

# COMP3308/COMP3608, Lecture 3a

## ARTIFICIAL INTELLIGENCE

### A\* Algorithm

Reference: Russell and Norvig, ch. 3

# Outline

- **A\* search algorithm**
- **How to invent admissible heuristics**

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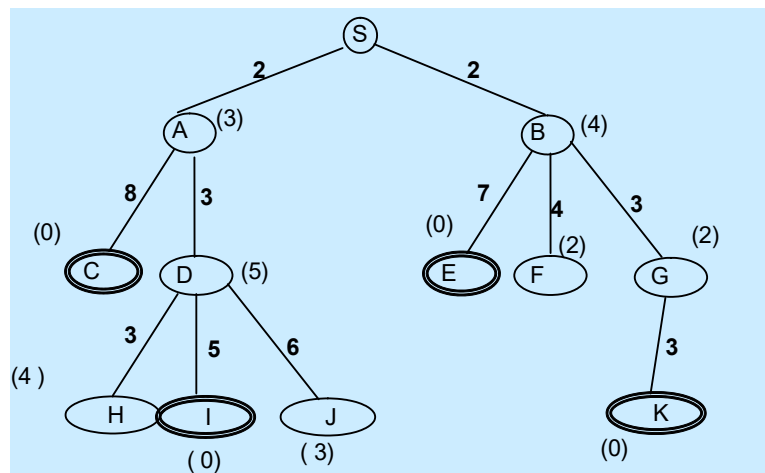
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# A\* Search

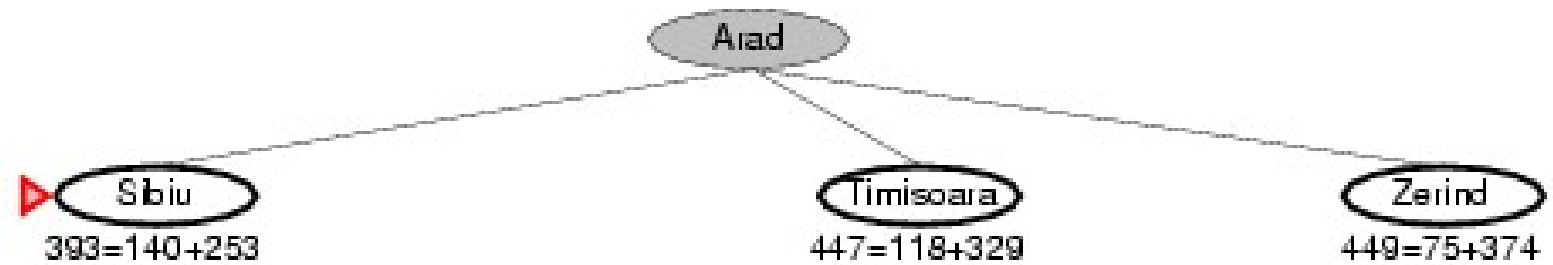
- UCS minimizes the cost so far  $g(n)$
- GS minimizes the estimated cost to the goal  $h(n)$
- A\* combines UCS and GS
- Evaluation function:  $f(n)=g(n)+h(n)$ 
  - $g(n)$  = cost so far to reach  $n$
  - $h(n)$  = estimated cost from  $n$  to the goal
  - $f(n)$  = estimated total cost of path through  $n$  to the goal



