Deep reinforcement learning (RL) has led to many recent and groundbreaking advances. However, these advances have often come at the cost of both increased scale in the underlying architectures being trained as well as increased complexity of the RL algorithms used to train them. These increases have in turn made it more difficult for researchers to rapidly prototype new ideas or reproduce published RL algorithms. To address these concerns this work describes Acme, a framework for constructing novel RL algorithms that is specifically designed to enable agents that are built using simple, modular components that can be used at various scales of execution. While the primary goal of Acme is to provide a framework for algorithm development, a secondary goal is to provide simple reference implementations of important or state-of-the-art algorithms. These implementations serve both as a validation of our design decisions as well as an important contribution to reproducibility in RL research. In this work we describe the major design decisions made within Acme and give further details as to how its components can be used to implement various algorithms. Our experiments provide baselines for a number of common and state-of-the-art algorithms as well as showing how these algorithms can be scaled up for much larger and more complex environments. This highlights one of the primary advantages of Acme, namely that it can be used to implement large, distributed RL algorithms that can run at massive scales while still maintaining the inherent readability of that implementation.

This work presents a second version of the paper which coincides with an increase in modularity, additional emphasis on offline, imitation and learning from demonstrations algorithms, as well as various new agents implemented as part of Acme.

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1. Introduction

Reinforcement learning (RL) provides an elegant formalization with which to study and design intelligent agents (Russell, 2016). At its broadest level we can think of an agent as an object which is able to interact with its environment, to make observations, and to use these observations in order to improve its own performance. This formulation and the algorithms developed to train these agents have a long history that goes back at least to the 1950s (Bellman, 1957, 1966), see Sutton and Barto (2018, Section 1.7) for an excellent and concise history. Modern deep RL combines advances in reinforcement learning with improved neural network architectures and increased computational resources. These advances have in turn led to dramatic increases in agent capabilities. This modern era was perhaps ushered in by huge leaps forward in game-playing agents (Mnih et al., 2015; Silver et al., 2016), a trend that continues to push the boundaries of RL research to this day (Berner et al., 2019; Vinyals et al., 2019). More recent works have begun to move toward real-world domains as varied as robotics (OpenAI et al., 2020), stratospheric balloon navigation (Bellemare et al., 2020), nuclear fusion (Degrave et al., 2022), and more. The pursuit of state-of-the-art performance on such large and varied domains has in turn contributed to a huge uptick in both the complexity and scale of agents developed by the
research community.

One characteristic that has contributed to the increasing complexity in RL research has been an integrationist approach to agent design in which modern agents often involve a combination of an ever-increasing number of smaller algorithmic components. This has led to a state in which state-of-the-art agents incorporate numerous independent components. Examples include modifications to the reward signals to include intrinsic rewards (Bellemare et al., 2016; Badia et al., 2020) or auxiliary tasks (Jaderberg et al., 2017; Jaques et al., 2019), as well as specialized neural network architectures (Wang et al., 2015), and model ensembles (Osband et al., 2018). Core techniques have been rethought including replay (Schaul et al., 2016), the form of value function backups (Bellemare et al., 2017), or the use of search within policy improvement (Silver et al., 2018). Various forms of variance reduction (Wang et al., 2017; Schulman et al., 2017; Espeholt et al., 2018), hierarchical learning (Kulkarni et al., 2016; Vezhnevets et al., 2017), or meta-learning (Al-Shedivat et al., 2018; Finn et al., 2017; Xu et al., 2018) have also been proposed.

The performance of modern reinforcement learning algorithms, like much of machine learning, has also benefited greatly from increases in scale. This question of scale can be considered along two related dimensions: the capacity of the function approximator and the amount of training data presented to the algorithm. The first is an active area of research due to the increased importance of model parallelism and the latter is of particular importance in the context of RL as the agent typically has to produce its own data by interacting with the environment. This motivates distributing data gathering across multiple parallel instances of an environment in order to generate data as fast as possible. This has led to the widespread use of increasingly large-scale distributed systems in RL agent training (Mnih et al., 2016; Horgan et al., 2018; Espeholt et al., 2018; Kapturowski et al., 2019; Espeholt et al., 2020). This approach introduces engineering and algorithmic challenges, and relies on significant amounts of infrastructure which can impede the reproducibility of research. This is also the case with the increasing size of models we have seen in recent years. It also motivates agent designs that may represent dramatic departures from canonical abstractions laid out in the reinforcement learning literature (Sutton and Barto, 2018). This means that scaling a simple prototype to a full distributed system may require a complete re-implementation of the agent.

To combat the growing complexity inherent in modern RL implementations, we developed Acme, a framework for expressing and training RL agents which attempts to address both the issues of complexity and scale within a unified framework. The goal of Acme is to allow for fast iteration of research ideas and scalable implementation of state-of-the-art agents. Acme does this by providing tools and components for constructing agents at various levels of abstraction, from basic modules and functions (e.g. networks, losses, policies), to workers which update the state of the learning process (actors, learners, replay buffers), and finally complete agents with the experimental apparatus necessary for robust measurement and evaluation, such as training loops, logging, and checkpointing. The agents written in the framework are state-of-the-art implementations that promote the use of common tools and components. Our modular design of Acme's agents makes them easy to combine or scale to large distributed systems, all while maintaining clear and straightforward abstractions. It simultaneously supports training in a simpler synchronous setting which can be both easier to understand and to debug.

In Section 2 we give a brief overview of modern reinforcement learning and discuss various software frameworks used to tackle such problems. Section 3 goes on to introduce the key structural contributions of our approach to designing RL agents. In Section 4 we build upon this design to show how this framework is used to implement a number of modern agent implementations. Finally, in Section 5 we experiment with these agents and demonstrate that they can be used to obtain state-of-the-art performance across a variety of domains.

Note that this work also represents a second version of the paper. In the interim Acme has seen an increase in its modularity due to the design of agent builders (Section 3.5). We have also put additional emphasis on offline and imitation algorithms including many algorithms that make use of the builder design to compose agents. The number of core algorithms implemented as part of Acme has also increased. Finally, although it is not the focus of this paper much of the algorithms implemented in Acme have increasingly transitioned to JAX (Bradbury et al., 2018) to implement the network architecture of policies, critics, etc. While much of the base interfaces are still platform agnostic maintaining one-to-one correspondence between e.g. TensorFlow (Abadi et al., 2015) and JAX has been de-emphasized due to its corresponding support burden.
2. Modern Reinforcement Learning

The standard setting for reinforcement learning involves a learning agent—an entity that perceives and acts—interacting with an environment in discrete time. At a high level this setting can be thought of as an interactive loop in which the agent produces actions based on its observations of the environment and the environment consumes those actions before returning a reward and subsequent observation. See Figure 1 for a brief illustration of this interaction. From a mathematical perspective, the interaction between an agent and its environment can generally be characterized as either a Markov Decision Process (MDP) (Puterman, 1994) or a Partially Observable MDP (POMDP) (Kaelbling et al., 1998). In both of these formulations the environment is assumed to be determined at any time \( t \) by some state \( x_t \). In the MDP setting agents directly observe this state and make decisions based on its value. The POMDP setting, however, generalizes this assumption such that the agent is only able to perceive observations \( o_t \) which are functionally (or stochastically) generated based on the hidden state. In other words an MDP can be written more generally as a POMDP where \( o_t = x_t \). For a simple example illustrating this distinction, consider the widely used Atari set of benchmarks (Bellemare et al., 2013), for which \( x_t \) corresponds to the internal state of a given game and \( o_t \) corresponds to the pixel observations rendered from this state. In general we will assume the more general POMDP setting for all environments, however we leave the question of how to address partial observability up to particular agent implementations. This assumption does not fundamentally alter the agent/environment interface illustrated above and in Section 3.1 we describe this interface and Acme’s implementation of it in more detail.

The mechanism by which an agent interacts with the environment is primarily determined by its policy, i.e. a function which maps its experienced history of observations to an action \( a_t \). While the policy can be represented as an arbitrary function, in this work we will assume for expository reasons that it is a deep neural network of some form. Under this assumption, the simplest instance of an agent’s mapping might be that of a feed-forward neural network evaluated on the most recent observation. However, in order to optimally act in more general settings (e.g. partially observable environments), an agent might be implemented using a recurrent network. Here the recurrent state of the network can act as a proxy for the environment’s internal (hidden) state. Section 3.2 describes in more detail the way in which policies are represented in Acme and how these are used to generate an action. As shown in Figure 1, given an action selected by the agent the environment updates its internal state and emits rewards and observations; Section 3.3 describes how this data can then be collected and used to update the agent’s behavior.

The typical objective of any RL agent is to optimize its policy \( \pi \) so as to maximize some aggregate measure of its expected future rewards. If we let \( R_t \) denote the random variable associated with rewards at time \( t \) (i.e. the reward yielded by the environment after following the policy \( \pi \)), we can then write the discounted future returns of this policy as

\[
G_t = R_t + y R_{t+1} + y^2 R_{t+2} + \cdots
\]

Here the discount factor \( y \in [0, 1) \) is simply a term that prioritizes near-term rewards over longer-term rewards. Note that this choice of aggregation—i.e. summed, discounted rewards—is one particular, albeit common
choice. Most of the agents that we focus on in this work target this infinite-horizon, discounted reward formulation, however agents in Acme are capable of optimizing other such measures. This choice is typically made by the learner component of an algorithm that we introduce in Section 3.4 and we discuss particular implementations of it in Section 4. Given this measure of performance we can define an agent’s optimal policy as \( \pi^* = \arg \max_\pi \mathbb{E}_\pi [G_t] \), i.e. the policy which leads to the best return in expectation. Here we have explicitly noted that the expectation is dependent on the policy \( \pi \), however we have left implicit all the other distributions involved, i.e. in practice this expectation should be evaluated with respect to any stochasticity in the environment as well. The question of how best to estimate and/or directly optimize this expectation is predominately what leads to different mechanisms for updating an agent’s policy.

Finally, while the description of reinforcement learning given in this section provides a high level overview, we can also divide this space into a number of alternative formulations that are also supported by Acme. In what remains of this section we will highlight a number of these settings.

