Mastering the Game of Go With Deep Neural Networks and Tree Search

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27th May 2016

AlphaGo by Google DeepMind

- Go: ancient Chinese board game. Simple rules, but far more complicated than Chess
- Oct '15: defeated Fan Hui (2-dan European Go champion) 5 – 0

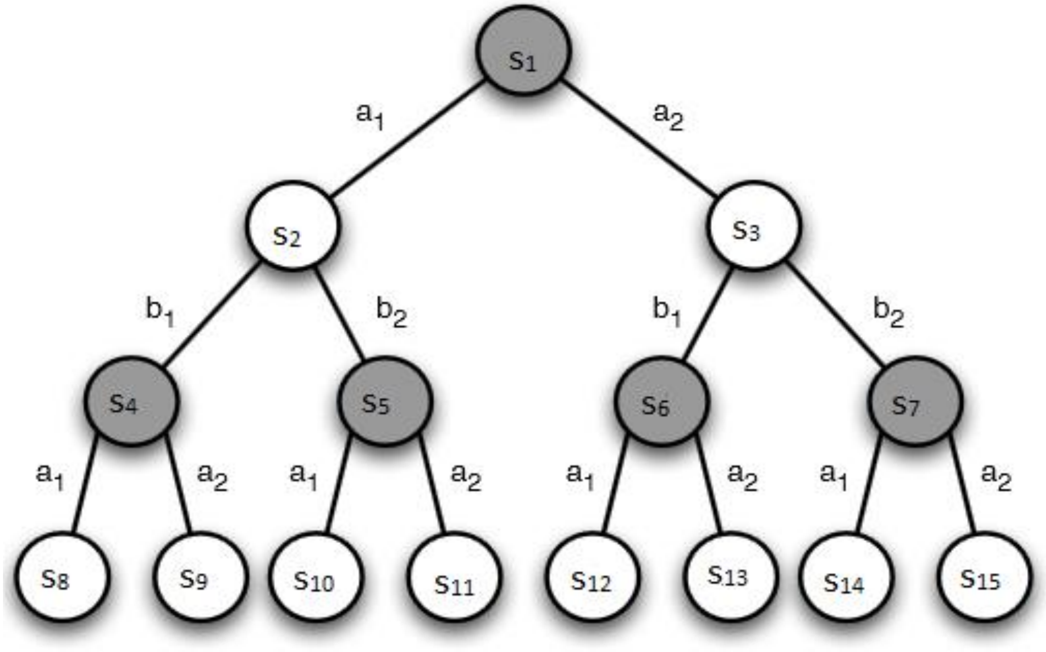
  (news delayed till January 2016 to coincide with the publication in Nature)
- Mar '16: defeated Lee Se-dol (9-dan South Korean Go player) 4 – 1
- "Last night was very gloomy… Many people drank alcohol": South Korean newspaper after Lee's first defeat

Before AlphaGo

The strongest previous Go programs were all based on Monte Carlo Tree Search (MCTS)

- Crazy Stone – 2006
- Mogo – 2007
- Fuego – 2010
- Pachi – 2012

Game Tree



s1
a1
a2
s2
s3
b1
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s6
s7
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s8
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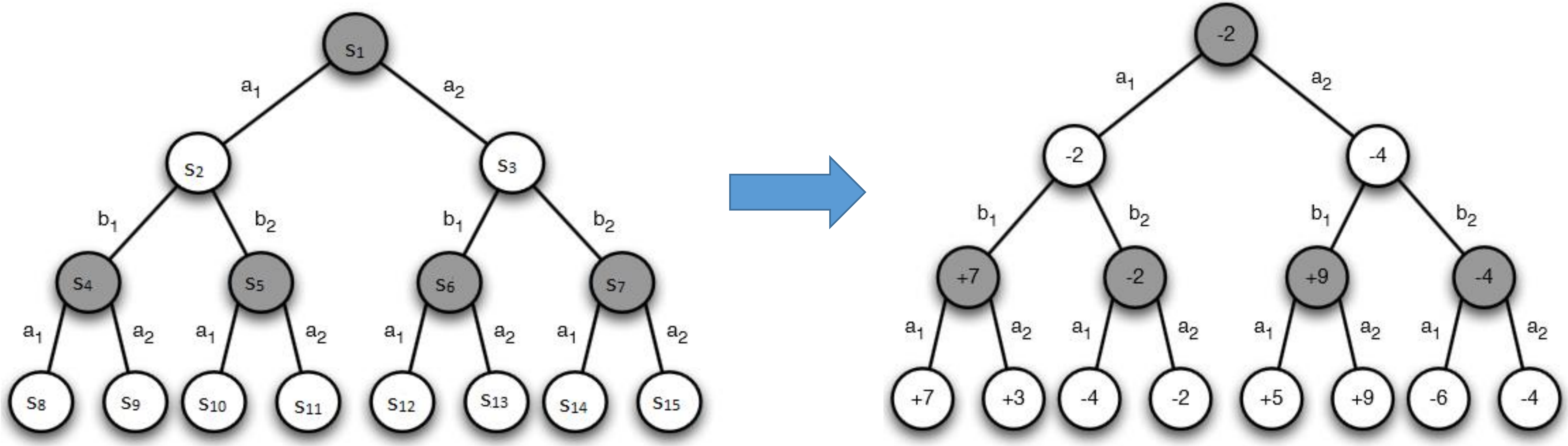
s10
s11
s12
s13
s14
s15

