Score Bounded Monte-Carlo Tree Search

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Abstract. Monte-Carlo Tree Search (MCTS) is a successful algorithm used in many state of the art game engines. We propose to improve a MCTS solver when a game has more than two outcomes. It is for example the case in games that can end in draw positions. In this case it improves significantly a MCTS solver to take into account bounds on the possible scores of a node in order to select the nodes to explore. We apply our algorithm to solving Seki in the game of Go and to Connect Four.

1 Introduction

Monte-Carlo Tree Search algorithms have been very successfully applied to the game of Go [7, 11]. They have also been used in state of the art programs for General Game Playing [9], for games with incomplete information such as Phantom Go [3], or for puzzles [4, 17, 5].

MCTS has also been used with an evaluation function instead of random playouts, in games such as Amazons [15] and Lines of Action [18].

In Lines of Action, MCTS has been successfully combined with exact results in a MCTS solver [19]. We propose to further extend this combination to games that have more than two outcomes. Example of such a game is playing a Seki in the game of Go: the game can be either lost, won or draw (i.e. Seki). Improving MCTS for Seki and Semeai is important for Monte-Carlo Go since this is one of the main weaknesses of current Monte-Carlo Go programs. We also address the application of our algorithm to Connect Four that can also end in a draw.

The second section deals with the state of the art in MCTS solver, the third section details our algorithm that takes bounds into account in a MCTS solver, the fourth section explains why Seki and Semeai are difficult for Monte-Carlo Go programs, the fifth section gives experimental results.

2 Monte-Carlo tree search solver

As the name suggests, MCTS builds a game tree in which each node is associated to a player, either *Max* or *Min*, and accordingly to values Q_{max} and Q_{min}. As the tree grows and more information is available, Q_{max} and Q_{min} are updated. The node value function is usually based on a combination of the mean of Monte Carlo playouts that went through the node [7, 13], and various heuristics such as All moves as first [10], or move urgencies [8, 6]. It can also involve an evaluation function as in [15, 18].

Monte-Carlo Tree Search is composed of four steps. First it descends a tree choosing at each node n the child of n maximizing the value for the player in n. When it reaches a nodes with that has unexplored children, it adds a new leaf to the tree. Then the corresponding position is scored through the result of an evaluation function or a random playout. The score is backpropagated to the nodes that have been traversed during the descent of the tree.

MCTS is able to converge to the optimal play given infinite time, however it is not able to prove the value of a position if it is not associated to a solver. MCTS is not good at finding narrow lines of tactical play. The association to a solver enables MCTS to alleviate this weakness and to find some of them.

Combining exact values with MCTS has been addressed by Winands et al. in their MCTS solver [19]. Two special values can be assigned to nodes : $+\infty$ and $-\infty$. When a node is associated to a solved position (for example a terminal position) it is associated to $+\infty$ for a won position and to $-\infty$ for a lost position. When a max node has a won child, the node is solved and the node value is set to $+\infty$. When a max node has all its children equal to $-\infty$ it is lost and set to $-\infty$. The descent of the tree is stopped as soon as a solved node is reached, in this case no simulation takes place and 1.0 is backpropagated for won positions, whereas -1.0 is backpropagated for lost ones.

Combining such a solver to MCTS improved a Lines Of Action (LOA) program, winning 65% of the time against the MCTS version without a solver. Winands et al. did not try to prove draws since draws are exceptional in LOA.

3 Integration of score bounds in MCTS

We assume the outcomes of the game belong to an interval $[minscore, maxscore]$ of $\mathbb{R}$, the player *Max* is trying to maximize the outcome while the player *Min* is trying to minimize the outcome.

In the following we are supposing that the tree is a minimax tree. It can be a partial tree of a sequential perfect information deterministic zero-sum game in which each node is either a *max-node* when the player *Max* is to play in the associated position or a *min-node* otherwise. Note that we do not require the child of a *max-node* to be a *min-node*, so a step-based approach to MCTS (for instance in Arimaa [14]) is possible. It can also be a partial tree of a perfect information deterministic one player puzzle. In this latter case, each node is a max-node and *Max* is the only player considered.

We assume that there are legal moves in a game position if and only if the game position is non terminal. Nodes corresponding to terminal game positions are called *terminal nodes*. Other nodes are called *internal nodes*.

