Ray: A Distributed Framework for Emerging AI Applications

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Abstract

The next generation of AI applications will continuously interact with the environment and learn from these interactions. These applications impose new and demanding systems requirements, both in terms of performance and flexibility. In this paper, we consider these requirements and present Ray-a distributed system to address them. Ray implements a dynamic task graph computation model that supports both the task-parallel and the actor programming models. To meet the performance requirements of AI applications, we propose an architecture that logically centralizes the system's control state using a sharded storage system and a novel bottom-up distributed scheduler. In our experiments, we demonstrate sub-millisecond remote task latencies and linear throughput scaling beyond 1.8 million tasks per second. We empirically validate that Ray speeds up challenging benchmarks and serves as both a natural and performant fit for an emerging class of reinforcement learning applications and algorithms.

1 Introduction

Artificial intelligence is currently emerging as the workhorse technology for a range of real-world applications [27]. To date, however, these applications have largely been based on a fairly restricted supervised learning paradigm in which a model is trained offline and deployed to serve predictions online. As the field matures, it will be necessary to consider a broader setting than standard supervised learning. Instead of making and serving a single prediction, machine learning applications must increasingly operate in dynamic environments, react to changes in the environment, and take sequences of actions to accomplish a goal [6, 34]. These broader requirements are naturally framed within the paradigm of reinforcement learning (RL), which deals with learning to operate continuously within an uncertain environment [44]. RL-based applications have already led to remarkable results, such as Google's AlphaGo beating a human world champion [43], and are finding their way into self-driving cars, UAVs [33], and robotic manipulation [23, 47].

There are three characteristics that distinguish RL applications from traditional supervised learning applications. First, they often rely heavily on simulations to explore states and discover the consequences of actions. A simulator could encode the rules of a computer game [11], the Newtonian dynamics of a physical system such as a robot [45], or the hybrid dynamics of virtual environments. This generally requires massive amounts of computation; for example, a realistic application might perform hundreds of millions of simulations. Second, the computation graph of an RL application is heterogeneous and evolves dynamically. A simulation can take from a few milliseconds to a few minutes, and the result of a simulation can determine the parameters of future simulations. Third, many RL applications, such as robotic control or autonomous driving, require actions to be taken *quickly* in response to a constantly changing environment. Furthermore, to choose the best action, the application may need to perform more simulations in real time. In summary, we need a computation framework that supports heterogeneous and dynamic computation graphs, while handling millions of tasks per second with millisecond-level latencies.

Existing cluster computing frameworks fall short of adequately satisfying these requirements. Map-Reduce [18], Apache Spark [50], Dryad [25], Dask [38], and CIEL [32] support neither the throughput nor the latencies required by general RL applications, while TensorFlow [5], Naiad [31], MPI [21], and Canary [37] generally assume static computation graphs.¹

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¹While deep learning frameworks like TensorFlow or MXNet are critical components of RL systems, they are not sufficient on their own. Existing distributed RL applications [3, 20, 39] that use these systems

In this paper, we propose Ray, a cluster computing framework that satisfies these requirements. To support the heterogeneous and dynamic workloads imposed by these applications, Ray implements a dynamic task graph computation model, similar to CIEL [32]. However, Ray also provides an actor programming abstraction on top of this execution model, in addition to the task-parallel abstraction provided by CIEL. The actor abstraction enables Ray to support stateful components, such as thirdparty simulators.

To achieve the stringent performance targets while supporting dynamic computation graphs, Ray employs a new distributed architecture that is horizontally scalable. The architecture is based on two key ideas. First, we store all of the control state of the system in a *global control store*, which enables all of the other components in the system to be stateless. As a result, each component can easily be scaled horizontally and restarted in the case of failures. In turn, the global control store can be scaled via sharding and made fault tolerant via replication.

Second, we introduce a new *bottom-up distributed scheduler*, where tasks are submitted by workers and drivers to *local schedulers* (there is one local scheduler per node). Local schedulers may choose to schedule tasks locally or to forward tasks to a replicated global scheduler. This decreases task latency by allowing local decisions, and increases the system throughput by reducing the burden on the global scheduler. We make the following **contributions**:

- We specify the systems requirements for emerging AI applications: support for (a) heterogeneous, concurrent computations, (b) dynamic task graphs, (c) high-throughput and low-latency scheduling, and (d) transparent fault tolerance.
- We provide the actor abstraction—in addition to the task-parallel programming abstraction—on top of a dynamic task graph computation model.
- We propose a horizontally scalable architecture to meet the above requirements, and build Ray, a cluster computing system that realizes this architecture.

2 Motivation and Requirements

While Ray can support a variety of workloads—as it provides both the task-parallel and the actor abstractions we focus on RL workloads in this paper, as they are representative of emerging AI applications, and were the primary driver behind Ray's design. Here, we consider a simple RL application to illustrate the key requirements for Ray.

An RL system consists of an *agent* that interacts repeatedly with the *environment* (see Figure 1(a)). The goal of the agent is to learn a policy that maximizes some *reward*. A *policy* is a mapping from the state of the environment to an *action* to take. The definitions of environment, agent, state, action, and reward are application-specific (Table 1).

Figure 2 shows an example of the pseudocode used by an agent to learn a policy. A typical procedure consists of two steps: (1) *evaluate* the current policy, and (2) *improve* the policy. To evaluate the policy, the pseudocode invokes **rollout**(*environment*, *policy*) to generate a set of rollouts, where a rollout is a trajectory of states and rewards collected by interacting with the environment using *environment*.**step**(*action*). An *action* is computed given the current *policy* and environment *state* via *policy*.**compute**(*state*). As trajectories are generated, **train_policy**() uses completed trajectories to improve the current policy via *policy*.**update**(*trajectories*). This process is repeated until the policy converges.

While simple, this application illustrates the key requirements of emerging AI applications. We group these requirements into three categories.

Flexibility. The flexibility of a system is typically measured in terms of the diversity of the workloads it can support. We consider two aspects of flexibility: the heterogeneity of concurrently executing tasks and the generality and dynamicity of the execution graph.

Concurrent, heterogeneous tasks. Concurrent tasks can be heterogeneous along three dimensions:

- *Functionality.* In the case of a robot, assessing the environment's state (e.g., *environment.step(action))* involves processing the inputs of multiple sensors, such as video, microphone, and radar. This requires running multiple tasks in parallel, each implementing a *different computation* (see Figure 1(b)).
- *Duration*. The time it takes to compute a trajectory can vary significantly (see **rollout**(*policy*, *environment*)). For example, in the case of a game, it could take just a few actions (moves) to lose the game, or it could take hundreds of moves to win it.
- *Resource types.* Computing an action by evaluating the policy (e.g., *policy.compute(state)*) is in many cases implemented by a deep neural network, which typically requires the use of GPUs. On the other hand, most of the other computations use CPUs.