Game Tree



s1
a1
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s3
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b2
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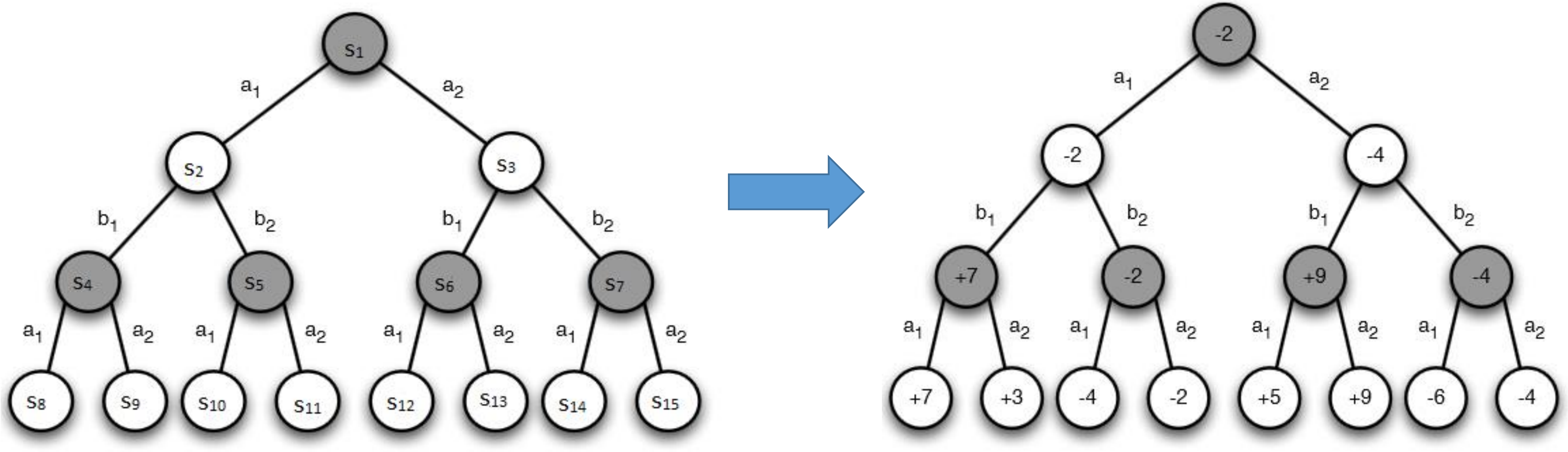
a1
a2
s8
s9
s10
s11
s12
s13
s14
s15
-2
a1
a2
-2
-4
b1
b2
b1
b2
+7
-2
+9
-4
a1
a2
a1
a2
a1
a2
a1
a2
+7
+3
-4
-2
+5
+9
-6
-4

Game Tree



- Optimal value of a node = best possible value the node's player can guarantee for himself
- Optimal value function: $f(node) \rightarrow optimal\ value$

Monte Carlo Simulations

Q: How do we estimate the value of a node?

Monte Carlo Simulations

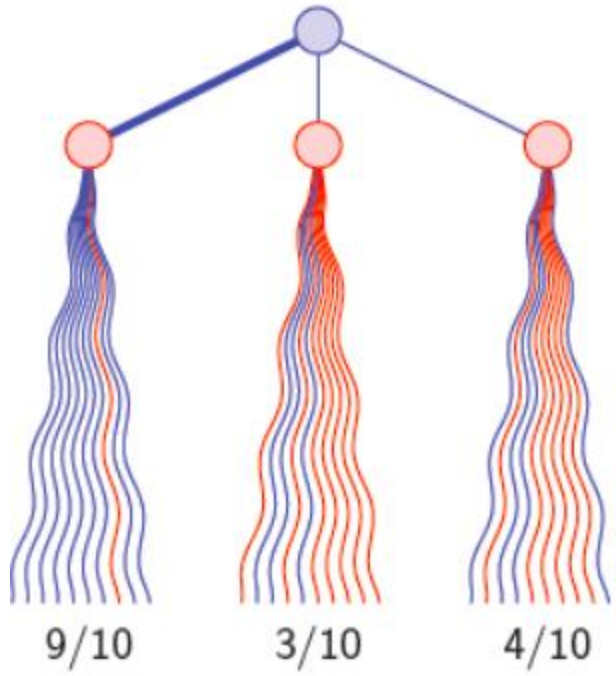
Q: How do we estimate the value of a node?

