Reinforcement Learning at the Hyperscale

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Outline

- The Hyperscale Revolution of Deep RL
- Unlock #1: Faster, diverse Eval (and curriculum learning)
- Unlock #2: Theory Inspired, simpler RL
- Unlock #3: Theory Inspired, scalable Meta-RL
    - Discovering RL Algorithms
- Bonus: AI Scientist – doing e2e science.. !

Note: this is a bit of a “choose your own adventure” talk.

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A tale of two revolutions: #1 The Deep Learning Revolution

AlexNet

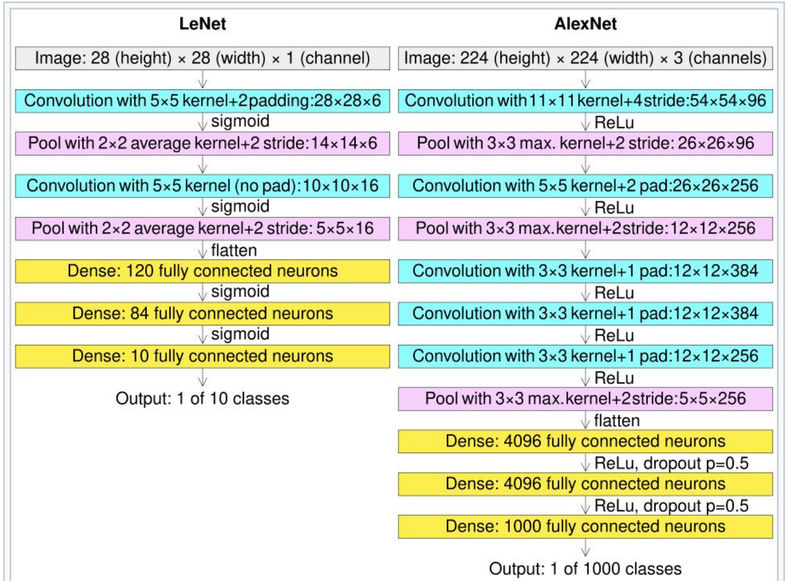
文A 10 languages

Article Talk Read Edit View history Tools

From Wikipedia, the free encyclopedia

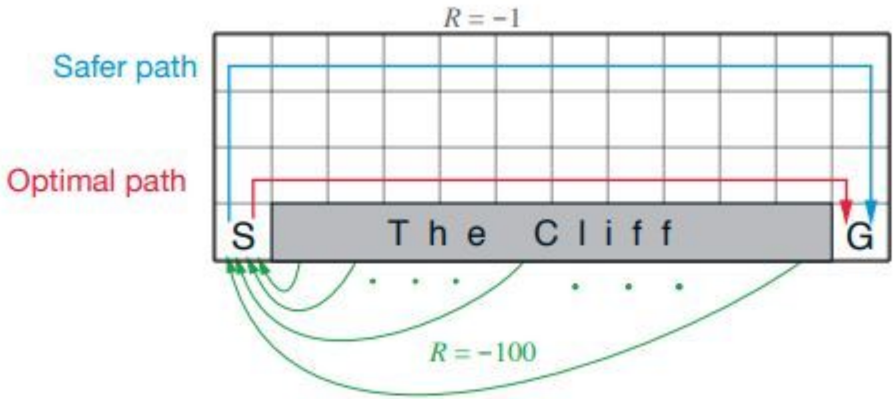
AlexNet is the name of a convolutional neural network (CNN) architecture, designed by Alex Krizhevsky in collaboration with Ilya Sutskever and Geoffrey Hinton, who was Krizhevsky's Ph.D. advisor at the University of Toronto.[1][2]

AlexNet competed in the ImageNet Large Scale Visual Recognition Challenge on September 30, 2012.[3] The network achieved a top-5 error of 15.3%, more than 10.8 percentage points lower than that of the runner up. The original paper's primary result was that the depth of the model was essential for its high performance, which was computationally expensive, but made feasible due to the utilization of graphics processing units (GPUs) during training.[2]

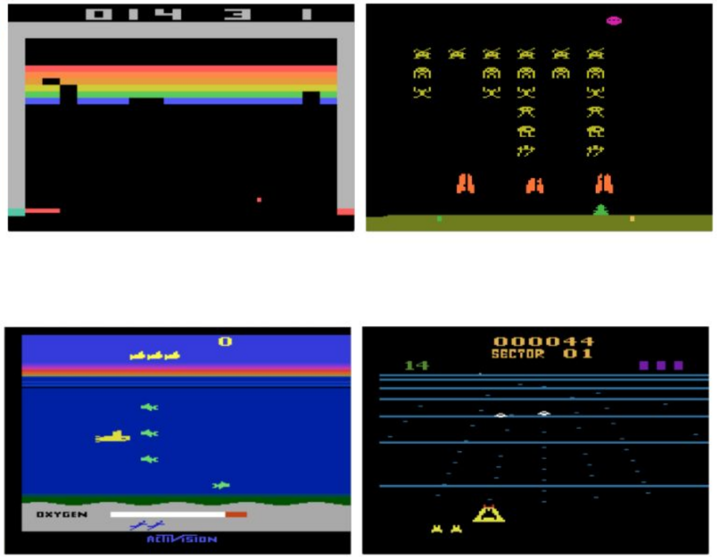


https://en.wikipedia.org/wiki/AlexNet

2: The Deep RL Revolution..



“Reinforcement Learning – An Introduction”,
Sutton and Barto



“Playing Atari with Deep Reinforcement Learning”, Mnih et al, NIPS Deep Learning Workshop 2013

Looking back 12+ years later…

Volodymyr Mnih

FOLLOW

DeepMind
Verified email at cs.toronto.edu - Homepage
Machine Learning

TITLE	CITED BY	YEAR
Human-level control through deep reinforcement learning V Mnih, K Kavukcuoglu, D Silver, AA Rusu, J Veness, MG Bellemare, ... Nature 518 (7540), 529-533	30723	2015
Playing Atari with Deep Reinforcement Learning V Mnih, K Kavukcuoglu, D Silver, A Graves, I Antonoglou, D Wierstra, ... arXiv preprint arXiv:1312.5602	15140	2013

Alex Krizhevsky

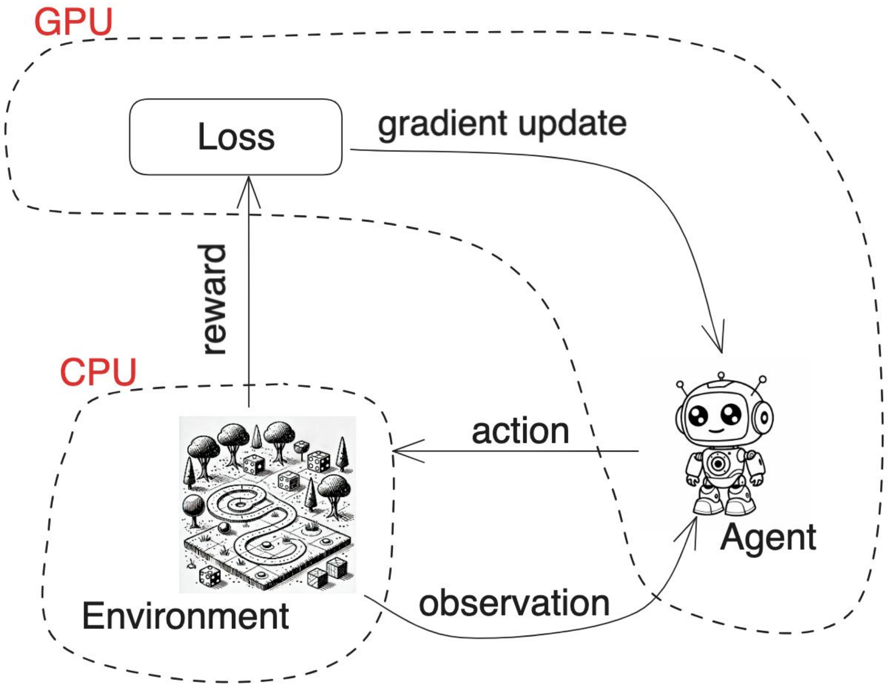
FOLLOW

University of Toronto
Verified email at cs.toronto.edu - Homepage
Machine Learning

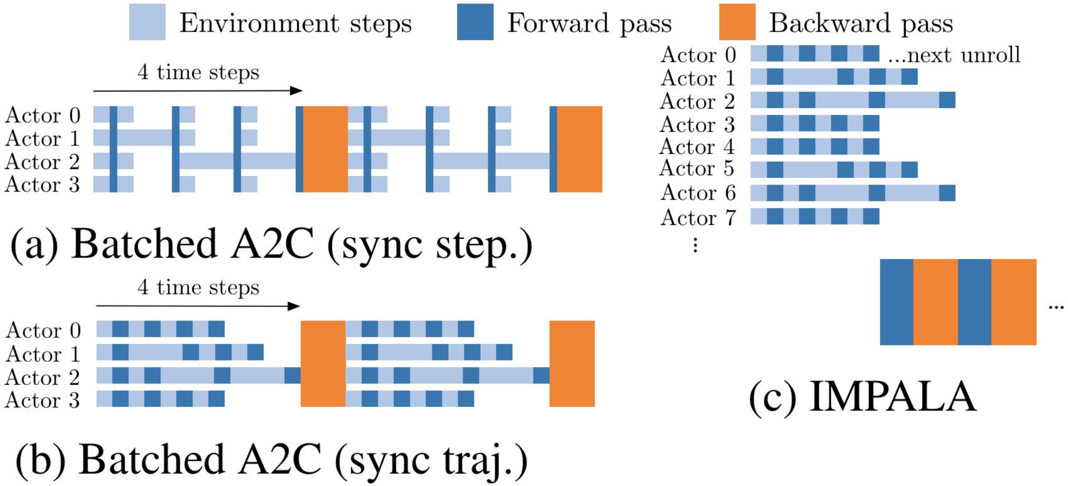
TITLE	CITED BY	YEAR
Imagenet classification with deep convolutional neural networks A Krizhevsky, I Sutskever, GE Hinton Advances in neural information processing systems 25	158869 *	2012

RL's Computational Inefficiency Problems

RL typically requires policy rollouts to happen in environments written for the CPU



From Computational Inefficiency to Algorithmic Complexity:



- Difficult to keep the GPU "busy"
- Data gets stale
- Algorithmic and Engineering Complexity

"IMPALA: Importance Weighted Actor-Learner Architectures", L Espeholt et al

What else does this mean? Example: Hanabi!

What else does this mean? Example: Hanabi!

Slow: “..Training a Rainbow agent for the *sample limited regime* of 100 million steps took approximately **seven days** using an NVIDIA V100 GPU.” [1]

- **165 steps / second on an NVIDIA V100**

Expensive: “.. agents for 20 billion steps. We estimate the computation took 100 CPU years for a population size of 30.. “ [1]

- **190 steps / CPU second**

1: “The Hanabi Challenge: A New Frontier for AI Research”, Bardt et al, https://arxiv.org/pdf/1902.00506

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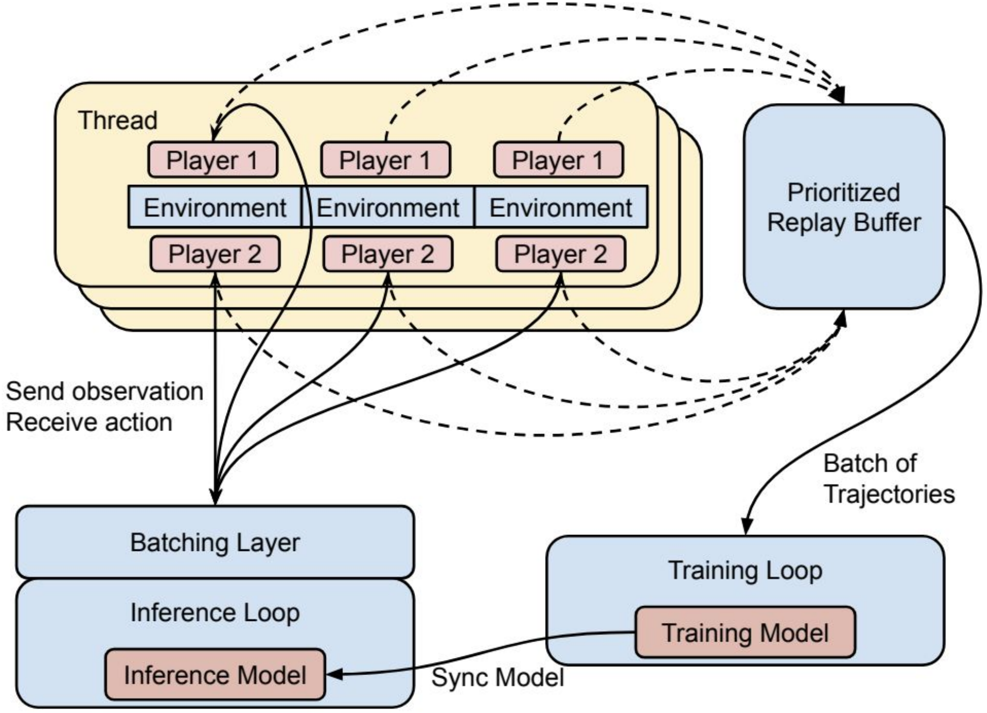
What else does this mean? Example: Hanabi!

Hyper-engineered: requiring C++ for env and training loop with complicated thread handling



However, this achieves roughly 12.000 SPS on 3 GPUs.

