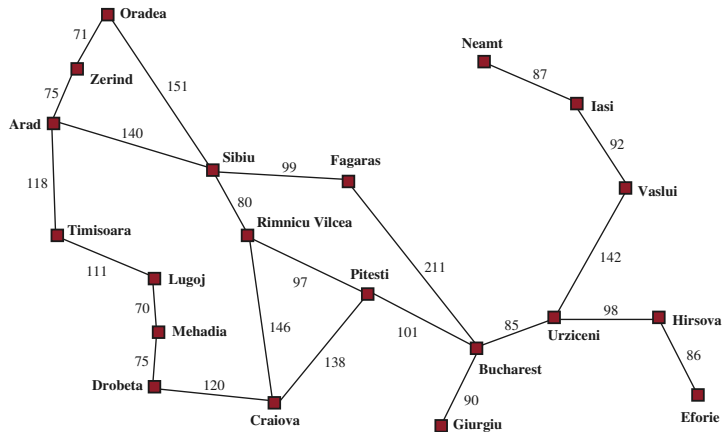


# Problem Solving

## Artificial Intelligence

Christopher Simpkins

# Problem-Solving Agents



- ▶ In this lesson we consider a *state* to be our location in one of these cities.
- ▶ A *goal* is a state in which we are located in a particular city.

This is the essence of problem solving: transforming a current state into a goal state. The first family of algorithms we'll study for problem solving are *search* algorithms.

# Problem Solving Process

To solve a problem, we

- ▶ Formulate a **goal**, e.g., “reach Bucharest”
- ▶ Formulate the **problem** as a set of states and actions that move us from one state to another.
  - ▶ Problem is a **model** – an *abstract* mathematical description.
  - ▶ Abstraction is essence and ignorance.
  - ▶ Key skill in problem formulation is finding the right **level of abstraction**.
- ▶ **Search** the possible sequences of action in our problem model that transforms our state from the current state to the goal state. A sequence of actions that gets us to the goal state is called a *solution*. May be many; pick one.
- ▶ **Execute** the actions in the solution.

# Open-Loop vs. Closed-Loop

- ▶ In an **open-loop** system the agent gets no feedback, i.e., sensor input, after executing an action.
  - ▶ If the agent's model is perfect and actions are deterministic, then the agent can operate in an open-loop fashion, simply executing the actions in the solution one after the other.
- ▶ In a **closed-loop** system gets sensory feedback after every action, so it can check whether the action had the expected effect.
  - ▶ If the environment is partially observable or actions are nondeterministic, closed-loop control is necessary.
  - ▶ Say the agent executes to **ToSibiu** action but ends up in **Zerind**. Closed-loop feedback will alert the agent to this fact so it can re-plan.

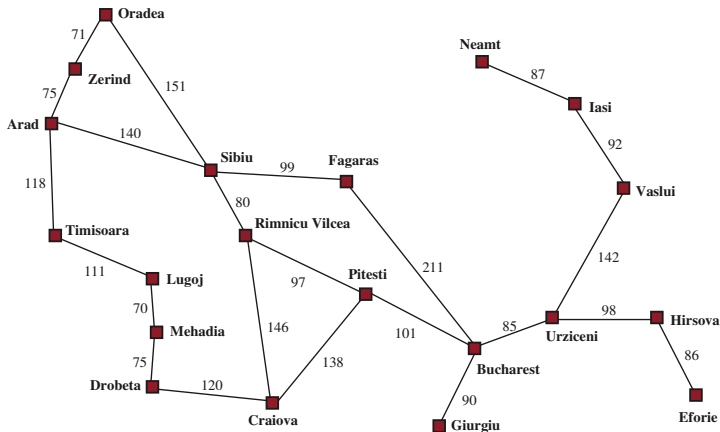
# Search Problems and Solutions

A search problem consists of:

- ▶ A set of **states**, which we call a **state space**.
- ▶ **Initial state**
- ▶ A set of **goal states**.
  - ▶ Typically use an **IS-GOAL**( $s$ ) predicate function to identify goal states.
- ▶ Sets of **actions** available in each state, **ACTION**( $s$ )
  - ▶ **ACTION**(Arad) = {ToSibiu, ToTimisoara, ToZerind}
- ▶ A **transition model**, **RESULT**( $s, a$ )
  - ▶ **RESULT**(Arad, ToZerind) = Zerind
- ▶ An **action cost function**, **ACTION-COST**( $s, a, s'$ ) or  $c(s, a, s')$  which returns the cost of executing action  $a$  in state  $s$  and reaching state  $s'$ .

