



AlphaGo

Go in numbers

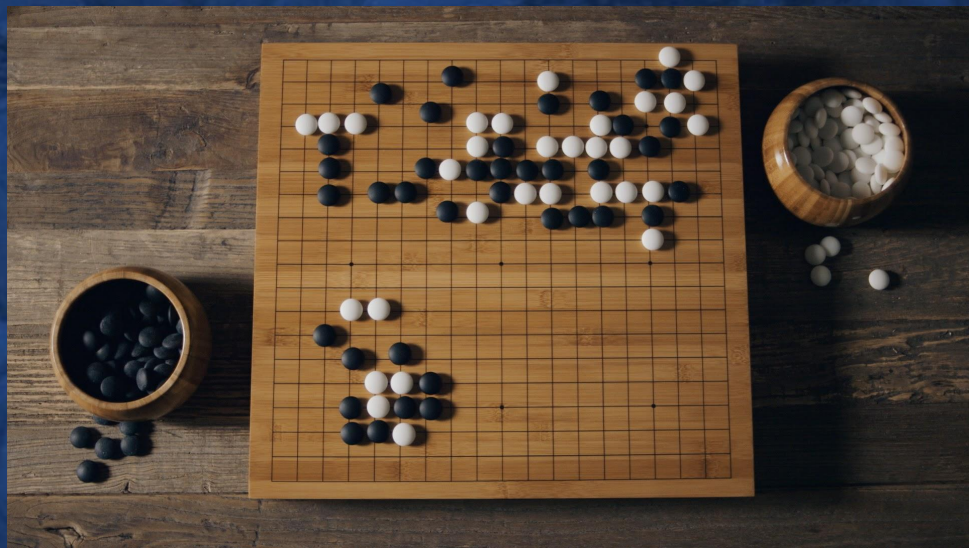


Why is Go hard for computers to play?

Game tree complexity = b^d

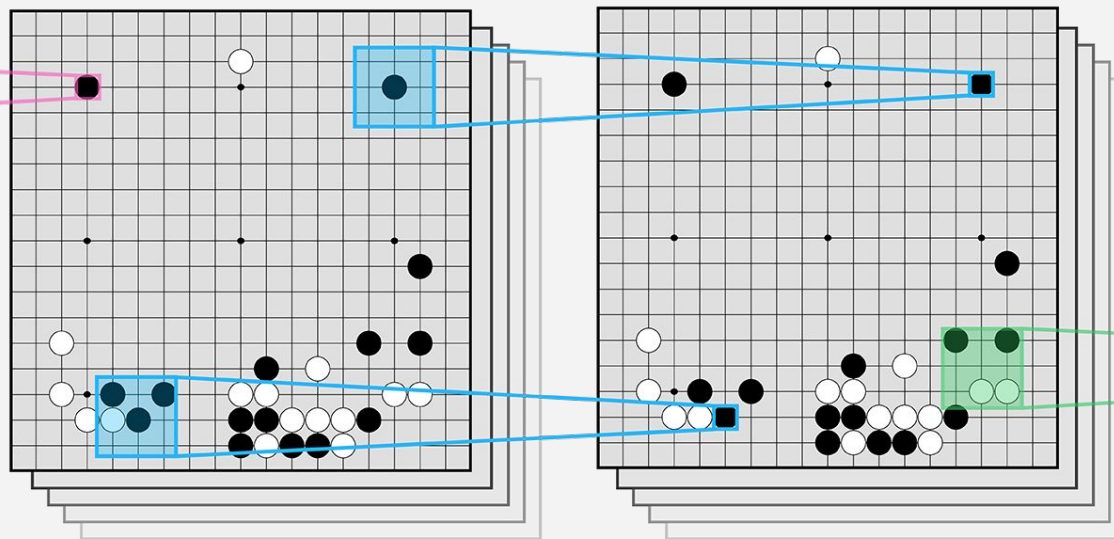
Brute force search intractable:

1. Search space is huge
2. “Impossible” for computers to evaluate who is winning

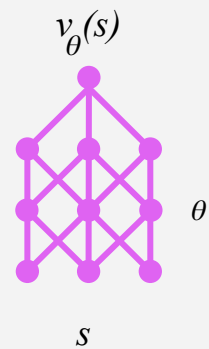
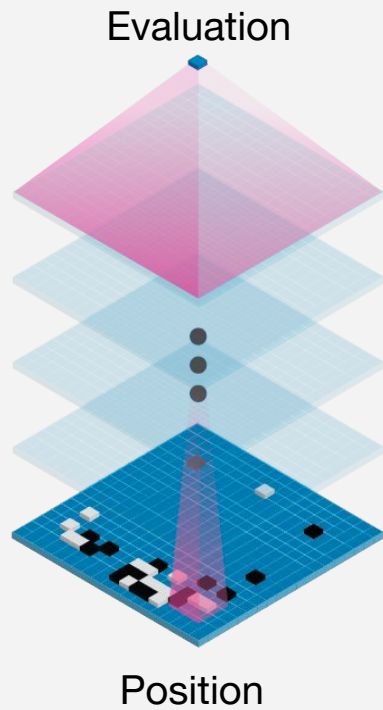




