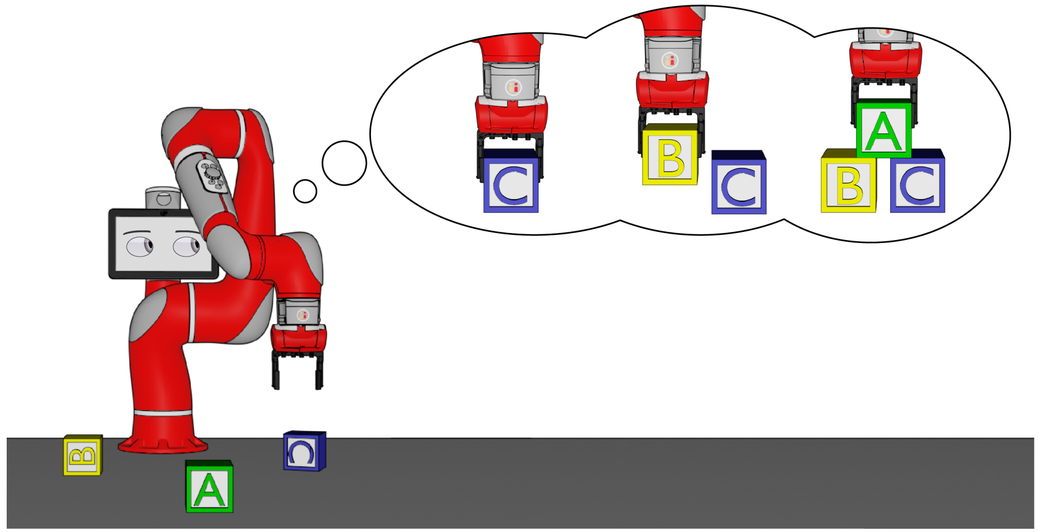
# Reinforcement Learning

## HSE, winter - spring 2025

## Lecture 9: Model-based RL



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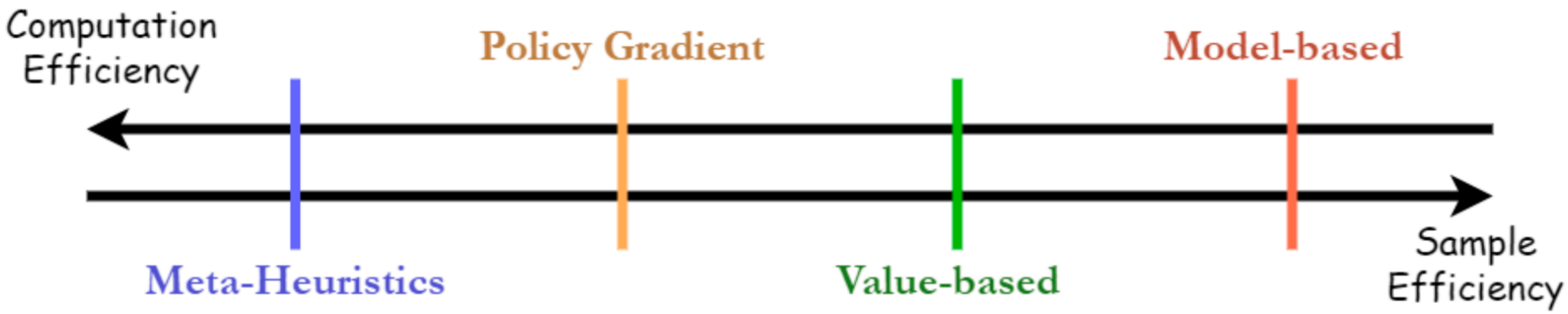
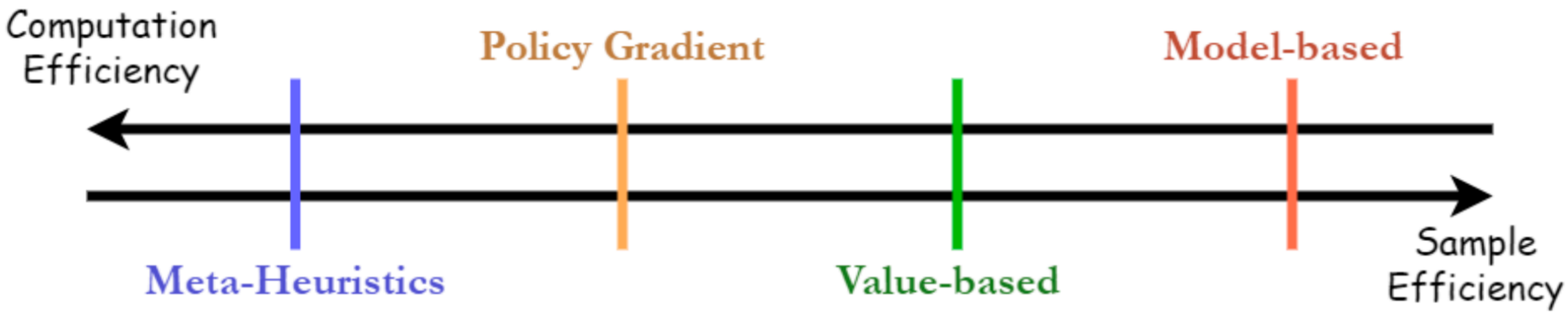
# Recap


Computation Efficiency
Policy Gradient
Model-based
Meta-Heuristics
Value-based
Sample Efficiency

# Recap




- CEM
- Evolution Strategies
- ARS

- REINFORCE
- A2C
- PPO
- SAC

- DQN
- RAINBOW

- Dynamic Programming

# Model-based Setup

The environment's dynamic is known or learnt:

- Stochastic case: $p(r, s' \mid s, a)$
- Deterministic case: $s' = S(s, a), r = R(s, a)$

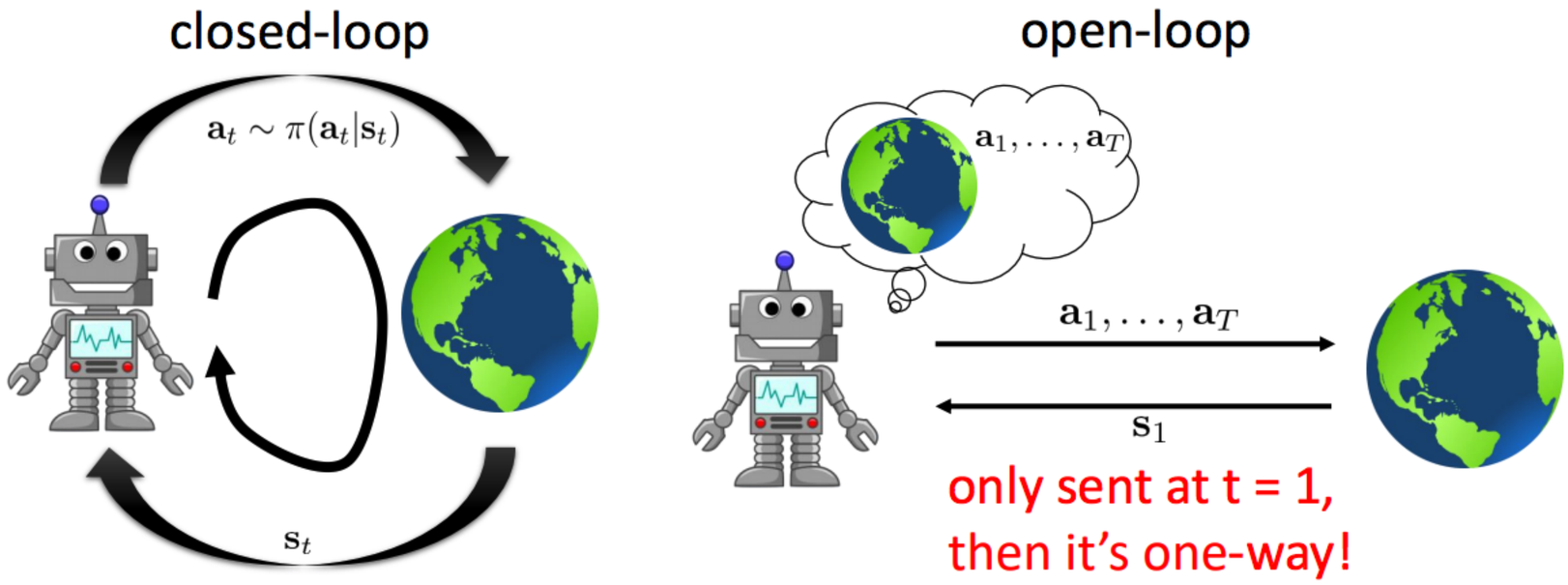
Examples:

- Games (Chess, Go, Shogi etc)

Further in this lecture, we will only consider deterministic environments.

