

# CS 561 Artificial Intelligence

## Lecture #

### SOLVING PROBLEMS BY SEARCHING INFORMED SEARCH

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Department of Computer Science & Engineering

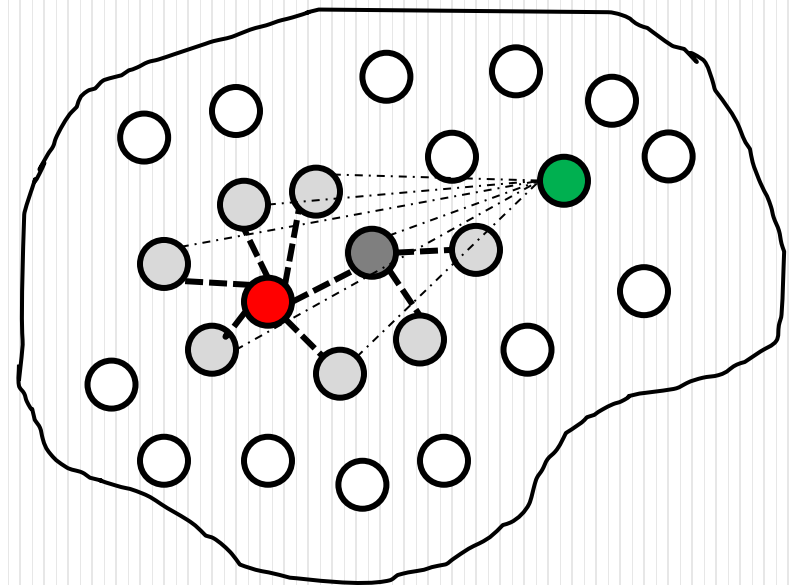
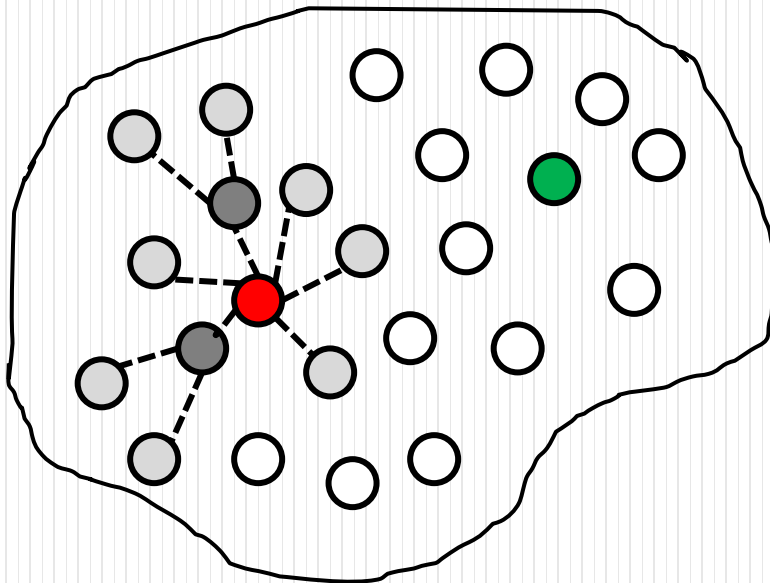
IIT Guwahati

# OUTLINE

- Informed (Heuristic) Search
  - Greedy Best-first Search
  - A\* Search
  - Iterative Deepening A\* (IDA\*)
  - Recursive Best First Search (RBFS)
- More about heuristics
- Applications

# INFORMED SEARCH STRATEGIES

Uses problem-specific knowledge beyond the definition of the problem itself



# BEST-FIRST SEARCH

- **Idea:** use an **evaluation function**  $f(n)$  for each node
  - $f(n)$  provides an estimate for the total cost.
    - Expand the node  $n$  with smallest  $f(n)$ .
    - Choice of  $f$  determines the search strategy
- **Implementation:**
  - Order the nodes in frontier by  $f(n)$  (lowest  $f(n)$  first)
- Special cases:
  - **greedy best-first search**
  - **$A^*$  search**

Evaluation function is an estimate of node quality.

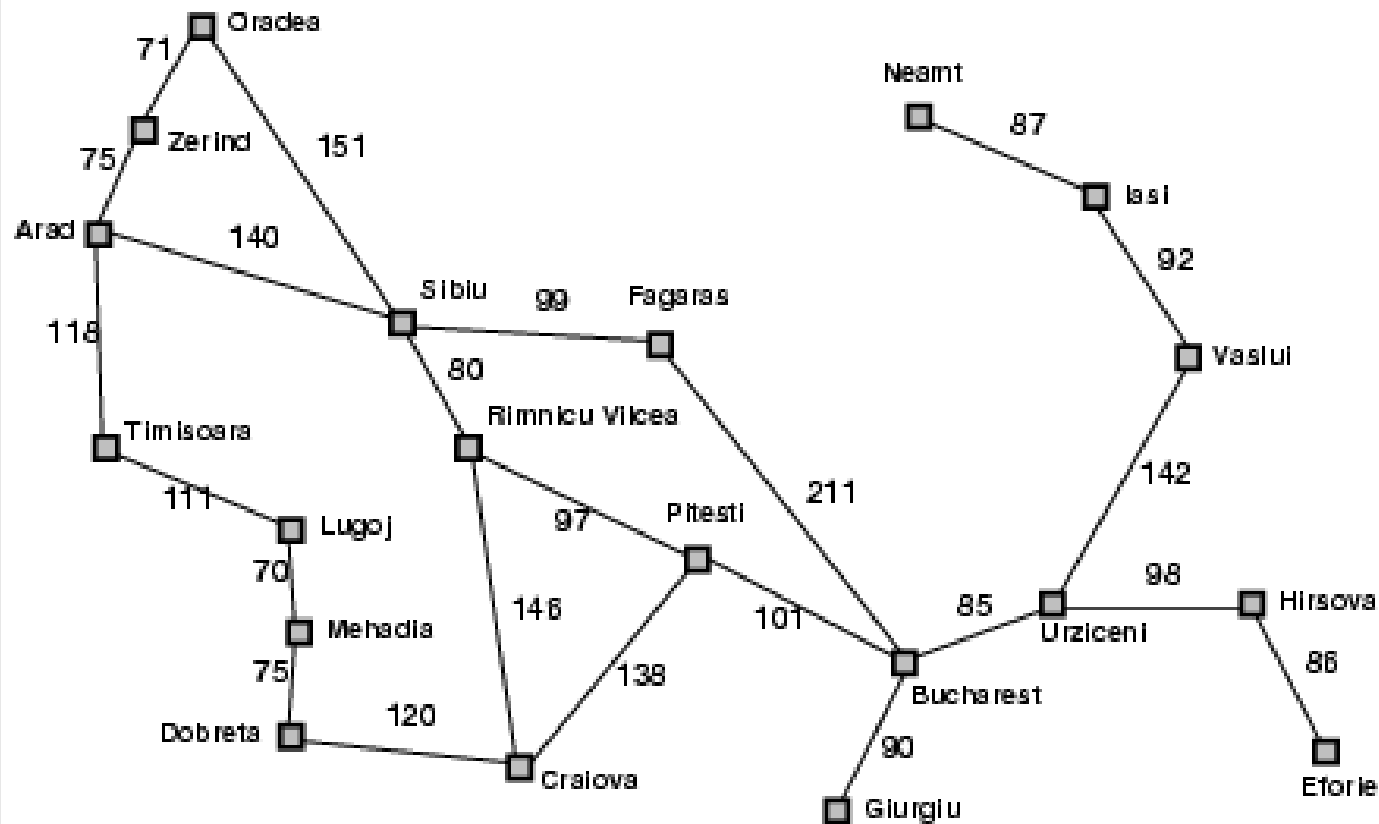
# HEURISTIC FUNCTION

- $f(n)$  consists of a heuristic function, denoted by  $h(n)$
- Heuristic: “using rules of thumb to find answers”
- **Heuristic function  $h(n)$** 
  - Non-negative and problem-specific function
  - Estimate of (optimal) cost from  $n$  to goal
  - $h(n) = 0$  if  $n$  is a goal node

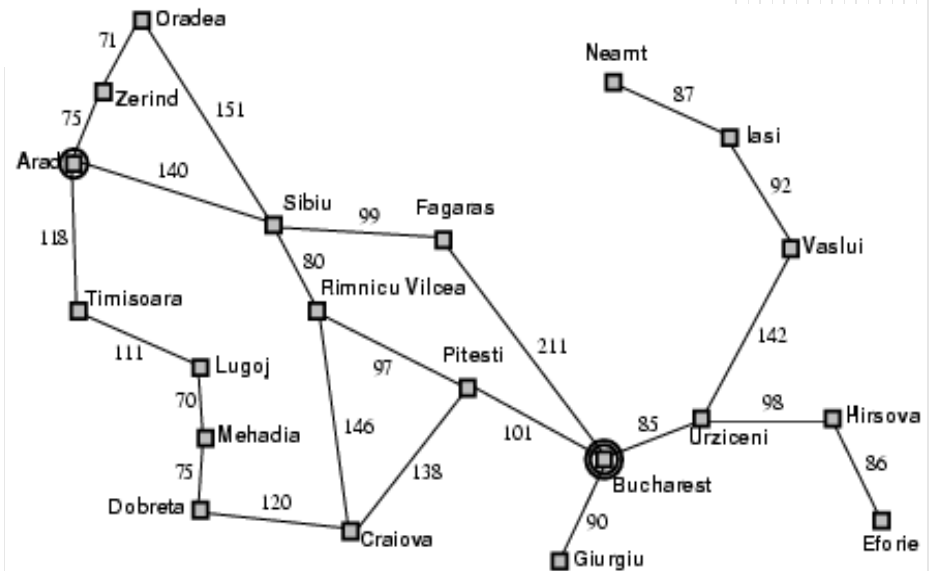
# GREEDY BEST-FIRST SEARCH

- Special case of best-first search
  - Uses  $h(n)$  = heuristic function as its evaluation function
    - Example: **straight line distance from n to Bucharest.**
- Expand the node that appears closest to goal

# ROMANIA EXAMPLE

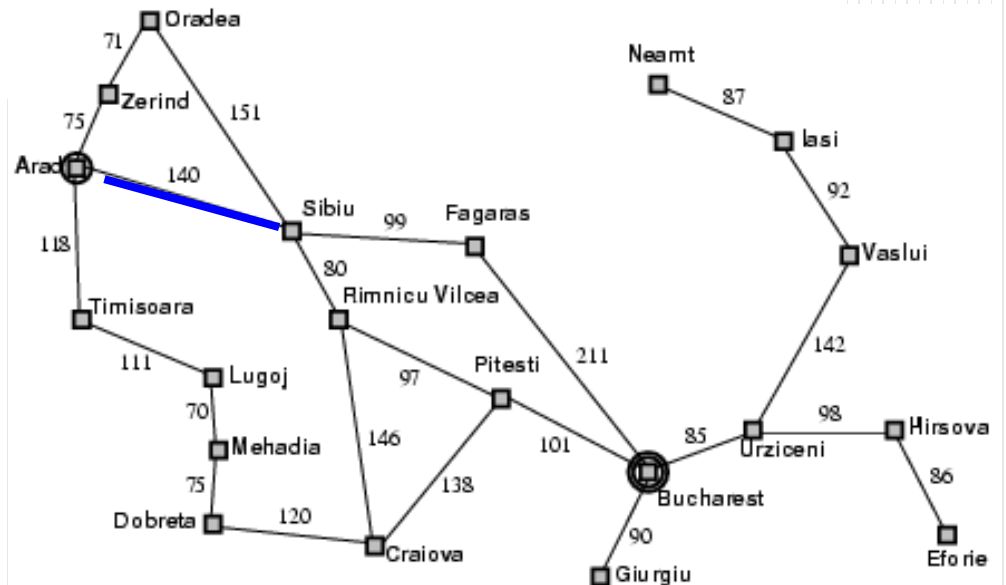


# GREEDY BEST-FIRST SEARCH EXAMPLE

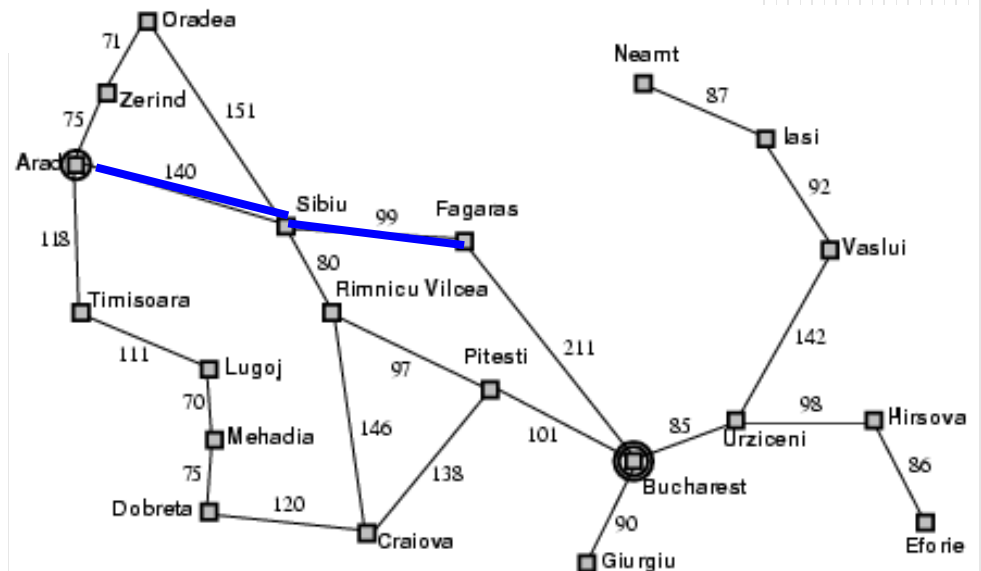
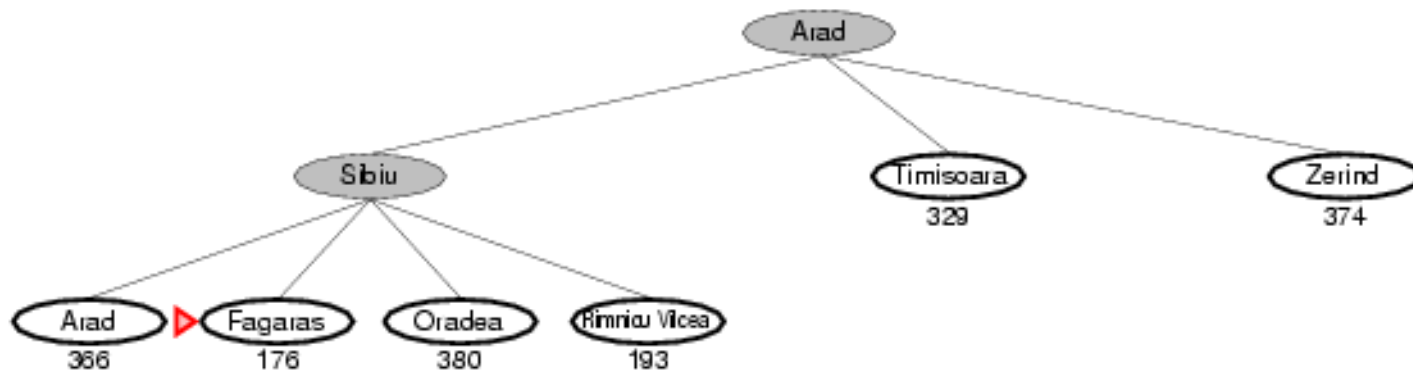




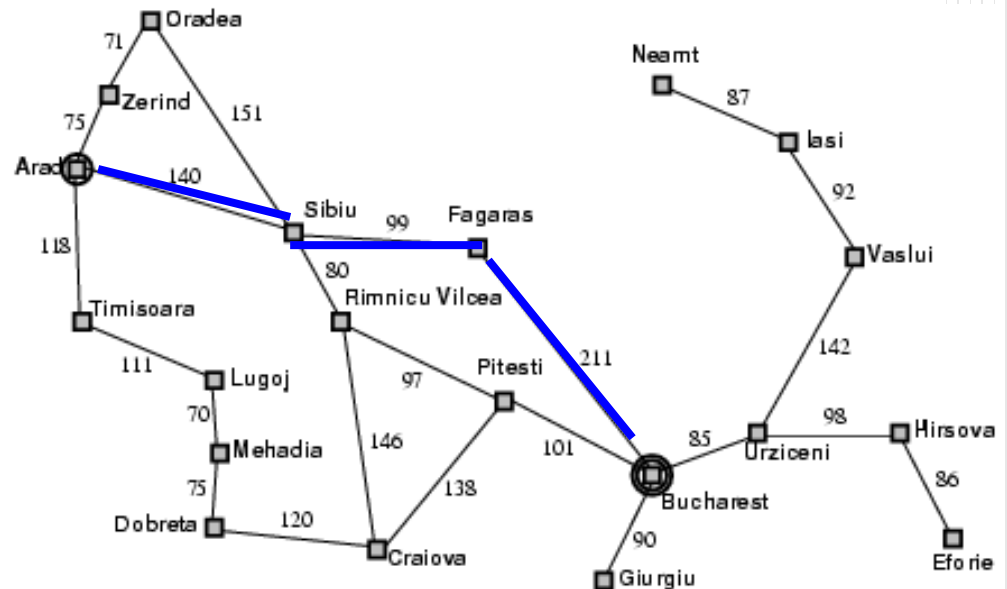
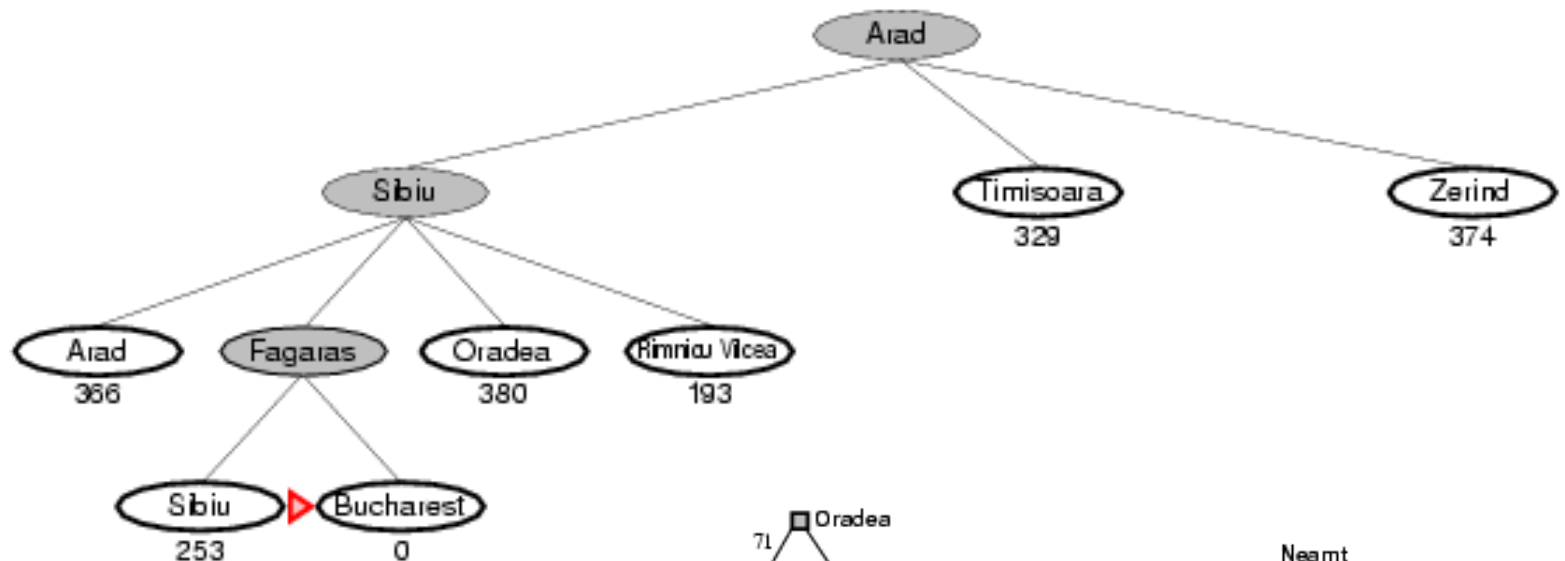
# GREEDY BEST-FIRST SEARCH EXAMPLE