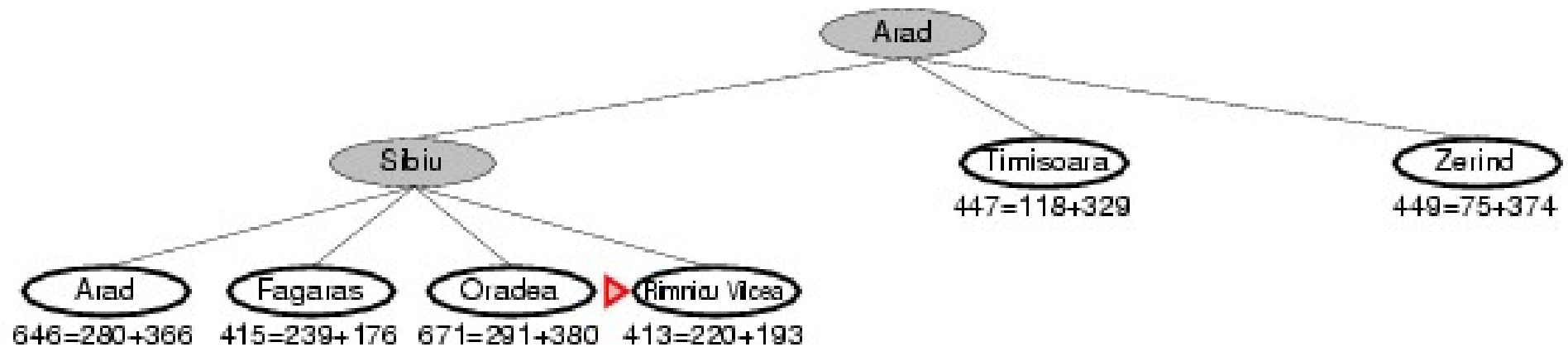
# A\* Search for Romania Example



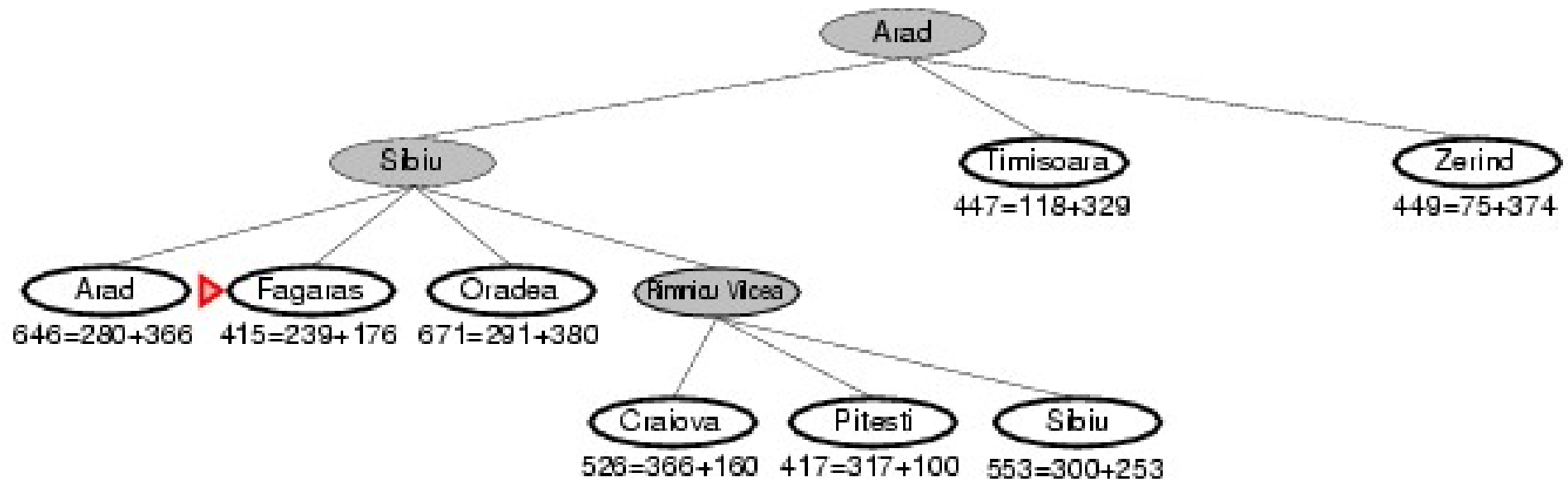
# A\* Search for Romania Example



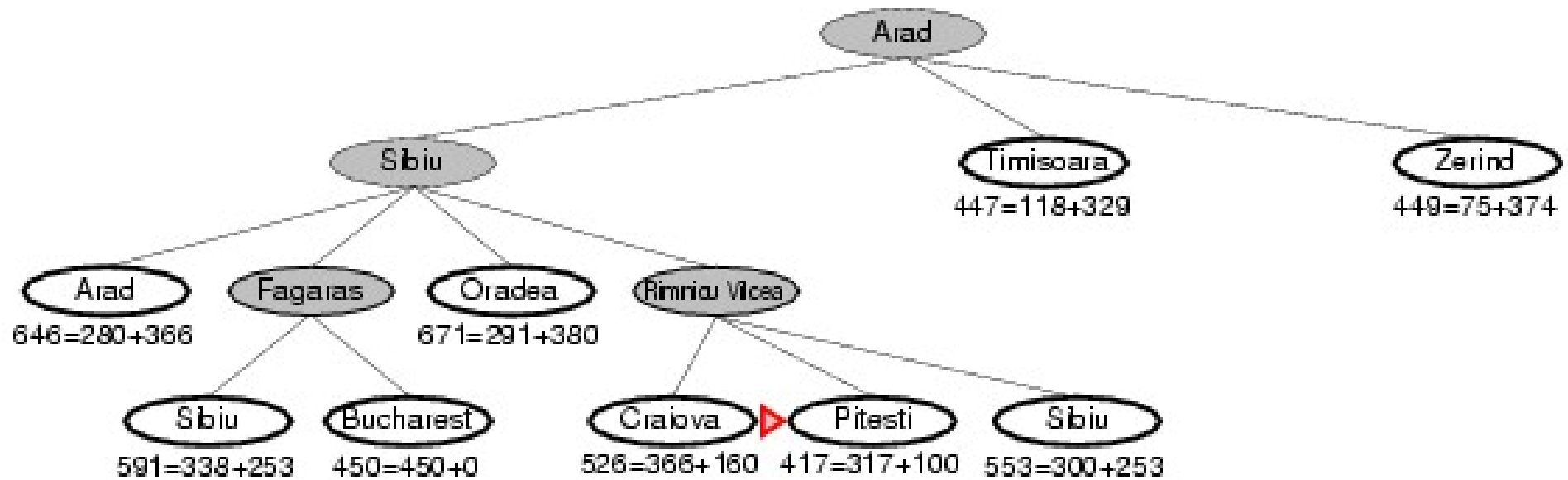
# A\* Search for Romania Example



# A\* Search for Romania Example

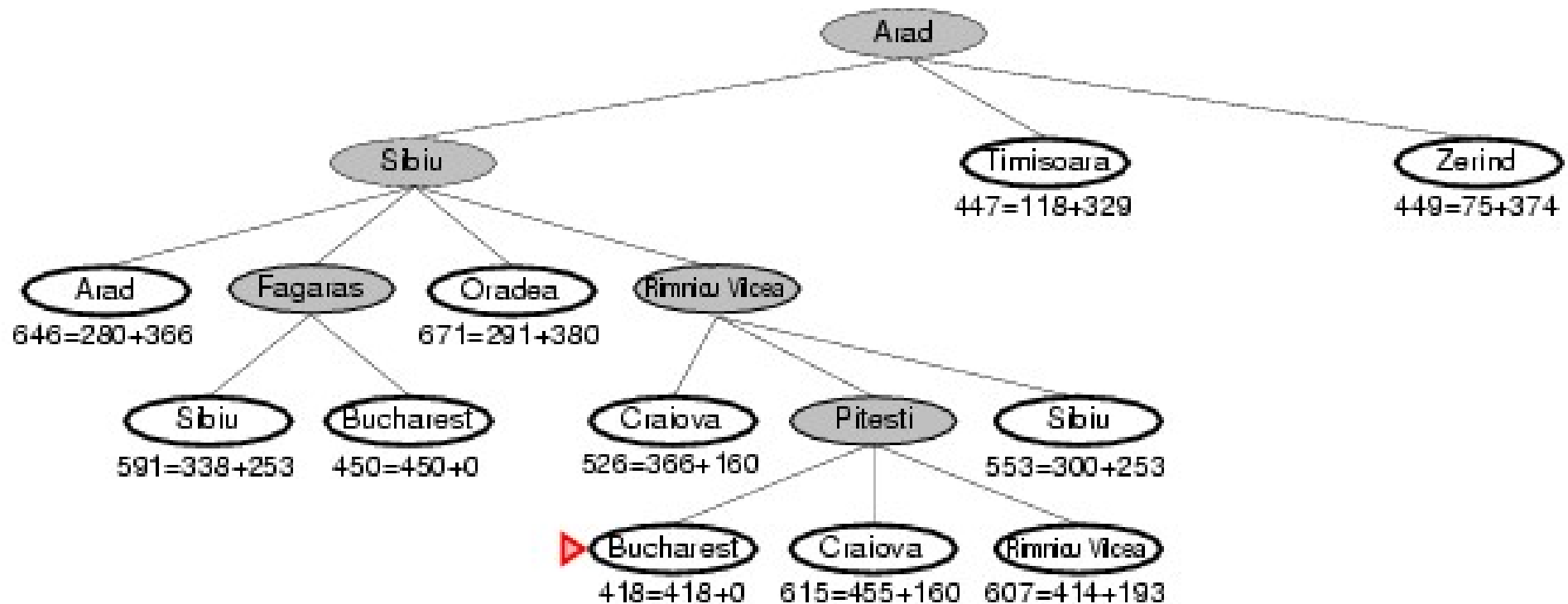


# A\* Search for Romania Example





# A\* Search for Romania Example

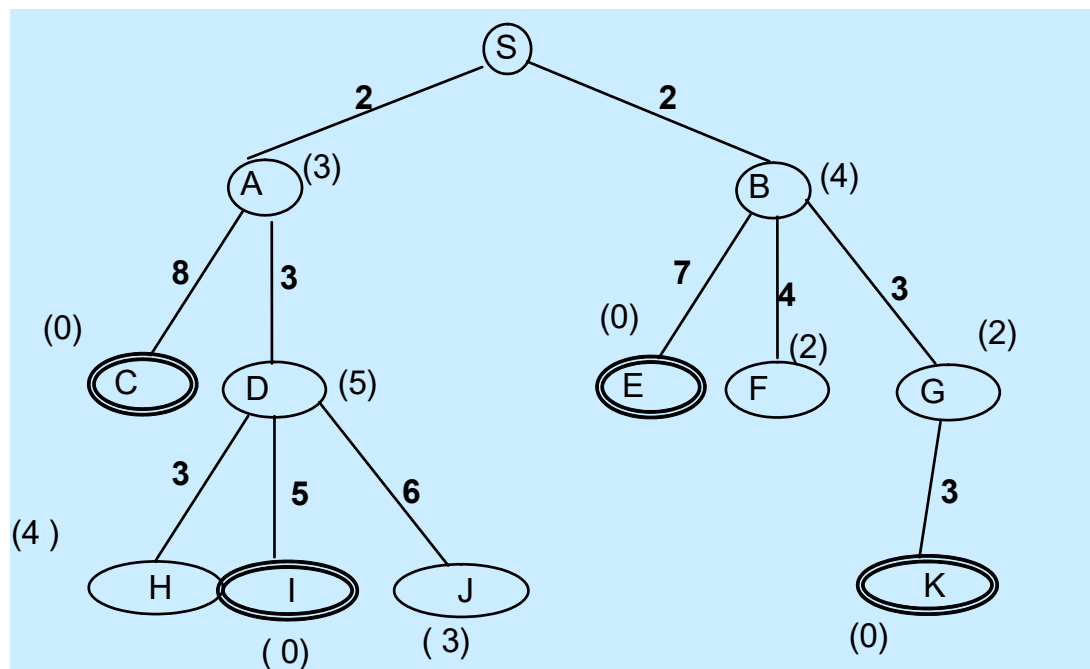