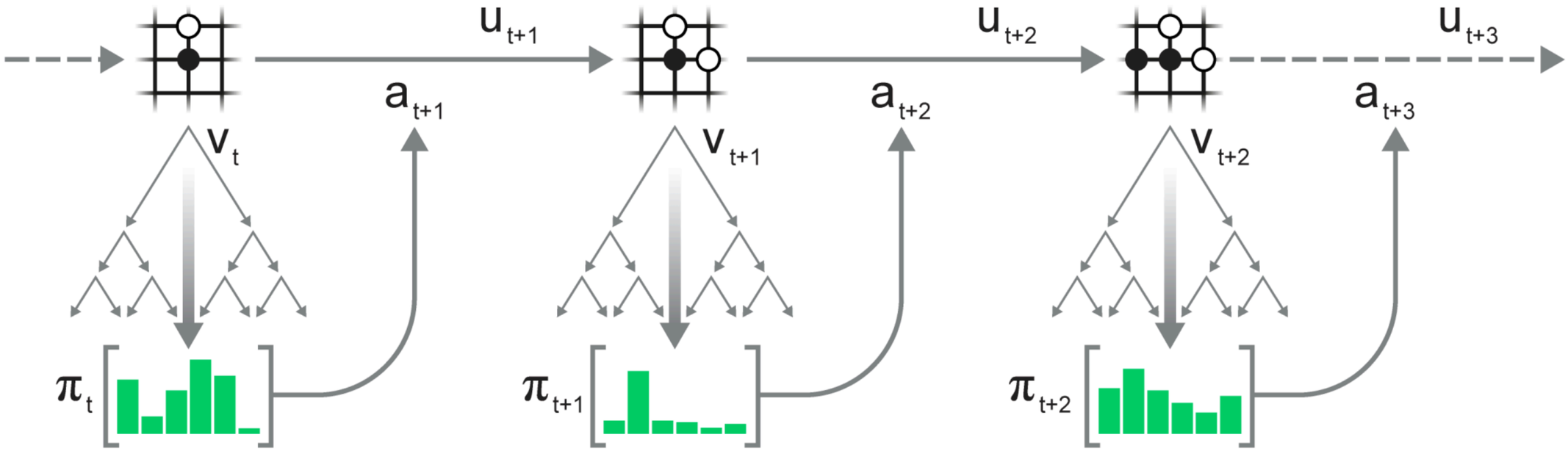
# Planning

Any computational process that takes an environment as input and produces or improves a policy for interacting with the modelled environment:

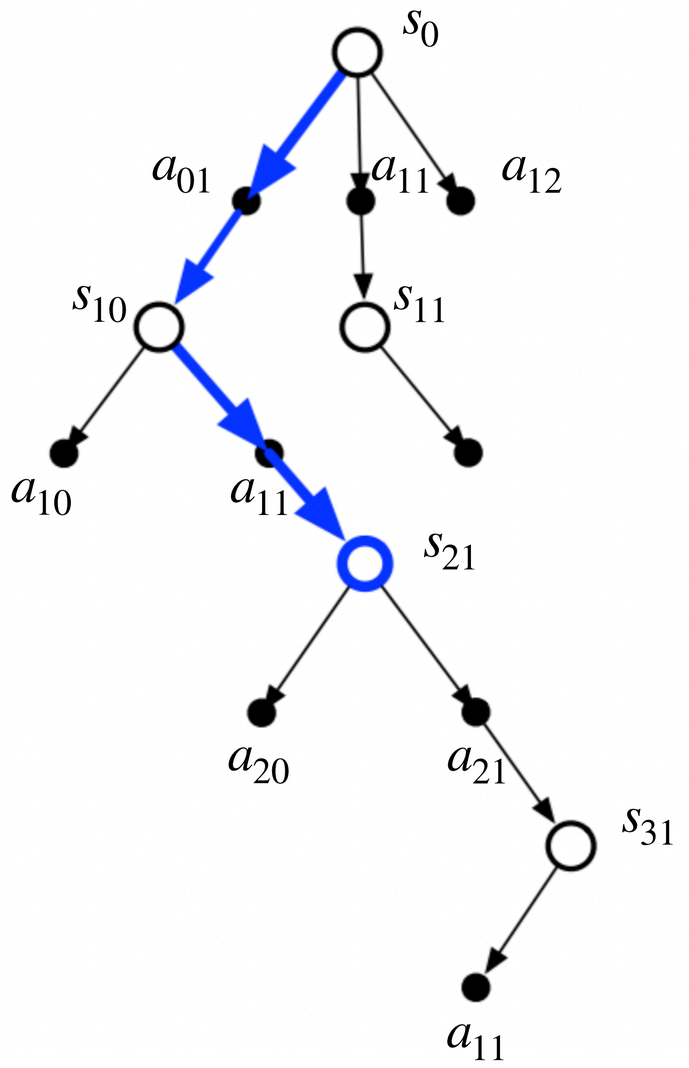



Source

# Planning in the Environment



# Monte-Carlo Tree Search



# Monte-Carlo Tree Search

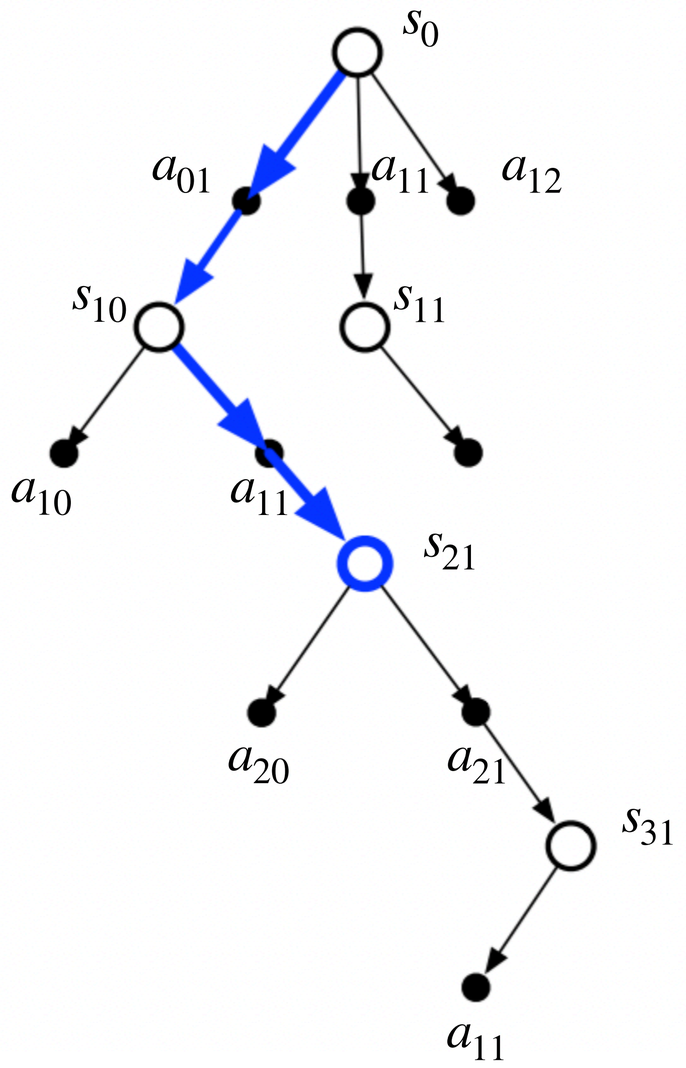
Each node storages a tuple $(G(s,a), n(s,a))$.