Our algorithm adds score bounds to nodes in the MCTS tree. It needs slight modifications of the backpropagation and descent steps. We first define the bounds that we consider and express a few desired properties. Then we show how bounds can be initially set and then incrementally adapted as the available information grows. We then show how such knowledge can be used to safely prune nodes and subtrees and how the bounds can be used to heuristically bias the descent of the tree.

3.1 Pessimistic and optimistic bounds

For each node n, we attach a pessimistic (noted $\mathrm{pess}(n)$) and an optimistic (noted $\mathrm{opti}(n)$) bound to n. Note that optimistic and pessimistic bounds in the context of game tree search were first introduced by Hans Berliner in his B* algorithm [2]. The names of the bounds are defined after *Max*'s point of view, for instance in both max- and min-nodes, the pessimistic bound is a lower bound of the best achievable outcome for *Max* (assuming rational play from *Min*). For a fixed node n, the bound $\mathrm{pess}(n)$ is increasing (resp. $\mathrm{opti}(n)$ is decreasing) as more and more information is available. This evolution is such that no false assumption is made on the expectation of n : the outcome of optimal play from node n on, noted $\mathrm{real}(n)$, is always between $\mathrm{pess}(n)$ and $\mathrm{opti}(n)$. That is $\mathrm{pess}(n) \leq \mathrm{real}(n) \leq \mathrm{opti}(n)$. If there is enough time allocated to information discovering in n, $\mathrm{pess}(n)$ and $\mathrm{opti}(n)$ will converge towards $\mathrm{real}(n)$. A position corresponding to a node n is solved if and only if $\mathrm{pess}(n) = \mathrm{real}(n) = \mathrm{opti}(n)$.

If the node n is terminal then the pessimistic and the optimistic values correspond to the score of the terminal position $\mathrm{pess}(n) = \mathrm{opti}(n) = \mathrm{score}(n)$. Initial bounds for internal nodes can either be set to the lowest and highest scores $\mathrm{pess}(n) = minscore$ and $\mathrm{opti}(n) = maxscore$, or to some values given by an appropriate admissible heuristic [12]. At a given time, the optimistic value of an internal node is the best possible outcome that *Max* can hope for, taking into account the information present in the tree and assuming rational play for both player. Conversely the pessimistic value of an internal node is the worst possible outcome that *Max* can fear, with the same hypothesis. Therefore it is sensible to update bounds of internal nodes in the following way.

If n is an internal max-node then	If n is an internal min-node then
$\mathrm{pess}(n) := \max_{s \in \mathrm{children}(n)} \mathrm{pess}(s)$	$\mathrm{pess}(n) := \min_{s \in \mathrm{children}(n)} \mathrm{pess}(s)$
$\mathrm{opti}(n) := \max_{s \in \mathrm{children}(n)} \mathrm{opti}(s)$	$\mathrm{opti}(n) := \min_{s \in \mathrm{children}(n)} \mathrm{opti}(s)$

3.2 Updating the tree

Knowledge about bounds appears at terminal nodes, for the pessimistic and optimistic values of a terminal node match its real value. This knowledge is then recursively upwards propagated as long as it adds information to some node. Using a fast incremental algorithm enables not to slow down the MCTS procedure.

Let s be a recently updated node whose parent is a max-node n. If $\mathrm{pess}(s)$ has just been increased, then we might want to increase $\mathrm{pess}(n)$ as well. It happens when the new pessimistic bound for s is greater than the pessimistic bound for n : $\mathrm{pess}(n) := \max(\mathrm{pess}(n), \mathrm{pess}(s))$. If $\mathrm{opti}(s)$ has just been decreased, then we might want to decrease $\mathrm{opti}(n)$ as well. It happens when the old optimistic bound for s was the greatest among the optimistic bounds of all children of n. $\mathrm{opti}(n) := \max_{s \in \mathrm{children}(n)} \mathrm{opti}(s)$. The converse update process takes place when s is the child of a min-node.

When n is not fully expanded, that is when some children of n have not been created yet, a dummy child d such that $\mathrm{pess}(d) = minscore$ and $\mathrm{opti}(d) = maxscore$ can be added to n to be able to compute conservative bounds for n despite bounds for some children being unavailable.

