

COMP 8620

Advanced Topics in AI

Lecturers:
Philip Kilby &
Jinbo Huang

Part 1: Search

Lecturer: Dr Philip Kilby

Philip.Kilby@nicta.com.au

Weeks 1-7

(Week 7 is assignment seminars)

Part 2: Probabilistic Reasoning with Bayesian networks

Lecturer: Dr Jinbo Huang

Jinbo.Huang@nicta.com.au

Weeks 8-13

Course Outline – Part 1

- | | | | |
|-----|--|-------|---|
| 1-2 | Introduction
Systematic Search | 7-8 | Constraint Programming
(Guest lecturer: Jason Li) |
| 3-4 | Linear Programming /
Integer Programming /
Branch and Bound | 9-10 | Case Studies: <ul style="list-style-type: none">• TSP• Planning (Jussi Rintanen) |
| 5-6 | Neighbourhood-based
methods: <ul style="list-style-type: none">• Simulated Annealing• Tabu Search• Genetic Algorithms | 11 | Dynamic Programming |
| 7-8 | Constraint Programming
(Guest lecturer: Jason Li) | 12 | Qualitative Reasoning
(Guest lecturer: Jason Li) |
| | | 13-14 | Seminars
(Guest Lecturers: You lot!) |

Assessment

- 40% Exam
- 60% Assignment
 - Search
 - 1 x Assignment (next week) 15%
 - 1 x Seminar 15%
 - Reasoning
 - 3 x Assignment (10% each) (*tentative*)

What is Search?

- Search finds a *solution* to a *problem*
- Landscape of solutions
- Some are “good”
- Lots (and lots and lots) are “bad”

How do we find the good ones?

What is Search?

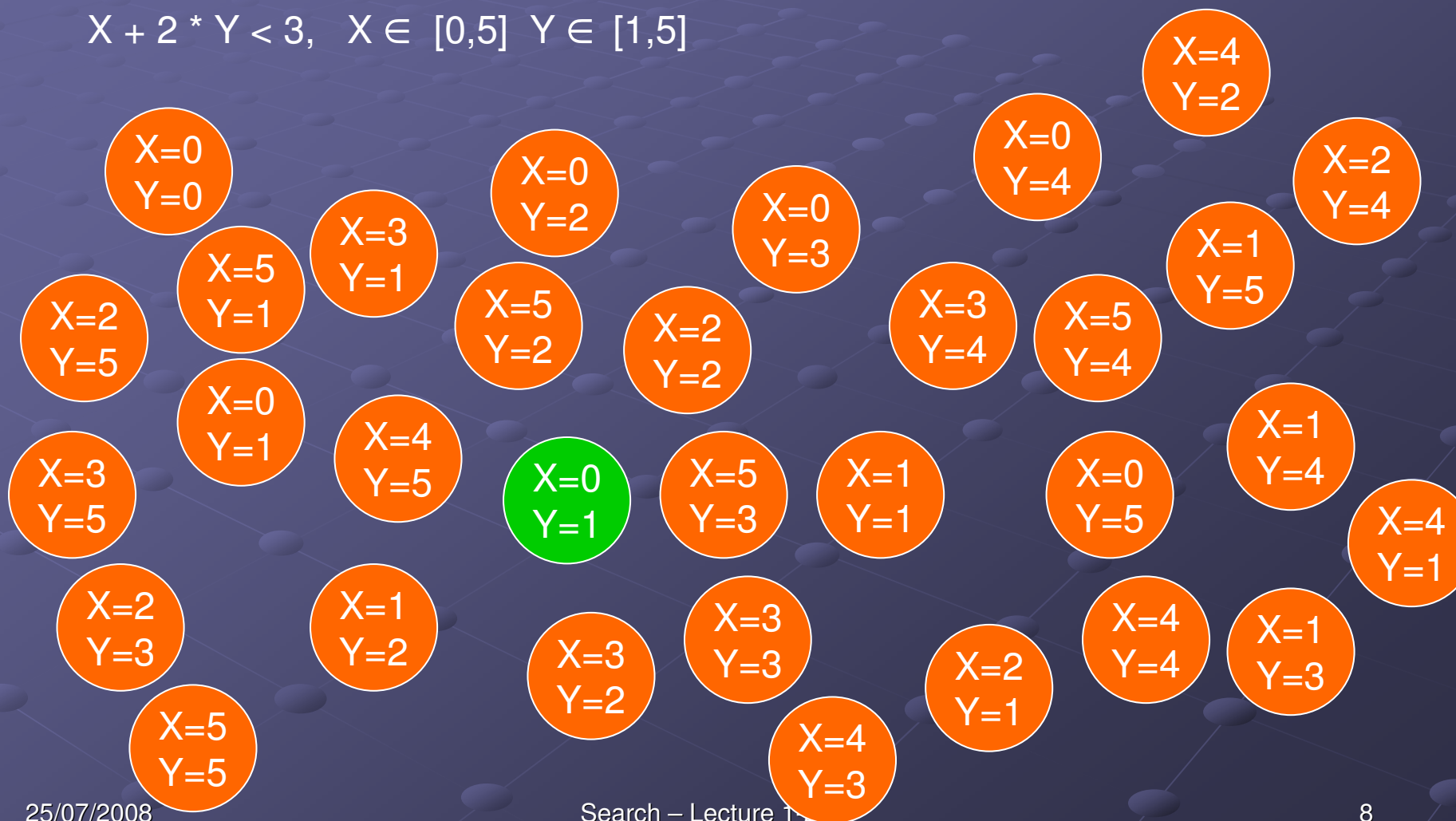
- Landscape can be continuous or discrete
- (We will only deal with discrete)
- Landscape can be (approximated by?) a *tree*
- Landscape can be (approximated by?) a *graph*

What is Search?

$$X + 2 * Y < 3, \quad X \in [0,5] \quad Y \in [1,5]$$

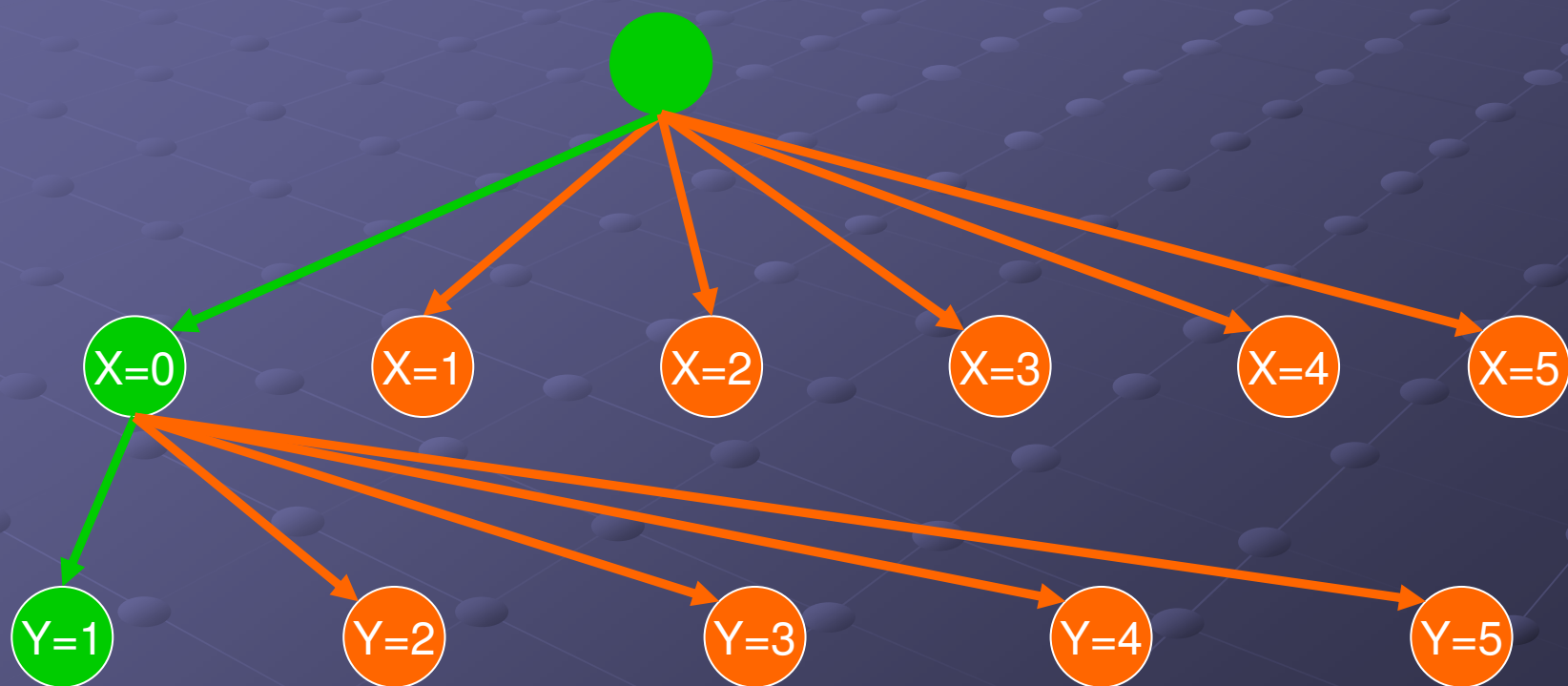
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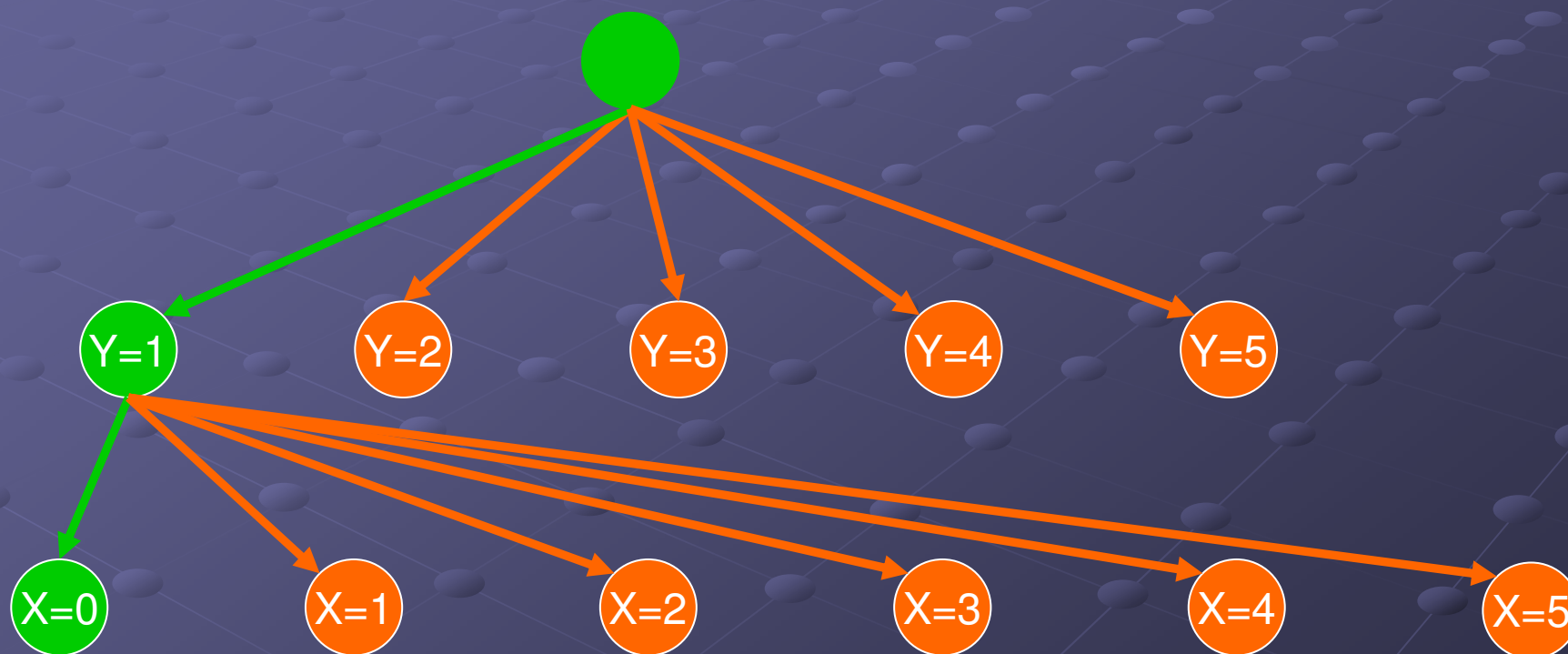
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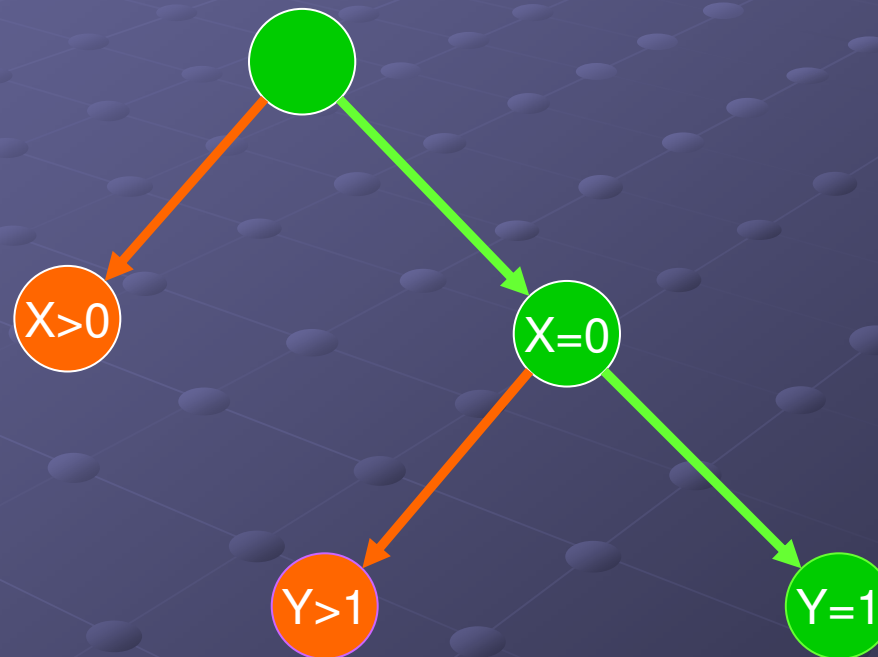
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What is Search?

$$X + 2 * Y < 3, \quad X \in [0,5] \quad Y \in [1,5]$$



What is Search?

- Different flavours

- Find a solution (Satisfaction/Decision)
- Find the *best* solution (Combinatorial Optimisation)

- Decision problems:

- Search variant: Find a solution (or show none exists)
- Decision variant: Does a solution exist?

What is Search

- Constructive Search – Find a solution by construction
- Local Search – Given a solution, explore the “neighbourhood” of that solution to find other (possibly better) solutions

What is Search?

Anytime algorithm (for optimisation prob):

- After a (short) startup time, an answer is available
- The longer the alg is run, the better the solution
- Quality guarantee may be available (e.g. solution is within 5% of optimal)

One-shot algorithm

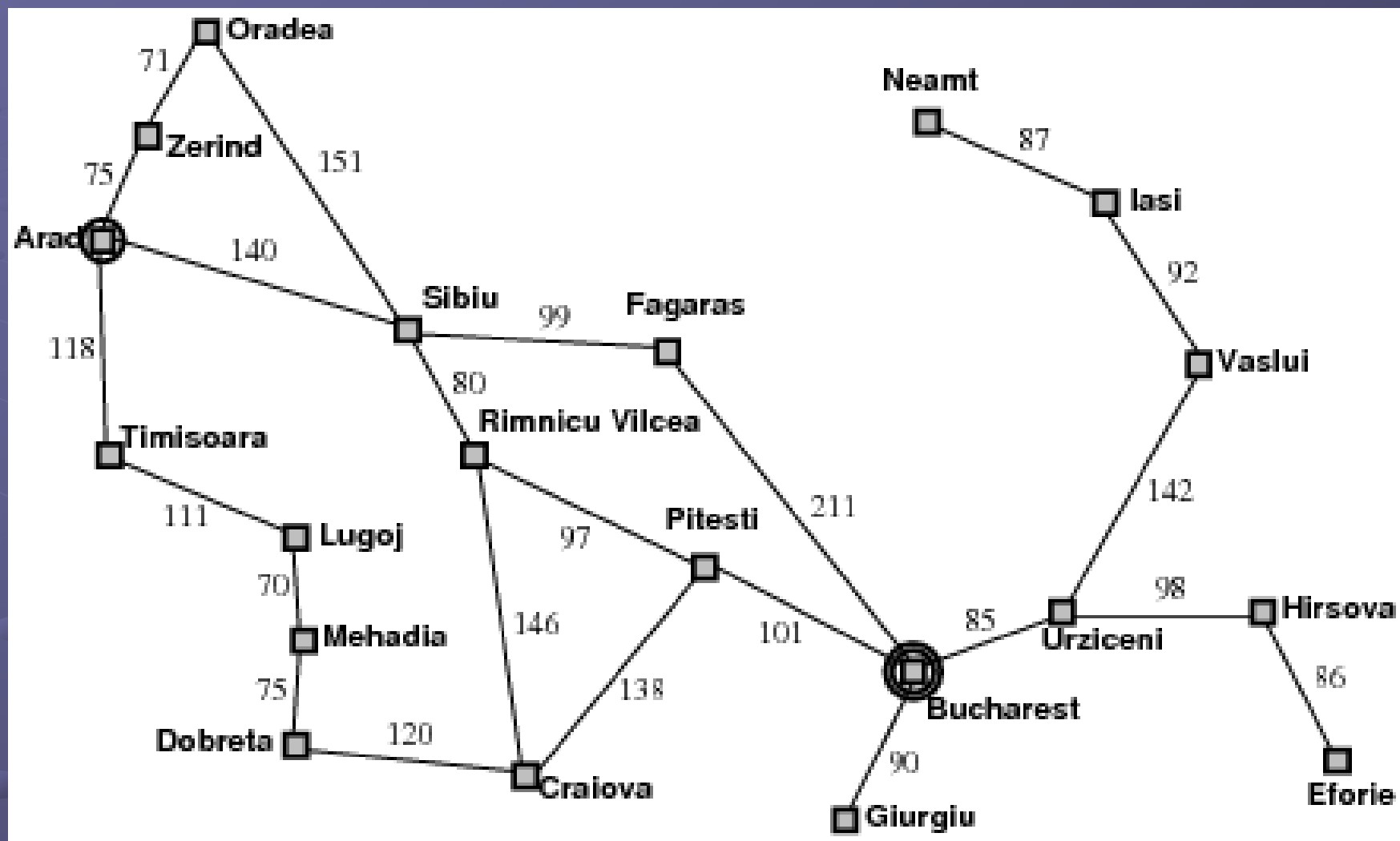
- Answer only available at completion

What is Search?

A problem is defined by

- Initial state
 - Successor function
(an action leading from one state to another)
 - Goal test
 - Path cost
-
- A solution is a sequence of actions leading from the start state to a goal state

Example: Romania



Problem formulation

- A problem is defined by four items:
- **initial state**
 - e.g., “at Arad”
- **successor function $S(x)$**
 - set of action–state pairs
 - e.g., $S(\text{Arad}) = \{ \langle \text{Arad} \rightarrow \text{Zerind}, \text{at Zerind} \rangle, \dots \}$
- **goal test** e.g., $x = \text{“at Bucharest”}$
 - can be implicit, e.g., $\text{HasAirport}(x)$
- **path cost** (additive)
 - e.g. sum of distances, number of actions executed, etc.
 - $c(x, a, y)$ is the step cost, assumed to be ≥ 0

Tree Search

function **Tree-Search** (*problem*, *fringe*) returns a solution, or failure

fringe $\leftarrow$ **Insert** (**Make-Node** (**Initial-State** (*problem*)), *fringe*)

loop do

if **Is-Empty** (*fringe*) then return failure

node $\leftarrow$ **Remove-Front** (*fringe*)

if **Goal-Test** (*problem*, **State**[*node*]) then return *node*

fringe $\leftarrow$ **InsertAll** (**Expand** (*node*, *problem*), *fringe*)

function **Expand** (*node*, *problem*) returns a set of nodes

successors $\leftarrow$ the empty set

for each (*action*, *result*) in **Successor-Fn** (*problem*, **State**[*node*]) do

s $\leftarrow$ a new Node

Parent-Node[*s*] $\leftarrow$ *node*; **Action**[*s*] $\leftarrow$ *action*; **State**[*s*] $\leftarrow$ *result*

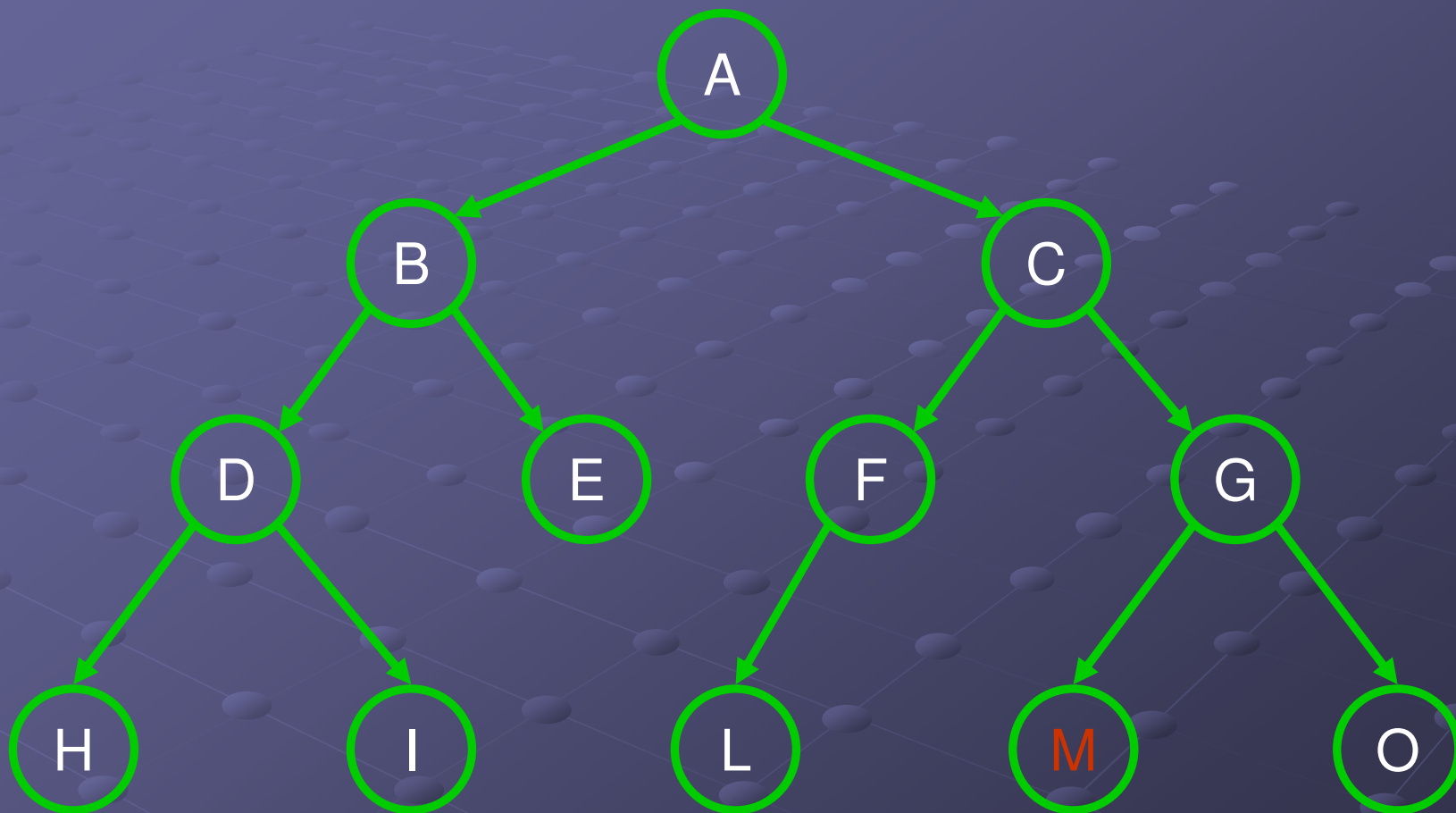
Path-Cost[*s*] $\leftarrow$ **Path-Cost**[*node*] + **Step-Cost**(**State**[*node*], *action*, *result*)

Depth[*s*] $\leftarrow$ **Depth**[*node*] + 1

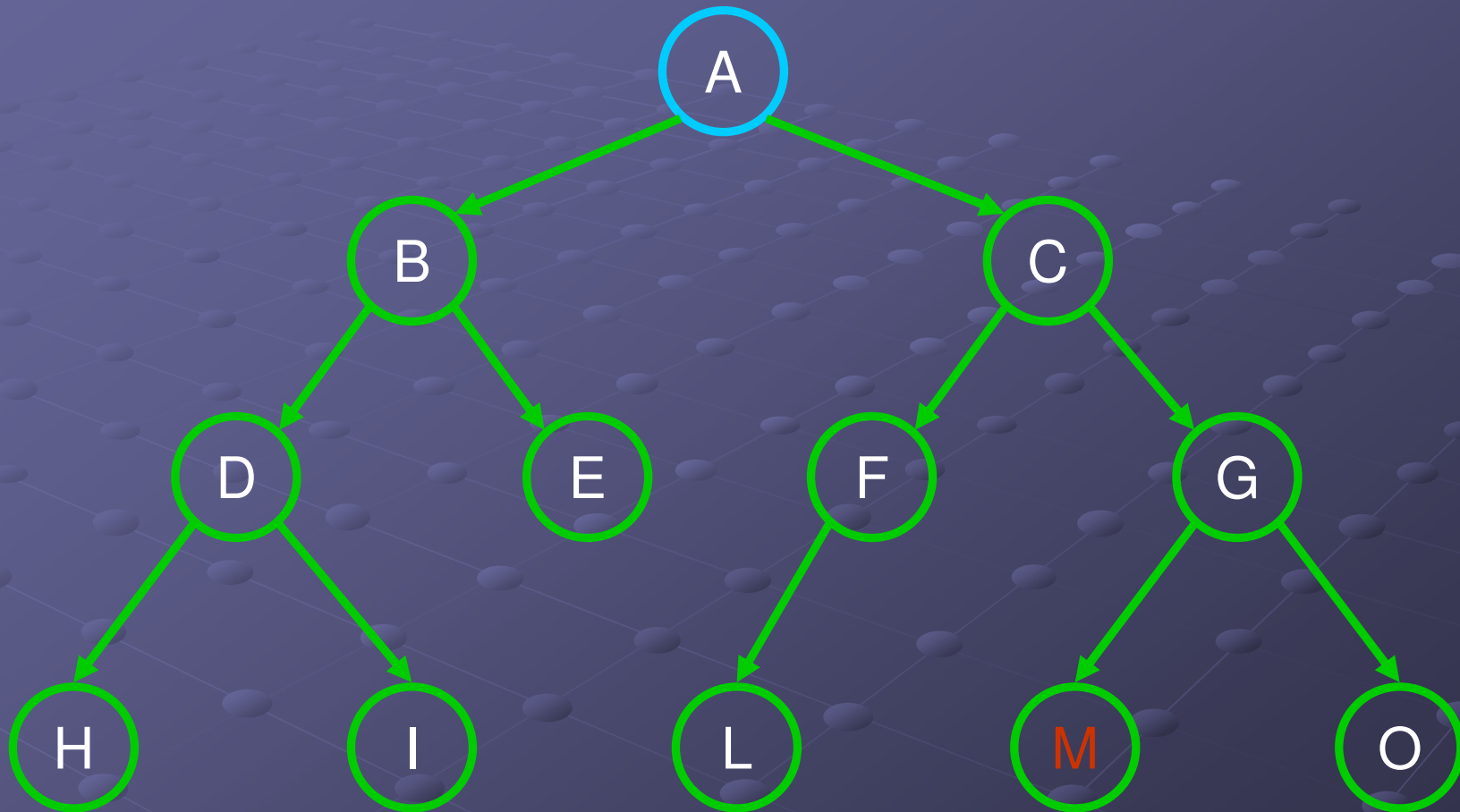
successors $\leftarrow$ **Insert** (*s*)