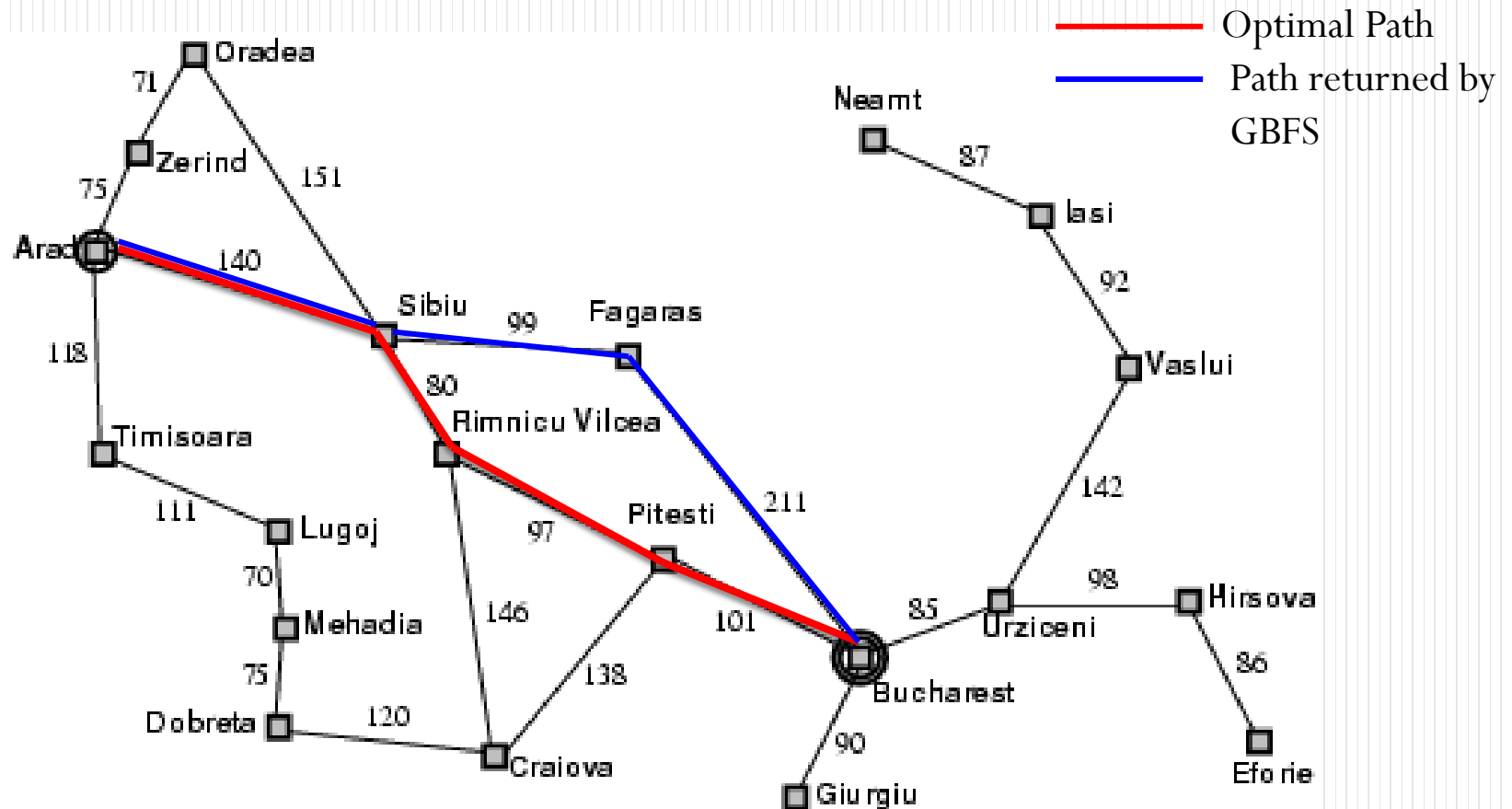
# GREEDY BEST-FIRST SEARCH EXAMPLE



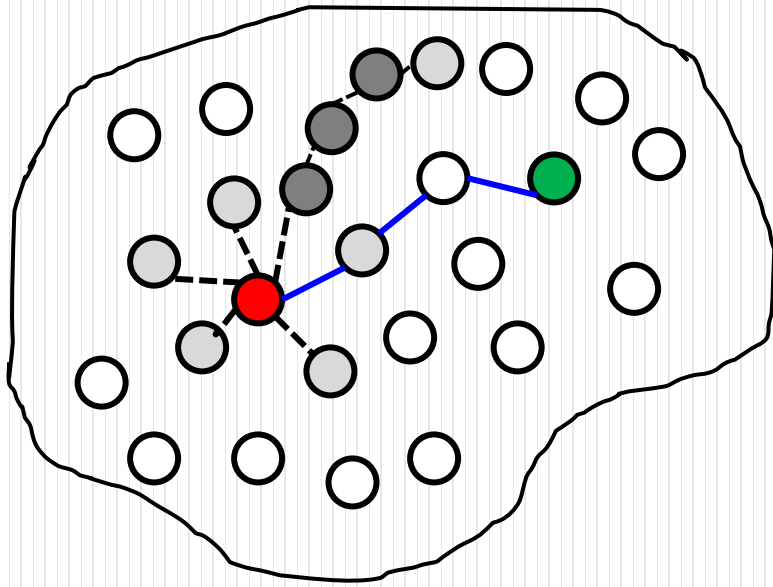
# GREEDY BEST-FIRST SEARCH EXAMPLE



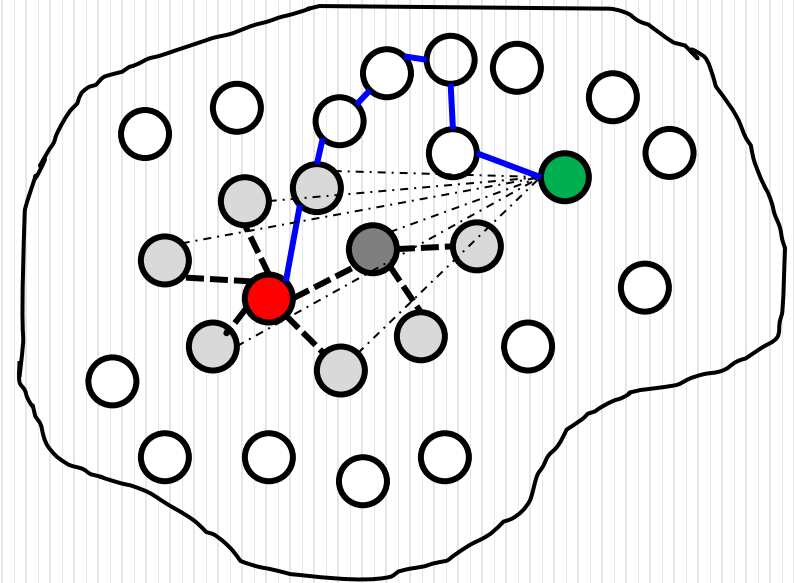
# Optimal Path







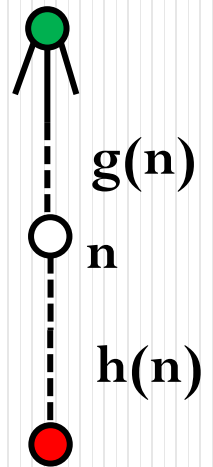
Uniform cost search  $f(n) = g(n)$



Greedy Best First Search  $f(n) = h(n)$

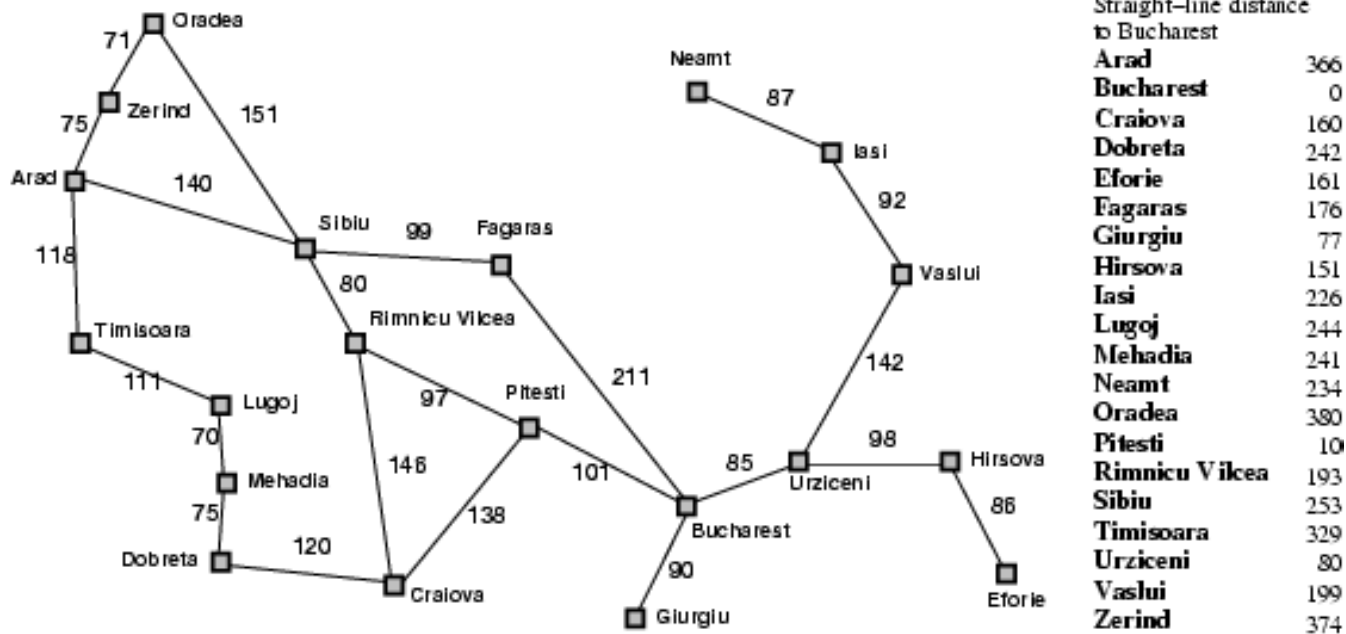
# A\* SEARCH

- Expand node based on estimate of total path cost through node
- Evaluation function  $f(n) = g(n) + h(n)$ 
  - $g(n)$  = cost so far to reach  $n$
  - $h(n)$  = estimated cost from  $n$  to goal
  - $f(n)$  = estimated total cost of path through  $n$  to goal
- Greedy Best First search has  $f(n)=h(n)$
- Uniform Cost search has  $f(n)=g(n)$



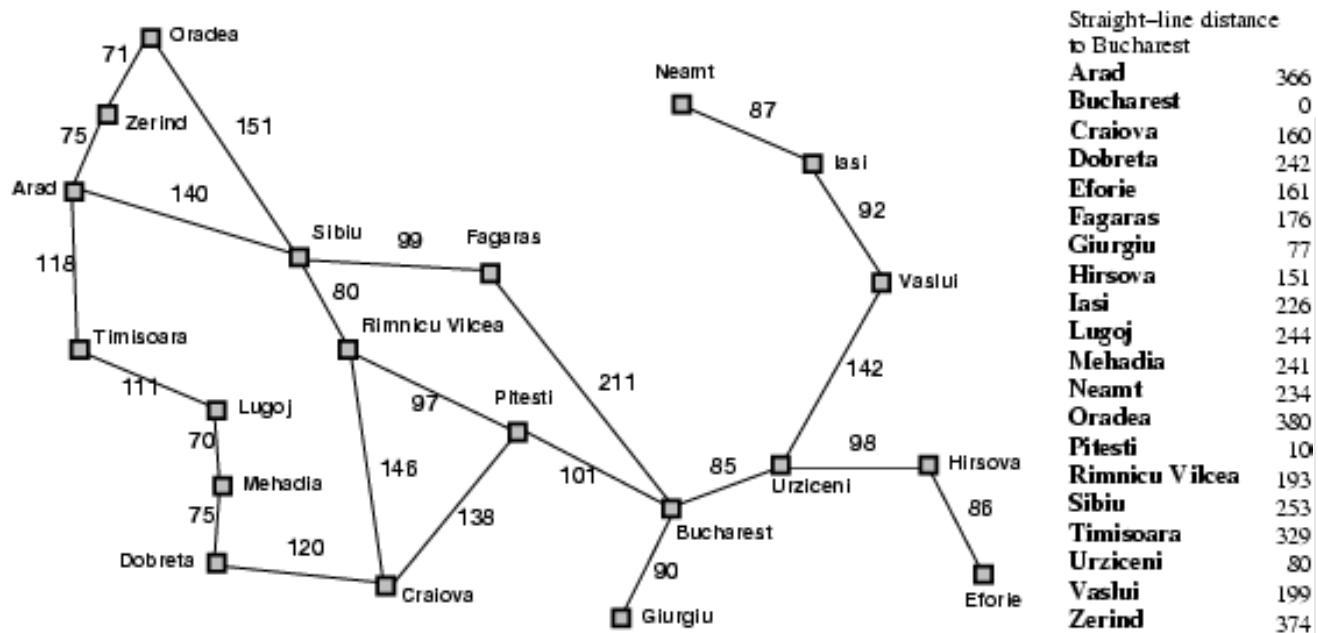
# A\* SEARCH EXAMPLE

Arad  
366=0+366

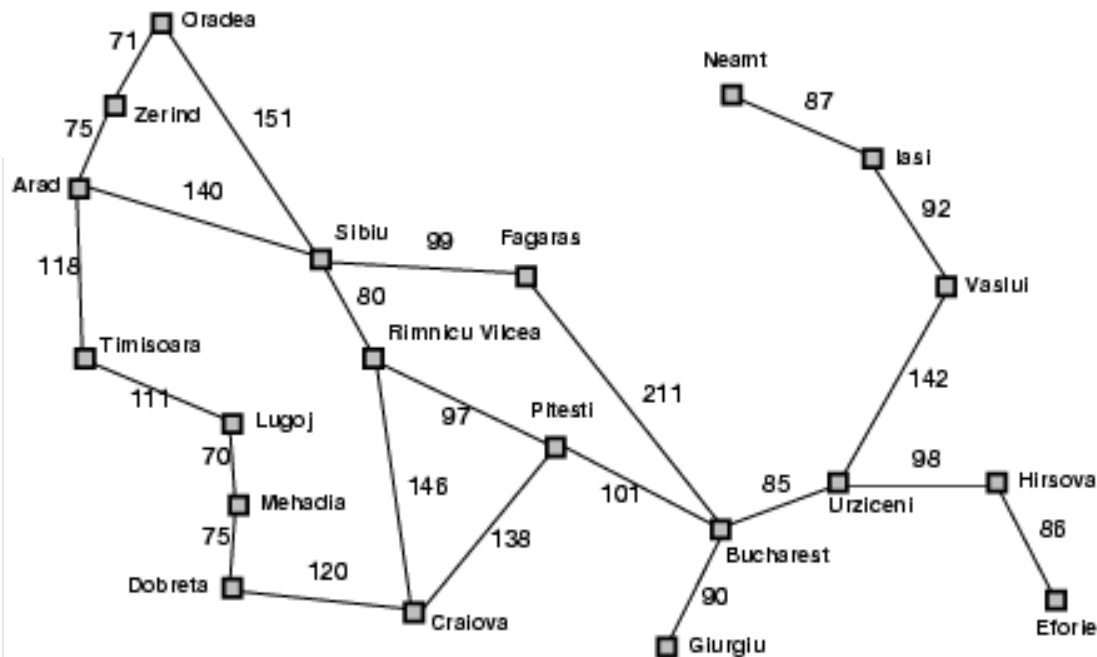
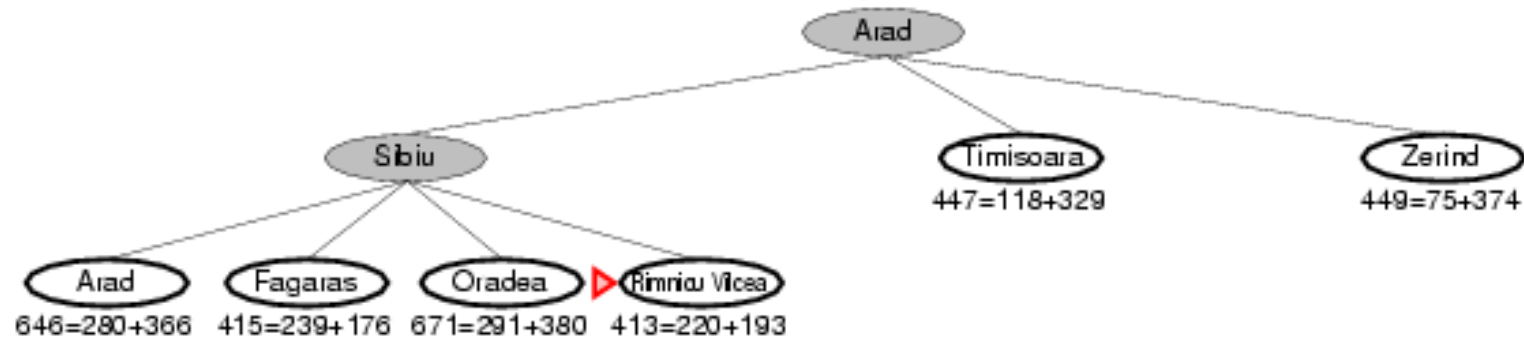




# A\* SEARCH EXAMPLE



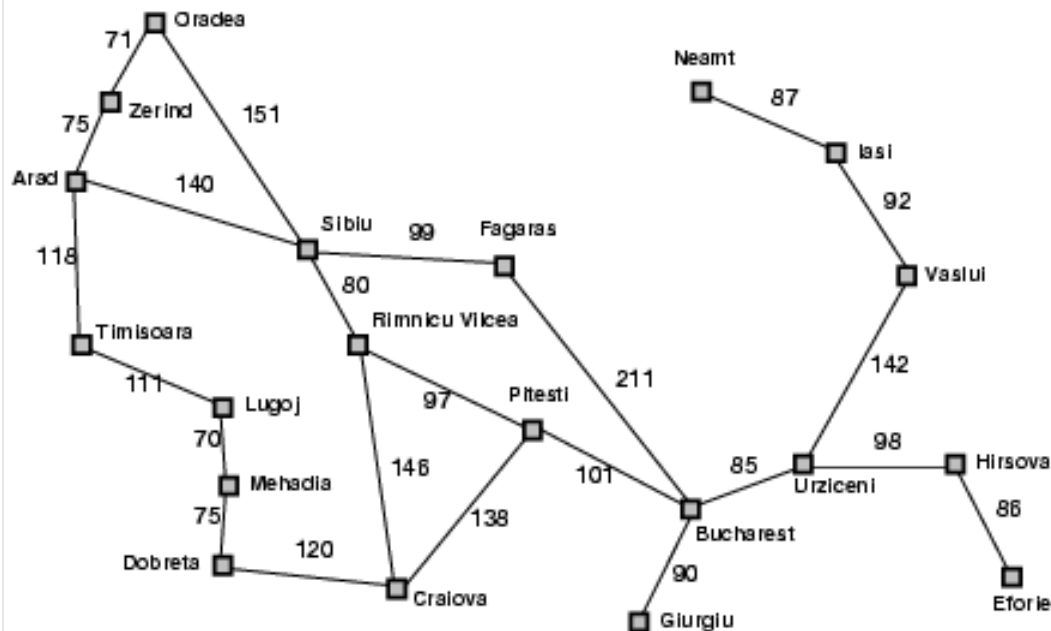
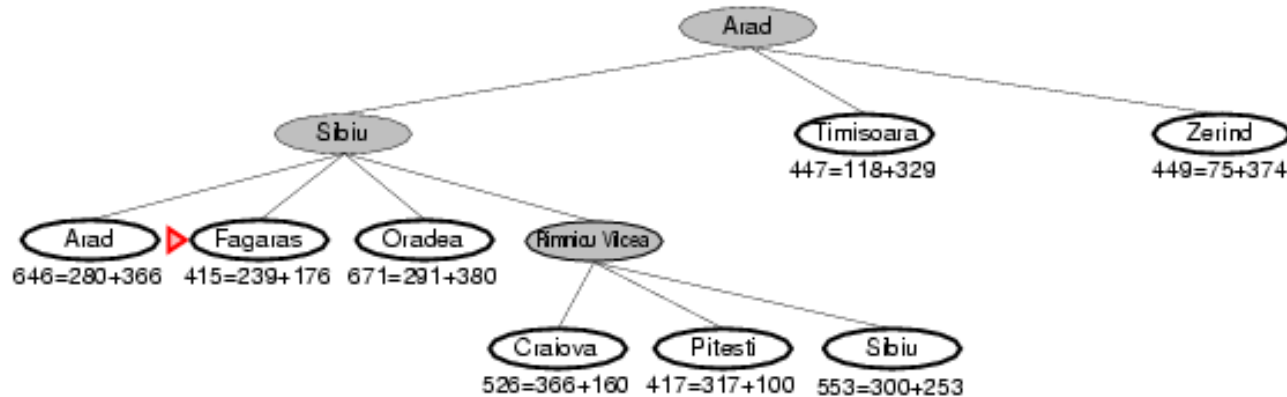
# A\* SEARCH EXAMPLE



Straight-line distance  
to Bucharest

Arad	366
Bucharest	0
Craiova	160
Dobreta	242
Eforie	161
Fagaras	176
Giurgiu	77
Hirsova	151
Iasi	226
Lugoj	244
Mehadia	241
Neamt	234
Oradea	380
Pitesti	10
Rimnicu Vilcea	193
Sibiu	253
Timisoara	329
Urziceni	80
Vaslui	199
Zerind	374

