

Q-2

IDA* use a heuristic function to evaluate the remaining cost to the goal from A* algorithm. It is very similar to IDS, but uses cost limit function instead of ~~depth~~ depth limit function.

IDA* algorithm:-

Threshold = $F(\text{start_Node})$

FoundGoal = False

~~while not found do~~

while not FoundGoal do:

DFS from start Node for nodes X .

Such that $F(X) \leq \text{Threshold}$

If Goal - Found:

FoundGoal = True

else:

Threshold = $\min \{ F(y) : \text{where } y \text{ is children of } N \text{ \& } F(y) > \text{Threshold} \}$

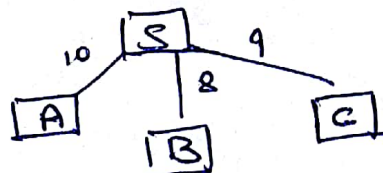
end

Note:- Assumptions \rightarrow IDA* doesn't store already visited nodes and can visit nodes again. There's also a possibility of a cycle. After discussing with the H-TA.

For the given graph:

Step-I or while loop iteration - I.

Threshold = $F(S)$ (where $F(S) = 0$)
= 0



$$F(A) = 10 + 0 = 10$$

$$F(B) = 8 + 4 = 12$$

$$F(C) = 9 + 3 = 12$$

min $\rightarrow 10$

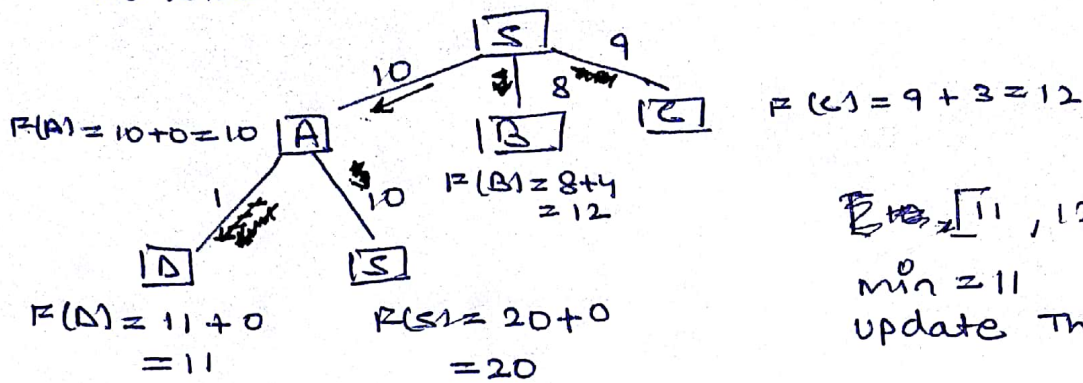
update Threshold with 10.

and run DFS again with updated Threshold.

