AlphaGo

Mastering the game of Go with deep neural networks and tree search

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Agenda

1. Problem setting
2. Policy and value networks
3. Features and architectures
4. Search algorithm

Problem setting

Game of perfect information:

- State space
- Action space
- A state transition function
- Policy
- Value function

$$v^p(s) = \mathbb{E}[z_t | s_t = s, a_{t \ldots T} \sim p]$$

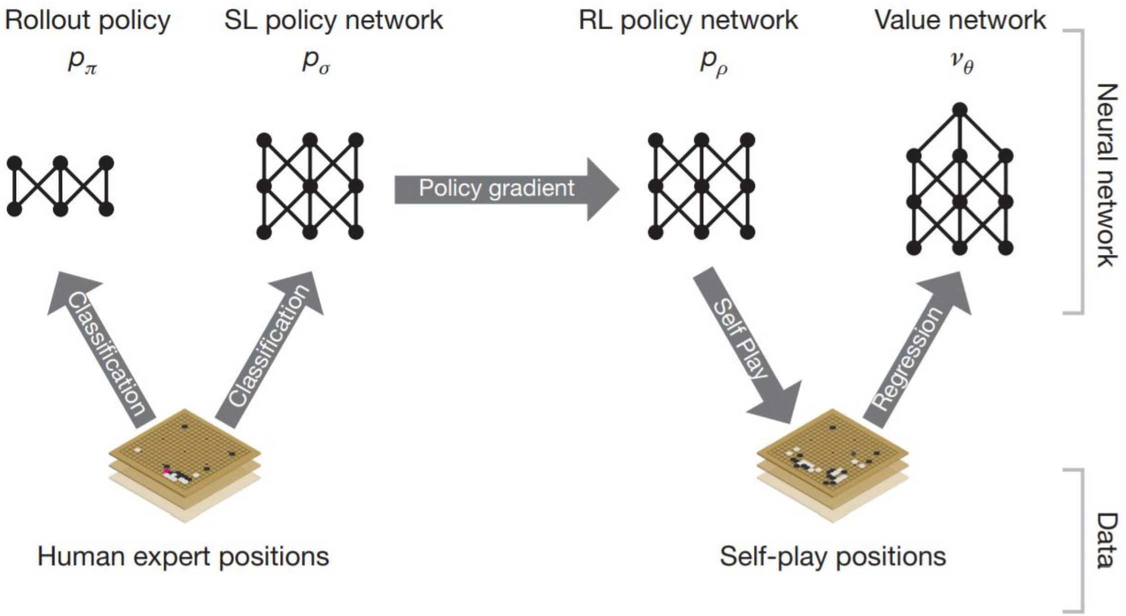
$$v^*(s) = \begin{cases} z_T & \text{if } s = s_T, \\ \max\limits_a - v^*(f(s,a)) & \text{otherwise} \end{cases}$$

Policy network: classification

- Train-test split - 1mil: 28 mil;
- Position - state and human action;
- Mini-batch gradient descent;
- 3 weeks of training

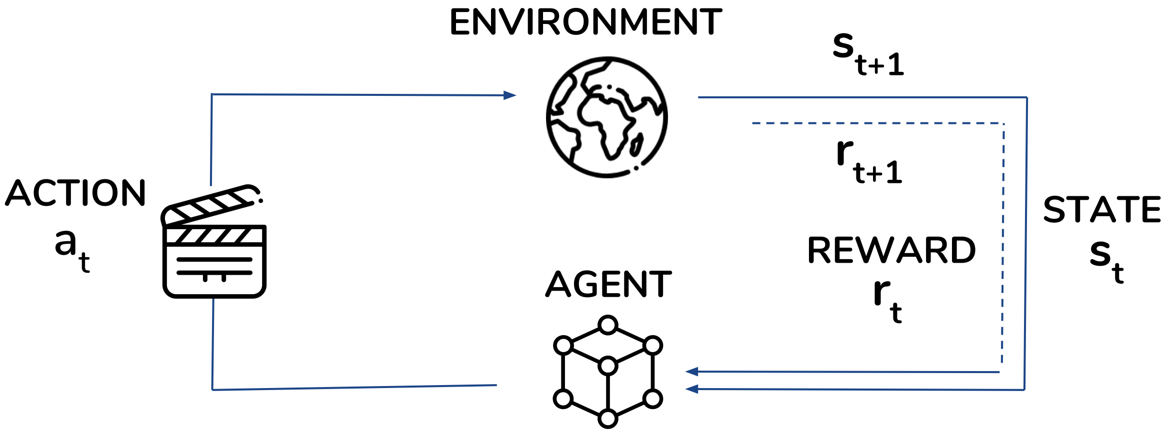
$$\Delta\sigma = \frac{\alpha}{m}\sum_{k=1}^{m}\frac{\partial \log p_\sigma(a^k|s^k)}{\partial\sigma}$$

