

• AlphaGo

Why is Go hard for computers to play?

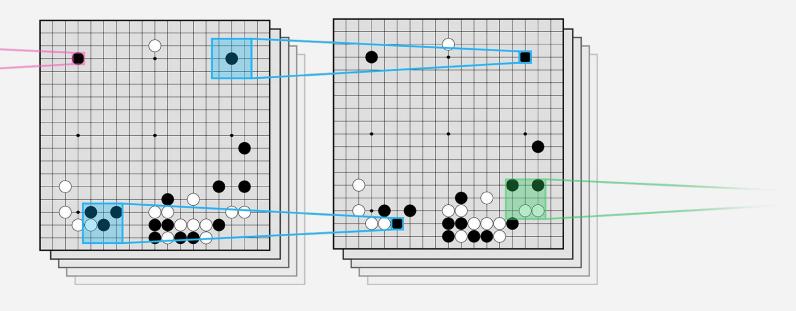
Game tree complexity = b^d

Brute force search intractable:

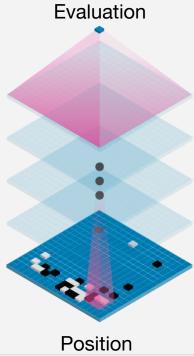
- 1. Search space is huge
- 2. "Impossible" for computers to evaluate who is winning

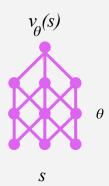


Convolutional neural network



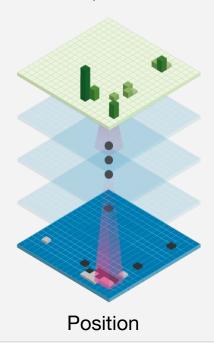
Value network





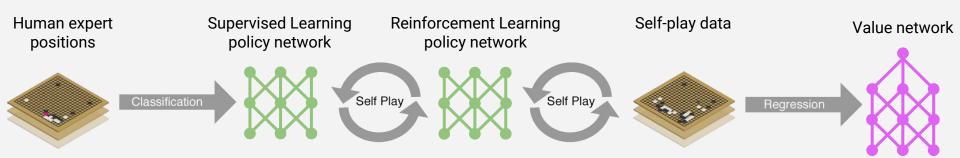
Policy network

Move probabilities





Neural network training pipeline



Supervised learning of policy networks

Policy network: 12 layer convolutional neural network

Training data: 30M positions from human expert games (KGS 5+ dan)



Training algorithm: maximise likelihood by stochastic gradient descent

$$\Delta\sigma \propto rac{\partial \log p_{\sigma}(a|s)}{\partial \sigma}$$

Training time: 4 weeks on 50 GPUs using Google Cloud

Results: 57% accuracy on held out test data (state-of-the art was 44%)

Reinforcement learning of policy networks

Policy network: 12 layer convolutional neural network

Training data: games of self-play between policy network



Training algorithm: maximise wins z by policy gradient reinforcement learning

$$\Delta\sigma \propto rac{\partial \log p_{\sigma}(a|s)}{\partial \sigma}z$$

Training time: 1 week on 50 GPUs using Google Cloud

Results: 80% vs supervised learning. Raw network ~3 amateur dan.

Reinforcement learning of value networks

Value network: 12 layer convolutional neural network

Training data: 30 million games of self-play



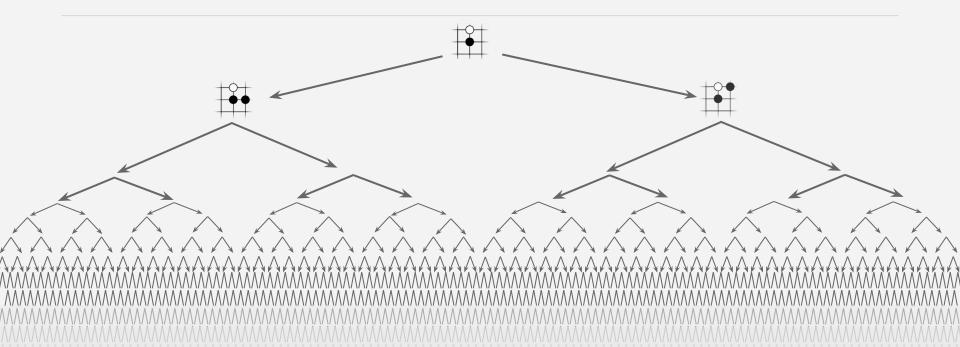
Training algorithm: minimise MSE by stochastic gradient descent

$$\Delta heta \propto rac{\partial v_{ heta}(s)}{\partial heta}(z - v_{ heta}(s))$$

