Derivative-free and Evolutionary Methods

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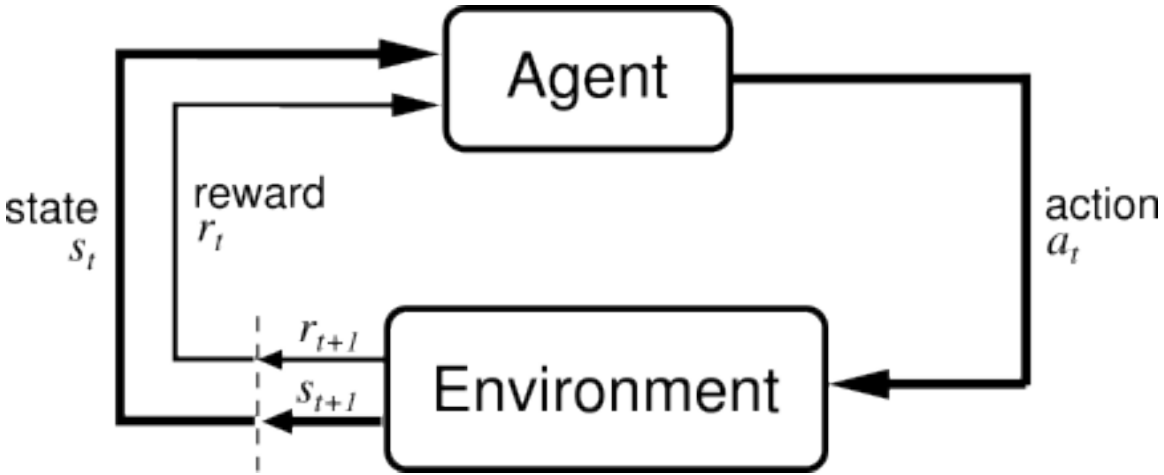
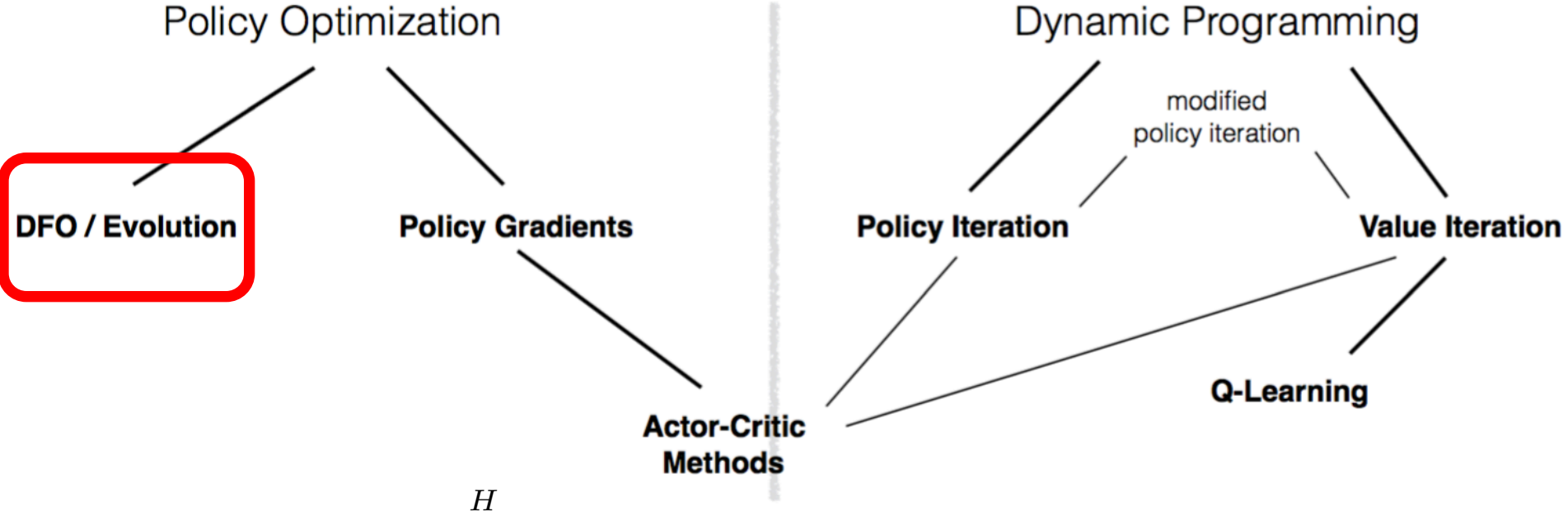
Reinforcement Learning



[Figure source: Sutton & Barto, 1998]

Policy Optimization in the RL Landscape



$$\max_\theta \; U(\theta) = \max_\theta \; \mathrm{E}[\sum_{t=0}^{H} R(s_t)|\pi_\theta]$$

