Machine Learning applied to Go

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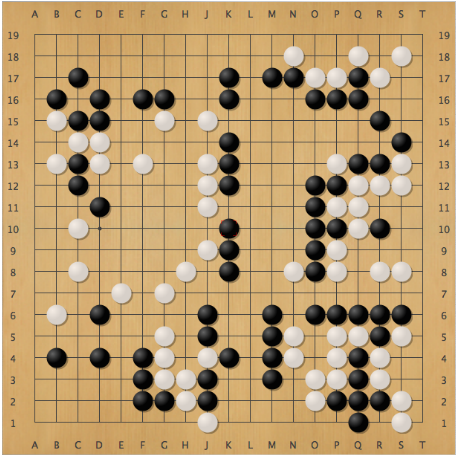
What is Go?



- Two-player deterministic board game
- Originated in ancient China. Today very popular in China, Japan and Korea
- 19x19 grid, also 9x9 grid for beginners
- Simple rules, but very complex strategy

Why study Go?

- *If there are sentient beings on other planets, then they play Go*
  – Emanuel Lasker, former chess world champion
- *Go is one of the grand challenges of AI*
  – Ron Rivest, professor of Computer Science at MIT
- *Go is like life and life is like Go*
  - Chinese proverb

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Monte Carlo

- Often used for problems that have no closed solution, e.g. computational physics
- Sample instances from some large population
- Use samples to approximate some common property of the population
- In search, select the next state based on some fixed distribution (usually uniform)
- Recently, have been very successful in Go, causing a mini-revolution

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K-armed bandit problem

- Slot machine with K arms. Each arm provides a reward based on some unknown, but fixed distribution
- Goal: to choose arms to play such that the total reward is maximized
- How should the gambler play at any given moment?
  - Choose arm with highest average reward seen so far (exploitation)
  - Choose a sub-optimal arm in the hope that it will lead to a greater reward (exploration)
  - Neither - need a combination of exploitation and exploration

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Upper Confidence Bounds

- Successive plays of arm i give rewards $X_{i,1}, X_{i,2}, \ldots$ which are i.i.d. with unknown $\mathbb{E}(X_i) = \mu_i$
- Let $T_i(n)$ be the number of times arm i has been played during the first n plays of machine
- Upper Confidence Bounds - UCB (Auer et al. 2002)
  - Initialization: Play each arm once
  - Loop: Play arm i that maximizes $\mu_i + \sqrt{\frac{2\log n}{T_i(n)}}$
- Proven to achieve optimal regret

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- UCB for minimax tree search (Kocsis and Szepesvari 2006)
- Start at the current board position p
- For i = 1 to 100,000 (number of simulations)
  - $p' \leftarrow p$
    until stopping criterion is reached (e.g. end of game)

    Evaluate leaf: value $\leftarrow$ winner of p'
    Update all the visited nodes with value
- At p play move with highest winning percentage

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MoGo

- First Go program to use UCT (Gelly et. al 2006)
- Store nodes and their statistics in a tree data structure
- Stopping criterion is a node that is not yet in the tree
- Leaf node evaluation:
- Pruning techniques, smart ordering of unexplored moves

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MoGo's success

- Ranked first on 9x9 Computer Go Server since August 2006
- Won two most recent tournaments on 9x9 and 13x13
- Expected to reach the level of human professional on 9x9 board

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Replacing UCB

- UCT is ad-hoc. Lack of theoretical analysis, because random variables (rewards X_i) are not i.i.d.
- Instead, use Beta distributions to model random variables
- Beta distribution is a conjugate prior to binomial distribution (game result)
- Here $\alpha =$ wins from node, $\beta =$ losses from node
- Let p be parent's winning percentage and $0 < a < 1$ parameter
- Pick a move that is most likely to have a winning percentage greater than $(1 - a)p + a$

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Improving node evaluation

- MoGo's node evaluation is fast, but not so meaningful
- Instead, use our cooperative scorer:
  - Initialization: Statically fill neutral territory with stones
  - Loop: players cooperate to make moves that do not affect the score
- Accurately predicts score: 96.3% on 9x9 and 89.2% on 19x19
- Only 15 times slower than pure random

