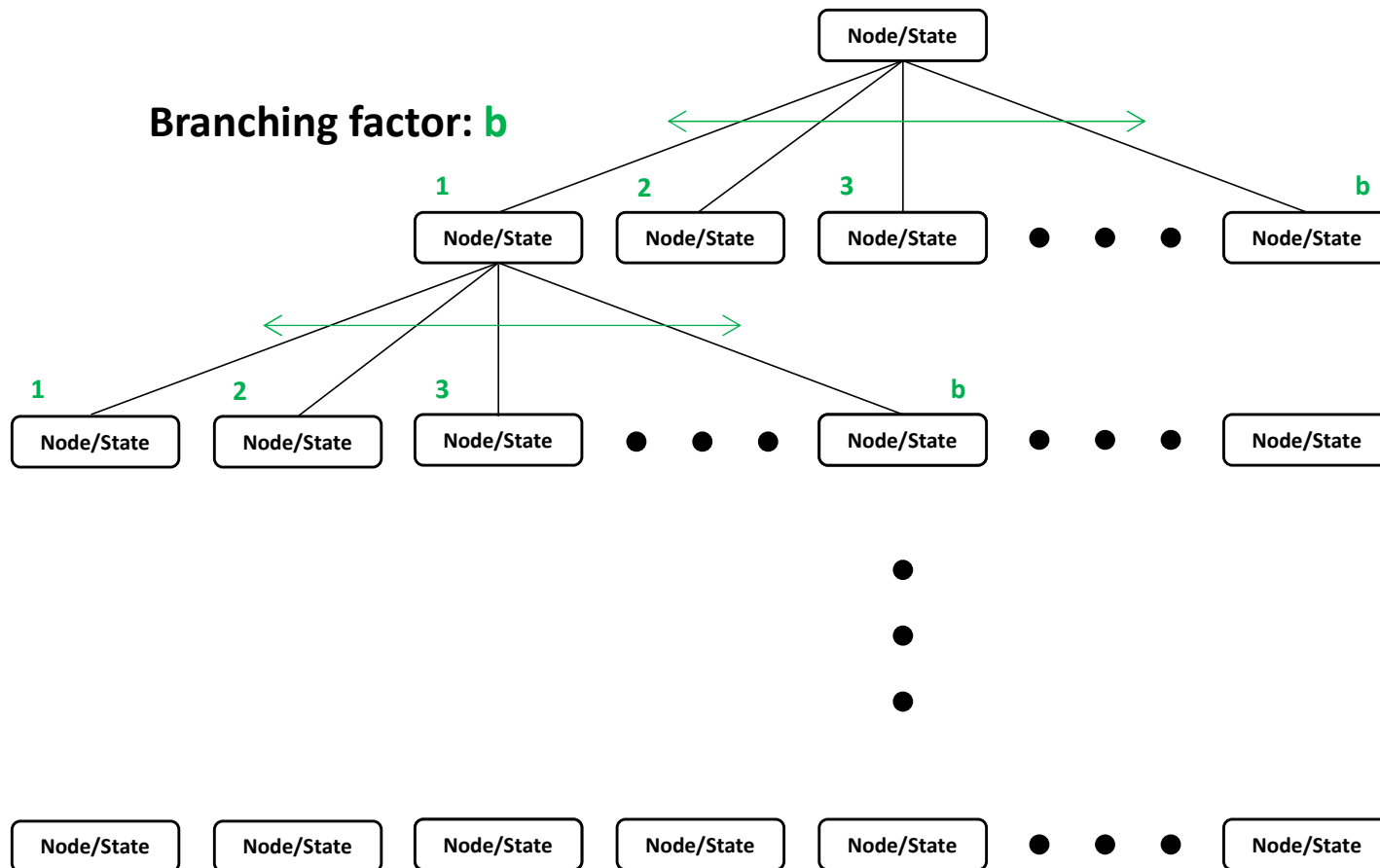
A, B, F, E

A, C, B, F, E

A, C, D, E



# Search Tree Challenges: Size



**Depth: 0 |  $N_0 = 1$**

Depth: 1 |  $N_1 = b$

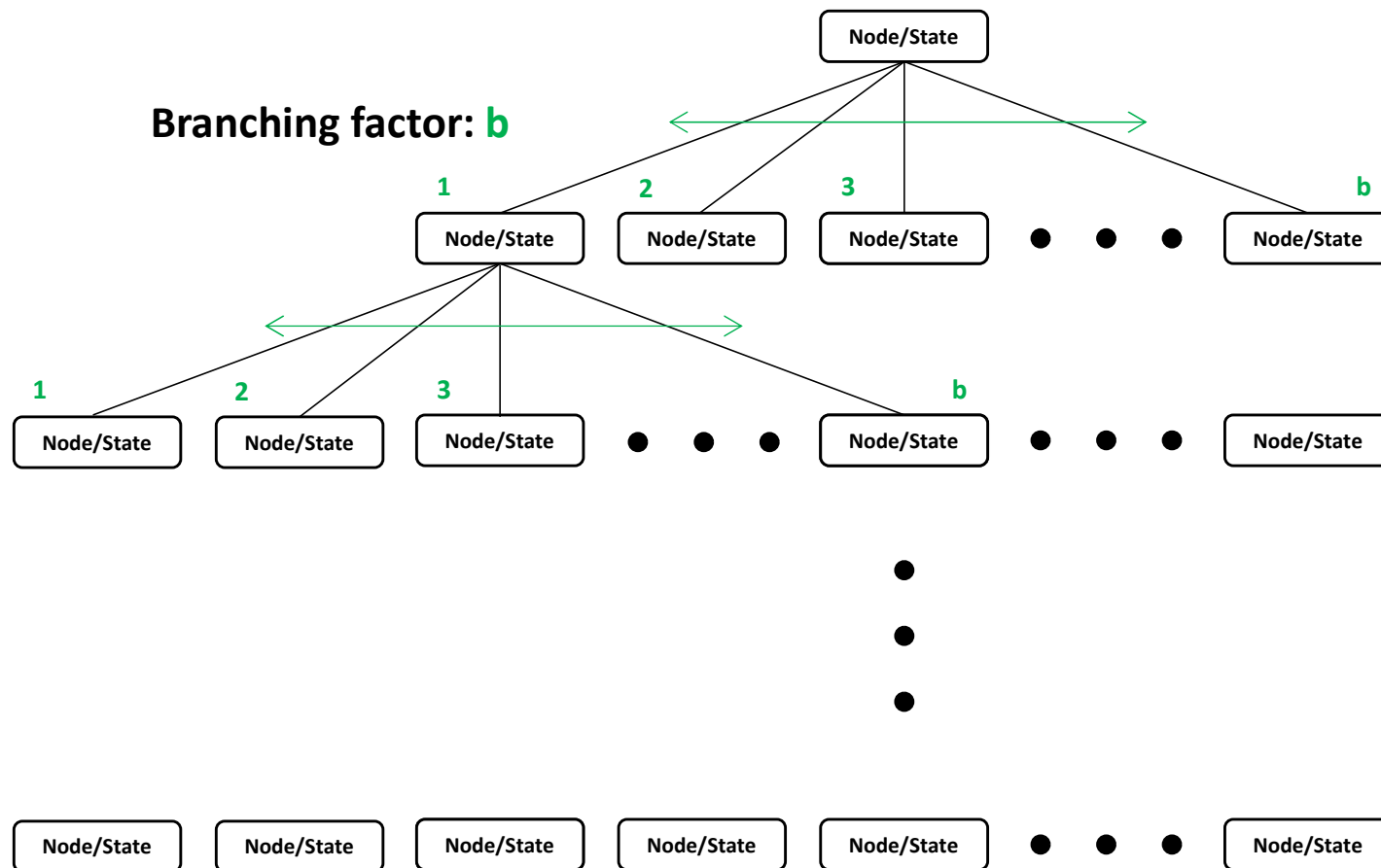
Depth: 2 |  $N_2 = b^2$

Depth:  $d$  |  $N_d = b^d$

**Total number of nodes / states:**  $1 + b + b^2 + b^3 + \dots + b^d \rightarrow O(b^d)$

**Quickly becomes unmanageable and impossible to search with brute force!