AlphaGo: Mastering the game of Go with neural networks and tree search

Silver et al. Nature 2016

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Machine Learning Reading Group at The Graduate Center, CUNY

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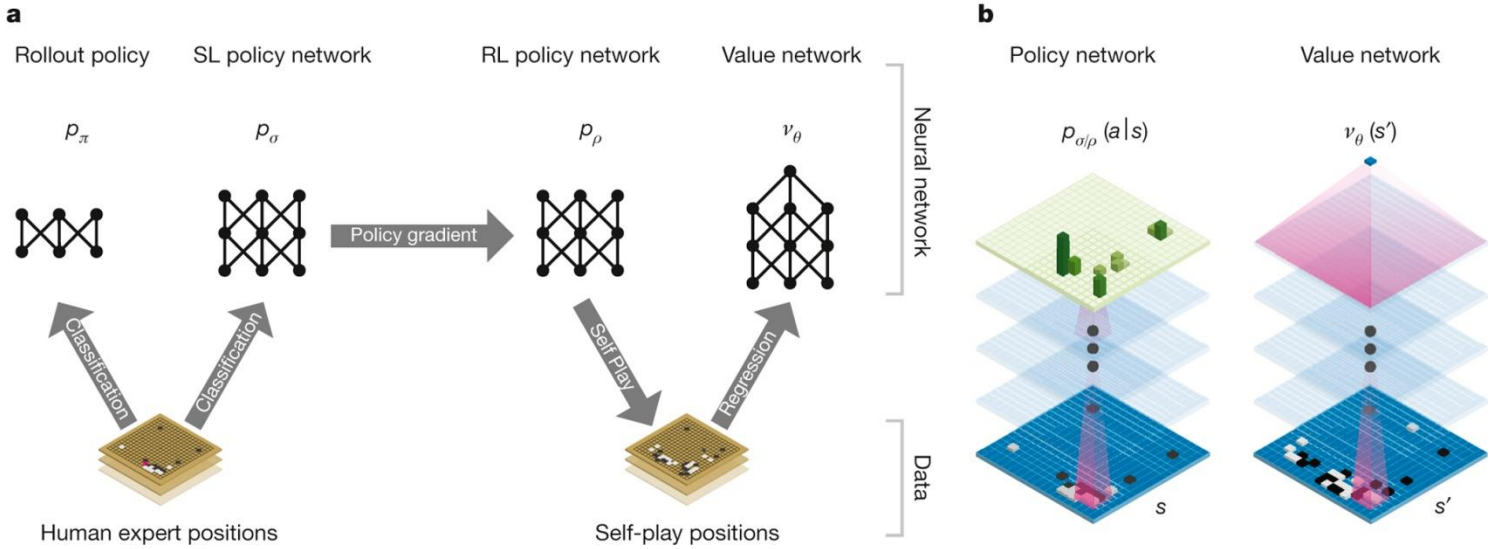
The Key Ingredients

- Convolutional Neural Networks
  - What is the state of the game board?
  - Reduce complexity of the game state.
- Reinforcement Learning
  - What moves to make? How good is a move?
  - Policy and value.
- Monte Carlo Tree Search
  - What moves lead to victory?
  - Approximate optimal minimax game tree.
- Distributed Computation
  - Do it all big and fast.

Neural network training pipeline and architecture



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- p_π and p_σ are trained to predict moves in human expert games, giving $p(a|s)$.
- The rollout policy is a small network used to quickly simulate entire games.
- p_ρ refines p_σ to predict winning moves in self-play simulation through reinforcement learning.
- v_θ predicts the probability of each player winning given a board state.

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Input Features

Extended Data Table 2: Input features for neural networks

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).

