Reliable RL: An Algorithmic Perspective

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CSAIL

Reinforcement Learning (RL)

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Is RL “real-world-ready”?

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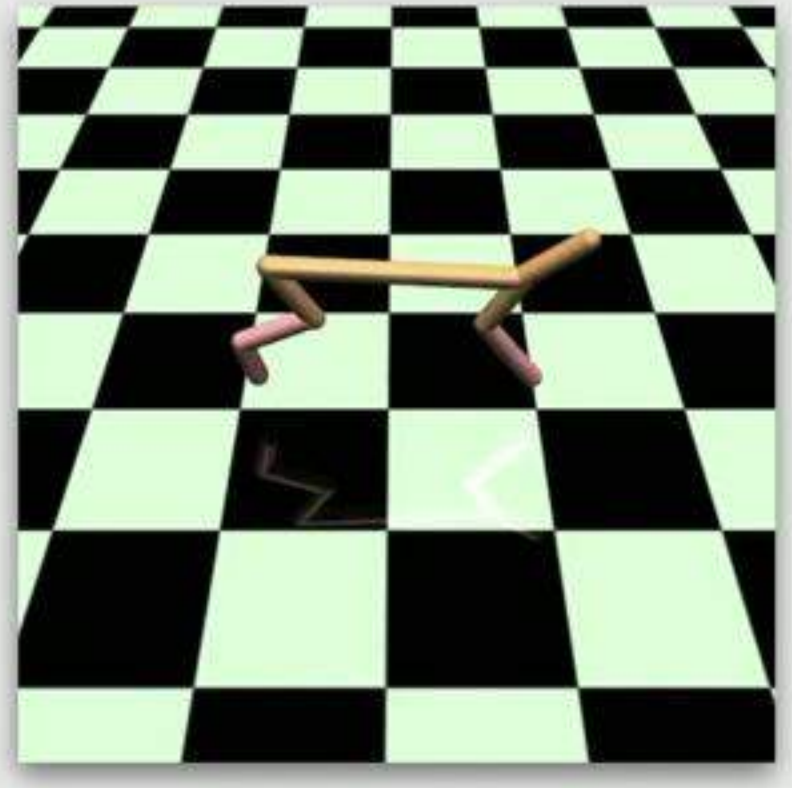
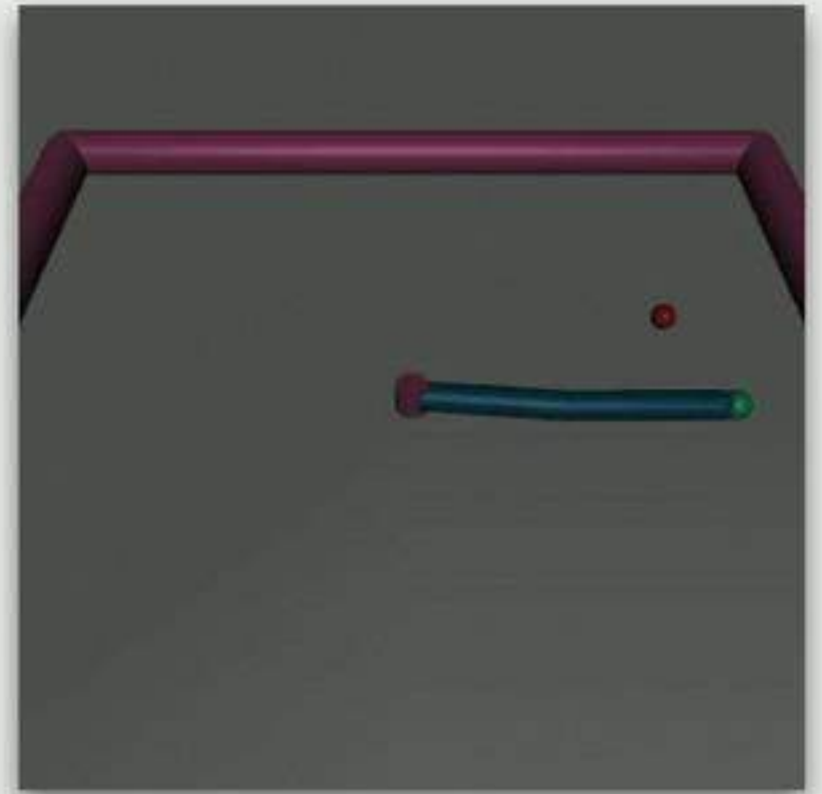
(Spoiler: No)

Deep RL is unreliable even in simple settings...





How do we get reliable RL?

An **algorithmic** understanding of
modern RL methods

The RL Setup

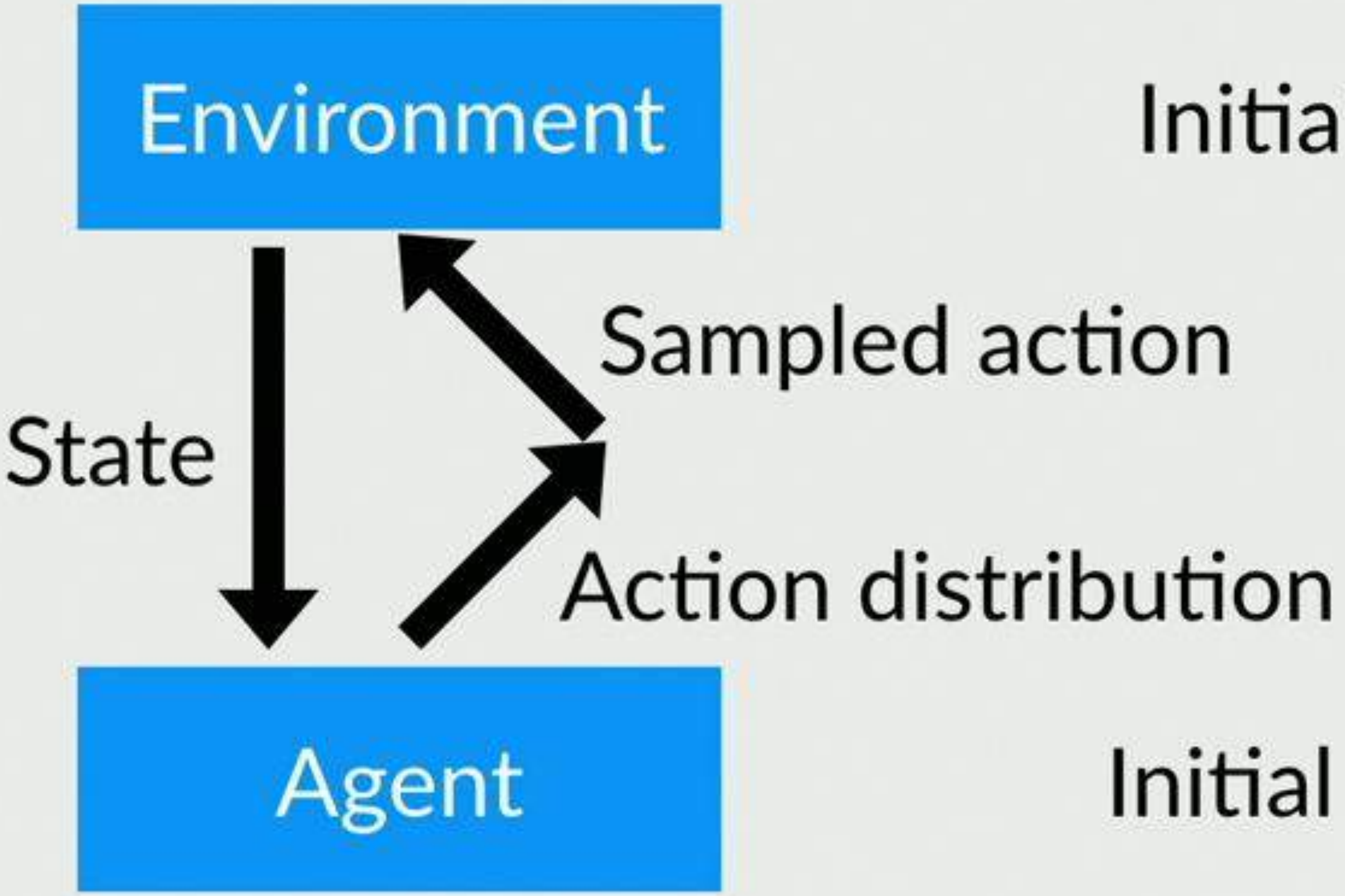
Environment

Initial state s_0

Agent

Initial policy π_0

The RL Setup



Initial state s_0

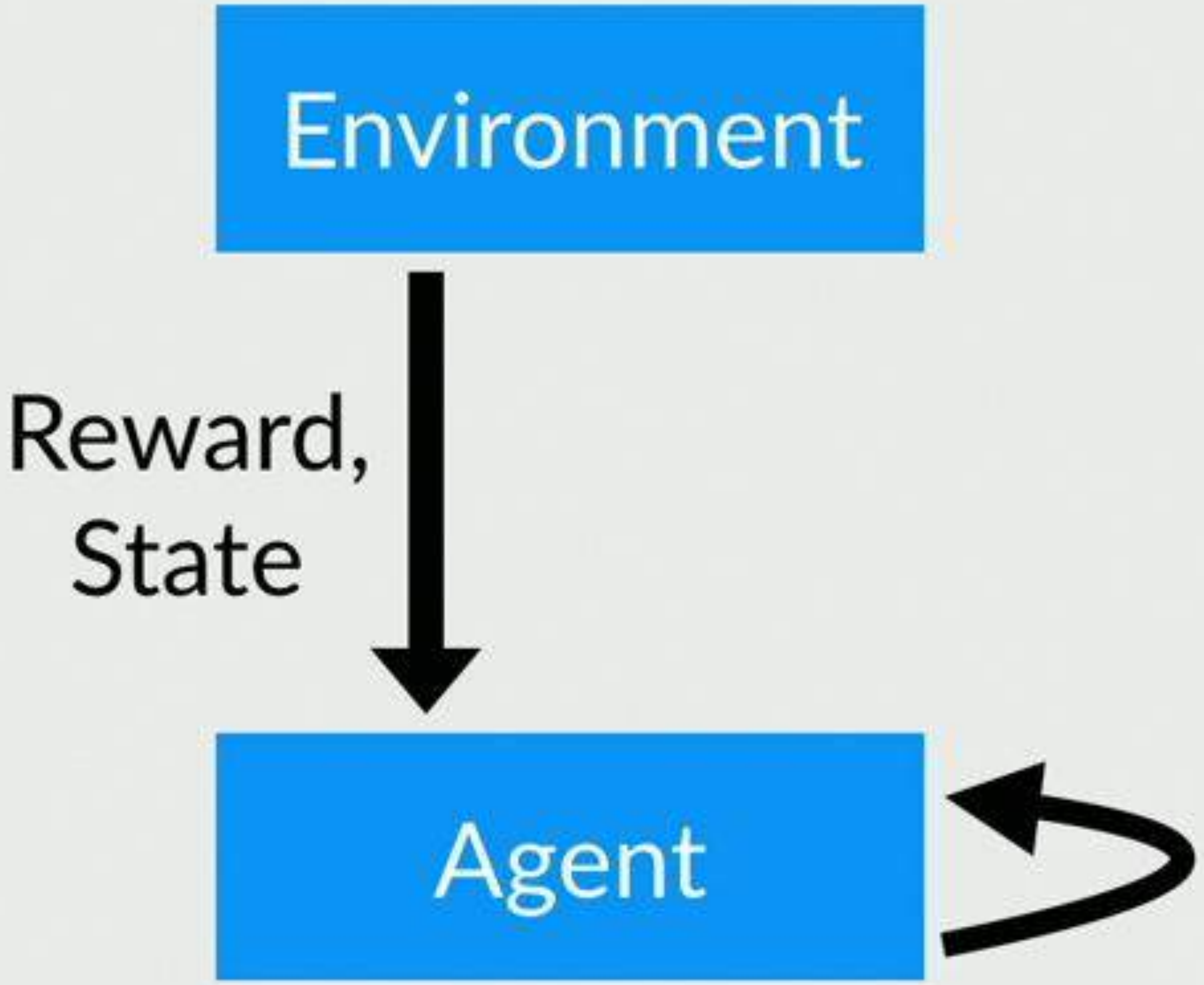
Initial policy π_0

The RL Setup

Next state s_t

Initial policy π_0

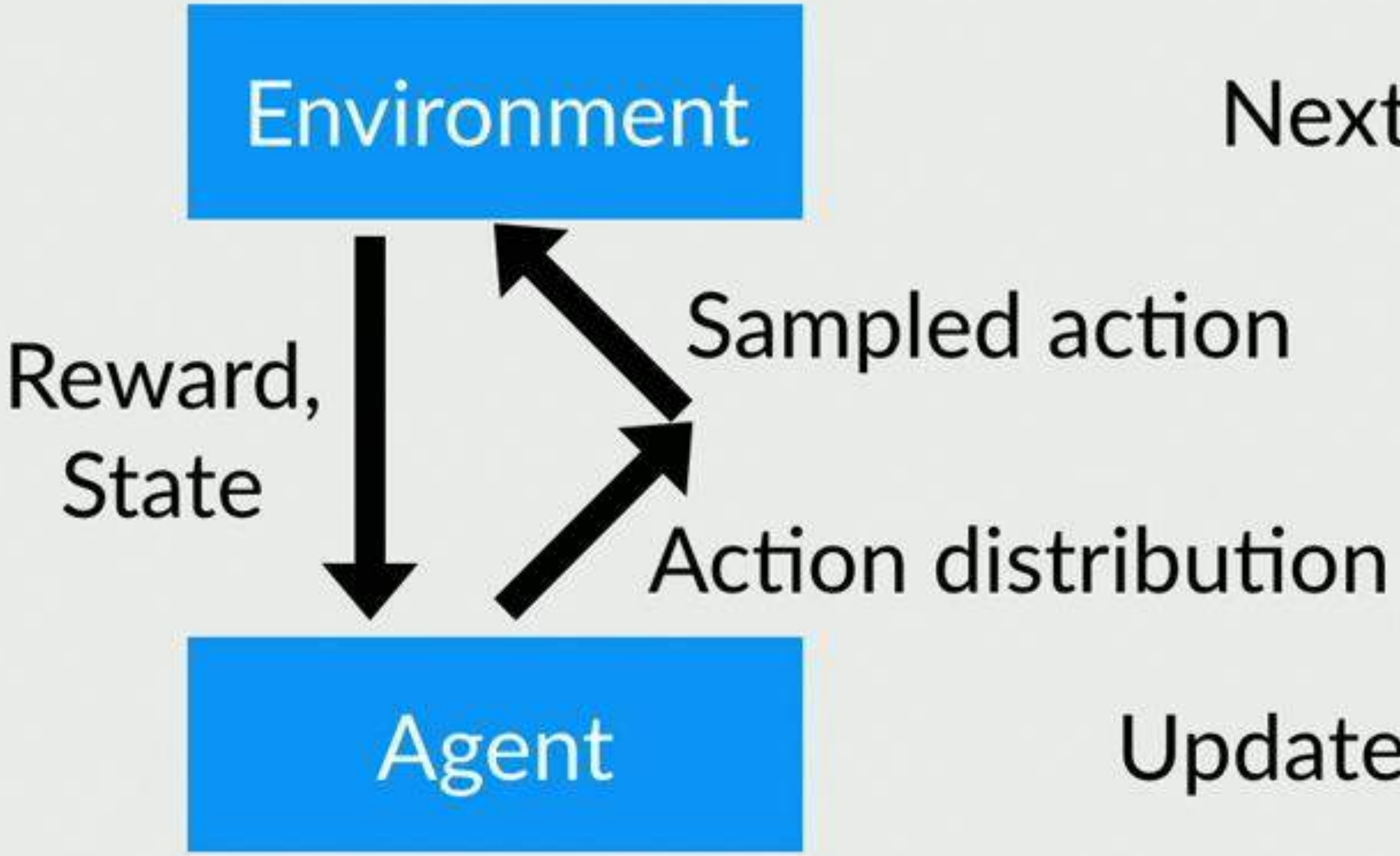
The RL Setup



Next state s_t

Updated policy π_t

The RL Setup



Next state s_t

Updated policy π_t

Goal: Maximize expected total reward

(over trajectories)

Policy Gradient Algorithms

Policy Gradients

Key Principle: View our goal as an optimization problem

$$\theta^* = \arg\max_{\theta} \mathbb{E}_{\tau \sim \pi_\theta} \left[\sum_{(s,a) \in \tau} r(s,a) \right]$$

Policy Gradients

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$$\theta^* = \arg\max_{\theta} \mathbb{E}_{\tau \sim \pi_\theta} \left[\sum_{(s,a) \in \tau} r(s,a) \right]$$

Expected value (over sampled trajectories) under current policy

Total reward

Policy Gradients

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Method of choice: gradient descent

Policy Gradients

Key Principle: View our goal as an optimization problem

$$\theta^* = \arg\max_\theta \boxed{\mathbb{E}_{\tau\sim\pi_\theta}\left[\sum_{(s,a)\in\tau} r(s,a)\right]}$$

No gradient access

Method of choice: gradient descent

Policy Gradients

Can we instead get a good *estimate* of the gradient?

$$\nabla_\theta \mathbb{E}_{\tau \sim \pi_\theta}\left[\sum_{(s,a)\in\tau} r(s,a)\right] = \textbf{???}$$

Policy Gradients

Can we instead get a good *estimate* of the gradient?

$$\nabla_\theta \mathbb{E}_{\tau\sim\pi_\theta}\left[\sum_{(s,a)\in\tau} r(s,a)\right] = \boxed{\mathbb{E}_{\tau\sim\pi_\theta}\left[g(\tau)\right]}$$

The Policy Gradient

Policy Gradients

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$$\approx \frac{1}{N}\sum_{\tau\sim\pi_\theta}\left[g(\tau)\right]$$

Policy Gradients

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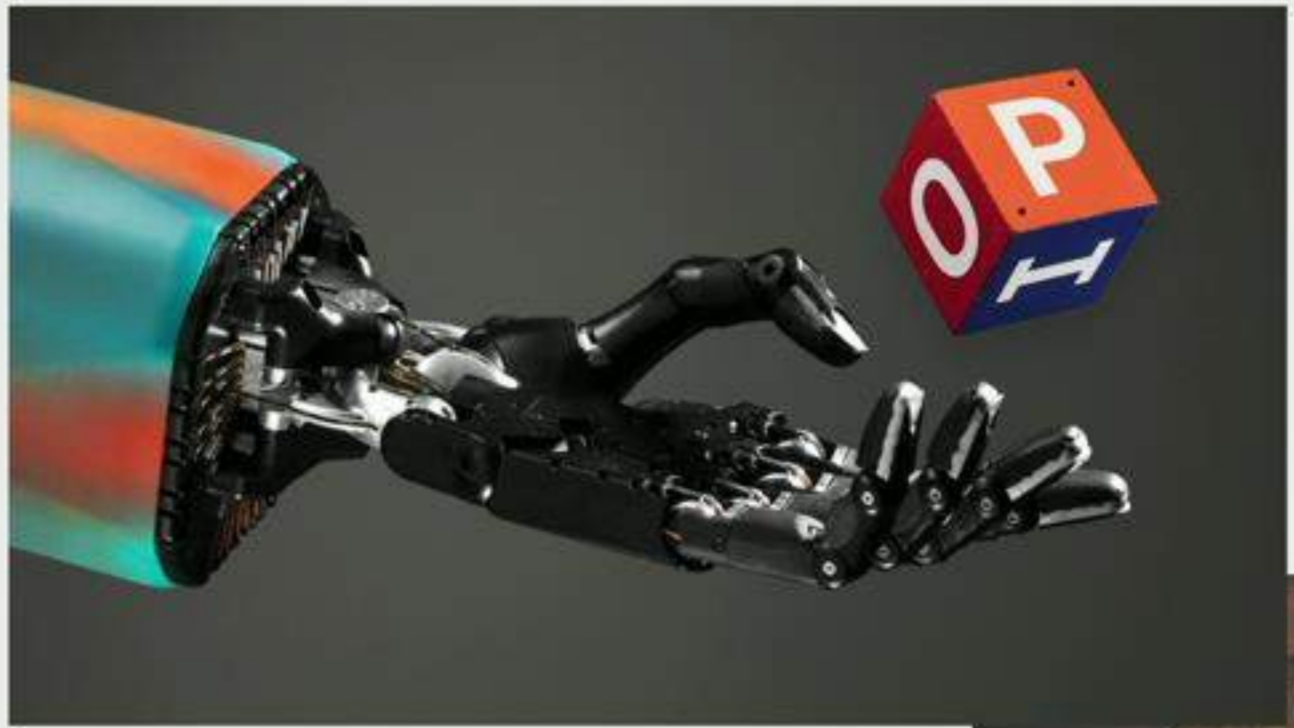
$$\approx \frac{1}{N} \sum_{\tau \sim \pi_\theta} \left[g(\tau) \right]$$

Then: use estimate in gradient descent!

Policy Gradient Successes



The Rotten Truth of Deep RL

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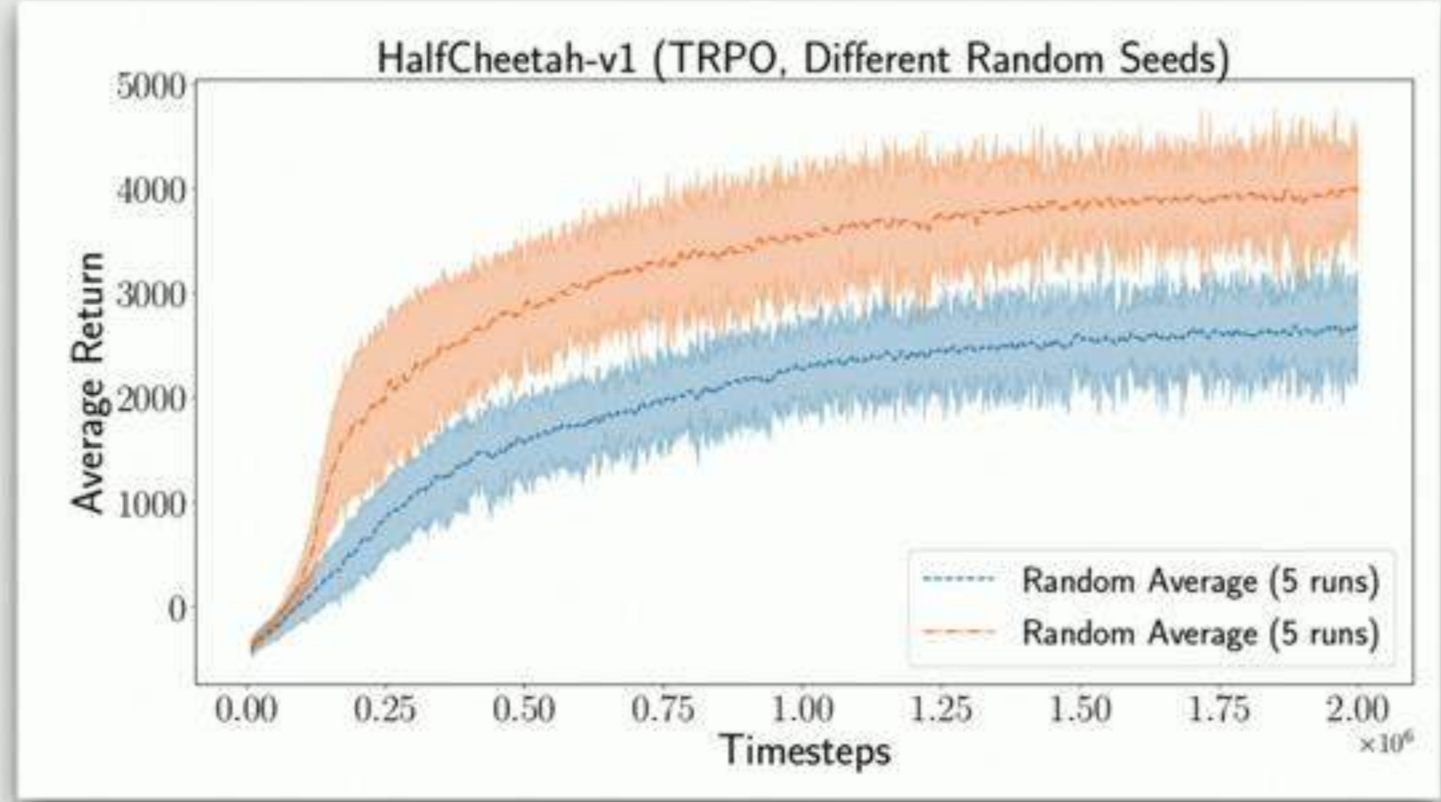
Deep RL can successfully solve tasks, **but has…**

- Poor reliability over repeated runs



[Henderson et al, 2017a,b] [Lewis et al, 2018]

The Rotten Truth of Deep RL

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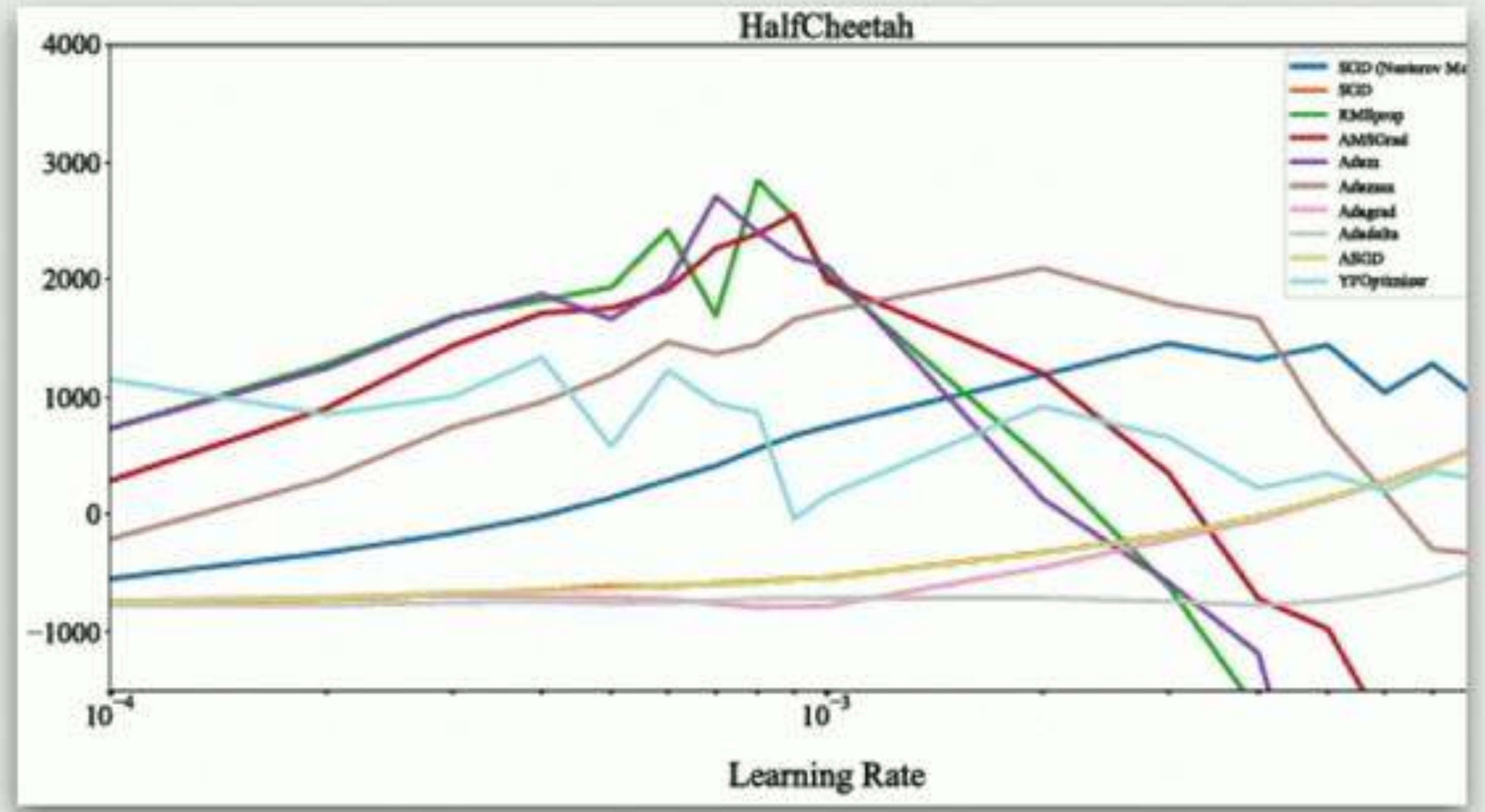

