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Deep Learning Assignment 3
Conditional GAN Skeleton Code.
Adopted from public sources, customized and improved for this assignment.
"""

#import necessary modules
import torch
import torch.nn as nn
from torchvision import transforms, datasets
from torch import optim as optim
# for visualization
from matplotlib import pyplot as plt
import math
import numpy as np
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# tells PyTorch to use an NVIDIA GPU, if one is available.
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# loading the dataset
training_parameters = {
    "img_size": 28,
    "n_epochs": 24, #24
    "batch_size": 64,
    "learning_rate_generator": 0.0002,
    "learning_rate_discriminator": 0.0002,
}
# define a transform to 1) scale the images and 2) convert them into tensors
transform = transforms.Compose([
    transforms.Resize(training_parameters['img_size']), # scales the smaller edge of the image to have this size
    transforms.ToTensor(),
])

# load the dataset
train_loader = torch.utils.data.DataLoader(
    datasets.FashionMNIST(
        './data', # specifies the directory to download the datafiles to, relative to the location of the notebook.
        train = True,
        download = True,
        transform = transform),
    batch_size = training_parameters["batch_size"],
    shuffle=True
    )

# Fashion MNIST has 10 classes, just like MNIST. Here's what they correspond to:
label_descriptions = {
      0: 'T-shirt/top',
      1 : 'Trouser',
      2 : 'Pullover',
      3 : 'Dress',
      4 : 'Coat',
      5 : 'Sandal',
      6 : 'Shirt',
      7 : 'Sneaker',
      8 : 'Bag',
      9 : 'Ankle boot'
}
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# Create the Generator model class, which will be used to initialize the generator
class Generator(nn.Module):
  def __init__(self, input_dim, output_dim, num_labels=10): # to initialize the model-wide parameters. When you run `generator
    super(Generator,self).__init__() # initialize the parent class
    # TODO (5.4) Turn this Generator into a Conditional Generator by
    # 1. Adjusting the input dimension of the first hidden layer.
    # 2. Modifying the input to the first hidden layer in the forward class.

    self.hidden_layer1 = nn.Sequential(
        nn.Linear(input_dim, 256),
        nn.LeakyReLU(0.2)
    )
    self.hidden_layer2 = nn.Sequential(
        nn.Linear(256, 512),
        nn.LeakyReLU(0.2)
    )
    self.hidden_layer3 = nn.Sequential(
        nn.Linear(512, 1024),
        nn.LeakyReLU(0.2)
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        )
        self.hidden_layer4 = nn.Sequential(
            nn.Linear(1024, output_dim),
            nn.Tanh()
        )
      def forward(self, x, labels):

          output = self.hidden_layer1(x)
          output = self.hidden_layer2(output)
          output = self.hidden_layer3(output)
          output = self.hidden_layer4(output)
          return output.to(device)


class Discriminator(nn.Module):
    def __init__(self, input_dim, output_dim=1, num_labels=None):
        super(Discriminator, self).__init__()

        #self.label_embedding = nn.Embedding(10, 10)
        # TODO (5.4) Modify this discriminator to function as a conditional discriminator.
        self.hidden_layer1 = nn.Sequential(
            nn.Linear(input_dim, 1024),
            nn.LeakyReLU(0.2),
            nn.Dropout(0.3)
        )

        self.hidden_layer2 = nn.Sequential(
            nn.Linear(1024, 512),
            nn.LeakyReLU(0.2),
            nn.Dropout(0.3)
        )

        self.hidden_layer3 = nn.Sequential(
            nn.Linear(512, 256),
            nn.LeakyReLU(0.2),
            nn.Dropout(0.3)
        )

        self.hidden_layer4 = nn.Sequential(
            nn.Linear(256, output_dim),
            nn.Sigmoid()
        )

    def forward(self, x, labels=None): # labels to be used in 5.4.

        output = self.hidden_layer1(x)
        output = self.hidden_layer2(output)
        output = self.hidden_layer3(output)
        output = self.hidden_layer4(output)
        return output.to(device)


discriminator = Discriminator(784,1).to(device) # initialize both models, and load them to the GPU or CPU.
generator = Generator(100,784).to(device)

discriminator_optimizer = optim.Adam(discriminator.parameters(), lr=training_parameters['learning_rate_discriminator'])
generator_optimizer = optim.Adam(generator.parameters(), lr=training_parameters['learning_rate_generator'])


# Establish convention for real and fake labels during training
real_label = 1.
fake_label = 0.



#Loss_D - discriminator loss calculated as the sum of losses for the all real and all fake batches $(\log (D(x))+\log (1- D(G(

loss_func = nn.BCELoss() # Binary Cross Entropy Loss
def train_generator(batch_size):
    """
    Performs a training step on the generator by
        1. Generating fake images from random noise.
        2. Running the discriminator on the fake images.
        3. Computing loss on the result.
    :arg batch_size: the number of training examples in the current batch
    Returns the average generator loss over the batch.
    """

