CS795-1c-b

April 19, 2022

[1]:
```
!pip install pytorch-ignite torchsummary
```

```
Requirement already satisfied: pytorch-ignite in
/home/pankaj/anaconda3/lib/python3.9/site-packages (0.4.8)
Requirement already satisfied: torchsummary in
/home/pankaj/anaconda3/lib/python3.9/site-packages (1.5.1)
Requirement already satisfied: torch<2,>=1.3 in
/home/pankaj/anaconda3/lib/python3.9/site-packages (from pytorch-ignite)
(1.10.0+cu113)
Requirement already satisfied: typing-extensions in
/home/pankaj/.local/lib/python3.9/site-packages (from torch<2,>=1.3->pytorch-
ignite) (4.0.0)
```

[2]:
```
import torch
import torchvision
import ignite

print(*map(lambda m: ": ".join((m.__name__, m.__version__)), (torch,␣
↪torchvision, ignite)), sep="\n")
```

```
torch: 1.10.0+cu113
torchvision: 0.11.1+cu113
ignite: 0.4.8
```

0.1 Import Libraries

Note: torchsummary is an optional dependency here.

[3]:
```
import os
import logging
import matplotlib.pyplot as plt

import numpy as np

from torchsummary import summary

import torch
import torch.nn as nn
import torch.optim as optim
```

```
import torchvision.transforms as transforms
import torchvision.utils as vutils

from ignite.engine import Engine, Events
import ignite.distributed as idist
```

0.2 Reproductibility and logging details

[4]:
```
ignite.utils.manual_seed(999)
```

[5]:
```
ignite.utils.setup_logger(name="ignite.distributed.auto.auto_dataloader",␣
 ↪level=logging.WARNING)
ignite.utils.setup_logger(name="ignite.distributed.launcher.Parallel",␣
 ↪level=logging.WARNING)
```

[5]: <Logger ignite.distributed.launcher.Parallel (WARNING)>

[6]:
```
import math
import torch
from torch.optim import Optimizer

required = object()


class Extragradient(Optimizer):

    def __init__(self, params, defaults):
        super(Extragradient, self).__init__(params, defaults)
        self.params_copy = []

    def update(self, p, group):
        raise NotImplementedError

    def extrapolation(self):

        # Check if a copy of the parameters was already made.
        is_empty = len(self.params_copy) == 0
        for group in self.param_groups:
            for p in group['params']:
                u = self.update(p, group)
                if is_empty:
                    # Save the current parameters for the update step.
                    # Several extrapolation step can be made before each update
                    # but only the parameters before the first extrapolation␣
 ↪step
                    # are saved.
```

```
                    self.params_copy.append(p.data.clone())
                if u is None:
                    continue
                # Update the current parameters
                p.data.add_(u)

    def step(self, closure=None):

        if len(self.params_copy) == 0:
            raise RuntimeError('Need to call extrapolation before calling step.
↪')

        loss = None
        if closure is not None:
            loss = closure()

        i = -1
        for group in self.param_groups:
            for p in group['params']:
                i += 1
                u = self.update(p, group)
                if u is None:
                    continue
                # Update the parameters saved during the extrapolation step
                p.data = self.params_copy[i].add_(u)

        # Free the old parameters
        self.params_copy = []
        return loss


class ExtraSGD(Extragradient):

    def __init__(self, params, lr=required, momentum=0, dampening=0,
                 weight_decay=0, nesterov=False):
        if lr is not required and lr < 0.0:
            raise ValueError("Invalid learning rate: {}".format(lr))
        if momentum < 0.0:
            raise ValueError("Invalid momentum value: {}".format(momentum))
        if weight_decay < 0.0:
            raise ValueError("Invalid weight_decay value: {}".
↪format(weight_decay))

        defaults = dict(lr=lr, momentum=momentum, dampening=dampening,
                        weight_decay=weight_decay, nesterov=nesterov)
        if nesterov and (momentum <= 0 or dampening != 0):
```

```
            raise ValueError("Nesterov momentum requires a momentum and zero␣
↪dampening")
        super(ExtraSGD, self).__init__(params, defaults)

    def __setstate__(self, state):
        super(ExtraSGD, self).__setstate__(state)
        for group in self.param_groups:
            group.setdefault('nesterov', False)

    def update(self, p, group):
        weight_decay = group['weight_decay']
        momentum = group['momentum']
        dampening = group['dampening']
        nesterov = group['nesterov']

        if p.grad is None:
            return None
        d_p = p.grad.data
        if weight_decay != 0:
            d_p.add_(weight_decay, p.data)
        if momentum != 0:
            param_state = self.state[p]
            if 'momentum_buffer' not in param_state:
                buf = param_state['momentum_buffer'] = torch.zeros_like(p.data)
                buf.mul_(momentum).add_(d_p)
            else:
                buf = param_state['momentum_buffer']
                buf.mul_(momentum).add_(1 - dampening, d_p)
            if nesterov:
                d_p = d_p.add(momentum, buf)
            else:
                d_p = buf

        return -group['lr'] * d_p
```

