AlphaGo or how DeepMind taught machine to win

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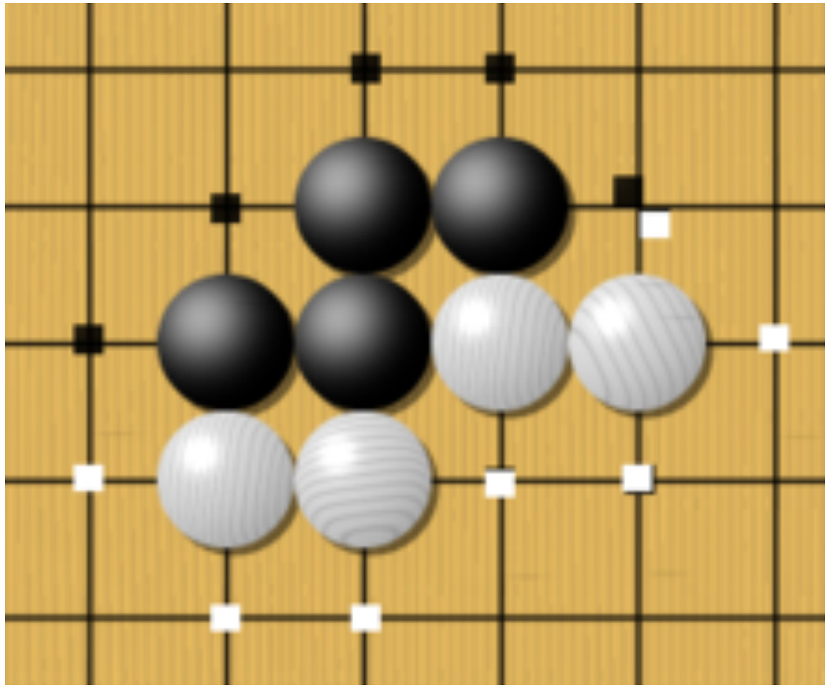
Go equipment

- Game board – goban
- Stones of two different colors, e.g. black and whites
- Bowls for storing stones
- Game clock at competitions

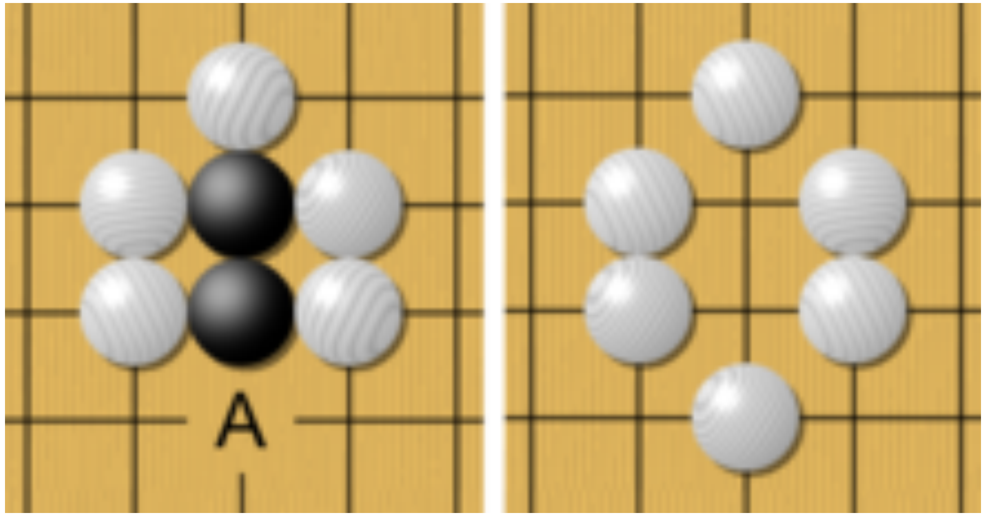
Rules of Go: basics

- Black goes first
- Stones are placed on vacant points of the grid
- Vertically and horizontally adjacent stones of the same color form a chain
- A vacant point adjacent to a stone is called a *liberty* for that stone
- Komi - awarding White some compensation for second move

