Mava: a research library for distributed multi-agent reinforcement learning in JAX

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Abstract

Multi-agent reinforcement learning (MARL) research is inherently computationally expensive and it is often difficult to obtain a sufficient number of experiment samples to test hypotheses and make robust statistical claims. Furthermore, MARL algorithms are typically complex in their design and can be tricky to implement correctly. These aspects of MARL present a difficult challenge when it comes to creating useful software for advanced research. Our criteria for such software is that it should be simple enough to use to implement new ideas quickly, while at the same time be scalable and fast enough to test those ideas in a reasonable amount of time. In this preliminary technical report, we introduce Mava, a research library for MARL written purely in JAX, that aims to fulfill these criteria. We discuss the design and core features of Mava, and demonstrate its use and performance across a variety of environments. In particular, we show Mava’s substantial speed advantage, with improvements of 10-100x compared to other popular MARL frameworks, while maintaining strong performance. This allows for researchers to test ideas in a few minutes instead of several hours. Finally, Mava forms part of an ecosystem of libraries that seamlessly integrate with each other to help facilitate advanced research in MARL. We hope Mava will benefit the community and help drive scientifically sound and statistically robust research in the field. The open-source repository for Mava is available at https://github.com/instadeepai/Mava.

1. Introduction

To facilitate advanced research in MARL from an engineering perspective presents a difficult challenge: to strike a balance between code that is highly performant, to run computationally expensive experiments efficiently, and code that is easy to understand, to enable conceptual and algorithmic development in a reasonable time frame. Software that is very simple to understand may likely be too slow to pursue any meaningful enquiries, yet software that is highly scalable and fast may be too rigid or opaque to quickly develop and test new ideas. There remains a need for tools that strike a fine balance between these two extremes for the purposes of conducting advanced research at scale.

Mava is a research library that aims to find such a balance, for online MARL research in particular. By leveraging the power of JAX as a machine learning framework (Bradbury et al., 2023), along with advances in distributed computing (Hessel et al., 2021), Mava is

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Figure 1: Depiction of how Mava fits into a broader multi-agent reinforcement learning ecosystem. Other components include OG-MARL, Jumanji, Flashbax, and MARL-eval. Further details for each of these components are given in Section 3.

able to train over millions of timesteps in a matter of minutes, enabling highly efficient experiment iteration. Yet, simultaneously, by intentionally adopting and adhering to the best practices of simple and readable code, Mava remains easy to parse, debug, and extend.

Importantly, Mava forms part of a broader ecosystem of research for MARL. Acting as an easy starting point for research ideas, Mava integrates naturally with a range of software libraries—spanning a corresponding framework for offline MARL (Formanek et al., 2023a) with accelerated replay buffers for off-policy and offline algorithms (Toledo et al., 2023), native RL environments written in JAX (Bonnet et al., 2023), and a robust and statistically reliable set of evaluation tools designed specifically for MARL (Gorsane et al., 2022). This ecosystem is depicted in Figure 1.

In this brief technical report, we provide an overview of the design and core features of Mava, and how it integrates into the broader MARL research ecosystem. Moreover, we conduct basic experiments demonstrating Mava’s speed and performance on various tasks.

2. Design and core features

A clean code philosophy. Moving away from completely modular MARL frameworks (Samvelyan et al., 2019a; Papoudakis et al., 2021; Hu et al., 2023; Bettini et al., 2023), Mava instead adopts a code philosophy akin to recent works such as CleanRL (Huang et al., 2022) and PureJAXRL (Lu et al., 2022) where all core algorithmic logic should be contained in a single easy-to-read file. This enables researchers to debug code easily and to adapt Mava to their particular use case with little friction and overhead. A notable difference
between CleanRL and Mava is that Mava has certain levels of abstraction; on environment
initialisation, reusable type definitions and flexible algorithm and environment configuration
management with Hydra (Yadan, 2019). This approach strikes a balance where code is easy
to understand but unnecessary boilerplate code is abstracted away.

**Strong baseline algorithms and training architectures.** Mava currently only supports
environments that are written in JAX. This constraint enables the (just-in-time) jit-
compilation of agent policy roll-outs and policy updates. In particular, Mava supports the
Anakin architecture (Hessel et al., 2021) for scalable distributed system training on hardware
accelerators, depicted in Figure 2. At the time of writing, Mava has implementations of
both recurrent and feedforward policy versions of multi-agent PPO systems that follow the
decentralised training with decentralised execution (DTDE) and centralised training with
decentralised execution (CTDE) paradigms. Next in our roadmap is to include off-policy
algorithms leveraging the Anakin architecture as well as both on and off-policy algorithms
supporting distributed non-JAX environment training using the Sebulba architecture (Hessel
et al., 2021).