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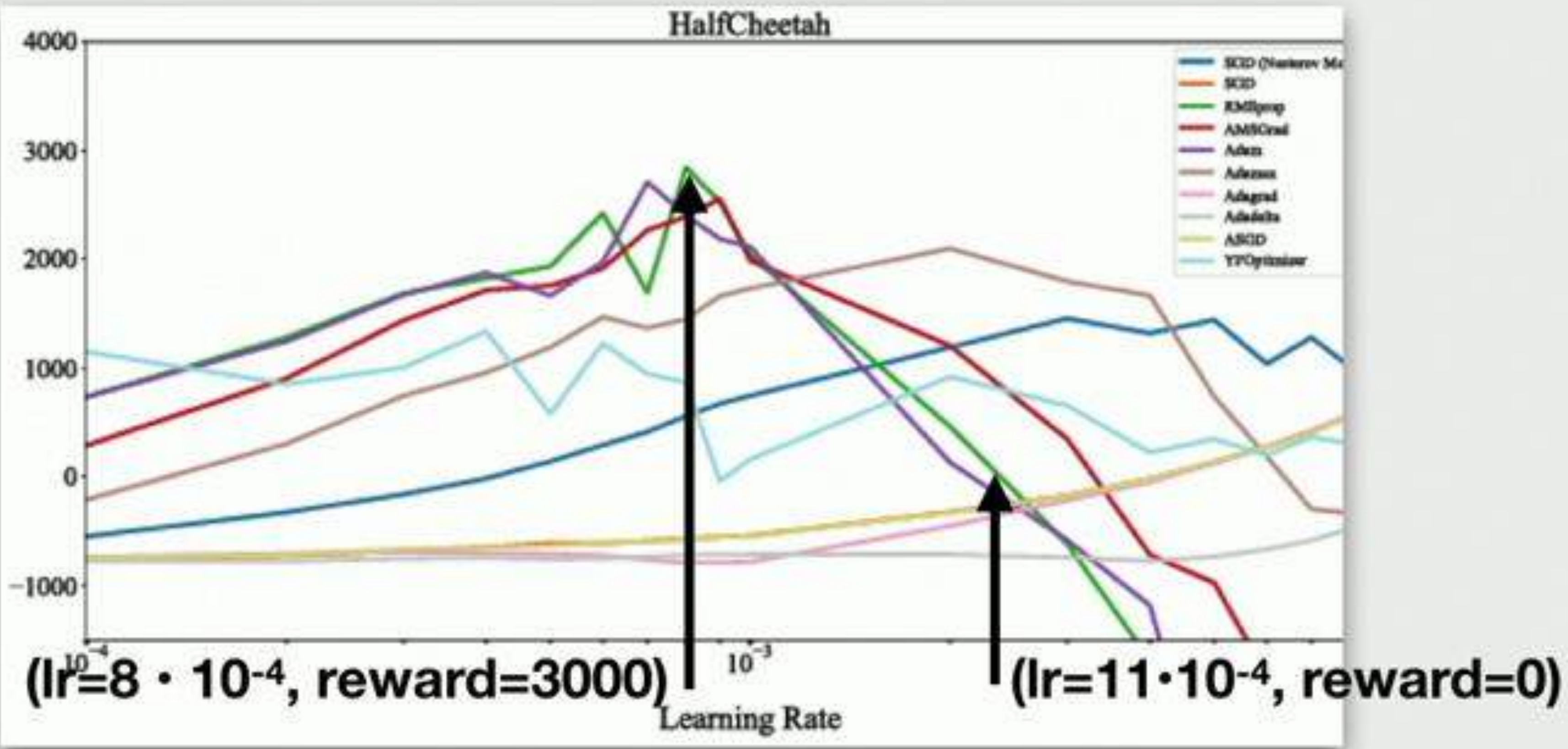

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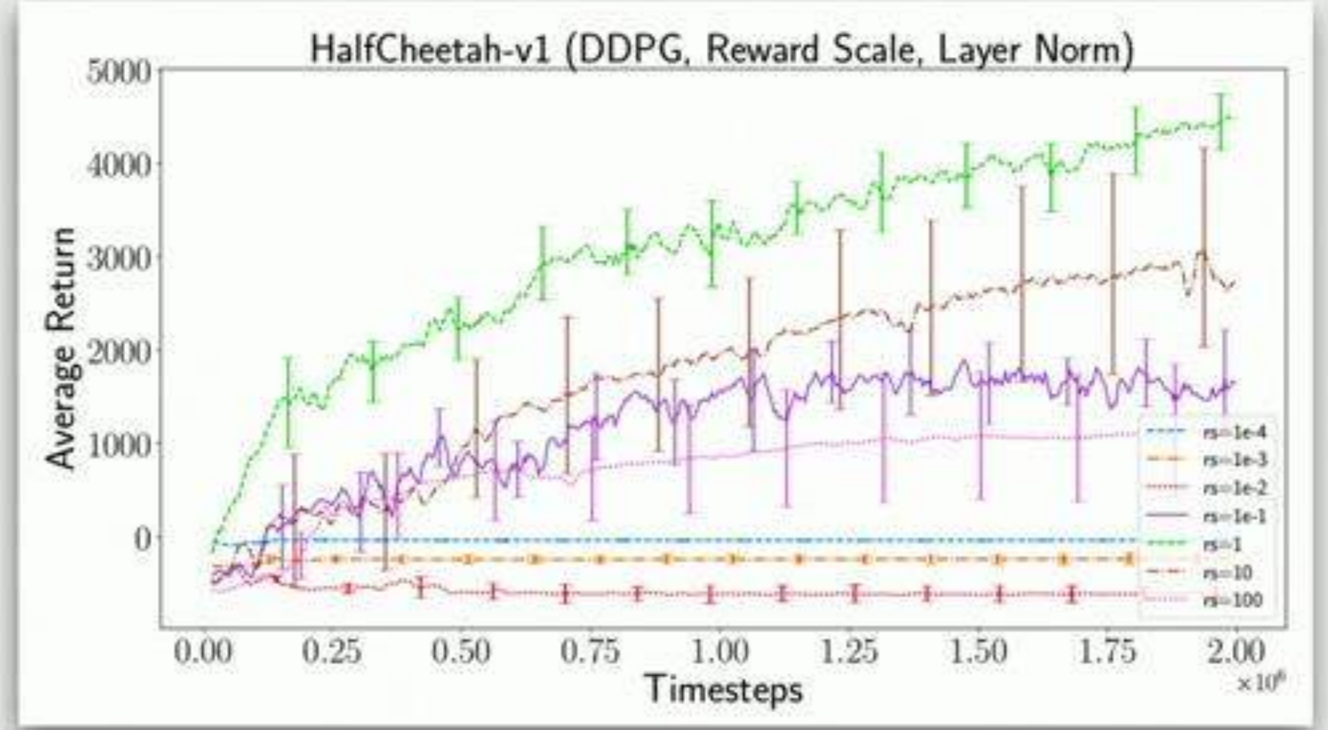

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Notably, benchmarks don't reveal these problems

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Notably, benchmarks don't reveal these problems

Where do such issues come from?

Hard to know: deep RL algorithms have many moving parts!

Implementation Obscures Deep RL Algorithms

openai / **baselines**

Watch 383 | Star 5,061 | Fork 1,455

<> Code | Issues 137 | Pull requests 71 | Projects 0 | Wiki | Insights

OpenAI Baselines: high-quality implementations of reinforcement learning algorithms

Source: GitHub issues

Implementation Obscures Deep RL Algorithms

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OpenAI Baselines: high-quality implementations of reinforcement learning algorithms

- Differences between the policies. ... an important modification ...

- Huge architectural differences. ...

Source: GitHub issues

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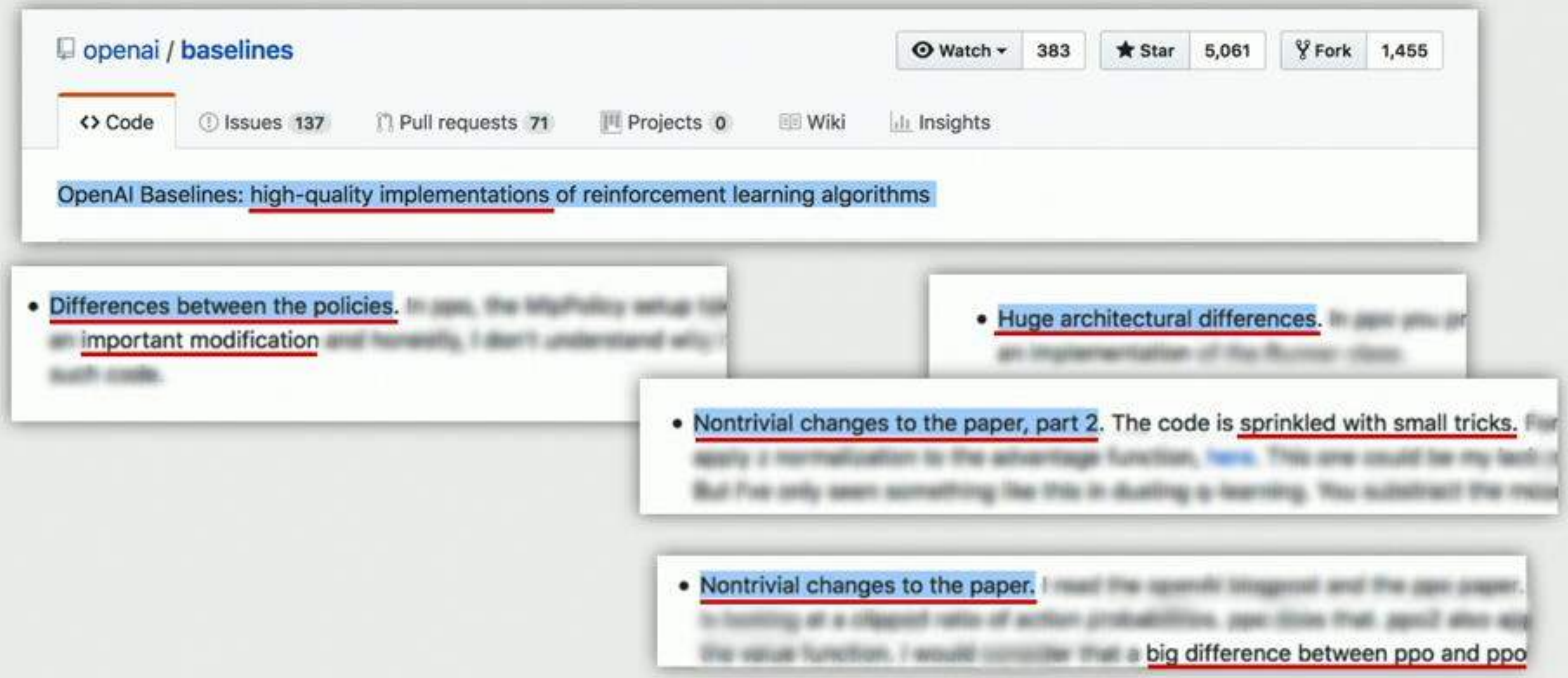

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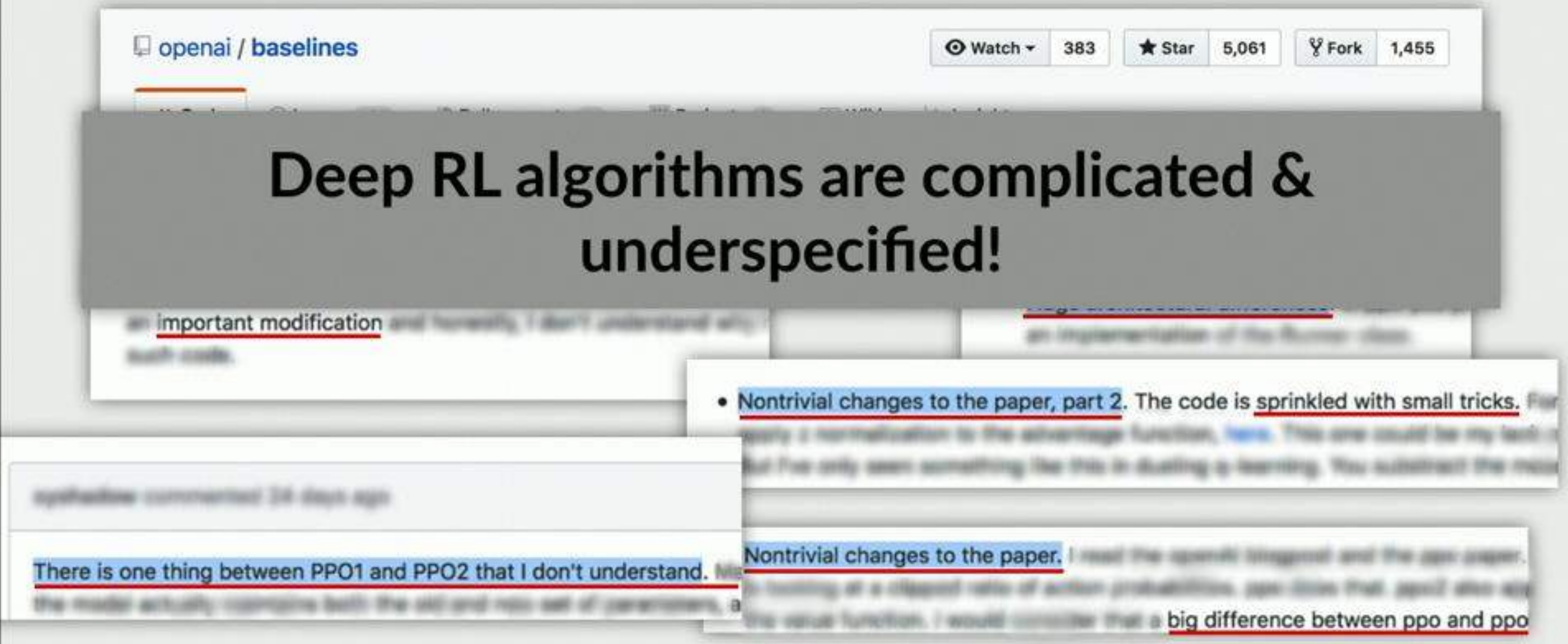

Deep RL algorithms are complicated & underspecified!

Source: GitHub issues

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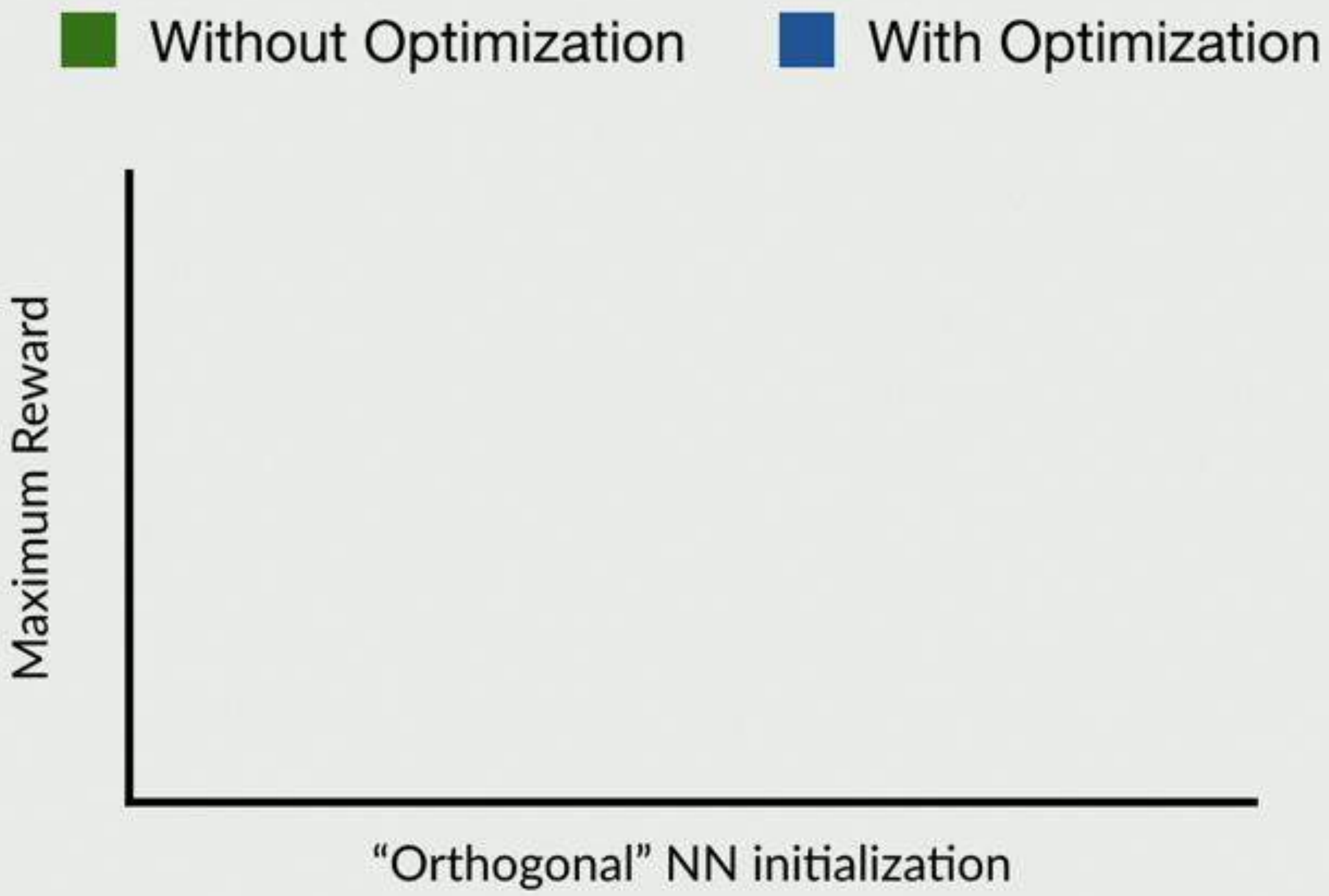

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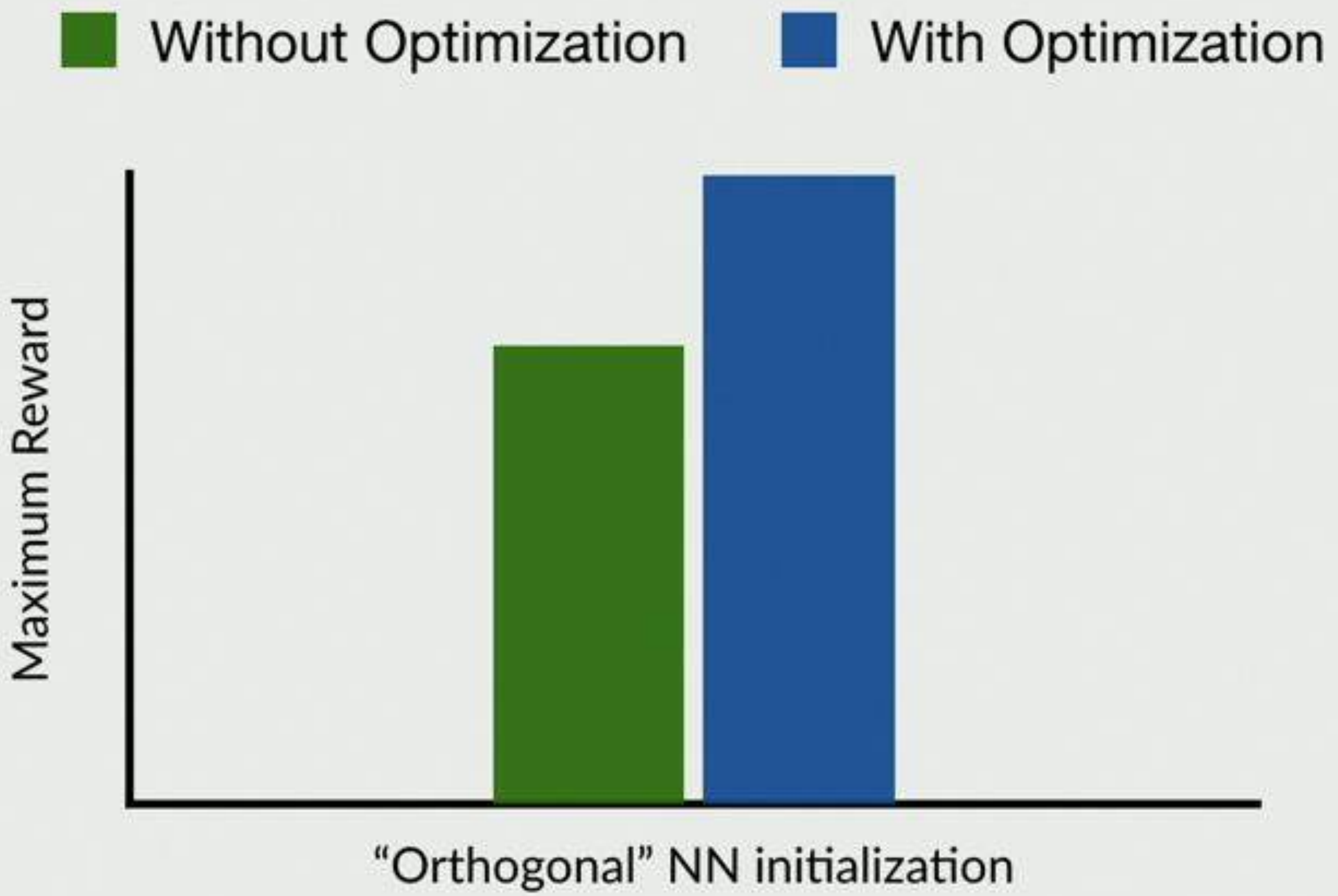

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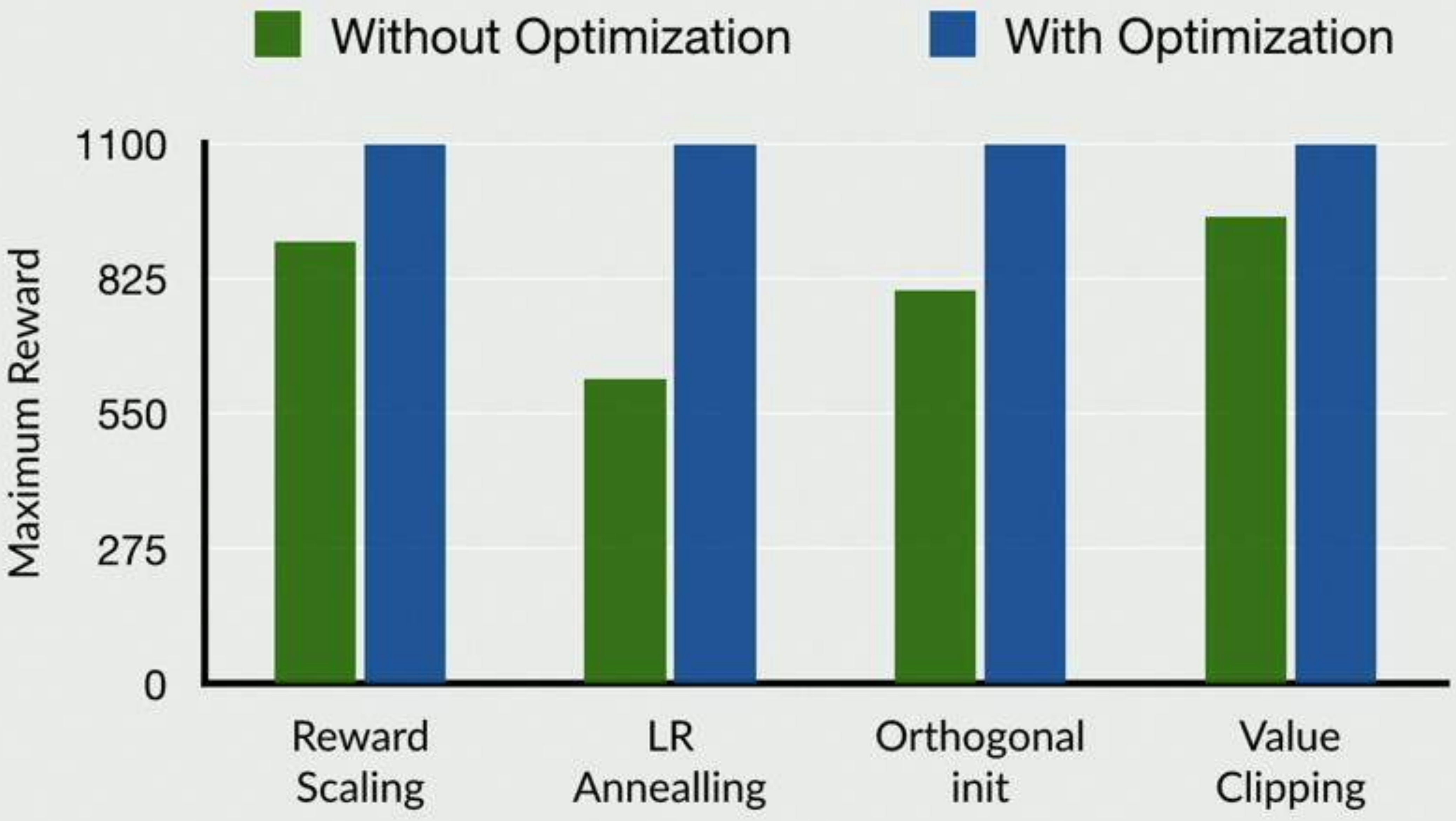

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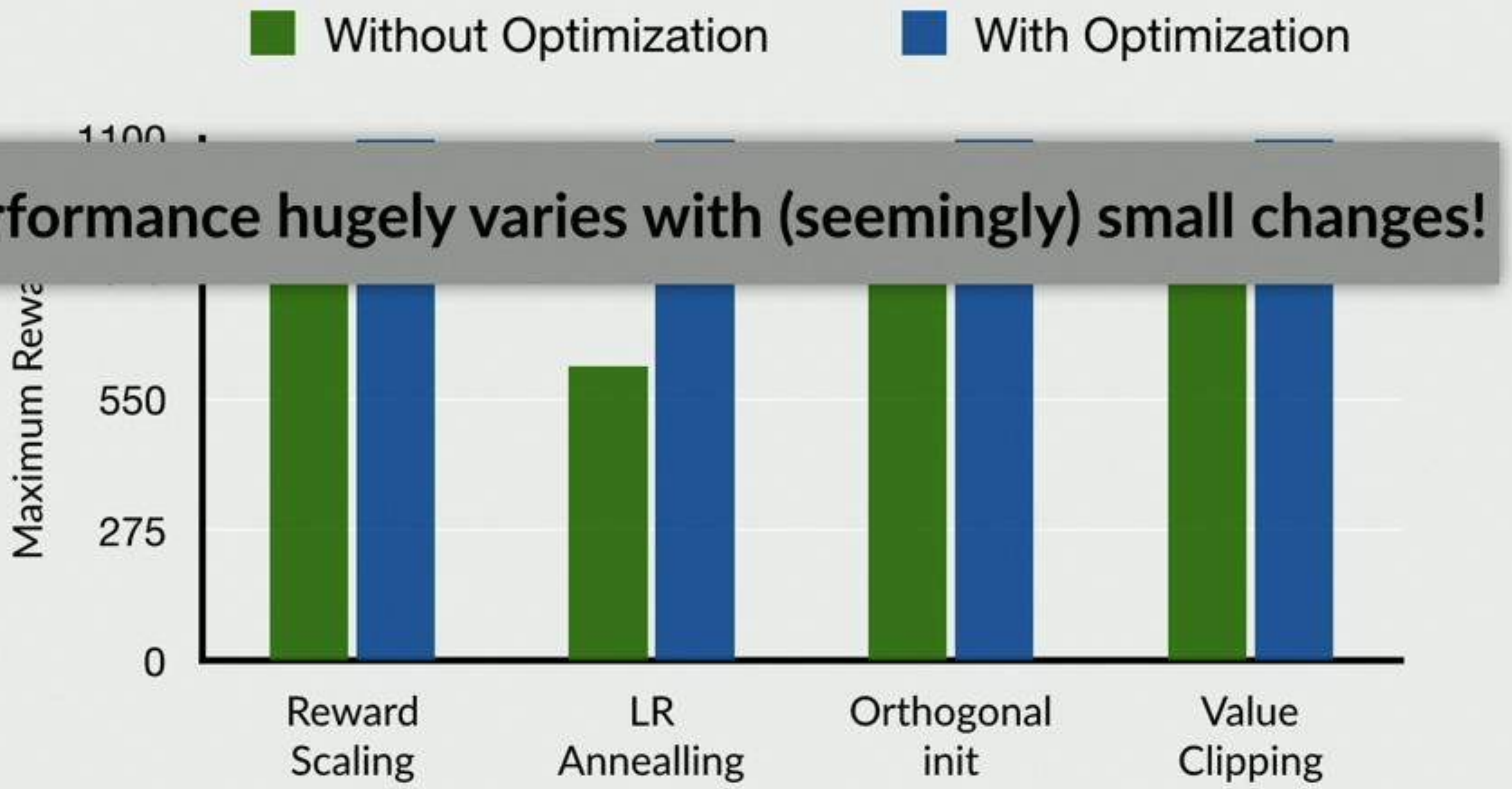


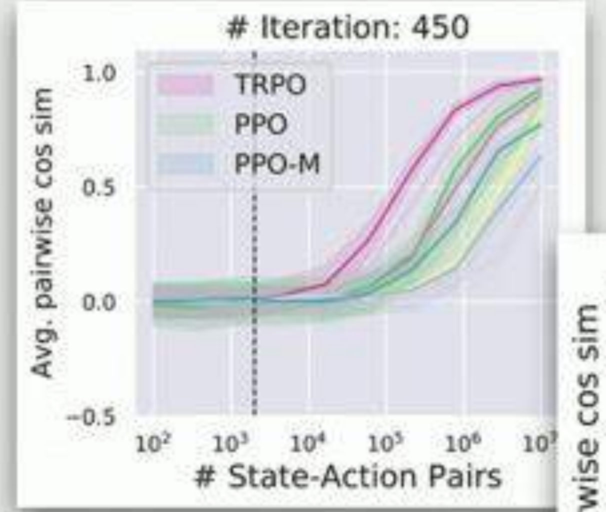
Implementation Obscures Deep RL Algorithms

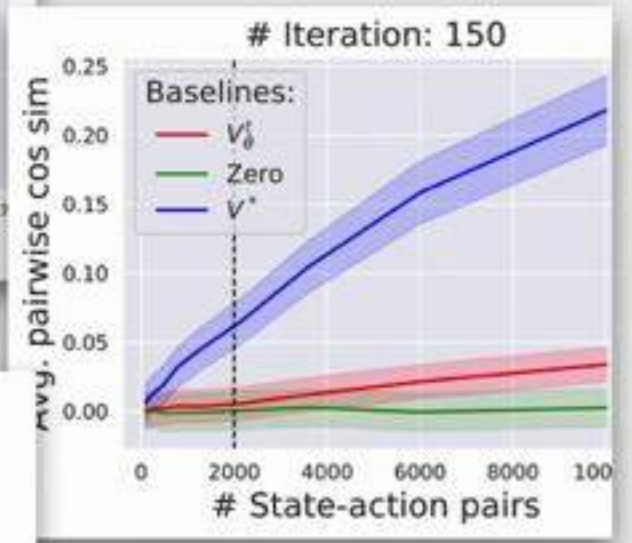
- Deep RL methods are complicated & underspecified
- Reasons for unreliability, performance are unclear
- **Deep RL methods are poorly understood!**