Note that these requirements are not naturally satisfied by the Bulk Synchronous Parallel (BSP) model [46], which is implemented by many of today's popular cluster computing frameworks [18, 50]. With BSP, all tasks within

rely on ad-hoc solutions or other distributed frameworks to implement task-parallelism and fault tolerance and to integrate stateful simulators.



Figure 1: (a) An RL system. (b) Task graph for processing sensor inputs. (c) Task graph for learning policy.

Application	Environment	Agent	State	Action	Reward
Go (game)	Board and opponent	Player	Board position	Place a piece	Game outcome
Atari Pong	Program	Player	Sequence of video frames	Control joystick	Pong score
Robot moving an object	Physical world	Control program	Object and robot pose	Actuate joints	Object moved

Table 1: Example RL applications.

```
train_policy(environment):
    policy ← initial_policy()
    while (policy has not converged):
        trajectories ← []
        // generate k rollouts and use them to update policy
        for i from 1 to k:
            trajectories.append(rollout(policy, environment))
        policy = policy.update(trajectories)
    return policy
```

Figure 2: Pseudocode for a typical RL training application.

the same stage² typically perform the same computations (albeit on different data partitions) and take roughly the same amounts of time.³

Dynamic task graphs. Consider the **train_policy**() function. Though not shown in Figure 2, it would be natural to update the policy as soon as a subset of rollouts finish (instead of waiting for all of them) and to launch new rollouts to maintain a pool of executing rollouts as in Figure 1(c). This makes the execution graph *dynamic*, as we cannot predict the order in which rollouts will complete or which rollouts will be used for a particular policy update.

Performance. In the case of a robot interacting with the physical environment, we need to infer the state of

the environment and compute a new action in a matter of milliseconds. Similarly, simulations might take on the order of milliseconds as well. As such, we need to be able to schedule tasks in less than one millisecond. Otherwise the scheduling overhead could be significant. Given that clusters with tens of thousands of cores are common, we need to be able to schedule hundreds of thousands or even millions of tasks per second. Consider a cluster consisting of 100 servers, each with 32 cores, and suppose each task takes 5ms to execute. To fully utilize this cluster, we would need to schedule 640K tasks/sec.

Ease of development. Since writing parallel applications is non-trivial, and since ML developers prefer to focus on their applications rather than on systems programming, simplifying development is paramount for the success of such a system.

Deterministic replay and fault tolerance. The ability to deterministically replay a job dramatically simplifies debugging. Transparent fault tolerance obviates the need for users to handle faults explicitly. It also enables users to use cheap preemptible resources (e.g., spot instances on AWS), leading to substantial cost savings when running in a public cloud.

Easy parallelization of existing algorithms. This involves providing a simple API and supporting existing languages, tools, and libraries. First, we need to provide support for Python, as Python is the language of choice for AI developers. Second, we need to provide tight integration with the wide range of available thirdparty libraries. These libraries include simulators such as OpenAI gym [13], DeepMind Lab [10], and the Mujoco physics simulator [45] as well as deep learning frameworks like TensorFlow [5], Theano [12], PyTorch [4], and Caffe [26]. As we will see, this requires augmenting the task-parallel model with an actor-like abstraction to wrap these third-party services.

²A stage is the unit of parallelism in BSP.

 $^{^{3}}$ Many straggler mitigation techniques depend on this assumption [8].

3 Programming and Computation Model

Ray implements a dynamic task graph computation model. On top, Ray provides both an actor and a taskparallel programming abstraction. This dual abstraction differentiates Ray from related systems, such as CIEL which only provides a task-parallel abstraction, and Orleans, which primarily provides an actor abstraction [14].

3.1 Programming Model and API

At its core, Ray provides a *task-parallel* programming model. Table 2 shows Ray's API. When a remote function is invoked, a *future* that represents the result of the task is returned immediately. Futures can be retrieved using **ray.get**() and composed, i.e., a future can be passed as an argument into another remote function. This allows the user to express parallelism while capturing data dependencies.

Remote functions operate on immutable objects, and are expected to be *stateless* and side-effect free: their outputs are determined solely by their inputs. This implies idempotence, which simplifies fault tolerance through function re-execution on failure.

To satisfy the requirements for heterogeneity, flexibility, and ease of development given in Section 2, we augment the task-parallel programming model in four ways.

First, to handle concurrent tasks with heterogeneous durations, we introduce **ray.wait**(). This call takes in a list of futures and returns the subset whose results are available, either after a timeout or when at least k are available. In contrast, **ray.get**() blocks until *all* requested futures are available. This is highly beneficial for RL applications, as simulations may have widely different durations, but complicates fault tolerance due to introduced nondeterminism.

Second, to handle resource-heterogeneous tasks, we enable developers to specify resource requirements so that the Ray scheduler can efficiently manage resources. The resources specified for a remote function are only allocated during the function's execution.

Third, to improve flexibility, we enable *nested remote functions*, meaning that remote functions can invoke other remote functions. This is also critical for achieving high scalability (see Section 4), as it enables multiple processes to invoke remote functions in parallel (otherwise the driver becomes a bottleneck for task invocations).

Finally, and most importantly, for ease of development and efficiency, we enhance our programming model with an *actor* abstraction. One limitation we encountered early in our development with stateless tasks was the inability to wrap third-party simulators, which do not expose their internal state. To address this limitation, Ray provides basic support for stateful components in the form of actors. In Ray, an actor is a stateful process that exposes a set of methods that can be invoked as remote functions and that executes these methods serially.

3.2 Computation Model

Ray employs a dynamic task graph computation model [19], in which the execution of both remote functions and actor methods is automatically triggered by the system when their inputs become available. In this section, we describe how the computation graph (Figure 3(b)) is constructed from a user program (Figure 3(a)). This program uses the API in Table 2 to implement the pseudocode from Figure 2.

Ignoring actors first, there are two types of nodes in a computation graph: data objects and remote function invocations, or tasks. There are also two types of edges: data edges and control edges. Data edges capture the dependencies between data objects and tasks. More precisely, if data object *D* is an output of task *T*, we add a data edge from *T* to *D*. Similarly, if *D* is an input to *T*, we add a data edge from *D* to *T*. Control edges capture the computation dependencies that result from nested remote functions (Section 3.1): if task T_1 invokes task T_2 , then we add a control edge from T_1 to T_2 .

Actor method invocations are also represented as nodes in the computation graph. They are identical to tasks with one key difference. To capture the state dependency across subsequent method invocations on the same actor, we add a third type of edge: a stateful edge. If method M_j is called right after method M_i on the same actor, then we add a stateful edge from M_i to M_j . Thus, all methods invoked on the same actor object form a chain connected by stateful edges (Figure 3(b)). This chain captures the order in which these methods were invoked.