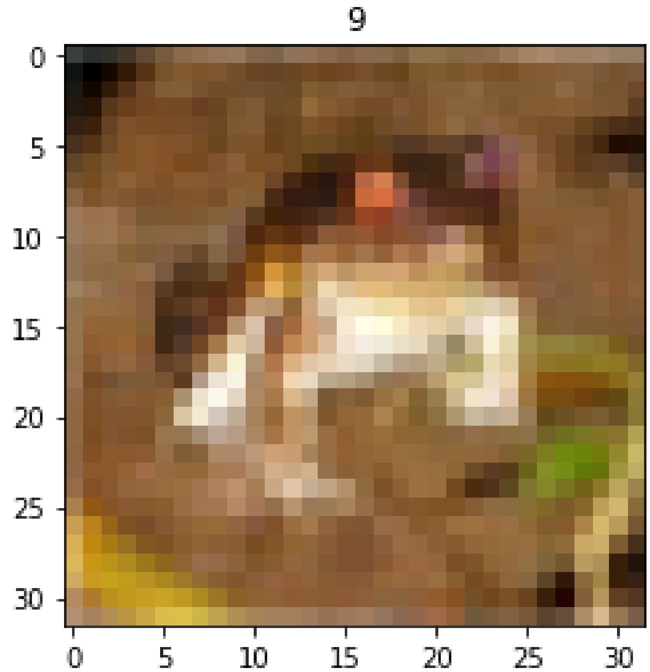
[7]:
```
from torchvision import datasets, transforms
from torchvision.transforms import ToTensor

image_size = 64
transform = transforms.Compose(
        [transforms.ToTensor(),
        transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

data_transform = transforms.Compose(
    [
        transforms.Resize(image_size),
        transforms.CenterCrop(image_size),
```

```
        transforms.ToTensor(),
        transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
    ]
)

train_data = datasets.CIFAR10(root='./data', train=True, transform =␣
 ↪data_transform, download=True)

test_data = datasets.CIFAR10(root='./data', train=False, transform =␣
 ↪data_transform, download=True)


print(train_data)
print(test_data)
```

```
Files already downloaded and verified
Files already downloaded and verified
Dataset CIFAR10
    Number of datapoints: 50000
    Root location: ./data
    Split: Train
    StandardTransform
Transform: Compose(
               Resize(size=64, interpolation=bilinear, max_size=None,
antialias=None)
               CenterCrop(size=(64, 64))
               ToTensor()
               Normalize(mean=(0.5, 0.5, 0.5), std=(0.5, 0.5, 0.5))
           )
Dataset CIFAR10
    Number of datapoints: 10000
    Root location: ./data
    Split: Test
    StandardTransform
Transform: Compose(
               Resize(size=64, interpolation=bilinear, max_size=None,
antialias=None)
               CenterCrop(size=(64, 64))
               ToTensor()
               Normalize(mean=(0.5, 0.5, 0.5), std=(0.5, 0.5, 0.5))
           )
```

