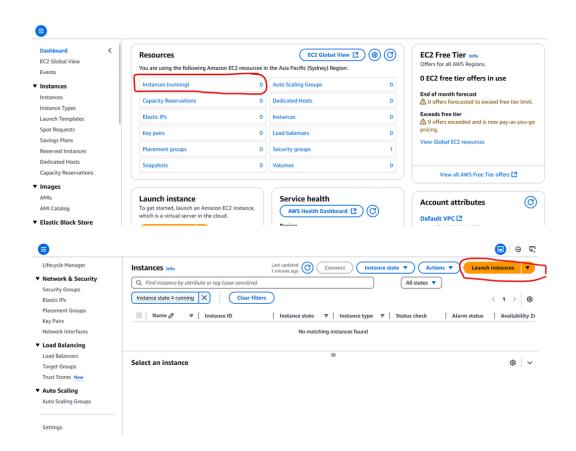
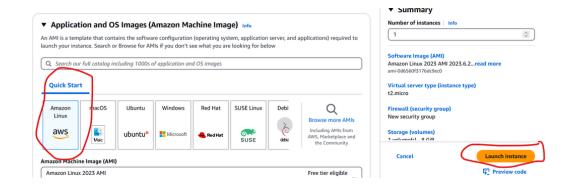
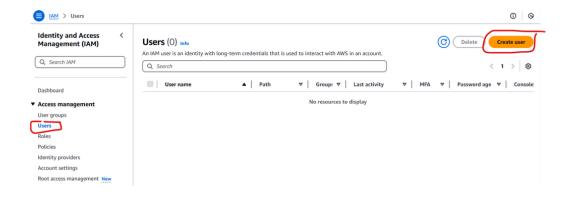
# AWS training: Ray cluster deployment

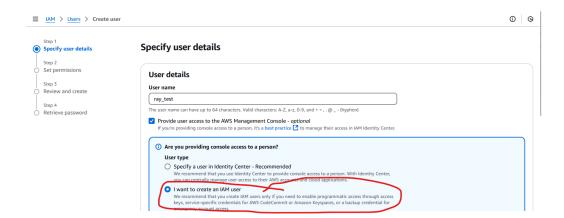
EC2 setup (free tier)
Installation
Credentials
Launch Ray cluster
EFS
Setup
IAM Role and EC2 Instance Profile
Accessing S3
Amazon CloudWatch
Train ML model

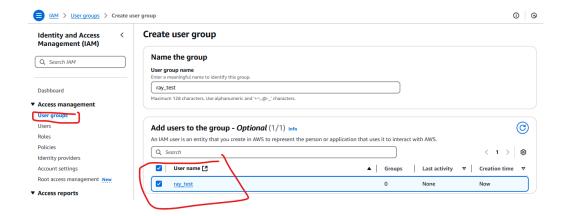
# EC2 setup (free tier)

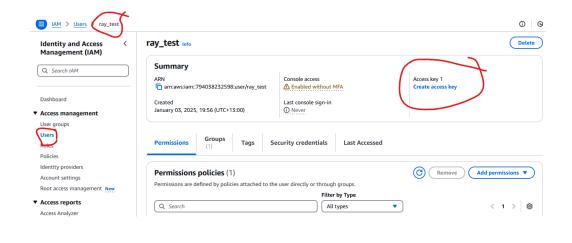


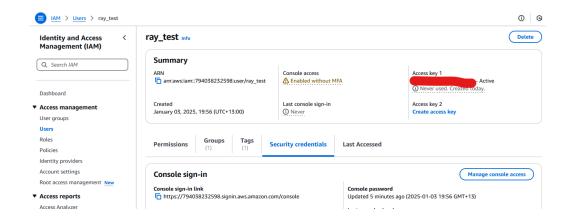












# Installation

poetry add boto3 botocore ray[default]

