Reinforcement Learning

Monte-Carlo Tree Search (MCTS)

Or how to combine learning and planning

Akka Zemmari

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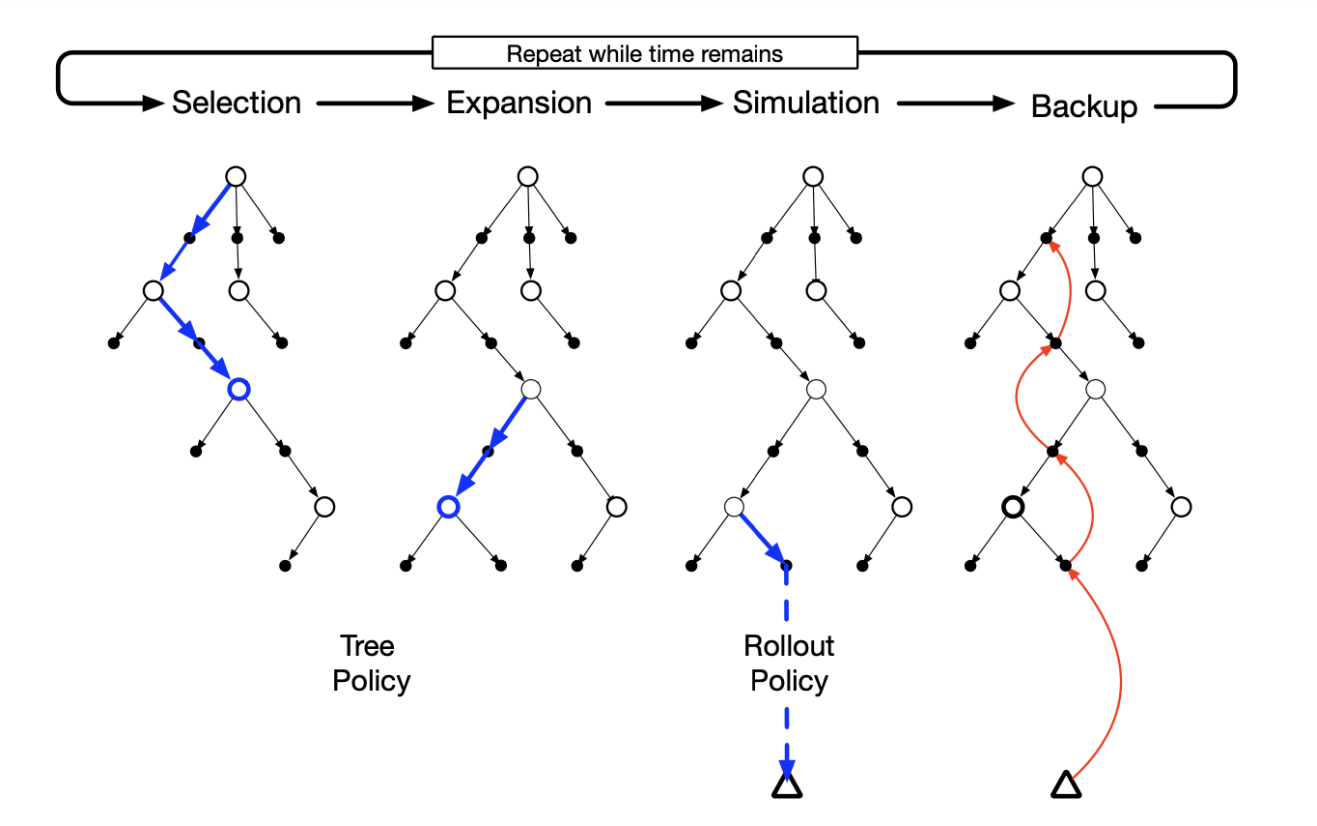
- Combines random sampling with systematic tree expansion.
- Widely used in board games (e.g., Go, Chess) and sequential decision-making problems.
- Effective for large and complex state spaces.

