WARPDRIVE: EXTREMELY FAST END-TO-END DEEP MULTI-AGENT REINFORCEMENT LEARNING ON A GPU

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ABSTRACT

Deep reinforcement learning (RL) is a powerful framework to train decision-making models in complex environments. However, RL can be slow as it requires repeated interaction with a simulation of the environment. In particular, there are key system engineering bottlenecks when using RL in complex environments that feature multiple agents with high-dimensional state, observation, or action spaces. We present WarpDrive, a flexible, lightweight, and easy-to-use open-source RL framework that implements end-to-end deep multi-agent RL on a single GPU (Graphics Processing Unit), built on PyCUDA and PyTorch. Using the extreme parallelization capability of GPUs, WarpDrive enables orders-of-magnitude faster RL compared to common implementations that blend CPU simulations and GPU models. Our design runs simulations and the agents in each simulation in parallel. It eliminates data copying between CPU and GPU. It also uses a single simulation data store on the GPU that is safely updated in-place. WarpDrive provides a lightweight Python interface and flexible environment wrappers that are easy to use and extend. Together, this allows the user to easily run thousands of concurrent multi-agent simulations and train on extremely large batches of experience. Through extensive experiments, we verify that WarpDrive provides high-throughput and scales almost linearly to many agents and parallel environments. For example, WarpDrive yields 2.9 million environment steps/second with 2000 environments and 1000 agents (at least \(10^2\times\) higher throughput compared to a CPU implementation) in a benchmark Tag simulation. As such, WarpDrive is a fast and extensible multi-agent RL platform to significantly accelerate research and development.

1 INTRODUCTION

Deep reinforcement learning (RL) is a powerful framework to train AI agents. RL agents have beaten humans at several strategy games (OpenAI, 2018; Vinyals et al., 2019), trained robotic arms (Gu et al., 2017), and have been used to design economic policies (Zheng et al., 2021; Trott et al., 2021).

However, it remains challenging to apply RL in complex simulations that feature multiple agents or high-dimensional state, observation, or action spaces, for example. In particular, multi-agent systems are a frontier for RL research and applications, especially those with (many) interacting agents, and are relevant to economics, dialogue agents, robotics, and many other fields. However, there are still many engineering and scientific challenges to the use of RL.

A central challenge is that RL experiments can take days or even weeks, especially with a large number of agents. The main reason is that the online RL-loop repeatedly runs simulation and trains agents. Here, the number of repetitions required can grow exponentially with the complexity of the learning problem. This is most salient in the model-free setting, where RL agents train with zero initial knowledge about the simulation or task at hand. This can lead to prohibitively long wall-clock training time because current deep RL implementations often combine CPU-based simulations with GPU neural network models. RL can be especially inefficient in the multi-agent setting, as CPUs have limited potential to parallelize computations across many agents and simulations, while CPU-GPU data transfer can be slow.

Several recent works have built domain-specific, GPU or TPU-based RL solutions, for Atari (Dalton et al., 2020), or learning robotic control in 3-D rigid-body simulations (Petrenko et al., 2021; Freeman et al., 2021; Makoviychuk et al., 2021). These frameworks have mostly focused on (specific) single-agent problems, and are challenging to extend to multi-agent RL. For example, Brax builds on JAX (Bradbury et al., 2018) and functional programming (FP) principles. While FP enables easy parallelization, it is challenging to use FP to build efficient multi-agent simulations, which may require manipulating complex multi-agent state representations (including mutable collections and hash tables) and graph-based or branch divergent logic to describe interactions between agents. These issues become prohibitive

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especially with simulations with a large number of agents.

Creating Fast RL Pipelines with WarpDrive. We built WarpDrive\(^1\), an open-source framework to build extremely fast deep (multi-agent) RL pipelines. WarpDrive runs the full RL workflow end-to-end on a single GPU, using a single store of data for simulation roll-outs, inference, and training. This minimizes costly communication and copying, and significantly increases simulation sampling and learning rates. WarpDrive also runs simulations and the agents in each simulation in tandem, capitalizing on the parallelization capabilities of GPUs. Taken together, these design choices enable running thousands of concurrent simulations, each containing thousands of agents, and training on extremely large batches of experience. Our benchmarks show that WarpDrive achieves orders-of-magnitude faster RL compared to common implementations that blend CPU simulations and GPU models. For example, WarpDrive yields at least 100× higher throughput with 2000 simulations and 1000 agents in a Tag simulation (see Section 5.1).

