Ray Documentation

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The Ray Team

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Installation

Ray is a fast and simple framework for building and running distributed applications.

Tip: Join our community slack to discuss Ray!

Ray is packaged with the following libraries for accelerating machine learning workloads:

- Tune: Scalable Hyperparameter Tuning
- RLlib: Scalable Reinforcement Learning
- Distributed Training

Install Ray with: `pip install ray`. For nightly wheels, see the Installation page.

View the codebase on GitHub.

CHAPTER 1

Quick Start

Execute Python functions in parallel.

```
import ray
ray.init()

@ray.remote
def f(x):
    return x * x

futures = [f.remote(i) for i in range(4)]
print(ray.get(futures))
```

To use Ray's actor model:

```
import ray
ray.init()

@ray.remote
class Counter():
    def __init__(self):
        self.n = 0

    def increment(self):
        self.n += 1

    def read(self):
        return self.n

counters = [Counter.remote() for i in range(4)]
[c.increment.remote() for c in counters]
futures = [c.read.remote() for c in counters]
print(ray.get(futures))
```

Visit the Walkthrough page a more comprehensive overview of Ray features.

Ray programs can run on a single machine, and can also seamlessly scale to large clusters. To execute the above Ray script in the cloud, just download this configuration file, and run:

```
ray submit [CLUSTER.YAML] example.py --start
```

Read more about launching clusters.

CHAPTER 2

Tune Quick Start

Tune is a library for hyperparameter tuning at any scale. With Tune, you can launch a multi-node distributed hyperparameter sweep in less than 10 lines of code. Tune supports any deep learning framework, including PyTorch, TensorFlow, and Keras.

Note: To run this example, you will need to install the following:

```
$ pip install ray torch torchvision filelock
```

This example runs a small grid search to train a CNN using PyTorch and Tune.

```
import torch.optim as optim
from ray import tune
from ray.tune.examples.mnist_pytorch import get_data_loaders, ConvNet, train, test


def train_mnist(config):
    train_loader, test_loader = get_data_loaders()
    model = ConvNet()
    optimizer = optim.SGD(model.parameters(), lr=config["lr"])
    for i in range(10):
        train(model, optimizer, train_loader)
        acc = test(model, test_loader)
        tune.track.log(mean_accuracy=acc)


analysis = tune.run(
    train_mnist, config={"lr": tune.grid_search([0.001, 0.01, 0.1])})

print("Best config: ", analysis.get_best_config(metric="mean_accuracy"))

# Get a dataframe for analyzing trial results.
df = analysis.dataframe()
```

If TensorBoard is installed, automatically visualize all trial results:

```
tensorboard --logdir ~/ray_results
```

CHAPTER 3

RLlib Quick Start

RLlib is an open-source library for reinforcement learning built on top of Ray that offers both high scalability and a unified API for a variety of applications.

```
pip install tensorflow  # or tensorflow-gpu
pip install ray[rllib]  # also recommended: ray[debug]
```

```
import gym
from gym.spaces import Discrete, Box
from ray import tune

class SimpleCorridor(gym.Env):
    def __init__(self, config):
        self.end_pos = config["corridor_length"]
        self.cur_pos = 0
        self.action_space = Discrete(2)
        self.observation_space = Box(0.0, self.end_pos, shape=(1, ))

    def reset(self):
        self.cur_pos = 0
        return [self.cur_pos]

    def step(self, action):
        if action == 0 and self.cur_pos > 0:
            self.cur_pos -= 1
        elif action == 1:
            self.cur_pos += 1
        done = self.cur_pos >= self.end_pos
        return [self.cur_pos], 1 if done else 0, done, {}

tune.run(
    "PPO",
    config={
        "env": SimpleCorridor,
```

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```
        "num_workers": 4,
        "env_config": {"corridor_length": 5}})
```

CHAPTER 4

More Information

- Tutorial
- Blog
- Ray paper
- Ray HotOS paper
- RLlib paper
- Tune paper

CHAPTER 5

Getting Involved

- ray-dev@googlegroups.com: For discussions about development or any general questions.
- StackOverflow: For questions about how to use Ray.
- GitHub Issues: For reporting bugs and feature requests.
- Pull Requests: For submitting code contributions.

5.1 Installing Ray

Ray supports Python 2 and Python 3 as well as MacOS and Linux. Windows support is planned for the future.

5.1.1 Latest stable version

You can install the latest stable version of Ray as follows.

```
pip install -U ray  # also recommended: ray[debug]
```

5.1.2 Latest Snapshots (Nightlies)

Here are links to the latest wheels (which are built for each commit on the master branch). To install these wheels, run the following command:

```
pip install -U [link to wheel]
```

Linux	MacOS
Linux Python 3.7	MacOS Python 3.7
Linux Python 3.6	MacOS Python 3.6
Linux Python 3.5	MacOS Python 3.5
Linux Python 2.7	MacOS Python 2.7

5.1.3 Building Ray from Source

Installing from `pip` should be sufficient for most Ray users.

However, should you need to build from source, follow instructions below for both Linux and MacOS.

Dependencies

To build Ray, first install the following dependencies. We recommend using Anaconda.

For Ubuntu, run the following commands:

```
sudo apt-get update
sudo apt-get install -y build-essential curl unzip psmisc

# If you are not using Anaconda, you need the following.
sudo apt-get install python-dev  # For Python 2.
sudo apt-get install python3-dev  # For Python 3.

pip install cython==0.29.0
```

For MacOS, run the following commands:

```
brew update
brew install wget

pip install cython==0.29.0
```

If you are using Anaconda, you may also need to run the following.

```
conda install libgcc
```

Install Ray

Ray can be built from the repository as follows.

```
git clone https://github.com/ray-project/ray.git

# Install Bazel.
ray/ci/travis/install-bazel.sh

# Optionally build the dashboard (requires Node.js, see below for more information).
pushd ray/python/ray/dashboard/client
npm ci
npm run build
popd

# Install Ray.
cd ray/python
pip install -e . --verbose  # Add --user if you see a permission denied error.
```

[Optional] Dashboard support

If you would like to use the dashboard, you will additionally need to install Node.js and build the dashboard before installing Ray. The relevant build steps are included in the installation instructions above.

The dashboard requires Python 3, and can be enabled by setting `include_webui=True` during initialization, i.e.

```
import ray
ray.init(include_webui=True)
```

5.1.4 Docker Source Images

Run the script to create Docker images.

```
cd ray
./build-docker.sh
```

This script creates several Docker images:

- The `ray-project/deploy` image is a self-contained copy of code and binaries suitable for end users.
- The `ray-project/examples` adds additional libraries for running examples.
- The `ray-project/base-deps` image builds from Ubuntu Xenial and includes Anaconda and other basic dependencies and can serve as a starting point for developers.

Review images by listing them:

```
docker images
```

Output should look something like the following:

```
REPOSITORY                          TAG                 IMAGE ID            CREATED␣
↪           SIZE
ray-project/examples                latest              7584bde65894        4 days␣
↪ago           3.257 GB
ray-project/deploy                  latest              970966166c71        4 days␣
↪ago           2.899 GB
ray-project/base-deps               latest              f45d66963151        4 days␣
↪ago           2.649 GB
ubuntu                              xenial              f49eec89601e        3 weeks␣
↪ago          129.5 MB
```

Launch Ray in Docker

Start out by launching the deployment container.

```
docker run --shm-size=<shm-size> -t -i ray-project/deploy
```

Replace `<shm-size>` with a limit appropriate for your system, for example `512M` or `2G`. The `-t` and `-i` options here are required to support interactive use of the container.

Note: Ray requires a **large** amount of shared memory because each object store keeps all of its objects in shared memory, so the amount of shared memory will limit the size of the object store.

You should now see a prompt that looks something like:

```
root@ebc78f68d100:/ray#
```

Test if the installation succeeded

To test if the installation was successful, try running some tests. This assumes that you've cloned the git repository.

```
python -m pytest -v python/ray/tests/test_mini.py
```

5.1.5 Troubleshooting installing Arrow

Some candidate possibilities.

You have a different version of Flatbuffers installed

Arrow pulls and builds its own copy of Flatbuffers, but if you already have Flatbuffers installed, Arrow may find the wrong version. If a directory like `/usr/local/include/flatbuffers` shows up in the output, this may be the problem. To solve it, get rid of the old version of flatbuffers.

There is some problem with Boost

If a message like `Unable to find the requested Boost libraries` appears when installing Arrow, there may be a problem with Boost. This can happen if you installed Boost using MacPorts. This is sometimes solved by using Brew instead.

5.2 Walkthrough

This walkthrough will overview the core concepts of Ray:

1. Using remote functions (tasks) [`ray.remote`]
2. Fetching results (object IDs) [`ray.put`, `ray.get`, `ray.wait`]
3. Using remote classes (actors) [`ray.remote`]

With Ray, your code will work on a single machine and can be easily scaled to a large cluster. To run this walkthrough, install Ray with `pip install -U ray`.

```
import ray

# Start Ray. If you're connecting to an existing cluster, you would use
# ray.init(address=<cluster-address>) instead.
ray.init()
```

See the Configuration documentation for the various ways to configure Ray. To start a multi-node Ray cluster, see the cluster setup page. You can stop ray by calling `ray.shutdown()`. To check if Ray is initialized, you can call `ray.is_initialized()`.

5.2.1 Remote functions (Tasks)

Ray enables arbitrary Python functions to be executed asynchronously. These asynchronous Ray functions are called "remote functions". The standard way to turn a Python function into a remote function is to add the `@ray.remote` decorator. Here is an example.

```
# A regular Python function.
def regular_function():
    return 1

# A Ray remote function.
@ray.remote
def remote_function():
    return 1
```

This causes a few things changes in behavior:

1. **Invocation:** The regular version is called with `regular_function()`, whereas the remote version is called with `remote_function.remote()`.
2. **Return values:** `regular_function` immediately executes and returns `1`, whereas `remote_function` immediately returns an object ID (a future) and then creates a task that will be executed on a worker process. The result can be retrieved with `ray.get`.

```
assert regular_function() == 1

object_id = remote_function.remote()

# The value of the original `regular_function`
assert ray.get(object_id) == 1
```

3. **Parallelism:** Invocations of `regular_function` happen **serially**, for example

```
# These happen serially.
for _ in range(4):
    regular_function()
```

whereas invocations of `remote_function` happen in **parallel**, for example

```
# These happen in parallel.
for _ in range(4):
    remote_function.remote()
```

See the ray.remote package reference page for specific documentation on how to use `ray.remote`.

Object IDs can also be passed into remote functions. When the function actually gets executed, **the argument will be a retrieved as a regular Python object**. For example, take this function:

```
@ray.remote
def remote_chain_function(value):
    return value + 1


y1_id = remote_function.remote()
assert ray.get(y1_id) == 1

chained_id = remote_chain_function.remote(y1_id)
assert ray.get(chained_id) == 2
```

Note the following behaviors:

- The second task will not be executed until the first task has finished executing because the second task depends on the output of the first task.

- If the two tasks are scheduled on different machines, the output of the first task (the value corresponding to `y1_id`) will be sent over the network to the machine where the second task is scheduled.

Oftentimes, you may want to specify a task's resource requirements (for example one task may require a GPU). The `ray.init()` command will automatically detect the available GPUs and CPUs on the machine. However, you can override this default behavior by passing in specific resources, e.g., `ray.init(num_cpus=8, num_gpus=4, resources={'Custom': 2})`.

To specify a task's CPU and GPU requirements, pass the `num_cpus` and `num_gpus` arguments into the remote decorator. The task will only run on a machine if there are enough CPU and GPU (and other custom) resources available to execute the task. Ray can also handle arbitrary custom resources.

Note:

- If you do not specify any resources in the `@ray.remote` decorator, the default is 1 CPU resource and no other resources.
- If specifying CPUs, Ray does not enforce isolation (i.e., your task is expected to honor its request).
- If specifying GPUs, Ray does provide isolation in forms of visible devices (setting the environment variable `CUDA_VISIBLE_DEVICES`), but it is the task's responsibility to actually use the GPUs (e.g., through a deep learning framework like TensorFlow or PyTorch).

```
@ray.remote(num_cpus=4, num_gpus=2)
def f():
    return 1
```

The resource requirements of a task have implications for the Ray's scheduling concurrency. In particular, the sum of the resource requirements of all of the concurrently executing tasks on a given node cannot exceed the node's total resources.

Below are more examples of resource specifications:

```
# Ray also supports fractional resource requirements
@ray.remote(num_gpus=0.5)
def h():
    return 1

# Ray support custom resources too.
@ray.remote(resources={'Custom': 1})
def f():
    return 1
```

Further, remote function can return multiple object IDs.

```
@ray.remote(num_return_vals=3)
def return_multiple():
    return 1, 2, 3

a_id, b_id, c_id = return_multiple.remote()
```

5.2.2 Objects in Ray

In Ray, we can create and compute on objects. We refer to these objects as **remote objects**, and we use **object IDs** to refer to them. Remote objects are stored in shared-memory **object stores**, and there is one object store per node in the cluster. In the cluster setting, we may not actually know which machine each object lives on.

An **object ID** is essentially a unique ID that can be used to refer to a remote object. If you're familiar with futures, our object IDs are conceptually similar.

Object IDs can be created in multiple ways.

1. They are returned by remote function calls.
2. They are returned by `ray.put`.

```
y = 1
object_id = ray.put(y)
```

`ray.`**`put`**(*value*, *weakref=False*)

Store an object in the object store.

The object may not be evicted while a reference to the returned ID exists. Note that this pinning only applies to the particular object ID returned by put, not object IDs in general.

Parameters

- **`value`** – The Python object to be stored.
- **`weakref`** – If set, allows the object to be evicted while a reference to the returned ID exists. You might want to set this if putting a lot of objects that you might not need in the future.

Returns The object ID assigned to this value.

Important: Remote objects are immutable. That is, their values cannot be changed after creation. This allows remote objects to be replicated in multiple object stores without needing to synchronize the copies.

5.2.3 Fetching Results

The command `ray.get(x_id)` takes an object ID and creates a Python object from the corresponding remote object. First, if the current node's object store does not contain the object, the object is downloaded. Then, if the object is a numpy array or a collection of numpy arrays, the `get` call is zero-copy and returns arrays backed by shared object store memory. Otherwise, we deserialize the object data into a Python object.

```
y = 1
obj_id = ray.put(y)
assert ray.get(obj_id) == 1
```

`ray.`**`get`**(*object_ids*)

Get a remote object or a list of remote objects from the object store.

This method blocks until the object corresponding to the object ID is available in the local object store. If this object is not in the local object store, it will be shipped from an object store that has it (once the object has been created). If object_ids is a list, then the objects corresponding to each object in the list will be returned.

Parameters **`object_ids`** – Object ID of the object to get or a list of object IDs to get.

Returns A Python object or a list of Python objects.

Raises `Exception` – An exception is raised if the task that created the object or that created one of the objects raised an exception.

After launching a number of tasks, you may want to know which ones have finished executing. This can be done with `ray.wait`. The function works as follows.

```
ready_ids, remaining_ids = ray.wait(object_ids, num_returns=1, timeout=None)
```

ray.**wait**(*object_ids*, *num_returns=1*, *timeout=None*)
Return a list of IDs that are ready and a list of IDs that are not.

> **Warning:** The **timeout** argument used to be in **milliseconds** (up through `ray==0.6.1`) and now it is in **seconds**.

If timeout is set, the function returns either when the requested number of IDs are ready or when the timeout is reached, whichever occurs first. If it is not set, the function simply waits until that number of objects is ready and returns that exact number of object IDs.

This method returns two lists. The first list consists of object IDs that correspond to objects that are available in the object store. The second list corresponds to the rest of the object IDs (which may or may not be ready).

Ordering of the input list of object IDs is preserved. That is, if A precedes B in the input list, and both are in the ready list, then A will precede B in the ready list. This also holds true if A and B are both in the remaining list.

Parameters

- **object_ids** (*List[ObjectID]*) – List of object IDs for objects that may or may not be ready. Note that these IDs must be unique.
- **num_returns** (*int*) – The number of object IDs that should be returned.
- **timeout** (*float*) – The maximum amount of time in seconds to wait before returning.

Returns A list of object IDs that are ready and a list of the remaining object IDs.

5.2.4 Object Eviction

When the object store gets full, objects will be evicted to make room for new objects. This happens in approximate LRU (least recently used) order. To avoid objects from being evicted, you can call `ray.get` and store their values instead. Numpy array objects cannot be evicted while they are mapped in any Python process. You can also configure memory limits to control object store usage by actors.

Note: Objects created with `ray.put` are pinned in memory while a Python reference to the object ID returned by the put exists. This only applies to the specific ID returned by put, not IDs in general or copies of that IDs.

5.2.5 Remote Classes (Actors)

Actors extend the Ray API from functions (tasks) to classes. The `ray.remote` decorator indicates that instances of the `Counter` class will be actors. An actor is essentially a stateful worker. Each actor runs in its own Python process.

```
@ray.remote
class Counter(object):
    def __init__(self):
        self.value = 0

    def increment(self):
        self.value += 1
        return self.value
```

To create a couple actors, we can instantiate this class as follows:

```
a1 = Counter.remote()
a2 = Counter.remote()
```

When an actor is instantiated, the following events happen.

1. A worker Python process is started on a node of the cluster.
2. A `Counter` object is instantiated on that worker.

You can specify resource requirements in Actors too (see the Actors section for more details.)

```
@ray.remote(num_cpus=2, num_gpus=0.5)
class Actor(object):
    pass
```

We can interact with the actor by calling its methods with the `.remote` operator. We can then call `ray.get` on the object ID to retrieve the actual value.

```
obj_id = a1.increment.remote()
ray.get(obj_id) == 1
```

Methods called on different actors can execute in parallel, and methods called on the same actor are executed serially in the order that they are called. Methods on the same actor will share state with one another, as shown below.

```
# Create ten Counter actors.
counters = [Counter.remote() for _ in range(10)]

# Increment each Counter once and get the results. These tasks all happen in
# parallel.
results = ray.get([c.increment.remote() for c in counters])
print(results)  # prints [1, 1, 1, 1, 1, 1, 1, 1, 1, 1]

# Increment the first Counter five times. These tasks are executed serially
# and share state.
results = ray.get([counters[0].increment.remote() for _ in range(5)])
print(results)  # prints [2, 3, 4, 5, 6]
```

To learn more about Ray Actors, see the Actors section.

5.3 Using Actors

An actor is essentially a stateful worker (or a service). When a new actor is instantiated, a new worker is created, and methods of the actor are scheduled on that specific worker and can access and mutate the state of that worker.

5.3.1 Creating an actor

You can convert a standard Python class into a Ray actor class as follows:

```
@ray.remote
class Counter(object):
    def __init__(self):
        self.value = 0
```

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```
    def increment(self):
        self.value += 1
        return self.value
```

Note that the above is equivalent to the following:

```
class Counter(object):
    def __init__(self):
        self.value = 0

    def increment(self):
        self.value += 1
        return self.value

Counter = ray.remote(Counter)
```

When the above actor is instantiated, the following events happen.

1. A node in the cluster is chosen and a worker process is created on that node for the purpose of running methods called on the actor.
2. A `Counter` object is created on that worker and the `Counter` constructor is run.

5.3.2 Actor Methods

Any method of the actor can return multiple object IDs with the `ray.method` decorator:

```
@ray.remote
class Foo(object):

    @ray.method(num_return_vals=2)
    def bar(self):
        return 1, 2

f = Foo.remote()

obj_id1, obj_id2 = f.bar.remote()
assert ray.get(obj_id1) == 1
assert ray.get(obj_id2) == 2
```

5.3.3 Resources with Actors

You can specify that an actor requires CPUs or GPUs in the decorator. While Ray has built-in support for CPUs and GPUs, Ray can also handle custom resources.

When using GPUs, Ray will automatically set the environment variable `CUDA_VISIBLE_DEVICES` for the actor after instantiated. The actor will have access to a list of the IDs of the GPUs that it is allowed to use via `ray.get_gpu_ids()`. This is a list of integers, like `[]`, or `[1]`, or `[2, 5, 6]`.

```
@ray.remote(num_cpus=2, num_gpus=1)
class GPUActor(object):
    pass
```

When an `GPUActor` instance is created, it will be placed on a node that has at least 1 GPU, and the GPU will be reserved for the actor for the duration of the actor's lifetime (even if the actor is not executing tasks). The GPU resources will be released when the actor terminates.

If you want to use custom resources, make sure your cluster is configured to have these resources (see configuration instructions):

Important:

- If you specify resource requirements in an actor class's remote decorator, then the actor will acquire those resources for its entire lifetime (if you do not specify CPU resources, the default is 1), even if it is not executing any methods. The actor will not acquire any additional resources when executing methods.
- If you do not specify any resource requirements in the actor class's remote decorator, then by default, the actor will not acquire any resources for its lifetime, but every time it executes a method, it will need to acquire 1 CPU resource.

```
@ray.remote(resources={'Resource2': 1})
class GPUActor(object):
    pass
```

If you need to instantiate many copies of the same actor with varying resource requirements, you can do so as follows.

```
@ray.remote(num_cpus=4)
class Counter(object):
    def __init__(self):
        self.value = 0

    def increment(self):
        self.value += 1
        return self.value

a1 = Counter._remote(num_cpus=1, resources={"Custom1": 1})
a2 = Counter._remote(num_cpus=2, resources={"Custom2": 1})
a3 = Counter._remote(num_cpus=3, resources={"Custom3": 1})
```

Note that to create these actors successfully, Ray will need to be started with sufficient CPU resources and the relevant custom resources.

5.3.4 Terminating Actors

Actor processes will be terminated automatically when the initial actor handle goes out of scope in Python. If we create an actor with `actor_handle = Counter.remote()`, then when `actor_handle` goes out of scope and is destructed, the actor process will be terminated. Note that this only applies to the original actor handle created for the actor and not to subsequent actor handles created by passing the actor handle to other tasks.

If necessary, you can manually terminate an actor by calling `ray.actor.exit_actor()` from within one of the actor methods. This will kill the actor process and release resources associated/assigned to the actor. This approach should generally not be necessary as actors are automatically garbage collected.

5.3.5 Passing Around Actor Handles

Actor handles can be passed into other tasks. To see an example of this, take a look at the asynchronous parameter server example. To illustrate this with a simple example, consider a simple actor definition.

```
@ray.remote
class Counter(object):
    def __init__(self):
        self.counter = 0

    def inc(self):
        self.counter += 1

    def get_counter(self):
        return self.counter
```

We can define remote functions (or actor methods) that use actor handles.

```
import time

@ray.remote
def f(counter):
    for _ in range(1000):
        time.sleep(0.1)
        counter.inc.remote()
```

If we instantiate an actor, we can pass the handle around to various tasks.

```
counter = Counter.remote()

# Start some tasks that use the actor.
[f.remote(counter) for _ in range(3)]

# Print the counter value.
for _ in range(10):
    time.sleep(1)
    print(ray.get(counter.get_counter.remote()))
```

5.4 GPU Support

GPUs are critical for many machine learning applications. Ray enables remote functions and actors to specify their GPU requirements in the `ray.remote` decorator.

5.4.1 Starting Ray with GPUs

Ray will automatically detect the number of GPUs available on a machine. If you need to, you can override this by specifying `ray.init(num_gpus=N)` or `ray start --num-gpus=N`.

Note: There is nothing preventing you from passing in a larger value of `num_gpus` than the true number of GPUs on the machine. In this case, Ray will act as if the machine has the number of GPUs you specified for the purposes of scheduling tasks that require GPUs. Trouble will only occur if those tasks attempt to actually use GPUs that don't exist.

5.4.2 Using Remote Functions with GPUs

If a remote function requires GPUs, indicate the number of required GPUs in the remote decorator.

```
import os

@ray.remote(num_gpus=1)
def use_gpu():
    print("ray.get_gpu_ids(): {}".format(ray.get_gpu_ids()))
    print("CUDA_VISIBLE_DEVICES: {}".format(os.environ["CUDA_VISIBLE_DEVICES"]))
```

Inside of the remote function, a call to `ray.get_gpu_ids()` will return a list of integers indicating which GPUs the remote function is allowed to use. Typically, it is not necessary to call `ray.get_gpu_ids()` because Ray will automatically set the `CUDA_VISIBLE_DEVICES` environment variable.

Note: The function `use_gpu` defined above doesn't actually use any GPUs. Ray will schedule it on a machine which has at least one GPU, and will reserve one GPU for it while it is being executed, however it is up to the function to actually make use of the GPU. This is typically done through an external library like TensorFlow. Here is an example that actually uses GPUs. Note that for this example to work, you will need to install the GPU version of TensorFlow.

```
import tensorflow as tf

@ray.remote(num_gpus=1)
def use_gpu():
    # Create a TensorFlow session. TensorFlow will restrict itself to use the
    # GPUs specified by the CUDA_VISIBLE_DEVICES environment variable.
    tf.Session()
```

Note: It is certainly possible for the person implementing `use_gpu` to ignore `ray.get_gpu_ids` and to use all of the GPUs on the machine. Ray does not prevent this from happening, and this can lead to too many workers using the same GPU at the same time. However, Ray does automatically set the `CUDA_VISIBLE_DEVICES` environment variable, which will restrict the GPUs used by most deep learning frameworks.

5.4.3 Fractional GPUs

If you want two tasks to share the same GPU, then the tasks can each request half (or some other fraction) of a GPU.

```
import ray
import time

ray.init(num_cpus=4, num_gpus=1)

@ray.remote(num_gpus=0.25)
def f():
    time.sleep(1)

# The four tasks created here can execute concurrently.
ray.get([f.remote() for _ in range(4)])
```

It is the developer's responsibility to make sure that the individual tasks don't use more than their share of the GPU memory. TensorFlow can be configured to limit its memory usage.

5.4.4 Using Actors with GPUs

When defining an actor that uses GPUs, indicate the number of GPUs an actor instance requires in the `ray.remote` decorator.

```
@ray.remote(num_gpus=1)
class GPUActor(object):
    def __init__(self):
        return "This actor is allowed to use GPUs {}.".format(ray.get_gpu_ids())
```

When the actor is created, GPUs will be reserved for that actor for the lifetime of the actor. If sufficient GPU resources are not available, then the actor will not be created.

The following is an example of how to use GPUs in an actor through TensorFlow.

```
@ray.remote(num_gpus=1)
class GPUActor(object):
    def __init__(self):
        # The call to tf.Session() will restrict TensorFlow to use the GPUs
        # specified in the CUDA_VISIBLE_DEVICES environment variable.
        self.sess = tf.Session()
```

5.4.5 Workers not Releasing GPU Resources

Note: Currently, when a worker executes a task that uses a GPU (e.g., through TensorFlow), the task may allocate memory on the GPU and may not release it when the task finishes executing. This can lead to problems the next time a task tries to use the same GPU. You can address this by setting `max_calls=1` in the remote decorator so that the worker automatically exits after executing the task (thereby releasing the GPU resources).

```
import tensorflow as tf

@ray.remote(num_gpus=1, max_calls=1)
def leak_gpus():
    # This task will allocate memory on the GPU and then never release it, so
    # we include the max_calls argument to kill the worker and release the
    # resources.
    sess = tf.Session()
```

5.5 Serialization

Since Ray processes do not share memory space, data transferred between workers and nodes will need to **serialized** and **deserialized**. Ray uses the Plasma object store to efficiently transfer objects across different processes and different nodes. Numpy arrays in the object store are shared between workers on the same node (zero-copy deserialization).

5.5.1 Plasma Object Store

Plasma is an in-memory object store that is being developed as part of Apache Arrow. Ray uses Plasma to efficiently transfer objects across different processes and different nodes. All objects in Plasma object store are **immutable** and held in shared memory. This is so that they can be accessed efficiently by many workers on the same node.

Each node has its own object store. When data is put into the object store, it does not get automatically broadcasted to other nodes. Data remains local to the writer until requested by another task or actor on another node.

5.5.2 Overview

Objects that are serialized for transfer among Ray processes go through three stages:

1. Serialize using pyarrow: Below is the set of Python objects that Ray can serialize using `pyarrow`:

1. Primitive types: ints, floats, longs, bools, strings, unicode, and numpy arrays.
2. Any list, dictionary, or tuple whose elements can be serialized by Ray.

2. ‘‘__dict__‘‘ serialization: If a direct usage of PyArrow is not possible, Ray will recursively extract the object's `__dict__` and serialize that using pyarrow. This behavior is not correct in all cases.

3. Cloudpickle: Ray falls back to `cloudpickle` as a final attempt for serialization. This may be slow.

5.5.3 Numpy Arrays

Ray optimizes for numpy arrays by using the Apache Arrow data format. The numpy array is stored as a read-only object, and all Ray workers on the same node can read the numpy array in the object store without copying (zero-copy reads). Each numpy array object in the worker process holds a pointer to the relevant array held in shared memory. Any writes to the read-only object will require the user to first copy it into the local process memory.

Tip: You can often avoid serialization issues by using only native types (e.g., numpy arrays or lists/dicts of numpy arrays and other primitive types), or by using Actors hold objects that cannot be serialized.

5.5.4 Serialization notes and limitations

- Ray currently handles certain patterns incorrectly, according to Python semantics. For example, a list that contains two copies of the same list will be serialized as if the two lists were distinct.

```
l1 = [0]
l2 = [l1, l1]
l3 = ray.get(ray.put(l2))

assert l2[0] is l2[1]
assert not l3[0] is l3[1]
```

- For reasons similar to the above example, we also do not currently handle objects that recursively contain themselves (this may be common in graph-like data structures).

```
l = []
l.append(l)

# Try to put this list that recursively contains itself in the object store.
ray.put(l)
```

  This will throw an exception with a message like the following.

```
This object exceeds the maximum recursion depth. It may contain itself␣
↪recursively.
```

- Whenever possible, use numpy arrays or Python collections of numpy arrays for maximum performance.

Last resort: Custom Serialization

If none of these options work, you can try registering a custom serializer.

ray.**register_custom_serializer**(*cls*, *use_pickle=False*, *use_dict=False*, *serializer=None*, *deserializer=None*, *local=False*, *job_id=None*, *class_id=None*)

Enable serialization and deserialization for a particular class.

This method runs the register_class function defined below on every worker, which will enable ray to properly serialize and deserialize objects of this class.

Parameters

- **cls** (*type*) – The class that ray should use this custom serializer for.
- **use_pickle** (*bool*) – If true, then objects of this class will be serialized using pickle.
- **use_dict** – If true, then objects of this class be serialized turning their __dict__ fields into a dictionary. Must be False if use_pickle is true.
- **serializer** – The custom serializer to use. This should be provided if and only if use_pickle and use_dict are False.
- **deserializer** – The custom deserializer to use. This should be provided if and only if use_pickle and use_dict are False.
- **local** – True if the serializers should only be registered on the current worker. This should usually be False.
- **job_id** – ID of the job that we want to register the class for.
- **class_id** – ID of the class that we are registering. If this is not specified, we will calculate a new one inside the function.

Raises Exception – An exception is raised if pickle=False and the class cannot be efficiently serialized by Ray. This can also raise an exception if use_dict is true and cls is not pickleable.

Below is an example of using ray.register_custom_serializer:

```
import ray

ray.init()

class Foo(object):
    def __init__(self, value):
        self.value = value

def custom_serializer(obj):
    return obj.value

def custom_deserializer(value):
    object = Foo()
    object.value = value
    return object

ray.register_custom_serializer(
    Foo, serializer=custom_serializer, deserializer=custom_deserializer)

object_id = ray.put(Foo(100))
assert ray.get(object_id).value == 100
```

If you find cases where Ray serialization doesn't work or does something unexpected, please let us know so we can fix it.

Advanced: Huge Pages

On Linux, it is possible to increase the write throughput of the Plasma object store by using huge pages. See the Configuration page for information on how to use huge pages in Ray.

5.6 Memory Management

This page describes how memory management works in Ray, and how you can set memory quotas to ensure memory-intensive applications run predictably and reliably.

5.6.1 Overview

There are several ways that Ray applications use memory:

Ray system memory: this is memory used internally by Ray

- **Redis**: memory used for storing task lineage and object metadata. When Redis becomes full, lineage will start to be be LRU evicted, which makes the corresponding objects ineligible for reconstruction on failure.
- **Raylet**: memory used by the C++ raylet process running on each node. This cannot be controlled, but is usually quite small.

Application memory: this is memory used by your application

- **Worker heap**: memory used by your application (e.g., in Python code or TensorFlow), best measured as the *resident set size (RSS)* of your application minus its *shared memory usage (SHR)* in commands such as `top`.
- **Object store memory**: memory used when your application creates objects in the objects store via `ray.put` and when returning values from remote functions. Objects are LRU evicted when the store is full. There is an object store server running on each node.
- **Object store shared memory**: memory used when your application reads objects via `ray.get`. Note that if an object is already present on the node, this does not cause additional allocations. This allows large objects to be efficiently shared among many actors and tasks.

By default, Ray will cap the memory used by Redis at `min(30% of node memory, 10GiB)`, and object store at `min(10% of node memory, 20GiB)`, leaving half of the remaining memory on the node available for use by worker heap. You can also manually configure this by setting `redis_max_memory=<bytes>` and `object_store_memory=<bytes>` on Ray init.

It is important to note that these default Redis and object store limits do not address the following issues:

- Actor or task heap usage exceeding the remaining available memory on a node.
- Heavy use of the object store by certain actors or tasks causing objects required by other tasks to be prematurely evicted.

To avoid these potential sources of instability, you can set *memory quotas* to reserve memory for individual actors and tasks.

5.6.2 Heap memory quota

When Ray starts, it queries the available memory on a node / container not reserved for Redis and the object store or being used by other applications. This is considered "available memory" that actors and tasks can request memory out of. You can also set `memory=<bytes>` on Ray init to tell Ray explicitly how much memory is available.

To tell the Ray scheduler a task or actor requires a certain amount of available memory to run, set the `memory` argument. The Ray scheduler will then reserve the specified amount of available memory during scheduling, similar to how it handles CPU and GPU resources:

```
# reserve 500MiB of available memory to place this task
@ray.remote(memory=500 * 1024 * 1024)
def some_function(x):
    pass

# reserve 2.5GiB of available memory to place this actor
@ray.remote(memory=2500 * 1024 * 1024)
class SomeActor(object):
    def __init__(self, a, b):
        pass
```

In the above example, the memory quota is specified statically by the decorator, but you can also set them dynamically at runtime using `_remote()` as follows:

```
# override the memory quota to 100MiB when submitting the task
some_function._remote(memory=100 * 1024 * 1024, kwargs={"x": 1})

# override the memory quota to 1GiB when creating the actor
SomeActor._remote(memory=1000 * 1024 * 1024, kwargs={"a": 1, "b": 2})
```

Enforcement: If an actor exceeds its memory quota, calls to it will throw `RayOutOfMemoryError` and it may be killed. Memory quota is currently enforced on a best-effort basis for actors only (but quota is taken into account during scheduling in all cases).

5.6.3 Object store memory quota

Use `@ray.remote(object_store_memory=<bytes>)` to cap the amount of memory an actor can use for `ray.put` and method call returns. This gives the actor its own LRU queue within the object store of the given size, both protecting its objects from eviction by other actors and preventing it from using more than the specified quota. This quota protects objects from unfair eviction when certain actors are producing objects at a much higher rate than others.

Ray takes this resource into account during scheduling, with the caveat that a node will always reserve ~30% of its object store for global shared use.

For the driver, you can set its object store memory quota with `driver_object_store_memory`. Setting object store quota is not supported for tasks.

5.6.4 Object store shared memory

Object store memory is also used to map objects returned by `ray.get` calls in shared memory. While an object is mapped in this way (i.e., there is a Python reference to the object), it is pinned and cannot be evicted from the object store. However, ray does not provide quota management for this kind of shared memory usage.

5.6.5 Summary

You can set memory quotas to ensure your application runs predictably on any Ray cluster configuration. If you're not sure, you can start with a conservative default configuration like the following and see if any limits are hit:

```
@ray.remote(
    memory=2000 * 1024 * 1024,
    object_store_memory=200 * 1024 * 1024)
```

5.7 Configuring Ray

This page discusses the various way to configure Ray, both from the Python API and from the command line. Take a look at the `ray.init` documentation for a complete overview of the configurations.

Important: For the multi-node setting, you must first run *ray start* on the command line before `ray.init` in Python. On a single machine, you can run `ray.init()` without *ray start*.

5.7.1 Cluster Resources

Ray by default detects available resources.

```
# This automatically detects available resources in the single machine.
ray.init()
```

If not running cluster mode, you can specify cluster resources overrides through `ray.init` as follows.

```
# If not connecting to an existing cluster, you can specify resources overrides:
ray.init(num_cpus=8, num_gpus=1)

# Specifying custom resources
ray.init(num_gpus=1, resources={'Resource1': 4, 'Resource2': 16})
```

When starting Ray from the command line, pass the `--num-cpus` and `--num-cpus` flags into `ray start`. You can also specify custom resources.

```
# To start a head node.
$ ray start --head --num-cpus=<NUM_CPUS> --num-gpus=<NUM_GPUS>

# To start a non-head node.
$ ray start --address=<address> --num-cpus=<NUM_CPUS> --num-gpus=<NUM_GPUS>

# Specifying custom resources
ray start [--head] --num-cpus=<NUM_CPUS> --resources='{"Resource1": 4, "Resource2":␣
↪16}'
```

If using the command line, connect to the Ray cluster as follow:

```
# Connect to ray. Notice if connected to existing cluster, you don't specify␣
↪resources.
ray.init(address=<address>)
```

5.7.2 Logging and Debugging

Each Ray session will have a unique name. By default, the name is `session_{timestamp}_{pid}`. The format of `timestamp` is `%Y-%m-%d_%H-%M-%S_%f` (See Python time format for details); the pid belongs to the startup

process (the process calling `ray.init()` or the Ray process executed by a shell in `ray start`).

For each session, Ray will place all its temporary files under the *session directory*. A *session directory* is a subdirectory of the *root temporary path* (`/tmp/ray` by default), so the default session directory is `/tmp/ray/{ray_session_name}`. You can sort by their names to find the latest session.

Change the *root temporary directory* in one of these ways:

- Pass `--temp-dir={your temp path}` to `ray start`
- Specify `temp_dir` when call `ray.init()`

You can also use `default_worker.py --temp-dir={your temp path}` to start a new worker with the given *root temporary directory*.

Layout of logs:

```
/tmp
└── ray
    └── session_{datetime}_{pid}
        ├── logs  # for logging
        │   ├── log_monitor.err
        │   ├── log_monitor.out
        │   ├── monitor.err
        │   ├── monitor.out
        │   ├── plasma_store.err  # outputs of the plasma store
        │   ├── plasma_store.out
        │   ├── raylet.err  # outputs of the raylet process
        │   ├── raylet.out
        │   ├── redis-shard_0.err   # outputs of redis shards
        │   ├── redis-shard_0.out
        │   ├── redis.err  # redis
        │   ├── redis.out
        │   ├── webui.err  # ipython notebook web ui
        │   ├── webui.out
        │   ├── worker-{worker_id}.err  # redirected output of workers
        │   ├── worker-{worker_id}.out
        │   └── {other workers}
        └── sockets  # for sockets
            ├── plasma_store
            └── raylet  # this could be deleted by Ray's shutdown cleanup.
```

5.7.3 Redis Port Authentication

Ray instances should run on a secure network without public facing ports. The most common threat for Ray instances is unauthorized access to Redis, which can be exploited to gain shell access and run arbitrary code. The best fix is to run Ray instances on a secure, trusted network.

Running Ray on a secured network is not always feasible. To prevent exploits via unauthorized Redis access, Ray provides the option to password-protect Redis ports. While this is not a replacement for running Ray behind a firewall, this feature is useful for instances exposed to the internet where configuring a firewall is not possible. Because Redis is very fast at serving queries, the chosen password should be long.

Note: The Redis passwords provided below may not contain spaces.

Redis authentication is only supported on the raylet code path.

To add authentication via the Python API, start Ray using:

```
ray.init(redis_password="password")
```

To add authentication via the CLI or to connect to an existing Ray instance with password-protected Redis ports:

```
ray start [--head] --redis-password="password"
```

While Redis port authentication may protect against external attackers, Ray does not encrypt traffic between nodes so man-in-the-middle attacks are possible for clusters on untrusted networks.

See the Redis security documentation for more information.

5.7.4 Using the Object Store with Huge Pages

Plasma is a high-performance shared memory object store originally developed in Ray and now being developed in Apache Arrow. See the relevant documentation.

On Linux, it is possible to increase the write throughput of the Plasma object store by using huge pages. You first need to create a file system and activate huge pages as follows.

```
sudo mkdir -p /mnt/hugepages
gid=`id -g`
uid=`id -u`
sudo mount -t hugetlbfs -o uid=$uid -o gid=$gid none /mnt/hugepages
sudo bash -c "echo $gid > /proc/sys/vm/hugetlb_shm_group"
# This typically corresponds to 20000 2MB pages (about 40GB), but this
# depends on the platform.
sudo bash -c "echo 20000 > /proc/sys/vm/nr_hugepages"
```

Note: Once you create the huge pages, they will take up memory which will never be freed unless you remove the huge pages. If you run into memory issues, that may be the issue.

You need root access to create the file system, but not for running the object store.

You can then start Ray with huge pages on a single machine as follows.

```
ray.init(huge_pages=True, plasma_directory="/mnt/hugepages")
```

In the cluster case, you can do it by passing `--huge-pages` and `--plasma-directory=/mnt/hugepages` into `ray start` on any machines where huge pages should be enabled.

See the relevant Arrow documentation for huge pages.

5.8 Debugging and Profiling

5.8.1 Observing Ray Work

You can run `ray stack` to dump the stack traces of all Ray workers on the current node. This requires `py-spy` to be installed. See the Troubleshooting page for more details.

5.8.2 Visualizing Tasks in the Ray Timeline

The most important tool is the timeline visualization tool. To visualize tasks in the Ray timeline, you can dump the timeline as a JSON file by running `ray timeline` from the command line or by using the following command.

```
ray.timeline(filename="/tmp/timeline.json")
```

Then open chrome://tracing in the Chrome web browser, and load `timeline.json`.

5.8.3 Profiling Using Python's CProfile

A second way to profile the performance of your Ray application is to use Python's native cProfile profiling module. Rather than tracking line-by-line of your application code, cProfile can give the total runtime of each loop function, as well as list the number of calls made and execution time of all function calls made within the profiled code.

Unlike `line_profiler` above, this detailed list of profiled function calls **includes** internal function calls and function calls made within Ray!

However, similar to `line_profiler`, cProfile can be enabled with minimal changes to your application code (given that each section of the code you want to profile is defined as its own function). To use cProfile, add an import statement, then replace calls to the loop functions as follows:

```
import cProfile  # Added import statement

def ex1():
    list1 = []
    for i in range(5):
        list1.append(ray.get(func.remote()))

def main():
    ray.init()
    cProfile.run('ex1()')  # Modified call to ex1
    cProfile.run('ex2()')
    cProfile.run('ex3()')

if __name__ == "__main__":
    main()
```

Now, when executing your Python script, a cProfile list of profiled function calls will be outputted to terminal for each call made to `cProfile.run()`. At the very top of cProfile's output gives the total execution time for `'ex1()'`:

```
601 function calls (595 primitive calls) in 2.509 seconds
```

Following is a snippet of profiled function calls for `'ex1()'`. Most of these calls are quick and take around 0.000 seconds, so the functions of interest are the ones with non-zero execution times:

```
ncalls  tottime  percall  cumtime  percall filename:lineno(function)
...
     1    0.000    0.000    2.509    2.509 your_script_here.py:31(ex1)
     5    0.000    0.000    0.001    0.000 remote_function.py:103(remote)
     5    0.000    0.000    0.001    0.000 remote_function.py:107(_submit)
...
    10    0.000    0.000    0.000    0.000 worker.py:2459(__init__)
     5    0.000    0.000    2.508    0.502 worker.py:2535(get)
     5    0.000    0.000    0.000    0.000 worker.py:2695(get_global_worker)
    10    0.000    0.000    2.507    0.251 worker.py:374(retrieve_and_deserialize)
     5    0.000    0.000    2.508    0.502 worker.py:424(get_object)
     5    0.000    0.000    0.000    0.000 worker.py:514(submit_task)
...
```

The 5 separate calls to Ray's `get`, taking the full 0.502 seconds each call, can be noticed at `worker.py:2535(get)`. Meanwhile, the act of calling the remote function itself at `remote_function.`

`py:103(remote)` only takes 0.001 seconds over 5 calls, and thus is not the source of the slow performance of `ex1()`.

Profiling Ray Actors with cProfile

Considering that the detailed output of cProfile can be quite different depending on what Ray functionalities we use, let us see what cProfile's output might look like if our example involved Actors (for an introduction to Ray actors, see our Actor documentation here).

Now, instead of looping over five calls to a remote function like in `ex1`, let's create a new example and loop over five calls to a remote function **inside an actor**. Our actor's remote function again just sleeps for 0.5 seconds:

```
# Our actor
@ray.remote
class Sleeper(object):
    def __init__(self):
        self.sleepValue = 0.5

    # Equivalent to func(), but defined within an actor
    def actor_func(self):
        time.sleep(self.sleepValue)
```

Recalling the suboptimality of `ex1`, let's first see what happens if we attempt to perform all five `actor_func()` calls within a single actor:

```
def ex4():
    # This is suboptimal in Ray, and should only be used for the sake of this example
    actor_example = Sleeper.remote()

    five_results = []
    for i in range(5):
        five_results.append(actor_example.actor_func.remote())

    # Wait until the end to call ray.get()
    ray.get(five_results)
```

We enable cProfile on this example as follows:

```
def main():
    ray.init()
    cProfile.run('ex4()')

if __name__ == "__main__":
    main()
```

Running our new Actor example, cProfile's abbreviated output is as follows:

```
12519 function calls (11956 primitive calls) in 2.525 seconds

ncalls  tottime  percall  cumtime  percall filename:lineno(function)
...
1    0.000    0.000    0.015    0.015 actor.py:546(remote)
1    0.000    0.000    0.015    0.015 actor.py:560(_submit)
1    0.000    0.000    0.000    0.000 actor.py:697(__init__)
...
1    0.000    0.000    2.525    2.525 your_script_here.py:63(ex4)
...
```

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```
9    0.000    0.000    0.000    0.000 worker.py:2459(__init__)
1    0.000    0.000    2.509    2.509 worker.py:2535(get)
9    0.000    0.000    0.000    0.000 worker.py:2695(get_global_worker)
4    0.000    0.000    2.508    0.627 worker.py:374(retrieve_and_deserialize)
1    0.000    0.000    2.509    2.509 worker.py:424(get_object)
8    0.000    0.000    0.001    0.000 worker.py:514(submit_task)
...
```

It turns out that the entire example still took 2.5 seconds to execute, or the time for five calls to `actor_func()` to run in serial. We remember in `ex1` that this behavior was because we did not wait until after submitting all five remote function tasks to call `ray.get()`, but we can verify on cProfile's output line `worker.py:2535(get)` that `ray.get()` was only called once at the end, for 2.509 seconds. What happened?

It turns out Ray cannot parallelize this example, because we have only initialized a single `Sleeper` actor. Because each actor is a single, stateful worker, our entire code is submitted and ran on a single worker the whole time.

To better parallelize the actors in `ex4`, we can take advantage that each call to `actor_func()` is independent, and instead create five `Sleeper` actors. That way, we are creating five workers that can run in parallel, instead of creating a single worker that can only handle one call to `actor_func()` at a time.

```
def ex4():
    # Modified to create five separate Sleepers
    five_actors = [Sleeper.remote() for i in range(5)]

    # Each call to actor_func now goes to a different Sleeper
    five_results = []
    for actor_example in five_actors:
        five_results.append(actor_example.actor_func.remote())

    ray.get(five_results)
```

Our example in total now takes only 1.5 seconds to run:

```
1378 function calls (1363 primitive calls) in 1.567 seconds

ncalls  tottime  percall  cumtime  percall filename:lineno(function)
...
5    0.000    0.000    0.002    0.000 actor.py:546(remote)
5    0.000    0.000    0.002    0.000 actor.py:560(_submit)
5    0.000    0.000    0.000    0.000 actor.py:697(__init__)
...
1    0.000    0.000    1.566    1.566 your_script_here.py:71(ex4)
...
21    0.000    0.000    0.000    0.000 worker.py:2459(__init__)
1    0.000    0.000    1.564    1.564 worker.py:2535(get)
25    0.000    0.000    0.000    0.000 worker.py:2695(get_global_worker)
3    0.000    0.000    1.564    0.521 worker.py:374(retrieve_and_deserialize)
1    0.000    0.000    1.564    1.564 worker.py:424(get_object)
20    0.001    0.000    0.001    0.000 worker.py:514(submit_task)
...
```

This document discusses some common problems that people run into when using Ray as well as some known problems. If you encounter other problems, please let us know.

5.8.4 Crashes

If Ray crashed, you may wonder what happened. Currently, this can occur for some of the following reasons.

- **Stressful workloads:** Workloads that create many many tasks in a short amount of time can sometimes interfere with the heartbeat mechanism that we use to check that processes are still alive. On the head node in the cluster, you can check the files `/tmp/ray/session_*/logs/monitor*`. They will indicate which processes Ray has marked as dead (due to a lack of heartbeats). However, it is currently possible for a process to get marked as dead without actually having died.
- **Starting many actors:** Workloads that start a large number of actors all at once may exhibit problems when the processes (or libraries that they use) contend for resources. Similarly, a script that starts many actors over the lifetime of the application will eventually cause the system to run out of file descriptors. This is addressable, but currently we do not garbage collect actor processes until the script finishes.
- **Running out of file descriptors:** As a workaround, you may be able to increase the maximum number of file descriptors with a command like `ulimit -n 65536`. If that fails, double check that the hard limit is sufficiently large by running `ulimit -Hn`. If it is too small, you can increase the hard limit as follows (these instructions work on EC2).
  - Increase the hard ulimit for open file descriptors system-wide by running the following.

    ```
    sudo bash -c "echo $USER hard nofile 65536 >> /etc/security/limits.conf"
    ```

  - Logout and log back in.

5.8.5 No Speedup

You just ran an application using Ray, but it wasn't as fast as you expected it to be. Or worse, perhaps it was slower than the serial version of the application! The most common reasons are the following.

- **Number of cores:** How many cores is Ray using? When you start Ray, it will determine the number of CPUs on each machine with `psutil.cpu_count()`. Ray usually will not schedule more tasks in parallel than the number of CPUs. So if the number of CPUs is 4, the most you should expect is a 4x speedup.
- **Physical versus logical CPUs:** Do the machines you're running on have fewer **physical** cores than **logical** cores? You can check the number of logical cores with `psutil.cpu_count()` and the number of physical cores with `psutil.cpu_count(logical=False)`. This is common on a lot of machines and especially on EC2. For many workloads (especially numerical workloads), you often cannot expect a greater speedup than the number of physical CPUs.
- **Small tasks:** Are your tasks very small? Ray introduces some overhead for each task (the amount of overhead depends on the arguments that are passed in). You will be unlikely to see speedups if your tasks take less than ten milliseconds. For many workloads, you can easily increase the sizes of your tasks by batching them together.
- **Variable durations:** Do your tasks have variable duration? If you run 10 tasks with variable duration in parallel, you shouldn't expect an N-fold speedup (because you'll end up waiting for the slowest task). In this case, consider using `ray.wait` to begin processing tasks that finish first.
- **Multi-threaded libraries:** Are all of your tasks attempting to use all of the cores on the machine? If so, they are likely to experience contention and prevent your application from achieving a speedup. This is very common with some versions of `numpy`, and in that case can usually be setting an environment variable like `MKL_NUM_THREADS` (or the equivalent depending on your installation) to `1`.

  For many - but not all - libraries, you can diagnose this by opening `top` while your application is running. If one process is using most of the CPUs, and the others are using a small amount, this may be the problem. The most common exception is PyTorch, which will appear to be using all the cores despite needing `torch.set_num_threads(1)` to be called to avoid contention.

If you are still experiencing a slowdown, but none of the above problems apply, we'd really like to know! Please create a GitHub issue and consider submitting a minimal code example that demonstrates the problem.

5.8.6 Outdated Function Definitions

Due to subtleties of Python, if you redefine a remote function, you may not always get the expected behavior. In this case, it may be that Ray is not running the newest version of the function.

Suppose you define a remote function `f` and then redefine it. Ray should use the newest version.

```
@ray.remote
def f():
    return 1

@ray.remote
def f():
    return 2

ray.get(f.remote())  # This should be 2.
```

However, the following are cases where modifying the remote function will not update Ray to the new version (at least without stopping and restarting Ray).

- **The function is imported from an external file:** In this case, `f` is defined in some external file `file.py`. If you `import file`, change the definition of `f` in `file.py`, then re-`import file`, the function `f` will not be updated.

  This is because the second import gets ignored as a no-op, so `f` is still defined by the first import.

  A solution to this problem is to use `reload(file)` instead of a second `import file`. Reloading causes the new definition of `f` to be re-executed, and exports it to the other machines. Note that in Python 3, you need to do `from importlib import reload`.

- **The function relies on a helper function from an external file:** In this case, `f` can be defined within your Ray application, but relies on a helper function `h` defined in some external file `file.py`. If the definition of `h` gets changed in `file.py`, redefining `f` will not update Ray to use the new version of `h`.

  This is because when `f` first gets defined, its definition is shipped to all of the workers, and is unpickled. During unpickling, `file.py` gets imported in the workers. Then when `f` gets redefined, its definition is again shipped and unpickled in all of the workers. But since `file.py` has been imported in the workers already, it is treated as a second import and is ignored as a no-op.

  Unfortunately, reloading on the driver does not update `h`, as the reload needs to happen on the worker.

  A solution to this problem is to redefine `f` to reload `file.py` before it calls `h`. For example, if inside `file.py` you have

  ```
  def h():
      return 1
  ```

  And you define remote function `f` as

  ```
  @ray.remote
  def f():
      return file.h()
  ```

  You can redefine `f` as follows.

```
@ray.remote
def f():
    reload(file)
    return file.h()
```

This forces the reload to happen on the workers as needed. Note that in Python 3, you need to do `from importlib import reload`.

5.9 Advanced Usage

This page will cover some more advanced examples of using Ray's flexible programming model.

5.9.1 Dynamic Remote Parameters

You can dynamically adjust resource requirements or return values of `ray.remote` during execution with `._remote`.

For example, here we instantiate many copies of the same actor with varying resource requirements. Note that to create these actors successfully, Ray will need to be started with sufficient CPU resources and the relevant custom resources:

```
@ray.remote(num_cpus=4)
class Counter(object):
    def __init__(self):
        self.value = 0

    def increment(self):
        self.value += 1
        return self.value

a1 = Counter._remote(num_cpus=1, resources={"Custom1": 1})
a2 = Counter._remote(num_cpus=2, resources={"Custom2": 1})
a3 = Counter._remote(num_cpus=3, resources={"Custom3": 1})
```

You can specify different resource requirements for tasks (but not for actor methods):

```
@ray.remote
def g():
    return ray.get_gpu_ids()

object_gpu_ids = g.remote()
assert ray.get(object_gpu_ids) == [0]

dynamic_object_gpu_ids = g._remote(args=[], num_cpus=1, num_gpus=1)
assert ray.get(dynamic_object_gpu_ids) == [0]
```

And vary the number of return values for tasks (and actor methods too):

```
@ray.remote
def f(n):
    return list(range(n))

id1, id2 = f._remote(args=[2], num_return_vals=2)
assert ray.get(id1) == 0
assert ray.get(id2) == 1
```

5.9.2 Nested Remote Functions

Remote functions can call other remote functions, resulting in nested tasks. For example, consider the following.

```
@ray.remote
def f():
    return 1

@ray.remote
def g():
    # Call f 4 times and return the resulting object IDs.
    return [f.remote() for _ in range(4)]

@ray.remote
def h():
    # Call f 4 times, block until those 4 tasks finish,
    # retrieve the results, and return the values.
    return ray.get([f.remote() for _ in range(4)])
```

Then calling `g` and `h` produces the following behavior.

```
>>> ray.get(g.remote())
[ObjectID(b1457ba0911ae84989aae86f89409e953dd9a80e),
 ObjectID(7c14a1d13a56d8dc01e800761a66f09201104275),
 ObjectID(99763728ffc1a2c0766a2000ebabded52514e9a6),
 ObjectID(9c2f372e1933b04b2936bb6f58161285829b9914)]

>>> ray.get(h.remote())
[1, 1, 1, 1]
```

One limitation is that the definition of `f` must come before the definitions of `g` and `h` because as soon as `g` is defined, it will be pickled and shipped to the workers, and so if `f` hasn't been defined yet, the definition will be incomplete.

5.9.3 Circular Dependencies

Consider the following remote function.

```
@ray.remote(num_cpus=1, num_gpus=1)
def g():
    return ray.get(f.remote())
```

When a `g` task is executing, it will release its CPU resources when it gets blocked in the call to `ray.get`. It will reacquire the CPU resources when `ray.get` returns. It will retain its GPU resources throughout the lifetime of the task because the task will most likely continue to use GPU memory.

5.9.4 Cython Code in Ray

To use Cython code in Ray, run the following from directory `$RAY_HOME/examples/cython`:

```
pip install scipy # For BLAS example
pip install -e .
python cython_main.py --help
```

You can import the `cython_examples` module from a Python script or interpreter.

Notes

- You **must** include the following two lines at the top of any `*.pyx` file:

```
#!python
# cython: embedsignature=True, binding=True
```

- You cannot decorate Cython functions within a `*.pyx` file (there are ways around this, but creates a leaky abstraction between Cython and Python that would be very challenging to support generally). Instead, prefer the following in your Python code:

```
some_cython_func = ray.remote(some_cython_module.some_cython_func)
```

- You cannot transfer memory buffers to a remote function (see `example8`, which currently fails); your remote function must return a value
- Have a look at `cython_main.py`, `cython_simple.pyx`, and `setup.py` for examples of how to call, define, and build Cython code, respectively. The Cython documentation is also very helpful.
- Several limitations come from Cython's own unsupported Python features.
- We currently do not support compiling and distributing Cython code to `ray` clusters. In other words, Cython developers are responsible for compiling and distributing any Cython code to their cluster (much as would be the case for users who need Python packages like `scipy`).
- For most simple use cases, developers need not worry about Python 2 or 3, but users who do need to care can have a look at the `language_level` Cython compiler directive (see here).

5.9.5 Inspecting Cluster State

Applications written on top of Ray will often want to have some information or diagnostics about the cluster. Some common questions include:

1. How many nodes are in my autoscaling cluster?
2. What resources are currently available in my cluster, both used and total?
3. What are the objects currently in my cluster?

For this, you can use the global state API.

Node Information

To get information about the current nodes in your cluster, you can use `ray.nodes()`:

`ray.nodes()`
Get a list of the nodes in the cluster.

Returns Information about the Ray clients in the cluster.

```
import ray

ray.init()

print(ray.nodes())

"""
[{'ClientID': 'a9e430719685f3862ed7ba411259d4138f8afb1e',
```

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```
  'IsInsertion': True,
  'NodeManagerAddress': '192.168.19.108',
  'NodeManagerPort': 37428,
  'ObjectManagerPort': 43415,
  'ObjectStoreSocketName': '/tmp/ray/session_2019-07-28_17-03-53_955034_24883/sockets/
↪plasma_store',
  'RayletSocketName': '/tmp/ray/session_2019-07-28_17-03-53_955034_24883/sockets/
↪raylet',
  'Resources': {'CPU': 4.0},
  'alive': True}]
"""
```

The above information includes:

- *ClientID*: A unique identifier for the raylet.
- *alive*: Whether the node is still alive.
- *NodeManagerAddress*: PrivateIP of the node that the raylet is on.
- *Resources*: The total resource capacity on the node.

Resource Information

To get information about the current total resource capacity of your cluster, you can use `ray.cluster_resources()`.

`ray.`**`cluster_resources`**`()`
Get the current total cluster resources.

Note that this information can grow stale as nodes are added to or removed from the cluster.

Returns

A dictionary mapping resource name to the total quantity of that resource in the cluster.

To get information about the current available resource capacity of your cluster, you can use `ray.available_resources()`.

`ray.`**`available_resources`**`()`
Get the current available cluster resources.

This is different from *cluster_resources* in that this will return idle (available) resources rather than total resources.

Note that this information can grow stale as tasks start and finish.

Returns

A dictionary mapping resource name to the total quantity of that resource in the cluster.

5.10 Ray Package Reference

ray.**init**(*address=None*, *redis_address=None*, *num_cpus=None*, *num_gpus=None*, *memory=None*, *object_store_memory=None*, *resources=None*, *driver_object_store_memory=None*, *redis_max_memory=None*, *log_to_driver=True*, *node_ip_address=None*, *object_id_seed=None*, *local_mode=False*, *redirect_worker_output=None*, *redirect_output=None*, *ignore_reinit_error=False*, *num_redis_shards=None*, *redis_max_clients=None*, *redis_password=None*, *plasma_directory=None*, *huge_pages=False*, *include_webui=False*, *job_id=None*, *configure_logging=True*, *logging_level=20*, *logging_format='%(asctime)s\t%(levelname)s %(filename)s:%(lineno)s – %(message)s'*, *plasma_store_socket_name=None*, *raylet_socket_name=None*, *temp_dir=None*, *load_code_from_local=False*, *_internal_config=None*)

Connect to an existing Ray cluster or start one and connect to it.

This method handles two cases. Either a Ray cluster already exists and we just attach this driver to it, or we start all of the processes associated with a Ray cluster and attach to the newly started cluster.

To start Ray and all of the relevant processes, use this as follows:

```
ray.init()
```

To connect to an existing Ray cluster, use this as follows (substituting in the appropriate address):

```
ray.init(address="123.45.67.89:6379")
```

Parameters

- **address** (*str*) – The address of the Ray cluster to connect to. If this address is not provided, then this command will start Redis, a raylet, a plasma store, a plasma manager, and some workers. It will also kill these processes when Python exits.
- **redis_address** (*str*) – Deprecated; same as address.
- **num_cpus** (*int*) – Number of cpus the user wishes all raylets to be configured with.
- **num_gpus** (*int*) – Number of gpus the user wishes all raylets to be configured with.
- **resources** – A dictionary mapping the name of a resource to the quantity of that resource available.
- **memory** – The amount of memory (in bytes) that is available for use by workers requesting memory resources. By default, this is autoset based on available system memory.
- **object_store_memory** – The amount of memory (in bytes) to start the object store with. By default, this is autoset based on available system memory, subject to a 20GB cap.
- **redis_max_memory** – The max amount of memory (in bytes) to allow each redis shard to use. Once the limit is exceeded, redis will start LRU eviction of entries. This only applies to the sharded redis tables (task, object, and profile tables). By default, this is autoset based on available system memory, subject to a 10GB cap.
- **log_to_driver** (*bool*) – If true, then output from all of the worker processes on all nodes will be directed to the driver.
- **node_ip_address** (*str*) – The IP address of the node that we are on.
- **object_id_seed** (*int*) – Used to seed the deterministic generation of object IDs. The same value can be used across multiple runs of the same driver in order to generate the object IDs in a consistent manner. However, the same ID should not be used for different drivers.

- **local_mode** (*bool*) – True if the code should be executed serially without Ray. This is useful for debugging.
- **driver_object_store_memory** (*int*) – Limit the amount of memory the driver can use in the object store for creating objects. By default, this is autoset based on available system memory, subject to a 20GB cap.
- **ignore_reinit_error** – True if we should suppress errors from calling ray.init() a second time.
- **num_redis_shards** – The number of Redis shards to start in addition to the primary Redis shard.
- **redis_max_clients** – If provided, attempt to configure Redis with this maxclients number.
- **redis_password** (*str*) – Prevents external clients without the password from connecting to Redis if provided.
- **plasma_directory** – A directory where the Plasma memory mapped files will be created.
- **huge_pages** – Boolean flag indicating whether to start the Object Store with hugetlbfs support. Requires plasma_directory.
- **include_webui** – Boolean flag indicating whether to start the web UI, which displays the status of the Ray cluster.
- **job_id** – The ID of this job.
- **configure_logging** – True if allow the logging cofiguration here. Otherwise, the users may want to configure it by their own.
- **logging_level** – Logging level, default will be logging.INFO.
- **logging_format** – Logging format, default contains a timestamp, filename, line number, and message. See ray_constants.py.
- **plasma_store_socket_name** (*str*) – If provided, it will specify the socket name used by the plasma store.
- **raylet_socket_name** (*str*) – If provided, it will specify the socket path used by the raylet process.
- **temp_dir** (*str*) – If provided, it will specify the root temporary directory for the Ray process.
- **load_code_from_local** – Whether code should be loaded from a local module or from the GCS.
- **_internal_config** (*str*) – JSON configuration for overriding RayConfig defaults. For testing purposes ONLY.

Returns Address information about the started processes.

Raises `Exception` – An exception is raised if an inappropriate combination of arguments is passed in.

`ray.`**is_initialized**`()`

Check if ray.init has been called yet.

Returns True if ray.init has already been called and false otherwise.

ray.**remote**(**args*, ***kwargs*)

Define a remote function or an actor class.

This can be used with no arguments to define a remote function or actor as follows:

```
@ray.remote
def f():
    return 1

@ray.remote
class Foo(object):
    def method(self):
        return 1
```

It can also be used with specific keyword arguments:

- **num_return_vals:** This is only for *remote functions*. It specifies the number of object IDs returned by the remote function invocation.
- **num_cpus:** The quantity of CPU cores to reserve for this task or for the lifetime of the actor.
- **num_gpus:** The quantity of GPUs to reserve for this task or for the lifetime of the actor.
- **resources:** The quantity of various custom resources to reserve for this task or for the lifetime of the actor. This is a dictionary mapping strings (resource names) to numbers.
- **max_calls:** Only for *remote functions*. This specifies the maximum number of times that a given worker can execute the given remote function before it must exit (this can be used to address memory leaks in third-party libraries or to reclaim resources that cannot easily be released, e.g., GPU memory that was acquired by TensorFlow). By default this is infinite.
- **max_reconstructions**: Only for *actors*. This specifies the maximum number of times that the actor should be reconstructed when it dies unexpectedly. The minimum valid value is 0 (default), which indicates that the actor doesn't need to be reconstructed. And the maximum valid value is ray.ray_constants.INFINITE_RECONSTRUCTIONS.

This can be done as follows:

```
@ray.remote(num_gpus=1, max_calls=1, num_return_vals=2)
def f():
    return 1, 2

@ray.remote(num_cpus=2, resources={"CustomResource": 1})
class Foo(object):
    def method(self):
        return 1
```

ray.**get**(*object_ids*)

Get a remote object or a list of remote objects from the object store.

This method blocks until the object corresponding to the object ID is available in the local object store. If this object is not in the local object store, it will be shipped from an object store that has it (once the object has been created). If object_ids is a list, then the objects corresponding to each object in the list will be returned.

Parameters **object_ids** – Object ID of the object to get or a list of object IDs to get.

Returns A Python object or a list of Python objects.

Raises Exception – An exception is raised if the task that created the object or that created one of the objects raised an exception.

ray.**wait**(*object_ids*, *num_returns=1*, *timeout=None*)
Return a list of IDs that are ready and a list of IDs that are not.

> **Warning:** The **timeout** argument used to be in **milliseconds** (up through `ray==0.6.1`) and now it is in **seconds**.

If timeout is set, the function returns either when the requested number of IDs are ready or when the timeout is reached, whichever occurs first. If it is not set, the function simply waits until that number of objects is ready and returns that exact number of object IDs.

This method returns two lists. The first list consists of object IDs that correspond to objects that are available in the object store. The second list corresponds to the rest of the object IDs (which may or may not be ready).

Ordering of the input list of object IDs is preserved. That is, if A precedes B in the input list, and both are in the ready list, then A will precede B in the ready list. This also holds true if A and B are both in the remaining list.

Parameters

- **object_ids** (*List[ObjectID]*) – List of object IDs for objects that may or may not be ready. Note that these IDs must be unique.
- **num_returns** (*int*) – The number of object IDs that should be returned.
- **timeout** (*float*) – The maximum amount of time in seconds to wait before returning.

Returns A list of object IDs that are ready and a list of the remaining object IDs.

ray.**put**(*value*, *weakref=False*)
Store an object in the object store.

The object may not be evicted while a reference to the returned ID exists. Note that this pinning only applies to the particular object ID returned by put, not object IDs in general.

Parameters

- **value** – The Python object to be stored.
- **weakref** – If set, allows the object to be evicted while a reference to the returned ID exists. You might want to set this if putting a lot of objects that you might not need in the future.

Returns The object ID assigned to this value.

ray.**get_gpu_ids**()
Get the IDs of the GPUs that are available to the worker.

If the CUDA_VISIBLE_DEVICES environment variable was set when the worker started up, then the IDs returned by this method will be a subset of the IDs in CUDA_VISIBLE_DEVICES. If not, the IDs will fall in the range [0, NUM_GPUS - 1], where NUM_GPUS is the number of GPUs that the node has.

Returns A list of GPU IDs.

ray.**get_resource_ids**()
Get the IDs of the resources that are available to the worker.

Returns A dictionary mapping the name of a resource to a list of pairs, where each pair consists of the ID of a resource and the fraction of that resource reserved for this worker.

ray.**get_webui_url**()
Get the URL to access the web UI.

Note that the URL does not specify which node the web UI is on.

Returns The URL of the web UI as a string.

ray.**shutdown**(*exiting_interpreter=False*)
Disconnect the worker, and terminate processes started by ray.init().

This will automatically run at the end when a Python process that uses Ray exits. It is ok to run this twice in a row. The primary use case for this function is to cleanup state between tests.

Note that this will clear any remote function definitions, actor definitions, and existing actors, so if you wish to use any previously defined remote functions or actors after calling ray.shutdown(), then you need to redefine them. If they were defined in an imported module, then you will need to reload the module.

Parameters **exiting_interpreter** (*bool*) – True if this is called by the atexit hook and false otherwise. If we are exiting the interpreter, we will wait a little while to print any extra error messages.

ray.**register_custom_serializer**(*cls*, *use_pickle=False*, *use_dict=False*, *serializer=None*, *deserializer=None*, *local=False*, *job_id=None*, *class_id=None*)
Enable serialization and deserialization for a particular class.

This method runs the register_class function defined below on every worker, which will enable ray to properly serialize and deserialize objects of this class.

Parameters

- **cls** (*type*) – The class that ray should use this custom serializer for.
- **use_pickle** (*bool*) – If true, then objects of this class will be serialized using pickle.
- **use_dict** – If true, then objects of this class be serialized turning their __dict__ fields into a dictionary. Must be False if use_pickle is true.
- **serializer** – The custom serializer to use. This should be provided if and only if use_pickle and use_dict are False.
- **deserializer** – The custom deserializer to use. This should be provided if and only if use_pickle and use_dict are False.
- **local** – True if the serializers should only be registered on the current worker. This should usually be False.
- **job_id** – ID of the job that we want to register the class for.
- **class_id** – ID of the class that we are registering. If this is not specified, we will calculate a new one inside the function.

Raises Exception – An exception is raised if pickle=False and the class cannot be efficiently serialized by Ray. This can also raise an exception if use_dict is true and cls is not pickleable.

ray.**profile**(*event_type*, *extra_data=None*)
Profile a span of time so that it appears in the timeline visualization.

Note that this only works in the raylet code path.

This function can be used as follows (both on the driver or within a task).

```
with ray.profile("custom event", extra_data={'key': 'value'}):
    # Do some computation here.
```

Optionally, a dictionary can be passed as the "extra_data" argument, and it can have keys "name" and "cname" if you want to override the default timeline display text and box color. Other values will appear at the bottom of the chrome tracing GUI when you click on the box corresponding to this profile span.

Parameters

- **event_type** – A string describing the type of the event.

- **extra_data** – This must be a dictionary mapping strings to strings. This data will be added to the json objects that are used to populate the timeline, so if you want to set a particular color, you can simply set the "cname" attribute to an appropriate color. Similarly, if you set the "name" attribute, then that will set the text displayed on the box in the timeline.

Returns An object that can profile a span of time via a "with" statement.

ray.**method**(**args*, ***kwargs*)
Annotate an actor method.

```
@ray.remote
class Foo(object):
    @ray.method(num_return_vals=2)
    def bar(self):
        return 1, 2

f = Foo.remote()

_, _ = f.bar.remote()
```

Parameters **num_return_vals** – The number of object IDs that should be returned by invocations of this actor method.

5.10.1 Inspect the Cluster State

ray.**nodes**()
Get a list of the nodes in the cluster.

Returns Information about the Ray clients in the cluster.

ray.**tasks**(*task_id=None*)
Fetch and parse the task table information for one or more task IDs.

Parameters **task_id** – A hex string of the task ID to fetch information about. If this is None, then the task object table is fetched.

Returns Information from the task table.

ray.**objects**(*object_id=None*)
Fetch and parse the object table info for one or more object IDs.

Parameters **object_id** – An object ID to fetch information about. If this is None, then the entire object table is fetched.

Returns Information from the object table.

ray.**timeline**(*filename=None*)
Return a list of profiling events that can viewed as a timeline.

To view this information as a timeline, simply dump it as a json file by passing in "filename" or using using json.dump, and then load go to chrome://tracing in the Chrome web browser and load the dumped file.

Parameters **filename** – If a filename is provided, the timeline is dumped to that file.

Returns

If filename is not provided, this returns a list of profiling events. Each profile event is a dictionary.

ray.**object_transfer_timeline**(*filename=None*)
Return a list of transfer events that can viewed as a timeline.

To view this information as a timeline, simply dump it as a json file by passing in "filename" or using using json.dump, and then load go to chrome://tracing in the Chrome web browser and load the dumped file. Make sure to enable "Flow events" in the "View Options" menu.

Parameters **filename** – If a filename is provided, the timeline is dumped to that file.

Returns

If filename is not provided, this returns a list of profiling events. Each profile event is a dictionary.

ray.**cluster_resources**()
Get the current total cluster resources.

Note that this information can grow stale as nodes are added to or removed from the cluster.

Returns

A dictionary mapping resource name to the total quantity of that resource in the cluster.

ray.**available_resources**()
Get the current available cluster resources.

This is different from *cluster_resources* in that this will return idle (available) resources rather than total resources.

Note that this information can grow stale as tasks start and finish.

Returns

A dictionary mapping resource name to the total quantity of that resource in the cluster.

ray.**errors**(*all_jobs=False*)
Get error messages from the cluster.

Parameters **all_jobs** – False if we should only include error messages for this specific job, or True if we should include error messages for all jobs.

Returns

Error messages pushed from the cluster. This will be a single list if all_jobs is False, or a dictionary mapping from job ID to a list of error messages for that job if all_jobs is True.

5.10.2 The Ray Command Line API

ray start

```
ray start [OPTIONS]
```

Options

--node-ip-address <node_ip_address>
the IP address of this node

--redis-address <redis_address>
the address to use for connecting to Redis

--address <address>
same as –redis-address

--redis-port <redis_port>
the port to use for starting Redis

--num-redis-shards <num_redis_shards>
the number of additional Redis shards to use in addition to the primary Redis shard

--redis-max-clients <redis_max_clients>
If provided, attempt to configure Redis with this maximum number of clients.

--redis-password <redis_password>
If provided, secure Redis ports with this password

--redis-shard-ports <redis_shard_ports>
the port to use for the Redis shards other than the primary Redis shard

--object-manager-port <object_manager_port>
the port to use for starting the object manager

--node-manager-port <node_manager_port>
the port to use for starting the node manager

--memory <memory>
The amount of memory (in bytes) to make available to workers. By default, this is set to the available memory on the node.

--object-store-memory <object_store_memory>
The amount of memory (in bytes) to start the object store with. By default, this is capped at 20GB but can be set higher.

--redis-max-memory <redis_max_memory>
The max amount of memory (in bytes) to allow redis to use. Once the limit is exceeded, redis will start LRU eviction of entries. This only applies to the sharded redis tables (task, object, and profile tables). By default this is capped at 10GB but can be set higher.

--num-cpus <num_cpus>
the number of CPUs on this node

--num-gpus <num_gpus>
the number of GPUs on this node

--resources <resources>
a JSON serialized dictionary mapping resource name to resource quantity

--head
provide this argument for the head node

--include-webui
provide this argument if the UI should be started

--block
provide this argument to block forever in this command

--plasma-directory <plasma_directory>
object store directory for memory mapped files

--huge-pages
enable support for huge pages in the object store

--autoscaling-config <autoscaling_config>
the file that contains the autoscaling config

--no-redirect-worker-output
do not redirect worker stdout and stderr to files

--no-redirect-output
do not redirect non-worker stdout and stderr to files

--plasma-store-socket-name <plasma_store_socket_name>
manually specify the socket name of the plasma store

--raylet-socket-name <raylet_socket_name>
manually specify the socket path of the raylet process

--temp-dir <temp_dir>
manually specify the root temporary dir of the Ray process

--include-java
Enable Java worker support.