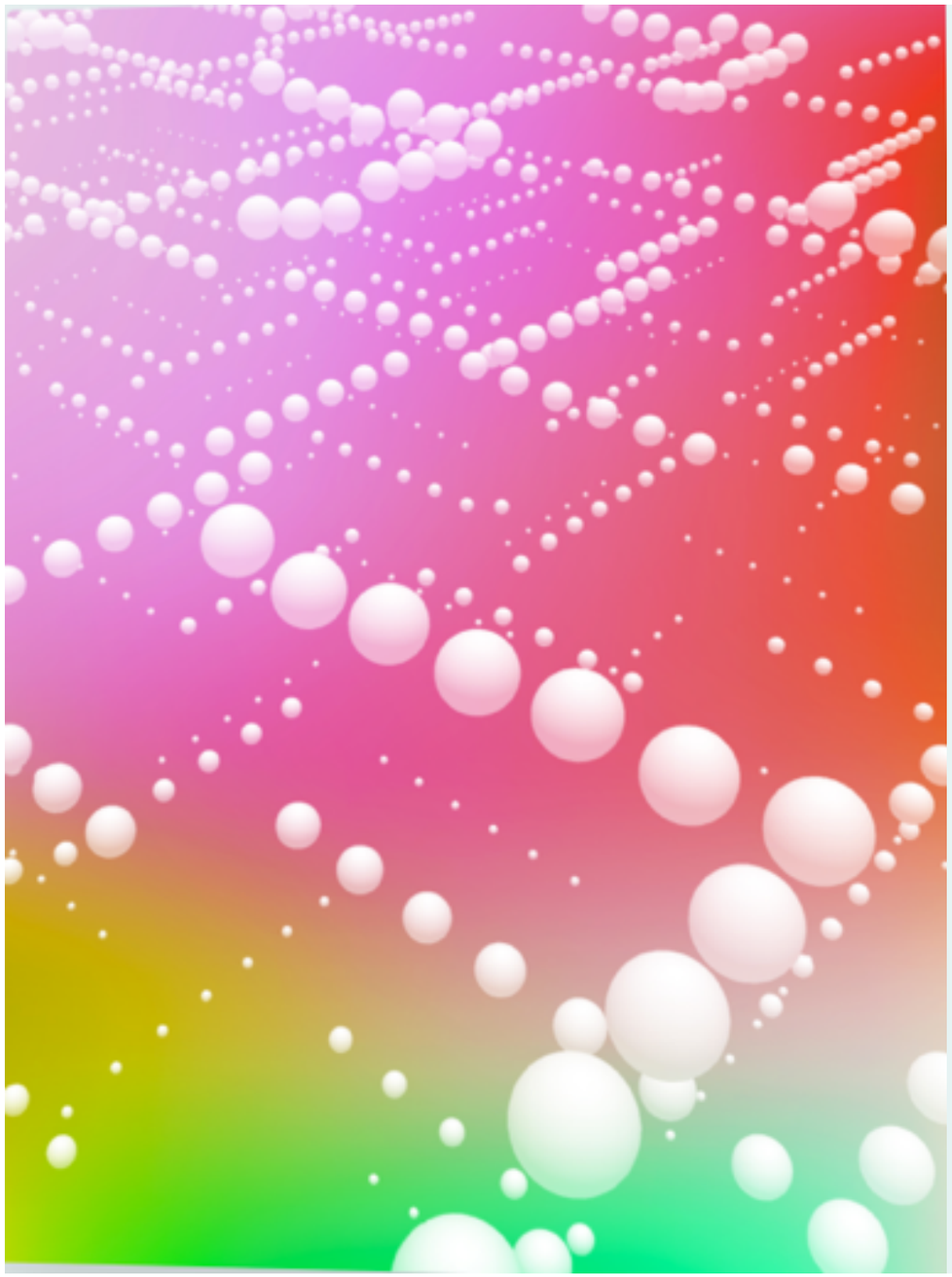
Evolution Strategies as a Scalable Alternative to Reinforcement Learning

OpenAI

Notations

- ES: Evolution Strategies
- RL: Reinforcement Learning
- PG: Policy Gradient
- BP: Backpropagation
- NN: Neural Network

A **Strong** Alternative



MARCH 24, 2017

Evolution Strategies as a Scalable Alternative to Reinforcement Learning

We've discovered that **evolution strategies (ES)**, an optimization technique that's been known for decades, rivals the performance of standard **reinforcement learning (RL)** techniques on modern RL benchmarks (e.g. Atari/MuJoCo), while overcoming many of RL's inconveniences.

History Repeats Itself

AlexNet

ImageNet Classification with Deep Convolutional Neural Networks

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Geoffrey E. Hinton University of Toronto hinton@cs.utoronto.ca

Abstract

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

DQN

Playing Atari with Deep Reinforcement Learning

Volodymyr Mnih **Koray Kavukcuoglu** **David Silver** **Alex Graves** **Ioannis Antonoglou** **Daan Wierstra** **Martin Riedmiller**

