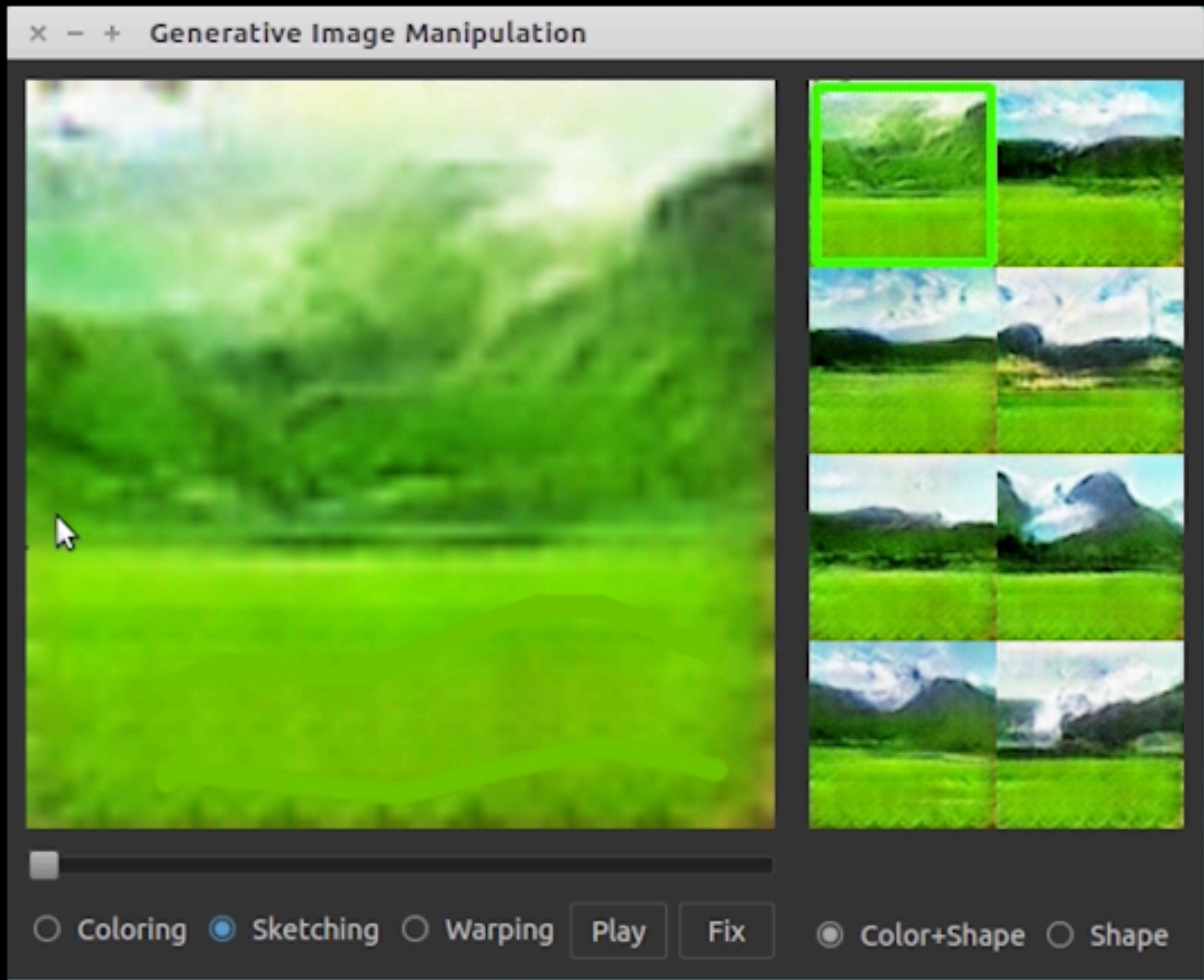




# Machine Creativity

“GAN Teddy” by Mario Klingemann using BigGAN model (2018)



Source: Generative Visual Manipulation on the Natural Image Manifold, Zhu et al. ECCV 2016

Select a feature brush & strength and enjoy painting:

tree

grass

door

sky

cloud

brick

dome

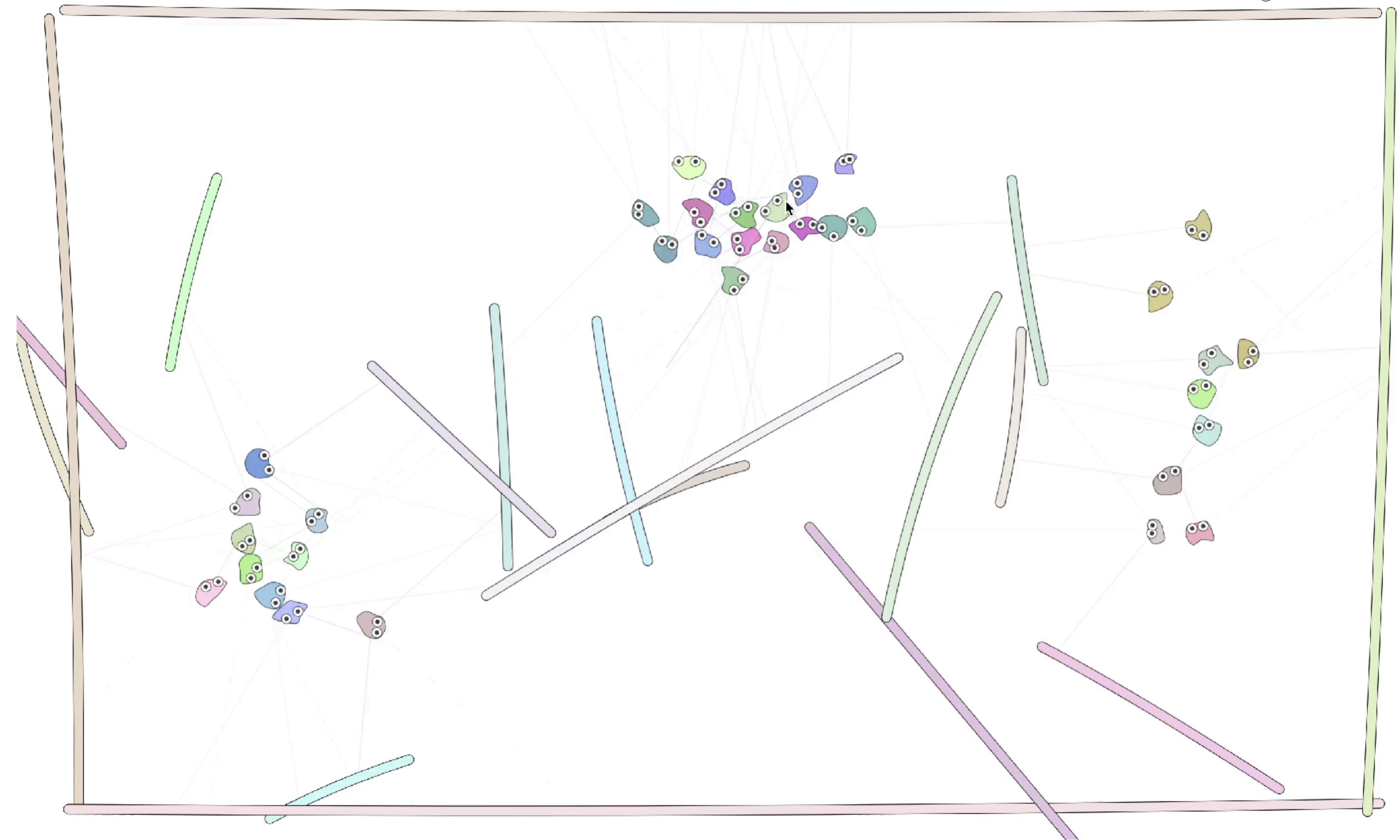
draw remove

undo reset

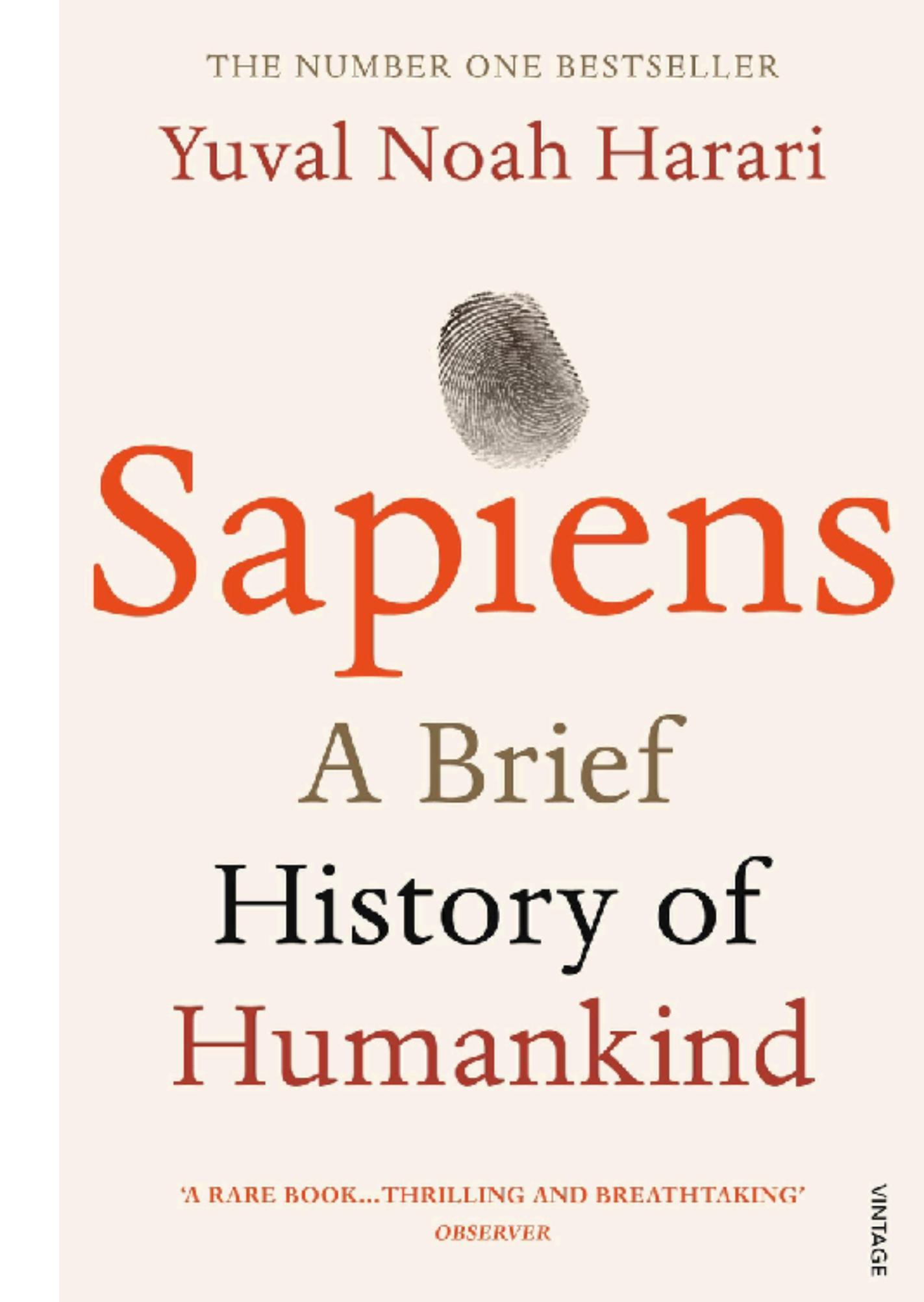
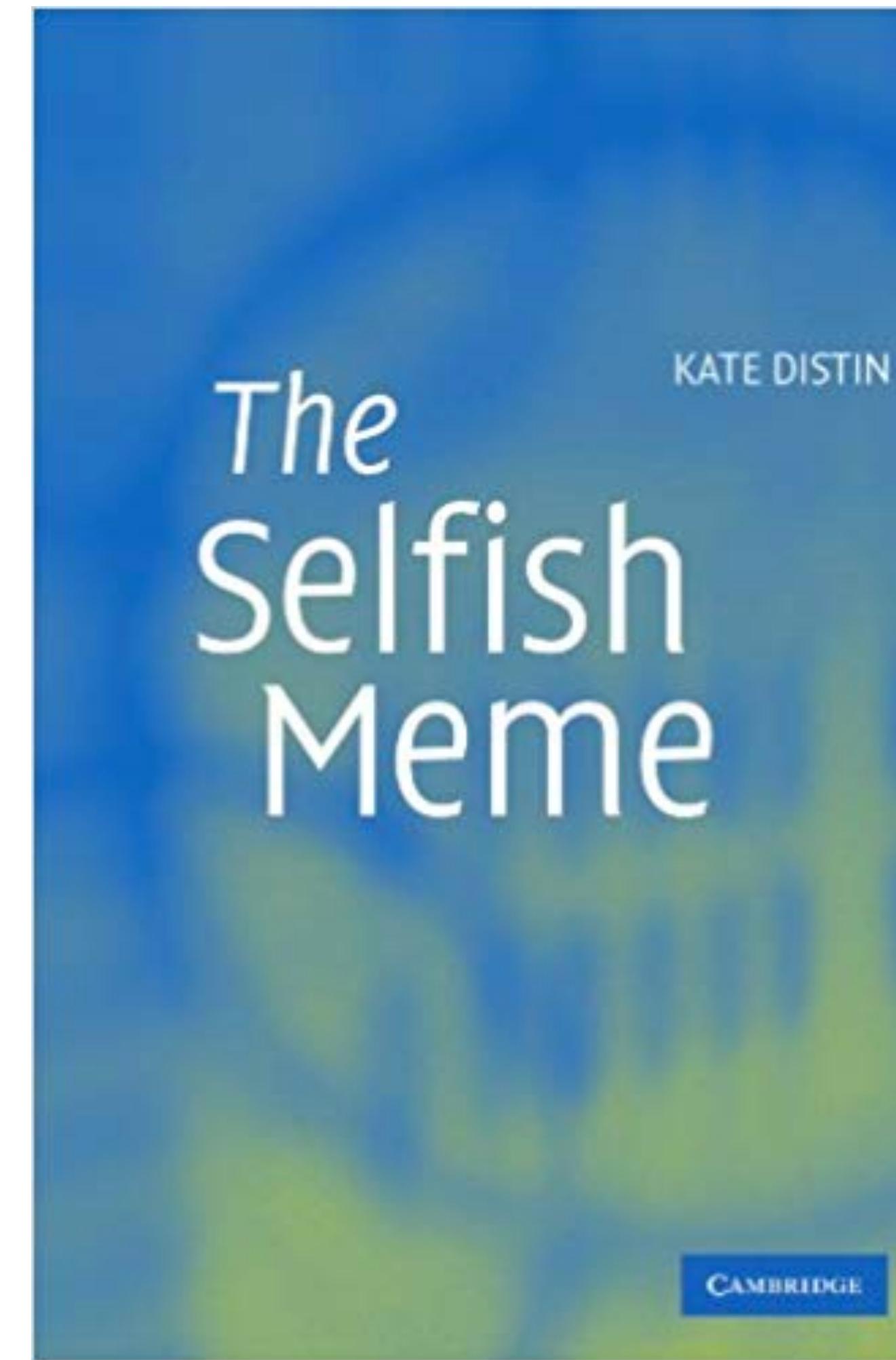
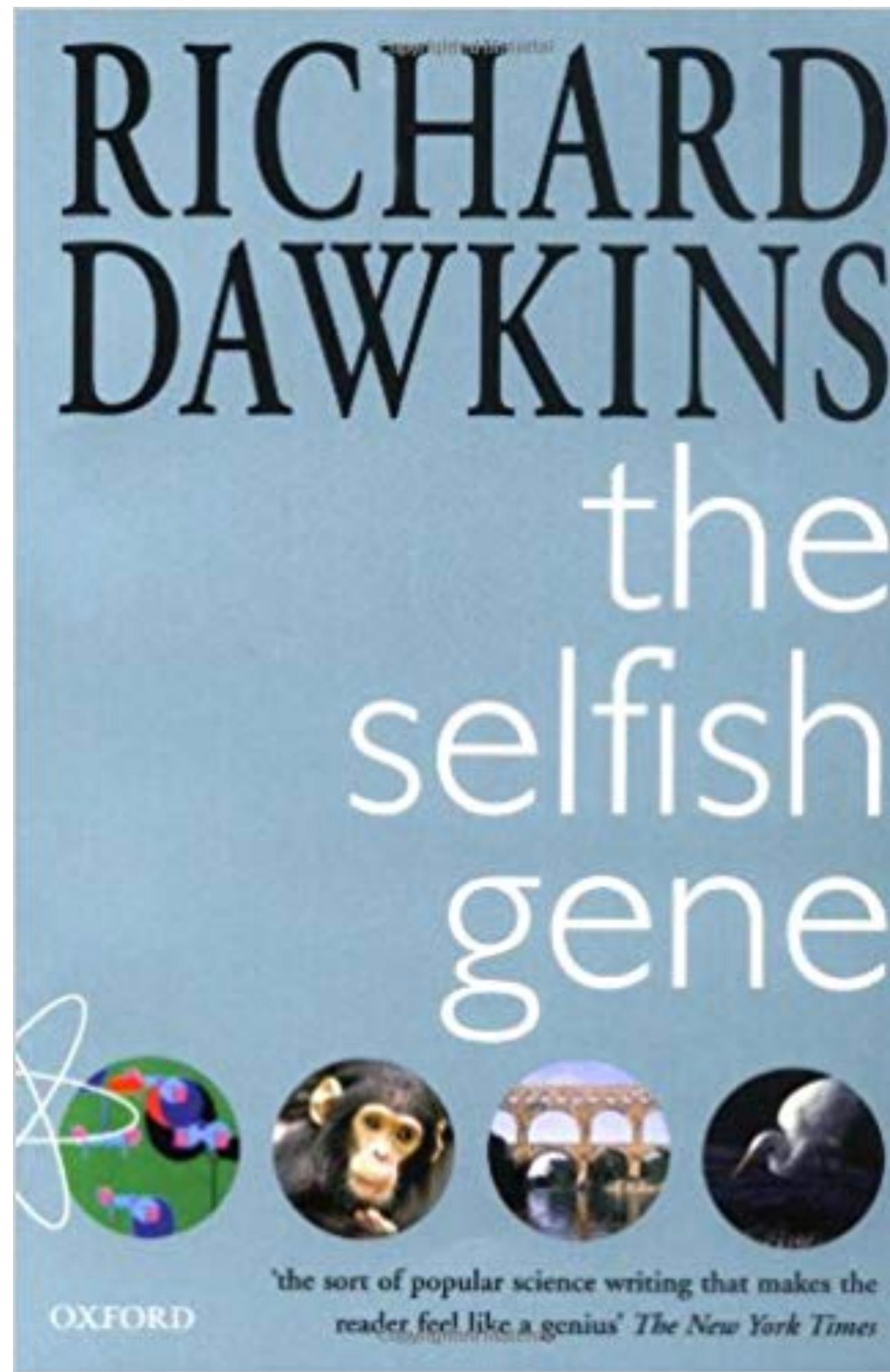