**Bucharest is selected for expansion and it is a goal node => stop**

**Solution path: Arad-Sibiu-Rimnicu Vilcea-Pitesti-Bucharest, cost=418**

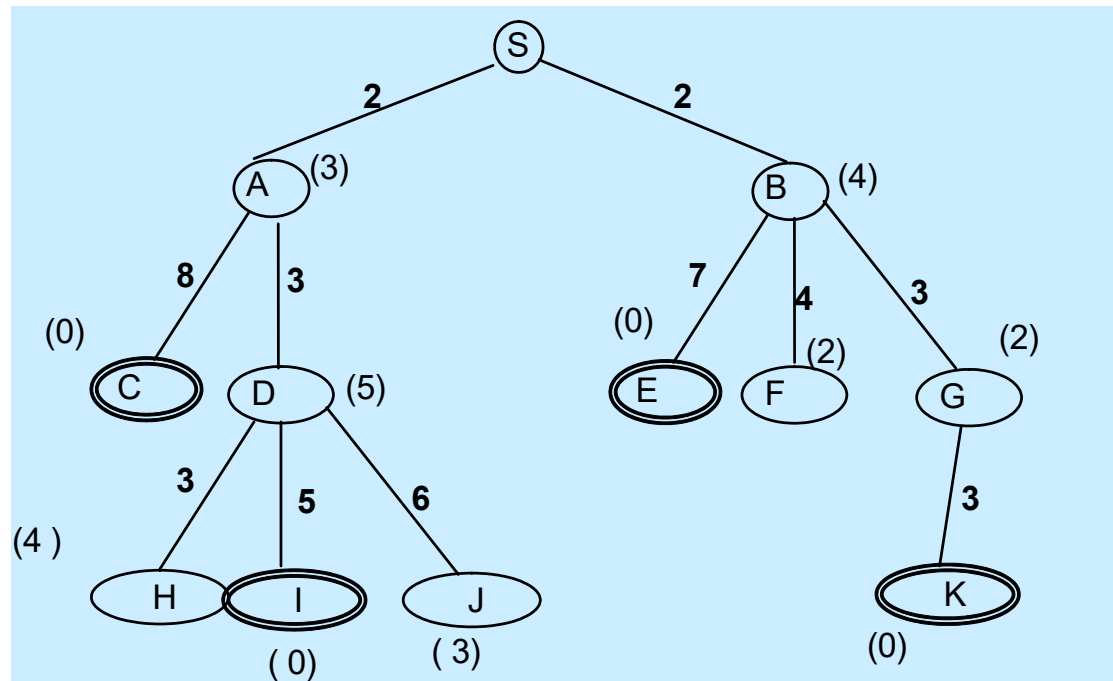
# A\* Search – Another Example

- **Given:**
  - **Goal nodes:** C, I, E and K
  - **Step path cost:** along the links
  - ***h* value of each node:** in brackets ()
  - **Same priority nodes** -> **expand the last added first**
- **Run A\***
  - **list of expanded nodes** =?
  - **solution path** =?
  - **cost of the solution**:=?



