Monte-Carlo Tree Search

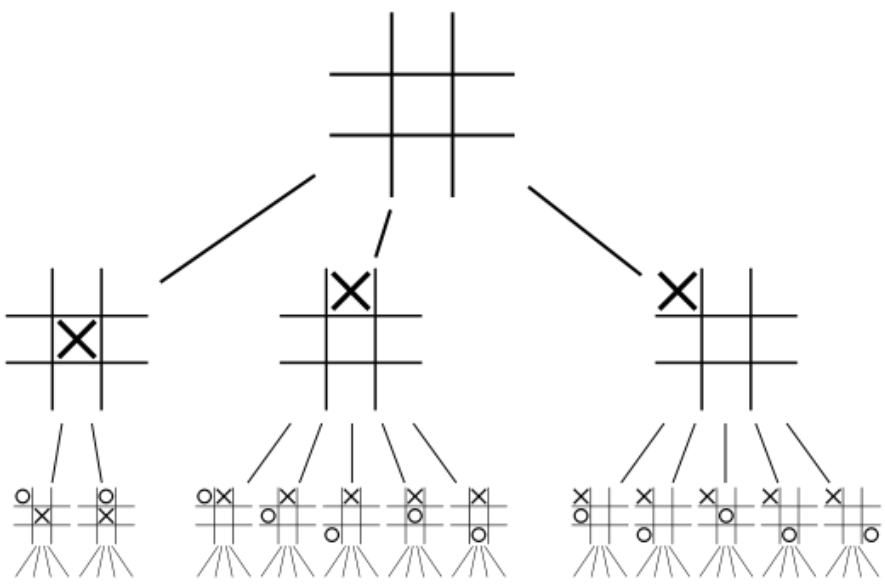
March 10, 2018 (http://matthewdeakos.me/2018/03/10/monte-carlo-tree-search/) *Matthew Deakos (http://matthewdeakos.me/author/admin/)* Machine Learning and Data Science (http://matthewdeakos.me/category/ml-data-science/)

3 Comments (http://matthewdeakos.me/2018/03/10/monte-carlo-tree-search/#comments)

This blog post will discuss Monte Carlo tree search – one particularly powerful reinforcement learning technique that's been employed in some of the most revolutionary game playing AI, including AlphaGo (https://en.wikipedia.org/wiki/AlphaGo) and AlphaZero (https://en.wikipedia.org/wiki/AlphaZero). Before jumping right in though, we need to first cover the introductory topic of Game Trees.

Game Trees

The idea of a game tree is very straightforward. The nodes of a tree represent a state of the game. Edges of a node tell you what possible states can be reached from the current state.

