Scaling Up RL Using Evolution Strategies

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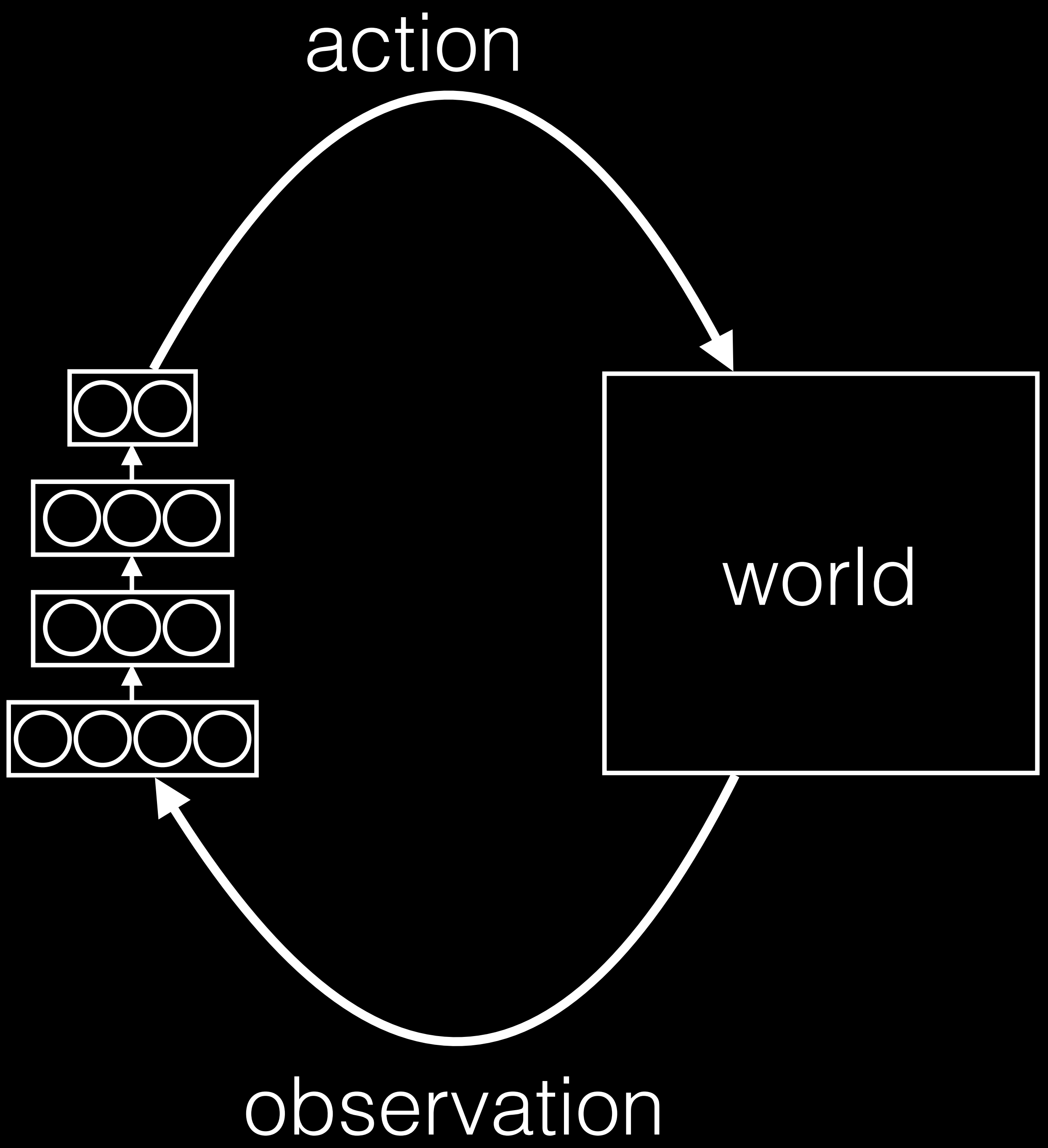
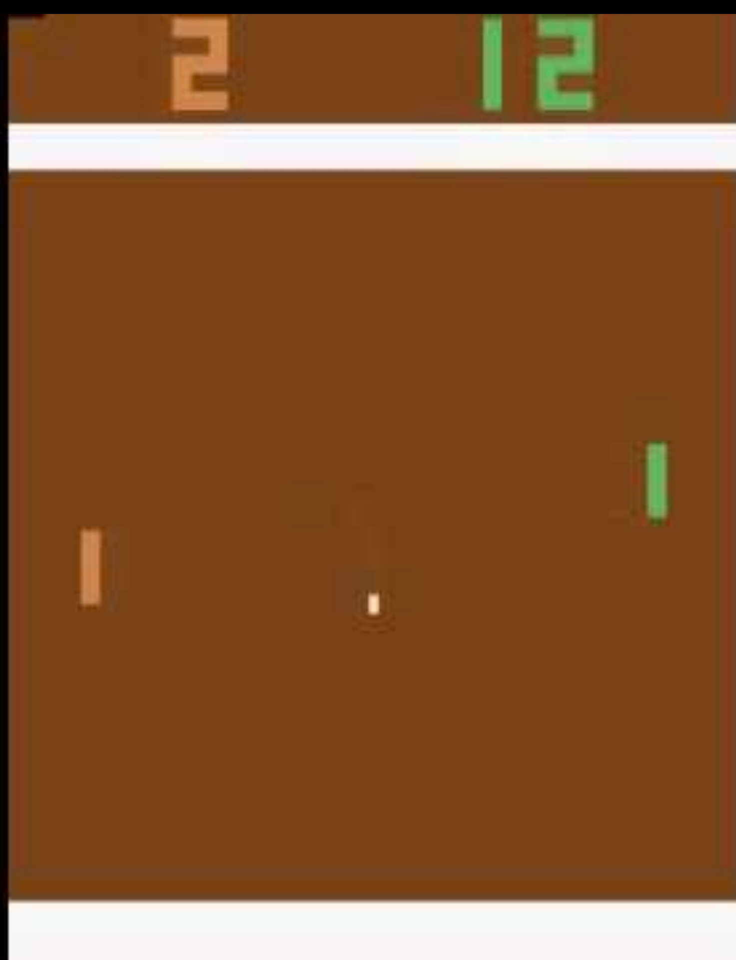
OpenAI