**Selection:**

- Starting from the root, walk down the tree until the leaf node is achieved
- UCB:

$$n(s) = \sum_a n(s,a)$$

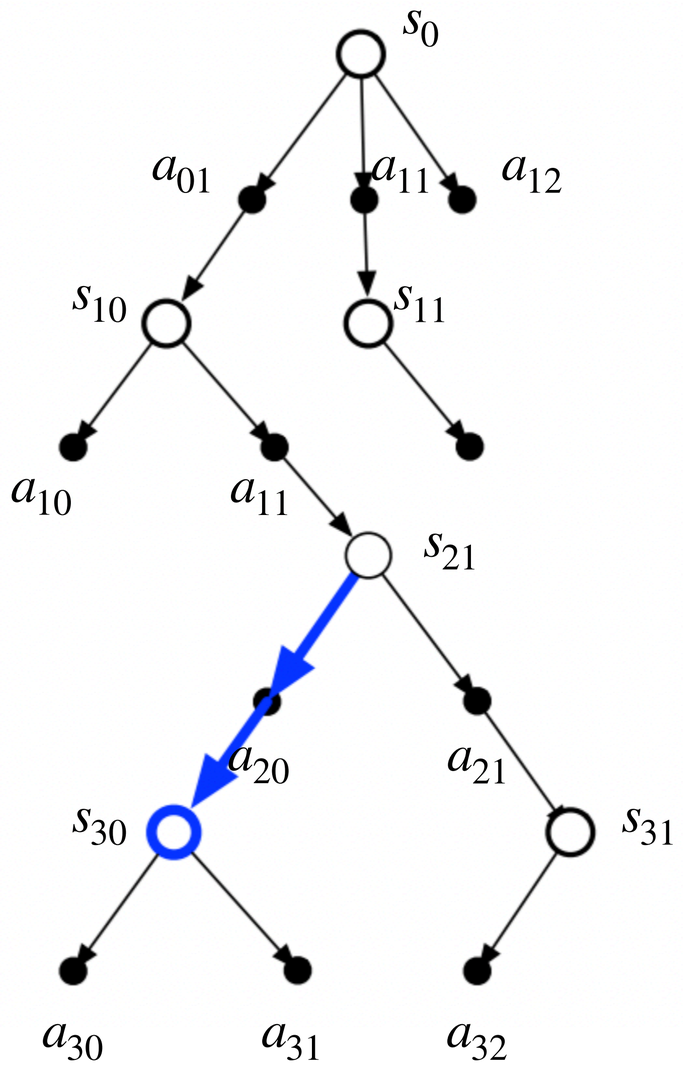
$$\hat{a} = argmax_a[Q(s,a) + C\sqrt{\frac{\log n(s)}{n(s,a)}}]$$



# Monte-Carlo Tree Search

**Expansion:**

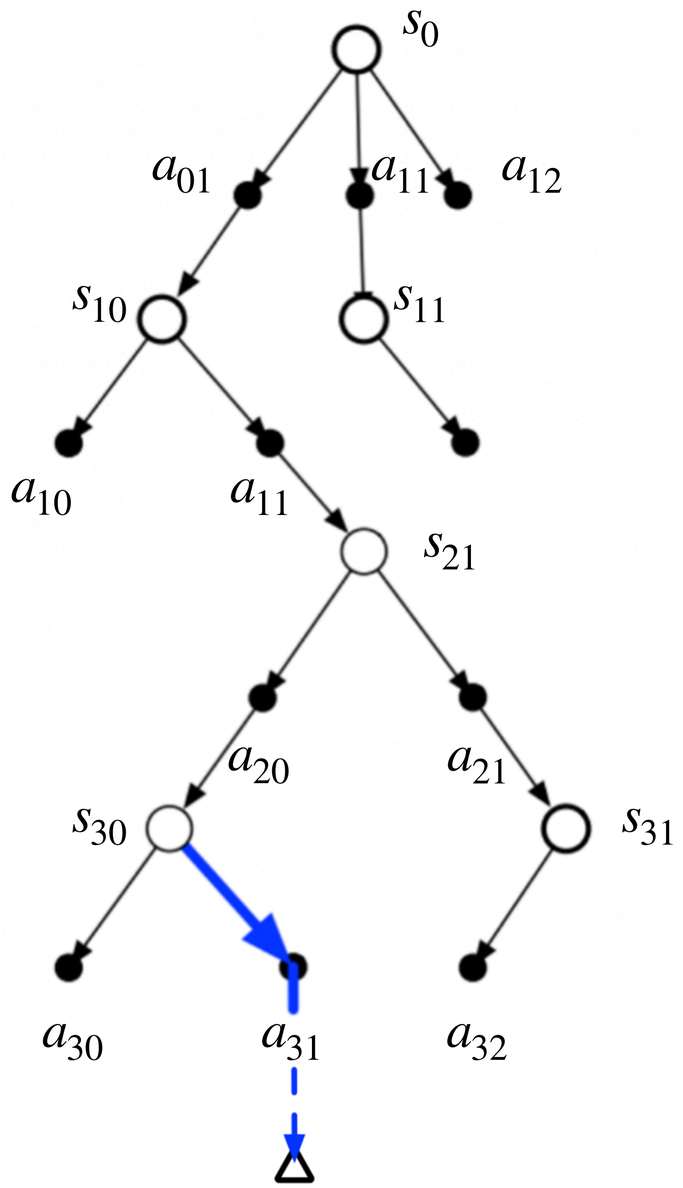
- Select an action $a$ to apply in the state $s$, either randomly or using a heuristic.



# Monte-Carlo Tree Search

**Simulation:**

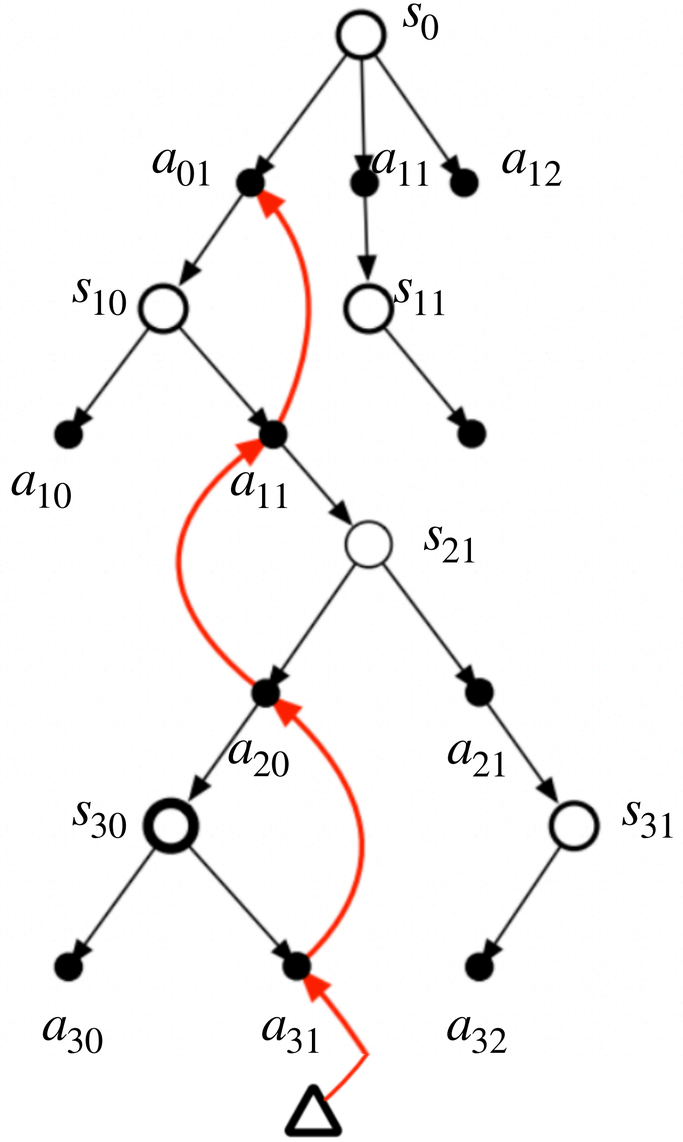
- Perform a randomised simulation of the MDP until we reach a terminating state.