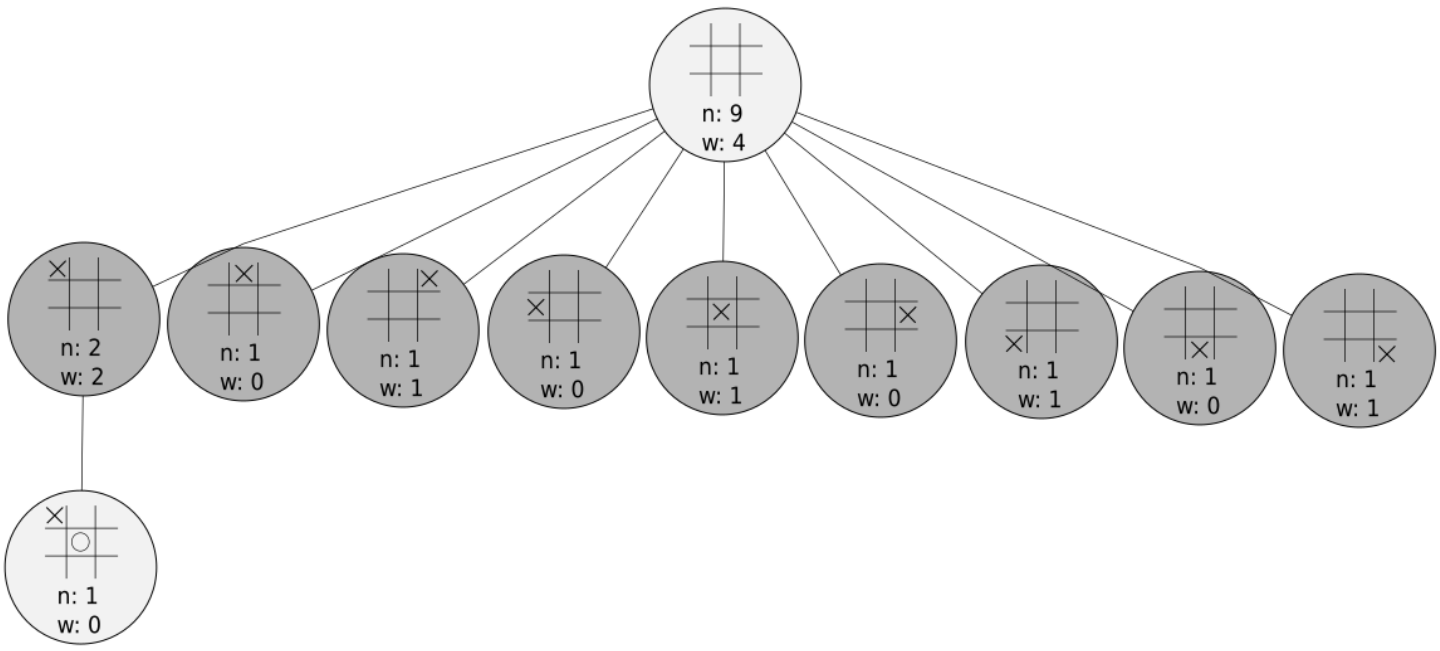


A *complete* game tree contains every possible state of the given game. If you are able to build a complete game tree then it becomes trivial to calculate which moves are more likely to lead to a win. This is pretty easy to do in games that have a low average *branching factor* (the number of possible states reachable from the current one) and a low number of possible states

But what do we do when the number of possible states is high? Take Go (https://en.wikipedia.org/wiki/Go_(game)) as the quintessential example – this game has an estimated 10^{172} states. This is more possible board positions than atoms in the universe! No matter how powerful your computer is, you just can't simulate enough moves to build a complete game tree. In fact, you'll never even scratch the surface. So what do we do here? Enter the Monte Carlo tree search.

Monte-Carlo Tree Search

Imagine we have an AI that's using Monte Carlo tree search (let's call him HAL). HAL is plugged in to a game of tic-tac-toe and has been thinking about his first move. At the moment, HAL's game tree looks like this:



First, let's break this down. Each node has two values associated with it: ***n*** and ***w***. ***n*** represents the number of times this state has been considered, and ***w*** represents the number of times the player who *just played* would have won from this position. That means that the ***w*** in the darker nodes tell us how many times player X has won from that position and the ***w*** lighter nodes tell us how many times player O has won from that position.

In most cases, we allow HAL a couple of seconds to make a decision. During that time, HAL *thinks* about what move he'd like to play. This is where the Monte Carlo tree search comes in.

Monte-Carlo Tree search is made up of four distinct operations:

1. Selection
2. Expansion
3. Simulation
4. Backpropagation

HAL is going to keep cycling through these four phases for as long as he's allowed to think. Each of these phases are covered in more detail below.

Selection

In the selection phase, we decide which action to *think* about taking. This is non-trivial – HAL doesn't want to waste too much time thinking about taking bad moves, but he also doesn't want to only consider moves that he feels good about because he might miss a big opportunity. This dilemma is referred to as the *exploration/exploitation* tradeoff.

