

Adversarial Search (Game Search)

Murray Shanahan

Notes based on Ch.6 of Russell & Norvig

Overview

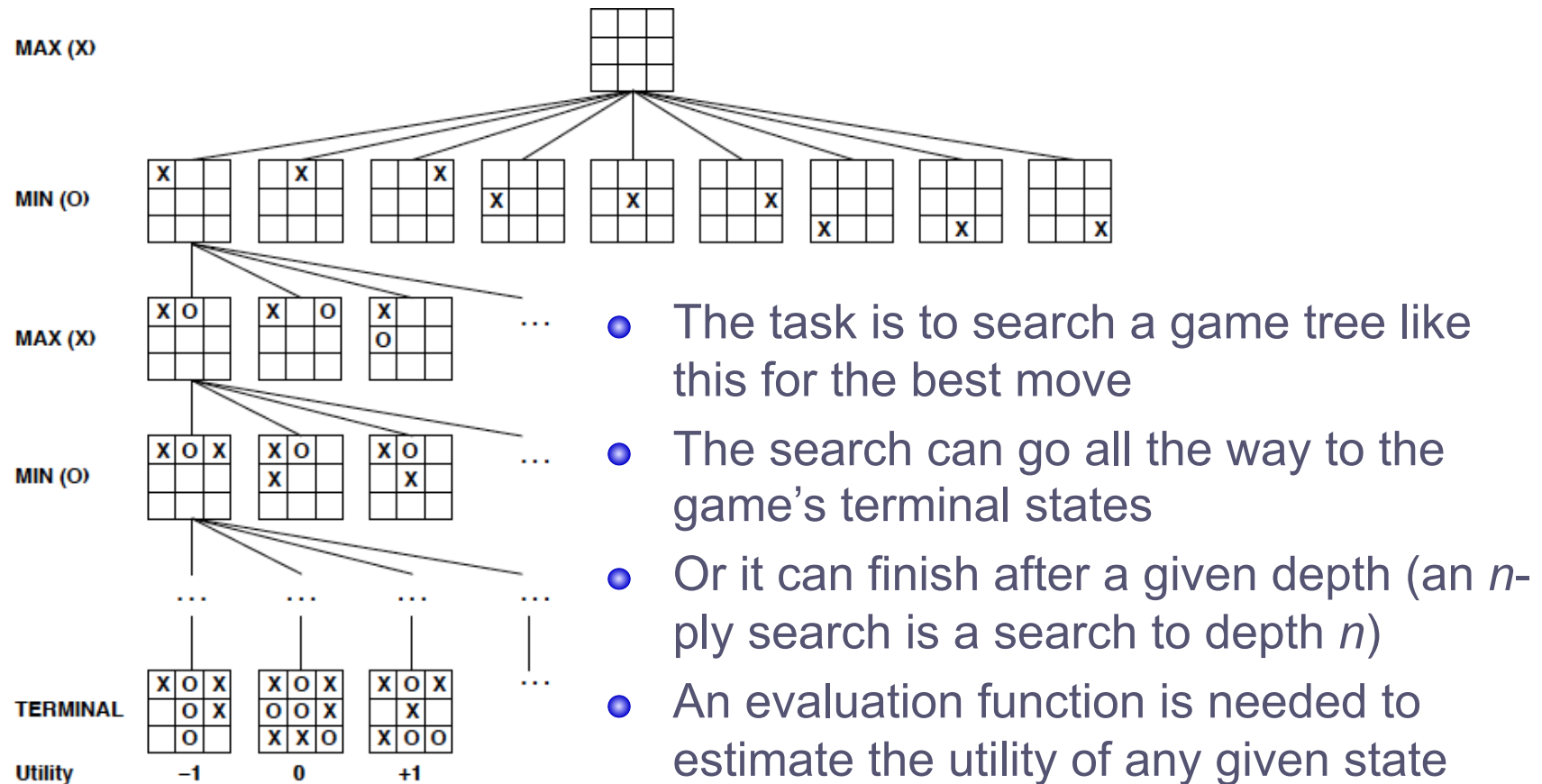
- Types of games
- Minimax
- α - β pruning

Types of Games

- Games search involves an unpredictable opponent
- Games can be classified along several dimensions
- We'll be looking at two-player deterministic games where there is perfect information, such as chess