return *successors*

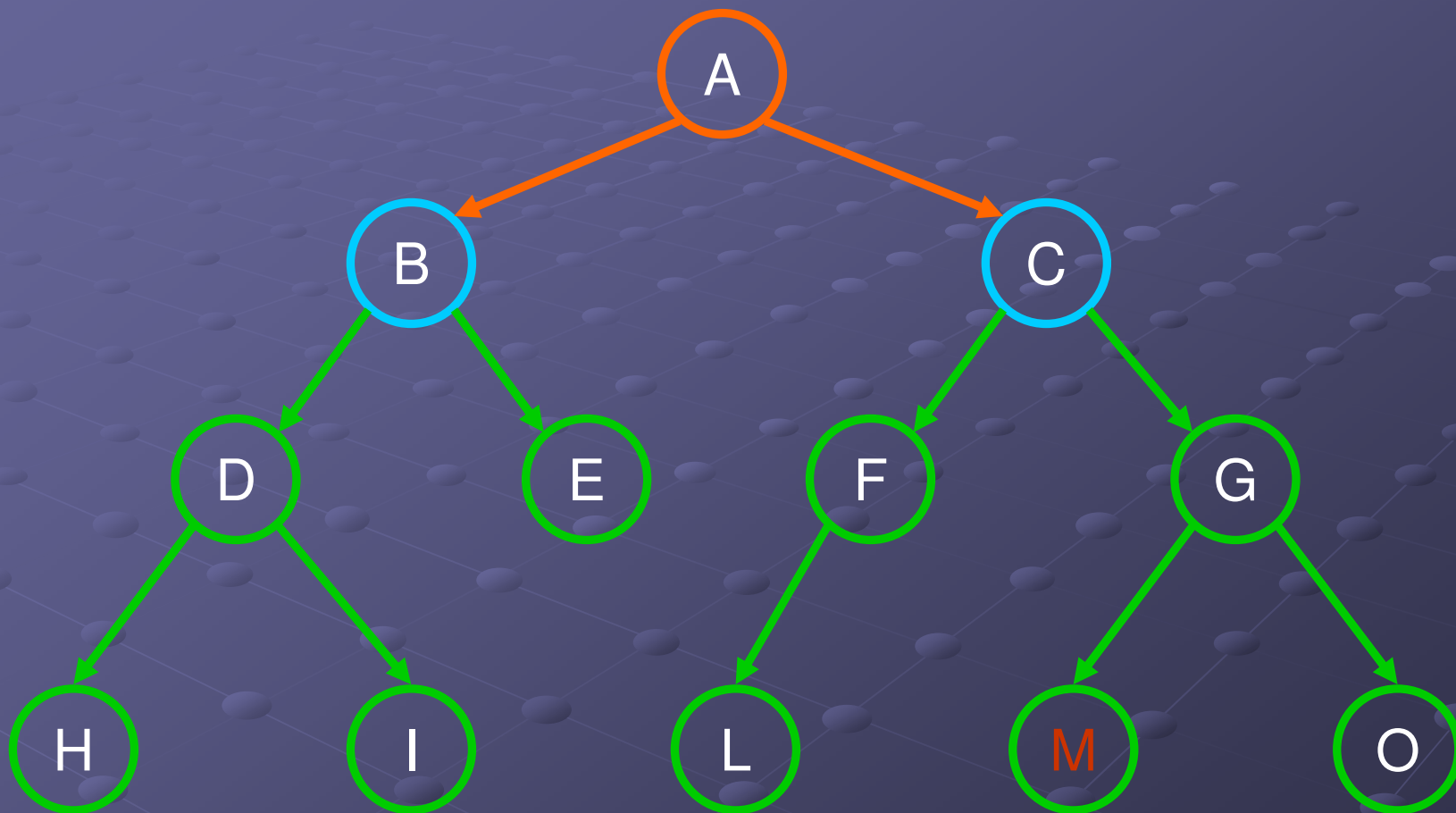
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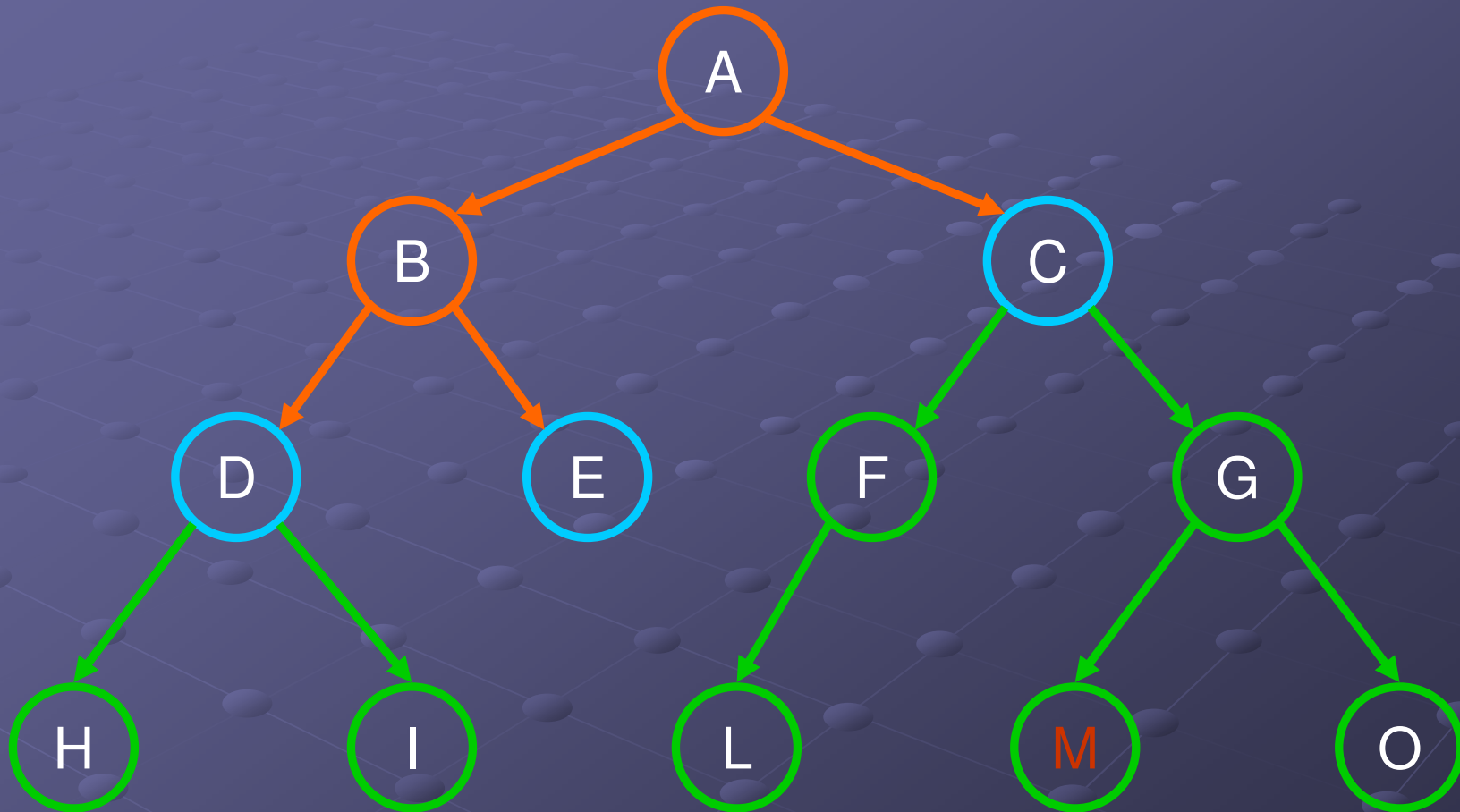
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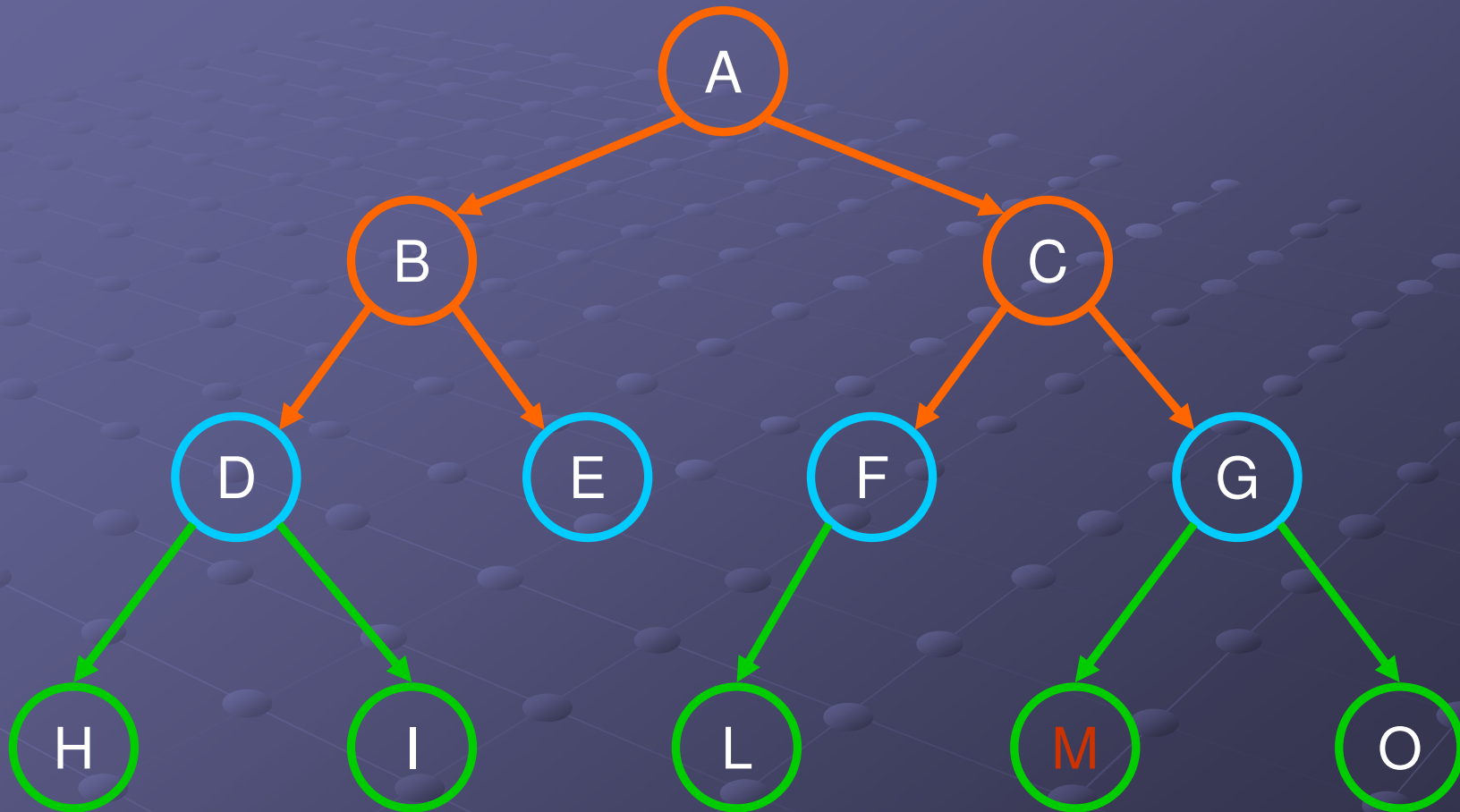
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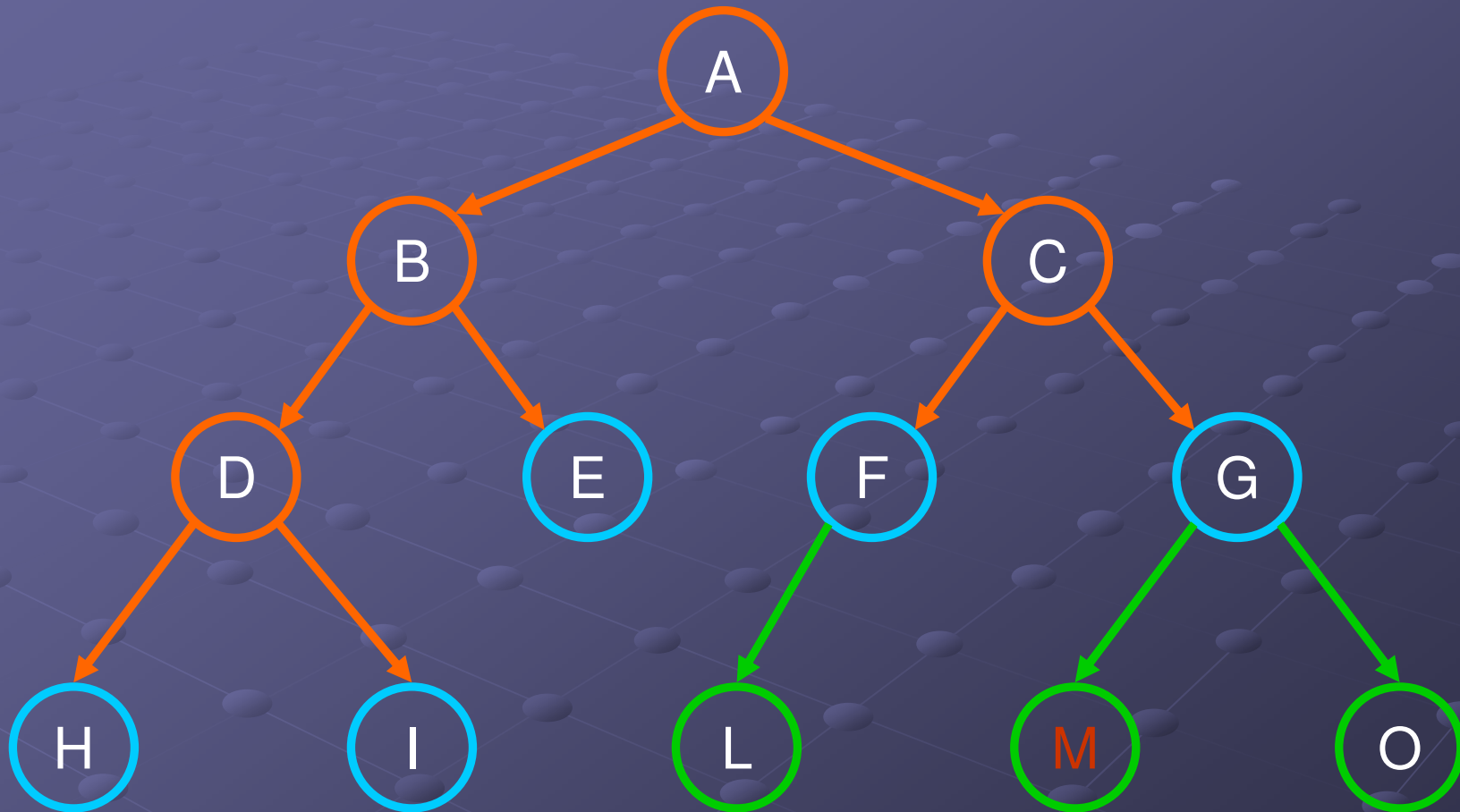
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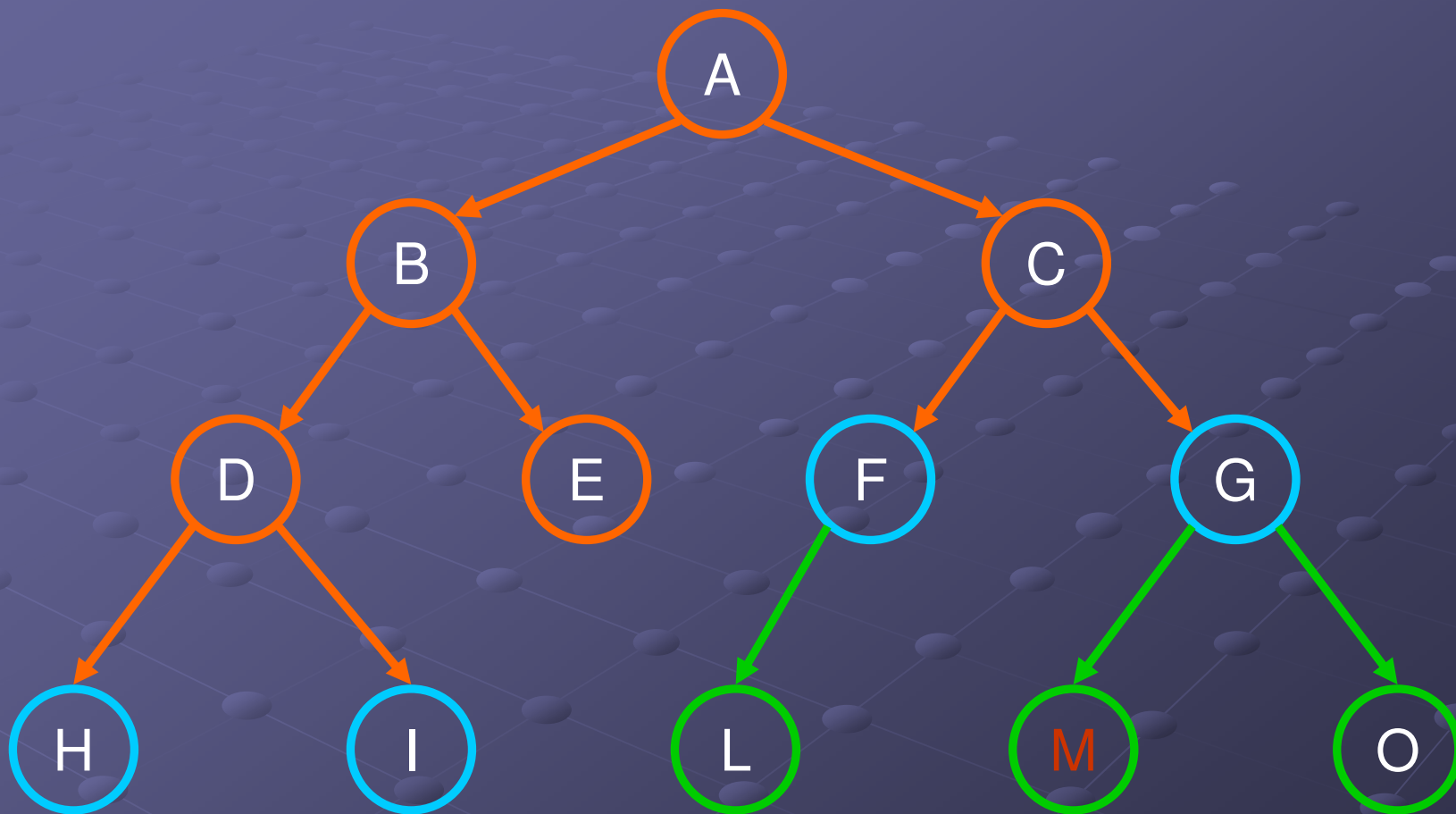
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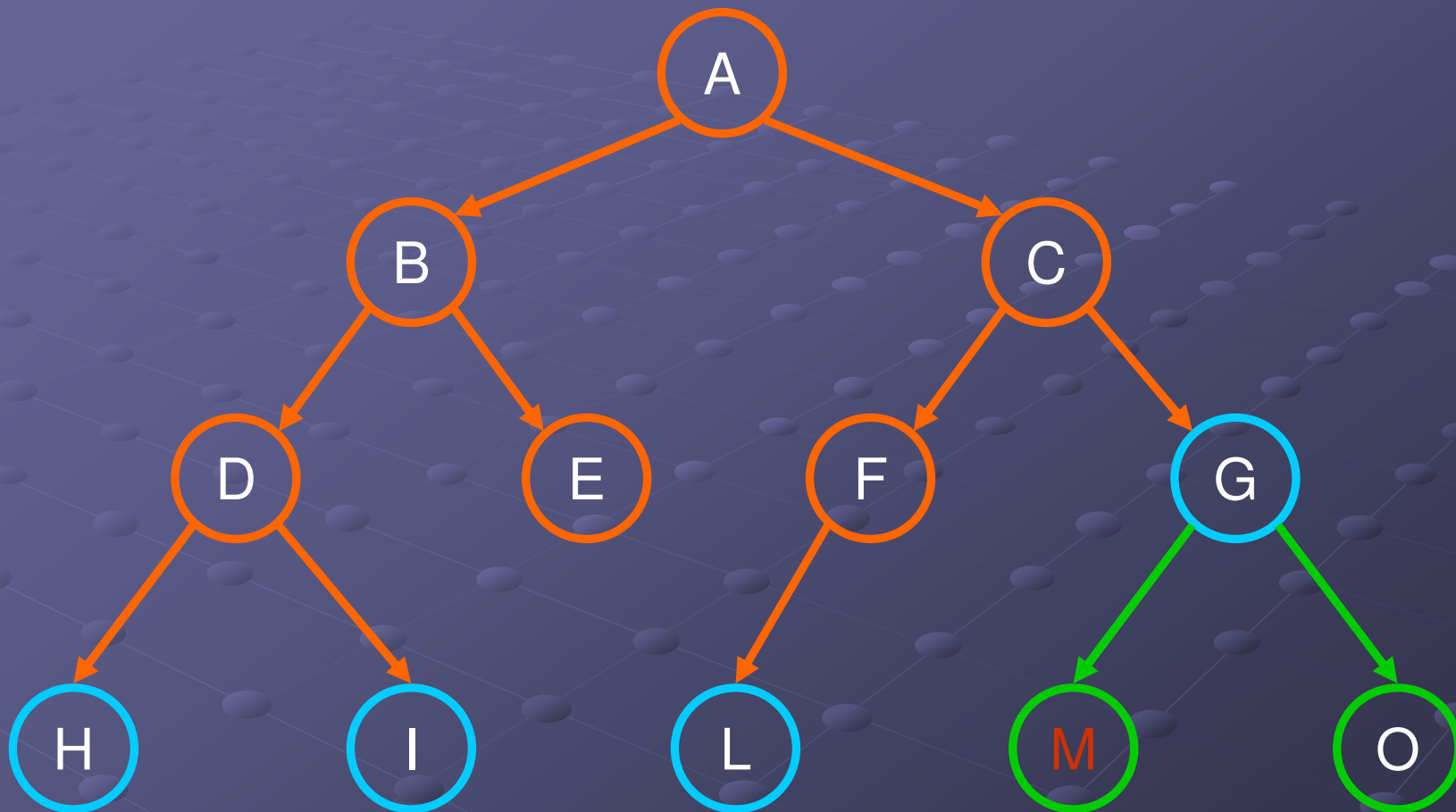
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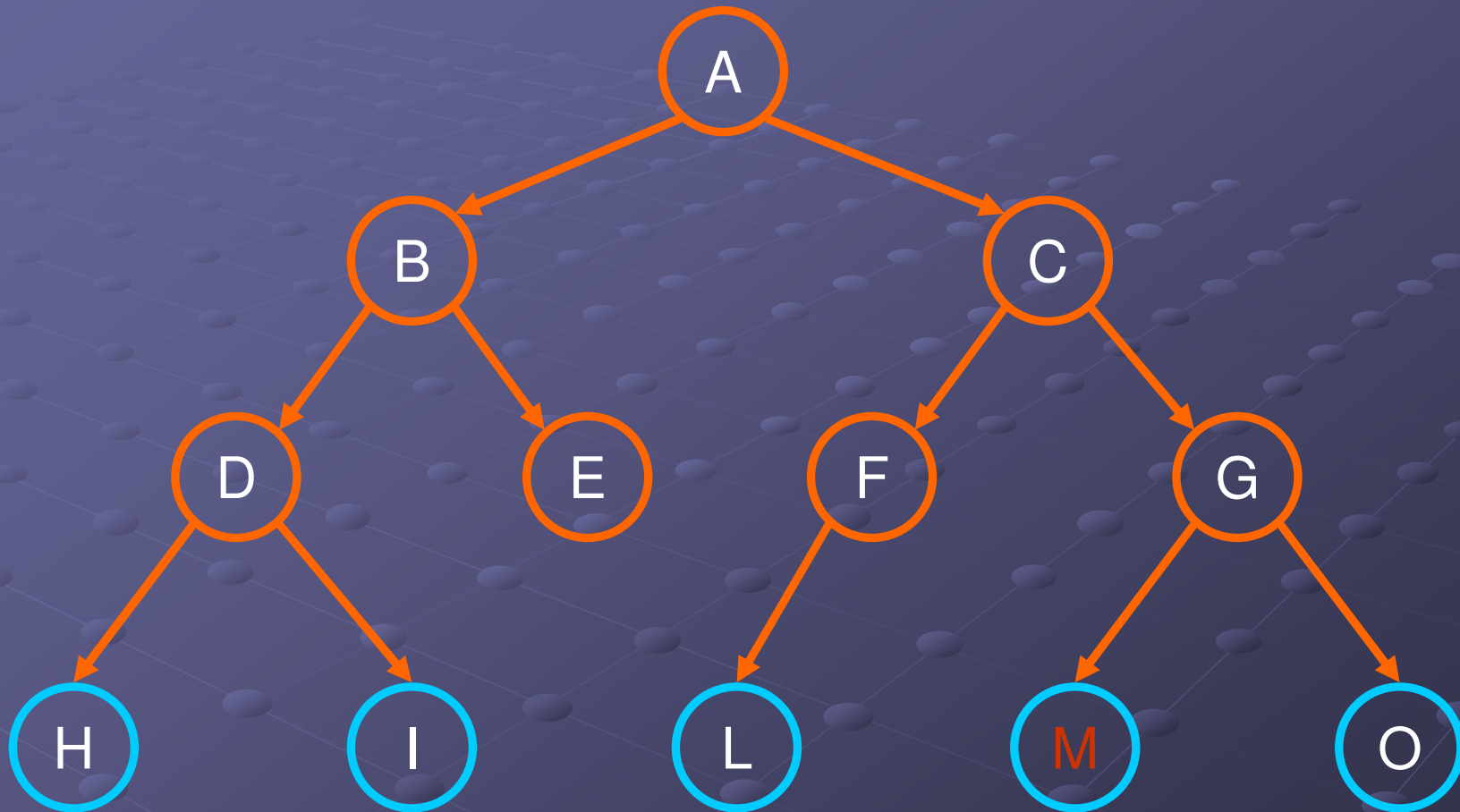
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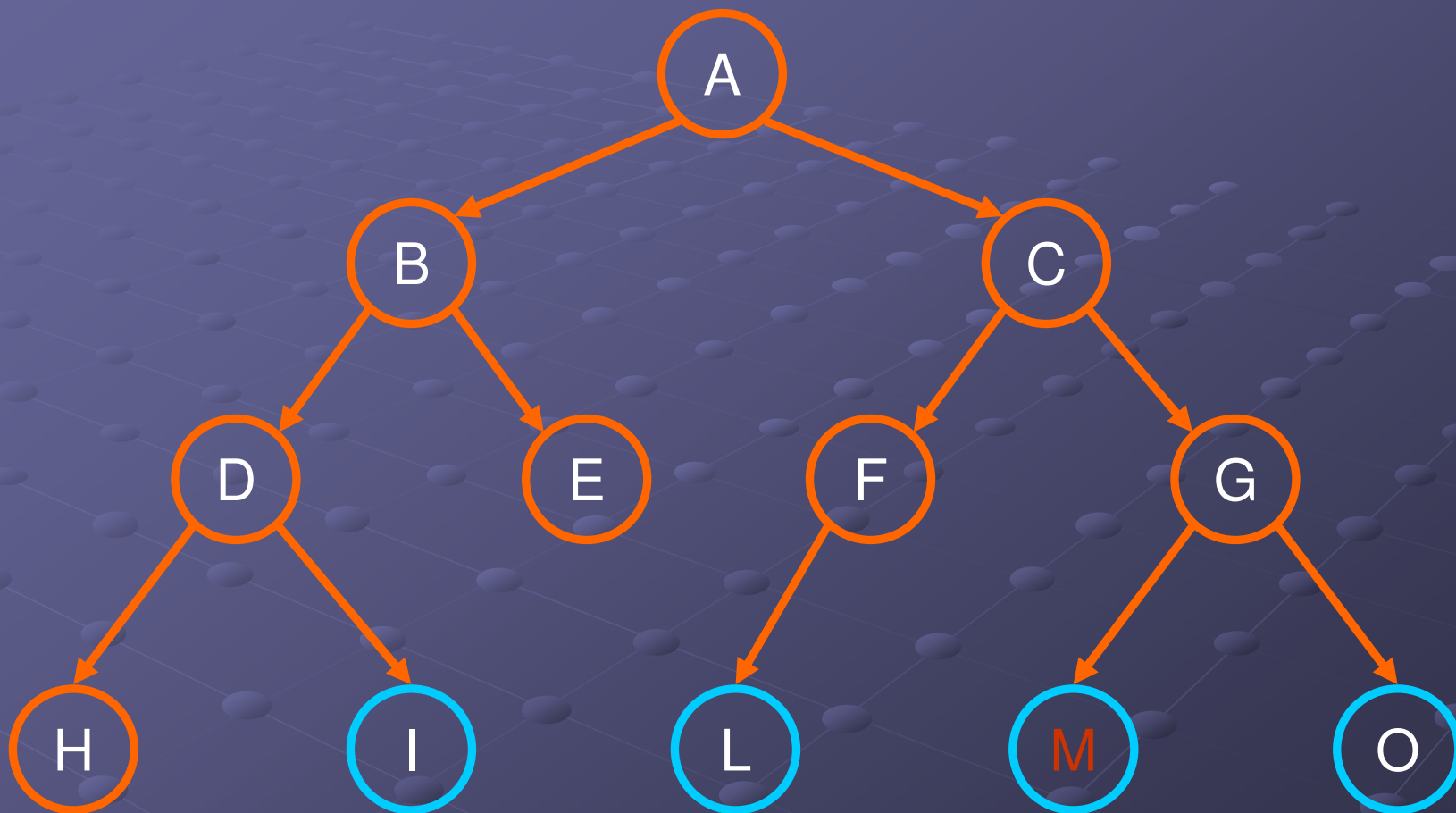
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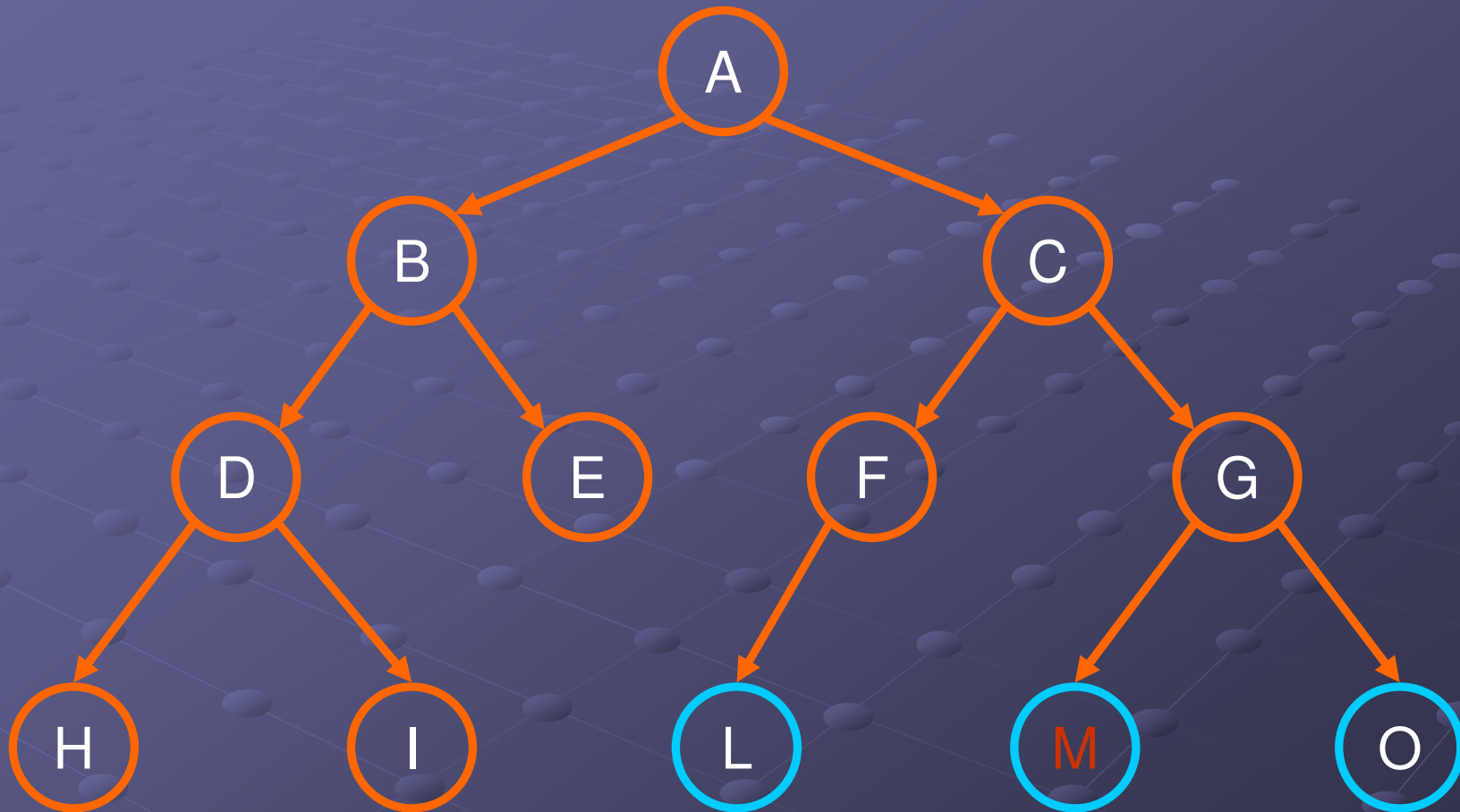
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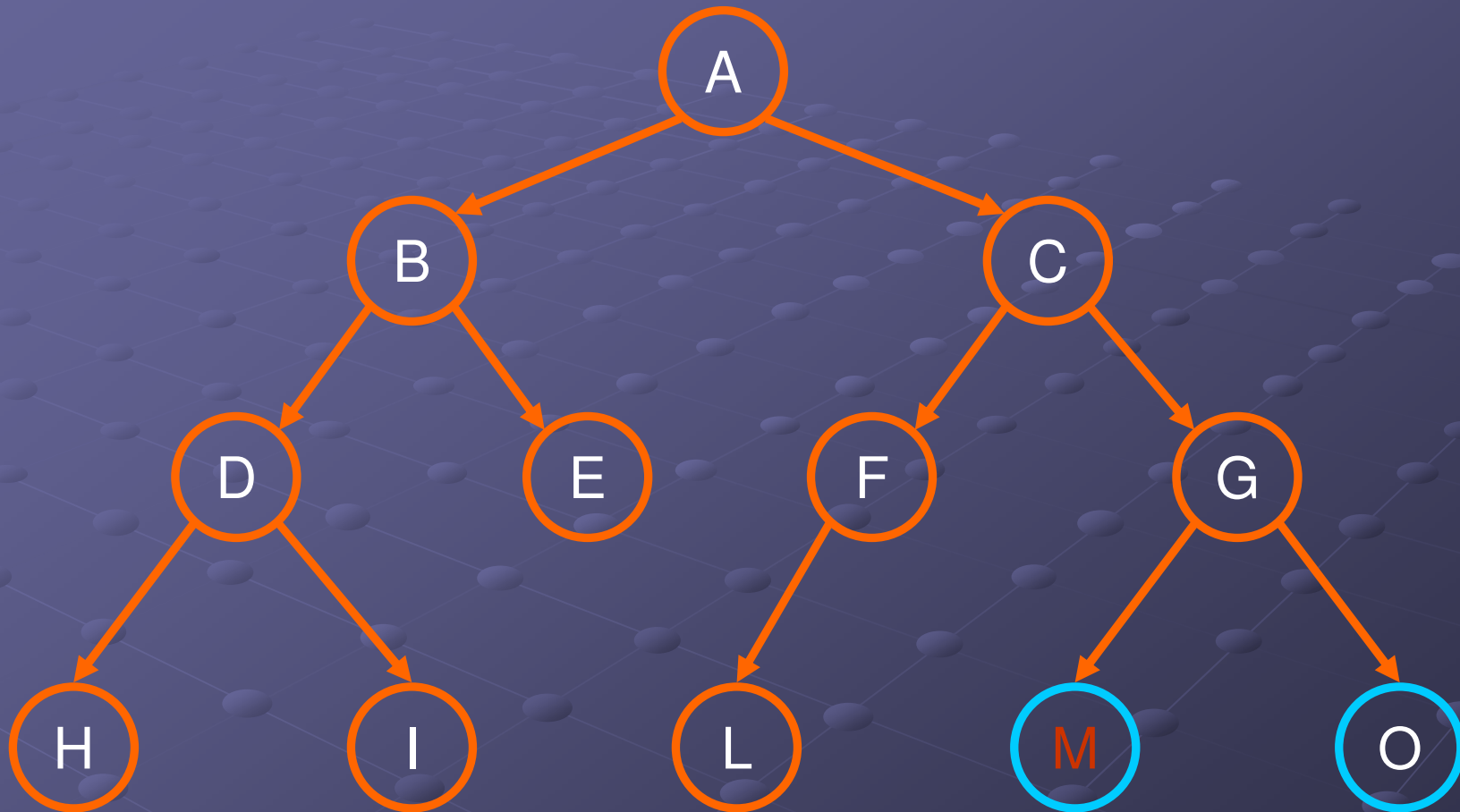
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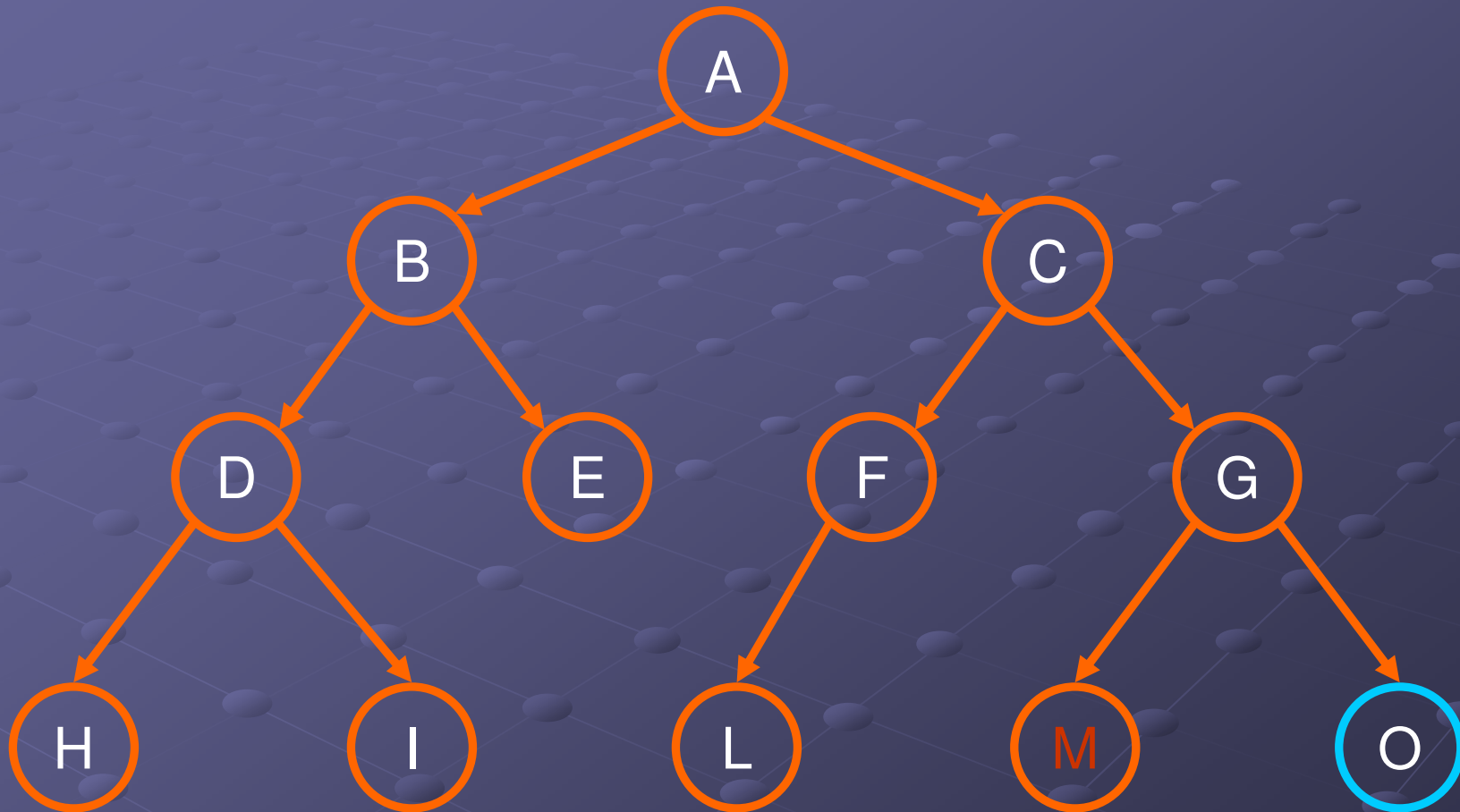
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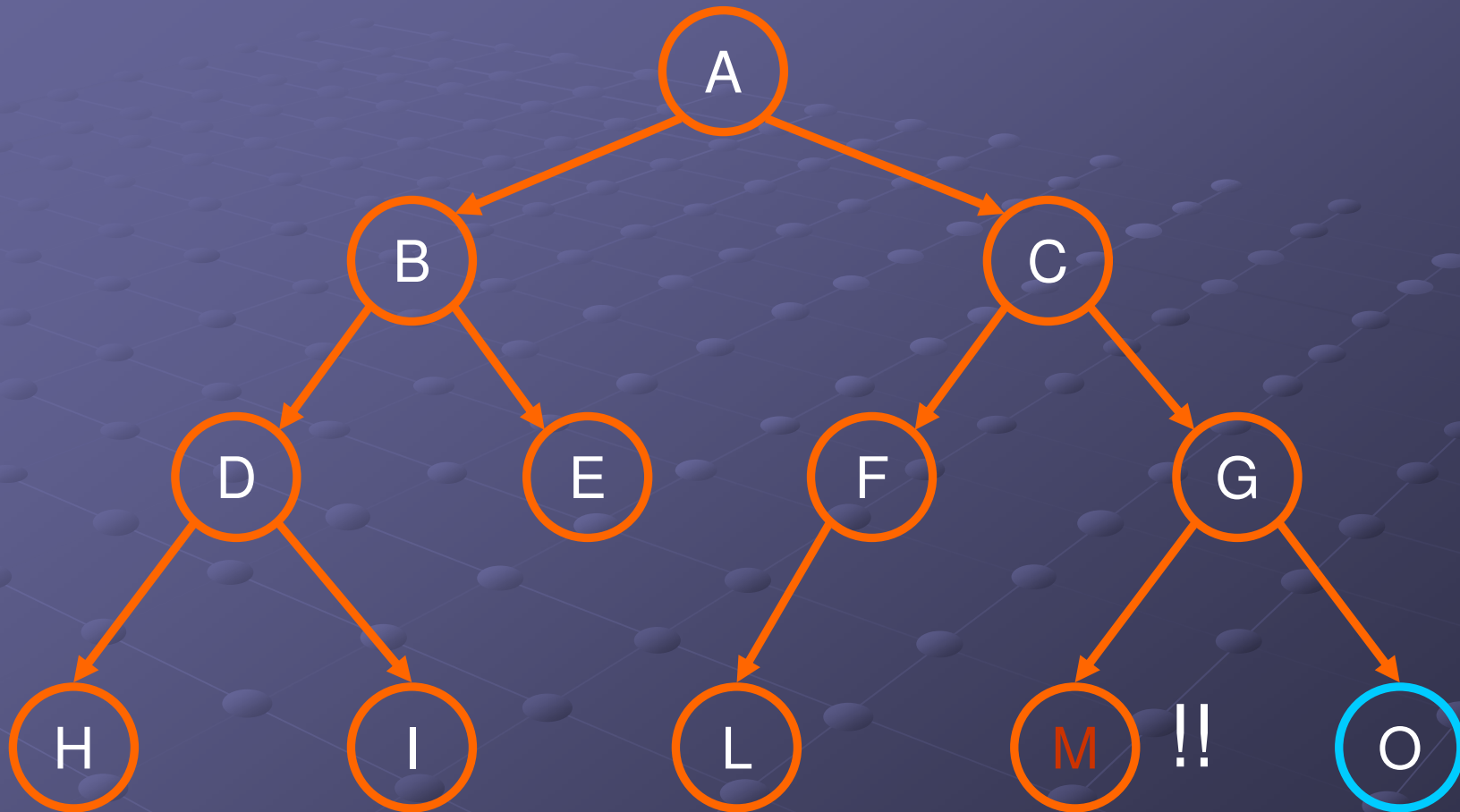
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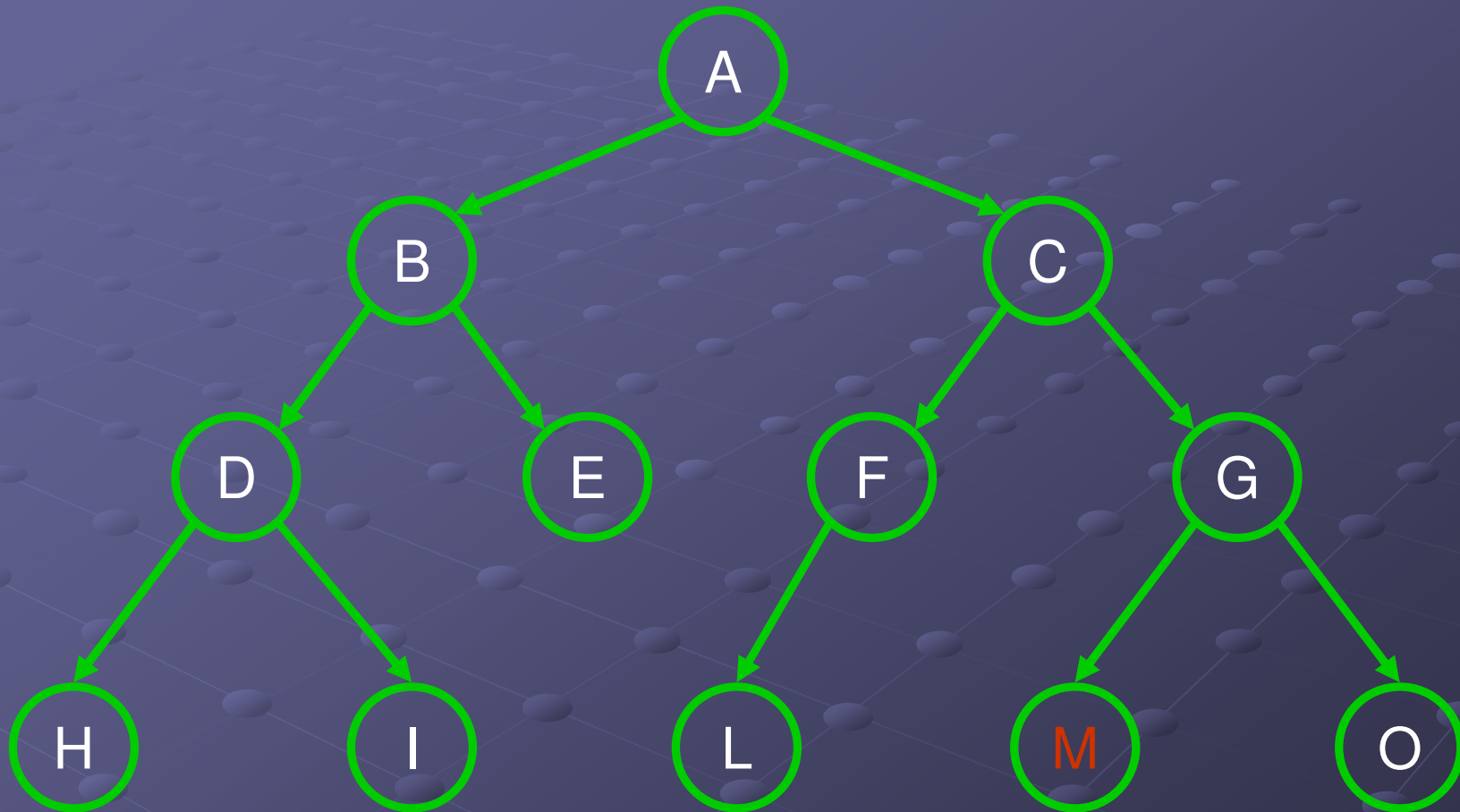
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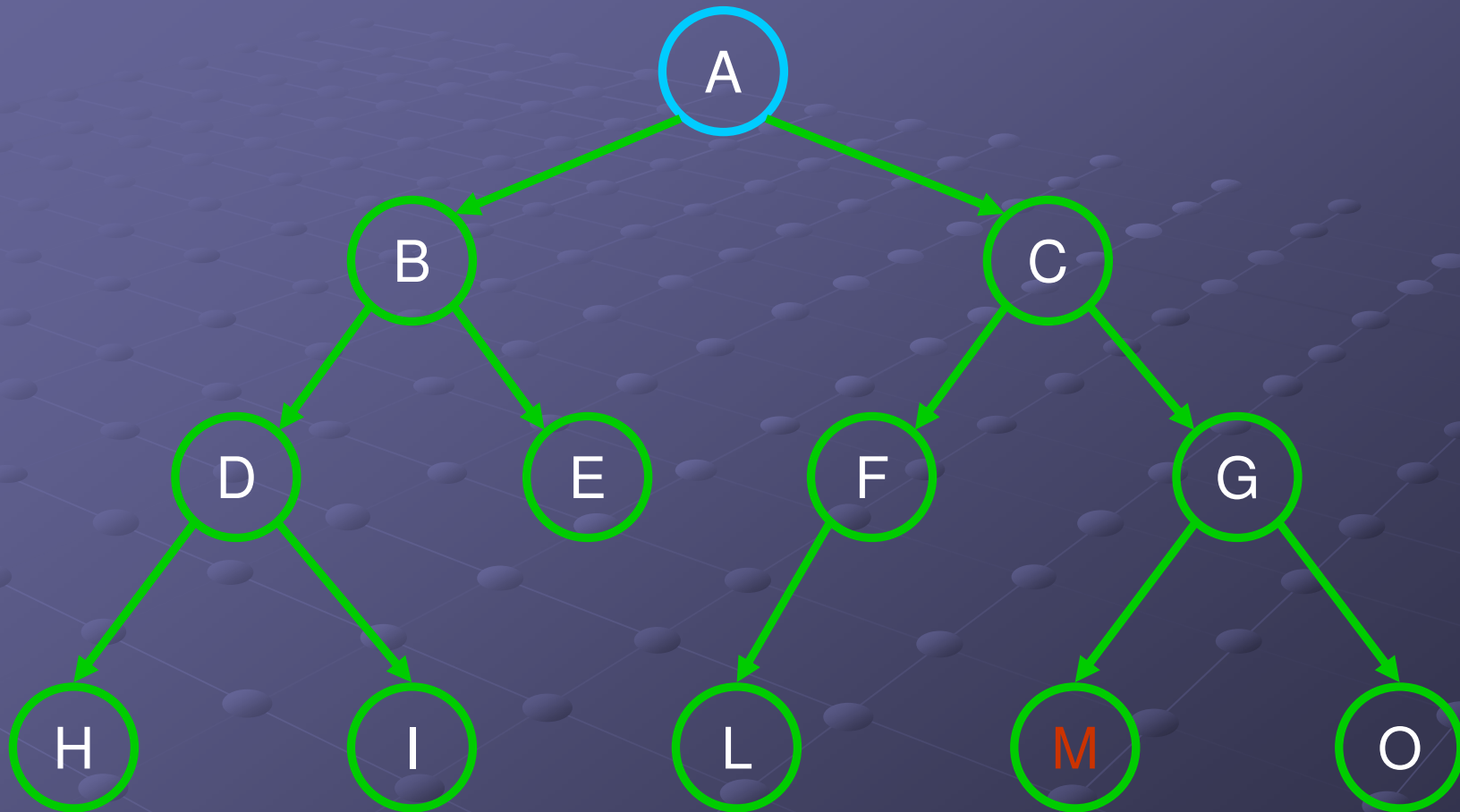
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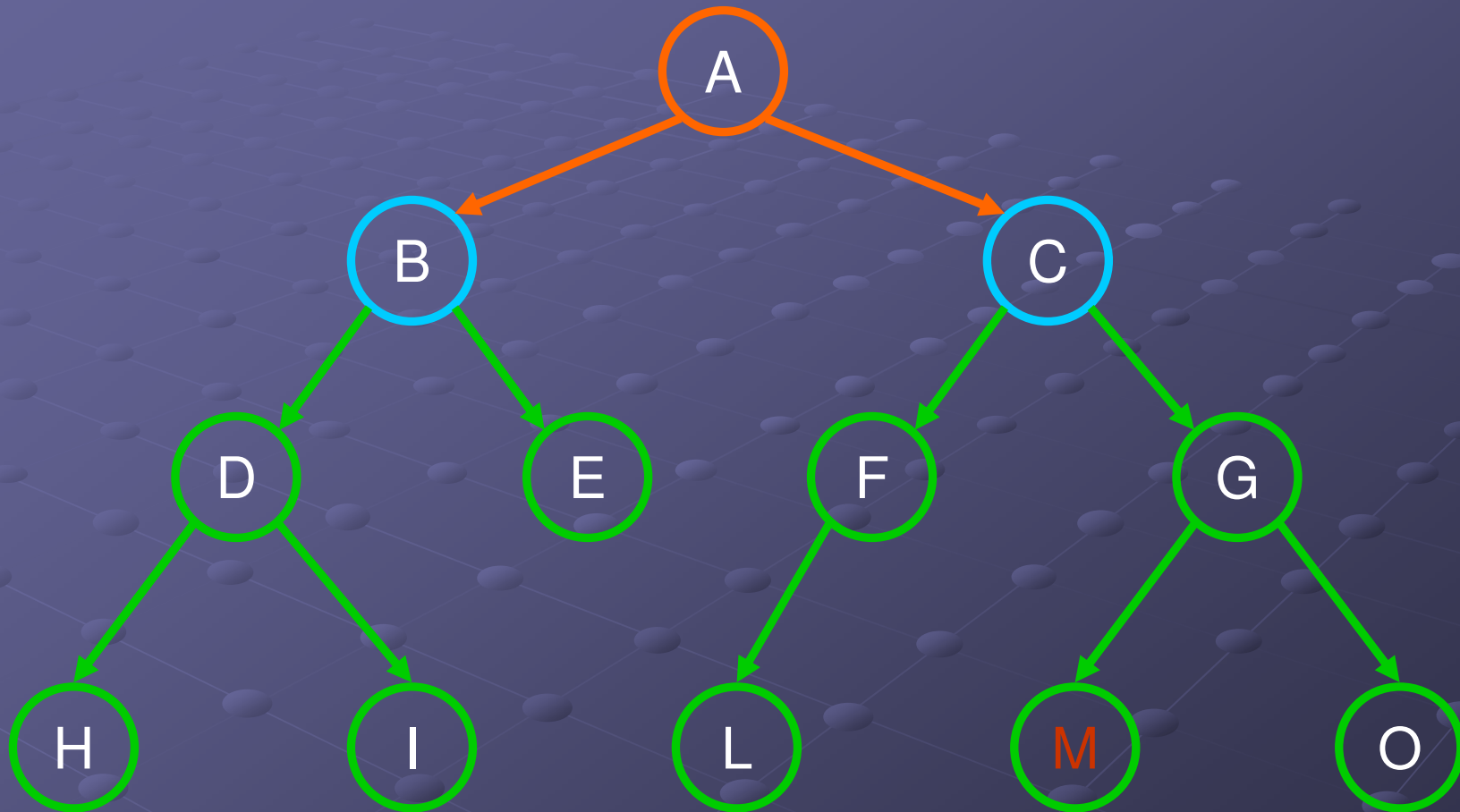
Depth-first Search