**Multi-device training with easy checkpointing and logging.** Mava offers some core
benefits over recent MARL offerings in JAX (Rutherford et al., 2023). The first of which is
out-of-the-box support for code to be pmap-ed over multiple devices on hardware accelerators
like TPUs for faster training times. The second is support for robust evaluation, system
checkpointing and continual metric logging. It is common in MARL systems to freeze
training periodically in order to evaluate current agent policies (Gorsane et al., 2022). This
is a challenge in end-to-end JAX-based RL since jit-compiling the agent training loop forces
one to wait for training to be complete before any performance feedback can be obtained.
Possible ways around this are to either (1) use JAX’s debug callback functionality, which
tends to lead to significant increases in training wallclock time, (2) to evaluate systems
once at the end of training, or (3) to forgo evaluation feedback altogether and only produce
training curves - none of which is desirable. Mava solves this problem by interleaving
evaluation blocks during system training. Here, both the training and evaluation blocks
are pmap-ed and run sequentially in a normal Python for loop. This has the benefit that it
maintains system performance while giving researchers continual insights into system training
dynamics. Since system performance and parameters are continually exposed, metrics can
be logged and policy parameters can be checkpointed continually throughout training. Mava
has native support for logging to Tensorboard and Neptune and also supports logging to
JSON files in a format that is supported by the MARL-eval (Gorsane et al., 2022) library
for downstream statistical aggregation and plotting, discussed further below.

3. Seamless integration between ecosystem libraries

As shown in Figure 1, Mava forms part of a wider and evolving ecosystem of software for RL
research. By design, this ecosystem allows for seamless integration between libraries.

**Accelerated JAX-native environments.** One of the main challenges in RL and MARL
is that algorithms tend to be sample inefficient, typically requiring millions of timesteps to
converge. This means that the speed at which the environment can step has a substantial

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Figure 2: A diagram of the Anakin podracer architecture (Hessel et al., 2021) implemented in Mava for fast training on hardware accelerators, such as a GPU or TPU. A set of parameters $\theta$ is taken as input, and is replicated across $D$ devices. On each device $d \in D$ (via `jax.pmap`), these parameters are further broadcast to $J$ update functions (via `jax.vmap`). Each update function $j \in J$ rolls out independent experience from $N$ copies of the environment (via `jax.vmap`), which is collected and given to a loss function, for which a gradient is computed. For device $d$ and update function $j$, the gradient is $\nabla_d^j$. On each device $d$, the gradients of the $J$ update functions are averaged via a `jax.pmean` operation, yielding $\bar{\nabla}_d$. These gradients are then averaged across devices, again via `jax.pmean`, yielding $\bar{\bar{\nabla}}$, which is used to calculate the new parameters, $\theta'$. 
impact on the time to convergence of algorithms. Recently, environments implemented directly in JAX have demonstrated significant speedups in environment interactions per second by effectively leveraging modern hardware accelerators such as GPUs and TPUs (Lange, 2022; Freeman et al., 2021). To take full advantage of this trend, Mava currently supports three suites of JAX-native multi-agent environments, namely **Matrax** (Pretorius, 2023), **Jumanji** (Bonnet et al., 2023) and **JaxMARL** (Rutherford et al., 2023).

- **Matrax** is a lightweight suite of common 2-player matrix games written in JAX. Matrix games are appealing for their simplicity and speed. As such, they provide a good starting point for testing new MARL algorithms and for discovering fundamental failure modes, even in simple settings.

- **Jumanji** provides a suite of environments related to combinatorial optimisation problems. Several environments in Jumanji lend themselves well to being solved by MARL algorithms, for example, Multi-Robot Warehouse (RWARE) (Christianos et al., 2020), Level-Based Foraging (LBF) (Albrecht and Ramamoorthy, 2015) and the Multi-Agent Capacitated Vehicle Routing Problem (MA-CVRP). In Mava, we have developed flexible wrappers for Jumanji to make it simple to train Mava systems in these environments.

- **JaxMARL** contains JAX implementations of many popular MARL benchmark environments, such as the StarCraft Multi-Agent Challenge (SMAC) (Samvelyan et al., 2019b), Overcooked (Carroll et al., 2019) and Multi-Agent MuJoCo (MAMuJoCo) (Peng et al., 2021). JaxMARL’s environment offering is appealing because of its close relationship with well-established non-JAX environments. However, while it may be tempting to directly compare results on JaxMARL environments to their non-JAX versions, it’s important to bear in mind that in some cases there can be subtle but important differences which make such comparisons invalid.