Rollout policy



- Linear softmax policy;
- Much more features than in SL policy network

Policy network: reinforcement learning



$$\Delta\rho = \frac{\alpha}{n}\sum_{i=1}^{n}\sum_{t=1}^{T^i}\frac{\partial \log p_\rho(a_t^i|s_t^i)}{\partial\rho}(z_t^i - v(s_t^i))$$

Value network

- Artificial datasets to prevent overfitting
- Learning only using single training example
- 1 extra feature

$$\Delta\theta = \frac{\alpha}{m}\sum_{k=1}^{m}\left(z^k - v_\theta(s^k)\right)\frac{\partial v_\theta(s^k)}{\partial\theta}$$

$$v^{p_\rho}(s_{U+1}) = \mathbb{E}[z_{U+1} | s_{U+1}, a_{U+1,\ldots T} \sim p_\rho]$$

Features

Input features for neural networks

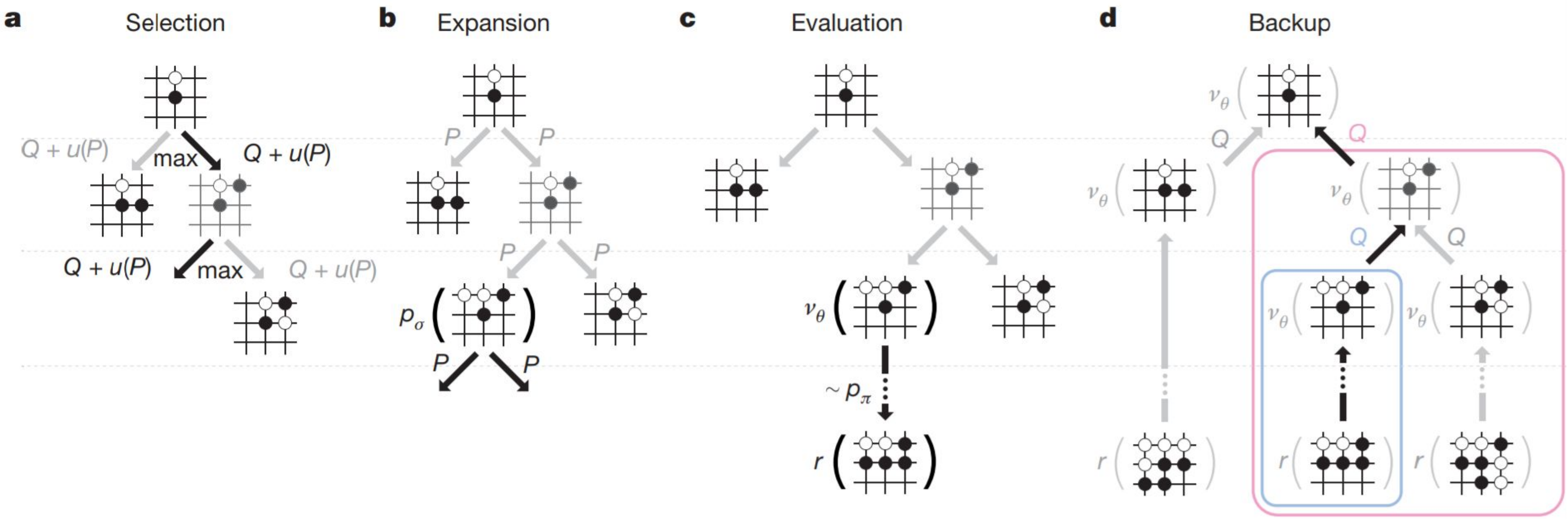
Feature	# of patterns	Description
Stone colour	3	Player stone / opponent stone / empty
Ones	1	A constant plane filled with 1
Turns science	8	How many turns since a move was played
Liberties	8	Number of liberties (empty adjacent points)
Capture size	8	How many opponent stones would be captured
Self-atari 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