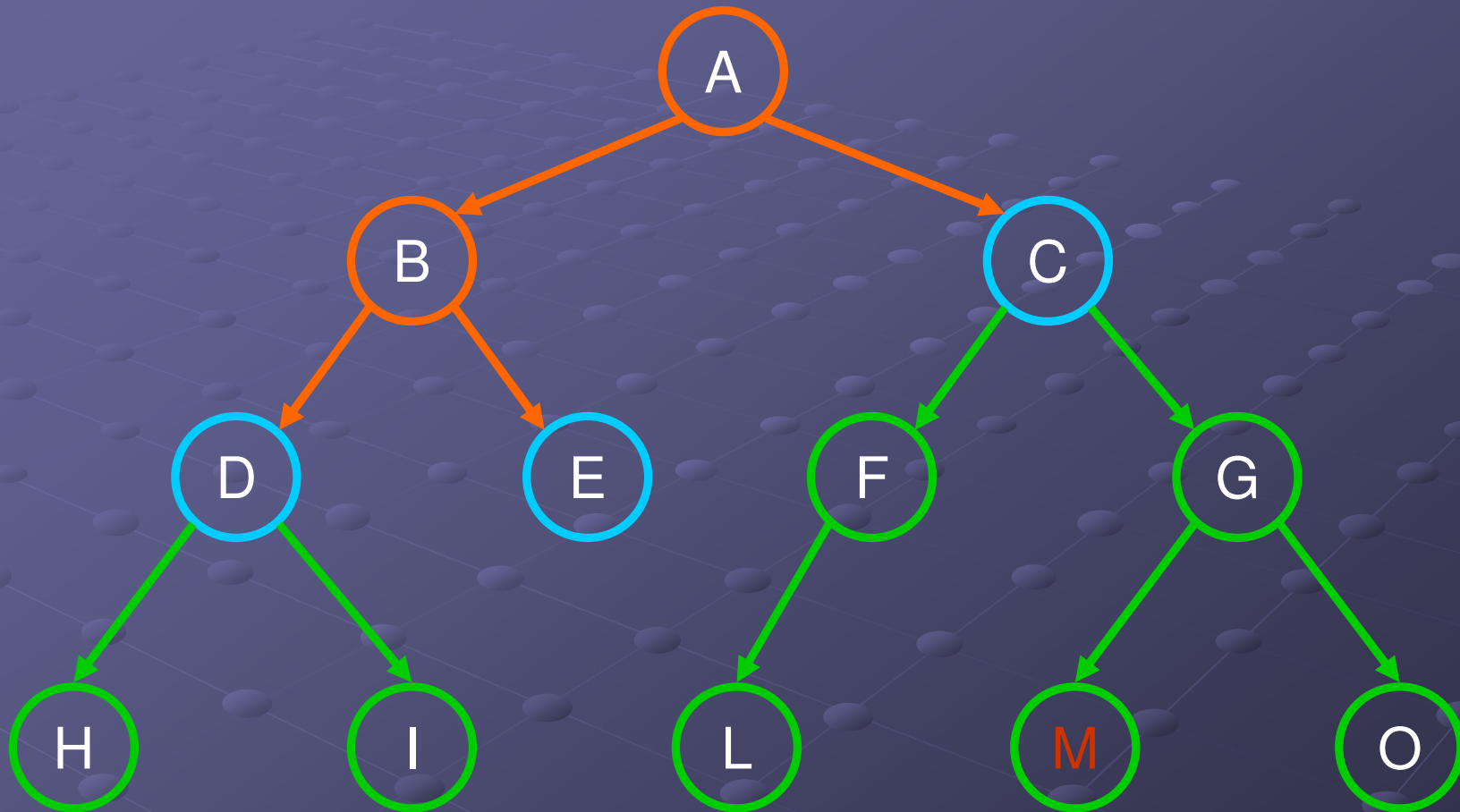
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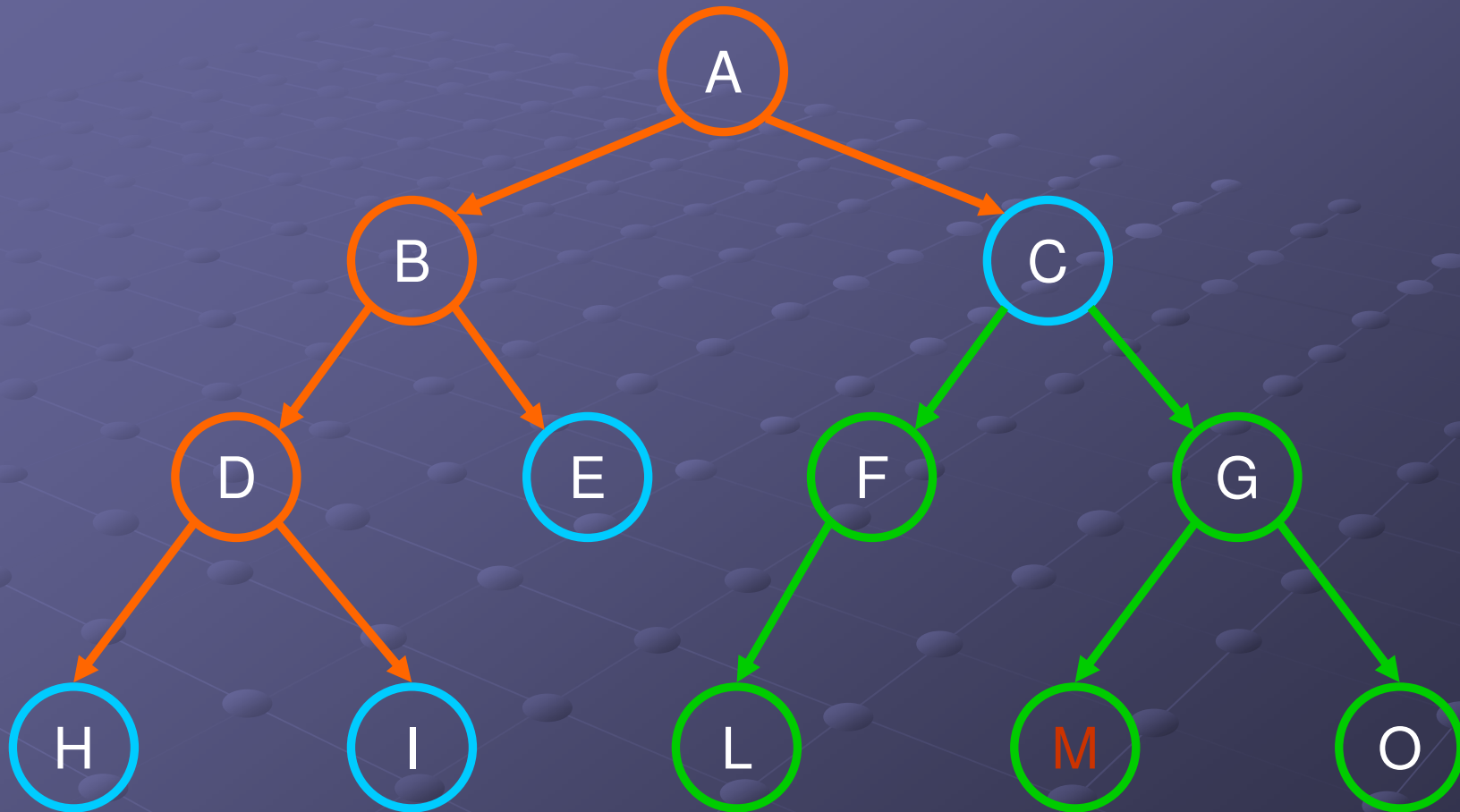
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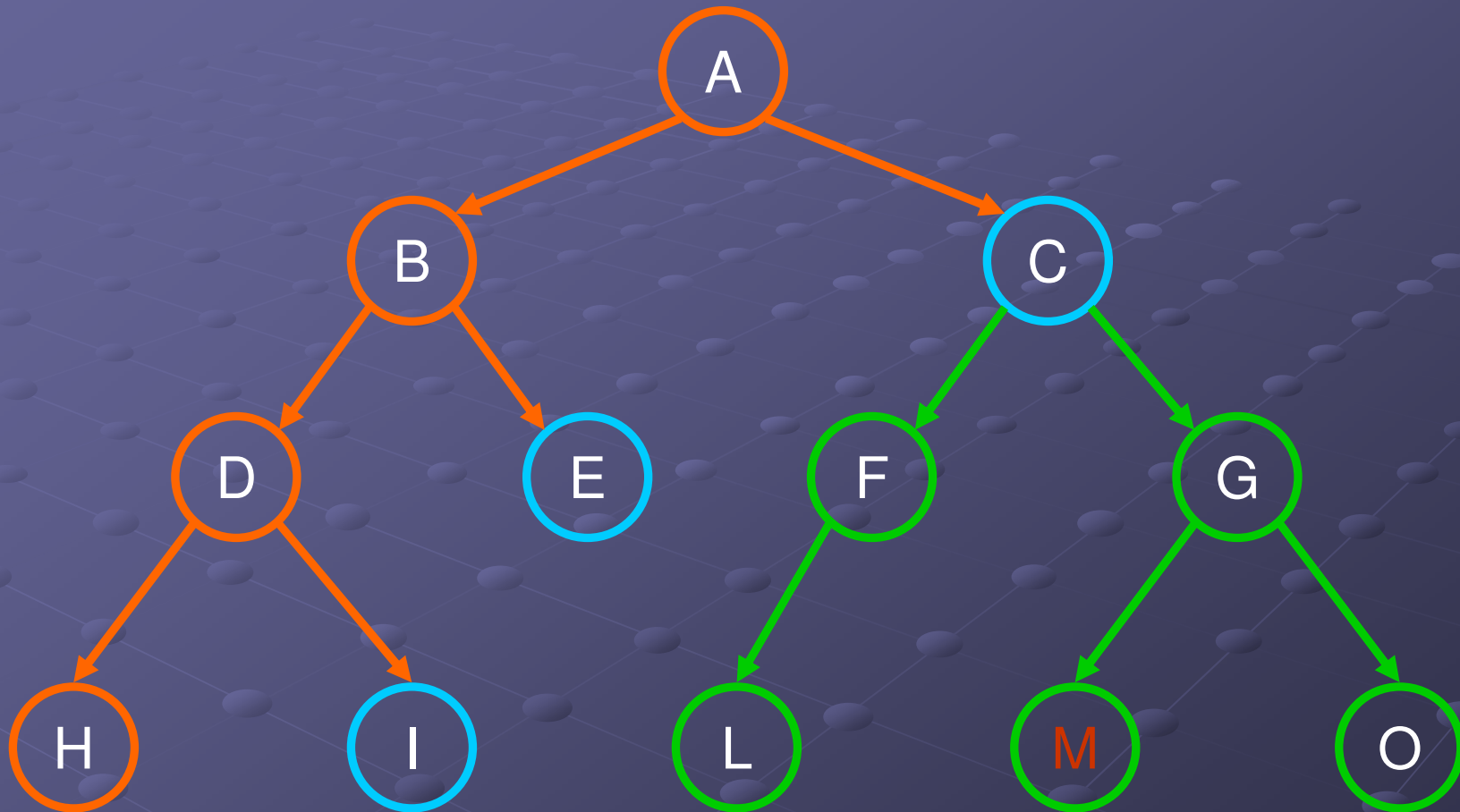
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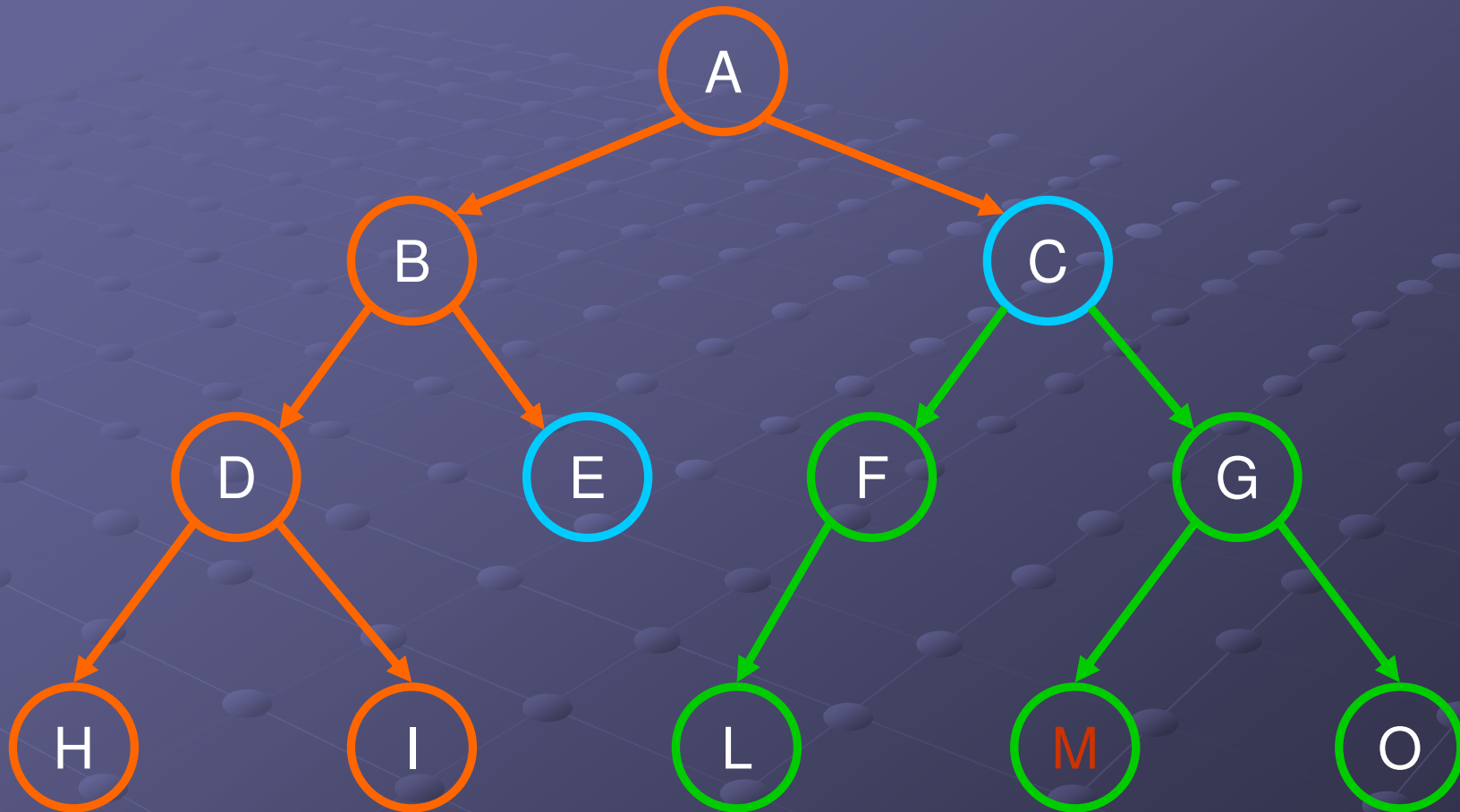
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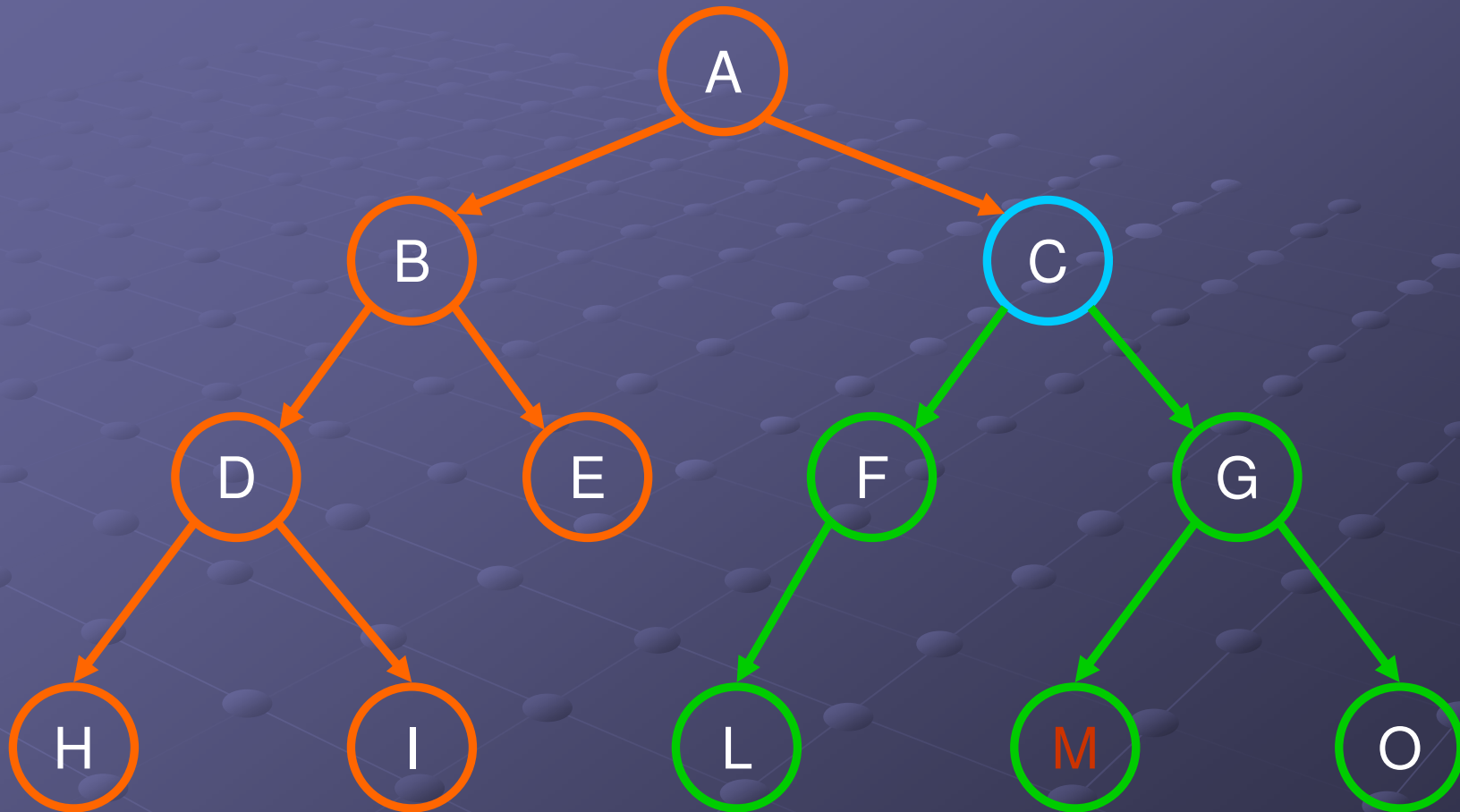
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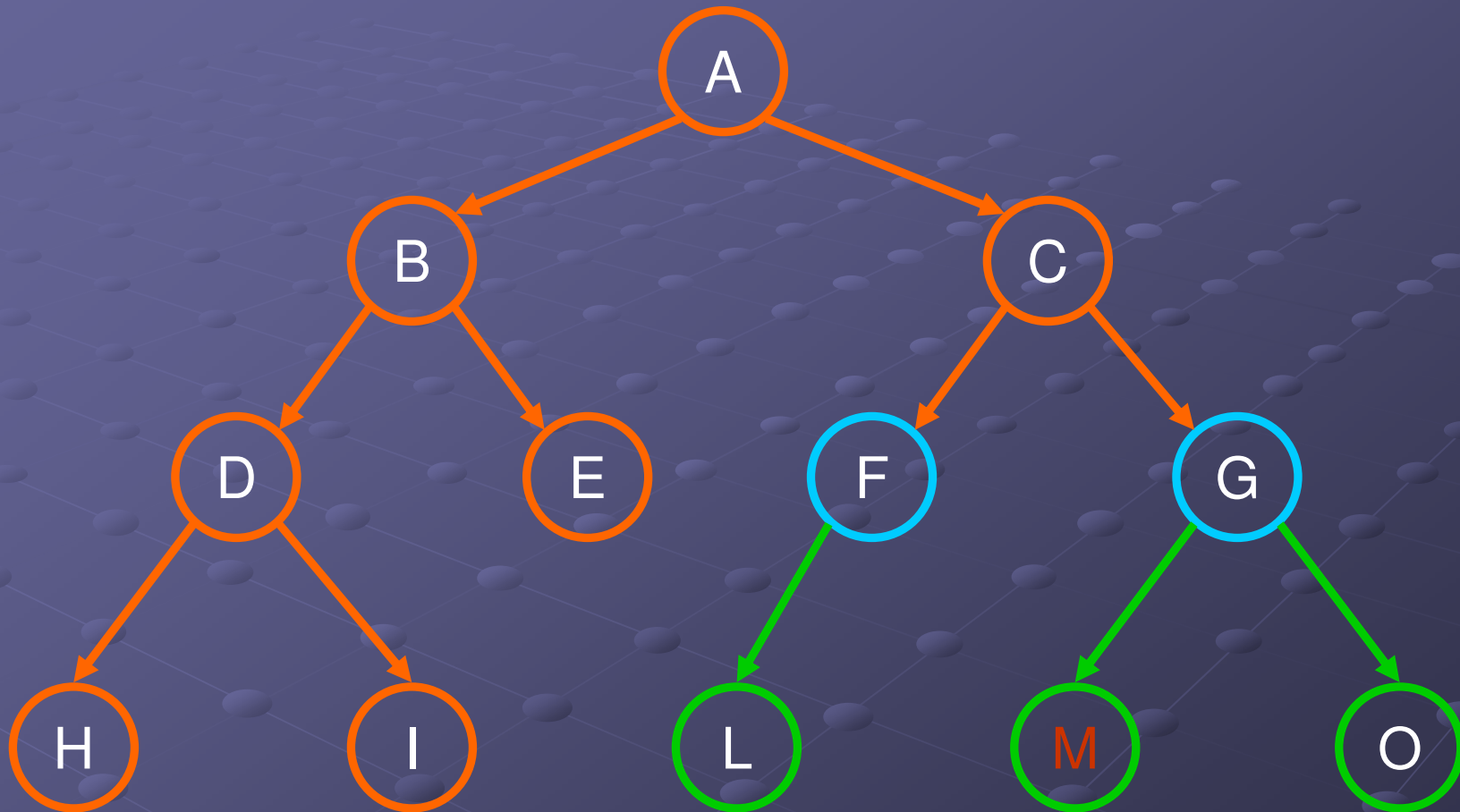
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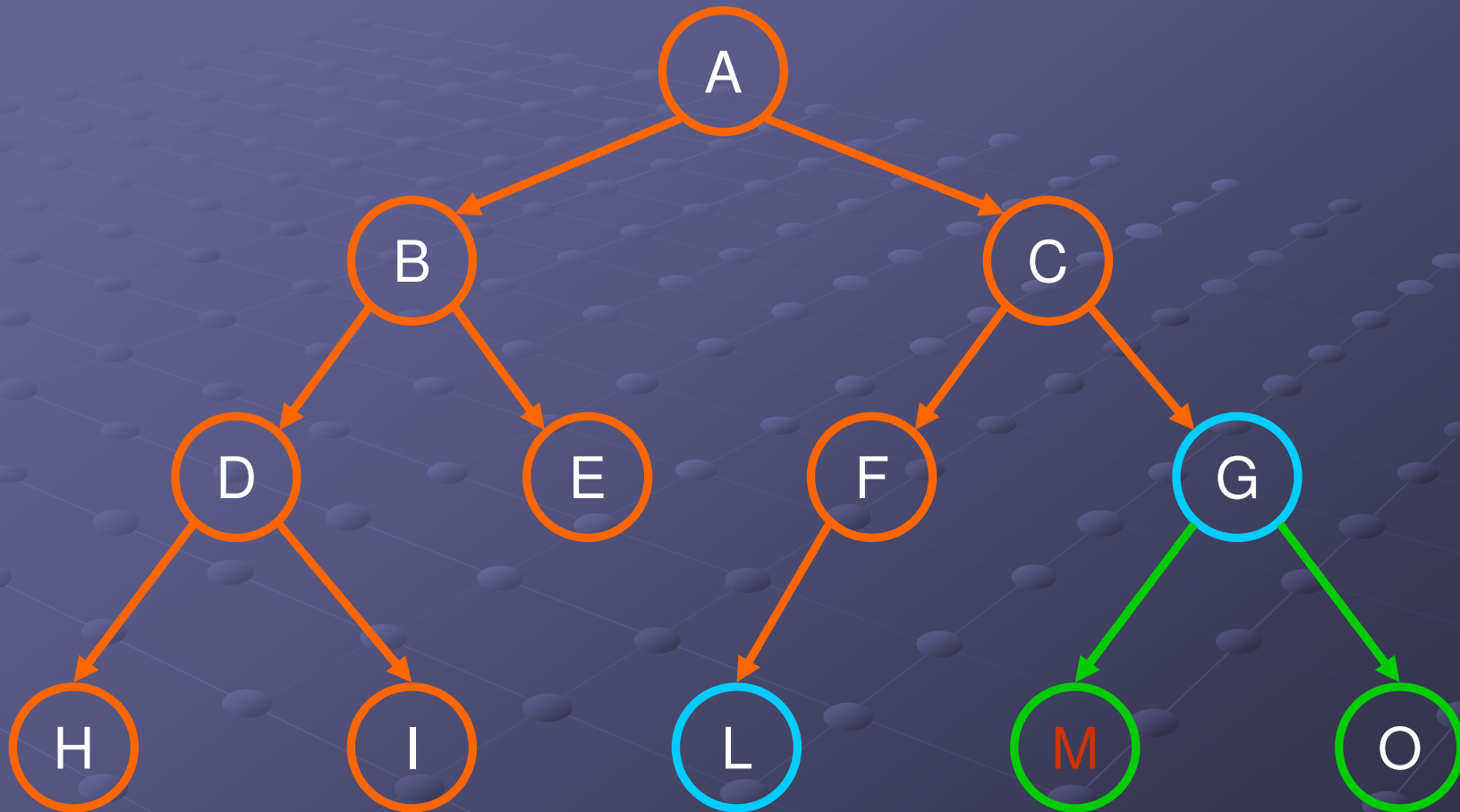
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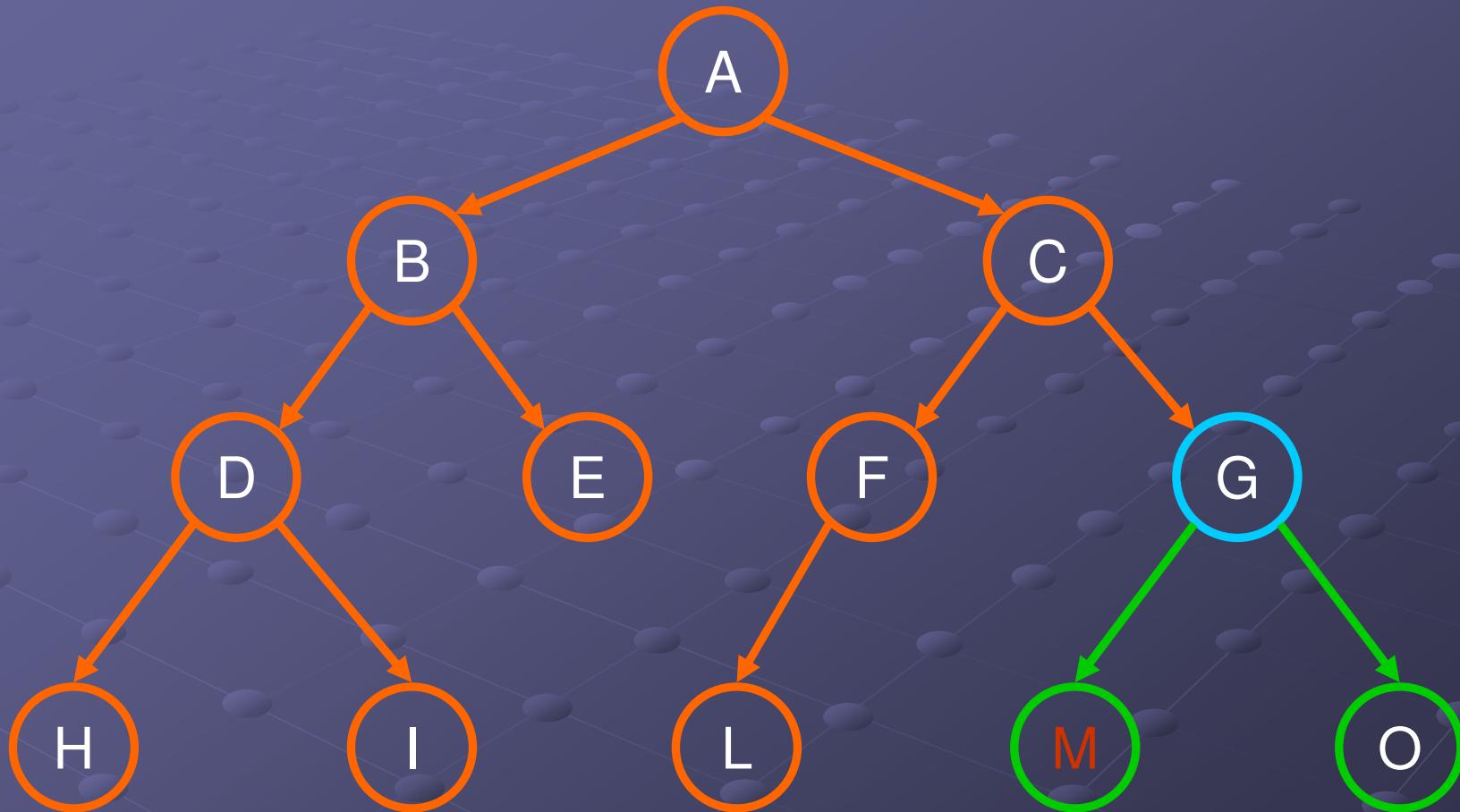
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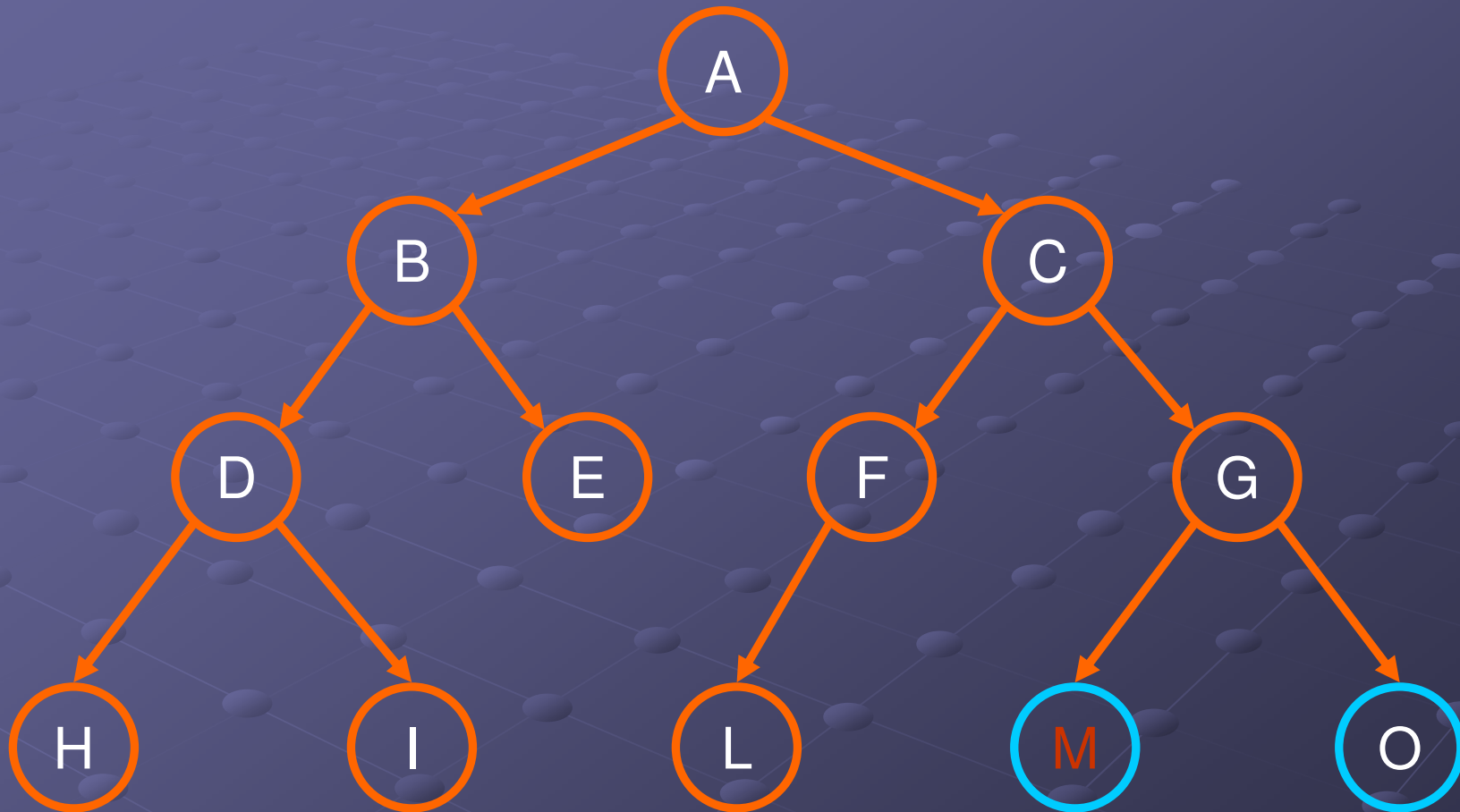
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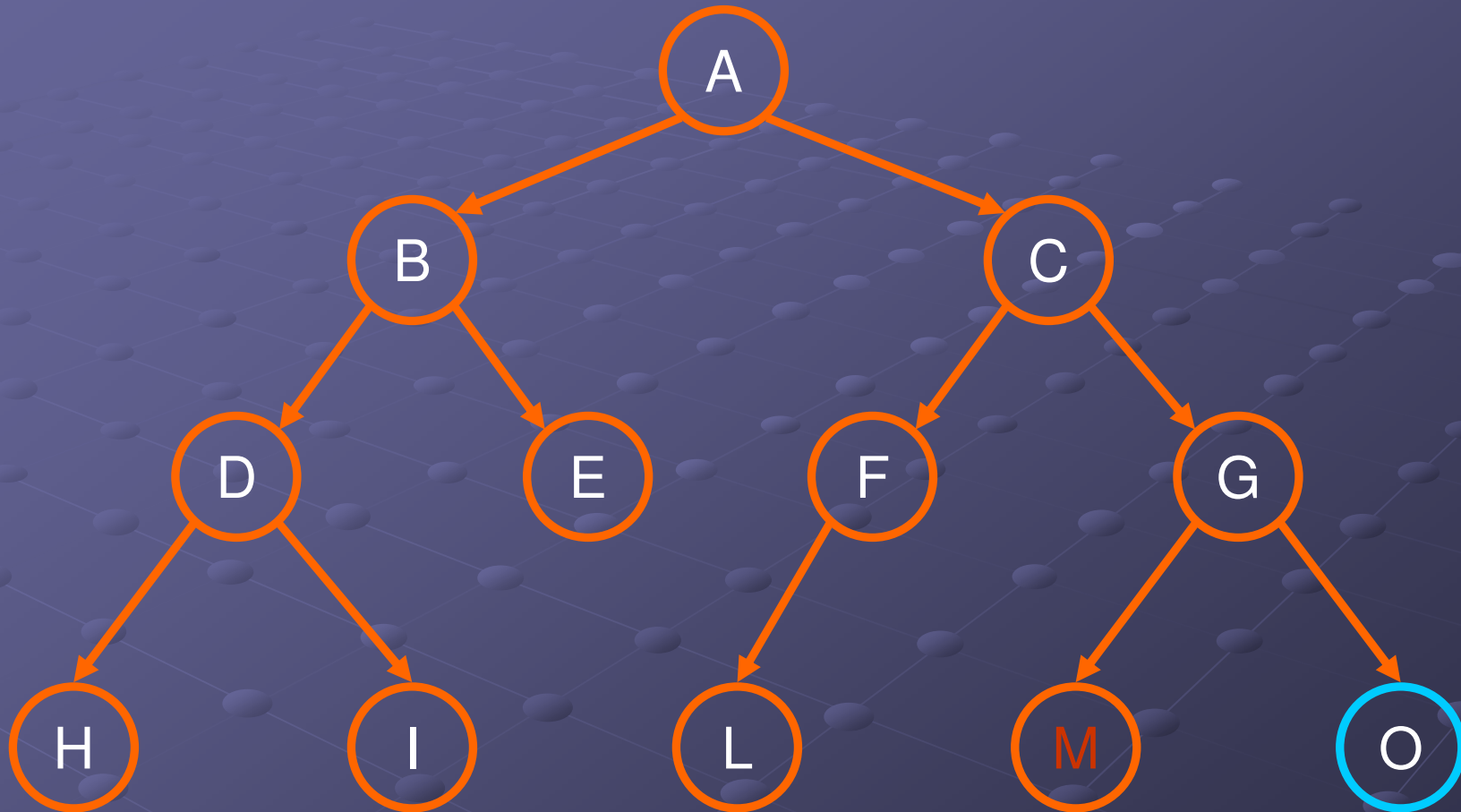
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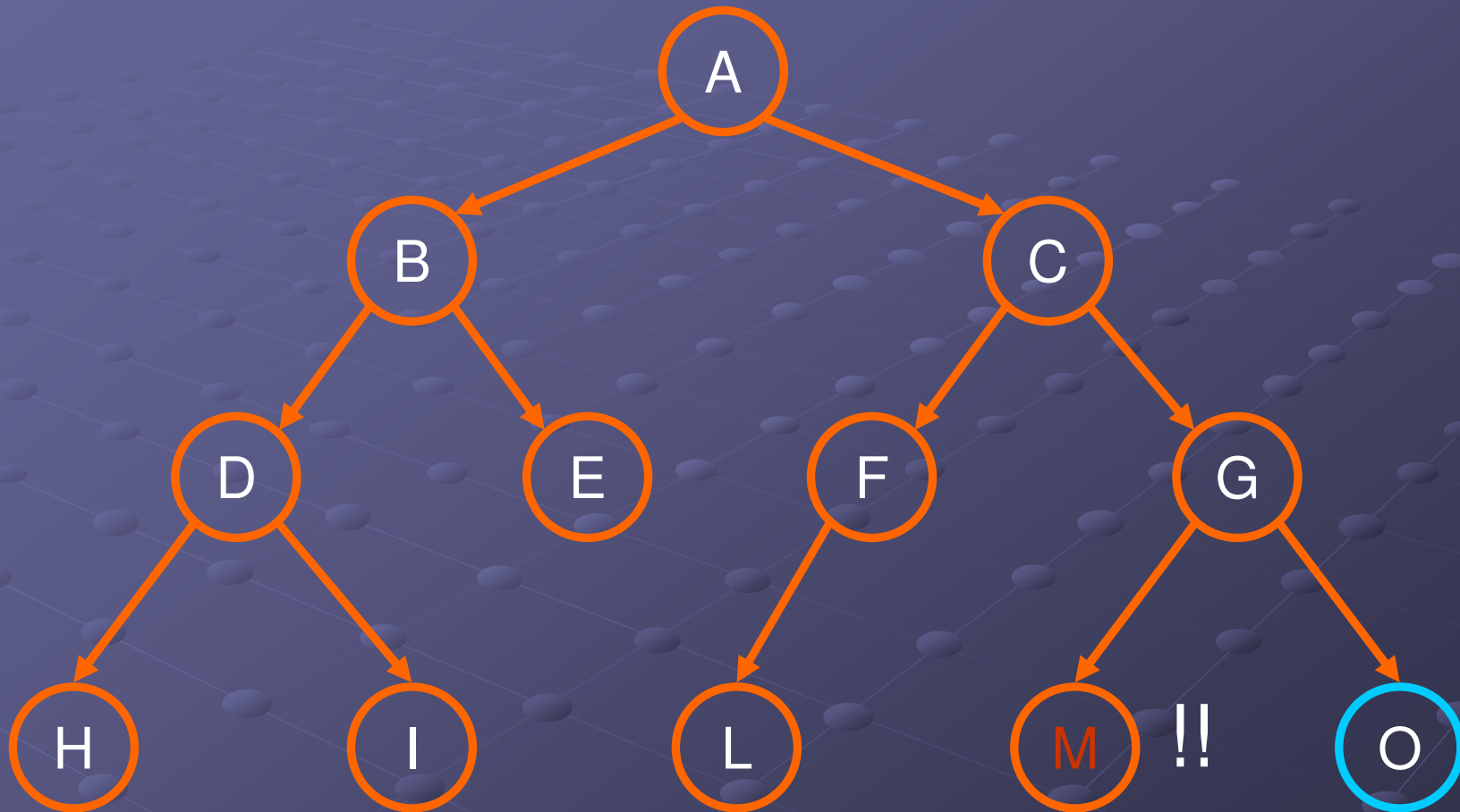
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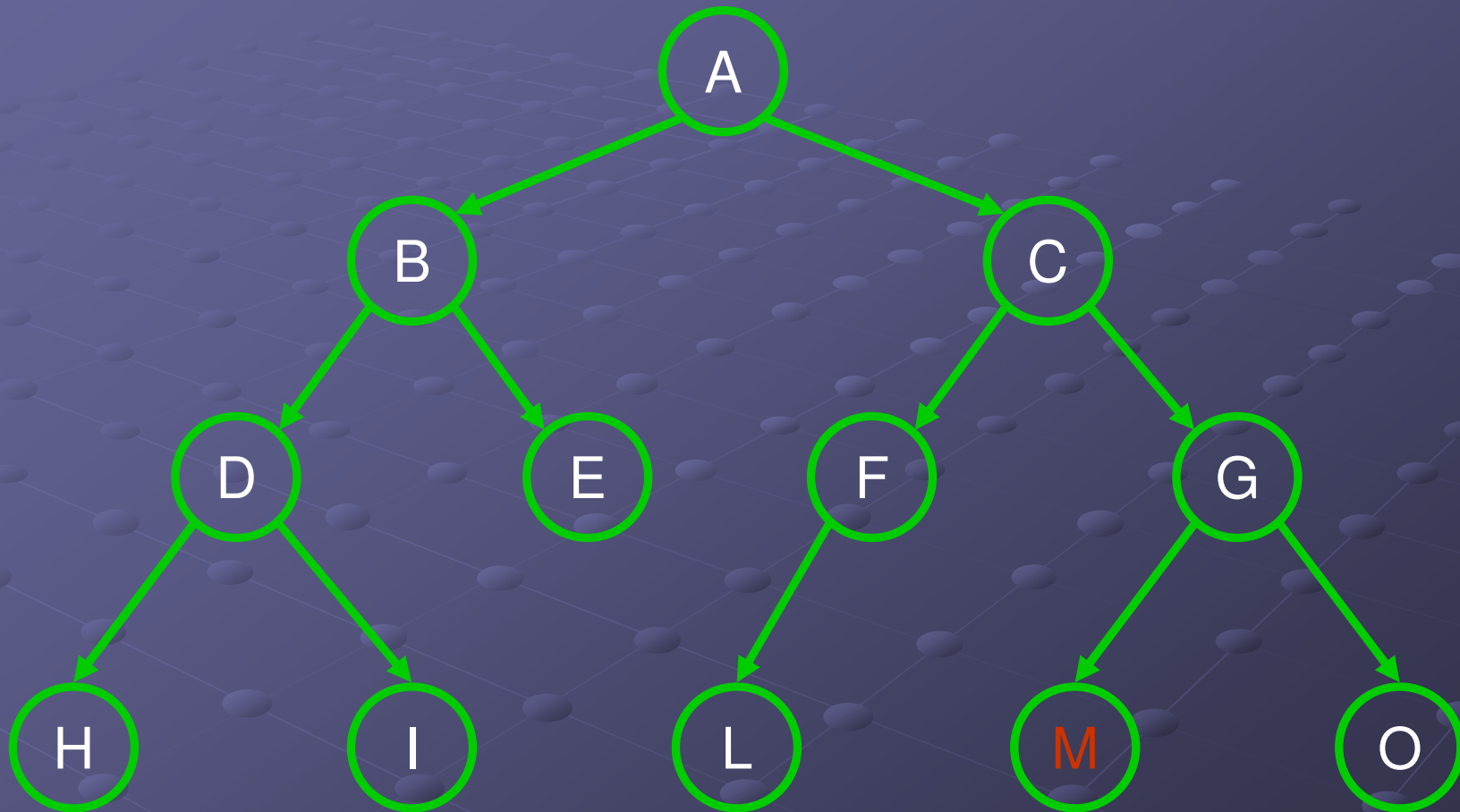
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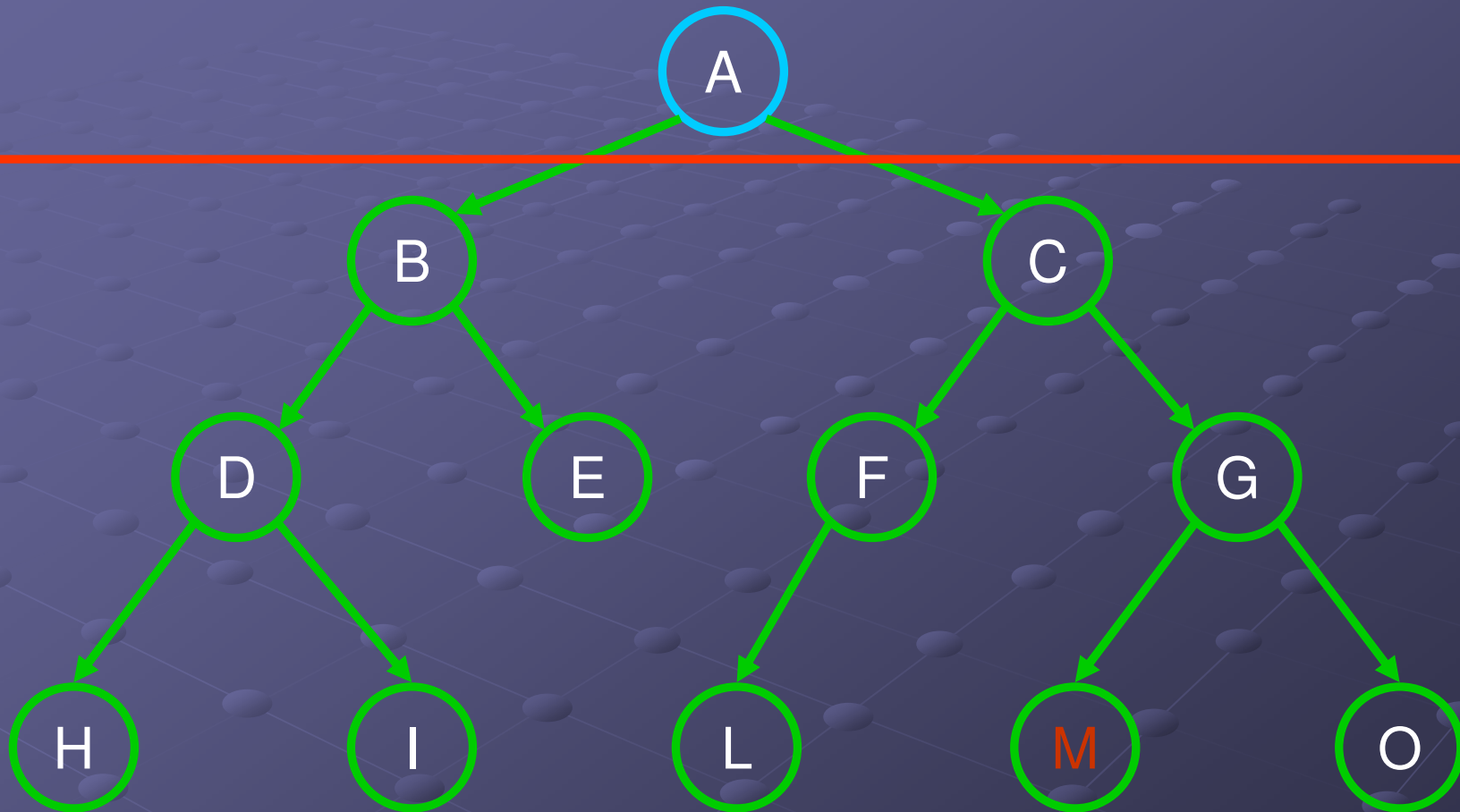
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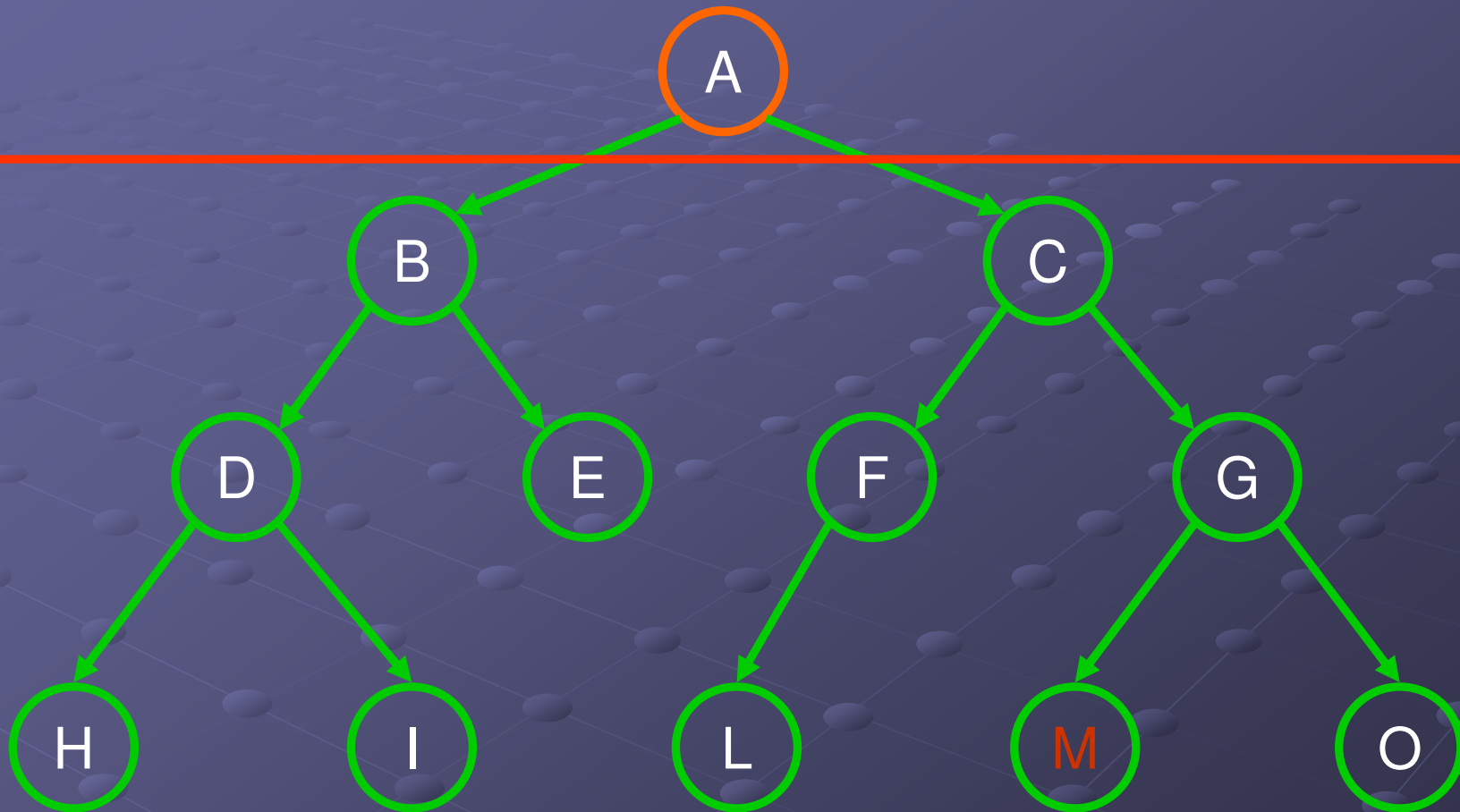
Iterative Deepening DFS Search



