PA 5: Generative Adversarial Networks

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0. Overview

This assignment is about Generative Adversarial Networks(GAN). The goal of this assignment is generating images with concepts of GAN. First problem is generating images from latent vector, the second problem is image-to-image translation, and the third problem is generating images from the caption.

1. [Problem #1] Training and Testing DC-GAN and Vector Arithmetic

Problem #1 is about training DC-GAN model. We can read and understand the DC-GAN using generator and discriminator network. And we can implement the DC-GAN model from github repository.

https://github.com/pytorch/examples/tree/main/dcgan

GitHub - Annusha/dcgan: train/test dcgan + arithmetic

man-woman-detection | Kaggle

Face Mask Detection ~12K Images Dataset | Kaggle

1.1. Try the efforts to improve the performance on your network. For example, your hyperparameter setting or collecting dataset or your network improvements that are not provided by the basic codes.

First, I implemented main.py based on the reference code in github. This main.py file will be used for training. Subsequently, code was additionally implemented to perform arithmetic. I implemented generator.py, arg_parse.py, and arthmetic.py based on another github reference code.

In the case of dataset, I downloaded it from Kaggle and used it. I downloaded the face mask dataset using the reference site. After that, the hyper-parameter was set and used for learning. It was set to batchSize=64, beta1=0.5, imageSize=64, lr=0.0002, ndf=64, and ngf=64. And in the case of the most important number of iteration, the test was conducted by adjusting it from 200 to 1000.

The entire training process started with main.py and used generator.py and arg_parse.py. From this, new data was created and noise value was stored along with it. And I tried to choose a clean image for arithmetic. It seemed good to choose a clean image and noise. So, I did arithmetic on the selected image and noise value using arithmetic.py.

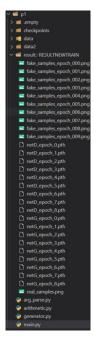
To proceed with the training, I used main.py as follows. Before that, the necessary package written in the requirement.txt file was installed (ex.lmdb). After that, learning was conducted after entering the parsing variable as follows.

```
(hhh) user@7ffe62bf4ffe:/home/DL/assn5/p1$ python main.py --dataset folder --dataroot '/home/DL/assn5/p1/data' --outf '/home/DL/assn5/p1/result/RESULTNEWTRAIN/' --niter 1000 --cuda &
```

Here, the "dataset" may specify the format of the dataset I used the data in the designated path using folder. "dataroot" is the path of the learning image, and "outf" is the path of output. "niter" determines the number of learning epochs, and "cuda" determines the GPU used for learning. Then, it can be seen that learning proceeds as follows.

```
1.3882 Loss_G: 6.8734 D(x): 0.9058 D(G(z)): 1.4597 Loss_G: 2.8750 D(x): 0.3440 D(G(z)):
1000][67/185]
                                                3.6001 D(x): 0.7197 D(G(z)): 3.5542 D(x): 0.6596 D(G(z)):
10001[70/185]
                 Loss D: 0.8254 Loss G:
1000][72/185
                 Loss_D: 0.9845 Loss_G:
                 Loss D: 0.6320 Loss G:
                                                4.7668 D(x): 0.8077
10001[75/185]
                                                7.0029 D(x): 0.7984
                            1.4200
                                                4.5892 D(x): 0.8491
2.6445 D(x): 0.5122
                 Loss D:
                                     Loss G:
      [80/185]
                 Loss D:
                            1.2405 Loss G:
                                                3.0656 D(x):
                                                                 0.5014
```

Then, it can be seen that the weight and image according to epoch are stored in the result folder made in advance as follows.



When learning is completed with main.py, new data is created based on the learned model. For this purpose, generator.py and arg_parse.py codes were implemented. The following is the arg_parse.py code, which sets variables that are used jointly by the generator and subsequent arithmetic.

```
parser = argparse.ArgumentParser()
# parser.add_argument('--dataset', required=True, help='cifar10 | lsun | imagenet | folder | lfw | fake')
parser.add_argument('--dataset', default='lsun', help='cifar10 | lsun | imagenet | folder | lfw | fake')
parser.add_argument('--dataroot', default='./data/', help='path to dataset')
parser.add_argument('--workers', type=int, help='number of data loading workers', default=4)
parser.add_argument('--batchSize', type=int, default=128, help='input batch size')
parser.add_argument('--imageSize', type=int, default=64, help='the height / width of the input image to network')
parser.add_argument('--ngf', type=int, default=100, help='size of the latent z vector')
parser.add_argument('--ndf', type=int, default=64)
parser.add_argument('--niter', type=int, default=1000, help='number of epochs to train for')
parser.add_argument('--niter', type=int, default=0.0002, help='learning rate, default=0.0002')
parser.add_argument('--niter', type=int, default=1000, help='number of epochs to train for')
parser.add_argument('--lr', type=float, default=0.0002, help='learning rate, default=0.0002')
parser.add_argument('--beta1', type=float, default=0.5, help='beta1 for adam. default=0.5')
parser.add_argument('--net6', default='/home/DL/assn5/p1/result/RESULTNENTRAIN/net6_epoch_999.pth', help="path to net6 (to continue training)")
parser.add_argument('--netD', default='/home/DL/assn5/p1/result/RESULTNENTRAIN/net0_epoch_999.pth', help="path to net0 (to continue training)")
parser.add_argument('--outf', default='/home/DL/assn5/p1/result/gimages/', help='folder to output images and model checkpoints')
parser.add_argument('--train_svm', action='store_true', help='enable train svm using saved features')
opt = parser.parse_args()
print(opt)
             os.makedirs(opt.outf)
  if opt.manualSeed is None:
               opt.manualSeed = random.randint(1, 10000)
 print("Random Seed: ", opt.manualSeed)
random.seed(opt.manualSeed)
   torch.manual_seed(opt.manualSeed)
 torch.cuda.manual_seed_all(opt.manualSeed)
   cudnn.benchmark = True
 kernels = []
strides = []
 pads = []
if opt.imageSize == 64:
                kernels = [4, 4, 4, 4, 4]
              strides - [1, 2, 2, 2, 2]
pads = [0, 1, 1, 1, 1]
   if opt.imageSize == 32:
               kernels = [2, 4, 4, 4, 4]
               pads = [0, 1, 1, 1, 1]
```

