High Performance Simulation for Scalable Multi-Agent Reinforcement Learning

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Abstract

Multi-agent reinforcement learning experiments and open-source training environments are typically limited in scale, supporting tens or sometimes up to hundreds of interacting agents. In this paper we demonstrate the use of Vogue, a high performance agent based model (ABM) framework. Vogue serves as a multi-agent training environment, supporting thousands to tens of thousands of interacting agents while maintaining high training throughput by running both the environment and reinforcement learning (RL) agents on the GPU. High performance multi-agent environments at this scale have the potential to enable the learning of robust and flexible policies for use in ABMs and simulations of complex systems. We demonstrate training performance with two newly developed, large scale multi-agent training environments. Moreover, we show that these environments can train shared RL policies on time-scales of minutes and hours.

1. Introduction

Increases in computational power and available data have led to an increase in the potential scale and fidelity of computer simulations such as agent based models (ABMs). In tandem, a desire has developed for complex agent behaviour which cannot be addressed solely by the often error-prone and challenging process of manually designing and implementing agent behaviours that are both flexible and robust to extreme states of the simulation.

In the context of agent-based models, multi-agent reinforcement learning (MARL) is a means of learning agent behaviours where the reward function is well known but the simulation has a complex state space. This motivates the development of fast and large-scale training environments, enabling the use of MARL to learn behaviours reflecting emergent systems such as crowds, flocks, social networks or markets.

2. High Performance MARL with Vogue

2.1. Vogue: An Agent-Based Modelling Framework

Vogue is a commercial Python framework for high performance ABMs. It is motivated by some key design principles:

- **Usability:** Vogue allows users to write ABM logic in native, idiomatic Python, as shown in code snippet 1.
This is then compiled by Vogue into high performance bytecode, and can be run in a standard Python process.

- **High Performance Execution**: Vogue maps model logic over agents using high performance, vectorised update patterns. This is efficient and obviates the need for modellers to consider the computational complexity and low-level implementation details of ABMs.

- **Composition**: Vogue model logic is described in small pieces of functionality following standard patterns. This allows modellers to easily combine and reuse model logic, and standardises how models are written.

- **Interoperability**: Vogue interacts seamlessly with the broader Python data science and machine learning (ML) ecosystem. This allows Vogue models to be easily employed in ML and data science pipelines.

These design choices allow users to quickly implement high performance ABMs without the need to write low-level code, as shown in code snippet 1. In comparison to other numerical Python compilation libraries such as JAX (Bradbury et al., 2018) or Numba (Lam et al., 2015), Vogue specifically implements common patterns encountered in ABMs, in particular interactions between spatially embedded agents (based on spatial proximity), and agents interacting via edges on a graph or network. These base interactions can then be combined into more complex model logic, including interactions between heterogeneous agent types.

Vogue is currently limited to models that update in discrete time-steps. It is designed such that individual interactions update agents simultaneously, in particular the GPU engine applies interactions to entities in parallel.

### 2.2. End-to-end GPU-based Reinforcement Learning

As well as allowing users to efficiently implement models, a major advantage of Vogue is that models can be executed completely on the GPU with minimal changes to the underlying code, leveraging the high degree of parallelism afforded by the GPU to efficiently update the state of the model. Vogue’s implementation allows data to be shared between Vogue and other ML and deep-learning libraries without copying (or transfer via the host) via the CUDA array interface. This means Vogue can interact directly with any ML framework that implements the CUDA array interface, including popular ML tools like PyTorch (Paszke et al., 2019) and JAX (Bradbury et al., 2018), or GPU based data tools like RAPIDS (Team, 2018). This allows the execution of both the Vogue training environment/simulation and the deep reinforcement learning (RL) agent on the GPU, removing the overhead of moving data to and from the GPU during training.

