

JaxMARL: Multi-Agent RL Environments and Algorithms in JAX

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ABSTRACT

Benchmarks play an important role in the development of machine learning algorithms. For example, research in reinforcement learning (RL) has been heavily influenced by available environments and benchmarks. However, RL environments are traditionally run on the CPU, limiting their scalability with typical academic compute. Recent advancements in JAX have enabled the wider use of hardware acceleration to overcome these computational hurdles, enabling massively parallel RL training pipelines and environments. This is particularly useful for multi-agent reinforcement learning (MARL) research. First of all, multiple agents must be considered at each environment step, adding *computational burden*, and secondly, the *sample complexity* is increased due to non-stationarity, decentralised partial observability, or other MARL challenges. In this paper, we present JaxMARL, the first open-source code base that combines ease-of-use with GPU enabled efficiency, and supports a large number of commonly used MARL environments as well as popular baseline algorithms. When considering wall clock time, our experiments show that per-run our JAX-based training pipeline is up to 12500x faster than existing approaches. This enables efficient and thorough evaluations, with the potential to alleviate the *evaluation crisis* of the field. We also introduce and benchmark SMAX, a vectorised, simplified version of the popular StarCraft Multi-Agent Challenge, which removes the need to run the StarCraft II game engine. This not only enables GPU acceleration, but also provides a more flexible MARL environment, unlocking the potential for self-play, meta-learning, and other future applications in MARL. We provide code at <https://github.com/flairox/jaxmarl>.

KEYWORDS

Multi-Agent Reinforcement Learning, JAX, Benchmarks

1 INTRODUCTION

Benchmarks play a pivotal role in the development of new single and multi-agent reinforcement learning (MARL) algorithms by defining problems, enabling comparisons, and focusing efforts. For example, in recent years, Go and Chess drove the development of MuZero [50] while decentralised StarCraft Micromanagement [17] and later the StarCraft Multi-Agent Challenge [SMAC, 49] resulted in the development of algorithms such as QMIX [46], a popular MARL technique.

Data transfer between the CPU (where the environment is simulated) and the GPU (where the agents are evaluated) is a crucial bottleneck for simulation speed. Simulation speed in turn is vital

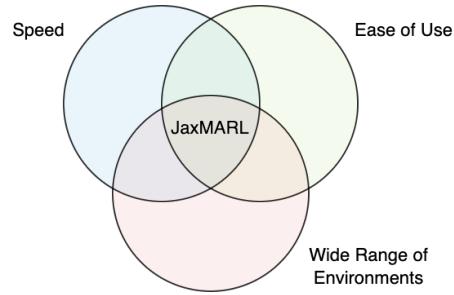


Figure 1: JaxMARL’s philosophy. JaxMARL combines a wide range of environments with ease of use and evaluation speed.

for progress in reinforcement learning (RL) because RL algorithms often require a large number of environment interactions. This problem is even worse in MARL, where non-stationarity and decentralised partial observability greatly worsen the sample complexity [4]. Hardware acceleration and parallelisation are crucial to alleviating this, but current acceleration and parallelisation methods are typically not implemented in Python, reducing their accessibility for most machine learning researchers [52, 61]. For example, the extremely efficient Hanabi library [21] from Meta-AI research is implemented in C++ and has seen relatively little adoption by the community. However, recent advances in JAX [7] have opened up new possibilities for using Python code directly with hardware accelerators, enabling the wider use of massively parallel RL training pipelines and environments.

The JAX [7] library provides composable function transformations, allowing for automatic vectorisation, device parallelisation, automatic differentiation and just-in-time (JIT) compilation with XLA [48], for device-agnostic optimisation. Using JAX, both the environment rollouts and model training can happen on a hardware accelerator (such as a GPU or TPU), removing the cost of data transfer between devices and allowing for significant parallelisation. Recently, PureJaxRL [33, 36] has demonstrated the power of this end-to-end JAX-based approach; running both the environment and the model training on a GPU yields a 4000x speedup over a “traditional” pipeline with a GPU-trained policy but a CPU-based environment.

These accelerations could substantially advance RL and MARL research by quickening the testing and iteration of ideas. Furthermore, they lower computational hurdles for in-depth MARL research, enabling researchers to utilise billions of frames and extract more performance from single GPUs.

Alongside the current computational issues faced by MARL researchers, recent work also highlights issues with the evaluation

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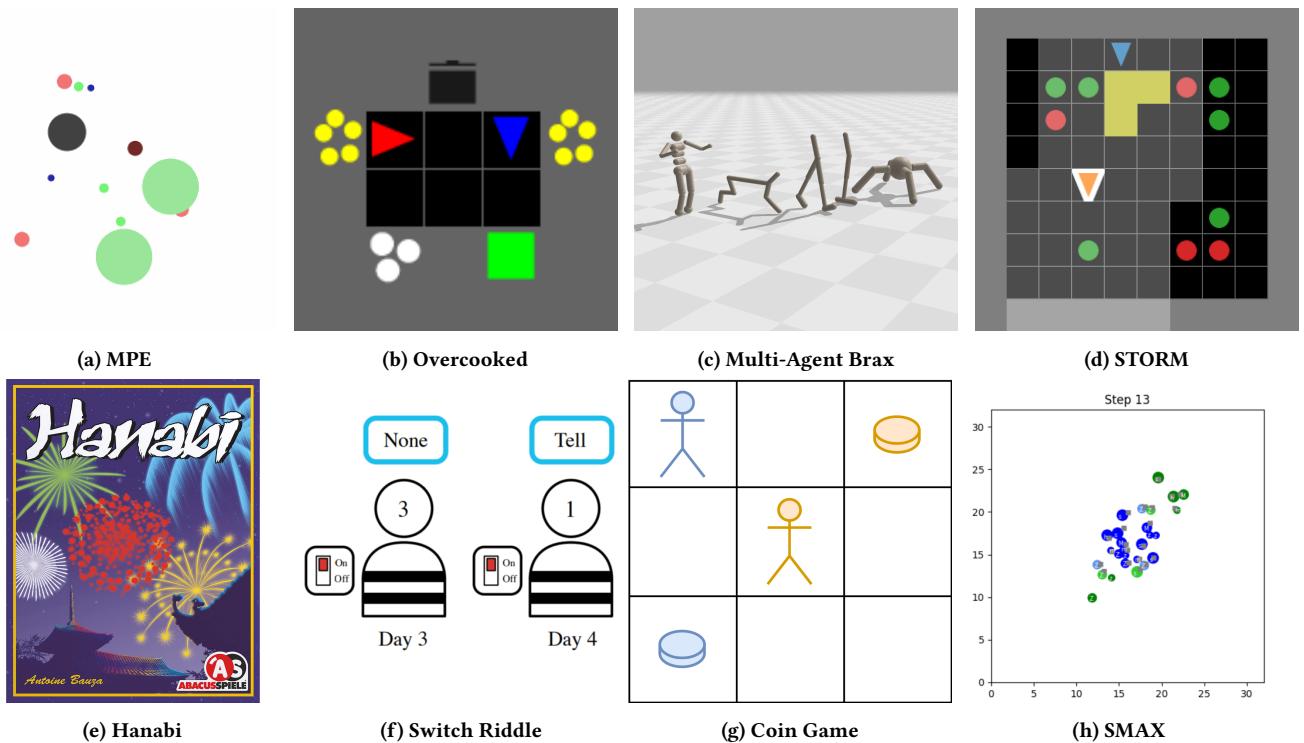


Figure 2: JaxMARL environments. We provide vectorised implementations of a wide range of environments from different MARL settings.

standards and use of benchmarks in the MARL community. In particular, MARL papers typically only test on a few domains. Of the 75 recent MARL papers analysed by [20], 50% used only one evaluation environment and a further 30% used only two. While SMAC and MPE [32], the two most used environments, have various tasks or maps, the lack of a standard set raises the risk of biased comparisons and incorrect conclusions. This leads to environment overfitting and unclear progress markers.