# Solution

- ▶ A solution is a path from the start state to the a goal state.
- ▶ An optimal solution is a solution with lowest cost among all solutions.

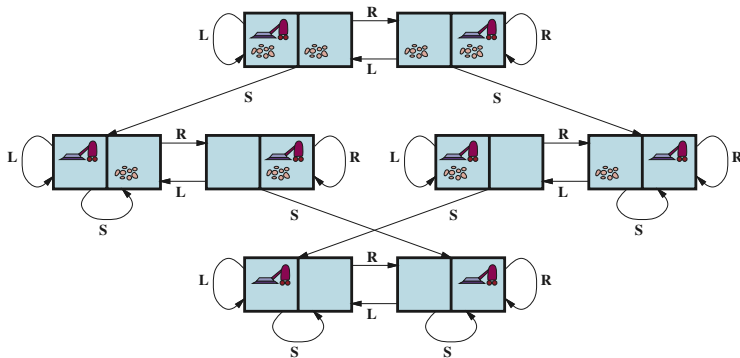


- ▶ How many paths are there from Arad to Bucharest?
- ▶ What is/are the solutions to the Arad-to-Bucharest problem (assume perfect information – fully observable, known dynamics, and deterministic actions)?

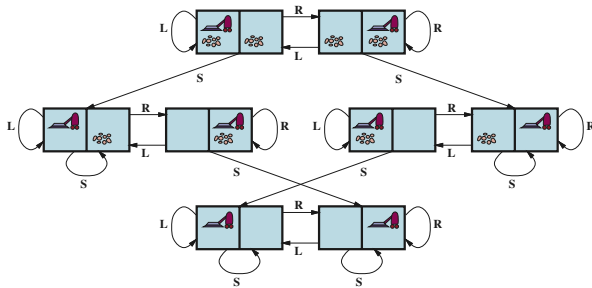
## Example Problems

- ▶ **Standardized problems** use idealized environments designed to illustrate or exercise various problem-solving methods. See, for example, [Gymnasium](#).
  - ▶ A **grid world** is a standardized environment whose states are organized as a grid, and whose actions include moving between adjacent grids.
- ▶ **Real-world problems** are formulated for specific real-world tasks, like the problem specification used for Roombas.

Here's a standardized environment for the vacuum cleaner agent, formulated as a grid world:



# Vacuum Cleaner Grid World



- ▶ **States** include both the agent's location, and characteristics of the environment. For the vacuum world, that's  $2 \cdot 2^2 = 8$  states.
- ▶ **Initial state** is an arbitrary choice of the possible states. Sometimes this choice is important.
- ▶ **Actions** for this vacuum world are **L**, **R**, and **Suck**.
  - ▶ For 2D grids we can choose between
    - ▶ **absolute** movement, like **Up** and **Right**, a.k.a., cardinal directions, or
    - ▶ **egocentric** movement, like **TurnRight**, **MoveForward**. How does this affect the state description?
- ▶ **Goal states** are those in which every location is clean.
- ▶ **Action cost** (path cost) is 1.



# Agents

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

# Route Finding

- ▶ **States:** a location (e.g., an airport) and the time.
  - ▶ If action cost (e.g., a flight segment) depends on previous segments, fares, etc., the state must include these details.
- ▶ **Initial state:** The user's home airport.
- ▶ **Actions:** Take any flight from the current location, in any seat class, leaving after the current time, or for connecting flights, after sufficient in-airport transfer time.
- ▶ **Transition model:** The state resulting from taking a flight will have the flight's destination as the new location and the flight's arrival time as the new time.
  - ▶ Example  $T(s, a, s')$ :  $T(S(ATL, 10:00), A(DL875), S(LGA, 12:00))$  (DL875 has a flight time of 2 hours).
- ▶ **Goal state:** A destination city. Sometimes the goal can be more complex, such as arrive at the destination on a nonstop flight. (Remember, a solution is a path, i.e., sequence of actions.)
- ▶ **Action cost:** A combination of monetary cost, waiting time, flight time, customs and immigration procedures, seat quality, time of day, type of airplane, frequent-flyer reward points, and so on.

