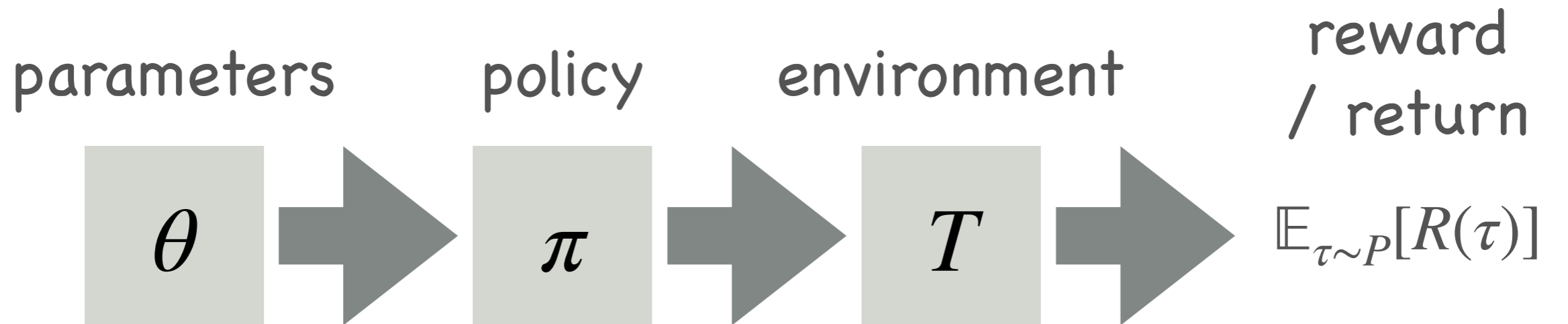


Gradient free optimization

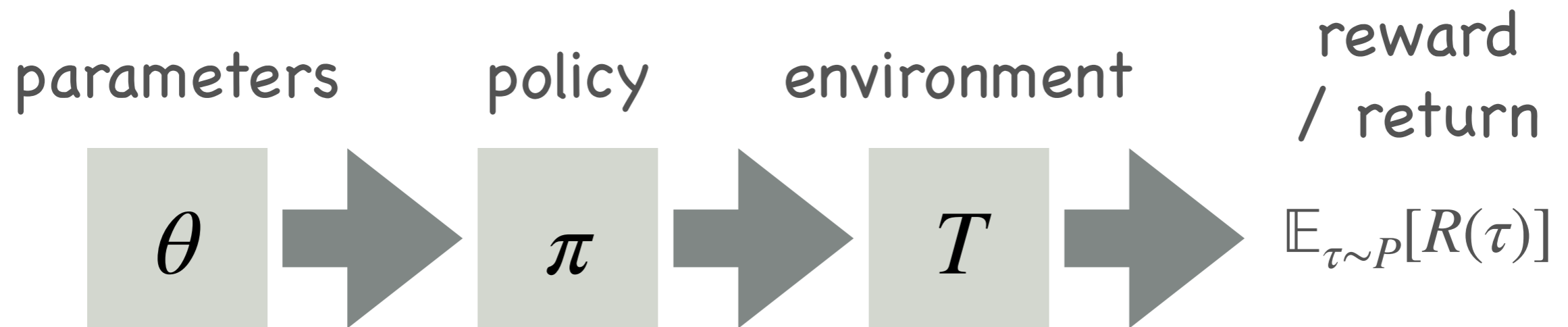
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Why do we need a gradient?



← getting good gradients is hard!

Why do we need a gradient?



