Computer Go: from the Beginnings to AlphaGo

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2017

Outline of the Talk

- Game of Go
- Short history - Computer Go from the beginnings to AlphaGo
- The science behind AlphaGo
- The legacy of AlphaGo

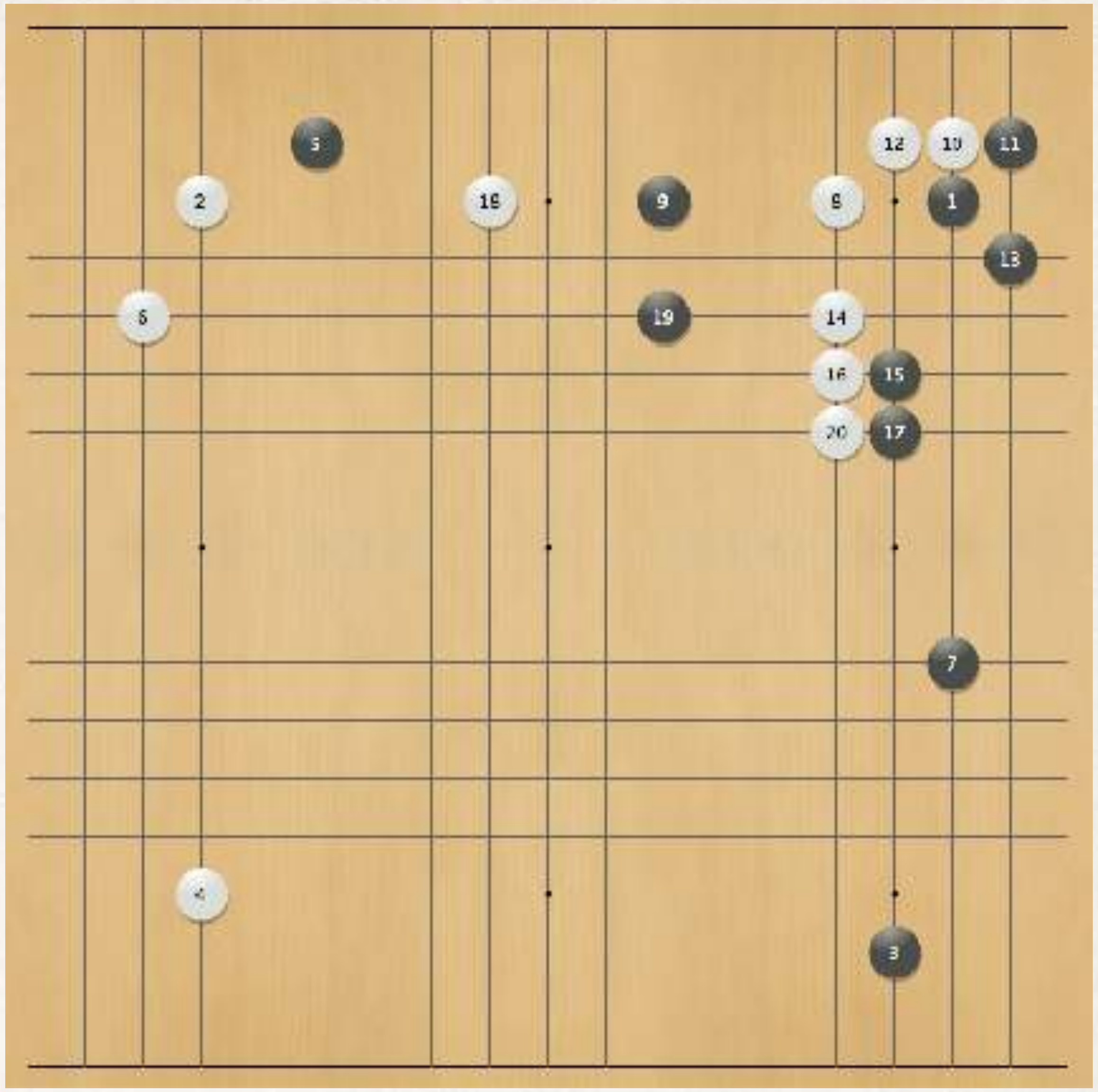
The Game of Go

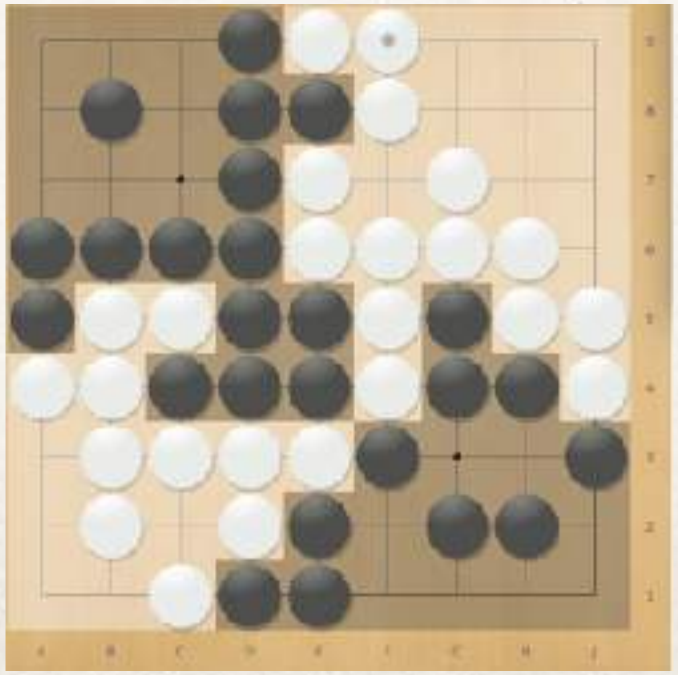
Go

- Classic two-player board game
- Invented in China thousands of years ago
- Simple rules, complex strategy
- Played by millions
- Hundreds of top experts - professional players
- Until 2016, computers weaker than humans

Go Rules

- Start with empty board
- Place stone of your own color
- Goal: surround empty points or opponent - capture
- Win: control more than half the board
- Komi: first player advantage





Final score, 9x9 board

Measuring Go Strength

- People in Europe and America use the traditional Japanese ranking system
- Kyu (student) and Dan (master) levels
  - Separate Dan ranks for professional players
- Kyu grades go down from 30 (absolute beginner) to 1 (best)
- Dan grades go up from 1 (weakest) to about 6
- There is also a numerical (Elo) system, e.g. 2500 = 5 Dan

Short History of Computer Go

Computer Go History - Beginnings

- 1960’s: initial ideas, designs on paper
- 1970’s: first serious program - Reitman & Wilcox
    - Interviews with strong human players
    - Try to build a model of human decision-making
    - Level: “advanced beginner”, 15-20 kyu
    - One game costs thousands of dollars in computer time

1980-89 The Arrival of PC

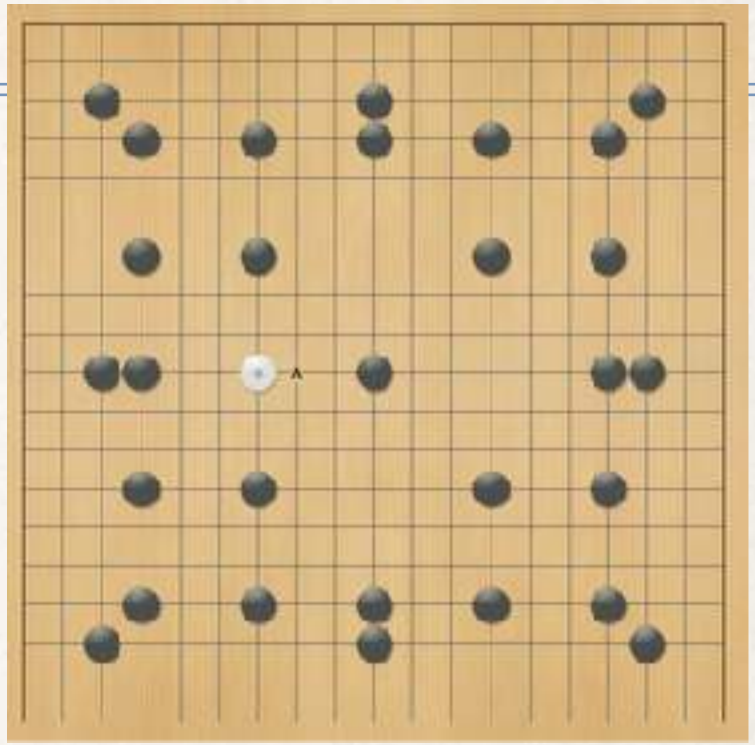
- From 1980: PC (personal computers) arrive
- Many people get cheap access to computers
- Many start writing Go programs
- First competitions, Computer Olympiad, Ing Cup
- Level 10-15 kyu

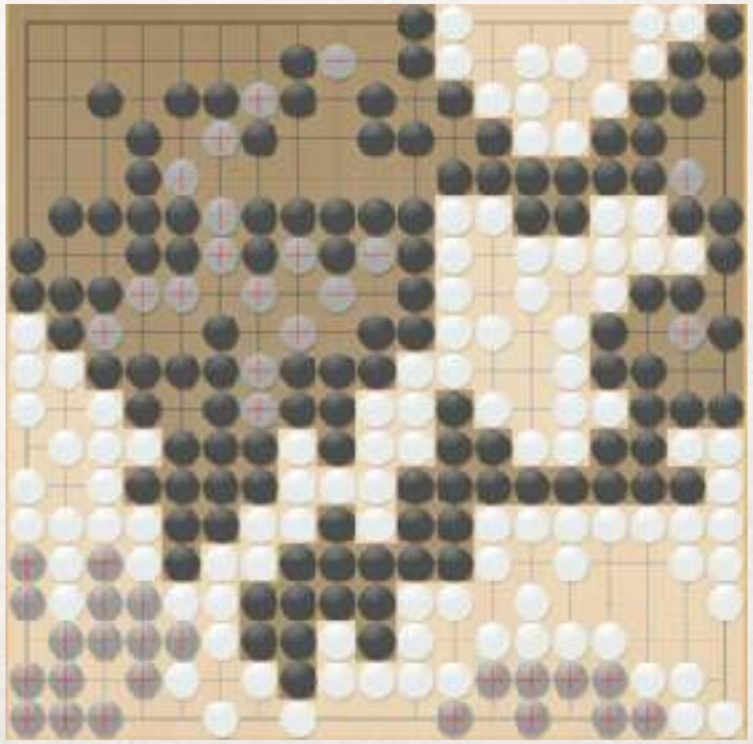
1990-2005: Slow Progress

- Slow progress, commercial successes
- 1990 Ing Cup in Beijing
- 1993 Ing Cup in Chengdu
- Top programs Handtalk (Prof. Chen Zhixing), Goliath (Mark Boon), Go++ (Michael Reiss), Many Faces of Go (David Fotland)
- GNU Go - open source program, almost equal to top commercial programs
- Level - maybe 5 Kyu, but some “blind spots”