“Off-Belief Learning”, Hu et al

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Take-Away:

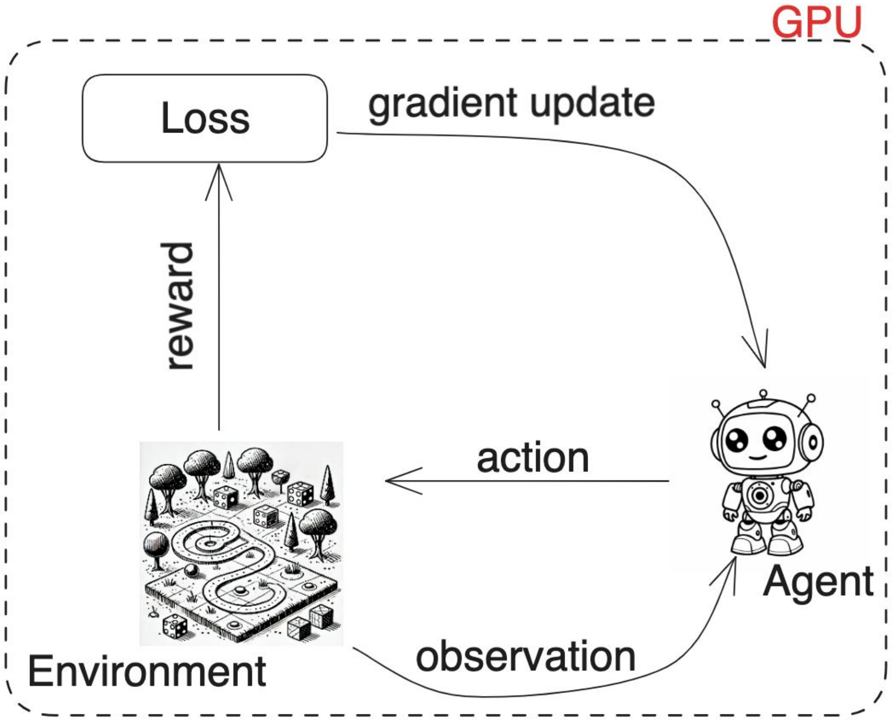
Deep RL had lost the “Hardware Lottery”

A Path Forward:

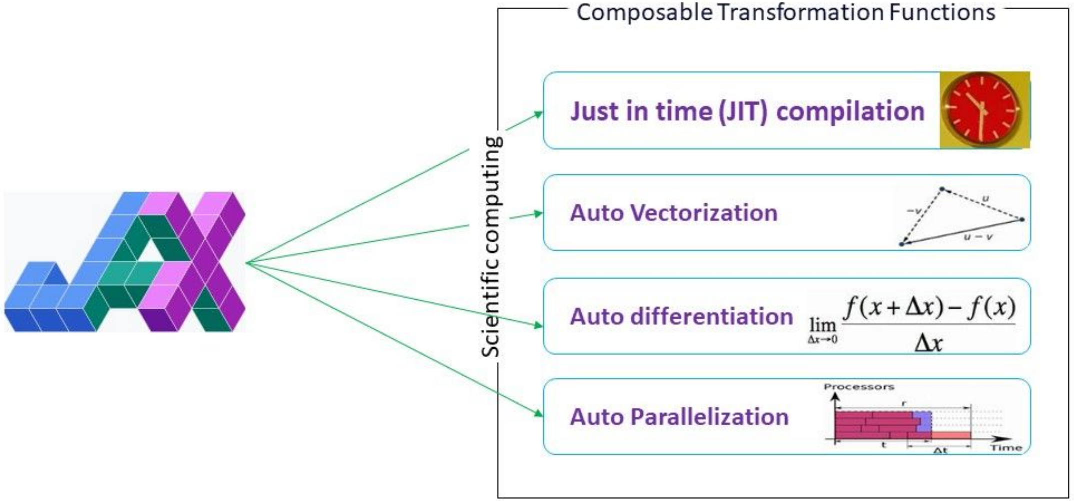
The Second Coming of the GPU (to deep RL)

The solution:

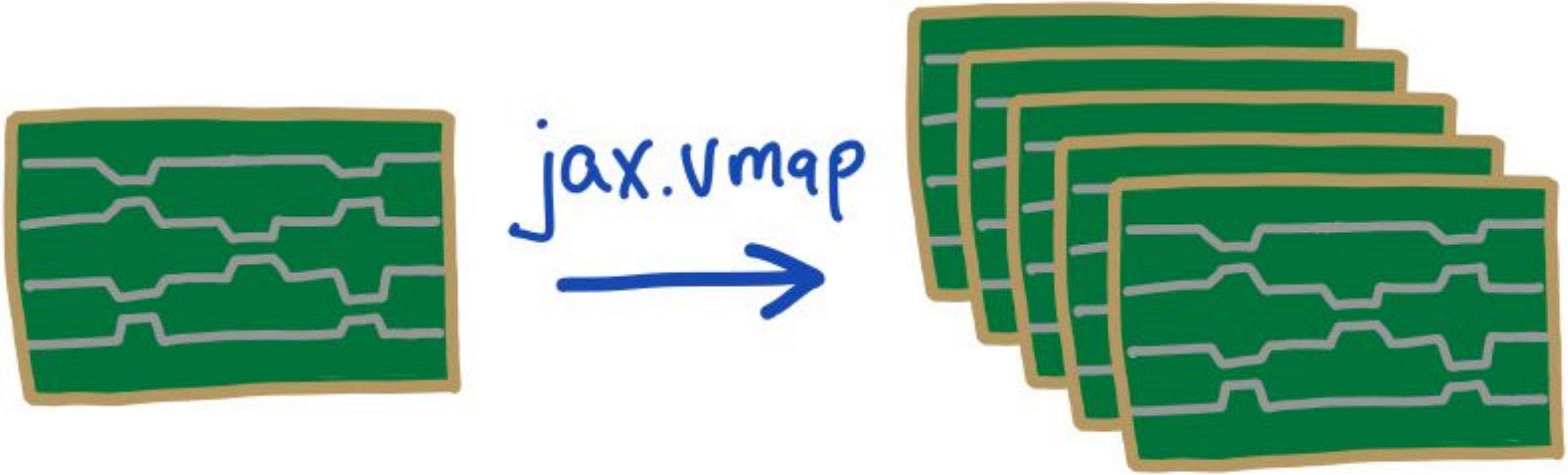
What if we run *everything* on the GPU instead? Wouldn't this be difficult?



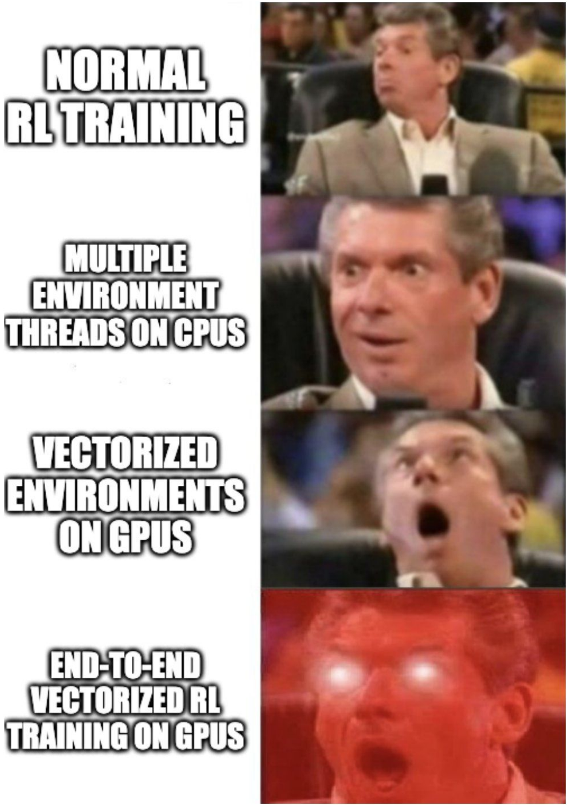
Solution: Jax!



Solution: Jax vmap!

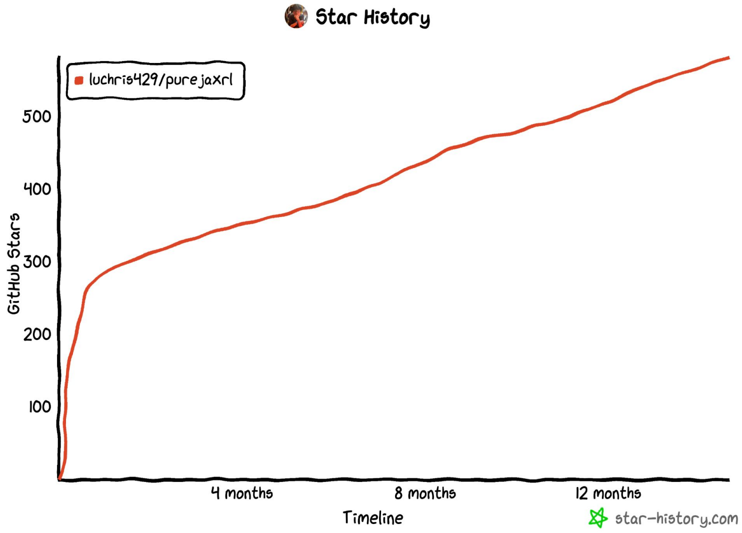


Scaling Up: PureJaxRL



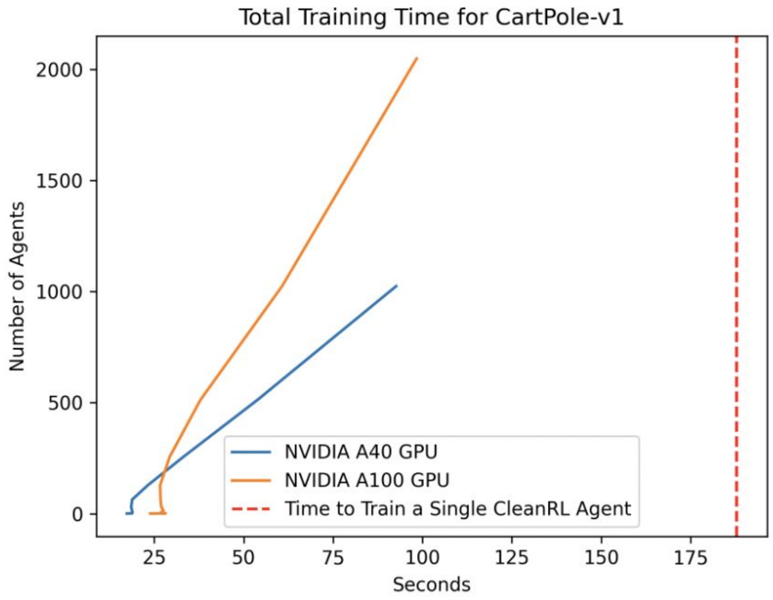
Achieving 4000x Speedups and Meta-Evolving Discoveries with PureJaxRL

AUTHORS	AFFILIATIONS	PUBLISHED	FULL PAPER
Chris Lu	University of Oxford, Foerster Lab for AI Research	April 3, 2023	arXiv



Chris Lu

PureJaxRL Speedups



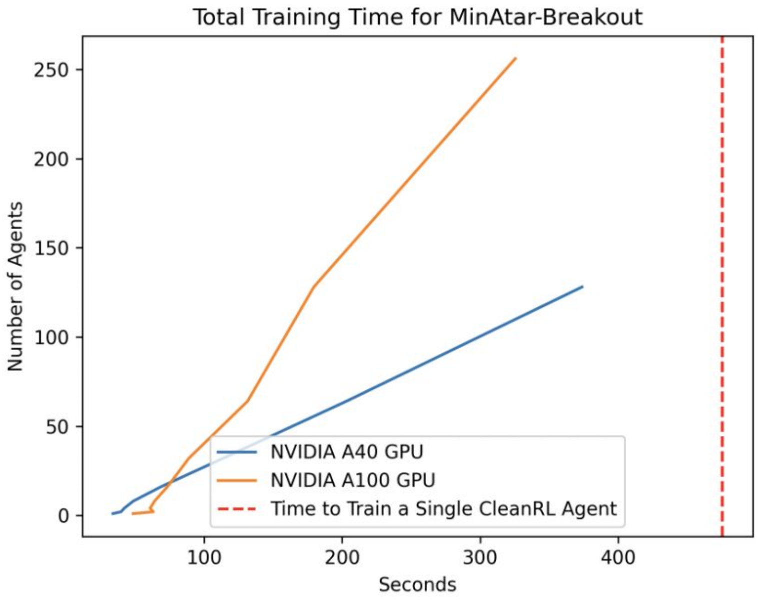


Figure 3: CleanRL vs. Our Jax PPO on CartPole-v1 and MinAtar-Breakout. We can parallelise the agent training itself! On CartPole-v1 we can train 2048 agents in about half the time it takes to train a single CleanRL agent!

Chris Lu

#1:

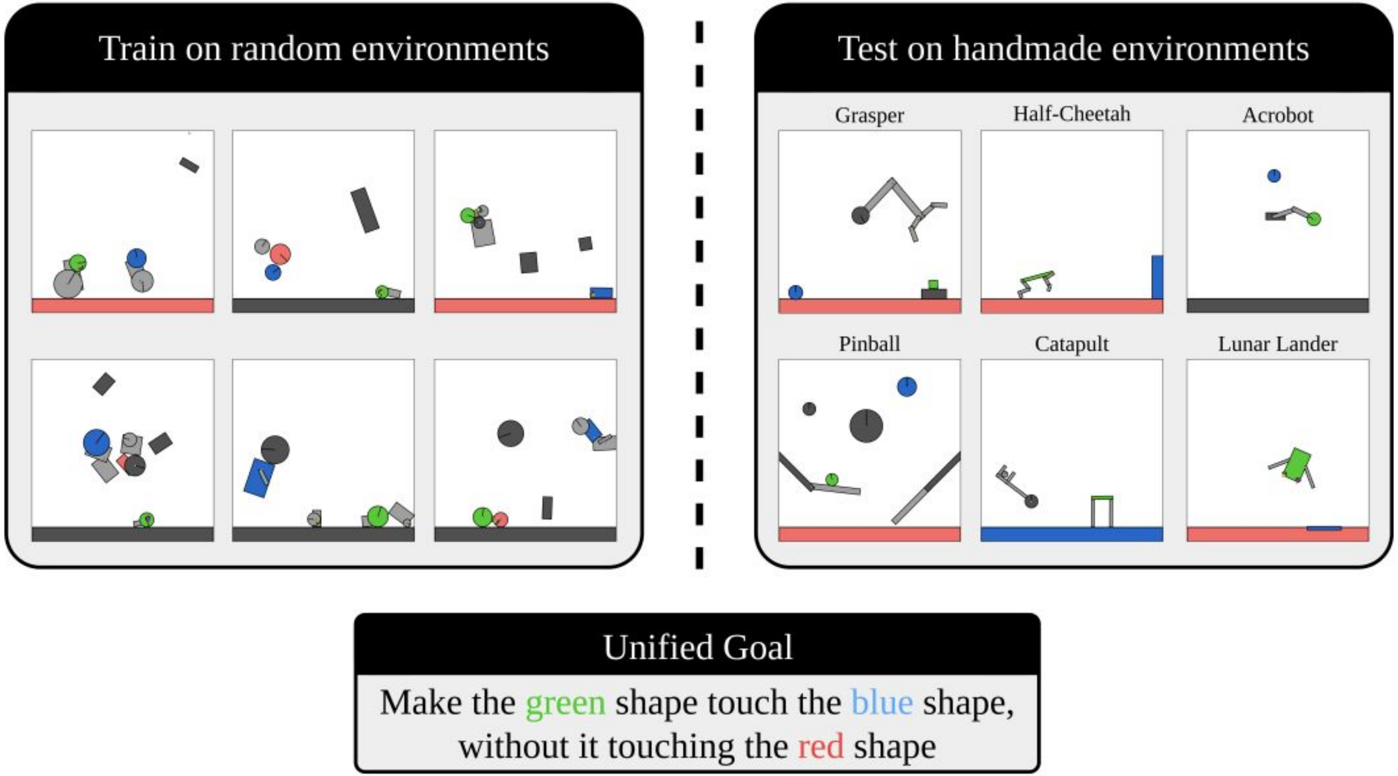
Faster, diverse Eval

(and curriculum discovery)

KINETIX: INVESTIGATING THE TRAINING OF GENERAL AGENTS THROUGH OPEN-ENDED PHYSICS-BASED CONTROL TASKS

Michael Matthews* **Michael Beukman*** **Chris Lu** **Jakob Foerster**
FLAIR, University of Oxford

ICLR 2025 Oral



Can we learn a _foundation model_ for
decision making?