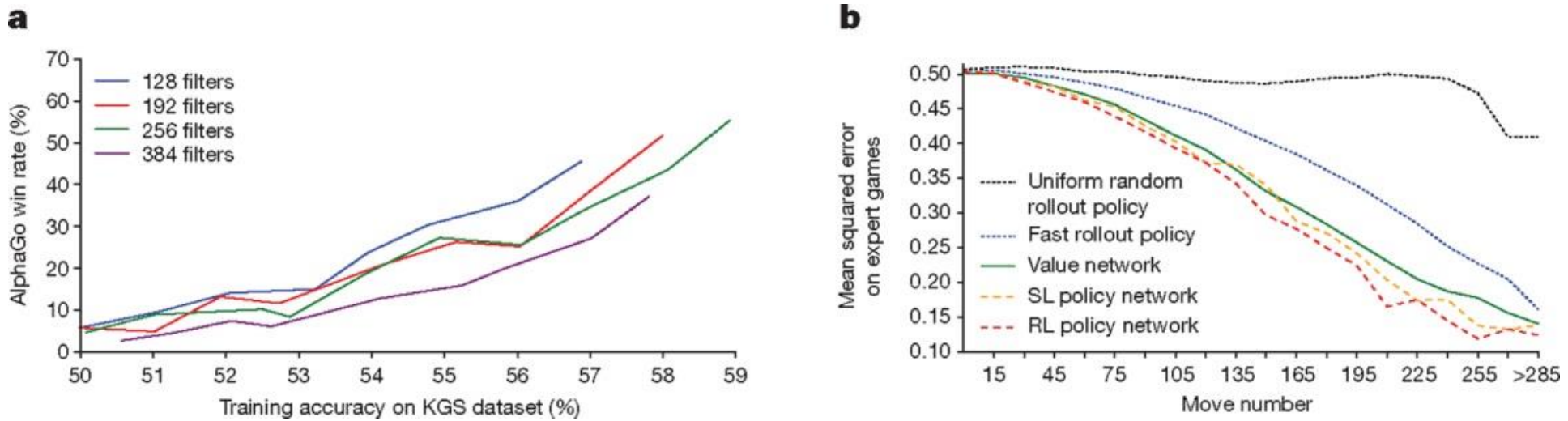
Input Features

Extended Data Table 4: Input features for rollout and tree policy

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 3×3 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, ≥3) at each intersection of the pattern.

Strength and accuracy of policy and value networks



- a) Comparison of policy networks with varying number of convolutional filters versus the match ready version of AlphaGo.
- b) Comparison of value network and mean of 100 rollouts by various policies on predictions of outcomes on human expert games.

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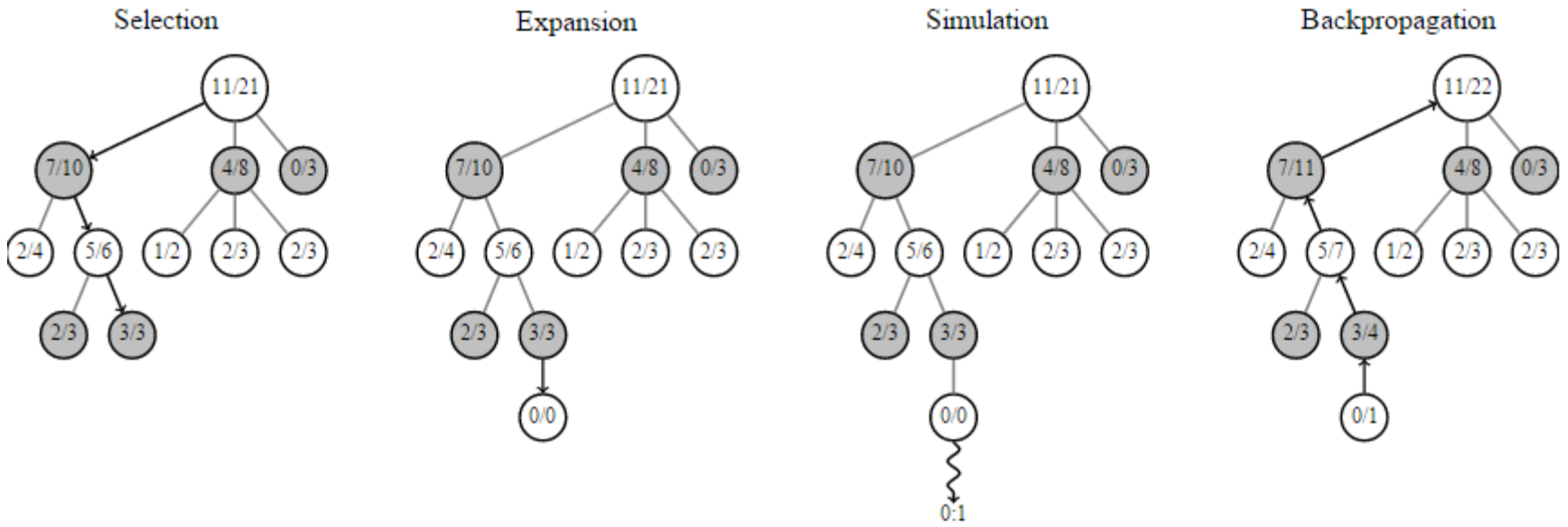
Reinforcement Learning