→ Step - 2

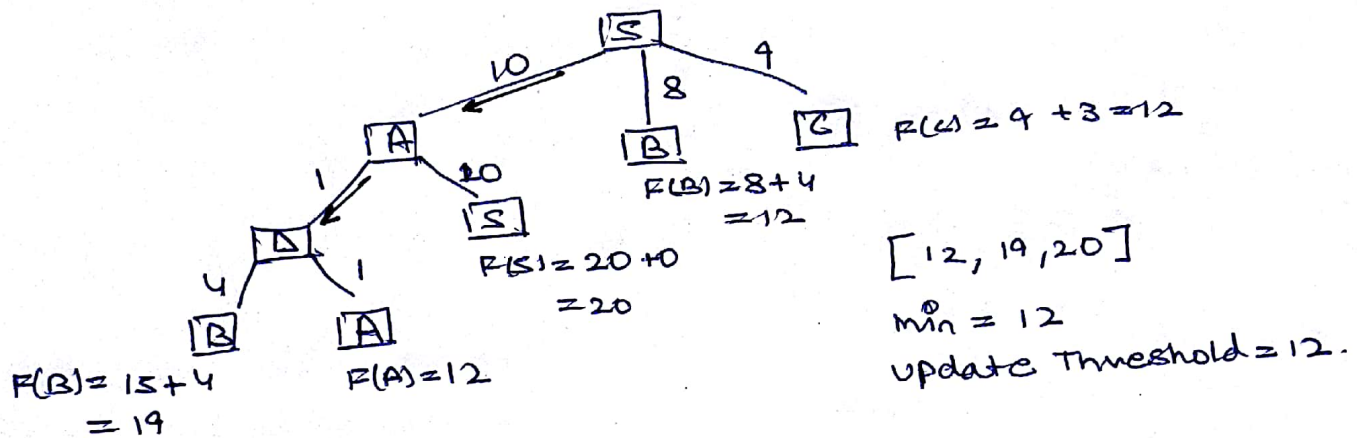
Threshold = 10

Do ~~not~~



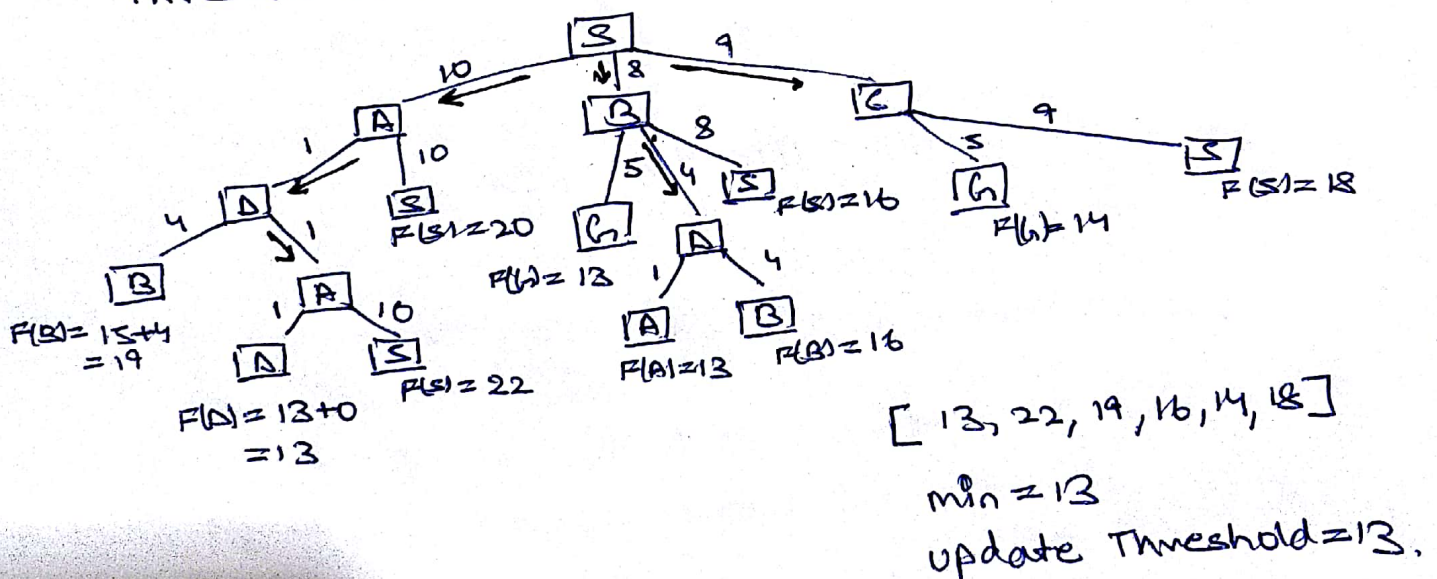
→ Step - 3

Threshold = 11



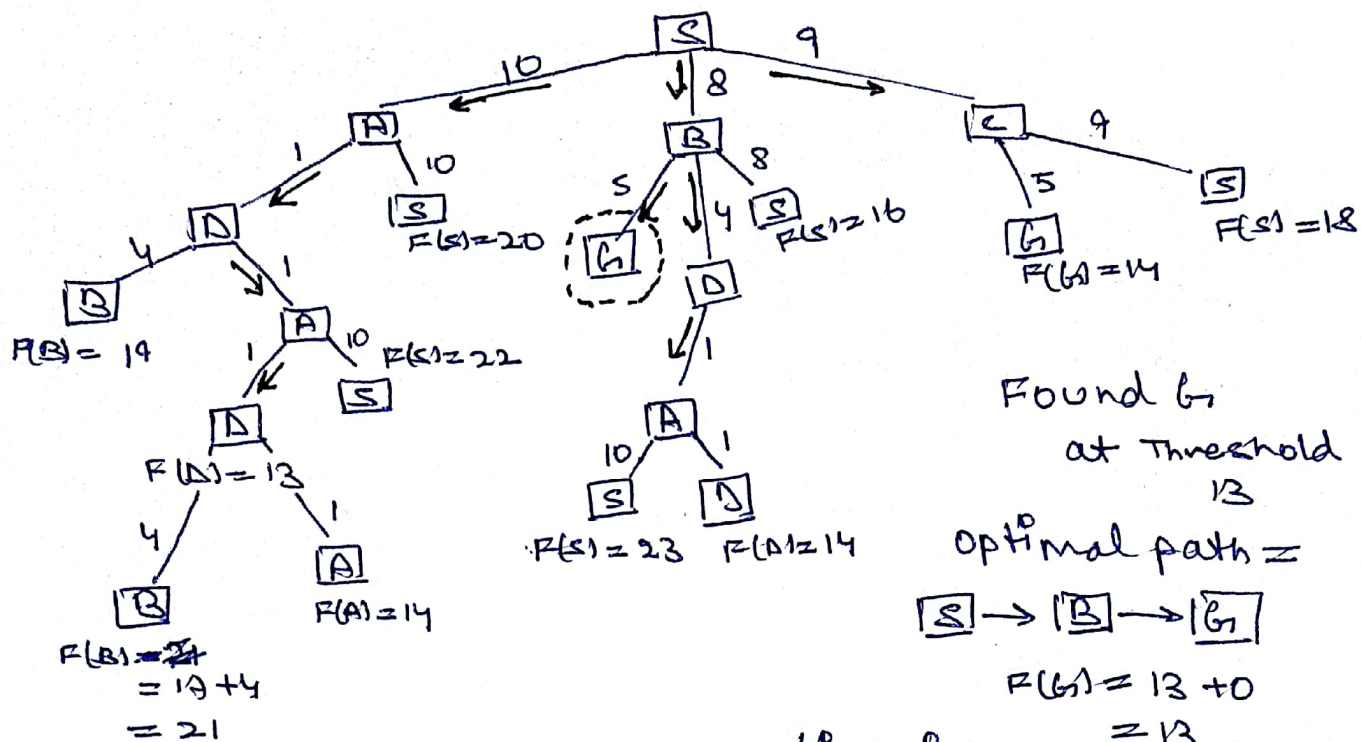
→ Step - 4

Threshold = 12



Step - 5

Threshold = 13



Since it's DFS that searches for the node, then it's possible that this path is visited after all other paths are exhausted

A3

one point cross over \rightarrow

A random crossover point is selected and heads of the two parents are swapped to get new off-springs

eg \rightarrow $\begin{matrix} 0 & 1 & 2 & 3 & 4 & 5 \\ 5 & 4 & 3 & 2 & 1 & 0 \end{matrix} \leftarrow \begin{matrix} \text{Parent 1 chromosome} \\ \text{Parent 2 chromosome} \end{matrix}$

New Off-springs

$\begin{matrix} 5 & 4 & 2 & 3 & 4 & 5 \\ 0 & 1 & 2 & 2 & 1 & 0 \end{matrix}$

To get an optimal solution of 10 $(00001010)_2$.

From Parents.

$P_1 \rightarrow 17 \rightarrow (00010001)_2$

$P_2 \rightarrow 21 \rightarrow (00010101)_2$

$P_3 \rightarrow 4 \rightarrow (00000100)_2$

$P_4 \rightarrow 28 \rightarrow (00011100)_2$

lets represent 10 in indexed array.

(4)

(0 0 0 0 1 0 1 0)²
 ↑ ↑ ↑ ↑ ↑ ↑ ↑
 0 1 2 3 4 5 6 7

Similarly for the rest of Parents.

We will first check whether this solution is possible from given parents.

For each index, Binary digit should also be present in any of the parents. If its present, then that binary digit can be achieved by using single point crossover.

For index 0,

0 0 0 0 1 0 1 0

↳ 1 is present in the parents.

P₁ → 0 0 0 1 0 0 0 1

P₂ → 0 0 0 1 0 1 0 1

P₃ → 0 0 0 0 0 1 0 0

P₄ → 0 0 0 1 1 1 0 0

Similarly, for index 5 all digits are present in at least one of the parents.

For index 5.