**

# Search Tree Challenges: Infiniteness



**Depth: 0**

## Depth: 1

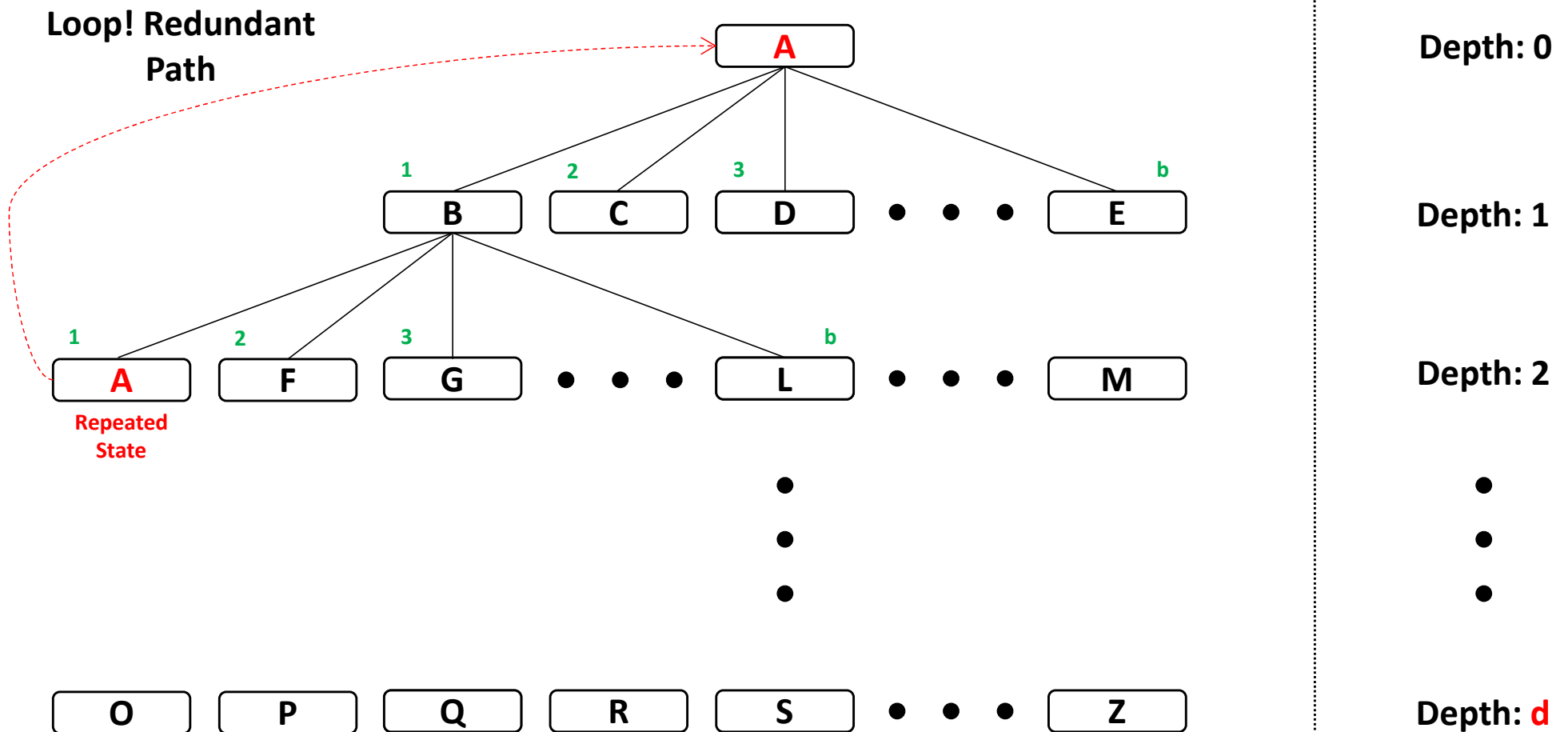
## Depth: 2

Depth: **d**  $\rightarrow \infty$

## Unmanageable and impossible to search with brute force!

## Memory and time use grows quickly!

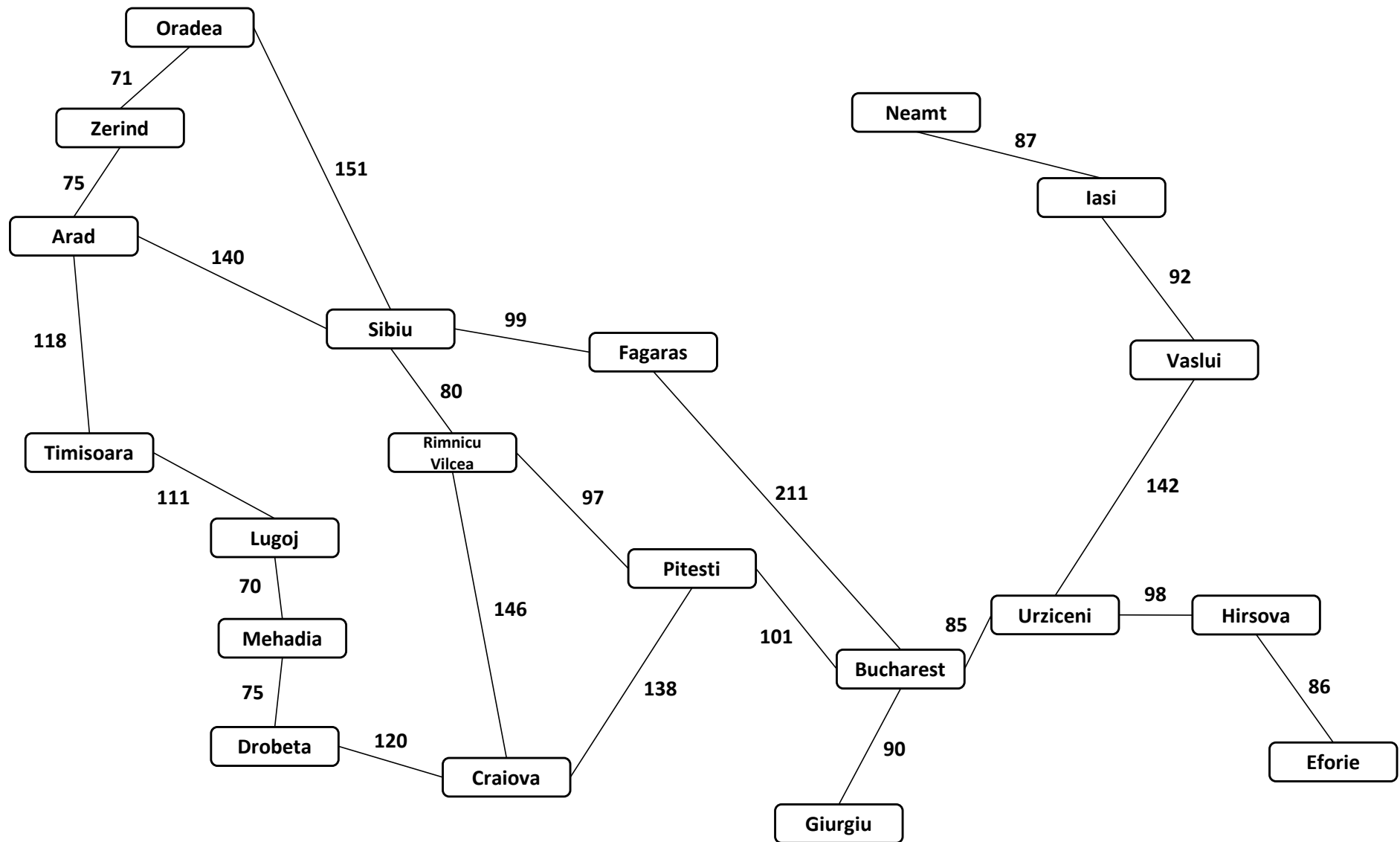
# Search Tree Challenges: Loops



This would lead to an infinite state sequence repetition if not handled!

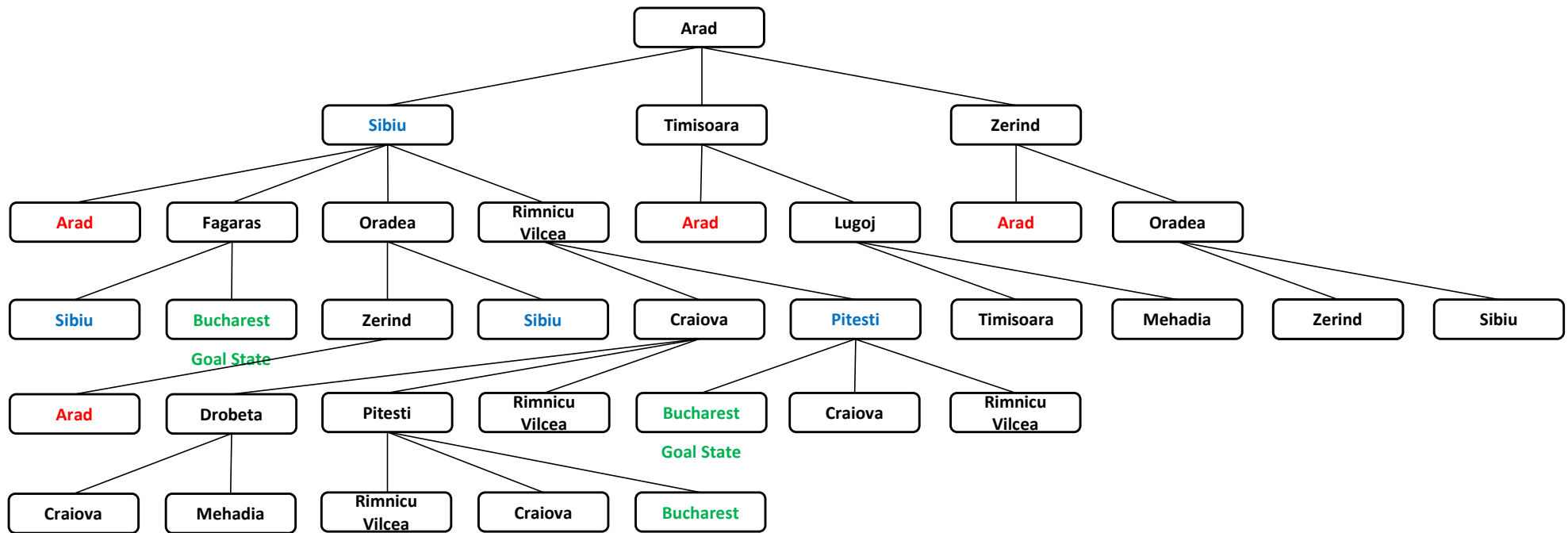
Memory and time use grows quickly!

