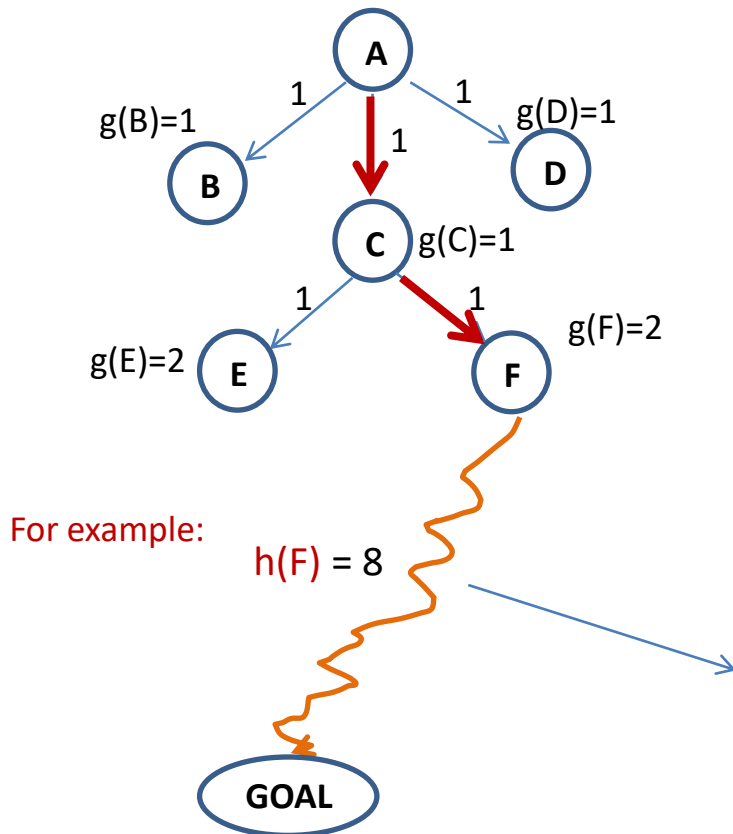


Heuristic

Informed (heuristic) search: one that uses problem-specific knowledge to guide search.

Heuristic function: *A rule of thumb, simplification, or educated guess that reduces or limits the search for solutions in domains that are difficult and poorly understood*



