CS 181V: Reinforcement Learning

Lecture 23
April 27, 2020
Neil Rhodes

Images from:

- **David Foster, Applied Data Science**
- ***Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm* by Silver, et al., 2017**
- ***Mastering the game of Go without human knowledge*, Silver, et al., 2017**

Outline

- **Monte Carlo Tree Search refresher**
- DeepMind’s AlphaGo (and successors)

MCTS Refresher

- Monte Carlo Tree Search takes a state, `root`, and rollout policy $\pi_{rollout}$ and produces an improved action
- Algorithm:

```
repeat many times:
  selected = Select(root)
  expanded = Expand(selected)
  reward = Simulate(expanded, π_rollout)
  Backup(expanded, reward)
Choose root's child action with highest n(v)
```

MCTS nodes in tree

- Each node, v stores:
  - $n(v)$: number of times that node has participated in a simulation
  - $q(v)$: total reward attributed to that node during simulations

MCTS Select

```
Select(v)
  if node is terminal or has an unexpanded
child, return v
 else  return child of v with highest
```

$$UCT(v) = \frac{q(v)}{n(v)} + c\sqrt{\frac{\log n(v.parent)}{n(v)}}$$

MCTS Expand

```
Expand(v)
  if node is terminal:
    return v
  c = create random child node of v
  q(c) = n(c) = 0
  return c
```

MCTS Simulate

```
Simulate(v, π_rollout)
  Choose actions starting from v according
to policy π_rollout until a terminal state is
reached
  return immediate reward leading to that
terminal state
```

MCTS Backup

```
Backup(v, reward)
  for all nodes from v up to the root:
    n(v) += 1
    q(v) += reward
```

Outline

- Monte Carlo Tree Search refresher
- **DeepMind’s AlphaGo (and successors)**

History

- AlphaGo, 2015
  - Hand-crafted features and trained on human plays
  - Two Neural Networks: One to learn the value function, one to learn policy function
  - Policy function trained on large body of human plays

History

- AlphaGo Zero, 2017
  - No prior knowledge of Go (no hand-crafted features, no training on human games). All self-play
  - Single Residual Neural Network learns both value and policy functions
  - Keeps best-neural-network-so-far (new champion if beats >55% of games against old champion)

History

- AlphaZero, 2017
  - No current best Neural Net. Always uses the latest NN.
  - Same network (other than input and head) with almost same hyper-parameters can learn Go, Chess, and Shogi
    - One hyper-parameter is scaled based on number of possible actions

History

- MuZero, 2019
    - Doesn't know the rules of the game (During MCTS, must use learned representation of the game dynamics)
    - Extended to work with Atari games as well as Go.

AlphaGo

3 Policy Networks

	SL	RL	Rollout
Initialized	Random	From SL	Random
Structure	NN	NN	Linear
Training	Human games	RL with self-play	Human games
Input	Hand-crafted features	Hand-crafted features	Low-level handcrafted features
Time to select action	3 ms	3 ms	2 μs

Given the game state, what is the value of an action?

AlphaGo

Hand-crafted Features

- SL/RL example features:
  - Is a move at this point a successful ladder capture
  - How many opponent stones would be captured playing at this point
- Rollout example features:
  - Move matches 3x3 pattern around the move (69938 features)
  - Move saves stones from capture

AlphaGo

Value network

- Like SL network, but has only a single output:

What is the value of a game state?

AlphaGo

Overview of Training

- Initialize Neural Network
- Repeat in parallel:
    1. Self-play a game. Do MCTS for each move.
       MCTS(P, s) is a new policy, π, more accurate than P.
        - For each state, record state, π(s), win_lose_or_draw_result
    2. Create mini batch of 2048 states from the most recent 500,000 games
        - Use mini batch to train RL network and value network

AlphaGo

How is Policy network used?

- As tree policy in MCTS to guide action selection

- When choosing an action from a node s_t in the MCTS tree:

$$a_t = \text{argmax}_a(Q(S_t, a) + U(s_t, a))$$

  - bonus (incorporates tree policy and exploration bonus):

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

AlphaGo

How is Value network used?

- To help get better simulation results
- After we have expanded node: n_e, we do simulation:
  - Do rollout (to obtain win/draw/lose) to estimate value: $v_1(n_e)$
  - Also use value network to estimate value: $v_2(n_e)$
- Use weighted average as value: $\lambda v_1(n_e) + (1 - \lambda) v_2(n_e)$

AlphaGo

Monte Carlo Tree Search (MCTS)

Each state has edges for all legal actions:
For each edge keep:

- ***N(s, a):*** **how many times has this state/action pair been seen**
- ***W(s, a)*****: total action-value**
- ***Q(s, a)*****: mean action-value:** ***W(s, a)/N(s, a)***
- ***P(s, a)*****: prior probability of selecting that edge**

AlphaGo

MCTS for AlphaGo

- Monte Carlo Tree Search takes a state, `root`, a tree policy π_{tree}, a rollout policy $\pi_{rollout}$, a state value approximator and produces an improved action
- Algorithm:

```
repeat many times:
  expanded = Select(root)
  reward = Evaluate(expanded, π_rollout, vapprox)
  Backup(expanded, reward)
Choose root's child action with highest n(v)
```

AlphaGo

MCTS: Select

- Different from MCTS we've seen:

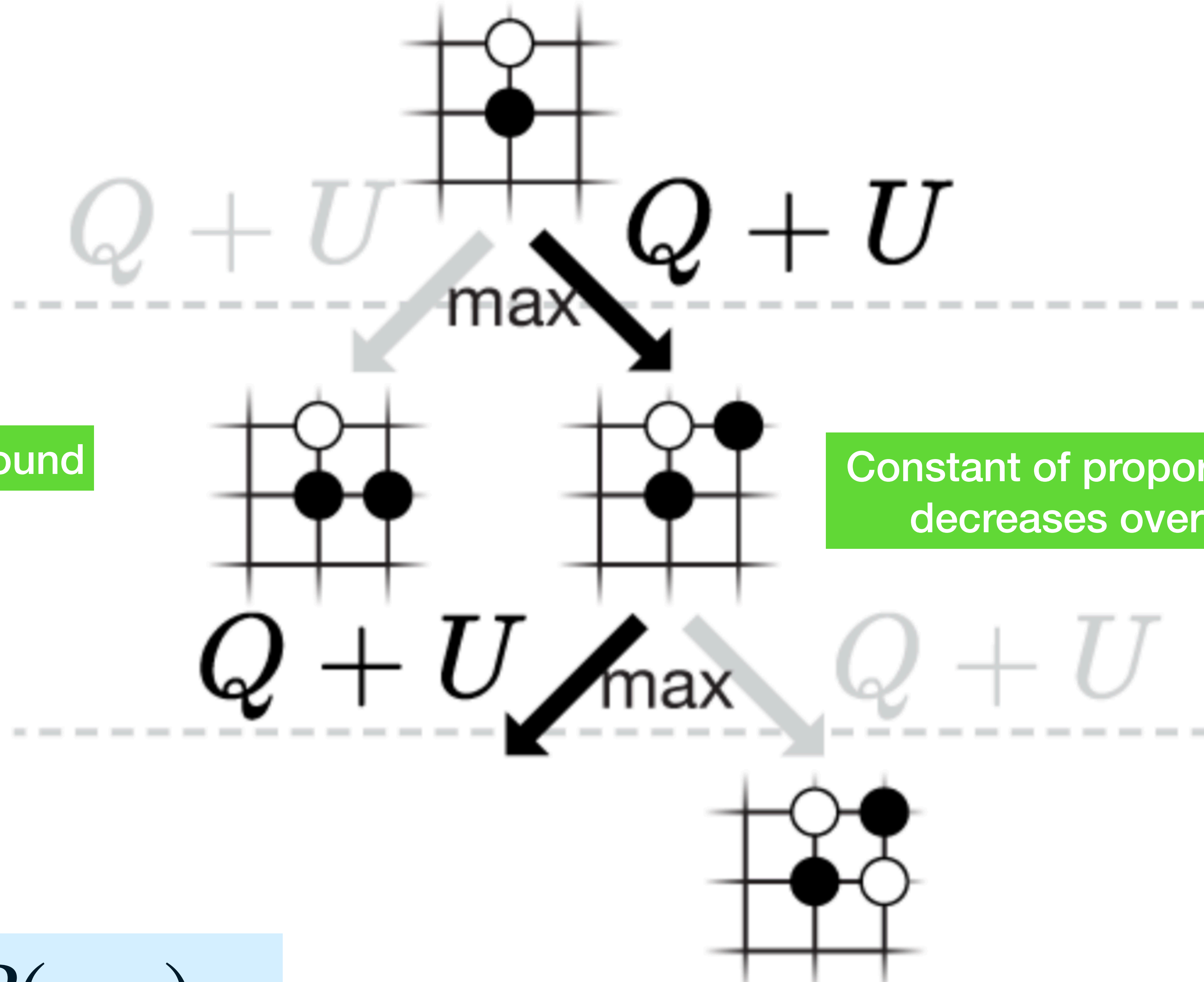
```
Select(n):
  if n is terminal:
    return n
  child = child with highest Q+U (including
    unexpanded children)
  if child is expanded:
    return Select(child)
  return Expand(child)
```

AlphaGo

MCTS Evaluate

```
Evaluate(n, π_rollout, vapprox)
  Choose actions starting from n according
to policy π_rollout until a terminal state is
reached
  v_1 is value of that terminal state
according to Go rules
  v_2 is vapprox(n)
  return λv_1 + (1 − λ)v_2
```

