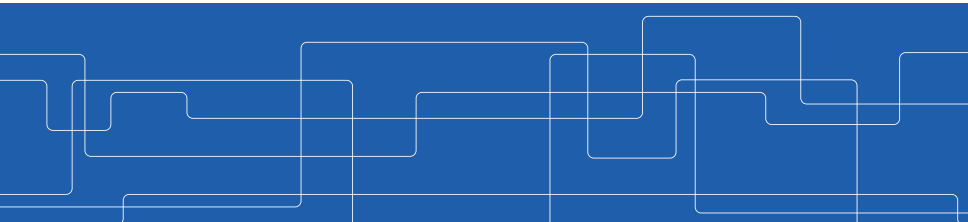




# Search in Games

Artificial Intelligence (DD2380)

KTH – Royal Institute of Technology  
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# Zero-sum games

- ▶ **Utility function**  $\psi(s, p)$ : numerical value for a game ending at state  $s$  by player  $p$ .
- ▶ **Zero-sum game**: game where the sum of the utility function for all players is zero. That is:  $\sum_i \psi(s, p_i) = 0$ .
  - ▶ Chess example:  $\psi(\text{win}, p) = 1$ ,  $\psi(\text{loss}, p) = -1$ , and  $\psi(\text{draw}, p) = 0$ .
- ▶ We consider **2-player, adversarial** games (no collaboration).
- ▶ We consider **perfect information** games: **deterministic** and **fully observable** environments.

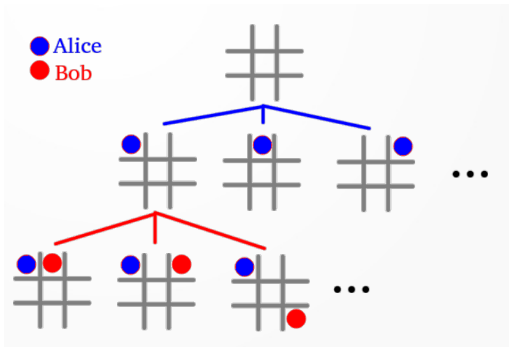
# Zero-sum games

## Tree representation:

- ▶ Nodes are states.
- ▶ Edges are moves (actions).

## Optimizing next move:

- ▶ Creating the game tree in the background.
- ▶ Assume the opponent is as smart as you.
- ▶ Search for the move that reaches the best state.





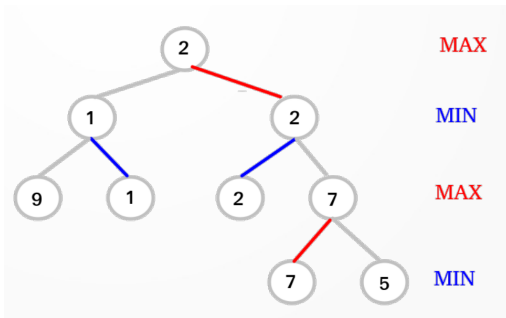
# Mini-Max Algorithm

- ▶ Strategy to find the best move.
- ▶ Two players taking turns: **MAX** and **MIN**.
  - ▶ **MAX** wants to **maximize** their gain.
  - ▶ **MIN** wants to **minimize** the other's gain.
- ▶ We want to explore the game tree to find the best outcome: → **Search!**
  - ▶ Depth First Search (DFS).

Two player types:

- ▶ **MAX**: selects highest value state.
- ▶ **MIN**: selects lowest value state.

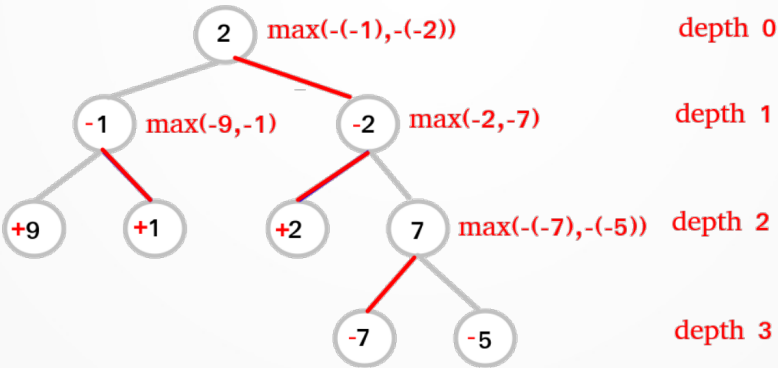
We assume both players are **equally smart!**