Features

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

Search algorithm



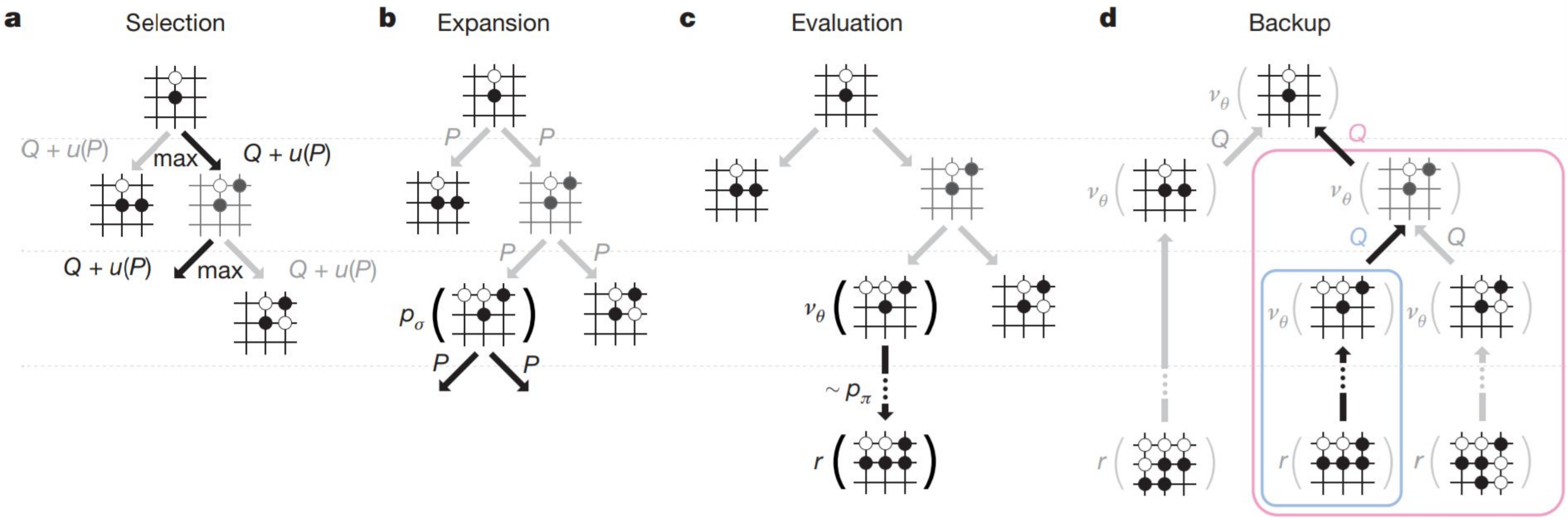
Selection

$$\{P(s,a),\ \ N_v(s,a),\ \ N_r(s,a),\ \ W_v(s,a),\ \ W_r(s,a),\ \ Q(s,a)\}$$

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

$$u(s,a) = c_{\text{puct}} P(s,a) \frac{\sqrt{\sum_b N_r(s,b)}}{1 + N_r(s,a)}$$

Search algorithm



Backup

$$N_r(s_t, a_t) \leftarrow N_r(s_t, a_t) + n_{vl}; W_r(s_t, a_t) \leftarrow W_r(s_t, a_t) - n_{vl}$$

$$N_r(s_t, a_t) \leftarrow N_r(s_t, a_t) - n_{\mathrm{vl}} + 1; \; W_r(s_t, a_t) \leftarrow W_r(s_t, a_t) + n_{\mathrm{vl}} + z_t$$

$$N_v(s_t, a_t) \leftarrow N_v(s_t, a_t) + 1, \; W_v(s_t, a_t) \leftarrow W_v(s_t, a_t) + v_\theta(s_L)$$

$$Q(s, a) = (1 - \lambda)\frac{W_v(s, a)}{N_v(s, a)} + \lambda\frac{W_r(s, a)}{N_r(s, a)}$$

Literature used

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THANK YOU
FOR LISTENING