Convolutional neural network

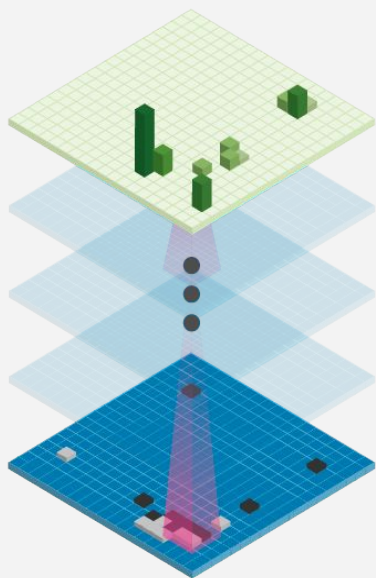


Value network



Policy network

Move probabilities



$$p_{\sigma}(a|s)$$

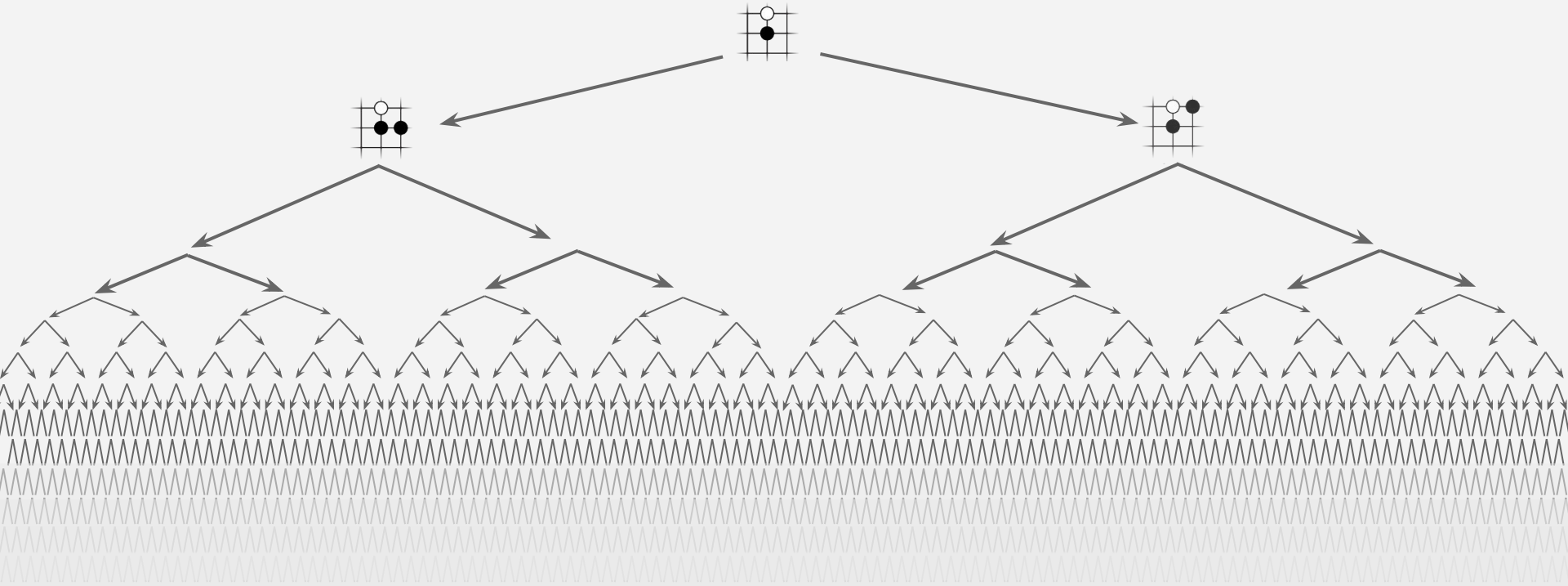


σ

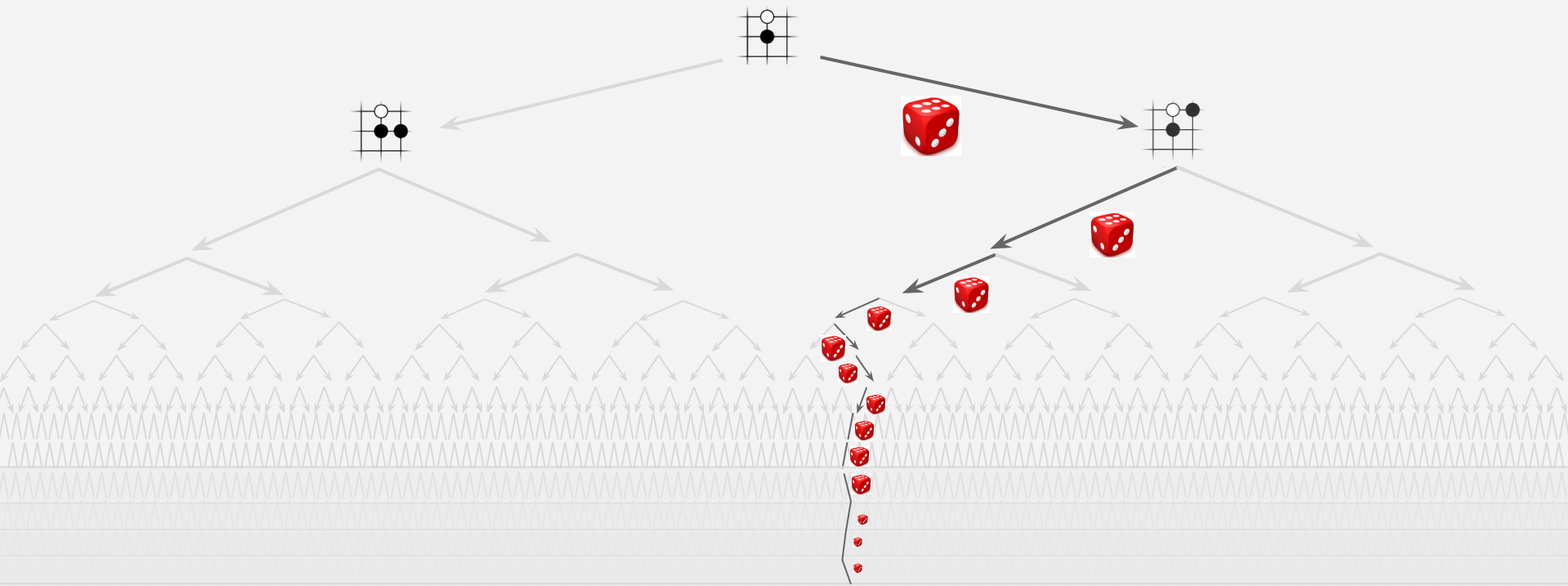
s

Position

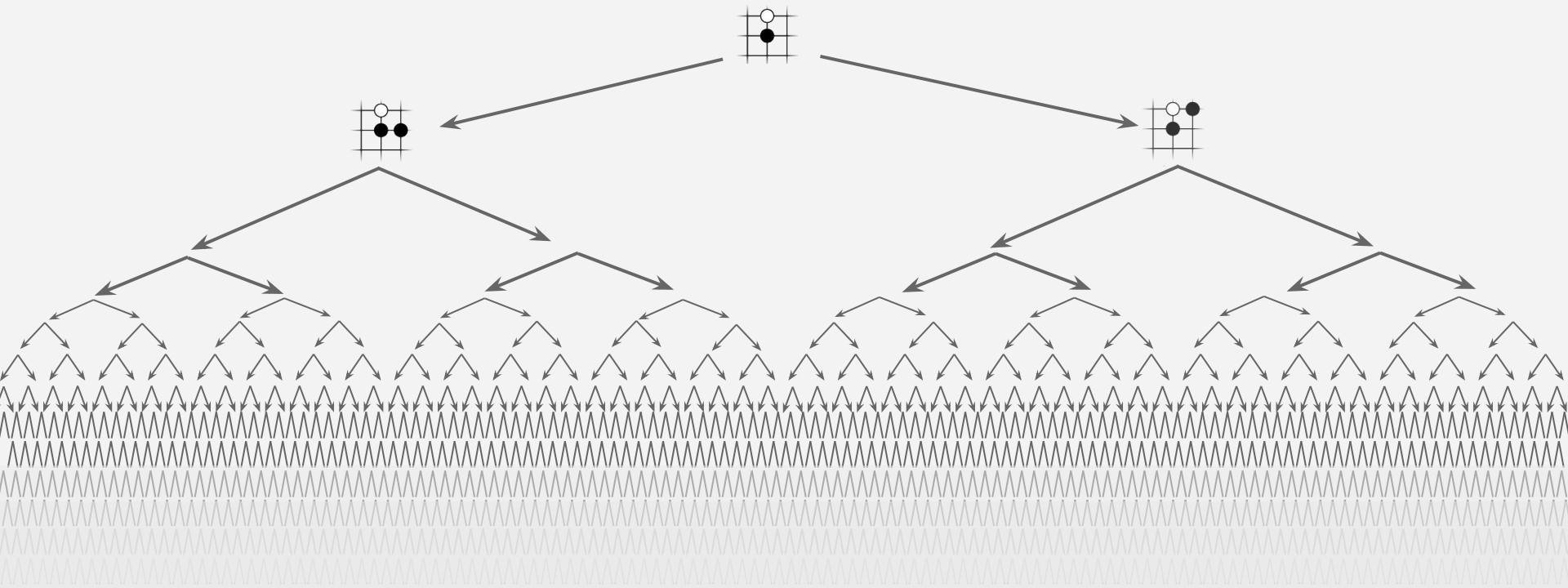
Exhaustive search



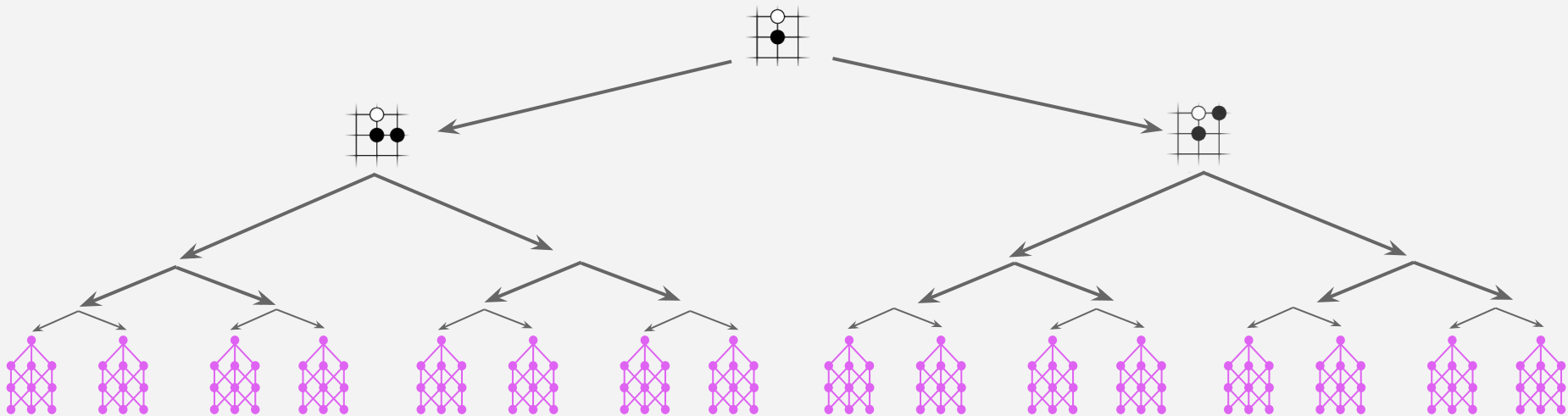
Monte-Carlo rollouts



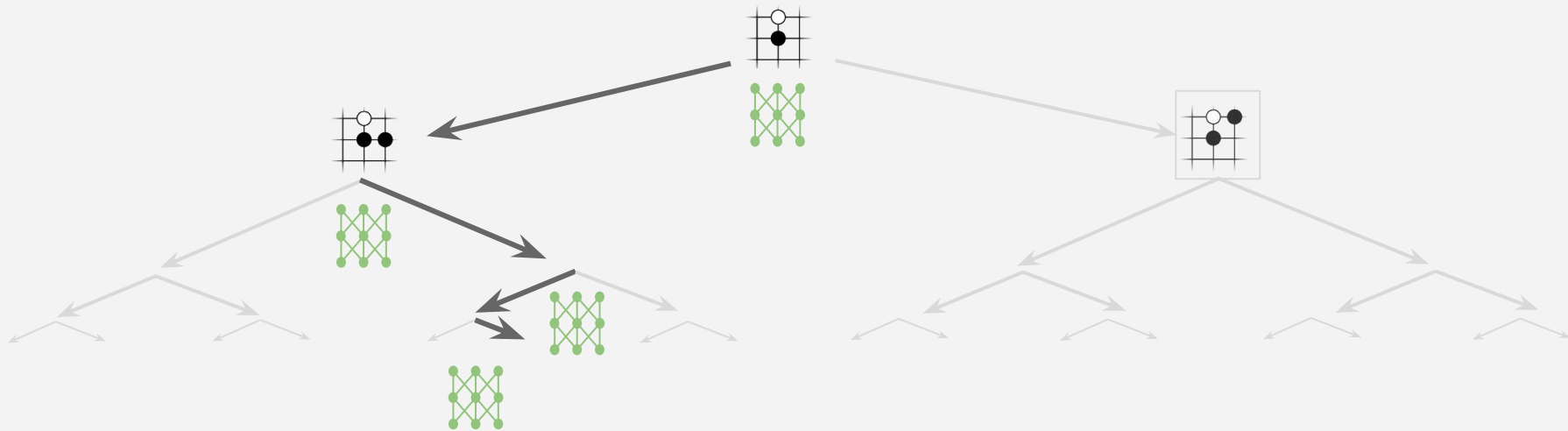