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```python
def update_opinion(  
    params: Params, person: Person  
) -> None:  
    person.opinion = person.new_opinion

@vogue.interaction.graph()
def social_influence(  
    params: Params, me: Person, you: Person,  
    edge: Friendship,  
) -> None:  
    d = abs(me.opinion - you.opinion)
    if d < params.threshold:
        w = params.strength * edge.weight
        me.new_opinion = (  
            (1.0 - w) * me.new_opinion +  
            w * you.opinion  
        )
```

Code Snippet 1. A Vogue implementation of a simple opinion dynamics model. The model is implemented as two interactions. A self interaction that updates the current opinion of entities, and a graph interaction that updates an entities opinion based on its neighbours opinions. Model logic in Vogue is expressed as interactions between pairs of agents, or updates of individual agents. The compilation of these interactions and execution of the model is handled by the Vogue engine.

### 3. Background

MARL has found a wide range of applications including distributed autonomous systems, socioeconomic and game theoretic problems (Busoniu et al., 2008). The number of learning agents in these systems typically ranges from single-digit to hundreds of interacting agents.

A major obstacle to applying MARL to systems with larger numbers of interacting agents is the lack of high performance simulation environments, as well as the technical challenges and cost associated with their development. Training environments are often implemented for execution on the CPU with the deep RL agent running on the GPU. However, the communication of data from the simulation on the host to the agent on the GPU can have a significant performance impact.

OpenAI Gym (Brockman et al., 2016) has become a de facto standard API for RL research, allowing training environments and RL agent implementations to be easily combined, though it does not have a standard API for multi-agent training. There are a number of open-source MARL envi-
Warpdrive (Lan et al., 2021) offers a framework for end-to-end MARL on GPU. It demonstrates high throughput, though is only tested (in Lan et al., 2021) on a maximum of 1,000 agents (executed across 2,000 environments simultaneously). Its end-to-end solution contrasts Vogue’s focus on ease of writing high performance models, and interoperability with existing Python tools. NVidia’s Issac Gym (Makoviychuk et al., 2021) takes a similar approach, sharing data between simulation and RL agent on the GPU directly. Their focus is on physics simulations for robotics, where Vogue is focused on ABM use cases, and ease of implementing and combining ABMs.

There are a number of ABM frameworks, sharing the broad aim of allowing users to more easily implement ABMs, or provide performance gains. Mesa (Kazil et al., 2020) is a popular Python ABM framework, though its performance is restricted by Python’s native performance. Netlogo (Wilensky, 1999) is instead implemented in Java, though this limits its interoperability with Python and requires users to implement models in Netlogo’s scripting language. A comparison of the performance of these libraries for a basic implementation of boids (with hard-coded behaviours) is shown in Figure 2. Both the CPU and GPU version of Vogue are several orders of magnitude faster than Mesa and NetLogo. The GPU engine demonstrates improved scaling over the CPU engine with increasing number of agents. Few frameworks support GPU execution; Flame (Richmond et al., 2021) is a notable example, implemented in C++ with an optional Python interface.

4. Training Environments

At the time of writing, we could not locate any documented training environments at the scale of 1,000+ interacting agents. Instead, we provide two simple examples by implementing extended versions of two popular models: flocking and tug. We note that extending the range and complexity of example environments is a priority for future work.

In both examples, to address the increased overall size of the simulation state space, the agents only observe their local neighbourhood of the simulation via a simple ray casting algorithm that divides an agent’s field of view into a fixed number, \( v \), of sectors. Internally, their view is represented by an array of \( v \) values representing the distance to the nearest object at that angle, as shown in Figure 3(a). An example time series showing an agent’s view during a training step is shown in Figure 3(b). This local view forms part of the training environment observation space, local to each agent in the environment.