Stateful edges help us embed actors in an otherwise stateless task graph, as they capture the implicit data dependency between successive method invocations sharing the internal state of an actor. Stateful edges also enable us to maintain lineage. As in other dataflow systems [50], we track data lineage to enable reconstruction. By explicitly including stateful edges in the lineage graph, we can easily reconstruct lost data, whether produced by remote functions or actor methods (Section 4.2.3).

4 Architecture

4.1 Application Layer

The application layer consists of three components:

• Driver: A process executing the user program.

Name	Description		
$futures_list = \mathbf{f}.\mathbf{remote}(args)$	Execute function $f()$ remotely. $f()$ takes either object values or futures as arguments,		
	and returns a list of futures. This is a non-blocking call.		
$obj_list = ray.get(futures_list)$	Return the values associated with a list of futures. This is a blocking call.		
futures_list_done =	Given a list of futures, return the futures whose corresponding tasks have completed		
ray.wait (<i>futures_list</i> , <i>k</i> , <i>timeout</i>)	as soon as either k of the tasks have completed or the timeout expires.		
actor = Class.remote $(args)$	Instantiate class <i>Class</i> as a remote actor, and return a reference to it. Call a method		
<i>futures_list</i> = <i>actor</i> . method . remote (<i>args</i>)	on the remote actor and return a list of futures. This is a non-blocking call.		

Table 2: Ray API



Figure 3: (a) Python code implementing the example in Figure 2 in Ray. Note that @ray.remote indicates remote functions and actors. Invocations of remote functions and actor methods return futures, which can be passed to subsequent remote functions or actor methods to encode task dependencies. Each actor has an environment object self.env shared between all of its methods. (b) The task graph corresponding to an invocation of train_policy.remote(). Remote function calls and the actor method calls correspond to tasks in the task graph. The figure shows two actors. The method invocations for each actor (the tasks labeled A_{1i} and A_{2i}) have stateful edges between them indicating that they share the mutable actor state. There are control edges from train_policy to the tasks that it invokes. To train multiple policies in parallel, we could call train_policy.remote() multiple times.

- *Worker*: A stateless process that executes tasks (remote functions) invoked by a driver or another worker. Workers are started automatically and assigned tasks by the system layer. When a remote function is declared, the function is automatically published to all workers. A worker executes tasks serially.
- Actor: A stateful process that executes, when invoked, the methods it exposes. Unlike a worker, an actor is explicitly instantiated by a worker or a driver. Like workers, actors execute methods serially.

Note that workers are stateless in that they do not maintain local state across tasks. Assuming deterministic execution, invoking the same remote function with the same arguments will return the same results no matter whether it is executed on the same worker or not. In contrast, an actor is a stateful process in that the results of a method invocation can depend on the previous methods executed by that actor.

4.2 System Layer

The system layer enables us to meet the performance and fault tolerance goals, as discussed in Section 2, by employing an architecture in which each component is horizontally scalable and fault-tolerant. This layer consists of three major components: a global control store, a distributed scheduler, and a distributed object store.

4.2.1 Global Control Store (GCS)

At its core, our system leverages a global control store (GCS), which stores all up-to-date metadata and control state information in the system. This includes (1) a speci-



Figure 4: Ray's architecture consists of two parts: an *application* layer and a *system* layer. The application layer implements the API and the computation model described in Section 3, the system layer implements task scheduling and data management to satisfy the performance and fault-tolerance requirements.

fication of every task, (2) the code for every remote function, (3) the computation graph, (4) the current locations of all objects, and (5) every scheduling event. The GCS also provides publish-subscribe infrastructure to facilitate communication between components.

By storing and managing the entire control state in a centralized fashion, the GCS enables every other component to be stateless. This not only simplifies the support for fault tolerance (i.e., on failure, components restart and read the latest state from the GCS), but also makes it easy to horizontally scale every other component, as all the state shared by the component's replicas or shards is accessible via the GCS.

To scale the GCS, we use sharding. Since we can associate pseudo-random IDs to virtually every data entry in the GCS (e.g., objects, tasks, functions), it is relatively easy to balance the load across multiple shards. To provide fault-tolerance, we use a hot replica for each shard.

Centralizing the system control information allows us to easily build debugging, profiling, and visualization tools on top of the GCS. The minimalist tools we've built so far have already proven useful in our development.

4.2.2 Bottom-Up Distributed Scheduler

Many existing cluster computing frameworks, such as Apache Spark [50], CIEL [32], Dryad [25] and Hadoop [49], implement a centralized scheduler. While this simplifies the design, it hurts scalability.

There are several approaches to improve scheduling scalability: (1) *batch scheduling*, where the scheduler submits tasks to worker nodes in batches to amortize fixed overheads related to task submission (e.g., Drizzle [48]); (2) *hierarchical scheduling*, where a global scheduler partitions the task graph across per-node local



Figure 5: Bottom-up distributed scheduler. Tasks are submitted bottom-up, from drivers and workers to a local scheduler and forwarded to the global scheduler only if needed (Section 4.2.2). The thickness of each arrow is proportional to its request rate.

schedulers (e.g., Canary [37]); (3) *parallel scheduling*, where multiple global schedulers schedule tasks concurrently on all worker nodes (e.g., Sparrow [36]). Unfortunately, none of these approaches addresses Ray's demands. Batch scheduling still requires the global scheduler to handle every task, which limits its scalability, hierarchical scheduling assumes the task graph is known in advance (i.e., the graph is static), and parallel scheduling assumes that every global scheduler schedules independent jobs. In contrast, we require a highly scalable scheduler to handle dynamic task graphs, possibly generated by a single job.

Like existing hierarchical scheduling solutions, we employ a global scheduler and per-node local schedulers. However, unlike prior solutions, tasks created on a node are submitted to the node's local scheduler first, not to a global scheduler (Figure 5). A local scheduler schedules tasks locally, unless the node is overloaded, or it cannot satisfy a task's requirements (e.g., lacks GPU), or a task's inputs are remote. If a local scheduler doesn't schedule a task, it sends the task to the global scheduler. To determine the load, the local scheduler checks the current length of its task queue. If the length exceeds some configurable threshold, it concludes that the local node is overloaded. The value of this threshold enables the scheduling policy to span the continuum from centralized, when all tasks are handed over to the global scheduler, to decentralized, when all tasks are handled locally.

Each local scheduler sends periodic heartbeats (e.g., every 100ms) to the GCS containing its load information. The GCS records this information and forwards it to the global scheduler. Upon receiving a task, the global scheduler uses the latest load information from every node along with the locations and sizes of the task's inputs (from the GCS's object metadata) to decide which node to assign the task to. If the global scheduler becomes a bottleneck, we can instantiate more replicas and have each local scheduler randomly pick a replica to send its tasks to. This makes our scheduler architecture highly scalable.

