# Mastering the game of Go with deep neural networks and tree search (Silver et al., 2016)

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# The Game of Go

Image 1: [2], Image 2: [3], Image 3: [4]

# Timeline

- 1952 – computer masters Tic-Tac-Toe
- 1994 – computer masters Checkers
- 1997 – IBM's Deep Blue defeats Garry Kasparov in Chess
- 2011 – IBM's Watson defeats Jeopardy champions
- 2014 – Google algorithms learn to play Atari games
- 2015 – Wikipedia: *"Thus, it is very unlikely that it will be possible to program a reasonably fast algorithm for playing the Go endgame flawlessly, let alone the whole Go game."*
- 2015 – Google's AlphaGo defeats Fan Hui (2-dan professional) in Go

# Timeline

AlphaGo

*"This is the first time that a computer program has defeated a human professional player in the full-sized game of Go, a feat previously thought to be at least a decade away."*

– Silver et al., 2016

Figure: David Silver

Image 1: [5], Image 2: [6]

# Overview

1. The Game of Go
   - Go Basics
   - Complexity of Go
2. The Architecture of AlphaGo
   - Monte Carlo Tree Search
   - Policy and Value Networks
   - Combining Neural Networks with MCTS
   - Playing Strength Evaluation
3. AlphaGo vs Lee Sedol

# Go Basics

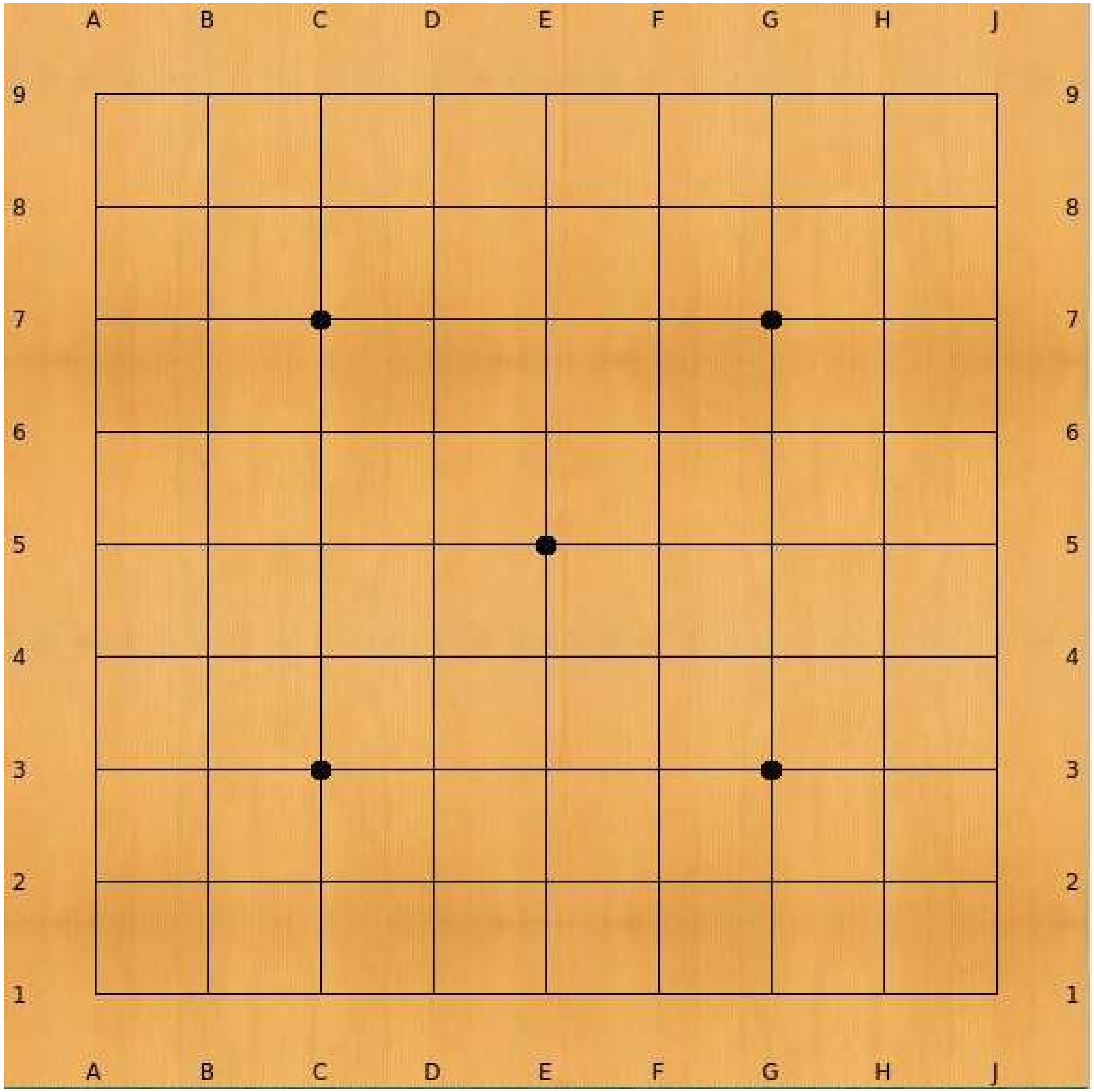
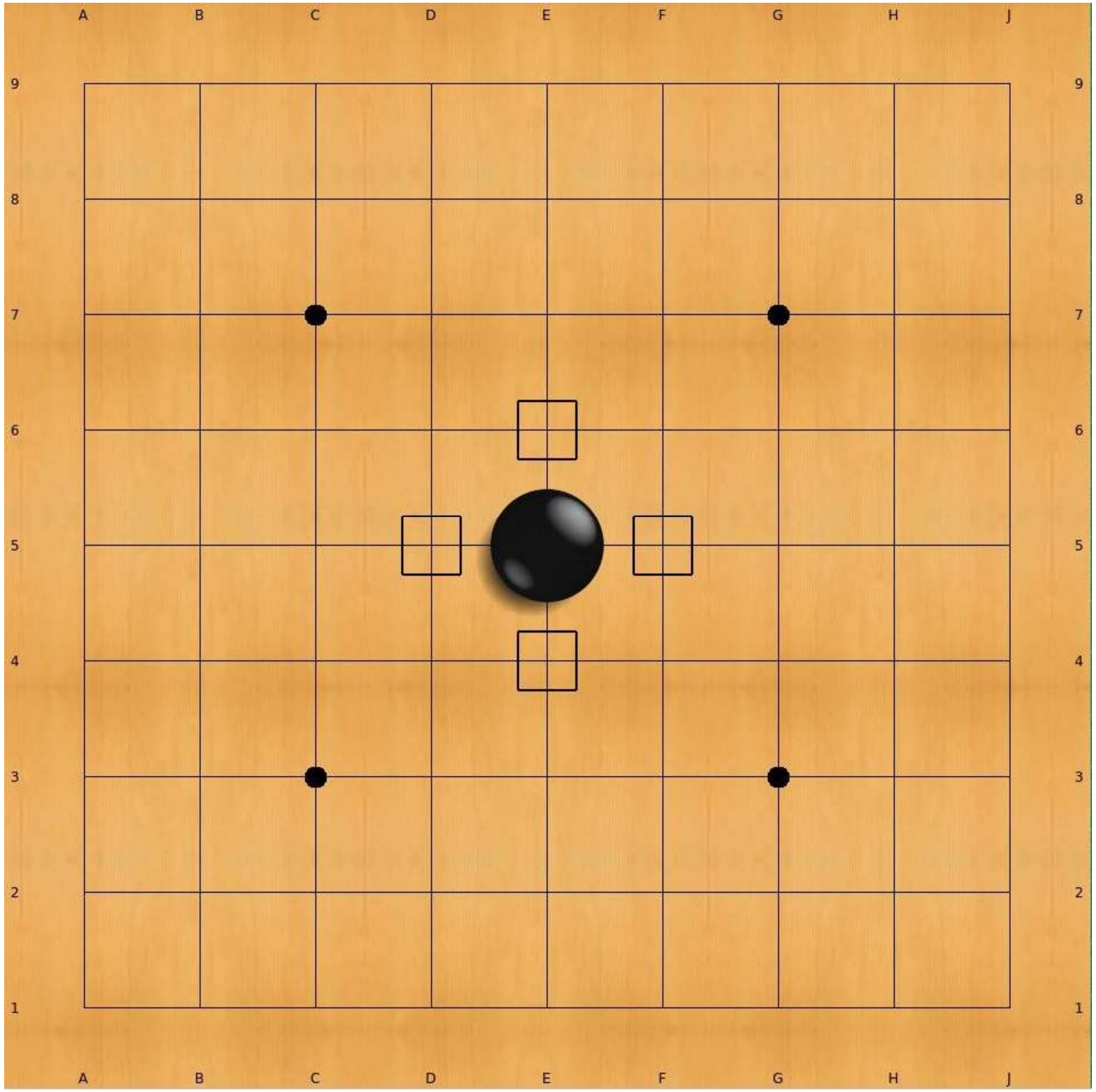



Image [7]

# Go Basics

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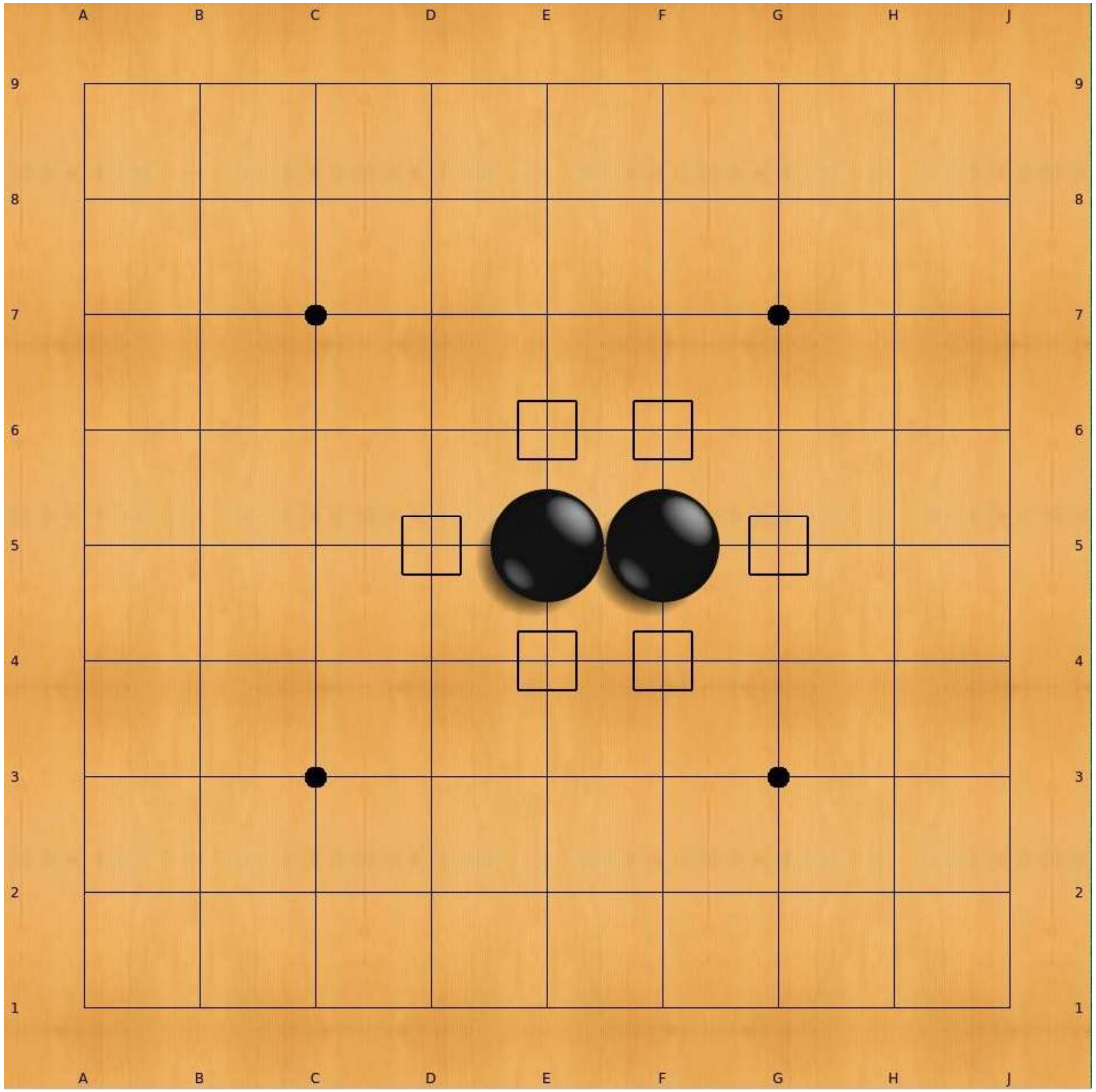