4.1. Flocking

This training environment is based on Reynolds’ Boids model (Reynolds, 1987), designed to mimic natural flocks and shoals. The training environment consists of a flock of agents navigating a 2d space, with no hard-coded navigation rules. Previous studies have looked at emergence of flocking from reinforcement learning (for example Durve et al., 2020; Shimada & Bentley, 2018) but in this work we aim to examine the feasibility of efficiently training flocking behaviours for 1,000-10,000+ interacting agents. A snapshot of a simulation state is shown in Figure 1.

The observation space of the environment (for an individual agent) is a 129 length vector containing the agent’s view, with \( v = 128 \) sectors, and the agent’s current speed. The action space is two dimensional. One dimension accelerates/decelerates the agent, in the range \([-\theta_{\text{max}}, \theta_{\text{max}}]\), updating the speed of the agent as \( s_{t+1} = \min(s_{\text{min}}, \max(s_t + a_t, s_{\text{max}})) \). The second dimension in the range \([-\theta_{\text{max}}, \theta_{\text{max}}]\)
4.2. Tag

This environment is based on Petting Zoo’s (in Terry et al., 2020) simple tag environment. It contains two agent types: runners and chasers. Chasers are rewarded for touching runners, and runners are rewarded for staying close to other runners, and penalised for touching a chaser. The view model of the agent has two simulated colour channels allowing agents to distinguish between neighbouring runners or chasers. The corresponding observation space is a 128 length vector, concatenating the two $v = 64$ colour channels. The two dimensional action space rotates the agent’s heading, in the range $[-\theta_{\text{max}}, \theta_{\text{max}}]$ and moves them along the heading, in the range $[0, s_{\text{max}}]$ where $s_{\text{max}}$ is the maximum speed of the agents.

4.3. Training

For both environments we used proximal policy optimisation (PPO) (Schulman et al., 2017) for a continuous action space, with the simulated agents sharing a single policy. In the tag environment, the runner and chaser types share independent policies, trained simultaneously. Instead of multiple parallel environments, we treat each individual agent as an independent learner, and gather trajectories across the full set of agents. If we have $n$ agents and run $t$ updates of the simulation each training step, we sample a total of $n \times t$ trajectories per training step. Vogue updates the state of the ABM in response to the actions sampled from the PPO policy, then copies the updated observations and rewards to the JAX experience buffer, as shown in Figure 5.
5. Performance Results

Benchmarking was performed on an Nvidia A100 GPU. Each full training run includes $T = 200$ training steps. Inside each training step the environment was updated for $t = 128$ steps, generating $m = n \times t$ individual trajectories. The policy was then updated for $p = 2$ epochs, across $b$ mini-batches sampled from the trajectories. The number of trajectories scales with the number of simulated agents, so the number of mini-batches is capped as $b = \min(m/|b|, b_{\text{max}})$ where $b_{\text{max}} = 512$ is the maximum number of batches, and $|b| = 512$ is the chosen mini-batch size. This means for the highest number of entities each training run performs $T \times p \times b = 204,800$ mini-batch updates of the PPO policy, and $T \times t = 25,600$ updates of the environment. The agents have a view distance equivalent to 1/10th of the width of the environment and a convex field of vision of approximately $250^\circ$. The RL agent update, and trajectory processing algorithms were implemented in JAX. The actor and critic PPO networks had two hidden layers with 64 nodes each, with a total of 1035 trainable parameters.

It should also be noted that performance of the simulation can be highly dependent on the parameters of the simulation. For example the view distance of the agents and their vision angle impact the number of interactions between agents that must be processed.

