Lyceum: An efficient and scalable ecosystem for robot learning

Colin Summers¹, Kendall Lowrey¹, Aravind Rajeswaran¹
Siddhartha Srinivasa¹, Emanuel Todorov¹,²

{colinxs, klowrey, aravraj, siddh, todorov}@cs.uw.edu
¹ University of Washington Seattle, ² Roboti LLC

Abstract

We introduce Lyceum, a high-performance computational ecosystem for robot learning. Lyceum is built on top of the Julia programming language and the MuJoCo physics simulator, combining the ease-of-use of a high-level programming language with the performance of native C. In addition, Lyceum has a straightforward API to support parallel computation across multiple cores and machines. Overall, depending on the complexity of the environment, Lyceum is 5-30X faster compared to other popular abstractions like OpenAI’s Gym and DeepMind’s dm-control. This substantially reduces training time for various reinforcement learning algorithms; and is also fast enough to support real-time model predictive control through MuJoCo. The code, tutorials, and demonstration videos can be found at: www.lyceum.ml.

1. Introduction

Progress in artificial intelligence has exploded in recent years, due in large part to advances computational infrastructure. The advent of massively parallel GPU computing, combined with powerful automatic-differentiation tools like TensorFlow (Abadi et al., 2016) and PyTorch (Paszke et al., 2017), have lead to new classes of deep learning algorithms by enabling what was once computationally intractable. These tools, alongside fast and accurate physics simulators like MuJoCo (Todorov et al., 2012), and associated frameworks like OpenAI’s Gym (Brockman et al., 2016) and DeepMind’s dm_control (Tassa et al., 2018), have similarly transformed various aspects of robotic control like Reinforcement Learning (RL), Model-Predictive Control (MPC), and motion planning. These platforms enable researchers to give their ideas computational form, share results with collaborators, and deploy their successes on real systems.

From these advances, simulation to real-world (sim2real) transfer has emerged as a promising paradigm for robotic control. A growing body of recent work suggests that robust control policies trained in simulation can successfully transfer to the real world (OpenAI, 2018; Rajeswaran et al., 2016; Sadeghi and Levine, 2016; Lowrey et al., 2018a; Tobin et al., 2017; Mordatch et al., 2015). However, many algorithms used in these works for controller synthesis are computationally intensive. Training control policies with state-of-the-art RL algorithms often takes many hours to days of compute time. For example, OpenAI’s landmark Dactyl work (OpenAI, 2018) required 50 hours of training time across 6144 CPU cores and 8 NVIDIA V100 GPUs. Such computational budgets are available only to a select few labs. Furthermore, such experiments are seldom run only once in deep learning and especially in deep RL. Indeed, RL algorithms are notoriously sensitive to choices of hyper-parameters (Rajeswaran et al., 2017; Henderson et al., 2017; Mania et al., 2018). Thus, many iterations of the learning process may be required, with humans in the loop, to improve hyperparameter choices and reward functions, before finally deploying solutions in the real world.
This computational bottleneck often leads to a scarcity of hardware results, relative to the number of papers that propose new algorithms on highly simplified and well tuned benchmark tasks. Exploring avenues to reduce experiment turn around time is thus crucial for scaling up to harder tasks and making resource-intensive algorithms and environments accessible to research labs without massive cloud computing budgets.

In a similar vein, computational considerations have also limited progress in model-based control algorithms. For real-time model predictive control (MPC), the computational restrictions manifest as the requirement to compute actions in bounded time with limited local resources. As we will show, existing frameworks such as Gym and dm_control, while providing a convenient abstraction in Python, are too slow to meet this real-time computation requirement. As a result, most planning algorithms are run offline and deployed in open-loop mode on hardware. This is unfortunate, since it does not take feedback into account which is well known to be critical for stochastic control.

**Our Contributions:** Our goal in this work is to overcome the aforementioned computational restrictions to enable faster training of policies with RL algorithms, facilitate real-time MPC with a detailed physics simulator, and ultimately enable researchers to engage with complex robotic tasks. To this end, we develop Lyceum, a computational ecosystem that uses the Julia programming language and the MuJoCo physics engine. Lyceum ships with the main OpenAI gym continuous control tasks, along with other environments representative of challenges in robotics. Julia’s unique features allow us to wrap MuJoCo with zero-cost abstractions, providing the flexibility of a high-level programming language to enable easy creation of environments, tasks, and algorithms, while retaining the performance of native C. This allows RL and MPC algorithms implemented in Lyceum to be 5-30X faster compared to Gym and dm_control. We hope that this speedup will enable RL researchers to scale up to harder problems with reduced computational costs, and also enable real-time MPC.