Idea:

- Run several simulations from that node by sampling actions from a policy distribution

$$a_t \sim p(a|s)$$

- Average the rewards from the simulations to obtain a Monte Carlo value estimate of the node



Monte Carlo Tree Search (MCTS)

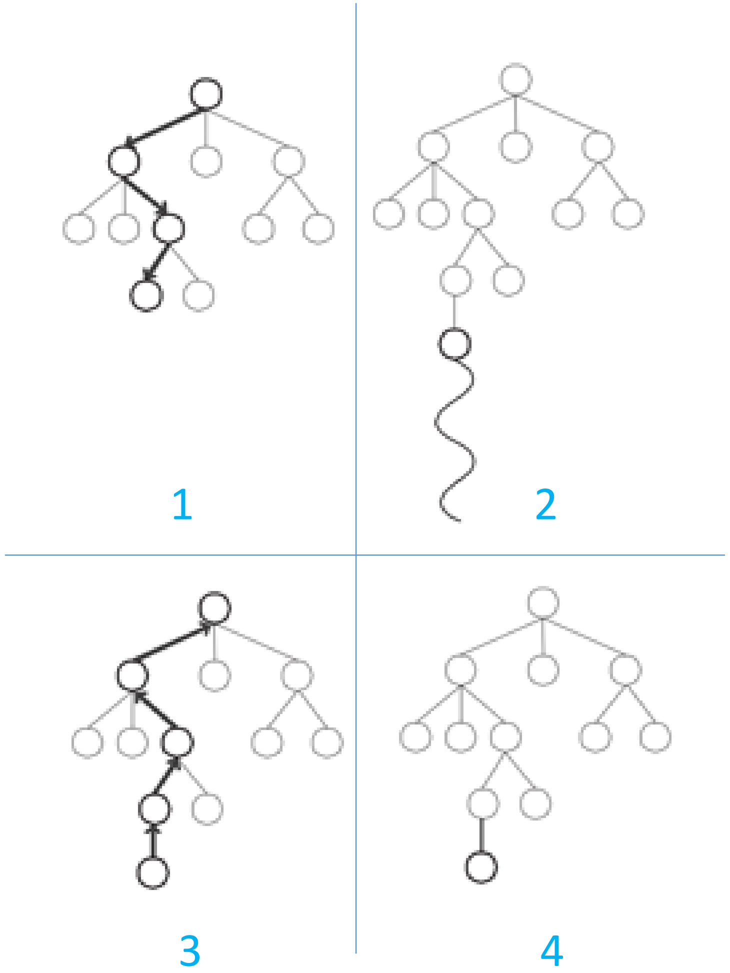
Combine Monte Carlo simulations with game tree search

1. Selection: Select the action leading to the node with highest value in the tree

2. Evaluation/Rollout: When a leaf is encountered in the tree, use a stochastic policy to select actions for both players, till the game terminates

3. Backup/Update: Update the statistics (# of visits, # of wins, prior probability) for each node of the tree visited during Selection phase

4. Growth: The first new node visited in the rollout phase is added to the tree, and its stats are initialized



MCTS: Advantages over Exhaustive Search

- The rollouts reduce the tree search breadth by sampling actions from a policy
- As more simulations are executed, the tree grows larger and the relevant values become more accurate, converging to optimal values
- The policy also improves over time (by selecting nodes with higher values), converging to optimal play

MCTS: Challenges

- Need to choose a good simulation policy that approximately chooses the optimal actions

- Need to estimate the value function based on the chosen policy

MCTS: Challenges

- In previous works, simulation policy has been chosen by training over human expert moves, or through reinforcement learning via self-play.

- Achieve superhuman performance in backgammon and scrabble, but only amateur level play in Go