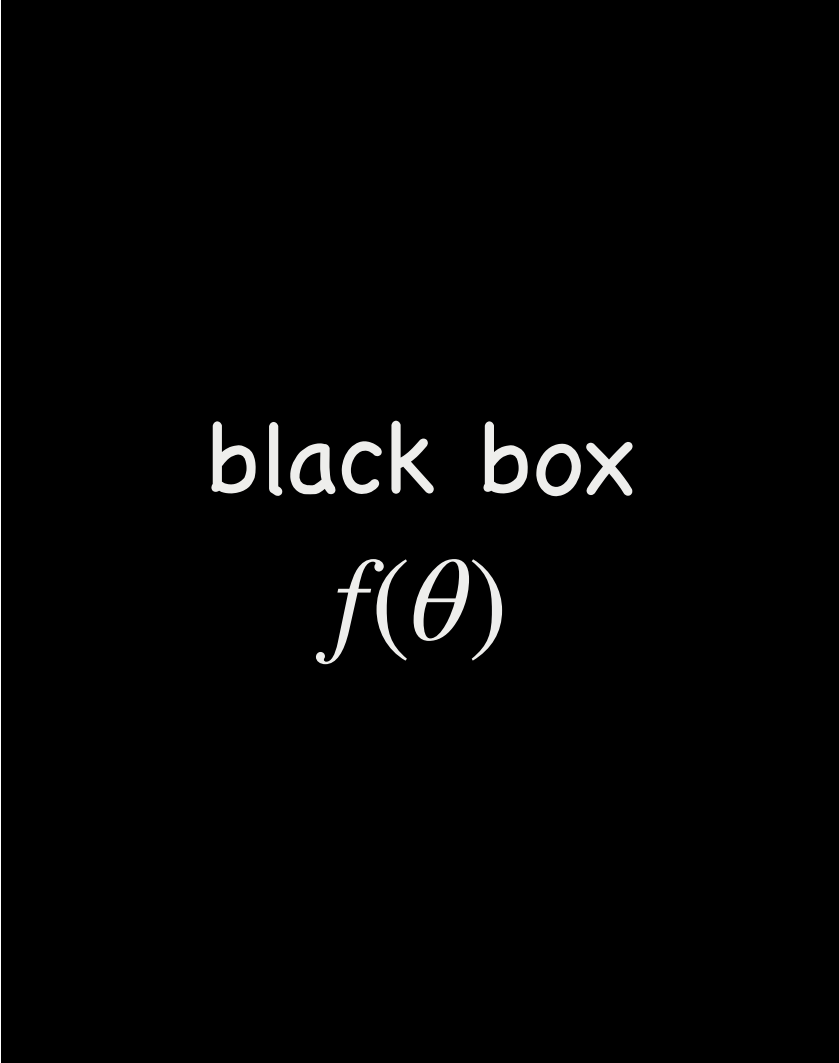
is the forward pass hard?

What if we had an oracle?

- Given policies π_A and π_B
- which one is better?
 - rollout and compute return

Gradient Free Optimization

- maximize $f(\theta)$ w.r.t. θ
 - can only evaluate function value
 - no gradients
 - f is smooth
 - similar θ produce similar $f(\theta)$