Core Idea of MCTS

- Incrementally builds a search tree based on simulations.

Monte Carlo Tree Search[1] in a Nutshell



[1] Sutton et al.

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  4. **Backpropagation**: Update node values based on simulation results.

Step 1: Selection

- Traverse the tree using a selection policy (e.g., UCT).
- Upper Confidence (Bounds) for trees (UCT):

$$UCT = \frac{w_i}{n_i} + C\sqrt{\frac{\ln N}{n_i}}$$

where:

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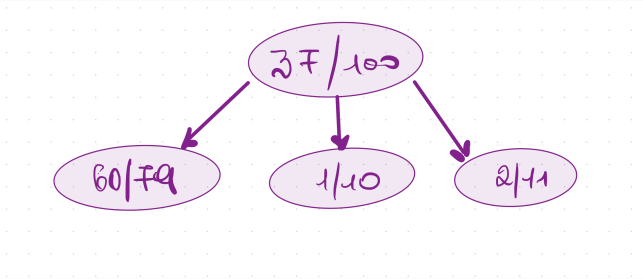

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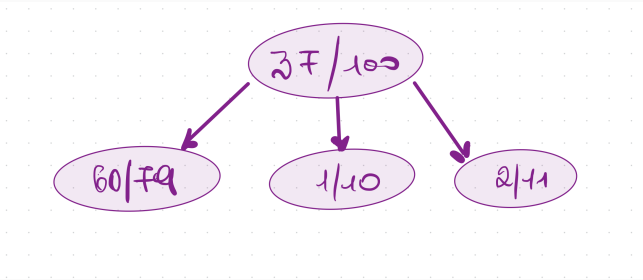

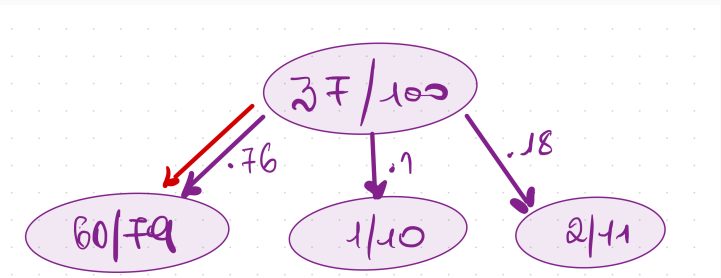

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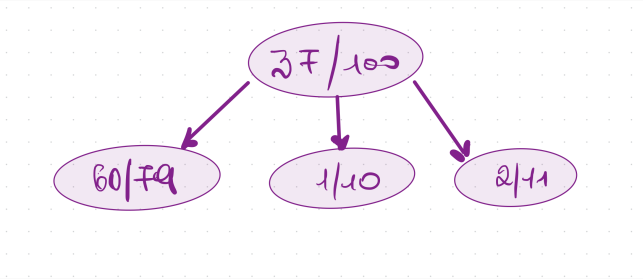

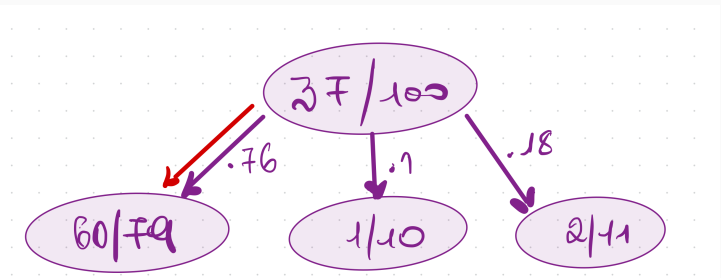

Remark: In the illustration, we do not realy use the UCB formula, but the idea is the same.