# Real-World Problems

- ▶ **Touring problems**
- ▶ **VLSI layout** – minimize area, minimize circuit delays, minimize stray capacitances, and maximize manufacturing yield
  - ▶ Cell layout – place cells on chip so they don't overlap and have room for connections
  - ▶ Channel routing – find routes for each wire between cells
- ▶ **Robot navigation**
- ▶ **Automatic assembly sequencing** – standard practice in manufacturing since the 1970s.
  - ▶ Solving some automatic assembly problems could earn you a [Nobel Prize!](#)

# Search Algorithms

A **search algorithm** takes a search problem as input and returns a solution, or an indication of failure.

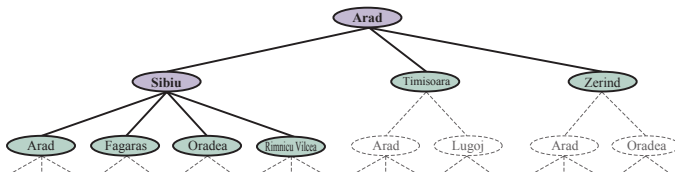
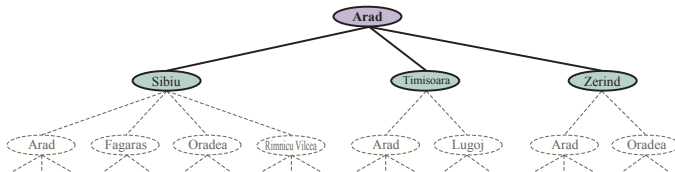
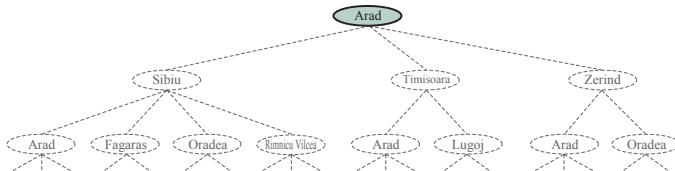
- ▶ In general, the states and actions of a problem create a state space graph.
- ▶ Here we consider algorithms that superimpose a **search tree** over the state-space graph.
- ▶ **Nodes** correspond to states, **edges** correspond to actions
  - ▶ May be many nodes for a given state, but each path is unique.

Don't confuse state space with search tree.

- ▶ State space describes the set of states and actions that case transitions from one state to another.
- ▶ Search tree describes paths between these states, reaching towards the goal(s).

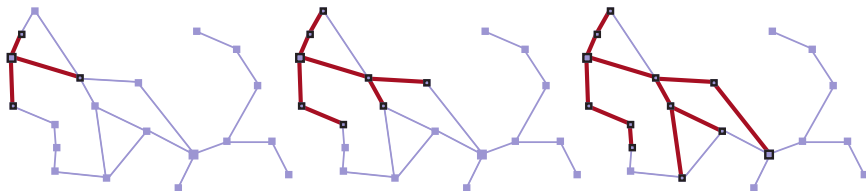
# Searching State Space

Root node is initial state. At each node we can **expand** the node, which grows the tree, by taking actions (adding edges) that lead to successor states (generate successor/child nodes).



# Search Tree Expansion

Here is a search tree being imposed on the Romania state space graph by a search algorithm.

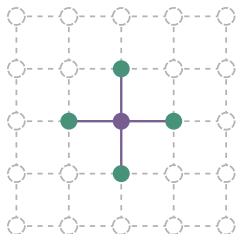


Essence of search:

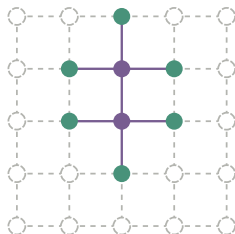
- ▶ Choose a child node to consider next.
- ▶ Put aside other nodes for later.

# Separation Property of Graph Search

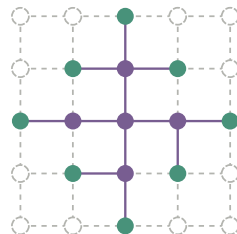
The **frontier** separates the interior region of expanded nodes from the exterior region of unexpanded nodes.



(a)



(b)



(c)

- ▶ (a) Only root expanded.
- ▶ (b) Top frontier node expanded.
- ▶ (c) Remaining successors of root expanded in clockwise order.