# Credentials

```
# setup AWS credentials using environment variables
export AWS_ACCESS_KEY_ID=foo

export AWS_SECRET_ACCESS_KEY=bar

export AWS_SESSION_TOKEN=baz

# alternatively, you can setup AWS credentials using ~/.aws/credentials file

echo "[default]

aws_access_key_id=foo

aws_secret_access_key=bar

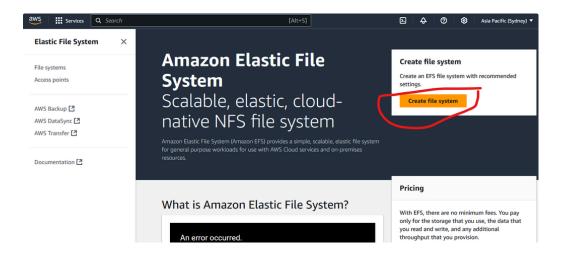
aws_session_token=baz" >> ~/.aws/credentials
```

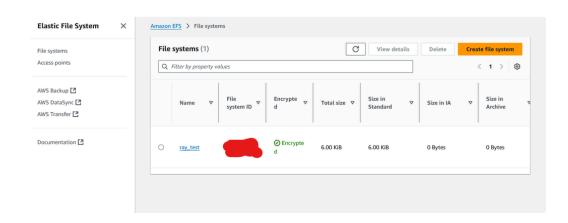
# Launch Ray cluster

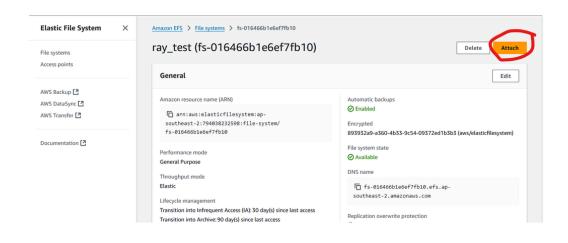
```
1  # Download the example-full.yaml
2  wget https://raw.githubusercontent.com/ray-project/ray/master/python/ray/autoscaler/aws/example-full.yaml
3
```

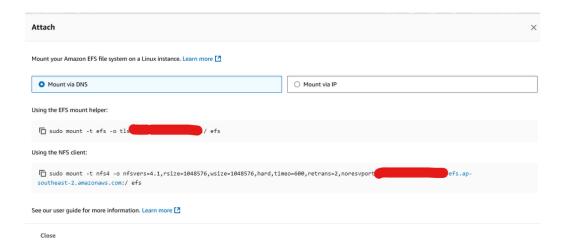
```
4 # Create or update the cluster. When the command finishes, it will print
5 # out the command that can be used to SSH into the cluster head node.
6 ray up example-full.yaml
7 # This will take a while...
8
  10
11 # Jump into the cluster
12 # Get a remote shell on the head node.
13 ray attach example-full.yaml
14
16
17 pwd
18 ls
19
20 # Try running a Ray program.
21 python -c 'import ray; ray.init()'
22 exit
23
24 # Tear down the cluster.
25 ray down example-full.yaml
```

## **EFS**









# Setup

Replace {{FileSystemId}} below

```
1 # Note You need to replace the {{FileSystemId}} with your own EFS ID before using the config.
2 # You may also need to modify the SecurityGroupIds for the head and worker nodes in the config file.
3
4 setup_commands:
5
       - sudo kill -9 `sudo lsof /var/lib/dpkg/lock-frontend | awk '{print $2}' | tail -n 1`;
6
            sudo pkill -9 apt-get;
7
            sudo pkill -9 dpkg;
8
            sudo dpkg --configure -a;
9
            sudo apt-get -y install binutils;
10
            cd $HOME;
11
            git clone https://github.com/aws/efs-utils;
            cd $HOME/efs-utils;
12
13
            ./build-deb.sh;
14
            sudo apt-get -y install ./build/amazon-efs-utils*deb;
15
            cd $HOME;
16
            mkdir efs;
17
            sudo mount -t efs {{FileSystemId}}:/ efs;
18
            sudo chmod 777 efs;
```