Online Reinforcement Learning The online setting largely corresponds to the description given above, and could be described more simply as the "standard" setting for reinforcement learning (Sutton and Barto, 2018). Under this problem formulation an agent interacts with its environment and maximizes the accumulated reward collected through trial-and-error. This formulation emphasizes an agent’s ability to learn by actively exploring its environment and can be contrasted against settings in which an agent makes more passive observations of the environment. Additionally, Online RL is often further split into on-policy or off-policy algorithms, a distinction which refers to whether data is generated by the same policy that is being optimized (on-policy) or a separate behavior policy. Finally, although it is not a strict one-to-one correspondence many off-policy algorithms also make use of experience replay, i.e. experience is stored as it is generated so that updates to the policy can query the entire history of generated data rather than the most recently generated samples. Off-policy algorithms also typically rely on what is known as bootstrapping wherein an estimates of the value of a given policy is used in a dynamic-programming-like fashion to improve its own estimate (i.e. the estimates bootstrap upon themselves).

Offline Reinforcement Learning The setting of offline RL (also referred to as batch RL) (Ernst et al., 2005; Riedmiller, 2005; Lange et al., 2012; Levine et al., 2020), is used when the agent cannot interact with its environment, and instead learns a policy from an existing collection of experience. This setting is particularly relevant if interactions with the environment are costly or dangerous and appeals to a natural motivation to facilitate learning by leveraging historical interactions. However, as policies learned in this setting do not receive feedback from the environment, such algorithms may wrongfully associate high returns with actions that were not taken in the collection of existing experience. Thus, methods in this offline setting frequently incorporate regularization that incentivizes the learned policy to avoid unknown or uncertain state-action regions. This can further be contrasted with online methods where uncertainty is often encouraged as a mechanism to fully explore the state space (often known as optimism in the face of uncertainty).

Imitation Learning For various tasks, the environment might not come with a reward which is well-defined. For instance, suppose that we have a game simulator, and that the goal is to design a policy that "plays like a beginner". The specification of a reward function that would explain the behavior of a beginner player is tedious. In the Imitation Learning (IL) setting (Pomerleau, 1991; Bagnell et al., 2007; Ross and Bagnell, 2010), the environment does not come with a reward, but instead a number of demonstrations which are trajectories of an agent interacting with the environment of interest. The objective is either to learn a policy whose behavior match the one in the provided demonstrations, or to infer the reward that best explains the behavior in the provided demonstrations (see also Ng and Russell, 2000; Russell, 1998; Ziebart et al., 2008; Abbeel and Ng, 2004).

Learning from Demonstrations In the Learning from Demonstrations (LfD) setting (Schaal, 1997; Hester et al., 2018; Vecerik et al., 2017a; Dadashi et al., 2022), similarly to the standard online RL setting, the goal is to learn a policy through trial and error by interacting with an environment, which has a well-defined reward to optimize. In addition, similarly to the IL setting, the learning agent has access to examples of trajectories that come from an "expert" agent. This is relevant in domains where the reward function is easy to define but is
challenging to optimize. For example, for tasks with sparse reward signals (e.g., a manipulation task that yields a positive reward only if the task is completed) the use of demonstrations facilitates the exploration problem.

3. Acme

At its core Acme is a framework designed to enable readable and efficient implementations of reinforcement learning algorithms that target the development of novel RL agents and their applications. One of the hallmarks of modern reinforcement learning is the scale at which such algorithms are run. As a result, algorithms implemented with Acme usually culminate in a distributed agent which involves many separate (parallel) acting, learning, as well as diagnostic and helper processes. However, one of the key design decisions of Acme is to re-use the same components between simple, single-process implementations and large, distributed agents. This gives researchers and algorithm developers the ability to implement RL algorithms once, regardless of how they will later be executed.

To keep things simple, we will begin by describing those components that should be readily familiar to anyone well-versed in the RL literature (e.g. Sutton and Barto, 2018) as illustrated in Figure 2. First and foremost among these components is the environment with which the agent interacts, described in Section 3.1. The agent itself is then broken down into three primary components: an actor which interacts with the environment to generate data, a replay system which stores that data, and a learner which updates the agent’s behavior based on data sampled from replay; these elements are described in Sections 3.2–3.4 respectively. Next, we will show how these components can be combined to train and evaluate the performance of a given agent. This includes builders which defines how to construct all the components of an agent (Section 3.5). We will also describe experiment runners for both local and distributed agents (Sections 3.6–3.7) along with their shared configuration. We will then describe how these agents can be reused for offline settings with limited (or even zero) modification.

Note, in what follows we will give a high-level overview of the core interfaces and building blocks of Acme. We are, however, very cognizant of the fact that Acme is a living framework and some of this design (particularly with respect to function inputs) may subtly shift over time. While the high-level components, methods, and their uses should be relatively stable, for up-to-date information on the precise APIs please refer to our documentation (https://dm-acme.readthedocs.io/).

![Figure 2](image-url) | An expanded view of the agent-environment interaction shown in Figure 1. This explicitly displays the environment loop which controls the interface between the agent and its environment; the communication between these components is now represented by a single, bidirectional link. We have also expanded the agent into into its three major components which include an actor which generates actions and receives observations, a replay system which stores data produced by the actor, and a learner which consumes this data to produce parameter updates.
3.1. Environments and environment loops

The environment with which an agent interacts is a core concept within reinforcement learning. In Acme we assume an environment which maintains its own state and that follows an interface defined by the dm_env package (Muldal et al., 2019). Ultimately, an environment is represented by an object which implements a `step` function that takes an action $a_t$ and produces a tuple $(r_t, d_t, o_{t+1}, e_{t+1})$ consisting of:

- the reward $r_t$, provided by the environment as it transitions to its new state;
- an environmental discount $0 \leq d_t \leq 1$ that allows for environment-specific discounting of future rewards—this acts like the discount factor $\gamma$ but is provided by the environment; this term is most often used to distinguish between episode termination and truncation (see below);
- a new observation $o_{t+1}$ that corresponds to any observable quantities of the new state provided by the environment;
- and an end-of-episode indicator $e_{t+1}$. Environments here are assumed to be episodic, and the end-of-episode indicator is a Boolean value which is true when the step is the final step of an episode, i.e. the lifetime of a single agent instance. This signal is often used to reset any internal agent state in order to begin a new episode.

Note that at the end of an episode (i.e. when $e_{t+1}$ is True) we can have $d_t = 0$, which signals the termination of the episode and therefore no more reward(s) can be obtained. This is in contrast to the case where $d_t > 0$, which signals the truncation of an episode—i.e. additional rewards could be obtained by continuing to interact with the environment but the environment is signaling that it will end the episode early and sample a new one. The distinction between these two cases is particularly relevant when learning a bootstrapped value function (which we will define more carefully in Section 4). In particular, bootstrapping should be used when an episode is truncated but not when it is terminated.

The interaction between an agent and its environment is mediated through use of an environment loop. This provides a simple entry point which, given actor and environment instances can be repeatedly called to interact with the environment for a given number of transitions or whole episodes. Instances of the actor interface, which will be introduced in the following section, can be roughly thought of as a wrapper around a raw policy which maintains the policy’s state. Given these two components, Listing 1 shows both pseudocode and a corresponding, albeit simplified, implementation of the environment loop. In particular this highlights the interleaved interaction between the actor and environment, where the environment generates observations, the actor consumes those observations to produce actions, and the environment loop maintains the state of this interaction. A full implementation of this loop largely corresponds with the given pseudocode, albeit here the pseudocode eliminates logging, checkpointing, and other bookkeeping operations.

Listing 1 | Pseudocode for a simplified environment loop. Also shown for comparison is an implementation of this loop using Acme components. The given code is broadly equivalent to the actual EnvironmentLoop class and is only lacking in additional bookkeeping operations.
3.2. Actors

In Acme, the agent's interaction with the environment is controlled by an environment loop, but the process of generating actions is performed by an actor. This component consumes the environment outputs—the rewards, observations, etc.—and produces actions that are passed to the environment. While it might be possible to combine this step into a single function, in Acme we explicitly split this into four methods:

- **select_action** consumes the observation \(o_t\) and returns the action \(a_t\) selected by the agent; any internal state for the agent should be computed and stored by this method.
- **observe** consumes the agent's selected action \(a_t\) and the timestep tuple \((r_t, d_t, o_{t+1}, e_{t+1})\) produced by the environment; this data can then be stored or otherwise used for learning.
- **observe_first** plays the same role as the **observe** method, but should be called on the first step of an episode when only the observation \(o_0\) has been produced.
- **update** allows the actor to perform any internal parameter updates. In distributed agents this usually corresponds to requesting the latest policy parameters from the learner.

By splitting these methods up we can clearly delineate the responsibility and inputs for each agent function. While it is possible to implement all of an agent's logic behind the **Actor** interface, we generally prefer to limit the use of this interface to only those functions necessary for generating actions and storing the experience data generated by this interaction. By separating the responsibilities for data generation and training (Section 3.4) the agent can be distributed and parallelized in a much simpler fashion as we will demonstrate in Section 3.7. With this in mind, the three primary methods defined by the actor interface can be seen as evaluating the policy, storing observed data, and retrieving updated parameters from an external variable source.

While the **select_action** of an actor is in charge of evaluating the agent's policy in order to select the next action, the policy is usually being learned (represented by its parameters) and we must be able to handle changes to these parameters when the **update** method is called. In order to seamlessly support both single-process and distributed execution, the processing of updating parameters on each **Actor** is performed by periodically polling some variable source for the most recent parameters. When an **Actor** is instantiated it is given an object implementing the **VariableSource** interface. This interface includes a **get_variables** method which can be used to retrieve the most recent set of policy parameters. While in most cases the role of the variable source is played by the **Learner** (introduced in Section 3.4), this has been generalized to include edge cases that may not yet be supported, e.g. a sources that read parameters from disk, or some other form of caching. Finally, rather than having each actor implement this polling procedure directly we also provide a **VariableClient** object which handles polling and other bookkeeping on a separate thread.

