Introduction to Deep RL, Part 2

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2.1: What is RL currently achieving?

What RL Can Currently Do: RL in Simulation

If you have infinite simulator data and well-defined rewards, you can make substantial progress on extremely hard problems!

- Atari
- Simulated robotics
- Go (Deepmind's AlphaZero)
- Dota (OpenAI Five)
- Starcraft (Deepmind's AlphaStar)

Spotlight on AlphaGo

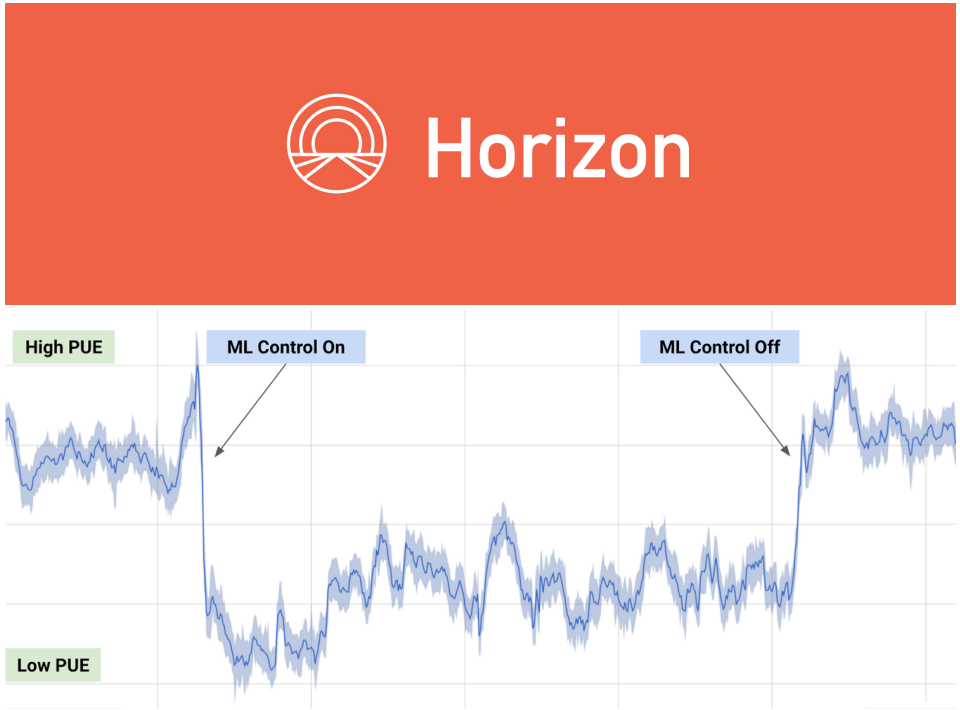
Hard to overstate what an unbelievable accomplishment this was

Previously: Go was considered unassailable stronghold for human experts, AI 10+ years away

What RL Can Currently Do: RL in the Real World

RL is beginning to see profitable real-world applications!

