Review: AlphaGo <https://storage.googleapis.com/deepmind-media/alphago/AlphaGoNaturePaper.pdf>

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Date: 15.03.2017

AlphaGo is an agent, which has defeated proficient players and other agents with a winning rate of 99.8% in game of Go. It is built by a combination of Monte Carlo Search Trees (MCTS) and deep neural networks. The difficulty of creating an agent for Go relies on the possible sequences of moves and thus exhaustive search is not viable. However, the search space can be reduced by the following technique. First, the search tree is truncated, where a state in the tree is replaced by its subtree evaluated with a value function. Second, the breadth of the search tree is reduced by sampling actions for a state according to a policy.

Prior work was limited to shallow policies and weakly designed value functions. AlphaGo takes advantage of deep neural networks to create a better policy network and value network.

Firstly, a neural network (SL) is trained for policy network p\_SL. The input of the samples is a board state and the output is expert human move for a given board state. The output is provided as a probability distribution over legal moves. The trained SL policy network can predict with an accuracy of 57% in 3ms as compared to 44% state-of-the-art policy. The improvements in accuracy lead to large improvements in the playing strength. For AlphaGo, in addition to p\_SL, a faster policy network p\_RO is trained with a smaller network, which achieves an accuracy of 24% but can predict a move in 2µs.

Second stage of training aims to improve the p\_SL by reinforcement learning. Another policy network p\_RL is introduced, which has the identical structure of p\_SL with weights initialized from p\_SL. The policy network p\_RL is then updated by self-playing against randomly selected previous iterations of the p\_RL. The optimized network tries to maximize a predefined reward for a move given a state. The trained p\_RL is able to defeat p\_SL in 80% of games, state-of-the-art Monte Carlo search program 85% of games. In comparison previous state-of-the-art supervised deep neural networks wins 11% against the Monte Carlo search program.

The final stage is training a value network v to estimate a value function using the policy network p\_RL, which predicts the outcome of a board state. This neural network is similar to the policy network, but outputs only a single prediction. A specific technique is followed here during training to avoid memorization of the game outcomes instead of generalizing to new board states. The generated self-play data sets sampled from separate games are used as training samples to overcome this problem. As compared to Monte Carlo rollouts with p\_RO, the value network v is consistently more accurate. Moreover, v achieves the accuracy of Monte Carlo rollouts with p\_RL using 15000 times less computation.

The policy and value networks are combined in a MCTS to select a move given a board state. Along the tree each move is evaluated with parameters action value, visit count and prior probability. Among all moves, the move with the maximum evaluation is selected. The action value is obtained by combining output of value network v and a random rollout played with policy network p\_RO. During tree traversal the visit counts of the moves are updated. The prior probability is simply the output of p\_SL given a board state for a move.

Evaluating the policy and value networks of AlphaGo is computation intensive and thus execution is done on multiple CPUs and networks are evaluated with GPUs in parallel. In tournaments, AlphaGo beats the strongest Go programs, all of which are based on MCTS algorithms, winning 494 of 495 games. In an experiment, it is also noticed that for a given action value without fast rollouts, AlphaGo exceeded the performance of other Go programs. It is also seen that a balanced mixed evaluation of value network v and policy network p\_RO performs best by winning 95% of games versus other variants. Accordingly, it can be suggested that the value network v approximates the outcome of the game played by a slow and strong p\_RL, while weaker but faster p\_RO can precisely score and evaluate the outcome of the game.

AlphaGo defeated for the first time a human professional player. In comparison to the chess match between Deep Blue and Kasparov, AlphaGo evaluated thousands of times less states by selecting states more intelligently using the policy network and evaluating them more precisely using the value network.