- Reliance on a linear combination of input features

AlphaGo

Leverage the power of deep convolutional neural networks (CNNs) in MCTS

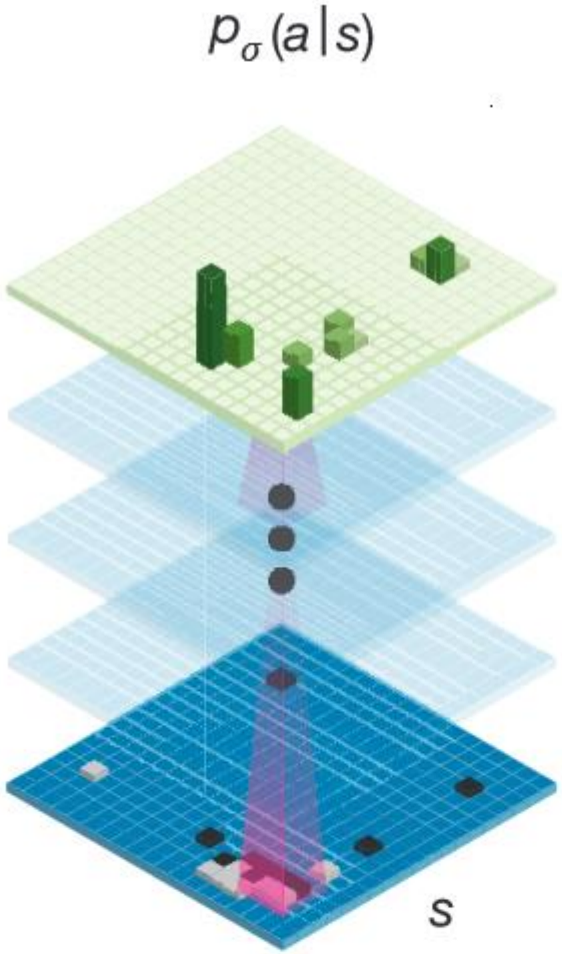
1. Policy network to compute a simulation policy $p(a|s)$
2. Value network to compute node values $v(s)$

AlphaGo Training Architecture

Main Components:

1. A Supervised Learning (SL) policy network $p_\sigma(a|s)$ (as well as a fast but less accurate rollout policy $p_\pi(a|s)$)
2. A Reinforcement Learning (RL) policy network $p_\rho(a|s)$
3. A value network $v_\theta(s)$

1. SL Policy Network



Goal: Predict the human expert's action at each step

Training Set: 30 million (s, a) pairs

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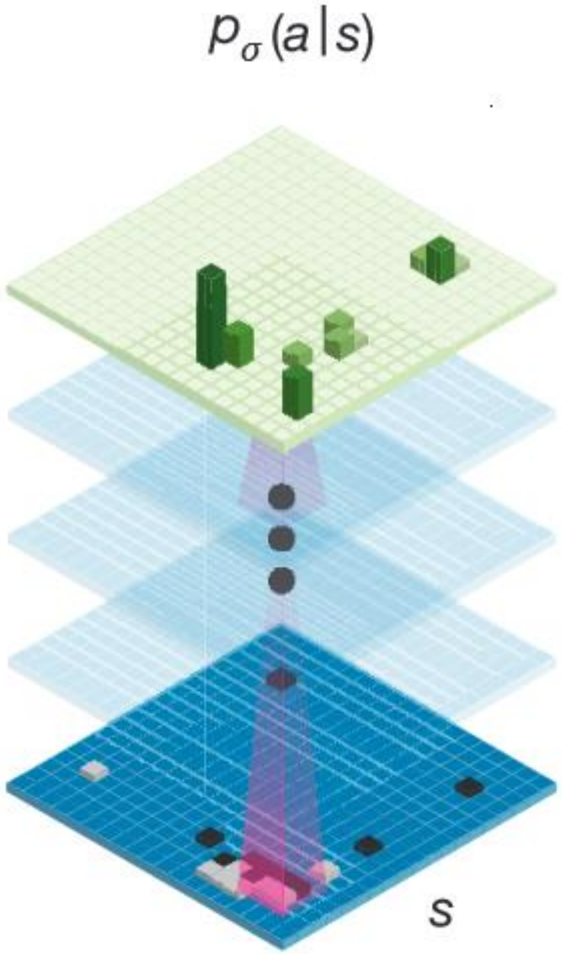

Goal: Predict the human expert's action at each step

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Input: Simple features – stone color, #liberties, #turns, etc

Output: a probability distribution $p_\sigma(a|s)$ over all legal actions in state s

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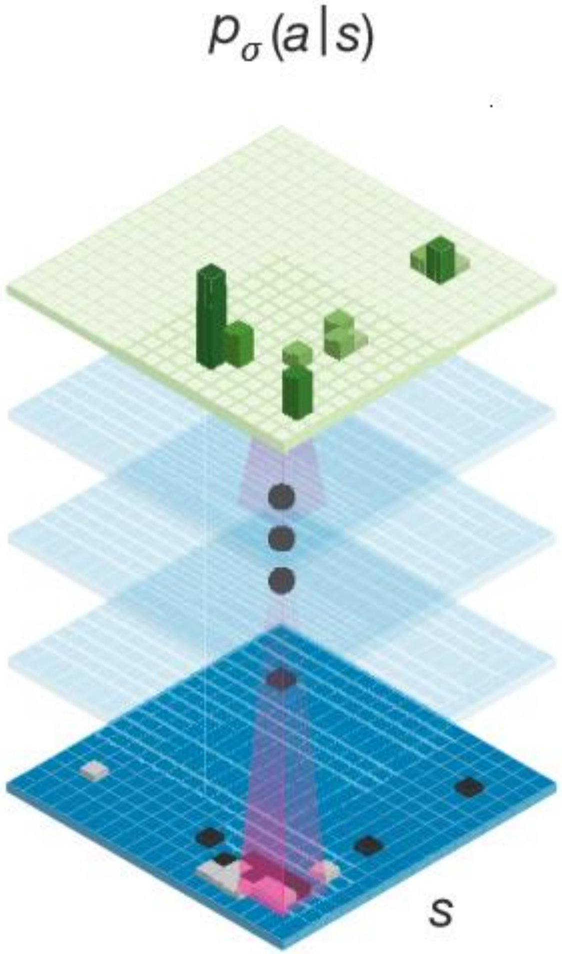