# Nega-Max Algorithm

- ▶ Strategy to find the best move.
- ▶ We exploit the fact that  $\text{max}(-a, -b) = -\text{min}(a, b)$ .
- ▶ We **negate utilities at odd depths** and always take  $\text{max}(-\text{child}_1, -\text{child}_2)$ .
- ▶ We want to explore the game tree to find the best outcome: → **Search!**
  - ▶ Depth First Search (DFS).



- ▶ We exploit the fact that  $\max(-a, -b) = -\min(a, b)$ .
- ▶ We **negate utilities at odd depths** and always take  $\max(-\text{child}_1, -\text{child}_2)$ .

# Alpha-Beta Pruning

- ▶ Some values are useless: Their value will not make any effect.
  - ▶ Example:  $\min(\max(7, \min(F(\cdot))), 2) = 2$  regardless of what  $F(\cdot)$  returns.
- ▶  $\alpha$ : Highest value found along the path to the root for MAX  $\rightarrow$  **Lower bound**
- ▶  $\beta$ : Lowest value found along the path to the root for MIN  $\rightarrow$  **Upper bound**
- ▶ Prune when  $\beta \leq \alpha$ . Why?
  - ▶ For MAX:  $\max(\alpha, \min(\beta, \text{sth})) = \alpha$ .
  - ▶ For MIN:  $\min(\beta, \max(\alpha, \text{sth})) = \beta$ .

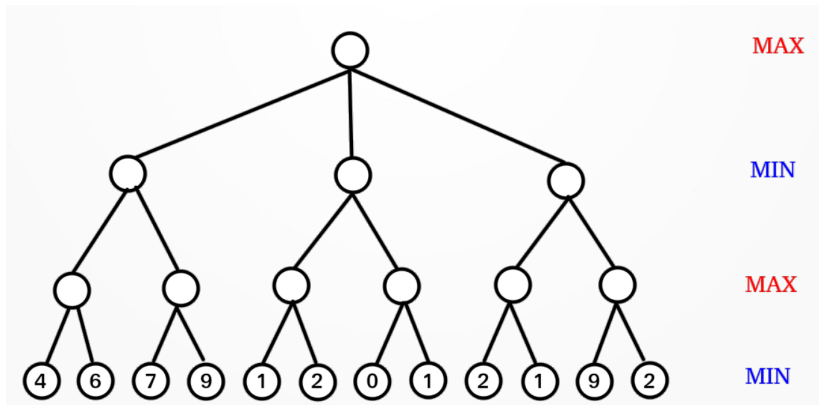




# Alpha-Beta Pruning

- ▶  $\alpha$  and  $\beta$  values are propagated down the tree.
- ▶  $\alpha$  and  $\beta$  values are **never** propagated up the tree.
- ▶  $\alpha$  values are evaluated in **MAX** nodes.
- ▶  $\beta$  values are evaluated in **MIN** nodes.

# Alpha-Beta Pruning



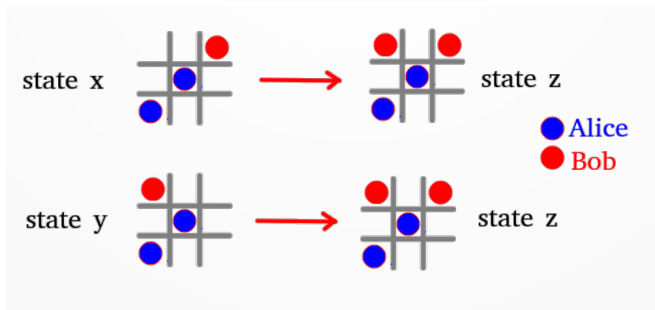




## Repeated States

- ▶ Search algorithms can visit the same state via different sequence of moves  
→ **Computationally expensive.**
- ▶ We can implement a data structure to avoid calculating the same states →  
**Hash function** and **transposition table.**
- ▶ Which states are equivalent?
  - ▶ Same placement of pieces.
  - ▶ **Symmetric** placements.
  - ▶ Is it important **who** made the move?