Instead, novel MARL methods should be tested on a wide range of domains to accurately evaluate their limits and enable better comparisons. The likely issue preventing this is the lack of a unified codebase and the computational burden of further evaluation.

This paper presents JaxMARL, a Python library that for the first time brings together JAX implementations of eight common MARL environments under one API. We additionally provide JAX implementations for four state-of-the-art algorithms, allowing for end-to-end JAX-based training pipelines in a similar fashion to PureJaxRL. As outlined in Figure 1, we present a library with end-to-end hardware-accelerated training, simple Python implementations, and a broad range of MARL environments. By alleviating computational constraints, JaxMARL allows rapid evaluation of novel methods across a broad set of domains, and hence has the potential to be a powerful tool to address MARL’s evaluation crisis. Specifically, we find that JaxMARL achieves over 12500x speedup compared to “conventional” approaches.

We also create SMAX, a JAX-based simplification of the centralised training with decentralised execution (CTDE) benchmarks

SMAC [49] and SMACv2 [14]. SMAX features simplified dynamics, greater flexibility and a more sophisticated but fully-decentralised heuristic AI, while retaining the high-dimensional observation space, complex unit type interactions and procedural scenario generation that lend SMAC and SMACv2 much of their difficulty.

As shown in Figure 2, in addition to SMAX, our library includes the most popular environments from several MARL settings. For centralised training with decentralised execution (CTDE), we include the Multi-Agent Particle Environments (MPE) [32], and Multi-Agent Brax (MABrax). Meanwhile, for zero-shot coordination (ZSC) and ad-hoc teamplay, we include Hanabi and Overcooked. Lastly, from the general-sum literature, we include the CoinGame and Spatial-Temporal Representations of Matrix Games (STORM), a representation of matrix games as grid-world scenarios with temporally extended actions. JaxMARL provides the first JAX implementation of these environments and unifies them in a single codebase.

We additionally provide JAX implementations of Independent PPO (IPPO) [13, 51], QMIX, VDN [55] and Independent Q-Learning (IQL) [40], four of the most common MARL algorithms, allowing new techniques to be easily benchmarked against existing practices. We will extend this list before the camera-ready copy, e.g. with the popular MAPPO [63] algorithm.

2 BACKGROUND

2.1 Hardware Accelerated Environments

JAX enables the use of Python code with any hardware accelerator, allowing researchers to write hardware-accelerated code easily. Within the RL community, writing environment code in JAX has gained recent popularity. This brings two chief advantages: firstly, environments written in JAX can be very easily parallelised by using JAX’s `vmap` operation, which vectorises a function across an input dimension, and secondly writing the environment in JAX allows the agent and environment to be co-located on the GPU, which eliminates the time taken to copy between CPU and GPU memory. Combined, these two factors bring significant increases in training speed, with PureJaxRL [33] achieving a 4000x speedup over traditional training in single-agent settings.

2.2 SMAC

StarCraft is a popular environment for testing RL algorithms. It typically features features a centralised controller issuing commands to balance *micromanagement*, the low-level control of individual units, and *macromanagement*, the high level plans for economy and resource management.

SMAC [49], instead, focuses on *decentralised* unit micromanagement across a range of scenarios divided into three broad categories: *symmetric*, where each side has the same units, *asymmetric*, where the enemy team has more units, and *micro-trick*, which are scenarios designed specifically to feature a particular StarCraft micromanagement strategy. SMACv2 [14] demonstrates that open-loop policies can be effective on SMAC and adds additional randomly generated scenarios to rectify SMAC’s lack of stochasticity. However, both of these environments rely on running the full game of StarCraft II, which severely increases their CPU and memory requirements. SMAClite [38] attempts to alleviate this computational burden by recreating the SMAC environment primarily in NumPy, with some core components written in C++. While this is much more lightweight than SMAC, it cannot be run on a GPU and therefore cannot be parallelised effectively with typical academic hardware, which commonly has very few CPU cores compared to industry clusters.

3 JAXMARL

We present JaxMARL, a library containing simple and accessible JAX implementations of popular MARL environments and algorithms. JAX enables significant acceleration and parallelisation over existing implementations. To the best of our knowledge, JaxMARL is the first open source library that provides JAX-based implementations of a wide range of MARL environments and baselines.

3.1 API

The interface of JaxMARL is inspired by PettingZoo [58] and Gymnasx. We designed it to be a simple and easy-to-use interface for a wide-range of MARL problems. An example of instantiating an environment from JaxMARL’s registry and executing one transition is presented in Figure 3. As JAX’s JIT compilation requires pure functions, our `step` method has two additional inputs compared to PettingZoo’s. The `state` object stores the environment’s internal state and is updated with each call to `step`, before being passed to

```
1 import jax
2 from jaxmarl import make
3
4 key = jax.random.PRNGKey(0)
5 key, key_reset, key_act, key_step = jax.random.split(key, 4)
6
7 # Initialise and reset the environment.
8 env = make('MPE_simple_world_comm_v3')
9 obs, state = env.reset(key_reset)
10
11 # Sample random actions.
12 key_act = jax.random.split(key_act, env.num_agents)
13 actions = {agent: env.action_space(agent).sample(key_act[i]) \
14             for i, agent in enumerate(env.agents)}
15
16 # Perform the step transition.
17 obs, state, reward, done, infos = env.step(key_step, state, actions)
```

Figure 3: An example of JaxMARL’s API, which is flexible and easy-to-use.

subsequent calls. Meanwhile, `key_step` is a pseudo-random key, consumed by JAX functions that require stochasticity. This key is separated from the internal state for clarity.

Similar to PettingZoo, the remaining inputs and outputs are dictionaries keyed by agent names, allowing for differing action and observation spaces. However, as JAX’s JIT compilation requires arrays to have static shapes, the total number of agents in an environment cannot vary during an episode. Thus, we do not use PettingZoo’s *agent iterator*. Instead, the maximum number of agents is set upon environment instantiation and any agents that terminate before the end of an episode pass dummy actions thereafter. As asynchronous termination is possible, we signal the end of an episode using a special “`__all__`” key within `done`. The same dummy action approach is taken for environments where agents act asynchronously (e.g. turn-based games).

To ensure clarity and reproducibility, we keep strict registration of environments with suffixed version numbers, for example “MPE Simple Spread V3”. Whenever JaxMARL environments correspond to existing CPU-based implementations, the version numbers match.

3.2 Environments

JaxMARL contains a diverse range of environments, all implemented in JAX. We also introduce SMAX, a SMAC-like environment implemented entirely in JAX. In this section we introduce these environments and provide details on their implementations.

SMAX. The StarCraft Multi-Agent Challenge (SMAC) is a popular benchmark but has a number of shortcomings. First, as noted and addressed in prior work [14], it is not sufficiently stochastic to require complex closed-loop policies. Additionally, SMAC relies on StarCraft II as a simulator. While this allows SMAC to use the wide range of units, objects and terrain available in StarCraft II, running an entire instance of StarCraft II is slow [38] and memory intensive. StarCraft II runs on the CPU and therefore SMAC’s parallelisation is severely limited with typical academic compute.

Using the StarCraft II game engine constrains environment design. For example, StarCraft II groups units into three *races* and does not allow units of different races on the same team, limiting the variety of scenarios that can be generated. Secondly, SMAC does not support a competitive self-play setting without significant

Table 1: SMAX scenarios. The first section corresponds to SMAC scenarios, while the second corresponds to SMACv2.