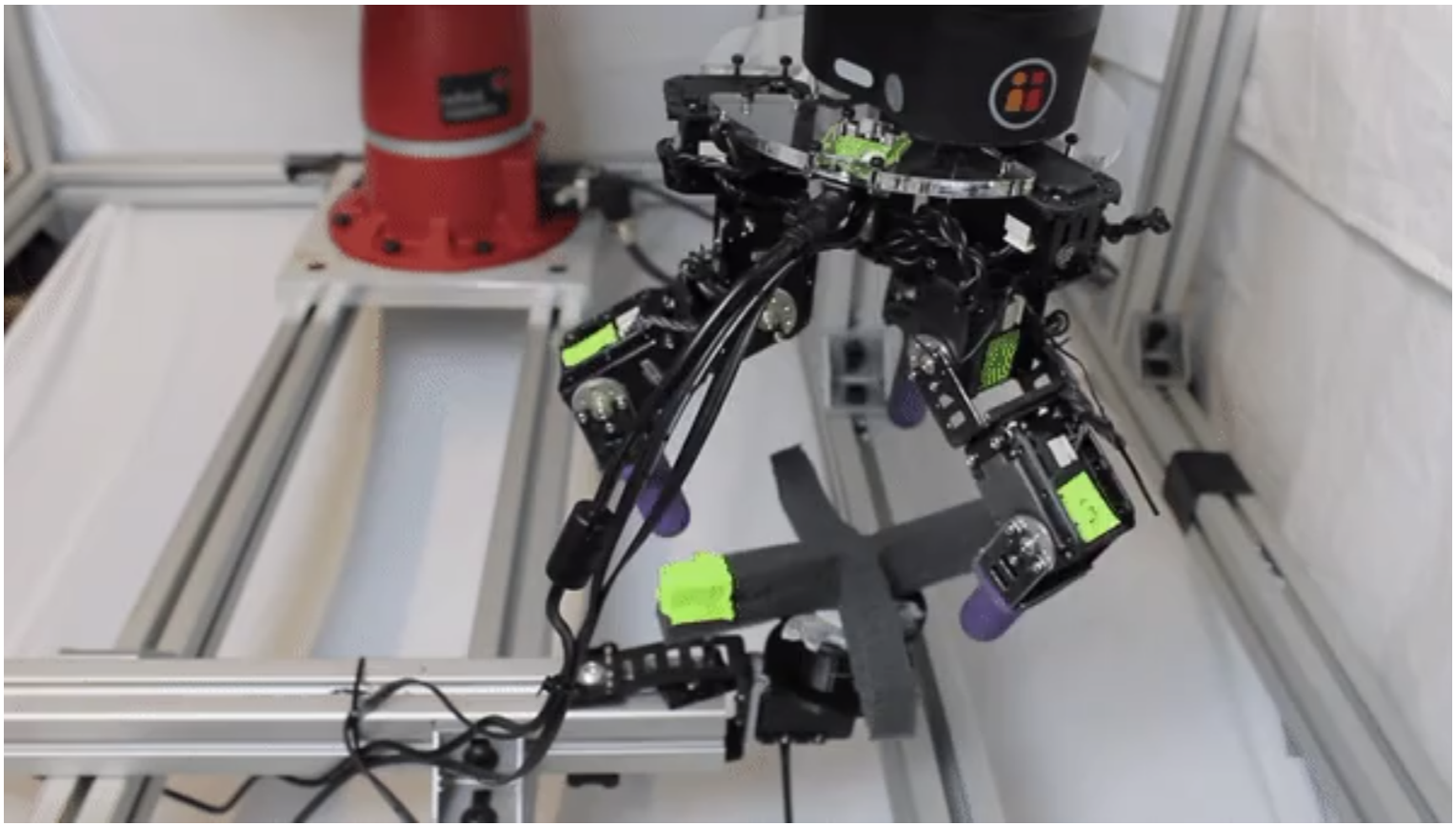
- Facebook uses RL (DQN) for push notifications (Horizon)
- DeepMind integrated RL into data center cooling
- Several promising early efforts at applying RL for robotics