DeepMind Technologies

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Abstract

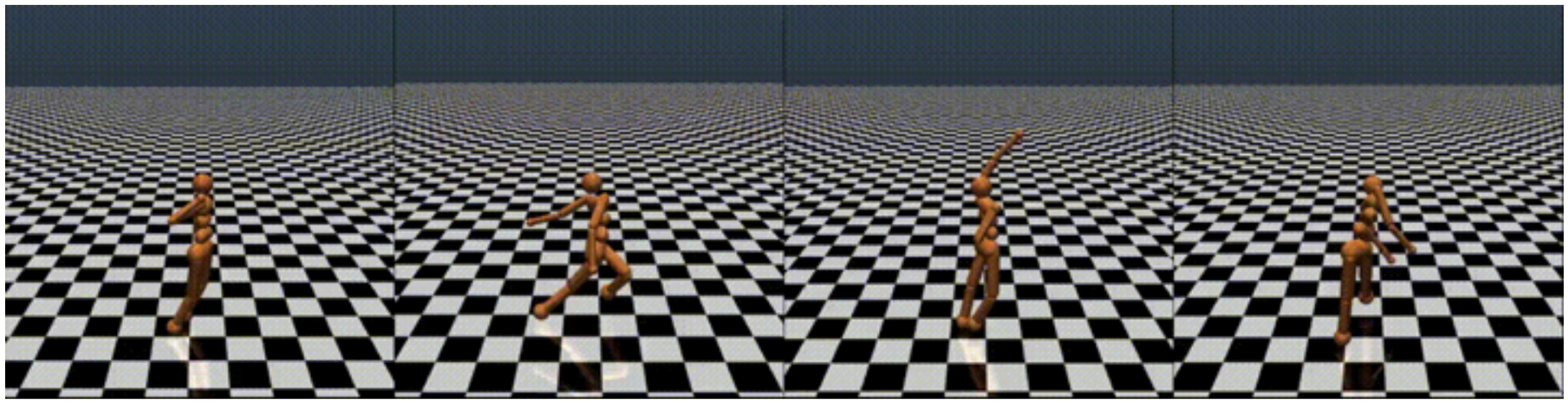
We present the first deep learning model to successfully learn control policies directly from high-dimensional sensory input using reinforcement learning. The model is a convolutional neural network, trained with a variant of Q-learning, whose input is raw pixels and whose output is a value function estimating future rewards. We apply our method to seven Atari 2600 games from the Arcade Learning Environment, with no adjustment of the architecture or learning algorithm. We find that it outperforms all previous approaches on six of the games and surpasses a human expert on three of them.

NN, RL are amazing when **computing power** is strong.

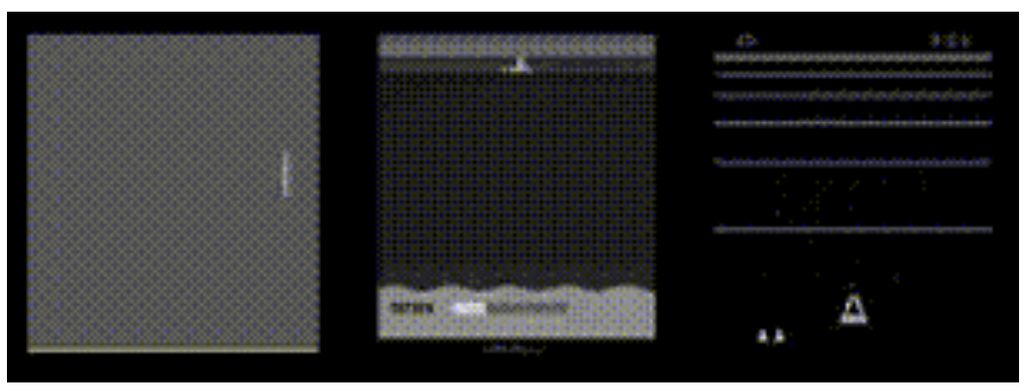
What about ES?