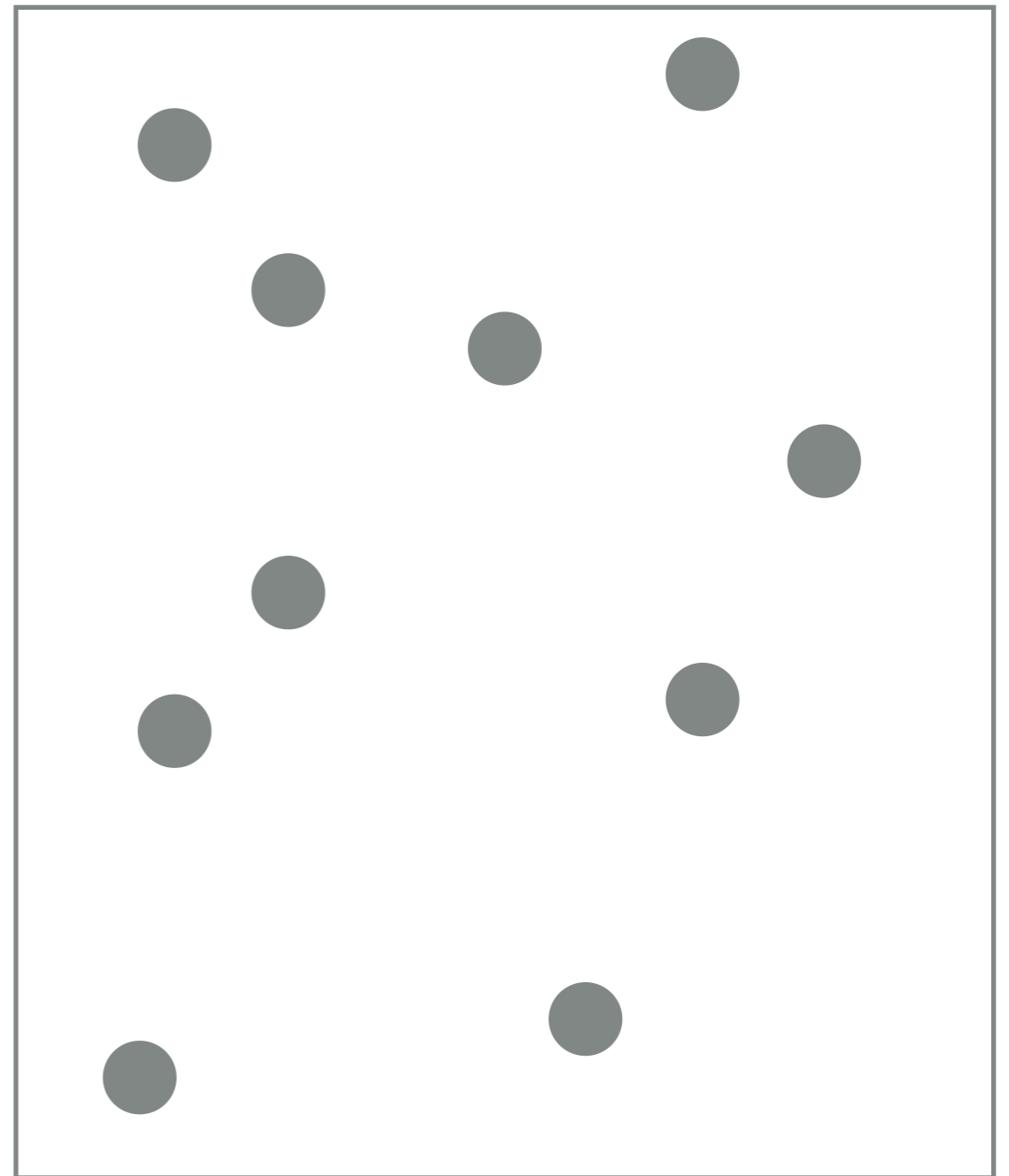


black box
 $f(\theta)$

Random Search

parameters space

