

# CPSC 322: Introduction to Artificial Intelligence

Search: A\* Optimality  
Branch and Bound, Pruning  
Textbook reference: [3.6,3.7.1,3.8.1]

Instructor: Varada Kolhatkar  
University of British Columbia

Credit: These slides are adapted from the slides of the previous offerings of the course. Thanks to all instructors for creating and improving the teaching material and making it available!

# Announcements

- Midterm time and location


**Time:** Friday, Oct 25th, from 6pm to 7pm

**Location:** Woodward 2

(Instructional Resources Centre-IRC) (WOOD) - 2

- If you cannot make this time, please contact me **ASAP**.
- Assignment 1 is due on Sept. 30th at 11:59pm
- My office hours: Fridays from 11am to noon at ICCS 185

# Lecture outline

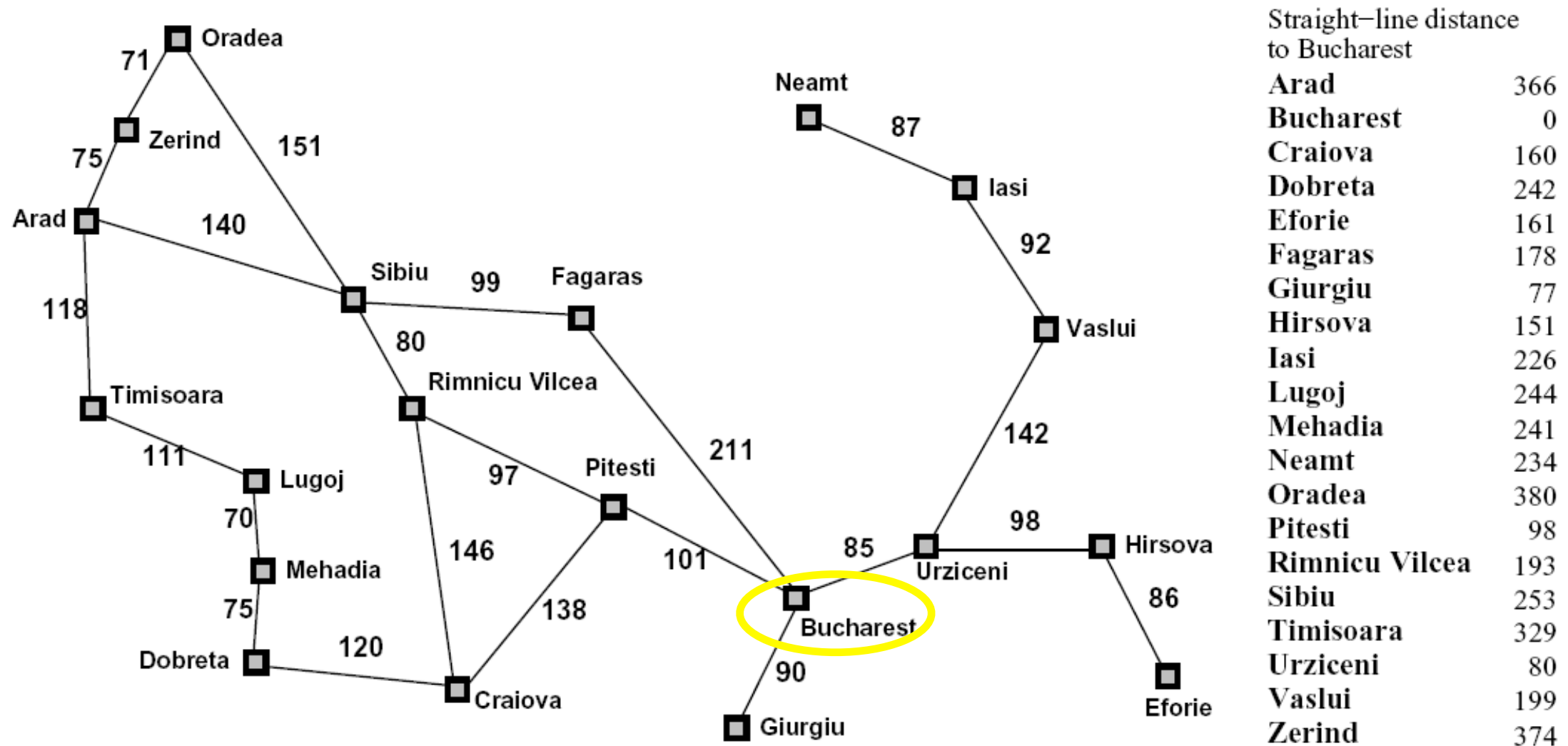
- **Recap from last lecture (~10 mins)** 
- A\* analysis (~15 mins)
- Branch and bound (~10 mins)
- A\* enhancements (~5 mins)
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- Pruning (~15 mins)
- Summary and wrap-up (~5 mins)

# Admissible heuristic

A search heuristic is **admissible** if it never overestimates the actual cost of the cheapest path from a node to a goal.

**Admissible heuristics are by nature optimistic because they think the cost of solving the problem is less than it actually is.**

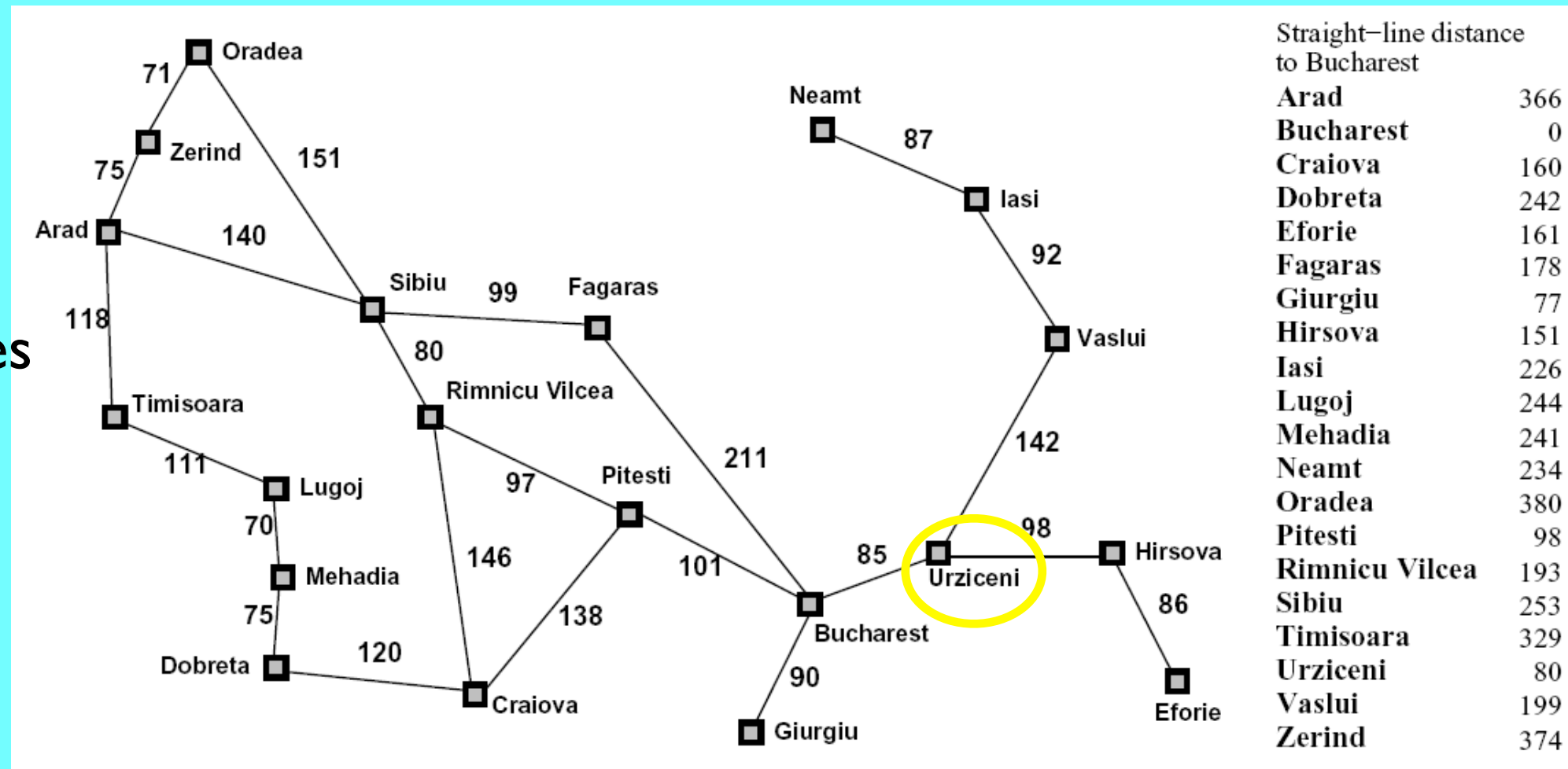
# Example: Travelling in Eastern Europe



Is the given heuristic admissible given the goal is Bucharest?

# Example: Travelling in Eastern Europe

Suppose goal =  
Urziceni  
But all we know is  
straight line distances  
(sld) to Bucharest.



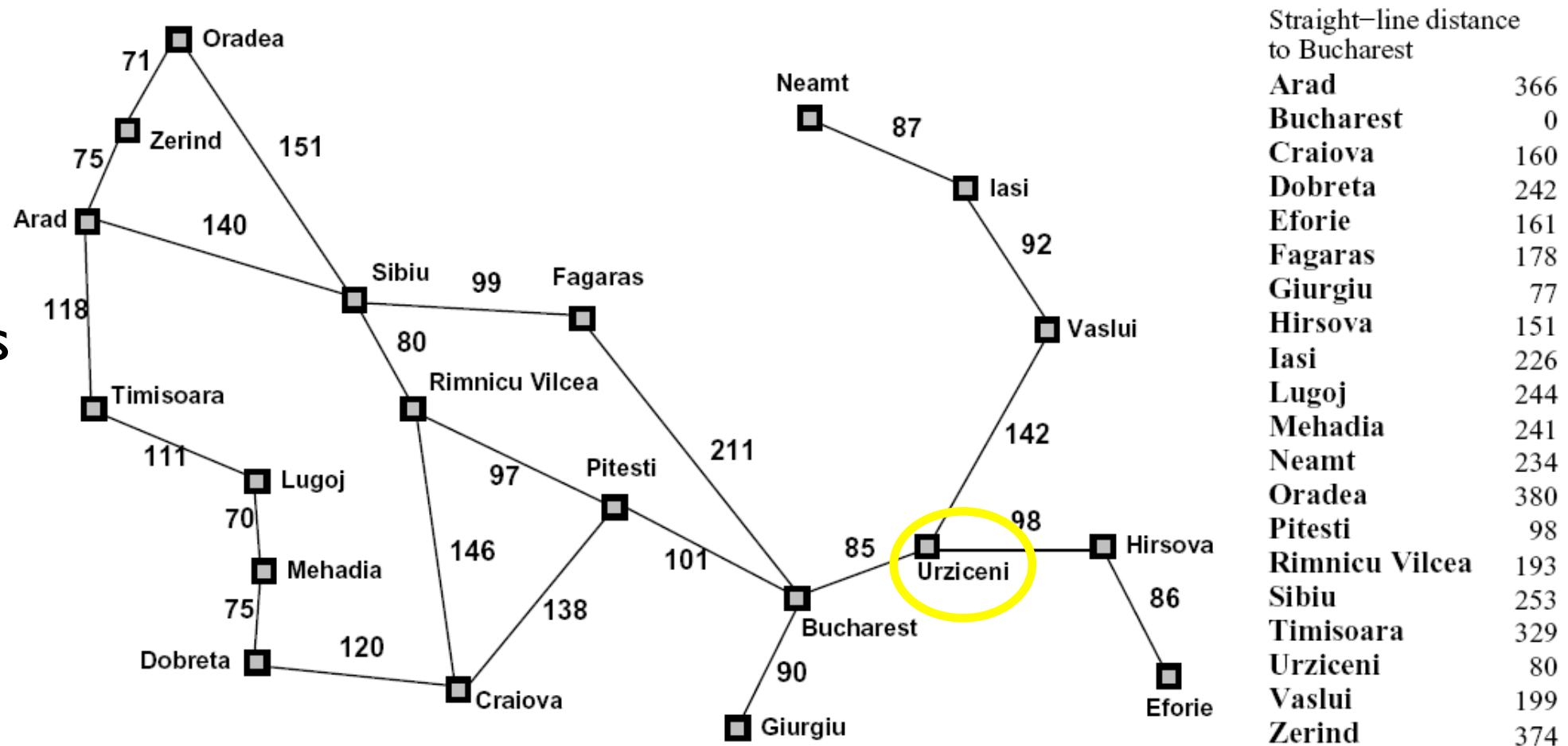
Possible  $h(n) = \text{sld}(n, \text{Bucharest}) + \text{cost}(\text{Bucharest to Urziceni})$   
Is this heuristic admissible?

A. Yes

B. No

# Example: Travelling in Eastern Europe

Suppose goal =  
Urziceni  
But all we know is  
straight line distances  
(sld) to Bucharest.