AMAZING Results of ES

3D MuJoCo humanoid walker



2D Atari games



AMAZING Results of ES

3D MuJoCo humanoid walker

- ES(1440 cores): 10 minutes
- A3C(32 cores): 10 hours

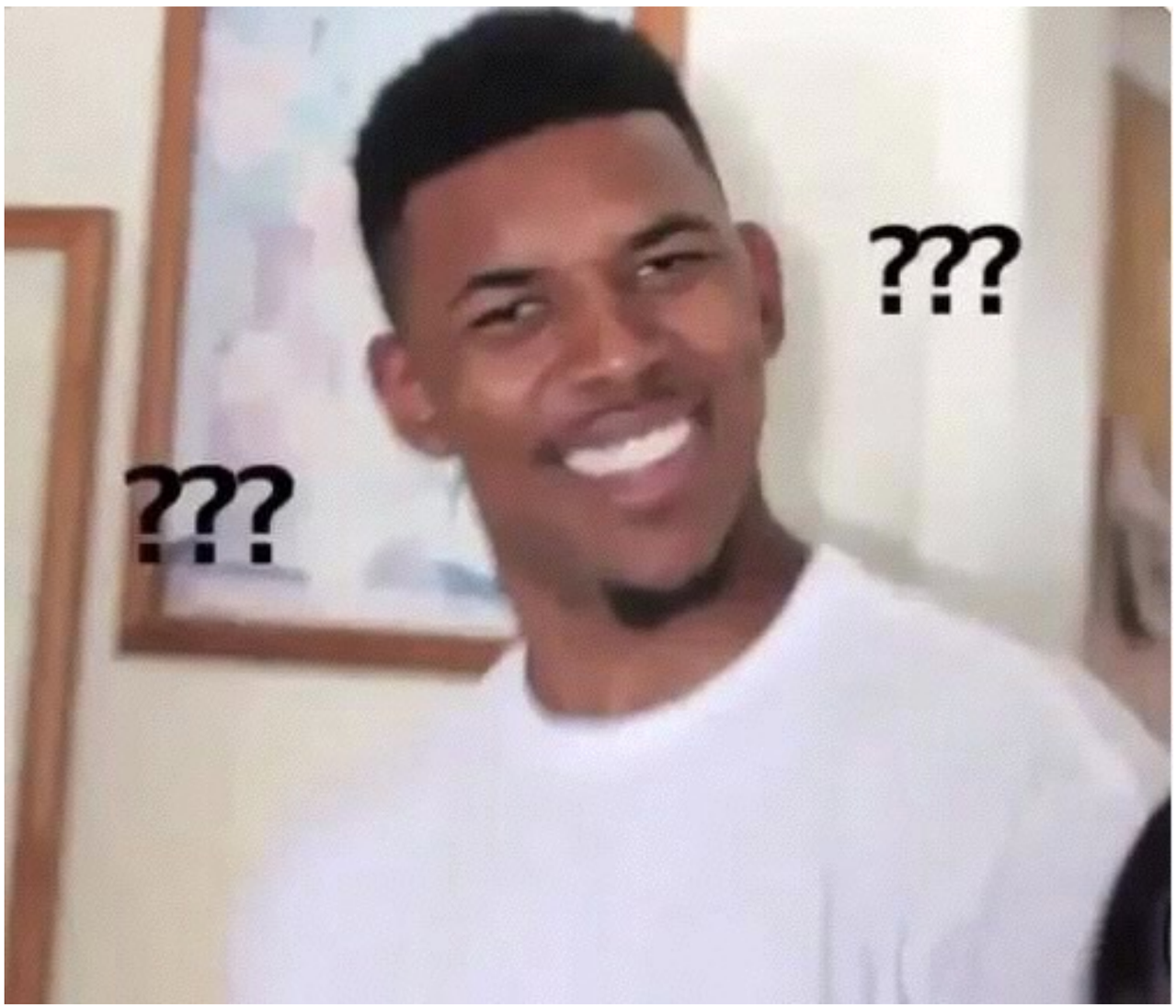
2D Atari games

- ES(720 cores): 1 hour
- A3C(32 cores): 1 day

Yet another example of

achieving strong results with decades-old ideas.

Why?



How ES Works?

Algorithm 1 Evolution Strategies

Input: Learning rate α, noise standard deviation σ, initial policy parameters θ_0

for $t = 0, 1, 2, \ldots$ **do**

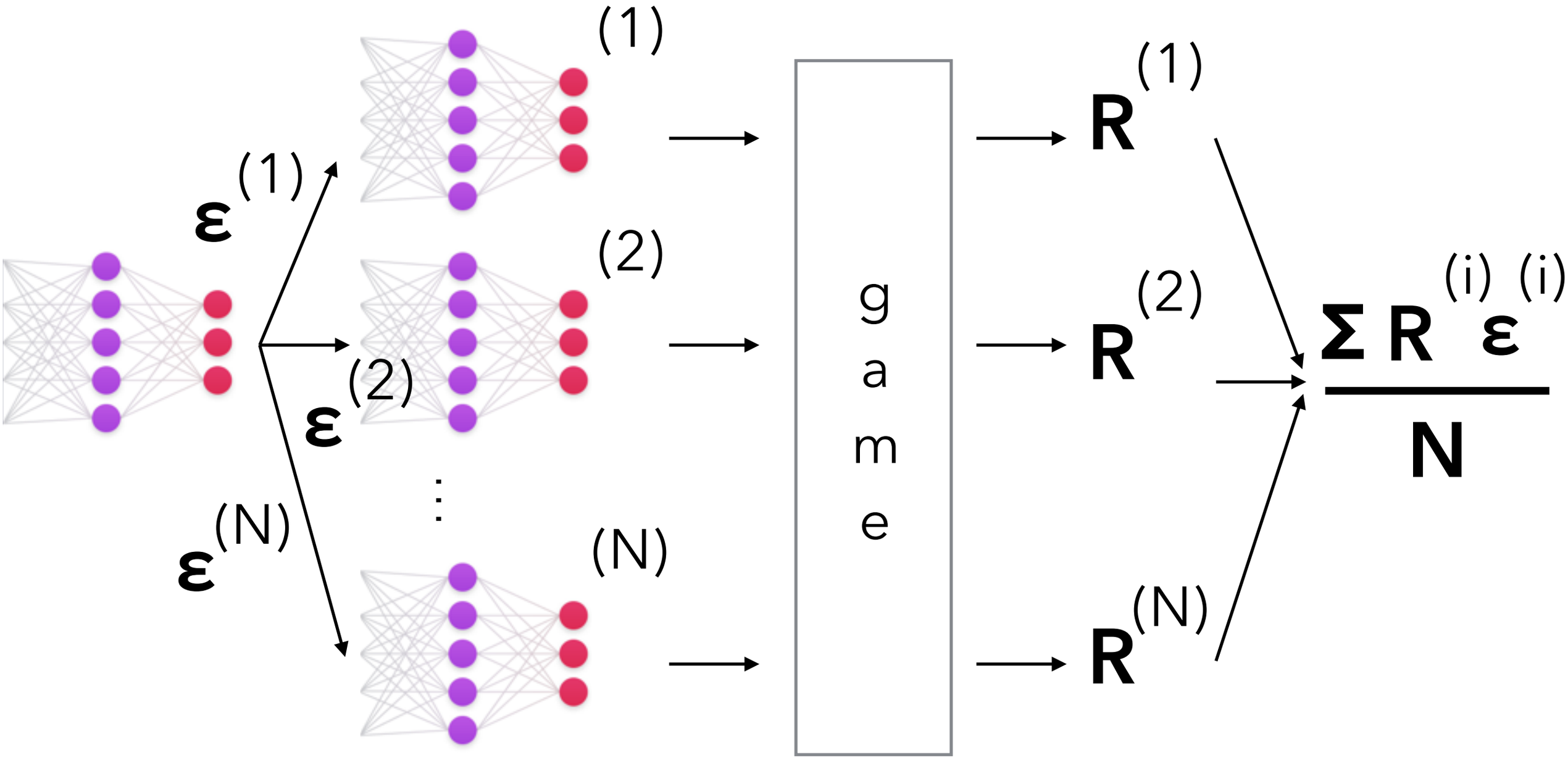
  Sample $\epsilon_1, \ldots \epsilon_n \sim \mathcal{N}(0, I)$