0 0 0 0 1 0 1 0

P₁ → 0 0 0 1 0 0 0 1 X

P₂ → 0 0 0 1 0 1 0 1 X

P₃ → 0 0 0 0 0 1 0 0 X

P₄ → 0 0 0 1 1 1 0 0 X

1 not present in any of the parents.

An optimal solution 10 is not achievable using one point crossover with given Parents.

So, probability to find an optimal solution 10 is 0.

A-4 (a) Medical Diagnosis system

- Performance measures: Cost of the system, ~~more~~ healthy patients, reputation
- Environment: Hospital, pharmacy, Patients, equipments, doctors, staff.
- Actuators: Screen Display, printing, email, tests
- Sensors: Buttons, keyboard, mouse, patient answers, camera, mic (for patient answer).

⑥ Refinery Controller →

- Performance measure: Maximize purity, wastage, safety, hours (no. of hours it can work without heating too much).
- Environment: machines, people, Refinery. (fuel, water etc), Systems that control these machines.
- Actuators: Pumps, displays, heater, valves, pipes, Display
- Sensors: Pressure, chemicals, Temperature, voltage Sensor.

⑦ Amazon Go →

- Performance measure: Usability, Product availability, Support, fast ~~see~~ Transaction, accurate Product detection.
- Environment: Camera, People, Carts, Products
- Actuators: Screen display
- Sensors: Cameras, RFID's, Scanners, motion sensor, weight sensor, QR reader.

A-b We can use A* algorithm to find optimal solution. Firstly we need to convert the problem into a form of graph or tree. We can represent position of keys in a node.

Class Node:

```
def __init__(self):
    key1
    key2
    steps
    distance
```

key1: Represent the station on which key1 is present.
key2: Represent station on which key2 is present.

Similarly each Neighbour can be represented ~~using this~~ in a form of Node.

Assumption → ~~key~~ Both keys are independent of each other's position. Any key can go from position x to $x+1$ or $x+4$. Independent of other key.

A* Algorithm

def A*

visited = []

Q = PriorityQueue()

Q.add(Root_node)

while Q not empty

 Current_node = Q.Pop()

 if Current_node is goal state

 return True

 Neighbours = Findallchild(Current_node)

 for child in Neighbours:

 if child not in visited:

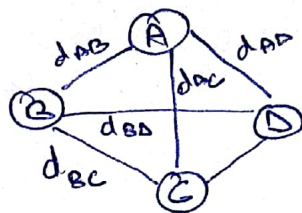
 Q.add(child)

 visited.add(child)

return False

A-1

Assumption: bomb squad team travel with const velocity 'v'.
To minimize casualty count we can use A* algorithm. Firstly we need to convert the problem into a graph. Each node will represent a bomb site. Node contains coordinates of the bomb site, casualty count, Time + c to detonate. We also know the distance to reach a bomb site y from every other bomb site. Our graph would be like: let's assume we have 4 bomb site.



In each Neighbour/child we will also store, the time it took to will take to reach that bomb site from $t=0$.

↳ let's denote this variable as "time from start".

~~Heuristic for A* algorithm~~

Our cost function consist of:

$$F = G + H.$$

G: denote population we have saved upto now.

H: denotes the population count of the Node.

our Priority Queue in A* algorithm implement Max heap.

will give max casualty count that can be saved.

When we pop a node from the Priority we will check

whether that bomb site population can be saved or not.

we will check by using the condition: $\text{Time from start} + C \leq t$

If this condition is true, then

we will take this node as our current node and ~~not~~ continue

A*. otherwise we will pick another node from the Priority Queue until we get a node in which the population can be saved.

C: Time to diffuse the bomb.