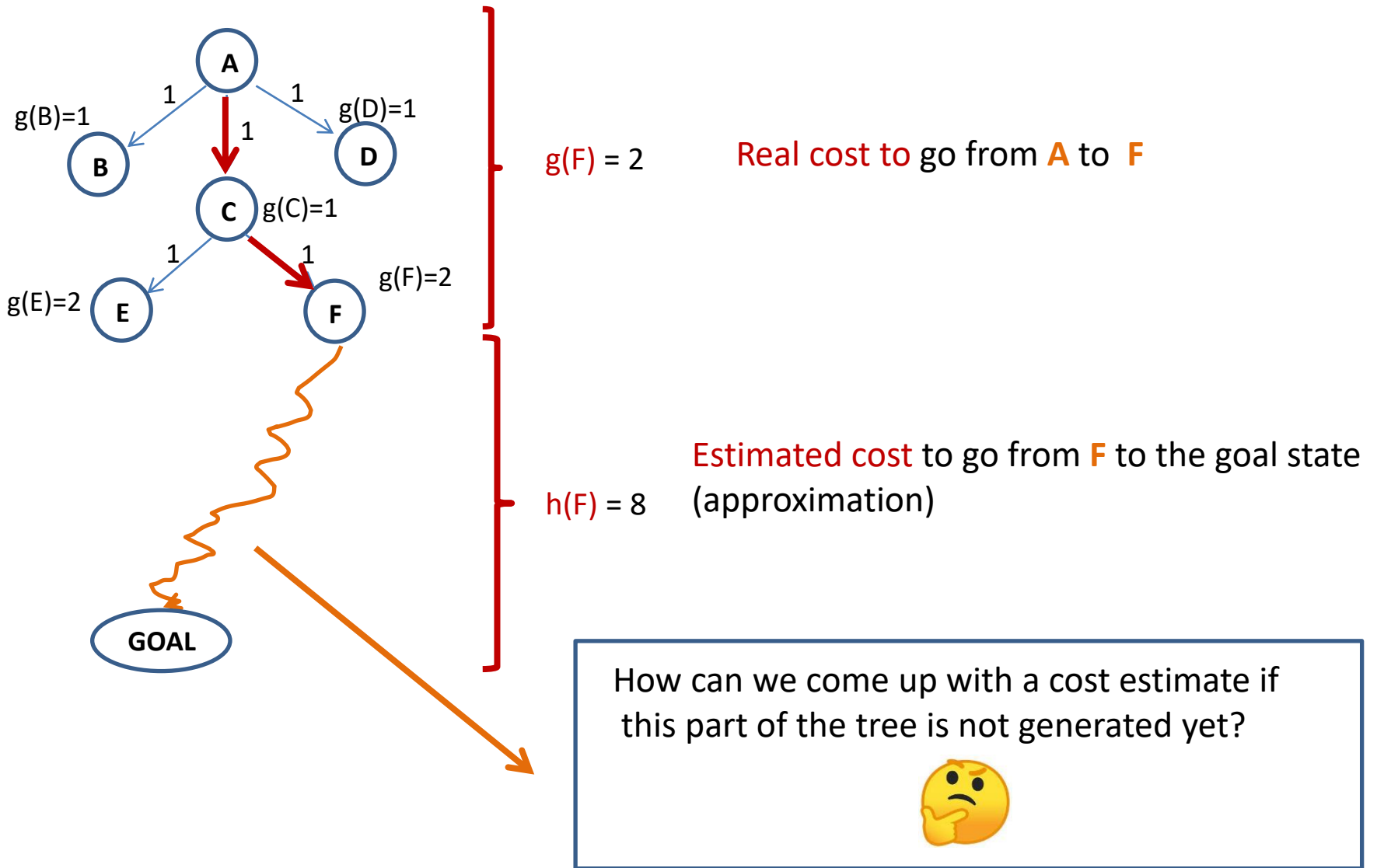
$g(n)$: cost function (the cost of a path from A to n)

$g(F) = 2$ because all operators have cost = 1

$h(n)$: heuristic function → function that **estimates** the cost of a node **n** to a GOAL node.