Exploration refers to HAL thinking about moves that he hasn't tried much already, where exploitation is taking advantage of HAL's current knowledge and pushing it further. One of the most popular ways to balance these two goals is with the **UCB1** formula. We choose the action that leads to the node for which the following equation is maximized.

$$\frac{w_i}{n_i} + c\sqrt{\frac{\ln N}{n_i}}$$

w_i represents the number of wins considered for that node

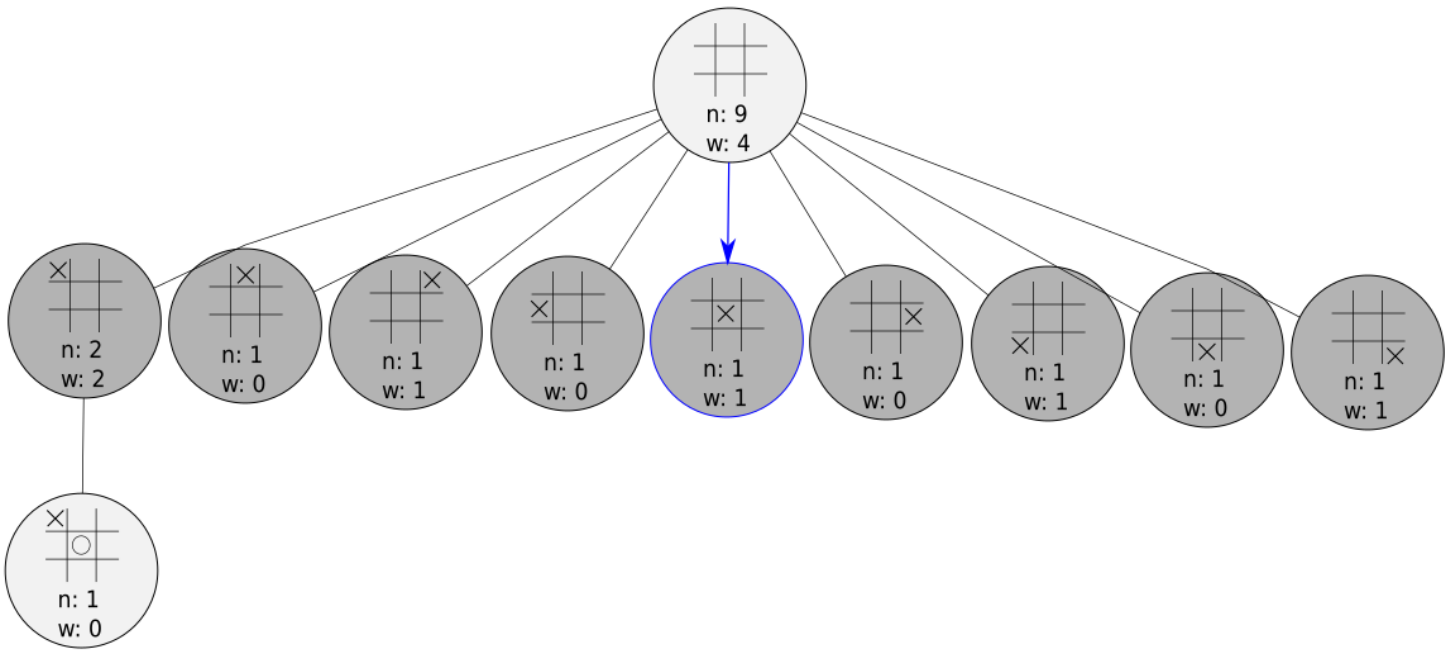
n_i represents the number of times that node has been considered (visit count)

N represents the number of times *all* reachable nodes have been considered (sum of the visit count of all reachable nodes)

c is a hyperparameter that we choose. The higher we set this hyperparameter, the more we value exploration over exploitation. This is typically set close to 1, but should be adjusted on a case-by-case basis.

If any nodes tie, we can choose between them at random.