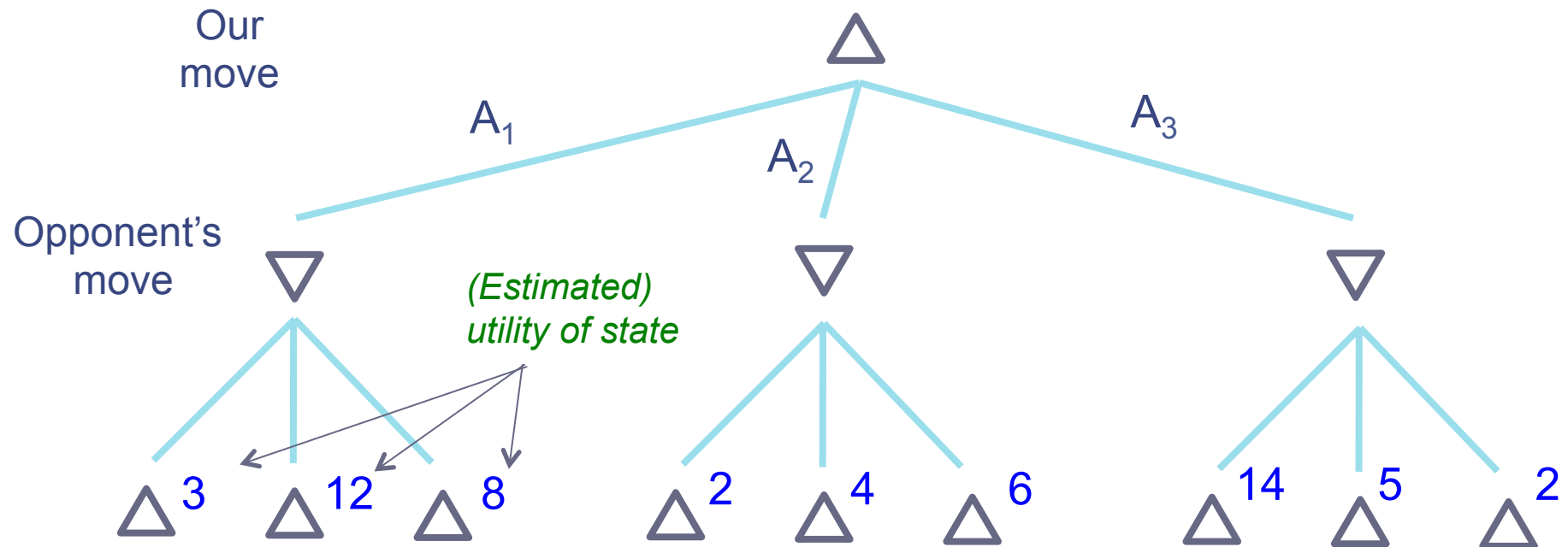
	Deterministic	Chance
Perfect information	chess, drafts, go, othello	backgammon, monopoly
Imperfect information	battleships	bridge, poker, scrabble

Game Trees



Choosing the Best Move

- Suppose we have the following search tree
- Should we select action A_1 , A_2 , or A_3 ?