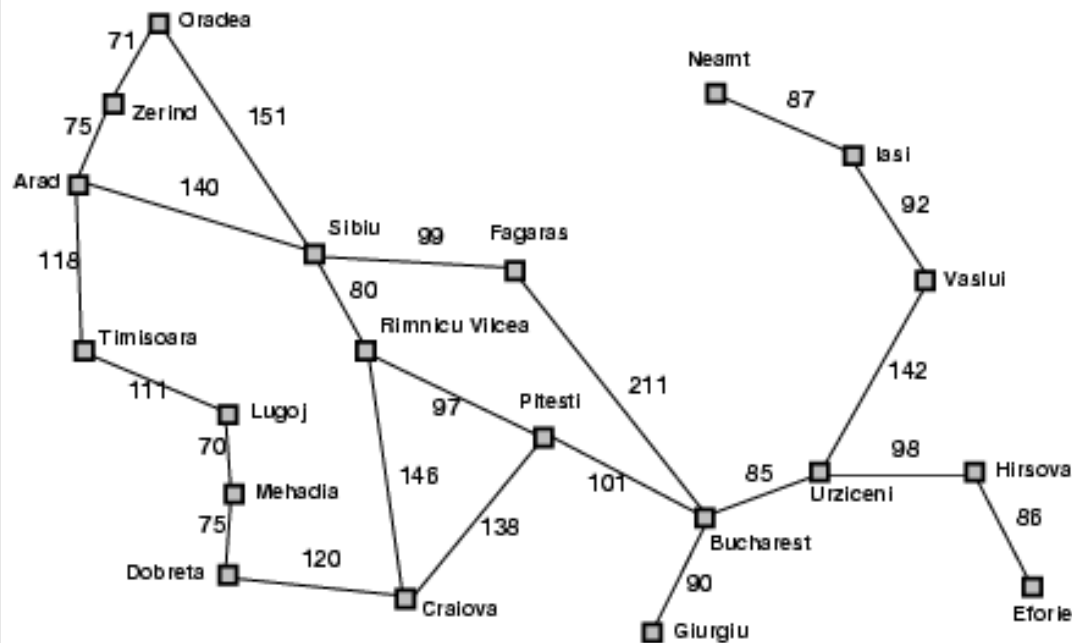
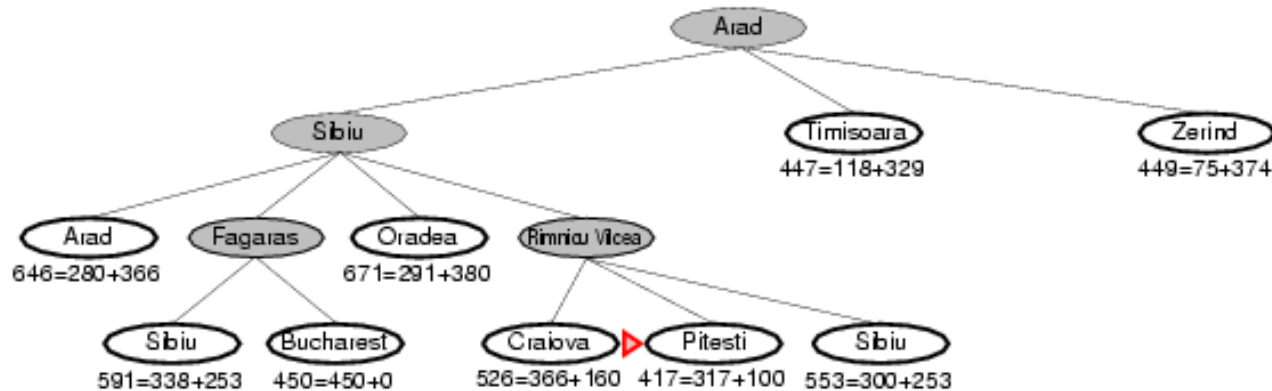
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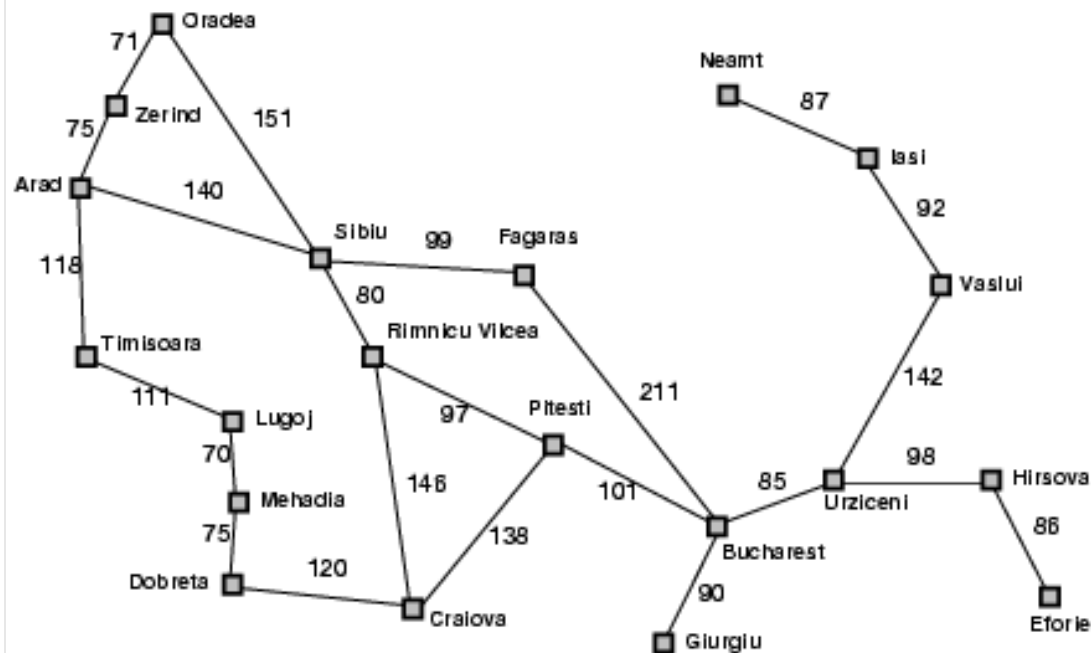
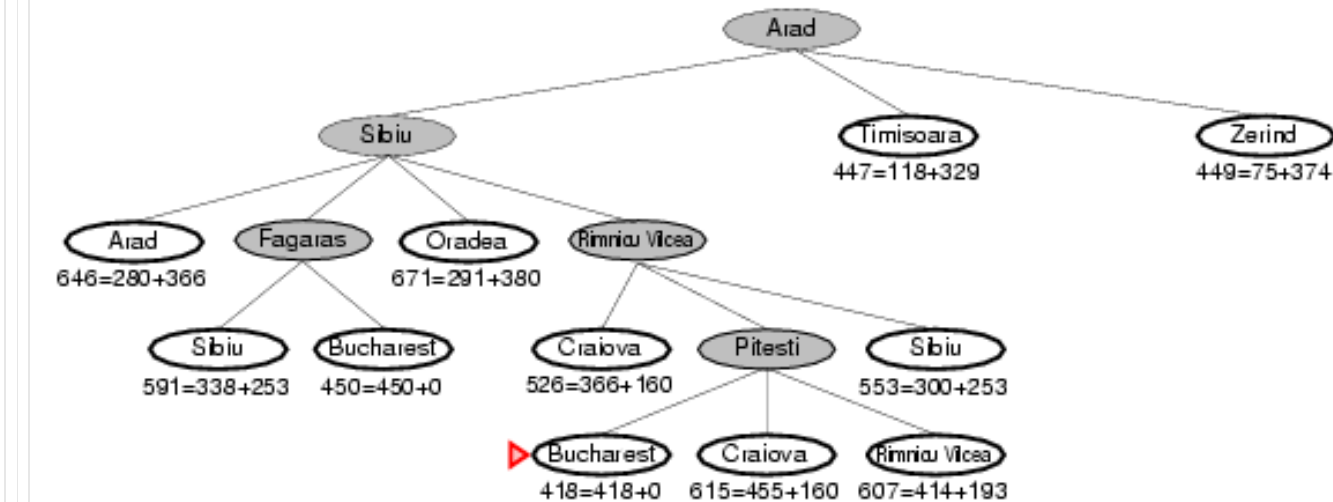
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# A\* SEARCH EXAMPLE



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# A\* SEARCH

- A\* search is both **complete** (finds a solution if one exists) and **optimal** (finds the optimal path to a goal) if:
  - the branching factor is finite
  - Step cost are  $> \epsilon > 0$
  - $h(n)$  satisfies the conditions of
    - **Admissibility**
    - **Consistency**

# ADMISSIBLE HEURISTICS

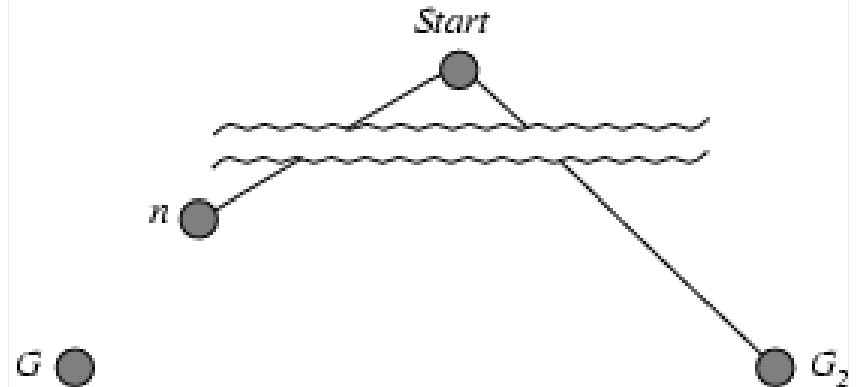
- A heuristic  $h(n)$  is **admissible** if for every node  $n$ ,  $h(n) \leq h^*(n)$ , where  $h^*(n)$  is the **true** cost to reach the goal state from  $n$ .
- An admissible heuristic **never overestimates** the cost to reach the goal, i.e., it is **optimistic**
- Example:  $h_{SLD}(n)$  (never overestimates the actual road distance)
- **Theorem:**  
If  $h(n)$  is admissible,  $A^*$  using TREE-SEARCH is optimal

# OPTIMALITY OF A\* (PROOF)

- Suppose some suboptimal goal  $G_2$  has been generated and is in the frontier. Let  $n$  be an unexpanded node in the frontier such that  $n$  is on a shortest path to an optimal goal  $G$ .

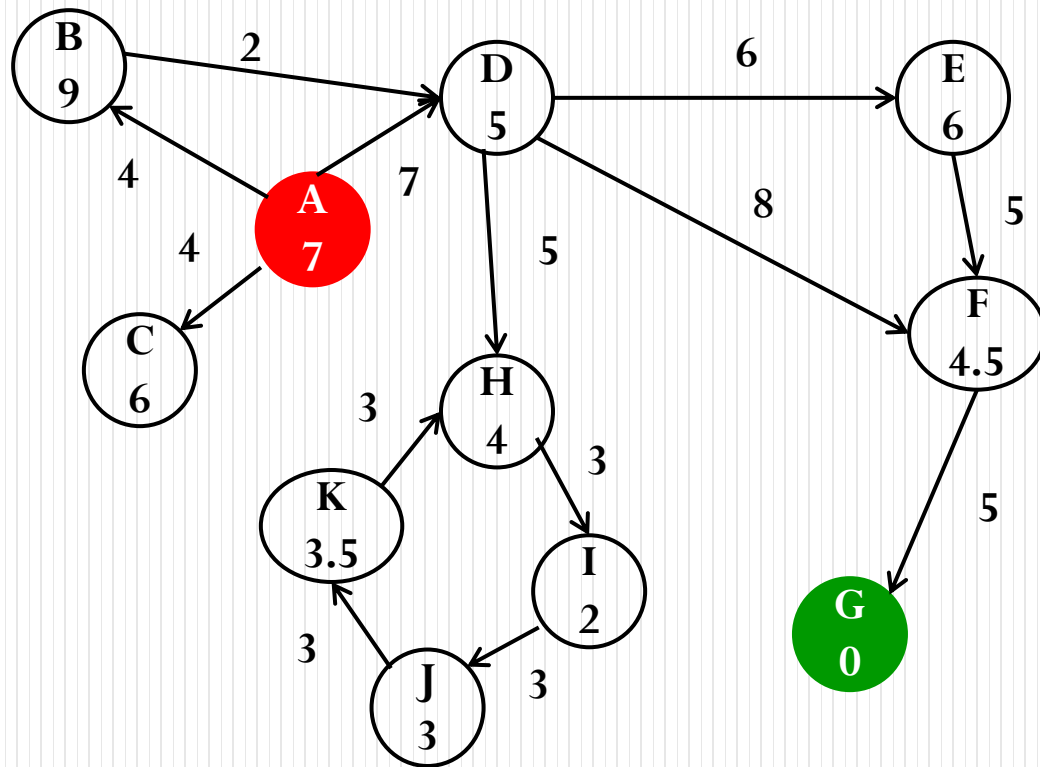
**We want to prove:**  
 **$f(n) < f(G_2)$**   
**(then A\* will prefer  $n$  over  $G_2$ )**

- $f(G_2) = g(G_2)$  since  $h(G_2) = 0$
- $f(G) = g(G)$  since  $h(G) = 0$
- $g(G_2) > g(G)$  since  $G_2$  is suboptimal
- $f(G_2) > f(G)$  from above
- $h(n) \leq h^*(n)$  since  $h$  is admissible (*under-estimate*)
- $g(n) + h(n) \leq g(n) + h^*(n)$  from above
- $f(n) \leq f(G)$  since  $g(n) + h(n) = f(n)$  &  $g(n) + h^*(n) = f(G)$
- $f(n) < f(G_2)$  since  $f(G) < f(G_2)$



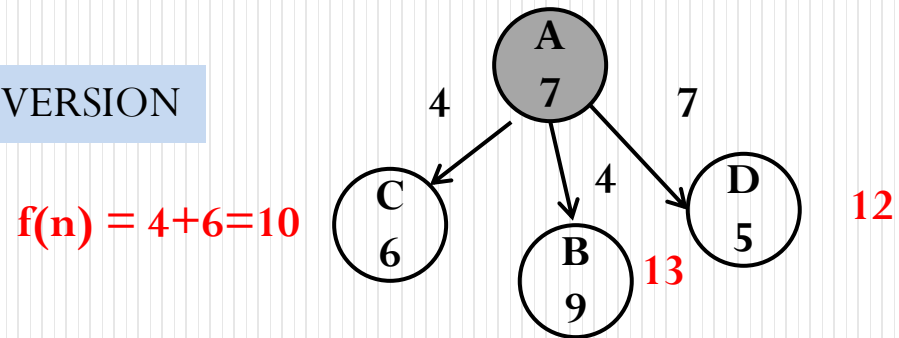


# A \* Example



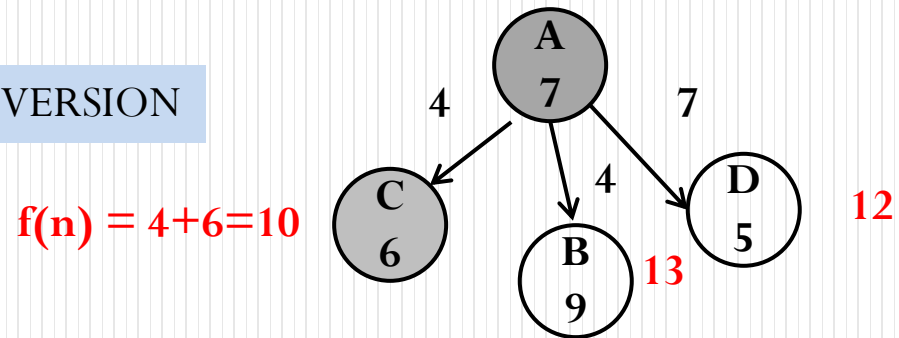
# A \* Example

TREE-SEARCH VERSION



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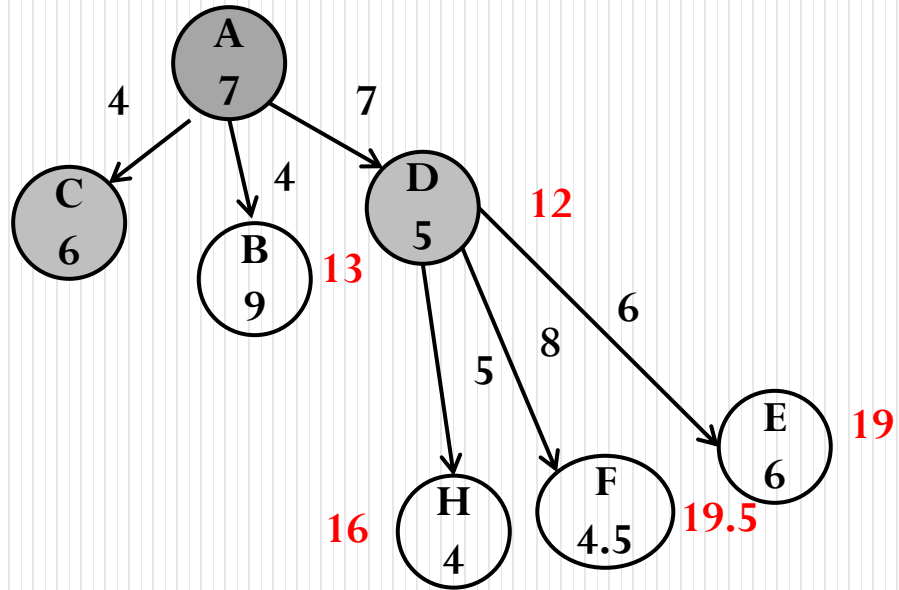
TREE-SEARCH VERSION



# A \* Example

TREE-SEARCH VERSION

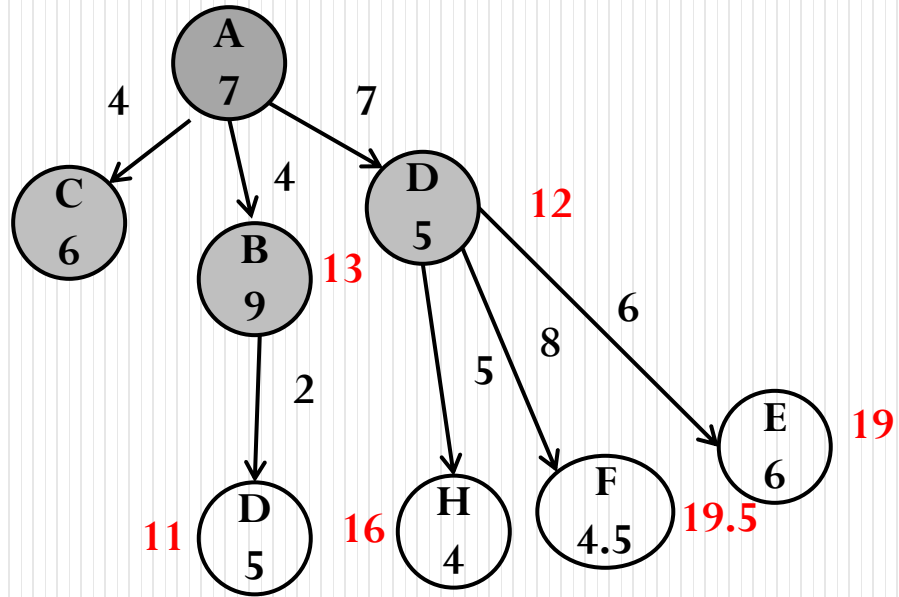
$$f(n) = 4 + 6 = 10$$



# A \* Example

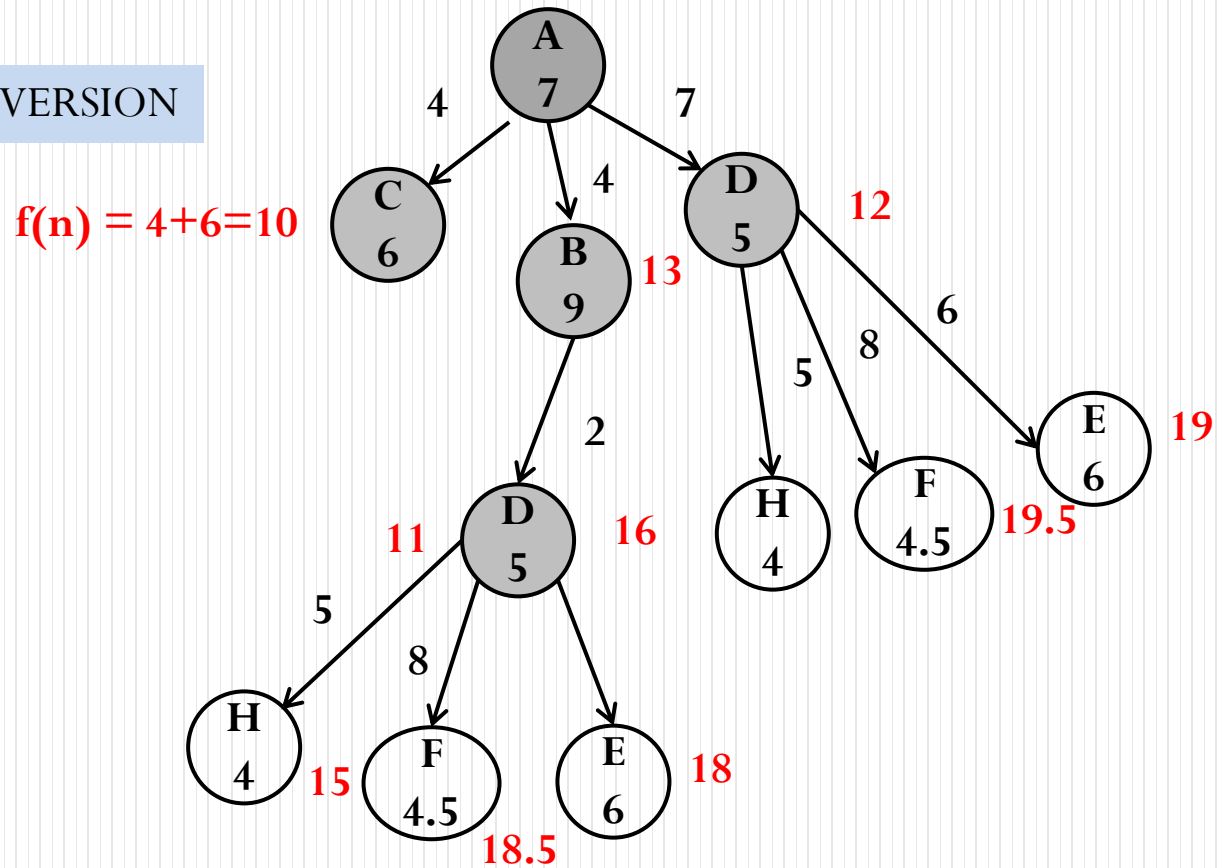
TREE-SEARCH VERSION

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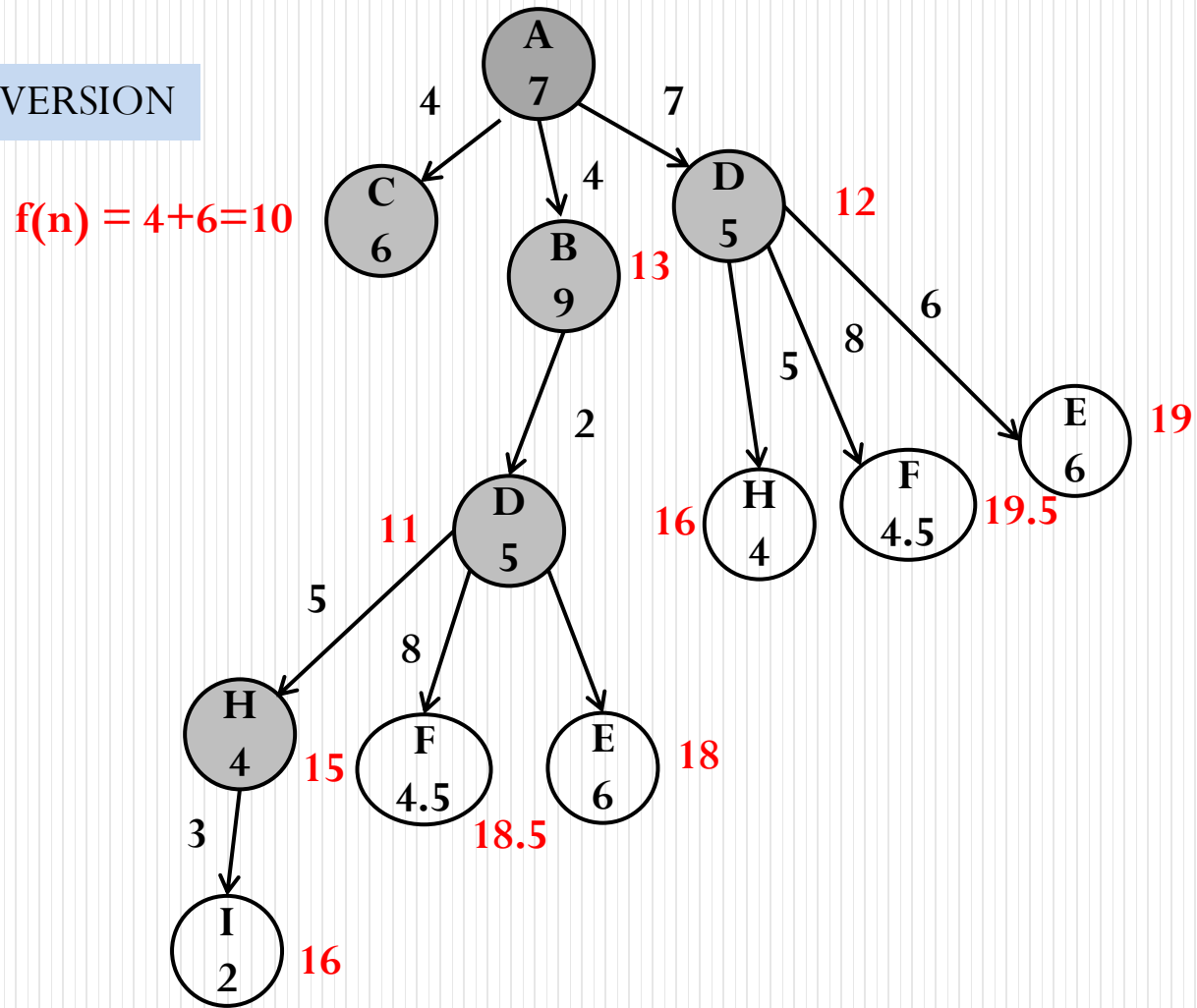
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TREE-SEARCH VERSION