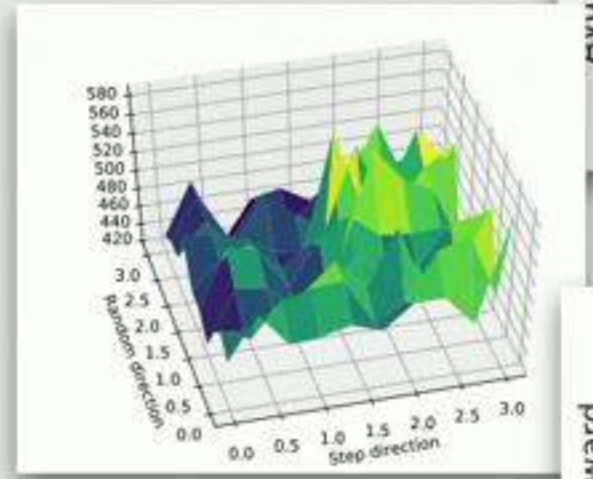
Back to First Principles

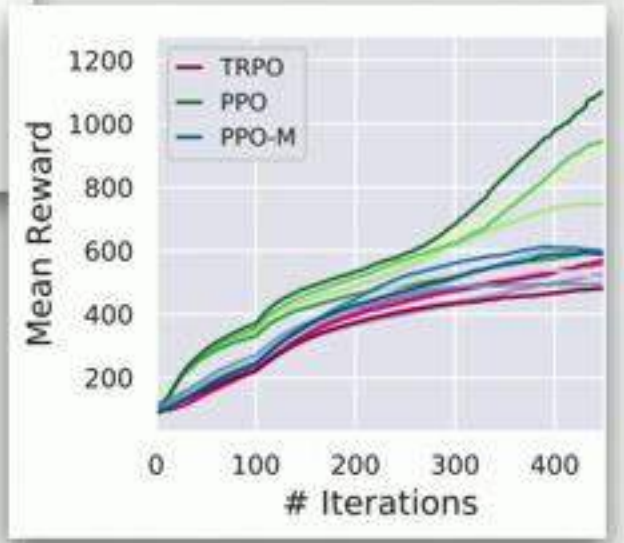
Back to First Principles

- Gradient Estimates
- Value Prediction
- Optimization Landscapes
- Trust Regions









Gradient Estimation

Key assumption of policy gradient framework:

$$\nabla_\theta \mathbb{E}_{\tau\sim\theta}[R(\theta)] \approx \frac{1}{N}\sum_{\tau\sim\theta} g(\tau)$$

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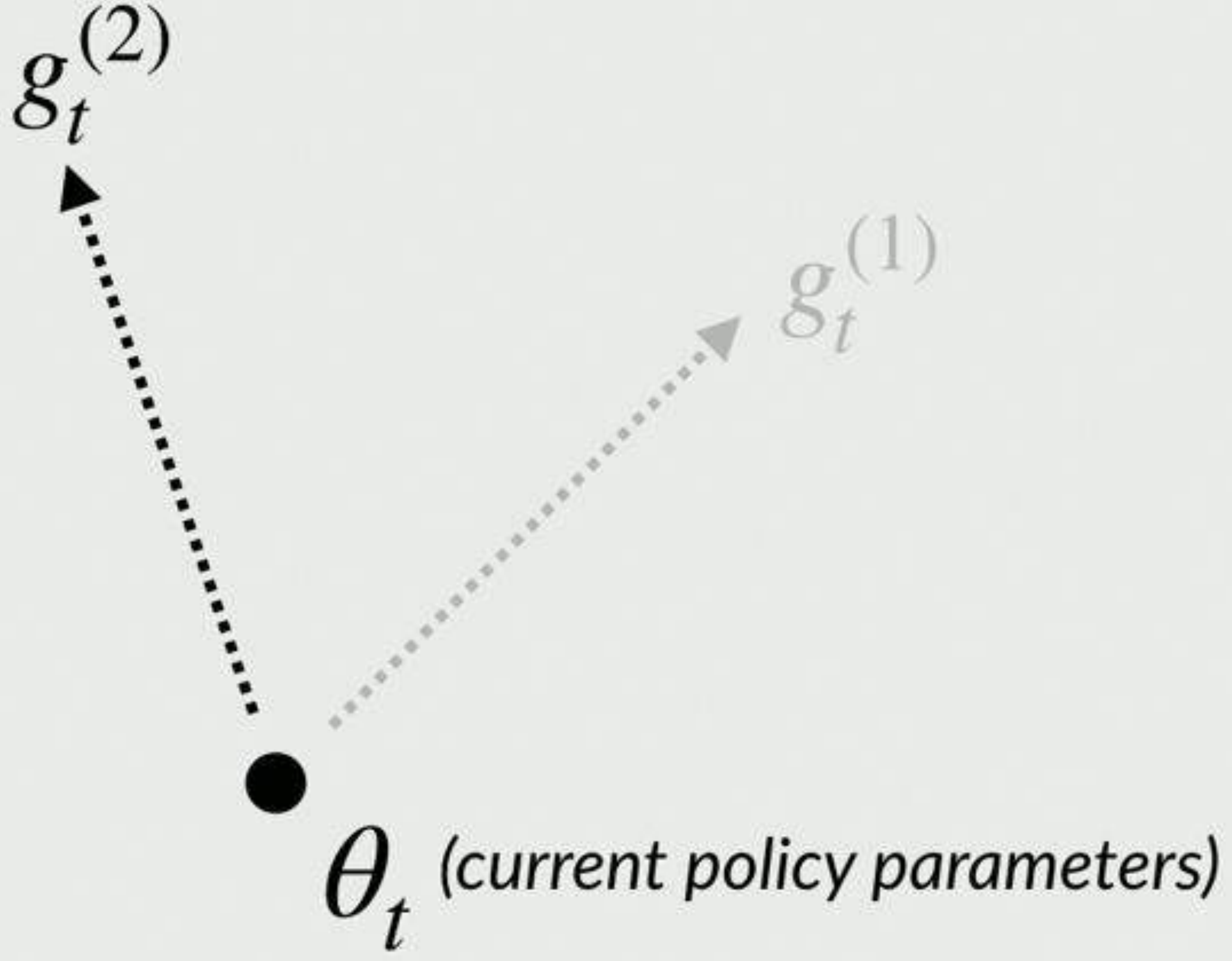
How valid is this?

Gradient Estimation

θ_t *(current policy parameters)*

Gradient Estimation



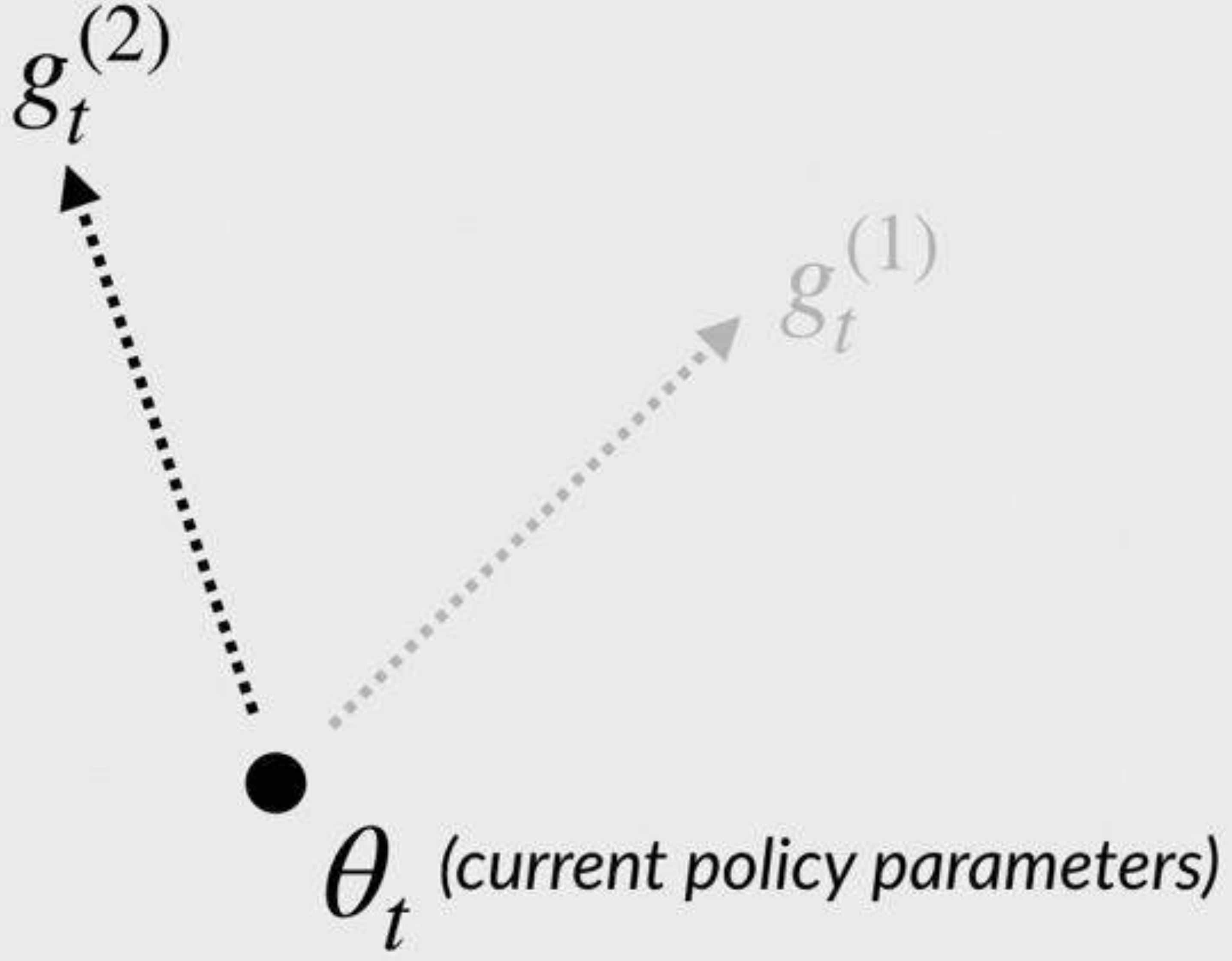
Gradient Estimation

$$g_t^{(1)} = \frac{1}{k}\sum_{i=1}^{k} \cdots$$

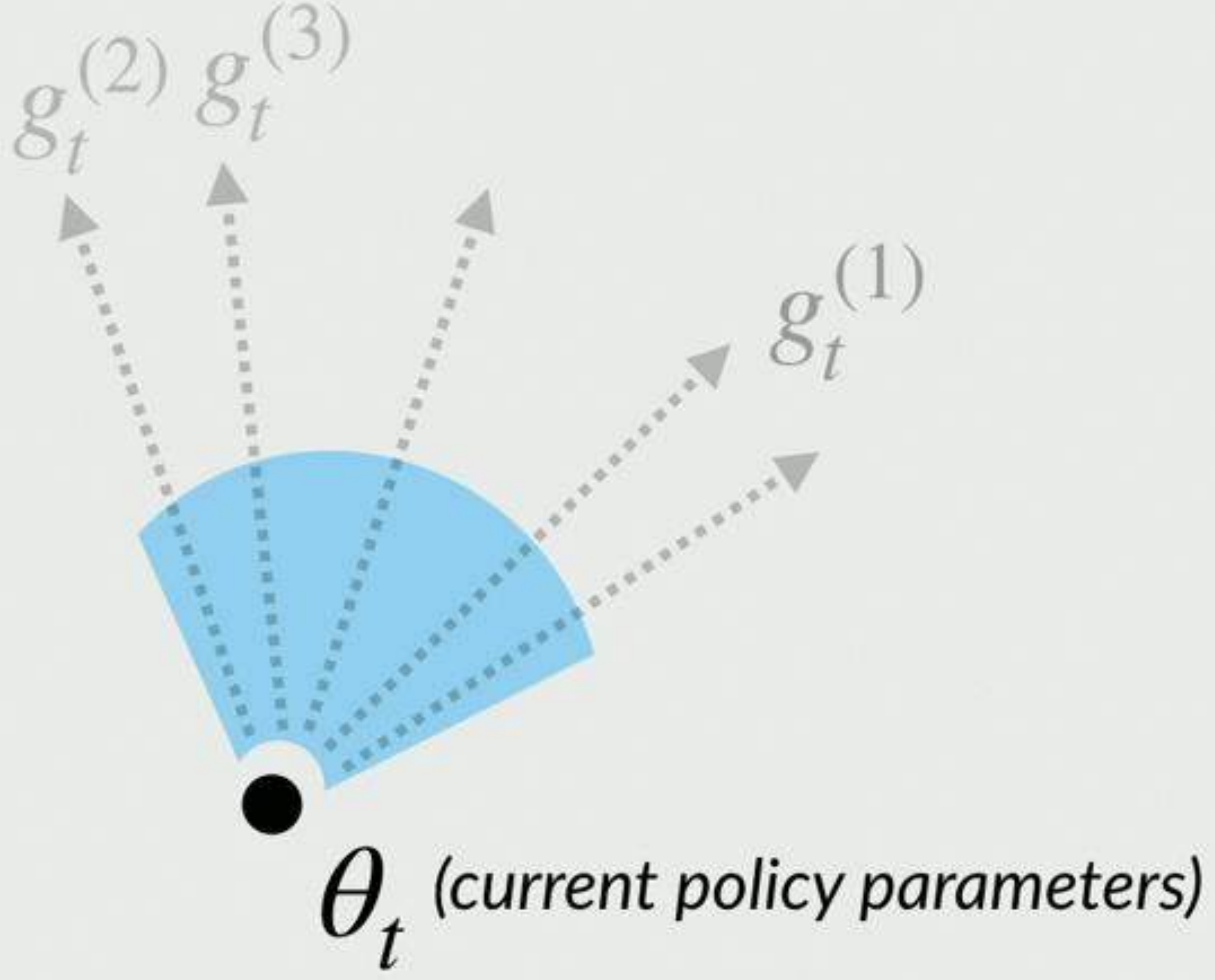
(k-sample gradient estimate)

θ_t *(current policy parameters)*

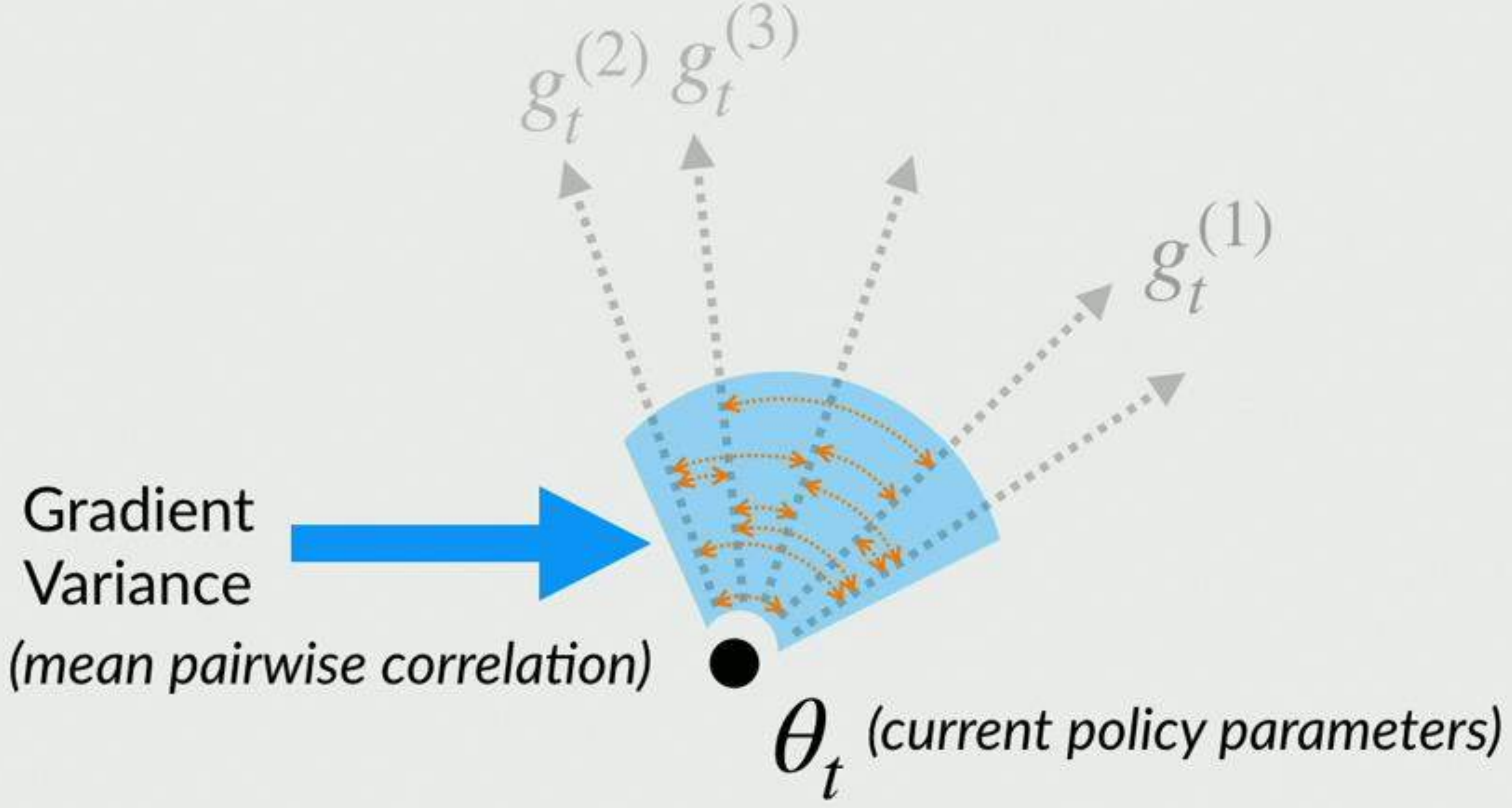
Gradient Estimation



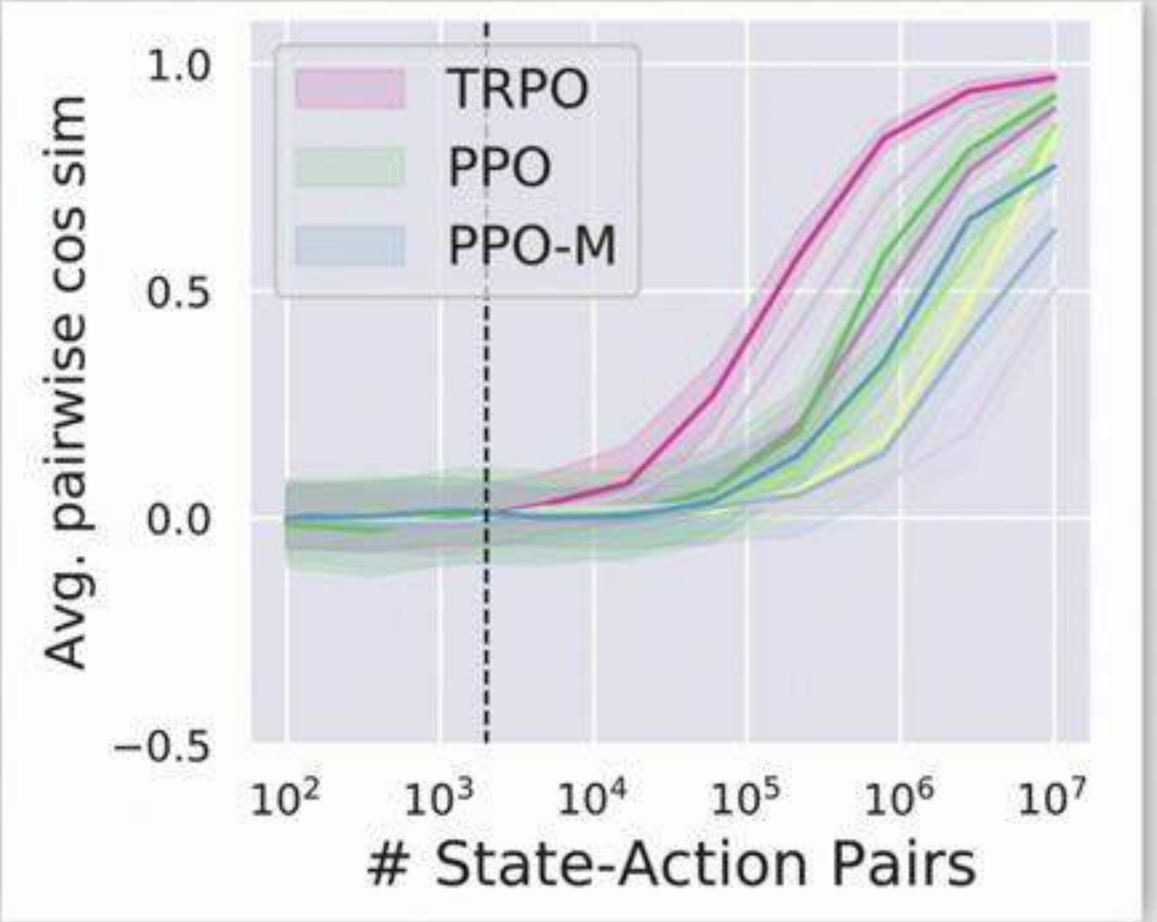
Gradient Estimation



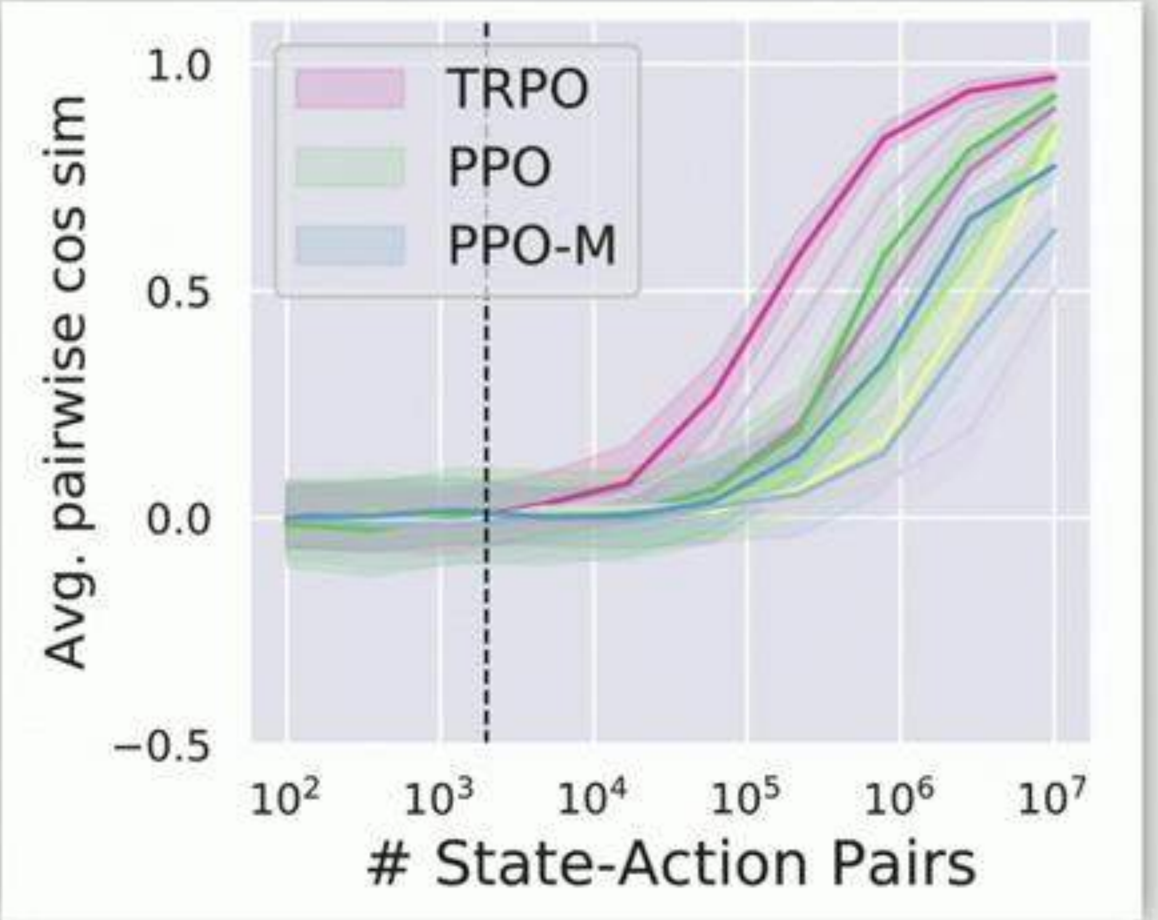
Gradient Estimation



Gradient Variance



Gradient Variance

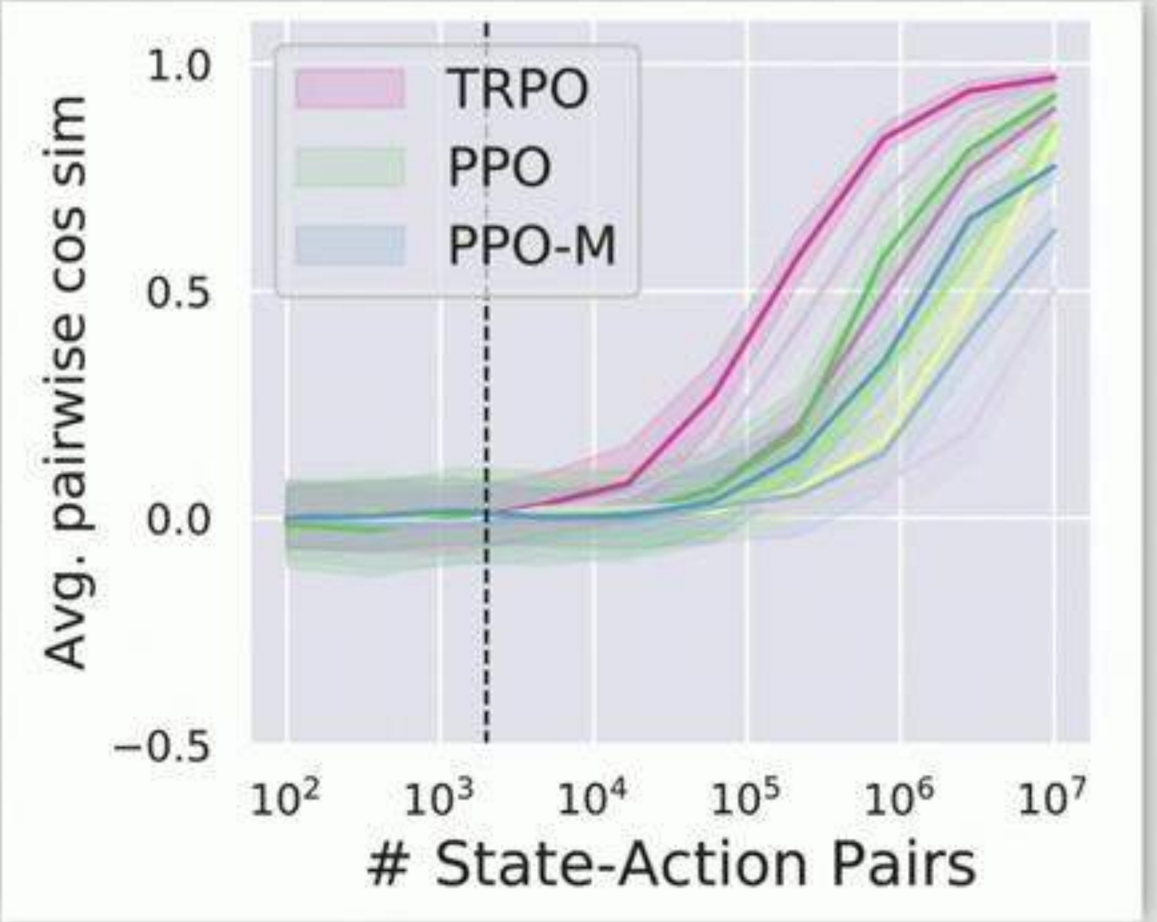


- **Black line**: relevant sample regime
- Gradients are less concentrated than they could be
- Less correlated for "harder" tasks, later iterations

Gradient Estimation

- **No good understanding of training dynamics**
  - How does variance influence optimization?
  - Can we use insights from stochastic opt?
- **Missing a link from reliability to sample size**

Gradient Variance



Gradient Estimation

- **No good understanding of training dynamics**
  - How does variance influence optimization?
  - Can we use insights from stochastic opt?
- **Missing a link from reliability to sample size**

Value Prediction

Gradient estimation is hindered by high variance!