1998 - 29 Stone Handicap Game

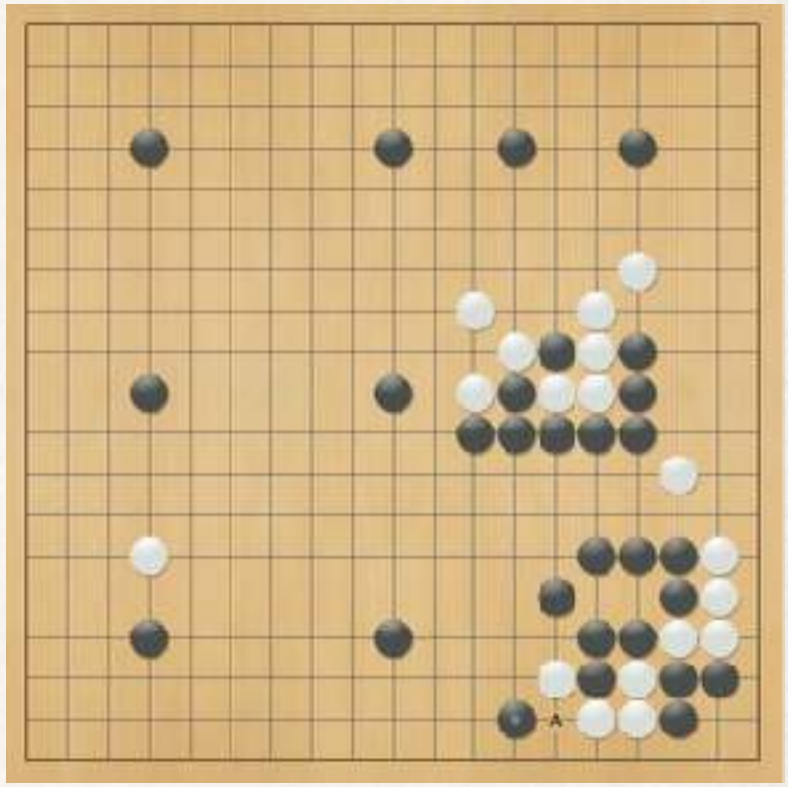
- Played at US Go Congress
- Black: Many Faces of Go, world champion and one of the top Go programs at the time
- White: Martin Müller, 5 Dan amateur
- Result: White won by 6 points





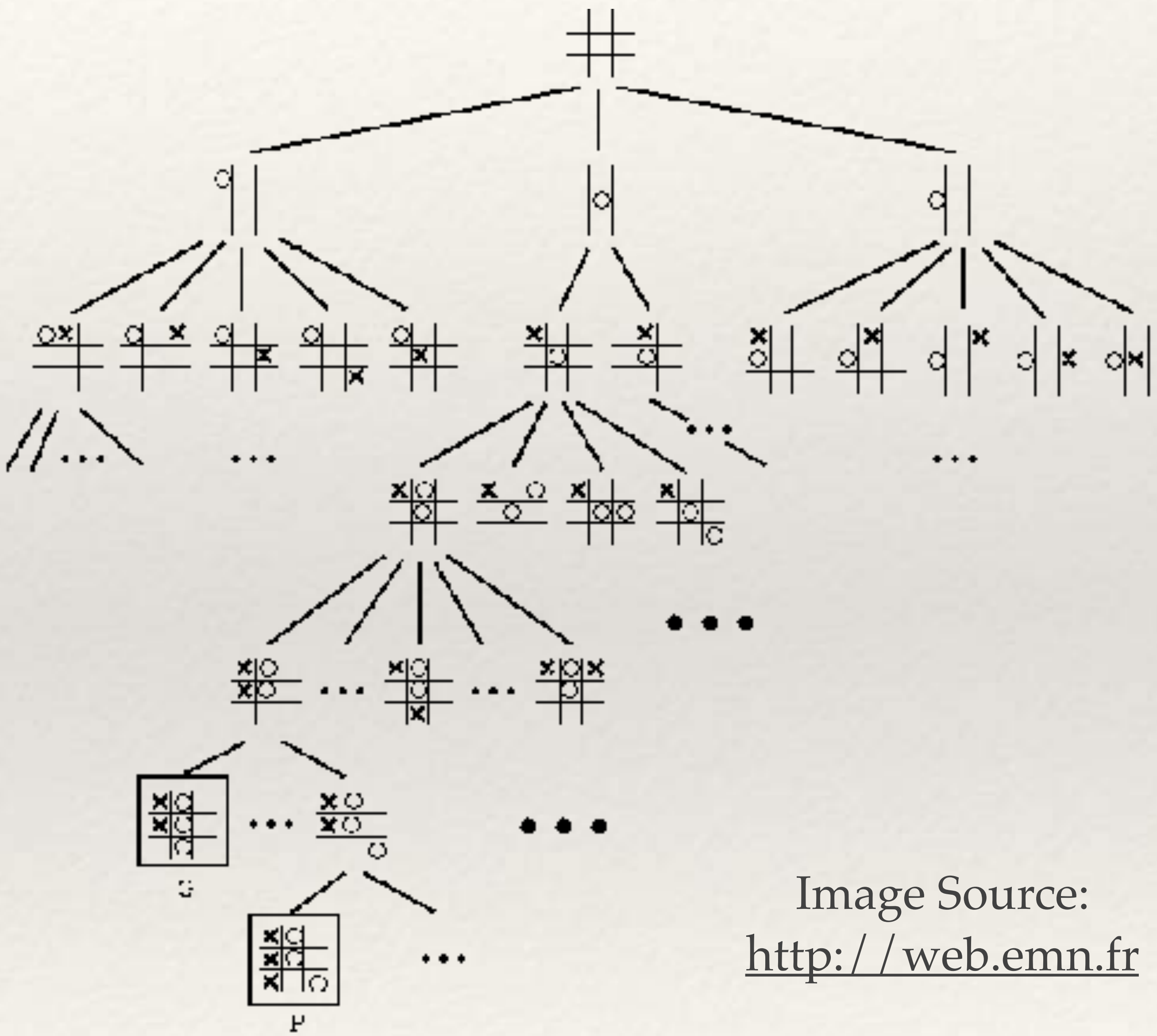
2006-08 Monte Carlo Revolution

- Remi Coulom, Crazy Stone program: Monte Carlo Tree Search (MCTS)
- Levente Kocsis and Csaba Szepesvari: UCT algorithm
- Sylvain Gelly, Olivier Teytaud et al: MoGo program
- Level: about 1 Dan



Search - Game Tree Search

- All possible move sequences
- Combined in a tree structure
- Root is the current game position
- Leaf node is end of game
- Search used to find good move sequences
- Minimax principle



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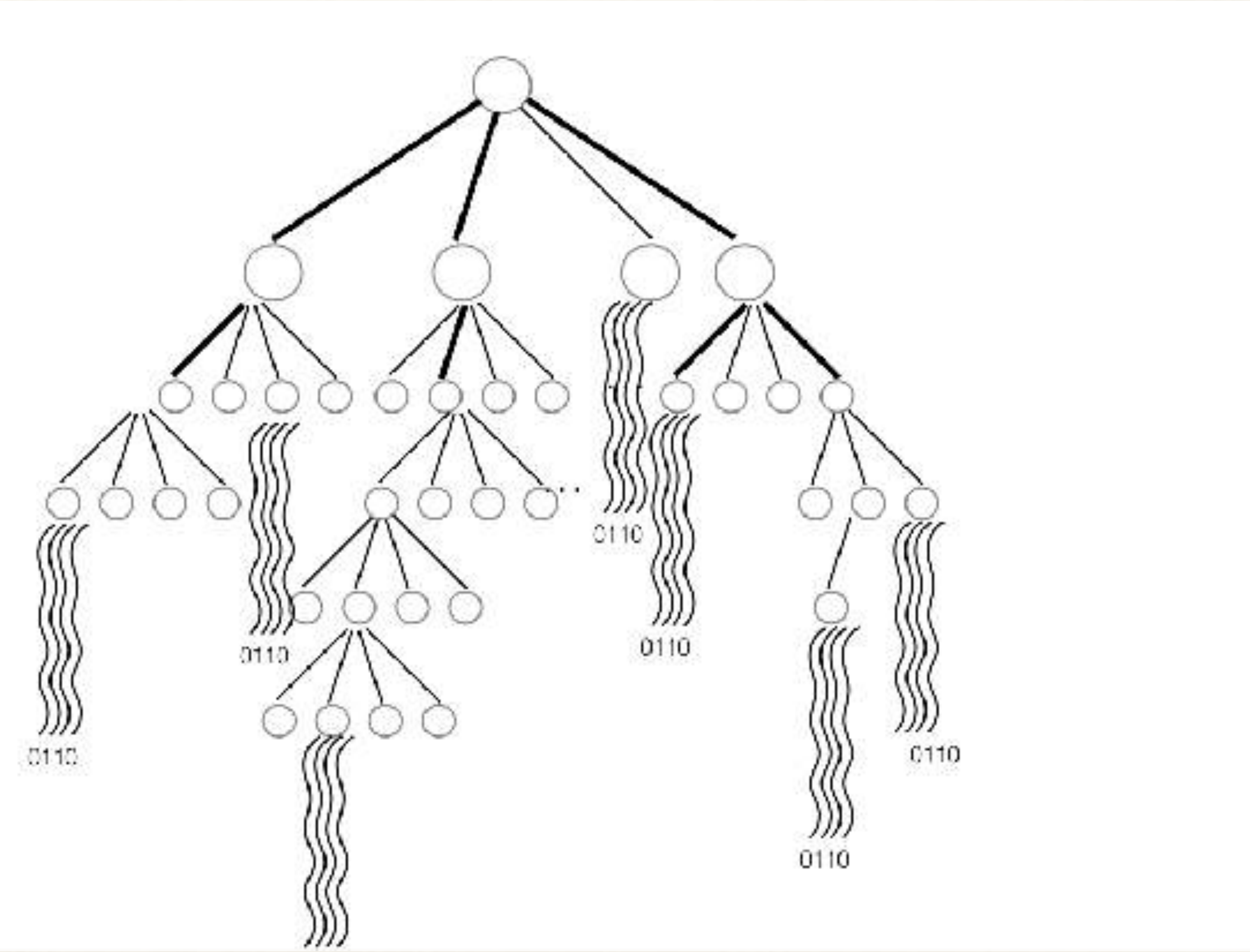
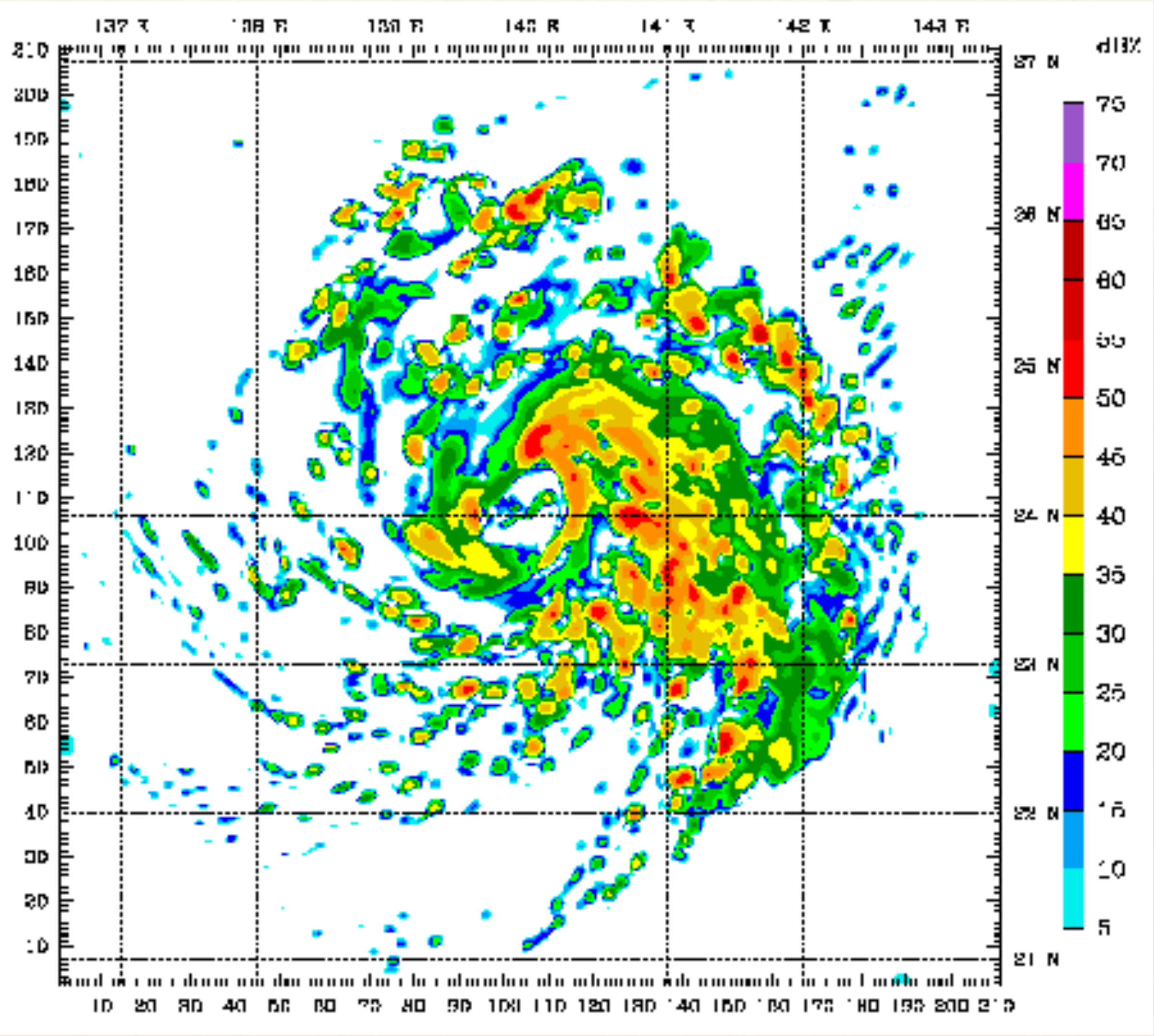
Search - Monte Carlo Tree Search