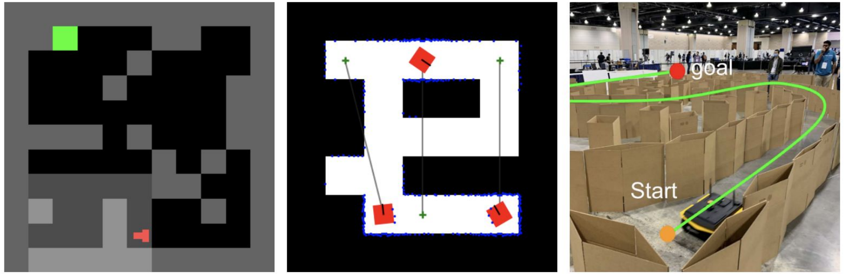
Interlude: Curriculum learning

No Regrets: Investigating and Improving Regret Approximations for Curriculum Discovery

Alex Rutherford* Michael Beukman*
Timon Willi Bruno Lacerda Nick Hawes Jakob Foerster

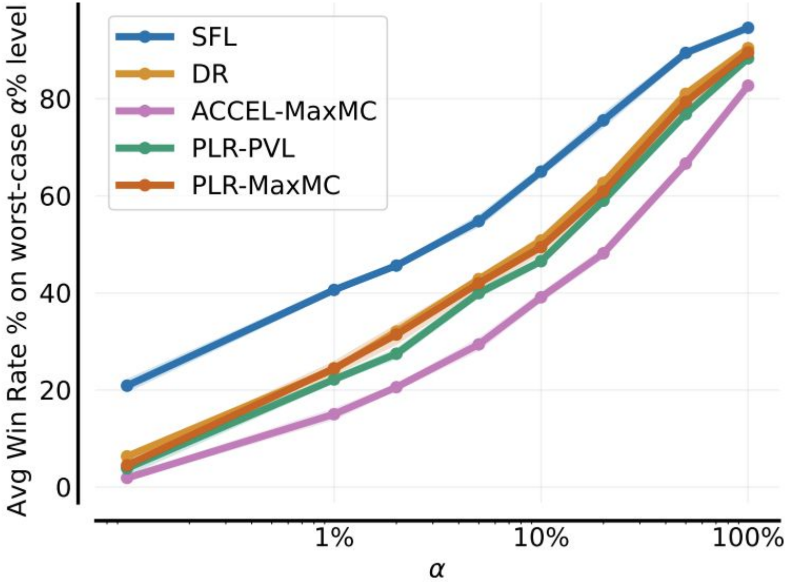
University of Oxford

NeurIPS 2024



(a) Minigrid (b) JaxNav (c) Real World (Source: [18])

Figure 1: JaxNAV (b) brings UED, often tested on Minigrid (a), closer to the real world (c)



P * (1- P) (SFL) *rocks*

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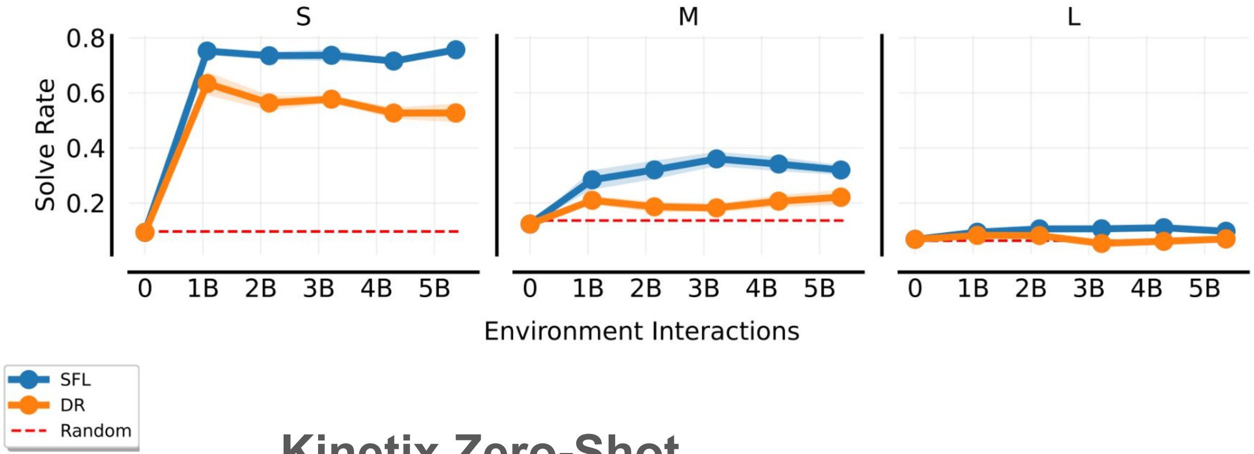
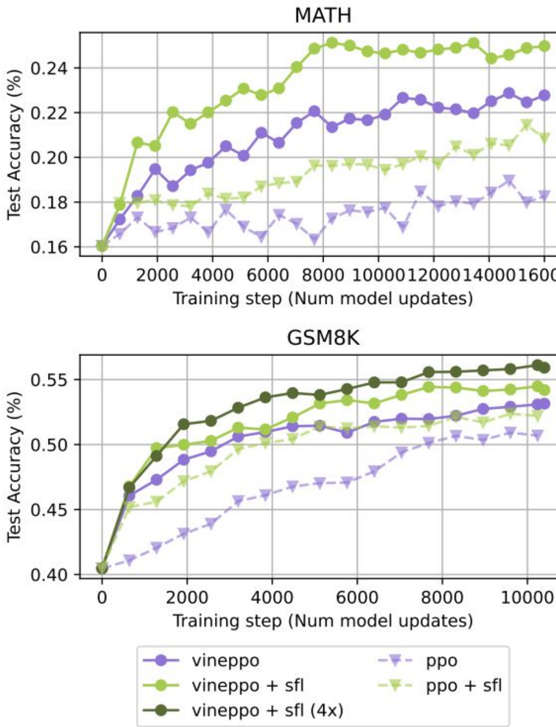
Interlude: Curriculum learning

Learning to Reason at the Frontier of Learnab

Thomas Foster [*1] Jakob Foerster [1 2]

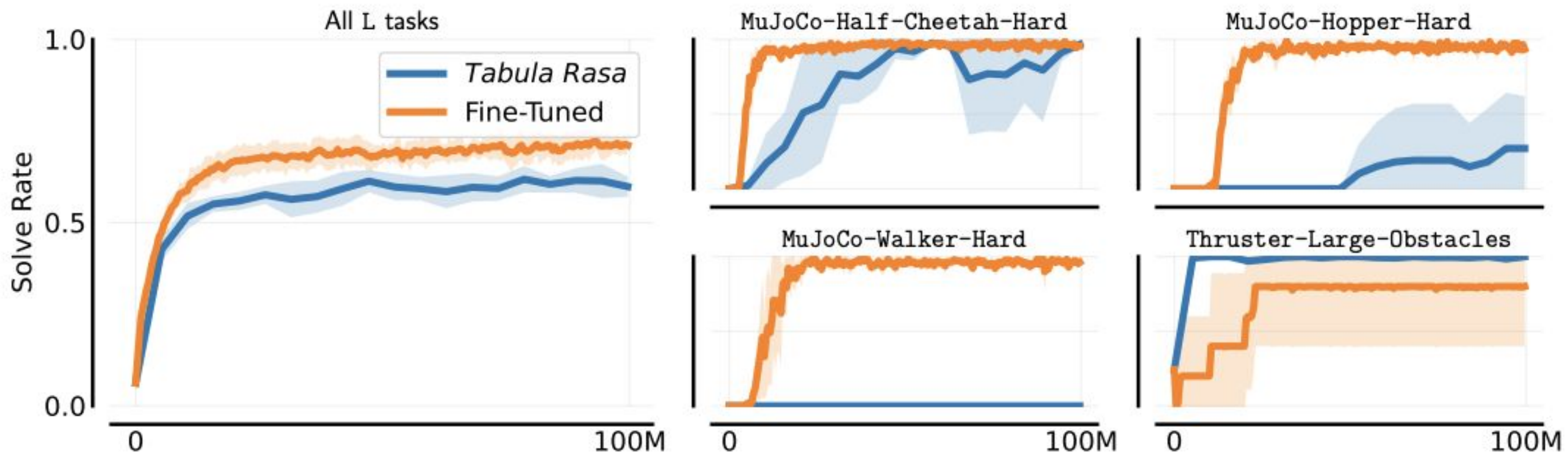


Kinetix Zero-Shot



P * (1- P) (SFL) *rocks*

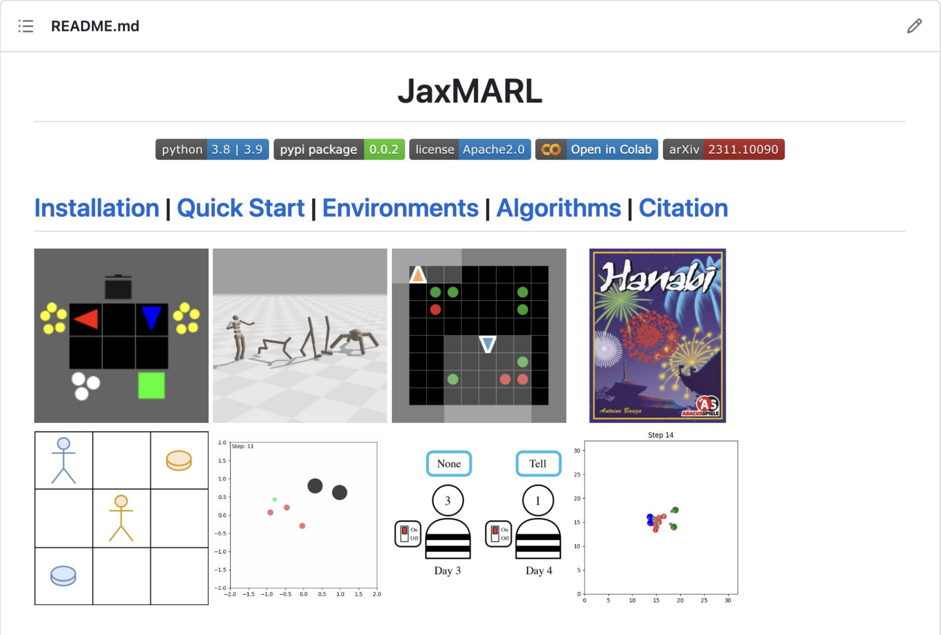
Fine-Tuning Results (..cause that's what you can do with a foundation model..)



JaxMARL: Multi-Agent RL Environments in JAX

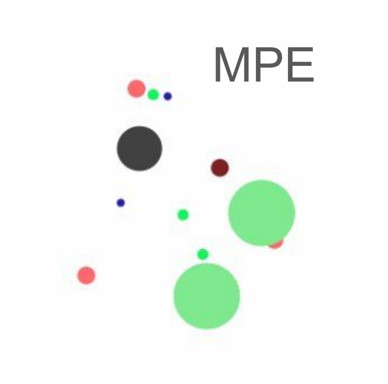
Alexander Rutherford[1*†], Benjamin Ellis[1*†], Matteo Gallici[2*†], Jonathan Cook[1*], Andrei Lupu[1*], Garðar Ingvarsson[3*], Timon Willi[1*], Akbir Khan[3], Christian Schroeder de Witt[1], Alexandra Souly[3], Saptarashmi Bandyopadhyay[4], Mikayel Samvelyan[3], Minqi Jiang[3], Robert Tjarko Lange[5], Shimon Whiteson[1], Bruno Lacerda[1], Nick Hawes[1], Tim Rocktäschel[3], Chris Lu[1*†], Jakob Nicolaus Foerster[1]

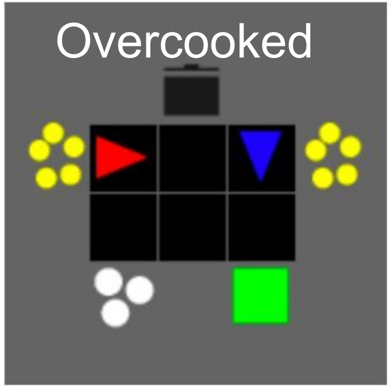
[1]University of Oxford [2]Universitat Politècnica de Catalunya [3]UCL [4]University of Maryland [5]Technical University Berlin

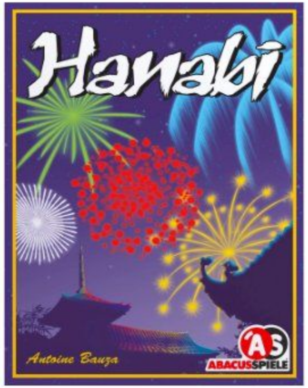


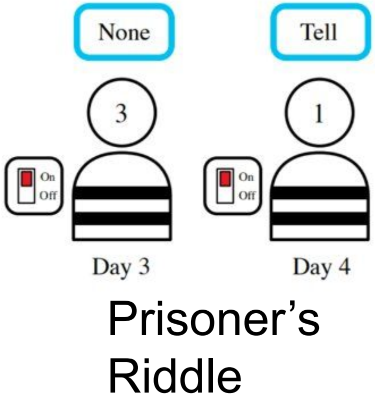
(Slides from Chris Lu)

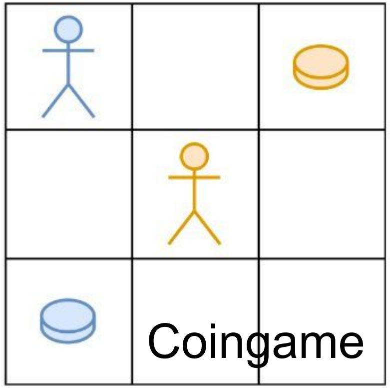
JaxMARL - So far Eight Environment Suites

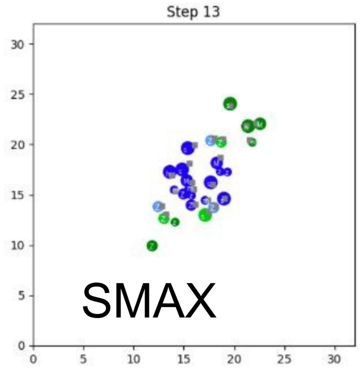










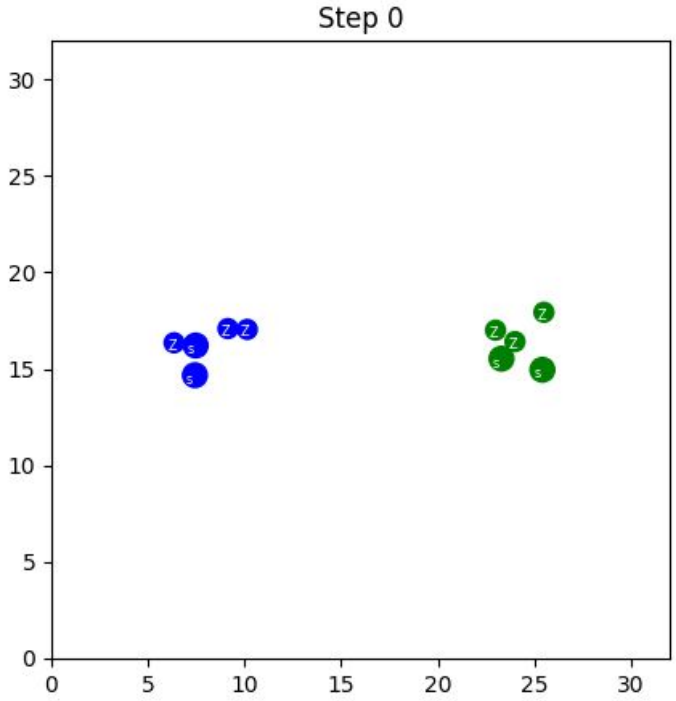


Environment Speedups

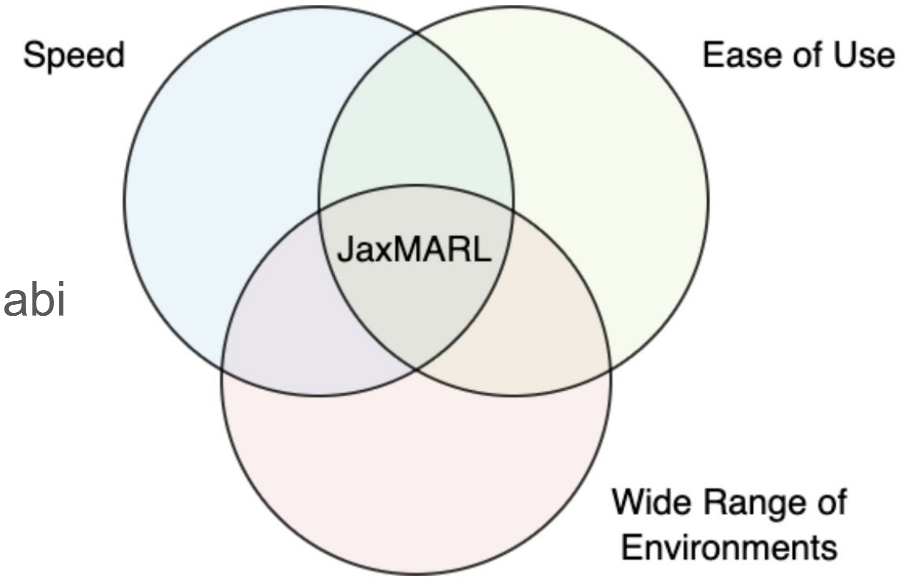
Table 2: Benchmark results for JAX-based MARL environments (steps-per-second) when taking random actions. All environments are significantly faster than existing CPU implementations.