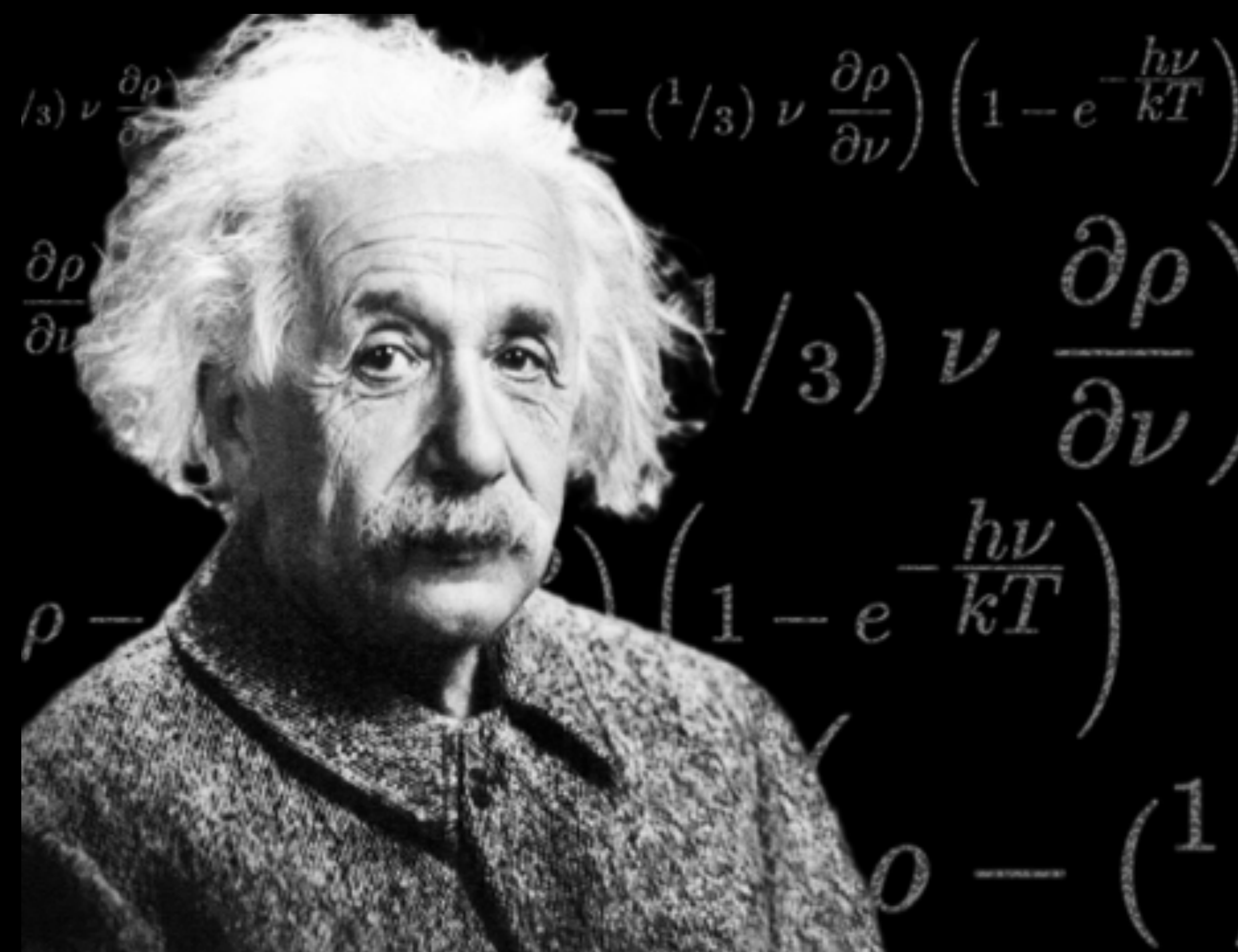
Reinforcement Learning = AI?

- Definition of “RL” broad enough to capture all that is needed for AGI
- Increased interest and improved algorithms
- Large investments are made



Still a long way to go…





What’s keeping us?

- Credit assignment
- Compute

- Many other things we will not discuss right now

Credit assignment is difficult for general MDPs

Credit assignment is difficult for general MDPs

- At state s_t take action a_t. Next get state s_{t+1}
- Receive return R after taking T actions
- No precisely timed rewards, no discounting, no value functions
- Currently this seems true for our hardest problems, like meta learning

  Duan et al (2016) "RL^2: Fast Reinforcement Learning via Slow Reinforcement Learning."
  Wang et al. (2016) "Learning to reinforcement learn."

Vanilla policy gradients

- Stochastic policy P(a | s,θ)
- Estimate gradient of expected return F = E[R] using REINFORCE

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

Vanilla policy gradients

- Correlation between return and individual actions is typically low

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

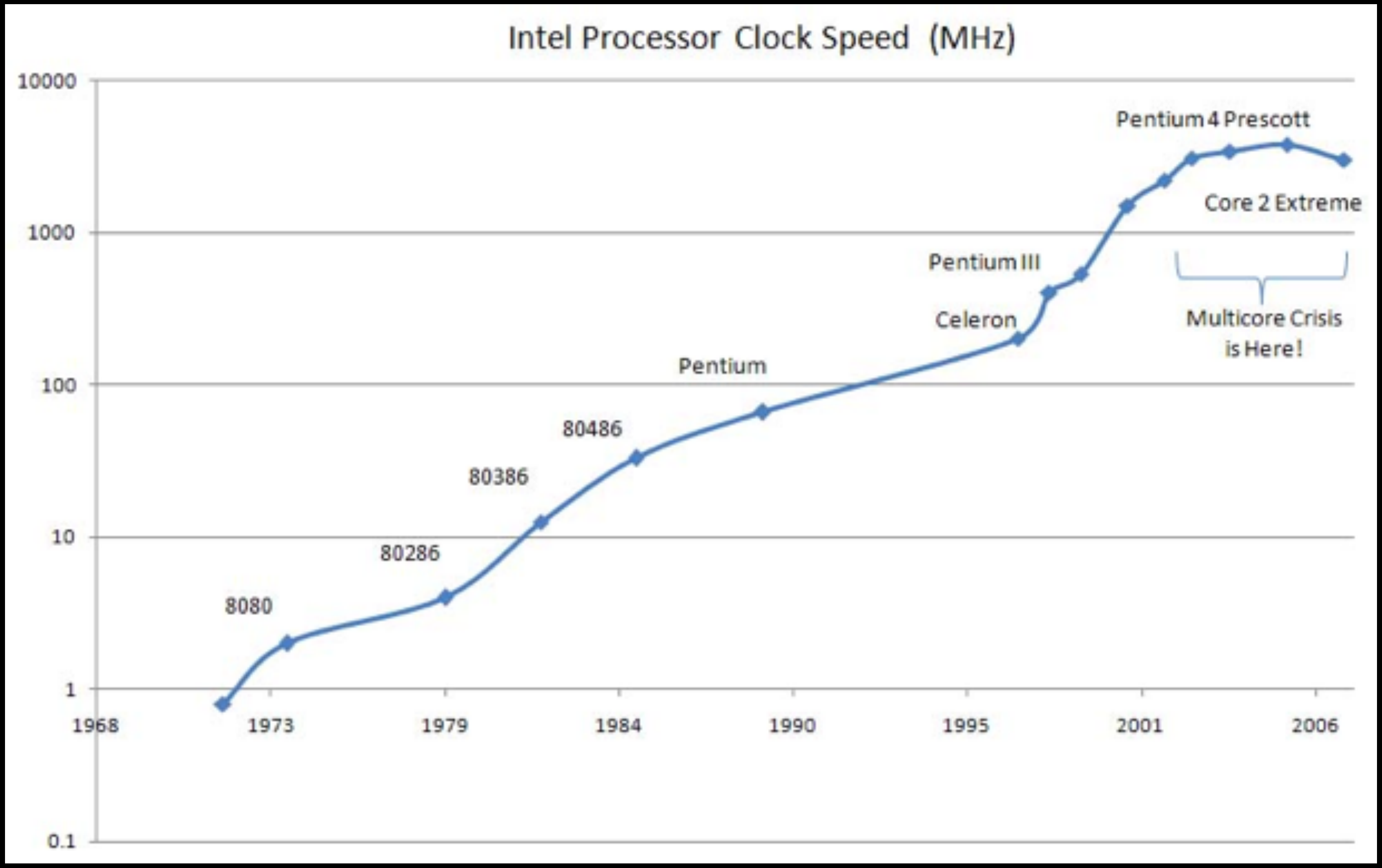
- Gradient of logprob is sum of T uncorrelated terms

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

- This means the variance grows linearly with T!