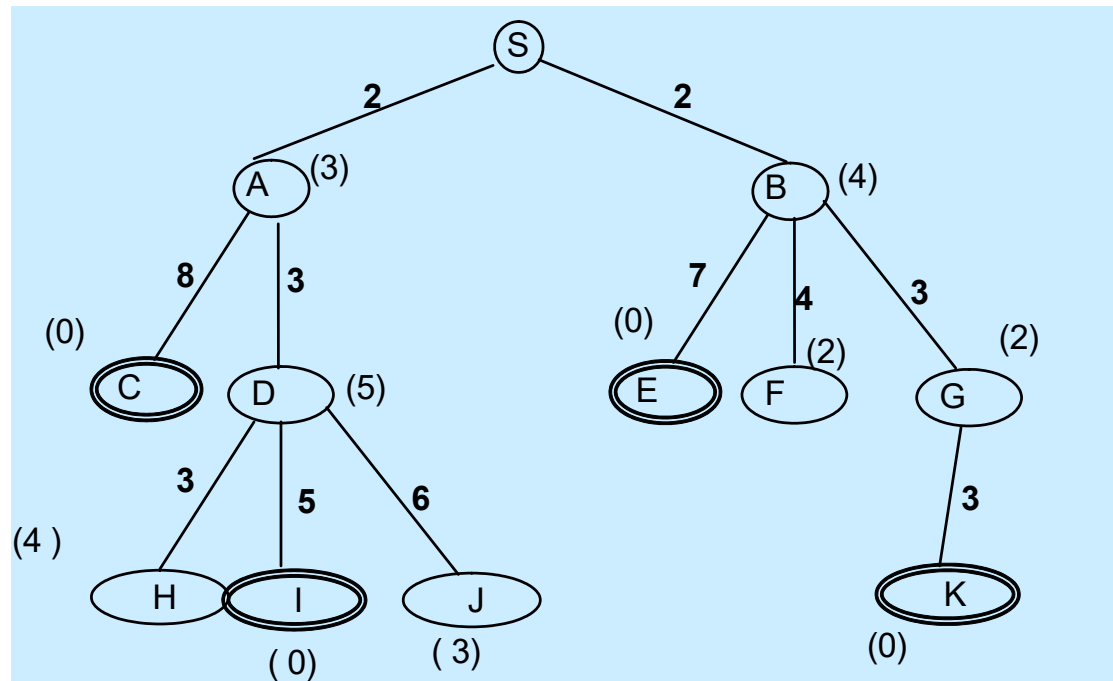
# Solution

- **Fringe:** S
- **Expanded:** nil



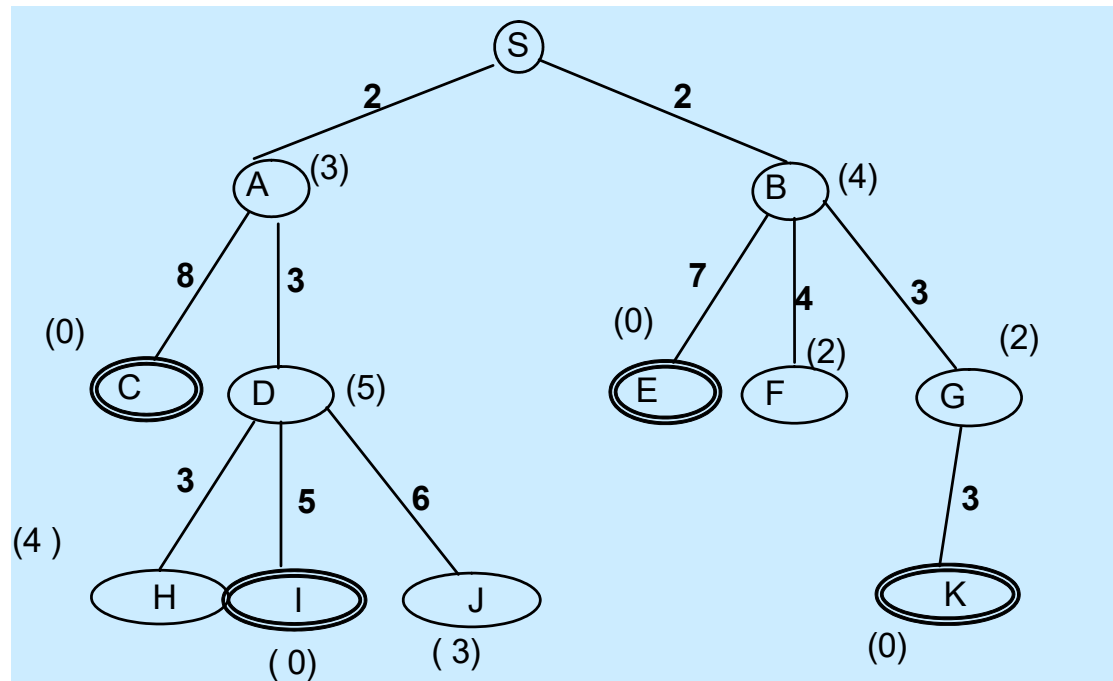
# Solution

- **Fringe:** (A, 5), (B, 6) //keep the fringe in sorted order
- **Expanded:** S



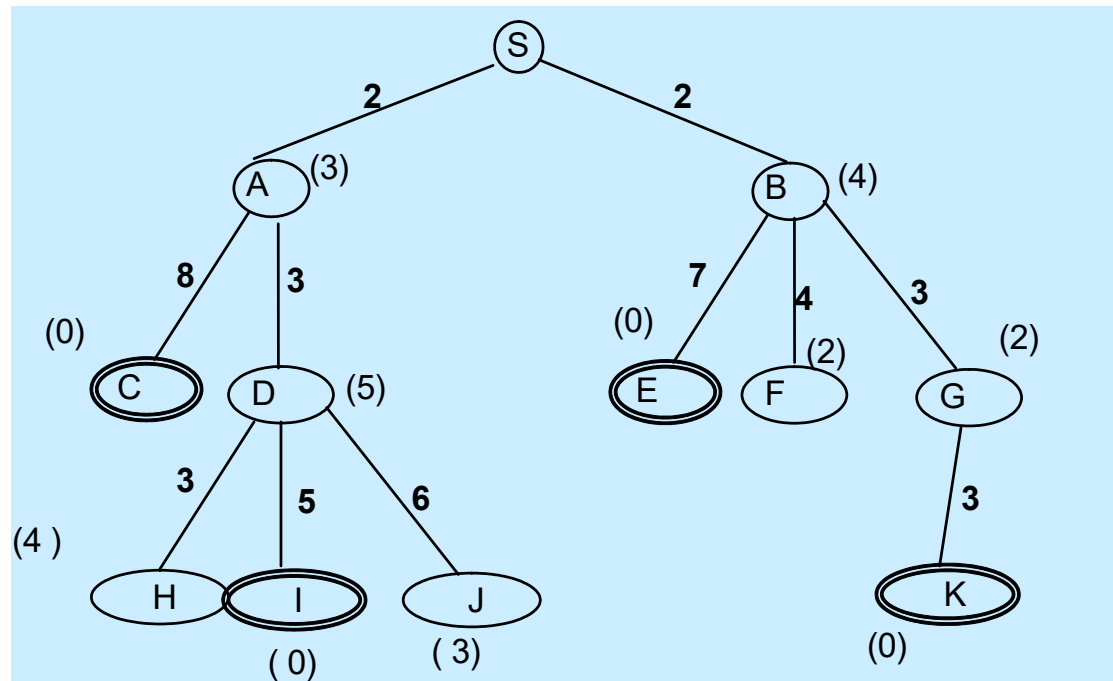
# Solution

- **Fringe:** (B, 6), (C, 10), (D, 10) //the added children are in blue
- **Expanded:** S, (A, 5)



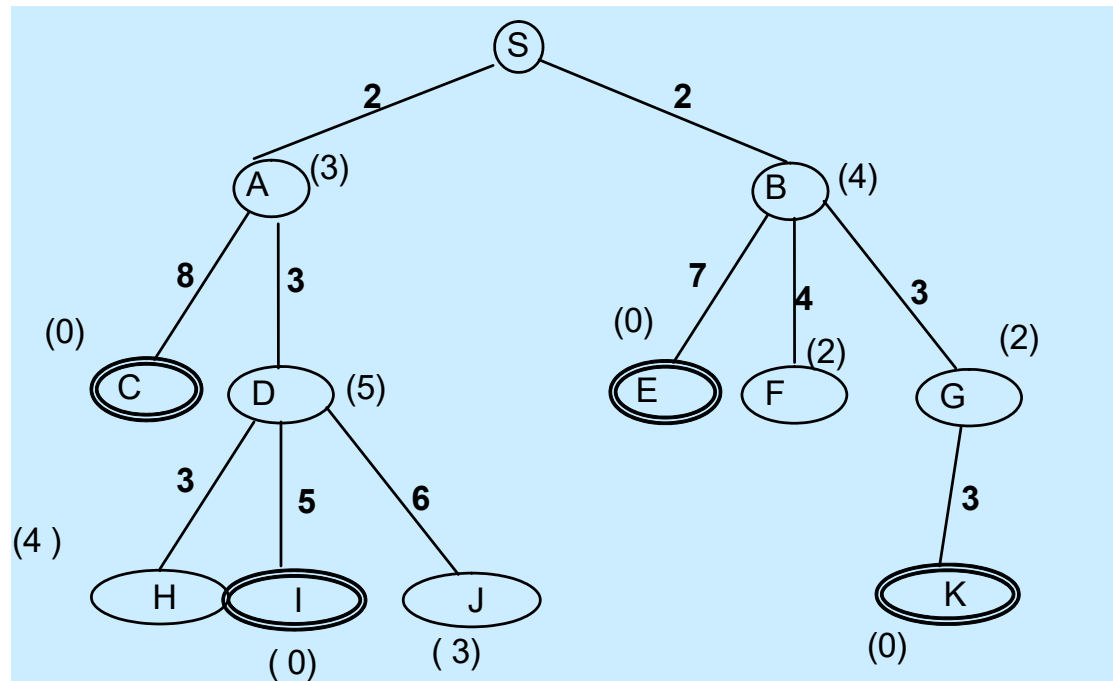
# Solution

- **Fringe:** (G, 7), (F, 8), (E, 9), (C, 10), (D, 10)
- **Expanded:** S, (A, 5), (B, 6)



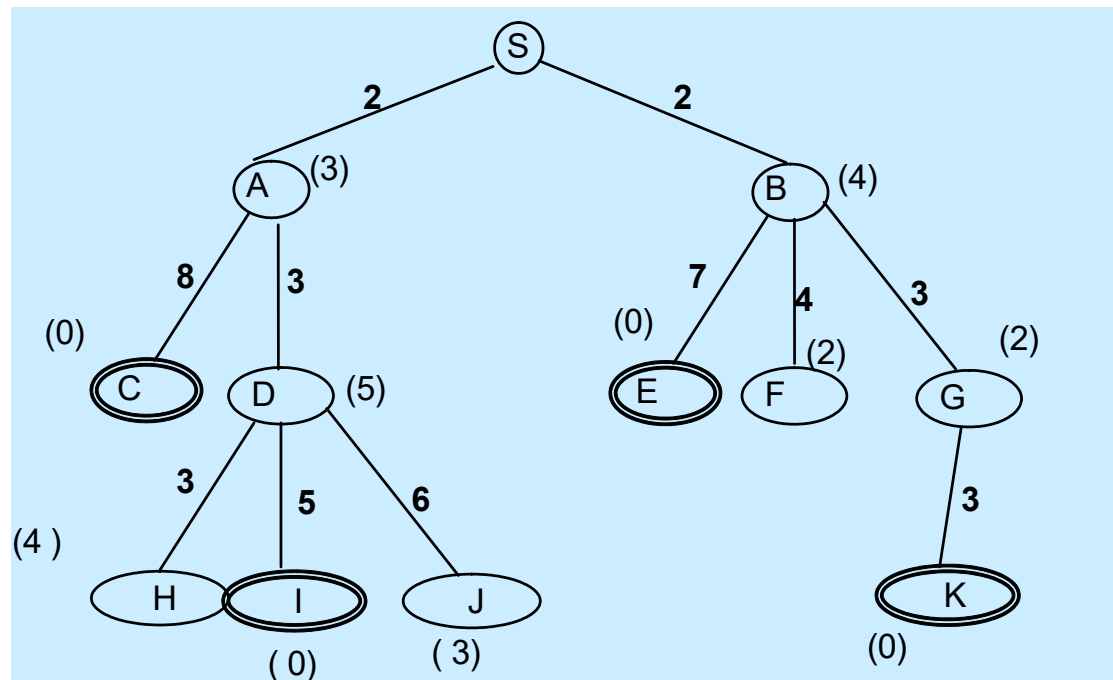
# Solution

- **Fringe:** (K, 8), (F, 8), (E, 9), (C, 10), (D, 10)
- **Expanded:** S, (A, 5), (B, 6), (G, 7)



## Solution

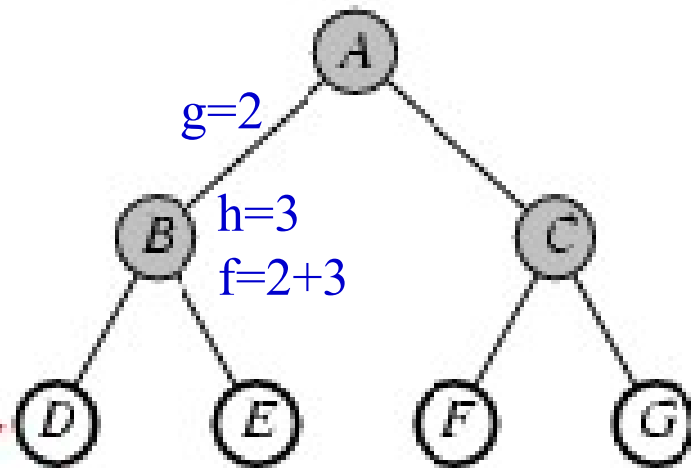
- **K is selected; Goal node? Yes => stop**
- **Expanded: S, A, B, G, K**
- **Solution path: SBGK, cost=8**
- **Is this the optimal solution=?**





# A\* and UCS

- UCS is a special case of A\* when  $h(n) = ?$
- In other words, when will A\* behave as UCS?