WarpDrive builds on CUDA (Compute Unified Device Architecture), a popular platform and programming model that allows users to run programs (called kernels) on (CUDA-enabled) GPU hardware. This enables users to use the full feature set of CUDA programming, including the GPU’s parallel computational elements, making it convenient to implement even complex multi-agent simulations. WarpDrive seamlessly integrates with any CUDA C-based simulation that has a gym-style API (Brockman et al., 2016) through a light-weight environment wrapper that executes the step on the GPU. It also provides a PyTorch-based trainer and training utilities that implement end-to-end RL training on the GPU. As such, WarpDrive is flexible and easy to use and extend, and allows users to create and extend custom RL pipelines that maximize the utility of GPUs.

2 The RL Problem

To set context, we summarize the RL problem (Sutton & Barto, 2018). RL is formalized as a Markov Decision Process (MDP) and extensions thereof. A Markov Game is a multi-agent extension of the MDP that formally describes a system of agents, indexed by \(i = 1, \ldots, N\) that interact with a (simulation) environment (Littman, 1994). The environment is further defined by a state space \(S\), action space \(A\), reward function \(r\), environment dynamics \(T(s_{t+1} | s_t, a_t)\), and a discount factor \(\gamma\). Boldface quantities denote vectors over agents, e.g., \(s = (s_1, \ldots, s_N)\). This process is shown for a single agent in Figure 1. Each RL agent uses a policy model \(\pi_i(a_i | s_i)\) to sample actions to execute. Given the actions, the dynamics \(T\) move the environment forward. A roll-out is a sequence of transitions \(\xi = ((s_t, a_t, r_t))_{t=0, \ldots, T}\), representing the experience of the agents in the simulation. Given roll-outs, the goal of RL is to optimize the policies \(\pi = (\pi_1, \ldots, \pi_N)\), each aiming to maximize its discounted expected reward:

\[
\pi^*_i = \arg\max_{\pi_i} \mathbb{E}_{s, r, T} \left[ \sum_{t=0}^{T} \gamma^t r_{i,t} \right].
\]

We focus on model-free, on-policy RL. This means that the agents do not explicitly learn a parametric “world model” of \(T\) and use the policy \(\pi_i\) for both exploration (collecting unseen experience) and exploitation (executing “optimal” behavior). This approach has shown its potential by yielding superhuman performance in games (Silver et al., 2017; Vinyals et al., 2019). However, a downside of model-free RL is that it often requires a significant amount of roll-out data, especially when applying RL to complex problems. As such, it is crucial to build high-throughput RL systems with fast RL-loops, as in Figure 1.

3 Distributed RL Systems

Distributed computing is a popular approach to accelerate and scale up RL systems. Distributed RL architectures typically comprise a large number of roll-out and trainer workers operating in tandem (see Figure 2). The roll-out workers repeatedly step through the environment to generate roll-outs in parallel, using the actions sampled from the policy models on the roll-out workers (Tian et al., 2017;
Espeholt et al., 2018; Hoffman et al., 2020; Pretorius et al., 2021) or provided by the trainer worker (Espeholt et al., 2020). Roll-out workers typically use CPU machines, and sometimes, GPU machines for richer environments. Trainer workers gather the roll-out data (asynchronously) from the roll-out workers and optimize policies on CPU or GPU machines. While these architectures are highly scalable, they have several shortcomings.

Expensive Communication. There is repeated data transfer between roll-out and trainer workers, e.g., experience from the roll-out workers to the trainer worker, and model parameters or actions from the trainer worker back to the roll-out workers. In particular, when the environment’s observation space is large and/or when the number of roll-out workers is large, the data transfer becomes very expensive.

Poor Utilization. The roll-out and trainer workers run different types of tasks with different compute requirements. This can lead to inefficient resource utilization. Calibrating the optimal ratio of worker and/or node types can be tedious.

