gan_mnist_pytorch

December 20, 2021

1 Thực hành về mạng GAN

[ ]:
```
# !nvidia-smi
# from google.colab import drive
# drive.mount('/content/drive')
# !pip3 install torchsummary
# !pip3 install torchvision
```

1.0.1 Chuẩn bị các thư viện cần thiết

[ ]:
```
import torch
import torch.nn as nn
import torch.optim as optim
import numpy as np
import glob
import cv2
import torch.nn.functional as F
from torch.autograd import Variable

import torchvision
import torchvision.transforms as transforms

from torch.nn import CrossEntropyLoss, Dropout, Softmax, Linear, Conv2d,␣
 ↪LayerNorm
import matplotlib.pyplot as plt
from torchsummary import summary
```

1.0.2 Thiết lập các hằng số cho tập MNIST

[ ]:
```
width    = 28
height   = 28
channels = 1
epochs   = 1000

img_shape = (width, height, channels)
```

1. Tải tập dữ liệu MNIST

Ta chỉ dùng tập huấn luyện, không dùng nhãn. Các điểm ảnh được chuẩn hoá về miền giá trị [-1, 1]

[ ]:
```
transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5), (0.5))])

batch_size = 32

trainset = torchvision.datasets.MNIST(root='./data', train=True,
                                        download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=batch_size,
                                          shuffle=True, num_workers=2)
```

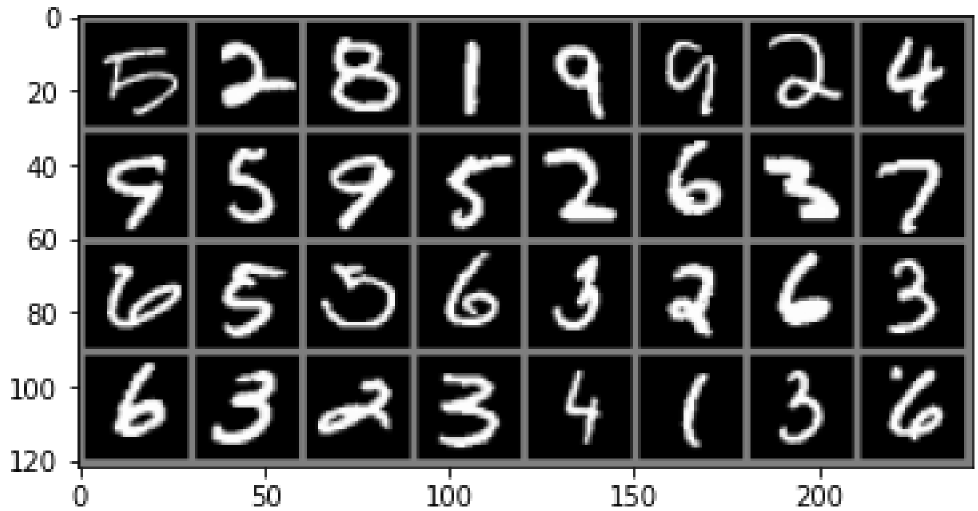
```
/usr/local/lib/python3.7/dist-packages/torchvision/datasets/mnist.py:498:
UserWarning: The given NumPy array is not writeable, and PyTorch does not
support non-writeable tensors. This means you can write to the underlying
(supposedly non-writeable) NumPy array using the tensor. You may want to copy
the array to protect its data or make it writeable before converting it to a
tensor. This type of warning will be suppressed for the rest of this program.
(Triggered internally at  /pytorch/torch/csrc/utils/tensor_numpy.cpp:180.)
  return torch.from_numpy(parsed.astype(m[2], copy=False)).view(*s)
```

Trực quan dữ liệu MNIST

[ ]:
```
def imshow(img):
    img = img / 2 + 0.5     # unnormalize
    npimg = img.numpy()
    plt.imshow(np.transpose(npimg, (1, 2, 0)))
    plt.show()

# get some random training images
dataiter = iter(trainloader)
images, labels = dataiter.next()

# show images
imshow(torchvision.utils.make_grid(images))
# print labels
print(' '.join('%5s' % labels[j].item() for j in range(batch_size)))
```




```
    5    2    8    1    9    9    2    4    9    5    9    5    2
  6    3    7    6    5    5    6    3    2    6    3    6    3    2
  3    4    1    3    6
```

2. Generator
   Lập trình kiến trúc Generator theo mô tả phía dưới

[ ]:
```python
""" Declare GENERATOR.
    + Its input is a 100-feature vector of random noise
    + Its output is a fake image with pixel values in [-1, 1]"""

class Generator(nn.Module):

    ##########################
    ###   YOUR CODE HERE   ###
    ##########################

G = Generator().cuda()
summary(G, (100, ), batch_size=-1, device='cuda')
print("_____________________ Generator Created_____________________")
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                 [-1, 256]          25,856
         LeakyReLU-2                 [-1, 256]               0
       BatchNorm1d-3                 [-1, 256]             512
            Linear-4                 [-1, 512]         131,584
         LeakyReLU-5                 [-1, 512]               0
       BatchNorm1d-6                 [-1, 512]           1,024
```

```
            Linear-7                 [-1, 1024]         525,312
         LeakyReLU-8                 [-1, 1024]               0
       BatchNorm1d-9                 [-1, 1024]           2,048
           Linear-10                  [-1, 784]         803,600
             Tanh-11                  [-1, 784]               0
================================================================
Total params: 1,489,936
Trainable params: 1,489,936
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.00
Forward/backward pass size (MB): 0.05
Params size (MB): 5.68
Estimated Total Size (MB): 5.74
----------------------------------------------------------------
_____________________ Generator Created_____________________
```