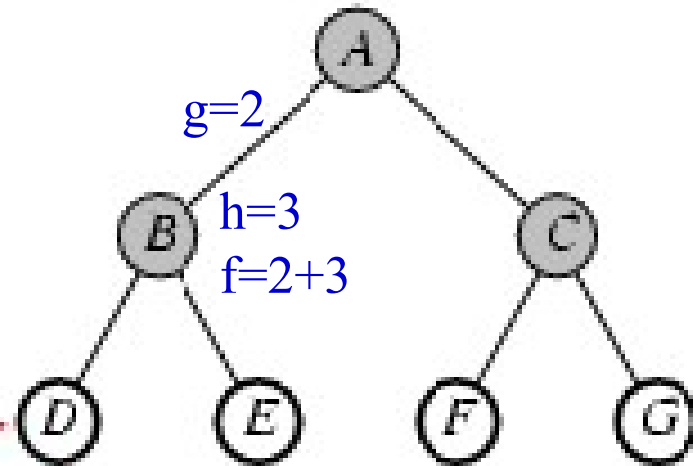


**Hint:**

- UCS uses which cost?
- A\* uses which cost?
- Relation between the 2 costs =?

# A\* and UCS (Answer)

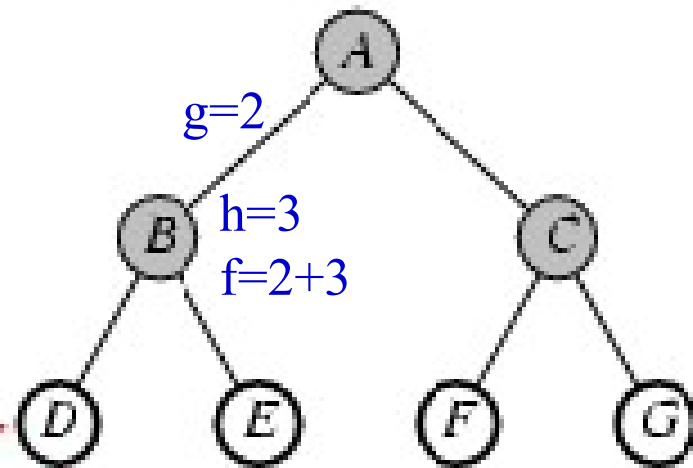
- UCS is a special case of A\* when  $h(n) = ?$
- In other words, when will A\* behave as UCS?



- UCS uses which cost?
- A\* uses which cost?
- UCS:  $g(n)$
- A\*:  $f(n) = g(n) + h(n)$
- if  $h(n) = 0 \Rightarrow f(n) = g(n)$ ,  
i.e. A\* becomes UCS

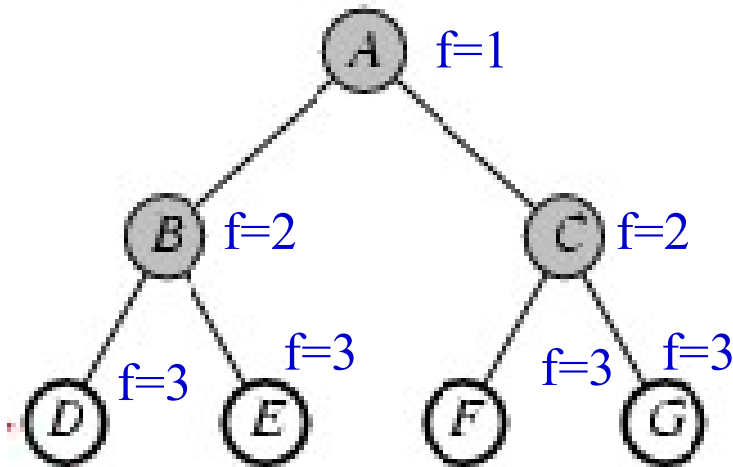
# A\* and BFS

- **BFS is a special case of A\* when  $f(n) = ?$**
- **When will A\* behave as BFS?**



# A\* and BFS (Answer)

- **BFS is a special case of A\* when  $f(n) = ?$**

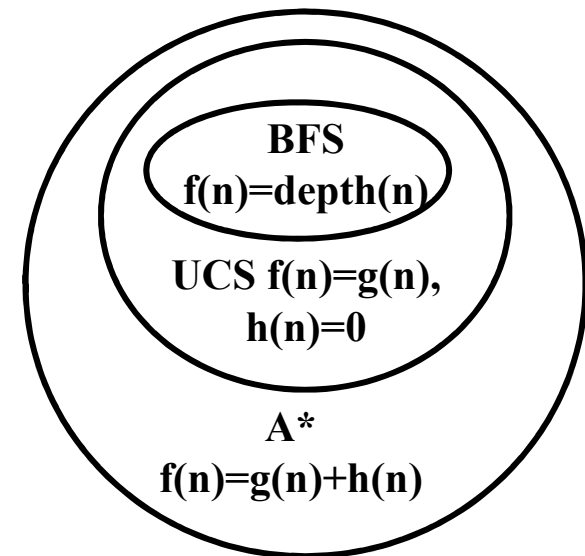
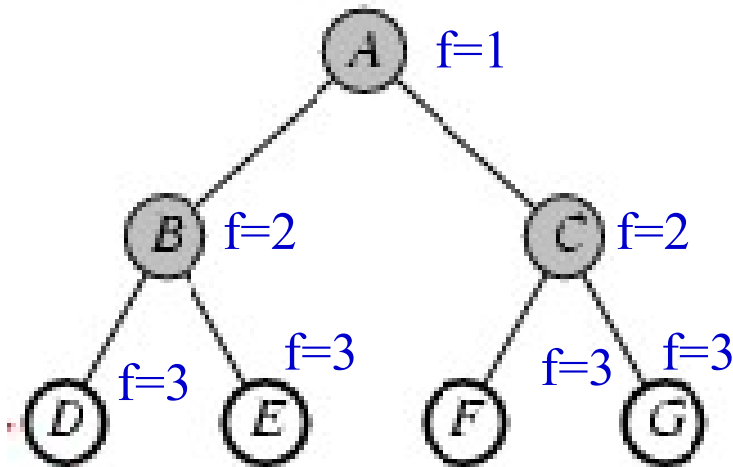


**when  $f(n) = \text{depth}(n)$**

- **And also when this assumption for resolving ties is true: among nodes with the same priority, the left most is expanded first**

# BFS, UCS and A\*

- **BFS** is a special case of A\* when  $f(n)=depth(n)$
- **BFS** is also a special case of UCS when  $g(n)=depth(n)$
- **UCS** is a special case of A\* when  $h(n)=0$



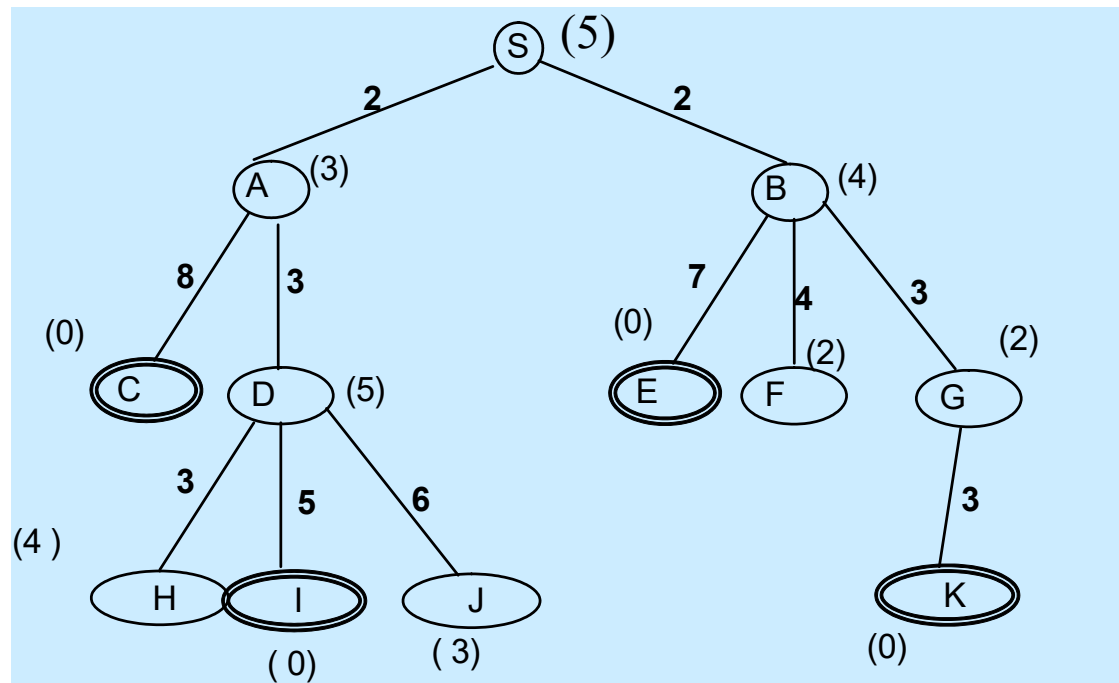
# Admissible Heuristic

- 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 a goal from  $n$
  - i.e. the estimate to reach a goal is smaller than (or equal to) the true cost to reach a goal
- Admissible heuristics are *optimistic* – they think that the cost of solving the problem is less than it actually is!
  - e.g. the straight line distance heuristic  $h_{SLD}(n)$  never overestimates the actual road distance (cost from  $n$  to goal) => it is admissible
- Theorem: If  $h$  is an *admissible heuristic*, then  $A^*$  is complete and optimal