Scenario	Ally Units	Enemy Units	Start Positions
2s3z	2 stalkers and 3 zealots	2 stalkers and 3 zealots	Fixed
3s5z	3 stalkers and 5 zealots	3 stalkers and 5 zealots	Fixed
5m_vs_6m	5 marines	6 marines	Fixed
10m_vs_11m	10 marines	11 marines	Fixed
27m_vs_30m	27 marines	30 marines	Fixed
3s5z_vs_3s6z	3 stalkers and 5 zealots	3 stalkers and 6 zealots	Fixed
3s_vs_5z	3 stalkers	5 zealots	Fixed
6h_vs_8z	6 hydralisks	8 zealots	Fixed
smacv2_5_units	5 uniformly randomly chosen	5 uniformly randomly chosen	SMACv2-style
smacv2_10_units	10 uniformly randomly chosen	10 uniformly randomly chosen	SMACv2-style
smacv2_20_units	20 uniformly randomly chosen	20 uniformly randomly chosen	SMACv2-style

engineering work. The purpose of SMAX is to address these limitations. It provides access to a SMAC-like, hardware-accelerated, customisable environment that supports self-play and custom unit types.

Units in SMAX are modelled as circles in a two-dimensional continuous space. SMAX makes a number of additional simplifications to the dynamics of StarCraft II, details of which are given in Appendix A.1.

SMAX also features a different, and more sophisticated, heuristic AI. The heuristic in SMAC simply moves to a fixed location [38], attacking any enemies it encounters along the way, and the heuristic in SMACv2 globally pursues the nearest agent. Thus the SMAC AI often does not aggressively pursue enemies that run away, and cannot generalise to the SMACv2 start positions, whereas the SMACv2 heuristic AI conditions on global information and is exploitable because of its tendency to flip-flop between two similarly close enemies. SMAC’s heuristic AI must be coded in the map editor, which does not provide a simple coding interface.

In contrast, SMAX features a *decentralised* heuristic AI that can effectively find enemies without requiring the global information of the SMACv2 heuristic. This guarantees that in principle a 50% win rate is always achievable by copying the decentralised heuristic policy exactly. This means any win-rate below 50% represents a concrete failure to learn.

SMAX scenarios incorporate both a number of the original scenarios from SMAC and scenarios similar to those found in SMACv2. The latter sample units uniformly across all SMAX unit types (stalker, zealot, hydralisk, zergling, marine, marauder) and ensure fairness by having identical team composition for the enemy and ally teams. We provide more details on SMAX in Appendix A.1.

Overcooked. Inspired by the popular videogame of the same name, Overcooked is commonly used for assessing fully cooperative and fully observable Human-AI task performance. The aim is to quickly prepare and deliver soup, which involves putting three onions in a pot, cooking the soup, and serving it into bowls. Two agents, or *cooks*, must coordinate to effectively divide the tasks to maximise their common reward signal. Our implementation mimics the original from Overcooked-AI [9], including all five original layouts and a simple method for creating additional ones. For a

discussion on the limitations of the Overcooked-AI environment, see [30].

Hanabi. Hanabi is a fully cooperative partially observable multiplayer card game, where players can observe other players’ cards but not their own. To win, the team must play a series of cards in a specific order while sharing only a limited amount of information between players. As reasoning about the beliefs and intentions of other agents is central to performance, it is a common benchmark for ZSC and ad-hoc teamplay research. Our implementation is inspired by the Hanabi Learning Environment [2] and includes custom configurations for varying game settings, such as the number of colours/ranks, number of players, and number of hint tokens. Compared to the Hanabi Learning Environment, which is written in C++ and split over dozens of files, our implementation is a single easy-to-read Python file, which simplifies interfacing with the library and running experiments.

Multi-Agent Particle Environments (MPE). The multi-agent particle environments feature a 2D world with simple physics where particle agents can move, communicate, and interact with fixed landmarks. Each specific environment varies the format of the world and the agents’ abilities, creating a diverse set of tasks that include both competitive and cooperative settings. We implement all the MPE scenarios featured in the PettingZoo library and the transitions of our implementation map exactly to theirs. We additionally include a fully cooperative predator-prey variant of *simple tag*, presented in [44]. The code is structured to allow for straightforward extensions, enabling further tasks to be added.

Multi-Agent Brax (MABrax). MABrax is a derivative of Multi-Agent MuJoCo [44], an extension of the MuJoCo Gym environment [59] that is commonly used for benchmarking continuous multi-agent robotic control. Our implementation utilises Brax[18] as the underlying physics engine and includes five of *Multi-Agent MuJoCo*’s multi-agent factorisation tasks, where each agent controls a subset of the joints and only observes the local state. The included tasks, illustrated in Figure 2, are: ant_4x2, halfcheetah_6x1, hopper_3x1, humanoid_9|8, and walker2d_2x3. The task descriptions mirror those from Gymnasium-Robotics [12].

Coin Game. Coin Game is a two-player grid-world environment which emulates social dilemmas such as the iterated prisoner’s dilemma [53]. Used as a benchmark for the general-sum setting, it

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

expands on simpler social dilemmas by adding a high-dimensional state. Two players, ‘red’ and ‘blue’ move in a grid world and are each awarded 1 point for collecting any coin. However, ‘red’ loses 2 points if ‘blue’ collects a red coin and vice versa. Thus, if both agents ignore colour when collecting coins their expected reward is 0. Further details are provided in Appendix A.2.

Spatial-Temporal Representations of Matrix Games (STORM). Inspired by the “in the Matrix” games in Melting Pot 2.0 [1], the STORM [26] environment expands on matrix games by representing them as grid-world scenarios. Agents collect resources which define their strategy during interactions and are rewarded based on a pre-specified payoff matrix. This allows for the embedding of fully cooperative, competitive or general-sum games, such as the prisoner’s dilemma [53]. Thus, STORM can be used for studying paradigms such as *opponent shaping*, where agents act with the intent to change other agents’ learning dynamics, which has been empirically shown to lead to more prosocial outcomes [16, 26, 35, 65]. Compared to the Coin Game or matrix games, the grid-world setting presents a variety of new challenges such as partial observability, multi-step agent interactions, temporally-extended actions, and longer time horizons. Unlike the “in the Matrix” games from Melting Pot, STORM features stochasticity, increasing the difficulty [14]. A further environment specification is provided in Appendix A.3.

Switch Riddle. Originally used to illustrate the Differentiable Inter-Agent Learning algorithm [15], Switch Riddle is a simple cooperative communication environment that we include as a debugging tool. n prisoners held by a warden can secure their release by collectively ensuring that each has passed through a room with a light bulb and a switch. Each day, a prisoner is chosen at random to enter this room. They have three choices: do nothing, signal to the next prisoner by toggling the light, or inform the warden they think all prisoners have been in the room. The game ends when a prisoner informs the warden or the maximum time steps are reached. The rewards are +1 if the prisoner informs the warden, and all prisoners have been in the room, -1 if the prisoner informs the warden before all prisoners have taken their turn, and 0 otherwise, including when the maximum time steps are reached. We benchmark using the implementation from [64].

3.3 Algorithms

In this section, we present our re-implementation of four well known MARL baseline algorithms using JAX. The primary objective of these baselines is to provide a structured framework for developing MARL algorithms leveraging the advantages of the Jax-MARL environments. All of the training pipelines are fully compatible with JAX’s JIT and VMAP functions, resulting in a significant acceleration of both the training and metric evaluation processes. This enables parallelisation of training across various seeds and hyperparameters on a single machine in parallel. We follow the CleanRL philosophy of providing clear, single-file implementations [24].

IPPO. Our Independent PPO (IPPO) [13, 51] implementation is based on PureJaxRL [33], with parameter sharing across homogeneous agents. We provide both feed-forward and RNN versions.

Q-learning Methods. Our Q-Learning baselines, including Independent Q-Learning (IQL) [57], Value Decomposition Networks (VDN) [56], and QMIX [47], have been implemented in accordance with the PyMARL codebase [47] to ensure consistency with published results and enable direct comparisons with PyTorch. Our baselines natively support aggregating trajectories from batched environments, simplifying parallelisation. This approach is more convenient than managing environments on distinct threads and subsequently aggregating results, as done in PyMARL. We provide a brief overview of the implemented baselines in the Appendix.

4 RESULTS

In our results, we aim to demonstrate the speed and correctness of our environments and algorithms. In several cases, minor changes to the environments mean that our environments do not exactly match the originals on a step-by-step level. We therefore demonstrate the correctness in different ways for each environment and discuss each separately. By combining this evidence, we demonstrate that our library provides overall correct and far quicker baselines on a wide range of sufficiently correct and easily-modifiable environments.