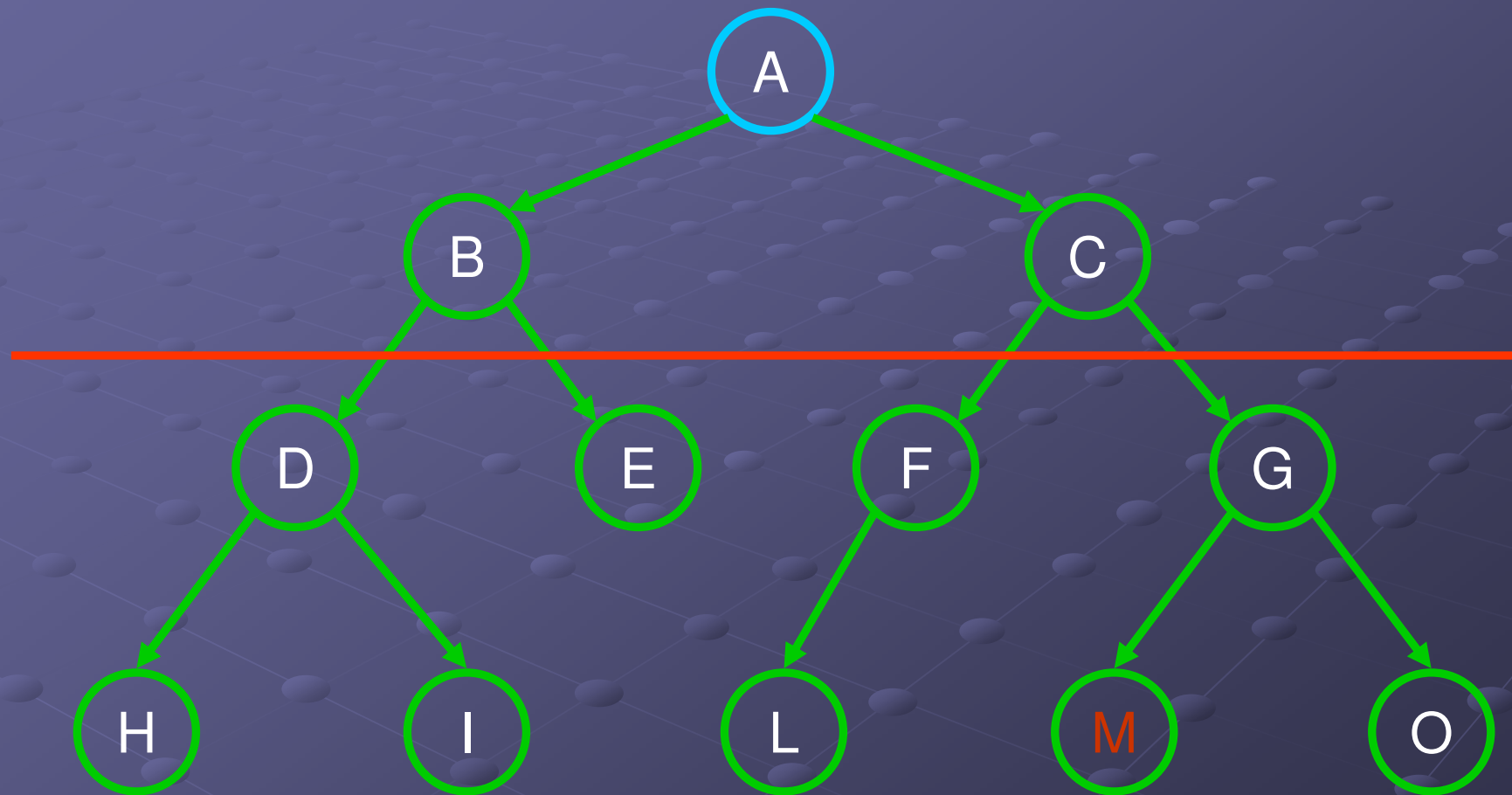
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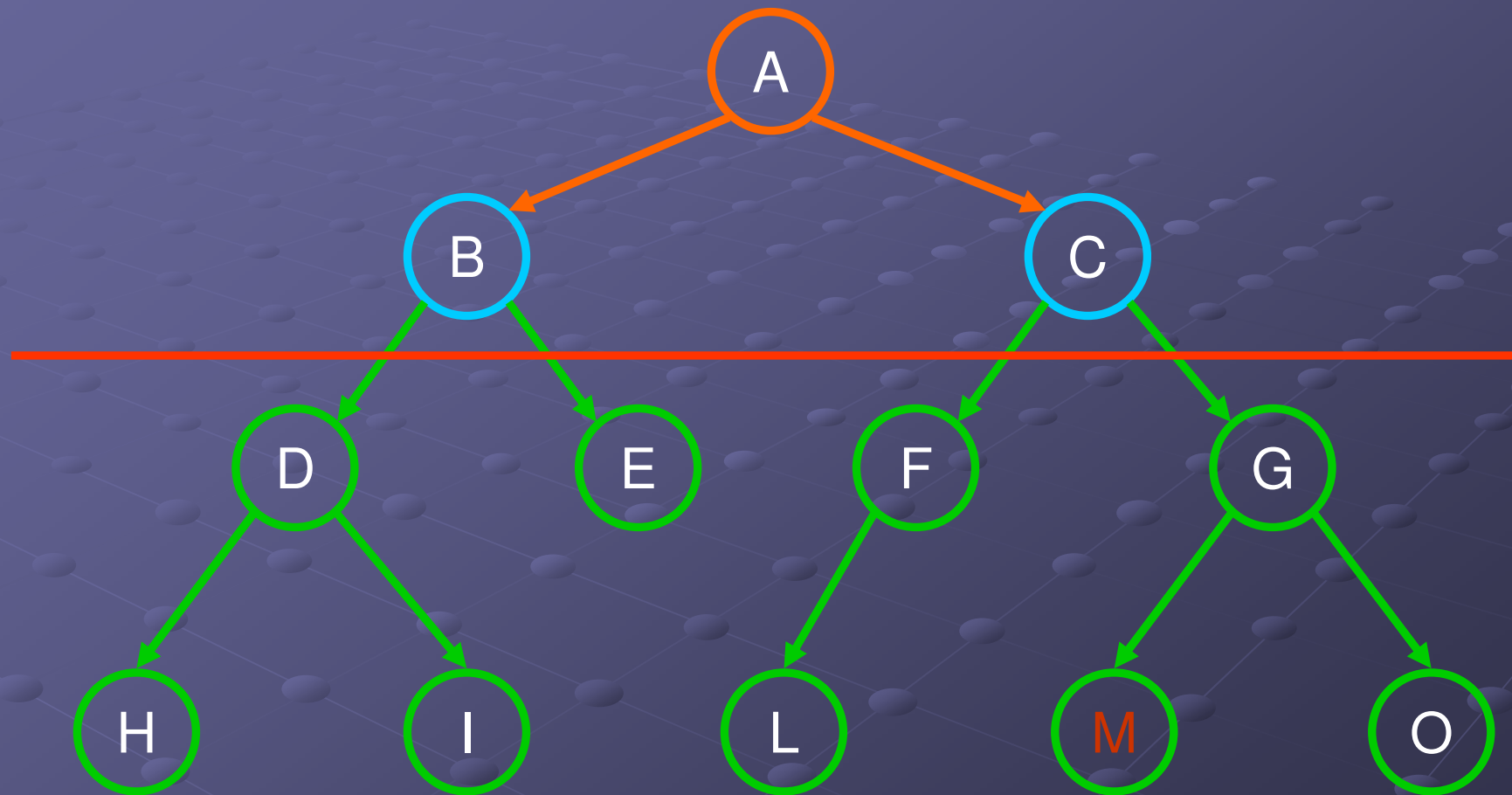
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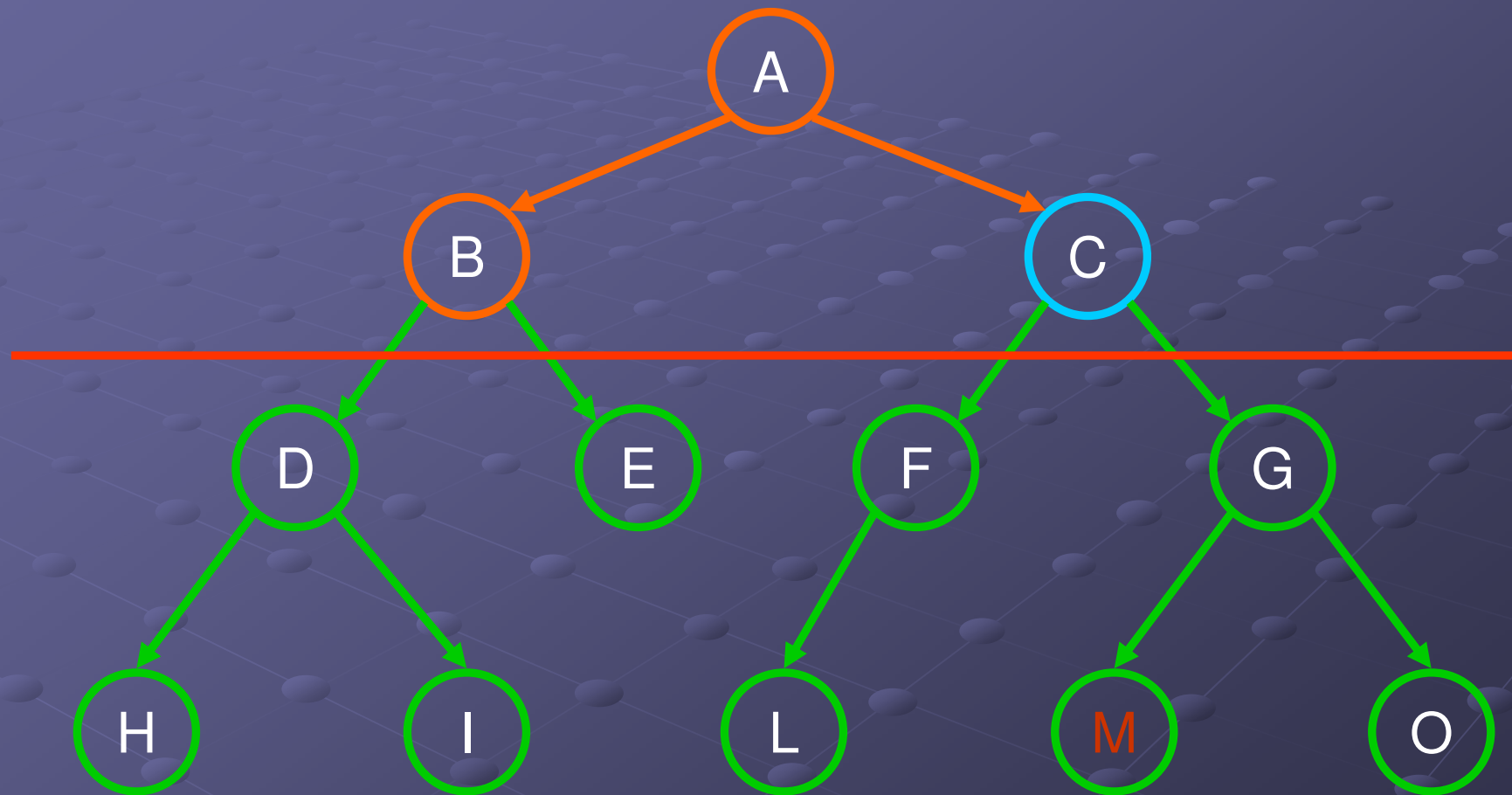
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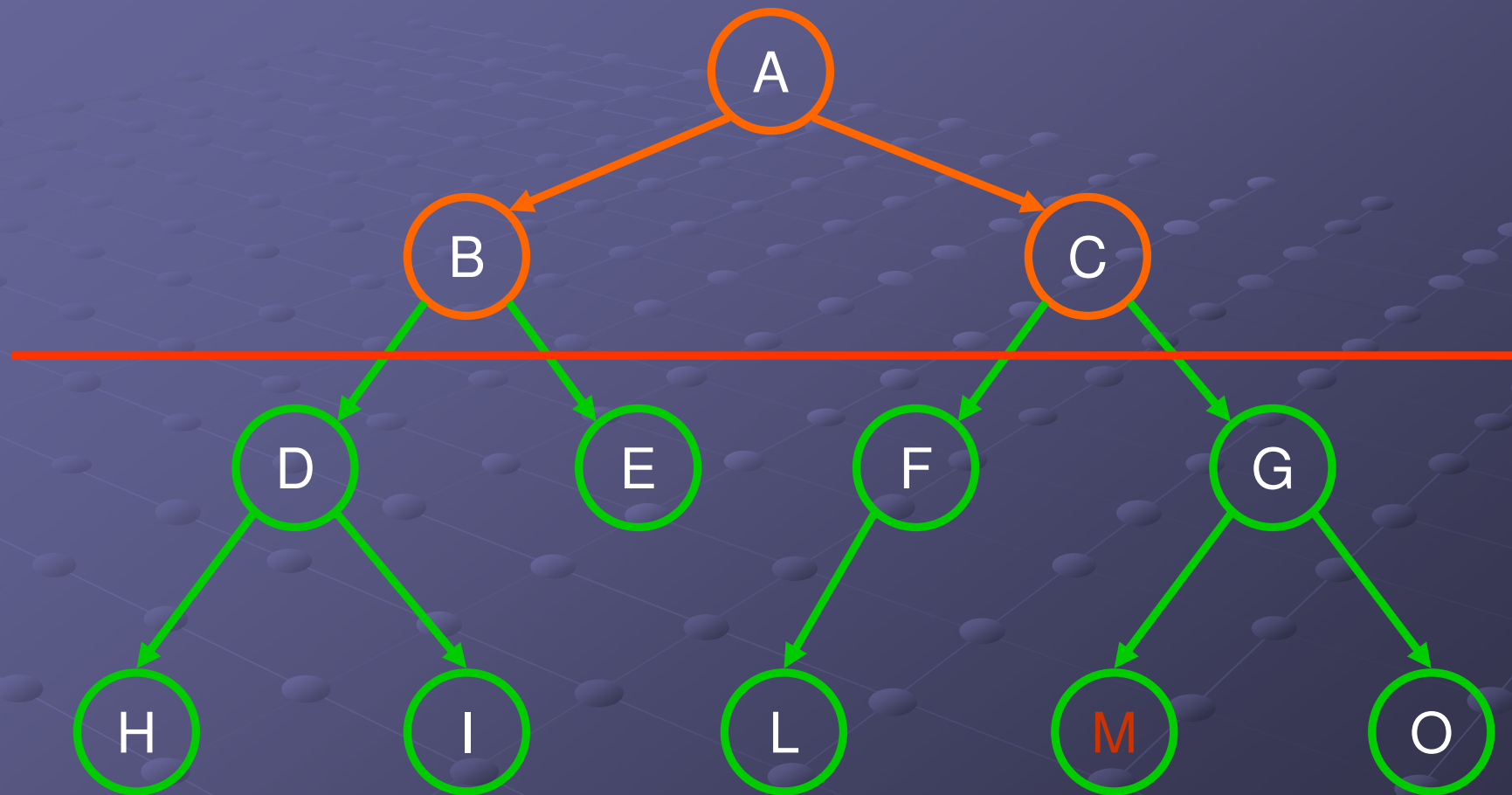
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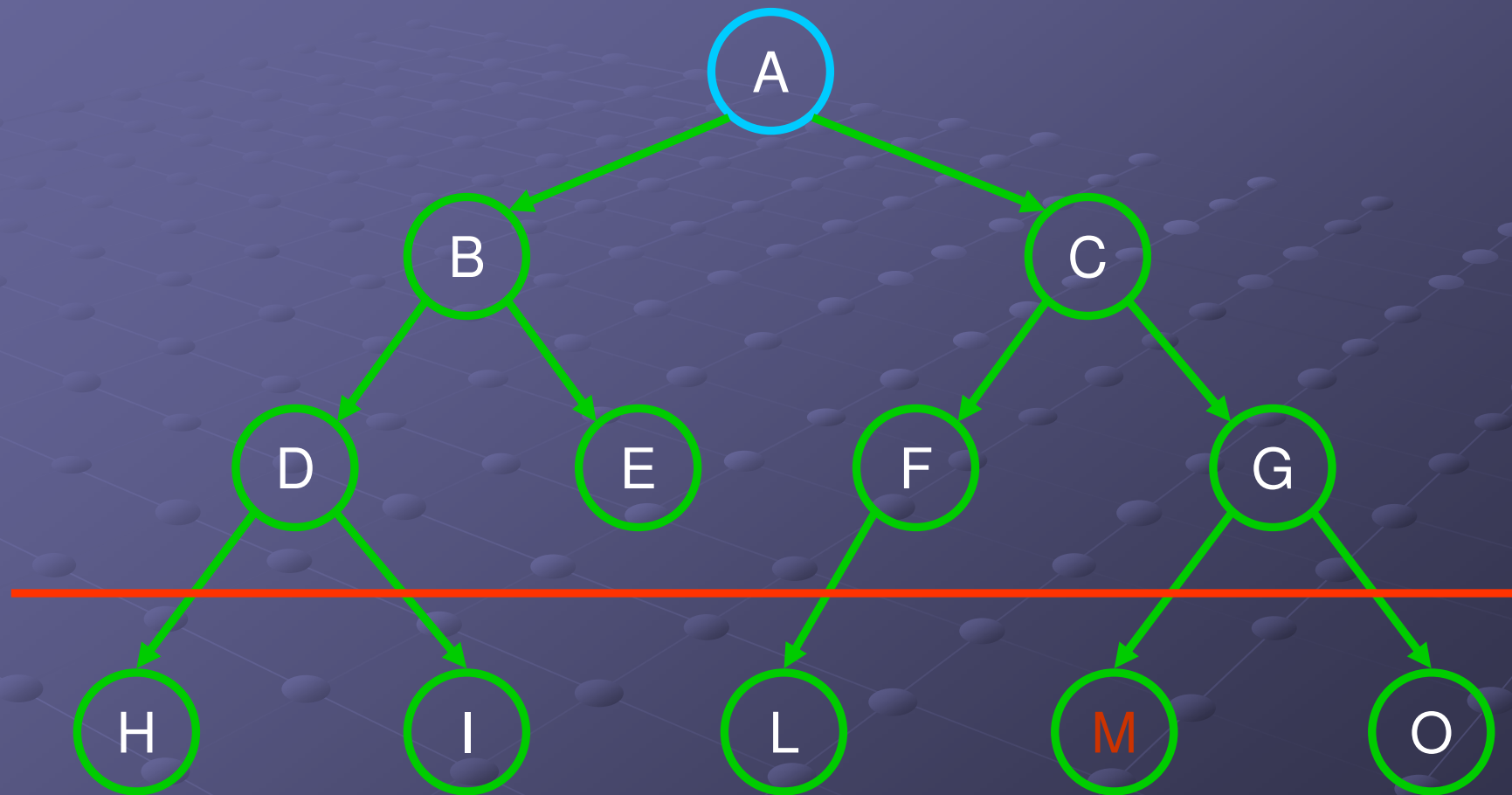
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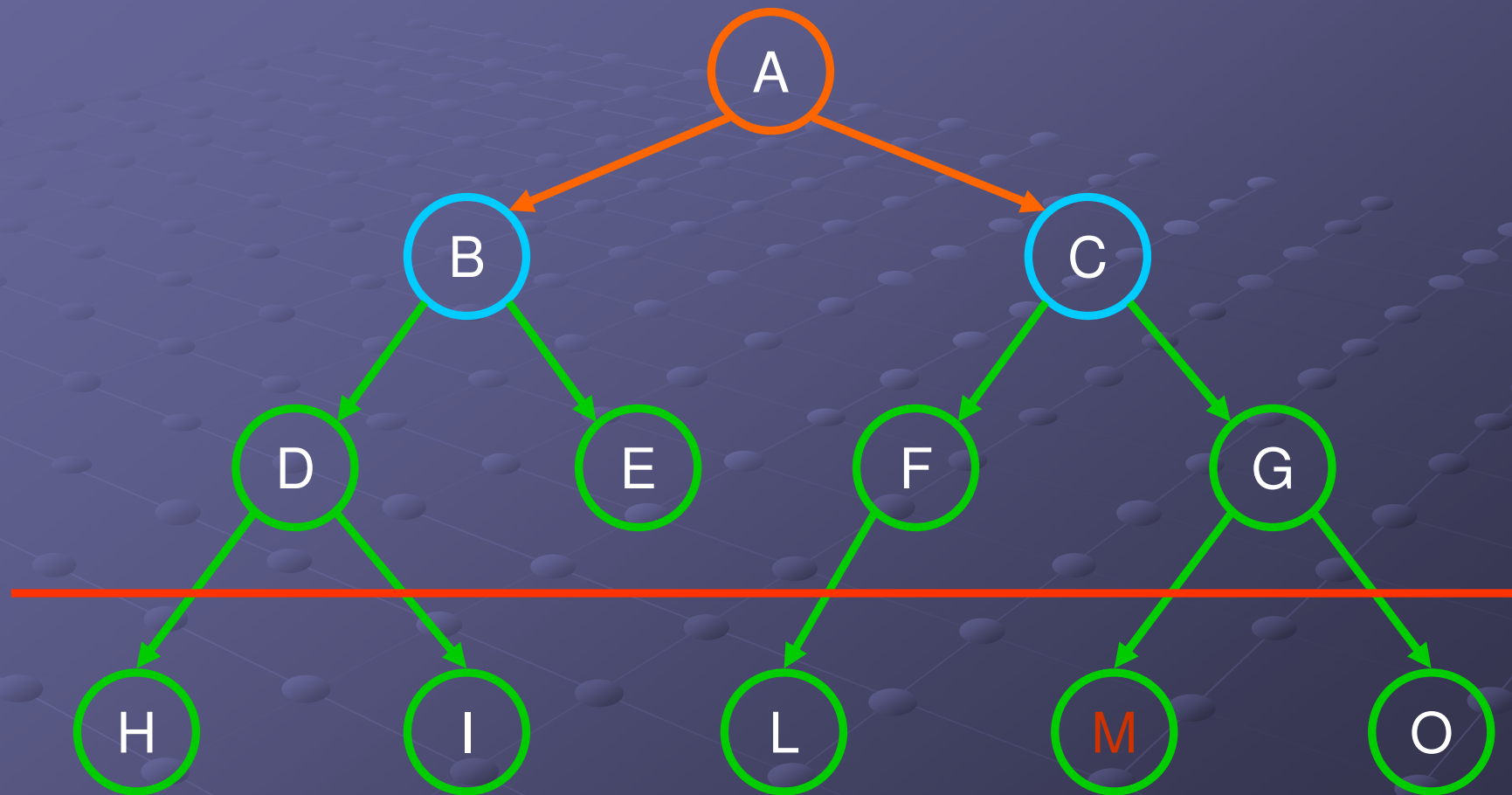
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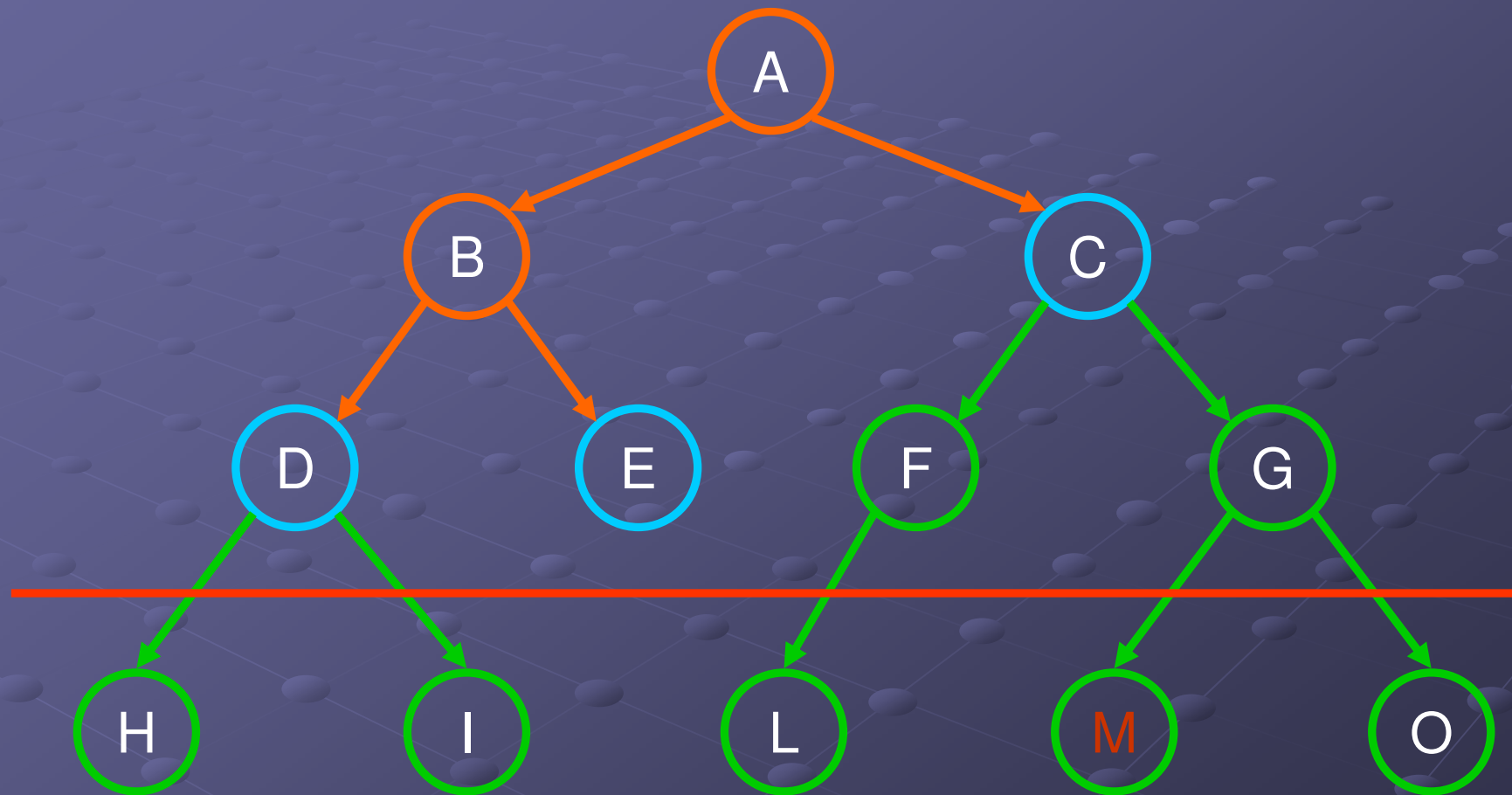
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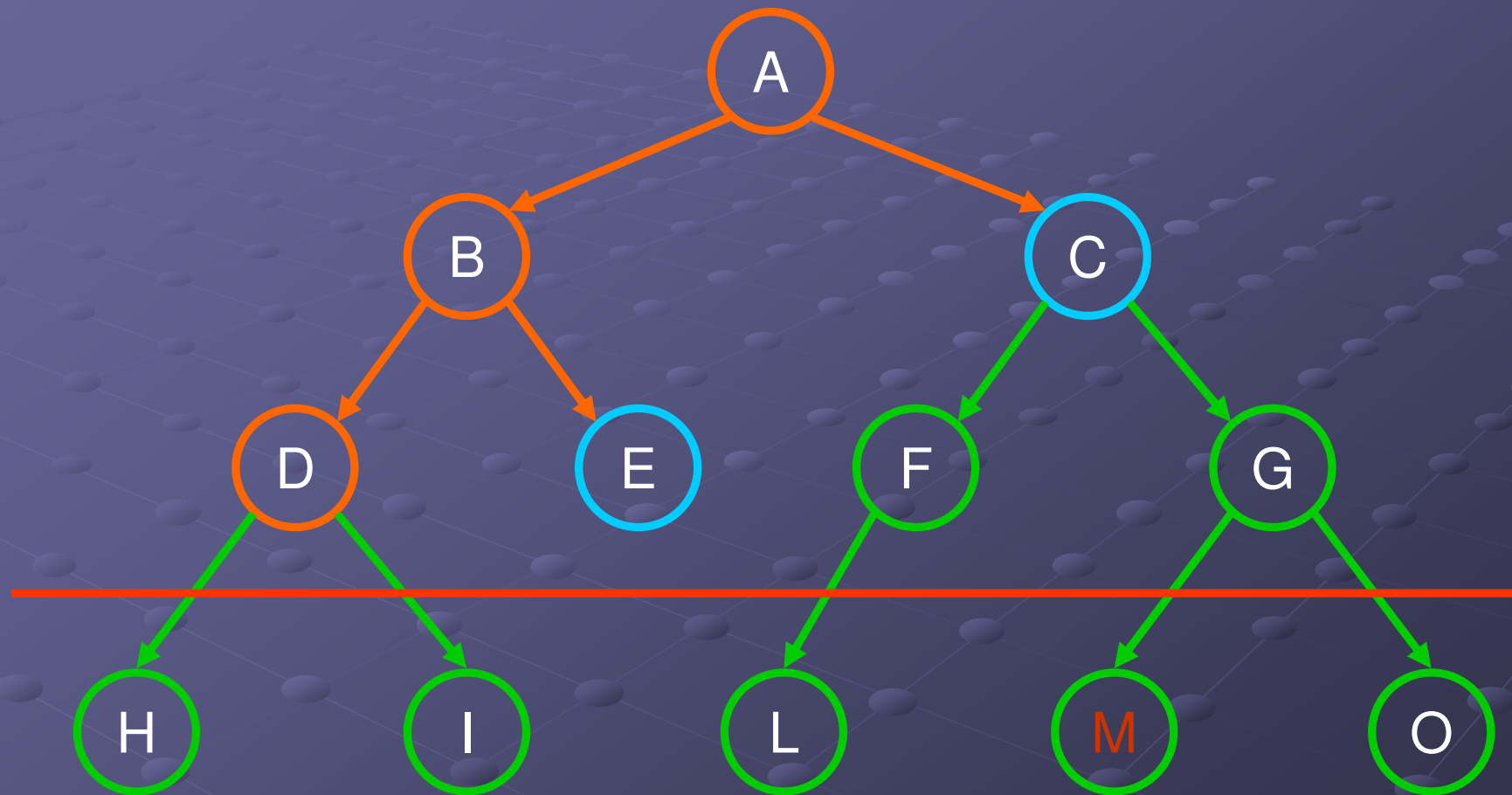
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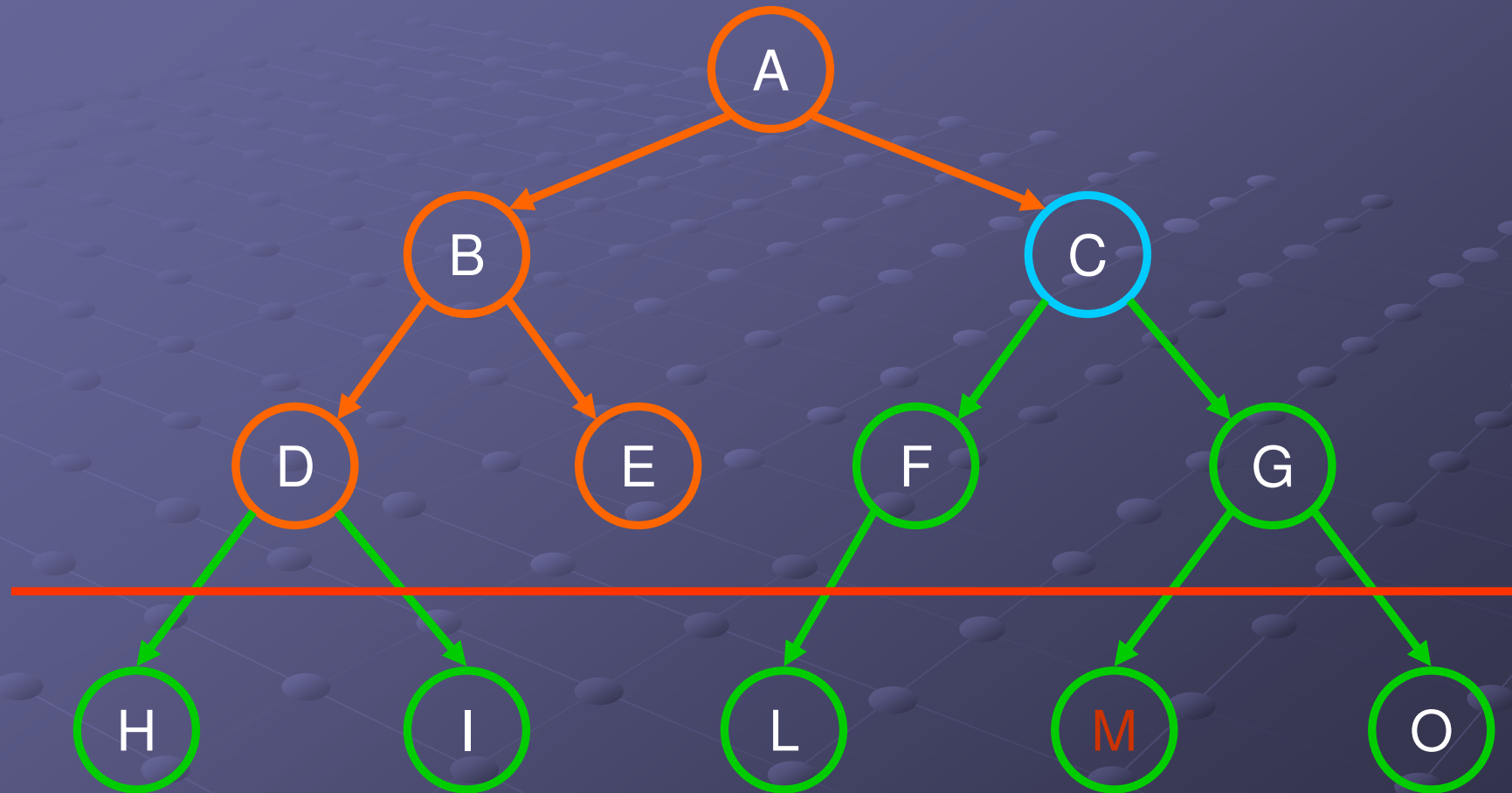