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Architecture: 13 layers; alternating between convolutional layers with weights σ and layers containing rectifiers

Objective: Maximize the likelihood $p_\sigma(a|s)$ using stochastic gradient ascent:

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

1. Rollout Policy

- Architecture: A linear softmax of small pattern features with weights π

- Output: a probability distribution $p_\pi(a|s)$ over all legal actions available in state s

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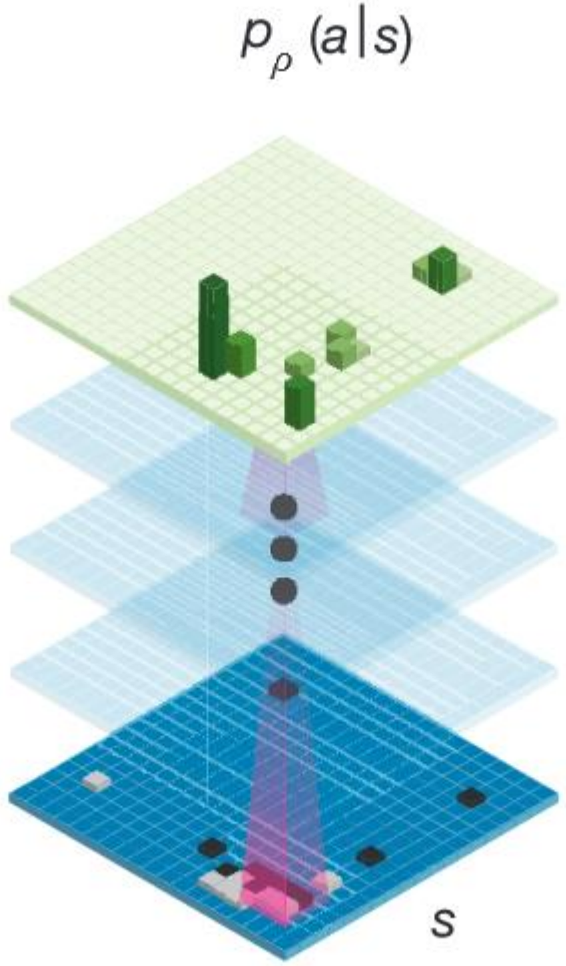
2. RL Policy Network



Structure: Same as SL policy network, with weights ρ initialized to σ

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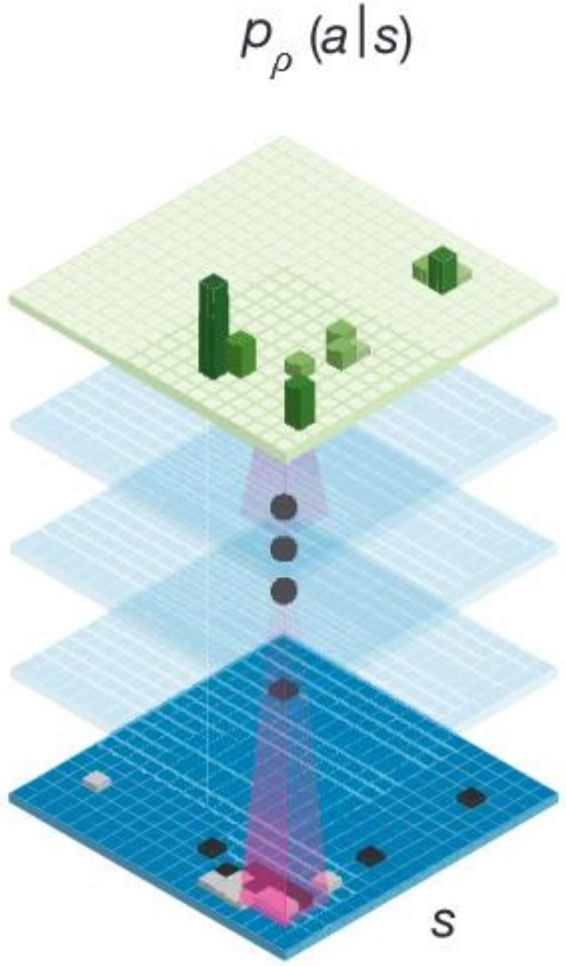