4.1 Environment Speed

We measure the performance of our environments in *steps per second* when using random actions and compare to the original environments in Table 2 and Figure 4. All results were collected on

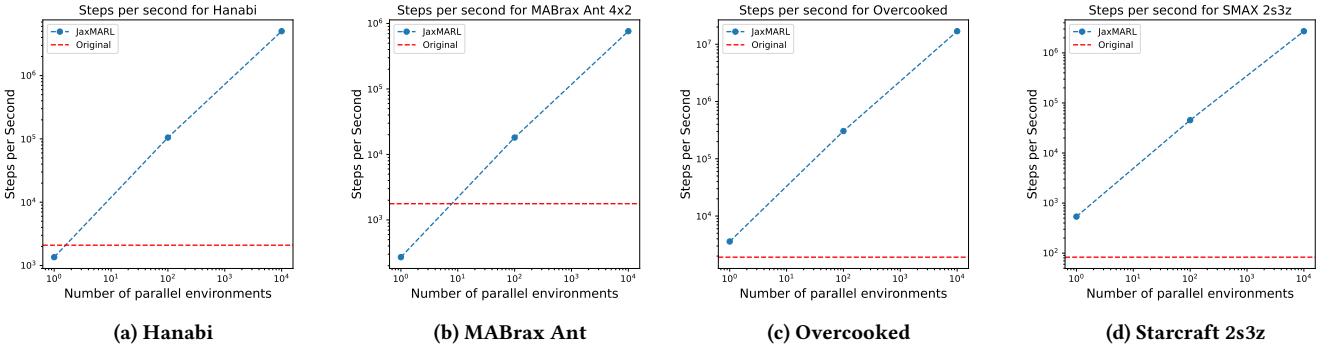


Figure 4: Speedup of four JaxMARL environments compared to singled-threaded CPU-based implementations.

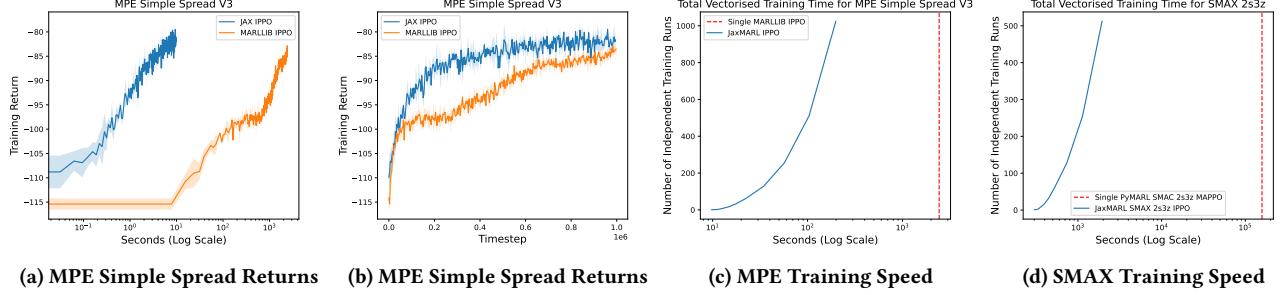


Figure 5: IPPO Speed and Performance in JaxMARL compared to MARLLIB and PyMARL in SMAX and MPE. Return results were averaged across 3 seeds. Performance results show 1 seed collected on the hardware described in Section 4.1.

a single NVIDIA A100 GPU and AMD EPYC 7763 64-core processor. Environments were rolled out for 1000 sequential steps. Many environments have comparable performance to JaxMARL when comparing single environments, but the ease of parallelisation with Jax allows for more efficient scaling compared to CPU-based environments. For example, MPE Simple Spread’s JAX implementation is $\tilde{20}$ x slower than the original when comparing a single environment, but even when only running 100 environments in parallel, the JAX environment is already over 6x faster. When considering 10000 environments, the JAX versions are much faster, achieving speedups of up to 8500x over the single-threaded environment (in the case of Overcooked). Running this many environments in parallel using CPU environments would require a large CPU cluster and sophisticated communication mechanisms. This engineering is typically beyond the resources of academic labs, and therefore JaxMARL can unlock new research directions for such institutions.

4.2 Algorithm Speed

We investigate the speed of our IPPO implementation in Figure 5. By vectorising over agents, it is possible to train a vast number of agents in a fraction of the time it takes to train a single agent without hardware acceleration. For MPE, it is possible to train 1024 teams in 198.4 seconds, which is less than 0.2 seconds per teams of agents. A single run of MARLLIB’s IPPO implementation on the same hardware takes around 2435.7 seconds on average. This represents a speedup of over 12500x.

Our JAX-based Q -learning algorithms also offer significant speed advantages. In Figure 6a, training a single IQN, VDN, or QMIX policy in MPE takes ~ 130 seconds while using PyMarl takes over an hour. Training 1024 QMIX learners in a batch requires 1670 seconds, which translates to 1.6 seconds per learner, indicating a 2700x speedup. This speedup is not as large as for IPPO because Q -learning baselines are typically trained with fewer parallel environments. In our experiments, we used 8 parallel environments for Q -learning compared to the 25 or 64 used for PPO. This difference is due to Q -learners benefiting more from a buffer with trajectories collected by different policies, resulting in a more frequent policy update, rather than collecting many trajectories with the same policy in parallel.

For SMAX, we compare our vectorised IPPO baseline to the MAPPO implementation provided in [54]. MAPPO utilises an RNN and IPPO uses a feed forward network. This was run on a machine with a 64-core CPU and NVIDIA 2080Ti GPU. Additionally, as discussed in Section 3.2, SMAC and SMAX are different environments. These caveats aside, the differences in performance are so striking that we believe this clearly demonstrates the advantages of our approach. We trained 512 SMAX teams on 2s3z in under 33 minutes, whereas a single training run of PyTorch IPPO implementation takes 44 hours on average. This is roughly a 40000x speedup.

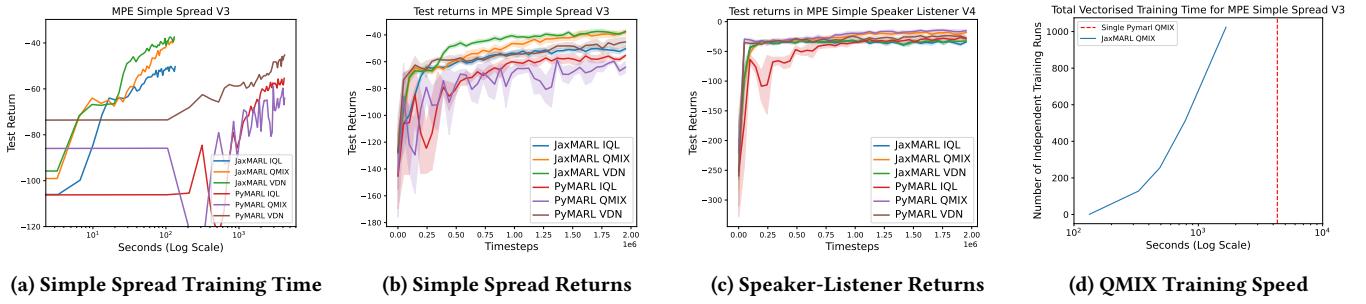


Figure 6: Performance and speed of JaxMARL Q-Learning baselines compared to PyMARL on MPE. Our implementations match PyMARL’s returns, while being over 2000x faster to train

4.3 Algorithm Correctness

We verify the correctness of our algorithm implementations by comparing to baselines from other libraries on the MPE Simple Spread and Simple Speaker Listener environments. For IPPO we report the mean return across 3 seeds in Figure 5b. Results were collected on the same hardware as listed in Section 4.1. Our IPPO implementation obtains the same performance as MARLLIB and runs 250x quicker, taking only ten seconds to train.