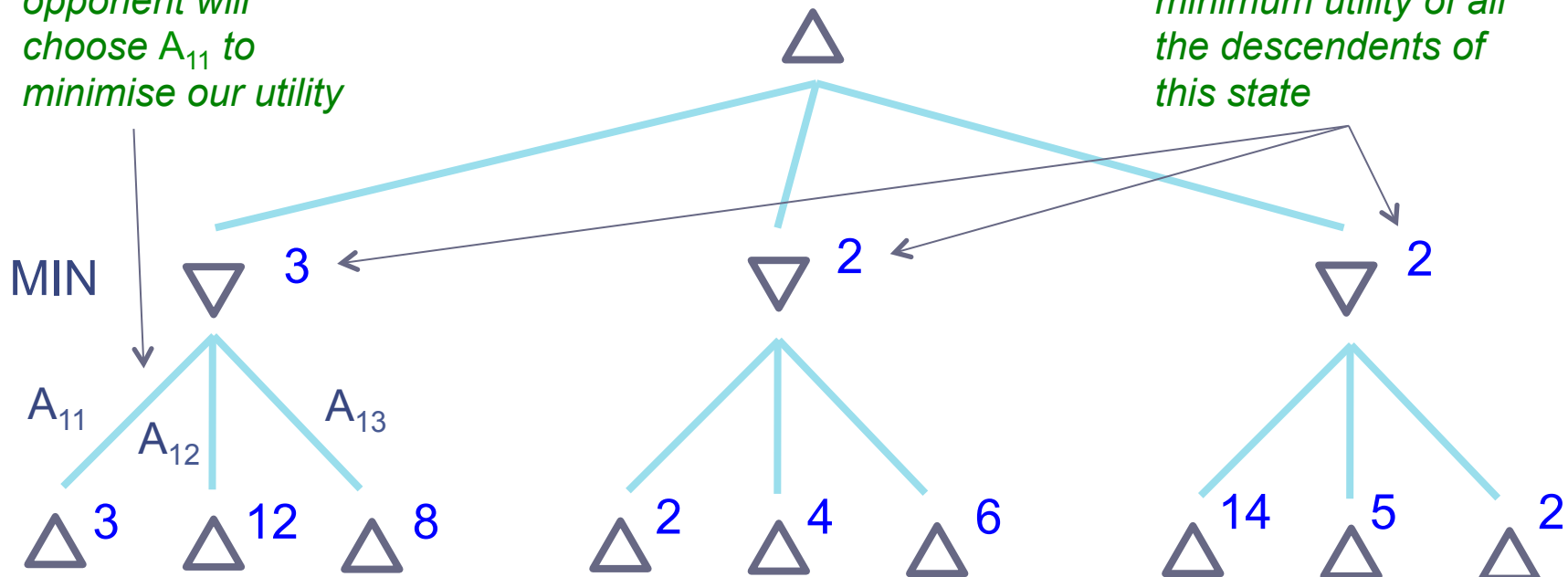
The Minimax Principle

- Assume that the opponent will always make the worst move for us
 - This is the action with the lowest estimated utility
- But we will always make the best move
- So utilities can be propagated up the tree, alternating between minimizing utility (opponent's move) and maximizing utility (our move)
- The move we make is the one with the maximum utility at the root

The Minimising Phase

In this state, opponent will choose A_{11} to minimise our utility

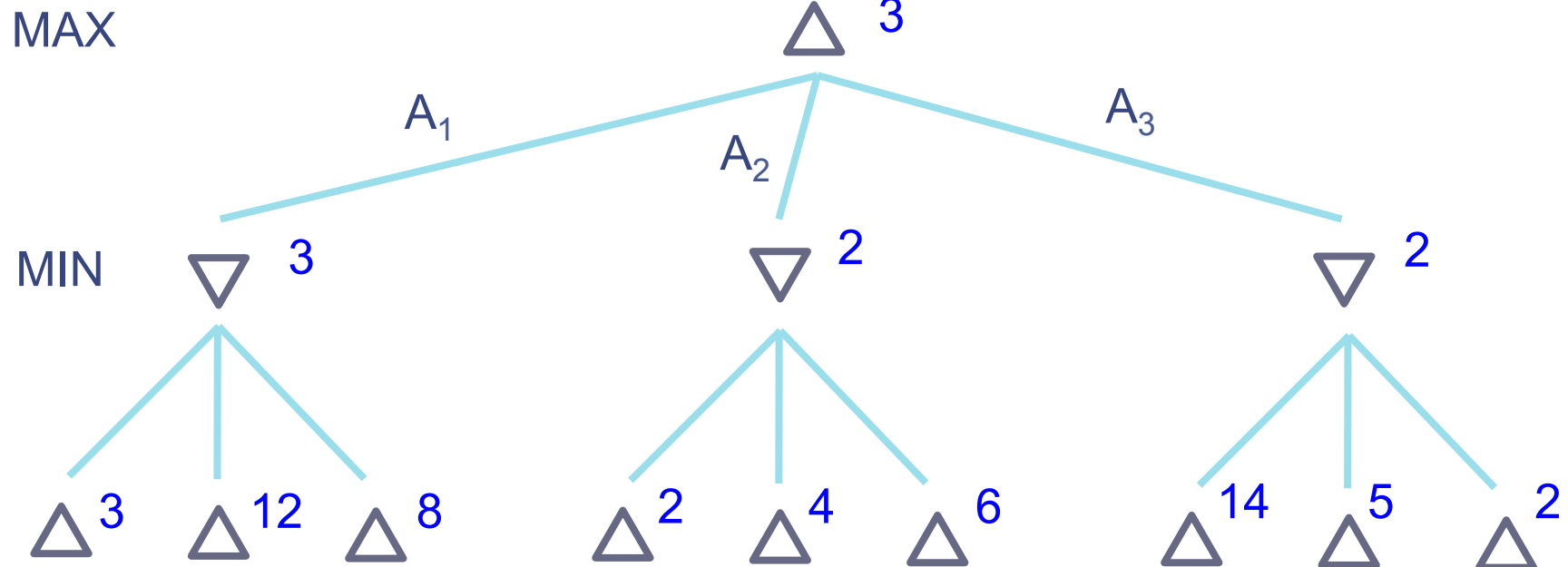
The utility here is the minimum utility of all the descendents of this state