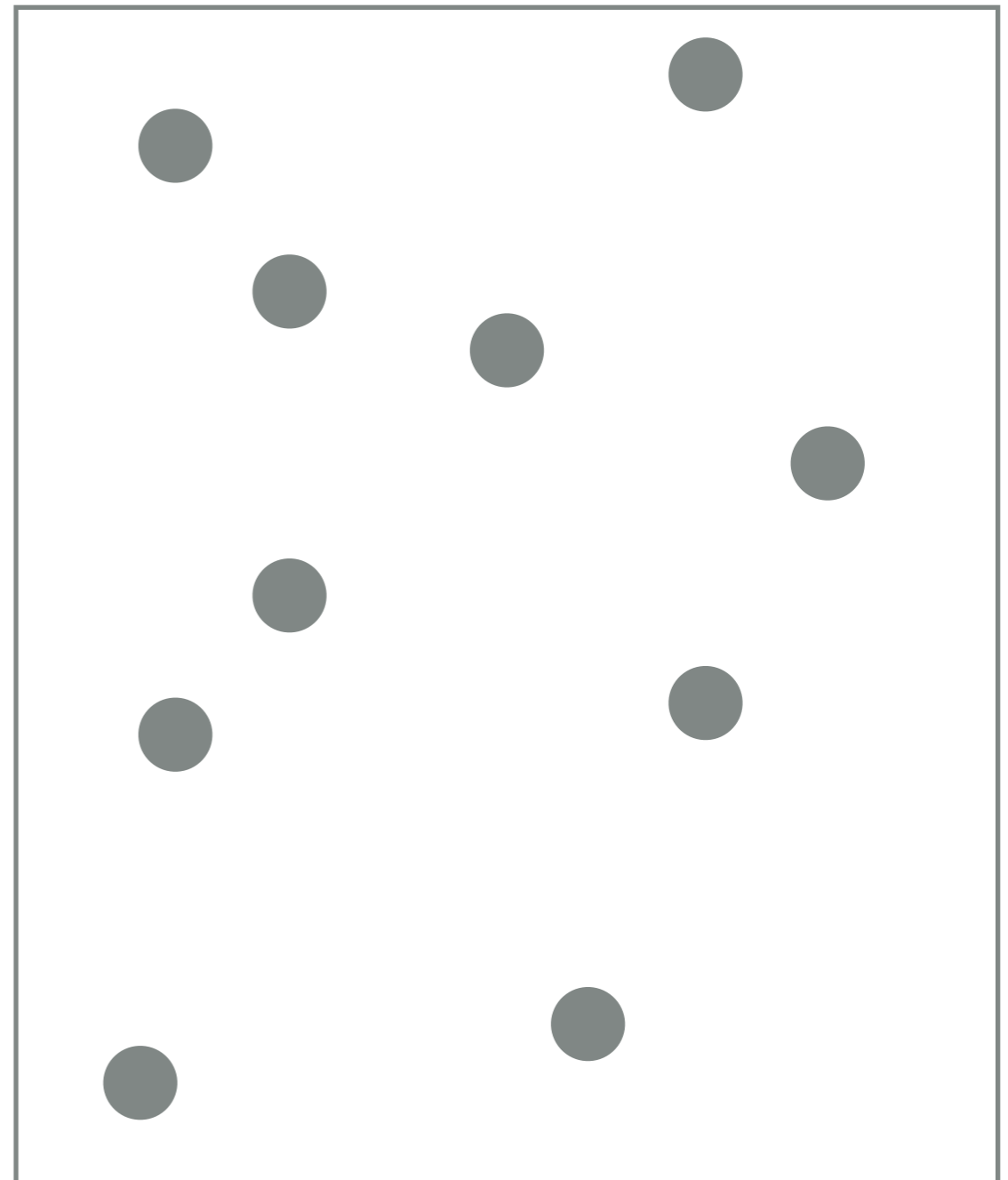
- Randomly sample θ
- pick highest $f(\theta)$