  Compute returns $F_i = F(\theta_t + \sigma\epsilon_i)$ for $i = 1, \ldots, n$

  Set $\theta_{t+1} \leftarrow \theta_t + \alpha \frac{1}{n\sigma} \sum_{i=1}^{n} F_i \epsilon_i$

end for

ES in a Nutshell



Another Cool View Point

- Agent: parameter tuner
- Policy: gaussian policy
- Action: parameter perturbation
- Environment: RL agent’s policy parameter + game

Advantages of ES

- No need for BP
- Easier to scale
- Immune to sparse rewards
- Robust to hyperparameters

Advantages of ES

- No need for BP
- Easier to scale
- Immune to sparse rewards
- Fewer hyperparameters

No Need for BP

- Write code faster / easier
- Code runs faster (only 1/3 computation)
- Use CPU instead of GPU
- No gradient explosion (common in RNN)
- Memory efficient

Advantages of ES

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Easier to Scale

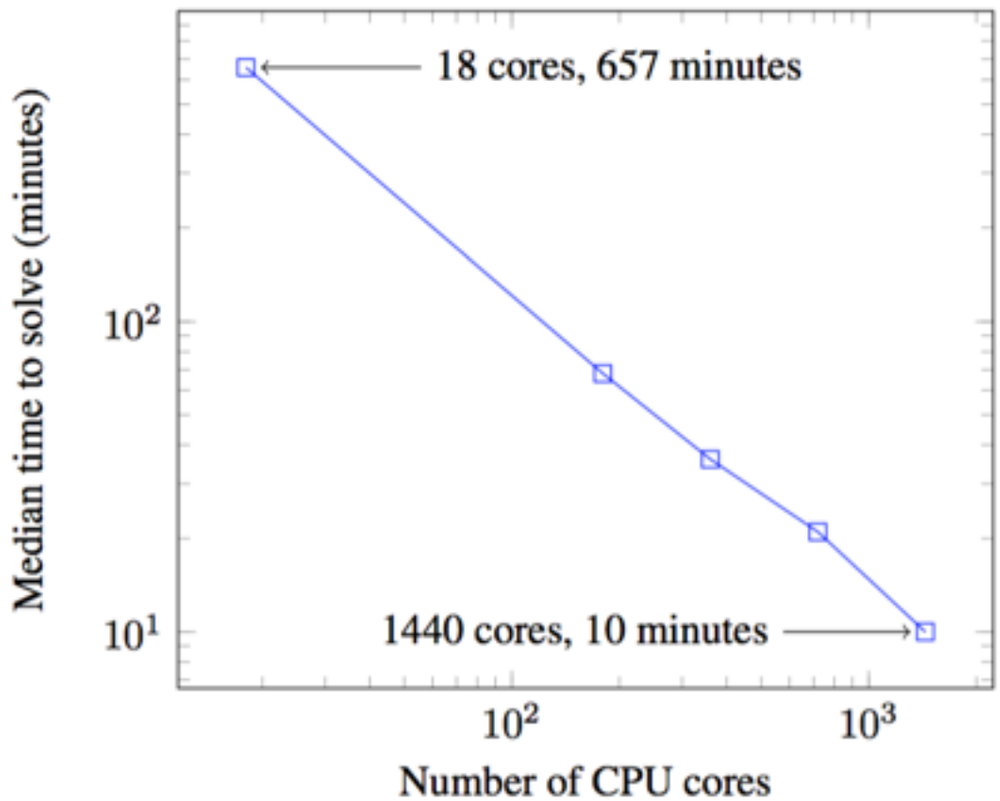

Figure 1. Time to reach a score of 6000 on 3D Humanoid with different number of CPU cores. Experiments are repeated 7 times and median time is reported.

