



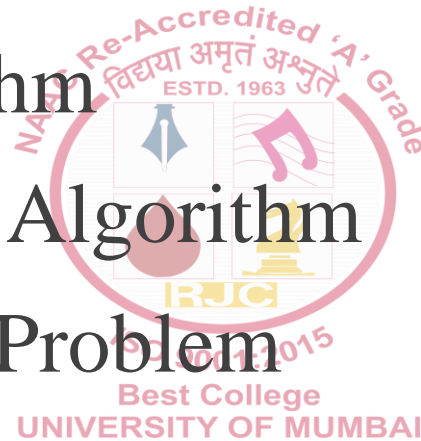
Department of Information Technology

RJITC04 ARTIFICIAL INTELLIGENCE

DAY 4/ AI Algorithm Part 3

Content Overview

- ❑ Introduction to Problem Solving
- ❑ Beam Search Algorithm
- ❑ Simulated Annealing Algorithm
- ❑ Travelling Salesman Problem



Problem Solving

□ ***Problem solving*** is a process of generating solutions from observed data.

- a '*problem*' is characterized by a set of goals,
- a set of *objects*, and
- a set of *operations*.



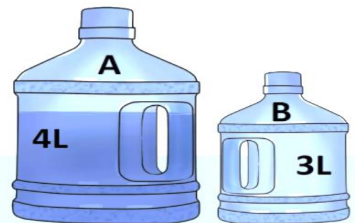
Problem space

- ❑ A '*problem space*' is an abstract space.
- A problem space encompasses all *valid states* that can be generated by the application of any combination of *operators* on any combination of *objects*.
- The problem space may contain one or more *solutions*.
- A solution is combination of *operations* and *objects* that achieve the *goals*.



Water Jug Problem

- You are given two jugs - a 4-gallon one and a 3-gallon one,
- A pump which has unlimited water which you can use to fill the jug
- Ground on which water may be poured.
- Neither jug has any measuring markings on it.
- We can pour water from one jug to another.
- How can you get exactly 2 gallons of water in the 4-gallon jug?



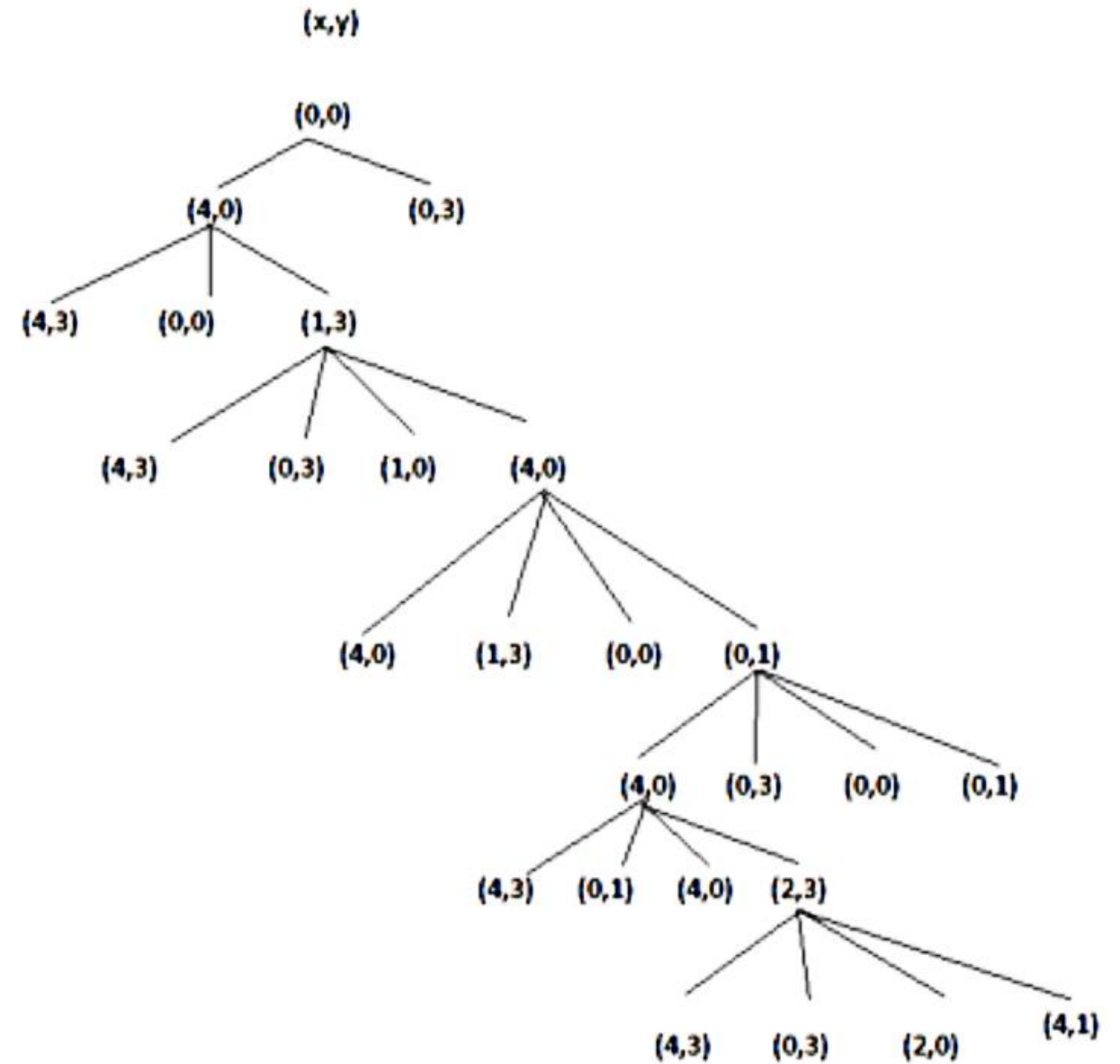
State Space Representation

- The state space for this problem can be described as the set of ordered pairs of integer (x,y) .
- x - water in 4- gallon jug
- y - water in 3- gallon jug
- The Start state is $(0,0)$.
- The Goal state is $(2,y)$



S.No	Initial State	Rules/Conditions	Final state	Description of action taken
1.	(x,y)	If $x < 4$	(4,y)	Fill the 4 gallon jug completely
2.	(x,y)	if $y < 3$	(x,3)	Fill the 3 gallon jug completely
3.	(x,y)	If $x > 0$	(x-d,y)	Pour some part from the 4 gallon jug
4.	(x,y)	If $y > 0$	(x,y-d)	Pour some part from the 3 gallon jug
5.	(x,y)	If $x > 0$	(0,y)	Empty the 4 gallon jug
6.	(x,y)	If $y > 0$	(x,0)	Empty the 3 gallon jug
7.	(x,y)	If $(x+y) < 7$	(4, $y-[4-x]$)	Pour some water from the 3 gallon jug to fill the 4 gallon jug
8.	(x,y)	If $(x+y) < 7$	($x-[3-y]$,y)	Pour some water from the 4 gallon jug to fill the 3 gallon jug.
9.	(x,y)	If $(x+y) < 4$	(x+y,0)	Pour all water from 3 gallon jug to the 4 gallon jug
10.	(x,y)	if $(x+y) < 3$	(0, x+y)	Pour all water from the 4 gallon jug to the 3 gallon jug

Gallons in the 4-gallon jug	Gallons in the 3-gallon jug	Rule applied
0	0	2
0	3	9
3	0	2
3	3	7
4	2	5 or 12
0	2	9 or 11
2	0	--



```
print("Water Jug Problem")
x=int(input("Enter X:"))
y=int(input("Enter Y:"))
while True:
    rno=int(input("Enter the Rule No"))
    if rno==1:
        if x<4:x=4
    if rno==2:
        if y<3:y=3
    if rno==3:
        if x>0:x=0
    if rno==4:
        if y>0:y=0
    if rno==5:
        if x+y>= 4 and y>0:x,y=4,y-(4-x)
    if rno==6:
        if x+y>=3 and x>0:x,y=x-(3-y),3
    if rno==7:
        if x+y<=4 and y>0:x,y=x+y,0
    if rno==8:
        if x+y<=3 and x>0:x,y=0,x+y
    print("X =" ,x)
    print("Y =" ,y)
    if (x==2):
        print(" The result is a Goal state")
        break
```

===== RESTART: D:/p

```
Water Jug Problem
Enter X:0
Enter Y:0
Enter the Rule No2
X = 0
Y = 3
Enter the Rule No7
X = 3
Y = 0
Enter the Rule No2
X = 3
Y = 3
Enter the Rule No5
X = 4
Y = 2
Enter the Rule No3
X = 0
Y = 2
Enter the Rule No7
X = 2
Y = 0
The result is a Goal state
>>> |
```

=====

```
Water Jug Problem
Enter X:0
Enter Y:0
Enter the Rule No1
X = 4
Y = 0
Enter the Rule No6
X = 1
Y = 3
Enter the Rule No4
X = 1
Y = 0
Enter the Rule No8
X = 0
Y = 1
Enter the Rule No1
X = 4
Y = 1
Enter the Rule No6
X = 2
Y = 3
The result is a Goal state
```

Search

- ❑ A '*search*' refers to the search for a solution in a problem space.
- ❑ The problem can then be solved by using the *rules*, in combination with an appropriate *control strategy*, to move through the *problem space* until a *path* from an *initial state* to a *goal state* is found. This process is known as '*search*'.
- ❑ *Search* is a general mechanism that can be used when a more direct method is not known.

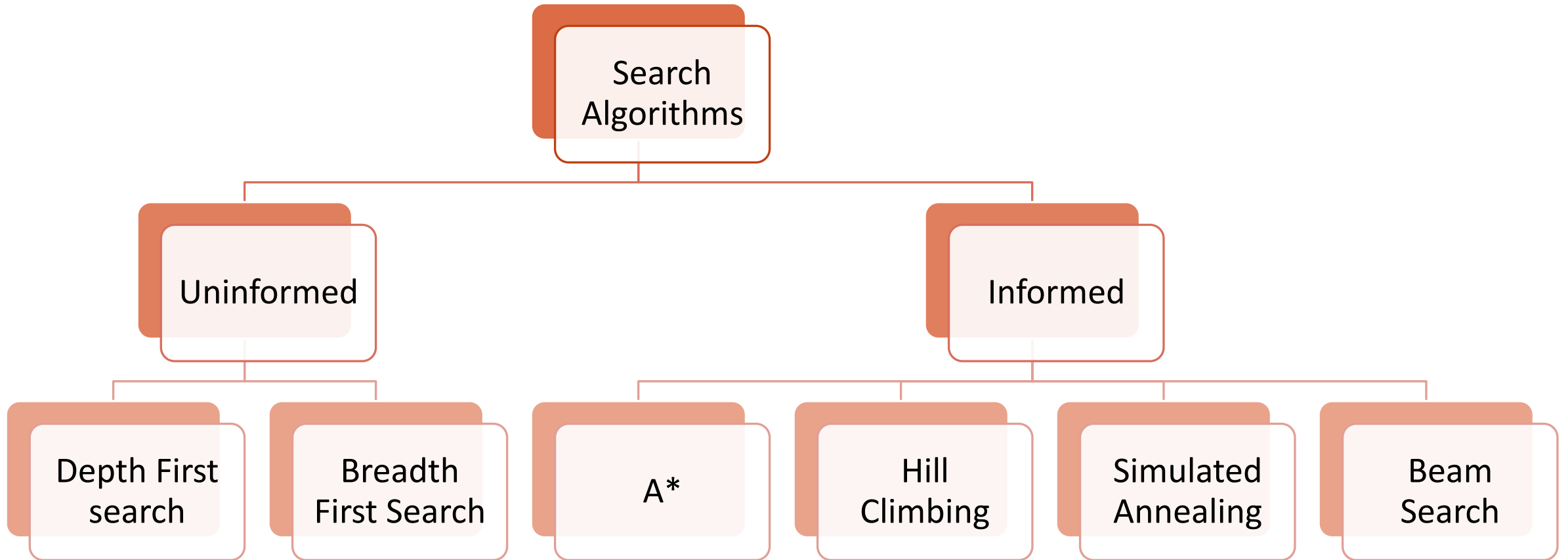
Search Algorithms

Uninformed search algorithms or **blind search, exhaustive or brute-force search,**

- Searches through the search space across all possible candidates for the solution checking whether each candidate satisfies the problem's statement.
- It uses no information about the problem to guide the search

Informed search algorithms use **heuristic functions** that are specific to the problem,

- It applies heuristic function to guide the search through the search space
- Guesses the distance to a goal state and it reduces the amount of time spent in searching.
- Heuristic algorithms are not really intelligent; they appear to be intelligent because they achieve better performance.



Beam Search Algorithm

- Search Algorithms like BFS, DFS and A* etc. are infeasible on large search spaces.
- Beam Search was developed in an attempt to achieve the optimal (or sub-optimal) solution.
- It is a heuristic approach where only the most promising β nodes (instead of all nodes) at each step of the search are retained for further branching.
- β is called Beam Width.
- Beam search is an optimization of best-first search that reduces its memory requirements.
- It is used in many machine translation systems.

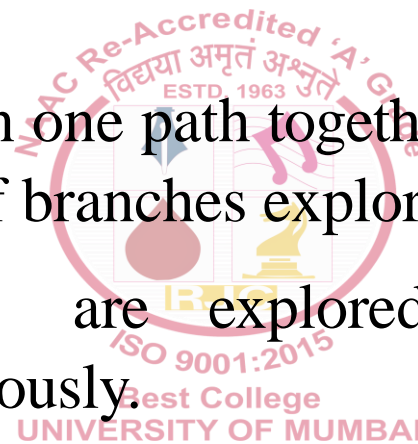


-
- ❑ The idea is that you just keep around those states that are relatively good, and just forget the rest.
 - ❑ **Local beam search: somewhat similar to Hill Climbing:**
 - ➔ Start from N initial states.
 - ➔ Expand all N states and keep k best successors.
 - ❑ **Local Beam Search Algorithm**
 - ❑ Keep track of k states instead of one
 - ➔ Initially: k random states
 - ➔ **Next:** determine all successors of k states
 - Extend **all paths** one step
 - Reject all paths with loops
 - **Sort all paths in queue by estimated distance to goal**
 - ➔ If any of successors is goal → finished
 - ➔ Else select k best from successors and repeat.



Hill Climbing Vs. Beam Search

- Hill climbing just explores all nodes in one branch until goal found or not being able to explore more nodes.
- Beam search explores more than one path together. A factor **k** (β **Beam Width**) is used to determine the number of branches explored at a time.
- If **k=2**, then two branches are explored at a time. For **k=4**, four branches are explored simultaneously.
- The branches selected are the **best branches** based on the used **heuristic evaluation function**.



Beam Search, k=2

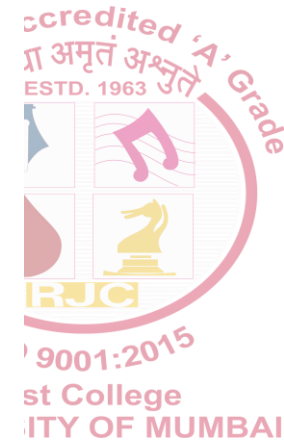
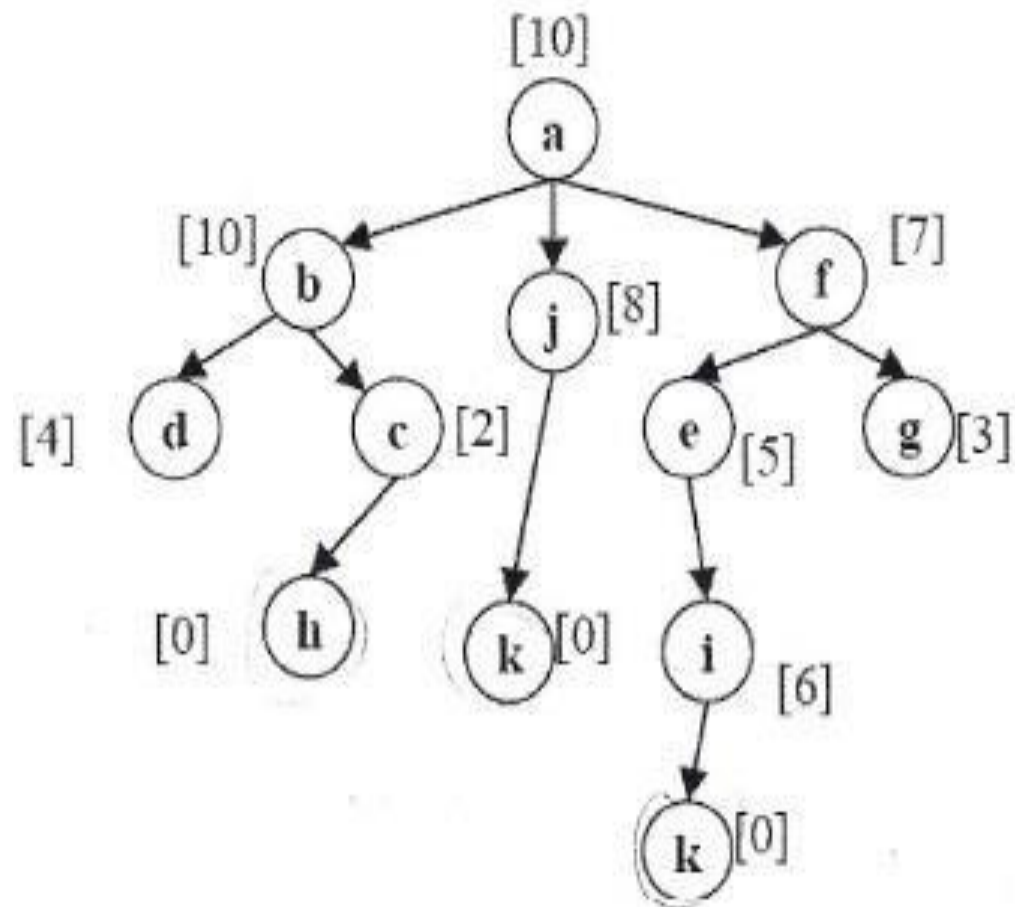
Start Node – A

Goal Node – K

Current

Children

a



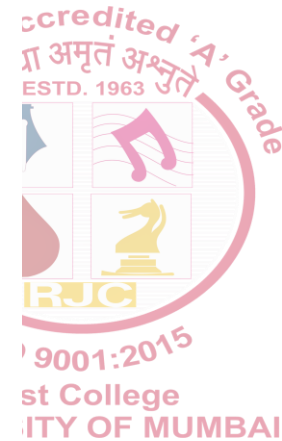
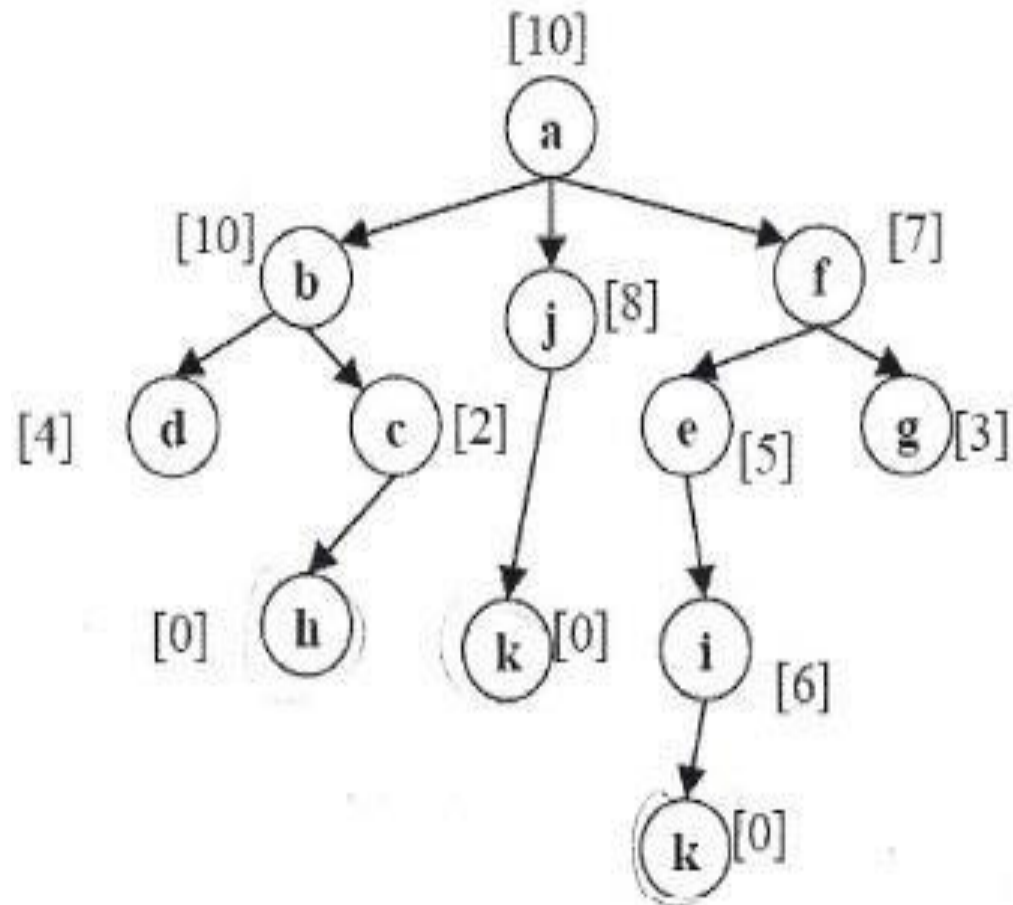
Beam Search

Goal Node - K

Current

a

Children



Beam Search

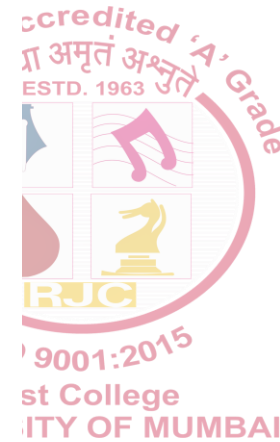
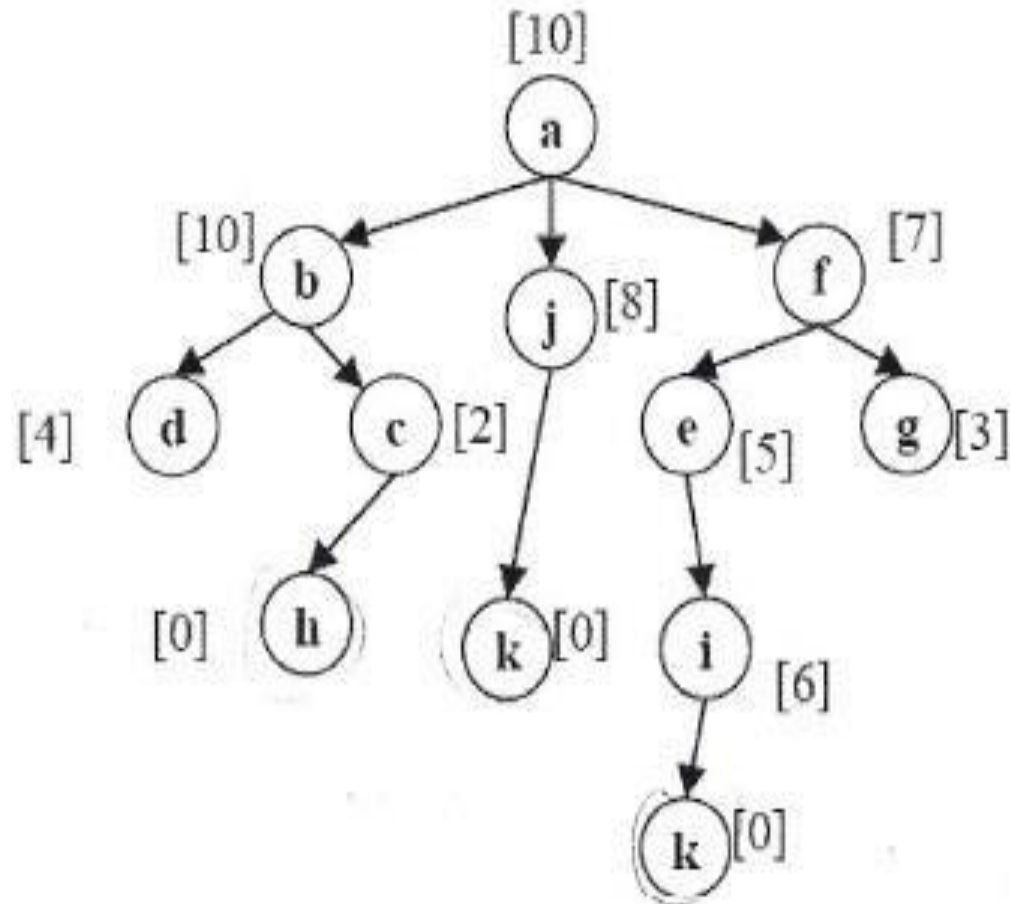
Goal Node - K

Current

a

a

Children



Beam Search

Goal Node - K

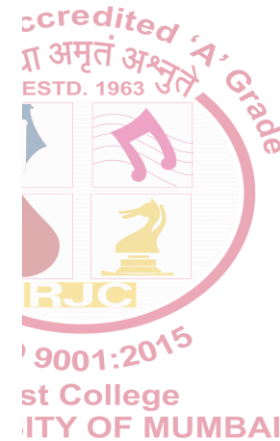
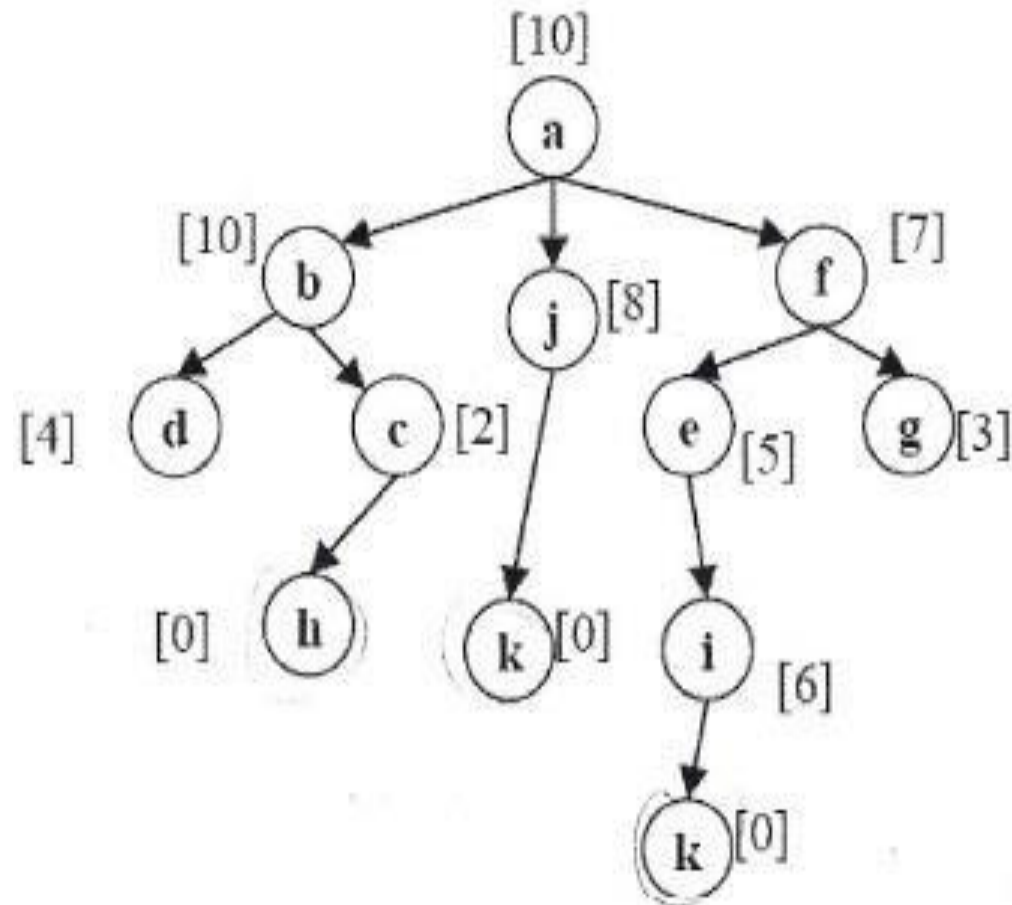
Current

