Mastering the Game of Go with Deep Neural Networks and Tree Search

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- John Nham, Ilya Sutskever – Google.

New Methods

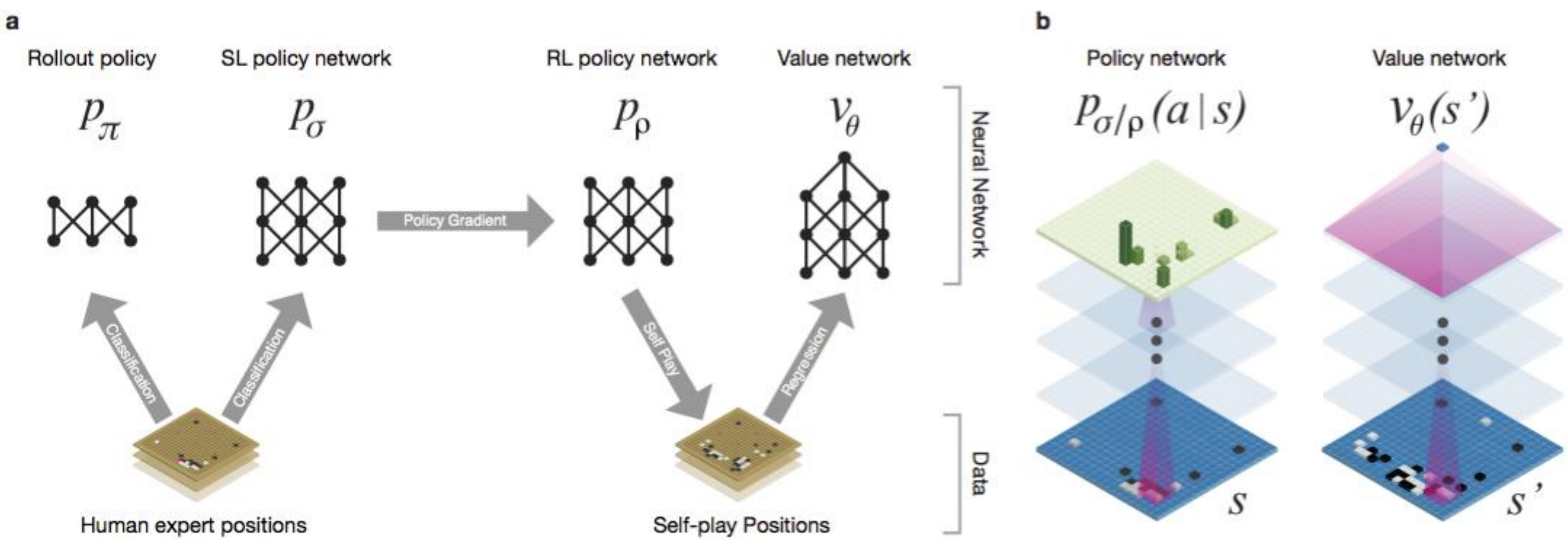
- A new approach to computer Go that uses value networks to evaluate board positions and policy networks to select moves.
- A new search algorithm that combines Monte-Carlo simulation with value and policy networks.

Deep convolutional neural networks

- They employ a similar architecture for the game of Go.
- Monte-Carlo tree search (MCTS) uses Monte-Carlo rollouts to estimate the value of each state in a search tree.
- They use these neural networks to reduce the effective depth and breadth of the search tree:

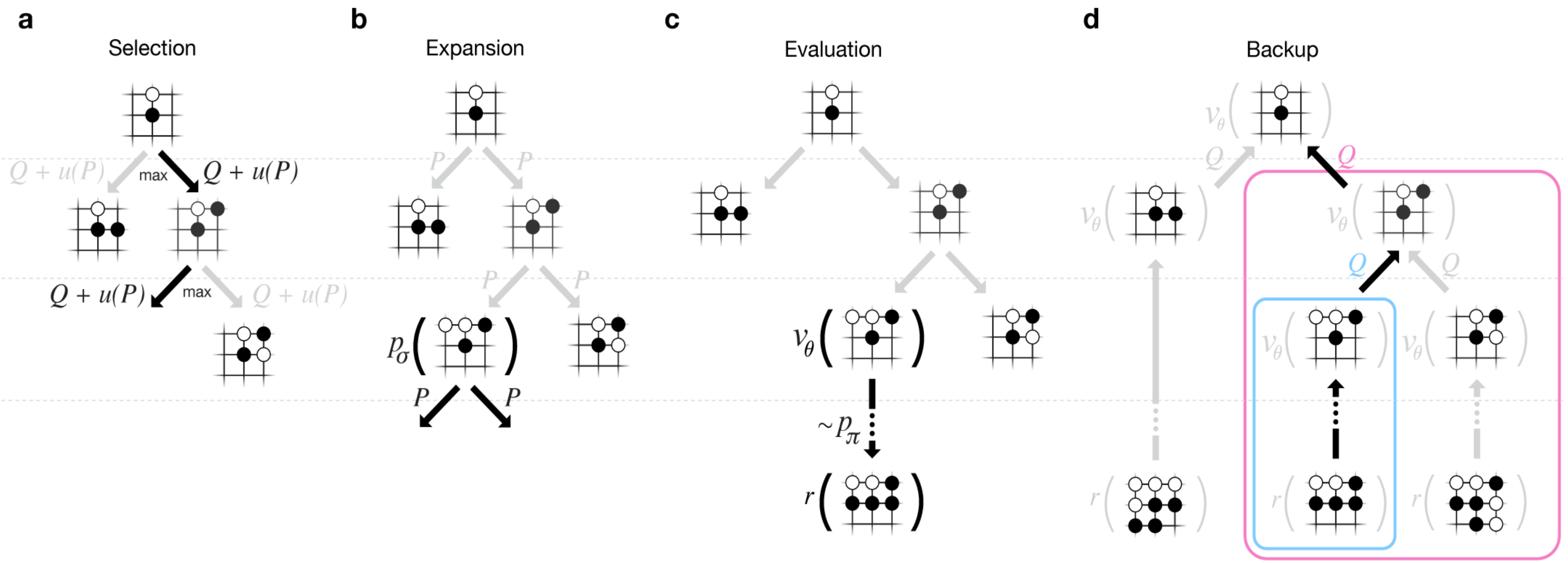
1. evaluating positions using a value network,
2. sampling actions using a policy network.