# The `yield` statement

A function containing a `yield` statement is a **generator**. Use a generator to turn a data generating process into an iterator.

```
1 In [36]: def by_twos(start: int, end: int):
2     ...:     x = start
3     ...:     while x < end:
4     ...:         yield x
5     ...:         x += 2
6     ...:
7
8 In [37]: by_twos(1, 9)
9 Out[37]: <generator object by_twos at 0x109010ee0>
10
11 In [38]: list(Out[37])
12 Out[38]: [1, 3, 5, 7]
13
14 In [39]: for x in by_twos(1, 10):
15     ...:     print(f"{x}")
16     ...:
17 x=1
18 x=3
19 x=5
20 x=7
21 x=9
```



# Search Data Structures

Node:

- ▶ `node.STATE`: the state to which the node corresponds;
- ▶ `node.PARENT`: the node in the tree that generated this node;
- ▶ `node.ACTION`: the action that was applied to the parent's state to generate this node;
- ▶ `node.PATH-COST`: the total cost of the path from the initial state to this node. In mathematical formulas, we use  $g(\text{node})$  as a synonym for PATH-COST.

Frontier is a **queue** with operations:

- ▶ `IS-EMPTY(frontier)` returns true only if there are no nodes in the frontier.
- ▶ `POP(frontier)` removes the top node from the frontier and returns it.
- ▶ `TOP(frontier)` returns (but does not remove) the top node of the frontier.
- ▶ `ADD(node, frontier)` inserts node into its proper place in the queue.

Queues used in search algorithms:

- ▶ A **priority queue** first pops the node with the minimum cost according to some evaluation function,  $f$ . It is used in best-first search.
- ▶ A **FIFO queue** or first-in-first-out queue first pops the node that was added to the queue first; we shall see it is used in breadth-first search.
- ▶ A **LIFO queue** or last-in-first-out queue (also known as a stack) pops first the most recently added node; we shall see it is used in depth-first search.

# Best-First Search Algorithm

$f(node)$  is an evaluation function, which imposes an ordering on the nodes in the priority queue.

```
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)
```

# Redundant Paths

Repeated states  
cycles  
redundant paths  
graph search  
tree-like search

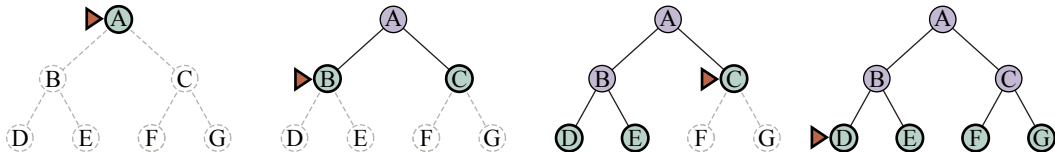
# Measuring Problem-Solving Performance

- ▶ **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? This can be measured in seconds, or more abstractly by the number of states and actions considered.
- ▶ **Space complexity:** How much memory is needed to perform the search?

# Uninformed Search Strategies

Strategy:

# Breadth-First Search



**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*

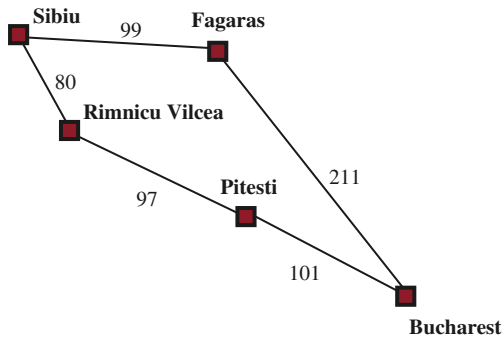
**if** *s* is not in *reached* **then**

add *s* to *reached*

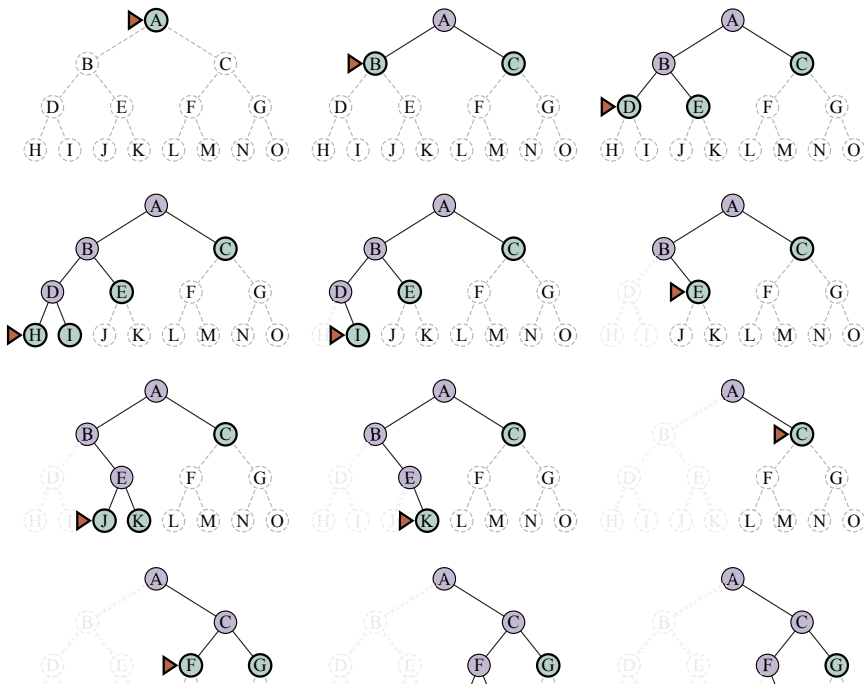
add *child* to *frontier*

**return** *failure*

# Dijkstra's Algorithm



# Depth-First Search





# Depth-Limited Search and Iterative Deepening Search

**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*

# Progression of Iterative Deepening Search

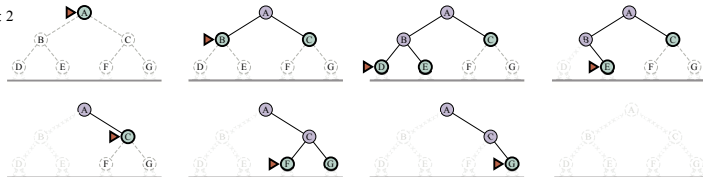
limit: 0



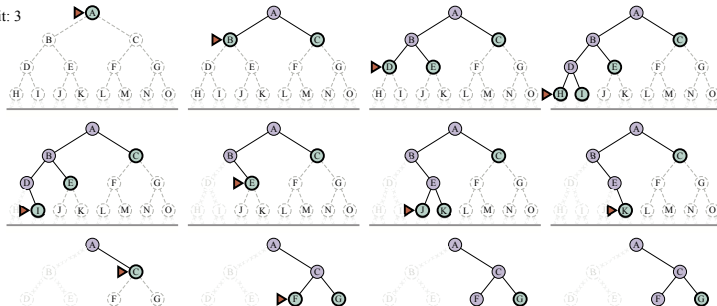
limit: 1



limit: 2



limit: 3



# Bidirectional Best-First Search

**function** BiBF-SEARCH( $problem_F, f_F, problem_B, f_B$ ) **returns** a solution node, or failure

$node_F \leftarrow \text{NODE}(problem_F.INITIAL)$  // Node for a start state

$node_B \leftarrow \text{NODE}(problem_B.INITIAL)$  // Node for a goal state

$frontier_F \leftarrow$  a priority queue ordered by  $f_F$ , with  $node_F$  as an element

$frontier_B \leftarrow$  a priority queue ordered by  $f_B$ , with  $node_B$  as an element

$reached_F \leftarrow$  a lookup table, with one key  $node_F.STATE$  and value  $node_F$

$reached_B \leftarrow$  a lookup table, with one key  $node_B.STATE$  and value  $node_B$

$solution \leftarrow failure$

**while not** TERMINATED( $solution, frontier_F, frontier_B$ ) **do**

**if**  $f_F(\text{TOP}(frontier_F)) < f_B(\text{TOP}(frontier_B))$  **then**

$solution \leftarrow \text{PROCEED}(F, problem_F, frontier_F, reached_F, reached_B, solution)$

**else**  $solution \leftarrow \text{PROCEED}(B, problem_B, frontier_B, reached_B, reached_F, solution)$

**return**  $solution$

**function** PROCEED( $dir, problem, frontier, reached, reached_2, solution$ ) **returns** a solution

    // Expand node on frontier; check against the other frontier in  $reached_2$ .

    // The variable “ $dir$ ” is the direction: either F for forward or B for backward.

$node \leftarrow \text{POP}(frontier)$

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

$s \leftarrow child.STATE$

**if**  $s$  not in  $reached$  **or**  $\text{PATH-COST}(child) < \text{PATH-COST}(reached[s])$  **then**

$reached[s] \leftarrow child$

            add  $child$  to  $frontier$

**if**  $s$  is in  $reached_2$  **then**

$solution_2 \leftarrow \text{JOIN-NODES}(dir, child, reached_2[s])$

**if**  $\text{PATH-COST}(solution_2) < \text{PATH-COST}(solution)$  **then**

$solution \leftarrow solution_2$

# Comparing 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	$O(b^d)$	$O(b^{1+\lceil C^*/\epsilon \rceil})$	$O(bm)$	$O(b\ell)$	$O(bd)$	$O(b^{d/2})$