For the Q -learning algorithms, we verify the correctness by comparing with PyMARL implementations of the same algorithms on the MPE Simple Spread and Simple Speaker Listener environments. IQL, VDN and QMIX all obtain the same or better results than their PyMARL counterparts. The returns are from greedy policies and averaged across 8 runs. The hyperparameters used are from the PyMARL library.

4.4 Environment Correctness

MPE. Our MPE environment corresponds exactly to the PettingZoo implementation. We validate this for each environment using a uniform-random policy on 1000 rollouts, ensuring all observations and rewards are within a tolerance of 1×10^{-4} at each transition. This tolerance accounts for non-determinism due to running floating point computation on the GPU. The correspondence is also shown through the performance of IPPO in Figure 5b and the Q -learning algorithms in Figures 6b and 6c respectively, as the performance of these algorithms is inline with existing baselines [63]. We additionally report training performance for IQL on the remaining MPE environments in Appendix C.2.

Overcooked. The transition dynamics of our Overcooked implementation match those of the Overcooked-AI implementation. We demonstrate this by training an IPPO policy on our implementation and evaluating the policy on both our Overcooked implementation and the original at regular intervals. Results are illustrated in Figure 7a and performance is similar, demonstrating their equivalence.

SMAX. SMAX and SMAC are different environments. However, we demonstrate some similarity between them by comparing our IPPO and MAPPO implementations against MAPPO results on SMAC, using the implementation from [54]. We show this in Figure 8. SMAX and SMAC have different opponent policies and dynamics, which makes this comparison more qualitative than precise. We describe the differences between the two in more depth in

in the supplementary material. However, despite these differences, the environments seem similarly difficult, with some environments being more difficult in SMAC, and some more difficult in SMAX. This is shown in Figure 8 and in the supplementary material.

MABrax. As Brax differs subtly from MuJoCo, MABrax does not correspond to MAMuJoCo but the learning dynamics are qualitatively similar. To demonstrate this, we report mean training return across 10 seeds for IPPO on ant_4x2 in Figure 7b, and our results are in line with the performance of TRPO reported in [28]. We report the performance of IPPO on HalfCheetah and Walker in Appendix C.1, the results are also in line with TRPO.

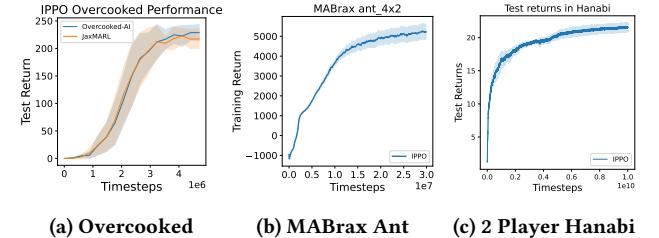


Figure 7: JaxMARL IPPO baseline results. These results correspond to similar baselines and therefore demonstrate the correctness of our implementations.

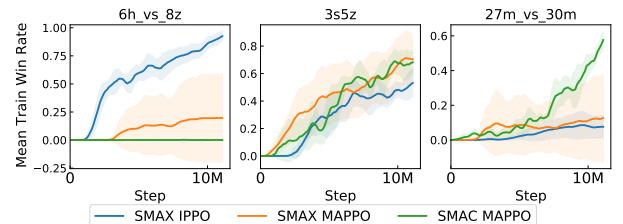


Figure 8: SMAX IPPO and MAPPO baselines compared to MAPPO in SMAC.

Table 3: Recommended Minimal Environment Evaluations for different research settings

Setting	Recommended Environments
CTDE	SMAX (all scenarios), Hanabi (2-5 players), Overcooked
Zero-shot Coordination	Hanabi (2 players), Overcooked (5 basic scenarios)
General-Sum	STORM (iterated prisoner’s dilemma), STORM (matching pennies)
Cooperative Continuous Actions	MABrax

Hanabi. Our implementation does not correspond exactly to the Hanabi Learning Environment as we use a subtly different observation space, with the reasoning given in Appendix A.4. To demonstrate qualitative similarity, we train IPPO on Hanabi in self-play with 2 players, with the mean test return across 3 seeds reported in Figure 7c.

STORM, Coin Game & Switch Riddle. STORM differs from Melting Pot 2.0 significantly, making direct comparisons challenging, with differences discussed in Appendix A.3. Furthermore, STORM and Coin Game are general-sum games, so the environment returns of IPPO in self-play would not be a good indicator of performance. Switch Riddle is a simple diagnostic environment – we do not use it for thorough evaluations.

5 EVALUATION RECOMMENDATIONS

Previous work [20] has found significant differences in the evaluation protocols between MARL research works. We identify four main research areas that would benefit from our library: cooperative centralised training with decentralised execution (CTDE) [15], zero-shot coordination [22], general-sum games, and cooperative continuous action methods.

To aid comparisons between methods, we recommend standard *minimal* sets of evaluation environments for each of these settings in Table 3. It’s important to note that these are *minimal* and we encourage as broad an evaluation as possible. For example, in the zero-shot coordination setting, all methods should be able to evaluate on Hanabi and Overcooked. However, it may also be possible to evaluate such methods on the SMACv2 settings of SMAX. Similarly, SMAX could be used to evaluate two-player zero-sum methods by training in self-play. For some settings, such as continuous action environments and general-sum games, there is only one difficult environment. We encourage further development of JAX-based environments in these settings to improve the quality of evaluation.

6 RELATED WORK

Several open-source libraries exist for both MARL algorithms and environments. The popular library PyMARL [49] provides PyTorch implementations of QMIX, VDN and IQL and integrates easily with SMAC. E-PyMARL [43] extends this by adding the actor-critic algorithms MADDPG [32], MAA2C [39], IA2C [39], and MAPPO, and supports the SMAC, Gym [8], Robot Warehouse [10], Level-Based Foraging [10], and MPE environments. Recently released MARLLib [23] is instead based on the open-source RL library RL-Lib [31] and combines a wide range of competitive, cooperative and mixed environments with a broad set of baseline algorithms. Meanwhile, MALib [66] focuses on population-based MARL across a wide range of environments. However, none of these frameworks feature

hardware-accelerated environments and thus lack the associated performance benefits.

There has also been a recent proliferation of hardware-accelerated and JAX-based RL environments. Isaac gym [37] provides a GPU-accelerated simulator for a range of robotics platforms and CuLE [11] is a CUDA reimplementation of the Atari Learning Environment [3]. Both of these environments are GPU-specific and cannot be extended to other hardware accelerators. Madrona [52] is an extensible game-engine written in C++ that allows for GPU acceleration and parallelisation across environments. However, it requires environment code to be written in C++, limiting its accessibility. VMAS [5] provides a vectorized 2D physics engine written in PyTorch and a set of challenging multi-robot scenarios, including those from the MPE environment. For RL environments implemented in JAX, Jumanji [6] features mostly single-agent environments with a strong focus on combinatorial problems. The authors also provide an actor-critic baseline in addition to random actions. PGX [27] includes several board-game environments written in JAX. Gymnax [29] provides JAX implementations of the BSuite [42], classic continuous control, MinAtar [62] and other assorted environments. Gymnax’s sister-library, gymnax-baselines, provides PPO and ES baselines. Further extensions to Gymnax [34] also include POPGym environments [41]. Brax [18] reimplements the MuJoCo simulator in JAX and also provides a PPO implementation as a baseline. Jax-LOB [19] implements a vectorized limit order book as an RL environment that runs on the accelerator. Perhaps the most similar to our work is Mava [45], which provides a MAPPO baseline, as well as integration with the Robot Warehouse environment. However, none of these libraries combine a range of JAX-based MARL environments with both value-based and actor-critic baselines.

Broadly, no other work provides implementations of a wide range of hardware-accelerated MARL environments, while also implementing value-based and actor-critic baselines. Secondly, no other JAX simplification of SMAC exists. All other versions are either tied to the StarCraft II simulator or not hardware accelerated.