The neural networks



Searching with Policy and Value Networks

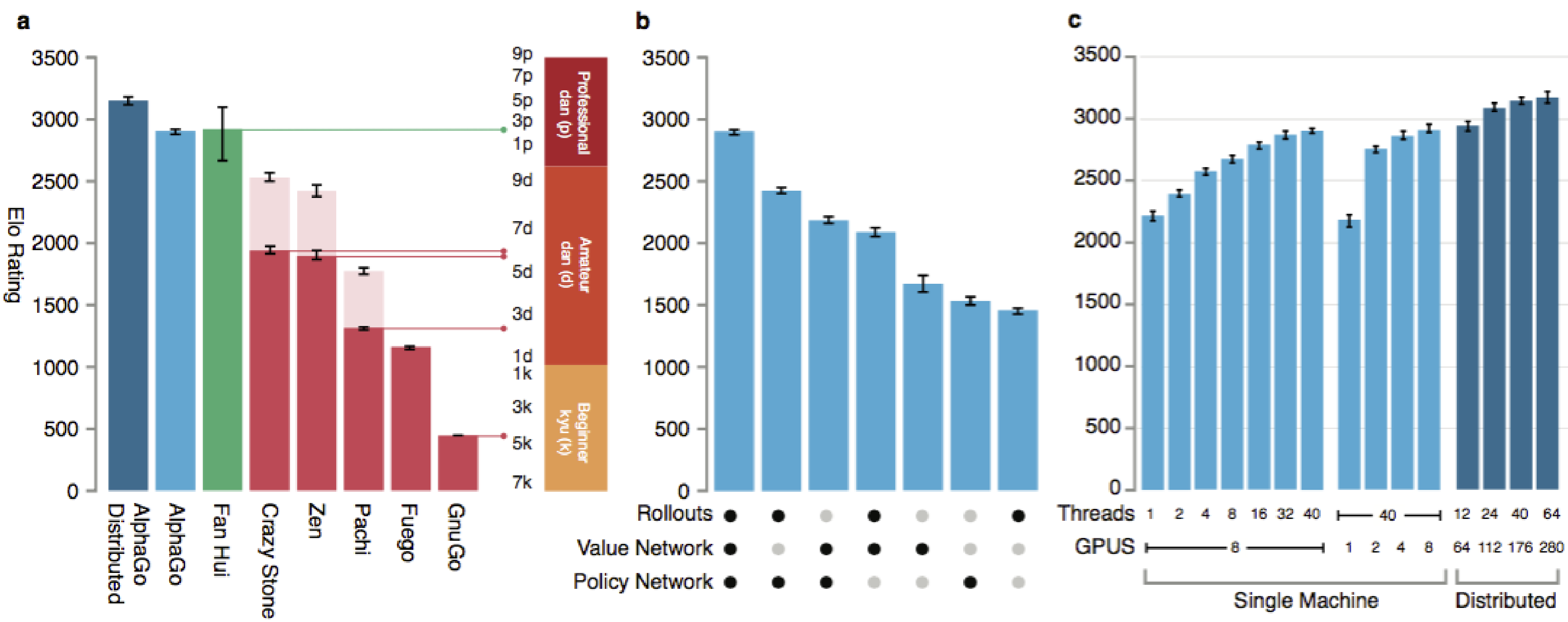
- AlphaGo combines the policy and value networks in an MCTS algorithm that selects actions by lookahead search.



Discussion

- They have developed effective move selection and position evaluation functions for Go, based on deep neural networks that are trained by a novel combination of supervised and reinforcement learning.
- They have introduced a new search algorithm that successfully combines neural network evaluations with Monte-Carlo rollouts
- AlphaGo won the human European champion (5-0)
- AlphaGo is more effective than other Go programs

Evaluating the Playing Strength of AlphaGo

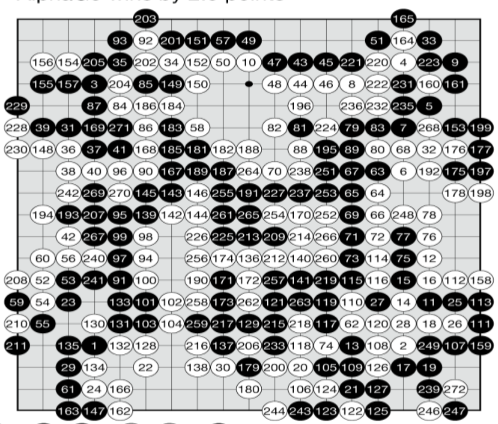


AlphaGo vs Fan Hui

Game 1

Fan Hui (Black), AlphaGo (White)

AlphaGo wins by 2.5 points

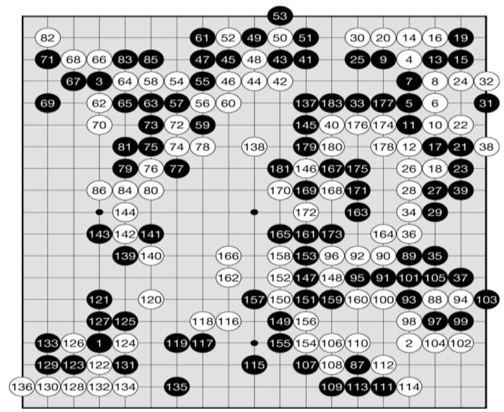


234 at 179 245 at 122 250 at 59

Game 2

AlphaGo (Black), Fan Hui (White)

