AlphaGo

IBM Deep Blue

Figure 1: First defeat of a world chess champion by a machine in 1997

Deep Blue was handcrafted by programmers & chess grandmasters

AlphaGo *learnt* from human moves & self play

AlphaGo evaluated fewer positions

- **width** - policy network select states more intelligently
- **depth** - value function evaluate states more precisely

Why Go?

Long held as the most challenging classic game for artificial intelligence

- massive search space
- more legal positions than atoms in universe
- difficult to evaluate positions & moves
- sparse & delayed reward

Difficult to evaluate positions

- chess you can evaluate positions by summing the value of all the peices
- go - it's just stones on the board, equal numbers each side

Components of the AlphaGo agent

Three policy networks $\pi(s)$

- fast rollout policy network – linear function
- supervised learning policy – 13 layer convolutional NN
- reinforcement learning policy – 13 layer convolutional NN

One value function $V(s)$ - convolutional neural network

Combined together using Monte Carlo tree search

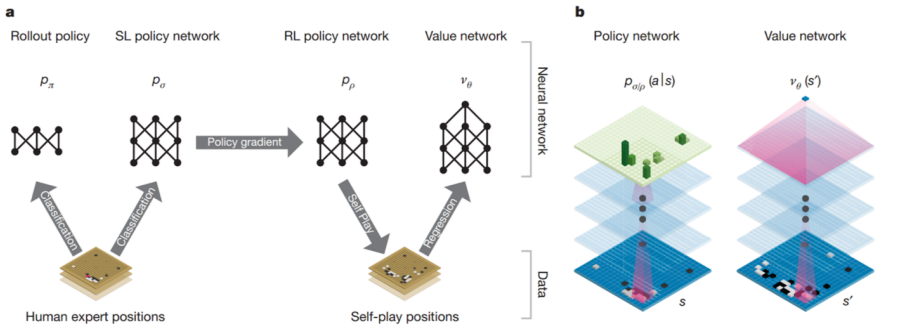


Figure 1 | Neural network training pipeline and architecture. a, A fast rollout policy p_π and supervised learning (SL) policy network p_σ are trained to predict human expert moves in a data set of positions. A reinforcement learning (RL) policy network p_ρ is initialized to the SL policy network, and is then improved by policy gradient learning to maximize the outcome (that is, winning more games) against previous versions of the policy network. A new data set is generated by playing games of self-play with the RL policy network. Finally, a value network v_θ is trained by regression to predict the expected outcome (that is, whether the current player wins) in positions from the self-play data set. **b**, Schematic representation of the neural network architecture used in AlphaGo. The policy network takes a representation of the board position s as its input, passes it through many convolutional layers with parameters σ (SL policy network) or ρ (RL policy network), and outputs a probability distribution $p_\sigma(a|s)$ or $p_\rho(a|s)$ over legal moves a, represented by a probability map over the board. The value network similarly uses many convolutional layers with parameters θ, but outputs a scalar value $v_\theta(s')$ that predicts the expected outcome in position s'.

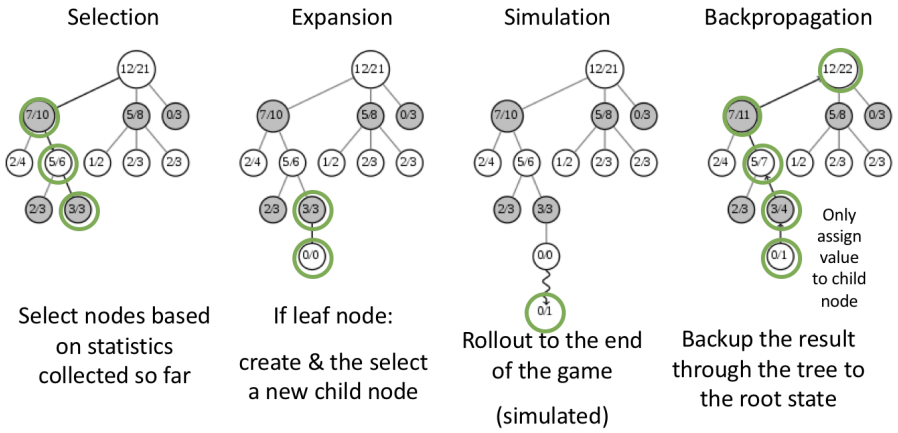
Figure 2: Learning of AlphaGo

Monte Carlo Tree Search

Value & policy networks combined using MCTS

Basic idea = analyse most promising next moves

Planning algorithm - simulated (not actual experience) - roll out to end of game (a simulated Monte Carlo return)