Environment	Original, 1 Env	Jax, 1 Env	Jax, 100 Envs	Jax, 10k Envs	Maximum Speedup
MPE Simple Spread	8.34×10^4	5.48×10^3	5.24×10^5	3.99×10^7	4.78×10^2
MPE Simple Reference	1.46×10^5	5.24×10^3	4.85×10^5	3.35×10^7	2.29×10^2
Switch Riddle	2.69×10^4	6.24×10^3	7.92×10^5	6.68×10^7	2.48×10^3
Hanabi	2.10×10^3	1.36×10^3	1.05×10^5	5.02×10^6	2.39×10^3
Overcooked	1.91×10^3	3.59×10^3	3.04×10^5	1.69×10^7	8.85×10^3
MABrax Ant 4x2	1.77×10^3	2.70×10^2	1.81×10^4	7.62×10^5	4.31×10^2
Starcraft 2s3z	8.31×10^1	5.37×10^2	4.53×10^4	2.71×10^6	3.26×10^4
Starcraft 27m vs 30m	2.73×10^1	1.45×10^2	1.12×10^4	1.90×10^5	6.96×10^3
STORM	–	2.48×10^3	1.75×10^5	1.46×10^7	–
Coin Game	1.97×10^4	4.67×10^3	4.06×10^5	4.03×10^7	2.05×10^3

SMAX



…e.g.
20k SPS on Hanabi



…Python based

…And growing

See our repo and blog post for more information

JaxMARL: Multi-Agent RL Environments and Algorithms in JAX

AUTHORS
Alex Rutherford, Ben Ellis, Chris Lu

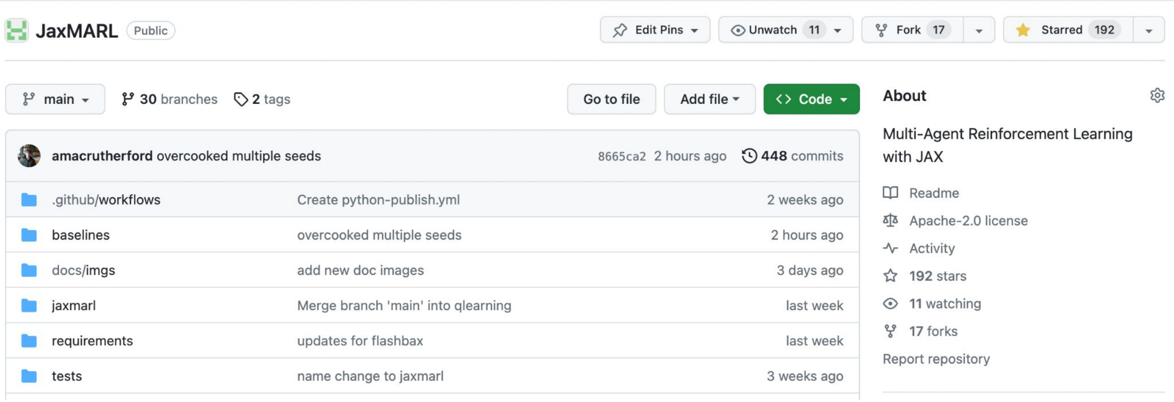
AFFILIATIONS
University of Oxford

PUBLISHED
Nov. 17, 2023

FULL PAPER
arXiv

Overview

We present JaxMARL, a library of multi-agent reinforcement learning (MARL) environments and algorithms based on end-to-end GPU acceleration that achieves up to 12500x speedups. The environments in JaxMARL span cooperative, competitive, and mixed games; discrete and continuous state and action spaces; and zero-shot and CTDE settings. We specifically include implementations of the Hanabi Learning Environment, Overcooked, Multi-Agent Brax, MPE, Switch Riddle, Coin Game, and Spatial-Temporal Representations of Matrix Games (STORM). **Because of JAX's hardware acceleration, our per-run training pipeline is 12500x faster than existing approaches**. We also introduce **SMAX**, a vectorised version of the popular StarCraft Multi-Agent Challenge, which removes the need to run the StarCraft II game engine. By significantly speeding up training, JaxMARL enables new research into areas such as multi-agent meta-learning, as well as significantly easing and improving evaluation in MARL. Try it out here: https://github.com/flairox/jaxmarl!



JAX-LOB: A GPU-Accelerated Limit Order Book Simulator to Unlock Large Scale Reinforcement Learning for Trading

International Conference on AI in Finance: ICAIF'23
Best Academic Paper

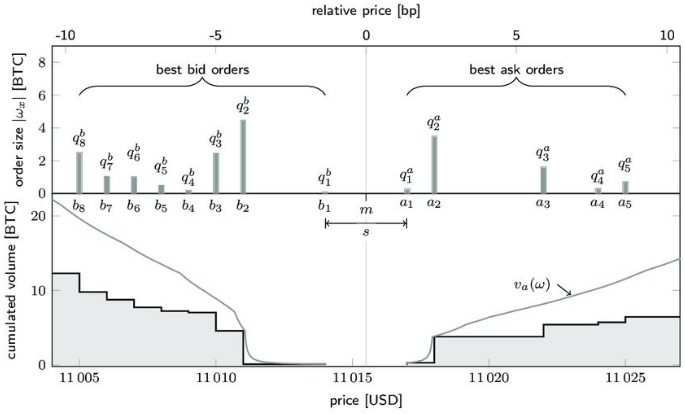
Sascha Frey, Kang Li, Peer Nagy, Silvia Sapora, Chris Lu,
Stefan Zohren, Jakob Foerster, Anisoara Calinescu

FLAIR Foerster Lab for AI Research
UNIVERSITY OF OXFORD
OXFORD-MAN INSTITUTE

(Slides from Sasha Frey)

The Financial Markets are a complex multi-agent System

Limit Order Book



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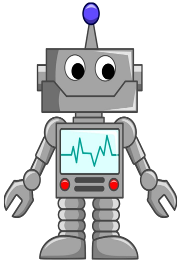
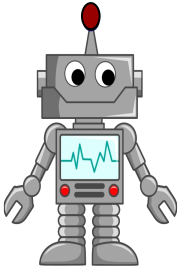
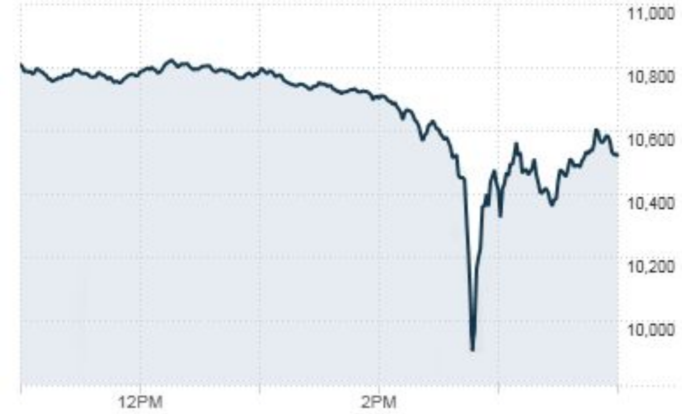


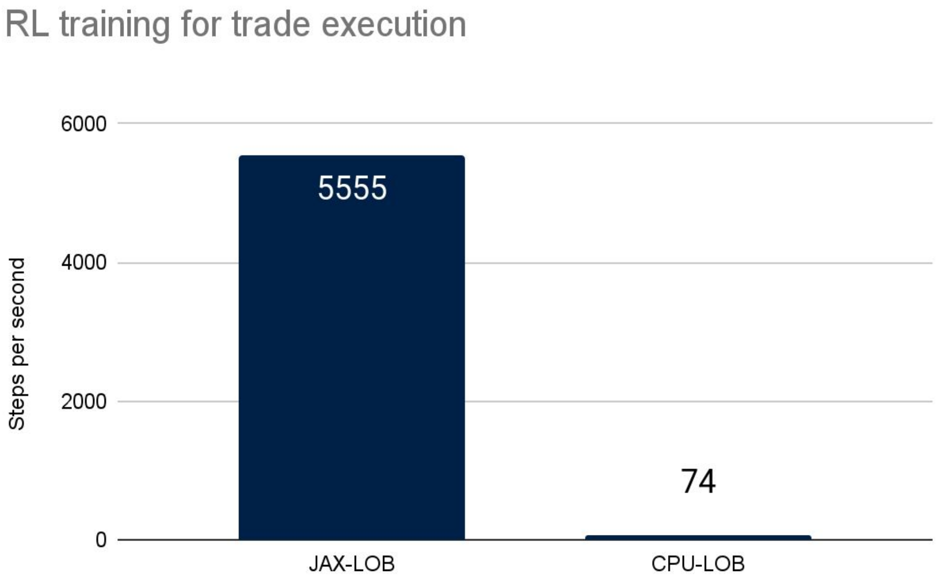


Interesting Emergent Dynamics



JAX-LOB Benefits: **75x Speed-Up** Over CPU Equivalent

Automatic parallelisation: major benefit for **RL** since the entire training loop is GPU native. Similar speed-up expected for **Monte Carlo** methods



Interlude 1:

Generative AI for End-to-End Limit Order Book Modelling

A Token-Level Autoregressive Generative Model of Message Flow Using a Deep State Space Network

Peer Nagy
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Oxford-Man Institute of Quantitative Finance, University of Oxford
UK

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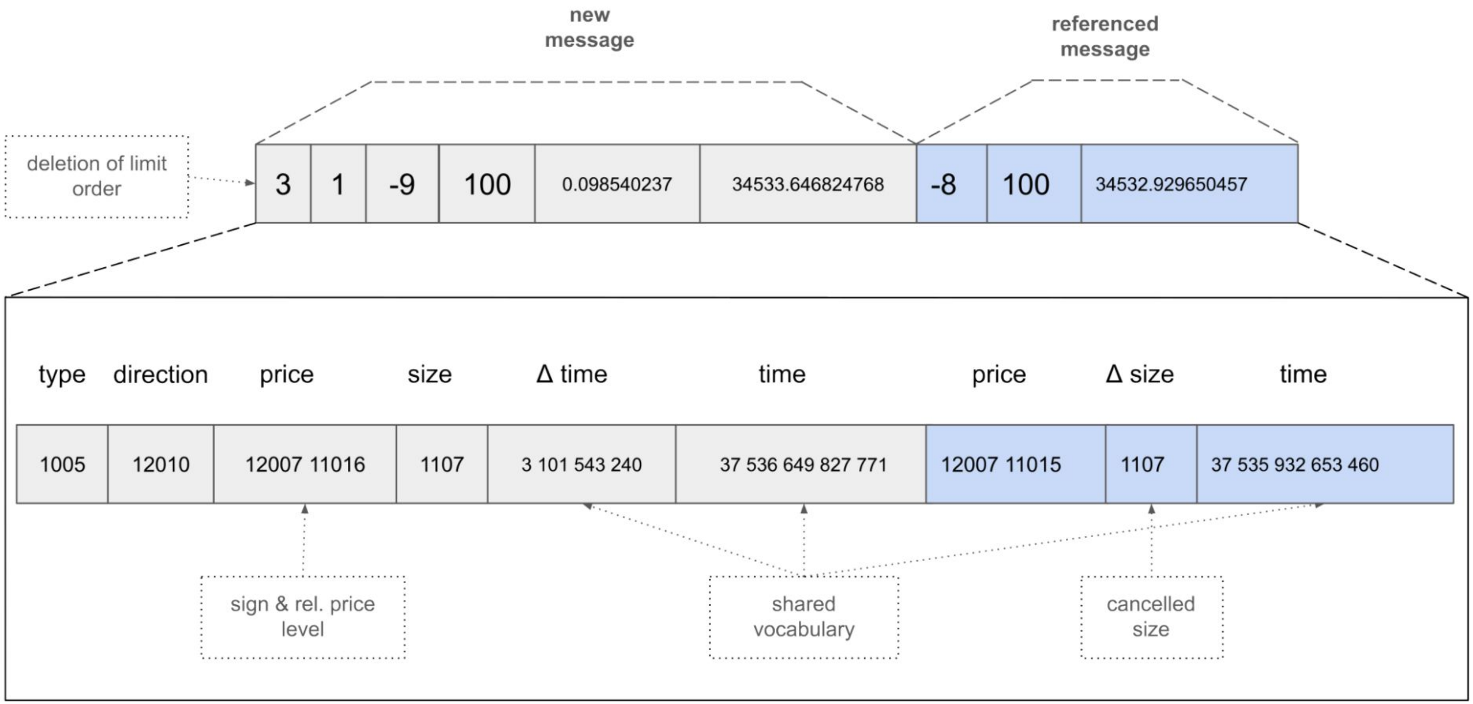
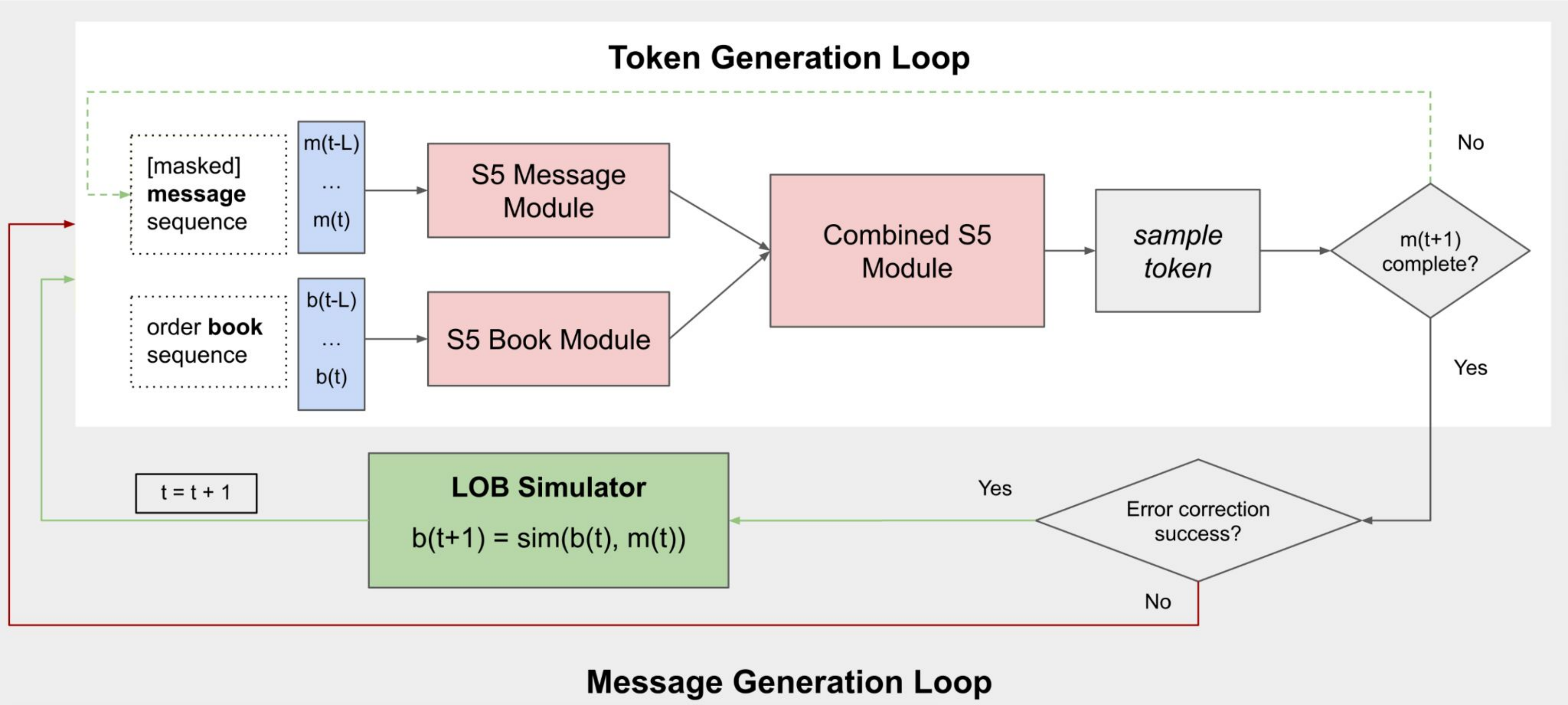
Oxford-Man Institute of Quantitative Finance, University of Oxford & Man Group
UK