a

a

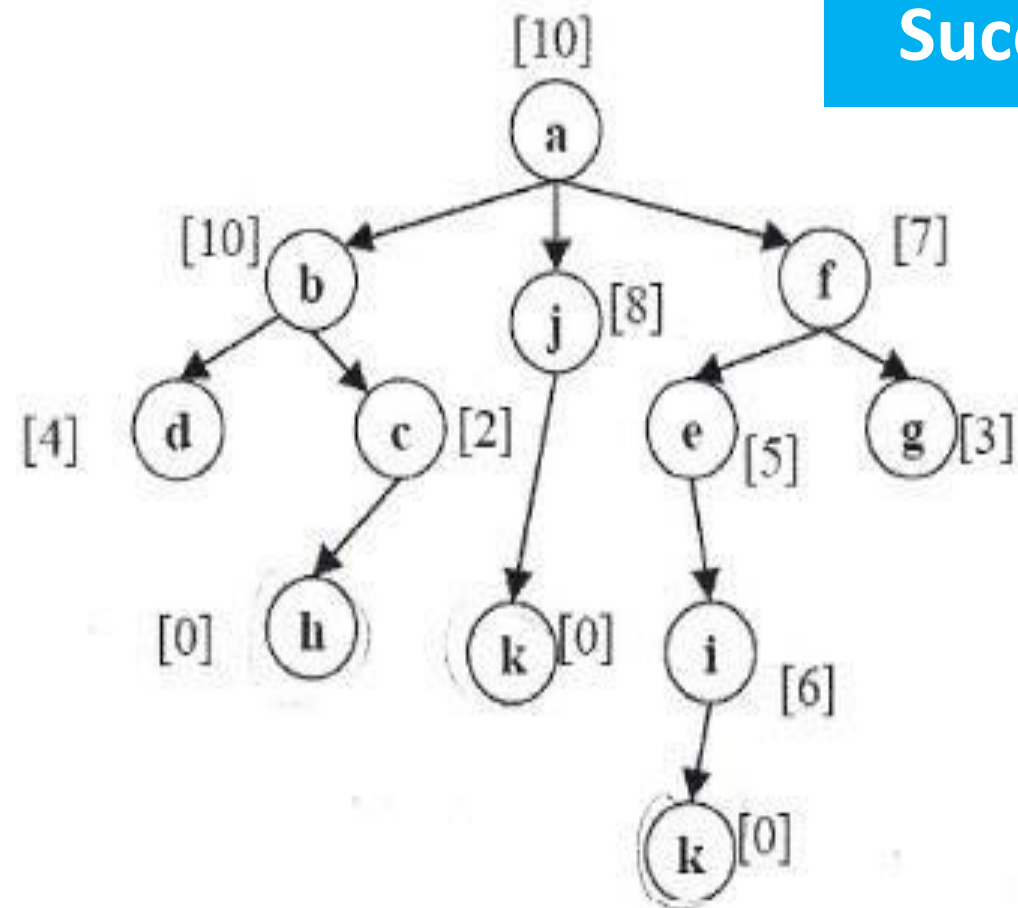
Children

f_7, j_8, b_{10}



Beam Search

Goal Node - K



**Best k
Successors**

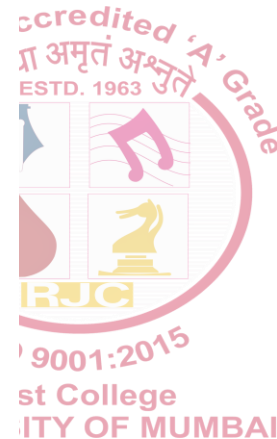
Current

a

a

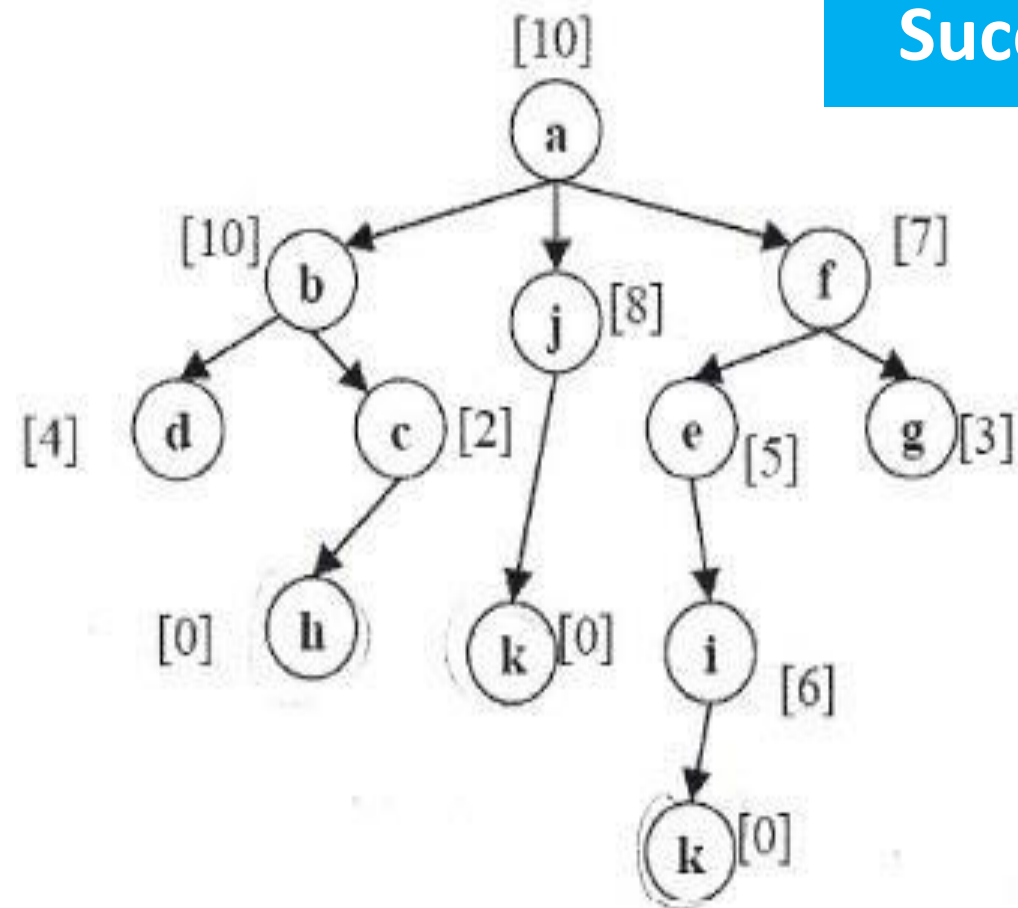
Children

f_7, j_8, b_{10}



Beam Search

Goal Node - K



Best k
Successors

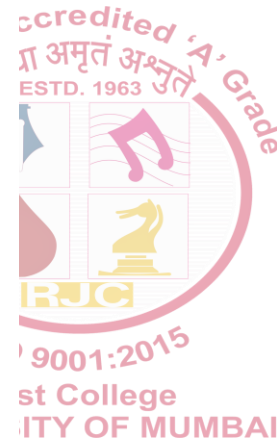
Current

a

a

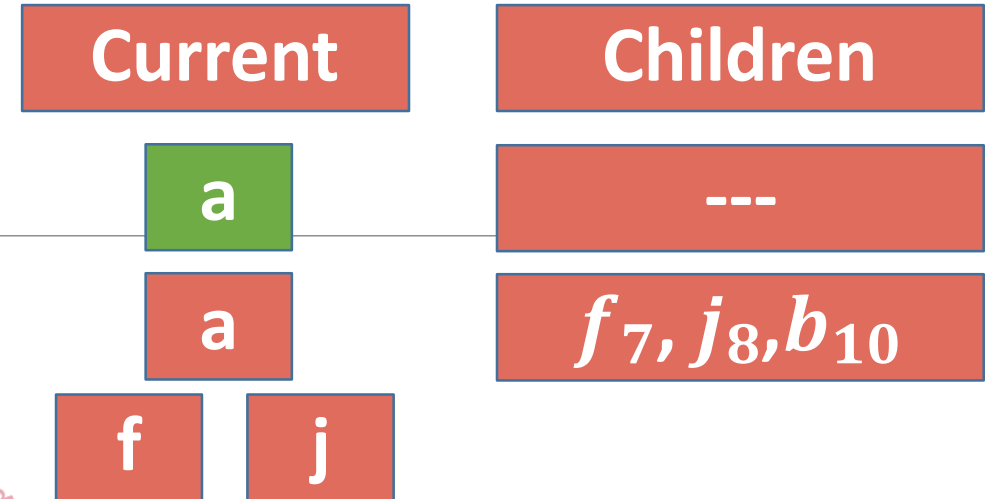
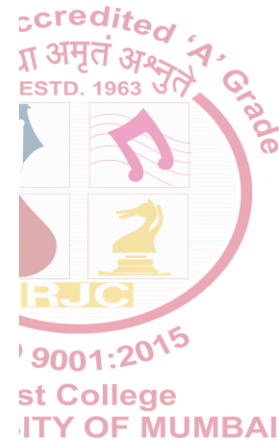
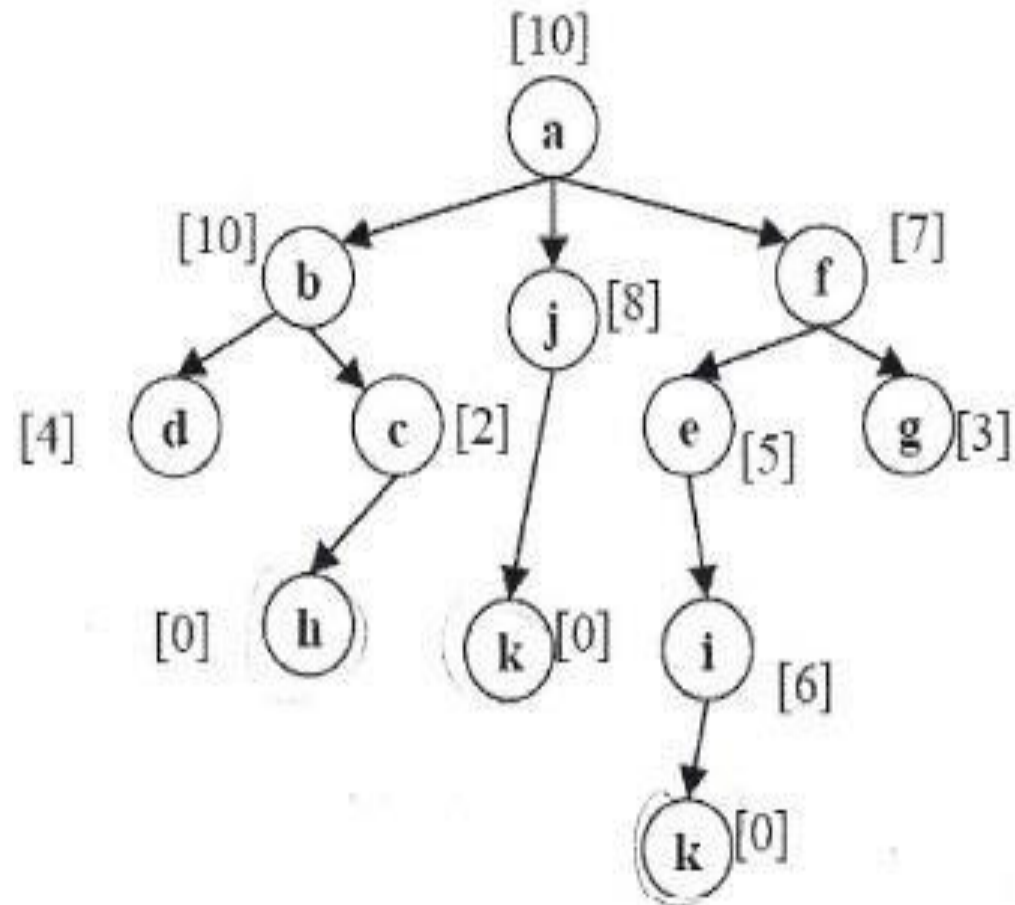
Children

f_7, j_8, b_{10}



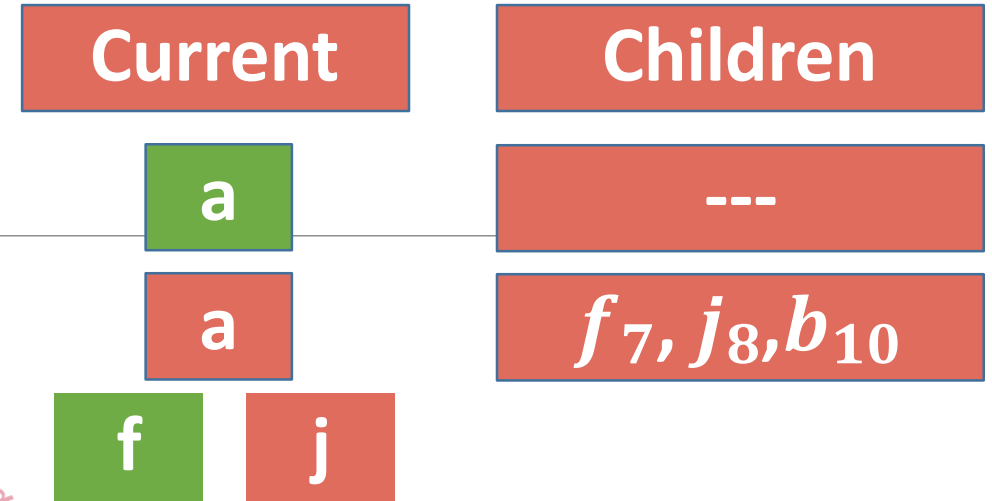
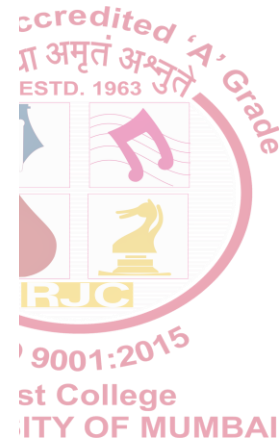
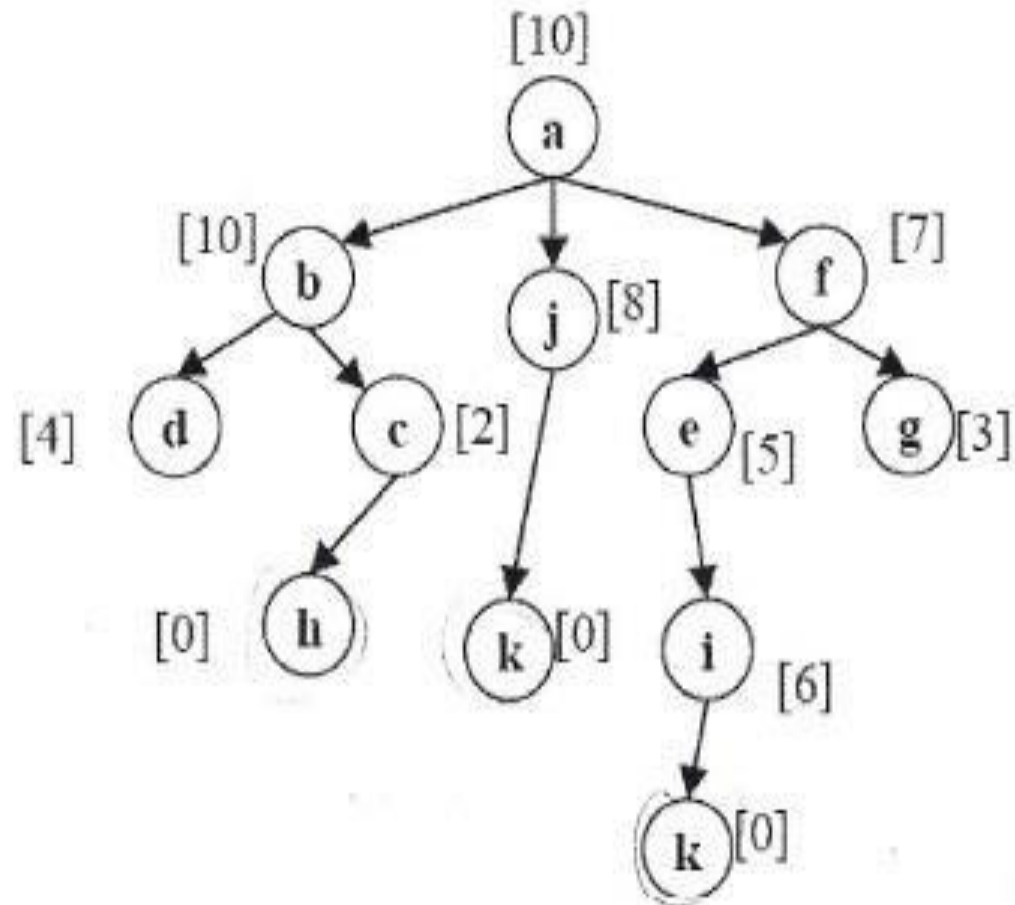
Beam Search

Goal Node - K



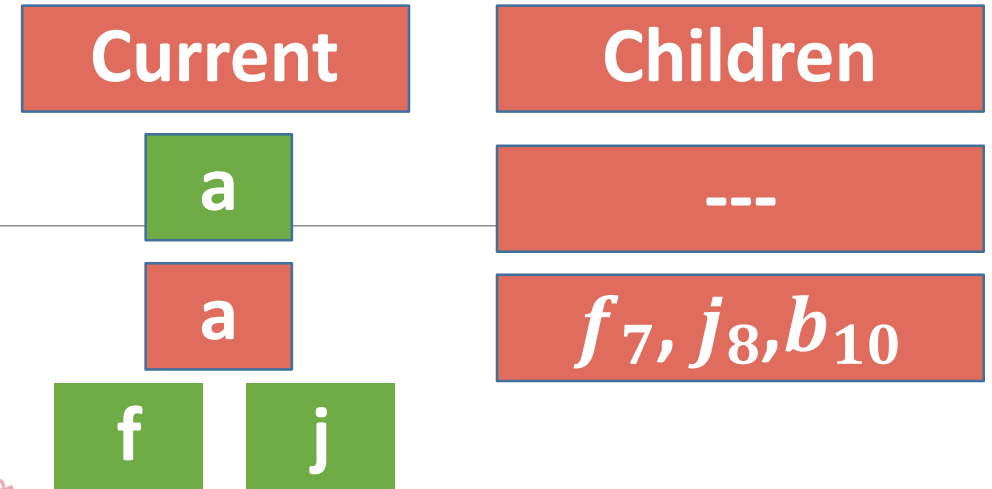
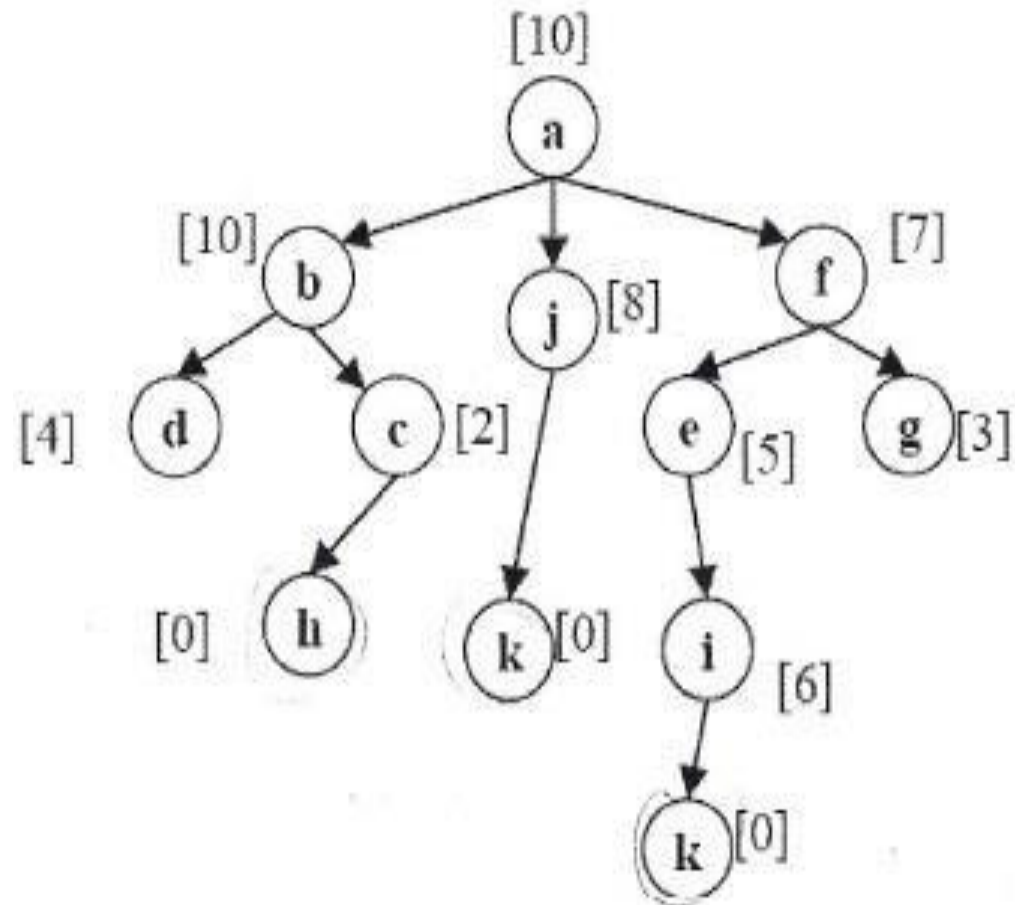
Beam Search

Goal Node - K



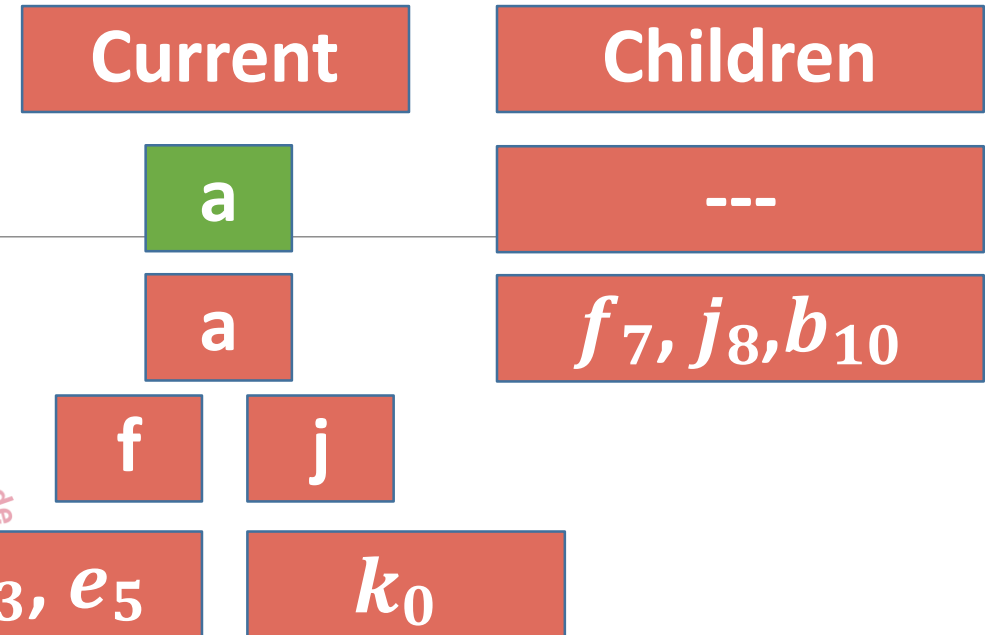
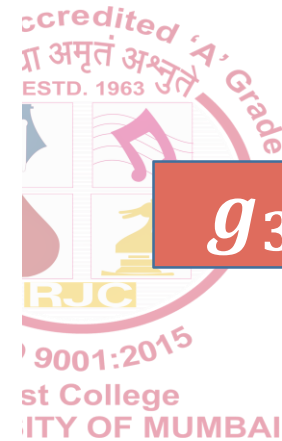
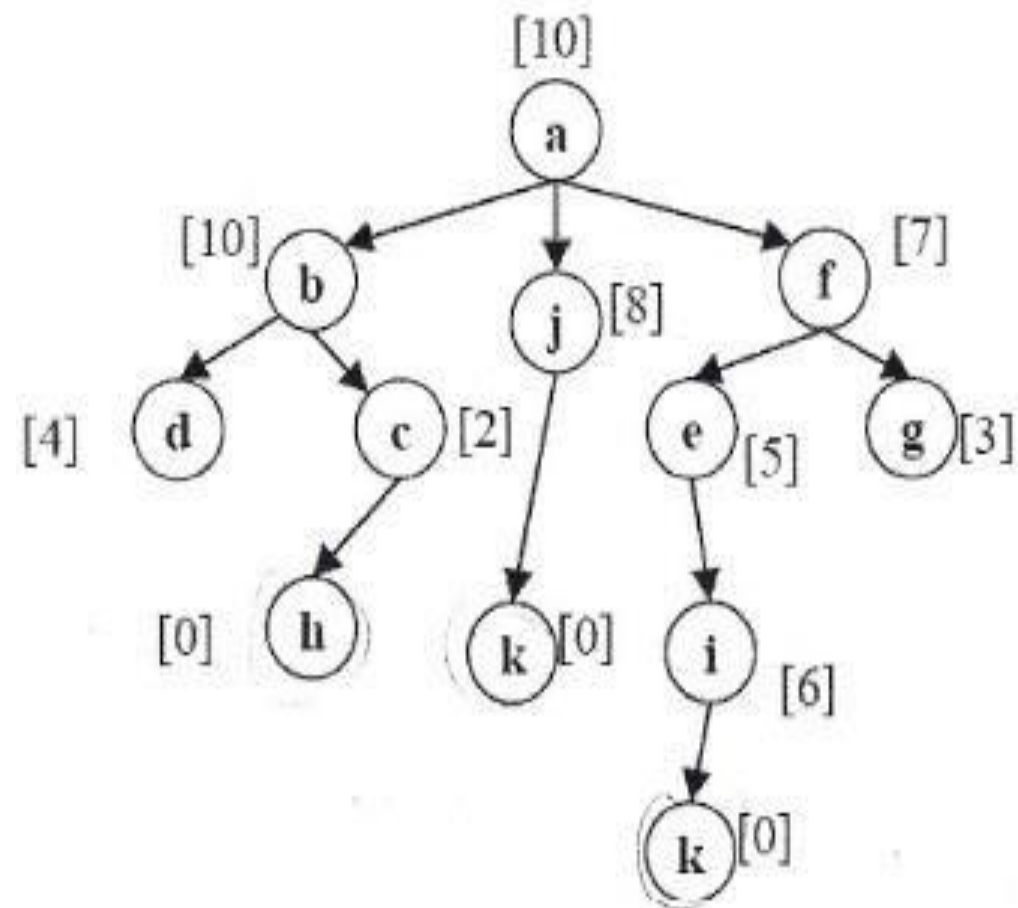
Beam Search

Goal Node - K



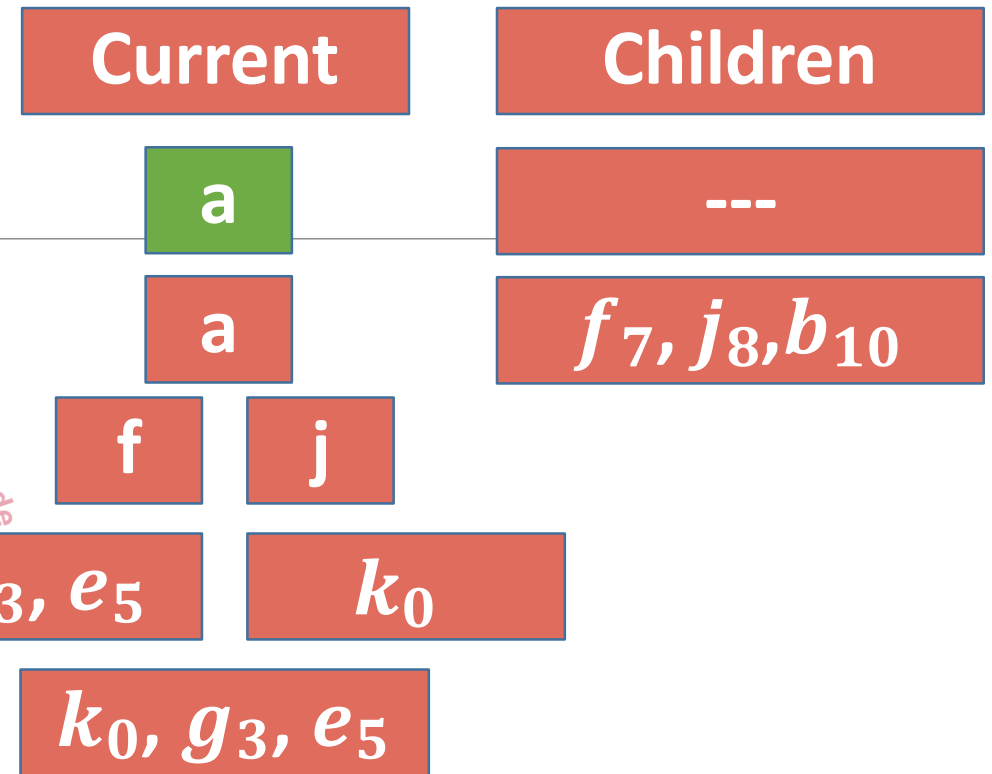
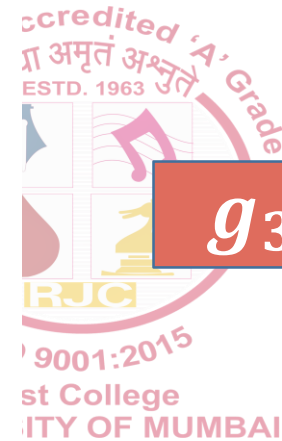
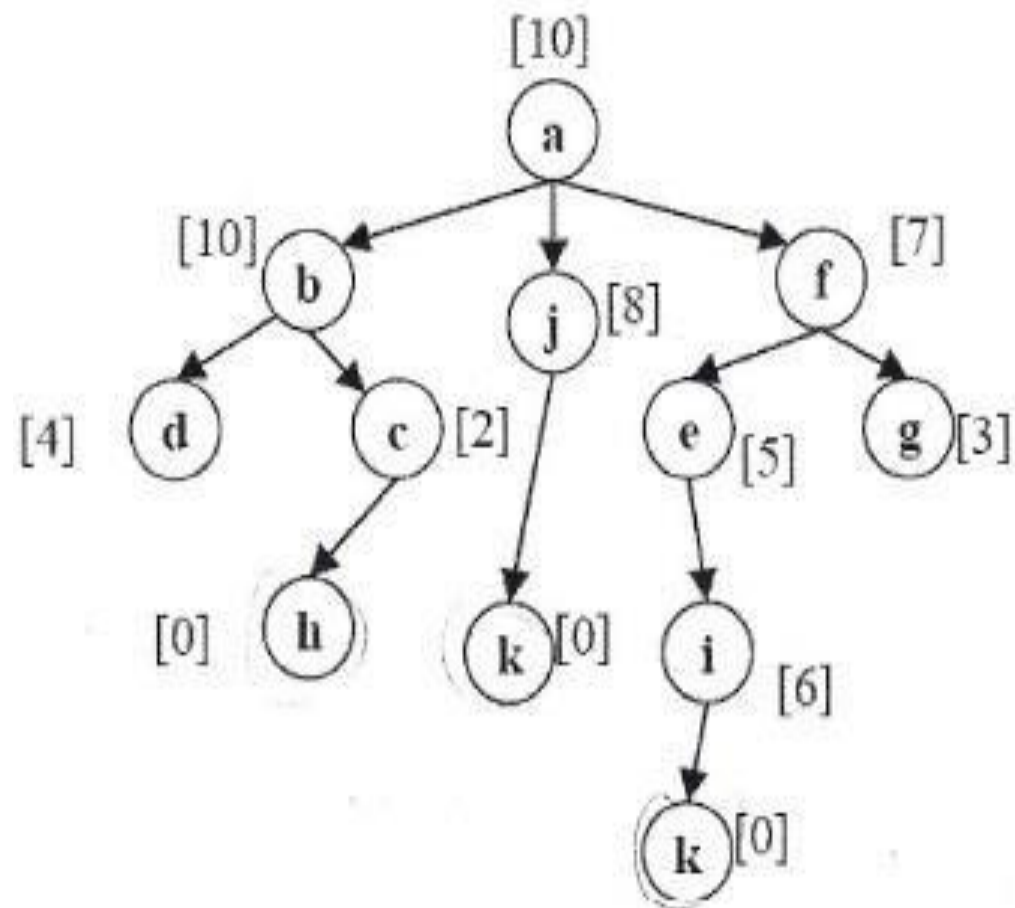
Beam Search