## IAM Role and EC2 Instance Profile

By default, Ray nodes in a Ray AWS cluster have full EC2 and S3 permissions (i.e. arn:aws:iam::aws:policy/AmazonEC2FullAccess and arn:aws:iam::aws:policy/AmazonS3FullAccess). This is a good default for trying out Ray clusters but you may want to change the permissions Ray nodes have for various reasons (e.g. to reduce the permissions for security reasons). You can do so by providing a custom IamInstanceProfile to the related node\_config:

#### **Accessing S3**

In various scenarios, worker nodes may need write access to an S3 bucket, e.g., Ray Tune has an option to write checkpoints to S3 instead of syncing them directly back to the driver.

If you see errors like "Unable to locate credentials", make sure that the correct IamInstanceProfile is configured for worker nodes in your cluster config file. This may look like:

You can verify if the set up is correct by SSHing into a worker node and running

```
1 aws configure list
2
```

You should see something like

```
Name
                          Value
                                        Type
                                               Location
2
      ----
                          ____
                                         ----
                                               _____
3
   profile
                      <not set>
                                        None
                                               None
             ***********XXXX
4 access key
                                     iam-role
            ************Y
5 secret_key
                                     iam-role
6
     region
                       <not set>
                                        None
                                              None
7
```

Please refer to this discussion for more details on accessing S3.

#### Amazon CloudWatch

Create cloudwatch-basic.yaml

```
# cloudwatch-basic.yaml

provider:
type: aws
region: us-west-2
availability_zone: us-west-2a
```

```
# Start by defining a `cloudwatch` section to enable CloudWatch integration with your Ray cluster.
8
       cloudwatch:
9
           agent:
10
               # Path to Unified CloudWatch Agent config file
11
               config: "cloudwatch/example-cloudwatch-agent-config.json"
12
13
               # CloudWatch Dashboard name
14
               name: "example-dashboard-name"
               # Path to the CloudWatch Dashboard config file
               config: "cloudwatch/example-cloudwatch-dashboard-config.json"
16
17
18 auth:
19
       ssh_user: ubuntu
20
21 available_node_types:
22
       ray.head.default:
23
           node_config:
24
           InstanceType: c5a.large
25
           ImageId: ami-0d88d9cbe28fac870 # Unified CloudWatch agent pre-installed AMI, us-west-2
26
           resources: {}
     ray.worker.default:
27
28
           node config:
29
               InstanceType: c5a.large
30
               ImageId: ami-0d88d9cbe28fac870 # Unified CloudWatch agent pre-installed AMI, us-west-2
               IamInstanceProfile:
31
32
                   Name: ray-autoscaler-cloudwatch-v1
33
           resources: {}
           min workers: 0
1 mkdir cloudwatch
2 cd cloudwatch
3 wget https://raw.githubusercontent.com/ray-project/ray/master/python/ray/autoscaler/aws/cloudwatch/example-
```

```
cd cloudwatch
wget https://raw.githubusercontent.com/ray-project/ray/master/python/ray/autoscaler/aws/cloudwatch/example-
cloudwatch-agent-config.json
wget https://raw.githubusercontent.com/ray-project/ray/master/python/ray/autoscaler/aws/cloudwatch/example-
cloudwatch-dashboard-config.json

cd ..
ray up cloudwatch-basic.yaml
```

