

Monte Carlo Tree Search

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September 8, 2025

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3 | $\alpha - \beta$ pruning

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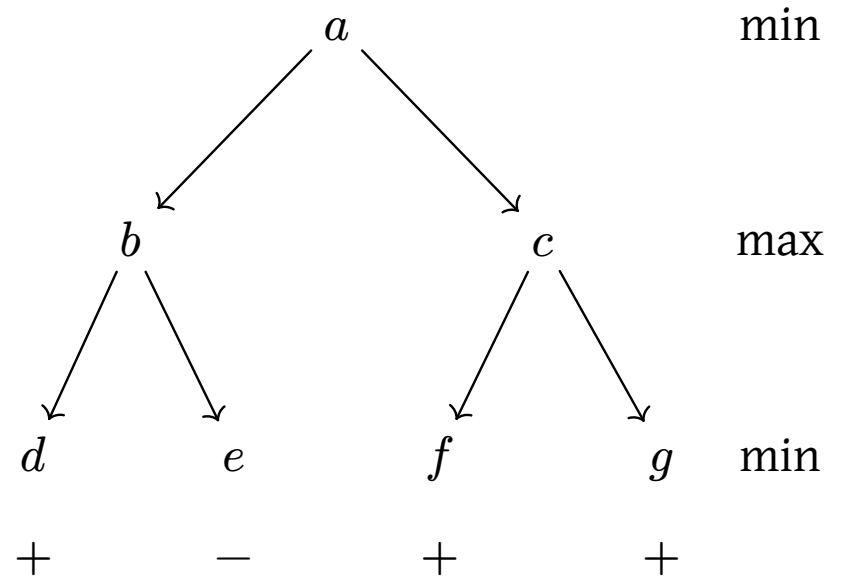
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1 | Introduction

The future is a garden of forking paths [1]. Action a at state s_t yields a new state s_{t+1} . A different action a' , however, might have yielded some different state s'_{t+1} .

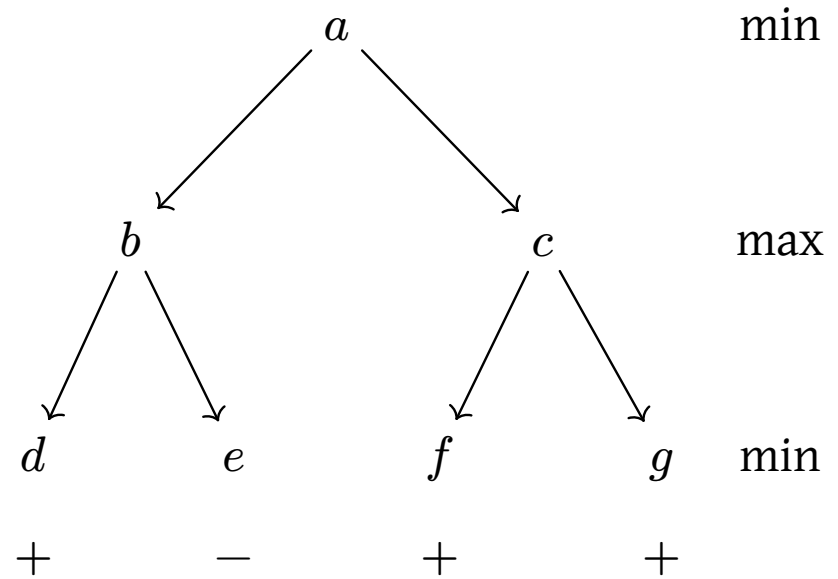
2 | Minimax

- ▶ Suppose we have a function that:
- ▶ given a state and an action returns a new state,
- ▶ and another that given a state returns who won
- ▶ What can we do?