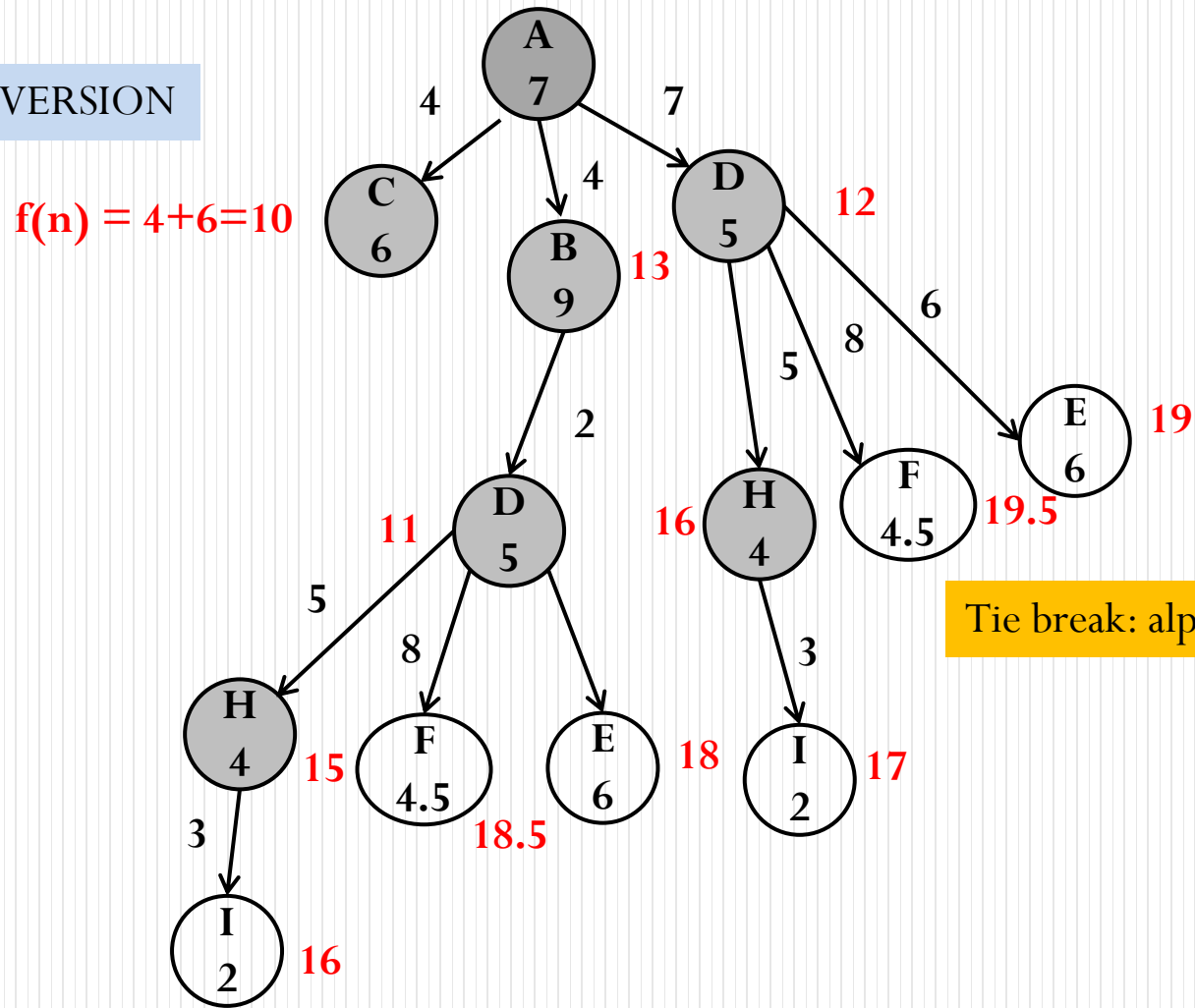
# A \* Example

TREE-SEARCH VERSION



# A \* Example

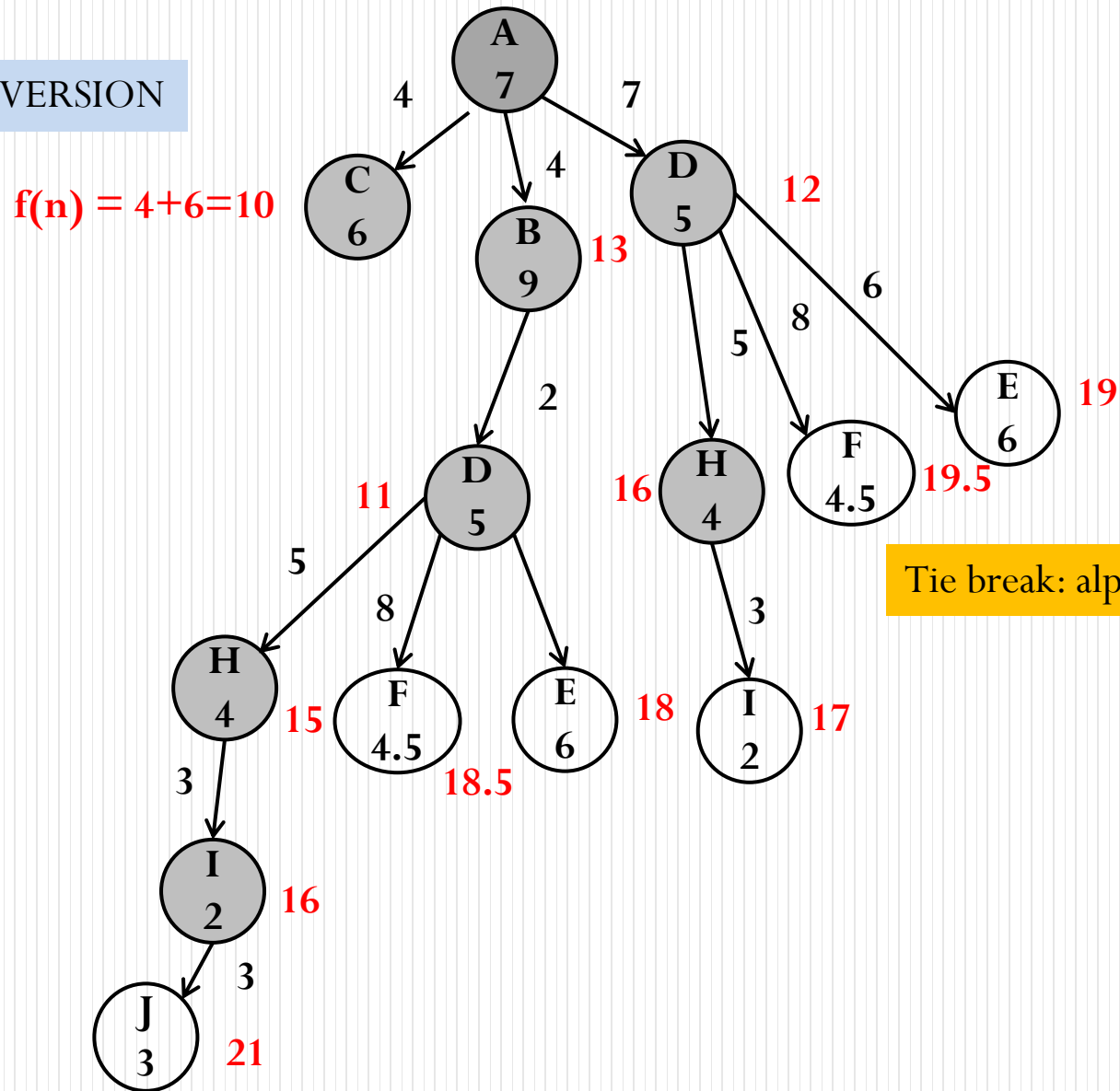
TREE-SEARCH VERSION





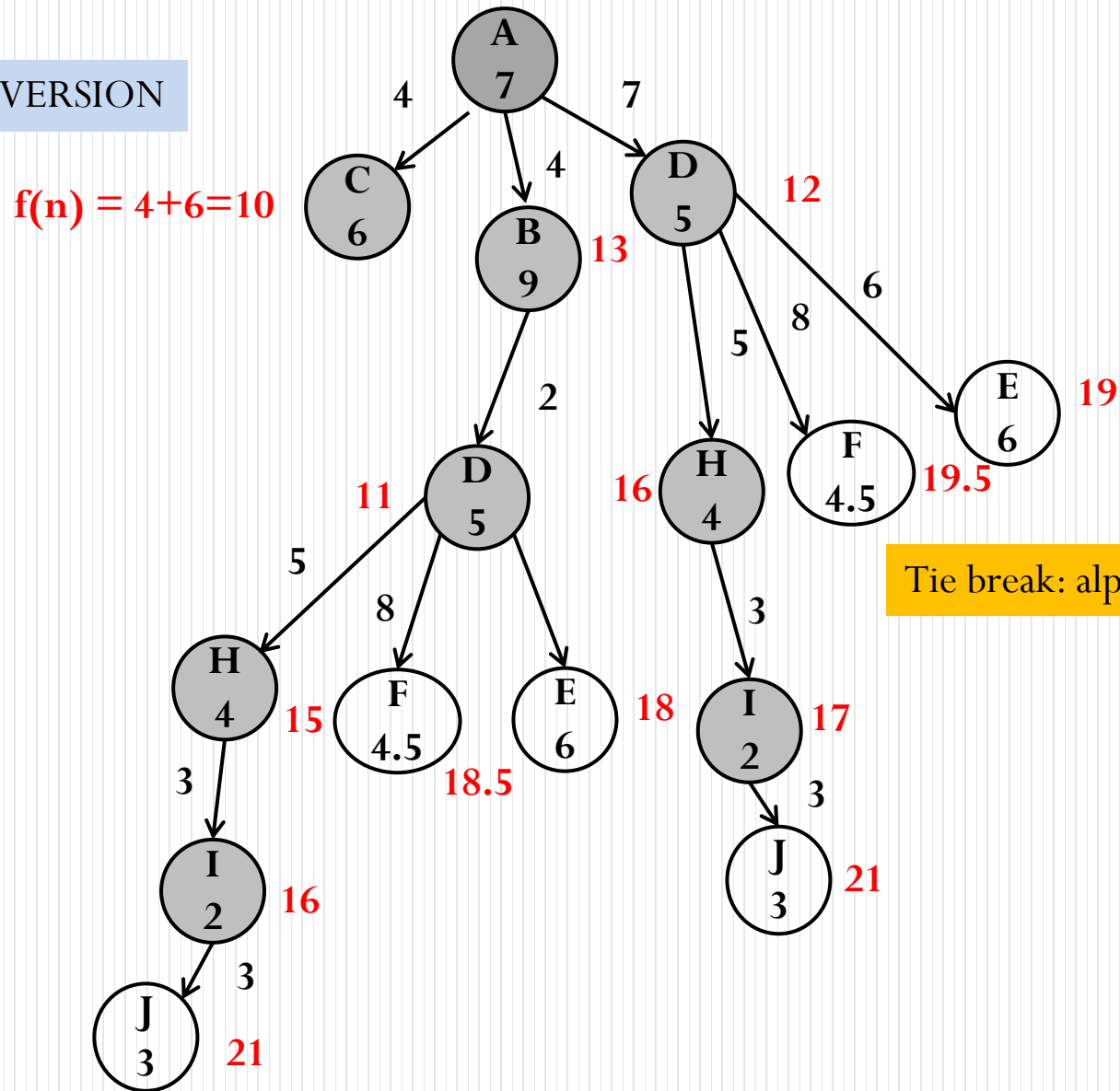
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TREE-SEARCH VERSION