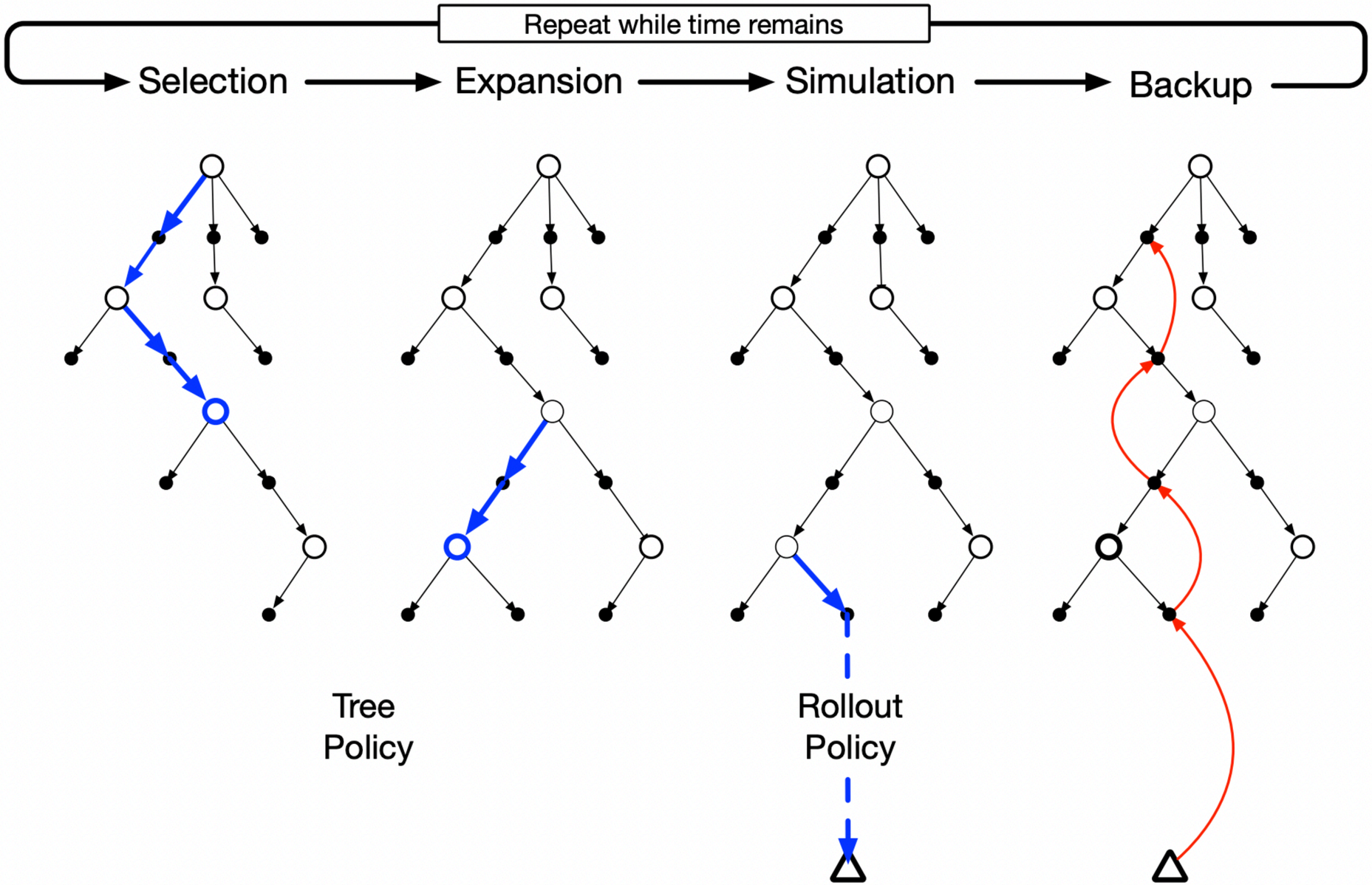
# Monte-Carlo Tree Search

**Propagation:**

- $n(s,a) \leftarrow n(s,a) + 1$
- $G \leftarrow r + \gamma G$
- $Q(s,a) \leftarrow Q(s,a) + \frac{1}{n(s,a)}[G - Q(s,a)]$



# Monte-Carlo Tree Search



# Monte-Carlo Tree Search

The result of the MCTS algorithm is a policy in the current environment's state:

- $\pi_{MCTS}(a \mid s) \propto n(s,a)^{\frac{1}{\tau}}$
- $\pi_{MCTS}(s) = argmax_a Q(s,a)$

# Self-Play

- The zero-sum game of two players
- $o = \begin{cases} 1, & \text{if now it's first player's turn} \\ -1, & \text{otherwise} \end{cases}$
- $Q_o(s,a) = oQ(s,a)$
- $\hat{a} = argmax_a[Q_o(s,a) + C\sqrt{\frac{\log n(s)}{n(s,a)}}]$
- $\pi_{MCTS}(a \mid s) \propto n(s,a)^{\frac{1}{\tau}}$

# MCTS

Two issues:

1. After applying an action sample from $\pi_{MCTS}(\,.\,|\,s)$ we probably remove the tree's nodes corresponding to not chosen actions.

2. We must play till the end to get an estimation of $V(s)$.

# MCTS

Two issues:

1. After applying an action sample from $\pi_{MCTS}(\,.\,|\,s)$ we probably remove the tree's nodes corresponding to not chosen actions.

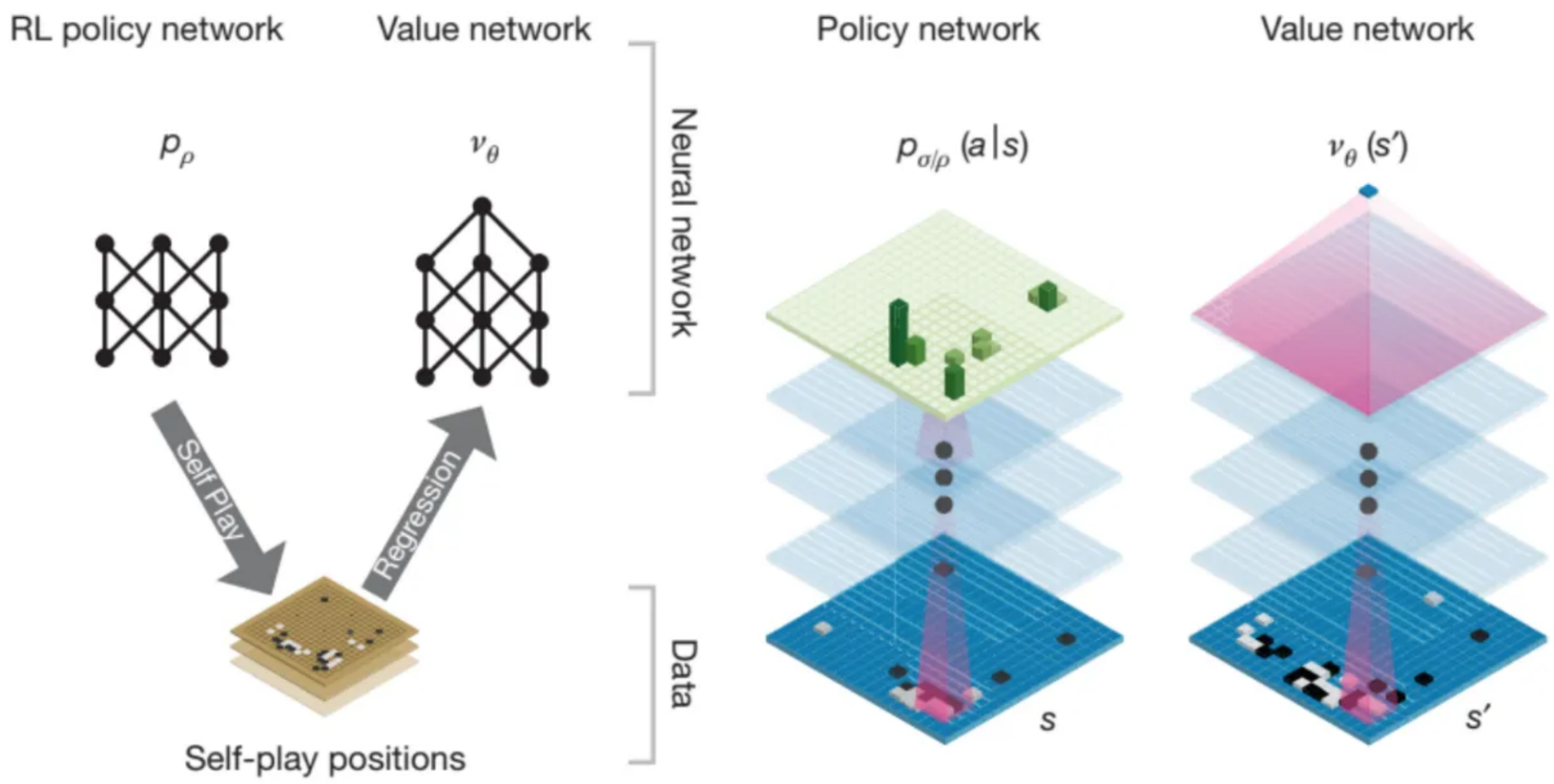
2. We must play till the end to get an estimation of $V(s)$.