Iterative Random Search

parameters space

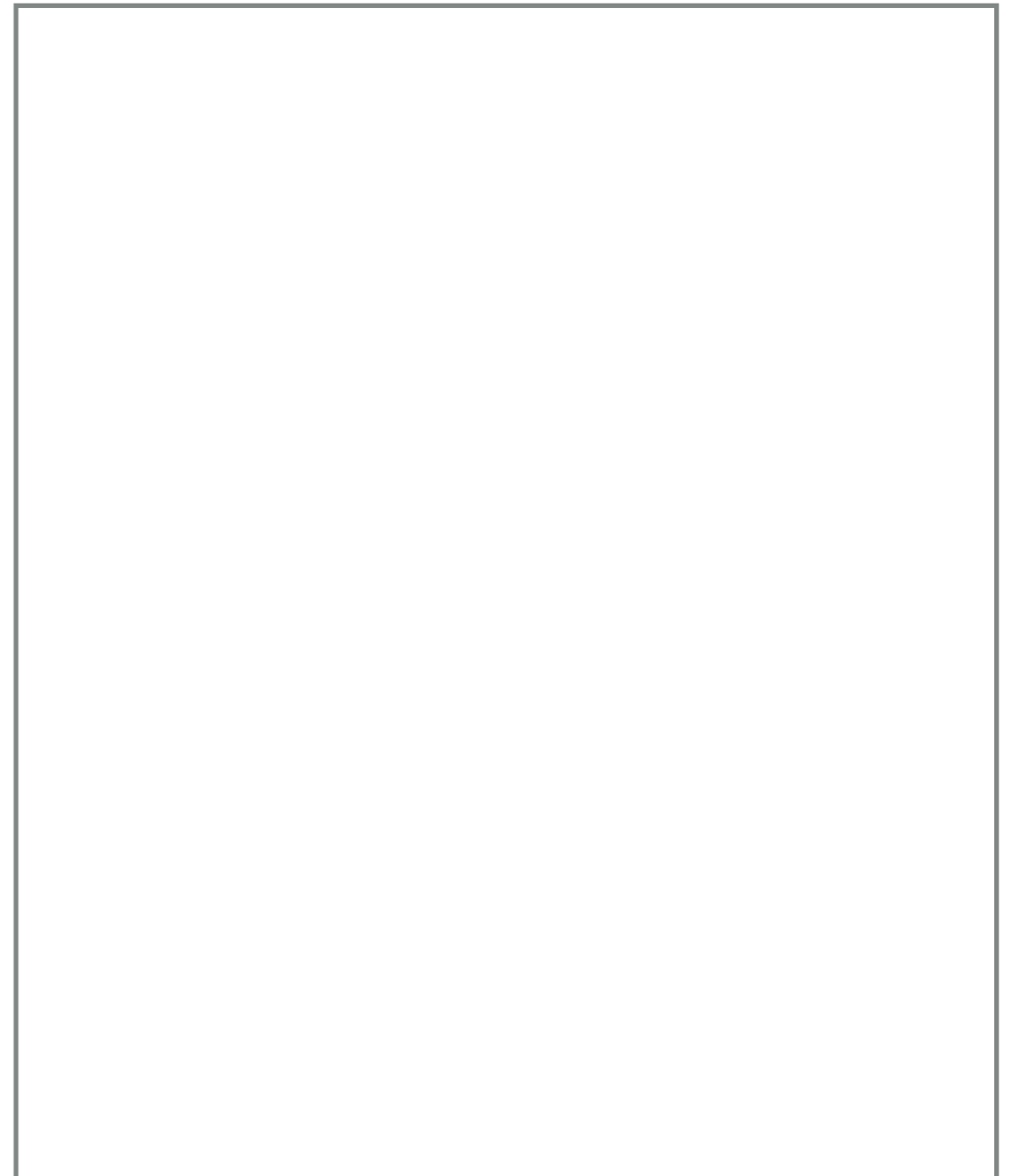
- Randomly sample θ
- pick highest $f(\theta)$
- Sample more points around maxima
- repeat