# Sample Problem: Dracula's Roadtrip



**Problem:** Get from Arad to Bucharest efficiently (for example: quickly or cheaply).

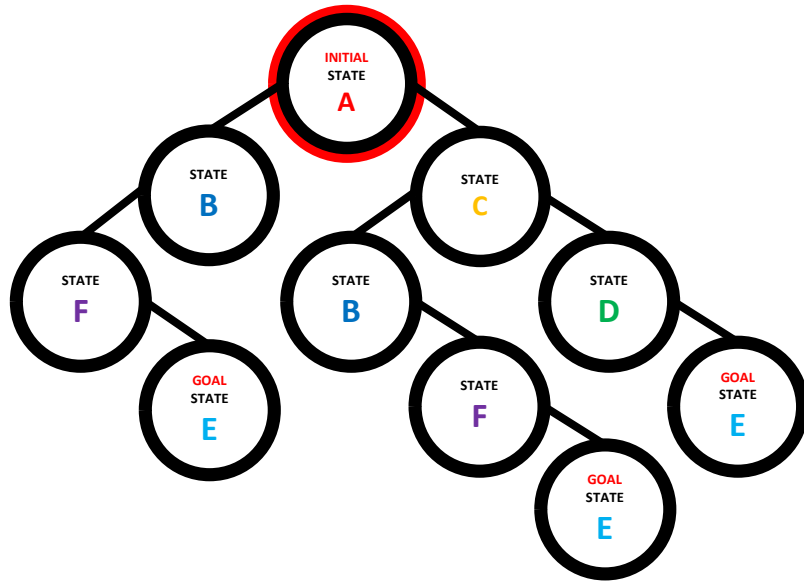
# Romanian Roadtrip as a Tree



INCOMPLETE! I need to redraw it in smarter way

# Search Tree: Implementations

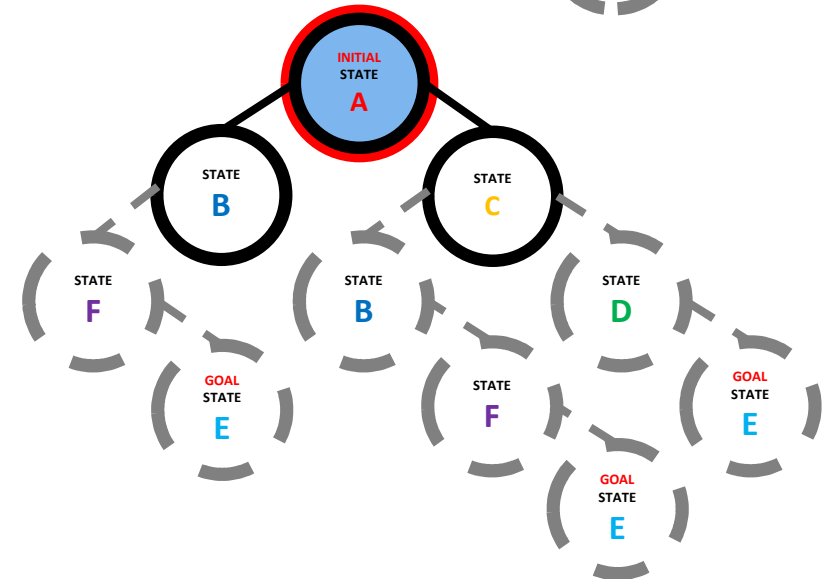
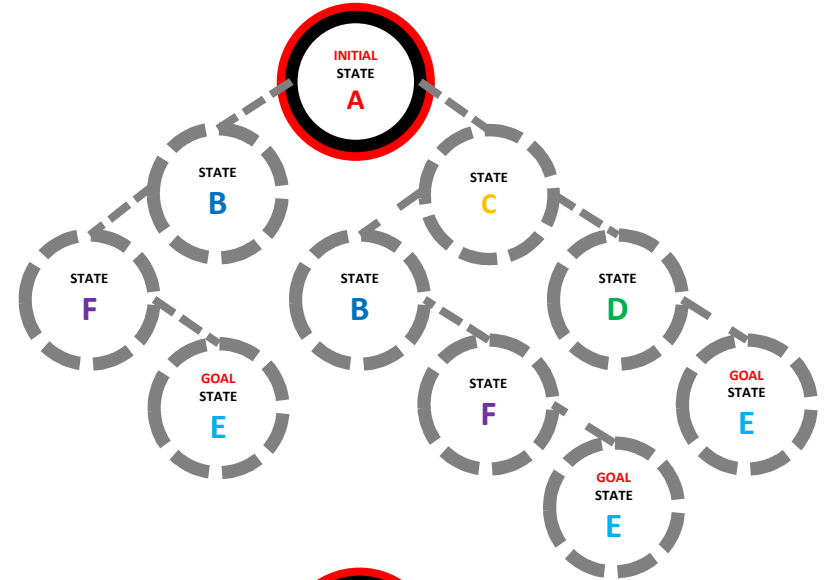
Build entire search tree



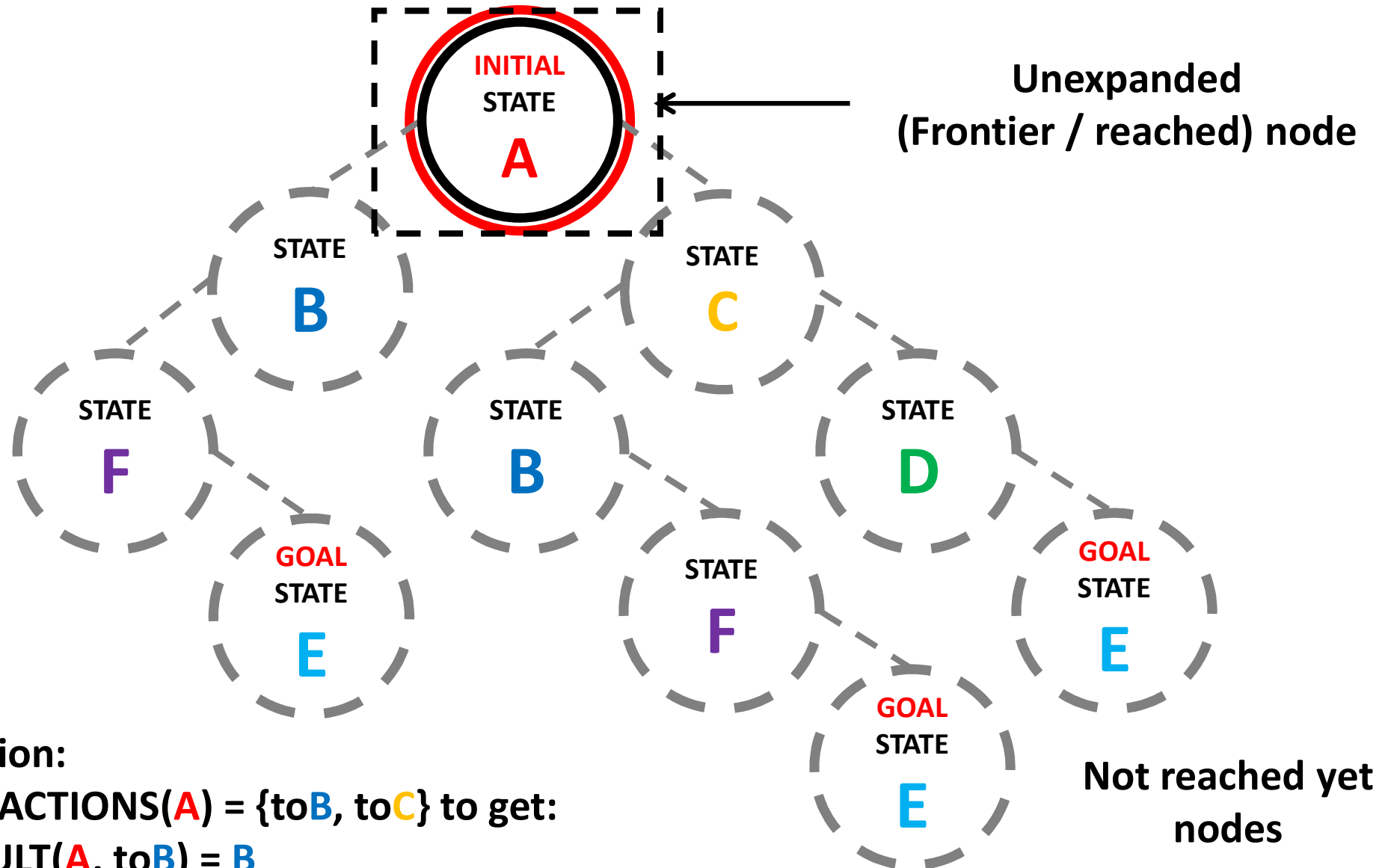
Challenges:

- memory requirements
- impossible for infinite number of states

Expand/generate nodes as you go



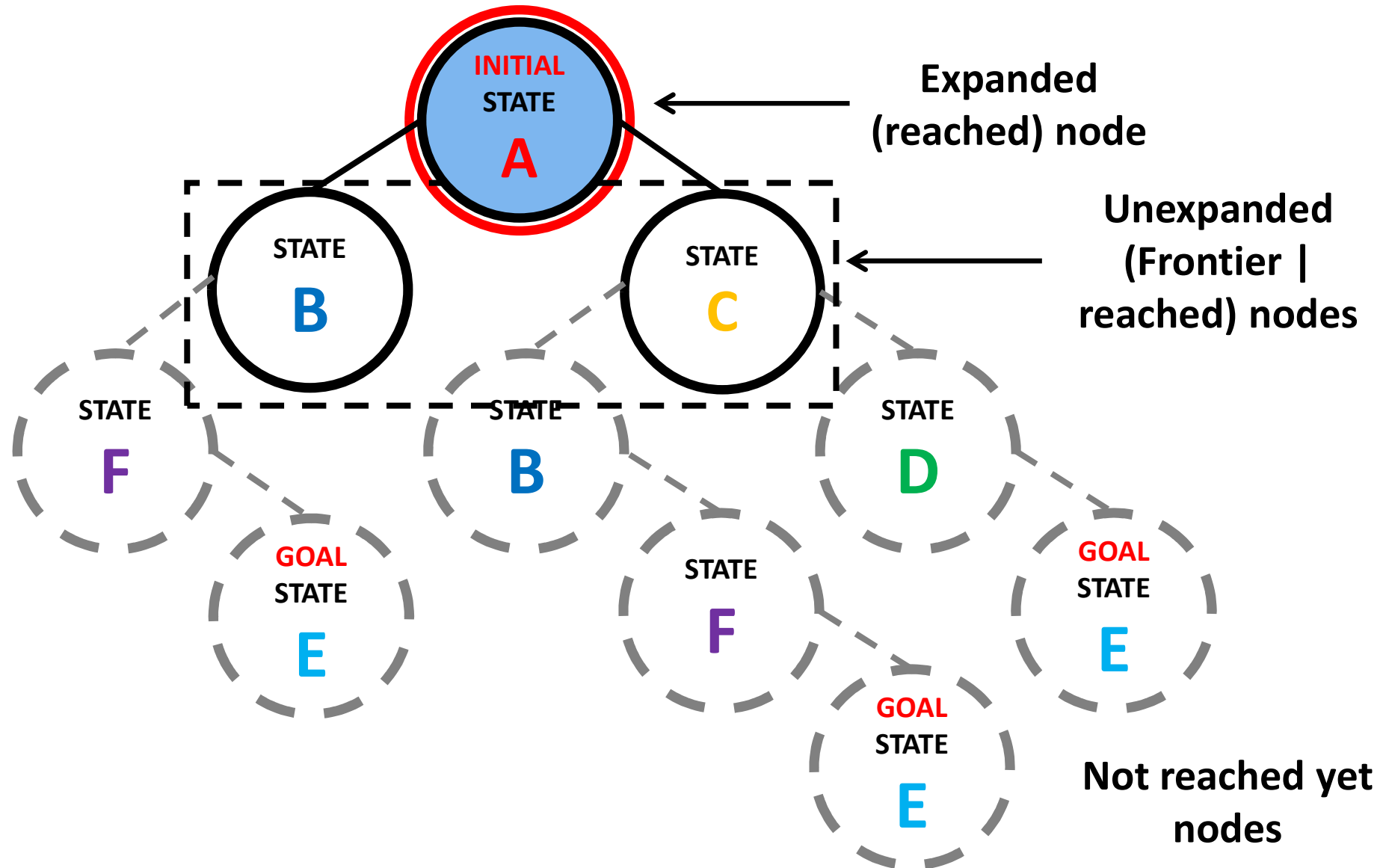
# Search Tree: Node Expansion



Expansion:

- Use  $\text{ACTIONS}(\text{A}) = \{\text{toB}, \text{toC}\}$  to get:
- $\text{RESULT}(\text{A}, \text{toB}) = \text{B}$
- $\text{RESULT}(\text{A}, \text{toC}) = \text{C}$

# Search Tree: Node Expansion



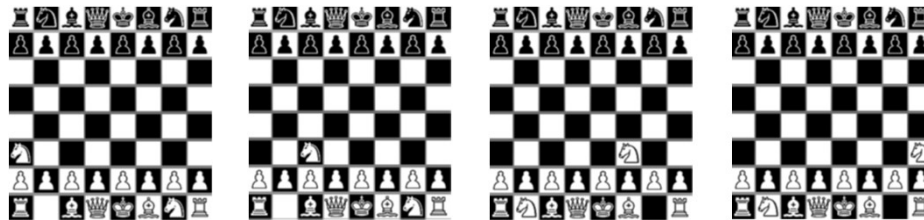


# Chess: State Node Expansion

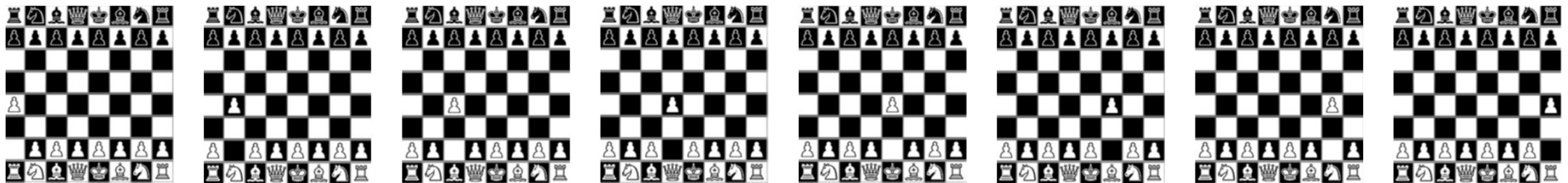
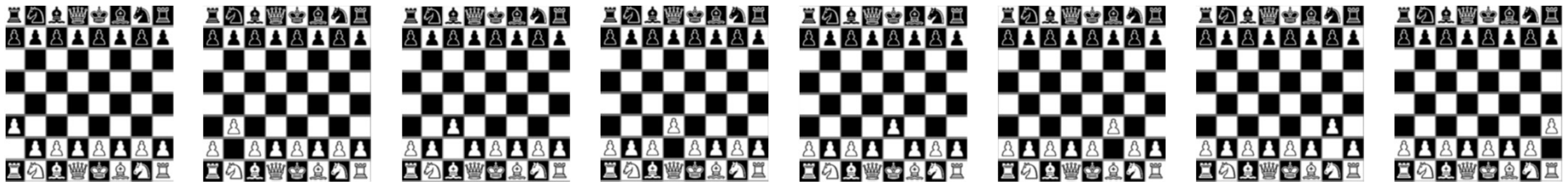
Initial  
State



Use game rules to generate subsequent possible game tree states / nodes!



20 Possible **legal** first moves:  
16 pawn moves  
4 knight moves



# Designing the Searching Problem

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**Select searching  
algorithm**

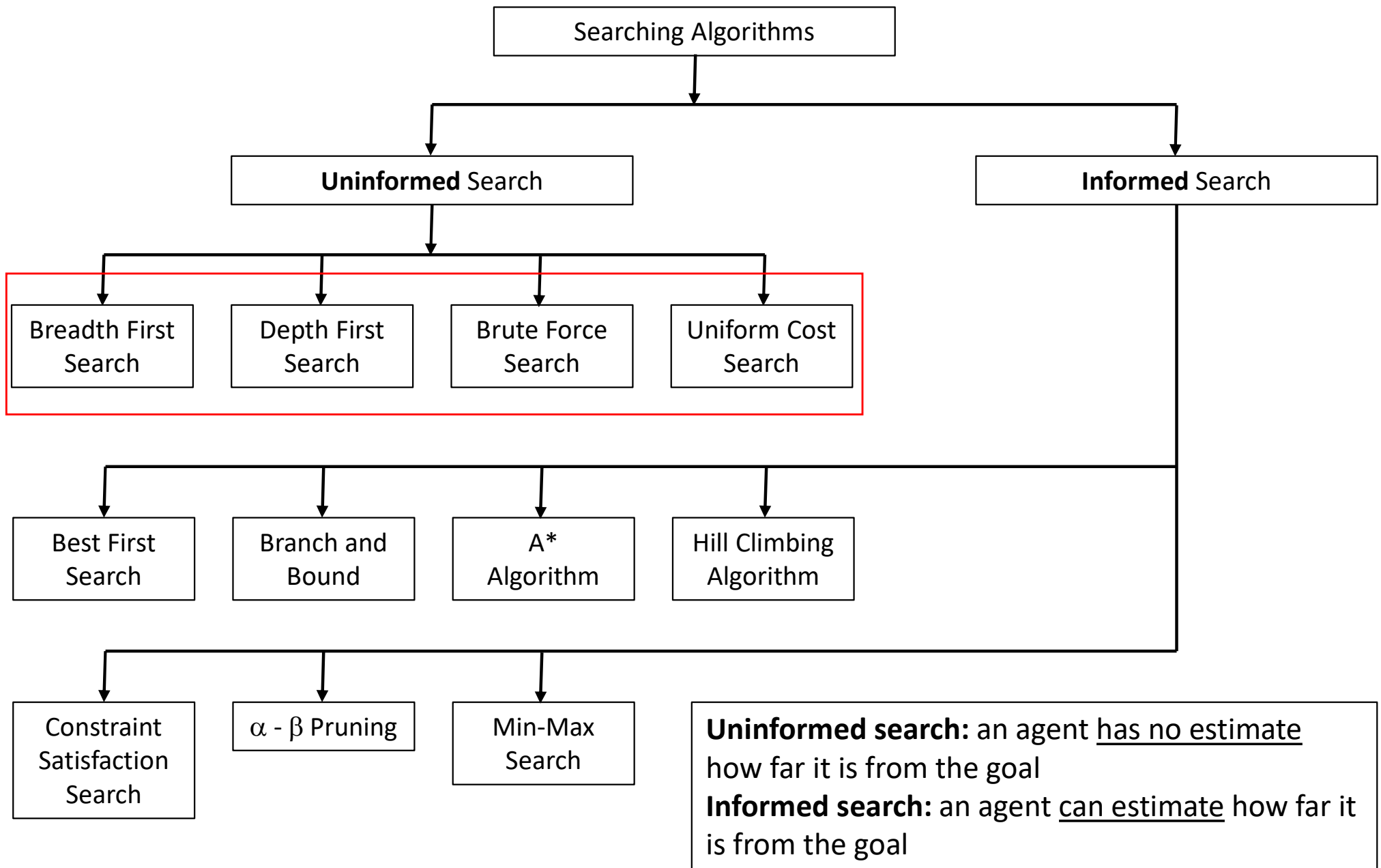
**Search**

# Measuring Searching Performance

Search algorithms can be evaluated in four ways:

- **Completeness**: Is the algorithm guaranteed to find a solution when there is one, and to correctly report failure when there is not?
- **Cost optimality**: Does it find a solution with the lowest path cost of all solutions?
- **Time complexity**: How long does it take to find a solution? (in seconds, actions, states, etc.)
- **Space complexity**: How much memory is needed to perform the search?