Jakob Foerster
Foerster Lab for AI Research, University of Oxford
UK

A Token Level Order-Book model based on the S5 state-space model.




Token Generation Loop
[masked] **message** sequence
m(t-L)
...
m(t)
S5 Message Module
order **book** sequence
b(t-L)
...
b(t)
S5 Book Module
Combined S5 Module
sample token
m(t+1) complete?
No
Yes
t = t + 1
LOB Simulator
b(t+1) = sim(b(t), m(t))
Yes
Error correction success?
No
Message Generation Loop

Craftax: A Lightning-Fast Benchmark for Open-Ended Reinforcement Learning

Michael Matthews [1] Michael Beukman [1] Benjamin Ellis [1] Mikayel Samvelyan [2] Matthew Jackson [1]
Samuel Coward [1] Jakob Foerster [1]

ICML 2024 - Spotlight Poster

Michael Matthews[1]

Michael Beukman[1]

Benjamin Ellis[1,2]

Mikayel Samvelyan[3]

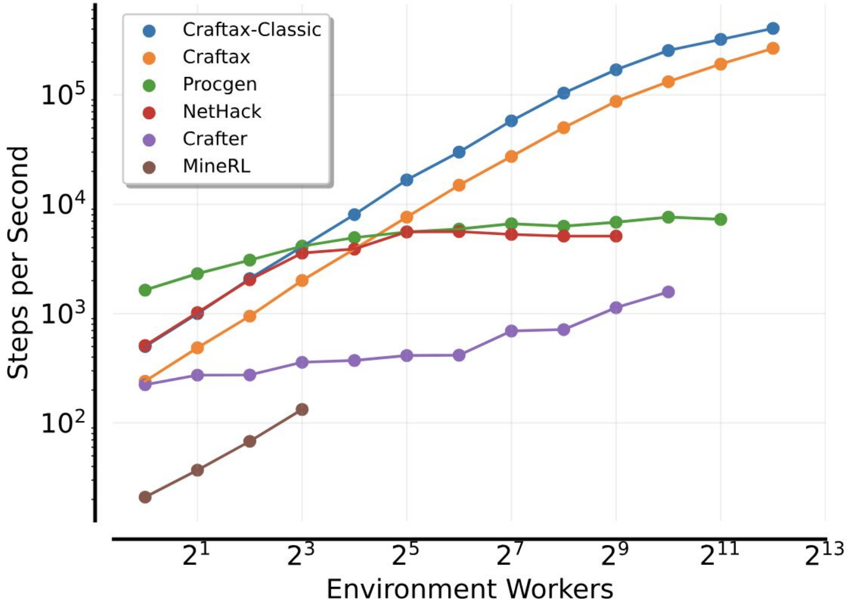
Matthew Jackson[1,2]

Samuel Coward[1]

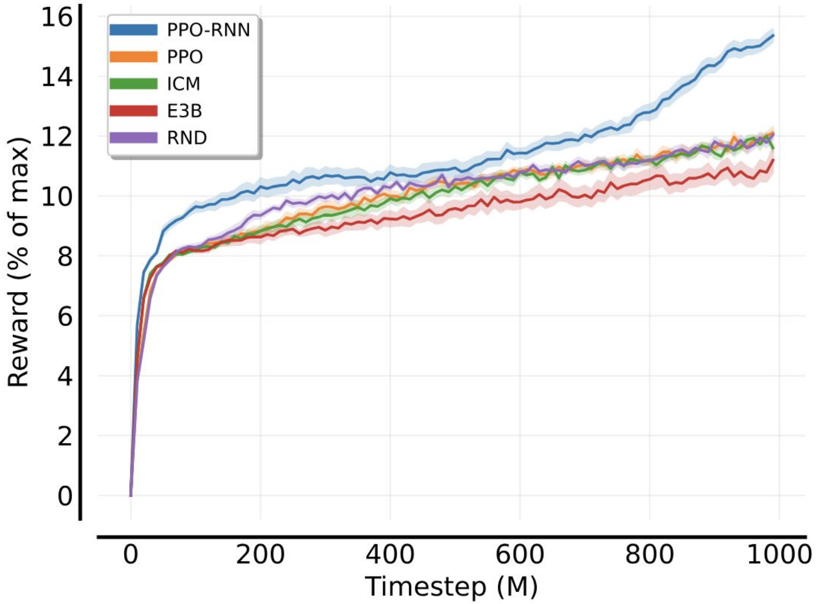
Jakob Foerster[1]

[1] FLAIR, University of Oxford [2] WhiRL, University of Oxford [3] DARK, University College London

Blazing Fast



Challenging…



#2:

GPU Acceleration + (some) Theory =

Simplified Reinforcement Learning

FLAIR

Simplifying Deep Temporal Difference Learning

Matteo Gallici[*1] **Mattie Fellows**[*2]
Benjamin Ellis[2] **Bartomeu Pou**[1,3] **Ivan Masmitja**[4]
Jakob Nicolaus Foerster[2] **Mario Martin**[1]
[1]Universitat Politècnica de Catalunya [2]University of Oxford
[3]Barcelona Supercomputing Center [4] Institut de Ciències del Mar
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bartomeu.poumulet@bsc.es masmitja@icm.csic.es

ICLR 2025 spotlight

Part 1: Analysing and Stabilizing TD….

Why is TD so unstable? It's not a gradient of anything

How can we analyse TD? Using the Jacobian

How can we stabilise TD? By introducing and LayerNorm
+ L2 regularisation

Slide by: Mattie Fellows

Theoretical insights - read the paper for details

1) Batchnorm layers make the policy myopic:

Theorem 1. *Under Assumption 1, using the* BatchNorm *Q-function defined in Eq.* (3) $\lim_{N\to\infty} \mathbb{E}_{x_t \sim d^\mu}\left[\mathcal{B}\left[Q_\phi\right](x_t)\right] = \mathbb{E}_{r \sim P_R(x_t), x_t \sim d^\mu}\left[r\right]$ *almost surely.*

2) LayerNorm + L2 regularisation instead mitigates Off-Policy Instability:

Theorem: *Under mild regularity assumptions, using the k width LayerNorm Q -function:*

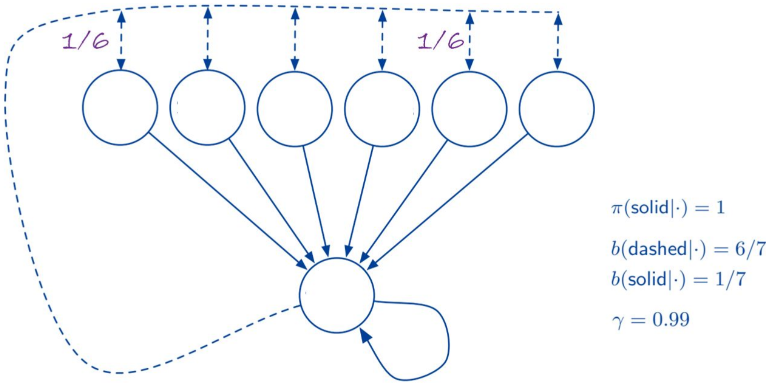
$$\frac{\left|\left(r(s,a) + \gamma Q_\omega(s',a') - Q_\omega(s,a)\right) x^\top \nabla^2_\omega Q_\omega(s,a) x\right|}{\|x\|^2} = \mathcal{O}\left(\frac{1}{\sqrt{k}}\right)$$

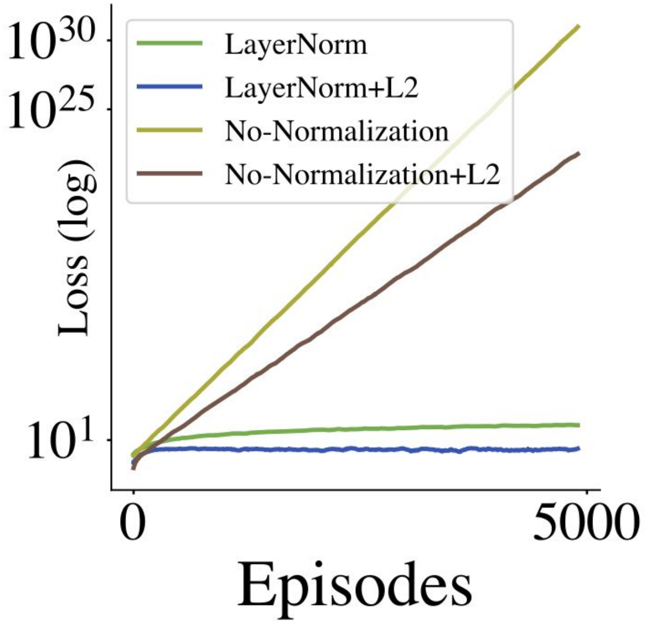
almost surely for a test vector x and any s, a, s', a'

Shrinks with increasing k

Tabular Validation

Baird's counterexample:
Simple MDP with linear function approximator and off-policy sampling





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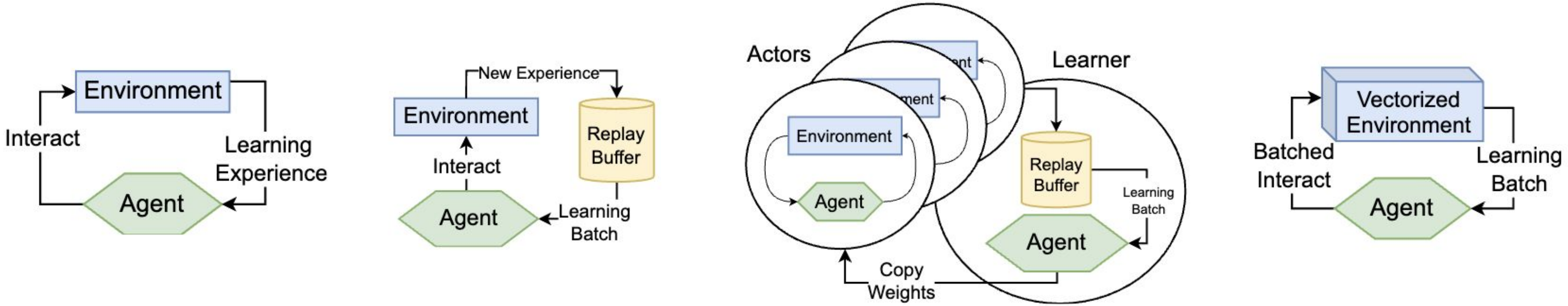
Part 2: Simplifying Temporal Difference Learning



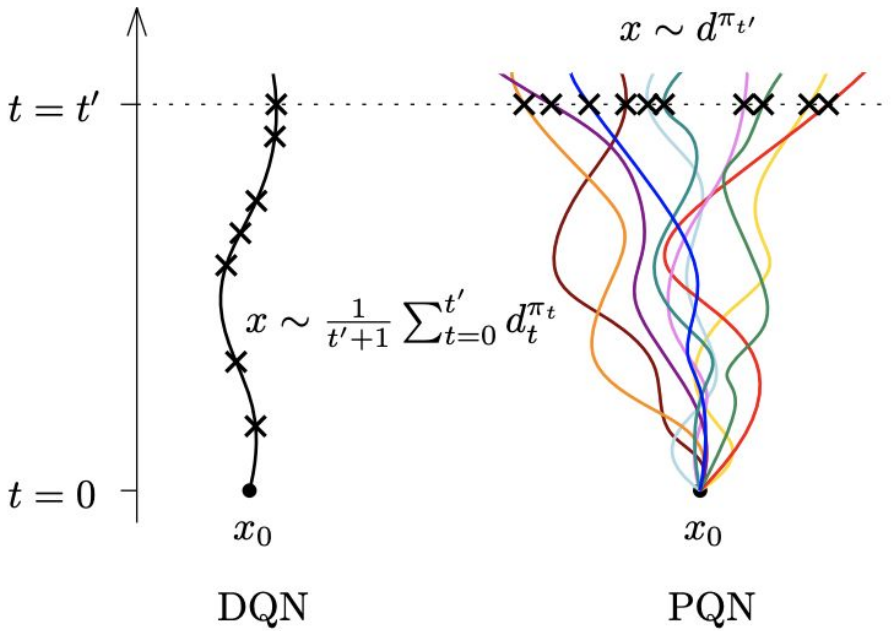
(a) Online Q-Learning (b) DQN (c) Distributed DQN (d) PQN