Cross entropy method

parameters space

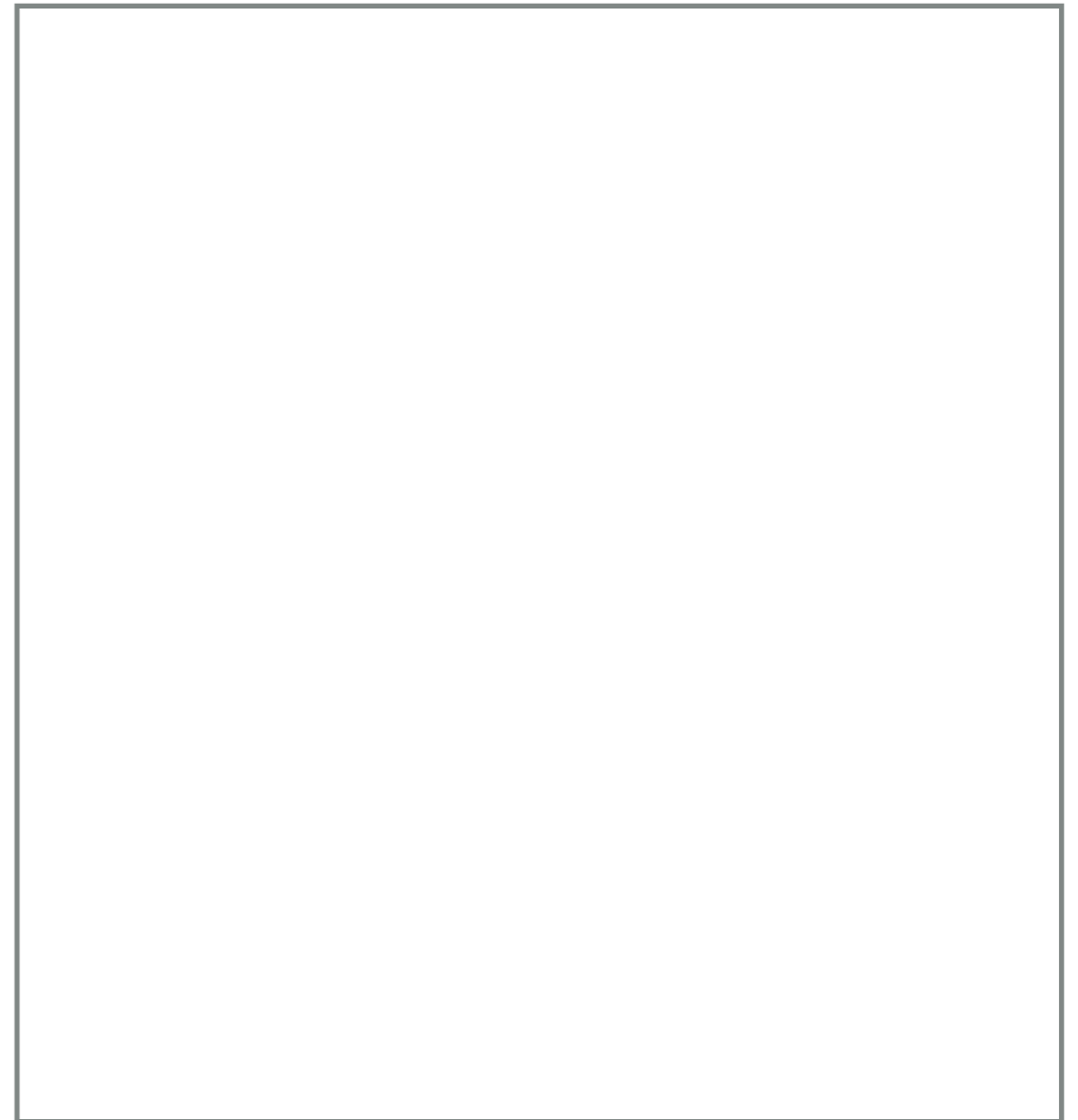
- Initialize μ, σ
 - sample $\theta \sim \mathcal{N}(\mu, \sigma^2)$
 - compute reward $f(\theta)$
 - select top p % ($p = 20$)
 - fit Gaussian for new μ, σ
 - repeat



Evolution Strategies

parameters space

- Initialize θ
- Iterate
 - Sample $\epsilon_0, \epsilon_1, \dots, \epsilon_n \sim \mathcal{N}(0, I)$
 - Compute returns $F_i = R(\theta + \sigma \epsilon_i)$
 - Normalize $\tilde{F}_i = \frac{F_i - \mu_F}{\sigma_F}$
 - Update $w := w + \frac{\alpha}{\sigma n} \sum_{i=1}^n \tilde{F}_i \epsilon_i$



