Information Sharing in MCTS

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Outline

1 Information Sharing

2 Current Concepts

3 Inspiration for the Future

Big Ideas

- Computer Go work: **Big Ideas** and **Essential Details**
- Natural tendency: Use big ideas of others and focus on essential details
- Essential details: Reach or somewhat surpass current state-of-art level
  Immediate reward
- Big ideas: Large leap in possibilities
  1% success rate (optimistic)

Big Ideas

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- Natural tendency: Use big ideas of others and focus on essential details
- Essential details: Reach or somewhat surpass current state-of-art level
  Immediate reward
- Big ideas: Large leap in possibilities
  1% success rate (optimistic)
- Still, please think of big ideas and work on them!
  - They are your new contributions to human understanding
  - You will be famous and your program will get very strong :-)

Information Sharing

- Common ways to improve a Computer Go program: Go knowledge, opening books, machine learning improvements, . . .
- Today's big idea: **Information sharing**

- By default, MCTS spends a lot of CPU resources on a simulation and then uses only a single number — result of the simulation!
- By default, MCTS does not share any data between branches of the tree, even though many areas of the board can be mostly independent
- Let's fix that!

- Information flow: From simulations to tree, from tree to simulations, between tree branches, between simulations

Framework: Monte Carlo Tree Search

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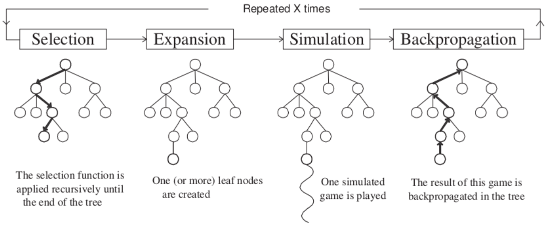
- Only root at the beginning, and we repeat:
  - Descending to the leaf, sons chosen by Multi-armed Bandit
  - If we visit a leaf *n* times, we create son nodes
  - In the leaf, we start a Monte Carlo simulation
  - The result is propagated back through the path to the root


Repeated X times
Selection
Expansion
Simulation
Backpropagation
The selection function is applied recursively until the end of the tree
One (or more) leaf nodes are created
One simulated game is played
The result of this game is backpropagated in the tree

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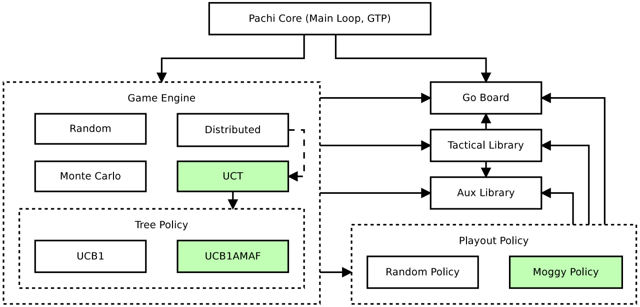
- The tree grows dynamically based on search direction
- RAVE Multi-armed Bandit: We search moves that worked well in simulations

Framework: Pachi Software

- Computer Go player
- Standard MCTS: RAVE algorithm and a set of heuristics
- Modular, fairly small; optimized C, open source



Framework: Pachi Software

- Computer Go player
- Standard MCTS: RAVE algorithm and a set of heuristics
- Modular, fairly small; optimized C, open source
- Play-testing infrastructure “autotest”
- Pattern harvesting infrastructure

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RAVE

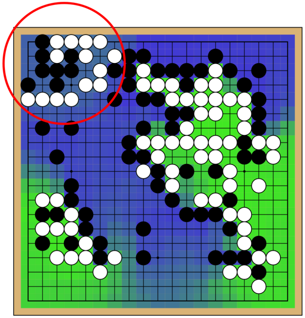
- Most strong programs are using it (except **Nomitan**!)
- Keystone of modern Computer Go, major method of information sharing; modern programs use it aggressively (even completely replacing UCT)
- Key questions of information sharing: *What information* to share, *the scope where* we share it, *how to use it?*
- **What information:** “All moves as first”
- **The scope:** Aggregating statistics by “common prefix” in the tree
- **How to use it:** The RAVE formula

$$\beta = \frac{sims_{RAVE}}{sims_{RAVE} + sims + sims_{RAVE}\, sims / sims_{EQUIV}}$$

$$\mu^{RAVE} = \beta \frac{wins_{RAVE}}{sims_{RAVE}} + (1-\beta)\frac{wins}{sims} \qquad \pi_{RAVE} = \mathrm{argmax}_i\, \mu_i^{RAVE}$$

Criticality

- First presented by Rémi Coulom at UEC 2009
- Some areas are essential for winning and unsettled!
- We should “somehow detect” and “somehow use” this to focus the search better