## Is $h$ Admissible for Our Example?

- No need to check goal nodes ( $h=0$  for them) and nodes that are not on a goal path
- $h(S)=5 \leq 8$  (shortest path from S to a goal, i.e. to goal K)
- $h(B)=4 \leq 6$
- $h(G)=2 \leq 3$
- $h(A)=3 \leq 8$
- $h(D)=5 \leq 5$
- $\Rightarrow h$  is admissible



# Optimality of A\* - Proof

**Optimal solution = the shortest (lowest cost) path to a goal node**

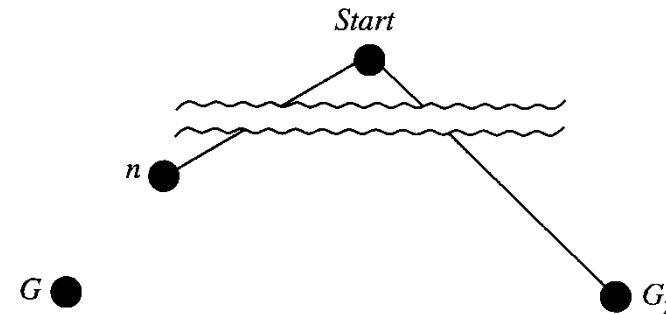
**Idea: Suppose that some sub-optimal goal  $G_2$  has been generated and it is in the fringe. We will show that  $G_2$  can not be selected from the fringe.**

**Given:**

**$G$  - the optimal goal**

**$G_2$  – a sub-optimal goal**

**$h$  is admissible**



**To prove:  $G_2$  can not be selected from the fringe for expansion**

**Proof:**

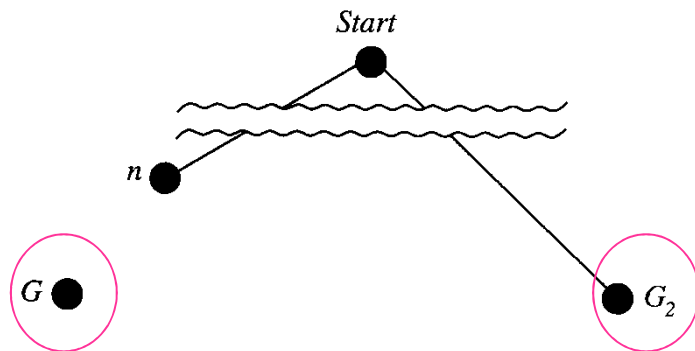
**Let  $n$  be an unexpanded node in the fringe such that  $n$  is on the optimal (shortest) path to  $G$  (there must be such a node). We will show that  $f(n) < f(G_2)$ , i.e.  $n$  will be expanded, not  $G_2$**



# Optimality of A\* - Proof (2)

Compare  $f(G_2)$  and  $f(G)$

- 1)  $f(G_2) = g(G_2) + h(G_2)$  (by definition)  $= g(G_2)$  as  $h(G_2) = 0$ ,  $G_2$  is a goal
- 2)  $f(G) = g(G) + h(G)$  (by definition)  $= g(G)$  as  $h(G) = 0$ ,  $G$  is a goal
- 3)  $g(G_2) > g(G)$  as  $G_2$  is suboptimal
- 4)  $\Rightarrow f(G_2) > f(G)$  by substituting 1) and 2) into 3)



# Optimality of A\* - Proof (3)

Compare  $f(n)$  and  $f(G)$

5)  $f(n) = g(n) + h(n)$  (by definition)

6)  $h(n) \leq h^*(n)$  where  $h^*(n)$  is the true cost from  $n$  to  $G$  (as  $h$  is admissible)

7)  $\Rightarrow f(n) \leq g(n) + h^*(n)$  (5 & 6)

8)  $\quad \quad \quad = g(G)$  path cost from  $S$  to  $G$  via  $n$

9)  $\quad \quad \quad g(G) = f(G)$  as  $f(G) = g(G) + h(G) = g(G) + 0$  as  $h(G) = 0$ ,  $G$  is a goal

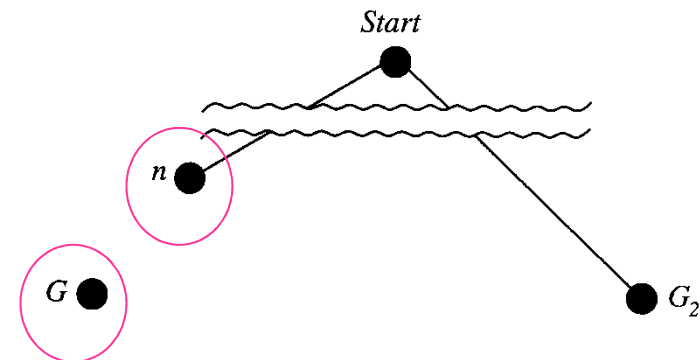
10)  $\Rightarrow f(n) \leq f(G)$  (7,8,9)

Thus  $f(G) < f(G_2)$  (4)

$f(n) \leq f(G)$  (10)

11)  $f(n) \leq f(G) < f(G_2)$  (10, 4)

12)  $f(n) < f(G_2) \Rightarrow n$  will be expanded not  $G_2$ ; A\* will not select  $G_2$  for expansion



# Admissible Heuristics for 8-puzzle – $h_1$

- $h_1(n)$  = number of misplaced tiles
- $h_1(\text{Start}) = ?$ 
  - 7 (7 of 8 tiles are out of position)
- Why is  $h_1$  admissible?
  - recall: admissible heuristics are optimistic – they never overestimate the number of steps to the goal
  - $h_1$ : any tile that is out of place must be moved once
  - true cost: higher; any tile that is out of place must be moved at least once

5	4	
6	1	8
7	3	2

Start State

1	2	3
8		4
7	6	5

Goal State

# Admissible Heuristics for 8-puzzle – $h_2$

- $h_2(n)$  = the sum of the distances of the tiles from their goal positions (Manhattan distance)
  - note: tiles can move only horizontally and vertically
- $h_2(\text{Start}) = ?$ 
  - 18 (2+3+3+2+4+2+0+2)
- Why is  $h_2$  admissible?
  - $h_2$ : at each step move a tile to an adjacent position so that it is 1 step closer to its goal position and you will reach the solution in  $h_2$  steps, e.g. move tile 1 up, then left
  - True cost: higher as moving a tile to an adjacent position is not always possible; depends on the position of the blank tile

5	4	
6	1	8
7	3	2

Start State

1	2	3
8		4
7	6	5

Goal State

# Dominance

- Definition of a *dominant heuristic*:
  - Given 2 admissible heuristics  $h_1$  and  $h_2$ ,
  - $h_2$  *dominates*  $h_1$  if for all nodes  $n$   $h_2(n) \geq h_1(n)$
- Theorem: A\* using  $h_2$  will expand fewer nodes than A\* using  $h_1$  (i.e.  $h_2$  is better for search)
  - $\forall n$  with  $f(n) < f^*$  will be expanded ( $f^*$ =cost of optimal solution path)
  - $\Rightarrow \forall n$  with  $h(n) < f^* - g(n)$  will be expanded
  - but  $h_2(n) \geq h_1(n)$
  - $\Rightarrow \forall n$  expanded by A\* using  $h_2$  will also be expanded by  $h_1$  and  $h_1$  may also expand other nodes
- Typical search costs for 8-puzzle with  $d=14$ :  
IDS = 3 473 941 nodes, A\*( $h_1$ ) = 539 nodes, A\*( $h_2$ ) = 113 nodes
- Dominant heuristics give a better estimate of the true cost to a goal G

## Question

- Suppose that  $h1$  and  $h2$  are two admissible heuristics for a given problem. We define two other heuristics:
  - $h3 = \min(h1, h2)$
  - $h4 = \max(h1, h2)$
- Q1. Is  $h3$  admissible?
- Q2. Is  $h4$  admissible?
- Q3. Which one is a better heuristic -  $h3$  or  $h4$ ?