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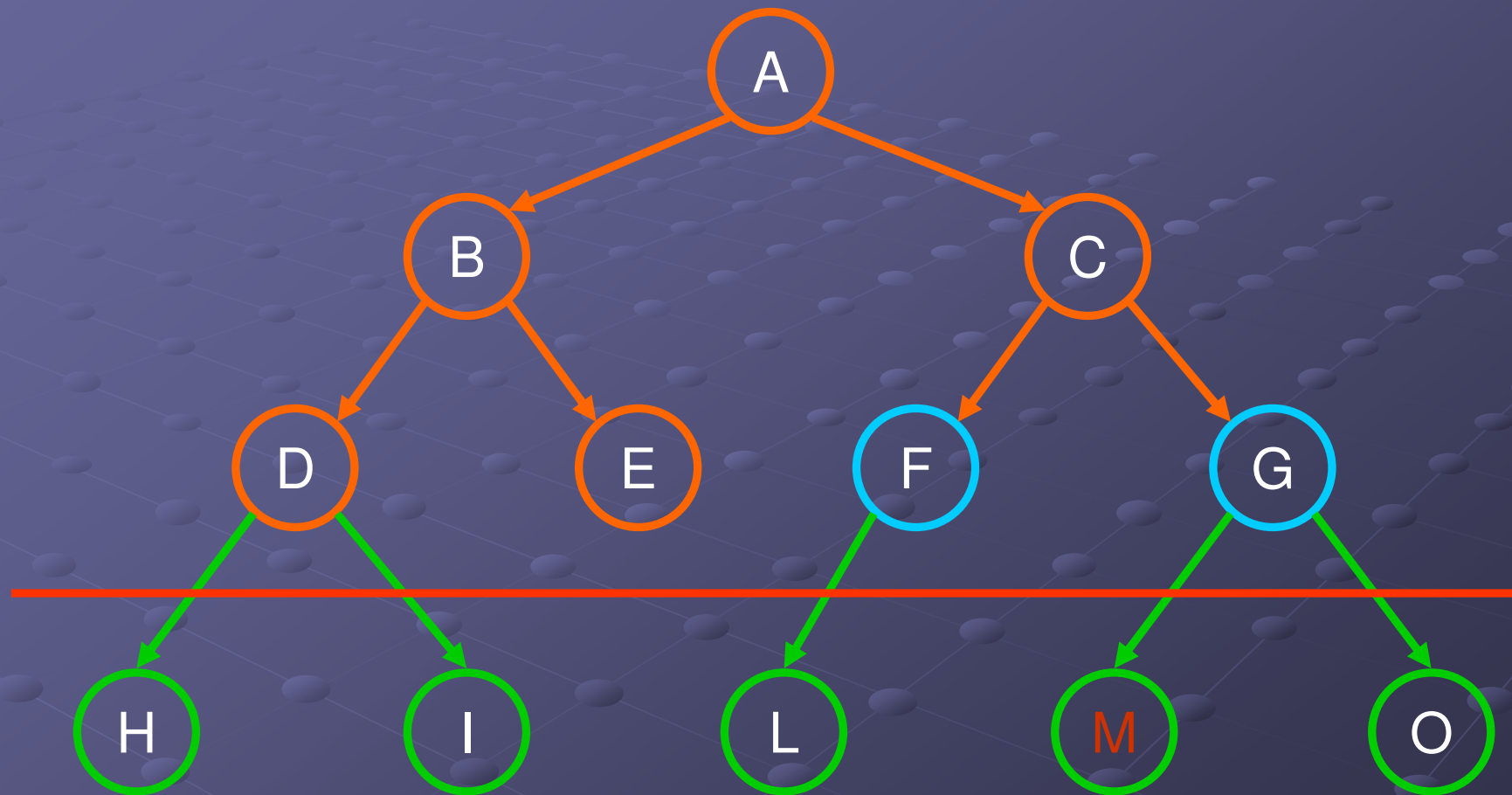
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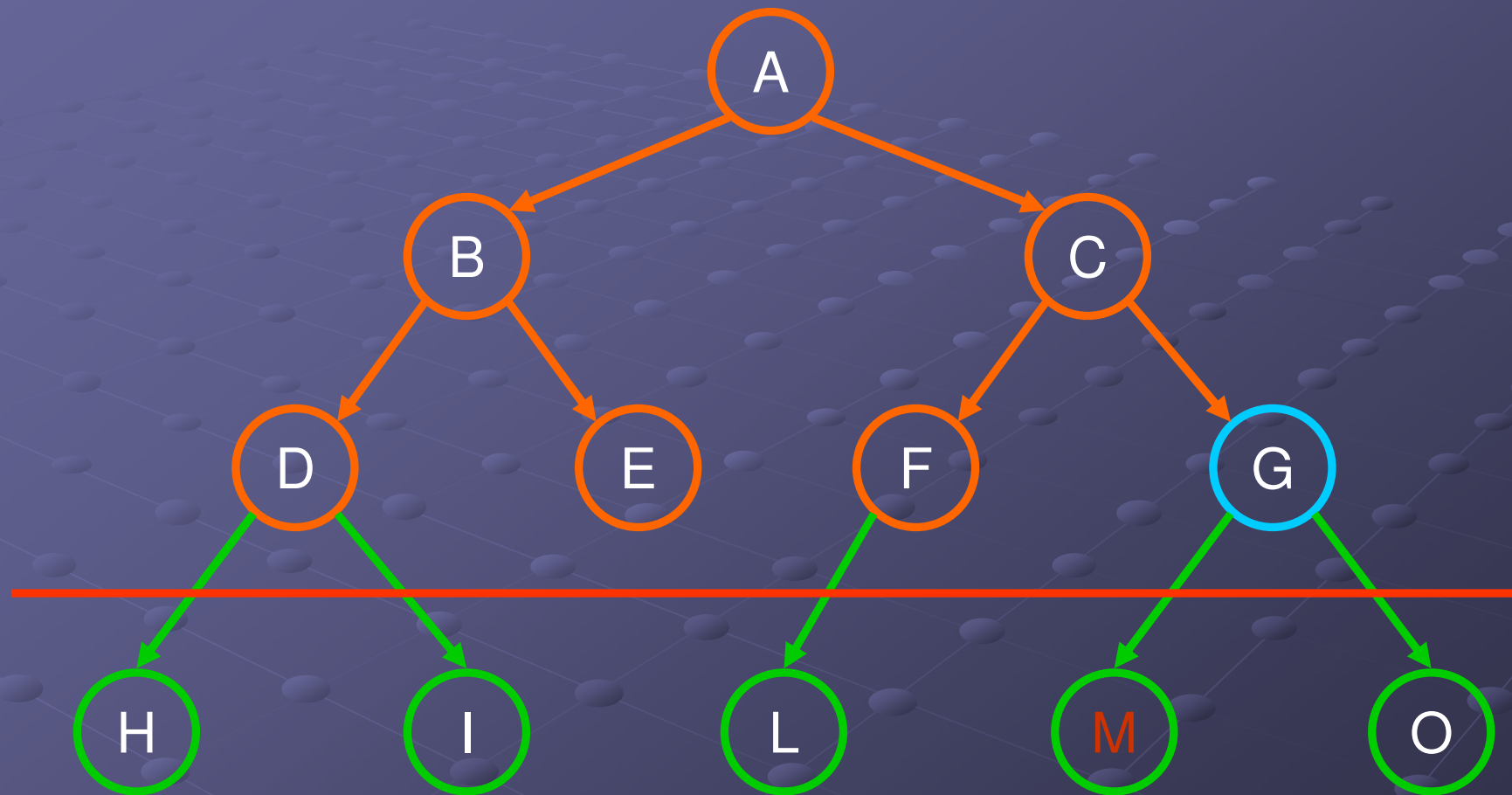
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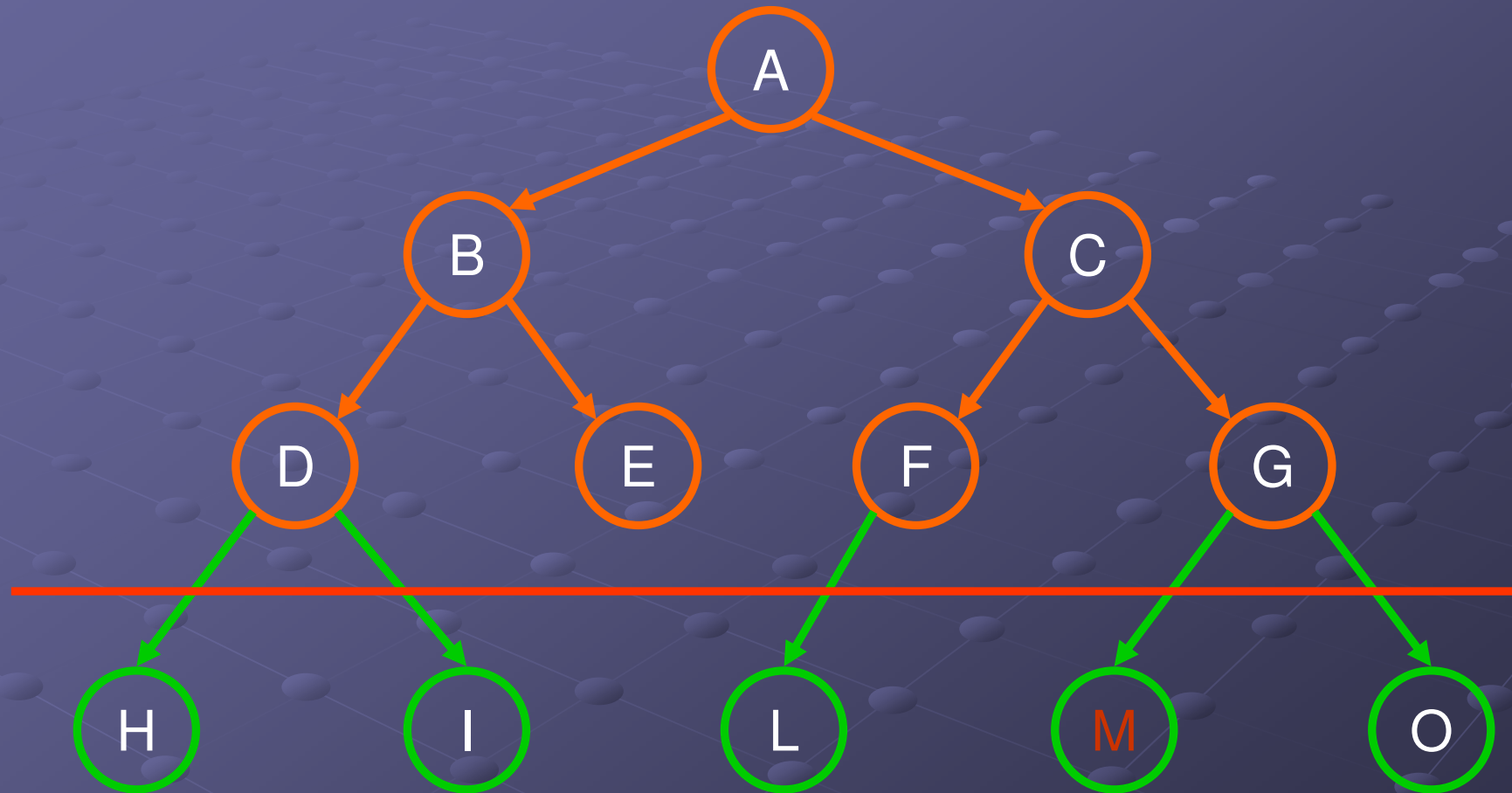
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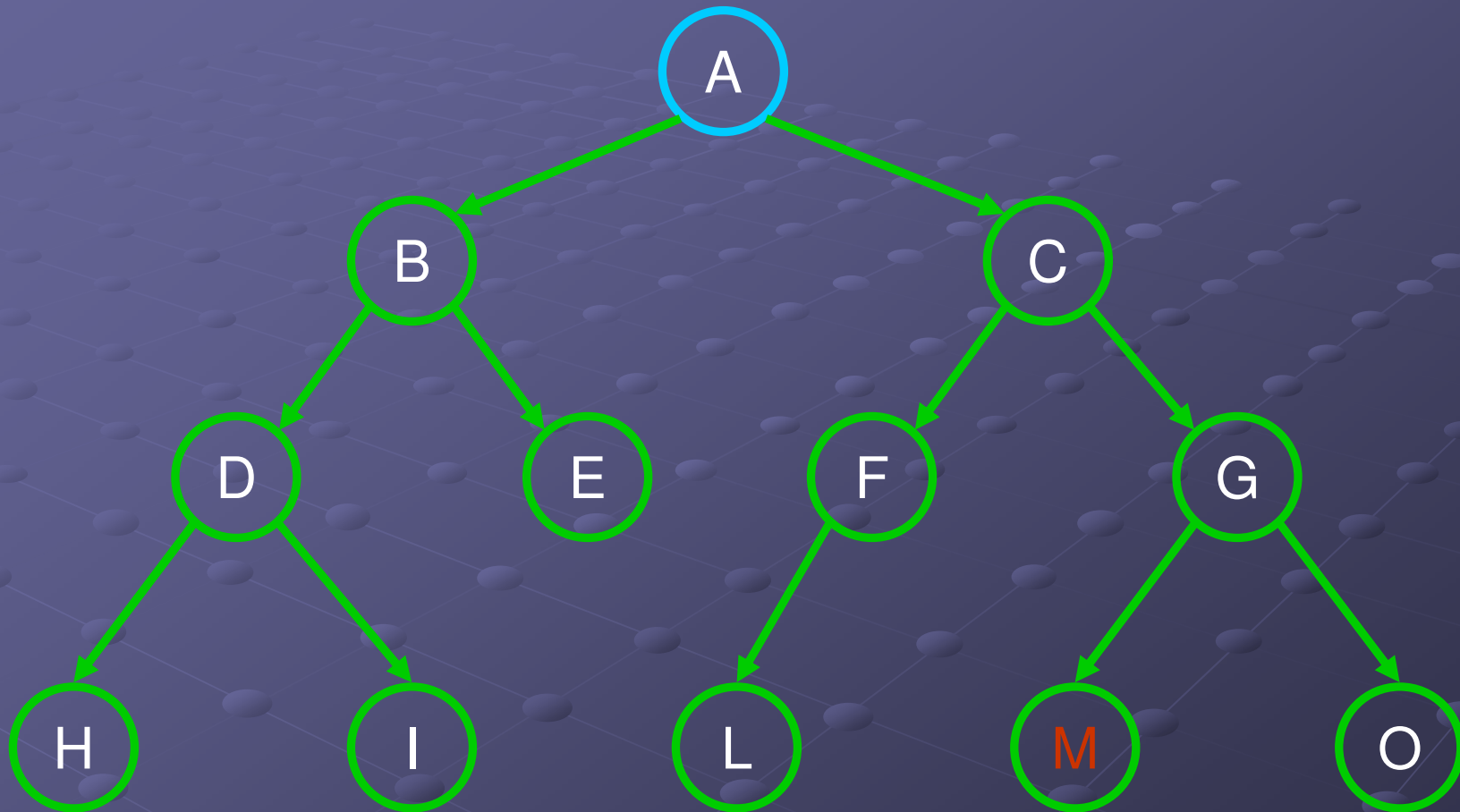
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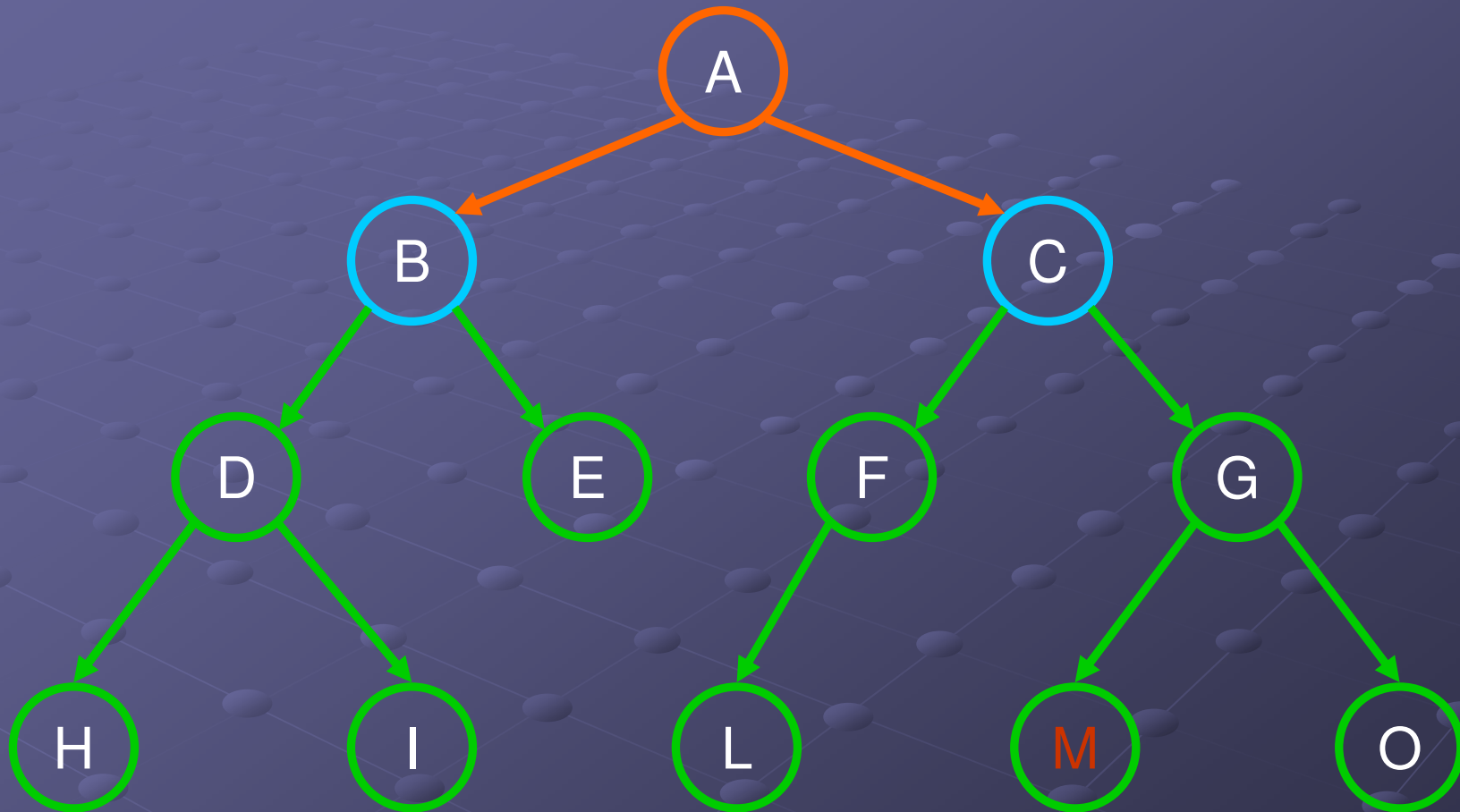
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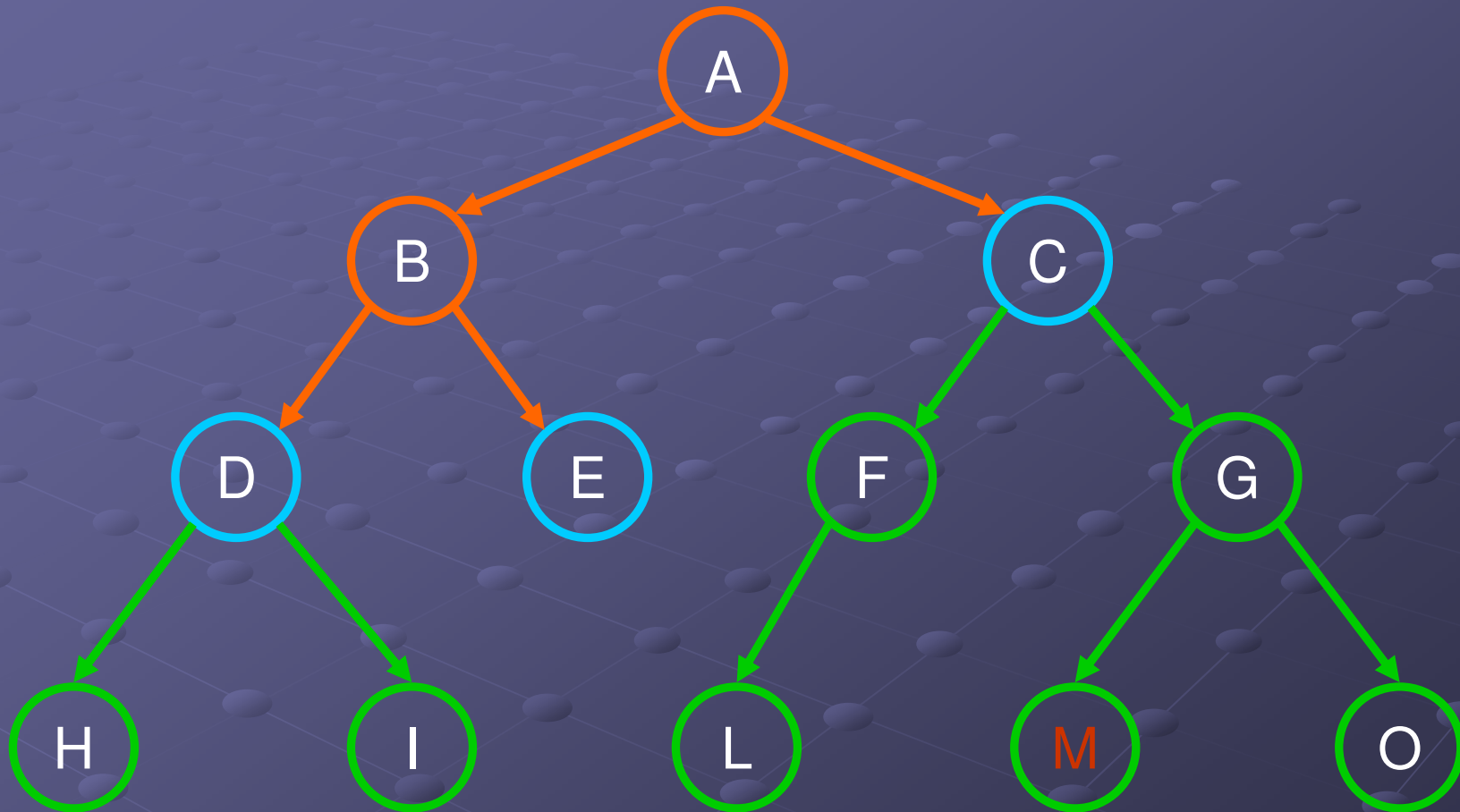
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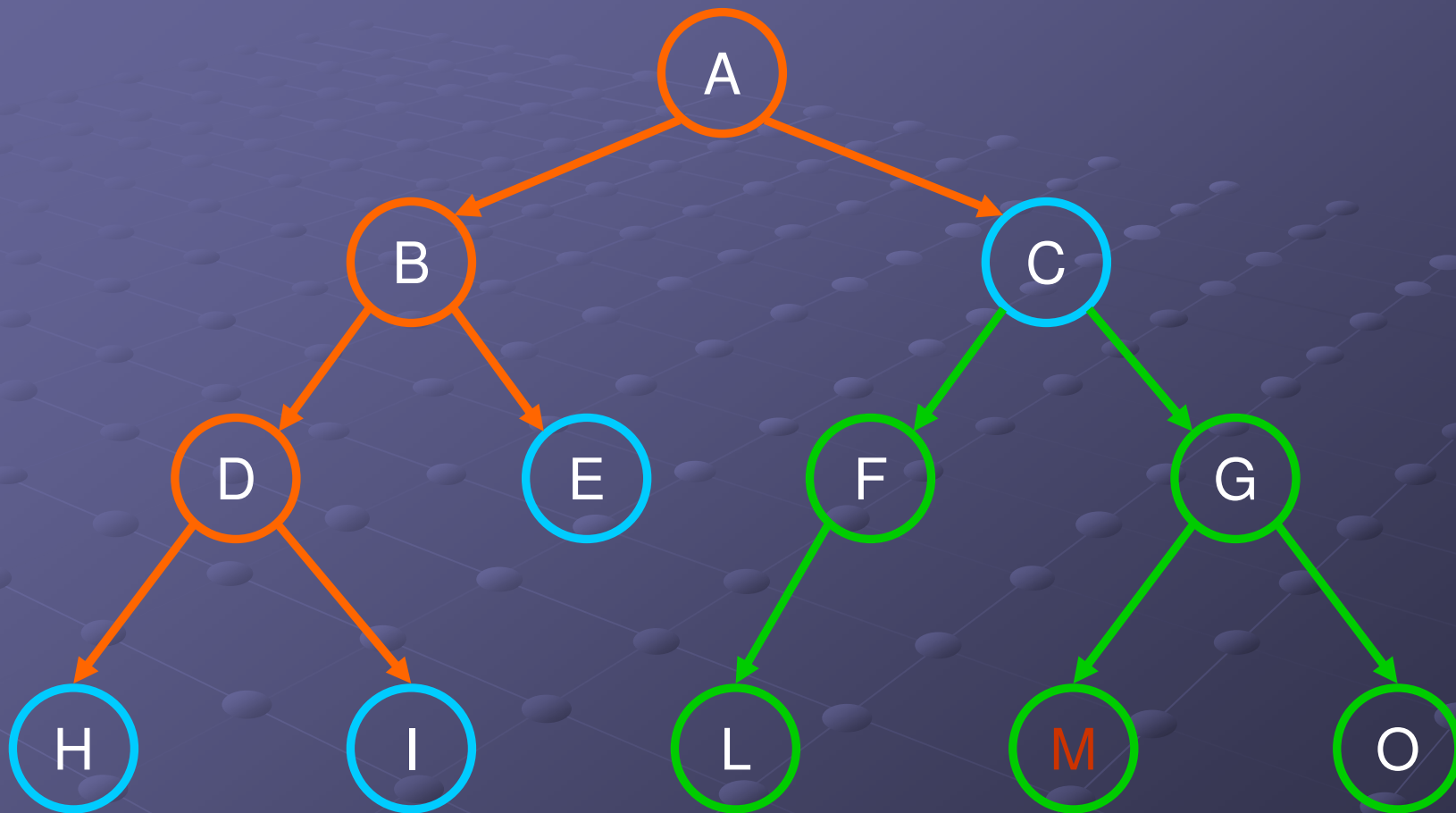
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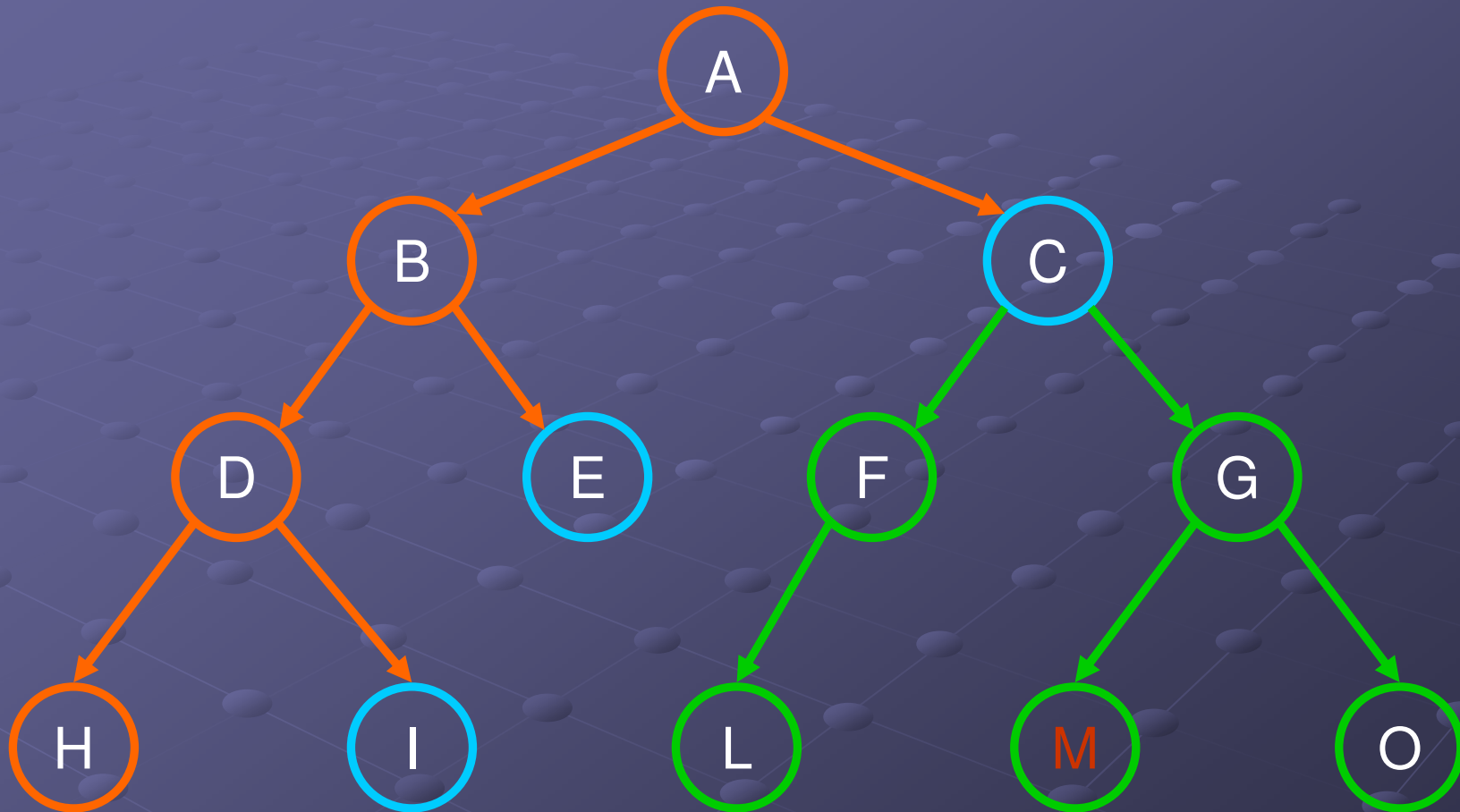
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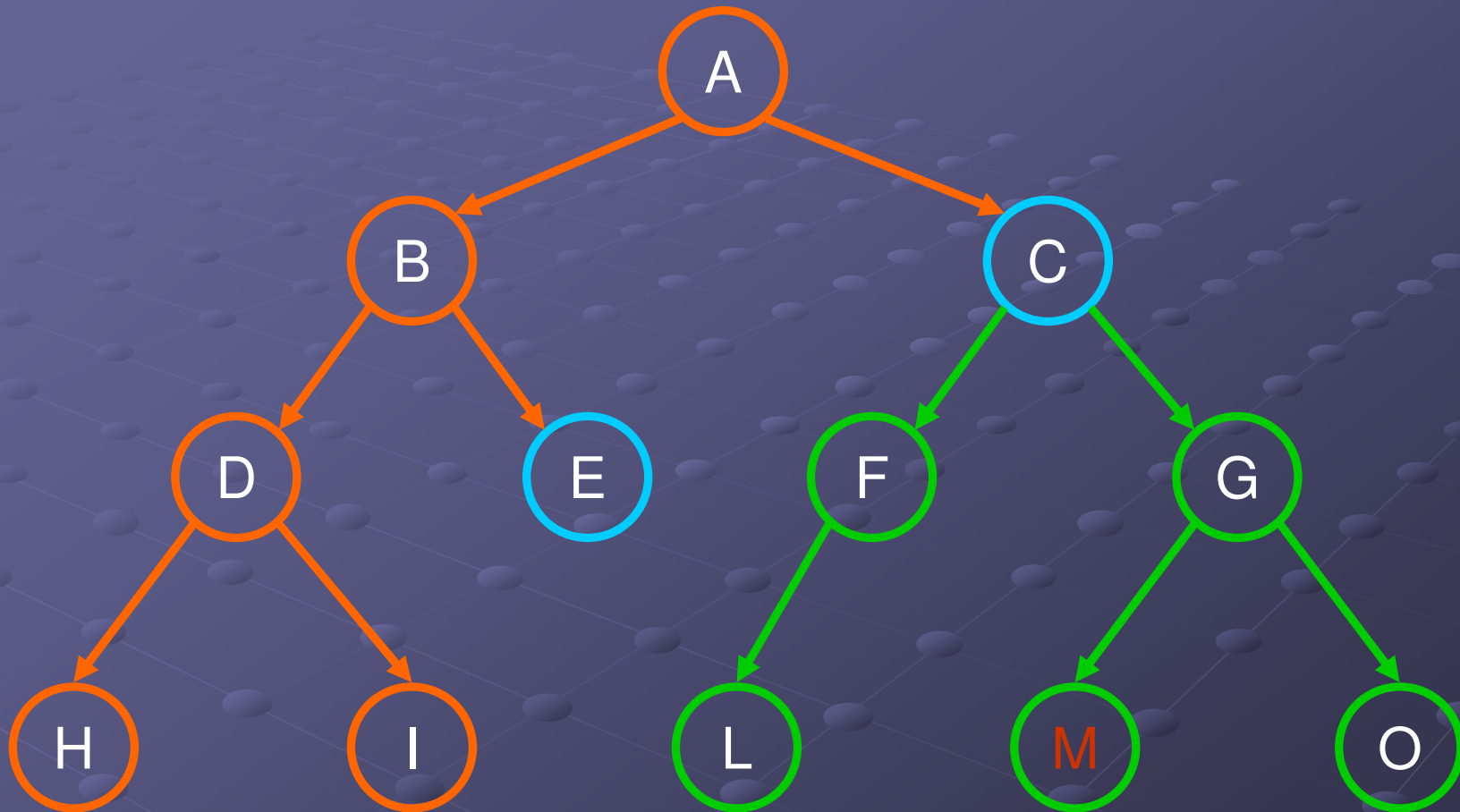