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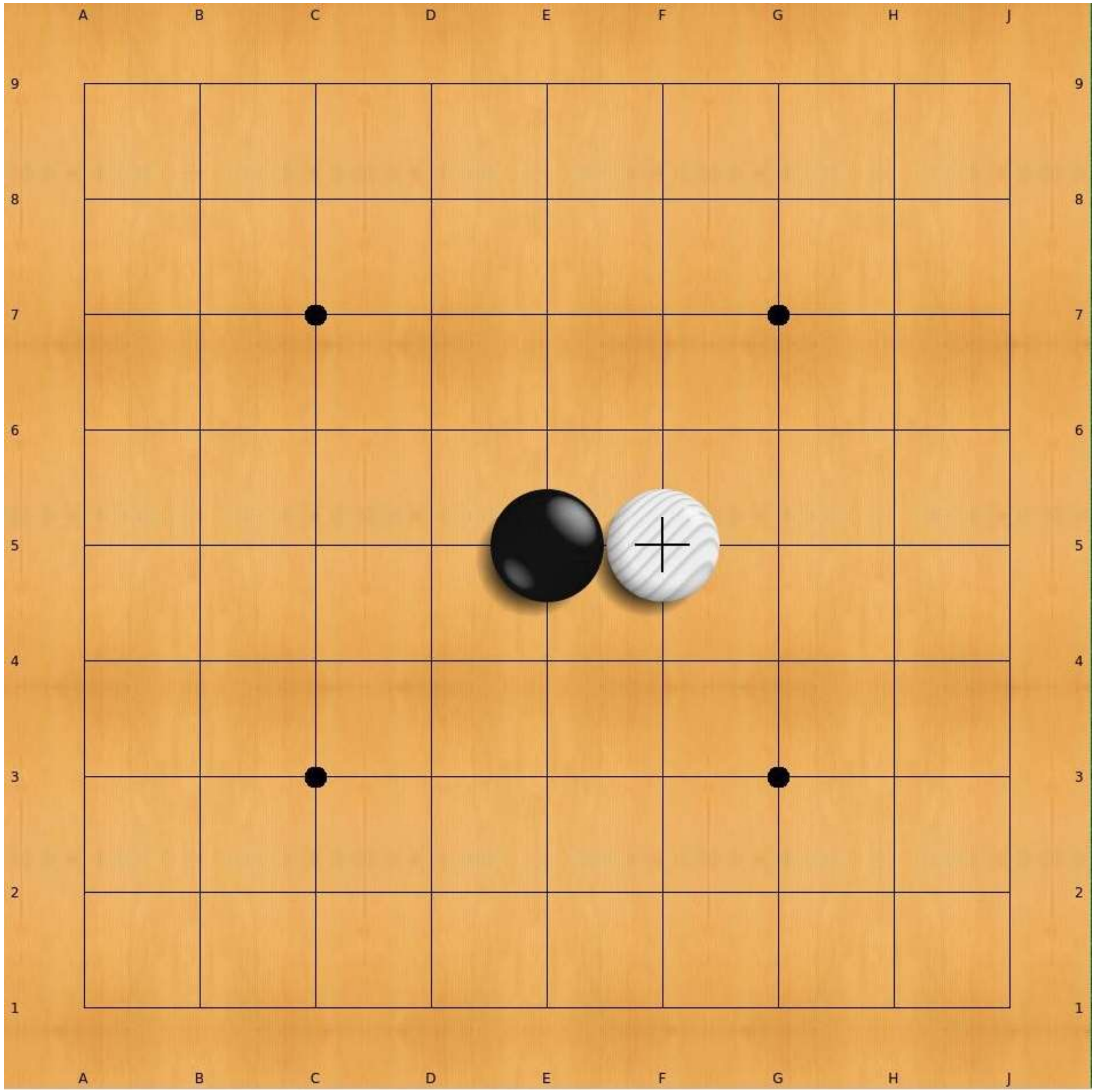


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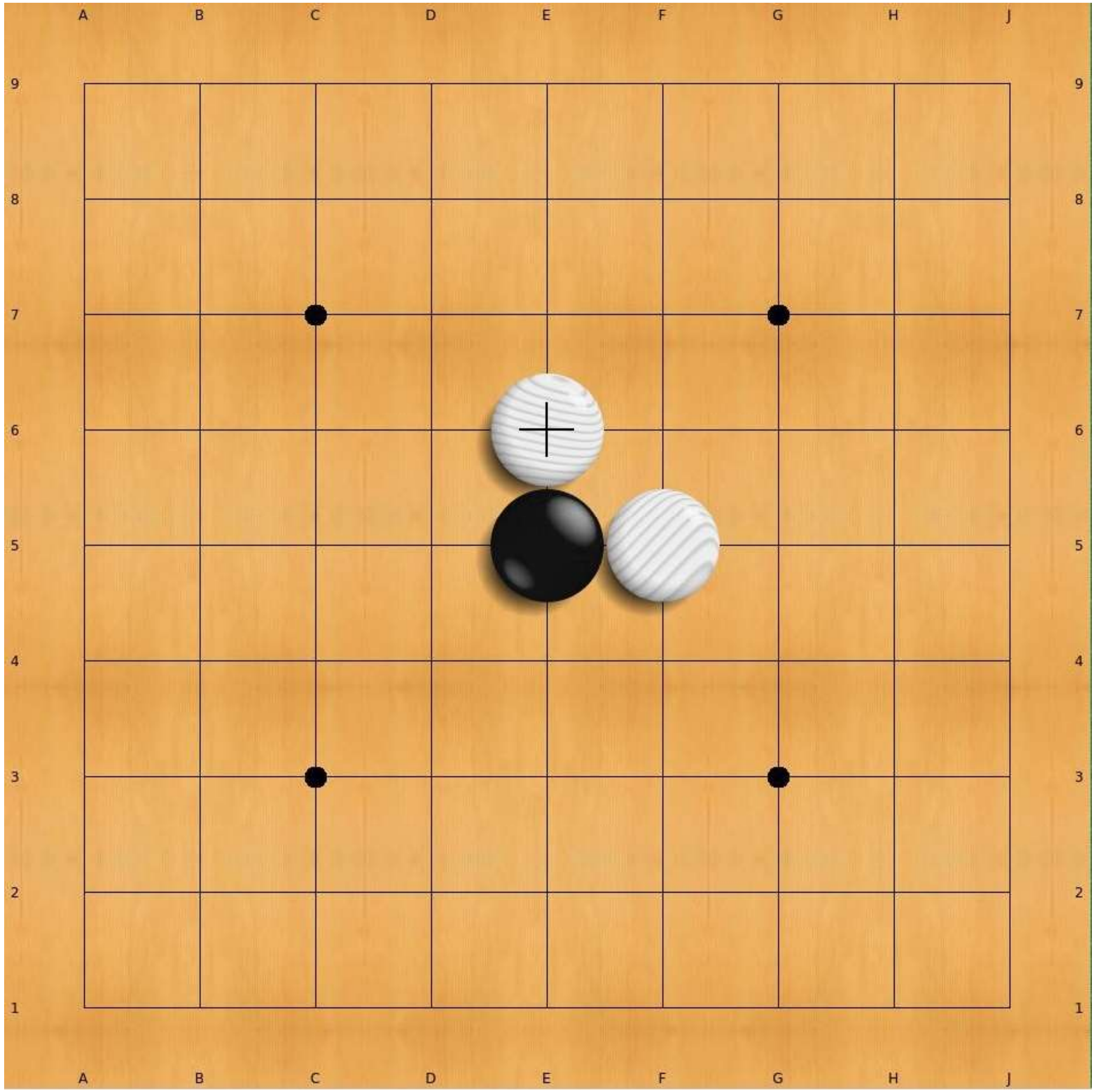


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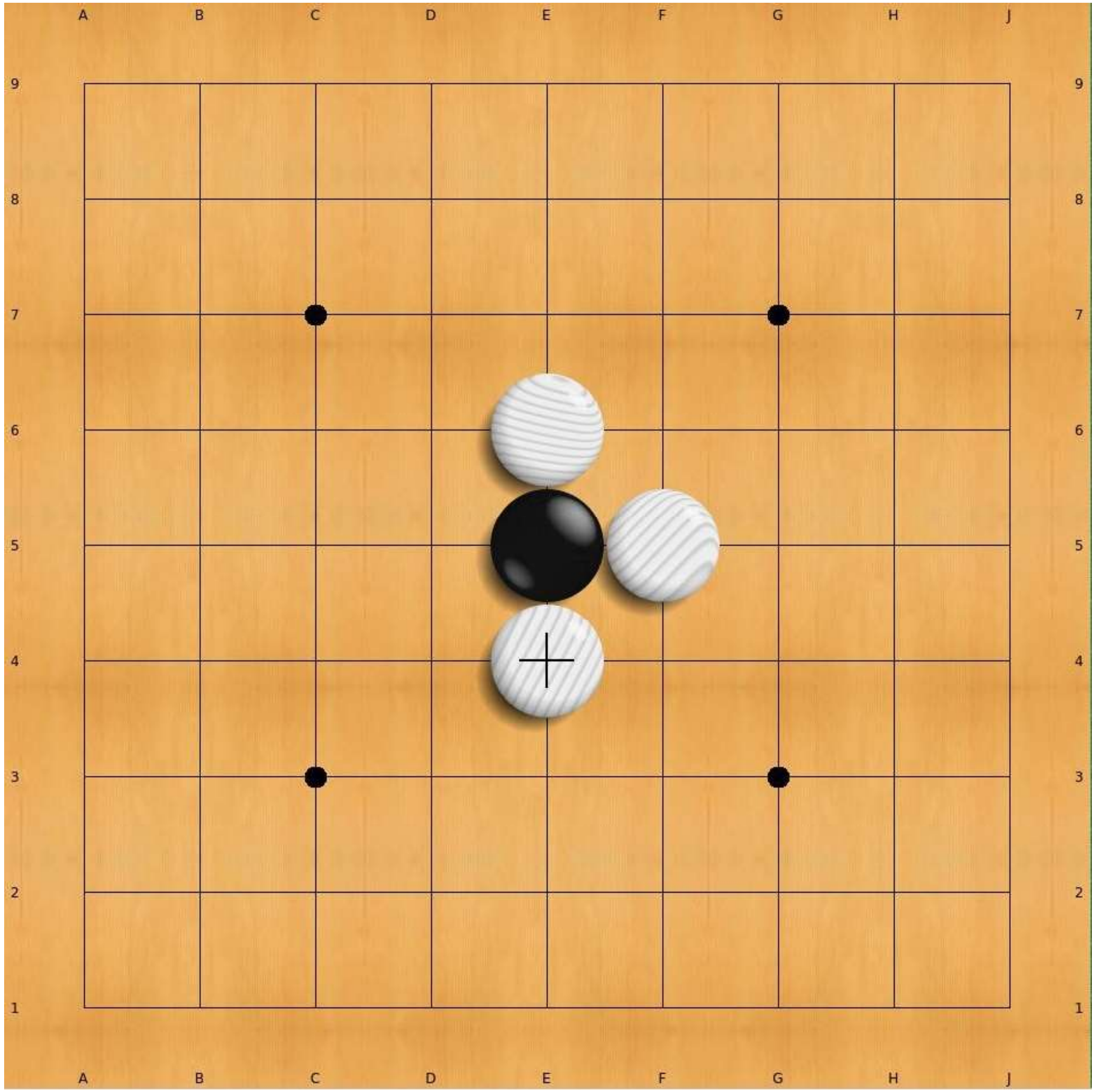


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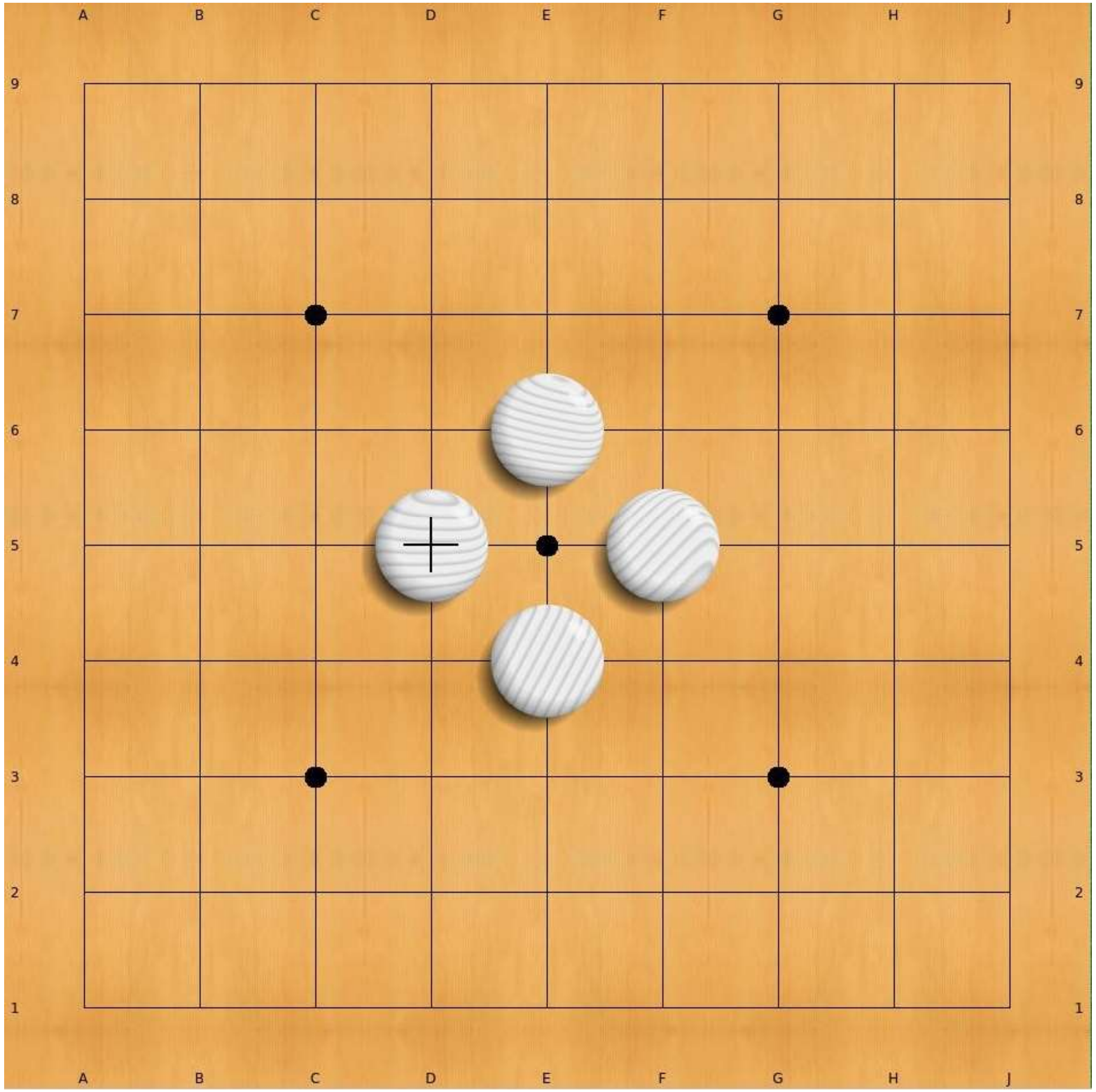