## Answer

- Suppose that  $h1$  and  $h2$  are two admissible heuristics for a given problem. We define two other heuristics:
  - $h3 = \min(h1, h2)$
  - $h4 = \max(h1, h2)$
- Q1. Is  $h3$  admissible?
- Q2. Is  $h4$  admissible?
- Q2. Which one is a better heuristic -  $h3$  or  $h4$ ?

### Answer:

- Q1 and Q2: Both  $h3$  and  $h4$  are admissible as their values are never greater than an admissible value  $h1$  or  $h2$
- Q3:  $h4$  is a better heuristic since it is closer to the real cost, i.e.  $h4$  is a dominant heuristic since  $h4(n) \geq h3(b)$

# How to Invent Admissible Heuristics?

- By formulating a *relaxed* version of the problem and finding the *exact* solution. This solution is an admissible heuristic.
- Relaxed problem – a problem with fewer restrictions on the actions
- 8-puzzle relaxed formulation 1:
  - a tile can move *anywhere*
  - How many steps do we need to reach the goal state from the initial state? (=solution)
  - solution = the number of misplaced tiles =  $h_1(n)$
- 8-puzzle relaxed formulation 2:
  - a tile can move to *any adjacent square*
  - solution = Manhattan distance =  $h_2(n)$



# Admissible Heuristics from Relaxed Problems

- **Theorem:** The optimal solution to a relaxed problem is an admissible heuristic for the original problem
- **Intuitively, this is true because:**  
The optimal solution to the original problem is also a solution to the relaxed version (by definition)  $\Rightarrow$  it must be at least as expensive as the optimal solution to the relaxed version  $\Rightarrow$  the solution to the relaxed version is less or equally expensive than the solution to the original problem  $\Rightarrow$  it is an admissible heuristic for the original problem

# Constructing Relaxed Problems Automatically

- Relaxed problems can be constructed automatically if the problem definition is written in a formal language
  - Problem:
    - A tile can move from square A to square B if A is adjacent to B and B is blank*
  - 3 relaxed problems generated by removing 1 or both conditions:
    - 1) A tile can move from square A to square B if A is adjacent to B*
    - 2) A tile can move from square A to square B if B is blank*
    - 3) A tile can move from square A to square B (always, no conditions)*
- ABSOLVER (1993) is a program that can generate heuristics automatically using the “relaxed problem” method and other methods
  - Generated a new heuristic for the 8-puzzle that was better than any existing heuristic
  - Found the first useful heuristic for the Rubik’s cube puzzle



# No Single Clearly Best Heuristic?

- Often we can't find a single heuristic that is clearly the best (i.e. dominant)
- We have a set of heuristics  $h_1, h_2, \dots, h_m$  but none of them dominates any of the others
- Which should we choose?
- Solution: define a composite heuristic:  
$$h(n) = \max\{h_1(n), h_2(n), \dots, h_m(n)\}$$

At a given node, it uses whichever heuristic is most accurate (dominant)
- Is  $h(n)$  admissible?  
Yes, because the individual heuristics are admissible

# Learning Heuristics from Experience

- **Example: 8-puzzle**
- **Experience = many 8-puzzle solutions (paths from A to B)**
- **Each previous solution provides a set of examples to learn  $h$**
- **Each example is a pair (state, associated  $h$ )**
  - $h$  is known for each state, i.e. we have a *labelled* dataset
- **The state is suitably represented as a set of useful features, e.g.**
  - $f1$  = number of misplaced tiles
  - $f2$  = number of adjacent tiles that should not be adjacent
  - $h$  is a function of the features but we don't know how exactly it depends on them, we will learn this relationship from the data
- **We can generate e.g. 100 random 8-puzzle configurations and record the values of  $f1$ ,  $f2$  and  $h$  to form a *training set* of examples. Using this training set, we build a classifier.**
- **We use this classifier on new data, i.e. given  $f1$  and  $f2$ , to predict  $h$  which is unknown. No guarantee that the learned heuristic is admissible or consistent.**

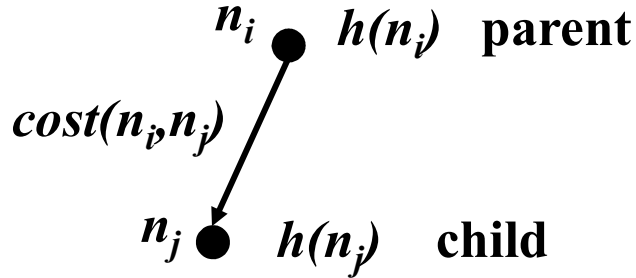
training data

Ex.#	f1	f2	h
Ex1	7	8	14
...			
Ex100	5	2	5

# Back to A\* and another property of the heuristics...

# Consistent (Monotonic) Heuristic

- Consider a pair of nodes  $ni$  and  $nj$ , where  $ni$  is the parent of  $nj$



- $h$  is a *consistent (monotonic) heuristic*, if for all such pairs in the search graph the following triangle inequality is satisfied:

$$h(ni) \leq cost(ni,nj) + h(nj) \text{ for all } n$$

**parent**

# child

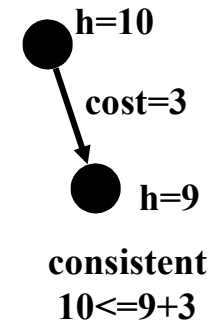
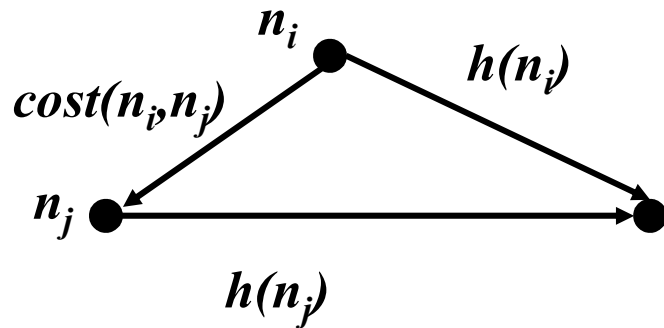


Diagram illustrating a node with  $h=10$  pointing to a child node with  $h=5$ . The edge is labeled  $\text{cost}=3$ . Below the diagram, it says "not consistent" and  $10 \neq 5+3$ .

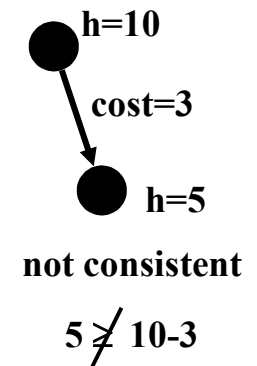
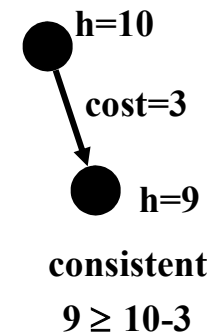
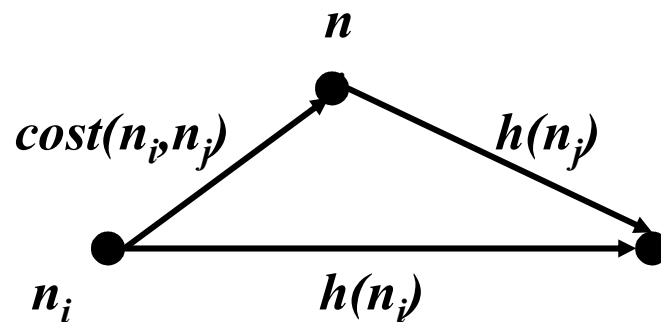
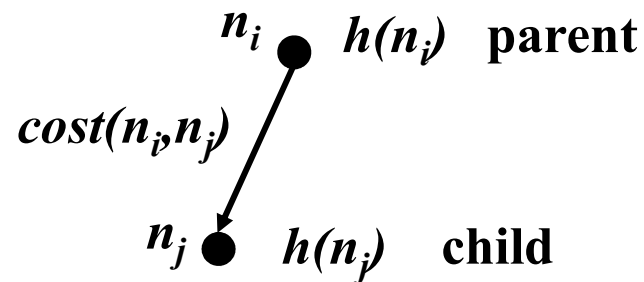
# Another Interpretation of the Triangle Inequality

$$h(n_i) \leq \text{cost}(n_i, n_j) + h(n_j) \text{ for all } n$$

parent

child

- $\Rightarrow h(n_j) \geq h(n_i) - \text{cost}(n_i, n_j)$ , i.e. along any path our estimate of the remaining cost to the goal cannot decrease by more than the arc cost