--java-worker-options <java_worker_options>
Overwrite the options to start Java workers.

--internal-config <internal_config>
Do NOT use this. This is for debugging/development purposes ONLY.

--load-code-from-local
Specify whether load code from local file or GCS serialization.

ray stop

```
ray stop [OPTIONS]
```

ray up

Create or update a Ray cluster.

```
ray up [OPTIONS] CLUSTER_CONFIG_FILE
```

Options

--no-restart
Whether to skip restarting Ray services during the update. This avoids interrupting running jobs.

--restart-only
Whether to skip running setup commands and only restart Ray. This cannot be used with 'no-restart'.

--min-workers <min_workers>
Override the configured min worker node count for the cluster.

--max-workers <max_workers>
Override the configured max worker node count for the cluster.

-n, --cluster-name <cluster_name>
Override the configured cluster name.

-y, --yes
Don't ask for confirmation.

Arguments

CLUSTER_CONFIG_FILE
Required argument

ray down

Tear down the Ray cluster.

```
ray down [OPTIONS] CLUSTER_CONFIG_FILE
```

Options

--workers-only
Only destroy the workers.

-y, --yes
Don't ask for confirmation.

-n, --cluster-name <cluster_name>
Override the configured cluster name.

Arguments

CLUSTER_CONFIG_FILE
Required argument

ray exec

```
ray exec [OPTIONS] CLUSTER_CONFIG_FILE CMD
```

Options

--docker
Runs command in the docker container specified in cluster_config.

--stop
Stop the cluster after the command finishes running.

--start
Start the cluster if needed.

--screen
Run the command in a screen.

--tmux
Run the command in tmux.

-n, --cluster-name <cluster_name>
Override the configured cluster name.

--port-forward <port_forward>
Port to forward.

Arguments

CLUSTER_CONFIG_FILE
Required argument

CMD
Required argument

ray attach

```
ray attach [OPTIONS] CLUSTER_CONFIG_FILE
```

Options

--start
Start the cluster if needed.

--screen
Run the command in screen.

--tmux
Run the command in tmux.

-n, --cluster-name <cluster_name>
Override the configured cluster name.

-N, --new
Force creation of a new screen.

Arguments

CLUSTER_CONFIG_FILE
Required argument

ray get_head_ip

```
ray get_head_ip [OPTIONS] CLUSTER_CONFIG_FILE
```

Options

-n, --cluster-name <cluster_name>
Override the configured cluster name.

Arguments

CLUSTER_CONFIG_FILE
Required argument

ray stack

```
ray stack [OPTIONS]
```

ray timeline

```
ray timeline [OPTIONS]
```

Options

--redis-address <redis_address>
Override the redis address to connect to.

5.11 Automatic Cluster Setup

Ray comes with a built-in autoscaler that makes deploying a Ray cluster simple, just run `ray up` from your local machine to start or update a cluster in the cloud or on an on-premise cluster. Once the Ray cluster is running, you can manually SSH into it or use provided commands like `ray attach`, `ray rsync-up`, and `ray-exec` to access it and run Ray programs.

5.11.1 Setup

This section provides instructions for configuring the autoscaler to launch a Ray cluster on AWS/GCP, an existing Kubernetes cluster, or on a private cluster of host machines.

Once you have finished configuring the autoscaler to create a cluster, see the Quickstart guide below for more details on how to get started running Ray programs on it.

AWS

First, install boto (`pip install boto3`) and configure your AWS credentials in `~/.aws/credentials`, as described in the boto docs.

Once boto is configured to manage resources on your AWS account, you should be ready to run the autoscaler. The provided ray/python/ray/autoscaler/aws/example-full.yaml cluster config file will create a small cluster with an m5.large head node (on-demand) configured to autoscale up to two m5.large spot workers.

Test that it works by running the following commands from your local machine:

```
# Create or update the cluster. When the command finishes, it will print
# out the command that can be used to SSH into the cluster head node.
$ ray up ray/python/ray/autoscaler/aws/example-full.yaml

# Get a remote screen on the head node.
$ ray attach ray/python/ray/autoscaler/aws/example-full.yaml
$ source activate tensorflow_p36
$ # Try running a Ray program with 'ray.init(address="auto")'.

# Tear down the cluster.
$ ray down ray/python/ray/autoscaler/aws/example-full.yaml
```

GCP

First, install the Google API client (`pip install google-api-python-client`), set up your GCP credentials, and create a new GCP project.

Once the API client is configured to manage resources on your GCP account, you should be ready to run the autoscaler. The provided ray/python/ray/autoscaler/gcp/example-full.yaml cluster config file will create a small cluster with a n1-standard-2 head node (on-demand) configured to autoscale up to two n1-standard-2 preemptible workers. Note that you'll need to fill in your project id in those templates.

Test that it works by running the following commands from your local machine:

```
# Create or update the cluster. When the command finishes, it will print
# out the command that can be used to SSH into the cluster head node.
$ ray up ray/python/ray/autoscaler/gcp/example-full.yaml

# Get a remote screen on the head node.
$ ray attach ray/python/ray/autoscaler/gcp/example-full.yaml
$ source activate tensorflow_p36
$ # Try running a Ray program with 'ray.init(address="auto")'.

# Tear down the cluster.
$ ray down ray/python/ray/autoscaler/gcp/example-full.yaml
```

Kubernetes

The autoscaler can also be used to start Ray clusters on an existing Kubernetes cluster. First, install the Kubernetes API client (`pip install kubernetes`), then make sure your Kubernetes credentials are set up properly to access the cluster (if a command like `kubectl get pods` succeeds, you should be good to go).

Once you have `kubectl` configured locally to access the remote cluster, you should be ready to run the autoscaler. The provided ray/python/ray/autoscaler/kubernetes/example-full.yaml cluster config file will create a small cluster of one pod for the head node configured to autoscale up to two worker node pods, with all pods requiring 1 CPU and 0.5GiB of memory.

Test that it works by running the following commands from your local machine:

```
# Create or update the cluster. When the command finishes, it will print
# out the command that can be used to get a remote shell into the head node.
$ ray up ray/python/ray/autoscaler/kubernetes/example-full.yaml

# List the pods running in the cluster. You shoud only see one head node
# until you start running an application, at which point worker nodes
# should be started. Don't forget to include the Ray namespace in your
# 'kubectl' commands ('ray' by default).
$ kubectl -n ray get pods

# Get a remote screen on the head node.
$ ray attach ray/python/ray/autoscaler/kubernetes/example-full.yaml
$ # Try running a Ray program with 'ray.init(address="auto")'.

# Tear down the cluster
$ ray down ray/python/ray/autoscaler/kubernetes/example-full.yaml
```

Private Cluster

The autoscaler can also be used to run a Ray cluster on a private cluster of hosts, specified as a list of machine IP addresses to connect to. You can get started by filling out the fields in the provided ray/python/ray/autoscaler/local/example-full.yaml. Be sure to specify the proper `head_ip`, list of `worker_ips`, and the `ssh_user` field.

Test that it works by running the following commands from your local machine:

```
# Create or update the cluster. When the command finishes, it will print
# out the command that can be used to get a remote shell into the head node.
$ ray up ray/python/ray/autoscaler/local/example-full.yaml

# Get a remote screen on the head node.
$ ray attach ray/python/ray/autoscaler/local/example-full.yaml
$ # Try running a Ray program with 'ray.init(address="auto")'.

# Tear down the cluster
$ ray down ray/python/ray/autoscaler/local/example-full.yaml
```

External Node Provider

Ray also supports external node providers (check node_provider.py implementation). You can specify the external node provider using the yaml config:

```
provider:
    type: external
    module: mypackage.myclass
```

The module needs to be in the format *package.provider_class* or *package.sub_package.provider_class*.

Additional Cloud Providers

To use Ray autoscaling on other Cloud providers or cluster management systems, you can implement the `NodeProvider` interface (~100 LOC) and register it in node_provider.py. Contributions are welcome!

5.11.2 Quickstart

Starting and updating a cluster

When you run `ray up` with an existing cluster, the command checks if the local configuration differs from the applied configuration of the cluster. This includes any changes to synced files specified in the `file_mounts` section of the config. If so, the new files and config will be uploaded to the cluster. Following that, Ray services will be restarted.

You can also run `ray up` to restart a cluster if it seems to be in a bad state (this will restart all Ray services even if there are no config changes).

If you don't want the update to restart services (e.g., because the changes don't require a restart), pass `--no-restart` to the update call.

```
# Replace '<your_backend>' with one of: 'aws', 'gcp', 'kubernetes', or 'local'.
$ BACKEND=<your_backend>

# Create or update the cluster.
```

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```
$ ray up ray/python/ray/autoscaler/$BACKEND/example-full.yaml

# Reconfigure autoscaling behavior without interrupting running jobs.
$ ray up ray/python/ray/autoscaler/$BACKEND/example-full.yaml \
    --max-workers=N --no-restart

# Tear down the cluster.
$ ray down ray/python/ray/autoscaler/$BACKEND/example-full.yaml
```

Running commands on new and existing clusters

You can use `ray exec` to conveniently run commands on clusters. Note that scripts you run should connect to Ray via `ray.init(address="auto")`.

```
# Run a command on the cluster
$ ray exec cluster.yaml 'echo "hello world"'

# Run a command on the cluster, starting it if needed
$ ray exec cluster.yaml 'echo "hello world"' --start

# Run a command on the cluster, stopping the cluster after it finishes
$ ray exec cluster.yaml 'echo "hello world"' --stop

# Run a command on a new cluster called 'experiment-1', stopping it after
$ ray exec cluster.yaml 'echo "hello world"' \
    --start --stop --cluster-name experiment-1

# Run a command in a detached tmux session
$ ray exec cluster.yaml 'echo "hello world"' --tmux

# Run a command in a screen (experimental)
$ ray exec cluster.yaml 'echo "hello world"' --screen
```

You can also use `ray submit` to execute Python scripts on clusters. This will `rsync` the designated file onto the cluster and execute it with the given arguments.

```
# Run a Python script in a detached tmux session
$ ray submit cluster.yaml --tmux --start --stop tune_experiment.py
```

Attaching to a running cluster

You can use `ray attach` to attach to an interactive screen session on the cluster.

```
# Open a screen on the cluster
$ ray attach cluster.yaml

# Open a screen on a new cluster called 'session-1'
$ ray attach cluster.yaml --start --cluster-name=session-1

# Attach to tmux session on cluster (creates a new one if none available)
$ ray attach cluster.yaml --tmux
```

Port-forwarding applications

If you want to run applications on the cluster that are accessible from a web browser (e.g., Jupyter notebook), you can use the `--port-forward` option for `ray exec`. The local port opened is the same as the remote port.

```
$ ray exec cluster.yaml --port-forward=8899 'source ~/anaconda3/bin/activate␣
↪tensorflow_p36 && jupyter notebook --port=8899'
```

Manually synchronizing files

To download or upload files to the cluster head node, use `ray rsync_down` or `ray rsync_up`:

```
$ ray rsync_down cluster.yaml '/path/on/cluster' '/local/path'
$ ray rsync_up cluster.yaml '/local/path' '/path/on/cluster'
```

Security

On cloud providers, nodes will be launched into their own security group by default, with traffic allowed only between nodes in the same group. A new SSH key will also be created and saved to your local machine for access to the cluster.

Autoscaling

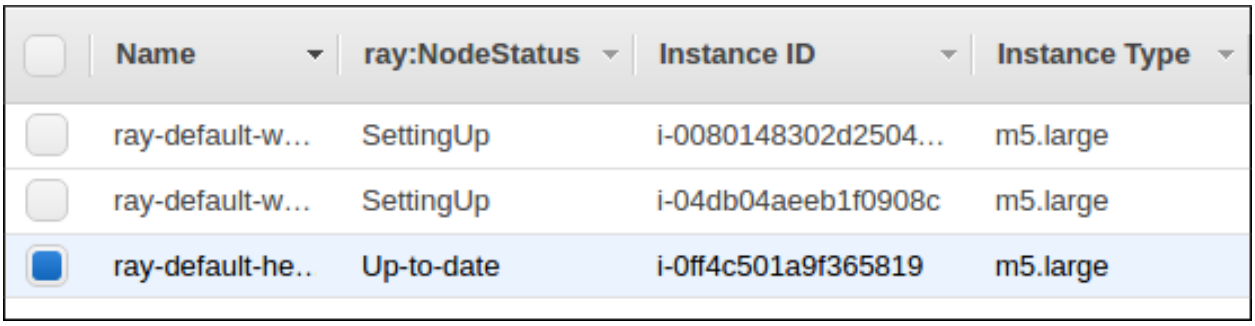
Ray clusters come with a load-based autoscaler. When cluster resource usage exceeds a configurable threshold (80% by default), new nodes will be launched up the specified `max_workers` limit. When nodes are idle for more than a timeout, they will be removed, down to the `min_workers` limit. The head node is never removed.

The default idle timeout is 5 minutes. This is to prevent excessive node churn which could impact performance and increase costs (in AWS / GCP there is a minimum billing charge of 1 minute per instance, after which usage is billed by the second).

Monitoring cluster status

You can monitor cluster usage and auto-scaling status by tailing the autoscaling logs in `/tmp/ray/session_*/logs/monitor*`.

The Ray autoscaler also reports per-node status in the form of instance tags. In your cloud provider console, you can click on a Node, go the the "Tags" pane, and add the `ray-node-status` tag as a column. This lets you see per-node statuses at a glance:



Name	ray:NodeStatus	Instance ID	Instance Type
ray-default-w...	SettingUp	i-0080148302d2504...	m5.large
ray-default-w...	SettingUp	i-04db04aeeb1f0908c	m5.large
ray-default-he..	Up-to-date	i-0ff4c501a9f365819	m5.large

Customizing cluster setup

You are encouraged to copy the example YAML file and modify it to your needs. This may include adding additional setup commands to install libraries or sync local data files.

Note: After you have customized the nodes, it is also a good idea to create a new machine image (or docker container) and use that in the config file. This reduces worker setup time, improving the efficiency of auto-scaling.

The setup commands you use should ideally be *idempotent*, that is, can be run more than once. This allows Ray to update nodes after they have been created. You can usually make commands idempotent with small modifications, e.g. `git clone foo` can be rewritten as `test -e foo || git clone foo` which checks if the repo is already cloned first.

Most of the example YAML file is optional. Here is a reference minimal YAML file, and you can find the defaults for optional fields in this YAML file.

Syncing git branches

A common use case is syncing a particular local git branch to all workers of the cluster. However, if you just put a *git checkout <branch>* in the setup commands, the autoscaler won't know when to rerun the command to pull in updates. There is a nice workaround for this by including the git SHA in the input (the hash of the file will change if the branch is updated):

```
file_mounts: {
    "/tmp/current_branch_sha": "/path/to/local/repo/.git/refs/heads/<YOUR_BRANCH_NAME>
↪",
}

setup_commands:
    - test -e <REPO_NAME> || git clone https://github.com/<REPO_ORG>/<REPO_NAME>.git
    - cd <REPO_NAME> && git fetch && git checkout `cat /tmp/current_branch_sha`
```

This tells `ray up` to sync the current git branch SHA from your personal computer to a temporary file on the cluster (assuming you've pushed the branch head already). Then, the setup commands read that file to figure out which SHA they should checkout on the nodes. Note that each command runs in its own session. The final workflow to update the cluster then becomes just this:

1. Make local changes to a git branch
2. Commit the changes with `git commit` and `git push`
3. Update files on your Ray cluster with `ray up`

Common cluster configurations

The `example-full.yaml` configuration is enough to get started with Ray, but for more compute intensive workloads you will want to change the instance types to e.g. use GPU or larger compute instance by editing the yaml file. Here are a few common configurations:

GPU single node: use Ray on a single large GPU instance.

```
max_workers: 0
head_node:
    InstanceType: p2.8xlarge
```

Docker: Specify docker image. This executes all commands on all nodes in the docker container, and opens all the necessary ports to support the Ray cluster. It will also automatically install Docker if Docker is not installed. This currently does not have GPU support.

```
docker:
    image: tensorflow/tensorflow:1.5.0-py3
    container_name: ray_docker
```

Mixed GPU and CPU nodes: for RL applications that require proportionally more CPU than GPU resources, you can use additional CPU workers with a GPU head node.

```
max_workers: 10
head_node:
    InstanceType: p2.8xlarge
worker_nodes:
    InstanceType: m4.16xlarge
```

Autoscaling CPU cluster: use a small head node and have Ray auto-scale workers as needed. This can be a cost-efficient configuration for clusters with bursty workloads. You can also request spot workers for additional cost savings.

```
min_workers: 0
max_workers: 10
head_node:
    InstanceType: m4.large
worker_nodes:
    InstanceMarketOptions:
        MarketType: spot
    InstanceType: m4.16xlarge
```

Autoscaling GPU cluster: similar to the autoscaling CPU cluster, but with GPU worker nodes instead.

```
min_workers: 0  # NOTE: older Ray versions may need 1+ GPU workers (#2106)
max_workers: 10
head_node:
    InstanceType: m4.large
worker_nodes:
    InstanceMarketOptions:
        MarketType: spot
    InstanceType: p2.xlarge
```

Questions or Issues?

You can post questions or issues or feedback through the following channels:

1. ray-dev@googlegroups.com: For discussions about development or any general questions and feedback.
2. StackOverflow: For questions about how to use Ray.
3. GitHub Issues: For bug reports and feature requests.

5.12 Manual Cluster Setup

Note: If you're using AWS or GCP you should use the automated setup commands.

The instructions in this document work well for small clusters. For larger clusters, consider using the pssh package: `sudo apt-get install pssh` or the setup commands for private clusters.

5.12.1 Deploying Ray on a Cluster

This section assumes that you have a cluster running and that the nodes in the cluster can communicate with each other. It also assumes that Ray is installed on each machine. To install Ray, follow the installation instructions.

Starting Ray on each machine

On the head node (just choose some node to be the head node), run the following. If the `--redis-port` argument is omitted, Ray will choose a port at random.

```
ray start --head --redis-port=6379
```

The command will print out the address of the Redis server that was started (and some other address information).

Then on all of the other nodes, run the following. Make sure to replace `<address>` with the value printed by the command on the head node (it should look something like `123.45.67.89:6379`).

```
ray start --address=<address>
```

If you wish to specify that a machine has 10 CPUs and 1 GPU, you can do this with the flags `--num-cpus=10` and `--num-gpus=1`. See the Configuration page for more information.

Now we've started all of the Ray processes on each node Ray. This includes

- Some worker processes on each machine.
- An object store on each machine.
- A raylet on each machine.
- Multiple Redis servers (on the head node).

To run some commands, start up Python on one of the nodes in the cluster, and do the following.

```
import ray
ray.init(address="<address>")
```

Now you can define remote functions and execute tasks. For example, to verify that the correct number of nodes have joined the cluster, you can run the following.

```
import time

@ray.remote
def f():
    time.sleep(0.01)
    return ray.services.get_node_ip_address()

# Get a list of the IP addresses of the nodes that have joined the cluster.
set(ray.get([f.remote() for _ in range(1000)]))
```

Stopping Ray

When you want to stop the Ray processes, run `ray stop` on each node.

5.13 Deploying on Kubernetes

Note: The easiest way to run a Ray cluster is by using the built-in autoscaler, which has support for running on top of Kubernetes. Please see the autoscaler documentation for details.

Warning: Running Ray on Kubernetes is still a work in progress. If you have a suggestion for how to improve them or want to request a missing feature, please get in touch using one of the channels in the *Questions or Issues?* section below.

This document assumes that you have access to a Kubernetes cluster and have `kubectl` installed locally and configured to access the cluster. It will first walk you through how to deploy a Ray cluster on your existing Kubernetes cluster, then explore a few different ways to run programs on the Ray cluster.

The configuration `yaml` files used here are provided in the Ray repository as examples to get you started. When deploying real applications, you will probably want to build and use your own container images, add more worker nodes to the cluster (or use the Kubernetes Horizontal Pod Autoscaler), and change the resource requests for the head and worker nodes. Refer to the provided `yaml` files to be sure that you maintain important configuration options for Ray to function properly.

5.13.1 Creating a Ray Namespace

First, create a Kubernetes Namespace for Ray resources on your cluster. The following commands will create resources under this Namespace, so if you want to use a different one than `ray`, please be sure to also change the *namespace* fields in the provided `yaml` files and anytime you see a `-n` flag passed to `kubectl`.

```
$ kubectl create -f ray/doc/kubernetes/ray-namespace.yaml
```

5.13.2 Starting a Ray Cluster

A Ray cluster consists of a single head node and a set of worker nodes (the provided `ray-cluster.yaml` file will start 3 worker nodes). In the example Kubernetes configuration, this is implemented as:

- A `ray-head` Kubernetes Service that enables the worker nodes to discover the location of the head node on start up.
- A `ray-head` Kubernetes Deployment that backs the `ray-head` Service with a single head node pod (replica).
- A `ray-worker` Kubernetes Deployment with multiple worker node pods (replicas) that connect to the `ray-head` pod using the `ray-head` Service.

Note that because the head and worker nodes are Deployments, Kubernetes will automatically restart pods that crash to maintain the correct number of replicas.

- If a worker node goes down, a replacement pod will be started and joined to the cluster.
- If the head node goes down, it will be restarted. This will start a new Ray cluster. Worker nodes that were connected to the old head node will crash and be restarted, connecting to the new head node when they come back up.

Try deploying a cluster with the provided Kubernetes config by running the following command:

```
$ kubectl apply -f ray/doc/kubernetes/ray-cluster.yaml
```

Verify that the pods are running by running `kubectl get pods -n ray`. You may have to wait up to a few minutes for the pods to enter the 'Running' state on the first run.

```
$ kubectl -n ray get pods
NAME                           READY   STATUS    RESTARTS   AGE
ray-head-5455bb66c9-6bxvz      1/1     Running   0          10s
ray-worker-5c49b7cc57-c6xs8    1/1     Running   0          5s
ray-worker-5c49b7cc57-d9m86    1/1     Running   0          5s
ray-worker-5c49b7cc57-kzk4s    1/1     Running   0          5s
```

Note: You might see a nonzero number of RESTARTS for the worker pods. That can happen when the worker pods start up before the head pod and the workers aren't able to connect. This shouldn't affect the behavior of the cluster.

To change the number of worker nodes in the cluster, change the `replicas` field in the worker deployment configuration in that file and then re-apply the config as follows:

```
# Edit 'ray/doc/kubernetes/ray-cluster.yaml' and change the 'replicas'
# field under the ray-worker deployment to, e.g., 4.

# Re-apply the new configuration to the running deployment.
$ kubectl apply -f ray/doc/kubernetes/ray-cluster.yaml
service/ray-head unchanged
deployment.apps/ray-head unchanged
deployment.apps/ray-worker configured

# Verify that there are now the correct number of worker pods running.
$ kubectl -n ray get pods
NAME                           READY   STATUS    RESTARTS   AGE
ray-head-5455bb66c9-6bxvz      1/1     Running   0          30s
ray-worker-5c49b7cc57-c6xs8    1/1     Running   0          25s
ray-worker-5c49b7cc57-d9m86    1/1     Running   0          25s
ray-worker-5c49b7cc57-kzk4s    1/1     Running   0          25s
ray-worker-5c49b7cc57-zzfg2    1/1     Running   0          0s
```

To validate that the restart behavior is working properly, try killing pods and checking that they are restarted by Kubernetes:

```
# Delete a worker pod.
$ kubectl -n ray delete ray-worker-5c49b7cc57-c6xs8
pod "ray-worker-5c49b7cc57-c6xs8" deleted

# Check that a new worker pod was started (this may take a few seconds).
$ kubectl -n ray get pods
NAME                           READY   STATUS    RESTARTS   AGE
ray-head-5455bb66c9-6bxvz      1/1     Running   0          45s
ray-worker-5c49b7cc57-d9m86    1/1     Running   0          40s
ray-worker-5c49b7cc57-kzk4s    1/1     Running   0          40s
ray-worker-5c49b7cc57-ypq8x    1/1     Running   0          0s

# Delete the head pod.
$ kubectl -n ray delete ray-head-5455bb66c9-6bxvz
pod "ray-head-5455bb66c9-6bxvz" deleted
```

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```
# Check that a new head pod was started and the worker pods were restarted.
$ kubectl -n ray get pods
NAME                           READY   STATUS    RESTARTS   AGE
ray-head-5455bb66c9-gqzql      1/1     Running   0          0s
ray-worker-5c49b7cc57-d9m86    1/1     Running   1          50s
ray-worker-5c49b7cc57-kzk4s    1/1     Running   1          50s
ray-worker-5c49b7cc57-ypq8x    1/1     Running   1          10s

# You can even try deleting all of the pods in the Ray namespace and checking
# that Kubernetes brings the right number back up.
$ kubectl -n ray delete pods --all
$ kubectl -n ray get pods
NAME                           READY   STATUS    RESTARTS   AGE
ray-head-5455bb66c9-7l6xj      1/1     Running   0          10s
ray-worker-5c49b7cc57-57tpv    1/1     Running   0          10s
ray-worker-5c49b7cc57-6m4kp    1/1     Running   0          10s
ray-worker-5c49b7cc57-jx2w2    1/1     Running   0          10s
```

5.13.3 Running Ray Programs

This section assumes that you have a running Ray cluster (if you don't, please refer to the section above to get started) and will walk you through three different options to run a Ray program on it:

1. Using *kubectl exec* to run a Python script.
2. Using *kubectl exec -it bash* to work interactively in a remote shell.
3. Submitting a Kubernetes Job.

Running a program using 'kubectl exec'

To run an example program that tests object transfers between nodes in the cluster, try the following commands (don't forget to replace the head pod name - you can find it by running `kubectl -n ray get pods`):

```
# Copy the test script onto the head node.
$ kubectl -n ray cp ray/doc/kubernetes/example.py ray-head-5455bb66c9-7l6xj:/example.
↪py

# Run the example program on the head node.
$ kubectl -n ray exec ray-head-5455bb66c9-7l6xj -- python example.py
# You should see repeated output for 10 iterations and then 'Success!'
```

Running a program in a remote shell

You can also run tasks interactively on the cluster by connecting a remote shell to one of the pods.

```
# Copy the test script onto the head node.
$ kubectl -n ray cp ray/doc/kubernetes/example.py ray-head-5455bb66c9-7l6xj:/example.
↪py

# Get a remote shell to the head node.
$ kubectl -n ray exec -it ray-head-5455bb66c9-7l6xj -- bash
```

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```
# Run the example program on the head node.
root@ray-head-6f566446c-5rdmb:/# python example.py
# You should see repeated output for 10 iterations and then 'Success!'
```

You can also start an IPython interpreter to work interactively:

```
# From your local machine.
$ kubectl -n ray exec -it ray-head-5455bb66c9-7l6xj -- ipython

# From a remote shell on the head node.
$ kubectl -n ray exec -it ray-head-5455bb66c9-7l6xj -- bash
root@ray-head-6f566446c-5rdmb:/# ipython
```

Once you have the IPython interpreter running, try running the following example program:

```
from collections import Counter
import socket
import time
import ray

ray.init(address="$RAY_HEAD_SERVICE_HOST:$RAY_HEAD_SERVICE_PORT_REDIS_PRIMARY")

@ray.remote
def f(x):
    time.sleep(0.01)
    return x + (socket.gethostname(), )

# Check that objects can be transferred from each node to each other node.
%time Counter(ray.get([f.remote(f.remote(())) for _ in range(100)]))
```

Submitting a Job

You can also submit a Ray application to run on the cluster as a Kubernetes Job. The Job will run a single pod running the Ray driver program to completion, then terminate the pod but allow you to access the logs.

To submit a Job that downloads and executes an example program that tests object transfers between nodes in the cluster, run the following command:

```
$ kubectl create -f ray/doc/kubernetes/ray-job.yaml
job.batch/ray-test-job-kw5gn created
```

To view the output of the Job, first find the name of the pod that ran it, then fetch its logs:

```
$ kubectl -n ray get pods
NAME                          READY   STATUS      RESTARTS   AGE
ray-head-5455bb66c9-7l6xj     1/1     Running     0          15s
ray-test-job-kw5gn-5g7tv      0/1     Completed   0          10s
ray-worker-5c49b7cc57-57tpv   1/1     Running     0          15s
ray-worker-5c49b7cc57-6m4kp   1/1     Running     0          15s
ray-worker-5c49b7cc57-jx2w2   1/1     Running     0          15s

# Fetch the logs. You should see repeated output for 10 iterations and then
# 'Success!'
$ kubectl -n ray logs ray-test-job-kw5gn-5g7tv
```

To clean up the resources created by the Job after checking its output, run the following:

```
# List Jobs run in the Ray namespace.
$ kubectl -n ray get jobs
NAME                 COMPLETIONS   DURATION   AGE
ray-test-job-kw5gn   1/1           10s        30s

# Delete the finished Job.
$ kubectl -n ray delete job ray-test-job-kw5gn

# Verify that the Job's pod was cleaned up.
$ kubectl -n ray get pods
NAME                           READY   STATUS      RESTARTS   AGE
ray-head-5455bb66c9-7l6xj      1/1     Running     0          60s
ray-worker-5c49b7cc57-57tpv    1/1     Running     0          60s
ray-worker-5c49b7cc57-6m4kp    1/1     Running     0          60s
ray-worker-5c49b7cc57-jx2w2    1/1     Running     0          60s
```

5.13.4 Cleaning Up

To delete a running Ray cluster, you can run the following command:

```
kubectl delete -f ray/doc/kubernetes/ray-cluster.yaml
```

5.13.5 Questions or Issues?

You can post questions or issues or feedback through the following channels:

1. ray-dev@googlegroups.com: For discussions about development or any general questions and feedback.
2. StackOverflow: For questions about how to use Ray.
3. GitHub Issues: For bug reports and feature requests.

5.14 Deploying on Slurm

Clusters managed by Slurm may require that Ray is initialized as a part of the submitted job. This can be done by using `srun` within the submitted script. For example:

```
#!/bin/bash

#SBATCH --job-name=test
#SBATCH --cpus-per-task=5
#SBATCH --mem-per-cpu=1GB
#SBATCH --nodes=3
#SBATCH --tasks-per-node 1

worker_num=2 # Must be one less that the total number of nodes

# module load Langs/Python/3.6.4 # This will vary depending on your environment
# source venv/bin/activate

nodes=$(scontrol show hostnames $SLURM_JOB_NODELIST) # Getting the node names
nodes_array=( $nodes )
```

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```
node1=${nodes_array[0]}

ip_prefix=$(srun --nodes=1 --ntasks=1 -w $node1 hostname --ip-address) # Making␣
↪address
suffix=':6379'
ip_head=$ip_prefix$suffix
redis_password=$(uuidgen)

export ip_head # Exporting for latter access by trainer.py

srun --nodes=1 --ntasks=1 -w $node1 ray start --block --head --redis-port=6379 --
↪redis-password=$redis_password & # Starting the head
sleep 5

for ((  i=1; i<=$worker_num; i++ ))
do
  node2=${nodes_array[$i]}
  srun --nodes=1 --ntasks=1 -w $node2 ray start --block --address=$ip_head --redis-
↪password=$redis_password & # Starting the workers
  sleep 5
done

python -u trainer.py $redis_password 15 # Pass the total number of allocated CPUs
```

```
# trainer.py
from collections import Counter
import os
import sys
import time
import ray

redis_password = sys.argv[1]
num_cpus = int(sys.argv[2])

ray.init(address=os.environ["ip_head"], redis_password=redis_password)

print("Nodes in the Ray cluster:")
print(ray.nodes())

@ray.remote
def f():
    time.sleep(1)
    return ray.services.get_node_ip_address()

# The following takes one second (assuming that ray was able to access all of the␣
↪allocated nodes).
for i in range(60):
    start = time.time()
    ip_addresses = ray.get([f.remote() for _ in range(num_cpus)])
    print(Counter(ip_addresses))
    end = time.time()
    print(end - start)
```

5.15 Tune: A Scalable Hyperparameter Tuning Library

Tip: Help make Tune better by taking our 3 minute Ray Tune User Survey!

Tune is a Python library for hyperparameter tuning at any scale. Core features:

- Launch a multi-node distributed hyperparameter sweep in less than 10 lines of code.
- Supports any machine learning framework, including PyTorch, XGBoost, MXNet, and Keras.
- Visualize results with TensorBoard.
- Choose among scalable SOTA algorithms such as Population Based Training (PBT), Vizier's Median Stopping Rule, HyperBand/ASHA.
- Tune integrates with many optimization libraries such as Facebook Ax, HyperOpt, and Bayesian Optimization and enables you to scale them transparently.

5.15.1 Quick Start

Note: To run this example, you will need to install the following:

```
$ pip install ray torch torchvision filelock
```

This example runs a small grid search to train a CNN using PyTorch and Tune.

```
import torch.optim as optim
from ray import tune
from ray.tune.examples.mnist_pytorch import get_data_loaders, ConvNet, train, test
```

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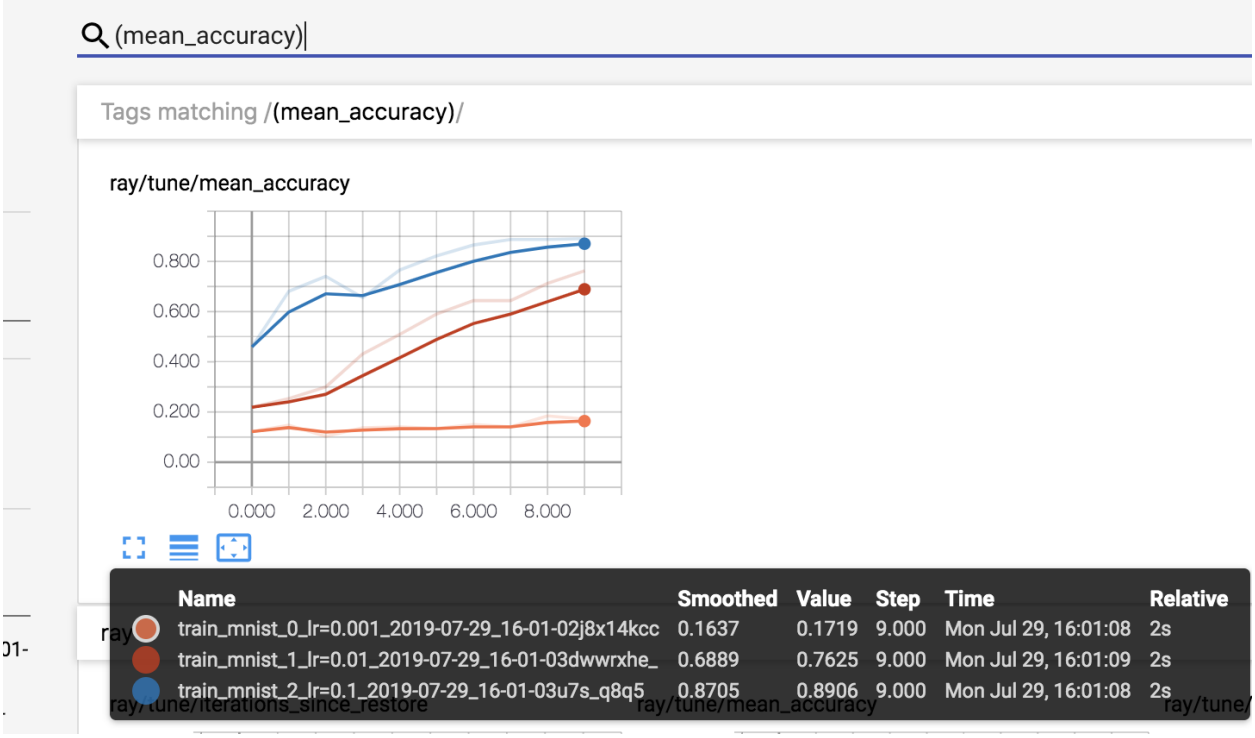
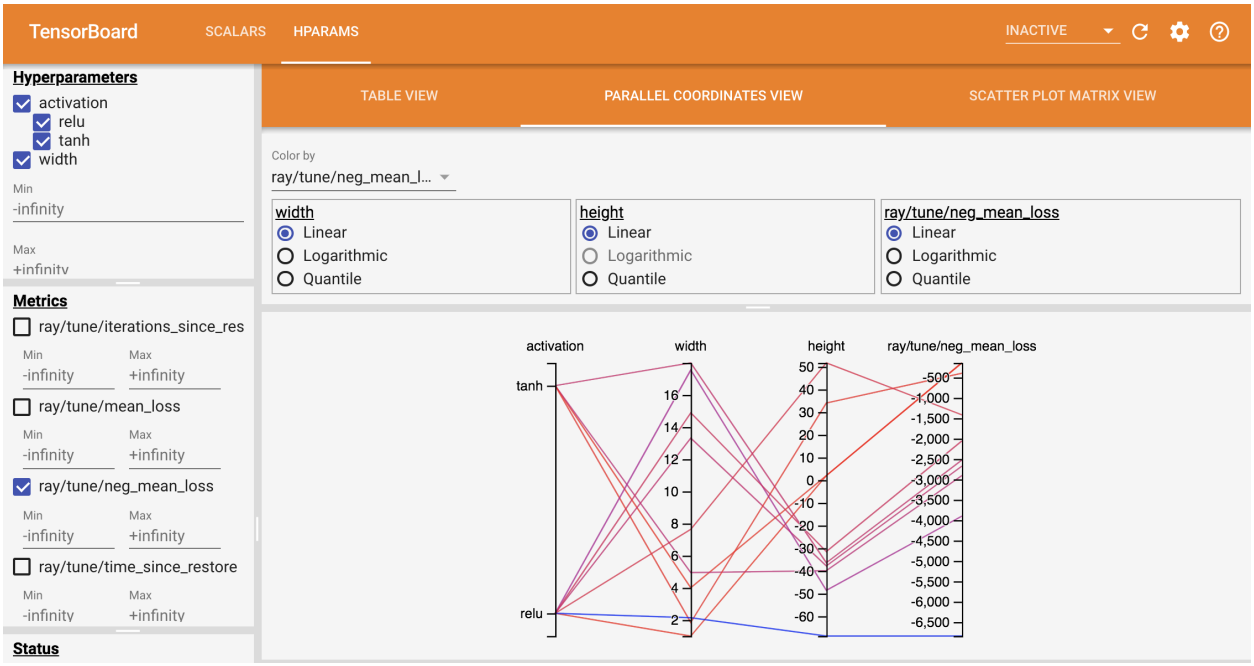
```
def train_mnist(config):
    train_loader, test_loader = get_data_loaders()
    model = ConvNet()
    optimizer = optim.SGD(model.parameters(), lr=config["lr"])
    for i in range(10):
        train(model, optimizer, train_loader)
        acc = test(model, test_loader)
        tune.track.log(mean_accuracy=acc)


analysis = tune.run(
    train_mnist, config={"lr": tune.grid_search([0.001, 0.01, 0.1])})

print("Best config: ", analysis.get_best_config(metric="mean_accuracy"))

# Get a dataframe for analyzing trial results.
df = analysis.dataframe()
```

If TensorBoard is installed, automatically visualize all trial results:

```
tensorboard --logdir ~/ray_results
```



If using TF2 and TensorBoard, Tune will also automatically generate TensorBoard HParams output:



5.15.2 Distributed Quick Start

1. Import and initialize Ray by appending the following to your example script.

```
# Append to top of your script
import ray
import argparse

parser = argparse.ArgumentParser()
parser.add_argument("--ray-address")
args = parser.parse_args()
ray.init(address=args.ray_address)
```

Alternatively, download a full example script here: `mnist_pytorch.py`

2. Download the following example Ray cluster configuration as `tune-local-default.yaml` and replace the appropriate fields:

```
cluster_name: local-default
provider:
    type: local
    head_ip: YOUR_HEAD_NODE_HOSTNAME
    worker_ips: [WORKER_NODE_1_HOSTNAME, WORKER_NODE_2_HOSTNAME, ... ]
auth: {ssh_user: YOUR_USERNAME, ssh_private_key: ~/.ssh/id_rsa}
## Typically for local clusters, min_workers == max_workers.
min_workers: 3
max_workers: 3
setup_commands:   # Set up each node.
    - pip install ray torch torchvision tabulate tensorboard
```

Alternatively, download it here: `tune-local-default.yaml`. See Ray cluster docs here.

3. Run `ray submit` like the following.

```
ray submit tune-local-default.yaml mnist_pytorch.py --args="--ray-
↪address=localhost:6379" --start
```

This will start Ray on all of your machines and run a distributed hyperparameter search across them.

To summarize, here are the full set of commands:

```
wget https://raw.githubusercontent.com/ray-project/ray/master/python/ray/tune/
↪examples/mnist_pytorch.py
wget https://raw.githubusercontent.com/ray-project/ray/master/python/ray/tune/tune-
↪local-default.yaml
ray submit tune-local-default.yaml mnist_pytorch.py --args="--ray-
↪address=localhost:6379" --start
```

Take a look at the Distributed Experiments documentation for more details, including:

1. Setting up distributed experiments on your local cluster
2. Using AWS and GCP
3. Spot instance usage/pre-emptible instances, and more.

5.15.3 Getting Started

- Code: GitHub repository for Tune.
- User Guide: A comprehensive overview on how to use Tune's features.
- Tutorial Notebook: Our tutorial notebooks of using Tune with Keras or PyTorch.

5.15.4 Contribute to Tune

Take a look at our Contributor Guide for guidelines on contributing.

5.15.5 Citing Tune

If Tune helps you in your academic research, you are encouraged to cite our paper. Here is an example bibtex:

```
@article{liaw2018tune,
    title={Tune: A Research Platform for Distributed Model Selection and Training},
    author={Liaw, Richard and Liang, Eric and Nishihara, Robert
            and Moritz, Philipp and Gonzalez, Joseph E and Stoica, Ion},
    journal={arXiv preprint arXiv:1807.05118},
    year={2018}
}
```

5.16 Tune Walkthrough

Tip: Help make Tune better by taking our 3 minute Ray Tune User Survey!

This tutorial will walk you through the following process to setup a Tune experiment. Specifically, we'll leverage ASHA and Bayesian Optimization (via HyperOpt) via the following steps:

1. Integrating Tune into your workflow
2. Specifying a TrialScheduler
3. Adding a SearchAlgorithm
4. Getting the best model and analyzing results

Note: To run this example, you will need to install the following:

```
$ pip install ray torch torchvision filelock
```

We first run some imports:

```
import numpy as np
import torch
import torch.optim as optim
from torchvision import datasets

from ray import tune
from ray.tune import track
from ray.tune.schedulers import ASHAScheduler
from ray.tune.examples.mnist_pytorch import get_data_loaders, ConvNet, train, test
```

Below, we have some boiler plate code for a PyTorch training function.

```
def train_mnist(config):
    model = ConvNet()
    train_loader, test_loader = get_data_loaders()
    optimizer = optim.SGD(
        model.parameters(), lr=config["lr"], momentum=config["momentum"])
    for i in range(10):
        train(model, optimizer, train_loader)
        acc = test(model, test_loader)
        track.log(mean_accuracy=acc)
        if i % 5 == 0:
            # This saves the model to the trial directory
            torch.save(model, "./model.pth")
```

Notice that there's a couple helper functions in the above training script. You can take a look at these functions in the imported module examples/mnist_pytorch; there's no black magic happening. For example, `train` is simply a for loop over the data loader.

```
def train(model, optimizer, train_loader):
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        if batch_idx * len(data) > EPOCH_SIZE:
            return
        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        loss.backward()
        optimizer.step()
```

Let's run 1 trial, randomly sampling from a uniform distribution for learning rate and momentum.

```
search_space = {
    "lr": tune.sample_from(lambda spec: 10**(-10 * np.random.rand())),
    "momentum": tune.uniform(0.1, 0.9)
}

# Uncomment this to enable distributed execution
# `ray.init(address=...)`

analysis = tune.run(train_mnist, config=search_space)
```

We can then plot the performance of this trial.

```
dfs = analysis.trial_dataframes
[d.mean_accuracy.plot() for d in dfs.values()]
```

Important: Tune will automatically run parallel trials across all available cores/GPUs on your machine or cluster. To limit the number of cores that Tune uses, you can call `ray.init(num_cpus=<int>, num_gpus=<int>)` before `tune.run`.

5.16.1 Early Stopping with ASHA

Let's integrate an early stopping algorithm to our search - ASHA, a scalable algorithm for principled early stopping.

How does it work? On a high level, it terminates trials that are less promising and allocates more time and resources to more promising trials. See this blog post for more details.

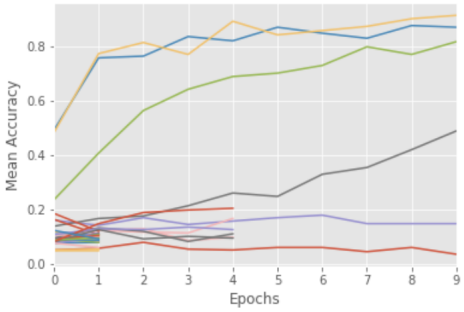
We can afford to **increase the search space by 5x**, by adjusting the parameter `num_samples`. See the Trial Scheduler section for more details of available schedulers and library integrations.

```
analysis = tune.run(
    train_mnist,
    num_samples=30,
    scheduler=ASHAScheduler(metric="mean_accuracy", mode="max"),
    config=search_space)

# Obtain a trial dataframe from all run trials of this `tune.run` call.
dfs = analysis.trial_dataframes
```

You can run the below in a Jupyter notebook to visualize trial progress.

```
# Plot by epoch
ax = None  # This plots everything on the same plot
for d in dfs.values():
    ax = d.mean_accuracy.plot(ax=ax, legend=False)
```

```
[25]: # Plot by epoch
ax = None
for d in dfs.values():
    ax = d.mean_accuracy.plot(ax=ax, legend=False)
ax.set_xlabel("Epochs")
ax.set_ylabel("Mean Accuracy");
```



You can also use Tensorboard for visualizing results.

```
$ tensorboard --logdir {logdir}
```

5.16.2 Search Algorithms in Tune

With Tune you can combine powerful hyperparameter search libraries such as HyperOpt and Ax with state-of-the-art algorithms such as HyperBand without modifying any model training code. Tune allows you to use different search algorithms in combination with different trial schedulers. See the Search Algorithm section for more details of available algorithms and library integrations.

```
from hyperopt import hp
from ray.tune.suggest.hyperopt import HyperOptSearch

space = {
    "lr": hp.loguniform("lr", 1e-10, 0.1),
    "momentum": hp.uniform("momentum", 0.1, 0.9),
}

hyperopt_search = HyperOptSearch(
    space, max_concurrent=2, reward_attr="mean_accuracy")

analysis = tune.run(train_mnist, num_samples=10, search_alg=hyperopt_search)
```

5.16.3 Evaluate your model

You can evaluate best trained model using the Analysis object to retrieve the best model:

```
import os

df = analysis.dataframe()
logdir = analysis.get_best_logdir("mean_accuracy", mode="max")
model = torch.load(os.path.join(logdir, "model.pth"))
```

Next Steps

Take a look at the Usage Guide for more comprehensive overview of Tune features.

5.17 Tune User Guide

Tip: Help make Tune better by taking our 3 minute Ray Tune User Survey!

5.17.1 Tune Overview

Tune takes a user-defined Python function or class and evaluates it on a set of hyperparameter configurations.

Each hyperparameter configuration evaluation is called a *trial*, and multiple trials are run in parallel. Configurations are either generated by Tune or drawn from a user-specified **search algorithm**. The trials are scheduled and managed by a **trial scheduler**.

More information about Tune's search algorithms can be found here. More information about Tune's trial schedulers can be found here. You can check out our examples page for more code examples.

5.17.2 Tune Training API

The Tune training API [`tune.run(Trainable)`] has two concepts:

1. The Trainable API, and
2. tune.run.

Training can be done with either the Trainable **Class API** or **function-based API**.

Trainable API

The class-based API will require users to subclass `ray.tune.Trainable`. The Trainable interface can be found here.

Here is an example:

```
class Example(Trainable):
    def _setup(self, config):
        ...

    def _train(self):
        # run training code
        result_dict = {"accuracy": 0.5, "f1": 0.1, ...}
        return result_dict
```

class ray.tune.**Trainable**(*config=None*, *logger_creator=None*)

Abstract class for trainable models, functions, etc.

A call to `train()` on a trainable will execute one logical iteration of training. As a rule of thumb, the execution time of one train call should be large enough to avoid overheads (i.e. more than a few seconds), but short enough to report progress periodically (i.e. at most a few minutes).

Calling `save()` should save the training state of a trainable to disk, and `restore(path)` should restore a trainable to the given state.

Generally you only need to implement `_setup`, `_train`, `_save`, and `_restore` when subclassing Trainable.

Other implementation methods that may be helpful to override are `_log_result`, `reset_config`, `_stop`, and `_export_model`.

When using Tune, Tune will convert this class into a Ray actor, which runs on a separate process. Tune will also change the current working directory of this process to *self.logdir*.

Tune function-based API

User-defined functions will need to have following signature and call `tune.track.log`, which will allow you to report metrics used for scheduling, search, or early stopping:

```
def trainable(config):
    """
    Args:
        config (dict): Parameters provided from the search algorithm
            or variant generation.
    """

    while True:
        # ...
        tune.track.log(**kwargs)
```

Tune will run this function on a separate thread in a Ray actor process. Note that this API is not checkpointable, since the thread will never return control back to its caller. `tune.track` documentation can be found here.

Both the Trainable and function-based API will have autofilled metrics in addition to the metrics reported.

Note: If you have a lambda function that you want to train, you will need to first register the function: `tune.register_trainable("lambda_id", lambda x: ...)`. You can then use `lambda_id` in place of `my_trainable`.

Note: See previous versions of the documentation for the `reporter` API.

Launching Tune

Use `tune.run` to generate and execute your hyperparameter sweep:

```
tune.run(trainable)

# Run a total of 10 evaluations of the Trainable. Tune runs in
# parallel and automatically determines concurrency.
tune.run(trainable, num_samples=10)
```

This function will report status on the command line until all Trials stop:

```
== Status ==
Using FIFO scheduling algorithm.
Resources used: 4/8 CPUs, 0/0 GPUs
Result logdir: ~/ray_results/my_experiment
 - train_func_0_lr=0.2,momentum=1:  RUNNING [pid=6778], 209 s, 20604 ts, 7.29 acc
 - train_func_1_lr=0.4,momentum=1:  RUNNING [pid=6780], 208 s, 20522 ts, 53.1 acc
 - train_func_2_lr=0.6,momentum=1:  TERMINATED [pid=6789], 21 s, 2190 ts, 100 acc
```

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```
 - train_func_3_lr=0.2,momentum=2:  RUNNING [pid=6791], 208 s, 41004 ts, 8.37 acc
 - train_func_4_lr=0.4,momentum=2:  RUNNING [pid=6800], 209 s, 41204 ts, 70.1 acc
 - train_func_5_lr=0.6,momentum=2:  TERMINATED [pid=6809], 10 s, 2164 ts, 100 acc
```

All results reported by the trainable will be logged locally to a unique directory per experiment, e.g. `~/ray_results/example-experiment` in the above example. On a cluster, incremental results will be synced to local disk on the head node.

Trial Parallelism

Tune automatically runs N concurrent trials, where N is the number of CPUs (cores) on your machine. By default, Tune assumes that each trial will only require 1 CPU. You can override this with `resources_per_trial`:

```
# If you have 4 CPUs on your machine, this will run 4 concurrent trials at a time.
tune.run(trainable, num_samples=10)

# If you have 4 CPUs on your machine, this will run 2 concurrent trials at a time.
tune.run(trainable, num_samples=10, resources_per_trial={"cpu": 2})

# If you have 4 CPUs on your machine, this will run 1 trial at a time.
tune.run(trainable, num_samples=10, resources_per_trial={"cpu": 4})
```

To leverage GPUs, you can set `gpu` in `resources_per_trial`. A trial will only be executed if there are resources available. See the section on‘resource allocation <tune-usage#resource-allocation-using-gpus>‘_, which provides more details about GPU usage and trials that are distributed:

```
# If you have 4 CPUs on your machine and 1 GPU, this will run 1 trial at a time.
tune.run(trainable, num_samples=10, resources_per_trial={"cpu": 2, "gpu": 1})
```

To attach to a Ray cluster or use `ray.init` manual resource overrides, simply run `ray.init` before `tune.run`:

```
# Setup a local ray cluster and override resources. This will run 50 trials in␣
↪parallel:
ray.init(num_cpus=100)
tune.run(trainable, num_samples=100, resources_per_trial={"cpu": 2})

# Connect to an existing distributed Ray cluster
ray.init(address=<ray_redis_address>)
tune.run(trainable, num_samples=100, resources_per_trial={"cpu": 2, "gpu": 1})
```

Tip: To run everything sequentially, use Ray Local Mode.

5.17.3 Analyzing Results

Tune provides an `ExperimentAnalysis` object for analyzing results from `tune.run`.

```
analysis = tune.run(
    trainable,
    name="example-experiment",
    num_samples=10,
)
```

You can use the `ExperimentAnalysis` object to obtain the best configuration of the experiment:

```
>>> print("Best config is", analysis.get_best_config(metric="mean_accuracy"))
Best config is: {'lr': 0.011537575723482687, 'momentum': 0.8921971713692662}
```

Here are some example operations for obtaining a summary of your experiment:

```
# Get a dataframe for the last reported results of all of the trials
df = analysis.dataframe()

# Get a dataframe for the max accuracy seen for each trial
df = analysis.dataframe(metric="mean_accuracy", mode="max")

# Get a dict mapping {trial logdir -> dataframes} for all trials in the experiment.
all_dataframes = analysis.trial_dataframes

# Get a list of trials
trials = analysis.trials
```

You may want to get a summary of multiple experiments that point to the same `local_dir`. For this, you can use the `Analysis` class.

```
from ray.tune import Analysis
analysis = Analysis("~/ray_results/example-experiment")
```

See the full documentation for the `Analysis` object.

5.17.4 Tune Search Space (Default)

You can use `tune.grid_search` to specify an axis of a grid search. By default, Tune also supports sampling parameters from user-specified lambda functions, which can be used independently or in combination with grid search.

Note: If you specify an explicit Search Algorithm such as any SuggestionAlgorithm, you may not be able to specify lambdas or grid search with this interface, as the search algorithm may require a different search space declaration.

Use `tune.sample_from(<func>)` to sample a value for a hyperparameter. The `func` should take in a `spec` object, which has a `config` namespace from which you can access other hyperparameters. This is useful for conditional distributions:

```
tune.run(
    ...,
    config={
        "alpha": tune.sample_from(lambda spec: np.random.uniform(100)),
        "beta": tune.sample_from(lambda spec: spec.config.alpha * np.random.normal())
    }
)
```

Tune provides a couple helper functions for common parameter distributions, wrapping numpy random utilities such as `np.random.uniform`, `np.random.choice`, and `np.random.randn`. See the Package Reference for more details.

The following shows grid search over two nested parameters combined with random sampling from two lambda functions, generating 9 different trials. Note that the value of `beta` depends on the value of `alpha`, which is represented by referencing `spec.config.alpha` in the lambda function. This lets you specify conditional parameter distributions.

```
tune.run(
    my_trainable,
    name="my_trainable",
    config={
        "alpha": tune.sample_from(lambda spec: np.random.uniform(100)),
        "beta": tune.sample_from(lambda spec: spec.config.alpha * np.random.
↪normal()),
        "nn_layers": [
            tune.grid_search([16, 64, 256]),
            tune.grid_search([16, 64, 256]),
        ],
    }
)
```

5.17.5 Custom Trial Names

To specify custom trial names, you can pass use the `trial_name_creator` argument to *tune.run*. This takes a function with the following signature:

```
def trial_name_string(trial):
    """
    Args:
        trial (Trial): A generated trial object.

    Returns:
        trial_name (str): String representation of Trial.
    """
    return str(trial)

tune.run(
    MyTrainableClass,
    name="example-experiment",
    num_samples=1,
    trial_name_creator=trial_name_string
)
```

An example can be found in logging_example.py.

5.17.6 Sampling Multiple Times

By default, each random variable and grid search point is sampled once. To take multiple random samples, add `num_samples: N` to the experiment config. If *grid_search* is provided as an argument, the grid will be repeated *num_samples* of times.

```
tune.run(
    my_trainable,
    name="my_trainable",
    config={
        "alpha": tune.sample_from(lambda spec: np.random.uniform(100)),
        "beta": tune.sample_from(lambda spec: spec.config.alpha * np.random.
↪normal()),
        "nn_layers": [
            tune.grid_search([16, 64, 256]),
            tune.grid_search([16, 64, 256]),
```

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```
        ],
    },
    num_samples=10
)
```

E.g. in the above, `num_samples=10` repeats the 3x3 grid search 10 times, for a total of 90 trials, each with randomly sampled values of `alpha` and `beta`.

5.17.7 Resource Allocation (Using GPUs)

Tune will allocate the specified GPU and CPU `resources_per_trial` to each individual trial (defaulting to 1 CPU per trial). Under the hood, Tune runs each trial as a Ray actor, using Ray's resource handling to allocate resources and place actors. A trial will not be scheduled unless at least that amount of resources is available in the cluster, preventing the cluster from being overloaded.

Fractional values are also supported, (i.e., `"gpu": 0.2`). You can find an example of this in the Keras MNIST example.

If GPU resources are not requested, the `CUDA_VISIBLE_DEVICES` environment variable will be set as empty, disallowing GPU access. Otherwise, it will be set to the GPUs in the list (this is managed by Ray).

5.17.8 Advanced Resource Allocation

Trainables can themselves be distributed. If your trainable function / class creates further Ray actors or tasks that also consume CPU / GPU resources, you will also want to set `extra_cpu` or `extra_gpu` to reserve extra resource slots for the actors you will create. For example, if a trainable class requires 1 GPU itself, but will launch 4 actors each using another GPU, then it should set `"gpu": 1, "extra_gpu": 4`.

```
tune.run(
    my_trainable,
    name="my_trainable",
    resources_per_trial={
        "cpu": 1,
        "gpu": 1,
        "extra_gpu": 4
    }
)
```

The `Trainable` also provides the `default_resource_requests` interface to automatically declare the `resources_per_trial` based on the given configuration.

classmethod `Trainable.`**default_resource_request**(*config*)

Returns the resource requirement for the given configuration.

This can be overriden by sub-classes to set the correct trial resource allocation, so the user does not need to.

Example

```
>>> def default_resource_request(cls, config):
        return Resources(
            cpu=0,
            gpu=0,
```

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```
            extra_cpu=config["workers"],
            extra_gpu=int(config["use_gpu"]) * config["workers"])
```

5.17.9 Save and Restore

When running a hyperparameter search, Tune can automatically and periodically save/checkpoint your model. Checkpointing is used for

- saving a model at the end of training
- modifying a model in the middle of training
- fault-tolerance in experiments with pre-emptible machines.
- enables certain Trial Schedulers such as HyperBand and PBT.

To enable checkpointing, you must implement a Trainable class (Trainable functions are not checkpointable, since they never return control back to their caller). The easiest way to do this is to subclass the pre-defined `Trainable` class and implement `_save`, and `_restore` abstract methods, as seen in this example.

For PyTorch model training, this would look something like this PyTorch example:

```
class MyTrainableClass(Trainable):
    def _save(self, tmp_checkpoint_dir):
        checkpoint_path = os.path.join(tmp_checkpoint_dir, "model.pth")
        torch.save(self.model.state_dict(), checkpoint_path)
        return tmp_checkpoint_dir

    def _restore(self, tmp_checkpoint_dir):
        checkpoint_path = os.path.join(tmp_checkpoint_dir, "model.pth")
        self.model.load_state_dict(torch.load(checkpoint_path))
```

Checkpoints will be saved by training iteration to `local_dir/exp_name/trial_name/checkpoint_<iter>`. You can restore a single trial checkpoint by using `tune.run(restore=<checkpoint_dir>)`.

Tune also generates temporary checkpoints for pausing and switching between trials. For this purpose, it is important not to depend on absolute paths in the implementation of `save`. See the below reference:

`Trainable.`**`_save`**(*tmp_checkpoint_dir*)

Subclasses should override this to implement `save()`.

> **Warning:** Do not rely on absolute paths in the implementation of `_save` and `_restore`.

Use `validate_save_restore` to catch `_save`/`_restore` errors before execution.

```
>>> from ray.tune.util import validate_save_restore
>>> validate_save_restore(MyTrainableClass)
>>> validate_save_restore(MyTrainableClass, use_object_store=True)
```

Parameters **`tmp_checkpoint_dir`** (*str*) – The directory where the checkpoint file must be stored. In a Tune run, if the trial is paused, the provided path may be temporary and moved.

Returns A dict or string. If string, the return value is expected to be prefixed by *tmp_checkpoint_dir*. If dict, the return value will be automatically serialized by Tune and passed to *_restore()*.

Examples

```
>>> print(trainable1._save("/tmp/checkpoint_1"))
"/tmp/checkpoint_1/my_checkpoint_file"
>>> print(trainable2._save("/tmp/checkpoint_2"))
{"some": "data"}
```

```
>>> trainable._save("/tmp/bad_example")
"/tmp/NEW_CHECKPOINT_PATH/my_checkpoint_file" # This will error.
```

`Trainable._restore`(*checkpoint*)

Subclasses should override this to implement restore().

Warning: In this method, do not rely on absolute paths. The absolute path of the checkpoint_dir used in `_save` may be changed.

If `_save` returned a prefixed string, the prefix of the checkpoint string returned by `_save` may be changed. This is because trial pausing depends on temporary directories.

The directory structure under the checkpoint_dir provided to `_save` is preserved.

See the example below.

```
class Example(Trainable):
    def _save(self, checkpoint_path):
        print(checkpoint_path)
        return os.path.join(checkpoint_path, "my/check/point")

    def _restore(self, checkpoint):
        print(checkpoint)

>>> trainer = Example()
>>> obj = trainer.save_to_object()  # This is used when PAUSED.
<logdir>/tmpc8k_c_6hsave_to_object/checkpoint_0/my/check/point
>>> trainer.restore_from_object(obj)  # Note the different prefix.
<logdir>/tmpb87b5axfrestore_from_object/checkpoint_0/my/check/point
```

Parameters **checkpoint** (*str|dict*) – If dict, the return value is as returned by *_save*. If a string, then it is a checkpoint path that may have a different prefix than that returned by *_save*. The directory structure underneath the *checkpoint_dir* *_save* is preserved.

5.17.10 Trainable (Trial) Checkpointing

Checkpointing assumes that the model state will be saved to disk on whichever node the Trainable is running on. You can checkpoint with three different mechanisms: manually, periodically, and at termination.

Manual Checkpointing: A custom Trainable can manually trigger checkpointing by returning `should_checkpoint: True` (or `tune.result.SHOULD_CHECKPOINT: True`) in the result dictionary of *_train*. This can be especially helpful in spot instances:

```
def _train(self):
    # training code
    result = {"mean_accuracy": accuracy}
    if detect_instance_preemption():
```

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```
        result.update(should_checkpoint=True)
    return result
```

Periodic Checkpointing: periodic checkpointing can be used to provide fault-tolerance for experiments. This can be enabled by setting `checkpoint_freq=<int>` and `max_failures=<int>` to checkpoint trials every *N* iterations and recover from up to *M* crashes per trial, e.g.:

```
tune.run(
    my_trainable,
    checkpoint_freq=10,
    max_failures=5,
)
```

Checkpointing at Termination: The checkpoint_freq may not coincide with the exact end of an experiment. If you want a checkpoint to be created at the end of a trial, you can additionally set the `checkpoint_at_end=True`:

```
tune.run(
    my_trainable,
    checkpoint_freq=10,
    checkpoint_at_end=True,
    max_failures=5,
)
```

The checkpoint will be saved at a path that looks like `local_dir/exp_name/trial_name/checkpoint_x/`, where the x is the number of iterations so far when the checkpoint is saved. To restore the checkpoint, you can use the `restore` argument and specify a checkpoint file. By doing this, you can change whatever experiments' configuration such as the experiment's name, the training iteration or so:

```
# Restored previous trial from the given checkpoint
tune.run(
    "PG",
    name="RestoredExp", # The name can be different.
    stop={"training_iteration": 10}, # train 5 more iterations than previous
    restore="~/ray_results/Original/PG_<xxx>/checkpoint_5/checkpoint-5",
    config={"env": "CartPole-v0"},
)
```

5.17.11 Fault Tolerance

Tune will automatically restart trials from the last checkpoint in case of trial failures/error (if `max_failures` is set), both in the single node and distributed setting.

In the distributed setting, if using the autoscaler with `rsync` enabled, Tune will automatically sync the trial folder with the driver. For example, if a node is lost while a trial (specifically, the corresponding Trainable actor of the trial) is still executing on that node and a checkpoint of the trial exists, Tune will wait until available resources are available to begin executing the trial again.

If the trial/actor is placed on a different node, Tune will automatically push the previous checkpoint file to that node and restore the remote trial actor state, allowing the trial to resume from the latest checkpoint even after failure.

Take a look at an example.

Recovering From Failures

Tune automatically persists the progress of your entire experiment (a `tune.run` session), so if an experiment crashes or is otherwise cancelled, it can be resumed by passing one of True, False, "LOCAL", "REMOTE", or "PROMPT" to `tune.run(resume=...)`. Note that this only works if trial checkpoints are detected, whether it be by manual or periodic checkpointing.

Settings:

- The default setting of `resume=False` creates a new experiment.
- `resume="LOCAL"` and `resume=True` restore the experiment from `local_dir/[experiment_name]`.
- `resume="REMOTE"` syncs the upload dir down to the local dir and then restores the experiment from `local_dir/experiment_name`.
- `resume="PROMPT"` will cause Tune to prompt you for whether you want to resume. You can always force a new experiment to be created by changing the experiment name.

Note that trials will be restored to their last checkpoint. If trial checkpointing is not enabled, unfinished trials will be restarted from scratch.

E.g.:

```
tune.run(
    my_trainable,
    checkpoint_freq=10,
    local_dir="~/path/to/results",
    resume=True
)
```

Upon a second run, this will restore the entire experiment state from `~/path/to/results/my_experiment_name`. Importantly, any changes to the experiment specification upon resume will be ignored. For example, if the previous experiment has reached its termination, then resuming it with a new stop criterion makes no effect: the new experiment will terminate immediately after initialization. If you want to change the configuration, such as training more iterations, you can do so restore the checkpoint by setting `restore=<path-to-checkpoint>` - note that this only works for a single trial.

> **Warning:** This feature is still experimental, so any provided Trial Scheduler or Search Algorithm will not be preserved. Only `FIFOScheduler` and `BasicVariantGenerator` will be supported.

5.17.12 Handling Large Datasets

You often will want to compute a large object (e.g., training data, model weights) on the driver and use that object within each trial. Tune provides a `pin_in_object_store` utility function that can be used to broadcast such large objects. Objects pinned in this way will never be evicted from the Ray object store while the driver process is running, and can be efficiently retrieved from any task via `get_pinned_object`.

```
import ray
from ray import tune
from ray.tune.util import pin_in_object_store, get_pinned_object

import numpy as np

ray.init()
```

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```
# X_id can be referenced in closures
X_id = pin_in_object_store(np.random.random(size=100000000))

def f(config, reporter):
    X = get_pinned_object(X_id)
    # use X

tune.run(f)
```

5.17.13 Custom Stopping Criteria

You can control when trials are stopped early by passing the `stop` argument to `tune.run`. This argument takes either a dictionary or a function.

If a dictionary is passed in, the keys may be any field in the return result of `tune.track.log` in the Function API or `train()` (including the results from `_train` and auto-filled metrics).

In the example below, each trial will be stopped either when it completes 10 iterations OR when it reaches a mean accuracy of 0.98. Note that *training_iteration* is an auto-filled metric by Tune.

```
tune.run(
    my_trainable,
    stop={"training_iteration": 10, "mean_accuracy": 0.98}
)
```

For more flexibility, you can pass in a function instead. If a function is passed in, it must take `(trial_id, result)` as arguments and return a boolean (`True` if trial should be stopped and `False` otherwise).

You can use this to stop all trials after the criteria is fulfilled by any individual trial:

```
class Stopper:
    def __init__(self):
        self.should_stop = False

    def stop(self, trial_id, result):
        if not self.should_stop and result['foo'] > 10:
            self.should_stop = True
        return self.should_stop

stopper = Stopper()
tune.run(my_trainable, stop=stopper.stop)
```

Note that in the above example all trials will not stop immediately, but will do so once their current iterations are complete.

5.17.14 Auto-Filled Results

During training, Tune will automatically fill certain fields if not already provided. All of these can be used as stopping conditions or in the Scheduler/Search Algorithm specification.

```
# (Optional/Auto-filled) training is terminated. Filled only if not provided.
DONE = "done"
```

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```
# (Optional) Enum for user controlled checkpoint
SHOULD_CHECKPOINT = "should_checkpoint"

# (Auto-filled) The hostname of the machine hosting the training process.
HOSTNAME = "hostname"

# (Auto-filled) The auto-assigned id of the trial.
TRIAL_ID = "trial_id"

# (Auto-filled) The node ip of the machine hosting the training process.
NODE_IP = "node_ip"

# (Auto-filled) The pid of the training process.
PID = "pid"

# (Optional) Mean reward for current training iteration
EPISODE_REWARD_MEAN = "episode_reward_mean"

# (Optional) Mean loss for training iteration
MEAN_LOSS = "mean_loss"

# (Optional) Mean accuracy for training iteration
MEAN_ACCURACY = "mean_accuracy"

# Number of episodes in this iteration.
EPISODES_THIS_ITER = "episodes_this_iter"

# (Optional/Auto-filled) Accumulated number of episodes for this experiment.
EPISODES_TOTAL = "episodes_total"

# Number of timesteps in this iteration.
TIMESTEPS_THIS_ITER = "timesteps_this_iter"

# (Auto-filled) Accumulated number of timesteps for this entire experiment.
TIMESTEPS_TOTAL = "timesteps_total"

# (Auto-filled) Time in seconds this iteration took to run.
# This may be overriden to override the system-computed time difference.
TIME_THIS_ITER_S = "time_this_iter_s"

# (Auto-filled) Accumulated time in seconds for this entire experiment.
TIME_TOTAL_S = "time_total_s"

# (Auto-filled) The index of this training iteration.
TRAINING_ITERATION = "training_iteration"
```

The following fields will automatically show up on the console output, if provided:

1. `episode_reward_mean`
2. `mean_loss`
3. `mean_accuracy`
4. `timesteps_this_iter` (aggregated into `timesteps_total`).

```
Example_0:  TERMINATED [pid=68248], 179 s, 2 iter, 60000 ts, 94 rew
```

5.17.15 TensorBoard

To visualize learning in tensorboard, install TensorFlow:

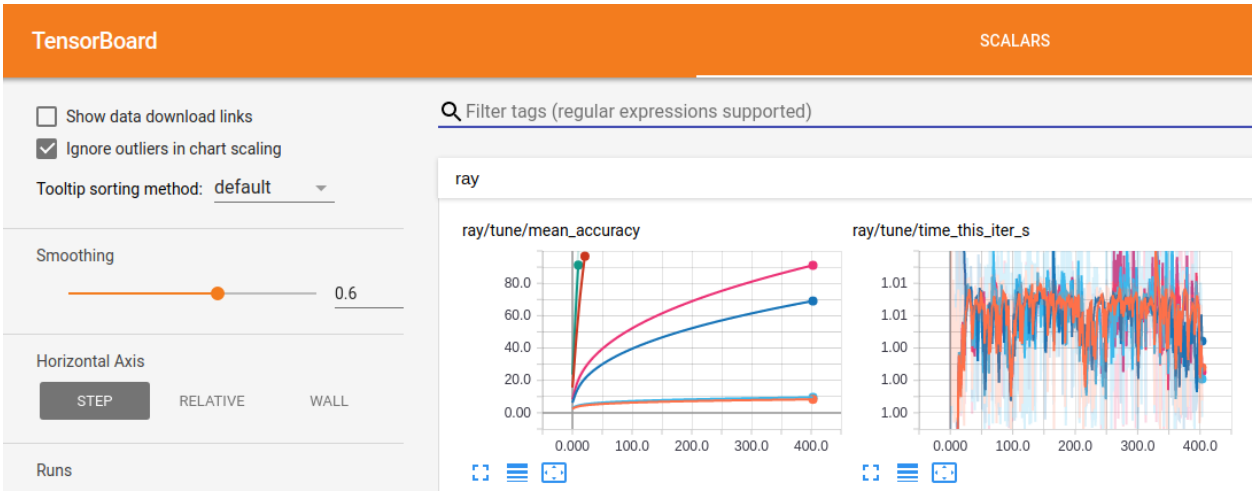
```
$ pip install tensorflow
```

Then, after you run a experiment, you can visualize your experiment with TensorBoard by specifying the output directory of your results. Note that if you running Ray on a remote cluster, you can forward the tensorboard port to your local machine through SSH using `ssh -L 6006:localhost:6006 <address>`:

```
$ tensorboard --logdir=~/ray_results/my_experiment
```

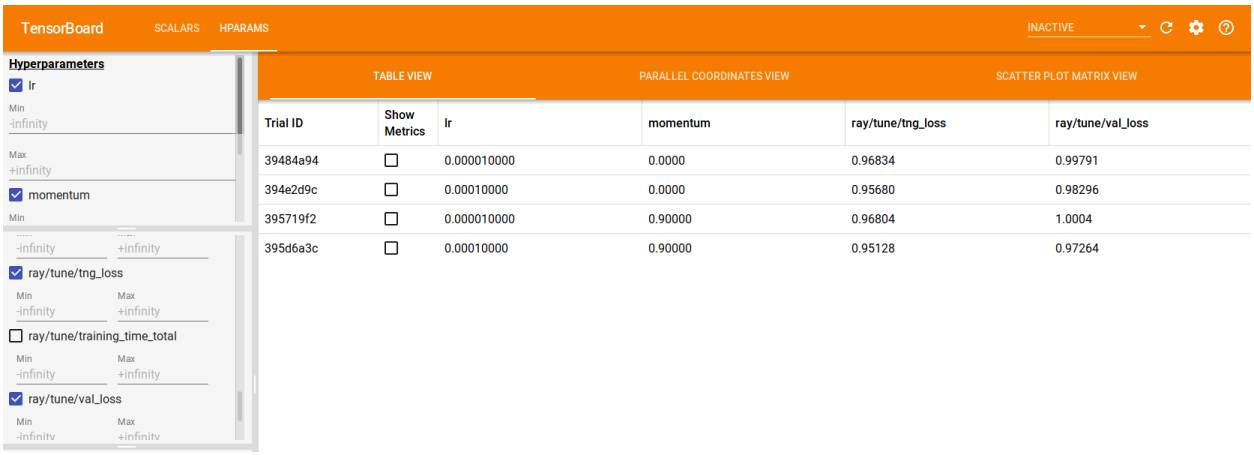
If you are running Ray on a remote multi-user cluster where you do not have sudo access, you can run the following commands to make sure tensorboard is able to write to the tmp directory:

```
$ export TMPDIR=/tmp/$USER; mkdir -p $TMPDIR; tensorboard --logdir=~/ray_results
```



If using TF2, Tune also automatically generates TensorBoard HParams output, as shown below:

```
tune.run(
    ...,
    config={
        "lr": tune.grid_search([1e-5, 1e-4]),
        "momentum": tune.grid_search([0, 0.9])
    }
)
```

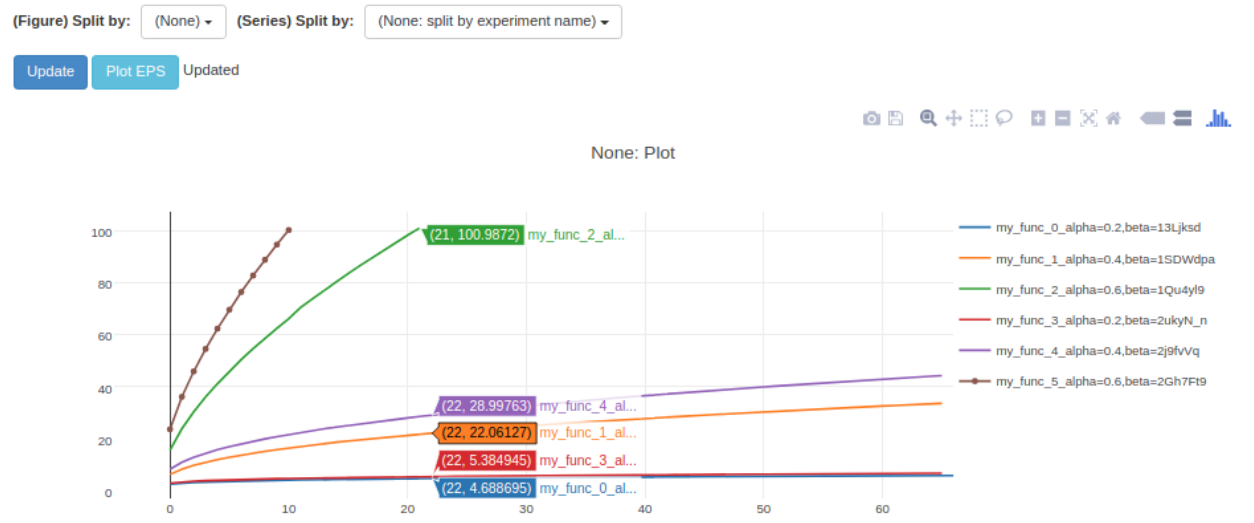


The nonrelevant metrics (like timing stats) can be disabled on the left to show only the relevant ones (like accuracy, loss, etc.).