4.2.3 In-Memory Distributed Object Store

To minimize task latency, we implement an in-memory distributed storage system to store the inputs and outputs of every task. This allows workers and actors to share data efficiently. On each node, we implement the object store via *shared memory*. This allows zero-copy data sharing between tasks running on the same node. Additionally, we use Apache Arrow [1], an efficient memory layout that is becoming the de facto standard in data analytics.

If a task's inputs are not local, the inputs are replicated to the local object store on the same node before execution. Tasks also write all outputs to the local object store. Replication eliminates the potential bottleneck due to hot data objects and minimizes task execution time as a task only reads and writes data in local memory. This increases throughput for computation-bound workloads, a profile shared by many AI applications.

As with existing cluster computing frameworks, such as Apache Spark [50], and Dryad [25], the object store is limited to *immutable data*, which significantly simplifies the system design by obviating the need for complex consistency protocols (as it avoids concurrent updates), and by simplifying support for fault tolerance.

For simplicity, our object store does not build in support for distributed objects, that is, each object fits on a single node. Distributed objects like large matrices or trees can be implemented at a higher level (e.g., the application level) as collections of futures.

Object reconstruction. Component failure may result in object loss, which Ray recovers from through lineage re-execution. Ray tracks lineage by recording task dependencies in the GCS during execution. This is similar to the solution employed by other cluster computing systems like Apache Spark [50] and CIEL [32]. Also, like these systems, Ray assumes that objects are immutable and operators (i.e., remote functions and actor methods) are deterministic. However, unlike these systems, Ray adds support for stateful operator (i.e., actor) reconstruction. By integrating stateful edges directly into the computation graph, we can leverage the same reconstruction mechanism for both remote functions and actors.

To reconstruct a lost object, we walk backward along data and stateful edges until we find tasks whose inputs are all present in the object store. We then replay the computation subgraph rooted at these inputs. Consider the example in Figure 3(b), and assume that $rollout_{12}$ has



(b) Returning the result of a remote task

Figure 6: An end-to-end example that adds a and b and returns c. Solid lines are data plane operations and dotted lines are control plane operations. (a) The function **add**() is registered with the GCS by node 1 (*N*1), invoked on *N*1, and executed on *N*2. (b) *N*1 gets **add**()'s result using **ray.get**(). The Object Table entry for c is created in step 4 and updated in step 6 after c is copied to *N*1.

been lost. By walking backwards along data and stateful edges we reach A_{10} which has no input.⁴ Thus, to reconstruct *rollout*₁₂, we need to re-instantiate the actor by executing A_{10} , and then executing the methods A_{11} and A_{12} in order.

Note that for any object whose lineage includes stateful edges, reconstruction will require reinstantiating the actor (e.g., A_{10}) and replaying a possibly long chain of stateful edges (e.g., A_{11}, A_{12} , etc). Since actors are commonly used to wrap third-party simulators, which have a finite lifetime, we expect these chains to be bounded. However, we've also found actors to be useful for managing more general forms of state. To improve recovery time in such cases, we checkpoint the actor's state periodically and allow the actor to recover from checkpoints.

For low latency, we keep objects entirely in memory and evict them as needed to disk using a least-recentlyused eviction policy.

In Section A, we briefly explain how our design satisfies the requirements outlined in Section 2.

⁴Since it has no input, all of its inputs are trivially in the object store.

4.3 Putting Everything Together

Figure 6 illustrates how Ray works end-to-end with a simple example that adds two objects a and b, which could be scalars or matrices, and returns result c. The remote function **add**() is automatically registered with the GCS upon initialization and distributed to every worker in the system (step 0 in Figure 6(a)).

Figure 6(a) shows the step-by-step operations triggered by a driver invoking add.remote(a, b), where a and b are stored on nodes N1 and N2, respectively. The driver submits add(a, b) to the local scheduler (step 1), which forwards it to a global scheduler (step 2).⁵ Next, the global scheduler looks up the locations of add(a, b)'s arguments in the GCS (step 3) and decides to schedule the task on node N2, which stores argument b (step 4). The local scheduler at node N2 checks whether the local object store contains add(a, b)'s arguments (step 5). Since the local store doesn't have object a, it looks up a's location in the GCS (step 6). Learning that a is stored at N1, N2's object store replicates it locally (step 7). As all arguments of add() are now stored locally, the local scheduler invokes add() at a local worker (step 8), which accesses the arguments via shared memory (step 9).

Figure 6(b) shows the step-by-step operations triggered by the execution of **ray.get(**) at *N*1, and of **add(**) at N2, respectively. Upon $ray.get(id_c)$'s invocation, the driver checks the local object store for the value c, using the future id_c returned by **add()** (step 1). Since the local object store doesn't store c, it looks up its location in the GCS. At this time, there is no entry for c, as c has not been created yet. As a result, N1's object store registers a callback with the Object Table to be triggered when c's entry has been created (step 2). Meanwhile, at N2, add() completes its execution, stores the result c in the local object store (step 3), which in turn adds c's entry to the GCS (step 4). As a result, the GCS triggers a callback to N1's object store with c's entry (step 5). Next, N1 replicates c from N2 (step 6), and returns c to **ray.get(**) (step 7), which finally completes the task.

While this example involves a large number of RPCs, in many cases this number is much smaller, as most tasks are scheduled locally, and the GCS replies are cached by the global and local schedulers.

5 Implementation

Ray is implemented in ≈ 40 K lines of code (LoC), 72% in C++ for the system layer, 28% in Python for the application layer. The object store and our zero-copy serialization libraries have been factored out as standalone projects that can be used independently of Ray.

The bottom-up distributed scheduler (Section 4.2.2) is 3.2KLoC and will undergo significant development as we refine Ray's scheduling policies. In this section, we focus on the implementation details for achieving the performance targets dictated by real-time AI applications: (a) scheduler performance, (b) object store performance, and (c) end-to-end system performance.

Bottom-up distributed scheduler. We implement both the local and global scheduler as event-driven, single-threaded processes. Internally, local schedulers maintain cached state for local object metadata, tasks waiting for inputs, and tasks ready for dispatch to a worker. As object dependencies become available, tasks become ready for dispatch. Worker availability triggers dispatch of as many tasks as possible under the node's capacity constraints.

The local scheduler sends periodic heartbeats (every 100ms) to the global schedulers, routed through the GCS via a publish-subscriber mechanism, containing the dispatch queue length and resource availability. This enables the global scheduler to balance the load across nodes.

Object store. Ray's object store is also implemented as a single-threaded event loop. It uses shared memory so workers on the same node can read data without copying it. Objects are immutable. An object is only made visible after a worker finishes creation. To minimize object creation overhead, the store pre-allocates a pool of large memory-mapped files. We use a SIMD-like memory copy to maximize the throughput of copying data from a worker to the object store's shared memory. We also parallelize computation of an object's content hash, which is used to detect non-deterministic computations. Ray uses Apache Arrow [1] to achieve high performance when serializing/deserializing Python objects.