https://en.wikipedia.org/wiki/Monte_Carlo_tree_search

Figure 3: fig

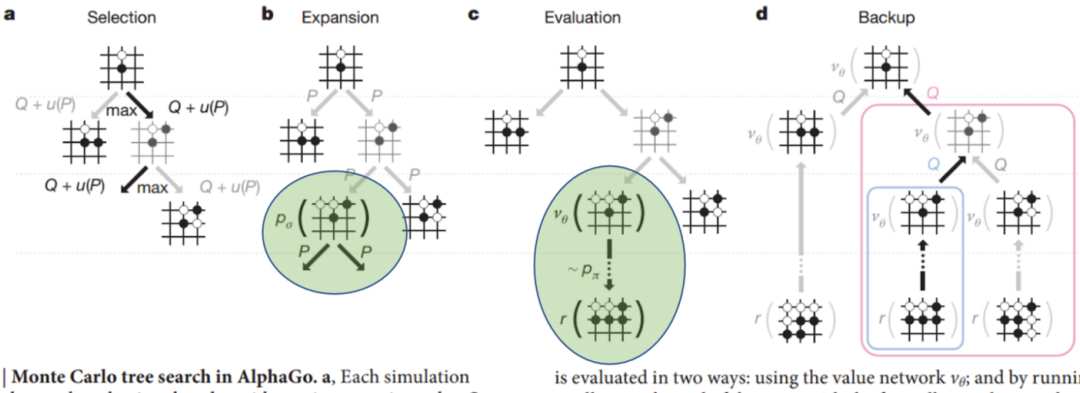
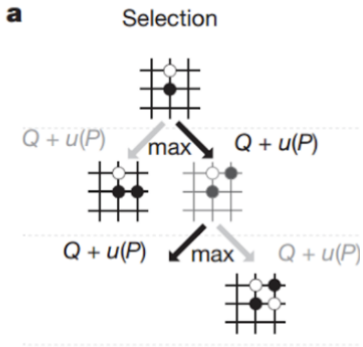


Figure 3 | Monte Carlo tree search in AlphaGo. a, Each simulation traverses the tree by selecting the edge with maximum action value Q, plus a bonus $u(P)$ that depends on a stored prior probability P for that edge. **b**, The leaf node may be expanded; the new node is processed once by the policy network p_σ and the output probabilities are stored as prior probabilities P for each action. **c**, At the end of a simulation, the leaf node is evaluated in two ways: using the value network v_θ; and by running a rollout to the end of the game with the fast rollout policy p_π, then computing the winner with function r. **d**, Action values Q are updated to track the mean value of all evaluations $r(\cdot)$ and $v_\theta(\cdot)$ in the subtree below that action.

Figure 4: MCTS in AlphaGo



Each edge (s, a) keeps track of statistics

action value	$Q(s,a)$
visit count	$N(s,a)$
prior probability	$P(s,a)$ SL policy network

Bonus $u(s,a)$ penalizes more visits to encourages exploration

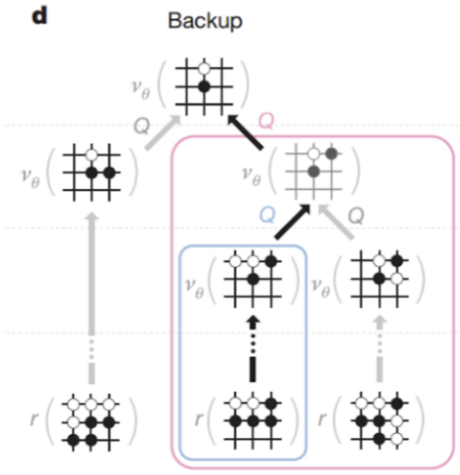
Action selected according too

$$a = \underset{a}{\text{argmax}}[Q(s,a) - u(s,a)]$$

where

$$u(s,a) \propto P(s,a)/[1 - N(s,a)]$$

Figure 5: fig



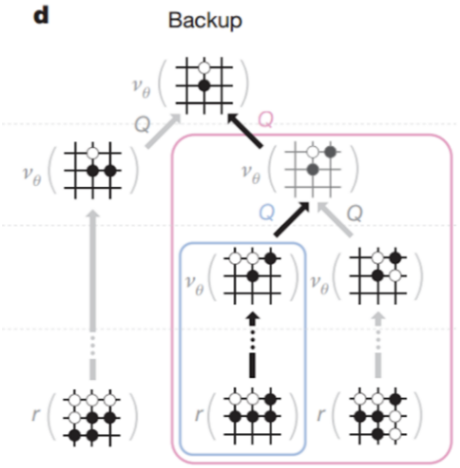
After we finish our rollout – we calculate a state value for our leaf node s_L

$$V(s_L) = (1-\lambda)v_\theta(s) + \lambda z$$

- λ mixing parameter
- v_θ value network estimate
- z simulated result of rollout