Slow Simulation. In the context of multi-agent simulations, especially with a large number of agents, running the environment step itself can become the bottleneck, since observations, rewards, and other information needs to be computed for multiple agents. While it’s often possible to parallelize operations across agents, the roll-out time only increases with increasing the number of agents.

Heavy Hardware Requirements. Complex simulations, e.g., with multiple agents, often need a lot of compute power. This often requires setting up a large (cluster of) node(s) with multiple processors, which can be non-trivial.

4 ACCELERATING RL WITH WARPDRIVE

WarpDrive addresses the above challenges by enabling RL workflows on a single GPU. WarpDrive provides a framework and quality-of-life tools to implement fast and flexible multi-agent RL systems.

We emphasize that WarpDrive is complementary to other RL systems, such as distributed RL. Future work could implement hybrid distributed versions of WarpDrive.

We now discuss the design principles and key benefits, followed by a bottom-up overview of the design and components of WarpDrive, and describe how our design choices enable extremely fast end-to-end RL.

4.1 Design Principles

WarpDrive is built following these design principles:

1. Run the full end-to-end RL workflow on a GPU, including roll-out generation and training.
2. Update data in-place to eliminate data communication.
3. Maximally parallelize, e.g., environments and agents.
4. Stay modular and flexible to easily accommodate using new environments, models and training algorithms.
5. Each part of the RL pipeline is separately testable.
6. Use imperative and stateful code to build complex multi-agent simulation logic with interacting agents.
7. Retain low-level control over thread mapping to environment replicas and agents for expressiveness.
8. Maximize quality-of-life by building easy-to-use APIs and utilities for common RL pipeline components.

4.2 Key Benefits

Together, these design choices enable fast end-to-end RL while fostering a scalable development ecosystem. That is:

1. **Minimal Communication.** There is only a one-time data transfer between the CPU and the GPU (after the first reset), and no required communication thereafter. During all the subsequent step and reset calls, the data arrays are stored exclusively on the GPU and modified in-place. All the data on the GPU is accessed and modified in-place, so there is no data copying cost.

2. **Extremely Fast Simulation.** Because each agent only uses a single thread on the GPU, we can simulate millions of agents and/or environments, making this paradigm extremely parallelized and efficient.

3. **Runs on a Single GPU.** Our current release requires only a single GPU and does not require communication between multiple GPU devices. It is an open direction to explore efficient multi-device RL systems.
4. Flexible Development Platform. The user owns the precise scheduling of each thread and has granular control over how the multi-agent logic is expressed. WarpDrive also provides RL components that are lightweight and well separated. It is easy to create and extend custom RL pipelines.

4.3 CUDA and GPU Structure

Figure 3 illustrates the fundamental architecture design of WarpDrive. Following the CUDA convention, the CPU is referred to as the host and the GPU as the device. Running any CUDA program involves three main steps:

1. Host-to-device transfer (push): Copying input data from the host to device memory, e.g., at the start.
2. Invoke CUDA kernels (execute): Loading CUDA functions to run and caching data on the GPU for speed.
3. Device-to-host transfer (pull): Copying data back from the device to host memory, e.g., once training finishes.

Following this paradigm, WarpDrive implements a DataManager and a FunctionManager: two key Python classes (residing on the CPU) to facilitate all host-device communication and interactions that are relevant to RL. The DataManager handles all host-device data transfers (push and pull). The FunctionManager allows the user to invoke CUDA programs (or compute kernels) from the CPU and execute them on the GPU. These Manager classes provide simple APIs to build high-level Python applications in WarpDrive.

A key feature of GPUs is that they can run many computational threads in parallel. Threads are organized into thread blocks. Additionally, multiple thread blocks are organized into a grid structure. A CUDA kernel can access and define parallel computations for these threads. In WarpDrive, each block is designed to contain an environment replica and each thread simulates an agent. Blocks can access a shared GPU memory that stores mini-batches of simulations data and neural network models.

4.4 Software Layers and Components of WarpDrive

Figure 4 provides a visual overview of module structures and their relationships in WarpDrive. At a high level, WarpDrive consists of four layers.