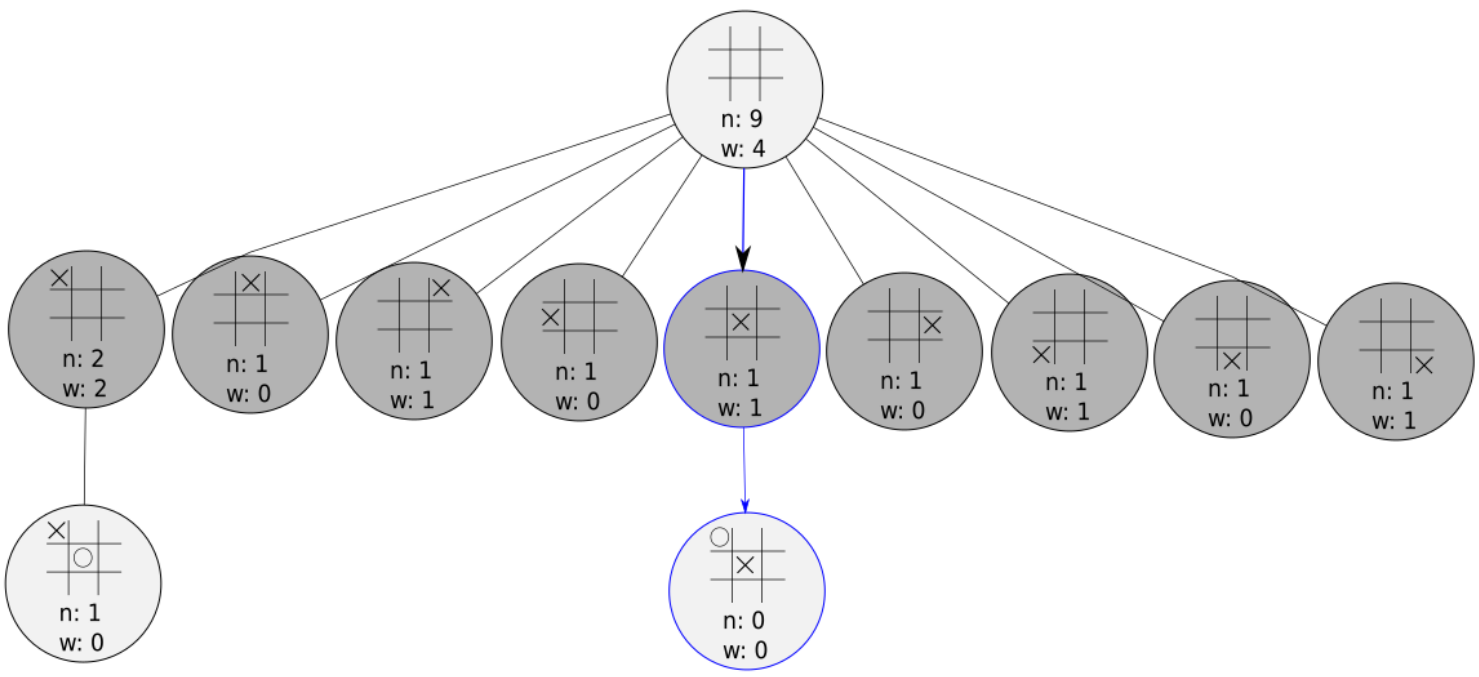
It's important to note that these phases always begin with the **current** state of the board in the very top node. Now let's imagine we chose ***C*** such that the following node was selected:



As you can see, the node we selected doesn't have any child nodes in the game tree. When this happens, we move into the expansion phase.