We are combining the value network with the MCTS rollout

Figure 6: fig



Then use our combined estimate $V(s_L)$ to update

action value $Q(s,a)$

visit count $N(s,a)$

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

We are averaging across all visits in the simulation

After all simulations finished - select the most visited action from the root state

Figure 7: fig

AlphaGo, in context – Andrej Karpathy

Convenient properties of Go

- fully deterministic
- fully observed
- discrete action space
- access to perfect simulator
- relatively short episodes
- evaluation is clear
- huge datasets of human play

DeepMind take advantage of properties of Go that will not be available in real world applications of reinforcement learning.

AlphaGo Zero

ARTICLE

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Mastering the game of Go without human knowledge

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Figure 8: fig

Key ideas

- simpler
- search
- adverserial
- machine knowledge only

Training time & performance

- AG Lee trained over several months
- AG Zero beat AG Lee 100-0 after 72 hours of training

Computational efficiency

- AG Lee = distributed w/ 48 TPU
- AG Zero = single machine w/ 4 TPU

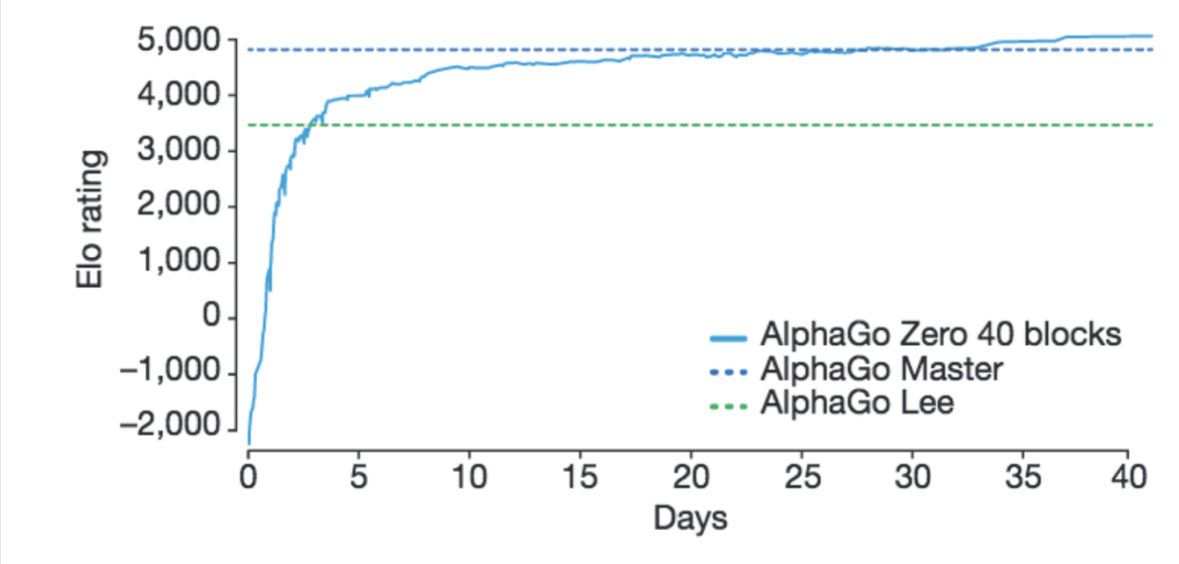

Figure 6 | Performance of AlphaGo Zero. a, Learning curve for AlphaGo Zero using a larger 40-block residual network over 40 days. The plot shows the performance of each player α_{θ_i} from each iteration i of our reinforcement learning algorithm. Elo ratings were computed from evaluation games between different players, using 0.4 s per search (see Methods)