Evolution strategies as a scalable alternative to reinforcement learning, Salimans et al., arXiv 2017

Augmented random search

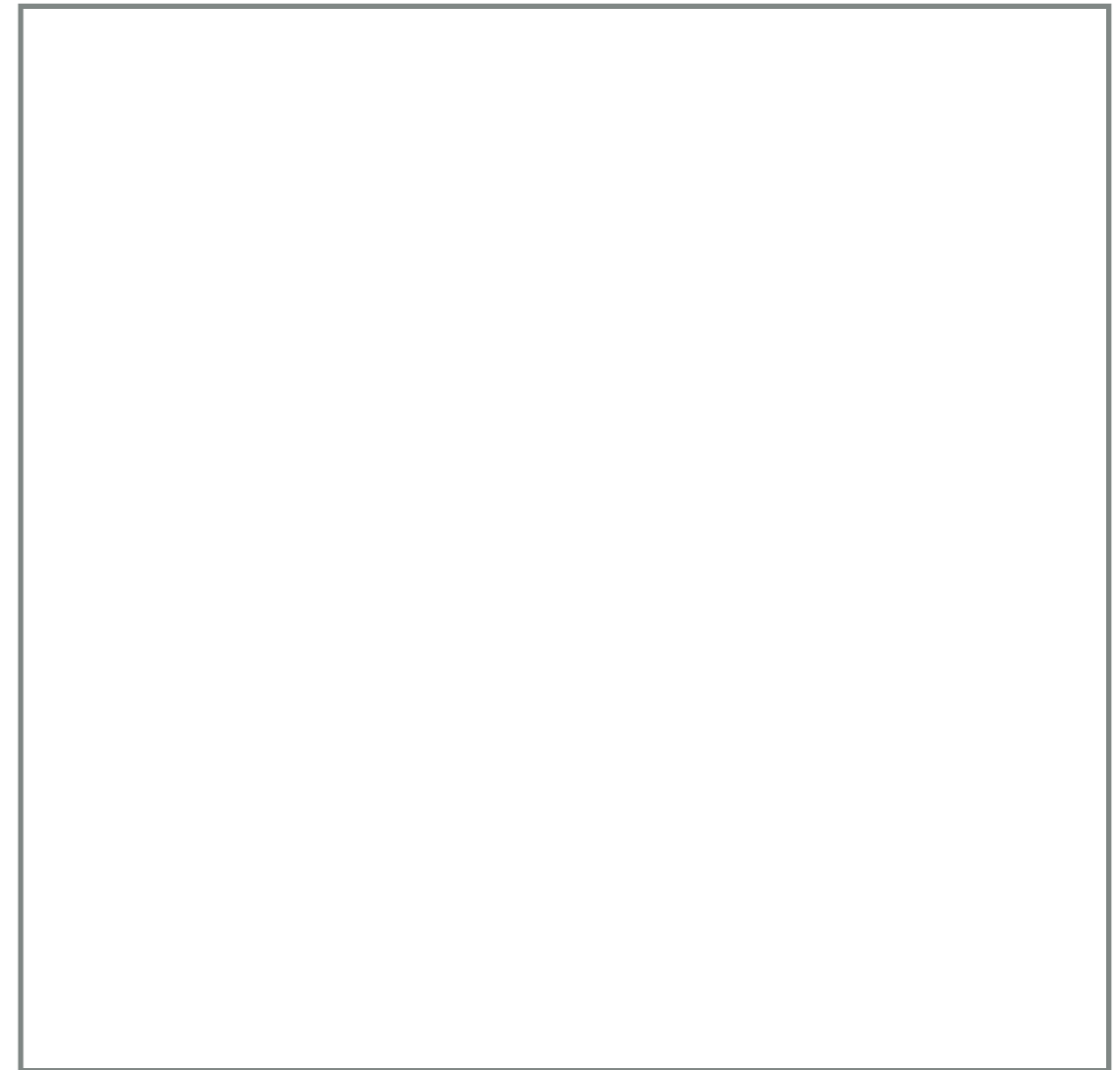
parameters space

- Initialize θ
- Iterate
 - Sample $\epsilon_0, \epsilon_1, \dots, \epsilon_n \sim \mathcal{N}(0, I)$
 - Compute returns $F_i^+ = R(\theta + \sigma\epsilon_i)$,
 $F_i^- = R(\theta - \sigma\epsilon_i)$