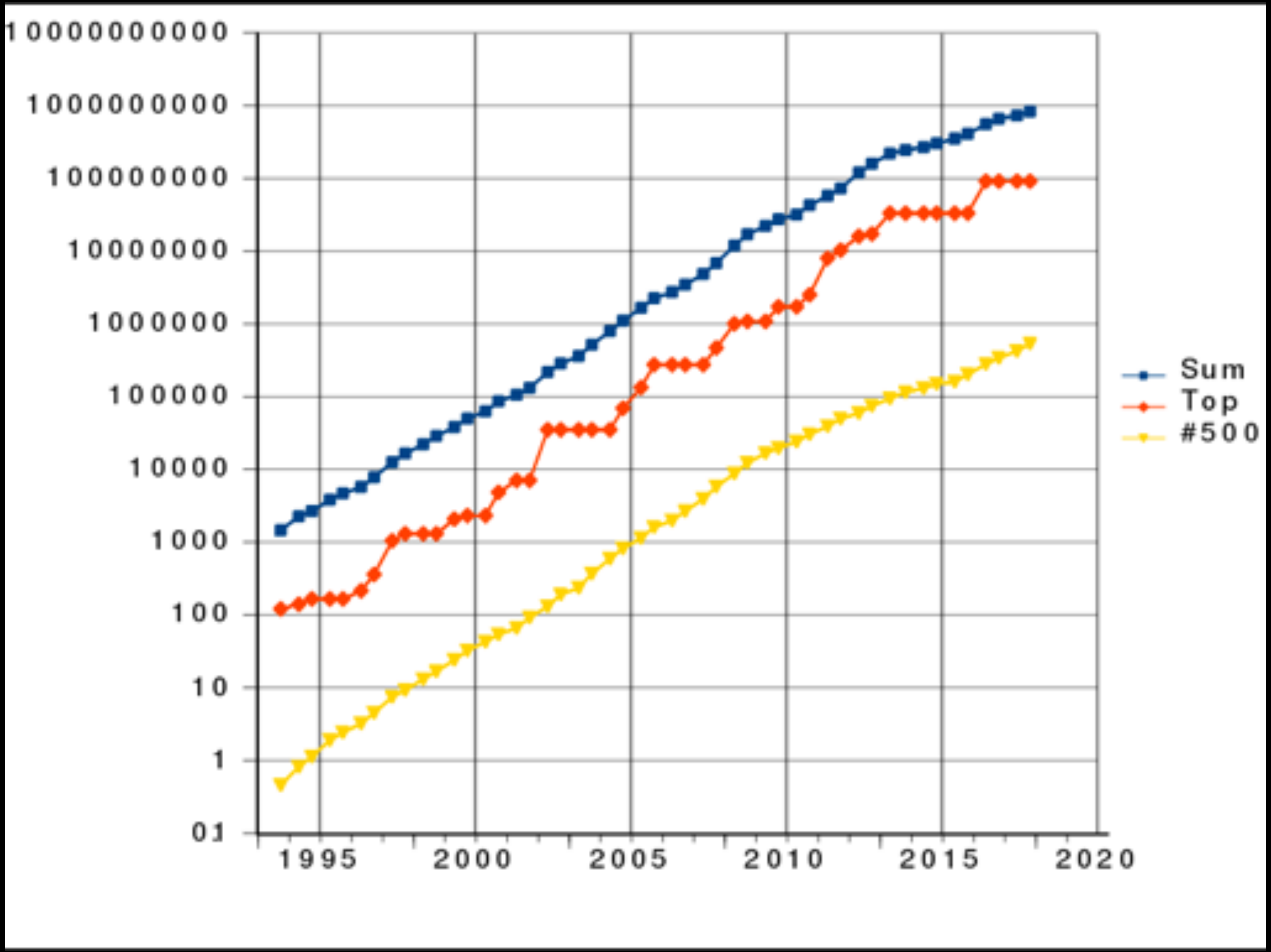
We can do only very little sequential computation

CPU clock speed has stopped improving long ago



source: https://smoothspan.com/2007/09/06/a-picture-of-the-multicore-crisis/

But increased parallelism keeps us going



Supercomputer GFLOPS over time. Source: WikiPedia

Communication is the eventual bottleneck

- Clock speed = constant
- Number of cores $\longrightarrow \infty$

$\longrightarrow$ **communication bandwidth between cores becomes bottleneck**

Thought experiment:
What's the optimal algorithm to calculate a policy gradient if…

- Sequence length $T \longrightarrow \infty$
- We cannot do credit assignment
- Communication is the only computational bottleneck

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Finite differences!

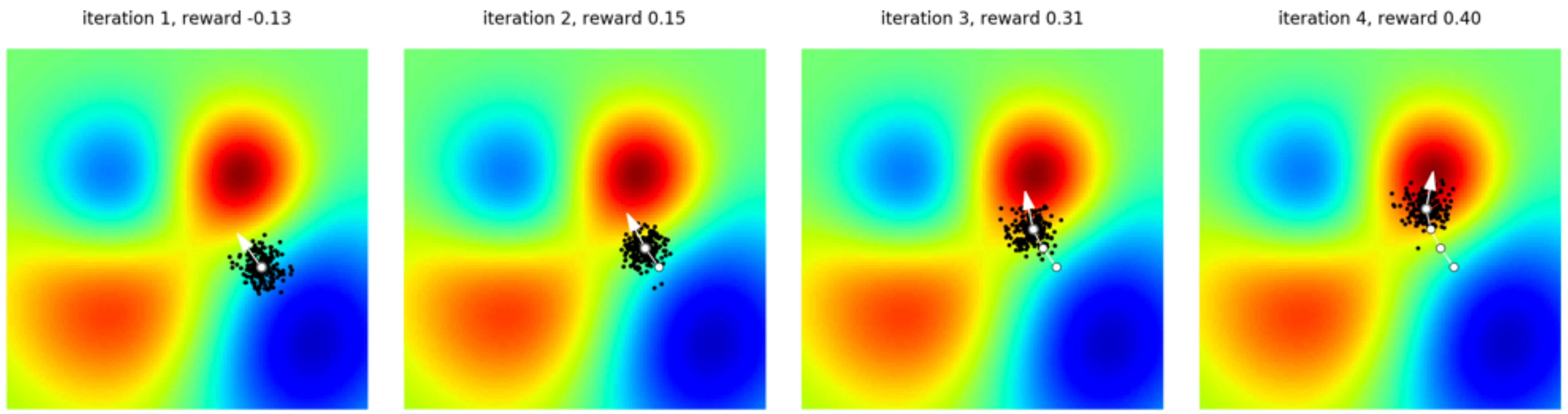
Finite differences and other black box optimizers

$$\nabla_{\theta_i} F_{PG}(\theta) \approx \frac{\mathbb{E}_{\mathbf{a}\sim p(\mathbf{a};\theta_i+\epsilon)}[R(\mathbf{a})] - \mathbb{E}_{\mathbf{a}\sim p(\mathbf{a};\theta_i-\epsilon)}[R(\mathbf{a})]}{2\epsilon}$$

- Each function evaluation only requires communicating a scalar result
- Variance independent of sequence length
- No credit assignment required

Evolution Strategies

- Old technique, known under many other names
- Randomized finite differences:
  - Add noise vector ε to the parameters
  - If the result improves, keep the change
  - Repeat