MCTS: Select



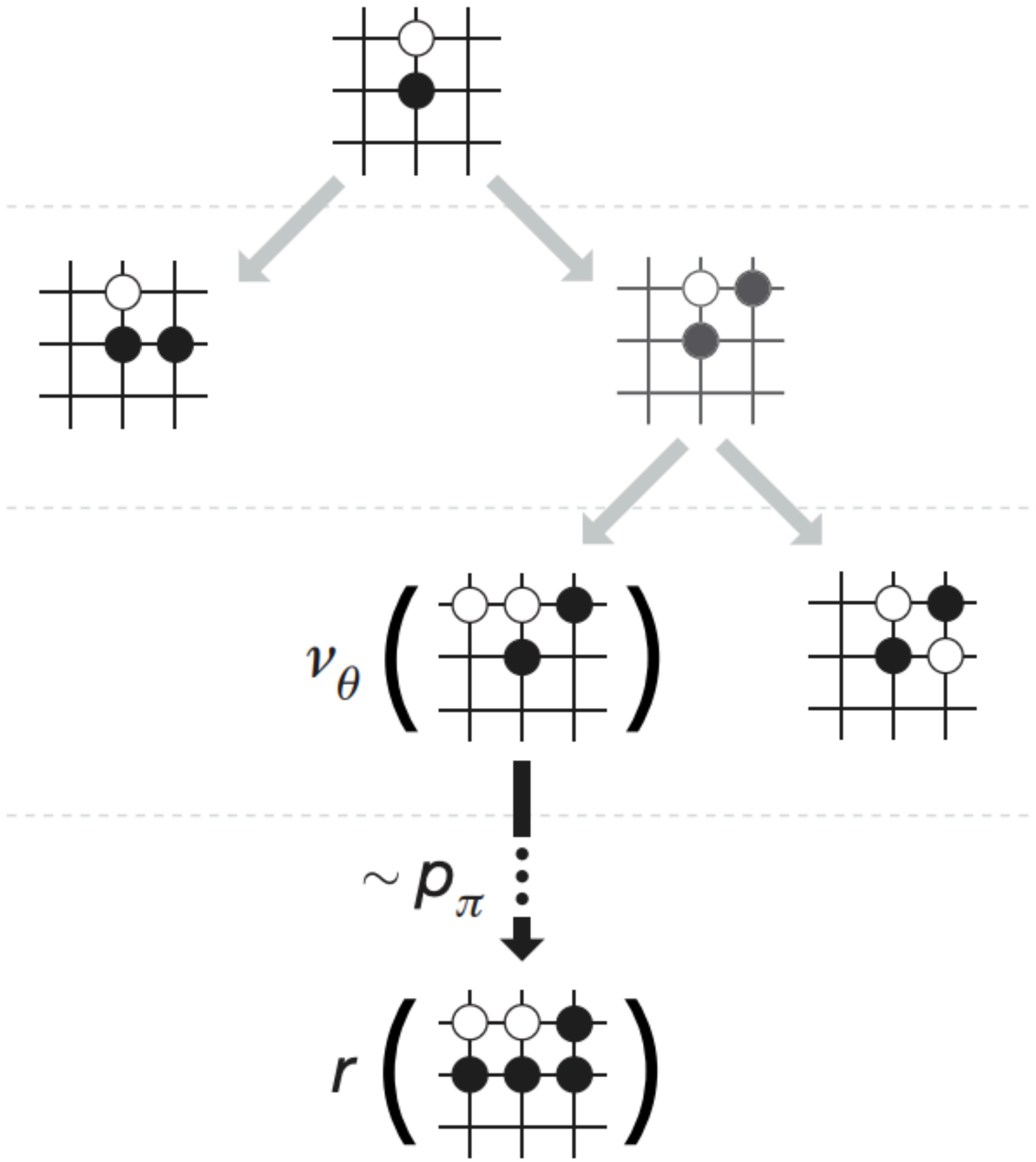
U Is upper-confidence bound

Constant of proportionality decreases over time

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

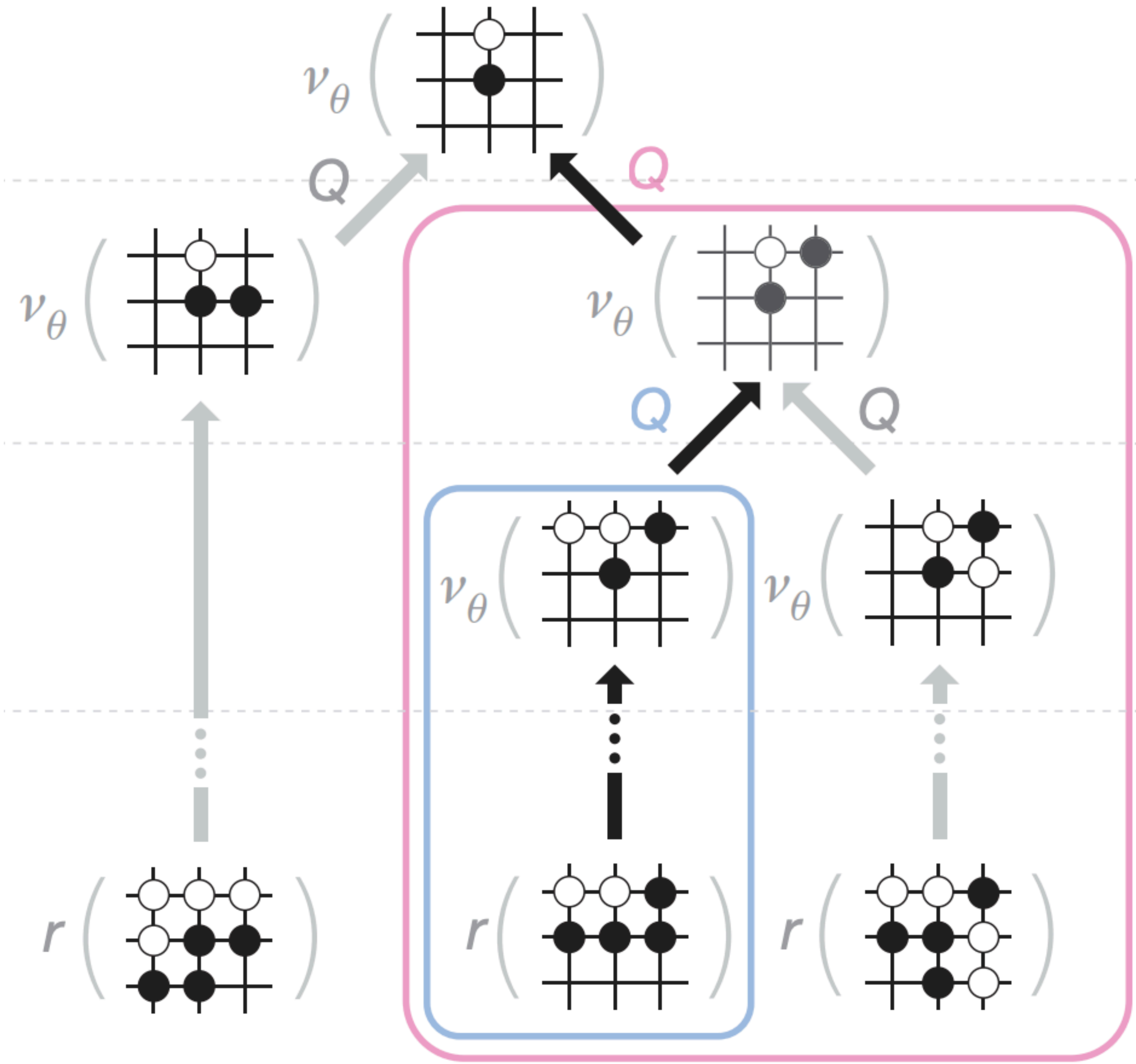
AlphaGo

MCTS: Expand & Evaluate



AlphaGo

MCTS: Backup



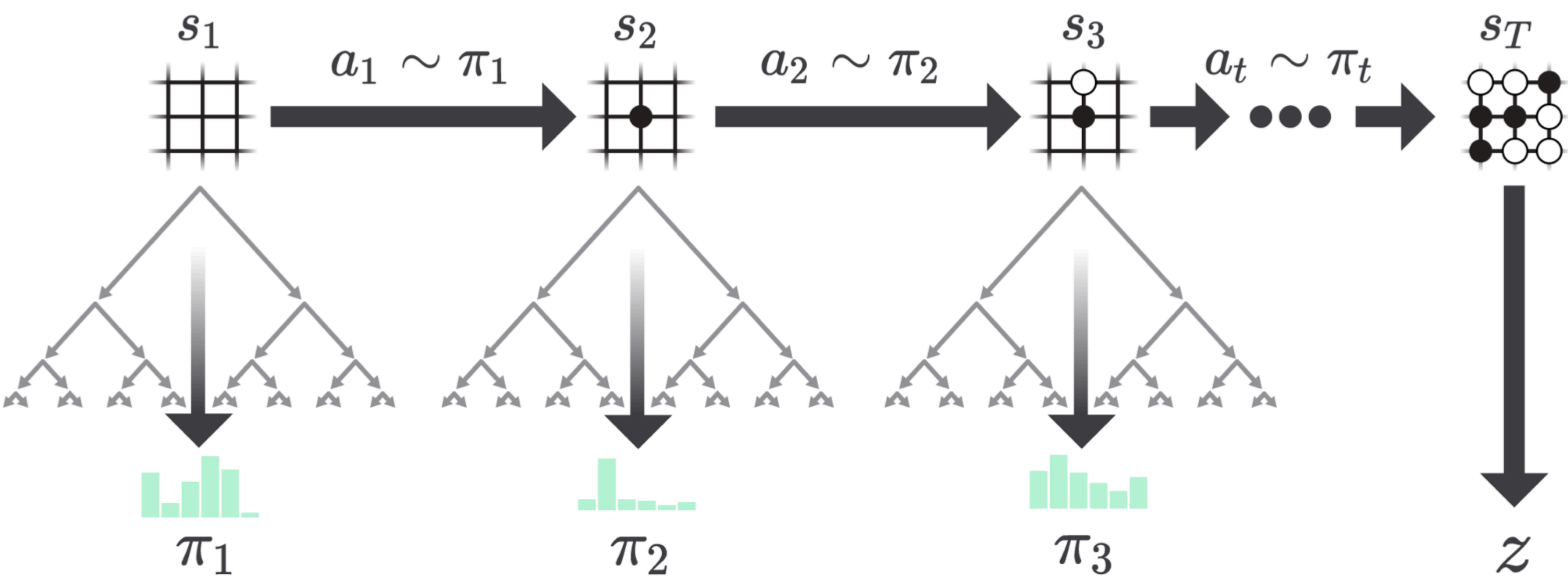
For each ancestor edge:

$$N(s,a) \mathrel{+}= 1$$

$$W(s,a) \mathrel{+}= r$$

AlphaGo

Self-play

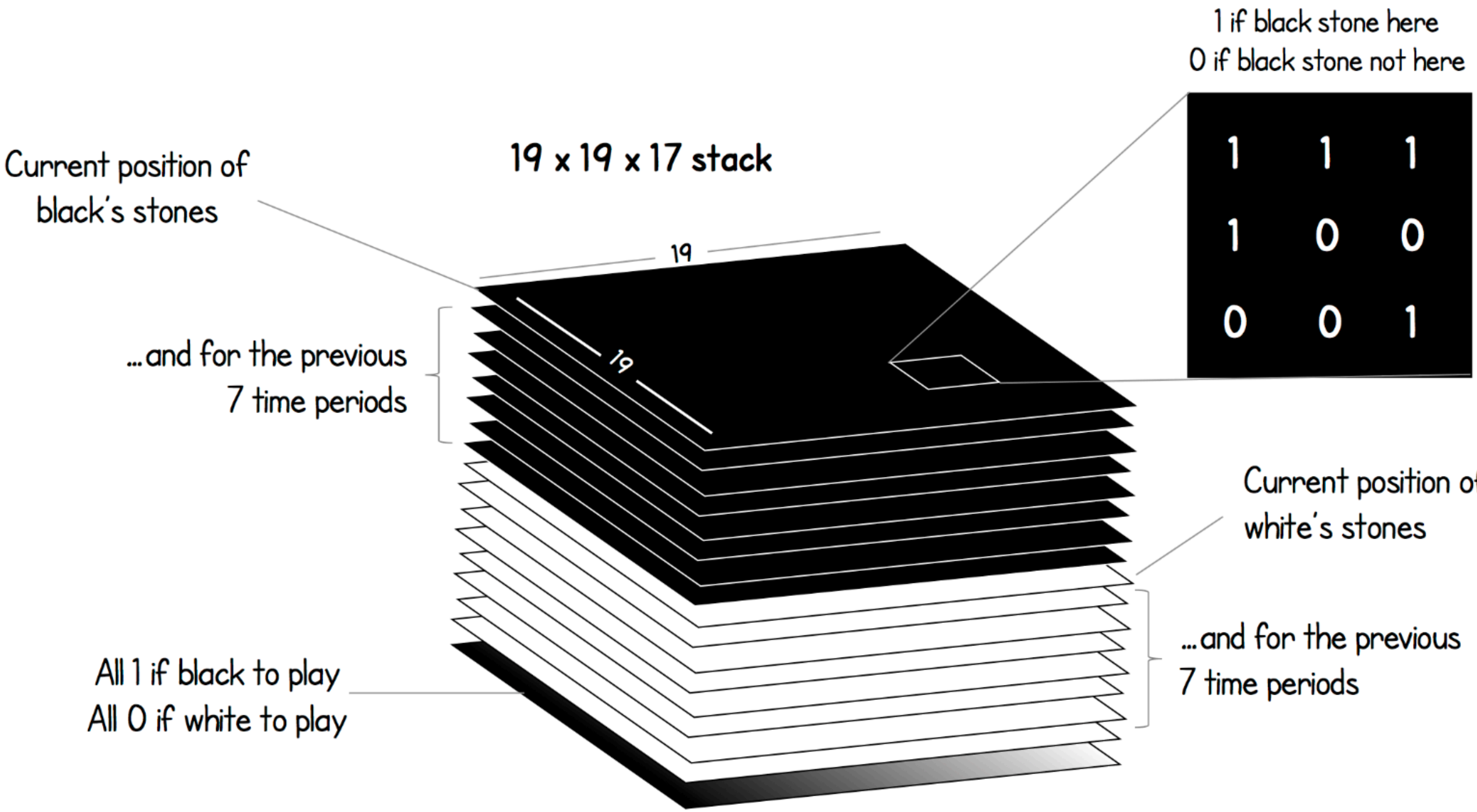


AlphaGo Zero

Learn through self-play

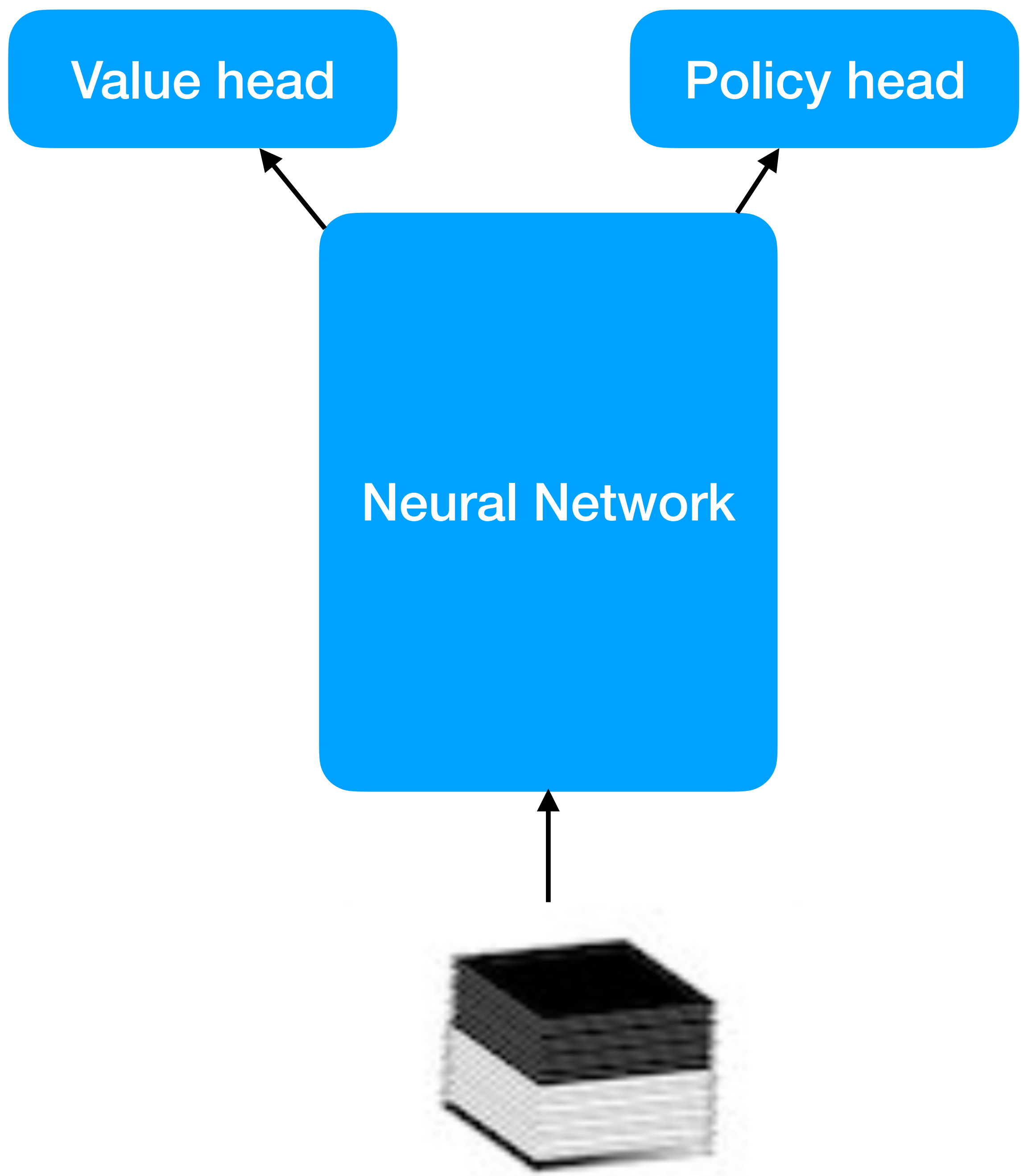
- Get rid of handcrafted features
- No network weights pretrained from human games
- One shared network to compute both policy and value
- Simplified MCTS: no rollouts!