CUDA Layer. The CUDA layer executes the CUDA kernel for RL step and reset. To execute this design, WarpDrive includes two major CUDA modules:

- The CUDA Service contains the CUDA C kernel version of the environment reset to reset individual environment replicas at the block level, and the kernel of sampler to sample actions at the thread level where each thread is handling one agent. This is the shared library for any environment.
- The CUDA Environment has the CUDA C kernel of the environment step and is separate from other WarpDrive CUDA Services. WarpDrive provides several default environments and the environment loader to load custom environments provided by the user. Details on how
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**Figure 4.** *WarpDrive code structure diagram.* The bottom-up overview of the main layers of WarpDrive and their relationships. Each layer or component is well separated and incrementally executable, so the user can easily create and extend custom RL pipelines.

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| Layer                              | Description                                      | Beispiel |
|------------------------------------|--------------------------------------------------|----------|
| **Python Layer**                   | Python classes serve as fundamental classes for the Python applications running in WarpDrive, and communicate directly with the CUDA kernels. In particular, there are two major modules: |          |
|                                   |  - *Python Service* contains the *Sampler* class that directly controls the CUDA *sampler* kernel to sample agent actions at the thread level and maintains the action-data on the GPU. It also provides the *EnvironmentReset* class that controls the CUDA *reset* kernel to reset each individual environment replica in-place and independently. |          |
|                                   |  - *Python Environment* provides the *Environment* class to control the CUDA *step* kernel. |          |
| **Manager Layer**                  | The *manager layer* provides a *DataManager* and *FunctionManager* to communicate with the CUDA layer. Using these managers, WarpDrive provides Python classes to host and manage the corresponding CUDA back-end and support the high-level applications built on WarpDrive. |          |
| **CUDA Layer**                     | WarpDrive provides a full development and training ecosystem for multi-agent RL on a GPU. The *application layer* supports a gym-style interface and provides pre-built RL modules and training utilities. WarpDrive provides several tools to simplify developing and running simulations on a GPU: |          |
|                                   |  - A light-weight wrapper class *EnvWrapper* that works with the Python Service and Environment modules to automatically build gym-style environment objects and run them on the GPU. |          |
|                                   |  - A *Trainer* class, *training utilities*, and *example scripts* that enable end-to-end RL on a GPU in a few lines of code and easy customization of the process. |          |

**Manager Layer.** The manager layer provides a DataManager and FunctionManager to communicate with the CUDA layer. Using these managers, WarpDrive provides Python classes to host and manage the corresponding CUDA back-end and support the high-level applications built on WarpDrive.

**Python Layer.** These Python classes serve as fundamental classes for the Python applications running in WarpDrive, and communicate directly with the CUDA kernels. In particular, there are two major modules:

- **Python Service** contains the Sampler class that directly controls the CUDA sampler kernel to sample agent actions at the thread level and maintains the action-data on the GPU. It also provides the EnvironmentReset class that controls the CUDA reset kernel to reset each individual environment replica in-place and independently.

- **Python Environment** provides the Environment class to control the CUDA step kernel.

**Application Layer and Quality-of-Life Tools.** WarpDrive provides a full development and training ecosystem for multi-agent RL on a GPU. The application layer supports a gym-style interface and provides pre-built RL modules and training utilities. WarpDrive provides several tools to simplify developing and running simulations on a GPU:

- A light-weight wrapper class EnvWrapper that works with the Python Service and Environment modules to automatically build gym-style environment objects and run them on the GPU.

- A Trainer class, training utilities, and example scripts that enable end-to-end RL on a GPU in a few lines of code and easy customization of the process.

**4.5 The WarpDrive RL Workflow**

Using WarpDrive, a typical RL workflow for gathering rollouts and training on the GPU involves the following steps:

1. **One-Time Data Copy.** Copy over all the data from the host to the device only once after the environment object is initialized and reset. The DataManager provides API methods to perform this push operation. The data copied from the host to the device may include environment configuration parameters, data arrays created at the end of the very first reset, as well as placeholders for the observations, actions, rewards and
“done” flags. The DataManager also helps maintain a copy of the variables that need to be re-initialized at every reset. After this point, there is no further data push from the host to the device.