While the **Actor** is a fundamental component of Acme, where possible we prefer and recommend using the **GenericActor** object which implements this interface; see Figure 3 for an illustration. The **GenericActor** handles much of the boiler plate logic that is most commonly necessary in distributed RL agents so that, as its name suggests, it is generic enough to be used by most of our agents. This can be done because the **GenericActor** defers the logic that differs between agents to a component called the **ActorCore** which can generally be thought of as the policy-specific components of an actor. The **ActorCore** is a simple container class, which holds the following three pure functions:

- **init** produces a new initial state, usually at episode beginnings. This state can hold, for example, the recurrent neural network (RNN) state of agents endowed with memory (e.g. the R2D2 agent).
- **select_action** mirrors the corresponding **Actor** function with the addition of state management.
- **get_extras** consumes the state and produces the extras information that should be stored along with the corresponding timestep. This is useful, for example, when learners require the log-probability of actions taken in the environment for V-trace or Retrace corrections (e.g. Impala or MPO).

3.3. Experience replay and data storage

Previous sections of this work have introduced actors which observe the data generated from their interactions with the environment. An algorithm can immediately consume that data in order to update its policy parameters or store it for later consumption and possible re-evaluation. This distinction is typically made when discussing on-policy algorithms in the first case and off-policy algorithms in the second, where the storage of data for later
Figure 3 | An expanded view of the GenericActor and ActorCore implementation of an Acme Actor.

use is often referred to as experience replay (Lin, 1992; Schaul et al., 2016). In this section we will discuss how Acme implements both ends of the spectrum by making use of Reverb (Cassirer et al., 2021), a special-purpose storage system build for this purpose.

Reverb is a high-throughput, in-memory storage system which is particularly suited for the task of experience replay—especially in distributed settings. In particular, Reverb exposes a client-server architecture where servers are tasked with storing data and can be either co-located with the rest of the agent infrastructure or run on a separate machine. Data can be written to the server via a client interface at a per-timestep level and a subset of data associated with one or more timesteps can be marked as sampleable units with an associated priority. The ability to mark specific subsets of timestep data as sampleable units enables one to efficiently expose different forms of data required by specific algorithm implementations. Data is also organized into different tables which allows actors to write data to separate tables which can then be individually sampled from. Reverb also defines multiple mechanisms by which units can be sampled from replay including first-in-first-out (FIFO), last-in-first-out (LIFO), and in proportion to given priorities. Similar selection mechanisms are used to define which elements should be removed from the replay when memory becomes full. For prioritized sampling mechanisms, the priority associated with a sampleable unit is a scalar value given when writing or updating the data to replay, i.e. it is computed on both the actor and the learner respectively. By marking units with a given priority (and later updating this priority) various forms of prioritized replay (Schaul et al., 2016) can be implemented.

Reverb directly exposes a client-server architecture for writing and sampling from replay, however in Acme it is typically not necessary to use this interface directly. Data sampled from replay is exposed to Learners (described in the next section) via a simple Python iterator where each iterate corresponds to a batch of sampled data. Similarly, while Reverb's client defines a low-level mechanism for writing data to replay, it is often simpler to define that data semantically by making use of the Adder interface. Adders implement an add method which consumes an action \( a_t \) and a timestep \( \eta_t \), i.e. equivalent to the observe method found in the actor interface. Instances of this object implement different styles of pre-processing and aggregation of observational data that occurs before insertion into the dataset. For example a given agent implementation might rely on sampling transitions, \( n \)-step transitions, sequences (overlapping or not), or entire episodes—all of which have existing adder implementations in Acme. The different adder implementations take care of any processing and data caching in order to write this data.

Although adders define what data to write to replay, they do not prescribe how or at what rate data is presented for consumption. In a traditional synchronous learning loop, it is relatively easy to control how many steps of acting in the environment an agent should perform between each learning step. The ratio between acting and learning can, in turn, have a dramatic effect not only on the sample efficiency of a given agent (i.e. the number of environment steps required to reach a given performance) but also on its long-term learning performance and stability. While the same is true for distributed learning settings, the asynchronous nature of training agents in this case makes it much more difficult to maintain a fixed ratio. Running the learner and actor processes independently easily results in higher variance which is often attributable to differences in the computational substrate (e.g. different hardware and network connectivity) between processes but pinpointing precise sources can be extremely challenging. Thus, maintaining a fixed ratio of acting to learning steps in distributed setting comes at the cost of either blocking the learner or actor processes and can be computationally
wasteful.

In Acme, these scaling issues can be mitigated through the use of Reverb’s RateLimiter. By adopting rate limitation, one can enforce a desired relative rate of learning to acting, allowing the actor and learner processes to run unblocked so long as they remain within some defined tolerance of the prescribed rate. In an ideal setting, learner and actor processes are given the correct proportion of computational resource to run unblocked by the rate limiter. However if due to network issues, insufficient resources, or otherwise, one of the processes starts lagging behind the other, the rate limiter will block the latter while the former catches up. While this may waste computational resource by keeping the latter idle, it does so only for as long as is necessary to ensure the relative rate of learning to acting stays within tolerance. Rate limitation can also be used to simulate a queue data structure which allows one to implement more purely online algorithms in conjunction with FIFO samplers/removers; in Section 4 we will highlight a number of algorithms that make use of this system.

3.4. Learners

Learners in Acme are the components which implement parameter updates given data. Often this data is gathered by actors and sampled from replay as introduced in the previous sections, however as we will see in Section 3.8 this interface can be completely reused for static datasets containing offline data. Learners also have the most general interface, due largely to the fact that they must accommodate the greatest amount of variation between different algorithm implementations. This interface consists largely of a step function which performs a single learning step updating the agent’s parameters—typically, although not exclusively, corresponding to a step of gradient descent. Learners also expose a get_variables method which returns the current state of its parameters. By defining this method Learners implement the VariableSource interface introduced when describing actors, and this method is primarily used to update actors as they interact with the environment.

In practice learner implementations should also be initialized using a dataset iterator. Although this iterator can be backed by experience replay, that is not a requirement and in fact it is precisely this design choice that greatly simplifies the process of defining offline algorithms. The offline setting for reinforcement learning, as introduced in Section 2, can be seen as an extreme version of off-policy learning in that such algorithms rely on a fixed dataset and no additional data generation. What this means is that any algorithm implemented via the Learner interface can be applied in the offline setting purely by eliminating the actor/replay part of their algorithm. Similarly many algorithms in the LfD setting can be constructed by adapting online algorithms and specially mixing online and offline data. However, while this means that any Acme algorithm can be easily adapted to offline settings this certainly does not mean that they will perform well—in fact most algorithms built for such settings have to be carefully designed to avoid over-generalization as we will highlight in Section 4.

Finally, while different algorithms implemented in Acme require different data formats (e.g. trajectories, sequences, etc.) for offline baselines and experiments, we generally rely on standard mechanisms for providing this data. In the online setting this is provided by the relevant Adder implementations, and in the offline setting the necessary formats are defined by the RL Datasets (RLDS) package (Ramos et al., 2021). This package stores data as full episodes, and provides utilities to transform them into the desired trajectory format.

3.5. Defining agents using Builders

As described at the beginning of this section, an RL agent is defined by its combination of actors, learners, and replay (although as we will see in Section 3.8 the actor may only be needed for evaluation and replay may be replaced by a static dataset). While these components can be used individually, in Acme we also provide general purpose mechanisms for running experiments which instantiate the agent and its environment and run its learning process. We will detail this in the following sections, however in order to do so we need a full definition of the agent. In Acme this is accomplished by agent builder objects which define how to construct the individual components.

The builder abstraction encapsulates the full definition of an agent algorithm in a way which allows applying those algorithms to a wide variety of learning tasks represented as environments. This means that each algorithm should make as few assumptions as possible about the environment they are interacting with (e.g. some environments provide image observations, others provide an encoding of the internal environment state).
To achieve this, all Acme algorithms can be configured with an environment spec and a network module. The environment spec object provides a lightweight specification of the types and shapes of environment inputs and outputs—knowledge required by many of the agent's components. The network module object defines the neural network architecture required to construct and learn the agent's policy. Specifying networks outside of the builder allows for reusing a single agent implementation for a wide variety of different environments. To simplify the process of training an agent from a user perspective, most algorithms provide a means to construct a default set of networks given an environment spec.

With that out of the way we can define the interface for builder objects, which includes the following functions:

- **make_policy** constructs the policy as a function of the environment spec and networks.
- **make_replay_tables** returns a list of replay tables, i.e. the Reverb collections to which data will be written; this allows adders to write data differently between multiple tables which can then be sampled on the learner side. As the format of the tables may depend on the shape of the inputs and outputs of the environment, as well as the outputs of the policy, this function accepts both the environment spec and policy as inputs.
- **make_adder** constructs the adder which will be used to record data to replay. This is a function of both the environment spec and networks for the same reasons as given above. It is also a function of the replay client which will be constructed from the replay tables; this allows low-level access necessary for the adder to write its data.
- **make_actor** returns an actor as a function of the policy, an adder, and a variable source; these are the necessary components to evaluate actions, add data, and synchronize parameters. Also passed are the environment spec which is necessary for initialization and a random key for seeding any stochasticity in the policy.
- **make_learner** returns the learner object which handles all parameter updates for the agent. This is primarily a function of the dataset iterator and network modules, however the environment spec is also necessary for initialization, and a random key is also provided to seed any randomness in the learning process.
- **make_dataset_iterator** constructs the dataset iterator as a function of the replay client.

Additionally, to allow for logging and diagnostic capabilities the learner is also equipped with shared counter and logger objects which respectively allow for maintaining metadata counts shared among the different agent components and logging this and other metadata; we will describe loggers in more detail in the following section.

The builder definition contains everything necessary to define an agent and situate it within an environment loop. While this can be done manually it is generally more useful to run a predefined experiment as we will describe in the next section. Ultimately, as we will show in Section 3.7 we can use the same interface to instantiate and run a distributed experiment. This also allows for some level of algorithmic composition (as we will see in Section 4.4) where higher-level algorithms are defined by composing builders. In the following section we will show how this interface can be used to construct and run an agent; see also Listing 2.

### 3.6. Running an agent

In Acme we refer to the combination of a builder, network definitions, and environment as an experiment. While the concept of an experiment is somewhat loosely defined, the components necessary to run an experiment can be concretely specified using the ExperimentConfig datatype. This datatype provides factories for network and environment instances along with a builder instance; note also that the builder itself can be seen as a collection of factories for lower-level modules. Given such a config, Acme provides a simple run_experiment function which will instantiate all of the necessary actor, learner, environment loop components, etc. Listing 2 shows a simplified version of this function which summarizes how all of the previously introduced components are connected together.