2. Related Works

Recently, various physics simulators and the computational ecosystems surrounding them have transformed robot learning research. They allow for exercising creativity to quickly generate new and interesting robotic scenes, as well as quickly prototype various learning and control solutions. We summarize the main threads of related work below.

**Physics simulators:** MuJoCo (Todorov et al., 2012) has quickly emerged as a leading physics simulator for robot learning research. It is fast and efficient, and particularly well suited for contact-rich tasks. Numerous recent works have also demonstrated simulation to reality transfer with MuJoCo through physically consistent system identification (Lowrey et al., 2018a) or domain randomization (OpenAI, 2018; Mordatch et al., 2015; Nachum et al., 2019). Our framework wraps MuJoCo in Julia and enables programming and research with a high level language, while retaining the speed of native C. While we primarily focus on MuJoCo, we believe that similar design principles can be extended to other simulators like Bullet (Coumans, 2013) and DART (Lee et al., 2018).

**Computational ecosystems:** OpenAI’s gym (Brockman et al., 2016) and DeepMind’s dm_control (Tassa et al., 2018) sparked a wave of interest by providing Python bindings for MuJoCo with a high-level API, as well as easy-to-use environments and algorithms. This has enabled the RL community to quickly access physics-based environments and prototype algorithms. Unfortunately, this flexibility comes at the price of computational efficiency. Existing ecosystems are slow due to inefficiencies and poor parallelization capabilities of Python. Prior works have tried to address
some of the shortcomings of Python-based frameworks by attempting to add JIT compilation to the language (Lam et al., 2015; Paszke et al., 2017; Agrawal et al., 2019) but only support a subset of the language, and do not achieve the same performance as Julia. Fan et al. (2018) developed a framework similar to Gym that supports distributed computing, but it still suffers the same performance issues of Python and multi-processing. Perhaps closest to our motivation is the work of Koolen and Deits (2019), which demonstrates the usefulness of Julia as a language for robotics. However, it uses a custom and minimalist rigid body simulator with limited contact support. In contrast, our work addresses the inefficiencies of existing computational ecosystems through use of Julia, and directly wraps a more capable simulator, MuJoCo, with zero overhead.

**Algorithmic toolkits and environments:** A number of algorithmic toolkits like OpenAI Baselines (Dhariwal et al., 2017), mjRL (Rajeswaran et al., 2017), Soft-Learning (Haarnoja et al., 2018), and RL-lab (Duan et al., 2016); as well as environments like Hand Manipulation Suite (Rajeswaran et al., 2018), Robel (Ahn et al., 2019), Door Gym (Urakami et al., 2019), and Surreal Robosuite (Fan et al., 2018) have been developed around existing computational ecosystems. Our framework supports all the underlying functionality needed to transfer these advances into our ecosystem (e.g. simulator wrappers and automatic differentiation through Flux). Lyceum comes with a few popular algorithms out of the box like NPG (Kakade, 2002; Rajeswaran et al., 2017) for RL and variants of MPPI (Lowrey et al., 2018b; Williams et al., 2016) for MPC. In the future, we plan to port further algorithms and advances into our ecosystem and look forward to community contributions as well.

### 3. The Lyceum ecosystem

The computational considerations are unique for designing infrastructure and ecosystems for robotic control with RL and MPC. We desire a computational ecosystem that is high-level and easy to use for research, can efficiently handle parallel operations, while ideally also matching serial operation speed of native C to be usable on robots. We found Julia to be well suited for these requirements, and we summarize some of these main advantages that prompted us to use Julia. Subsequently, we outline some salient features of Lyceum.

#### 3.1. Julia for robotics and RL

Julia is a general-purpose programming language developed in 2012 at MIT with a focus on technical computing (Bezanson et al., 2017). While a full description of Julia is beyond the scope of this paper, we highlight a few key aspects that we leverage in Lyceum and believe make Julia an excellent tool for robotics and RL researchers.

**Just-in-time compilation** Julia feels like a dynamic, interpreted scripting language, enabling an interactive programming experience. Under the hood, however, Julia leverages the LLVM backend to "just-in-time" (JIT) compile native machine code that is as fast as C for a variety of hardware platforms (Bezanson et al., 2017). This enables researchers to quickly prototype ideas and optimize for performance with the same language.