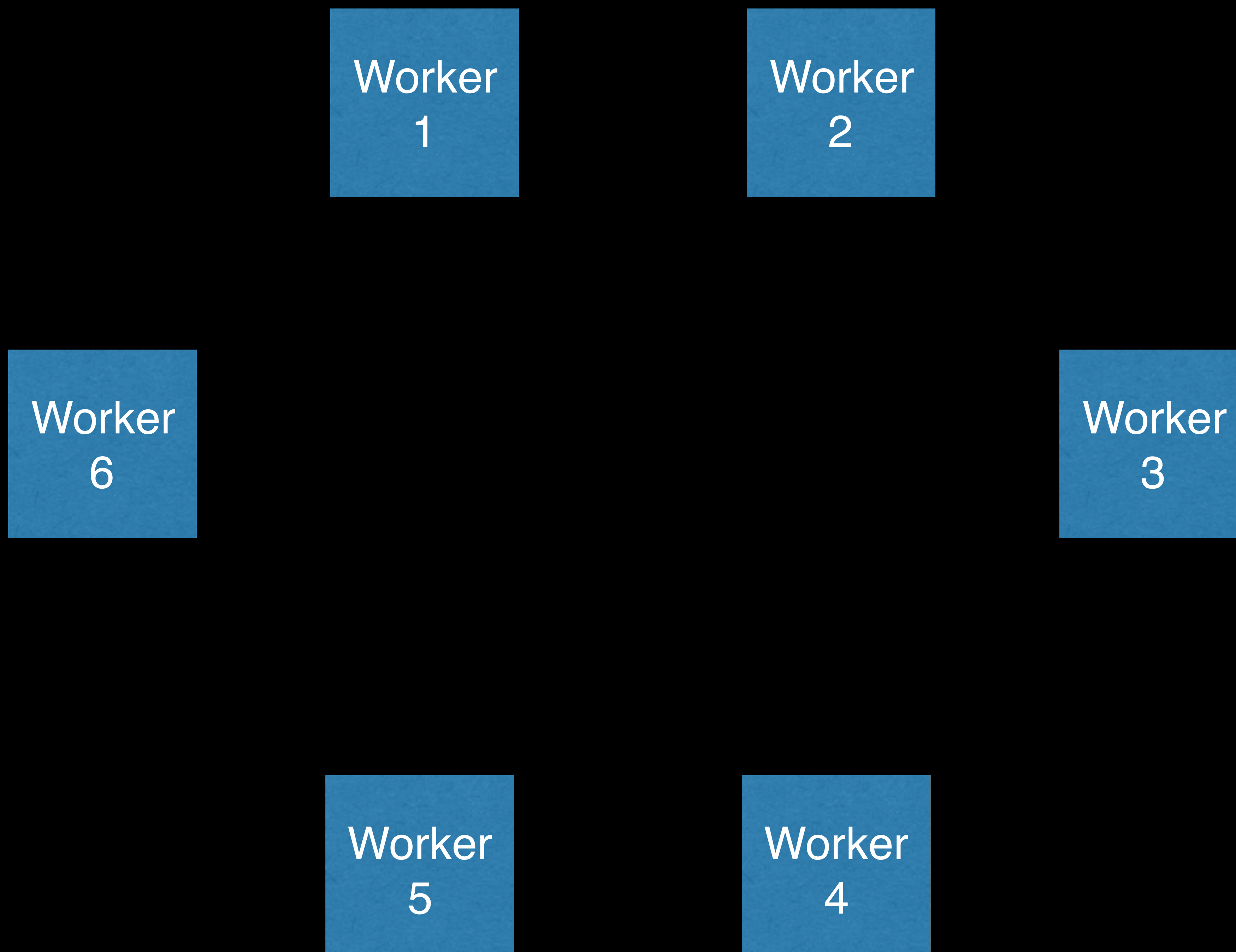
Parallelization

- You have a bunch of workers
- They all try on different random noise
- Then they report how good the random noise was
- But they *don't need to communicate the noise vector*
- Because they know each other's seeds!

Parallelization

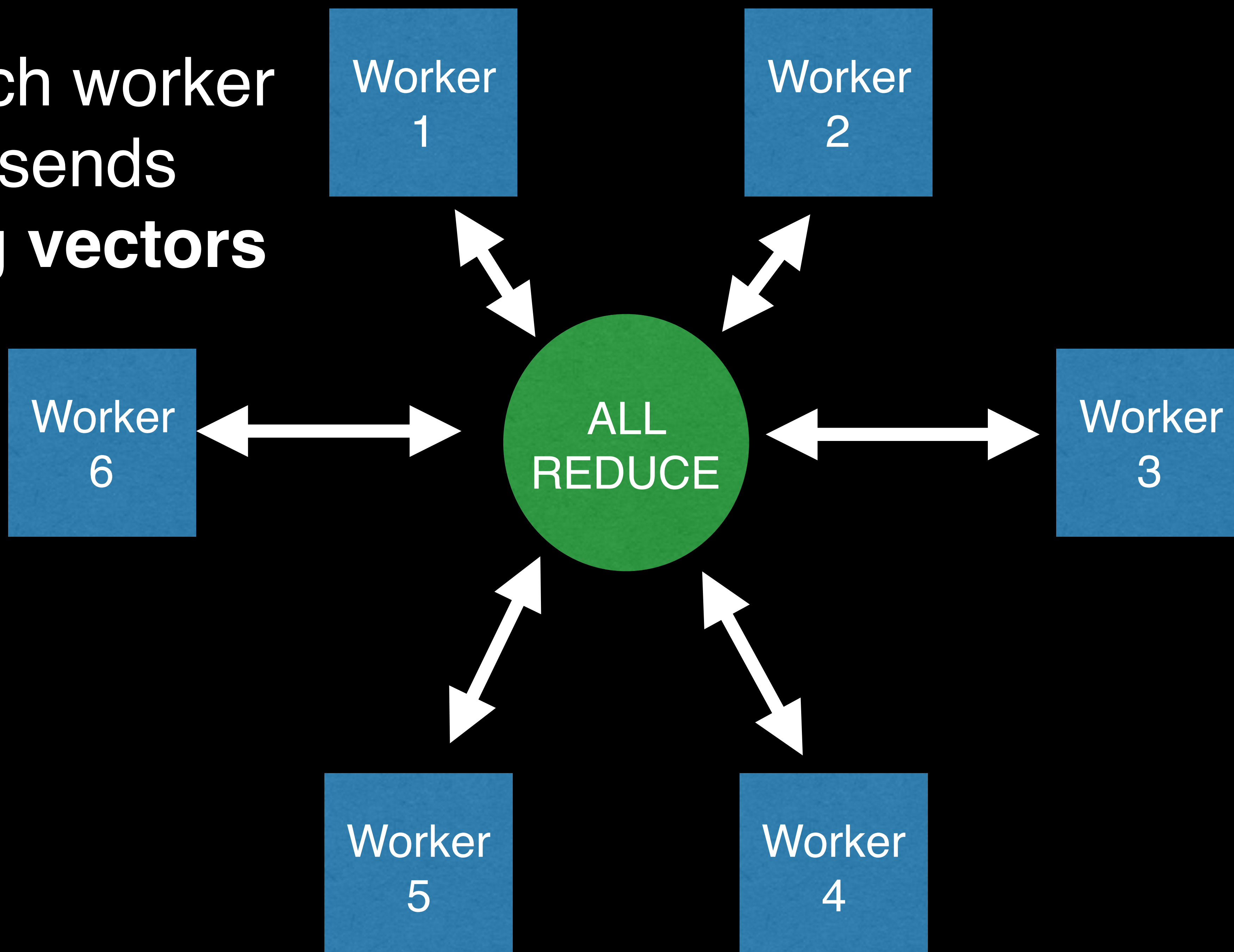
Input: Learning rate α, noise standard deviation σ, initial policy parameters θ_0
Initialize: n workers with known random seeds, and initial parameters θ_0
for $t = 0, 1, 2, \ldots$ **do**
  for each worker $i = 1, \ldots, n$ **do**
    Sample $\epsilon_i \sim \mathcal{N}(0, I)$
    Compute returns $F_i = F(\theta_t + \sigma\epsilon_i)$
  end for
  Send all scalar returns F_i from each worker to every other worker
  for each worker $i = 1, \ldots, n$ **do**
    Reconstruct all perturbations ϵ_j for $j = 1, \ldots, n$ using known random seeds
    Set $\theta_{t+1} \leftarrow \theta_t + \alpha \frac{1}{n\sigma} \sum_{j=1}^{n} F_j \epsilon_j$
  end for
end for