Criticality

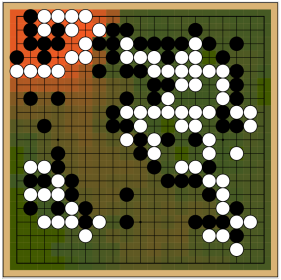
Point Criticality: Covariance of random variables “owning an intersection” and “winning a game”

$$Cov(Owning, Winning) = \mathbb{E}Owning \cdot Winning - $$
$$-\mathbb{E}Owning \cdot \mathbb{E}Winning$$

$$C_{\mathrm{Coulom}}(x) = \mu_{win(x)} - (\mu_{b(x)}\mu_{\mathrm{b}} + \mu_{w(x)}\mu_{\mathrm{w}})$$

$$C_{\mathrm{Pell.}}(x) = \mu_{\mathrm{b},b(x)}\mu_{\mathrm{w},w(x)} - \mu_{\mathrm{w},b(x)}\mu_{\mathrm{b},w(x)}$$

$$C_{\mathrm{Pachi}}(x) = \mu_{win(x)} - (2\mu_{b(x)}\mu_{\mathrm{b}} - \mu_{b(x)} - \mu_{\mathrm{b}} + 1)$$



Criticality

- We have a *number* ($C \in [-1, 1]$)
- Scope: Global table or common prefix like RAVE
- Usage: This makes the real difference
- CrazyStone: Progressive widening criterion, pattern feature
- Orego: $\mu_{Crit} = \mu_{UCT} + 2C$ (RAVE replacement!)
- Pachi: Proportionally adding RAVE wins or losses

$$sims_{Crit} = |C_{\mathrm{Pachi}}(x)| \cdot sims_{AMAF}$$

$$wins_{Crit} = \begin{cases} C_{\mathrm{Pachi}}(x) > 0 & sims_{Crit} \\ C_{\mathrm{Pachi}}(x) < 0 & 0 \end{cases}$$

$$sims_{RAVE} = sims_{AMAF} + sims_{Crit}$$

$$wins_{RAVE} = wins_{AMAF} + wins_{Crit}$$

Last Good Reply

- Let's make the simulations adaptive! (Drake et al., Henrik Baier)
- Maintain function $LGR_n \colon a_1, \ldots, a_n \rightarrow a^*$ that stores whether a move a^* preceded by a sequence of other moves
- Usage: If our context matches an entry in LGR_n, play the stored move! $n = 2$ is common
- Forgetting: We remove a^* if we lost the simulation
- Very nice thesis of Henrik Baier explores also (bad) performance of scoping and variations

Other

- Dynamic komi — add/substract extra virtual komi based on average result of previous simulations
- Monte Carlo point owner — simpler alternative or complement to criticality
- Some others that I have probably forgot

- The first method for information sharing you implement has by far the largest impact
- RAVE is the popular first choice, but it seems RAVE might not be so essential!

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Local Trees

- Motivation: Let's combat the horizon effect!
- Idea: Aggregate *local sequences* from various branches of the Monte Carlo tree
- (L_B, L_W) pair of "local trees" storing black-first (or white-first, respectively) local sequences
- Sequences are aggregatd from all branches of the main tree
- Sequences are paused when tenuki happens in the main tree

- Ideally, if we e.g. misevaluate some corner in simulations, and keep pushing out the correct solution from the main tree, we will still learn the correct solution sequence in the local tree

Local Trees

- Big problem (as usual): How to *use* this information?
- Simple approach: Bias main tree search based on local sequences
- Experience: Difficult to overcome bias from simulations flowing in by RAVE
- How to bias the simulations based on local tree information? Not so clear!
- **Forcing:** Play out *n* sequences from local tree (chosen by UCT) just before a simulation begins
- Negligible improvement (for now?)

Liberty Maps

- Biasing simulations based on previous experience: Alternatives to local trees? (together with Kroon and van Niekerk)
- **Liberty maps:** A way to aggregate information on moves regarding a group *in the same situation*
- **Liberty map of group** G**:** Zobrist hash of G's liberties, taking *their* liberties into account (rotating the hash)
- $\Rightarrow$ Liberty map is a hash number (index in hash table)
- Information stored: Track success of tactical heuristics candidate moves
- Usage: Prefer moves with better success rates — either over threshold or UCB (sort of local UCT-ish transposition table arises!)
- Only small improvement (for now?)

Goal-based Search

- Generalizing liberty maps: tracking success of moves to achieve goals
- Goal (high-level): Killing or surviving with a given group
- Goal (low-level): Coloring an intersection with a given color *(what about eyes?)*
- Fill goal-achieving moves from simulation heuristics and "touching moves" anywhere in the tree
- Possible optimization: Consider only groups present in the tree as possible goals
- Opportunities for sharing results of one-time static analysis
- Usage: Heuristic choice preference, maybe also explicitly try to achieve goals in simulations?

Conclusion

- Information sharing allows us to mine maximum amount of information from simulations — best return for CPU time invested
- Our simulations could learn from past mistakes (or good choices) and eventually solve even unexpected situations
- Maybe we can approach pro strength by better ways to share information (but *essential details* are still essential, I'm sorry)
- Try out your big ideas with Pachi! ;-)

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Thanks!