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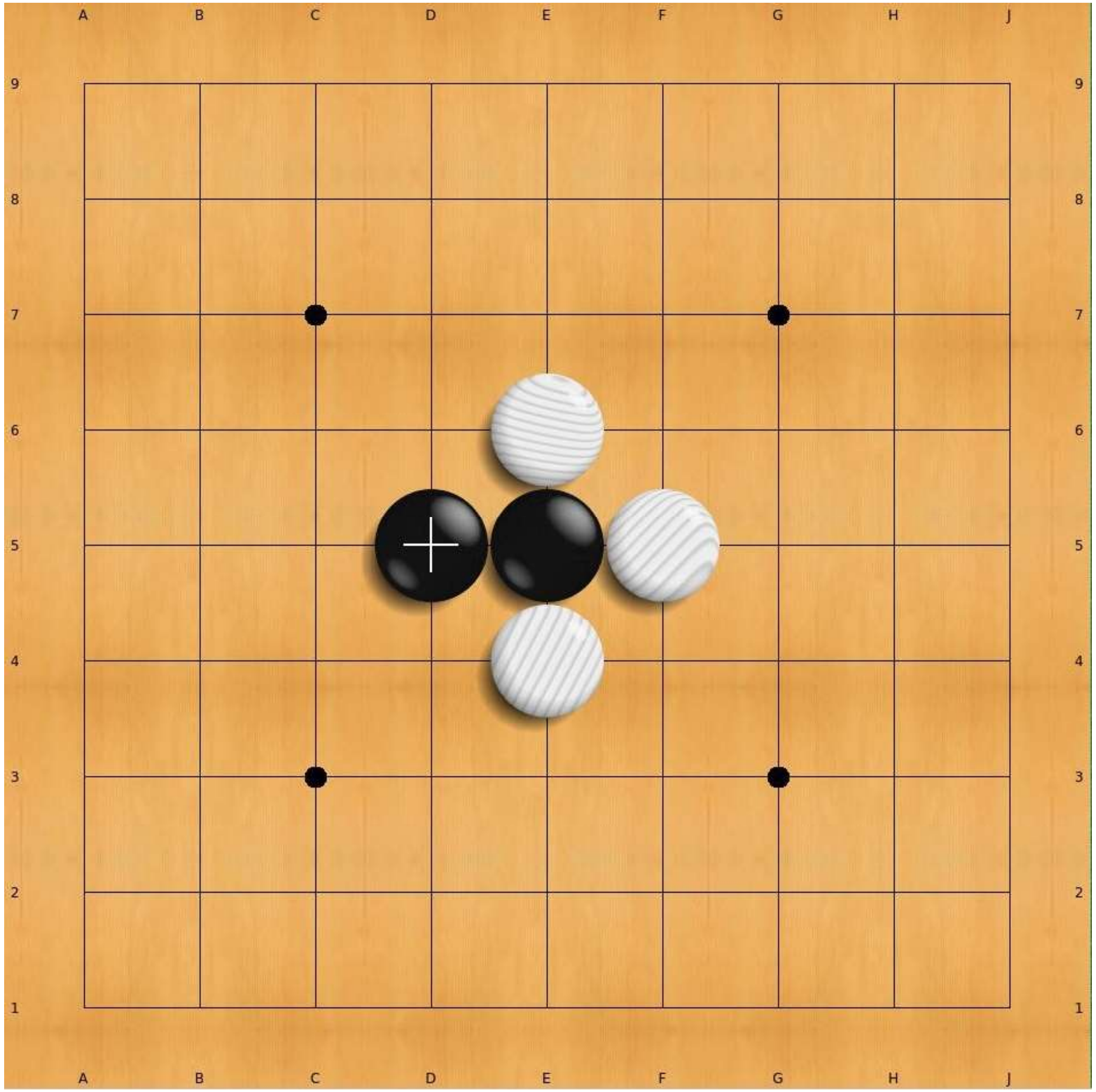


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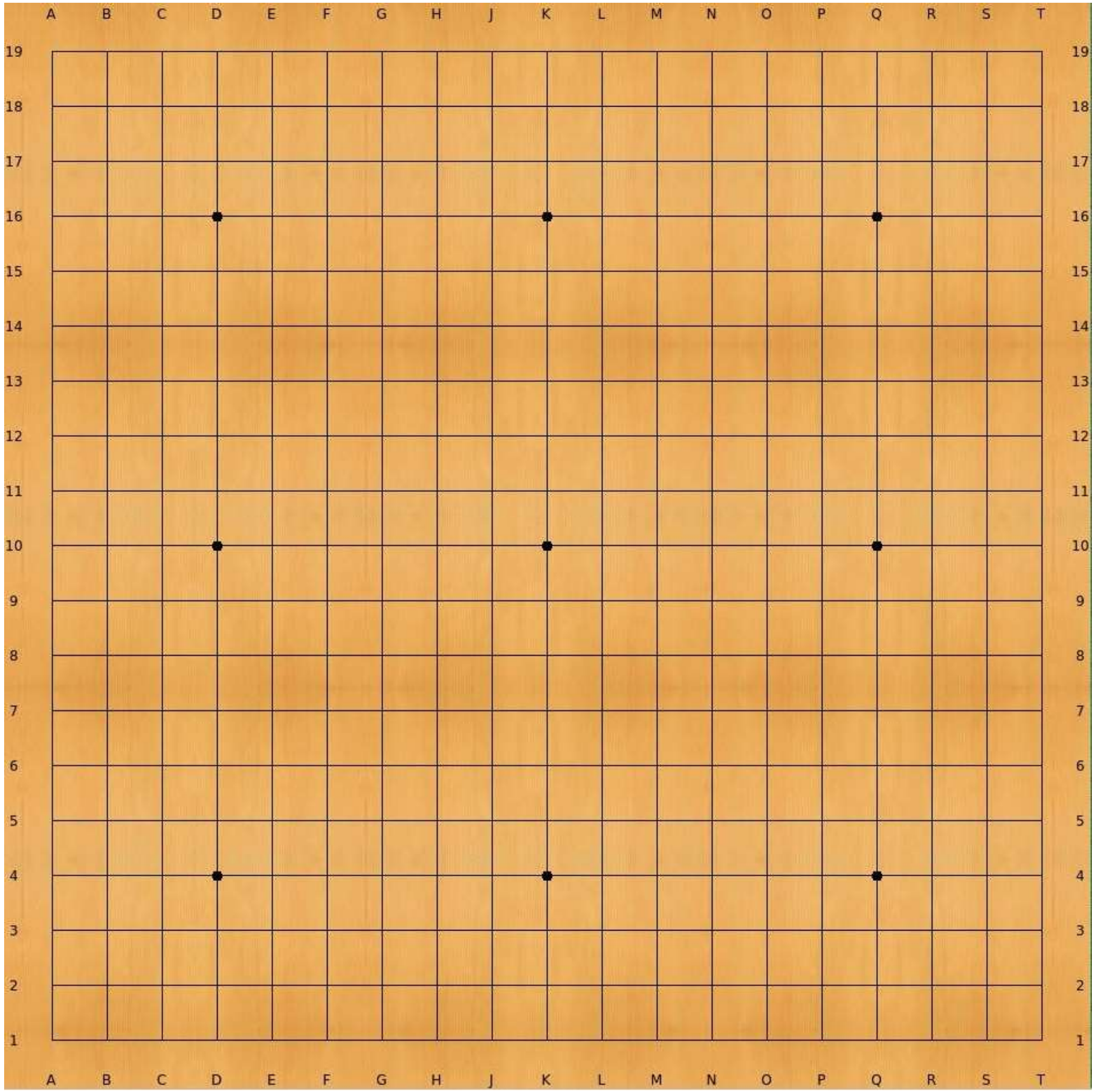


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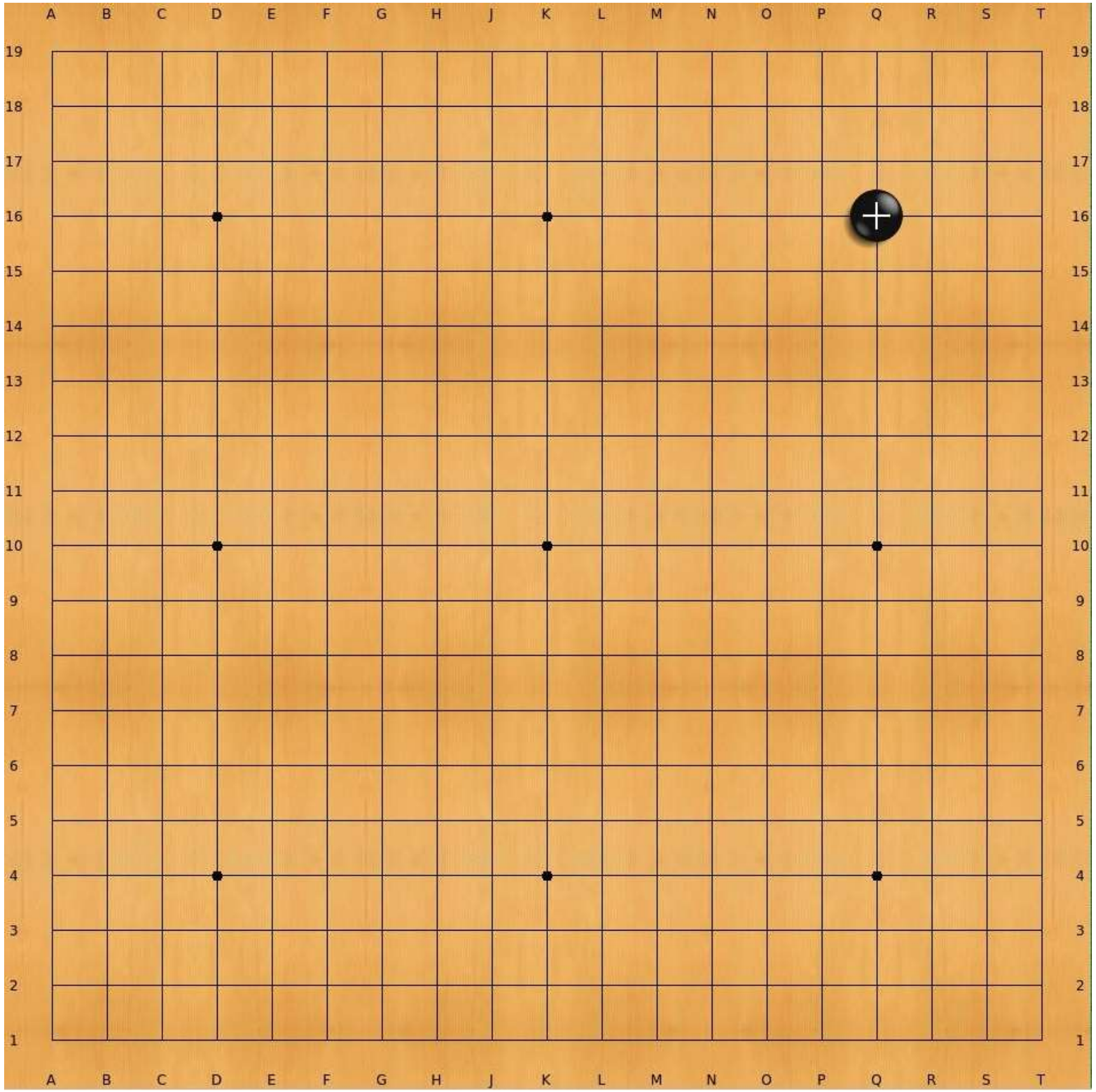


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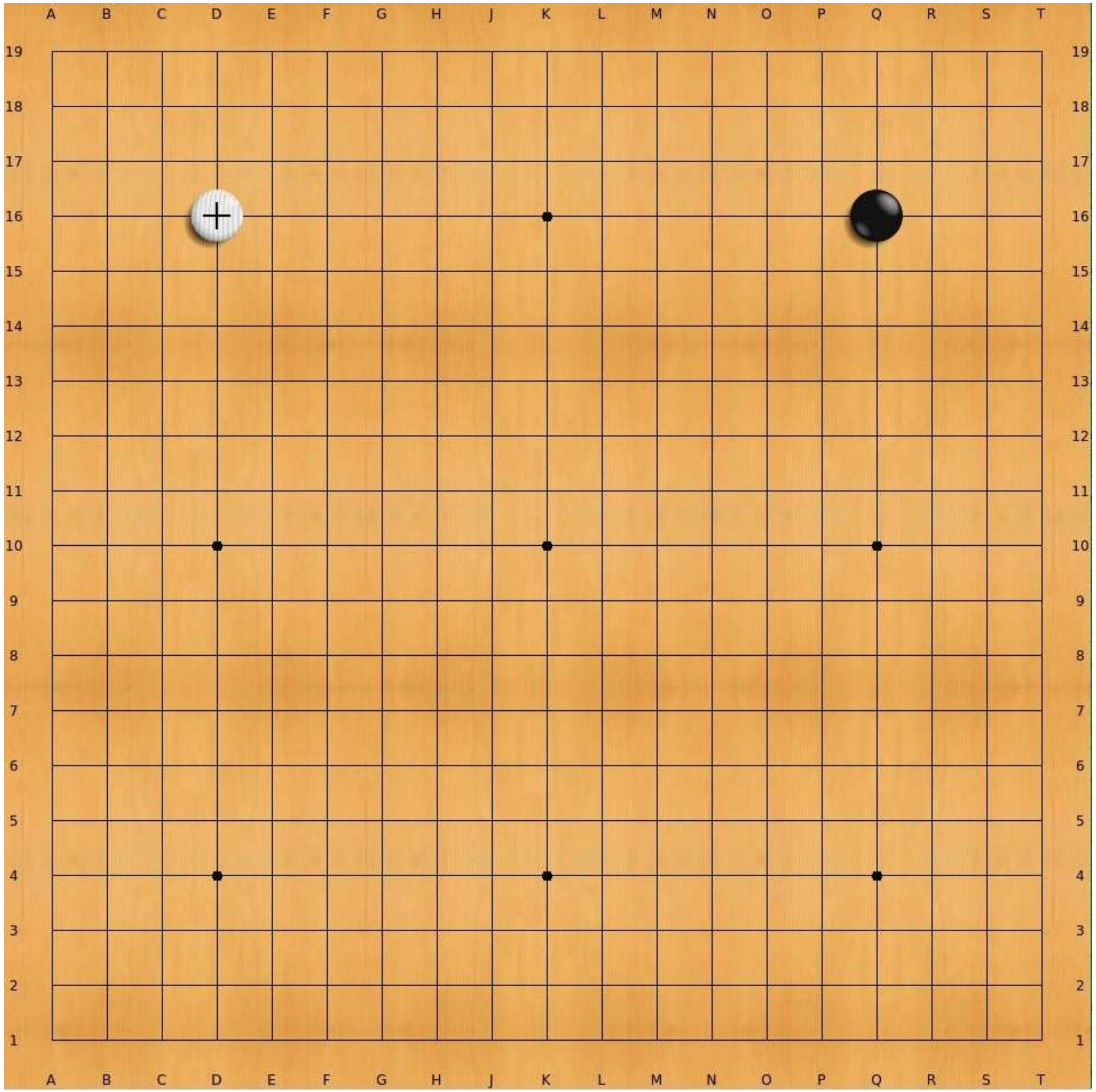