2 | Minimax

- ▶ Suppose we have a function that:
- ▶ given a state and an action returns a new state,
- ▶ and another that given a state returns who won
- ▶ What can we do? Play perfectly and never loose



2 | Minimax

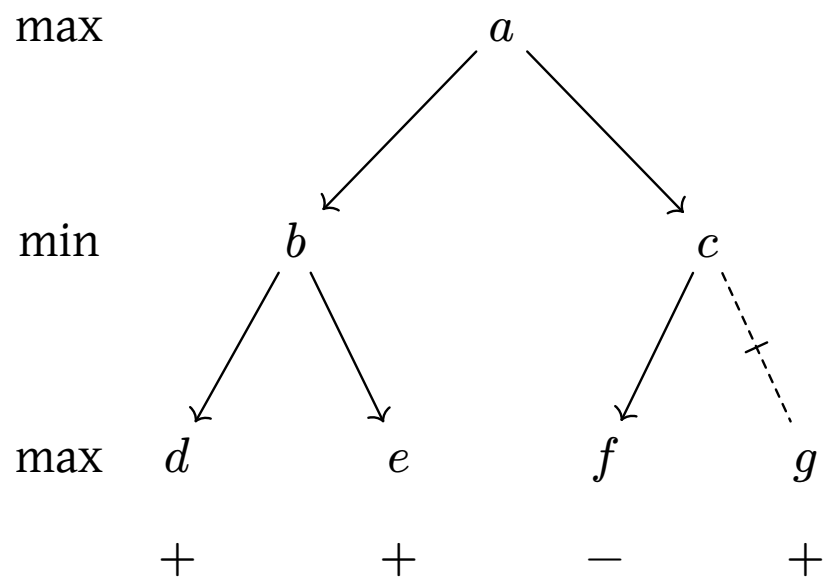
- ▶ We can win (or at least not loose) any game¹ by:
 1. Calling the minimax function for all actions
 2. Storing the values of each action in a list
 3. Taking the action with the highest value
- ▶ How can we do better? What are the issues?

Algorithm 1: minimax(state, maxim) \rightarrow value

```
1 if node is terminal
2   | return the value of node
3 temp =  $-\infty$  if maxim else  $\infty$ 
4 for each child of state
5   | value = minimax(child, not maxim)
6   | temp = (max if maxim else min)(temp,
7   | value)
7 return temp
```

¹that is two player, winnable, deterministic, etc.

3 | $\alpha - \beta$ pruning



- ▶ Skip branches worse than current floor
- ▶ α and β refer to those precisely floors

3 | $\alpha - \beta$ pruning

- ▶ Algorithm 2 looks daunting but the idea is:
- ▶ Stop exploring paths you already know are bad

Algorithm 2: $\alpha - \beta$ pruning(node, maxim, α , β)

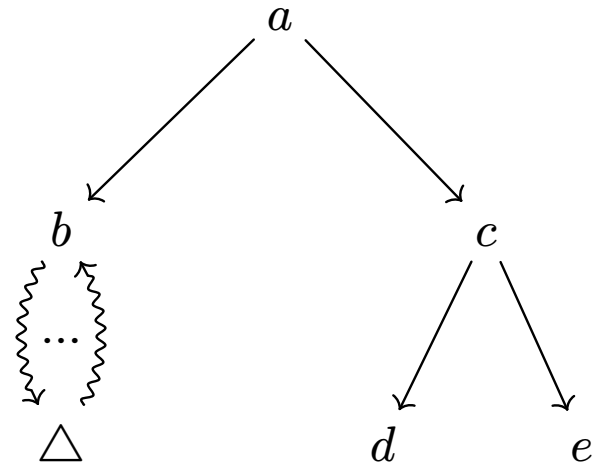
```
1  if node is terminal
2    return the value of node
3  bestValue =  $-\infty$  if maxim else  $\infty$ 
4  condition = max if maxim else min
5  for each child of node
6    value = minimax(child, not maxim,  $\alpha$ ,  $\beta$ )
7    bestValue = condition(bestValue, value)
8     $\alpha$  = (condition( $\alpha$ , value) if maxim else  $\alpha$ )
9       $\beta$  = (condition( $\beta$ , value) if not maxim else
10         $\beta$ )
11  if  $\alpha \geq \beta$ ; break
12 return bestValue
```

4 | MCTS

- ▶ We haven't actually looked at the board
- ▶ Humans don't mentally finish n games

4 | MCTS

- ▶ Monte Carlo (random) tree search [2]
- ▶ Core idea: sample from bottom of each branch
- ▶ How much to sample from each branch?
- ▶ How should we reach the bottom?