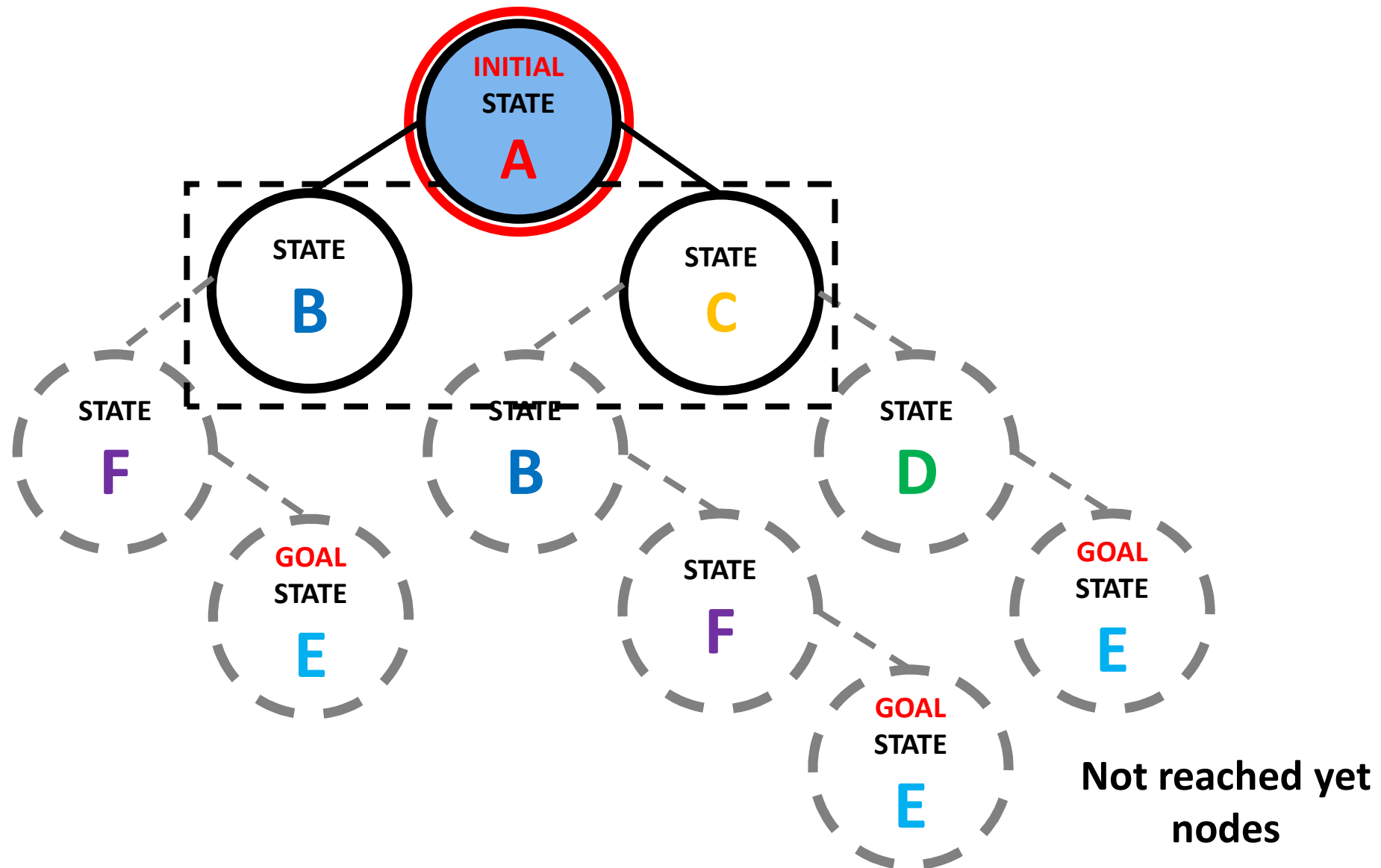
# Selected Searching Algorithms



# Uninformed Searching

- **Breadth First Search (BFS):**
  - Will find a solution with a minimal number of actions
  - Large memory requirement
  - Only relatively small problem instances are tractable
- **Depth First Search:**
  - May NOT find a solution with a minimal number of actions
  - Requires less memory than BFS (for tree search)
  - Backtracking (one child / successor generated at a time)
- **Brute Force Search:** depends on the approach -> bad
- **Uniform Cost Search:** minimize solution / path cost

# Expansion: Which Node to Expand?



# Evaluation function

**Calculate / obtain:**

$$f(n) = f(\text{State } n)$$

$$f(n) = f(\text{relevant information about State } n)$$

**A state  $n$  with minimum  $f(n)$  should be  
chosen for expansion**

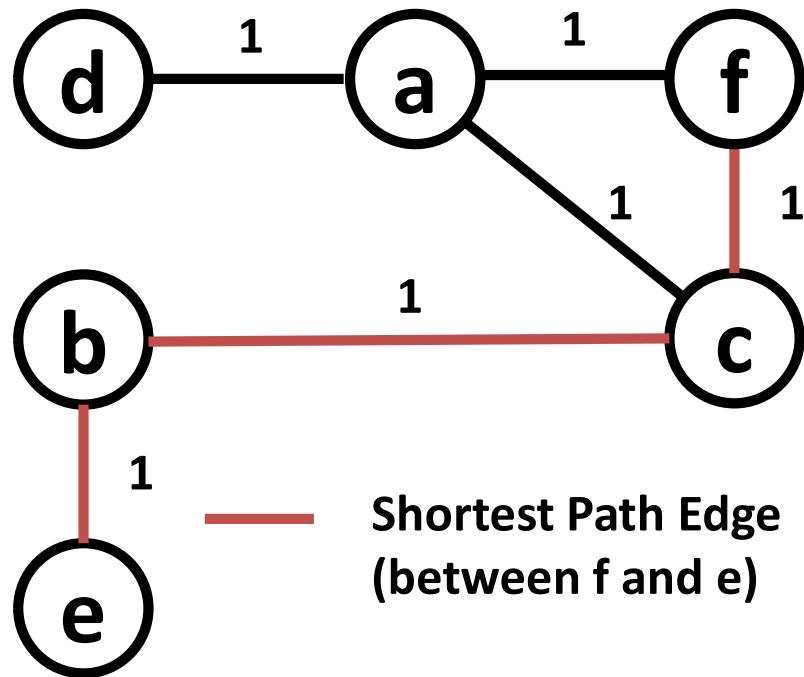
**What about ties?**

[illegible]



# Uniform Cost Search | Dijkstra's Algo

Weighted Graph G



Popular algorithms:

- Dijkstra's algorithm

## Shortest Path Problem

**Shortest path problem:**

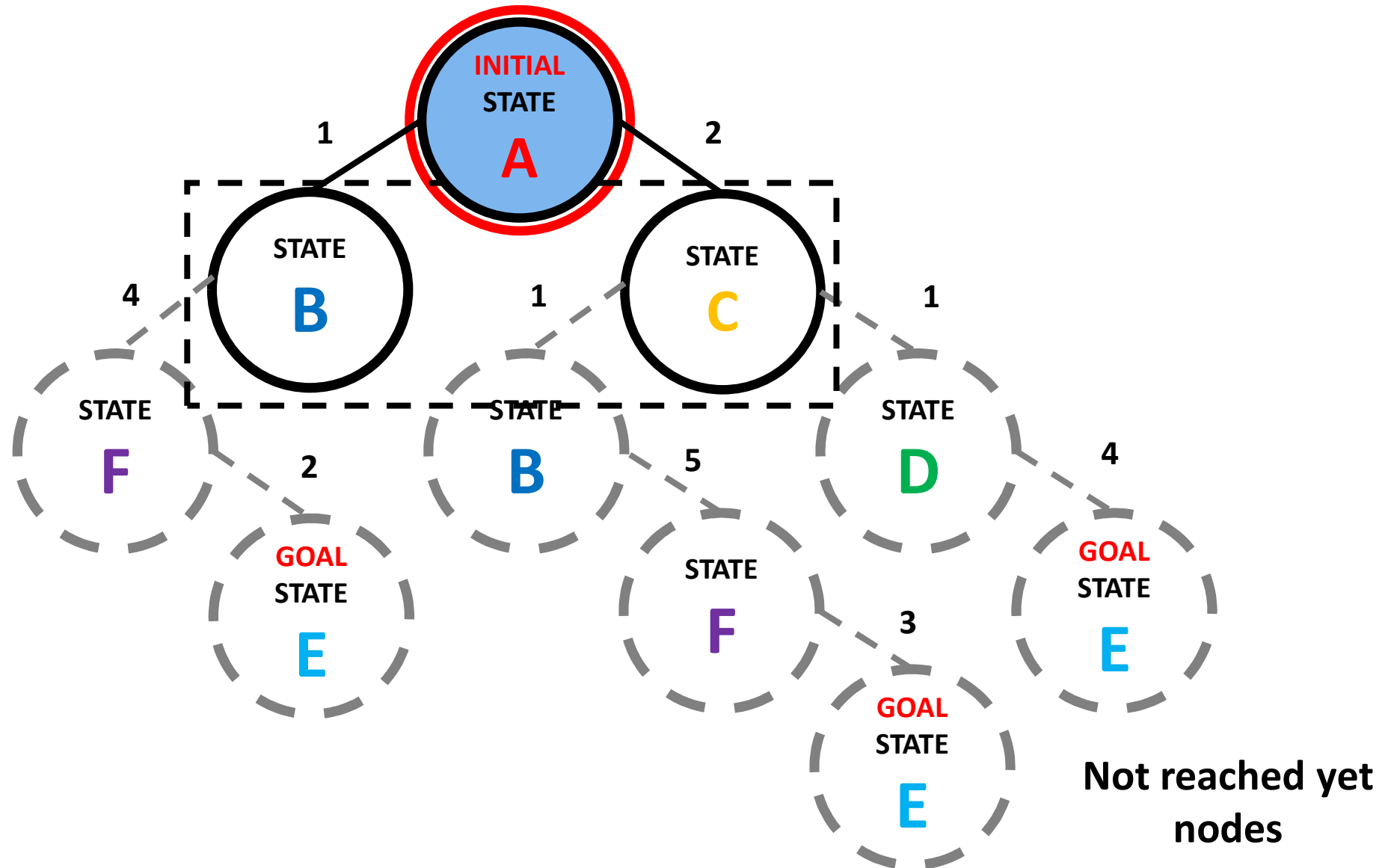
Given a weighted graph  $G(V, E, w)$  and two vertices  $a, b$  in  $V$ , find the shortest path between vertices  $a$  and  $b$  (**all edge weights are equal**).