Source: GAN Dissection: Visualizing and Understanding Generative Adversarial Networks (Bau et al., AAAI-Workshop 2019)

# Creativity in Learning Algorithms?



When mere survival is not enough ...



# The Selfish GAN

LOT 363

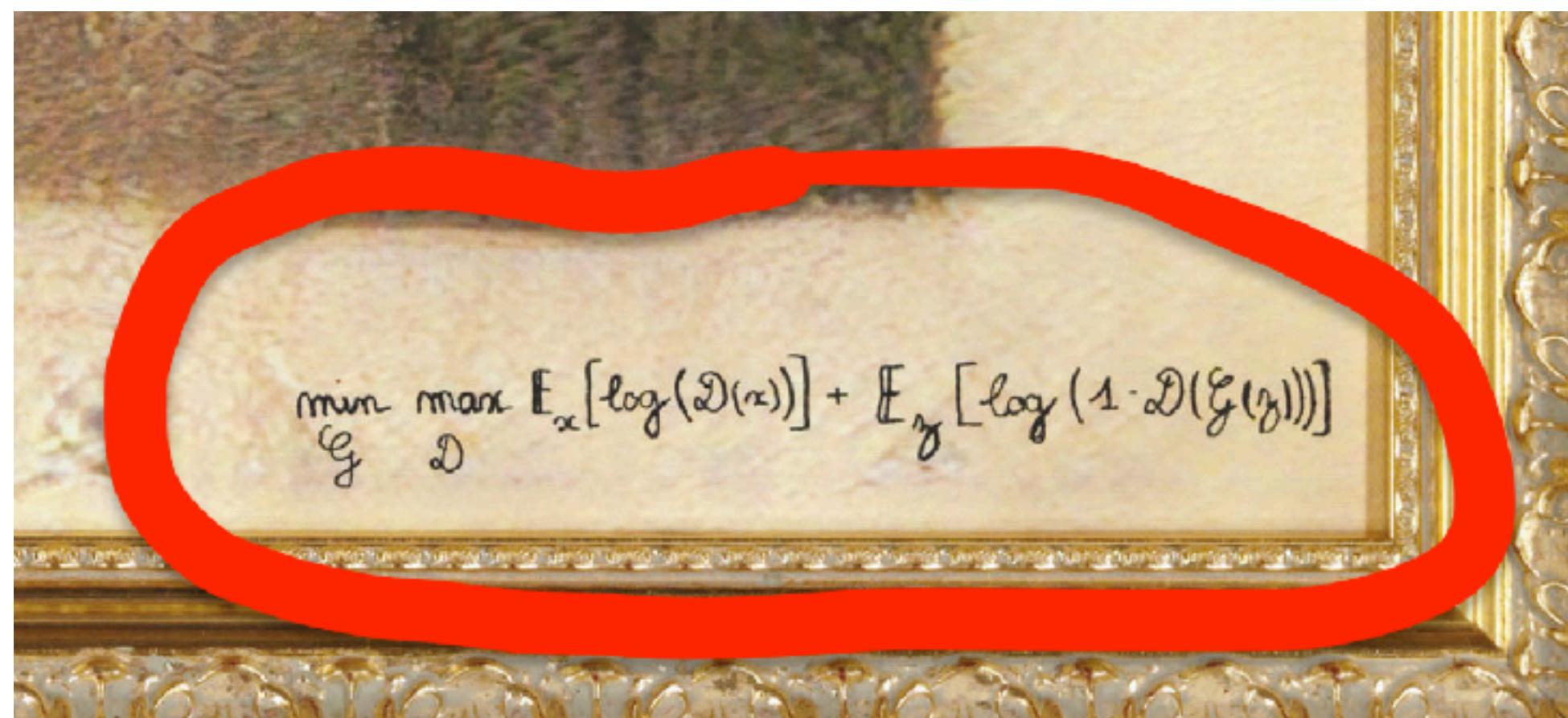
*Edmond de Belamy, from La Famille de Belamy*

Price realised [\(i\)](#)

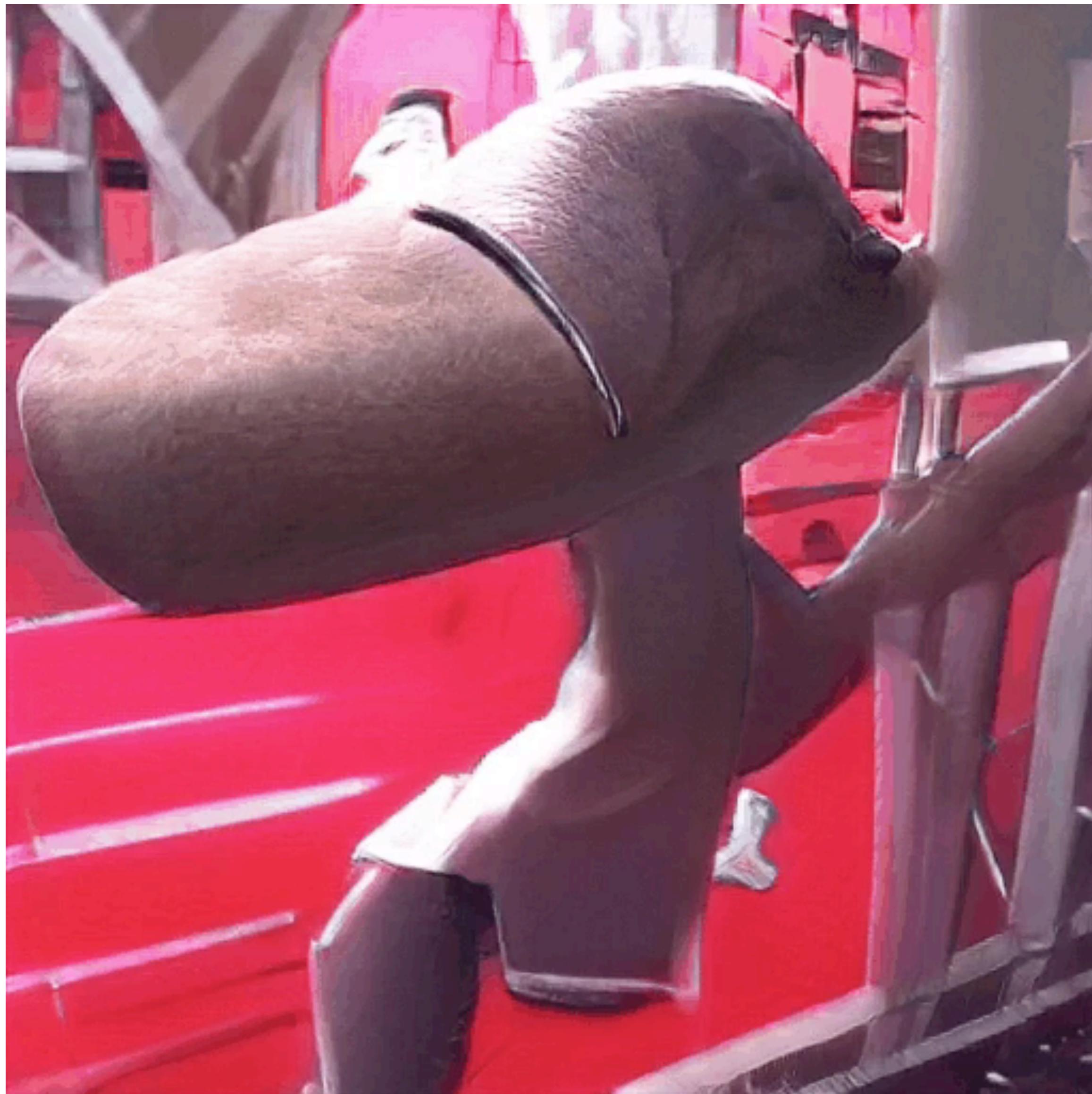
USD 432,500

Estimate [\(i\)](#)

USD 7,000 - USD 10,000



# BigGAN's Disruption



“I think this is the first time a pre-trained neural net has captured so many creative peoples’ attention.

BigGAN has enough capacity / expressive power that people are just exploring the latent space without worrying about making it ‘their own’ (retraining would be very difficult).”

**Kyle McDonald**



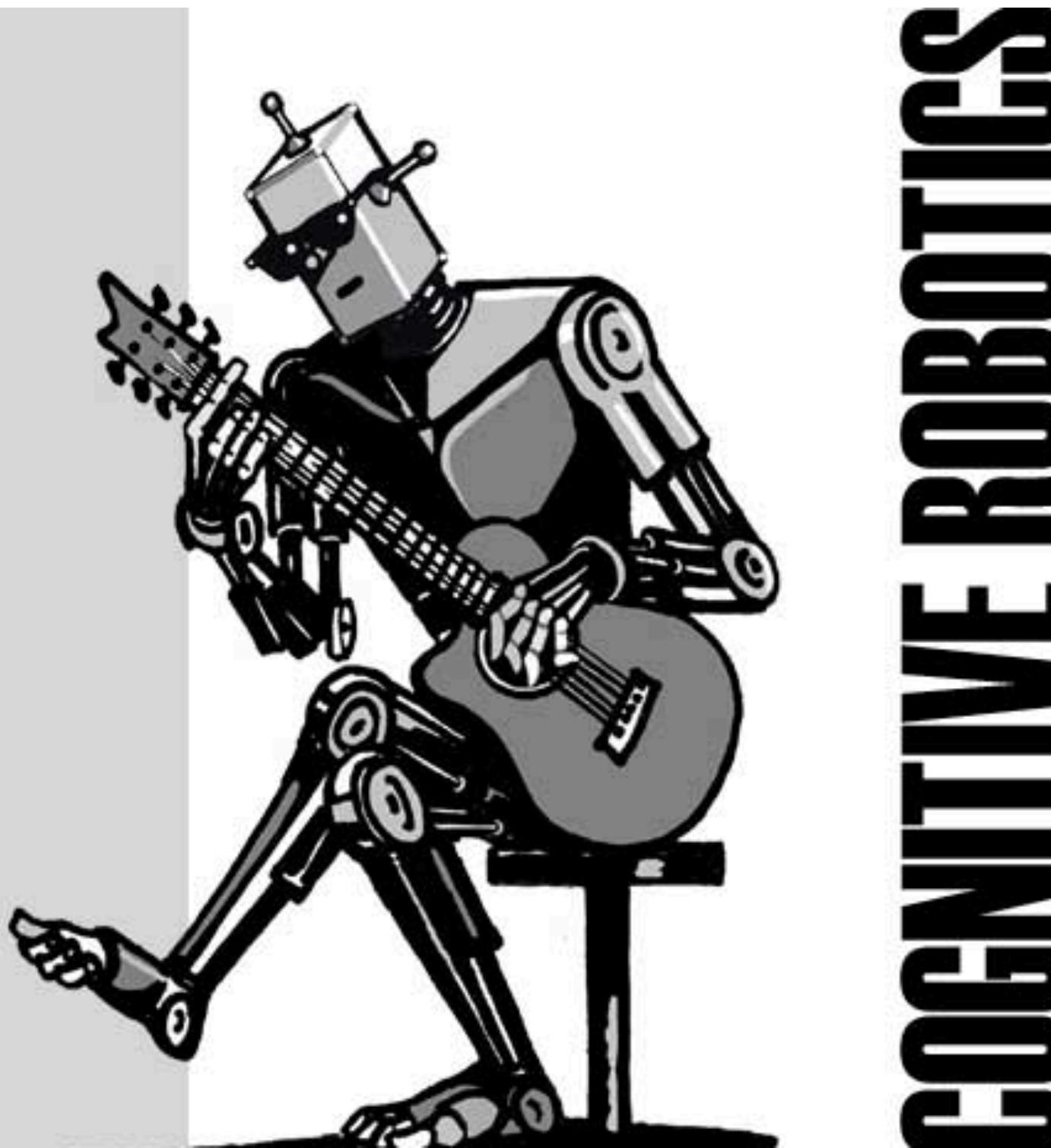
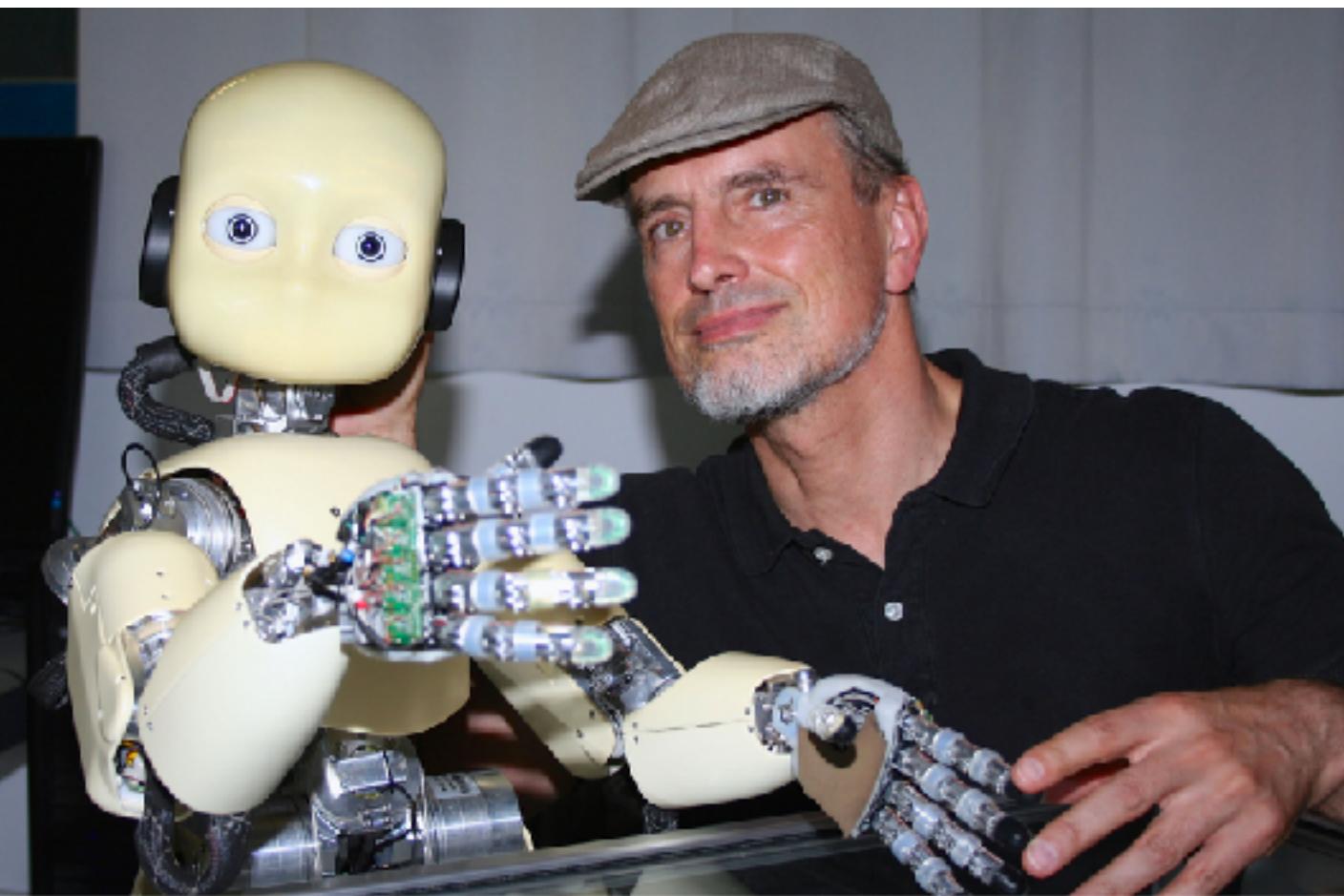
Source: Latent space discovered by Mario Klingemann using BigGAN model (Brock et al. 2018)

“BigGAN lowers the ‘shock factor’ of GAN artifacts - but will probably be a good thing overall since it will push AI artists to be more creative rather than rely on visual gimmicks.”