Reducing depth with value network



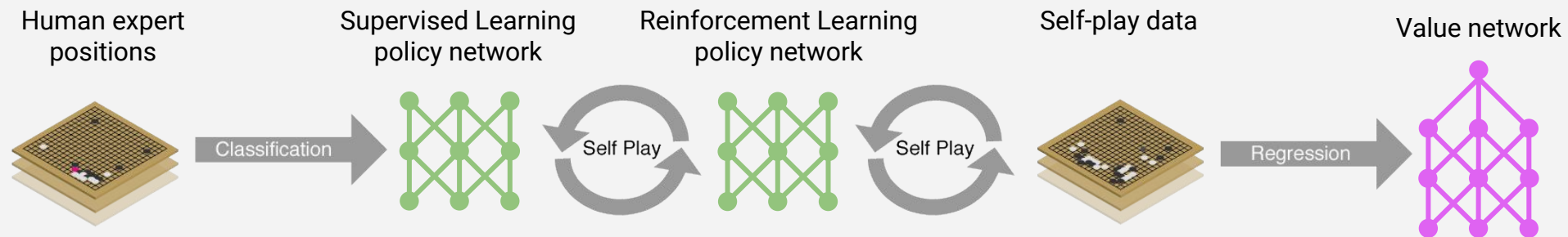
Reducing depth with value network



Reducing breadth with policy network



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

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

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

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