[8]:

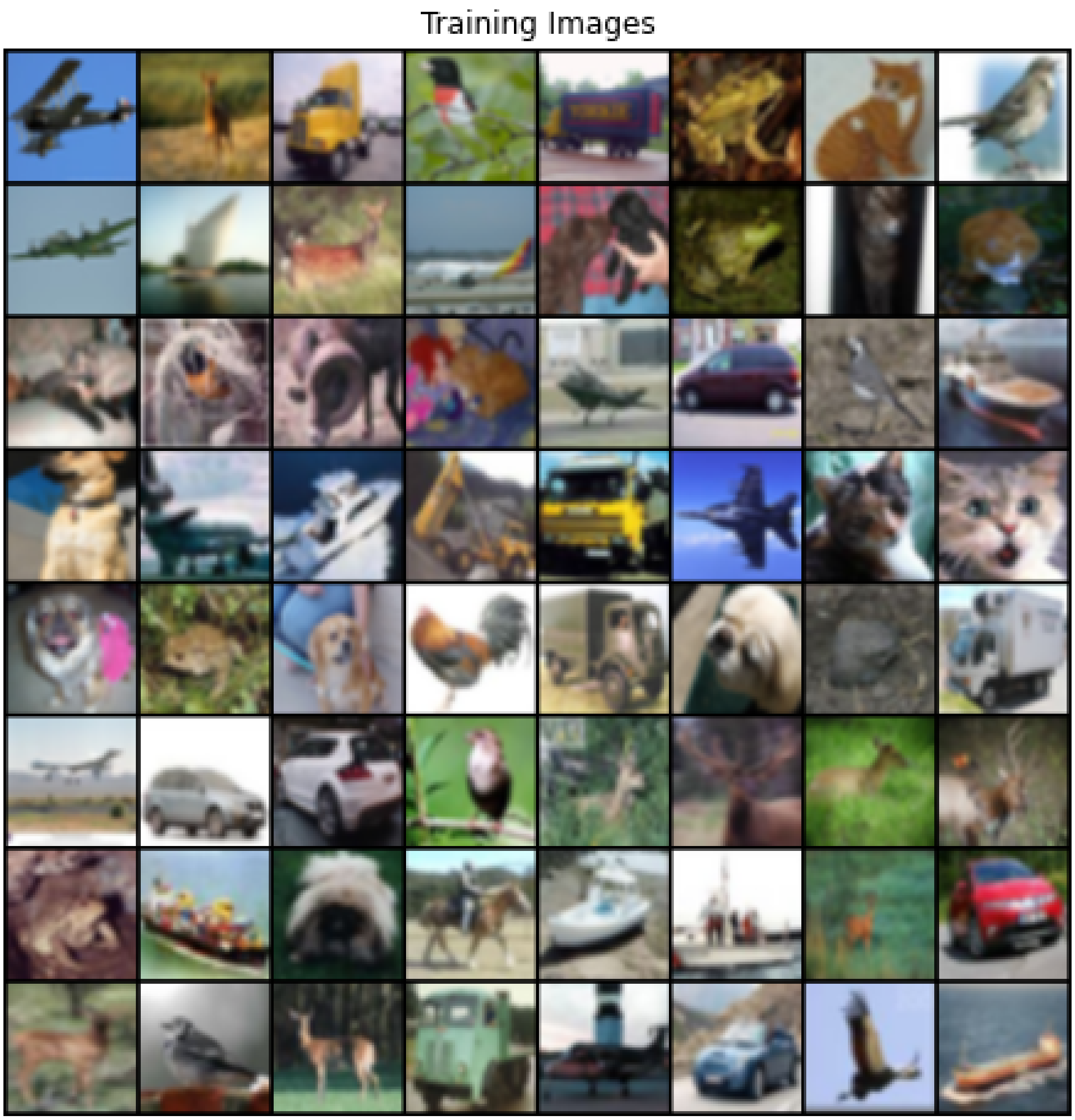
```
import matplotlib.pyplot as plt
plt.imshow(train_data.data[0])
plt.title('%i' % train_data.targets[1])
plt.show()
```