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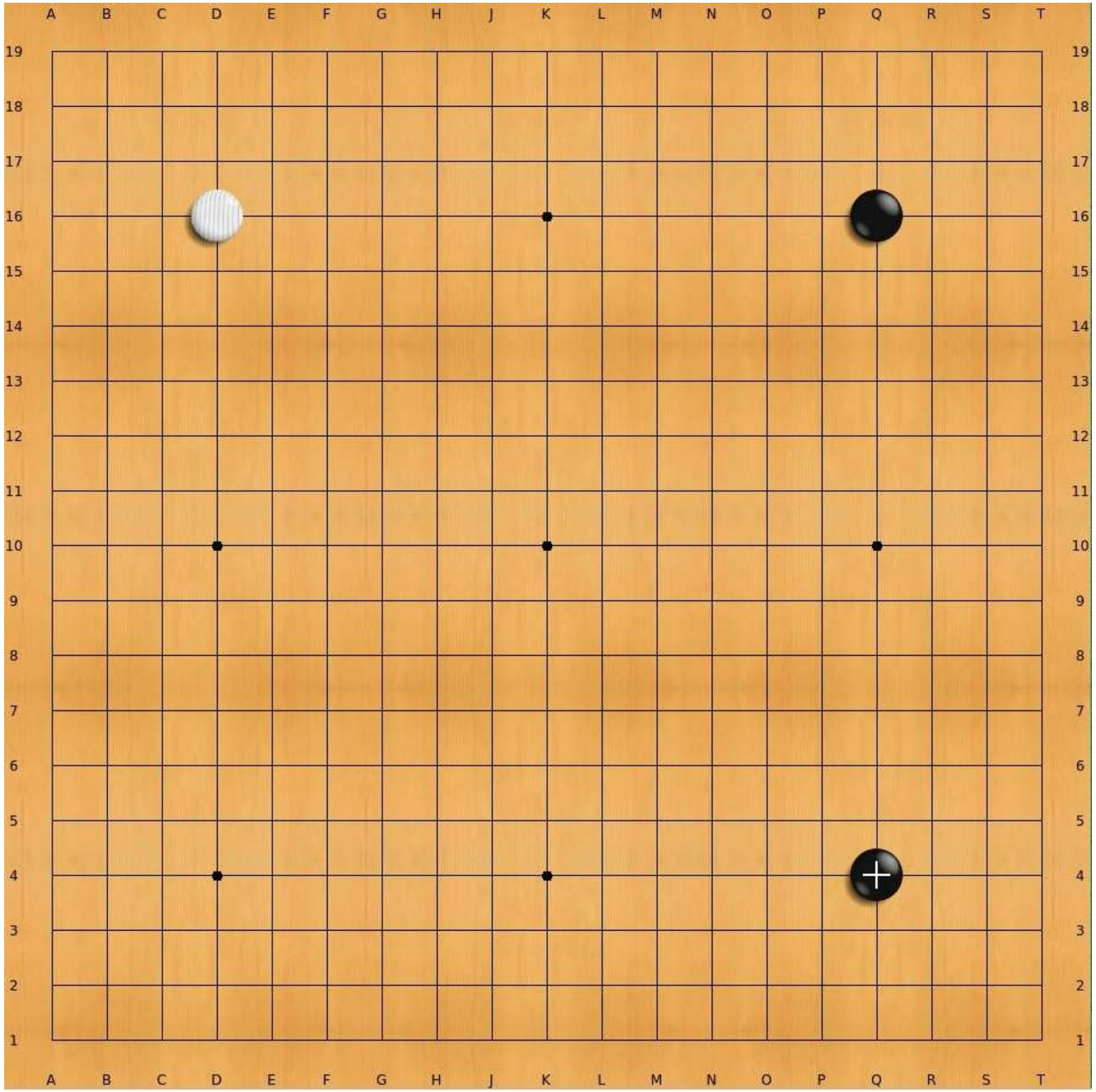


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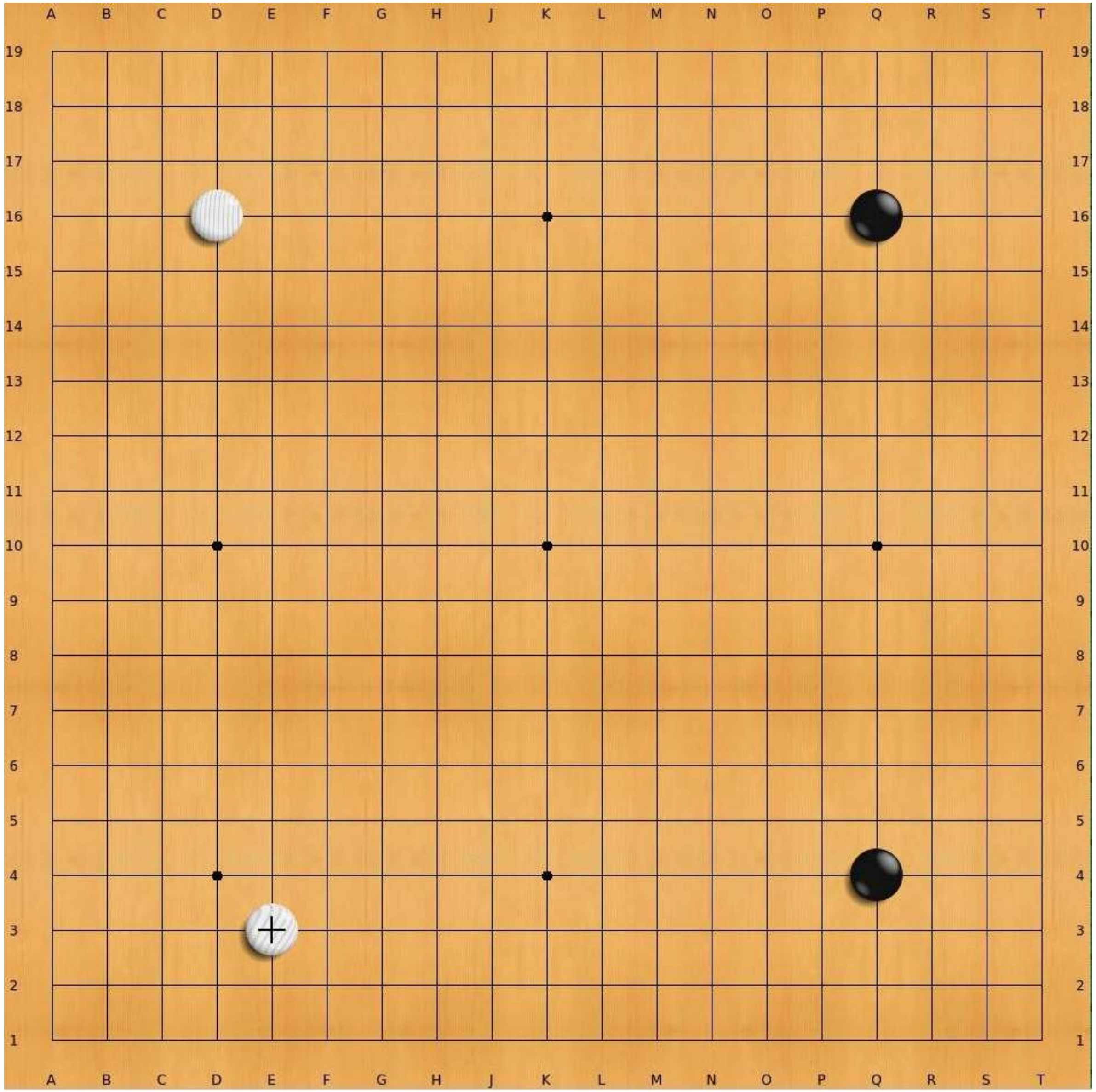


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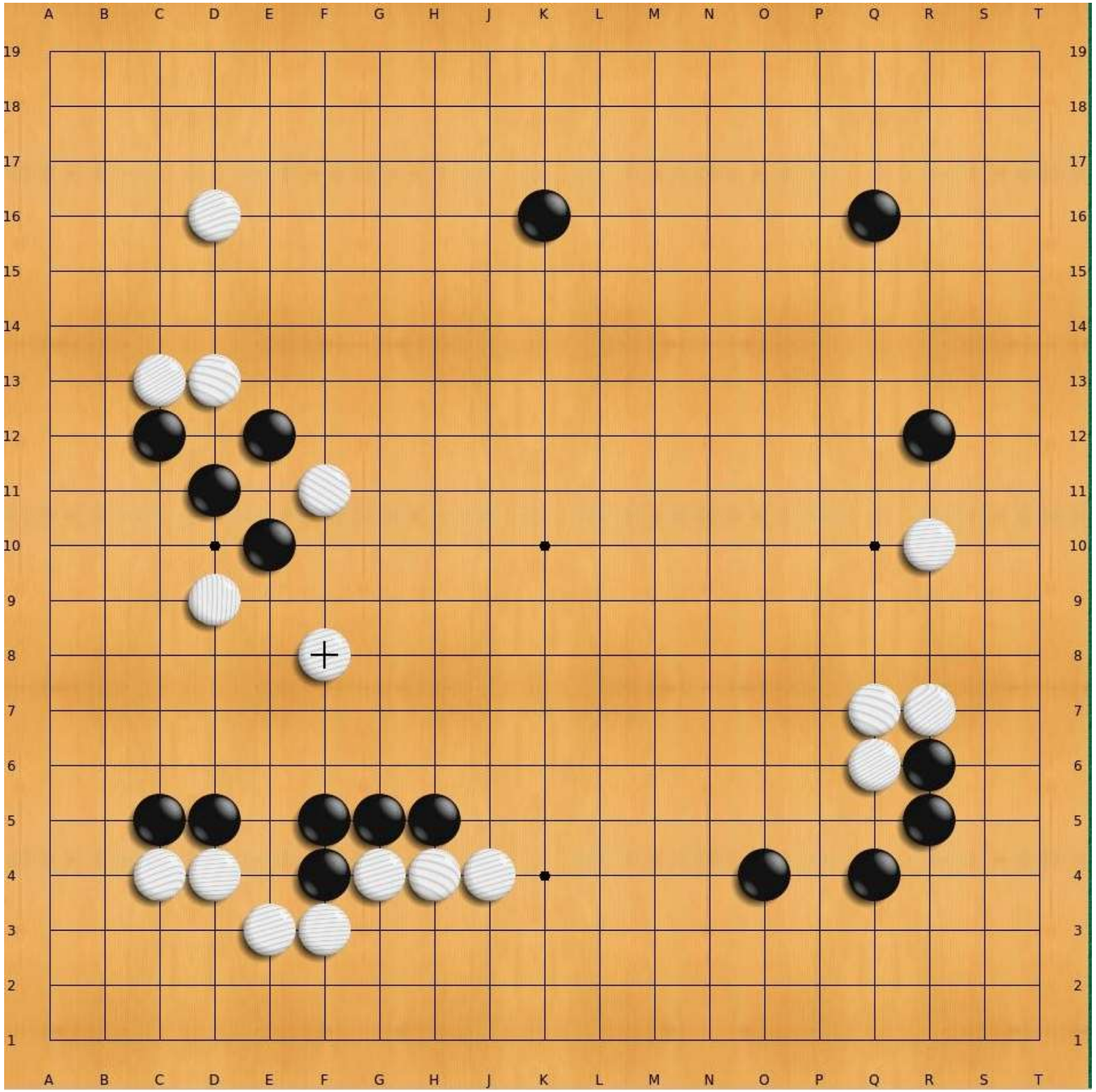


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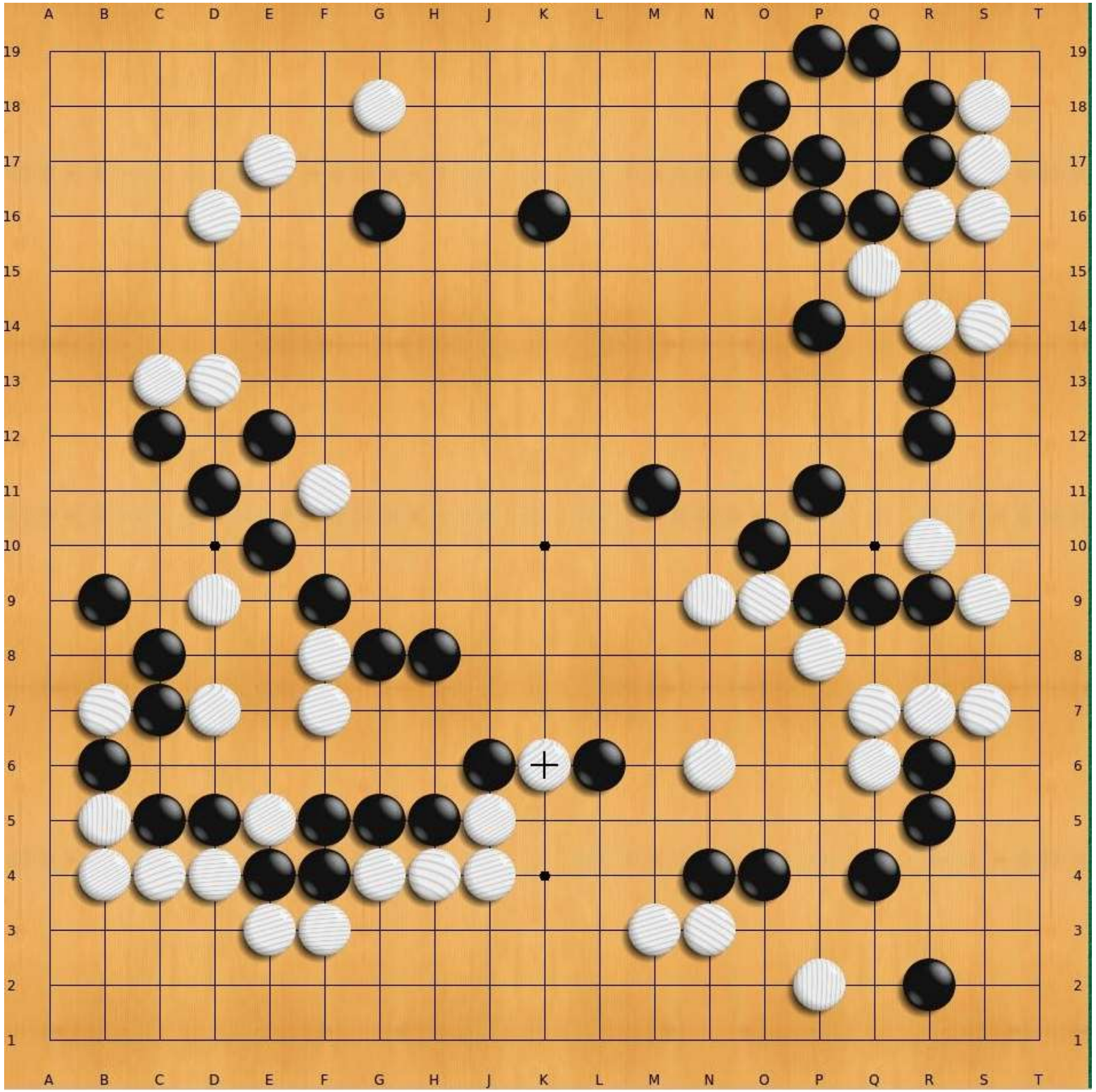