Global control store. We implement Ray's Global Control Store (GCS) using one Redis [40] key-value store per shard (Redis can be easily swapped with other key-value stores). We shard the GCS tables by object and task IDs to scale, and we replicate every shard for fault tolerance. As we scale up the experiment, we distribute the shards across multiple nodes. Though our GCS implementation uses multiple Redis servers, our performance and fault tolerance requirements could also be met by existing systems like RAMCloud [35].

Lastly, Ray's monitor tracks system component liveness and reflects component failures in the GCS. Tasks and objects on failed cluster nodes are marked as lost, and objects are later reconstructed with lineage information, as necessary.

⁵Note that the N1 local scheduler could also decide to schedule the task locally.



Figure 7: End-to-end scalability of the system is achieved in a linear fashion, leveraging the GCS and bottom-up distributed scheduler. Ray reaches 1 million tasks per second throughput with 60 m4.16xlarge nodes and processes 100 million tasks in under a minute. We omit $x \in \{70, 80, 90\}$ due to cost.

6 Evaluation

In this section, we demonstrate three key points. First, we examine the scalability of the system as a whole as well as the performance of its individual components (Section 6.1). Second, we demonstrate robustness and fault tolerance (Section 6.2). Third, we demonstrate that Ray is a natural fit for reinforcement learning applications, both in terms of performance and ease of development (Section 6.3). All experiments were run on Amazon Web Services. The specific instance types are reported below.

6.1 Scalability and Performance

End-to-end scalability. One of the key benefits of the Global Control Store (GCS) is the ability to horizontally scale the system. We evaluate this ability in this section. In Fig. 7, we benchmark an embarrassingly parallel workload, increasing the cluster size on the x-axis. We observe near-perfect linearity in progressively increasing task throughput. Ray exceeds 1 million tasks per second throughput at 60 nodes and continues to scale linearly beyond 1.8 million tasks per second at 100 nodes. The rightmost datapoint shows that Ray can process 100 million tasks in less than a minute (54s). Variability (shown with black error bars) is minimal. As expected, increasing task duration, but the overall scalability remains linear.

The global scheduler's primary responsibility is to maintain balanced load throughout the system. In Figure 8, 100K tasks submitted on a single node are rebalanced across the available resources. Note that the node where the load originates processes more tasks as it maximizes utilization of the local node before forwarding tasks to the global scheduler.



Figure 8: Ray maintains balanced load. A driver on the first node submits 100K tasks, which are rebalanced by the global scheduler across the 21 available nodes.



Figure 9: Object store write throughput and IOPS. From a single client, throughput exceeds 15GB/s (red) for large objects and 18K IOPS (cyan) for small objects on a 16 core instance (m4.4xlarge). It uses 8 threads to copy objects larger than 0.5MB and 1 thread for small objects. Bar plots report throughput with 1, 2, 4, 8, 16 threads. Results are averaged over 5 runs.

Object store performance. We track two metrics for object store performance: IOPS (for small objects) and write throughput (for large objects) in Figure 9. As object size increases, the write throughput from a single client reaches 15GB/s. For larger objects, copying the object from the client dominates the time spent on object creation. For smaller objects, completion time is dominated by serialization overhead and IPC between the client and object store. The object store peaks at 18K IOPS, which corresponds to 56μ s per operation.

6.2 Fault Tolerance

Recovering from object failures. In Figure 10, we demonstrate Ray's ability to transparently recover from worker node failures and elastically scale. The driver submits rounds of tasks where each task is dependent on a task in the previous round. As worker nodes are killed (at 25s, 50s, 100s), the surviving local schedulers automatically trigger reconstruction of the lost objects. During periods of reconstruction, the tasks originally submitted by the driver stall, since their dependencies cannot be satisfied. However, the overall task throughput remains



Figure 10: Fully transparent fault tolerance for distributed tasks. The dashed line represents the number of nodes in the cluster. Curves show the throughput of new tasks (cyan) and re-executed tasks (red). The driver continually submits and re-trieves rounds of 10000 tasks. Each task takes 100ms and depends on a task in the previous round. Each task has input and output of size 100KB.



Figure 11: Fully transparent fault tolerance for actor methods. The driver continually submits tasks to the actors in the cluster. At t = 200s, we kill 2 of the 10 nodes, causing 400 of the 2000 actors in the cluster to be recovered on the remaining nodes.

stable, fully utilizing the available resources until the lost dependencies are reconstructed. Furthermore, as more nodes are added back to the system at 210s, Ray is able to fully recover to its initial throughput.

Recovering from actor failures. Next, we demonstrate Ray's ability to transparently recover lost actors. By encoding each actor's method calls into the dependency graph, we can reuse the same object reconstruction mechanism as in Figure 10. The workload in Figure 11a demonstrates the extreme case where no intermediate actor state is saved. All previous method calls for each lost actor must be re-executed serially (t = 210-330s). Lost actors are automatically redistributed across the available nodes, and throughput fully recovers after reconstruction.

To improve reconstruction time for long-lived actors, we provide transparent checkpointing of intermediate actor state. Figure 11b shows the same workload, but with an automatic checkpoint task on each actor every 10 method calls. The initial throughput is comparable to that without checkpointing. After node failure, the majority of reconstruction is done by executing checkpoint tasks to reconstruct the actor's state (t = 210-270s). As a result, only 500 tasks need to be re-executed, and new method calls stall for 60s, versus 10K re-executions and 120s without checkpointing, respectively. In the future, we hope to further reduce actor reconstruction time, e. g. by allowing user annotations for read-only methods.

Overhead from GCS replication. To make the GCS fault tolerant, we replicate each of the database shards. When a client writes to one of the shards of the GCS, it duplicates the writes to all replicas. For workloads in which we artificially make the GCS the bottleneck by reducing the number of GCS shards, the overhead of two-way replication is less than 10%. In most real workloads the slowdown is undetectable.

6.3 **RL** Applications

Given the diverse and demanding requirements of reinforcement learning applications described in Section 2, reinforcement learning algorithms today are implemented on top of special-purpose ad-hoc systems that typically require substantial engineering effort to develop and which do not generalize to other algorithms.

In this section, we implement two types of reinforcement learning algorithms in Ray and show that we are able to match or outperform the performance of specialized systems built *specifically for these algorithms*. Furthermore, using Ray to distribute these algorithms over clusters requires *changing only a few lines of code* in serial implementations of the algorithms.

In addition, we test Ray in a latency-sensitive setting in which Ray is used to control a simulated robot under varying real-time requirements.