[9]:
```
batch_size = 128

train_dataloader = idist.auto_dataloader(
    train_data,
    batch_size=batch_size,
    num_workers=2,
    shuffle=True,
    drop_last=True,
)

test_dataloader = idist.auto_dataloader(
    test_data,
    batch_size=batch_size,
    num_workers=2,
    shuffle=False,
    drop_last=True,
)
```

[10]:
```
batch_size = 128
real_batch = next(iter(train_dataloader))

plt.figure(figsize=(8,8))
plt.axis("off")
plt.title("Training Images")
```

```
plt.imshow(np.transpose(vutils.make_grid(real_batch[0][:64], padding=2,␣
 ↪normalize=True).cpu(),(1,2,0)))
plt.show()
```



0.3 Models for GAN

0.3.1 Generator

The latent space dimension of input vectors for the generator is a key parameter of GAN.

[11]:
```
latent_dim = 100
```

[12]:
```
class Generator3x64x64(nn.Module):
    def __init__(self, latent_dim):
        super(Generator3x64x64, self).__init__()
        self.model = nn.Sequential(
            nn.ConvTranspose2d(latent_dim, 512, 4, 1, 0, bias=False),
            nn.BatchNorm2d(512),
            nn.ReLU(True),
            # state size. 512 x 4 x 4
            nn.ConvTranspose2d(512, 256, 4, 2, 1, bias=False),
            nn.BatchNorm2d(256),
            nn.ReLU(True),
            # state size. 256 x 8 x 8
            nn.ConvTranspose2d(256, 128, 4, 2, 1, bias=False),
            nn.BatchNorm2d(128),
            nn.ReLU(True),
            # state size. 128 x 16 x 16
            nn.ConvTranspose2d(128, 64, 4, 2, 1, bias=False),
            nn.BatchNorm2d(64),
            nn.ReLU(True),
            # state size. 64 x 32 x 32
            nn.ConvTranspose2d(64, 3, 4, 2, 1, bias=False),
            nn.Tanh()
            # final state size. 3 x 64 x 64
        )

    def forward(self, x):
        x = self.model(x)
        return x
```

As for dataloading, distributed models requires some specifics that `idist` adresses providing the `auto_model` helper.

[13]:
```
netG = idist.auto_model(Generator3x64x64(latent_dim))
```

Note that the model is automatically moved to the best device detected by `idist`.

[14]:
```
idist.device()
```

[14]:
```
device(type='cuda')
```

[15]:
```
summary(netG, (latent_dim, 1, 1))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
   ConvTranspose2d-1            [-1, 512, 4, 4]         819,200
       BatchNorm2d-2            [-1, 512, 4, 4]           1,024
              ReLU-3            [-1, 512, 4, 4]               0
   ConvTranspose2d-4            [-1, 256, 8, 8]       2,097,152
```

```
      BatchNorm2d-5            [-1, 256, 8, 8]             512
             ReLU-6            [-1, 256, 8, 8]               0
  ConvTranspose2d-7          [-1, 128, 16, 16]         524,288
      BatchNorm2d-8          [-1, 128, 16, 16]             256
             ReLU-9          [-1, 128, 16, 16]               0
 ConvTranspose2d-10           [-1, 64, 32, 32]         131,072
     BatchNorm2d-11           [-1, 64, 32, 32]             128
            ReLU-12           [-1, 64, 32, 32]               0
 ConvTranspose2d-13            [-1, 3, 64, 64]           3,072
            Tanh-14            [-1, 3, 64, 64]               0
================================================================
Total params: 3,576,704
Trainable params: 3,576,704
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.00
Forward/backward pass size (MB): 3.00
Params size (MB): 13.64
Estimated Total Size (MB): 16.64
----------------------------------------------------------------
```