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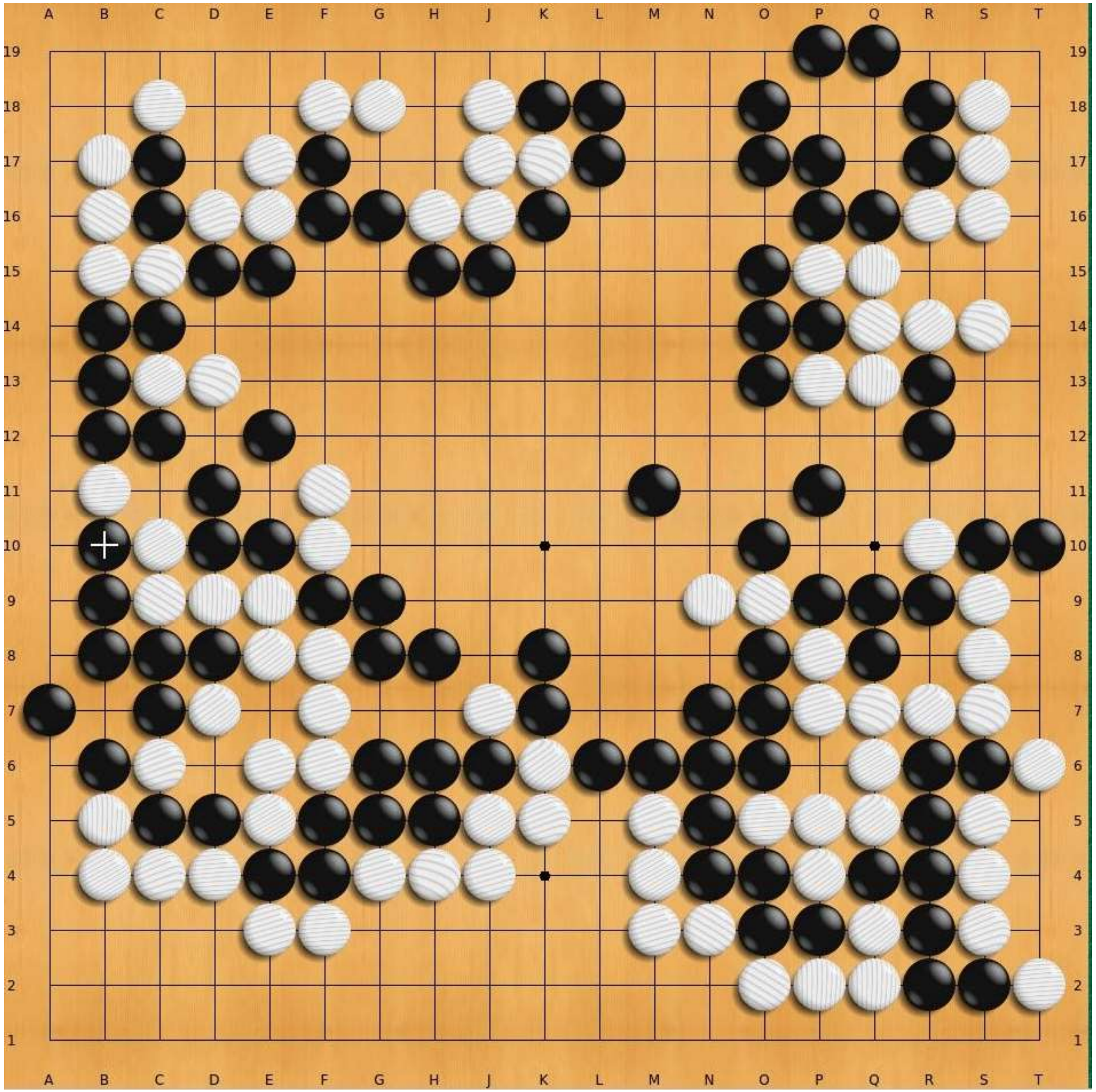


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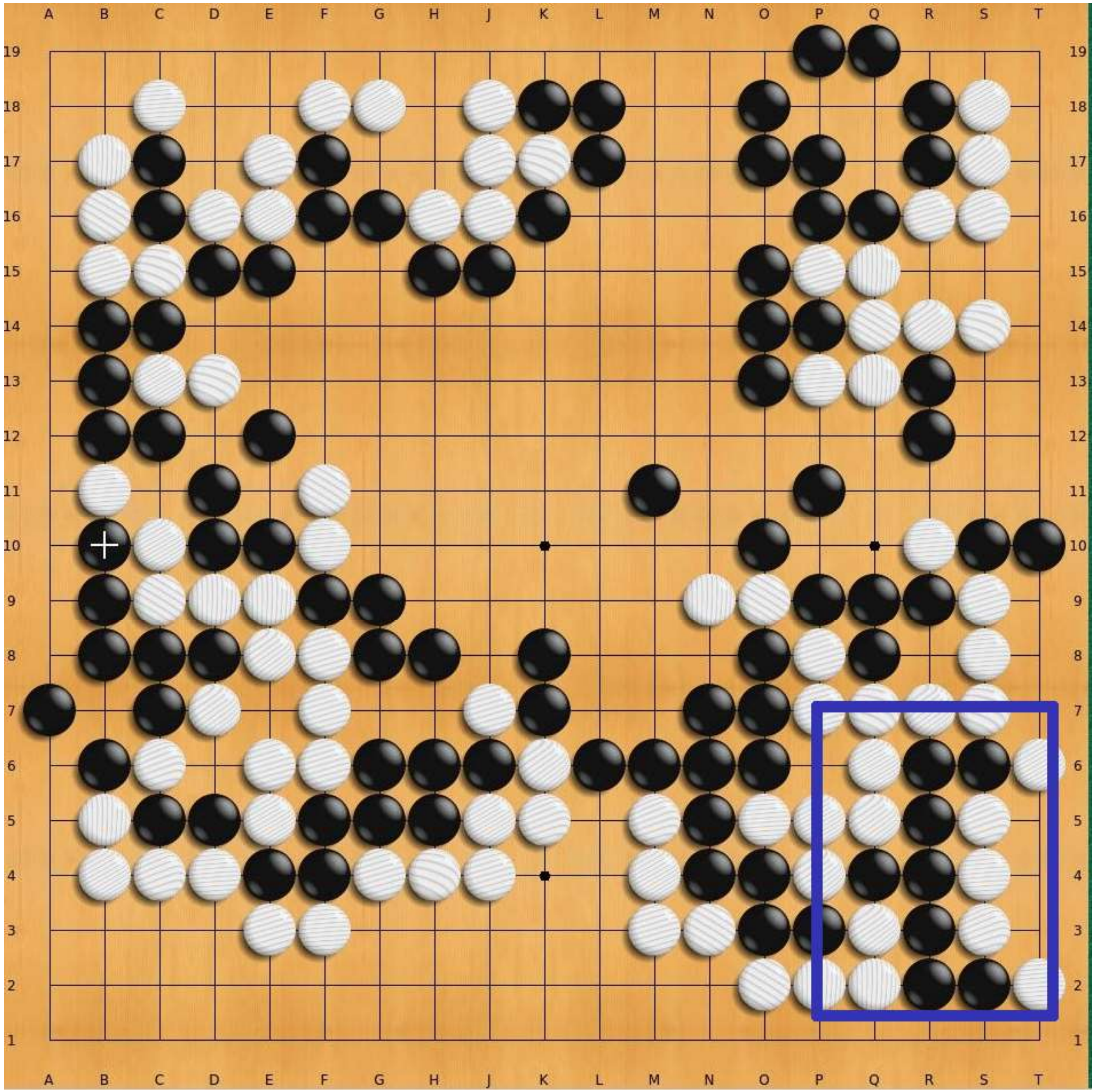


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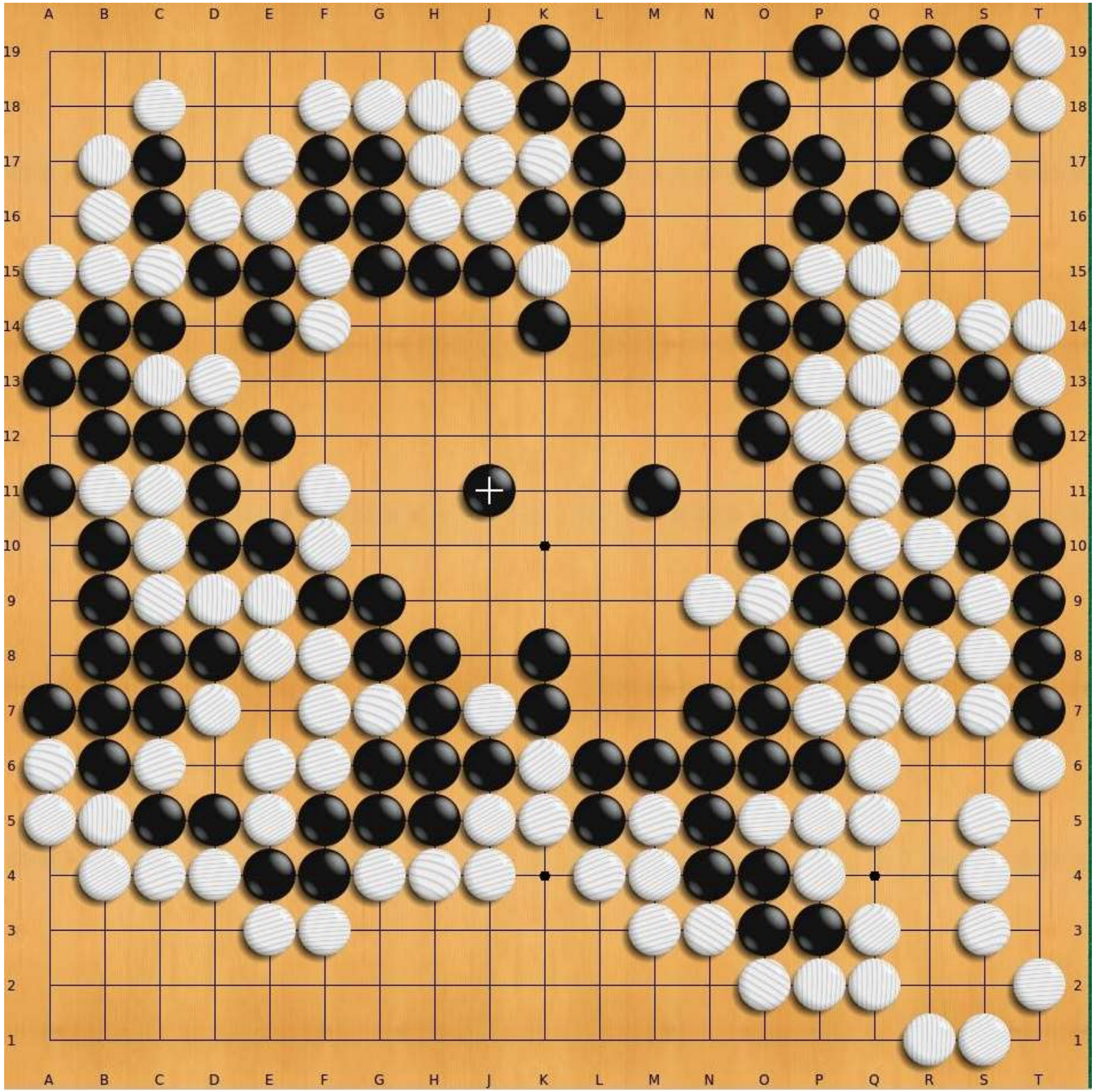