7 CONCLUSION

Hardware acceleration offers important opportunities for MARL research by lowering computational barriers, increasing the speed at which ideas can be iterated, and allowing for more thorough evaluation. We present JaxMARL, an open-source library of popular MARL environments and baseline algorithms implemented in JAX. We combine ease of use with hardware accelerator enabled efficiency to give significant speed-ups compared to traditional CPU-based implementations. Furthermore, by bringing together a wide range of MARL environments under one codebase, we have the potential to help alleviate issues with MARL’s evaluation standards.

We hope that JaxMARL will help advance MARL by improving the ability of academic labs to conduct research with thorough, fast, and effective evaluations.

8 AUTHOR CONTRIBUTIONS

This project is a large-scale effort spanning many labs and contributors.

AR*[†] led the design of the JaxMARL API and interface the implementation of IPPO and MPE environments. BE*[†] led the design and implementation of the SMAX environments and IPPO evaluations. AR and BE also led the writing of this manuscript. MG[†] led the implementation of the off-policy MARL algorithms, their evaluations., and the implementation of the Switch Riddle environment.

JC* led the implementation of the Hanabi environment and heavily assisted with benchmarking and verifying its performance. AL* led the implementation of the Overcooked environments. GI* led the implementation of the Multi-Agent Brax environments. TW* led the implementation of the STORM environments. AK and AS worked on the STORM environments. CSW led the implementation of the Predator-Prey environment.

CSW, SB, MS, MJ, and RL provided invaluable discussions for project planning and implementations across the project. SB helped initiate the project plan. MS worked on the Multi-Agent Brax environments. MJ worked on the Overcooked and Hanabi environments. RL assisted with the design of the API and testing infrastructure.

SW, BL, NH, and TR provided invaluable feedback on the project, manuscript, and results.

^{CL*}[†] initiated the project and led the organizational and planning efforts, speed-based benchmarking, and Coin Game implementation.

JF is the primary advisor for the project.

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A FURTHER DETAILS ON ENVIRONMENTS

A.1 SMAX

Observations in SMAX are structured similarly to SMAC. Each agent observes the health, previous action, position, weapon cooldown and unit type of all allies and enemies in its sight range. Like SMACv2[14], we use the sight and attack ranges as prescribed by StarCraft II rather than the fixed values used in SMAC.

SMAX and SMAC have different returns. SMAC’s reward function, like SMAX’s, is split into two parts: one part for depleting enemy health, and another for winning the episode. However, in SMAC, the part which rewards depleting enemy health scales with the number of agents. This is most clearly demonstrated in 27m_vs_30m, where a random policy gets a return of around 10 out of a maximum of 20 because almost all the reward is for depleting enemy health or killing agents, rather than winning the episode. In SMAX, however, 50% of the total return is always for depleting enemy health, and 50% for winning. Unlike StarCraft II, where all actions happen in a randomised order in the game loop, some actions in SMAX are simultaneous, meaning draws are possible. In this case both teams get 0 reward.

Like SMAC, each environment step in SMAX consists of eight individual time ticks. SMAX uses a discrete action space, consisting of movement in the four cardinal directions, a stop action, and a shoot action per enemy.

SMAX makes three notable simplifications of the StarCraft II dynamics to reduce complexity. First, zerg units do not regenerate health. This health regeneration is slow at 0.38 health per second, and so likely has little impact on the game. Protoss units also do not have shields. Shields only recharge after 10 seconds out of combat, and therefore are unlikely to recharge during a single micromanagement task. Protoss units have additional health to compensate for their lost shields. Finally, the available unit types are reduced compared to SMAC. SMAX has no medivac, colossus or banling units. Each of these unit types has special mechanics that were left out for the sake of simplicity. For the SMACv2 scenarios, the start positions are generated as in SMACv2, with the small difference that the ‘surrounded’ start positions now treat allies and enemies identically, rather than always spawning allies in the middle of the map. This symmetry guarantees that a 50% win rate is always achievable.

Collisions are handled by moving agents to their desired location first and then pushing them out from one another.

A.2 Coin Game

Two agents, ‘red’ and ‘blue’, move in a wrap-around grid and collect red and blue coloured coins. When an agent collects any coin, the agent receives a reward of 1. However, when ‘red’ collects a blue coin, ‘blue’ receives a reward of -2 and vice versa. Once a coin is collected, a new coin of the same colour appears at a random location within the grid. If a coin is collected by both agents simultaneously, the coin is duplicated and both agents collect it. Episodes are of a set length.

A.3 Spatial-Temporal Representations of Matrix Games (STORM)

This environment features directional agents within an 8x8 grid-world with a restricted field of view. Agents cannot move backwards or share the same location. Collisions are resolved by either giving priority to the stationary agent or randomly if both are moving. Agents collect two unique resources: *cooperate* and *defect* coins. Once an agent picks up any coin, the agent’s colour shifts, indicating its readiness to interact. The agents can then release an *interact* beam directly ahead; when this beam intersects with another ready agent, both are rewarded based on the specific matrix game payoff matrix. The agents’ coin collections determine their strategies. For instance, if an agent has 1 *cooperate* coin and 3 *defect* coins, there’s a 25% likelihood of the agent choosing to cooperate. After an interaction, the two agents involved are frozen for five steps, revealing their coin collections to surrounding agents. After five steps, they respawn in a new location, with their coin count set back to zero. Once an episode concludes, the coin placements are shuffled. This grid-based approach to matrix games can be adapted for n-player versions. While STORM is inspired by MeltingPot 2.0, there are noteworthy differences:

- Meltingpot uses pixel-based observations while we allow for direct grid access.
- Meltingpot’s grid size is typically 23x15, while ours is 8x8.
- Meltingpot features walls within its layout, ours does not.
- Our environment introduces stochasticity by shuffling the coin placements, which remain static in Meltingpot.
- Our agents begin with an empty coin inventory, making it easier for them to adopt pure cooperate or defect tactics, unlike in Meltingpot where they start with one of each coin.
- MeltingPot is implemented in Lua [25] where as ours is a vectorized implementation in Jax.

We deem the coin shuffling especially crucial because even large environments representing POMDPs, such as SMAC, can be solved without the need for memory if they lack sufficient randomness [14].

A.4 Hanabi

There are a few details that differ between our Hanabi implementation and the original Hanabi Learning Environment (HLE). The most notable of these is how we choose to represent card knowledge information in the agents’ observation. In the HLE, card knowledge is observed as a colour/rank if there has been an explicit hint about a given card. As a separate feature, implicit card knowledge is represented as possible colours/ranks if there has not been an explicit hint that indicates a given card is not that colour/rank. We, on the other hand, combine implicit and explicit card knowledge, by only maintaining a representation of implicit card knowledge, which reduces to explicit card knowledge in the event an explicit hint is given about a card. This is because all possible colours/ranks are represented as 1s, whilst all ruled out colours/ranks are represented as 0s. By giving an explicit hint, all but one colour/rank are ruled out, leaving a one-hot encoding of the explicit card knowledge. We implement card knowledge this way, because knowledge updates are implemented via tensor calculus using JAX Numpy arrays of fixed shape and data type.

B VALUE-BASED MARL METHODS AND IMPLEMENTATION DETAILS

Key features of our framework include parameter sharing, a recurrent neural network (RNN) for agents, an epsilon-greedy exploration strategy with linear decay, a uniform experience replay buffer, and the incorporation of Double Deep Q -Learning (DDQN) [60] techniques to enhance training stability.

Unlike PyMARL, we use the Adam optimizer as the default optimization algorithm. Below is an introduction to common value-based MARL methods.

IQL (Independent Q -Learners) is a straightforward adaptation of Deep Q -Learning to multi-agent scenarios. It features multiple Q -Learner agents that operate independently, optimizing their individual returns. This approach follows a decentralized learning and decentralized execution pipeline.

VDN (Value Decomposition Networks) extends Q -Learning to multi-agent scenarios with a centralized-learning-decentralized-execution framework. Individual agents approximate their own action's Q -Value, which is then summed during training to compute a jointed Q_{tot} for the global state-action pair. Back-propagation of the global DDQN loss in respect to a global team reward optimizes the factorization of the jointed Q -Value.