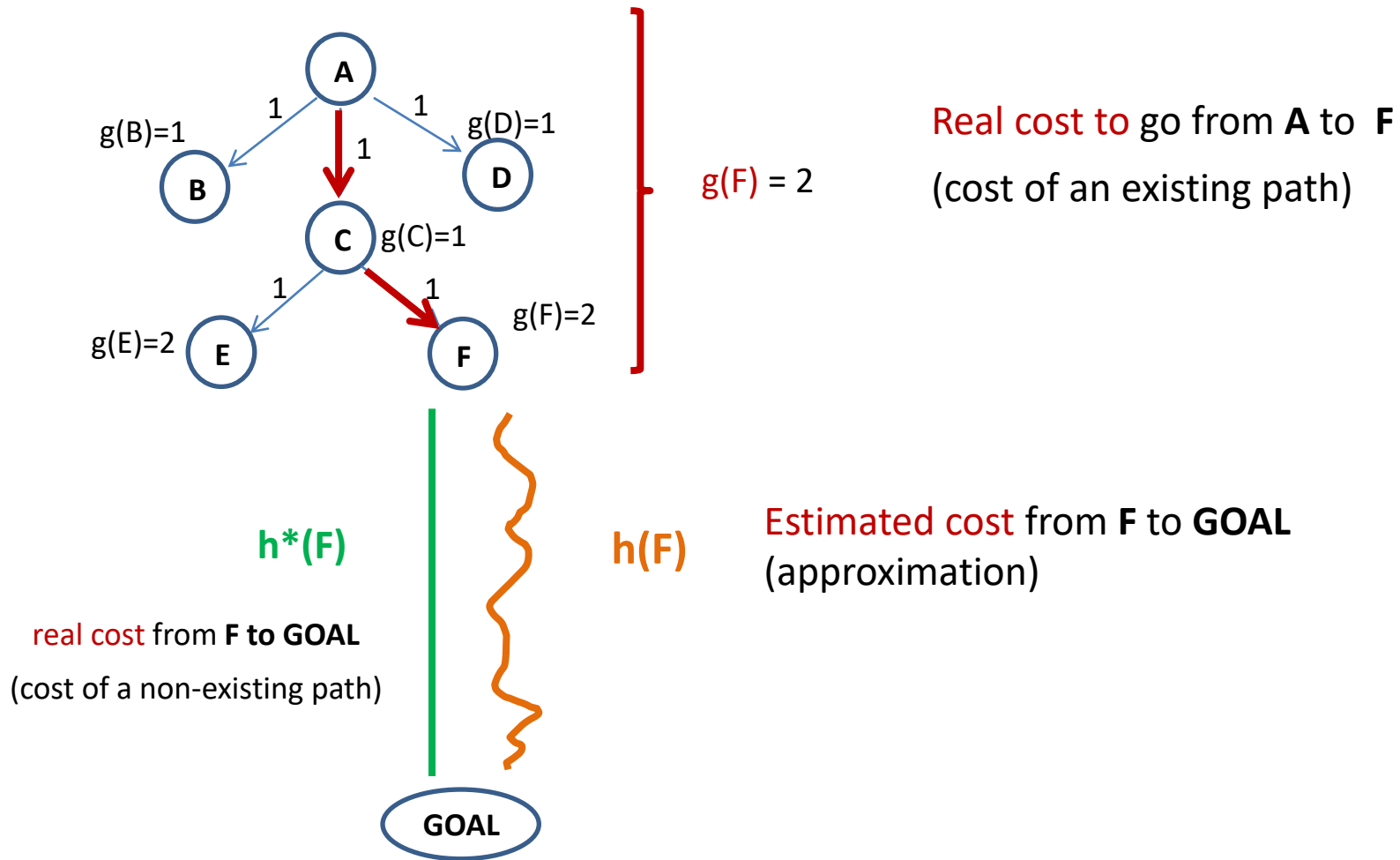
It means there is an estimation that the cost of the optimal path from **F** to **GOAL** is 8
(8 moves or operators because all operators have the same cost = 1)

Heuristic



Exploiting problem-specific knowledge

In summary ...