- Invented about 10 years ago (Coulom - Crazystone, UCT)
- Grow tree using win/loss statistics of simulations
- First successful use of simulations for classical two-player games
- Scaled up to massively parallel
  - MoGo; Fuego on several thousand cores



Simulation

- For complex problems, there are far too many possible future states
- Example:
  predict the path of a storm
- Sometimes, there is no good evaluation
- We can sample long-term consequences by simulating many future trajectories



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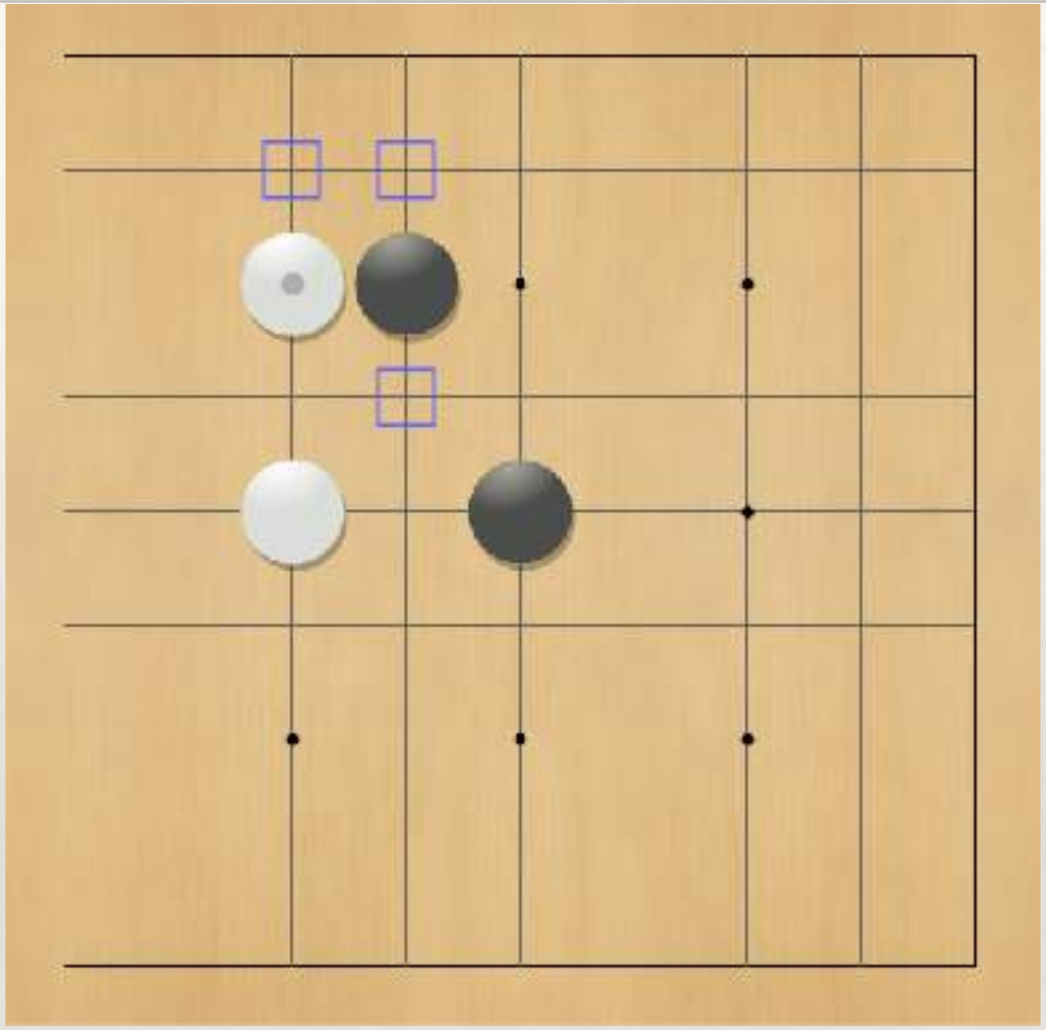
Simulation in Computer Go

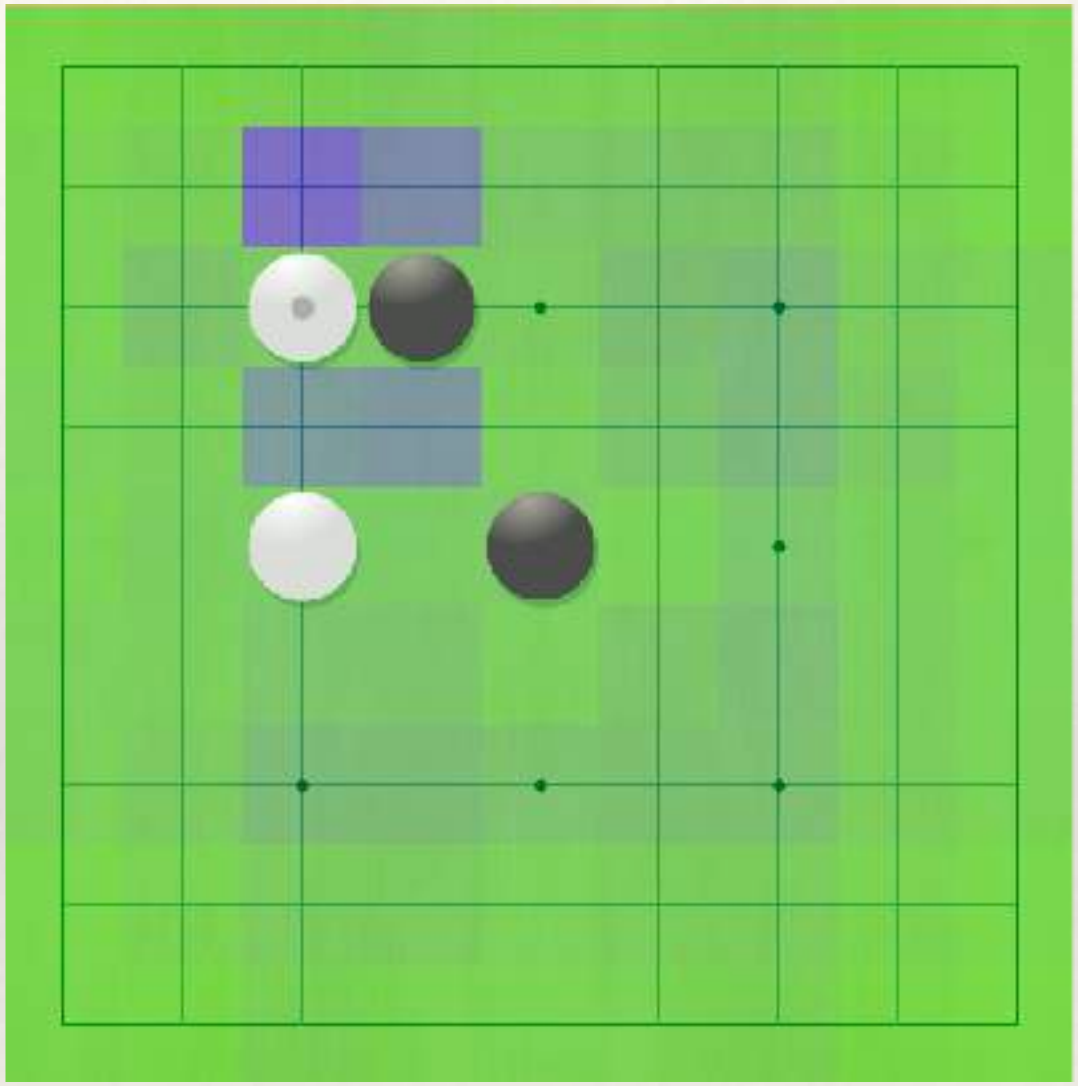
- Play until end of game
- Find who wins at end (easy)
- Moves in simulation: random + simple rules
- Early rules hand-made