Distributed Deep Learning



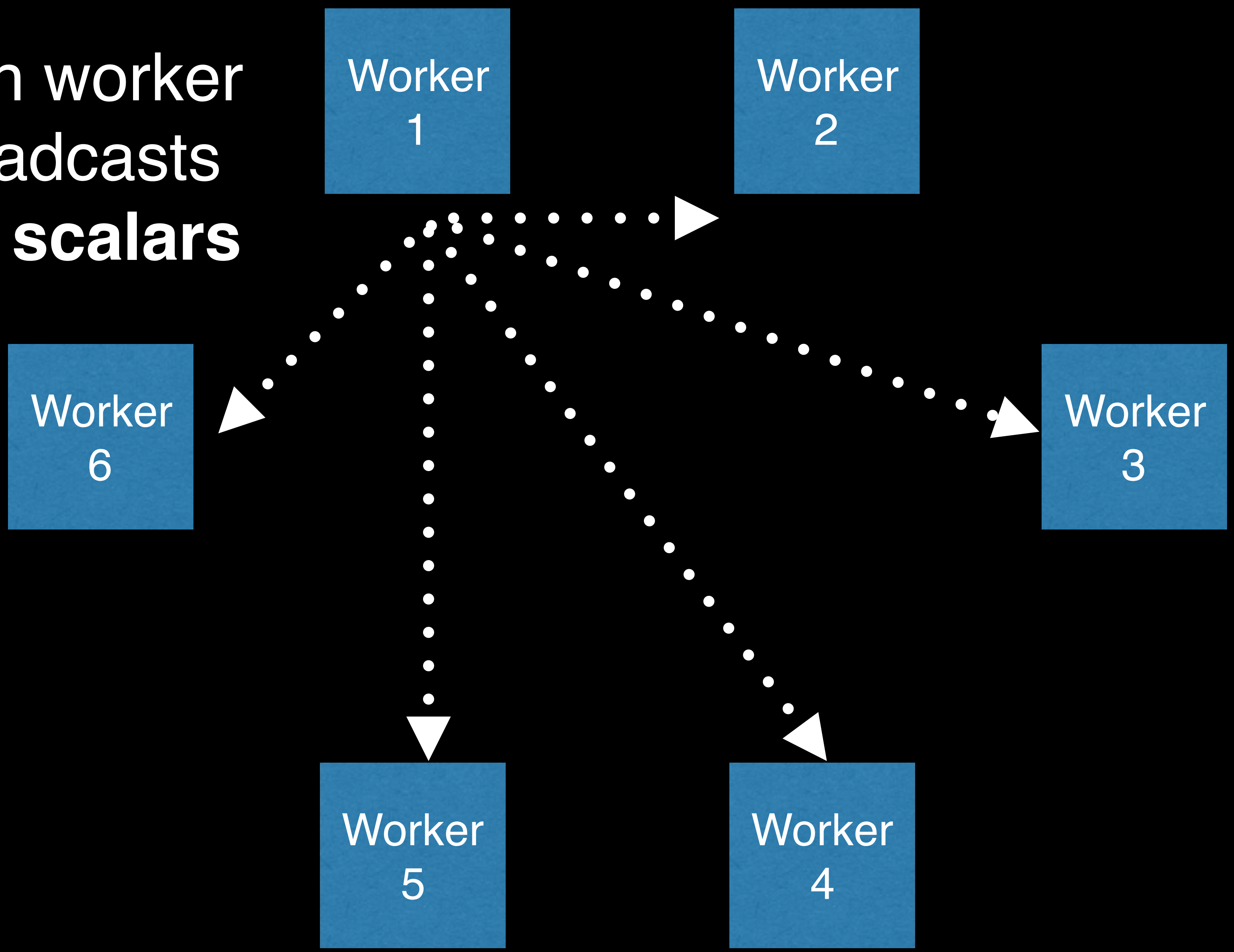
Distributed Deep Learning

Each worker sends **big vectors**



Distributed Evolution Strategies

Each worker broadcasts **tiny scalars**



Distributed Evolution Strategies

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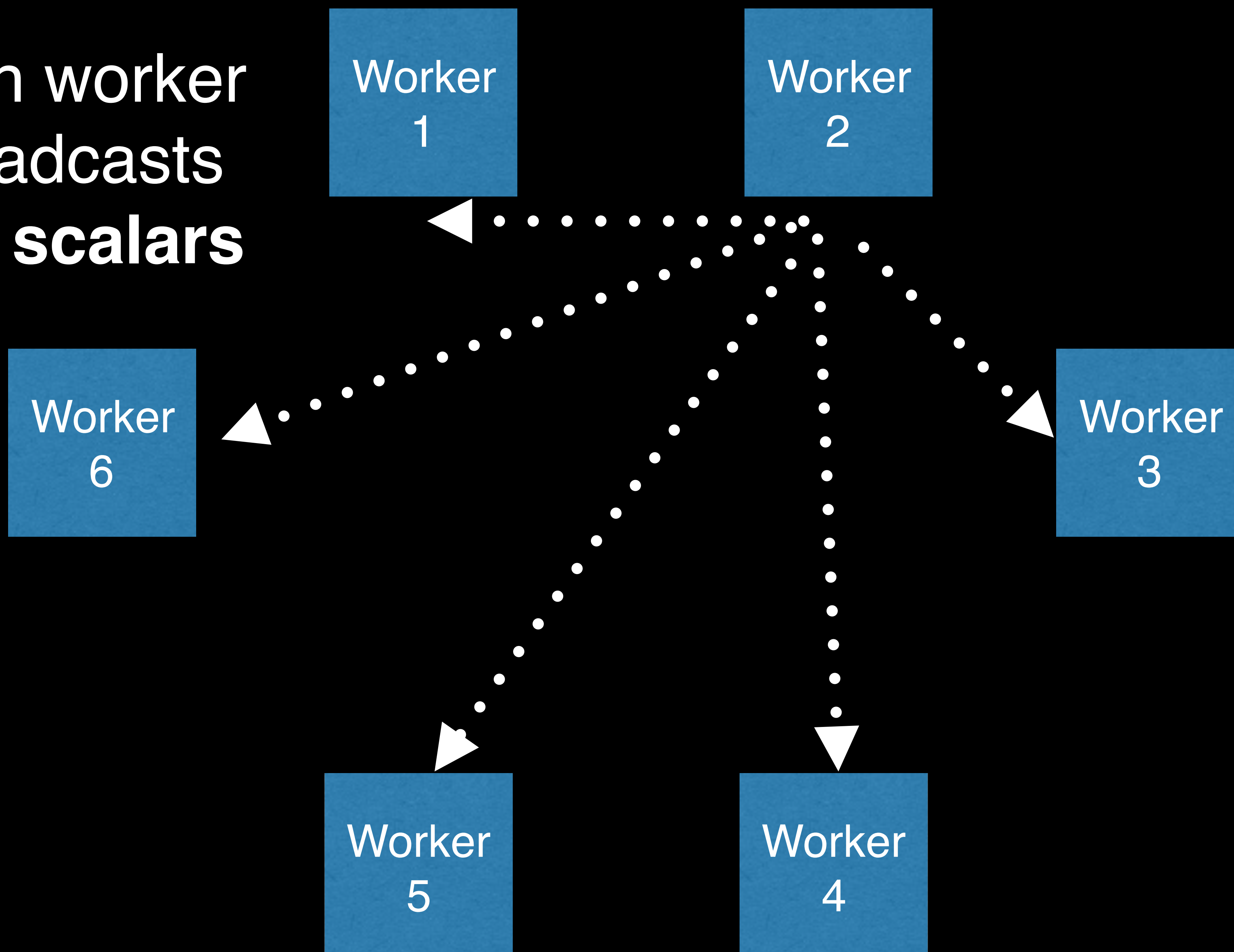