AlphaGo wins by resignation

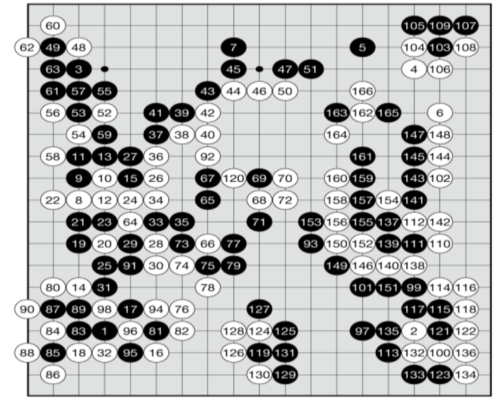


182 at 169

Game 3

Fan Hui (Black), AlphaGo (White)

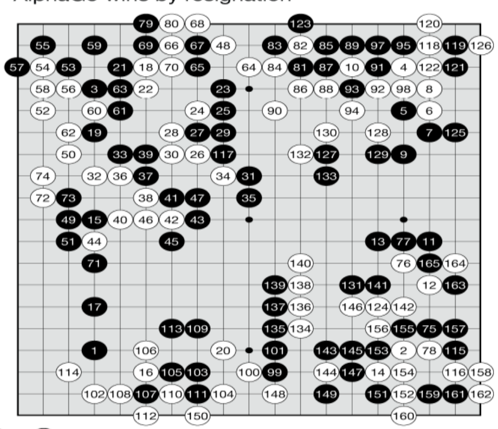
AlphaGo wins by resignation



Game 4

AlphaGo (Black), Fan Hui (White)

AlphaGo wins by resignation

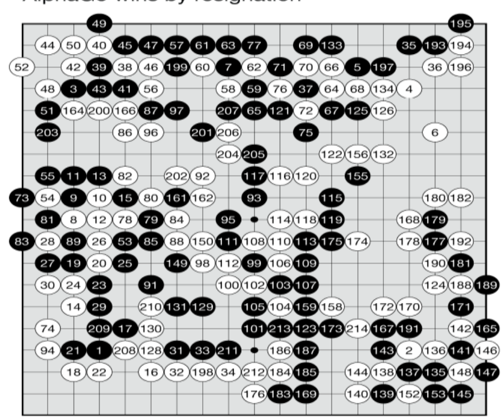


96 at 10

Game 5

Fan Hui (Black), AlphaGo (White)

AlphaGo wins by resignation



90 at 15 127 at 37 151 at 141 154 at 148 157 at 141 160 at 148

163 at 141

- Спасибо за внимание!

Functions at each step

- Supervised Learning of Policy Networks

$$\Delta\sigma \propto \frac{\partial \log p_\sigma(a|s)}{\partial \sigma}$$

- Reinforcement Learning of Policy Networks

$$\Delta\rho \propto \frac{\partial \log p_\rho(a_t|s_t)}{\partial \rho} z_t$$

- Reinforcement Learning of Value Networks

$$v^p(s) = \mathbb{E}\left[z_t \mid s_t = s, a_{t\ldots T} \sim p\right] \qquad \Delta\theta \propto \frac{\partial v_\theta(s)}{\partial \theta}(z - v_\theta(s))$$

Monte-Carlo tree search in AlphaGo.

- Each edge (s; a) of the search tree stores an action value Q(s; a), visit count N(s; a), and prior probability P(s; a).

$$a_t = \operatorname*{argmax}_a \left(Q(s_t, a) + u(s_t, a) \right)$$

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

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

$$V(s_L) = (1 - \lambda) v_\theta(s_L) + \lambda z_L \, .$$

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