0.3.2 Discriminator

[16]:
```python
class Discriminator3x64x64(nn.Module):
    def __init__(self):
        super(Discriminator3x64x64, self).__init__()
        self.model = nn.Sequential(
            # input is 3 x 64 x 64
            nn.Conv2d(3, 64, 4, 2, 1, bias=False),
            nn.LeakyReLU(0.2, inplace=True),
            # state size. 64 x 32 x 32
            nn.Conv2d(64, 128, 4, 2, 1, bias=False),
            nn.BatchNorm2d(128),
            nn.LeakyReLU(0.2, inplace=True),
            # state size. 128 x 16 x 16
            nn.Conv2d(128, 256, 4, 2, 1, bias=False),
            nn.BatchNorm2d(256),
            nn.LeakyReLU(0.2, inplace=True),
            # state size. 256 x 8 x 8
            nn.Conv2d(256, 512, 4, 2, 1, bias=False),
            nn.BatchNorm2d(512),
            nn.LeakyReLU(0.2, inplace=True),
            # state size. 512 x 4 x 4
            nn.Conv2d(512, 1, 4, 1, 0, bias=False),
            nn.Sigmoid()
        )
```

```python
    def forward(self, x):
        x = self.model(x)
        return x
```

[17]:
```python
netD = idist.auto_model(Discriminator3x64x64())
summary(netD, (3, 64, 64))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 64, 32, 32]           3,072
         LeakyReLU-2           [-1, 64, 32, 32]               0
            Conv2d-3          [-1, 128, 16, 16]         131,072
       BatchNorm2d-4          [-1, 128, 16, 16]             256
         LeakyReLU-5          [-1, 128, 16, 16]               0
            Conv2d-6            [-1, 256, 8, 8]         524,288
       BatchNorm2d-7            [-1, 256, 8, 8]             512
         LeakyReLU-8            [-1, 256, 8, 8]               0
            Conv2d-9            [-1, 512, 4, 4]       2,097,152
      BatchNorm2d-10            [-1, 512, 4, 4]           1,024
        LeakyReLU-11            [-1, 512, 4, 4]               0
           Conv2d-12              [-1, 1, 1, 1]           8,192
          Sigmoid-13              [-1, 1, 1, 1]               0
================================================================
Total params: 2,765,568
Trainable params: 2,765,568
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.05
Forward/backward pass size (MB): 2.31
Params size (MB): 10.55
Estimated Total Size (MB): 12.91
----------------------------------------------------------------
```

[18]:
```python
criterion = nn.BCELoss()
```

A batch of 64 fixed samples will be used for generating images from throughout the training. This will allow a qualitative evaluation throughout the training progress.

[19]:
```python
fixed_noise = torch.randn(64, latent_dim, 1, 1, device=idist.device())
```

Finally, two separate optimizers are set up, one for the generator, and one for the discriminator. Yet, another helper method `auto_optim` provided by `idist` will help to adapt optimizer for distributed configurations.

[20]:
```python
optimizerD = idist.auto_optim(
    ExtraSGD(netD.parameters(), lr=0.0002)
)
```

```
optimizerG = idist.auto_optim(
    ExtraSGD(netG.parameters(), lr=0.0002)
)
```