Goal Node - K



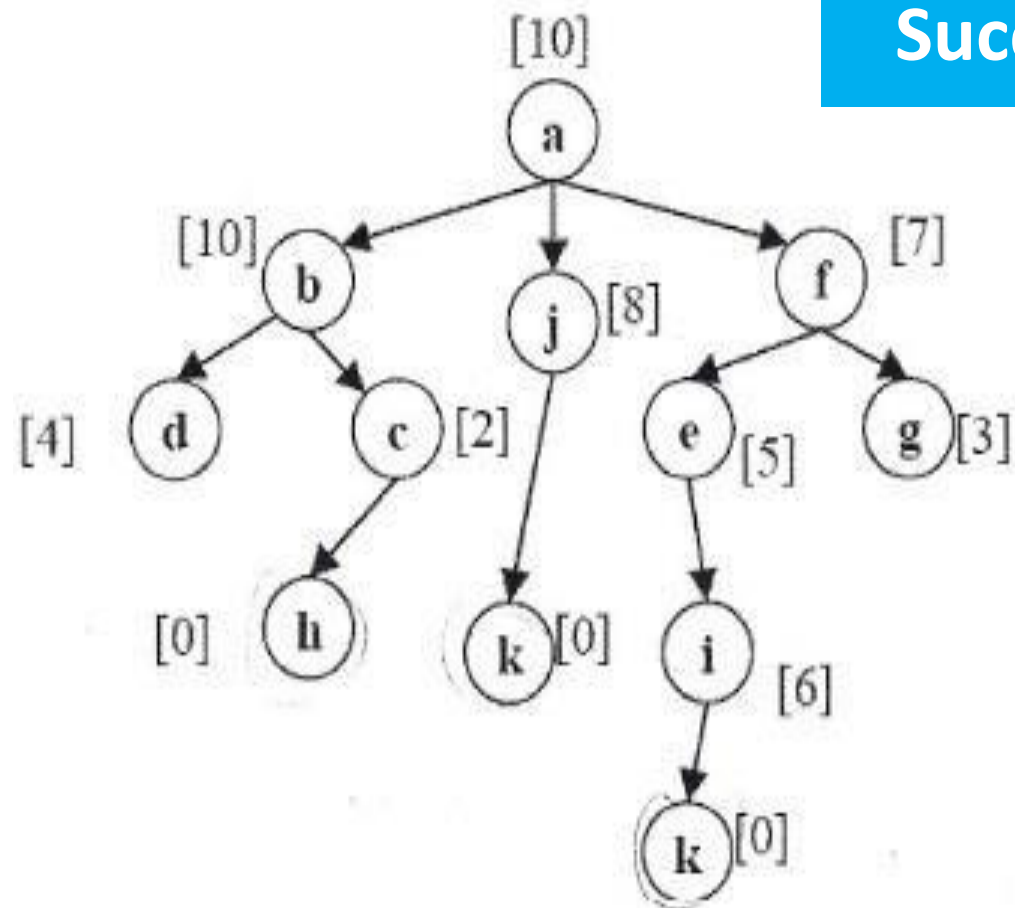
Beam Search

Goal Node - K

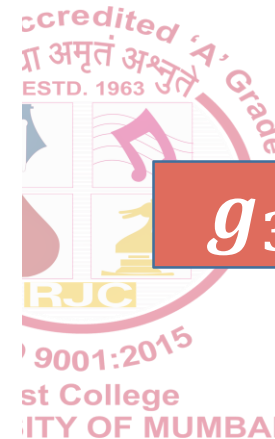
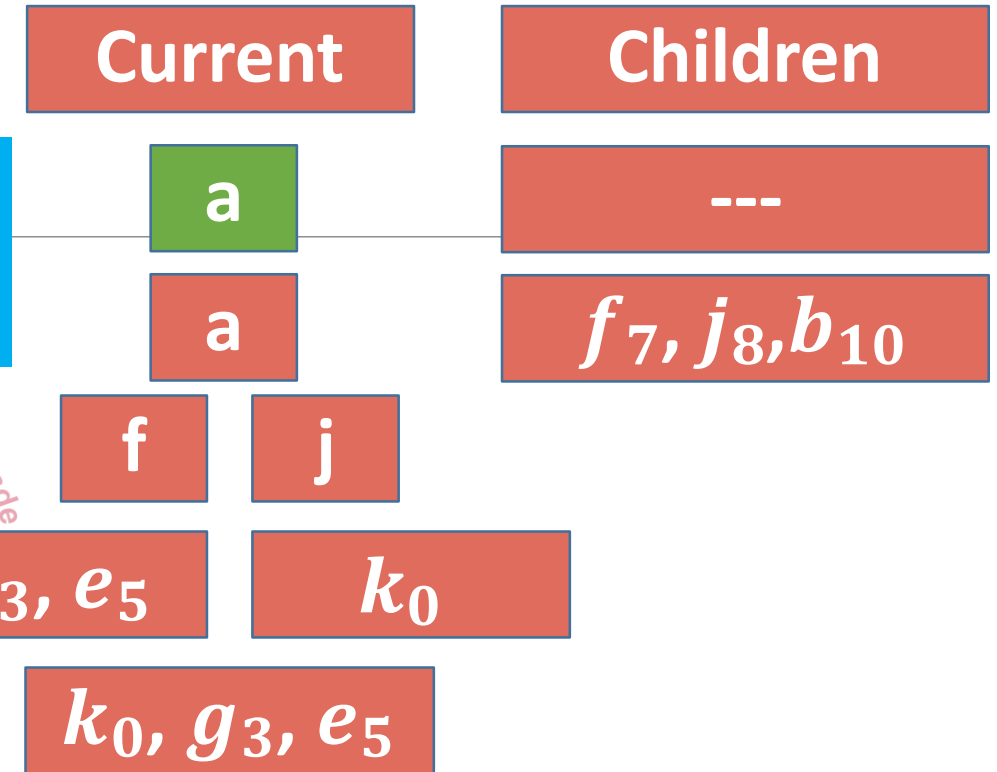


Beam Search

Goal Node - K

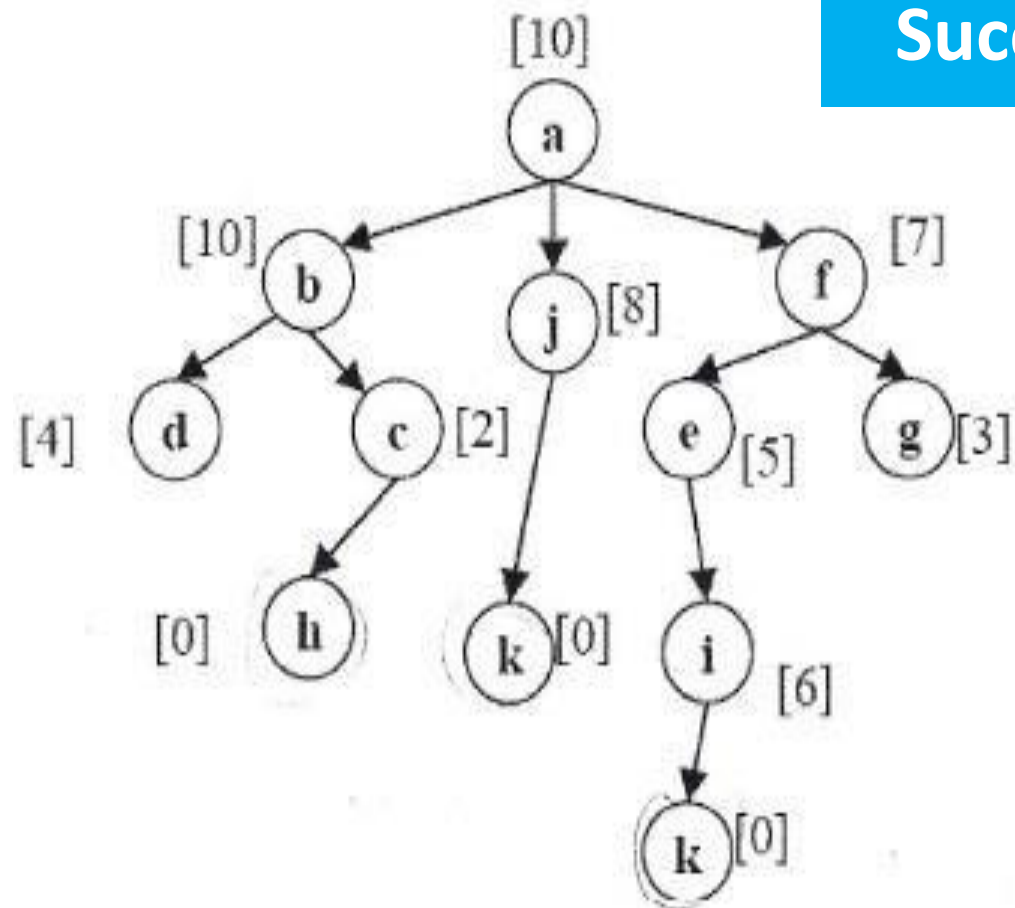


**Best k
Successors**



Beam Search

Goal Node - K



**Best k
Successors**

Current

Children

a

a

f_7, j_8, b_{10}

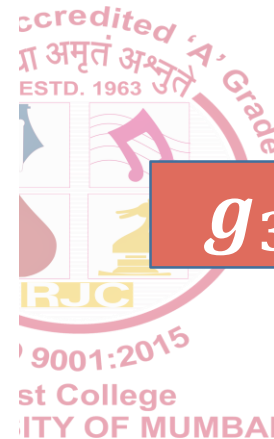
f

j

g_3, e_5

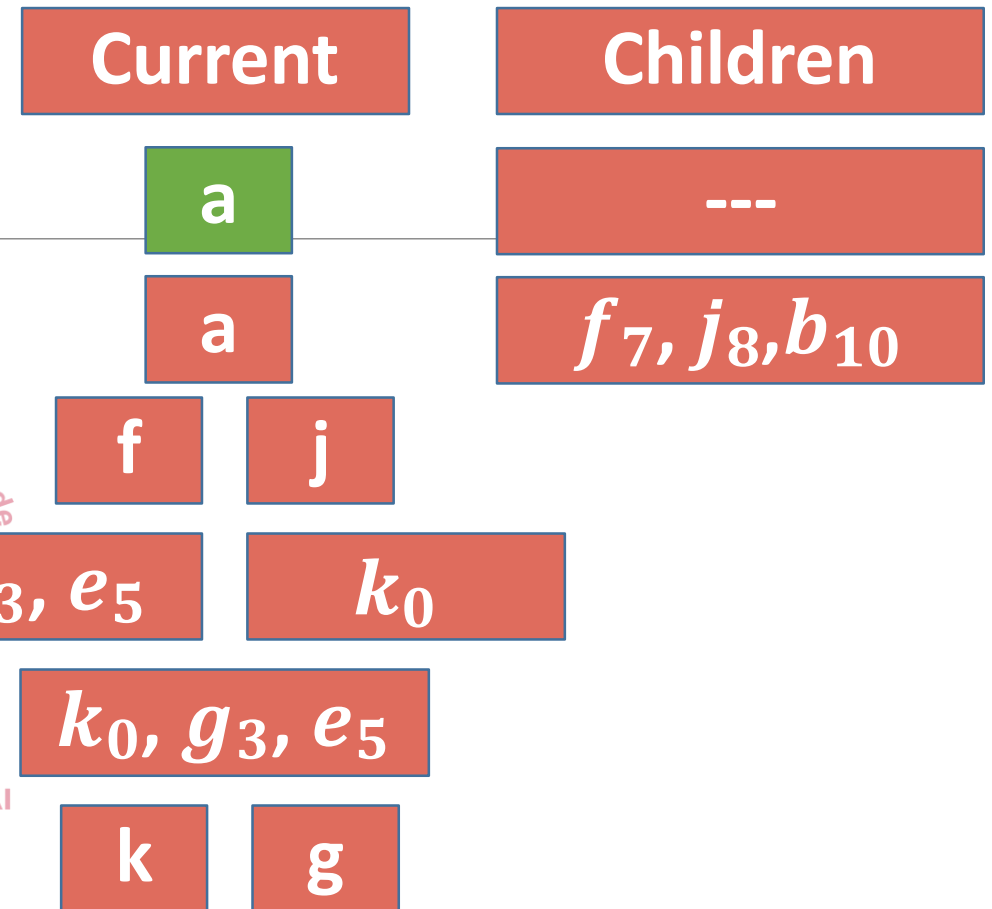
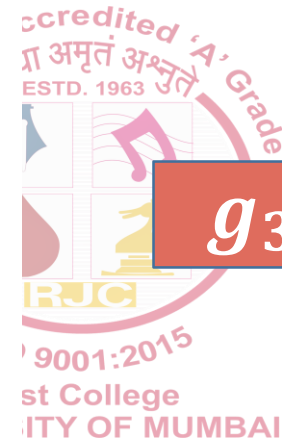
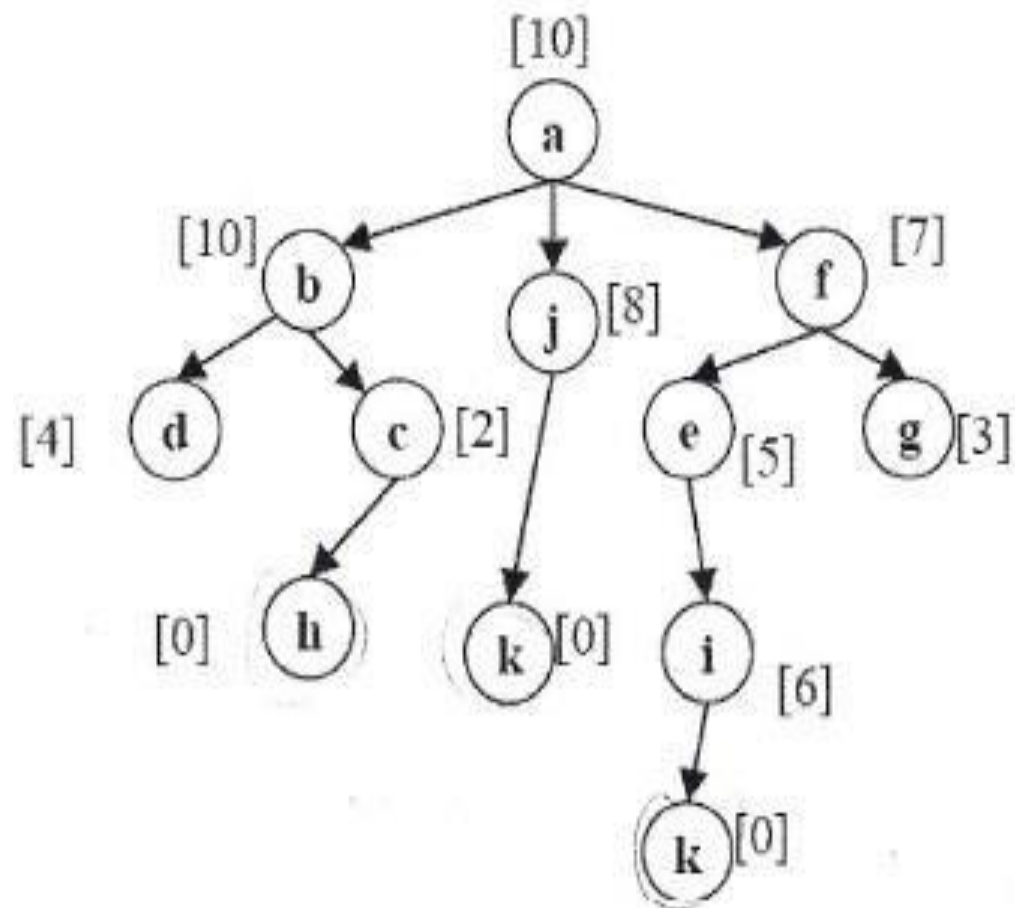
k_0

k_0, g_3, e_5



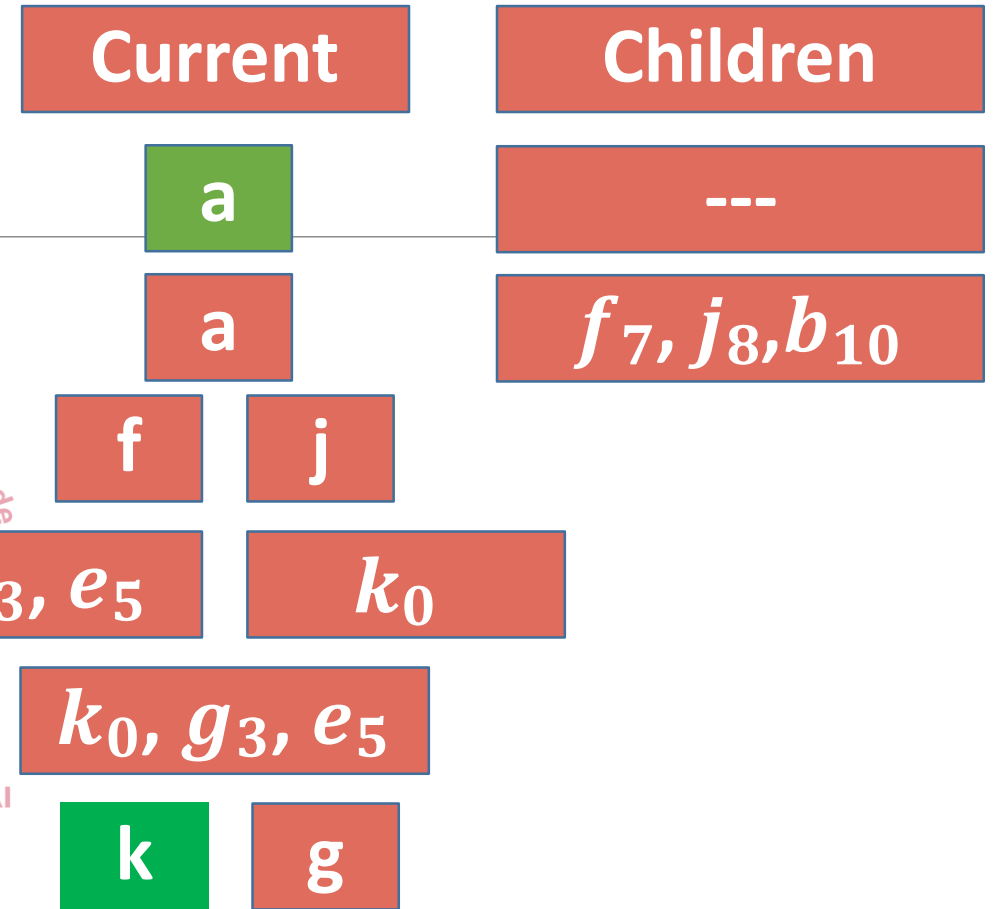
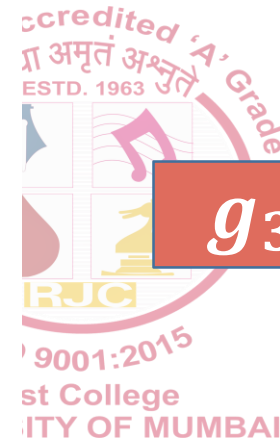
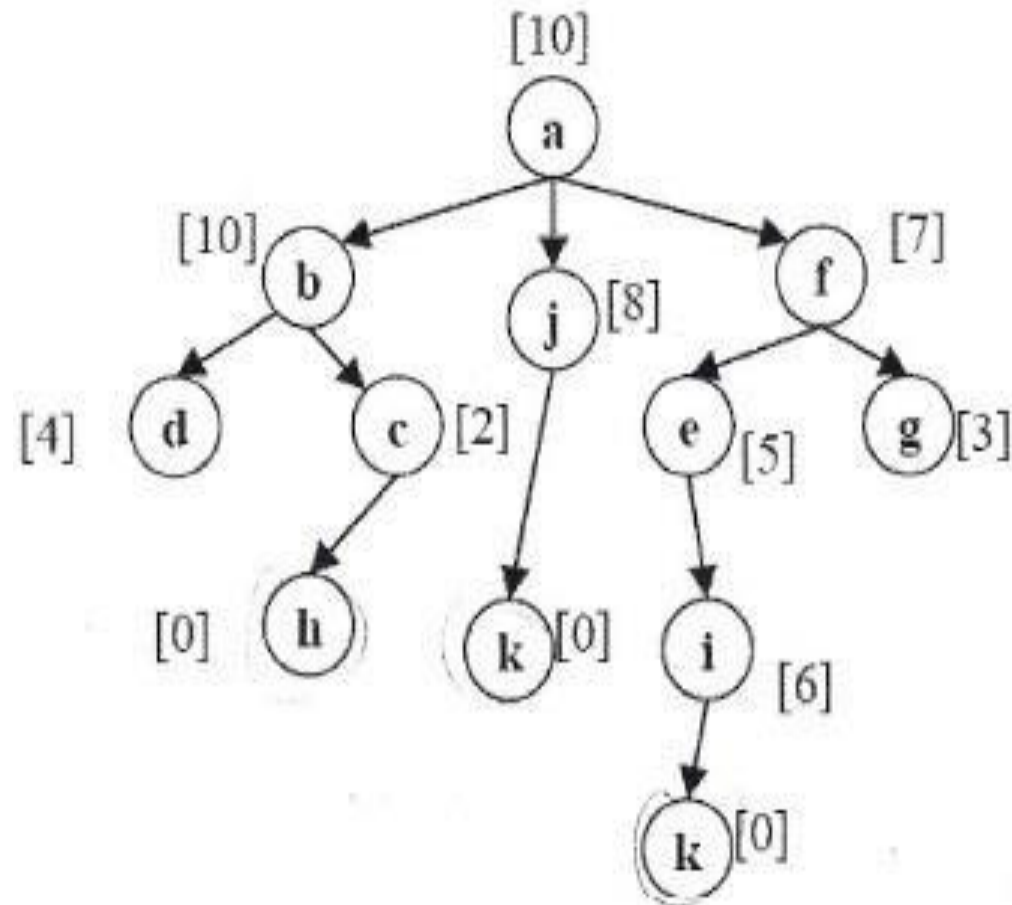
Beam Search

Goal Node - K



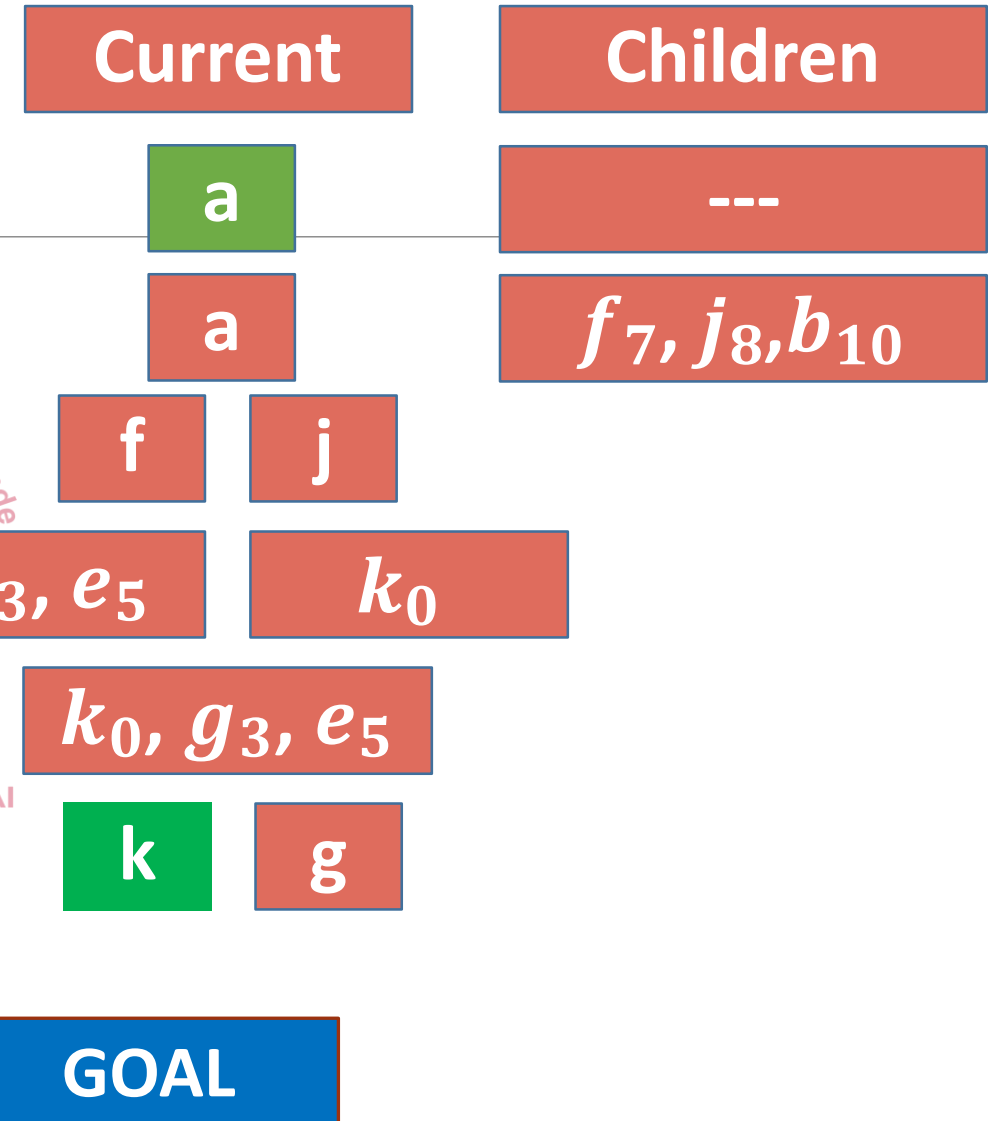
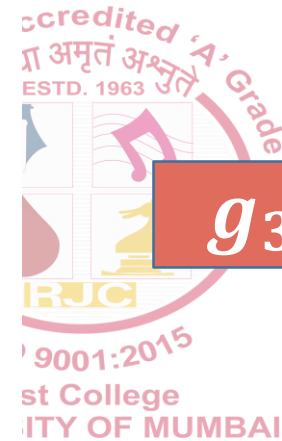
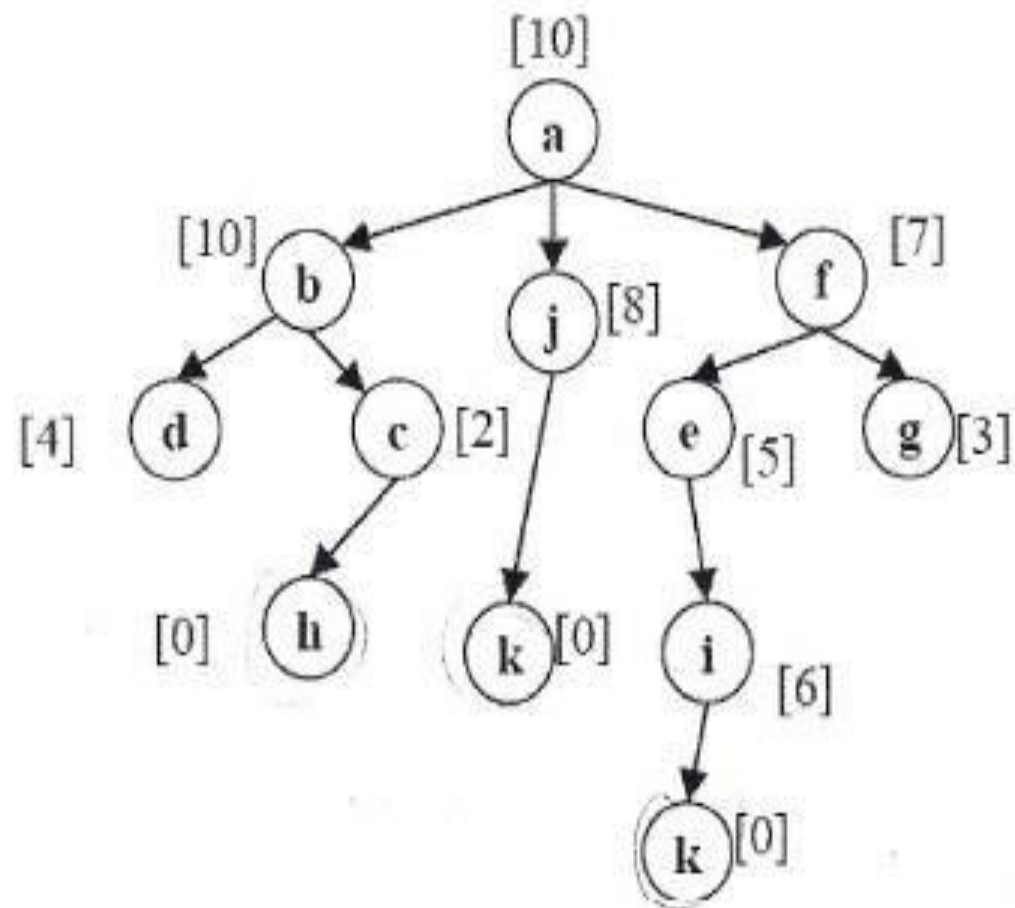
Beam Search

