

# Monte Carlo Tree Search

This is the first of three labs. Its purpose is to 1) allow you to get hands-on experience with game trees, and 2) to ensure that your computer setup is up and running. Having installed `uv`<sup>1</sup>, and cloned our repo<sup>2</sup>, run `uv sync` to install all dependencies. I recommend using Zed<sup>3</sup> or VS Code as your editor, but anything (including Notepad++) will do. We will explore this lab in the coming sessions.

## 1 | Connect four

`aigs/games.py` contains an implementation of Tic-Tac-Toe. You have to:

- ▶ Look at the code and understand it
- ▶ Create a child class of `Env` called `ConnectFour`
- ▶ Implement an `init()` → State method
- ▶ Implement a `step(state, action)` → State method.

## 2 | Minimax

The minimax function has the signature  $f : S \rightarrow \mathbb{B} \rightarrow \mathbb{Z}$ . In plain English: it takes a state and a boolean (indicating player) and returns an integer (representing value). When we want to take an action, then, we call minimax for each of our potential actions, and take the action with the highest value. You have to:

- ▶ Implement the minimax function
- ▶ Call it for every potential action at time  $t$
- ▶ Then take the action that yielded the highest value

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<sup>1</sup>[docs.astral.sh/uv](https://docs.astral.sh/uv)

<sup>2</sup>[github.com/syrkis/aigs](https://github.com/syrkis/aigs)

<sup>3</sup>[zed.dev](https://zed.dev)

### 3 | $\alpha - \beta$ pruning

One common sense modification to minimax is to break early when a particular branch allows the oponent something better than what we are already guaranteed to have. The function signature then becomes  $f : S \rightarrow \mathbb{B} \rightarrow \mathbb{Z} \rightarrow \mathbb{Z} \rightarrow \mathbb{Z}$ , with the second to last two values representing  $\alpha$  and  $\beta$  (the values to beat for the two players). You have to:

- ▶ Copy your minimax function
- ▶ Add input parameters  $\alpha$  and  $\beta$
- ▶ Modify the function to break early when appropriate

### 4 | Heuristic variations

Notice how we never actually *looked* at the game board to gague its value, but instead we fully complete games, exhaustively exploring the game tree. Since already for connect-four, the combinatoric explosion leaves exhaustive search intractable, Shannon's 1950s chess program used heuristics [1]. Rather than always fully finishing every simulated game, he'd maximally look  $n$  steps into the future, and then evaluate the board using a *heuristic*—a linear combination of manually crafted features (e.g.,  $0.3 \times \text{number of pawns in the center} + 0.1 \times \text{mean distance from ally pawn to enemy king, or whatever.}$ ) You have to:

- ▶ Create a heuristic function that given a board returns a value
- ▶ Copy your minimax function, and add a depth parameter
- ▶ Modify the function to return winner if terminated or heuristic value of depth is 0

### 5 | Monte Carlo tree search

Even with  $\alpha - \beta$  pruning, we are still exhaustively searching through the game tree (in what we know for sure not to be dead ends). Why not just sample? When faced with a choice of making move  $a$  or  $b$  we could simulate  $n$  potential futures for each possibility and count outcomes. There are many variations and smart tricks to MCTS [2]. You have to

- ▶ Implement a rollout function

- ▶ Implement a backpropagation function
- ▶ Implement a selection function
- ▶ Implement an expansion function
- ▶ Combine the above into MCTS

## Index of Sources

- [1] C. E. Shannon, “Programming a Computer for Playing Chess,” *Computer Chess Compendium*, pp. 2–13, 1950, doi: 10.1007/978-1-4757-1968-0\_1.
- [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/TCLIAIG.2012.2186810.