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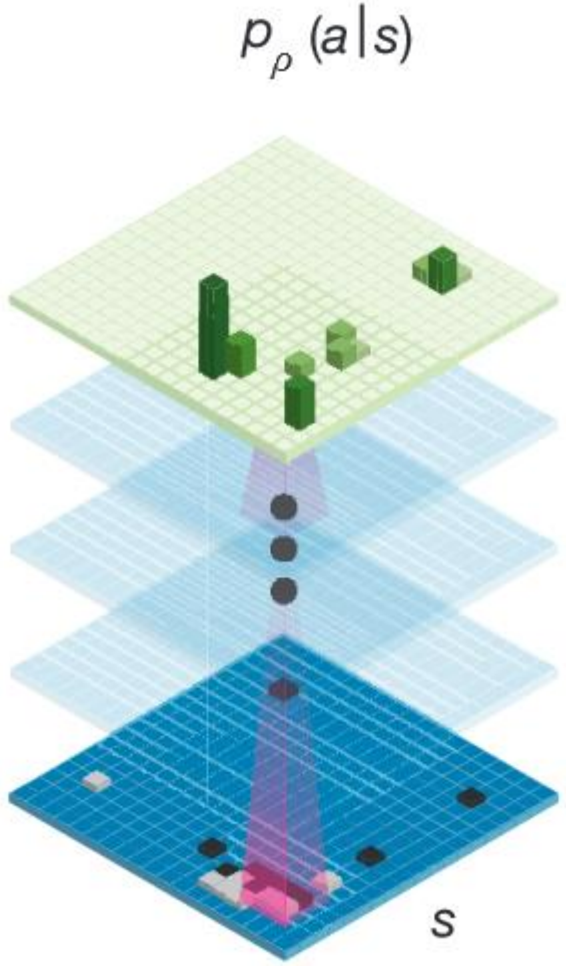
Output: a probability distribution $p_\rho(a|s)$ over all legal actions available in state s



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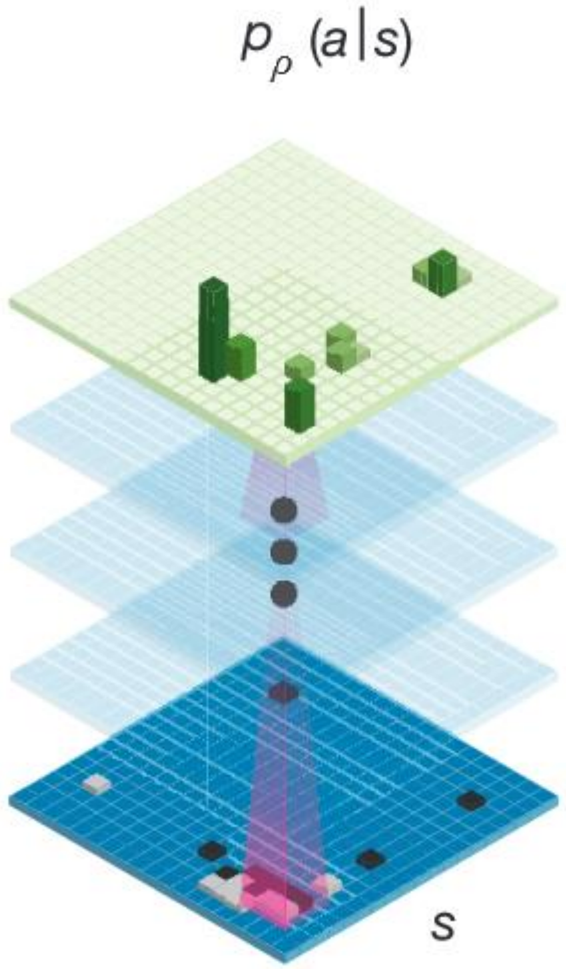


Structure: Same as SL policy network, with weights ρ initialized to σ

Goal: Improve the SL policy network through reinforcement learning

Output: a probability distribution $p_\rho(a|s)$ over all legal actions available in state s

Objective: Play p_ρ against a randomly selected previous iteration. Update weights through stochastic gradient ascent to maximize expected outcome:

$$\Delta\rho \propto \frac{\partial \log p_\rho(a_t|s_t)}{\partial \rho} z_t$$

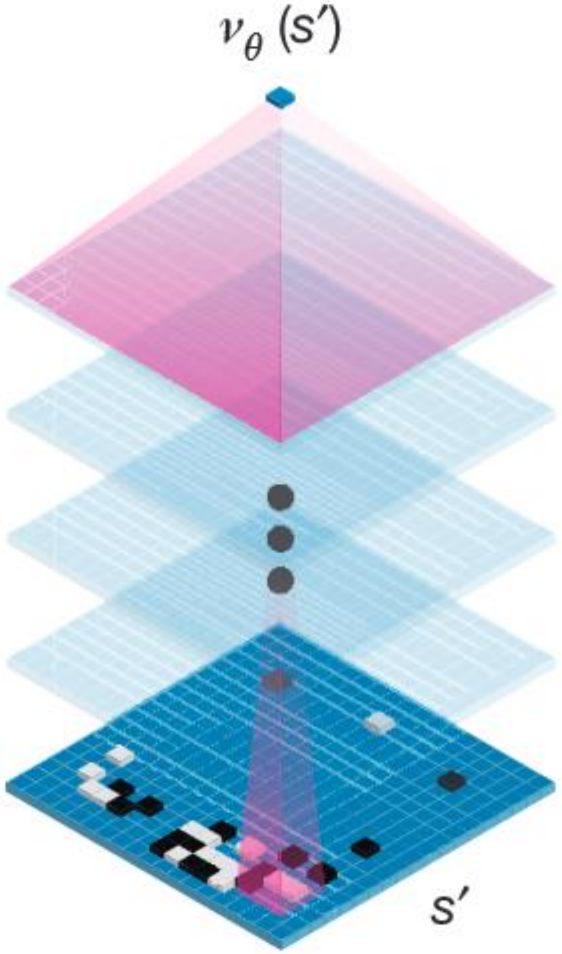
AlphaGo Training Architecture

Main Components:

1. A Supervised Learning (SL) policy network $p_\sigma(a|s)$ (as well as a fast but less accurate rollout policy $p_\pi(a|s)$) ✓
2. A Reinforcement Learning (RL) policy network $p_\rho(a|s)$ ✓
3. A value network $v_\theta(s) \approx v^*(s)$

3. Value Network

Structure: Similar to SL/RL policy network with weights θ



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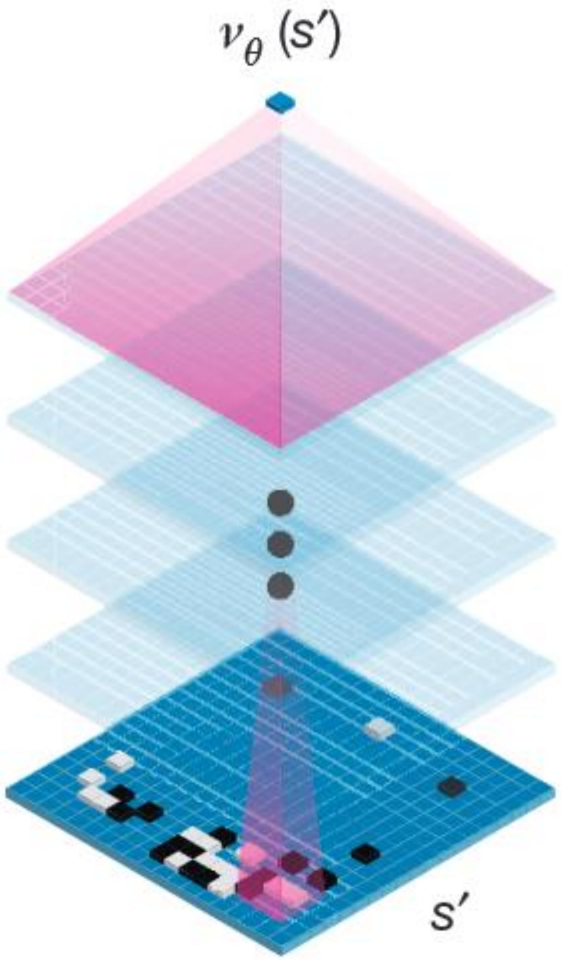

Structure: Similar to SL/RL policy network with weights θ

Goal: Estimate the value function $v^p(s)$ to predict outcome at state s, using policy p for both players:

$$v^p(s) = \mathbb{E}[z_t | s_t = s,\ a_{t...T} \sim p]$$

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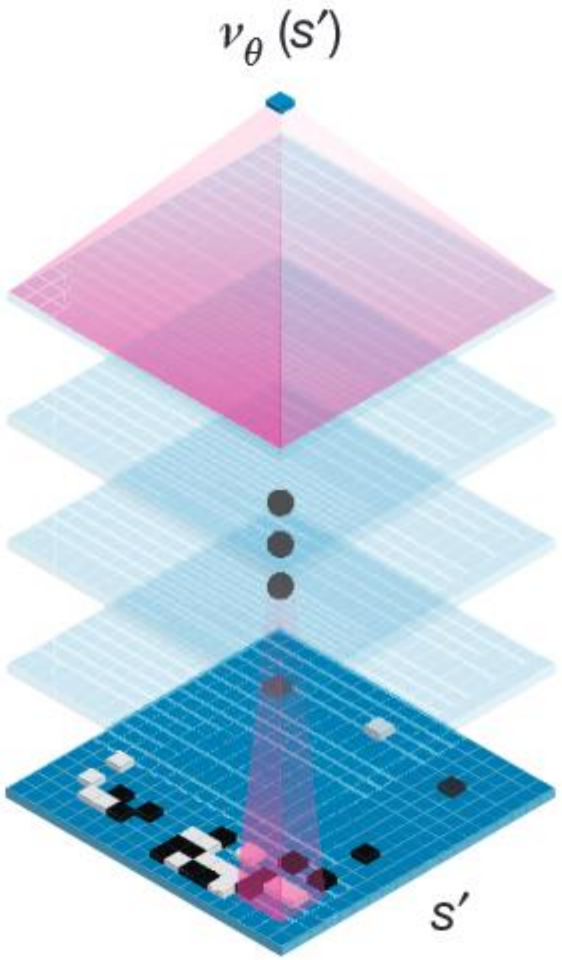
Data: 30 million (s, z) pairs, from games played between RL network and itself