Algorithm 1 Pseudo-code for propagating pessimistic bounds

```
procedure prop-pess
arguments node $s$
if $s$ is not the root node then
    Let $n$ be the parent of $s$
    Let $old\_pess := \mathrm{pess}(n)$
    if $old\_pess < \mathrm{pess}(s)$ then
        if $n$ is a Max node then
            $\mathrm{pess}(n) := \mathrm{pess}(s)$
            prop-pess($n$)
        else
            $\mathrm{pess}(n) := \min_{s' \in \mathrm{children}(n)} \mathrm{pess}(s')$
            if $old\_pess > \mathrm{pess}(n)$ then
                prop-pess($n$)
            end if
        end if
    end if
end if
```

Algorithm 2 Pseudo-code for propagating optimistic bounds

```
procedure prop-opti
arguments node $s$
if $s$ is not the root node then
    Let $n$ be the parent of $s$
    Let $old\_opti := \mathrm{opti}(n)$
    if $old\_opti > \mathrm{opti}(s)$ then
        if $n$ is a Max node then
            $\mathrm{opti}(n) := \max_{s' \in \mathrm{children}(n)} \mathrm{opti}(s')$
            if $old\_opti > \mathrm{opti}(n)$ then
                prop-opti($n$)
            end if
        else
            $\mathrm{opti}(n) := \mathrm{opti}(s)$
            prop-opti($n$)
        end if
    end if
end if
```

3.3 Pruning nodes with alpha-beta style cuts

Once pessimistic and optimistic bounds are available, it is possible to prune subtrees using simple rules. Given a max-node (resp. min-node) n and a child s of n, the subtree starting at s can safely be pruned if $\mathrm{opti}(s) \leq \mathrm{pess}(n)$ (resp. $\mathrm{pess}(s) \geq opti(n)$).

To prove that the rules are safe, let's suppose n is an unsolved max-node and s is a child of n such that $\mathrm{opti}(s) \leq \mathrm{pess}(n)$. We want to prove it is not useful to explore the child s. On the one hand, n has at least one child left unpruned. That is, there is at least a child of n, s^+, such that $\mathrm{opti}(s') > \mathrm{pess}(n)$. This comes directly from the fact that as n is unsolved, $\mathrm{opti}(n) > \mathrm{pess}(n)$, or equivalently $\max_{s^+ \in \mathrm{children}(n)} \mathrm{opti}(s^+) > \mathrm{pess}(n)$. s^+ is not solved. On the other hand, let us show that there exists at least one other child of n better worth choosing than s. By definition of the pessimistic bound of n, there is at least a child of n, s', such that $\mathrm{pess}(s') = \mathrm{pess}(n)$. The optimistic outcome in s is smaller than the pessimistic outcome in s' : $\mathrm{real}(s) \leq \mathrm{opti}(s) \leq \mathrm{pess}(s') \leq \mathrm{real}(s')$. Now either $s \neq s'$ and s' can be explored instead of s with no loss, or $s = s'$ and s is solved and does not need to be explored any further, in the latter case s^+ could be explored instead of s.

An example of a cut node is given in Figure 1. In this figure, the *min-node* d has a solved child (f) with a 0.5 score, therefore the best *Max* can hope for this node is 0.5. Node a has also a solved child (c) that scores 0.5. This makes node d useless to explore since it cannot improve upon c.

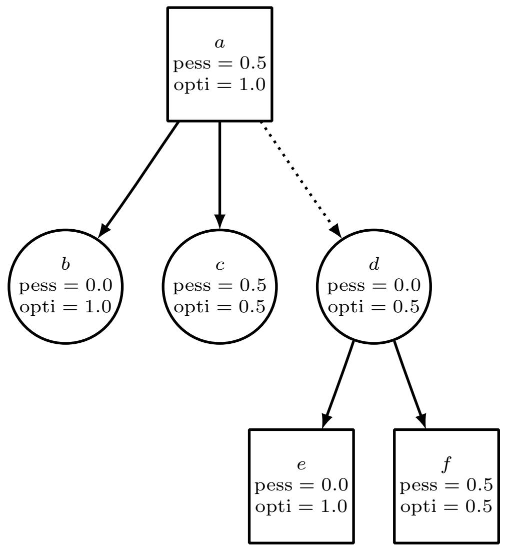

Fig. 1. Example of a cut. The d node is cut because its optimistic value is smaller or equal to the pessimistic value of its father.

3.4 Bounds based node value bias

The pessimistic and optimistic bounds of nodes can also be used to influence the choice among uncut children in a complementary heuristic manner. In a max-node n, the chosen node is the one maximizing a value function Q_{max}.