6.3.1 Evolution Strategies

To evaluate Ray on large-scale RL workloads, we implement the evolution strategies (ES) algorithm and compare to the reference implementation [39], which is a special-purpose system built for this algorithm. It uses a hierarchy of Redis servers as message buses and relies on low-level multiprocessing libraries for sharing data.

As shown in Figure 12, a straightforward implementation on top of Ray is more scalable, scaling to 8192 physical cores, whereas the special-purpose system stops running after 1024 cores. The Ray implementation runs in a median time of 3.7 minutes, which is more than twice as fast as the best published result (10 minutes). The Ray implementation was also substantially simpler to develop. Parallelizing a serial implementation using Ray required modifying only 7 lines of code. In contrast,



Figure 12: Time to reach a score of 6000 in the Humanoidv1 task [13]. The Ray ES implementation scales well to 8192 cores. The special-purpose system failed to run beyond 1024 cores. With 8192 cores, we achieve a median time of 3.7 minutes, which is over twice as fast as the best published result. ES is faster than PPO (Section 6.3.2) on this benchmark but exhibits greater runtime variance.



Figure 13: Time to reach a score of 6000 in the Humanoid-v1 task [13]. The Ray PPO implementation outperforms a specialized MPI implementation [3] with fewer GPUs and at a fraction of the cost. The MPI implementation required 1 GPU for every 8 CPUs, whereas the Ray version required at most 8 GPUs (and never more than 1 GPU per 8 CPUs).

the reference implementation required several hundred lines of code to develop a custom protocol for communicating tasks and data between workers and could not be easily adapted to different algorithms or communication patterns. We include pseudocode illustrating this point in Section B.1.

6.3.2 Proximal Policy Optimization

To evaluate Ray on single node and small cluster RL workloads, we implement Proximal Policy Optimization (PPO) [41] in Ray and compare to a highly-optimized reference implementation [3] that uses OpenMPI communication primitives.⁶ All experiments were run us-

ing p2.16xlarge (GPU) and m4.16xlarge (high CPU) instances, each of which has 32 physical cores.

Ray's API made it easy to take advantage of heterogeneous resources *decreasing costs by a factor of 4.5* [2]. Ray tasks and actors can specify distinct resource requirements, allowing CPU-only tasks to be scheduled on cheaper high-CPU instances. In contrast, MPI applications often exhibit symmetric architectures, in which all processes run the same code and require identical resources, in this case preventing the use of CPU-only machines for scale-out.

As shown in Figure 13, the Ray implementation outperforms the optimized MPI implementation in all experiments (hyperparameters listed in Section D) with a fraction of the GPUs. As with ES, we were able to parallelize PPO using Ray with minimal changes to the structure of the serial program.

6.3.3 Controlling a Simulated Robot

We show that Ray can meet soft real-time requirements by controlling a simulated robot in real time. A Ray driver runs the simulated robot and takes actions at fixed time steps varying from 1 millisecond to 30 milliseconds to simulate different real-time requirements. The driver submits tasks that compute actions to be taken using a policy that was trained offline. However, the actions are only taken if they are received by the driver within the relevant time step (otherwise the prior action is repeated). Latency budgets for real robots are on the order of 10 milliseconds, and we find that even if we run the simulation faster than real time (using a 3 millisecond time step), Ray is able to produce a stable walk. Table 3 shows the fraction of tasks that did not arrive fast enough to be used by the robot.

Time budget (ms)	30	20	10	5	3	2	1
% actions dropped	0	0	0	0	0.4	40	65
Stable walk?	Yes	Yes	Yes	Yes	Yes	No	No

Table 3: Low-latency robot simulation results

7 Related Work

Dynamic task graphs. Ray is closely related to CIEL [32]. They both support dynamic task graphs with nested tasks, implement the futures abstraction, and provide lineage-based fault tolerance. However, they differ in two important aspects. First, Ray extends the task model with an actor abstraction. Second, Ray employs a fully distributed control plane and scheduler, instead of relying on a single master. In addition, Ray adds the **ray.wait**() method, employs an in-memory (instead of a

⁶Both implementations use TensorFlow to define neural networks but rely on the distributed frameworks (OpenMPI and Ray) for communication between processes. Though this algorithm could be implemented using TensorFlow alone, single-machine performance would be slow due to the Python global interpreter lock and distributed versions would look similar to MPI implementations (sending and receiving data via queues).

file-based) object store, and extends an existing programming language (Python), while CIEL provides its own scripting language (Skywriting). Ray is also closely related to Dask [38], which supports dynamic task graphs, including a wait-like primitive, and employs the futures abstraction in a Python environment. However, Dask uses a centralized scheduler, doesn't offer an actor-like abstraction, and doesn't provide fault tolerance.

Data flow systems. Popular dataflow systems, such as MapReduce [18], Spark [51], and Dryad [25] have widespread adoption for analytics and ML workloads, but their computation model is more restrictive. Spark and MapReduce implement the BSP execution model, which assumes that tasks within the same stage perform the same computation and take roughly the same amount of time. Dryad relaxes this restriction but lacks support for dynamic task graphs. Furthermore, none of these systems provide an actor abstraction, nor implement a distributed scalable control plane and scheduler. Finally, Naiad [31] is a dataflow system that provides improved scalability for some workloads, but only supports static task graphs.

Actor systems. Orleans [14] provides a *virtual* actorbased abstraction. Actors are perpetual and their state persists across invocations. For scaling out, Orleans also allows multiple instances of an actor to run in parallel when the actor operates on immutable state or has no state. These stateless actors can act as tasks in Ray. However, unlike Ray, the Orleans developer must explicitly checkpoint actor state and intermediate responses. In addition, Orleans provides at-least-once semantics. In contrast, Ray provides transparent fault tolerance and exactly-once semantics, as each method call is logged in the GCS and both arguments and results are immutable. We find that in practice these limitations do not affect the performance of our applications.

Erlang [9] and C++ Actor Framework (CAF) [16], two other actor-based systems, also require the application to explicitly handle fault tolerance. Also, Erlang's global state store is not suitable for sharing large objects such as ML models, while CAF does not support data sharing.

Global control state and scheduling. The concept of logically centralizing the control plane has been previously proposed in software defined networks (SDNs) [15], distributed file systems (e.g., GFS [22]), resource management (e.g., Omega [42]), and distributed frameworks (e.g., MapReduce [18], BOOM [7]), to name a few. Ray draws inspiration from these pioneering efforts, but provides significant improvements. In contrast with SDNs, BOOM, and GFS which couple the control plane data and computation, Ray decouples the storage of the control plane information (e.g., GCS) from the logic implementation (e.g., schedulers). This allows both storage and computation layers to scale independently, which is key to achieving our scalability targets. Omega uses a distributed architecture in which schedulers coordinate via globally shared state. To this architecture, Ray adds global schedulers to balance load across local schedulers, and targets ms-level, not second-level, task scheduling.