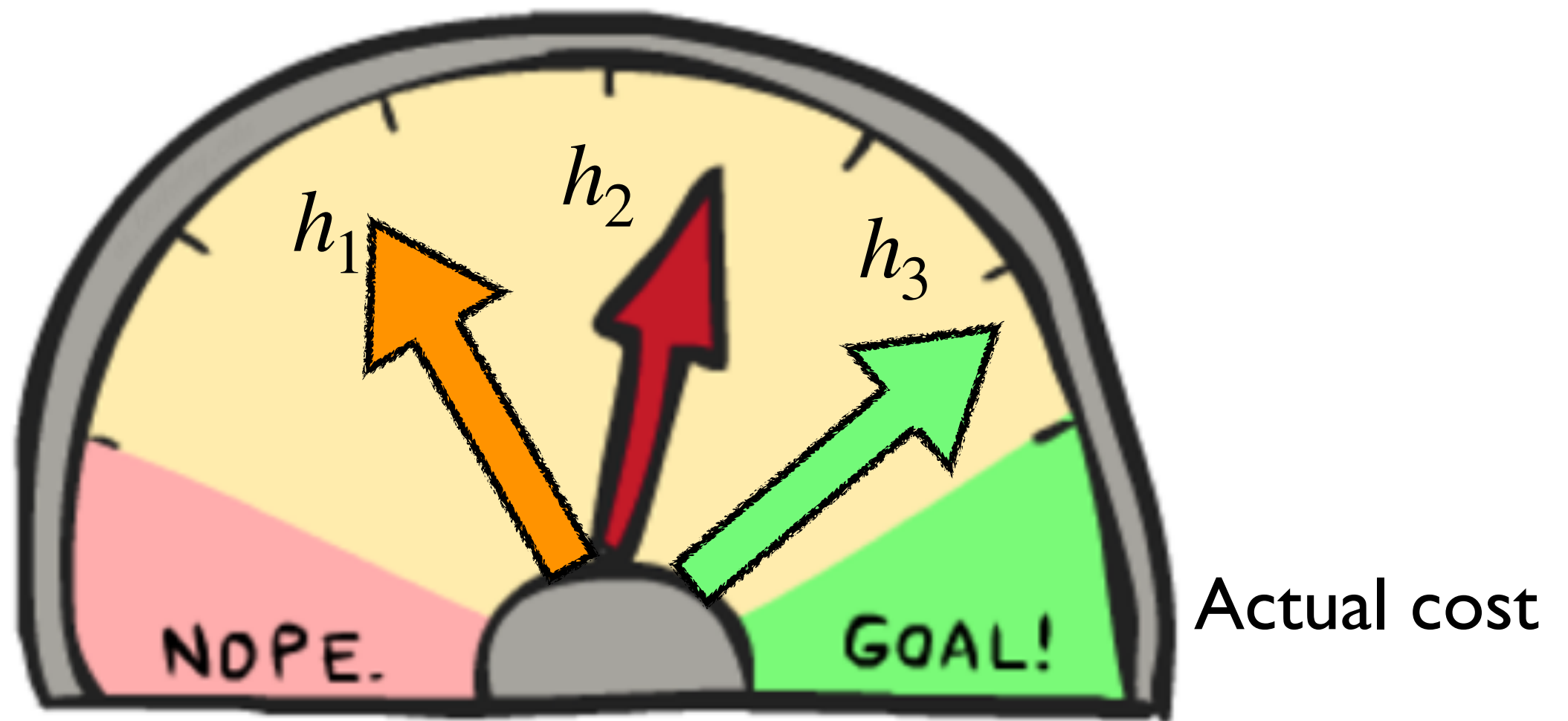
Possible  $h(n) = \text{sld}(n, \text{Bucharest}) + \text{cost}(\text{Bucharest to Urziceni})$   
Is this heuristic admissible?

A. Yes

B. No 

# Heuristic dominance

All admissible heuristics but the ones closer to the actual cost are more efficient (expand fewer paths).



$$h(n) = 0$$



# Heuristics dominance

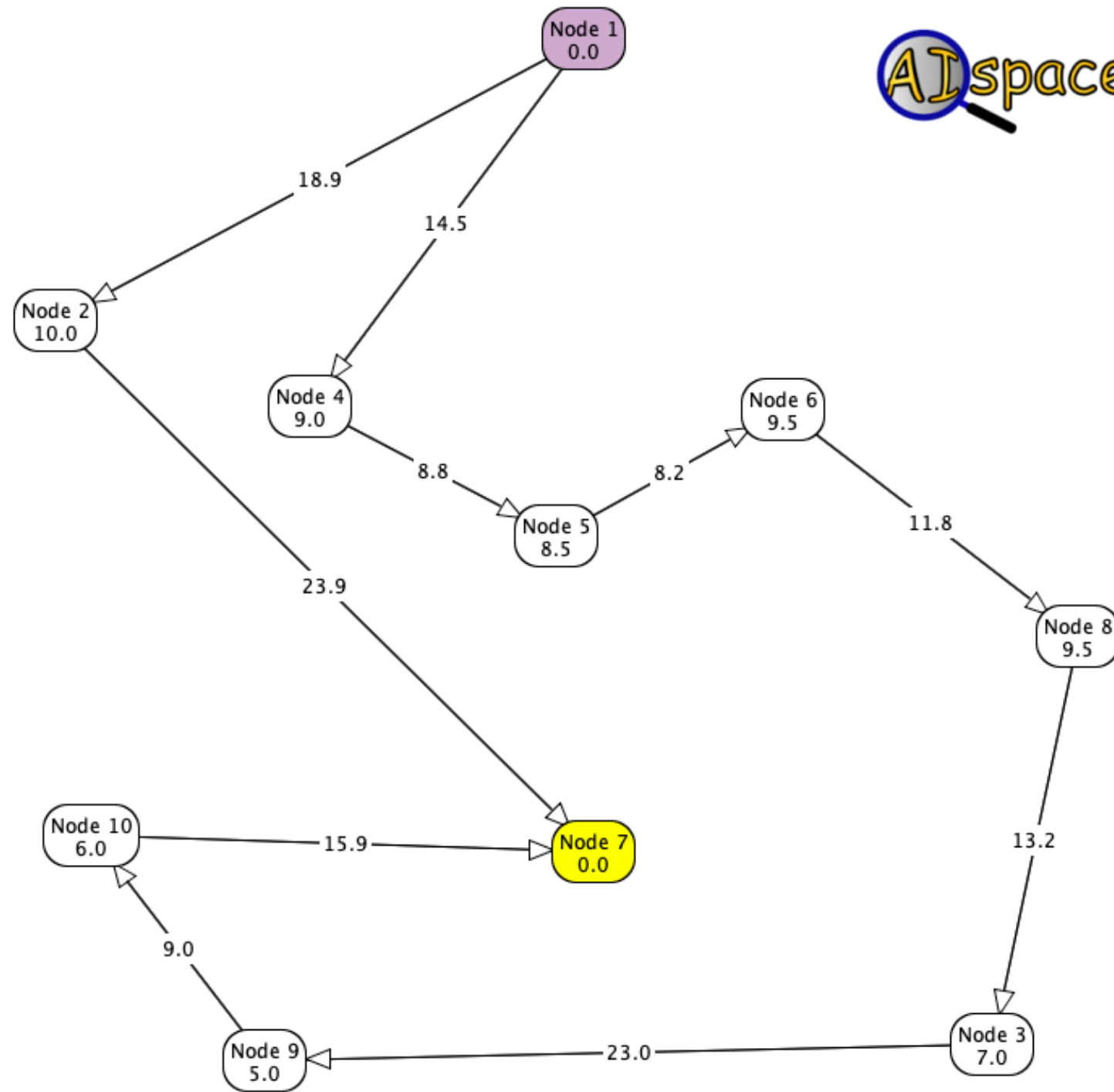
Search costs for the 8-puzzle (average number of paths expanded). Averaged over 100 instances of the 8-puzzle, for various solutions.

$$h_2(n) \geq h_1(n)$$

	$d = 12$	$d = 24$
IDS	3,644,035 paths	too many paths
$A^*(h_1)$	227 paths	39,135 paths
$A^*(h_2)$	73 paths	1,641 paths

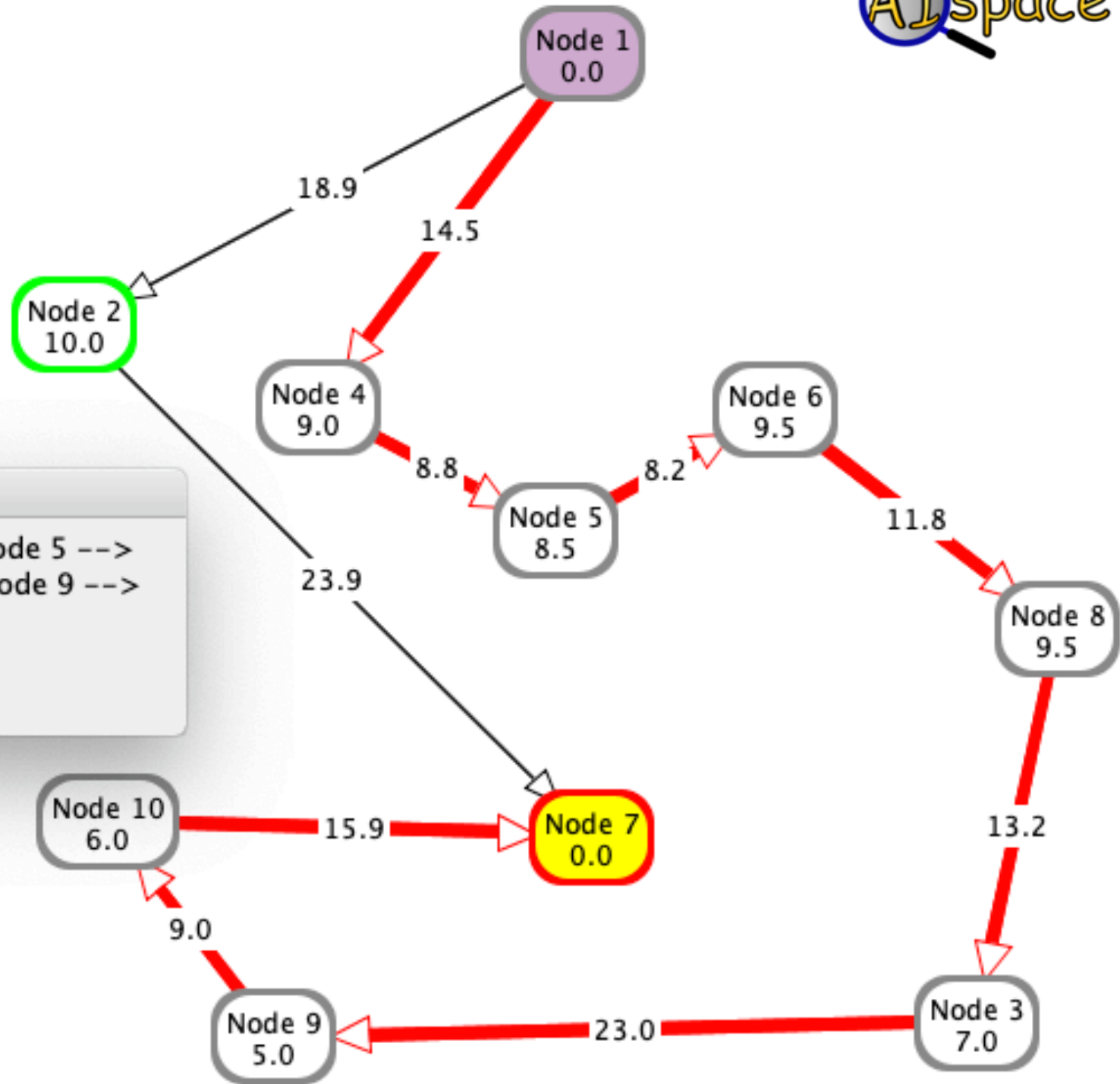
# Best-First Search (BestFS)

Selects a path  
on the frontier  
with minimum  
*h*-value



# Best-First Search (BestFS)

Selects a path  
on the frontier  
with minimum  
 $h$ -value



Goal Node Reached

Path found: Node 1 --> Node 4 --> Node 5 --> Node 6 --> Node 8 --> Node 3 --> Node 9 --> Node 10 --> Node 7 (Goal)