In the following example, we assume the outcomes to be reals from $[0, 1]$ and for sake of simplicity the Q function is assumed to be the mean of random playouts. Figure 2 shows an artificial tree with given bounds and given results of Monte-Carlo evaluations. The node a has two children b and c. Random simulations seem to indicate that the position corresponding to node c is less favorable to *Max* than the position corresponding to b. However the lower and upper bounds of the outcome in c and b seem to mitigate this estimation.

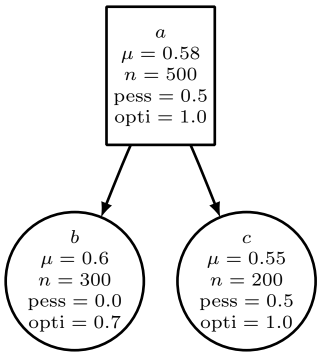

Fig. 2. Artificial tree in which the bounds could be useful to guide the selection.

This example intuitively shows that taking bounds into account could improve the node selection process. It is possible to add bound induced bias to the node values of a son s of n by setting two bias terms γ and δ, and rather using adapted Q' node values defined as $Q'_{max}(s) = Q_{max}(s) + \gamma\,\mathrm{pess}(s) + \delta\,\mathrm{opti}(s)$ and $Q'_{min}(s) = Q_{min}(s) - \gamma\,\mathrm{opti}(s) - \delta\,\mathrm{pess}(s)$.

4 Why Seki and Semeai are hard for MCTS

The figure 3 shows two Semeai. The first one is unsettled, the first player wins. In this position, random playouts give a probability of 0.5 for Black to win the Semeai if he plays the first move of the playout. However if Black plays perfectly he always wins the Semeai.

The second Semeai of figure 3 is won for Black even if White plays first. The probability for White to win the Semeai in a random game starting with a White move is 0.45. The true value with perfect play should be 0.0.

We have written a dynamic programming program to compute the exact probabilities of winning the Semeai for Black if he plays first. A probability p of playing in the

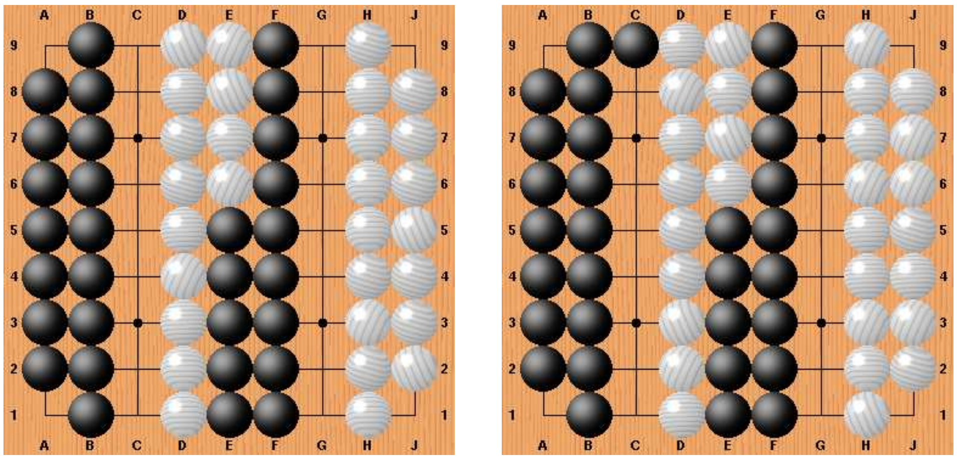

Fig. 3. An unsettled Semeai and Semeai lost for White.

Semeai is used to model what would happen on a 19x19 board where the Semeai is only a part of the board. In this case playing moves outside of the Semeai during the playout has to be modeled.

The table 1 gives the probabilities of winning the Semeai for Black if he plays first according to the number of liberties of Black (the rows) and the number of liberties of White (the column). The table was computed with the dynamic programming algorithm and with a probability $p = 0.0$ of playing outside the Semeai. We can now confirm, looking at row 9, column 9 that the probability for Black to win the first Semeai of figure 3 is 0.50.