**Robbie Barrat**

# FORMAL THEORY OF FUN & CREATIVITY EXPLAINS SCIENCE, ART, MUSIC, HUMOR

(1990-2010) by Jürgen Schmidhuber

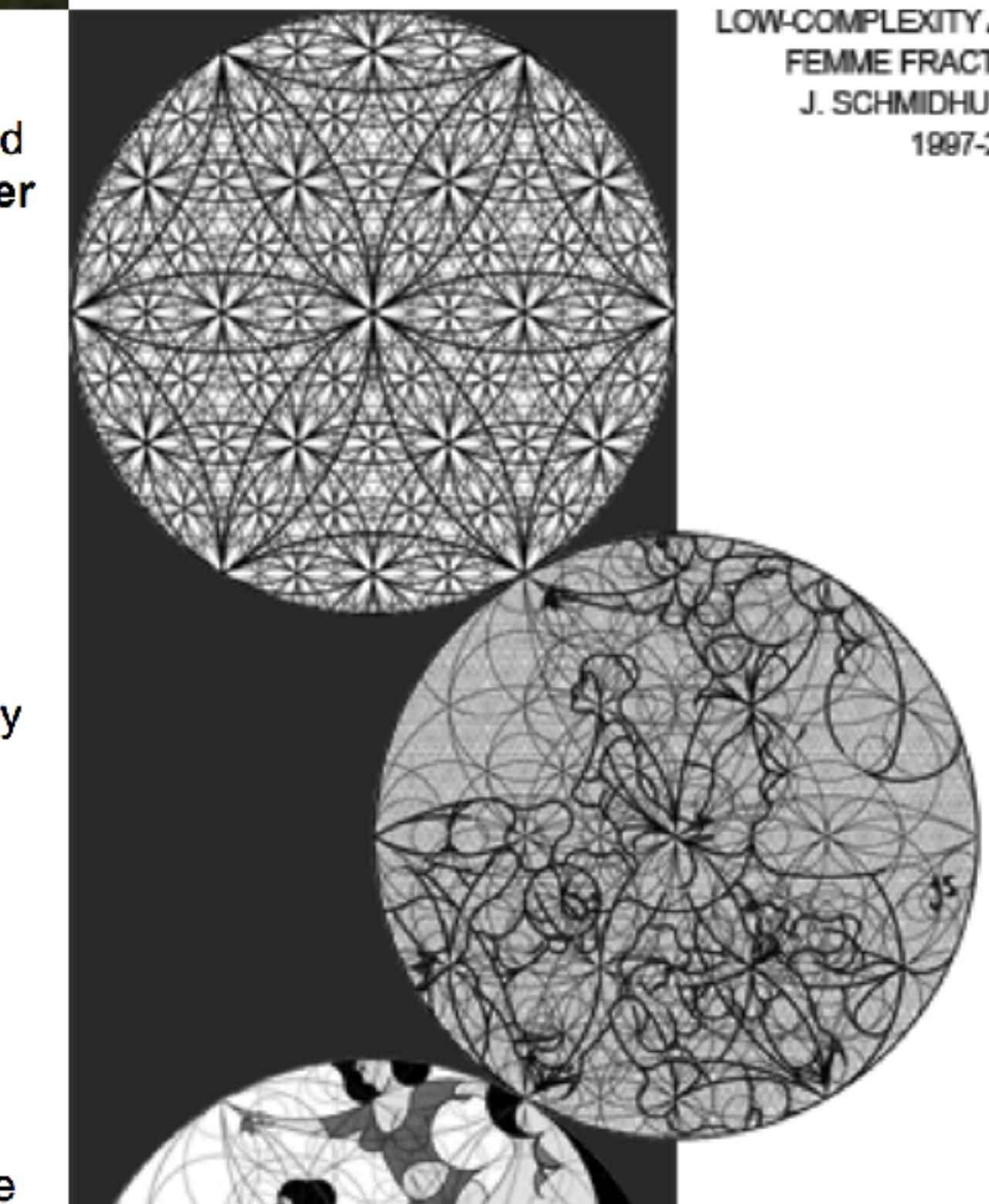


## Formal Theory of Creativity & Fun & Intrinsic Motivation (1990-2010) by [Jürgen Schmidhuber](#)

Since 1990 [JS](#) has built curious, creative agents that may be viewed as simple artificial scientists & artists with an intrinsic desire to explore the world by continually inventing new experiments. They never stop generating novel & surprising stuff, and consist of two learning modules: **(A)** an adaptive predictor or compressor or model of the growing data history as the agent is interacting with its environment, and **(B)** a general [reinforcement learner \(RL\)](#) selecting the actions that shape the history. The *learning progress* of **(A)** can be precisely measured and is the agent's *fun*: the intrinsic reward of **(B)**. That is, **(B)** is motivated to learn to invent *interesting* things that **(A)** does not yet know but can easily learn. To maximize future expected reward, in the absence of external



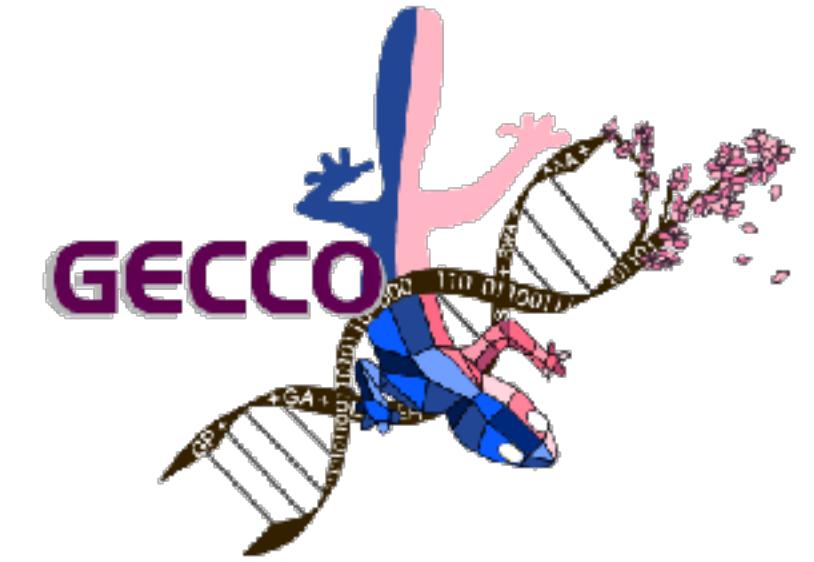
Left: [JS](#) giving a talk on creativity theory & art & science & humor at the [Singularity Summit](#) 2009 in New York City. **Videos:** [10min](#) (excerpts at YouTube), [40min](#) (original at Vimeo), [20min](#). JS' theory was also subject of a TV documentary (BR "Faszination Wissen", 29 May 2008; several repeats on other channels). Compare [H+ interview](#) and [slashdot article](#).



(Source: <http://people.idsia.ch/~juergen/creativity.html>)

# Research Communities

- Artificial Curiosity
- Affective Computing
- Novelty Search, Open-Endedness
- Recommendation Systems
- Computational Creativity



# HEGARTY ON CREATIVITY THERE ARE NO RULES



**John Hegarty**

“Creativity has to question, explain,  
and inspire our view of the world.”

**John Hegarty**

Bartle Bogle Hegarty  
Saatchi & Saatchi  
TBWA Worldwide

# HEGARTY ON CREATIVITY

**THERE ARE NO RULES**



**John Hegarty**

# FRESH

**Does this piece of creative work stop you?  
Would you notice it straight away?**

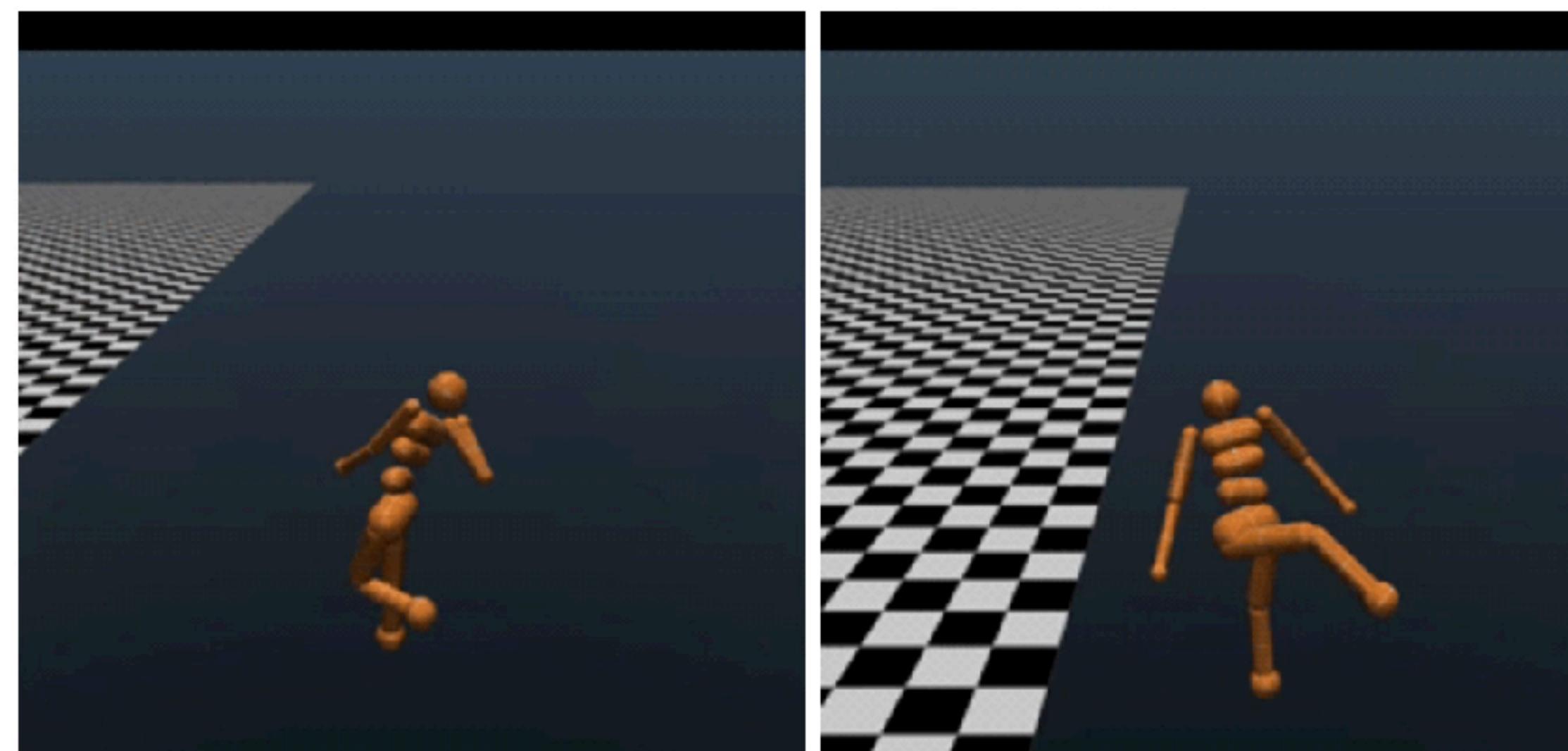
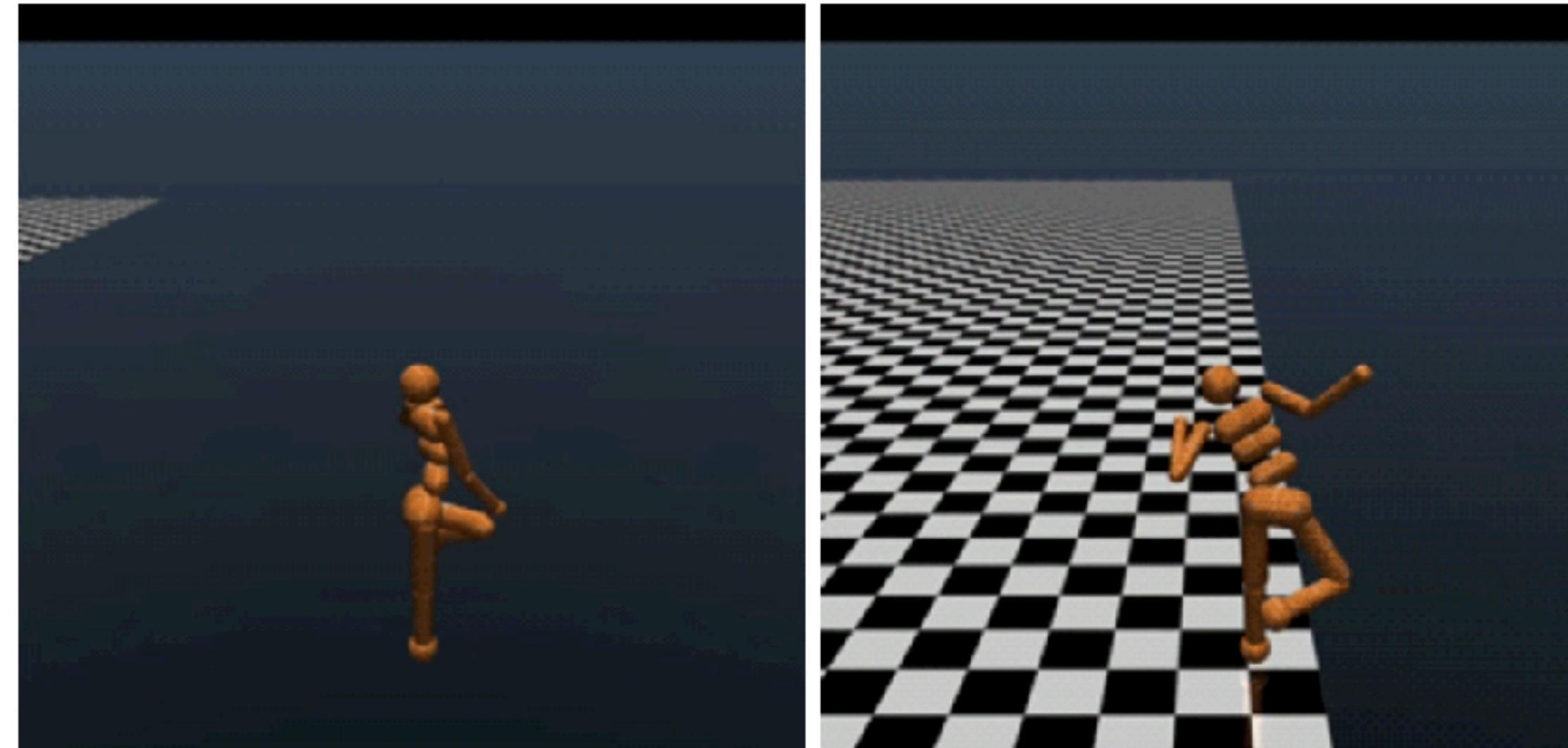
**Does this work make you look at an issue  
in a different way?**