Two ideas:

1. Distill $\pi_{MCTS}$ in $p_\theta$.

2. $V \approx V_\phi$

# Architecture

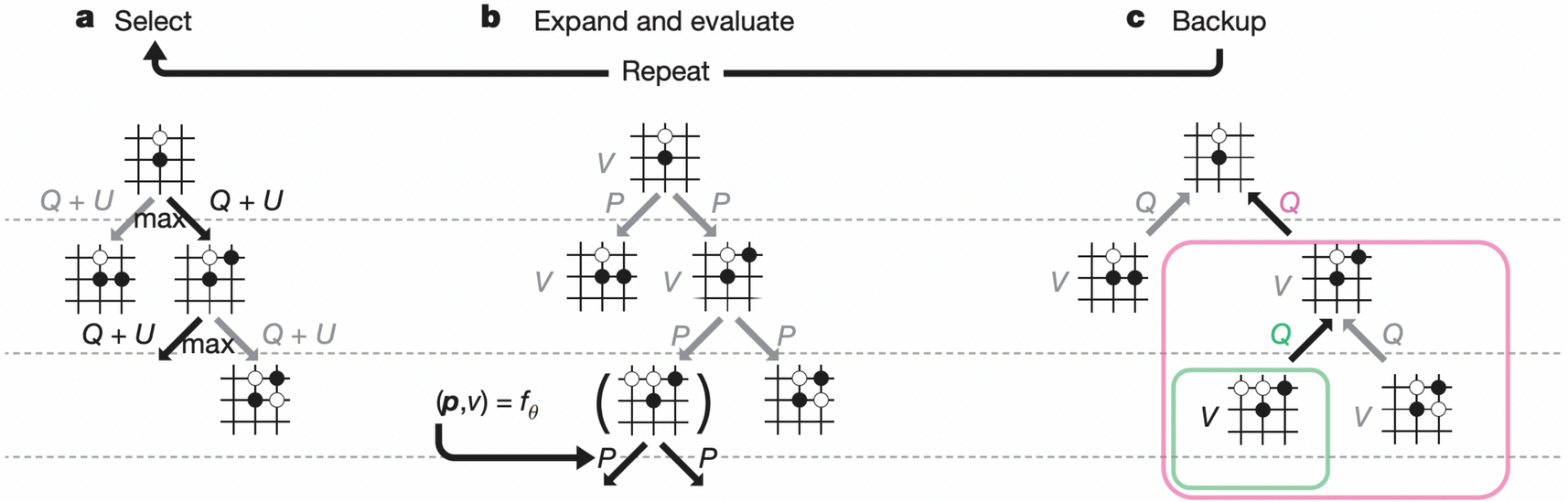



Policy and Value networks are indeed combined

# MCTS in AlphaZero

$f_\theta(s) = (\mathbf{p}, V)$ is a two-head neural network.

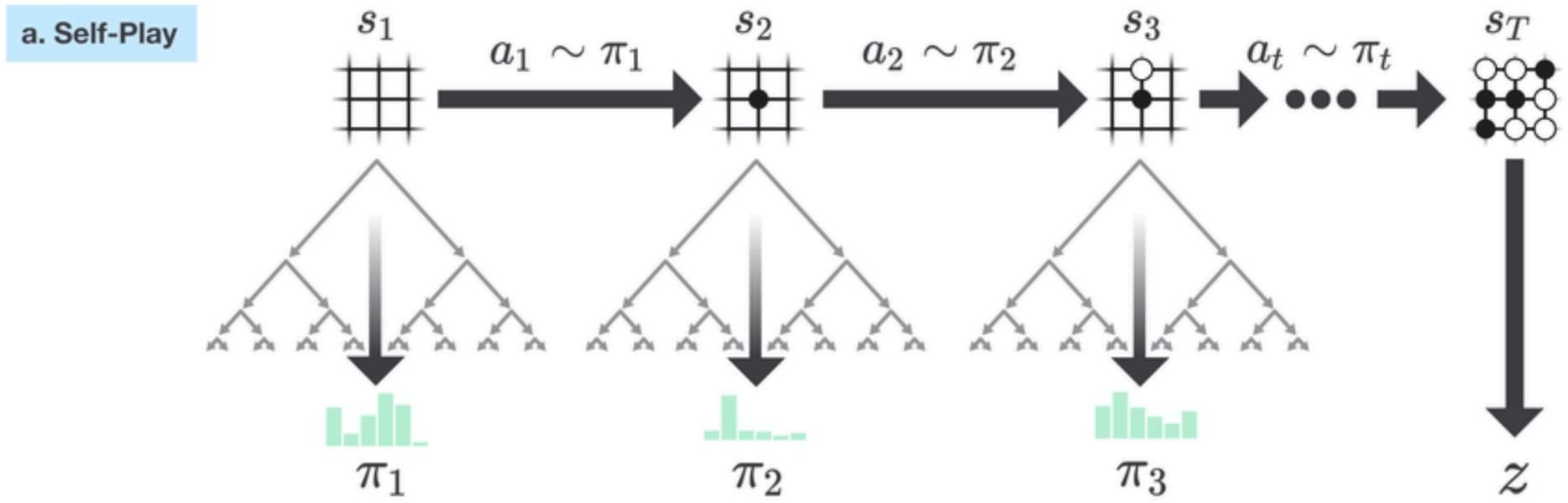
1. Selection: $\hat{a} = argmax_a[\hat{Q}(s,a) + C\, p_\theta(a \mid s) \dfrac{\sqrt{n(s)}}{n(s,a)+1}]$
2. Expansion
3. Propagation: for leaf state $s_{leaf}$ use $V_\theta(s_{leaf})$



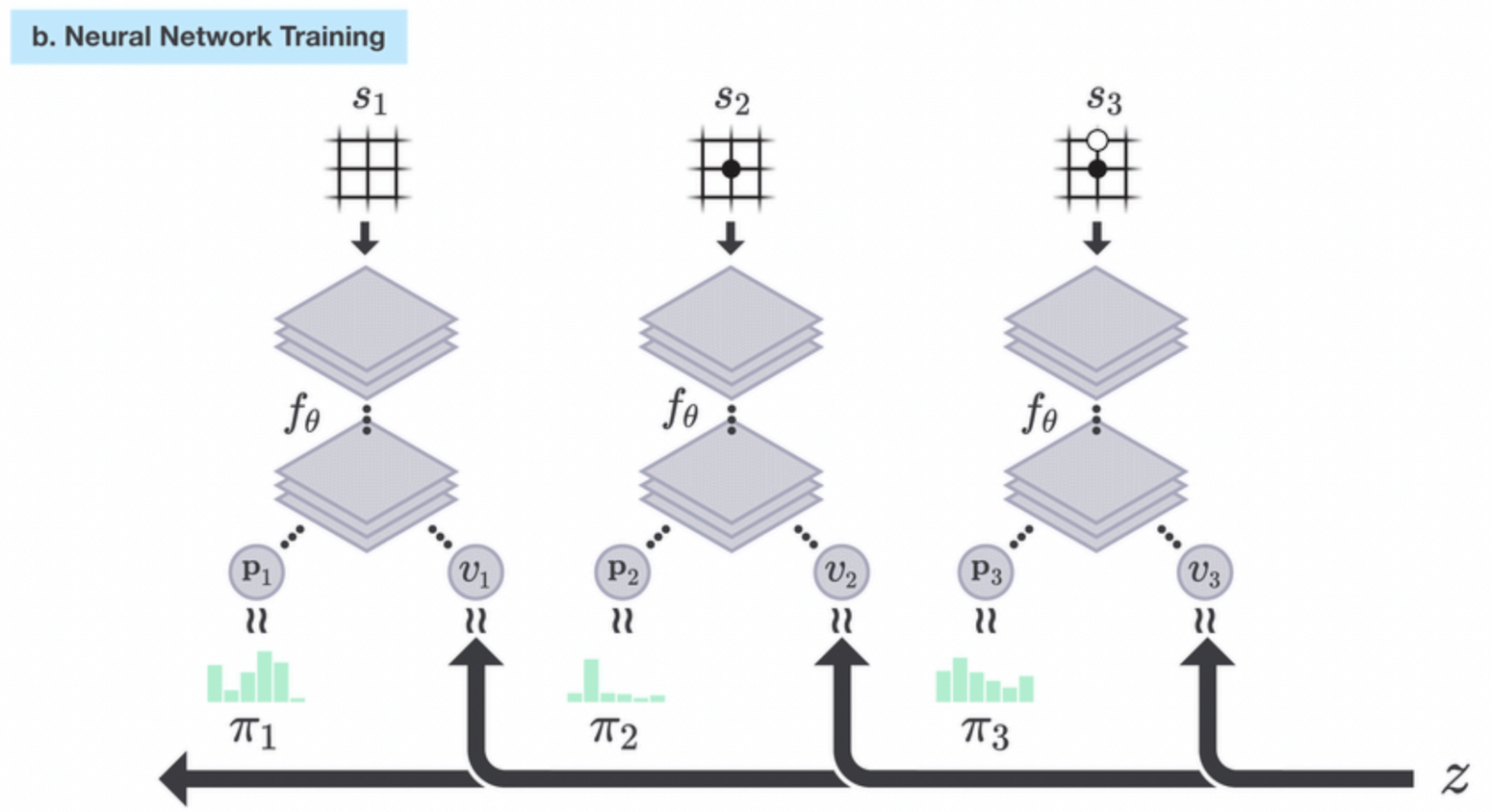
# AlphaZero Network Training

1. Many self-play games: in each state, an agent plans with MCTS and executes action $a \sim \pi(\,.\,|\,s) \propto n(s,a)^{\frac{1}{\tau}}$