2. Call GPU Kernels from the CPU. The FunctionManager provides API methods to initialize and invoke the CUDA C kernel functions required for performing the environment step, generating observations, and computing rewards from the host node. These functions execute only on the device, and all the data arrays are modified in-place. Data may be pulled by the host from time to time for visualization or analysis purposes, but all the data can essentially reside on the GPU only during training.

3. Block-parallelized Environment Runs. Within the GPU, we execute several replicas of the environment in parallel. Each environment runs on a separate thread block. Because a typical GPU has thousands of blocks, we can execute thousands of environments in parallel on just a single GPU.

4. Thread-parallelized Multi-agent Steps. Within each environment (running in its own block), each agent in the environment can also execute its own logic on an agent-exclusive thread. Figure 3 shows an example in which agents $i$, $j$ and $k$ operate in parallel on individual threads $i$, $j$ and $k$, respectively. This becomes very useful in the context of multi-agent RL, since we can fully parallelize the agents’ operations during the environment step, thus the simulation time complexity remains constant even as the number of agents increases (up to the number of available threads).

5. Automatic Environment Resetting. Any environment may reach a terminal state and be “done”. WarpDrive provides an EnvironmentReset class designed to automatically identify and reset those environments that are done. At this point, those environments are also reset and given (new) initial data. For example, they may use the initial data arrays that were copied over at the initial reset.

6. Thread-parallelized Action Sampling. WarpDrive also provides a Sampler class for sampling actions in order to step through the environment. Actions are sampled using the probabilities computed by the policy models. Our sampler runs in parallel on each agent thread, and runs about $4 \times$ faster than equivalent PyTorch implementation. See Section 5 for details.

7. PyTorch-based Multi-agent RL Training. Once rollout data is gathered from several environments and agents into a training data batch, we can also perform end-to-end training with WarpDrive. The initial release of WarpDrive includes an example training script and Trainer class which currently implements Advantage Actor Critic (A2C) (Mnih et al., 2016) and Proximal Policy Optimization (PPO) (Schulman et al., 2017), and a fully-connected neural network policy model. The Trainer builds on PyTorch, and calls all CUDA kernels and PyTorch operations (that run on the GPU device) from the CPU host. However, PyTorch can directly access and interpret the WarpDrive data batches (states, actions, rewards and done flags) stored on the device as a torch.Tensor. This allows the user to compute losses and modify the model parameters, while eliminating data copying. Given the modular design of WarpDrive, it is straightforward to integrate existing implementations of other RL algorithms and model classes.

4.6 Extensibility and Quality-of-Life Tools

WarpDrive’s modular structure makes it easy to integrate custom Python RL environments and develop an equivalent CUDA C implementation that can run on a GPU. At the core, the first version of WarpDrive uses simulations that are implemented using CUDA C (see Figure 5 for a sample function signature). Implementing and testing programs in CUDA C can take longer than in Python. A key reason is that memory and threads need to be carefully managed in CUDA C programs. This is especially relevant when using GPUs, which feature multiple types of memory.

Checking Consistency. To ensure correctness of CUDA C simulations, an effective approach is to implement the simulation logic in Python and NumPy first and verify its
```python
class Env:
    def __init__(self, **env_config):
        ...

    def reset(self):
        ...
        return obs

    def get_data_dictionary(self):
        # Specify the data that needs to be pushed to the GPU.
        data_feed = DataFeed()
        data_feed.add_data(
            name="variable_name",
            data=self.variable,
            save_copy_and_apply_at_reset=True,
        )
        ...
        return data_feed

    def step(self, actions):
        if self.use_cuda:
            self.cuda_step(
                # Pass the relevant data
                # feed keys as arguments
                # to cuda_step.
                # Note: cuda_data_manager
                # is created by the
                # EnvWrapper.
                self.cuda_data_manager.device_data(...),
            )
        else:
            ...
            return obs, rew, done, info
```

Figure 6. Augmenting Python Environments for WarpDrive. To use an existing Python Environment with WarpDrive, one needs to add two augmentations. First, a get_data_dictionary() method that returns a dictionary-like DataFeed object with data arrays and parameters that should be pushed to the GPU. Second, the step-function should call the cuda_step with the data arrays that the CUDA C step function should have access to. Given these additions, the EnvironmentWrapper class can automatically build a CUDA C Environment that handles other parts of the simulation pipeline, which includes a DataManager, see Figure 7.