As the ecosystem evolves, we plan to add support for additional environments. For researchers who are interested in using Mava on any currently unsupported environment, it should be quite easy to develop an environment wrapper similar to those for Jumanji or JaxMARL to make their new environment conform to the API Mava algorithms expect.

**Standardised and statistically robust evaluation reporting.** To ensure a high level of standardisation and statistical rigour in the evaluation of experimental outcomes, Mava can log raw experimental data in such a way that it conforms to the format expected by **MARL-eval** (Gorsane et al., 2022). MARL-eval implements the data aggregation and reporting proposed by Gorsane et al. (2022), based on the principles established in (Agarwal et al., 2021). This equips MARL-eval with statistically sound plotting tools, enabling robust and reliable analysis of cooperative MARL experiments.

**Offline MARL.** A promising and increasingly popular research direction in MARL is offline training (Yang et al., 2021; Tseng et al., 2022; Meng et al., 2023; Tian et al., 2023; Wang et al., 2023). In offline MARL, agents are trained on a static dataset of experience without any additional online interactions in the environment. Offline MARL is an appealing paradigm because it avoids online environment interactions which can be slow, expensive and dangerous if a simulator is not readily available. Another promising approach is combining offline with
As a minimal demonstration of how Mava can be integrated into an offline MARL experiment pipeline, we trained an online Mava PPO system on RWARE and recorded its experience using a Flashbax Vault. We then reloaded the Vault in OG-MARL and trained the MAICQ algorithm completely offline on the Mava data. The entire online-to-offline experiment was repeated for 10 independent seeds. The mean and standard error across seeds are plotted.

Online training to make online training significantly more sample efficient (Nair et al., 2020; Wagenmaker and Pacchiano, 2023; Ball et al., 2023). Formanek et al. (2023b) demonstrated that a similar approach can significantly speed up online training in MARL.

Recently, Off-the-Grid MARL (Formanek et al., 2023a) was proposed as a framework for offline MARL research. To demonstrate how Mava can be utilised in an offline research workflow, we recorded online transitions from a Mava PPO system on RWARE using a Flashbax Vault (see below) and reloaded these transitions as a dataset (directly into VRAM) to train a fully jit-compilable JAX version of the offline algorithm MAICQ (Yang et al., 2021) implemented in OG-MARL. A plot of the online and offline training curves is given in Figure 3.

Flashbax Vault (Toledo et al., 2023) serves as the intermediary between Mava and OG-MARL. Vault offers an efficient mechanism to save Flashbax buffers, which essentially hold JAX arrays, to persistent data storage. Consider a Flashbax buffer which has experience data of dimensionality \((B, T, \ast E)\), where \(B\) is a batch dimension (for the sake of recording independent trajectories synchronously), \(T\) is a temporal dimension, and \(\ast E\) indicates the multiple dimensions of the experience data. Since large quantities of data may be generated for a given environment, Vault extends the \(T\) dimension to a virtually unconstrained degree by reading and writing slices of buffers along this time axis. In doing so, gigantic buffer stores can reside on disk, from which sub-buffers can be loaded into RAM/VRAM for efficient offline training.
Figure 4: Performance comparison between Mava and EPyMARL training a feedforward MAPPO on the tiny-2ag, tiny-4ag, and small-4ag tasks. Highlighting the comparable implementations between Jumanji’s non-collision RWARE and the original RWARE, Mava’s feedforward MAPPO shows equal or enhanced performance at significantly reduced wallclock time (from hours to minutes), with further speed gains observed when systems are scaled to use 256 vmap-ed achieving convergence in roughly 2 minutes.

4. Speed and Performance

This section outlines a series of early experiments conducted to demonstrate the use and effectiveness of Mava. We stress that these experiments are not meant to serve as an extensive investigation, and in several cases, we suspect significant improvements can still be obtained through proper hyperparameter tuning. Nonetheless, these simple experiments show how Mava scales with respect to the number of vectorized environments leading to a significant reduction in experiment wallclock time (from several hours to only a few minutes), while simultaneously maintaining good performance.

We first compare Mava’s speed and performance with a popular PyTorch-based MARL framework EPyMARL (Papoudakis et al., 2021), which itself is an extension of PyMARL (Samvelyan et al., 2019a), arguably one of the most popular frameworks in MARL. We conduct experiments in various Level-Based Foraging (LBF) (Albrecht and Ramamoorthy, 2015) and Multi-Robotic Warehouse (RWARE) (Papoudakis et al., 2021) scenarios, utilizing both feedforward and recurrent architectures for Independent PPO (IPPO) and Multi-Agent PPO (MAPPO) with a centralised critic. Following these experiments, we provide a very preliminary comparison between Mava and the recently released JAX-based PPO baselines from JaxMARL on their StarCraft Multi-Agent Challenge in JAX (SMAX) environment (Rutherford et al., 2023). SMAX represents a JAX-based simplification of the original SMAC environment (Samvelyan et al., 2019a), streamlining its complexity for more flexible and fast experimentation. In all our experiments, we follow the evaluation guideline as proposed by Gorsane et al. (2022).