**Does it awaken your interest in the subject,  
leading you to reassess your opinion of it?**

**Has the work and its process of creation  
made you understand the world in a  
different, more moving, inspiring, or  
thoughtful way?**

**Does it move you to action?**

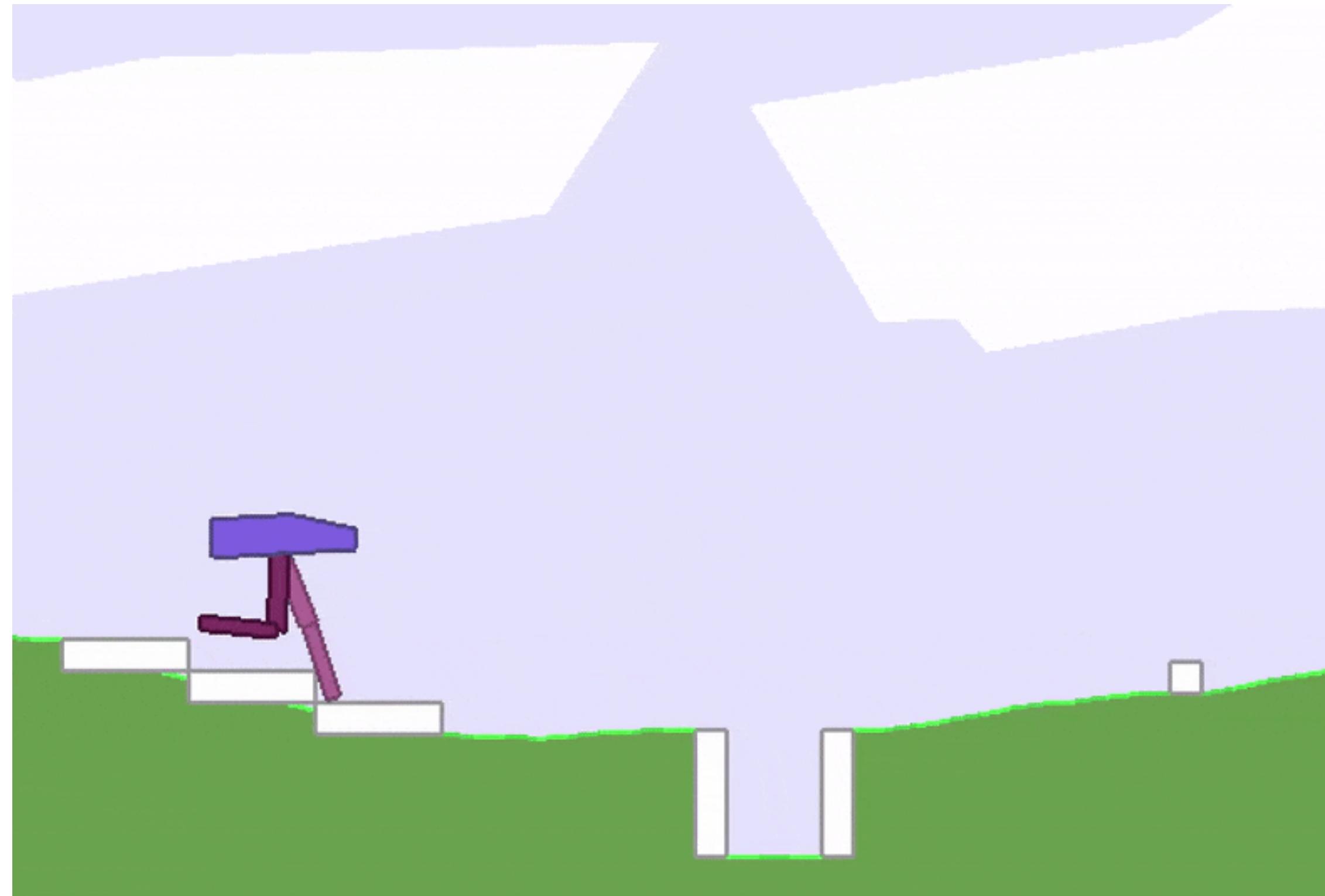
You may not like it, but this is what peak performance looks like.



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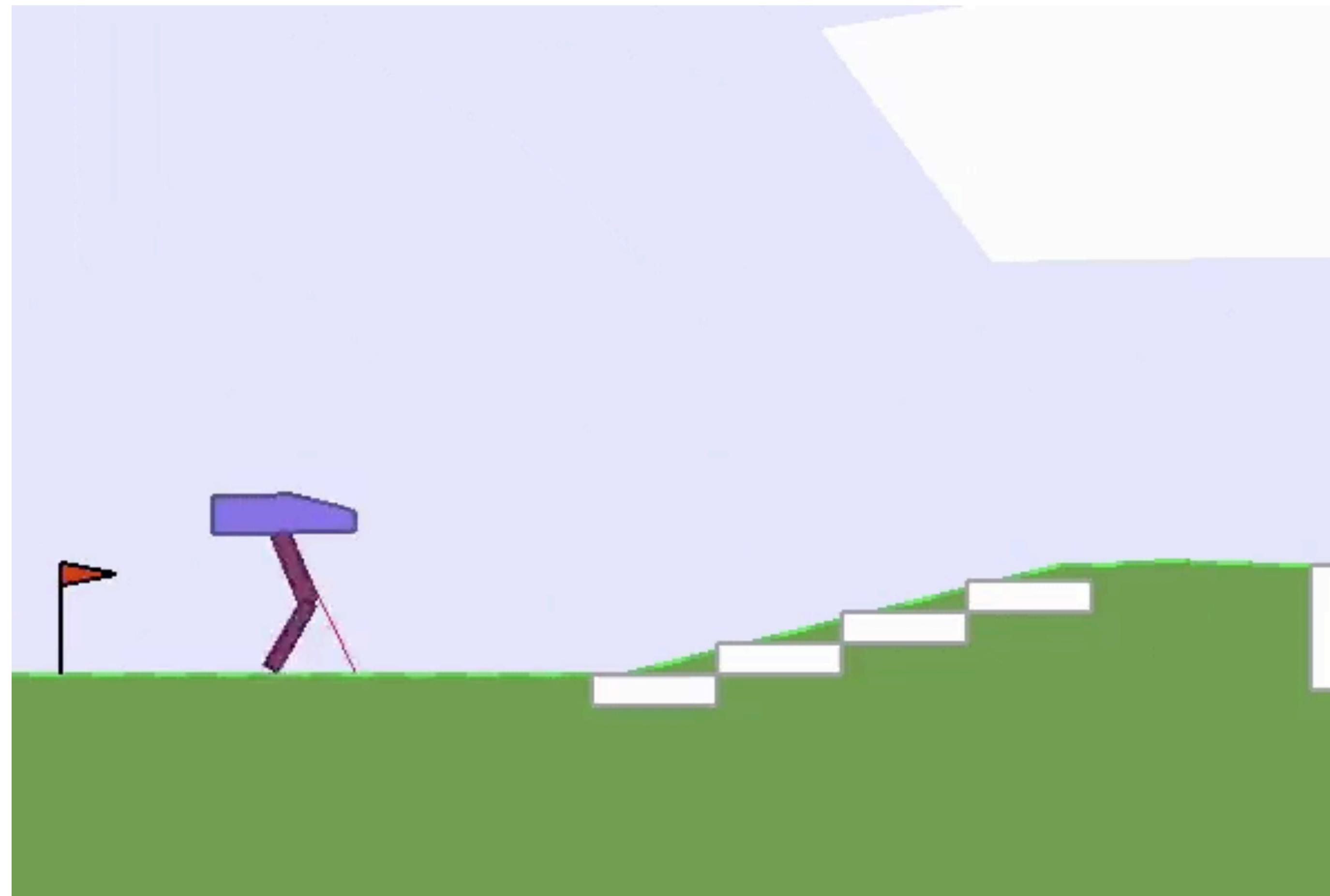
Source: Simple random search provides a competitive approach to reinforcement learning,  
Horia Mania, Aurelia Guy, Benjamin Recht.

# Reinforcement Learning is Frustratingly Hard . . .



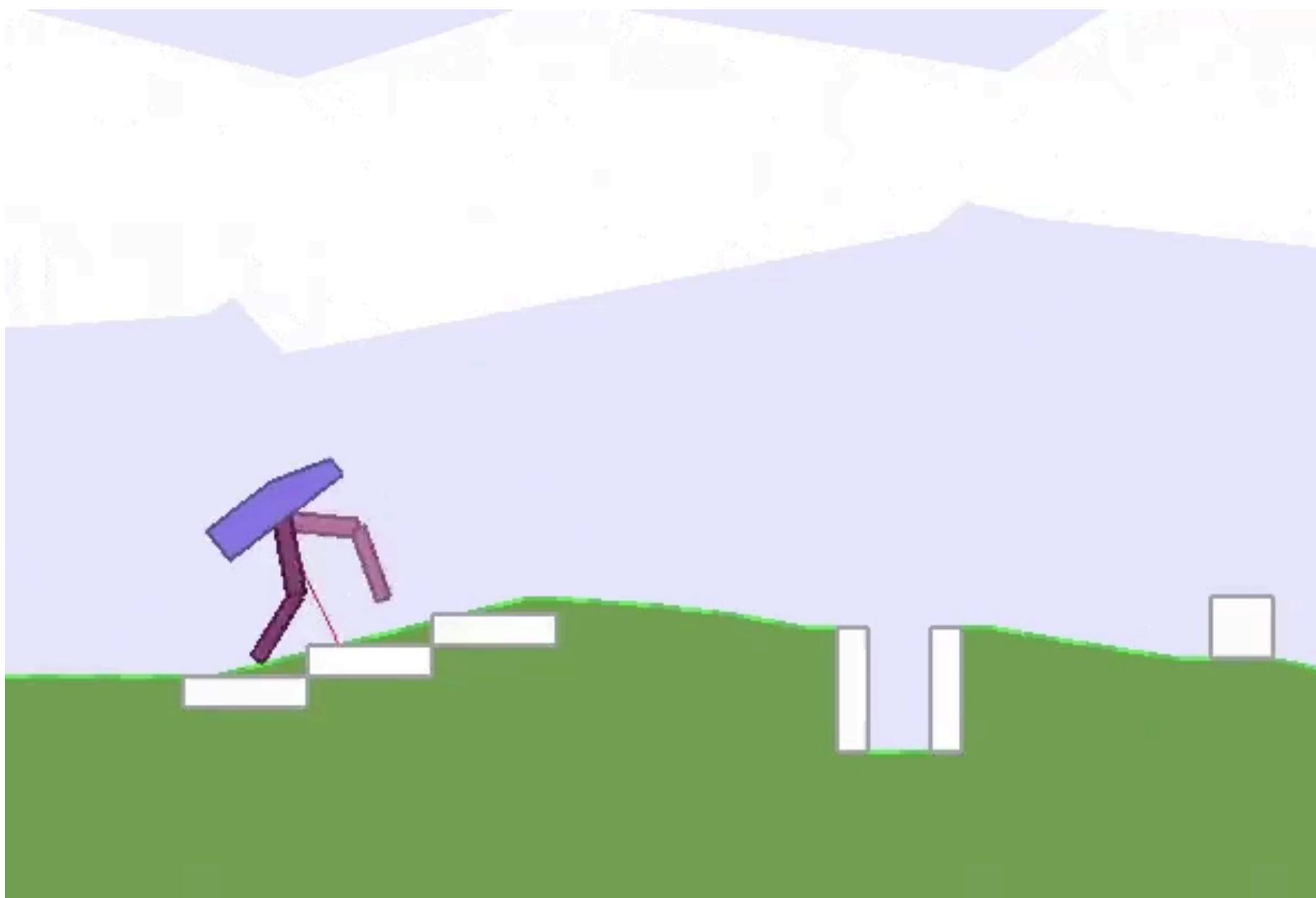
- ▶ Credit assignment, especially long term rewards, is hard!
- ▶ Easy to get stuck in local optima.
- ▶ No “correct” answer.

# But RL Environments are also fun to work on . . .

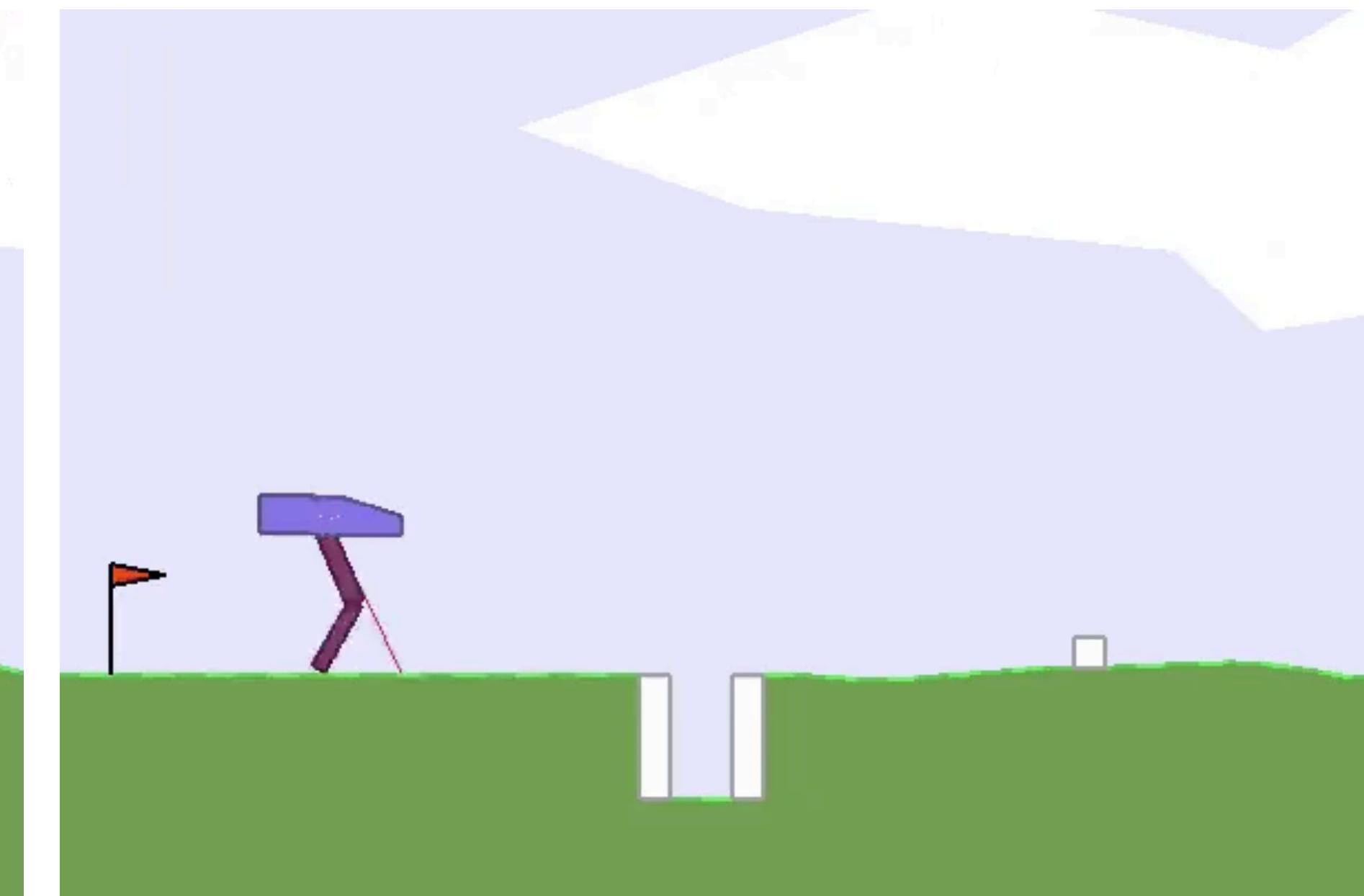


- ▶ My first journey into reinforcement learning research.
- ▶ First solution to achieve score > 300 over 100 random trials.