QMIX improves upon VDN by relaxing the full factorization requirement. It ensures that a global $argmax$ operation on the total Q -Value (Q_{tot}) is equivalent to individual $argmax$ operations on each agent's Q -Value. This is achieved using a feed-forward neural network as the mixing network, which combines agent network outputs to produce Q_{tot} values. The global DDQN loss is computed using a single shared reward function and is back-propagated through the mixer network to the agents' parameters. Hypernetworks generate the mixing network's weights and biases, ensuring non-negativity using an absolute activation function. These hypernetworks are two-layered multi-layer perceptrons with ReLU non-linearity.

C TRAINING RESULTS

C.1 MABrax

The performance of IPPO on HalfCheetah and Walker is reported in Figure 9, with hyperparameters reported in Table 4.

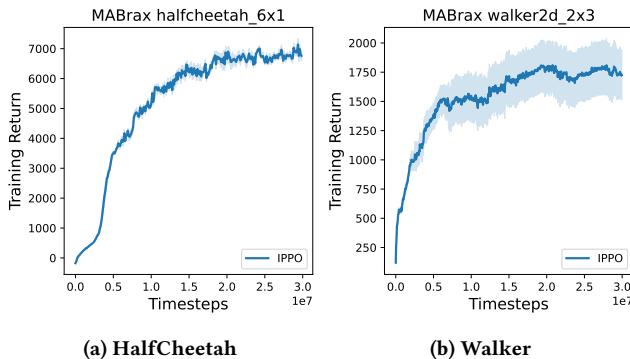


Figure 9: Performance of IPPO on MABrax Tasks

C.2 MPE

Performance of Q -Learning baselines in all the MPE scenarios are reported in Figure 10. The upper row represents cooperative scenarios, with results for all our Q -learning baselines reported. The bottom row refers to competitive scenarios, and results for IQL are divided by agent types. Hyperparameters are given in Table 9

C.3 SMAX

The performance of IPPO in SMAX versus MAPPO in SMAC is shown in Figure 11 while the performance of our Q -learning baselines is reported in Figure 12. We do not report them together because their hyperparameters were tuned over a different number of timesteps. Hyperparameters for IPPO and the Q -learning methods are given in Tables 6 and 10 respectively.

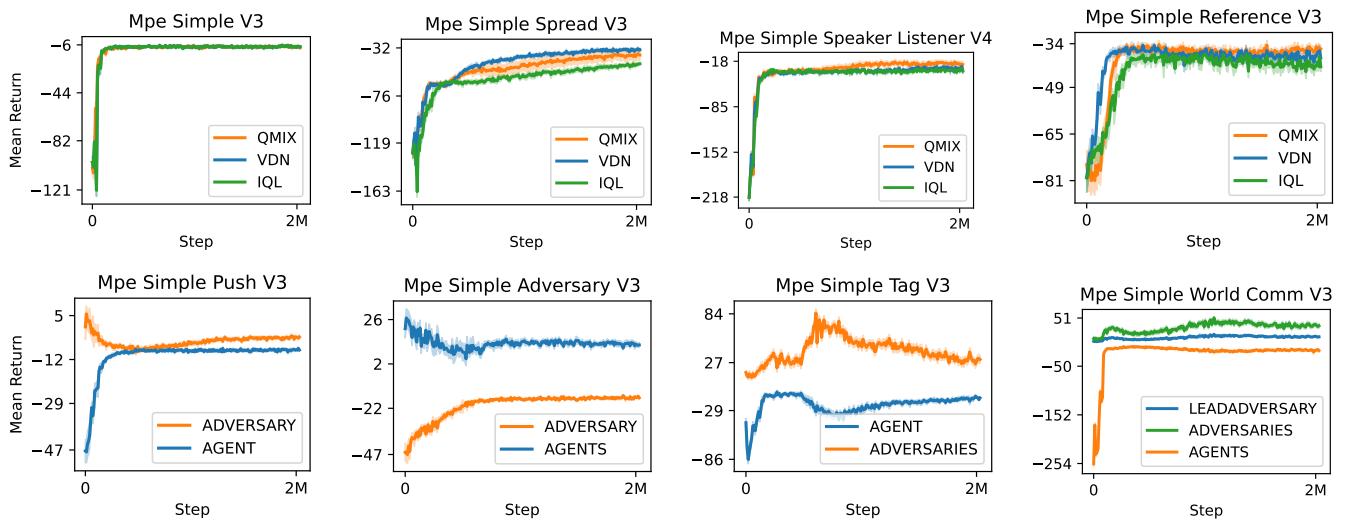


Figure 10: *Q*-Learning Baselines in all MPE scenarios. Where no algorithm names are given, the results represent IQL.

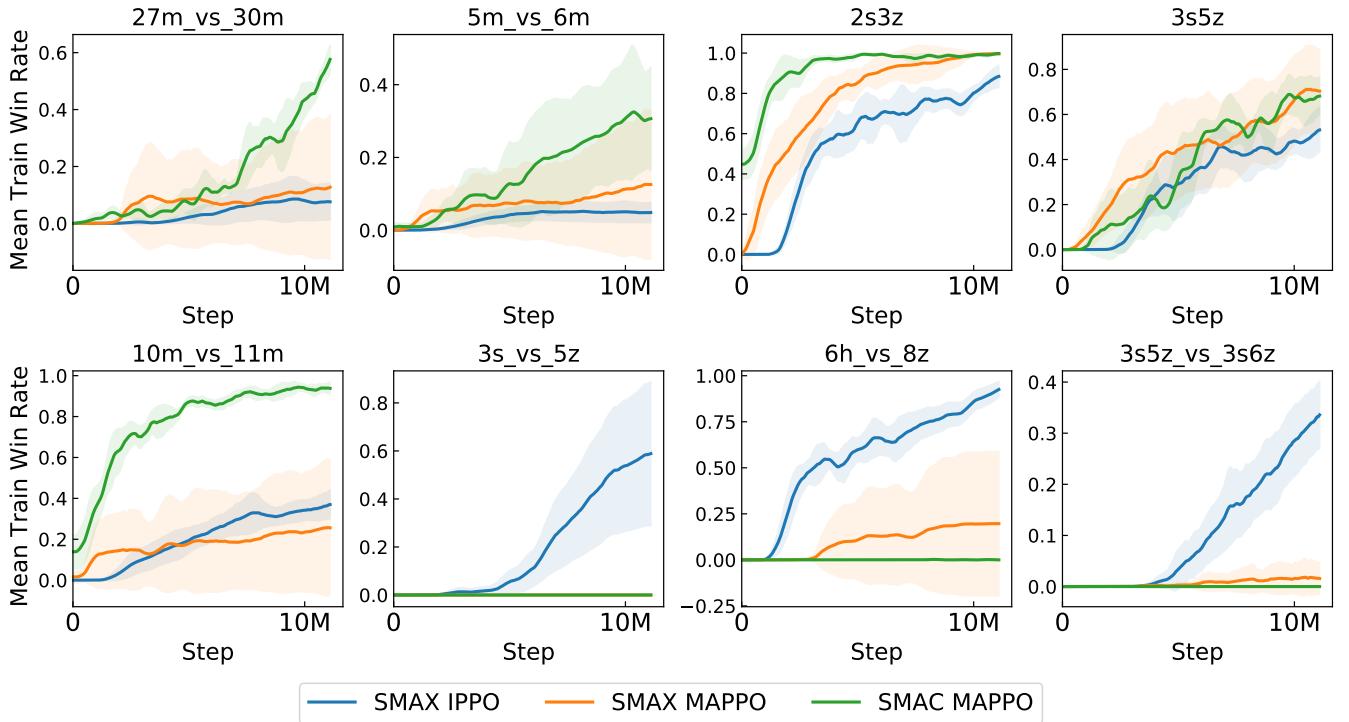


Figure 11: IPPO and MAPPO in SMAX versus MAPPO in SMAC for all SMAC maps.