17,600 agents (16,000 runners and 1,600 chasers) training takes around 12 minutes. The tag environment demonstrates roughly linear growth in training time with number of agents, we speculate because of the added complexity of multiple interactions between different agent types.

6. Conclusion

We have demonstrated that joining forward simulation and training of MARL systems into a single end-to-end RL process can lead to drastic improvements in performance. Using the commercial software Vogue, high performance ABMs can be executed directly on the GPU, while the high level of interoperability enables direct communication between Vogue and many Python based RL or deep learning frameworks. Vogue is currently available for academic research – please contact the authors.

References

Brockman, G., Cheung, V., Pettersson, L., Schneider, J., Schulman, J., Tang, J., and Zaremba, W. OpenAI gym, 2016.

Busoniu, L., Babuska, R., and De Schutter, B. A comprehensive survey of multiagent reinforcement learning. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, 38:156 – 172, 04 2008. doi: 10.1109/TSMCC.2007.913919.

Durve, M., Peruani, F., and Celani, A. Learning to flock through reinforcement. *Physical Review E*, 102(1), jul 2020. doi: 10.1103/physreve.102.012601. URL https://doi.org/10.1103%2Fphysreve.102.012601.

Kazil, J., Masad, D., and Crooks, A. Utilizing python for agent-based modeling: The mesa framework. In Thompson, R., Bisgin, H., Dancy, C., Hyder, A., and Hussain, M. (eds.), *Social, Cultural, and Behavioral Modeling*, pp. 308–317, Cham, 2020. Springer International Publishing. ISBN 978-3-030-61255-9.

Lam, S. K., Pitrou, A., and Seibert, S. Numba: A llvm-based python jit compiler. In *Proceedings of the Second Workshop on the LLVM Compiler Infrastructure in HPC*, pp. 1–6, 2015.

Lan, T., Srinivasa, S., and Zheng, S. Warpdrive: Extremely fast end-to-end deep multi-agent reinforcement learning
on a GPU. CoRR, abs/2108.13976, 2021. URL https://arxiv.org/abs/2108.13976.

Liang, E., Liaw, R., Nishihara, R., Moritz, P., Fox, R., Gonzalez, J., Goldberg, K., and Stoica, I. Ray rllib: A composable and scalable reinforcement learning library. CoRR, abs/1712.09381, 2017. URL http://arxiv.org/abs/1712.09381.

Makoviychuk, V., Wawrzyniak, L., Guo, Y., Lu, M., Storey, K., Macklin, M., Hoeller, D., Rudin, N., Allshire, A., Handa, A., and State, G. Isaac gym: High performance gpu-based physics simulation for robot learning, 2021.

Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., Desmaison, A., Kopf, A., Yang, E., DeVito, Z., Raison, M., Tejani, A., Chilamkurthy, S., Steiner, B., Fang, L., Bai, J., and Chintala, S. Pytorch: An imperative style, high-performance deep learning library. In Advances in Neural Information Processing Systems 32, pp. 8024–8035. Curran Associates, Inc., 2019. URL http://papers.neurips.cc/paper/9015-pytorch-an-imperative-style-high-performance-deep-learning-library.pdf.

Reynolds, C. W. Flocks, herds and schools: A distributed behavioral model. In Proceedings of the 14th Annual Conference on Computer Graphics and Interactive Techniques, SIGGRAPH ’87, pp. 25–34, New York, NY, USA, 1987. Association for Computing Machinery. ISBN 0897912276. doi: 10.1145/37401.37406. URL https://doi.org/10.1145/37401.37406.

Richmond, P., Chisholm, R., Heywood, P., Leach, M., and Kabiri Chimeh, M. Flame gpu, December 2021. URL https://doi.org/10.5281/zenodo.5769677.

Schulman, J., Wolski, F., Dhariwal, P., Radford, A., and Klimov, O. Proximal policy optimization algorithms. CoRR, abs/1707.06347, 2017. URL http://arxiv.org/abs/1707.06347.

Shimada, K. and Bentley, P. J. Learning how to flock: deriving individual behaviour from collective behaviour with multi-agent reinforcement learning and natural evolution strategies. Proceedings of the Genetic and Evolutionary Computation Conference Companion, 2018.

Team, R. D. RAPIDS: Collection of Libraries for End to End GPU Data Science, 2018. URL https://rapi ds.ai.

Terry, J. K., Black, B., Grammel, N., Jayakumar, M., Hari, A., Sullivan, R., Santos, L., Perez, R., Horsch, C., Dief fendale, C., Williams, N. L., Lokesh, Y., Sullivan, R., and Ravi, P. Pettingzoo: Gym for multi-agent reinforcement learning. arXiv preprint arXiv:2009.14471, 2020.

Wilensky, U. Netlogo. http://ccl.northwestern.edu/netlogo/, Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL, 1999. URL http://ccl.northwestern.edu/netlogo/.