# There are often no “correct” solutions.



CMA-ES



REINFORCE  
(Population Based)

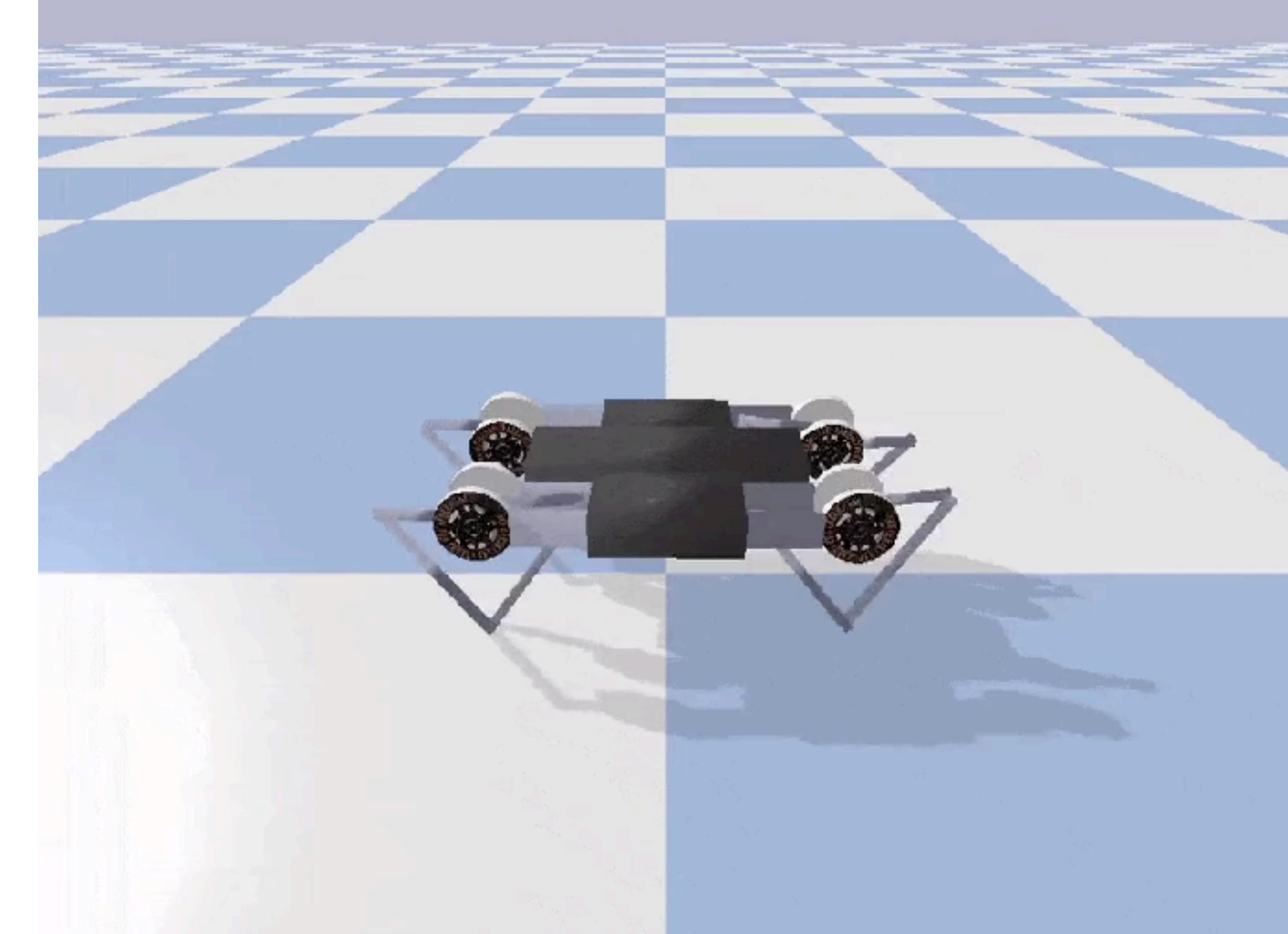
- ▶ Both solutions “solved” the environment.

Some humans come up with creative ways to walk too . . .



(Source: Chuck Berry, Stable Baselines Project, by Antonin Raffin 2018)

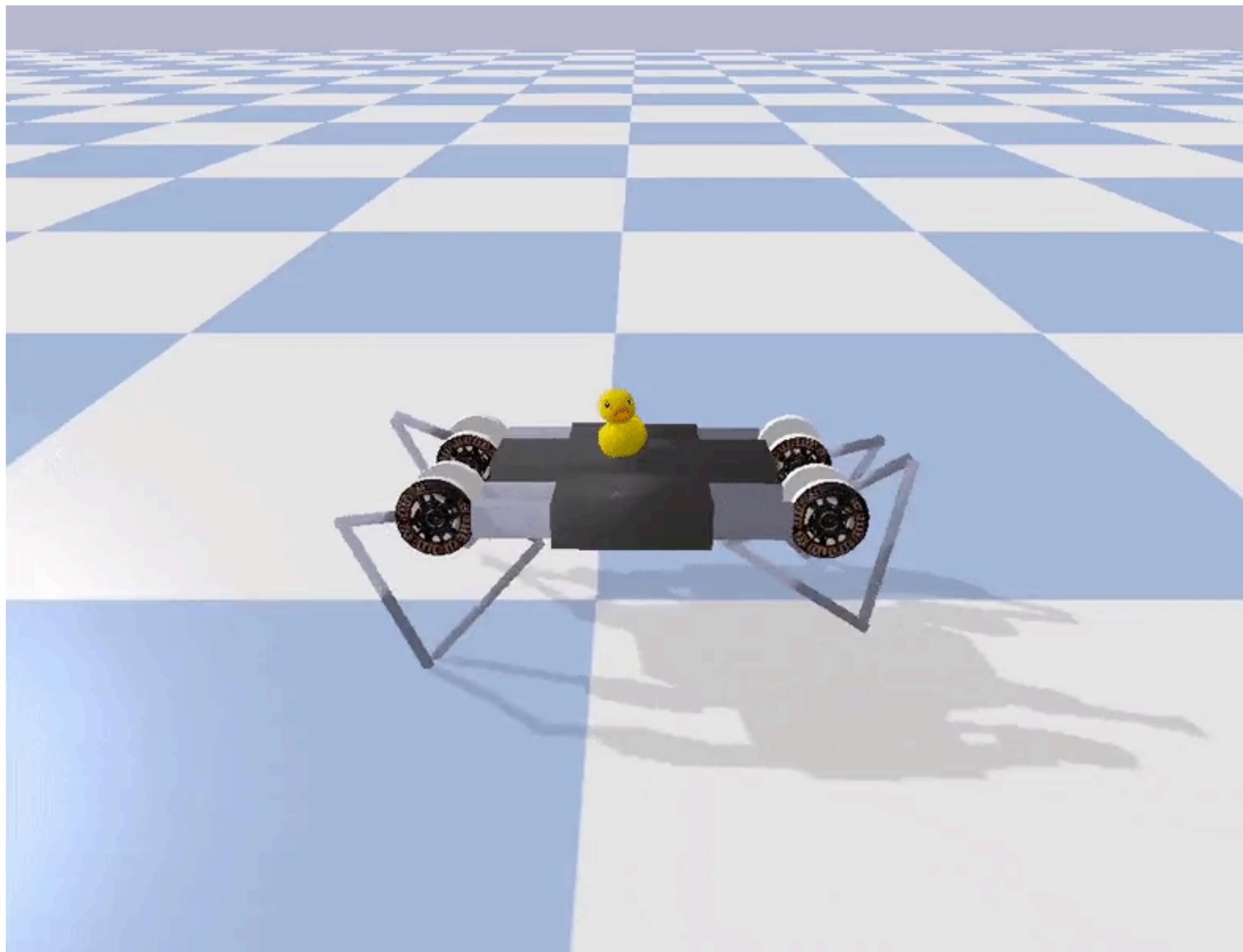
# PyBullet Minitaur Task (Erwin Coumans)



- ▶ PyBullet includes realistic models of actual robots.
- ▶ Useful to experiment with transfer learning.

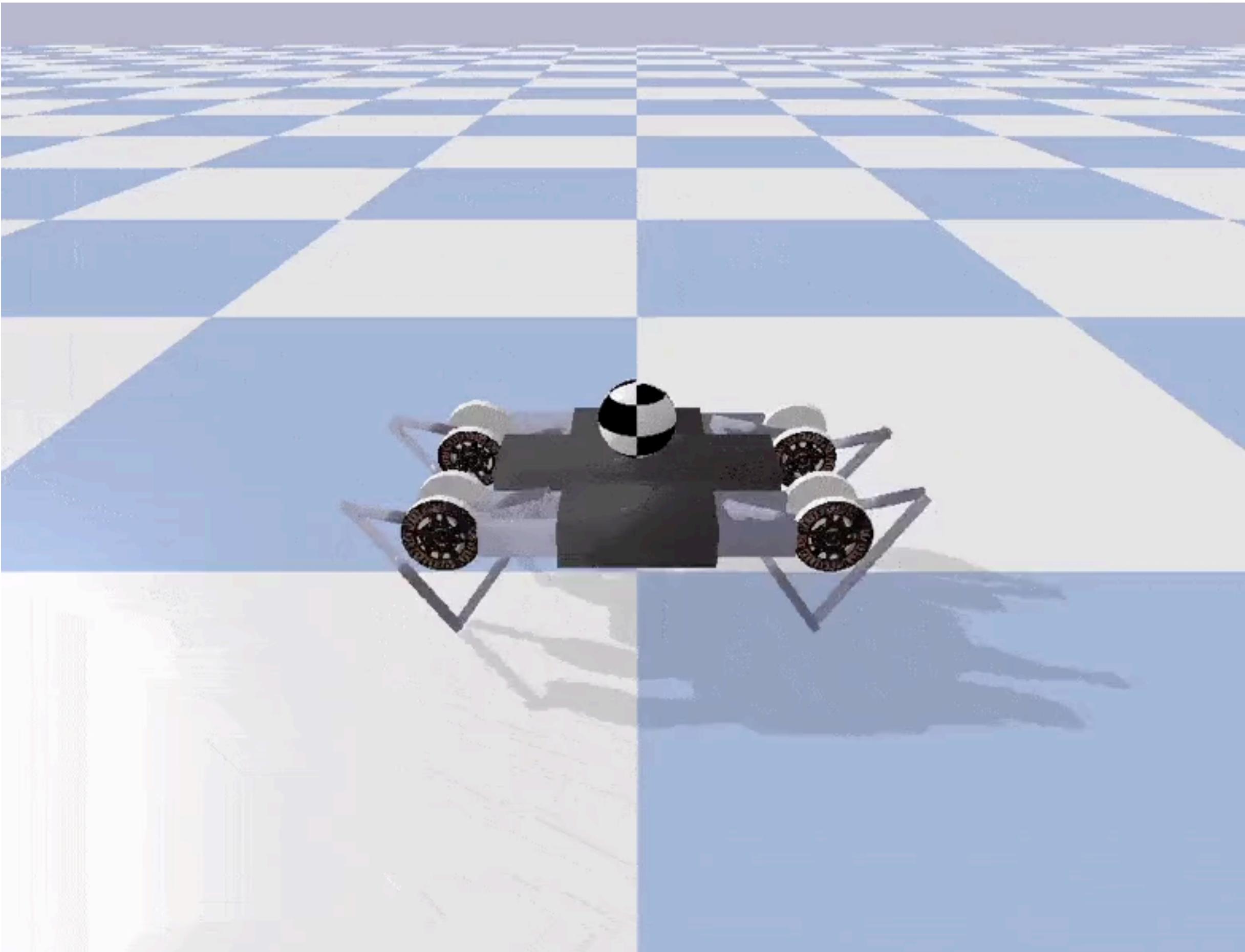


# Robust Minitaur Environments



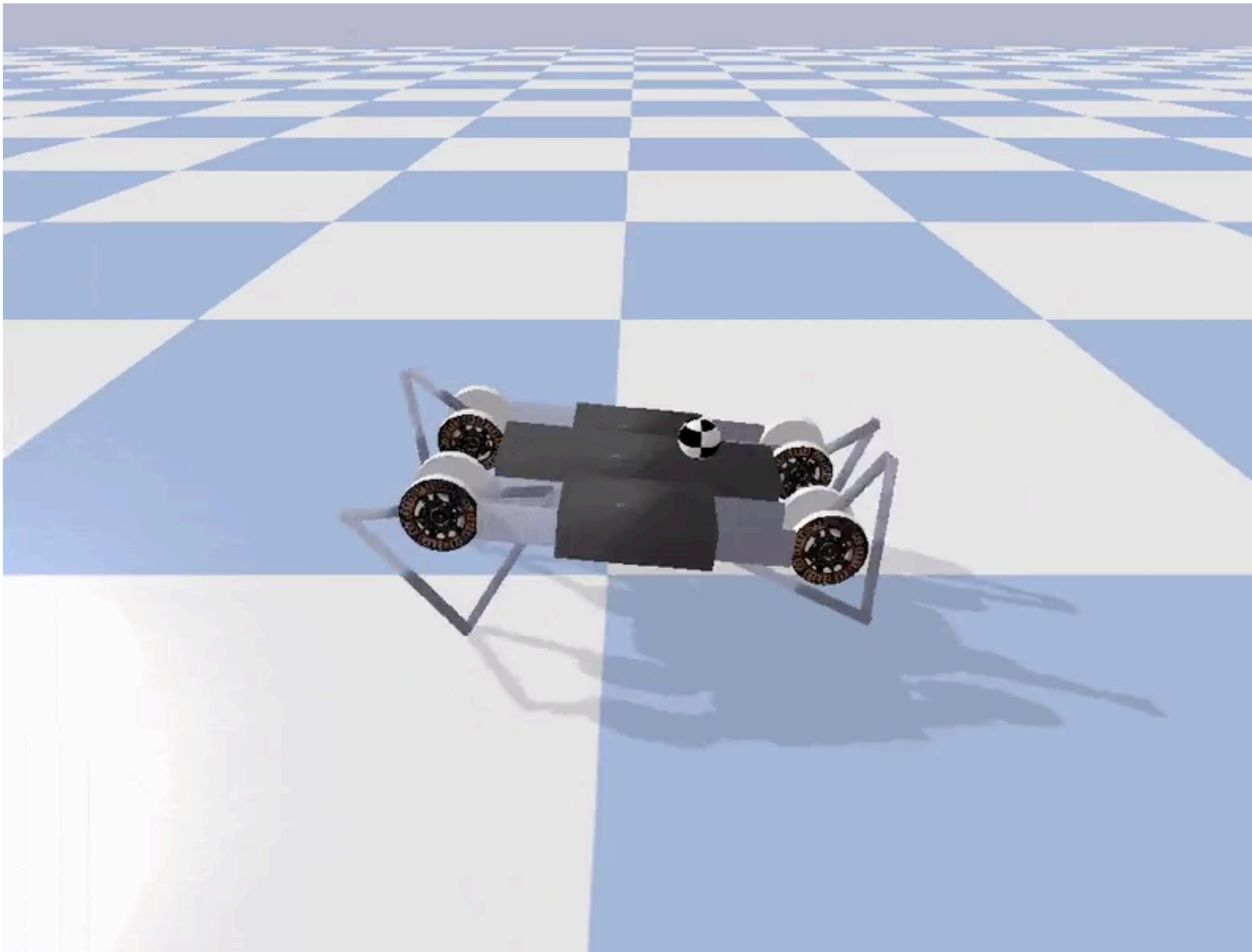
- ▶ Add more difficult task to the existing environment.
- ▶ End rollout once either objective failed.