# BFS and UCS: Pseudocode

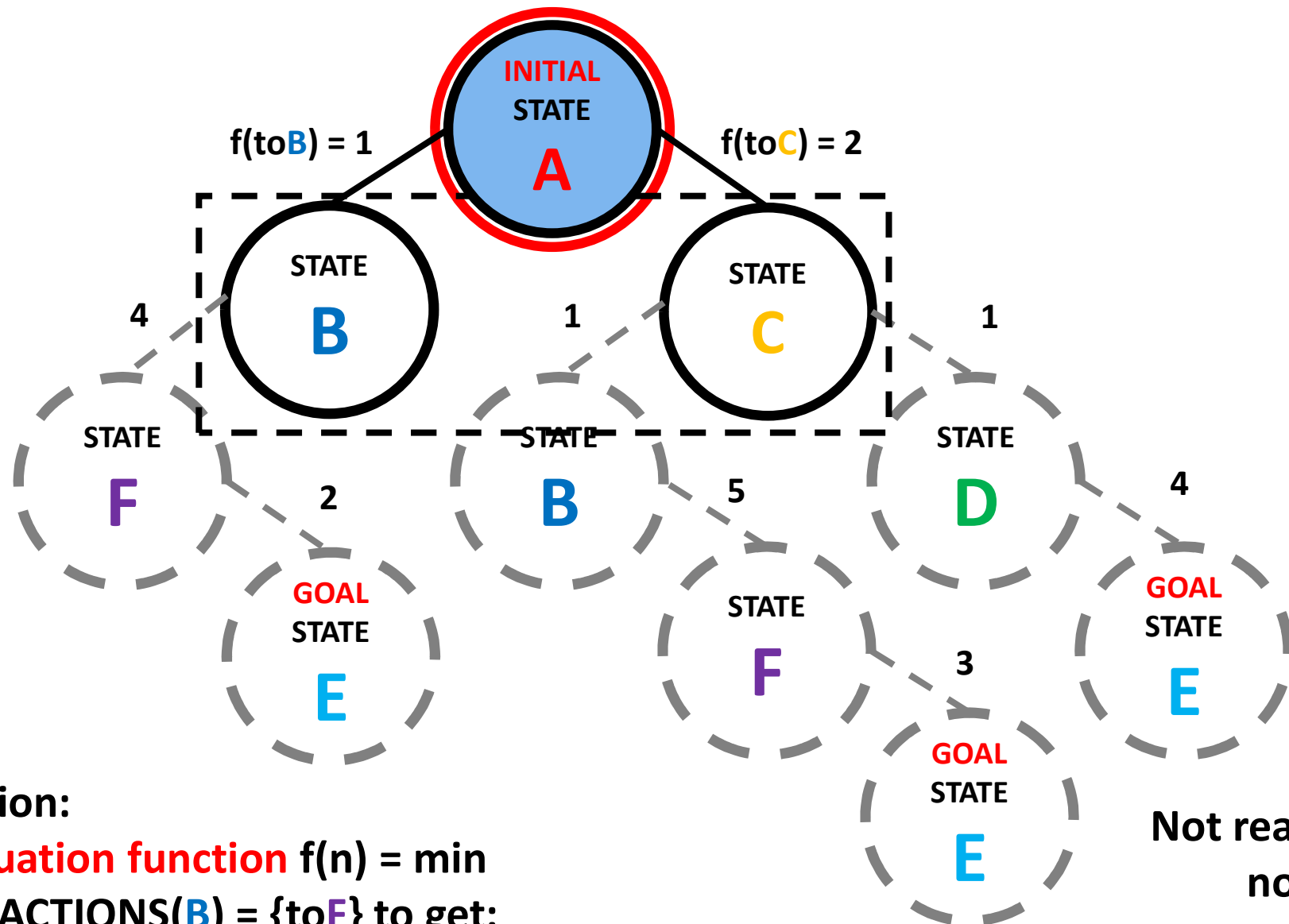
```
function BREADTH-FIRST-SEARCH(problem) returns a solution node or failure  
  node  $\leftarrow$  NODE(problem.INITIAL)  
  if problem.IS-GOAL(node.STATE) then return node  
  frontier  $\leftarrow$  a FIFO queue, with node as an element  
  reached  $\leftarrow$  {problem.INITIAL}  
  while not IS-EMPTY(frontier) do  
    node  $\leftarrow$  POP(frontier)  
    for each child in EXPAND(problem, node) do  
      s  $\leftarrow$  child.STATE  
      if problem.IS-GOAL(s) then return child  
      if s is not in reached then  
        add s to reached  
        add child to frontier  
  return failure
```

```
function UNIFORM-COST-SEARCH(problem) returns a solution node, or failure  
  return BEST-FIRST-SEARCH(problem, PATH-COST)
```

# Search Tree: Variable Action Cost



# Search Tree: Variable Action Cost



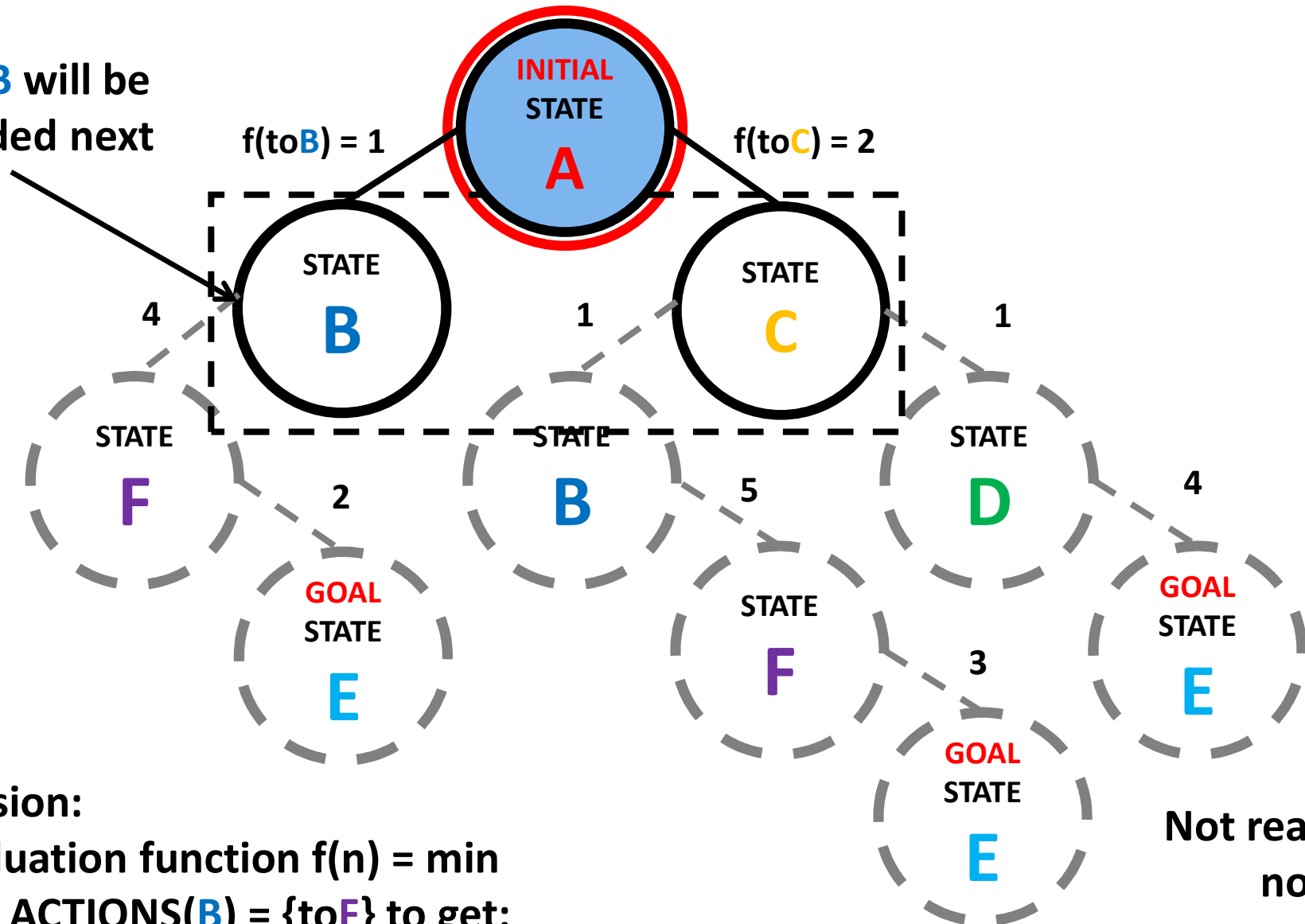
Expansion:

- **Evaluation function**  $f(n) = \min$
- Use  $\text{ACTIONS}(\text{B}) = \{\text{toF}\}$  to get:
- $\text{RESULT}(\text{B}, \text{toF}) = \text{F}$

Not reached yet  
nodes

# Search Tree: Best-First Search

Node **B** will be expanded next



Expansion:

- Evaluation function  $f(n) = \min$
- Use  $\text{ACTIONS}(\mathbf{B}) = \{\text{toF}\}$  to get:
- $\text{RESULT}(\mathbf{B}, \text{toF}) = \mathbf{F}$