    # Start by zeroing the gradients of the optimizer
    generator_optimizer.zero_grad()
    # 1. Create a new batch of fake images (since the discriminator has just been trained on the old ones)
    noise = torch.randn(batch_size,100).to(device) # whenever you create new variables for the model to process, send them to
    generated_labels = torch.randint(0, 10, (batch_size,)).to(device)
    generator_output = generator(noise, labels = generated_labels)
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        # 2. Run the discriminator on the fake images
        discriminator_output = discriminator(generator_output, labels = generated_labels)
        ###----copied----
        real_label_vector = torch.full((batch_size,), real_label, dtype=torch.float, device=device)
        real_label_vector = real_label_vector.view(-1, 1)
        #-------
        # 3. Compute the loss
        loss = loss_func(discriminator_output, real_label_vector)
        loss.backward()
        generator_optimizer.step()

        loss = loss.mean().item()
        return loss

    def train_discriminator(batch_size, images, labels=None): # labels to be used in 5.4.
        """
        Performs a training step on the discriminator by
            1. Generating fake images from random noise.
            2. Running the discriminator on the fake images.
            3. Running the discriminator on the real images
            3. Computing loss on the results.
        :arg batch_size: the number of training examples in the current batch
        :arg images: the current batch of images, a tensor of size BATCH x 1 x 64 x 64
        :arg labels: the labels corresponding to images, a tensor of size BATCH
        Returns the average loss over the batch.
        """

        discriminator_optimizer.zero_grad()
        ###----fake images----###
        # 1. Create a new batch of fake images (since the discriminator has just been trained on the old ones)
        noise = torch.randn(batch_size,100).to(device) # whenever you create new variables for the model to process, send them to
        generated_labels = torch.randint(0, 10, (batch_size,)).to(device)
        generator_output = generator(noise, labels = generated_labels)
        # 2. Run the discriminator on the fake images
        discriminator_output = discriminator(generator_output, labels = generated_labels)
        # 3. Compute the loss
        fake_label_vector = torch.full((batch_size,), fake_label, dtype=torch.float, device=device)
        fake_label_vector = fake_label_vector.view(-1, 1)
        loss_fake = loss_func(discriminator_output, fake_label_vector)

        ###----real images----###
        # 1. Run the discriminator on the real images
        images = torch.flatten(images, start_dim=1)
        discriminator_output = discriminator(images, labels = labels)
        # 2. Compute the loss
        real_label_vector = torch.full((batch_size,), real_label, dtype=torch.float, device=device)
        real_label_vector = real_label_vector.view(-1, 1)
        loss_real = loss_func(discriminator_output, real_label_vector)

        #combine losses
        loss = loss_real + loss_fake
        loss.backward()
        discriminator_optimizer.step()

        loss = loss.mean().item()
        return loss



    for epoch in range(training_parameters['n_epochs']):
        G_loss = []  # for plotting the losses over time
        D_loss = []
        for batch, (imgs, labels) in enumerate(train_loader):
            batch_size = labels.shape[0]  # if the batch size doesn't evenly divide the dataset length, this may change on the las
            #generator first training
            lossG = train_generator(batch_size)
            G_loss.append(lossG)
            #single discriminator training
            lossD = train_discriminator(batch_size, imgs, labels)
            D_loss.append(lossD)

            if ((batch + 1) % 500 == 0 and (epoch + 1) % 1 == 0):
                # Display a batch of generated images and print the loss
                print("Training Steps Completed: ", batch)
                with torch.no_grad():  # disables gradient computation to speed things up
                    noise = torch.randn(batch_size, 100).to(device)
                    fake_labels = torch.randint(0, 10, (batch_size,)).to(device)
                    generated_data = generator(noise, fake_labels).cpu().view(batch_size, 28, 28)

                    # display generated images
                    batch_sqrt = int(training_parameters['batch_size'] ** 0.5)
                    fig, ax = plt.subplots(batch_sqrt, batch_sqrt, figsize=(15, 15))
                    for i, x in enumerate(generated_data):
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        #ax[math.floor(i / batch_sqrt)][i % batch_sqrt].set_title(label_descriptions[int(fake_labels[i].item())])
        ax[math.floor(i / batch_sqrt)][i % batch_sqrt].imshow(x.detach().numpy(), interpolation='nearest', cmap='g
        ax[math.floor(i / batch_sqrt)][i % batch_sqrt].get_xaxis().set_visible(False)
        ax[math.floor(i / batch_sqrt)][i % batch_sqrt].get_yaxis().set_visible(False)
    plt.show()
    #fig.savefig(f"./results/CGAN_Generations_Epoch_{epoch}")
    #fig.savefig(f"pset/pset3/results/CGAN_Generations_Epoch_{epoch}")
    fig.savefig(f"CGAN_Generations_Epoch_{epoch}")
    print(
        f"Epoch {epoch}: loss_d: {torch.mean(torch.FloatTensor(D_loss))}, loss_g: {torch.mean(torch.FloatTensor(G_
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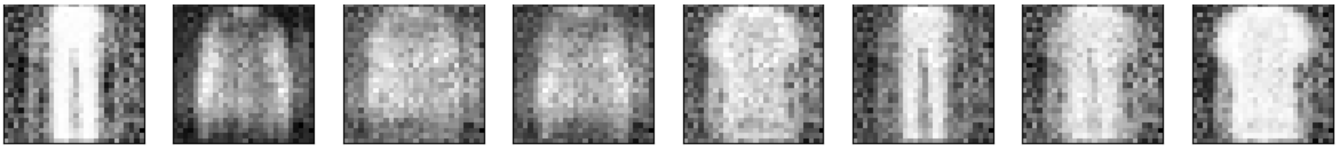

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Epoch 10: loss_d: 0.9024223685264587, loss_g: 1.4600729942321777
Training Steps Completed:  499
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