Goal Node - K



Beam Search

Goal Node - K



Applications of Beam Search

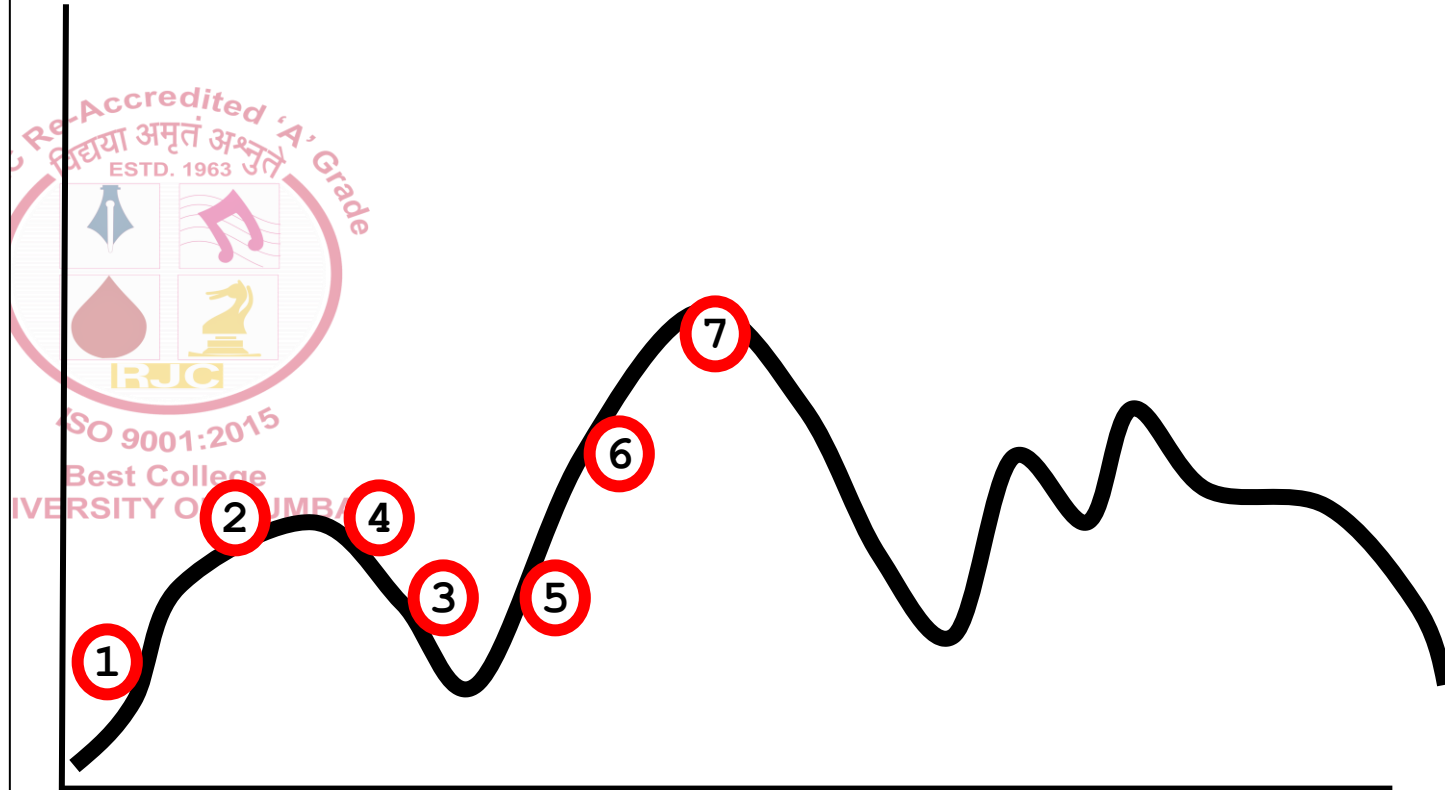
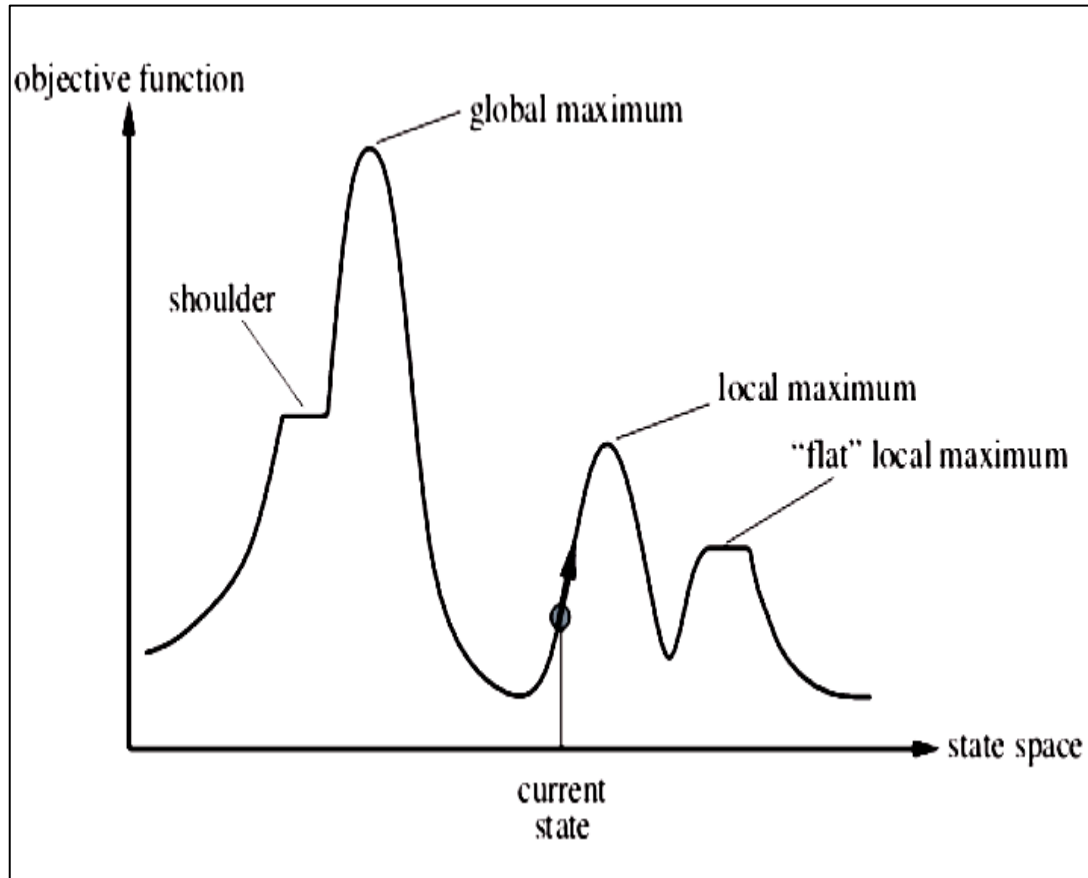
- Job Scheduling - early/tardy scheduling problem
- Phrase-Based Translation Model
- Speech recognition, vision, planning, and machine learning



Simulated Annealing

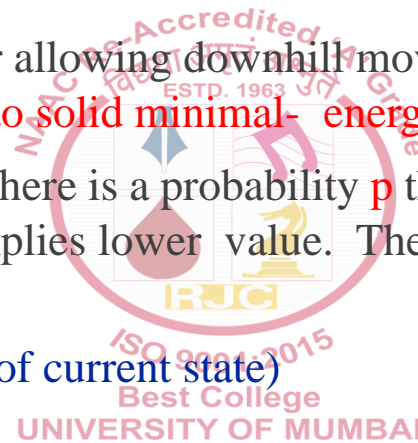
- ❑ Motivated by the physical annealing process
- ❑ **Annealing**: harden metals and glass by heating them to a high temperature and then gradually cooling them
- ❑ At the start, make lots of moves and then gradually slow down
- ❑ More formally...
 - ➡ Instead of picking the best move (as in Hill Climbing),
 - ➡ Generate a random new neighbor from current state,
 - ➡ If it's better take it,
 - ➡ If it's worse then take it with some probability proportional to the temperature and the delta between the new and old states,
 - ➡ Probability gets smaller as time passes and by the amount of “badness” of the move,
- ❑ Compared to hill climbing the main difference is that SA allows downwards steps; (moves to higher cost successors).
- ❑ Simulated annealing also differs from hill climbing in that a move is selected at random and then decides whether to accept it.

Simulated Annealing



Simulated Annealing

- ❑ The probability of making a downhill move decreases with time (length of the exploration path from a start state).
- ❑ The choice of probability distribution for allowing downhill moves is derived from the physical process of annealing metals (cooling molten metal to solid minimal-energy state).
- ❑ During the annealing process in metals, there is a probability p that a transition to a higher energy state (which is sub-optimal) occurs. Higher energy implies lower value. The probability of going to a higher energy state is $e^{\Delta/T}$ where
 - ➡ $\Delta = (\text{energy of next state}) - (\text{energy of current state})$
 - ➡ T is the temperature of the metal.
- ❑ p is higher when T is higher, and movement to higher energy states become less likely as the temperature cools down.
- ❑ For both real and simulated annealing, the rate at which a system is cooled is called the *annealing schedule*, or just the “schedule.”



Simulated Annealing Algorithm

- ❑ Select a start node (root node).
- ❑ Randomly select a child of the current node, calculate a value reflecting how good such child is like $value(node) = -heuristic(node)$.
- ❑ Select the child if it is better than the current node. Else try another child.

A node is better than the current node if $\Delta E = value(next) - value(current) > 0$.

Else if $\Delta E < 0$, then try to find another child.

- ❑ If the child was not better than the current node then it will be selected with probability equal to $p = e^{\frac{\Delta E}{T}}$
where $\Delta E = value[next] - value[current]$
 T is a temperature.

- ❑ Stop if no improvement can be found or after a fixed time.

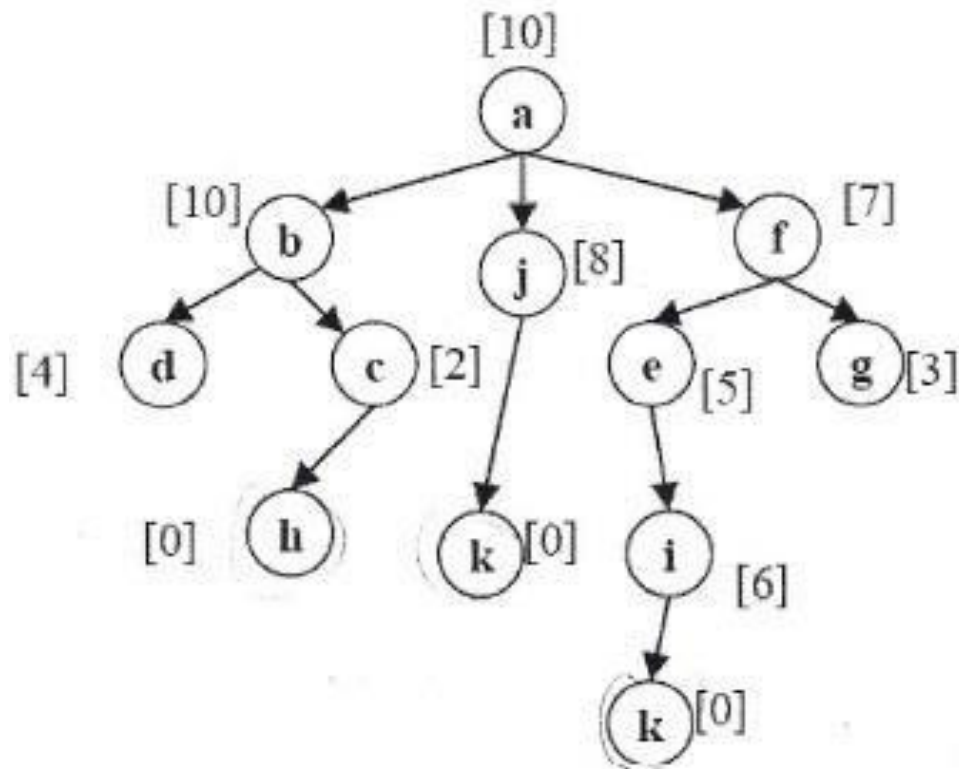
Simulated Annealing

Example – $T=10$

Current

Children

a

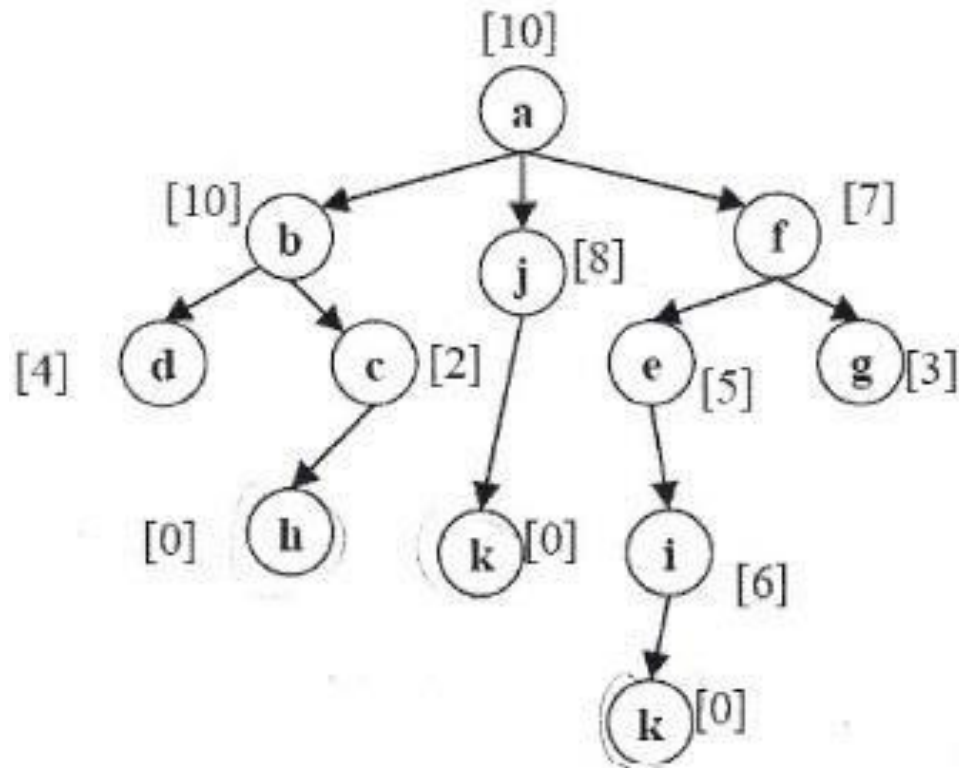


Simulated Annealing Starting from Node a

Current

Children

a

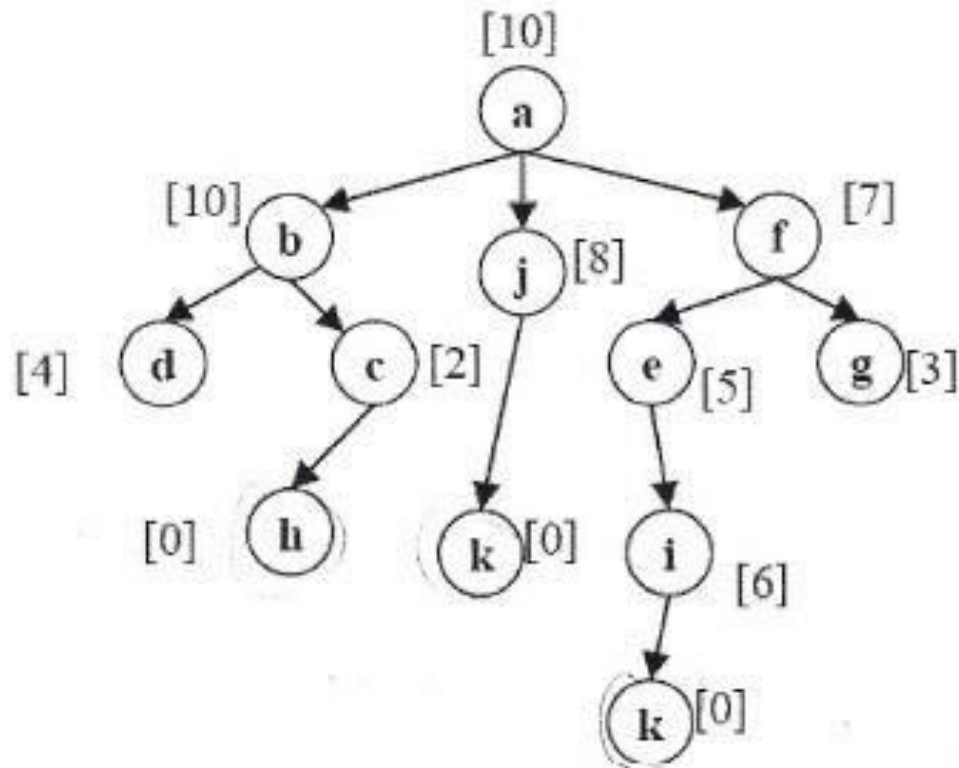


Simulated Annealing Starting from Node a

Current

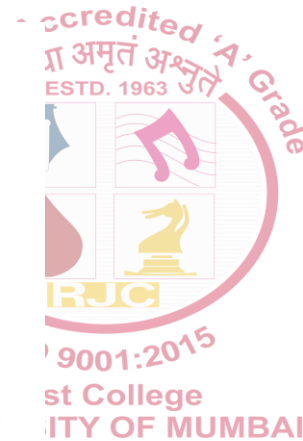
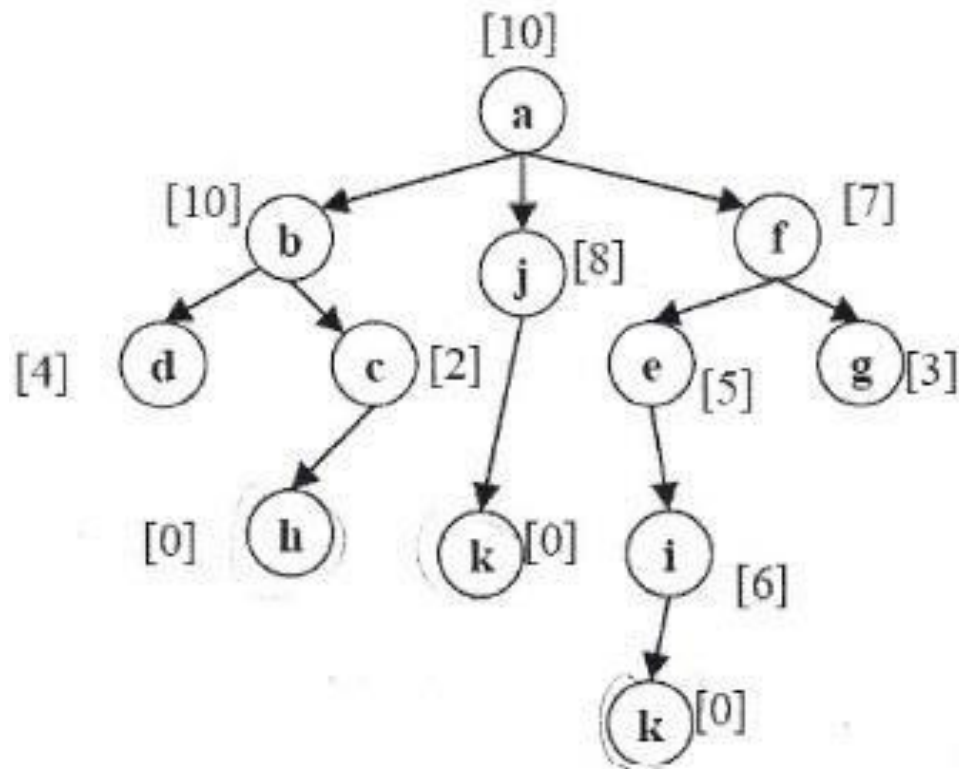
Children

a



Simulated Annealing

Current	Children
a	---
a	f_7, j_8, b_{10}



Simulated Annealing

Current

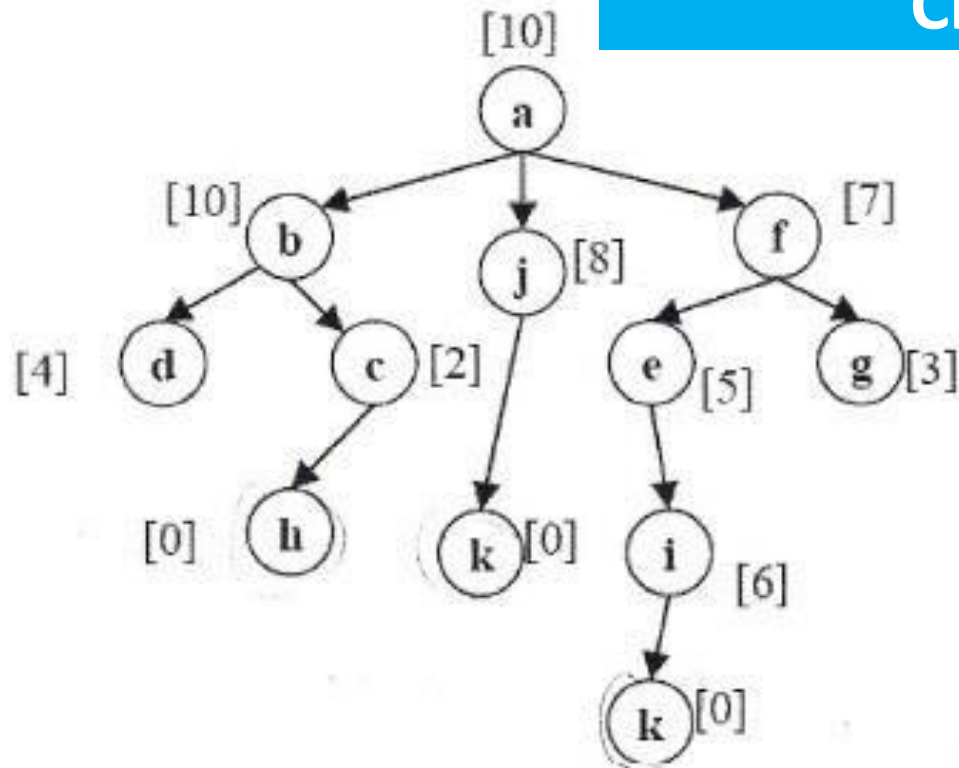
Children

a

a

f_7, j_8, b_{10}

Randomly Select a Child



Simulated Annealing

Current

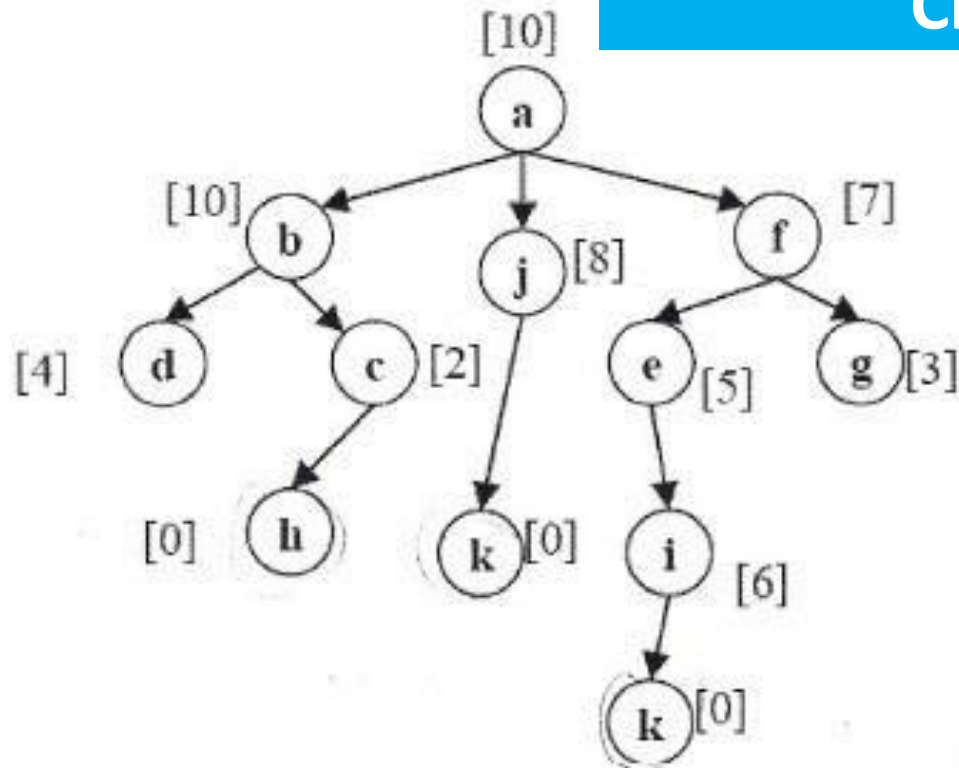
Children

a

a

f_7, j_8, b_{10}

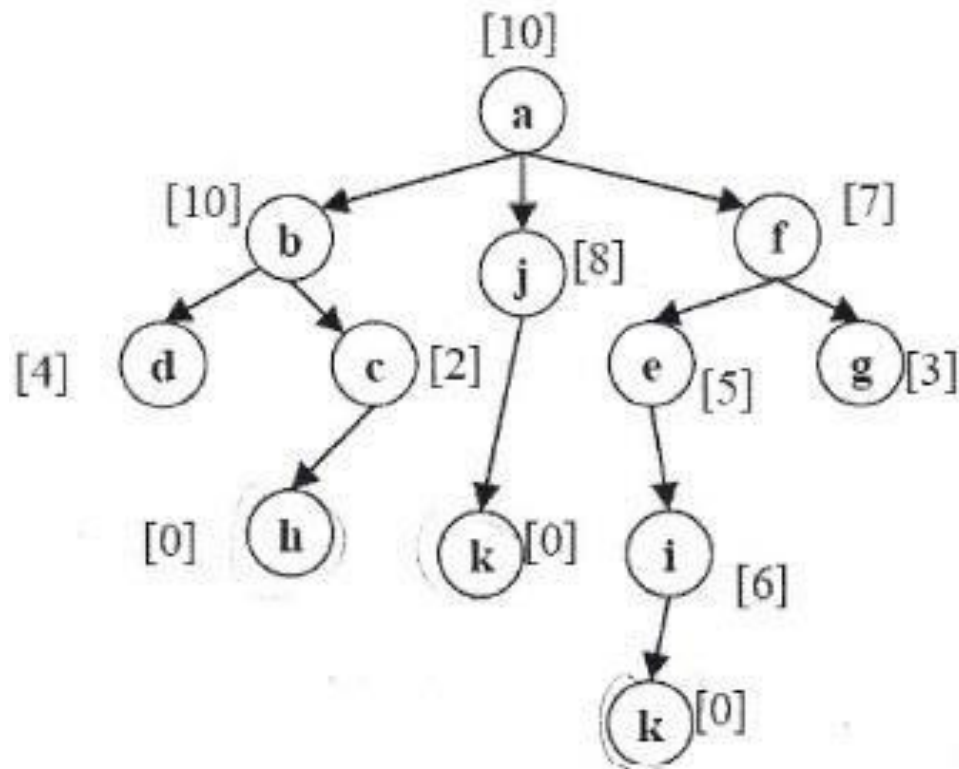
Randomly Select a
Child



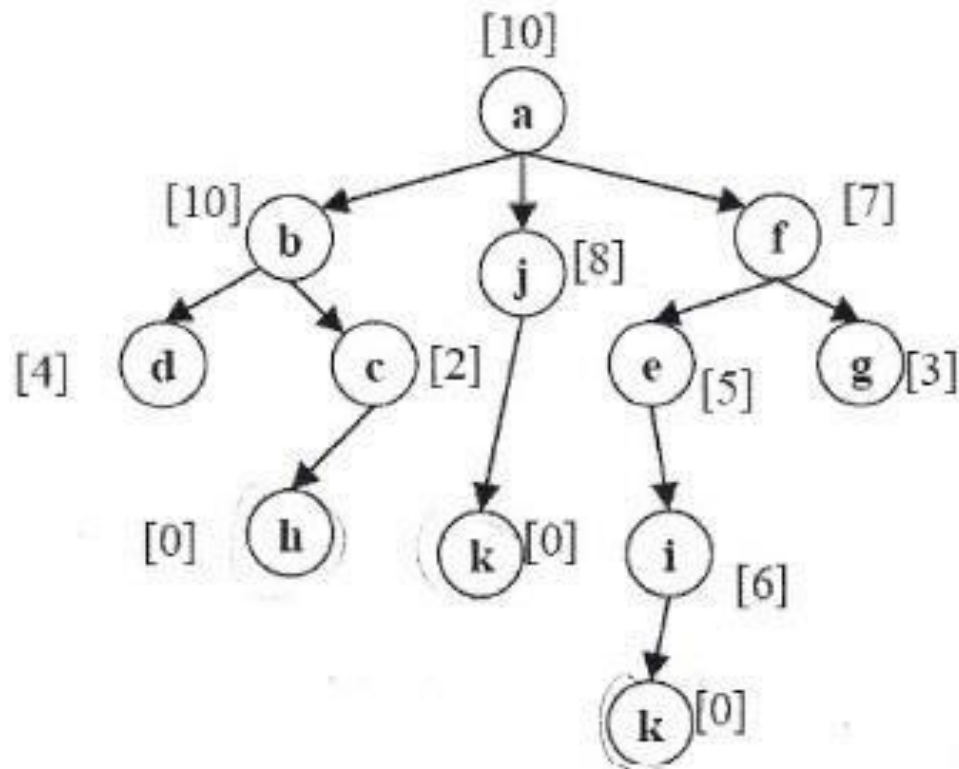
Simulated Annealing

Current	Children
a	---
a	f_7, j_8, b_{10}

Check if next node f_7 is better than current node



Simulated Annealing

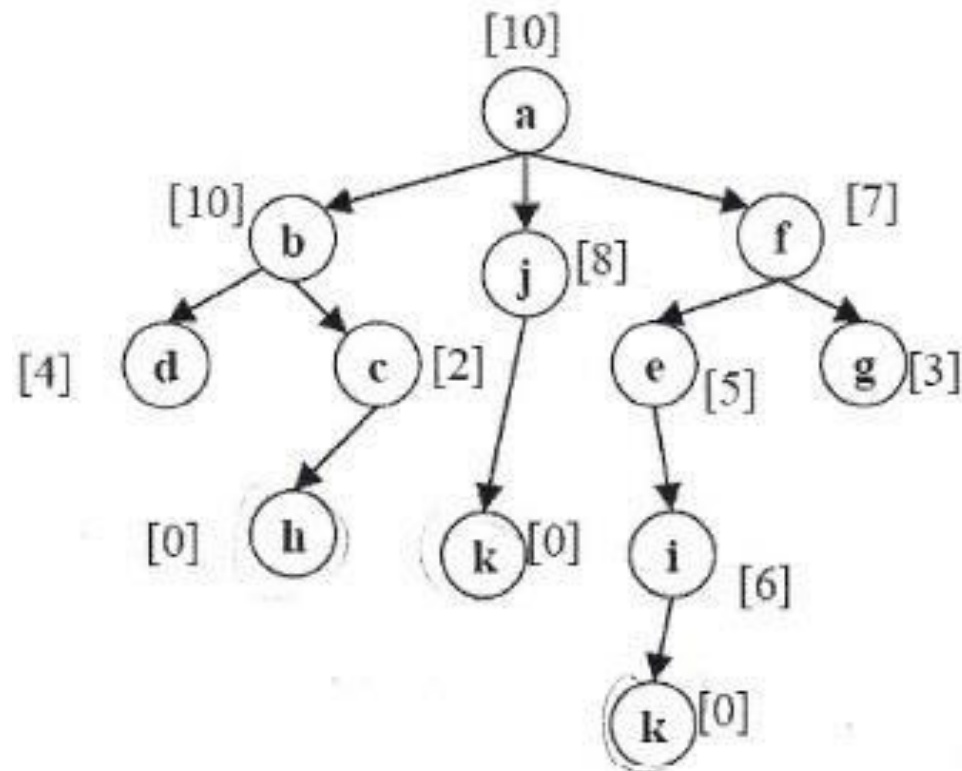


Current	Children
a	---
a	f_7, j_8, b_{10}

Check if next node f_7 is better than current node

$$\Delta E > 0$$

Simulated Annealing



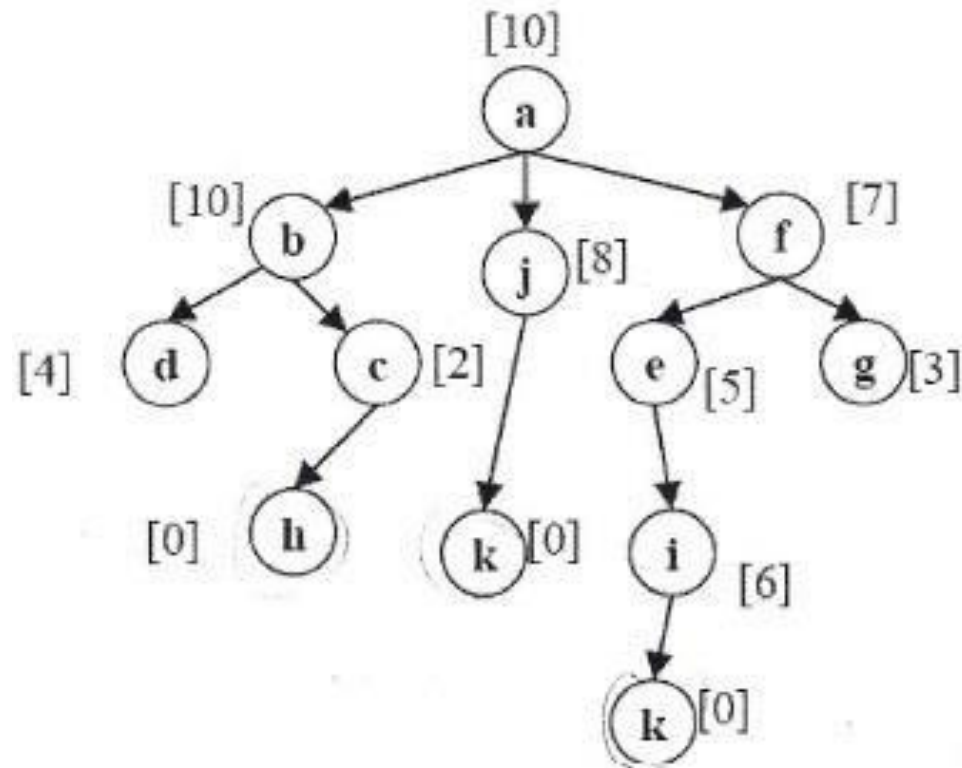
Current	Children
a	---
a	f_7, j_8, b_{10}