3. Discriminator
   Lập trình kiến trúc Discriminator

[ ]:
```python
""" Declare DISCRIMINATOR
    Its input is REAL IMAGE (in a form of a vector 28x28)
    Its ouput is the probability of image type (REAL IMAGE or FAKE IMAGE)
    the values in the range of [0, 1] """

class Discriminator(nn.Module):
    ##########################
    ###   YOUR CODE HERE   ###
    ##########################

D = Discriminator().cuda()
summary(D, img_shape, batch_size=-1, device='cuda')
print("____________________ Discriminator Created____________________")
```

4. Generative model

Xây dựng GAN và huấn luyện

[ ]:
```python
##########################
###   YOUR CODE HERE   ###
##########################

losses_G = []
losses_D = []
samples = []
```

[ ]:
```python
for epoch in range(epochs):
    for (i, (imgs, _)) in enumerate(trainloader, start=1):
        # Adversarial ground truths
```

```
        valid = Variable(torch.cuda.FloatTensor(imgs.size(0), 1).fill_(1.0),␣
↪requires_grad=False)
        fake = Variable(torch.cuda.FloatTensor(imgs.size(0), 1).fill_(0.0),␣
↪requires_grad=False)

        # Configure input
        real_imgs = Variable(imgs.type(torch.cuda.FloatTensor))

        # -----------------
        #  Train Generator
        # -----------------

        optimizer_G.zero_grad()

        # Sample noise as generator input
        z = Variable(torch.cuda.FloatTensor(np.random.normal(0, 1, (imgs.
↪shape[0], 100))))

        # Generate a batch of images
        gen_imgs = G(z)

        # Loss measures generator's ability to fool the discriminator

        ##########################
        ###    YOUR CODE HERE    ###
        ##########################

        g_loss.backward()
        optimizer_G.step()

        # ---------------------
        #  Train Discriminator
        # ---------------------

        optimizer_D.zero_grad()

        # Loss measures discriminator's ability to classify real from generated␣
↪samples

        ##########################
        ###    YOUR CODE HERE    ###
        ##########################

        d_loss.backward()
        optimizer_D.step()

        if epoch % 10 == 0 and i == len(trainloader):
```

```
            print(
                "[Epoch %d/%d] [Batch %d/%d] [D loss: %f] [G loss: %f]"
                % (epoch, epochs, i, len(trainloader), d_loss.item(), g_loss.
↪item())
            )

            losses_G.append(g_loss.item())
            losses_D.append(d_loss.item())
            samples.append(gen_imgs)
```

```
[Epoch 0/1000] [Batch 1875/1875] [D loss: 0.567250] [G loss: 0.849551]
[Epoch 10/1000] [Batch 1875/1875] [D loss: 0.615487] [G loss: 0.989828]
[Epoch 20/1000] [Batch 1875/1875] [D loss: 0.644482] [G loss: 0.857566]
[Epoch 30/1000] [Batch 1875/1875] [D loss: 0.449982] [G loss: 1.188688]
[Epoch 40/1000] [Batch 1875/1875] [D loss: 0.435769] [G loss: 1.717387]
[Epoch 50/1000] [Batch 1875/1875] [D loss: 0.545302] [G loss: 0.907160]
[Epoch 60/1000] [Batch 1875/1875] [D loss: 0.604432] [G loss: 1.368047]
[Epoch 70/1000] [Batch 1875/1875] [D loss: 0.473351] [G loss: 1.126326]
[Epoch 80/1000] [Batch 1875/1875] [D loss: 0.516999] [G loss: 1.188379]
[Epoch 90/1000] [Batch 1875/1875] [D loss: 0.458347] [G loss: 1.528381]
[Epoch 100/1000] [Batch 1875/1875] [D loss: 0.534393] [G loss: 1.319414]
[Epoch 110/1000] [Batch 1875/1875] [D loss: 0.425020] [G loss: 1.788332]
[Epoch 120/1000] [Batch 1875/1875] [D loss: 0.480867] [G loss: 1.442632]
[Epoch 130/1000] [Batch 1875/1875] [D loss: 0.338395] [G loss: 1.911445]
[Epoch 140/1000] [Batch 1875/1875] [D loss: 0.453917] [G loss: 1.691558]
[Epoch 150/1000] [Batch 1875/1875] [D loss: 0.336953] [G loss: 2.119481]
[Epoch 160/1000] [Batch 1875/1875] [D loss: 0.351745] [G loss: 2.208638]
[Epoch 170/1000] [Batch 1875/1875] [D loss: 0.437646] [G loss: 1.892489]
[Epoch 180/1000] [Batch 1875/1875] [D loss: 0.332448] [G loss: 2.235240]
[Epoch 190/1000] [Batch 1875/1875] [D loss: 0.390249] [G loss: 2.321619]
[Epoch 200/1000] [Batch 1875/1875] [D loss: 0.398770] [G loss: 2.007938]
[Epoch 210/1000] [Batch 1875/1875] [D loss: 0.331310] [G loss: 2.265262]
[Epoch 220/1000] [Batch 1875/1875] [D loss: 0.312279] [G loss: 2.224203]
[Epoch 230/1000] [Batch 1875/1875] [D loss: 0.212925] [G loss: 2.046962]
[Epoch 240/1000] [Batch 1875/1875] [D loss: 0.291377] [G loss: 2.234614]
[Epoch 250/1000] [Batch 1875/1875] [D loss: 0.265238] [G loss: 2.627646]
[Epoch 260/1000] [Batch 1875/1875] [D loss: 0.252542] [G loss: 2.080127]
[Epoch 270/1000] [Batch 1875/1875] [D loss: 0.319955] [G loss: 2.812288]
[Epoch 280/1000] [Batch 1875/1875] [D loss: 0.180922] [G loss: 3.096547]
[Epoch 290/1000] [Batch 1875/1875] [D loss: 0.197178] [G loss: 2.714063]
[Epoch 300/1000] [Batch 1875/1875] [D loss: 0.238466] [G loss: 2.448203]
[Epoch 310/1000] [Batch 1875/1875] [D loss: 0.114808] [G loss: 2.446286]
[Epoch 320/1000] [Batch 1875/1875] [D loss: 0.204256] [G loss: 2.293240]
[Epoch 330/1000] [Batch 1875/1875] [D loss: 0.214994] [G loss: 2.082977]
[Epoch 340/1000] [Batch 1875/1875] [D loss: 0.130408] [G loss: 3.432069]
[Epoch 350/1000] [Batch 1875/1875] [D loss: 0.175108] [G loss: 2.724875]
[Epoch 360/1000] [Batch 1875/1875] [D loss: 0.107969] [G loss: 2.920527]
[Epoch 370/1000] [Batch 1875/1875] [D loss: 0.349168] [G loss: 3.319548]
```

```
[Epoch 380/1000] [Batch 1875/1875] [D loss: 0.236485] [G loss: 3.356713]
[Epoch 390/1000] [Batch 1875/1875] [D loss: 0.213364] [G loss: 2.520835]
[Epoch 400/1000] [Batch 1875/1875] [D loss: 0.097428] [G loss: 3.194795]
[Epoch 410/1000] [Batch 1875/1875] [D loss: 0.191139] [G loss: 3.006736]
[Epoch 420/1000] [Batch 1875/1875] [D loss: 0.219425] [G loss: 2.950970]
[Epoch 430/1000] [Batch 1875/1875] [D loss: 0.082084] [G loss: 2.983739]
[Epoch 440/1000] [Batch 1875/1875] [D loss: 0.118818] [G loss: 2.294273]
[Epoch 450/1000] [Batch 1875/1875] [D loss: 0.123423] [G loss: 2.666441]
```