Output: a single prediction value $v_\theta(s) \approx v^p(s) \approx v^*(s)$



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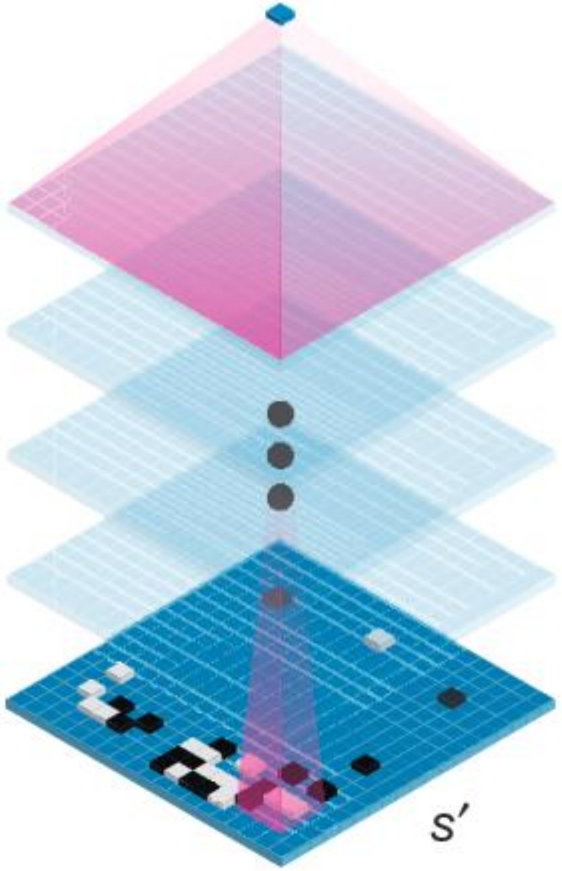

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Data: 30 million (s, z) pairs, from games played between RL network and itself

Output: a single prediction value $v_\theta(s) \approx v^p(s) \approx v^*(s)$

Objective: minimize MSE between $v_\theta(s)$ and outcome z through SGD:

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

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Main Components:

1. A Supervised Learning (SL) policy network $p_\sigma(a|s)$ (as well as a fast but less accurate rollout policy $p_\pi(a|s)$) ✓ 50 GPUs, 3 weeks
2. A Reinforcement Learning (RL) policy network $p_\rho(a|s)$ ✓ 50 GPUs, 1 day
3. A value network $v_\theta(s) \approx v^*(s)$ ✓ 50 GPUs, 1 week

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PUT IT ALL TOGETHER USING MCTS

SETUP: MCTS in AlphaGo

Each edge (s, a) of the search tree stores:

- $Q(s, a)$**:** the action value
- $N(s, a)$**:** visit count
- $P(s, a)$**:** prior probability
- $u(s, a)$**:** exploration bonus

$$u(s,a) \propto \frac{P(s,a)}{1+N(s,a)}$$

MCTS in AlphaGo

At time step t:

1. Selection: $\boxed{a_t = \underset{a}{\operatorname{argmax}}(Q(s_t, a) + u(s_t, a))}$

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2. Evaluation: When a leaf s_L is encountered in the tree:
   - set $P(s_L, a) := p_{\sigma/\rho}(a|s_L)$ for each edge
   - evaluate the node $\boxed{V(s_L) = (1 - \lambda)v_\theta(s_L) + \lambda z_L}$, where z_L = outcome of a random rollout using p_π

MCTS in AlphaGo

At time step t:

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3. Update: Update the statistics of the visited edges:

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

MCTS in AlphaGo

At time step t:

1. Selection: $\boxed{a_t = \operatorname*{argmax}_a (Q(s_t, a) + u(s_t, a))}$

2. Evaluation: When a leaf s_L is encountered in the tree:

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4. Growth: When $N(s,a) > threshold$ for a node s', add the node to the tree, initialize it to all zeros and set

$$\boxed{P(s',a) := p_{\sigma/\rho}(a|s')}$$

Resource Usage

Final version of AlphaGo:

- 40 search threads, 48 CPUs (for simulation)
- 8 GPUs (to compute policy and value networks)

Distributed version:

- 40 search threads, 1202 CPUs
- 176 GPUs