



SRM

INSTITUTE OF SCIENCE & TECHNOLOGY
(Deemed to be University u/s 3 of UGC Act, 1956)

18CSC305J – ARTIFICIAL INTELLIGENCE LAB

Exp-6: Min-Max Algorithm for Alpha-Beta Pruning

Submitted by-

Name:- Anannya P. Neog

Reg. No. :- RA1911003010367

Course :- Btech

Section :- F1

Branch:- Computer Science Engineering

Sem:- 6th Sem

AI LAB Ex – 6:- Min-Max Algorithm for Alpha-Beta Pruning

Team Members:

- ✓ Richa - 357
- ✓ Anannya - 367
- ✓ Pushan - 371
- ✓ Ankit - 372
- ✓ Tanay - 377

Aim:

To implement Min-Max Algorithm for Alpha-Beta Pruning

Objective:

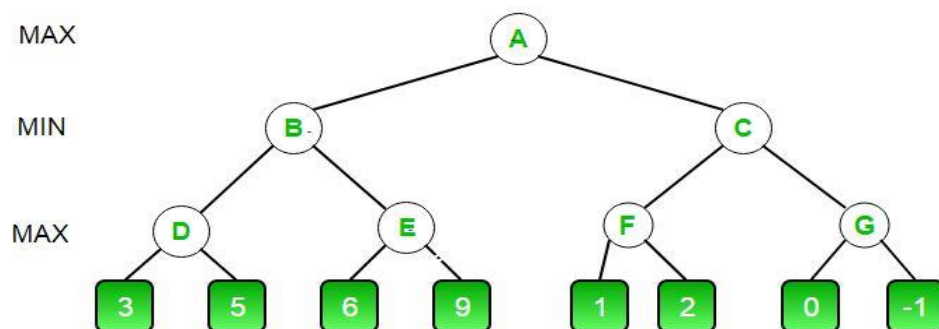
The Minmax problem seeks to minimize the maximum value of a number of decision variables. It is sometimes applied to minimize the possible loss for a worst case (maximum loss) scenario.

- **Alpha** is the best value that the **maximizer** currently can guarantee at that level or above.
- **Beta** is the best value that the **minimizer** currently can guarantee at that level or above.

Time Complexity:

$$O(B^{(D/2)})$$

Example:



Algorithm:

- The initial call starts from **A**. The value of alpha here is **-INFINITY** and the value of beta is **+INFINITY**. These values are passed down to subsequent nodes in the tree. At **A** the maximizer must choose max of **B** and **C**, so **A** calls **B** first
- At **B** it the minimizer must choose min of **D** and **E** and hence calls **D** first.
- At **D**, it looks at its left child which is a leaf node. This node returns a value of 3. Now the value of alpha at **D** is $\max(-\text{INF}, 3)$ which is 3.