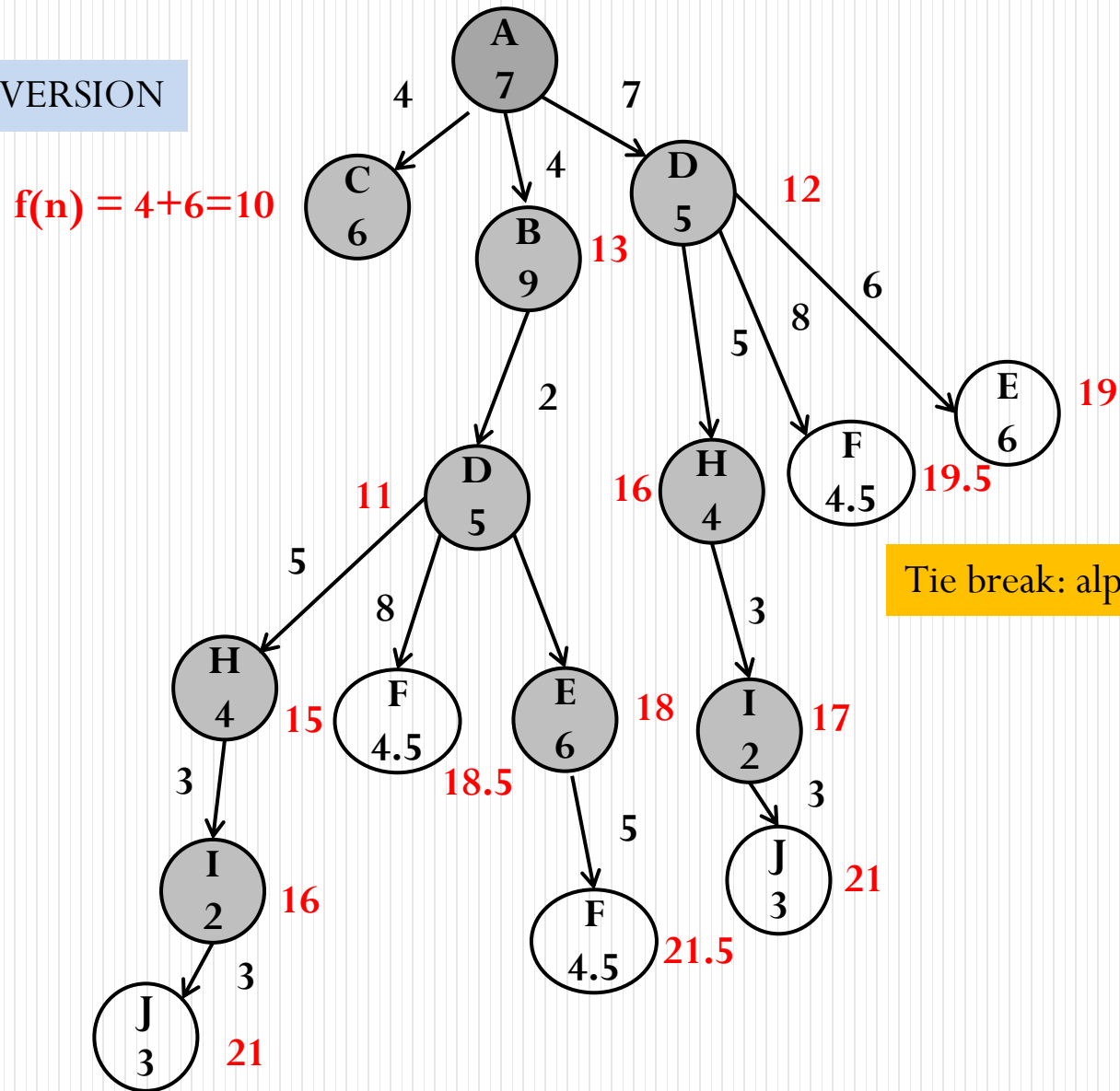
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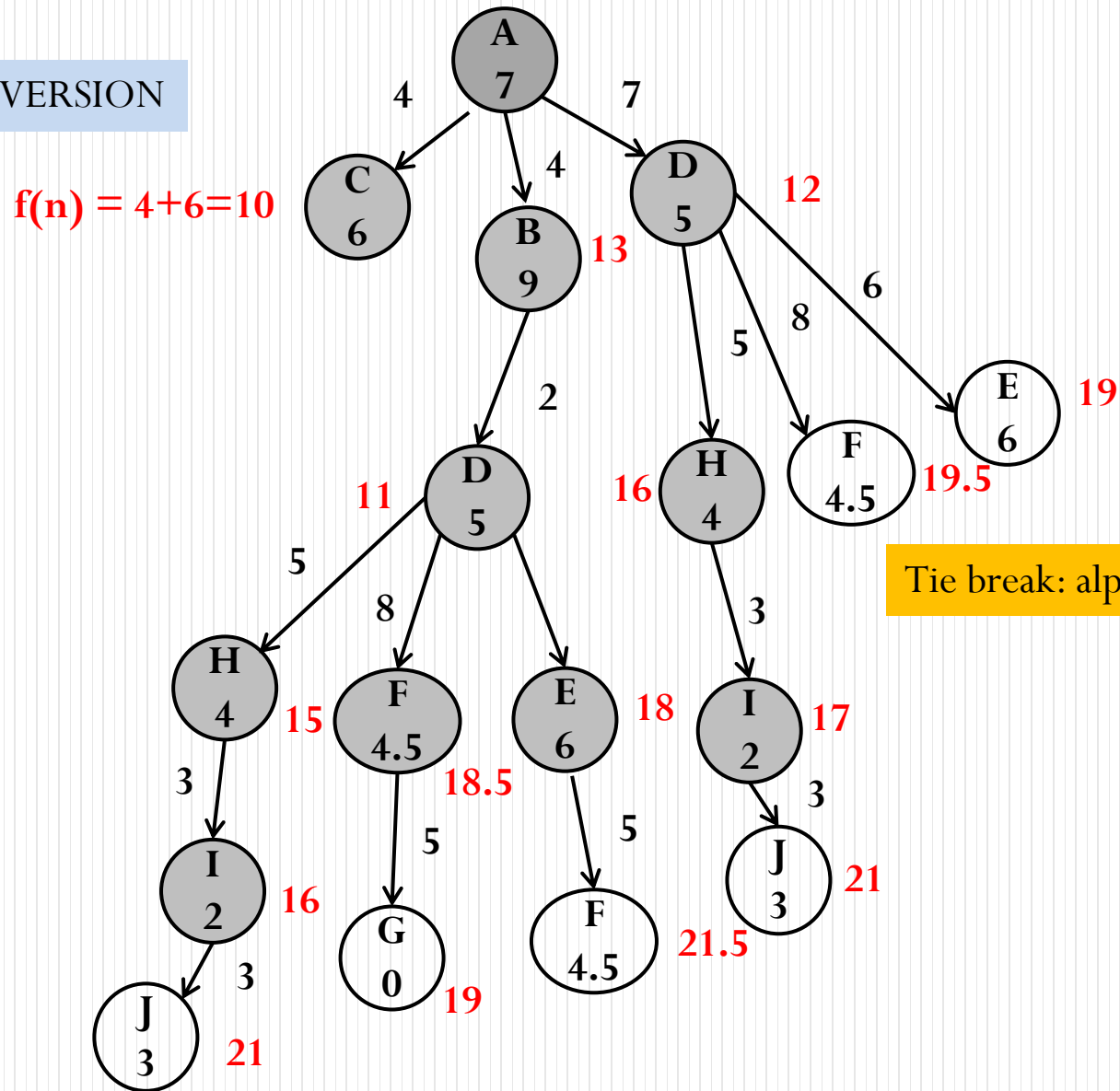
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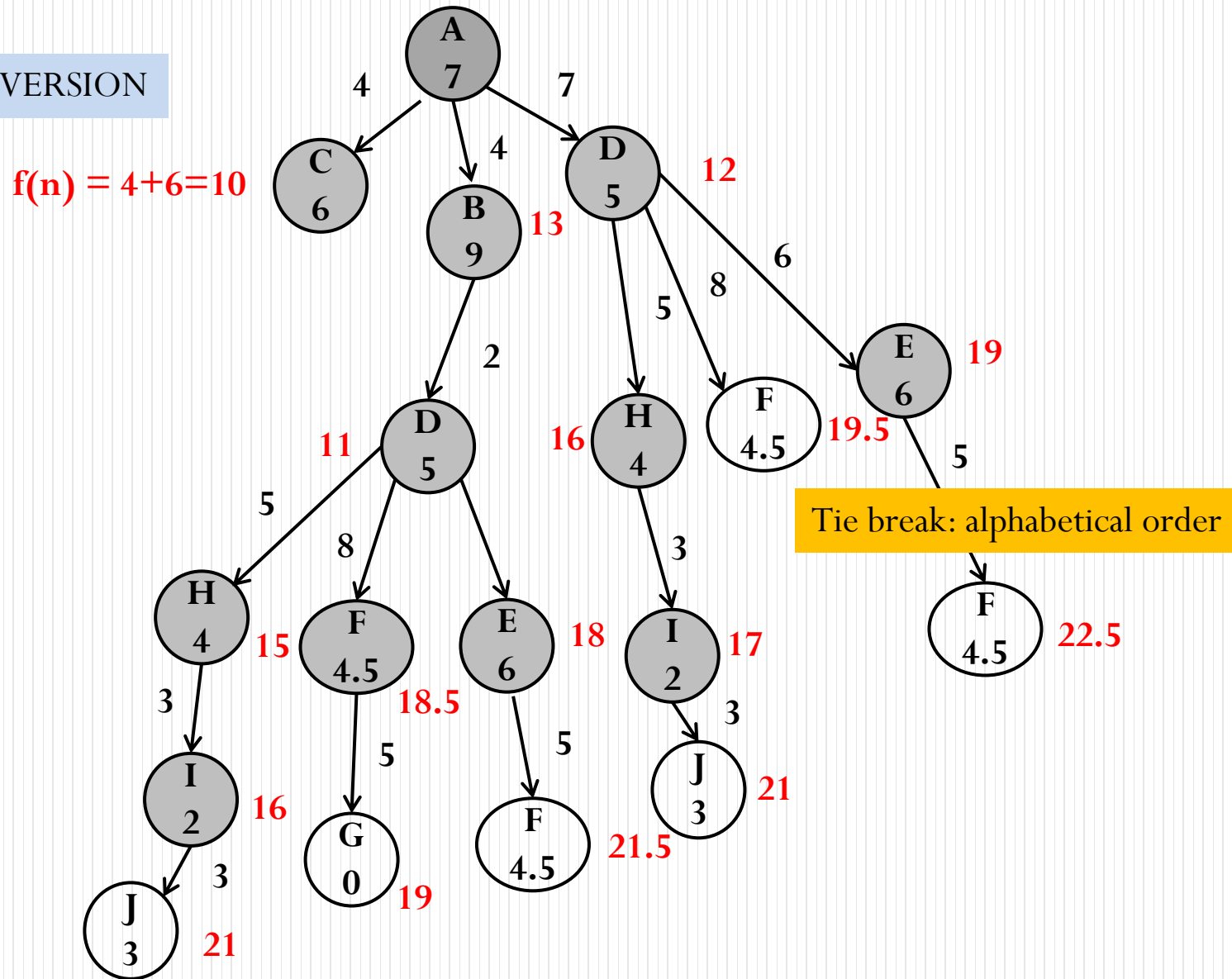
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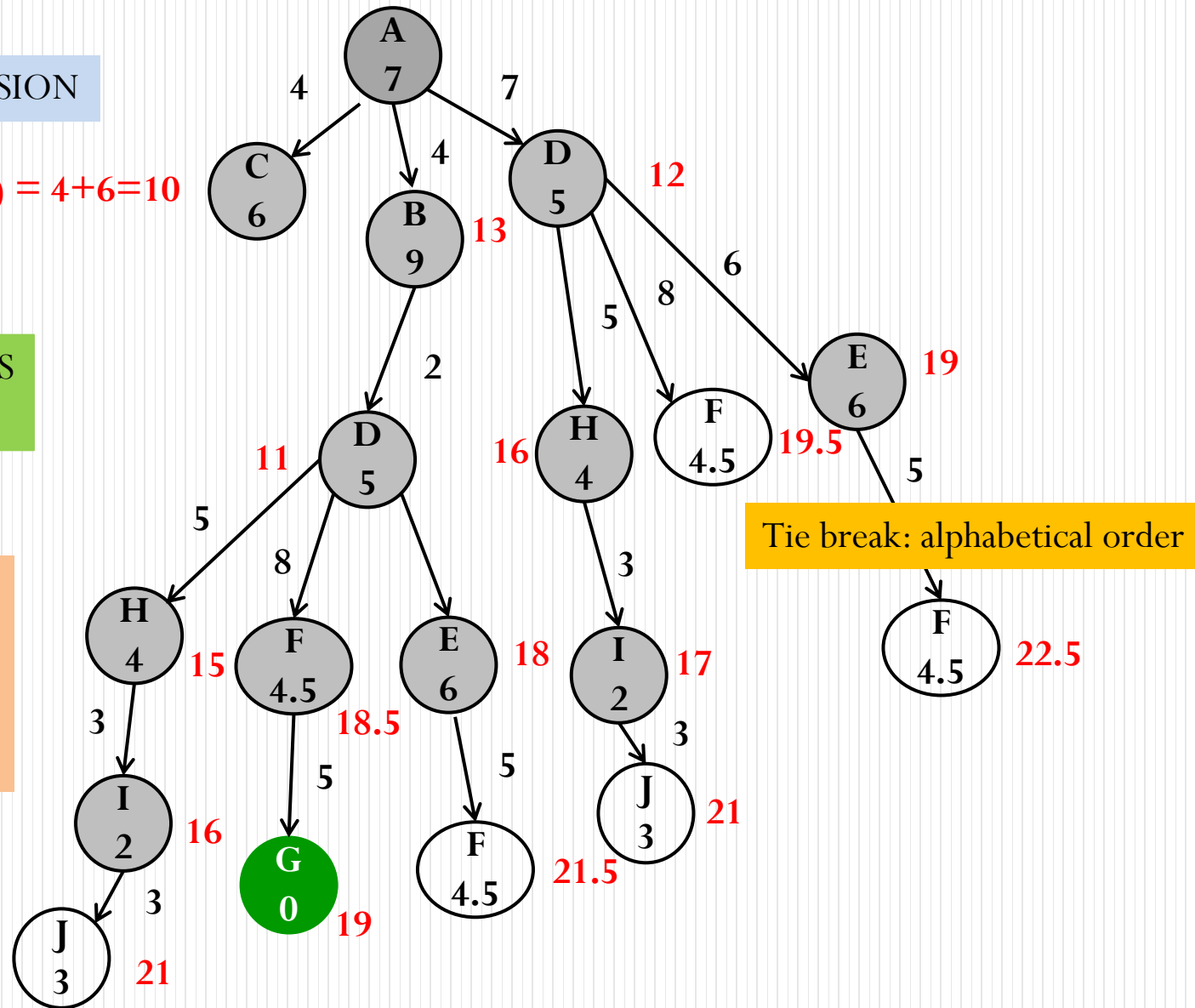
# A \* Example

TREE-SEARCH VERSION

$$f(n) = 4 + 6 = 10$$

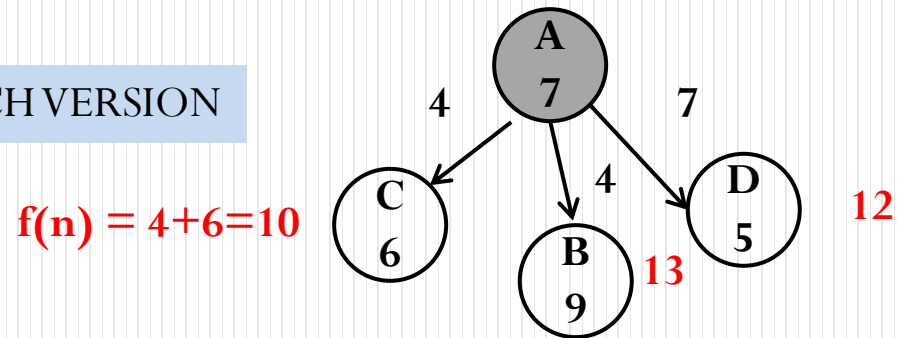
COMPLETE ? – YES  
OPTIMAL ? – YES

Search is duplicated  
from D, identical  
sub-trees hanging  
below



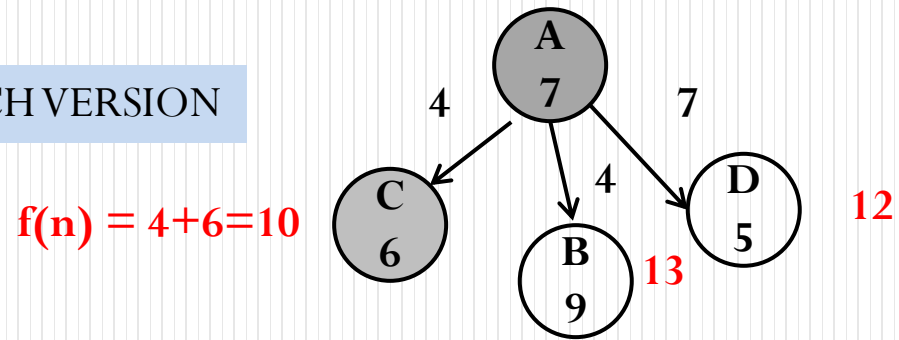
# A \* Example

GRAPH-SEARCH VERSION



# A \* Example

GRAPH-SEARCH VERSION

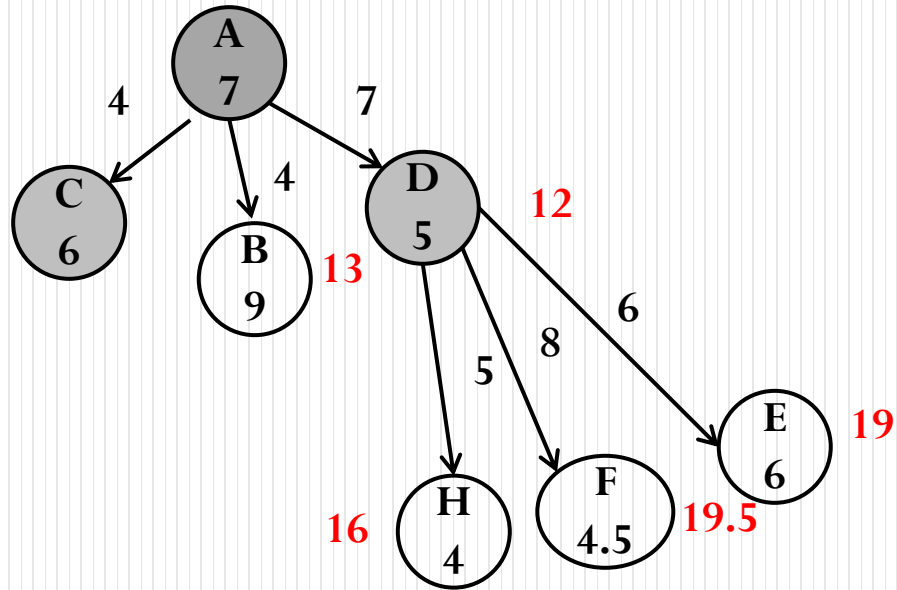




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GRAPH-SEARCH VERSION

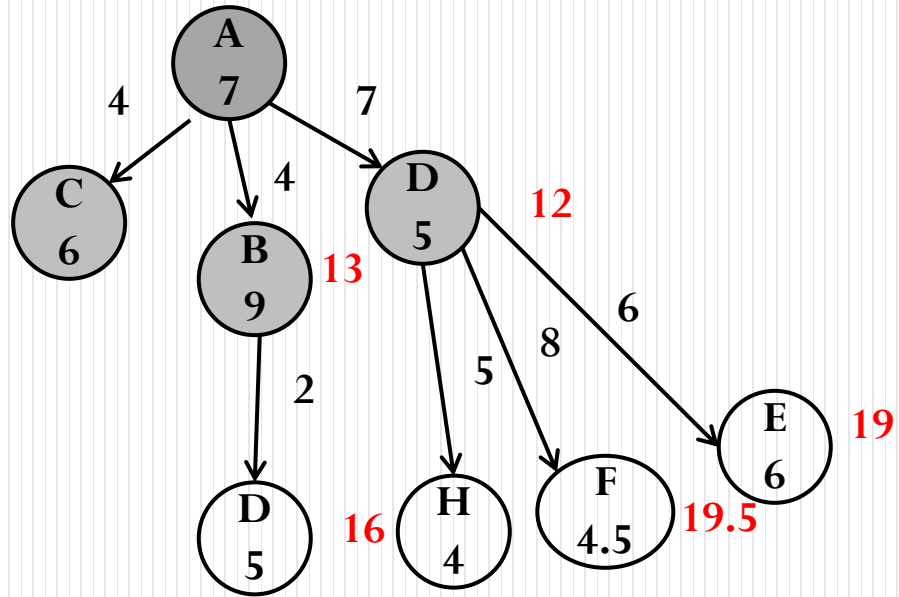
$$f(n) = 4 + 6 = 10$$



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GRAPH-SEARCH VERSION

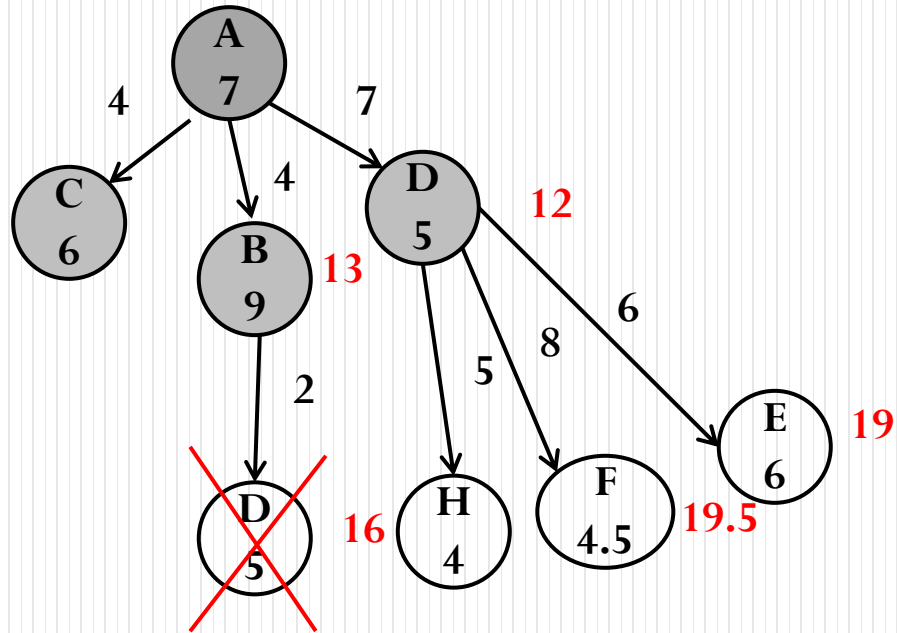
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GRAPH-SEARCH VERSION

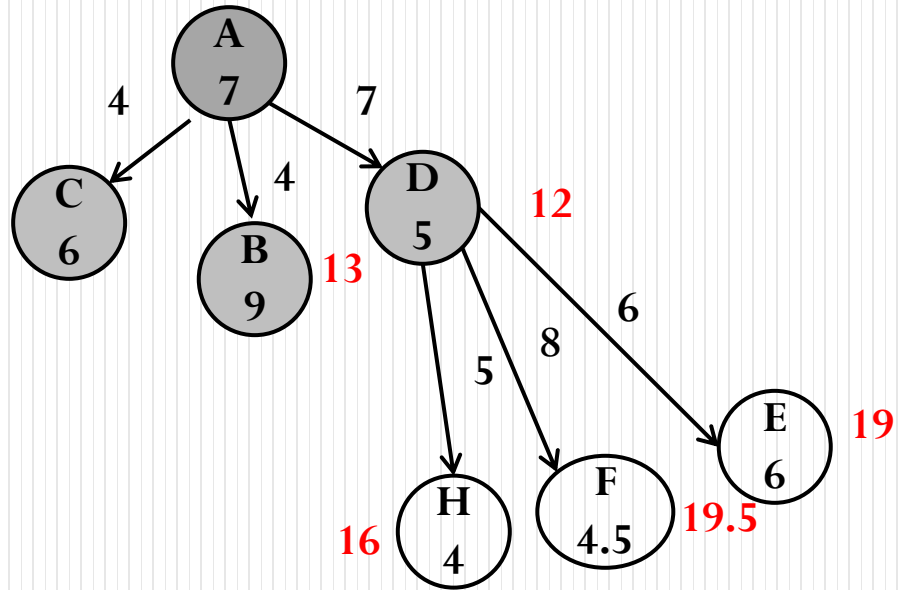
$$f(n) = 4 + 6 = 10$$



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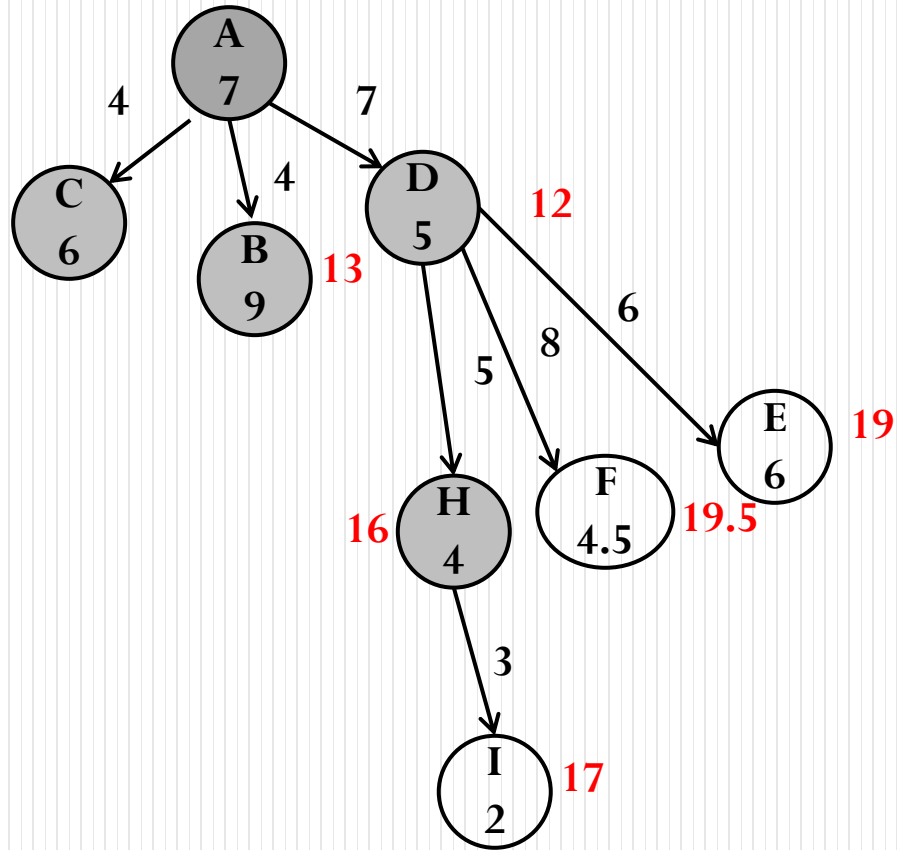
$$f(n) = 4 + 6 = 10$$