5.17.16 Viskit

To use VisKit (you may have to install some dependencies), run:

```
$ git clone https://github.com/rll/rllab.git
$ python rllab/rllab/viskit/frontend.py ~/ray_results/my_experiment
```



5.17.17 Logging

You can pass in your own logging mechanisms to output logs in custom formats as follows:

```
from ray.tune.logger import DEFAULT_LOGGERS

tune.run(
    MyTrainableClass
    name="experiment_name",
    loggers=DEFAULT_LOGGERS + (CustomLogger1, CustomLogger2)
)
```

These loggers will be called along with the default Tune loggers. All loggers must inherit the Logger interface. Tune enables default loggers for Tensorboard, CSV, and JSON formats. You can also check out logger.py for implementation details. An example can be found in logging_example.py.

MLFlow

Tune also provides a default logger for MLFlow. You can install MLFlow via `pip install mlflow`. An example can be found mlflow_example.py. Note that this currently does not include artifact logging support. For this, you can use the native MLFlow APIs inside your Trainable definition.

5.17.18 Uploading/Syncing

Tune automatically syncs the trial folder on remote nodes back to the head node. This requires the ray cluster to be started with the autoscaler. By default, local syncing requires rsync to be installed. You can customize the sync command with the `sync_to_driver` argument in `tune.run` by providing either a function or a string.

If a string is provided, then it must include replacement fields `{source}` and `{target}`, like `rsync -savz -e "ssh -i ssh_key.pem" {source} {target}`. Alternatively, a function can be provided with the following signature:

```
def custom_sync_func(source, target):
    sync_cmd = "rsync {source} {target}".format(
        source=source,
        target=target)
    sync_process = subprocess.Popen(sync_cmd, shell=True)
    sync_process.wait()

tune.run(
    MyTrainableClass,
    name="experiment_name",
    sync_to_driver=custom_sync_func,
)
```

When syncing results back to the driver, the source would be a path similar to `ubuntu@192.0.0.1:/home/ubuntu/ray_results/trial1`, and the target would be a local path. This custom sync command would be also be used in node failures, where the source argument would be the path to the trial directory and the target would be a remote path. The *sync_to_driver* would be invoked to push a checkpoint to new node for a queued trial to resume.

If an upload directory is provided, Tune will automatically sync results to the given directory, natively supporting standard S3/gsutil commands. You can customize this to specify arbitrary storages with the `sync_to_cloud` argument. This argument is similar to `sync_to_cloud` in that it supports strings with the same replacement fields and arbitrary functions. See syncer.py for implementation details.

```
tune.run(
    MyTrainableClass,
    name="experiment_name",
    sync_to_cloud=custom_sync_func,
)
```

5.17.19 Tune Client API

You can interact with an ongoing experiment with the Tune Client API. The Tune Client API is organized around REST, which includes resource-oriented URLs, accepts form-encoded requests, returns JSON-encoded responses, and uses standard HTTP protocol.

To allow Tune to receive and respond to your API calls, you have to start your experiment with `with_server=True`:

```
tune.run(..., with_server=True, server_port=4321)
```

The easiest way to use the Tune Client API is with the built-in TuneClient. To use TuneClient, verify that you have the `requests` library installed:

```
$ pip install requests
```

Then, on the client side, you can use the following class. If on a cluster, you may want to forward this port (e.g. `ssh -L <local_port>:localhost:<remote_port> <address>`) so that you can use the Client on your local machine.

class ray.tune.web_server.**TuneClient**(*tune_address*, *port_forward*)
Client to interact with an ongoing Tune experiment.

Requires a TuneServer to have started running.

tune_address
Address of running TuneServer

Type str

port_forward
Port number of running TuneServer

Type int

get_all_trials()
Returns a list of all trials' information.

get_trial(*trial_id*)
Returns trial information by trial_id.

add_trial(*name*, *specification*)
Adds a trial by name and specification (dict).

stop_trial(*trial_id*)
Requests to stop trial by trial_id.

For an example notebook for using the Client API, see the Client API Example.

The API also supports curl. Here are the examples for getting trials (`GET /trials/[:id]`):

```
$ curl http://<address>:<port>/trials
$ curl http://<address>:<port>/trials/<trial_id>
```

And stopping a trial (`PUT /trials/:id`):

```
$ curl -X PUT http://<address>:<port>/trials/<trial_id>
```

5.17.20 Debugging

By default, Tune will run hyperparameter evaluations on multiple processes. However, if you need to debug your training process, it may be easier to do everything on a single process. You can force all Ray functions to occur on a single process with `local_mode` by calling the following before `tune.run`.

```
ray.init(local_mode=True)
```

Note that some behavior such as writing to files by depending on the current working directory in a Trainable and setting global process variables may not work as expected. Local mode with multiple configuration evaluations will interleave computation, so it is most naturally used when running a single configuration evaluation.

5.17.21 Tune CLI (Experimental)

`tune` has an easy-to-use command line interface (CLI) to manage and monitor your experiments on Ray. To do this, verify that you have the `tabulate` library installed:

```
$ pip install tabulate
```

Here are a few examples of command line calls.

- `tune list-trials`: List tabular information about trials within an experiment. Empty columns will be dropped by default. Add the `--sort` flag to sort the output by specific columns. Add the `--filter` flag to filter the output in the format `"<column> <operator> <value>"`. Add the `--output` flag to write the trial information to a specific file (CSV or Pickle). Add the `--columns` and `--result-columns` flags to select specific columns to display.

```
$ tune list-trials [EXPERIMENT_DIR] --output note.csv

+------------------+-----------------------+------------+
| trainable_name   | experiment_tag        | trial_id   |
|------------------+-----------------------+------------|
| MyTrainableClass | 0_height=40,width=37  | 87b54a1d   |
| MyTrainableClass | 1_height=21,width=70  | 23b89036   |
| MyTrainableClass | 2_height=99,width=90  | 518dbe95   |
| MyTrainableClass | 3_height=54,width=21  | 7b99a28a   |
| MyTrainableClass | 4_height=90,width=69  | ae4e02fb   |
+------------------+-----------------------+------------+
Dropped columns: ['status', 'last_update_time']
Please increase your terminal size to view remaining columns.
Output saved at: note.csv

$ tune list-trials [EXPERIMENT_DIR] --filter "trial_id == 7b99a28a"

+------------------+-----------------------+------------+
| trainable_name   | experiment_tag        | trial_id   |
|------------------+-----------------------+------------|
| MyTrainableClass | 3_height=54,width=21  | 7b99a28a   |
+------------------+-----------------------+------------+
Dropped columns: ['status', 'last_update_time']
Please increase your terminal size to view remaining columns.
```

5.17.22 Further Questions or Issues?

You can post questions or issues or feedback through the following channels:

1. ray-dev@googlegroups.com: For discussions about development or any general questions and feedback.
2. StackOverflow: For questions about how to use Ray.
3. GitHub Issues: For bug reports and feature requests.

5.18 Tune Distributed Experiments

Tune is commonly used for large-scale distributed hyperparameter optimization. This page will overview:

1. How to setup and launch a distributed experiment,
2. commonly used commands, including fast file mounting, one-line cluster launching, and result uploading to cloud storage.

Quick Summary: To run a distributed experiment with Tune, you need to:

1. Make sure your script has `ray.init(address=...)` to connect to the existing Ray cluster.
2. If a ray cluster does not exist, start a Ray cluster (instructions for local machines, cloud).
3. Run the script on the head node (or use `ray submit`).

5.18.1 Running a distributed experiment

Running a distributed (multi-node) experiment requires Ray to be started already. You can do this on local machines or on the cloud (instructions for local machines, cloud).

Across your machines, Tune will automatically detect the number of GPUs and CPUs without you needing to manage `CUDA_VISIBLE_DEVICES`.

To execute a distributed experiment, call `ray.init(address=XXX)` before `tune.run`, where `XXX` is the Ray redis address, which defaults to `localhost:6379`. The Tune python script should be executed only on the head node of the Ray cluster.

One common approach to modifying an existing Tune experiment to go distributed is to set an `argparse` variable so that toggling between distributed and single-node is seamless.

```
import ray
import argparse

parser = argparse.ArgumentParser()
parser.add_argument("--ray-address")
args = parser.parse_args()
ray.init(address=args.ray_address)

tune.run(...)
```

```
# On the head node, connect to an existing ray cluster
$ python tune_script.py --ray-address=localhost:XXXX
```

If you used a cluster configuration (starting a cluster with `ray up` or `ray submit --start`), use:

```
ray submit tune-default.yaml tune_script.py --args="--ray-address=localhost:6379"
```

Tip:

1. In the examples, the Ray redis address commonly used is `localhost:6379`.
2. If the Ray cluster is already started, you should not need to run anything on the worker nodes.

5.18.2 Local Cluster Setup

If you have already have a list of nodes, you can follow the local private cluster setup instructions here. Below is an example cluster configuration as `tune-default.yaml`:

```
cluster_name: local-default
provider:
    type: local
    head_ip: YOUR_HEAD_NODE_HOSTNAME
    worker_ips: [WORKER_NODE_1_HOSTNAME, WORKER_NODE_2_HOSTNAME, ... ]
auth: {ssh_user: YOUR_USERNAME, ssh_private_key: ~/.ssh/id_rsa}
## Typically for local clusters, min_workers == max_workers.
min_workers: 3
max_workers: 3
setup_commands:  # Set up each node.
    - pip install ray torch torchvision tabulate tensorboard
```

`ray up` starts Ray on the cluster of nodes.

```
ray up tune-default.yaml
```

`ray submit` uploads `tune_script.py` to the cluster and runs `python tune_script.py [args]`.

```
ray submit tune-default.yaml tune_script.py --args="--ray-address=localhost:6379"
```

Manual Local Cluster Setup

If you run into issues using the local cluster setup (or want to add nodes manually), you can use the manual cluster setup. Full documentation here. At a glance,

On the head node:

```
# If the ``--redis-port`` argument is omitted, Ray will choose a port at random.
$ ray start --head --redis-port=6379
```

The command will print out the address of the Redis server that was started (and some other address information).

Then on all of the other nodes, run the following. Make sure to replace `<address>` with the value printed by the command on the head node (it should look something like `123.45.67.89:6379`).

```
$ ray start --address=<address>
```

Then, you can run your Tune Python script on the head node like:

```
# On the head node, execute using existing ray cluster
$ python tune_script.py --ray-address=<address>
```

5.18.3 Launching a cloud cluster

Tip: If you have already have a list of nodes, go to the *Local Cluster Setup* section.

Ray currently supports AWS and GCP. Below, we will launch nodes on AWS that will default to using the Deep Learning AMI. See the cluster setup documentation. Save the below cluster configuration (`tune-default.yaml`):

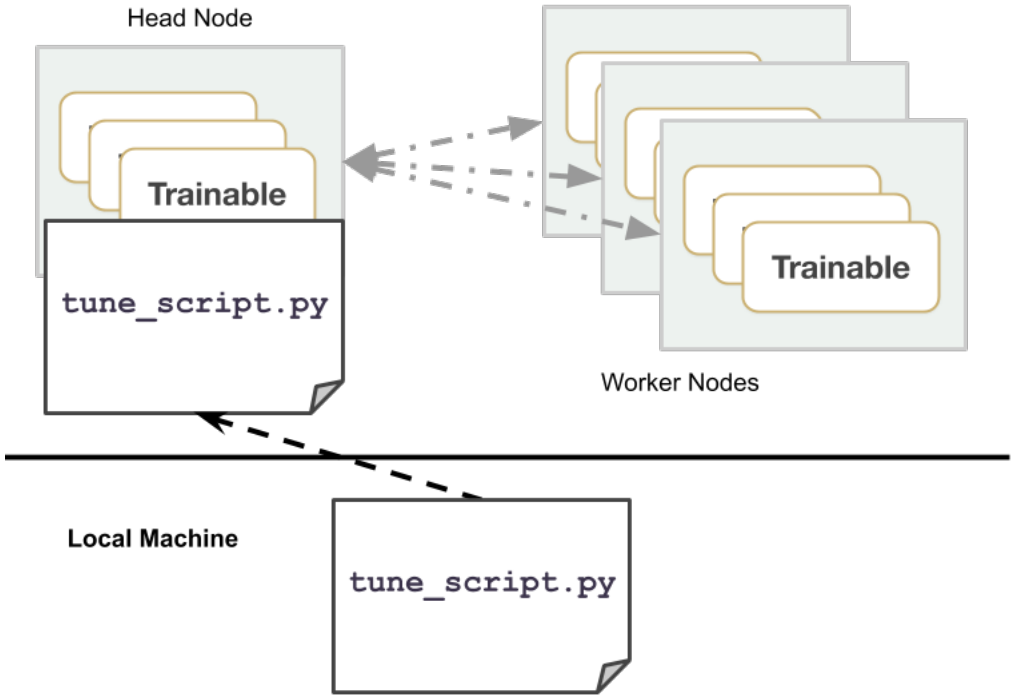
```
cluster_name: tune-default
provider: {type: aws, region: us-west-2}
auth: {ssh_user: ubuntu}
min_workers: 3
max_workers: 3
# Deep Learning AMI (Ubuntu) Version 21.0
head_node: {InstanceType: c5.xlarge, ImageId: ami-0b294f219d14e6a82}
worker_nodes: {InstanceType: c5.xlarge, ImageId: ami-0b294f219d14e6a82}
setup_commands: # Set up each node.
    - pip install ray torch torchvision tabulate tensorboard
```

`ray up` starts Ray on the cluster of nodes.

```
ray up tune-default.yaml
```

`ray submit --start` starts a cluster as specified by the given cluster configuration YAML file, uploads `tune_script.py` to the cluster, and runs `python tune_script.py [args]`.

```
ray submit tune-default.yaml tune_script.py --start --args="--ray-
↪address=localhost:6379"
```



Analyze your results on TensorBoard by starting TensorBoard on the remote head machine.

```
# Go to http://localhost:6006 to access TensorBoard.
ray exec tune-default.yaml 'tensorboard --logdir=~/ray_results/ --port 6006' --port-
↪forward 6006
```

Note that you can customize the directory of results by running: `tune.run(local_dir=..)`. You can then point TensorBoard to that directory to visualize results. You can also use awless for easy cluster management on AWS.

5.18.4 Pre-emptible Instances (Cloud)

Running on spot instances (or pre-emptible instances) can reduce the cost of your experiment. You can enable spot instances in AWS via the following configuration modification:

```
# Provider-specific config for worker nodes, e.g. instance type.
worker_nodes:
    InstanceType: m5.large
    ImageId: ami-0b294f219d14e6a82 # Deep Learning AMI (Ubuntu) Version 21.0

    # Run workers on spot by default. Comment this out to use on-demand.
    InstanceMarketOptions:
        MarketType: spot
        SpotOptions:
            MaxPrice: 1.0  # Max Hourly Price
```

In GCP, you can use the following configuration modification:

```
worker_nodes:
    machineType: n1-standard-2
    disks:
      - boot: true
        autoDelete: true
        type: PERSISTENT
        initializeParams:
          diskSizeGb: 50
          # See https://cloud.google.com/compute/docs/images for more images
          sourceImage: projects/deeplearning-platform-release/global/images/family/tf-
↪1-13-cpu

    # Run workers on preemtible instances.
    scheduling:
      - preemptible: true
```

Spot instances may be removed suddenly while trials are still running. Often times this may be difficult to deal with when using other distributed hyperparameter optimization frameworks. Tune allows users to mitigate the effects of this by preserving the progress of your model training through checkpointing.

The easiest way to do this is to subclass the pre-defined `Trainable` class and implement `_save`, and `_restore` abstract methods, as seen in the example below:

```
class TrainMNIST(tune.Trainable):
    def _setup(self, config):
        use_cuda = config.get("use_gpu") and torch.cuda.is_available()
        self.device = torch.device("cuda" if use_cuda else "cpu")
        self.train_loader, self.test_loader = get_data_loaders()
        self.model = ConvNet().to(self.device)
        self.optimizer = optim.SGD(
            self.model.parameters(),
            lr=config.get("lr", 0.01),
            momentum=config.get("momentum", 0.9))

    def _train(self):
        train(
            self.model, self.optimizer, self.train_loader, device=self.device)
        acc = test(self.model, self.test_loader, self.device)
        return {"mean_accuracy": acc}
```

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```
    def _save(self, checkpoint_dir):
        checkpoint_path = os.path.join(checkpoint_dir, "model.pth")
        torch.save(self.model.state_dict(), checkpoint_path)
        return checkpoint_path

    def _restore(self, checkpoint_path):
        self.model.load_state_dict(torch.load(checkpoint_path))
```

This can then be used similarly to the Function API as before:

```
search_space = {
    "lr": tune.sample_from(lambda spec: 10**(-10 * np.random.rand())),
    "momentum": tune.uniform(0.1, 0.9)
}

analysis = tune.run(
    TrainMNIST, config=search_space, stop={"training_iteration": 10})
```

Example for using spot instances (AWS)

Here is an example for running Tune on spot instances. This assumes your AWS credentials have already been setup (`aws configure`):

1. Download a full example Tune experiment script here. This includes a Trainable with checkpointing: `mnist_pytorch_trainable.py`. To run this example, you will need to install the following:

```
$ pip install ray torch torchvision filelock
```

2. Download an example cluster yaml here: `tune-default.yaml`
3. Run `ray submit` as below to run Tune across them. Append `[--start]` if the cluster is not up yet. Append `[--stop]` to automatically shutdown your nodes after running.

```
ray submit tune-default.yaml mnist_pytorch_trainable.py \
    --args="--ray-address=localhost:6379" \
    --start
```

4. Optionally for testing on AWS or GCP, you can use the following to kill a random worker node after all the worker nodes are up

```
$ ray kill-random-node tune-default.yaml --hard
```

To summarize, here are the commands to run:

```
wget https://raw.githubusercontent.com/ray-project/ray/master/python/ray/tune/
↪examples/mnist_pytorch_trainable.py
wget https://raw.githubusercontent.com/ray-project/ray/master/python/ray/tune/tune-
↪default.yaml
ray submit tune-default.yaml mnist_pytorch_trainable.py --args="--ray-
↪address=localhost:6379" --start

# wait a while until after all nodes have started
ray kill-random-node tune-default.yaml --hard
```

You should see Tune eventually continue the trials on a different worker node. See the Save and Restore section for more details.

You can also specify `tune.run(upload_dir=...)` to sync results with a cloud storage like S3, persisting results in case you want to start and stop your cluster automatically.

5.18.5 Common Commands

Below are some commonly used commands for submitting experiments. Please see the Autoscaler page to see find more comprehensive documentation of commands.

```
# Upload `tune_experiment.py` from your local machine onto the cluster. Then,
# run `python tune_experiment.py --address=localhost:6379` on the remote machine.
$ ray submit CLUSTER.YAML tune_experiment.py --args="--address=localhost:6379"

# Start a cluster and run an experiment in a detached tmux session,
# and shut down the cluster as soon as the experiment completes.
# In `tune_experiment.py`, set `tune.run(upload_dir="s3://...")` to persist results
$ ray submit CLUSTER.YAML --tmux --start --stop tune_experiment.py  --args="--
↪address=localhost:6379"

# To start or update your cluster:
$ ray up CLUSTER.YAML [-y]

# Shut-down all instances of your cluster:
$ ray down CLUSTER.YAML [-y]

# Run Tensorboard and forward the port to your own machine.
$ ray exec CLUSTER.YAML 'tensorboard --logdir ~/ray_results/ --port 6006' --port-
↪forward 6006

# Run Jupyter Lab and forward the port to your own machine.
$ ray exec CLUSTER.YAML 'jupyter lab --port 6006' --port-forward 6006

# Get a summary of all the experiments and trials that have executed so far.
$ ray exec CLUSTER.YAML 'tune ls ~/ray_results'

# Upload and sync file_mounts up to the cluster with this command.
$ ray rsync-up CLUSTER.YAML

# Download the results directory from your cluster head node to your local machine on␣
↪``~/cluster_results``.
$ ray rsync-down CLUSTER.YAML '~/ray_results' ~/cluster_results

# Launching multiple clusters using the same configuration.
$ ray up CLUSTER.YAML -n="cluster1"
$ ray up CLUSTER.YAML -n="cluster2"
$ ray up CLUSTER.YAML -n="cluster3"
```

5.18.6 Troubleshooting

Sometimes, your program may freeze. Run this to restart the Ray cluster without running any of the installation commands.

```
$ ray up CLUSTER.YAML --restart-only
```

5.19 Tune Trial Schedulers

By default, Tune schedules trials in serial order with the `FIFOScheduler` class. However, you can also specify a custom scheduling algorithm that can early stop trials or perturb parameters.

```
tune.run( ... , scheduler=AsyncHyperBandScheduler())
```

Tune includes distributed implementations of early stopping algorithms such as Median Stopping Rule, HyperBand, and an asynchronous version of HyperBand. These algorithms are very resource efficient and can outperform Bayesian Optimization methods in many cases. All schedulers take in a `metric`, which is a value returned in the result dict of your Trainable and is maximized or minimized according to `mode`.

Current Available Trial Schedulers:

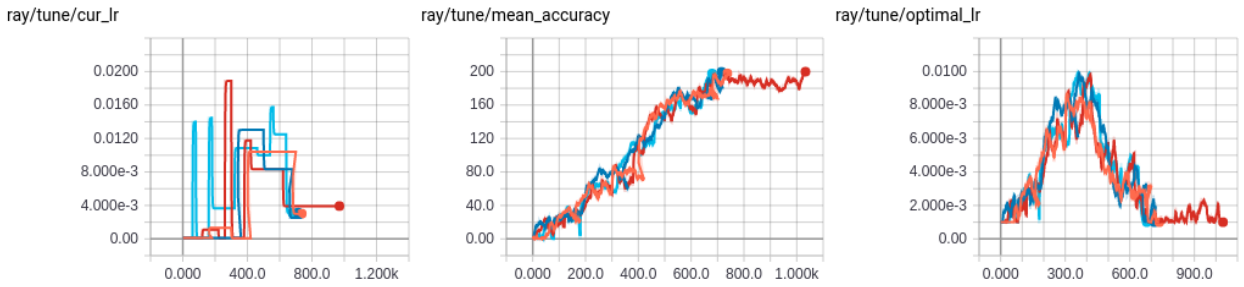
5.19.1 Population Based Training (PBT)

Tune includes a distributed implementation of Population Based Training (PBT). This can be enabled by setting the `scheduler` parameter of `tune.run`, e.g.

```
pbt_scheduler = PopulationBasedTraining(
        time_attr='time_total_s',
        metric='mean_accuracy',
        mode='max',
        perturbation_interval=600.0,
        hyperparam_mutations={
            "lr": [1e-3, 5e-4, 1e-4, 5e-5, 1e-5],
            "alpha": lambda: random.uniform(0.0, 1.0),
            ...
        })
tune.run( ... , scheduler=pbt_scheduler)
```

When the PBT scheduler is enabled, each trial variant is treated as a member of the population. Periodically, top-performing trials are checkpointed (this requires your Trainable to support save and restore). Low-performing trials clone the checkpoints of top performers and perturb the configurations in the hope of discovering an even better variation.

You can run this toy PBT example to get an idea of how how PBT operates. When training in PBT mode, a single trial may see many different hyperparameters over its lifetime, which is recorded in its `result.json` file. The following figure generated by the example shows PBT with optimizing a LR schedule over the course of a single experiment:



class ray.tune.schedulers.**PopulationBasedTraining**(*time_attr='time_total_s'*, *reward_attr=None*, *metric='episode_reward_mean'*, *mode='max'*, *perturbation_interval=60.0*, *hyperparam_mutations={}*, *quantile_fraction=0.25*, *resample_probability=0.25*, *custom_explore_fn=None*, *log_config=True*)

Implements the Population Based Training (PBT) algorithm.

https://deepmind.com/blog/population-based-training-neural-networks

PBT trains a group of models (or agents) in parallel. Periodically, poorly performing models clone the state of the top performers, and a random mutation is applied to their hyperparameters in the hopes of outperforming the current top models.

Unlike other hyperparameter search algorithms, PBT mutates hyperparameters during training time. This enables very fast hyperparameter discovery and also automatically discovers good annealing schedules.

This Tune PBT implementation considers all trials added as part of the PBT population. If the number of trials exceeds the cluster capacity, they will be time-multiplexed as to balance training progress across the population. To run multiple trials, use *tune.run(num_samples=<int>)*.

Parameters

- **time_attr** (*str*) – The training result attr to use for comparing time. Note that you can pass in something non-temporal such as *training_iteration* as a measure of progress, the only requirement is that the attribute should increase monotonically.
- **metric** (*str*) – The training result objective value attribute. Stopping procedures will use this attribute.
- **mode** (*str*) – One of {min, max}. Determines whether objective is minimizing or maximizing the metric attribute.
- **perturbation_interval** (*float*) – Models will be considered for perturbation at this interval of *time_attr*. Note that perturbation incurs checkpoint overhead, so you shouldn't set this to be too frequent.
- **hyperparam_mutations** (*dict*) – Hyperparams to mutate. The format is as follows: for each key, either a list or function can be provided. A list specifies an allowed set of categorical values. A function specifies the distribution of a continuous parameter. You must specify at least one of *hyperparam_mutations* or *custom_explore_fn*.
- **quantile_fraction** (*float*) – Parameters are transferred from the top *quantile_fraction* fraction of trials to the bottom *quantile_fraction* fraction. Needs to be between 0 and 0.5. Setting it to 0 essentially implies doing no exploitation at all.

- **resample_probability** (*float*) – The probability of resampling from the original distribution when applying *hyperparam_mutations*. If not resampled, the value will be perturbed by a factor of 1.2 or 0.8 if continuous, or changed to an adjacent value if discrete.
- **custom_explore_fn** (*func*) – You can also specify a custom exploration function. This function is invoked as *f(config)* after built-in perturbations from *hyperparam_mutations* are applied, and should return *config* updated as needed. You must specify at least one of *hyperparam_mutations* or *custom_explore_fn*.
- **log_config** (*bool*) – Whether to log the ray config of each model to local_dir at each exploit. Allows config schedule to be reconstructed.

Example

```
>>> pbt = PopulationBasedTraining(
>>>     time_attr="training_iteration",
>>>     metric="episode_reward_mean",
>>>     mode="max",
>>>     perturbation_interval=10,  # every 10 `time_attr` units
>>>                                # (training_iterations in this case)
>>>     hyperparam_mutations={
>>>         # Perturb factor1 by scaling it by 0.8 or 1.2. Resampling
>>>         # resets it to a value sampled from the lambda function.
>>>         "factor_1": lambda: random.uniform(0.0, 20.0),
>>>         # Perturb factor2 by changing it to an adjacent value, e.g.
>>>         # 10 -> 1 or 10 -> 100. Resampling will choose at random.
>>>         "factor_2": [1, 10, 100, 1000, 10000],
>>>     })
>>> tune.run({...}, num_samples=8, scheduler=pbt)
```

5.19.2 Asynchronous HyperBand

The asynchronous version of HyperBand scheduler can be used by setting the `scheduler` parameter of `tune.run`, e.g.

```
async_hb_scheduler = AsyncHyperBandScheduler(
    time_attr='training_iteration',
    metric='episode_reward_mean',
    mode='max',
    max_t=100,
    grace_period=10,
    reduction_factor=3,
    brackets=3)
tune.run( ... , scheduler=async_hb_scheduler)
```

Compared to the original version of HyperBand, this implementation provides better parallelism and avoids straggler issues during eliminations. An example of this can be found in async_hyperband_example.py. **We recommend using this over the standard HyperBand scheduler.**

class ray.tune.schedulers.**AsyncHyperBandScheduler**(*time_attr='training_iteration'*, *reward_attr=None*, *metric='episode_reward_mean'*, *mode='max'*, *max_t=100*, *grace_period=1*, *reduction_factor=4*, *brackets=1*)

Implements the Async Successive Halving.

This should provide similar theoretical performance as HyperBand but avoid straggler issues that HyperBand faces. One implementation detail is when using multiple brackets, trial allocation to bracket is done randomly with over a softmax probability.

See https://arxiv.org/abs/1810.05934

Parameters

- **time_attr** (*str*) – A training result attr to use for comparing time. Note that you can pass in something non-temporal such as *training_iteration* as a measure of progress, the only requirement is that the attribute should increase monotonically.
- **metric** (*str*) – The training result objective value attribute. Stopping procedures will use this attribute.
- **mode** (*str*) – One of {min, max}. Determines whether objective is minimizing or maximizing the metric attribute.
- **max_t** (*float*) – max time units per trial. Trials will be stopped after max_t time units (determined by time_attr) have passed.
- **grace_period** (*float*) – Only stop trials at least this old in time. The units are the same as the attribute named by *time_attr*.
- **reduction_factor** (*float*) – Used to set halving rate and amount. This is simply a unit-less scalar.
- **brackets** (*int*) – Number of brackets. Each bracket has a different halving rate, specified by the reduction factor.

5.19.3 HyperBand

Note: Note that the HyperBand scheduler requires your trainable to support saving and restoring, which is described in Tune User Guide. Checkpointing enables the scheduler to multiplex many concurrent trials onto a limited size cluster.

Tune also implements the standard version of HyperBand. You can use it as such:

```
tune.run( ... , scheduler=HyperBandScheduler())
```

An example of this can be found in hyperband_example.py. The progress of one such HyperBand run is shown below.

```
== Status ==
Using HyperBand: num_stopped=0 total_brackets=5
Round #0:
  Bracket(n=5, r=100, completed=80%): {'PAUSED': 4, 'PENDING': 1}
  Bracket(n=8, r=33, completed=23%): {'PAUSED': 4, 'PENDING': 4}
  Bracket(n=15, r=11, completed=4%): {'RUNNING': 2, 'PAUSED': 2, 'PENDING': 11}
  Bracket(n=34, r=3, completed=0%): {'RUNNING': 2, 'PENDING': 32}
  Bracket(n=81, r=1, completed=0%): {'PENDING': 38}
Resources used: 4/4 CPUs, 0/0 GPUs
Result logdir: ~/ray_results/hyperband_test
PAUSED trials:
 - my_class_0_height=99,width=43:   PAUSED [pid=11664], 0 s, 100 ts, 97.1 rew
 - my_class_11_height=85,width=81:  PAUSED [pid=11771], 0 s, 33 ts, 32.8 rew
 - my_class_12_height=0,width=52:   PAUSED [pid=11785], 0 s, 33 ts, 0 rew
 - my_class_19_height=44,width=88:  PAUSED [pid=11811], 0 s, 11 ts, 5.47 rew
```

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```
 - my_class_27_height=96,width=84:  PAUSED [pid=11840], 0 s, 11 ts, 12.5 rew
  ... 5 more not shown
PENDING trials:
 - my_class_10_height=12,width=25:  PENDING
 - my_class_13_height=90,width=45:  PENDING
 - my_class_14_height=69,width=45:  PENDING
 - my_class_15_height=41,width=11:  PENDING
 - my_class_16_height=57,width=69:  PENDING
  ... 81 more not shown
RUNNING trials:
 - my_class_23_height=75,width=51:  RUNNING [pid=11843], 0 s, 1 ts, 1.47 rew
 - my_class_26_height=16,width=48:  RUNNING
 - my_class_31_height=40,width=10:  RUNNING
 - my_class_53_height=28,width=96:  RUNNING
```

class ray.tune.schedulers.**HyperBandScheduler**(*time_attr='training_iteration'*, *reward_attr=None*, *metric='episode_reward_mean'*, *mode='max'*, *max_t=81*, *reduction_factor=3*)

Implements the HyperBand early stopping algorithm.

HyperBandScheduler early stops trials using the HyperBand optimization algorithm. It divides trials into brackets of varying sizes, and periodically early stops low-performing trials within each bracket.

To use this implementation of HyperBand with Tune, all you need to do is specify the max length of time a trial can run *max_t*, the time units *time_attr*, the name of the reported objective value *metric*, and if *metric* is to be maximized or minimized (*mode*). We automatically determine reasonable values for the other HyperBand parameters based on the given values.

For example, to limit trials to 10 minutes and early stop based on the *episode_mean_reward* attr, construct:

```
HyperBand('time_total_s', 'episode_reward_mean', max_t=600)
```

Note that Tune's stopping criteria will be applied in conjunction with HyperBand's early stopping mechanisms.

See also: https://people.eecs.berkeley.edu/~kjamieson/hyperband.html

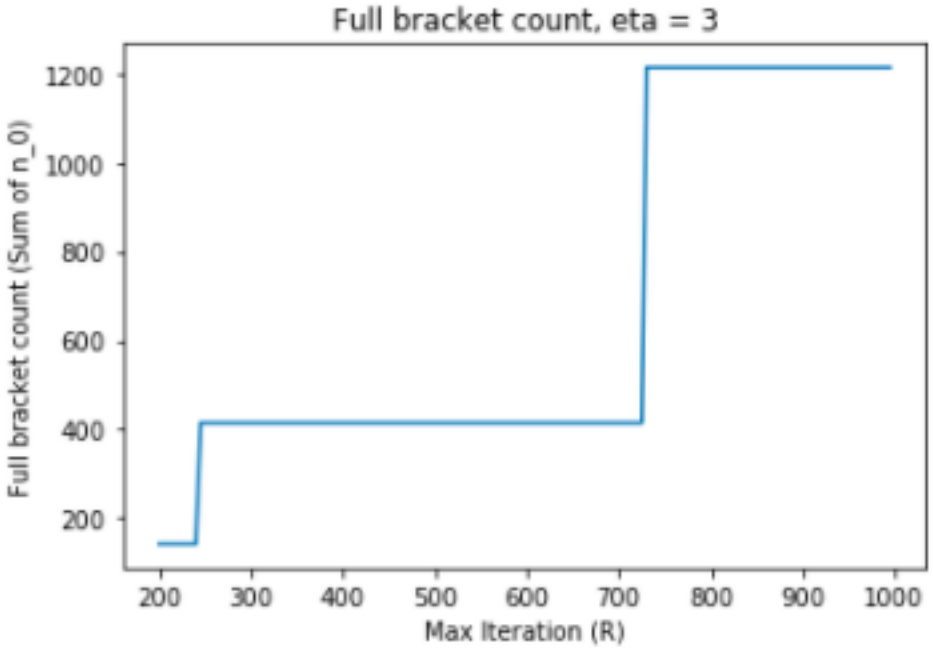
Parameters

- **time_attr** (*str*) – The training result attr to use for comparing time. Note that you can pass in something non-temporal such as *training_iteration* as a measure of progress, the only requirement is that the attribute should increase monotonically.
- **metric** (*str*) – The training result objective value attribute. Stopping procedures will use this attribute.
- **mode** (*str*) – One of {min, max}. Determines whether objective is minimizing or maximizing the metric attribute.
- **max_t** (*int*) – max time units per trial. Trials will be stopped after max_t time units (determined by time_attr) have passed. The scheduler will terminate trials after this time has passed. Note that this is different from the semantics of *max_t* as mentioned in the original HyperBand paper.
- **reduction_factor** (*float*) – Same as *eta*. Determines how sharp the difference is between bracket space-time allocation ratios.

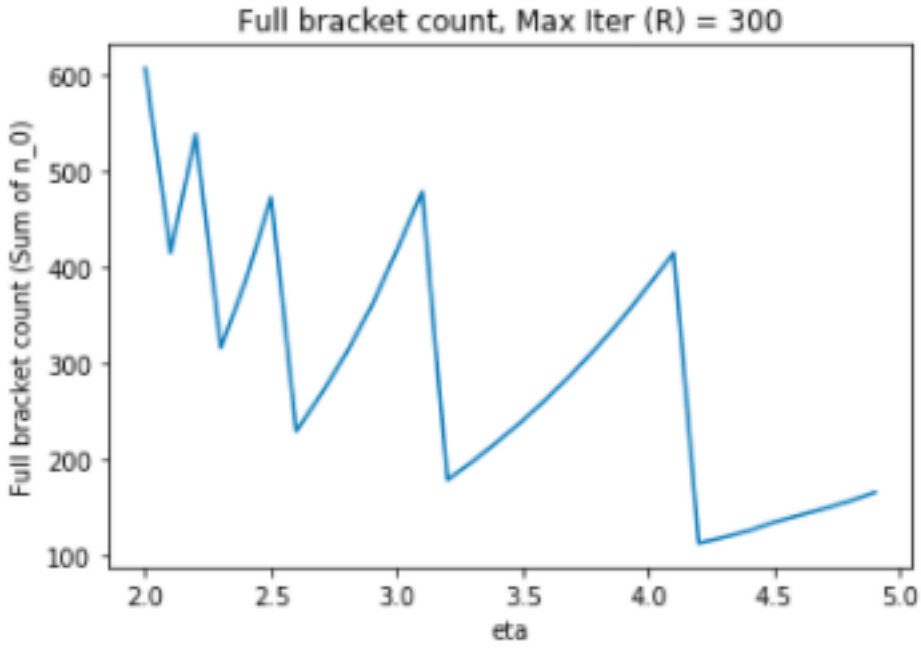
HyperBand Implementation Details

Implementation details may deviate slightly from theory but are focused on increasing usability. Note: `R`, `s_max`, and `eta` are parameters of HyperBand given by the paper. See this post for context.

1. Both `s_max` (representing the `number of brackets - 1`) and `eta`, representing the downsampling rate, are fixed. In many practical settings, `R`, which represents some resource unit and often the number of training iterations, can be set reasonably large, like `R >= 200`. For simplicity, assume `eta = 3`. Varying `R` between `R = 200` and `R = 1000` creates a huge range of the number of trials needed to fill up all brackets.

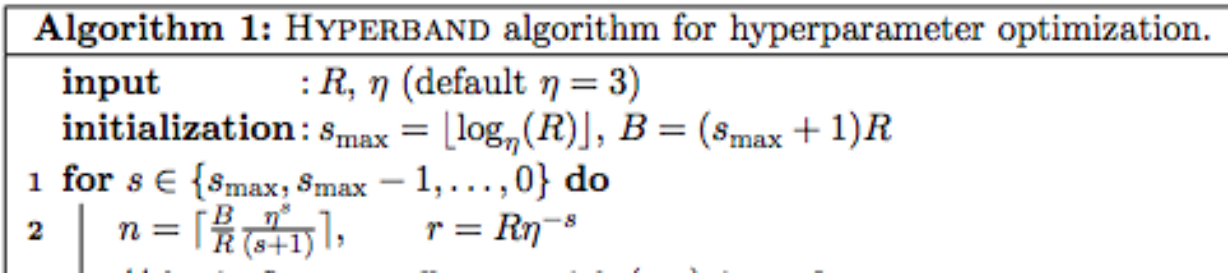


On the other hand, holding `R` constant at `R = 300` and varying `eta` also leads to HyperBand configurations that are not very intuitive:



The implementation takes the same configuration as the example given in the paper and exposes `max_t`, which is not a parameter in the paper.

2. The example in the post to calculate `n_0` is actually a little different than the algorithm given in the paper. In this implementation, we implement `n_0` according to the paper (which is n in the below example):



3. There are also implementation specific details like how trials are placed into brackets which are not covered in the paper. This implementation places trials within brackets according to smaller bracket first - meaning that with low number of trials, there will be less early stopping.

5.19.4 HyperBand (BOHB)

Tip: This implementation is still experimental. Please report issues on https://github.com/ray-project/ray/issues/. Thanks!

This class is a variant of HyperBand that enables the BOHB Algorithm. This implementation is true to the original HyperBand implementation and does not implement pipelining nor straggler mitigation.

This is to be used in conjunction with the Tune BOHB search algorithm. See TuneBOHB for package requirements, examples, and details.

An example of this in use can be found in bohb_example.py.

class ray.tune.schedulers.**HyperBandForBOHB**(*time_attr='training_iteration'*, *reward_attr=None*, *metric='episode_reward_mean'*, *mode='max'*, *max_t=81*, *reduction_factor=3*)

Extends HyperBand early stopping algorithm for BOHB.

This implementation removes the `HyperBandScheduler` pipelining. This class introduces key changes:

1. Trials are now placed so that the bracket with the largest size is filled first.

2. Trials will be paused even if the bracket is not filled. This allows BOHB to insert new trials into the training.

See ray.tune.schedulers.HyperBandScheduler for parameter docstring.

5.19.5 Median Stopping Rule

The Median Stopping Rule implements the simple strategy of stopping a trial if its performance falls below the median of other trials at similar points in time. You can set the `scheduler` parameter as such:

```
tune.run( ... , scheduler=MedianStoppingRule())
```

class ray.tune.schedulers.**MedianStoppingRule**(*time_attr='time_total_s'*, *reward_attr=None*, *metric='episode_reward_mean'*, *mode='max'*, *grace_period=60.0*, *min_samples_required=3*, *min_time_slice=0*, *hard_stop=True*)

Implements the median stopping rule as described in the Vizier paper:

https://research.google.com/pubs/pub46180.html

Parameters

- **time_attr** (*str*) – The training result attr to use for comparing time. Note that you can pass in something non-temporal such as *training_iteration* as a measure of progress, the only requirement is that the attribute should increase monotonically.
- **metric** (*str*) – The training result objective value attribute. Stopping procedures will use this attribute.
- **mode** (*str*) – One of {min, max}. Determines whether objective is minimizing or maximizing the metric attribute.
- **grace_period** (*float*) – Only stop trials at least this old in time. The mean will only be computed from this time onwards. The units are the same as the attribute named by *time_attr*.
- **min_samples_required** (*int*) – Minimum number of trials to compute median over.
- **min_time_slice** (*float*) – Each trial runs at least this long before yielding (assuming it isn't stopped). Note: trials ONLY yield if there are not enough samples to evaluate performance for the current result AND there are other trials waiting to run. The units are the same as the attribute named by *time_attr*.
- **hard_stop** (*bool*) – If False, pauses trials instead of stopping them. When all other trials are complete, paused trials will be resumed and allowed to run FIFO.

5.20 Tune Search Algorithms

Tune provides various hyperparameter search algorithms to efficiently optimize your model. Tune allows you to use different search algorithms in combination with different trial schedulers. Tune will by default implicitly use the Variant Generation algorithm to create trials.

You can utilize these search algorithms as follows:

```
tune.run(my_function, search_alg=SearchAlgorithm(...))
```

Currently, Tune offers the following search algorithms (and library integrations):

- Grid Search and Random Search
- BayesOpt
- HyperOpt
- SigOpt
- Nevergrad
- Scikit-Optimize
- Ax
- BOHB

5.20.1 Variant Generation (Grid Search/Random Search)

By default, Tune uses the default search space and variant generation process to create and queue trials. This supports random search and grid search as specified by the `config` parameter of `tune.run`.

class `ray.tune.suggest.`**BasicVariantGenerator**(*shuffle=False*)

Bases: `ray.tune.suggest.search.SearchAlgorithm`

Uses Tune's variant generation for resolving variables.

See also: *ray.tune.suggest.variant_generator*.

Example

```
>>> searcher = BasicVariantGenerator()
>>> searcher.add_configurations({"experiment": { ... }})
>>> list_of_trials = searcher.next_trials()
>>> searcher.is_finished == True
```

Note that other search algorithms will not necessarily extend this class and may require a different search space declaration than the default Tune format.

5.20.2 BayesOpt Search

The `BayesOptSearch` is a SearchAlgorithm that is backed by the bayesian-optimization package to perform sequential model-based hyperparameter optimization. Note that this class does not extend `ray.tune.suggest.BasicVariantGenerator`, so you will not be able to use Tune's default variant generation/search space declaration when using BayesOptSearch.

In order to use this search algorithm, you will need to install Bayesian Optimization via the following command:

```
$ pip install bayesian-optimization
```

This algorithm requires setting a search space and defining a utility function. You can use BayesOptSearch like follows:

```
tune.run(... , search_alg=BayesOptSearch(bayesopt_space, utility_kwargs=utility_
↪params, ... ))
```

An example of this can be found in bayesopt_example.py.

class ray.tune.suggest.bayesopt.**BayesOptSearch**(*space*, *max_concurrent=10*, *reward_attr=None*, *metric='episode_reward_mean'*, *mode='max'*, *utility_kwargs=None*, *random_state=1*, *verbose=0*, ***kwargs*)

Bases: ray.tune.suggest.suggestion.SuggestionAlgorithm

A wrapper around BayesOpt to provide trial suggestions.

Requires BayesOpt to be installed. You can install BayesOpt with the command: *pip install bayesian-optimization*.

Parameters

- **space** (*dict*) – Continuous search space. Parameters will be sampled from this space which will be used to run trials.
- **max_concurrent** (*int*) – Number of maximum concurrent trials. Defaults to 10.
- **metric** (*str*) – The training result objective value attribute.
- **mode** (*str*) – One of {min, max}. Determines whether objective is minimizing or maximizing the metric attribute.
- **utility_kwargs** (*dict*) – Parameters to define the utility function. Must provide values for the keys *kind*, *kappa*, and *xi*.
- **random_state** (*int*) – Used to initialize BayesOpt.
- **verbose** (*int*) – Sets verbosity level for BayesOpt packages.

Example

```
>>> space = {
>>>     'width': (0, 20),
>>>     'height': (-100, 100),
>>> }
>>> algo = BayesOptSearch(
>>>     space, max_concurrent=4, metric="mean_loss", mode="min")
```

5.20.3 HyperOpt Search (Tree-structured Parzen Estimators)

The HyperOptSearch is a SearchAlgorithm that is backed by HyperOpt to perform sequential model-based hyperparameter optimization. Note that this class does not extend ray.tune.suggest.BasicVariantGenerator, so you will not be able to use Tune's default variant generation/search space declaration when using HyperOptSearch.

In order to use this search algorithm, you will need to install HyperOpt via the following command:

```
$ pip install --upgrade git+git://github.com/hyperopt/hyperopt.git
```

This algorithm requires using the HyperOpt search space specification. You can use HyperOptSearch like follows:

```
tune.run(... , search_alg=HyperOptSearch(hyperopt_space, ... ))
```

An example of this can be found in hyperopt_example.py.

class ray.tune.suggest.hyperopt.**HyperOptSearch**(*space*, *max_concurrent=10*, *reward_attr=None*, *metric='episode_reward_mean'*, *mode='max'*, *points_to_evaluate=None*, *n_initial_points=20*, *random_state_seed=None*, *gamma=0.25*, ***kwargs*)

Bases: ray.tune.suggest.suggestion.SuggestionAlgorithm

A wrapper around HyperOpt to provide trial suggestions.

Requires HyperOpt to be installed from source. Uses the Tree-structured Parzen Estimators algorithm, although can be trivially extended to support any algorithm HyperOpt uses. Externally added trials will not be tracked by HyperOpt. Trials of the current run can be saved using save method, trials of a previous run can be loaded using restore method, thus enabling a warm start feature.

Parameters

- **space** (*dict*) – HyperOpt configuration. Parameters will be sampled from this configuration and will be used to override parameters generated in the variant generation process.
- **max_concurrent** (*int*) – Number of maximum concurrent trials. Defaults to 10.
- **metric** (*str*) – The training result objective value attribute.
- **mode** (*str*) – One of {min, max}. Determines whether objective is minimizing or maximizing the metric attribute.
- **points_to_evaluate** (*list*) – Initial parameter suggestions to be run first. This is for when you already have some good parameters you want hyperopt to run first to help the TPE algorithm make better suggestions for future parameters. Needs to be a list of dict of hyperopt-named variables. Choice variables should be indicated by their index in the list (see example)
- **n_initial_points** (*int*) – number of random evaluations of the objective function before starting to aproximate it with tree parzen estimators. Defaults to 20.
- **random_state_seed** (*int, array_like, None*) – seed for reproducible results. Defaults to None.
- **gamma** (*float in range (0,1)*) – parameter governing the tree parzen estimators suggestion algorithm. Defaults to 0.25.

Example

```
>>> space = {
>>>     'width': hp.uniform('width', 0, 20),
>>>     'height': hp.uniform('height', -100, 100),
>>>     'activation': hp.choice("activation", ["relu", "tanh"])
>>> }
>>> current_best_params = [{
```

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```
>>>     'width': 10,
>>>     'height': 0,
>>>     'activation': 0, # The index of "relu"
>>> }]
>>> algo = HyperOptSearch(
>>>     space, max_concurrent=4, metric="mean_loss", mode="min",
>>>     points_to_evaluate=current_best_params)
```

5.20.4 SigOpt Search

The `SigOptSearch` is a SearchAlgorithm that is backed by SigOpt to perform sequential model-based hyperparameter optimization. Note that this class does not extend `ray.tune.suggest.BasicVariantGenerator`, so you will not be able to use Tune's default variant generation/search space declaration when using SigOptSearch.

In order to use this search algorithm, you will need to install SigOpt via the following command:

```
$ pip install sigopt
```

This algorithm requires the user to have a SigOpt API key to make requests to the API. Store the API token as an environment variable named `SIGOPT_KEY` like follows:

```
$ export SIGOPT_KEY= ...
```

This algorithm requires using the SigOpt experiment and space specification. You can use SigOptSearch like follows:

```
tune.run(... , search_alg=SigOptSearch(sigopt_space, ... ))
```

An example of this can be found in sigopt_example.py.

class ray.tune.suggest.sigopt.**SigOptSearch**(*space*, *name='Default Tune Experiment'*, *max_concurrent=1*, *reward_attr=None*, *metric='episode_reward_mean'*, *mode='max'*, ***kwargs*)

Bases: `ray.tune.suggest.suggestion.SuggestionAlgorithm`

A wrapper around SigOpt to provide trial suggestions.

Requires SigOpt to be installed. Requires user to store their SigOpt API key locally as an environment variable at *SIGOPT_KEY*.

Parameters

- **space** (*list of dict*) – SigOpt configuration. Parameters will be sampled from this configuration and will be used to override parameters generated in the variant generation process.
- **name** (*str*) – Name of experiment. Required by SigOpt.
- **max_concurrent** (*int*) – Number of maximum concurrent trials supported based on the user's SigOpt plan. Defaults to 1.
- **metric** (*str*) – The training result objective value attribute.
- **mode** (*str*) – One of {min, max}. Determines whether objective is minimizing or maximizing the metric attribute.

Example

```
>>> space = [
>>>     {
>>>         'name': 'width',
>>>         'type': 'int',
>>>         'bounds': {
>>>             'min': 0,
>>>             'max': 20
>>>         },
>>>     },
>>>     {
>>>         'name': 'height',
>>>         'type': 'int',
>>>         'bounds': {
>>>             'min': -100,
>>>             'max': 100
>>>         },
>>>     },
>>> ]
>>> algo = SigOptSearch(
>>>     space, name="SigOpt Example Experiment",
>>>     max_concurrent=1, metric="mean_loss", mode="min")
```

5.20.5 Nevergrad Search

The `NevergradSearch` is a SearchAlgorithm that is backed by Nevergrad to perform sequential model-based hyperparameter optimization. Note that this class does not extend `ray.tune.suggest.BasicVariantGenerator`, so you will not be able to use Tune's default variant generation/search space declaration when using NevergradSearch.

In order to use this search algorithm, you will need to install Nevergrad via the following command.:

```
$ pip install nevergrad
```

Keep in mind that `nevergrad` is a Python 3.6+ library.

This algorithm requires using an optimizer provided by `nevergrad`, of which there are many options. A good rundown can be found on their README's Optimization section. You can use `NevergradSearch` like follows:

```
tune.run(... , search_alg=NevergradSearch(optimizer, parameter_names, ... ))
```

An example of this can be found in nevergrad_example.py.

class ray.tune.suggest.nevergrad.**NevergradSearch**(*optimizer*, *parameter_names*, *max_concurrent=10*, *reward_attr=None*, *metric='episode_reward_mean'*, *mode='max'*, ***kwargs*)

Bases: `ray.tune.suggest.suggestion.SuggestionAlgorithm`

A wrapper around Nevergrad to provide trial suggestions.

Requires Nevergrad to be installed. Nevergrad is an open source tool from Facebook for derivative free optimization of parameters and/or hyperparameters. It features a wide range of optimizers in a standard ask and tell interface. More information can be found at https://github.com/facebookresearch/nevergrad.

Parameters

- **optimizer** (*nevergrad.optimization.Optimizer*) – Optimizer provided from Nevergrad.
- **parameter_names** (*list*) – List of parameter names. Should match the dimension of the optimizer output. Alternatively, set to None if the optimizer is already instrumented with kwargs (see nevergrad v0.2.0+).
- **max_concurrent** (*int*) – Number of maximum concurrent trials. Defaults to 10.
- **metric** (*str*) – The training result objective value attribute.
- **mode** (*str*) – One of {min, max}. Determines whether objective is minimizing or maximizing the metric attribute.

Example

```
>>> from nevergrad.optimization import optimizerlib
>>> instrumentation = 1
>>> optimizer = optimizerlib.OnePlusOne(instrumentation, budget=100)
>>> algo = NevergradSearch(optimizer, ["lr"], max_concurrent=4,
>>>                        metric="mean_loss", mode="min")
```

Note: In nevergrad v0.2.0+, optimizers can be instrumented. For instance, the following will specifies searching for "lr" from 1 to 2.

```
>>> from nevergrad.optimization import optimizerlib
>>> from nevergrad import instrumentation as inst
>>> lr = inst.var.Array(1).bounded(1, 2).asfloat()
>>> instrumentation = inst.Instrumentation(lr=lr)
>>> optimizer = optimizerlib.OnePlusOne(instrumentation, budget=100)
>>> algo = NevergradSearch(optimizer, None, max_concurrent=4,
>>>                        metric="mean_loss", mode="min")
```

5.20.6 Scikit-Optimize Search

The `SkOptSearch` is a SearchAlgorithm that is backed by Scikit-Optimize to perform sequential model-based hyperparameter optimization. Note that this class does not extend `ray.tune.suggest.BasicVariantGenerator`, so you will not be able to use Tune's default variant generation/search space declaration when using SkOptSearch.

In order to use this search algorithm, you will need to install Scikit-Optimize via the following command:

```
$ pip install scikit-optimize
```

This algorithm requires using the Scikit-Optimize ask and tell interface. This interface requires using the Optimizer provided by Scikit-Optimize. You can use SkOptSearch like follows:

```
optimizer = Optimizer(dimension, ...)
tune.run(... , search_alg=SkOptSearch(optimizer, parameter_names, ... ))
```

An example of this can be found in skopt_example.py.

class ray.tune.suggest.skopt.**SkOptSearch**(*optimizer*, *parameter_names*, *max_concurrent=10*, *reward_attr=None*, *metric='episode_reward_mean'*, *mode='max'*, *points_to_evaluate=None*, *evaluated_rewards=None*, ***kwargs*)

Bases: ray.tune.suggest.suggestion.SuggestionAlgorithm

A wrapper around skopt to provide trial suggestions.

Requires skopt to be installed.

Parameters

- **optimizer** (*skopt.optimizer.Optimizer*) – Optimizer provided from skopt.
- **parameter_names** (*list*) – List of parameter names. Should match the dimension of the optimizer output.
- **max_concurrent** (*int*) – Number of maximum concurrent trials. Defaults to 10.
- **metric** (*str*) – The training result objective value attribute.
- **mode** (*str*) – One of {min, max}. Determines whether objective is minimizing or maximizing the metric attribute.
- **points_to_evaluate** (*list of lists*) – A list of points you'd like to run first before sampling from the optimiser, e.g. these could be parameter configurations you already know work well to help the optimiser select good values. Each point is a list of the parameters using the order definition given by parameter_names.
- **evaluated_rewards** (*list*) – If you have previously evaluated the parameters passed in as points_to_evaluate you can avoid re-running those trials by passing in the reward attributes as a list so the optimiser can be told the results without needing to re-compute the trial. Must be the same length as points_to_evaluate. (See tune/examples/skopt_example.py)

Example

```
>>> from skopt import Optimizer
>>> optimizer = Optimizer([(0,20),(-100,100)])
>>> current_best_params = [[10, 0], [15, -20]]
>>> algo = SkOptSearch(optimizer,
>>>     ["width", "height"],
>>>     max_concurrent=4,
>>>     metric="mean_loss",
>>>     mode="min",
>>>     points_to_evaluate=current_best_params)
```

5.20.7 Ax Search

The AxSearch is a SearchAlgorithm that is backed by Ax to perform sequential model-based hyperparameter optimization. Ax is a platform for understanding, managing, deploying, and automating adaptive experiments. Ax provides an easy to use interface with BoTorch, a flexible, modern library for Bayesian optimization in PyTorch. Note that this class does not extend ray.tune.suggest.BasicVariantGenerator, so you will not be able to use Tune's default variant generation/search space declaration when using AxSearch.

In order to use this search algorithm, you will need to install PyTorch, Ax, and sqlalchemy. Instructions to install PyTorch locally can be found here. You can install Ax and sqlalchemy via the following command:

```
$ pip install ax-platform sqlalchemy
```

This algorithm requires specifying a search space and objective. You can use *AxSearch* like follows:

```
client = AxClient(enforce_sequential_optimization=False)
client.create_experiment( ... )
tune.run(... , search_alg=AxSearch(client))
```

An example of this can be found in ax_example.py.

class ray.tune.suggest.ax.**AxSearch**(*ax_client*, *max_concurrent=10*, ***kwargs*)

Bases: ray.tune.suggest.suggestion.SuggestionAlgorithm

A wrapper around Ax to provide trial suggestions.

Requires Ax to be installed. Ax is an open source tool from Facebook for configuring and optimizing experiments. More information can be found in https://ax.dev/.

Parameters

- **parameters** (*list[dict]*) – Parameters in the experiment search space. Required elements in the dictionaries are: "name" (name of this parameter, string), "type" (type of the parameter: "range", "fixed", or "choice", string), "bounds" for range parameters (list of two values, lower bound first), "values" for choice parameters (list of values), and "value" for fixed parameters (single value).
- **objective_name** (*str*) – Name of the metric used as objective in this experiment. This metric must be present in *raw_data* argument to *log_data*. This metric must also be present in the dict reported/returned by the Trainable.
- **max_concurrent** (*int*) – Number of maximum concurrent trials. Defaults to 10.
- **minimize** (*bool*) – Whether this experiment represents a minimization problem. Defaults to False.
- **parameter_constraints** (*list[str]*) – Parameter constraints, such as "x3 >= x4" or "x3 + x4 >= 2".
- **outcome_constraints** (*list[str]*) – Outcome constraints of form "metric_name >= bound", like "m1 <= 3."

Example

```
>>> parameters = [
>>>     {"name": "x1", "type": "range", "bounds": [0.0, 1.0]},
>>>     {"name": "x2", "type": "range", "bounds": [0.0, 1.0]},
>>> ]
>>> algo = AxSearch(parameters=parameters,
>>>     objective_name="hartmann6", max_concurrent=4)
```

5.20.8 BOHB

Tip: This implementation is still experimental. Please report issues on https://github.com/ray-project/ray/issues/. Thanks!

BOHB (Bayesian Optimization HyperBand) is a SearchAlgorithm that is backed by HpBandSter to perform sequential model-based hyperparameter optimization in conjunction with HyperBand. Note that this class does not extend `ray.tune.suggest.BasicVariantGenerator`, so you will not be able to use Tune's default variant generation/search space declaration when using BOHB.

Importantly, BOHB is intended to be paired with a specific scheduler class: HyperBandForBOHB.

This algorithm requires using the ConfigSpace search space specification. In order to use this search algorithm, you will need to install `HpBandSter` and `ConfigSpace`:

```
$ pip install hpbandster ConfigSpace
```

You can use `TuneBOHB` in conjunction with `HyperBandForBOHB` as follows:

```
# BOHB uses ConfigSpace for their hyperparameter search space
import ConfigSpace as CS

config_space = CS.ConfigurationSpace()
config_space.add_hyperparameter(
    CS.UniformFloatHyperparameter("height", lower=10, upper=100))
config_space.add_hyperparameter(
    CS.UniformFloatHyperparameter("width", lower=0, upper=100))

experiment_metrics = dict(metric="episode_reward_mean", mode="min")
bohb_hyperband = HyperBandForBOHB(
    time_attr="training_iteration", max_t=100, **experiment_metrics)
bohb_search = TuneBOHB(
    config_space, max_concurrent=4, **experiment_metrics)

tune.run(MyTrainableClass,
    name="bohb_test",
    scheduler=bohb_hyperband,
    search_alg=bohb_search,
    num_samples=5)
```

Take a look at an example here. See the BOHB paper for more details.

class ray.tune.suggest.bohb.**TuneBOHB**(*space*, *bohb_config=None*, *max_concurrent=10*, *metric='neg_mean_loss'*, *mode='max'*)

Bases: `ray.tune.suggest.suggestion.SuggestionAlgorithm`

BOHB suggestion component.

Requires HpBandSter and ConfigSpace to be installed. You can install HpBandSter and ConfigSpace with: *pip install hpbandster ConfigSpace*.

This should be used in conjunction with HyperBandForBOHB.

Parameters

- **space** (*ConfigurationSpace*) – Continuous ConfigSpace search space. Parameters will be sampled from this space which will be used to run trials.
- **bohb_config** (*dict*) – configuration for HpBandSter BOHB algorithm
- **max_concurrent** (*int*) – Number of maximum concurrent trials. Defaults to 10.
- **metric** (*str*) – The training result objective value attribute.
- **mode** (*str*) – One of {min, max}. Determines whether objective is minimizing or maximizing the metric attribute.

Example

```
>>> import ConfigSpace as CS
>>> config_space = CS.ConfigurationSpace()
>>> config_space.add_hyperparameter(
        CS.UniformFloatHyperparameter('width', lower=0, upper=20))
>>> config_space.add_hyperparameter(
        CS.UniformFloatHyperparameter('height', lower=-100, upper=100))
>>> config_space.add_hyperparameter(
        CS.CategoricalHyperparameter(
            name='activation', choices=['relu', 'tanh']))
>>> algo = TuneBOHB(
        config_space, max_concurrent=4, metric='mean_loss', mode='min')
>>> bohb = HyperBandForBOHB(
        time_attr='training_iteration',
        metric='mean_loss',
        mode='min',
        max_t=100)
>>> run(MyTrainableClass, scheduler=bohb, search_alg=algo)
```

5.20.9 Contributing a New Algorithm

If you are interested in implementing or contributing a new Search Algorithm, the API is straightforward:

class ray.tune.suggest.**SearchAlgorithm**

Interface of an event handler API for hyperparameter search.

Unlike TrialSchedulers, SearchAlgorithms will not have the ability to modify the execution (i.e., stop and pause trials).

Trials added manually (i.e., via the Client API) will also notify this class upon new events, so custom search algorithms should maintain a list of trials ID generated from this class.

See also: *ray.tune.suggest.BasicVariantGenerator*.

add_configurations(*experiments*)

Tracks given experiment specifications.

Parameters **experiments** (*Experiment | list | dict*) – Experiments to run.

next_trials()

Provides Trial objects to be queued into the TrialRunner.

Returns Returns a list of trials.

Return type trials (list)

on_trial_result(*trial_id*, *result*)

Called on each intermediate result returned by a trial.

This will only be called when the trial is in the RUNNING state.

Parameters **trial_id** – Identifier for the trial.

on_trial_complete(*trial_id*, *result=None*, *error=False*, *early_terminated=False*)

Notification for the completion of trial.

Parameters

- **trial_id** – Identifier for the trial.

- **result** (*dict*) – Defaults to None. A dict will be provided with this notification when the trial is in the RUNNING state AND either completes naturally or by manual termination.
- **error** (*bool*) – Defaults to False. True if the trial is in the RUNNING state and errors.
- **early_terminated** (*bool*) – Defaults to False. True if the trial is stopped while in PAUSED or PENDING state.

is_finished()
Returns True if no trials left to be queued into TrialRunner.

Can return True before all trials have finished executing.

Model-Based Suggestion Algorithms

Often times, hyperparameter search algorithms are model-based and may be quite simple to implement. For this, one can extend the following abstract class and implement `on_trial_result`, `on_trial_complete`, and `_suggest`. The abstract class will take care of Tune-specific boilerplate such as creating Trials and queuing trials:

class ray.tune.suggest.**SuggestionAlgorithm**
Bases: ray.tune.suggest.search.SearchAlgorithm

Abstract class for suggestion-based algorithms.

Custom search algorithms can extend this class easily by overriding the *_suggest* method provide generated parameters for the trials.

To track suggestions and their corresponding evaluations, the method *_suggest* will be passed a trial_id, which will be used in subsequent notifications.

Example

```
>>> suggester = SuggestionAlgorithm()
>>> suggester.add_configurations({ ... })
>>> new_parameters = suggester._suggest()
>>> suggester.on_trial_complete(trial_id, result)
>>> better_parameters = suggester._suggest()
```

_suggest(*trial_id*)
Queries the algorithm to retrieve the next set of parameters.

Parameters **trial_id** – Trial ID used for subsequent notifications.

Returns

Configuration for a trial, if possible. Else, returns None, which will temporarily stop the TrialRunner from querying.

Return type dict|None

Example

```
>>> suggester = SuggestionAlgorithm(max_concurrent=1)
>>> suggester.add_configurations({ ... })
>>> parameters_1 = suggester._suggest()
```

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```
>>> parameters_2 = suggester._suggest()
>>> parameters_2 is None
>>> suggester.on_trial_complete(trial_id, result)
>>> parameters_2 = suggester._suggest()
>>> parameters_2 is not None
```

5.21 Tune Package Reference

5.21.1 ray.tune

ray.tune.**grid_search**(*values*)
Convenience method for specifying grid search over a value.

Parameters **values** – An iterable whose parameters will be gridded.

ray.tune.**register_env**(*name*, *env_creator*)
Register a custom environment for use with RLlib.

Parameters

- **name** (*str*) – Name to register.
- **env_creator** (*obj*) – Function that creates an env.

ray.tune.**register_trainable**(*name*, *trainable*)
Register a trainable function or class.

Parameters

- **name** (*str*) – Name to register.
- **trainable** (*obj*) – Function or tune.Trainable class. Functions must take (config, status_reporter) as arguments and will be automatically converted into a class during registration.

ray.tune.**run**(*run_or_experiment*, *name=None*, *stop=None*, *config=None*, *resources_per_trial=None*, *num_samples=1*, *local_dir=None*, *upload_dir=None*, *trial_name_creator=None*, *loggers=None*, *sync_to_cloud=None*, *sync_to_driver=None*, *checkpoint_freq=0*, *checkpoint_at_end=False*, *keep_checkpoints_num=None*, *checkpoint_score_attr=None*, *global_checkpoint_period=10*, *export_formats=None*, *max_failures=3*, *restore=None*, *search_alg=None*, *scheduler=None*, *with_server=False*, *server_port=4321*, *verbose=2*, *resume=False*, *queue_trials=False*, *reuse_actors=False*, *trial_executor=None*, *raise_on_failed_trial=True*, *return_trials=False*, *ray_auto_init=True*, *sync_function=None*)
Executes training.

Parameters

- **run_or_experiment** (*function|class|str|Experiment*) – If function|class|str, this is the algorithm or model to train. This may refer to the name of a built-on algorithm (e.g. RLLib's DQN or PPO), a user-defined trainable function or class, or the string identifier of a trainable function or class registered in the tune registry. If Experiment, then Tune will execute training based on Experiment.spec.
- **name** (*str*) – Name of experiment.

- **stop** (*dict|func*) – The stopping criteria. If dict, the keys may be any field in the return result of 'train()', whichever is reached first. If function, it must take (trial_id, result) as arguments and return a boolean (True if trial should be stopped, False otherwise).
- **config** (*dict*) – Algorithm-specific configuration for Tune variant generation (e.g. env, hyperparams). Defaults to empty dict. Custom search algorithms may ignore this.
- **resources_per_trial** (*dict*) – Machine resources to allocate per trial, e.g. `{"cpu": 64, "gpu": 8}`. Note that GPUs will not be assigned unless you specify them here. Defaults to 1 CPU and 0 GPUs in `Trainable.default_resource_request()`.
- **num_samples** (*int*) – Number of times to sample from the hyperparameter space. Defaults to 1. If *grid_search* is provided as an argument, the grid will be repeated *num_samples* of times.
- **local_dir** (*str*) – Local dir to save training results to. Defaults to `~/ray_results`.
- **upload_dir** (*str*) – Optional URI to sync training results to (e.g. `s3://bucket`).
- **trial_name_creator** (*func*) – Optional function for generating the trial string representation.
- **loggers** (*list*) – List of logger creators to be used with each Trial. If None, defaults to ray.tune.logger.DEFAULT_LOGGERS. See *ray/tune/logger.py*.
- **sync_to_cloud** (*func|str*) – Function for syncing the local_dir to and from upload_dir. If string, then it must be a string template that includes *{source}* and *{target}* for the syncer to run. If not provided, the sync command defaults to standard S3 or gsutil sync comamnds.
- **sync_to_driver** (*func|str*) – Function for syncing trial logdir from remote node to local. If string, then it must be a string template that includes *{source}* and *{target}* for the syncer to run. If not provided, defaults to using rsync.
- **checkpoint_freq** (*int*) – How many training iterations between checkpoints. A value of 0 (default) disables checkpointing.
- **checkpoint_at_end** (*bool*) – Whether to checkpoint at the end of the experiment regardless of the checkpoint_freq. Default is False.
- **keep_checkpoints_num** (*int*) – Number of checkpoints to keep. A value of *None* keeps all checkpoints. Defaults to *None*. If set, need to provide *checkpoint_score_attr*.
- **checkpoint_score_attr** (*str*) – Specifies by which attribute to rank the best checkpoint. Default is increasing order. If attribute starts with *min-* it will rank attribute in decreasing order, i.e. *min-validation_loss*.
- **global_checkpoint_period** (*int*) – Seconds between global checkpointing. This does not affect *checkpoint_freq*, which specifies frequency for individual trials.
- **export_formats** (*list*) – List of formats that exported at the end of the experiment. Default is None.
- **max_failures** (*int*) – Try to recover a trial from its last checkpoint at least this many times. Only applies if checkpointing is enabled. Setting to -1 will lead to infinite recovery retries. Defaults to 3.
- **restore** (*str*) – Path to checkpoint. Only makes sense to set if running 1 trial. Defaults to None.
- **search_alg** (`SearchAlgorithm`) – Search Algorithm. Defaults to BasicVariantGenerator.

- **scheduler** (TrialScheduler) – Scheduler for executing the experiment. Choose among FIFO (default), MedianStopping, AsyncHyperBand, and HyperBand.
- **with_server** (*bool*) – Starts a background Tune server. Needed for using the Client API.
- **server_port** (*int*) – Port number for launching TuneServer.
- **verbose** (*int*) – 0, 1, or 2. Verbosity mode. 0 = silent, 1 = only status updates, 2 = status and trial results.
- **resume** (*str|bool*) – One of "LOCAL", "REMOTE", "PROMPT", or bool. LOCAL/True restores the checkpoint from the local_checkpoint_dir. REMOTE restores the checkpoint from remote_checkpoint_dir. PROMPT provides CLI feedback. False forces a new experiment. If resume is set but checkpoint does not exist, ValueError will be thrown.
- **queue_trials** (*bool*) – Whether to queue trials when the cluster does not currently have enough resources to launch one. This should be set to True when running on an autoscaling cluster to enable automatic scale-up.
- **reuse_actors** (*bool*) – Whether to reuse actors between different trials when possible. This can drastically speed up experiments that start and stop actors often (e.g., PBT in time-multiplexing mode). This requires trials to have the same resource requirements.
- **trial_executor** (*TrialExecutor*) – Manage the execution of trials.
- **raise_on_failed_trial** (*bool*) – Raise TuneError if there exists failed trial (of ERROR state) when the experiments complete.
- **ray_auto_init** (*bool*) – Automatically starts a local Ray cluster if using a RayTrialExecutor (which is the default) and if Ray is not initialized. Defaults to True.
- **sync_function** – Deprecated. See *sync_to_cloud* and *sync_to_driver*.

Returns List of Trial objects.

Raises TuneError if any trials failed and *raise_on_failed_trial* is True.

Examples

```
>>> tune.run(mytrainable, scheduler=PopulationBasedTraining())
```

```
>>> tune.run(mytrainable, num_samples=5, reuse_actors=True)
```

```
>>> tune.run(
        "PG",
        num_samples=5,
        config={
            "env": "CartPole-v0",
            "lr": tune.sample_from(lambda _: np.random.rand())
        }
    )
```

ray.tune.**run_experiments**(*experiments*, *search_alg=None*, *scheduler=None*, *with_server=False*, *server_port=4321*, *verbose=2*, *resume=False*, *queue_trials=False*, *reuse_actors=False*, *trial_executor=None*, *raise_on_failed_trial=True*)

Runs and blocks until all trials finish.

Examples

```
>>> experiment_spec = Experiment("experiment", my_func)
>>> run_experiments(experiments=experiment_spec)
```

```
>>> experiment_spec = {"experiment": {"run": my_func}}
>>> run_experiments(experiments=experiment_spec)
```

```
>>> run_experiments(
>>>     experiments=experiment_spec,
>>>     scheduler=MedianStoppingRule(...))
```

```
>>> run_experiments(
>>>     experiments=experiment_spec,
>>>     search_alg=SearchAlgorithm(),
>>>     scheduler=MedianStoppingRule(...))
```

Returns List of Trial objects, holding data for each executed trial.

class ray.tune.**Experiment**(*name*, *run*, *stop=None*, *config=None*, *resources_per_trial=None*, *num_samples=1*, *local_dir=None*, *upload_dir=None*, *trial_name_creator=None*, *loggers=None*, *sync_to_driver=None*, *checkpoint_freq=0*, *checkpoint_at_end=False*, *keep_checkpoints_num=None*, *checkpoint_score_attr=None*, *export_formats=None*, *max_failures=3*, *restore=None*, *repeat=None*, *trial_resources=None*, *sync_function=None*)

Bases: object

Tracks experiment specifications.

Implicitly registers the Trainable if needed.

Examples

```
>>> experiment_spec = Experiment(
>>>     "my_experiment_name",
>>>     my_func,
>>>     stop={"mean_accuracy": 100},
>>>     config={
>>>         "alpha": tune.grid_search([0.2, 0.4, 0.6]),
>>>         "beta": tune.grid_search([1, 2]),
>>>     },
>>>     resources_per_trial={
>>>         "cpu": 1,
>>>         "gpu": 0
>>>     },
>>>     num_samples=10,
>>>     local_dir="~/ray_results",
>>>     checkpoint_freq=10,
>>>     max_failures=2)
```

classmethod from_json(*name*, *spec*)

Generates an Experiment object from JSON.

Parameters

- **name** (*str*) – Name of Experiment.
- **spec** (*dict*) – JSON configuration of experiment.

class ray.tune.**sample_from**(*func*)
Bases: object

Specify that tune should sample configuration values from this function.

Parameters **func** – An callable function to draw a sample from.

ray.tune.**uniform**(**args*, ***kwargs*)
Wraps tune.sample_from around np.random.uniform.

tune.uniform(1, 10) is equivalent to tune.sample_from(lambda _: np.random.uniform(1, 10))

ray.tune.**choice**(**args*, ***kwargs*)
Wraps tune.sample_from around np.random.choice.

tune.choice(10) is equivalent to tune.sample_from(lambda _: np.random.choice(10))

ray.tune.**randint**(**args*, ***kwargs*)
Wraps tune.sample_from around np.random.randint.

tune.randint(10) is equivalent to tune.sample_from(lambda _: np.random.randint(10))

ray.tune.**randn**(**args*, ***kwargs*)
Wraps tune.sample_from around np.random.randn.

tune.randn(10) is equivalent to tune.sample_from(lambda _: np.random.randn(10))

ray.tune.**loguniform**(*min_bound*, *max_bound*, *base=10*)
Sugar for sampling in different orders of magnitude.