Distributed Evolution Strategies

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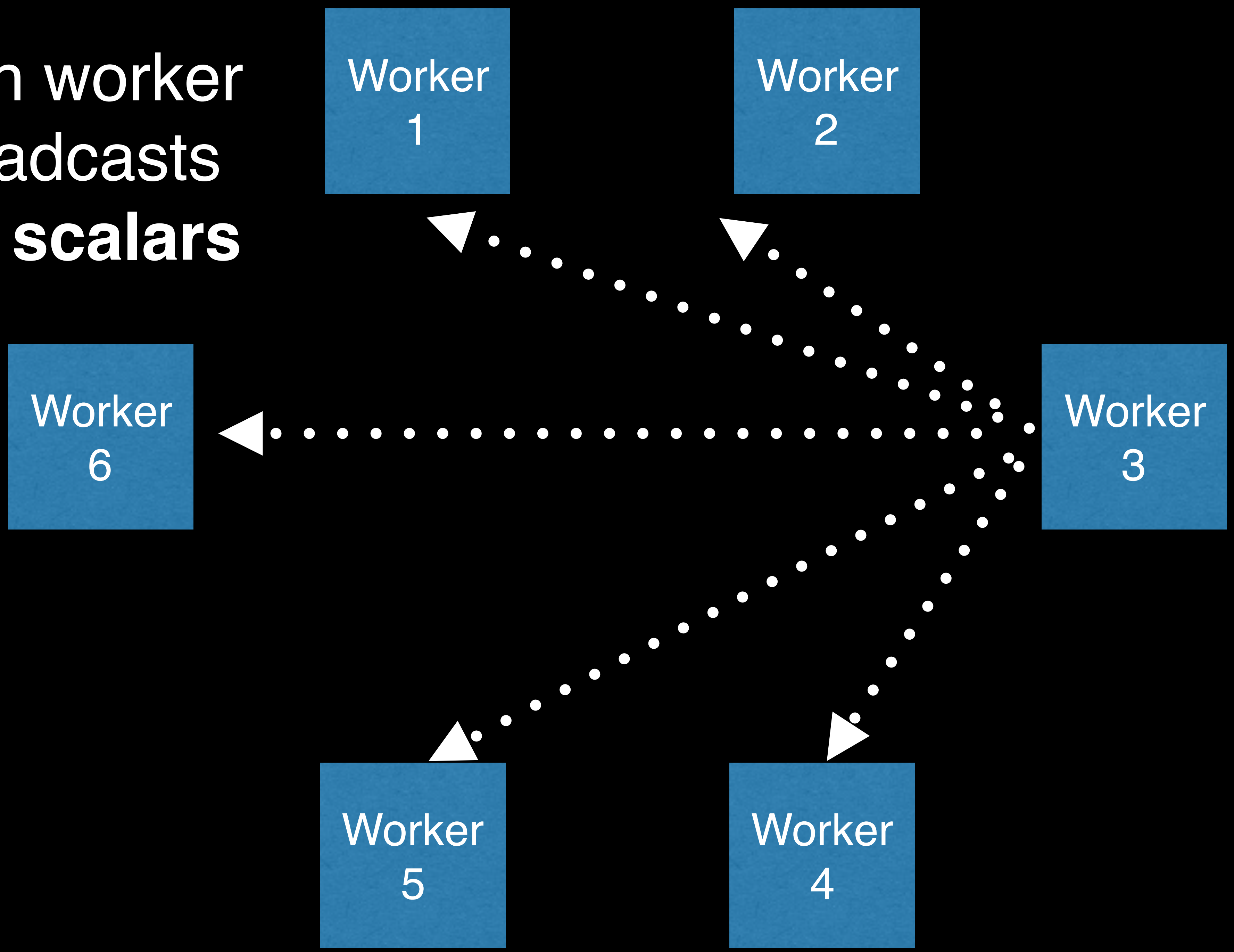
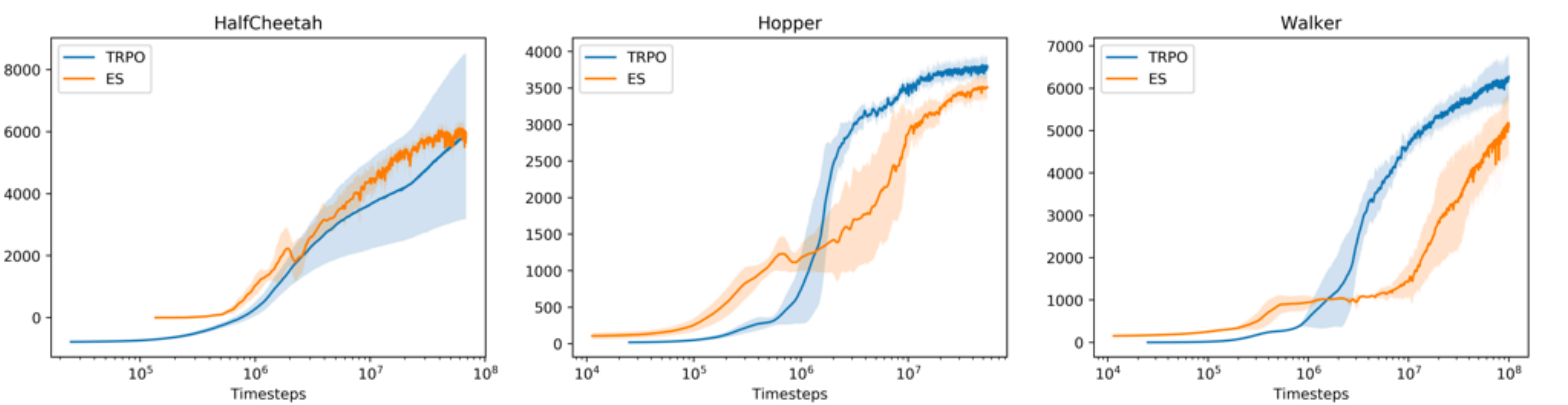


Does it work in practice?

- Surprisingly competitive with popular RL techniques in terms of data efficiency
    - need 3-10x more data than TRPO / A3C on MuJoCo and Atari
- No backward pass, no need to store activations in memory
- Near perfect scaling

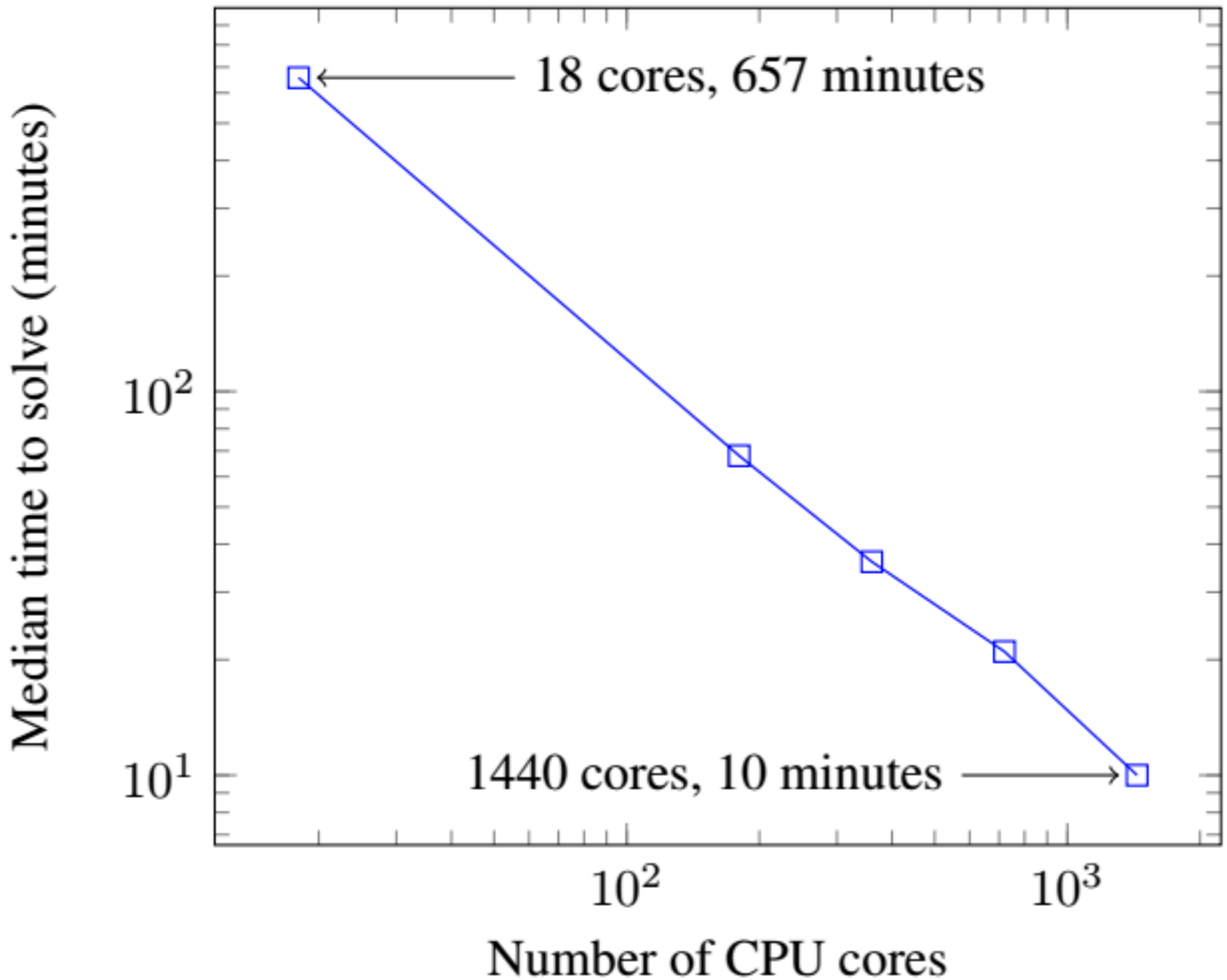
MuJoCo results

- ES needs more data, but it achieves nearly the same result
- If we use 1440 cores, we need **10 minutes** to solve the humanoid task, which takes 1 day with TRPO on a single machine