2.1.1: Spotlight on RL for Real-World Robotics

Tasks that can't easily be simulated

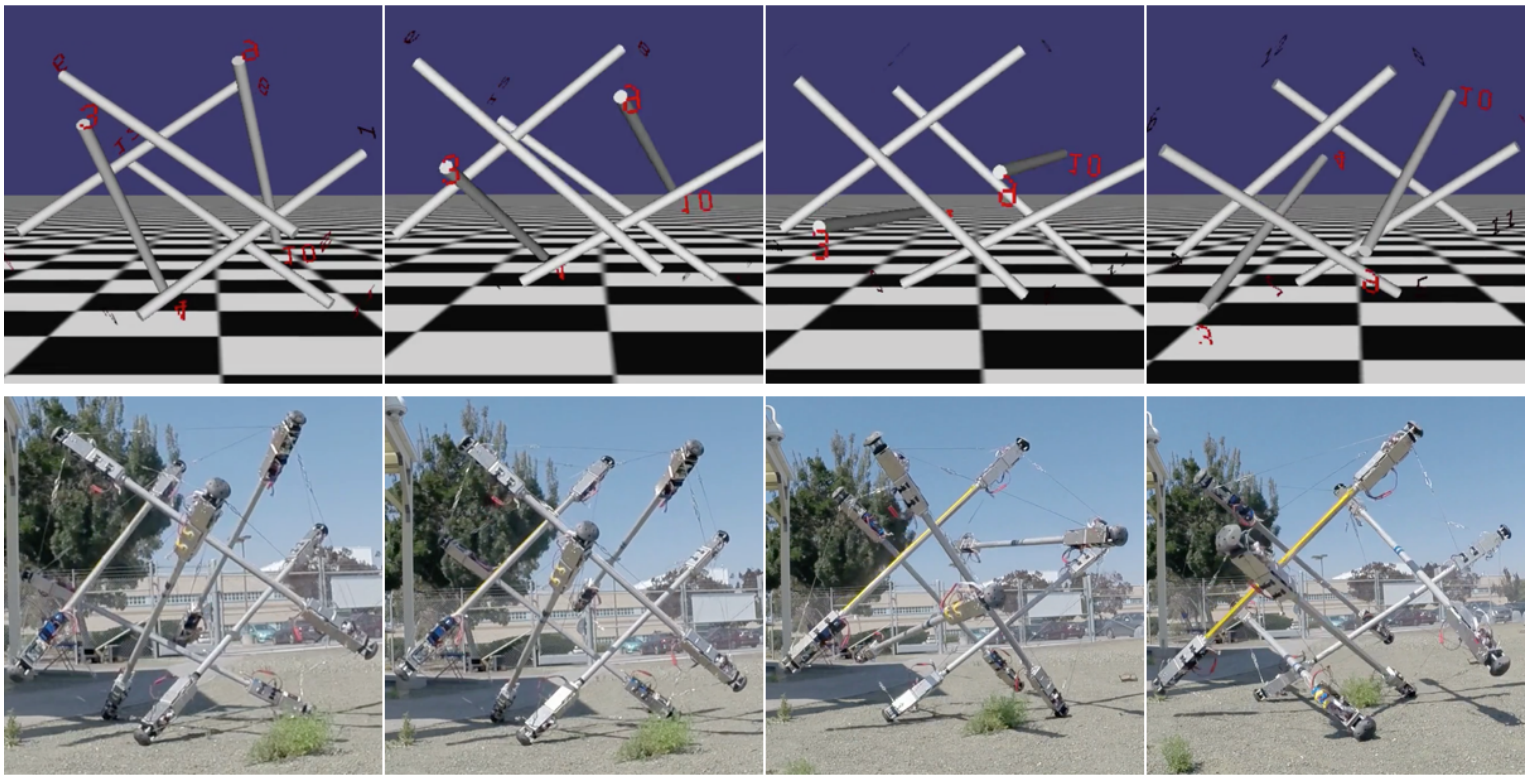
Zhu et al. trained low-cost robots from scratch in the real world on hard-to-simulate tasks using natural policy gradient. (Note: observation space here is hand state and valve state)



[1]Zhu et al, 2018: "Dexterous Manipulation with Deep Reinforcement Learning: Efficient, General, and Low-Cost"