- To decide whether its worth looking at its right node or not, it checks the condition $\beta \leq \alpha$. This is false since $\beta = +\text{INF}$ and $\alpha = 3$. So it continues the search.
- **D** now looks at its right child which returns a value of 5. At **D**, $\alpha = \max(3, 5)$ which is 5. Now the value of node **D** is 5
- **D** returns a value of 5 to **B**. At **B**, $\beta = \min(+\text{INF}, 5)$ which is 5. The minimizer is now guaranteed a value of 5 or lesser. **B** now calls **E** to see if he can get a lower value than 5.
- At **E** the values of alpha and beta is not $-\text{INF}$ and $+\text{INF}$ but instead $-\text{INF}$ and 5 respectively, because the value of beta was changed at **B** and that is what **B** passed down to **E**
- Now **E** looks at its left child which is 6. At **E**, $\alpha = \max(-\text{INF}, 6)$ which is 6. Here the condition becomes true. β is 5 and α is 6. So $\beta \leq \alpha$ is true. Hence it breaks and **E** returns 6 to **B**
- Note how it did not matter what the value of **E**'s right child is. It could have been $+\text{INF}$ or $-\text{INF}$, it still wouldn't matter, We never even had to look at it because the minimizer was guaranteed a value of 5 or lesser. So as soon as the maximizer saw the 6 he knew the minimizer would never come this way because he can get a 5 on the left side of **B**. This way we dint have to look at that 9 and hence saved computation time.
- **E** returns a value of 6 to **B**. At **B**, $\beta = \min(5, 6)$ which is 5. The value of node **B** is also 5
- **B** returns 5 to **A**. At **A**, $\alpha = \max(-\text{INF}, 5)$ which is 5. Now the maximizer is guaranteed a value of 5 or greater. **A** now calls **C** to see if it can get a higher value than 5.
- At **C**, $\alpha = 5$ and $\beta = +\text{INF}$. **C** calls **F**
- At **F**, $\alpha = 5$ and $\beta = +\text{INF}$. **F** looks at its left child which is a 1. $\alpha = \max(5, 1)$ which is still 5.
- **F** looks at its right child which is a 2. Hence the best value of this node is 2. Alpha still remains 5
- **F** returns a value of 2 to **C**. At **C**, $\beta = \min(+\text{INF}, 2)$. The condition $\beta \leq \alpha$ becomes true as $\beta = 2$ and $\alpha = 5$. So it breaks and it does not even have to compute the entire sub-tree of **G**.
- The intuition behind this break off is that, at **C** the minimizer was guaranteed a value of 2 or lesser. But the maximizer was already guaranteed a value of 5 if he choose **B**. So why would the maximizer ever choose **C** and get a value less than 2 ? Again you can see that it did not matter what those last 2 values were. We also saved a lot of computation by skipping a whole sub tree.
- **C** now returns a value of 2 to **A**. Therefore the best value at **A** is $\max(5, 2)$ which is a 5.
- Hence the optimal value that the maximizer can get is 5.

Code:

MAX, MIN = 1000, -1000

```
def minimax(depth, nodeIndex, maximizingPlayer,
            values, alpha, beta):
```

```
    if depth == 3:
        return values[nodeIndex]
```

```
    if maximizingPlayer:
```

```
        best = MIN
```

```

        for i in range(0, 2):

            val = minimax(depth + 1, nodeIndex * 2 + i,
                           False, values, alpha, beta)

            best = max(best, val)
            alpha = max(alpha, best)

            if beta <= alpha:
                break

        return best

    else:
        best = MAX
        for i in range(0, 2):

            val = minimax(depth + 1, nodeIndex * 2 + i,
                           True, values, alpha, beta)

            best = min(best, val)
            beta = min(beta, best)
            if beta <= alpha:
                break

        return best

if __name__ == "__main__":

    values = []
    for i in range(0, 8):

        x = int(input(f"Enter Value {i} : "))
        values.append(x)

    print ("The optimal value is :", minimax(0, 0, True, values, MIN, MAX))

```

```

In [1]: MAX, MIN = 1000, -1000
def minimax(depth, nodeIndex, maximizingPlayer,
            values, alpha, beta):

    if depth == 3:
        return values[nodeIndex]

    if maximizingPlayer:
        best = MIN

        for i in range(0, 2):
            val = minimax(depth + 1, nodeIndex * 2 + i,
                          False, values, alpha, beta)
            best = max(best, val)
            alpha = max(alpha, best)

            if beta <= alpha:
                break

        return best
    else:
        best = MAX
        for i in range(0, 2):
            val = minimax(depth + 1, nodeIndex * 2 + i,
                          True, values, alpha, beta)
            best = min(best, val)
            beta = min(beta, best)
            if beta <= alpha:
                break

        return best

if __name__ == "__main__":
    values = []
    for i in range(0, 8):
        x = int(input(f"Enter Value {i} : "))
        values.append(x)

    print ("The optimal value is :", minimax(0, 0, True, values, MIN, MAX))

```

Output:

```

Enter Value 0 : 3
Enter Value 1 : 5
Enter Value 2 : 6
Enter Value 3 : 9
Enter Value 4 : 1
Enter Value 5 : 2
Enter Value 6 : 0
Enter Value 7 : -1
The optimal value is : 5

```