Check if next node f_7 is better than current node

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

Simulated Annealing

Current	Children
a	---
a	f_7, j_8, b_{10}

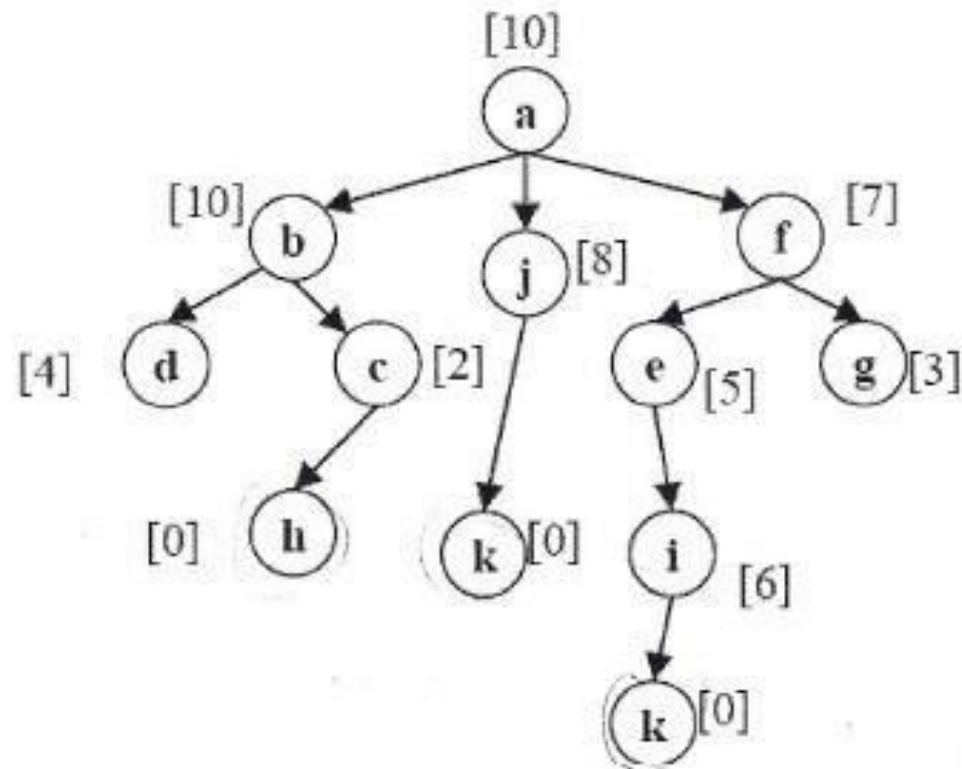


Check if next node f_7 is better than current node

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(f_7) - \text{value}(a_{10})$$

Simulated Annealing



Current

Children

a

a

f_7, j_8, b_{10}

Check if next node f_7 is better than current node

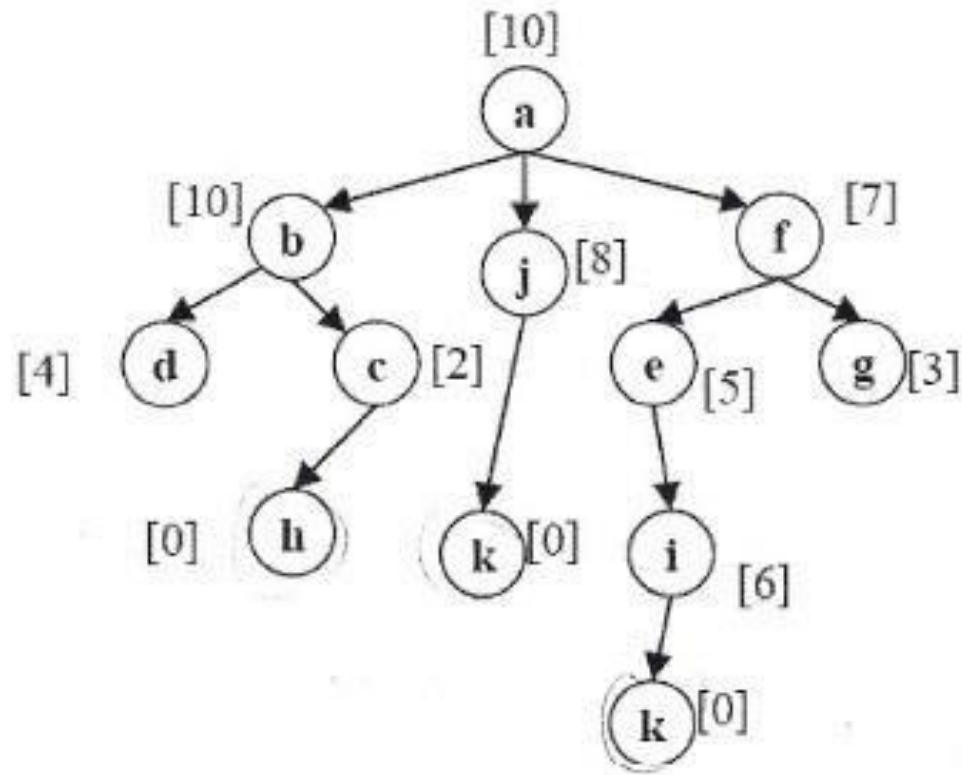
$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(f_7) - \text{value}(a_{10})$$

$$\text{value}(f_7) = -\text{heuristic}(f_7) = -7$$



Simulated Annealing



Current

Children

a

a

f_7, j_8, b_{10}

Check if next node f_7 is better than current node

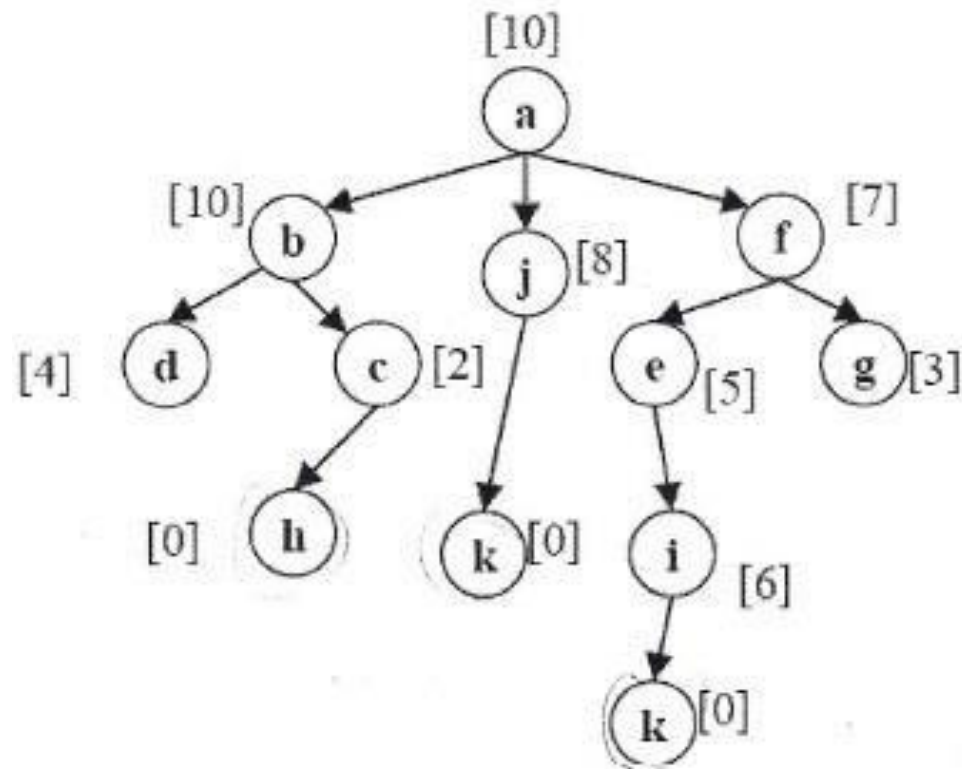
$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(f_7) - \text{value}(a_{10})$$

$$\text{value}(f_7) = -\text{heuristic}(f_7) = -7$$

$$\text{value}(a_{10}) = -\text{heuristic}(a_{10}) = -10$$

Simulated Annealing



Current

a

a

Children

f_7, j_8, b_{10}

Check if next node f_7 is better than current node

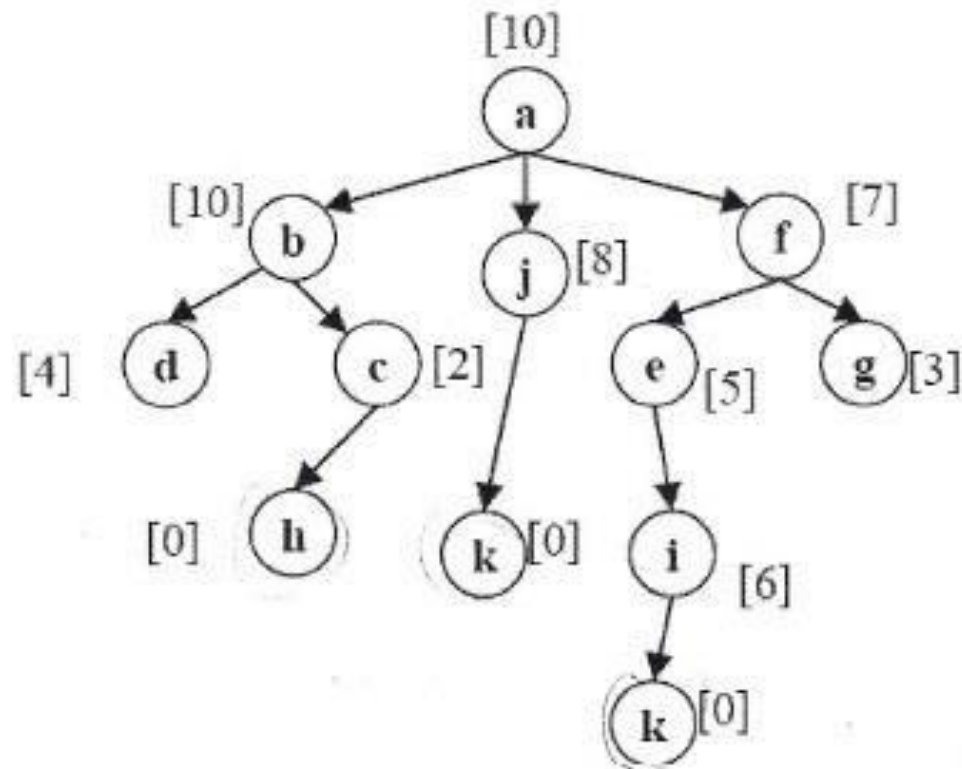
$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(f_7) - \text{value}(a_{10})$$

$$\Delta E = -7 - (-10) = +3$$



Simulated Annealing



Current

a

a

Children

f_7, j_8, b_{10}

Check if next node f_7 is better than current node

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(f_7) - \text{value}(a_{10})$$

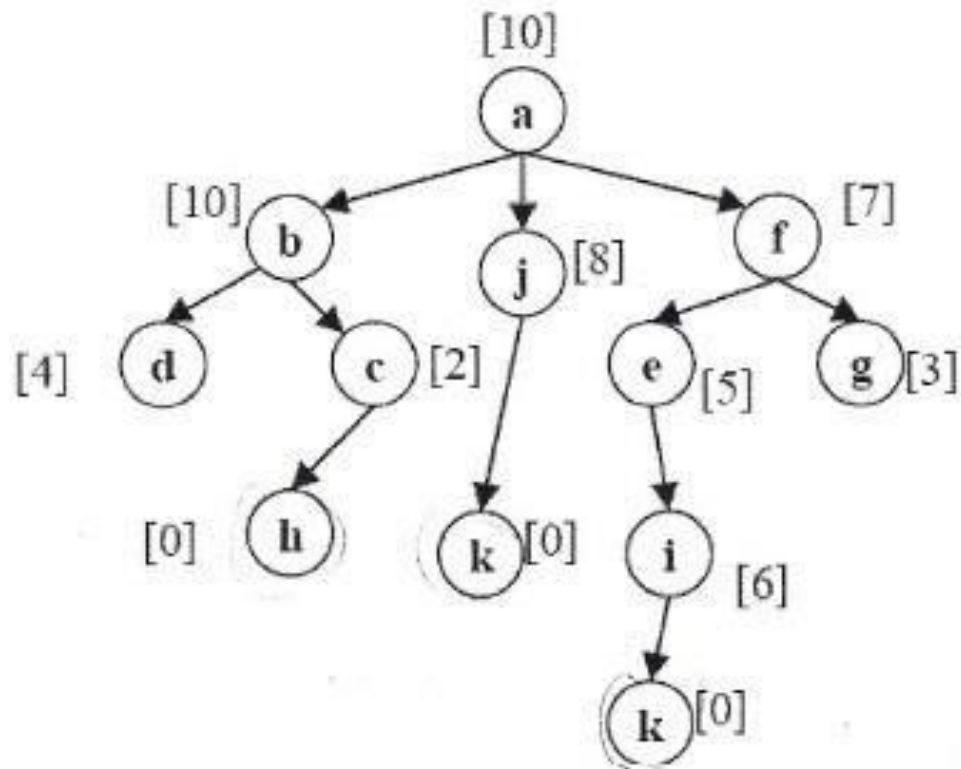
$$\Delta E = -7 - (-10) = +3$$

$$\therefore \Delta E > 0$$

$\therefore f_7$ will be selected with probability 1

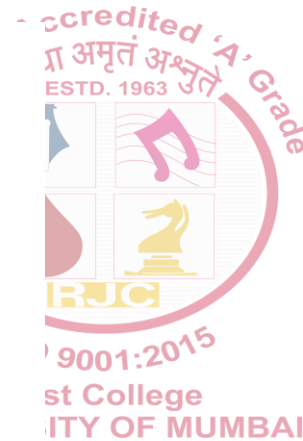
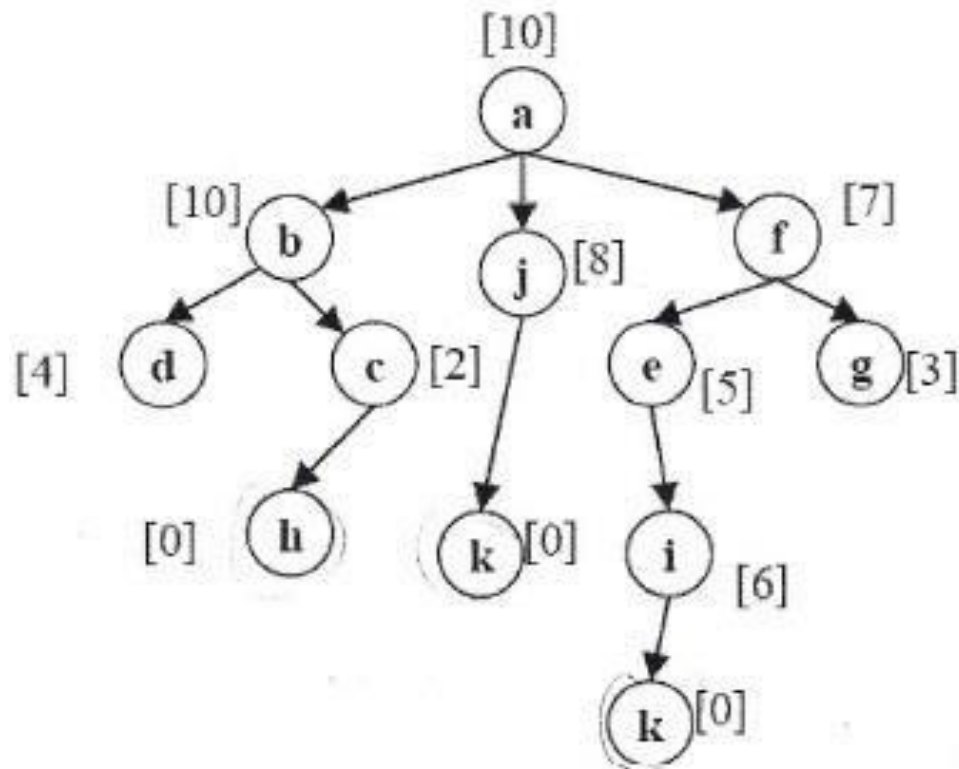
Simulated Annealing

Current	Children
a	---
a	f_7, j_8, b_{10}
f	

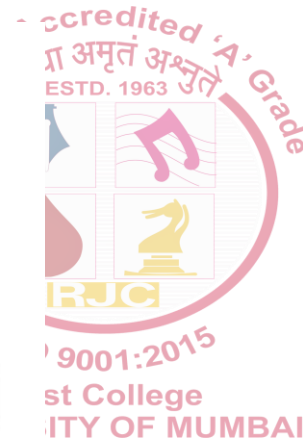
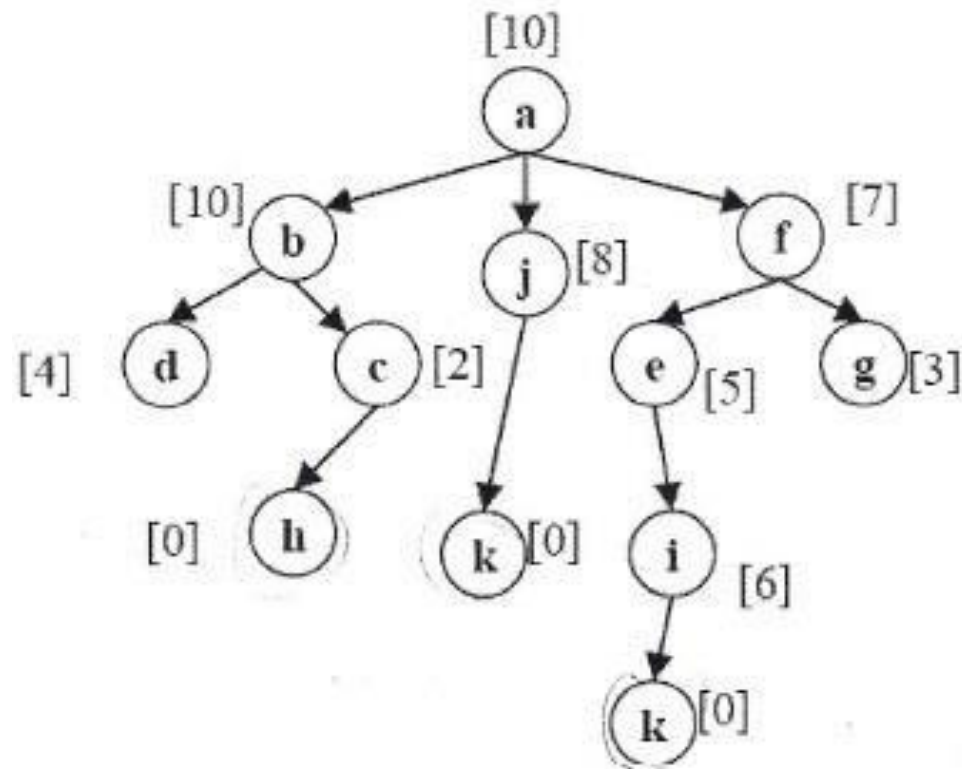


Simulated Annealing

Current	Children
a	---
a	f_7, j_8, b_{10}
f	



Simulated Annealing



Current

a

a

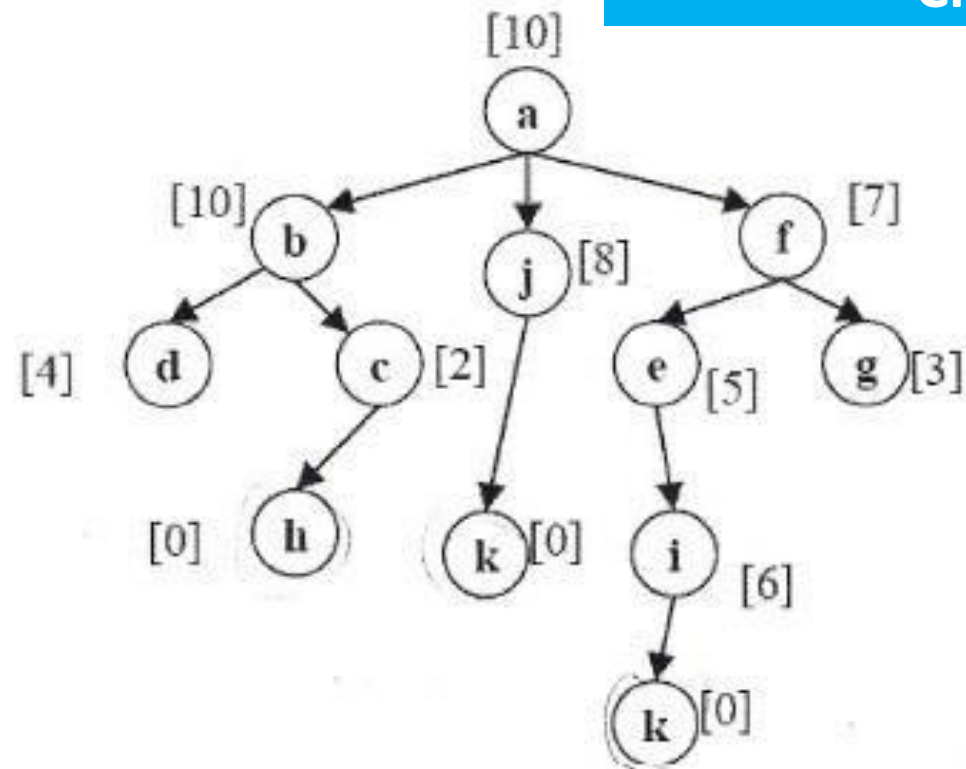
f

Children

f_7, j_8, b_{10}

e_5, g_3

Simulated Annealing



Randomly Select a Child

Current

a

a

f

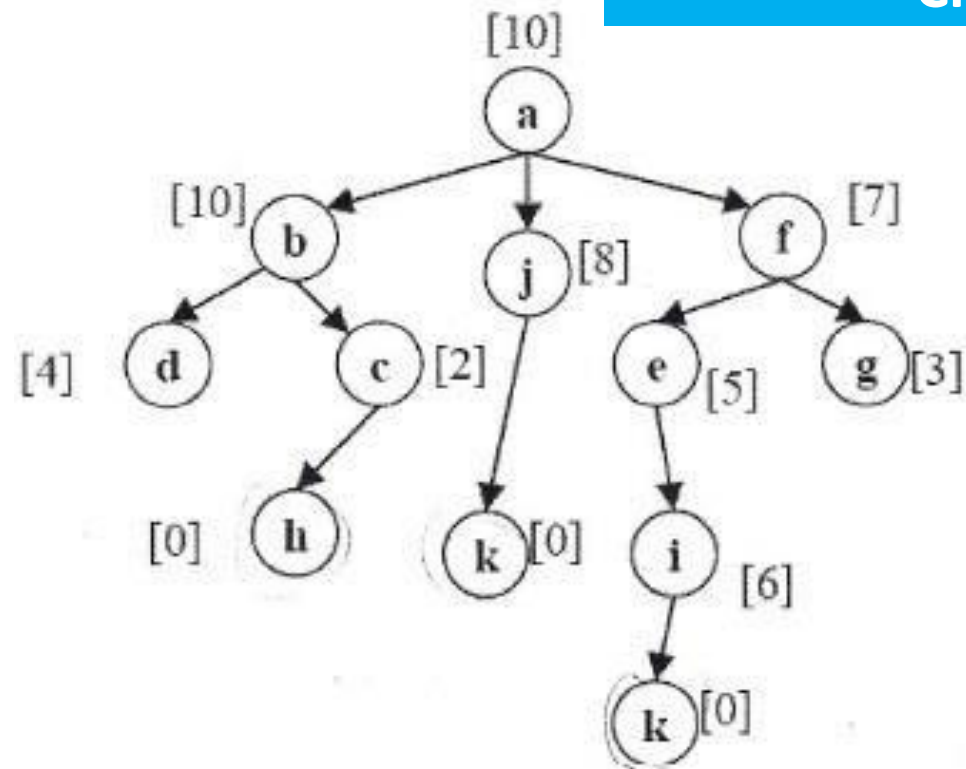
Children

f_7, j_8, b_{10}

e_5, g_3



Simulated Annealing



Randomly Select a Child

Current

a

a

f

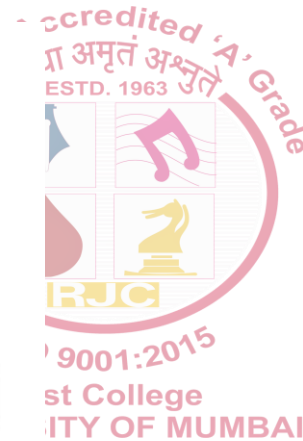
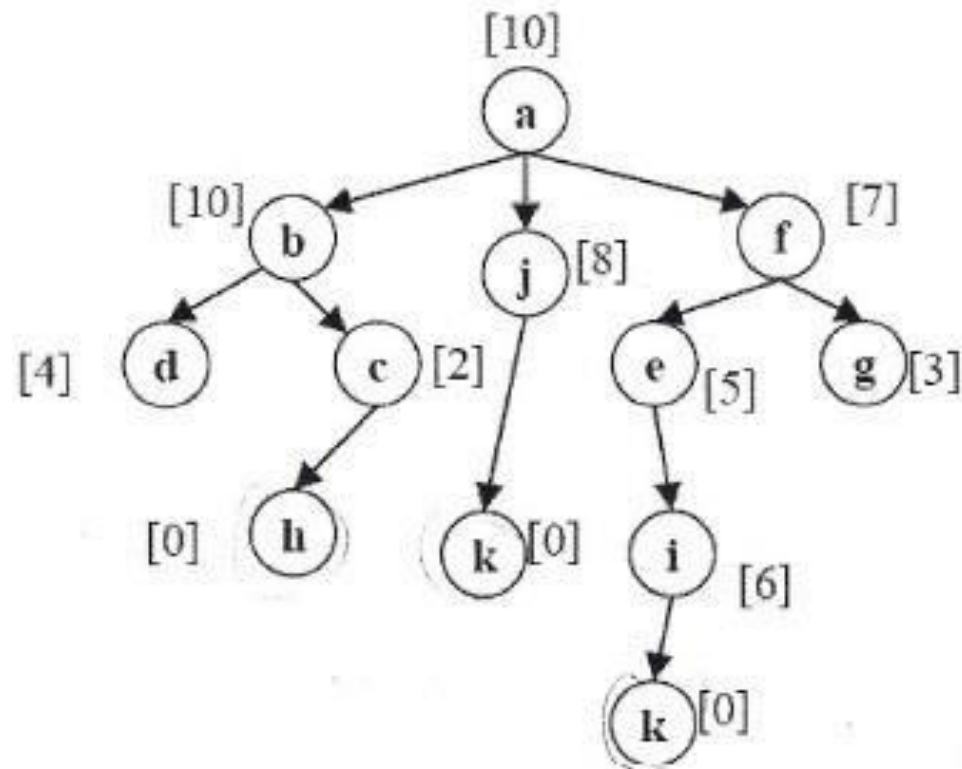
Children

f_7, j_8, b_{10}

e_5, g_3

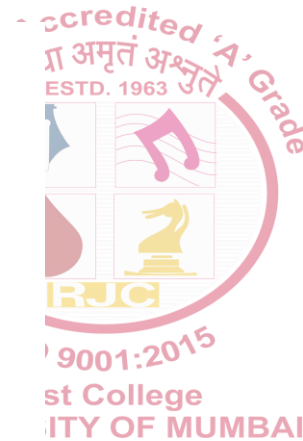
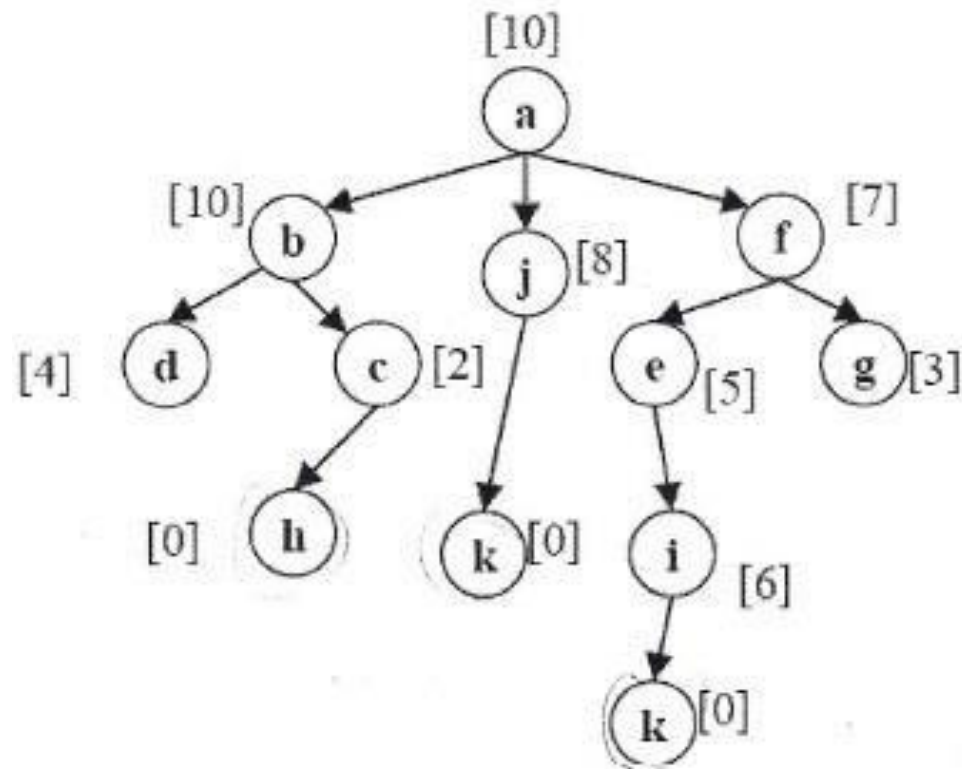