No Target network, no replay – just TD Learning

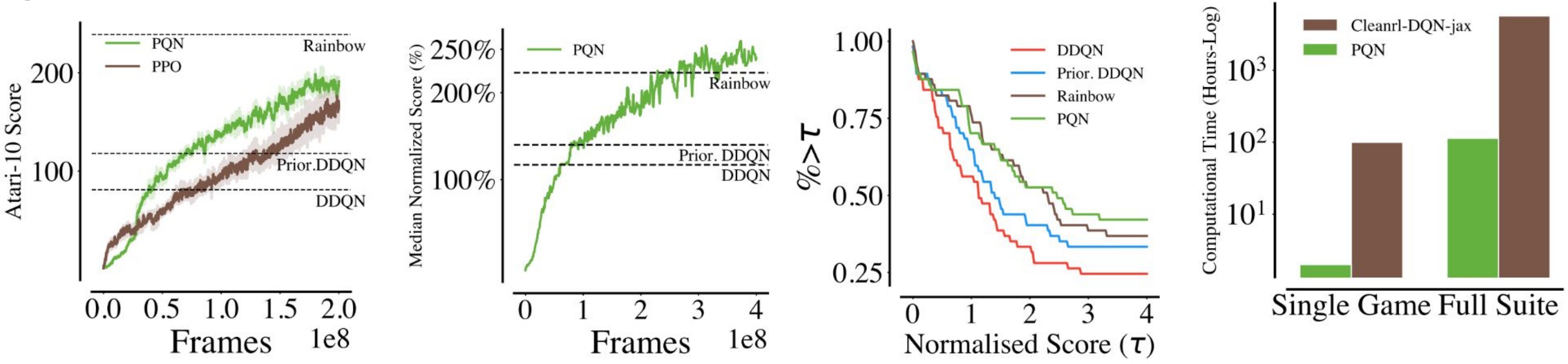
Algorithm 1 PQN (s, a, s', r, target are B-dim vectors)

$\phi \leftarrow$ initialise regularised Q-network parameters
$s \leftarrow$ intial state $s_0 \sim P_0$,
for *each episode* **do**
  for *each* $i \in B$ *(in parallel)* **do**
    $a_i \leftarrow \begin{cases} a_i \sim \text{Unif}(\mathcal{A}), & \text{with prob. } \epsilon, \\ \arg\max_{a'} Q_\phi(s_i, a'), & \text{otherwise,} \end{cases}$
    $s'_i, r_i \leftarrow s'_i \sim P_S(s_i, a_i), r_i \sim P_R(s_i, a_i)$,
    $\text{target}_i \leftarrow r_i + \gamma \mathbb{1}(\textbf{not } \textit{terminal}) \max_{a'} Q_\phi(s'_i, a')$
  end for
  $\phi \leftarrow \phi - \alpha \nabla_\phi \|\text{StopGrad}[\text{target}] - Q_\phi(s, a)\|^2$
end for

The sampling regime of PQN



Results



(a) Atari-10 Score (b) Atari-57 Median (c) Atari-57 Score Profile (d) Speed Comparison

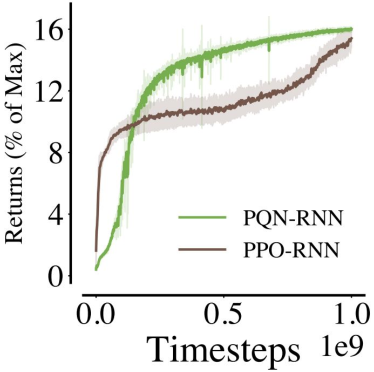
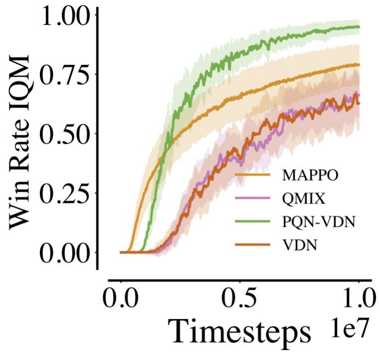
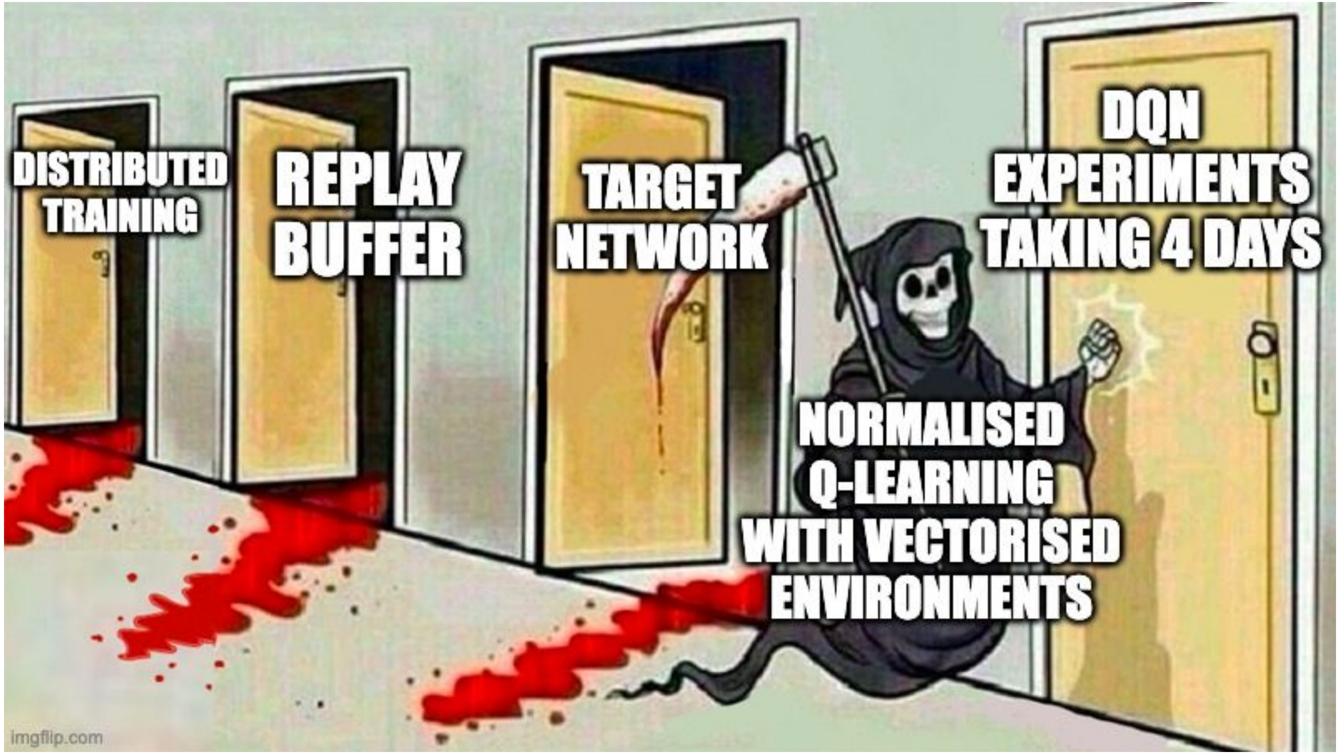


Figure 4: Craftax Score



(a) Smax

A competitive and simple algorithm!
Q-learning *is back!*


DISTRIBUTED TRAINING
REPLAY BUFFER
TARGET NETWORK
DQN EXPERIMENTS TAKING 4 DAYS
NORMALISED Q-LEARNING WITH VECTORISED ENVIRONMENTS
imgflip.com

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#3: GPU Acceleration + (some) Theory = Scalable Meta - RL

Mirror Learning Framework (ICML 2022)

Mirror Learning: A Unifying Framework of Policy Optimisation

Jakub Grudzien Kuba [1] Christian Schroeder de Witt [1] Jakob Foerster [1]

Slides from Chris Lu

Mirror Learning: The Update Formula (Simplified)

At every iteration, maximize

$$\mathbb{E}_{\mathrm{a}\sim\pi_{\mathrm{new}}}\left[Q_{\pi_{\mathrm{old}}}(s,\mathrm{a})\right] - \mathfrak{D}_{\pi_{\mathrm{old}}}(\pi_{\mathrm{new}}|s)$$

Drift Function

Mirror Learning: Properties

Theorem 1 (The Fundamental Theorem of Mirror Learning). *Let $\mathfrak{D}^{\nu}$ be a drift, $\mathcal{N}$ be a neighbourhood operator, and the sampling distribution β_π depend continuously on π. Let $\pi_0 \in \Pi$, and the sequence of policies $(\pi_n)_{n=0}^{\infty}$ be obtained by mirror learning induced by $\mathfrak{D}^{\nu}$, $\mathcal{N}$, and β_π. Then, the learned policies*

1. *Attain the strict monotonic improvement property,*

$$\eta(\pi_{n+1}) \geqslant \eta(\pi_n) + \mathbb{E}_{\mathrm{s}\sim d}\left[\frac{\nu_{\pi_n}^{\pi_{n+1}}(\mathrm{s})}{\beta_{\pi_n}(\mathrm{s})}\mathfrak{D}_{\pi_n}(\pi_{n+1}|\mathrm{s})\right],$$

2. *Their value functions converge to the optimal one,*

$$\lim_{n\to\infty} V_{\pi_n} = V^*,$$

3. *Their expected returns converge to the optimal return,*

$$\lim_{n\to\infty} \eta(\pi_n) = \eta^*,$$

4. *Their ω-limit set consists of the optimal policies.*

Space of RL Algorithms

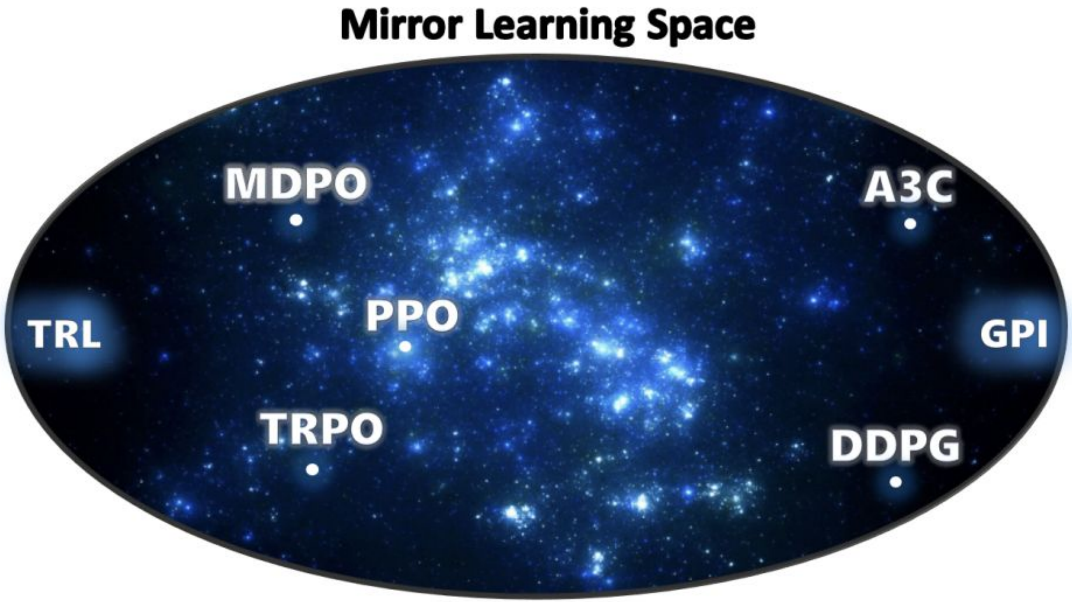

Figure 1. Known RL frameworks and algorithms as points in the infinite space of *theoretically sound* mirror learning algorithms.

Space of RL Algorithms

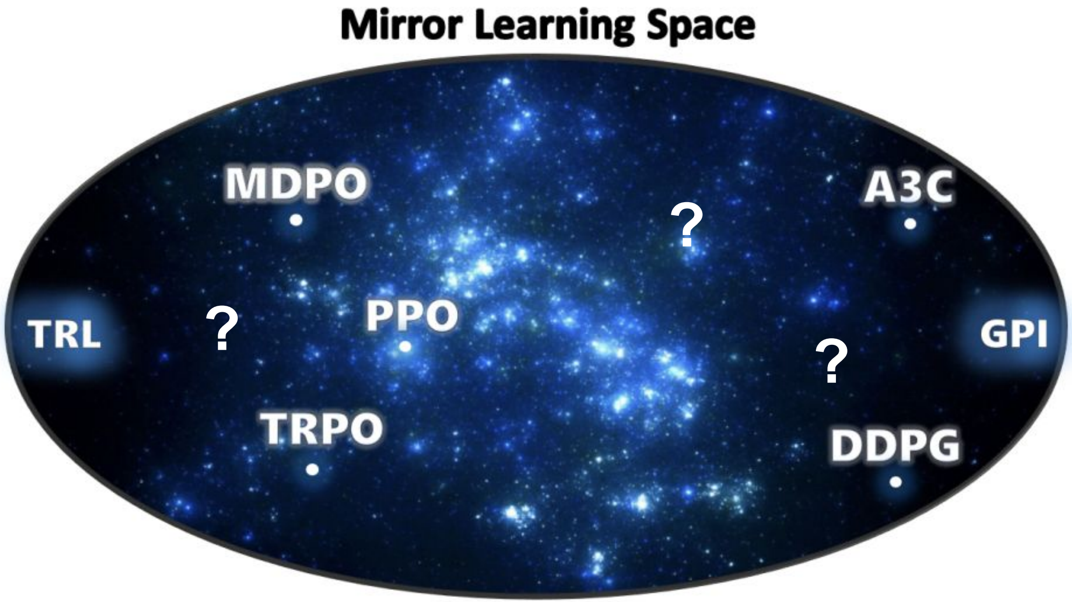

Figure 1. Known RL frameworks and algorithms as points in the infinite space of *theoretically sound* mirror learning algorithms.