- Performance boosts linearly with #CPUs
- Different workers only need to pass reward to each other, not gradient
- $CPU << $GPU

The Killer Feature of ES

- Every worker's random seed are shared
- Can directly reconstruct other worker's parameter
- Only need to pass scalar **R**

Advantages of ES

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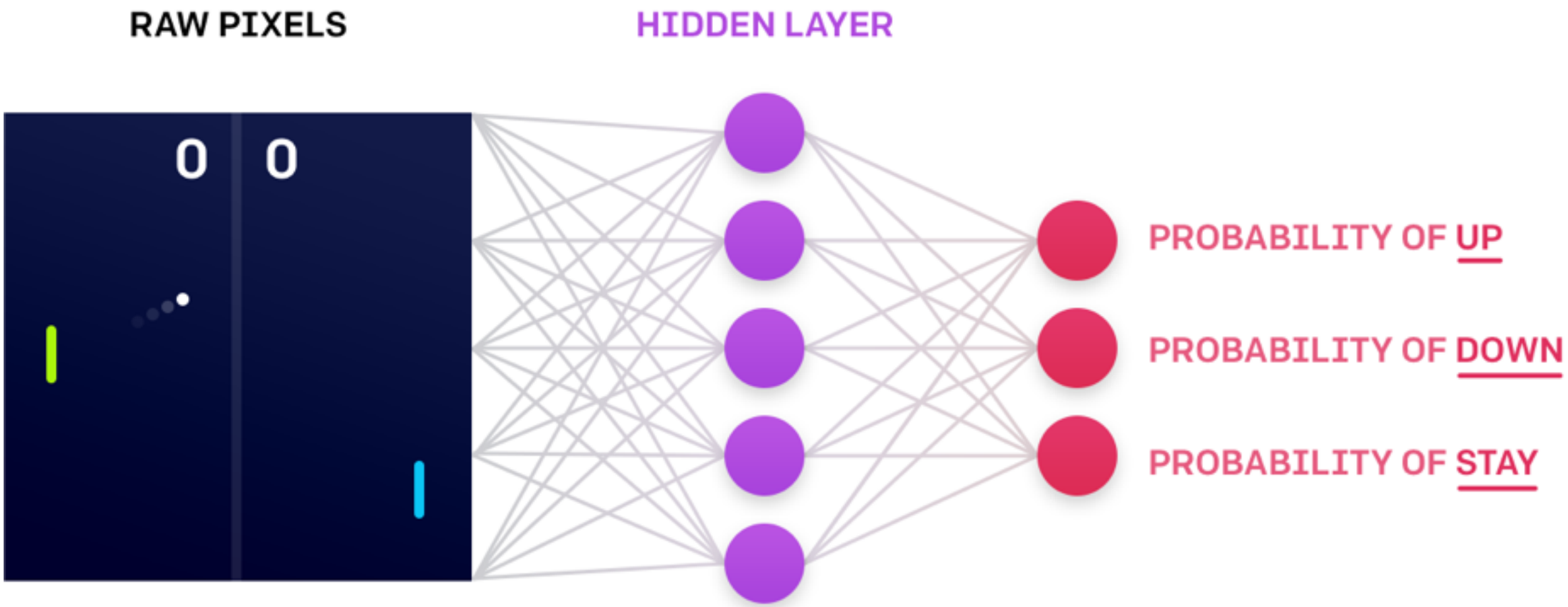
Recap: Deep RL