Parameters

- **min_bound** (*float*) – Lower boundary of the output interval (1e-4)
- **max_bound** (*float*) – Upper boundary of the output interval (1e-2)
- **base** (*float*) – Base of the log. Defaults to 10.

class ray.tune.**ExperimentAnalysis**(*experiment_checkpoint_path*, *trials=None*)
Bases: ray.tune.analysis.experiment_analysis.Analysis

Analyze results from a Tune experiment.

Parameters **experiment_checkpoint_path** (*str*) – Path to a json file representing an experiment state. Corresponds to Experiment.local_dir/Experiment.name/experiment_state.json

Example

```
>>> tune.run(my_trainable, name="my_exp", local_dir="~/tune_results")
>>> analysis = ExperimentAnalysis(
>>>     experiment_checkpoint_path="~/tune_results/my_exp/state.json")
```

stats()
Returns a dictionary of the statistics of the experiment.

runner_data()
Returns a dictionary of the TrialRunner data.

class ray.tune.**Analysis**(*experiment_dir*)
Bases: object

Analyze all results from a directory of experiments.

dataframe(*metric=None*, *mode=None*)
Returns a pandas.DataFrame object constructed from the trials.

Parameters

- **metric** (*str*) – Key for trial info to order on. If None, uses last result.
- **mode** (*str*) – One of [min, max].

get_best_config(*metric*, *mode='max'*)
Retrieve the best config corresponding to the trial.

Parameters

- **metric** (*str*) – Key for trial info to order on.
- **mode** (*str*) – One of [min, max].

get_best_logdir(*metric*, *mode='max'*)
Retrieve the logdir corresponding to the best trial.

Parameters

- **metric** (*str*) – Key for trial info to order on.
- **mode** (*str*) – One of [min, max].

get_all_configs(*prefix=False*)
Returns a list of all configurations.

Parameters **prefix** (*bool*) – If True, flattens the config dict and prepends *config/*.

trial_dataframes
List of all dataframes of the trials.

class ray.tune.**Trainable**(*config=None*, *logger_creator=None*)
Abstract class for trainable models, functions, etc.

A call to `train()` on a trainable will execute one logical iteration of training. As a rule of thumb, the execution time of one train call should be large enough to avoid overheads (i.e. more than a few seconds), but short enough to report progress periodically (i.e. at most a few minutes).

Calling `save()` should save the training state of a trainable to disk, and `restore(path)` should restore a trainable to the given state.

Generally you only need to implement `_setup`, `_train`, `_save`, and `_restore` when subclassing Trainable.

Other implementation methods that may be helpful to override are `_log_result`, `reset_config`, `_stop`, and `_export_model`.

When using Tune, Tune will convert this class into a Ray actor, which runs on a separate process. Tune will also change the current working directory of this process to *self.logdir*.

classmethod default_resource_request(*config*)
Returns the resource requirement for the given configuration.

This can be overriden by sub-classes to set the correct trial resource allocation, so the user does not need to.

Example

```
>>> def default_resource_request(cls, config):
        return Resources(
            cpu=0,
            gpu=0,
            extra_cpu=config["workers"],
            extra_gpu=int(config["use_gpu"]) * config["workers"])
```

classmethod resource_help(*config*)
Returns a help string for configuring this trainable's resources.

train()
Runs one logical iteration of training.

Subclasses should override `_train()` instead to return results. This class automatically fills the following fields in the result:

done (bool): training is terminated. Filled only if not provided.

time_this_iter_s (float): Time in seconds this iteration took to run. This may be overriden in order to override the system-computed time difference.

time_total_s (float): Accumulated time in seconds for this entire experiment.

experiment_id (str): Unique string identifier for this experiment. This id is preserved across checkpoint / restore calls.

training_iteration (int): The index of this training iteration, e.g. call to train(). This is incremented after *_train()* is called.

pid (str): The pid of the training process.

date (str): A formatted date of when the result was processed.

timestamp (str): A UNIX timestamp of when the result was processed.

hostname (str): Hostname of the machine hosting the training process.

node_ip (str): Node ip of the machine hosting the training process.

Returns A dict that describes training progress.

delete_checkpoint(*checkpoint_dir*)
Removes subdirectory within checkpoint_folder

Parameters **checkpoint_dir** – path to checkpoint

save(*checkpoint_dir=None*)
Saves the current model state to a checkpoint.

Subclasses should override `_save()` instead to save state. This method dumps additional metadata alongside the saved path.

Parameters **checkpoint_dir** (*str*) – Optional dir to place the checkpoint.

Returns Checkpoint path or prefix that may be passed to restore().

save_to_object()
Saves the current model state to a Python object.

It also saves to disk but does not return the checkpoint path.

Returns Object holding checkpoint data.

restore(*checkpoint_path*)
Restores training state from a given model checkpoint.

These checkpoints are returned from calls to save().

Subclasses should override `_restore()` instead to restore state. This method restores additional metadata saved with the checkpoint.

restore_from_object(*obj*)
Restores training state from a checkpoint object.

These checkpoints are returned from calls to save_to_object().

export_model(*export_formats*, *export_dir=None*)
Exports model based on export_formats.

Subclasses should override _export_model() to actually export model to local directory.

Parameters

- **export_formats** (*list*) – List of formats that should be exported.
- **export_dir** (*str*) – Optional dir to place the exported model. Defaults to self.logdir.

Returns A dict that maps ExportFormats to successfully exported models.

reset_config(*new_config*)
Resets configuration without restarting the trial.

This method is optional, but can be implemented to speed up algorithms such as PBT, and to allow performance optimizations such as running experiments with reuse_actors=True.

Parameters **new_config** (*dir*) – Updated hyperparameter configuration for the trainable.

Returns True if reset was successful else False.

stop()
Releases all resources used by this trainable.

logdir
Directory of the results and checkpoints for this Trainable.

Tune will automatically sync this folder with the driver if execution is distributed.

Note that the current working directory will also be changed to this.

iteration
Current training iteration.

This value is automatically incremented every time *train()* is called and is automatically inserted into the training result dict.

get_config()
Returns configuration passed in by Tune.

_train()
Subclasses should override this to implement train().

The return value will be automatically passed to the loggers. Users can also return *tune.result.DONE* or *tune.result.SHOULD_CHECKPOINT* as a key to manually trigger termination or checkpointing of this trial. Note that manual checkpointing only works when subclassing Trainables.

Returns A dict that describes training progress.

_save(*tmp_checkpoint_dir*)
Subclasses should override this to implement `save()`.

> **Warning:** Do not rely on absolute paths in the implementation of `_save` and `_restore`.

Use `validate_save_restore` to catch `_save`/`_restore` errors before execution.

```
>>> from ray.tune.util import validate_save_restore
>>> validate_save_restore(MyTrainableClass)
>>> validate_save_restore(MyTrainableClass, use_object_store=True)
```

Parameters **tmp_checkpoint_dir** (*str*) – The directory where the checkpoint file must be stored. In a Tune run, if the trial is paused, the provided path may be temporary and moved.

Returns A dict or string. If string, the return value is expected to be prefixed by *tmp_checkpoint_dir*. If dict, the return value will be automatically serialized by Tune and passed to *_restore()*.

Examples

```
>>> print(trainable1._save("/tmp/checkpoint_1"))
"/tmp/checkpoint_1/my_checkpoint_file"
>>> print(trainable2._save("/tmp/checkpoint_2"))
{"some": "data"}
```

```
>>> trainable._save("/tmp/bad_example")
"/tmp/NEW_CHECKPOINT_PATH/my_checkpoint_file" # This will error.
```

_restore(*checkpoint*)
Subclasses should override this to implement restore().

> **Warning:** In this method, do not rely on absolute paths. The absolute path of the checkpoint_dir used in `_save` may be changed.

If `_save` returned a prefixed string, the prefix of the checkpoint string returned by `_save` may be changed. This is because trial pausing depends on temporary directories.

The directory structure under the checkpoint_dir provided to `_save` is preserved.

See the example below.

```
class Example(Trainable):
    def _save(self, checkpoint_path):
        print(checkpoint_path)
        return os.path.join(checkpoint_path, "my/check/point")

    def _restore(self, checkpoint):
        print(checkpoint)

>>> trainer = Example()
>>> obj = trainer.save_to_object()  # This is used when PAUSED.
```

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```
<logdir>/tmpc8k_c_6hsave_to_object/checkpoint_0/my/check/point
>>> trainer.restore_from_object(obj)  # Note the different prefix.
<logdir>/tmpb87b5axfrestore_from_object/checkpoint_0/my/check/point
```

Parameters **checkpoint** (*str|dict*) – If dict, the return value is as returned by *_save*. If a string, then it is a checkpoint path that may have a different prefix than that returned by *_save*. The directory structure underneath the *checkpoint_dir _save* is preserved.

_setup(*config*)
Subclasses should override this for custom initialization.

Parameters **config** (*dict*) – Hyperparameters and other configs given. Copy of *self.config*.

_log_result(*result*)
Subclasses can optionally override this to customize logging.

Parameters **result** (*dict*) – Training result returned by _train().

_stop()
Subclasses should override this for any cleanup on stop.

If any Ray actors are launched in the Trainable (i.e., with a RLlib trainer), be sure to kill the Ray actor process here.

You can kill a Ray actor by calling *actor.__ray_terminate__.remote()* on the actor.

_export_model(*export_formats*, *export_dir*)
Subclasses should override this to export model.

Parameters

- **export_formats** (*list*) – List of formats that should be exported.
- **export_dir** (*str*) – Directory to place exported models.

Returns A dict that maps ExportFormats to successfully exported models.

class ray.tune.function_runner.**StatusReporter**(*result_queue*, *continue_semaphore*, *logdir=None*)
Object passed into your function that you can report status through.

Example

```
>>> def trainable_function(config, reporter):
>>>     assert isinstance(reporter, StatusReporter)
>>>     reporter(timesteps_this_iter=1)
```

__call__(***kwargs*)
Report updated training status.

Pass in *done=True* when the training job is completed.

Parameters **kwargs** – Latest training result status.

Example

```
>>> reporter(mean_accuracy=1, training_iteration=4)
>>> reporter(mean_accuracy=1, training_iteration=4, done=True)
```

Raises `StopIteration` – A StopIteration exception is raised if the trial has been signaled to stop.

5.21.2 ray.tune.schedulers

class ray.tune.schedulers.**TrialScheduler**
Bases: `object`

Interface for implementing a Trial Scheduler class.

CONTINUE = 'CONTINUE'
Status for continuing trial execution

PAUSE = 'PAUSE'
Status for pausing trial execution

STOP = 'STOP'
Status for stopping trial execution

on_trial_add(*trial_runner*, *trial*)
Called when a new trial is added to the trial runner.

on_trial_error(*trial_runner*, *trial*)
Notification for the error of trial.

This will only be called when the trial is in the RUNNING state.

on_trial_result(*trial_runner*, *trial*, *result*)
Called on each intermediate result returned by a trial.

At this point, the trial scheduler can make a decision by returning one of CONTINUE, PAUSE, and STOP. This will only be called when the trial is in the RUNNING state.

on_trial_complete(*trial_runner*, *trial*, *result*)
Notification for the completion of trial.

This will only be called when the trial is in the RUNNING state and either completes naturally or by manual termination.

on_trial_remove(*trial_runner*, *trial*)
Called to remove trial.

This is called when the trial is in PAUSED or PENDING state. Otherwise, call *on_trial_complete*.

choose_trial_to_run(*trial_runner*)
Called to choose a new trial to run.

This should return one of the trials in trial_runner that is in the PENDING or PAUSED state. This function must be idempotent.

If no trial is ready, return None.

debug_string()
Returns a human readable message for printing to the console.

class ray.tune.schedulers.**HyperBandScheduler**(*time_attr='training_iteration'*, *reward_attr=None*, *metric='episode_reward_mean'*, *mode='max'*, *max_t=81*, *reduction_factor=3*)
Bases: `ray.tune.schedulers.trial_scheduler.FIFOScheduler`

Implements the HyperBand early stopping algorithm.

HyperBandScheduler early stops trials using the HyperBand optimization algorithm. It divides trials into brackets of varying sizes, and periodically early stops low-performing trials within each bracket.

To use this implementation of HyperBand with Tune, all you need to do is specify the max length of time a trial can run *max_t*, the time units *time_attr*, the name of the reported objective value *metric*, and if *metric* is to be maximized or minimized (*mode*). We automatically determine reasonable values for the other HyperBand parameters based on the given values.

For example, to limit trials to 10 minutes and early stop based on the *episode_mean_reward* attr, construct:

```
HyperBand('time_total_s', 'episode_reward_mean', max_t=600)
```

Note that Tune's stopping criteria will be applied in conjunction with HyperBand's early stopping mechanisms.

See also: https://people.eecs.berkeley.edu/~kjamieson/hyperband.html

Parameters

- **time_attr** (*str*) – The training result attr to use for comparing time. Note that you can pass in something non-temporal such as *training_iteration* as a measure of progress, the only requirement is that the attribute should increase monotonically.
- **metric** (*str*) – The training result objective value attribute. Stopping procedures will use this attribute.
- **mode** (*str*) – One of {min, max}. Determines whether objective is minimizing or maximizing the metric attribute.
- **max_t** (*int*) – max time units per trial. Trials will be stopped after max_t time units (determined by time_attr) have passed. The scheduler will terminate trials after this time has passed. Note that this is different from the semantics of *max_t* as mentioned in the original HyperBand paper.
- **reduction_factor** (*float*) – Same as *eta*. Determines how sharp the difference is between bracket space-time allocation ratios.

on_trial_add(*trial_runner*, *trial*)
Adds new trial.

On a new trial add, if current bracket is not filled, add to current bracket. Else, if current band is not filled, create new bracket, add to current bracket. Else, create new iteration, create new bracket, add to bracket.

on_trial_result(*trial_runner*, *trial*, *result*)
If bracket is finished, all trials will be stopped.

If a given trial finishes and bracket iteration is not done, the trial will be paused and resources will be given up.

This scheduler will not start trials but will stop trials. The current running trial will not be handled, as the trialrunner will be given control to handle it.

on_trial_remove(*trial_runner*, *trial*)
Notification when trial terminates.

Trial info is removed from bracket. Triggers halving if bracket is not finished.

on_trial_complete(*trial_runner*, *trial*, *result*)
Cleans up trial info from bracket if trial completed early.

on_trial_error(*trial_runner*, *trial*)
Cleans up trial info from bracket if trial errored early.

choose_trial_to_run(*trial_runner*)
Fair scheduling within iteration by completion percentage.

List of trials not used since all trials are tracked as state of scheduler. If iteration is occupied (ie, no trials to run), then look into next iteration.

debug_string()
This provides a progress notification for the algorithm.

For each bracket, the algorithm will output a string as follows:

Bracket(Max Size (n)=5, Milestone (r)=33, completed=14.6%): {PENDING: 2, RUNNING: 3, TERMINATED: 2}

"Max Size" indicates the max number of pending/running experiments set according to the Hyperband algorithm.

"Milestone" indicates the iterations a trial will run for before the next halving will occur.

"Completed" indicates an approximate progress metric. Some brackets, like ones that are unfilled, will not reach 100%.

class ray.tune.schedulers.**AsyncHyperBandScheduler**(*time_attr='training_iteration'*, *reward_attr=None*, *metric='episode_reward_mean'*, *mode='max'*, *max_t=100*, *grace_period=1*, *reduction_factor=4*, *brackets=1*)
Bases: ray.tune.schedulers.trial_scheduler.FIFOScheduler

Implements the Async Successive Halving.

This should provide similar theoretical performance as HyperBand but avoid straggler issues that HyperBand faces. One implementation detail is when using multiple brackets, trial allocation to bracket is done randomly with over a softmax probability.

See https://arxiv.org/abs/1810.05934

Parameters

- **time_attr** (*str*) – A training result attr to use for comparing time. Note that you can pass in something non-temporal such as *training_iteration* as a measure of progress, the only requirement is that the attribute should increase monotonically.
- **metric** (*str*) – The training result objective value attribute. Stopping procedures will use this attribute.
- **mode** (*str*) – One of {min, max}. Determines whether objective is minimizing or maximizing the metric attribute.
- **max_t** (*float*) – max time units per trial. Trials will be stopped after max_t time units (determined by time_attr) have passed.
- **grace_period** (*float*) – Only stop trials at least this old in time. The units are the same as the attribute named by *time_attr*.
- **reduction_factor** (*float*) – Used to set halving rate and amount. This is simply a unit-less scalar.
- **brackets** (*int*) – Number of brackets. Each bracket has a different halving rate, specified by the reduction factor.

on_trial_add(*trial_runner*, *trial*)
Called when a new trial is added to the trial runner.

on_trial_result(*trial_runner*, *trial*, *result*)
Called on each intermediate result returned by a trial.

At this point, the trial scheduler can make a decision by returning one of CONTINUE, PAUSE, and STOP. This will only be called when the trial is in the RUNNING state.

on_trial_complete(*trial_runner*, *trial*, *result*)
Notification for the completion of trial.

This will only be called when the trial is in the RUNNING state and either completes naturally or by manual termination.

on_trial_remove(*trial_runner*, *trial*)
Called to remove trial.

This is called when the trial is in PAUSED or PENDING state. Otherwise, call *on_trial_complete*.

debug_string()
Returns a human readable message for printing to the console.

ray.tune.schedulers.**ASHAScheduler**
alias of ray.tune.schedulers.async_hyperband.AsyncHyperBandScheduler

class ray.tune.schedulers.**MedianStoppingRule**(*time_attr='time_total_s'*, *reward_attr=None*, *metric='episode_reward_mean'*, *mode='max'*, *grace_period=60.0*, *min_samples_required=3*, *min_time_slice=0*, *hard_stop=True*)
Bases: ray.tune.schedulers.trial_scheduler.FIFOScheduler

Implements the median stopping rule as described in the Vizier paper:

https://research.google.com/pubs/pub46180.html

Parameters

- **time_attr** (*str*) – The training result attr to use for comparing time. Note that you can pass in something non-temporal such as *training_iteration* as a measure of progress, the only requirement is that the attribute should increase monotonically.
- **metric** (*str*) – The training result objective value attribute. Stopping procedures will use this attribute.
- **mode** (*str*) – One of {min, max}. Determines whether objective is minimizing or maximizing the metric attribute.
- **grace_period** (*float*) – Only stop trials at least this old in time. The mean will only be computed from this time onwards. The units are the same as the attribute named by *time_attr*.
- **min_samples_required** (*int*) – Minimum number of trials to compute median over.
- **min_time_slice** (*float*) – Each trial runs at least this long before yielding (assuming it isn't stopped). Note: trials ONLY yield if there are not enough samples to evaluate performance for the current result AND there are other trials waiting to run. The units are the same as the attribute named by *time_attr*.
- **hard_stop** (*bool*) – If False, pauses trials instead of stopping them. When all other trials are complete, paused trials will be resumed and allowed to run FIFO.

on_trial_result(*trial_runner*, *trial*, *result*)
Callback for early stopping.

This stopping rule stops a running trial if the trial's best objective value by step *t* is strictly worse than the median of the running averages of all completed trials' objectives reported up to step *t*.

on_trial_complete(*trial_runner*, *trial*, *result*)
Notification for the completion of trial.

This will only be called when the trial is in the RUNNING state and either completes naturally or by manual termination.

debug_string()
Returns a human readable message for printing to the console.

class ray.tune.schedulers.**FIFOScheduler**
Bases: ray.tune.schedulers.trial_scheduler.TrialScheduler

Simple scheduler that just runs trials in submission order.

on_trial_add(*trial_runner*, *trial*)
Called when a new trial is added to the trial runner.

on_trial_error(*trial_runner*, *trial*)
Notification for the error of trial.

This will only be called when the trial is in the RUNNING state.

on_trial_result(*trial_runner*, *trial*, *result*)
Called on each intermediate result returned by a trial.

At this point, the trial scheduler can make a decision by returning one of CONTINUE, PAUSE, and STOP. This will only be called when the trial is in the RUNNING state.

on_trial_complete(*trial_runner*, *trial*, *result*)
Notification for the completion of trial.

This will only be called when the trial is in the RUNNING state and either completes naturally or by manual termination.

on_trial_remove(*trial_runner*, *trial*)
Called to remove trial.

This is called when the trial is in PAUSED or PENDING state. Otherwise, call *on_trial_complete*.

choose_trial_to_run(*trial_runner*)
Called to choose a new trial to run.

This should return one of the trials in trial_runner that is in the PENDING or PAUSED state. This function must be idempotent.

If no trial is ready, return None.

debug_string()
Returns a human readable message for printing to the console.

class ray.tune.schedulers.**PopulationBasedTraining**(*time_attr='time_total_s'*, *reward_attr=None*, *metric='episode_reward_mean'*, *mode='max'*, *perturbation_interval=60.0*, *hyperparam_mutations={}*, *quantile_fraction=0.25*, *resample_probability=0.25*, *custom_explore_fn=None*, *log_config=True*)
Bases: ray.tune.schedulers.trial_scheduler.FIFOScheduler

Implements the Population Based Training (PBT) algorithm.

https://deepmind.com/blog/population-based-training-neural-networks

PBT trains a group of models (or agents) in parallel. Periodically, poorly performing models clone the state of the top performers, and a random mutation is applied to their hyperparameters in the hopes of outperforming the current top models.

Unlike other hyperparameter search algorithms, PBT mutates hyperparameters during training time. This enables very fast hyperparameter discovery and also automatically discovers good annealing schedules.

This Tune PBT implementation considers all trials added as part of the PBT population. If the number of trials exceeds the cluster capacity, they will be time-multiplexed as to balance training progress across the population. To run multiple trials, use *tune.run(num_samples=<int>)*.

Parameters

- **time_attr** (*str*) – The training result attr to use for comparing time. Note that you can pass in something non-temporal such as *training_iteration* as a measure of progress, the only requirement is that the attribute should increase monotonically.
- **metric** (*str*) – The training result objective value attribute. Stopping procedures will use this attribute.
- **mode** (*str*) – One of {min, max}. Determines whether objective is minimizing or maximizing the metric attribute.
- **perturbation_interval** (*float*) – Models will be considered for perturbation at this interval of *time_attr*. Note that perturbation incurs checkpoint overhead, so you shouldn't set this to be too frequent.
- **hyperparam_mutations** (*dict*) – Hyperparams to mutate. The format is as follows: for each key, either a list or function can be provided. A list specifies an allowed set of categorical values. A function specifies the distribution of a continuous parameter. You must specify at least one of *hyperparam_mutations* or *custom_explore_fn*.
- **quantile_fraction** (*float*) – Parameters are transferred from the top *quantile_fraction* fraction of trials to the bottom *quantile_fraction* fraction. Needs to be between 0 and 0.5. Setting it to 0 essentially implies doing no exploitation at all.
- **resample_probability** (*float*) – The probability of resampling from the original distribution when applying *hyperparam_mutations*. If not resampled, the value will be perturbed by a factor of 1.2 or 0.8 if continuous, or changed to an adjacent value if discrete.
- **custom_explore_fn** (*func*) – You can also specify a custom exploration function. This function is invoked as *f(config)* after built-in perturbations from *hyperparam_mutations* are applied, and should return *config* updated as needed. You must specify at least one of *hyperparam_mutations* or *custom_explore_fn*.
- **log_config** (*bool*) – Whether to log the ray config of each model to local_dir at each exploit. Allows config schedule to be reconstructed.

Example

```
>>> pbt = PopulationBasedTraining(
>>>     time_attr="training_iteration",
>>>     metric="episode_reward_mean",
>>>     mode="max",
>>>     perturbation_interval=10,  # every 10 `time_attr` units
>>>                                # (training_iterations in this case)
>>>     hyperparam_mutations={
```

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```
>>>         # Perturb factor1 by scaling it by 0.8 or 1.2. Resampling
>>>         # resets it to a value sampled from the lambda function.
>>>         "factor_1": lambda: random.uniform(0.0, 20.0),
>>>         # Perturb factor2 by changing it to an adjacent value, e.g.
>>>         # 10 -> 1 or 10 -> 100. Resampling will choose at random.
>>>         "factor_2": [1, 10, 100, 1000, 10000],
>>>     })
>>> tune.run({...}, num_samples=8, scheduler=pbt)
```

on_trial_add(*trial_runner*, *trial*)
Called when a new trial is added to the trial runner.

on_trial_result(*trial_runner*, *trial*, *result*)
Called on each intermediate result returned by a trial.

At this point, the trial scheduler can make a decision by returning one of CONTINUE, PAUSE, and STOP. This will only be called when the trial is in the RUNNING state.

choose_trial_to_run(*trial_runner*)
Ensures all trials get fair share of time (as defined by time_attr).

This enables the PBT scheduler to support a greater number of concurrent trials than can fit in the cluster at any given time.

debug_string()
Returns a human readable message for printing to the console.

class ray.tune.schedulers.**HyperBandForBOHB**(*time_attr='training_iteration'*, *reward_attr=None*, *metric='episode_reward_mean'*, *mode='max'*, *max_t=81*, *reduction_factor=3*)
Bases: ray.tune.schedulers.hyperband.HyperBandScheduler

Extends HyperBand early stopping algorithm for BOHB.

This implementation removes the HyperBandScheduler pipelining. This class introduces key changes:

1. Trials are now placed so that the bracket with the largest size is filled first.

2. Trials will be paused even if the bracket is not filled. This allows BOHB to insert new trials into the training.

See ray.tune.schedulers.HyperBandScheduler for parameter docstring.

on_trial_add(*trial_runner*, *trial*)
Adds new trial.

On a new trial add, if current bracket is not filled, add to current bracket. Else, if current band is not filled, create new bracket, add to current bracket. Else, create new iteration, create new bracket, add to bracket.

on_trial_result(*trial_runner*, *trial*, *result*)
If bracket is finished, all trials will be stopped.

If a given trial finishes and bracket iteration is not done, the trial will be paused and resources will be given up.

This scheduler will not start trials but will stop trials. The current running trial will not be handled, as the trialrunner will be given control to handle it.

choose_trial_to_run(*trial_runner*)
Fair scheduling within iteration by completion percentage.

List of trials not used since all trials are tracked as state of scheduler. If iteration is occupied (ie, no trials to run), then look into next iteration.

5.21.3 ray.tune.suggest

class ray.tune.suggest.**SearchAlgorithm**
Bases: object

Interface of an event handler API for hyperparameter search.

Unlike TrialSchedulers, SearchAlgorithms will not have the ability to modify the execution (i.e., stop and pause trials).

Trials added manually (i.e., via the Client API) will also notify this class upon new events, so custom search algorithms should maintain a list of trials ID generated from this class.

See also: *ray.tune.suggest.BasicVariantGenerator*.

add_configurations(*experiments*)
Tracks given experiment specifications.

Parameters **experiments** (*Experiment | list | dict*) – Experiments to run.

next_trials()
Provides Trial objects to be queued into the TrialRunner.

Returns Returns a list of trials.

Return type trials (list)

on_trial_result(*trial_id*, *result*)
Called on each intermediate result returned by a trial.

This will only be called when the trial is in the RUNNING state.

Parameters **trial_id** – Identifier for the trial.

on_trial_complete(*trial_id*, *result=None*, *error=False*, *early_terminated=False*)
Notification for the completion of trial.

Parameters

- **trial_id** – Identifier for the trial.
- **result** (*dict*) – Defaults to None. A dict will be provided with this notification when the trial is in the RUNNING state AND either completes naturally or by manual termination.
- **error** (*bool*) – Defaults to False. True if the trial is in the RUNNING state and errors.
- **early_terminated** (*bool*) – Defaults to False. True if the trial is stopped while in PAUSED or PENDING state.

is_finished()
Returns True if no trials left to be queued into TrialRunner.

Can return True before all trials have finished executing.

class ray.tune.suggest.**BasicVariantGenerator**(*shuffle=False*)
Bases: ray.tune.suggest.search.SearchAlgorithm

Uses Tune's variant generation for resolving variables.

See also: *ray.tune.suggest.variant_generator*.

Example

```
>>> searcher = BasicVariantGenerator()
>>> searcher.add_configurations({"experiment": { ... }})
>>> list_of_trials = searcher.next_trials()
>>> searcher.is_finished == True
```

add_configurations(*experiments*)
Chains generator given experiment specifications.

Parameters **experiments** (*Experiment | list | dict*) – Experiments to run.

next_trials()
Provides Trial objects to be queued into the TrialRunner.

Returns Returns a list of trials.

Return type trials (list)

is_finished()
Returns True if no trials left to be queued into TrialRunner.

Can return True before all trials have finished executing.

class ray.tune.suggest.**TuneBOHB**(*space*, *bohb_config=None*, *max_concurrent=10*, *metric='neg_mean_loss'*, *mode='max'*)
Bases: ray.tune.suggest.suggestion.SuggestionAlgorithm

BOHB suggestion component.

Requires HpBandSter and ConfigSpace to be installed. You can install HpBandSter and ConfigSpace with: *pip install hpbandster ConfigSpace*.

This should be used in conjunction with HyperBandForBOHB.

Parameters

- **space** (*ConfigurationSpace*) – Continuous ConfigSpace search space. Parameters will be sampled from this space which will be used to run trials.
- **bohb_config** (*dict*) – configuration for HpBandSter BOHB algorithm
- **max_concurrent** (*int*) – Number of maximum concurrent trials. Defaults to 10.
- **metric** (*str*) – The training result objective value attribute.
- **mode** (*str*) – One of {min, max}. Determines whether objective is minimizing or maximizing the metric attribute.

Example

```
>>> import ConfigSpace as CS
>>> config_space = CS.ConfigurationSpace()
>>> config_space.add_hyperparameter(
        CS.UniformFloatHyperparameter('width', lower=0, upper=20))
>>> config_space.add_hyperparameter(
        CS.UniformFloatHyperparameter('height', lower=-100, upper=100))
>>> config_space.add_hyperparameter(
        CS.CategoricalHyperparameter(
            name='activation', choices=['relu', 'tanh']))
>>> algo = TuneBOHB(
```

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```
        config_space, max_concurrent=4, metric='mean_loss', mode='min')
>>> bohb = HyperBandForBOHB(
        time_attr='training_iteration',
        metric='mean_loss',
        mode='min',
        max_t=100)
>>> run(MyTrainableClass, scheduler=bohb, search_alg=algo)
```

on_trial_result(*trial_id*, *result*)
Called on each intermediate result returned by a trial.

This will only be called when the trial is in the RUNNING state.

Parameters **trial_id** – Identifier for the trial.

on_trial_complete(*trial_id*, *result=None*, *error=False*, *early_terminated=False*)
Notification for the completion of trial.

Parameters

- **trial_id** – Identifier for the trial.
- **result** (*dict*) – Defaults to None. A dict will be provided with this notification when the trial is in the RUNNING state AND either completes naturally or by manual termination.
- **error** (*bool*) – Defaults to False. True if the trial is in the RUNNING state and errors.
- **early_terminated** (*bool*) – Defaults to False. True if the trial is stopped while in PAUSED or PENDING state.

class ray.tune.suggest.**SuggestionAlgorithm**
Bases: ray.tune.suggest.search.SearchAlgorithm

Abstract class for suggestion-based algorithms.

Custom search algorithms can extend this class easily by overriding the *_suggest* method provide generated parameters for the trials.

To track suggestions and their corresponding evaluations, the method *_suggest* will be passed a trial_id, which will be used in subsequent notifications.

Example

```
>>> suggester = SuggestionAlgorithm()
>>> suggester.add_configurations({ ... })
>>> new_parameters = suggester._suggest()
>>> suggester.on_trial_complete(trial_id, result)
>>> better_parameters = suggester._suggest()
```

add_configurations(*experiments*)
Chains generator given experiment specifications.

Parameters **experiments** (*Experiment | list | dict*) – Experiments to run.

next_trials()
Provides a batch of Trial objects to be queued into the TrialRunner.

A batch ends when self._trial_generator returns None.

Returns Returns a list of trials.

Return type trials (list)

_generate_trials(*experiment_spec*, *output_path=''*)
Generates trials with configurations from *_suggest*.

Creates a trial_id that is passed into *_suggest*.

Yields Trial objects constructed according to *spec*

is_finished()
Returns True if no trials left to be queued into TrialRunner.

Can return True before all trials have finished executing.

_suggest(*trial_id*)
Queries the algorithm to retrieve the next set of parameters.

Parameters **trial_id** – Trial ID used for subsequent notifications.

Returns

Configuration for a trial, if possible. Else, returns None, which will temporarily stop the TrialRunner from querying.

Return type dict|None

Example

```
>>> suggester = SuggestionAlgorithm(max_concurrent=1)
>>> suggester.add_configurations({ ... })
>>> parameters_1 = suggester._suggest()
>>> parameters_2 = suggester._suggest()
>>> parameters_2 is None
>>> suggester.on_trial_complete(trial_id, result)
>>> parameters_2 = suggester._suggest()
>>> parameters_2 is not None
```

5.21.4 ray.tune.track

ray.tune.track.**init**(*ignore_reinit_error=True*, ***session_kwargs*)
Initializes the global trial context for this process.

This creates a TrackSession object and the corresponding hooks for logging.

Examples

```
>>> from ray.tune import track
>>> track.init()
```

ray.tune.track.**shutdown**()
Cleans up the trial and removes it from the global context.

ray.tune.track.**log**(***kwargs*)
Applies TrackSession.log to the trial in the current context.

ray.tune.track.**trial_dir**()
Returns the directory where trial results are saved.

This includes json data containing the session's parameters and metrics.

class ray.tune.track.**TrackSession**(*trial_name=''*, *experiment_dir=None*, *upload_dir=None*, *trial_config=None*, *_tune_reporter=None*)

Manages results for a single session.

Represents a single Trial in an experiment.

trial_name
Custom trial name.

Type str

experiment_dir
Directory where results for all trials are stored. Each session is stored into a unique directory inside experiment_dir.

Type str

upload_dir
Directory to sync results to.

Type str

trial_config
Parameters that will be logged to disk.

Type dict

_tune_reporter
For rerouting when using Tune. Will not instantiate logging if not None.

Type *StatusReporter*

log(***metrics*)
Logs all named arguments specified in *metrics*.

This will log trial metrics locally, and they will be synchronized with the driver periodically through ray.

Parameters **metrics** – named arguments with corresponding values to log.

logdir
Trial logdir (subdir of given experiment directory)

5.21.5 ray.tune.logger

class ray.tune.logger.**Logger**(*config*, *logdir*, *trial=None*)
Logging interface for ray.tune.

By default, the UnifiedLogger implementation is used which logs results in multiple formats (TensorBoard, rllab/viskit, plain json, custom loggers) at once.

Parameters

- **config** – Configuration passed to all logger creators.
- **logdir** – Directory for all logger creators to log to.

on_result(*result*)
Given a result, appends it to the existing log.

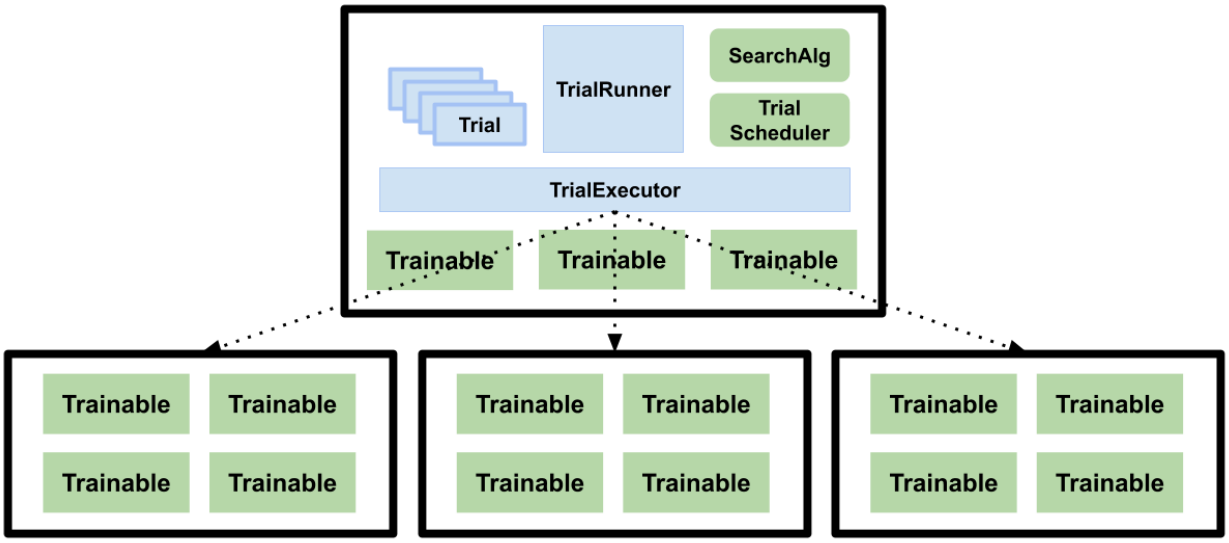
update_config(*config*)
Updates the config for logger.

close()
Releases all resources used by this logger.

flush()
Flushes all disk writes to storage.

5.22 Tune Design Guide

In this part of the documentation, we overview the design and architecture of Tune.



The blue boxes refer to internal components, and green boxes are public-facing. Please refer to the package reference for user-facing APIs.

5.22.1 Main Components

Tune's main components consist of TrialRunner, Trial objects, TrialExecutor, SearchAlg, TrialScheduler, and Trainable.

TrialRunner

[source code] This is the main driver of the training loop. This component uses the TrialScheduler to prioritize and execute trials, queries the SearchAlgorithm for new configurations to evaluate, and handles the fault tolerance logic.

Fault Tolerance: The TrialRunner executes checkpointing if `checkpoint_freq` is set, along with automatic trial restarting in case of trial failures (if `max_failures` is set). For example, if a node is lost while a trial (specifically, the corresponding Trainable of the trial) is still executing on that node and checkpointing is enabled, the trial will then be reverted to a `"PENDING"` state and resumed from the last available checkpoint when it is run. The TrialRunner is also in charge of checkpointing the entire experiment execution state upon each loop iteration. This allows users to restart their experiment in case of machine failure.

Trial objects

[source code] This is an internal data structure that contains metadata about each training run. Each Trial object is mapped one-to-one with a Trainable object but are not themselves distributed/remote. Trial objects transition among the following states: `"PENDING"`, `"RUNNING"`, `"PAUSED"`, `"ERRORED"`, and `"TERMINATED"`.

TrialExecutor

[source code] The TrialExecutor is a component that interacts with the underlying execution framework. It also manages resources to ensure the cluster isn't overloaded. By default, the TrialExecutor uses Ray to execute trials.

SearchAlg

[source code] The SearchAlgorithm is a user-provided object that is used for querying new hyperparameter configurations to evaluate.

SearchAlgorithms will be notified every time a trial finishes executing one training step (of `train()`), every time a trial errors, and every time a trial completes.

TrialScheduler

[source code] TrialSchedulers operate over a set of possible trials to run, prioritizing trial execution given available cluster resources.

TrialSchedulers are given the ability to kill or pause trials, and also are given the ability to reorder/prioritize incoming trials.

Trainables

[source code] These are user-provided objects that are used for the training process. If a class is provided, it is expected to conform to the Trainable interface. If a function is provided. it is wrapped into a Trainable class, and the function itself is executed on a separate thread.

Trainables will execute one step of `train()` before notifying the TrialRunner.

5.23 Tune Examples

In our repository, we provide a variety of examples for the various use cases and features of Tune.

If any example is broken, or if you'd like to add an example to this page, feel free to raise an issue on our Github repository.

5.23.1 General Examples

- async_hyperband_example: Example of using a Trainable class with AsyncHyperBandScheduler.
- hyperband_example: Example of using a Trainable class with HyperBandScheduler. Also uses the Experiment class API for specifying the experiment configuration. Also uses the AsyncHyperBandScheduler.
- pbt_example: Example of using a Trainable class with PopulationBasedTraining scheduler.
- pbt_ppo_example: Example of optimizing a distributed RLlib algorithm (PPO) with the PopulationBasedTraining scheduler.
- logging_example: Example of custom loggers and custom trial directory naming.
- pbt_memnn_example: Example of training a Memory NN on bAbI with Keras using PBT.

5.23.2 Search Algorithm Examples

- Ax example: Optimize a Hartmann function with Ax with 4 parallel workers.
- HyperOpt Example: Optimizes a basic function using the function-based API and the HyperOptSearch (SearchAlgorithm wrapper for HyperOpt TPE).
- Nevergrad example: Optimize a simple toy function with the gradient-free optimization package Nevergrad with 4 parallel workers.
- Bayesian Optimization example: Optimize a simple toy function using Bayesian Optimization with 4 parallel workers.

5.23.3 Keras Examples

- tune_mnist_keras: Converts the Keras MNIST example to use Tune with the function-based API and a Keras callback. Also shows how to easily convert something relying on argparse to use Tune.

5.23.4 PyTorch Examples

- mnist_pytorch: Converts the PyTorch MNIST example to use Tune with the function-based API. Also shows how to easily convert something relying on argparse to use Tune.
- mnist_pytorch_trainable: Converts the PyTorch MNIST example to use Tune with Trainable API. Also uses the HyperBandScheduler and checkpoints the model at the end.

5.23.5 TensorFlow Examples

- tune_mnist_ray: A basic example of tuning a TensorFlow model on MNIST using the Trainable class.
- tune_mnist_ray_hyperband: A basic example of tuning a TensorFlow model on MNIST using the Trainable class and the HyperBand scheduler.
- tune_mnist_async_hyperband: Example of tuning a TensorFlow model on MNIST using AsyncHyperBand.

5.23.6 XGBoost Example

- xgboost_example: Trains a basic XGBoost model with Tune with the function-based API and a XGBoost callback.

5.23.7 LightGBM Example

- lightgbm_example: Trains a basic LightGBM model with Tune with the function-based API and a LightGBM callback.

5.23.8 Contributed Examples

- pbt_tune_cifar10_with_keras: A contributed example of tuning a Keras model on CIFAR10 with the PopulationBasedTraining scheduler.
- genetic_example: Optimizing the michalewicz function using the contributed GeneticSearch search algorithm with AsyncHyperBandScheduler.

- tune_cifar10_gluon: MXNet Gluon example to use Tune with the function-based API on CIFAR-10 dataset.

5.24 Contributing to Tune

We welcome (and encourage!) all forms of contributions to Tune, including and not limited to:

- Code reviewing of patches and PRs.
- Pushing patches.
- Documentation and examples.
- Community participation in forums and issues.
- Code readability and code comments to improve readability.
- Test cases to make the codebase more robust.
- Tutorials, blog posts, talks that promote the project.

5.24.1 Setting up a development environment

If you have Ray installed via pip (`pip install -U [link to wheel]` - you can find the link to the latest wheel here), you can develop Tune locally without needing to compile Ray.

First, you will need your own fork to work on the code. Press the Fork button on the ray project page. Then, clone the project to your machine and connect your repository to the upstream (main project) ray repository.

```
git clone https://github.com/[your username]/ray.git [path to ray directory]
cd [path to ray directory]
git remote add upstream https://github.com/ray-project/ray.git
```

Before continuing, make sure that your git branch is in sync with the installed Ray binaries (i.e., you are up-to-date on master and have the latest wheel installed.)

Then, run *[path to ray directory]/python/ray/setup-dev.py* (also here on Github) script. This sets up links between the `tune` dir (among other directories) in your local repo and the one bundled with the `ray` package.

As a last step make sure to install all packages required for development of tune. This can be done by running:

```
pip install -r [path to ray directory]/python/ray/tune/requirements-dev.txt
```

5.24.2 What can I work on?

We use Github to track issues, feature requests, and bugs. Take a look at the ones labeled "good first issue" and "help wanted" for a place to start. Look for issues with "[tune]" in the title.

Note: If raising a new issue or PR related to Tune, be sure to include "[tune]" in the beginning of the title.

For project organization, Tune maintains a relatively up-to-date organization of issues on the Tune Github Project Board. Here, you can track and identify how issues are organized.

5.24.3 Submitting and Merging a Contribution

There are a couple steps to merge a contribution.

1. First rebase your development branch on the most recent version of master.

```
git remote add upstream https://github.com/ray-project/ray.git
git fetch upstream
git rebase upstream/master
```

2. Make sure all existing tests pass.
3. If introducing a new feature or patching a bug, be sure to add new test cases in the relevant file in *tune/tests/*.
4. Document the code. Public functions need to be documented, and remember to provide an usage example if applicable.
5. Request code reviews from other contributors and address their comments. One fast way to get reviews is to help review others' code so that they return the favor. You should aim to improve the code as much as possible before the review. We highly value patches that can get in without extensive reviews.
6. Reviewers will merge and approve the pull request; be sure to ping them if the pull request is getting stale.

5.24.4 Testing

Even though we have hooks to run unit tests automatically for each pull request, we recommend you to run unit tests locally beforehand to reduce reviewers' burden and speedup review process.

```
pytest ray/python/ray/tune/tests/
```

Documentation should be documented in Google style format.

We also have tests for code formatting and linting that need to pass before merge. Install *yapf==0.23, flake8, flake8-quotes* (these are also in the *requirements-dev.txt* found in `python/ray/tune`). You can run the following locally:

```
ray/scripts/format.sh
```

5.24.5 Becoming a Reviewer

We identify reviewers from active contributors. Reviewers are individuals who not only actively contribute to the project and are also willing to participate in the code review of new contributions. A pull request to the project has to be reviewed by at least one reviewer in order to be merged. There is currently no formal process, but active contributors to Tune will be solicited by current reviewers.

Note: These tips are based off of the TVM contributor guide.

5.25 RLlib: Scalable Reinforcement Learning

RLlib is an open-source library for reinforcement learning that offers both high scalability and a unified API for a variety of applications. RLlib natively supports TensorFlow, TensorFlow Eager, and PyTorch, but most of its internals are framework agnostic.

To get started, take a look over the custom env example and the API documentation. If you're looking to develop custom algorithms with RLlib, also check out concepts and custom algorithms.

5.25.1 RLlib in 60 seconds

The following is a whirlwind overview of RLlib. For a more in-depth guide, see also the full table of contents and RLlib blog posts. You may also want to skim the list of built-in algorithms.

Running RLlib

RLlib has extra dependencies on top of `ray`. First, you'll need to install either PyTorch or TensorFlow. Then, install the RLlib module:

```
pip install ray[rllib]  # also recommended: ray[debug]
```

Then, you can try out training in the following equivalent ways:

```
rllib train --run=PPO --env=CartPole-v0  # --eager [--trace] for eager execution
```

```
from ray import tune
from ray.rllib.agents.ppo import PPOTrainer
tune.run(PPOTrainer, config={"env": "CartPole-v0"})  # "eager": True for eager␣
↪execution
```

Next, we'll cover three key concepts in RLlib: Policies, Samples, and Trainers.

Policies

Policies are a core concept in RLlib. In a nutshell, policies are Python classes that define how an agent acts in an environment. Rollout workers query the policy to determine agent actions. In a gym environment, there is a single agent and policy. In vector envs, policy inference is for multiple agents at once, and in multi-agent, there may be multiple policies, each controlling one or more agents:

Policies can be implemented using any framework. However, for TensorFlow and PyTorch, RLlib has build_tf_policy and build_torch_policy helper functions that let you define a trainable policy with a functional-style API, for example:

```
def policy_gradient_loss(policy, model, dist_class, train_batch):
    logits, _ = model.from_batch(train_batch)
    action_dist = dist_class(logits, model)
    return -tf.reduce_mean(
        action_dist.logp(train_batch["actions"]) * train_batch["rewards"])

# <class 'ray.rllib.policy.tf_policy_template.MyTFPolicy'>
MyTFPolicy = build_tf_policy(
    name="MyTFPolicy",
    loss_fn=policy_gradient_loss)
```

Sample Batches

Whether running in a single process or large cluster, all data interchange in RLlib is in the form of sample batches. Sample batches encode one or more fragments of a trajectory. Typically, RLlib collects batches of size

`sample_batch_size` from rollout workers, and concatenates one or more of these batches into a batch of size `train_batch_size` that is the input to SGD.

A typical sample batch looks something like the following when summarized. Since all values are kept in arrays, this allows for efficient encoding and transmission across the network:

```
{ 'action_logp': np.ndarray((200,), dtype=float32, min=-0.701, max=-0.685, mean=-0.
↪694),
  'actions': np.ndarray((200,), dtype=int64, min=0.0, max=1.0, mean=0.495),
  'dones': np.ndarray((200,), dtype=bool, min=0.0, max=1.0, mean=0.055),
  'infos': np.ndarray((200,), dtype=object, head={}),
  'new_obs': np.ndarray((200, 4), dtype=float32, min=-2.46, max=2.259, mean=0.018),
  'obs': np.ndarray((200, 4), dtype=float32, min=-2.46, max=2.259, mean=0.016),
  'rewards': np.ndarray((200,), dtype=float32, min=1.0, max=1.0, mean=1.0),
  't': np.ndarray((200,), dtype=int64, min=0.0, max=34.0, mean=9.14)}
```

In multi-agent mode, sample batches are collected separately for each individual policy.

Training

Policies each define a `learn_on_batch()` method that improves the policy given a sample batch of input. For TF and Torch policies, this is implemented using a *loss function* that takes as input sample batch tensors and outputs a scalar loss. Here are a few example loss functions:

- Simple policy gradient loss
- Simple Q-function loss
- Importance-weighted APPO surrogate loss

RLlib Trainer classes coordinate the distributed workflow of running rollouts and optimizing policies. They do this by leveraging policy optimizers that implement the desired computation pattern. The following figure shows *synchronous sampling*, the simplest of these patterns:

Fig. 1: Synchronous Sampling (e.g., A2C, PG, PPO)

RLlib uses Ray actors to scale training from a single core to many thousands of cores in a cluster. You can configure the parallelism used for training by changing the `num_workers` parameter.

Customization

RLlib provides ways to customize almost all aspects of training, including the environment, neural network model, action distribution, and policy definitions:

To learn more, proceed to the table of contents.

5.26 RLlib Table of Contents

5.26.1 Training APIs

- Command-line
- Configuration

5.26.2 Environments

5.26.3 Models, Preprocessors, and Action Distributions

- Variable-length / Parametric Action Spaces
- Autoregressive Action Distributions

5.26.4 Algorithms

- High-throughput architectures
  - Distributed Prioritized Experience Replay (Ape-X)
  - Importance Weighted Actor-Learner Architecture (IMPALA)
  - Asynchronous Proximal Policy Optimization (APPO)
- Gradient-based
  - Advantage Actor-Critic (A2C, A3C)
  - Deep Deterministic Policy Gradients (DDPG, TD3)
  - Deep Q Networks (DQN, Rainbow, Parametric DQN)
  - Policy Gradients
  - Proximal Policy Optimization (PPO)
  - Soft Actor Critic (SAC)
- Derivative-free
  - Augmented Random Search (ARS)
  - Evolution Strategies
- Multi-agent specific
  - QMIX Monotonic Value Factorisation (QMIX, VDN, IQN)
  - Multi-Agent Deep Deterministic Policy Gradient (contrib/MADDPG)
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5.26.5 Offline Datasets

- Working with Offline Datasets
- Input Pipeline for Supervised Losses
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- Output API

5.26.6 Concepts and Custom Algorithms

- Policies
  - Policies in Multi-Agent
  - Building Policies in TensorFlow
  - Building Policies in TensorFlow Eager

  - Building Policies in PyTorch
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5.26.7 Examples

- Tuned Examples
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- Development Install
- API Stability
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5.26.9 Package Reference

- ray.rllib.agents
- ray.rllib.env
- ray.rllib.evaluation
- ray.rllib.models
- ray.rllib.optimizers
- ray.rllib.utils

5.26.10 Troubleshooting

If you encounter errors like *blas_thread_init: pthread_create: Resource temporarily unavailable* when using many workers, try setting `OMP_NUM_THREADS=1`. Similarly, check configured system limits with *ulimit -a* for other resource limit errors.

If you encounter out-of-memory errors, consider setting `redis_max_memory` and `object_store_memory` in `ray.init()` to reduce memory usage.

For debugging unexpected hangs or performance problems, you can run `ray stack` to dump the stack traces of all Ray workers on the current node, and `ray timeline` to dump a timeline visualization of tasks to a file.

5.27 RLlib Training APIs

5.27.1 Getting Started

At a high level, RLlib provides an `Trainer` class which holds a policy for environment interaction. Through the trainer interface, the policy can be trained, checkpointed, or an action computed. In multi-agent training, the trainer manages the querying and optimization of multiple policies at once.

You can train a simple DQN trainer with the following command:

```
rllib train --run DQN --env CartPole-v0  # --eager [--trace] for eager execution
```

By default, the results will be logged to a subdirectory of `~/ray_results`. This subdirectory will contain a file `params.json` which contains the hyperparameters, a file `result.json` which contains a training summary for each episode and a TensorBoard file that can be used to visualize training process with TensorBoard by running

```
tensorboard --logdir=~/ray_results
```

The `rllib train` command (same as the `train.py` script in the repo) has a number of options you can show by running:

```
rllib train --help
-or-
python ray/rllib/train.py --help
```

The most important options are for choosing the environment with `--env` (any OpenAI gym environment including ones registered by the user can be used) and for choosing the algorithm with `--run` (available options are `SAC`, `PPO`, `PG`, `A2C`, `A3C`, `IMPALA`, `ES`, `DDPG`, `DQN`, `MARWIL`, `APEX`, and `APEX_DDPG`).

Evaluating Trained Policies

In order to save checkpoints from which to evaluate policies, set `--checkpoint-freq` (number of training iterations between checkpoints) when running `rllib train`.

An example of evaluating a previously trained DQN policy is as follows:

```
rllib rollout \
    ~/ray_results/default/DQN_CartPole-v0_0upjmdgr0/checkpoint_1/checkpoint-1 \
    --run DQN --env CartPole-v0 --steps 10000
```

The `rollout.py` helper script reconstructs a DQN policy from the checkpoint located at `~/ray_results/default/DQN_CartPole-v0_0upjmdgr0/checkpoint_1/checkpoint-1` and renders its behavior in the environment specified by `--env`.

5.27.2 Configuration

Specifying Parameters

Each algorithm has specific hyperparameters that can be set with `--config`, in addition to a number of common hyperparameters. See the algorithms documentation for more information.

In an example below, we train A2C by specifying 8 workers through the config flag.

```
rllib train --env=PongDeterministic-v4 --run=A2C --config '{"num_workers": 8}'
```

Specifying Resources

You can control the degree of parallelism used by setting the `num_workers` hyperparameter for most algorithms. The number of GPUs the driver should use can be set via the `num_gpus` option. Similarly, the resource allocation to workers can be controlled via `num_cpus_per_worker`, `num_gpus_per_worker`, and `custom_resources_per_worker`. The number of GPUs can be a fractional quantity to allocate only a fraction of a GPU. For example, with DQN you can pack five trainers onto one GPU by setting `num_gpus: 0.2`.

Common Parameters

The following is a list of the common algorithm hyperparameters:

```
COMMON_CONFIG = {
    # === Debugging ===
    # Whether to write episode stats and videos to the agent log dir
    "monitor": False,
    # Set the ray.rllib.* log level for the agent process and its workers.
    # Should be one of DEBUG, INFO, WARN, or ERROR. The DEBUG level will also
    # periodically print out summaries of relevant internal dataflow (this is
    # also printed out once at startup at the INFO level).
    "log_level": "INFO",
    # Callbacks that will be run during various phases of training. These all
    # take a single "info" dict as an argument. For episode callbacks, custom
    # metrics can be attached to the episode by updating the episode object's
    # custom metrics dict (see examples/custom_metrics_and_callbacks.py). You
    # may also mutate the passed in batch data in your callback.
    "callbacks": {
        "on_episode_start": None,     # arg: {"env": .., "episode": ...}
        "on_episode_step": None,      # arg: {"env": .., "episode": ...}
        "on_episode_end": None,       # arg: {"env": .., "episode": ...}
        "on_sample_end": None,        # arg: {"samples": .., "worker": ...}
        "on_train_result": None,      # arg: {"trainer": ..., "result": ...}
        "on_postprocess_traj": None,  # arg: {
                                      #   "agent_id": ..., "episode": ...,
                                      #   "pre_batch": (before processing),
                                      #   "post_batch": (after processing),
                                      #   "all_pre_batches": (other agent ids),
                                      # }
    },
    # Whether to attempt to continue training if a worker crashes.
    "ignore_worker_failures": False,
    # Log system resource metrics to results.
    "log_sys_usage": True,
    # Enable TF eager execution (TF policies only).
    "eager": False,
    # Enable tracing in eager mode. This greatly improves performance, but
    # makes it slightly harder to debug since Python code won't be evaluated
    # after the initial eager pass.
    "eager_tracing": False,
    # Disable eager execution on workers (but allow it on the driver). This
    # only has an effect is eager is enabled.
```

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```
    "no_eager_on_workers": False,

    # === Policy ===
    # Arguments to pass to model. See models/catalog.py for a full list of the
    # available model options.
    "model": MODEL_DEFAULTS,
    # Arguments to pass to the policy optimizer. These vary by optimizer.
    "optimizer": {},

    # === Environment ===
    # Discount factor of the MDP
    "gamma": 0.99,
    # Number of steps after which the episode is forced to terminate. Defaults
    # to `env.spec.max_episode_steps` (if present) for Gym envs.
    "horizon": None,
    # Calculate rewards but don't reset the environment when the horizon is
    # hit. This allows value estimation and RNN state to span across logical
    # episodes denoted by horizon. This only has an effect if horizon != inf.
    "soft_horizon": False,
    # Don't set 'done' at the end of the episode. Note that you still need to
    # set this if soft_horizon=True, unless your env is actually running
    # forever without returning done=True.
    "no_done_at_end": False,
    # Arguments to pass to the env creator
    "env_config": {},
    # Environment name can also be passed via config
    "env": None,
    # Whether to clip rewards prior to experience postprocessing. Setting to
    # None means clip for Atari only.
    "clip_rewards": None,
    # Whether to np.clip() actions to the action space low/high range spec.
    "clip_actions": True,
    # Whether to use rllib or deepmind preprocessors by default
    "preprocessor_pref": "deepmind",
    # The default learning rate
    "lr": 0.0001,

    # === Evaluation ===
    # Evaluate with every `evaluation_interval` training iterations.
    # The evaluation stats will be reported under the "evaluation" metric key.
    # Note that evaluation is currently not parallelized, and that for Ape-X
    # metrics are already only reported for the lowest epsilon workers.
    "evaluation_interval": None,
    # Number of episodes to run per evaluation period.
    "evaluation_num_episodes": 10,
    # Extra arguments to pass to evaluation workers.
    # Typical usage is to pass extra args to evaluation env creator
    # and to disable exploration by computing deterministic actions
    # TODO(kismuz): implement determ. actions and include relevant keys hints
    "evaluation_config": {},

    # === Resources ===
    # Number of actors used for parallelism
    "num_workers": 2,
    # Number of GPUs to allocate to the trainer process. Note that not all
    # algorithms can take advantage of trainer GPUs. This can be fractional
    # (e.g., 0.3 GPUs).
```

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```
    "num_gpus": 0,
    # Number of CPUs to allocate per worker.
    "num_cpus_per_worker": 1,
    # Number of GPUs to allocate per worker. This can be fractional.
    "num_gpus_per_worker": 0,
    # Any custom resources to allocate per worker.
    "custom_resources_per_worker": {},
    # Number of CPUs to allocate for the trainer. Note: this only takes effect
    # when running in Tune.
    "num_cpus_for_driver": 1,

    # === Memory quota ===
    # You can set these memory quotas to tell Ray to reserve memory for your
    # training run. This guarantees predictable execution, but the tradeoff is
    # if your workload exceeeds the memory quota it will fail.
    # Heap memory to reserve for the trainer process (0 for unlimited). This
    # can be large if your are using large train batches, replay buffers, etc.
    "memory": 0,
    # Object store memory to reserve for the trainer process. Being large
    # enough to fit a few copies of the model weights should be sufficient.
    # This is enabled by default since models are typically quite small.
    "object_store_memory": 0,
    # Heap memory to reserve for each worker. Should generally be small unless
    # your environment is very heavyweight.
    "memory_per_worker": 0,
    # Object store memory to reserve for each worker. This only needs to be
    # large enough to fit a few sample batches at a time. This is enabled
    # by default since it almost never needs to be larger than ~200MB.
    "object_store_memory_per_worker": 0,

    # === Execution ===
    # Number of environments to evaluate vectorwise per worker.
    "num_envs_per_worker": 1,
    # Default sample batch size (unroll length). Batches of this size are
    # collected from workers until train_batch_size is met. When using
    # multiple envs per worker, this is multiplied by num_envs_per_worker.
    "sample_batch_size": 200,
    # Training batch size, if applicable. Should be >= sample_batch_size.
    # Samples batches will be concatenated together to this size for training.
    "train_batch_size": 200,
    # Whether to rollout "complete_episodes" or "truncate_episodes"
    "batch_mode": "truncate_episodes",
    # Use a background thread for sampling (slightly off-policy, usually not
    # advisable to turn on unless your env specifically requires it)
    "sample_async": False,
    # Element-wise observation filter, either "NoFilter" or "MeanStdFilter"
    "observation_filter": "NoFilter",
    # Whether to synchronize the statistics of remote filters.
    "synchronize_filters": True,
    # Configure TF for single-process operation by default
    "tf_session_args": {
        # note: overriden by `local_tf_session_args`
        "intra_op_parallelism_threads": 2,
        "inter_op_parallelism_threads": 2,
        "gpu_options": {
            "allow_growth": True,
        },
```

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```
        "log_device_placement": False,
        "device_count": {
            "CPU": 1
        },
        "allow_soft_placement": True,  # required by PPO multi-gpu
    },
    # Override the following tf session args on the local worker
    "local_tf_session_args": {
        # Allow a higher level of parallelism by default, but not unlimited
        # since that can cause crashes with many concurrent drivers.
        "intra_op_parallelism_threads": 8,
        "inter_op_parallelism_threads": 8,
    },
    # Whether to LZ4 compress individual observations
    "compress_observations": False,
    # Wait for metric batches for at most this many seconds. Those that
    # have not returned in time will be collected in the next iteration.
    "collect_metrics_timeout": 180,
    # Smooth metrics over this many episodes.
    "metrics_smoothing_episodes": 100,
    # If using num_envs_per_worker > 1, whether to create those new envs in
    # remote processes instead of in the same worker. This adds overheads, but
    # can make sense if your envs can take much time to step / reset
    # (e.g., for StarCraft). Use this cautiously; overheads are significant.
    "remote_worker_envs": False,
    # Timeout that remote workers are waiting when polling environments.
    # 0 (continue when at least one env is ready) is a reasonable default,
    # but optimal value could be obtained by measuring your environment
    # step / reset and model inference perf.
    "remote_env_batch_wait_ms": 0,
    # Minimum time per iteration
    "min_iter_time_s": 0,
    # Minimum env steps to optimize for per train call. This value does
    # not affect learning, only the length of iterations.
    "timesteps_per_iteration": 0,
    # This argument, in conjunction with worker_index, sets the random seed of
    # each worker, so that identically configured trials will have identical
    # results. This makes experiments reproducible.
    "seed": None,

    # === Offline Datasets ===
    # Specify how to generate experiences:
    #  - "sampler": generate experiences via online simulation (default)
    #  - a local directory or file glob expression (e.g., "/tmp/*.json")
    #  - a list of individual file paths/URIs (e.g., ["/tmp/1.json",
    #    "s3://bucket/2.json"])
    #  - a dict with string keys and sampling probabilities as values (e.g.,
    #    {"sampler": 0.4, "/tmp/*.json": 0.4, "s3://bucket/expert.json": 0.2}).
    #  - a function that returns a rllib.offline.InputReader
    "input": "sampler",
    # Specify how to evaluate the current policy. This only has an effect when
    # reading offline experiences. Available options:
    #  - "wis": the weighted step-wise importance sampling estimator.
    #  - "is": the step-wise importance sampling estimator.
    #  - "simulation": run the environment in the background, but use
    #    this data for evaluation only and not for learning.
    "input_evaluation": ["is", "wis"],
```

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```
    # Whether to run postprocess_trajectory() on the trajectory fragments from
    # offline inputs. Note that postprocessing will be done using the *current*
    # policy, not the *behaviour* policy, which is typically undesirable for
    # on-policy algorithms.
    "postprocess_inputs": False,
    # If positive, input batches will be shuffled via a sliding window buffer
    # of this number of batches. Use this if the input data is not in random
    # enough order. Input is delayed until the shuffle buffer is filled.
    "shuffle_buffer_size": 0,
    # Specify where experiences should be saved:
    #  - None: don't save any experiences
    #  - "logdir" to save to the agent log dir
    #  - a path/URI to save to a custom output directory (e.g., "s3://bucket/")
    #  - a function that returns a rllib.offline.OutputWriter
    "output": None,
    # What sample batch columns to LZ4 compress in the output data.
    "output_compress_columns": ["obs", "new_obs"],
    # Max output file size before rolling over to a new file.
    "output_max_file_size": 64 * 1024 * 1024,

    # === Multiagent ===
    "multiagent": {
        # Map from policy ids to tuples of (policy_cls, obs_space,
        # act_space, config). See rollout_worker.py for more info.
        "policies": {},
        # Function mapping agent ids to policy ids.
        "policy_mapping_fn": None,
        # Optional whitelist of policies to train, or None for all policies.
        "policies_to_train": None,
    },
}
```

Tuned Examples

Some good hyperparameters and settings are available in the repository (some of them are tuned to run on GPUs). If you find better settings or tune an algorithm on a different domain, consider submitting a Pull Request!

You can run these with the `rllib train` command as follows:

```
rllib train -f /path/to/tuned/example.yaml
```

5.27.3 Python API

The Python API provides the needed flexibility for applying RLlib to new problems. You will need to use this API if you wish to use custom environments, preprocessors, or models with RLlib.

Here is an example of the basic usage (for a more complete example, see custom_env.py):

```
import ray
import ray.rllib.agents.ppo as ppo
from ray.tune.logger import pretty_print

ray.init()
config = ppo.DEFAULT_CONFIG.copy()
```

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```
config["num_gpus"] = 0
config["num_workers"] = 1
config["eager"] = False
trainer = ppo.PPOTrainer(config=config, env="CartPole-v0")

# Can optionally call trainer.restore(path) to load a checkpoint.

for i in range(1000):
   # Perform one iteration of training the policy with PPO
   result = trainer.train()
   print(pretty_print(result))

   if i % 100 == 0:
       checkpoint = trainer.save()
       print("checkpoint saved at", checkpoint)
```

Note: It's recommended that you run RLlib trainers with Tune, for easy experiment management and visualization of results. Just set `"run": ALG_NAME, "env": ENV_NAME` in the experiment config.

All RLlib trainers are compatible with the Tune API. This enables them to be easily used in experiments with Tune. For example, the following code performs a simple hyperparam sweep of PPO:

```
import ray
from ray import tune

ray.init()
tune.run(
    "PPO",
    stop={"episode_reward_mean": 200},
    config={
        "env": "CartPole-v0",
        "num_gpus": 0,
        "num_workers": 1,
        "lr": tune.grid_search([0.01, 0.001, 0.0001]),
        "eager": False,
    },
)
```

Tune will schedule the trials to run in parallel on your Ray cluster:

```
== Status ==
Using FIFO scheduling algorithm.
Resources requested: 4/4 CPUs, 0/0 GPUs
Result logdir: ~/ray_results/my_experiment
PENDING trials:
 - PPO_CartPole-v0_2_lr=0.0001:     PENDING
RUNNING trials:
 - PPO_CartPole-v0_0_lr=0.01:       RUNNING [pid=21940], 16 s, 4013 ts, 22 rew
 - PPO_CartPole-v0_1_lr=0.001:      RUNNING [pid=21942], 27 s, 8111 ts, 54.7 rew
```

Custom Training Workflows

In the basic training example, Tune will call `train()` on your trainer once per iteration and report the new training results. Sometimes, it is desirable to have full control over training, but still run inside Tune. Tune supports custom

trainable functions that can be used to implement custom training workflows (example).

For even finer-grained control over training, you can use RLlib's lower-level building blocks directly to implement fully customized training workflows.

Accessing Policy State

It is common to need to access a trainer's internal state, e.g., to set or get internal weights. In RLlib trainer state is replicated across multiple *rollout workers* (Ray actors) in the cluster. However, you can easily get and update this state between calls to `train()` via `trainer.workers.foreach_worker()` or `trainer.workers.foreach_worker_with_index()`. These functions take a lambda function that is applied with the worker as an arg. You can also return values from these functions and those will be returned as a list.

You can also access just the "master" copy of the trainer state through `trainer.get_policy()` or `trainer.workers.local_worker()`, but note that updates here may not be immediately reflected in remote replicas if you have configured `num_workers > 0`. For example, to access the weights of a local TF policy, you can run `trainer.get_policy().get_weights()`. This is also equivalent to `trainer.workers.local_worker().policy_map["default_policy"].get_weights()`:

```
# Get weights of the default local policy
trainer.get_policy().get_weights()

# Same as above
trainer.workers.local_worker().policy_map["default_policy"].get_weights()

# Get list of weights of each worker, including remote replicas
trainer.workers.foreach_worker(lambda ev: ev.get_policy().get_weights())

# Same as above
trainer.workers.foreach_worker_with_index(lambda ev, i: ev.get_policy().get_weights())
```

Accessing Model State

Similar to accessing policy state, you may want to get a reference to the underlying neural network model being trained. For example, you may want to pre-train it separately, or otherwise update its weights outside of RLlib. This can be done by accessing the `model` of the policy:

Example: Preprocessing observations for feeding into a model

```
>>> import gym
>>> env = gym.make("Pong-v0")

# RLlib uses preprocessors to implement transforms such as one-hot encoding
# and flattening of tuple and dict observations.
>>> from ray.rllib.models.preprocessors import get_preprocessor
>>> prep = get_preprocessor(env.observation_space)(env.observation_space)
<ray.rllib.models.preprocessors.GenericPixelPreprocessor object at 0x7fc4d049de80>

# Observations should be preprocessed prior to feeding into a model
>>> env.reset().shape
(210, 160, 3)
>>> prep.transform(env.reset()).shape
(84, 84, 3)
```

Example: Querying a policy's action distribution

```
# Get a reference to the policy
>>> from ray.rllib.agents.ppo import PPOTrainer
>>> trainer = PPOTrainer(env="CartPole-v0", config={"eager": True, "num_workers": 0})
>>> policy = trainer.get_policy()
<ray.rllib.policy.eager_tf_policy.PPOTFPolicy_eager object at 0x7fd020165470>

# Run a forward pass to get model output logits. Note that complex observations
# must be preprocessed as in the above code block.
>>> logits, _ = policy.model.from_batch({"obs": np.array([[0.1, 0.2, 0.3, 0.4]])})
(<tf.Tensor: id=1274, shape=(1, 2), dtype=float32, numpy=...>, [])

# Compute action distribution given logits
>>> policy.dist_class
<class_object 'ray.rllib.models.tf.tf_action_dist.Categorical'>
>>> dist = policy.dist_class(logits, policy.model)
<ray.rllib.models.tf.tf_action_dist.Categorical object at 0x7fd02301d710>

# Query the distribution for samples, sample logps
>>> dist.sample()
<tf.Tensor: id=661, shape=(1,), dtype=int64, numpy=..>
>>> dist.logp([1])
<tf.Tensor: id=1298, shape=(1,), dtype=float32, numpy=...>

# Get the estimated values for the most recent forward pass
>>> policy.model.value_function()
<tf.Tensor: id=670, shape=(1,), dtype=float32, numpy=...>

>>> policy.model.base_model.summary()
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   Connected to
=================================================================
observations (InputLayer)    [(None, 4)]               0
_________________________________________________________________
fc_1 (Dense)                 (None, 256)               1280      observations[0][0]
_________________________________________________________________
fc_value_1 (Dense)           (None, 256)               1280      observations[0][0]
_________________________________________________________________
fc_2 (Dense)                 (None, 256)               65792     fc_1[0][0]
_________________________________________________________________
fc_value_2 (Dense)           (None, 256)               65792     fc_value_1[0][0]
_________________________________________________________________
fc_out (Dense)               (None, 2)                 514       fc_2[0][0]
_________________________________________________________________
value_out (Dense)            (None, 1)                 257       fc_value_2[0][0]
=================================================================
Total params: 134,915
Trainable params: 134,915
Non-trainable params: 0
_________________________________________________________________
```

Example: Getting Q values from a DQN model

```
# Get a reference to the model through the policy
>>> from ray.rllib.agents.dqn import DQNTrainer
>>> trainer = DQNTrainer(env="CartPole-v0", config={"eager": True})
>>> model = trainer.get_policy().model
```

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```
<ray.rllib.models.catalog.FullyConnectedNetwork_as_DistributionalQModel ...>

# List of all model variables
>>> model.variables()
[<tf.Variable 'default_policy/fc_1/kernel:0' shape=(4, 256) dtype=float32>, ...]

# Run a forward pass to get base model output. Note that complex observations
# must be preprocessed. An example of preprocessing is examples/saving_experiences.py
>>> model_out = model.from_batch({"obs": np.array([[0.1, 0.2, 0.3, 0.4]])})
(<tf.Tensor: id=832, shape=(1, 256), dtype=float32, numpy=...)

# Access the base Keras models (all default models have a base)
>>> model.base_model.summary()
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   Connected to
=================================================================
observations (InputLayer)    [(None, 4)]               0
_________________________________________________________________
fc_1 (Dense)                 (None, 256)               1280      observations[0][0]
_________________________________________________________________
fc_out (Dense)               (None, 256)               65792     fc_1[0][0]
_________________________________________________________________
value_out (Dense)            (None, 1)                 257       fc_1[0][0]
=================================================================
Total params: 67,329
Trainable params: 67,329
Non-trainable params: 0
_________________________________________________________________

# Access the Q value model (specific to DQN)
>>> model.get_q_value_distributions(model_out)
[<tf.Tensor: id=891, shape=(1, 2)>, <tf.Tensor: id=896, shape=(1, 2, 1)>]

>>> model.q_value_head.summary()
Model: "model_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
model_out (InputLayer)       [(None, 256)]             0
_________________________________________________________________
lambda (Lambda)              [(None, 2), (None, 2, 1), 66306
=================================================================
Total params: 66,306
Trainable params: 66,306
Non-trainable params: 0
_________________________________________________________________

# Access the state value model (specific to DQN)
>>> model.get_state_value(model_out)
<tf.Tensor: id=913, shape=(1, 1), dtype=float32>

>>> model.state_value_head.summary()
Model: "model_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
```

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```
model_out (InputLayer)       [(None, 256)]             0
_________________________________________________________________
lambda_1 (Lambda)            (None, 1)                 66049
=================================================================
Total params: 66,049
Trainable params: 66,049
Non-trainable params: 0
_________________________________________________________________
```

This is especially useful when used with custom model classes.

Global Coordination

Sometimes, it is necessary to coordinate between pieces of code that live in different processes managed by RLlib. For example, it can be useful to maintain a global average of a certain variable, or centrally control a hyperparameter used by policies. Ray provides a general way to achieve this through *named actors* (learn more about Ray actors here). As an example, consider maintaining a shared global counter that is incremented by environments and read periodically from your driver program:

```
from ray.experimental import named_actors

@ray.remote
class Counter:
   def __init__(self):
      self.count = 0
   def inc(self, n):
      self.count += n
   def get(self):
      return self.count

# on the driver
counter = Counter.remote()
named_actors.register_actor("global_counter", counter)
print(ray.get(counter.get.remote()))  # get the latest count

# in your envs
counter = named_actors.get_actor("global_counter")
counter.inc.remote(1)  # async call to increment the global count
```

Ray actors provide high levels of performance, so in more complex cases they can be used implement communication patterns such as parameter servers and allreduce.