► Example: **tic-tac-toe**





## Scoring Function / Heuristic

- ▶ **Heuristic** or **scoring function**  $h(s, p)$ : **experience-based** approximation of the utility function:  $h(s, p) \approx \psi(s, p)$ .
- ▶ To calculate the utility function we need to explore the tree until the leaves → Potentially **very computationally expensive**.
- ▶ There are many number of heuristics and strategies → Usually none is optimal.
- ▶ Example: **checkers**
  - ▶ Count the number of your pieces and subtract the enemy pieces.



## The problem with DFS

- ▶ In some games, the depth of the state is very large (almost infinite).
- ▶ Possible solution: **search to a fixed depth**.
- ▶ But, what is the appropriate depth? And what if the branching factor is very big?
  - ▶ Branching factor of chess:  $\approx 35$ .
  - ▶ Branching factor of Go:  $\approx 250$ .



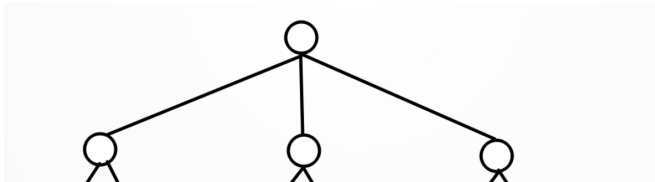
## Iterative Deepening Search (IDS)

Iterate the search depth: start at depth 0, then 1, then 2, and so on until the resources run out.



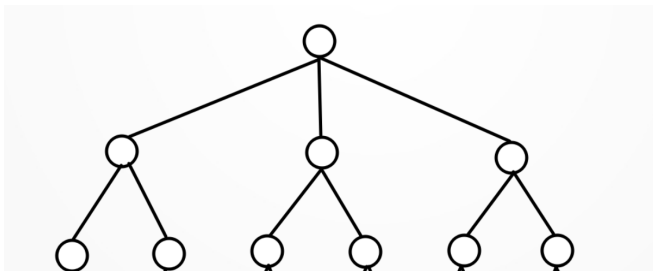
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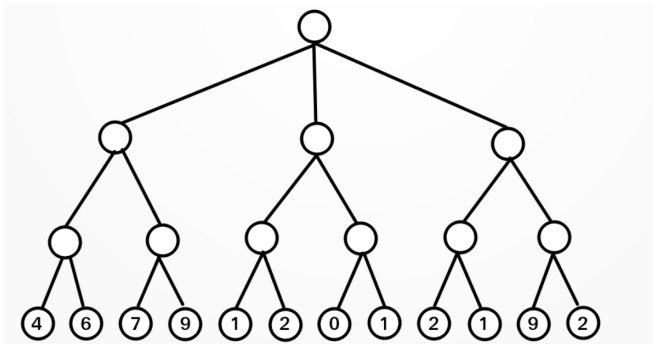
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## IDS and move ordering

Order the nodes at depth  $d + 1$  based on the estimation from depth  $d$ :

- ▶ If better nodes are searched first, **AlphaBeta** will prune large portions of the tree → **faster exploration**



## Tips and Questions

1. Make sure your **MiniMax/NegaMax** works.
2. Make sure your **Alpha-Beta** pruning works.
3. Check for **repeated states**.
  - ▶ Apply symmetry breaking.
4. Implement **iterative deepening** for exploration.
5. Almost EOG? Search until the end.
6. Implement move ordering for **Alpha-Beta** pruning.
7. Implement an ending states **look-up table**.



## Tips and Questions

- ▶ Kattis has a time limit, return the best in hand when time is up.
- ▶ Questions?
- ▶ **Have fun! :).**