Path cost: 104.4

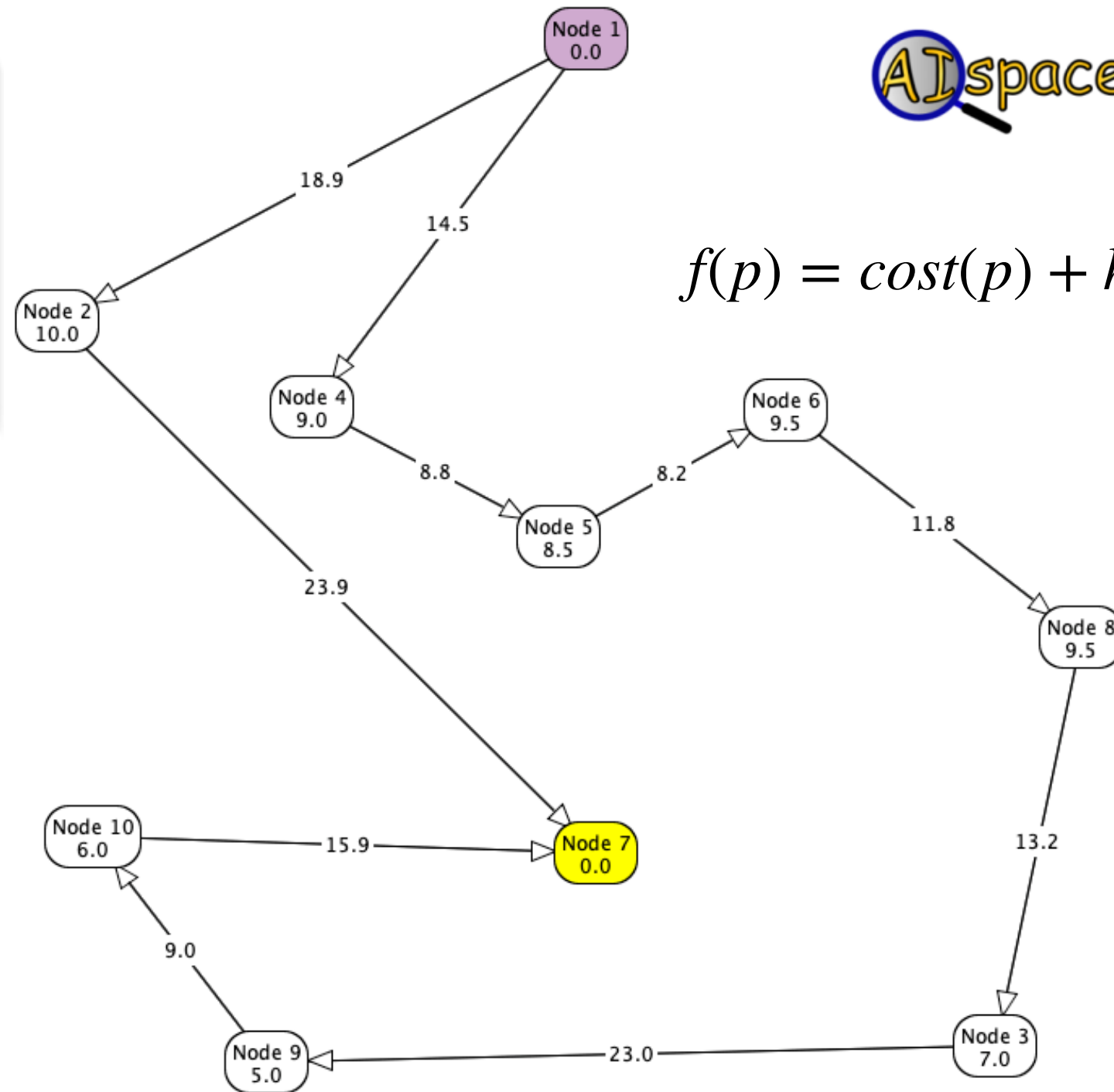
Nodes expanded: 9

# A\* search

Selects a path on the frontier with minimum  $f$ -value



$$f(p) = cost(p) + h(p)$$

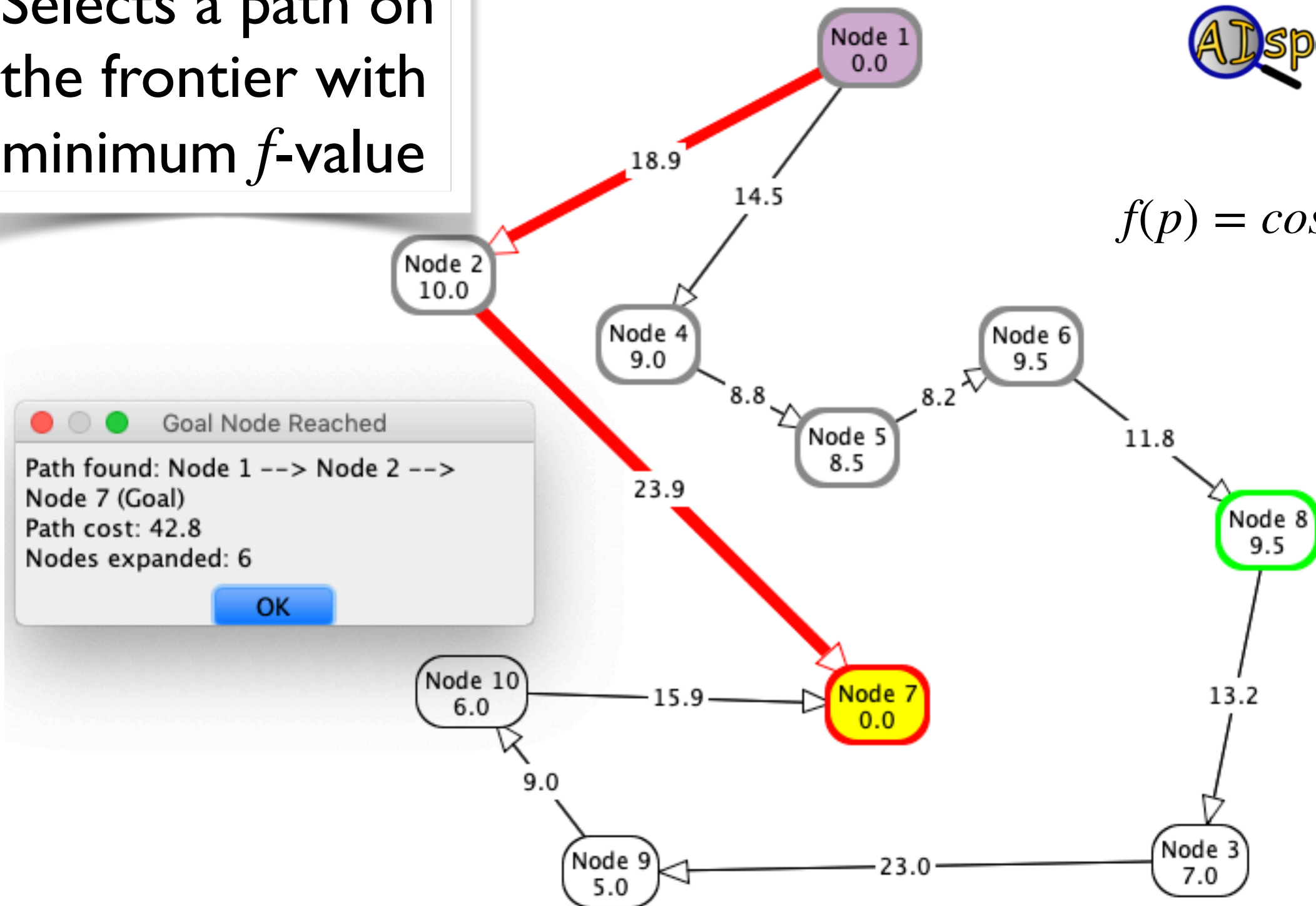


# A\* search

Selects a path on the frontier with minimum  $f$ -value

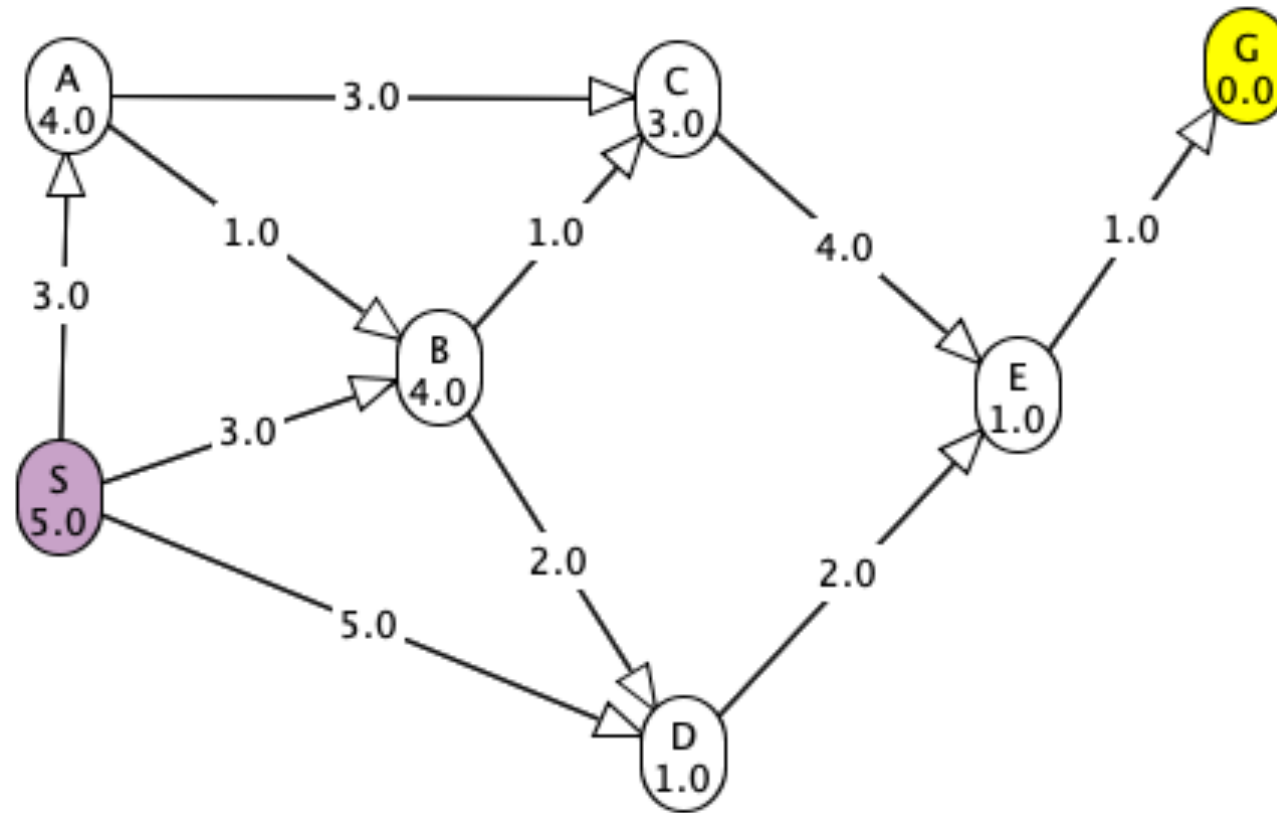


$$f(p) = cost(p) + h(p)$$



# Computing $f$ -values

The  $f$ -value is an estimate of the cost of getting to the goal via this node (path).



What is  $f$ -value of  $s \rightarrow A \rightarrow B \rightarrow D$ ?

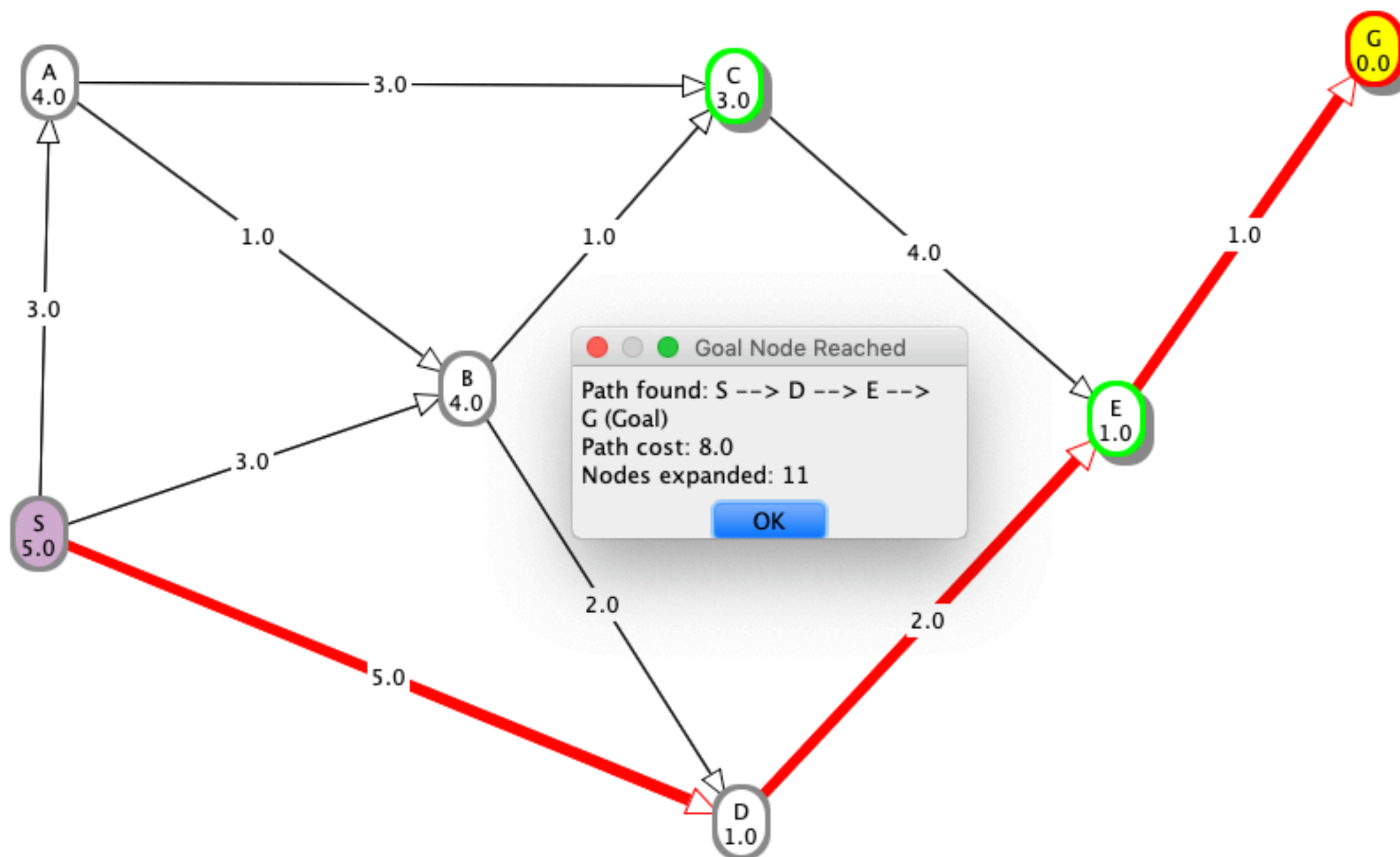
$$\text{cost}(s \rightarrow A \rightarrow B \rightarrow D) + h(D)$$

$$= (3 + 1 + 2) + 1 = 7$$

# RECAP: A\* search



$$f(p) = cost(p) + h(p)$$




# Today: Learning outcomes

From this lecture, students are expected to be able to:

- Analyze  $A^*$ 
  - Formally prove  $A^*$  optimality
- Define optimally efficient
- Define/read/write/trace/debug branch and bound search algorithm and other enhancements of  $A^*$
- Explain pruning




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# A\* search



If the heuristic is completely uninformative (e.g.,  $h = 0$  for all nodes) and the edge costs are all the same, A\* is equivalent to

- A. LCFS
- B. BFS 
- C. DFS
- D. A and B

# Analysis of A\*

When the arc costs are strictly positive. The heuristic could be completely uninformative, and the edge costs could all be the same, meaning that A\* would do the same thing as BFS.

- Time complexity:  $O(b^m)$
- Space complexity:  $O(b^m)$
- Completeness: Yes
- Optimality: ??