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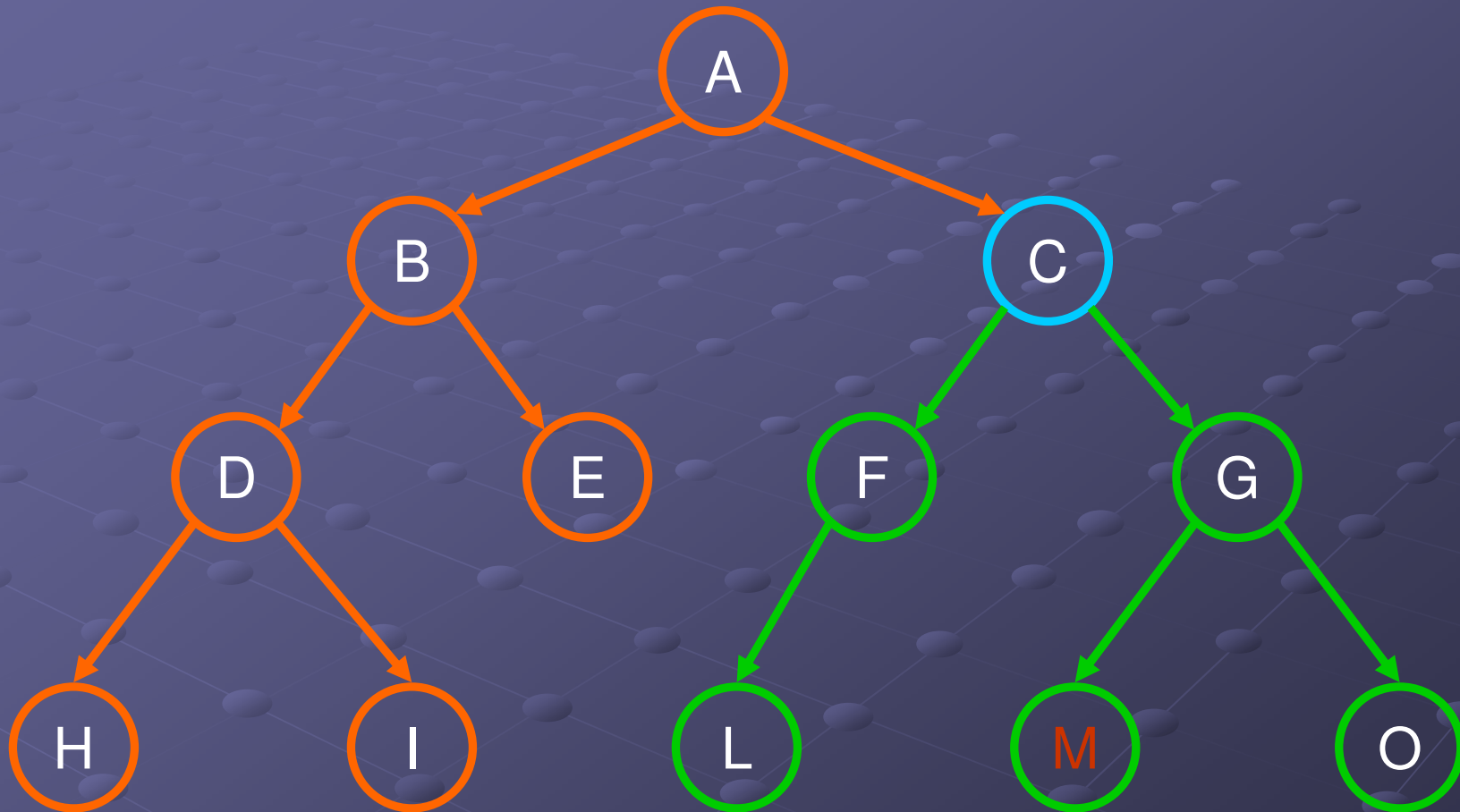
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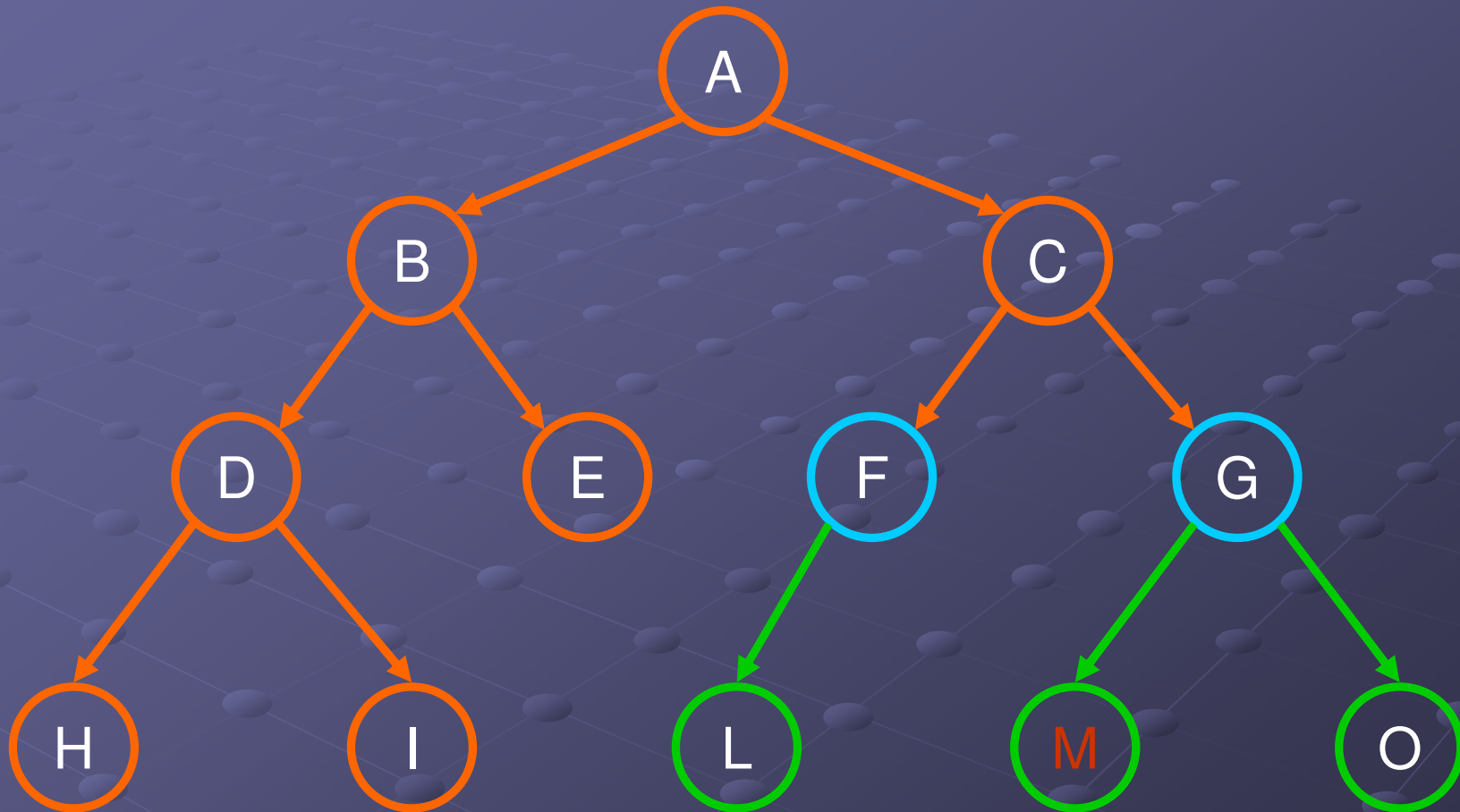
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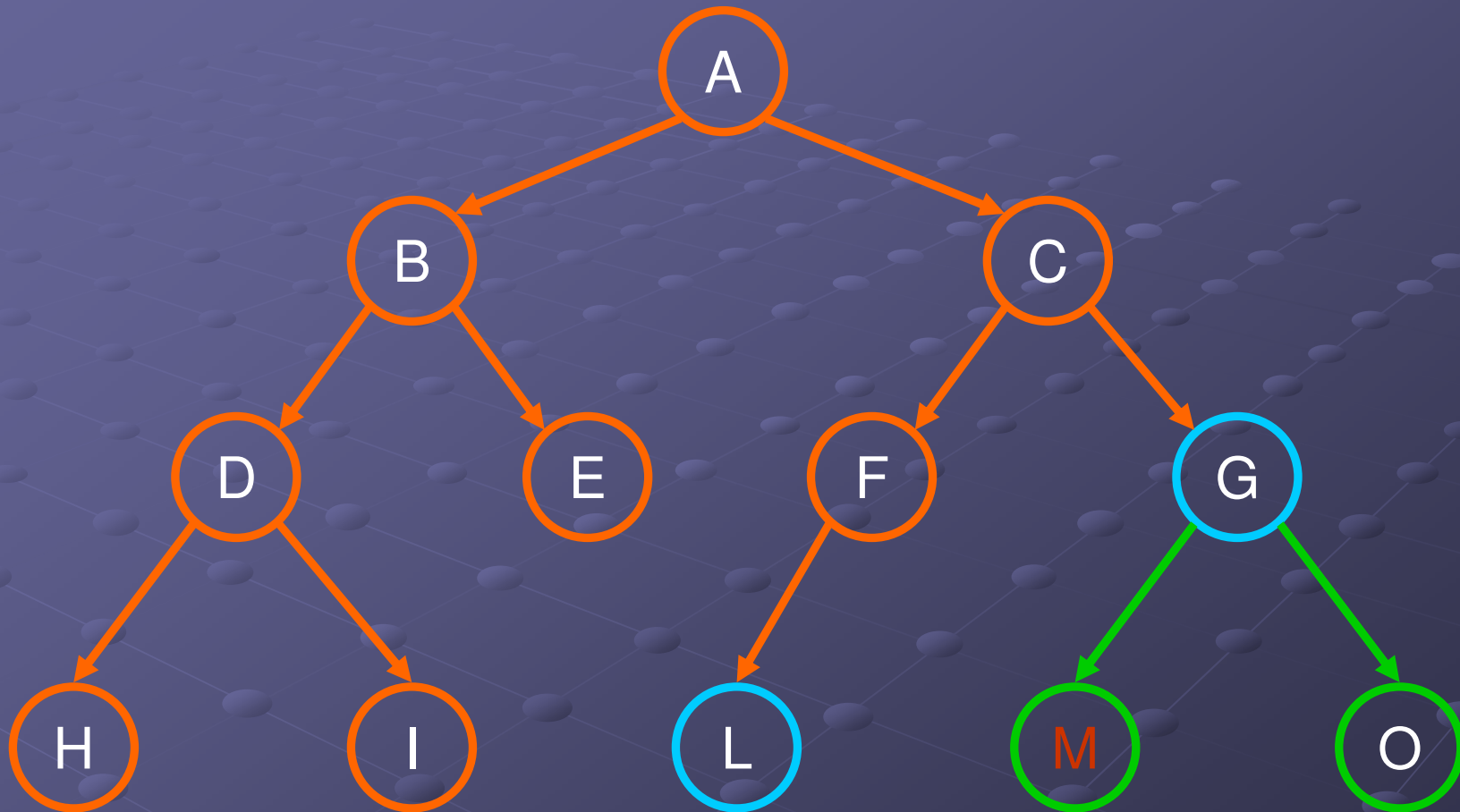
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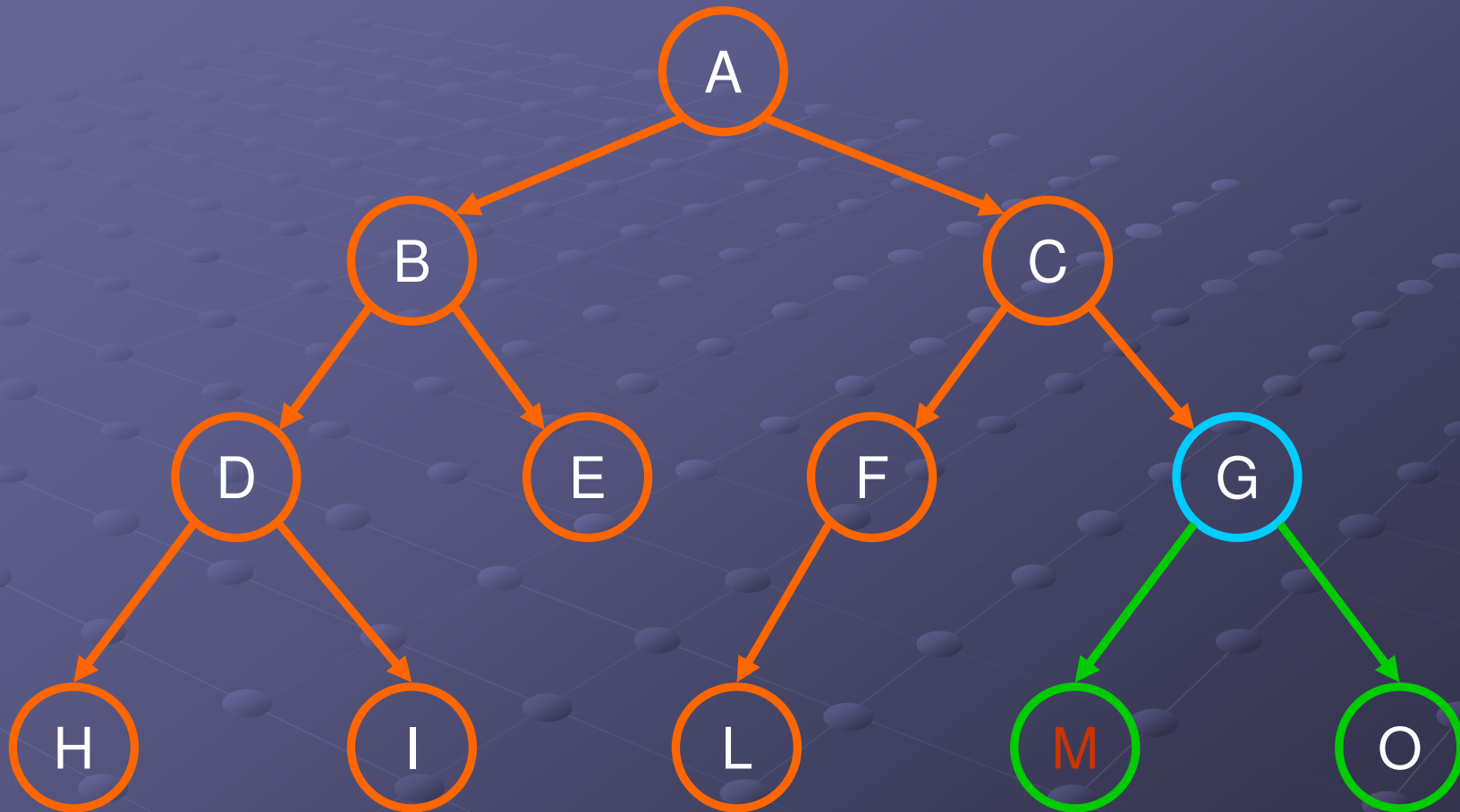
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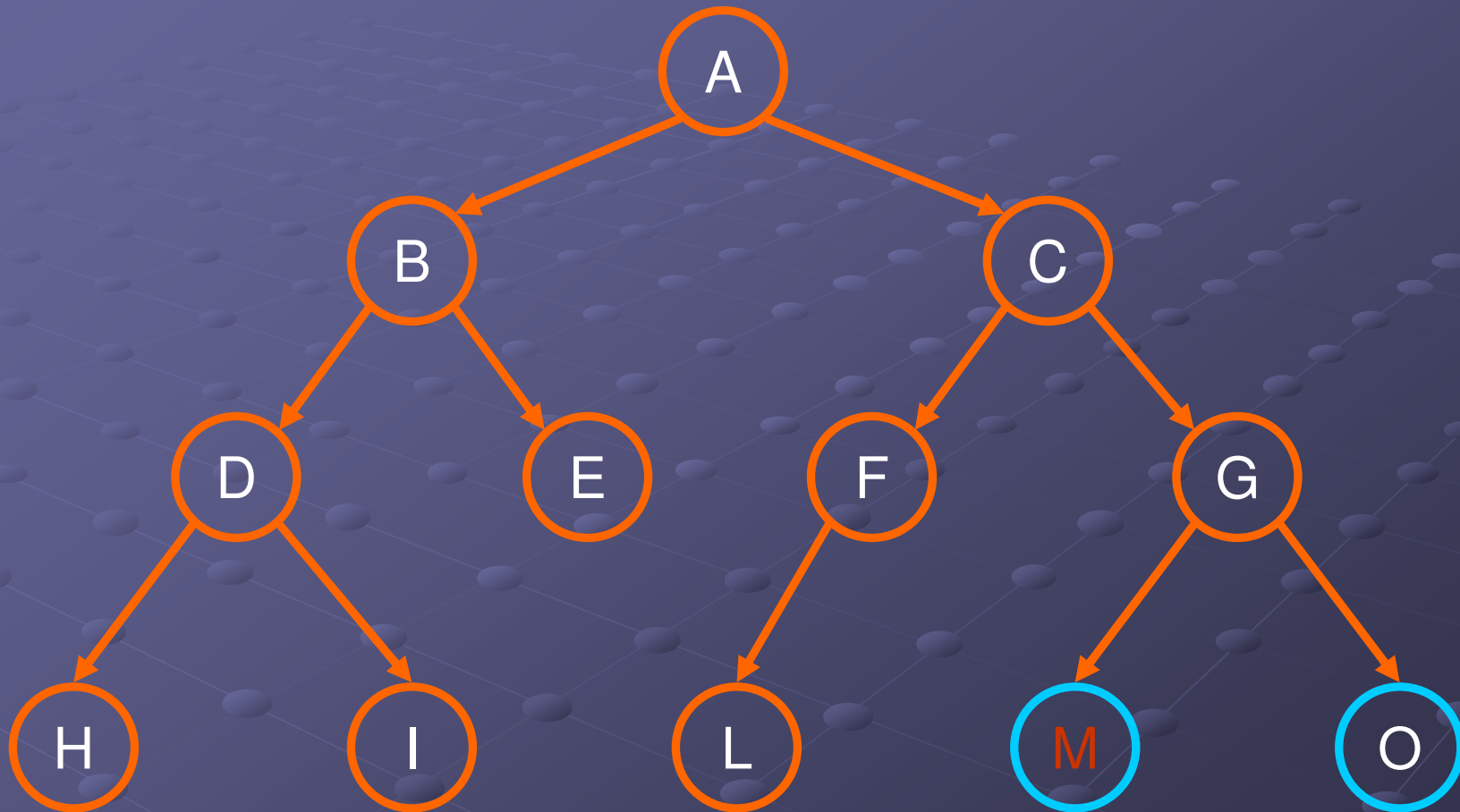
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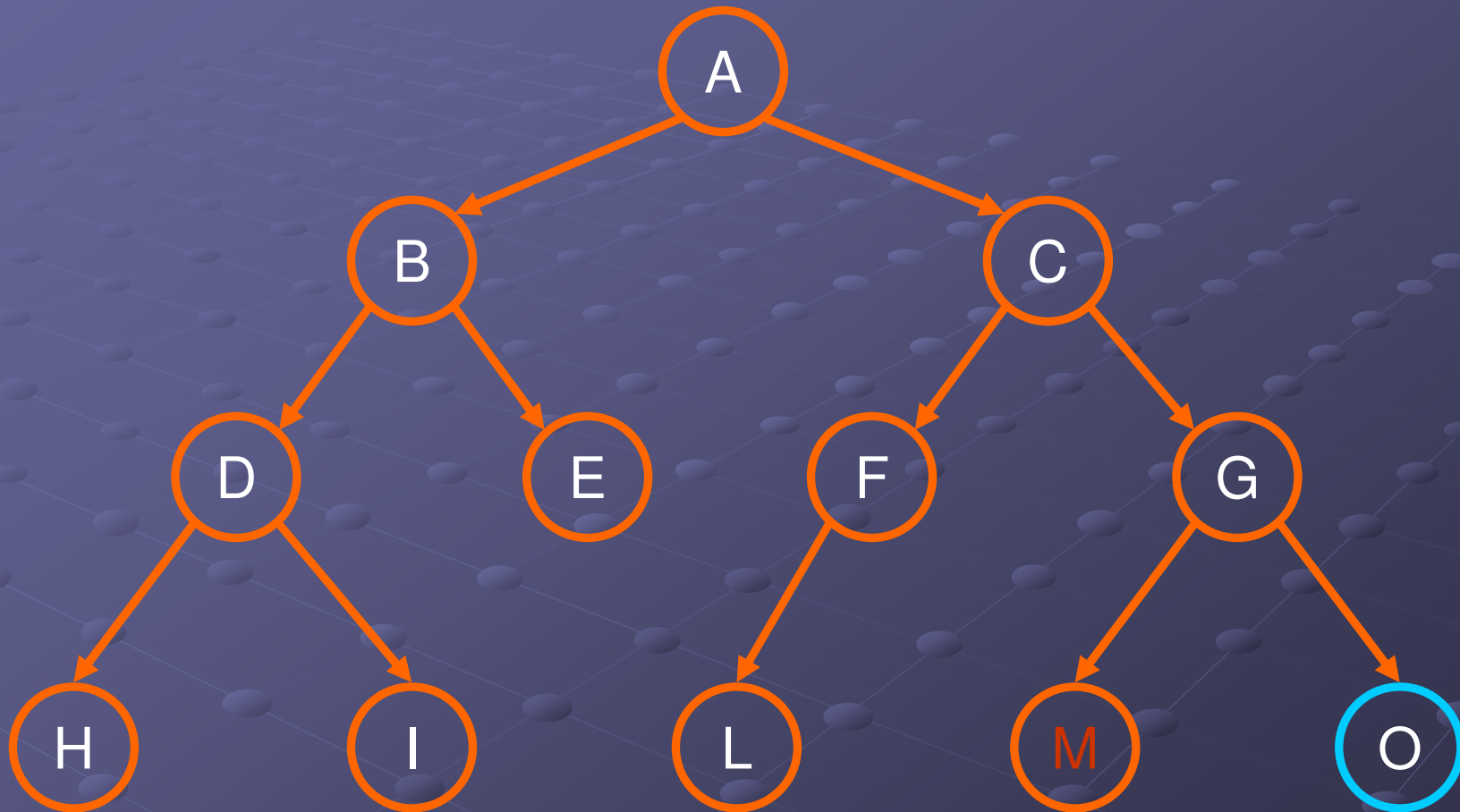
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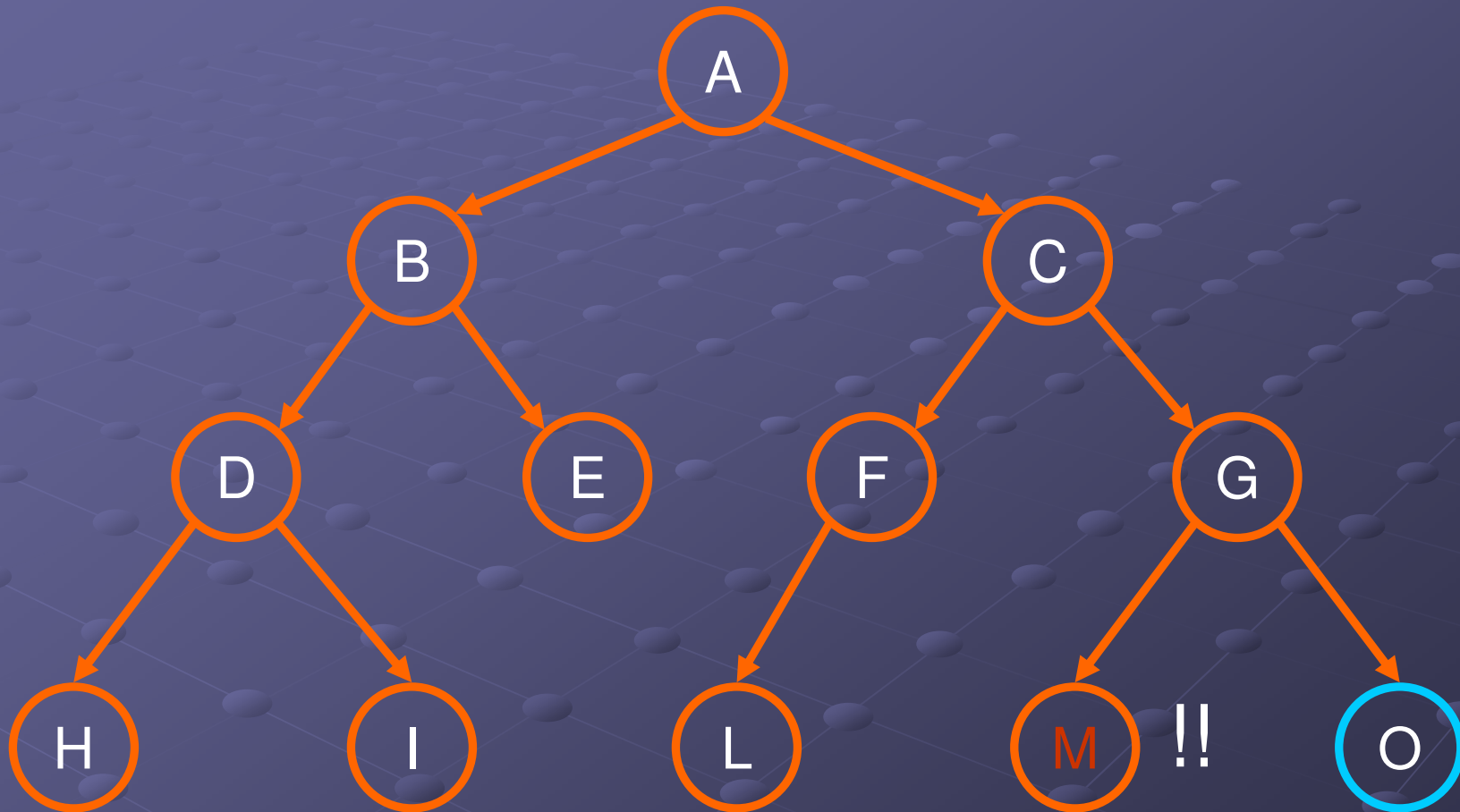
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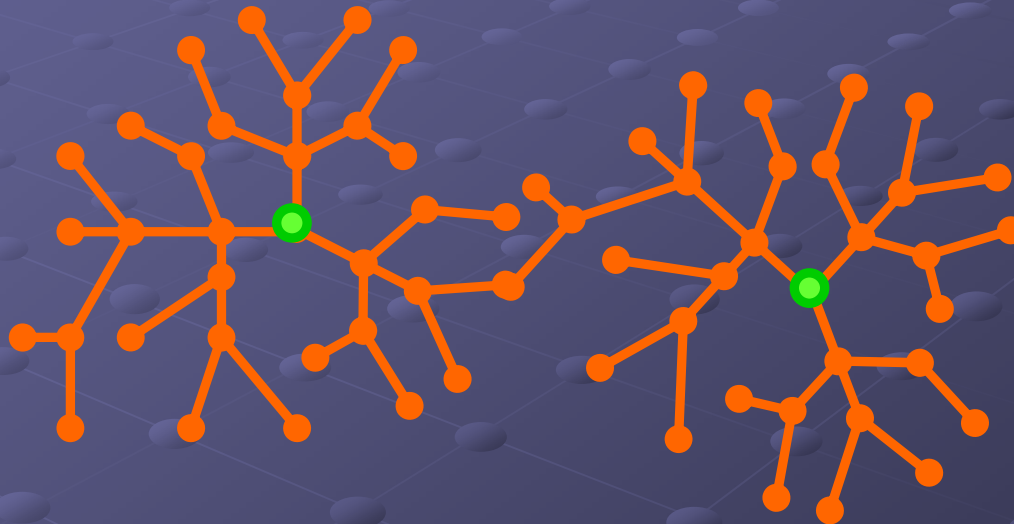