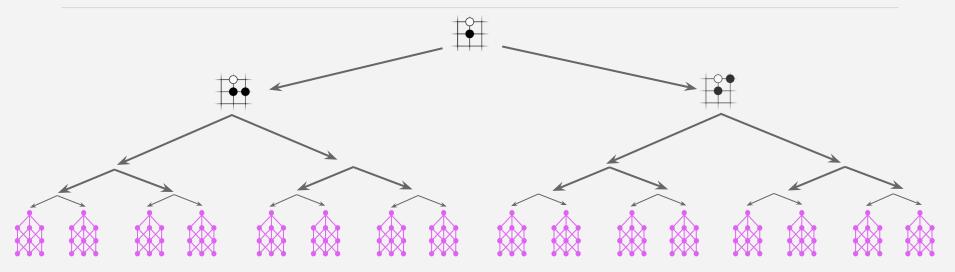
Training time: 1 week on 50 GPUs using Google Cloud

Results: First strong position evaluation function - previously thought impossible

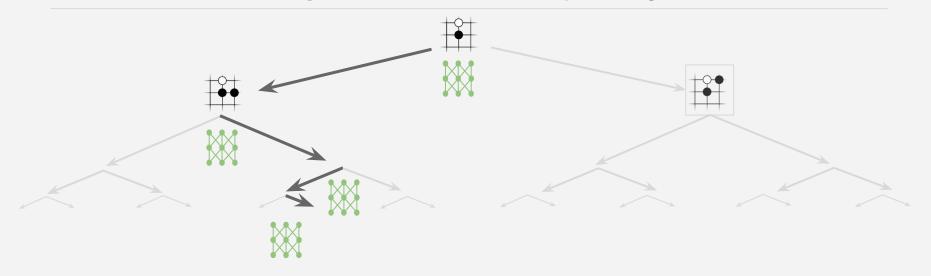
Exhaustive search



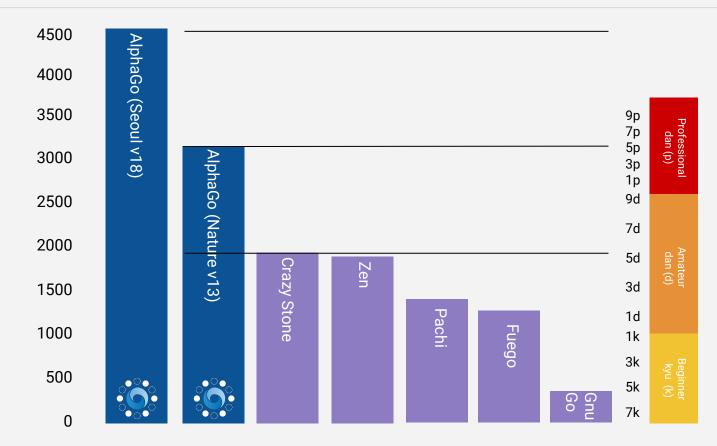
Reducing depth with value network

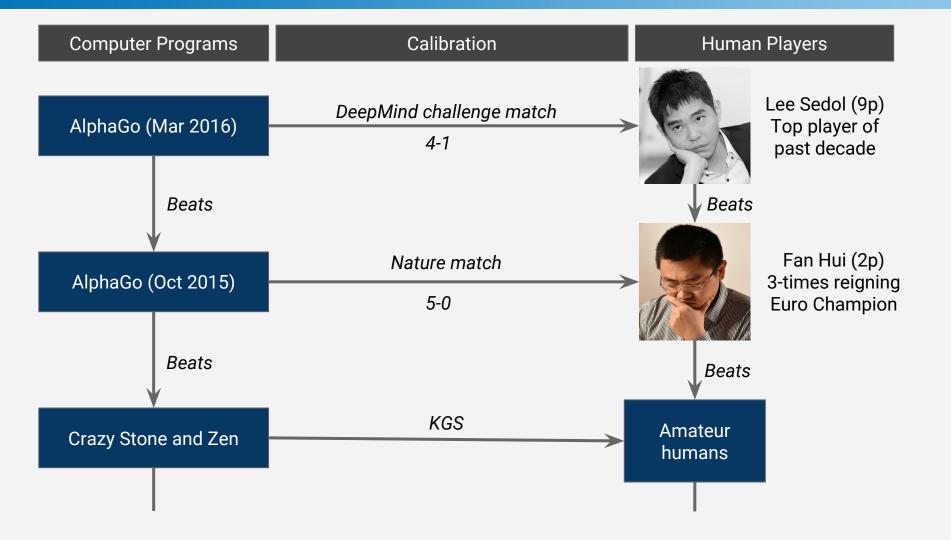


Reducing breadth with policy network



Evaluating AlphaGo against computers





What's Next?