The Maximising Phase

Now we're maximising. The utility is the maximum utility of all the descendents of this state

So the action to choose is A_1



The Minimax Algorithm 1

- The algorithm is expressed as a pair of mutually recursive functions `MinValue` and `MaxValue`
- `Eval(s)` is the evaluation function. It yields an estimate of the utility of state `s`

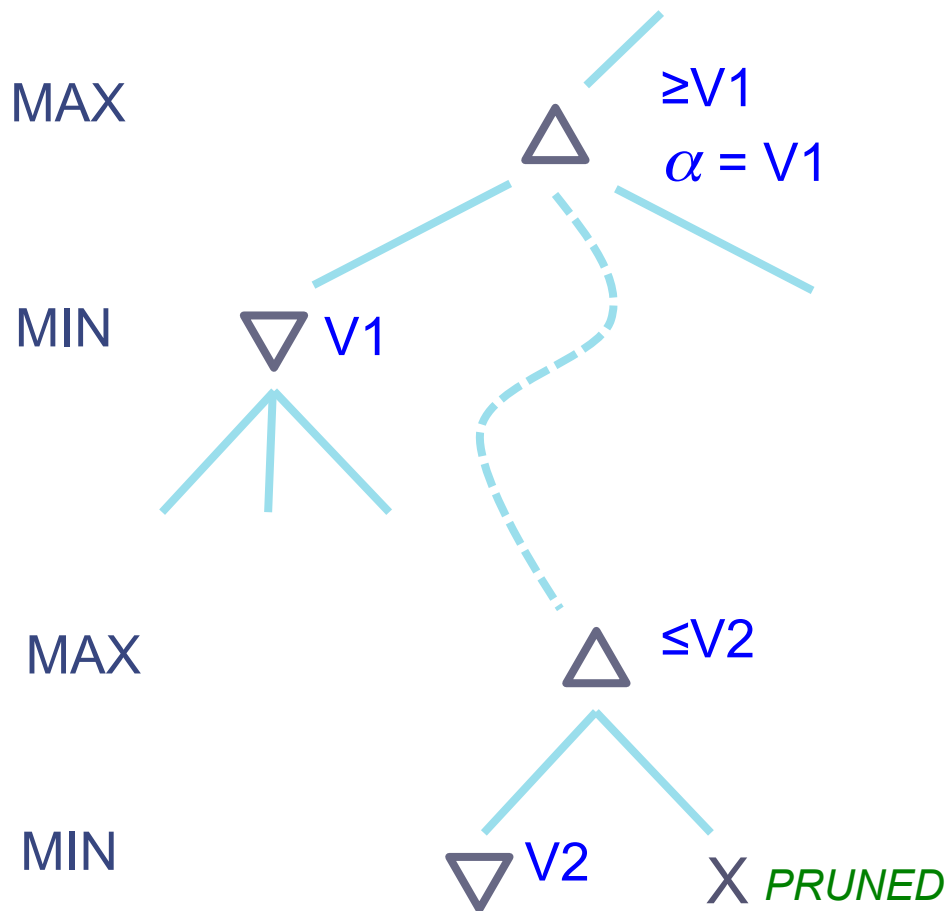
```
function MinValue(s,d)
    if s is a terminal state or d = MaxDepth
        return Eval(s)
    else
        v := ∞
        for each action a possible in s
            v := Min(v,MaxValue(Result(a,s),d+1)
        return v
```