Robots that are hard to control conventionally

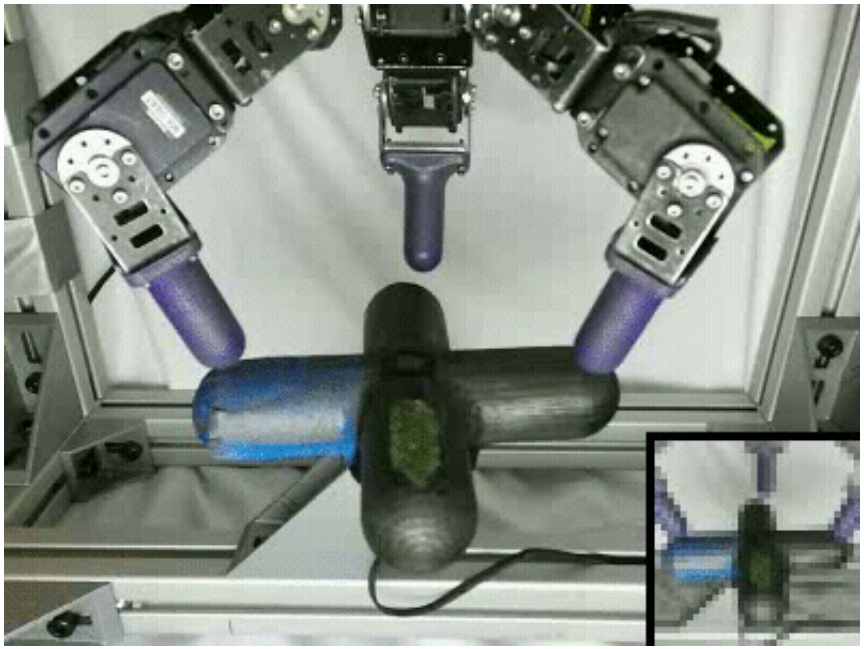
Zhang et al. trained a tensegrity robot with deep RL in simulation and demonstrated transfer to the real world



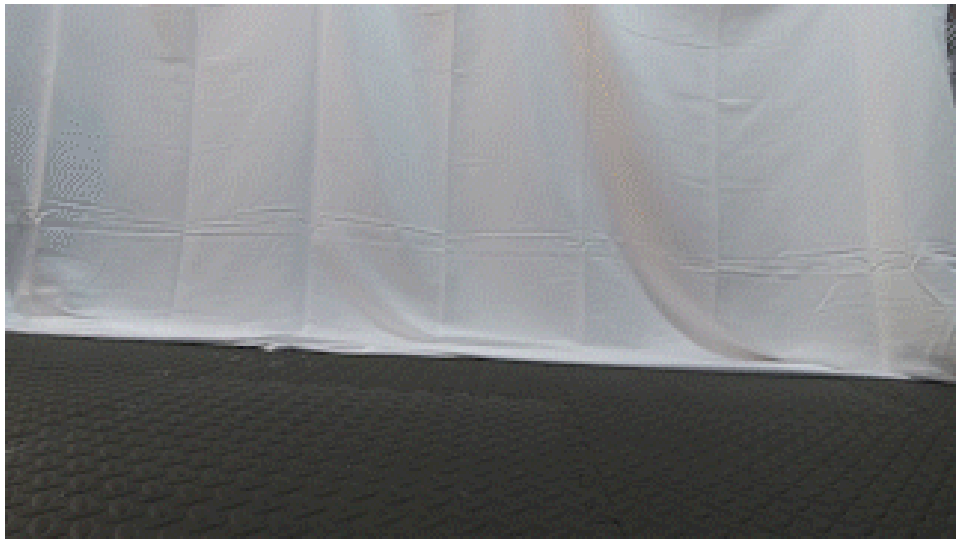
[1] Zhang et al, 2016: "Deep Reinforcement Learning for Tensegrity Robot Locomotion"

Soft Actor-Critic

Haarnoja et al. trained robots in the real world with Soft Actor-Critic, and demonstrated efficient and robust control on hard domains



Manipulation from visual input, agent sees lower-right (took 20 hours to learn)



Robust control of a legged robot (took 2 hours to learn)

[1] Haarnoja et al, 2018: "Soft Actor-Critic Algorithms and Applications"