Expansion

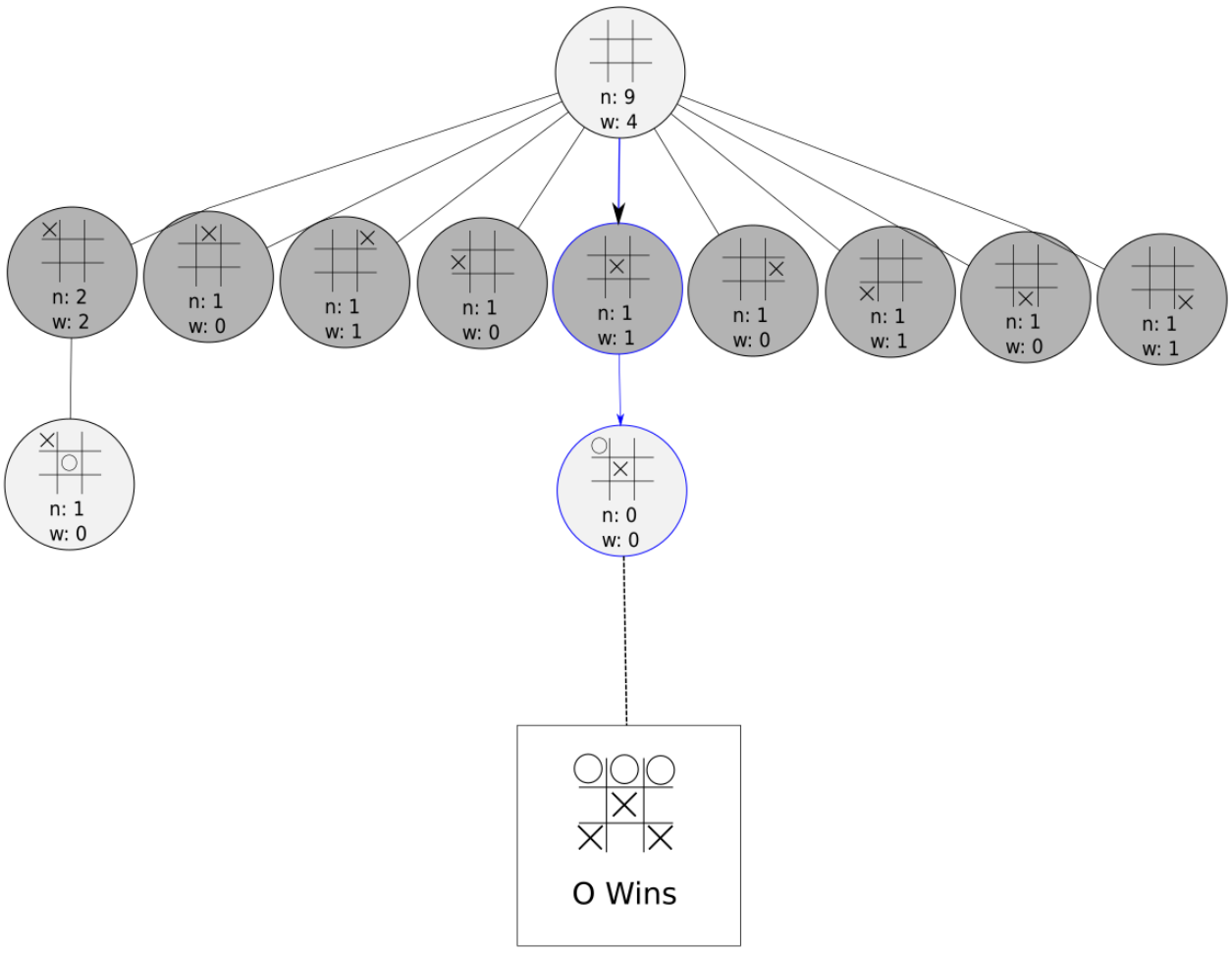
HAL doesn't have enough information to select a node anymore, so we grow our tree! Here we'll just choose an action at random – this is called a *light rollout*.



In more complex games, it is common to use *heavy rollout* – this means using some deep heuristic knowledge to choose an action, or even a neural net trained to evaluate board position. This can lead to faster convergence to a more optimal tree. If the game's not over yet, we move through to the simulation phase.