The Minimax Algorithm 2

- The best move is the action a that maximises $\text{MinValue}(\text{Result}(a, S_0), 1)$ where S_0 is the current state of the game

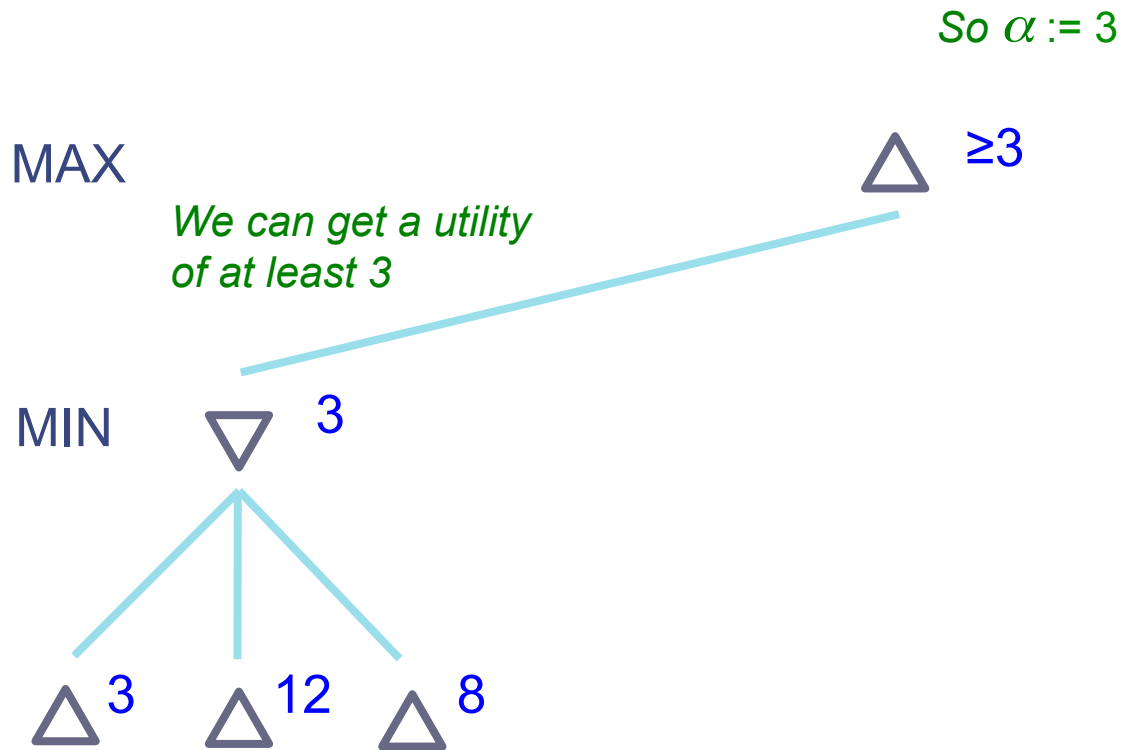
```
function MaxValue(s,d)
    if s is a terminal state or d = MaxDepth
        return Eval(s)
    else
        v :=  $-\infty$ 
        for each action a possible in s
            v := Max(v, MinValue(Result(a,s), d+1))
        return v
```