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

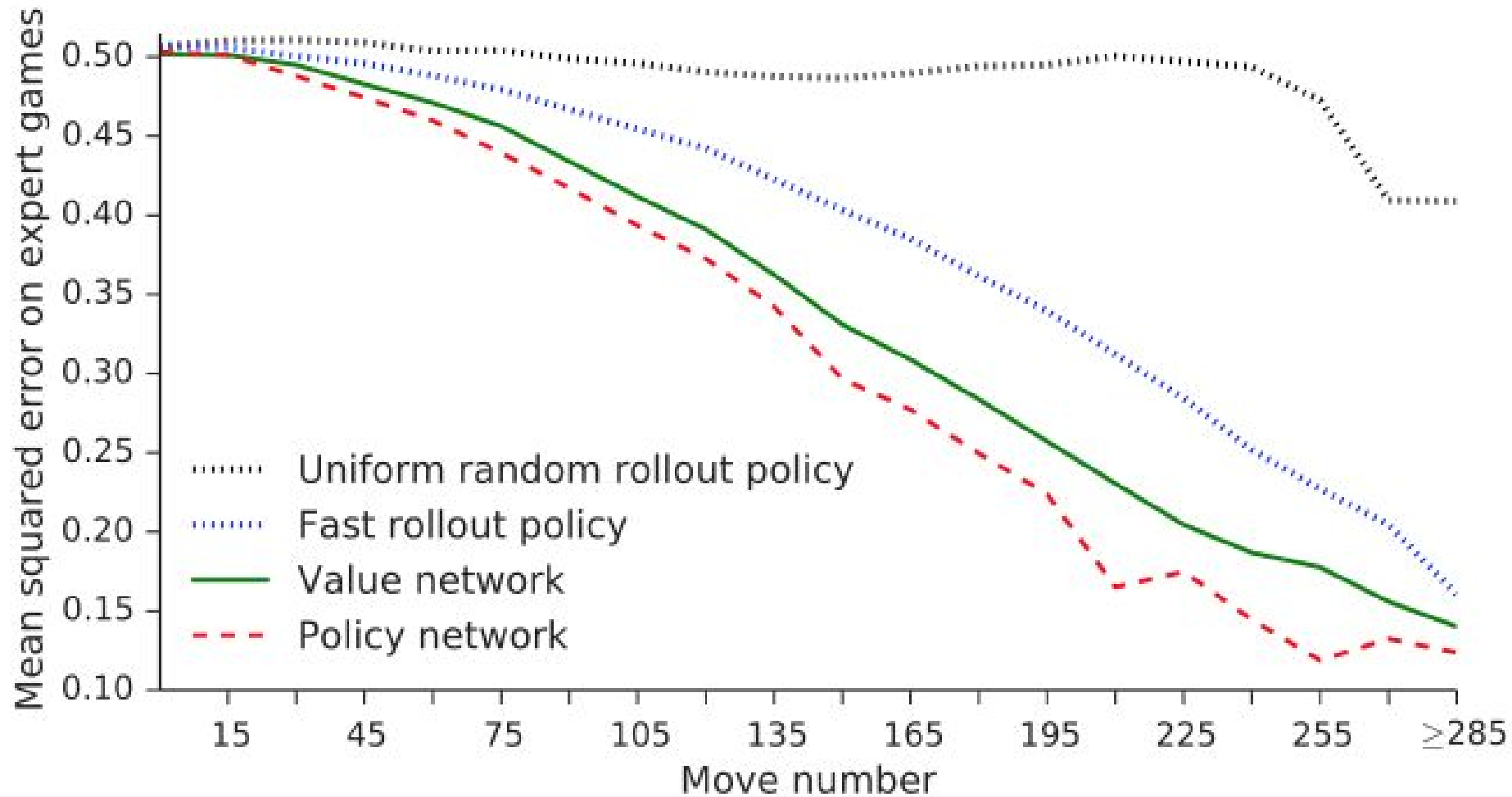
Training algorithm: minimise MSE by stochastic gradient descent

$$\Delta\theta \propto \frac{\partial v_{\theta}(s)}{\partial \theta} (z - v_{\theta}(s))$$

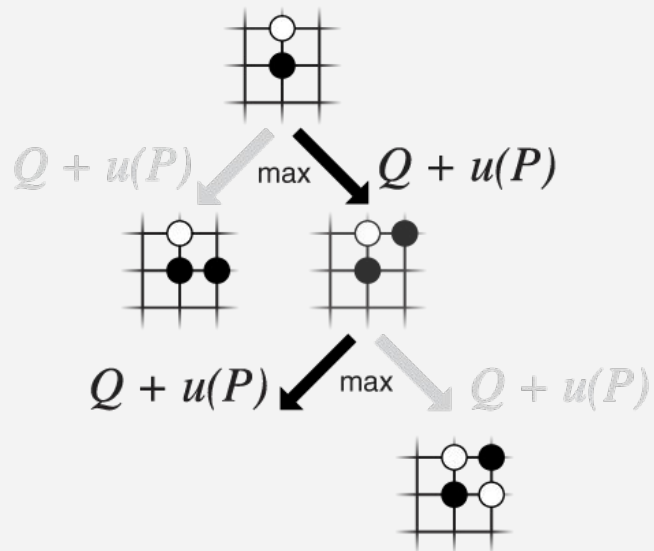
Training time: 1 week on 50 GPUs using Google Cloud

Results: First strong position evaluation function - previously thought impossible