# Optimality of $A^*$

If  $A^*$  returns a solution, that solution is guaranteed to be optimal, as long as

- the branching factor is finite
- arc costs are  $> \epsilon > 0$
- $h(n)$  is admissible (an underestimate of the length of the shortest path from  $n$  to a goal node and non-negative)

This property of  $A^*$  is called admissibility of  $A^*$

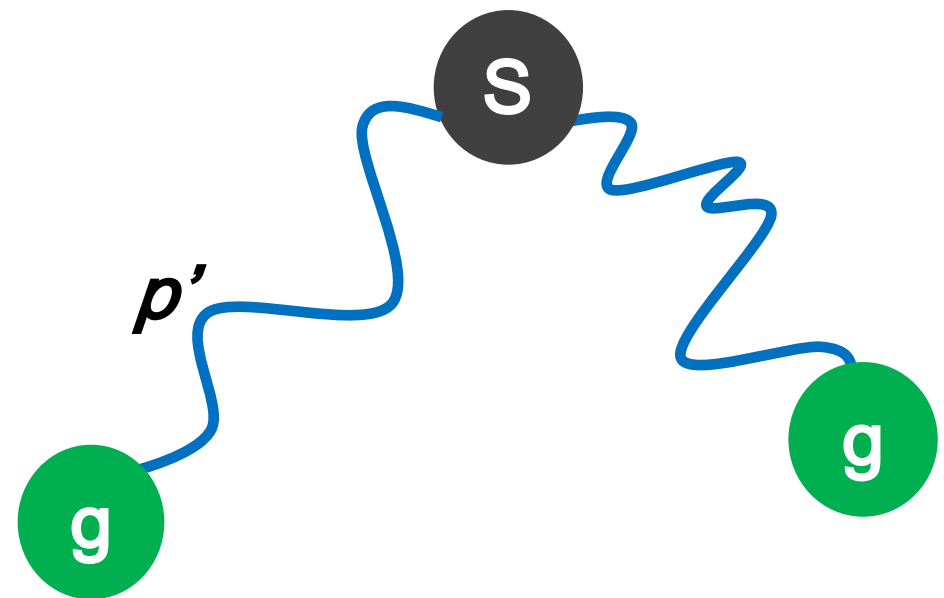
# A\* optimality proof

Theorem: If  $A^*$  selects a path  $p$  as the solution, then  $p$  is an optimal (i.e., lowest-cost) path.

## Proof by contradiction

Suppose  $A^*$  returns path  $p$ .

Assume that there exists some other path  $p'$  that is a better path to a goal.



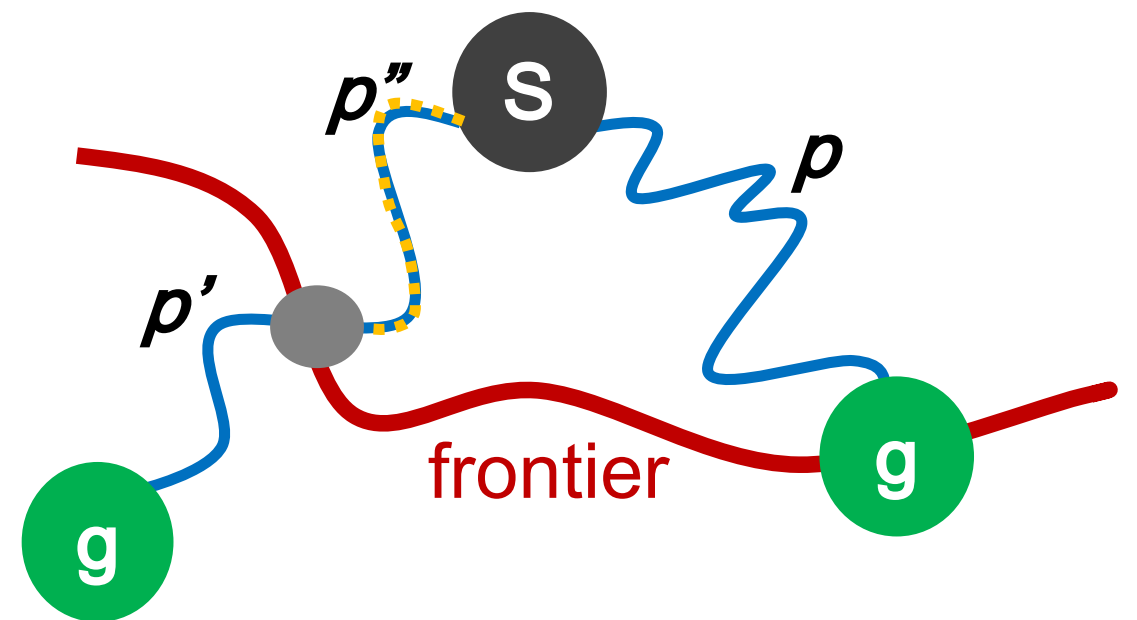
# A\* optimality proof

Theorem: If  $A^*$  selects a path  $p$  as the solution, then  $p$  is an optimal (i.e., lowest-cost) path.

## Proof by contradiction

Consider the moment when  $p$  is selected from the frontier.

Some part of  $p'$  will also be on the frontier. Let's call this part  $p''$



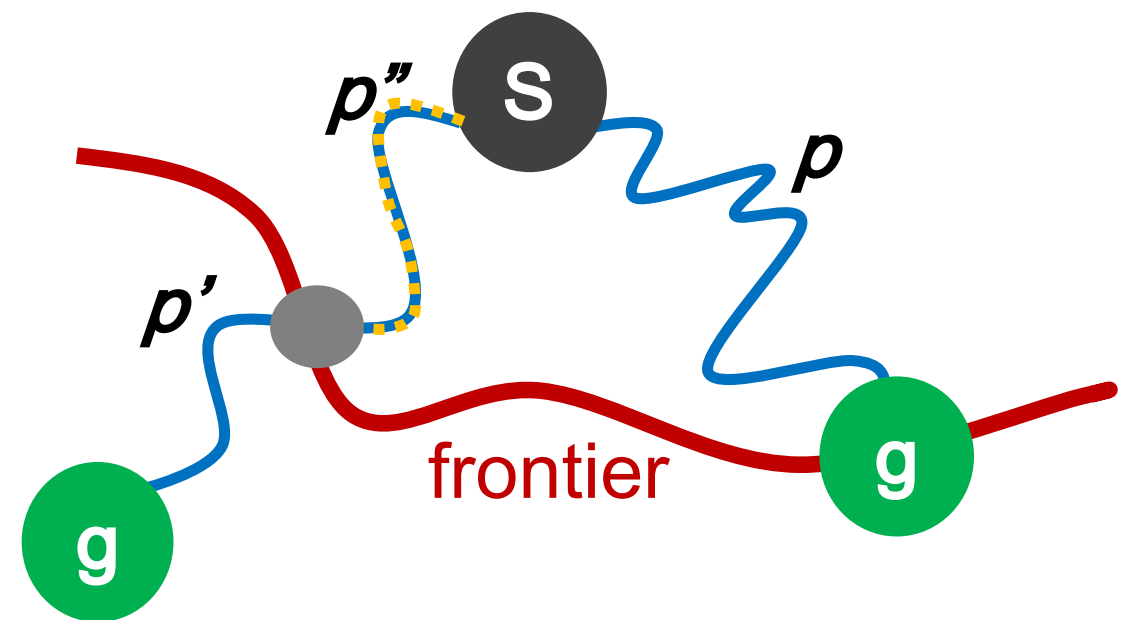
# A\* optimality proof

Theorem: If A\* selects a path  $p$  as the solution, then  $p$  is an optimal (i.e., lowest-cost) path.

## Proof by contradiction

Because  $p$  was expanded before  $p''$ ,  $f(p) \leq f(p'')$  and so

$$\text{cost}(p) + h(p) \leq \text{cost}(p'') + h(p'')$$



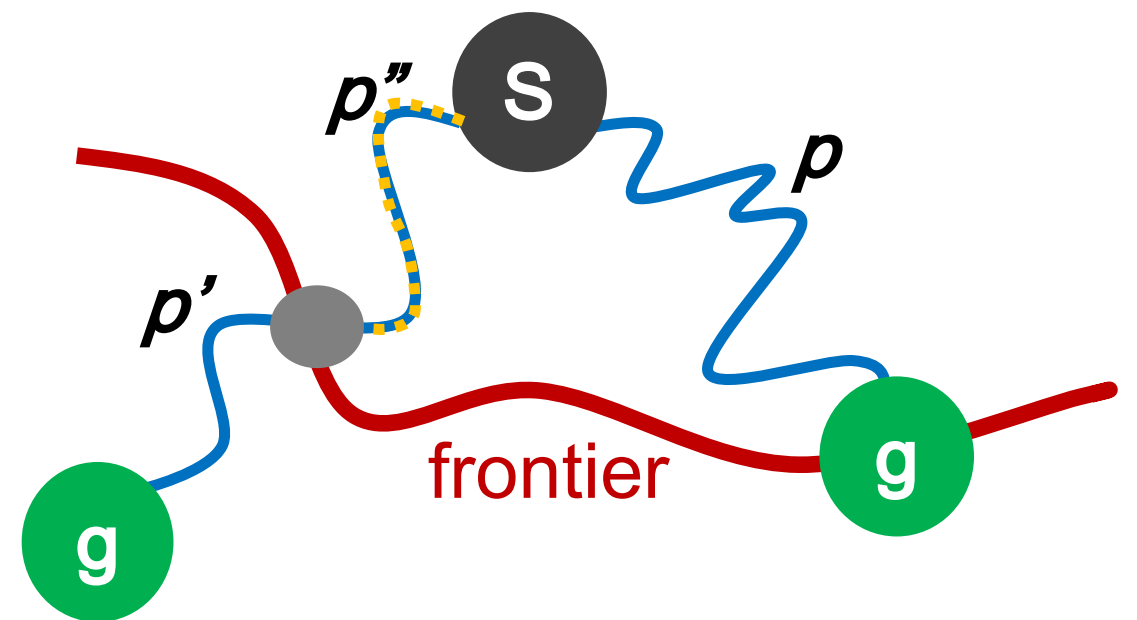
# A\* optimality proof

Theorem: If A\* selects a path  $p$  as the solution, then  $p$  is an optimal (i.e., lowest-cost) path.

Proof by contradiction

Because  $p$  ends at goal,  
 $h(p) = 0$

$$\text{cost}(p) + \cancel{h(p)} \leq \text{cost}(p'') + h(p'')$$





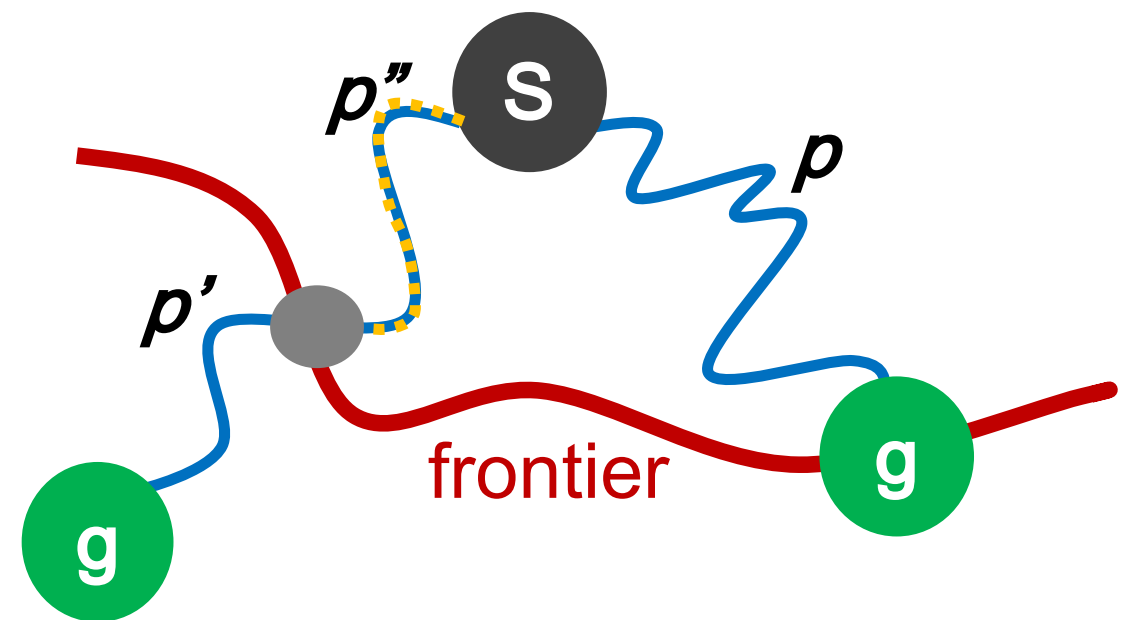
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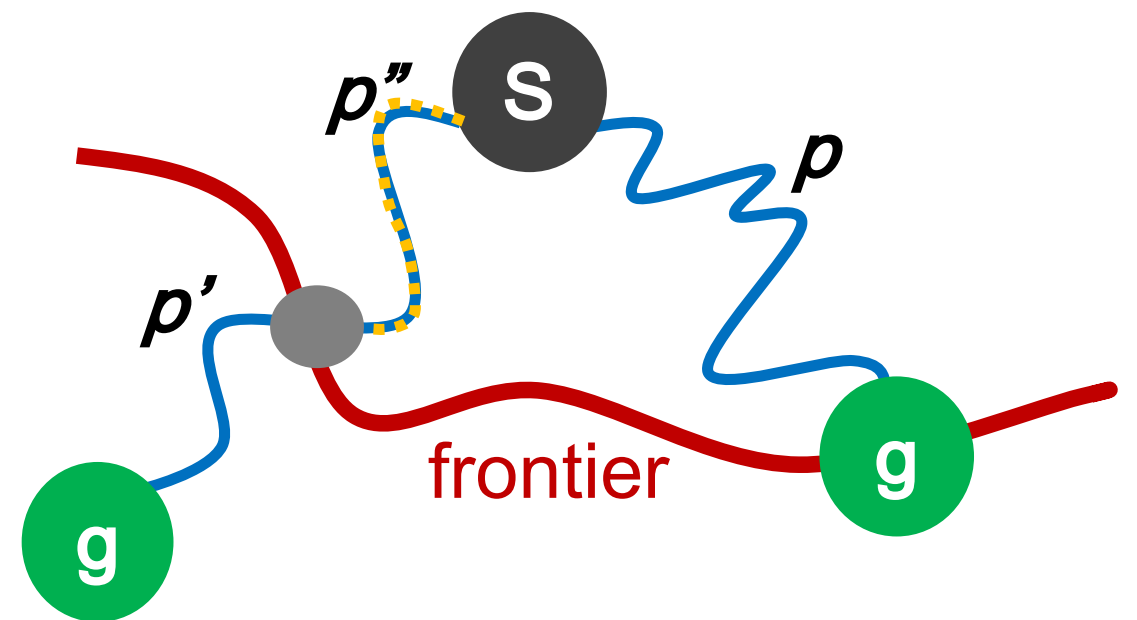
# A\* optimality proof

Theorem: If A\* selects a path  $p$  as the solution, then  $p$  is an optimal (i.e., lowest-cost) path.