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GRAPH-SEARCH VERSION

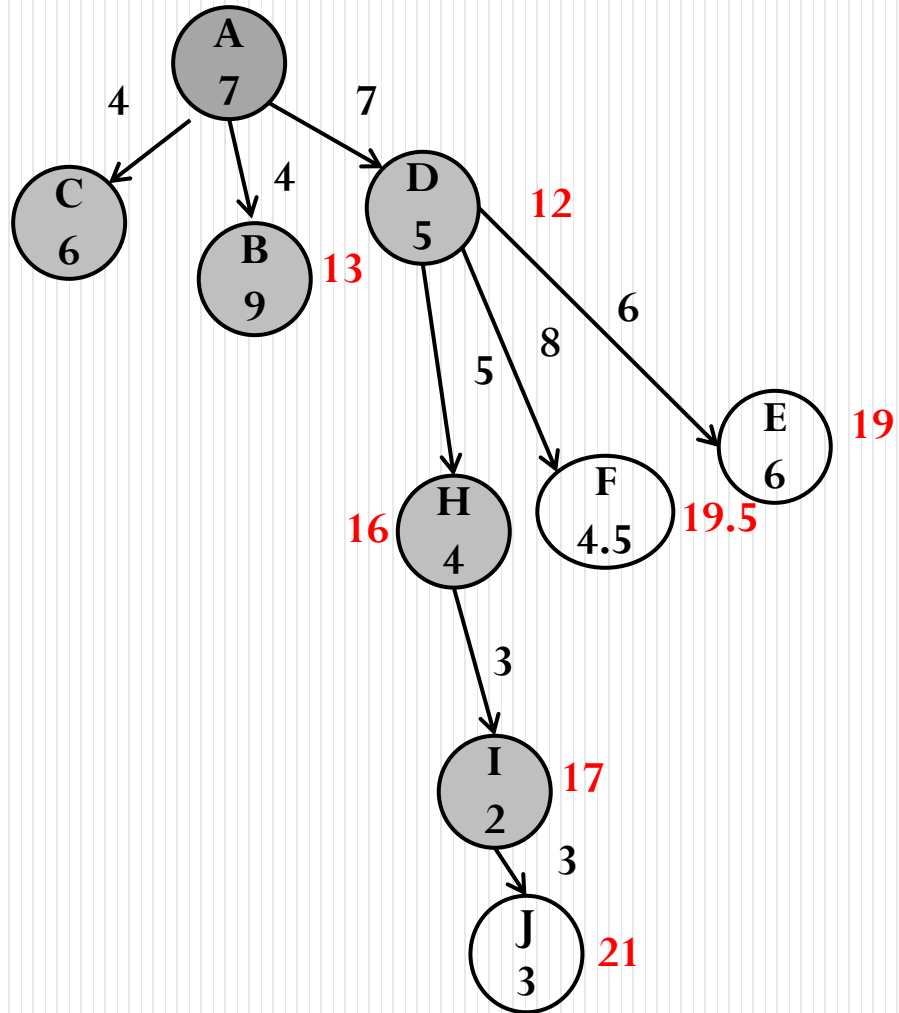
$$f(n) = 4 + 6 = 10$$



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GRAPH-SEARCH VERSION

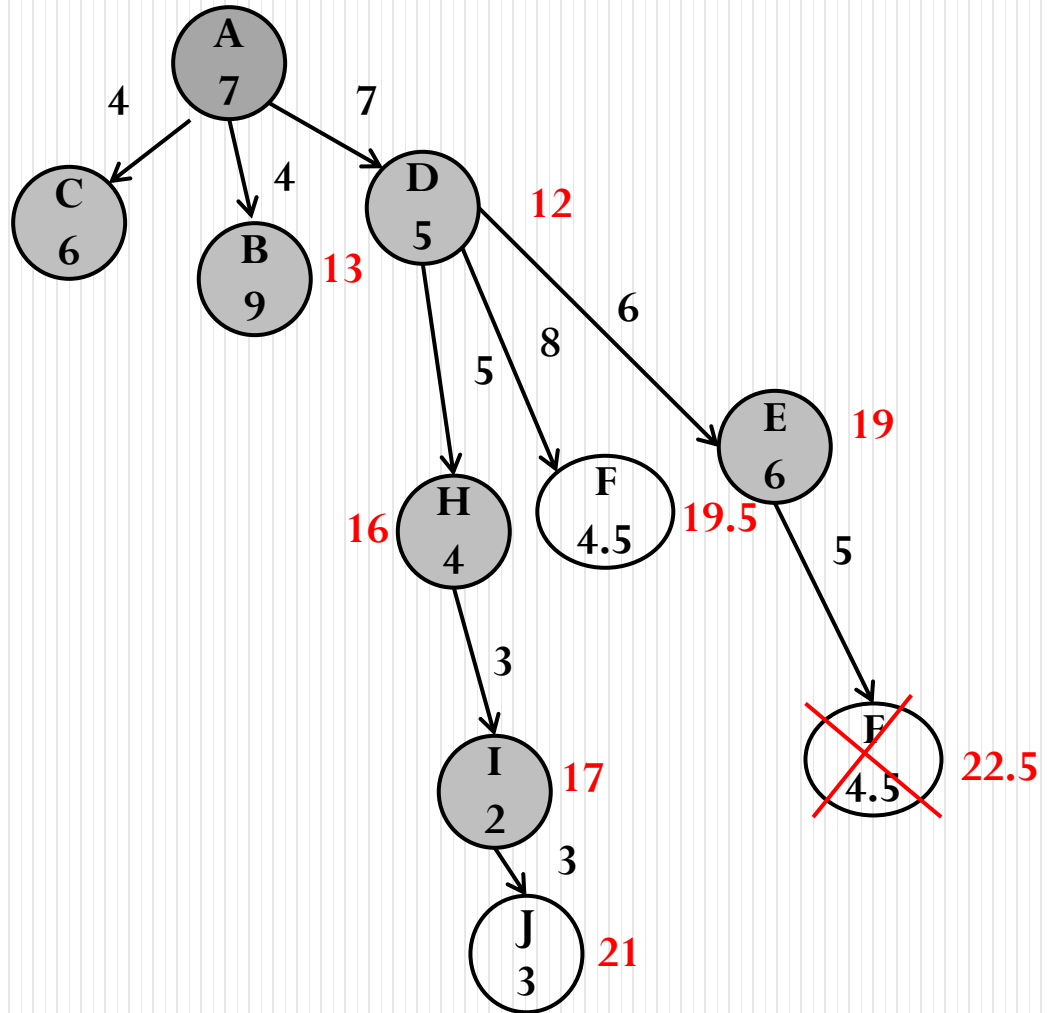
$$f(n) = 4 + 6 = 10$$



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GRAPH-SEARCH VERSION

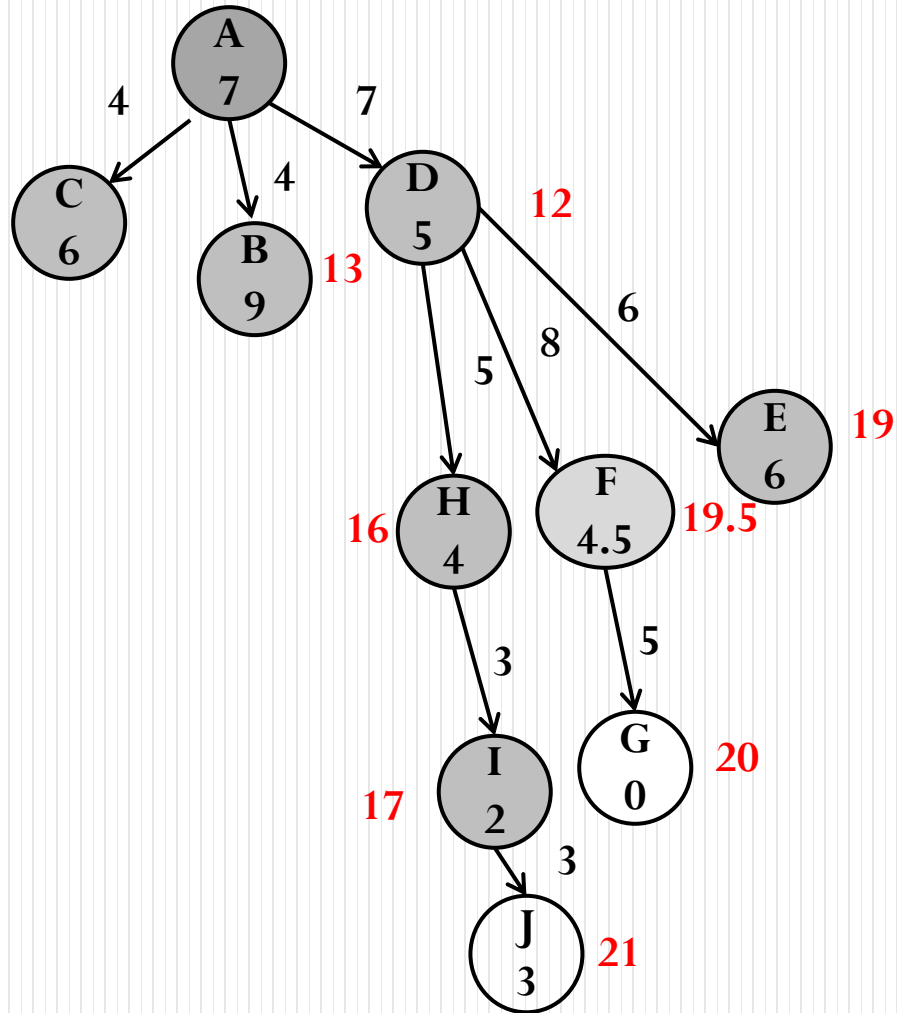
$$f(n) = 4 + 6 = 10$$



# A \* Example

GRAPH-SEARCH VERSION

$$f(n) = 4 + 6 = 10$$

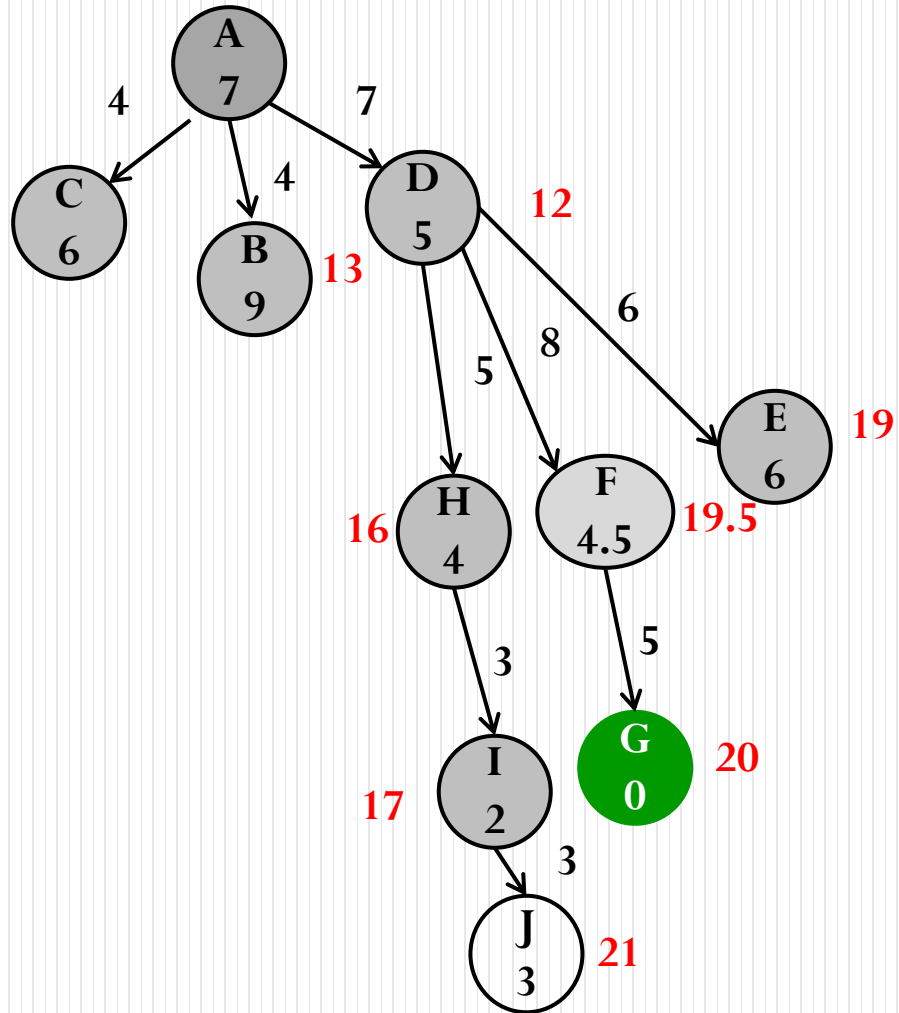




# A \* Example

GRAPH-SEARCH VERSION

$$f(n) = 4 + 6 = 10$$



# A \* Example

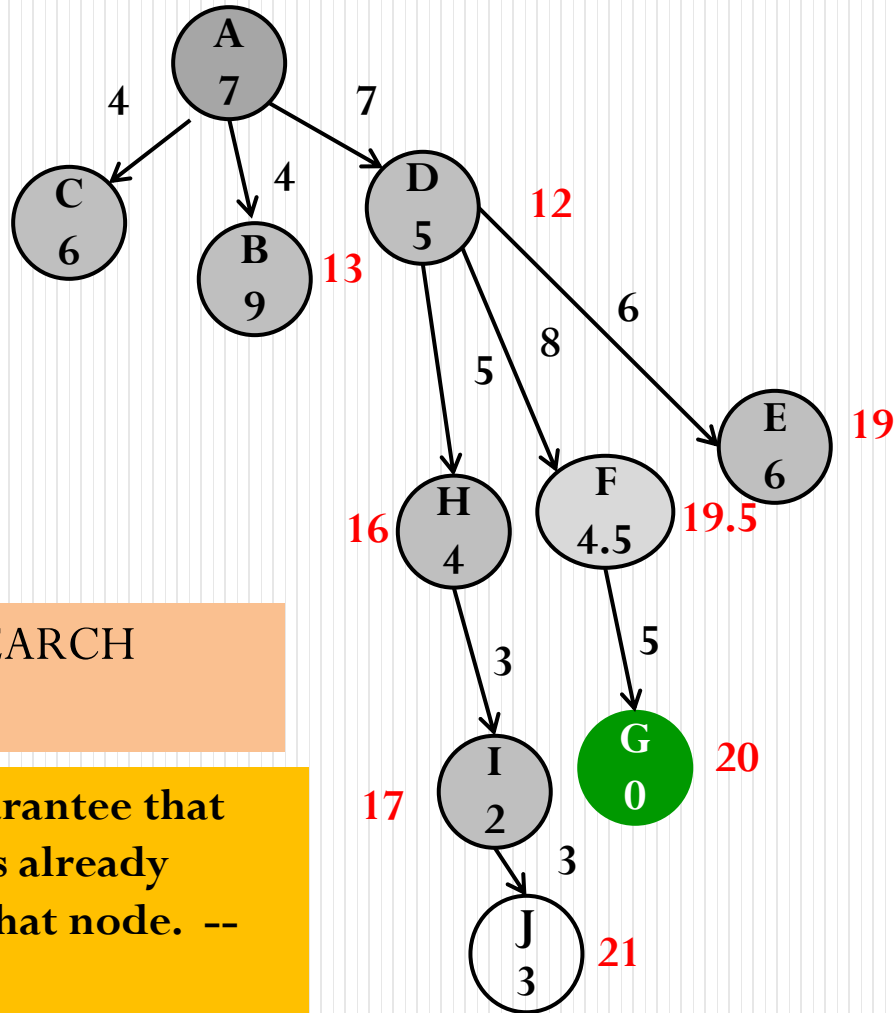
GRAPH-SEARCH VERSION

$$f(n) = 4 + 6 = 10$$

COMPLETE ? – YES  
OPTIMAL ? - NO

Allow 'REOPEN' in GRAPH-SEARCH  
Version

Impose condition on  $f$  that guarantee that  
when A\* expands a node, it has already  
found the least costly path to that node. --  
CONSISTENCY

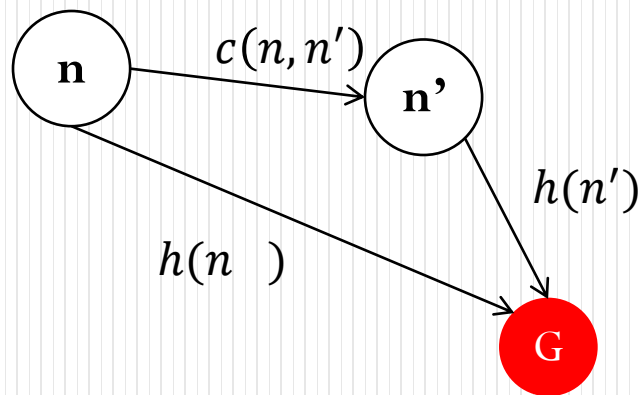


# A\* Search

- If  $n'$  is successor of  $n$ ,  $h$  is **consistent** if  $\forall n, n'$   
$$h(n) \leq c(n, n') + h(n')$$

where  $c(n, n')$  is the step cost from  $n$  to  $n'$

i.e. the estimated cost of reaching the goal from  $n$  is no greater than the step cost of getting to  $n'$  plus the estimated cost of reaching the goal from  $n'$



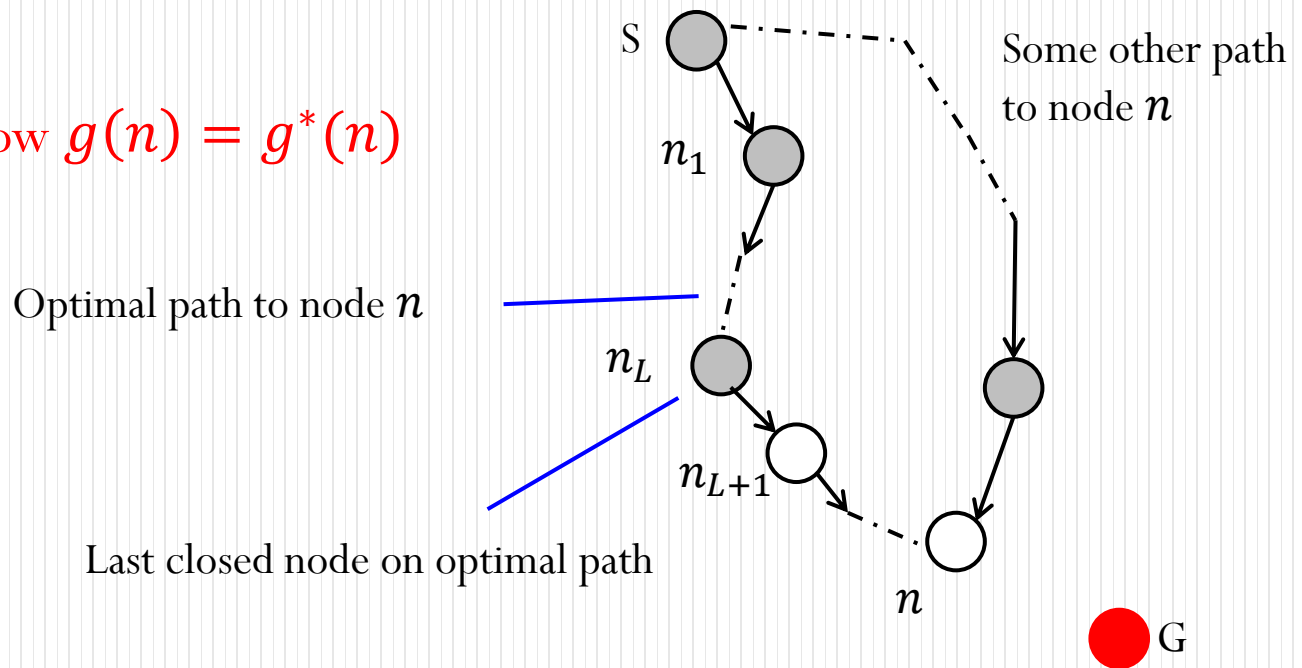
If  $h(n)$  is consistent, then the values of  $f(n)$  along any path are non-decreasing

# A\* Search

- **Theorem:** if the consistency condition on  $h$  is satisfied, then when A\* expands a node  $n$ , it has already found an optimal path to  $n$ .

- Proof:

we will try to show  $g(n) = g^*(n)$



# A\* Search

- Proof (contd.) : let A\* is about to pick up node  $n$  with a value  $g(n)$ . Let there be a (known) optimal path from  $S$  to  $n$  via  $n_L$  and  $n_{L+1}$ .
- Let A\* expand node  $n$  with cost  $g(n)$ .
- Let  $n_L$  be the last node on the optimal path from  $S$  to  $n$  that has been expanded.
- Let  $n_{L+1}$  be the successor of  $n_L$  that must be on OPEN.
- The following property holds
  - $h(n_L) \leq h(n_{L+1}) + C(n_L, n_{L+1})$
  - $h(n_L) + g(n_L) \leq h(n_{L+1}) + C(n_L, n_{L+1}) + g(n_L)$  (add  $g(n_L)$ )
  - $h(n_L) + g(n_L) \leq h(n_{L+1}) + g(n_{L+1})$
  - $h(n_L) + g^*(n_L) \leq h(n_{L+1}) + g^*(n_{L+1})$  (as both are in optimal path)

# A\* Search

- By transitivity of  $\leq$ , the above property holds true for any two nodes on the optimal path, in particular it holds for  $n_{L+1}$  and node  $n$ .
  - $h(n_{L+1}) + g^*(n_{L+1}) \leq h(n) + g^*(n)$  -----(1)
  - $f(n_{L+1}) \leq h(n) + g^*(n)$  (because  $n_{L+1}$  is on the optimal path to  $n$ )

- But since A\* is about to pick node  $n$  instead,

- $f(n) \leq f(n_{L+1})$  or
- $h(n) + g(n) \leq h(n_{L+1}) + g^*(n_{L+1})$  -----(2)

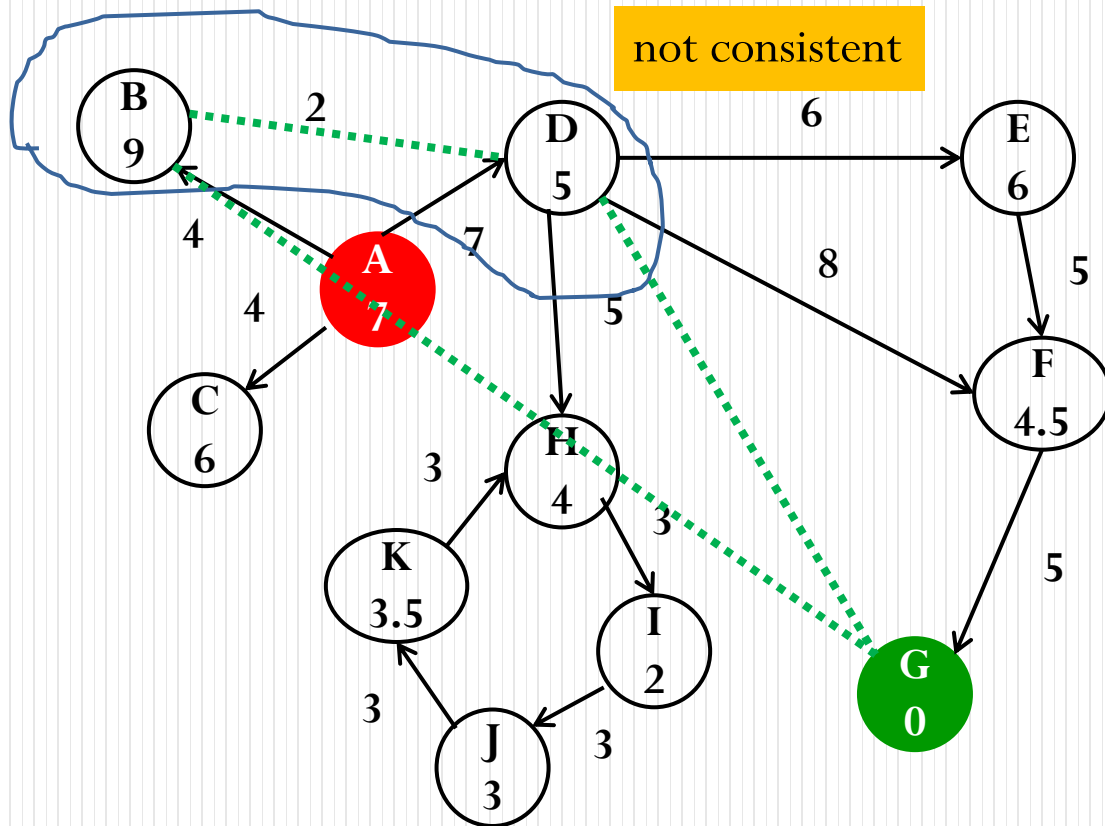
Combining (1) and (2)

- $h(n) + g(n) \leq h(n_{L+1}) + g^*(n_{L+1}) \leq h(n) + g^*(n)$
- $h(n) + g(n) \leq h(n) + g^*(n)$
- $g(n) \leq g^*(n)$

$g(n)$  cannot be less than  $g^*(n)$  as  $g^*(n)$  is the optimal cost.

$$g(n) = g^*(n)$$

# A \* Example



# Iterative Deepening A\* Search

- Heuristic search can perform as bad as Breadth first search (specially in terms of space) if a *good* heuristic is not chosen.
- Basic idea of IDA\* is to achieve similar benefits as iterative deepening DFS for heuristic search.
  - While finding minimal cost path the memory grows only linearly with depth of goal.
- Perform a depth-first search at each iteration with cut-off value as  $f$  cost.

