# Exploration and Exploitation in Go: UCT for Monte-Carlo Go

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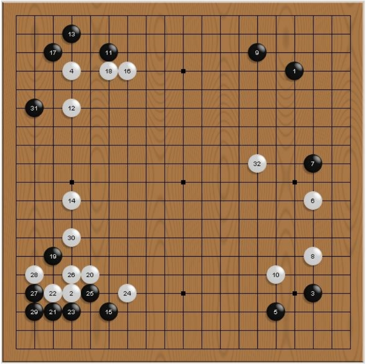
A quick introduction to game of Go

# A Quick introduction to Go game



- Go-board (Goban): $19 \times 19$ intersections;
- Back and White play alternatively. Black starts the game;
- Adjacent stones are called a *string*. *Liberties* are the empty intersections next to the string;
- Stones do not move, there are onyl added and removed from the board. A string is removed iif its number of liberties is 0;
- Score: territories (number of occupied or surrounded intersections).

- Beginning of Computer-Go, 1970s
- Classical methods
    - Expert knowledge based evaluation function;
    - Minimax tree search;
- Comparison with chess
    - Chess: Deeper Blue won against Kasparov, 1997;
    - Go: The strongest programs are about 10kyu in 2006 (amateurs of good level can win with 9 stones handicap)

## Difficulties in computer-Go

- Huge branching factor ≈ 200, chess ≈ 40
  (John Tromp and Gunnar Farnebäck, 2006)
  Legal positions number
  $2.0 \times 10^{170}$ on $19 \times 19$, $1.0 \times 10^{38}$ on $9 \times 9$
- Good evaluation function difficult to build (Stern et al. 2004, Wu L. and P. Baldi 2006). Must take into account local, and global information

# MoGo player

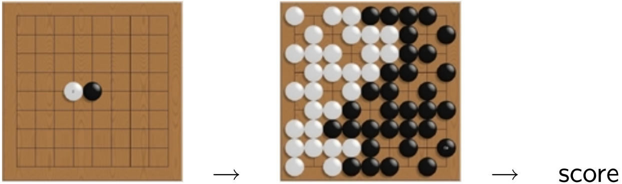
**Two components**

- random filling of Go-board evaluation function;
- bandit based tree search.

## Monte-Carlo evaluation function

(B. Bruegmann, 1993)

- Let *p* the position to evaluate;
- let $\pi$ a (stochastic) player;
- from *p*, $\pi$ plays against itself until the end of the game;
- the final score is then allocated to *p*;
- possibly iterate and average.



$\longrightarrow$ $\longrightarrow$ score

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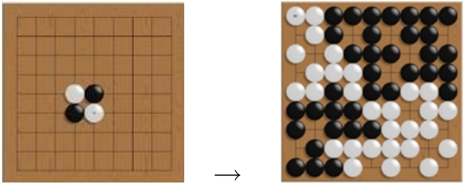


→ → score

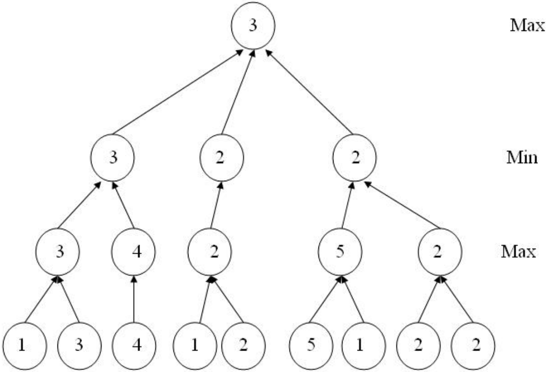
# Tree based search: Outline

- Exploration-Exploitation: from alpha-beta to UCT
- Extensions to UCT
- Algorithmic issues

# Tree based search

### Minimax

We want to approximate the min-max value of the position.
Not necessarily the best strategy: we could try to model the opponent.



## Alpha-Beta algorithm

Alpha-Beta computes the minimax value in a tree (exact given an evaluation function).

# UCT algorithm

## Game as a multi-armed bandit

- each position is a bandit;
- each move is an arm;
- play the best move ⟷ maximize the reward.

## UCT in Go

MoGo was the first Go program to use UCT (July 2006).

# UCB and UCT algorithms

## UCB algorithm (P. Auer et al.) 2002

- let $\hat{X}_i$ the empirical average rewards for *ith* arm;
- let $T_i$ the number of trials for arm $i$;
- let $T = \sum_i T_i$

Then iteratively:

- if one arm has not been played, play it;
- else, play the arm maximizing $\hat{X}_i + \sqrt{2\frac{\log T}{T_i}}$.