Callbacks and Custom Metrics

You can provide callback functions to be called at points during policy evaluation. These functions have access to an info dict containing state for the current episode. Custom state can be stored for the episode in the `info["episode"].user_data` dict, and custom scalar metrics reported by saving values to the `info["episode"].custom_metrics` dict. These custom metrics will be aggregated and reported as part of training results. The following example (full code here) logs a custom metric from the environment:

```
def on_episode_start(info):
    print(info.keys())  # -> "env", 'episode"
    episode = info["episode"]
```

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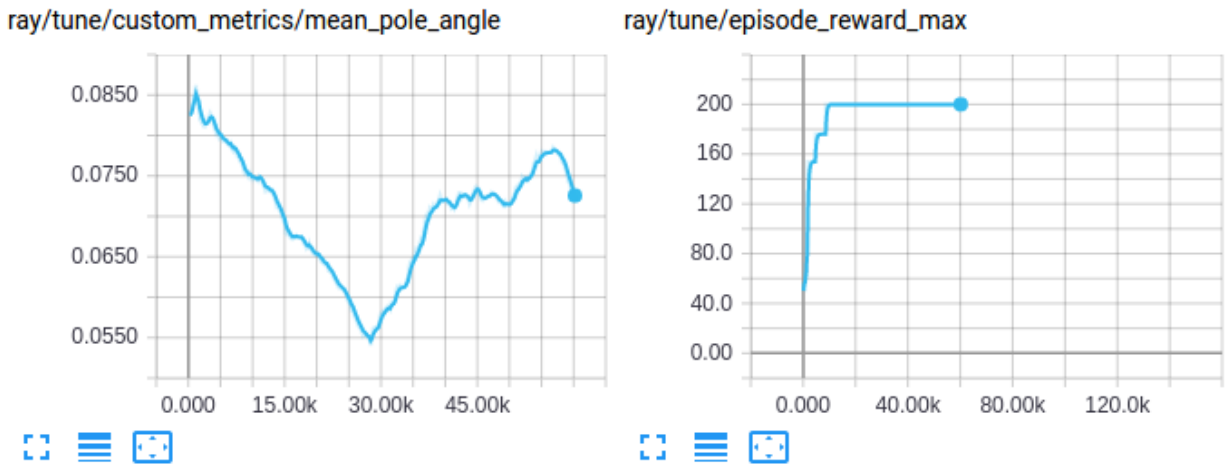
```
    print("episode {} started".format(episode.episode_id))
    episode.user_data["pole_angles"] = []

def on_episode_step(info):
    episode = info["episode"]
    pole_angle = abs(episode.last_observation_for()[2])
    episode.user_data["pole_angles"].append(pole_angle)

def on_episode_end(info):
    episode = info["episode"]
    pole_angle = np.mean(episode.user_data["pole_angles"])
    print("episode {} ended with length {} and pole angles {}".format(
        episode.episode_id, episode.length, pole_angle))
    episode.custom_metrics["pole_angle"] = pole_angle

def on_train_result(info):
    print("trainer.train() result: {} -> {} episodes".format(
        info["trainer"].__name__, info["result"]["episodes_this_iter"]))

def on_postprocess_traj(info):
    episode = info["episode"]
    batch = info["post_batch"]  # note: you can mutate this
    print("postprocessed {} steps".format(batch.count))

ray.init()
analysis = tune.run(
    "PG",
    config={
        "env": "CartPole-v0",
        "callbacks": {
            "on_episode_start": on_episode_start,
            "on_episode_step": on_episode_step,
            "on_episode_end": on_episode_end,
            "on_train_result": on_train_result,
            "on_postprocess_traj": on_postprocess_traj,
        },
    },
)
```

Visualizing Custom Metrics

Custom metrics can be accessed and visualized like any other training result:



Rewriting Trajectories

Note that in the `on_postprocess_batch` callback you have full access to the trajectory batch (`post_batch`) and other training state. This can be used to rewrite the trajectory, which has a number of uses including:

- Backdating rewards to previous time steps (e.g., based on values in `info`).
- Adding model-based curiosity bonuses to rewards (you can train the model with a custom model supervised loss).

Curriculum Learning

Let's look at two ways to use the above APIs to implement curriculum learning. In curriculum learning, the agent task is adjusted over time to improve the learning process. Suppose that we have an environment class with a `set_phase()` method that we can call to adjust the task difficulty over time:

Approach 1: Use the Trainer API and update the environment between calls to `train()`. This example shows the trainer being run inside a Tune function:

```
import ray
from ray import tune
from ray.rllib.agents.ppo import PPOTrainer

def train(config, reporter):
    trainer = PPOTrainer(config=config, env=YourEnv)
    while True:
        result = trainer.train()
        reporter(**result)
        if result["episode_reward_mean"] > 200:
            phase = 2
        elif result["episode_reward_mean"] > 100:
            phase = 1
        else:
            phase = 0
        trainer.workers.foreach_worker(
            lambda ev: ev.foreach_env(
                lambda env: env.set_phase(phase)))
```

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```
ray.init()
tune.run(
    train,
    config={
        "num_gpus": 0,
        "num_workers": 2,
    },
    resources_per_trial={
        "cpu": 1,
        "gpu": lambda spec: spec.config.num_gpus,
        "extra_cpu": lambda spec: spec.config.num_workers,
    },
)
```

Approach 2: Use the callbacks API to update the environment on new training results:

```
import ray
from ray import tune

def on_train_result(info):
    result = info["result"]
    if result["episode_reward_mean"] > 200:
        phase = 2
    elif result["episode_reward_mean"] > 100:
        phase = 1
    else:
        phase = 0
    trainer = info["trainer"]
    trainer.workers.foreach_worker(
        lambda ev: ev.foreach_env(
            lambda env: env.set_phase(phase)))

ray.init()
tune.run(
    "PPO",
    config={
        "env": YourEnv,
        "callbacks": {
            "on_train_result": on_train_result,
        },
    },
)
```

5.27.4 Debugging

Gym Monitor

The `"monitor": true` config can be used to save Gym episode videos to the result dir. For example:

```
rllib train --env=PongDeterministic-v4 \
    --run=A2C --config '{"num_workers": 2, "monitor": true}'

# videos will be saved in the ~/ray_results/<experiment> dir, for example
openaigym.video.0.31401.video000000.meta.json
```

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```
openaigym.video.0.31401.video000000.mp4
openaigym.video.0.31403.video000000.meta.json
openaigym.video.0.31403.video000000.mp4
```

Eager Mode

Policies built with `build_tf_policy` (most of the reference algorithms are) can be run in eager mode by setting the `"eager": True` / `"eager_tracing": True` config options or using `rllib train --eager [--trace]`. This will tell RLlib to execute the model forward pass, action distribution, loss, and stats functions in eager mode.

Eager mode makes debugging much easier, since you can now use normal Python functions such as `print()` to inspect intermediate tensor values. However, it can be slower than graph mode unless tracing is enabled.

Episode Traces

You can use the data output API to save episode traces for debugging. For example, the following command will run PPO while saving episode traces to `/tmp/debug`.

```
rllib train --run=PPO --env=CartPole-v0 \
    --config='{"output": "/tmp/debug", "output_compress_columns": []}'

# episode traces will be saved in /tmp/debug, for example
output-2019-02-23_12-02-03_worker-2_0.json
output-2019-02-23_12-02-04_worker-1_0.json
```

Log Verbosity

You can control the trainer log level via the `"log_level"` flag. Valid values are "INFO" (default), "DEBUG", "WARN", and "ERROR". This can be used to increase or decrease the verbosity of internal logging. For example:

```
rllib train --env=PongDeterministic-v4 \
    --run=A2C --config '{"num_workers": 2, "log_level": "DEBUG"}'
```

Stack Traces

You can use the `ray stack` command to dump the stack traces of all the Python workers on a single node. This can be useful for debugging unexpected hangs or performance issues.

5.27.5 REST API

In some cases (i.e., when interacting with an externally hosted simulator or production environment) it makes more sense to interact with RLlib as if were an independently running service, rather than RLlib hosting the simulations itself. This is possible via RLlib's external agents interface.

class ray.rllib.utils.policy_client.**PolicyClient**(*address*)

REST client to interact with a RLlib policy server.

start_episode(*episode_id=None*, *training_enabled=True*)

Record the start of an episode.

Parameters

- **episode_id** (*str*) – Unique string id for the episode or None for it to be auto-assigned.
- **training_enabled** (*bool*) – Whether to use experiences for this episode to improve the policy.

Returns Unique string id for the episode.

Return type episode_id (str)

get_action(*episode_id*, *observation*)
Record an observation and get the on-policy action.

Parameters

- **episode_id** (*str*) – Episode id returned from start_episode().
- **observation** (*obj*) – Current environment observation.

Returns Action from the env action space.

Return type action (obj)

log_action(*episode_id*, *observation*, *action*)
Record an observation and (off-policy) action taken.

Parameters

- **episode_id** (*str*) – Episode id returned from start_episode().
- **observation** (*obj*) – Current environment observation.
- **action** (*obj*) – Action for the observation.

log_returns(*episode_id*, *reward*, *info=None*)
Record returns from the environment.

The reward will be attributed to the previous action taken by the episode. Rewards accumulate until the next action. If no reward is logged before the next action, a reward of 0.0 is assumed.

Parameters

- **episode_id** (*str*) – Episode id returned from start_episode().
- **reward** (*float*) – Reward from the environment.

end_episode(*episode_id*, *observation*)
Record the end of an episode.

Parameters

- **episode_id** (*str*) – Episode id returned from start_episode().
- **observation** (*obj*) – Current environment observation.

class ray.rllib.utils.policy_server.**PolicyServer**(*external_env*, *address*, *port*)
REST server than can be launched from a ExternalEnv.

This launches a multi-threaded server that listens on the specified host and port to serve policy requests and forward experiences to RLlib.

Examples

```
>>> class CartpoleServing(ExternalEnv):
       def __init__(self):
           ExternalEnv.__init__(
               self, spaces.Discrete(2),
               spaces.Box(
                   low=-10,
                   high=10,
                   shape=(4,),
                   dtype=np.float32))
       def run(self):
           server = PolicyServer(self, "localhost", 8900)
           server.serve_forever()
>>> register_env("srv", lambda _: CartpoleServing())
>>> pg = PGTrainer(env="srv", config={"num_workers": 0})
>>> while True:
        pg.train()
```

```
>>> client = PolicyClient("localhost:8900")
>>> eps_id = client.start_episode()
>>> action = client.get_action(eps_id, obs)
>>> ...
>>> client.log_returns(eps_id, reward)
>>> ...
>>> client.log_returns(eps_id, reward)
```

For a full client / server example that you can run, see the example client script and also the corresponding server script, here configured to serve a policy for the toy CartPole-v0 environment.

5.28 RLlib Environments

RLlib works with several different types of environments, including OpenAI Gym, user-defined, multi-agent, and also batched environments.

5.28.1 Feature Compatibility Matrix

Algorithm	Discrete Actions	Continuous	Multi-Agent	Model Support
A2C, A3C	**Yes** +parametric	**Yes**	**Yes**	+RNN, +autoreg
PPO, APPO	**Yes** +parametric	**Yes**	**Yes**	+RNN, +autoreg
PG	**Yes** +parametric	**Yes**	**Yes**	+RNN, +autoreg
IMPALA	**Yes** +parametric	**Yes**	**Yes**	+RNN, +autoreg
DQN, Rainbow	**Yes** +parametric	No	**Yes**	
DDPG, TD3	No	**Yes**	**Yes**	
APEX-DQN	**Yes** +parametric	No	**Yes**	
APEX-DDPG	No	**Yes**	**Yes**	
SAC	(todo)	**Yes**	**Yes**	
ES	**Yes**	**Yes**	No	
ARS	**Yes**	**Yes**	No	
QMIX	**Yes**	No	**Yes**	+RNN
MARWIL	**Yes** +parametric	**Yes**	**Yes**	+RNN

5.28.2 Configuring Environments

You can pass either a string name or a Python class to specify an environment. By default, strings will be interpreted as a gym environment name. Custom env classes passed directly to the trainer must take a single `env_config` parameter in their constructor:

```
import gym, ray
from ray.rllib.agents import ppo

class MyEnv(gym.Env):
    def __init__(self, env_config):
        self.action_space = <gym.Space>
        self.observation_space = <gym.Space>
    def reset(self):
        return <obs>
    def step(self, action):
        return <obs>, <reward: float>, <done: bool>, <info: dict>

ray.init()
trainer = ppo.PPOTrainer(env=MyEnv, config={
    "env_config": {},  # config to pass to env class
})

while True:
    print(trainer.train())
```

You can also register a custom env creator function with a string name. This function must take a single `env_config` parameter and return an env instance:

```
from ray.tune.registry import register_env

def env_creator(env_config):
    return MyEnv(...)  # return an env instance

register_env("my_env", env_creator)
trainer = ppo.PPOTrainer(env="my_env")
```

For a full runnable code example using the custom environment API, see custom_env.py.

Warning: The gym registry is not compatible with Ray. Instead, always use the registration flows documented above to ensure Ray workers can access the environment.

In the above example, note that the `env_creator` function takes in an `env_config` object. This is a dict containing options passed in through your trainer. You can also access `env_config.worker_index` and `env_config.vector_index` to get the worker id and env id within the worker (if `num_envs_per_worker > 0`). This can be useful if you want to train over an ensemble of different environments, for example:

```
class MultiEnv(gym.Env):
    def __init__(self, env_config):
        # pick actual env based on worker and env indexes
        self.env = gym.make(
            choose_env_for(env_config.worker_index, env_config.vector_index))
        self.action_space = self.env.action_space
        self.observation_space = self.env.observation_space
    def reset(self):
```

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```
        return self.env.reset()
    def step(self, action):
        return self.env.step(action)

register_env("multienv", lambda config: MultiEnv(config))
```

5.28.3 OpenAI Gym

RLlib uses Gym as its environment interface for single-agent training. For more information on how to implement a custom Gym environment, see the gym.Env class definition. You may find the SimpleCorridor example useful as a reference.

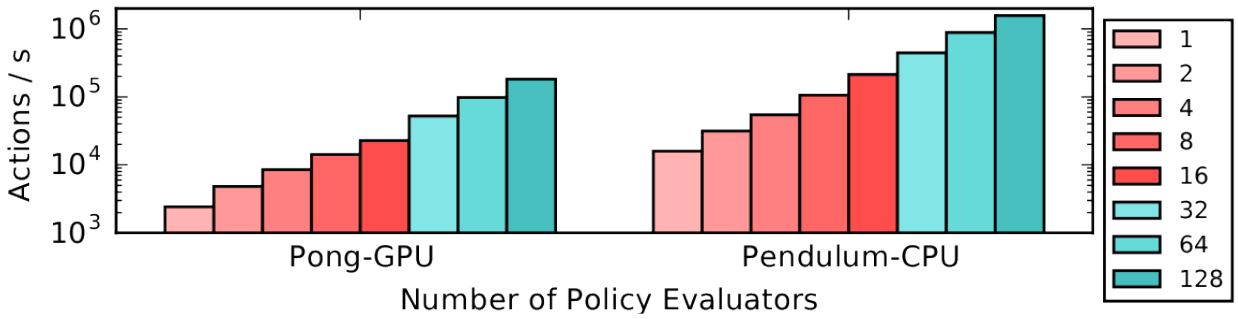
Performance

There are two ways to scale experience collection with Gym environments:

1. **Vectorization within a single process:** Though many envs can achieve high frame rates per core, their throughput is limited in practice by policy evaluation between steps. For example, even small TensorFlow models incur a couple milliseconds of latency to evaluate. This can be worked around by creating multiple envs per process and batching policy evaluations across these envs.

   You can configure `{"num_envs_per_worker": M}` to have RLlib create `M` concurrent environments per worker. RLlib auto-vectorizes Gym environments via VectorEnv.wrap().

2. **Distribute across multiple processes:** You can also have RLlib create multiple processes (Ray actors) for experience collection. In most algorithms this can be controlled by setting the `{"num_workers": N}` config.



You can also combine vectorization and distributed execution, as shown in the above figure. Here we plot just the throughput of RLlib policy evaluation from 1 to 128 CPUs. PongNoFrameskip-v4 on GPU scales from 2.4k to 200k actions/s, and Pendulum-v0 on CPU from 15k to 1.5M actions/s. One machine was used for 1-16 workers, and a Ray cluster of four machines for 32-128 workers. Each worker was configured with `num_envs_per_worker=64`.

Expensive Environments

Some environments may be very resource-intensive to create. RLlib will create `num_workers + 1` copies of the environment since one copy is needed for the driver process. To avoid paying the extra overhead of the driver copy, which is needed to access the env's action and observation spaces, you can defer environment initialization until `reset()` is called.

5.28.4 Vectorized

RLlib will auto-vectorize Gym envs for batch evaluation if the `num_envs_per_worker` config is set, or you can define a custom environment class that subclasses VectorEnv to implement `vector_step()` and `vector_reset()`.

Note that auto-vectorization only applies to policy inference by default. This means that policy inference will be batched, but your envs will still be stepped one at a time. If you would like your envs to be stepped in parallel, you can set `"remote_worker_envs": True`. This will create env instances in Ray actors and step them in parallel. These remote processes introduce communication overheads, so this only helps if your env is very expensive to step / reset.

When using remote envs, you can control the batching level for inference with `remote_env_batch_wait_ms`. The default value of 0ms means envs execute asynchronously and inference is only batched opportunistically. Setting the timeout to a large value will result in fully batched inference and effectively synchronous environment stepping. The optimal value depends on your environment step / reset time, and model inference speed.

5.28.5 Multi-Agent and Hierarchical

A multi-agent environment is one which has multiple acting entities per step, e.g., in a traffic simulation, there may be multiple "car" and "traffic light" agents in the environment. The model for multi-agent in RLlib as follows: (1) as a user you define the number of policies available up front, and (2) a function that maps agent ids to policy ids. This is summarized by the below figure:

The environment itself must subclass the MultiAgentEnv interface, which can returns observations and rewards from multiple ready agents per step:

```
# Example: using a multi-agent env
> env = MultiAgentTrafficEnv(num_cars=20, num_traffic_lights=5)

# Observations are a dict mapping agent names to their obs. Not all agents
# may be present in the dict in each time step.
> print(env.reset())
{
    "car_1": [[...]],
    "car_2": [[...]],
    "traffic_light_1": [[...]],
}

# Actions should be provided for each agent that returned an observation.
> new_obs, rewards, dones, infos = env.step(actions={"car_1": ..., "car_2": ...})

# Similarly, new_obs, rewards, dones, etc. also become dicts
> print(rewards)
{"car_1": 3, "car_2": -1, "traffic_light_1": 0}

# Individual agents can early exit; env is done when "__all__" = True
> print(dones)
{"car_2": True, "__all__": False}
```

If all the agents will be using the same algorithm class to train, then you can setup multi-agent training as follows:

```
trainer = pg.PGAgent(env="my_multiagent_env", config={
    "multiagent": {
        "policies": {
            # the first tuple value is None -> uses default policy
```

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```
            "car1": (None, car_obs_space, car_act_space, {"gamma": 0.85}),
            "car2": (None, car_obs_space, car_act_space, {"gamma": 0.99}),
            "traffic_light": (None, tl_obs_space, tl_act_space, {}),
        },
        "policy_mapping_fn":
            lambda agent_id:
                "traffic_light"  # Traffic lights are always controlled by this policy
                if agent_id.startswith("traffic_light_")
                else random.choice(["car1", "car2"])  # Randomly choose from car␣
↪policies
    },
})

while True:
    print(trainer.train())
```

RLlib will create three distinct policies and route agent decisions to its bound policy. When an agent first appears in the env, `policy_mapping_fn` will be called to determine which policy it is bound to. RLlib reports separate training statistics for each policy in the return from `train()`, along with the combined reward.

Here is a simple example training script in which you can vary the number of agents and policies in the environment. For how to use multiple training methods at once (here DQN and PPO), see the two-trainer example. Metrics are reported for each policy separately, for example:

```
Result for PPO_multi_cartpole_0:
  episode_len_mean: 34.025862068965516
  episode_reward_max: 159.0
  episode_reward_mean: 86.06896551724138
  info:
    policy_0:
      cur_lr: 4.999999873689376e-05
      entropy: 0.6833480000495911
      kl: 0.010264254175126553
      policy_loss: -11.95590591430664
      total_loss: 197.7039794921875
      vf_explained_var: 0.0010995268821716309
      vf_loss: 209.6578826904297
    policy_1:
      cur_lr: 4.999999873689376e-05
      entropy: 0.6827034950256348
      kl: 0.01119876280426979
      policy_loss: -8.787769317626953
      total_loss: 88.26161193847656
      vf_explained_var: 0.0005457401275634766
      vf_loss: 97.0471420288086
  policy_reward_mean:
    policy_0: 21.194444444444443
    policy_1: 21.798387096774192
```

To scale to hundreds of agents, MultiAgentEnv batches policy evaluations across multiple agents internally. It can also be auto-vectorized by setting `num_envs_per_worker > 1`.

Rock Paper Scissors Example

The rock_paper_scissors_multiagent.py example demonstrates several types of policies competing against each other: heuristic policies of repeating the same move, beating the last opponent move, and learned LSTM and feedforward

policies.

Fig. 2: TensorBoard output of running the rock-paper-scissors example, where a learned policy faces off between a random selection of the same-move and beat-last-move heuristics. Here the performance of heuristic policies vs the learned policy is compared with LSTM enabled (blue) and a plain feed-forward policy (red). While the feedforward policy can easily beat the same-move heuristic by simply avoiding the last move taken, it takes a LSTM policy to distinguish between and consistently beat both policies.

Variable-Sharing Between Policies

Note: With ModelV2, you can put layers in global variables and straightforwardly share those layer objects between models instead of using variable scopes.

RLlib will create each policy's model in a separate `tf.variable_scope`. However, variables can still be shared between policies by explicitly entering a globally shared variable scope with `tf.VariableScope(reuse=tf.AUTO_REUSE)`:

```
with tf.variable_scope(
        tf.VariableScope(tf.AUTO_REUSE, "name_of_global_shared_scope"),
        reuse=tf.AUTO_REUSE,
        auxiliary_name_scope=False):
    <create the shared layers here>
```

There is a full example of this in the example training script.

Implementing a Centralized Critic

Here are two ways to implement a centralized critic compatible with the multi-agent API:

Strategy 1: Sharing experiences in the trajectory preprocessor:

The most general way of implementing a centralized critic involves modifying the `postprocess_trajectory` method of a custom policy, which has full access to the policies and observations of concurrent agents via the `other_agent_batches` and `episode` arguments. The batch of critic predictions can then be added to the post-processed trajectory. Here's an example:

```
def postprocess_trajectory(policy, sample_batch, other_agent_batches, episode):
    agents = ["agent_1", "agent_2", "agent_3"]  # simple example of 3 agents
    global_obs_batch = np.stack(
        [other_agent_batches[agent_id][1]["obs"] for agent_id in agents],
        axis=1)
    # add the global obs and global critic value
```

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```
    sample_batch["global_obs"] = global_obs_batch
    sample_batch["central_vf"] = self.sess.run(
        self.critic_network, feed_dict={"obs": global_obs_batch})
    return sample_batch
```

To update the critic, you'll also have to modify the loss of the policy. For an end-to-end runnable example, see examples/centralized_critic.py.

Strategy 2: Sharing observations through the environment:

Alternatively, the env itself can be modified to share observations between agents. In this strategy, each observation includes all global state, and policies use a custom model to ignore state they aren't supposed to "see" when computing actions. The advantage of this approach is that it's very simple and you don't have to change the algorithm at all – just use an env wrapper and custom model. However, it is a bit less principled in that you have to change the agent observation spaces and the environment. You can find a runnable example of this strategy at examples/centralized_critic_2.py.

Grouping Agents

It is common to have groups of agents in multi-agent RL. RLlib treats agent groups like a single agent with a Tuple action and observation space. The group agent can then be assigned to a single policy for centralized execution, or to specialized multi-agent policies such as Q-Mix that implement centralized training but decentralized execution. You can use the `MultiAgentEnv.with_agent_groups()` method to define these groups:

```
    @PublicAPI
    def with_agent_groups(self, groups, obs_space=None, act_space=None):
        """Convenience method for grouping together agents in this env.

        An agent group is a list of agent ids that are mapped to a single
        logical agent. All agents of the group must act at the same time in the
        environment. The grouped agent exposes Tuple action and observation
        spaces that are the concatenated action and obs spaces of the
        individual agents.

        The rewards of all the agents in a group are summed. The individual
        agent rewards are available under the "individual_rewards" key of the
        group info return.

        Agent grouping is required to leverage algorithms such as Q-Mix.

        This API is experimental.

        Arguments:
            groups (dict): Mapping from group id to a list of the agent ids
                of group members. If an agent id is not present in any group
                value, it will be left ungrouped.
            obs_space (Space): Optional observation space for the grouped
                env. Must be a tuple space.
            act_space (Space): Optional action space for the grouped env.
                Must be a tuple space.

        Examples:
            >>> env = YourMultiAgentEnv(...)
            >>> grouped_env = env.with_agent_groups(env, {
            ...   "group1": ["agent1", "agent2", "agent3"],
            ...   "group2": ["agent4", "agent5"],
```

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```
            ... })
        """

        from ray.rllib.env.group_agents_wrapper import _GroupAgentsWrapper
        return _GroupAgentsWrapper(self, groups, obs_space, act_space)
```

For environments with multiple groups, or mixtures of agent groups and individual agents, you can use grouping in conjunction with the policy mapping API described in prior sections.

Hierarchical Environments

Hierarchical training can sometimes be implemented as a special case of multi-agent RL. For example, consider a three-level hierarchy of policies, where a top-level policy issues high level actions that are executed at finer timescales by a mid-level and low-level policy. The following timeline shows one step of the top-level policy, which corresponds to two mid-level actions and five low-level actions:

```
top_level ----------------------------------------------------------------> top_level -
↪-->
mid_level_0 -------------------------------> mid_level_0 ----------------> mid_level_
↪1 ->
low_level_0 -> low_level_0 -> low_level_0 -> low_level_1 -> low_level_1 -> low_level_
↪2 ->
```

This can be implemented as a multi-agent environment with three types of agents. Each higher-level action creates a new lower-level agent instance with a new id (e.g., `low_level_0`, `low_level_1`, `low_level_2` in the above example). These lower-level agents pop in existence at the start of higher-level steps, and terminate when their higher-level action ends. Their experiences are aggregated by policy, so from RLlib's perspective it's just optimizing three different types of policies. The configuration might look something like this:

```
"multiagent": {
    "policies": {
        "top_level": (custom_policy or None, ...),
        "mid_level": (custom_policy or None, ...),
        "low_level": (custom_policy or None, ...),
    },
    "policy_mapping_fn":
        lambda agent_id:
            "low_level" if agent_id.startswith("low_level_") else
            "mid_level" if agent_id.startswith("mid_level_") else "top_level"
    "policies_to_train": ["top_level"],
},
```

In this setup, the appropriate rewards for training lower-level agents must be provided by the multi-agent env implementation. The environment class is also responsible for routing between the agents, e.g., conveying goals from higher-level agents to lower-level agents as part of the lower-level agent observation.

See this file for a runnable example: hierarchical_training.py.

5.28.6 Interfacing with External Agents

In many situations, it does not make sense for an environment to be "stepped" by RLlib. For example, if a policy is to be used in a web serving system, then it is more natural for an agent to query a service that serves policy decisions, and for that service to learn from experience over time. This case also naturally arises with **external simulators** that run independently outside the control of RLlib, but may still want to leverage RLlib for training.

RLlib provides the ExternalEnv class for this purpose. Unlike other envs, ExternalEnv has its own thread of control. At any point, agents on that thread can query the current policy for decisions via `self.get_action()` and reports rewards via `self.log_returns()`. This can be done for multiple concurrent episodes as well.

ExternalEnv can be used to implement a simple REST policy server that learns over time using RLlib. In this example RLlib runs with `num_workers=0` to avoid port allocation issues, but in principle this could be scaled by increasing `num_workers`.

Logging off-policy actions

ExternalEnv also provides a `self.log_action()` call to support off-policy actions. This allows the client to make independent decisions, e.g., to compare two different policies, and for RLlib to still learn from those off-policy actions. Note that this requires the algorithm used to support learning from off-policy decisions (e.g., DQN).

Data ingest

The `log_action` API of ExternalEnv can be used to ingest data from offline logs. The pattern would be as follows: First, some policy is followed to produce experience data which is stored in some offline storage system. Then, RLlib creates a number of workers that use a ExternalEnv to read the logs in parallel and ingest the experiences. After a round of training completes, the new policy can be deployed to collect more experiences.

Note that envs can read from different partitions of the logs based on the `worker_index` attribute of the env context passed into the environment constructor.

See also:

Offline Datasets provide higher-level interfaces for working with offline experience datasets.

5.28.7 Advanced Integrations

For more complex / high-performance environment integrations, you can instead extend the low-level BaseEnv class. This low-level API models multiple agents executing asynchronously in multiple environments. A call to `BaseEnv:poll()` returns observations from ready agents keyed by their environment and agent ids, and actions for those agents are sent back via `BaseEnv:send_actions()`. BaseEnv is used to implement all the other env types in RLlib, so it offers a superset of their functionality. For example, `BaseEnv` is used to implement dynamic batching of observations for inference over multiple simulator actors.

5.29 RLlib Models, Preprocessors, and Action Distributions

The following diagram provides a conceptual overview of data flow between different components in RLlib. We start with an `Environment`, which given an action produces an observation. The observation is preprocessed by a `Preprocessor` and `Filter` (e.g. for running mean normalization) before being sent to a neural network `Model`. The model output is in turn interpreted by an `ActionDistribution` to determine the next action.

The components highlighted in green can be replaced with custom user-defined implementations, as described in the next sections. The purple components are RLlib internal, which means they can only be modified by changing the algorithm source code.

5.29.1 Default Behaviours

Built-in Models and Preprocessors

RLlib picks default models based on a simple heuristic: a vision network for image observations, and a fully connected network for everything else. These models can be configured via the `model` config key, documented in the model catalog. Note that you'll probably have to configure `conv_filters` if your environment observations have custom sizes, e.g., `"model": {"dim": 42, "conv_filters": [[16, [4, 4], 2], [32, [4, 4], 2], [512, [11, 11], 1]]}` for 42x42 observations.

In addition, if you set `"model": {"use_lstm": true}`, then the model output will be further processed by a LSTM cell. More generally, RLlib supports the use of recurrent models for its policy gradient algorithms (A3C, PPO, PG, IMPALA), and RNN support is built into its policy evaluation utilities.

For preprocessors, RLlib tries to pick one of its built-in preprocessor based on the environment's observation space. Discrete observations are one-hot encoded, Atari observations downscaled, and Tuple and Dict observations flattened (these are unflattened and accessible via the `input_dict` parameter in custom models). Note that for Atari, RLlib defaults to using the DeepMind preprocessors, which are also used by the OpenAI baselines library.

Built-in Model Parameters

The following is a list of the built-in model hyperparameters:

```
MODEL_DEFAULTS = {
    # === Built-in options ===
    # Filter config. List of [out_channels, kernel, stride] for each filter
    "conv_filters": None,
    # Nonlinearity for built-in convnet
    "conv_activation": "relu",
    # Nonlinearity for fully connected net (tanh, relu)
    "fcnet_activation": "tanh",
    # Number of hidden layers for fully connected net
    "fcnet_hiddens": [256, 256],
    # For control envs, documented in ray.rllib.models.Model
    "free_log_std": False,
    # Whether to skip the final linear layer used to resize the hidden layer
    # outputs to size `num_outputs`. If True, then the last hidden layer
    # should already match num_outputs.
    "no_final_linear": False,
    # Whether layers should be shared for the value function.
    "vf_share_layers": True,

    # == LSTM ==
    # Whether to wrap the model with a LSTM
    "use_lstm": False,
    # Max seq len for training the LSTM, defaults to 20
    "max_seq_len": 20,
    # Size of the LSTM cell
    "lstm_cell_size": 256,
    # Whether to feed a_{t-1}, r_{t-1} to LSTM
    "lstm_use_prev_action_reward": False,
    # When using modelv1 models with a modelv2 algorithm, you may have to
    # define the state shape here (e.g., [256, 256]).
    "state_shape": None,

    # == Atari ==
```

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```
    # Whether to enable framestack for Atari envs
    "framestack": True,
    # Final resized frame dimension
    "dim": 84,
    # (deprecated) Converts ATARI frame to 1 Channel Grayscale image
    "grayscale": False,
    # (deprecated) Changes frame to range from [-1, 1] if true
    "zero_mean": True,

    # === Options for custom models ===
    # Name of a custom preprocessor to use
    "custom_preprocessor": None,
    # Name of a custom model to use
    "custom_model": None,
    # Name of a custom action distribution to use
    "custom_action_dist": None,
    # Extra options to pass to the custom classes
    "custom_options": {},
}
```

5.29.2 TensorFlow Models

Note: TFModelV2 replaces the previous `rllib.models.Model` class, which did not support Keras-style reuse of variables. The `rllib.models.Model` class is deprecated and should not be used.

Custom TF models should subclass TFModelV2 to implement the `__init__()` and `forward()` methods. Forward takes in a dict of tensor inputs (the observation `obs`, `prev_action`, and `prev_reward`, `is_training`), optional RNN state, and returns the model output of size `num_outputs` and the new state. You can also override extra methods of the model such as `value_function` to implement a custom value branch. Additional supervised / self-supervised losses can be added via the `custom_loss` method:

class ray.rllib.models.tf.tf_modelv2.**TFModelV2**(*obs_space*, *action_space*, *num_outputs*, *model_config*, *name*)

TF version of ModelV2.

Note that this class by itself is not a valid model unless you implement forward() in a subclass.

__init__(*obs_space*, *action_space*, *num_outputs*, *model_config*, *name*)

Initialize a TFModelV2.

Here is an example implementation for a subclass `MyModelClass(TFModelV2)`:

```
def __init__(self, *args, **kwargs):
    super(MyModelClass, self).__init__(*args, **kwargs)
    input_layer = tf.keras.layers.Input(...)
    hidden_layer = tf.keras.layers.Dense(...)(input_layer)
    output_layer = tf.keras.layers.Dense(...)(hidden_layer)
    value_layer = tf.keras.layers.Dense(...)(hidden_layer)
    self.base_model = tf.keras.Model(
        input_layer, [output_layer, value_layer])
    self.register_variables(self.base_model.variables)
```

forward(*input_dict*, *state*, *seq_lens*)

Call the model with the given input tensors and state.

Any complex observations (dicts, tuples, etc.) will be unpacked by __call__ before being passed to forward(). To access the flattened observation tensor, refer to input_dict["obs_flat"].

This method can be called any number of times. In eager execution, each call to forward() will eagerly evaluate the model. In symbolic execution, each call to forward creates a computation graph that operates over the variables of this model (i.e., shares weights).

Custom models should override this instead of __call__.

Parameters

- **input_dict** (*dict*) – dictionary of input tensors, including "obs", "obs_flat", "prev_action", "prev_reward", "is_training"
- **state** (*list*) – list of state tensors with sizes matching those returned by get_initial_state + the batch dimension
- **seq_lens** (*Tensor*) – 1d tensor holding input sequence lengths

Returns

The model output tensor of size [BATCH, num_outputs]

Return type (outputs, state)

Sample implementation for the `MyModelClass` example:

```
def forward(self, input_dict, state, seq_lens):
    model_out, self._value_out = self.base_model(input_dict["obs"])
    return model_out, state
```

value_function()

Return the value function estimate for the most recent forward pass.

Returns value estimate tensor of shape [BATCH].

Sample implementation for the `MyModelClass` example:

```
def value_function(self):
    return self._value_out
```

custom_loss(*policy_loss*, *loss_inputs*)

Override to customize the loss function used to optimize this model.

This can be used to incorporate self-supervised losses (by defining a loss over existing input and output tensors of this model), and supervised losses (by defining losses over a variable-sharing copy of this model's layers).

You can find an runnable example in examples/custom_loss.py.

Parameters

- **policy_loss** (*Tensor*) – scalar policy loss from the policy.
- **loss_inputs** (*dict*) – map of input placeholders for rollout data.

Returns Scalar tensor for the customized loss for this model.

metrics()

Override to return custom metrics from your model.

The stats will be reported as part of the learner stats, i.e.,

info:

learner:

model: key1: metric1 key2: metric2

Returns Dict of string keys to scalar tensors.

update_ops()
Return the list of update ops for this model.

For example, this should include any BatchNorm update ops.

register_variables(*variables*)
Register the given list of variables with this model.

variables()
Returns the list of variables for this model.

trainable_variables()
Returns the list of trainable variables for this model.

Once implemented, the model can then be registered and used in place of a built-in model:

```
import ray
import ray.rllib.agents.ppo as ppo
from ray.rllib.models import ModelCatalog
from ray.rllib.models.tf.tf_modelv2 import TFModelV2

class MyModelClass(TFModelV2):
    def __init__(self, obs_space, action_space, num_outputs, model_config, name): ...
    def forward(self, input_dict, state, seq_lens): ...
    def value_function(self): ...

ModelCatalog.register_custom_model("my_model", MyModelClass)

ray.init()
trainer = ppo.PPOTrainer(env="CartPole-v0", config={
    "model": {
        "custom_model": "my_model",
        "custom_options": {},  # extra options to pass to your model
    },
})
```

For a full example of a custom model in code, see the keras model example. You can also reference the unit tests for Tuple and Dict spaces, which show how to access nested observation fields.

Recurrent Models

Instead of using the `use_lstm: True` option, it can be preferable use a custom recurrent model. This provides more control over postprocessing of the LSTM output and can also allow the use of multiple LSTM cells to process different portions of the input. For a RNN model it is preferred to subclass `RecurrentTFModelV2` to implement `__init__()`, `get_initial_state()`, and `forward_rnn()`. You can check out the custom_keras_rnn_model.py model as an example to implement your own model:

class ray.rllib.models.tf.recurrent_tf_modelv2.**RecurrentTFModelV2**(*obs_space*, *action_space*, *num_outputs*, *model_config*, *name*)

Helper class to simplify implementing RNN models with TFModelV2.

Instead of implementing forward(), you can implement forward_rnn() which takes batches with the time dimension added already.

__init__(*obs_space*, *action_space*, *num_outputs*, *model_config*, *name*)
Initialize a TFModelV2.

Here is an example implementation for a subclass `MyRNNClass(RecurrentTFModelV2)`:

```
def __init__(self, *args, **kwargs):
    super(MyModelClass, self).__init__(*args, **kwargs)
    cell_size = 256

    # Define input layers
    input_layer = tf.keras.layers.Input(
        shape=(None, obs_space.shape[0]))
    state_in_h = tf.keras.layers.Input(shape=(256, ))
    state_in_c = tf.keras.layers.Input(shape=(256, ))
    seq_in = tf.keras.layers.Input(shape=(), dtype=tf.int32)

    # Send to LSTM cell
    lstm_out, state_h, state_c = tf.keras.layers.LSTM(
        cell_size, return_sequences=True, return_state=True,
        name="lstm")(
            inputs=input_layer,
            mask=tf.sequence_mask(seq_in),
            initial_state=[state_in_h, state_in_c])
    output_layer = tf.keras.layers.Dense(...)(lstm_out)

    # Create the RNN model
    self.rnn_model = tf.keras.Model(
        inputs=[input_layer, seq_in, state_in_h, state_in_c],
        outputs=[output_layer, state_h, state_c])
    self.register_variables(self.rnn_model.variables)
    self.rnn_model.summary()
```

forward_rnn(*inputs*, *state*, *seq_lens*)
Call the model with the given input tensors and state.

Parameters

- **inputs** (*dict*) – observation tensor with shape [B, T, obs_size].
- **state** (*list*) – list of state tensors, each with shape [B, T, size].
- **seq_lens** (*Tensor*) – 1d tensor holding input sequence lengths.

Returns

The model output tensor of shape [B, T, num_outputs] and the list of new state tensors each with shape [B, size].

Return type (outputs, new_state)

Sample implementation for the `MyRNNClass` example:

```
def forward_rnn(self, inputs, state, seq_lens):
    model_out, h, c = self.rnn_model([inputs, seq_lens] + state)
    return model_out, [h, c]
```

get_initial_state()
Get the initial recurrent state values for the model.

Returns list of np.array objects, if any

Sample implementation for the `MyRNNClass` example:

```
def get_initial_state(self):
    return [
        np.zeros(self.cell_size, np.float32),
        np.zeros(self.cell_size, np.float32),
    ]
```

Batch Normalization

You can use `tf.layers.batch_normalization(x, training=input_dict["is_training"])` to add batch norm layers to your custom model: code example. RLlib will automatically run the update ops for the batch norm layers during optimization (see tf_policy.py and multi_gpu_impl.py for the exact handling of these updates).

In case RLlib does not properly detect the update ops for your custom model, you can override the `update_ops()` method to return the list of ops to run for updates.

5.29.3 PyTorch Models

Similarly, you can create and register custom PyTorch models for use with PyTorch-based algorithms (e.g., A2C, PG, QMIX). See these examples of fully connected, convolutional, and recurrent torch models.

class ray.rllib.models.torch.torch_modelv2.**TorchModelV2**(*obs_space*, *action_space*, *num_outputs*, *model_config*, *name*)

Torch version of ModelV2.

Note that this class by itself is not a valid model unless you inherit from nn.Module and implement forward() in a subclass.

__init__(*obs_space*, *action_space*, *num_outputs*, *model_config*, *name*)

Initialize a TorchModelV2.

Here is an example implementation for a subclass `MyModelClass(TorchModelV2, nn.Module)`:

```
def __init__(self, *args, **kwargs):
    TorchModelV2.__init__(self, *args, **kwargs)
    nn.Module.__init__(self)
    self._hidden_layers = nn.Sequential(...)
    self._logits = ...
    self._value_branch = ...
```

forward(*input_dict*, *state*, *seq_lens*)

Call the model with the given input tensors and state.

Any complex observations (dicts, tuples, etc.) will be unpacked by __call__ before being passed to forward(). To access the flattened observation tensor, refer to input_dict["obs_flat"].

This method can be called any number of times. In eager execution, each call to forward() will eagerly evaluate the model. In symbolic execution, each call to forward creates a computation graph that operates over the variables of this model (i.e., shares weights).

Custom models should override this instead of __call__.

Parameters

- **input_dict** (*dict*) – dictionary of input tensors, including "obs", "obs_flat", "prev_action", "prev_reward", "is_training"
- **state** (*list*) – list of state tensors with sizes matching those returned by get_initial_state + the batch dimension
- **seq_lens** (*Tensor*) – 1d tensor holding input sequence lengths

Returns

The model output tensor of size [BATCH, num_outputs]

Return type (outputs, state)

Sample implementation for the `MyModelClass` example:

```
def forward(self, input_dict, state, seq_lens):
    features = self._hidden_layers(input_dict["obs"])
    self._value_out = self._value_branch(features)
    return self._logits(features), state
```

value_function()

Return the value function estimate for the most recent forward pass.

Returns value estimate tensor of shape [BATCH].

Sample implementation for the `MyModelClass` example:

```
def value_function(self):
    return self._value_out
```

custom_loss(*policy_loss*, *loss_inputs*)

Override to customize the loss function used to optimize this model.

This can be used to incorporate self-supervised losses (by defining a loss over existing input and output tensors of this model), and supervised losses (by defining losses over a variable-sharing copy of this model's layers).

You can find an runnable example in examples/custom_loss.py.

Parameters

- **policy_loss** (*Tensor*) – scalar policy loss from the policy.
- **loss_inputs** (*dict*) – map of input placeholders for rollout data.

Returns Scalar tensor for the customized loss for this model.

metrics()

Override to return custom metrics from your model.

The stats will be reported as part of the learner stats, i.e.,

info:

learner:

model: key1: metric1 key2: metric2

Returns Dict of string keys to scalar tensors.

get_initial_state()

Get the initial recurrent state values for the model.

Returns list of np.array objects, if any

Once implemented, the model can then be registered and used in place of a built-in model:

```
import torch.nn as nn

import ray
from ray.rllib.agents import a3c
from ray.rllib.models import ModelCatalog
from ray.rllib.models.torch.torch_modelv2 import TorchModelV2

class CustomTorchModel(nn.Module, TorchModelV2):
    def __init__(self, obs_space, action_space, num_outputs, model_config, name): ...
    def forward(self, input_dict, state, seq_lens): ...
    def value_function(self): ...

ModelCatalog.register_custom_model("my_model", CustomTorchModel)

ray.init()
trainer = a3c.A2CTrainer(env="CartPole-v0", config={
    "use_pytorch": True,
    "model": {
        "custom_model": "my_model",
        "custom_options": {},  # extra options to pass to your model
    },
})
```

5.29.4 Custom Preprocessors

Custom preprocessors should subclass the RLlib preprocessor class and be registered in the model catalog. Note that you can alternatively use gym wrapper classes around your environment instead of preprocessors.

```
import ray
import ray.rllib.agents.ppo as ppo
from ray.rllib.models import ModelCatalog
from ray.rllib.models.preprocessors import Preprocessor

class MyPreprocessorClass(Preprocessor):
    def _init_shape(self, obs_space, options):
        return new_shape  # can vary depending on inputs

    def transform(self, observation):
        return ...  # return the preprocessed observation

ModelCatalog.register_custom_preprocessor("my_prep", MyPreprocessorClass)

ray.init()
trainer = ppo.PPOTrainer(env="CartPole-v0", config={
    "model": {
        "custom_preprocessor": "my_prep",
        "custom_options": {},  # extra options to pass to your preprocessor
    },
})
```

5.29.5 Custom Action Distributions

Similar to custom models and preprocessors, you can also specify a custom action distribution class as follows. The action dist class is passed a reference to the `model`, which you can use to access `model.model_config` or other attributes of the model. This is commonly used to implement *autoregressive action outputs*.

```
import ray
import ray.rllib.agents.ppo as ppo
from ray.rllib.models import ModelCatalog
from ray.rllib.models.preprocessors import Preprocessor

class MyActionDist(ActionDistribution):
    @staticmethod
    def required_model_output_shape(action_space, model_config):
        return 7  # controls model output feature vector size

    def __init__(self, inputs, model):
        super(MyActionDist, self).__init__(inputs, model)
        assert model.num_outputs == 7

    def sample(self): ...
    def logp(self, actions): ...
    def entropy(self): ...

ModelCatalog.register_custom_action_dist("my_dist", MyActionDist)

ray.init()
trainer = ppo.PPOTrainer(env="CartPole-v0", config={
    "model": {
        "custom_action_dist": "my_dist",
    },
})
```

5.29.6 Supervised Model Losses

You can mix supervised losses into any RLlib algorithm through custom models. For example, you can add an imitation learning loss on expert experiences, or a self-supervised autoencoder loss within the model. These losses can be defined over either policy evaluation inputs, or data read from offline storage.

TensorFlow: To add a supervised loss to a custom TF model, you need to override the `custom_loss()` method. This method takes in the existing policy loss for the algorithm, which you can add your own supervised loss to before returning. For debugging, you can also return a dictionary of scalar tensors in the `metrics()` method. Here is a runnable example of adding an imitation loss to CartPole training that is defined over a offline dataset.

PyTorch: There is no explicit API for adding losses to custom torch models. However, you can modify the loss in the policy definition directly. Like for TF models, offline datasets can be incorporated by creating an input reader and calling `reader.next()` in the loss forward pass.

5.29.7 Variable-length / Parametric Action Spaces

Custom models can be used to work with environments where (1) the set of valid actions varies per step, and/or (2) the number of valid actions is very large. The general idea is that the meaning of actions can be completely conditioned on the observation, i.e., the `a` in `Q(s, a)` becomes just a token in `[0, MAX_AVAIL_ACTIONS)` that only has meaning in the context of `s`. This works with algorithms in the DQN and policy-gradient families and can be implemented as follows:

1. The environment should return a mask and/or list of valid action embeddings as part of the observation for each step. To enable batching, the number of actions can be allowed to vary from 1 to some max number:

```
class MyParamActionEnv(gym.Env):
    def __init__(self, max_avail_actions):
        self.action_space = Discrete(max_avail_actions)
        self.observation_space = Dict({
            "action_mask": Box(0, 1, shape=(max_avail_actions, )),
            "avail_actions": Box(-1, 1, shape=(max_avail_actions, action_embedding_
↪sz)),
            "real_obs": ...,
        })
```

2. A custom model can be defined that can interpret the `action_mask` and `avail_actions` portions of the observation. Here the model computes the action logits via the dot product of some network output and each action embedding. Invalid actions can be masked out of the softmax by scaling the probability to zero:

```
class ParametricActionsModel(TFModelV2):
    def __init__(self,
                 obs_space,
                 action_space,
                 num_outputs,
                 model_config,
                 name,
                 true_obs_shape=(4,),
                 action_embed_size=2):
        super(ParametricActionsModel, self).__init__(
            obs_space, action_space, num_outputs, model_config, name)
        self.action_embed_model = FullyConnectedNetwork(...)

    def forward(self, input_dict, state, seq_lens):
        # Extract the available actions tensor from the observation.
        avail_actions = input_dict["obs"]["avail_actions"]
        action_mask = input_dict["obs"]["action_mask"]

        # Compute the predicted action embedding
        action_embed, _ = self.action_embed_model({
            "obs": input_dict["obs"]["cart"]
        })

        # Expand the model output to [BATCH, 1, EMBED_SIZE]. Note that the
        # avail actions tensor is of shape [BATCH, MAX_ACTIONS, EMBED_SIZE].
        intent_vector = tf.expand_dims(action_embed, 1)

        # Batch dot product => shape of logits is [BATCH, MAX_ACTIONS].
        action_logits = tf.reduce_sum(avail_actions * intent_vector, axis=2)

        # Mask out invalid actions (use tf.float32.min for stability)
        inf_mask = tf.maximum(tf.log(action_mask), tf.float32.min)
        return action_logits + inf_mask, state
```

Depending on your use case it may make sense to use just the masking, just action embeddings, or both. For a runnable example of this in code, check out parametric_action_cartpole.py. Note that since masking introduces `tf.float32.min` values into the model output, this technique might not work with all algorithm options. For example, algorithms might crash if they incorrectly process the `tf.float32.min` values. The cartpole example has working configurations for DQN (must set `hiddens=[]`), PPO (must disable running mean and set `vf_share_layers=True`), and several other algorithms. Not all algorithms support parametric actions; see the feature compatibility matrix.

5.29.8 Autoregressive Action Distributions

In an action space with multiple components (e.g., `Tuple(a1, a2)`), you might want `a2` to be conditioned on the sampled value of `a1`, i.e., `a2_sampled ~ P(a2 | a1_sampled, obs)`. Normally, `a1` and `a2` would be sampled independently, reducing the expressivity of the policy.

To do this, you need both a custom model that implements the autoregressive pattern, and a custom action distribution class that leverages that model. The autoregressive_action_dist.py example shows how this can be implemented for a simple binary action space. For a more complex space, a more efficient architecture such as a MADE is recommended. Note that sampling a *N-part* action requires *N* forward passes through the model, however computing the log probability of an action can be done in one pass:

```
class BinaryAutoregressiveOutput(ActionDistribution):
    """Action distribution P(a1, a2) = P(a1) * P(a2 | a1)"""

    @staticmethod
    def required_model_output_shape(self, model_config):
        return 16  # controls model output feature vector size

    def sample(self):
        # first, sample a1
        a1_dist = self._a1_distribution()
        a1 = a1_dist.sample()

        # sample a2 conditioned on a1
        a2_dist = self._a2_distribution(a1)
        a2 = a2_dist.sample()

        # return the action tuple
        return TupleActions([a1, a2])

    def logp(self, actions):
        a1, a2 = actions[:, 0], actions[:, 1]
        a1_vec = tf.expand_dims(tf.cast(a1, tf.float32), 1)
        a1_logits, a2_logits = self.model.action_model([self.inputs, a1_vec])
        return (Categorical(a1_logits, None).logp(a1) + Categorical(
            a2_logits, None).logp(a2))

    def _a1_distribution(self):
        BATCH = tf.shape(self.inputs)[0]
        a1_logits, _ = self.model.action_model(
            [self.inputs, tf.zeros((BATCH, 1))])
        a1_dist = Categorical(a1_logits, None)
        return a1_dist

    def _a2_distribution(self, a1):
        a1_vec = tf.expand_dims(tf.cast(a1, tf.float32), 1)
        _, a2_logits = self.model.action_model([self.inputs, a1_vec])
        a2_dist = Categorical(a2_logits, None)
        return a2_dist

class AutoregressiveActionsModel(TFModelV2):
    """Implements the `.action_model` branch required above."""

    def __init__(self, obs_space, action_space, num_outputs, model_config,
                 name):
        super(AutoregressiveActionsModel, self).__init__(
            obs_space, action_space, num_outputs, model_config, name)
```

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```
        if action_space != Tuple([Discrete(2), Discrete(2)]):
            raise ValueError(
                "This model only supports the [2, 2] action space")

        # Inputs
        obs_input = tf.keras.layers.Input(
            shape=obs_space.shape, name="obs_input")
        a1_input = tf.keras.layers.Input(shape=(1, ), name="a1_input")
        ctx_input = tf.keras.layers.Input(
            shape=(num_outputs, ), name="ctx_input")

        # Output of the model (normally 'logits', but for an autoregressive
        # dist this is more like a context/feature layer encoding the obs)
        context = tf.keras.layers.Dense(
            num_outputs,
            name="hidden",
            activation=tf.nn.tanh,
            kernel_initializer=normc_initializer(1.0))(obs_input)

        # P(a1 | obs)
        a1_logits = tf.keras.layers.Dense(
            2,
            name="a1_logits",
            activation=None,
            kernel_initializer=normc_initializer(0.01))(ctx_input)

        # P(a2 | a1)
        # --note: typically you'd want to implement P(a2 | a1, obs) as follows:
        # a2_context = tf.keras.layers.Concatenate(axis=1)(
        #     [ctx_input, a1_input])
        a2_context = a1_input
        a2_hidden = tf.keras.layers.Dense(
            16,
            name="a2_hidden",
            activation=tf.nn.tanh,
            kernel_initializer=normc_initializer(1.0))(a2_context)
        a2_logits = tf.keras.layers.Dense(
            2,
            name="a2_logits",
            activation=None,
            kernel_initializer=normc_initializer(0.01))(a2_hidden)

        # Base layers
        self.base_model = tf.keras.Model(obs_input, context)
        self.register_variables(self.base_model.variables)
        self.base_model.summary()

        # Autoregressive action sampler
        self.action_model = tf.keras.Model([ctx_input, a1_input],
                                           [a1_logits, a2_logits])
        self.action_model.summary()
        self.register_variables(self.action_model.variables)
```

Note: Not all algorithms support autoregressive action distributions; see the feature compatibility matrix.

5.30 RLlib Algorithms

5.30.1 High-throughput architectures

Distributed Prioritized Experience Replay (Ape-X)

[paper] [implementation] Ape-X variations of DQN, DDPG, and QMIX (APEX_DQN, APEX_DDPG, APEX_QMIX) use a single GPU learner and many CPU workers for experience collection. Experience collection can scale to hundreds of CPU workers due to the distributed prioritization of experience prior to storage in replay buffers.

Fig. 3: Ape-X architecture

Tuned examples: PongNoFrameskip-v4, Pendulum-v0, MountainCarContinuous-v0, {BeamRider,Breakout,Qbert,SpaceInvaders}NoFrameskip-v4.

Atari results @10M steps: more details

Atari env	RLlib Ape-X 8-workers	Mnih et al Async DQN 16-workers
BeamRider	6134	~6000
Breakout	123	~50
Qbert	15302	~1200
SpaceInvaders	686	~600

Scalability:

Atari env	RLlib Ape-X 8-workers @1 hour	Mnih et al Async DQN 16-workers @1 hour
BeamRider	4873	~1000
Breakout	77	~10
Qbert	4083	~500
SpaceInvaders	646	~300

Ape-X specific configs (see also common configs):

```
APEX_DEFAULT_CONFIG = merge_dicts(
    DQN_CONFIG,  # see also the options in dqn.py, which are also supported
    {
        "optimizer": merge_dicts(
            DQN_CONFIG["optimizer"], {
                "max_weight_sync_delay": 400,
                "num_replay_buffer_shards": 4,
                "debug": False
            }),
        "n_step": 3,
        "num_gpus": 1,
        "num_workers": 32,
        "buffer_size": 2000000,
        "learning_starts": 50000,
        "train_batch_size": 512,
        "sample_batch_size": 50,
        "target_network_update_freq": 500000,
        "timesteps_per_iteration": 25000,
        "per_worker_exploration": True,
```

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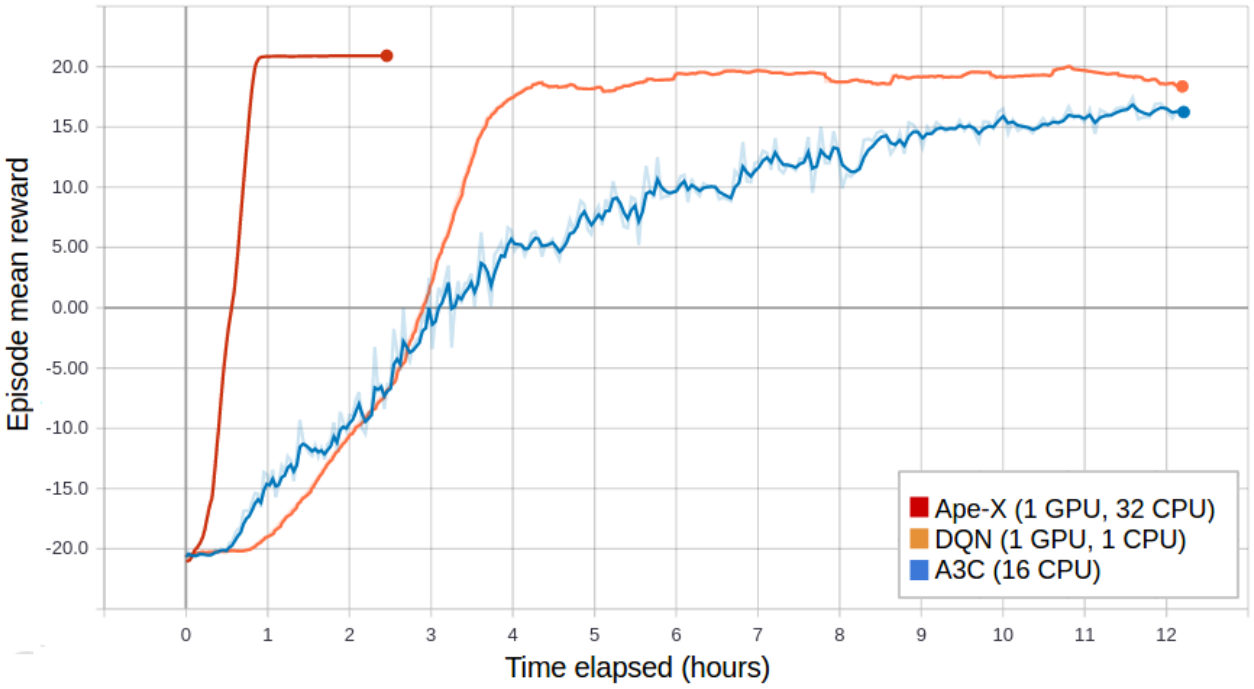

Fig. 4: Ape-X using 32 workers in RLlib vs vanilla DQN (orange) and A3C (blue) on PongNoFrameskip-v4.

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```
        "worker_side_prioritization": True,
        "min_iter_time_s": 30,
    },
)
```

Importance Weighted Actor-Learner Architecture (IMPALA)

[paper] [implementation] In IMPALA, a central learner runs SGD in a tight loop while asynchronously pulling sample batches from many actor processes. RLlib's IMPALA implementation uses DeepMind's reference V-trace code. Note that we do not provide a deep residual network out of the box, but one can be plugged in as a custom model. Multiple learner GPUs and experience replay are also supported.

Fig. 5: IMPALA architecture

Tuned examples: PongNoFrameskip-v4, vectorized configuration, multi-gpu configuration, {BeamRider,Breakout,Qbert,SpaceInvaders}NoFrameskip-v4

Atari results @10M steps: more details

Atari env	RLlib IMPALA 32-workers	Mnih et al A3C 16-workers
BeamRider	2071	~3000
Breakout	385	~150
Qbert	4068	~1000
SpaceInvaders	719	~600

Scalability:

Atari env	RLlib IMPALA 32-workers @1 hour	Mnih et al A3C 16-workers @1 hour
BeamRider	3181	~1000
Breakout	538	~10
Qbert	10850	~500
SpaceInvaders	843	~300

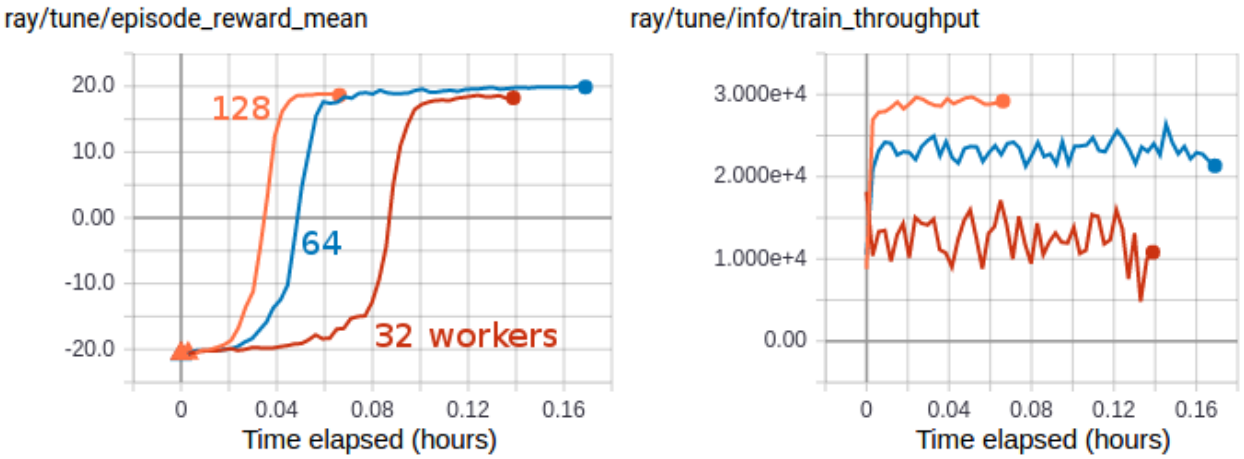

Fig. 6: Multi-GPU IMPALA scales up to solve PongNoFrameskip-v4 in ~3 minutes using a pair of V100 GPUs and 128 CPU workers. The maximum training throughput reached is ~30k transitions per second (~120k environment frames per second).

IMPALA-specific configs (see also common configs):

```
DEFAULT_CONFIG = with_common_config({
    # V-trace params (see vtrace.py).
    "vtrace": True,
    "vtrace_clip_rho_threshold": 1.0,
    "vtrace_clip_pg_rho_threshold": 1.0,

    # System params.
    #
    # == Overview of data flow in IMPALA ==
    # 1. Policy evaluation in parallel across `num_workers` actors produces
    #    batches of size `sample_batch_size * num_envs_per_worker`.
    # 2. If enabled, the replay buffer stores and produces batches of size
    #    `sample_batch_size * num_envs_per_worker`.
    # 3. If enabled, the minibatch ring buffer stores and replays batches of
    #    size `train_batch_size` up to `num_sgd_iter` times per batch.
    # 4. The learner thread executes data parallel SGD across `num_gpus` GPUs
    #    on batches of size `train_batch_size`.
    #
    "sample_batch_size": 50,
    "train_batch_size": 500,
    "min_iter_time_s": 10,
    "num_workers": 2,
    # number of GPUs the learner should use.
    "num_gpus": 1,
    # set >1 to load data into GPUs in parallel. Increases GPU memory usage
    # proportionally with the number of buffers.
    "num_data_loader_buffers": 1,
```

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```
    # how many train batches should be retained for minibatching. This conf
    # only has an effect if `num_sgd_iter > 1`.
    "minibatch_buffer_size": 1,
    # number of passes to make over each train batch
    "num_sgd_iter": 1,
    # set >0 to enable experience replay. Saved samples will be replayed with
    # a p:1 proportion to new data samples.
    "replay_proportion": 0.0,
    # number of sample batches to store for replay. The number of transitions
    # saved total will be (replay_buffer_num_slots * sample_batch_size).
    "replay_buffer_num_slots": 0,
    # max queue size for train batches feeding into the learner
    "learner_queue_size": 16,
    # wait for train batches to be available in minibatch buffer queue
    # this many seconds. This may need to be increased e.g. when training
    # with a slow environment
    "learner_queue_timeout": 300,
    # level of queuing for sampling.
    "max_sample_requests_in_flight_per_worker": 2,
    # max number of workers to broadcast one set of weights to
    "broadcast_interval": 1,
    # use intermediate actors for multi-level aggregation. This can make sense
    # if ingesting >2GB/s of samples, or if the data requires decompression.
    "num_aggregation_workers": 0,

    # Learning params.
    "grad_clip": 40.0,
    # either "adam" or "rmsprop"
    "opt_type": "adam",
    "lr": 0.0005,
    "lr_schedule": None,
    # rmsprop considered
    "decay": 0.99,
    "momentum": 0.0,
    "epsilon": 0.1,
    # balancing the three losses
    "vf_loss_coeff": 0.5,
    "entropy_coeff": 0.01,
    "entropy_coeff_schedule": None,

    # use fake (infinite speed) sampler for testing
    "_fake_sampler": False,
})
```

Asynchronous Proximal Policy Optimization (APPO)

[paper] [implementation] We include an asynchronous variant of Proximal Policy Optimization (PPO) based on the IMPALA architecture. This is similar to IMPALA but using a surrogate policy loss with clipping. Compared to synchronous PPO, APPO is more efficient in wall-clock time due to its use of asynchronous sampling. Using a clipped loss also allows for multiple SGD passes, and therefore the potential for better sample efficiency compared to IMPALA. V-trace can also be enabled to correct for off-policy samples.

APPO is not always more efficient; it is often better to simply use PPO or IMPALA.

Tuned examples: PongNoFrameskip-v4

APPO-specific configs (see also common configs):

Fig. 7: APPO architecture (same as IMPALA)

```
DEFAULT_CONFIG = with_base_config(impala.DEFAULT_CONFIG, {
    # Whether to use V-trace weighted advantages. If false, PPO GAE advantages
    # will be used instead.
    "vtrace": False,

    # == These two options only apply if vtrace: False ==
    # If true, use the Generalized Advantage Estimator (GAE)
    # with a value function, see https://arxiv.org/pdf/1506.02438.pdf.
    "use_gae": True,
    # GAE(lambda) parameter
    "lambda": 1.0,

    # == PPO surrogate loss options ==
    "clip_param": 0.4,

    # == PPO KL Loss options ==
    "use_kl_loss": False,
    "kl_coeff": 1.0,
    "kl_target": 0.01,

    # == IMPALA optimizer params (see documentation in impala.py) ==
    "sample_batch_size": 50,
    "train_batch_size": 500,
    "min_iter_time_s": 10,
    "num_workers": 2,
    "num_gpus": 0,
    "num_data_loader_buffers": 1,
    "minibatch_buffer_size": 1,
    "num_sgd_iter": 1,
    "replay_proportion": 0.0,
    "replay_buffer_num_slots": 100,
    "learner_queue_size": 16,
    "learner_queue_timeout": 300,
    "max_sample_requests_in_flight_per_worker": 2,
    "broadcast_interval": 1,
    "grad_clip": 40.0,
    "opt_type": "adam",
    "lr": 0.0005,
    "lr_schedule": None,
    "decay": 0.99,
    "momentum": 0.0,
    "epsilon": 0.1,
    "vf_loss_coeff": 0.5,
    "entropy_coeff": 0.01,
    "entropy_coeff_schedule": None,
})
```

5.30.2 Gradient-based

Advantage Actor-Critic (A2C, A3C)

[paper] [implementation] RLlib implements A2C and A3C using SyncSamplesOptimizer and AsyncGradientsOpti-

mizer respectively for policy optimization. These algorithms scale to up to 16-32 worker processes depending on the environment. Both a TensorFlow (LSTM), and PyTorch version are available.

Fig. 8: A2C architecture

Tuned examples: PongDeterministic-v4, PyTorch version, {BeamRider,Breakout,Qbert,SpaceInvaders}NoFrameskip-v4

Tip: Consider using *IMPALA* for faster training with similar timestep efficiency.

Atari results @10M steps: more details

Atari env	RLlib A2C 5-workers	Mnih et al A3C 16-workers
BeamRider	1401	~3000
Breakout	374	~150
Qbert	3620	~1000
SpaceInvaders	692	~600

A3C-specific configs (see also common configs):

```
DEFAULT_CONFIG = with_common_config({
    # Size of rollout batch
    "sample_batch_size": 10,
    # Use PyTorch as backend - no LSTM support
    "use_pytorch": False,
    # GAE(gamma) parameter
    "lambda": 1.0,
    # Max global norm for each gradient calculated by worker
    "grad_clip": 40.0,
    # Learning rate
    "lr": 0.0001,
    # Learning rate schedule
    "lr_schedule": None,
    # Value Function Loss coefficient
    "vf_loss_coeff": 0.5,
    # Entropy coefficient
    "entropy_coeff": 0.01,
    # Min time per iteration
    "min_iter_time_s": 5,
    # Workers sample async. Note that this increases the effective
    # sample_batch_size by up to 5x due to async buffering of batches.
    "sample_async": True,
})
```

Deep Deterministic Policy Gradients (DDPG, TD3)

[paper] [implementation] DDPG is implemented similarly to DQN (below). The algorithm can be scaled by increasing the number of workers, switching to AsyncGradientsOptimizer, or using Ape-X. The improvements from TD3 are available as `TD3`.

Fig. 9: DDPG architecture (same as DQN)

Tuned examples: Pendulum-v0, MountainCarContinuous-v0, HalfCheetah-v2, TD3 Pendulum-v0, TD3 InvertedPendulum-v2, TD3 Mujoco suite (Ant-v2, HalfCheetah-v2, Hopper-v2, Walker2d-v2).

DDPG-specific configs (see also common configs):

```
DEFAULT_CONFIG = with_common_config({
    # === Twin Delayed DDPG (TD3) and Soft Actor-Critic (SAC) tricks ===
    # TD3: https://spinningup.openai.com/en/latest/algorithms/td3.html
    # In addition to settings below, you can use "exploration_noise_type" and
    # "exploration_gauss_act_noise" to get IID Gaussian exploration noise
    # instead of OU exploration noise.
    # twin Q-net
    "twin_q": False,
    # delayed policy update
    "policy_delay": 1,
    # target policy smoothing
    # (this also replaces OU exploration noise with IID Gaussian exploration
    # noise, for now)
    "smooth_target_policy": False,
    # gaussian stddev of target action noise for smoothing
    "target_noise": 0.2,
    # target noise limit (bound)
    "target_noise_clip": 0.5,

    # === Evaluation ===
    # Evaluate with epsilon=0 every `evaluation_interval` training iterations.
    # The evaluation stats will be reported under the "evaluation" metric key.
    # Note that evaluation is currently not parallelized, and that for Ape-X
    # metrics are already only reported for the lowest epsilon workers.
    "evaluation_interval": None,
    # Number of episodes to run per evaluation period.
    "evaluation_num_episodes": 10,

    # === Model ===
    # Apply a state preprocessor with spec given by the "model" config option
    # (like other RL algorithms). This is mostly useful if you have a weird
    # observation shape, like an image. Disabled by default.
    "use_state_preprocessor": False,
    # Postprocess the policy network model output with these hidden layers. If
    # use_state_preprocessor is False, then these will be the *only* hidden
    # layers in the network.
    "actor_hiddens": [400, 300],
    # Hidden layers activation of the postprocessing stage of the policy
    # network
    "actor_hidden_activation": "relu",
    # Postprocess the critic network model output with these hidden layers;
    # again, if use_state_preprocessor is True, then the state will be
    # preprocessed by the model specified with the "model" config option first.
    "critic_hiddens": [400, 300],
    # Hidden layers activation of the postprocessing state of the critic.
    "critic_hidden_activation": "relu",
    # N-step Q learning
    "n_step": 1,

    # === Exploration ===
    # Turns on annealing schedule for exploration noise. Exploration is
    # annealed from 1.0 to exploration_final_eps over schedule_max_timesteps
    # scaled by exploration_fraction. Original DDPG and TD3 papers do not
```

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```
    # anneal noise, so this is False by default.
    "exploration_should_anneal": False,
    # Max num timesteps for annealing schedules.
    "schedule_max_timesteps": 100000,
    # Number of env steps to optimize for before returning
    "timesteps_per_iteration": 1000,
    # Fraction of entire training period over which the exploration rate is
    # annealed
    "exploration_fraction": 0.1,
    # Final scaling multiplier for action noise (initial is 1.0)
    "exploration_final_scale": 0.02,
    # valid values: "ou" (time-correlated, like original DDPG paper),
    # "gaussian" (IID, like TD3 paper)
    "exploration_noise_type": "ou",
    # OU-noise scale; this can be used to scale down magnitude of OU noise
    # before adding to actions (requires "exploration_noise_type" to be "ou")
    "exploration_ou_noise_scale": 0.1,
    # theta for OU
    "exploration_ou_theta": 0.15,
    # sigma for OU
    "exploration_ou_sigma": 0.2,
    # gaussian stddev of act noise for exploration (requires
    # "exploration_noise_type" to be "gaussian")
    "exploration_gaussian_sigma": 0.1,
    # If True parameter space noise will be used for exploration
    # See https://blog.openai.com/better-exploration-with-parameter-noise/
    "parameter_noise": False,
    # Until this many timesteps have elapsed, the agent's policy will be
    # ignored & it will instead take uniform random actions. Can be used in
    # conjunction with learning_starts (which controls when the first
    # optimization step happens) to decrease dependence of exploration &
    # optimization on initial policy parameters. Note that this will be
    # disabled when the action noise scale is set to 0 (e.g during evaluation).
    "pure_exploration_steps": 1000,
    # Extra configuration that disables exploration.
    "evaluation_config": {
        "exploration_fraction": 0,
        "exploration_final_eps": 0,
    },

    # === Replay buffer ===
    # Size of the replay buffer. Note that if async_updates is set, then
    # each worker will have a replay buffer of this size.
    "buffer_size": 50000,
    # If True prioritized replay buffer will be used.
    "prioritized_replay": True,
    # Alpha parameter for prioritized replay buffer.
    "prioritized_replay_alpha": 0.6,
    # Beta parameter for sampling from prioritized replay buffer.
    "prioritized_replay_beta": 0.4,
    # Fraction of entire training period over which the beta parameter is
    # annealed
    "beta_annealing_fraction": 0.2,
    # Final value of beta
    "final_prioritized_replay_beta": 0.4,
    # Epsilon to add to the TD errors when updating priorities.
    "prioritized_replay_eps": 1e-6,
```

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```
    # Whether to LZ4 compress observations
    "compress_observations": False,

    # === Optimization ===
    # Learning rate for the critic (Q-function) optimizer.
    "critic_lr": 1e-3,
    # Learning rate for the actor (policy) optimizer.
    "actor_lr": 1e-3,
    # Update the target network every `target_network_update_freq` steps.
    "target_network_update_freq": 0,
    # Update the target by \tau * policy + (1-\tau) * target_policy
    "tau": 0.002,
    # If True, use huber loss instead of squared loss for critic network
    # Conventionally, no need to clip gradients if using a huber loss
    "use_huber": False,
    # Threshold of a huber loss
    "huber_threshold": 1.0,
    # Weights for L2 regularization
    "l2_reg": 1e-6,
    # If not None, clip gradients during optimization at this value
    "grad_norm_clipping": None,
    # How many steps of the model to sample before learning starts.
    "learning_starts": 1500,
    # Update the replay buffer with this many samples at once. Note that this
    # setting applies per-worker if num_workers > 1.
    "sample_batch_size": 1,
    # Size of a batched sampled from replay buffer for training. Note that
    # if async_updates is set, then each worker returns gradients for a
    # batch of this size.
    "train_batch_size": 256,

    # === Parallelism ===
    # Number of workers for collecting samples with. This only makes sense
    # to increase if your environment is particularly slow to sample, or if
    # you're using the Async or Ape-X optimizers.
    "num_workers": 0,
    # Whether to use a distribution of epsilons across workers for exploration.
    "per_worker_exploration": False,
    # Whether to compute priorities on workers.
    "worker_side_prioritization": False,
    # Prevent iterations from going lower than this time span
    "min_iter_time_s": 1,
})
```

Deep Q Networks (DQN, Rainbow, Parametric DQN)

[paper] [implementation] RLlib DQN is implemented using the SyncReplayOptimizer. The algorithm can be scaled by increasing the number of workers, using the AsyncGradientsOptimizer for async DQN, or using Ape-X. Memory usage is reduced by compressing samples in the replay buffer with LZ4. All of the DQN improvements evaluated in Rainbow are available, though not all are enabled by default. See also how to use parametric-actions in DQN.