4.1 | Explore / exploit

- ▶ When do we exploit the best tool we have?
- ▶ When should we explore for a new tool?
- ▶ There is a good entropy based solution [3]

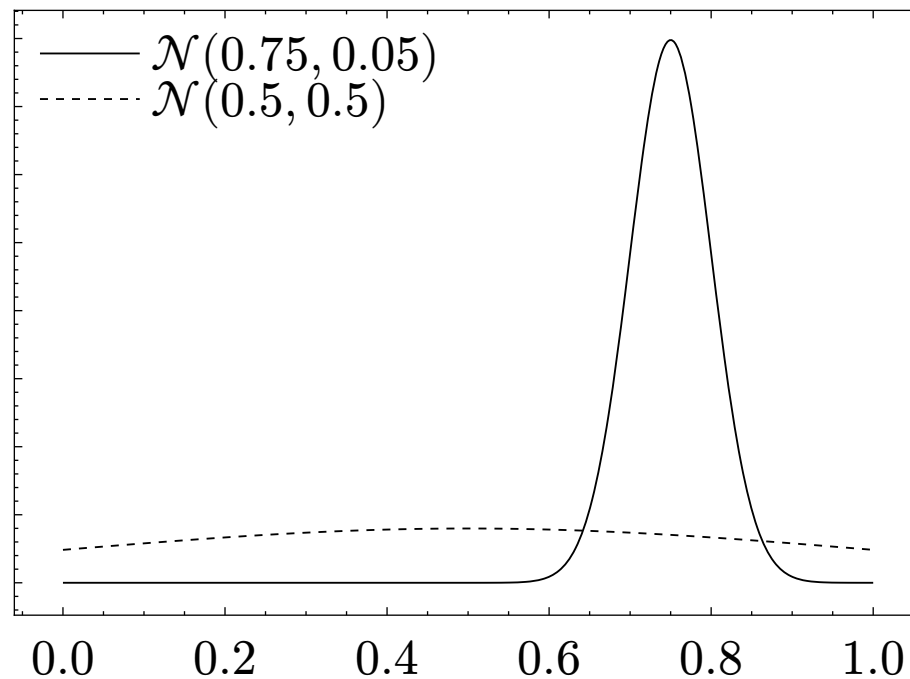


Figure 4: Which distribution would you sample from? Which is more likely to reach 1?

5 | Python

- ▶ You will see code that looks like Script 1
- ▶ In some games $s \neq o$, so we need separate obs
- ▶ Multi player setup will have inner player loop

```
import gymnasium as gym
env = gym.game("tic_tac_toe")
state, done = env.init()
```

```
while not done:
    action = action_fn(state)
    state, done = env.step(state, action)
```

Script 1: Playing games in Python usually look
something like this

5 | Python

- ▶ Some useful packages
- ▶ Understanding gymnasium is a must
- ▶ Get comfy with `.reset` and `.step`
- ▶ Sometimes state has a valid action mask!

<code>aigs</code>	package for our course
<code>gymnasium[4]</code>	Basic env package
<code>petting-zoo[5]</code>	gym for multiplayer

References

- [1] J. L. Borges, “The Garden of Forking Paths,” Ficciones. Grove Press, New York, 1962.
- [2] C. B. Browne et al., “A Survey of Monte Carlo Tree Search Methods,” IEEE Transactions on Computational Intelligence and AI in Games, vol. 4, no. 1, pp. 1–43, Mar. 2012, doi: 10.1109/TCIAIG.2012.2186810.
- [3] H. Robbins, “SOME ASPECTS OF THE SEQUENTIAL DESIGN OF EXPERIMENTS,” 1952.
- [4] M. Towers et al., “Gymnasium: A Standard Interface for Reinforcement Learning Environments.” Mar. 2025.
- [5] J. Terry et al., “Pettingzoo: Gym for Multi-Agent Reinforcement Learning,” Advances in Neural Information Processing Systems, vol. 34, pp. 15032–15043, 2021.