Figure 4 breaks down the different elements necessary to configure and run an experiment. In particular we have also loosely split these components into different levels at which they sit within Acme's framework.
Figure 4 | This diagram illustrates how experiments are configured and run in the Acme framework.

Listing 2 | Pseudocode for a simplified version of run_experiment. This requires environment and network factories as well as a builder specifying the agent. The pseudocode below will then construct and run the agent in an environment loop. For simplicity this omits logging operations as well as some simple helper functions. Also not shown is a _make_learning_actor wrapper which is necessary for running learning operations, but for a full overview one should refer to the code.

Require: environment_factory, network_factory, builder.

# Create an environment and get a spec describing inputs/outputs.
1: environment ← environment_factory()
2: environment_spec ← _make_environment_spec(environment)

# Create the networks and use this to build a policy which generates actions.
3: networks ← network_factory()
4: policy ← builder.make_policy(environment_spec, networks)

# Create replay and the dataset.
5: replay_tables ← builder.make_replay_tables(environment_spec, policy)
6: replay ← _make_replay(replay_tables)
7: dataset ← builder.make_dataset_iterator(replay)

# Create the learner which updates parameters.
8: learner ← builder.make_learner(environment_spec, networks, dataset, replay)

# Create an adder (to add data) and an actor (to generate data).
9: adder ← builder.make_adder(replay, environment_spec, policy)
10: actor ← builder.make_actor(environment_spec, policy, learner, adder)

# Wrap the actor to periodically run training steps on the learner.
11: actor ← _make_learning_actor(actor, learner, ...)

# Create the main loop and run it.
12: environment_loop ← EnvironmentLoop(environment, actor)
13: environment_loop.run()

At the lowest (left-most) level is the tooling provided by Acme which defines the configuration and the run_experiment function; from a practitioner or agent developer perspective these should be usable as-is. Going up one level, a user who is interested in developing a new algorithm can do so by creating a new agent builder, which may require modifying or creating new learners, actors, etc. (which are in turn constructed by the builder). However, from the perspective of a practitioner who is interested in using an algorithm for a novel environment or network architecture they need only specify environment and network factories and any agent-specific configuration.

Experiments can additionally contain a logger factory which controls where and how performance and debugging data is written. Loggers, which also allow for rate control and aggregation, are simple objects that implement a write method taking a dictionary of numerical data. These objects are then passed to the learner.
Figure 5 | This diagram illustrates a distributed training loop. Here two environment loops are running on different machines, feeding data to a single replay, which is co-located with the Learner process on a third machine.

and to any created environment loops. While loggers control where and how to record data they say nothing about what data should be recorded. In the case of any loggers passed to a learner object, the learner directly controls what data is recorded. However, when using a generic actor and environment loop it may be desirable to record additional data that is environment-specific. To account for this, each experiment can additionally be given an observer factory which will be constructed and passed to any created environment loops. This shares a similar interface to the actor and allows a user to record additional data that can then be written by the logger. Importantly this is purely a user-side callback and requires no additional change to the algorithm (i.e. the builder).

Another feature typically required of an experiment in Acme is the ability to periodically evaluate the agent’s performance during training. This problem of evaluation is related but distinct from both the losses optimized by the learner and the performance of the experience-collecting actors. The losses are often just a proxy for the actual performance whereas the actors are typically exploratory in some manner and will take under-explored actions to achieve this at the cost of degraded performance. Acme provides a default evaluation mechanism that instantiates an environment loop and actor/policy that runs in parallel with training. Such actors do not record their experience so as to not affect the learning process. The policy factory associated with the agent is allowed to take a Boolean-valued parameter eval which allows configuring them for the needs of the evaluation (e.g. turn off exploration in the policy). In addition, experiments can be given generic evaluator factories which allow users to define and compute custom evaluation metrics specific to their experiments (e.g. to evaluate the distribution of a given policy).

3.7. Distributed agents

A major, ongoing aspect of RL research is the question of how to scale these algorithms up in terms of the amount of data that can be both produced and consumed. A particularly successful—and general—strategy for addressing this question relies on generating data asynchronously by making use of distributed data generation, typically by interacting with multiple environments in parallel (see e.g. Nair et al., 2015; Mnih et al., 2016; Horgan et al., 2018; Barth-Maron et al., 2018). This has two benefits: the first being that environment interactions can occur asynchronously with the learning process, i.e. we allow the learning process to proceed as quickly as possible regardless of the speed of data gathering. The second benefit is that by making use of more actors in parallel we can accelerate the data generation process. See Figure 5 for an illustration of a distributed agent with two data generation processes.

In previous sections we have already introduced the primary split in Acme agents between acting, learning,
and storage components. While this was primarily introduced through the lens of composability, it serves another crucial purpose: namely, by running these components in different threads, processes, or in particular on different machines we can implement a distributed agent using all of the same agent building blocks. To this end Acme exposes a `make_distributed_experiment` function which roughly shares the same interface as `run_experiment` introduced in the previous section, albeit with some additional control over distributed-specific parameters such as the number of data-generating actors. Rather than running the experiment, this function returns a `program` data structure that describes the distributed computation and how to launch it. This datatype is defined by `Launchpad` (Yang et al., 2021), the package we use to build and launch these programs. In what follows we will briefly describe Launchpad and its use within Acme.

Launchpad provides a programming model that simplifies the process of defining and launching instances of distributed computation. The fundamental concept of this model is that of a Launchpad `program` which represents computation as a directed graph of service `nodes`. Edges in this graph denote communication between nodes which are made via remote procedure calls. By making the graph representation explicit Launchpad makes it easy to both design and later modify a program’s topology in a single, centralized way. Launchpad also provides a `launch` function which takes a program, a `launch type`, and potentially a collection of `resource types`. The `launch type` can be used to specify the distribution mechanism—e.g. multi-processing, multi-threading, distributed machines, etc. Similarly the resource specification can be used to specify resource requirements such CPU, RAM, etc. where required by the launch type. This model is also extensible to different launch platforms, in particular one platform specifically targeted by Launchpad is that of Google Cloud.

In Acme our use of Launchpad is entirely contained within the `make_distributed_experiment` function introduced earlier. This method is tasked with constructing the program and adding all of the associated nodes. The Launchpad nodes in our case correspond exactly to the top-level components introduced in the previous section(s)—i.e. the environment loops (containing the actor and environment), learners (which perform the update loop), and the Reverb service itself. The program datatype is then returned by this function and launching the distributed experiment can be performed by using Launchpad’s `launch` mechanism directly. Note that in the previous section we briefly alluded to a `learning actor` which controlled the rate at which learner steps are taken as a function of the data gathered by the actor(s). In the distributed case this is no longer necessary as access to the dataset is purely asynchronous and use of a rate-limiter via Reverb handles this rate naturally.

Given this mechanism, combined with the particular split between components that we have chosen in Acme, results in a system that largely divorces the question of how to run (and scale) an algorithm from what to run. Many performance optimizations can be implemented directly in the background during program construction (i.e. the `make_distributed_experiment` function) allowing for algorithms to be developed without worrying about these optimizations. In the following section we introduce a number of agents built with Acme and describe at a high level how these are constructed.

### 3.8. Modifications for offline agents

Finally, alternate experiment `runners` can be exposed for defining this loop in different problem settings. For example, Acme also includes a `run_offline_experiment` function which runs a simplified experiment with no data-generation processes (i.e. the actor and adder components) and a fixed dataset. Note that this can—and often does—make use of an environment for evaluation purposes (Paine et al., 2020), although as noted above this can be replaced with an arbitrary evaluation mechanism. As noted earlier in Section 3.4, this process can make use of an `OfflineBuilder` which doesn’t define components such as the adder. However, this function also takes as input agents defined using the general `Builder` interface, allowing for all algorithms to be used in the offline setting. In a nutshell, implementing an offline agent amounts to implementing a learner and using the offline versions of the builder, the experiment config and the runner. Therefore, any online agent can readily be used in an offline setup.

### 4. Agent Algorithms

In this section, we describe a collection of agents which have been implemented and included with Acme. Our intention is for these agents to serve both as clear and succinct reference implementations of their respective RL algorithms as well as strong research baselines in their own right. We are periodically running regression tests
to ensure their performance stays stable.

As described in Section 3 the implementation of an agent comprises the entire apparatus to both collect new data as well as continually learn improved policies from that data. For many of the agents we introduce, however, their primary differences will be contained within the learner, i.e. the module which consumes data and updates the agent’s policy parameters.

In Section 4.1 we will first give a brief presentation of a number of common principles shared across agents implemented in Acme. Then, we will describe the individual agents, focusing primarily on the major distinctive elements of each particular agent. The agents have also been separated based on their primary problem setting—as introduced in Section 2—and we have labeled each agent with tags (e.g. Off-Policy) to highlight their specific characteristics. While the tags we use should be well-explained by the given agent descriptions, they are detailed more clearly in Appendix A. For historical reasons we will also highlight agents for which distributed data generation was a primary contribution of the original work. However, beyond the distinction on- and off-policy data generation this is not a significant algorithmic distinction in Acme, as all algorithms built using Acme’s modular interfaces can readily be run in a distributed fashion. Finally, note that while this collection of agents is meant to serve both as a snapshot of currently implemented agents as well as a broad overview of Acme’s capabilities, it is not meant to be comprehensive.

4.1. Preliminaries

As introduced by Equation (1) in Section 2, the objective of nearly all of the agents we will cover is to maximize the expected return $E_x[G_t] = E_x[\sum_{t=0}^{\infty} \gamma^t R_{t+i}]$ with respect to their policy $\pi$. As noted in the introduction the expectation is explicitly dependent on the policy $\pi$, however we have left implicit all the other distributions involved which arise from the environment. This is important because $G_t$ is a function of entire trajectories which depends on both the stochasticity of the policy and the environment. However, in what follows we will leave these additional distributions implicit and will introduce more detail as necessary.