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- Expand the tree by adding a new child node to the selected node.
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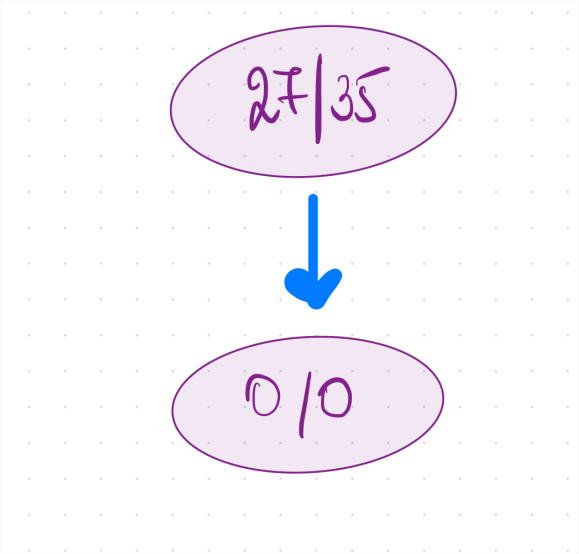

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- Perform a random simulation (rollout) from the newly added node.
- Continue until reaching a terminal state.
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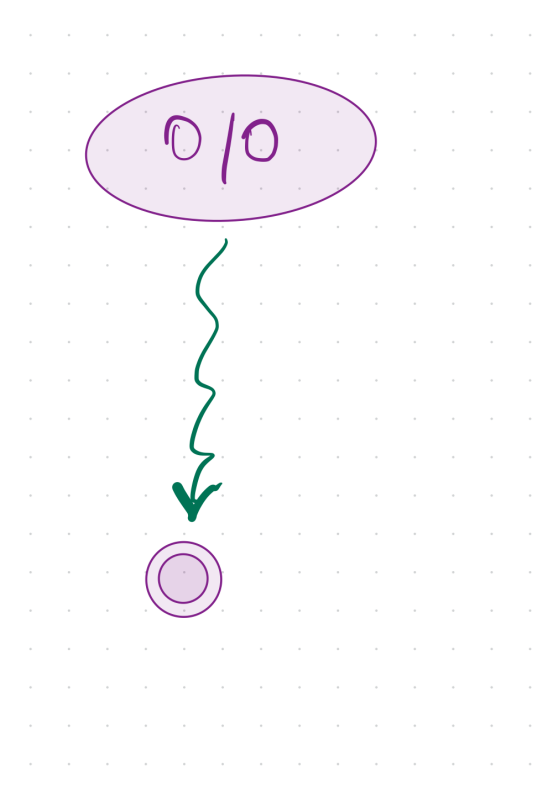

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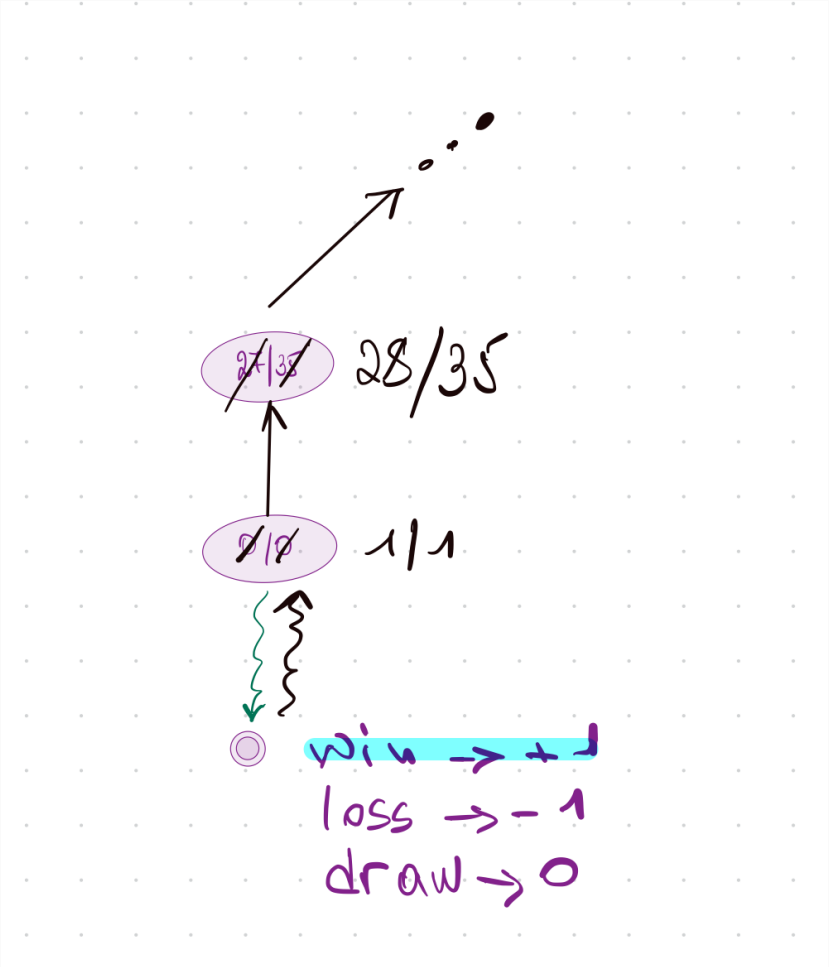