Simulated Annealing



Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3
Check if next node e_5 is better than current node	

Simulated Annealing

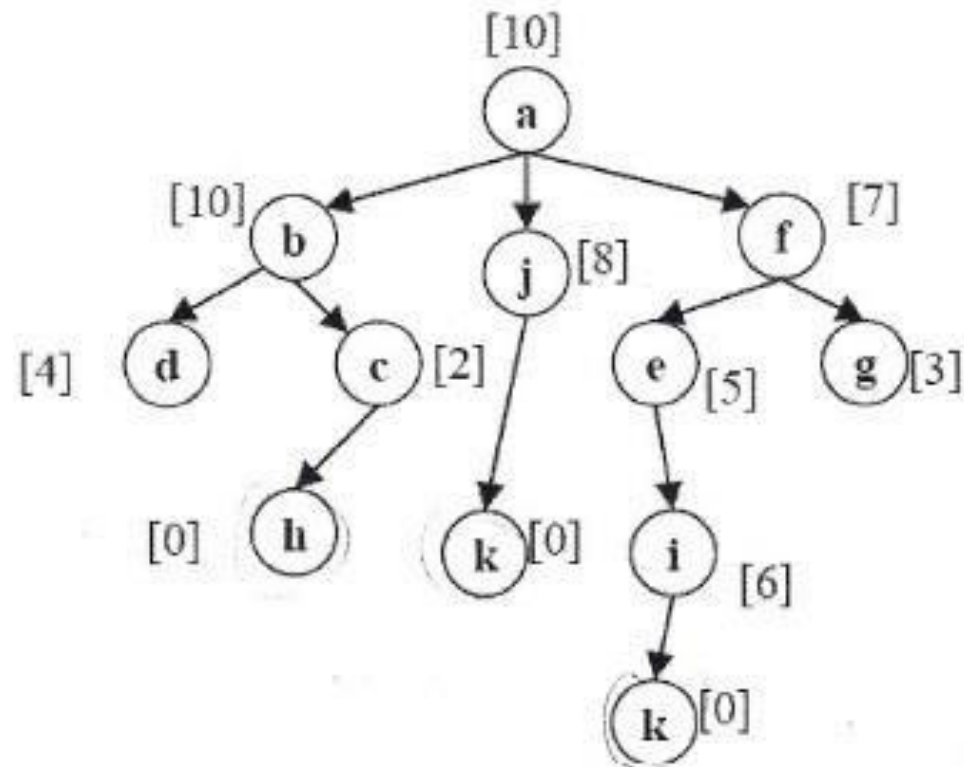


Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3

Check if next node e_5 is better than current node

$$\Delta E > 0$$

Simulated Annealing



Current

Children

a

a

f_7, j_8, b_{10}

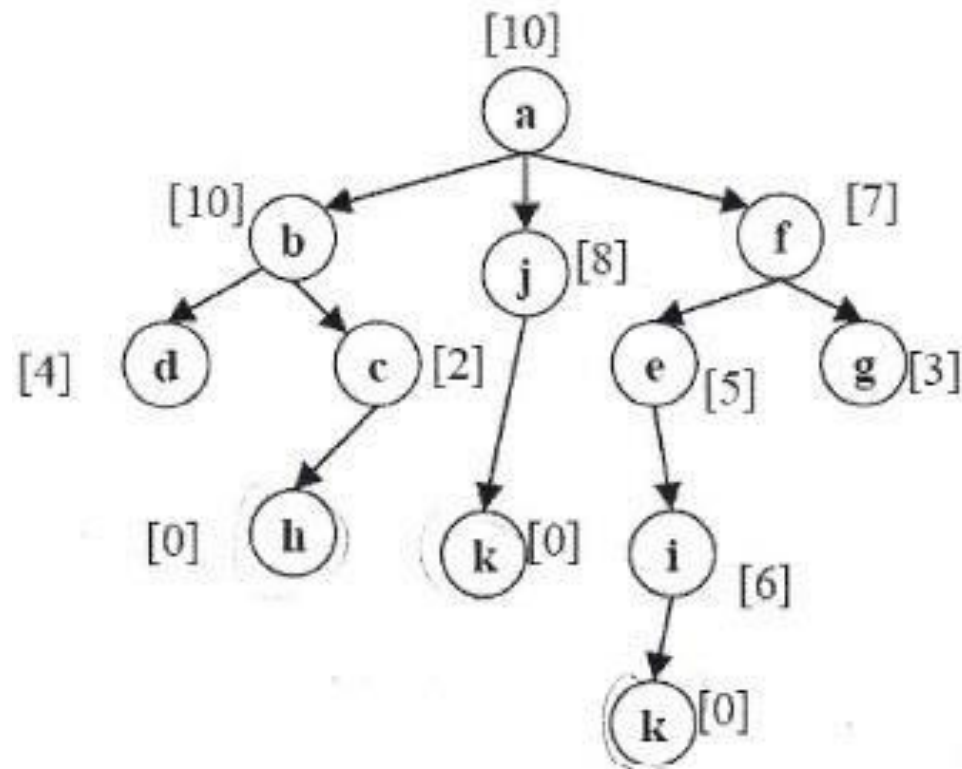
f

e_5, g_3

Check if next node e_5 is better than current node

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

Simulated Annealing



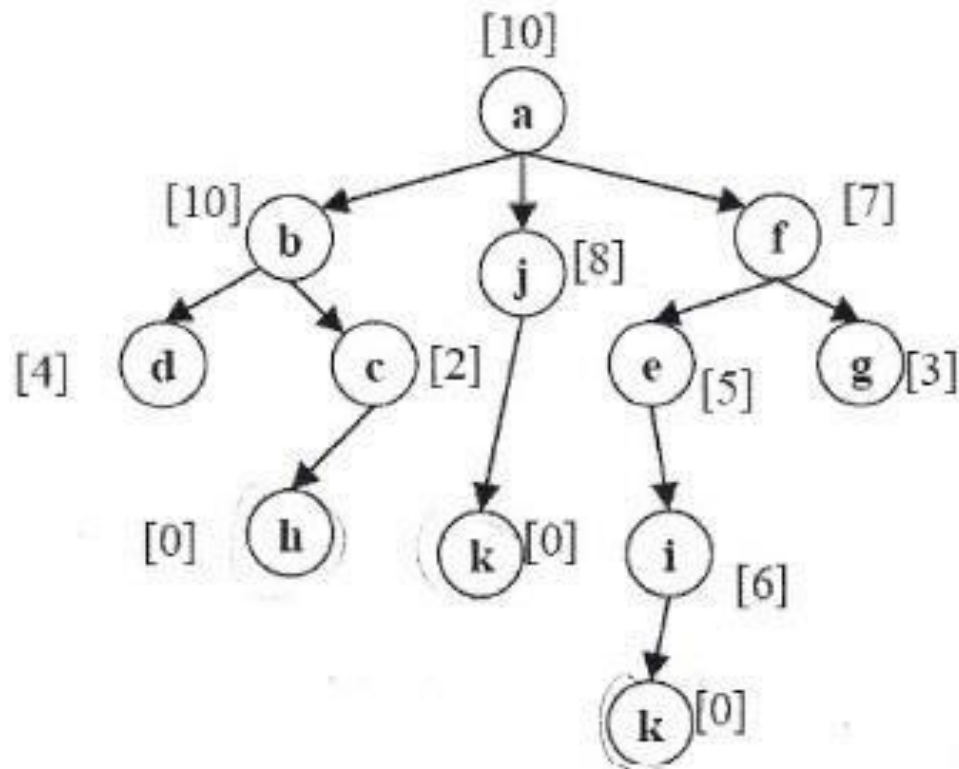
Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3

Check if next node e_5 is better than current node

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(e_5) - \text{value}(f_7)$$

Simulated Annealing



Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3

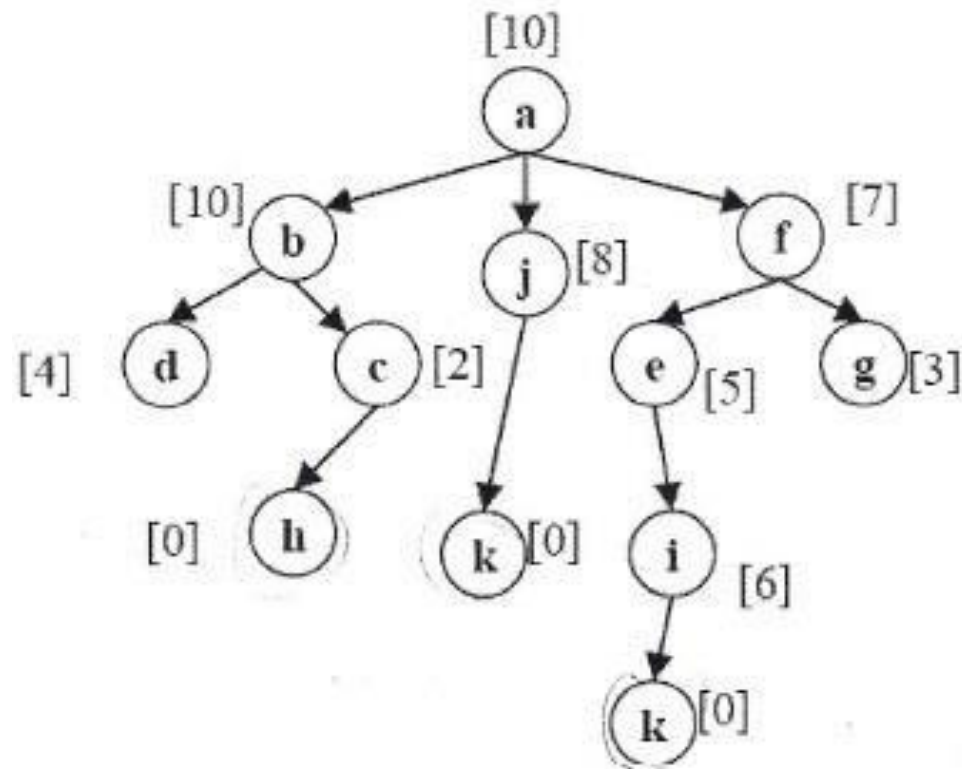
Check if next node e_5 is better than current node

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(e_5) - \text{value}(f_7)$$

$$\text{value}(e_5) = -\text{heuristic}(e_5) = -5$$

Simulated Annealing



Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3

Check if next node e_5 is better than current node

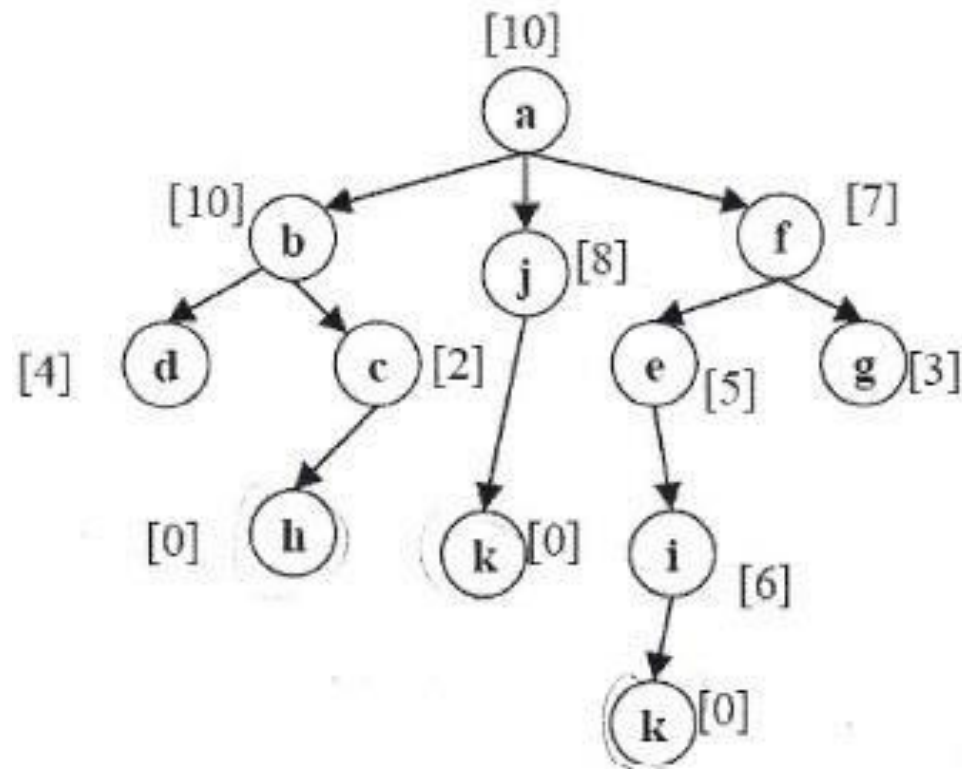
$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(e_5) - \text{value}(f_7)$$

$$\text{value}(e_5) = -\text{heuristic}(e_5) = -5$$

$$\text{value}(f_7) = -\text{heuristic}(f_7) = -7$$

Simulated Annealing



Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3

Check if next node e_5 is better than current node

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

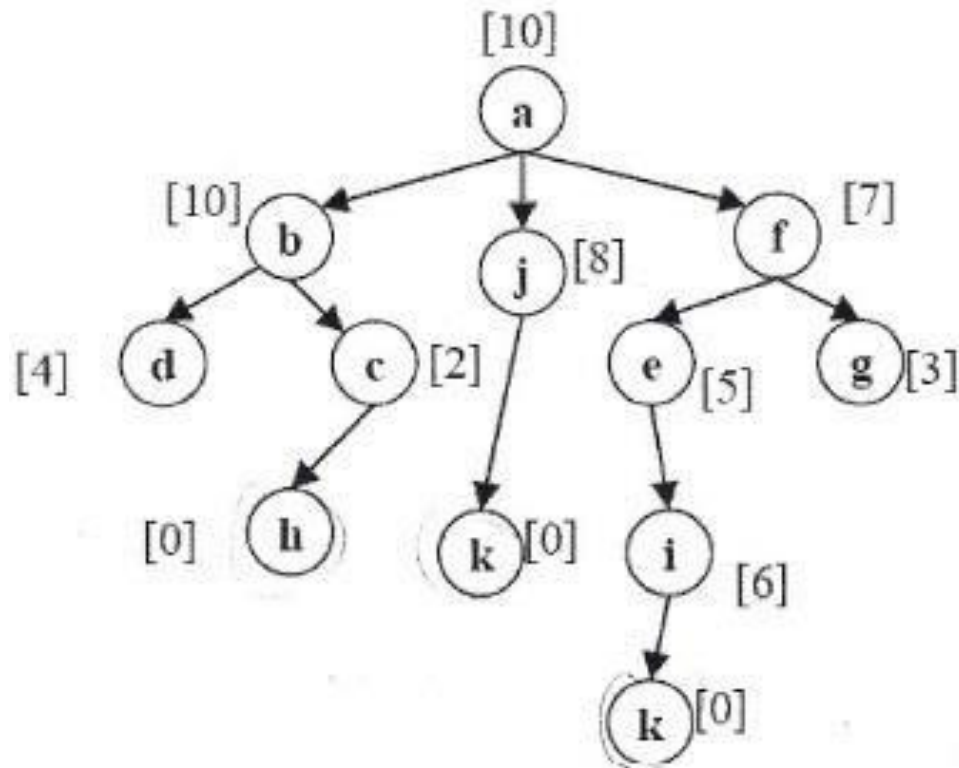
$$\Delta E = \text{value}(e_5) - \text{value}(f_7)$$

$$\Delta E = -5 - (-7) = +2$$

Simulated Annealing

$$\because \Delta E > 0$$

$\therefore e_5$ will be selected with probability 1



Current

Children

a

a

f_7, j_8, b_{10}

f

e_5, g_3

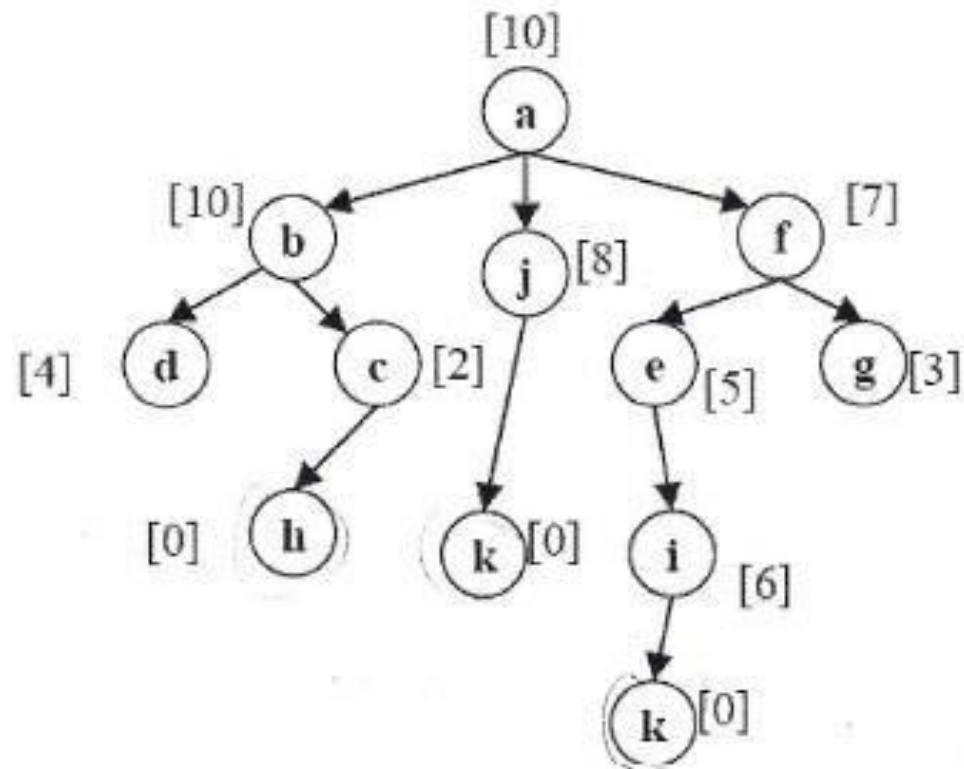
Check if next node e_5 is better than current node

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(e_5) - \text{value}(f_7)$$

$$\Delta E = -5 - (-7) = +2$$

Simulated Annealing



Current

a

a

f

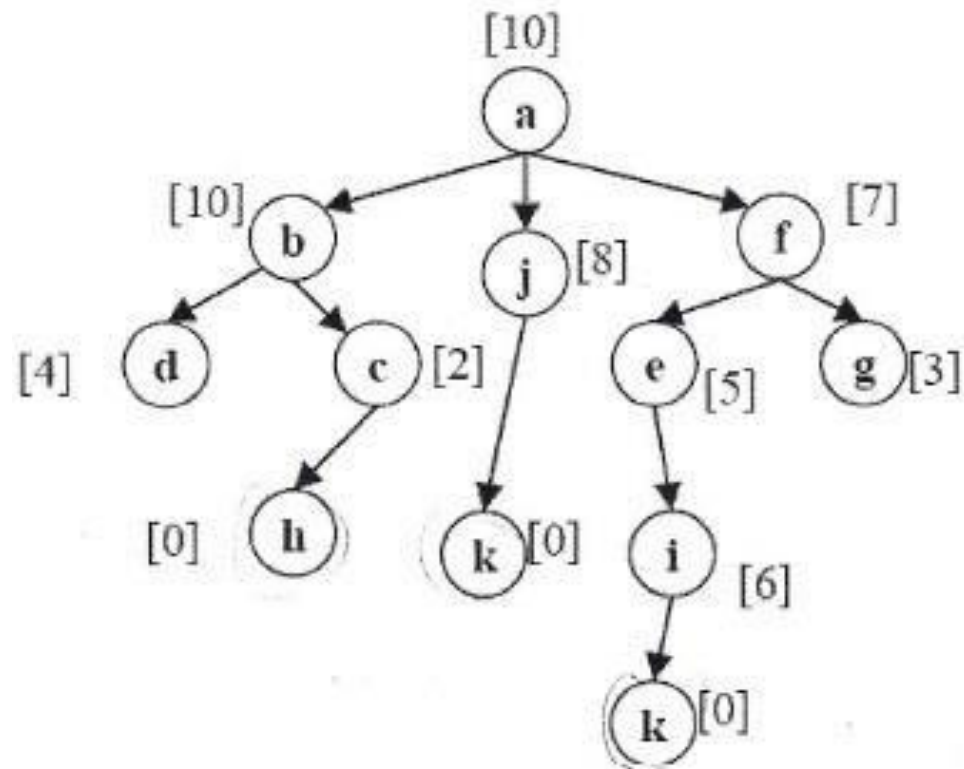
e

Children

f_7, j_8, b_{10}

e_5, g_3

Simulated Annealing



Current

a

a

f

e

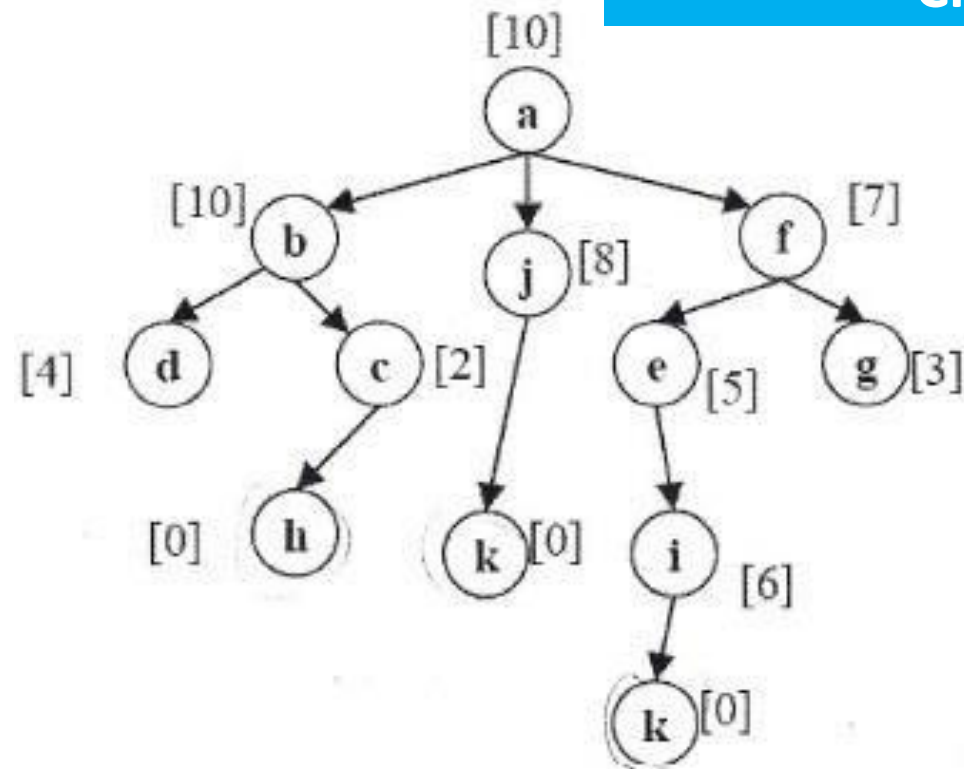
Children

f_7, j_8, b_{10}

e_5, g_3

i_6

Simulated Annealing



Randomly Select a Child

Current

a

a

f

e

Children

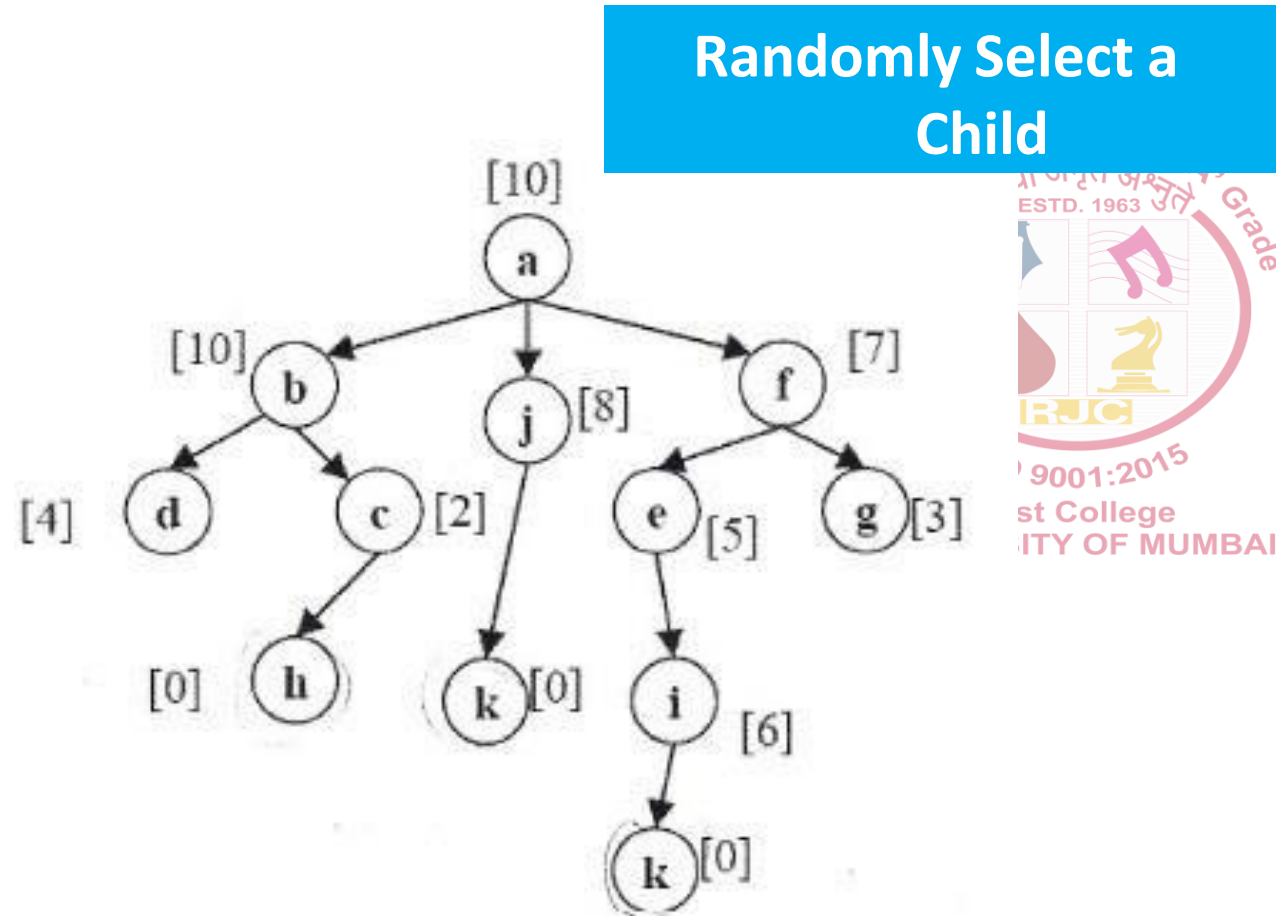
f_7, j_8, b_{10}

e_5, g_3

i_6



Simulated Annealing



Current

a

a

f

e

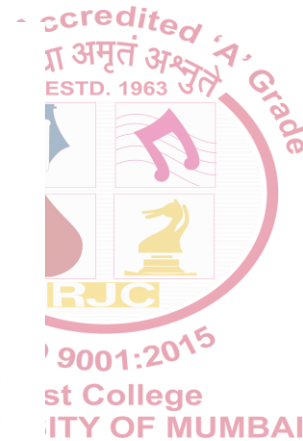
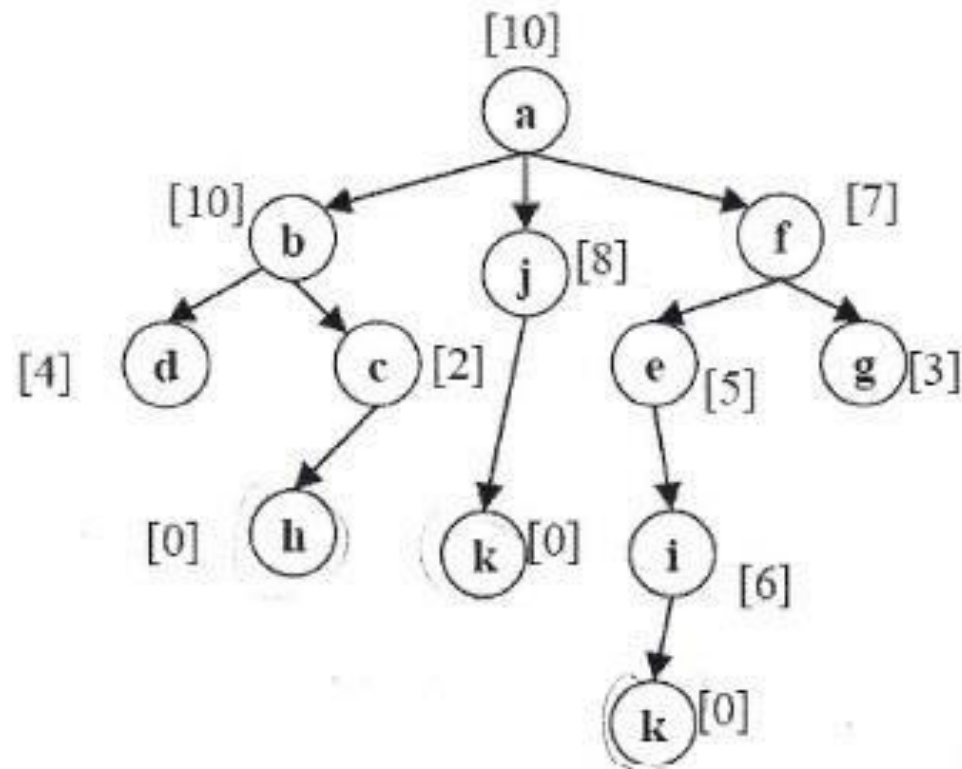
Children