Ray implements a unique distributed bottom-up scheduler that is horizontally scalable, and can handle dynamically constructed task graphs. Unlike Ray, most existing cluster computing systems [18, 50, 32] use a centralized scheduler architecture. While Sparrow [36] is decentralized, its schedulers make independent decisions, limiting the possible scheduling policies, and all tasks of a job are handled by the same global scheduler. Mesos [24] implements a two-level hierarchical scheduler, but its top-level scheduler can be a bottleneck. Canary [37] achieves impressive performance by having each scheduler instance handle a portion of the task graph, but does not handle dynamic computation graphs.

Machine learning frameworks. TensorFlow [5] and MXNet [17] target deep learning workloads and efficiently leverage both CPUs and GPUs. While they achieve great performance for workloads consisting of static DAGs of linear algebra operations, they have limited support for more general workloads. Tensor-Flow Fold [29] provides some support for dynamic task graphs, as well as MXNet through its internal C++ APIs, but neither fully supports the ability to modify the DAG during execution in response to task progress, task completion times, or faults. TensorFlow and MXNet in principle achieve generality by allowing the programmer to simulate low-level message-passing and synchronization primitives, but the pitfalls and user experience in this case are similar to those of MPI. OpenMPI [21] can achieve high performance, but it is relatively hard to program as it requires explicit coordination to handle heterogeneous and dynamic task graphs. Furthermore, it forces the programmer to explicitly handle fault tolerance.

8 Discussion and Experiences

Since we released Ray several months ago, over one hundred people have downloaded and used it. Here we discuss our experience developing and using Ray, as well as some of the feedback we've received from early users.

API. In designing the API, we have emphasized minimalism. Initially we started with a basic *task* abstraction. Later, we added the **wait()** primitive to accommodate rollouts with heterogeneous durations and the *actor* abstraction to accommodate third-party simulators and amortize the overhead of expensive initializations. While the resulting API is relatively low-level, it has proven both powerful and simple to use. Indeed, some teams report instructing developers to first write serial implementations and then to parallelize them using Ray.

To illustrate this point, next we briefly describe our experience with two other algorithms: Asynchronous Advantage Actor Critic (A3C) and hyperparameter search.

A3C [30] is a state-of-the-art RL algorithm which leverages asynchronous policy updates to significantly improve training times over previous algorithms. To scale out this algorithm, we use a simple hierarchical scheme where multiple instances of A3C are trained in parallel and periodically aggregated to form an improved model. Implementing hierarchical A3C in Ray was straightforward, requiring 20 lines of Python code to extend the non-hierarchical version. Furthermore, this simple extension improved performance on the same hardware by 30%.

We were able to implement a state-of-the-art hyperparameter search algorithm [28] in roughly 30 lines of Python code using Ray. Ray's support for nested tasks was critical because multiple experiments had to be run in parallel, and each experiment typically used parallelism internally. The **wait()** primitive allowed us to process the results of experiments in the order that they completed and to adaptively launch new ones. The actor abstraction allowed us to pause and resume stateful experiments based on the progress of other experiments (see Section B.3). In contrast, most existing implementations have to wait for *all* experiments in the round to complete, leading to inefficient resource utilization.

Ray's API is still a work in progress. Based on early user feedback, we are considering enhancing the API to include higher level primitives, such as simple aggregation and map. These could also inform scheduling decisions in the Ray system layer (Section 4.2).

Limitations. Given the workload generality, specialized optimizations are hard. For example, we must make scheduling decisions without full knowledge of the computation graph. Scheduling optimizations in Ray might require more complex runtime profiling. In addition, storing lineage for each task requires the implementation of garbage collection policies to bound storage costs in the GCS, a feature we are actively developing.

Fault tolerance. We are often asked if fault tolerance is really needed for AI applications. After all, due to the statistical nature of many AI algorithms, one could simply ignore failed rollouts. Based on our experience, our answer is an unqualified "yes". First, the ability to ignore failures makes applications much easier to write and reason about. Second, our particular implementation of fault tolerance via deterministic replay dramatically simplifies debugging as it allows us to easily reproduce most errors. This is particularly important since, due to their stochasticity, AI algorithms are notoriously hard to debug. Third, fault tolerance helps save money since it allows us to run on cheap resources like spot instances on AWS. Furthermore, as workloads scale, we expect fault tolerance to become even more important. Of course, this comes at the price of some overhead. However, we found this overhead to be minimal for our target workloads.

GCS and Horizontal Scalability. The GCS dramatically simplified Ray development and debugging. Basic failure handling and horizontal scaling for all other components took less than a week to implement. The GCS enabled us to query the entire system state while debugging (instead of having to manually expose internal component state). This helped us find numerous bugs and generally understand system behavior.

The GCS is instrumental to Ray's horizontal scalability. In the experiments reported in Section 6.1, we were able to scale the results by adding more shards whenever the GCS became a bottleneck. The GCS also enables the global scheduler to scale by simply adding more replicas. While currently we are manually configuring the number of GCS shards and global schedulers, we are planning to develop adaptive algorithms in the future. Due to these advantages, we believe that centralizing control state will be a key design component of future distributed systems.

9 Conclusion

Emerging AI applications present challenging computational demands. To meet these demands, Ray introduces a global control store and a bottom-up distributed scheduler. Together, this architecture implements dynamic task graph execution, which in turn supports both a task-parallel and an actor programming model. This programming flexibility is particularly important for RL workloads, which produce tasks diverse in resource requirements, duration, and functionality. Our evaluation demonstrates linear scalability past 1M tasks per second, transparent fault tolerance, and substantial performance improvements on several contemporary RL workloads. Thus, Ray provides a powerful combination of flexibility, performance, and ease of use for the development of future AI applications.

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A Satisfying the Requirements

In this section, we briefly explain how our design satisfies the requirements outlined in Section 2.

Flexibility: Ray extends the already general dynamic task model [32], by adding the **ray.wait**() primitive to efficiently handle tasks whose completion times are not known in advance, and the *actor* abstraction to handle third part simulators and amortize expensive setups. Finally, Ray supports heterogeneous resources, such as GPUs.

Performance: Table 4 summarizes techniques for scaling each component and the associated overhead. The last column shows the average number of requests/sec that each component should handle as a function of system and workload parameters, where *N* is the number of nodes, *s* the number of GCS shards, *g* the number of global schedulers, *w* the average number of tasks/sec generated by a node, and ε , the percentage of tasks submitted to the global scheduler. For instance, on average, the local scheduler handles a number of requests proportional to *w* tasks/sec, where α_1 , includes assigning the task to a worker or sending/receiving the task to/from the global scheduler. Similarly, the global scheduler handles a number of tasks/sec it receives ($\varepsilon Nw/g$) times α , a factor that includes querying the GCS for task's inputs' locations; *h* represents the number of heartbeats/sec.

