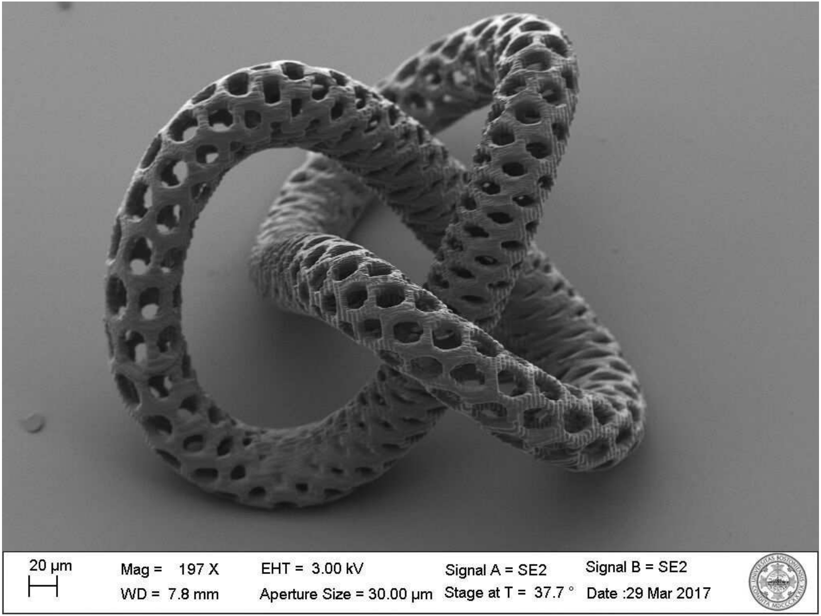
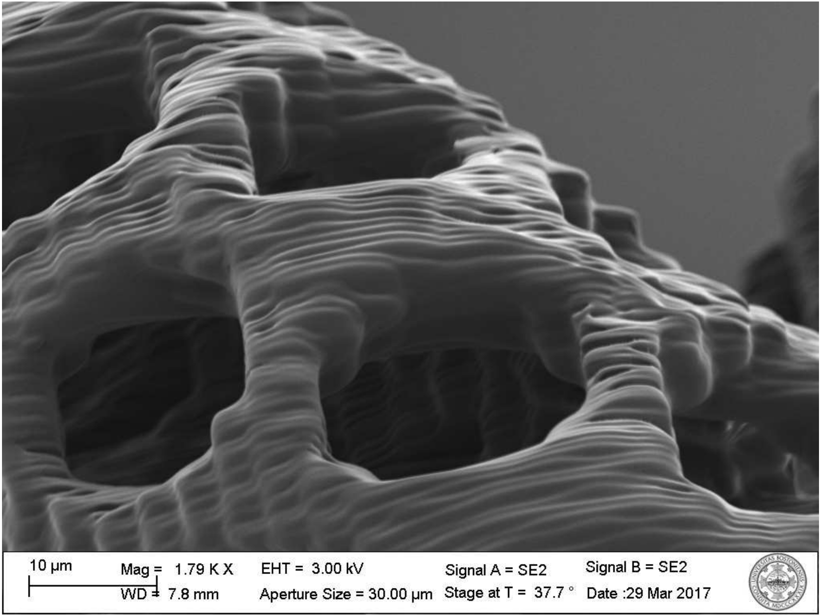
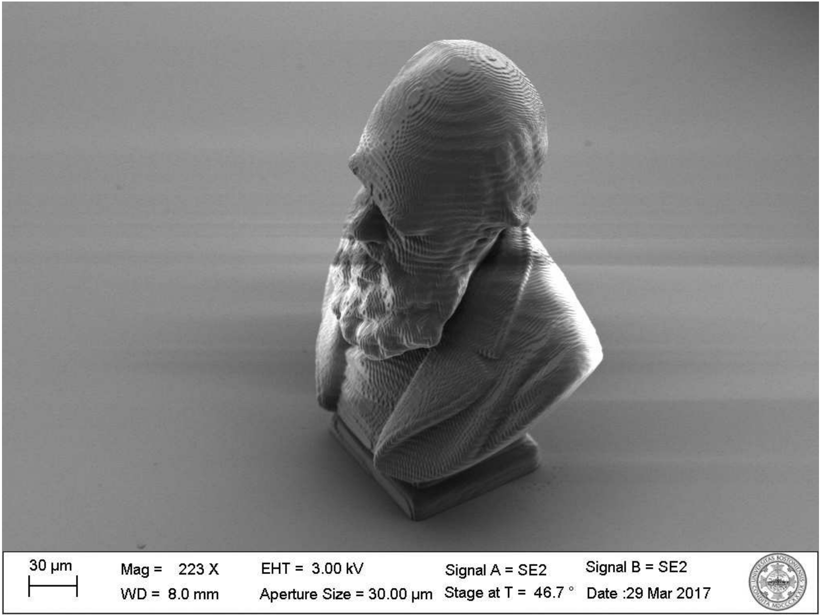