- Initialize p_ρ with p_σ, policy from human expert moves.
- Simulate game of $p_\rho^{(k)}$ with randomly selected $p_\rho^{k'}, k' < k$.
- Outcome at move t, z_t = +1 for winning and -1 for losing.
- SGD for each game move: $\Delta\rho \propto \frac{\partial \log p_\rho(a_t|s_t)}{\partial \rho} \cdot z_t$.
- 80% win rate versus p_σ.
- 85% win rate versus Pachi (previous best Go AI, search-based).

Reinforcement Learning

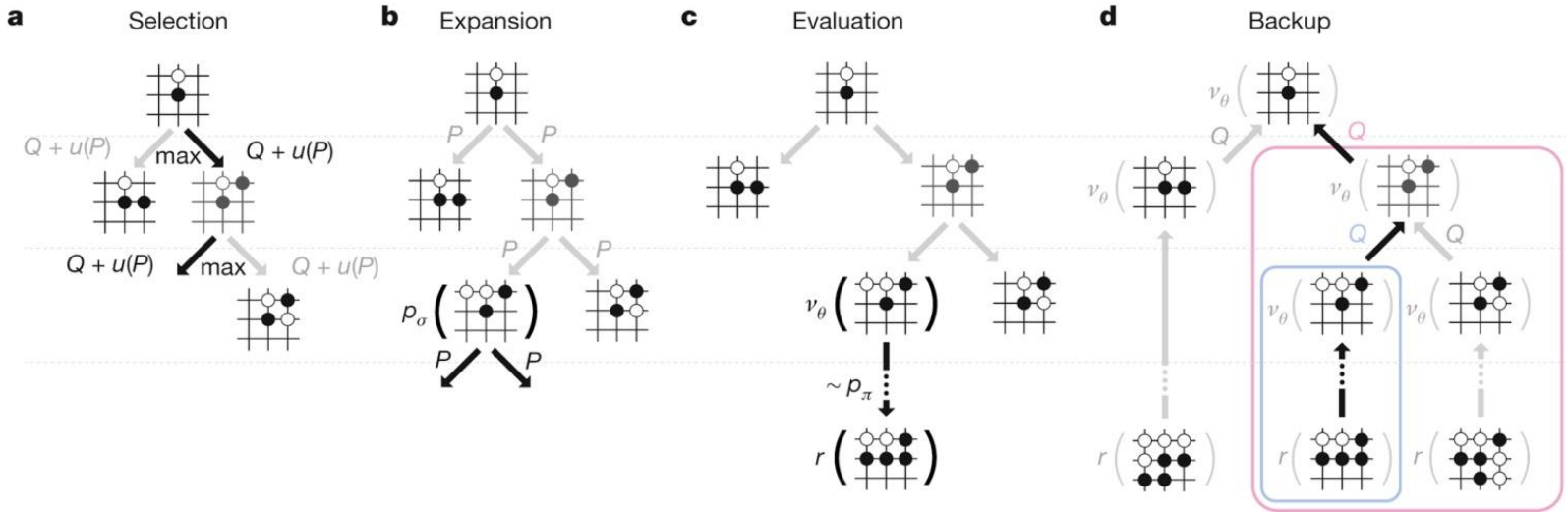
- $v^p(s) = \mathbb{E}[z_t \mid s_t = s, a_{t\ldots T} \sim p]$
- $v_\theta(s) \approx v^{p_\rho}(s) \approx v^*(s)$
- For state-outcome pairs (s, z), $\Delta\theta \propto \frac{\partial v_\theta(s)}{\partial \theta} \cdot \big(z - v_\theta(s)\big)$
- Successive positions in the same game are too strongly correlated, leads to overfitting.
- Sample (s, z) from different games in the self-play simulations.
- Approaches accuracy of rollouts of p_ρ with 15,000x less computation.