2. Store the dataset of triplets $(s, \pi_{MCTS}(\,.\,|\,s), z)$.

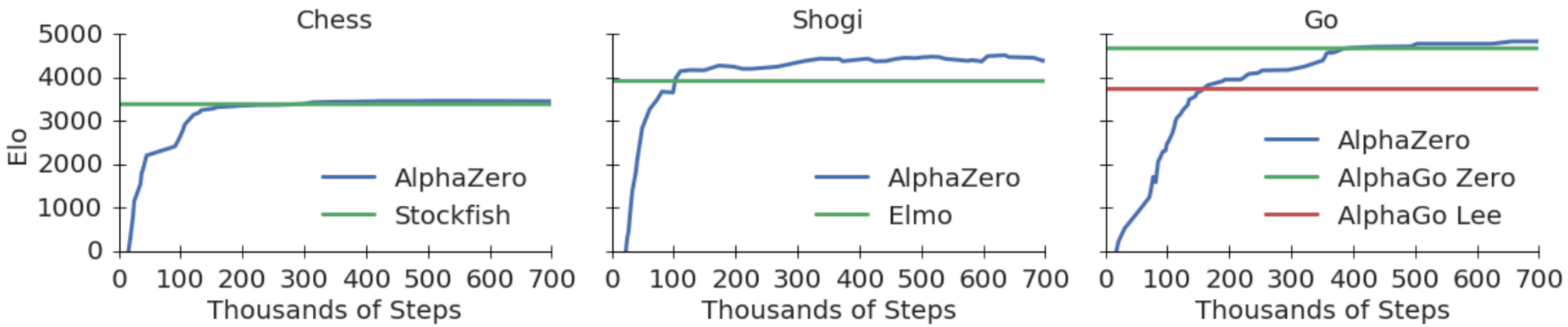


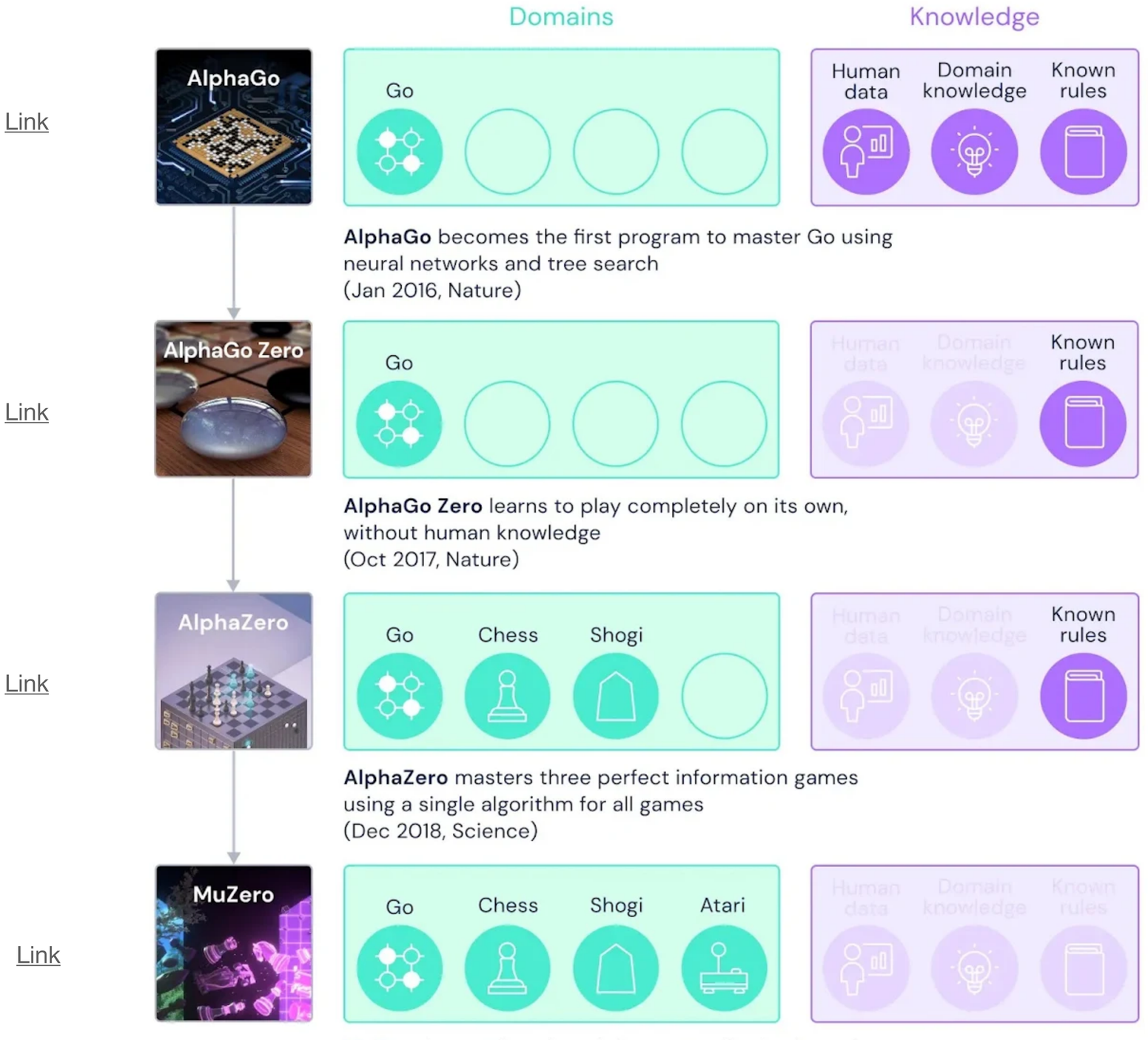
# AlphaZero Network Training




$$(z - V_\theta(s))^2 + \sum_a \pi_{MCTS}(s\,|\,a)\log p_\theta(s\,|\,a) + c\,||\theta||_2^2 \rightarrow \min_\theta$$

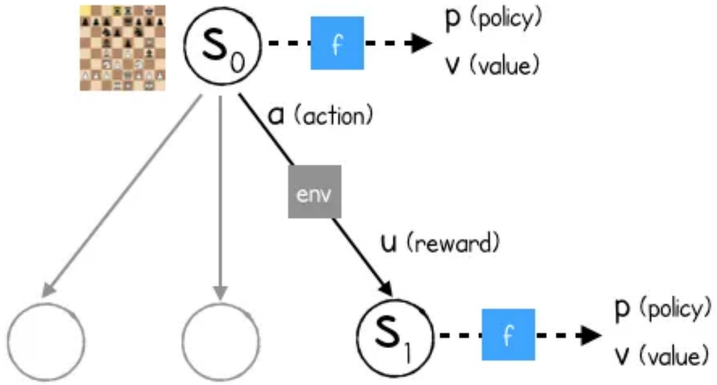
# AlphaZero Results




Domains
Knowledge
Link
AlphaGo
Go
Human data
Domain knowledge
Known rules
AlphaGo becomes the first program to master Go using neural networks and tree search
(Jan 2016, Nature)
Link
AlphaGo Zero
Go
Known rules
AlphaGo Zero learns to play completely on its own, without human knowledge
(Oct 2017, Nature)
Link
AlphaZero
Go
Chess
Shogi
Known rules
AlphaZero masters three perfect information games using a single algorithm for all games
(Dec 2018, Science)
Link
MuZero
Go
Chess
Shogi
Atari