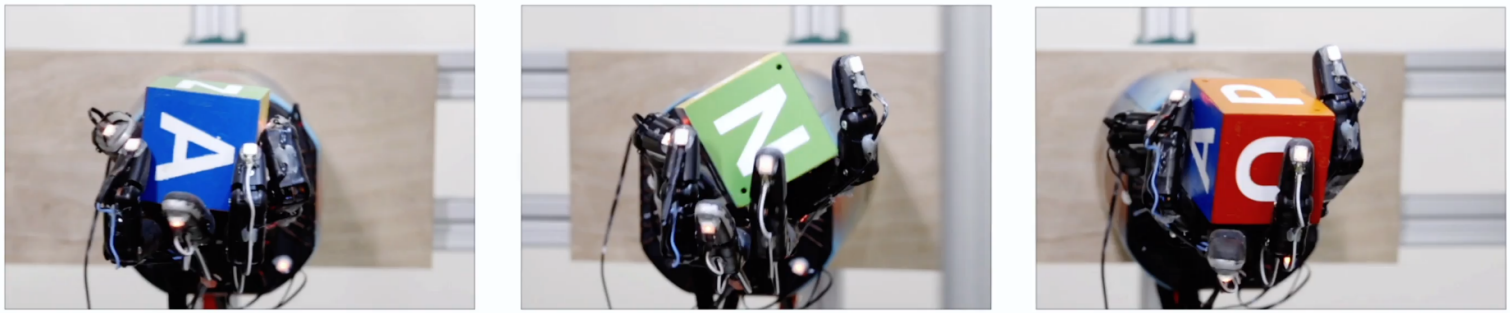
Anymal

Hwangbo et al. used real data to learn a better simulator, and then used lots of simulator data to train complex locomotion and recovery policies with TRPO for the Anymal robot:

[1] Hwangbo et al, 2018: "Learning agile and dynamic motor skills for legged robots"

Learning Dexterity

OpenAI et al. trained policies with PPO to dextrously manipulate a complex hand robot, using sim2real by domain randomization:



[1] OpenAI et al, 2018: "Learning Dexterous In-Hand Manipulation"

2.2: What are the challenges in modern RL?

Some grand challenges for RL

Let's talk about where RL fails, what we need that we aren't getting, and what research is happening.

- **Sample efficiency**: Modern deep RL algorithms are very inefficient with data, requiring in some cases 100x or more experience than a human to achieve good performance. How can we make them faster?

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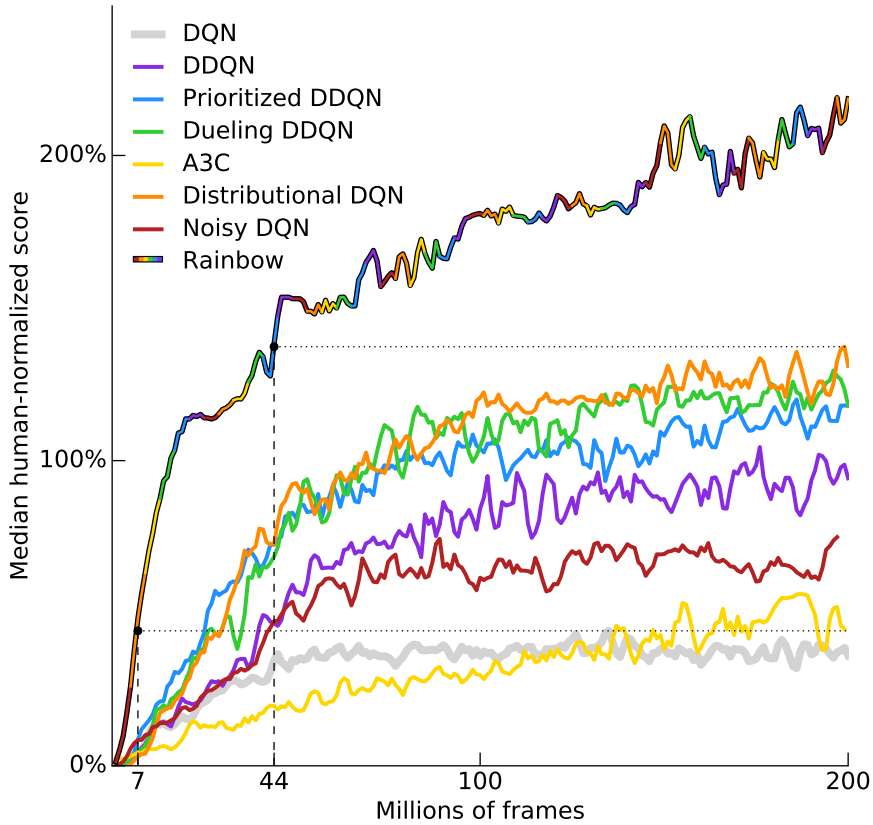
- **Safety**: How can we make sure that agents trained by deep RL behave in ways consistent with human preferences?