Observation: If we can estimate the **value** of a state, can significantly lower variance

(The **value of a state** is the cumulative expected reward received after visiting the state)

Intuition: Need to separate action quality from state quality

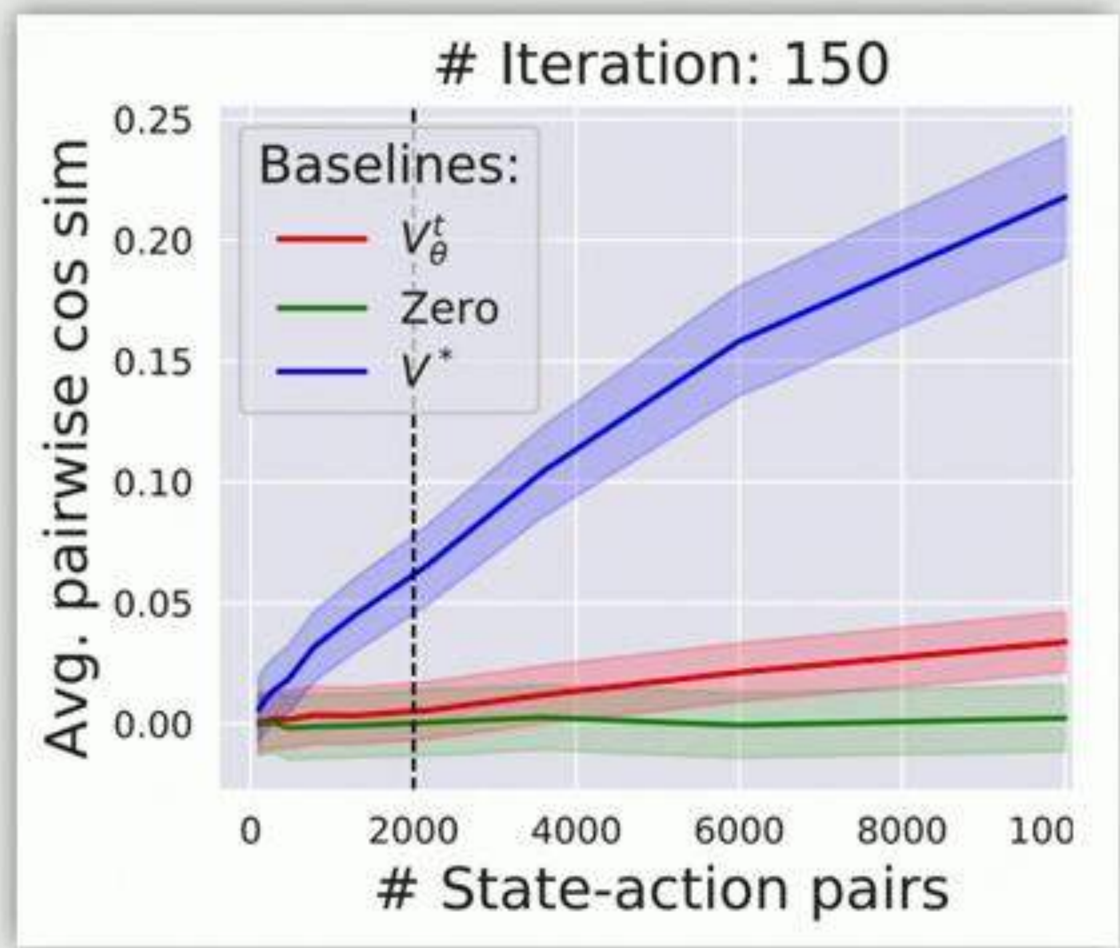
Value Prediction

Variance reduction needs **good value estimates**

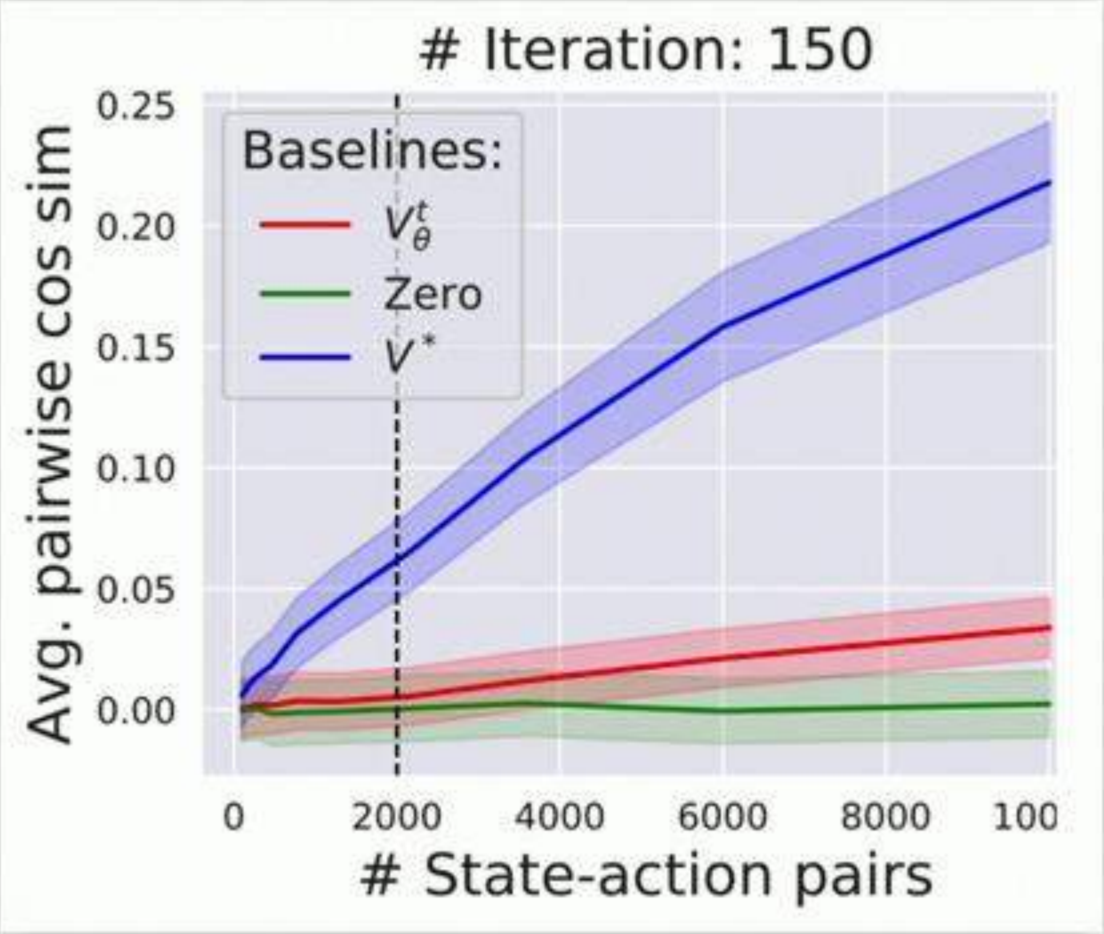
In Deep RL, values come from a neural network

To what degree do we actually reduce variance?

Value Prediction



Value Prediction



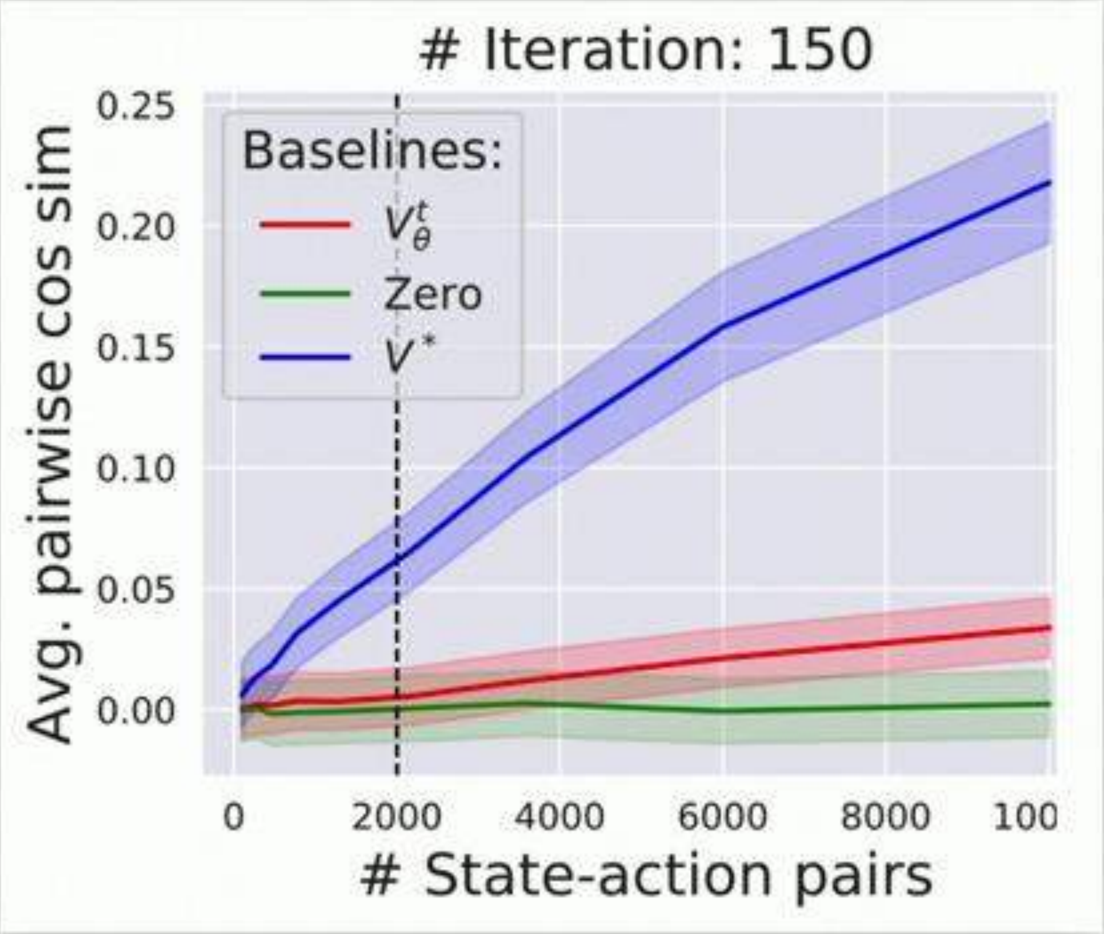
True value function

Agent's value function

No value function

Agent does significantly worse than optimal!

Value Prediction



True value function

Agent's value function

No value function

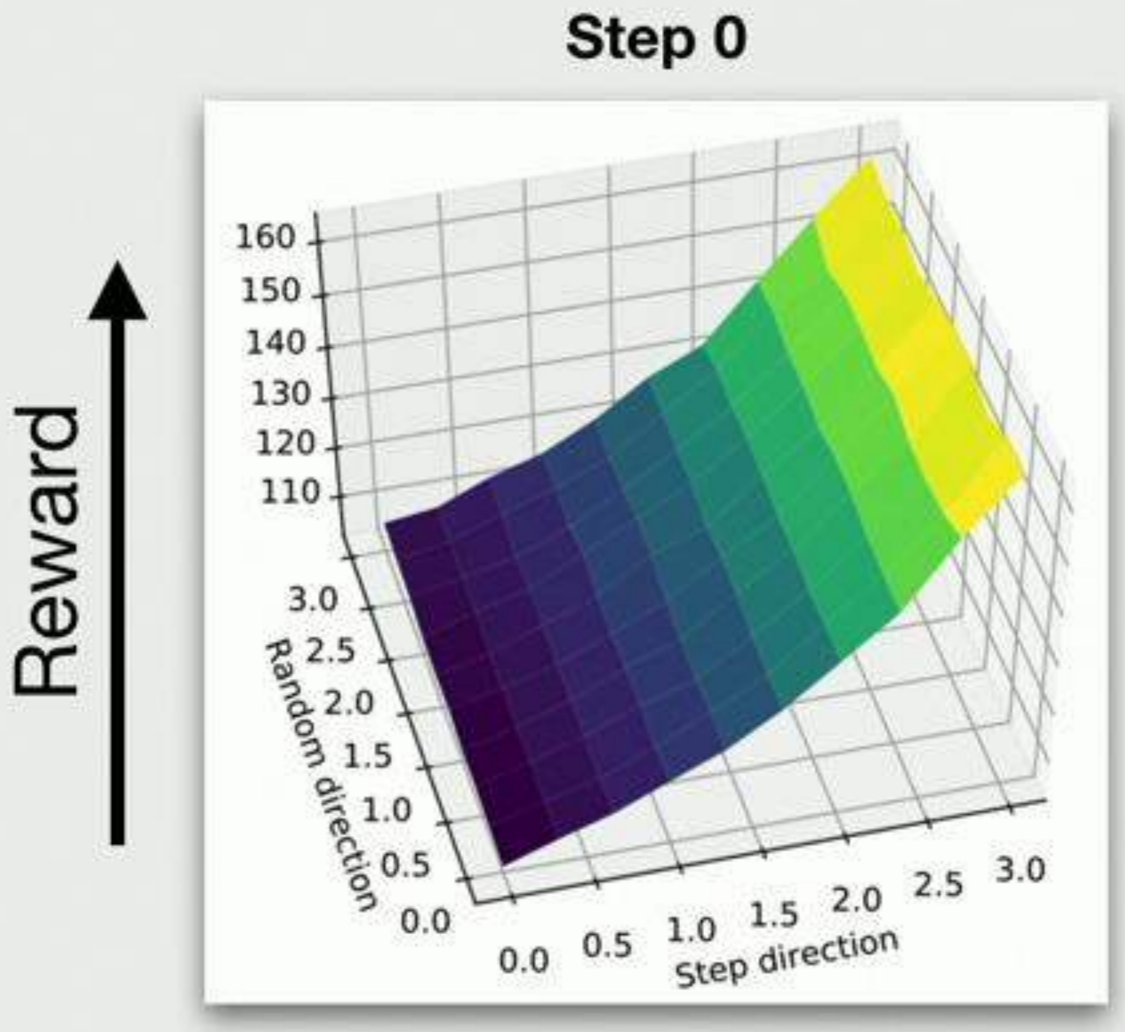
- Might **look** small, but using a value network makes **big** difference
- How would using the true value affect training?
- Can we get better value estimates?

Optimization Landscapes

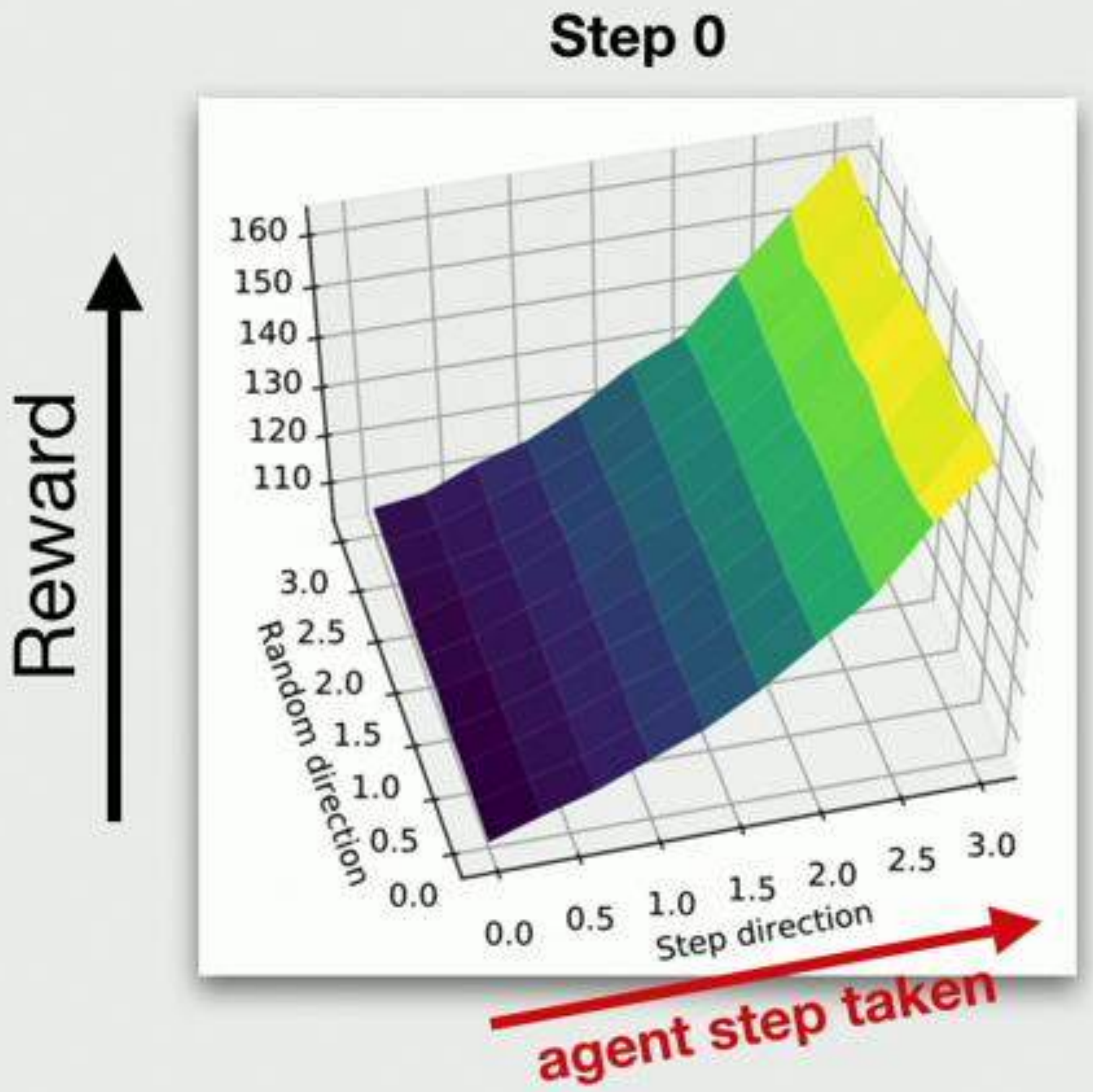
Assumption: taking gradient steps increases reward

How valid is this assumption in practice?

Optimization Landscapes



Optimization Landscapes



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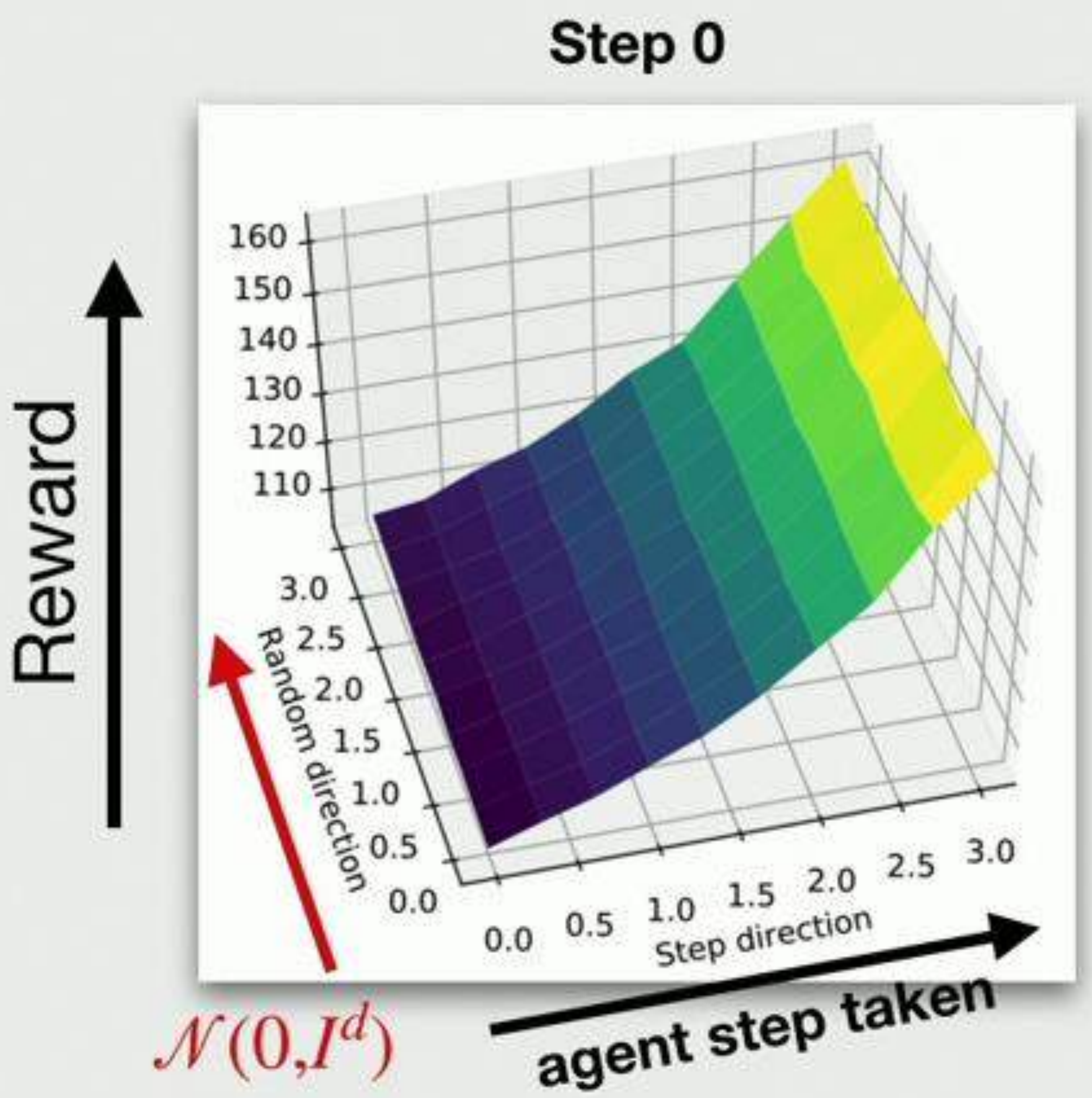

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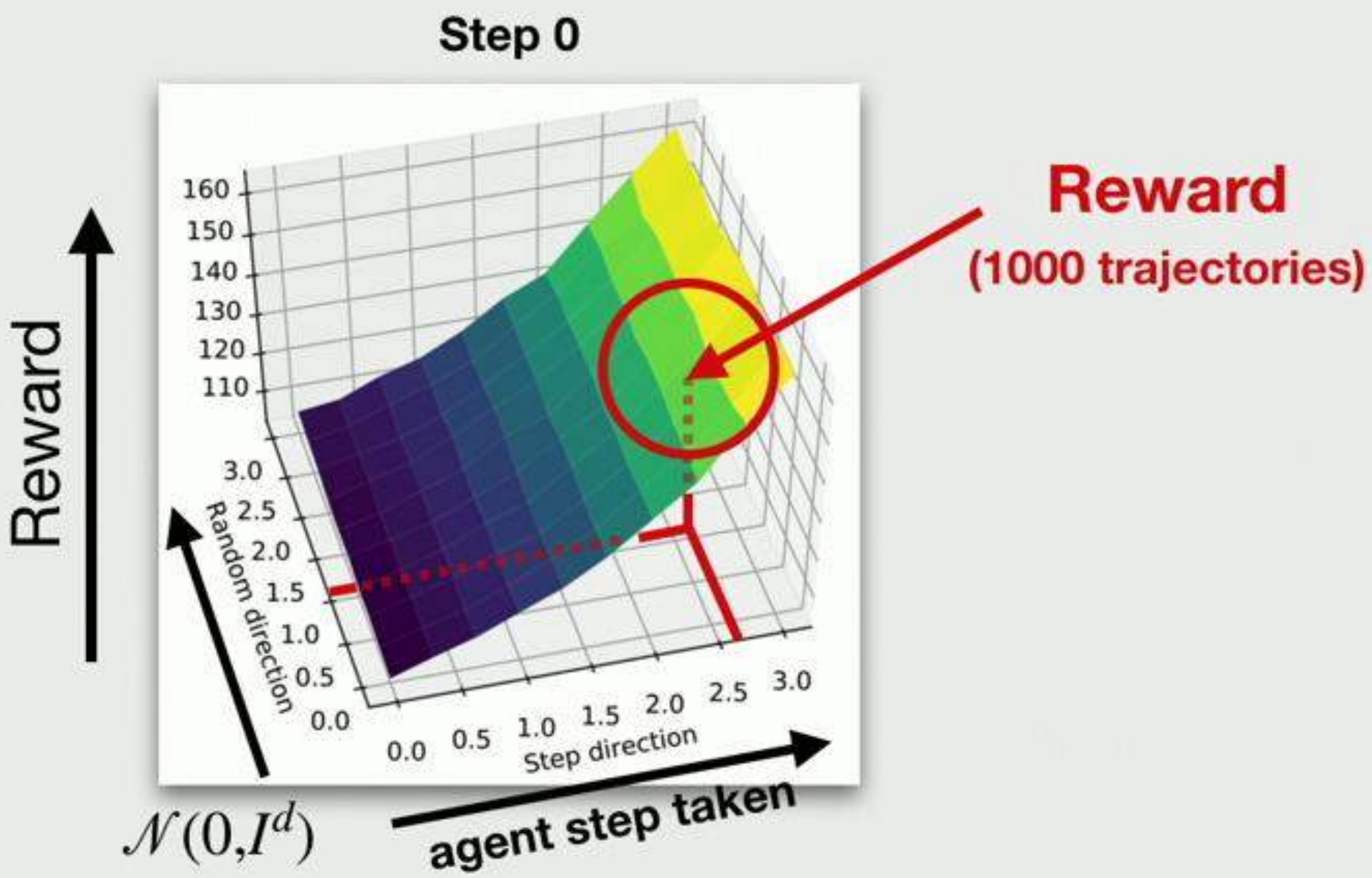

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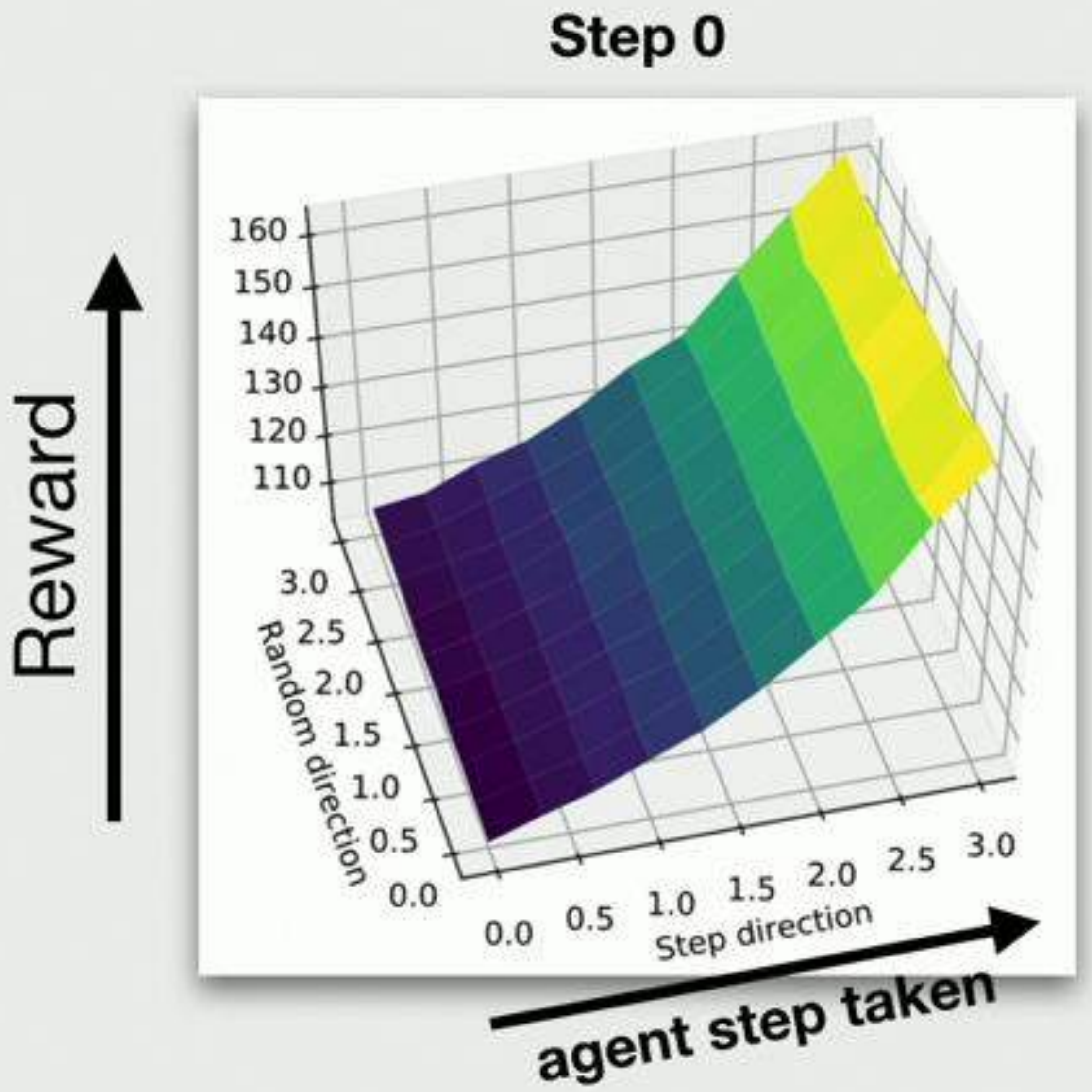