Example:
Simple rule-based policy

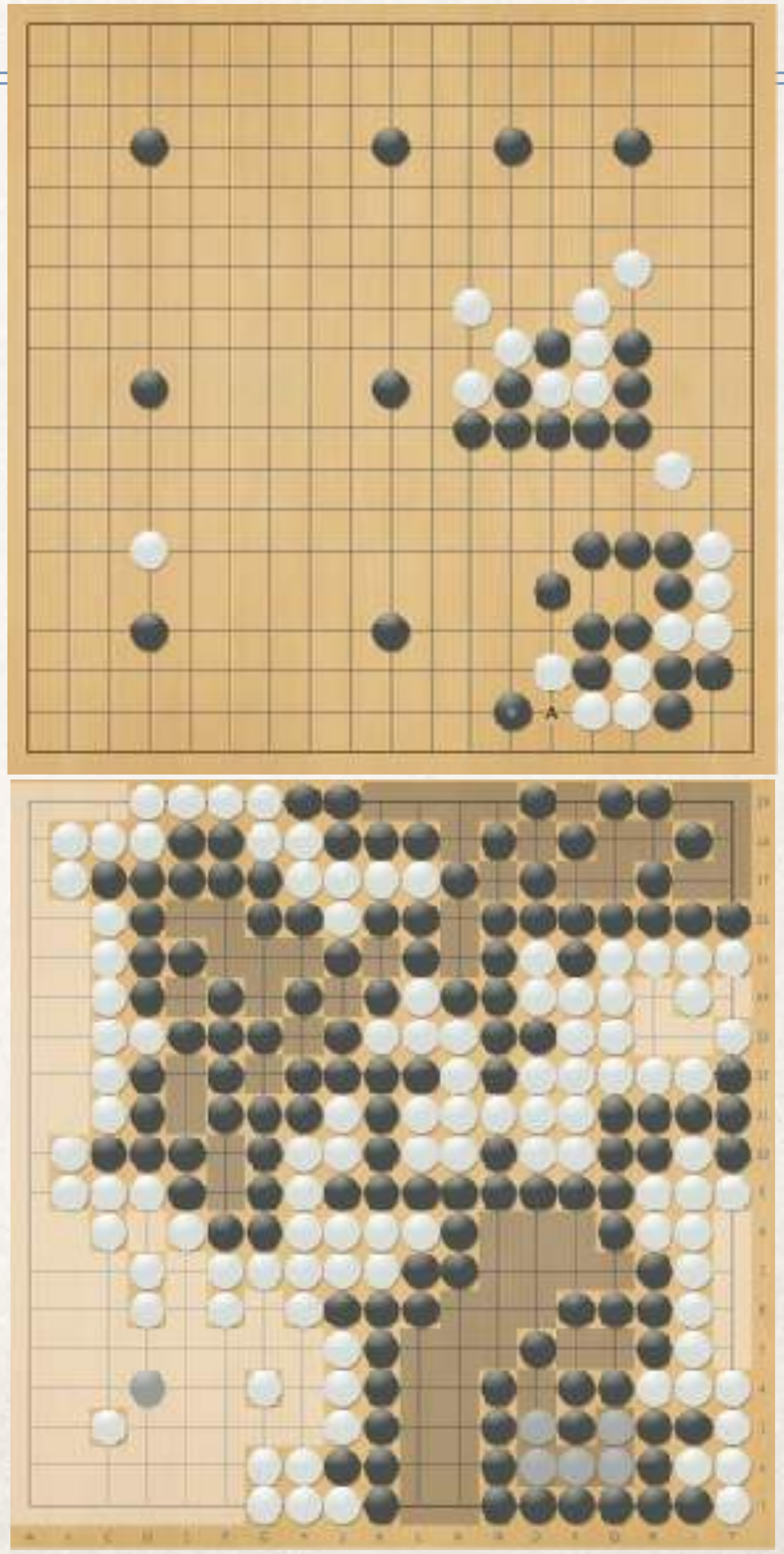
Simulation in Computer Go (2)

- Later improvement:
- Machine-learned policy based on simple features
- Probability for each move
- AlphaGo: machine-trained simple network
- Fast: goal is about 1,000,000 moves / second / CPU



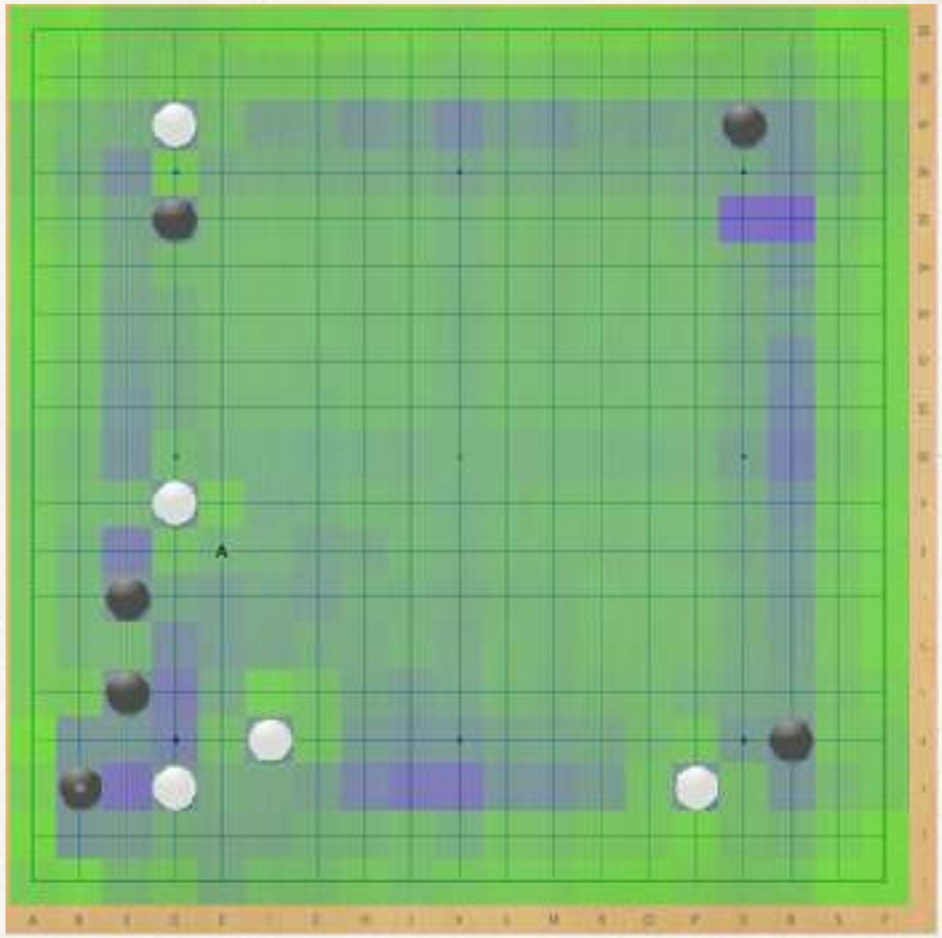
2008 First win on 9 Stones

- MoGo program
- Used supercomputer with 3200 CPUs
- Won with 9 stones handicap vs Myungwan Kim, 8 Dan professional



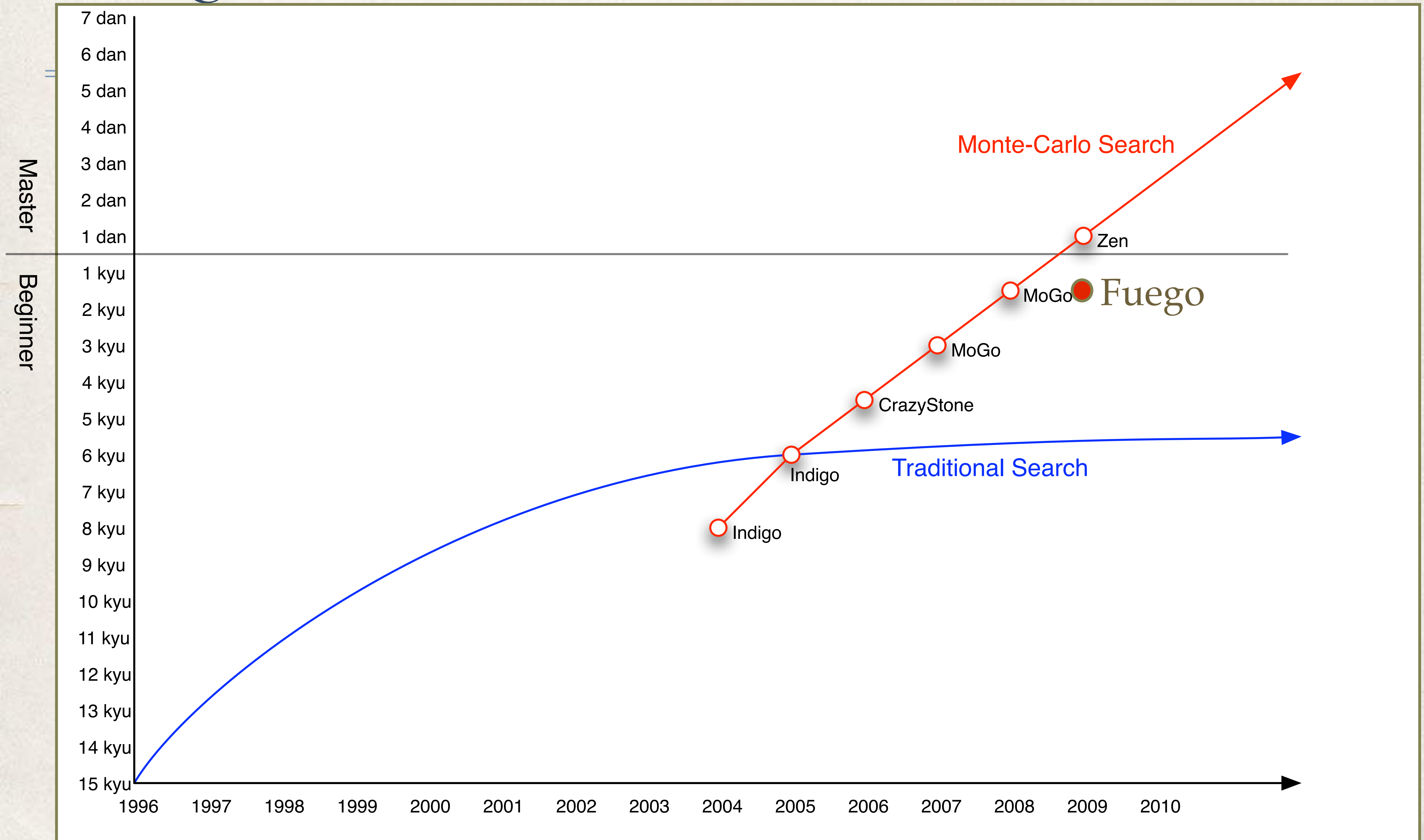
2008-15: Rapid Improvement

- Improve Monte Carlo Tree Search
- Better simulation policies
  (trial and error)
- Add Go knowledge in tree
  - Simple features, learn weights
    by machine learning
- Level: about 5-6 Dan
  3-4 stones handicap from top human players