20 µm
Mag = 197 X
WD = 7.8 mm
EHT = 3.00 kV
Aperture Size = 30.00 µm
Signal A = SE2
Stage at T = 37.7 °
Signal B = SE2
Date :29 Mar 2017



10 µm
Mag = 1.79 K X
WD = 7.8 mm
EHT = 3.00 kV
Aperture Size = 30.00 µm
Signal A = SE2
Stage at T = 37.7 °
Signal B = SE2
Date :29 Mar 2017


30 µm
Mag = 223 X
WD = 8.0 mm
EHT = 3.00 kV
Aperture Size = 30.00 µm
Signal A = SE2
Stage at T = 46.7 °
Signal B = SE2
Date :29 Mar 2017


周文矩重屏會棋圖真蹟

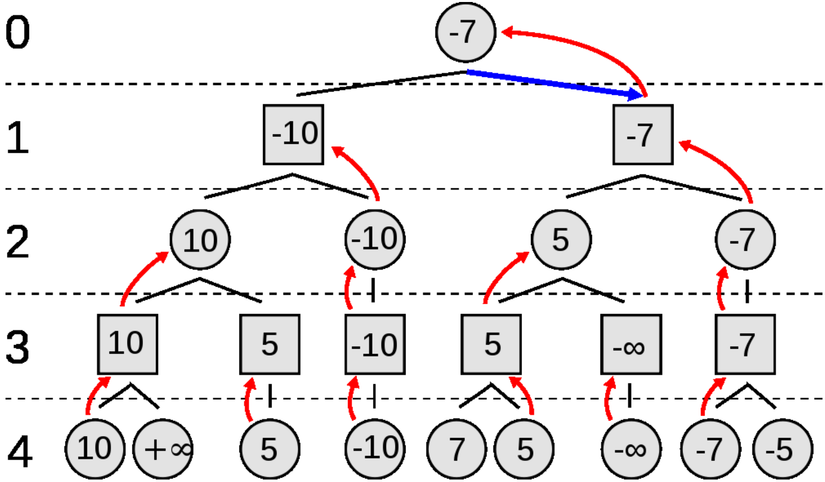

本朝英雄鏡
佐藤四郎兵衛忠信
国芳画


Google DeepM
Challenge Ma
8 - 15 March 2
AlphaGo
Lee Sedol

Go tutorial. . .

▸ The Way To Go

Machine play with Minimax:



How big is the game tree?

Branching factor: At each position, n possible moves

Length: game lasts m moves

n^m possible games

Size of games

Game	Branching factor	Length	$\log_{10}$ (# Games)
Tic-Tac-Toe	4	9	5
Connect Four	4	36	21
Checkers (8×8)	2.8	70	31
Chess	35	70	108
Backgammon	250	55	132
Carcassonne	55	71	195
Go	250	150	360

Reducing the computational complexity

Length:

- Estimate the value of non-terminal states

Branching factor:

- α-β Pruning
  - $O\left(\sqrt{n^m}\right)$ if moves are sorted
- Monte Carlo Tree Search *of promising moves*

Estimating the value of non-terminal states

Checkers:

- Material
- Position of non-kings

Chess:

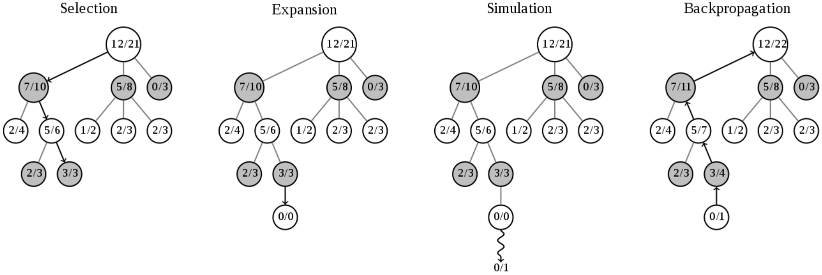
- Material
- Mobility
- Control centre of board

Go:

- "Strength" / "Influence"
  - Um...