One common construction used to optimize the expected return is a value function which writes the return as a function of the current state of the system. This can either be phrased as a state-action value function $Q^*(s_t, a_t) = E_x[G_t|s_t, a_t]$, also known as the Q-function, or as a a state-only version $V^*(s_t) = E_x[G_t|s_t]$. Also frequently used is the advantage function $Q_{adv}^{*}(s_t, a_t) = Q^*(s_t, a_t) - V^*(s_t)$ which denotes the advantage gained by taking action $a_t$ rather than following the policy $\pi$. Note that in this section we have returned to the fully-observable MDP setting i.e. where the states $s_t = s_o$ are equivalent to the observations. This is purely to simplify notation due to the fact that the Markov assumption is necessary to derive many of the following equations. In practice, and as noted in Section 2, such methods can be applied directly to the partially-observable setting (while sacrificing any performance guarantees) or by utilizing recurrent networks to approximate the fully history of observations. Later in this section we will highlight specific algorithms that make use of recurrence to attack partial observability.

While estimates of the value function can be used directly without explicit parameterization—often leading to so-called Monte Carlo methods—they can also be defined recursively, i.e. with the Q-function being written as

$$Q^*(s_t, a_t) = E_x[R_{t+1} + \gamma Q^*(S_{t+1}, A_{t+1})|s_t, a_t].$$

This construction is commonly referred to as the Bellman equation (Bellman, 1957) and a similar approach can also be used for $V^*$. Note again that the expectation is with respect to any stochasticity in the reward and dynamics models where the subsequent action $A_{t+1}$ is drawn according to the distribution $\pi(S_{t+1})$. If the policy is deterministic the action selection can be written more simply as $A_{t+1} = \pi(S_{t+1})$. By examining the recursive formulation in Eq. (2) we can see that the true value function associated with any given policy $\pi$ is a fixed-point of the Bellman equation. Solving this recursion naively with function approximators, however, can prove to be unstable (Baird, 1995). To avoid this instability, a common approach is to compute the right-hand-side of the equation using a previous estimate of the value function—held fixed for a certain window of time—and use this as a target for the left-hand-side. This can be formulated as minimization of the loss function

$$L(\phi) = \frac{1}{2}E_{\rho_x}[ (Q_{\phi}(S_t, A_t) - Y_t)^2 ]$$

where $Y_t = R_{t+1} + \gamma E_{A \sim \pi(S_{t+1})} [Q_{\phi}(S_{t+1}, A)]$.

Here outer expectation is taken with respect to the visitation distribution $S_t, A_t, R_t, S_{t+1} \sim \rho_x(·)$ transitions under the policy $\pi$ and the expectation of the target $Y_t$ is taken with respect to the policy $\pi$. This loss is also
known as the Temporal Difference (TD) error (Sutton and Barto, 2018). In the context of deep RL the network associated with parameters \( \phi \), i.e. those that are being optimized, are referred to as the online network while the target network is associated with the fixed set of parameters \( \phi' \). This entire process is also known as bootstrapping due to the way in which an older version of the value function is used to to recursively improve an estimate of itself. The use of bootstrapping also allows us to eliminate expectations of entire trajectories and instead focus on individual transitions.

Above we have distinguished two ends of the spectrum defined by direct and recursive value function formulations, numerous methods exist between these two ends (see e.g. Schulman et al., 2016) and are fully supported in Acme. One simple technique that is used frequently relies on the \( n \)-step TD error; this generalizes the TD error and simply replaces the single reward in the bootstrap target \( Y_t \) with a discounted sum of \( n \) rewards and the following state and action pair with \((S_{t+n}, A_{t+n})\). This behavior is supported in Acme by the choice of Reverb adder, either by storing length \( n \) sequences or using the more efficient \( n \)-step transition adder.

Given a value estimate, we can then turn to the question of how to use this to improve the agent’s policy. One special, albeit very common case is that of finite, discrete action spaces in which the Q-function can be estimated. This estimate was introduced by (Silver et al., 2014) who also showed that it is the limiting case of the stochastic prioritized experience replay distribution cannot be represented exactly it is also common to make use of prioritised experience replay wherein...
the probability of each sample is reweighted by some priority, typically in proportion to their TD error (Schaul et al., 2016).

Additionally, while many of the standard tools and machinery of supervised learning can be directly applied in an RL context, frequently these techniques must be adapted to the fact that in RL the supervisory signal (long-term value) is only indirectly observed via the immediate rewards. One such technique that has seen a recent resurgence in interest is the use of distributional value functions, i.e. value functions which estimate the entire distribution of expected return rather than only its expectation (Bellemare et al., 2017; Dabney et al., 2018; Barth-Maron et al., 2018); this results in a modified version of the TD error introduced earlier. The network architecture used for representing the value function can also play an important role in the performance of an agent. This is shown most clearly in Dueling DQN (Wang et al., 2015) which learns a separate state-only value function and an advantage function (representing the advantage/disadvantage of a single immediate action over the expected value) all with a shared embedding. One technique that is particularly unique to RL is typified by the use of separate networks for action selection and computing the target value function when estimating the Q-function. This technique, known as Double Q-Learning is frequently used to avoid overestimation bias; see Hasselt (2010) for more details. Finally, the use of regularization is also just as commonly used RL as it is in supervised learning. In an RL context this often takes the form of an additional penalty defined by the Kullback-Leibler (KL) divergence between the agent’s policy and some reference distribution. For example, previous iterates of the policy (often the target parameters) can be used as a reference. This constrains the magnitude of allowable updates (Abdolmaleki et al., 2018; Levine, 2018; Vieillard et al., 2020) in order to stabilize the learning process.

4.2. Online RL

DQN

Deep Q-Networks (DQN) (Mnih et al., 2013, 2015) is a modern variation on the classical Q-Learning algorithm (Watkins and Dayan, 1992), which uses a deep neural network to estimate the Q-function in discrete action spaces. DQN learns $Q_\phi$ by iteratively applying the recursive update described in the previous section and calculated by minimizing the loss in Equation (3) (with actions selected by the greedy policy). One optimization implemented by this algorithm relies on the fact that it is specifically targeted at discrete action spaces. Rather than implement $Q_\phi$ as a function of both observations and actions, DQN actually learns a vector-valued function of the observations where the $a$-th output is the value of the associated action, i.e. $Q_\phi(s,a) = [Q_\phi(s)]_a$. This entire vector can then be calculated using a single pass through the network. In terms of data-generation DQN relies on an $\epsilon$-greedy behavior policy for exploration, i.e. one in which with probability $\epsilon < 1$ a uniformly random action is selected and otherwise the greedy, maximum valued action is taken. As done in many other algorithms the value of $\epsilon$ is frequently annealed towards zero as learning proceeds. Data generated by this process is added to replay as $n$-step transitions which are used to form $n$-step returns during learning. In our implementation of DQN, and following in the spirit of Rainbow DQN (Hessel et al., 2018), we also include a number of recent enhancements including Double Q-Learning, dueling networks, and prioritized experience replay using the TD error as the priority.

Munchausen DQN

Munchausen DQN (MDQN) (Vieillard et al., 2020) is an explicitly entropy-regularized and implicitly KL-regularized version of DQN. In order to apply this regularization MDQN uses a stochastic policy given by a softmax of the Q-function, $\pi_\phi(a_t|s_t) \propto \exp(\frac{1}{\tau} Q_\phi(s_t,a_t))$ with temperature $\tau$; note that we have written the policy $\pi_\phi$ due to the fact that it is indirectly parameterized by $\phi$ via the Q-function. The target from Eq. (3) can then be modified to add the log-policy (scaled by $\alpha \in (0,1)$) to the reward function and replace the argmax policy by expectation over the softmax, resulting in

$$Y_t = R_t + \gamma \mathbb{E}_{A \sim \pi_\phi(A|S_{t+1})} \left[ Q_\phi(S_{t+1}, A) - \tau \log \pi_\phi(A_t|S_t) \right] + \alpha \tau \log \pi_\phi(A_t|S_t).$$

Note that the additional regularization terms have been highlighted in red and that when $\tau \to 0$ we recover Q-learning. This implicitly regularizes the policy towards the previous one and widens the action-gap. Note that in the above equation the target $Y_t$ is a random variable whose expectation we will take with respect to the state, action, and next-state.
R2D2  Discrete Actions  Off-Policy  Q-Network  Bootstrapping

Recurrent Replay Distributed DQN (R2D2) is a distributed, recurrent extension of DQN. This involves a Q-function computed by a recurrent network, which is arguably better adapted to partially observable environments. From an implementation perspective this replaces the feed-forward networks used in DQN with recurrent networks, adding full sequences (rather than transitions) to replay, and adapting the learning process to deal with these trajectories. For arbitrary trajectories sampled from replay, the initial state of the recurrent network can be set by replaying some initial set of states that will not be used for learning, referred to as burn-in. R2D2 additionally makes use of an invertible value rescaling to enhance robustness to different reward scales; for more details see Pohlen et al. (2018).

D4PG  Continuous Actions  Off-Policy  Q-Network  Policy-Network  Bootstrapping

Distributed Distributional Deterministic Policy Gradients (D4PG) (Barth-Maron et al., 2018) is an off-policy, actor-critic algorithm adapted for continuous action spaces. In particular D4PG is a distributed extension of the Deep Deterministic Policy Gradient (DDPG) approach of Lillicrap et al. (2016), which also adds a distributional critic and n-step transitions. The original implementation of this work makes use of a Q-function represented by a categorical distribution (Bellemare et al., 2017), although a mixture-of-Gaussians critic was also experimented with (see also MPO, introduced later). D4PG makes use of n-step returns, again implemented via the n-step transition adder. The other major contribution of the original work was its use of distributed experience generation, however as all agents in Acme are distributed this is not a major axis of variation with other algorithms. Note that in our later experiments we will also utilize a single-actor, non-distributed version of D4PG to simplify comparison with the other continuous control methods.

TD3  Continuous Actions  Off-Policy  Q-Network  Policy-Network  Bootstrapping

The Twin Delayed DDPG (TD3) algorithm (Fujimoto et al., 2018) also extends DDPG with three primary additions. All of these modifications are restricted to the algorithm’s computation of loss and as a result strictly occur on the learner. First, this algorithm utilizes a technique similar to Double Q-learning, which uses two estimates of Q_d in its target to avoid overestimation, however the variation introduced by this work always uses the smaller of the two estimates. Second, TD3 introduces a delay under which the policy \( \pi_\theta \) is updated less frequently than the Q-function during optimization. This is an attempt to delay policy updates until the value estimate has converged. Finally, TD3 also introduces a modification to the critic estimate where noise is added to actions calculated at subsequent states in order to smooth the target estimate in an effort to avoid policies which exploit errors in the Q-function.