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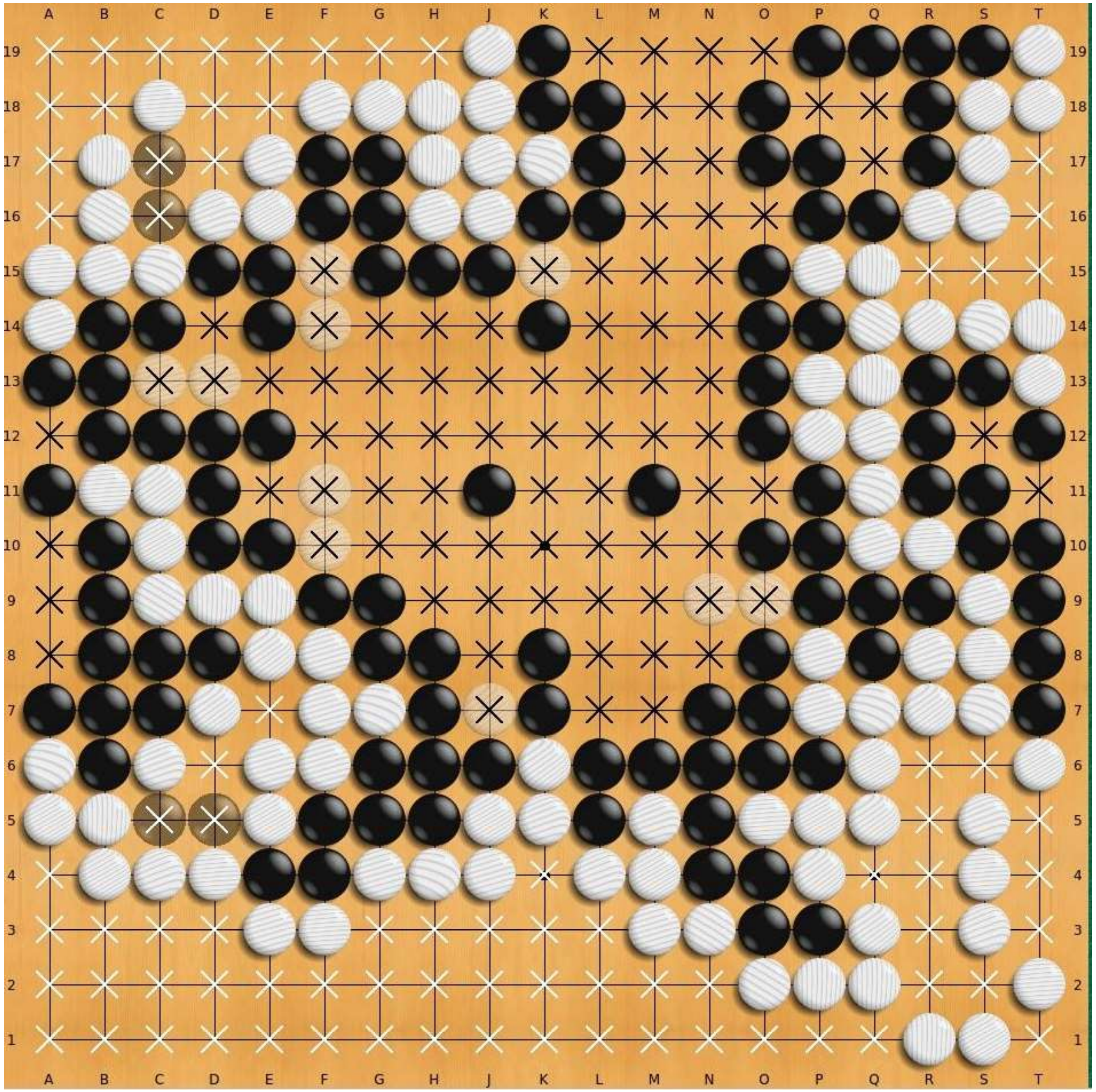



Image [7]

# Complexity of Go

**Why is Go so hard?**

- Board size usually 19x19
- Almost every move is legal
- Average branching factor of Go: 250
- Amount of possible game states: $10^{171}$ (Chess: $10^{43}$)

# Complexity of Go

| | breadth | depth |
|---|---|---|
| Tic-Tac-Toe | 4 | 9 |
| Checkers | 2.8 | 70 |
| Chess | 35 | 80 |
| Go | 250 | 150 |

Table: Game tree's breadths and depths

$\Rightarrow$ For Go: $b^d \approx 10^{360}$

# Reducing Search Space

- Reduce depth: position evaluation
  - Truncate the search tree at state $s$ and replace subtree below $s$ by an approximate value function $v(s) \approx v^*(s)$
- Reduce breadth: sampling actions from a policy
  - Policy $p(a|s)$: probability distribution over possible moves $a$ in state $s$

# Monte Carlo Tree Search

- Use Monte Carlo rollouts to estimate the value of each state in a search tree
- Policy during search improved over time by selecting children with higher values
- Policy converges to optimal play asymptotically

# Rollout policy $p_\pi$

- Training data: 8M board positions from games between human expert players
- Accuracy: 24.2%
- Time required to select an action: $2\mu s$

# Features (Rollout Policy $p_\pi$)

| Feature | # of patterns | Description |
|---|---|---|
| Response | 1 | Whether move matches one or more response pattern features |
| Save atari | 1 | Move saves stone(s) from capture |
| Neighbour | 8 | Move is 8-connected to previous move |
| Nakade | 8192 | Move matches a *nakade* pattern at captured stone |
| Response pattern | 32207 | Move matches 12-point diamond pattern near previous move |
| Non-response pattern | 69338 | Move matches $3 \times 3$ pattern around move |
| Self-atari | 1 | Move allows stones to be captured |
| Last move distance | 34 | Manhattan distance to previous two moves |
| Non-response pattern | 32207 | Move matches 12-point diamond pattern centred around move |

Features used by the rollout policy (first set) and tree policy (first and second set). Patterns are based on stone colour (black/white/empty) and liberties (1, 2, $\geq$3) at each intersection of the pattern.

Table: [1]

# Supervised Learning Policy Network $p_\sigma$

- Training data: 30M board positions from games between human expert players
- Stochastic gradient ascent to maximize likelihood of selecting the same move as the human did
- Architecture: 13-layer network
- Accuracy: 55.7% vs 44.4% (state-of-the-art) (55.7% using board position and move history only)
- Time required to select an action: $3ms$

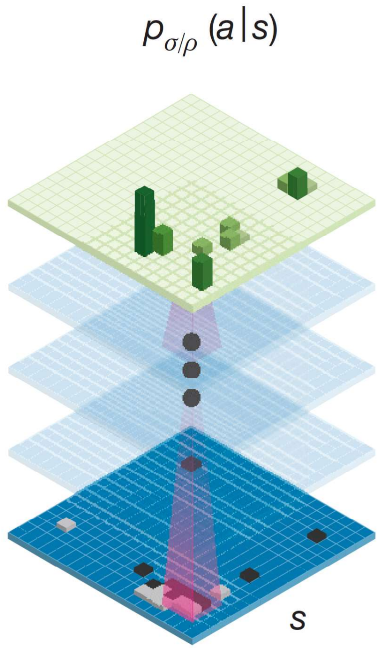



Image: [1]

# Reinforcement Learning Policy Network $p_\rho$

- Goal: Improve policy by policy gradient reinforcement learning
  Bias towards actually winning games rather than predictive accuracy
- Architecture: Identical to SL policy network
  weight initialization $\rho = \sigma$
- Training: games between current policy network and a randomly selected previous iteration of itself
- Reward function only rewards for winning a game
- Performance:
  - 80% of games won against SL policy network
  - 85% of games won against Pachi (using no search at all)
  - state-of-the-art, based on SL of convolutional networks, only won 11% of games against Pachi

# Value Network $v_\theta$

- Goal: Estimate a value function $v^p(s)$ that predicts the outcome from position $s$
- Ideally: optimal value function under perfect play $v^*(s)$
- Instead: approximate value function using value network $v_\theta(s)$
- Architecture: similar to policy network, however, output is a single prediction instead of a probability distribution
- Training: state-outcome pairs $(s, z)$ using SGD and MSE

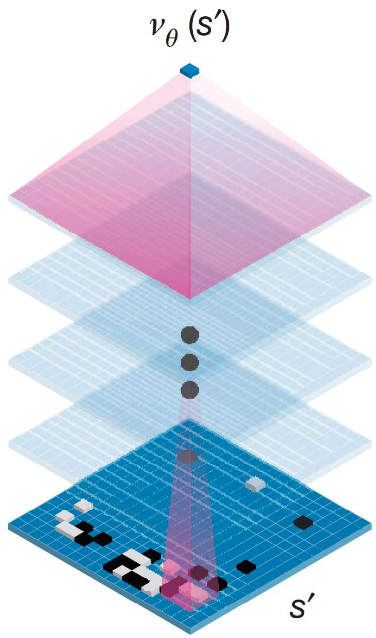



Image: [1]

# Feature Planes (Policy Network and Value Network)

| Feature | # of planes | Description |
|---|---|---|
| Stone colour | 3 | Player stone / opponent stone / empty |
| Ones | 1 | A constant plane filled with 1 |
| Turns since | 8 | How many turns since a move was played |
| Liberties | 8 | Number of liberties (empty adjacent points) |
| Capture size | 8 | How many opponent stones would be captured |
| Self-atari size | 8 | How many of own stones would be captured |
| Liberties after move | 8 | Number of liberties after this move is played |
| Ladder capture | 1 | Whether a move at this point is a successful ladder capture |
| Ladder escape | 1 | Whether a move at this point is a successful ladder escape |
| Sensibleness | 1 | Whether a move is legal and does not fill its own eyes |
| Zeros | 1 | A constant plane filled with 0 |
| Player color | 1 | Whether current player is black |

Feature planes used by the policy network (all but last feature) and value network (all features).

Table: [1]

# Training the Value Network

- Naive approach:
  - Predicting game outcomes from data consisting of complete games
  - Problem: Successive positions are strongly correlated
  - MSE $\Rightarrow$ Train: 0.19 / Test: 0.37
- Actual approach:
  - Generate self-play data set (30M distinct positions)
  - Each position sampled from a separate game
  - Games played between RL policy network and itself until termination
  - MSE $\Rightarrow$ Train: 0.226 / Test: 0.234

# Evaluation Accuracies

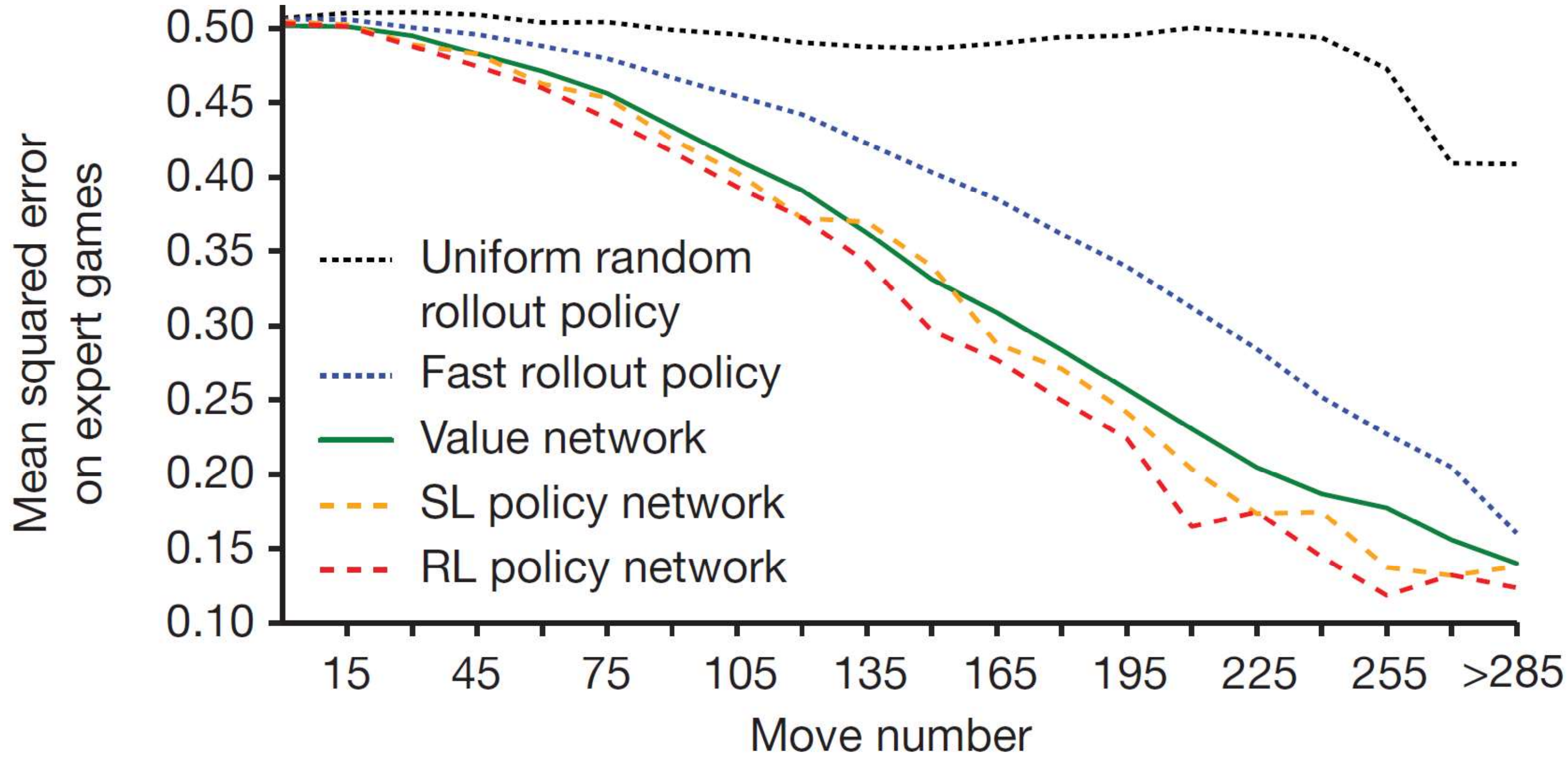



Image: [1]