Figure 9: fig

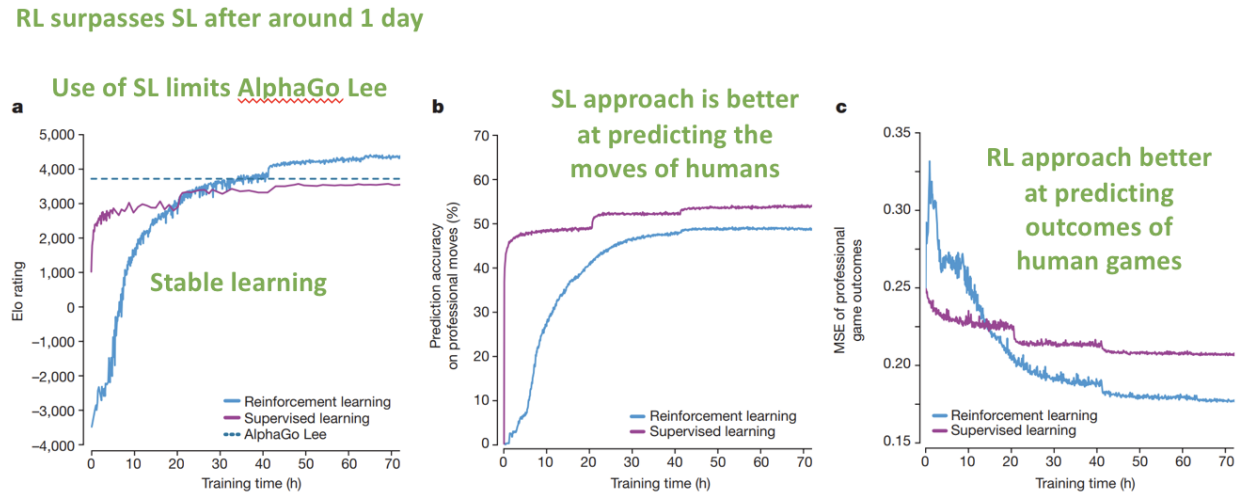

Figure 3 | Empirical evaluation of AlphaGo Zero. a, Performance of self-play reinforcement learning. The plot shows the performance of each MCTS player α_{θ_i} from each iteration i of reinforcement learning in AlphaGo Zero. Elo ratings were computed from evaluation games between different players, using 0.4 s of thinking time per move (see Methods). For comparison, a similar player trained by supervised learning from human data, using the KGS dataset, is also shown. **b**, Prediction accuracy on human professional moves. The plot shows the accuracy of the neural network f_{θ_i}, at each iteration of self-play i, in predicting human professional moves from the GoKifu dataset. The accuracy measures the percentage of positions in which the neural network assigns the highest probability to the human move. The accuracy of a neural network trained by supervised learning is also shown. **c**, Mean-squared error (MSE) of human professional game outcomes. The plot shows the MSE of the neural network f_{θ_i}, at each iteration of self-play i, in predicting the outcome of human professional games from the GoKifu dataset. The MSE is between the actual outcome $z \in \{-1, +1\}$ and the neural network value v, scaled by a factor of $\frac{1}{4}$ to the range of 0–1. The MSE of a neural network trained by supervised learning is also shown.

Figure 10: fig

AlphaGo Zero innovations

Learns using only self play

- no learning from human expert games
- no feature engineering
- learn purely from board positions

Single neural network - combine the policy & value networks

MCTS only during acting (not during learning)

