Accelerating Goal-Conditioned RL Algorithms and Research

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Outline

- What are the obstacles to scale up RL?
- Obstacle 1.
- JaxGCRL our solution for speeding up and scaling up GCRL.
- Obstacle 2 and our results.

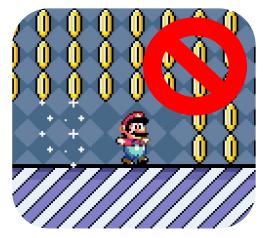
I have a dream... of Reinforcement Learning



New emergent behaviours

Unstructured Interaction



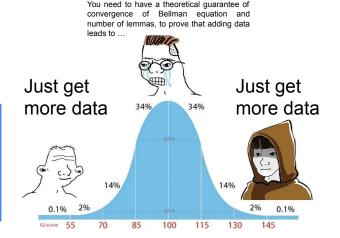


No reward shaping

Scaling up RL

Two main obstacles to scaling up RL:

 Need for massive amounts of data.
We use relatively small datasets of ~10⁶ transitions.

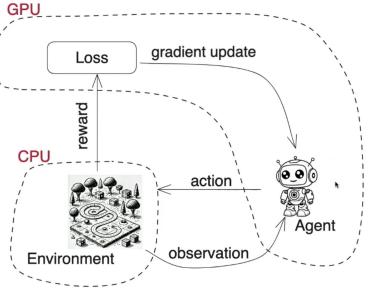


- Stable algorithms and architectures that utilize that data.
 - Data is not enough. We need proper algorithms.

Obstacle 1 - The data problem

- Time lost on transferring data between GPU and CPU.
- Small GPU utilisation.
- A lot of CPU threads to gather data.

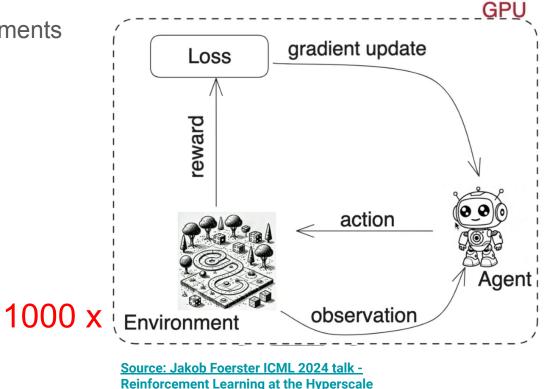
Training takes ~ 4-8 hours for DMC environments.



Source: Jakob Foerster ICML 2024 talk -Reinforcement Learning at the Hyperscale

The solution

- Use JAX vectorize environments
- Run everything on GPU
- JIT compile training loop.



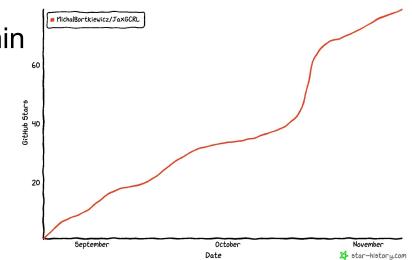
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JaxGCRL – benchmark + codebase

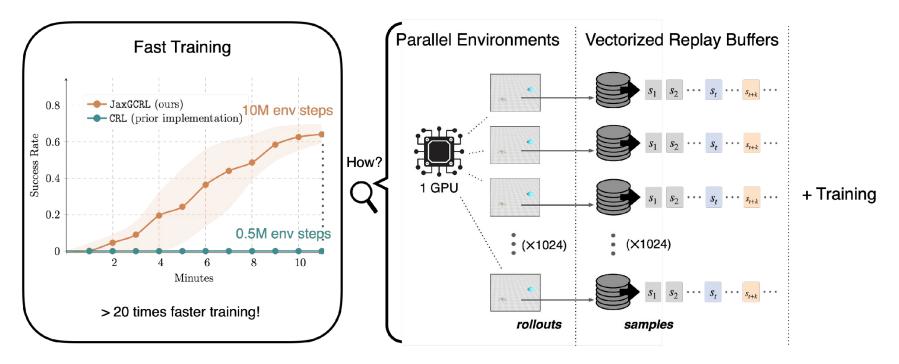
- 10+ GPU-accelerated BRAX/MJX environments.
- Fully JIT-compiled training.
 - ant training 10M steps < 10 min
- Easy to modify and extend.