# Robust Minitaur Environments



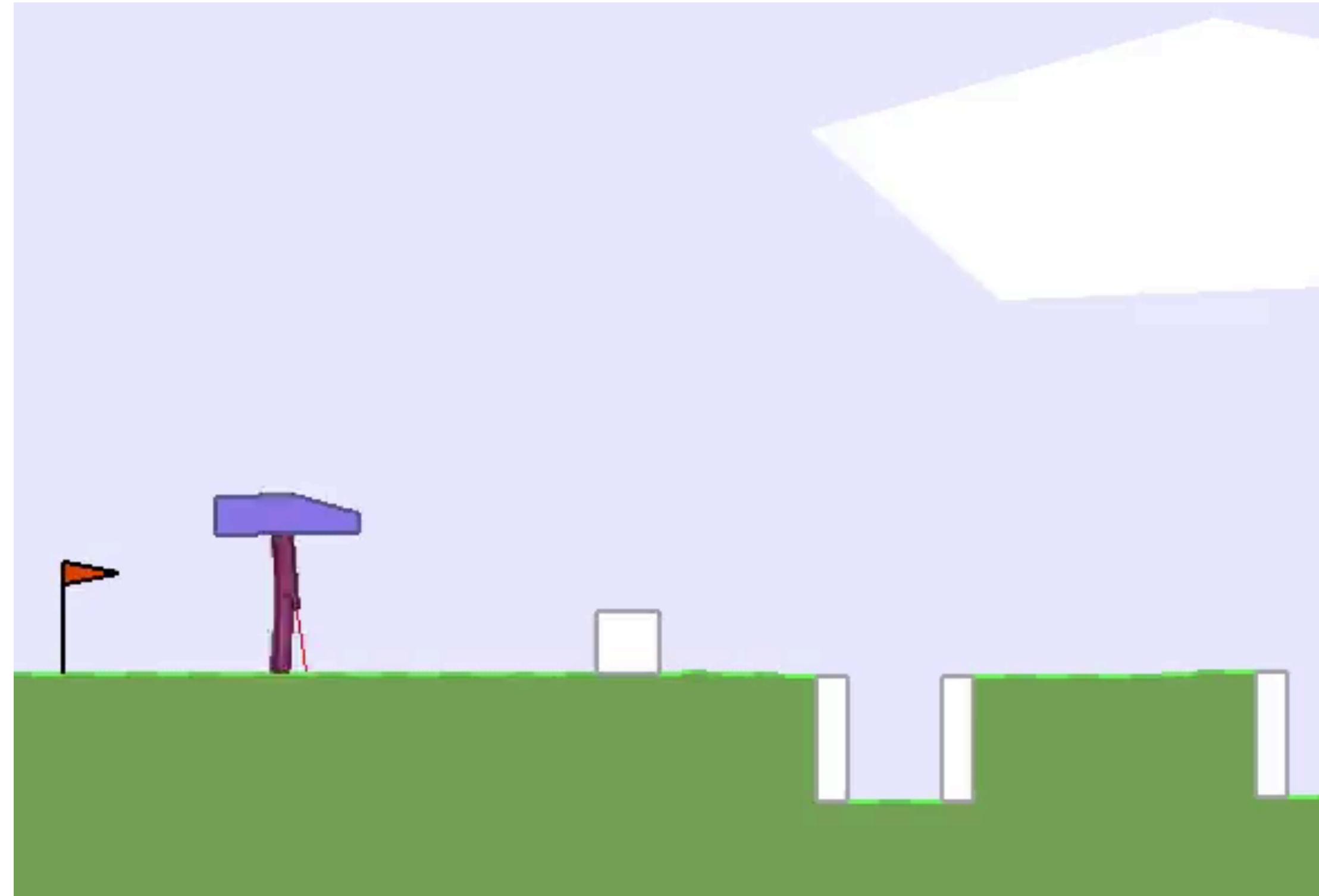
- ▶ It learned to cheat.

# Robust Minitaur Environments



- ▶ Showed it who is boss.

# Reinforcement Learning for Improving Agent Design (NIPS 2018 Deep RL Workshop) [designrl.github.io](https://designrl.github.io)



Self-Modifying Agents: Agent learns a better body design jointly with the navigation

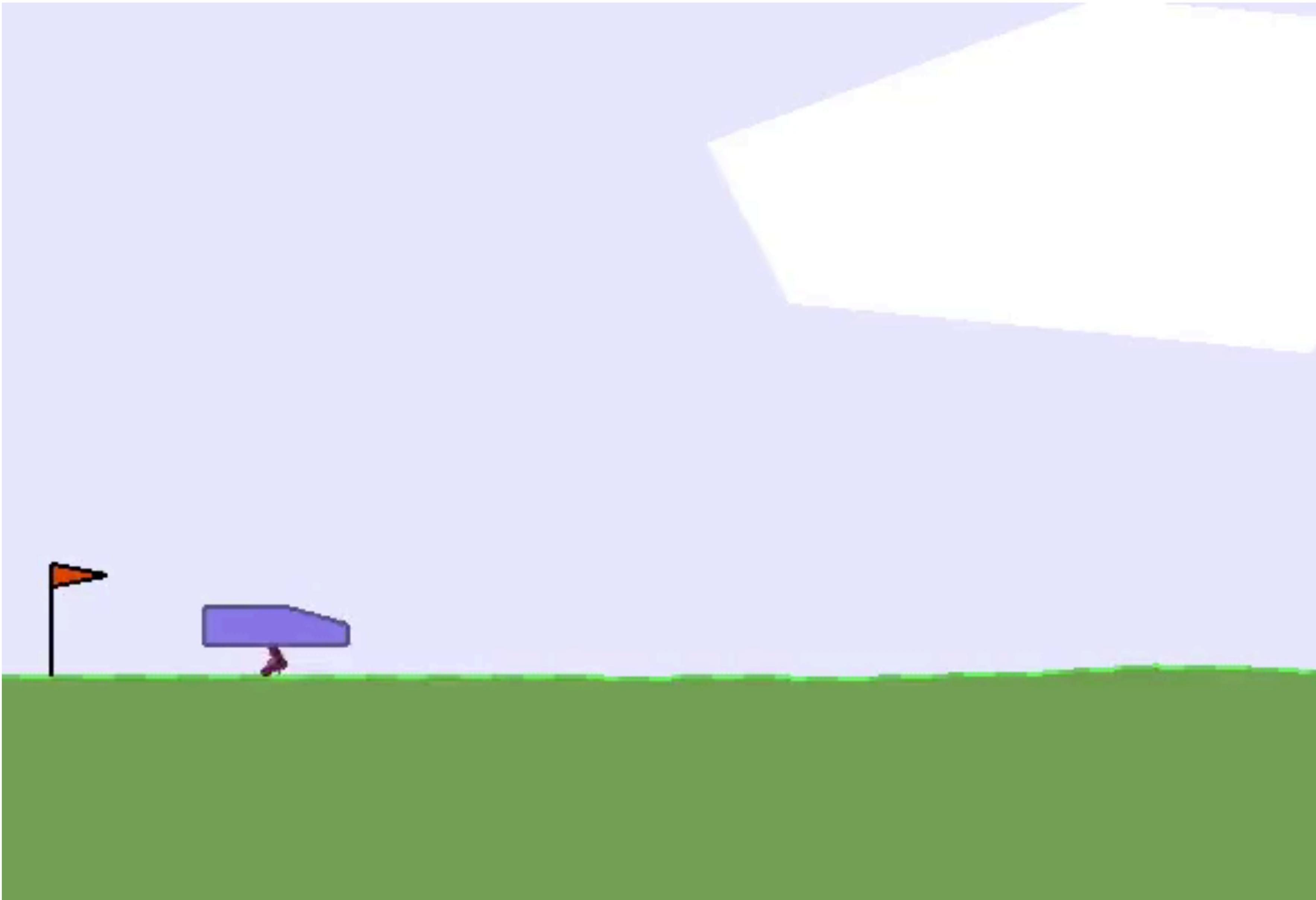
# Creativity from Passive Dynamics and Evolution



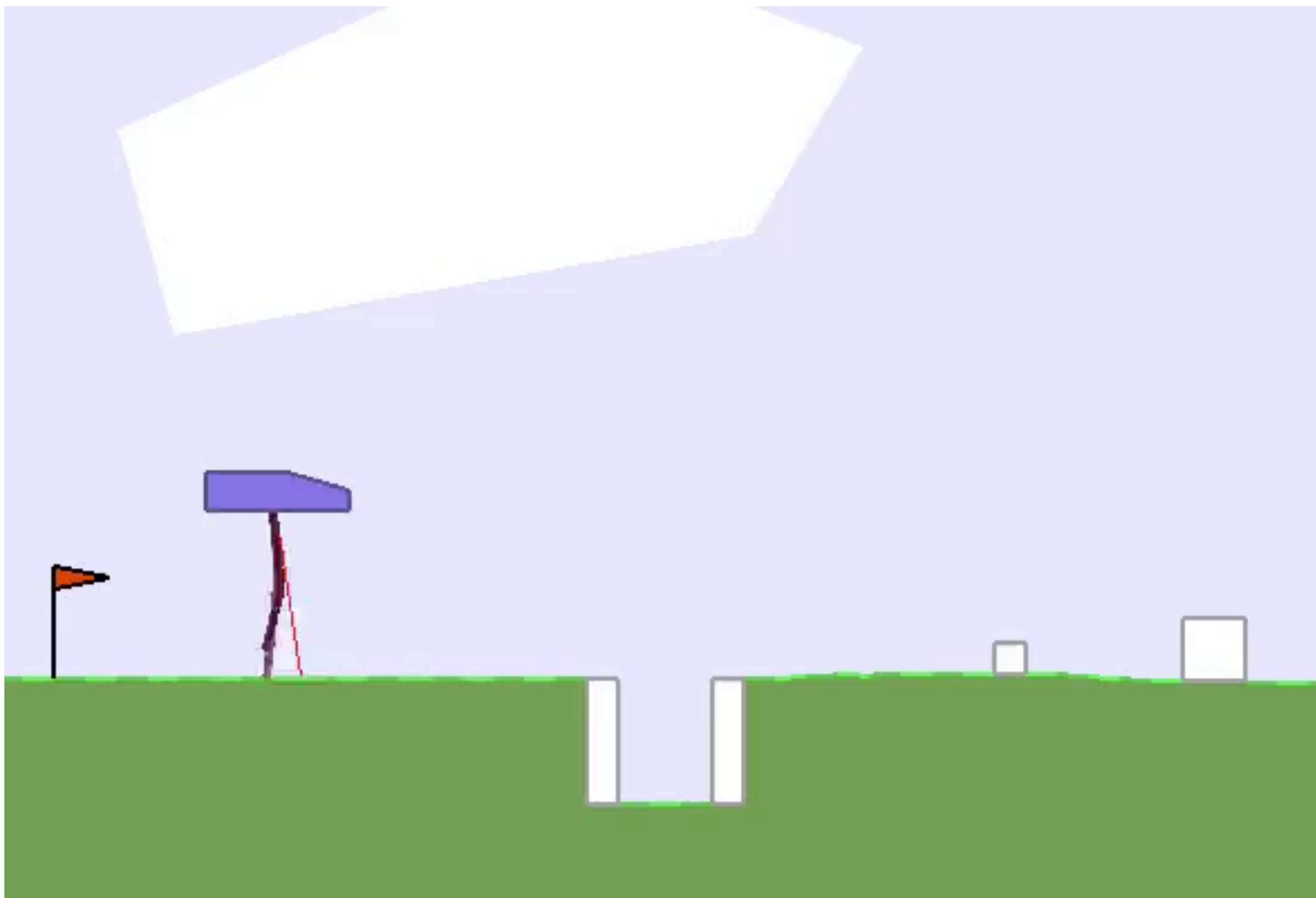
Agent learns a body to allow it to bounce forward efficiently.