Fig. 10: DQN architecture

Tuned examples: PongDeterministic-v4, Rainbow configuration, {BeamRider,Breakout,Qbert,SpaceInvaders}NoFrameskip-

v4, with Dueling and Double-Q, with Distributional DQN.

Tip: Consider using *Ape-X* for faster training with similar timestep efficiency.

Atari results @10M steps: more details

Atari env	RLlib DQN	RLlib Dueling DDQN	RLlib Dist. DQN	Hessel et al. DQN
BeamRider	2869	1910	4447	~2000
Breakout	287	312	410	~150
Qbert	3921	7968	15780	~4000
SpaceInvaders	650	1001	1025	~500

DQN-specific configs (see also common configs):

```
DEFAULT_CONFIG = with_common_config({
    # === Model ===
    # Number of atoms for representing the distribution of return. When
    # this is greater than 1, distributional Q-learning is used.
    # the discrete supports are bounded by v_min and v_max
    "num_atoms": 1,
    "v_min": -10.0,
    "v_max": 10.0,
    # Whether to use noisy network
    "noisy": False,
    # control the initial value of noisy nets
    "sigma0": 0.5,
    # Whether to use dueling dqn
    "dueling": True,
    # Whether to use double dqn
    "double_q": True,
    # Postprocess model outputs with these hidden layers to compute the
    # state and action values. See also the model config in catalog.py.
    "hiddens": [256],
    # N-step Q learning
    "n_step": 1,

    # === Exploration ===
    # Max num timesteps for annealing schedules. Exploration is annealed from
    # 1.0 to exploration_fraction over this number of timesteps scaled by
    # exploration_fraction
    "schedule_max_timesteps": 100000,
    # Minimum env steps to optimize for per train call. This value does
    # not affect learning, only the length of iterations.
    "timesteps_per_iteration": 1000,
    # Fraction of entire training period over which the exploration rate is
    # annealed
    "exploration_fraction": 0.1,
    # Final value of random action probability
    "exploration_final_eps": 0.02,
    # Update the target network every `target_network_update_freq` steps.
    "target_network_update_freq": 500,
    # Use softmax for sampling actions. Required for off policy estimation.
    "soft_q": False,
    # Softmax temperature. Q values are divided by this value prior to softmax.
    # Softmax approaches argmax as the temperature drops to zero.
```

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```
    "softmax_temp": 1.0,
    # If True parameter space noise will be used for exploration
    # See https://blog.openai.com/better-exploration-with-parameter-noise/
    "parameter_noise": False,
    # Extra configuration that disables exploration.
    "evaluation_config": {
        "exploration_fraction": 0,
        "exploration_final_eps": 0,
    },

    # === Replay buffer ===
    # Size of the replay buffer. Note that if async_updates is set, then
    # each worker will have a replay buffer of this size.
    "buffer_size": 50000,
    # If True prioritized replay buffer will be used.
    "prioritized_replay": True,
    # Alpha parameter for prioritized replay buffer.
    "prioritized_replay_alpha": 0.6,
    # Beta parameter for sampling from prioritized replay buffer.
    "prioritized_replay_beta": 0.4,
    # Fraction of entire training period over which the beta parameter is
    # annealed
    "beta_annealing_fraction": 0.2,
    # Final value of beta
    "final_prioritized_replay_beta": 0.4,
    # Epsilon to add to the TD errors when updating priorities.
    "prioritized_replay_eps": 1e-6,
    # Whether to LZ4 compress observations
    "compress_observations": True,

    # === Optimization ===
    # Learning rate for adam optimizer
    "lr": 5e-4,
    # Learning rate schedule
    "lr_schedule": None,
    # Adam epsilon hyper parameter
    "adam_epsilon": 1e-8,
    # If not None, clip gradients during optimization at this value
    "grad_norm_clipping": 40,
    # How many steps of the model to sample before learning starts.
    "learning_starts": 1000,
    # Update the replay buffer with this many samples at once. Note that
    # this setting applies per-worker if num_workers > 1.
    "sample_batch_size": 4,
    # Size of a batched sampled from replay buffer for training. Note that
    # if async_updates is set, then each worker returns gradients for a
    # batch of this size.
    "train_batch_size": 32,

    # === Parallelism ===
    # Number of workers for collecting samples with. This only makes sense
    # to increase if your environment is particularly slow to sample, or if
    # you"re using the Async or Ape-X optimizers.
    "num_workers": 0,
    # Whether to use a distribution of epsilons across workers for exploration.
    "per_worker_exploration": False,
    # Whether to compute priorities on workers.
```

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```
    "worker_side_prioritization": False,
    # Prevent iterations from going lower than this time span
    "min_iter_time_s": 1,
})
```

Policy Gradients

[paper] [implementation] We include a vanilla policy gradients implementation as an example algorithm in both TensorFlow and PyTorch. This is usually outperformed by PPO.

Fig. 11: Policy gradients architecture (same as A2C)

Tuned examples: CartPole-v0

PG-specific configs (see also common configs):

```
DEFAULT_CONFIG = with_common_config({
    # No remote workers by default
    "num_workers": 0,
    # Learning rate
    "lr": 0.0004,
    # Use PyTorch as backend
    "use_pytorch": False,
})
```

Proximal Policy Optimization (PPO)

[paper] [implementation] PPO's clipped objective supports multiple SGD passes over the same batch of experiences. RLlib's multi-GPU optimizer pins that data in GPU memory to avoid unnecessary transfers from host memory, substantially improving performance over a naive implementation. RLlib's PPO scales out using multiple workers for experience collection, and also with multiple GPUs for SGD.

Fig. 12: PPO architecture

Tuned examples: Humanoid-v1, Hopper-v1, Pendulum-v0, PongDeterministic-v4, Walker2d-v1, HalfCheetah-v2, {BeamRider,Breakout,Qbert,SpaceInvaders}NoFrameskip-v4

Atari results: more details

Atari env	RLlib PPO @10M	RLlib PPO @25M	Baselines PPO @10M
BeamRider	2807	4480	~1800
Breakout	104	201	~250
Qbert	11085	14247	~14000
SpaceInvaders	671	944	~800

Scalability: more details

MuJoCo env	RLlib PPO 16-workers @ 1h	Fan et al PPO 16-workers @ 1h
HalfCheetah	9664	~7700

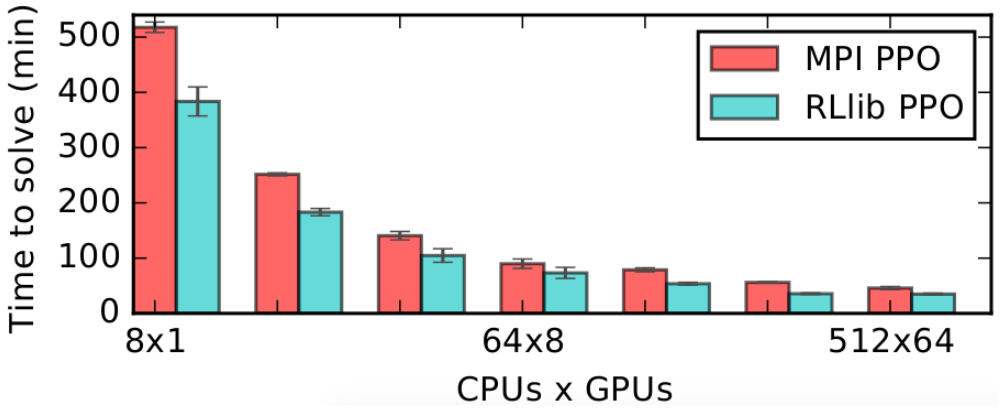

Fig. 13: RLlib's multi-GPU PPO scales to multiple GPUs and hundreds of CPUs on solving the Humanoid-v1 task. Here we compare against a reference MPI-based implementation.

PPO-specific configs (see also common configs):

```
DEFAULT_CONFIG = with_common_config({
    # If true, use the Generalized Advantage Estimator (GAE)
    # with a value function, see https://arxiv.org/pdf/1506.02438.pdf.
    "use_gae": True,
    # GAE(lambda) parameter
    "lambda": 1.0,
    # Initial coefficient for KL divergence
    "kl_coeff": 0.2,
    # Size of batches collected from each worker
    "sample_batch_size": 200,
    # Number of timesteps collected for each SGD round
    "train_batch_size": 4000,
    # Total SGD batch size across all devices for SGD
    "sgd_minibatch_size": 128,
    # Whether to shuffle sequences in the batch when training (recommended)
    "shuffle_sequences": True,
    # Number of SGD iterations in each outer loop
    "num_sgd_iter": 30,
    # Stepsize of SGD
    "lr": 5e-5,
    # Learning rate schedule
    "lr_schedule": None,
    # Share layers for value function. If you set this to True, it's important
    # to tune vf_loss_coeff.
    "vf_share_layers": False,
    # Coefficient of the value function loss. It's important to tune this if
    # you set vf_share_layers: True
    "vf_loss_coeff": 1.0,
    # Coefficient of the entropy regularizer
    "entropy_coeff": 0.0,
    # Decay schedule for the entropy regularizer
    "entropy_coeff_schedule": None,
    # PPO clip parameter
    "clip_param": 0.3,
    # Clip param for the value function. Note that this is sensitive to the
    # scale of the rewards. If your expected V is large, increase this.
    "vf_clip_param": 10.0,
```

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```
    # If specified, clip the global norm of gradients by this amount
    "grad_clip": None,
    # Target value for KL divergence
    "kl_target": 0.01,
    # Whether to rollout "complete_episodes" or "truncate_episodes"
    "batch_mode": "truncate_episodes",
    # Which observation filter to apply to the observation
    "observation_filter": "NoFilter",
    # Uses the sync samples optimizer instead of the multi-gpu one. This does
    # not support minibatches.
    "simple_optimizer": False,
})
```

Soft Actor Critic (SAC)

[paper] [implementation]

Fig. 14: SAC architecture (same as DQN)

RLlib's soft-actor critic implementation is ported from the official SAC repo to better integrate with RLlib APIs. Note that SAC has two fields to configure for custom models: `policy_model` and `Q_model`, and currently has no support for non-continuous action distributions. It is also currently *experimental*.

Tuned examples: Pendulum-v0

SAC-specific configs (see also common configs):

```
DEFAULT_CONFIG = with_common_config({
    # === Model ===
    "twin_q": True,
    "use_state_preprocessor": False,
    "policy": "GaussianLatentSpacePolicy",
    # RLlib model options for the Q function
    "Q_model": {
        "hidden_activation": "relu",
        "hidden_layer_sizes": (256, 256),
    },
    # RLlib model options for the policy function
    "policy_model": {
        "hidden_activation": "relu",
        "hidden_layer_sizes": (256, 256),
    },

    # === Learning ===
    # Update the target by \tau * policy + (1-\tau) * target_policy
    "tau": 5e-3,
    # Target entropy lower bound. This is the inverse of reward scale,
    # and will be optimized automatically.
    "target_entropy": "auto",
    # Disable setting done=True at end of episode.
    "no_done_at_end": True,
    # N-step target updates
    "n_step": 1,
```

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```
    # === Evaluation ===
    # The evaluation stats will be reported under the "evaluation" metric key.
    "evaluation_interval": 1,
    # Number of episodes to run per evaluation period.
    "evaluation_num_episodes": 1,
    # Extra configuration that disables exploration.
    "evaluation_config": {
        "exploration_enabled": False,
    },

    # === Exploration ===
    # Number of env steps to optimize for before returning
    "timesteps_per_iteration": 100,
    "exploration_enabled": True,

    # === Replay buffer ===
    # Size of the replay buffer. Note that if async_updates is set, then
    # each worker will have a replay buffer of this size.
    "buffer_size": int(1e6),
    # If True prioritized replay buffer will be used.
    # TODO(hartikainen): Make sure this works or remove the option.
    "prioritized_replay": False,
    "prioritized_replay_alpha": 0.6,
    "prioritized_replay_beta": 0.4,
    "prioritized_replay_eps": 1e-6,
    "beta_annealing_fraction": 0.2,
    "final_prioritized_replay_beta": 0.4,
    "compress_observations": False,

    # === Optimization ===
    "optimization": {
        "actor_learning_rate": 3e-4,
        "critic_learning_rate": 3e-4,
        "entropy_learning_rate": 3e-4,
    },
    # If not None, clip gradients during optimization at this value
    "grad_norm_clipping": None,
    # How many steps of the model to sample before learning starts.
    "learning_starts": 1500,
    # Update the replay buffer with this many samples at once. Note that this
    # setting applies per-worker if num_workers > 1.
    "sample_batch_size": 1,
    # Size of a batched sampled from replay buffer for training. Note that
    # if async_updates is set, then each worker returns gradients for a
    # batch of this size.
    "train_batch_size": 256,
    # Update the target network every `target_network_update_freq` steps.
    "target_network_update_freq": 0,

    # === Parallelism ===
    # Whether to use a GPU for local optimization.
    "num_gpus": 0,
    # Number of workers for collecting samples with. This only makes sense
    # to increase if your environment is particularly slow to sample, or if
    # you"re using the Async or Ape-X optimizers.
    "num_workers": 0,
    # Whether to allocate GPUs for workers (if > 0).
```

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```
    "num_gpus_per_worker": 0,
    # Whether to allocate CPUs for workers (if > 0).
    "num_cpus_per_worker": 1,
    # Whether to compute priorities on workers.
    "worker_side_prioritization": False,
    # Prevent iterations from going lower than this time span
    "min_iter_time_s": 1,

    # TODO(ekl) these are unused; remove them from sac config
    "per_worker_exploration": False,
    "exploration_fraction": 0.1,
    "schedule_max_timesteps": 100000,
    "exploration_final_eps": 0.02,
})
```

5.30.3 Derivative-free

Augmented Random Search (ARS)

[paper] [implementation] ARS is a random search method for training linear policies for continuous control problems. Code here is adapted from https://github.com/modestyachts/ARS to integrate with RLlib APIs.

Tuned examples: CartPole-v0, Swimmer-v2

ARS-specific configs (see also common configs):

```
DEFAULT_CONFIG = with_common_config({
    "noise_stdev": 0.02,  # std deviation of parameter noise
    "num_rollouts": 32,  # number of perturbs to try
    "rollouts_used": 32,  # number of perturbs to keep in gradient estimate
    "num_workers": 2,
    "sgd_stepsize": 0.01,  # sgd step-size
    "observation_filter": "MeanStdFilter",
    "noise_size": 250000000,
    "eval_prob": 0.03,  # probability of evaluating the parameter rewards
    "report_length": 10,  # how many of the last rewards we average over
    "offset": 0,
})
```

Evolution Strategies

[paper] [implementation] Code here is adapted from https://github.com/openai/evolution-strategies-starter to execute in the distributed setting with Ray.

Tuned examples: Humanoid-v1

Scalability:

ES-specific configs (see also common configs):

```
DEFAULT_CONFIG = with_common_config({
    "l2_coeff": 0.005,
    "noise_stdev": 0.02,
    "episodes_per_batch": 1000,
    "train_batch_size": 10000,
```

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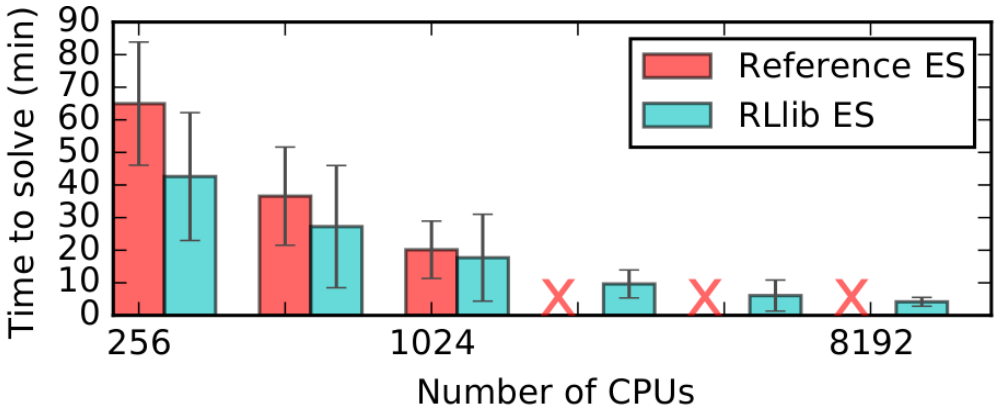

Fig. 15: RLlib's ES implementation scales further and is faster than a reference Redis implementation on solving the Humanoid-v1 task.

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```
    "eval_prob": 0.003,
    "return_proc_mode": "centered_rank",
    "num_workers": 10,
    "stepsize": 0.01,
    "observation_filter": "MeanStdFilter",
    "noise_size": 250000000,
    "report_length": 10,
})
```

QMIX Monotonic Value Factorisation (QMIX, VDN, IQN)

[paper] [implementation] Q-Mix is a specialized multi-agent algorithm. Code here is adapted from https://github.com/oxwhirl/pymarl_alpha to integrate with RLlib multi-agent APIs. To use Q-Mix, you must specify an agent grouping in the environment (see the two-step game example). Currently, all agents in the group must be homogeneous. The algorithm can be scaled by increasing the number of workers or using Ape-X.

Q-Mix is implemented in PyTorch and is currently *experimental*.

Tuned examples: Two-step game

QMIX-specific configs (see also common configs):

```
DEFAULT_CONFIG = with_common_config({
    # === QMix ===
    # Mixing network. Either "qmix", "vdn", or None
    "mixer": "qmix",
    # Size of the mixing network embedding
    "mixing_embed_dim": 32,
    # Whether to use Double_Q learning
    "double_q": True,
    # Optimize over complete episodes by default.
    "batch_mode": "complete_episodes",

    # === Evaluation ===
    # Evaluate with epsilon=0 every `evaluation_interval` training iterations.
    # The evaluation stats will be reported under the "evaluation" metric key.
    # Note that evaluation is currently not parallelized, and that for Ape-X
```

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```
    # metrics are already only reported for the lowest epsilon workers.
    "evaluation_interval": None,
    # Number of episodes to run per evaluation period.
    "evaluation_num_episodes": 10,

    # === Exploration ===
    # Max num timesteps for annealing schedules. Exploration is annealed from
    # 1.0 to exploration_fraction over this number of timesteps scaled by
    # exploration_fraction
    "schedule_max_timesteps": 100000,
    # Number of env steps to optimize for before returning
    "timesteps_per_iteration": 1000,
    # Fraction of entire training period over which the exploration rate is
    # annealed
    "exploration_fraction": 0.1,
    # Final value of random action probability
    "exploration_final_eps": 0.02,
    # Update the target network every `target_network_update_freq` steps.
    "target_network_update_freq": 500,

    # === Replay buffer ===
    # Size of the replay buffer in steps.
    "buffer_size": 10000,

    # === Optimization ===
    # Learning rate for adam optimizer
    "lr": 0.0005,
    # RMSProp alpha
    "optim_alpha": 0.99,
    # RMSProp epsilon
    "optim_eps": 0.00001,
    # If not None, clip gradients during optimization at this value
    "grad_norm_clipping": 10,
    # How many steps of the model to sample before learning starts.
    "learning_starts": 1000,
    # Update the replay buffer with this many samples at once. Note that
    # this setting applies per-worker if num_workers > 1.
    "sample_batch_size": 4,
    # Size of a batched sampled from replay buffer for training. Note that
    # if async_updates is set, then each worker returns gradients for a
    # batch of this size.
    "train_batch_size": 32,

    # === Parallelism ===
    # Number of workers for collecting samples with. This only makes sense
    # to increase if your environment is particularly slow to sample, or if
    # you"re using the Async or Ape-X optimizers.
    "num_workers": 0,
    # Whether to use a distribution of epsilons across workers for exploration.
    "per_worker_exploration": False,
    # Whether to compute priorities on workers.
    "worker_side_prioritization": False,
    # Prevent iterations from going lower than this time span
    "min_iter_time_s": 1,

    # === Model ===
    "model": {
```

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```
        "lstm_cell_size": 64,
        "max_seq_len": 999999,
    },
})
```

Multi-Agent Deep Deterministic Policy Gradient (contrib/MADDPG)

[paper] [implementation] MADDPG is a specialized multi-agent algorithm. Code here is adapted from https://github.com/openai/maddpg to integrate with RLlib multi-agent APIs. Please check wsjeon/maddpg-rllib for examples and more information.

MADDPG-specific configs (see also common configs):

Tuned examples: Multi-Agent Particle Environment, Two-step game

```
DEFAULT_CONFIG = with_common_config({
    # === Settings for each individual policy ===
    # ID of the agent controlled by this policy
    "agent_id": None,
    # Use a local critic for this policy.
    "use_local_critic": False,

    # === Evaluation ===
    # Evaluation interval
    "evaluation_interval": None,
    # Number of episodes to run per evaluation period.
    "evaluation_num_episodes": 10,

    # === Model ===
    # Apply a state preprocessor with spec given by the "model" config option
    # (like other RL algorithms). This is mostly useful if you have a weird
    # observation shape, like an image. Disabled by default.
    "use_state_preprocessor": False,
    # Postprocess the policy network model output with these hidden layers. If
    # use_state_preprocessor is False, then these will be the *only* hidden
    # layers in the network.
    "actor_hiddens": [64, 64],
    # Hidden layers activation of the postprocessing stage of the policy
    # network
    "actor_hidden_activation": "relu",
    # Postprocess the critic network model output with these hidden layers;
    # again, if use_state_preprocessor is True, then the state will be
    # preprocessed by the model specified with the "model" config option first.
    "critic_hiddens": [64, 64],
    # Hidden layers activation of the postprocessing state of the critic.
    "critic_hidden_activation": "relu",
    # N-step Q learning
    "n_step": 1,
    # Algorithm for good policies
    "good_policy": "maddpg",
    # Algorithm for adversary policies
    "adv_policy": "maddpg",

    # === Replay buffer ===
    # Size of the replay buffer. Note that if async_updates is set, then
    # each worker will have a replay buffer of this size.
```

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```
    "buffer_size": int(1e6),
    # Observation compression. Note that compression makes simulation slow in
    # MPE.
    "compress_observations": False,

    # === Optimization ===
    # Learning rate for the critic (Q-function) optimizer.
    "critic_lr": 1e-2,
    # Learning rate for the actor (policy) optimizer.
    "actor_lr": 1e-2,
    # Update the target network every `target_network_update_freq` steps.
    "target_network_update_freq": 0,
    # Update the target by \tau * policy + (1-\tau) * target_policy
    "tau": 0.01,
    # Weights for feature regularization for the actor
    "actor_feature_reg": 0.001,
    # If not None, clip gradients during optimization at this value
    "grad_norm_clipping": 0.5,
    # How many steps of the model to sample before learning starts.
    "learning_starts": 1024 * 25,
    # Update the replay buffer with this many samples at once. Note that this
    # setting applies per-worker if num_workers > 1.
    "sample_batch_size": 100,
    # Size of a batched sampled from replay buffer for training. Note that
    # if async_updates is set, then each worker returns gradients for a
    # batch of this size.
    "train_batch_size": 1024,
    # Number of env steps to optimize for before returning
    "timesteps_per_iteration": 0,

    # === Parallelism ===
    # Number of workers for collecting samples with. This only makes sense
    # to increase if your environment is particularly slow to sample, or if
    # you're using the Async or Ape-X optimizers.
    "num_workers": 1,
    # Prevent iterations from going lower than this time span
    "min_iter_time_s": 0,
})
```

Advantage Re-Weighted Imitation Learning (MARWIL)

[paper] [implementation] MARWIL is a hybrid imitation learning and policy gradient algorithm suitable for training on batched historical data. When the `beta` hyperparameter is set to zero, the MARWIL objective reduces to vanilla imitation learning. MARWIL requires the offline datasets API to be used.

Tuned examples: CartPole-v0

MARWIL-specific configs (see also common configs):

```
DEFAULT_CONFIG = with_common_config({
    # You should override this to point to an offline dataset (see agent.py).
    "input": "sampler",
    # Use importance sampling estimators for reward
    "input_evaluation": ["is", "wis"],

    # Scaling of advantages in exponential terms
```

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```
    # When beta is 0, MARWIL is reduced to imitation learning
    "beta": 1.0,
    # Balancing value estimation loss and policy optimization loss
    "vf_coeff": 1.0,
    # Whether to calculate cumulative rewards
    "postprocess_inputs": True,
    # Whether to rollout "complete_episodes" or "truncate_episodes"
    "batch_mode": "complete_episodes",
    # Learning rate for adam optimizer
    "lr": 1e-4,
    # Number of timesteps collected for each SGD round
    "train_batch_size": 2000,
    # Number of steps max to keep in the batch replay buffer
    "replay_buffer_size": 100000,
    # Number of steps to read before learning starts
    "learning_starts": 0,
    # === Parallelism ===
    "num_workers": 0,
})
```

5.31 RLlib Offline Datasets

5.31.1 Working with Offline Datasets

RLlib's offline dataset APIs enable working with experiences read from offline storage (e.g., disk, cloud storage, streaming systems, HDFS). For example, you might want to read experiences saved from previous training runs, or gathered from policies deployed in web applications. You can also log new agent experiences produced during online training for future use.

RLlib represents trajectory sequences (i.e., `(s, a, r, s', ...)` tuples) with SampleBatch objects. Using a batch format enables efficient encoding and compression of experiences. During online training, RLlib uses policy evaluation actors to generate batches of experiences in parallel using the current policy. RLlib also uses this same batch format for reading and writing experiences to offline storage.

Example: Training on previously saved experiences

Note: For custom models and enviroments, you'll need to use the Python API.

In this example, we will save batches of experiences generated during online training to disk, and then leverage this saved data to train a policy offline using DQN. First, we run a simple policy gradient algorithm for 100k steps with `"output": "/tmp/cartpole-out"` to tell RLlib to write simulation outputs to the `/tmp/cartpole-out` directory.

```
$ rllib train
    --run=PG \
    --env=CartPole-v0 \
    --config='{"output": "/tmp/cartpole-out", "output_max_file_size": 5000000}' \
    --stop='{"timesteps_total": 100000}'
```

The experiences will be saved in compressed JSON batch format:

```
$ ls -l /tmp/cartpole-out
total 11636
-rw-rw-r-- 1 eric eric 5022257 output-2019-01-01_15-58-57_worker-0_0.json
-rw-rw-r-- 1 eric eric 5002416 output-2019-01-01_15-59-22_worker-0_1.json
-rw-rw-r-- 1 eric eric 1881666 output-2019-01-01_15-59-47_worker-0_2.json
```

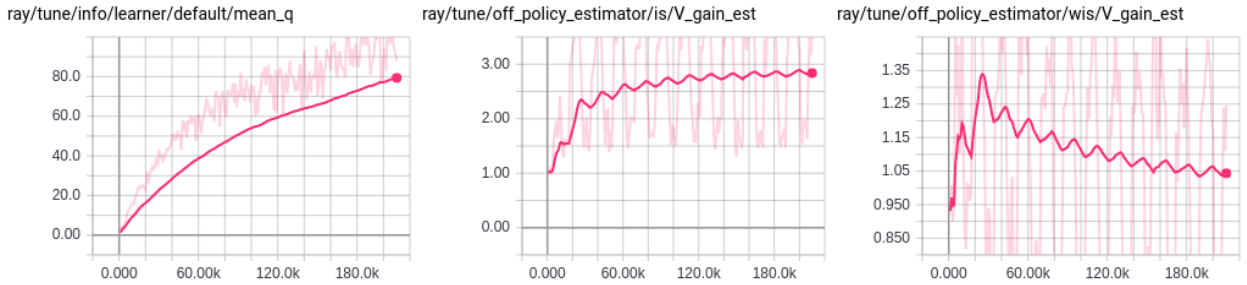
Then, we can tell DQN to train using these previously generated experiences with `"input": "/tmp/cartpole-out"`. We disable exploration since it has no effect on the input:

```
$ rllib train \
    --run=DQN \
    --env=CartPole-v0 \
    --config='{
        "input": "/tmp/cartpole-out",
        "input_evaluation": [],
        "exploration_final_eps": 0,
        "exploration_fraction": 0}'
```

Off-policy estimation: Since the input experiences are not from running simulations, RLlib cannot report the true policy performance during training. However, you can use `tensorboard --logdir=~/ray_results` to monitor training progress via other metrics such as estimated Q-value. Alternatively, off-policy estimation can be used, which requires both the source and target action probabilities to be available (i.e., the `action_prob` batch key). For DQN, this means enabling soft Q learning so that actions are sampled from a probability distribution:

```
$ rllib train \
    --run=DQN \
    --env=CartPole-v0 \
    --config='{
        "input": "/tmp/cartpole-out",
        "input_evaluation": ["is", "wis"],
        "soft_q": true,
        "softmax_temp": 1.0}'
```

This example plot shows the Q-value metric in addition to importance sampling (IS) and weighted importance sampling (WIS) gain estimates (>1.0 means there is an estimated improvement over the original policy):



Estimator Python API: For greater control over the evaluation process, you can create off-policy estimators in your Python code and call `estimator.estimate(episode_batch)` to perform counterfactual estimation as needed. The estimators take in a policy object and gamma value for the environment:

```
trainer = DQNTrainer(...)
...  # train policy offline

from ray.rllib.offline.json_reader import JsonReader
from ray.rllib.offline.wis_estimator import WeightedImportanceSamplingEstimator
```

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```
estimator = WeightedImportanceSamplingEstimator(trainer.get_policy(), gamma=0.99)
reader = JsonReader("/path/to/data")
for _ in range(1000):
    batch = reader.next()
    for episode in batch.split_by_episode():
        print(estimator.estimate(episode))
```

Simulation-based estimation: If true simulation is also possible (i.e., your env supports `step()`), you can also set `"input_evaluation": ["simulation"]` to tell RLlib to run background simulations to estimate current policy performance. The output of these simulations will not be used for learning. Note that in all cases you still need to specify an environment object to define the action and observation spaces. However, you don't need to implement functions like reset() and step().

Example: Converting external experiences to batch format

When the env does not support simulation (e.g., it is a web application), it is necessary to generate the `*.json` experience batch files outside of RLlib. This can be done by using the JsonWriter class to write out batches. This runnable example shows how to generate and save experience batches for CartPole-v0 to disk:

```
import gym
import numpy as np

from ray.rllib.models.preprocessors import get_preprocessor
from ray.rllib.evaluation.sample_batch_builder import SampleBatchBuilder
from ray.rllib.offline.json_writer import JsonWriter

if __name__ == "__main__":
    batch_builder = SampleBatchBuilder()  # or MultiAgentSampleBatchBuilder
    writer = JsonWriter("/tmp/demo-out")

    # You normally wouldn't want to manually create sample batches if a
    # simulator is available, but let's do it anyways for example purposes:
    env = gym.make("CartPole-v0")

    # RLlib uses preprocessors to implement transforms such as one-hot encoding
    # and flattening of tuple and dict observations. For CartPole a no-op
    # preprocessor is used, but this may be relevant for more complex envs.
    prep = get_preprocessor(env.observation_space)(env.observation_space)
    print("The preprocessor is", prep)

    for eps_id in range(100):
        obs = env.reset()
        prev_action = np.zeros_like(env.action_space.sample())
        prev_reward = 0
        done = False
        t = 0
        while not done:
            action = env.action_space.sample()
            new_obs, rew, done, info = env.step(action)
            batch_builder.add_values(
                t=t,
                eps_id=eps_id,
                agent_index=0,
                obs=prep.transform(obs),
                actions=action,
```

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```
                action_prob=1.0,  # put the true action probability here
                rewards=rew,
                prev_actions=prev_action,
                prev_rewards=prev_reward,
                dones=done,
                infos=info,
                new_obs=prep.transform(new_obs))
            obs = new_obs
            prev_action = action
            prev_reward = rew
            t += 1
        writer.write(batch_builder.build_and_reset())
```

On-policy algorithms and experience postprocessing

RLlib assumes that input batches are of postprocessed experiences. This isn't typically critical for off-policy algorithms (e.g., DQN's post-processing is only needed if `n_step > 1` or `worker_side_prioritization: True`). For off-policy algorithms, you can also safely set the `postprocess_inputs: True` config to auto-postprocess data.

However, for on-policy algorithms like PPO, you'll need to pass in the extra values added during policy evaluation and postprocessing to `batch_builder.add_values()`, e.g., `logits`, `vf_preds`, `value_target`, and `advantages` for PPO. This is needed since the calculation of these values depends on the parameters of the *behaviour* policy, which RLlib does not have access to in the offline setting (in online training, these values are automatically added during policy evaluation).

Note that for on-policy algorithms, you'll also have to throw away experiences generated by prior versions of the policy. This greatly reduces sample efficiency, which is typically undesirable for offline training, but can make sense for certain applications.

Mixing simulation and offline data

RLlib supports multiplexing inputs from multiple input sources, including simulation. For example, in the following example we read 40% of our experiences from `/tmp/cartpole-out`, 30% from `hdfs:/archive/cartpole`, and the last 30% is produced via policy evaluation. Input sources are multiplexed using np.random.choice:

```
$ rllib train \
    --run=DQN \
    --env=CartPole-v0 \
    --config='{
        "input": {
            "/tmp/cartpole-out": 0.4,
            "hdfs:/archive/cartpole": 0.3,
            "sampler": 0.3,
        },
        "exploration_final_eps": 0,
        "exploration_fraction": 0}'
```

Scaling I/O throughput

Similar to scaling online training, you can scale offline I/O throughput by increasing the number of RLlib workers via the `num_workers` config. Each worker accesses offline storage independently in parallel, for linear scaling of I/O throughput. Within each read worker, files are chosen in random order for reads, but file contents are read sequentially.

5.31.2 Input Pipeline for Supervised Losses

You can also define supervised model losses over offline data. This requires defining a custom model loss. We provide a convenience function, `InputReader.tf_input_ops()`, that can be used to convert any input reader to a TF input pipeline. For example:

```
def custom_loss(self, policy_loss):
    input_reader = JsonReader("/tmp/cartpole-out")
    # print(input_reader.next())  # if you want to access imperatively

    input_ops = input_reader.tf_input_ops()
    print(input_ops["obs"])  # -> output Tensor shape=[None, 4]
    print(input_ops["actions"])  # -> output Tensor shape=[None]

    supervised_loss = some_function_of(input_ops)
    return policy_loss + supervised_loss
```

See custom_loss.py for a runnable example of using these TF input ops in a custom loss.

5.31.3 Input API

You can configure experience input for an agent using the following options:

```
    # Specify how to generate experiences:
    #  - "sampler": generate experiences via online simulation (default)
    #  - a local directory or file glob expression (e.g., "/tmp/*.json")
    #  - a list of individual file paths/URIs (e.g., ["/tmp/1.json",
    #    "s3://bucket/2.json"])
    #  - a dict with string keys and sampling probabilities as values (e.g.,
    #    {"sampler": 0.4, "/tmp/*.json": 0.4, "s3://bucket/expert.json": 0.2}).
    #  - a function that returns a rllib.offline.InputReader
    "input": "sampler",
    # Specify how to evaluate the current policy. This only has an effect when
    # reading offline experiences. Available options:
    #  - "wis": the weighted step-wise importance sampling estimator.
    #  - "is": the step-wise importance sampling estimator.
    #  - "simulation": run the environment in the background, but use
    #    this data for evaluation only and not for learning.
    "input_evaluation": ["is", "wis"],
    # Whether to run postprocess_trajectory() on the trajectory fragments from
    # offline inputs. Note that postprocessing will be done using the *current*
    # policy, not the *behaviour* policy, which is typically undesirable for
    # on-policy algorithms.
    "postprocess_inputs": False,
    # If positive, input batches will be shuffled via a sliding window buffer
    # of this number of batches. Use this if the input data is not in random
    # enough order. Input is delayed until the shuffle buffer is filled.
    "shuffle_buffer_size": 0,
```

The interface for a custom input reader is as follows:

class ray.rllib.offline.**InputReader**

Input object for loading experiences in policy evaluation.

next()

Return the next batch of experiences read.

Returns SampleBatch or MultiAgentBatch read.

tf_input_ops(*queue_size=1*)
Returns TensorFlow queue ops for reading inputs from this reader.

The main use of these ops is for integration into custom model losses. For example, you can use tf_input_ops() to read from files of external experiences to add an imitation learning loss to your model.

This method creates a queue runner thread that will call next() on this reader repeatedly to feed the TensorFlow queue.

Parameters **queue_size** (*int*) – Max elements to allow in the TF queue.

Example

```
>>> class MyModel(rllib.model.Model):
...     def custom_loss(self, policy_loss, loss_inputs):
...         reader = JsonReader(...)
...         input_ops = reader.tf_input_ops()
...         logits, _ = self._build_layers_v2(
...             {"obs": input_ops["obs"]},
...             self.num_outputs, self.options)
...         il_loss = imitation_loss(logits, input_ops["action"])
...         return policy_loss + il_loss
```

You can find a runnable version of this in examples/custom_loss.py.

Returns dict of Tensors, one for each column of the read SampleBatch.

5.31.4 Output API

You can configure experience output for an agent using the following options:

```
    # Specify where experiences should be saved:
    #  - None: don't save any experiences
    #  - "logdir" to save to the agent log dir
    #  - a path/URI to save to a custom output directory (e.g., "s3://bucket/")
    #  - a function that returns a rllib.offline.OutputWriter
    "output": None,
    # What sample batch columns to LZ4 compress in the output data.
    "output_compress_columns": ["obs", "new_obs"],
    # Max output file size before rolling over to a new file.
    "output_max_file_size": 64 * 1024 * 1024,
```

The interface for a custom output writer is as follows:

class ray.rllib.offline.**OutputWriter**
Writer object for saving experiences from policy evaluation.

write(*sample_batch*)
Save a batch of experiences.

Parameters **sample_batch** – SampleBatch or MultiAgentBatch to save.

5.32 RLlib Concepts and Custom Algorithms

This page describes the internal concepts used to implement algorithms in RLlib. You might find this useful if modifying or adding new algorithms to RLlib.

5.32.1 Policies

Policy classes encapsulate the core numerical components of RL algorithms. This typically includes the policy model that determines actions to take, a trajectory postprocessor for experiences, and a loss function to improve the policy given postprocessed experiences. For a simple example, see the policy gradients policy definition.

Most interaction with deep learning frameworks is isolated to the Policy interface, allowing RLlib to support multiple frameworks. To simplify the definition of policies, RLlib includes *Tensorflow* and *PyTorch-specific* templates. You can also write your own from scratch. Here is an example:

```
class CustomPolicy(Policy):
    """Example of a custom policy written from scratch.

    You might find it more convenient to use the `build_tf_policy` and
    `build_torch_policy` helpers instead for a real policy, which are
    described in the next sections.
    """

    def __init__(self, observation_space, action_space, config):
        Policy.__init__(self, observation_space, action_space, config)
        # example parameter
        self.w = 1.0

    def compute_actions(self,
                        obs_batch,
                        state_batches,
                        prev_action_batch=None,
                        prev_reward_batch=None,
                        info_batch=None,
                        episodes=None,
                        **kwargs):
        # return action batch, RNN states, extra values to include in batch
        return [self.action_space.sample() for _ in obs_batch], [], {}

    def learn_on_batch(self, samples):
        # implement your learning code here
        return {}  # return stats

    def get_weights(self):
        return {"w": self.w}

    def set_weights(self, weights):
        self.w = weights["w"]
```

The above basic policy, when run, will produce batches of observations with the basic `obs`, `new_obs`, `actions`, `rewards`, `dones`, and `infos` columns. There are two more mechanisms to pass along and emit extra information:

Policy recurrent state: Suppose you want to compute actions based on the current timestep of the episode. While it is possible to have the environment provide this as part of the observation, we can instead compute and store it as part of the Policy recurrent state:

```
def get_initial_state(self):
    """Returns initial RNN state for the current policy."""
    return [0]  # list of single state element (t=0)
                # you could also return multiple values, e.g., [0, "foo"]

def compute_actions(self,
                    obs_batch,
                    state_batches,
                    prev_action_batch=None,
                    prev_reward_batch=None,
                    info_batch=None,
                    episodes=None,
                    **kwargs):
    assert len(state_batches) == len(self.get_initial_state())
    new_state_batches = [[
        t + 1 for t in state_batches[0]
    ]]
    return ..., new_state_batches, {}

def learn_on_batch(self, samples):
    # can access array of the state elements at each timestep
    # or state_in_1, 2, etc. if there are multiple state elements
    assert "state_in_0" in samples.keys()
    assert "state_out_0" in samples.keys()
```

Extra action info output: You can also emit extra outputs at each step which will be available for learning on. For example, you might want to output the behaviour policy logits as extra action info, which can be used for importance weighting, but in general arbitrary values can be stored here (as long as they are convertible to numpy arrays):

```
def compute_actions(self,
                    obs_batch,
                    state_batches,
                    prev_action_batch=None,
                    prev_reward_batch=None,
                    info_batch=None,
                    episodes=None,
                    **kwargs):
    action_info_batch = {
        "some_value": ["foo" for _ in obs_batch],
        "other_value": [12345 for _ in obs_batch],
    }
    return ..., [], action_info_batch

def learn_on_batch(self, samples):
    # can access array of the extra values at each timestep
    assert "some_value" in samples.keys()
    assert "other_value" in samples.keys()
```

Policies in Multi-Agent

Beyond being agnostic of framework implementation, one of the main reasons to have a Policy abstraction is for use in multi-agent environments. For example, the rock-paper-scissors example shows how you can leverage the Policy abstraction to evaluate heuristic policies against learned policies.

Building Policies in TensorFlow

This section covers how to build a TensorFlow RLlib policy using `tf_policy_template.build_tf_policy()`.

To start, you first have to define a loss function. In RLlib, loss functions are defined over batches of trajectory data produced by policy evaluation. A basic policy gradient loss that only tries to maximize the 1-step reward can be defined as follows:

```
import tensorflow as tf
from ray.rllib.policy.sample_batch import SampleBatch

def policy_gradient_loss(policy, model, dist_class, train_batch):
    actions = train_batch[SampleBatch.ACTIONS]
    rewards = train_batch[SampleBatch.REWARDS]
    logits, _ = model.from_batch(train_batch)
    action_dist = dist_class(logits, model)
    return -tf.reduce_mean(action_dist.logp(actions) * rewards)
```

In the above snippet, `actions` is a Tensor placeholder of shape `[batch_size, action_dim...]`, and `rewards` is a placeholder of shape `[batch_size]`. The `action_dist` object is an ActionDistribution that is parameterized by the output of the neural network policy model. Passing this loss function to `build_tf_policy` is enough to produce a very basic TF policy:

```
from ray.rllib.policy.tf_policy_template import build_tf_policy

# <class 'ray.rllib.policy.tf_policy_template.MyTFPolicy'>
MyTFPolicy = build_tf_policy(
    name="MyTFPolicy",
    loss_fn=policy_gradient_loss)
```

We can create a *Trainer* and try running this policy on a toy env with two parallel rollout workers:

```
import ray
from ray import tune
from ray.rllib.agents.trainer_template import build_trainer

# <class 'ray.rllib.agents.trainer_template.MyCustomTrainer'>
MyTrainer = build_trainer(
    name="MyCustomTrainer",
    default_policy=MyTFPolicy)

ray.init()
tune.run(MyTrainer, config={"env": "CartPole-v0", "num_workers": 2})
```

If you run the above snippet (runnable file here), you'll probably notice that CartPole doesn't learn so well:

```
== Status ==
Using FIFO scheduling algorithm.
Resources requested: 3/4 CPUs, 0/0 GPUs
Memory usage on this node: 4.6/12.3 GB
Result logdir: /home/ubuntu/ray_results/MyAlgTrainer
Number of trials: 1 ({'RUNNING': 1})
RUNNING trials:
 - MyAlgTrainer_CartPole-v0_0:      RUNNING, [3 CPUs, 0 GPUs], [pid=26784],
                                    32 s, 156 iter, 62400 ts, 23.1 rew
```

Let's modify our policy loss to include rewards summed over time. To enable this advantage calculation, we need to

define a *trajectory postprocessor* for the policy. This can be done by defining `postprocess_fn`:

```
from ray.rllib.evaluation.postprocessing import compute_advantages, \
    Postprocessing

def postprocess_advantages(policy,
                           sample_batch,
                           other_agent_batches=None,
                           episode=None):
    return compute_advantages(
        sample_batch, 0.0, policy.config["gamma"], use_gae=False)

def policy_gradient_loss(policy, model, dist_class, train_batch):
    logits, _ = model.from_batch(train_batch)
    action_dist = dist_class(logits, model)
    return -tf.reduce_mean(
        action_dist.logp(train_batch[SampleBatch.ACTIONS]) *
        train_batch[Postprocessing.ADVANTAGES])

MyTFPolicy = build_tf_policy(
    name="MyTFPolicy",
    loss_fn=policy_gradient_loss,
    postprocess_fn=postprocess_advantages)
```

The `postprocess_advantages()` function above uses calls RLlib's `compute_advantages` function to compute advantages for each timestep. If you re-run the trainer with this improved policy, you'll find that it quickly achieves the max reward of 200.

You might be wondering how RLlib makes the advantages placeholder automatically available as `train_batch[Postprocessing.ADVANTAGES]`. When building your policy, RLlib will create a "dummy" trajectory batch where all observations, actions, rewards, etc. are zeros. It then calls your `postprocess_fn`, and generates TF placeholders based on the numpy shapes of the postprocessed batch. RLlib tracks which placeholders that `loss_fn` and `stats_fn` access, and then feeds the corresponding sample data into those placeholders during loss optimization. You can also access these placeholders via `policy.get_placeholder(<name>)` after loss initialization.

Example 1: Proximal Policy Optimization

In the above section you saw how to compose a simple policy gradient algorithm with RLlib. In this example, we'll dive into how PPO was built with RLlib and how you can modify it. First, check out the PPO trainer definition:

```
PPOTrainer = build_trainer(
    name="PPOTrainer",
    default_config=DEFAULT_CONFIG,
    default_policy=PPOTFPolicy,
    make_policy_optimizer=choose_policy_optimizer,
    validate_config=validate_config,
    after_optimizer_step=update_kl,
    before_train_step=warn_about_obs_filter,
    after_train_result=warn_about_bad_reward_scales)
```

Besides some boilerplate for defining the PPO configuration and some warnings, there are two important arguments to take note of here: `make_policy_optimizer=choose_policy_optimizer`, and `after_optimizer_step=update_kl`.

The `choose_policy_optimizer` function chooses which *Policy Optimizer* to use for distributed training. You can think of these policy optimizers as coordinating the distributed workflow needed to improve the policy. Depending on the trainer config, PPO can switch between a simple synchronous optimizer, or a multi-GPU optimizer that implements minibatch SGD (the default):

```
def choose_policy_optimizer(workers, config):
    if config["simple_optimizer"]:
        return SyncSamplesOptimizer(
            workers,
            num_sgd_iter=config["num_sgd_iter"],
            train_batch_size=config["train_batch_size"])

    return LocalMultiGPUOptimizer(
        workers,
        sgd_batch_size=config["sgd_minibatch_size"],
        num_sgd_iter=config["num_sgd_iter"],
        num_gpus=config["num_gpus"],
        sample_batch_size=config["sample_batch_size"],
        num_envs_per_worker=config["num_envs_per_worker"],
        train_batch_size=config["train_batch_size"],
        standardize_fields=["advantages"],
        straggler_mitigation=config["straggler_mitigation"])
```

Suppose we want to customize PPO to use an asynchronous-gradient optimization strategy similar to A3C. To do that, we could define a new function that returns `AsyncGradientsOptimizer` and override the `make_policy_optimizer` component of `PPOTrainer`.

```
from ray.rllib.agents.ppo import PPOTrainer
from ray.rllib.optimizers import AsyncGradientsOptimizer

def make_async_optimizer(workers, config):
    return AsyncGradientsOptimizer(workers, grads_per_step=100)

CustomTrainer = PPOTrainer.with_updates(
    make_policy_optimizer=make_async_optimizer)
```

The `with_updates` method that we use here is also available for Torch and TF policies built from templates.

Now let's take a look at the `update_kl` function. This is used to adaptively adjust the KL penalty coefficient on the PPO loss, which bounds the policy change per training step. You'll notice the code handles both single and multi-agent cases (where there are be multiple policies each with different KL coeffs):

```
def update_kl(trainer, fetches):
    if "kl" in fetches:
        # single-agent
        trainer.workers.local_worker().for_policy(
            lambda pi: pi.update_kl(fetches["kl"]))
    else:

        def update(pi, pi_id):
            if pi_id in fetches:
                pi.update_kl(fetches[pi_id]["kl"])
            else:
                logger.debug("No data for {}, not updating kl".format(pi_id))

        # multi-agent
        trainer.workers.local_worker().foreach_trainable_policy(update)
```

The `update_kl` method on the policy is defined in PPOTFPolicy via the `KLCoeffMixin`, along with several other advanced features. Let's look at each new feature used by the policy:

```
PPOTFPolicy = build_tf_policy(
    name="PPOTFPolicy",
    get_default_config=lambda: ray.rllib.agents.ppo.ppo.DEFAULT_CONFIG,
    loss_fn=ppo_surrogate_loss,
    stats_fn=kl_and_loss_stats,
    extra_action_fetches_fn=vf_preds_and_logits_fetches,
    postprocess_fn=postprocess_ppo_gae,
    gradients_fn=clip_gradients,
    before_loss_init=setup_mixins,
    mixins=[LearningRateSchedule, KLCoeffMixin, ValueNetworkMixin])
```

`stats_fn`: The stats function returns a dictionary of Tensors that will be reported with the training results. This also includes the `kl` metric which is used by the trainer to adjust the KL penalty. Note that many of the values below reference `policy.loss_obj`, which is assigned by `loss_fn` (not shown here since the PPO loss is quite complex). RLlib will always call `stats_fn` after `loss_fn`, so you can rely on using values saved by `loss_fn` as part of your statistics:

```
def kl_and_loss_stats(policy, train_batch):
    policy.explained_variance = explained_variance(
        train_batch[Postprocessing.VALUE_TARGETS], policy.model.value_function())

    stats_fetches = {
        "cur_kl_coeff": policy.kl_coeff,
        "cur_lr": tf.cast(policy.cur_lr, tf.float64),
        "total_loss": policy.loss_obj.loss,
        "policy_loss": policy.loss_obj.mean_policy_loss,
        "vf_loss": policy.loss_obj.mean_vf_loss,
        "vf_explained_var": policy.explained_variance,
        "kl": policy.loss_obj.mean_kl,
        "entropy": policy.loss_obj.mean_entropy,
    }

    return stats_fetches
```

`extra_actions_fetches_fn`: This function defines extra outputs that will be recorded when generating actions with the policy. For example, this enables saving the raw policy logits in the experience batch, which e.g. means it can be referenced in the PPO loss function via `batch[BEHAVIOUR_LOGITS]`. Other values such as the current value prediction can also be emitted for debugging or optimization purposes:

```
def vf_preds_and_logits_fetches(policy):
    return {
        SampleBatch.VF_PREDS: policy.model.value_function(),
        BEHAVIOUR_LOGITS: policy.model.last_output(),
    }
```

`gradients_fn`: If defined, this function returns TF gradients for the loss function. You'd typically only want to override this to apply transformations such as gradient clipping:

```
def clip_gradients(policy, optimizer, loss):
    if policy.config["grad_clip"] is not None:
        grads = tf.gradients(loss, policy.model.trainable_variables())
        policy.grads, _ = tf.clip_by_global_norm(grads,
                                                 policy.config["grad_clip"])
        clipped_grads = list(zip(policy.grads, policy.model.trainable_variables()))
        return clipped_grads
    else:
```

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```
        return optimizer.compute_gradients(
            loss, colocate_gradients_with_ops=True)
```

`mixins`: To add arbitrary stateful components, you can add mixin classes to the policy. Methods defined by these mixins will have higher priority than the base policy class, so you can use these to override methods (as in the case of `LearningRateSchedule`), or define extra methods and attributes (e.g., `KLCoeffMixin`, `ValueNetworkMixin`). Like any other Python superclass, these should be initialized at some point, which is what the `setup_mixins` function does:

```
def setup_mixins(policy, obs_space, action_space, config):
    ValueNetworkMixin.__init__(policy, obs_space, action_space, config)
    KLCoeffMixin.__init__(policy, config)
    LearningRateSchedule.__init__(policy, config["lr"], config["lr_schedule"])
```

In PPO we run `setup_mixins` before the loss function is called (i.e., `before_loss_init`), but other callbacks you can use include `before_init` and `after_init`.

Example 2: Deep Q Networks

Let's look at how to implement a different family of policies, by looking at the SimpleQ policy definition:

```
SimpleQPolicy = build_tf_policy(
    name="SimpleQPolicy",
    get_default_config=lambda: ray.rllib.agents.dqn.dqn.DEFAULT_CONFIG,
    make_model=build_q_models,
    action_sampler_fn=build_action_sampler,
    loss_fn=build_q_losses,
    extra_action_feed_fn=exploration_setting_inputs,
    extra_action_fetches_fn=lambda policy: {"q_values": policy.q_values},
    extra_learn_fetches_fn=lambda policy: {"td_error": policy.td_error},
    before_init=setup_early_mixins,
    after_init=setup_late_mixins,
    obs_include_prev_action_reward=False,
    mixins=[
        ExplorationStateMixin,
        TargetNetworkMixin,
    ])
```

The biggest difference from the policy gradient policies you saw previously is that SimpleQPolicy defines its own `make_model` and `action_sampler_fn`. This means that the policy builder will not internally create a model and action distribution, rather it will call `build_q_models` and `build_action_sampler` to get the output action tensors.

The model creation function actually creates two different models for DQN: the base Q network, and also a target network. It requires each model to be of type `SimpleQModel`, which implements a `get_q_values()` method. The model catalog will raise an error if you try to use a custom ModelV2 model that isn't a subclass of SimpleQModel. Similarly, the full DQN policy requires models to subclass `DistributionalQModel`, which implements `get_q_value_distributions()` and `get_state_value()`:

```
def build_q_models(policy, obs_space, action_space, config):
    ...

    policy.q_model = ModelCatalog.get_model_v2(
        obs_space,
        action_space,
        num_outputs,
```

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```
        config["model"],
        framework="tf",
        name=Q_SCOPE,
        model_interface=SimpleQModel,
        q_hiddens=config["hiddens"])

    policy.target_q_model = ModelCatalog.get_model_v2(
        obs_space,
        action_space,
        num_outputs,
        config["model"],
        framework="tf",
        name=Q_TARGET_SCOPE,
        model_interface=SimpleQModel,
        q_hiddens=config["hiddens"])

    return policy.q_model
```

The action sampler is straightforward, it just takes the q_model, runs a forward pass, and returns the argmax over the actions:

```
def build_action_sampler(policy, q_model, input_dict, obs_space, action_space,
                         config):
    # do max over Q values...
    ...
    return action, action_logp
```

The remainder of DQN is similar to other algorithms. Target updates are handled by a `after_optimizer_step` callback that periodically copies the weights of the Q network to the target.

Finally, note that you do not have to use `build_tf_policy` to define a TensorFlow policy. You can alternatively subclass `Policy`, `TFPolicy`, or `DynamicTFPolicy` as convenient.

Building Policies in TensorFlow Eager

Policies built with `build_tf_policy` (most of the reference algorithms are) can be run in eager mode by setting the `"eager": True` / `"eager_tracing": True` config options or using `rllib train --eager [--trace]`. This will tell RLlib to execute the model forward pass, action distribution, loss, and stats functions in eager mode.

Eager mode makes debugging much easier, since you can now use normal Python functions such as `print()` to inspect intermediate tensor values. However, it can be slower than graph mode unless tracing is enabled.

You can also selectively leverage eager operations within graph mode execution with tf.py_function. Here's an example of using eager ops embedded within a loss function.

Building Policies in PyTorch

Defining a policy in PyTorch is quite similar to that for TensorFlow (and the process of defining a trainer given a Torch policy is exactly the same). Here's a simple example of a trivial torch policy (runnable file here):

```
from ray.rllib.policy.sample_batch import SampleBatch
from ray.rllib.policy.torch_policy_template import build_torch_policy

def policy_gradient_loss(policy, model, dist_class, train_batch):
```

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```
    logits, _ = model.from_batch(train_batch)
    action_dist = dist_class(logits)
    log_probs = action_dist.logp(train_batch[SampleBatch.ACTIONS])
    return -train_batch[SampleBatch.REWARDS].dot(log_probs)

# <class 'ray.rllib.policy.torch_policy_template.MyTorchPolicy'>
MyTorchPolicy = build_torch_policy(
    name="MyTorchPolicy",
    loss_fn=policy_gradient_loss)
```

Now, building on the TF examples above, let's look at how the A3C torch policy is defined:

```
A3CTorchPolicy = build_torch_policy(
    name="A3CTorchPolicy",
    get_default_config=lambda: ray.rllib.agents.a3c.a3c.DEFAULT_CONFIG,
    loss_fn=actor_critic_loss,
    stats_fn=loss_and_entropy_stats,
    postprocess_fn=add_advantages,
    extra_action_out_fn=model_value_predictions,
    extra_grad_process_fn=apply_grad_clipping,
    optimizer_fn=torch_optimizer,
    mixins=[ValueNetworkMixin])
```

`loss_fn`: Similar to the TF example, the actor critic loss is defined over `batch`. We imperatively execute the forward pass by calling `model()` on the observations followed by `dist_class()` on the output logits. The output Tensors are saved as attributes of the policy object (e.g., `policy.entropy = dist.entropy.mean()`), and we return the scalar loss:

```
def actor_critic_loss(policy, model, dist_class, train_batch):
    logits, _ = model.from_batch(train_batch)
    values = model.value_function()
    action_dist = dist_class(logits)
    log_probs = action_dist.logp(train_batch[SampleBatch.ACTIONS])
    policy.entropy = action_dist.entropy().mean()
    ...
    return overall_err
```

`stats_fn`: The stats function references `entropy`, `pi_err`, and `value_err` saved from the call to the loss function, similar in the PPO TF example:

```
def loss_and_entropy_stats(policy, train_batch):
    return {
        "policy_entropy": policy.entropy.item(),
        "policy_loss": policy.pi_err.item(),
        "vf_loss": policy.value_err.item(),
    }
```

`extra_action_out_fn`: We save value function predictions given model outputs. This makes the value function predictions of the model available in the trajectory as `batch[SampleBatch.VF_PREDS]`:

```
def model_value_predictions(policy, input_dict, state_batches, model):
    return {SampleBatch.VF_PREDS: model.value_function().cpu().numpy()}
```

`postprocess_fn` and `mixins`: Similar to the PPO example, we need access to the value function during postprocessing (i.e., `add_advantages` below calls `policy._value()`. The value function is exposed through a mixin class that defines the method:

```
def add_advantages(policy,
                   sample_batch,
                   other_agent_batches=None,
                   episode=None):
    completed = sample_batch[SampleBatch.DONES][-1]
    if completed:
        last_r = 0.0
    else:
        last_r = policy._value(sample_batch[SampleBatch.NEXT_OBS][-1])
    return compute_advantages(sample_batch, last_r, policy.config["gamma"],
                              policy.config["lambda"])

class ValueNetworkMixin(object):
    def _value(self, obs):
        with self.lock:
            obs = torch.from_numpy(obs).float().unsqueeze(0).to(self.device)
            _, _, vf, _ = self.model({"obs": obs}, [])
            return vf.detach().cpu().numpy().squeeze()
```

You can find the full policy definition in a3c_torch_policy.py.

In summary, the main differences between the PyTorch and TensorFlow policy builder functions is that the TF loss and stats functions are built symbolically when the policy is initialized, whereas for PyTorch (or TensorFlow Eager) these functions are called imperatively each time they are used.

Extending Existing Policies

You can use the `with_updates` method on Trainers and Policy objects built with `make_*` to create a copy of the object with some changes, for example:

```
from ray.rllib.agents.ppo import PPOTrainer
from ray.rllib.agents.ppo.ppo_policy import PPOTFPolicy

CustomPolicy = PPOTFPolicy.with_updates(
    name="MyCustomPPOTFPolicy",
    loss_fn=some_custom_loss_fn)

CustomTrainer = PPOTrainer.with_updates(
    default_policy=CustomPolicy)
```

5.32.2 Policy Evaluation

Given an environment and policy, policy evaluation produces batches of experiences. This is your classic "environment interaction loop". Efficient policy evaluation can be burdensome to get right, especially when leveraging vectorization, RNNs, or when operating in a multi-agent environment. RLlib provides a RolloutWorker class that manages all of this, and this class is used in most RLlib algorithms.

You can use rollout workers standalone to produce batches of experiences. This can be done by calling `worker.sample()` on a worker instance, or `worker.sample.remote()` in parallel on worker instances created as Ray actors (see WorkerSet).

Here is an example of creating a set of rollout workers and using them gather experiences in parallel. The trajectories are concatenated, the policy learns on the trajectory batch, and then we broadcast the policy weights to the workers for the next round of rollouts:

```
# Setup policy and rollout workers
env = gym.make("CartPole-v0")
policy = CustomPolicy(env.observation_space, env.action_space, {})
workers = WorkerSet(
    policy=CustomPolicy,
    env_creator=lambda c: gym.make("CartPole-v0"),
    num_workers=10)

while True:
    # Gather a batch of samples
    T1 = SampleBatch.concat_samples(
        ray.get([w.sample.remote() for w in workers.remote_workers()]))

    # Improve the policy using the T1 batch
    policy.learn_on_batch(T1)

    # Broadcast weights to the policy evaluation workers
    weights = ray.put({"default_policy": policy.get_weights()})
    for w in workers.remote_workers():
        w.set_weights.remote(weights)
```

5.32.3 Policy Optimization

Similar to how a gradient-descent optimizer can be used to improve a model, RLlib's policy optimizers implement different strategies for improving a policy.

For example, in A3C you'd want to compute gradients asynchronously on different workers, and apply them to a central policy replica. This strategy is implemented by the AsyncGradientsOptimizer. Another alternative is to gather experiences synchronously in parallel and optimize the model centrally, as in SyncSamplesOptimizer. Policy optimizers abstract these strategies away into reusable modules.

This is how the example in the previous section looks when written using a policy optimizer:

```
# Same setup as before
workers = WorkerSet(
    policy=CustomPolicy,
    env_creator=lambda c: gym.make("CartPole-v0"),
    num_workers=10)

# this optimizer implements the IMPALA architecture
optimizer = AsyncSamplesOptimizer(workers, train_batch_size=500)

while True:
    optimizer.step()
```

5.32.4 Trainers

Trainers are the boilerplate classes that put the above components together, making algorithms accessible via Python API and the command line. They manage algorithm configuration, setup of the rollout workers and optimizer, and collection of training metrics. Trainers also implement the Trainable API for easy experiment management.

Example of three equivalent ways of interacting with the PPO trainer, all of which log results in `~/ray_results`:

```
trainer = PPOTrainer(env="CartPole-v0", config={"train_batch_size": 4000})
while True:
    print(trainer.train())
```

```
rllib train --run=PPO --env=CartPole-v0 --config='{"train_batch_size": 4000}'
```

```
from ray import tune
tune.run(PPOTrainer, config={"env": "CartPole-v0", "train_batch_size": 4000})
```

5.33 RLlib Examples

This page is an index of examples for the various use cases and features of RLlib.

If any example is broken, or if you'd like to add an example to this page, feel free to raise an issue on our Github repository.

5.33.1 Tuned Examples

- **Tuned examples:** Collection of tuned algorithm hyperparameters.
- **Atari benchmarks:** Collection of reasonably optimized Atari results.

5.33.2 Blog Posts

- **Scaling Multi-Agent Reinforcement Learning:** This blog post is a brief tutorial on multi-agent RL and its design in RLlib.
- **Functional RL with Keras and TensorFlow Eager:** Exploration of a functional paradigm for implementing reinforcement learning (RL) algorithms.

5.33.3 Training Workflows

- **Custom training workflows:** Example of how to use Tune's support for custom training functions to implement custom training workflows.
- **Curriculum learning:** Example of how to adjust the configuration of an environment over time.
- **Custom metrics:** Example of how to output custom training metrics to TensorBoard.
- **Using rollout workers directly for control over the whole training workflow:** Example of how to use RLlib's lower-level building blocks to implement a fully customized training workflow.

5.33.4 Custom Envs and Models

- **Registering a custom env and model:** Example of defining and registering a gym env and model for use with RLlib.
- **Custom Keras model:** Example of using a custom Keras model.
- **Custom Keras RNN model:** Example of using a custom Keras RNN model.

- **Registering a custom model with supervised loss:** Example of defining and registering a custom model with a supervised loss.
- **Subprocess environment:** Example of how to ensure subprocesses spawned by envs are killed when RLlib exits.
- **Batch normalization:** Example of adding batch norm layers to a custom model.
- **Parametric actions:** Example of how to handle variable-length or parametric action spaces.
- **Eager execution:** Example of how to leverage TensorFlow eager to simplify debugging and design of custom models and policies.

5.33.5 Serving and Offline

- **CartPole server:** Example of online serving of predictions for a simple CartPole policy.
- **Saving experiences:** Example of how to externally generate experience batches in RLlib-compatible format.

5.33.6 Multi-Agent and Hierarchical

- **Rock-paper-scissors:** Example of different heuristic and learned policies competing against each other in rock-paper-scissors.
- **Two-step game:** Example of the two-step game from the QMIX paper.
- **PPO with centralized critic on two-step game:** Example of customizing PPO to leverage a centralized value function.
- **Centralized critic in the env:** A simpler method of implementing a centralized critic by augmentating agent observations with global information.
- **Hand-coded policy:** Example of running a custom hand-coded policy alongside trainable policies.
- **Weight sharing between policies:** Example of how to define weight-sharing layers between two different policies.
- **Multiple trainers:** Example of alternating training between two DQN and PPO trainers.
- **Hierarchical training:** Example of hierarchical training using the multi-agent API.

5.33.7 Community Examples

- **CARLA:** Example of training autonomous vehicles with RLlib and CARLA simulator.
- **GFootball:** Example of setting up a multi-agent version of GFootball with RLlib.
- **NeuroCuts:** Example of building packet classification trees using RLlib / multi-agent in a bandit-like setting.
- **Roboschool / SageMaker:** Example of training robotic control policies in SageMaker with RLlib.
- **StarCraft2:** Example of training in StarCraft2 maps with RLlib / multi-agent.
- **Traffic Flow:** Example of optimizing mixed-autonomy traffic simulations with RLlib / multi-agent.
- **Sequential Social Dilemma Games:** Example of using the multi-agent API to model several social dilemma games.

5.34 RLlib Development

5.34.1 Development Install

You can develop RLlib locally without needing to compile Ray by using the setup-dev.py script. This sets up links between the `rllib` dir in your git repo and the one bundled with the `ray` package. When using this script, make sure that your git branch is in sync with the installed Ray binaries (i.e., you are up-to-date on master and have the latest wheel installed.)

5.34.2 API Stability

Objects and methods annotated with `@PublicAPI` or `@DeveloperAPI` have the following API compatibility guarantees:

`ray.rllib.utils.annotations.`**`PublicAPI`**(*obj*)
Annotation for documenting public APIs.

Public APIs are classes and methods exposed to end users of RLlib. You can expect these APIs to remain stable across RLlib releases.

Subclasses that inherit from a `@PublicAPI` base class can be assumed part of the RLlib public API as well (e.g., all trainer classes are in public API because Trainer is `@PublicAPI`).

In addition, you can assume all trainer configurations are part of their public API as well.

`ray.rllib.utils.annotations.`**`DeveloperAPI`**(*obj*)
Annotation for documenting developer APIs.

Developer APIs are classes and methods explicitly exposed to developers for the purposes of building custom algorithms or advanced training strategies on top of RLlib internals. You can generally expect these APIs to be stable sans minor changes (but less stable than public APIs).

Subclasses that inherit from a `@DeveloperAPI` base class can be assumed part of the RLlib developer API as well (e.g., all policy optimizers are developer API because PolicyOptimizer is `@DeveloperAPI`).

5.34.3 Features

Feature development and upcoming priorities are tracked on the RLlib project board (note that this may not include all development efforts). For discussion of issues and new features, we use the Ray dev list and GitHub issues page.

5.34.4 Benchmarks

A number of training run results are available in the rl-experiments repo, and there is also a list of working hyperparameter configurations in tuned_examples. Benchmark results are extremely valuable to the community, so if you happen to have results that may be of interest, consider making a pull request to either repo.

5.34.5 Contributing Algorithms

These are the guidelines for merging new algorithms into RLlib:

- **Contributed algorithms (rllib/contrib):**
  - must subclass Trainer and implement the `_train()` method
  - must include a lightweight test (example) to ensure the algorithm runs

  - should include tuned hyperparameter examples and documentation
  - should offer functionality not present in existing algorithms

- **Fully integrated algorithms (rllib/agents) have the following additional requirements:**
  - must fully implement the Trainer API
  - must offer substantial new functionality not possible to add to other algorithms
  - should support custom models and preprocessors
  - should use RLlib abstractions and support distributed execution

Both integrated and contributed algorithms ship with the `ray` PyPI package, and are tested as part of Ray's automated tests. The main difference between contributed and fully integrated algorithms is that the latter will be maintained by the Ray team to a much greater extent with respect to bugs and integration with RLlib features.

How to add an algorithm to `contrib`

It takes just two changes to add an algorithm to contrib. A minimal example can be found here. First, subclass Trainer and implement the `_init` and `_train` methods:

```
class RandomAgent(Trainer):
    """Policy that takes random actions and never learns."""

    _name = "RandomAgent"
    _default_config = with_common_config({
        "rollouts_per_iteration": 10,
    })

    @override(Trainer)
    def _init(self, config, env_creator):
        self.env = env_creator(config["env_config"])

    @override(Trainer)
    def _train(self):
        rewards = []
        steps = 0
        for _ in range(self.config["rollouts_per_iteration"]):
            obs = self.env.reset()
            done = False
            reward = 0.0
            while not done:
                action = self.env.action_space.sample()
                obs, r, done, info = self.env.step(action)
                reward += r
                steps += 1
            rewards.append(reward)
        return {
            "episode_reward_mean": np.mean(rewards),
            "timesteps_this_iter": steps,
        }
```

Second, register the trainer with a name in contrib/registry.py.

```
def _import_random_agent():
    from ray.rllib.contrib.random_agent.random_agent import RandomAgent
    return RandomAgent
```

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```
def _import_random_agent_2():
    from ray.rllib.contrib.random_agent_2.random_agent_2 import RandomAgent2
    return RandomAgent2

CONTRIBUTED_ALGORITHMS = {
    "contrib/RandomAgent": _import_random_trainer,
    "contrib/RandomAgent2": _import_random_trainer_2,
    # ...
}
```

After registration, you can run and visualize training progress using `rllib train`:

```
rllib train --run=contrib/RandomAgent --env=CartPole-v0
tensorboard --logdir=~/ray_results
```

5.35 RLlib Package Reference

5.35.1 ray.rllib.policy

class ray.rllib.policy.**Policy**(*observation_space*, *action_space*, *config*)

An agent policy and loss, i.e., a TFPolicy or other subclass.

This object defines how to act in the environment, and also losses used to improve the policy based on its experiences. Note that both policy and loss are defined together for convenience, though the policy itself is logically separate.

All policies can directly extend Policy, however TensorFlow users may find TFPolicy simpler to implement. TFPolicy also enables RLlib to apply TensorFlow-specific optimizations such as fusing multiple policy graphs and multi-GPU support.

observation_space

Observation space of the policy.

Type gym.Space

action_space

Action space of the policy.

Type gym.Space

compute_actions(*obs_batch*, *state_batches*, *prev_action_batch=None*, *prev_reward_batch=None*, *info_batch=None*, *episodes=None*, ***kwargs*)

Compute actions for the current policy.

Parameters

- **obs_batch** (*np.ndarray*) – batch of observations
- **state_batches** (*list*) – list of RNN state input batches, if any
- **prev_action_batch** (*np.ndarray*) – batch of previous action values
- **prev_reward_batch** (*np.ndarray*) – batch of previous rewards
- **info_batch** (*info*) – batch of info objects

- **episodes** (*list*) – MultiAgentEpisode for each obs in obs_batch. This provides access to all of the internal episode state, which may be useful for model-based or multiagent algorithms.
- **kwargs** – forward compatibility placeholder

Returns

batch of output actions, with shape like [BATCH_SIZE, ACTION_SHAPE].

state_outs (list): list of RNN state output batches, if any, with shape like [STATE_SIZE, BATCH_SIZE].

info (dict): dictionary of extra feature batches, if any, with shape like {"f1": [BATCH_SIZE, ...], "f2": [BATCH_SIZE, ...]}.

Return type actions (np.ndarray)

compute_single_action(*obs*, *state*, *prev_action=None*, *prev_reward=None*, *info=None*, *episode=None*, *clip_actions=False*, ***kwargs*)

Unbatched version of compute_actions.

Parameters

- **obs** (*obj*) – single observation
- **state_batches** (*list*) – list of RNN state inputs, if any
- **prev_action** (*obj*) – previous action value, if any
- **prev_reward** (*int*) – previous reward, if any
- **info** (*dict*) – info object, if any
- **episode** (MultiAgentEpisode) – this provides access to all of the internal episode state, which may be useful for model-based or multi-agent algorithms.
- **clip_actions** (*bool*) – should the action be clipped
- **kwargs** – forward compatibility placeholder

Returns single action state_outs (list): list of RNN state outputs, if any info (dict): dictionary of extra features, if any

Return type actions (obj)

postprocess_trajectory(*sample_batch*, *other_agent_batches=None*, *episode=None*)

Implements algorithm-specific trajectory postprocessing.

This will be called on each trajectory fragment computed during policy evaluation. Each fragment is guaranteed to be only from one episode.

Parameters

- **sample_batch** (SampleBatch) – batch of experiences for the policy, which will contain at most one episode trajectory.
- **other_agent_batches** (*dict*) – In a multi-agent env, this contains a mapping of agent ids to (policy, agent_batch) tuples containing the policy and experiences of the other agents.
- **episode** (MultiAgentEpisode) – this provides access to all of the internal episode state, which may be useful for model-based or multi-agent algorithms.

Returns postprocessed sample batch.

Return type *SampleBatch*

learn_on_batch(*samples*)
Fused compute gradients and apply gradients call.

Either this or the combination of compute/apply grads must be implemented by subclasses.

Returns dictionary of extra metadata from compute_gradients().

Return type grad_info

Examples

```
>>> batch = ev.sample()
>>> ev.learn_on_batch(samples)
```

compute_gradients(*postprocessed_batch*)
Computes gradients against a batch of experiences.

Either this or learn_on_batch() must be implemented by subclasses.

Returns List of gradient output values info (dict): Extra policy-specific values

Return type grads (list)

apply_gradients(*gradients*)
Applies previously computed gradients.

Either this or learn_on_batch() must be implemented by subclasses.

get_weights()
Returns model weights.

Returns Serializable copy or view of model weights

Return type weights (obj)

set_weights(*weights*)
Sets model weights.

Parameters **weights** (*obj*) – Serializable copy or view of model weights

get_initial_state()
Returns initial RNN state for the current policy.

get_state()
Saves all local state.

Returns Serialized local state.

Return type state (obj)

set_state(*state*)
Restores all local state.

Parameters **state** (*obj*) – Serialized local state.

on_global_var_update(*global_vars*)
Called on an update to global vars.

Parameters **global_vars** (*dict*) – Global variables broadcast from the driver.

export_model(*export_dir*)
Export Policy to local directory for serving.

Parameters **export_dir** (*str*) – Local writable directory.

export_checkpoint(*export_dir*)
Export Policy checkpoint to local directory.

Argument: export_dir (str): Local writable directory.

class ray.rllib.policy.**TFPolicy**(*observation_space*, *action_space*, *sess*, *obs_input*, *action_sampler*, *loss*, *loss_inputs*, *model=None*, *action_logp=None*, *state_inputs=None*, *state_outputs=None*, *prev_action_input=None*, *prev_reward_input=None*, *seq_lens=None*, *max_seq_len=20*, *batch_divisibility_req=1*, *update_ops=None*)
An agent policy and loss implemented in TensorFlow.

Extending this class enables RLlib to perform TensorFlow specific optimizations on the policy, e.g., parallelization across gpus or fusing multiple graphs together in the multi-agent setting.

Input tensors are typically shaped like [BATCH_SIZE, . . .].

observation_space
observation space of the policy.