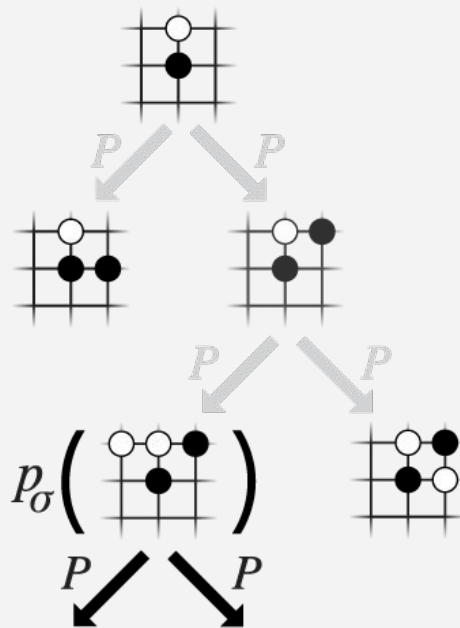


Monte-Carlo tree search in AlphaGo: **selection**



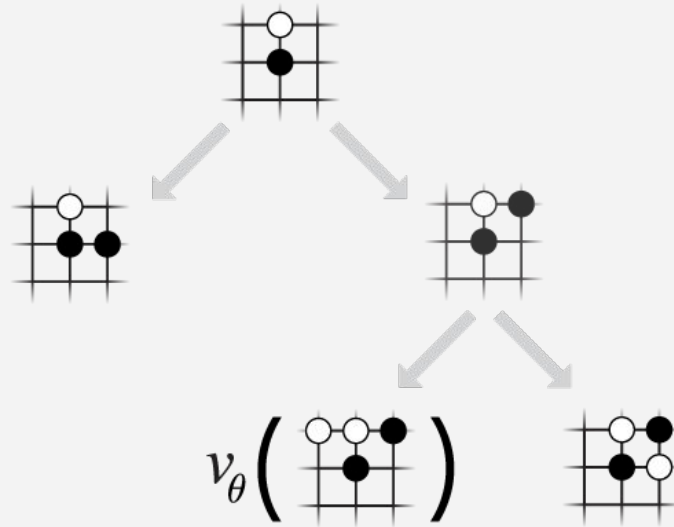
P prior probability
 Q action value

Monte-Carlo tree search in AlphaGo: **expansion**



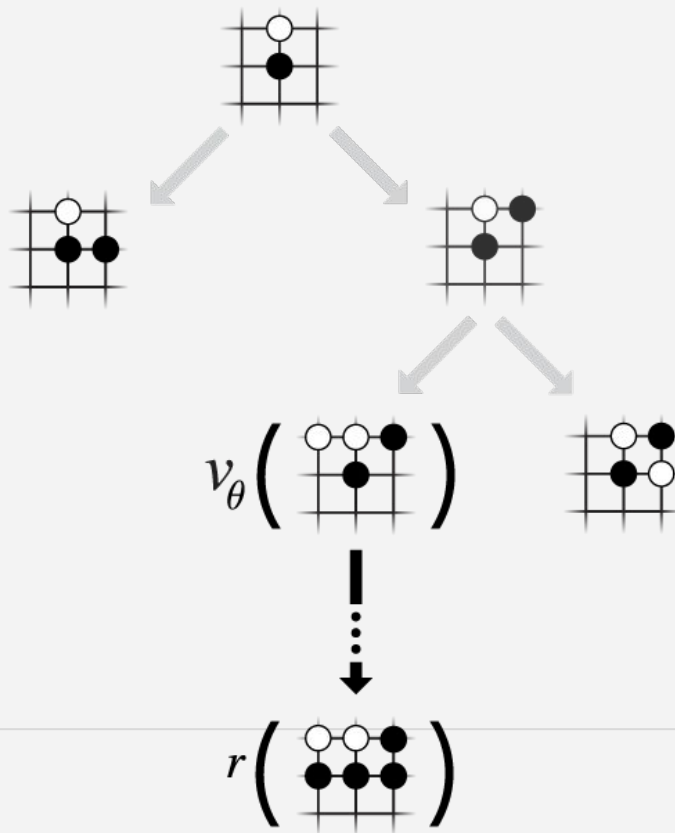
p_σ Policy network
 P prior probability

Monte-Carlo tree search in AlphaGo: **evaluation**



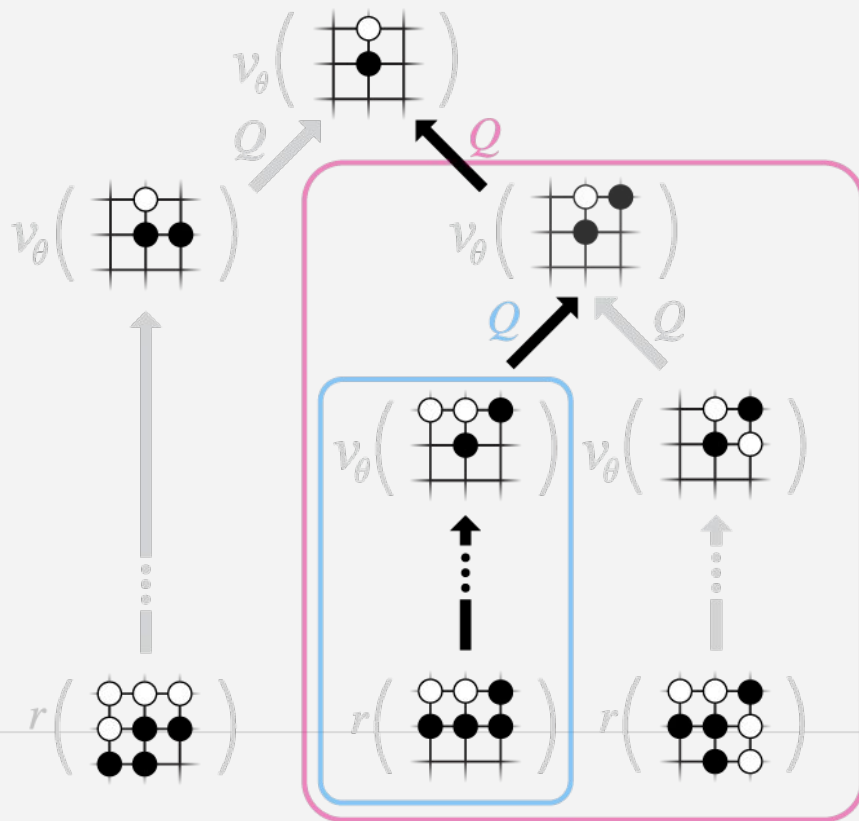
v_{θ} Value network

Monte-Carlo tree search in AlphaGo: rollout



v_{θ} Value network
 r Game scorer

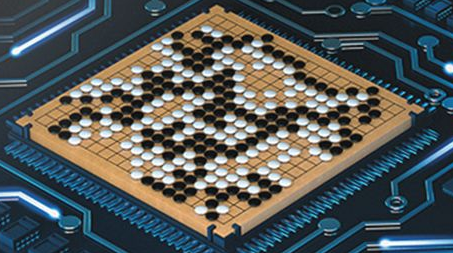
Monte-Carlo tree search in AlphaGo: **backup**



Q Action value
 v_θ Value network
 r Game scorer

nature

THE INTERNATIONAL WEEKLY JOURNAL OF SCIENCE



At last — a computer program that
can beat a champion Go player **PAGE 484**

ALL SYSTEMS GO

CONSERVATION

SONGBIRDS À LA CARTE

Illegal harvest of millions
of Mediterranean birds

PAGE 452

RESEARCH ETHICS

SAFEGUARD TRANSPARENCY

Don't let openness backfire
on individuals

PAGE 459

POPULAR SCIENCE

WHEN GENES GOT 'SELFISH'

Darwin's 'cutting
card' 40 years on

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NATUREASIA.COM

29 January 2015

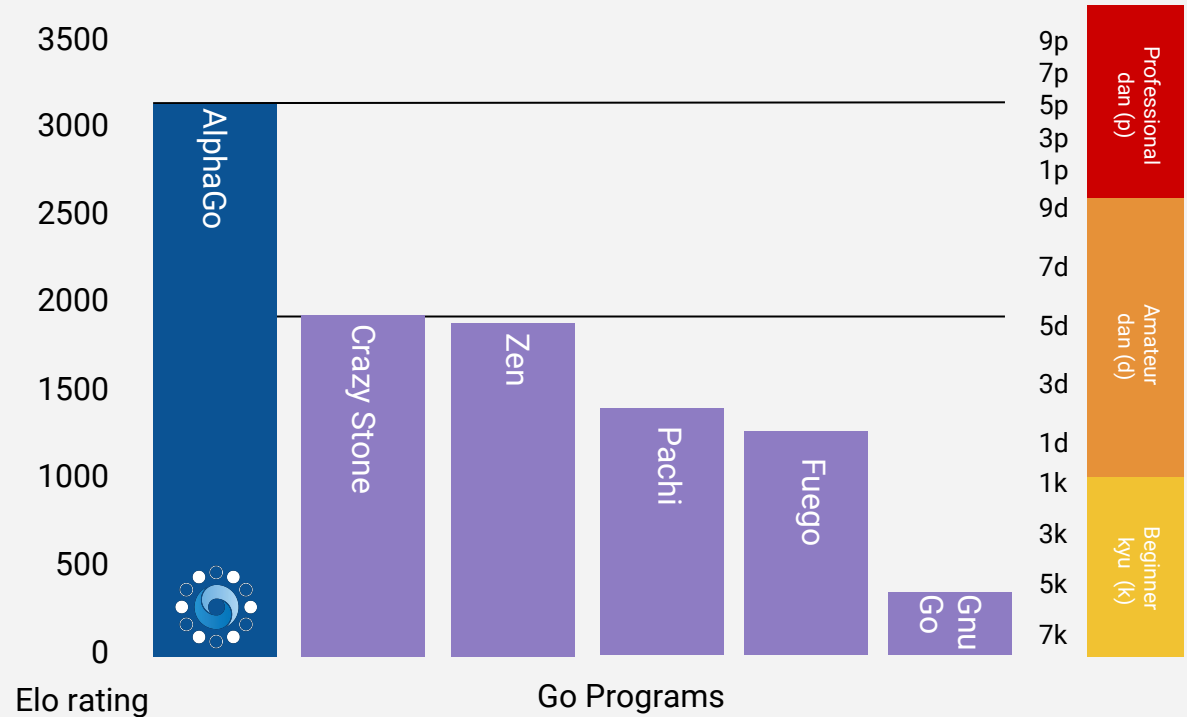
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Evaluating Nature AlphaGo against computers