Open-source: GPU-accelerated sim:





Training speedup in JaxGCRL

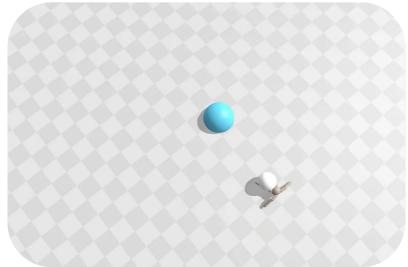


Takeaway:

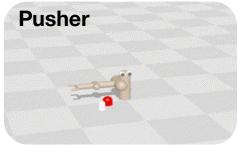
Training, data collection, and replay buffer are all run on a single GPU device.

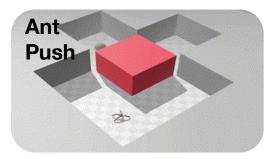
What exactly does JaxGCRL enable?

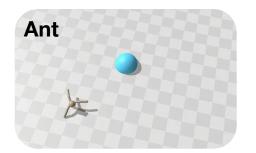
- You can work with RL projects, like data science projects, with a quick feedback loop.
- Anyone with access to a single GPU can contribute to SOTA GCRL research.
- You can have a working policy like this one in ~10 minutes.

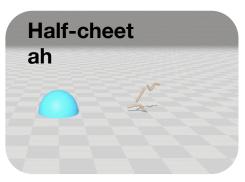


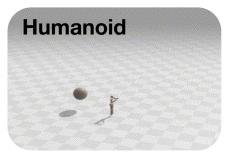
Environments

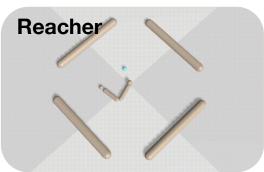


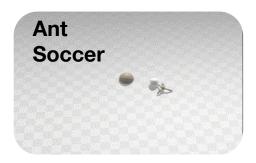




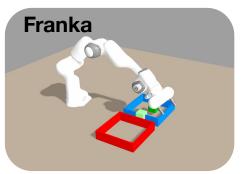








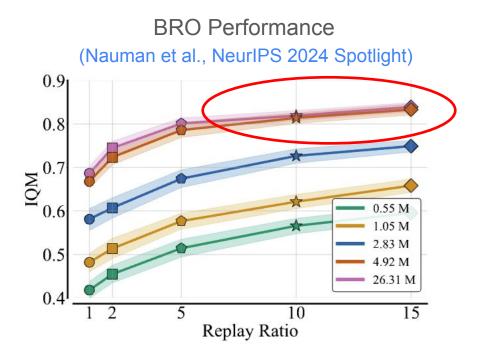




Obstacle 2 – algorithms and architectures that scale

Obstacle 2 - algorithms and architectures

- We use relatively small model architectures.
- The performance saturates quickly with model size.

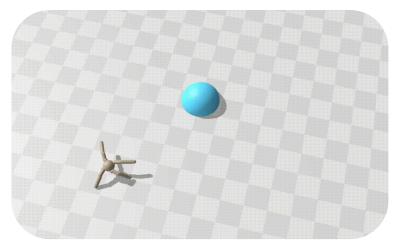


Goal-Conditioned Reinforcement Learning

- The objective is to reach the **goal** state.
- The **goal** can be defined as a subset of state space, i.e., just x and y coordinates.
- Often used in sparse reward settings.