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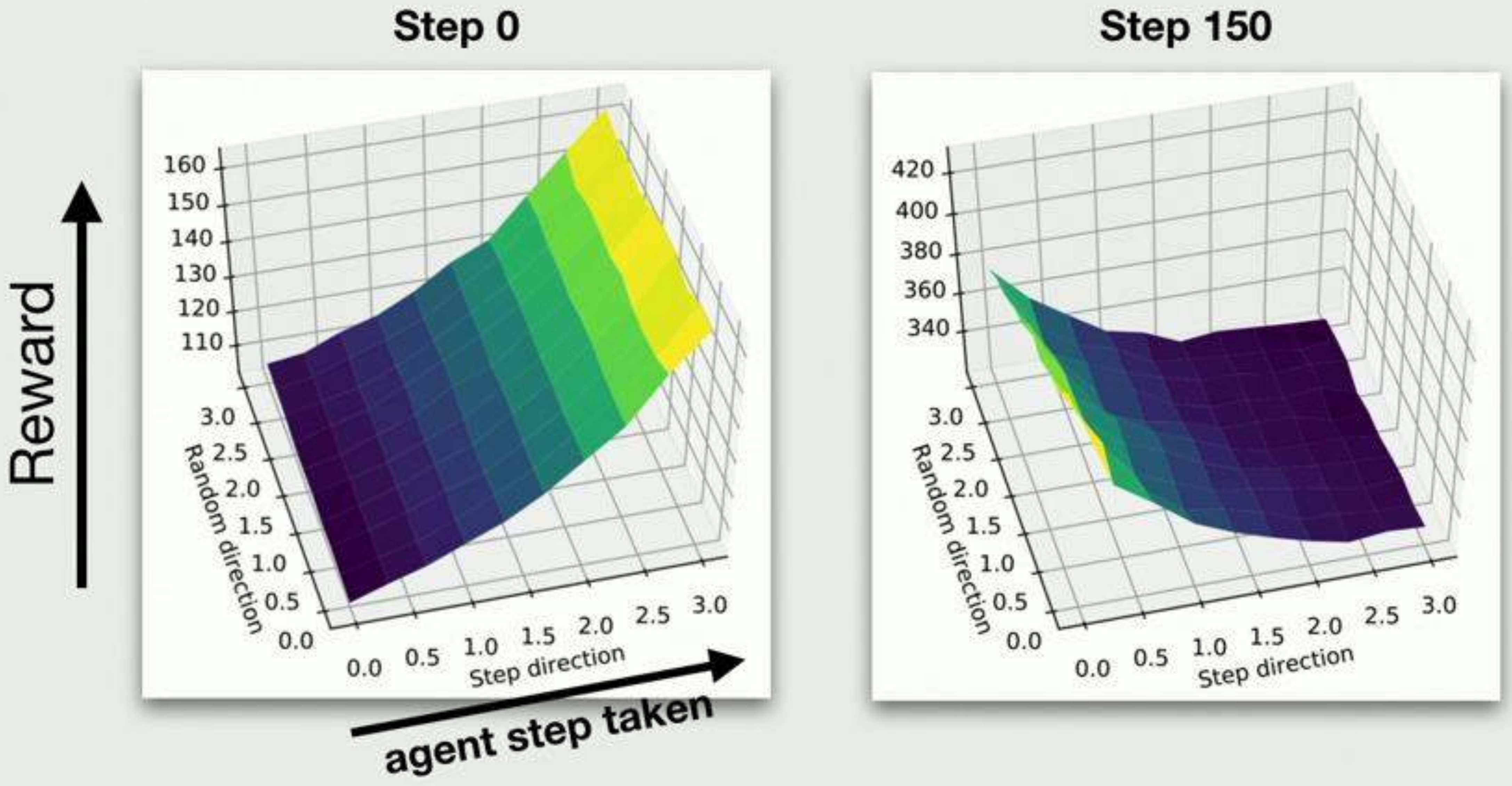

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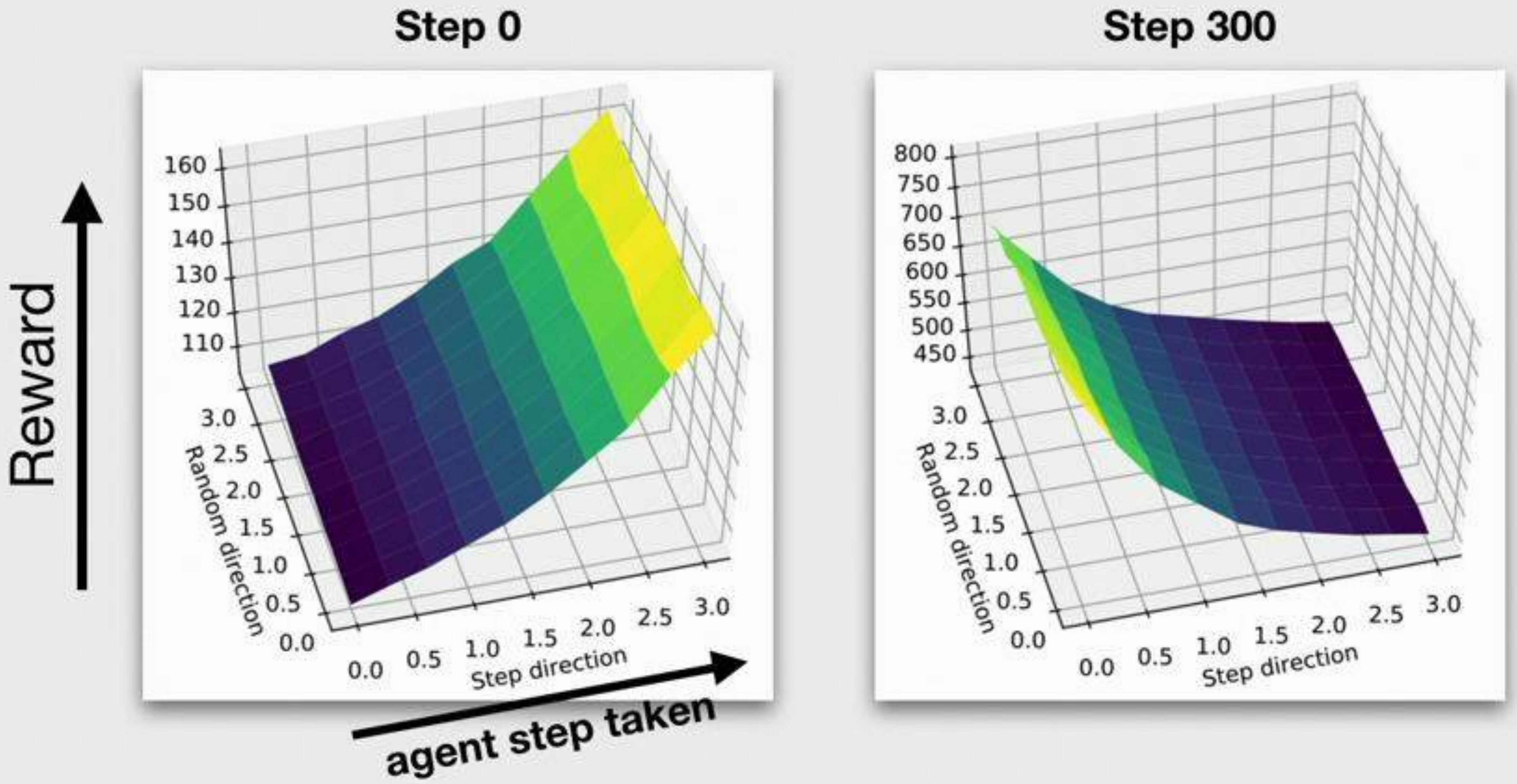
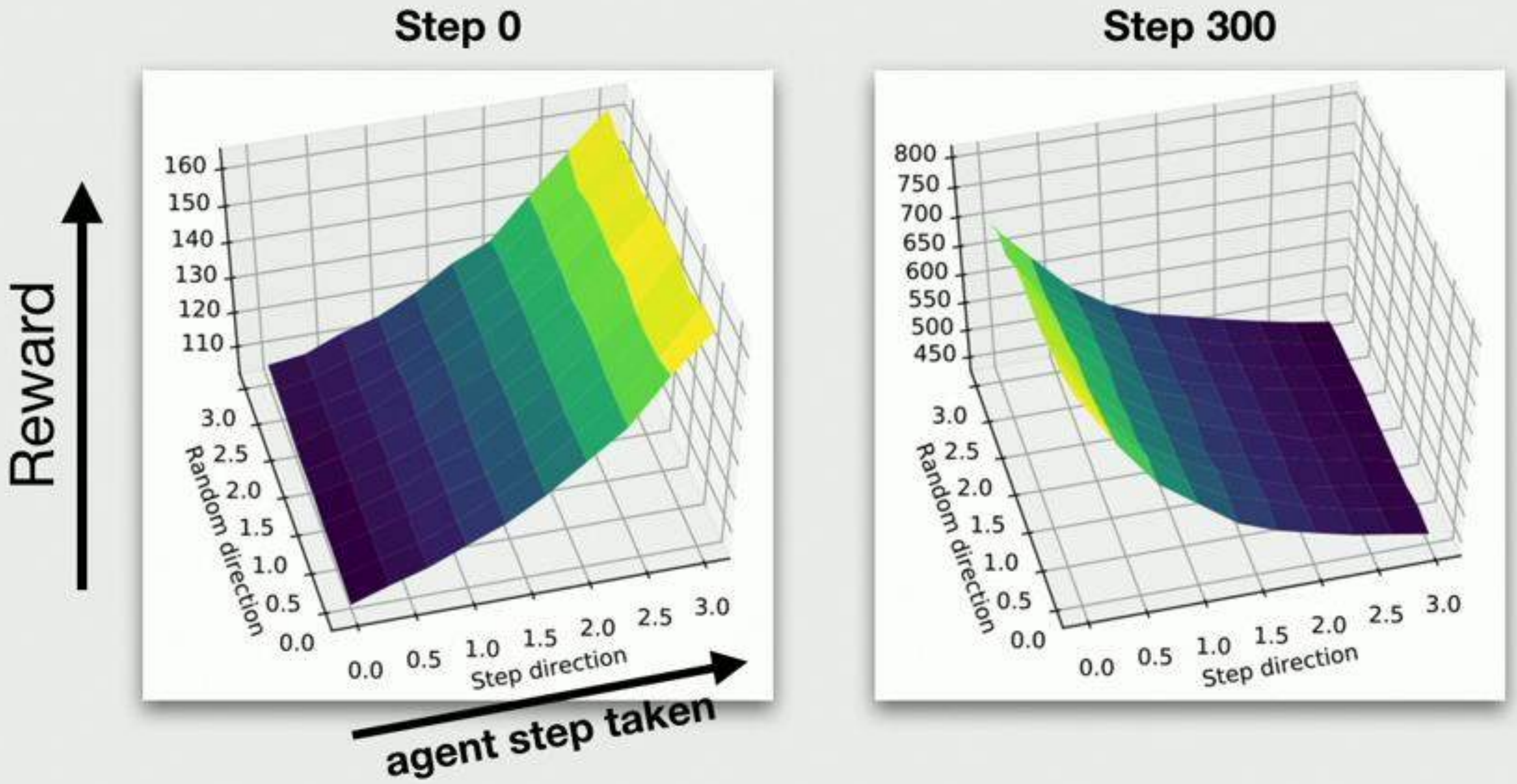


Steps are often not predictive

Optimization Landscapes



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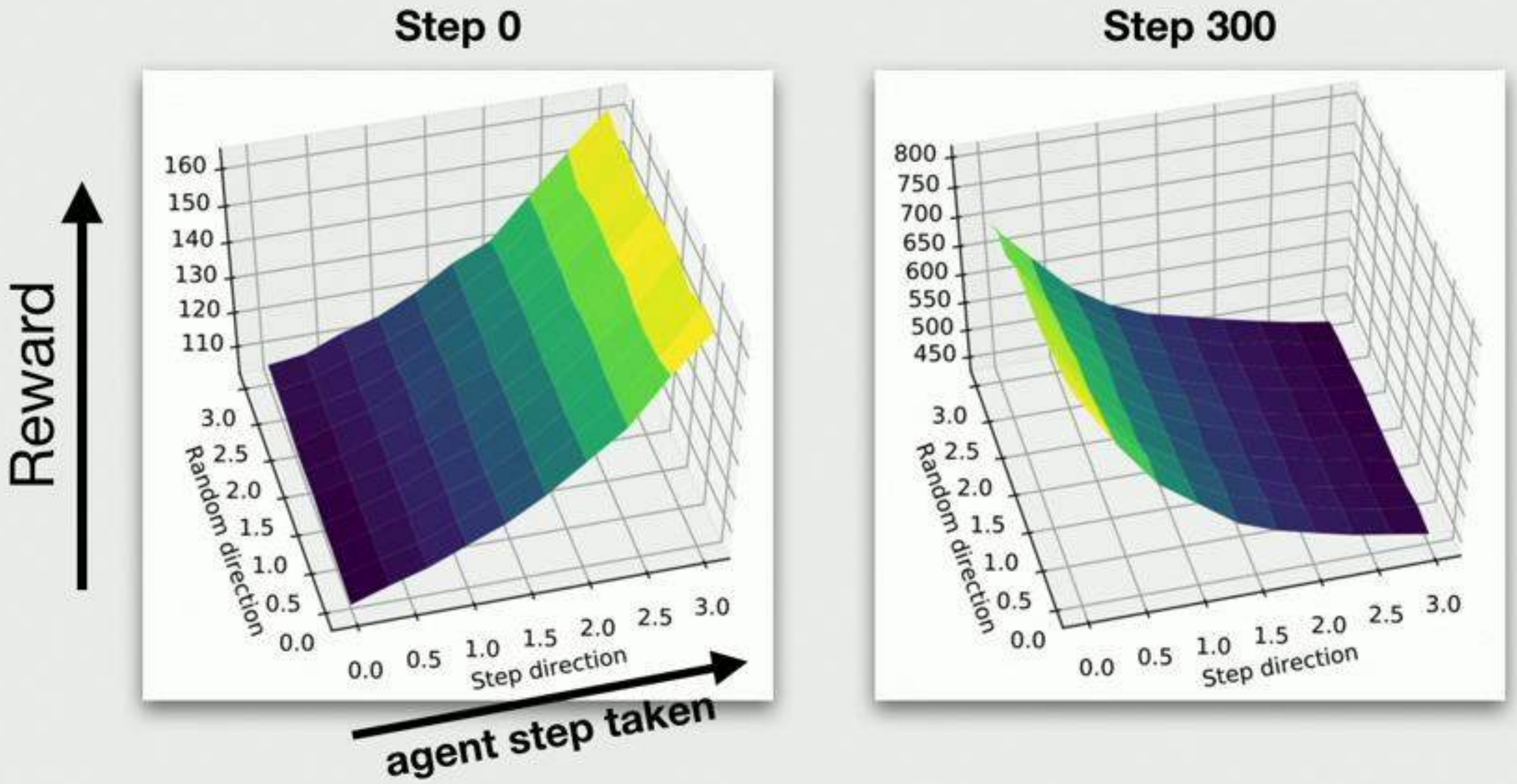
What's going on here?

Optimization Landscapes

Methods iteratively maximize a “surrogate reward”

(not the true reward!)

Optimization Landscapes



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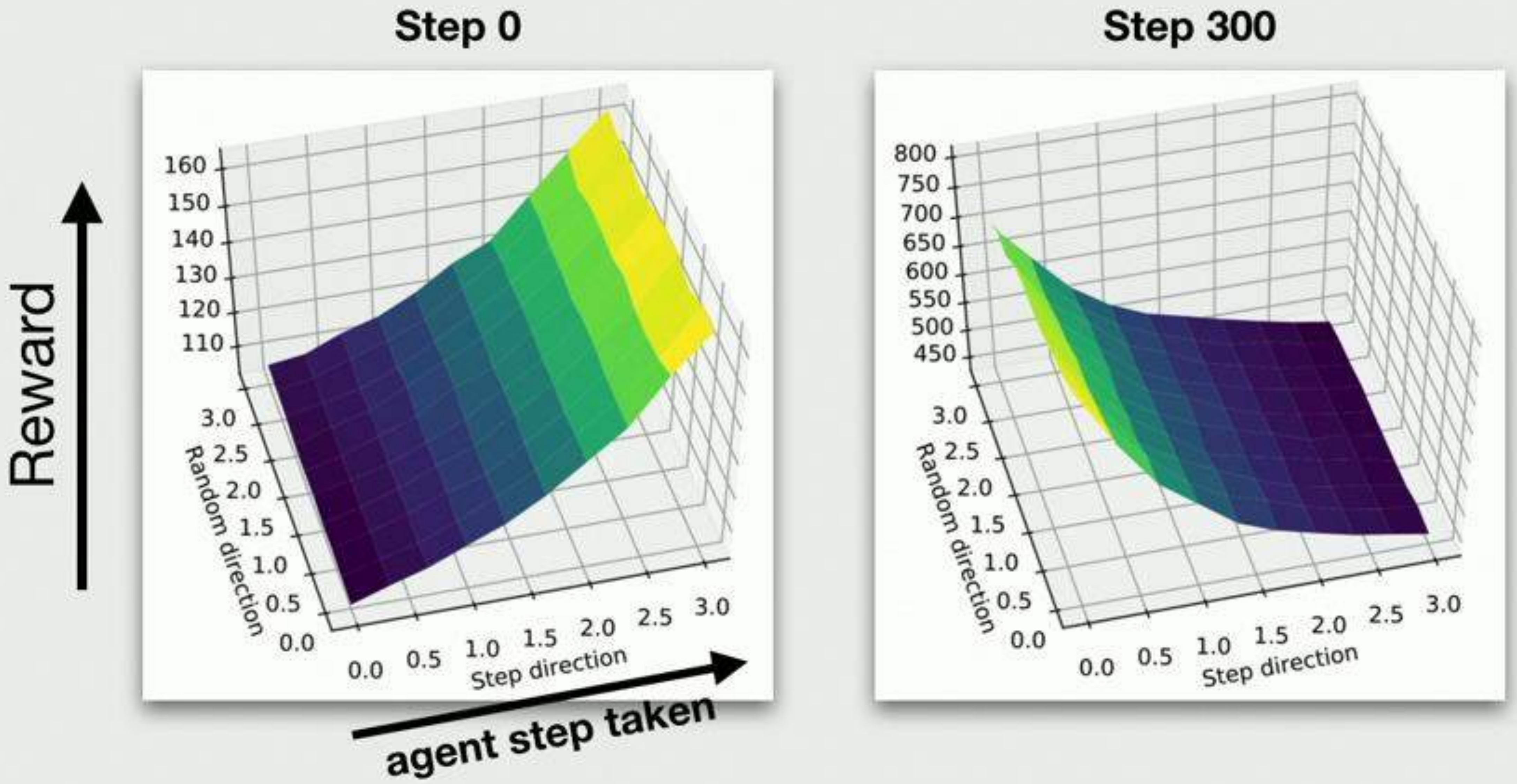

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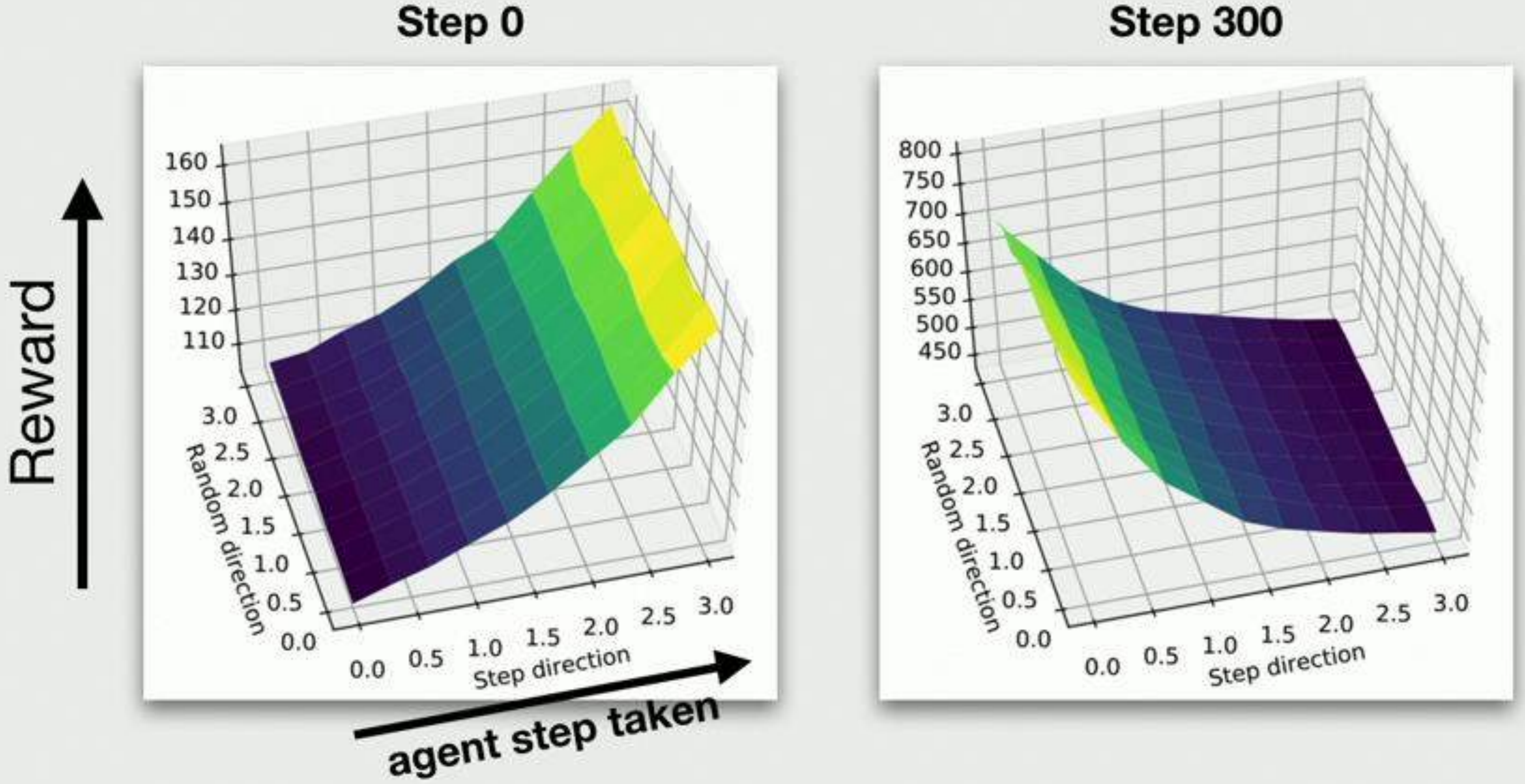

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What's going on here?

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Methods iteratively maximize a "surrogate reward"

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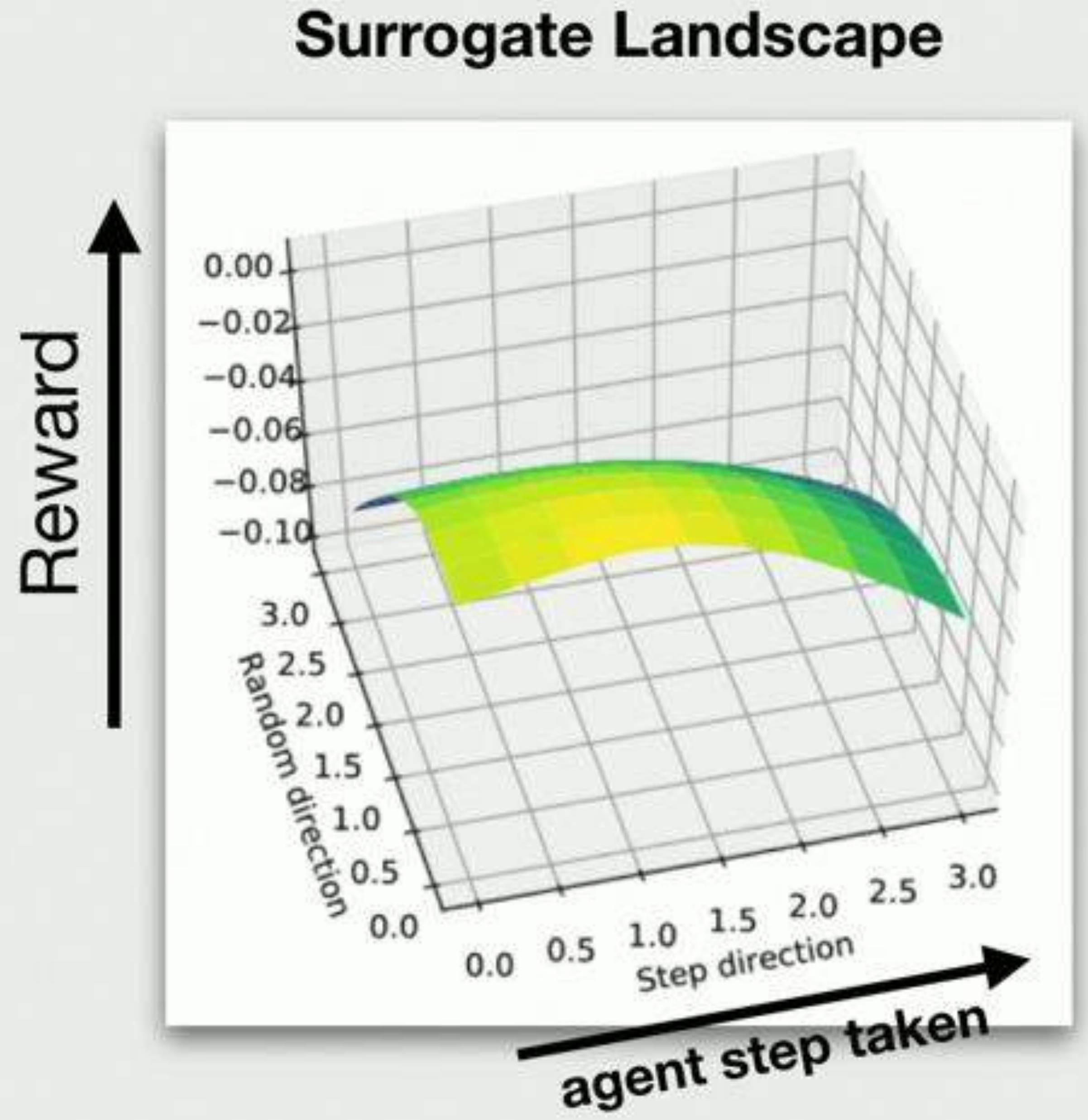
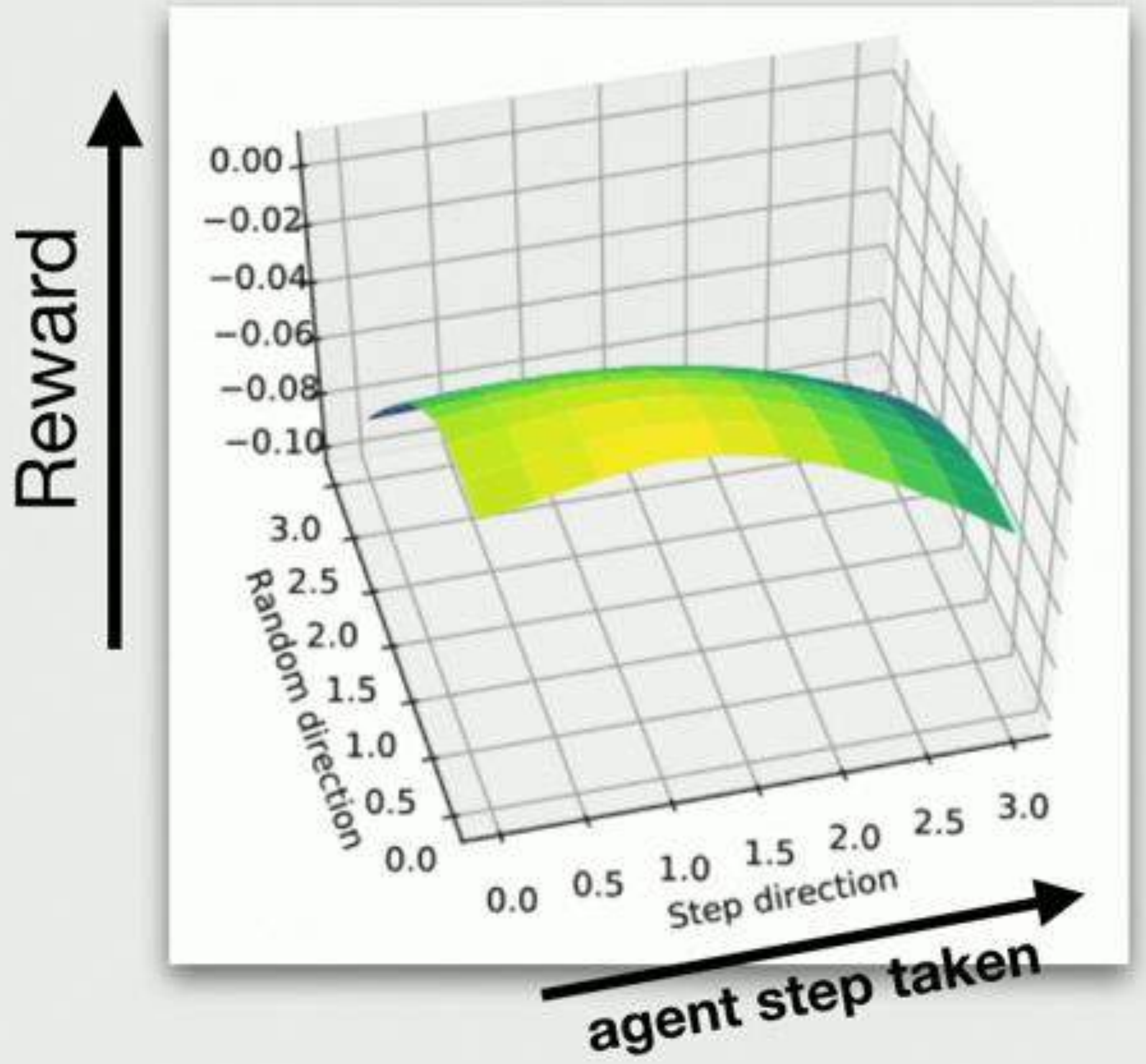
How do **surrogate rewards** compare with **true rewards**?