AlphaGo Zero: What is a game state for Go?



AlphaGo Zero

The Neural Network



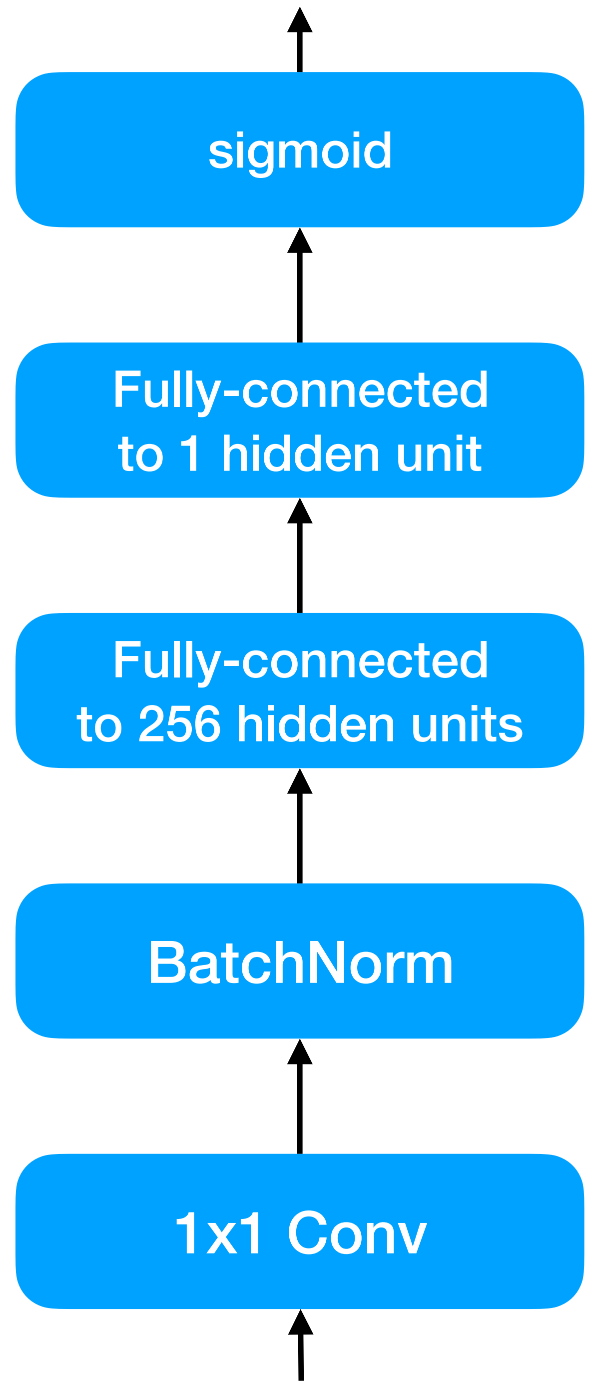
Input (Game state)

Multi-task learning!

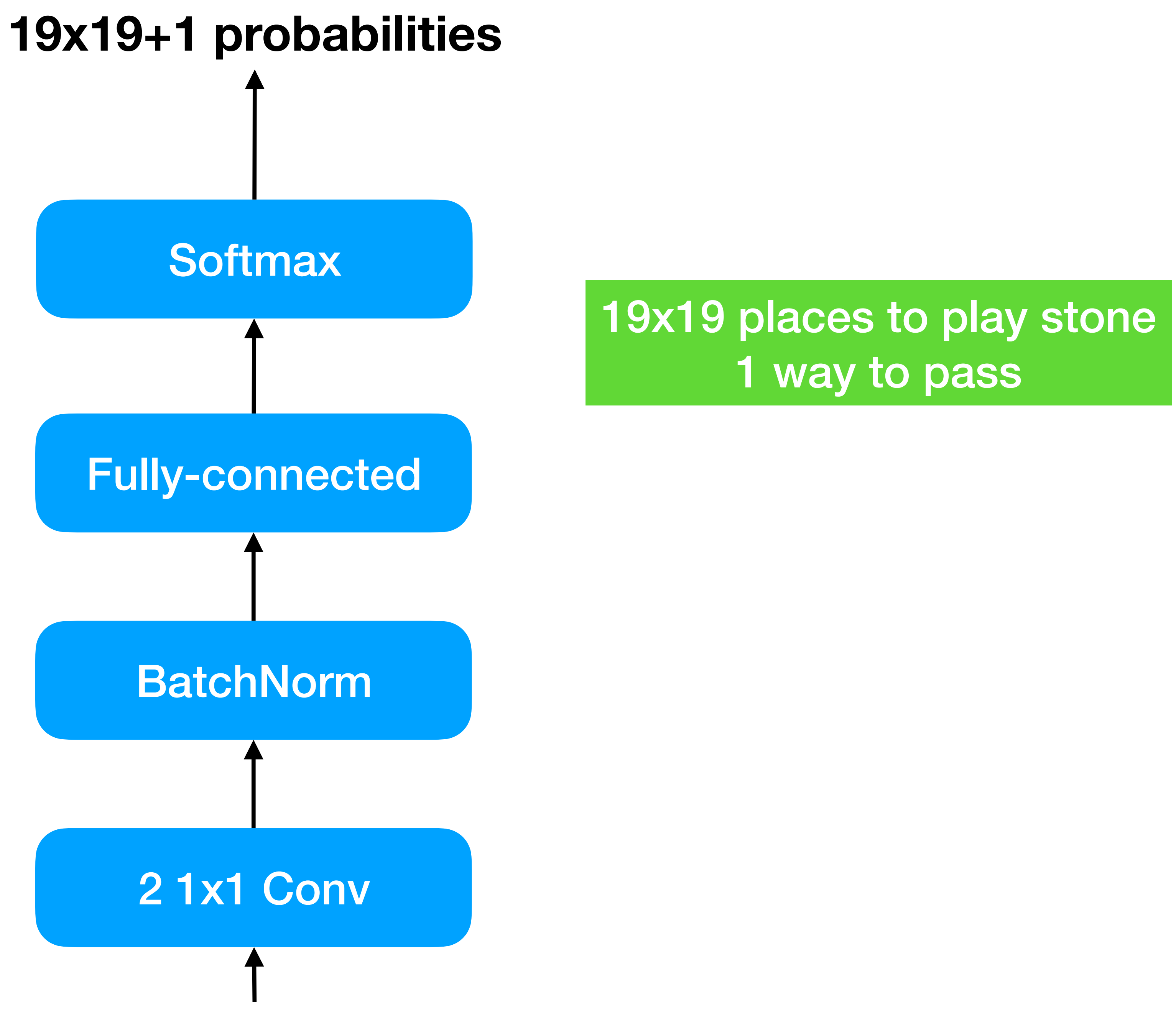
AlphaGo Zero

Value (V) Head

$\mathbb{R}\in$[0, 1]: probability of winning for current player



Policy (P) Head



AlphaGo Zero

Overview of Training

- Initialize Neural Network

- Repeat in parallel:

1. Self-play 44 million games (800 Monte Carlo Tree Search [MCTS] simulations/move).
   MCTS(P, s) is a new policy, π, more accurate than P.