Simulation

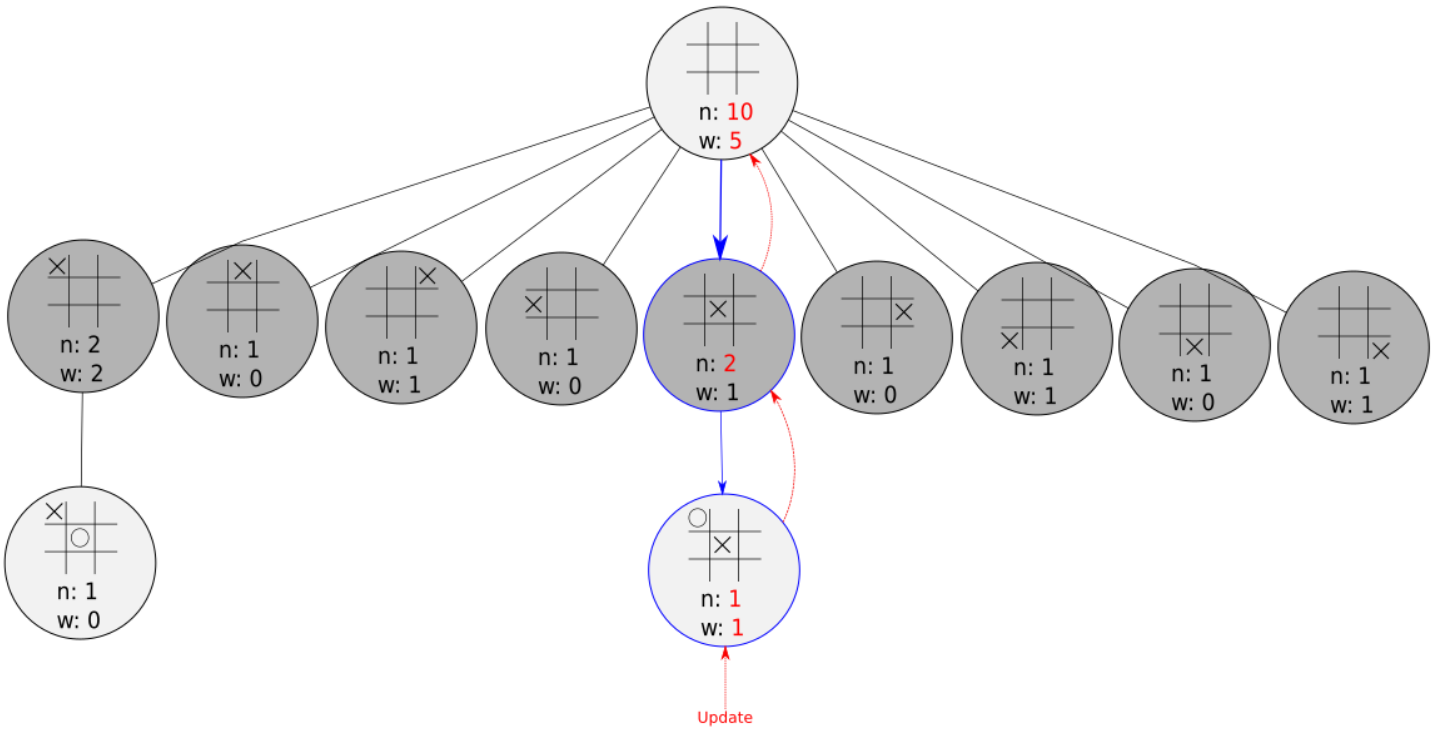
At this point, we just simulate the game from our current node to the end and see who won! Actions along the simulation are chosen randomly. It's important to note that we *do not* add states visited in the simulation phase to our game tree – the purpose of the simulation is just to help us evaluate the position of our current node.



We've simulated out a game and O won it. Time to move to the next phase!