In summary

It always holds $\forall n \ h(n) \leq h^*(n)$

$h(n)$ is called an **admissible heuristic**

Reminder

we know that if it always holds $\forall n \ h(n) \leq h^*(n)$

$h(n)$ is called an **admissible heuristic**

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

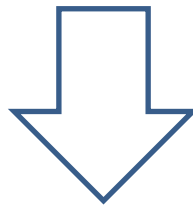


A algorithm

if $h(n)$ is **admissible**



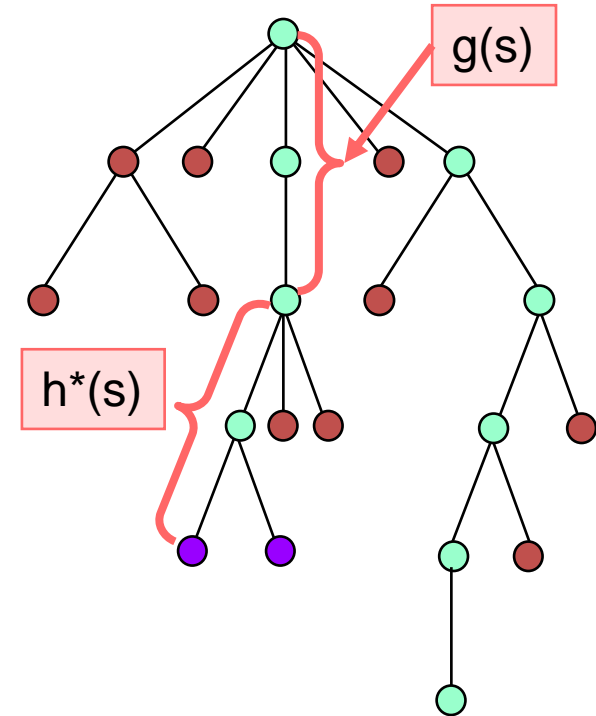
A* algorithm



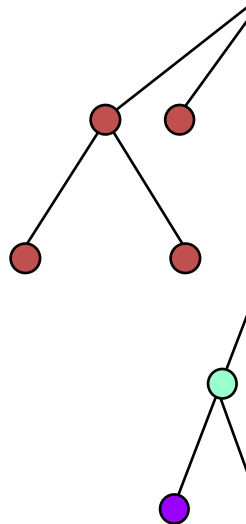
guarantees OPTIMAL SOLUTION

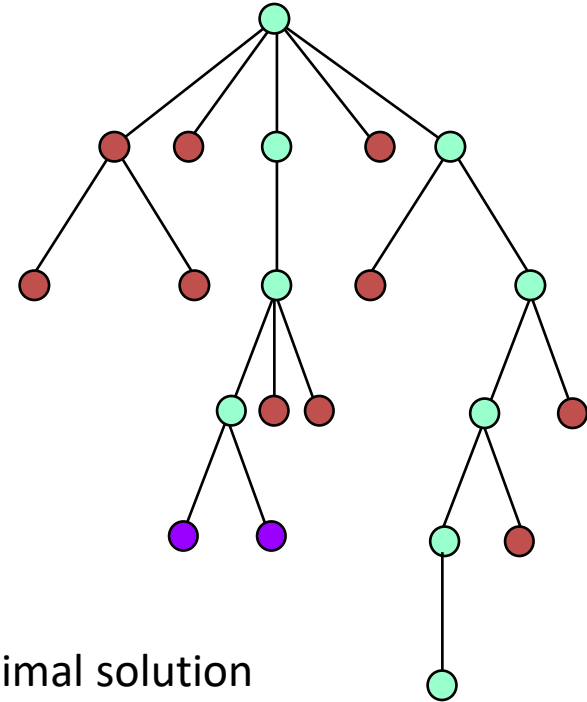
Node-Selection Heuristic

- Suppose we're searching a **tree** in which each edge (s,s') has a cost $c(s,s')$
 - If p is a path, let $c(p)$ = sum of the edge costs
 - For classical planning, this is the length of p
 - For every state s , let
 - $g(s)$ = cost of the path from s_0 to s
 - $h^*(s)$ = least cost of all paths from s to goal nodes
 - $f^*(s) = g(s) + h^*(s)$ = least cost of all paths from s_0 to goal nodes that go through s
 - Suppose $h(s)$ is an estimate of $h^*(s)$
 - Let $f(s) = g(s) + h(s)$
 - $f(s)$ is an estimate of $f^*(s)$
 - h is *admissible* if for every state s , $0 \leq h(s) \leq h^*(s)$
 - If h is admissible then f is a lower bound on f^*
-

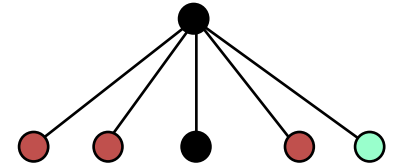


The A* Algorithm

- A* on trees:
 - loop
 - choose the leaf node s such that $f(s)$ is smallest
 - if s is a solution then return it and exit
 - expand it (generate its children)
 - On graphs, A* is more complicated
 - additional machinery to deal with multiple paths to the same node
 - If a solution exists (and certain other conditions are satisfied), then:
 - If $h(s)$ is admissible, then A* is guaranteed to find an optimal solution
 - The more “informed” the heuristic is (i.e., the closer it is to h^*), the smaller the number of nodes A* expands
 - If $h(s)$ is within c of being admissible, then A* is guaranteed to find a solution that’s within c of optimal
- 