SAC  Continuous Actions  Off-Policy  Q-Network  Policy-Network  Bootstrapping

Soft Actor-Critic (SAC) (Haarnoja et al., 2018a,b) is an off-policy, actor-critic algorithm that optimizes an entropy regularized objective. Much like MDQN this approach requires a stochastic policy, however unlike MDQN (which this algorithm predates) SAC utilizes a separate parameterized policy \( \pi_\theta \) that outputs the parameters of some underlying distribution, often a Gaussian much like D4PG and TD3. The critic objective is derived from Equation (3) where the target includes an additional entropy term, i.e.

\[
y_t = r_t + \gamma \mathbb{E}_{A \sim \pi_\varphi(\cdot | S_{t+1})} \left[ Q_{\psi}(S_{t+1}, A) - \alpha \log \pi_\theta(A | S_{t+1}) \right]
\]

and where the objective used to optimize the policy similarly corresponds to the expected return regularized by the log-policy,

\[
J(\theta) = \mathbb{E}_{S \sim \rho_{\psi, A \sim \pi_\varphi(\cdot | S)}} \left[ Q_{\psi}(S, A) - \alpha \log \pi_\theta(A | S) \right].
\]

The amount of regularization is controlled by a temperature \( \alpha \) which can be either set or learned. Finally, it is worth highlighting that SAC makes use of the reparameterization trick to parameterize its stochastic policy as a deterministic policy and independent noise.
MPO  Continuous Actions  Off-Policy  Q-Network  Policy-Network  Bootstrapping

Introduced by Abdolmaleki et al. (2018), Maximum a posteriori Policy Optimization (MPO) is another actor-critic algorithm which employs KL-regularization in the policy optimization step. Due to the fact that MPO is agnostic to the choice of how its Q-function is learned our implementation does so in an equivalent manner to DDPG. Its main contribution, instead, lies in terms of how its policy is learned. In the literature it is often formulated as under the guise of RL as inference (Levine, 2018) and is solved using the classical expectation-maximization (EM) algorithm. Because of this particular approach, the objective minimized by gradient descent takes the following peculiar form:

\[
J_{\alpha}(\theta) = \mathbb{E}_{S\sim \rho_0} \left[ E_{A\sim \pi_\theta(\cdot|S)} \left[ \exp \left( \frac{1}{\alpha} Q_\phi(S, A) \right) \log \pi_\theta(A|S) \right] - \alpha D_{KL}(\pi_{\theta}(\cdot|S) \parallel \pi_{\theta}(\cdot|S)) \right] \tag{9}
\]

where the second term is the KL divergence regularization. Optimization of this objective corresponds to the M-step of the EM algorithm, where the second term is the KL divergence regularization. Optimization of this objective corresponds to the M-step of the EM algorithm. Because of this particular approach, the objective minimized by gradient descent takes the form:

\[
J(\theta) = \mathbb{E}_{S\sim \rho_0,A\sim \pi_\theta(\cdot|S)} \left[ \min \left( \frac{\pi_\theta(A|S)}{\pi_{\theta'}(A|S)} Q_{\phi}^{\text{adv}}(S, A), \text{clip}(\frac{\pi_\theta(A|S)}{\pi_{\theta'}(A|S)}, 1 - \epsilon, 1 + \epsilon) Q_{\phi}^{\text{adv}}(S, A) \right) \right]. \tag{10}
\]

Here the \(Q_{\phi}^{\text{adv}}(S, A)\) term is a Generalized Advantage Estimate (Schulman et al., 2016) which is related to the standard Q-function and expresses the advantage that action A has over the expected value of the given policy. An estimate of this advantage is derived by mixing direct Monte-Carlo return estimates with a state-value function estimate (learned through Bellman updates) similarly to TD(\(\lambda\)). The term \(\epsilon\) is a hyperparameter that controls how much the new policy \(\pi_\theta\) can deviate from the past iterate \(\pi_{\theta'}\).

IMPALA  Continuous Actions  On-Policy  Policy-Network  V-Network  NC  Bootstrapping

IMPALA (Espeholt et al., 2018) is an actor-critic algorithm that uses an importance correction mechanism called V-trace to learn from on-policy and potentially off-policy data. The n-step V-trace TD target for values is

\[
Y_t = V_{\phi'}(S_t) + \sum_{i=1}^{n-1} y^{i-1} \delta_{t+i}(R_{t+i} + yV_{\phi'}(S_{t+i+1}) - V_{\phi'}(S_{t+i})), \tag{11}
\]

with \(\delta_t = \min(\delta_t, \pi_{\theta}(A|S_t))\) and \(c_t = \min(c_t, \pi_{\theta}(A|S_t))\) truncated importance sampling weights. It uses a distributed set of actors that write sequences of interaction data in a queue with FIFO insertion order that the learner gets updates from.

4.3. Offline RL

BC  Continuous Actions  Off-Policy  Policy-Network

Behavior Cloning (BC) (Pomerleau, 1991) is a supervised learning method for offline RL and imitation learning which does not require online interactions with the environment. Given an offline dataset of interactions with the system and a parameterized policy BC minimizes the error between the policy’s actions, conditional on the
recorded state, and the recorded action. Additionally, this approach is quite general-purpose and acts more like a family of algorithms based on the distance metric used. In particular BC can make use of a regression loss (e.g. for continuous control) or a classification loss (e.g. for discrete control).

**TD3 + BC**

Owing to their off-policy nature, algorithms such as TD3 can directly support offline RL due to the fact that they learn from interactions not generated by the current version of the policy. However, the lack of feedback from the environment usually leads to divergence at least partly because of the extrapolation of actions not taken in states from the offline dataset $D$. Adding a BC regularization term (Fujimoto and Gu, 2021) in the actor objective helps mitigate this phenomenon

$$J(\theta) = \mathbb{E}_{S,A \sim D} [Q_\phi(S, \pi_\theta(S)) - \lambda \| A - \pi_\theta(S) \|^2].$$

**CQL**

Similarly to TD3 + BC, Conservative Q-learning (CQL) attempts to prevent action extrapolation by using a regularization term when estimating the Q-function (Kumar et al., 2020). In particular it does so by adding an additional term to the critic loss which amounts to a penalty on deviations of the critic’s estimate under an alternative reference policy $\mu$. This results in a loss that combines the standard TD-error with this additional penalty

$$L(\phi) = \mathbb{E}_{S,A,R,S',D} \left[ \mathbb{E}_{A \sim \pi_0(\cdot|S')} \left( R + \gamma Q_\psi(S', A) - Q_\phi(S, A) \right)^2 \right] + \alpha \mathbb{E}_{A \sim \mu(\cdot|S)} \left[ Q_\phi(S, A) - Q_\phi(S, A') \right].$$

In practice the reference measure $\mu$ can be chosen in a min-max fashion where typical values result in it being proportional to the exponential of the Q-function (and thus the penalty term becomes a log-sum-exp of the Q-function). For more details see the referenced work.

**CRR**

Critic-Regularized Regression (CRR) (Wang et al., 2020) is a modification of behavior cloning that restricts training to those example transitions whose advantage (i.e. the difference between the Q- and V-functions) is positive. Here the Q-function can be trained by simply minimizing the TD-error (e.g. as in TD3) and the V-function can be written as the expected value of the Q-function evaluated under the current policy. As a result the policy updates can be written to maximize the log-probability of an observed transition only if this advantage is positive, i.e.

$$J(\theta) = \mathbb{E}_{S,A \sim D} \left[ \log \pi_\theta(A|S) \ 1_{\cdot \cdot}[Q(S, A) - E_{\pi_\psi}[Q(S, A')]] \right]$$

where $1_{\cdot \cdot}$ is an indicator function which takes on a value of one when its argument is greater than zero (and is zero otherwise). Note that different variants of CRR exist that correspond to replacing the indicator function with an exponential $\exp(\cdot/\beta)$ whose sharpness is controlled by the temperature $\beta$. Additionally the inner expectation can be replaced with a maximum over the Q-function with samples taken from the policy.

**One-Step CRR**

While the above methods attempt to learn a Q-function that can be used for policy improvement, they must contend with potential extrapolation and over-estimation of actions not present in the dataset. An alternative strategy is to completely avoid evaluating the critic on any other policy than the observed one as suggested by Brandfonbrener et al. (2021). The resulting critic is used to separately improve a learned policy, via similar techniques to that employed by CRR. This corresponds to simply replacing actions sampled from the policy with actions sampled directly from the replay buffer, i.e. by modifying the inner expectation from CRR.
Behavior value estimation (BVE) (Gulcehre et al., 2021) is a one-step policy improvement algorithm where the agent, instead of trying to recover the optimal policy, learns a Q-function that estimates the behavior value $Q^\beta(s, a)$ from the dataset. To achieve this, BVE eliminates the max-operator from the target network when computing the Bellman updates for the TD-learning. The behavior values can be learned with the SARSA tuples or directly predict the Monte Carlo returns in the offline RL with discrete actions. For example

$$L(\phi) = \mathbb{E}_{S,A,R,S' \sim D} \left[ (R + \gamma Q_\theta(S', A') - Q_\phi(S, A))^2 \right]$$

or,

$$L(\phi) = \mathbb{E}_{S,A,R,S' \sim D} \left[ \left( \sum_t r_t - Q_\phi(S, A) \right)^2 \right].$$

Gulcehre et al. (2021) found that for Atari, during the training, just using the SARSA tuples with will bootstrapping and doing a single step of policy improvement when the agent is evaluated in the environment works the best, and this is the setup we use in this paper.

Random ensemble mixtures (REM) (Agarwal et al., 2020) is an offline-RL agent that makes use of ensemble of Q-functions parameterized by neural networks to estimate the Q-values. The key insight behind REM is that the convex combination of multiple Q-value provides a robust estimate of the Q-value

$$L(\phi) = \mathbb{E}_{S,A,R,S' \sim D} \left[ E_{\alpha \sim P_\Delta} \left[ (R + \gamma \max_{a} \sum_k \alpha_k Q_\phi^k(S', a) - \sum_k \alpha_k Q_\phi^k(S, A))^2 \right] \right].$$

where $P_\Delta$ represents the probability distribution over a $(K-1)$ simplex with $\Delta^{K-1} = \{\alpha \in \mathbb{R}^K : \sum_{i=1}^K a_i = 1, a_k \geq 0, \forall k \in [1, K]\}$. During the training $\alpha$’s are sampled from uniform distribution such that $\alpha_k \sim U(0, 1)$ and then normalized $\alpha_k = \frac{\alpha_k}{\sum_{i=1}^K \alpha_i}$ to be in the $(K-1)$ simplex. For action-selection in the environment, REM uses the average of the Q-value estimates, i.e $Q(s, a) = \sum_k Q_\phi^k(s, a)/K$.