Note that given the cluster size, N, and the average load generated by a node, w, we could pick the number of GCS shards, s and global schedulers, s to bound the load on each shard or global scheduler. This makes both GCS and the global scheduler horizontally scalable.

Ease of development: Ray handles a variety of component failures, relieving the developer from writing complex software to handle failures. Ray achieves fault tolerance by using a variety of techniques, including stateless components, replication and, replay, summarized in Table 5. This also enables a user to run the system on cheap infrastructures where nodes may be preempted (e.g., AWS spot instances). The API shown in Table 2, while low-level, has proven to be a good fit for the RL applications in our experience. The fact that the API is provided in Python, the most popular language in the AI community, has been a big plus.

Component	Scaling Techniques	Requests/sec
Local Sched.	By default, use 1 per node.	$\alpha_1 w$
Object Store	By default, use 1 per node.	$\alpha_2 w$
GCS	Use more shards (s).	$\beta\left(\frac{N}{s}\right)w+h\left(\frac{Ng}{s}\right)$
Global Sched.	Use more replicas (g).	$\alpha \varepsilon \left(\frac{N}{g}\right) s + h$
Data Object	Replicate objects to local	N/A
	node before task execution.	
Driver	Use nested tasks; spawn	N/A
	tasks from workers.	

Table 4: Achieving scalability in Ray. By increasing the number of GCS shards *s* and the number of global scheduler replicas *g*, we can reduce the load on each GCS shard and global scheduler replica to a constant. *N* is the total number of nodes, *w* avg. number of tasks/node/sec, *h* avg. number of node heartbeats/sec, and α , α_1 , α_2 , β , and ε are constants.

Component	Description	
Global Control Store (GCS)	Replicate each shard.	
Local and Global	Stateless processes; restart and	
Schedulers, Workers	read state from the GCS.	
Object Store, Actor	Use lineage stored in the GCS to	
	reconstruct objects (Section 4.2.3).	
Driver	Restart it; can reuse objects already	
	present in the Object Store.	

Table 5: Techniques for achieving fault tolerance in Ray

B Ease of Development

B.1 Evolution Strategies

In this section, we give code examples to illustrate why the evolution strategies algorithm from Section 6.3.1 is so easy to implement and customize on top of Ray and so difficult in the special-purpose reference system that we compare to. Suppose we wish to parallelize the following serial Python code.

```
1 def f():
2    return result
3 
4 def g(N):
5    return [f() for _ in range(N)]
6 
7 results = [g(N) for _ in range(M)]
```

Attempting to implement this code in MPI, distributed TensorFlow, or many specialized systems would involve writing a single program that is run by all workers. As shown in the code below, programs would need to branch based on the role of that worker and would likely only work for predetermined values of M and N.

```
if WORKER_INDEX == 0:
1
2
       results = []
3
       for i in range(M):
           child_index = 1 + i
4
           results.append(RECEIVE(child_index), i)
5
   elif 1 <= WORKER_INDEX < M:</pre>
6
7
       intermediate_results = []
8
       for i in range(N):
           child_index = M + 1 + WORKER_INDEX + M * i
9
10
           intermediate_results.append(RECEIVE(child_index))
       SEND(intermediate_results, 0)
11
12
   else:
13
       result = f()
14
       parent_index = (WORKER_INDEX - M - 1) % M
15
       SEND(result, parent_index)
```

This is complex for a number of reasons. Each worker has to decide what tasks to execute and has to explicitly dictate logic for optimizations such as batching, which normally a task scheduler could take care of. Secondly, allowing variable values of M and N would substantially complicate the program, but hard coding the values M and N will make it even more difficult to extend the code to deeper hierarchies in the future.

Finally, this violates the lockstep assumptions that these frameworks make and would sacrifice performance by restricting the algorithm to a predefined scheduling layout.

In contrast, the Ray version is clean, simple, and extensible.

```
@ray.remote
1
  def f():
2
3
       return result
4
5
  @ray.remote
6
  def g(N):
7
       return ray.get([f.remote() for _ in range(N)])
8
9
  results = ray.get([g.remote(N) for _ in range(M)])
```

We believe that Ray's API will allow developers to easily develop more complex distributed schemes.

B.2 Tree Reduce

Consider the scenario where one wants to perform an aggregation operation on multiple data points in a distributed fashion. With Ray, the programmer would be able to easily aggregate data in an efficient manner.

Note that this implementation can be written in a more concise fashion.

```
1 while len(data) > 1:
2 data = data[2:] + [aggregate.remote(data[0], data[1])]
3 4 result = ray.get(data[0])
```

In contrast, systems such as MPI and Spark provide specialize tree-reduction operators (i.e. MPI_Allreduce and rdd.treeAggregate), since hierarchical computations are not easily expressed in their APIs.

B.3 Hyperparameter Search

Ray enables developers to build hyperparameter search programs in a readable and simple manner.

In this example, assume we have an experiment class with the following interface. We add a single decorator to the class to convert it into an actor.

Assume also that we have these helper functions predefined.

is_promising(results) returns True if the model is doing well and False otherwise. In practice, this function will may more information than the current result.

generate_hyperparameters defines a queue for many hyperparameter configurations, enumerating the space that the programmer wants to search over.

```
1 def is_promising(results):
2    return True
3 
4 def generate_hyperparameters():
5    return hyperparameter_queue
```

Here is a simple and straightforward implementation of a hyperparameter search program. Notice that more complicated management schemes can be implemented fairly easily, but we chose to leave those out in favor of readability.

```
1 hp_queue = generate_hyperparameters()
  experiment_list = [Experiment.remote(next(hp_queue)) for i in range(10)]
2
3
  paused = []
   current_exps = {exp.training_step.remote(): exp for exp in experiment_list}
4
5
6
   while True:
       experiment_futures = current_exps.keys()
7
       [ready_id], remaining = Oray.wait(experiment_futures, num_returns=1)
8
9
       current_exp = current_exps[ready_id]
10
       current_accuracy = ray.get(ready_id)
11
12
       if is_promising(current_accuracy):
           current_exps[current_exp.training_step.remote()] = current_exp
13
14
       else:
15
           paused.append(current_exp)
           new_exp = Experiment.remote(next(hp_queue))
16
           current_exps[new_exp.training_step.remote()] = new_exp
17
```

C Hyperparameters for Evolution Strategies

Hyperparameter	Value
Noise standard deviation	0.02
Adam stepsize	0.01
L2 coefficient	0.005
Episodes per batch	5000

D Hyperparameters for Proximal Policy Optimization

Hyperparameter	Value	
Timesteps per batch	320000	
SGD minibatch size	32768	
SGD epochs per iteration	20	
Adam stepsize	1e-4	
PPO clip param	0.2	
GAE parameter (λ)	0.95	
Discount (γ)	0.995	