**Julia can easily call functions in Python and C** In addition to the current ecosystem of Julia packages, users can interact with Python and C as illustrated below. This allows researchers to benefit from existing body of deep learning research (in Python), and also interact easily with low-level robot hardware drivers.
using PyCall
so = pyimport("scipy.optimize")
so.newton(x -> cos(x) - x, 1)
ccall((:mjr_getError,libmujoco),Cint,())

**Easy parallelization** Julia comes with extensive support for distributed and shared-memory multi-threading that allows users to trivially parallelize their code. The following example splits the indices of \( X \) across all the available cores and performs in-place multiplication in parallel:

```julia
@threads for i in eachindex(X)
    X[i] *= 2
end
```

Julia can also transpile to alternative hardware backends, allowing use of parallel processors like GPUs by writing high level Julia code.

**Simple package management** To handle the 3000+ packages available, Julia comes with a built-in package manager, avoiding "dependency hell", and facilitating collaboration and replication. This means less time is spent getting things to run and more time for focusing on the task at hand.

### 3.2. Salient Features of **Lyceum**

Lyceum consists of the following packages

1. **LyceumBase.jl**: A "base" package which defines a set of abstract environment and controller interfaces, along with several utilities.
2. **MuJoCo.jl**: A low-level Julia wrapper for the MuJoCo physics simulator.
3. **LyceumMuJoCo.jl**: A high-level "environment" abstraction similar to Gym and dm_control.
4. **LyceumMuJoCoViz.jl**: A flexible policy and trajectory visualizer with interaction.
5. **LyceumAI.jl**: A collection of various algorithms for robotic control.

**LyceumBase.jl** At the highest level we provide **LyceumBase.jl**, which contains several convenience utilities used throughout the Lyceum ecosystem for data logging, multi-threading, and controller benchmarking (i.e. measuring throughput, jitter, etc.). **LyceumBase.jl** also contains interface definitions, such as **AbstractEnvironment** which **LyceumMuJoCo.jl** implements. See the appendix for the full **AbstractEnvironment** interface.

This interface is similar to the popular Python frameworks Gym and dm_control, where an agent’s observations are defined, actions are chosen, and the simulator can step. A few key differences are as follows:

1. The ability to arbitrarily get/set the state of the simulator, a necessary feature for model-based methods like MPC or motion planning. An important component of this is defining a proper notion of a state, which is often missing from existing frameworks, as it can include more than just the position and velocities of the dynamics.
2. Optional, in-place versions for all functions (e.g. `getstate!(:·)`) which store the return value in a pre-allocated data structure. This eliminates unnecessary memory allocations and garbage collection, enabling environments to be used in tight, real-time control loops.
3. An optional "evaluation" metric. Often times reward functions are heavily "shaped" and hard to interpret. For example, the reward function for bipedal walking may include root pose, ZMP terms, control costs, etc., while success can instead be simply evaluated by distance of the root along an axis.

We expect most users will be interested in implementing their own environments, which forms a crucial part of robotics research. Indeed, different researchers may be interested in different robots performing different tasks, ranging from whole arm manipulators to legged locomotion to dexterous anthropomorphic hands. To aid this process, we provide sensible defaults for most of the API, making it easy to get started and experiment with different environments. The separation of interface and implementation also allows for other simulators and back-ends (e.g. RigidBodySim.jl or DART) to be used in lieu of the MuJoCo-based environments we provide, should the user desire.

_MuJoCo.jl, LyceumMuJoCo.jl, and LyceumMuJoCoViz.jl_ MuJoCo.jl is a low-level Julia wrapper for MuJoCo that has a one-to-one correspondence to MuJoCo 2.0’s C interface and includes soft body dynamics. All data is memory mapped with no overhead, and named fields in a MuJoCo.xml file are exposed to the data structures, enabling field access as `d.qpos[:, :arm]`. We then build LyceumMuJoCo.jl, the MuJoCo implementation of our AbstractEnvironment API, on top of MuJoCo.jl. This is the construction of an environment based in MuJoCo, and allows the user to configure tasks rewards and programatically modify dynamics before passing the structure to algorithms for processing. Finally the LyceumMuJoCoViz.jl package visualizes the results of MuJoCo based models. Data is passed in as a list of trajectories for viewing or control function; a trained policy or MPC controller, for example, can be passed to the visualizer, which has hooks for keyboard and mouse interaction. Robots in the real world encounter perturbations and disturbances, and with LyceumMuJoCoViz.jl the user can interact with the simulated environment to test the robustness of a controller.