Uniform cost search

- Expand in order of cost
- Identical to Breadth-First Search if all step costs are equal
- Number of nodes expanded depends on $\epsilon > 0$ – the smallest cost action cost.
- (If $\epsilon = 0$, uniform-Cost search may infinite-loop)

Bi-directional Search

- Extend BFS from Start and Goal states simultaneously



$$b^{d/2} + b^{d/2} \ll b^d$$

Bi-directional Search

Restrictions:

- Can only use if 1 (or a few) *known* goal nodes
- Can only use if actions are reversible
i.e. if we can efficiently calculate $\text{Pred}(s)$ (for state s)
where

$$\text{Pred}(s) = \{r : \exists a \ r \xrightarrow{a} s\}$$

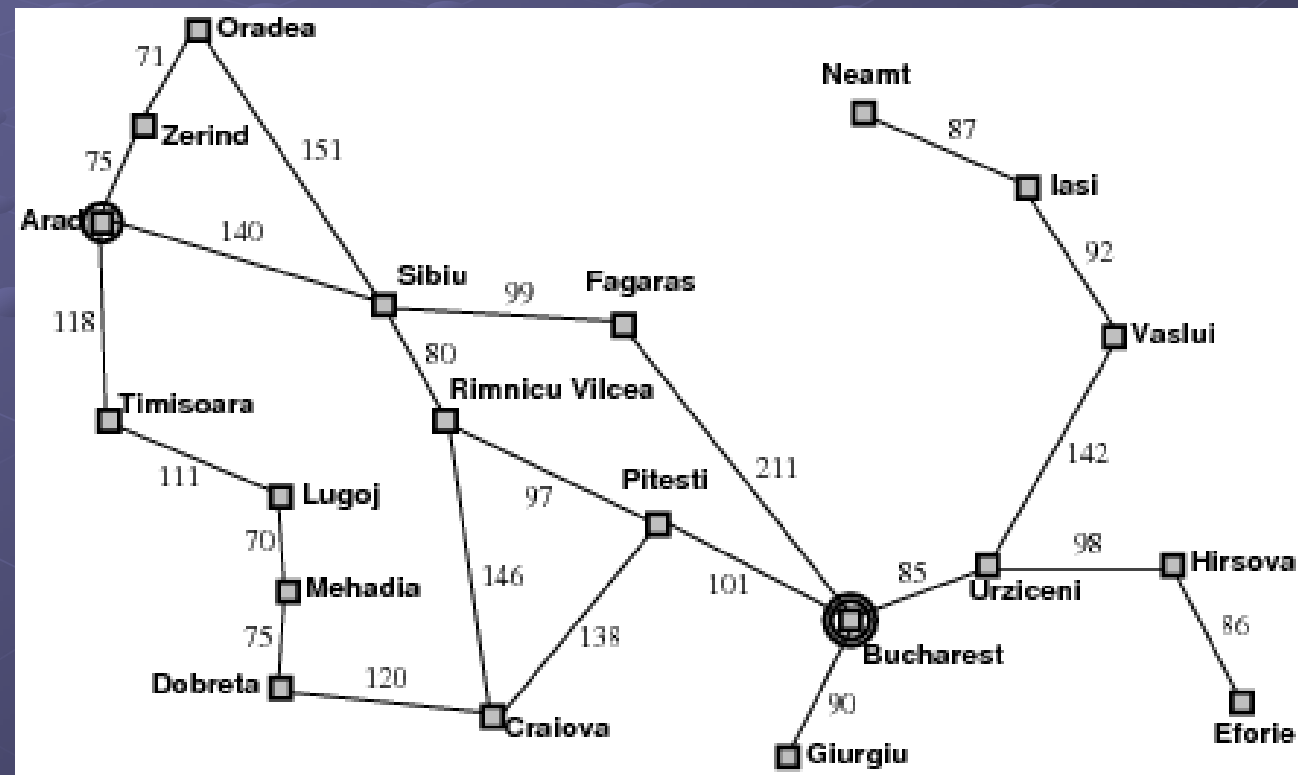
Summary

Criterion	BFS	DFS	IDDFS	Uniform Cost	Bi-directional
Complete	Yes	No	Yes	Yes	Yes
Time	$O(b^{d+1})$	$O(b^m)$	$O(b^d)$	$O(b^{C^*/\epsilon})$	$O(b^{d/2})$
Space	$O(b^{d+1})$	$O(bm)$	$O(bd)$	$O(b^{C^*/\epsilon})$	$O(b^{d/2})$
Optimal	Yes, for unit cost	No	Yes, for unit cost	Yes	Yes, for unit cost

b = branching factor ; m = max depth of tree ; d = depth of goal node
 C^* = cost of goal ; ϵ = min action cost

Repeated State Detection

- Test for previously-seen states
- Essentially, search graph mimics state graph



Repeated State Detection

- ✓ Can make exponential improvement in time
- ✓ Can make DFS complete
- ✗ DFS now has potentially exponential space requirement
- ✗ Have to be careful to guarantee optimality

In practice, almost always use repeated state detection

A* Search

Idea: avoid expanding paths that are already expensive

Evaluation function $f(n) = g(n) + h(n)$

$g(n)$ = cost so far to reach n

$h(n)$ = estimated cost from n to the closest goal

$f(n)$ = estimated total cost of path through n to goal

A* search uses an *admissible* heuristic

i.e., $h(n) \leq h^*(n)$ where $h^*(n)$ is the true cost from n .

(Also require $h(n) \geq 0$, so $h(G) = 0$ for any goal G .)

E.g., $h_{\text{SLD}}(n)$ never overestimates the actual road distance

When $h(n)$ is admissible, $f(n)$ never overestimates the total cost of the shortest path through n to the goal

Theorem: A* search is optimal

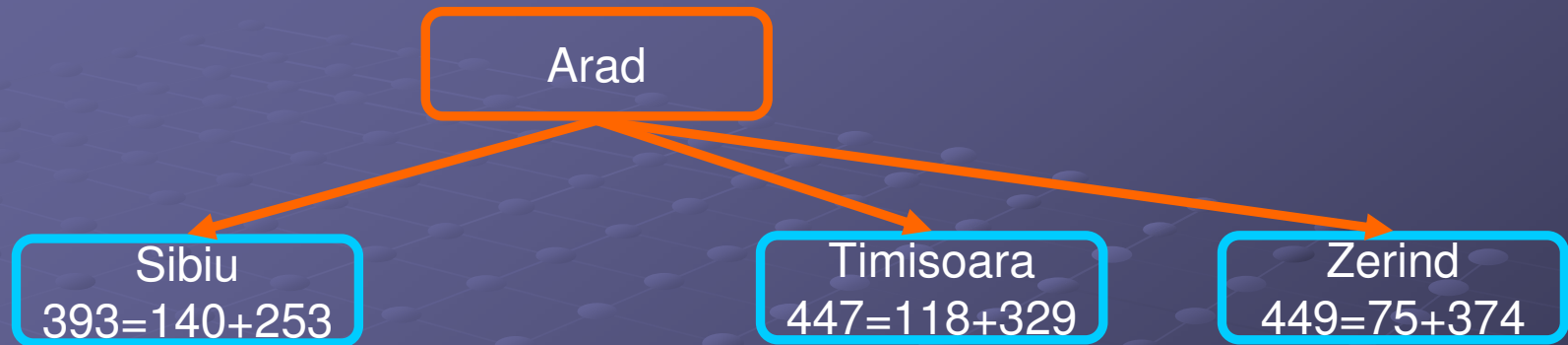
A* Example

Arad
 $366 = 0 + 366$

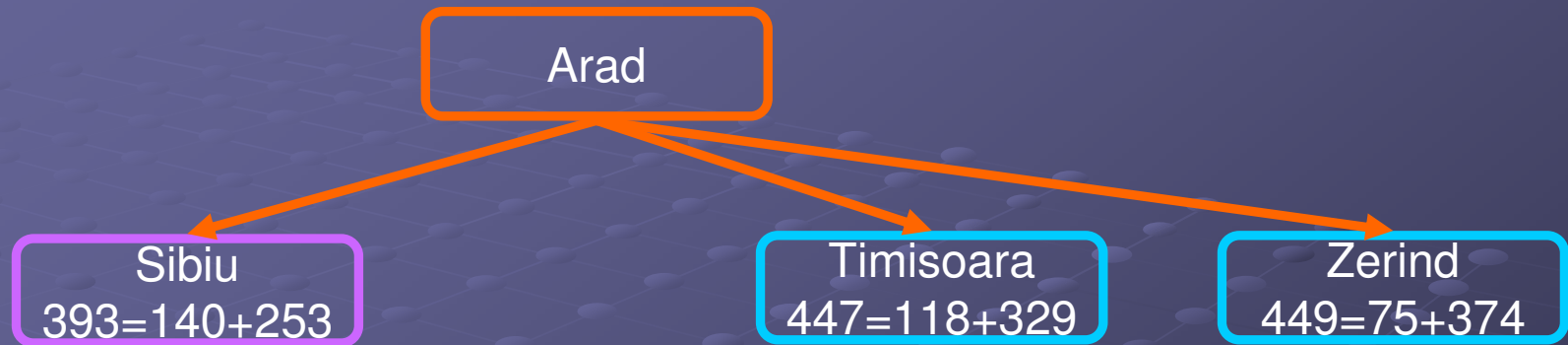
A* Example

Arad
 $366 = 0 + 366$

A* Example



A* Example



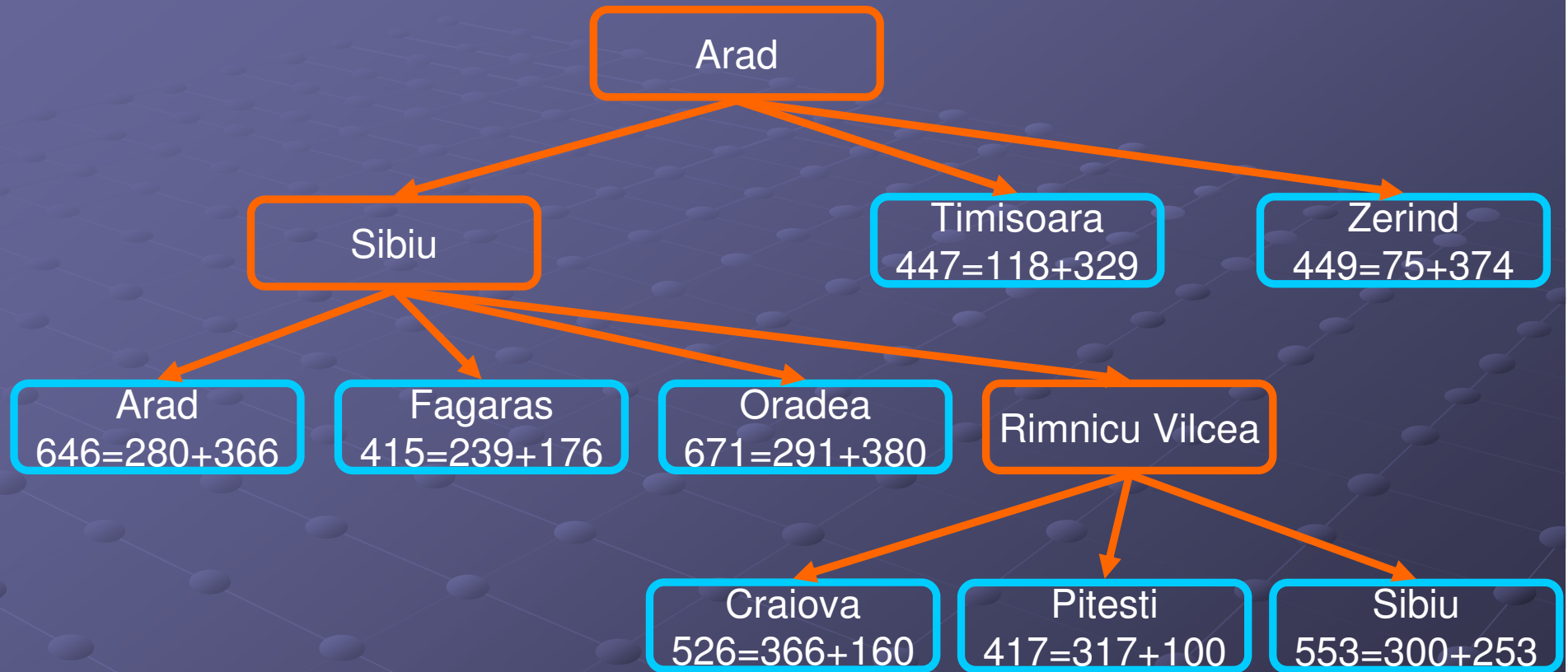
A* Example



A* Example



A* Example



A* Example



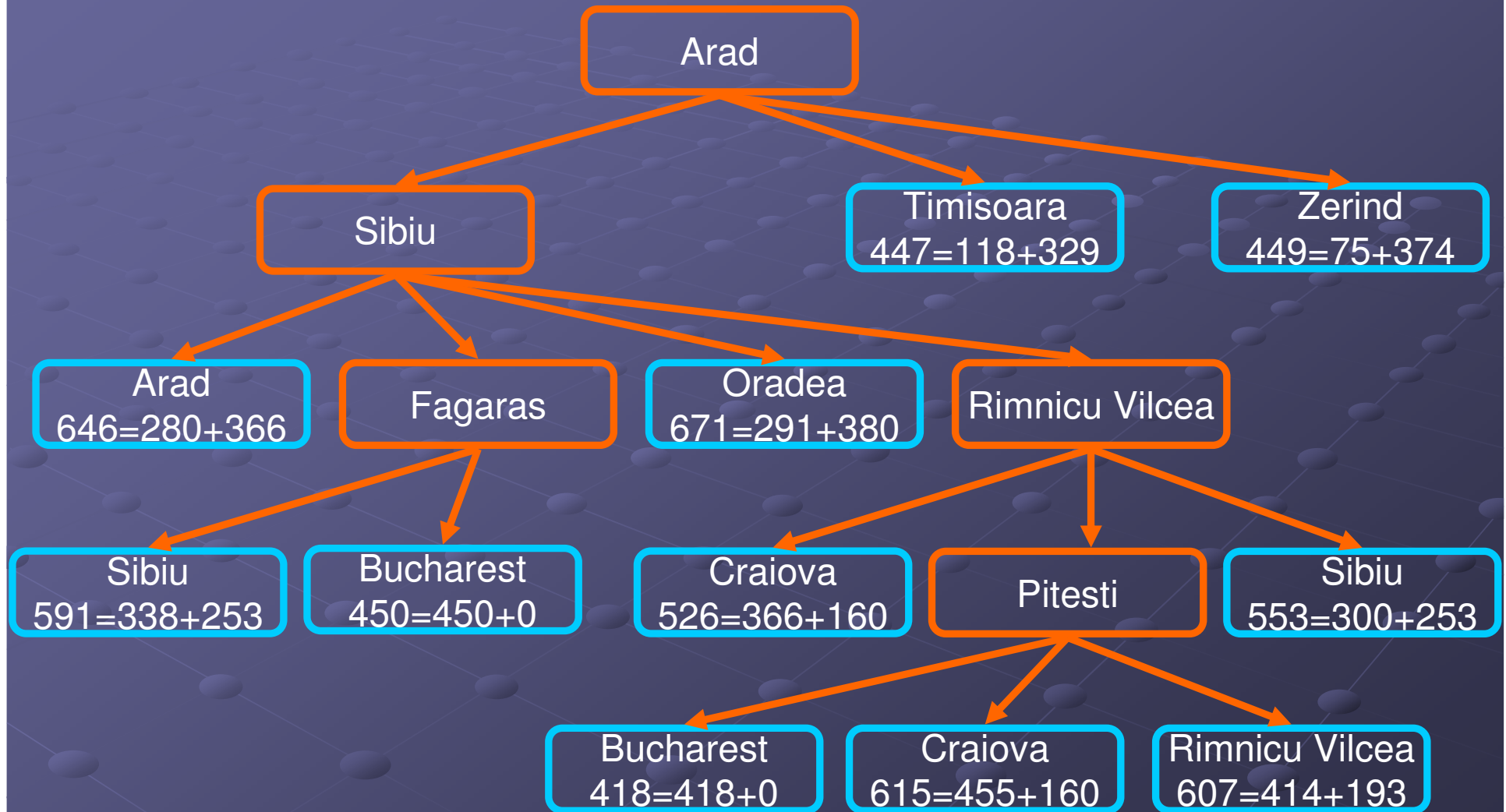
A* Example



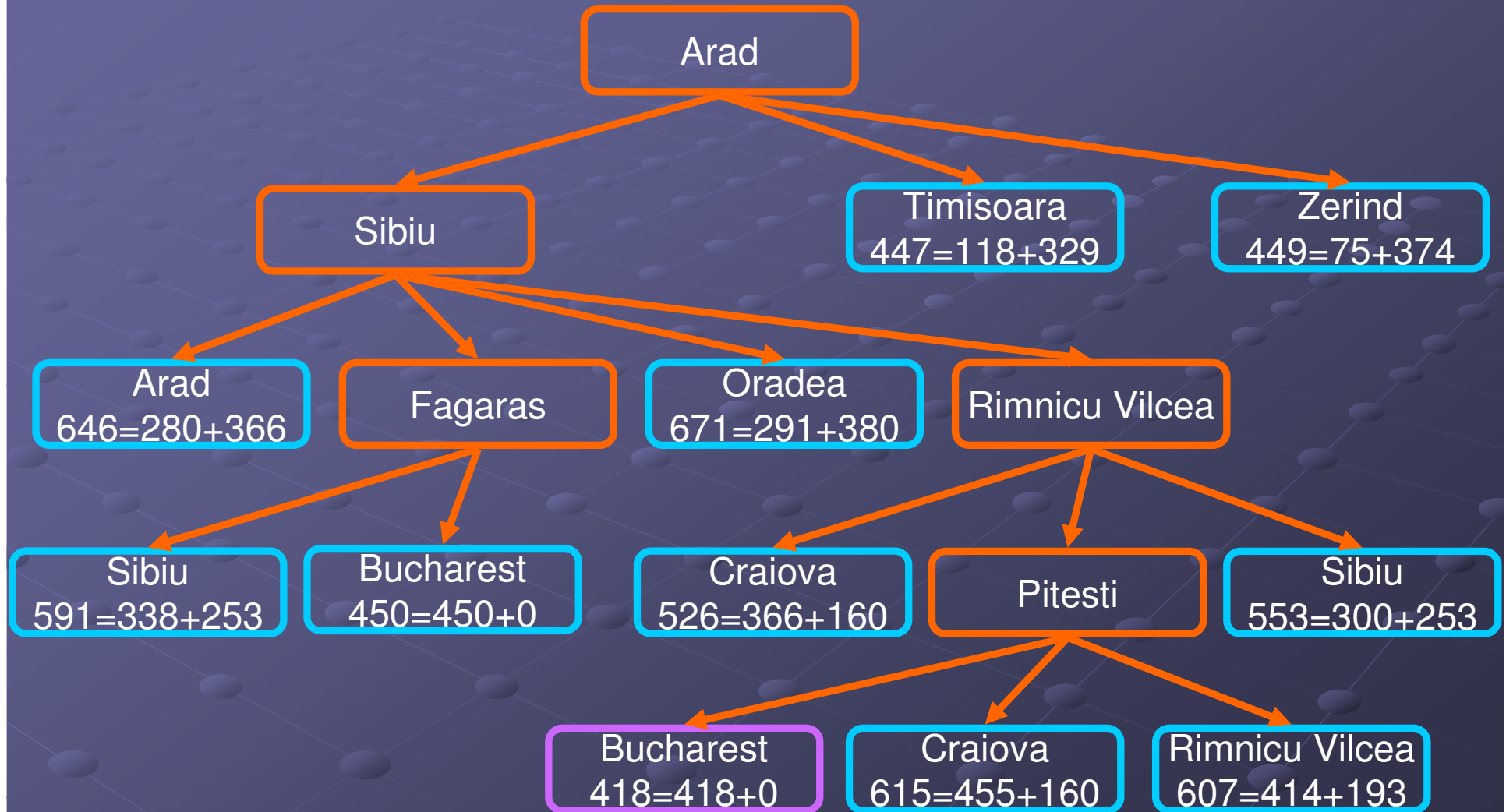
A* Example



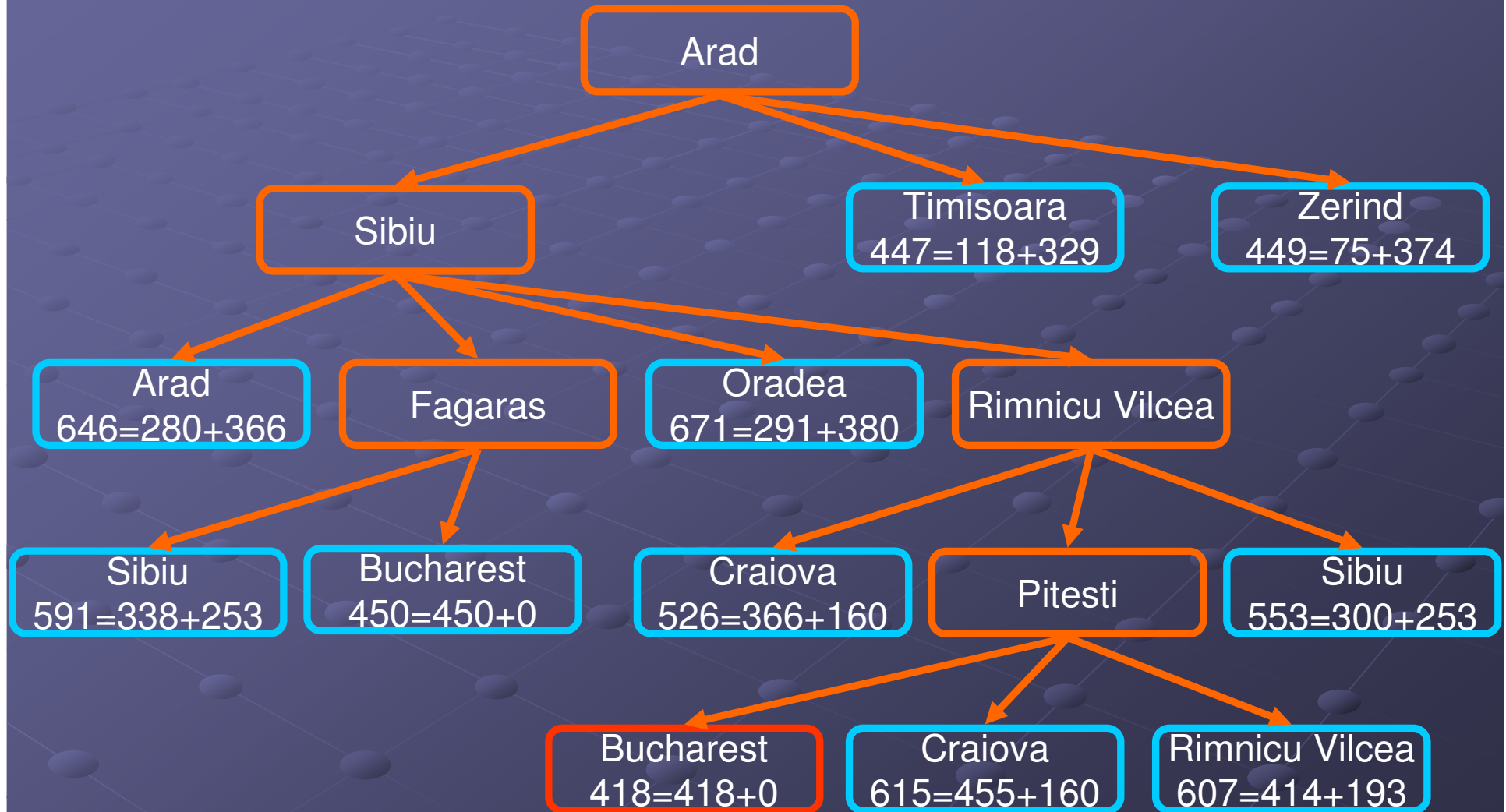
A* Example



A* Example



A* Example



A* Search

- ✓ Optimal
- ✓ No other optimal algorithm expands fewer nodes (modulo order of expansion of nodes with same cost)
- ✗ Exponential space requirement

Greedy Search

- Use (always admissible) $h(n) = 0$ in $f(n) = g(n) + h(n)$
- *i.e.* always use the cheapest found so far

Variants of A* Search

Many variants of A* developed

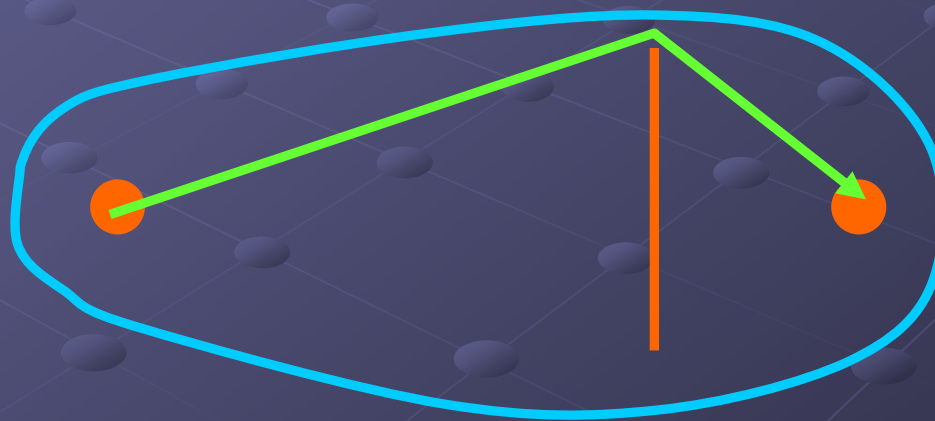
- Weighted A*: $f(n) = g(n) + W h(n)$

- Not exact
- Faster
- Answer is within W of optimal

Variants of A* Search

Many variants of A* developed

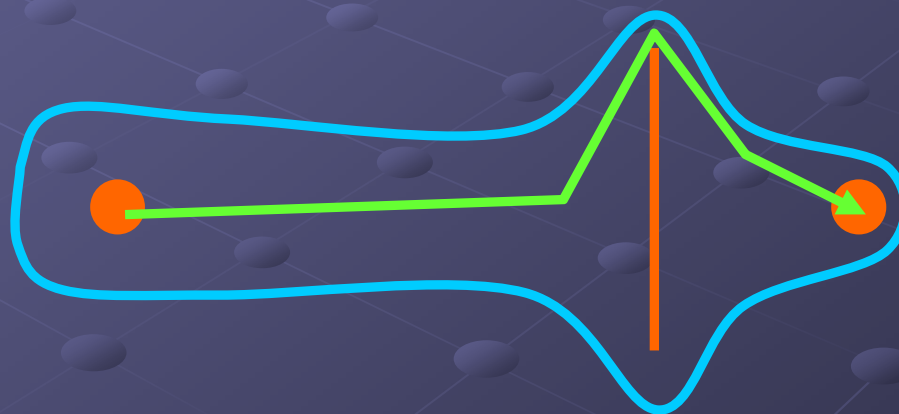
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Weighted
A*

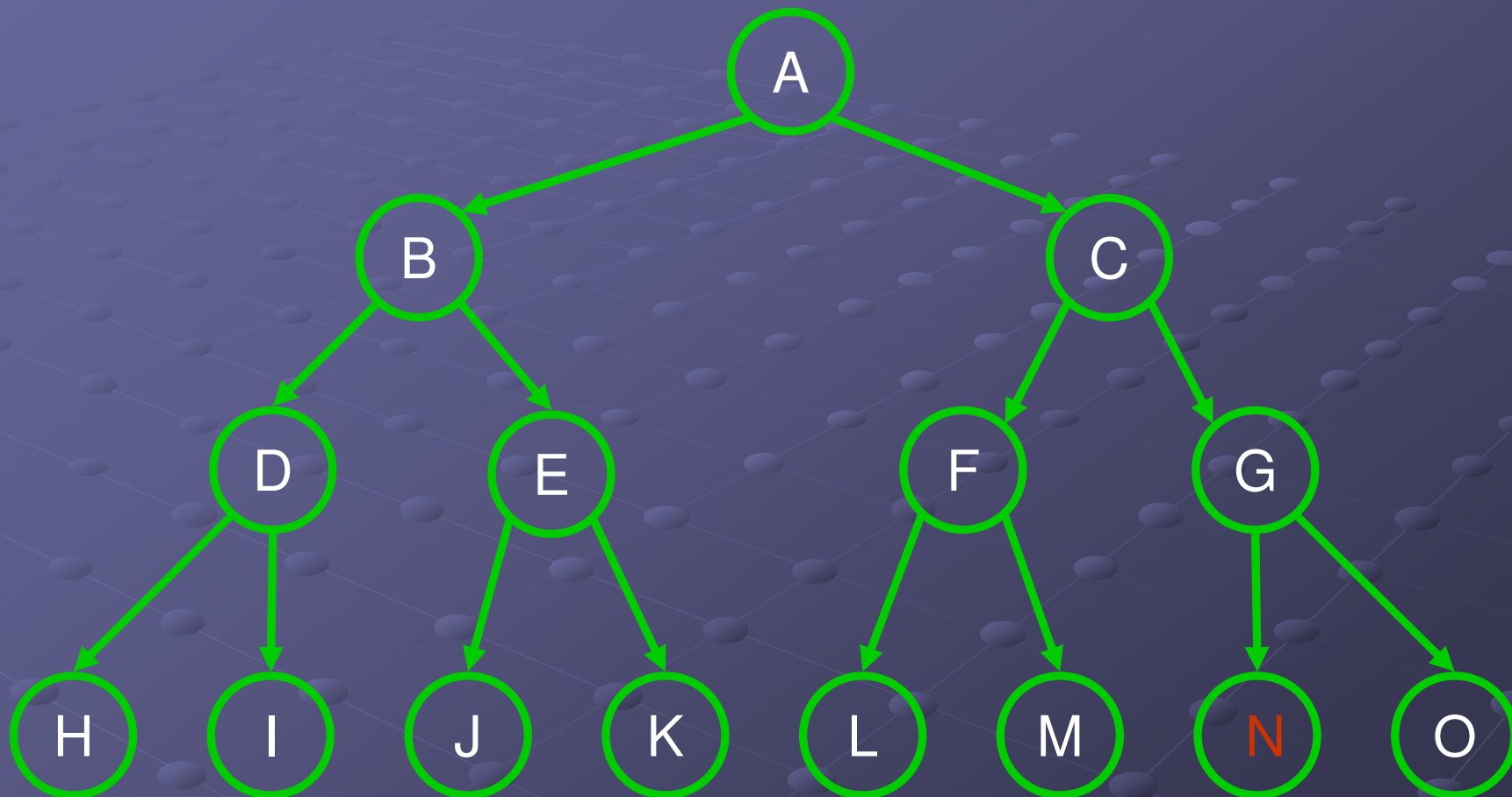
Variants of A* Search

- Iterative Deepening A* (IDA*)
 - Incrementally increase max depth
- Memory-bounded A*
 - Impose bound on memory
 - Discard nodes with largest $f(x)$ if necessary
- Others to come in seminars...