α - β Pruning

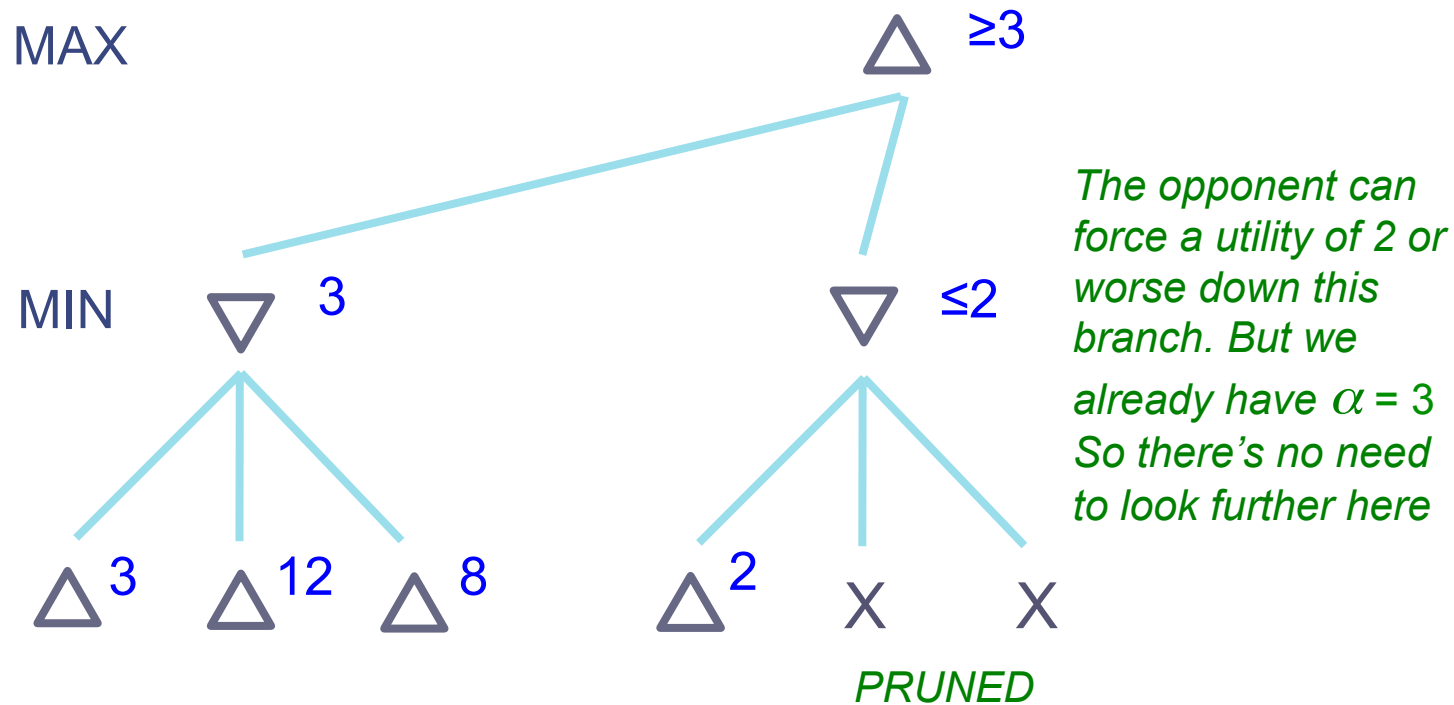


- Minimax performs a lot of redundant search
- It can be improved by keeping track of the best MAX value found so far (α) and the worst MIN value (β)
- There is no point in exploring MAX branches worse than α or MIN branches better than β
- Here, if we have $V2 < \alpha$ there is no need for MAX to explore more branches for that node