_LyceumAI.jl_ Coupled with these environments is LyceumAI.jl, a collection of algorithms for robotic control that similarly leverage Julia’s performance and multi-threading abilities. Currently we provide implementations of "Model Predictive Path Integral Control" (MPPI), a stochastic shooting method for model-predictive control and Natural Policy Gradient. We compare these methods with a Python implementation in the next sections. Both of these methods benefit from multi-threaded rollouts, either with respect to controls or a policy, which can be performed in parallel. Neural networks and automatic differentiation for objects like control policies or fitted value functions are handled by Flux.jl and Zygote.jl (Innes et al., 2018; Innes, 2018), which are also Julia based. The combination of efficient compute utilization, flexible high level programming, and an ecosystem of tools should allow both robotics and RL researchers to experiment with different robotic systems, algorithm design, and hopefully deploy to real systems.

4. Benchmark Experiments and Results

We designed our experiments and timing benchmarks to answer the following questions: (a) Do the implementations of Gym RL environments and algorithms in Lyceum produce comparable results? (b) Does Lyceum lead to faster environment sampling and experiment turn-around time when compared to Gym and dm_control?
**Experiment Setup** All experiments are performed on a 16-core Intel i9-7960X with the CPU governor pinned at 1.2GHz so as to prevent dynamic scaling or thermal throttling from affecting results. As Gym and dm_control do not come with built-in support for parallel computing, the authors implement this functionality using Python’s `multiprocessing` library as recommended in several GitHub Issues by the respective library authors. Below we describe the various benchmarks we considered and their results.

**Sampling Throughput** In the first benchmark, we study the sampling throughput and parallel scaling performance of LyceumMuJoCo.jl against Gym, dm_control, and a native C implementation using an OpenMP thread pool. To do so, we consider various models of increasing complexity: CartPole, Ant, HERB, and Humanoid. In the first experiment, we use all 16 of the available cores to measure the number of samples we can collect per second. Figure 1 (left) shows the results, which are presented in two forms: as a fraction of native C’s throughput, and as samples per second. We see that Lyceum and native C significantly outperform Gym and dm_control in all cases. In particular, for CartPole, Lyceum is more than 200x faster compared to Gym.

In the second experiment, we study how the sampling performance scales with the number of cores for the various implementations. To do so, we consider the Humanoid model and measure the number of samples that can be generated per second with varying number of cores. The results are presented in Figure 1 (right), where we see substantial gains for Lyceum. In particular, the scaling is near linear with the number of cores for C and Lyceum, while there are diminishing returns for Gym and dm_control. This is due to inherent multi-threading limitations of (pure) Python. When using more cores (e.g. on a cluster), the performance difference is likely to be even larger.

**Reinforcement Learning with Policy Gradients** In the second benchmark, we compare the learning curves and wall clock time of Natural Policy Gradient (Kakade, 2002; Rajeswaran et al.,...
Figure 2: Reinforcement learning with NPG in the Gym and Lyceum frameworks, training for one million time-steps. Top row presents environment reward vs experiment (i.e. wall clock time), and bottom row presents environment reward vs number of simulated timesteps. Performance of the underlying deterministic policy is reported.

2017), which is closely related to TRPO (Schulman et al., 2015), between Gym and Lyceum. Our implementation of NPG, closely based on the algorithm as described in Rajeswaran et al. (2017) and consistent with majority practice in the community, considers 2 layer neural network policies. Details about hyperparameters are provided in the appendix. We compare based on three representative tasks (Swimmer, Hopper, and Walker) and find that the learning curves match across the two frameworks. The results are summarized in Figure 2, and we find that the performance curves match well. We note that RL algorithms are known to be sensitive to many implementation details (Henderson et al., 2017; Ilyas et al., 2018), and thus even approximately matching results is a promising sign for both the original code base and Lyceum. We expect that with further code-level optimization, the performance of RL algorithms in Lyceum can match their counterparts in Gym.