# Comparison

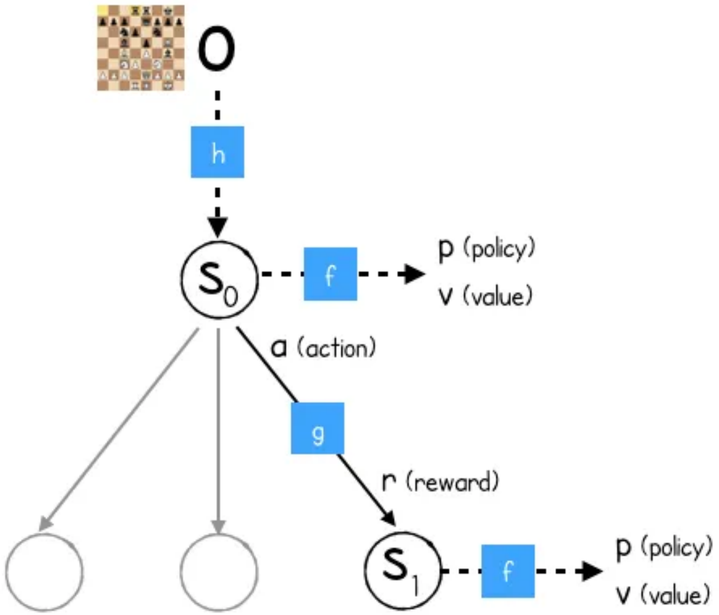
## AlphaZero




AlphaZero has 1 network

| | | from | to |
|---|---|---|---|
| prediction | f: | s | p, v |

## MuZero




MuZero has 3 networks

| | | from | to |
|---|---|---|---|
| prediction | f: | s | p, v |
| dynamics | g: | s, a | r, s |
| representation | h: | o | s |

Source

- Representation:

$$h_\theta(o_1, \ldots, o_t) = s_t^0$$

- Prediction:

$$f_\theta(s_t^k) = (\mathbf{p}_t^k, v_t^k)$$

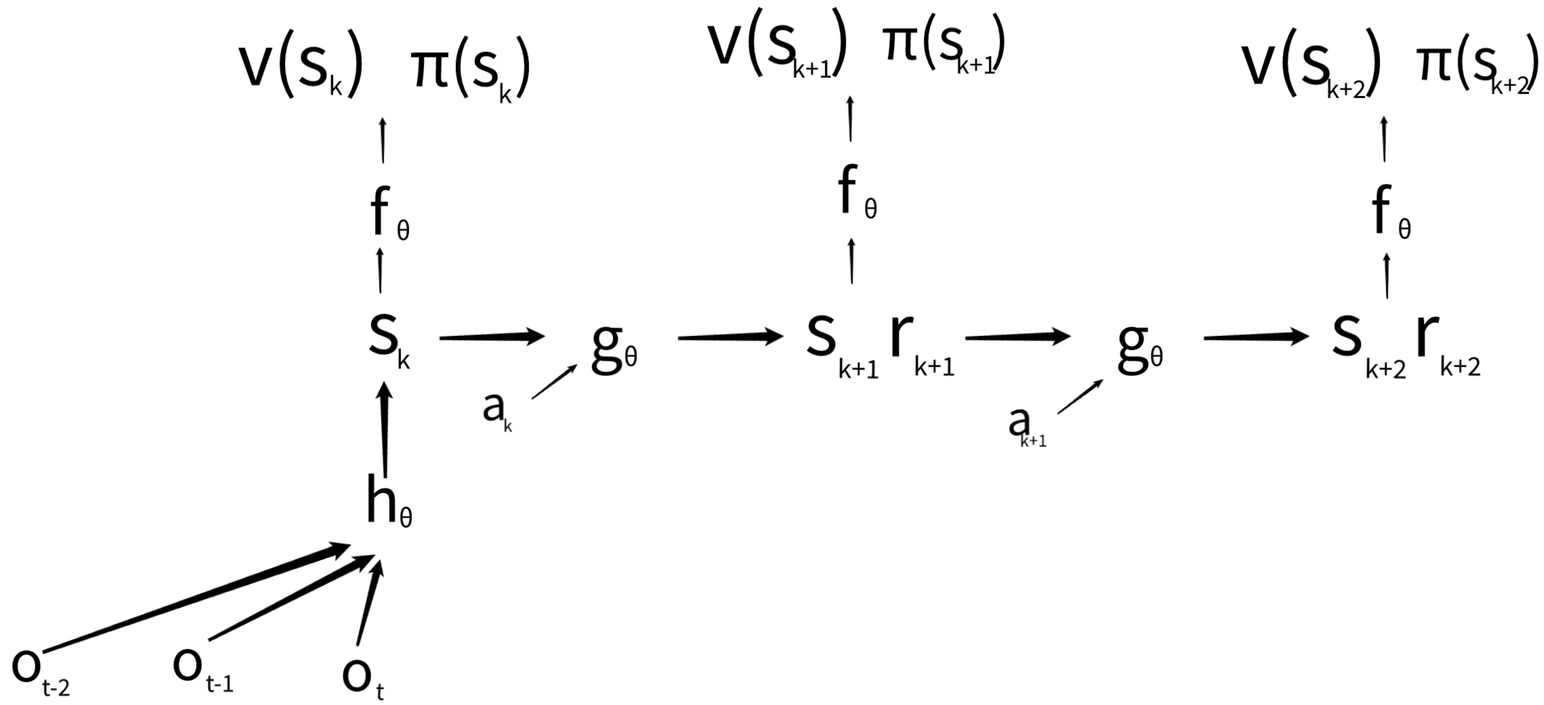
- Dynamics:

$$g_\theta(s_t^{k-1}, a_t^k) = (r_t^k, s_t^k)$$

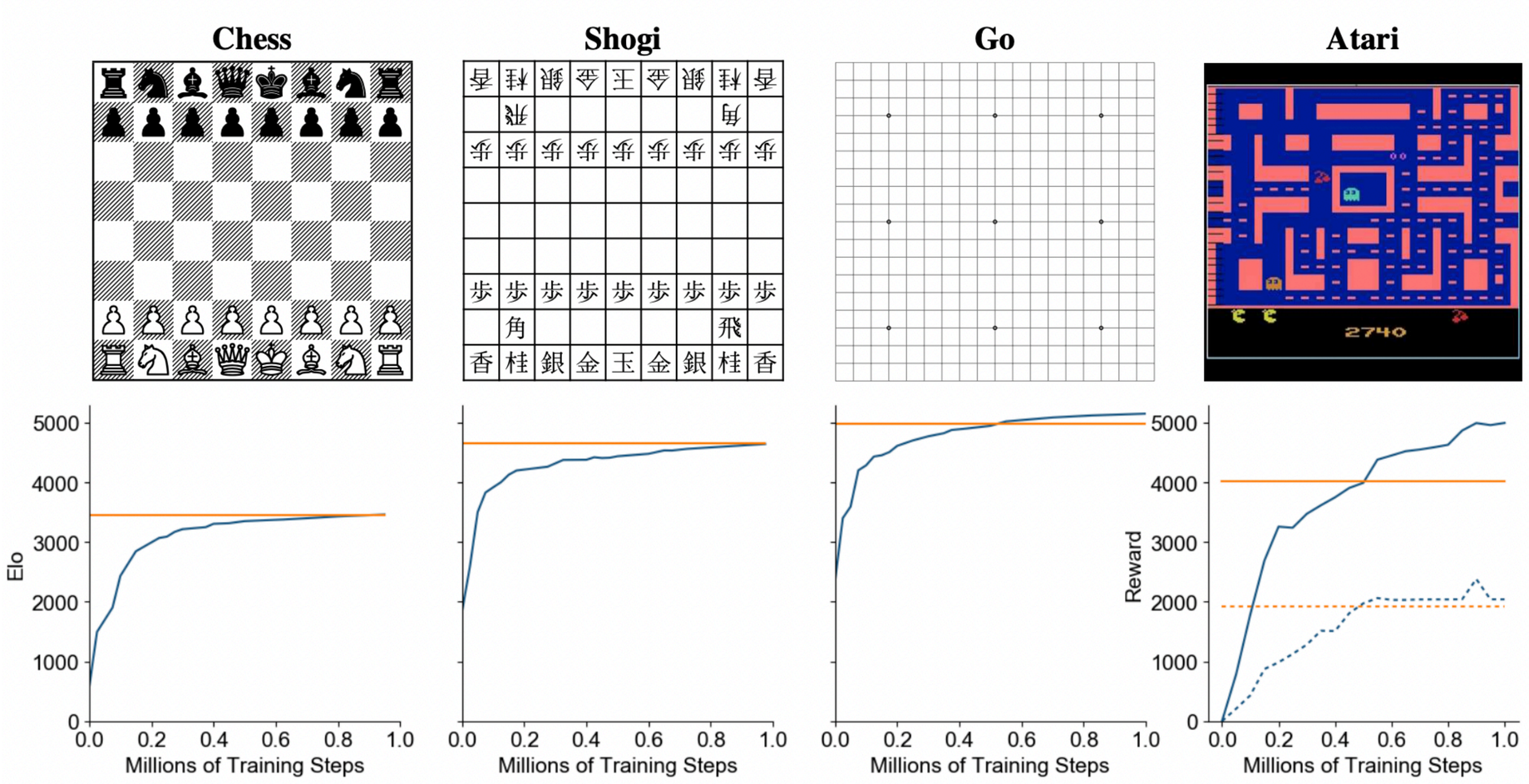
# MuZero Loss

$$l_t(\theta) = \sum_{k=0}^{K} [(u_{t+k} - r_t^k)^2 + (z_{t+k} - v_t^k)^2 + \pi_{t+k} \log p_t^k] + c\,||\theta||_2^2 \to \min_{\theta}$$