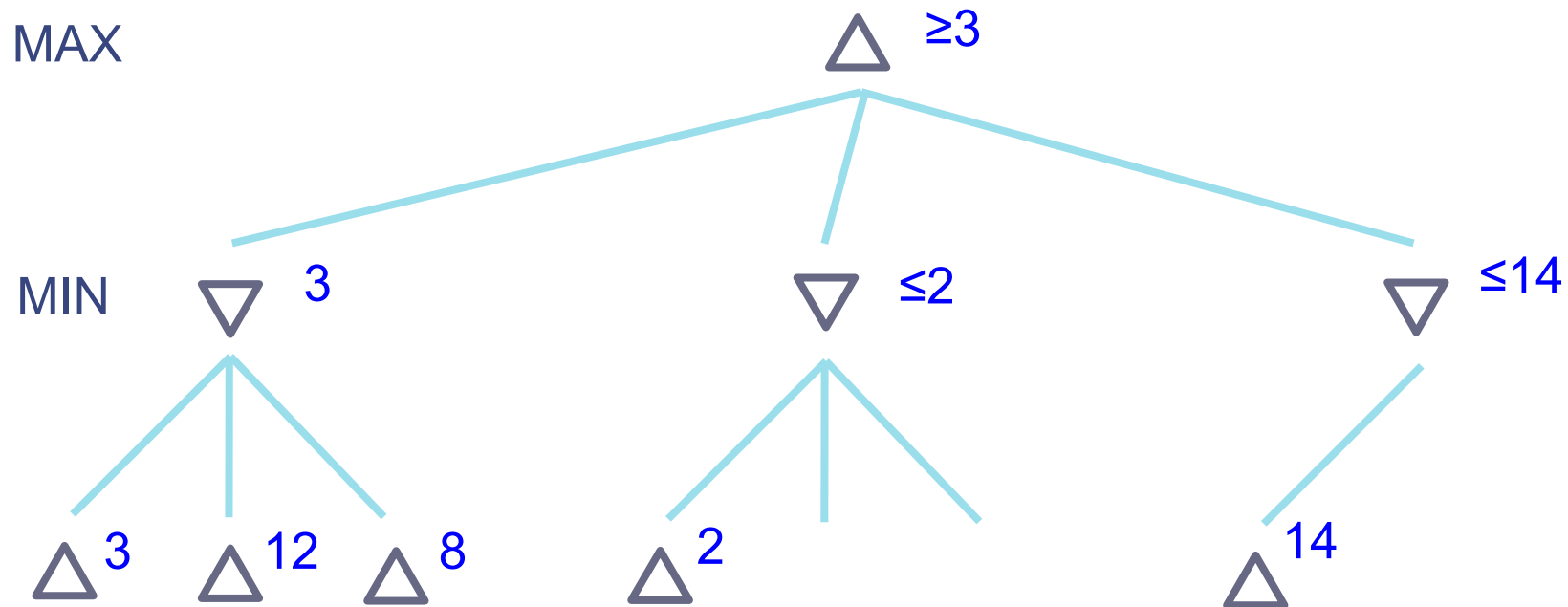
α - β Pruning Example



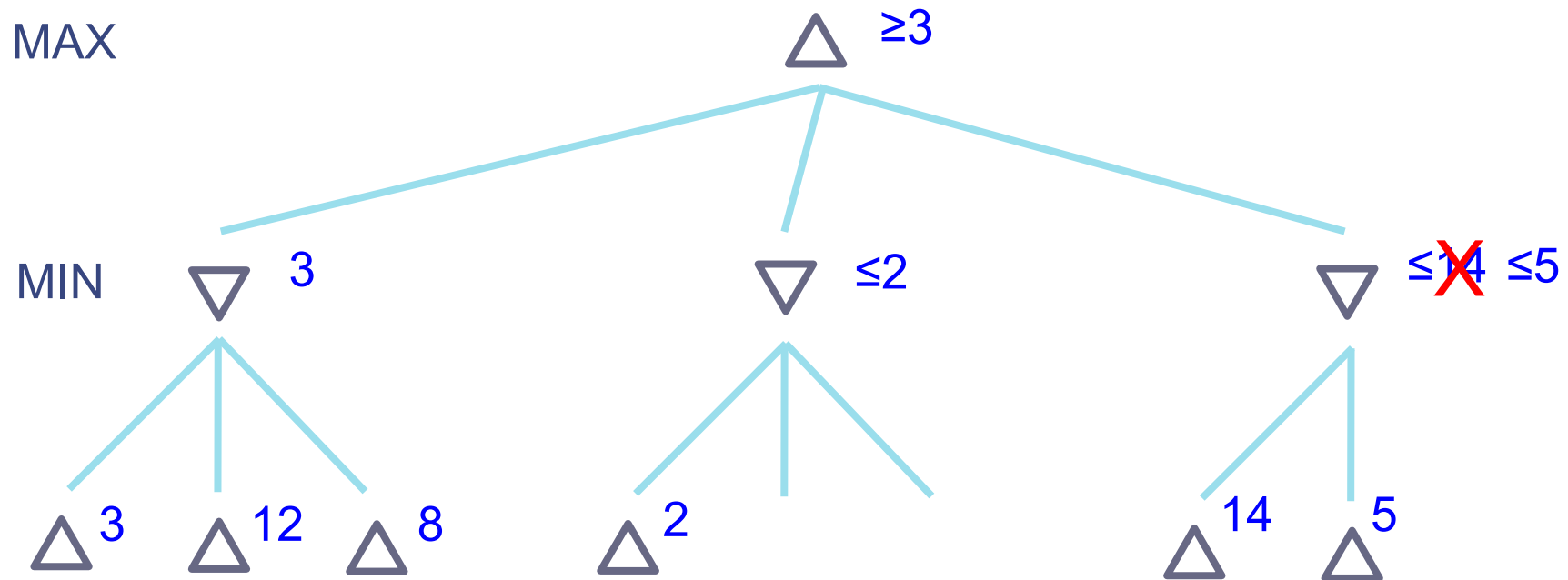
α - β Pruning Example



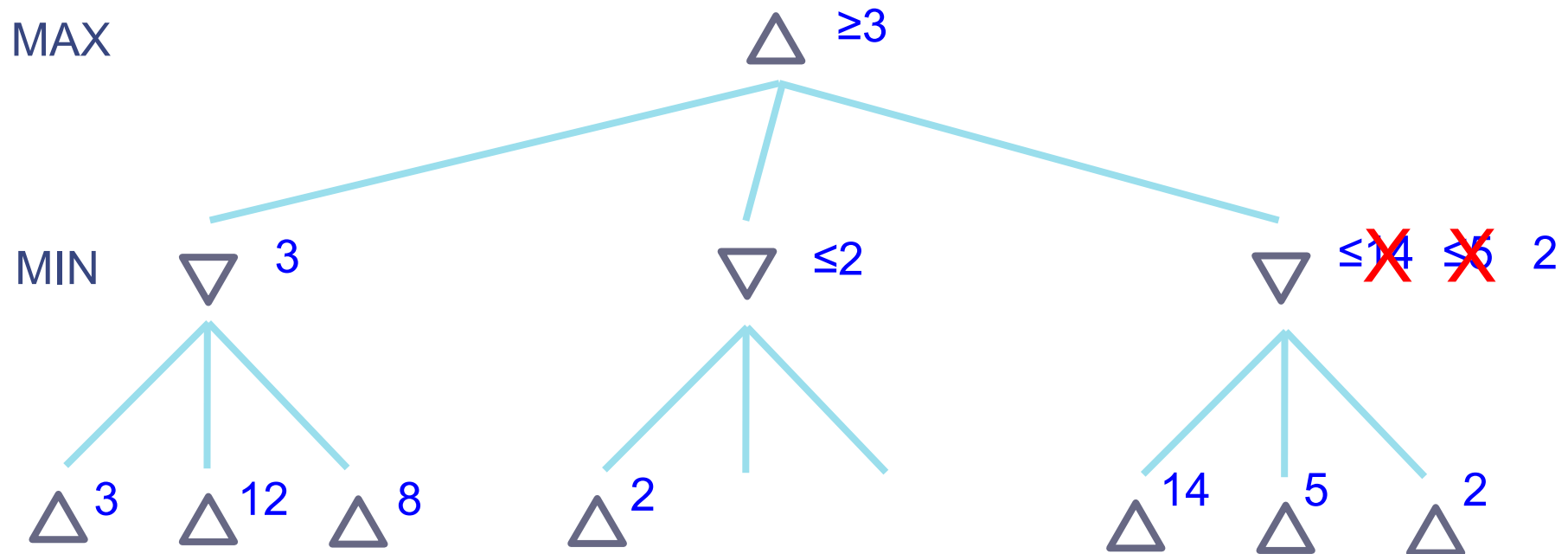
α - β Pruning Example



α - β Pruning Example



α - β Pruning Example



The Alpha-Beta Algorithm

- The Minimax algorithm is extended. Here's the new MinValue. MaxValue is analogous with roles of α and β reversed
- Need to maximise $\text{MinValue}(\text{Result}(a, S_0), -\infty, \infty, 1)$

```
function MinValue(s,  $\alpha$ ,  $\beta$ , d)
  if s is a terminal state or d = MaxDepth
    return Eval(s)
  else
    v :=  $\infty$ 
    for each action a possible in s
      v := Min(v, MaxValue(Result(a, s),  $\alpha$ ,  $\beta$ , d+1))
      if v  $\leq$   $\alpha$  return v
      else  $\beta$  := Min( $\beta$ , v)
    return v
```

Optimality

- If there is no depth limit, minimax is guaranteed to find the optimal move against an optimal opponent
- Alpha-beta will find the same move as minimax (but faster)
- If the opponent is not optimal ...
 - Consider an opponent that picks random moves. Then minimax might not be the best strategy for maximising expected reward
- If there is a depth limit, then minimax finds the optimal move for the given limit and evaluation function

Expected Utility

- If the opponent picks random moves, we should pick the move with maximum *expected* utility
- Here, minimax would choose A_1 , but the best move is A_3