Rules of Go: example of chains and liberties

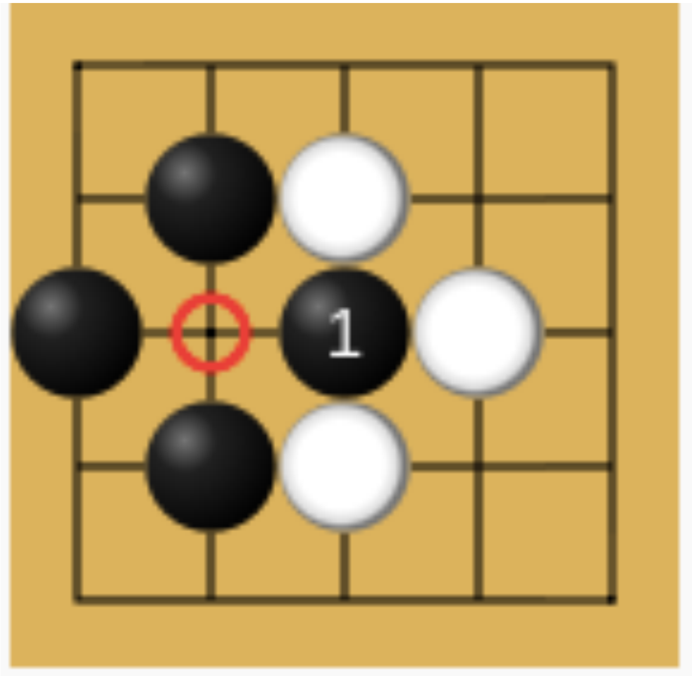


One black chain and two white chains, with their liberties marked with dots.