Intuition!

Monte Carlo Tree Search



Selecting a move for roll-out

Early:

- High prior probability?
- Low visit count

Later:

- Success rate

Return

The most visited move

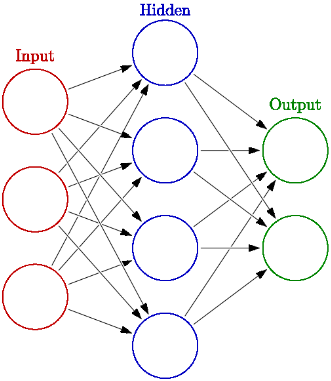
Ignoring questionable moves

Only examine promising moves.

Intuition

In the beginner's mind there are many possibilities. In the expert's mind there are few. –Shunryu Suzuki

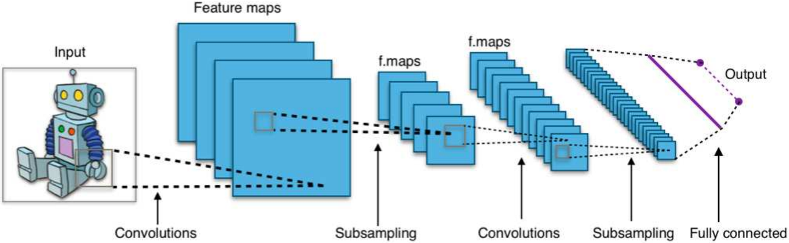
Neural Networks



- Input pattern ξ
- Weights W
- $y = W_1 \tanh(W_0 \xi)$
- W_i are trained with backpropagation of errors

Convolutional Neural Networks

Inspired by Hubel & Wiesel 1968?



▸ LeNet

Supervised learning of policy networks: $p_\sigma(a|s)$

Predict the expert's move:

- Given board state s, predict probability of move a
- 13 convolutional layers
  - Input: 48 features
  - Layer 1: 192 of 5×5
  - Layers 2–12: 192 of 3×3
  - Rectifier nonlinearities
- Training: 30 million positions from KGS
- 57% accurate
- Evaluation time: 3 ms

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

Supervised learning of policy networks II: $p_\pi(a|s)$

Predict the expert's move (faster):

- Given board state s, predict probability of move a
- Small pattern features
- Training: 8 million positions from Tygem (?)
- 24% accurate
- Evaluation time: 2 μs

Why? To be continued...

Reinforcement learning of policy networks: $p_\rho(a|s)$

Don't predict expert moves: Win!

- Start with the supervised move predictor: $\rho \leftarrow \sigma$
- Training: self-play vs. a previous iteration of ρ
- Result of game is z

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

p_ρ won 80% of its games vs. p_σ

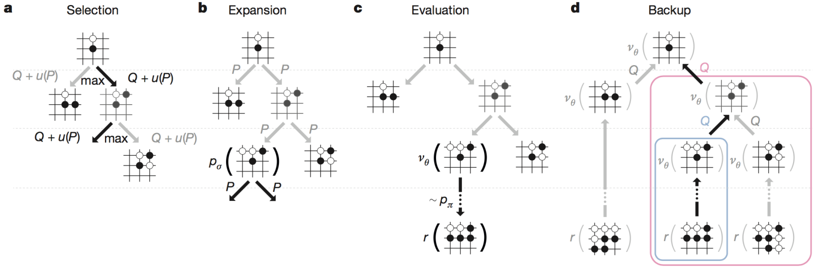
Reinforcement learning of value networks: $v^p(s)$

Predict the likelihood of winning from any board position

- $v^p(s) = \mathbb{E}\left[z | s = s_t, a_{t \dots T} \sim p\right]$
- Similar architecture to p_ρ, but outputs scalar v
- Trained from 30 million samples from self-play by $p_\rho(s, a)$
  - Decorrelate sequences of moves

$$\Delta\theta \propto \frac{\partial v_\theta(s)}{\partial \theta}(z - v_\theta(s))$$

Monte Carlo Tree Search II



Selecting a move for roll-out

Early:

- High prior probability from $p_\sigma(s, a)$!
- Low visit count

Later:

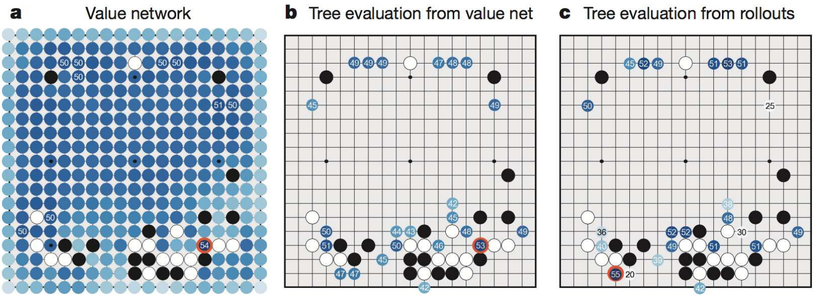
- Success rate

Return

The most visited move

Choosing a move

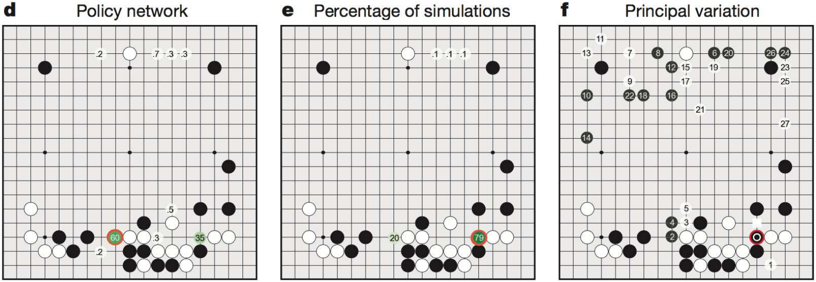
- Evaluate potential new position s' in 2 ways:
  - $v_\theta(s')$
  - Monte Carlo rollout (using the fast policy p_π)
    - Initialise MCTS priors $\forall a$ from $p_\sigma(s', a)$ + exploration term
- Combine the evaluations (λ).



Evaluation of all successors s of the root position s, using the value network $v_\theta(s)$; estimated winning percentages are shown for the top evaluations.

Action values $Q(s, a)$ for each edge (s, a) in the tree from root position s; averaged over value network evaluations only $(\lambda = 0)$.

Action values $Q(s, a)$, averaged over rollout evaluations only $(\lambda = 1)$.

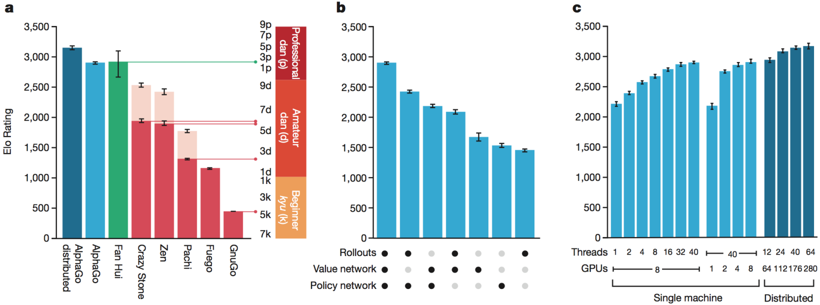


Move probabilities directly from the SL policy network, $p_\sigma(a|s)$; reported as a percentage (if above 0.1%)

Percentage frequency with which actions were selected from the root during simulations.

AlphaGo's move, and the most likely continuation of the game.

Results


a
Elo Rating
3,500
3,000
2,500
2,000
1,500
1,000
500
0
AlphaGo distributed
AlphaGo
Fan Hui
Crazy Stone
Zen
Pachi
Fuego
GnuGo
9p
7p
5p
3p
1p
9d
7d
5d
3d
1d
1k
3k
5k
7k
Professional dan (p)
Amateur dan (d)
Beginner kyu (k)
b
Rollouts
Value network
Policy network
c
Threads 1 2 4 8 16 32 40 40 12 24 40 64
GPUs 8 1 2 4 8 64 112 176 280
Single machine
Distributed

Victory!

- Beat Fan Hui 2p 5-0
- Beat Lee Sedol 9p 4-1
  - One of 'em!
- 10^3 times fewer position evaluations than Deep Blue!
  - Learns to aggressively examine only a few promising moves
  - Learns intuition for values of intermediate positions
  - Plays like a human?
- "AlphaGo's play makes us feel free, that no move is impossible. Now everyone is trying to play in a style that hasn't been tried before." –Zhou Ruiyang 9p

Future work

- Ke Jie 9p
  - May 23–27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