4.4. Imitation Learning

In this section, we describe Imitation Learning algorithms which include a direct RL method. The tags are left blank as the overall algorithm inherits properties from its direct RL method.

Adversarial Imitation Learning (AIL) is a framework introduced by Ho and Ermon (2016) that follows the two-player game paradigm set forth by Generative Adversarial Networks (GANs). In this setting an agent (the generator) is trained to produce trajectories that are indistinguishable from demonstrations as determined by a trained discriminator. The objective consists of matching the state-action occupancy measure of the policy, denoted $d_{\pi_{\theta_1}}$, with that of an expert, denoted $d_e$. This matching is done by minimizing their Jensen-Shannon divergence between the two occupancy measures (Ho and Ermon, 2016; Ke et al., 2020). In practice, the policy is trained with an online RL algorithm whose reward is given by a classifier which tells whether a transition comes from the demonstration data or the agent interaction data. Letting $D(s, a)$ denote the probability of classifying a given state-action pair as expert-generated, the policy can be trained via the base RL algorithm with a reward of $r(s, a) = -\log(1 - D_e(s, a))$. The discriminator itself can be trained by maximizing the following objective

$$K(\omega) = \mathbb{E}_{O,A \sim d_{\pi_{\theta_1}}} [\log D_w(O, A)] - \mathbb{E}_{O,A \sim d_e} [\log(1 - D_w(O, A))].$$

A number of variants of GAIL have been proposed and have showed to improve performance using an off-policy agent rather than an on-policy agent (Kostrikov et al., 2019), using regularization in the discriminator (Miyato et al., 2018; Gulrajani et al., 2017) or using different formulation of the rewards (Fu et al., 2018). We refer the reader to Orsini et al. (2021) for an extensive review of the different variants and their influence on performance. In the rest of the paper, the GAIL variant studied uses TD3 as the direct RL method similarly to DAC (Kostrikov et al., 2019) with the original GAIL reward.
SQIL  Discrete & Continuous Actions

Soft Q Imitation Learning (Reddy et al., 2020) is a method based on a limit case of AIL, since it consists in using a constant positive reward if the transition comes from the expert demonstrations and a zero reward if the transition comes from the agent interactions. The agent learns from balanced batches between expert demonstrations and agent interactions using an off-policy online RL agent (in our study, the agent used is SAC).

PWIL  Continuous Actions

Primal Wasserstein Imitation Learning (Dadashi et al., 2021) is a non-adversarial imitation learning method that aims at minimizing the primal formulation of the Wasserstein distance between the state-action occupancy measure of the agent and the one of the expert. The reward is derived from an upper bound of the Wasserstein distance. In the following, the direct RL agent considered is D4PG.

4.5. Learning from Demonstrations

SACfD/TD3fD  Continuous Actions  Off-Policy  Q-Network  Policy-Network  Bootstrapping

We propose two natural modifications to the SAC agent and the TD3 agent compatible with the Learning from Demonstrations setting and inspired from Vecerik et al. (2017b). In this setting, contrary to the Imitation Learning setting, the environment has a well-defined reward function and the demonstrations come with environment rewards. We can thus modify any off-policy agent (in this case, SAC and TD3) to sample batches of transitions either from environment interactions or from demonstration data with a ratio that is a hyperparameter.

5. Experiments

In order to showcase Acme agents, we provide in this section a set of experiments from multiple agents tackling the settings described in Section 2. This further highlights the flexibility of our framework due to the fact that a number of agents can be evaluated in multiple setups, e.g. TD3 alone can be used online, offline by making use of TD3+BC, AIL can be used with TD3 as its direct RL agent, and TD3fD can be used to learn from demonstrations. Note however that while the learning curves are representative and should be informative they are not meant to establish a strict hierarchy between the different agents since these could be further improved by tweaking hyperparameters on a per-environment basis. Instead these results should demonstrate that the agents are implemented correctly and are able to reproduce the published baselines. Additionally, one can reproduce these baselines by simply using the runfiles in the baselines/ folder of Acme. Similarly, all hyperparameters used the experiment can be read directly in these provided scripts.

5.1. Protocol

For each setup, we evaluate agents on a common set of tasks that are standard in the literature (e.g. Atari games for discrete control) for a fixed number of interactions with the environment. Most agents can have two policies: a training policy that interacts with the environment while balancing exploration and exploitation, and an evaluation policy that is fully exploitative. Each experimental setup will specify which policy is used in the corresponding figures. For each evaluated agent, we performed a hyperparameter search for a configuration that is reasonably consistent with performance reported in the literature across all tasks. Agent performance is computed across multiple random seeds (specified for each setup), and episode returns are grouped in 50 contiguous equal size windows of steps (actor steps for online algorithms and learner steps for offline algorithms). The figures below show the resulting average and standard deviation. The standard deviation captures both the inter-seed and intra-seed variability. In the presented results, a single hyperparameter configuration is run across the full setup. One can thus tweak further the hyperparameter of each algorithm for a specific task and reach much higher performance.
5.2. Environments

**Arcade Learning Environment** The Arcade Learning Environment (ALE) (Bellemare et al., 2013) provides a simulator for Atari 2600 games. ALE is one of the most commonly used benchmark environments for RL research. The action space ranges between 4 to 18 discrete actions (joystick controls) depending on the game. The observation space consists of 210 x 160 RGB image. We use a representative subset of five Atari games to broadcast the performance of our discrete agents. We also use several pre-processing methods on the Atari frames including giving zero-discount on life loss, action repeats with frame pooling, greyscaling, rescaling to 84x84, reward clipping, and observation stacking, following Machado et al. (2018).

**DeepMind Control suite** The DeepMind Control suite (Tassa et al., 2018) provides a set of continuous control tasks in MuJoCo (Todorov et al., 2012) and has been widely used as a benchmark to assess performance of continuous control algorithms. The tasks vary from the simple control problems with a single degree of freedom (DOF) such as the cartpole and pendulum, to the control of complex multi-joint bodies such as the humanoid (21 DOF). The DeepMind Control suite enables to control an agent both in a feature-based observation space and a raw pixel-based observation space. The following results are limited to the former.

**Gym environments** The Gym suite (Brockman et al., 2016) provides a wide range of continuous control tasks in MuJoCo and is a testbed for continuous control algorithms. In the following, we focus on locomotion tasks, that share similarities with the ones defined in the DeepMind Control suite. We also consider the Adroit manipulation tasks (Rajeswaran et al., 2017), a collection of 4 tasks with a 24-DOF simulated hand.

![Continuous Control](image)

**Figure 6** Continuous Control. Episode returns obtained by the evaluation policies. Here we plot the means and standard deviations over 25 seeds. Gym environments are run for 10 million environment steps, DM Control environments for 4 million, except for DM Control humanoid which is run for 25 million steps.
5.3. Results

**Continuous Control** We evaluate PPO, TD3, SAC, D4PG and MPO (as well as MPO variants) on the environments described in Section 5.1. Policy and value networks have a common three hidden layer architecture with 256 units. Hyperparameters are kept constant across environments for each algorithm, except for D4PG for which we change the support of the distributional critic for Gym and DM Control. We report the results in Figure 6, where we can observe the average episode return for the evaluation policy (without exploration noise) as a function of the environment steps. For the sake of completeness, we also include the results of PPO at convergence as a dashed horizontal line. To obtain this value, we run the exact same configuration of PPO with 256 actors for 50M environment steps and plot the average and standard deviation of the episode return obtained between 45M and 50M steps, where the algorithm has converged.

**Discrete Control** We evaluate DQN, R2D2, Impala and Munchausen-DQN on 5 Atari games: Asterix, Breakout, MsPacman, Pong and SpaceInvaders. For DQN and M-DQN, both algorithms use the same network, the original three convolutional layer followed by one dense layer from Mnih et al. (2013). For R2D2 and Impala, the network architecture is recurrent. Note that both DQN and M-DQN use Adam as their optimizer, which considerably improves results compared to RMSProp. The results depicted in Figure 7 are computed across 5 random seeds, in a distributed setup. Although the unified setup (distributed actors, sticky actions, zero-discount on life loss, 200M frames) makes it harder to compare to all specific reference papers, performance of the resulting policies overall match the results provided in the literature. In the chosen 200M frames regime, which uses an order of magnitude less samples than in the original papers of recurrent agents (R2D2/IMPALA), recurrent architectures still seem to help with performance.

![Graphs showing results for Asterix, Breakout, MsPacman, Pong, and SpaceInvaders](image)

**Figure 7** | **Discrete Control.** Episode returns obtained by the training policies. Here we plot the means and standard deviations over 5 seeds. Each environment is run for 50 million environment steps, which corresponds to 200 million frames, due to the agent’s actions being repeated four times on the environment side (Mnih et al., 2013).
**Offline Reinforcement Learning** We evaluate TD3, TD3+BC, CQL, CRR and CRR+SARSA on the Gym MuJoCo (Brockman et al., 2016) locomotion environments mentioned in Section 5.1 with D4RL datasets (Fu et al., 2020). The D4RL datasets is a collection of datasets generated by agents trained online. Figure 8 compares the performance of these algorithms on different D4RL levels (medium-expert, medium, medium-replay). For CQL, we observed that an initial pre-training of the policy for 50K steps significantly improves the performance. We also trained and evaluated BC, BVE, REM, and offline DQN on offline Atari datasets from RL Unplugged offline RL benchmark suite (Gulcehre et al., 2020) with the best hyperparameters reported in the paper. We noticed in Figure 9 that on dense reward games, such as Pong and Asterix, the one-step RL agent BVE performs better than REM and DQN. However, on Gravitar, a sparse reward game, the methods that do multiple steps of policy improvement, such as DQN and REM, perform better than BVE.