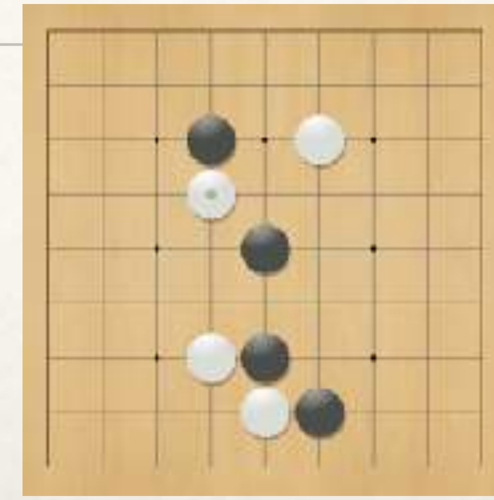
Knowledge based
on simple features
in Fuego

Progress In 19x19 Go, 1996-2010



2009 - First 9x9 Win vs Top Pro

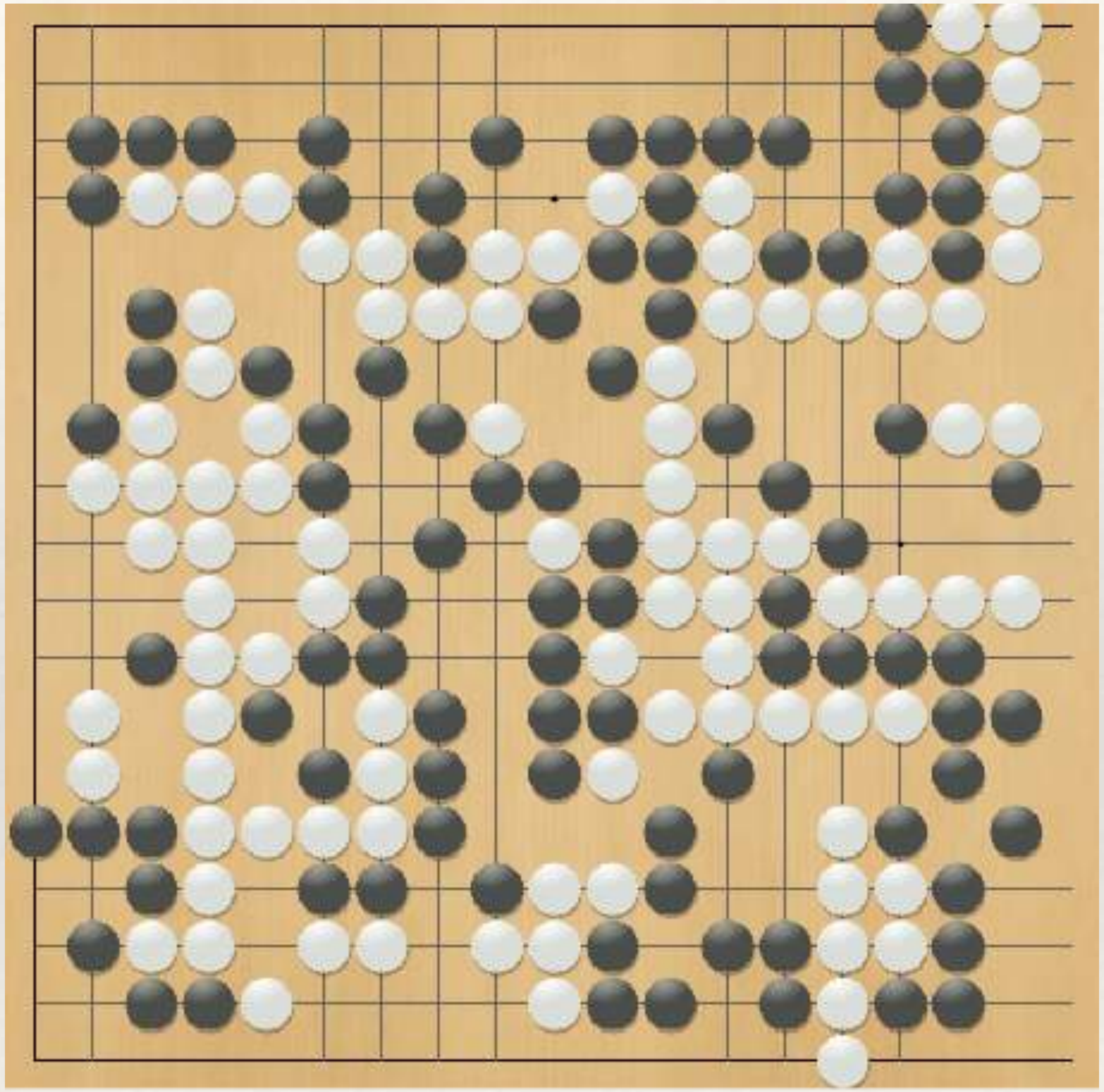
- Fuego open source program
  - Mostly developed at University of Alberta
- First win against top human professional on 9x9 board
- MCTS, deep searches
- 80 core parallel machine



White: Fuego
Black: Chou Chun-Hsun 9 Dan
White wins by 2.5 points

Computer Go Before AlphaGo

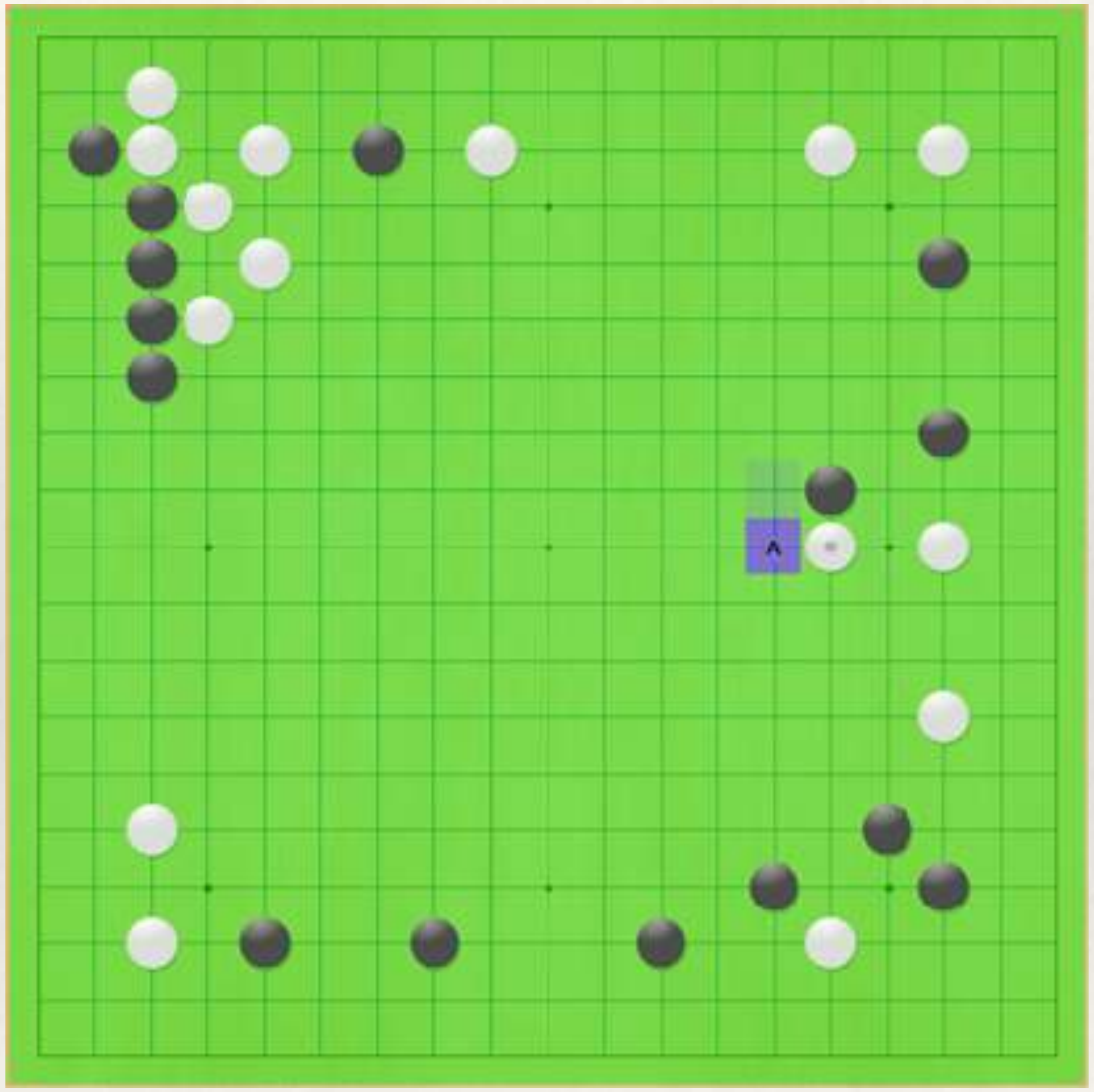
- Summary of state of the art before AlphaGo:
- Search - quite strong
- Simulations - OK, but hard to improve
- **Knowledge**
  - Good for move selection
  - **Considered hopeless for position evaluation**



Who is better here?

2015 - Deep Neural Nets Arrive

- Two papers within a few weeks
  - First by Clark and Storkey, University of Edinburgh
  - Second paper by group at DeepMind, stronger results
- Deep convolutional neural nets (DCNN) used for move prediction in Go
- Much better prediction than old feature-based systems



AlphaGo

- Program by DeepMind
- Based in London, UK **and Edmonton (from 2017)**
- Bought by Google
- Expertise in Reinforcement Learning and search
- 2014-16: worked on Go program for about 2 years, mostly in secret
- One paper on move prediction (previous slide)