   - For each state, record state, π(s), win_lose_or_draw_result

2. Create mini batch of 2048 states from the most recent 500,000 games

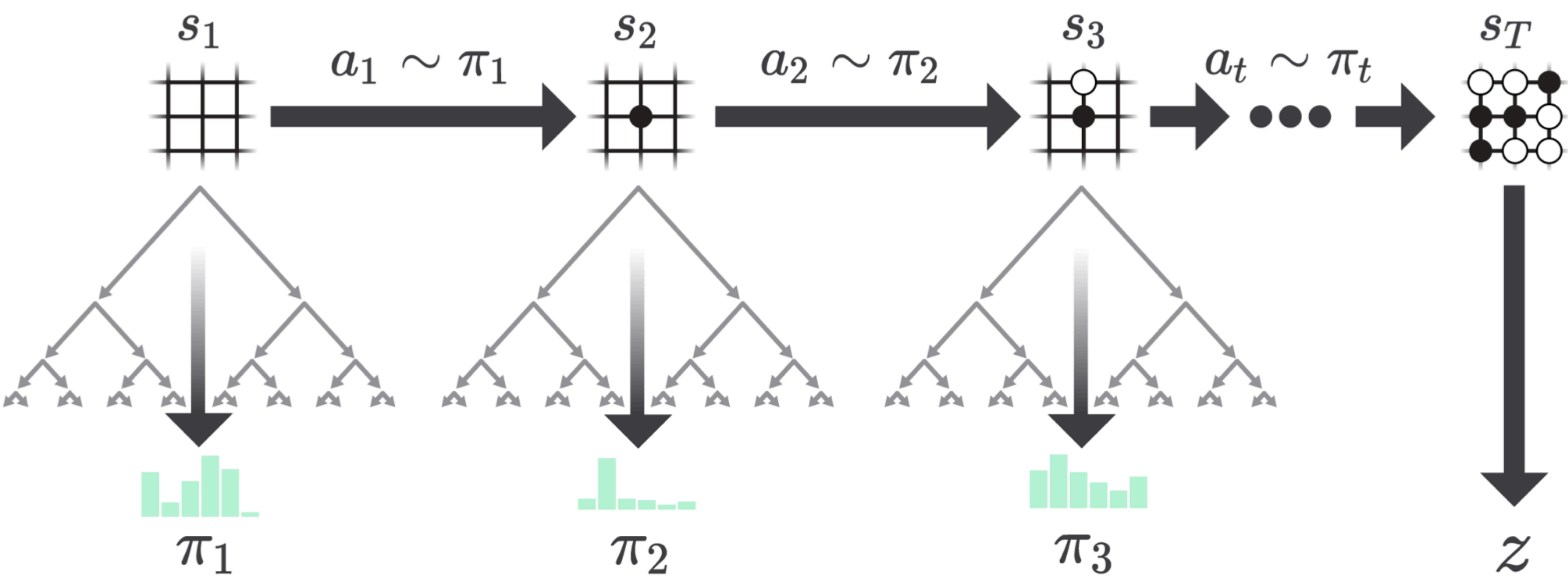
   - Use mini batch to train Neural Network

For chess, took 9 hours to run

Total of 700,000 mini batches

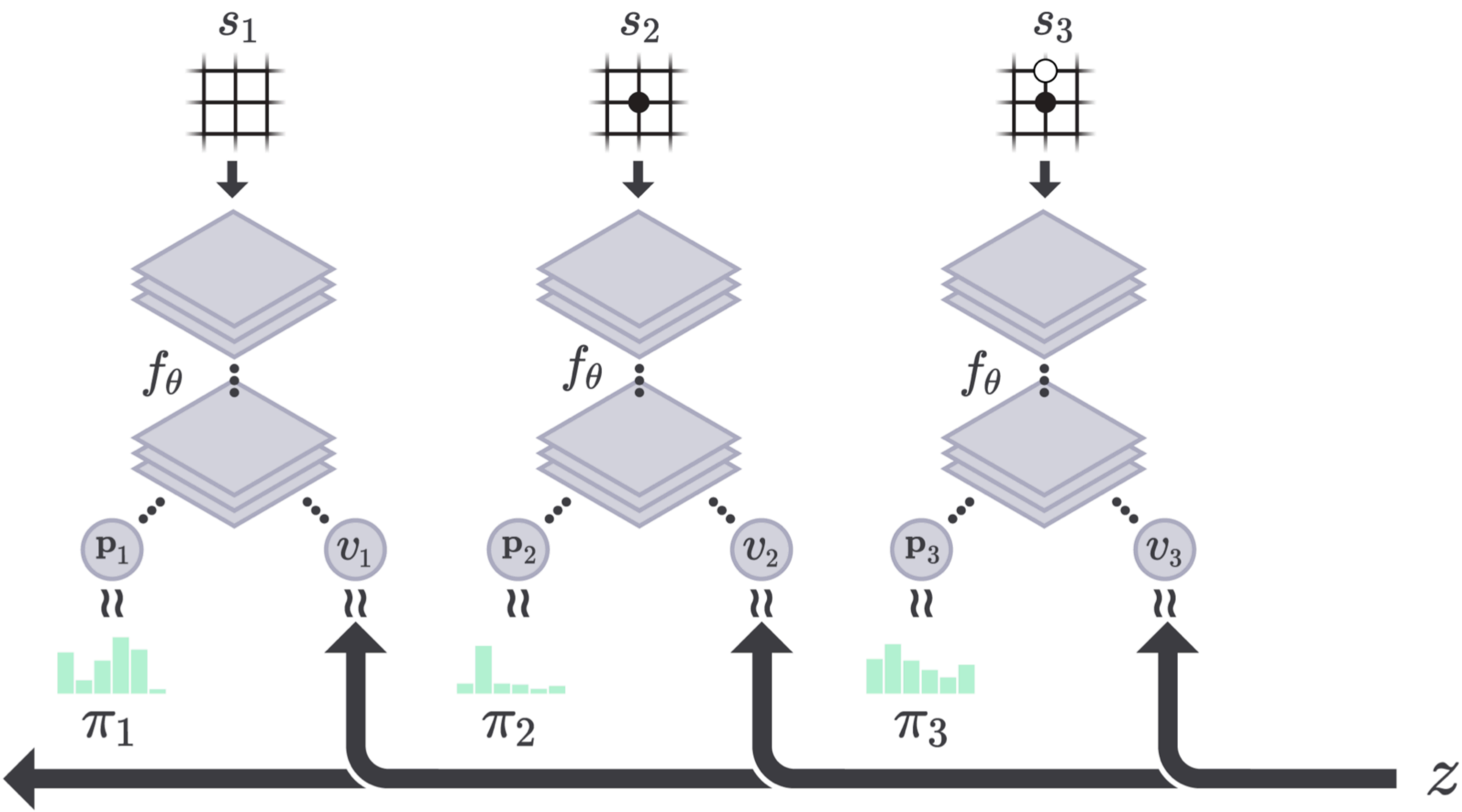
AlphaGo Zero

Self-play



AlphaGo Zero

Neural Net Training



$$L = (z - v)^2 - \pi^T \log p + c\|\Theta\|^2$$

AlphaGo Zero

Neural Net Training

- Update Θ so that:
  - Given an input state, s_i, f_Θ produces output that is closer to:
    - For value portion: z, the actual result of the game
    - For action portion: π_i, the MCTS-improved policy based on the neural net's p_i