Monte Carlo Tree Search



- Explore move and simulate to game conclusion.
- Balance exploration vs exploitation.
- Converges to optimal value function with infinite simulations.

Monte Carlo tree search in AlphaGo



- a) Traverse tree from root to leaf my selecting actions with $\text{argmax}_a Q(s,a) + u(s,a)$, the action value plus a prior-based bonus $u(s,a) \propto \frac{P(s,a)}{1+N(s,a)}$, that decays with repeated visits.

- b) Expand leaf node and set prior $P(s,a) = p_\sigma(a|s)$.

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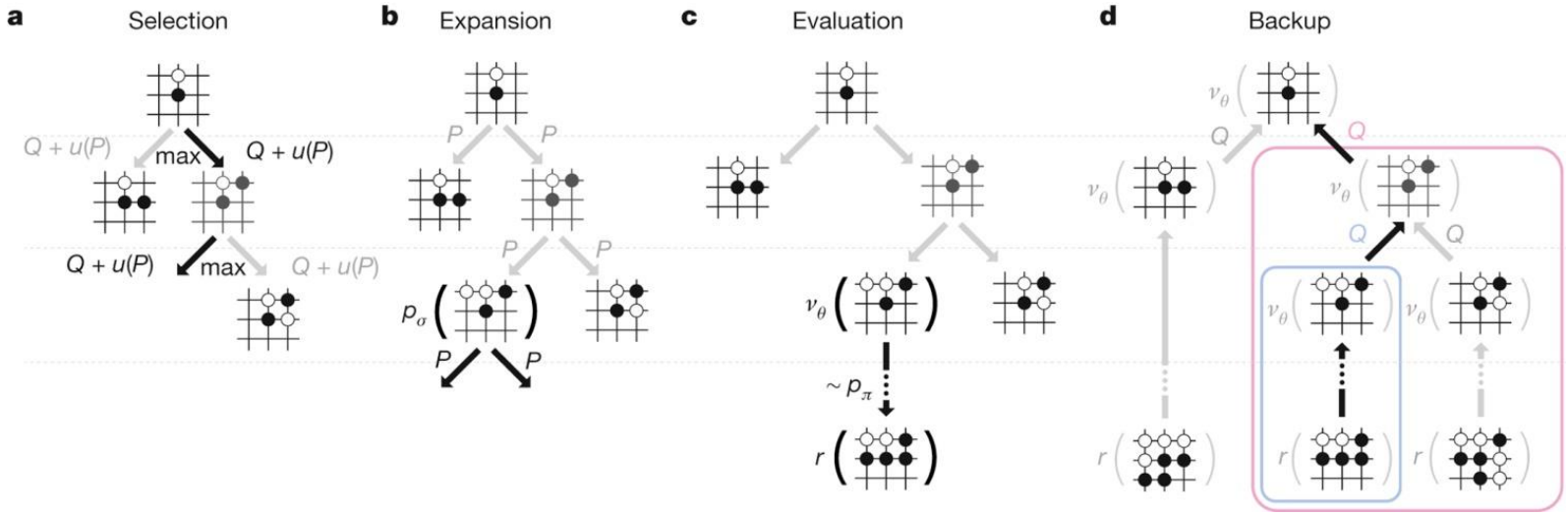
Monte Carlo tree search in AlphaGo



- c) Evaluate leaf node, $V(s_L) = (1-\lambda)v_\theta(s_L) + \lambda z_L$ where z_L is the rollout outcome using p_π.

- d) Update Q along tree path to track mean action value.