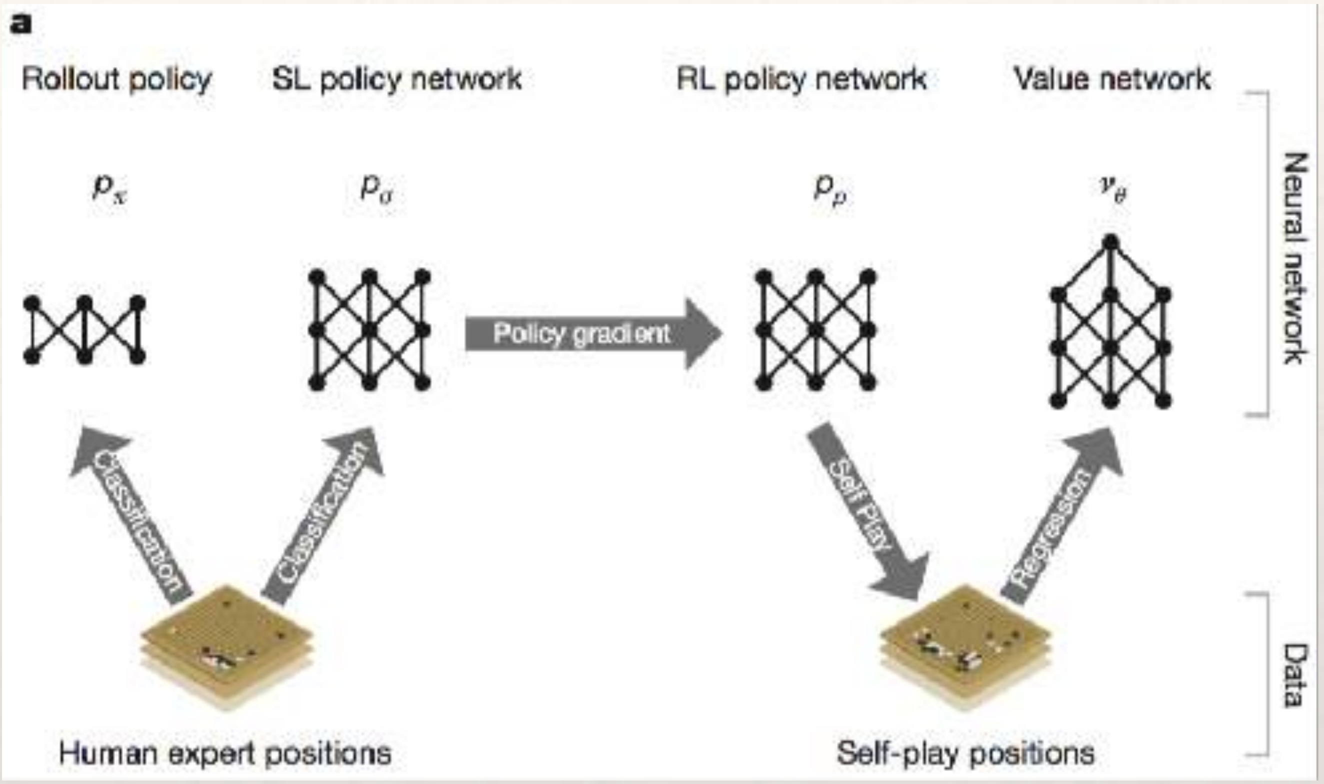
AlphaGo Matches

- Fall 2015 - beat European champion Fan Hui by 5:0 (kept secret)
- January 2016 paper in Nature, announced win vs Fan Hui
- March 2016 match vs Lee Sedol Wins 4:1
- January 2017, wins fast games 60:0 against many top players
- May 2017 match vs Ke Jie Wins 3:0 then retires

The Science Behind AlphaGo

The Science Behind AlphaGo

- AlphaGo builds on decades of research in:
  - Building high performance game playing programs
  - Reinforcement Learning
  - (Deep) neural networks

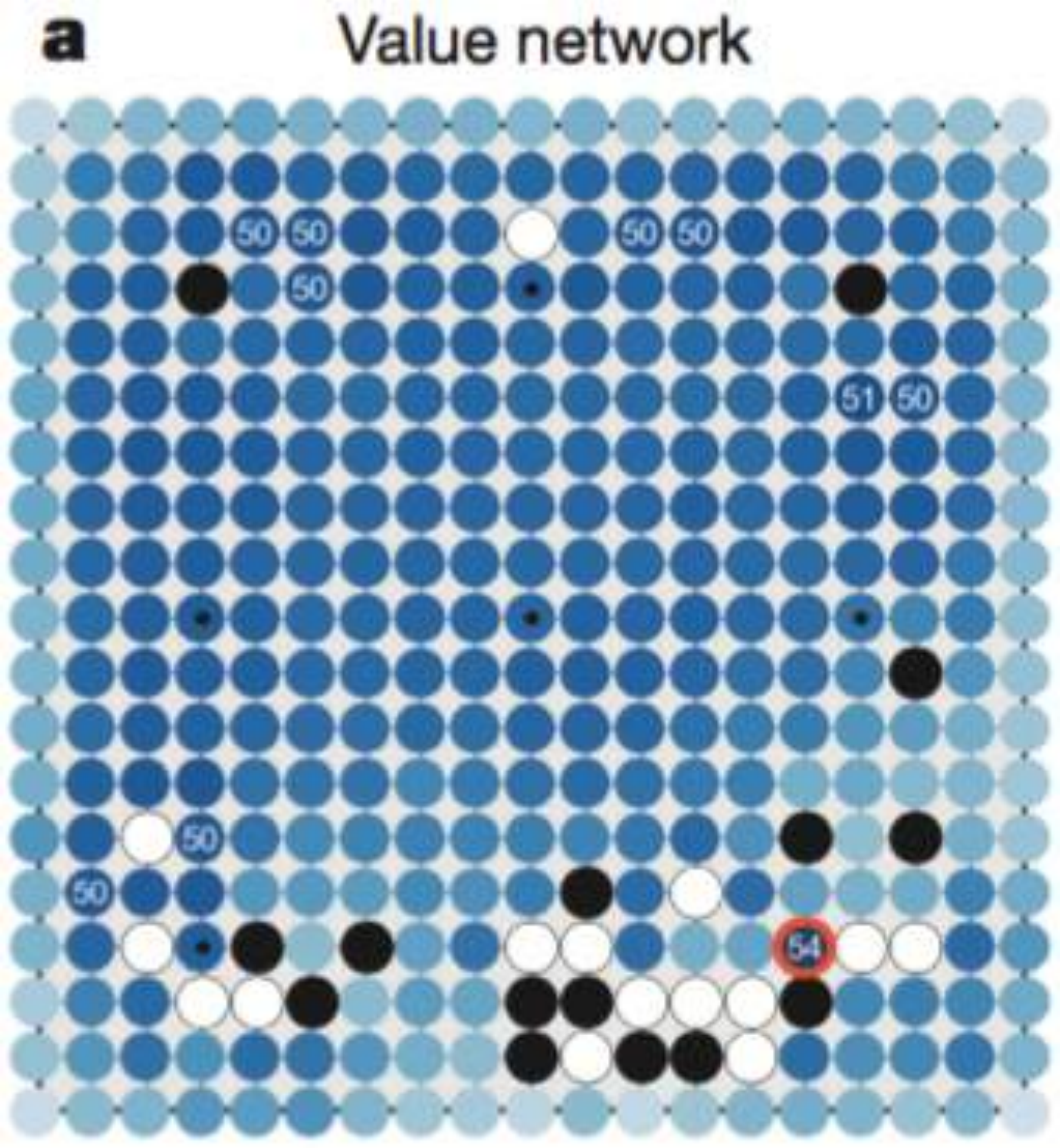


Main Components of AlphaGo

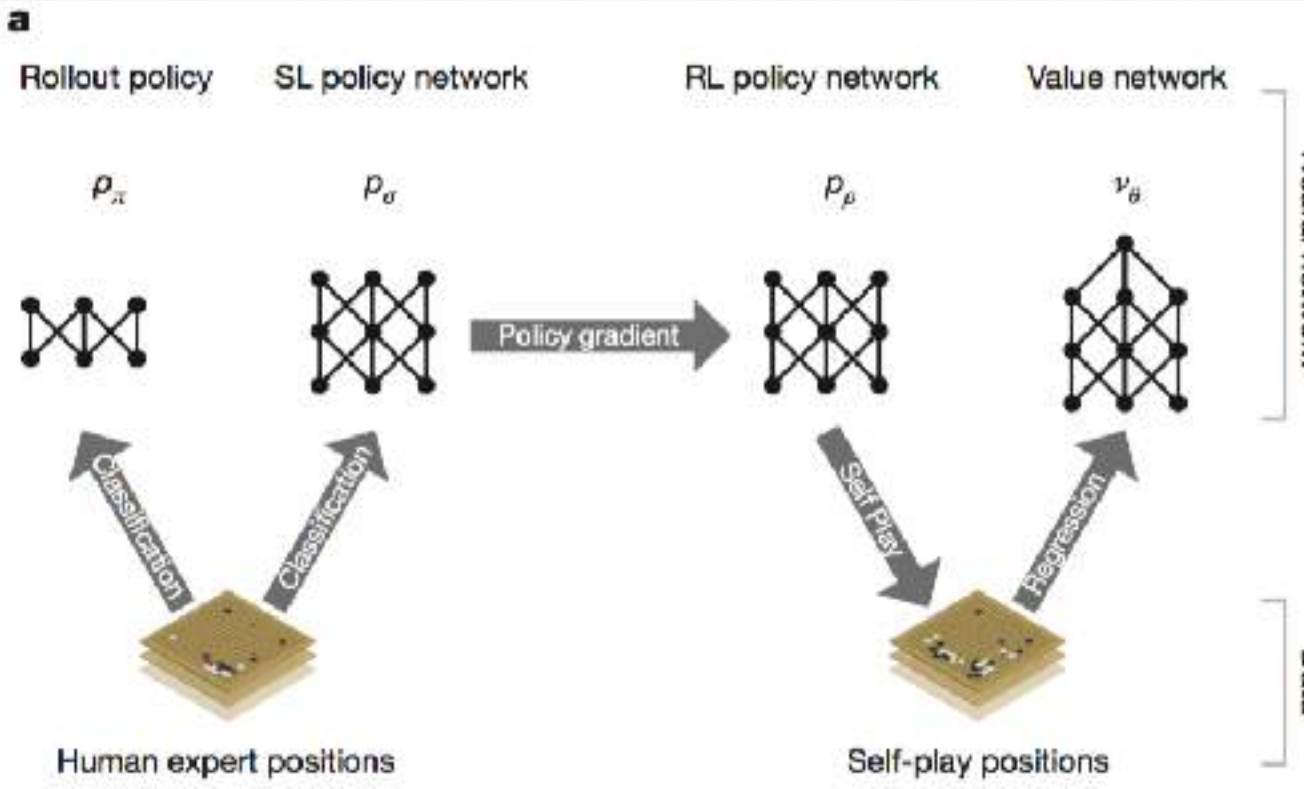
- AlphaGo shares the same main components with many other modern heuristic search programs:
  - Search - MCTS (normal)
  - Knowledge created by machine learning (**new types of knowledge**)
  - Simulations (normal)

Knowledge - Policy and Evaluation

- Two types of knowledge
- Encoded in deep convolutional neural networks
- *Policy network*
  selects good moves for the search (as in move prediction)
- *Value network*:
  evaluation function,
  measures probability of winning



Deep Neural Networks in AlphaGo



- Three different deep neural networks
- Supervised Learning (SL) policy network as in 2015 paper
  - Learn from master games: improved in details, more data
- New: **Reinforcement Learning (RL)** from self-play for **policy network**
- New: **value network** trained from labeled data from self-play games