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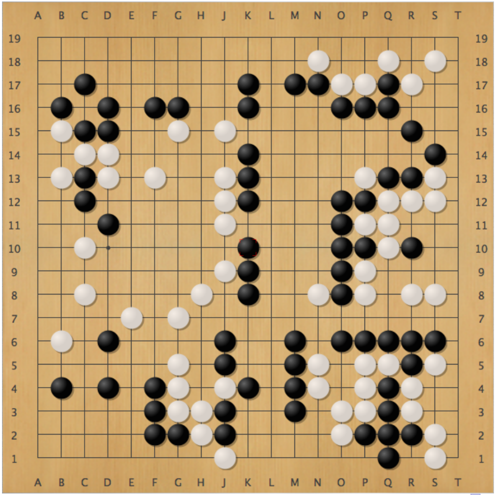

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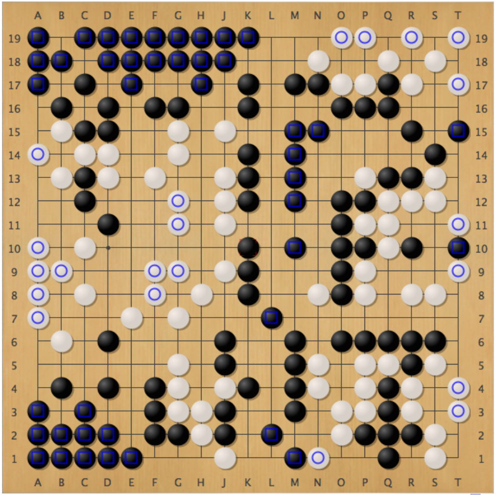

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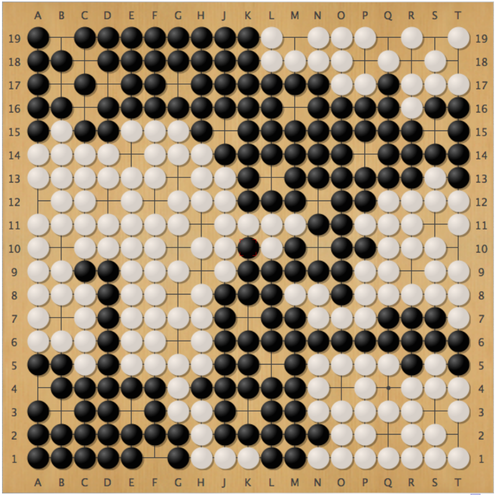

Improving memory management

- Tree data structure is memory-inefficient
- Instead, use a hash table:
    - For each visited position p, key = ZobristHash(p)
    - Store statistics of p: hashTable[key] = (#wins, #runs, depth)
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- Use a small hash table with more information for frequently visited nodes

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Learning evaluation function

- Convert the board position into a graph:
  - Collapse regions of the same colour into one node
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- Use Condition Random Fields (CRF) to learn from this graph:
- Can use this with the scorer or for move generation

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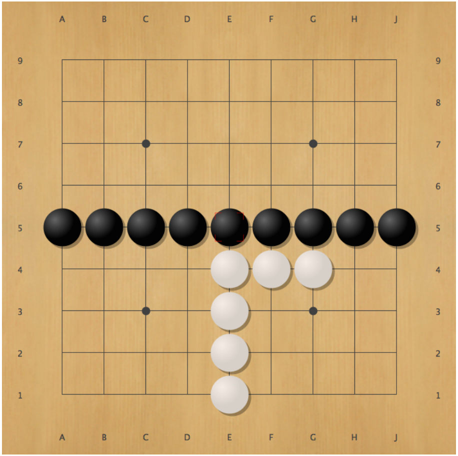

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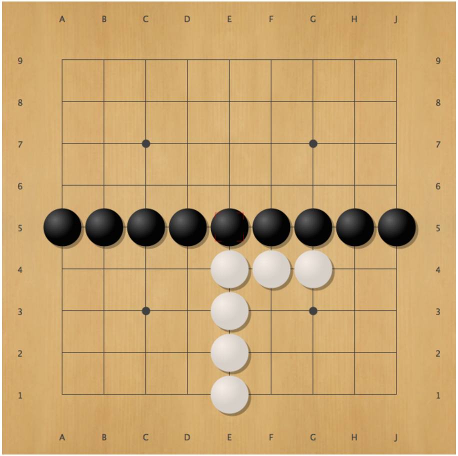

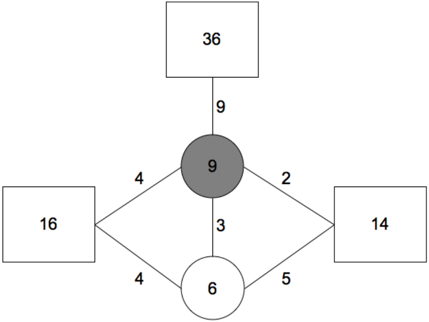

Questions?

- You never ever know if you never ever GO!