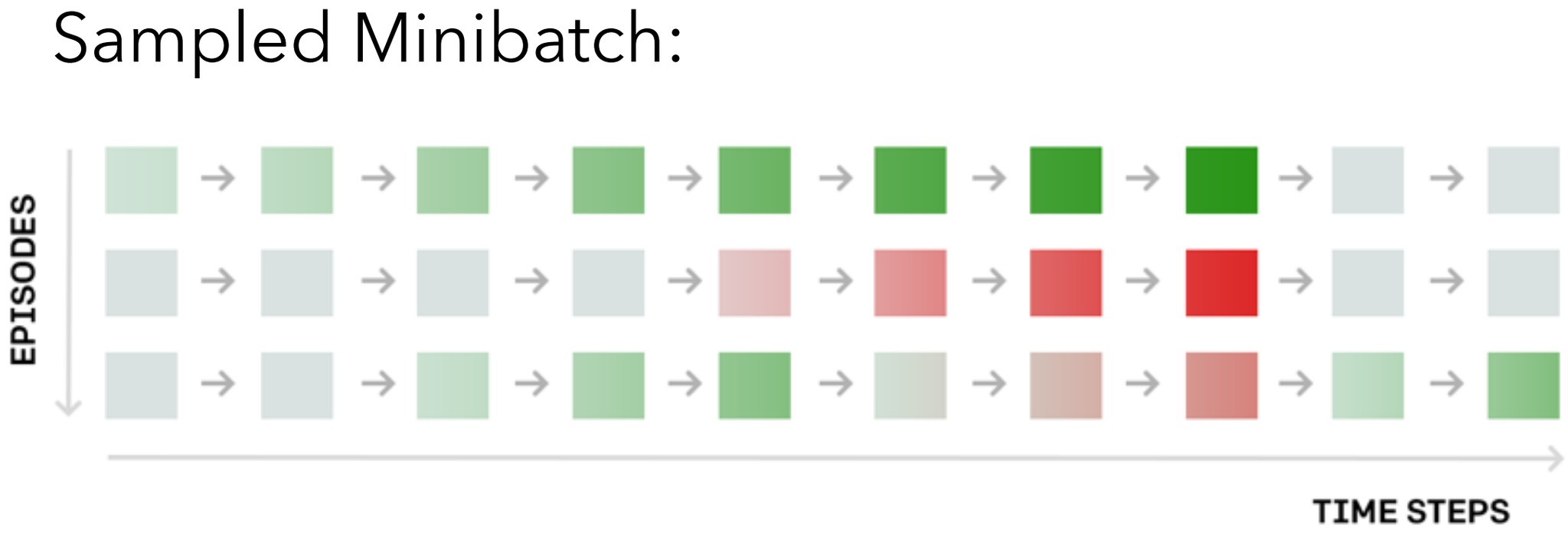


Recap: Deep RL Training Process

: + reward

: - reward

Sampled Minibatch:



Gradient of RL & ES

- PG adds noise in action space

$$\nabla_\theta F_{PG}(\theta) = \mathbb{E}_\epsilon \left\{ R(\mathbf{a}(\epsilon, \theta)) \nabla_\theta \log p(\mathbf{a}(\epsilon, \theta); \theta) \right\}.$$

- ES adds noise in parameter space

$$\nabla_\theta F_{ES}(\theta) = \mathbb{E}_\xi \left\{ R(\mathbf{a}(\xi, \theta)) \nabla_\theta \log p(\tilde{\theta}(\xi, \theta); \theta) \right\}.$$

Immune to Sparse Rewards

- Policy Gradient:

$$\mathrm{Var}[\nabla_\theta F_{PG}(\theta)] \approx \mathrm{Var}[R(\mathbf{a})]\,\mathrm{Var}[\nabla_\theta \log p(\mathbf{a};\theta)],$$

$$\nabla_\theta \log p(\mathbf{a};\theta) = \sum_{t=1}^{T} \nabla_\theta \log p(a_t;\theta)$$

- ES:

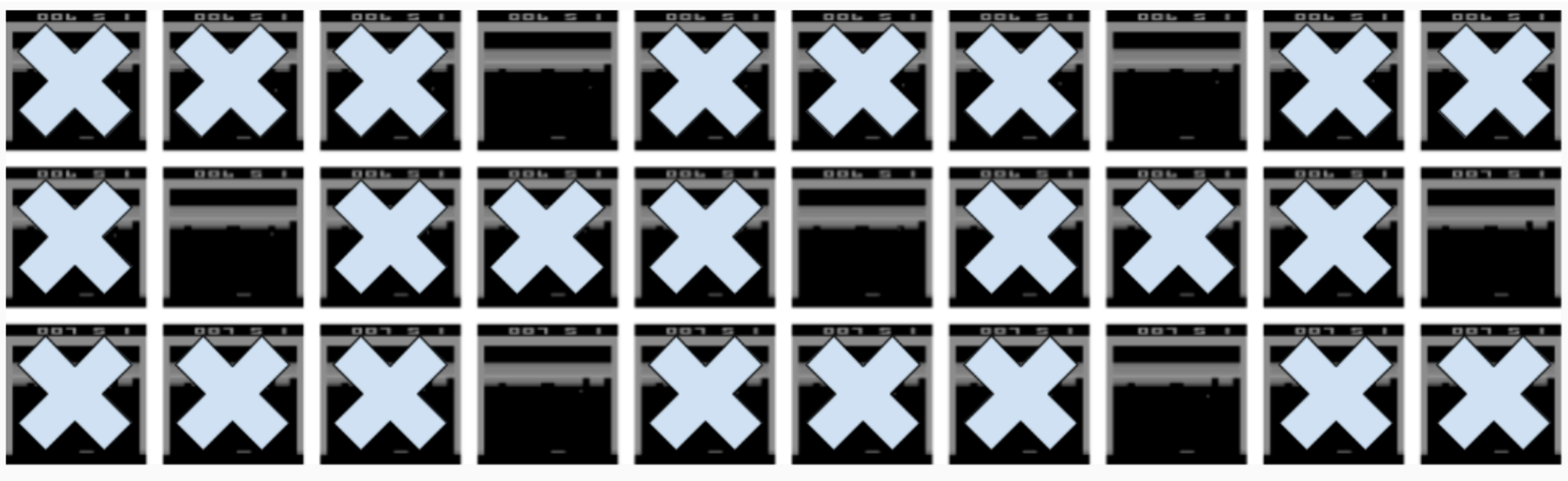
$$\mathrm{Var}[\nabla_\theta F_{ES}(\theta)] \approx \mathrm{Var}[R(\mathbf{a})]\,\mathrm{Var}[\nabla_\theta \log p(\tilde{\theta};\theta)].$$