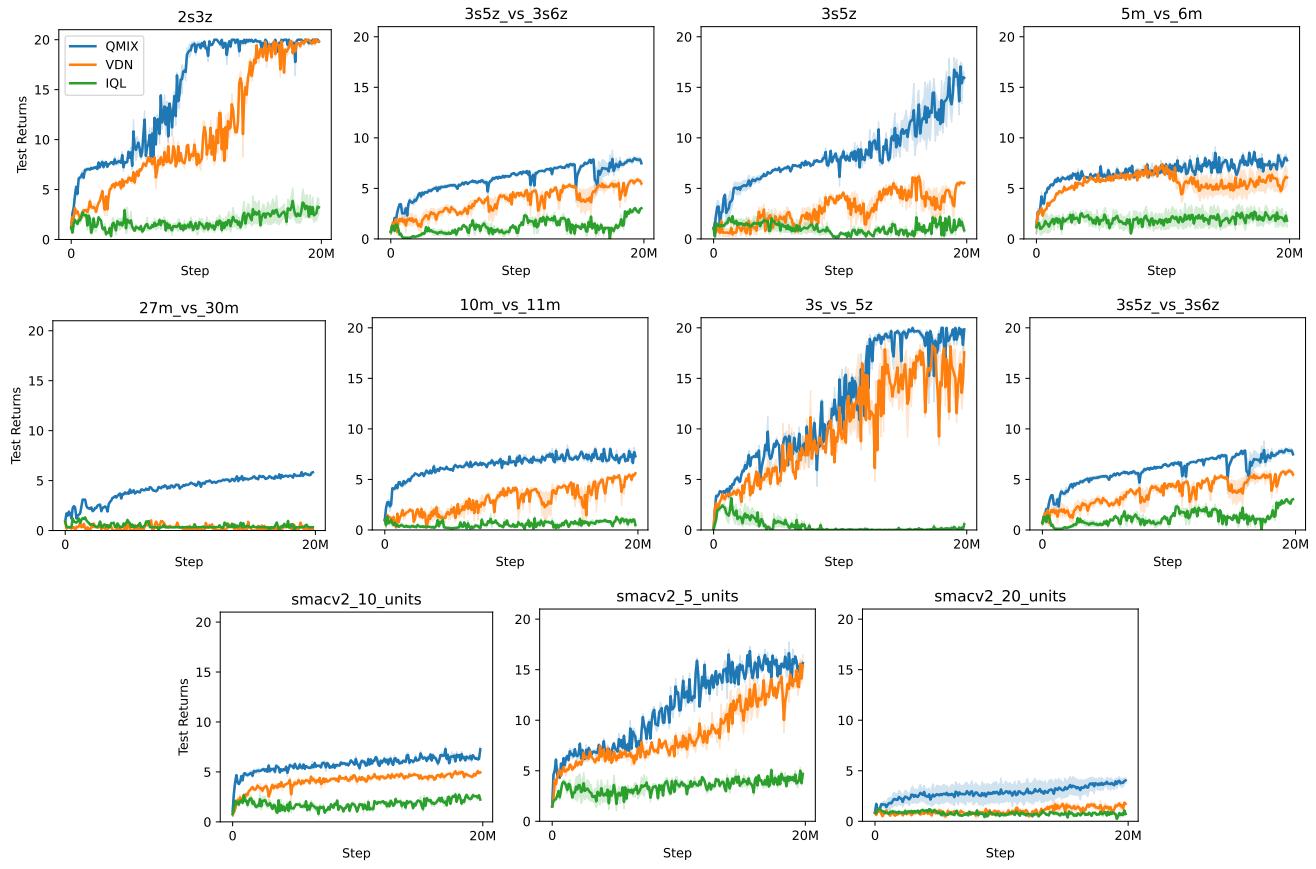


Figure 12: Performance of Q -Learning Baselines for all SMAX scenarios

D HYPERPARAMETERS

Value	Ant	HalfCheetah	Walker
VF_COEF	4.5	0.14	1.9
ENT_COEF	2×10^{-6}	4.5×10^{-3}	1×10^{-3}
LR	1×10^{-3}	6×10^{-4}	7×10^{-3}
NUM_ENVS	64	–	–
NUM_STEPS	300	–	–
TOTAL_TIMESTEPS	1×10^8	–	–
NUM_MINIBATCHES	4	–	–
GAMMA	0.99	–	–
GAE_LAMBDA	1.0	–	–
CLIP_EPS	0.2	–	–
MAX_GRAD_NORM	0.5	–	–
ACTIVATION	tanh	–	–
ANNEAL_LR	True	–	–

Table 4: MABrax Hyperparameters, where – indicates repeated parameters

Hyperparameter	Value
LR	0.0005
NUM_ENVS	25
NUM_STEPS	128
TOTAL_TIMESTEPS	1×10^6
UPDATE_EPOCHS	5
NUM_MINIBATCHES	2
GAMMA	0.99
GAE_LAMBDA	1.0
CLIP_EPS	0.3
ENT_COEF	0.01
VF_COEF	1.0
MAX_GRAD_NORM	0.5
ACTIVATION	tanh
ANNEAL_LR	True

Table 5: Hyperparameters for MPE IPPO

Hyperparameter	Value
LR	0.004
NUM_ENVS	64
NUM_STEPS	128
TOTAL_TIMESTEPS	1×10^7
UPDATE_EPOCHS	2
NUM_MINIBATCHES	2
GAMMA	0.99
GAE_LAMBDA	0.95
CLIP_EPS	0.2
SCALE_CLIP_EPS	False
ENT_COEF	0.0
VF_COEF	0.5
MAX_GRAD_NORM	0.5
ACTIVATION	relu

Table 6: Hyperparameters for SMAX IPPO

Hyperparameter	Value
LR	5×10^{-4}
NUM_ENVS	1024
NUM_STEPS	128
TOTAL_TIMESTEPS	1×10^{10}
UPDATE_EPOCHS	4
NUM_MINIBATCHES	4
GAMMA	0.99
GAE_LAMBDA	0.95
CLIP_EPS	0.2
ENT_COEF	0.01
VF_COEF	0.5
MAX_GRAD_NORM	0.5
ACTIVATION	relu
ANNEAL_LR	True
NUM_FC_LAYERS	2
LAYER_WIDTH	512

Table 7: Hyperparameters for Hanabi IPPO

Hyperparameter	Value
LR	2.5×10^{-4}
NUM_ENVS	16
NUM_STEPS	128
TOTAL_TIMESTEPS	5×10^6
UPDATE_EPOCHS	4
NUM_MINIBATCHES	4
GAMMA	0.99
GAE_LAMBDA	0.95
CLIP_EPS	0.2
ENT_COEF	0.01
VF_COEF	0.5
MAX_GRAD_NORM	0.5
ACTIVATION	tanh
ANNEAL_LR	True
NUM_EVALS	16

Table 8: Hyperparameters for Overcooked IPPO

Hyperparameter	Value
NUM_ENVS	8
NUM_STEPS	25
BUFFER_SIZE	5000
BUFFER_BATCH_SIZE	32
TOTAL_TIMESTEPS	2×10^6
AGENT_HIDDEN_DIM	64
AGENT_INIT_SCALE	2.0
EPSILON_START	1.0
EPSILON_FINISH	0.05
EPSILON_ANNEAL_TIME	100000
MIXER_EMBEDDING_DIM*	32
MIXER_HYPERNET_HIDDEN_DIM*	64
MIXER_INIT_SCALE*	0.00001
MAX_GRAD_NORM	25
TARGET_UPDATE_INTERVAL	200
LR	0.005
EPS_ADAM	0.001
WEIGHT_DECAY_ADAM	0.00001
GAMMA	0.9
NUM_TEST_EPISODES	32
TEST_INTERVAL	50000

Table 9: Hyperparameters for MPE Q-Learning Algorithms Table 10: Hyperparameters for SMAX Q-Learning Algorithms

(* Parameters specific to QMix.)

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