```
import numpy as np
    import torch
    import torch.nn as nn
    import torchvision
    import torchvision.transforms as T
    import torch.optim as optim
    from torch.utils.data import sampler
10
    import PIL
    NOISE DIM = 96
    dtype = torch.FloatTensor
15
    #dtype = torch.cuda.FloatTensor ## UNCOMMENT THIS LINE IF YOU'RE ON A GPU!
    def sample_noise(batch_size, dim, seed=None):
       Generate a PyTorch Tensor of uniform random noise.
20
       Input:
       - batch size: Integer giving the batch size of noise to generate.
       - dim: Integer giving the dimension of noise to generate.
25
       Output:
       - A PyTorch Tensor of shape (batch_size, dim) containing uniform
        random noise in the range (-1, 1).
       if seed is not None:
30
          torch.manual_seed(seed)
       # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)****
       sample = torch.rand((batch size, dim)) * 2 - 1
35
       return sample
       # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
40
    def discriminator(seed=None):
       Build and return a PyTorch model implementing the architecture above.
45
       if seed is not None:
          torch.manual_seed(seed)
       model = None
50
       # TODO: Implement architecture
       # HINT: nn. Sequential might be helpful.
       55
       # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
       model = nn.Sequential(
               Flatten(),
                nn.Linear(784, 256),
60
                nn.LeakyReLU(negative_slope=0.01, inplace=True),
               nn.Linear(256, 256),
                nn.LeakyReLU(negative_slope=0.01, inplace=True),
               nn.Linear(256, 1)
65
       # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
       END OF YOUR CODE
```

```
70
        return model
     def generator(noise_dim=NOISE_DIM, seed=None):
        Build and return a PyTorch model implementing the architecture above.
75
        if seed is not None:
            torch.manual seed(seed)
80
        model = None
        # TODO: Implement architecture
85
        # HINT: nn.Sequential might be helpful.
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)***
        model = nn.Sequential(
90
               nn.Linear(noise dim, 1024),
               nn.ReLU(inplace=True),
               nn.Linear(1024, 1024),
               nn.ReLU(inplace=True),
               nn.Linear(1024, 784),
95
               nn.Tanh()
        )
        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)****
        100
                                    END OF YOUR CODE
        return model
     def bce loss(input, target):
105
        Numerically stable version of the binary cross-entropy loss function.
        As per https://github.com/pytorch/pytorch/issues/751
        See the TensorFlow docs for a derivation of this formula:
        https://www.tensorflow.org/api_docs/python/tf/nn/sigmoid_cross_entropy_with_logits
110
        Inputs:
        - input: PyTorch Tensor of shape (N, ) giving scores.
        - target: PyTorch Tensor of shape (N,) containing 0 and 1 giving targets.
115
        - A PyTorch Tensor containing the mean BCE loss over the minibatch
          of input data.
120
        neg abs = - input.abs()
        loss = input.clamp(min=0) - input * target + (1 + neg_abs.exp()).log()
        return loss.mean()
     def discriminator_loss(logits_real, logits_fake):
125
        Computes the discriminator loss described above.
        Inputs:
        - logits real: PyTorch Tensor of shape (N,) giving scores for the real data.
130
        - logits fake: PyTorch Tensor of shape (N,) giving scores for the fake data.
        Returns:
        - loss: PyTorch Tensor containing (scalar) the loss for the discriminator.
135
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)****
        # Target label vector, the discriminator shoud be aiming
```

```
true_labels = torch.ones(logits_real.size()).type(dtype)
140
          # Discriminator loss has 2 parts: how well it classifies real images
          # and how well it classifies fake images.
          real_image_loss = bce_loss(logits_real, true_labels)
          fake_image_loss = bce_loss(logits_fake, 1 - true_labels)
145
          loss = real_image_loss + fake_image_loss
          # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
150
          return loss
      def generator_loss(logits_fake):
          Computes the generator loss described above.
155
          Inputs:
          - logits_fake: PyTorch Tensor of shape (N,) giving scores for the fake data.