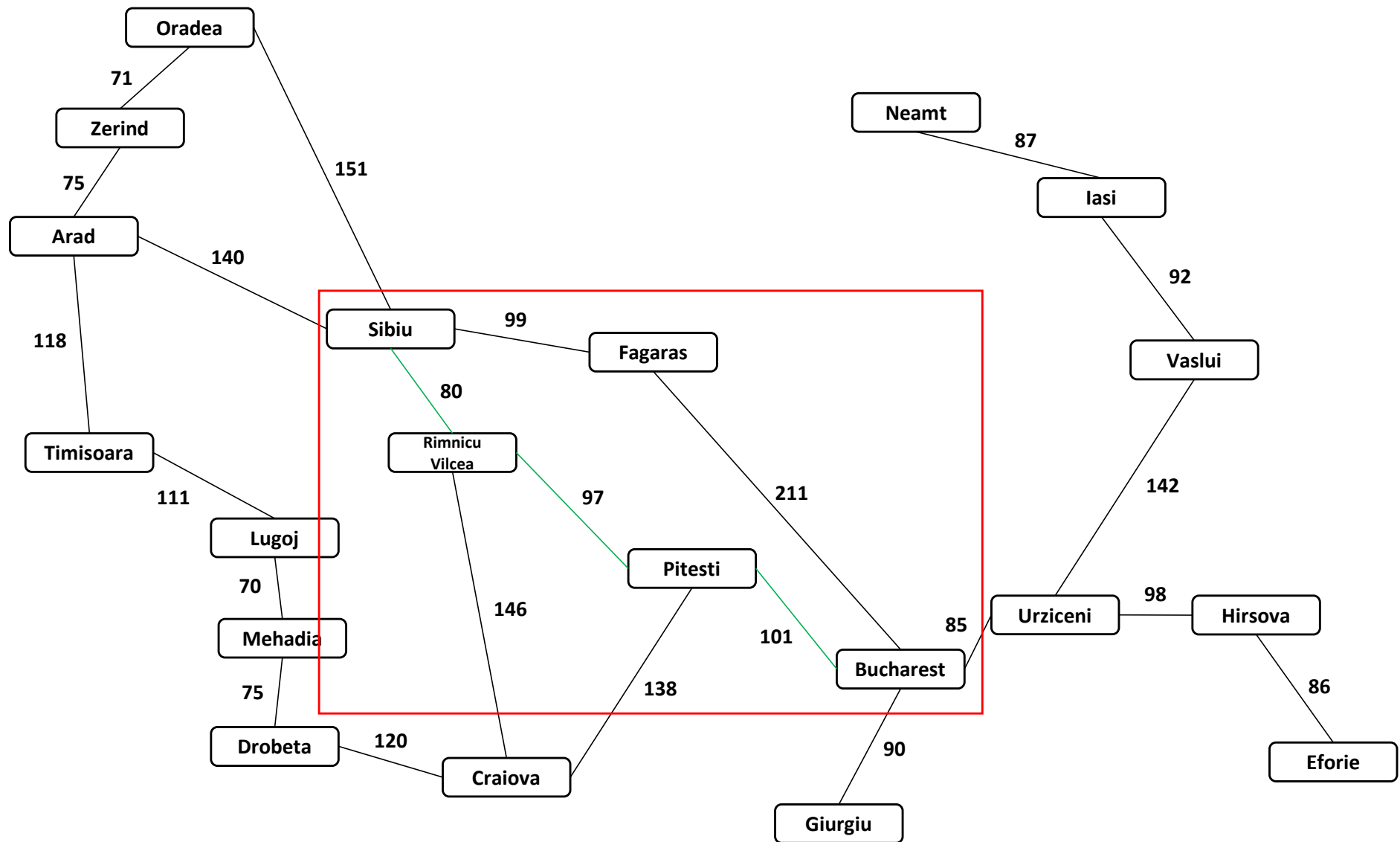


# Best-First Search: Pseudocode

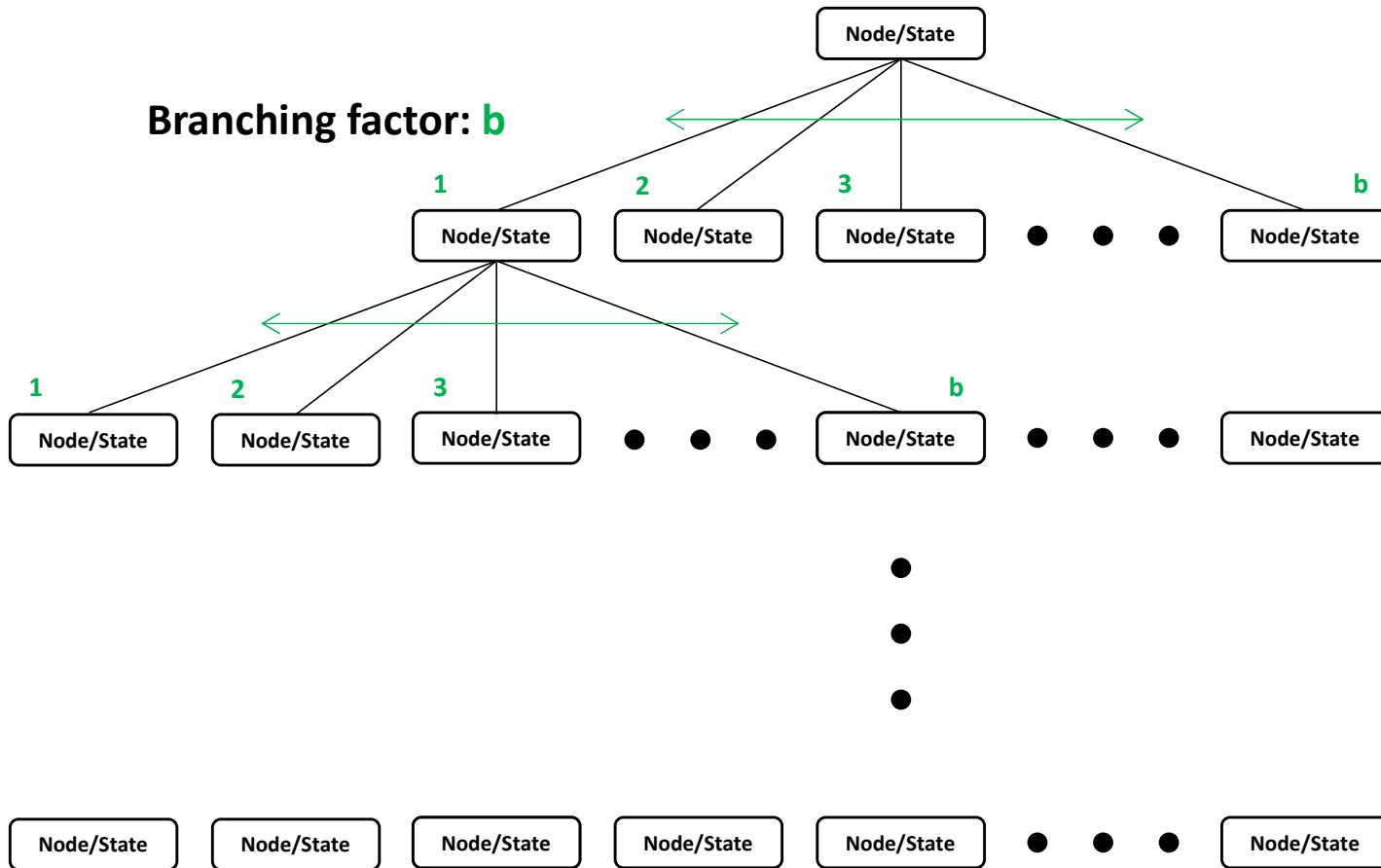
```
function BEST-FIRST-SEARCH(problem, f) returns a solution node or failure  
  node  $\leftarrow$  NODE(STATE=problem.INITIAL)  
  frontier  $\leftarrow$  a priority queue ordered by f, with node as an element  
  reached  $\leftarrow$  a lookup table, with one entry with key problem.INITIAL and value node  
  while not IS-EMPTY(frontier) do  
    node  $\leftarrow$  POP(frontier)  
    if problem.IS-GOAL(node.STATE) then return node  
    for each child in EXPAND(problem, node) do  
      s  $\leftarrow$  child.STATE  
      if s is not in reached or child.PATH-COST < reached[s].PATH-COST then  
        reached[s]  $\leftarrow$  child  
        add child to frontier  
  return failure
```

```
function EXPAND(problem, node) yields nodes  
  s  $\leftarrow$  node.STATE  
  for each action in problem.ACTIONS(s) do  
    s'  $\leftarrow$  problem.RESULT(s, action)  
    cost  $\leftarrow$  node.PATH-COST + problem.ACTION-COST(s, action, s')  
    yield NODE(STATE=s', PARENT=node, ACTION=action, PATH-COST=cost)
```

# Best First Search: Issue



# Let's Go Back to Depth First Search



**Depth: 0 |  $N_0 = 1$**

Depth: 1 |  $N_1 = b$

Depth: 2 |  $N_2 = b^2$

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•

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**Depth:  $d$  |  $N_d = b^d$**

# Tree depth is an issue!



# “Controlled” DFS: Pseudocode

**function** ITERATIVE-DEEPENING-SEARCH(*problem*) **returns** a solution node or *failure*

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

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

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

**function** DEPTH-LIMITED-SEARCH(*problem*,  $\ell$ ) **returns** a node or *failure* or *cutoff*

*frontier*  $\leftarrow$  a LIFO queue (stack) with NODE(*problem*.INITIAL) as an element

*result*  $\leftarrow$  *failure*

**while not** IS-EMPTY(*frontier*) **do**

*node*  $\leftarrow$  POP(*frontier*)

**if** *problem*.IS-GOAL(*node*.STATE) **then return** *node*

**if** DEPTH(*node*) >  $\ell$  **then**

*result*  $\leftarrow$  *cutoff*

**else if not** IS-CYCLE(*node*) **do**

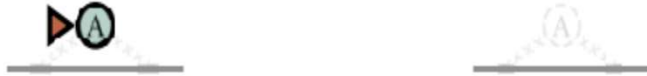
**for each** *child* **in** EXPAND(*problem*, *node*) **do**