Model Predictive Control In the final benchmark, we compare the performance of a model-based trajectory optimizer on Gym and Lyceum. For this purpose, we consider the Model Predictive Path Integral (MPPI) algorithm (Williams et al., 2016), which in conjunction with learning based techniques have demonstrated impressive results in tasks like aggressive driving and dexterous hand manipulation (Lowrey et al., 2018a; Nagabandi et al., 2019). MPPI is a sampling based algorithm where different candidate action sequences are considered to generate many potential trajectories
Figure 3: (Left) Illustration of the 30-DOF in-hand manipulation task with a Shadow Hand (Adroit). The goal is to manipulate the (blue) pen to match the (green) desired pose. (Middle) Illustration of the reaching task with a 7-DOF Sawyer arm. Goal is to make the end-effector (blue) reach the (green) target. (Right) comparison of time taken and success percentage in gym and Lyceum. Time refers to the time taken to execute a single episode with the MPPI controller (in MPC mode). Success % measures the number of successful episodes when the robot is controlled using the MPPI algorithm. 95% confidence intervals are also reported. See appendix for additional details and hyperparameters.

starting from the current state. Rewards are calculated for each of these trajectories, and the candidate action sequences are combined with exponentially weighted trajectory rewards.

We consider two tasks for the MPPI comparison: a 7-DOF sawyer arm that reaches various spatial goals with the end effector, and a 30-DOF in-hand manipulation task where a Shadow hand (Adroit) (Kumar, 2016) has to perform in-hand manipulation of a pen to match a desired configuration. We compare the times taken by MPPI to optimize a trajectory and also the fraction of times MPPI optimized a successful trajectory. The results are provided in Figure 3. In summary, we find that the MPPI success percentage are comparable in both Gym and Lyceum, and the Lyceum implementation is approx. 30x faster for the Sawyer arm task and 3x faster for the Shadow Hand task. This trend is consistent with the earlier trend, where the relative differences are larger for lower dimensional systems with fewer contacts. This is because for complex models with many contacts like the Shadow Hand, most of the computational work is performed by MuJoCo, thereby diminishing the impact of overheads in Gym. We also note, however, that we found the performance scaling with cores to be better in Lyceum compared to Gym, and thus the difference between the frameworks is likely larger when using more cores (e.g. on a cluster).

5. Conclusion and Future Work

We introduced Lyceum, a new computational ecosystem for robot learning in Julia that provides the rapid prototyping and ease-of-use benefits of a high-level programming language, yet retaining the performance of a low-level language like C. We demonstrated that this ecosystem can obtain substantial speedups compared to existing ecosystems like OpenAI gym and dm_control. We also demonstrated that this speed up enables faster experimental times for RL and MPC algorithms. In the future, we hope to port over algorithmic infrastructures like OpenAI’s baselines (Dhariwal et al., 2017). We also hope to include and support models and environments involving real robots like Cassie, HERB (Srinivasa et al., 2009), ROBEL (Ahn et al., 2019), and Shadow Hand (Kumar, 2016; Rajeswaran et al., 2018; Jain et al., 2019), and also support for fast rendering to enable research integrating perception and control.
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Appendix A. AbstractEnvironment Interface

For a more thorough description of the AbstractEnvironment interface and more, see the documentation at docs.lyceum.ml/dev.

```julia
# Task evaluation metric
geteval(s, a, o, env)
# that can differ from reward
reset!(env)
# Reset to a fixed initial state.
randreset!(env)
# Reset to a random initial state.
step!(env)
# Step the environment.
isdone(env)
# return `true` if `env` terminated early
```

Appendix B. Example MuJoCo Environment

The following is an example of a the OpenAI Gym hopper environment ported to Lyceum. Functions that are not defined from the previous section use the default behaviors of the AbstractEnvironment type.

```julia
import LyceumMujoco: getobs!, randreset!, geteval, step!
struct HopperV2 <: AbstractEnvironment
    # This thread safe data structure
    sim::MJSim
    # stores the simulator and other
    # user-desired values

    function HopperV2()
        new(MJSim("hopper.xml"))
    end
end

function getobs!(o, env::HopperV2) # writes data to pre-allocated o
    nq = env.sim.m.nq
    qpos = env.sim.d.qpos[2:end] # and accessing its fields provides the
    qvel = copy(env.sim.d.qvel) # desired observations
    clamp!(qvel, -10, 10)
end
```
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copyto!(o, vcat(qpos, qvel))
return o
end