Optimization Landscapes

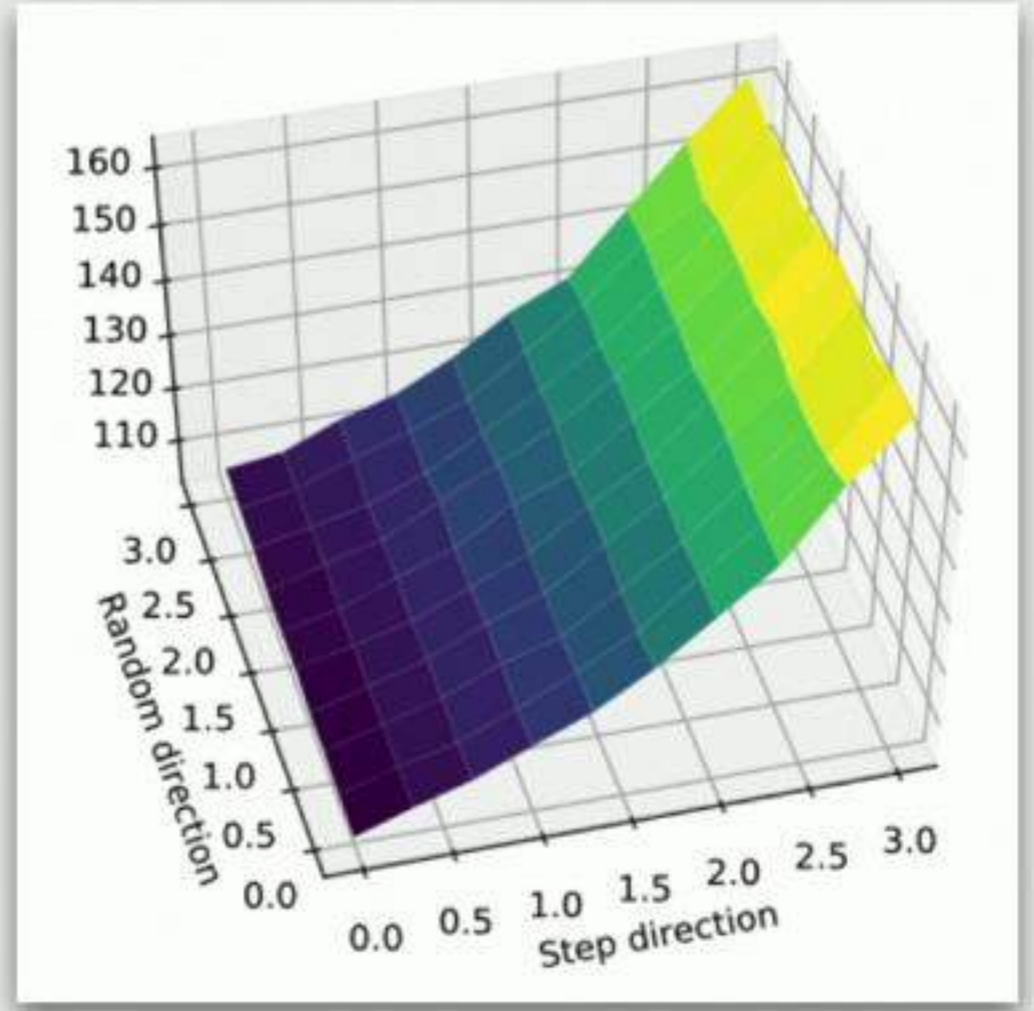


Optimization Landscapes

Surrogate Landscape

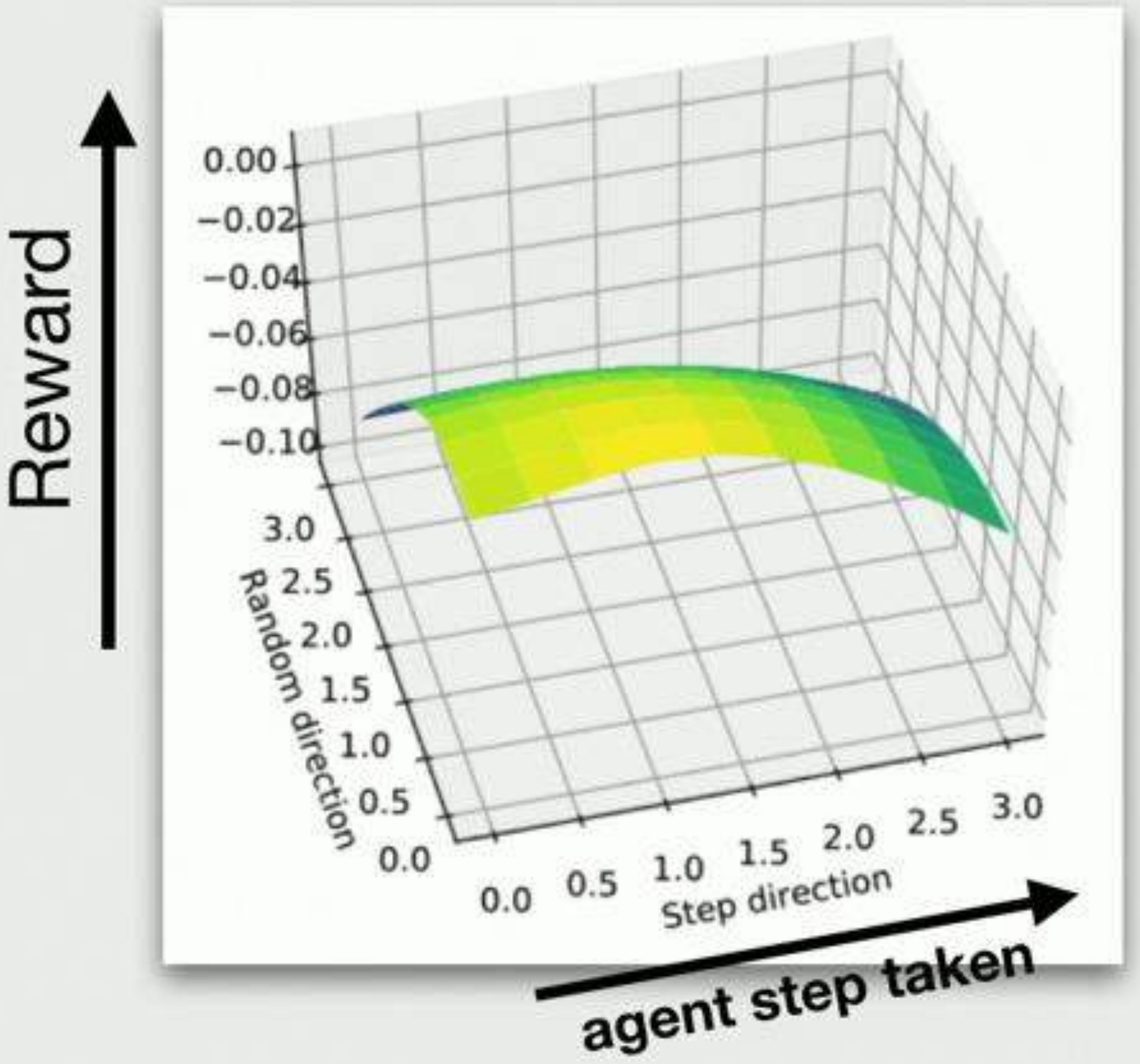


Reward Landscape

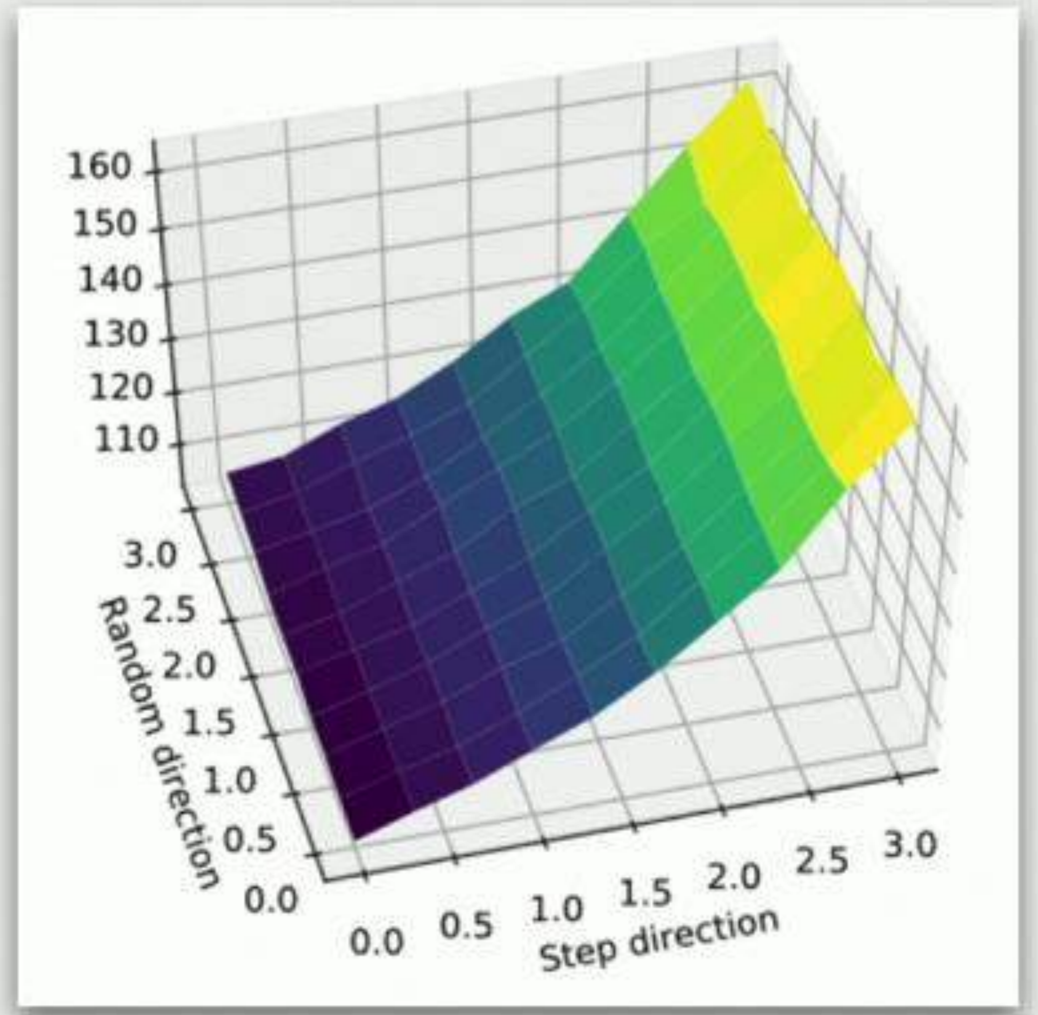


Optimization Landscapes

Surrogate Landscape

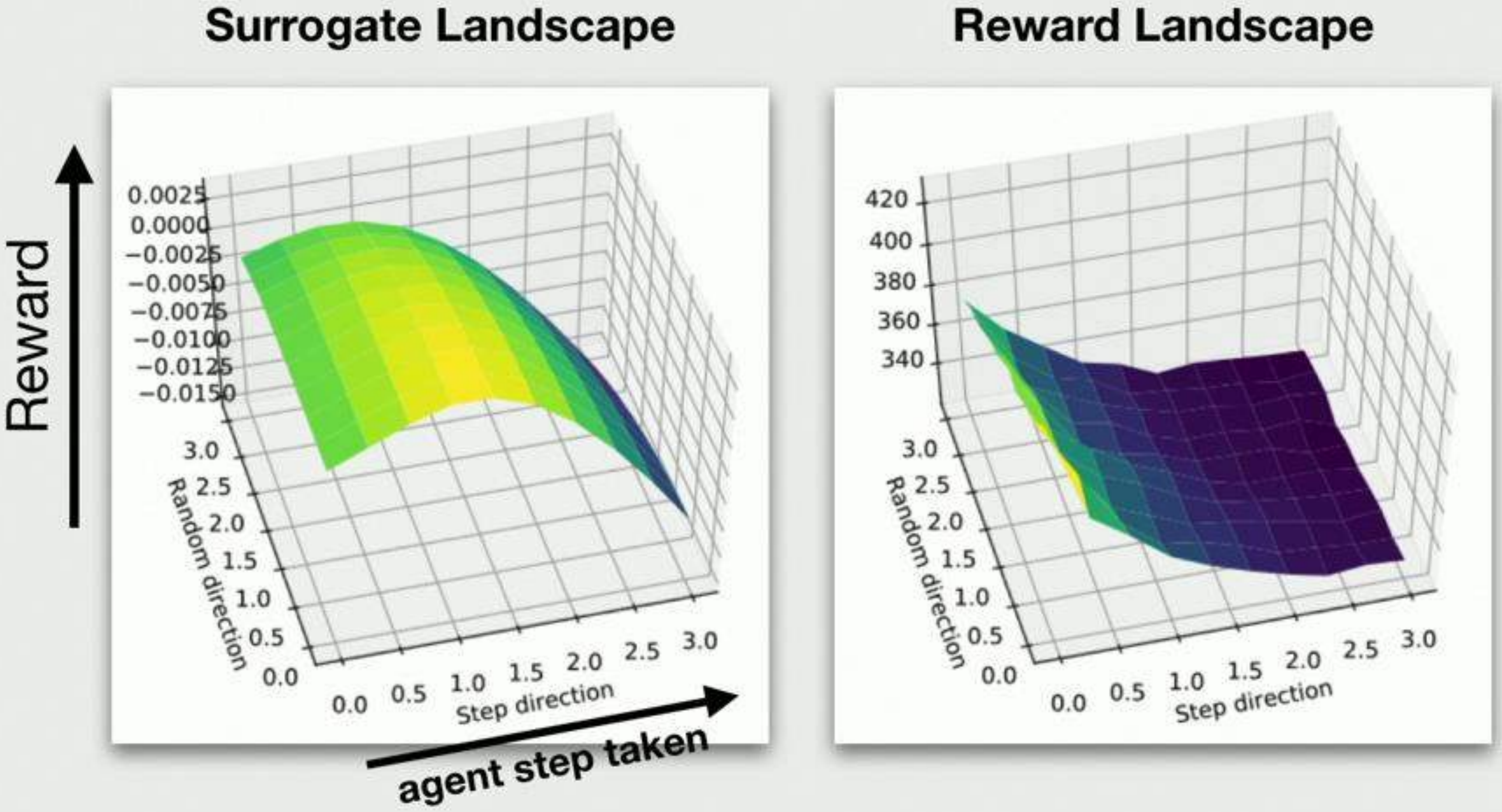


Reward Landscape



Step 0

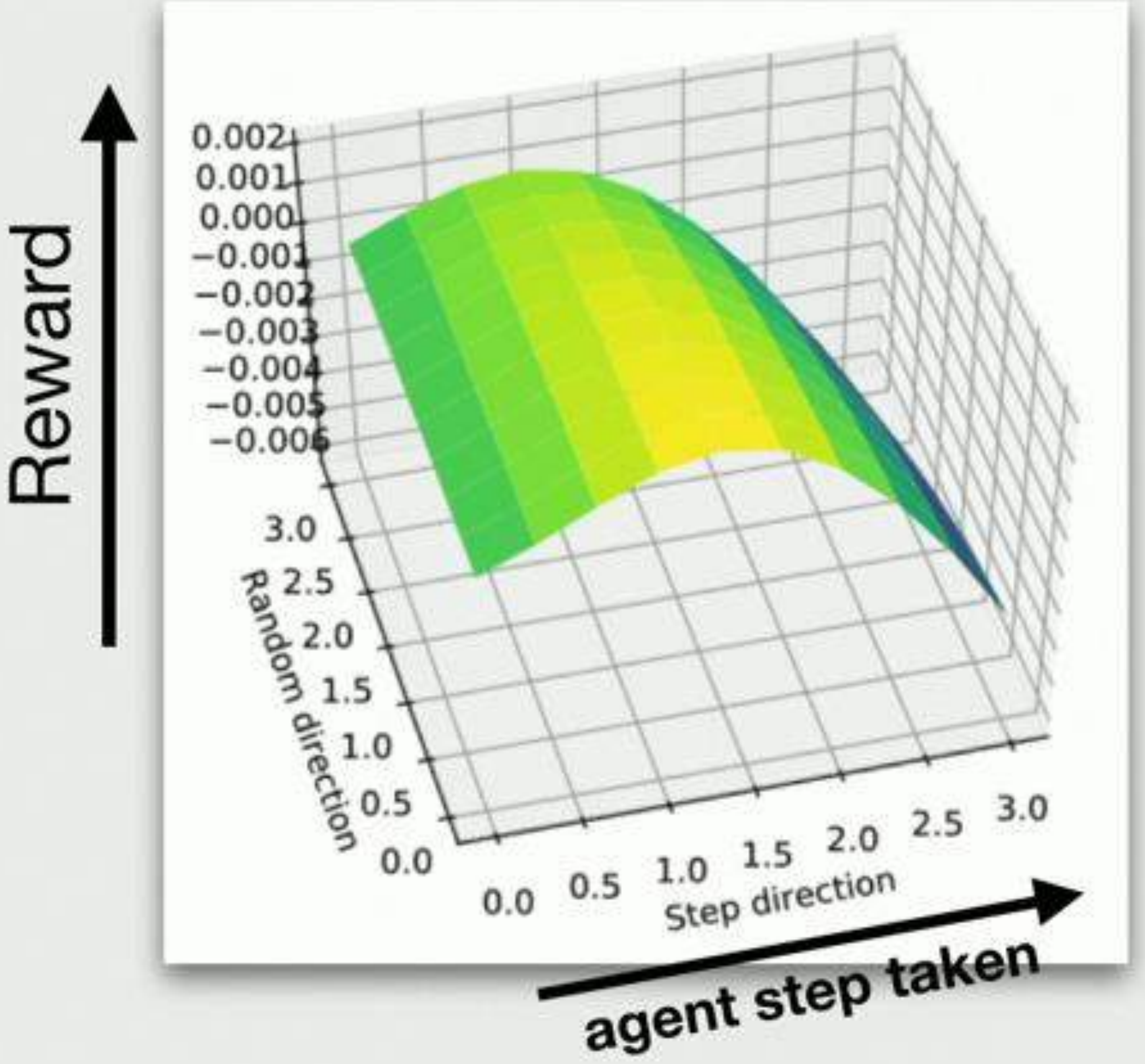
Optimization Landscapes



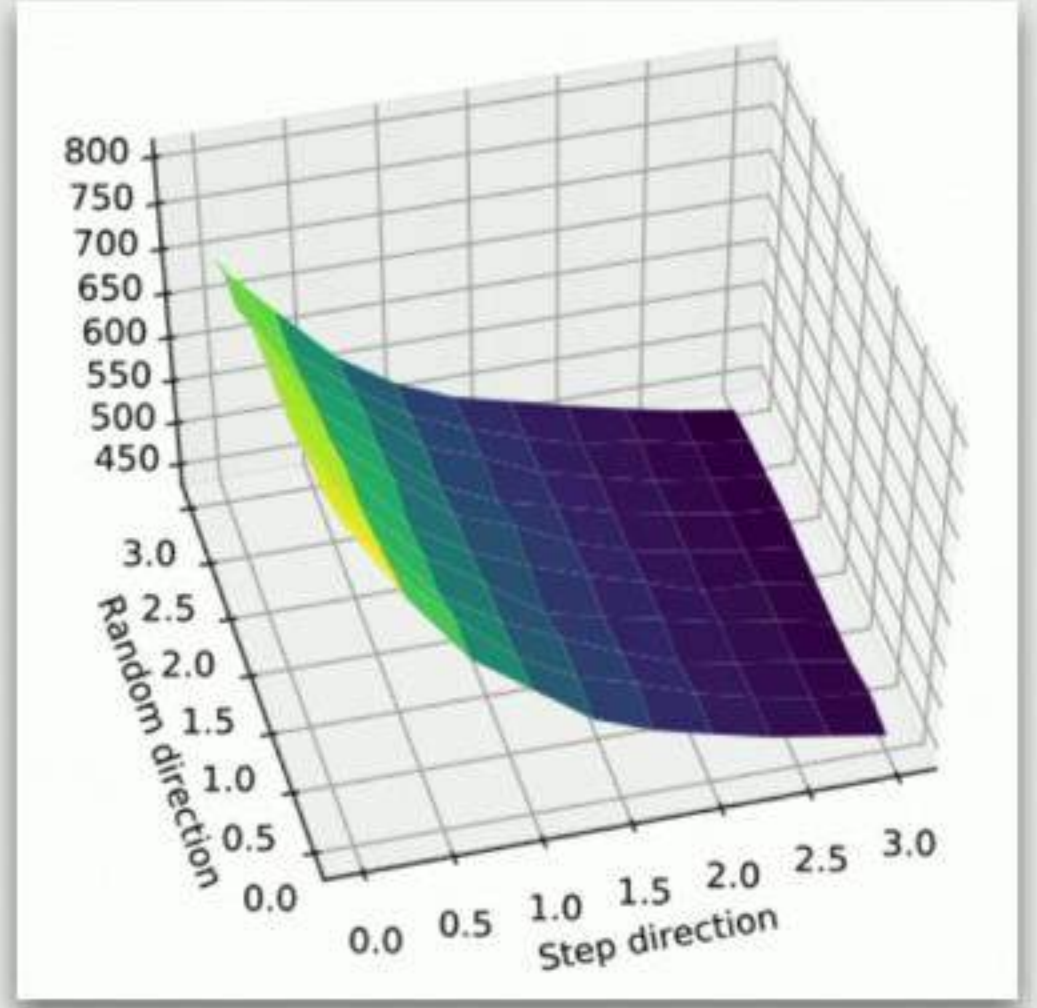
Step 150

Optimization Landscapes

Surrogate Landscape



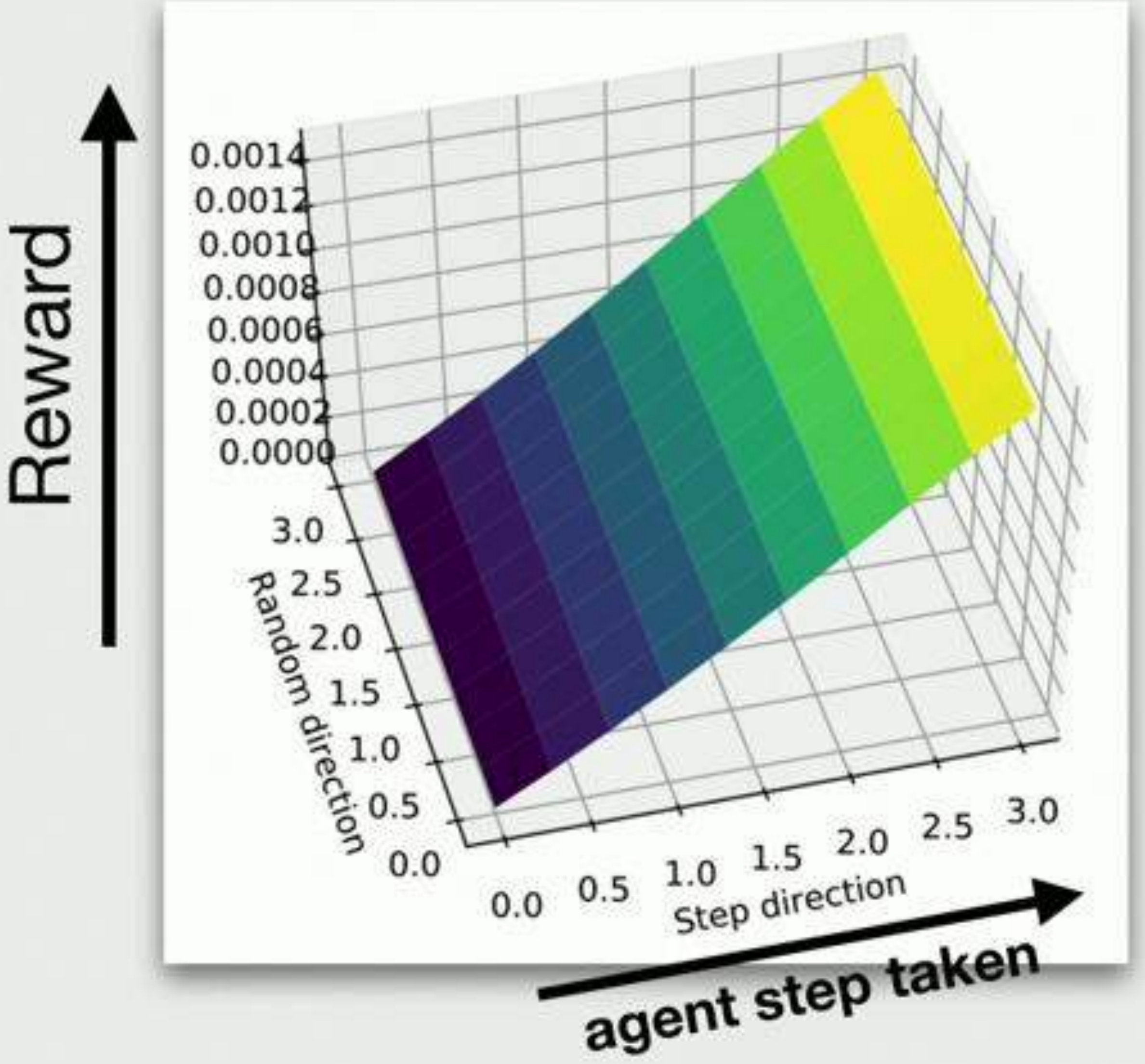
Reward Landscape



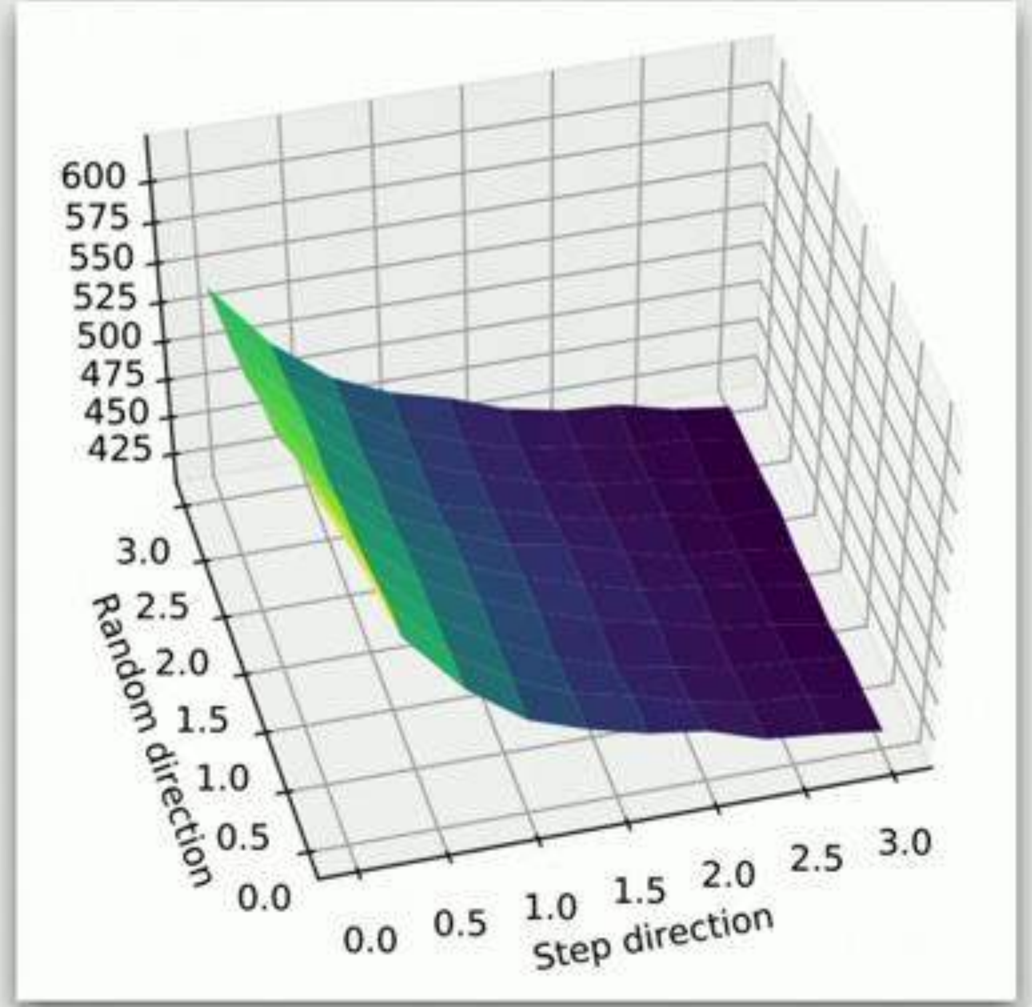
Step 300

Optimization Landscapes

Surrogate Landscape



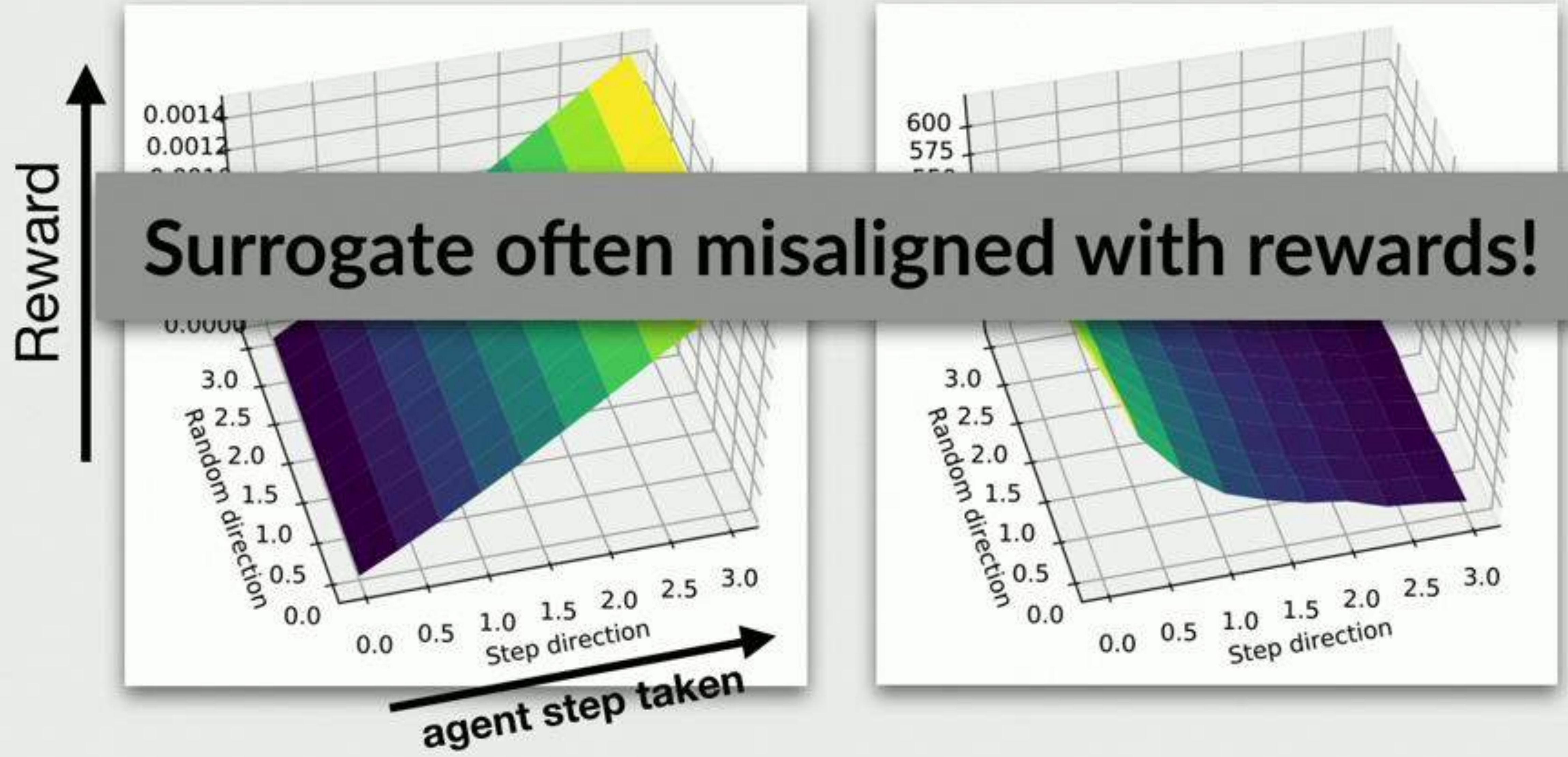
Reward Landscape



Step 450

Optimization Landscapes

Surrogate Landscape | **Reward Landscape**

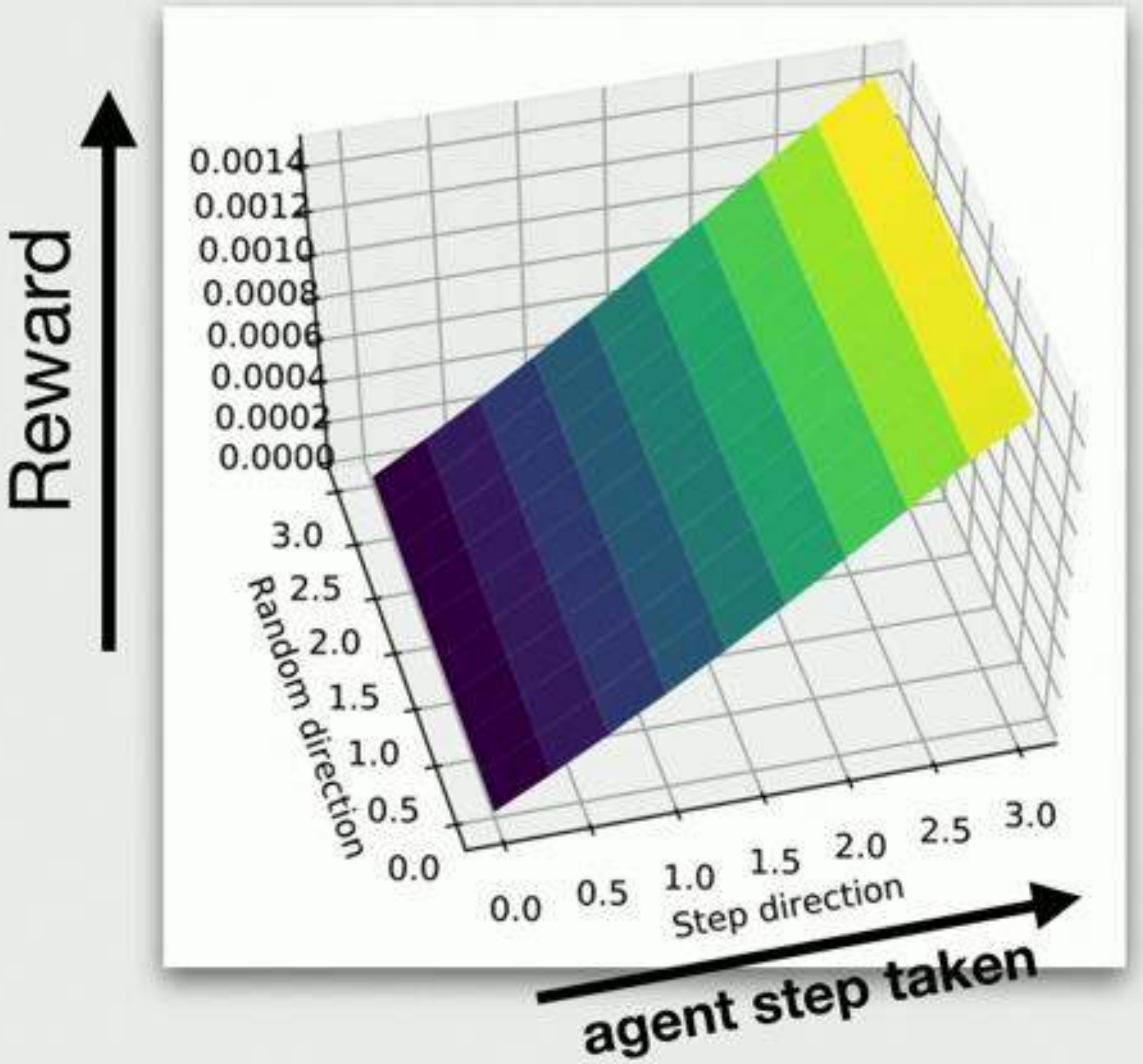


Surrogate often misaligned with rewards!

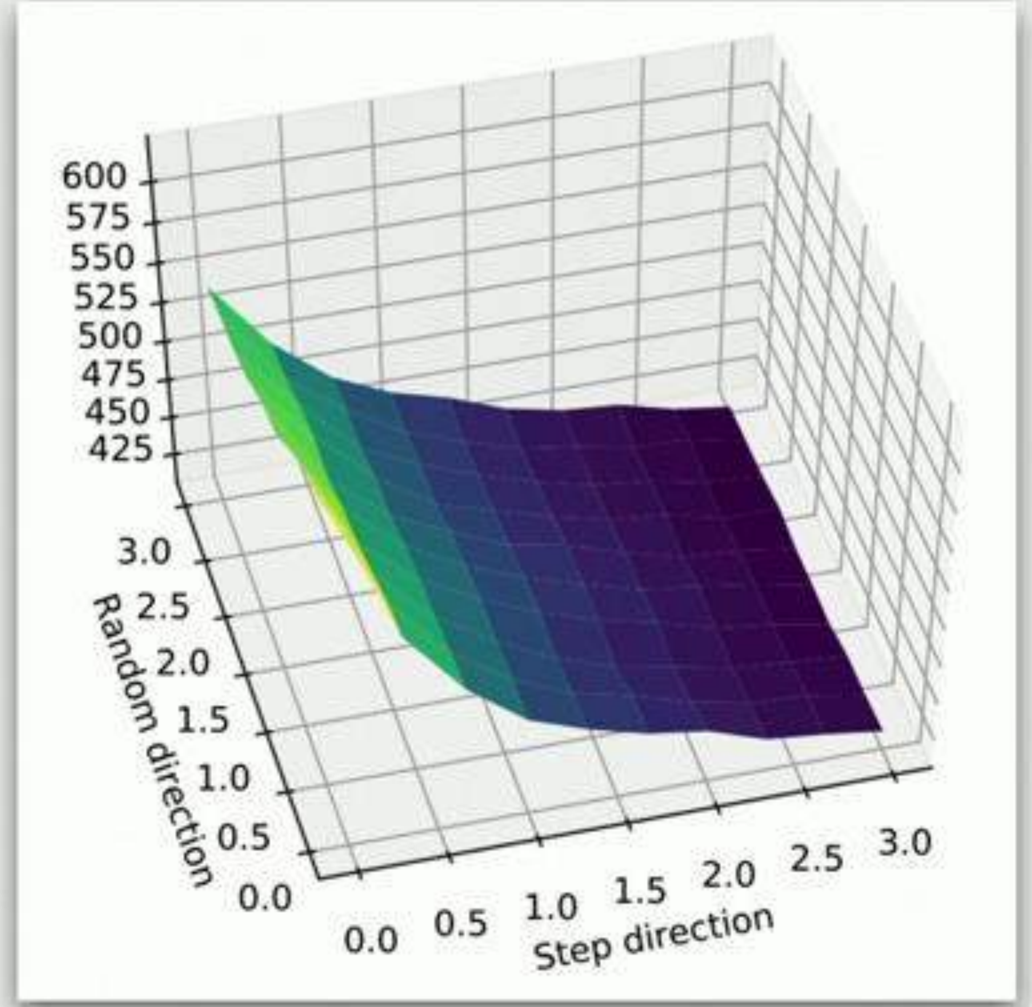
Step 450