# Putting It All Together

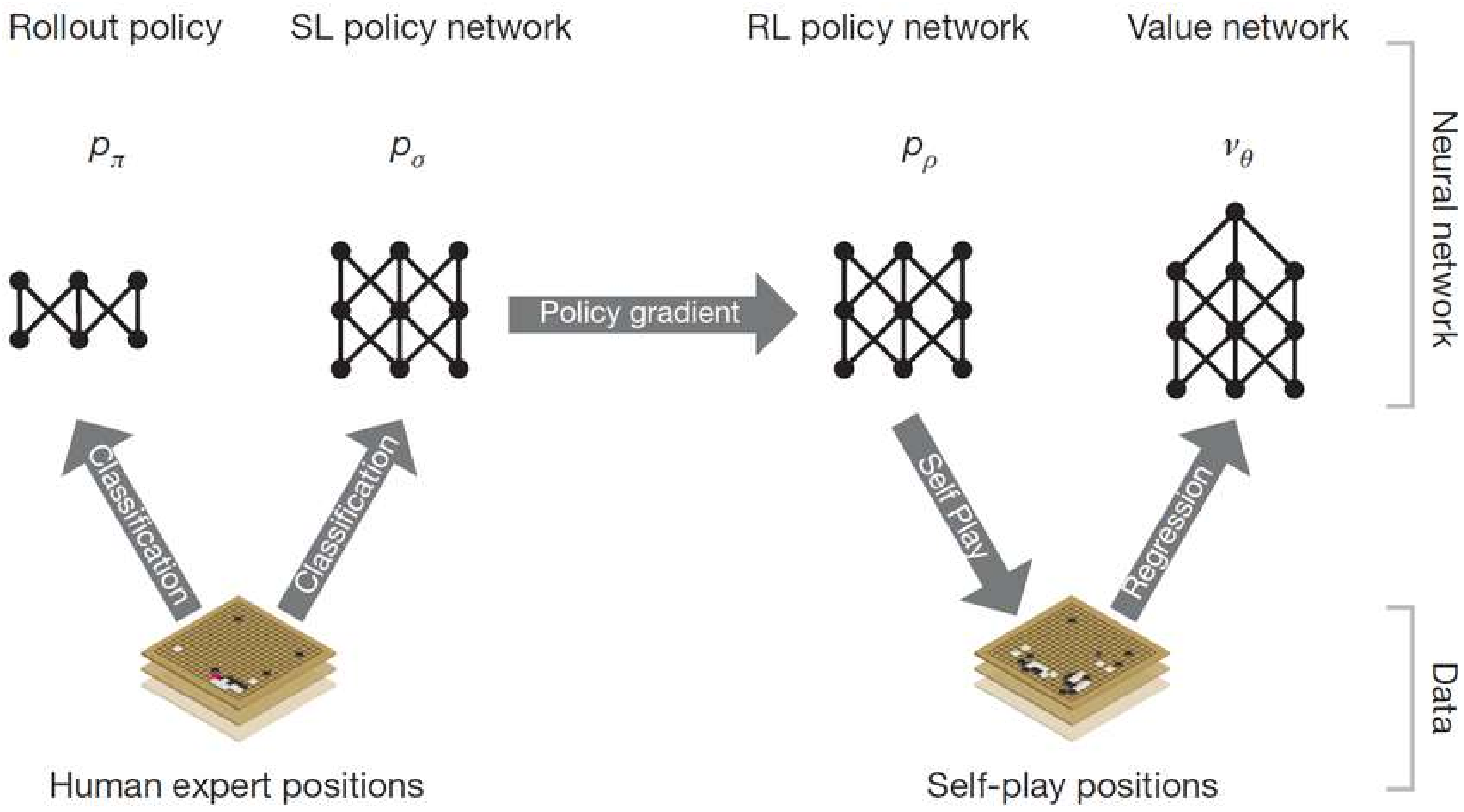
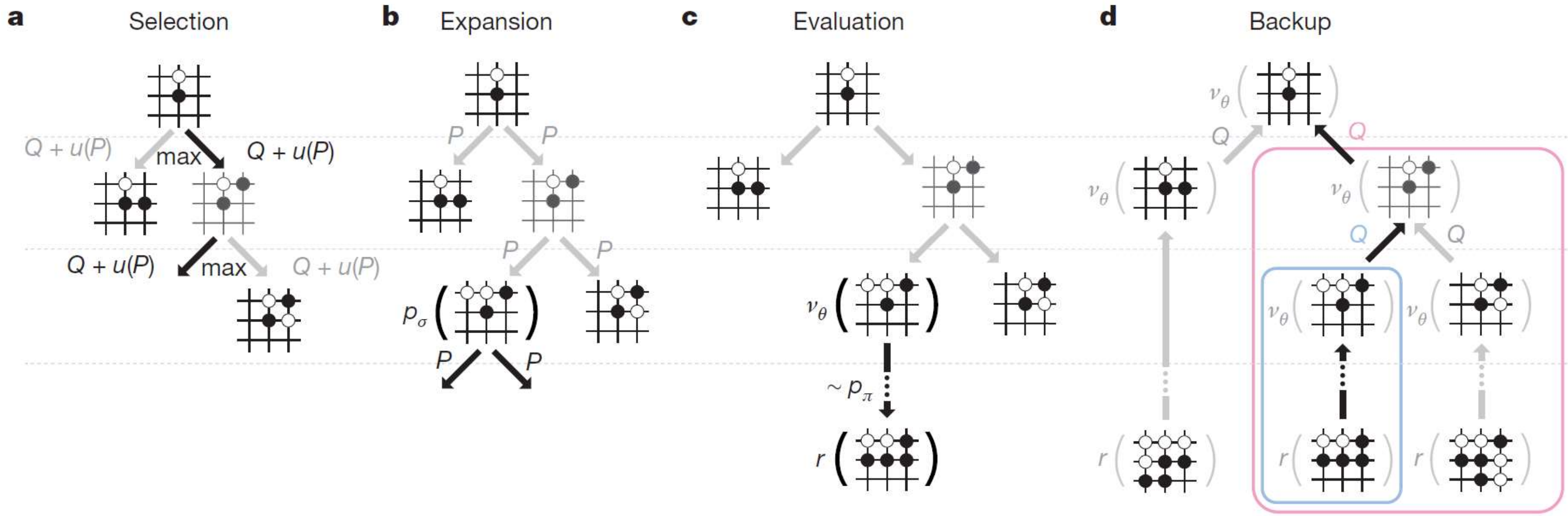



Image: [1]

# Searching with Policy and Value Networks



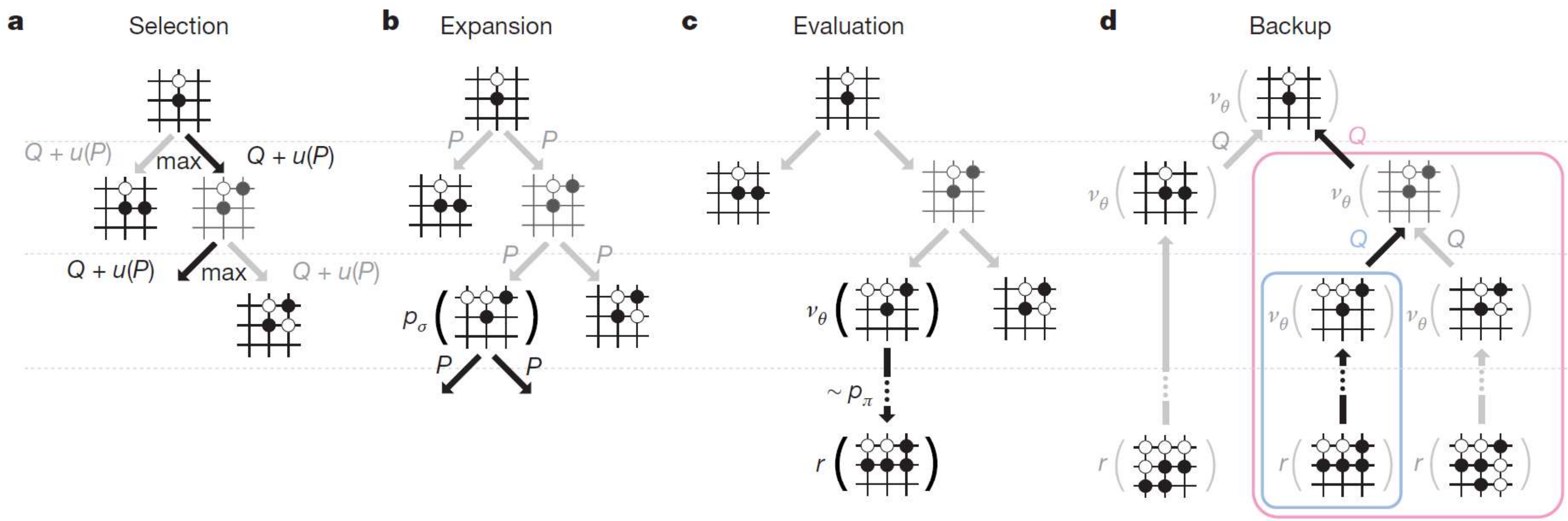

## Action selection at timestep t

$$a_t = \underset{a}{\operatorname{argmax}}(Q(s_t, a) + u(s_t, a))$$

$$u(s, a) \propto \frac{P(s, a)}{1 + N(s, a)}$$

Image: [1]

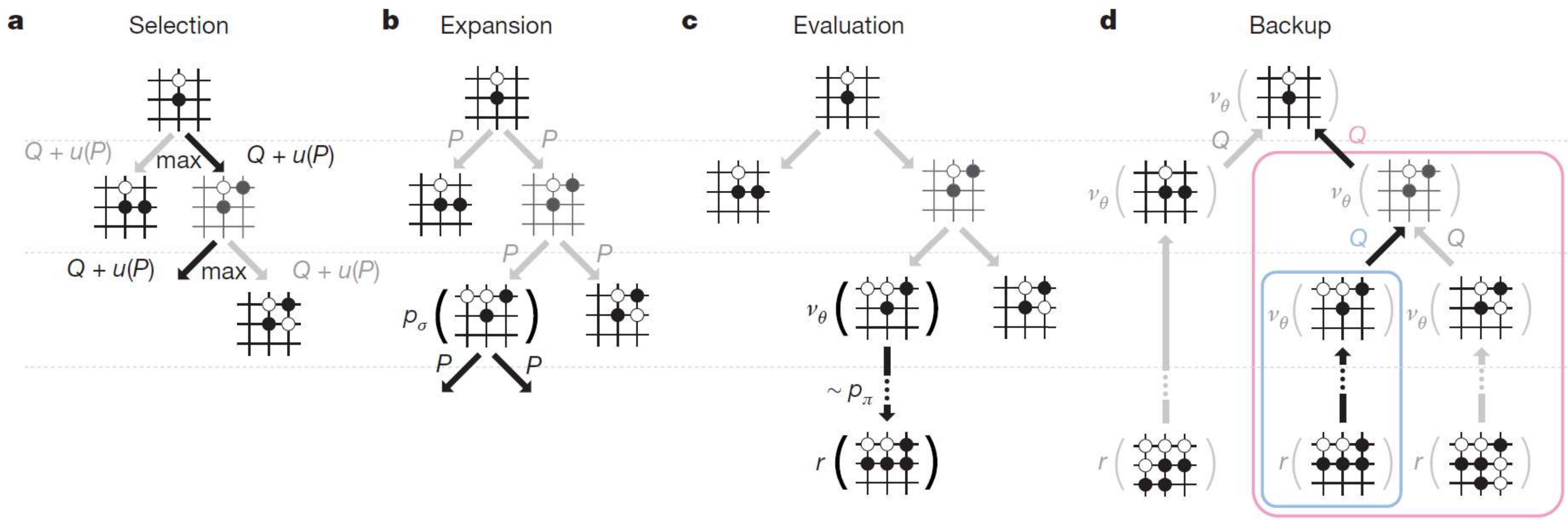
# Searching with Policy and Value Networks




## Leaf evaluation

$$V(S_L) = (1 - \lambda) v_\theta(S_L) + \lambda z_L$$

Image: [1]




## Backpropagation

$$N(s,a) = \sum_{i=1}^{n} 1(s,a,i)$$

$$Q(s,a) = \frac{1}{N(s,a)} \sum_{i=1}^{n} 1(s,a,i) V(s_L^i)$$

Image: [1]

# AlphaGo's Playing Strength

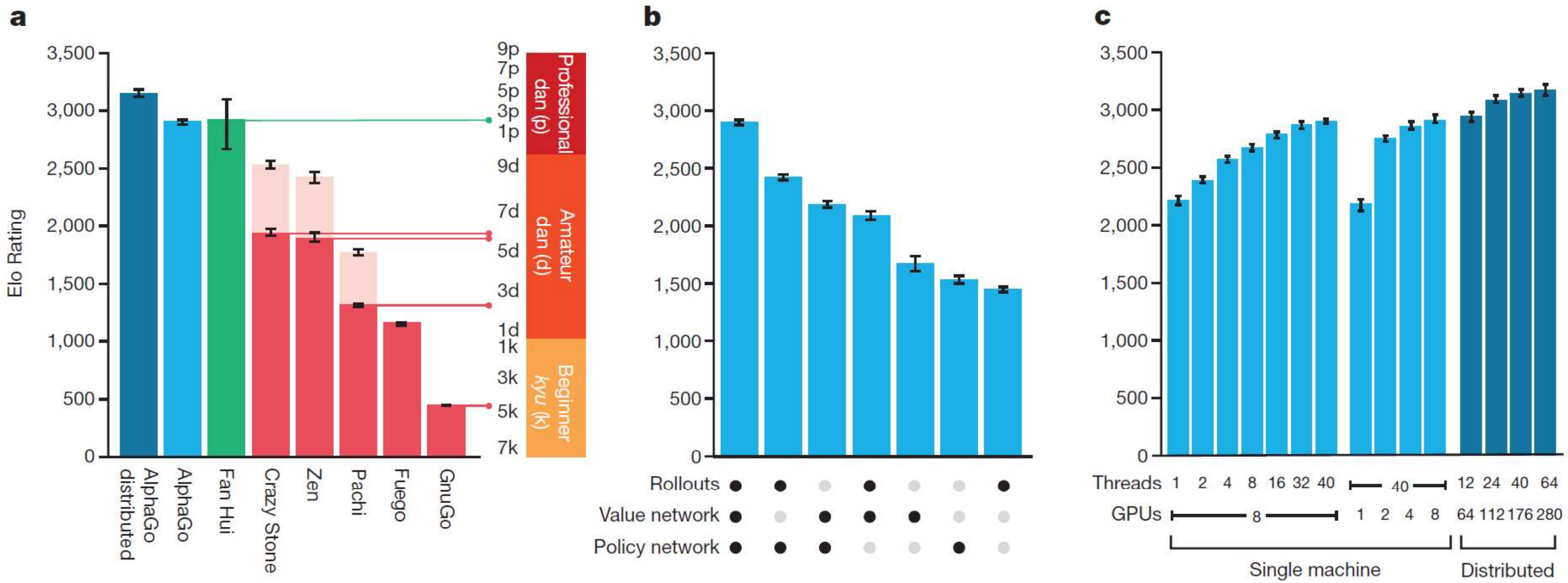



Image: [1]