#### Train ML model

```
1 ray up example-full.yaml
2
4
5 # Jump into the cluster
6 # Get a remote shell on the head node.
7 ray attach example-full.yaml
8
10
11 python -c """
12 import math
13 import torch
14 import gpytorch
15 from matplotlib import pyplot as plt
16 import ray
```

```
17
18 ray.init()
19
20 @ray.remote
21 def get_data():
22
       train_x = torch.linspace(0, 1, 100)
23
       # True function is sin(2*pi*x) with Gaussian noise
24
       train_y = torch.sin(train_x * (2 * math.pi)) + torch.randn(train_x.size()) * math.sqrt(0.04)
25
       test x = torch.linspace(0, 1, 51)
26
27
        return train_x, train_y, test_x
28
29
30 # We will use the simplest form of GP model, exact inference
31 class ExactGPModel(gpytorch.models.ExactGP):
       def __init__(self, train_x, train_y, likelihood):
32
33
            super(ExactGPModel, self).__init__(train_x, train_y, likelihood)
34
            self.mean module = gpytorch.means.ConstantMean()
35
            self.covar_module = gpytorch.kernels.ScaleKernel(gpytorch.kernels.RBFKernel())
36
37
       def forward(self, x):
38
           mean x = self.mean module(x)
           covar x = self.covar module(x)
39
40
            return gpytorch.distributions.MultivariateNormal(mean_x, covar_x)
41
42 @ray.remote
43 def get model():
44
        # initialize likelihood and model
45
       likelihood = gpytorch.likelihoods.GaussianLikelihood()
46
        model = ExactGPModel(train_x, train_y, likelihood)
47
48
       # Find optimal model hyperparameters
49
       model.train()
50
       likelihood.train()
51
52
       # Use the adam optimizer
       optimizer = torch.optim.Adam(model.parameters(), lr=0.1) # Includes GaussianLikelihood parameters
53
54
55
       # "Loss" for GPs - the marginal log likelihood
56
       mll = gpytorch.mlls.ExactMarginalLogLikelihood(likelihood, model)
57
58
        return model, likelihood, mll, optimizer
59
60 train_x, train_y, test_x = ray.get(get_data.remote())
61 model, likelihood, mll, optimizer = ray.get(get model.remote())
62
63 @ray.remote
64 def train_model(training_iter, model, mll, optimizer):
65
66
        for i in range(training iter):
67
           # Zero gradients from previous iteration
           optimizer.zero grad()
68
69
           # Output from model
70
           output = model(train x)
71
           # Calc loss and backprop gradients
72
           loss = -mll(output, train_y)
73
           loss.backward()
74
            print('Iter %d/%d - Loss: %.3f lengthscale: %.3f noise: %.3f' % (
```

```
75
                i + 1, training iter, loss.item(),
 76
                model.covar_module.base_kernel.lengthscale.item(),
                model.likelihood.noise.item()
77
 78
            ))
79
            optimizer.step()
80
81
        return model, mll, optimizer
82
 83 training iter = 5
84 model, mll, optimizer = ray.get(train_model.remote(
85
        training_iter, model, mll, optimizer
86 ))
87
88 @ray.remote
89 def eval_model(model, likelihood, train_x, train_y, test_x):
        # Get into evaluation (predictive posterior) mode
90
91
        model.eval()
        likelihood.eval()
92
93
94
        # Test points are regularly spaced along [0,1]
95
        # Make predictions by feeding model through likelihood
        with torch.no grad(), gpytorch.settings.fast pred var():
96
            observed_pred = likelihood(model(test_x))
97
98
99
        with torch.no grad():
100
            # Initialize plot
101
            f, ax = plt.subplots(1, 1, figsize=(4, 3))
102
103
            # Get upper and lower confidence bounds
104
            lower, upper = observed_pred.confidence_region()
            # Plot training data as black stars
105
            ax.plot(train_x.numpy(), train_y.numpy(), 'k*')
106
107
            # Plot predictive means as blue line
108
            ax.plot(test_x.numpy(), observed_pred.mean.numpy(), 'b')
109
            # Shade between the lower and upper confidence bounds
110
            ax.fill between(test x.numpy(), lower.numpy(), upper.numpy(), alpha=0.5)
111
            ax.set_ylim([-3, 3])
            ax.legend(['Observed Data', 'Mean', 'Confidence'])
112
113
114
            f.savefig('/tmp/gp_plot.png')
115
116 ray.get(eval model.remote(
117
        model, likelihood, train_x, train_y, test_x
118 ))
119
120 ray.shutdown()
121 """
122
123 ls /tmp
124 exit
125
127
128 # Tear down the cluster.
129 ray down example-full.yaml
```