f_7, j_8, b_{10}

e_5, g_3

i_6

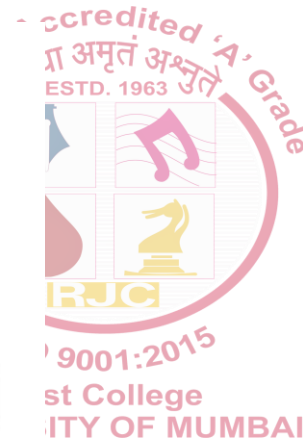
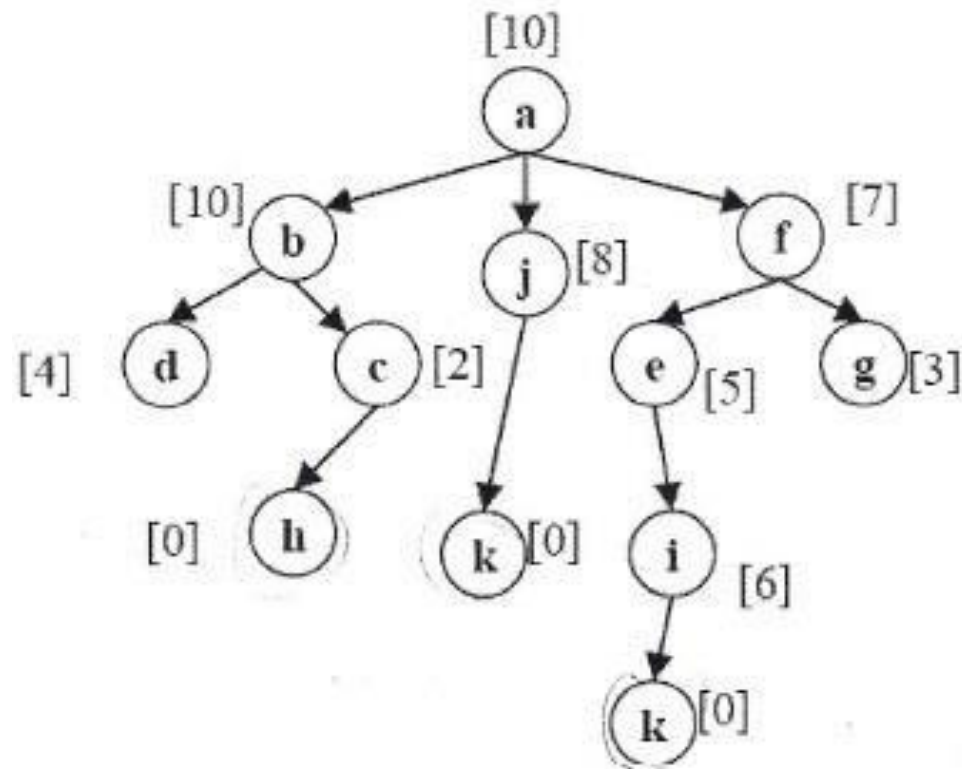
Simulated Annealing



Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3
e	i_6

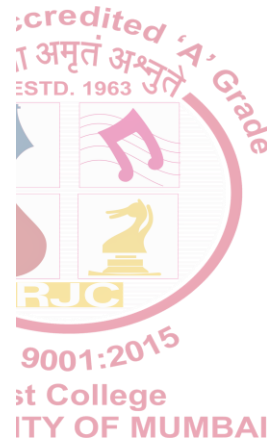
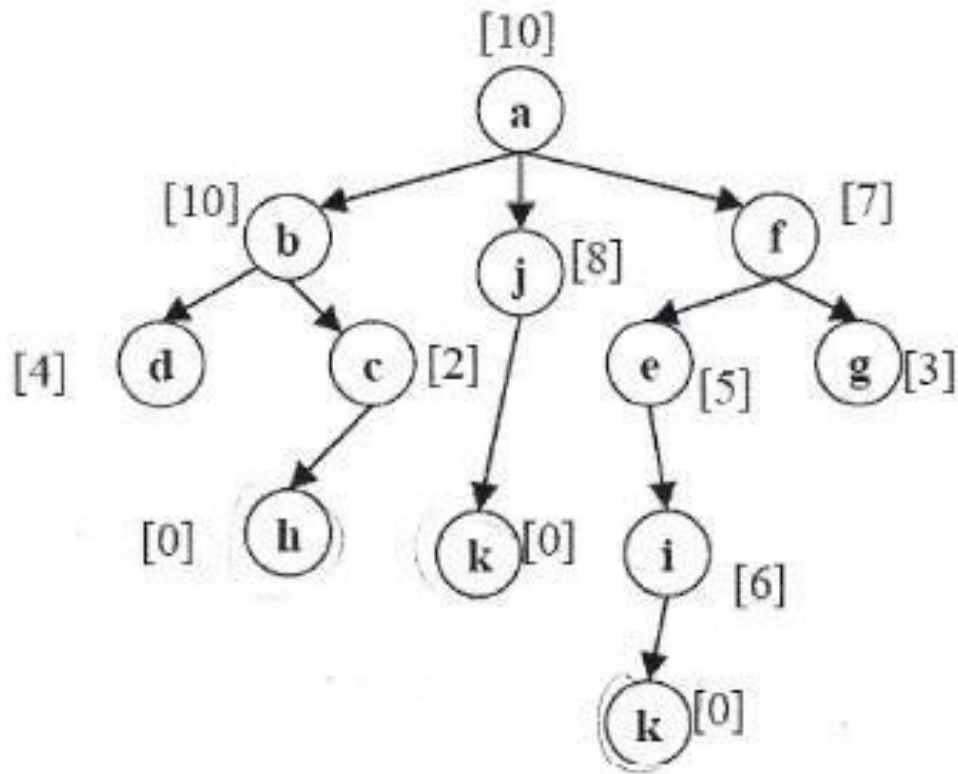
Check if next node i_6 is better than current node

Simulated Annealing



Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3
e	i_6
Check if next node i_6 is better than current node	
$\Delta E > 0$	

Simulated Annealing



Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3
e	i_6

Check if next node i_6 is better than current node

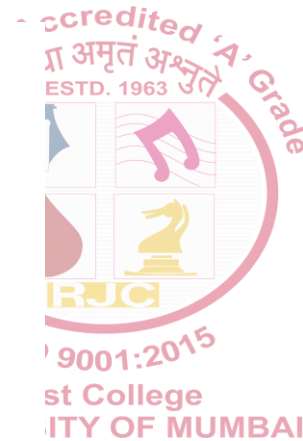
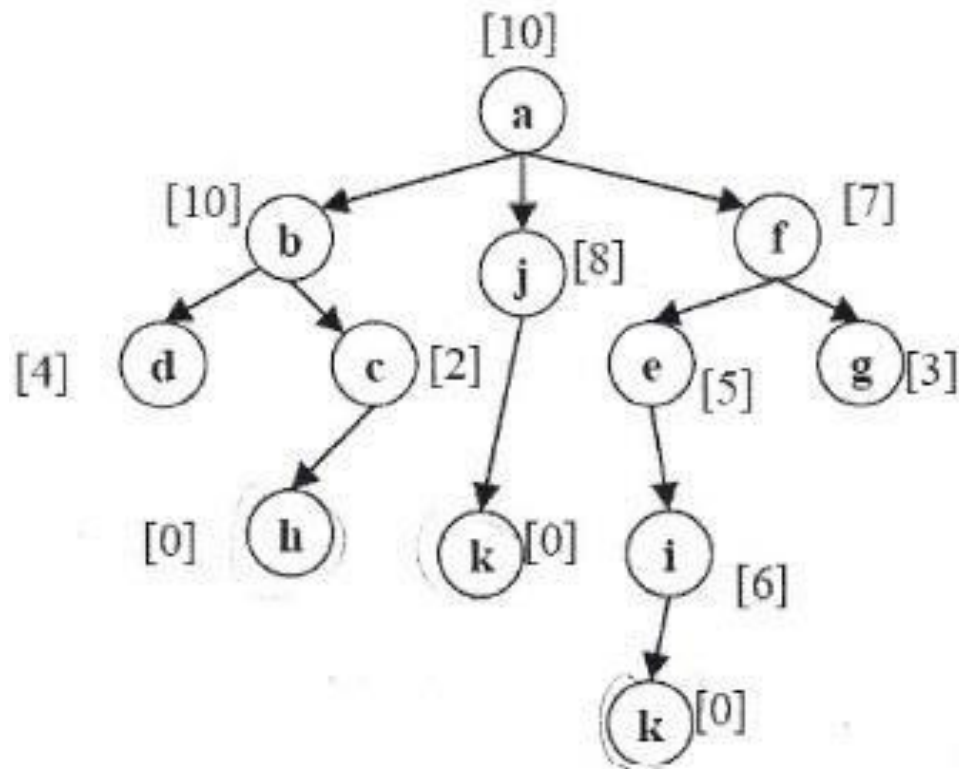
$$\Delta E > 0$$

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(i_6) - \text{value}(e_5)$$

Simulated Annealing

$$\text{value}(i_6) = -\text{heuristic}(i_6) = -6$$



Current

Children

a

a

f_7, j_8, b_{10}

f

e_5, g_3

e

i_6

Check if next node i_6 is better than current node

$$\Delta E > 0$$

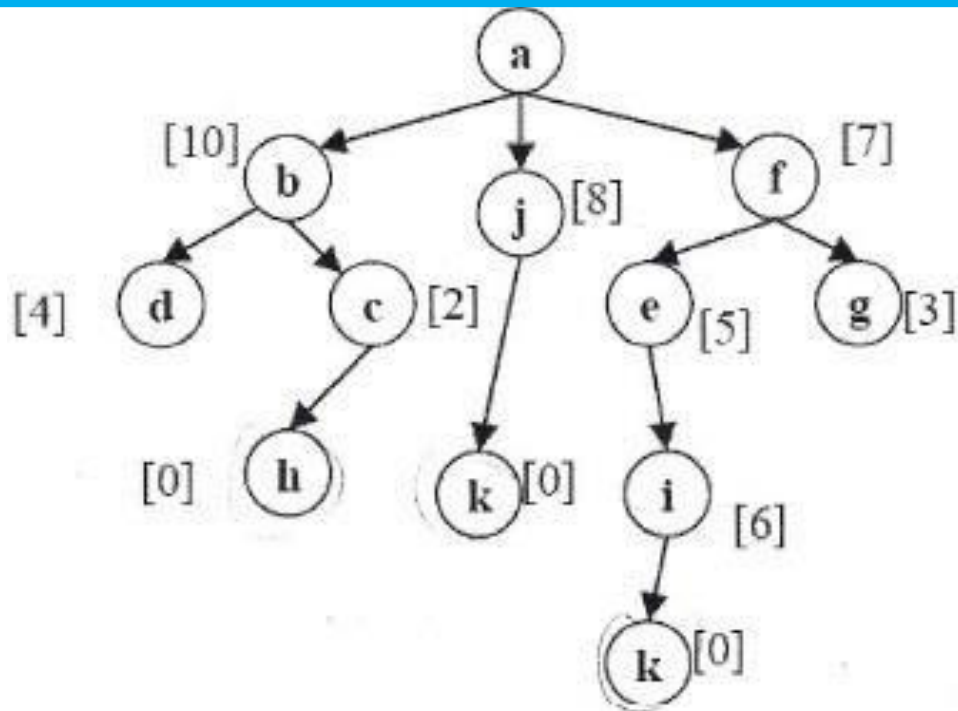
$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(i_6) - \text{value}(e_5)$$

Simulated Annealing

$$\text{value}(i_6) = -\text{heuristic}(i_6) = -6$$

$$\text{value}(e_5) = -\text{heuristic}(e_5) = -5$$



Current

Children

a

a

f_7, j_8, b_{10}

f

e_5, g_3

e

i_6

Check if next node i_6 is better than current node

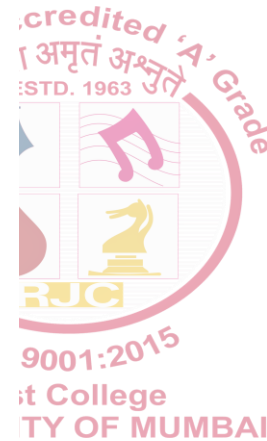
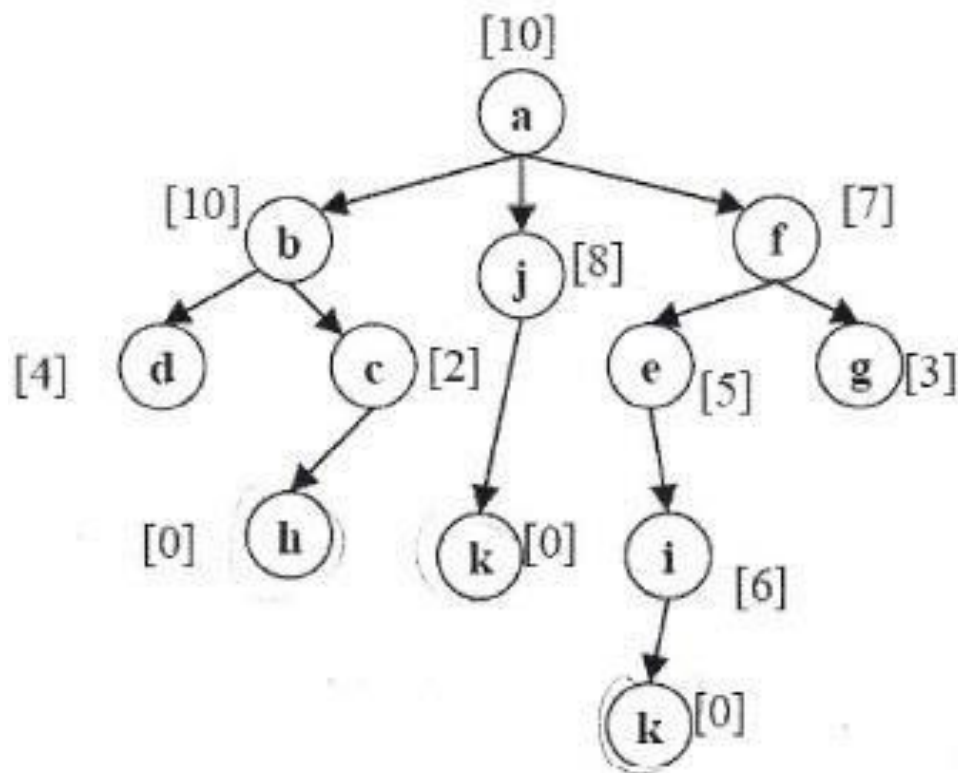
$$\Delta E > 0$$

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(i_6) - \text{value}(e_5)$$

Simulated Annealing

$$\Delta E = -6 - (-5) = -1$$



Current

Children

a

a

f_7, j_8, b_{10}

f

e_5, g_3

e

i_6

Check if next node i_6 is better than current node

$$\Delta E > 0$$

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(i_6) - \text{value}(e_5)$$

Simulated Annealing

$\because \Delta E < 0$
 $\therefore i_6$ can be selected with
 probability $p = e^{\frac{\Delta E}{T}}$



Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3
e	i_6

Check if next node e_5 is better than current node

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(e_5) - \text{value}(f_7)$$

$$\Delta E = -5 - (-7) = +2$$

Simulated Annealing

$\because \Delta E < 0$
 $\therefore i_6$ can be selected with
 probability $p = e^{\frac{\Delta E}{T}}$

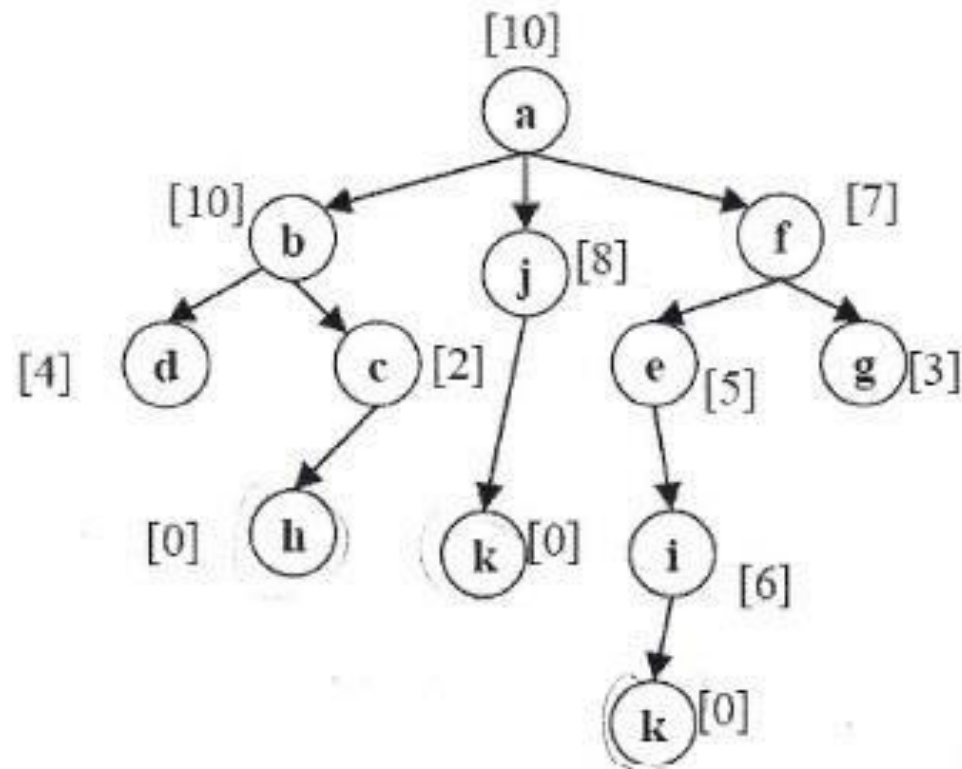


Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3
e	i_6

Check if next node e_5 is better than current node

$$p = e^{\frac{-1}{10}} = e^{\frac{-1}{10}} = .905$$

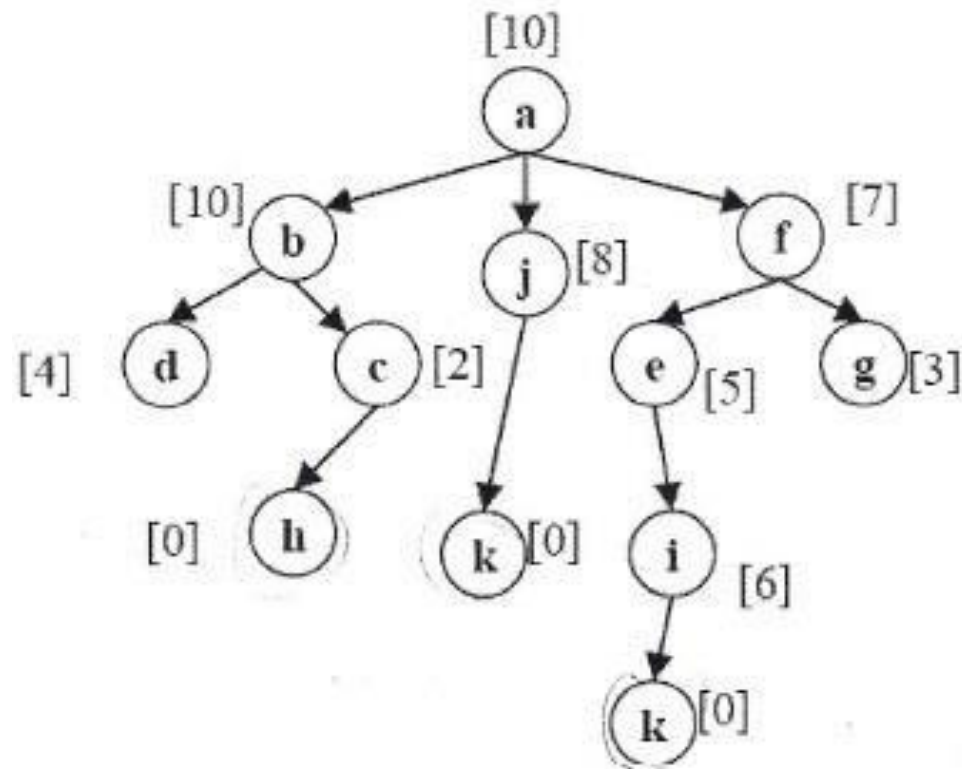
Simulated Annealing



Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3
e	i_6

Because the only child of e_5 is i_6 then it will be selected even if its probability is not 1.