Proof by contradiction

Because  $h$  is admissible,

$$\text{cost}(p'') + h(p'') \leq \text{cost}(p')$$



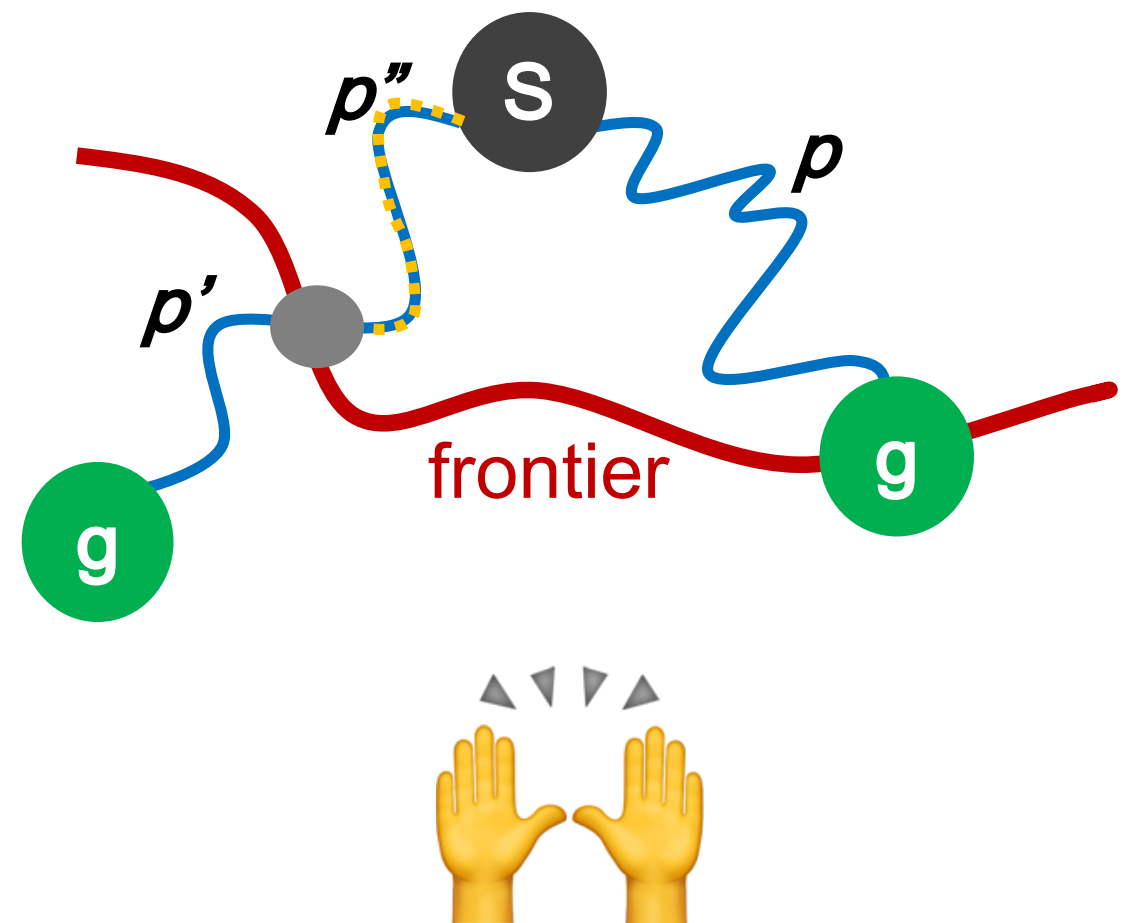
# A\* optimality proof

Theorem: If A\* selects a path  $p$  as the solution, then  $p$  is an optimal (i.e., lowest-cost) path.

## Proof by contradiction

$cost(p) \leq cost(p'') + h(p'')$  and  
 $cost(p'') + h(p'') \leq cost(p')$   
implies that  
 $cost(p) \leq cost(p')$

This contradicts our assumption  
that  $p'$  is a better path.



# Optimal efficiency of $A^*$

In fact, we can prove something even stronger about  $A^*$ : Given the particular heuristic that is available, **no search algorithm could do better!**

**Optimal efficiency:** Among all optimal algorithms, that start from the same start node and use the same heuristic  $h$ ,  $A^*$  expands the minimum number of paths.

# Search: summary table

Uninformed

Informed

	complete?	optimal?	time $O()$	space $O()$
DFS	No	No	$b^m$	$mb$
BFS	Yes	Yes*	$b^m$	$b^m$
IDS	Yes	Yes*	$b^m$	$mb$
LCFS	Yes <sup>^</sup>	Yes <sup>^</sup>	$b^m$	$b^m$
BestFS	No	No	$b^m$	$b^m$
A*	Yes	Yes <sup>^+</sup>	$b^m$	$b^m$

\*Assuming arc costs are equal


<sup>^</sup> Assuming arc costs are positive

<sup>+</sup> Assuming  $h(n)$  is admissible

# ASIDE: History of $A^*$

- The algorithm was first published in 1968 at Stanford Research Institute as part of the Shakey project for Shakey's path planning.
- They started with Dijkstra's algorithm.
- Then created extensions  $A1$ ,  $A2$ , and then collectively named them as  $A^*$ .

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# Is $A^*$ the answer to all searching needs?

- Informed 
- Complete 
- Optimal 
- Optimally efficient 

For most problems, the number of states is still a problem; it is exponential in the length of the solution 😞. So **space** is still an issue.



# Branch and bound search (B&B)

- Follow exactly the same search path as depth-first search
  - Treat the frontier as a stack
  - Expand the most-recently added path first
- The order in which neighbours are added to the frontier can be governed by some arbitrary node-ordering approach
  - Assignment 1 specified alphabetical ordering
  - We could also use some ordering based on  $f$ -score

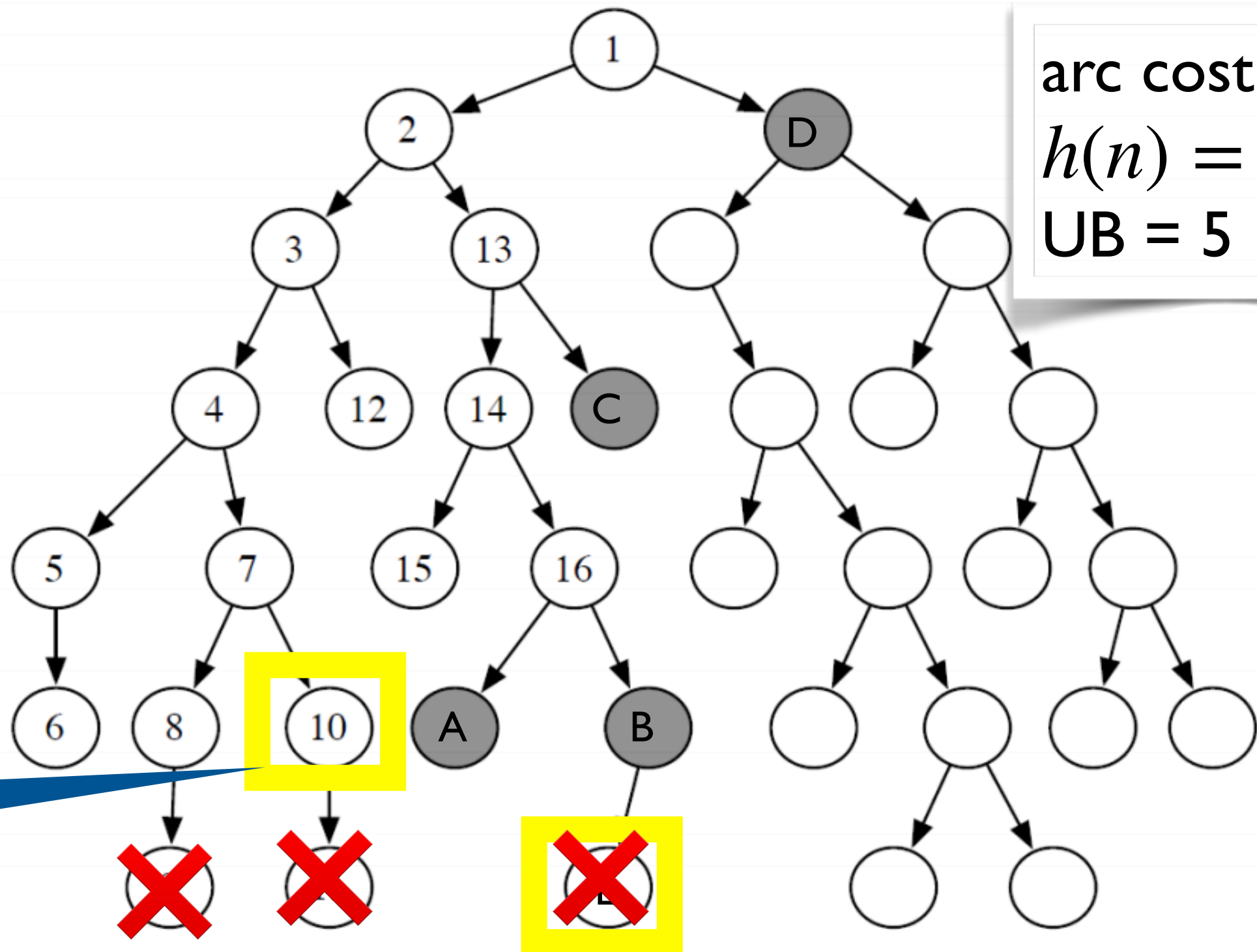
# B&B

- A way to combine DFS with heuristic guidance
- Follows exactly the same search path as DFS but to ensure optimality, it does not stop at the first solution found
- Then prune all paths encountered that have cost  $\geq$  the cost of the best solution so far

# B&B

- Keep track of a lower bound and upper bound on solution cost at each path.
- Lower bound:  $LB(p) = f(p) = cost(p) + h(p)$
- Upper bound:  $UB(p) = \text{cost of the best solution found so far}$
- Initialize  $UB = \infty$  or some overestimate of the solution cost
- When path  $p$  is selected for expansion, if  $LB(p) \geq UB$ , remove  $p$  from frontier without expanding it (pruning) else expand  $p$  adding all of its neighbours to the frontier.

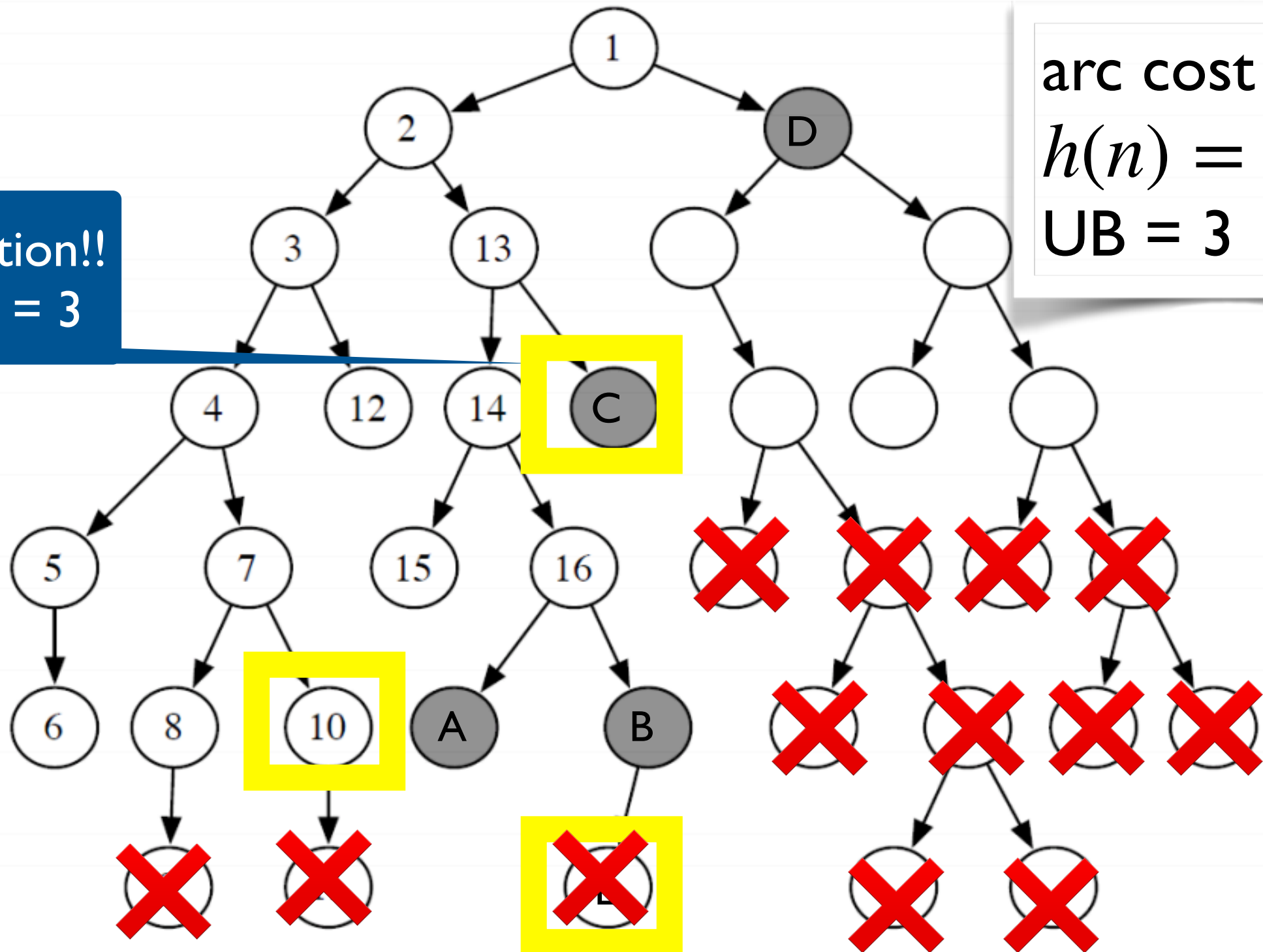
# Example: B&B



# Example: B&B

Solution!!  
UB = 3


arc cost = 1  
 $h(n) = 1 \forall n$   
UB = 3



# B&B



Once B&B has found a solution, what does it do next?