Backpropagation

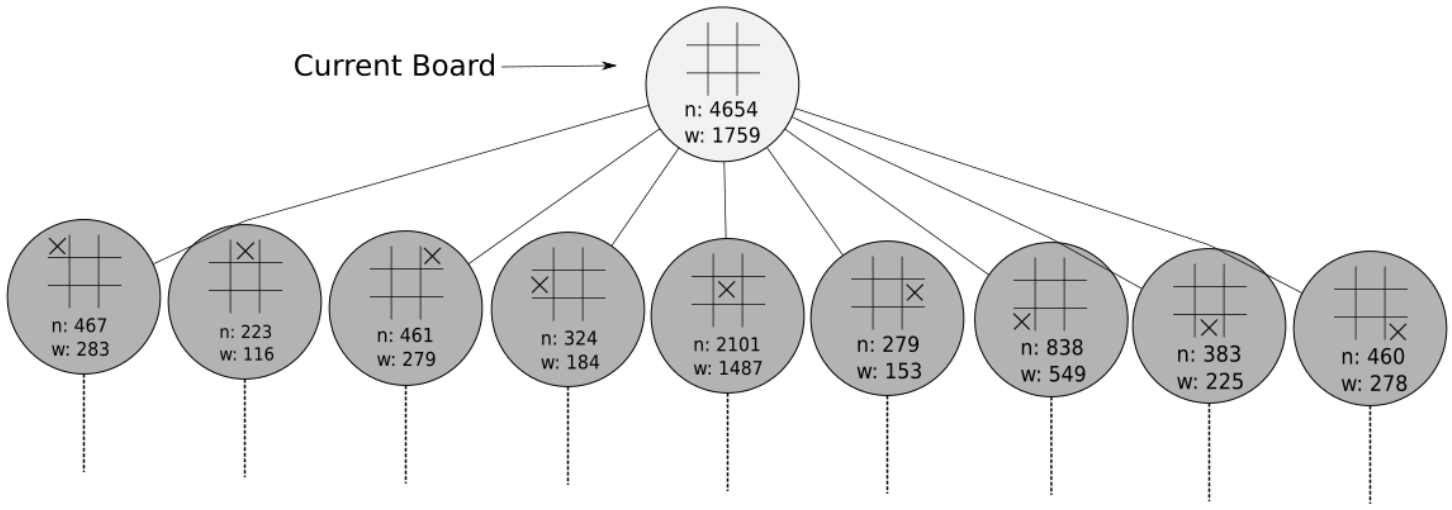
In this phase, we simply update our selected nodes with the result of the simulation. We increment the visit count ***n*** in each node, and we update our win count ***w*** for only the light gray nodes.



One simulation is noisy, and we can't really be very certain of the results. But after hundreds or thousands of simulations, we start to get a clearer picture of what the value at each node might be.

Making a move

HAL still hasn't even made his first move – this whole time HAL has just been *thinking* about which move he should make. After a couple of seconds, HAL has iterated through this 4-step process thousands of times, each node has had its win count and visit count update over and over again. I actually ran a MCTS on a simple tic-tac-toe environment, and here are the first couple nodes of the game tree:



So which one does HAL pick? There are actually a few strategies here, and in *most* cases they all lead to the same answer. He can pick the action that leads to the node with the highest *winning percentage* or to the node with the highest *visit count* – the logic being that more interesting nodes are explored more. After HAL makes his choice, he'll repeat this process over and over again until the end of the game.

And that's it – the prolific Monte Carlo Tree Search! Please feel free to leave any comments or suggested changes below.

Thanks for reading!

3 Replies to "Monte-Carlo Tree Search"

Kelsy Fontaine
March 21, 2018 at 2:10 am (http://matthewdeakos.me/2018/03/10/monte-carlo-tree-search/#comment-2)

Great!! Thanks, this was very easy to understand! 🙂

Phil
April 3, 2018 at 9:43 pm (http://matthewdeakos.me/2018/03/10/monte-carlo-tree-search/#comment-3)

How could you modify this to eliminate searches through redundant branches? For example there are really only three opening moves in Tic-Tac-Toe; center, center edge, and corner. All other moves are congruent.

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admin
April 20, 2018 at 10:26 pm (http://matthewdeakos.me/2018/03/10/monte-carlo-tree-search/#comment-4)

That's a really good question! I was looking into this, and I couldn't actually find examples of this sort of implementation. I've been thinking about it, and I do think there's one efficient way we could use this information without seriously modifying the inner workings of MCTS. If we can define a function that can give us a list of symmetrical states that we visited, we can sum their visit counts and win counts to achieve much faster convergence. I think this would be the simplest way to take advantage of board symmetry in light-rollout MCTS.

That said, in *heavy rollout* MCTS (tutorial coming soon) random rotations of states actually are used fairly often. By randomly rotating states that are visited, we can generate more training data for a neural network without computing more games. I believe the original version of AlphaGo did this.

‹ A Practical Introduction to PCA in Python (http://matthewdeakos.me/2018/02/26/principal-component-analysis/)

Integrating Monte Carlo Tree Search and Neural Networks › (http://matthewdeakos.me/2018/07/03/integrating-monte-carlo-tree-search-and-neural-networks/)