Simulated Annealing



Current

a

a

f

e

i

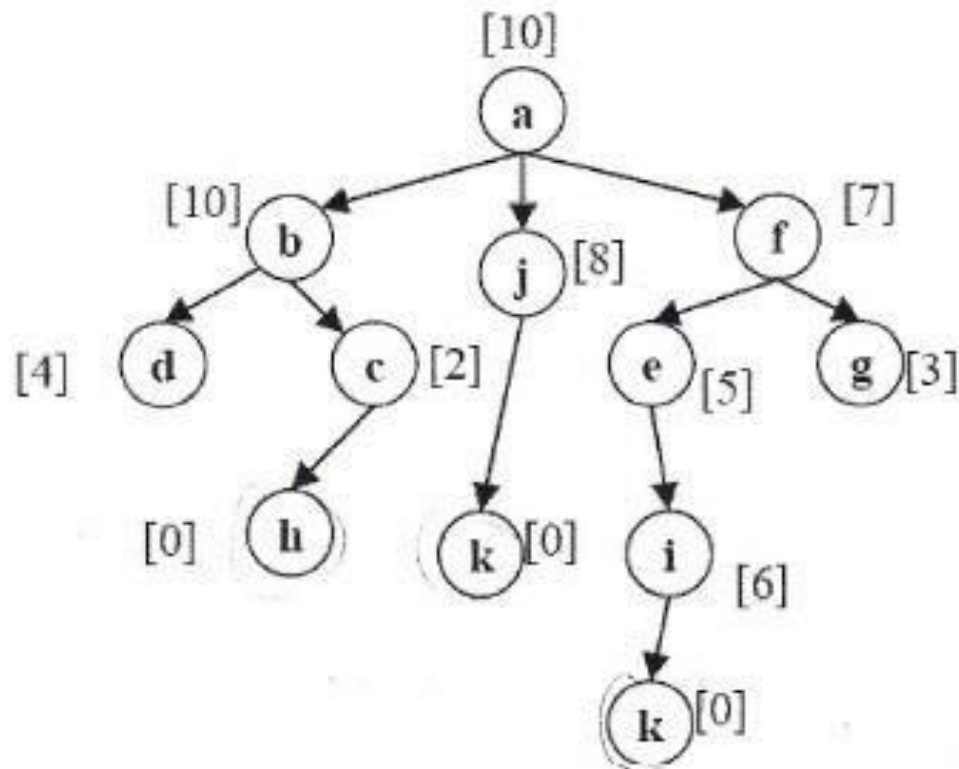
Children

f_7, j_8, b_{10}

e_5, g_3

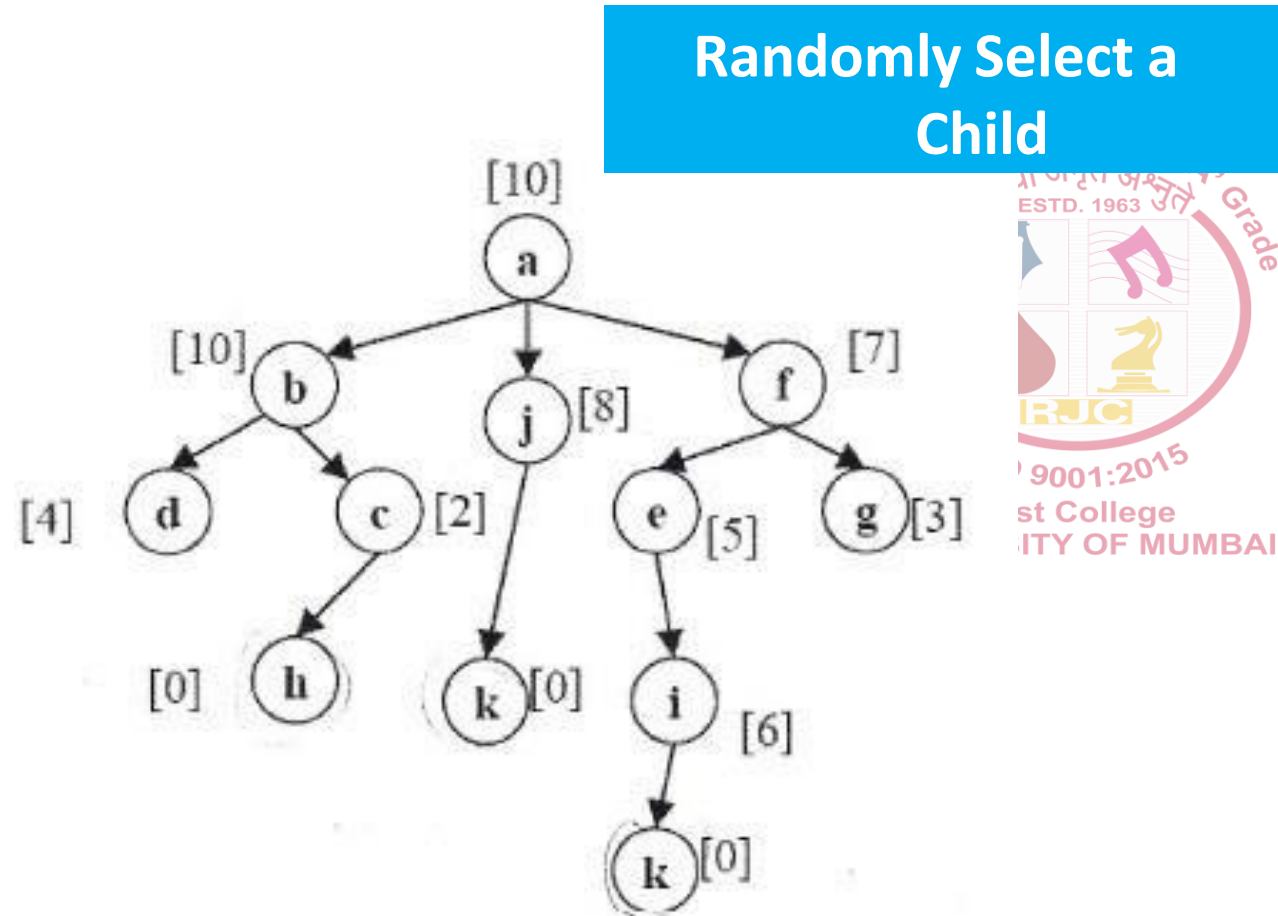
i_6

Simulated Annealing



Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3
e	i_6
i	k_0

Simulated Annealing



Current

Children

a

a

f_7, j_8, b_{10}

f

e_5, g_3

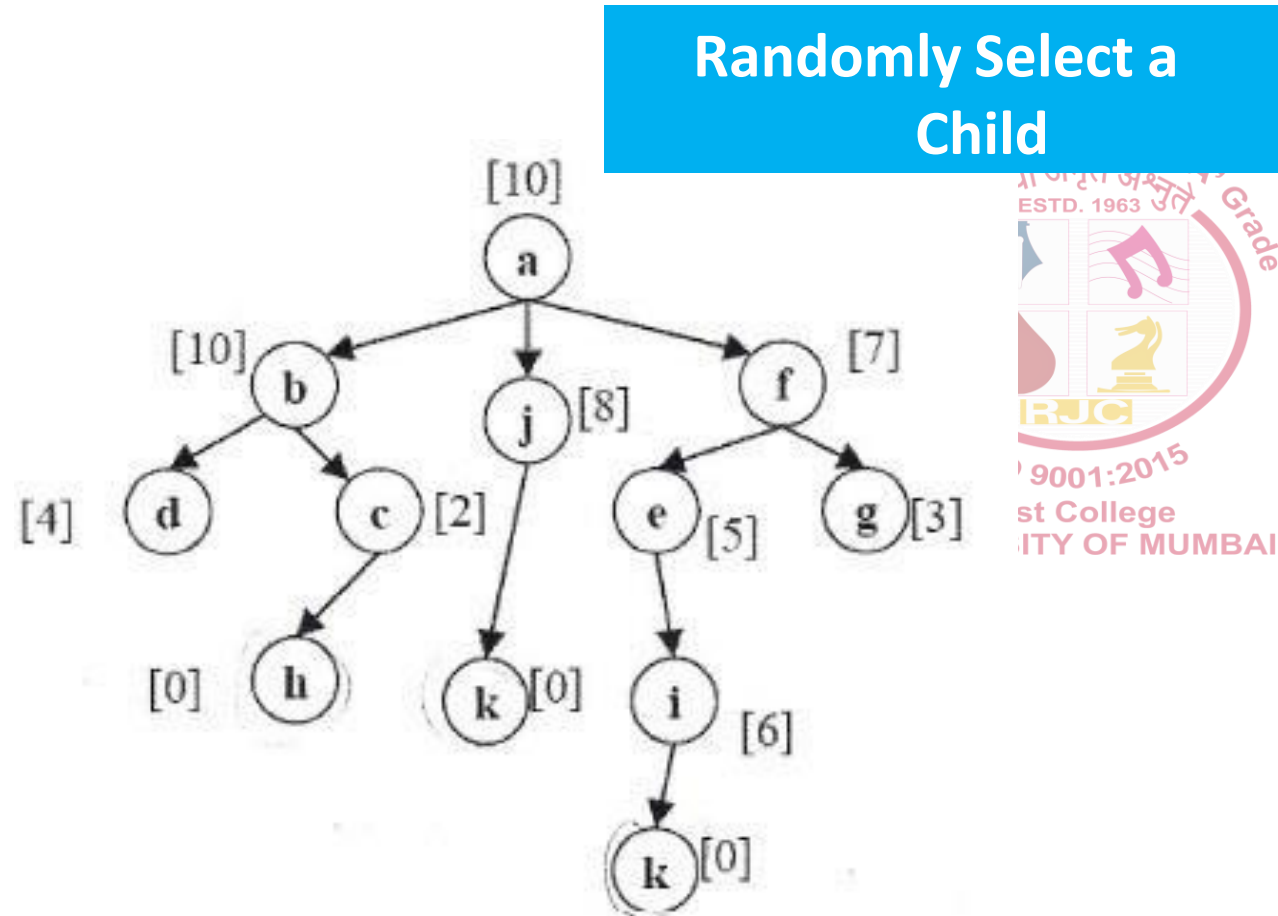
e

i_6

i

k_0

Simulated Annealing



Current

a

a

f

e

i

Children

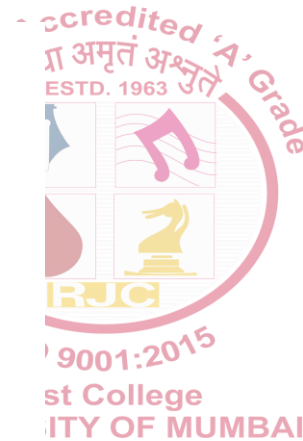
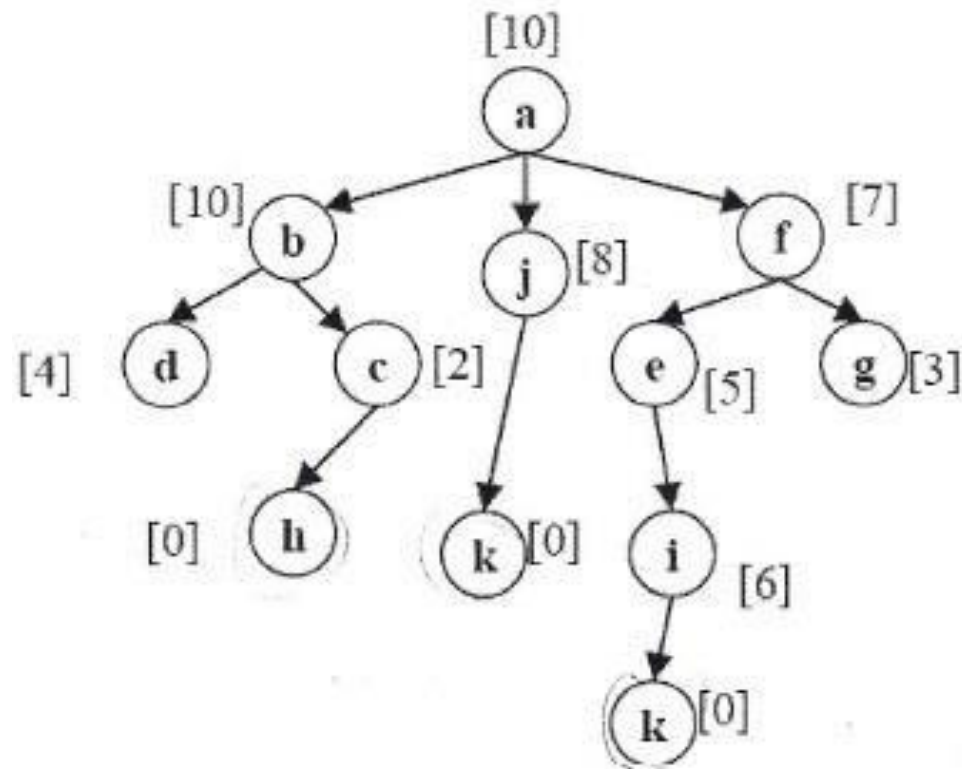
f_7, j_8, b_{10}

e_5, g_3

i_6

k_0

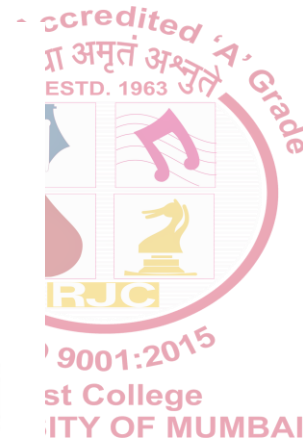
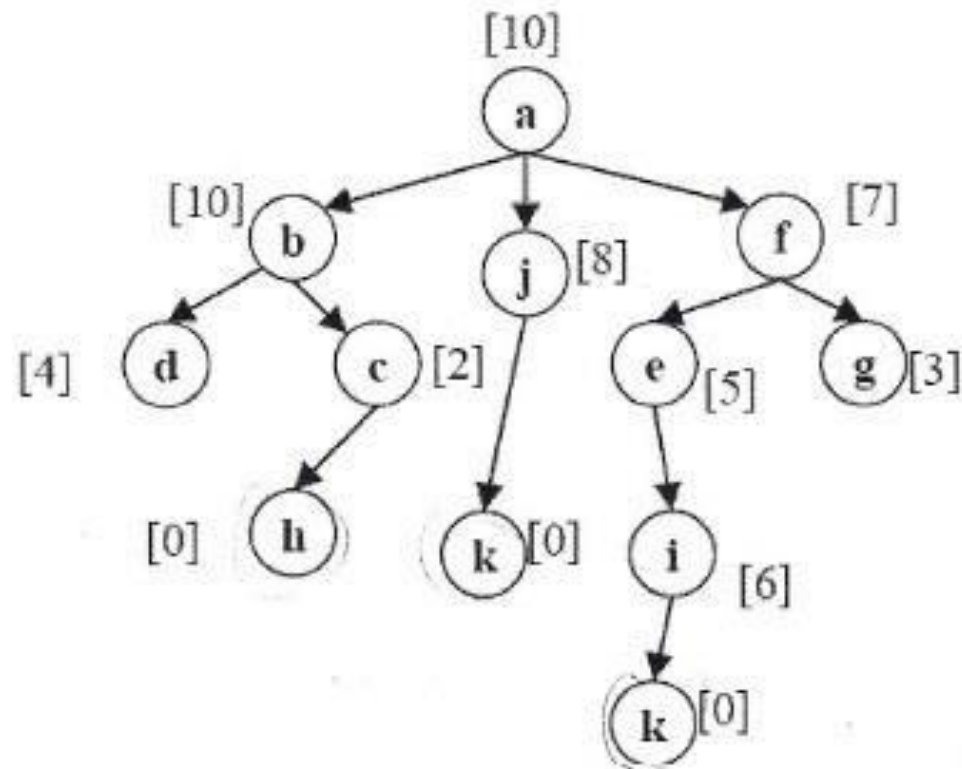
Simulated Annealing



Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3
e	i_6
i	k_0

Check if next node k_0 is better than current node

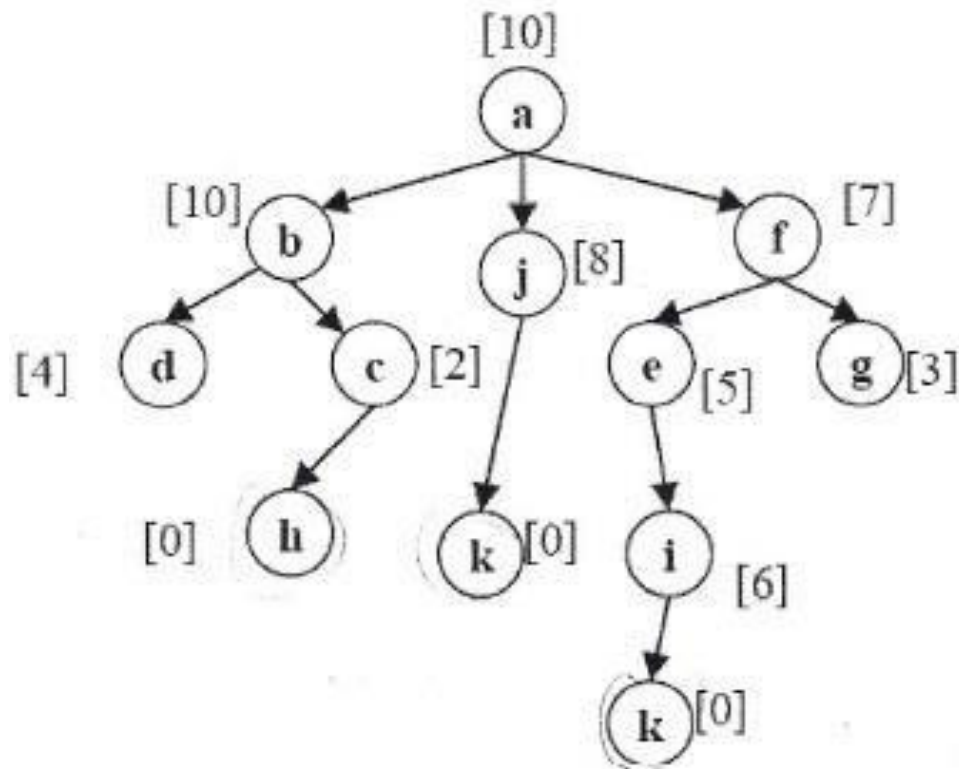
Simulated Annealing



Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3
e	i_6
i	k_0
Check if next node k_0 is better than current node	
$\Delta E > 0$	

Simulated Annealing

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

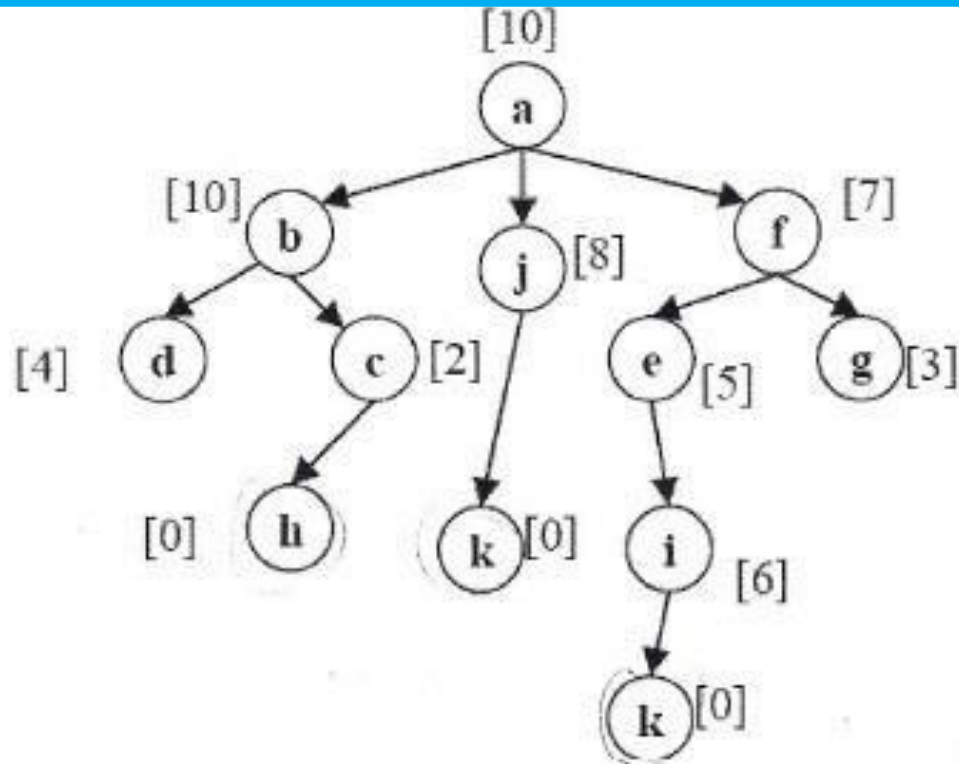


Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3
e	i_6
i	k_0
Check if next node k_0 is better than current node	
$\Delta E > 0$	

Simulated Annealing

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(k_0) - \text{value}(i_6)$$



Current

Children

a

a

f_7, j_8, b_{10}

f

e_5, g_3

e

i_6

i

k_0

Check if next node k_0 is better than current node

$$\Delta E > 0$$

Simulated Annealing

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(k_0) - \text{value}(i_6)$$

$$\text{value}(k_0) = -\text{heuristic}(k_0) = 0$$



Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3
e	i_6
i	k_0

Check if next node k_0 is better than current node

$$\Delta E > 0$$

Simulated Annealing

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(k_0) - \text{value}(i_6)$$

$$\text{value}(k_0) = -\text{heuristic}(k_0) = 0$$

$$\text{value}(i_6) = -\text{heuristic}(i_6) = -6$$

ISO 9001:2015
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Current

a

a

f

e

i

Children

f_7, j_8, b_{10}

e_5, g_3

i_6

k_0

Check if next node k_0 is better than current node

$$\Delta E > 0$$

Simulated Annealing

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(k_0) - \text{value}(i_6)$$

$$\text{value}(k_0) = -\text{heuristic}(k_0) = 0$$

$$\text{value}(i_6) = -\text{heuristic}(i_6) = -6$$

$$\Delta E = 0 - (-6) = +6$$

Current	Children
a	---
a	f_7, j_8, b_{10}
f	e_5, g_3
e	i_6
i	k_0

Check if next node k_0 is better than current node

$$\Delta E > 0$$

Simulated Annealing

$$\Delta E = \text{value}(\text{next}) - \text{value}(\text{current})$$

$$\Delta E = \text{value}(k_0) - \text{value}(i_6)$$

$$\text{value}(k_0) = -\text{heuristic}(k_0) = 0$$

$$\text{value}(i_6) = -\text{heuristic}(i_6) = -6$$

$$\Delta E = 0 - (-6) = +6$$

$$\because \Delta E > 0$$

$\therefore k_0$ will be selected with
probability 1

Current

a

a

f

e

i

Children

f_7, j_8, b_{10}

e_5, g_3

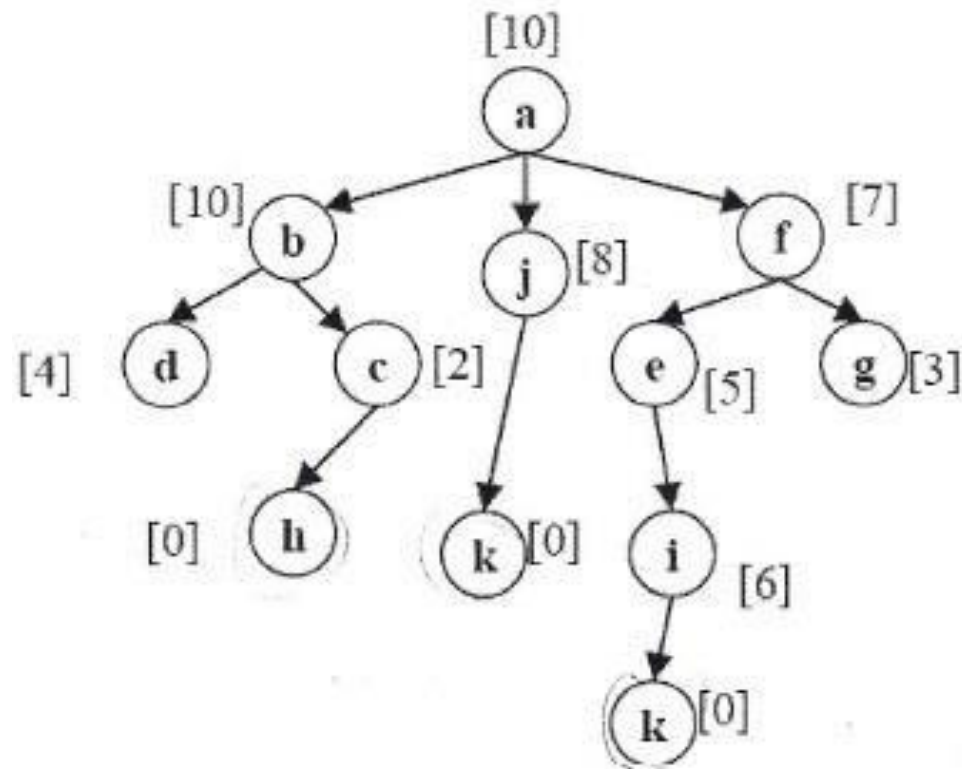
i_6

k_0

Check if next node k_0 is
better than current node

$$\Delta E > 0$$

Simulated Annealing



Current

a

a

f

e

i

k

Children

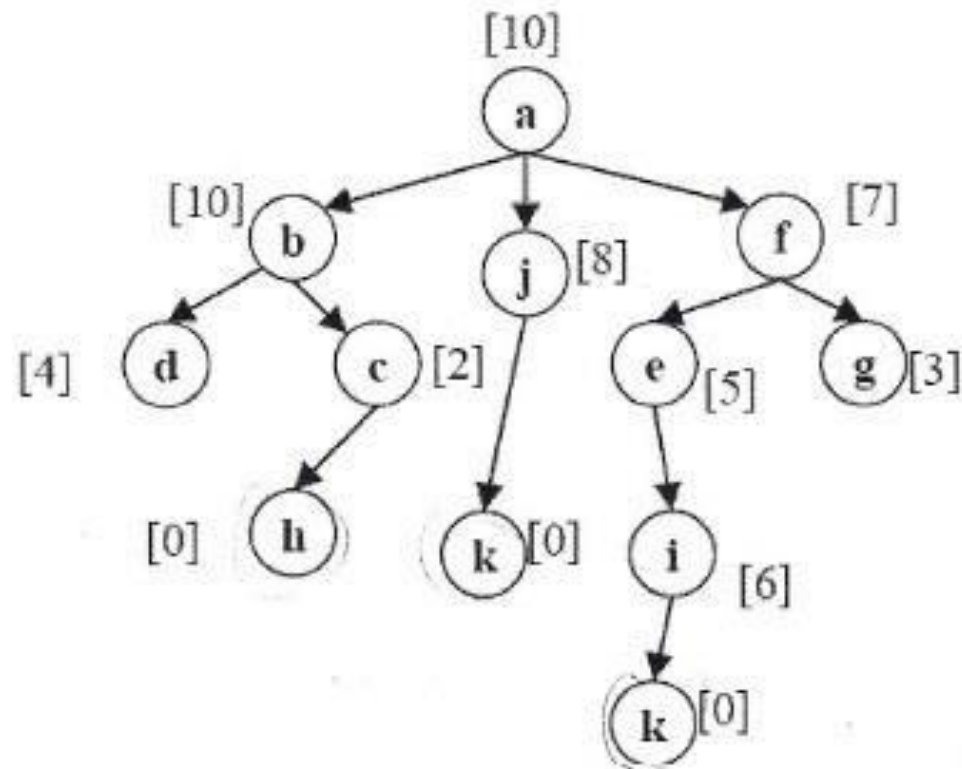
f_7, j_8, b_{10}

e_5, g_3

i_6

k_0

Simulated Annealing



Current

a

a

f

e

i

k

GOAL

Children

f_7, j_8, b_{10}

e_5, g_3

i_6

k_0

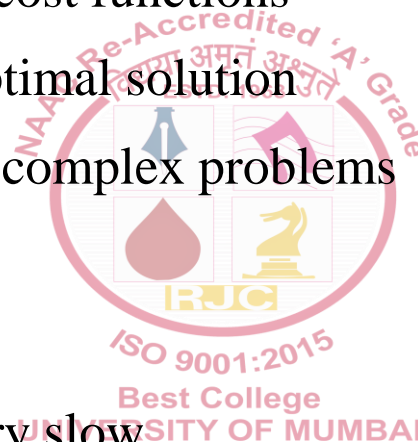
Advantages & Disadvantages of Simulated Annealing

❑ Advantages

- Can deal with arbitrary systems and cost functions
- Statistically guarantees finding an optimal solution
- It is relatively easy to code, even for complex problems
- Generally gives a ``good" solution

❑ Disadvantages

- Repeatedly annealing schedule is very slow
- For problems where the energy landscape is smooth, or there are few local minima, SA is overkill
- The method cannot tell whether it has found an optimal solution. Some other method (e.g. branch and bound) is required to do this



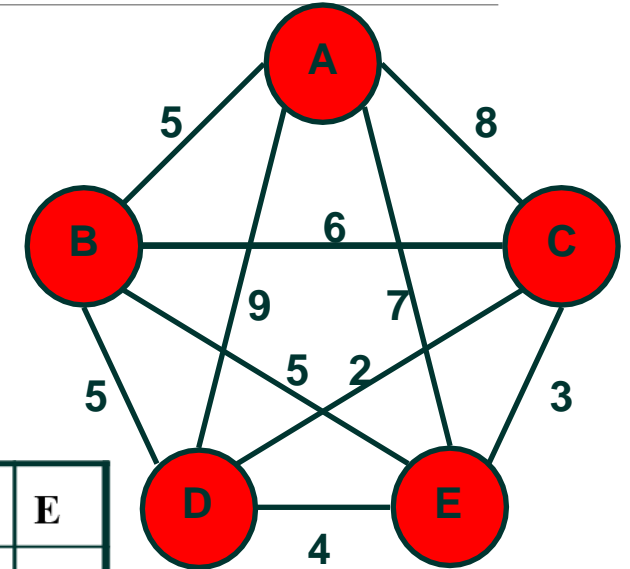
Uses of Simulated Annealing

- Used to solve combinatorial problems
- Applied to the travelling salesman problem to minimize the length of a route
- Formulation of power system optimization



Travelling Salesman Problem

- ❑ A salesman wants to visit a list of cities
 - ➡ Stopping in each city only once
 - ➡ Returning to the first city
 - ➡ Traveling the shortest distance
- ❑ Nodes are cities
- ❑ Arcs are labeled with distances between cities



	A	B	C	D	E
A	0	5	8	9	7
B	5	0	6	5	5
C	8	6	0	2	3
D	9	5	2	0	4
E	7	5	3	4	0

□ A solution is a permutation of cities, called a **tour**

□ How many solutions exist?

➔ $(n-1)!/2$ where $n = \#$ of cities

$n = 5$ results in 12 tours

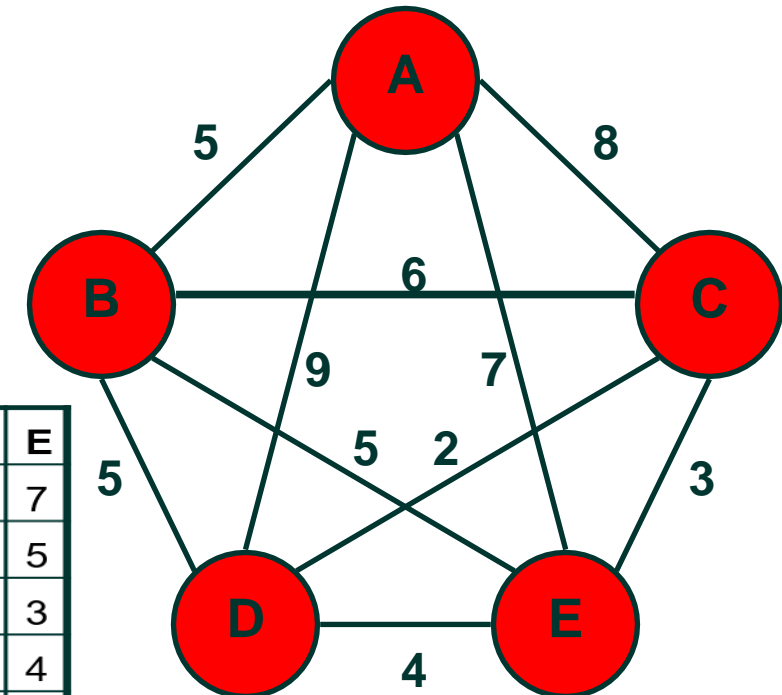
$n = 10$ results in 181440 tours

$n = 20$ results in $\sim 6 \times 10^{16}$ tours



	A	B	C	D	E
A	0	5	8	9	7
B	5	0	6	5	5
C	8	6	0	2	3
D	9	5	2	0	4
E	7	5	3	4	0

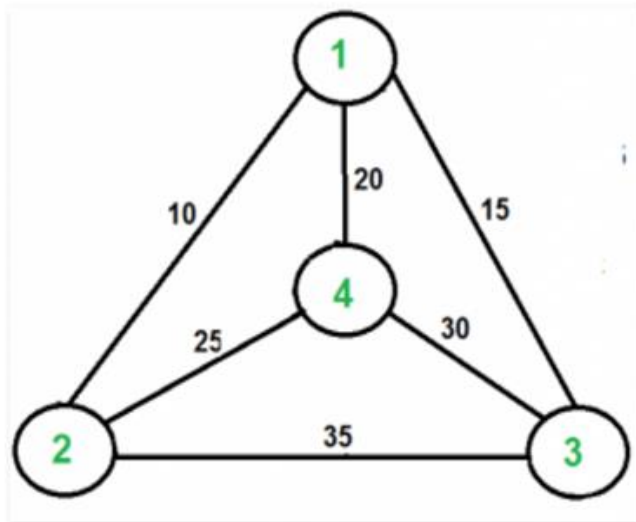
5 City TSP



Naive Approach

- ❑ Consider city 1 as the starting and ending point. Since the route is cyclic, we can consider any point as a starting point.
- ❑ Generate all $(n-1)!$ permutations of cities.
- ❑ Calculate the cost of every permutation and keep track of the minimum cost permutation.
- ❑ Return the permutation with minimum cost.





	1	2	3	4
1	0	10	15	20
2	10	0	35	25
3	15	35	0	30
4	20	25	30	0

graph = [[0, 10, 15, 20], [10, 0, 35, 25], [15, 35, 0, 30], [20, 25, 30, 0]]

Permutations:

1-2-3-4-1 -> Cost = 95 , 1-4-2-3-1 -> Cost = 95

1-3-4-2-1 -> Cost = 80

```

# Python program to implement traveling salesman
# problem using naive approach.
from sys import maxsize
from itertools import permutations
V = 4

# implementation of traveling Salesman Problem
def travellingSalesmanProblem(graph, s):

    # store all vertex apart from source vertex
    vertex = []
    for i in range(V):
        if i != s:
            vertex.append(i)

    # store minimum weight Hamiltonian Cycle
    min_path = maxsize
    next_permutation=permutations(vertex)
    for i in next_permutation:

        # store current Path weight(cost)
        current_pathweight = 0

        # compute current path weight
        k = s
        for j in i:
            current_pathweight += graph[k][j]
            k = j
        current_pathweight += graph[k][s]

        # update minimum
        min_path = min(min_path, current_pathweight)

    return min_path

```

```

def next_permutation(L):
    ''' Permute the list L in-place to generate the next lexicographic permutation.
    Return True if such a permutation exists, else return False.
    '''
    n = len(L)

    # Step 1: find rightmost position i such that L[i] < L[i+1]
    i = n - 2
    while i >= 0 and L[i] >= L[i+1]:
        i -= 1

    if i == -1:
        return False

    # Step 2: find rightmost position j to the right of i such that L[j] > L[i]
    j = i + 1
    while j < n and L[j] > L[i]:
        j += 1
    j -= 1

    # Step 3: swap L[i] and L[j]
    L[i], L[j] = L[j], L[i]

    # Step 4: reverse everything to the right of i
    left = i + 1
    right = n - 1

    while left < right:
        L[left], L[right] = L[right], L[left]
        left += 1
        right -= 1

    return True

```

```
# Main Code
```

```
if __name__ == "__main__":
```

```
    # matrix representation of graph
```

```
    graph = [[0, 10, 15, 20], [10, 0, 35, 25], [15, 35, 0, 30], [20, 25, 30, 0]]
```

```
    s = 0
```

```
    print(travellingSalesmanProblem(graph, s))
```

IDLE Shell 3.9.2

File Edit Shell Debug Options Window Help

Python 3.9.2 (tags/v3.9.2:1a79785, Feb 19 2021, 13:44:55) [MSC v.1928 64 bit (AMD64)] on win32

Type "help", "copyright", "credits" or "license()" for more information.

>>>

===== RESTART: D:\python\tsp2.py =====

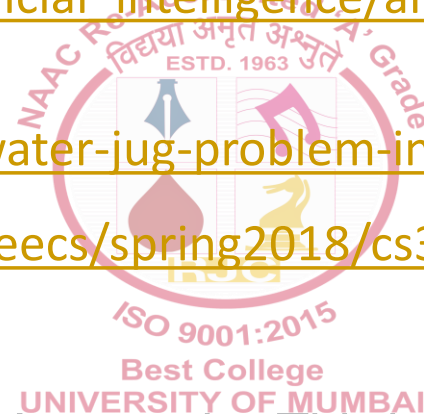
80

>>> |

References

Web references:

- https://www.tutorialspoint.com/artificial_intelligence/artificial_intelligence_popular_search_algorithms.htm
- <https://www.goeduhub.com/7743/water-jug-problem-in-artificial-intelligence>
- <http://classes.engr.oregonstate.edu/eecs/spring2018/cs331/slides/LocalSearch.2pp.pdf>
- Book:
- **Artificial Intelligence: A Modern Approach** · Third edition, Stuart **Russell** and Peter Norvig



Assignment

- **Problem:** Given 3 jugs of capacities 8, 5 and 3 liters respectively. These are initially filled with 8, 0 and 0 liters. In the goal state they should be filled with 4, 4 and 0 liters. (There is no marking in the jugs)
- Write solution steps and python code to solve the above problem
- Prepare a Case Study on :Use of Beam search algorithm in Translation
- Solving Travelling Salesman Problem using dynamic Approach .Explain with a simple example