- $u_{t+k}$ is an immediate reward
- $z_{t+k}$ is $n$-step Bellman target



# MuZero Results



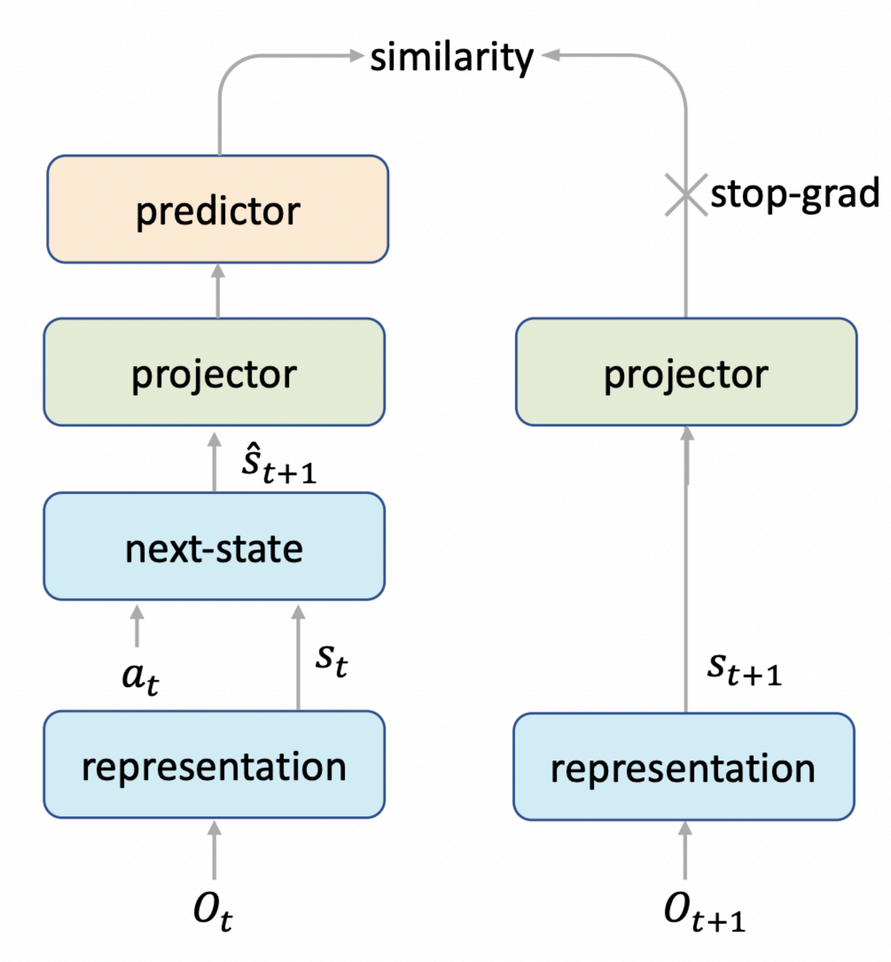
# EfficientZero

MuZero issues:

1. Lack of supervision on environment model:
    - The reward can be sparse
    - Targets are calculated with bootstrapping
2. Hardness to deal with aleatoric uncertainty:
    - the predicted rewards still have large prediction errors.
3. Off-policy issues of multi-step value

# Self-Supervised Consistency Loss

1. Compare the latent representation of consecutive observations with negative cosine similarity and optimise for it.



# End-To-End Prediction of the Value Prefix

2. Predict the value prefix, not immediate rewards:

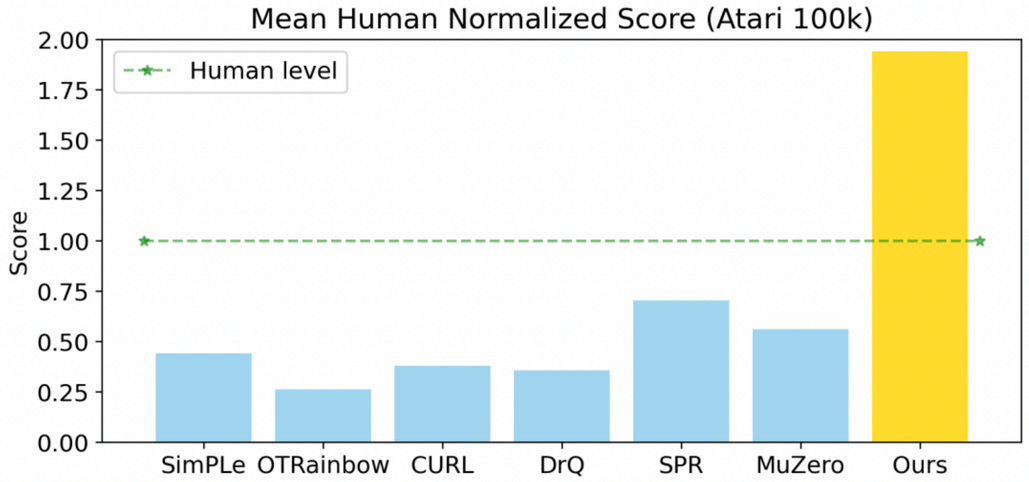
$$Q(s_t, a) = \sum_{k=0}^{K-1} \gamma^k r_{t+k} + \gamma^K V(s_{t+K})$$

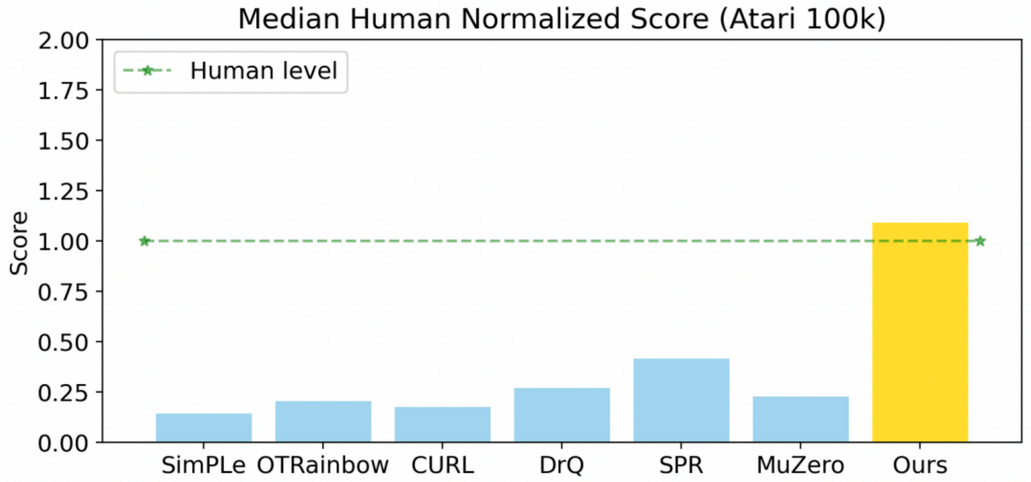
# Model-Based Off-Policy Correction

3. Use rewards of a dynamic horizon $L$ from the old trajectory and redo an MCTS search with the current policy on the last state $s_{t+L}$ and compute the empirical mean value at the root node.:

$$z_t = \sum_{k=0}^{L-1} \gamma^k u_{t+k} + \gamma^L V^{MCTS}(s_{t+L}), L < K$$

# EfficientZero Results



# Dreamer-V1

World Model Learning

Learning Value and Actor Networks

Environment Interaction

# Learning the World Model

# Efficient Behaviour Learning

$o_1$

# Background

1. Practical RL course by YSDA, week 10
2. Reinforcement Learning Textbook (in Russian): 7.2-7.3
3. DreamerV3
4. EfficientZeroV2

# Thank you for your attention!