- A. Stop and return that solution
- B. Keep searching looking for deeper solutions
- C. Keep searching but only for shorter solutions 
- D. None of the above
- E. Create a start up with this novel algorithm

# B&B completeness

iclicker®

Is branch and bound complete?

A. Yes

B. No 

# B&B completeness

- Not in general, for the same reasons that DFS isn't complete.
- But complete if initialized with some finite upper bound (an overestimate of the solution cost).
- For many problems of interest there are no infinite paths and no cycles.
- Hence, for many problems B&B is complete.



# B&B optimality



Is branch and bound optimal?


A. Yes 

B. No

# B&B time and space complexity

- Time complexity:  $O(b^m)$
- Space complexity:  $O(mb)$  like DFS!
- Big improvement over  $A^*$

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# Other A\* tricks

The primary problem with A\* is that in the worst case, it uses exponential space. Branch and bound is a way around this problem. Are there other ways?

- Iterative Deepening A\* (IDA\*)
- Memory-bounded A\*

# Heuristic iterative deepening (IDA\*)

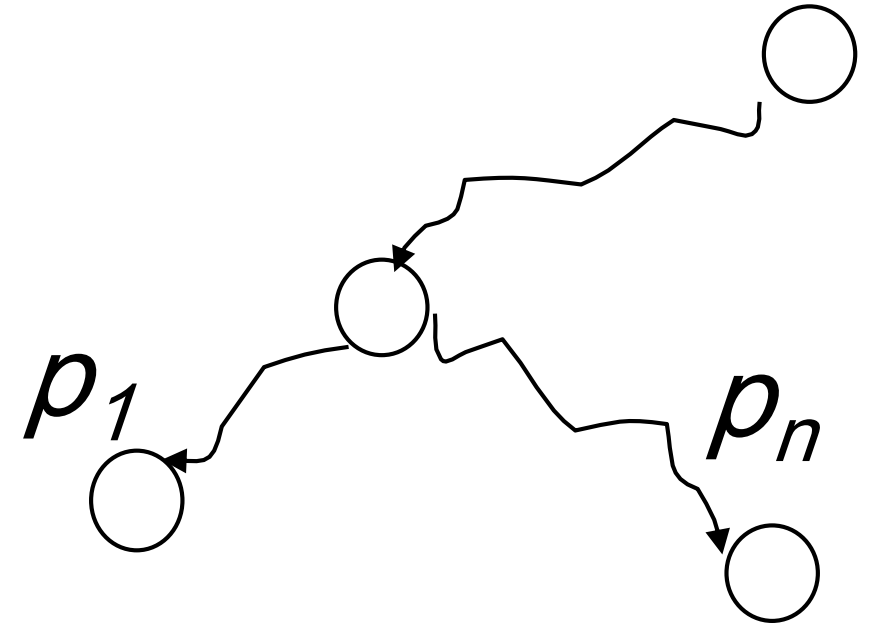
- Branch and bound improves over A\* but it can still get stuck in infinite (extremely long) paths
- Search depth-first but to a fixed depth/bound
- Depth is measured in  $f$ -values
- If you do not find a solution, update the bound with the lowest  $f$  that passed the previous bound and try again

# Analysis of IDA\*

- Complete and optimal? Same conditions as A\*
  - the branching factor is finite
  - arc costs are  $> \epsilon > 0$
  - $h(n)$  is admissible
- Space complexity?  $O(mb)$  😊
- Time complexity?  $O(b^m)$

# Memory-bounded A\*

- IDA\* and B&B use a tiny amount of memory  
What if we have more memory available?  
Keep as much of the frontier in memory as we can
- If we have to delete something:
  - delete the “worst” paths (with highest f-values.)
  - “back them up” to a common ancestor
- Update the heuristic value of the ancestor if possible




# Analysis of MBA\*

- Complete?  
Yes, as long as there is enough memory to store the solution
- Optimal?  
Yes, if  $h$  is admissible and if there is enough memory to store the solution
- Space complexity?  $O(b^m)$
- Time complexity?  $O(b^m)$



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# Class activity (10 mins)


Analysis of search methods and teaching feedback

	selection	complete?	optimal?	time $O()$	space $O()$
DFS					
BFS					
IDS					
LCFS					
BestFS					
A*					
B&B					
IDA*					
MBA*					

# Search strategies: summary

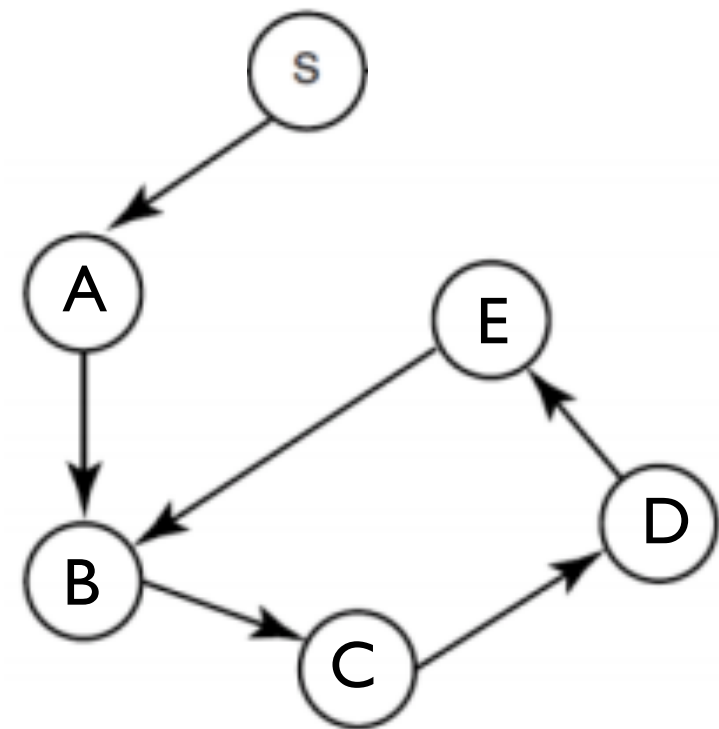
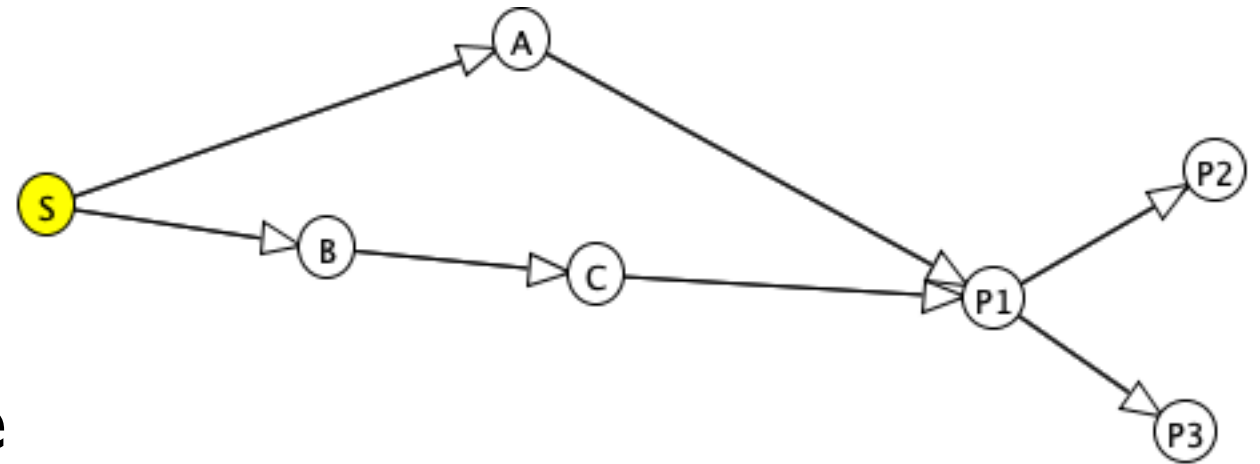
	Method	Selection	Complete	Optimal	Time $\mathcal{O}()$	Space $\mathcal{O}()$
Uninformed	<b>DFS</b>	LIFO	N (Y if no cycles)	N	$b^m$	$mb$
	<b>BFS</b>	FIFO	Y	Y	$b^m$	$b^m$
	<b>IDS</b>	LIFO	Y	Y	$b^m$	$mb$
	<b>LCFS</b> (when arc costs available)	min cost	Y (if costs $> 0$ )	Y (if costs $\geq 0$ )	$b^m$	$b^m$
informed	<b>BestFS</b> (When $h$ available)	min $h$	N	N	$b^m$	$b^m$
	<b>A*</b> (when arc costs and $h$ available)	min $f$	Y if branching factor finite, $h$ is admissible, and costs $> 0$	Y if branching factor finite, $h$ is admissible, and costs $> 0$	$b^m$	$b^m$
	<b>Branch and Bound</b>	LIFO + pruning	N (Y UB finite)	Y	$b^m$	$mb$
	<b>IDA*</b>	LIFO	Y (same as A*)	Y	$b^m$	$mb$
	<b>MBA*</b>	min $f$	Y if enough memory	Y if enough memory and $h$ is admissible	$b^m$	$b^m$

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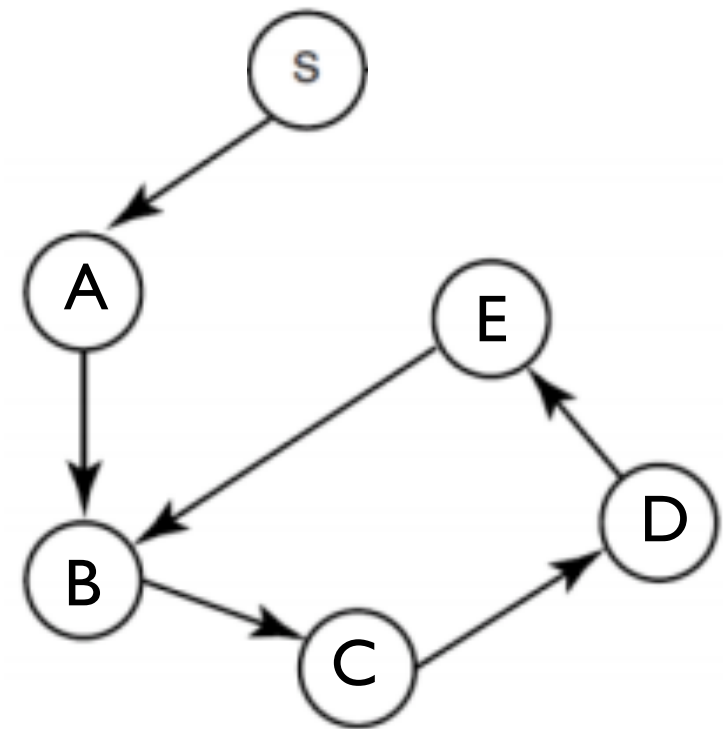
# Pruning: if we only want optimal solutions

- Often there are multiple paths to a node and we only need one path.
- The search algorithms we have seen so far can be improved using pruning strategies
- Cycle pruning: Avoid using paths with cycles
- Multiple-path pruning: Only consider one path to a node and prune all other paths



# Cycle checking

- Ensure that the algorithm does not consider neighbours that are already on the path from the start.
- Check whether the last node on the path already appears earlier on the path from the start node to that node.
- What is the computational cost of cycle checking?



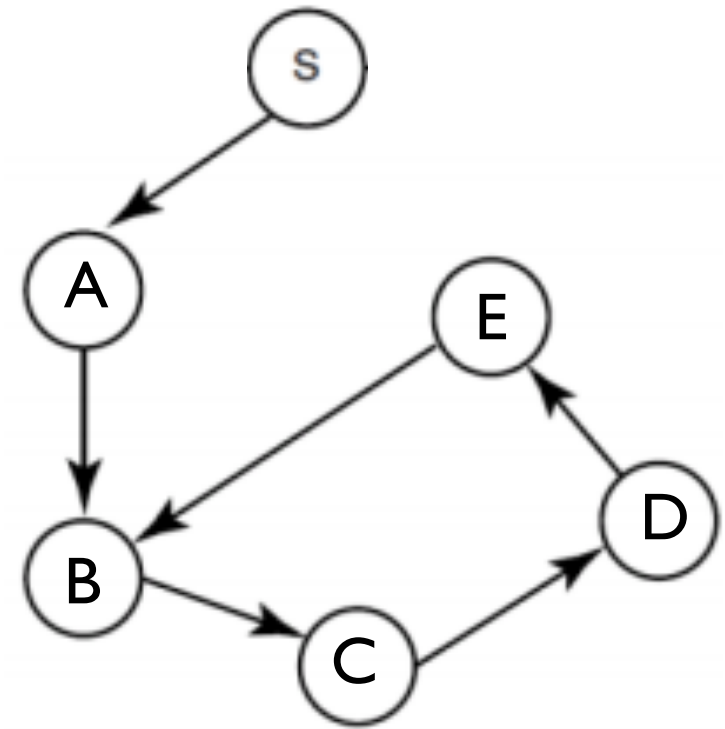
[<S,A,B,C,D,E>]

[<S,A,B,C,D,E,**B**>]

Do not add the path on the frontier.