Variance of gradient estimated by ES doest not grow linearly with T

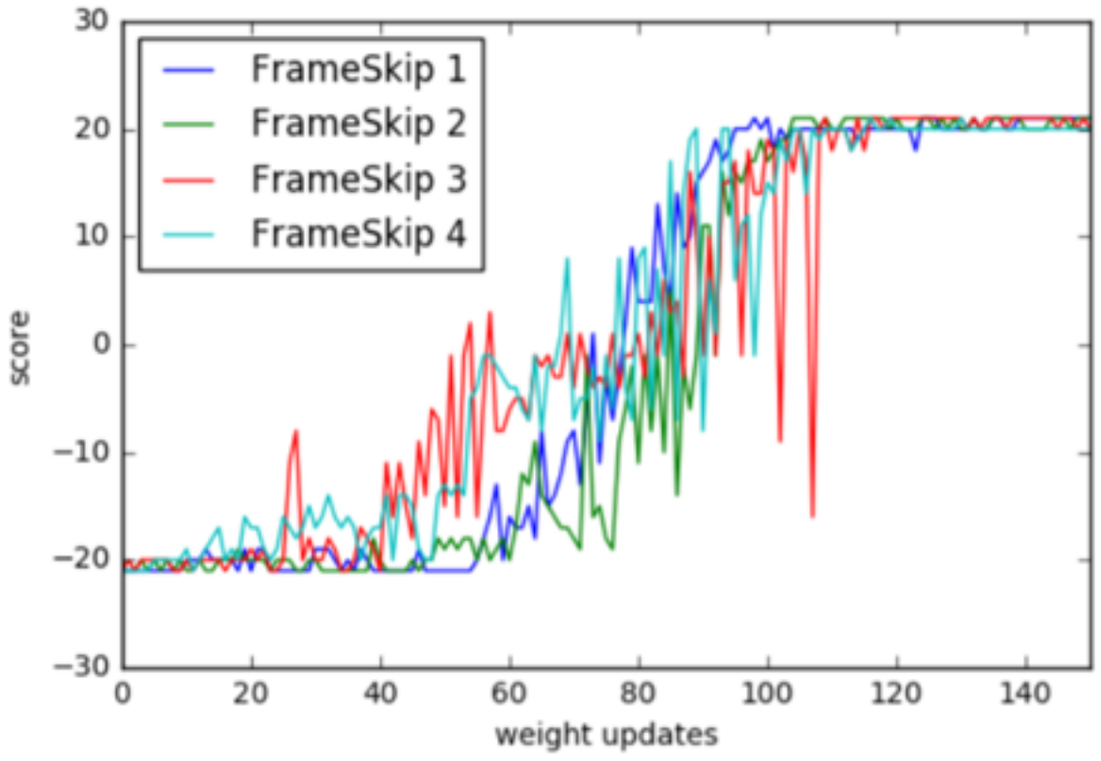
Advantages of ES

- No need for BP
- Easier to scale
- Immune to sparse rewards
- Robust to hyperparameters

Frame Skip



Insensitive to Hyperparameters



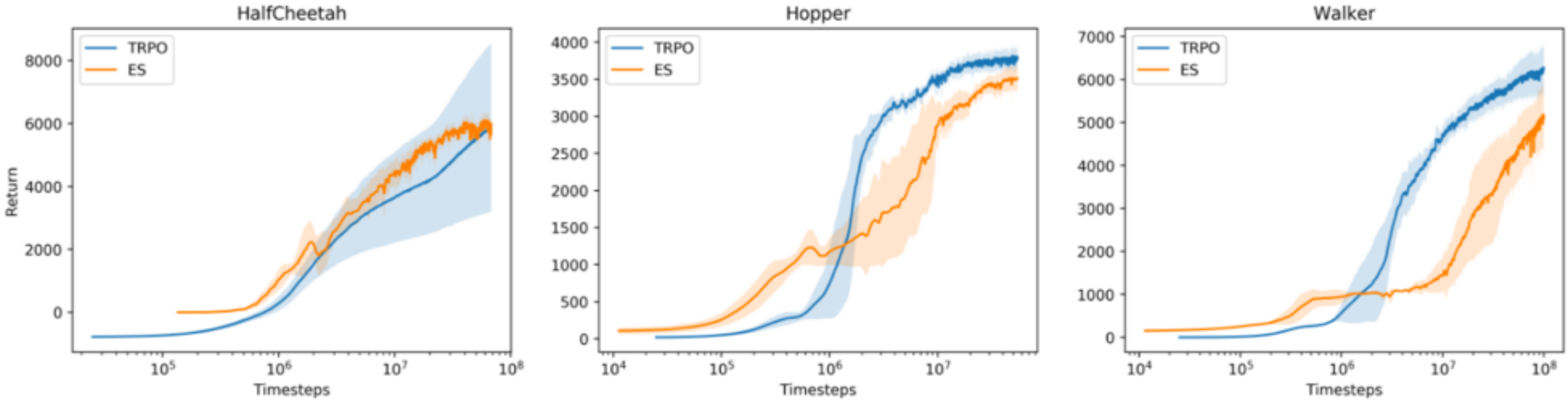
- No need to tune annoying hyperparameters.

Advantages of ES

- No need for BP
- Easier to scale 👍
- Immune to sparse rewards 🤔
- Robust to hyperparameters

Disadvantage of ES

- Less data efficient



At most needs 7.8x data on Mujoco, looks acceptable

RL v.s ES

“There are open-loop domain and closed-loop domain for RL.

In open-loop domain such as self-driving car, everything could happen.

In closed-loop domain such as electricity control, we can define our own MDP.”

– Honglak Lee

My Two Cents

- Open-loop: RL

  Cost of data is **high**, e.g., robotics

- Closed-loop: ES

  Cost of data is **low**, e.g., simulation