Iteration 1

cost cut-off is  $h(n_0)$ ,  $n_0$  is the start node.

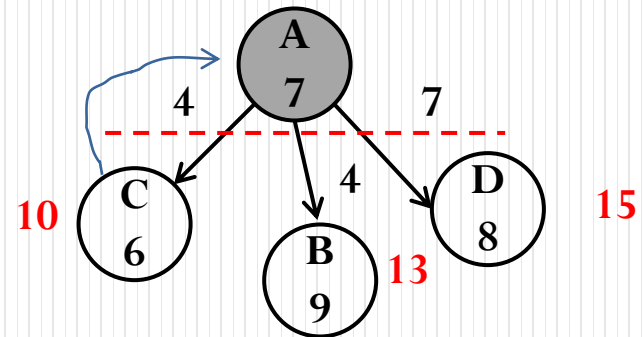
cut-off value is the smallest  $f$  cost of any node that exceeded the cut-off on previous iteration.

Successive  
Iterations



# Iterative Deepening A\*

- Expand nodes in depth-first fashion-backtracking whenever the  $f$  value of a successor of an expanded node exceeds the cut-off value

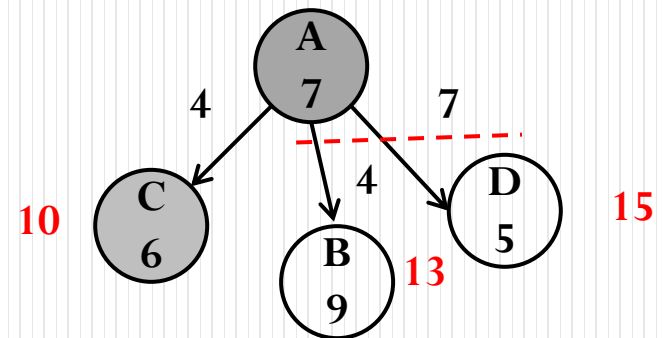


- Iteration 1:**

- $\text{cut-off} = f(A) = h(A) = 7$

- Iteration 2:**

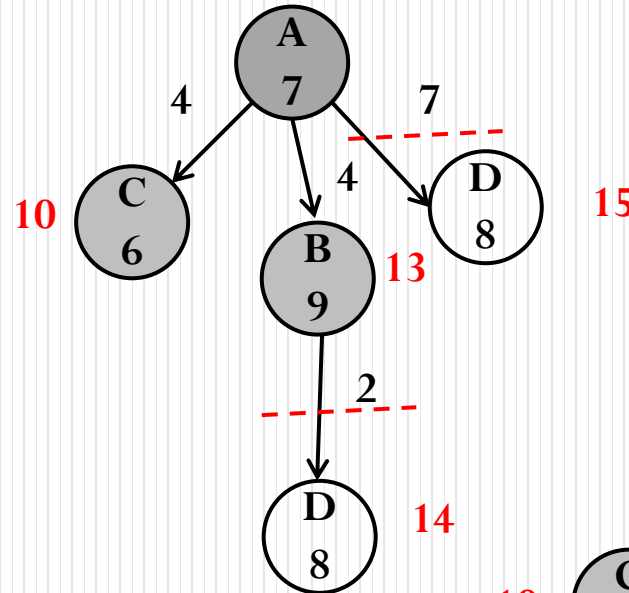
- $\text{cut-off} = f(C) = 10$
- Lowest of the  $f$  value of the nodes visited (but not expanded) in the previous DFS



# Iterative Deepening A\*

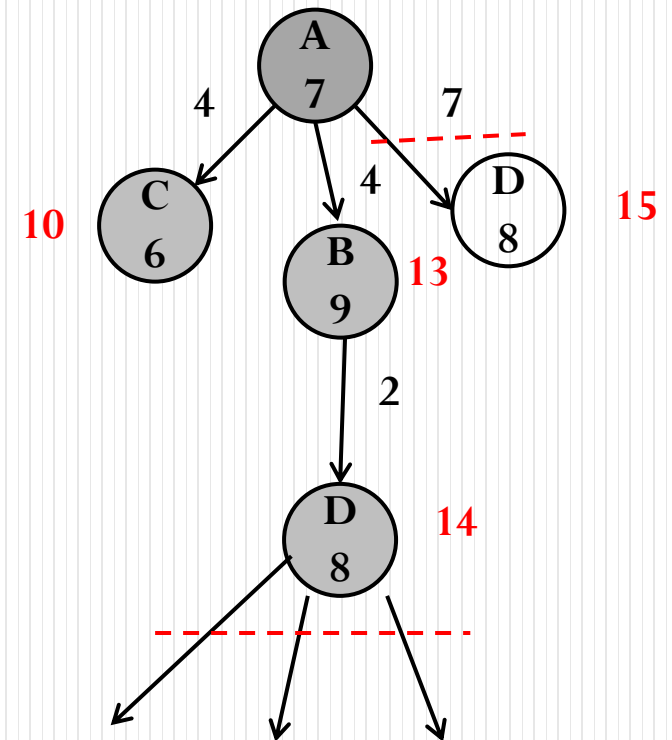
- **Iteration 3:**

- cut-off =  $f(B) = 13$



- **Iteration 4:**

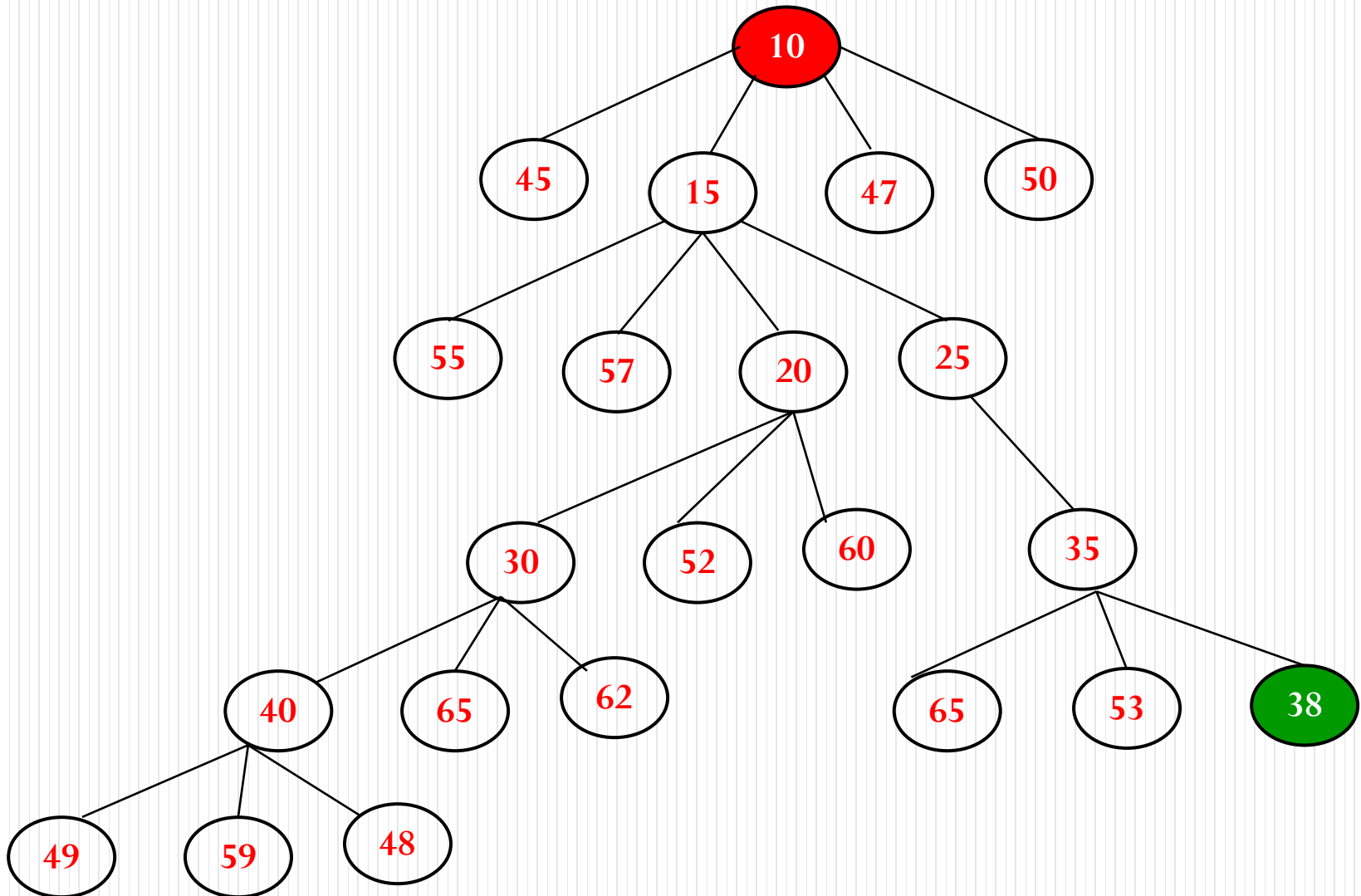
- cut-off =  $f(D) = 14$



# Recursive Best First Search

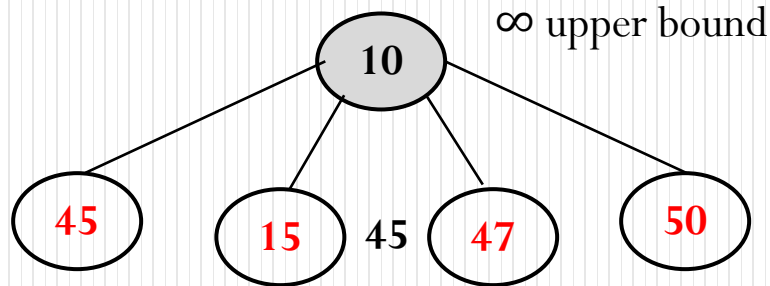
- Mimics best first search with linear space
- Similar to recursive depth-first but **do not continue indefinitely down the current path**
  - keeps track of the  $f$  value of the best alternative path available
  - if current  $f$  value exceeds this alternative  $f$  value then backtrack to alternative path
  - upon backtracking replace the  $f$  value of each node along the path with a **backed-up** value- the best  $f$  value of the children
- Like A\* (Tree search) , RBFS is **optimal** if the heuristic is admissible.
- **Space complexity** is  $O(bd)$  and **time complexity** depends on the heuristic function and how often the best path changes as nodes are expanded.

# RBFS Example



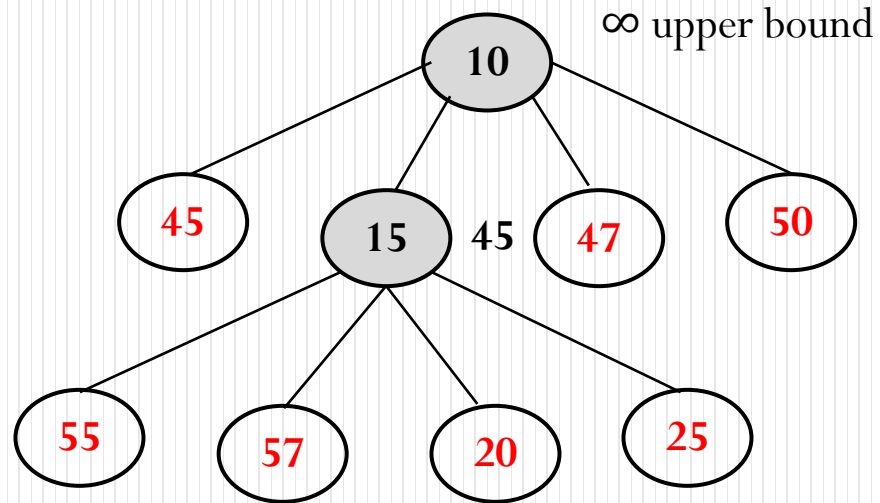
# RBFS Example

**Upperbound (n) =  
min [upperbound(n's  
parent), current value of  
lowest cost brother]**

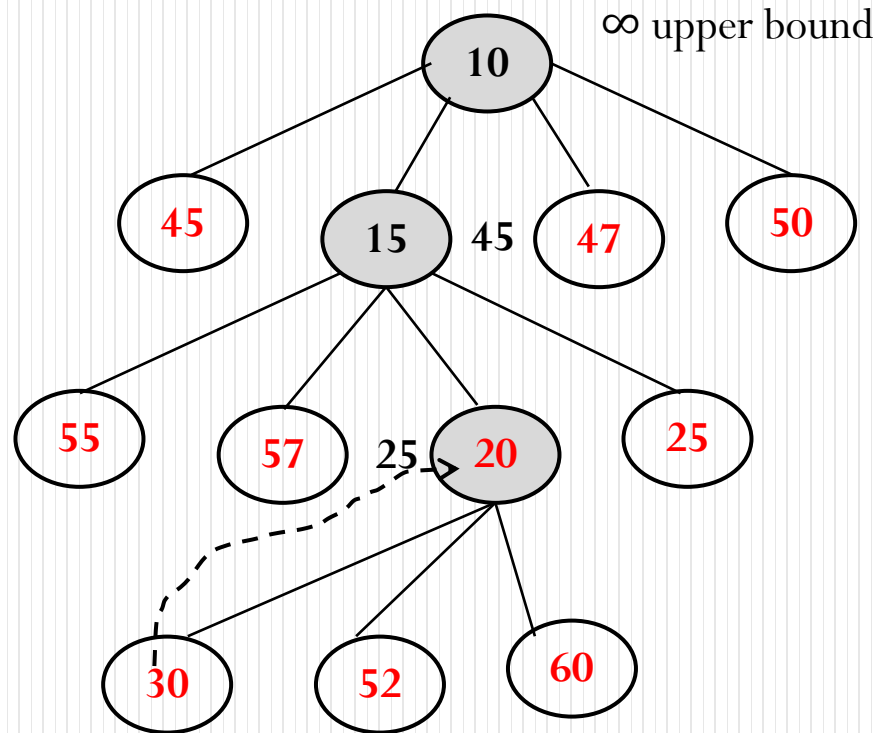


$f_{\text{backed-up}}(n) = f(n)$  /\*if n is leaf\*/  
 $f_{\text{backed-up}}(n) = f_{\text{backed-up}}(\text{child})$ ,  
child is successor of n /\*if n is not a leaf node\*/