Type gym.Space

action_space
action space of the policy.

Type gym.Space

model
RLlib model used for the policy.

Type *rllib.models.Model*

Examples

```
>>> policy = TFPolicySubclass(
    sess, obs_input, action_sampler, loss, loss_inputs)
```

```
>>> print(policy.compute_actions([1, 0, 2]))
(array([0, 1, 1]), [], {})
```

```
>>> print(policy.postprocess_trajectory(SampleBatch({...})))
SampleBatch({"action": ..., "advantages": ..., ...})
```

get_placeholder(*name*)
Returns the given action or loss input placeholder by name.

If the loss has not been initialized and a loss input placeholder is requested, an error is raised.

get_session()
Returns a reference to the TF session for this policy.

loss_initialized()
Returns whether the loss function has been initialized.

compute_actions(*obs_batch*, *state_batches=None*, *prev_action_batch=None*, *prev_reward_batch=None*, *info_batch=None*, *episodes=None*, ***kwargs*)
Compute actions for the current policy.

Parameters

- **obs_batch** (*np.ndarray*) – batch of observations
- **state_batches** (*list*) – list of RNN state input batches, if any
- **prev_action_batch** (*np.ndarray*) – batch of previous action values
- **prev_reward_batch** (*np.ndarray*) – batch of previous rewards
- **info_batch** (*info*) – batch of info objects
- **episodes** (*list*) – MultiAgentEpisode for each obs in obs_batch. This provides access to all of the internal episode state, which may be useful for model-based or multiagent algorithms.
- **kwargs** – forward compatibility placeholder

Returns

batch of output actions, with shape like [BATCH_SIZE, ACTION_SHAPE].

state_outs (list): list of RNN state output batches, if any, with shape like [STATE_SIZE, BATCH_SIZE].

info (dict): dictionary of extra feature batches, if any, with shape like {"f1": [BATCH_SIZE, ...], "f2": [BATCH_SIZE, ...]}.

Return type actions (np.ndarray)

compute_gradients (*postprocessed_batch*)
Computes gradients against a batch of experiences.

Either this or learn_on_batch() must be implemented by subclasses.

Returns List of gradient output values info (dict): Extra policy-specific values

Return type grads (list)

apply_gradients (*gradients*)
Applies previously computed gradients.

Either this or learn_on_batch() must be implemented by subclasses.

learn_on_batch (*postprocessed_batch*)
Fused compute gradients and apply gradients call.

Either this or the combination of compute/apply grads must be implemented by subclasses.

Returns dictionary of extra metadata from compute_gradients().

Return type grad_info

Examples

```
>>> batch = ev.sample()
>>> ev.learn_on_batch(samples)
```

get_weights ()
Returns model weights.

Returns Serializable copy or view of model weights

Return type weights (obj)

set_weights (*weights*)
Sets model weights.

Parameters **weights** (*obj*) – Serializable copy or view of model weights

export_model(*export_dir*)
Export tensorflow graph to export_dir for serving.

export_checkpoint(*export_dir*, *filename_prefix='model'*)
Export tensorflow checkpoint to export_dir.

copy(*existing_inputs*)
Creates a copy of self using existing input placeholders.

Optional, only required to work with the multi-GPU optimizer.

extra_compute_action_feed_dict()
Extra dict to pass to the compute actions session run.

extra_compute_action_fetches()
Extra values to fetch and return from compute_actions().

By default we only return action probability info (if present).

extra_compute_grad_feed_dict()
Extra dict to pass to the compute gradients session run.

extra_compute_grad_fetches()
Extra values to fetch and return from compute_gradients().

optimizer()
TF optimizer to use for policy optimization.

gradients(*optimizer*, *loss*)
Override for custom gradient computation.

build_apply_op(*optimizer*, *grads_and_vars*)
Override for custom gradient apply computation.

class ray.rllib.policy.**TorchPolicy**(*observation_space*, *action_space*, *model*, *loss*, *action_distribution_class*)
Template for a PyTorch policy and loss to use with RLlib.

This is similar to TFPolicy, but for PyTorch.

observation_space
observation space of the policy.

Type gym.Space

action_space
action space of the policy.

Type gym.Space

config
config of the policy

Type dict

model
Torch model instance

Type TorchModel

dist_class
Torch action distribution class

Type type

compute_actions(*obs_batch*, *state_batches=None*, *prev_action_batch=None*, *prev_reward_batch=None*, *info_batch=None*, *episodes=None*, ***kwargs*)

Compute actions for the current policy.

Parameters

- **obs_batch** (*np.ndarray*) – batch of observations
- **state_batches** (*list*) – list of RNN state input batches, if any
- **prev_action_batch** (*np.ndarray*) – batch of previous action values
- **prev_reward_batch** (*np.ndarray*) – batch of previous rewards
- **info_batch** (*info*) – batch of info objects
- **episodes** (*list*) – MultiAgentEpisode for each obs in obs_batch. This provides access to all of the internal episode state, which may be useful for model-based or multiagent algorithms.
- **kwargs** – forward compatibility placeholder

Returns

batch of output actions, with shape like [BATCH_SIZE, ACTION_SHAPE].

state_outs (list): list of RNN state output batches, if any, with shape like [STATE_SIZE, BATCH_SIZE].

info (dict): dictionary of extra feature batches, if any, with shape like {"f1": [BATCH_SIZE, ...], "f2": [BATCH_SIZE, ...]}.

Return type actions (np.ndarray)

learn_on_batch(*postprocessed_batch*)

Fused compute gradients and apply gradients call.

Either this or the combination of compute/apply grads must be implemented by subclasses.

Returns dictionary of extra metadata from compute_gradients().

Return type grad_info

Examples

```
>>> batch = ev.sample()
>>> ev.learn_on_batch(samples)
```

compute_gradients(*postprocessed_batch*)

Computes gradients against a batch of experiences.

Either this or learn_on_batch() must be implemented by subclasses.

Returns List of gradient output values info (dict): Extra policy-specific values

Return type grads (list)

apply_gradients(*gradients*)

Applies previously computed gradients.

Either this or learn_on_batch() must be implemented by subclasses.

get_weights()

Returns model weights.

Returns Serializable copy or view of model weights

Return type weights (obj)

set_weights(*weights*)
Sets model weights.

Parameters **weights** (*obj*) – Serializable copy or view of model weights

get_initial_state()
Returns initial RNN state for the current policy.

extra_grad_process()
Allow subclass to do extra processing on gradients and return processing info.

extra_action_out(*input_dict*, *state_batches*, *model*)
Returns dict of extra info to include in experience batch.

Parameters

- **input_dict** (*dict*) – Dict of model input tensors.
- **state_batches** (*list*) – List of state tensors.
- **model** (TorchModelV2) – Reference to the model.

extra_grad_info(*train_batch*)
Return dict of extra grad info.

optimizer()
Custom PyTorch optimizer to use.

ray.rllib.policy.**build_tf_policy**(*name*, *loss_fn*, *get_default_config=None*, *postprocess_fn=None*, *stats_fn=None*, *optimizer_fn=None*, *gradients_fn=None*, *apply_gradients_fn=None*, *grad_stats_fn=None*, *extra_action_fetches_fn=None*, *extra_learn_fetches_fn=None*, *before_init=None*, *before_loss_init=None*, *after_init=None*, *make_model=None*, *action_sampler_fn=None*, *mixins=None*, *get_batch_divisibility_req=None*, *obs_include_prev_action_reward=True*)
Helper function for creating a dynamic tf policy at runtime.

Functions will be run in this order to initialize the policy:

1. Placeholder setup: postprocess_fn
2. Loss init: loss_fn, stats_fn
3. **Optimizer init: optimizer_fn, gradients_fn, apply_gradients_fn,** grad_stats_fn

This means that you can e.g., depend on any policy attributes created in the running of *loss_fn* in later functions such as *stats_fn*.

In eager mode, the following functions will be run repeatedly on each eager execution: loss_fn, stats_fn, gradients_fn, apply_gradients_fn, and grad_stats_fn.

This means that these functions should not define any variables internally, otherwise they will fail in eager mode execution. Variable should only be created in make_model (if defined).

Parameters

- **name** (*str*) – name of the policy (e.g., "PPOTFPolicy")
- **loss_fn** (*func*) – function that returns a loss tensor as arguments (policy, model, dist_class, train_batch)

- **get_default_config** (*func*) – optional function that returns the default config to merge with any overrides
- **postprocess_fn** (*func*) – optional experience postprocessing function that takes the same args as Policy.postprocess_trajectory()
- **stats_fn** (*func*) – optional function that returns a dict of TF fetches given the policy and batch input tensors
- **optimizer_fn** (*func*) – optional function that returns a tf.Optimizer given the policy and config
- **gradients_fn** (*func*) – optional function that returns a list of gradients given (policy, optimizer, loss). If not specified, this defaults to optimizer.compute_gradients(loss)
- **apply_gradients_fn** (*func*) – optional function that returns an apply gradients op given (policy, optimizer, grads_and_vars)
- **grad_stats_fn** (*func*) – optional function that returns a dict of TF fetches given the policy, batch input, and gradient tensors
- **extra_action_fetches_fn** (*func*) – optional function that returns a dict of TF fetches given the policy object
- **extra_learn_fetches_fn** (*func*) – optional function that returns a dict of extra values to fetch and return when learning on a batch
- **before_init** (*func*) – optional function to run at the beginning of policy init that takes the same arguments as the policy constructor
- **before_loss_init** (*func*) – optional function to run prior to loss init that takes the same arguments as the policy constructor
- **after_init** (*func*) – optional function to run at the end of policy init that takes the same arguments as the policy constructor
- **make_model** (*func*) – optional function that returns a ModelV2 object given (policy, obs_space, action_space, config). All policy variables should be created in this function. If not specified, a default model will be created.
- **action_sampler_fn** (*func*) – optional function that returns a tuple of action and action prob tensors given (policy, model, input_dict, obs_space, action_space, config). If not specified, a default action distribution will be used.
- **mixins** (*list*) – list of any class mixins for the returned policy class. These mixins will be applied in order and will have higher precedence than the DynamicTFPolicy class
- **get_batch_divisibility_req** (*func*) – optional function that returns the divisibility requirement for sample batches
- **obs_include_prev_action_reward** (*bool*) – whether to include the previous action and reward in the model input

Returns a DynamicTFPolicy instance that uses the specified args

ray.rllib.policy.**build_torch_policy**(*name*, *loss_fn*, *get_default_config=None*, *stats_fn=None*, *postprocess_fn=None*, *extra_action_out_fn=None*, *extra_grad_process_fn=None*, *optimizer_fn=None*, *before_init=None*, *after_init=None*, *make_model_and_action_dist=None*, *mixins=None*)

Helper function for creating a torch policy at runtime.

Parameters

- **name** (*str*) – name of the policy (e.g., "PPOTorchPolicy")
- **loss_fn** (*func*) – function that returns a loss tensor as arguments (policy, model, dist_class, train_batch)
- **get_default_config** (*func*) – optional function that returns the default config to merge with any overrides
- **stats_fn** (*func*) – optional function that returns a dict of values given the policy and batch input tensors
- **postprocess_fn** (*func*) – optional experience postprocessing function that takes the same args as Policy.postprocess_trajectory()
- **extra_action_out_fn** (*func*) – optional function that returns a dict of extra values to include in experiences
- **extra_grad_process_fn** (*func*) – optional function that is called after gradients are computed and returns processing info
- **optimizer_fn** (*func*) – optional function that returns a torch optimizer given the policy and config
- **before_init** (*func*) – optional function to run at the beginning of policy init that takes the same arguments as the policy constructor
- **after_init** (*func*) – optional function to run at the end of policy init that takes the same arguments as the policy constructor
- **make_model_and_action_dist** (*func*) – optional func that takes the same arguments as policy init and returns a tuple of model instance and torch action distribution class. If not specified, the default model and action dist from the catalog will be used
- **mixins** (*list*) – list of any class mixins for the returned policy class. These mixins will be applied in order and will have higher precedence than the TorchPolicy class

Returns a TorchPolicy instance that uses the specified args

5.35.2 ray.rllib.env

class ray.rllib.env.**BaseEnv**

The lowest-level env interface used by RLlib for sampling.

BaseEnv models multiple agents executing asynchronously in multiple environments. A call to poll() returns observations from ready agents keyed by their environment and agent ids, and actions for those agents can be sent back via send_actions().

All other env types can be adapted to BaseEnv. RLlib handles these conversions internally in RolloutWorker, for example:

gym.Env => rllib.VectorEnv => rllib.BaseEnv rllib.MultiAgentEnv => rllib.BaseEnv rllib.ExternalEnv => rllib.BaseEnv

action_space

Action space. This must be defined for single-agent envs. Multi-agent envs can set this to None.

Type gym.Space

observation_space

Observation space. This must be defined for single-agent envs. Multi-agent envs can set this to None.

Type gym.Space

Examples

```
>>> env = MyBaseEnv()
>>> obs, rewards, dones, infos, off_policy_actions = env.poll()
>>> print(obs)
{
    "env_0": {
        "car_0": [2.4, 1.6],
        "car_1": [3.4, -3.2],
    },
    "env_1": {
        "car_0": [8.0, 4.1],
    },
    "env_2": {
        "car_0": [2.3, 3.3],
        "car_1": [1.4, -0.2],
        "car_3": [1.2, 0.1],
    },
}
>>> env.send_actions(
    actions={
        "env_0": {
            "car_0": 0,
            "car_1": 1,
        }, ...
    })
>>> obs, rewards, dones, infos, off_policy_actions = env.poll()
>>> print(obs)
{
    "env_0": {
        "car_0": [4.1, 1.7],
        "car_1": [3.2, -4.2],
    }, ...
}
>>> print(dones)
{
    "env_0": {
        "__all__": False,
        "car_0": False,
        "car_1": True,
    }, ...
}
```

static to_base_env(*env*, *make_env=None*, *num_envs=1*, *remote_envs=False*, *remote_env_batch_wait_ms=0*)

Wraps any env type as needed to expose the async interface.

poll()

Returns observations from ready agents.

The returns are two-level dicts mapping from env_id to a dict of agent_id to values. The number of agents and envs can vary over time.

Returns

- **obs (dict)** (*New observations for each ready agent.*)
- **rewards (dict)** (*Reward values for each ready agent. If the*) – episode is just started, the value will be None.

- **dones (dict)** (*Done values for each ready agent. The special key*) – "__all__" is used to indicate env termination.
- **infos (dict)** (*Info values for each ready agent.*)
- **off_policy_actions (dict)** (*Agents may take off-policy actions. When*) – that happens, there will be an entry in this dict that contains the taken action. There is no need to send_actions() for agents that have already chosen off-policy actions.

send_actions(*action_dict*)
Called to send actions back to running agents in this env.

Actions should be sent for each ready agent that returned observations in the previous poll() call.

Parameters **action_dict** (*dict*) – Actions values keyed by env_id and agent_id.

try_reset(*env_id*)
Attempt to reset the env with the given id.

If the environment does not support synchronous reset, None can be returned here.

Returns Resetted observation or None if not supported.

Return type obs (dict|None)

get_unwrapped()
Return a reference to the underlying gym envs, if any.

Returns Underlying gym envs or [].

Return type envs (list)

stop()
Releases all resources used.

class ray.rllib.env.**MultiAgentEnv**
An environment that hosts multiple independent agents.

Agents are identified by (string) agent ids. Note that these "agents" here are not to be confused with RLlib agents.

Examples

```
>>> env = MyMultiAgentEnv()
>>> obs = env.reset()
>>> print(obs)
{
    "car_0": [2.4, 1.6],
    "car_1": [3.4, -3.2],
    "traffic_light_1": [0, 3, 5, 1],
}
>>> obs, rewards, dones, infos = env.step(
    action_dict={
        "car_0": 1, "car_1": 0, "traffic_light_1": 2,
    })
>>> print(rewards)
{
    "car_0": 3,
    "car_1": -1,
    "traffic_light_1": 0,
}
```

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```
>>> print(dones)
{
    "car_0": False,    # car_0 is still running
    "car_1": True,     # car_1 is done
    "__all__": False,  # the env is not done
}
>>> print(infos)
{
    "car_0": {},  # info for car_0
    "car_1": {},  # info for car_1
}
```

reset()
Resets the env and returns observations from ready agents.

Returns New observations for each ready agent.

Return type obs (dict)

step(*action_dict*)
Returns observations from ready agents.

The returns are dicts mapping from agent_id strings to values. The number of agents in the env can vary over time.

Returns

- **obs (dict)** (*New observations for each ready agent.*)
- **rewards (dict)** (*Reward values for each ready agent. If the*) – episode is just started, the value will be None.
- **dones (dict)** (*Done values for each ready agent. The special key*) – "__all__" (required) is used to indicate env termination.
- **infos (dict)** (*Optional info values for each agent id.*)

with_agent_groups(*groups*, *obs_space=None*, *act_space=None*)
Convenience method for grouping together agents in this env.

An agent group is a list of agent ids that are mapped to a single logical agent. All agents of the group must act at the same time in the environment. The grouped agent exposes Tuple action and observation spaces that are the concatenated action and obs spaces of the individual agents.

The rewards of all the agents in a group are summed. The individual agent rewards are available under the "individual_rewards" key of the group info return.

Agent grouping is required to leverage algorithms such as Q-Mix.

This API is experimental.

Parameters

- **groups** (*dict*) – Mapping from group id to a list of the agent ids of group members. If an agent id is not present in any group value, it will be left ungrouped.
- **obs_space** (*Space*) – Optional observation space for the grouped env. Must be a tuple space.
- **act_space** (*Space*) – Optional action space for the grouped env. Must be a tuple space.

Examples

```
>>> env = YourMultiAgentEnv(...)
>>> grouped_env = env.with_agent_groups(env, {
...   "group1": ["agent1", "agent2", "agent3"],
...   "group2": ["agent4", "agent5"],
... })
```

class ray.rllib.env.**ExternalEnv**(*action_space*, *observation_space*, *max_concurrent=100*)

An environment that interfaces with external agents.

Unlike simulator envs, control is inverted. The environment queries the policy to obtain actions and logs observations and rewards for training. This is in contrast to gym.Env, where the algorithm drives the simulation through env.step() calls.

You can use ExternalEnv as the backend for policy serving (by serving HTTP requests in the run loop), for ingesting offline logs data (by reading offline transitions in the run loop), or other custom use cases not easily expressed through gym.Env.

ExternalEnv supports both on-policy actions (through self.get_action()), and off-policy actions (through self.log_action()).

This env is thread-safe, but individual episodes must be executed serially.

action_space

Action space.

Type gym.Space

observation_space

Observation space.

Type gym.Space

Examples

```
>>> register_env("my_env", lambda config: YourExternalEnv(config))
>>> trainer = DQNTrainer(env="my_env")
>>> while True:
      print(trainer.train())
```

run()

Override this to implement the run loop.

Your loop should continuously:

1. Call self.start_episode(episode_id)
2. **Call self.get_action(episode_id, obs)** -or- self.log_action(episode_id, obs, action)
3. Call self.log_returns(episode_id, reward)
4. Call self.end_episode(episode_id, obs)
5. Wait if nothing to do.

Multiple episodes may be started at the same time.

start_episode(*episode_id=None*, *training_enabled=True*)

Record the start of an episode.

Parameters

- **episode_id** (*str*) – Unique string id for the episode or None for it to be auto-assigned.
- **training_enabled** (*bool*) – Whether to use experiences for this episode to improve the policy.

Returns Unique string id for the episode.

Return type episode_id (str)

get_action(*episode_id*, *observation*)
Record an observation and get the on-policy action.

Parameters

- **episode_id** (*str*) – Episode id returned from start_episode().
- **observation** (*obj*) – Current environment observation.

Returns Action from the env action space.

Return type action (obj)

log_action(*episode_id*, *observation*, *action*)
Record an observation and (off-policy) action taken.

Parameters

- **episode_id** (*str*) – Episode id returned from start_episode().
- **observation** (*obj*) – Current environment observation.
- **action** (*obj*) – Action for the observation.

log_returns(*episode_id*, *reward*, *info=None*)
Record returns from the environment.

The reward will be attributed to the previous action taken by the episode. Rewards accumulate until the next action. If no reward is logged before the next action, a reward of 0.0 is assumed.

Parameters

- **episode_id** (*str*) – Episode id returned from start_episode().
- **reward** (*float*) – Reward from the environment.
- **info** (*dict*) – Optional info dict.

end_episode(*episode_id*, *observation*)
Record the end of an episode.

Parameters

- **episode_id** (*str*) – Episode id returned from start_episode().
- **observation** (*obj*) – Current environment observation.

class ray.rllib.env.**VectorEnv**
An environment that supports batch evaluation.

Subclasses must define the following attributes:

action_space
Action space of individual envs.

Type gym.Space

observation_space
Observation space of individual envs.

Type gym.Space

num_envs
Number of envs in this vector env.

Type int

vector_reset()
Resets all environments.

Returns Vector of observations from each environment.

Return type obs (list)

reset_at(*index*)
Resets a single environment.

Returns Observations from the resetted environment.

Return type obs (obj)

vector_step(*actions*)
Vectorized step.

Parameters **actions** (*list*) – Actions for each env.

Returns New observations for each env. rewards (list): Reward values for each env. dones (list): Done values for each env. infos (list): Info values for each env.

Return type obs (list)

get_unwrapped()
Returns the underlying env instances.

ray.rllib.env.**ServingEnv**
alias of ray.rllib.env.external_env.ExternalEnv

class ray.rllib.env.**EnvContext**(*env_config*, *worker_index*, *vector_index=0*, *remote=False*)
Wraps env configurations to include extra rllib metadata.

These attributes can be used to parameterize environments per process. For example, one might use *worker_index* to control which data file an environment reads in on initialization.

RLlib auto-sets these attributes when constructing registered envs.

worker_index
When there are multiple workers created, this uniquely identifies the worker the env is created in.

Type int

vector_index
When there are multiple envs per worker, this uniquely identifies the env index within the worker.

Type int

remote
Whether environment should be remote or not.

Type bool

5.35.3 ray.rllib.evaluation

class ray.rllib.evaluation.**EvaluatorInterface**
This is the interface between policy optimizers and policy evaluation.

See also: RolloutWorker

sample()

Returns a batch of experience sampled from this evaluator.

This method must be implemented by subclasses.

Returns A columnar batch of experiences (e.g., tensors), or a multi-agent batch.

Return type SampleBatch|MultiAgentBatch

Examples

```
>>> print(ev.sample())
SampleBatch({"obs": [1, 2, 3], "action": [0, 1, 0], ...})
```

learn_on_batch(*samples*)

Update policies based on the given batch.

This is the equivalent to apply_gradients(compute_gradients(samples)), but can be optimized to avoid pulling gradients into CPU memory.

Either this or the combination of compute/apply grads must be implemented by subclasses.

Returns dictionary of extra metadata from compute_gradients().

Return type info

Examples

```
>>> batch = ev.sample()
>>> ev.learn_on_batch(samples)
```

compute_gradients(*samples*)

Returns a gradient computed w.r.t the specified samples.

Either this or learn_on_batch() must be implemented by subclasses.

Returns A list of gradients that can be applied on a compatible evaluator. In the multi-agent case, returns a dict of gradients keyed by policy ids. An info dictionary of extra metadata is also returned.

Return type (grads, info)

Examples

```
>>> batch = ev.sample()
>>> grads, info = ev2.compute_gradients(samples)
```

apply_gradients(*grads*)

Applies the given gradients to this evaluator's weights.

Either this or learn_on_batch() must be implemented by subclasses.

Examples

```
>>> samples = ev1.sample()
>>> grads, info = ev2.compute_gradients(samples)
>>> ev1.apply_gradients(grads)
```

get_weights()
Returns the model weights of this Evaluator.

This method must be implemented by subclasses.

Returns weights that can be set on a compatible evaluator. info: dictionary of extra metadata.

Return type object

Examples

```
>>> weights = ev1.get_weights()
```

set_weights(*weights*)
Sets the model weights of this Evaluator.

This method must be implemented by subclasses.

Examples

```
>>> weights = ev1.get_weights()
>>> ev2.set_weights(weights)
```

get_host()
Returns the hostname of the process running this evaluator.

apply(*func*, **args*)
Apply the given function to this evaluator instance.

class ray.rllib.evaluation.**RolloutWorker**(*env_creator*, *policy*, *policy_mapping_fn=None*, *policies_to_train=None*, *tf_session_creator=None*, *batch_steps=100*, *batch_mode='truncate_episodes'*, *episode_horizon=None*, *preprocessor_pref='deepmind'*, *sample_async=False*, *compress_observations=False*, *num_envs=1*, *observation_filter='NoFilter'*, *clip_rewards=None*, *clip_actions=True*, *env_config=None*, *model_config=None*, *policy_config=None*, *worker_index=0*, *monitor_path=None*, *log_dir=None*, *log_level=None*, *callbacks=None*, *input_creator=<function RolloutWorker.<lambda>>*, *input_evaluation=frozenset()*, *output_creator=<function RolloutWorker.<lambda>>*, *remote_worker_envs=False*, *remote_env_batch_wait_ms=0*, *soft_horizon=False*, *no_done_at_end=False*, *seed=None*, *_fake_sampler=False*)

Common experience collection class.

This class wraps a policy instance and an environment class to collect experiences from the environment. You can create many replicas of this class as Ray actors to scale RL training.

This class supports vectorized and multi-agent policy evaluation (e.g., VectorEnv, MultiAgentEnv, etc.)

Examples

```
>>> # Create a rollout worker and using it to collect experiences.
>>> worker = RolloutWorker(
...   env_creator=lambda _: gym.make("CartPole-v0"),
...   policy=PGTFPolicy)
>>> print(worker.sample())
SampleBatch({
    "obs": [[...]], "actions": [[...]], "rewards": [[...]],
    "dones": [[...]], "new_obs": [[...]]})
```

```
>>> # Creating a multi-agent rollout worker
>>> worker = RolloutWorker(
...   env_creator=lambda _: MultiAgentTrafficGrid(num_cars=25),
...   policies={
...       # Use an ensemble of two policies for car agents
...       "car_policy1":
...         (PGTFPolicy, Box(...), Discrete(...), {"gamma": 0.99}),
...       "car_policy2":
...         (PGTFPolicy, Box(...), Discrete(...), {"gamma": 0.95}),
...       # Use a single shared policy for all traffic lights
...       "traffic_light_policy":
...         (PGTFPolicy, Box(...), Discrete(...), {}),
...   },
...   policy_mapping_fn=lambda agent_id:
...     random.choice(["car_policy1", "car_policy2"])
...     if agent_id.startswith("car_") else "traffic_light_policy")
>>> print(worker.sample())
MultiAgentBatch({
    "car_policy1": SampleBatch(...),
    "car_policy2": SampleBatch(...),
    "traffic_light_policy": SampleBatch(...)})
```

sample()
Evaluate the current policies and return a batch of experiences.

Returns SampleBatch|MultiAgentBatch from evaluating the current policies.

sample_with_count()
Same as sample() but returns the count as a separate future.

get_weights(*policies=None*)
Returns the model weights of this Evaluator.

This method must be implemented by subclasses.

Returns weights that can be set on a compatible evaluator. info: dictionary of extra metadata.

Return type object

Examples

```
>>> weights = ev1.get_weights()
```

set_weights(*weights*)
Sets the model weights of this Evaluator.

This method must be implemented by subclasses.

Examples

```
>>> weights = ev1.get_weights()
>>> ev2.set_weights(weights)
```

compute_gradients(*samples*)
Returns a gradient computed w.r.t the specified samples.

Either this or learn_on_batch() must be implemented by subclasses.

Returns A list of gradients that can be applied on a compatible evaluator. In the multi-agent case, returns a dict of gradients keyed by policy ids. An info dictionary of extra metadata is also returned.

Return type (grads, info)

Examples

```
>>> batch = ev.sample()
>>> grads, info = ev2.compute_gradients(samples)
```

apply_gradients(*grads*)
Applies the given gradients to this evaluator's weights.

Either this or learn_on_batch() must be implemented by subclasses.

Examples

```
>>> samples = ev1.sample()
>>> grads, info = ev2.compute_gradients(samples)
>>> ev1.apply_gradients(grads)
```

learn_on_batch(*samples*)
Update policies based on the given batch.

This is the equivalent to apply_gradients(compute_gradients(samples)), but can be optimized to avoid pulling gradients into CPU memory.

Either this or the combination of compute/apply grads must be implemented by subclasses.

Returns dictionary of extra metadata from compute_gradients().

Return type info

Examples

```
>>> batch = ev.sample()
>>> ev.learn_on_batch(samples)
```

get_metrics()
Returns a list of new RolloutMetric objects from evaluation.

foreach_env(*func*)
Apply the given function to each underlying env instance.

get_policy(*policy_id='default_policy'*)
Return policy for the specified id, or None.

Parameters **policy_id** (*str*) – id of policy to return.

for_policy(*func*, *policy_id='default_policy'*)
Apply the given function to the specified policy.

foreach_policy(*func*)
Apply the given function to each (policy, policy_id) tuple.

foreach_trainable_policy(*func*)
Apply the given function to each (policy, policy_id) tuple.

This only applies func to policies in *self.policies_to_train*.

sync_filters(*new_filters*)
Changes self's filter to given and rebases any accumulated delta.

Parameters **new_filters** (*dict*) – Filters with new state to update local copy.

get_filters(*flush_after=False*)
Returns a snapshot of filters.

Parameters **flush_after** (*bool*) – Clears the filter buffer state.

Returns Dict for serializable filters

Return type return_filters (dict)

ray.rllib.evaluation.**PolicyGraph**
alias of ray.rllib.utils.renamed_class.<locals>.DeprecationWrapper

ray.rllib.evaluation.**TFPolicyGraph**
alias of ray.rllib.utils.renamed_class.<locals>.DeprecationWrapper

ray.rllib.evaluation.**TorchPolicyGraph**
alias of ray.rllib.utils.renamed_class.<locals>.DeprecationWrapper

class ray.rllib.evaluation.**SampleBatch**(**args*, ***kw*)

class ray.rllib.evaluation.**MultiAgentBatch**(**args*, ***kw*)

class ray.rllib.evaluation.**SampleBatchBuilder**
Util to build a SampleBatch incrementally.

For efficiency, SampleBatches hold values in column form (as arrays). However, it is useful to add data one row (dict) at a time.

add_values(***values*)
Add the given dictionary (row) of values to this batch.

add_batch(*batch*)
Add the given batch of values to this batch.

build_and_reset()
Returns a sample batch including all previously added values.

class ray.rllib.evaluation.**MultiAgentSampleBatchBuilder**(*policy_map*, *clip_rewards*, *postp_callback*)
Util to build SampleBatches for each policy in a multi-agent env.

Input data is per-agent, while output data is per-policy. There is an M:N mapping between agents and policies. We retain one local batch builder per agent. When an agent is done, then its local batch is appended into the corresponding policy batch for the agent's policy.

total()
Returns summed number of steps across all agent buffers.

has_pending_data()
Returns whether there is pending unprocessed data.

add_values(*agent_id*, *policy_id*, ***values*)
Add the given dictionary (row) of values to this batch.

Parameters

- **agent_id** (*obj*) – Unique id for the agent we are adding values for.
- **policy_id** (*obj*) – Unique id for policy controlling the agent.
- **values** (*dict*) – Row of values to add for this agent.

postprocess_batch_so_far(*episode*)
Apply policy postprocessors to any unprocessed rows.

This pushes the postprocessed per-agent batches onto the per-policy builders, clearing per-agent state.

Parameters **episode** – current MultiAgentEpisode object or None

build_and_reset(*episode*)
Returns the accumulated sample batches for each policy.

Any unprocessed rows will be first postprocessed with a policy postprocessor. The internal state of this builder will be reset.

Parameters **episode** – current MultiAgentEpisode object or None

class ray.rllib.evaluation.**SyncSampler**(*env*, *policies*, *policy_mapping_fn*, *preprocessors*, *obs_filters*, *clip_rewards*, *unroll_length*, *callbacks*, *horizon=None*, *pack=False*, *tf_sess=None*, *clip_actions=True*, *soft_horizon=False*, *no_done_at_end=False*)

class ray.rllib.evaluation.**AsyncSampler**(*env*, *policies*, *policy_mapping_fn*, *preprocessors*, *obs_filters*, *clip_rewards*, *unroll_length*, *callbacks*, *horizon=None*, *pack=False*, *tf_sess=None*, *clip_actions=True*, *blackhole_outputs=False*, *soft_horizon=False*, *no_done_at_end=False*)

run()
Method representing the thread's activity.

You may override this method in a subclass. The standard run() method invokes the callable object passed to the object's constructor as the target argument, if any, with sequential and keyword arguments taken from the args and kwargs arguments, respectively.

ray.rllib.evaluation.**compute_advantages**(*rollout*, *last_r*, *gamma=0.9*, *lambda_=1.0*, *use_gae=True*)

Given a rollout, compute its value targets and the advantage.

Parameters

- **rollout** (SampleBatch) – SampleBatch of a single trajectory
- **last_r** (*float*) – Value estimation for last observation
- **gamma** (*float*) – Discount factor.
- **lambda** (*float*) – Parameter for GAE
- **use_gae** (*bool*) – Using Generalized Advantage Estimation

Returns

Object with experience from rollout and processed rewards.

Return type *SampleBatch* (*SampleBatch*)

ray.rllib.evaluation.**collect_metrics**(*local_worker=None*, *remote_workers=[]*, *to_be_collected=[]*, *timeout_seconds=180*)

Gathers episode metrics from RolloutWorker instances.

class ray.rllib.evaluation.**MultiAgentEpisode**(*policies*, *policy_mapping_fn*, *batch_builder_factory*, *extra_batch_callback*)

Tracks the current state of a (possibly multi-agent) episode.

new_batch_builder
Create a new MultiAgentSampleBatchBuilder.

Type func

add_extra_batch
Return a built MultiAgentBatch to the sampler.

Type func

batch_builder
Batch builder for the current episode.

Type obj

total_reward
Summed reward across all agents in this episode.

Type float

length
Length of this episode.

Type int

episode_id
Unique id identifying this trajectory.

Type int

agent_rewards
Summed rewards broken down by agent.

Type dict

custom_metrics
Dict where the you can add custom metrics.

Type dict

user_data
Dict that you can use for temporary storage.

Type dict

Use case 1: Model-based rollouts in multi-agent: A custom compute_actions() function in a policy can inspect the current episode state and perform a number of rollouts based on the policies and state of other agents in the environment.

Use case 2: Returning extra rollouts data. The model rollouts can be returned back to the sampler by calling:

```
>>> batch = episode.new_batch_builder()
>>> for each transition:
       batch.add_values(...)  # see sampler for usage
>>> episode.extra_batches.add(batch.build_and_reset())
```

soft_reset()
Clears rewards and metrics, but retains RNN and other state.

This is used to carry state across multiple logical episodes in the same env (i.e., if *soft_horizon* is set).

policy_for(*agent_id='agent0'*)
Returns the policy for the specified agent.

If the agent is new, the policy mapping fn will be called to bind the agent to a policy for the duration of the episode.

last_observation_for(*agent_id='agent0'*)
Returns the last observation for the specified agent.

last_raw_obs_for(*agent_id='agent0'*)
Returns the last un-preprocessed obs for the specified agent.

last_info_for(*agent_id='agent0'*)
Returns the last info for the specified agent.

last_action_for(*agent_id='agent0'*)
Returns the last action for the specified agent, or zeros.

prev_action_for(*agent_id='agent0'*)
Returns the previous action for the specified agent.

prev_reward_for(*agent_id='agent0'*)
Returns the previous reward for the specified agent.

rnn_state_for(*agent_id='agent0'*)
Returns the last RNN state for the specified agent.

last_pi_info_for(*agent_id='agent0'*)
Returns the last info object for the specified agent.

ray.rllib.evaluation.**PolicyEvaluator**
alias of ray.rllib.utils.renamed_class.<locals>.DeprecationWrapper

5.35.4 ray.rllib.models

class ray.rllib.models.**ActionDistribution**(*inputs*, *model*)
The policy action distribution of an agent.

inputs
input vector to compute samples from.

Type Tensors

model
reference to model producing the inputs.

Type ModelV2

sample()
Draw a sample from the action distribution.

sampled_action_logp()
Returns the log probability of the last sampled action.

logp(*x*)
The log-likelihood of the action distribution.

kl(*other*)
The KL-divergence between two action distributions.

entropy()
The entropy of the action distribution.

multi_kl(*other*)
The KL-divergence between two action distributions.

This differs from kl() in that it can return an array for MultiDiscrete. TODO(ekl) consider removing this.

multi_entropy()
The entropy of the action distribution.

This differs from entropy() in that it can return an array for MultiDiscrete. TODO(ekl) consider removing this.

static required_model_output_shape(*action_space*, *model_config*)
Returns the required shape of an input parameter tensor for a particular action space and an optional dict of distribution-specific options.

Parameters

- **action_space** (*gym.Space*) – The action space this distribution will be used for, whose shape attributes will be used to determine the required shape of the input parameter tensor.
- **model_config** (*dict*) – Model's config dict (as defined in catalog.py)

Returns

size of the required input vector (minus leading batch dimension).

Return type model_output_shape (int or np.ndarray of ints)

class ray.rllib.models.**ModelCatalog**
Registry of models, preprocessors, and action distributions for envs.

Examples

```
>>> prep = ModelCatalog.get_preprocessor(env)
>>> observation = prep.transform(raw_observation)
```

```
>>> dist_class, dist_dim = ModelCatalog.get_action_dist(
        env.action_space, {})
>>> model = ModelCatalog.get_model(inputs, dist_dim, options)
>>> dist = dist_class(model.outputs, model)
>>> action = dist.sample()
```

static get_action_dist(*action_space*, *config*, *dist_type=None*, *torch=False*)
Returns action distribution class and size for the given action space.

Parameters

- **action_space** (*Space*) – Action space of the target gym env.
- **config** (*dict*) – Optional model config.
- **dist_type** (*str*) – Optional identifier of the action distribution.
- **torch** (*bool*) – Optional whether to return PyTorch distribution.

Returns Python class of the distribution. dist_dim (int): The size of the input vector to the distribution.

Return type dist_class (*ActionDistribution*)

static get_action_shape(*action_space*)
Returns action tensor dtype and shape for the action space.

Parameters **action_space** (*Space*) – Action space of the target gym env.

Returns Dtype and shape of the actions tensor.

Return type (dtype, shape)

static get_action_placeholder(*action_space*)
Returns an action placeholder consistent with the action space

Parameters **action_space** (*Space*) – Action space of the target gym env.

Returns A placeholder for the actions

Return type action_placeholder (Tensor)

static get_model_v2(*obs_space*, *action_space*, *num_outputs*, *model_config*, *framework*, *name='default_model'*, *model_interface=None*, *default_model=None*, ***model_kwargs*)
Returns a suitable model compatible with given spaces and output.

Parameters

- **obs_space** (*Space*) – Observation space of the target gym env. This may have an *original_space* attribute that specifies how to unflatten the tensor into a ragged tensor.
- **action_space** (*Space*) – Action space of the target gym env.
- **num_outputs** (*int*) – The size of the output vector of the model.
- **framework** (*str*) – Either "tf" or "torch".
- **name** (*str*) – Name (scope) for the model.
- **model_interface** (*cls*) – Interface required for the model
- **default_model** (*cls*) – Override the default class for the model. This only has an effect when not using a custom model
- **model_kwargs** (*dict*) – args to pass to the ModelV2 constructor

Returns Model to use for the policy.

Return type model (ModelV2)

static get_preprocessor(*env*, *options=None*)
Returns a suitable preprocessor for the given env.

This is a wrapper for get_preprocessor_for_space().

static get_preprocessor_for_space(*observation_space*, *options=None*)
Returns a suitable preprocessor for the given observation space.

Parameters

- **observation_space** (*Space*) – The input observation space.
- **options** (*dict*) – Options to pass to the preprocessor.

Returns Preprocessor for the observations.

Return type preprocessor (*Preprocessor*)

static register_custom_preprocessor(*preprocessor_name*, *preprocessor_class*)
Register a custom preprocessor class by name.

The preprocessor can be later used by specifying {"custom_preprocessor": preprocesor_name} in the model config.

Parameters

- **preprocessor_name** (*str*) – Name to register the preprocessor under.
- **preprocessor_class** (*type*) – Python class of the preprocessor.

static register_custom_model(*model_name*, *model_class*)
Register a custom model class by name.

The model can be later used by specifying {"custom_model": model_name} in the model config.

Parameters

- **model_name** (*str*) – Name to register the model under.
- **model_class** (*type*) – Python class of the model.

static register_custom_action_dist(*action_dist_name*, *action_dist_class*)
Register a custom action distribution class by name.

The model can be later used by specifying {"custom_action_dist": action_dist_name} in the model config.

Parameters

- **model_name** (*str*) – Name to register the action distribution under.
- **model_class** (*type*) – Python class of the action distribution.

static get_model(*input_dict*, *obs_space*, *action_space*, *num_outputs*, *options*, *state_in=None*, *seq_lens=None*)
Deprecated: use get_model_v2() instead.

class ray.rllib.models.**Model**(*input_dict*, *obs_space*, *action_space*, *num_outputs*, *options*, *state_in=None*, *seq_lens=None*)
This class is deprecated, please use TFModelV2 instead.

value_function()
Builds the value function output.

This method can be overridden to customize the implementation of the value function (e.g., not sharing hidden layers).

Returns Tensor of size [BATCH_SIZE] for the value function.

custom_loss(*policy_loss*, *loss_inputs*)
Override to customize the loss function used to optimize this model.

This can be used to incorporate self-supervised losses (by defining a loss over existing input and output tensors of this model), and supervised losses (by defining losses over a variable-sharing copy of this model's layers).

You can find an runnable example in examples/custom_loss.py.

Parameters

- **policy_loss** (*Tensor*) – scalar policy loss from the policy.
- **loss_inputs** (*dict*) – map of input placeholders for rollout data.

Returns Scalar tensor for the customized loss for this model.

custom_stats()
Override to return custom metrics from your model.

The stats will be reported as part of the learner stats, i.e.,

info:

learner:

model: key1: metric1 key2: metric2

Returns Dict of string keys to scalar tensors.

loss()
Deprecated: use self.custom_loss().

class ray.rllib.models.**Preprocessor**(*obs_space*, *options=None*)
Defines an abstract observation preprocessor function.

shape
Shape of the preprocessed output.

Type obj

transform(*observation*)
Returns the preprocessed observation.

write(*observation*, *array*, *offset*)
Alternative to transform for more efficient flattening.

check_shape(*observation*)
Checks the shape of the given observation.

class ray.rllib.models.**FullyConnectedNetwork**(*input_dict*, *obs_space*, *action_space*, *num_outputs*, *options*, *state_in=None*, *seq_lens=None*)
Generic fully connected network.

class ray.rllib.models.**VisionNetwork**(*input_dict*, *obs_space*, *action_space*, *num_outputs*, *options*, *state_in=None*, *seq_lens=None*)
Generic vision network.

5.35.5 ray.rllib.optimizers

class ray.rllib.optimizers.**PolicyOptimizer**(*workers*)
Policy optimizers encapsulate distributed RL optimization strategies.

Policy optimizers serve as the "control plane" of algorithms.

For example, AsyncOptimizer is used for A3C, and LocalMultiGPUOptimizer is used for PPO. These optimizers are all pluggable, and it is possible to mix and match as needed.

config
The JSON configuration passed to this optimizer.

Type dict

workers
The set of rollout workers to use.

Type WorkerSet

num_steps_trained
Number of timesteps trained on so far.

Type int

num_steps_sampled
Number of timesteps sampled so far.

Type int

step()
Takes a logical optimization step.

This should run for long enough to minimize call overheads (i.e., at least a couple seconds), but short enough to return control periodically to callers (i.e., at most a few tens of seconds).

Returns Optional fetches from compute grads calls.

Return type fetches (dict|None)

stats()
Returns a dictionary of internal performance statistics.

save()
Returns a serializable object representing the optimizer state.

restore(*data*)
Restores optimizer state from the given data object.

stop()
Release any resources used by this optimizer.

collect_metrics(*timeout_seconds*, *min_history=100*, *selected_workers=None*)
Returns worker and optimizer stats.

Parameters

- **timeout_seconds** (*int*) – Max wait time for a worker before dropping its results. This usually indicates a hung worker.
- **min_history** (*int*) – Min history length to smooth results over.
- **selected_workers** (*list*) – Override the list of remote workers to collect metrics from.

Returns

A training result dict from worker metrics with *info* replaced with stats from self.

Return type res (dict)

reset(*remote_workers*)
Called to change the set of remote workers being used.

foreach_worker(*func*)
Apply the given function to each worker instance.

foreach_worker_with_index(*func*)
Apply the given function to each worker instance.

The index will be passed as the second arg to the given function.

class ray.rllib.optimizers.**AsyncReplayOptimizer**(*workers*, *learning_starts=1000*, *buffer_size=10000*, *prioritized_replay=True*, *prioritized_replay_alpha=0.6*, *prioritized_replay_beta=0.4*, *prioritized_replay_eps=1e-06*, *train_batch_size=512*, *sample_batch_size=50*, *num_replay_buffer_shards=1*, *max_weight_sync_delay=400*, *debug=False*, *batch_replay=False*)
Main event loop of the Ape-X optimizer (async sampling with replay).

This class coordinates the data transfers between the learner thread, remote workers (Ape-X actors), and replay buffer actors.

This has two modes of operation:

- normal replay: replays independent samples.
- **batch replay: simplified mode where entire sample batches are** replayed. This supports RNNs, but not prioritization.

This optimizer requires that rollout workers return an additional "td_error" array in the info return of compute_gradients(). This error term will be used for sample prioritization.

step()
Takes a logical optimization step.

This should run for long enough to minimize call overheads (i.e., at least a couple seconds), but short enough to return control periodically to callers (i.e., at most a few tens of seconds).

Returns Optional fetches from compute grads calls.

Return type fetches (dict|None)

stop()
Release any resources used by this optimizer.

reset(*remote_workers*)
Called to change the set of remote workers being used.

stats()
Returns a dictionary of internal performance statistics.

class ray.rllib.optimizers.**AsyncSamplesOptimizer**(*workers*, *train_batch_size=500*, *sample_batch_size=50*, *num_envs_per_worker=1*, *num_gpus=0*, *lr=0.0005*, *replay_buffer_num_slots=0*, *replay_proportion=0.0*, *num_data_loader_buffers=1*, *max_sample_requests_in_flight_per_worker=2*, *broadcast_interval=1*, *num_sgd_iter=1*, *minibatch_buffer_size=1*, *learner_queue_size=16*, *learner_queue_timeout=300*, *num_aggregation_workers=0*, *_fake_gpus=False*)

Main event loop of the IMPALA architecture.

This class coordinates the data transfers between the learner thread and remote workers (IMPALA actors).

step()

Takes a logical optimization step.

This should run for long enough to minimize call overheads (i.e., at least a couple seconds), but short enough to return control periodically to callers (i.e., at most a few tens of seconds).

Returns Optional fetches from compute grads calls.

Return type fetches (dict|None)

stop()

Release any resources used by this optimizer.

reset(*remote_workers*)

Called to change the set of remote workers being used.

stats()

Returns a dictionary of internal performance statistics.

class ray.rllib.optimizers.**AsyncGradientsOptimizer**(*workers*, *grads_per_step=100*)

An asynchronous RL optimizer, e.g. for implementing A3C.

This optimizer asynchronously pulls and applies gradients from remote workers, sending updated weights back as needed. This pipelines the gradient computations on the remote workers.

step()

Takes a logical optimization step.

This should run for long enough to minimize call overheads (i.e., at least a couple seconds), but short enough to return control periodically to callers (i.e., at most a few tens of seconds).

Returns Optional fetches from compute grads calls.

Return type fetches (dict|None)

stats()

Returns a dictionary of internal performance statistics.

class ray.rllib.optimizers.**SyncSamplesOptimizer**(*workers*, *num_sgd_iter=1*, *train_batch_size=1*, *sgd_minibatch_size=0*, *standardize_fields=frozenset()*)

A simple synchronous RL optimizer.

In each step, this optimizer pulls samples from a number of remote workers, concatenates them, and then updates a local model. The updated model weights are then broadcast to all remote workers.

step()
Takes a logical optimization step.

This should run for long enough to minimize call overheads (i.e., at least a couple seconds), but short enough to return control periodically to callers (i.e., at most a few tens of seconds).

Returns Optional fetches from compute grads calls.

Return type fetches (dict|None)

stats()
Returns a dictionary of internal performance statistics.

class ray.rllib.optimizers.**SyncReplayOptimizer**(*workers*, *learning_starts=1000*, *buffer_size=10000*, *prioritized_replay=True*, *prioritized_replay_alpha=0.6*, *prioritized_replay_beta=0.4*, *prioritized_replay_eps=1e-06*, *schedule_max_timesteps=100000*, *beta_annealing_fraction=0.2*, *final_prioritized_replay_beta=0.4*, *train_batch_size=32*, *sample_batch_size=4*, *before_learn_on_batch=None*, *synchronize_sampling=False*)
Variant of the local sync optimizer that supports replay (for DQN).

This optimizer requires that rollout workers return an additional "td_error" array in the info return of compute_gradients(). This error term will be used for sample prioritization.

step()
Takes a logical optimization step.

This should run for long enough to minimize call overheads (i.e., at least a couple seconds), but short enough to return control periodically to callers (i.e., at most a few tens of seconds).

Returns Optional fetches from compute grads calls.

Return type fetches (dict|None)

stats()
Returns a dictionary of internal performance statistics.

class ray.rllib.optimizers.**LocalMultiGPUOptimizer**(*workers*, *sgd_batch_size=128*, *num_sgd_iter=10*, *sample_batch_size=200*, *num_envs_per_worker=1*, *train_batch_size=1024*, *num_gpus=0*, *standardize_fields=[]*, *shuffle_sequences=True*)
A synchronous optimizer that uses multiple local GPUs.

Samples are pulled synchronously from multiple remote workers, concatenated, and then split across the memory of multiple local GPUs. A number of SGD passes are then taken over the in-memory data. For more details, see *multi_gpu_impl.LocalSyncParallelOptimizer*.

This optimizer is Tensorflow-specific and require the underlying Policy to be a TFPolicy instance that support *.copy()*.

Note that all replicas of the TFPolicy will merge their extra_compute_grad and apply_grad feed_dicts and fetches. This may result in unexpected behavior.

step()
Takes a logical optimization step.

This should run for long enough to minimize call overheads (i.e., at least a couple seconds), but short enough to return control periodically to callers (i.e., at most a few tens of seconds).

Returns Optional fetches from compute grads calls.

Return type fetches (dict|None)

stats()
Returns a dictionary of internal performance statistics.

class ray.rllib.optimizers.**SyncBatchReplayOptimizer**(*workers*, *learning_starts=1000*, *buffer_size=10000*, *train_batch_size=32*)
Variant of the sync replay optimizer that replays entire batches.

This enables RNN support. Does not currently support prioritization.

step()
Takes a logical optimization step.

This should run for long enough to minimize call overheads (i.e., at least a couple seconds), but short enough to return control periodically to callers (i.e., at most a few tens of seconds).

Returns Optional fetches from compute grads calls.

Return type fetches (dict|None)

stats()
Returns a dictionary of internal performance statistics.

5.35.6 ray.rllib.utils

ray.rllib.utils.**renamed_class**(*cls*, *old_name*)
Helper class for renaming classes with a warning.

class ray.rllib.utils.**Filter**
Processes input, possibly statefully.

apply_changes(*other*, **args*, ***kwargs*)
Updates self with "new state" from other filter.

copy()
Creates a new object with same state as self.

Returns A copy of self.

sync(*other*)
Copies all state from other filter to self.

clear_buffer()
Creates copy of current state and clears accumulated state

class ray.rllib.utils.**FilterManager**
Manages filters and coordination across remote evaluators that expose *get_filters* and *sync_filters*.

static synchronize(*local_filters*, *remotes*, *update_remote=True*)
Aggregates all filters from remote evaluators.

Local copy is updated and then broadcasted to all remote evaluators.

Parameters

- **local_filters** (*dict*) – Filters to be synchronized.
- **remotes** (*list*) – Remote evaluators with filters.
- **update_remote** (*bool*) – Whether to push updates to remote filters.

class ray.rllib.utils.**PolicyClient**(*address*)
REST client to interact with a RLlib policy server.

start_episode(*episode_id=None*, *training_enabled=True*)
Record the start of an episode.

Parameters

- **episode_id** (*str*) – Unique string id for the episode or None for it to be auto-assigned.
- **training_enabled** (*bool*) – Whether to use experiences for this episode to improve the policy.

Returns Unique string id for the episode.

Return type episode_id (str)

get_action(*episode_id*, *observation*)
Record an observation and get the on-policy action.

Parameters

- **episode_id** (*str*) – Episode id returned from start_episode().
- **observation** (*obj*) – Current environment observation.

Returns Action from the env action space.

Return type action (obj)

log_action(*episode_id*, *observation*, *action*)
Record an observation and (off-policy) action taken.

Parameters

- **episode_id** (*str*) – Episode id returned from start_episode().
- **observation** (*obj*) – Current environment observation.
- **action** (*obj*) – Action for the observation.

log_returns(*episode_id*, *reward*, *info=None*)
Record returns from the environment.

The reward will be attributed to the previous action taken by the episode. Rewards accumulate until the next action. If no reward is logged before the next action, a reward of 0.0 is assumed.

Parameters

- **episode_id** (*str*) – Episode id returned from start_episode().
- **reward** (*float*) – Reward from the environment.

end_episode(*episode_id*, *observation*)
Record the end of an episode.

Parameters

- **episode_id** (*str*) – Episode id returned from start_episode().
- **observation** (*obj*) – Current environment observation.

class ray.rllib.utils.**PolicyServer**(*external_env*, *address*, *port*)
REST server than can be launched from a ExternalEnv.

This launches a multi-threaded server that listens on the specified host and port to serve policy requests and forward experiences to RLlib.

Examples

```
>>> class CartpoleServing(ExternalEnv):
       def __init__(self):
           ExternalEnv.__init__(
               self, spaces.Discrete(2),
               spaces.Box(
                   low=-10,
                   high=10,
                   shape=(4,),
                   dtype=np.float32))
       def run(self):
           server = PolicyServer(self, "localhost", 8900)
           server.serve_forever()
>>> register_env("srv", lambda _: CartpoleServing())
>>> pg = PGTrainer(env="srv", config={"num_workers": 0})
>>> while True:
        pg.train()
```

```
>>> client = PolicyClient("localhost:8900")
>>> eps_id = client.start_episode()
>>> action = client.get_action(eps_id, obs)
>>> ...
>>> client.log_returns(eps_id, reward)
>>> ...
>>> client.log_returns(eps_id, reward)
```

ray.rllib.utils.**merge_dicts**(*d1*, *d2*)
Returns a new dict that is d1 and d2 deep merged.

ray.rllib.utils.**deep_update**(*original*, *new_dict*, *new_keys_allowed*, *whitelist*)
Updates original dict with values from new_dict recursively. If new key is introduced in new_dict, then if new_keys_allowed is not True, an error will be thrown. Further, for sub-dicts, if the key is in the whitelist, then new subkeys can be introduced.

Parameters

- **original** (*dict*) – Dictionary with default values.
- **new_dict** (*dict*) – Dictionary with values to be updated
- **new_keys_allowed** (*bool*) – Whether new keys are allowed.
- **whitelist** (*list*) – List of keys that correspond to dict values where new subkeys can be introduced. This is only at the top level.

5.36 Distributed Training (Experimental)

Ray's `PyTorchTrainer` simplifies distributed model training for PyTorch. The `PyTorchTrainer` is a wrapper around `torch.distributed.launch` with a Python API to easily incorporate distributed training into a larger Python application, as opposed to needing to execute training outside of Python.

With Ray:

Wrap your training with this:

```
ray.init(args.address)
trainer1 = PyTorchTrainer(
    model_creator,
    data_creator,
    optimizer_creator,
    num_replicas=<NUM_GPUS_YOU_HAVE> * <NUM_NODES>,
    use_gpu=True,
    batch_size=512,
    backend="gloo")

trainer1.train()
```

Then, start a Ray cluster via autoscaler or manually.

```
ray up CLUSTER.yaml
python train.py --address="localhost:<PORT>"
```

Before, with Pytorch:

In your training program, insert the following:

```
torch.distributed.init_process_group(backend='YOUR BACKEND',
                                     init_method='env://')

model = torch.nn.parallel.DistributedDataParallel(model,
                                                   device_ids=[arg.local_rank],
                                                   output_device=arg.local_rank)
```

Then, separately, on each machine:

```
# Node 1: *(IP: 192.168.1.1, and has a free port: 1234)*
$ python -m torch.distributed.launch --nproc_per_node=NUM_GPUS_YOU_HAVE
           --nnodes=4 --node_rank=0 --master_addr="192.168.1.1"
           --master_port=1234 YOUR_TRAINING_SCRIPT.py (--arg1 --arg2 --arg3
           and all other arguments of your training script)
# Node 2:
$ python -m torch.distributed.launch --nproc_per_node=NUM_GPUS_YOU_HAVE
           --nnodes=4 --node_rank=1 --master_addr="192.168.1.1"
           --master_port=1234 YOUR_TRAINING_SCRIPT.py (--arg1 --arg2 --arg3
           and all other arguments of your training script)
# Node 3:
$ python -m torch.distributed.launch --nproc_per_node=NUM_GPUS_YOU_HAVE
           --nnodes=4 --node_rank=2 --master_addr="192.168.1.1"
           --master_port=1234 YOUR_TRAINING_SCRIPT.py (--arg1 --arg2 --arg3
```

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```
            and all other arguments of your training script)
# Node 4:
$ python -m torch.distributed.launch --nproc_per_node=NUM_GPUS_YOU_HAVE
            --nnodes=4 --node_rank=3 --master_addr="192.168.1.1"
            --master_port=1234 YOUR_TRAINING_SCRIPT.py (--arg1 --arg2 --arg3
            and all other arguments of your training script)
```

5.36.1 PyTorchTrainer Example

Below is an example of using Ray's PyTorchTrainer. Under the hood, `PytorchTrainer` will create *replicas* of your model (controlled by `num_replicas`) which are each managed by a worker.

```
from __future__ import absolute_import
from __future__ import division
from __future__ import print_function

import argparse
import numpy as np
import torch
import torch.nn as nn

from ray.experimental.sgd.pytorch.pytorch_trainer import PyTorchTrainer


class LinearDataset(torch.utils.data.Dataset):
    """y = a * x + b"""

    def __init__(self, a, b, size=1000):
        x = np.random.random(size).astype(np.float32) * 10
        x = np.arange(0, 10, 10 / size, dtype=np.float32)
        self.x = torch.from_numpy(x)
        self.y = torch.from_numpy(a * x + b)

    def __getitem__(self, index):
        return self.x[index, None], self.y[index, None]

    def __len__(self):
        return len(self.x)


def model_creator(config):
    return nn.Linear(1, 1)


def optimizer_creator(model, config):
    """Returns criterion, optimizer"""
    criterion = nn.MSELoss()
    optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)
    return criterion, optimizer


def data_creator(config):
    """Returns training set, validation set"""
    return LinearDataset(2, 5), LinearDataset(2, 5, size=400)
```

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```
def train_example(num_replicas=1, use_gpu=False):
    trainer1 = PyTorchTrainer(
        model_creator,
        data_creator,
        optimizer_creator,
        num_replicas=num_replicas,
        use_gpu=use_gpu,
        batch_size=512,
        backend="gloo")
    trainer1.train()
    trainer1.shutdown()
    print("success!")


if __name__ == "__main__":
    parser = argparse.ArgumentParser()
    parser.add_argument(
        "--redis-address",
        required=False,
        type=str,
        help="the address to use for Redis")
    parser.add_argument(
        "--num-replicas",
        "-n",
        type=int,
        default=1,
        help="Sets number of replicas for training.")
    parser.add_argument(
        "--use-gpu",
        action="store_true",
        default=False,
        help="Enables GPU training")
    parser.add_argument(
        "--tune", action="store_true", default=False, help="Tune training")

    args, _ = parser.parse_known_args()

    import ray

    ray.init(redis_address=args.redis_address)
    train_example(num_replicas=args.num_replicas, use_gpu=args.use_gpu)
```

5.36.2 Hyperparameter Optimization on Distributed Pytorch

`PyTorchTrainer` naturally integrates with Tune via the `PyTorchTrainable` interface. The same arguments to `PyTorchTrainer` should be passed into the `tune.run(config=...)` as shown below.

```
from __future__ import absolute_import
from __future__ import division
from __future__ import print_function

import numpy as np
import torch
import torch.nn as nn
```

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```
import ray
from ray import tune
from ray.experimental.sgd.pytorch.pytorch_trainer import PyTorchTrainable


class LinearDataset(torch.utils.data.Dataset):
    """y = a * x + b"""

    def __init__(self, a, b, size=1000):
        x = np.random.random(size).astype(np.float32) * 10
        x = np.arange(0, 10, 10 / size, dtype=np.float32)
        self.x = torch.from_numpy(x)
        self.y = torch.from_numpy(a * x + b)

    def __getitem__(self, index):
        return self.x[index, None], self.y[index, None]

    def __len__(self):
        return len(self.x)


def model_creator(config):
    return nn.Linear(1, 1)


def optimizer_creator(model, config):
    """Returns criterion, optimizer"""
    criterion = nn.MSELoss()
    optimizer = torch.optim.SGD(model.parameters(), lr=config.get("lr", 1e-4))
    return criterion, optimizer


def data_creator(config):
    """Returns training set, validation set"""
    return LinearDataset(2, 5), LinearDataset(2, 5, size=400)


def tune_example(num_replicas=1, use_gpu=False):
    config = {
        "model_creator": tune.function(model_creator),
        "data_creator": tune.function(data_creator),
        "optimizer_creator": tune.function(optimizer_creator),
        "num_replicas": num_replicas,
        "use_gpu": use_gpu,
        "batch_size": 512,
        "backend": "gloo"
    }

    analysis = tune.run(
        PyTorchTrainable,
        num_samples=12,
        config=config,
        stop={"training_iteration": 2},
        verbose=1)

    return analysis.get_best_config(metric="validation_loss", mode="min")
```

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```
if __name__ == "__main__":
    import argparse
    parser = argparse.ArgumentParser()
    parser.add_argument(
        "--redis-address",
        type=str,
        help="the address to use for Redis")
    parser.add_argument(
        "--num-replicas",
        "-n",
        type=int,
        default=1,
        help="Sets number of replicas for training.")
    parser.add_argument(
        "--use-gpu",
        action="store_true",
        default=False,
        help="Enables GPU training")
    parser.add_argument(
        "--tune", action="store_true", default=False, help="Tune training")

    args, _ = parser.parse_known_args()

    ray.init(redis_address=args.redis_address)
    tune_example(num_replicas=args.num_replicas, use_gpu=args.use_gpu)
```

5.36.3 Package Reference

class ray.experimental.sgd.pytorch.**PyTorchTrainer**(*model_creator*, *data_creator*, *optimizer_creator=<function sgd_mse_optimizer>*, *config=None*, *num_replicas=1*, *use_gpu=False*, *batch_size=16*, *backend='auto'*)

Train a PyTorch model using distributed PyTorch.

Launches a set of actors which connect via distributed PyTorch and coordinate gradient updates to train the provided model.

__init__(*model_creator*, *data_creator*, *optimizer_creator=<function sgd_mse_optimizer>*, *config=None*, *num_replicas=1*, *use_gpu=False*, *batch_size=16*, *backend='auto'*)

Sets up the PyTorch trainer.

Parameters

- **model_creator** (*dict -> torch.nn.Module*) – creates the model using the config.
- **data_creator** (*dict -> Dataset, Dataset*) – creates the training and validation data sets using the config.
- **optimizer_creator** (*torch.nn.Module, dict -> loss, optimizer*) – creates the loss and optimizer using the model and the config.
- **config** (*dict*) – configuration passed to 'model_creator', 'data_creator', and 'optimizer_creator'.

- **num_replicas** (*int*) – the number of workers used in distributed training.
- **use_gpu** (*bool*) – Sets resource allocation for workers to 1 GPU if true.
- **batch_size** (*int*) – batch size for an update.
- **backend** (*string*) – backend used by distributed PyTorch.

train()
Runs a training epoch.

validate()
Evaluates the model on the validation data set.

get_model()
Returns the learned model.

save(*checkpoint*)
Saves the model at the provided checkpoint.

Parameters **checkpoint** (*str*) – Path to target checkpoint file.

restore(*checkpoint*)
Restores the model from the provided checkpoint.

Parameters **checkpoint** (*str*) – Path to target checkpoint file.

shutdown()
Shuts down workers and releases resources.

class ray.experimental.sgd.pytorch.**PyTorchTrainable**(*config=None*, *logger_creator=None*)

classmethod default_resource_request(*config*)
Returns the resource requirement for the given configuration.

This can be overriden by sub-classes to set the correct trial resource allocation, so the user does not need to.

Example

```
>>> def default_resource_request(cls, config):
        return Resources(
            cpu=0,
            gpu=0,
            extra_cpu=config["workers"],
            extra_gpu=int(config["use_gpu"]) * config["workers"])
```

5.37 TensorFlow Distributed Training API (Experimental)

Ray's `TFTrainer` simplifies distributed model training for Tensorflow. The `TFTrainer` is a wrapper around `MultiWorkerMirroredStrategy` with a Python API to easily incorporate distributed training into a larger Python application, as opposed to write custom logic of setting environments and starting separate processes.

Important: This API has only been tested with TensorFlow2.0rc.

With Ray:

Wrap your training with this:

```
ray.init(args.address)

trainer = TFTrainer(
    model_creator=model_creator,
    data_creator=data_creator,
    num_replicas=4,
    use_gpu=True,
    verbose=True,
    config={
        "fit_config": {
            "steps_per_epoch": num_train_steps,
        },
        "evaluate_config": {
            "steps": num_eval_steps,
        }
    })
```

Then, start a Ray cluster via autoscaler or manually.

```
ray up CLUSTER.yaml
python train.py --address="localhost:<PORT>"
```

Before, with Tensorflow:

In your training program, insert the following, and **customize** for each worker:

```
os.environ['TF_CONFIG'] = json.dumps({
    'cluster': {
        'worker': ["localhost:12345", "localhost:23456"]
    },
    'task': {'type': 'worker', 'index': 0}
})

...
strategy = tf.distribute.experimental.MultiWorkerMirroredStrategy()
with strategy.scope():
  multi_worker_model = model_creator()
```

And on each machine, launch a separate process that contains the index of the worker and information about all other nodes of the cluster.

5.37.1 TFTrainer Example

Below is an example of using Ray's TFTrainer. Under the hood, `TFTrainer` will create *replicas* of your model (controlled by `num_replicas`) which are each managed by a worker.

```
from __future__ import absolute_import
from __future__ import division
from __future__ import print_function

import argparse
```

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```
from tensorflow.data import Dataset
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
import numpy as np

import ray
from ray import tune
from ray.experimental.sgd.tf.tf_trainer import TFTrainer, TFTrainable

NUM_TRAIN_SAMPLES = 1000
NUM_TEST_SAMPLES = 400


def create_config(batch_size):
    return {
        "batch_size": batch_size,
        "fit_config": {
            "steps_per_epoch": NUM_TRAIN_SAMPLES // batch_size
        },
        "evaluate_config": {
            "steps": NUM_TEST_SAMPLES // batch_size,
        }
    }


def linear_dataset(a=2, size=1000):
    x = np.random.rand(size)
    y = x / 2

    x = x.reshape((-1, 1))
    y = y.reshape((-1, 1))

    return x, y


def simple_dataset(config):
    batch_size = config["batch_size"]
    x_train, y_train = linear_dataset(size=NUM_TRAIN_SAMPLES)
    x_test, y_test = linear_dataset(size=NUM_TEST_SAMPLES)

    train_dataset = Dataset.from_tensor_slices((x_train, y_train))
    test_dataset = Dataset.from_tensor_slices((x_test, y_test))
    train_dataset = train_dataset.shuffle(NUM_TRAIN_SAMPLES).repeat().batch(
        batch_size)
    test_dataset = test_dataset.repeat().batch(batch_size)

    return train_dataset, test_dataset


def simple_model(config):
    model = Sequential([Dense(10, input_shape=(1, )), Dense(1)])

    model.compile(
        optimizer="sgd",
        loss="mean_squared_error",
        metrics=["mean_squared_error"])
```

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```
    return model


def train_example(num_replicas=1, batch_size=128, use_gpu=False):
    trainer = TFTrainer(
        model_creator=simple_model,
        data_creator=simple_dataset,
        num_replicas=num_replicas,
        use_gpu=use_gpu,
        verbose=True,
        config=create_config(batch_size))

    train_stats1 = trainer.train()
    train_stats1.update(trainer.validate())
    print(train_stats1)

    train_stats2 = trainer.train()
    train_stats2.update(trainer.validate())
    print(train_stats2)

    val_stats = trainer.validate()
    print(val_stats)
    print("success!")


def tune_example(num_replicas=1, use_gpu=False):
    config = {
        "model_creator": tune.function(simple_model),
        "data_creator": tune.function(simple_dataset),
        "num_replicas": num_replicas,
        "use_gpu": use_gpu,
        "trainer_config": create_config(batch_size=128)
    }

    analysis = tune.run(
        TFTrainable,
        num_samples=2,
        config=config,
        stop={"training_iteration": 2},
        verbose=1)

    return analysis.get_best_config(metric="validation_loss", mode="min")


if __name__ == "__main__":
    parser = argparse.ArgumentParser()
    parser.add_argument(
        "--redis-address",
        required=False,
        type=str,
        help="the address to use for Redis")
    parser.add_argument(
        "--num-replicas",
        "-n",
        type=int,
        default=1,
        help="Sets number of replicas for training.")
```

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```
    parser.add_argument(
        "--use-gpu",
        action="store_true",
        default=False,
        help="Enables GPU training")
    parser.add_argument(
        "--tune", action="store_true", default=False, help="Tune training")

    args, _ = parser.parse_known_args()

    ray.init(redis_address=args.redis_address)

    if args.tune:
        tune_example(num_replicas=args.num_replicas, use_gpu=args.use_gpu)
    else:
        train_example(num_replicas=args.num_replicas, use_gpu=args.use_gpu)
```

5.37.2 Package Reference

class ray.experimental.sgd.tf.**TFTrainer**(*model_creator*, *data_creator*, *config=None*, *num_replicas=1*, *use_gpu=False*, *verbose=False*)

__init__(*model_creator*, *data_creator*, *config=None*, *num_replicas=1*, *use_gpu=False*, *verbose=False*)

Sets up the TensorFlow trainer.

Parameters

- **model_creator** (*dict -> Model*) – This function takes in the *config* dict and returns a compiled TF model.
- **data_creator** (*dict -> tf.Dataset, tf.Dataset*) – Creates the training and validation data sets using the config. *config* dict is passed into the function.
- **config** (*dict*) – configuration passed to 'model_creator', 'data_creator'. Also contains *fit_config*, which is passed into *model.fit(data, **fit_config)* and *evaluate_config* which is passed into *model.evaluate*.
- **num_replicas** (*int*) – Sets number of workers used in distributed training. Workers will be placed arbitrarily across the cluster.
- **use_gpu** (*bool*) – Enables all workers to use GPU.
- **verbose** (*bool*) – Prints output of one model if true.

train()

Runs a training epoch.

validate()

Evaluates the model on the validation data set.

get_model()

Returns the learned model.

save(*checkpoint*)

Saves the model at the provided checkpoint.

Parameters **checkpoint** (*str*) – Path to target checkpoint file.

restore(*checkpoint*)
Restores the model from the provided checkpoint.

Parameters **checkpoint** (*str*) – Path to target checkpoint file.

shutdown()
Shuts down workers and releases resources.

5.38 Pandas on Ray

Pandas on Ray has moved to Modin!

Pandas on Ray has moved into the Modin project with the intention of unifying the DataFrame APIs.

5.39 Ray Projects (Experimental)

Ray projects make it easy to package a Ray application so it can be rerun later in the same environment. They allow for the sharing and reliable reuse of existing code.

5.39.1 Quick start (CLI)

```
# Creates a project in the current directory. It will create a
# project.yaml defining the code and environment and a cluster.yaml
# describing the cluster configuration. Both will be created in the
# .rayproject subdirectory of the current directory.
$ ray project create <project-name>

# Create a new session from the given project.  Launch a cluster and run
# the command, which must be specified in the project.yaml file. If no
# command is specified, the "default" command in .rayproject/project.yaml
# will be used. Alternatively, use --shell to run a raw shell command.
$ ray session start <command-name> [arguments] [--shell]

# Open a console for the given session.
$ ray session attach

# Stop the given session and terminate all of its worker nodes.
$ ray session stop
```

5.39.2 Examples

See the readme for instructions on how to run these examples:

- Open Tacotron: A TensorFlow implementation of Google's Tacotron speech synthesis with pre-trained model (unofficial)
- PyTorch Transformers: A library of state-of-the-art pretrained models for Natural Language Processing (NLP)

5.39.3 Project file format (project.yaml)

A project file contains everything required to run a project. This includes a cluster configuration, the environment and dependencies for the application, and the specific inputs used to run the project.

Here is an example for a minimal project format:

```
name: test-project
description: "This is a simple test project"
repo: https://github.com/ray-project/ray

# Cluster to be instantiated by default when starting the project.
cluster: .rayproject/cluster.yaml

# Commands/information to build the environment, once the cluster is
# instantiated. This can include the versions of python libraries etc.
# It can be specified as a Python requirements.txt, a conda environment,
# a Dockerfile, or a shell script to run to set up the libraries.
environment:
  requirements: requirements.txt

# List of commands that can be executed once the cluster is instantiated
# and the environment is set up.
# A command can also specify a cluster that overwrites the default cluster.
commands:
  - name: default
    command: python default.py
    help: "The command that will be executed if no command name is specified"
  - name: test
    command: python test.py --param1={{param1}} --param2={{param2}}
    help: "A test command"
    params:
      - name: "param1"
        help: "The first parameter"
        # The following line indicates possible values this parameter can take.
        choices: ["1", "2"]
      - name: "param2"
        help: "The second parameter"
```

Project files have to adhere to the following schema:

type	*object*		
properties			
• **name**	The name of the project		
	type	*string*	
• description	A short description of the project		
	type	*string*	
• repo	The URL of the repo this project is part of		
	type	*string*	
• tags	Relevant tags for this project		
	type	*array*	
	items		
	•	type	*string*
• documentation	Link to the documentation of this project		

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Table 1 – continued from previous page

	type	*string*		
• **cluster**	Path to a .yaml cluster configuration file (relative to the project root)			
	type	*string*		
• environment	The environment that needs to be set up to run the project			
	type	*object*		
	properties			
	• dockerimage	URL to a docker image that can be pulled to run the project in		
		type	*string*	
	• dockerfile	Path to a Dockerfile to set up an image the project can run in (relative to the project root)		
		type	*string*	
	• requirements	Path to a Python requirements.txt file to set up project dependencies (relative to the project root)		
		type	*string*	
	• shell	A sequence of shell commands to run to set up the project environment		
		type	*array*	
		items		
		•	type	*string*
• commands	type	*array*		
	items			
	•	Possible commands to run to start a session		
		type	*object*	
		properties		
		• name	Name of the command	
			type	*string*
		• command	Shell command to run on the cluster	
			type	*string*
		• params	type	*array*
			items	
			•	Possible parameters in the command
				type *object*
				properties
				• name: Name of the parameter; type *string*
				• help: Help string for the parameter; type *string*
				• choices: Possible values the parameter can take; type *array*
		• config	type	*object*

5.39.4 Cluster file format (cluster.yaml)

This is the same as for the autoscaler, see Cluster Launch page.

5.40 Signal API (Experimental)

This experimental API allows tasks and actors to generate signals which can be received by other tasks and actors. In addition, task failures and actor method failures generate error signals. The error signals enable applications to detect failures and potentially recover from failures.

ray.experimental.signal.**send**(*signal*)
Send signal.

The signal has a unique identifier that is computed from (1) the id of the actor or task sending this signal (i.e., the actor or task calling this function), and (2) an index that is incremented every time this source sends a signal. This index starts from 1.

Parameters **signal** – Signal to be sent.

Here is a simple example of a remote function that sends a user-defined signal.

```
import ray.experimental.signal as signal

# Define an application level signal.
class UserSignal(signal.Signal):
    def __init__(self, value):
          self.value = value

    def get_value(self):
          return self.value

# Define a remote function that sends a user-defined signal.
@ray.remote
def send_signal(value):
    signal.send(UserSignal(value))
```

ray.experimental.signal.**receive**(*sources*, *timeout=None*)
Get all outstanding signals from sources.