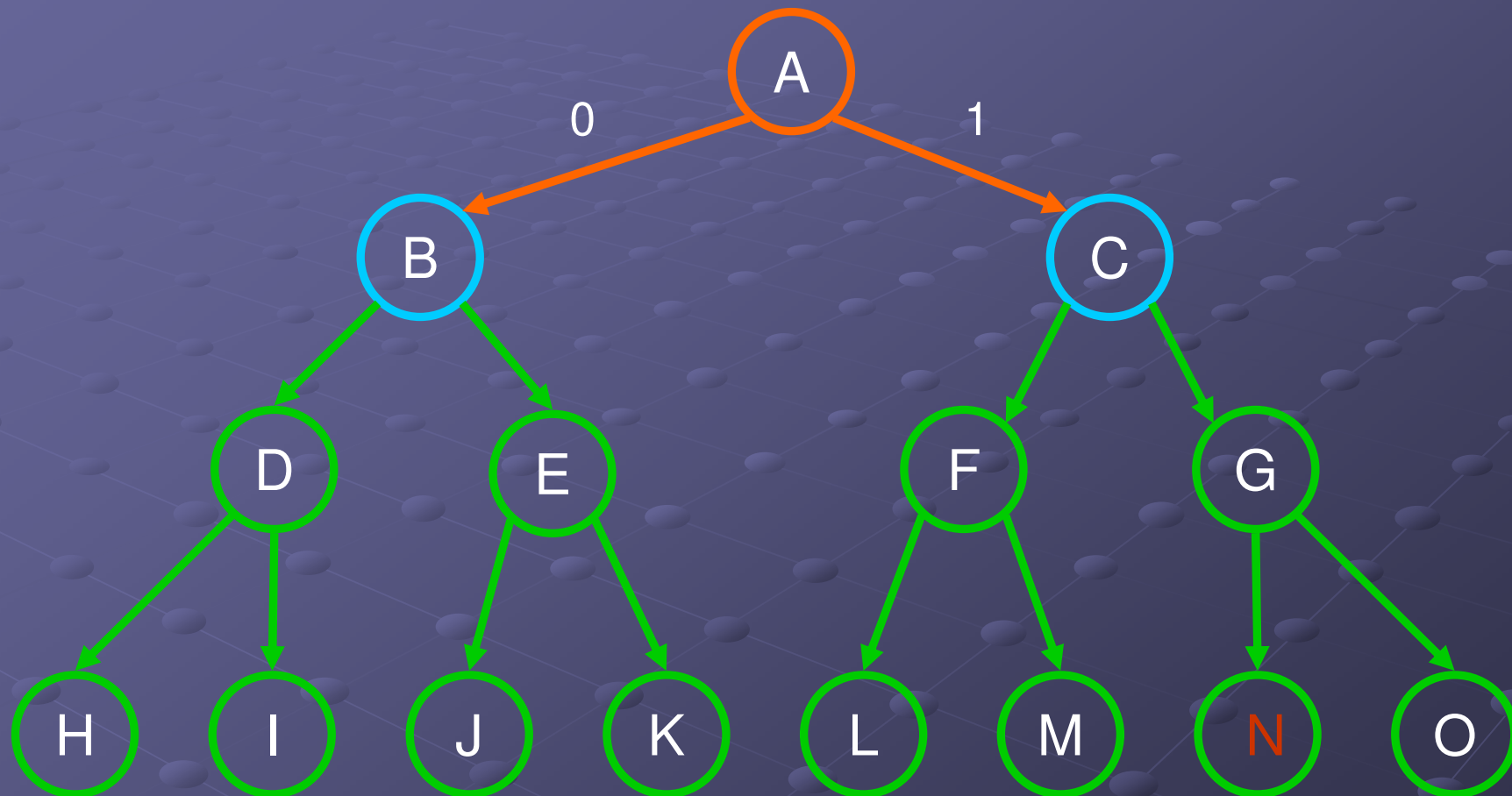
Limited Discrepancy Search

- Requires a heuristic to order choices (e.g. admissible heuristic, but don't require underestimate)
- If heuristic was right, we could always take the choice given by the heuristic
- LDS allows the heuristic to make mistakes: k -LDS allows k mistakes.

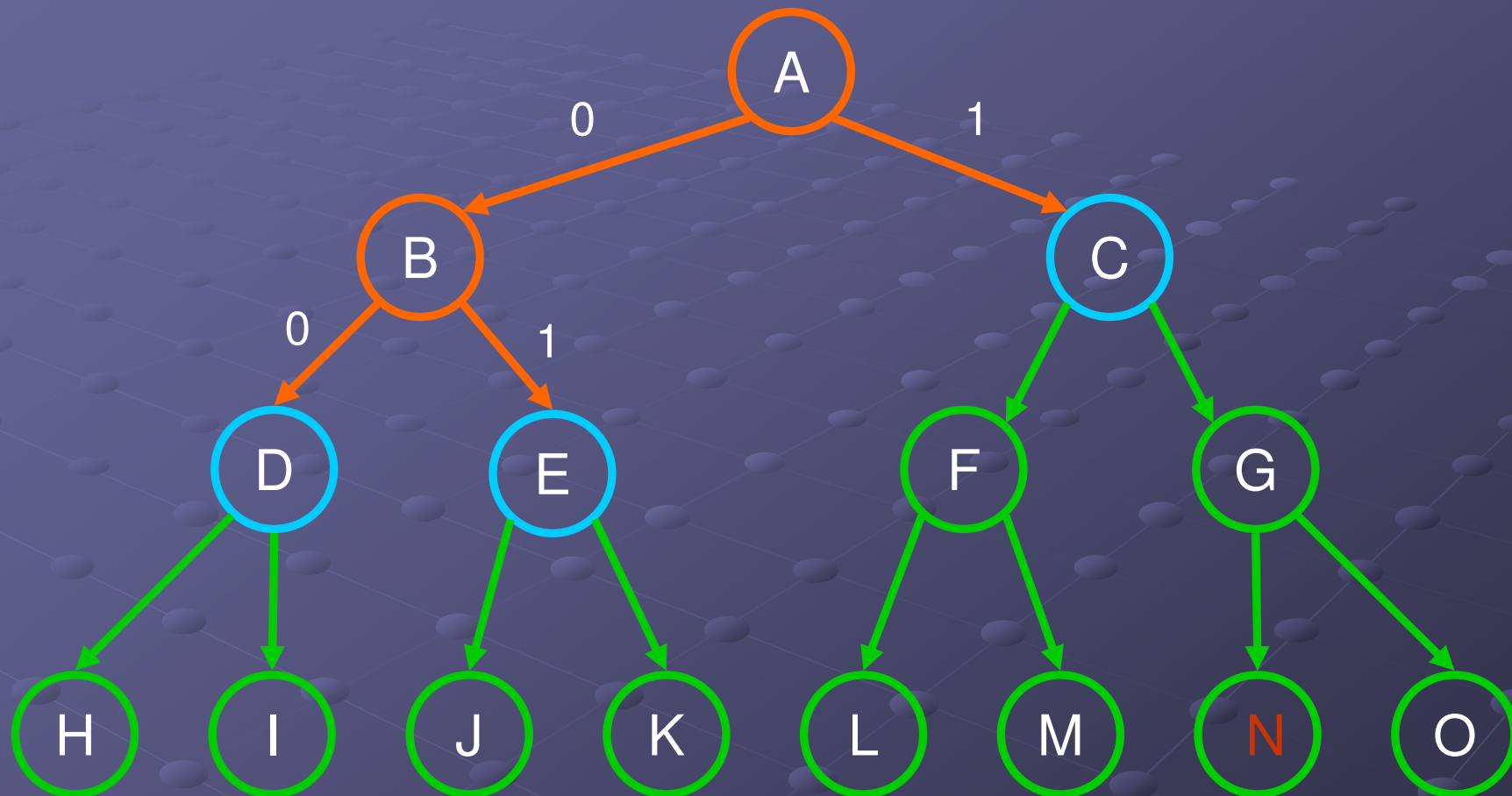
Limited Discrepancy Search ($k = 1$)



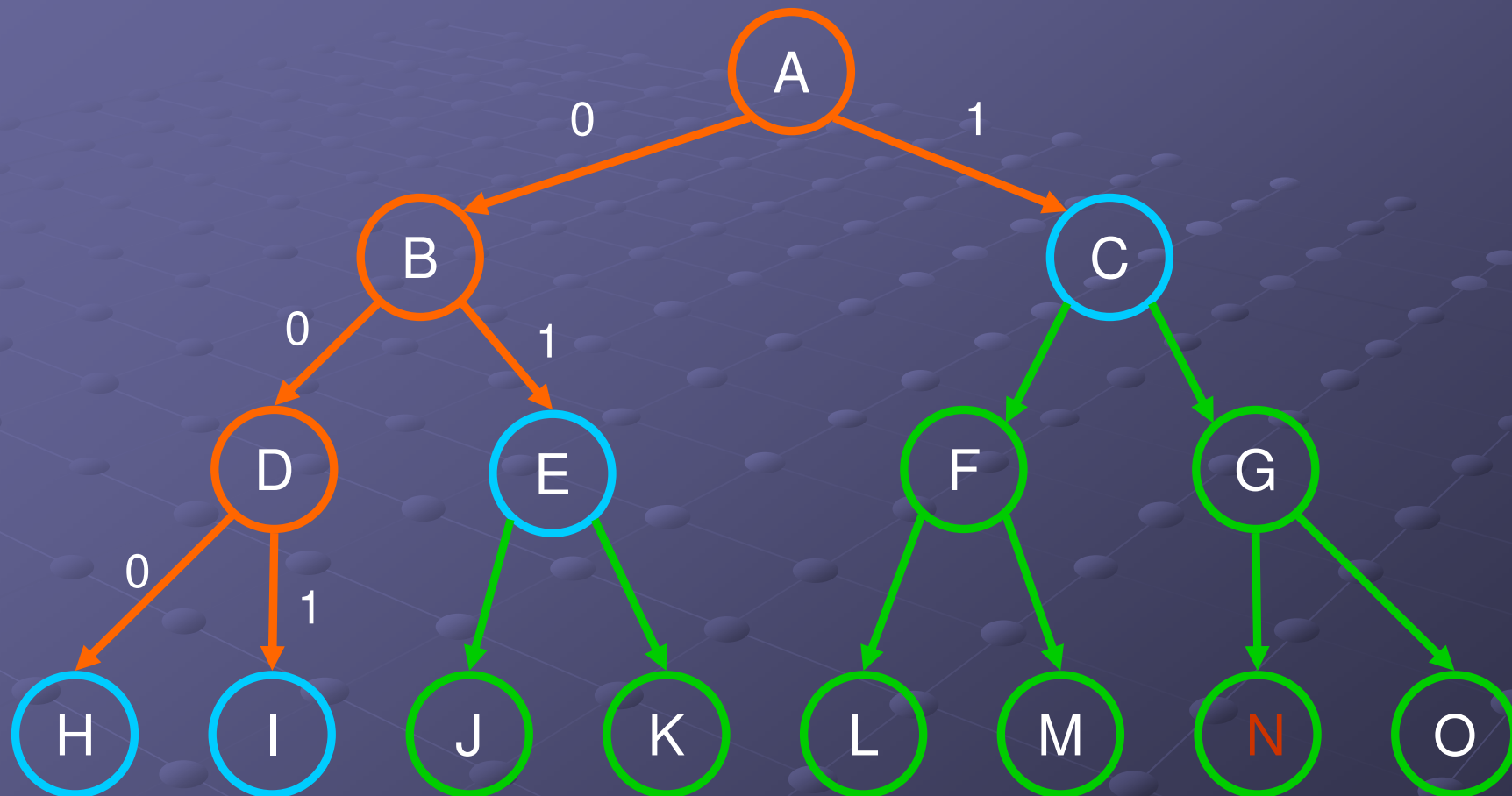
Limited Discrepancy Search ($k = 1$)



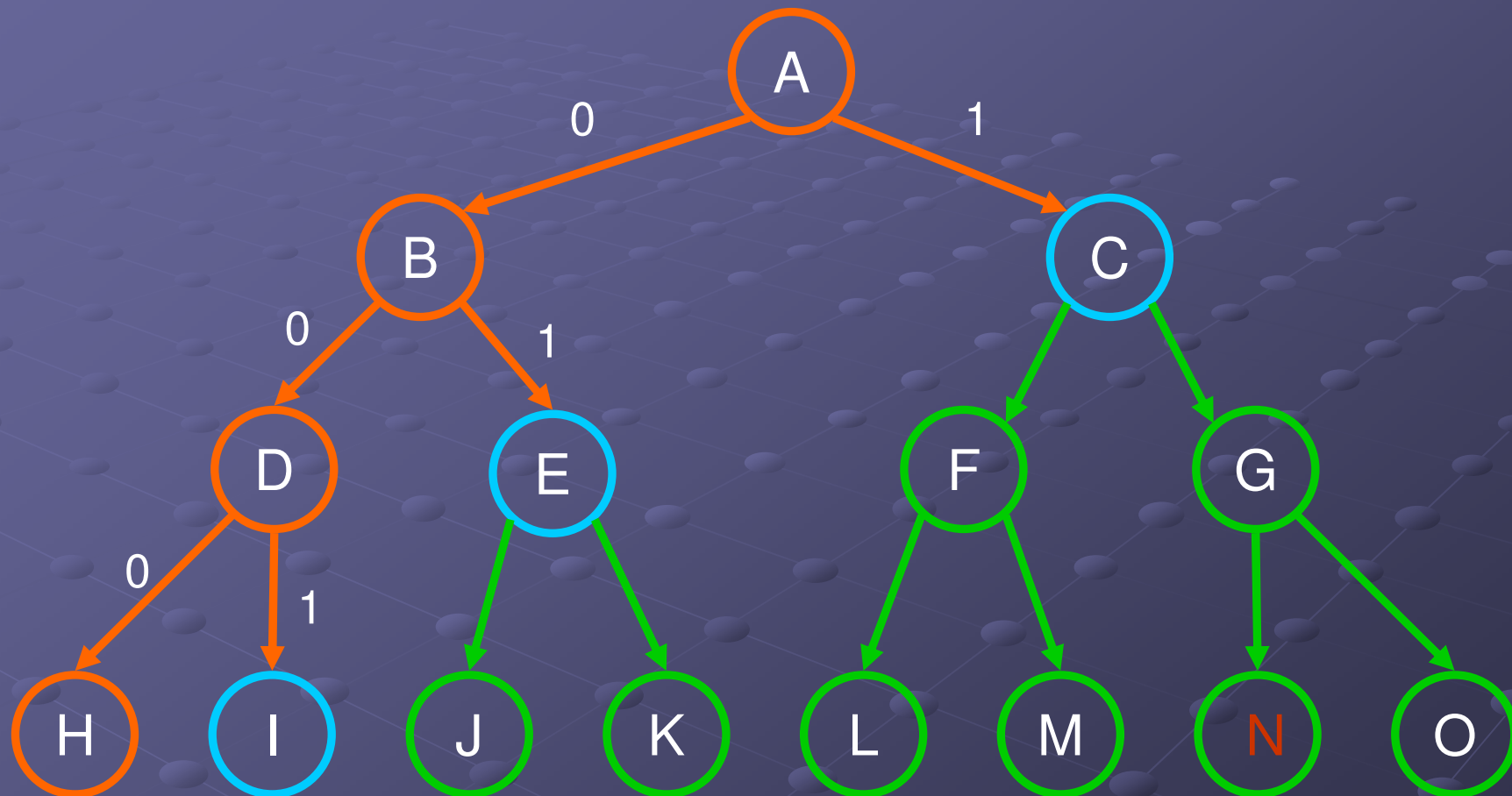
Limited Discrepancy Search ($k = 1$)



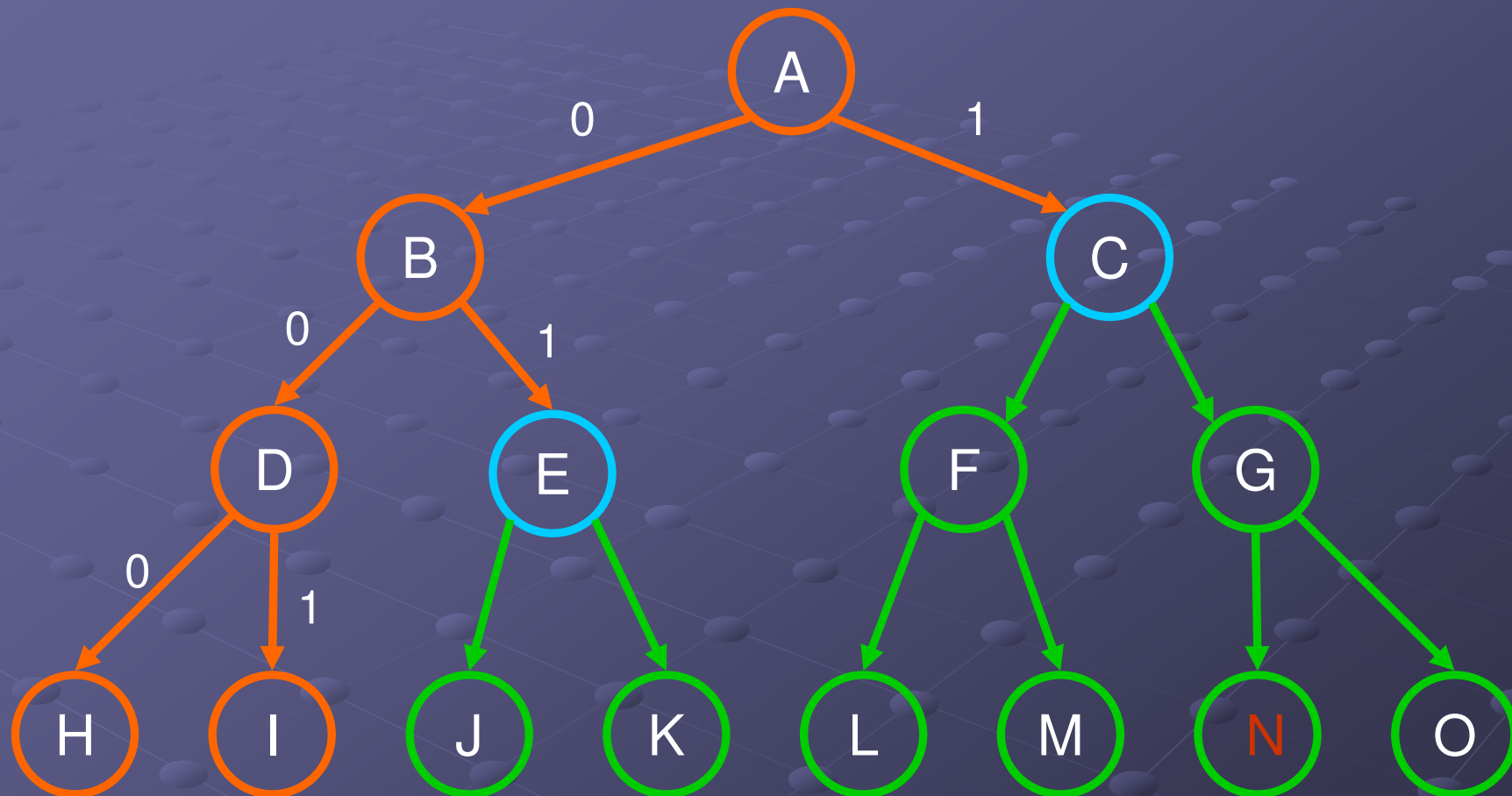
Limited Discrepancy Search ($k = 1$)



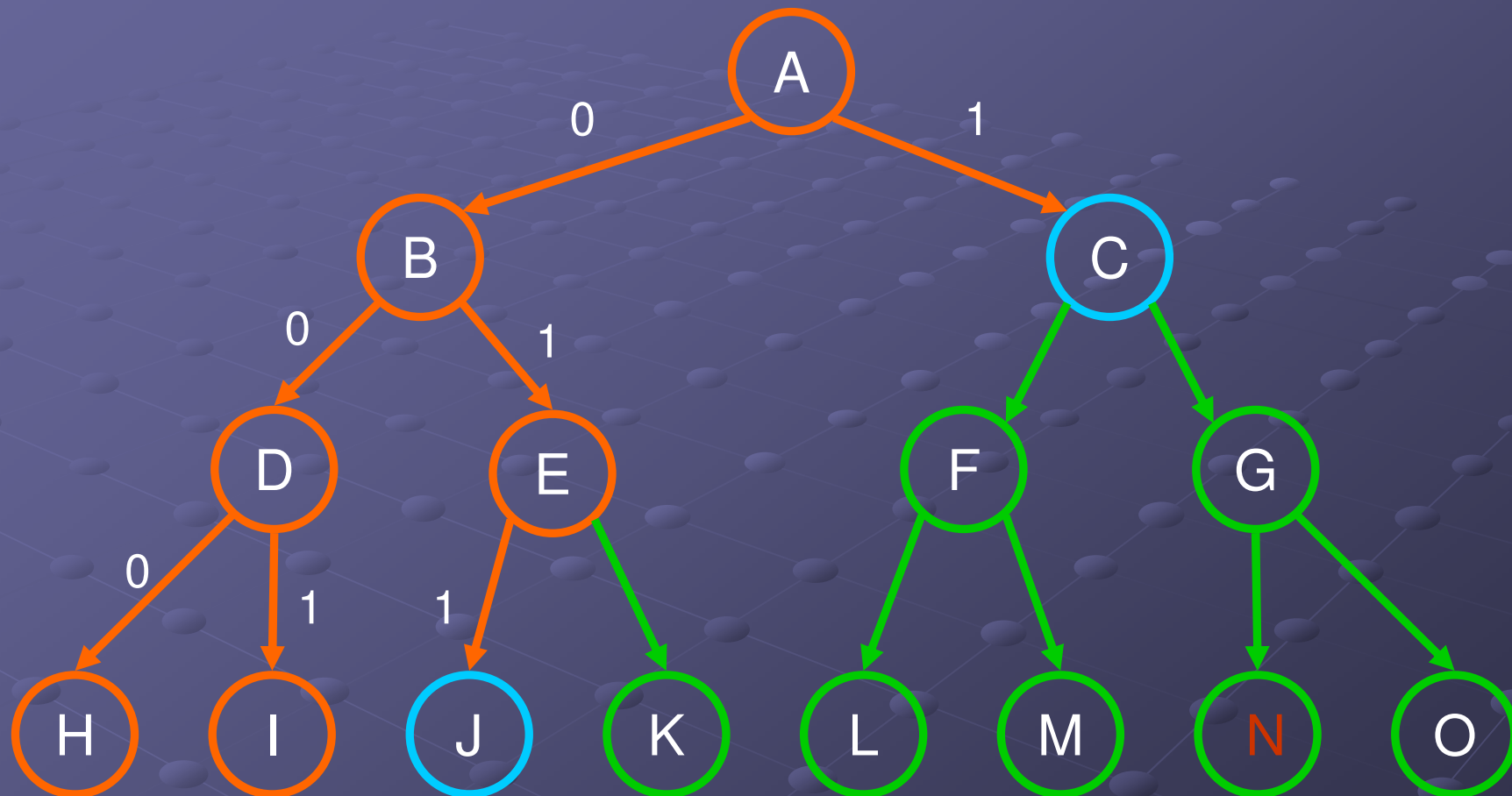
Limited Discrepancy Search ($k = 1$)



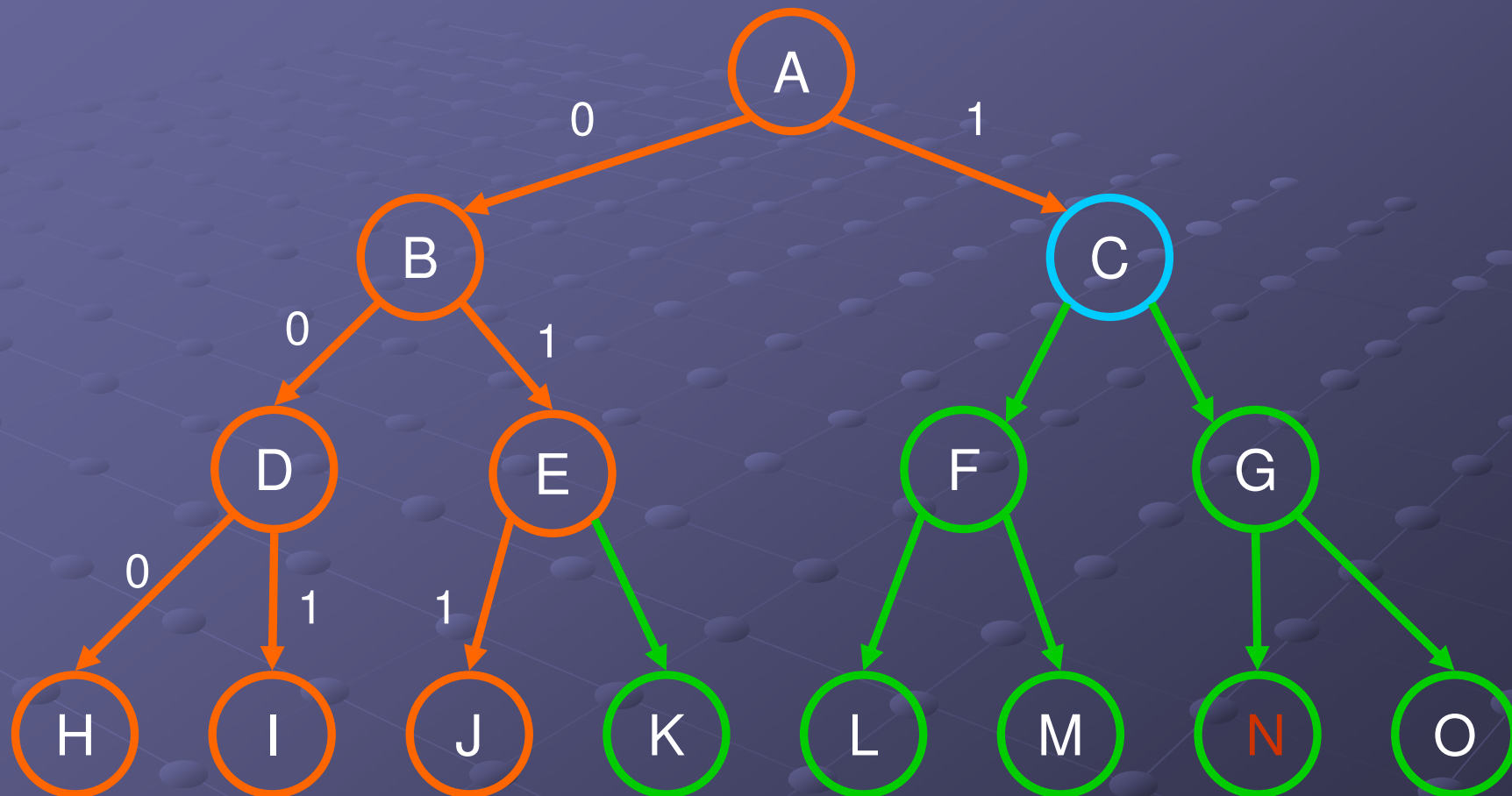
Limited Discrepancy Search ($k = 1$)



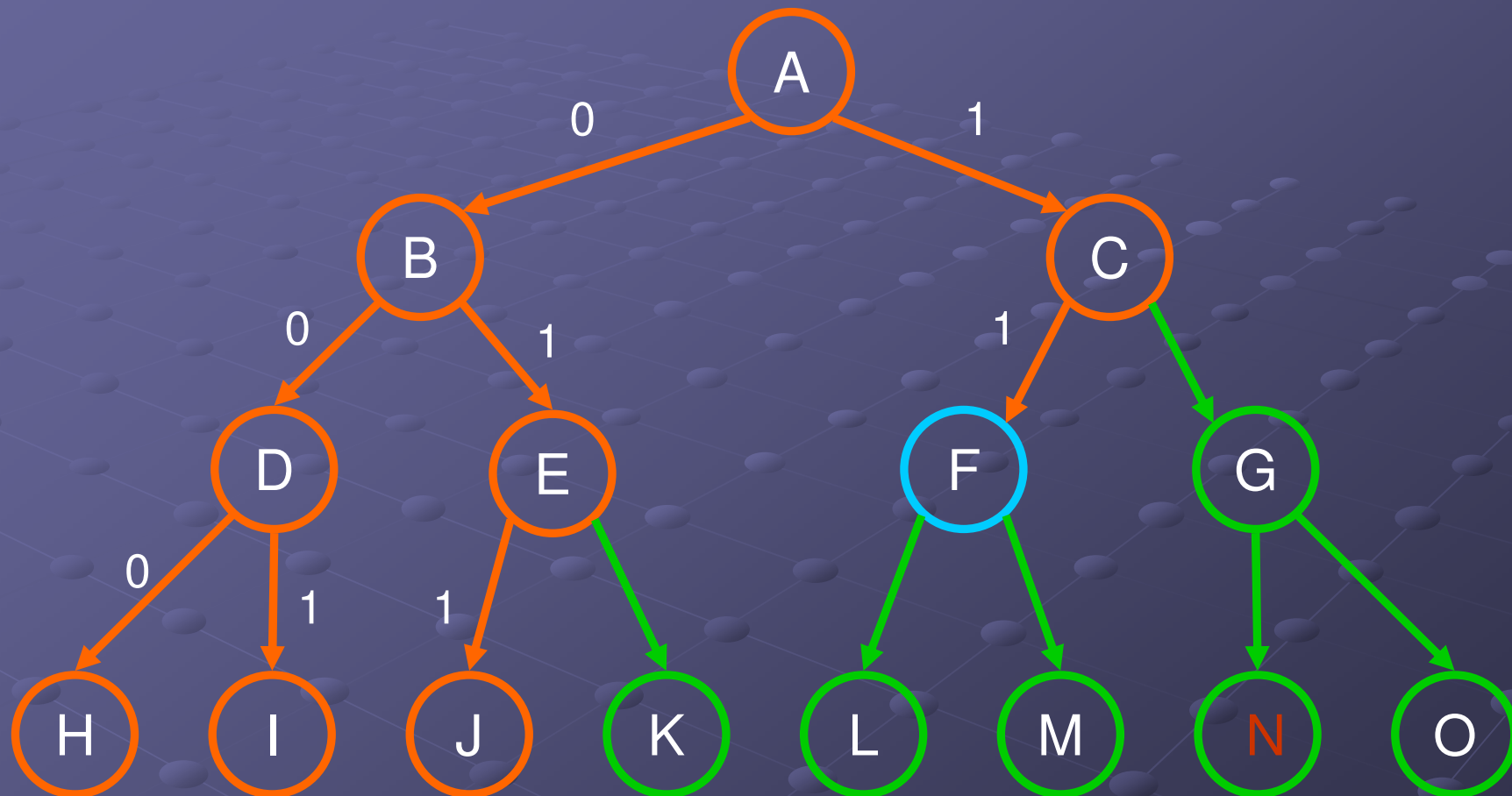
Limited Discrepancy Search ($k = 1$)



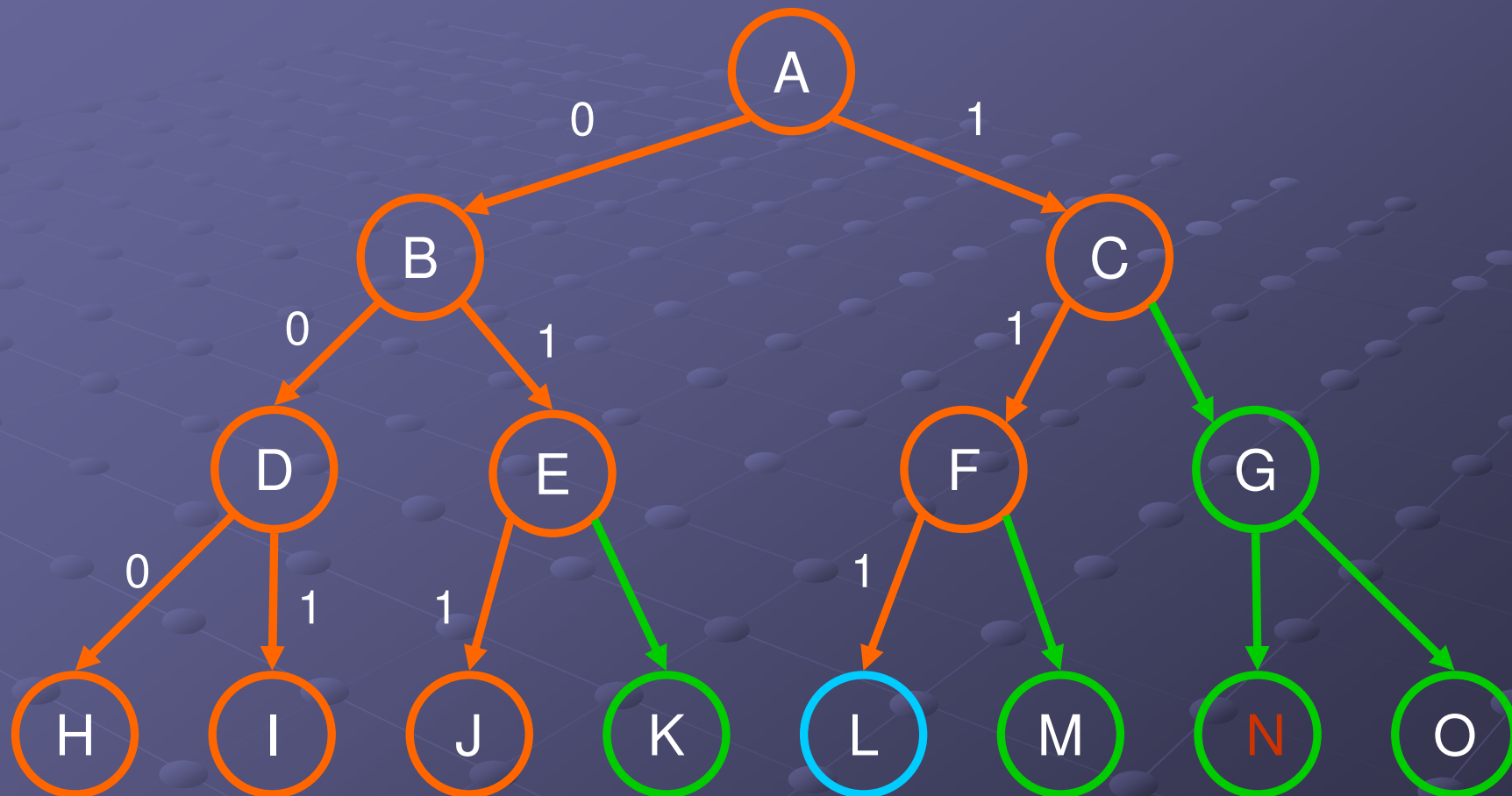
Limited Discrepancy Search ($k = 1$)



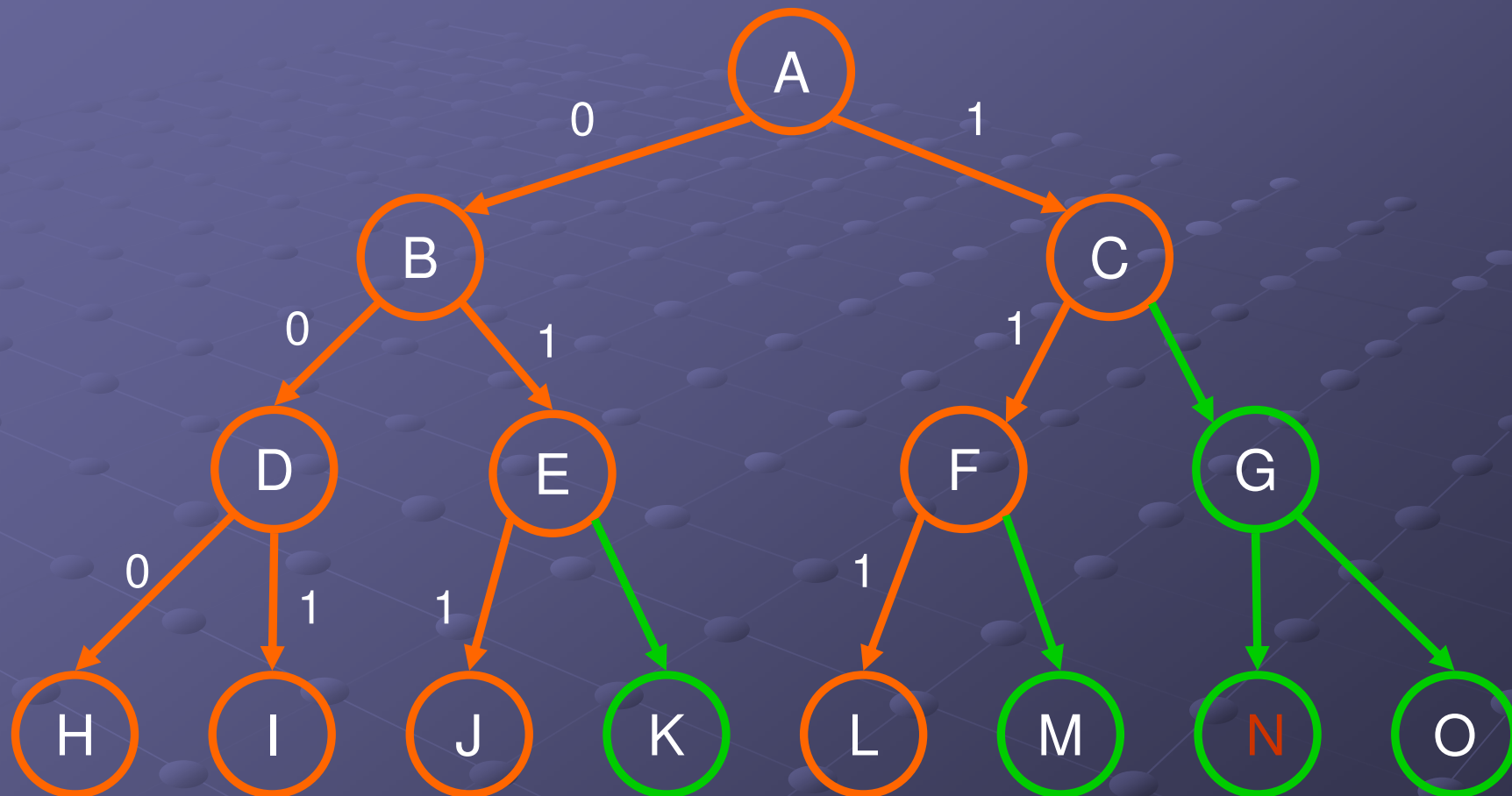
Limited Discrepancy Search ($k = 1$)



Limited Discrepancy Search ($k = 1$)



Limited Discrepancy Search ($k = 1$)



Next week....

(Integer) Linear Programming and Branch & Bound