[21]:
```
real_label = 1
fake_label = 0


def training_step(engine, data):
    # Set the models for training
    netG.train()
    netD.train()

    ############################
    # (1) Update D network: maximize log(D(x)) + log(1 - D(G(z)))
    ###########################
    ## Train with all-real batch
    netD.zero_grad()
    # Format batch
    real = data[0].to(idist.device())
    b_size = real.size(0)
    label = torch.full((b_size,), real_label, dtype=torch.float, device=idist.
 ↪device())
    # Forward pass real batch through D
    output1 = netD(real).view(-1)
    # Calculate loss on all-real batch
    errD_real = criterion(output1, label)
    # Calculate gradients for D in backward pass
    errD_real.backward()

    ## Train with all-fake batch
    # Generate batch of latent vectors
    noise = torch.randn(b_size, latent_dim, 1, 1, device=idist.device())
    # Generate fake image batch with G
    fake = netG(noise)
    label.fill_(fake_label)
    # Classify all fake batch with D
    output2 = netD(fake.detach()).view(-1)
    # Calculate D's loss on the all-fake batch
    errD_fake = criterion(output2, label)
    # Calculate the gradients for this batch, accumulated (summed) with␣
 ↪previous gradients
    errD_fake.backward()
    # Compute error of D as sum over the fake and the real batches
    errD = errD_real + errD_fake
    optimizerD.extrapolation()
    # Update D
```

```
    optimizerD.step()

    ############################
    # (2) Update G network: maximize log(D(G(z)))
    ###########################
    netG.zero_grad()
    label.fill_(real_label)  # fake labels are real for generator cost
    # Since we just updated D, perform another forward pass of all-fake batch␣
↪through D
    output3 = netD(fake).view(-1)
    # Calculate G's loss based on this output
    errG = criterion(output3, label)
    # Calculate gradients for G
    errG.backward()
    optimizerG.extrapolation()
    # Update G
    optimizerG.step()

    return {
        "Loss_G" : errG.item(),
        "Loss_D" : errD.item(),
        "D_x": output1.mean().item(),
        "D_G_z1": output2.mean().item(),
        "D_G_z2": output3.mean().item(),
    }
```

[22]:
```
trainer = Engine(training_step)
```

[23]:
```
def initialize_fn(m):
    classname = m.__class__.__name__
    if classname.find('Conv') != -1:
        nn.init.normal_(m.weight.data, 0.0, 0.02)
    elif classname.find('BatchNorm') != -1:
        nn.init.normal_(m.weight.data, 1.0, 0.02)
        nn.init.constant_(m.bias.data, 0)
```

[24]:
```
@trainer.on(Events.STARTED)
def init_weights():
    netD.apply(initialize_fn)
    netG.apply(initialize_fn)
```

[25]:
```
G_losses = []
D_losses = []



@trainer.on(Events.ITERATION_COMPLETED)
def store_losses(engine):
```

```
    o = engine.state.output
    G_losses.append(o["Loss_G"])
    D_losses.append(o["Loss_D"])
```

[26]:
```
img_list = []


@trainer.on(Events.ITERATION_COMPLETED(every=500))
def store_images(engine):
    with torch.no_grad():
        fake = netG(fixed_noise).cpu()
    img_list.append(fake)
```

[27]:
```
from ignite.metrics import FID, InceptionScore
```

[28]:
```
fid_metric = FID(device=idist.device())
```

[29]:
```
is_metric = InceptionScore(device=idist.device(), output_transform=lambda x:␣
 ↪x[0])
```

[30]:
```
import PIL.Image as Image


def interpolate(batch):
    arr = []
    for img in batch:
        pil_img = transforms.ToPILImage()(img)
        resized_img = pil_img.resize((299,299), Image.BILINEAR)
        arr.append(transforms.ToTensor()(resized_img))
    return torch.stack(arr)


def evaluation_step(engine, batch):
    with torch.no_grad():
        noise = torch.randn(batch_size, latent_dim, 1, 1, device=idist.device())
        netG.eval()
        fake_batch = netG(noise)
        fake = interpolate(fake_batch)
        real = interpolate(batch[0])
        return fake, real
```

[31]:
```
evaluator = Engine(evaluation_step)
fid_metric.attach(evaluator, "fid")
is_metric.attach(evaluator, "is")
```

[32]:
```
fid_values = []
is_values = []
```

```python


@trainer.on(Events.EPOCH_COMPLETED)
def log_training_results(engine):
    evaluator.run(test_dataloader,max_epochs=1)
    metrics = evaluator.state.metrics
    fid_score = metrics['fid']
    is_score = metrics['is']
    fid_values.append(fid_score)
    is_values.append(is_score)
    print(f"Epoch [{engine.state.epoch}/5] Metric Scores")
    print(f"*   FID : {fid_score:4f}")
    print(f"*    IS : {is_score:4f}")
```