          Returns:
          - loss: PyTorch Tensor containing the (scalar) loss for the generator.
160
          loss = None
          # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)****
          # Generator is trying to make the discriminator output 1 for all
# its image. So we create a 'target' label vector of ones for computing
165
          # generator loss.
          true_labels = torch.ones(logits_fake.size()).type(dtype)
170
          # Compute the generator loss comparing
          loss = bce_loss(logits_fake, true_labels)
          # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)****
          return loss
175
      def get_optimizer(model):
          Construct and return an Adam optimizer for the model with learning rate 1e-3,
          beta1=0.5, and beta2=0.999.
180
          Input:
          - model: A PyTorch model that we want to optimize.
          Returns:
185
          - An Adam optimizer for the model with the desired hyperparameters.
          optimizer = None
          # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE) *****
190
          optimizer = optim.Adam(model.parameters(), lr=1e-3,betas=(0.5, 0.999))
          # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)****
          return optimizer
195
      def ls_discriminator_loss(scores_real, scores_fake):
          Compute the Least-Squares GAN loss for the discriminator.
          Inputs:
200
          - scores_real: PyTorch Tensor of shape (N,) giving scores for the real data.
          - scores_fake: PyTorch Tensor of shape (N,) giving scores for the fake data.
          Outputs:
          - loss: A PyTorch Tensor containing the loss.
205
          # ****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)****
```

```
true label = torch.ones(scores real.size()).type(dtype)
210
         real image loss = torch.mean((scores real - true label)**2)
        fake_image_loss = torch.mean(scores_fake**2)
        loss = 0.5 * fake_image_loss + 0.5 * real_image_loss
215
        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        return loss
     def ls_generator_loss(scores_fake):
220
        Computes the Least-Squares GAN loss for the generator.
        Inputs:
         - scores fake: PyTorch Tensor of shape (N,) giving scores for the fake data.
225
        Outputs:
         - loss: A PyTorch Tensor containing the loss.
        loss = None
230
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)****
        true label = torch.ones(scores fake.size()).type(dtype)
        loss = 0.5 * torch.mean((scores_fake - true_label)**2)
235
        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)****
        return loss
     def build_dc_classifier(batch_size):
240
        Build and return a PyTorch model for the DCGAN discriminator implementing
         the architecture above.
245
        # TODO: Implement architecture
        # HINT: nn. Sequential might be helpful.
        250
        # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)****
        model = nn.Sequential(
            Unflatten(batch_size, 1, 28, 28),
            nn.Conv2d(in channels=1, out channels=32, kernel size=5, stride=1),
            nn.LeakyReLU(negative_slope=0.01, inplace=True),
255
            nn.MaxPool2d(kernel_size=2, stride=2),
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size=5, stride=1),
            nn.LeakyReLU(negative slope=0.01, inplace=True),
            nn.MaxPool2d(kernel_size=2, stride=2),
260
            Flatten(),
            nn.Linear(in_features=64*4*4, out_features=64*4*4),
            nn.LeakyReLU(negative slope=0.1, inplace=True),
            nn.Linear(in_features=64*4*4, out_features=1)
265
        return model
        # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
        END OF YOUR CODE
        270
     def build_dc_generator(noise_dim=NOISE_DIM):
275
        Build and return a PyTorch model implementing the DCGAN generator using
        the architecture described above.
```

```
280
         # TODO: Implement architecture
                                                                              #
         # HINT: nn. Sequential might be helpful.
         # *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)**
285
         batch size = 128
         model = nn.Sequential(
            nn.Linear(in features=noise dim, out features=1024),
            nn.ReLU(inplace=True),
290
            nn.BatchNorm1d(num_features=1024),
            nn.Linear(in features=1024, out features=7*7*128),
            nn.ReLU(inplace=True),
            nn.BatchNorm1d(num_features=7*7*128),
            Unflatten(N=batch_size, C=128, H=7, W=7),
295
            nn.ConvTranspose2d(in_channels=128, out_channels=64, kernel_size=4, \
                stride=2, padding=1),
            nn.ReLU(inplace=True),
            nn.BatchNorm2d(num_features=64),
            nn.ConvTranspose2d(in_channels=64, out_channels=1, kernel_size=4, \
300
                stride=2, padding=1),
            nn.Tanh(),
            Flatten()
         )
305
         return model
         # *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
         END OF YOUR CODE
         310
     def run_a_gan(D, G, D_solver, G_solver, discriminator_loss, generator_loss, \
         loader train, show every=250, batch size=128, noise size=96, num epochs=10):
         Train a GAN!