Optimization Landscapes

Surrogate Landscape



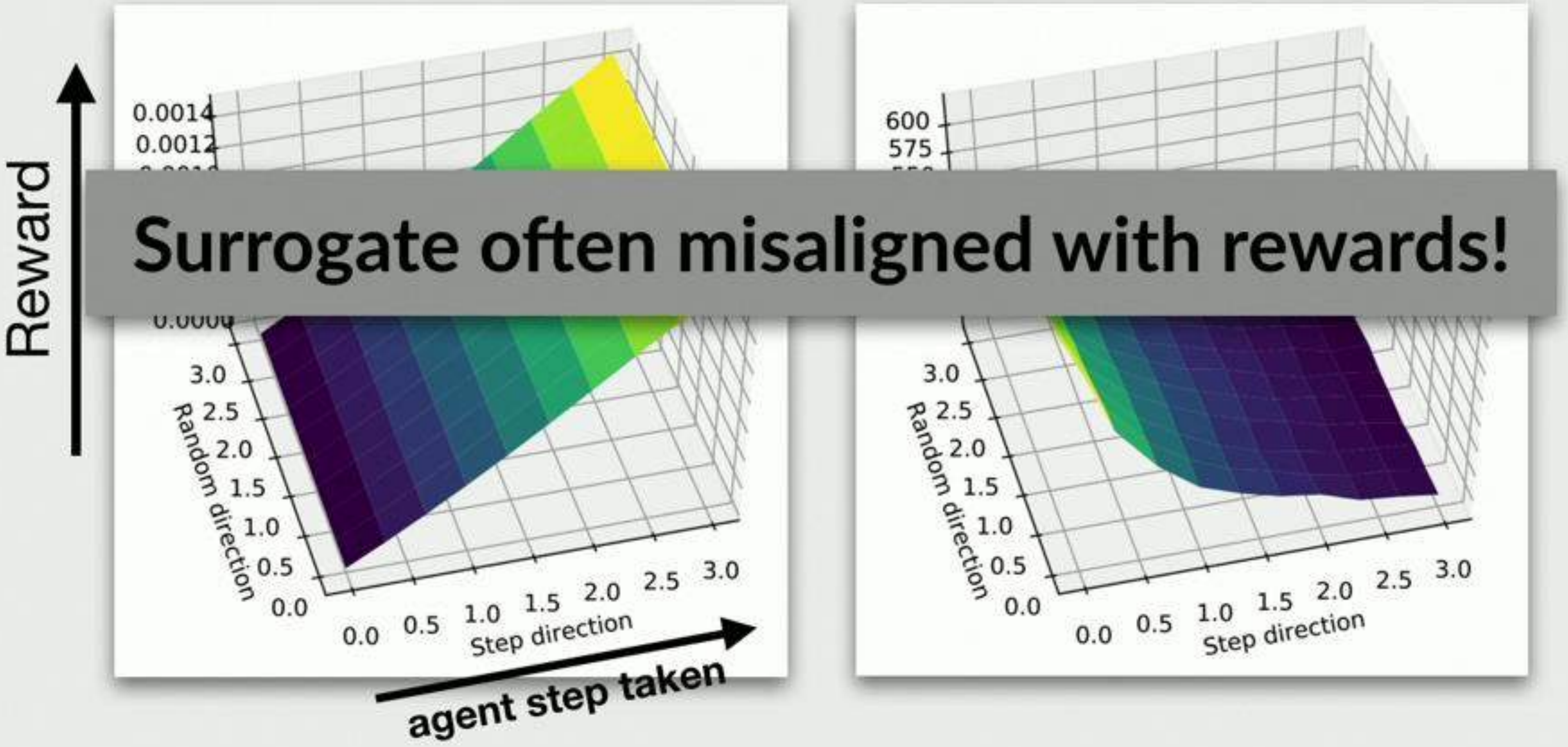
Reward Landscape



Step 450

Optimization Landscapes

Surrogate Landscape | **Reward Landscape**

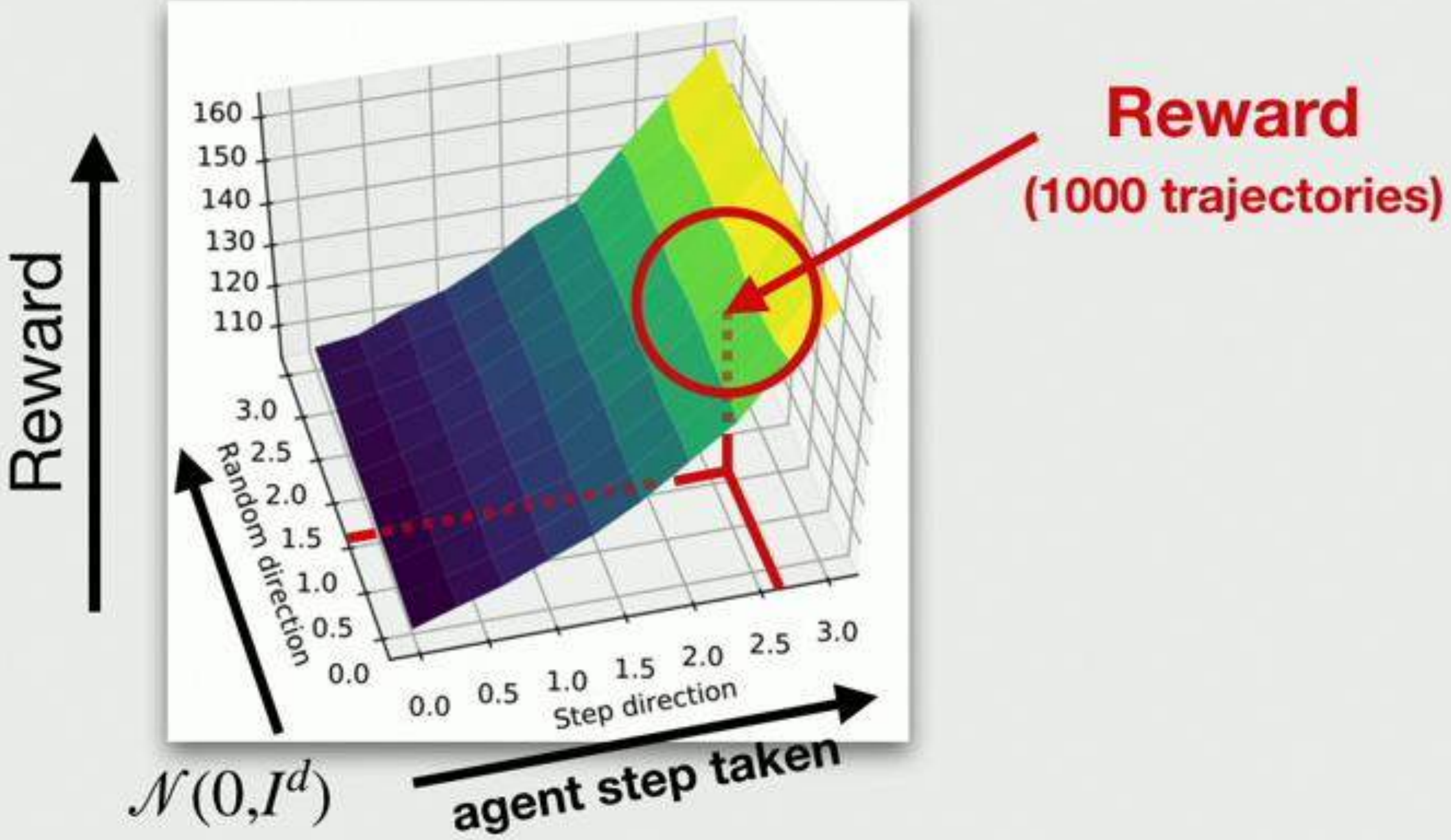


Surrogate often misaligned with rewards!

Step 450

Optimization Landscapes

All landscapes so far are in the **high sample** regime

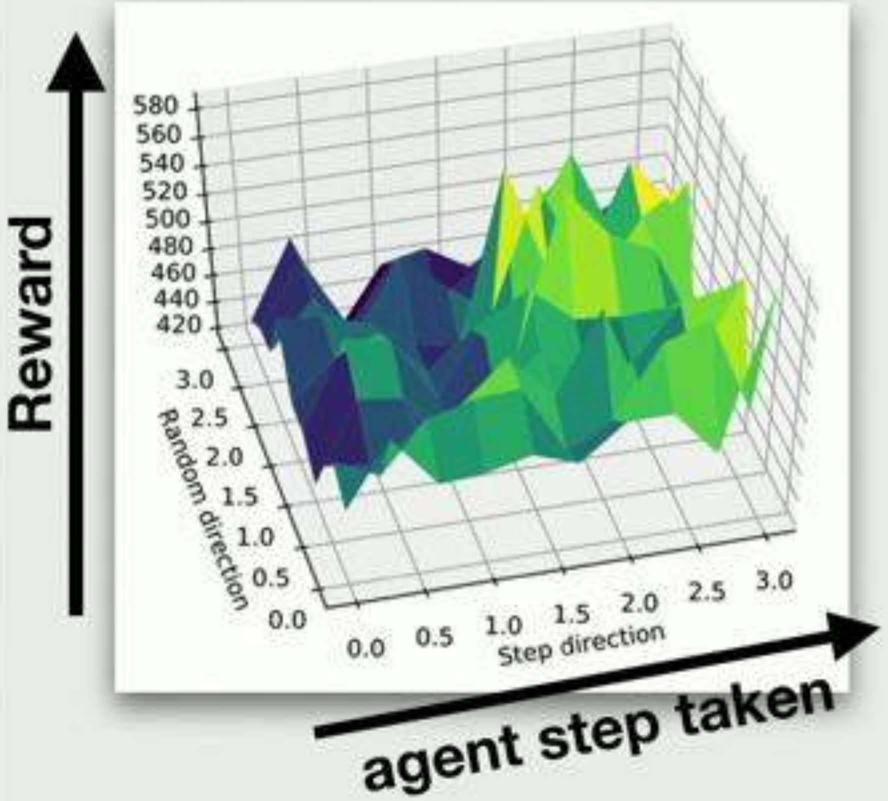


How do landscapes appear to the agent?

(~20 trajectories)

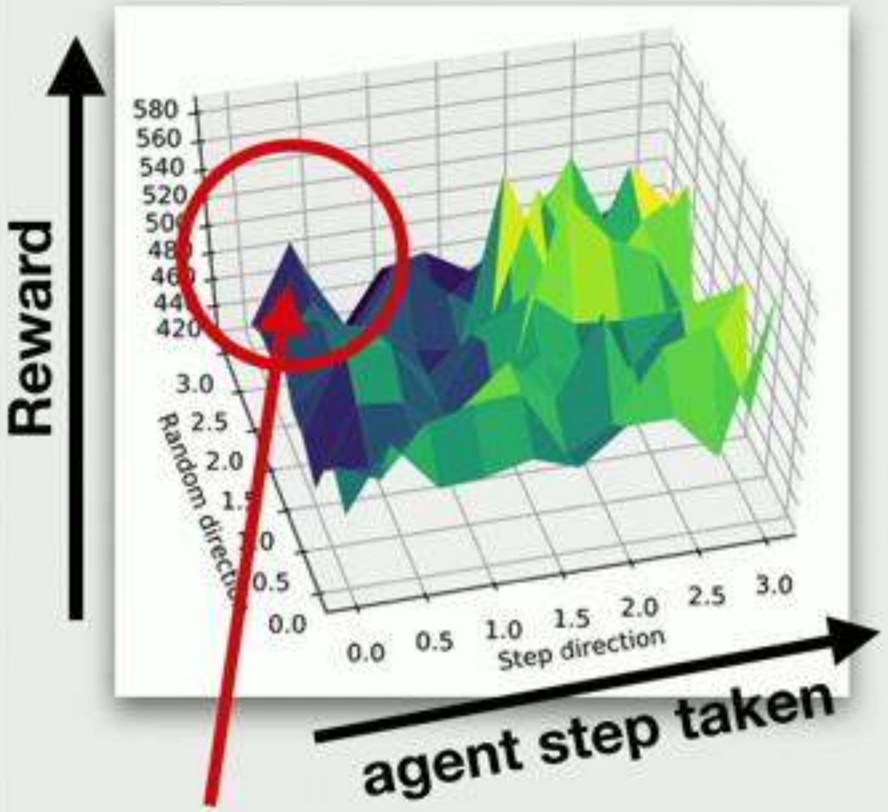
Optimization Landscapes

20-sample estimates



Optimization Landscapes

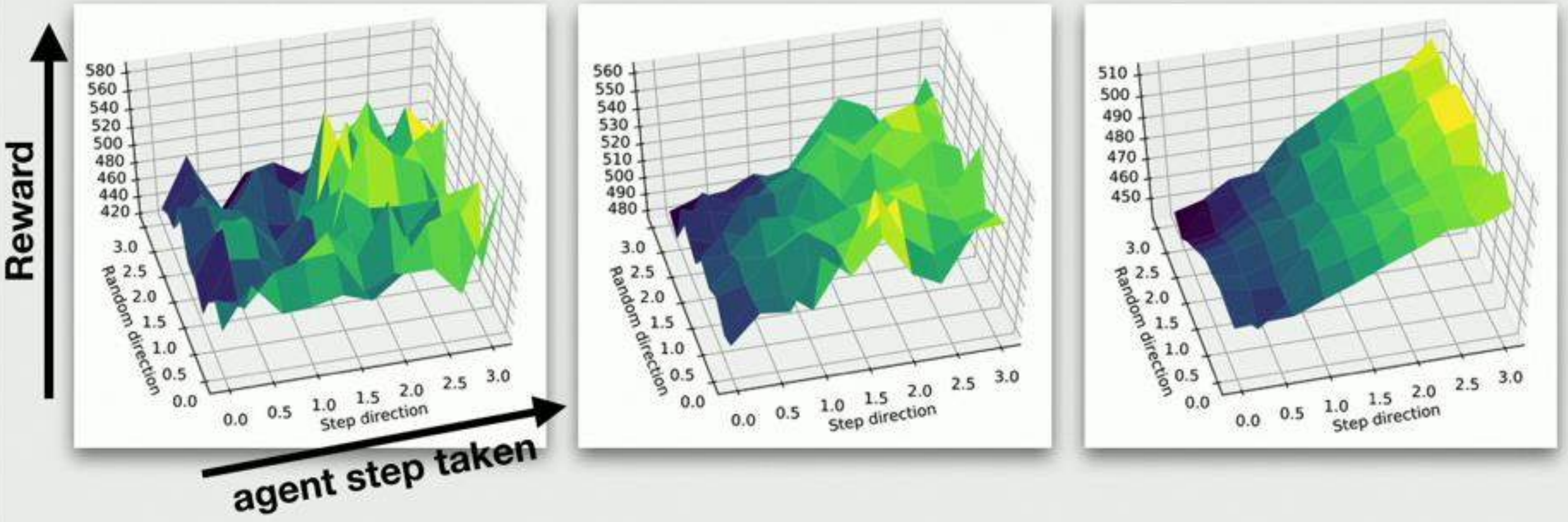
20-sample estimates



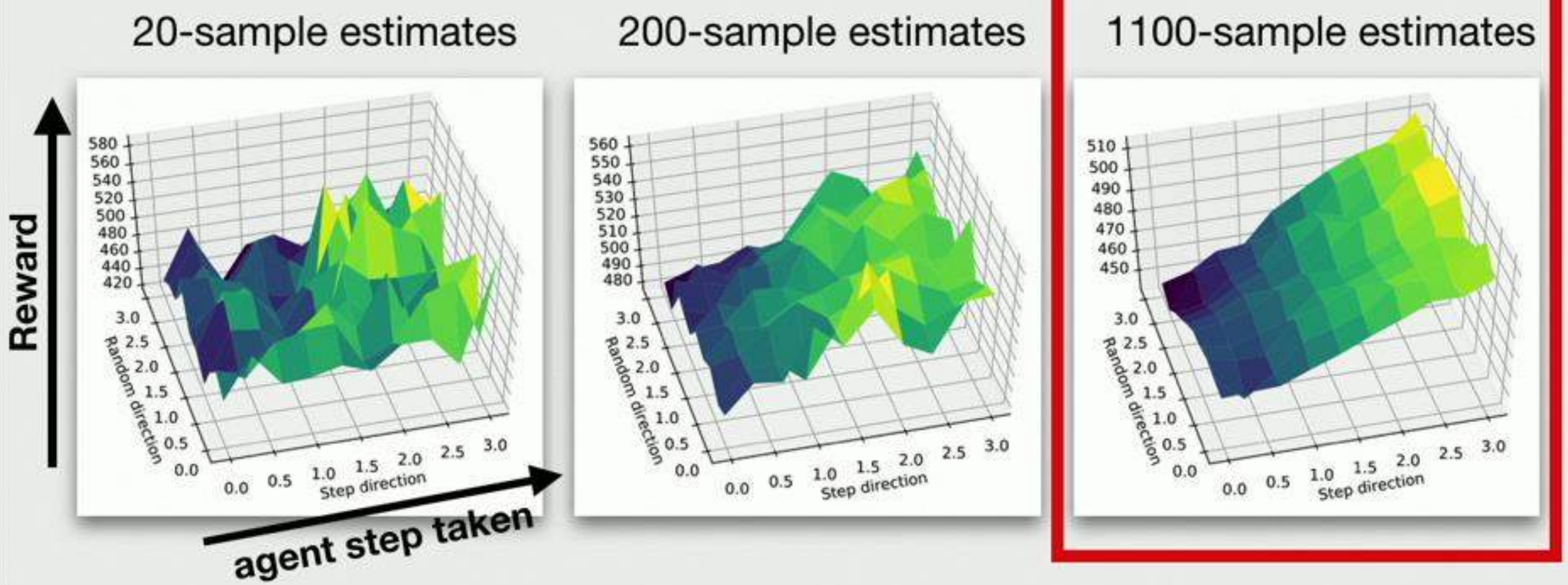
20 trajectories per reward estimate

Optimization Landscapes

20-sample estimates 200-sample estimates 1000-sample estimates

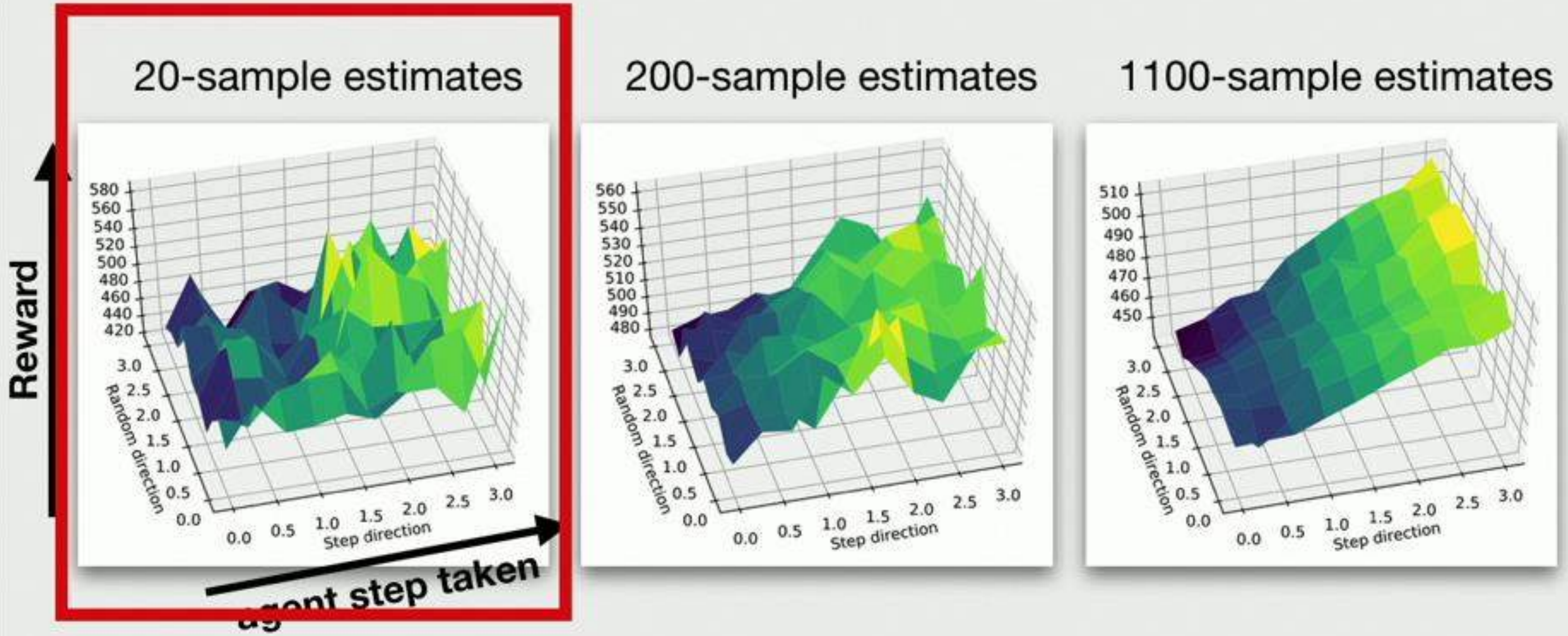


Optimization Landscapes



using many samples induces a smooth landscape...