![Figure 8](image1.png) ![Figure 8](image2.png) ![Figure 8](image3.png)

**Figure 8** | **Offline RL.** Mean and standard deviation of the episode return obtained by the evaluation policies over 25 seeds in 1M learner steps. Each column is a different D4RL level. Each row is a different environment.

![Figure 9](image4.png) ![Figure 9](image5.png) ![Figure 9](image6.png)

**Figure 9** | **Offline RL for Atari.** Mean and standard deviation of the episode return obtained by the evaluating policies over 5 seeds in 2M learner steps for BVE, REM, DQN and BC on 3 Atari games.


**Imitation Learning**  We evaluate AIL, PWIL, SQIL and BC on the locomotion environments mentioned in Section 5.1. We use the demonstrations generated by Orsini et al. (2021) which consists in 50 trajectories of a SAC agent trained to convergence on the original reward of the environment. For each seed, a fixed number of demonstration trajectories is sampled (1, 4 or 11); we did not subsample the trajectories. Figure 10 indicates that the performance of all methods improves with the number of demonstrations.

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**Figure 10 | Imitation Learning.** Episode return obtained by the evaluation policies over 25 seeds in 1M environment steps. Each column corresponds to a different number of demonstration trajectories. Each row is a different environment. The BC algorithm, which is trained offline, is depicted as an dashed line.
Learning from Demonstrations  We evaluate TD3fD and SACfD on a sparse version of Adroit environments which rewards the agent with 1 if the goal is achieved and 0 otherwise. We use the same demonstrations as Rajeswaran et al. (2017), which consists in 25 trajectories acquired by a human controller through a virtual reality system. In Figure 11 we show the influence of the ratio of demonstration transitions in the replay buffer against the agent’s historical transitions. The learning curves clearly illustrate that using demonstration data lead to better performance. We did not include learning curves on the Relocate task since none of the methods was able to get non-zero performance.

Figure 11 | Learning from Demonstrations. Mean and standard deviation of the episode return obtained by the evaluation policies over 25 seeds in 1M environment steps. Each column corresponds to a different ratio of demonstration transitions in the replay buffer against agent’s experienced transitions. Each row is a different environment.

Speed  In order to showcase how easily Acme agents can be sped up by simply scaling the learner hardware, we repeated an experiment three times on three different machines: a GPU-V100, a TPU-v2 1x1 and a TPU-v2 2x2. To be clear, the agent and its algorithmic logic is identical in all three cases, only the hardware its learner is running on varies. For this comparison we focussed on Pong. In order to ensure that the experiment is bottlenecked by the learner’s SGD step, we launched distributed R2D2 experiments with 256 actors and scaled the ResNet torso up to have channels of sizes $64, 128, 128, 64$ per group instead of $16, 32, 32$. The parameters are otherwise the default ones presented in Figure 7. As expected, the three experiments lead to the same episode return, yet TPU-v2 1x1 yields a 1.7x speed-up over GPU-V100, while running on the full 2x2 topology leads to a 5.6x speed-up over GPU. Results are presented on Figure 12.

6. Related work

Numerous open-source software libraries and frameworks have been developed in recent years. In this section we give a brief review of recent examples, and situate Acme within the broader context of similar projects. OpenAI baselines (Dhariwal et al., 2017) and TF-Agents (Guadarrama et al., 2018) are both examples of
established deep RL frameworks written in TensorFlow 1.X. They both strive to express numerous algorithms in single-process format. Dopamine (Castro et al., 2018) is a framework focusing on single-process agents in the DQN (Mnih et al., 2015) family, and various distributional variants including Rainbow (Hessel et al., 2018), and Implicit Quantile Networks (Dabney et al., 2018). Fiber (Zhi et al., 2020) and Ray (Moritz et al., 2017) are both generic tools for expressing distributed computations, similar to Launchpad, described below. ReAgent (Gauci et al., 2018) is primarily aimed at offline/batch RL from large datasets in production settings. SEED RL (Espeholt et al., 2018) is a highly scalable implementation of IMPALA (Espeholt et al., 2018) that uses batched inference on accelerators to maximize compute efficiency and throughput. Similarly, TorchBeast (Kiitter et al., 2019) is another IMPALA implementation written in Torch. SURREAL (Fan et al., 2018) expresses continuous control agents in a distributed training framework. Arena (Song et al., 2020) is targeted at expressing multi-agent reinforcement learning.

The design philosophy behind Acme is to strike a balance between simplicity and that of modularity and scale. This is often a difficult target to hit—often it is much easier to lean heavily into one and neglect the other. Instead, in Acme we have designed a framework and collection of agents that can be easily modified and experimented with at small scales, or expanded to high levels of data throughput at the other end of the spectrum.

7. Conclusion

This work introduces Acme, a modular light-weight framework that supports scalable and fast iteration of research ideas in RL. Acme naturally supports both single-actor and distributed training paradigms and provides a variety of agent baselines with state-of-the-art performance. This work also represents a second version of the paper which has seen an increase focus on modularity as well as additional emphasis on offline and imitation algorithms. The number of core algorithms implemented as part of Acme has also increased.

By providing these tools, we hope that Acme will help improve the status of reproducibility in RL, and empower the academic research community with simple building blocks to create new RL agents. Additionally, our baselines should provide additional yardsticks to measure progress in the field. We are excited to share Acme with the research community and look forward to contributions from everyone, as well as feedback to keep improving and extending Acme.

8. Author Contributions & Acknowledgments

Matt Hoffman, Gabriel Barth-Maron, John Aslanides, and Bobak Shahriari co-designed and implemented the first version of Acme that was released on June 1, 2020. This was based heavily on an initial prototype designed by Gabriel Barth-Maron, who provided much of the implementation for this initial prototype, and Matt Hoffman. Matt and Gabriel also contributed heavily to the design of Launchpad, which enabled distributed agents. Gabriel was also an important contributor to open-sourcing Reverb, which is used for experience replay. John Aslanides played a significant role in the underlying design for Actors, policies, and environment loops; he also contributed both the first DQN implementation as well as designing the first JAX agents in Acme (which
at that point were purely TensorFlow). Matt and Bobak later updated these designs to use JAX more centrally, helped integrate the Builder mechanism, and contributed ongoing maintenance and design. Matt was also the primary author of the first and second versions of the accompanying paper and Bobak coordinated these experiments. Bobak contributed the MPO agent for both TensorFlow and JAX and was heavily involved in core agent design.

Nikola Momchev contributed the Builder design along with its first implementation with contributions from Danila Sinopalnikov and Piotr Stanczyk. They worked to integrate this into Acme along with modular agents built using this system. Their work also enabled the incorporation of a number of imitation learning agents. They were also heavily involved in the continuing design and ongoing maintenance of Acme. Danila Sinopalnikov, in addition, contributed significantly to Acme’s agent testing infrastructure. Piotr Stanczyk contributed to the joint experiment configuration between single-process and distributed agents; he also contributed to ongoing maintenance for both Launchpad and Reverb, including their integration with Acme, and was instrumental in open sourcing Launchpad.

Sabela Ramos incorporated policy construction into the Builder interface as well as implementing structured Adders. Anton Raichuk provided numerous speed and efficiency improvements, implemented the first version of configurable policy and evaluator callbacks, and implemented SAC.

Léonard Hussenot and Robert Dadashi contributed to a number of agents—including TD3, PWIL, and SACFD—and were heavily involved in designing the experimental setup for the second version of the paper. Léonard led the coordination of experiments for the paper as well as writing the experimental section and providing plots. Both Robert and Léonard were also heavily involved in writing the paper as a whole, particularly the experimental and algorithm-specific descriptions (Sections 4 and 5).

Gabriel Dulac-Arnold contributed to running continuous control experiments, and helped with writing an early draft of Section 4, provided editing support, as well as contributing important design feedback for future generalizations. Manu Orsini, Alexis Jacq, Damien Vincent, Johan Ferret, Nino Vieillard implemented or made improvements upon a number of agents including GAIL, DQN, R2D2. Seyed Kamyar Seyed Ghasemipour made a number of agent improvements for supporting large-scale PPO, alongside Acme infrastructure contributions for supporting multi-learner agents. Sertan Gürin contributed bug fixes and a number of helpers for experiment launchers. Olivier Pietquin provided support and coordination throughout the second version of both the code and paper.

Feryal Behbahani helped document the first version of Acme, including writing tutorial notebooks, and wrote algorithm descriptions in the accompanying paper. Tamara Norman provided a number of efficiency improvements throughout the initial codebase. Abbas Abdolmaleki tuned all MPO variants, as well as being instrumental in its development, for both versions of the paper. Albin Cassirer helped integrate Acme with Reverb and provided the first version of Adders. Fan Yang helped integrate Acme with Launchpad. Kate Baumli provided initial documentation, notebook tutorials, and the initial version of the JAX R2D2 agent. Sarah Henderson provided support and coordination for releasing the code and writing the paper. Abe Friesen contributed code and tuning for the updated MPO agent. Ruba Haroun provided documentation and tutorials for the second version. Alex Novikov provided a number of bug fixes and initial offline agents for the first version of the paper. Sergio Gómez Colmenarejo provided bug fixes and helped with snapshot and checkpoint code for the first version. Serkan Cabi provided feedback and bug fixes for the initial JAX version of D4PG. Caglar Gulcehre and Tom Le Paine provided offline algorithms and experiments for both versions of the paper; Srivatsan Srinivasan contributed to these algorithms for the second version. Andrew Cowie provided bug fixes and an initial implementation of BCQ for the first version of the paper. Ziyu Wang and Alex Novikov contributed to an initial version of CRR. Bilal Piot provided feedback and design for the initial versions of R2D2 and MPO. Nando de Freitas provided support and feedback for both versions of the code and paper.

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A. Algorithm Tag Descriptions

- **Discrete Actions** and **Continuous Actions** describe the nature of actions space supported by the agents.

- **On-Policy**, **Off-Policy**, and **Offline** describe the training regimes of the agents, whether the learned policy is being played to gather data (on-policy), or another policy is being played to gather data (off-policy) or no data is being gathered (offline).

- **Q-Network**, **V-Network**, and **Policy-Network** describe the functions approximated with neural networks required by the agents.

- **MC** and **Bootstrapping** describe the learning logic of the value, either by unrolling full trajectories (Monte-Carlo rollouts), or by using its own estimate to define the target (bootstrapping).