The policy is conditioned on both state and goal:

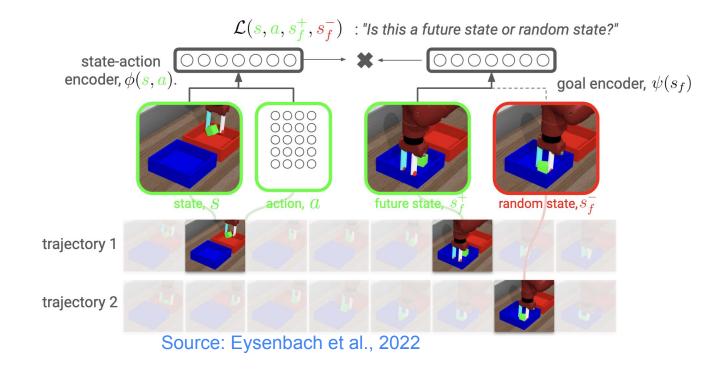
$$\pi(a \mid s,g)$$





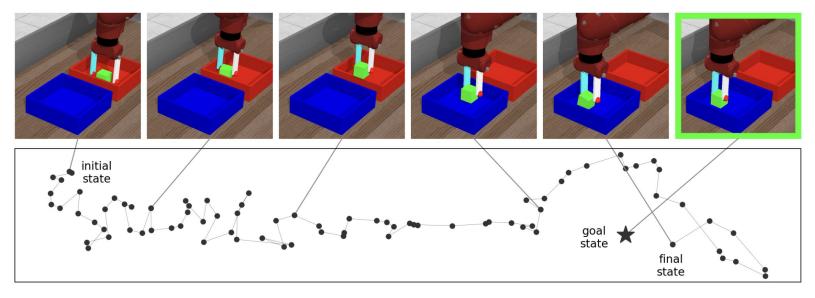
Contrastive Learning as Goal-Conditioned RL (Eysenbach et al., NeurIPS 2022)

Objective: Discriminate future states from random states.



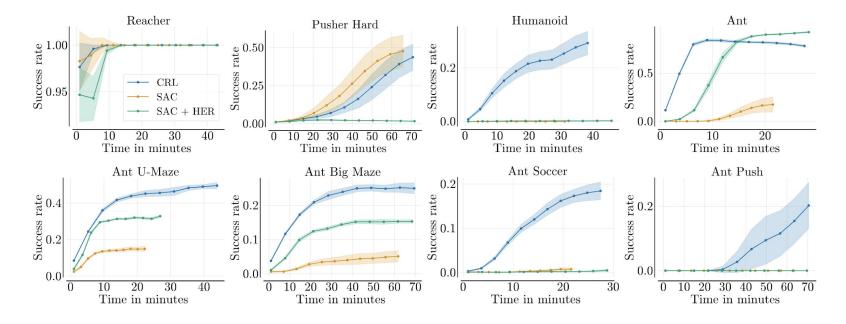
Why it works?

• Meaningful environment dynamics representations



Source: Eysenbach et al., 2022

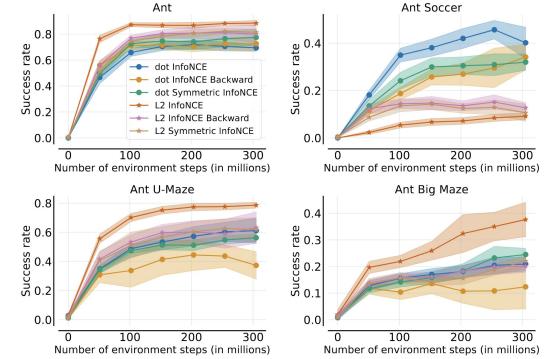
JaxGCRL Benchmark results



• Contrastive RL learns non-trivial policy in every environment.

What if we scale the number of env steps?

Currently, CRL does not scale effectively
with large amounts of data.



How important are energy and contrastive functions?

• Different contrastive energy functions and contrastive objectives based on InfoNCE (and DPO) perform on-pair.

Where is the bottleneck, then?

Contrastive objectives

Energy functions

Is architecture scale a bottleneck?

- Architecture size helps but needs to be scaled up correctly.
 - Performance per architecture epth 2 epth 3 epth 4 epth 4

Layer Normalization is helping in



Takeaways

- Obstacles: Data and Algorithms/Architectures.
- JaxGCRL addresses Obstacle 1 and speeds up research on Obstacle 2.
- Experiments with 10M steps can be completed in minutes, while those with billions of environment steps can be done in a few hours.
- *"We are experiencing another seismic shift in (RL) field"* Jakob Foerster 2024

Thank you! michalbortkiewicz8@gmail.com, wladek.palucki@gmail.com

github.com/MichalBortkiewicz/JaxGCRL