2.2.1: Research on Improving Sample Efficiency

Combining Model-Free Improvements

Rainbow DQN: combines...

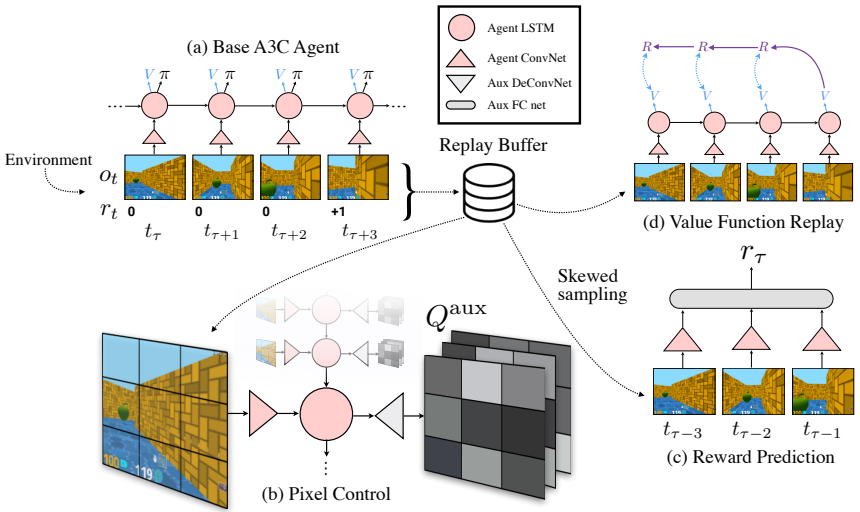
- Dueling architecture
- Double Q-Learning
- Prioritized experience replay
- N-step Q-Learning
- Distributional Q-Learning
- Parameter-space noise

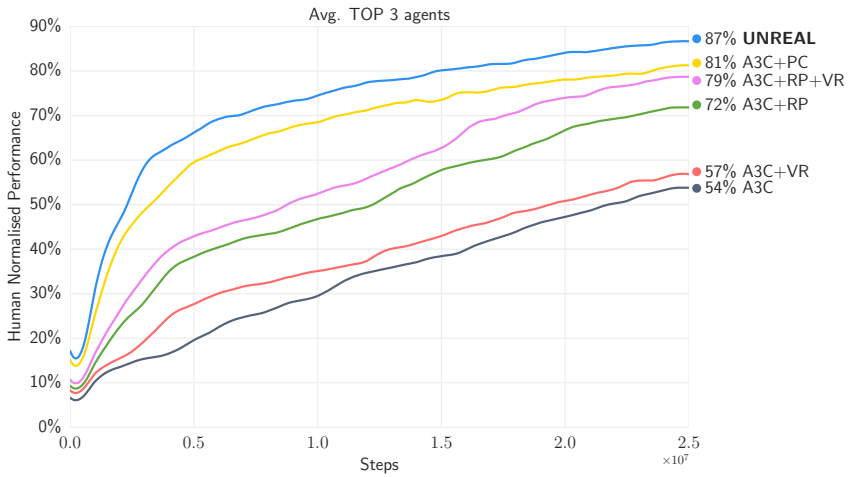


[1]Hessel et al, 2017: "Rainbow: Combining Improvements in Deep Reinforcement Learning"

Accelerating Feature Learning with Unsupervised Learning

UNREAL uses various unsupervised auxilliary tasks to speed up learning:





[1] Jaderberg et al, 2016: "Reinforcement Learning with Unsupervised Auxiliary Tasks"

Combining with Memory Mechanisms