315
         Inputs:
         - D, G: PyTorch models for the discriminator and generator
         - D solver, G solver: torch.optim Optimizers to use for training the
          discriminator and generator.
         - discriminator_loss, generator_loss: Functions to use for computing the generator and discriminator loss, respectively.
320
         - show_every: Show samples after every show_every iterations.
         - batch size: Batch size to use for training.
         - noise size: Dimension of the noise to use as input to the generator.
325
         - num_epochs: Number of epochs over the training dataset to use for training.
         images = []
         iter_count = 0
         for epoch in range(num_epochs):
                    in loader_train:
330
            for x,
                if len(x) != batch size:
                    continue
                D solver.zero grad()
                real_data = x.type(dtype)
                logits_real = D(2* (real_data - 0.5)).type(dtype)
335
                g_fake_seed = sample_noise(batch_size, noise_size).type(dtype)
                fake_images = G(g_fake_seed).detach()
                logits_fake = D(fake_images.view(batch_size, 1, 28, 28))
340
                d_total_error = discriminator_loss(logits_real, logits fake)
                d_total_error.backward()
                D solver.step()
345
                G_solver.zero_grad()
```

```
g_fake_seed = sample_noise(batch_size, noise_size).type(dtype)
                  fake images = G(g \text{ fake seed})
                  gen logits fake = D(fake images.view(batch size, 1, 28, 28))
                  g_error = generator_loss(gen_logits_fake)
350
                  g_error.backward()
                  G_solver.step()
                  if (iter count % show every == 0):
355
                      print('Iter: {}, D: {:.4}, G:{:.4}'.format(iter_count,\)
                          d_total_error.item(),g_error.item()))
                      imgs_numpy = fake_images.data.cpu().numpy()
                      images.append(imgs_numpy[0:16])
360
                  iter count += 1
          return images
365
      class ChunkSampler(sampler.Sampler):
          """Samples elements sequentially from some offset.
          Arguments:
              num samples: # of desired datapoints
370
              start: offset where we should start selecting from
                _init__(self, num_samples, start=0):
              self.num samples = num samples
              self.start = start
375
          def __iter__(self):
              return iter(range(self.start, self.start + self.num_samples))
               __len__(self):
380
              return self.num samples
      class Flatten(nn.Module):
          def forward(self, x):
385
              # read in N, C, H, W
              N, C, H, W = x.size()
              \# "flatten" the C * H * W values into a single vector per image
              return x.view(N, -1)
390
      class Unflatten(nn.Module):
          An Unflatten module receives an input of shape (N, C*H*W) and reshapes it
          to produce an output of shape (N, C, H, W).
                     (self, N=-1, C=128, H=7, W=7):
395
              super(Unflatten, self). init ()
              self.N = N
              self.C = C
              self.H = H
400
              self.W = W
          def forward(self, x):
              return x.view(self.N, self.C, self.H, self.W)
      def initialize weights(m):
405
          if isinstance(m, nn.Linear) or isinstance(m, nn.ConvTranspose2d):
              nn.init.xavier_uniform_(m.weight.data)
      def preprocess_img(x):
          return 2 * x - 1.0
410
      def deprocess_img(x):
          return (x + 1.0) / 2.0
      def rel_error(x,y):
```

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```
415     return np.max(np.abs(x - y) / (np.maximum(le-8, np.abs(x) + np.abs(y))))

def count_params(model):
    """Count the number of parameters in the current TensorFlow graph """
    param_count = np.sum([np.prod(p.size()) for p in model.parameters()])
    return param_count
```