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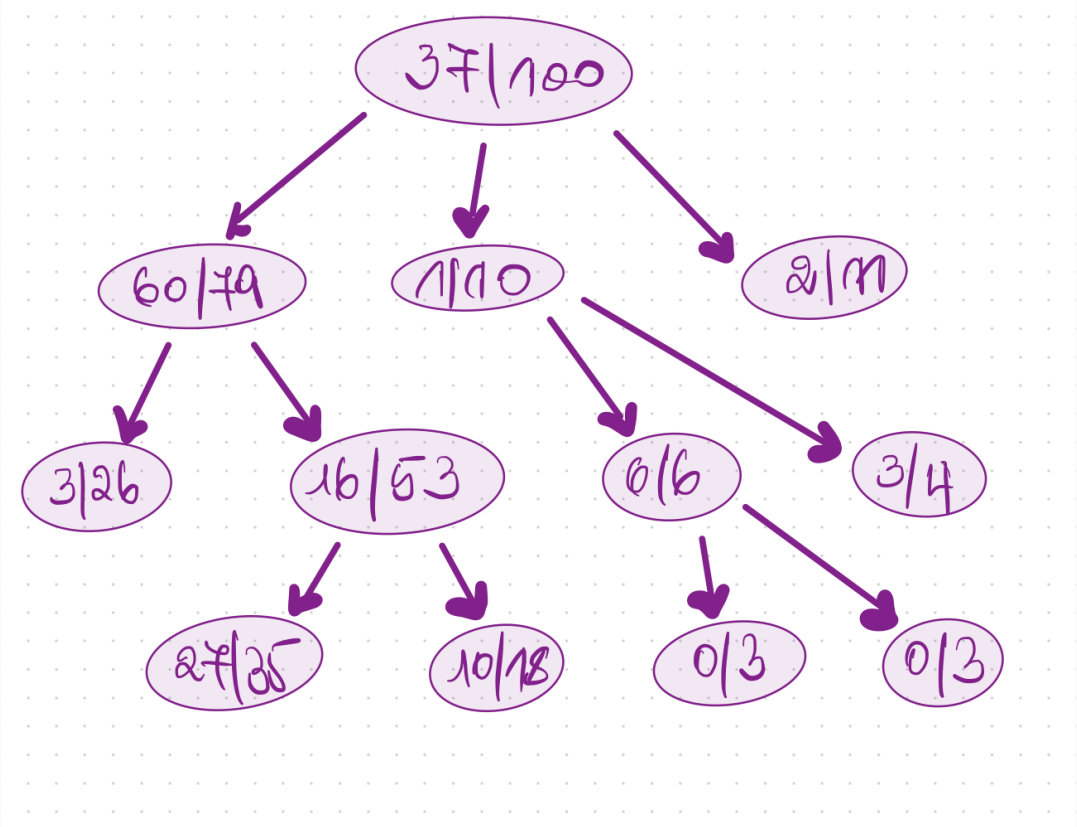