Own liberties	Opponent liberties								
	1	2	3	4	5	6	7	8	9
1	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	1.00	0.50	0.30	0.20	0.14	0.11	0.08	0.07	0.05
3	1.00	0.70	0.50	0.37	0.29	0.23	0.18	0.15	0.13
4	1.00	0.80	0.63	0.50	0.40	0.33	0.28	0.24	0.20
5	1.00	0.86	0.71	0.60	0.50	0.42	0.36	0.31	0.27
6	1.00	0.89	0.77	0.67	0.58	0.50	0.44	0.38	0.34
7	1.00	0.92	0.82	0.72	0.64	0.56	0.50	0.45	0.40
8	1.00	0.93	0.85	0.76	0.69	0.62	0.55	0.50	0.45
9	1.00	0.95	0.87	0.80	0.73	0.66	0.60	0.55	0.50

Table 1. Proportion of wins for random play on the liberties when always playing in the Semeai

In this table, when the strings have six liberties or more, the values for lost positions are close to the values for won positions, so MCTS is not well guided by the mean of the playouts.

5 Experimental Results

In order to apply the score bounded MCTS algorithm, we have chosen games that can often finish as draws. Such two games are playing a Seki in the game of Go and Connect Four. The first subsection details the application to Seki, the second subsection is about Connect Four.

5.1 Seki problems

We have tested Monte-Carlo with bounds on Seki problems since there are three possible exact values for a Seki: Won, Lost or Draw. Monte-Carlo with bounds can only cut nodes when there are exact values, and if the values are only Won and Lost the nodes are directly cut without any need for bounds.

Solving Seki problems has been addressed in [16]. We use more simple and easy to define problems than in [16]. Our aim is to show that Monte-Carlo with bounds can improve on Monte-Carlo without bounds as used in [19].

We used Seki problems with liberties for the players ranging from one to six liberties. The number of shared liberties is always two. The *Max* player (usually Black) plays first. The figure 4 shows the problem that has three liberties for *Max* (Black), four liberties for *Min* (White) and two shared liberties. The other problems of the test suite are very similar except for the number of liberties of Black and White. The results of these Seki problems are given in table 2. We can see that when *Max* has the same number of liberties than *Min* or one liberty less, the result is Draw.

Min liberties	*Max* liberties					
	1	2	3	4	5	6
1	Draw	Won	Won	Won	Won	Won
2	Draw	Draw	Won	Won	Won	Won
3	Lost	Draw	Draw	Won	Won	Won
4	Lost	Lost	Draw	Draw	Won	Won
5	Lost	Lost	Lost	Draw	Draw	Won
6	Lost	Lost	Lost	Lost	Draw	Draw

Table 2. Results for Sekis with two shared liberties

The first algorithm we have tested is simply to use a solver that cuts nodes when a child is won for the color to play as in [19]. The search was limited to 1 000 000 playouts. Each problem is solved thirty times and the results in the tables are the average

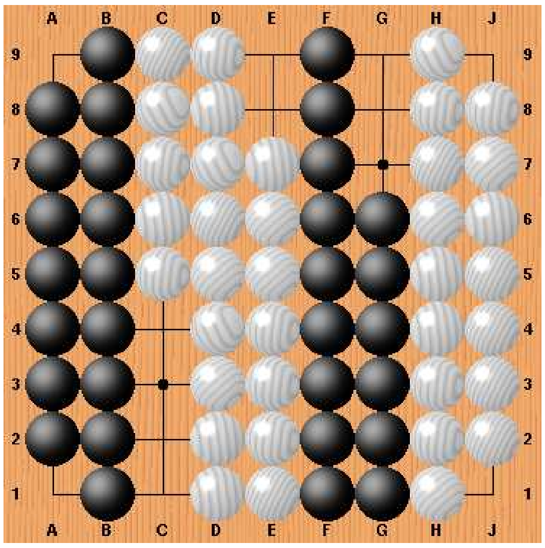

Fig. 4. A test seki with two shared liberties, three liberties for the *Max* player (Black) and four liberties for the *Min* player (White).

number of playouts required to solve a problem. An optimized Monte-Carlo tree search algorithm using the Rave heuristic is used. The results are given in table 3. The result corresponding to the problem of figure 4 is at row labeled *4 min lib* and at column labeled *3 max lib*, it is not solved in 1 000 000 playouts.

Min liberties	*Max* liberties					
	1	2	3	4	5	6
1	359	479	1535	2059	10 566	25 670
2	1389	11 047	12 627	68 718	98 155	28 9324
3	7219	60 755	541 065	283 782	516 514	79 1945
4	41 385	422 975	>1 000 000	>1 000 000	>989 407	>999 395
5	275 670	>1 000 000	>1 000 000	>1 000 000	>1 000 000	>1 000 000
6	>1 000 000	>1 000 000	>1 000 000	>1 000 000	>1 000 000	>1 000 000

Table 3. Number of playouts for solving Sekis with two shared liberties

The next algorithm uses bounds on score, node pruning and no bias on move selection (i.e. $\gamma = 0$ and $\delta = 0$). Its results are given in table 4. Table 4 shows that Monte-Carlo with bounds and node pruning works better than a Monte-Carlo solver without bounds.