[33]:
```python
from ignite.metrics import RunningAverage


RunningAverage(output_transform=lambda x: x["Loss_G"]).attach(trainer, 'Loss_G')
RunningAverage(output_transform=lambda x: x["Loss_D"]).attach(trainer, 'Loss_D')
```

[34]:
```python
from ignite.contrib.handlers import ProgressBar


ProgressBar().attach(trainer, metric_names=['Loss_G','Loss_D'])
ProgressBar().attach(evaluator)
```

[35]:
```python
def training(*args):
    trainer.run(train_dataloader, max_epochs=5)
```

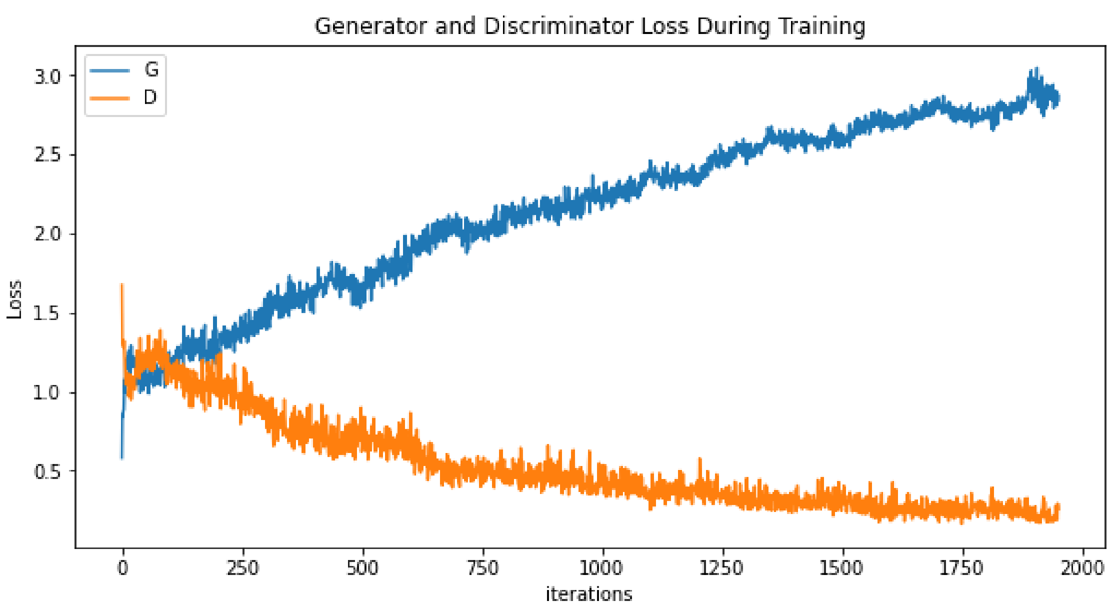
[36]:
```python
with idist.Parallel(backend='nccl') as parallel:
    parallel.run(training)
```

```
[1/390]   0%|           [00:00<?]

[1/78]   1%|1           [00:00<?]

Epoch [1/5] Metric Scores
*   FID : 0.154986
*    IS : 1.032711

[1/390]   0%|           [00:00<?]

[1/78]   1%|1           [00:00<?]

Epoch [2/5] Metric Scores
*   FID : 0.156611
*    IS : 1.037504

[1/390]   0%|           [00:00<?]

[1/78]   1%|1           [00:00<?]
```