Discovered Policy Optimisation

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NeurIPS 2022

A Meta Learning Approach

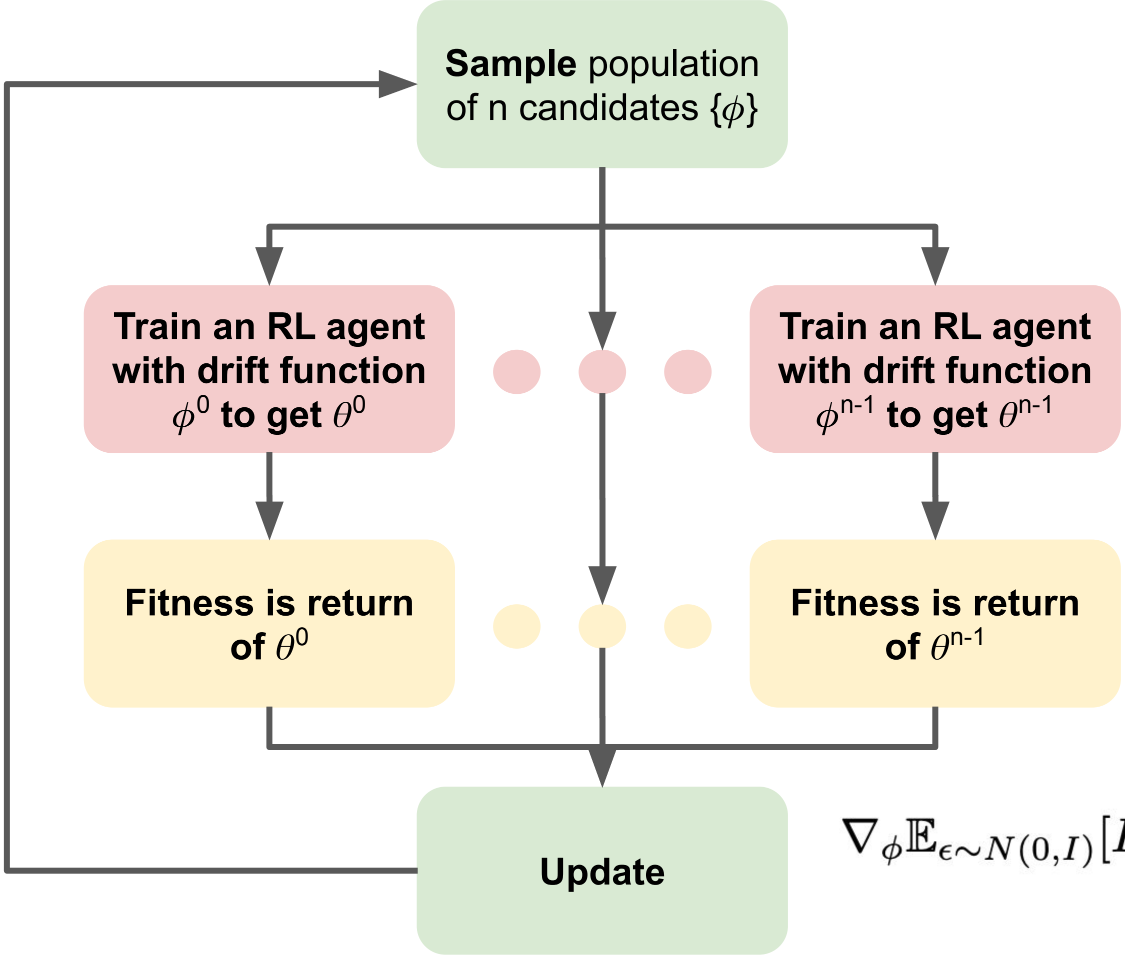
At every iteration, maximize

$$\mathbb{E}_{\mathrm{a}\sim\pi_{\mathrm{new}}}\left[Q_{\pi_{\mathrm{old}}}(s,\mathrm{a})\right]-\mathfrak{D}_{\pi_{\mathrm{old}}}(\pi_{\mathrm{new}}|s)$$

Drift Function

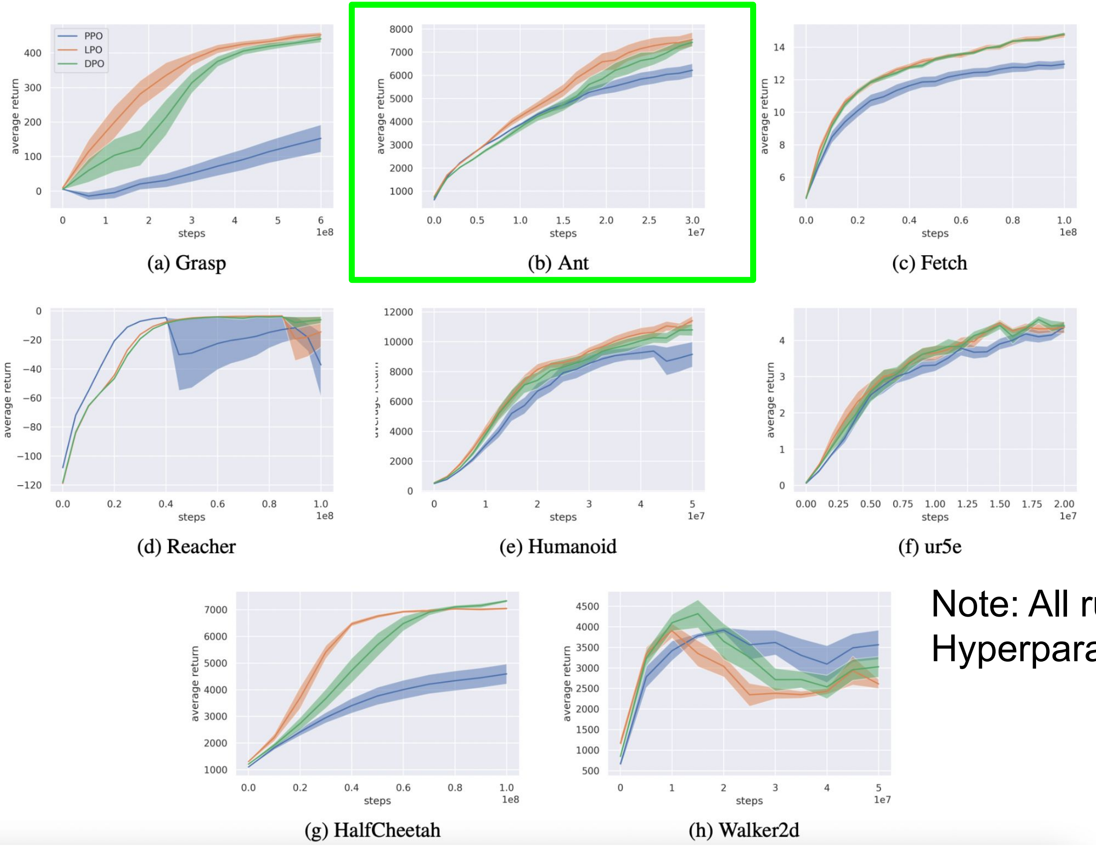
Parameterise as a neural network, ϕ, compliant with theory

How to estimate Meta-Gradients?



$$\nabla_\phi \mathbb{E}_{\epsilon \sim N(0,I)}[F(\phi + \sigma\epsilon)] = \frac{1}{\sigma}\mathbb{E}_{\epsilon \sim N(0,I)}[F(\phi + \sigma\epsilon)\epsilon],$$

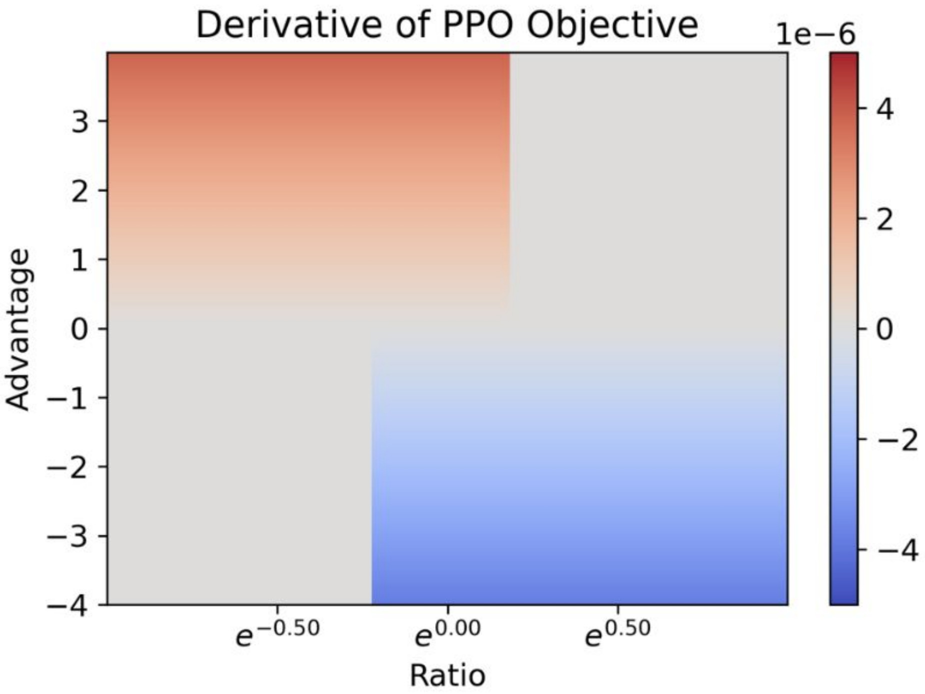
Learned Policy Optimisation (LPO) Performance



Note: All runs use BRAX default Hyperparameters *for PPO*

Visualizing Objective Functions: PPO

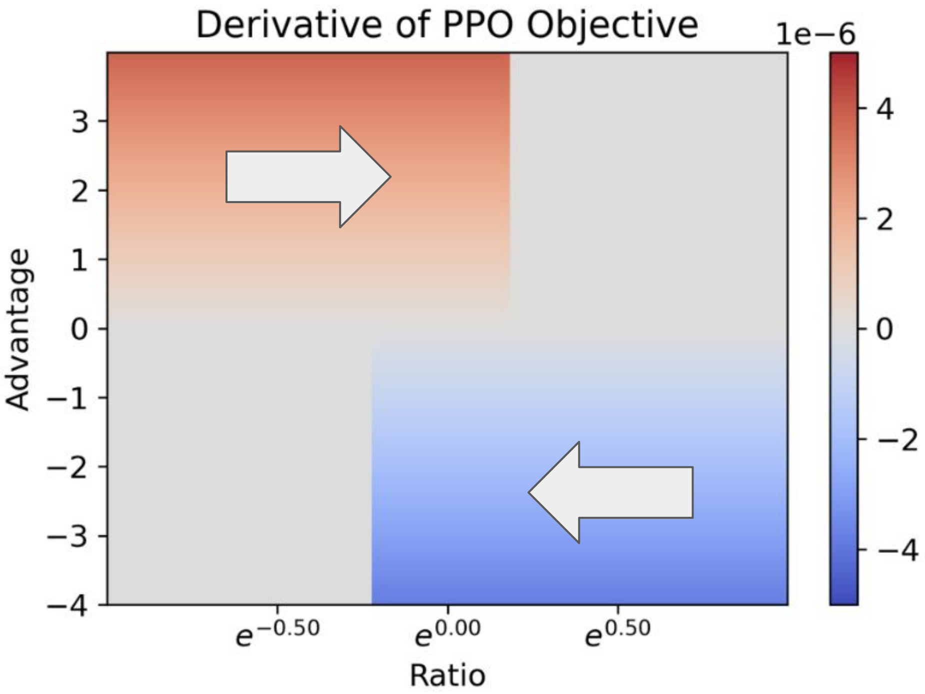
$$A_\pi(s,a)$$



$$\mathrm{r}(\bar{\pi}) \triangleq \bar{\pi}(a|s)/\pi(a|s)$$

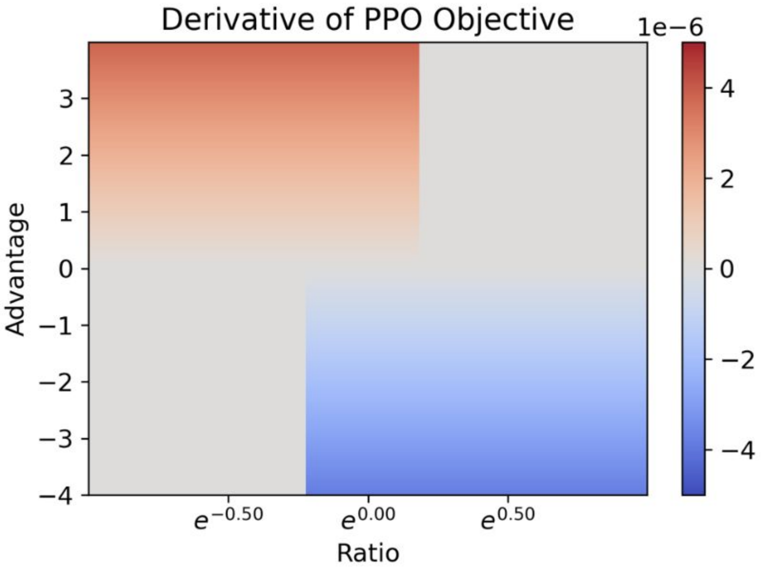
Visualizing Objective Functions: PPO

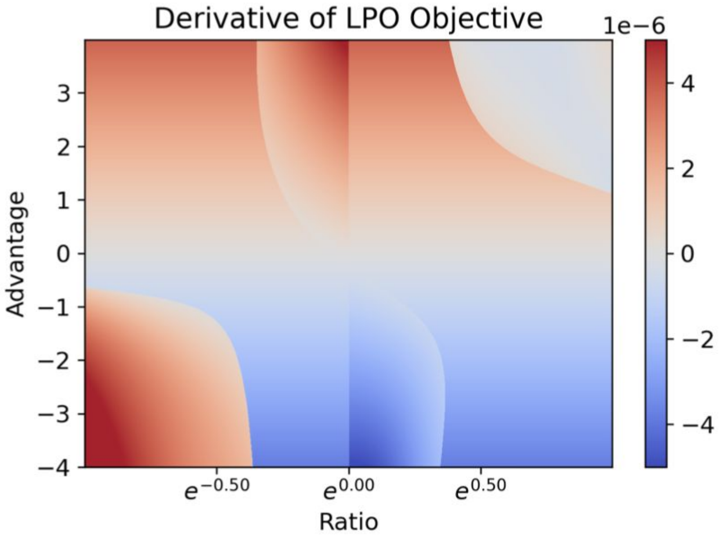
$$A_\pi(s,a)$$



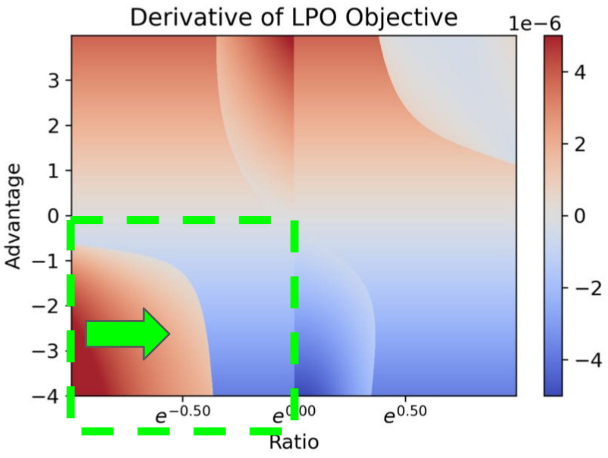
$$\mathrm{r}(\bar{\pi}) \triangleq \bar{\pi}(a|s)/\pi(a|s)$$

Visualizing Objective Functions: LPO



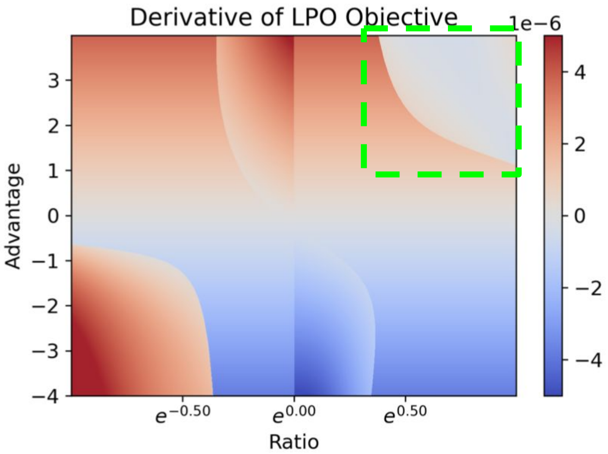


Interpreting LPO



1. "Rollback" for Negative Advantage
2. Cautious Optimism for Positive Advantage
3. Implicit Entropy Maximisation
4. Secondary Features