# Consistency Theorems

- Theorem 1:** If  $h(n)$  is consistent, then  $f(n_j) \geq f(n_i)$ , i.e.  $f$  is non-decreasing along any path  

child
parent

**Given:**  $h(n_i) \leq c(n_i, n_j) + h(n_j)$

**To prove:**  $f(n_j) \geq f(n_i)$

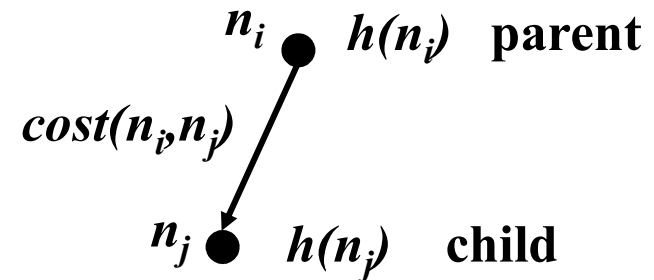
**Proof:**  $f(n_j) = g(n_j) + h(n_j) =$

$$= g(n_i) + c(n_i, n_j) + h(n_j) =$$

$$\geq g(n_i) + h(n_i) =$$

$$= f(n_i)$$

$$\Rightarrow f(n_j) \geq f(n_i)$$



deff.  $h(n)$  consistent

- Theorem 2:** If  $f(n_j) \geq f(n_i)$ , i.e.  $f$  is non-decreasing along any path, then  $h(n)$  is consistent



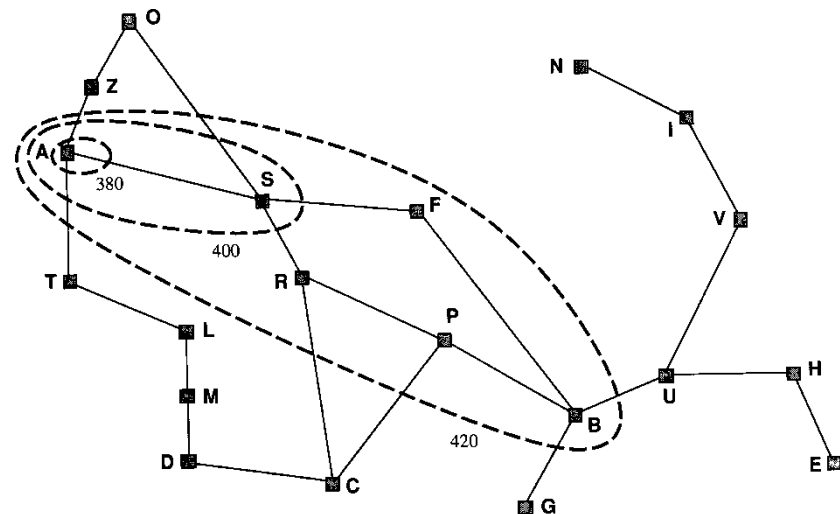
# Admissibility and Consistency

- Consistency is the stronger condition
- Theorems:
  - If a heuristic is consistent, it is also admissible  
*consistent  $\Rightarrow$  admissible*
  - If a heuristic is admissible, there is no guarantee that it is consistent  
*admissible  $\nRightarrow$  consistent*

# Completeness of A\* with Consistent Heuristic – Intuitive Idea

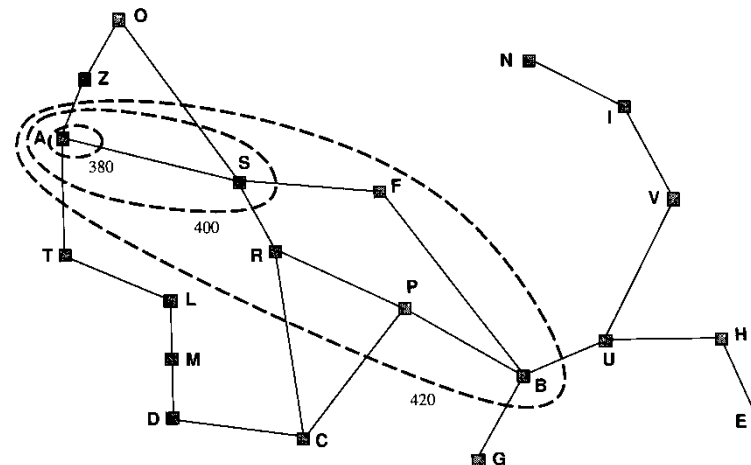
- A\* uses the f-cost to select nodes for expansion
- If  $h$  is consistent, the f-costs are non-decreasing  $\Rightarrow$  we can draw f-contours in the state space
- A\* expands nodes in order of increasing f-values, i.e.
  - It gradually adds f-contours of nodes
  - Nodes inside a contour have f-cost less than or equal to the contour value

- Completeness – as we add bands of increasing f, we must eventually reach a band where  $f=h(G)+g(G)=h(G)$



# Optimality of A\* with Consistent Heuristic – Intuitive Idea

- A\* finds the optimal solution, i.e. the one with smallest path cost  $g(n)$  among all solutions
- The first solution must be the optimal one, as subsequent contours will have higher f-cost, and thus higher g-cost ( $h(n)=0$  for goal nodes):
  - Bands  $f_1 < f_2 < f_3 \dots$
  - Compare 2 solutions at band 2 and 3: G2 and G3 (G2 will be found first)
  - $f(G_2) = g(G_2) + h(G_2)$ ,  $f(G_3) = g(G_3) + h(G_3)$
  - But  $f(G_2) < f(G_3)$  and  $h(G_2) = h(G_3) = 0 \Rightarrow g(G_2) < g(G_3)$ , i.e. the first solution found is the optimal



# A\* with Consistent Heuristic is Optimally Efficient

- **Theorem:** If  $h$  is a consistent heuristic, then A\* is *optimally efficient* among all optimal search algorithms using  $h$ 
  - no other optimal algorithm using  $h$  is guaranteed to expand fewer nodes than A\*
- Which are the optimal algorithms we have studied so far?
- Which are the optimal heuristic algorithms we have studied so far?

## Properties of A\*

- **Complete?** Yes, unless there are infinitely many nodes with  $f \leq f(G)$ ,  $G$  – optimal goal state
- **Optimal?** Yes, with admissible heuristic
- **Time?** Exponential  $O(b^d)$
- **Space?** Exponential, keeps all nodes in memory
- For most problems, the number of nodes which have to be expanded is exponential
- Both time and space are problems for A\* but space is the bigger problem - A\* runs out of space long before it runs out of time; solution: Iterative Deepening A\* (IDA\*) or Simplified Memory-Bounded A\* (SMA\*)

## Summary of A\*

- An admissible heuristic never overestimates the true distance to a goal
- A consistent (monotonic) heuristic satisfies the triangle equation
- $h(n)$  satisfies the triangle equation  $\Leftrightarrow f(n)$  does not decrease along any path
- Admissible  $\nRightarrow$  consistent
- Consistent  $\Rightarrow$  admissible
- Dominant heuristic
  - given 2 admissible heuristics  $h_1$  and  $h_2$ ,  $h_2$  is dominant if it gives a better estimate of the true cost to a goal node
  - A\* with a dominant heuristic will expand fewer nodes

## Summary of A\* (2)

- If  $h(n)$  is admissible, A\* is optimal
- If  $h(n)$  is consistent, A\* is optimally efficient - A\* will expand less or equal number of nodes than any other optimal algorithm using  $h(n)$
- However, theoretical completeness and optimality do not mean practical completeness and optimality if it takes too long to get the solution (time and space are exponential)
- $\Rightarrow$  If we can't design an accurate admissible or consistent heuristic, it may be better to settle for a non-admissible heuristic that works well in practice or for a local search algorithm (next lecture) even though completeness and optimality are no longer guaranteed.
- $\Rightarrow$  Also, although dominant (i.e. good) heuristics are better, they may need a lot of time to compute; it may be better to use a simpler heuristic - more nodes will be expanded but overall the search may be faster.