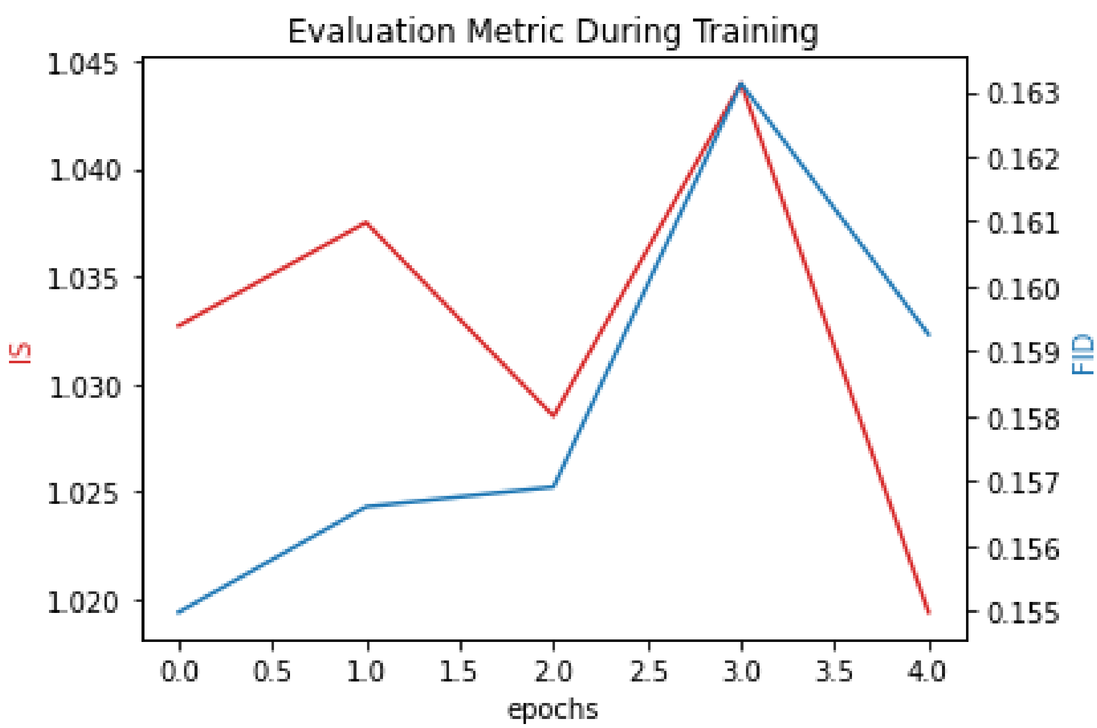
```
Epoch [3/5] Metric Scores
*   FID : 0.156914
*    IS : 1.028521

[1/390]    0%|             [00:00<?]

[1/78]    1%|1            [00:00<?]

Epoch [4/5] Metric Scores
*   FID : 0.163128
*    IS : 1.043960

[1/390]    0%|             [00:00<?]

[1/78]    1%|1            [00:00<?]

Epoch [5/5] Metric Scores
*   FID : 0.159262
*    IS : 1.019424
```

[37]:
```
%matplotlib inline

plt.figure(figsize=(10,5))
plt.title("Generator and Discriminator Loss During Training")
plt.plot(G_losses,label="G")
plt.plot(D_losses,label="D")
plt.xlabel("iterations")
plt.ylabel("Loss")
plt.legend()
```

[37]:
```
<matplotlib.legend.Legend at 0x7fcaa37d6ca0>
```



[38]:
```
fig, ax1 = plt.subplots()

plt.title("Evaluation Metric During Training")

color = 'tab:red'
ax1.set_xlabel('epochs')
ax1.set_ylabel('IS', color=color)
ax1.plot(is_values, color=color)

ax2 = ax1.twinx()

color = 'tab:blue'
ax2.set_ylabel('FID', color=color)
ax2.plot(fid_values, color=color)

fig.tight_layout()
```



[39]:
```
%matplotlib inline

# Grab a batch of real images from the dataloader
real_batch = next(iter(train_dataloader))
```

```
# Plot the real images
plt.figure(figsize=(15,15))
plt.subplot(1,2,1)
plt.axis("off")
plt.title("Real Images")
plt.imshow(np.transpose(vutils.make_grid(real_batch[0][:64], padding=5,␣
↪normalize=True).cpu(),(1,2,0)))

# Plot the fake images from the last epoch
plt.subplot(1,2,2)
plt.axis("off")
plt.title("Fake Images")
plt.imshow(np.transpose(vutils.make_grid(img_list[-1], padding=2,␣
↪normalize=True).cpu(),(1,2,0)))
```

[39]: <matplotlib.image.AxesImage at 0x7fcaccd56460>