# Example: How AlphaGo Selects Its Moves

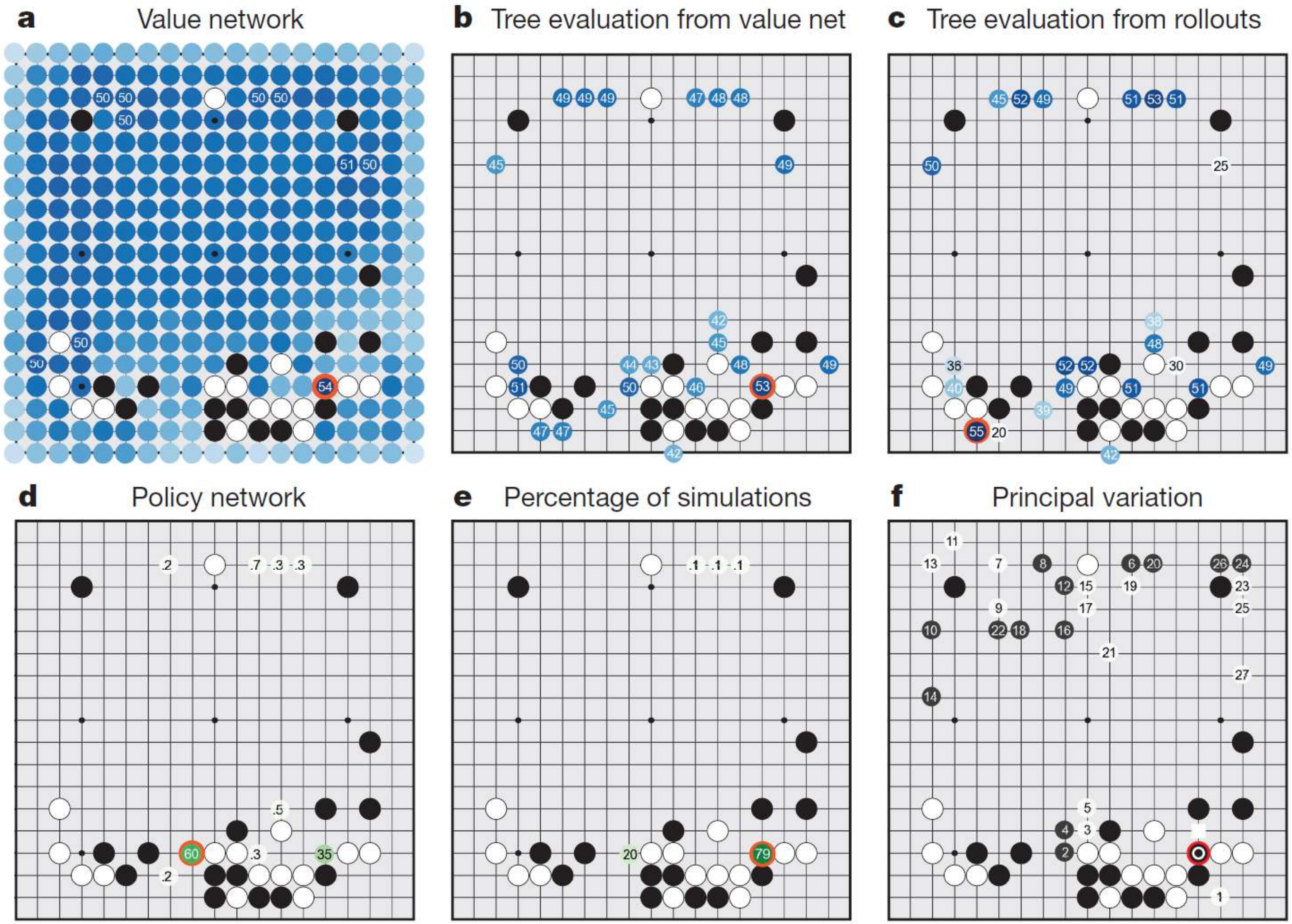



Image: [1]

# Why Use Policy and Value Networks?

- Value network and policy network work hand in hand
- Value network alone:
  - Would have to exhaustive compare the value of all children
    $\Rightarrow$ Policy network predicts best move, narrows the search space
- Policy network alone:
  - Unable to directly compare nodes in different parts of the tree
  - Value network gives an estimate of winner as if the game was played according to policy network
    $\Rightarrow$ Values direct later searches to moves that are actually evaluated to be better

# Why Combine Neural Networks with MCTS?

- How does MCTS improve a Policy Network?
    - Recall: MCTS (Pachi) won 15% of games against Policy Network
    - Policy Network is just a *prediction*
    - MCTS and Monte Carlo rollouts help the policy adjust towards moves that are actually evaluated to be good
- How doe Neural Networks improve MCTS?
    - The Slow Policy guides tree exploration more intelligently
    - The Fast Policy guides simulations more intelligently
    - Value Network and Simulation Value are complementary

# AlphaGo vs Lee Sedol


Image: [8]

# AlphaGo vs Lee Sedol

# Game 2 – Move 37 (AlphaGo)

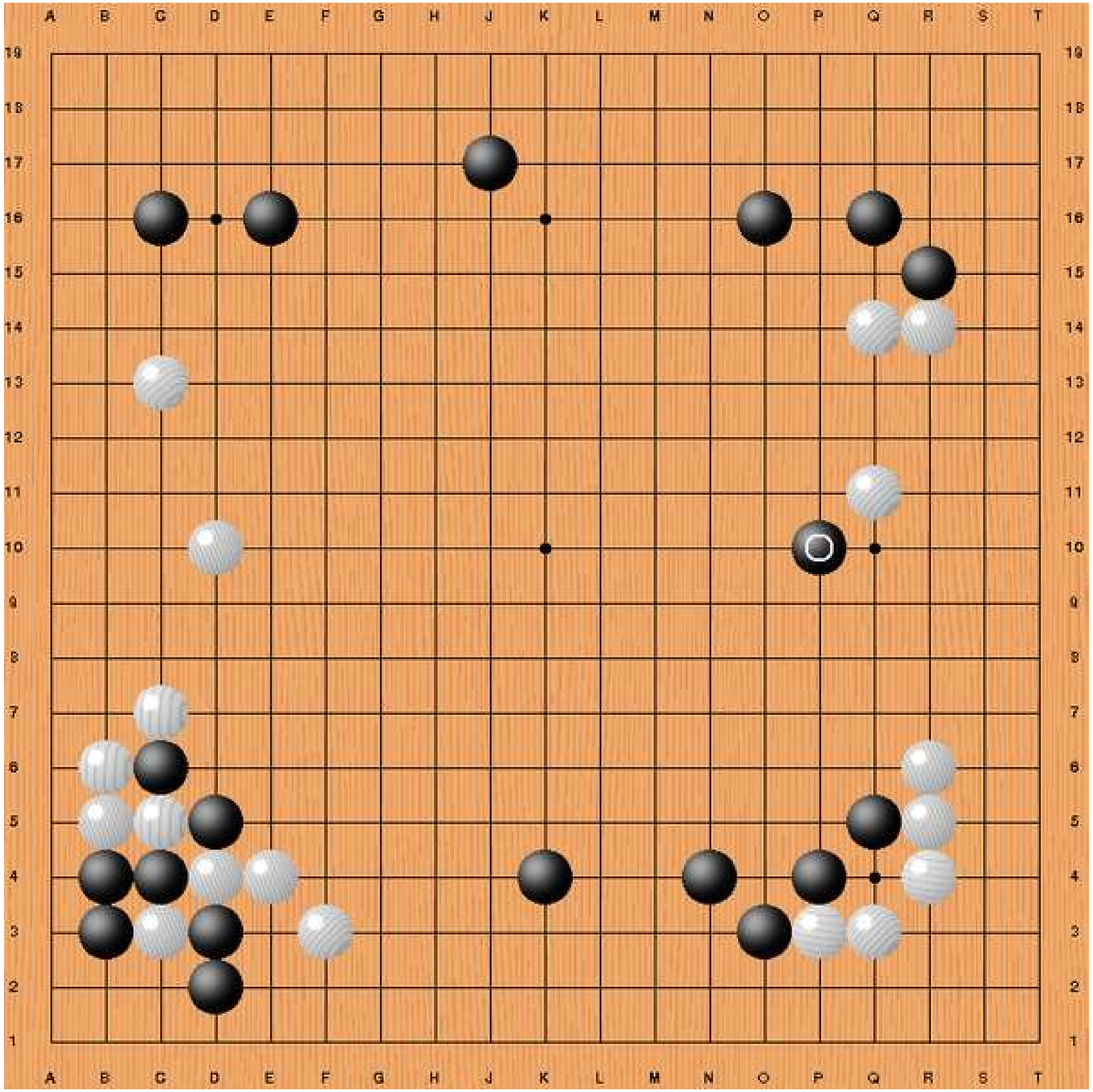



Image: [9]

# Game 2 – Move 37 (AlphaGo)

*"It's not a human move, I've never seen a human play this move. So beautiful. Beautiful. Beautiful."*

– Fan Hui (2p)

Image: [10]

# Game 4 – Move 78 (Lee Sedol) – "God's Touch"

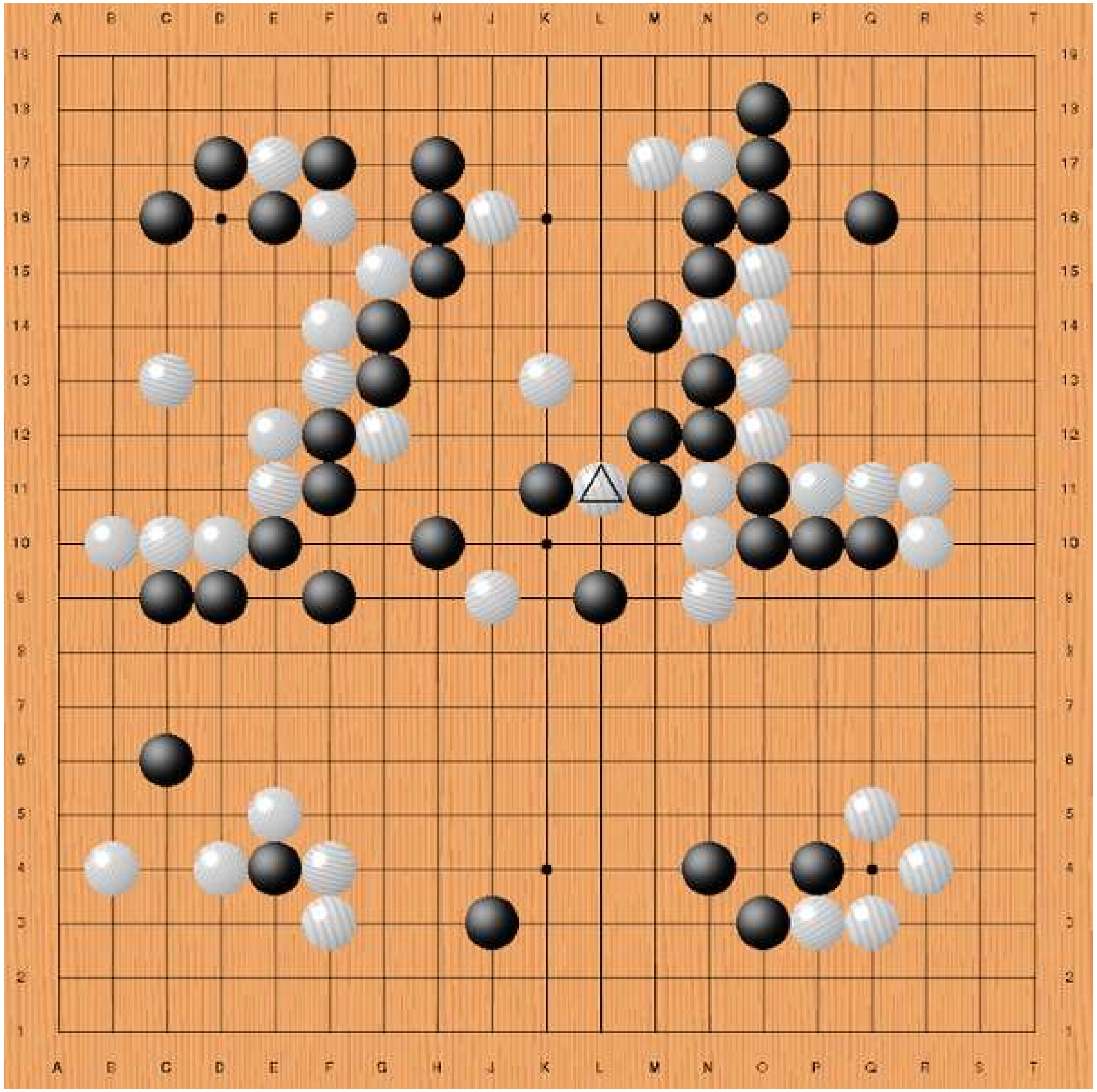


Image: [11]


ALPHAGO
TRIBECA FILM FESTIVAL 2017
BFI LONDON FILM FESTIVAL
OFFICIAL SELECTION 2017
WINNER
TRAVERSE CITY FILM FESTIVAL
2017
OFFICIAL SELECTION
MILL VALLEY FILM FESTIVAL
2017
Official Selection
WARSAW FILM FESTIVAL
VIFF
Official Selection
2017

Image: [12]

Thank you for your attention!

# References I


[1] Silver et al. (2016)
Mastering the game of Go with deep neural networks and tree search
*NATURE* 529, 484 – 489.
URL: https://vk.com/doc-44016343_437229031?dl=56ce06e325d42fbc72

[2] Korean couple playing Go
URL: https://upload.wikimedia.org/wikipedia/commons/e/e3/Korean_Game_from_the_Carpenter_Collection%2C_ca._1910-1920.jpg

[3] Woman playing Go
URL: https://upload.wikimedia.org/wikipedia/commons/thumb/9/9d/Anonymous-Astana_Graves_Wei_Qi_Player.jpg/1280px-Anonymous-Astana_Graves_Wei_Qi_Player.jpg

[4] Go Board
URL: https://i1.wp.com/cdn0.vox-cdn.com/thumbor/cxHFEPUtYJkaAz2Uf0dV5qLtc90=/cdn0.vox-cdn.com/uploads/chorus_asset/file/6160055/akrales_160307_0970_a_0127.0.png

# References II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[6] David Silver
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[7] Tobias Pfeiffer (2016)
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[9] Move 37
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[11] Move 78
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[12] AlphaGo Documentary
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