Building a CUDA-compatible Environment. Assuming the Python and CUDA C step functions are consistent, WarpDrive simplifies creating an augmented environment object that uses the CUDA C step. First, the Python Env class should be extended with a get_data_dictionary() method that defines which data should reside on the GPU, see Figure 6. The EnvWrapper provided by WarpDrive will automatically build an augmented Environment object that handles the low-level data transfer flow. This includes pushing all the data to the GPU after the very first reset, and providing gym-style step and reset Python methods for running the simulation on the GPU. Using this augmented environment enables RL on a GPU in a few lines of code, as shown in Figure 7.

5 PERFORMANCE BENCHMARKS

We use three environments to benchmark WarpDrive’s performance: two versions of the game of Tag and a more complex COVID-19 economic simulation. Our results show that the performance of WarpDrive scales linearly to thousands
5.1 Benchmark Environments

The Tag Environment. In Tag, $N_{\text{tag}} \geq 1$ taggers work together to catch $N_{\text{run}} \geq 1$ runners. There are $N = N_{\text{tag}} + N_{\text{run}}$ agents in total. See Figure 8 for a visualization. Runners are tagged once a tagger gets close enough. Each simulation episode ends after the maximum time steps, or when all runners have been tagged. The percentage of runners that were tagged defines how successful the taggers were. The goal for each agent is to learn how to optimally accelerate (or brake) and turn around on the 2-D playing field. Taggers and runners can have different skill levels; the higher the skill, the higher the maximal speed.

We use a discrete (simple) and continuous (advanced) version of Tag. In discrete Tag, agents move on a discrete 2-D grid. Every agent can choose to move up, down, left, right by one cell, or to not move. In continuous Tag, agents move in a continuous 2-D world. Here, every agent can accelerate, brake and/or turn around, still via a discrete set of actions, and the agents' movements follow classical mechanics.

For benchmarking, we also use two semantic variations, where agents have partial or full observations. With partial observations, agents can only see the closest $K$ agents. RL can optimize the tagger and runner policies. Here, taggers are positively rewarded (e.g., $+1$) for each successful tag, so they are incentivized to tag the runners. Once a runner is tagged, it receives a penalty (e.g., $-1$) and leaves the game. Therefore, runners learn to avoid being tagged. Tag can become a complicated decision-making problem once agents are strategic (e.g., trained by RL) and as more and more taggers and runners participate. For instance, taggers may learn cooperative strategies, e.g., taggers might learn to encircle runners. As such, Tag is an interesting benchmark environment for WarpDrive.

COVID-19 Economic Environment. We also show that WarpDrive scales to more complex environments, by evaluating it in a COVID-19 simulation (Trott et al., 2021). This simulation models health and economic dynamics amidst the COVID-19 pandemic, based on real-world data. Figure 8 shows its structure. The simulation step is substantially more complex compared to Tag and so takes a larger fraction of each iteration’s run-time.

The simulation comprises 52 agents: 51 governors corresponding to each US state and Washington D.C., and another one for the (USA) federal government. This is a complicated two-level multi-agent environment where the US state agents decide the stringency level of the policy response to the pandemic, while the US federal government provides subsidies to eligible individuals. Actions taken by each agent affect its health and economic outcomes, such as deaths, unemployment, and GDP. In addition, the actions of environments and agents, and yields orders of magnitude faster RL compared to CPU implementations.
of the federal government can change the health-economic trade-off and optimization objective for the US states, making it a complex, unstable two-level RL problem.

5.2 End-to-End Training Throughput

We benchmark WarpDrive by comparing performance across agents, across environment replicas, and between a 16-CPU N1 node (on GCP) and WarpDrive on an Nvidia A100 GPU. All our benchmarks results average over 5 repetitions. Across the board, WarpDrive is extremely fast and yields orders of magnitude higher throughput than when using CPU-simulations and GPU models.