AlphaGo Zero

Monte Carlo Tree Search (MCTS)

Each state has edges for all legal actions:
For each edge keep:
- ***N(s, a):*** **how many times has this state/action pair been seen**
- ***W(s, a)*****: total action-value**
- ***Q(s, a)*****: mean action-value:** ***W(s, a)/N(s, a)***
- ***P(s, a)*****: prior probability of selecting that edge**

AlphaGo Zero

Explore/Exploit

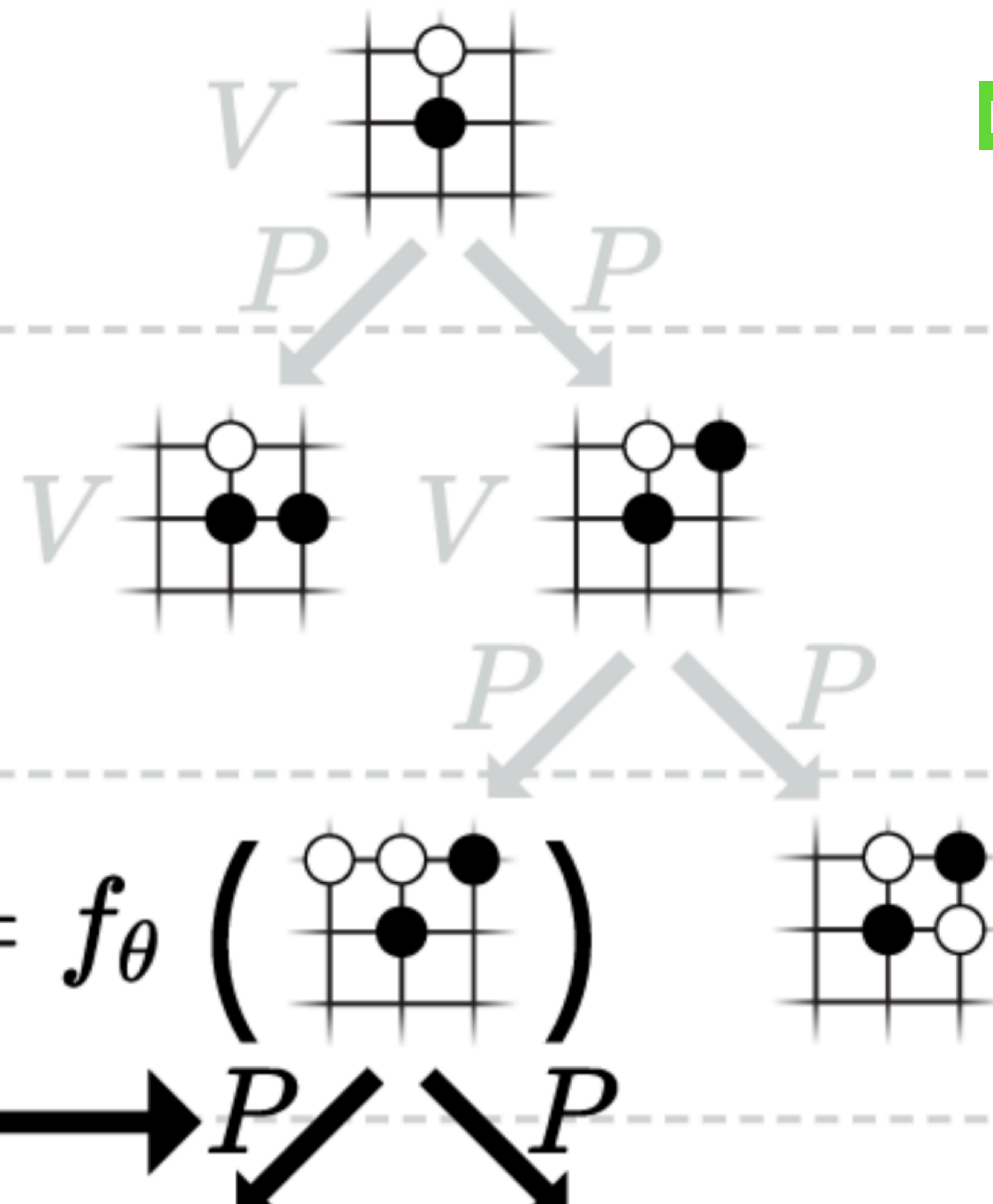
- Two sources to encourage exploration:
  - Dirichlet noise added to top-level P(s) of MCTS
    - Non-zero chance of any move happening
- Upper-confidence bound when evaluating move in MCTS
  - Encourage actions whose confidence is low

Dirichlet noise: sums to given value (so can be a probability), and, with parameter used in AlphaGoZero,
makes most of the probability focused in small area