# Cycle checking

- What is the computational cost of cycle checking?
- In general, linear in path length.



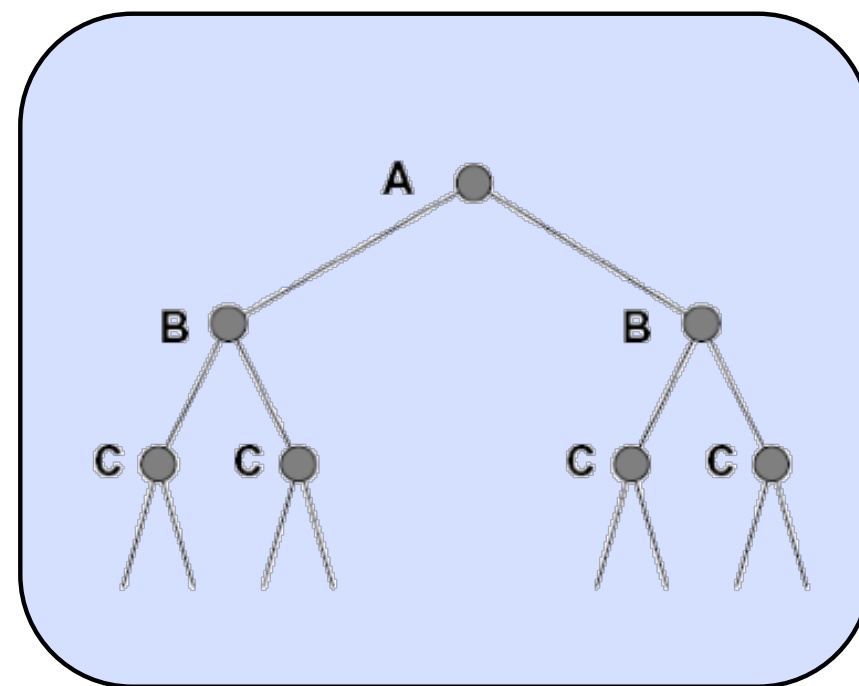
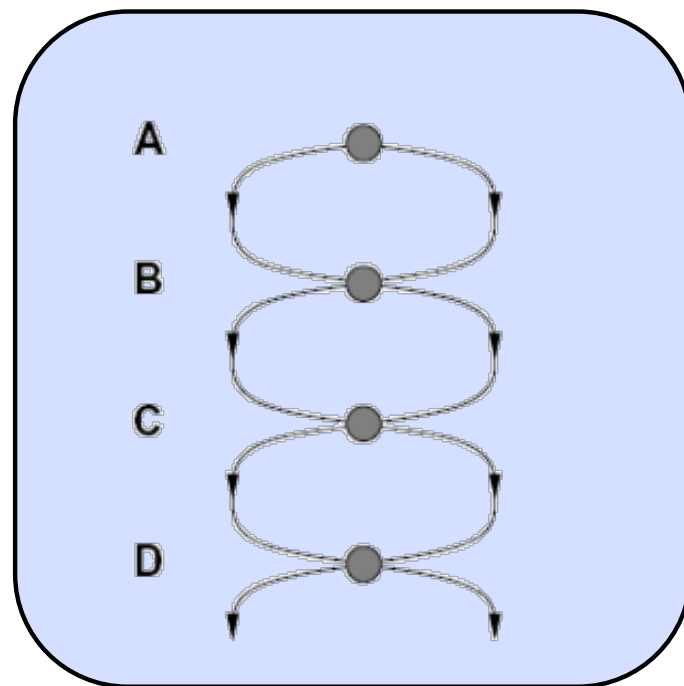
[<S,A,B,C,D,E>]

Do not add the path on the frontier.

[<S,A,B,C,D,E,**B**>]

# Repeated states/multiple paths

Failure to detect repeated states can turn a linear problem into an exponential one!

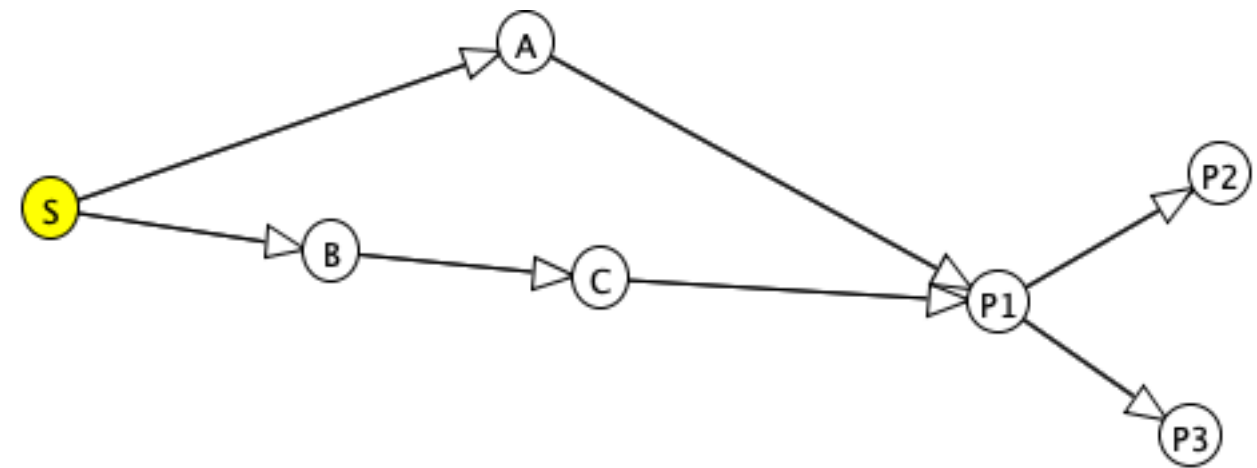


State space: 2 actions from each state to the next with  $d+1$  states, search tree has depth  $d$  and there are  $2^d$  possible paths.



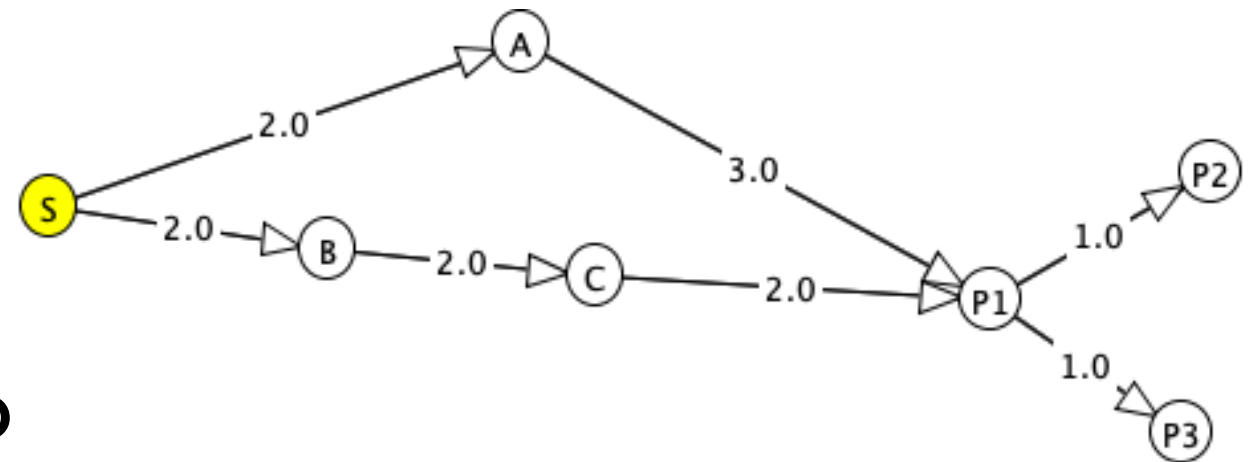
# Multiple path pruning

- The search algorithm can prune from the frontier any path that leads to a node to which it already has found paths.
- Implemented by **maintaining an explored set** (also called closed list), which is empty at the beginning, and is populated with the last node on the selected paths from the frontier.



# Multiple path pruning

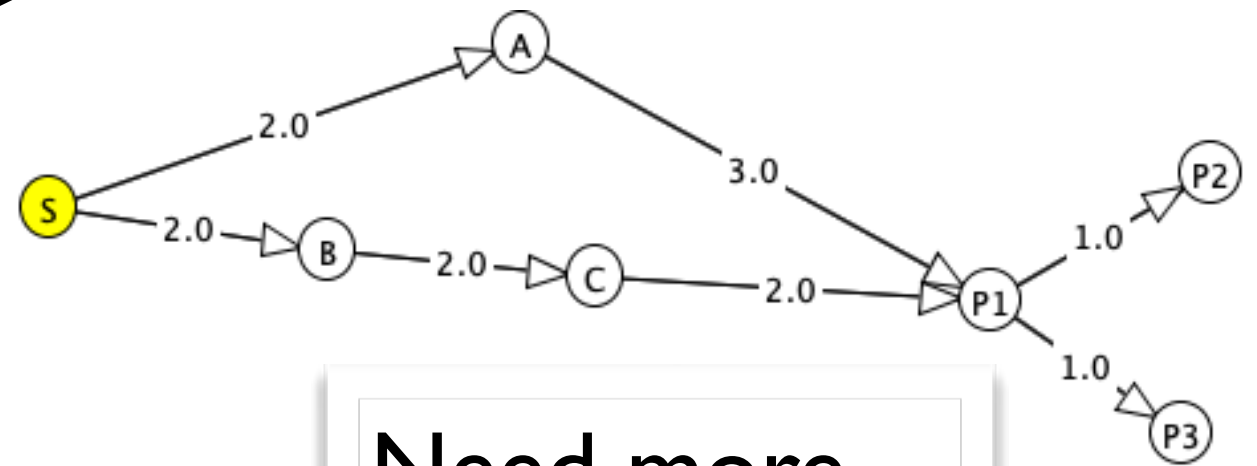
- Maintain an explored set.
- When a path  $\langle n_0, n_1, \dots, n_k \rangle$  is selected from the frontier, check if  $n_k$  is already in the explored set.
- If yes, it can be discarded. If no we add  $n_k$  to the explored set.



Does this method guarantee that the least-cost path is not discarded?

# Multiple path pruning

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Need more  
sophisticated  
approaches

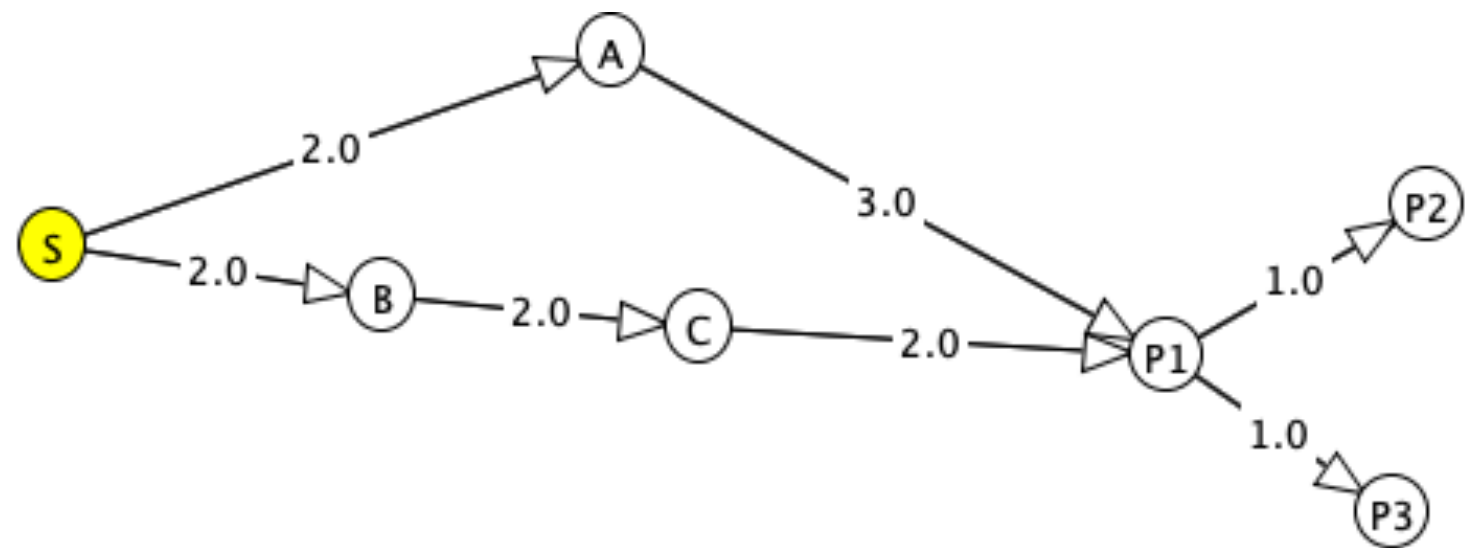
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# Multiple path pruning