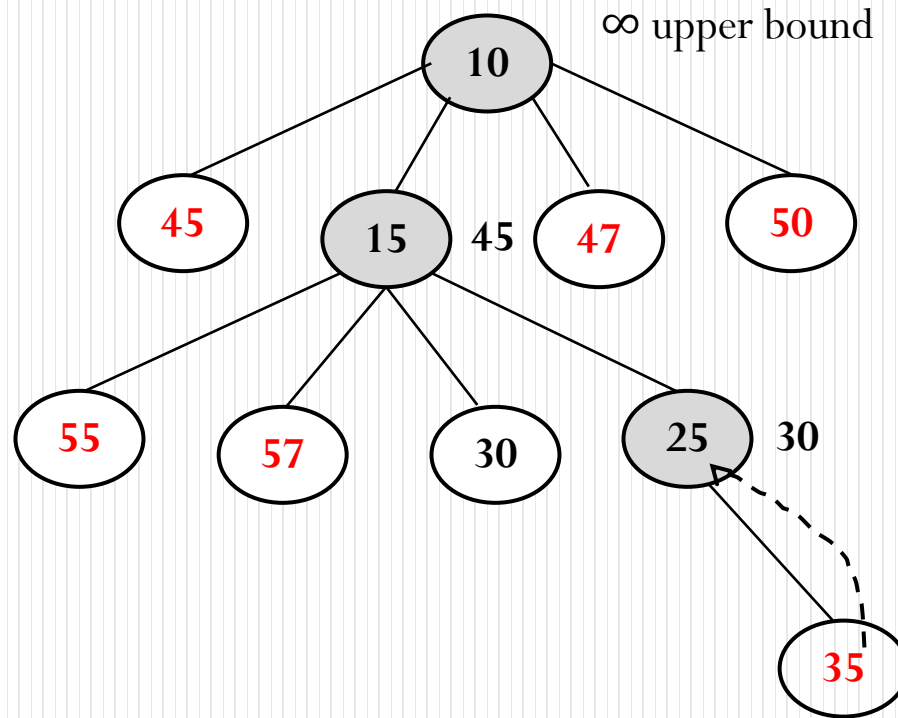
# RBFS Example



# RBFS Example

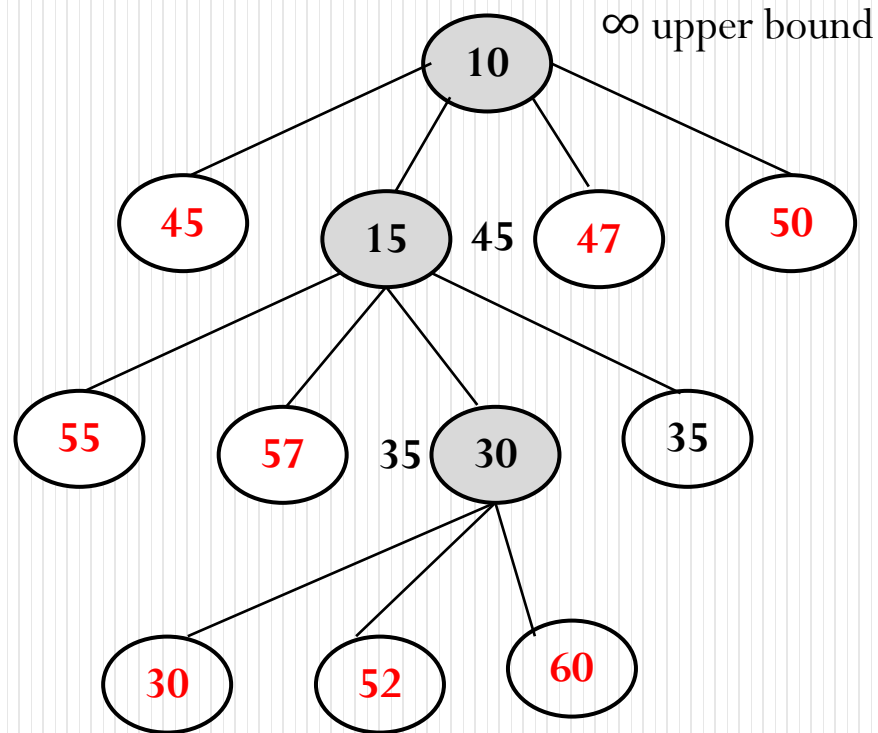


# RBFS Example

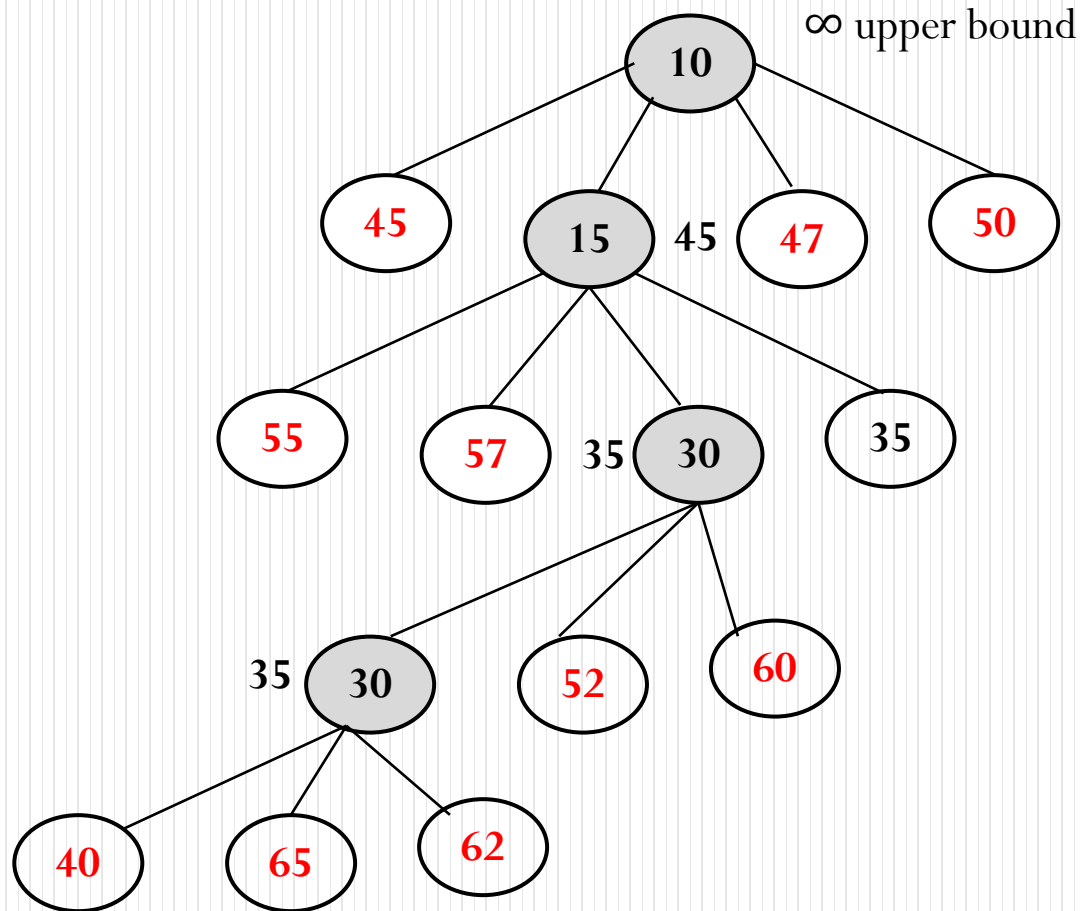




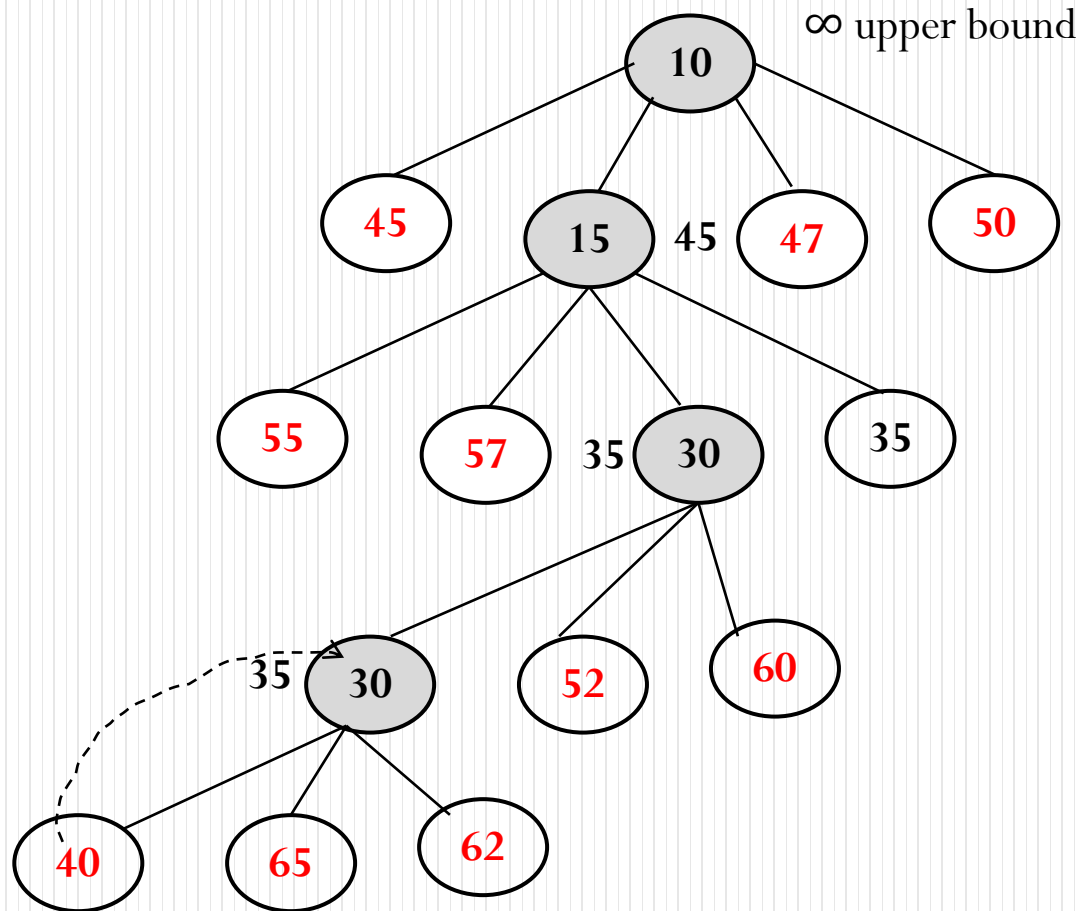
# RBFS Example



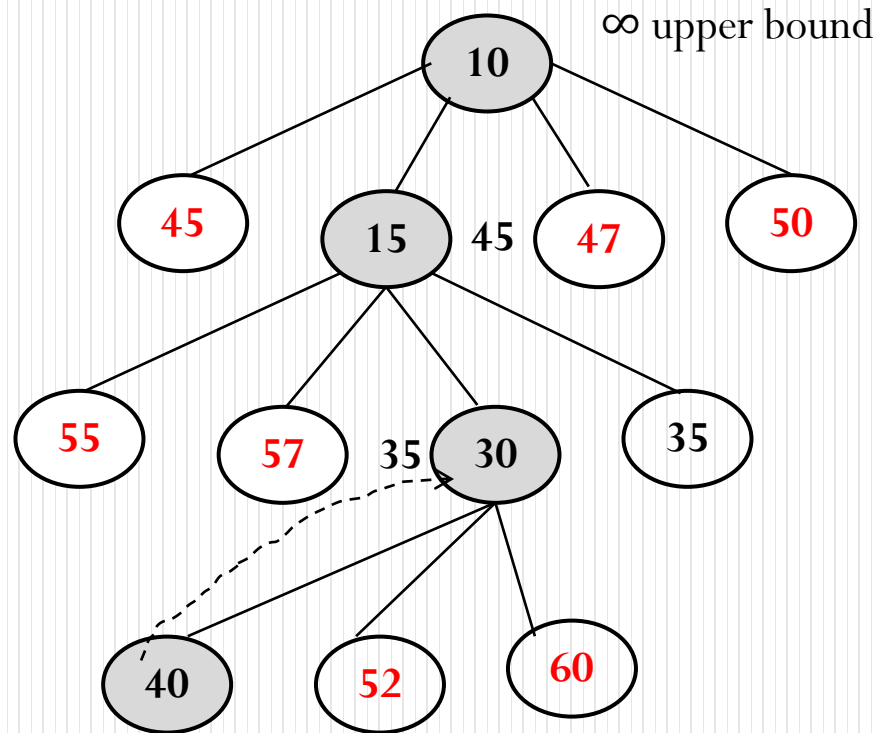
# RBFS Example



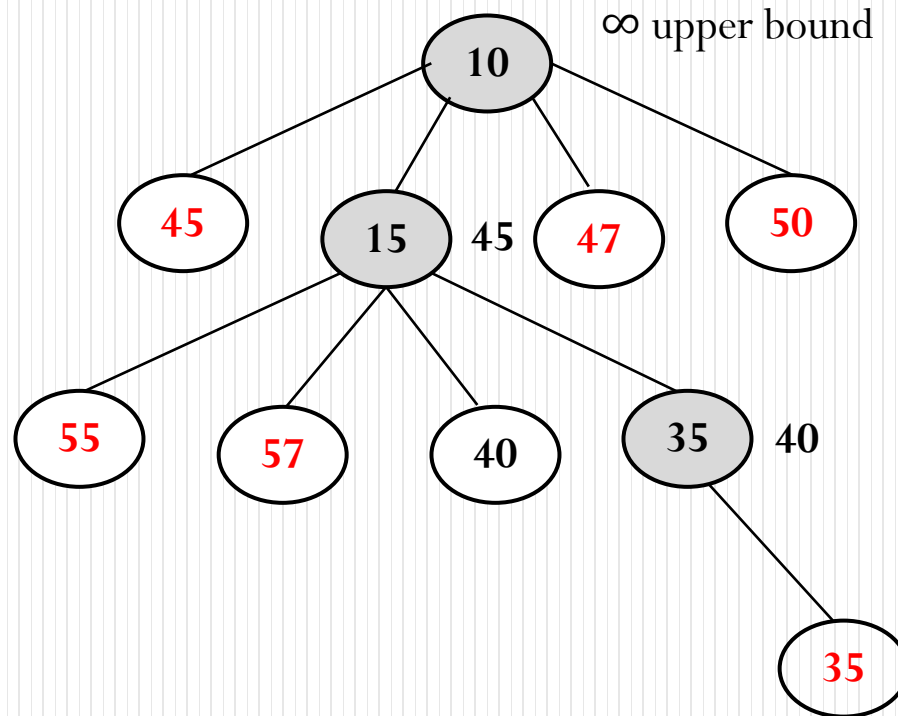
# RBFS Example



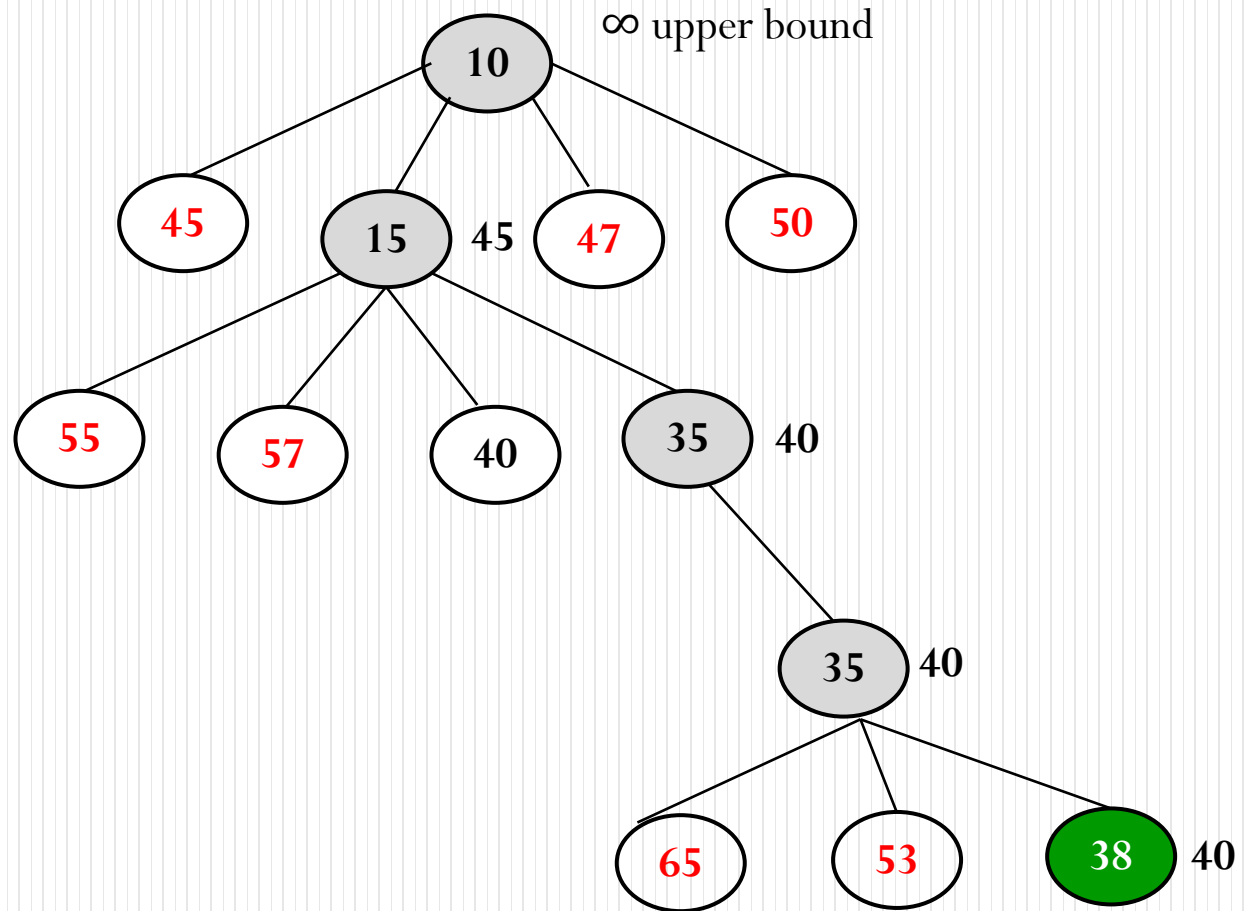
# RBFS Example



# RBFS Example



# RBFS Example



# More about Heuristics

- How to generate heuristics?
  - Relaxing problem definitions
  - Solution cost of a subproblem of a given problem
  - Learning from experience
- When more than one heuristic is available for the same problem, which one to choose?

# Heuristics

- Generating heuristics from Relaxed Problems
  - A problem with fewer restrictions on the actions is called a **relaxed problem**
  - The cost of an optimal solution to a relaxed problem is an admissible heuristic for the original problem.
- Example: 8-puzzle problem
  - A tile can move from square A to square B if **A is horizontally or vertically adjacent to B** and **B is blank**.
  - If the rules of the 8-puzzle are **relaxed** so that a tile can move **anywhere**, then  $h_1(n) = \text{number of misplaced tiles}$ .



# Heuristics

- If the rules are **relaxed** so that a tile can move to **any adjacent square**, then  $h_2(n)$  = sum of horizontal and vertical distances of the tiles from their goal positions (Manhattan distance)

$h_1(n) = 8$ , admissible because any tile that is out of place must be moved at least once.

$h_2(n) = 3+1+2+2+2+2+3+3+3+2 = 18$ , admissible because any move can slide tile one step closer to the goal.

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

Goal State

# Heuristics

- Generating Heuristics from subproblems
  - Admissible heuristics can also be derived from the solution cost of a subproblem of a given problem.
  - This cost is a lower bound on the cost of the real problem.

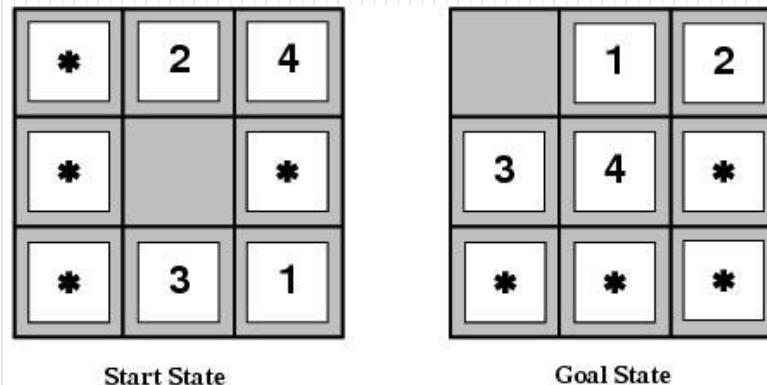


Fig. A subproblem of the 8-puzzle instance. The task is to get the tiles 1, 2, 3, and 4 into their correct positions without worrying about other tiles

# Heuristics

- **Pattern databases** (PDB) store the exact solution costs for every possible subproblem instance (every possible configuration of four tiles and the blank).
- The complete heuristic is constructed using the patterns in the DB

PDB consists of the set of all patterns which can be obtained by permutations of a target pattern

Pattern: partial specification of state  
i.e. tiles occupying certain states are unspecified

*	2	4
*		*
*	3	1

Start State

	1	2
3	4	*
*	*	*

Goal State

Target Pattern:  
partial specification  
of goal state

# Heuristics

- **Learning Heuristics from Experience**
  - Allow the agent to learn heuristic function  $h(n)$  from experience.
  - Experience – solving lots of 8-puzzles
  - Each optimal solution to an 8-puzzle problem = examples from which  $h(n)$  can be learned.
  - Example : (state from solution path, actual cost of solution path from that point)
  - Apply a learning algorithm to such examples to construct a function  $h(n)$  that predicts solution costs for other states that arise during search.

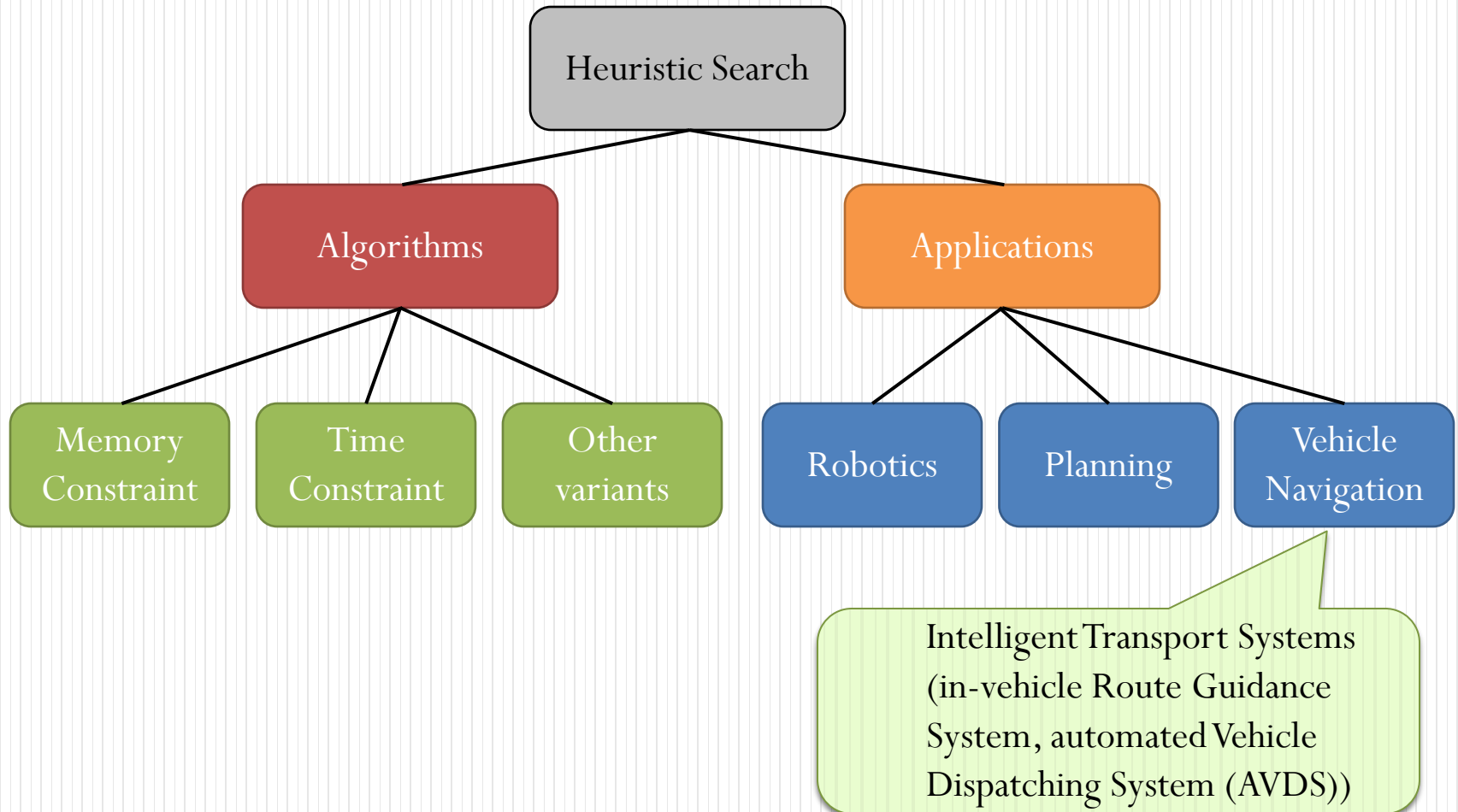
state1	$g(\text{state1})$
state2	$g(\text{state2})$

feature 11	feature 12	$g(\text{state1})$
feature 21	feature 22	$g(\text{State2})$

# Heuristics

- Could try to learn a heuristic function based on “features” rather than state itself
  - For example,  $x_1(n)$  = number of misplaced tiles,  $x_2(n)$  = number of goal-adjacent-pairs that are currently adjacent
  - $h(n) = w_1 x_1(n) + w_2 x_2(n)$ 
    - Weights could be learned to identify which features are predictive of path cost
- **More than one heuristic for the same problem?**
  - If for any node  $n$ ,  $h_2(n) > h_1(n)$  then we say that  $h_2(n)$  **dominates**  $h_1(n)$
  - use  $h_2$  provided it is consistent and that the computation time for the heuristic is not too long.
  - Given  $h_1, h_2, \dots, h_m$ , if none of them dominates the other then use
$$h(n) = \max \{h_1(n), \dots, h_m(n)\}$$

# Heuristic search: Trends



# Summary

- We discussed various **informed search strategies** that an agent can use to select actions before execution.
- **Heuristics and heuristic (informed) search:** Greedy Best-first search, A\* search, IDA\* , RBFS
- **Performance** of search strategies in terms of completeness, optimality, time complexity, and space complexity.
- How to generate admissible heuristics?