Use of residual networks

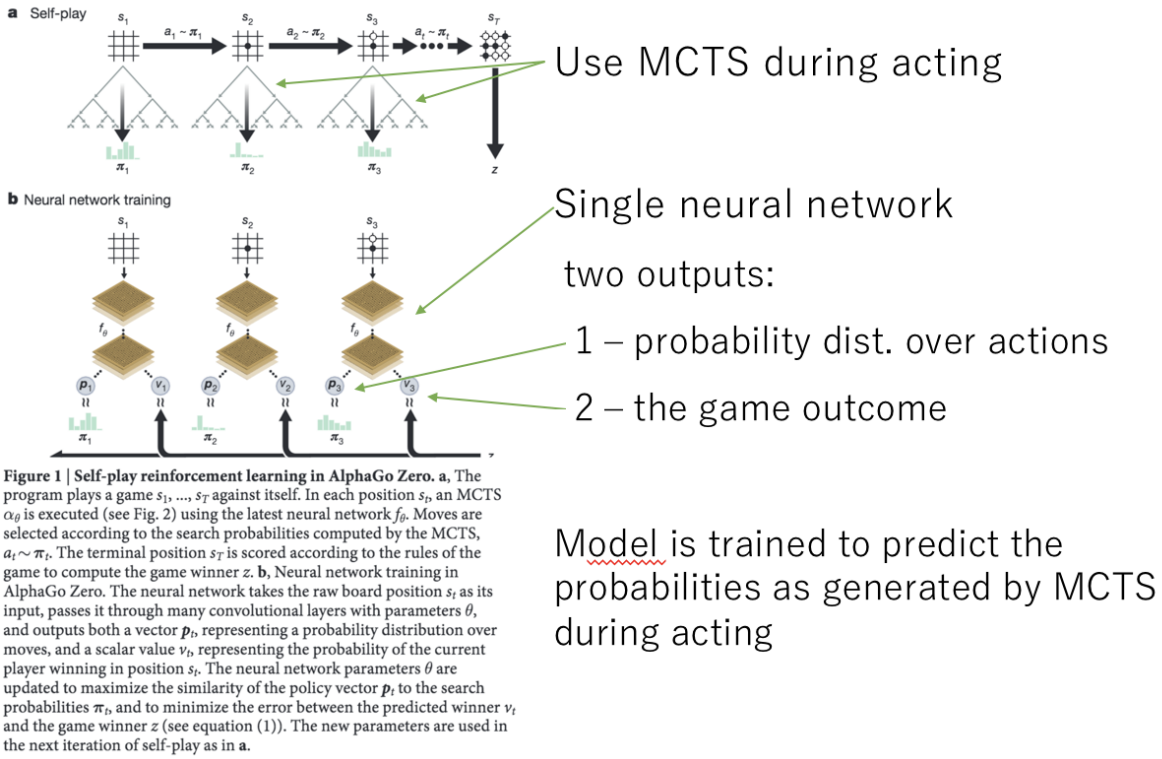

Figure 1 | Self-play reinforcement learning in AlphaGo Zero. a, The program plays a game $s_1, ..., s_T$ against itself. In each position s_t, an MCTS α_θ is executed (see Fig. 2) using the latest neural network f_θ. Moves are selected according to the search probabilities computed by the MCTS, $a_t \sim \pi_t$. The terminal position s_T is scored according to the rules of the game to compute the game winner z. **b**, Neural network training in AlphaGo Zero. The neural network takes the raw board position s_t as its input, passes it through many convolutional layers with parameters θ, and outputs both a vector $\boldsymbol{p}_t$, representing a probability distribution over moves, and a scalar value v_t, representing the probability of the current player winning in position s_t. The neural network parameters θ are updated to maximize the similarity of the policy vector $\boldsymbol{p}_t$ to the search probabilities π_t, and to minimize the error between the predicted winner v_t and the game winner z (see equation (1)). The new parameters are used in the next iteration of self-play as in **a**.

Figure 11: Acting and learning

Search in AlphaGo Zero

Policy evaluation

Policy is evaluated through self play

This creates high quality training signals - the game result

Policy improvement

MCTS is used during acting to create the improved policy

The improved policy generated during acting becomes the target policy during training

Keynote David Silver NIPS 2017 Deep Reinforcement Learning Symposium AlphaZero

DeepMind AlphaGo AMA

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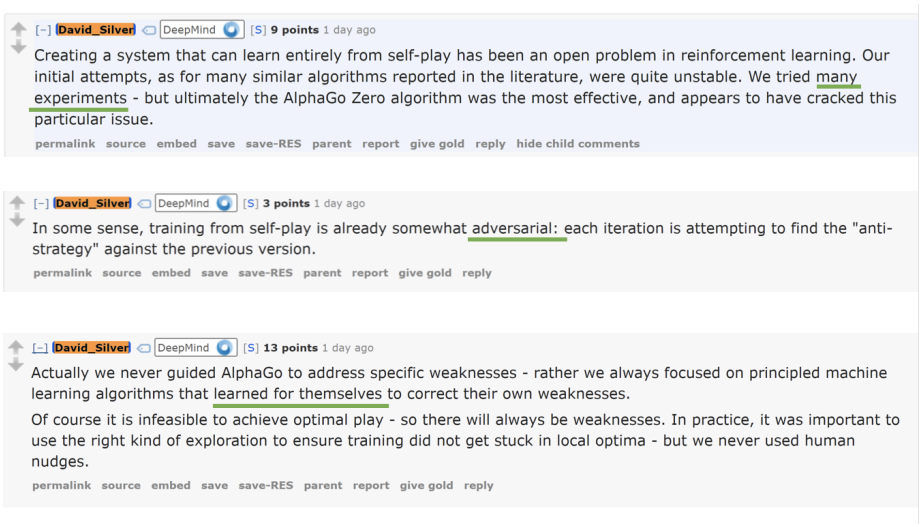

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