Optimization Landscapes



using many samples induces a smooth landscape…

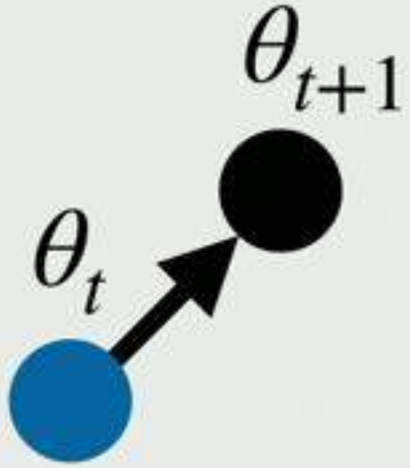
… but improvement is hard to detect in the agent's sample regime

Optimization Landscapes

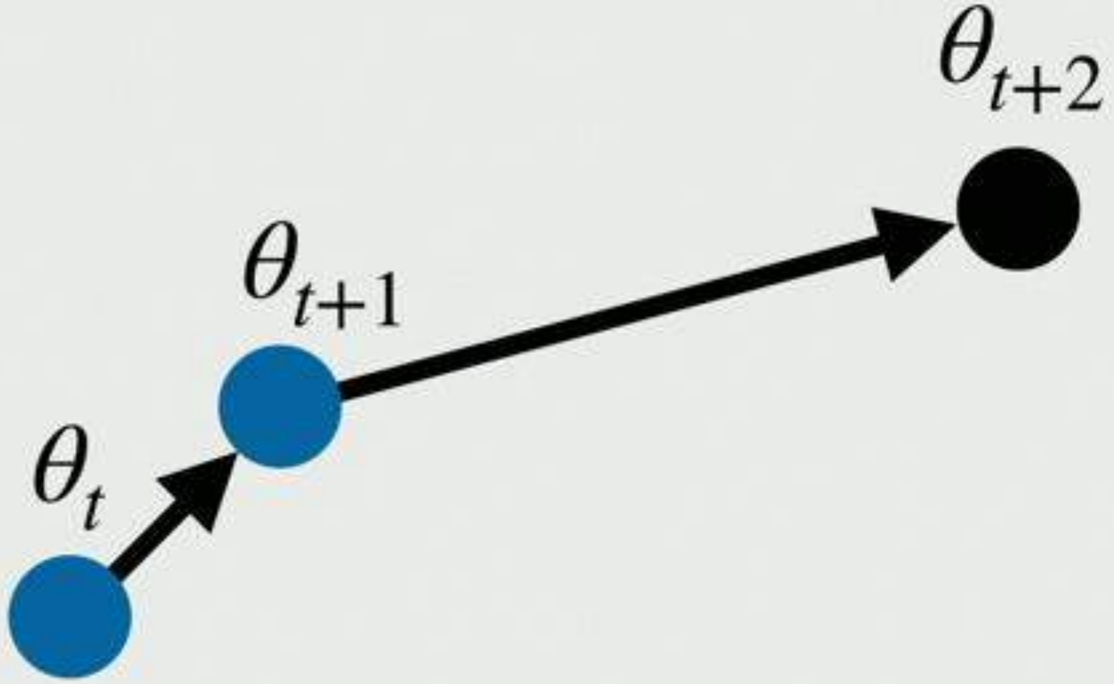
- Surrogate landscapes are often not reflective of rewards
- How can we better navigate the reward landscape?

Trust Regions

Trust Regions

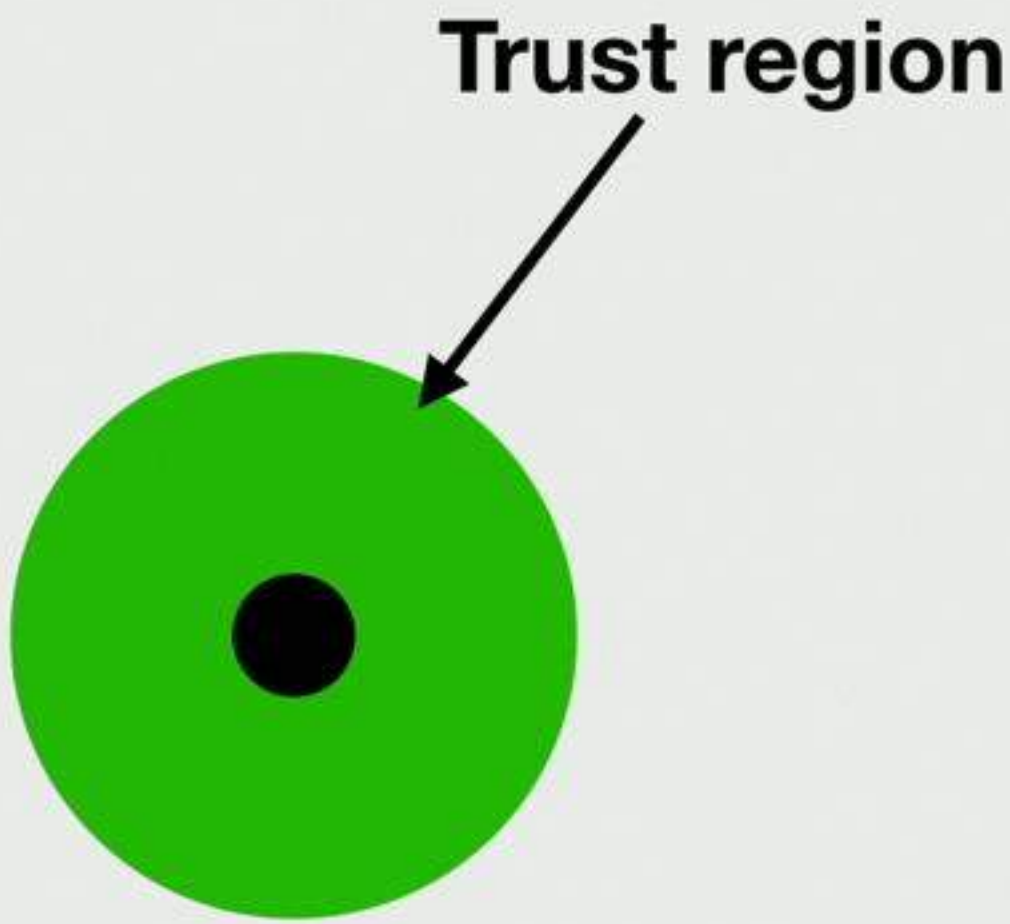


Trust Regions

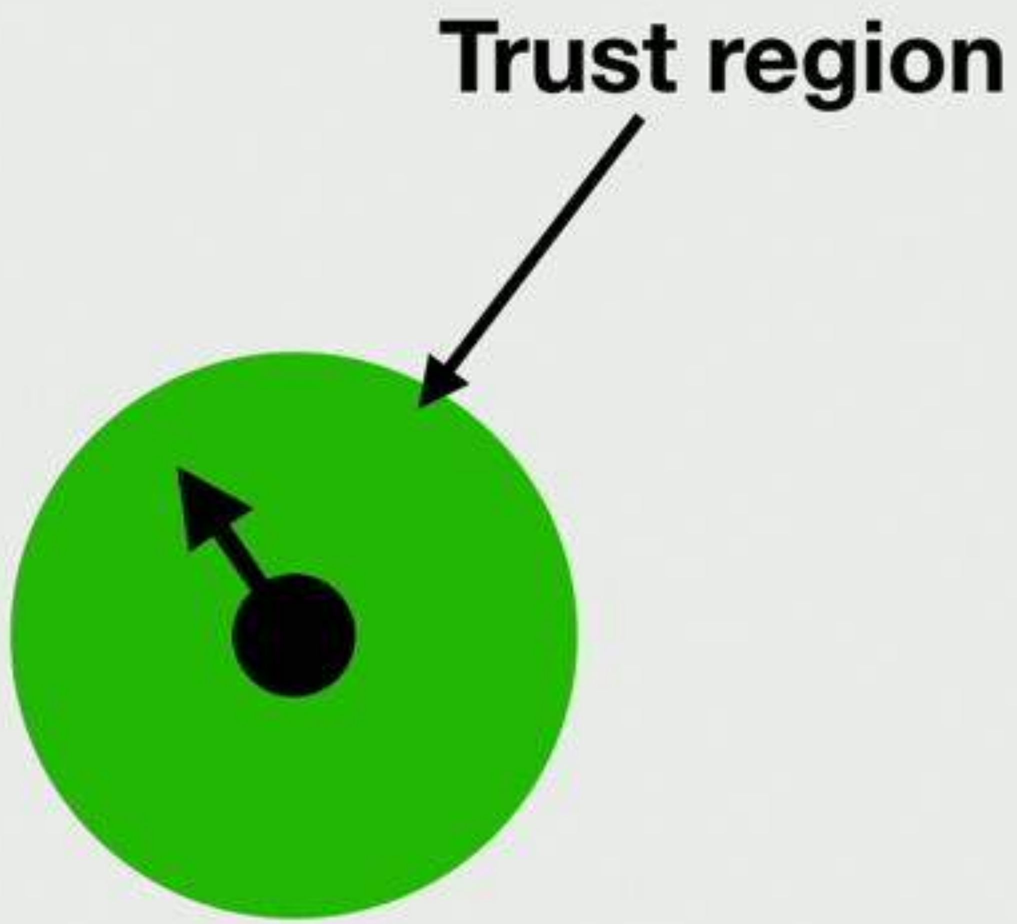


Trust Regions

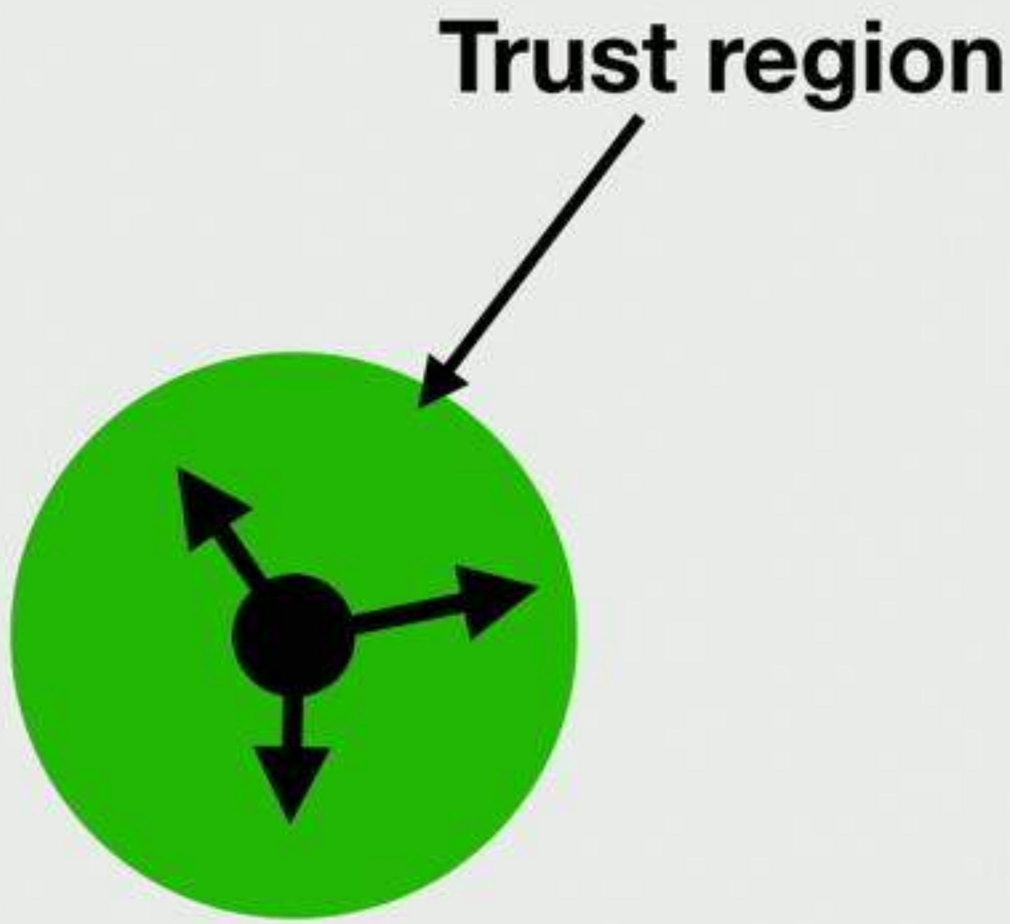
Trust Regions



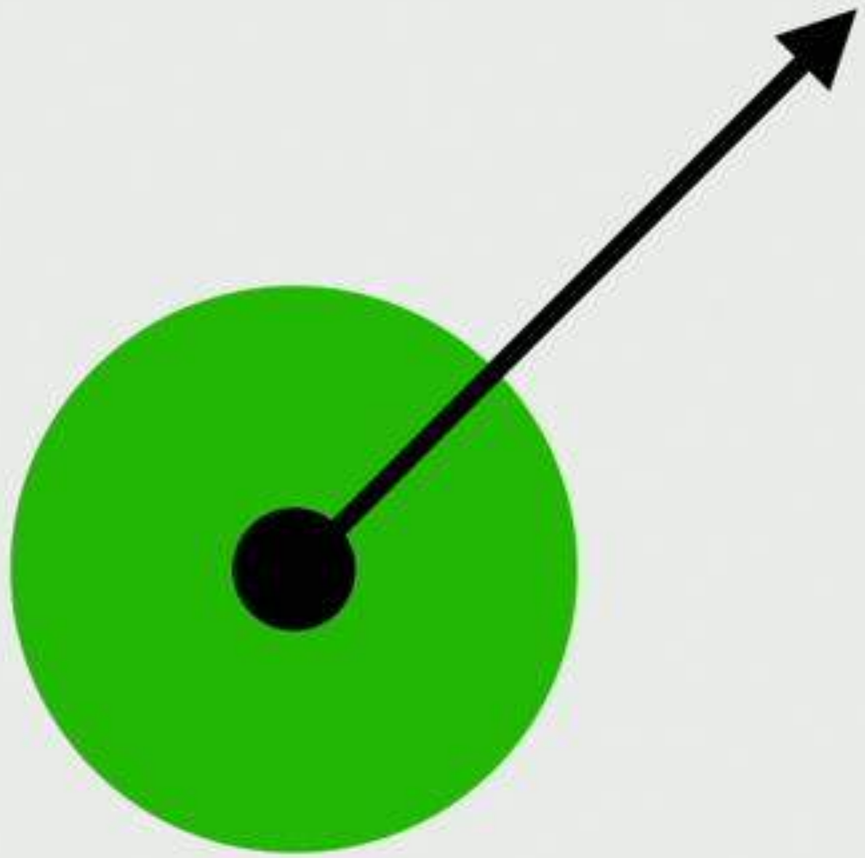
Trust Regions



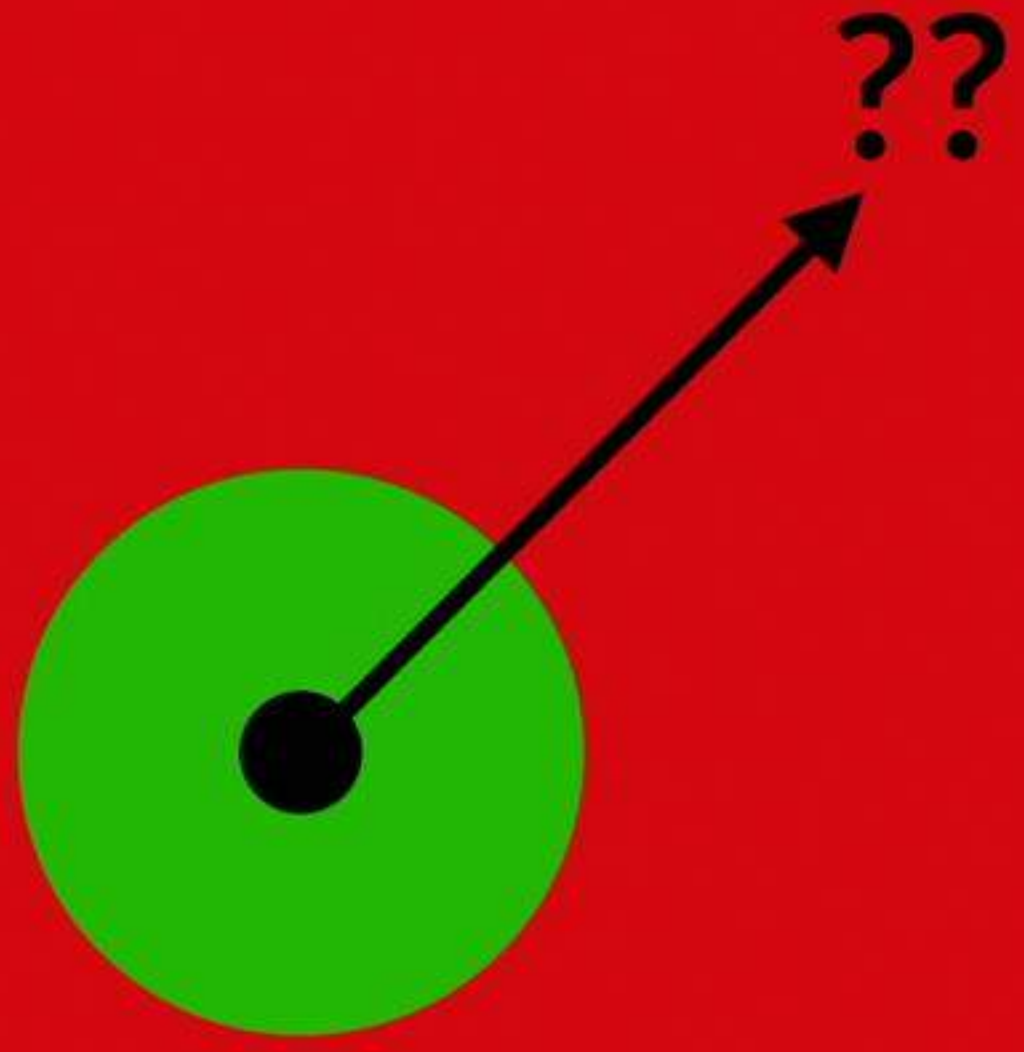
Trust Regions



Trust Regions



Trust Regions



Trust Regions

TRPO and PPO: Motivated by KL-based trust region:

$$\max_{s} D_{KL}\left(\pi_{\theta_{t+1}}(\,\cdot\,|\,s)\,\Big|\Big|\,\pi_{\theta_t}(\,\cdot\,|\,s)\right) \leq \delta$$

"keep the max distance between action distributions small"

But relax to an expectation:

$$\mathbb{E}_{s\sim\theta_t}\left[D_{KL}\left(\pi_{\theta_{t+1}}(\,\cdot\,|\,s)\,\Big|\Big|\,\pi_{\theta_t}(\,\cdot\,|\,s)\right)\right] \leq \delta$$

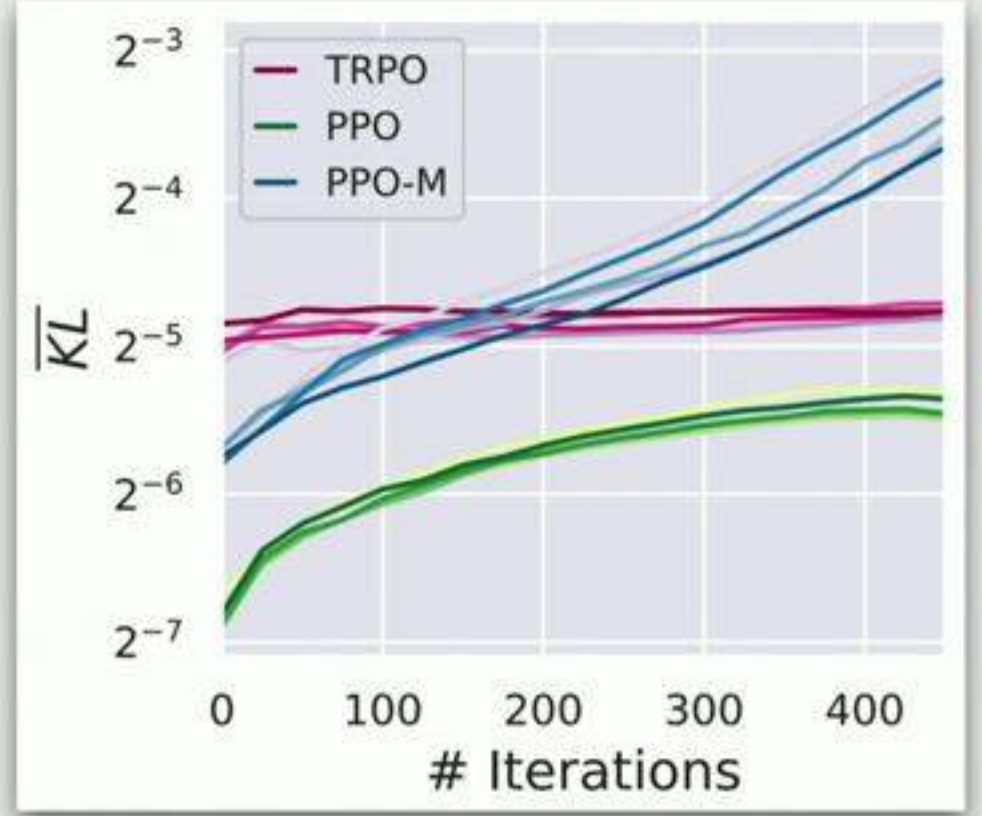
"keep the mean distance between action distributions small"

Trust Regions

What happens in practice?

Trust Regions

Mean KL Distance



- **TRPO** maintains trust region
- **PPO** algorithm does not!
- … but **optimizations** help

Trust Regions

- What part of algorithms keep trust regions?
- How do we reason about algorithms when they use such loose relaxations?
- How can we capture different kinds of uncertainty in our trust regions?

Takeaways

Recap

- Deep RL methods are complicated
- Deep RL training dynamics are poorly understood
  - Steps are often uncorrelated
  - Surrogate rewards do not match true rewards
  - Trust regions do not hold

How do we proceed?

- **Reconciling RL with our conceptual framework**
  - How can we make algorithms better follow our conceptual framework?
- **Rethinking primitives for modern settings**
  - How do we deal with *high dimensionality? Algorithm "optimizations?" Non-convex function approximators?*
- **Better evaluation for RL systems**
  - Benchmarks don't capture *reliability*, *safety*, *or robustness* of RL agents

Read more

Paper


Revisiting the Primitives of Deep Policy Gradient Algorithms

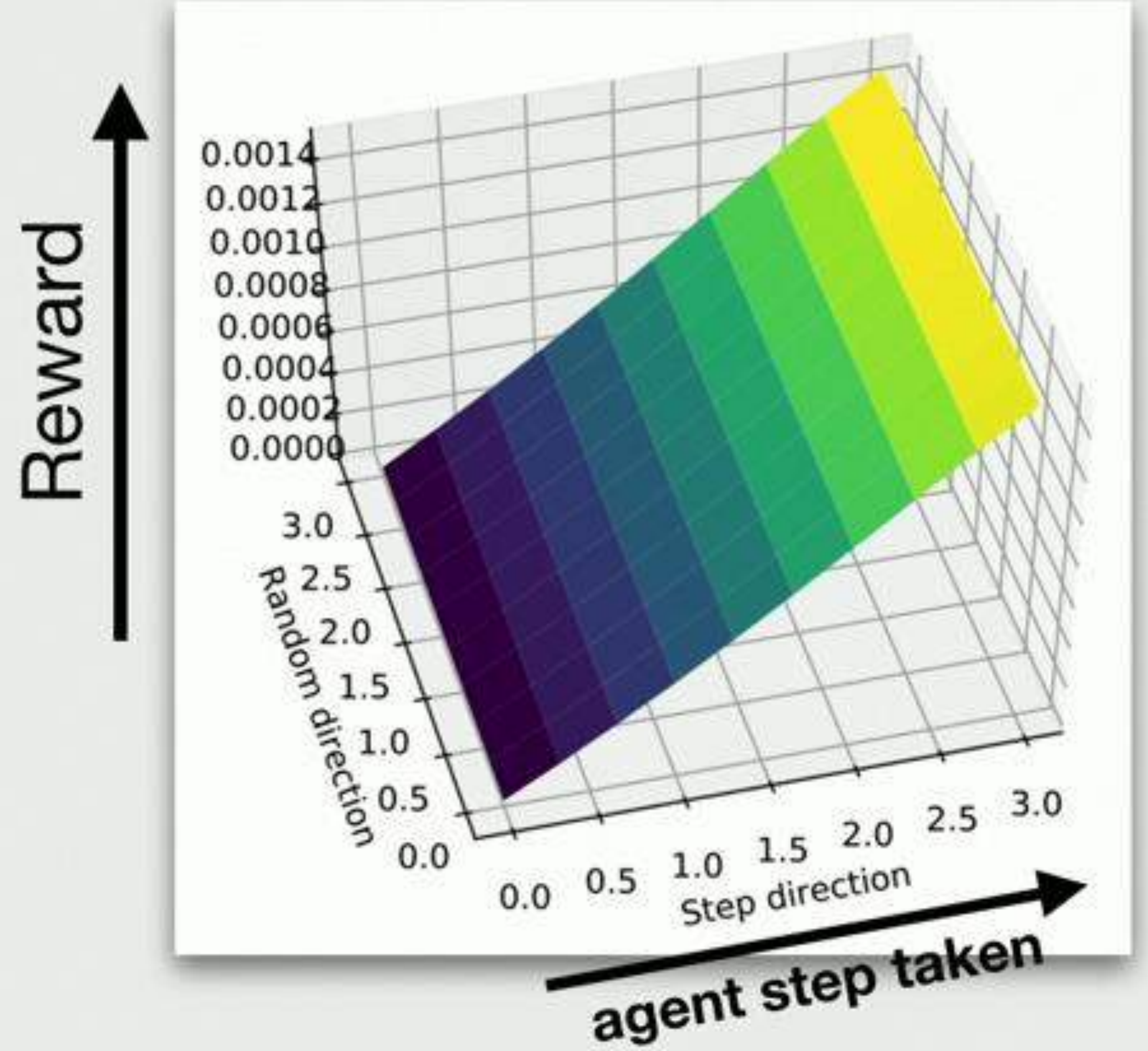
https://bit.ly/2UQGpad

Blog Posts

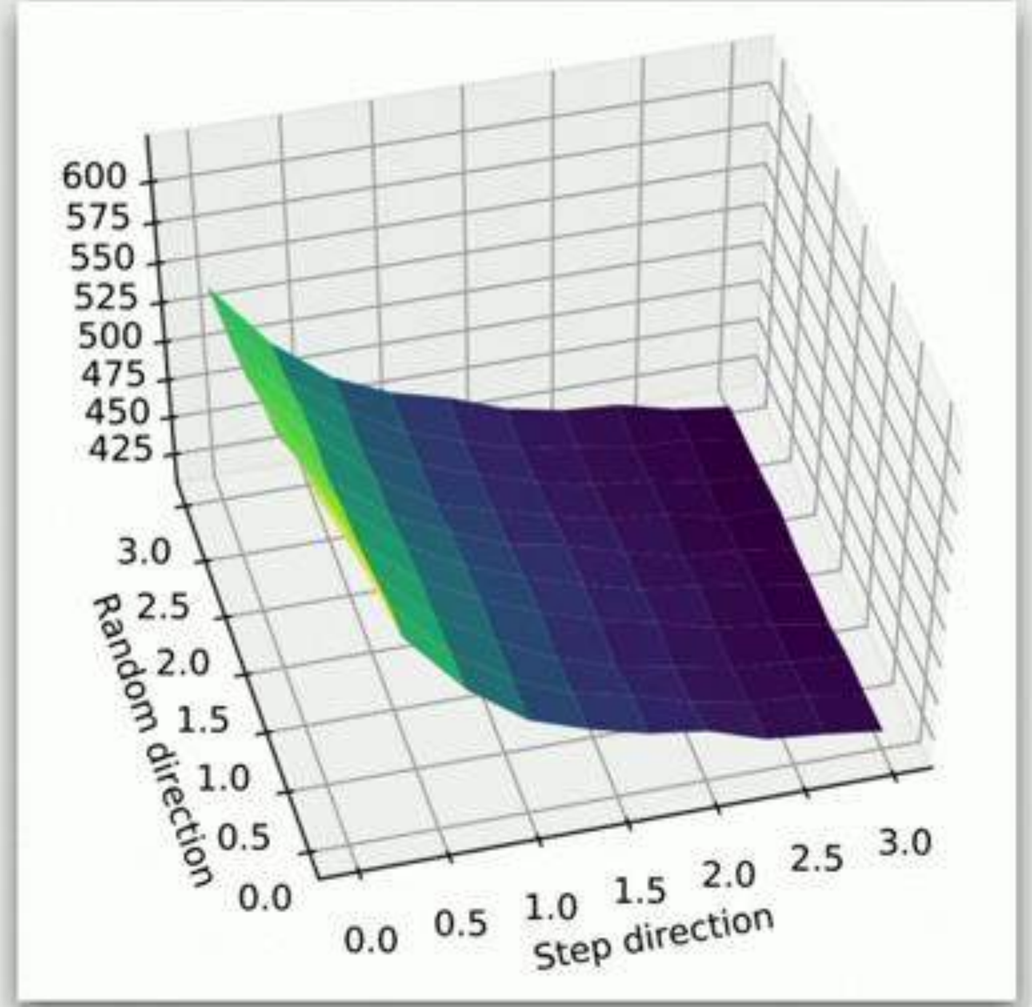
https://bit.ly/2WVPjAn

Optimization Landscapes

Surrogate Landscape



Reward Landscape



Step 450

Read more

Paper


Revisiting the Primitives of Deep Policy Gradient Algorithms

Anonymous Authors[1]

Abstract

1. Introduction

1.1. Our contributions

https://bit.ly/2UQGpad

Blog Posts

https://bit.ly/2WVPjAn