Multi-Robot Warehouse (RWARE). We train on 2 and 4-agent tasks, using Jumanji’s RWARE for Mava and the original (non-JAX) RWARE for EPyMARL. We use the recommended hyperparameters from (Papoudakis et al., 2021) for EPyMARL and conduct a basic grid search for Mava, training across 16 vectorized environments for up to 20 million steps. Notably, Jumanji’s RWARE variant used in Mava terminates the episode on collisions,
Figure 5: Scalability and training time analysis: (a) illustrates the steps per second achieved by recurrent and feedforward IPPO and MAPPO as the number of vectorised environments increases, and (b) The bar chart compares the run time of Mava’s implementations against EPyMARL’s across the experiments from Figure 4 for the case of 16 vmap-ed environments, showcasing Mava’s speed with about a 10x improvement across all tasks. At 256 vectorised environments we obtain improvements of more than 100x.

Figure 6: Performance comparison between Mava and EPyMARL training a recurrent MAPPO on the 15x15-4p-3f and 2s-8x8-2p-2f tasks. Mava achieves superior performance at 10x the speed. Moreover, by leveraging specialised hardware accelerators (in this case a TPU-V3), Mava is able to train to convergence in under five minutes.

adding complexity; to ensure a fair comparison, we include Mava’s performance with and without this feature. All experiments were conducted on an NVIDIA Quadro RTX 4000 GPU with 8GB Memory, leading to the showcased performance of FF-MAPPO in Figure 4 and the speed comparison in Figure 5. Mava’s speed is about 10x faster for the same number of parallel environments, and at 256 parallel environments, we obtain improvements of more than 100x in speed while maintaining good performance.

Level-Based Foraging (LBF). We compare the performance of Mava’s MAPPO recurrent system with those from EPyMARL in two settings: one involving 2 agents and the other with 4 agents, over 20 million timesteps. We utilize Jumanji’s LBF for Mava and the original LBF for EPyMARL. Both setups are trained on 16 vectorized environments using a GPU (NVIDIA A-100 for EPyMARL and NVIDIA GeForce RTX 3050 with 4GB Memory for Mava). Additionally, Mava is tested with 16 parallel environments on a TPU-V3 to
Figure 7: Performance of Recurrent IPPO and MAPPO from Mava and JaxMARL on SMAX Scenarios: 2s3z, 3s5z, and 6h vs 8z. Dashed lines indicate the estimated final win rates for JaxMARL taken from the plots in (Rutherford et al., 2023). In all experiments, we performed no hyperparameter tuning for Mava systems but simply used the hyperparameters from JaxMARL.

demonstrate scalability on specialised hardware. EPyMARL’s hyperparameters are sourced from (Papoudakis et al., 2021), whereas we employ a basic grid search for Mava.

**StarCraft Multi-Agent Challenge in JAX (SMAX).** We train Mava’s recurrent systems on a similar subset of SMAX scenarios as used in the main text of (Rutherford et al., 2023). We stress again that we do not consider these experiments to be extensive or sufficiently comprehensive to provide strong evidence to our claims, but only provide some preliminary results for interest. For all our experiments, we perform no hyperparameter tuning and simply use the hyperparameters from (Rutherford et al., 2023), training for 10 million timesteps using 64 parallel environments. Figure 7 illustrates that Mava’s recurrent IPPO and MAPPO algorithms match the performance of JaxMARL’s baselines. However, we suspect additional performance gains could be achieved with proper hyperparameter tuning. In terms of speed, we note that our FF-IPPO trains to convergence, achieving around 85% win rate, on 2s3z in under a minute (54 seconds). From our interpretation of the speeds on 2s3z reported by Rutherford et al. (2023) (in their Figure 5 (d)), the authors seem to claim single-run training times of roughly 5 seconds. However, we are unsure if we are interpreting these results correctly. In future we plan to run Mava (using both on and off-policy algorithms) across all SMAX scenarios (the minimal set suggested for research by Rutherford et al. (2023) following the advice from Gorsane et al. (2022)).

5. Conclusion

Mava is a flexible and performant JAX-based library for MARL that integrates seamlessly with several other powerful libraries forming a broader and continuously evolving ecosystem for MARL. By open-sourcing Mava we hope it can benefit the research community and help drive progress in the field.
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