Distributed Evolution Strategies

- Quantitative results on the Humanoid MuJoCo task:

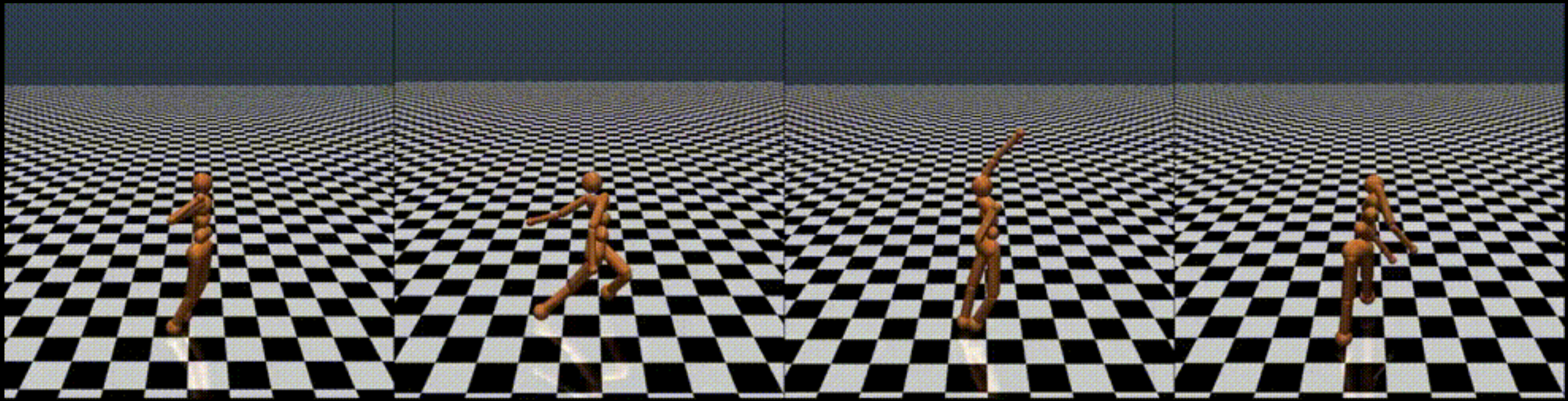


Distributed Evolution Strategies

- Networking requirements very limited
- Cheap! $12 to rent 1440 cores for an hour on Amazon EC2 with spot pricing
- Can run the experiment 6 times for $12!

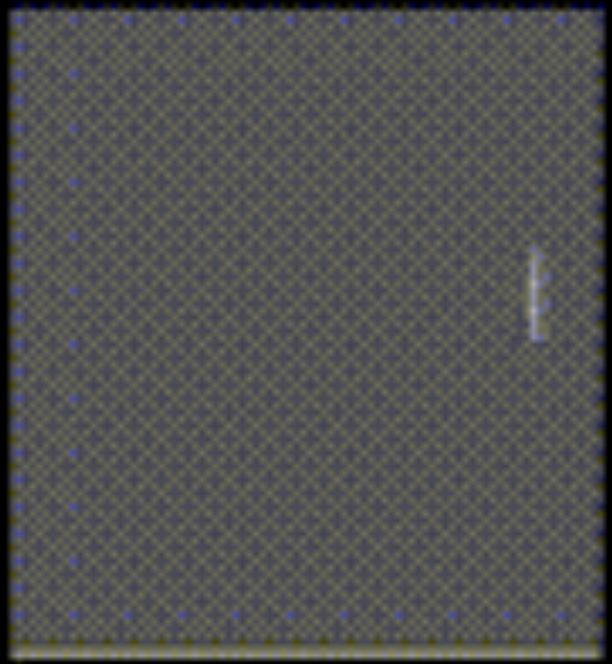
MuJoCo Results

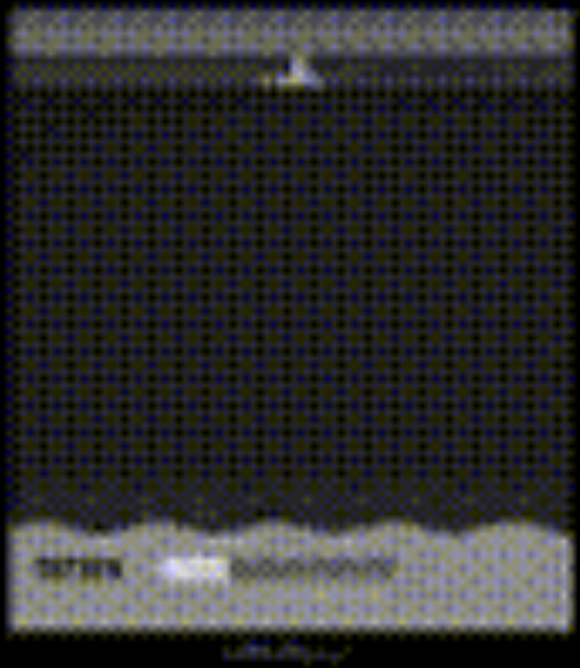
- Humanoid walker

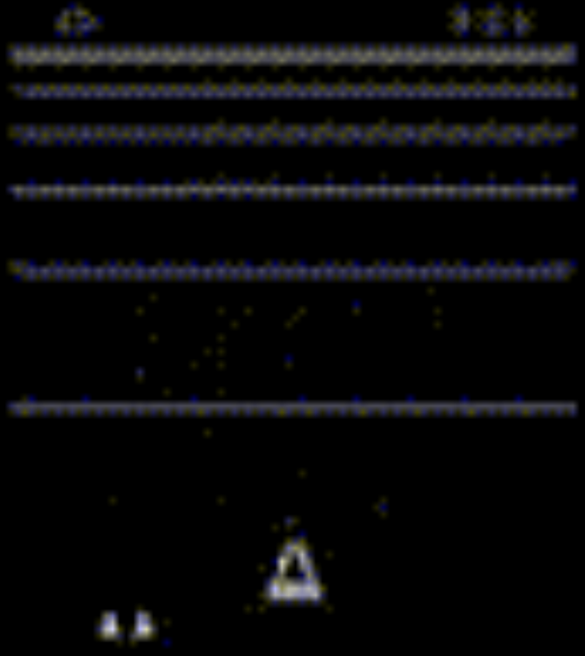


Atari Results

- We can match one-day A3C on Atari games on average (better on 50%, worse on 50% of games) in **1 hour** of our distributed implementation with 720 cores