A source can be either (1) an object ID returned by the task (we want to receive signals from), or (2) an actor handle.

When invoked by the same entity E (where E can be an actor, task or driver), for each source S in sources, this function returns all signals generated by S since the last receive() was invoked by E on S. If this is the first call on S, this function returns all past signals generated by S so far. Note that different actors, tasks or drivers that call receive() on the same source S will get independent copies of the signals generated by S.

Parameters

- **sources** – List of sources from which the caller waits for signals. A source is either an object ID returned by a task (in this case the object ID is used to identify that task), or an actor handle. If the user passes the IDs of multiple objects returned by the same task, this function returns a copy of the signals generated by that task for each object ID.
- **timeout** – Maximum time (in seconds) this function waits to get a signal from a source in sources. If None, the timeout is infinite.

Returns

A list of pairs (S, sig), where S is a source in the sources argument, and sig is a signal generated by S since the last time receive() was called on S. Thus, for each S in sources, the return list can contain zero or multiple entries.

Here is a simple example of how to receive signals from an actor or task identified by `a`. Note that an actor is identified by its handle, and a task by one of its object ID return values.

```
import ray.experimental.signal as signal

# This returns a possibly empty list of all signals that have been sent by 'a'
# since the last invocation of signal.receive from within this process. If 'a'
# did not send any signals, then this will wait for up to 10 seconds to receive
# a signal from 'a'.
signal_list = signal.receive([a], timeout=10)
```

ray.experimental.signal.**reset**()
Reset the worker state associated with any signals that this worker has received so far.

If the worker calls receive() on a source next, it will get all the signals generated by that source starting with index = 1.

5.40.1 Example: sending a user signal

The code below show a simple example in which a task, called `send_signal()` sends a user signal and the driver gets it by invoking `signal.receive()`.

```
import ray.experimental.signal as signal

# Define a user signal.
class UserSignal(signal.Signal):
    def __init__(self, value):
          self.value = value

    def get_value(self):
          return self.value

@ray.remote
def send_signal(value):
    signal.send(UserSignal(value))
    return

signal_value = 'simple signal'
object_id = send_signal.remote(signal_value)
# Wait up to 10sec to receive a signal from the task. Note the task is
# identified by the object_id it returns.
result_list = signal.receive([object_id], timeout=10)
# Print signal values. This should print "simple_signal".
# Note that result_list[0] is the signal we expect from the task.
# The signal is a tuple where the first element is the first object ID
# returned by the task and the second element is the signal object.
print(result_list[0][1].get_value())
```

5.40.2 Example: Getting an error signals

This is a simple example in which a driver gets an error signal caused by the failure of `task()`.

```
@ray.remote
def task():
    raise Exception('exception message')

object_id = task.remote()
```

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```
try:
    ray.get(object_id)
except Exception as e:
    pass
finally:
    result_list = signal.receive([object_id], timeout=10)
    # Expected signal is 'ErrorSignal'.
    assert type(result_list[0][1]) == signal.ErrorSignal
    # Print the error.
    print(result_list[0][1].get_error())
```

5.40.3 Example: Sending signals between multiple actors

This is a more involved example in which two actors `a1` and `a2` each generate five signals, and another actor `b` waits to receive all signals generated by `a1` and `a2`, respectively. Note that `b` recursively calls its own method `get_signals()` until it gets all signals it expects.

```
@ray.remote
class ActorSendSignals(object):
    def send_signals(self, value, count):
        for i in range(count):
            signal.send(UserSignal(value + str(i)))

@ray.remote
class ActorGetAllSignals(object):
    def __init__(self, num_expected_signals, *source_ids):
        self.received_signals = []
        self.num_expected_signals = num_expected_signals
        self.source_ids = source_ids

    def register_handle(self, handle):
        self.this_actor = handle

    def get_signals(self):
        new_signals = signal.receive(self.source_ids, timeout=10)
        self.received_signals.extend(new_signals)
        if len(self.received_signals) < self.num_expected_signals:
            self.this_actor.get_signals.remote()

    def get_count(self):
        return len(self.received_signals)

# Create two actors to send signals.
a1 = ActorSendSignals.remote()
a2 = ActorSendSignals.remote()
signal_value = 'simple signal'
count = 5
# Each actor sends five signals.
a1.send_signals.remote(signal_value, count)
a2.send_signals.remote(signal_value, count)

# Create an actor that waits for all five signals sent by each actor.
b = ActorGetAllSignals.remote(2 * count, *[a1, a2])
# Provide actor to its own handle, so it can recursively call itself
# to get all signals from a1, and a2, respectively. This enables the actor
```

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```
# execute other methods if needed.
ray.get(b.register_handle.remote(b))
b.get_signals.remote()
# Print total number of signals. This should be 2*count = 10.
print(ray.get(b.get_count.remote()))
```

5.40.4 Note

A failed actor (e.g., an actor that crashed) generates an error message only when another actor or task invokes one of its methods.

Please let us know any issues you encounter.

5.41 Async API (Experimental)

Since Python 3.5, it is possible to write concurrent code using the `async/await` syntax.

This document describes Ray's support for asyncio, which enables integration with popular async frameworks (e.g., aiohttp, aioredis, etc.) for high performance web and prediction serving.

5.41.1 Converting Ray objects into asyncio futures

Ray object IDs can be converted into asyncio futures with `ray.experimental.async_api`.

```
import asyncio
import time
import ray
from ray.experimental import async_api

@ray.remote
def f():
    time.sleep(1)
    return {'key1': ['value']}

ray.init()
future = async_api.as_future(f.remote())
asyncio.get_event_loop().run_until_complete(future)  # {'key1': ['value']}
```

`ray.experimental.async_api.`**`as_future`**(*object_id*)

Turn an object_id into a Future object.

Parameters **`object_id`** – A Ray object_id.

Returns A future object that waits the object_id.

Return type PlasmaObjectFuture

5.41.2 Example Usage

Basic Python

```
# Execute f serially.


def f():
  time.sleep(1)
  return 1



results = [f() for i in range(4)]
```

Distributed with Ray

```
# Execute f in parallel.


@ray.remote
def f():
    time.sleep(1)
    return 1

ray.init()
results = ray.get([f.remote() for i in␣
↪range(4)])
```

Async Python

```
# Execute f asynchronously.




async def f():
    await asyncio.sleep(1)
    return 1


loop = asyncio.get_event_loop()
tasks = [f() for i in range(4)]

results = loop.run_until_complete(
    asyncio.gather(tasks))
```

Async Ray

```
# Execute f asynchronously with Ray/
↪asyncio.

from ray.experimental import async_api

@ray.remote
def f():
    time.sleep(1)
    return 1

ray.init()
loop = asyncio.get_event_loop()
tasks = [async_api.as_future(f.remote())
         for i in range(4)]
results = loop.run_until_complete(
    asyncio.gather(tasks))
```

5.41.3 Known Issues

Async API support is experimental, and we are working to improve its performance. Please let us know any issues you encounter.

5.42 Ray Serve (Experimental)

Ray Serve is a serving library that exposes python function/classes to HTTP. It has built-in support for flexible traffic policy. This means you can easy split incoming traffic to multiple implementations.

With Ray Serve, you can deploy your services at any scale.

Warning: Ray Serve is Python 3 only.

5.42.1 Quickstart

```
"""
Full example of ray.serve module
"""

import ray
import ray.experimental.serve as serve
from ray.experimental.serve.utils import pformat_color_json
import requests
import time

# initialize ray serve system.
# blocking=True will wait for HTTP server to be ready to serve request.
serve.init(blocking=True)

# an endpoint is associated with an http URL.
serve.create_endpoint("my_endpoint", "/echo")


# a backend can be a function or class.
# it can be made to be invoked from web as well as python.
def echo_v1(flask_request, response="hello from python!"):
    if serve.context.web:
        response = flask_request.url
    return response


serve.create_backend(echo_v1, "echo:v1")

# We can link an endpoint to a backend, the means all the traffic
# goes to my_endpoint will now goes to echo:v1 backend.
serve.link("my_endpoint", "echo:v1")

print(requests.get("http://127.0.0.1:8000/echo").json())
# The service will be reachable from http

print(ray.get(serve.get_handle("my_endpoint").remote(response="hello")))

# as well as within the ray system.


# We can also add a new backend and split the traffic.
def echo_v2(flask_request):
    # magic, only from web.
    return "something new"


serve.create_backend(echo_v2, "echo:v2")

# The two backend will now split the traffic 50%-50%.
serve.split("my_endpoint", {"echo:v1": 0.5, "echo:v2": 0.5})

# Observe requests are now split between two backends.
for _ in range(10):
    print(requests.get("http://127.0.0.1:8000/echo").json())
    time.sleep(0.5)
```

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```
# You can also scale each backend independently.
serve.scale("echo:v1", 2)
serve.scale("echo:v2", 2)

# As well as retrieving relevant system metrics
print(pformat_color_json(serve.stat()))
```

5.42.2 API

ray.experimental.serve.**init**(*blocking=False*, *object_store_memory=100000000*, *gc_window_seconds=3600*)

Initialize a serve cluster.

Calling *ray.init* before *serve.init* is optional. When there is not a ray cluster initialized, serve will call *ray.init* with *object_store_memory* requirement.

Parameters

- **blocking** (*bool*) – If true, the function will wait for the HTTP server to be healthy, and other components to be ready before returns.
- **object_store_memory** (*int*) – Allocated shared memory size in bytes. The default is 100MiB. The default is kept low for latency stability reason.
- **gc_window_seconds** (*int*) – How long will we keep the metric data in memory. Data older than the gc_window will be deleted. The default is 3600 seconds, which is 1 hour.

ray.experimental.serve.**create_backend**(*func_or_class*, *backend_tag*, **actor_init_args*)

Create a backend using func_or_class and assign backend_tag.

Parameters

- **func_or_class** (*callable, class*) – a function or a class implements __call__ protocol.
- **backend_tag** (*str*) – a unique tag assign to this backend. It will be used to associate services in traffic policy.
- ***actor_init_args** (*optional*) – the argument to pass to the class initialization method.

ray.experimental.serve.**create_endpoint**(*endpoint_name*, *route_expression*, *blocking=True*)

Create a service endpoint given route_expression.

Parameters

- **endpoint_name** (*str*) – A name to associate to the endpoint. It will be used as key to set traffic policy.
- **route_expression** (*str*) – A string begin with "/". HTTP server will use the string to match the path.
- **blocking** (*bool*) – If true, the function will wait for service to be registered before returning

ray.experimental.serve.**link**(*endpoint_name*, *backend_tag*)

Associate a service endpoint with backend tag.

Example:

```
>>> serve.link("service-name", "backend:v1")
```

Note: This is equivalent to

```
>>> serve.split("service-name", {"backend:v1": 1.0})
```

ray.experimental.serve.**split**(*endpoint_name*, *traffic_policy_dictionary*)
Associate a service endpoint with traffic policy.

Example:

```
>>> serve.split("service-name", {
    "backend:v1": 0.5,
    "backend:v2": 0.5
})
```

Parameters

- **endpoint_name** (*str*) – A registered service endpoint.
- **traffic_policy_dictionary** (*dict*) – a dictionary maps backend names to their traffic weights. The weights must sum to 1.

ray.experimental.serve.**rollback**(*endpoint_name*)
Rollback a traffic policy decision.

Parameters **endpoint_name** (*str*) – A registered service endpoint.

ray.experimental.serve.**get_handle**(*endpoint_name*)
Retrieve RayServeHandle for service endpoint to invoke it from Python.

Parameters **endpoint_name** (*str*) – A registered service endpoint.

Returns RayServeHandle

ray.experimental.serve.**stat**(*percentiles=[50, 90, 95], agg_windows_seconds=[10, 60, 300, 600, 3600]*)
Retrieve metric statistics about ray serve system.

Parameters

- **percentiles** (*List[int]*) – The percentiles for aggregation operations. Default is 50th, 90th, 95th percentile.
- **agg_windows_seconds** (*List[int]*) – The aggregation windows in seconds. The longest aggregation window must be shorter or equal to the gc_window_seconds.

ray.experimental.serve.**scale**(*backend_tag*, *num_replicas*)
Set the number of replicas for backend_tag.

Parameters

- **backend_tag** (*str*) – A registered backend.
- **num_replicas** (*int*) – Desired number of replicas

5.43 Examples Overview

5.44 Batch L-BFGS

This document provides a walkthrough of the L-BFGS example. To run the application, first install these dependencies.

```
pip install tensorflow
pip install scipy
```

You can view the code for this example.

Then you can run the example as follows.

```
python ray/doc/examples/lbfgs/driver.py
```

Optimization is at the heart of many machine learning algorithms. Much of machine learning involves specifying a loss function and finding the parameters that minimize the loss. If we can compute the gradient of the loss function, then we can apply a variety of gradient-based optimization algorithms. L-BFGS is one such algorithm. It is a quasi-Newton method that uses gradient information to approximate the inverse Hessian of the loss function in a computationally efficient manner.

5.44.1 The serial version

First we load the data in batches. Here, each element in `batches` is a tuple whose first component is a batch of `100` images and whose second component is a batch of the `100` corresponding labels. For simplicity, we use TensorFlow's built in methods for loading the data.

```
from tensorflow.examples.tutorials.mnist import input_data
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
batch_size = 100
num_batches = mnist.train.num_examples // batch_size
batches = [mnist.train.next_batch(batch_size) for _ in range(num_batches)]
```

Now, suppose we have defined a function which takes a set of model parameters `theta` and a batch of data (both images and labels) and computes the loss for that choice of model parameters on that batch of data. Similarly, suppose we've also defined a function that takes the same arguments and computes the gradient of the loss for that choice of model parameters.

```
def loss(theta, xs, ys):
    # compute the loss on a batch of data
    return loss

def grad(theta, xs, ys):
    # compute the gradient on a batch of data
    return grad

def full_loss(theta):
    # compute the loss on the full data set
    return sum([loss(theta, xs, ys) for (xs, ys) in batches])

def full_grad(theta):
    # compute the gradient on the full data set
    return sum([grad(theta, xs, ys) for (xs, ys) in batches])
```

Since we are working with a small dataset, we don't actually need to separate these methods into the part that operates on a batch and the part that operates on the full dataset, but doing so will make the distributed version clearer.

Now, if we wish to optimize the loss function using L-BFGS, we simply plug these functions, along with an initial choice of model parameters, into `scipy.optimize.fmin_l_bfgs_b`.

```
theta_init = 1e-2 * np.random.normal(size=dim)
result = scipy.optimize.fmin_l_bfgs_b(full_loss, theta_init, fprime=full_grad)
```

5.44.2 The distributed version

In this example, the computation of the gradient itself can be done in parallel on a number of workers or machines.

First, let's turn the data into a collection of remote objects.

```
batch_ids = [(ray.put(xs), ray.put(ys)) for (xs, ys) in batches]
```

We can load the data on the driver and distribute it this way because MNIST easily fits on a single machine. However, for larger data sets, we will need to use remote functions to distribute the loading of the data.

Now, lets turn `loss` and `grad` into methods of an actor that will contain our network.

```
class Network(object):
    def __init__():
        # Initialize network.

    def loss(theta, xs, ys):
        # compute the loss
        return loss

    def grad(theta, xs, ys):
        # compute the gradient
        return grad
```

Now, it is easy to speed up the computation of the full loss and the full gradient.

```
def full_loss(theta):
    theta_id = ray.put(theta)
    loss_ids = [actor.loss(theta_id) for actor in actors]
    return sum(ray.get(loss_ids))

def full_grad(theta):
    theta_id = ray.put(theta)
    grad_ids = [actor.grad(theta_id) for actor in actors]
    return sum(ray.get(grad_ids)).astype("float64") # This conversion is necessary␣
↪for use with fmin_l_bfgs_b.
```

Note that we turn `theta` into a remote object with the line `theta_id = ray.put(theta)` before passing it into the remote functions. If we had written

```
[actor.loss(theta_id) for actor in actors]
```

instead of

```
theta_id = ray.put(theta)
[actor.loss(theta_id) for actor in actors]
```

then each task that got sent to the scheduler (one for every element of `batch_ids`) would have had a copy of `theta` serialized inside of it. Since `theta` here consists of the parameters of a potentially large model, this is inefficient. *Large objects should be passed by object ID to remote functions and not by value*.

We use remote actors and remote objects internally in the implementation of `full_loss` and `full_grad`, but the user-facing behavior of these methods is identical to the behavior in the serial version.

We can now optimize the objective with the same function call as before.

```
theta_init = 1e-2 * np.random.normal(size=dim)
result = scipy.optimize.fmin_l_bfgs_b(full_loss, theta_init, fprime=full_grad)
```

5.45 News Reader

This document shows how to implement a simple news reader using Ray. The reader consists of a simple Vue.js frontend and a backend consisting of a Flask server and a Ray actor. View the code for this example.

To run this example, you will need to install NPM and a few python dependencies.

```
pip install atoma
pip install flask
```

To use this example you need to

- In the `ray/doc/examples/newsreader` directory, start the server with `python server.py`.
- Clone the client code with `git clone https://github.com/ray-project/qreader`
- Start the client with `cd qreader; npm install; npm run dev`
- You can now add a channel by clicking "Add channel" and for example pasting `http://news.ycombinator.com/rss` into the field.
- Star some of the articles and dump the database by running `sqlite3 newsreader.db` in a terminal in the `ray/doc/examples/newsreader` directory and entering `SELECT * FROM news;`.

Note: Click *here* to download the full example code

5.46 Simple Parallel Model Selection

In this example, we'll demonstrate how to quickly write a hyperparameter tuning script that evaluates a set of hyperparameters in parallel.

This script will demonstrate how to use two important parts of the Ray API: using `ray.remote` to define remote functions and `ray.wait` to wait for their results to be ready.

Important: For a production-grade implementation of distributed hyperparameter tuning, use Tune, a scalable hyperparameter tuning library built using Ray's Actor API.

```
import os
import numpy as np
from filelock import FileLock
```

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```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torchvision import datasets, transforms

import ray

ray.init()

# The number of sets of random hyperparameters to try.
num_evaluations = 10


# A function for generating random hyperparameters.
def generate_hyperparameters():
    return {
        "learning_rate": 10**np.random.uniform(-5, 1),
        "batch_size": np.random.randint(1, 100),
        "momentum": np.random.uniform(0, 1)
    }


def get_data_loaders(batch_size):
    mnist_transforms = transforms.Compose(
        [transforms.ToTensor(),
         transforms.Normalize((0.1307, ), (0.3081, ))])

    # We add FileLock here because multiple workers will want to
    # download data, and this may cause overwrites since
    # DataLoader is not threadsafe.
    with FileLock(os.path.expanduser("~/data.lock")):
        train_loader = torch.utils.data.DataLoader(
            datasets.MNIST(
                "~/data",
                train=True,
                download=True,
                transform=mnist_transforms),
            batch_size=batch_size,
            shuffle=True)
    test_loader = torch.utils.data.DataLoader(
        datasets.MNIST("~/data", train=False, transform=mnist_transforms),
        batch_size=batch_size,
        shuffle=True)
    return train_loader, test_loader


class ConvNet(nn.Module):
    """Simple two layer Convolutional Neural Network."""

    def __init__(self):
        super(ConvNet, self).__init__()
        self.conv1 = nn.Conv2d(1, 3, kernel_size=3)
        self.fc = nn.Linear(192, 10)

    def forward(self, x):
```

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```
        x = F.relu(F.max_pool2d(self.conv1(x), 3))
        x = x.view(-1, 192)
        x = self.fc(x)
        return F.log_softmax(x, dim=1)


def train(model, optimizer, train_loader, device=torch.device("cpu")):
    """Optimize the model with one pass over the data.

    Cuts off at 1024 samples to simplify training.
    """
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        if batch_idx * len(data) > 1024:
            return
        data, target = data.to(device), target.to(device)
        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        loss.backward()
        optimizer.step()


def test(model, test_loader, device=torch.device("cpu")):
    """Checks the validation accuracy of the model.

    Cuts off at 512 samples for simplicity.
    """
    model.eval()
    correct = 0
    total = 0
    with torch.no_grad():
        for batch_idx, (data, target) in enumerate(test_loader):
            if batch_idx * len(data) > 512:
                break
            data, target = data.to(device), target.to(device)
            outputs = model(data)
            _, predicted = torch.max(outputs.data, 1)
            total += target.size(0)
            correct += (predicted == target).sum().item()

    return correct / total


@ray.remote
def evaluate_hyperparameters(config):
    model = ConvNet()
    train_loader, test_loader = get_data_loaders(config["batch_size"])
    optimizer = optim.SGD(
        model.parameters(),
        lr=config["learning_rate"],
        momentum=config["momentum"])
    train(model, optimizer, train_loader)
    return test(model, test_loader)


# Keep track of the best hyperparameters and the best accuracy.
```

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```
best_hyperparameters = None
best_accuracy = 0
# A list holding the object IDs for all of the experiments that we have
# launched but have not yet been processed.
remaining_ids = []
# A dictionary mapping an experiment's object ID to its hyperparameters.
# hyerparameters used for that experiment.
hyperparameters_mapping = {}

# Randomly generate sets of hyperparameters and launch a task to test each set.
for i in range(num_evaluations):
    hyperparameters = generate_hyperparameters()
    accuracy_id = evaluate_hyperparameters.remote(hyperparameters)
    remaining_ids.append(accuracy_id)
    hyperparameters_mapping[accuracy_id] = hyperparameters

# Fetch and print the results of the tasks in the order that they complete.
while remaining_ids:
    # Use ray.wait to get the object ID of the first task that completes.
    done_ids, remaining_ids = ray.wait(remaining_ids)
    # There is only one return result by default.
    result_id = done_ids[0]

    hyperparameters = hyperparameters_mapping[result_id]
    accuracy = ray.get(result_id)
    print("""We achieve accuracy {:.3}% with
        learning_rate: {:.2}
        batch_size: {}
        momentum: {:.2}
      """.format(100 * accuracy, hyperparameters["learning_rate"],
                 hyperparameters["batch_size"], hyperparameters["momentum"]))
    if accuracy > best_accuracy:
        best_hyperparameters = hyperparameters
        best_accuracy = accuracy

# Record the best performing set of hyperparameters.
print("""Best accuracy over {} trials was {:.3} with
      learning_rate: {:.2}
      batch_size: {}
      momentum: {:.2}
      """.format(num_evaluations, 100 * best_accuracy,
                 best_hyperparameters["learning_rate"],
                 best_hyperparameters["batch_size"],
                 best_hyperparameters["momentum"]))
```

Total running time of the script: (0 minutes 0.000 seconds)

Note: Click *here* to download the full example code

5.47 Learning to Play Pong

In this example, we'll train a **very simple** neural network to play Pong using the OpenAI Gym.

At a high level, we will use multiple Ray actors to obtain simulation rollouts and calculate gradient simultaneously.

We will then centralize these gradients and update the neural network. The updated neural network will then be passed back to each Ray actor for more gradient calculation.

This application is adapted, with minimal modifications, from Andrej Karpathy's source code (see the accompanying blog post).

To run the application, first install some dependencies.

```
pip install gym[atari]
```

At the moment, on a large machine with 64 physical cores, computing an update with a batch of size 1 takes about 1 second, a batch of size 10 takes about 2.5 seconds. A batch of size 60 takes about 3 seconds. On a cluster with 11 nodes, each with 18 physical cores, a batch of size 300 takes about 10 seconds. If the numbers you see differ from these by much, take a look at the **Troubleshooting** section at the bottom of this page and consider submitting an issue.

Note that these times depend on how long the rollouts take, which in turn depends on how well the policy is doing. For example, a really bad policy will lose very quickly. As the policy learns, we should expect these numbers to increase.

```
import numpy as np
import os
import ray
import time

import gym
```

5.47.1 Hyperparameters

Here we'll define a couple of the hyperparameters that are used.

```
H = 200  # The number of hidden layer neurons.
gamma = 0.99  # The discount factor for reward.
decay_rate = 0.99  # The decay factor for RMSProp leaky sum of grad^2.
D = 80 * 80  # The input dimensionality: 80x80 grid.
learning_rate = 1e-4  # Magnitude of the update.
```

5.47.2 Helper Functions

We first define a few helper functions:

1. Preprocessing: The `preprocess` function will preprocess the original 210x160x3 uint8 frame into a one-dimensional 6400 float vector.

2. Reward Processing: The `process_rewards` function will calculate a discounted reward. This formula states that the "value" of a sampled action is the weighted sum of all rewards afterwards, but later rewards are exponentially less important.

3. Rollout: The `rollout` function plays an entire game of Pong (until either the computer or the RL agent loses).

```
def preprocess(img):
    # Crop the image.
    img = img[35:195]
    # Downsample by factor of 2.
    img = img[::2, ::2, 0]
    # Erase background (background type 1).
    img[img == 144] = 0
    # Erase background (background type 2).
```

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```
    img[img == 109] = 0
    # Set everything else (paddles, ball) to 1.
    img[img != 0] = 1
    return img.astype(np.float).ravel()


def process_rewards(r):
    """Compute discounted reward from a vector of rewards."""
    discounted_r = np.zeros_like(r)
    running_add = 0
    for t in reversed(range(0, r.size)):
        # Reset the sum, since this was a game boundary (pong specific!).
        if r[t] != 0:
            running_add = 0
        running_add = running_add * gamma + r[t]
        discounted_r[t] = running_add
    return discounted_r


def rollout(model, env):
    """Evaluates  env and model until the env returns "Done".

    Returns:
        xs: A list of observations
        hs: A list of model hidden states per observation
        dlogps: A list of gradients
        drs: A list of rewards.

    """
    # Reset the game.
    observation = env.reset()
    # Note that prev_x is used in computing the difference frame.
    prev_x = None
    xs, hs, dlogps, drs = [], [], [], []
    done = False
    while not done:
        cur_x = preprocess(observation)
        x = cur_x - prev_x if prev_x is not None else np.zeros(D)
        prev_x = cur_x

        aprob, h = model.policy_forward(x)
        # Sample an action.
        action = 2 if np.random.uniform() < aprob else 3

        # The observation.
        xs.append(x)
        # The hidden state.
        hs.append(h)
        y = 1 if action == 2 else 0  # A "fake label".
        # The gradient that encourages the action that was taken to be
        # taken (see http://cs231n.github.io/neural-networks-2/#losses if
        # confused).
        dlogps.append(y - aprob)

        observation, reward, done, info = env.step(action)

        # Record reward (has to be done after we call step() to get reward
```

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```
        # for previous action).
        drs.append(reward)
    return xs, hs, dlogps, drs
```

5.47.3 Neural Network

Here, a neural network is used to define a "policy" for playing Pong (that is, a function that chooses an action given a state).

To implement a neural network in NumPy, we need to provide helper functions for calculating updates and computing the output of the neural network given an input, which in our case is an observation.

```
class Model():
    """This class holds the neural network weights."""

    def __init__(self):
        self.weights = {}
        self.weights["W1"] = np.random.randn(H, D) / np.sqrt(D)
        self.weights["W2"] = np.random.randn(H) / np.sqrt(H)

    def policy_forward(self, x):
        h = np.dot(self.weights["W1"], x)
        h[h < 0] = 0  # ReLU nonlinearity.
        logp = np.dot(self.weights["W2"], h)
        # Softmax
        p = 1.0 / (1.0 + np.exp(-logp))
        # Return probability of taking action 2, and hidden state.
        return p, h

    def policy_backward(self, eph, epx, epdlogp):
        """Backward pass to calculate gradients.

        Arguments:
            eph: Array of intermediate hidden states.
            epx: Array of experiences (observations.
            epdlogp: Array of logps (output of last layer before softmax/

        """
        dW2 = np.dot(eph.T, epdlogp).ravel()
        dh = np.outer(epdlogp, self.weights["W2"])
        # Backprop relu.
        dh[eph <= 0] = 0
        dW1 = np.dot(dh.T, epx)
        return {"W1": dW1, "W2": dW2}

    def update(self, grad_buffer, rmsprop_cache, lr, decay):
        """Applies the gradients to the model parameters with RMSProp."""
        for k, v in self.weights.items():
            g = grad_buffer[k]
            rmsprop_cache[k] = (decay * rmsprop_cache[k] + (1 - decay) * g**2)
            self.weights[k] += lr * g / (np.sqrt(rmsprop_cache[k]) + 1e-5)


def zero_grads(grad_buffer):
    """Reset the batch gradient buffer."""
```

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```
    for k, v in grad_buffer.items():
        grad_buffer[k] = np.zeros_like(v)
```

5.47.4 Parallelizing Gradients

We define an **actor**, which is responsible for taking a model and an env and performing a rollout + computing a gradient update.

```
ray.init()


@ray.remote
class RolloutWorker(object):
    def __init__(self):
        # Tell numpy to only use one core. If we don't do this, each actor may
        # try to use all of the cores and the resulting contention may result
        # in no speedup over the serial version. Note that if numpy is using
        # OpenBLAS, then you need to set OPENBLAS_NUM_THREADS=1, and you
        # probably need to do it from the command line (so it happens before
        # numpy is imported).
        os.environ["MKL_NUM_THREADS"] = "1"
        self.env = gym.make("Pong-v0")

    def compute_gradient(self, model):
        # Compute a simulation episode.
        xs, hs, dlogps, drs = rollout(model, self.env)
        reward_sum = sum(drs)
        # Vectorize the arrays.
        epx = np.vstack(xs)
        eph = np.vstack(hs)
        epdlogp = np.vstack(dlogps)
        epr = np.vstack(drs)

        # Compute the discounted reward backward through time.
        discounted_epr = process_rewards(epr)
        # Standardize the rewards to be unit normal (helps control the gradient
        # estimator variance).
        discounted_epr -= np.mean(discounted_epr)
        discounted_epr /= np.std(discounted_epr)
        # Modulate the gradient with advantage (the policy gradient magic
        # happens right here).
        epdlogp *= discounted_epr
        return model.policy_backward(eph, epx, epdlogp), reward_sum
```

5.47.5 Running

This example is easy to parallelize because the network can play ten games in parallel and no information needs to be shared between the games.

In the loop, the network repeatedly plays games of Pong and records a gradient from each game. Every ten games, the gradients are combined together and used to update the network.

```
iterations = 20
batch_size = 4
model = Model()
actors = [RolloutWorker.remote() for _ in range(batch_size)]

running_reward = None
# "Xavier" initialization.
# Update buffers that add up gradients over a batch.
grad_buffer = {k: np.zeros_like(v) for k, v in model.weights.items()}
# Update the rmsprop memory.
rmsprop_cache = {k: np.zeros_like(v) for k, v in model.weights.items()}

for i in range(1, 1 + iterations):
    model_id = ray.put(model)
    gradient_ids = []
    # Launch tasks to compute gradients from multiple rollouts in parallel.
    start_time = time.time()
    gradient_ids = [
        actor.compute_gradient.remote(model_id) for actor in actors
    ]
    for batch in range(batch_size):
        [grad_id], gradient_ids = ray.wait(gradient_ids)
        grad, reward_sum = ray.get(grad_id)
        # Accumulate the gradient over batch.
        for k in model.weights:
            grad_buffer[k] += grad[k]
        running_reward = (reward_sum if running_reward is None else
                          running_reward * 0.99 + reward_sum * 0.01)
    end_time = time.time()
    print("Batch {} computed {} rollouts in {} seconds, "
          "running mean is {}".format(i, batch_size, end_time - start_time,
                                      running_reward))
    model.update(grad_buffer, rmsprop_cache, learning_rate, decay_rate)
    zero_grads(grad_buffer)
```

Total running time of the script: (0 minutes 0.000 seconds)

5.48 ResNet

This code uses ResNet to do data parallel training across multiple GPUs using Ray. View the code for this example.

To run the example, you will need to install TensorFlow (at least version `1.0.0`). Then you can run the example as follows.

First download the CIFAR-10 or CIFAR-100 dataset.

```
# Get the CIFAR-10 dataset.
curl -o cifar-10-binary.tar.gz https://www.cs.toronto.edu/~kriz/cifar-10-binary.tar.gz
tar -xvf cifar-10-binary.tar.gz

# Get the CIFAR-100 dataset.
curl -o cifar-100-binary.tar.gz https://www.cs.toronto.edu/~kriz/cifar-100-binary.tar.
↪gz
tar -xvf cifar-100-binary.tar.gz
```

Then run the training script that matches the dataset you downloaded.

```
# Train Resnet on CIFAR-10.
python ray/doc/examples/resnet/resnet_main.py \
    --eval_dir=/tmp/resnet-model/eval \
    --train_data_path=cifar-10-batches-bin/data_batch* \
    --eval_data_path=cifar-10-batches-bin/test_batch.bin \
    --dataset=cifar10 \
    --num_gpus=1

# Train Resnet on CIFAR-100.
python ray/doc/examples/resnet/resnet_main.py \
    --eval_dir=/tmp/resnet-model/eval \
    --train_data_path=cifar-100-binary/train.bin \
    --eval_data_path=cifar-100-binary/test.bin \
    --dataset=cifar100 \
    --num_gpus=1
```

To run the training script on a cluster with multiple machines, you will need to also pass in the flag `--address=<address>`, where `<address>` is the address of the Redis server on the head node.

The script will print out the IP address that the log files are stored on. In the single-node case, you can ignore this and run tensorboard on the current machine.

```
python -m tensorflow.tensorboard --logdir=/tmp/resnet-model
```

If you are running Ray on multiple nodes, you will need to go to the node at the IP address printed, and run the command.

The core of the script is the actor definition.

```
@ray.remote(num_gpus=1)
class ResNetTrainActor(object):
    def __init__(self, data, dataset, num_gpus):
        # data is the preprocessed images and labels extracted from the dataset.
        # Thus, every actor has its own copy of the data.
        # Set the CUDA_VISIBLE_DEVICES environment variable in order to restrict
        # which GPUs TensorFlow uses. Note that this only works if it is done before
        # the call to tf.Session.
        os.environ['CUDA_VISIBLE_DEVICES'] = ','.join([str(i) for i in ray.get_gpu_
↪ids()])
        with tf.Graph().as_default():
            with tf.device('/gpu:0'):
                # We omit the code here that actually constructs the residual network
                # and initializes it. Uses the definition in the Tensorflow Resnet␣
↪Example.

    def compute_steps(self, weights):
        # This method sets the weights in the network, runs some training steps,
        # and returns the new weights. self.model.variables is a TensorFlowVariables
        # class that we pass the train operation into.
        self.model.variables.set_weights(weights)
        for i in range(self.steps):
            self.model.variables.sess.run(self.model.train_op)
        return self.model.variables.get_weights()
```

The main script first creates one actor for each GPU, or a single actor if `num_gpus` is zero.

```
train_actors = [ResNetTrainActor.remote(train_data, dataset, num_gpus) for _ in␣
↪range(num_gpus)]
```

Then the main loop passes the same weights to every model, performs updates on each model, averages the updates, and puts the new weights in the object store.

```
while True:
    all_weights = ray.get([actor.compute_steps.remote(weight_id) for actor in train_
↪actors])
    mean_weights = {k: sum([weights[k] for weights in all_weights]) / num_gpus for k␣
↪in all_weights[0]}
    weight_id = ray.put(mean_weights)
```

5.49 Streaming MapReduce

This document walks through how to implement a simple streaming application using Ray's actor capabilities. It implements a streaming MapReduce which computes word counts on wikipedia articles.

You can view the code for this example.

To run the example, you need to install the dependencies

```
pip install wikipedia
```

and then execute the script as follows:

```
python ray/doc/examples/streaming/streaming.py
```

For each round of articles read, the script will output the top 10 words in these articles together with their word count:

```
article index = 0
   the 2866
   of 1688
   and 1448
   in 1101
   to 593
   a 553
   is 509
   as 325
   are 284
   by 261
article index = 1
   the 3597
   of 1971
   and 1735
   in 1429
   to 670
   a 623
   is 578
   as 401
   by 293
   for 285
article index = 2
   the 3910
   of 2123
   and 1890
   in 1468
   to 658
   a 653
```

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```
   is 488
   as 364
   by 362
   for 297
article index = 3
   the 2962
   of 1667
   and 1472
   in 1220
   a 546
   to 538
   is 516
   as 307
   by 253
   for 243
article index = 4
   the 3523
   of 1866
   and 1690
   in 1475
   to 645
   a 583
   is 572
   as 352
   by 318
   for 306
...
```

Note that this examples uses distributed actor handles, which are still considered experimental.

There is a `Mapper` actor, which has a method `get_range` used to retrieve word counts for words in a certain range:

```
@ray.remote
class Mapper(object):

    def __init__(self, title_stream):
        # Constructor, the title stream parameter is a stream of wikipedia
        # article titles that will be read by this mapper

    def get_range(self, article_index, keys):
        # Return counts of all the words with first
        # letter between keys[0] and keys[1] in the
        # articles that haven't been read yet with index
        # up to article_index
```

The `Reducer` actor holds a list of mappers, calls `get_range` on them and accumulates the results.

```
@ray.remote
class Reducer(object):

    def __init__(self, keys, *mappers):
         # Constructor for a reducer that gets input from the list of mappers
         # in the argument and accumulates word counts for words with first
         # letter between keys[0] and keys[1]

    def next_reduce_result(self, article_index):
         # Get articles up to article_index that haven't been read yet,
```

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```
        # accumulate the word counts and return them
```

On the driver, we then create a number of mappers and reducers and run the streaming MapReduce:

```
streams = # Create list of num_mappers streams
keys = # Partition the keys among the reducers.

# Create a number of mappers.
mappers = [Mapper.remote(stream) for stream in streams]

# Create a number of reduces, each responsible for a different range of keys.
# This gives each Reducer actor a handle to each Mapper actor.
reducers = [Reducer.remote(key, *mappers) for key in keys]

article_index = 0
while True:
    counts = ray.get([reducer.next_reduce_result.remote(article_index)
                      for reducer in reducers])
    article_index += 1
```

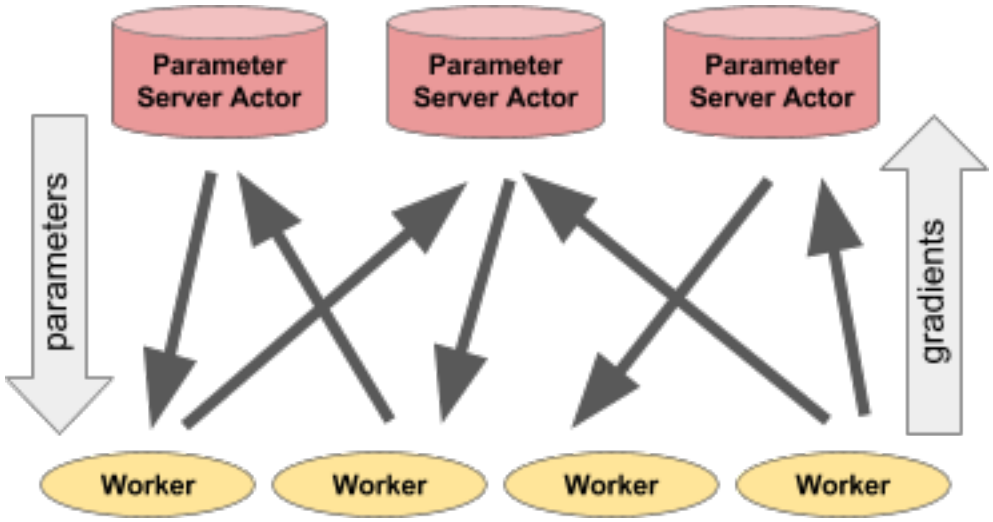
The actual example reads a list of articles and creates a stream object which produces an infinite stream of articles from the list. This is a toy example meant to illustrate the idea. In practice we would produce a stream of non-repeating items for each mapper.

Note: Click *here* to download the full example code

5.50 Parameter Server

The parameter server is a framework for distributed machine learning training.

In the parameter server framework, a centralized server (or group of server nodes) maintains global shared parameters of a machine-learning model (e.g., a neural network) while the data and computation of calculating updates (i.e., gradient descent updates) are distributed over worker nodes.



Parameter servers are a core part of many machine learning applications. This document walks through how to implement simple synchronous and asynchronous parameter servers using Ray actors.

To run the application, first install some dependencies.

```
pip install torch torchvision filelock
```

Let's first define some helper functions and import some dependencies.

```
import os
import torch
import torch.nn as nn
import torch.nn.functional as F
from torchvision import datasets, transforms
from filelock import FileLock
import numpy as np

import ray


def get_data_loader():
    """Safely downloads data. Returns training/validation set dataloader."""
    mnist_transforms = transforms.Compose(
        [transforms.ToTensor(),
         transforms.Normalize((0.1307, ), (0.3081, ))])

    # We add FileLock here because multiple workers will want to
    # download data, and this may cause overwrites since
    # DataLoader is not threadsafe.
    with FileLock(os.path.expanduser("~/data.lock")):
        train_loader = torch.utils.data.DataLoader(
            datasets.MNIST(
                "~/data",
                train=True,
                download=True,
                transform=mnist_transforms),
            batch_size=128,
            shuffle=True)
        test_loader = torch.utils.data.DataLoader(
            datasets.MNIST("~/data", train=False, transform=mnist_transforms),
            batch_size=128,
            shuffle=True)
    return train_loader, test_loader


def evaluate(model, test_loader):
    """Evaluates the accuracy of the model on a validation dataset."""
    model.eval()
    correct = 0
    total = 0
    with torch.no_grad():
        for batch_idx, (data, target) in enumerate(test_loader):
            # This is only set to finish evaluation faster.
            if batch_idx * len(data) > 1024:
                break
            outputs = model(data)
            _, predicted = torch.max(outputs.data, 1)
            total += target.size(0)
```

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```
            correct += (predicted == target).sum().item()
    return 100. * correct / total
```

5.50.1 Setup: Defining the Neural Network

We define a small neural network to use in training. We provide some helper functions for obtaining data, including getter/setter methods for gradients and weights.

```
class ConvNet(nn.Module):
    """Small ConvNet for MNIST."""

    def __init__(self):
        super(ConvNet, self).__init__()
        self.conv1 = nn.Conv2d(1, 3, kernel_size=3)
        self.fc = nn.Linear(192, 10)

    def forward(self, x):
        x = F.relu(F.max_pool2d(self.conv1(x), 3))
        x = x.view(-1, 192)
        x = self.fc(x)
        return F.log_softmax(x, dim=1)

    def get_weights(self):
        return {k: v.cpu() for k, v in self.state_dict().items()}

    def set_weights(self, weights):
        self.load_state_dict(weights)

    def get_gradients(self):
        grads = []
        for p in self.parameters():
            grad = None if p.grad is None else p.grad.data.cpu().numpy()
            grads.append(grad)
        return grads

    def set_gradients(self, gradients):
        for g, p in zip(gradients, self.parameters()):
            if g is not None:
                p.grad = torch.from_numpy(g)
```

5.50.2 Defining the Parameter Server

The parameter server will hold a copy of the model. During training, it will:

1. Receive gradients and apply them to its model.
2. Send the updated model back to the workers.

The `@ray.remote` decorator defines a remote process. It wraps the ParameterServer class and allows users to instantiate it as a remote actor.

```
@ray.remote
class ParameterServer(object):
    def __init__(self, lr):
```

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```
        self.model = ConvNet()
        self.optimizer = torch.optim.SGD(self.model.parameters(), lr=lr)

    def apply_gradients(self, *gradients):
        summed_gradients = [
            np.stack(gradient_zip).sum(axis=0)
            for gradient_zip in zip(*gradients)
        ]
        self.optimizer.zero_grad()
        self.model.set_gradients(summed_gradients)
        self.optimizer.step()
        return self.model.get_weights()

    def get_weights(self):
        return self.model.get_weights()
```

5.50.3 Defining the Worker

The worker will also hold a copy of the model. During training. it will continuously evaluate data and send gradients to the parameter server. The worker will synchronize its model with the Parameter Server model weights.

```
@ray.remote
class DataWorker(object):
    def __init__(self):
        self.model = ConvNet()
        self.data_iterator = iter(get_data_loader()[0])

    def compute_gradients(self, weights):
        self.model.set_weights(weights)
        try:
            data, target = next(self.data_iterator)
        except StopIteration:  # When the epoch ends, start a new epoch.
            self.data_iterator = iter(get_data_loader()[0])
            data, target = next(self.data_iterator)
        self.model.zero_grad()
        output = self.model(data)
        loss = F.nll_loss(output, target)
        loss.backward()
        return self.model.get_gradients()
```

5.50.4 Synchronous Parameter Server Training

We'll now create a synchronous parameter server training scheme. We'll first instantiate a process for the parameter server, along with multiple workers.

```
iterations = 200
num_workers = 2

ray.init(ignore_reinit_error=True)
ps = ParameterServer.remote(1e-2)
workers = [DataWorker.remote() for i in range(num_workers)]
```

We'll also instantiate a model on the driver process to evaluate the test accuracy during training.

```
model = ConvNet()
test_loader = get_data_loader()[1]
```

Training alternates between:

1. Computing the gradients given the current weights from the server
2. Updating the parameter server's weights with the gradients.

```
print("Running synchronous parameter server training.")
current_weights = ps.get_weights.remote()
for i in range(iterations):
    gradients = [
        worker.compute_gradients.remote(current_weights) for worker in workers
    ]
    # Calculate update after all gradients are available.
    current_weights = ps.apply_gradients.remote(*gradients)

    if i % 10 == 0:
        # Evaluate the current model.
        model.set_weights(ray.get(current_weights))
        accuracy = evaluate(model, test_loader)
        print("Iter {}: \taccuracy is {:.1f}".format(i, accuracy))

print("Final accuracy is {:.1f}.".format(accuracy))
# Clean up Ray resources and processes before the next example.
ray.shutdown()
```

5.50.5 Asynchronous Parameter Server Training

We'll now create a synchronous parameter server training scheme. We'll first instantiate a process for the parameter server, along with multiple workers.

```
print("Running Asynchronous Parameter Server Training.")

ray.init(ignore_reinit_error=True)
ps = ParameterServer.remote(1e-2)
workers = [DataWorker.remote() for i in range(num_workers)]
```

Here, workers will asynchronously compute the gradients given its current weights and send these gradients to the parameter server as soon as they are ready. When the Parameter server finishes applying the new gradient, the server will send back a copy of the current weights to the worker. The worker will then update the weights and repeat.

```
current_weights = ps.get_weights.remote()

gradients = {}
for worker in workers:
    gradients[worker.compute_gradients.remote(current_weights)] = worker

for i in range(iterations * num_workers):
    ready_gradient_list, _ = ray.wait(list(gradients))
    ready_gradient_id = ready_gradient_list[0]
    worker = gradients.pop(ready_gradient_id)

    # Compute and apply gradients.
    current_weights = ps.apply_gradients.remote(*[ready_gradient_id])
```

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```
    gradients[worker.compute_gradients.remote(current_weights)] = worker

    if i % 10 == 0:
        # Evaluate the current model after every 10 updates.
        model.set_weights(ray.get(current_weights))
        accuracy = evaluate(model, test_loader)
        print("Iter {}: \taccuracy is {:.1f}".format(i, accuracy))

print("Final accuracy is {:.1f}.".format(accuracy))
```

5.50.6 Final Thoughts

This approach is powerful because it enables you to implement a parameter server with a few lines of code as part of a Python application. As a result, this simplifies the deployment of applications that use parameter servers and to modify the behavior of the parameter server.

For example, sharding the parameter server, changing the update rule, switch between asynchronous and synchronous updates, ignoring straggler workers, or any number of other customizations, will only require a few extra lines of code.

Total running time of the script: (0 minutes 0.000 seconds)

5.51 Asynchronous Advantage Actor Critic (A3C)

This document walks through A3C, a state-of-the-art reinforcement learning algorithm. In this example, we adapt the OpenAI Universe Starter Agent implementation of A3C to use Ray.

View the code for this example.

Note: For an overview of Ray's reinforcement learning library, see RLlib.

To run the application, first install **ray** and then some dependencies:

```
pip install tensorflow
pip install six
pip install gym[atari]
pip install opencv-python-headless
pip install scipy
```

You can run the code with

```
rllib train --env=Pong-ram-v4 --run=A3C --config='{"num_workers": N}'
```

5.51.1 Reinforcement Learning

Reinforcement Learning is an area of machine learning concerned with **learning how an agent should act in an environment** so as to maximize some form of cumulative reward. Typically, an agent will observe the current state of the environment and take an action based on its observation. The action will change the state of the environment and will provide some numerical reward (or penalty) to the agent. The agent will then take in another observation and the process will repeat. **The mapping from state to action is a policy**, and in reinforcement learning, this policy is often represented with a deep neural network.

The **environment** is often a simulator (for example, a physics engine), and reinforcement learning algorithms often involve trying out many different sequences of actions within these simulators. These **rollouts** can often be done in parallel.

Policies are often initialized randomly and incrementally improved via simulation within the environment. To improve a policy, gradient-based updates may be computed based on the sequences of states and actions that have been observed. The gradient calculation is often delayed until a termination condition is reached (that is, the simulation has finished) so that delayed rewards have been properly accounted for. However, in the Actor Critic model, we can begin the gradient calculation at any point in the simulation rollout by predicting future rewards with a Value Function approximator.

In our A3C implementation, each worker, implemented as a Ray actor, continuously simulates the environment. The driver will create a task that runs some steps of the simulator using the latest model, computes a gradient update, and returns the update to the driver. Whenever a task finishes, the driver will use the gradient update to update the model and will launch a new task with the latest model.

There are two main parts to the implementation - the driver and the worker.

5.51.2 Worker Code Walkthrough

We use a Ray Actor to simulate the environment.

```
import numpy as np
import ray

@ray.remote
class Runner(object):
    """Actor object to start running simulation on workers.
        Gradient computation is also executed on this object."""
    def __init__(self, env_name, actor_id):
        # starts simulation environment, policy, and thread.
        # Thread will continuously interact with the simulation environment
        self.env = env = create_env(env_name)
        self.id = actor_id
        self.policy = LSTMPolicy()
        self.runner = RunnerThread(env, self.policy, 20)
        self.start()

    def start(self):
        # starts the simulation thread
        self.runner.start_runner()

    def pull_batch_from_queue(self):
        # Implementation details removed - gets partial rollout from queue
        return rollout

    def compute_gradient(self, params):
        self.policy.set_weights(params)
        rollout = self.pull_batch_from_queue()
        batch = process_rollout(rollout, gamma=0.99, lambda_=1.0)
        gradient = self.policy.compute_gradients(batch)
        info = {"id": self.id,
                "size": len(batch.a)}
        return gradient, info
```

5.51.3 Driver Code Walkthrough

The driver manages the coordination among workers and handles updating the global model parameters. The main training script looks like the following.

```
import numpy as np
import ray

def train(num_workers, env_name="PongDeterministic-v4"):
    # Setup a copy of the environment
    # Instantiate a copy of the policy - mainly used as a placeholder
    env = create_env(env_name, None, None)
    policy = LSTMPolicy(env.observation_space.shape, env.action_space.n, 0)
    obs = 0

    # Start simulations on actors
    agents = [Runner.remote(env_name, i) for i in range(num_workers)]

    # Start gradient calculation tasks on each actor
    parameters = policy.get_weights()
    gradient_list = [agent.compute_gradient.remote(parameters) for agent in agents]

    while True: # Replace with your termination condition
        # wait for some gradient to be computed - unblock as soon as the earliest␣
↪arrives
        done_id, gradient_list = ray.wait(gradient_list)

        # get the results of the task from the object store
        gradient, info = ray.get(done_id)[0]
        obs += info["size"]

        # apply update, get the weights from the model, start a new task on the same␣
↪actor object
        policy.apply_gradients(gradient)
        parameters = policy.get_weights()
        gradient_list.extend([agents[info["id"]].compute_gradient(parameters)])
    return policy
```

5.51.4 Benchmarks and Visualization

For the `PongDeterministic-v4` and an Amazon EC2 m4.16xlarge instance, we are able to train the agent with 16 workers in around 15 minutes. With 8 workers, we can train the agent in around 25 minutes.

You can visualize performance by running `tensorboard --logdir [directory]` in a separate screen, where `[directory]` is defaulted to `~/ray_results/`. If you are running multiple experiments, be sure to vary the directory to which Tensorflow saves its progress (found in `a3c.py`).

5.52 Best Practices: Ray with Tensorflow

This document describes best practices for using Ray with TensorFlow. Feel free to contribute if you think this document is missing anything.

5.52.1 Use Actors for Parallel Models

If you are training a deep network in the distributed setting, you may need to ship your deep network between processes (or machines). However, shipping the model is not always straightforward.

Tip: Avoid sending the Tensorflow model directly. A straightforward attempt to pickle a TensorFlow graph gives mixed results. Furthermore, creating a TensorFlow graph can take tens of seconds, and so serializing a graph and recreating it in another process will be inefficient.

It is recommended to replicate the same TensorFlow graph on each worker once at the beginning and then to ship only the weights between the workers.

Suppose we have a simple network definition (this one is modified from the TensorFlow documentation).

```
import tensorflow as tf
from tensorflow.keras import layers


def create_keras_model():
    model = tf.keras.Sequential()
    # Adds a densely-connected layer with 64 units to the model:
    model.add(layers.Dense(64, activation="relu", input_shape=(32, )))
    # Add another:
    model.add(layers.Dense(64, activation="relu"))
    # Add a softmax layer with 10 output units:
    model.add(layers.Dense(10, activation="softmax"))

    model.compile(
        optimizer=tf.train.RMSPropOptimizer(0.01),
        loss=tf.keras.losses.categorical_crossentropy,
        metrics=[tf.keras.metrics.categorical_accuracy])
    return model
```

It is strongly recommended you create actors to handle this. To do this, first initialize ray and define an Actor class:

```
import ray
import numpy as np

ray.init()

def random_one_hot_labels(shape):
    n, n_class = shape
    classes = np.random.randint(0, n_class, n)
    labels = np.zeros((n, n_class))
    labels[np.arange(n), classes] = 1
    return labels


# Use GPU wth
# @ray.remote(num_gpus=1)
@ray.remote
class Network():
    def __init__(self):
        self.model = create_keras_model()
        self.dataset = np.random.random((1000, 32))
        self.labels = random_one_hot_labels((1000, 10))
```

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```
    def train(self):
        history = self.model.fit(self.dataset, self.labels, verbose=False)
        return history.history

    def get_weights(self):
        return self.model.get_weights()

    def set_weights(self, weights):
        # Note that for simplicity this does not handle the optimizer state.
        self.model.set_weights(weights)
```

Then, we can instantiate this actor and train it on the separate process:

```
NetworkActor = Network.remote()
result_object_id = NetworkActor.train.remote()
ray.get(result_object_id)
```

We can then use `set_weights` and `get_weights` to move the weights of the neural network around. This allows us to manipulate weights between different models running in parallel without shipping the actual TensorFlow graphs, which are much more complex Python objects.

```
NetworkActor2 = Network.remote()
NetworkActor2.train.remote()
weights = ray.get(
    [NetworkActor.get_weights.remote(),
     NetworkActor2.get_weights.remote()])

averaged_weights = [(layer1 + layer2) / 2
                    for layer1, layer2 in zip(weights[0], weights[1])]

weight_id = ray.put(averaged_weights)
[
    actor.set_weights.remote(weight_id)
    for actor in [NetworkActor, NetworkActor2]
]
ray.get([actor.train.remote() for actor in [NetworkActor, NetworkActor2]])
```

5.52.2 Lower-level TF Utilities

Given a low-level TF definition:

```
import tensorflow as tf
import numpy as np

x_data = tf.placeholder(tf.float32, shape=[100])
y_data = tf.placeholder(tf.float32, shape=[100])

w = tf.Variable(tf.random_uniform([1], -1.0, 1.0))
b = tf.Variable(tf.zeros([1]))
y = w * x_data + b

loss = tf.reduce_mean(tf.square(y - y_data))
optimizer = tf.train.GradientDescentOptimizer(0.5)
grads = optimizer.compute_gradients(loss)
```

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```
train = optimizer.apply_gradients(grads)

init = tf.global_variables_initializer()
sess = tf.Session()
```

To extract the weights and set the weights, you can use the following helper method.

```
import ray.experimental.tf_utils
variables = ray.experimental.tf_utils.TensorFlowVariables(loss, sess)
```

The `TensorFlowVariables` object provides methods for getting and setting the weights as well as collecting all of the variables in the model.

Now we can use these methods to extract the weights, and place them back in the network as follows.

```
sess = tf.Session()
# First initialize the weights.
sess.run(init)
# Get the weights
weights = variables.get_weights()  # Returns a dictionary of numpy arrays
# Set the weights
variables.set_weights(weights)
```

Note: If we were to set the weights using the `assign` method like below, each call to `assign` would add a node to the graph, and the graph would grow unmanageably large over time.

```
w.assign(np.zeros(1))  # This adds a node to the graph every time you call it.
b.assign(np.zeros(1))  # This adds a node to the graph every time you call it.
```

class ray.experimental.tf_utils.**TensorFlowVariables**(*output*, *sess=None*, *input_variables=None*)

A class used to set and get weights for Tensorflow networks.

sess
The tensorflow session used to run assignment.

Type tf.Session

variables
Extracted variables from the loss or additional variables that are passed in.

Type Dict[str, tf.Variable]

placeholders
Placeholders for weights.

Type Dict[str, tf.placeholders]

assignment_nodes
Nodes that assign weights.

Type Dict[str, tf.Tensor]

set_session(*sess*)
Sets the current session used by the class.

Parameters **sess** (*tf.Session*) – Session to set the attribute with.

get_flat_size()
Returns the total length of all of the flattened variables.

Returns The length of all flattened variables concatenated.

get_flat()
Gets the weights and returns them as a flat array.

Returns 1D Array containing the flattened weights.

set_flat(*new_weights*)
Sets the weights to new_weights, converting from a flat array.

Note: You can only set all weights in the network using this function, i.e., the length of the array must match get_flat_size.

Parameters **new_weights** (*np.ndarray*) – Flat array containing weights.

get_weights()
Returns a dictionary containing the weights of the network.

Returns Dictionary mapping variable names to their weights.

set_weights(*new_weights*)
Sets the weights to new_weights.

Note: Can set subsets of variables as well, by only passing in the variables you want to be set.

Parameters **new_weights** (*Dict*) – Dictionary mapping variable names to their weights.

Note: This may not work with *tf.Keras*.

Troubleshooting

Note that `TensorFlowVariables` uses variable names to determine what variables to set when calling `set_weights`. One common issue arises when two networks are defined in the same TensorFlow graph. In this case, TensorFlow appends an underscore and integer to the names of variables to disambiguate them. This will cause `TensorFlowVariables` to fail. For example, if we have a class definiton `Network` with a `TensorFlowVariables` instance:

```
import ray
import tensorflow as tf

class Network(object):
    def __init__(self):
        a = tf.Variable(1)
        b = tf.Variable(1)
        c = tf.add(a, b)
        sess = tf.Session()
        init = tf.global_variables_initializer()
        sess.run(init)
        self.variables = ray.experimental.tf_utils.TensorFlowVariables(c, sess)

    def set_weights(self, weights):
```

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```
        self.variables.set_weights(weights)

    def get_weights(self):
        return self.variables.get_weights()
```

and run the following code:

```
a = Network()
b = Network()
b.set_weights(a.get_weights())
```

the code would fail. If we instead defined each network in its own TensorFlow graph, then it would work:

```
with tf.Graph().as_default():
    a = Network()
with tf.Graph().as_default():
    b = Network()
b.set_weights(a.get_weights())
```

This issue does not occur between actors that contain a network, as each actor is in its own process, and thus is in its own graph. This also does not occur when using `set_flat`.

Another issue to keep in mind is that `TensorFlowVariables` needs to add new operations to the graph. If you close the graph and make it immutable, e.g. creating a `MonitoredTrainingSession` the initialization will fail. To resolve this, simply create the instance before you close the graph.

5.53 Best Practices: Ray with PyTorch

This document describes best practices for using Ray with PyTorch. Feel free to contribute if you think this document is missing anything.

5.53.1 Downloading Data

It is very common for multiple Ray actors running PyTorch to have code that downloads the dataset for training and testing.

```
# This is running inside a Ray actor
# ...
torch.utils.data.DataLoader(
    datasets.MNIST(
        "../data", train=True, download=True,
        transform=transforms.Compose([
            transforms.ToTensor(),
            transforms.Normalize((0.1307,), (0.3081,))
        ])),
    128, shuffle=True, **kwargs)
# ...
```

This may cause different processes to simultaneously download the data and cause data corruption. One easy workaround for this is to use `Filelock`:

```
from filelock import FileLock

with FileLock("./data.lock"):
    torch.utils.data.DataLoader(
        datasets.MNIST(
            "./data", train=True, download=True,
            transform=transforms.Compose([
                transforms.ToTensor(),
                transforms.Normalize((0.1307,), (0.3081,))
            ])),
        128, shuffle=True, **kwargs)
```

5.53.2 Use Actors for Parallel Models

One common use case for using Ray with PyTorch is to parallelize the training of multiple models.

Tip: Avoid sending the PyTorch model directly. Send `model.state_dict()`, as PyTorch tensors are natively supported by the Plasma Object Store.

Suppose we have a simple network definition (this one is modified from the PyTorch documentation).

```
import torch
import torch.nn as nn
import torch.nn.functional as F


class Model(nn.Module):
    def __init__(self):
        super(Model, self).__init__()
        self.conv1 = nn.Conv2d(1, 20, 5, 1)
        self.conv2 = nn.Conv2d(20, 50, 5, 1)
        self.fc1 = nn.Linear(4 * 4 * 50, 500)
        self.fc2 = nn.Linear(500, 10)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        x = F.max_pool2d(x, 2, 2)
        x = F.relu(self.conv2(x))
        x = F.max_pool2d(x, 2, 2)
        x = x.view(-1, 4 * 4 * 50)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return F.log_softmax(x, dim=1)
```

Along with these helper training functions:

```
from filelock import FileLock
from torchvision import datasets, transforms


def train(model, device, train_loader, optimizer):
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        # This break is for speeding up the tutorial.
```

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```
        if batch_idx * len(data) > 1024:
            return
        data, target = data.to(device), target.to(device)
        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        loss.backward()
        optimizer.step()


def test(model, device, test_loader):
    model.eval()
    test_loss = 0
    correct = 0
    with torch.no_grad():
        for data, target in test_loader:
            data, target = data.to(device), target.to(device)
            output = model(data)

            # sum up batch loss
            test_loss += F.nll_loss(
                output, target, reduction="sum").item()
            pred = output.argmax(
                dim=1,
                keepdim=True)
            correct += pred.eq(target.view_as(pred)).sum().item()

    test_loss /= len(test_loader.dataset)
    return {
        "loss": test_loss,
        "accuracy": 100. * correct / len(test_loader.dataset)
    }


def dataset_creators(use_cuda):
    kwargs = {"num_workers": 1, "pin_memory": True} if use_cuda else {}
    with FileLock("./data.lock"):
        train_loader = torch.utils.data.DataLoader(
            datasets.MNIST(
                "./data",
                train=True,
                download=True,
                transform=transforms.Compose([
                    transforms.ToTensor(),
                    transforms.Normalize((0.1307, ), (0.3081, ))
                ])),
            128,
            shuffle=True,
            **kwargs)
    test_loader = torch.utils.data.DataLoader(
        datasets.MNIST(
            "./data",
            train=False,
            transform=transforms.Compose([
                transforms.ToTensor(),
                transforms.Normalize((0.1307, ), (0.3081, ))
            ])),
```

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```
        128,
        shuffle=True,
        **kwargs)

    return train_loader, test_loader
```

Let's now define a class that captures the training process.

```
import torch.optim as optim


class Network():
    def __init__(self, lr=0.01, momentum=0.5):
        use_cuda = torch.cuda.is_available()
        self.device = device = torch.device("cuda" if use_cuda else "cpu")
        self.train_loader, self.test_loader = dataset_creators(use_cuda)

        self.model = Model().to(device)
        self.optimizer = optim.SGD(
            self.model.parameters(), lr=lr, momentum=momentum)

    def train(self):
        train(self.model, self.device, self.train_loader, self.optimizer)
        return test(self.model, self.device, self.test_loader)

    def get_weights(self):
        return self.model.state_dict()

    def set_weights(self, weights):
        self.model.load_state_dict(weights)

    def save(self):
        torch.save(self.model.state_dict(), "mnist_cnn.pt")


net = Network()
net.train()
```

To train multiple models, you can convert the above class into a Ray Actor class.

```
import ray
ray.init()

RemoteNetwork = ray.remote(Network)
# Use the below instead of `ray.remote(network)` to leverage the GPU.
# RemoteNetwork = ray.remote(num_gpus=1)(Network)
```

Then, we can instantiate multiple copies of the Model, each running on different processes. If GPU is enabled, each copy runs on a different GPU. See the GPU guide for more information.

```
NetworkActor = RemoteNetwork.remote()
NetworkActor2 = RemoteNetwork.remote()

ray.get([NetworkActor.train.remote(), NetworkActor2.train.remote()])
```

We can then use `set_weights` and `get_weights` to move the weights of the neural network around. The below example averages the weights of the two networks and sends them back to update the original actors.

```
weights = ray.get(
    [NetworkActor.get_weights.remote(),
     NetworkActor2.get_weights.remote()])

from collections import OrderedDict
averaged_weights = OrderedDict(
    [(k, (weights[0][k] + weights[1][k]) / 2) for k in weights[0]])

weight_id = ray.put(averaged_weights)
[
    actor.set_weights.remote(weight_id)
    for actor in [NetworkActor, NetworkActor2]
]
ray.get([actor.train.remote() for actor in [NetworkActor, NetworkActor2]])
```

5.54 Development Tips

5.54.1 Compilation

To speed up compilation, be sure to install Ray with

```
cd ray/python
pip install -e . --verbose
```

The `-e` means "editable", so changes you make to files in the Ray directory will take effect without reinstalling the package. In contrast, if you do `python setup.py install`, files will be copied from the Ray directory to a directory of Python packages (often something like `/home/ubuntu/anaconda3/lib/python3.6/site-packages/ray`). This means that changes you make to files in the Ray directory will not have any effect.

If you run into **Permission Denied** errors when running `pip install`, you can try adding `--user`. You may also need to run something like `sudo chown -R $USER /home/ubuntu/anaconda3` (substituting in the appropriate path).

If you make changes to the C++ files, you will need to recompile them. However, you do not need to rerun `pip install -e .`. Instead, you can recompile much more quickly by doing

```
cd ray
bazel build //:ray_pkg
```

This command is not enough to recompile all C++ unit tests. To do so, see *Testing locally*.

5.54.2 Debugging

Starting processes in a debugger

When processes are crashing, it is often useful to start them in a debugger. Ray currently allows processes to be started in the following:

- valgrind
- the valgrind profiler
- the perftools profiler
- gdb

- tmux

To use any of these tools, please make sure that you have them installed on your machine first (`gdb` and `valgrind` on MacOS are known to have issues). Then, you can launch a subset of ray processes by adding the environment variable `RAY_{PROCESS_NAME}_{DEBUGGER}=1`. For instance, if you wanted to start the raylet in `valgrind`, then you simply need to set the environment variable `RAY_RAYLET_VALGRIND=1`.

To start a process inside of `gdb`, the process must also be started inside of `tmux`. So if you want to start the raylet in `gdb`, you would start your Python script with the following:

```
RAY_RAYLET_GDB=1 RAY_RAYLET_TMUX=1 python
```

You can then list the `tmux` sessions with `tmux ls` and attach to the appropriate one.

You can also get a core dump of the `raylet` process, which is especially useful when filing issues. The process to obtain a core dump is OS-specific, but usually involves running `ulimit -c unlimited` before starting Ray to allow core dump files to be written.

Inspecting Redis shards

To inspect Redis, you can use the global state API. The easiest way to do this is to start or connect to a Ray cluster with `ray.init()`, then query the API like so:

```
ray.init()
ray.nodes()
# Returns current information about the nodes in the cluster, such as:
# [{'ClientID': '2a9d2b34ad24a37ed54e4fcd32bf19f915742f5b',
#   'IsInsertion': True,
#   'NodeManagerAddress': '1.2.3.4',
#   'NodeManagerPort': 43280,
#   'ObjectManagerPort': 38062,
#   'ObjectStoreSocketName': '/tmp/ray/session_2019-01-21_16-28-05_4216/sockets/
↪plasma_store',
#   'RayletSocketName': '/tmp/ray/session_2019-01-21_16-28-05_4216/sockets/raylet',
#   'Resources': {'CPU': 8.0, 'GPU': 1.0}}]
```

To inspect the primary Redis shard manually, you can also query with commands like the following.

```
r_primary = ray.worker.global_worker.redis_client
r_primary.keys("*")
```

To inspect other Redis shards, you will need to create a new Redis client. For example (assuming the relevant IP address is `127.0.0.1` and the relevant port is `1234`), you can do this as follows.

```
import redis
r = redis.StrictRedis(host='127.0.0.1', port=1234)
```

You can find a list of the relevant IP addresses and ports by running

```
r_primary.lrange('RedisShards', 0, -1)
```

Backend logging

The `raylet` process logs detailed information about events like task execution and object transfers between nodes. To set the logging level at runtime, you can set the `RAY_BACKEND_LOG_LEVEL` environment variable before starting Ray. For example, you can do:

```
export RAY_BACKEND_LOG_LEVEL=debug
ray start
```

This will print any `RAY_LOG(DEBUG)` lines in the source code to the `raylet.err` file, which you can find in the Temporary Files.

5.54.3 Testing locally

Suppose that one of the tests (e.g., `test_basic.py`) is failing. You can run that test locally by running `python -m pytest -v python/ray/tests/test_basic.py`. However, doing so will run all of the tests which can take a while. To run a specific test that is failing, you can do

```
cd ray
python -m pytest -v python/ray/tests/test_basic.py::test_keyword_args
```

When running tests, usually only the first test failure matters. A single test failure often triggers the failure of subsequent tests in the same script.

To compile and run all C++ tests, you can run:

```
cd ray
bazel test $(bazel query 'kind(cc_test, ...)')
```

5.54.4 Linting

Running linter locally: To run the Python linter on a specific file, run something like `flake8 ray/python/ray/worker.py`. You may need to first run `pip install flake8`.

Autoformatting code. We use yapf for linting, and the config file is located at `.style.yapf`. We recommend running `scripts/yapf.sh` prior to pushing to format changed files. Note that some projects such as dataframes and rllib are currently excluded.

5.55 Profiling for Ray Developers

This document details, for Ray developers, how to use `pprof` to profile Ray binaries.

5.55.1 Installation

These instructions are for Ubuntu only. Attempts to get `pprof` to correctly symbolize on Mac OS have failed.

```
sudo apt-get install google-perftools libgoogle-perftools-dev
```

5.55.2 Launching the to-profile binary

If you want to launch Ray in profiling mode, define the following variables:

```
export RAYLET_PERFTOOLS_PATH=/usr/lib/x86_64-linux-gnu/libprofiler.so
export RAYLET_PERFTOOLS_LOGFILE=/tmp/pprof.out
```

The file `/tmp/pprof.out` will be empty until you let the binary run the target workload for a while and then `kill` it via `ray stop` or by letting the driver exit.

5.55.3 Visualizing the CPU profile

The output of `pprof` can be visualized in many ways. Here we output it as a zoomable `.svg` image displaying the call graph annotated with hot paths.

```
# Use the appropriate path.
RAYLET=ray/python/ray/core/src/ray/raylet/raylet

google-pprof -svg $RAYLET /tmp/pprof.out > /tmp/pprof.svg
# Then open the .svg file with Chrome.

# If you realize the call graph is too large, use -focus=<some function> to zoom
# into subtrees.
google-pprof -focus=epoll_wait -svg $RAYLET /tmp/pprof.out > /tmp/pprof.svg
```

Here's a snapshot of an example svg output, taken from the official documentation:

5.55.4 Running Microbenchmarks

To run a set of single-node Ray microbenchmarks, use:

```
ray microbenchmark
```

The following are the results for the 0.7.5 release on a Python 3 / a m4.16xl instance:

```
single core get calls per second 12169.8 +- 386.41
single core put calls per second 3117.45 +- 94.17
single core put gigabytes per second 11.32 +- 3.4
multi core put calls per second 16221.06 +- 895.13
multi core put gigabytes per second 24.14 +- 0.29
single core tasks sync per second 887.77 +- 3.69
single core tasks async per second 4524.45 +- 196.39
multi core tasks async per second 6963.49 +- 161.31
single core actor calls sync per second 762.4 +- 56.47
single core actor calls async per second 1030.44 +- 45.42
multi core actor calls async per second 6065.92 +- 175.05
```

5.55.5 References

- The pprof documentation.
- A Go version of pprof.
- The gperftools, including libprofiler, tcmalloc, and other goodies.

5.56 Fault Tolerance

This document describes the handling of failures in Ray.

5.56.1 Machine and Process Failures

Each **raylet** (the scheduler process) sends heartbeats to a **monitor** process. If the monitor does not receive any heartbeats from a given raylet for some period of time (about ten seconds), then it will mark that process as dead.

5.56.2 Lost Objects

If an object is needed but is lost or was never created, then the task that created the object will be re-executed to create the object. If necessary, tasks needed to create the input arguments to the task being re-executed will also be re-executed. This is the standard *lineage-based fault tolerance* strategy used by other systems like Spark.

5.56.3 Actors

When an actor dies (either because the actor process crashed or because the node that the actor was on died), by default any attempt to get an object from that actor that cannot be created will raise an exception. Subsequent releases will include an option for automatically restarting actors.

5.56.4 Current Limitations

At the moment, Ray does not handle all failure scenarios. We are working on addressing these known problems.

Process Failures

1. Ray does not recover from the failure of any of the following processes: any of the Redis servers and the monitor process.
2. If a driver fails, that driver will not be restarted and the job will not complete.

Lost Objects

1. If an object is constructed by a call to `ray.put` on the driver, is then evicted, and is later needed, Ray will not reconstruct this object.
2. If an object is constructed by an actor method, is then evicted, and is later needed, Ray will not reconstruct this object.

5.57 Getting Involved

We welcome (and encourage!) all forms of contributions to Ray, including and not limited to:

- Code reviewing of patches and PRs.
- Pushing patches.
- Documentation and examples.
- Community participation in forums and issues.
- Code readability and code comments to improve readability.
- Test cases to make the codebase more robust.
- Tutorials, blog posts, talks that promote the project.

5.57.1 What can I work on?

We use Github to track issues, feature requests, and bugs. Take a look at the ones labeled "good first issue" and "help wanted" for a place to start.

5.57.2 Submitting and Merging a Contribution

There are a couple steps to merge a contribution.

1. First rebase your development branch on the most recent version of master.

```
git remote add upstream https://github.com/ray-project/ray.git
git fetch upstream
git rebase upstream/master
```

2. Make sure all existing tests pass.
3. If introducing a new feature or patching a bug, be sure to add new test cases in the relevant file in *ray/python/ray/tests/*.
4. Document the code. Public functions need to be documented, and remember to provide an usage example if applicable.
5. Request code reviews from other contributors and address their comments. One fast way to get reviews is to help review others' code so that they return the favor. You should aim to improve the code as much as possible before the review. We highly value patches that can get in without extensive reviews.
6. Reviewers will merge and approve the pull request; be sure to ping them if the pull request is getting stale.

5.57.3 Testing

Even though we have hooks to run unit tests automatically for each pull request, we recommend you to run unit tests locally beforehand to reduce reviewers' burden and speedup review process.

```
pytest ray/python/ray/Ray/tests/
```

Documentation should be documented in Google style format.

We also have tests for code formatting and linting that need to pass before merge. Install `yapf==0.23, flake8, flake8-quotes`. You can run the following locally:

```
ray/scripts/format.sh
```

5.57.4 Becoming a Reviewer

We identify reviewers from active contributors. Reviewers are individuals who not only actively contribute to the project and are also willing to participate in the code review of new contributions. A pull request to the project has to be reviewed by at least one reviewer in order to be merged. There is currently no formal process, but active contributors to Ray will be solicited by current reviewers.

5.57.5 More Resources for Getting Involved

- ray-dev@googlegroups.com: For discussions about development or any general questions.

- StackOverflow: For questions about how to use Ray.
- GitHub Issues: For reporting bugs and feature requests.
- Pull Requests: For submitting code contributions.
- Meetup Group: Join our meetup group.
- Community Slack: Join our Slack workspace.
- Twitter: Follow updates on Twitter.

Note: These tips are based off of the TVM contributor guide.

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