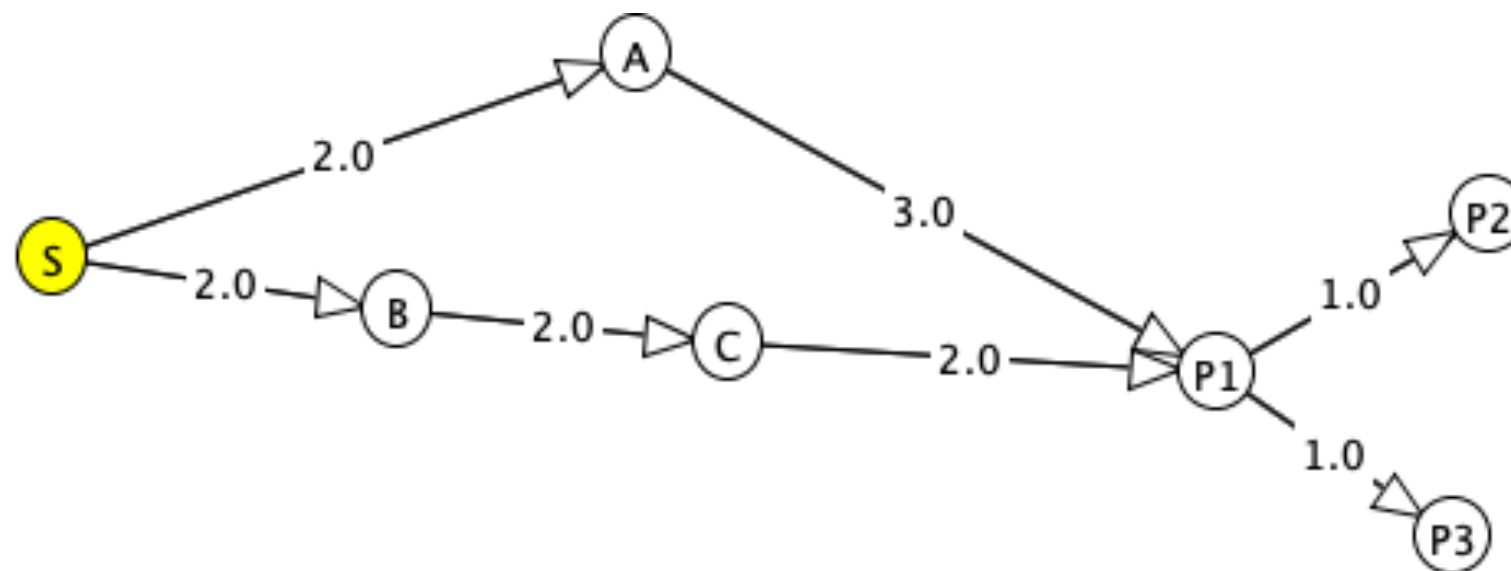
Approach 1: Make sure that the first path found to any node is a lowest-cost path to that node, then prune all subsequent paths found to that node.

Works for LCFS  
but not for A\*



# Multiple path pruning

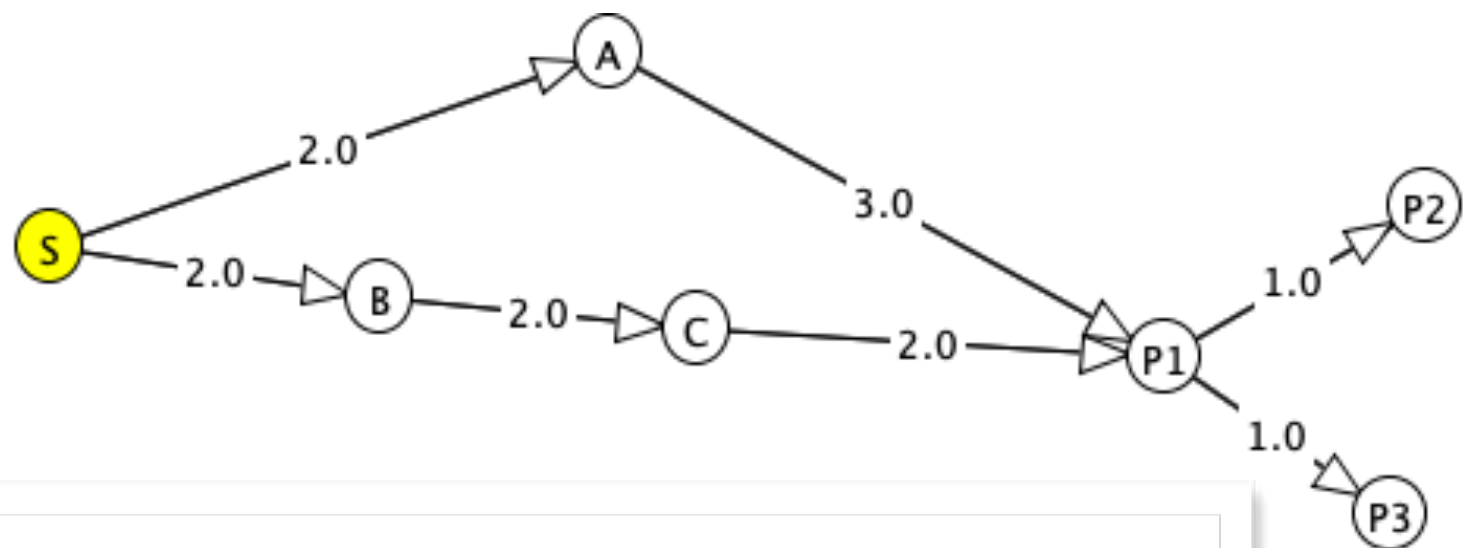
Approach 2: If the search algorithm finds a lower-cost path to a node than one already found, it could remove all paths that used the higher-cost path to the node because they cannot be on an optimal solution.



If  $cost(p) < cost(p')$ , remove all paths from the frontier with prefix  $p'$

# Multiple path pruning

Approach 3: Whenever the search finds a lower-cost path to a node than a path to that node already found, change the initial segment of the paths on the frontier to use the lowest-cost path.

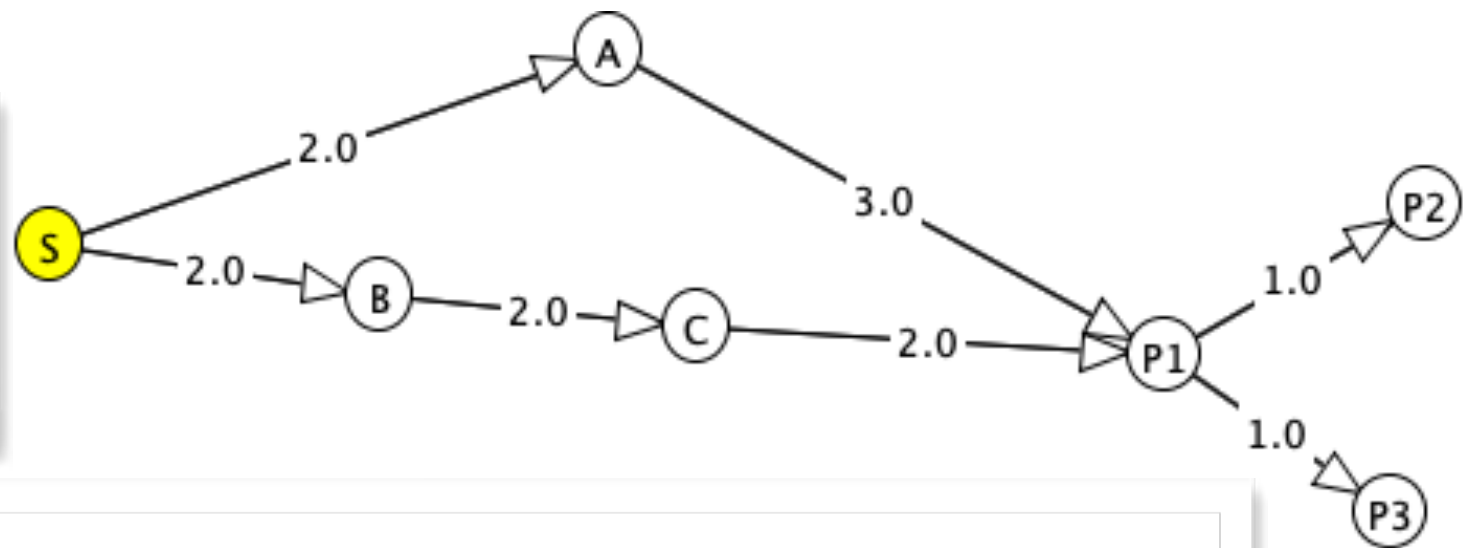


If  $cost(p) < cost(p')$ , replace prefixes in those paths (replace  $p'$  with  $p$ )

# Multiple path pruning

Approach 3: Whenever the search finds a lower-cost path to a node than a path to that node already found, change the initial segment of the paths on the frontier to use the lowest-cost path.

Would it guarantee optimality for A\*?

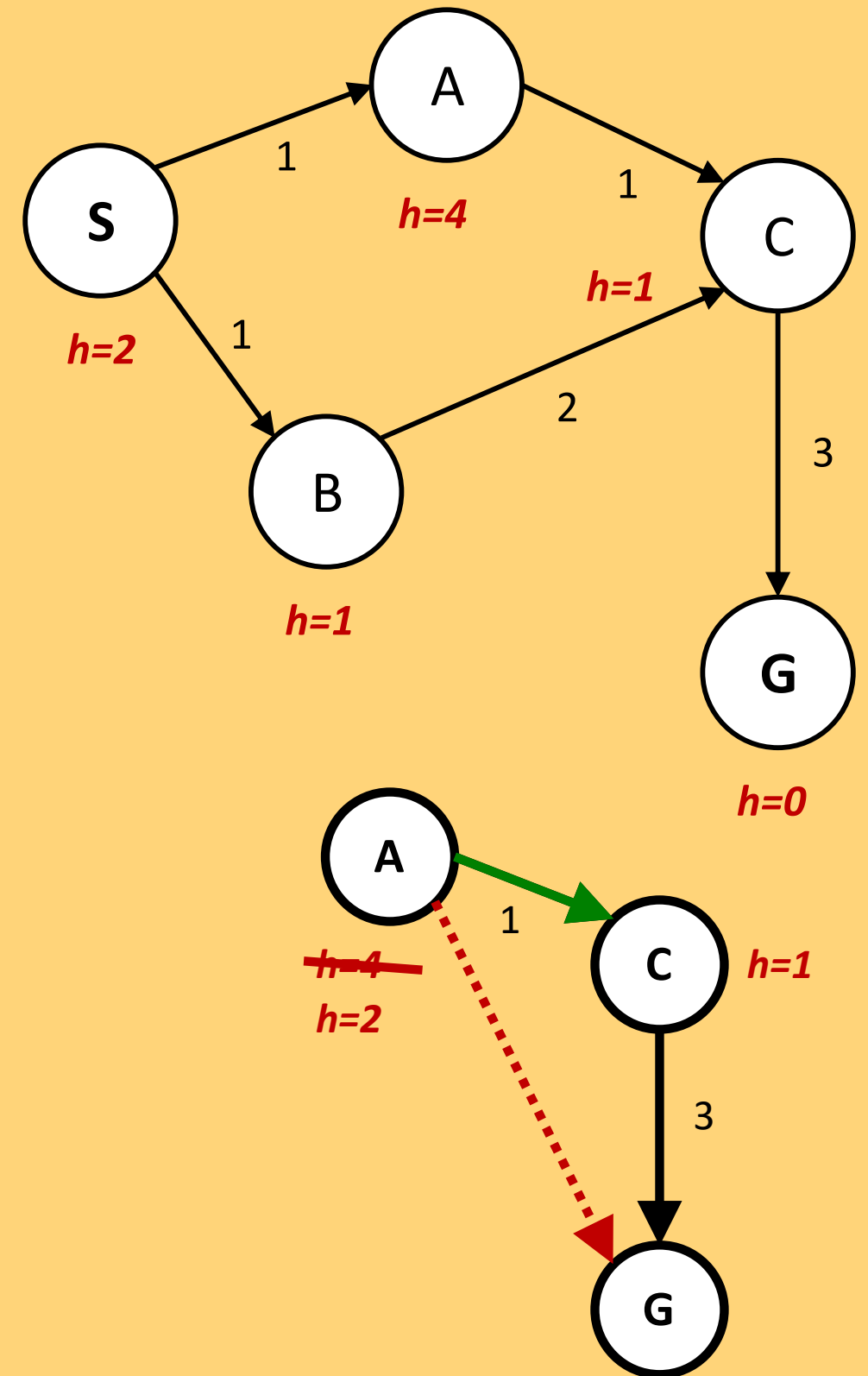


If  $cost(p) < cost(p')$ , replace prefixes in those paths (replace  $p'$  with  $p$ )

# ASIDE: Consistency of heuristics


Main idea: estimated heuristic cost  $\leq$  actual cost

- Admissibility: heuristic cost  $\leq$  actual cost to goal
  - $h(A) \leq$  actual cost from A to G
- Consistency: heuristic “arc” cost  $\leq$  actual cost for each arc
  - $h(A) - h(C) \leq \text{cost}(A \text{ to } C)$
- The f value along a path never decreases
  - $h(A) \leq \text{cost}(A \text{ to } C) + h(C)$





# Lecture outline

- Recap from last lecture (~10 mins)
- $A^*$  analysis (~15 mins)
- Branch and bound (~10 mins)
- $A^*$  enhancements (~5 mins)
- Class activity (~10 mins)
- Pruning (~15 mins)
- **Summary and wrap-up (~5 mins)** 

# Revisiting learning outcomes for search

Important for exams

- Identify real world examples that make use of deterministic, goal-driven search agents
- Assess the size of the search space of a given search problem.
- Implement the generic solution to a search problem.
- Apply basic properties of search algorithms: completeness, optimality, time and space complexity
- Select the most appropriate search algorithms for specific problems.

# Revisiting learning outcomes for search

Important for exams

- Define/read/write/trace/debug different search algorithms
- Construct heuristic functions for specific search problems
- Formally prove  $A^*$  optimality.
- Define optimally efficient

# A rough CPSC 322 overview

Representation  
and reasoning

Environment

Deterministic

Stochastic

Problem

Constraint  
satisfaction

Static

Query

Sequential

Planning

STRIPS

Search

Search is  
everywhere!

Arc consistency

Variables +  
constraints

Search

Logics

Search

Belief networks

Variable elimination

Decision networks

Variable elimination

Markov decision  
processes

Value iteration

# Coming up

- Submit your assignment on Sept. 30
- Start Constraint Satisfaction Problems (Chapter 4)