        add *child* to *frontier*

**return** *result*

# Iterative Deepening DFS: Illustration

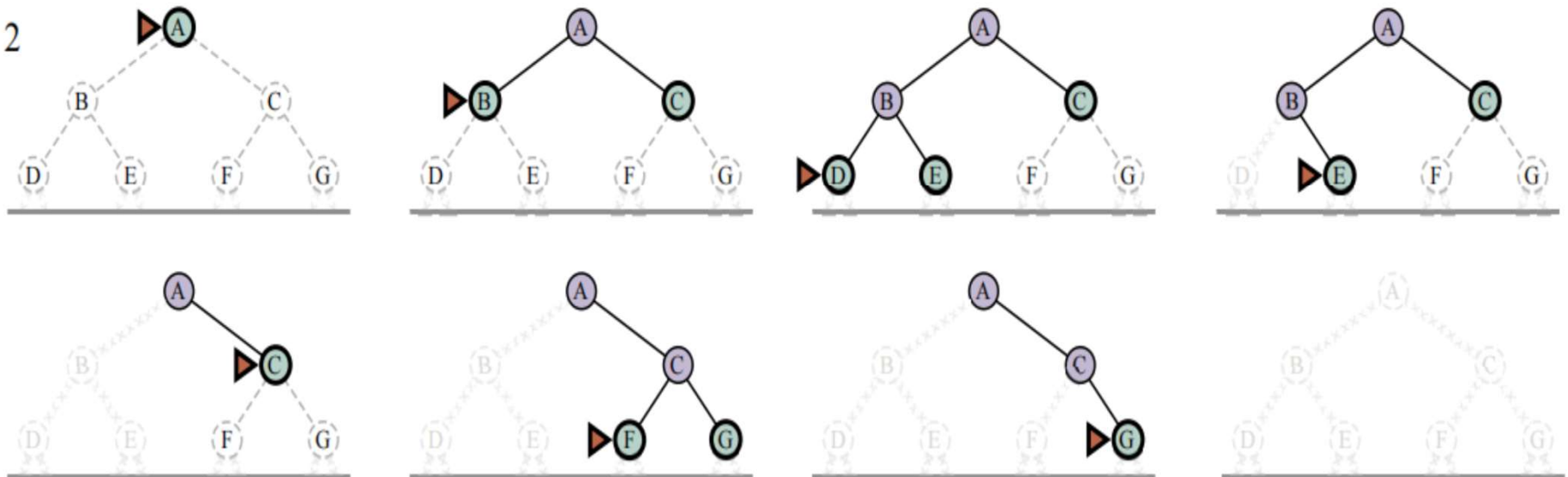
limit: 0



limit: 1

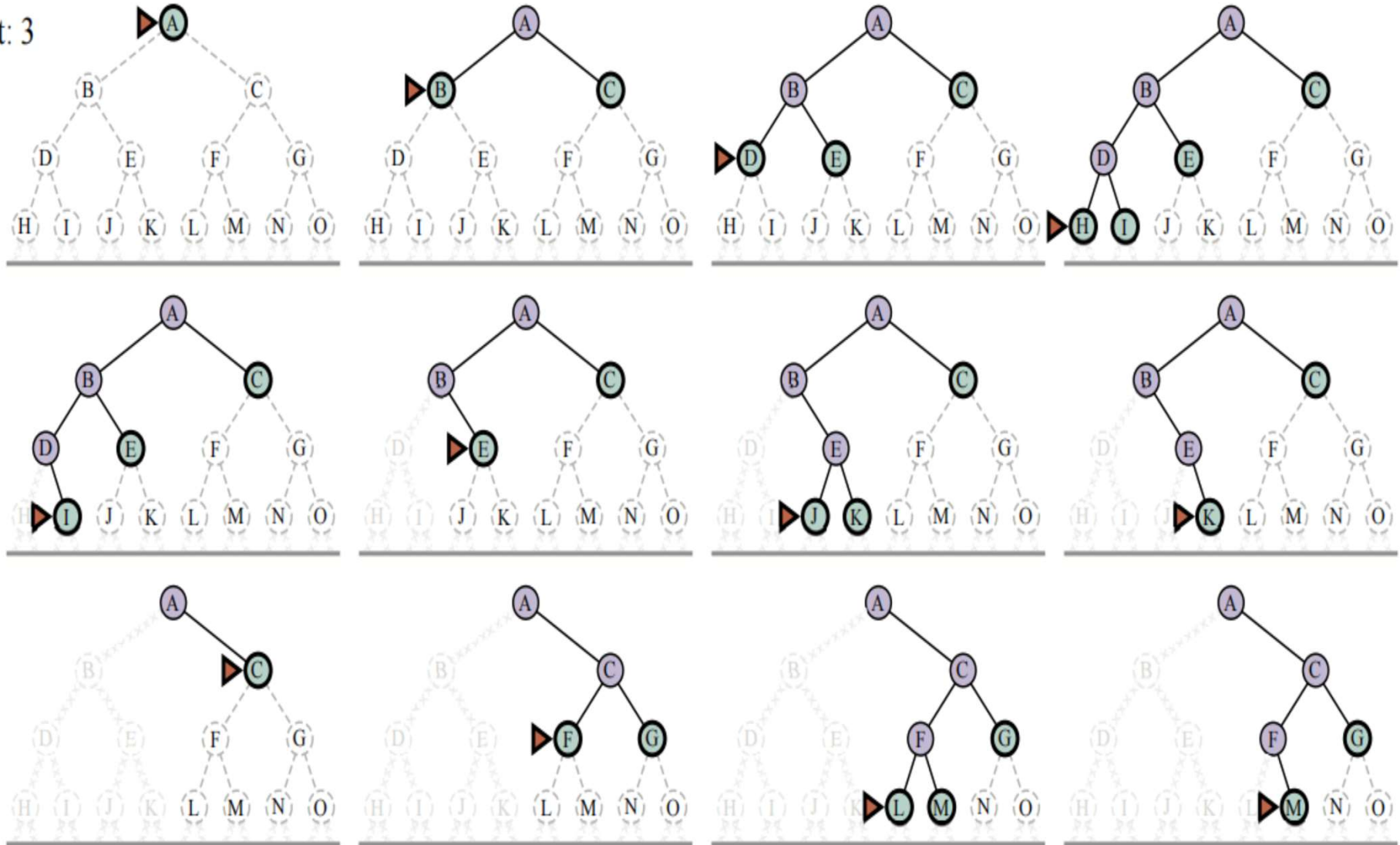


limit: 2



# Iterative Deepening DFS: Illustration

limit: 3



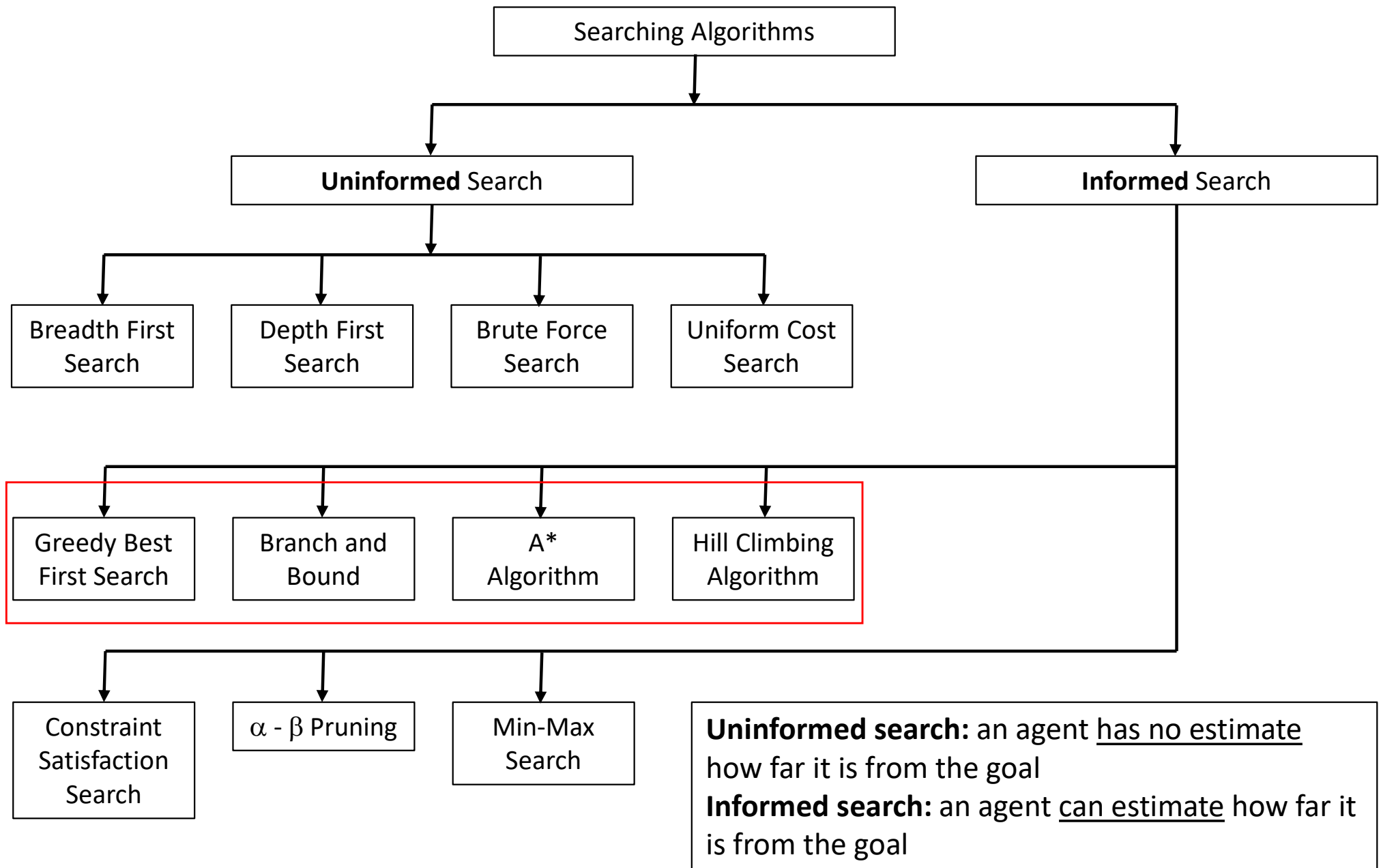


# Uninformed Search Algorithms

Criterion	Breadth-First	Uniform-Cost	Depth-First	Depth-Limited	Iterative Deepening	Bidirectional (if applicable)
Complete?	Yes <sup>1</sup>	Yes <sup>1,2</sup>	No	No	Yes <sup>1</sup>	Yes <sup>1,4</sup>
Optimal cost?	Yes <sup>3</sup>	Yes	No	No	Yes <sup>3</sup>	Yes <sup>3,4</sup>
Time	$O(b^d)$	$O(b^{1+\lceil C^*/\epsilon \rceil})$	$O(b^m)$	$O(b^\ell)$	$O(b^d)$	$O(b^{d/2})$
Space	$O(b^d)$	$O(b^{1+\lceil C^*/\epsilon \rceil})$	$O(bm)$	$O(b\ell)$	$O(bd)$	$O(b^{d/2})$

**Figure 3.15** Evaluation of search algorithms.  $b$  is the branching factor;  $m$  is the maximum depth of the search tree;  $d$  is the depth of the shallowest solution, or is  $m$  when there is no solution;  $\ell$  is the depth limit. Superscript caveats are as follows: <sup>1</sup> complete if  $b$  is finite, and the state space either has a solution or is finite. <sup>2</sup> complete if all action costs are  $\geq \epsilon > 0$ ; <sup>3</sup> cost-optimal if action costs are all identical; <sup>4</sup> if both directions are breadth-first or uniform-cost.

# Selected Searching Algorithms



# Informed Search and Heuristics

Informed search relies on **domain-specific knowledge / hints** that help locate the goal state.

$$h(n) = h(\text{State } n)$$

$$h(n) = n(\text{relevant information about State } n)$$

**$h(n)$  : heuristic function - estimated cost of the cheapest path from State  $n$  to the goal state**