494/495 against
computer opponents

>75% winning rate with
4 stone handicap

Even stronger using
distributed machines



Evaluating Nature AlphaGo against humans

Fan Hui (2p): European Champion 2013 - 2016

Match was played in October 2015

AlphaGo won the match 5-0

First program ever to beat a professional
on a full size 19x19 in an even game



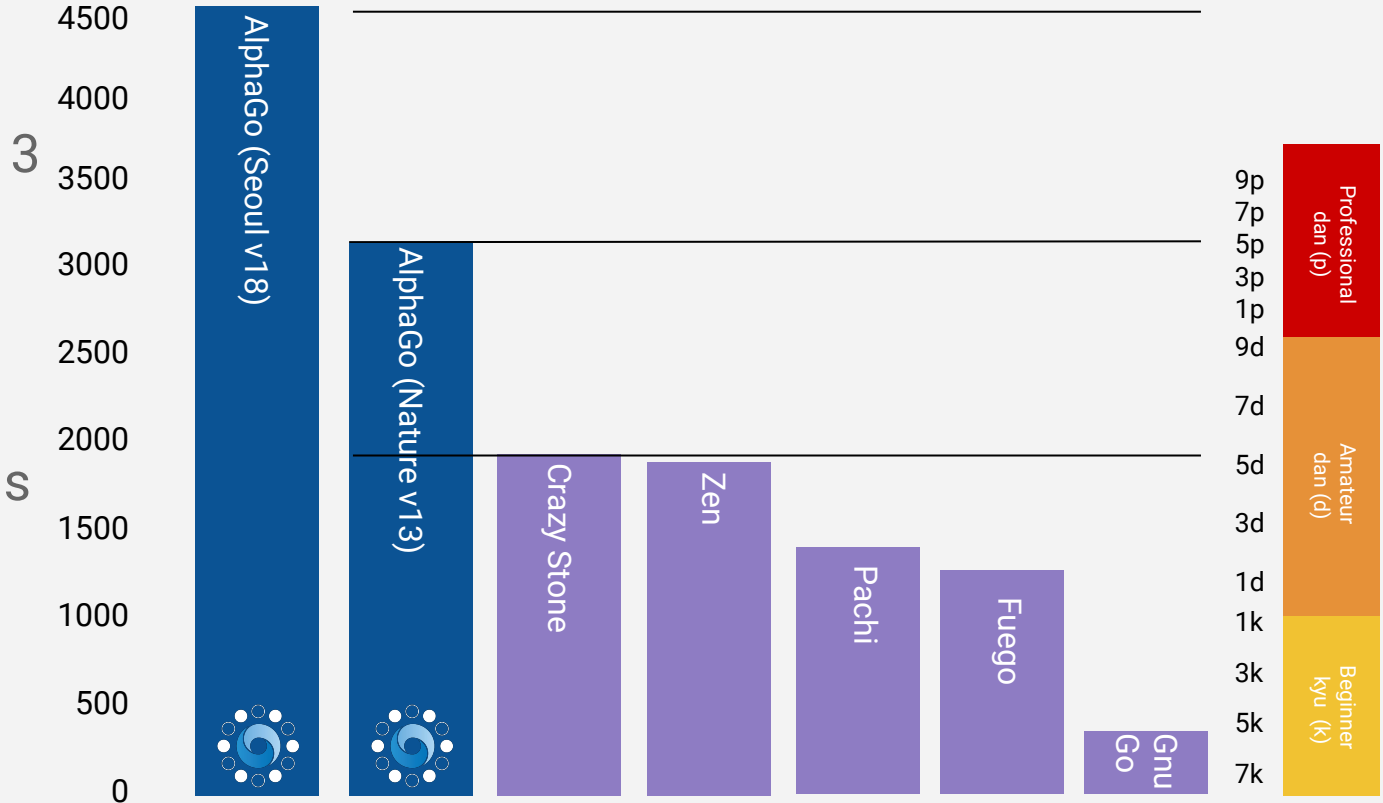
Seoul AlphaGo: Improvements

- Improved value network
- Improved policy network
- Improved search
- Improved hardware (TPU vs GPU)

Evaluating Seoul AlphaGo against computers

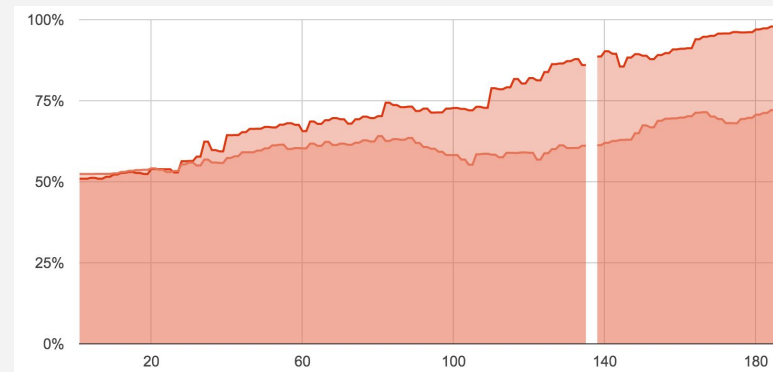
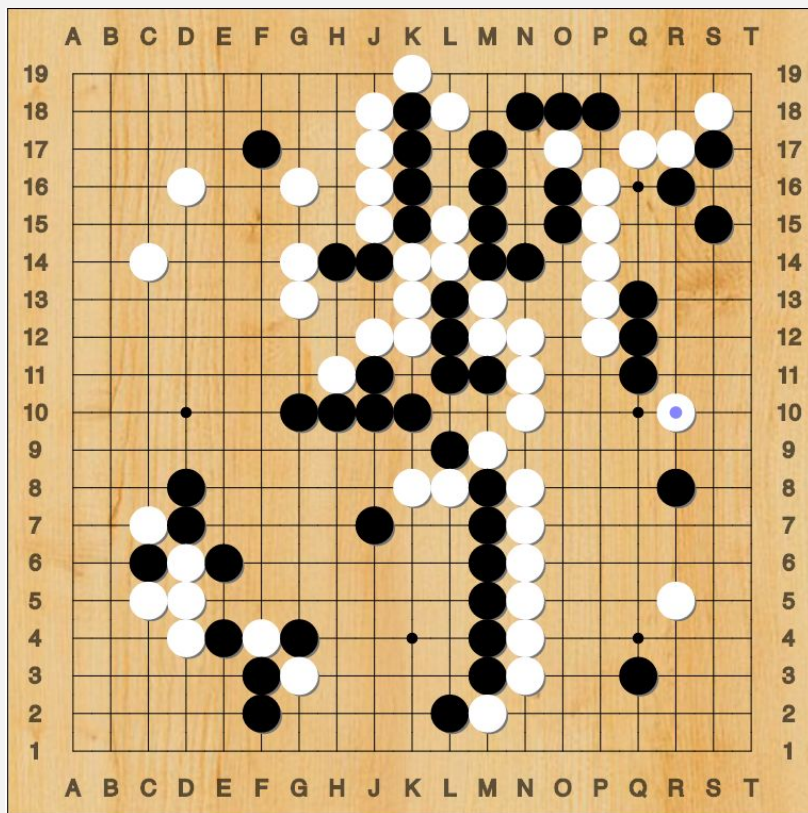
Beats Nature
AlphaGo with
to 4 stones
handicap