RL Policy Network

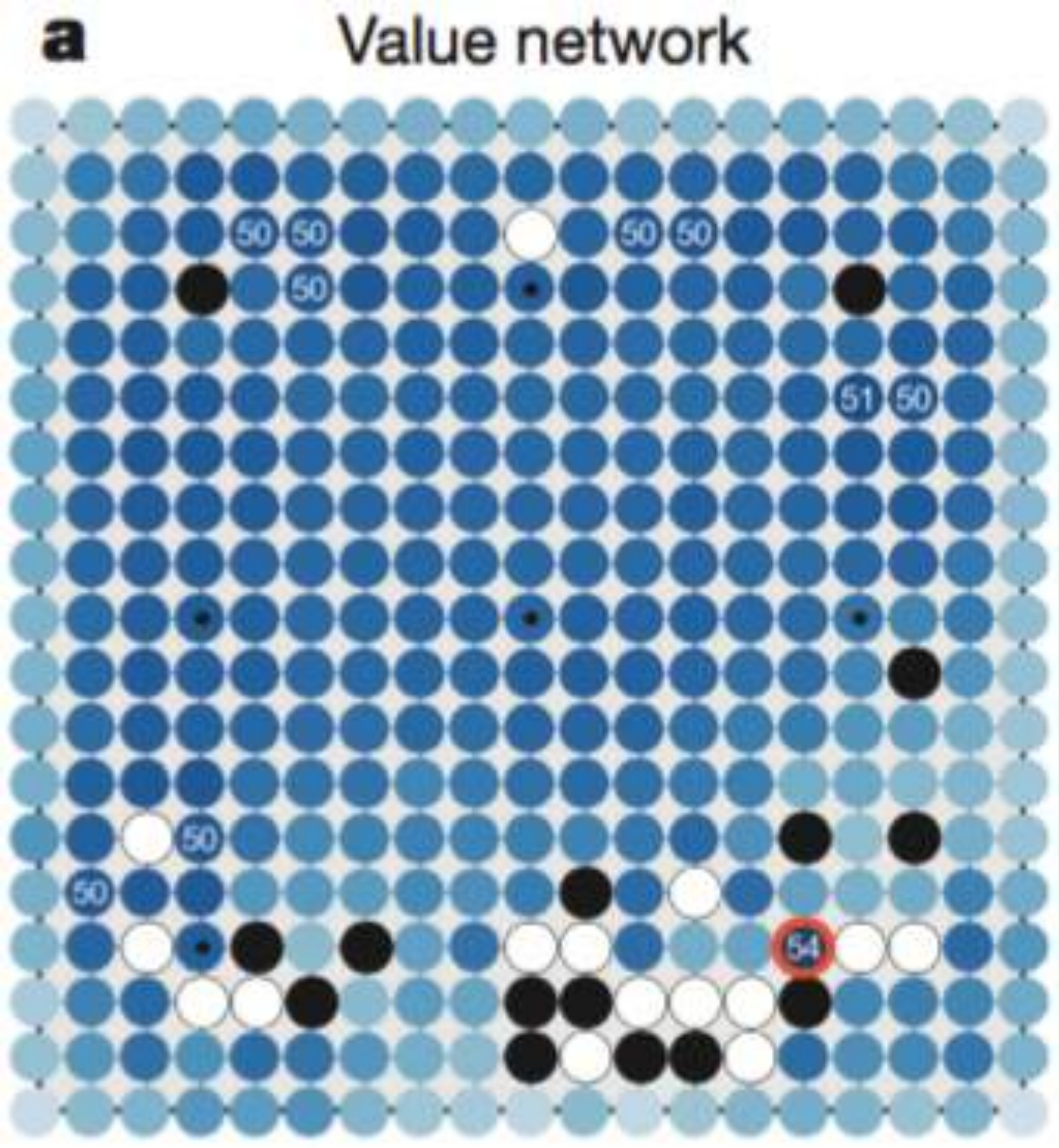
- Deep neural network, same architecture as SL network
- Given a Go position
- Computes probability of each move being best
- Initialized with SL policy weights
- Trained by Reinforcement Learning from millions of self-play games
- Adjust weights in network from win/loss result at end of game only

Data for Training Value Network

- Policy network can be used as a strong and relatively fast player
- Randomize moves according to their learned probability
- After training, played 30 million self-play games
- Pick a single position from each game randomly
- Label it with the win/loss result of the game
- Result: data set of 30 million Go positions, each labeled as win or loss
- Next step: train the value network on those positions

Value Network

- Another deep neural network
- Given a Go position
- Computes probability of winning
- Static evaluation function
- Trained from the 30 million labeled game positions
- Trained to minimize the prediction error on the (win/loss) labels



Putting it All Together

- A huge engineering effort
- Many other technical contributions
- Massive amounts of self-play training for the neural networks
- Massive amounts of testing/tuning
- Large parallel hardware in earlier matches
- "Single TPU machine" in 2017

What's New in AlphaGo 2017?

- Few details known as of now
- More publications promised
- Main change: better games data for training the value net
- Old system: 30 million games played by RL policy net
- New system: unknown number of games played by the full AlphaGo system

- Consequences:
  - Much better quality of games
  - Much better quality of final result labels
  - From strong amateur (RL network) to full AlphaGo strength
- Most likely,
  many other improvements
  in all parts of the system

The Legacy of AlphaGo

Legacy of AlphaGo

- Research contributions, the path leading to AlphaGo
- Impact on communities
  - Go players
  - Computer Go researchers
  - Computing science
  - General public

Review: Contributions to AlphaGo

- Deepmind developed AlphaGo, with many great breakthrough ideas
- AlphaGo is *also* based on decades of research in heuristic search and machine learning
- Much of that research was done at University of Alberta
- Next slide: references from AlphaGo paper in Nature
  - Over 40% of references have a University of Alberta (co-)author

U. Alberta Research and Training

- Citation list from AlphaGo paper in Nature
- Papers with Alberta faculty or trainees in yellow

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Impact on Game of Go

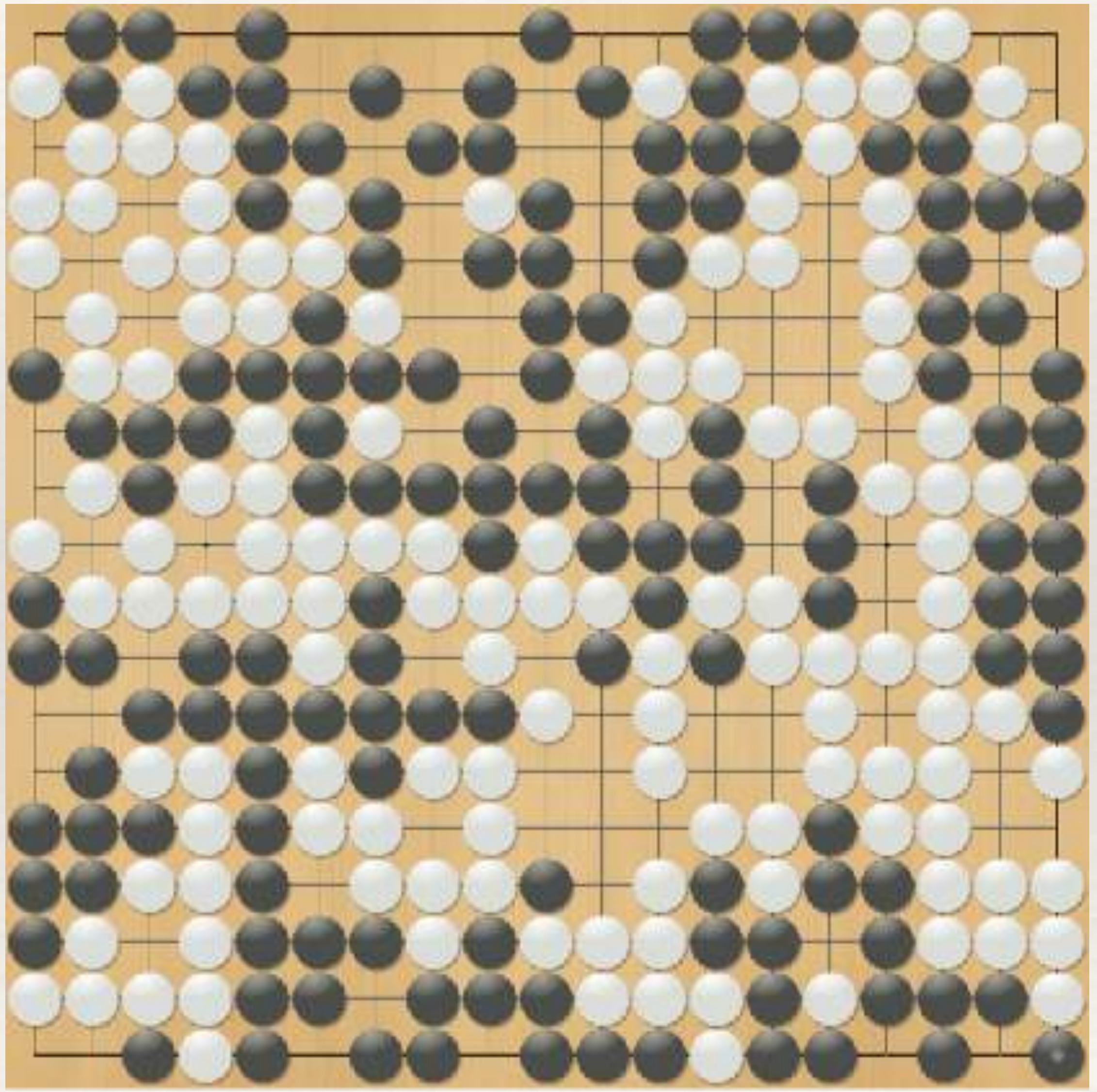
- AlphaGo received honorary 9 Dan diploma from both Chinese and Korean Go associations
- Strong impact on professional players
- Many new ideas, for example Ke Jie has experimented a lot with AlphaGo style openings
- Goal: Go programs as teaching tools
- Potential problem: cheating in tournaments?

What’s Next in Computer Go?

- Currently, developing a top Go program is *Big Science*
  - Needs a large team of engineers
  - Example: Tencent's FineArt
- What can a small-scale university project contribute?
- One idea: work on *solving* parts of the game

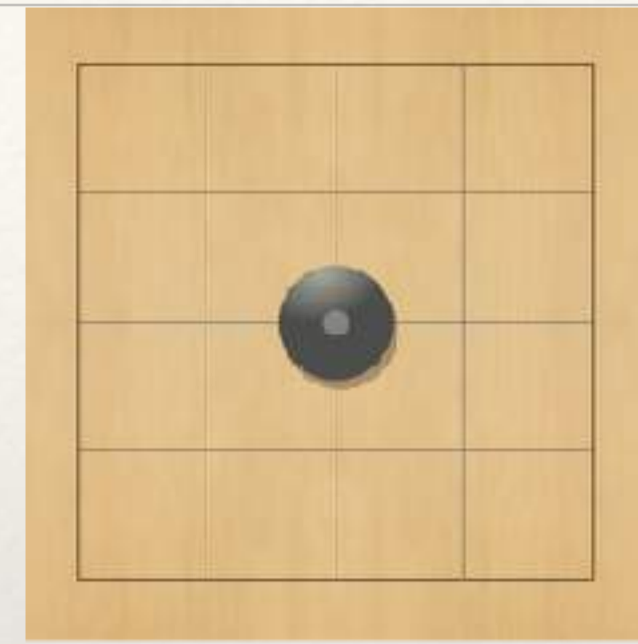
Is the Game of Go Solved Now?