Comparing table 4 to table 3 we can also observe that Monte-Carlo with bounds and node pruning is up to five time faster than a simple Monte-Carlo solver. The problem with three *Min* liberties and three *Max* liberties is solved in 107 353 playouts when it is solved in 541 065 playouts by a plain Monte-Carlo solver.

Min liberties	*Max* liberties					
	1	2	3	4	5	6
1	192	421	864	2000	4605	14521
2	786	3665	3427	17 902	40 364	116 749
3	4232	22 021	107 353	94 844	263 485	588 912
4	21 581	177 693	>964 871	>1 000 000	878 072	>1 000 000
5	125 793	>1 000 000	>1 000 000	>1 000 000	>1 000 000	>1 000 000
6	825 760	>1 000 000	>1 000 000	>1 000 000	>1 000 000	>1 000 000

Table 4. Number of playouts for solving Sekis with two shared liberties, bounds on score, node pruning, no bias

The third algorithm uses bounds on score, node pruning and biases move selection with $\delta = 10000$. The results are given in table 5. We can see in this table that the number of playouts is divided by up to ten. For example the problem with three *Max* lib and three *Min* lib is now solved in 9208 playouts (it was 107 353 playouts without biasing move selection and 541 065 playouts without bounds). We can see that eight more problems can be solved within the 1 000 000 playouts limit.

Min liberties	*Max* liberties					
	1	2	3	4	5	6
1	137	259	391	1135	2808	7164
2	501	1098	1525	3284	13 034	29 182
3	1026	5118	9208	19 523	31 584	141 440
4	2269	10 094	58 397	102 314	224 109	412 043
5	6907	27 947	127 588	737 774	>999 587	>1 000 000
6	16 461	85 542	372 366	>1 000 000	>1 000 000	>1 000 000

Table 5. Number of playouts for solving Sekis with two shared liberties, bounds on score, node pruning, biasing with $\gamma = 0$ and $\delta = 10000$

5.2 Connect Four

Connect Four was solved for the standard size 7x6 by L. V. Allis in 1988 [1]. We tested a plain MCTS Solver as described in [19] (plain), a score bounded MCTS with alpha-beta style cuts but no selection guidance that is with $\gamma = 0$ and $\delta = 0$ (cuts) and a score bounded MCTS with cuts and selection guidance with $\gamma = 0$ and $\delta = -0.1$ (guided cuts). We tried multiple values for γ and δ and we observed that the value of γ does not matter much and that the best value for δ was consistently $\delta = -0.1$. We solved various small sizes of Connect Four. We recorded the average over thirty runs of the number of playouts needed to solve each size. The results are given in table 6.

	Size			
	3×3	3×4	4×3	4×4
plain MCTS Solver	2700.9	26 042.7	227 617.6	>5 000 000
MCTS Solver with cuts	2529.2	12 496.7	31 772.9	386 324.3
MCTS Solver with guided cuts	1607.1	9792.7	24 340.2	351 320.3

Table 6. Comparison of solvers for various sizes of Connect Four

Concerning 7x6 Connect Four we did a 200 games match between a Monte-Carlo with alpha-beta style cuts on bounds and a Monte-Carlo without it. Each program played 10 000 playouts before choosing each move. The result was that the program with cuts scored 114.5 out of 200 against the program without cuts (a win scores 1, a draw scores 0.5 and a loss scores 0).

6 Conclusion and Future Works

We have presented an algorithm that takes into account bounds on the possible values of a node to select nodes to explore in a MCTS solver. For games that have more than two outcomes, the algorithm improves significantly on a MCTS solver that does not use bounds.

In our solver we avoided solved nodes during the descent of the MCTS tree. As [19] points out, it may be problematic for a heuristic program to avoid solved nodes as it can lead MCTS to overestimate a node.

It could be interesting to make γ and δ vary with the number of playout of a node as in RAVE. We may also investigate alternative ways to let score bounds influence the child selection process, possibly taking into account the bounds of the father.

We currently backpropagate the real score of a playout, it could be interesting to adjust the propagated score to keep it consistent with the bounds of each node during the backpropagation.

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