function randreset!(env::HopperV2)  # Reset environment to a random state
reset!(env)
dist = Uniform(-0.005, 0.005)  # Uniform sampler, called multiple times
env.sim.d.qpos .+= rand.(dist)  # to fill the qpos, qvel vectors
env.sim.d.qvel .+= rand.(dist)  # '.' notation vectorizes call to `rand`
forward!(env.sim)  # MuJoCo's forward dynamics
return env  # to propagate changes
end

function geteval(s, a, o, env::HopperV2)  # We evaluate distance along x axis
    statespace(env)(s).qpos[1]
end

function getreward(s, a, o, env::HopperV2)
    shapedstate = statespace(env)(s)
    qpos = shapedstate.qpos
    qvel = shapedstate.qvel
    x0 = qpos[1]
    step!(env.sim, a)
    x1, height, ang = qpos[1:3]
    alive_bonus = 1.0
    reward = (x0 - x1) / dt(env)
    reward += alive_bonus
    reward -= 1e-3 * sum(x->x^2, a)  # lambda function squares 'a'
    return reward
end

# # # # # # # # # # # # # # # # # # # # # #
# After creation of the environment we can use it with LyceumAI.
# we first include LyceumAI and other packages.
using LyceumAI, Flux

hop = HopperV2()

dobs, dact = length(obsspace(hop)), length(actionspace(hop))

# A policy and value function are created using helper
# functions built on Flux.jl
policy = DiagGaussianPolicy(
    multilayer_perceptron(dobs, 64, 64, dact),
    ones(dact) .*= -0.5
)

value = multilayer_perceptron(dobs, 128, 128, 1)
valueloss(bl, X, Y) = mse(vec(bl(X)), vec(Y))

# FluxTrainer is thing you can iterate on. The result at each
# loop is passed to stopcb below, so you can quit after
# a number of epochs, convergence, both, or never
valuetrainer = FluxTrainer(
optimiser = ADAM(1e-3),
szbatch = 64,
lossfn = valueloss,
stopcb = s->s.nepochs > 2
)

# The LyceumAI NaturalPolicyGradient is an iterator, where each loop
# the data is returned to the for-loop below. We construct nthreads
# number of Hopper Environments to be parallel evaluated.
npg = NaturalPolicyGradient(
    (HopperV2() for _=1:Threads.nthreads()),
policy,
value,
gamma = 0.995,
gaelambda = 0.97,
valuetrainer,
Hmax=1000,
norm_step_size=0.1,
N=10000
)

# We iterate on NPG for 100 iterations, printing useful information
# every 25 iterations.
for (i, state) in enumerate(npg)
  if i > 100
    break
  end
  if mod(i, 25) == 0
    println("stocreward = ", state.stoctraj_reward)
  end
end
Appendix C. Details on MPC experiments

For the MPC comparison with MPPI, we considered two environments. A 7-DOF Sawyer robot reaching various spatial goals with the end effector, and a 30-DOF in-hand manipulation task where a Shadow Hand has to manipulate a pen to match a desired orientation. Both tasks are episodic, where at the start of an episode, a random initial configuration and a random target configuration are generated. Each episode is 75 time-steps. The specific MPPI algorithm we used was based on Lowrey et al. (2018a), where the authors first observed that correlated noise sequences were important for hand manipulation tasks. Our observations are consistent with this finding. The main hyper-parameters used are summarized in the below table.

| Parameter             | Shadow Hand experiment | Sawyer experiment |
|-----------------------|------------------------|-------------------|
| Planning horizon      | 32                     | 16                |
| # trajectories sampled| 160                    | 30                |
| Temperature           | 1.0                    | 5.0               |
| Smoothing parameters  | $\beta_0 = 0.25, \beta_1 = 0.8$ | $\beta_0 = 0.25, \beta_1 = 0.8$ |

Appendix D. Details on RL experiments

As a representative RL experiment, we use the NPG algorithm and compared Lyceum with Gym. We study the learning curve as a function of both the number of environment interactions as well as wall clock time. As a function of environment interactions, we found Gym and Lyceum to be comparable (as expected), however Lyceum was substantially faster in wall clock time. The hyper-parameters for the RL experiment are mentioned in Table 2.

| Parameter                        | Value          |
|----------------------------------|----------------|
| # NPG steps                      | 100            |
| Samples per NPG step             | 10,000         |
| NPG step size (normalized)       | 0.1            |
| Policy size                      | (64, 64)       |
| Value function size              | (128, 128)     |
| Discount ($\gamma$)              | 0.995          |
| GAE ($\lambda$)                  | 0.97           |