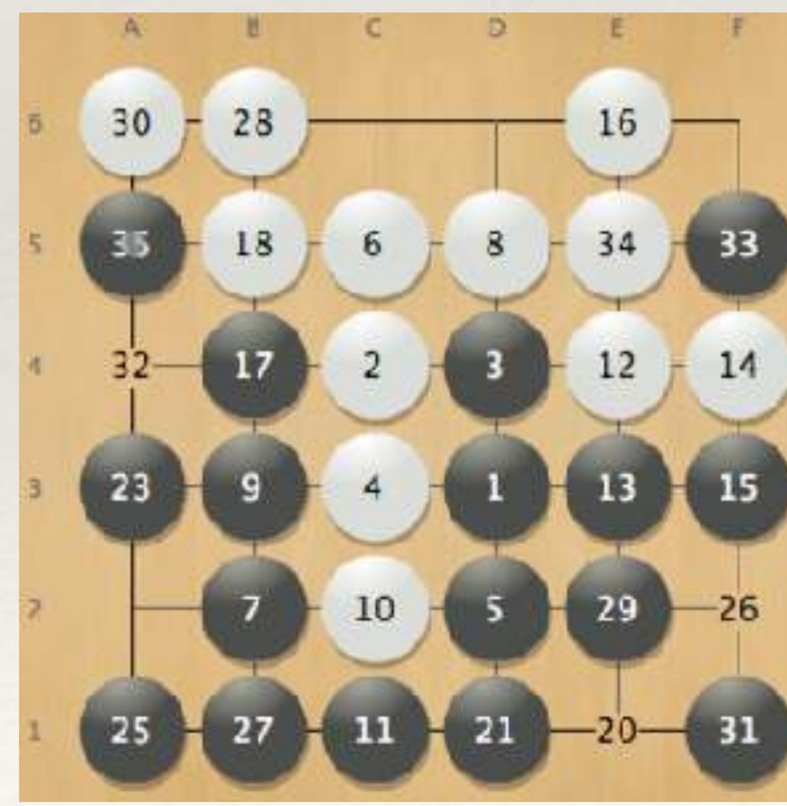
- **No!**
- AlphaGo is incredibly strong but…
  - … it is all based on heuristics
- AlphaGo still makes mistakes
- Example: 50 self-play games
  - Which color should win?
  - 38 wins for White
  - 12 wins for Black
  - One of these results must be wrong



Solving Go on Small Boards

- Solving means *proving* the best result *against any possible* opponent play
- Much harder to scale up than heuristic play
- 5x5, 5x6 Go are the largest solved board sizes (v.d.Werf 2003, 2009)
- Much work to be done: 6x6, 7x7, …

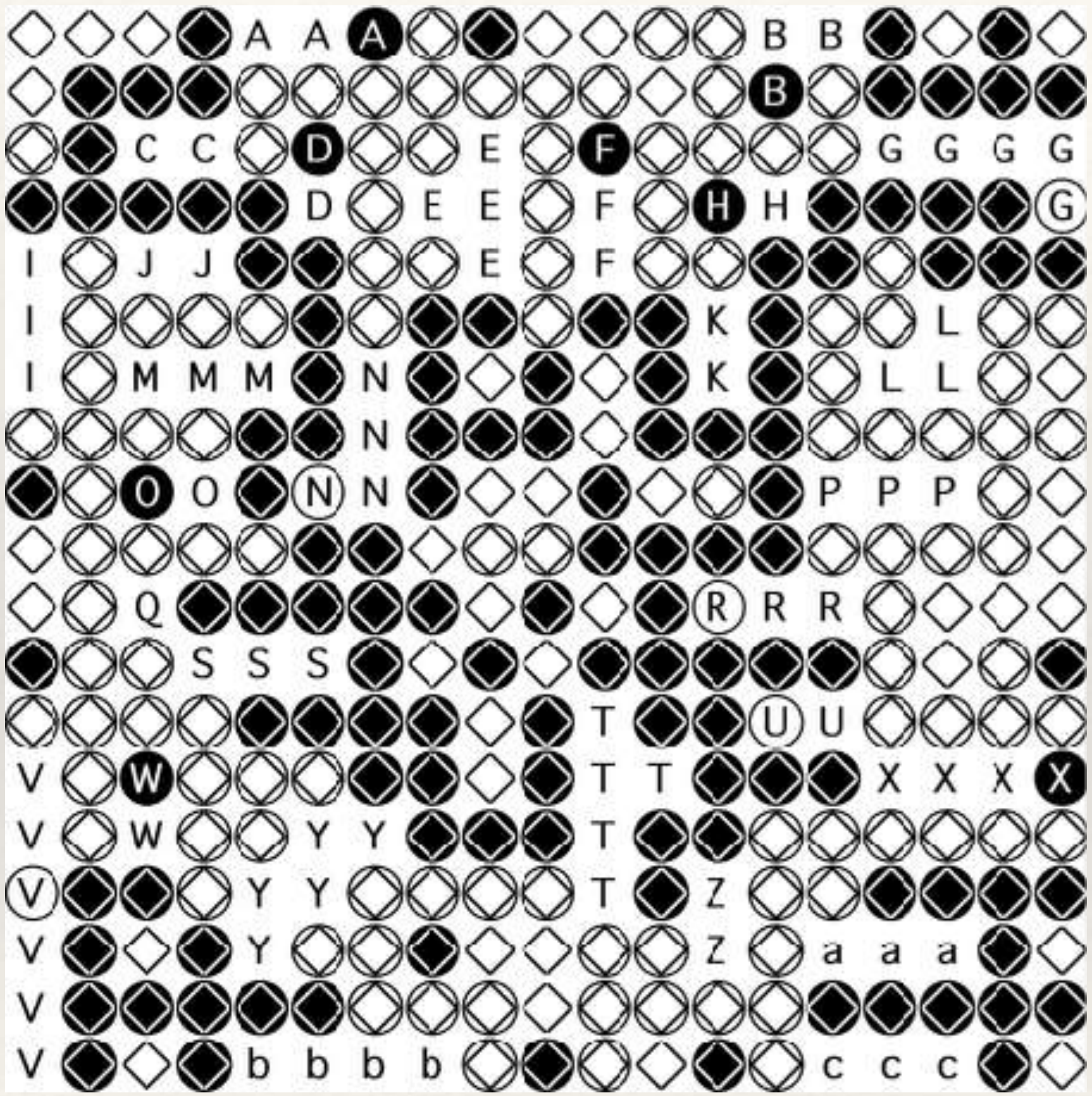


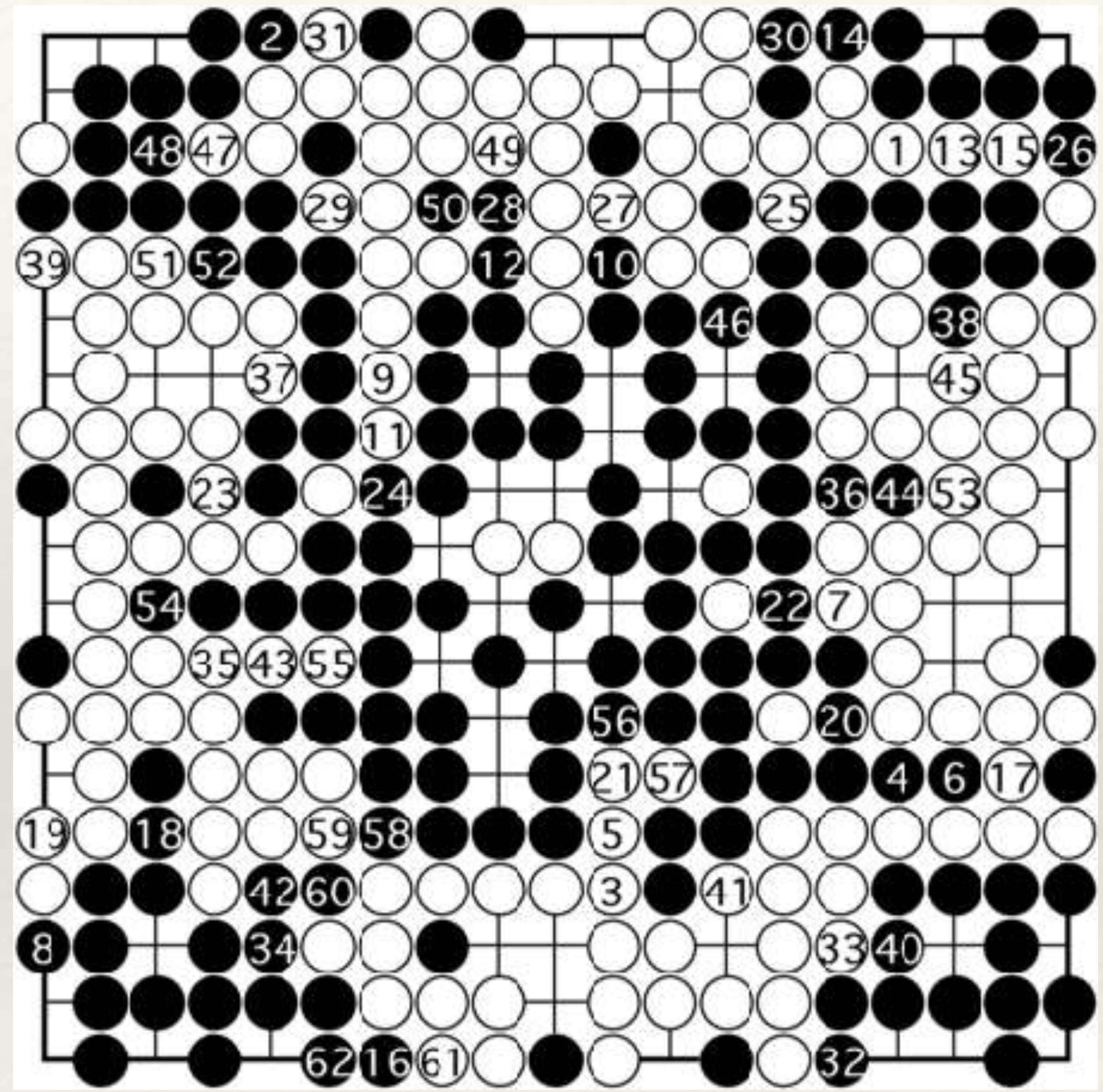


Solving Go Endgames

- How about solving 19x19 Go?
- Completely impossible, much too hard
- Solving endgames is more promising
- Can play *some* full-board 19x19 puzzles perfectly
    - Algorithms based on *combinatorial game theory* (Berlekamp+Wolfe 1994, Müller 1995)

Solving Go Endgame Puzzles





(Theory Berlekamp+Wolfe 1994,
computer program Müller 1995)

Impact on Computing Science, AI

- The promise of AlphaGo: methods are general, little game-specific engineering
- Shown that we have algorithms to acquire strong knowledge from very complex domains
- Challenge: what about real life applications?
    - Rules are not clear and change, hard to simulate
    - Even more actions
    - Less precise goals and evaluation

Impact on General Public

- Massive publicity about AlphaGo's success
- Illustration of the power of AI methods
- Feelings of both opportunities and fear
    - We can solve many complex problems with AI
    - Will AI destroy many good human jobs?
      Or replace boring jobs with better ones?

Summary and Outlook

- DeepMind's AlphaGo program is an incredible research breakthrough
- Landmark achievement for Computing Science
- Reviewed the main techniques that made this progress possible
- One big question: will the techniques apply to other problems?