Interpreting LPO



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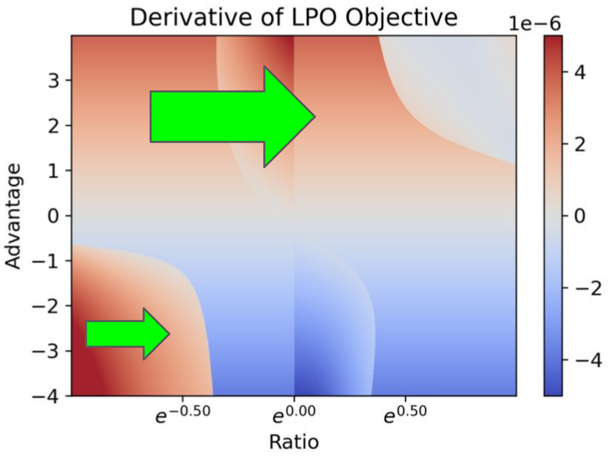
Interpreting LPO



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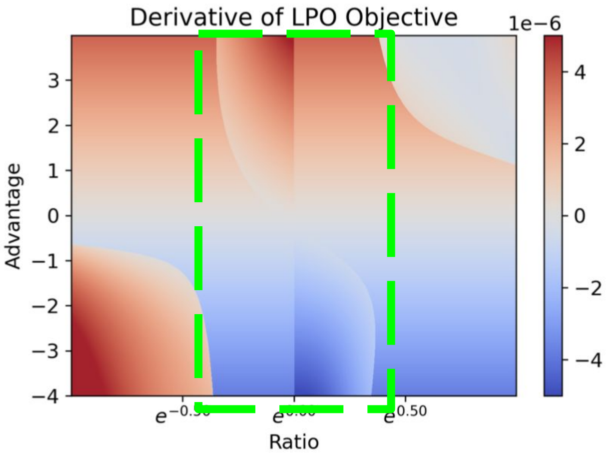
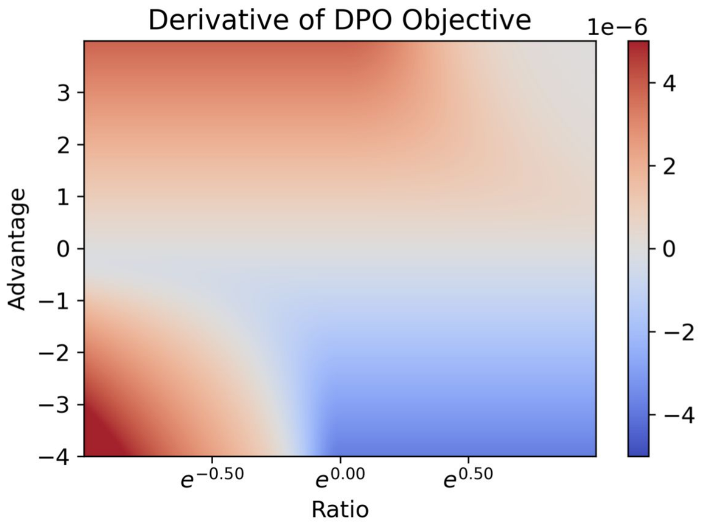
Interpreting LPO



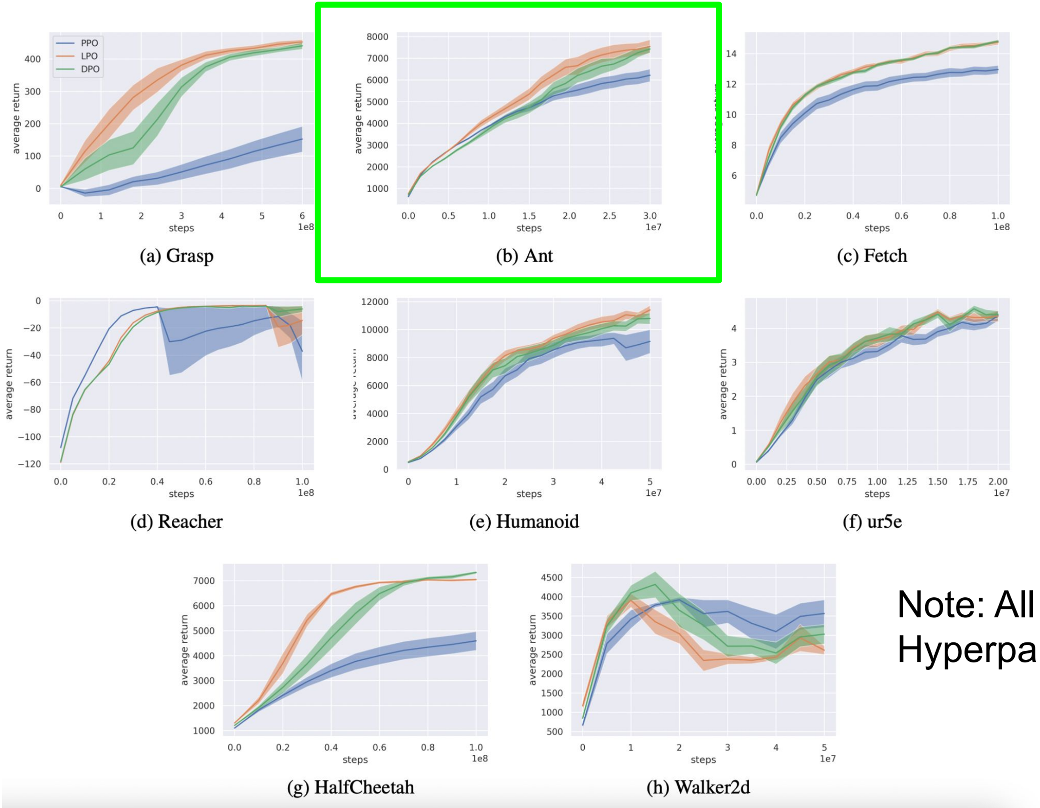
1. Rollback for Negative Advantage
2. Cautious Optimism for Positive Advantage
3. Implicit Entropy Maximisation
4. Secondary Features

Discovered Policy Optimisation (DPO)

$$f(r, A) = \begin{cases} \mathrm{ReLU}\big((r-1)A - \alpha \tanh((r-1)A/\alpha)\big) & A \geq 0 \\ \mathrm{ReLU}\big(\log(r)A - \beta \tanh(\log(r)A/\beta)\big) & A < 0 \end{cases}$$

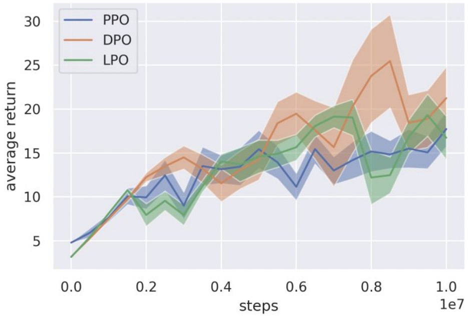


Discovered Policy Optimisation Performance

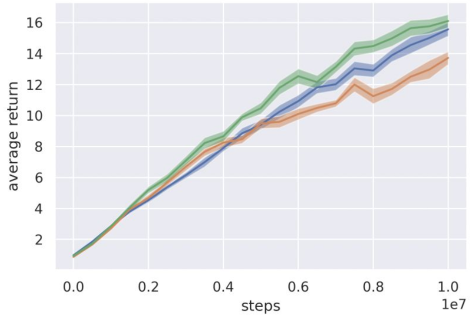


Note: All runs use BRAX default Hyperparameters *for PPO*

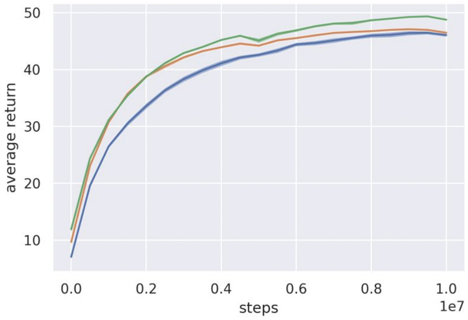
Discovered Policy Optimisation: Far OOD Performance



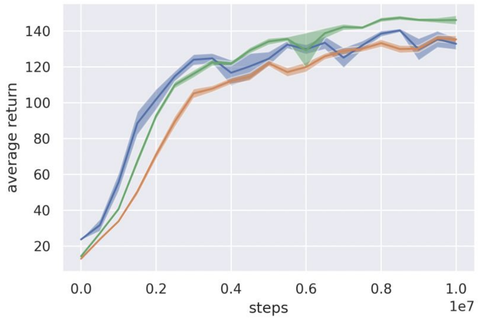
(a) Breakout-Minatar



(b) Asterix-Minatar



(c) Freeway-Minatar



(d) SpaceInvaders-Minatar

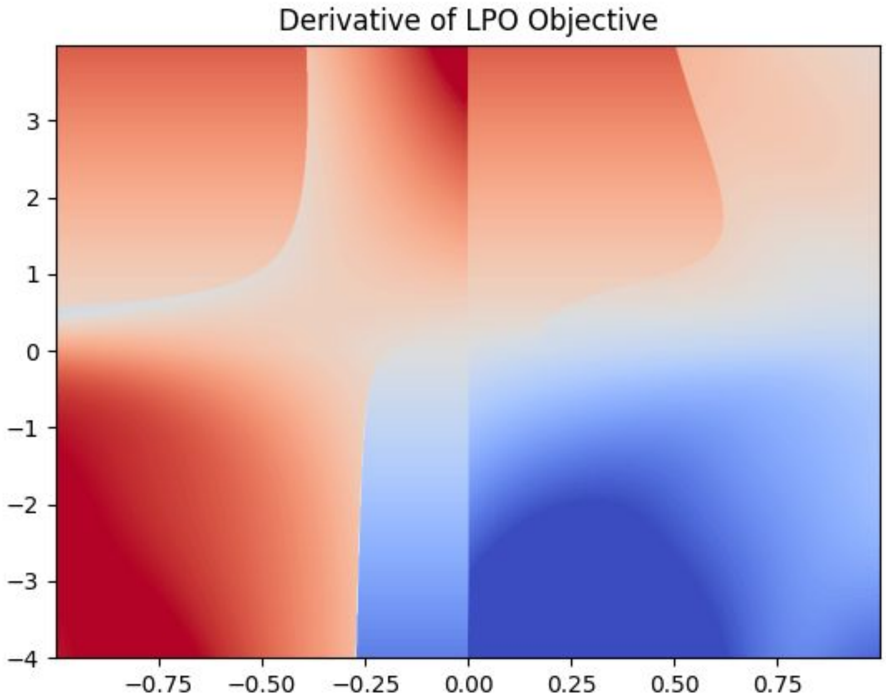
Discovery: DPO

1. Picked ϕ that corresponds to a core part of hand-crafted RL objective functions. Parameterised based on theory

2. Meta-Optimized ϕ using evolution and PureJaxRL

3. Analyzed ϕ to gain insight into policy optimization and create Discovered Policy Optimisation

Temporally-Adaptive LPO (ICLR 2024)



Matthew Jackson*, Chris Lu*, Louis Kirsch, Robert Lange, Shimon Whiteson, Jakob Foerster, *ICLR 2024*
*equal contribution

We get much better performance!

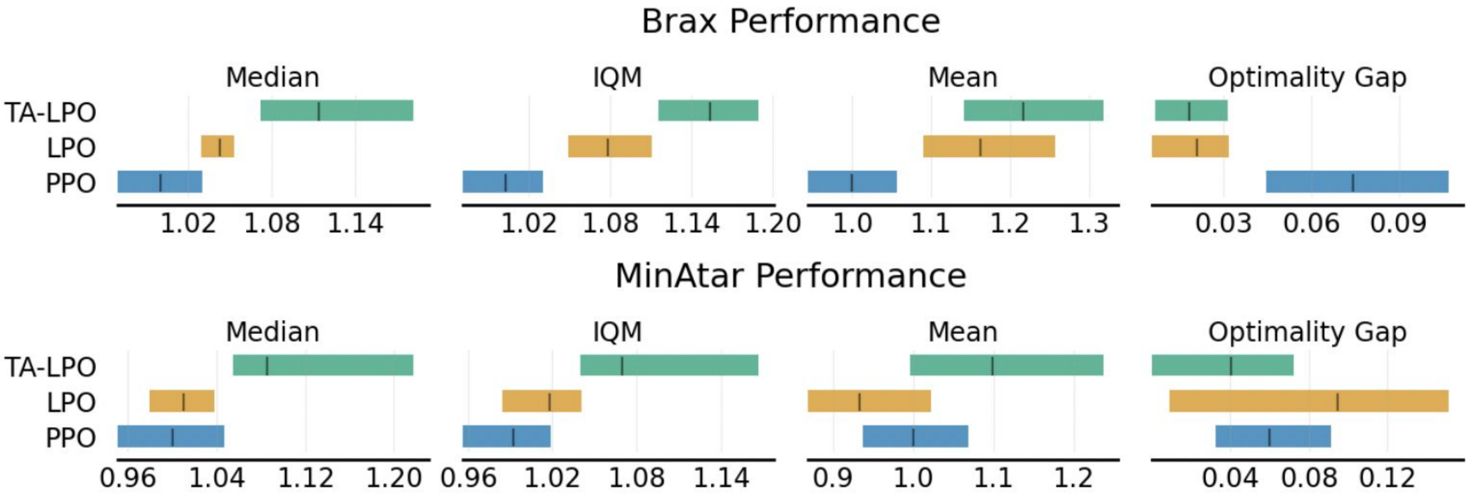


Figure 2: **TA-LPO leverages lifetime information and generalizes to a wide range of environments.** Results of TA-LPO, LPO and PPO on the Brax and MinAtar suites across three seeds. TA-LPO was only meta-trained on SpaceInvaders-MinAtar. We provide complete training curves in Appendix B.

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Further example work from FLAIR at the *Hyperscale*..

1. **Reward Functions**
    a. Sapora, Silvia, et al. "EvIL: Evolution Strategies for Generalisable Imitation Learning." *ICML 2024*
2. **Expert Datasets**
    a. Lupu, Andrei, et al. "Behaviour Distillation." *ICLR 2024*
3. **High-Dimensional Opponent Shaping**
    a. Khan, Akbir, et al. "Scaling Opponent Shaping to High Dimensional Games." *AAMAS 2023*
4. **Better Environments**
    a. Matthews, Michael et al. "Craftax" *ICML 2024*
    b. Frey, Sasha et al, "JAX-LOB" *ICAIF 2023*
5. **Synthetic Environments**
    a. Lu, Chris et al. "Adversarial Cheap Talk." *ICML 2023*
    b. Liesen, Jarek et al. "Discovering Minimal Reinforcement Learning Environments"
6. **Learned RL Optimizers**
    a. Goldie, Alexander et al. "Can Learned Optimization Make Reinforcement Learning Less Difficult?" ***ICML 2024*** *AutoRL Workshop (Spotlight)*

All of these experiments would have taken *years* to run in the old paradigm…

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Conclusion

- We are in the middle of a revolution for deep RL: *end-to-end GPU acceleration*
- Speed-ups of many orders of magnitude are possible
- We have implemented a number of environments in JAX
- This unlocks theory-inspired, simpler, highly performant algorithms
- It also pushes the frontier for meta-RL
- All code and many tools are open source on our github
- Thanks for listening!

Open questions:

- RL at the hyperscale in the Age of (Agentic) LLMs?
- Breaking out of the (JAX) Box?

Thanks for listening!

More info and code @j_foerst and www.foersterlab.com