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

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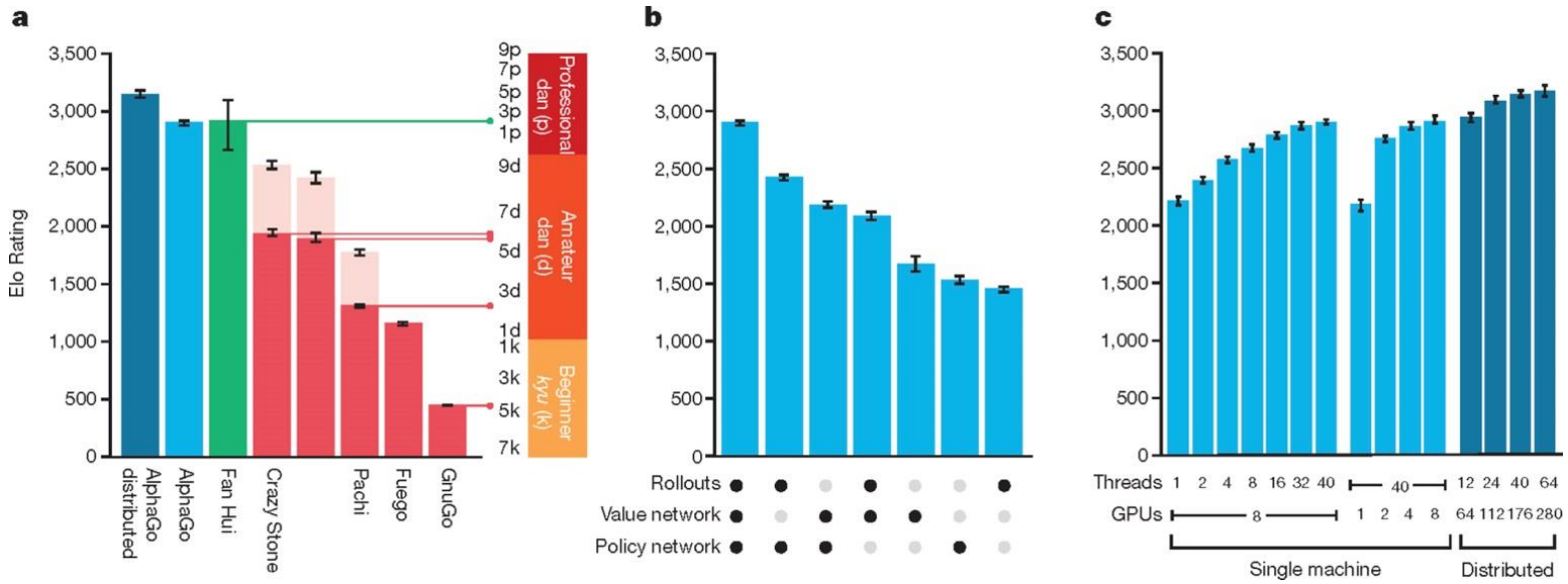
The Networks in AlphaGo MCTS

- Note that p_σ served as a better prior than p_ρ, presumably because humans consider a diverse beam of moves whereas RL optimizes for a single best move.
- However the value network derived from the RL policy network was better than the value network derived from the SL policy network.
- NNs are relatively expensive search heuristics for MCTS.
- Asynchronous multithreaded search:
  - 40 search threads, 48 CPUs, 8 GPUs.
- Distributed AlphaGo:
  - 40 search threads, 1202 CPUs, 176 GPUs.
- See the paper for more technical details.

Tournament evaluation of AlphaGo



- Each program used about 5s per move.
- Pale bar indicates games where a four stone handicap was given.
- Games against human European champion Fan Hui used longer time control.
- Elo rating: 100 point gap $\sim 64\%$ win rate, 200 point gap $\sim 76\%$ win rate.