**Tag Benchmarks.** Overall, WarpDrive achieves very fast end-to-end RL training speeds. With 2000 discrete Tag environments and 5 agents for each environment, WarpDrive achieves 1.3 million end-to-end RL training iterations per second. With 2000 environments and 1000 agents, it yields 0.38 million training iterations per second. We emphasize that increasing the number of agents by 200×, from 5 to 1000, resulted in only 50% lower throughput. In continuous Tag, with 2000 environments and 5 agents, WarpDrive achieves 0.57 million training iterations per second, or 0.15 million training iterations per second with 45 agents.

Figure 10 compares training speed between an N1 16-CPU node and a single A100 GPU in continuous Tag with 10 runners and 2 taggers, both using 60 environment replicas. With the same environment and training parameters, WarpDrive on a GPU is 5× faster, even with just 12 agents.

**COVID-19 Benchmarks.** For the COVID-19 economic environment, WarpDrive achieves 24× more steps per second with 60 environment replicas, compared to a 16 CPU node. Across different timing categories (see Figure 11, the performance gains comprise a 24× speed-up during the environment roll-out, a zero data transfer time, and a 30× speed-up for training the policy models. Moreover, WarpDrive can scale almost linearly to 1000 parallel COVID-19 environments, resulting in even higher throughput gains.

5.3 Scaling to Many Environments and Agents

WarpDrive achieves nearly perfect parallelism over thousands of environments and up to one thousand agents, running on one single GPU.

Figure 12 (Left) shows WarpDrive’s performance in discrete Tag. WarpDrive scales linearly to over thousands of environments (fixed number of agents) and yields almost perfect parallelism over environments. For example, WarpDrive runs at 9.8 million environment steps per second with 5 agents and 2000 discrete Tag environments. With 1000 agents, it achieves 2.9 million environment steps per second.

Figure 13 shows performance per discrete Tag environment as the number of agents grows. For each environment replica, WarpDrive is at least 50× faster compared to a NumPy version on a single CPU, for up to 1000 agents.

Continuous Tag is significantly faster too. Figure 14 shows that throughput scales linearly to over thousands of environment replicas in continuous Tag. In particular, WarpDrive reaches 8.3 million environment steps per second with 5
agents and 2000 environments. For each replica, WarpDrive yields at least 500× more environment steps per second compared to a single CPU, for up to 820 agents.

5.4 Faster Sampling

The improved performance of the WarpDrive sampler contributes to overall faster training. In discrete Tag, WarpDrive samples 18 million actions per second per agent with 2000 environments, independent of the number of agents (see Figure 12, right). This is 3.6× faster compared to the equivalent PyTorch operator, which yields 5 million samples per second. In continuous Tag, WarpDrive samples 16 million actions per action category per second per agent with 2000 environments, independent of the number of agents.

5.5 Impact of Simulation Complexity

The complexity of the simulation logic, as implemented in the step and reset function, impacts performance. To quantify the impact of this aspect, we compared two variations of Tag: with agents using partial observation vectors or full observation vectors. When using partial observations, each agent can only see its $K$ nearest neighbors. In discrete Tag, using partial observations yields an environment step function with close to $O(N)$ time complexity, better than $O(N^2)$. More generally, using partial observations can enable better scaling behavior when using GPUs. Constructing partial observations for any agent may require less information and communication between (other) agent threads, and thus benefits more from parallelizing across agents. However, this depends on the specific implementation of each simulation and is an important design choice.

Finally, we note that the speed gains persist under the more complex COVID-19 economic simulation, see Section 5.2.

6 Future Directions

Future work could explore how multi-GPU setups can further improve throughput. Furthermore, a key remaining bottleneck is to build robust CUDA simulations. Towards making RL usable and useful, we hope WarpDrive encourages the creation of new tools to simplify simulation development in CUDA. Being modular, we hope to extend WarpDrive and integrate other tools for building machine learning workflows on GPUs and other accelerators. In all, we hope that WarpDrive contributes to the democratization of high-performance RL systems and future advances in AI.
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