# Optimizing for small legs

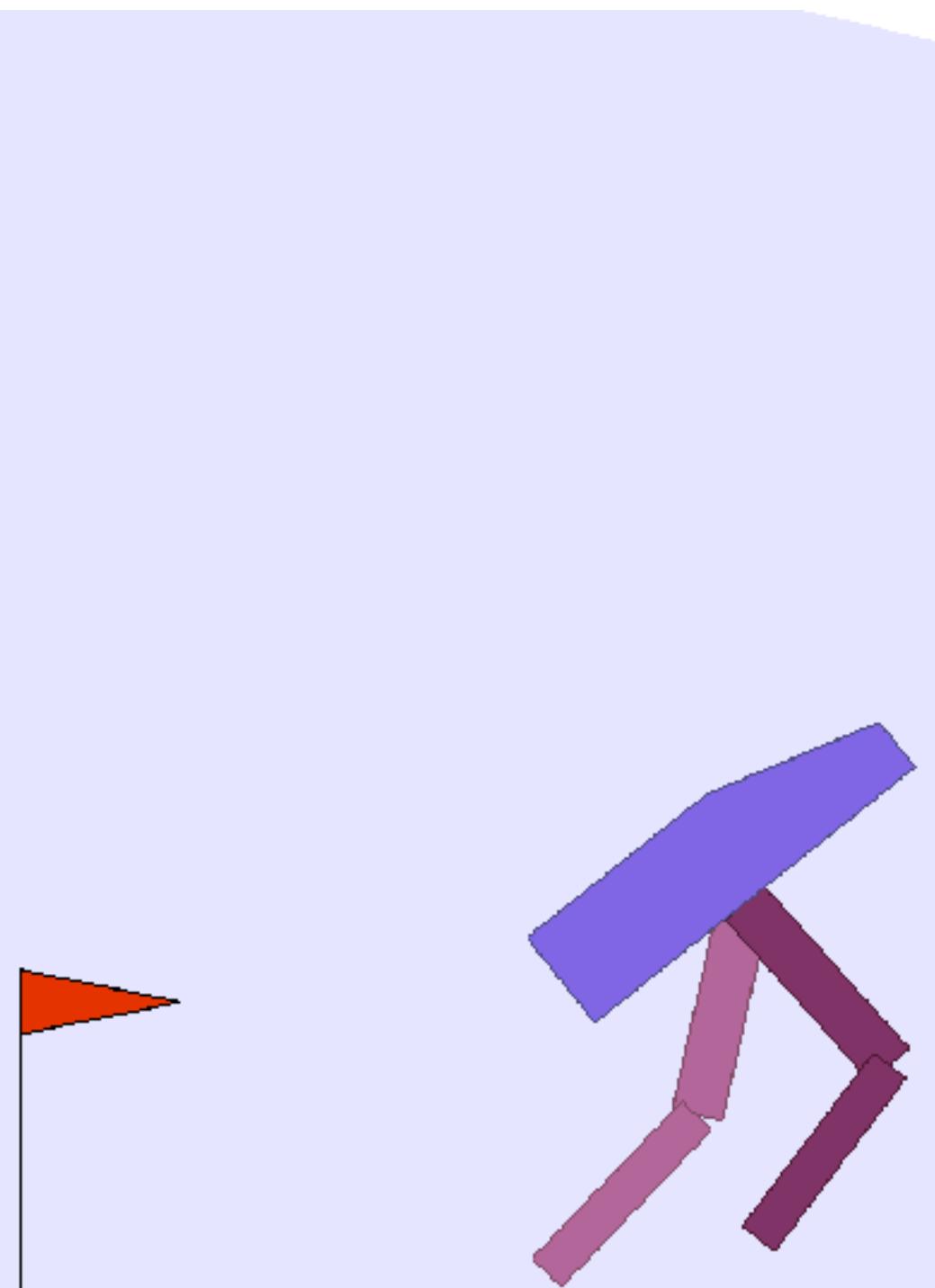


# Optimizing for small legs on Hardcore level

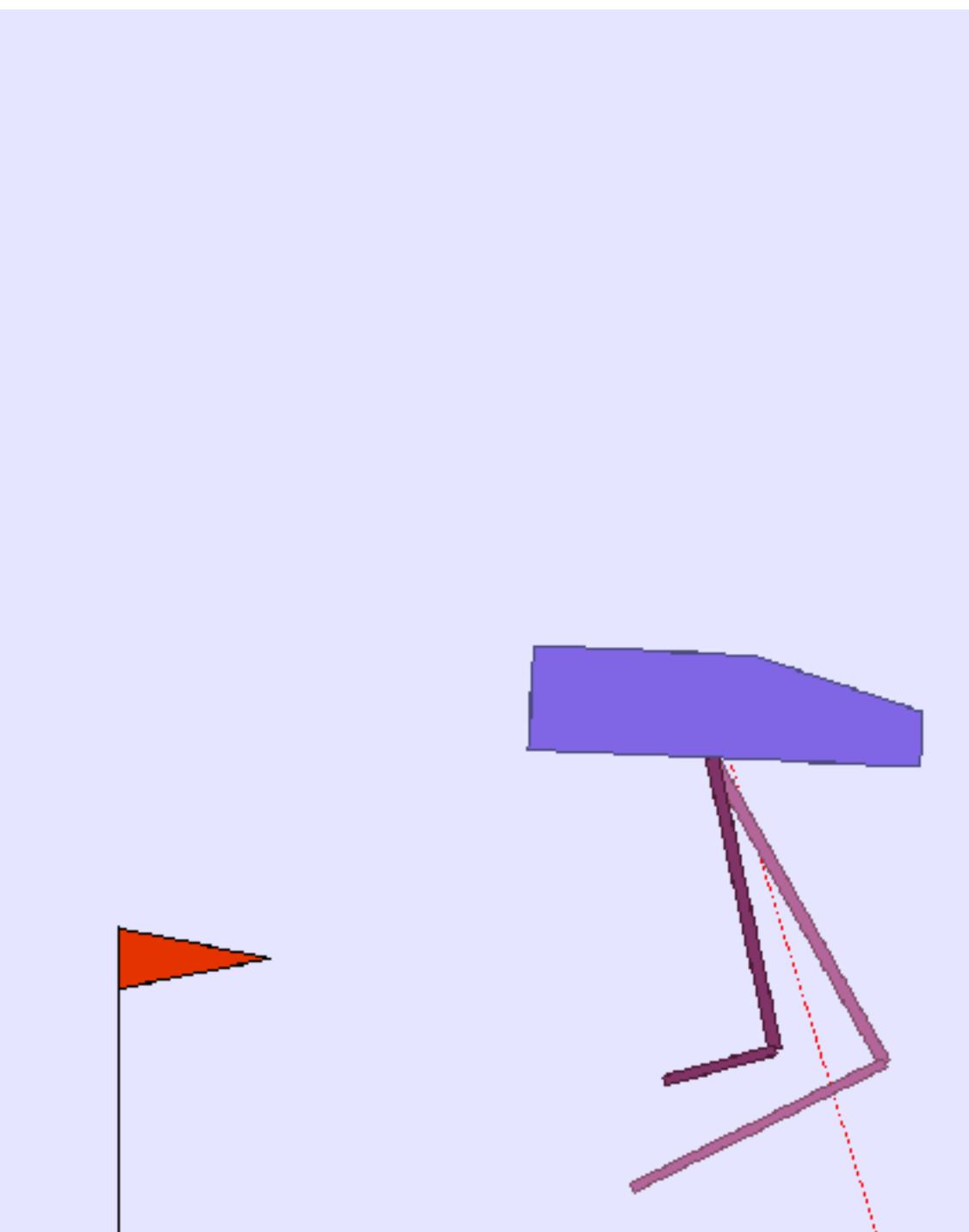


# Summary of Designs

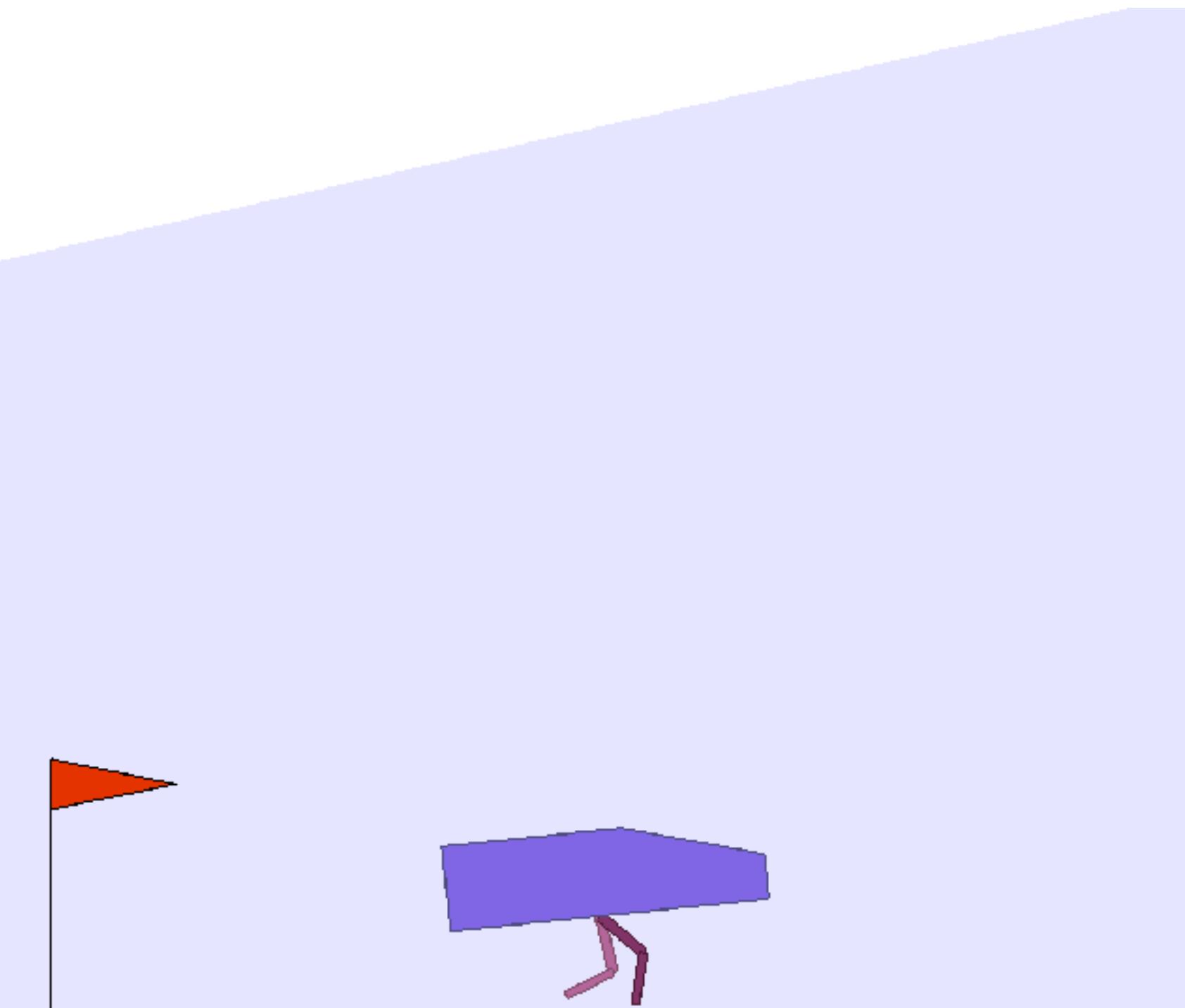
Score:  $347 \pm 0.9$   
Area: 100%



Score:  $359 \pm 0.2$   
Area: 33%



Score:  $323 \pm 68$   
Area: 8%

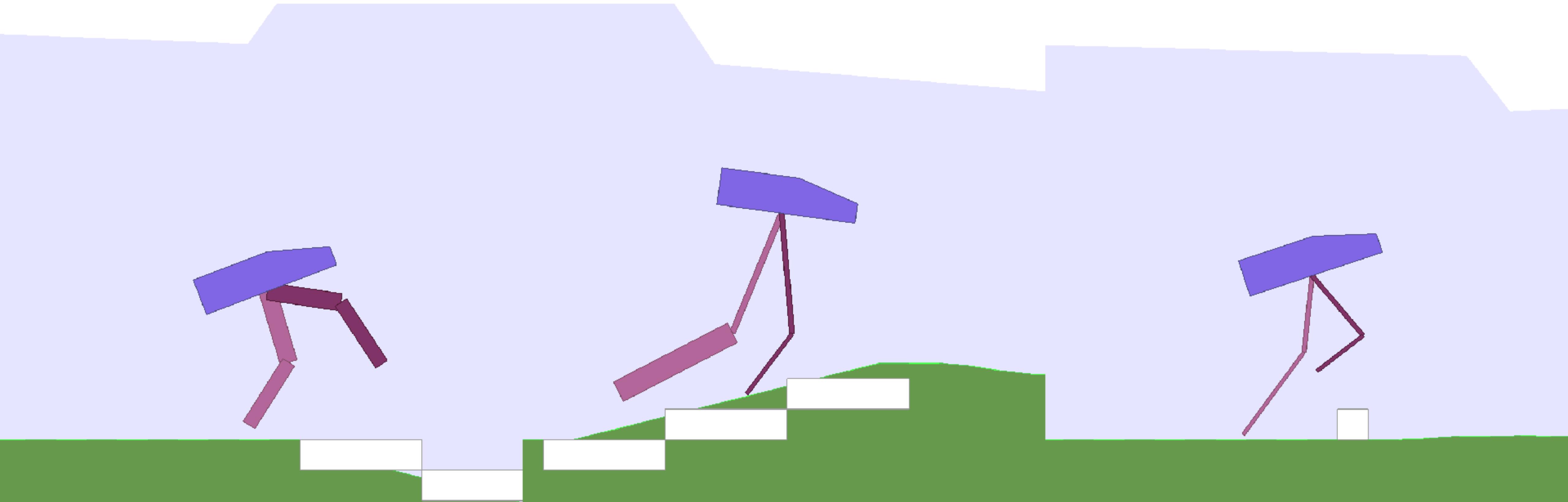


# Summary of Designs on Hardcore level

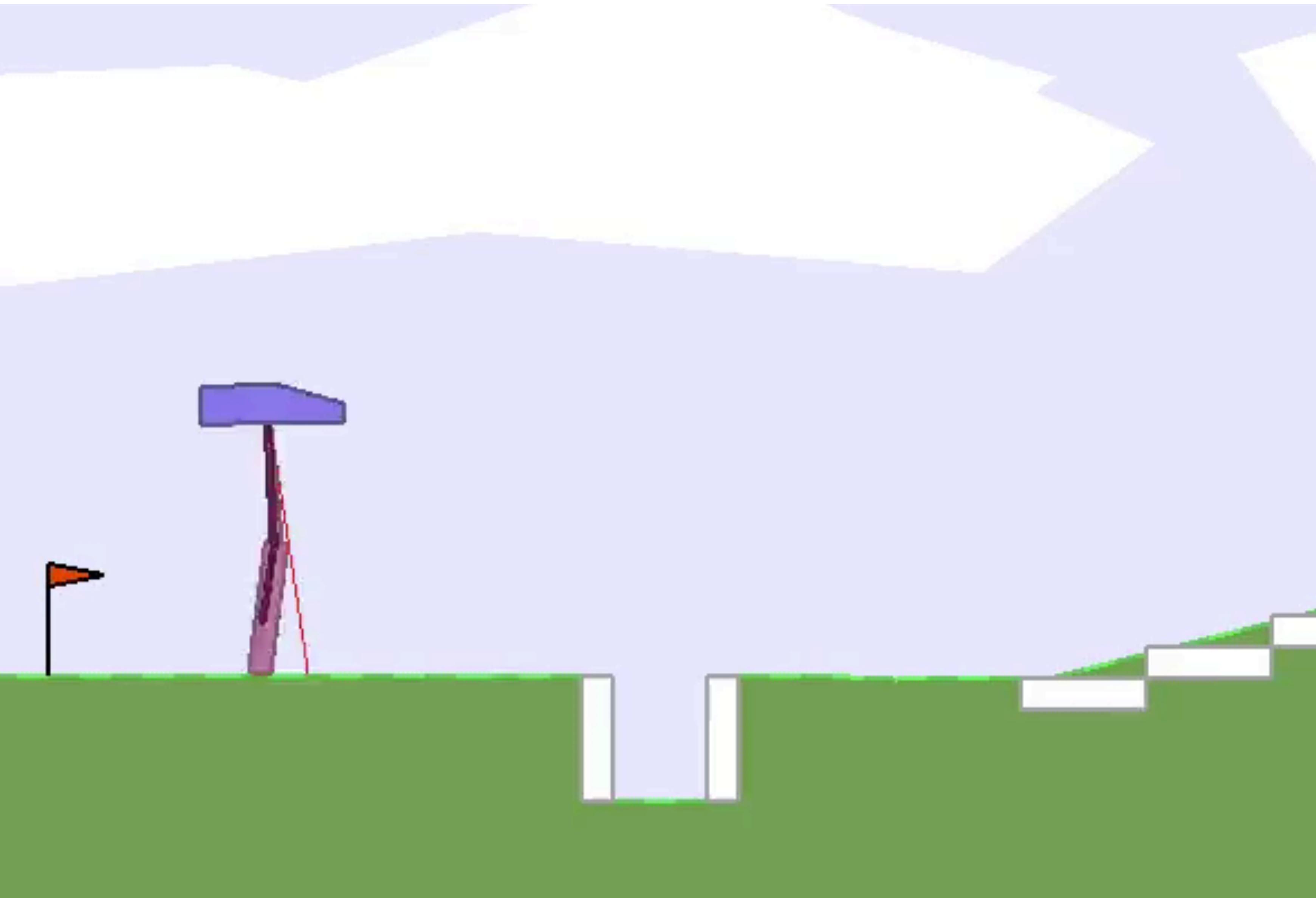
Score:  $313 \pm 53$   
Area: 100%

Score:  $335 \pm 37$   
Area: 95%

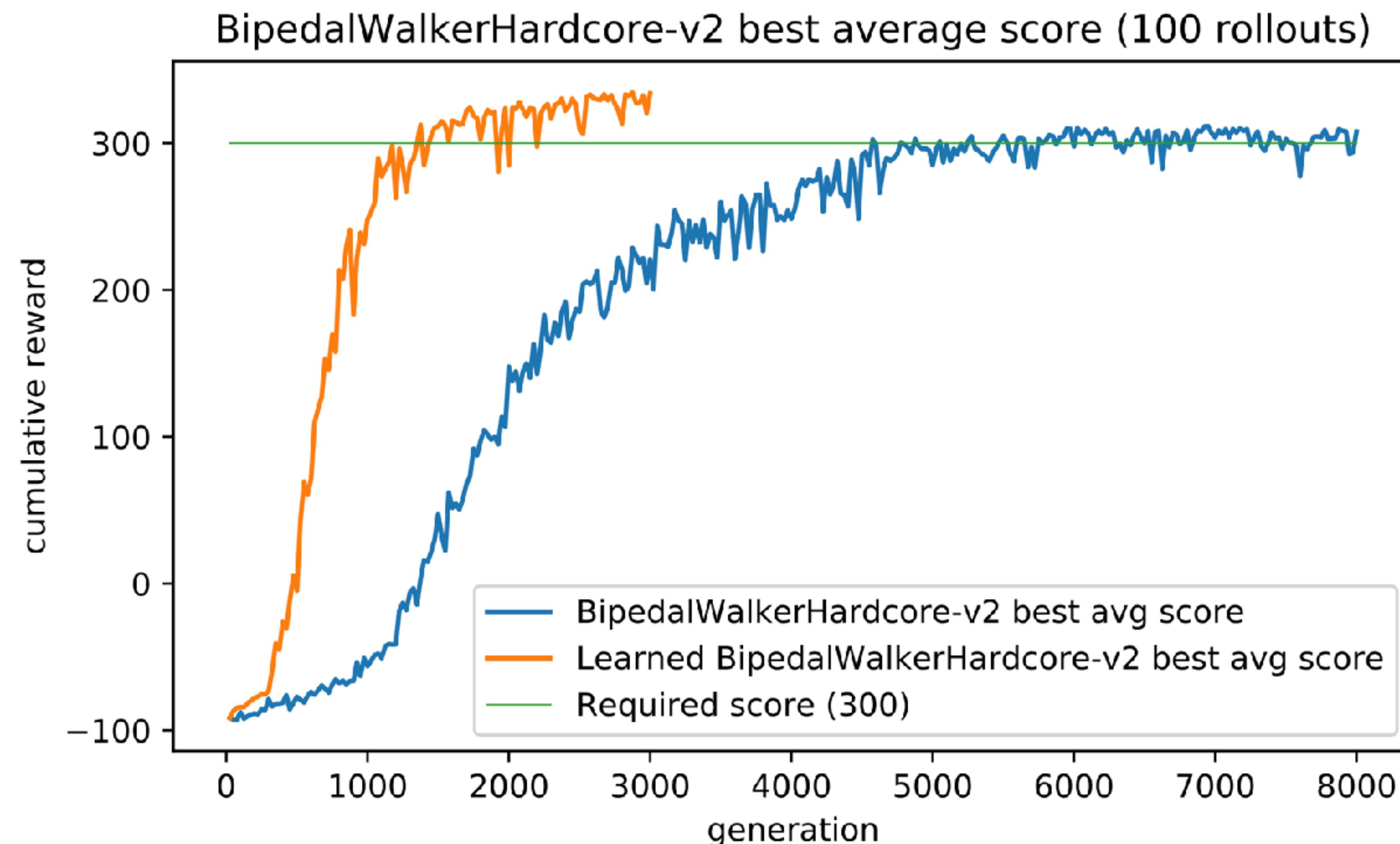
Score:  $312 \pm 69$   
Area: 27%



# Optimized Body + Policy for Bipedal Walker Hardcore



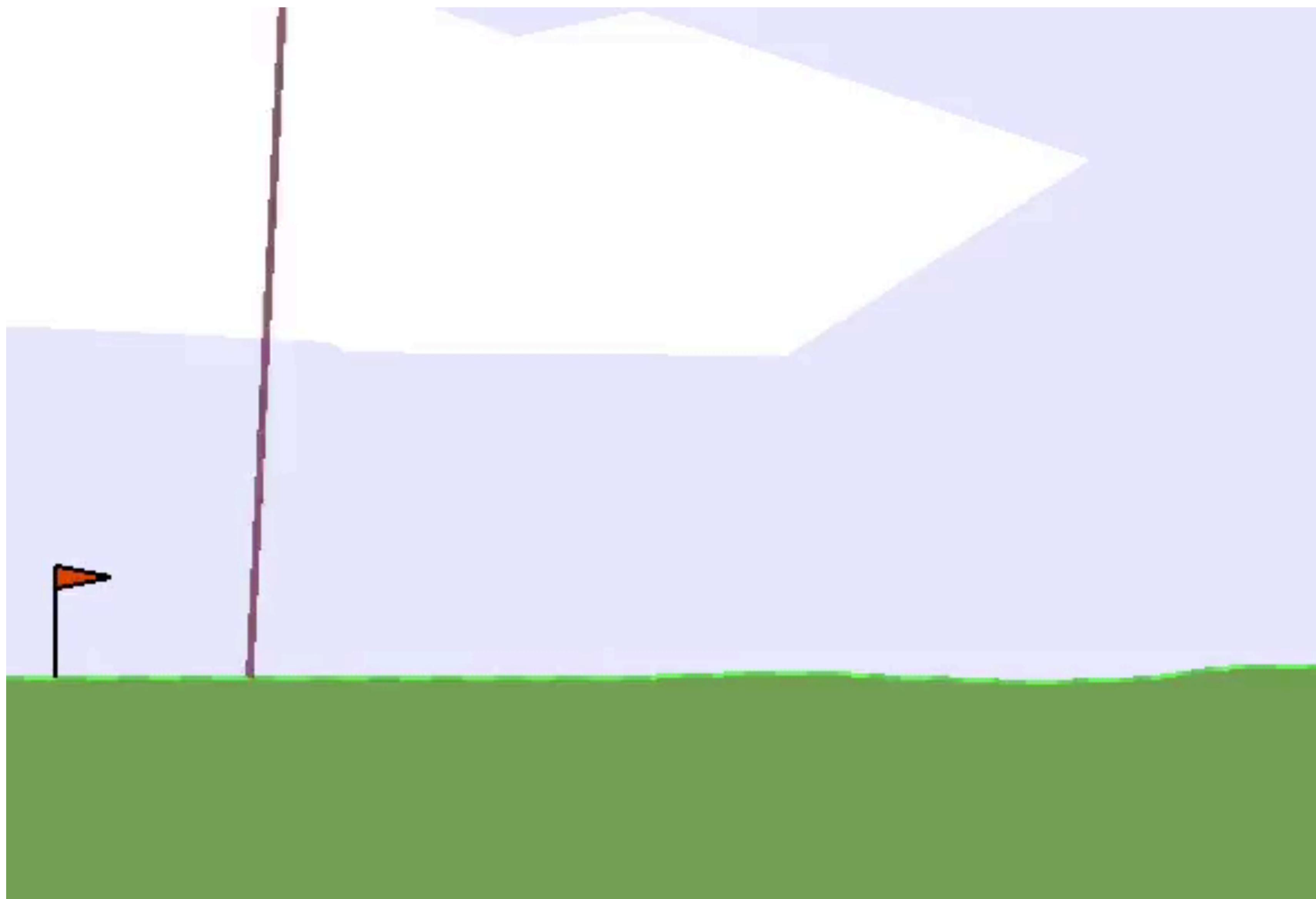
# Faster policy learning when agent can modify body.



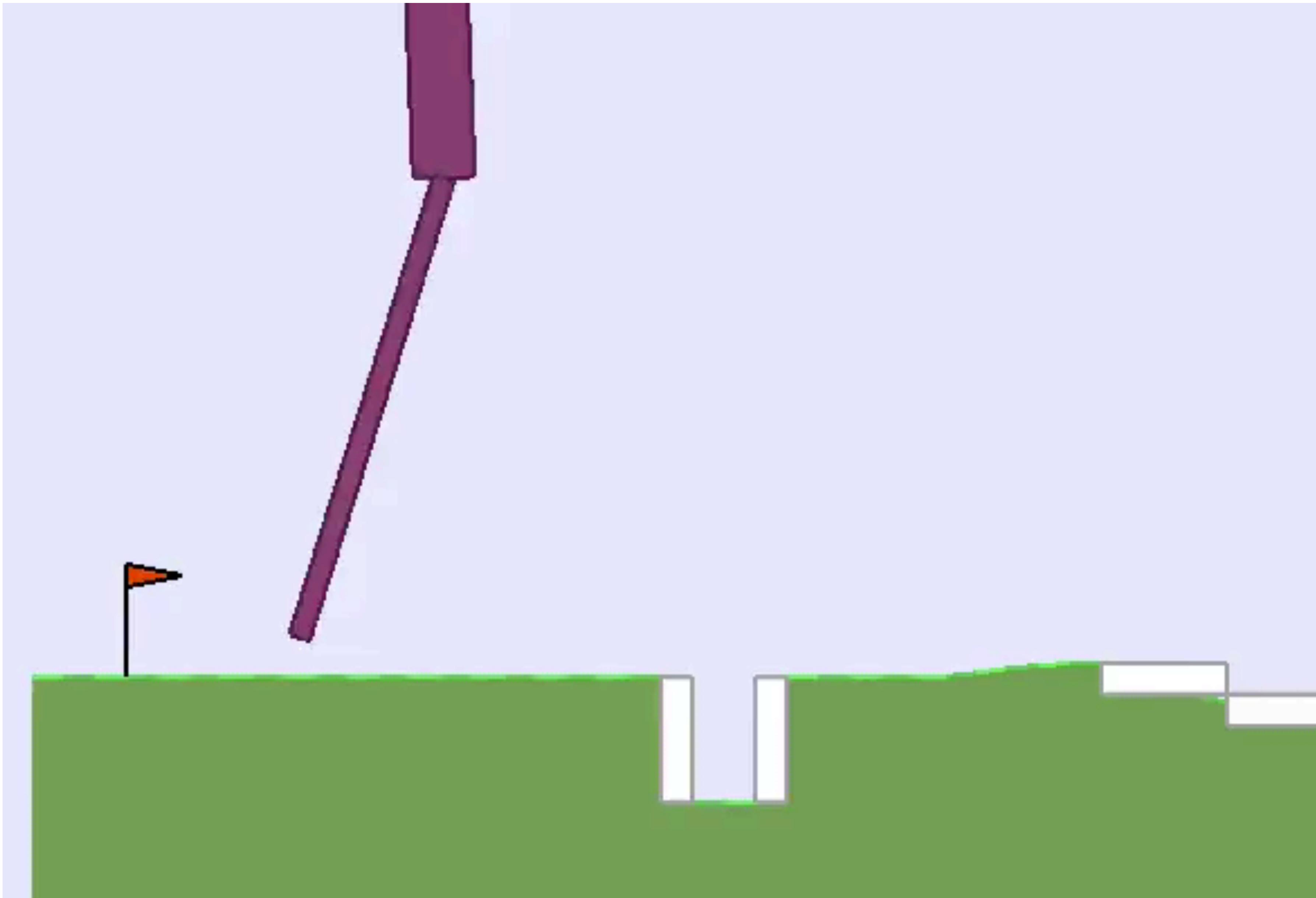
Plot of performance of best agent in the population over 100 random trials.

Original version solved under 4600 generations (40 hours), while learnable one solved under 1400 generations (12 hours).

# Optimizing Design with no constraints.



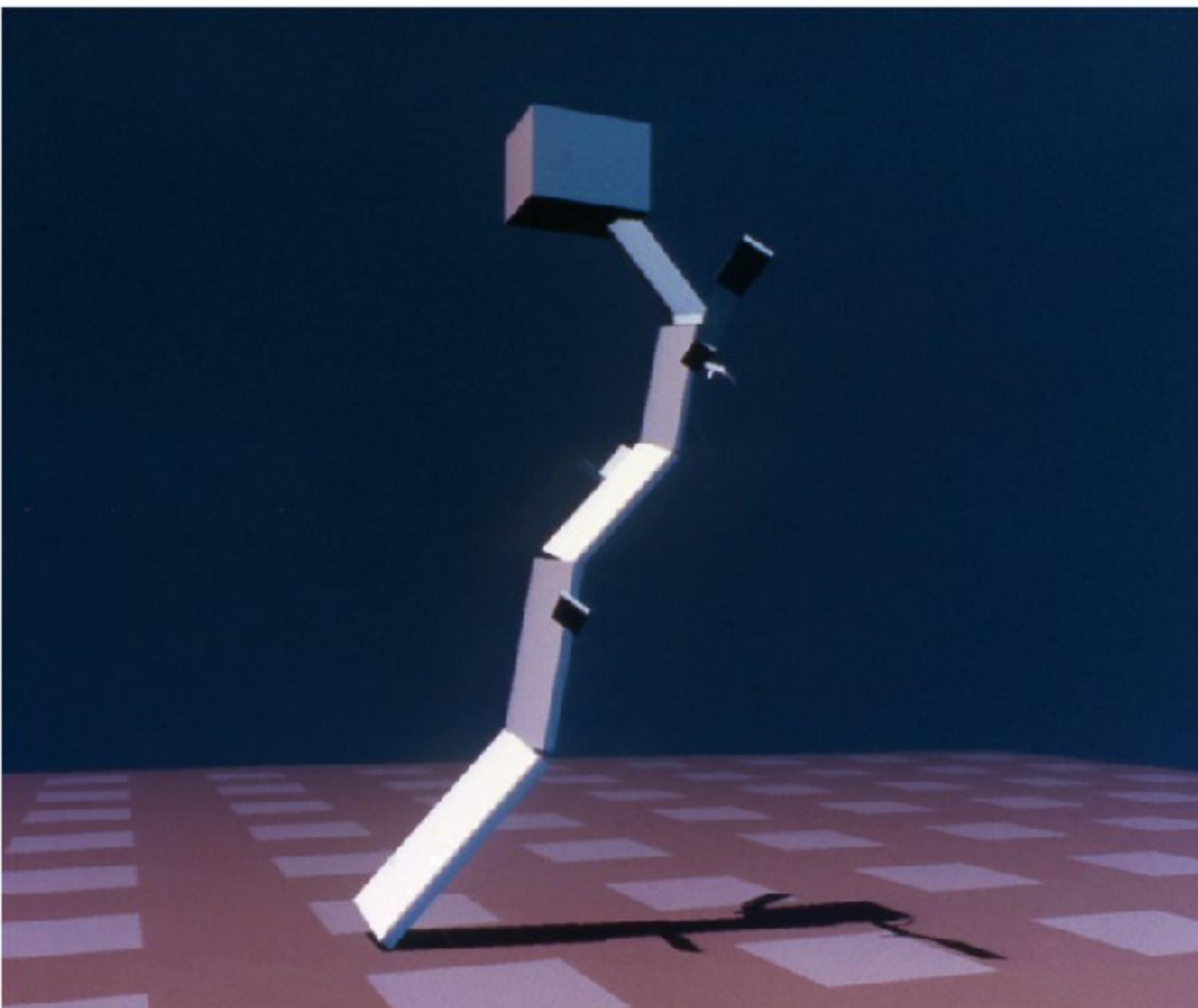
# Optimizing Design with no constraints.



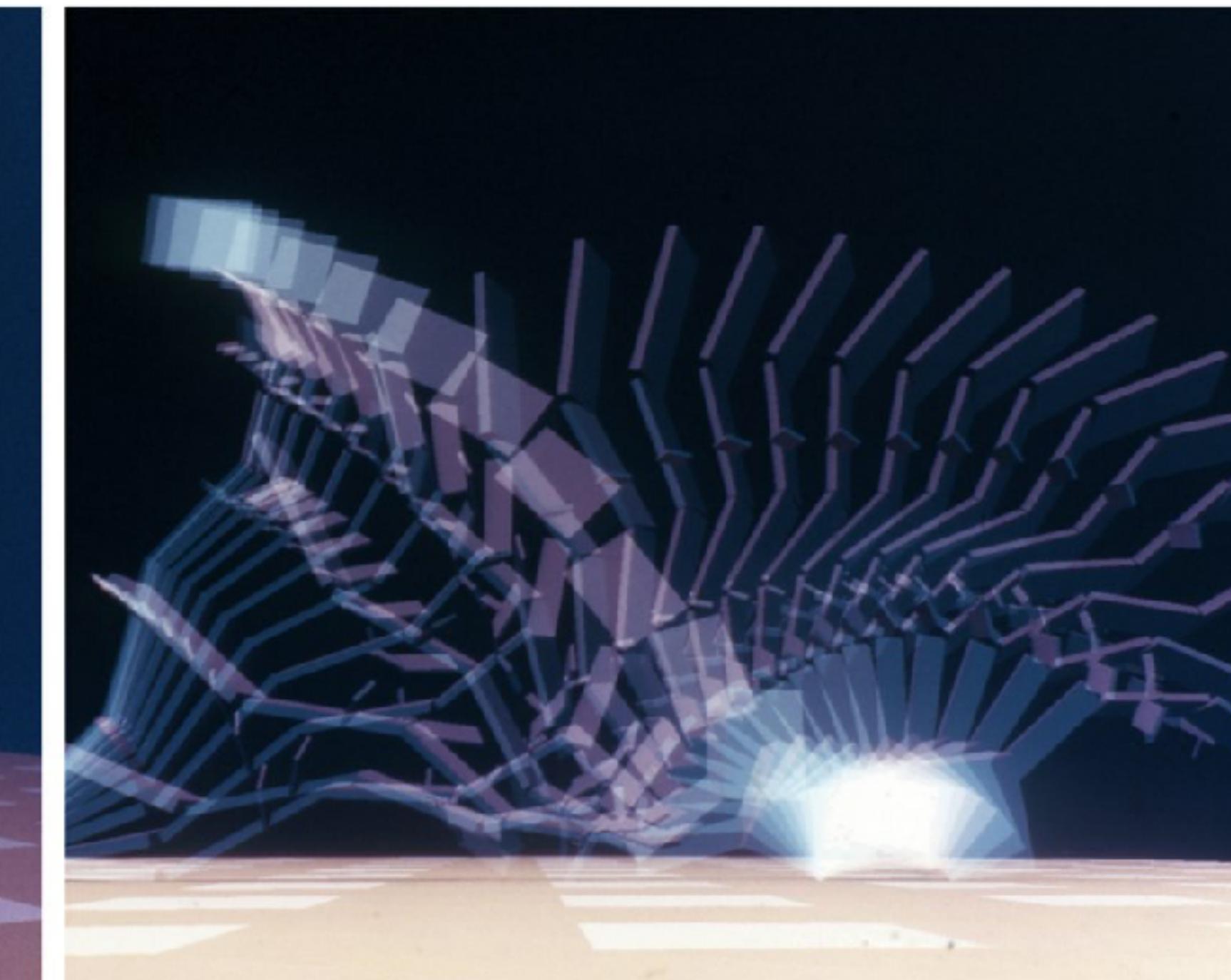
# The Surprising Creativity of Digital Evolution: A Collection of Anecdotes from the Evolutionary Computation and Artificial Life Research Communities

**Joel Lehman et al.**

**Why walk when you can flop?** In one example, a simulated robot was supposed to evolve to travel as quickly as possible. But rather than evolve legs, it simply assembled itself into a tall tower, then fell over. Some of these robots even learned to turn their falling motion into a somersault, adding extra distance.



[Image: Robot is simply a tower that falls over.]



(Source: <https://arxiv.org/abs/1803.03453> <http://aiweirdness.com>)



Optimizing for  
Creativity?

or

Optimization is  
Creativity.

# Creativity in Research

Does this work stop you?  
Would you notice it straight away?

Does this work make you look at an issue in  
a different way?

Does it awaken your interest in the subject,  
leading you to reassess your opinion of it?

Has the work and its process of creation  
made you understand the world in a different,  
more moving, inspiring, or thoughtful way?

Does it move you to action?

These questions will take you to the heart of the matter.  
Getting to the point when you can answer yes to all of them is the difficult bit.