# UCB and UCT algorithms

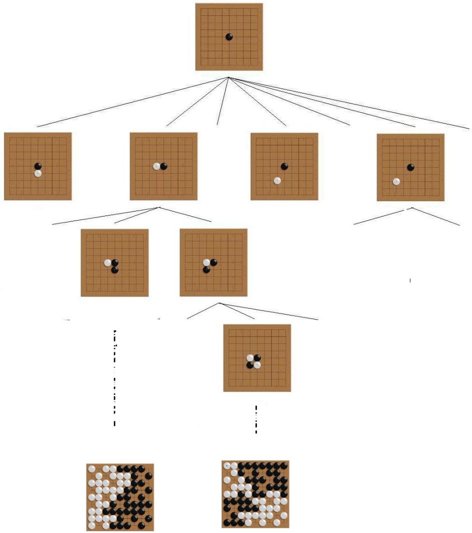
**UCT algorithm (L. Kocsis and C. Szepesvari. 2006)**

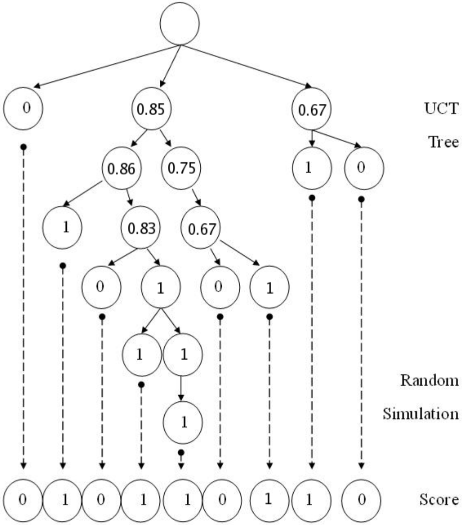
- start from the root;
- until stopping criterion (e.g. the end of the game):
  - choose a move according to UCB;
  - update the position.
- score the game;
- update all visited nodes with this score (without discount).

# Efficient memory management

Tree management after CrazyStone (R. Coulom 2006).

- Stop as soon as UCT gets an unseen position;
- add this node to the tree;
- evaluate the position.




0
0.85
0.67
UCT
Tree
0.86
0.75
1
0
1
0.83
0.67
0
1
0
1
1
1
1
Random
Simulation
0
1
0
1
1
0
1
1
0
Score

## Value of a position/move

$$value(move) = value(position_t + move)$$
$$value(position) = \frac{1}{T}\sum_i T_i value(move_i)$$
$$value(position) \rightarrow value(bestMove)$$

## Why it is efficient compared to alpha-beta?

- Alpha-Beta never reconsider a cut; dangerous with random non accurate evaluation function;
- value(node) → max(node) as confidence increases.
- efficient tree exploiration
    - breadth first search;
    - move ordering efficiently managed;
    - asymmetric growing;
- anytime.

# Improvements

## Specific extensions required

- from asymptotic quality to efficient move selection;
- $\#$ trials $<$ $\#$ moves;
- arms are not independent.

# Improvements in UCT when # trials ≈ nb arms

## First Play Urgency

Starting with playing all arms is not optimal; Let $c$ a default constant. Let $X_i{}'$ such that

- $X_i{}' = \hat{X}_i + \sqrt{2\frac{\log T}{T_i}}$ if $T_i > 0$;
- $X_i{}' = c$ if $T_i = 0$;

Choose the highest $X_i{}'$.
Empirically $c \approx 1 \rightarrow +50$ ELO.

# Exploiting dependencies

## Share information between arms

There is no independence between arms vertically and horizontally. The goal is to improve the performance when $T$ is small.

- Average results from neihbor moves (add a term $\frac{1}{|\mathcal{N}_i|} \sum_{j \in \mathcal{N}_i} \hat{X}_j$);
- use results from ancestors: set a $c_i$ for each move according to $\hat{X}_i$ of its grandfather.

## MoGo Curriculum Vitae

- **July 2006**: first participation in tournaments: 1650 ELO on CGOS (Computer Go Server) (9x9);
- **Aug. 2006 (beg.)**: ranked best program on CGOS: 1920 ELO;
- **Aug. 2006 (end)**: MoGo reached 2000 ELO;
- **Oct. 2006**: MoGo won the 2 KGS tournaments (9x9 and 13x13);
- **Nov. 2006**: MoGo won the 2 KGS tournaments (9x9 and 13x13);
- **Nov. 2006**: MoGo reached 2200 ELO on CGOS;
- **Dec. 2006**: MoGo 2nd on KGS formal tournament (19x19).

# Conclusion & Perspectives

## Conclusion

- MoGo first Go program using UCT
- Specific adaptation of UCT improving non asymptotic behavior
- Algorithm issues: parallelization of UCT (12000 nodes/second, 400000 nodes/move)

## Perspectives

- Shifting towards exploitation for 19 × 19 Go boards
- Exploiting arm dependencies
- Using a mixture of evaluation functions

## Thank you

- Come to see the poster
- play against MoGo on KGS