CAUTION: ratings
based on self-
play results

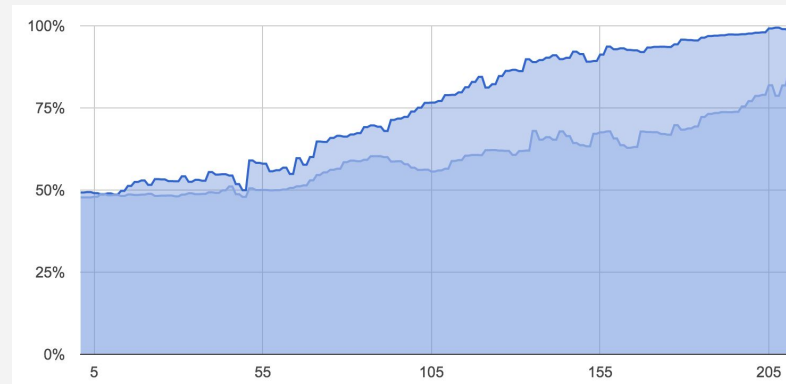
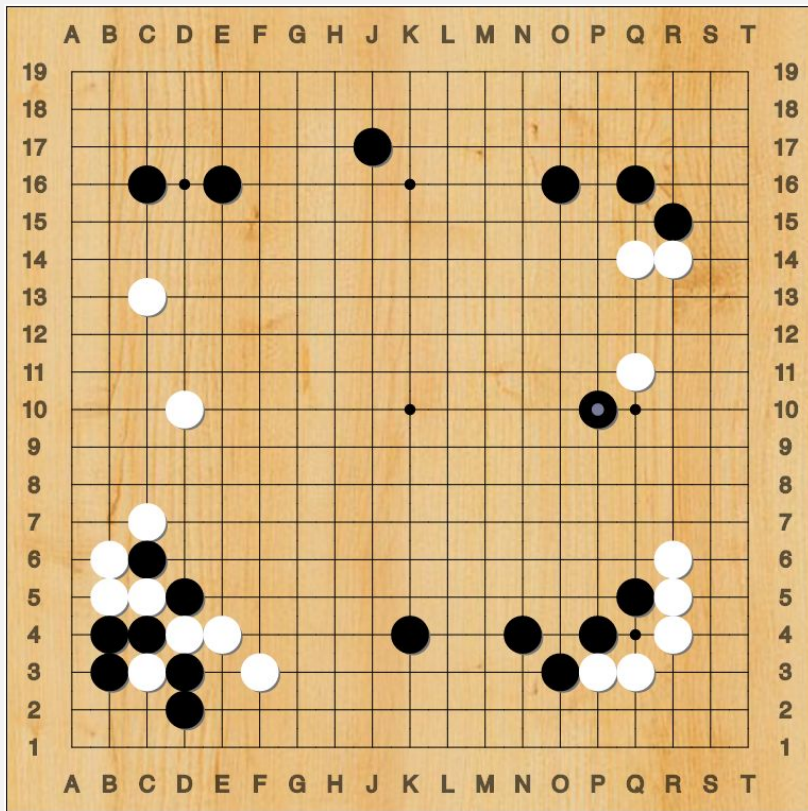




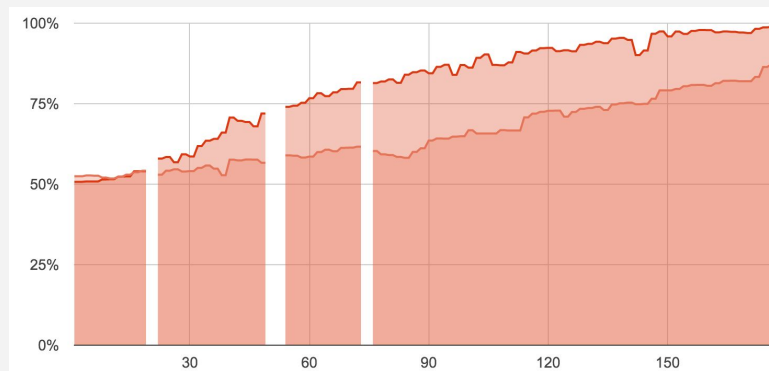
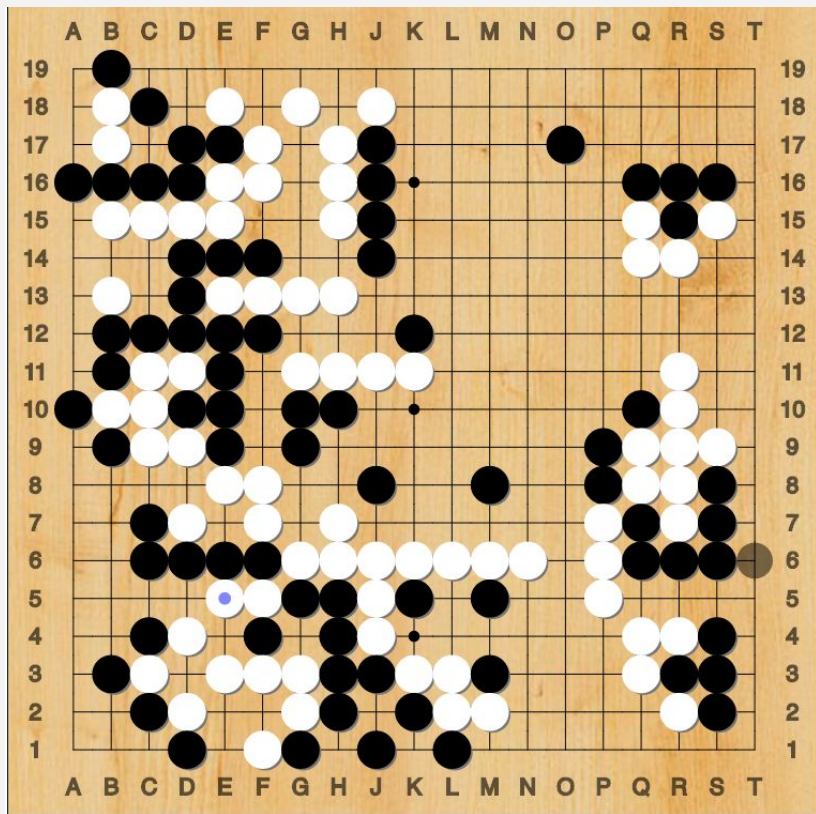
AlphaGo vs Lee Sedol: Game 1