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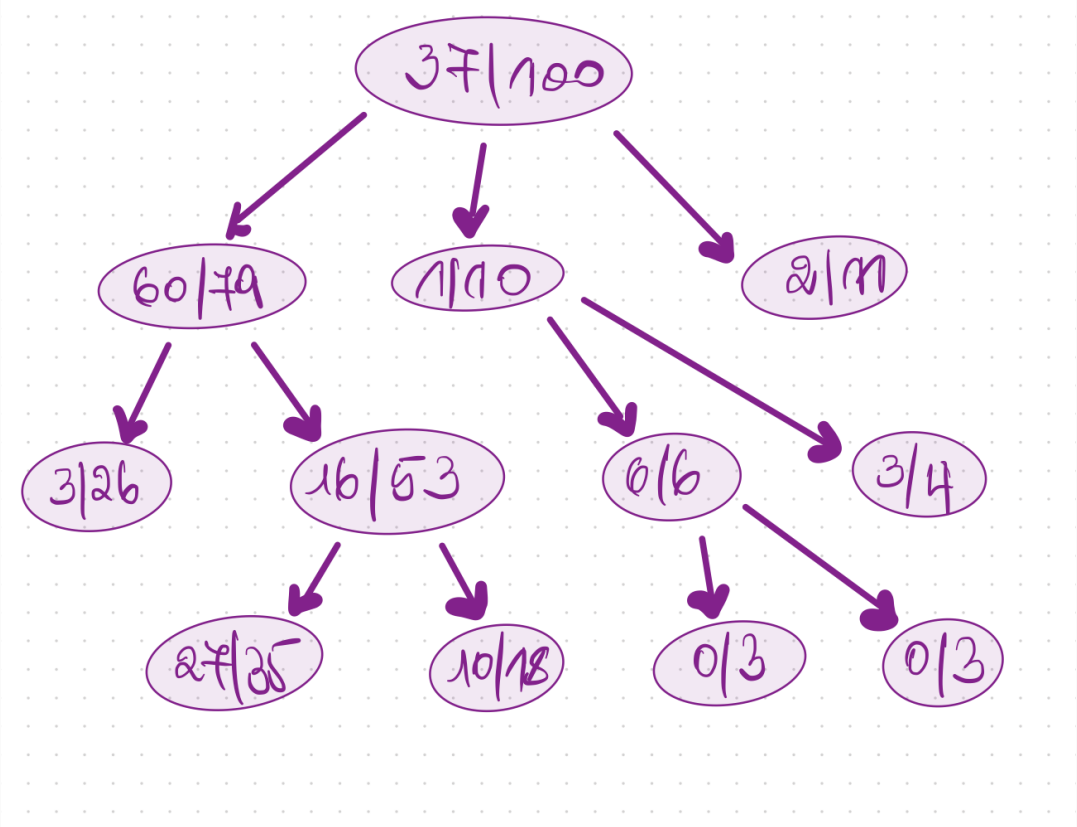

Whiteboard time!

Exploration vs Exploitation

- MCTS balances:
  - **Exploration**: Sampling less visited nodes.
  - **Exploitation**: Focusing on nodes with high win rates.
- UCT guides this balance effectively.

Advantages and Limitations of MCTS

- **Advantages**:
  - Effective for large search spaces.
  - Requires no prior knowledge.
  - Adaptable to various domains.
- **Limitations**:
  - Computationally expensive.
  - Results depend on the number of simulations.

Applications of MCTS

- Board games: Go, Chess, ...
- Planning and robotics.
- Real-time strategy games.
- General decision-making problems.

Conclusion

- MCTS is a versatile and powerful search algorithm.
- Balances random sampling with tree-based exploration.
- Widely applicable across domains with complex decision trees.