- Update

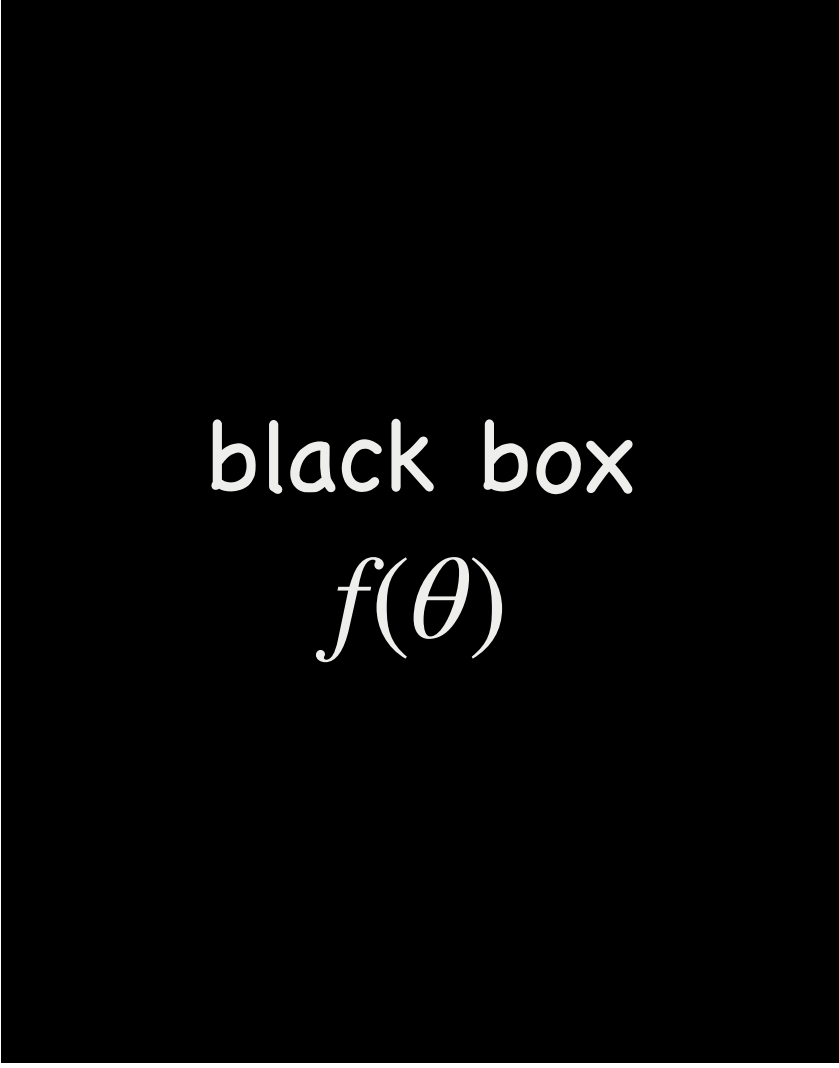
$$w := w + \frac{\alpha}{\sigma n} \sum_{i=1}^n (F_i^+ - F_i^-) \epsilon_i$$

- Simple random search provides a competitive approach to reinforcement learning, Mania et al., NIPS 2018
- Multivariate Stochastic Approximation Using a Simultaneous Perturbation Gradient Approximation, Spall, *Automatic Control*, 1992



Gradient free optimization

- Exponential in parameter space
- works better if
 - parameter space small
 - parameters correlate with expected return



black box
 $f(\theta)$