The Monte-Carlo Revolution in Go

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Game Complexity

Game	Complexity*	Status
Tic-tac-toe	10^3	Solved manually
Connect 4	10^{14}	Solved in 1988
Checkers	10^{20}	Solved in 2007
Chess	10^{50}	Programs $>$ best humans
Go	10^{171}	Programs $\ll$ best humans

*Complexity: number of board configurations

How can we deal with complexity ?

Some formal methods

- Use symmetries
- Use transpositions
- Combinatorial game theory

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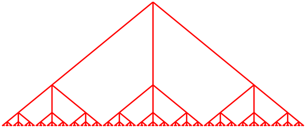
When formal methods fail

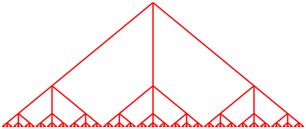
- Approximate evaluation
- Reasoning with uncertainty

Dealing with Huge Trees



Full tree

Dealing with Huge Trees



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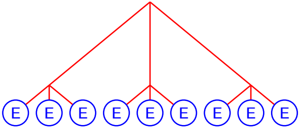

Classical approach =
depth limit + pos. evaluation (E)
(chess, shogi, . . .)

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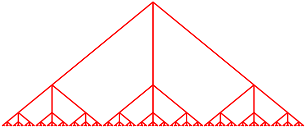

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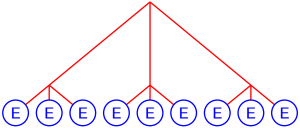

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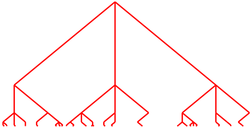
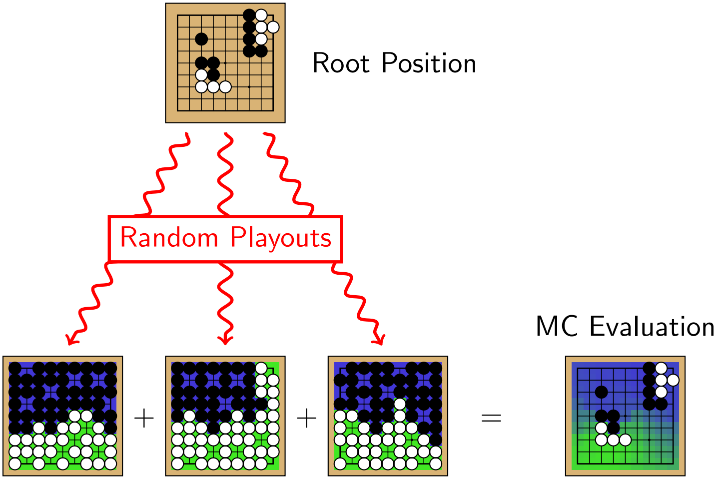


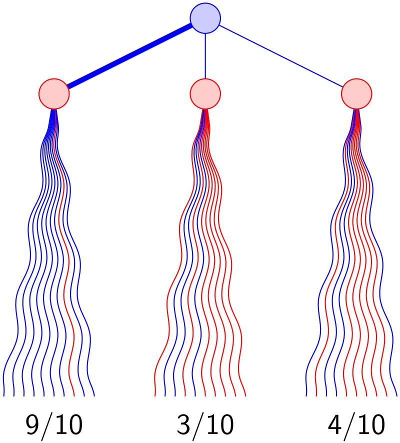
Monte-Carlo approach =
random playouts

A Random Playout

Principle of Monte-Carlo Evaluation



Basic Monte-Carlo Move Selection



Algorithm

- N playouts for every move
- Pick the best winning rate
- 5,000 playouts/s on 19x19

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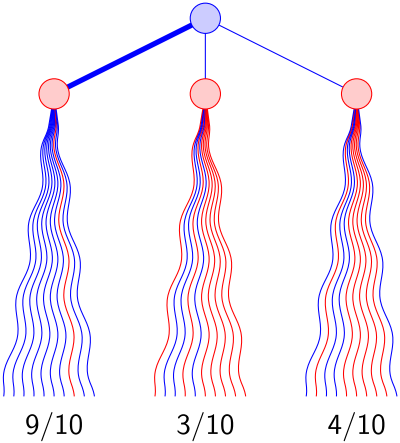

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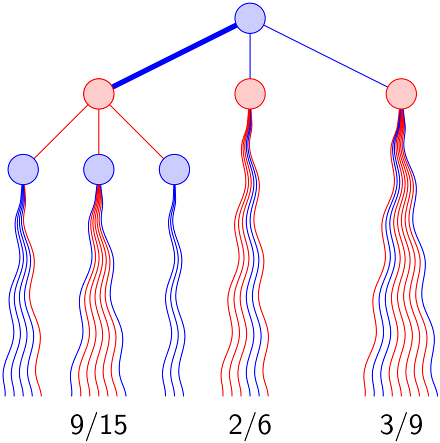
Problems

- Evaluation may be wrong
- For instance, if all moves lose immediately, except one that wins immediately.

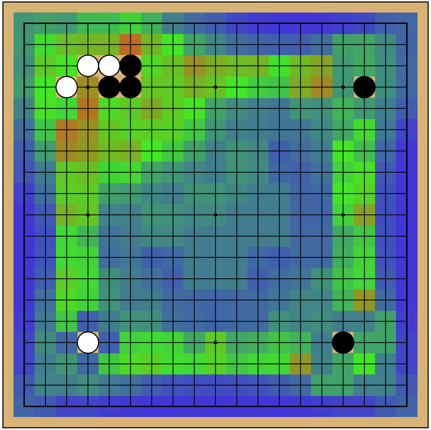
Monte-Carlo Tree Search



Principle

- More playouts to best moves
- Apply recursively
- Under some simple conditions: proven convergence to optimal move when #playouts$\rightarrow \infty$

Incorporating Domain Knowledge with Patterns

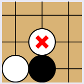


◯ to move

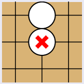
Patterns

- Library of local shapes
- Automatically generated
- Used for playouts
- Cut branches in the tree

Examples (out of ~30k)



Good



Bad

History (1/2)

Pioneers

- 1993: Brügmann: first MC program, not taken seriously
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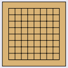
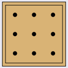
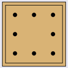
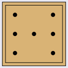
Victories against classical programs

- 2006: Crazy Stone (Coulom) wins 9×9 Computer Olympiad
- 2007: MoGo (Wang, Gelly, Munos, ...) wins 19×19

History (2/2)

Victories against professional players

- 2008-03:  MoGo beats Catalin Taranu (5p) on 9×9
- 2008-08:  MoGo beats Kim Myungwan (9p) at H9
- 2008-09:  Crazy Stone beats Kaori Aoba (4p) at H8
- 2008-12:  Crazy Stone beats Kaori Aoba (4p) at H7

Conclusion

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- A major breakthrough for computer Go
- Works similar games (Hex, Amazons) and automated planning

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- Path to top-level human Go ?
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More information: `http://remi.coulom.free.fr/CrazyStone/`

- Slides, papers, and game records
- Demo version of Crazy Stone (soon)