The FastForward Planner



- Use a heuristic function similar to $h(s) = \Delta^g(s, g)$
 - Some ways to improve it (I'll skip the details)
- Don't want an A*-style search (takes too much memory)
- Instead, use a greedy procedure:

until we have a solution, do

expand the current state s

$s :=$ the child of s for which $h(s)$ is smallest

(i.e., the child we think is closest to a solution)

The FastForward Planner

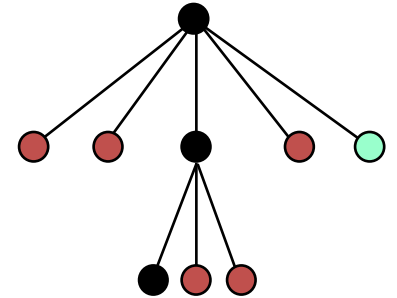
- Use a heuristic function $h(s)$ = relaxed plan
- Don't want an A*-style search (takes too much memory)
- Instead, use a greedy procedure:

until we have a solution, do

expand the current state s

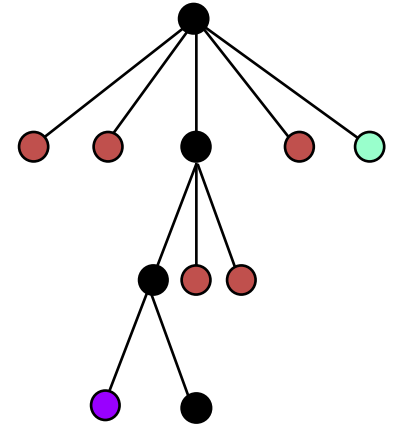
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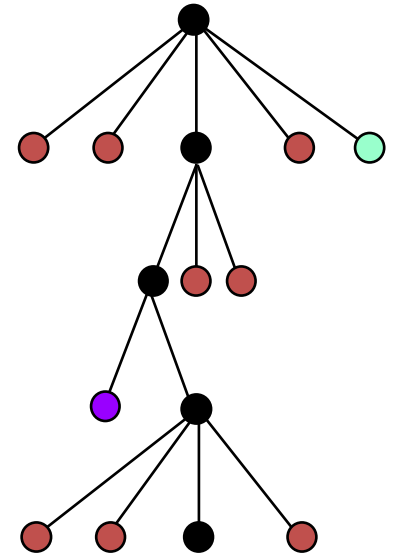
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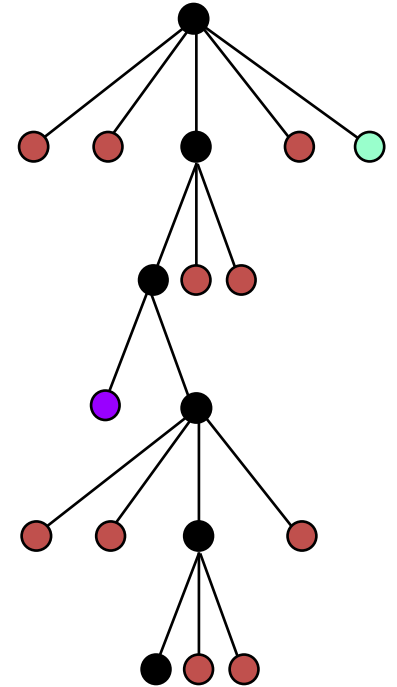


The FastForward Planner

- Use a heuristic function $h(s)$ = relaxed plan
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The FastForward Planner



- Use a heuristic function similar to $h(s) = \text{relaxed plan}$
- Don't want an A*-style search (takes too much memory)
- Instead, use a greedy procedure:
 - until we have a solution, do
 - expand the current state s
 - $s := \text{the child of } s \text{ for which } h(s) \text{ is smallest}$
(i.e., the child we think is closest to a solution)
- There are some ways FF improves on this
 - e.g. a way to escape from local minima
 - breadth-first search, stopping when a node with lower cost is found
- Can't guarantee how fast it will find a solution, or how good a solution it will find
 - However, it works pretty well on many problems