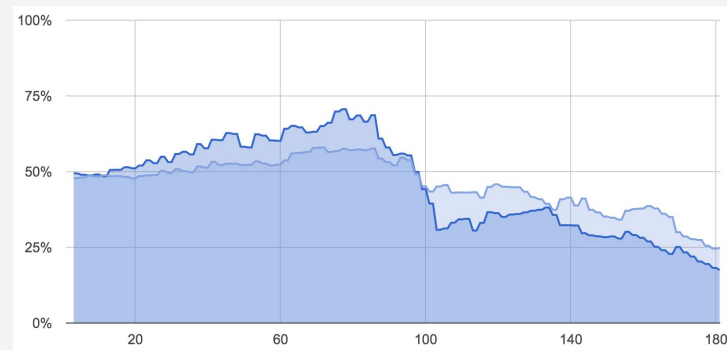
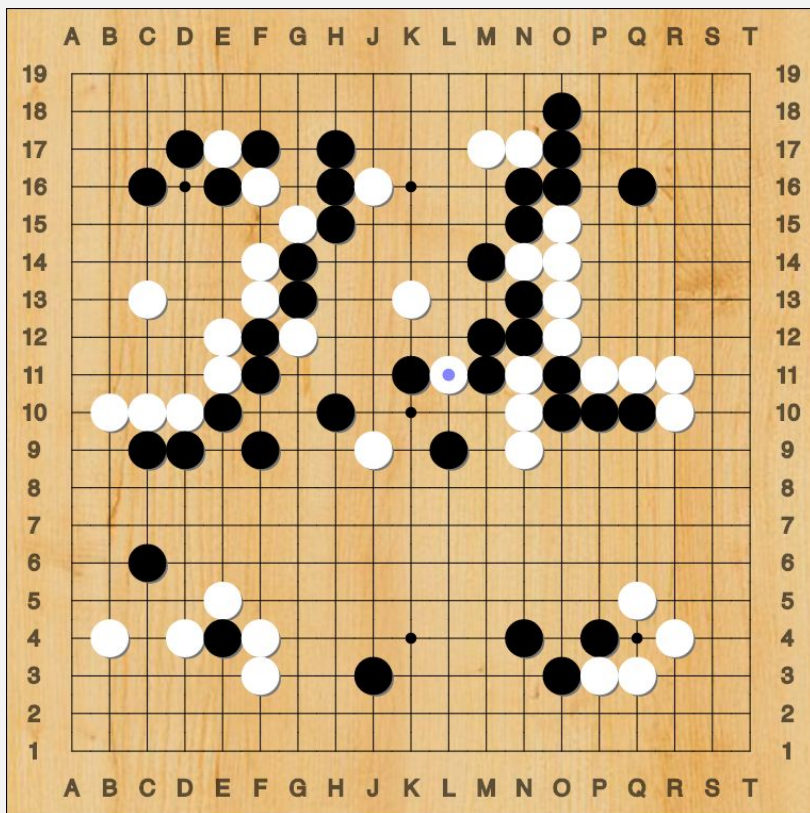
AlphaGo vs Lee Sedol: Game 2



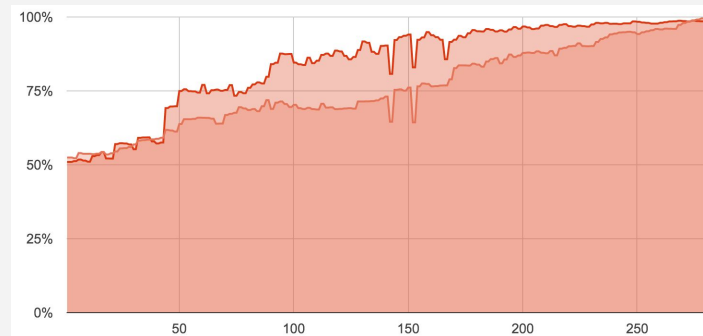
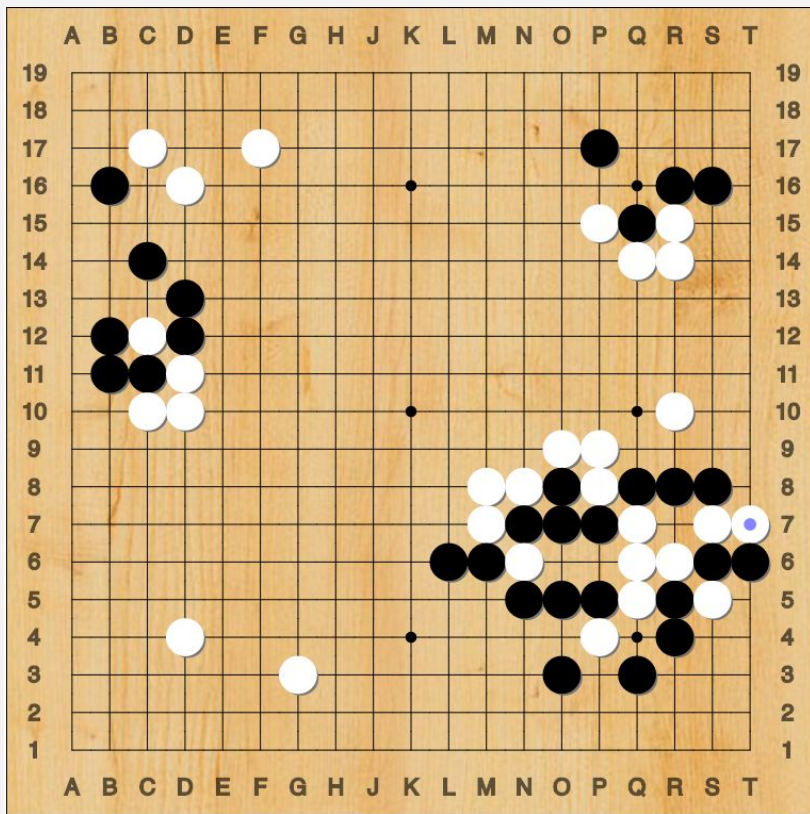
AlphaGo vs Lee Sedol: Game 3



AlphaGo vs Lee Sedol: Game 4



AlphaGo vs Lee Sedol: Game 5



Deep Blue

Handcrafted chess knowledge

Alpha-beta search guided by
heuristic evaluation function

200 million positions / second

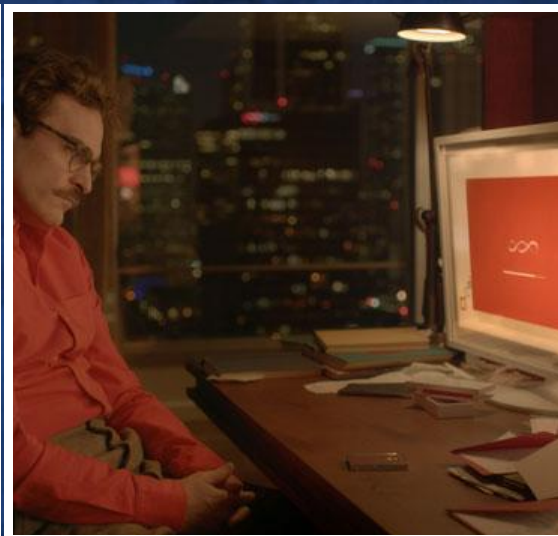
AlphaGo

Knowledge learned from expert
games and self-play

Monte-Carlo search guided by
policy and value networks

60,000 positions / second

What's Next?





AlphaGo Team



With thanks to: Lucas Baker, David Szepesvari, Malcolm Reynolds, Ziyu Wang, Nando De Freitas, Mike Johnson, Ilya Sutskever, Jeff Dean, Mike Marty, Sanjay Ghemawat.



Google DeepMind