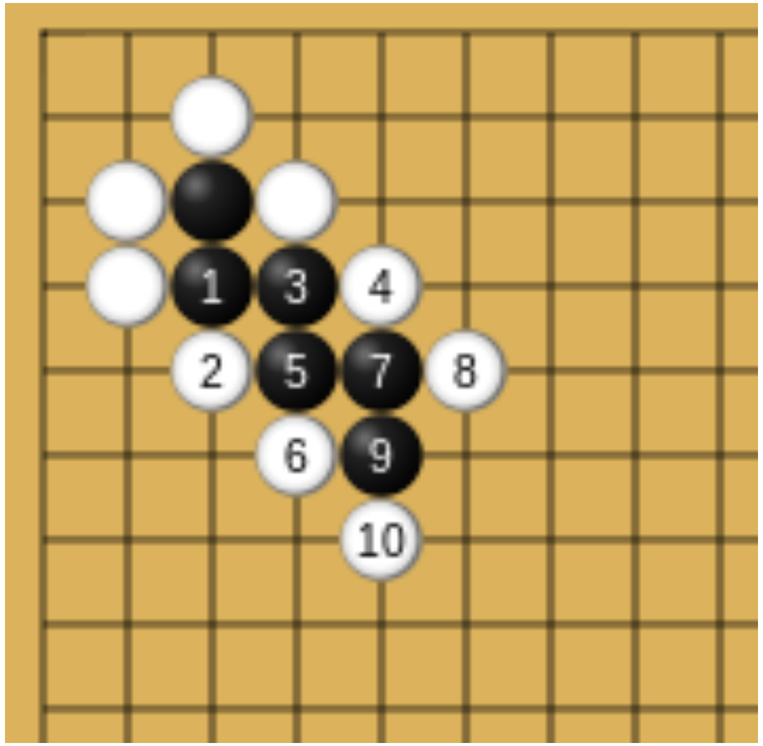
Example of capturing stones

Rules of Go: ko rule



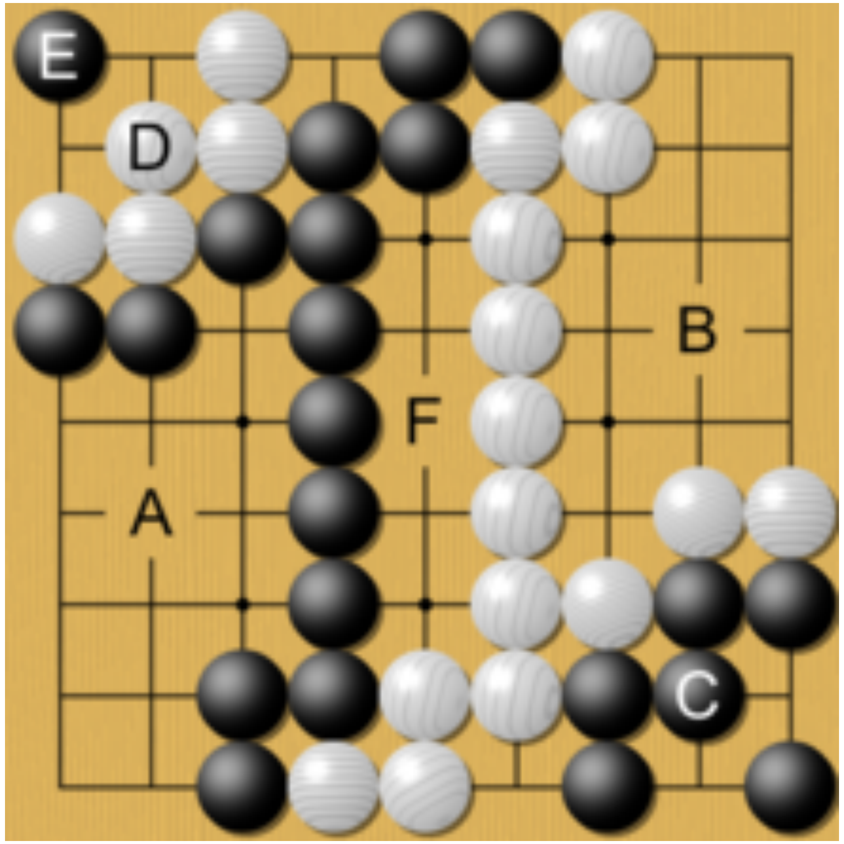
An example of a situation in which the ko rule applies

Basic capturing tactic: ladder



A ladder. Black cannot escape unless the ladder connects to black stones further down the board that will intercept with the ladder.

Rules of Go: scoring



Possible end
of the game

Obstacles to computer performance

- Size of the board (19x19, 361 intersections)
- Number of legal moves
- Much harder in comparison with chess
- Position or move evaluation function