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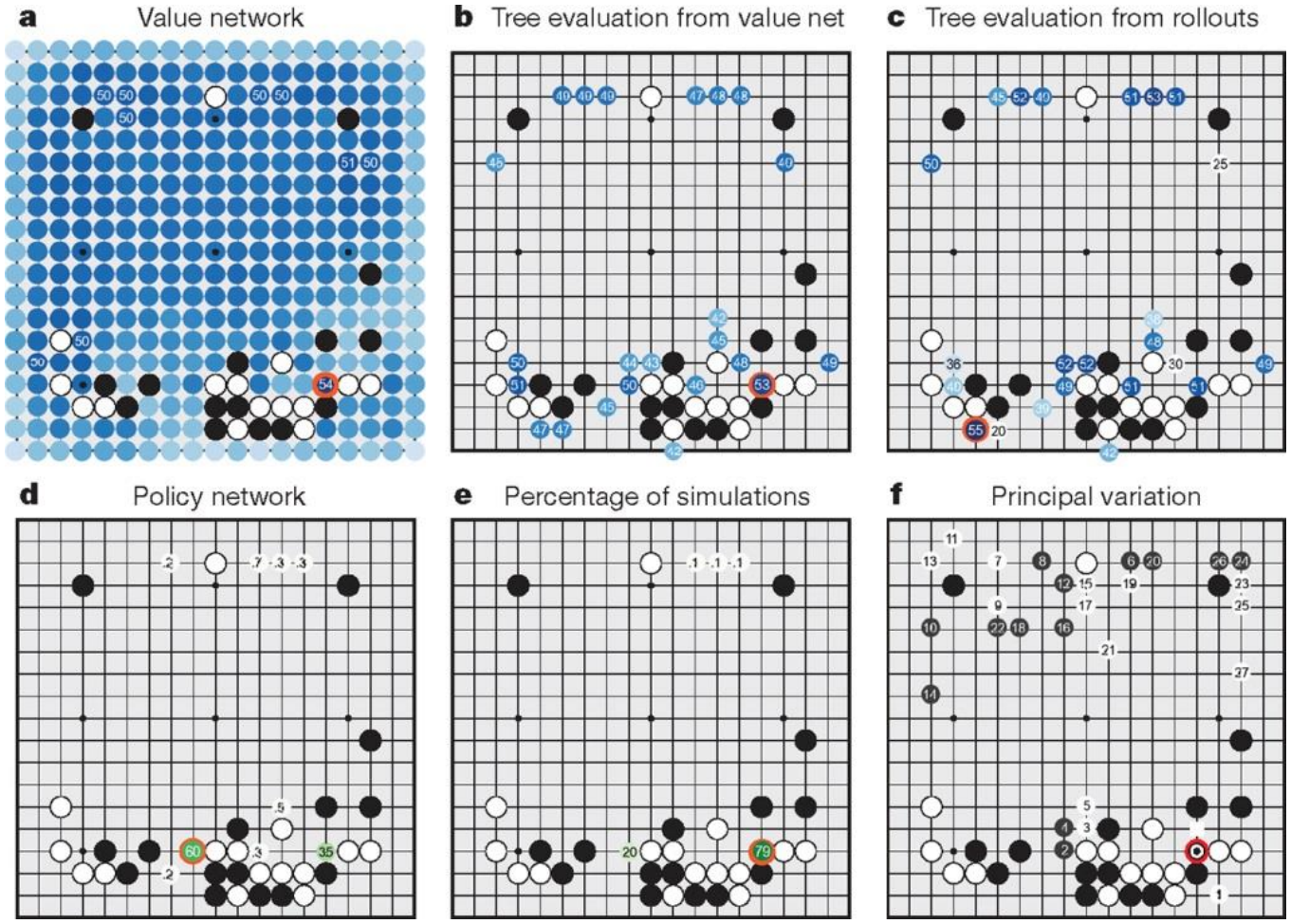
How AlphaGo (black, to play) selected its move in an informal game against Fan Hui



a) $v_\theta(a|s)$
b) MCTS using only $v_\theta(s)$ $(\lambda = 0)$
c) MCTS using only $p_\pi(s)$ $(\lambda = 1)$
d) $p_\sigma(a|s) > 0.1\%$
e) % selections during MCTS
f) Most visited path is selected. White square indicates Fan Hui's move. In post-game commentary he preferred the move labeled 1 predicted by AlphaGo.

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Comparison with Deep Blue

- AlphaGo evaluated thousands of times fewer positions in its matches against Fan Hui than Deep Blue against Garry Kasparov.
- Deep Blue used a handcrafted evaluation function while AlphaGo was trained directly from gameplay data.
  - Some AlphaGo features are still handcrafted, particularly for rollout.
- AlphaGo demonstrates a better capability of approximately solving a seemingly intractable problem using less brute-force effort.

AlphaGo vs Lee Se-dol

- AlphaGo is the first AI Go system to beat a human pro player.
- Fan Hui is the European champion and a 2 dan pro.
- Lee Se-dol has won 18 international titles and is a 9 dan pro.
- Based on Elo ratings, Lee would win 75% of games against Fan, and this may be an underestimate since 9 dan is the maximum rank.

- AlphaGo plays Lee Se-dol on March 9^{th},10^{th} ,12^{th} ,13^{th} ,and 15^{th} at 11:00pm ET. Matches are expected to take 4 - 5 hours.
- The winner will get a $1,000,000 prize.