1.0.3 Vẽ đồ thị hàm loss huấn luyện

[ ]:
```
plt.figure(figsize=(12, 6))
plt.plot(list(range(len(losses_G)/10)*10), losses_G, label="G_loss")
plt.plot(list(range(len(losses_D)/10)*10), losses_D, label="D_loss")
plt.title("Training losses", fontsize=16)
plt.xlabel("Epochs", fontsize=14)
plt.ylabel("Losses", fontsize=14)
plt.legend(loc="upper right", fontsize=14)
plt.show()
```

1.0.4 Trực quan hoá kết quả sinh dữ liệu của mô hình đã huấn luyện

[ ]:
```
i = 0
for i in range(0, len(samples), 10):
    images = samples[i].data.cpu().numpy()
    print("    ____________________ Step = %d ____________________" % i*10)
    plt.figure(figsize=(6, 6))
    for i in range(16):
        plt.subplot(4, 4, i+1)
        image = images[i, :, :, :]
        image = np.reshape(image, [height, width])
        plt.imshow(image, cmap='gray')
        plt.axis('off')
    plt.tight_layout()
    plt.show()
    print("\n")
```

[ ]:
```
noise = torch.Tensor(np.random.normal(0, 1, (16, 100))).cuda()
gen_images = G(noise)
images = gen_images.data.cpu().numpy()
plt.figure(figsize=(6, 6))
for i in range(16):
    plt.subplot(4, 4, i+1)
    image = images[i, :, :, :]
    image = np.reshape(image, [height, width])
    plt.imshow(image, cmap='gray')
    plt.axis('off')
```

```
plt.tight_layout()
plt.show()
```