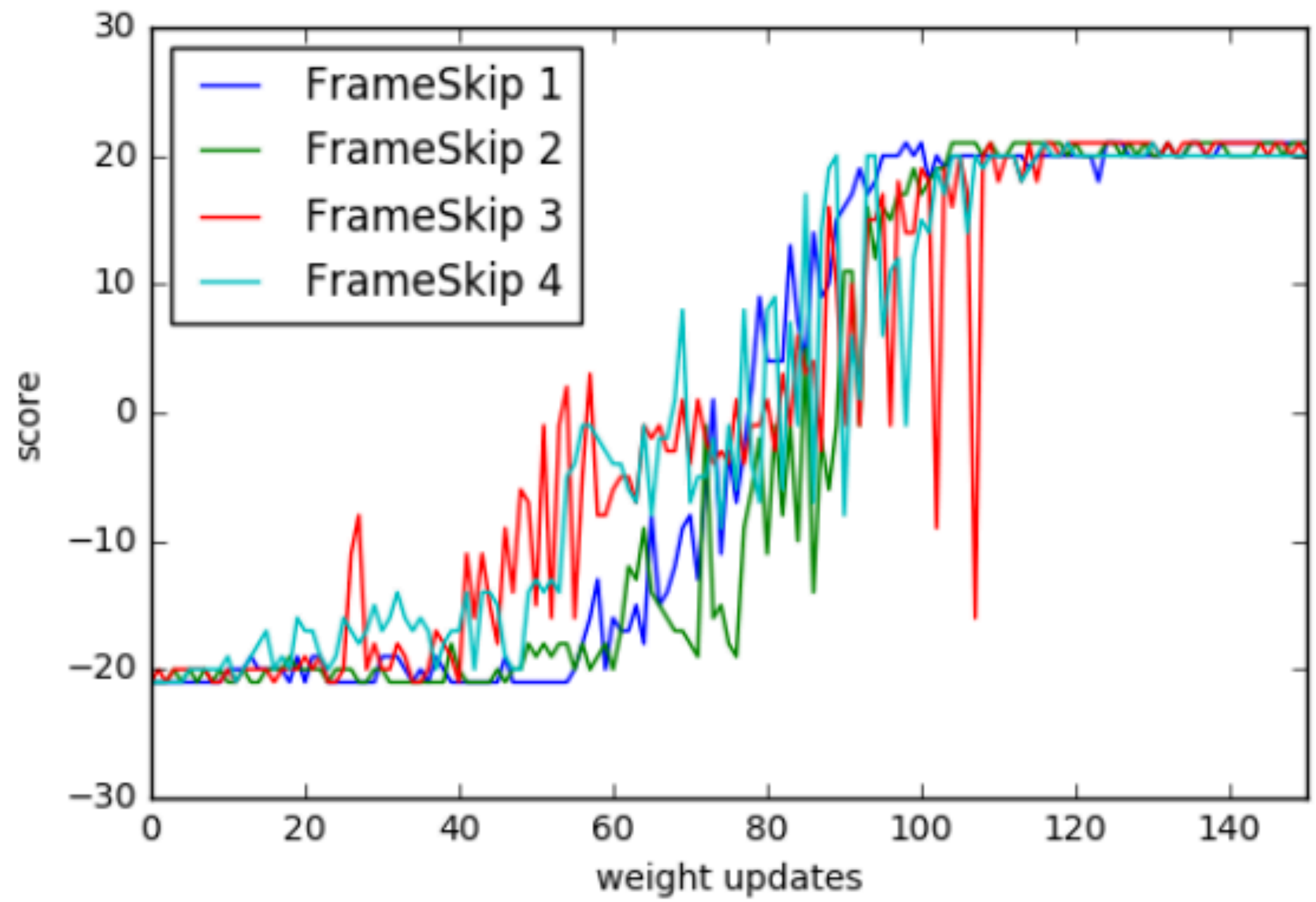




Long Horizons

- Long horizons are hard for RL
- RL is sensitive to action frequency
- Higher frequency of actions makes the RL problem more difficult
- Not so for Evolution Strategies

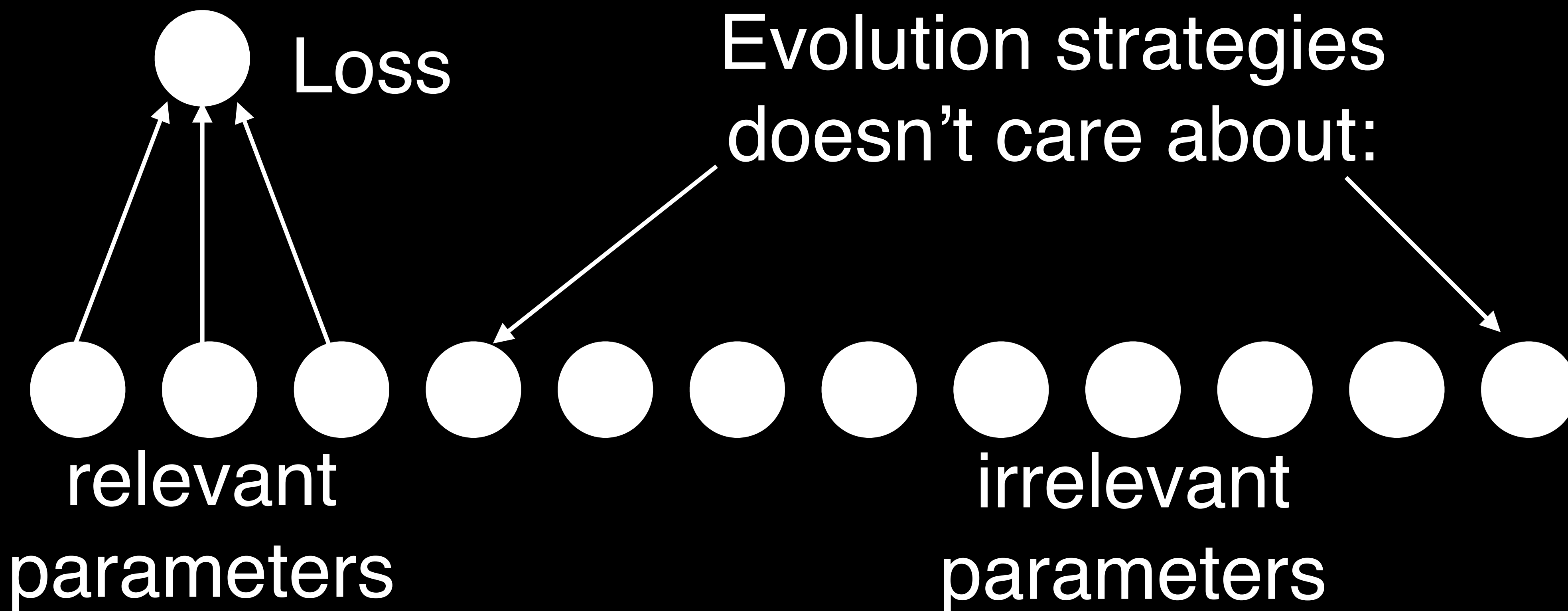
Long Horizons



How can it work in high dimensions?

- Fact: the speed of Evolution Strategies depends on the intrinsic dimensionality of the problem, not on the actual dimensionality of the neural net policy

Intrinsic Dimensionality



- Evolution strategies *automatically discards* the irrelevant dimensions — even when they live on a complicated subspace!

Intrinsic Dimensionality

- One explanation for how hill-climbing can succeed in a million-dimensional space!

- Parameterization of policy matters more than number of parameters

    - Virtual batch normalization helps a lot

      Salimans et al. (2016) "Improved techniques for training GANs."

    - Future advances to be made?

Backprop vs Evolution Strategies

- Evolution strategies does not use backprop
- So scale of initialization, vanishing gradients, etc, are not important?

Backprop vs Evolution Strategies

- Counterintuitive result: *every* trick that helps backprop, also helps evolution strategies
    - scale of random init, batch norm, ResNet…
- Why? Because evolution strategies tries to estimate *the gradient*!
    - If the gradient is vanishing, we won't get much by estimating it!

Conclusion: pros

- Though experiment: black box methods optimal if long horizon, no credit assignment, bandwidth limited
- Scales extremely well
- Competitive with other RL techniques
- Possibility proof for evolution of intelligence: us

Conclusion: cons

- Natural evolution seems much more sophisticated
  - Better parameterization?
  - Evolution of evolvability?
- Assumption that we cannot solve credit assignment / communication may be pessimistic
  - We should not give up on improvements in credit assignment, value functions, hierarchical RL, networking, and communication strategies!