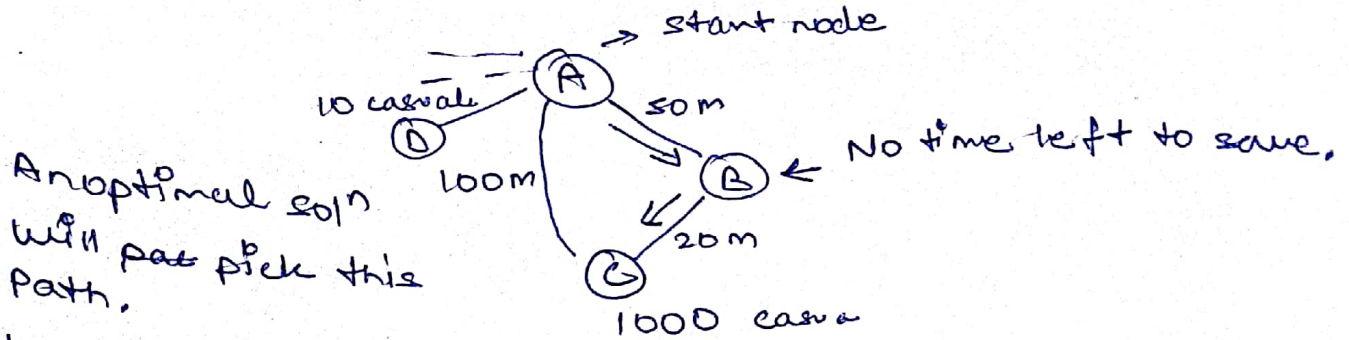
t: Time left for detonation.

Why am I taking all ~~other~~ bomb sites as Neighbour?

because we can visit all ~~other~~ ^{bomb site}, and it's possible that some bomb site are closer to some bomb site.

↳ This will be better explainable with an example.

lets take a graph



An optimal soln will pick this path.

Heuristic I am using will only underestimate these path. because of this path. these cases. My heuristic select maximum casuality count at each level of graph / tree,

A* Algorithm will be run by taking each bomb site as a start state. Then this will give us max ~~casuality~~ ^{casualties} saved population that can be saved. A* will return minimum casualties after visiting all bomb site. ~~that~~ ^{condition} BSC \rightarrow denotes bomb site i^{th} .

For P in Range (N) $N \rightarrow$ no. of Bomb site

run A* for start state as ~~each~~ BSC.

update ~~max~~ ^{proper} minimum casuality.

return minimum casuality.

Time for this algorithm = $O(N \times b \times \log(b))$
 $= O(N \times (b \times \log(b))^M)$
 \downarrow \rightarrow Priority Queue
 we will run A* N times
 where N is no. of Bomb site.

space complexity $\rightarrow O(b^M)$

Given in the Question:

- $h(x)$ over estimate $h^*(x)$
- $h^*(x)$ is the optimal heuristic, ~~there~~
- ~~h(x) is the shortest distance b/w x & goal state.~~
- $h^*(x)$ is the shortest distance b/w x & goal state.
- $h(x) \leq h^*(x) + \epsilon$

(9)

$h(.)$ is a heuristic that over estimates $h^*(x)$.

Then $h(.)$ ~~will~~ will give an sub optimal path using A^* algorithm.

\Rightarrow There must be a node, that is present in optimal path given by A^* using $h^*(x)$ and, that is ~~not~~ not present in sub optimal path given by $h(.)$ using A^* algorithm.

Let's take that node as x .

Now, we know that F function cost of a state that ~~appeared after~~ was explored after visiting state x will be greater than $F(x)$.

So let's take, $F(t)$ where t is goal state.

$$\text{Then, } F(t) \leq F(x)$$

(Note:- If $F(x) \leq F(t)$ then it would have been included in the optimal path. ~~But~~ Since $F(x)$ is greater than $F(t)$, it definitely doesn't belong to optimal path ~~so~~.)

$$\Rightarrow G(t) + H(t) \leq G(x) + H(x)$$

It's given that $H(t)$ is 0 for all goal states.

then,

$$G(t) \leq G(x) + H(x)$$

It's given that

$$H(x) \leq h^*(x) + \epsilon$$

so,

$$G(t) \leq G(x) + h^*(x) + \epsilon \quad \text{--- (1)}$$

We know that

$$F(s) \leq F(x) \quad (\text{This is always true}).$$

~~It's a start state~~

~~$$G(s) + h^*(s) \leq G(x) + h(x)$$

$$\text{It's given that } h(x) \leq h^*(x) + \epsilon$$

$$h^*(s) \leq G(x) + h^*(x) + \epsilon$$~~

~~6.3~~

$$f(x) \leq f(y)$$

$$G(x) + h^*(x) \leq G(y) + h^*(y) \quad \text{--- (1)}$$

\downarrow
 0 is a start state

Then using eq (1) & (1) ~~to~~

$$G(x) \leq h^*(x) + \epsilon //$$