AlphaGo Zero

MCTS: Evaluate

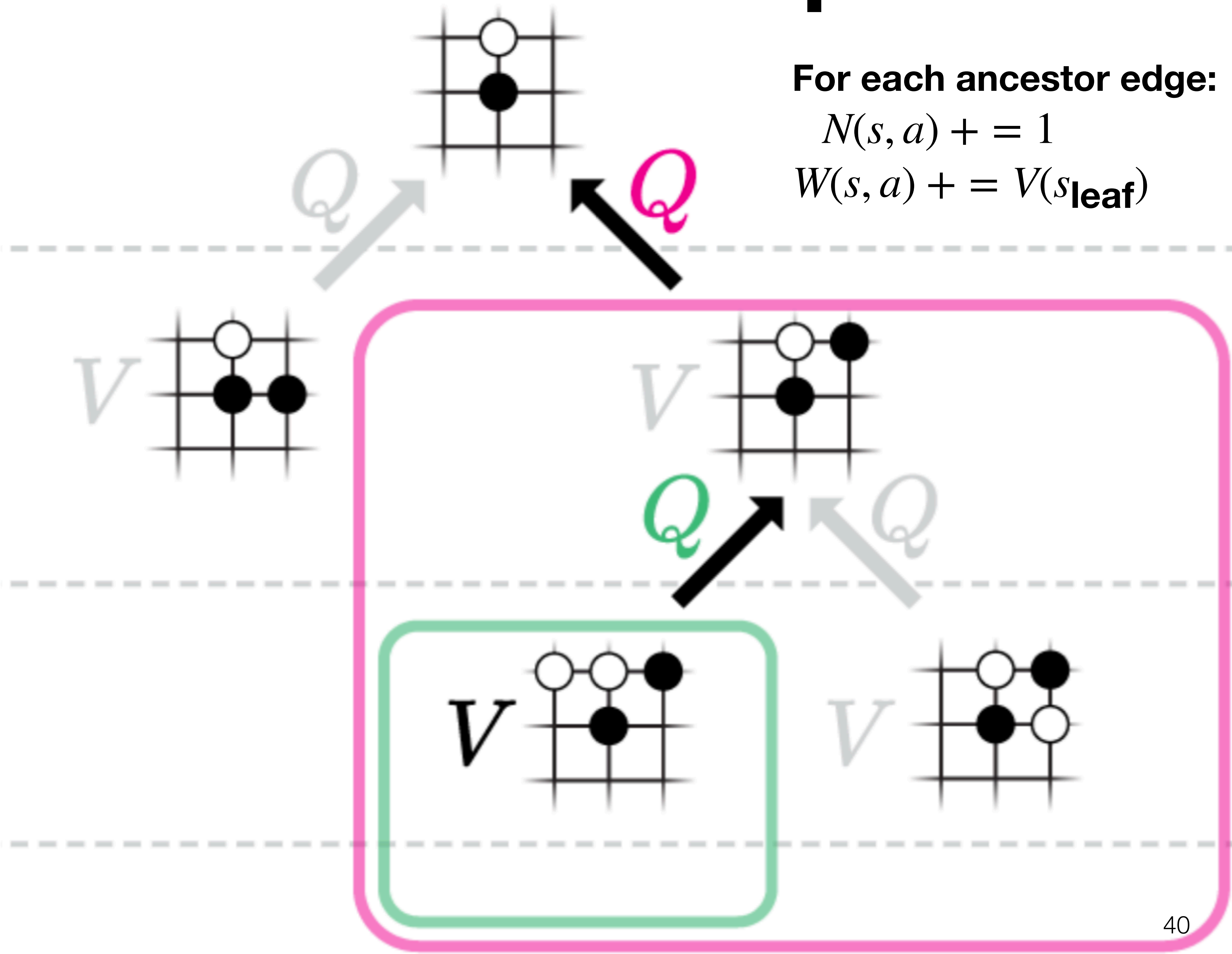
No rollout!



$$(\mathbf{p}, v) = f_\theta(\ \cdot\ )$$

AlphaGo Zero

MCTS: Backup

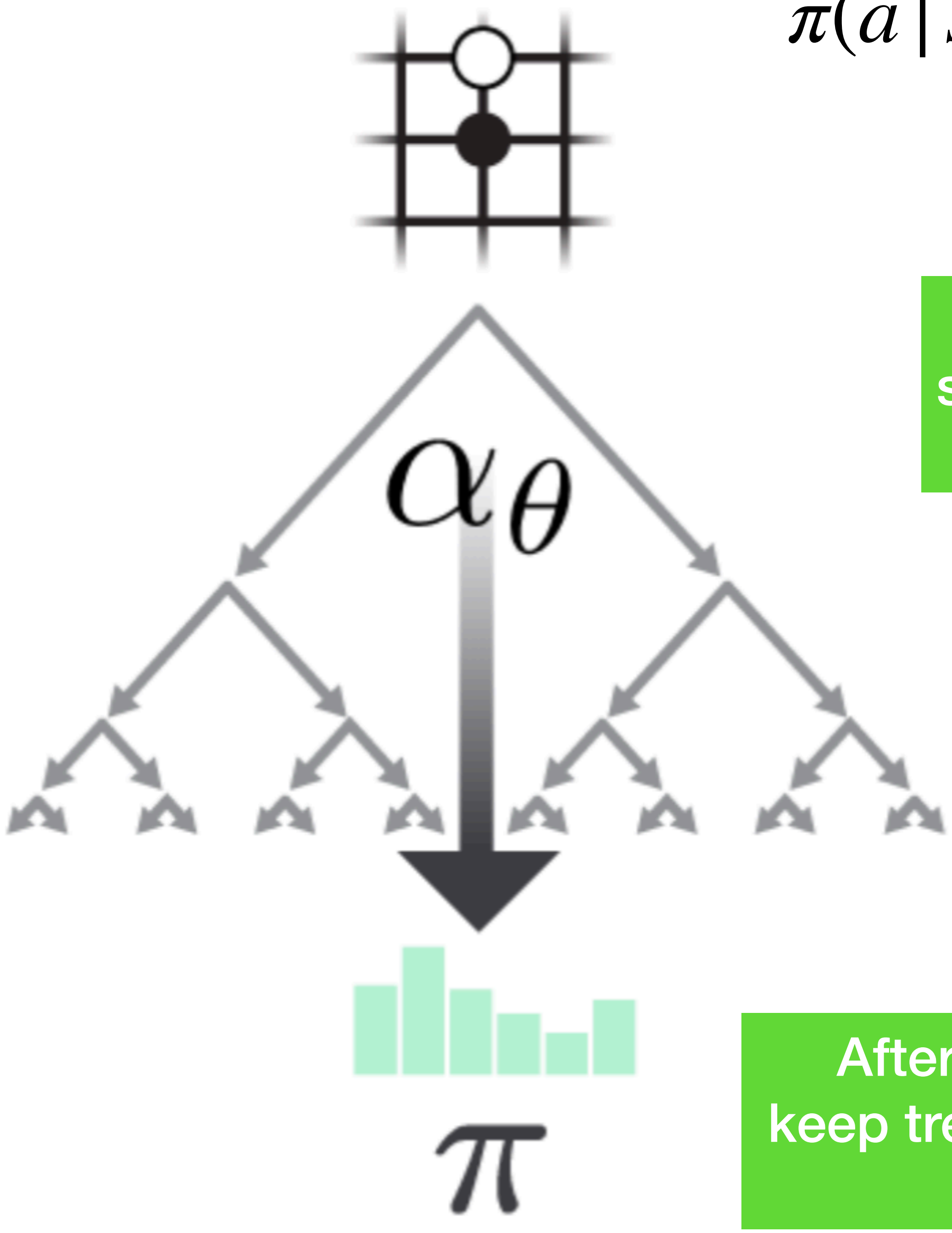


For each ancestor edge:

$N(s,a) += 1$

$W(s,a) += V(s_{\textbf{leaf}})$

MCTS: Play



$$\pi(a \mid s_0) = \frac{N(s_0, a)^{1/\tau}}{\sum_b N(s_0, b)^{1/\tau}}$$

τ is a temperature constant: starts near 1 and ends close to zero. For play: close to zero

After an action is chosen from π, keep tree starting from resulting state, clear rest of tree

AlphaGo Zero

What Go-specific knowledge is used?

- Network knows input format (19x19 board, etc.)
- Network knows how many possible actions (19x19+1)
- MCTS knows which actions lead to which states
- MCTS knows whether a state is terminal
- MCTS knows how to score a terminal state
- MCTS does dihedral reflection or rotation (takes advantage of symmetry of Go board)