Approaches to solving problems

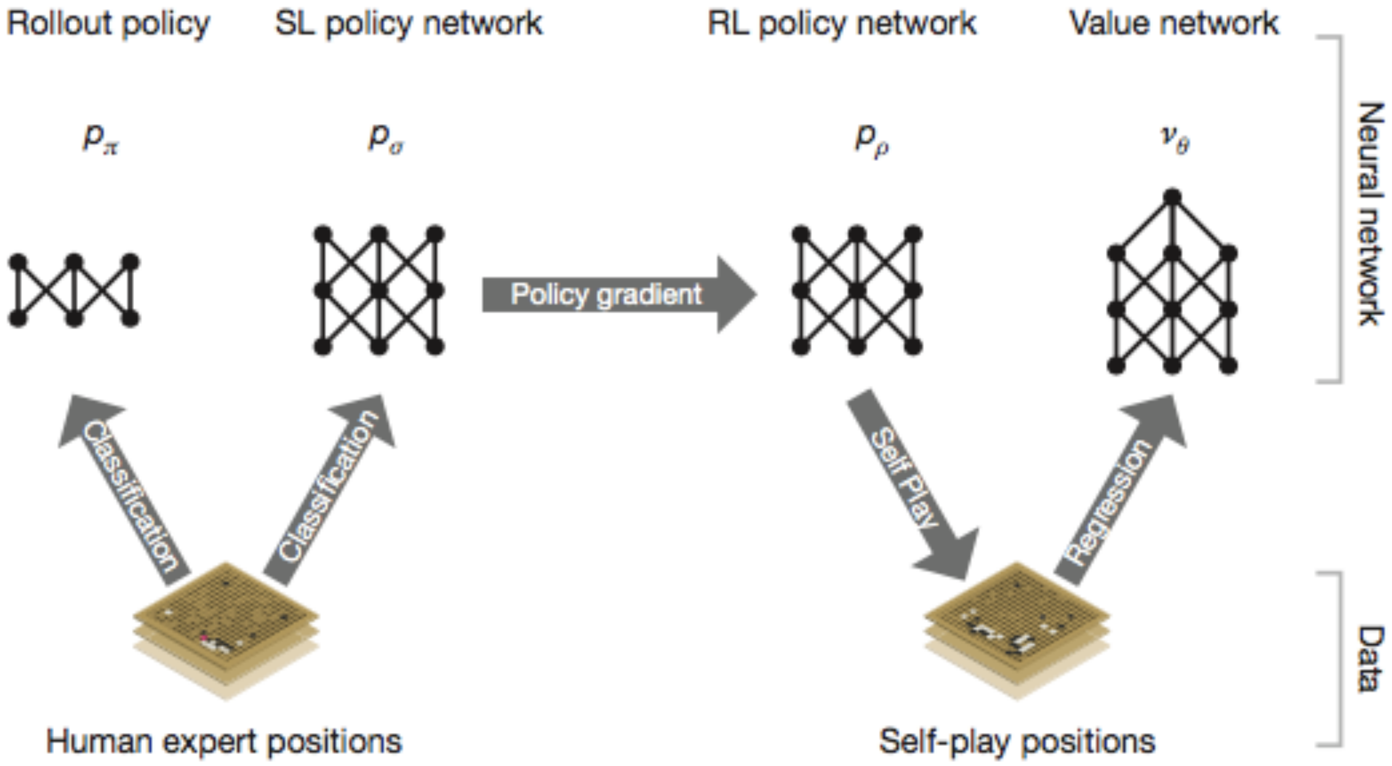
- Go – game of perfect information

- All games of perfect information have optimal value function

- Two general principles to reduce effective search space

  - Reduce depth of the search with position evaluation
  - Reduce breadth of the search with sampling from probability distribution over possible moves from fixed position

AlphaGo learning pipeline



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SL policy network: data preparation

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).

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SL policy network: architecture of p_σ

- Input Layer: 19x19x48 image stack

- 1 hidden layer:
  - zero padding to 23x23
  - convolving 192 filters of size 5x5 with stride equal to 1
  - applying rectifier unit

- 2-12 hidden layer:
  - zero padding to 21x21
  - convolving 192 filters of size 3x3 with stride equal to 1
  - applying rectifier unit

- Output layer:
  - convolving 1 filter of size 1x1 with stride equal to 1
  - applying softmax to get probability distribution over all possible moves

SL policy network: training

- Each training step:
  - Randomly get m samples from prepared data set
  - Maximize log likelihood of the action by stochastic gradient descent:

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

Rollout policy: fast linear softmax p_π

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, $\geq$3) at each intersection of the pattern.

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RL policy network: training p_ρ by self-play

- Each iteration of training consists of **n** games

- p_ρ - network being trained
- $p_{\rho'}$ - network from randomly chosen previous iteration

- Weights ρ and ρ' were initialized to σ from SL policy network

- Every 500 iterations the current parameters ρ were added to the opponent pool.

RL policy network: training p_ρ by self-play

- Play out each game i until termination step T^i
- Score game to get the outcome z_t^i = $\pm r(s_{T^i})$
- Replay games for policy gradient update using SGD
  - $\Delta p = \frac{\alpha}{n}\sum_{i=1}^{n}\sum_{t=1}^{T^i}\frac{\partial log p_\rho(a_t^i \mid s_t^i)}{\partial \rho}(z_t^i - v(s_t^i))$
- 10.000 iterations of 128 games took one day

Value network: overfitting on KGS data

- Data consisting of complete games leads to overfitting due to:
  - difference between successive positions is just one stone
  - but regression target is shared for the whole game
- As the result we get:
  - 0.19 MSE on the training set
  - 0.37 MSE on the test set
  - Memorized outcomes

Value network: let's generate own data

- Each game was generated by successive sampling:

  - Time step $U \sim unif\{1, 450\}$
  - First $t = 1 \ldots U - 1$ moves: $a_t \sim p_\sigma(\cdot\,|s_t)$
  - $a_U \sim \mathrm{Unif}\{1, 361\}$ repeatedly until a_U is legal
  - Remaining $t = U + 1\ \ldots T$ moves: $a_t \sim p_\rho(\cdot\,|s_t)$

- Score game to get the outcome $z_t = \pm r(s_t)$
- Add only $(s_{U+1}\ ;\ z_{U+1})$ to new data set from each game

Value network: architecture of v_θ

- Input to the CNN:
  - the same as in SL policy network
  - plus additional player colour binary feature
- Hidden layers:
  - also the same
  - plus one more convolutional layer is added.
- Output Layer:
  - fully connected layer with 256 units
  - applying single tanh unit

Value network: training v_θ

- Also the same as in SL policy network, but maximizing MSE

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

- 50 million mini batches of 32 positions.
- Training took one week

Search algorithm

- Each node s contains edges (s, a) for all legal actions

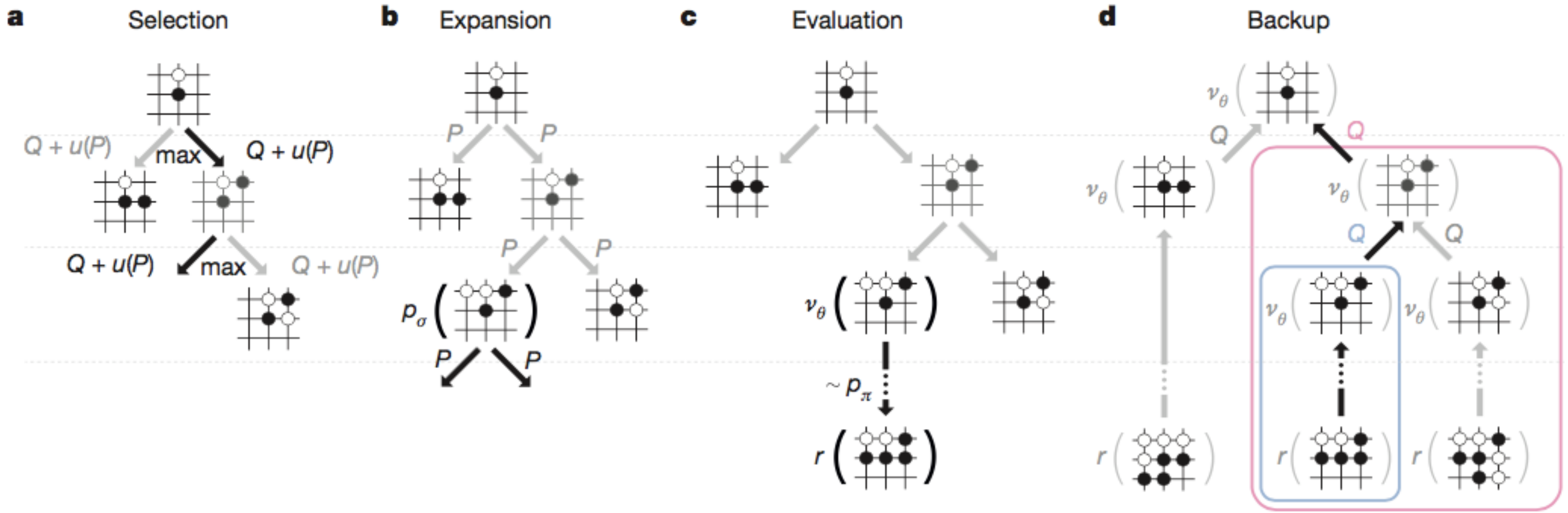
- Each edge stores a set of statistics:

  - P(s, a) – prior probability

  - $W_v(s, a)$ and $W_r(s, a)$ – Monte Carlo estimates of total action value, accumulated over leaf evaluations $N_v(s, a)$ and rollout rewards $N_r(s, a)$

  - Q(s, a) - combined mean action value for that edge.

Search algorithm



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