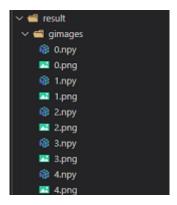
generator.py will randomly generate noise. Thus, an image may be generated through a generator. The following is code for generator network and noise generation and image generation and storage.

```
nz = int(arg_parse.opt.nz)
ngf = int(arg_parse.opt.ngf)
ndf - int(arg_parse.opt.ndf)
nc = 3
class Generator(nn.Module):
       self.main = nn.Sequential(
           nn.ConvTranspose2d( nz, ngf * 8, 4, 1, 0, bias=False),
nn.BatchNorm2d(ngf * 8),
           nn.ReLU(True),
           nn.ConvTranspose2d(ngf * 8, ngf * 4, 4, 2, 1, bias=False),
           nn.BatchNorm2d(ngf * 4),
           nn.ConvTranspose2d(ngf * 4, ngf * 2, 4, 2, 1, bias=False),
           nn.BatchNorm2d(ngf * 2),
           nn.ConvTranspose2d(ngf * 2,
                                          ngf, 4, 2, 1, bias=False),
           nn.BatchNorm2d(ngf),
           nn.ConvTranspose2d( ngf,
    def forward(self, input):
        output = self.main(input)
        return output
```

```
_create_and_save(netG):
   number = len(os.listdir(opt.outf))
   for i in range(number, number + opt.niter):
       noise = torch.FloatTensor(1, opt.nz, 1, 1).normal_(0, 1)
       noise = Variable(noise)
       noise - noise.cuda()
       noise_np - noise.cpu().numpy()
       np.save(opt.outf + '%d' % i, noise_np)
       fake - netG(noise)
   vutils.save_image(fake.data, opt.outf + '%d.png' % i, normalize=True, nrow=4)
if __name__ -- '__main__':
   netG = Generator()
   if opt.dataset == 'imagenet' :
       path_root - opt.dataroot
       path_Gs = [os.path.join(path_root, i) for i in os.listdir(path_root) if 'netG' in i]
       for path G in path Gs:
           digit = int(re.findall(r'\d+', path_G)[0])
           if digit < 30:
              print('save from epoch %d'%digit)
               netG.load_state_dict(torch.load(path_G))
              netG.cuda()
              netG.eval()
              __create_and_save(netG)
       if opt.netG -- ":
          print('load weights for generator')
           exit(-1)
       netG.load_state_dict(torch.load(opt.netG))
       print(netG)
       netG.eval()
       _create_and_save(net6)
```

The generator can be executed using the stored weight. The normal function, which produced the best image by testing by changing the noise generation method, was used. The noise value is also stored along with the generated image, and only one image is set to be generated at a time.

```
(hhh) user@7ffe62bf4ffe:/home/DL/assn5/p1$ python generator.py
Namespace(batchSize=128, beta1=0.5, dataroot='./data/', dataset='lsun', imageSize=64, lr=0.0002, manua es/', train_sym=False, workers=4)
Random Seed: 1485
Generator(
  (main): Sequential(
      (0): ConvTranspose2d(3, 512, kernel_size=(4, 4), stride=(1, 1), bias=False)
      (1): BatchNorm2d(512, eps=1e=05, momentum=0.1, affine=True, track_running_stats=True)
      (2): ReLU(inplace=True)
      (3): ConvTranspose2d(512, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
      (4): BatchNorm2d(256, eps=1e=05, momentum=0.1, affine=True, track_running_stats=True)
      (5): ReLU(inplace=True)
      (6): ConvTranspose2d(256, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
      (7): BatchNorm2d(128, eps=1e=05, momentum=0.1, affine=True, track_running_stats=True)
      (8): ReLU(inplace=True)
      (9): ConvTranspose2d(128, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
      (10): BatchNorm2d(64, eps=1e=05, momentum=0.1, affine=True, track_running_stats=True)
      (11): ReLU(inplace=True)
      (12): ConvTranspose2d(64, 3, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
      (13): Tanh()
    }
}
```



I would like to do arithmetical using the noise generated in this way. It is intended to create an image in a desired direction using the properties of Latent z.

```
lef preprocess_img(img_v):
   img = img_v.data.cpu().numpy()
   img = img.transpose(0, 2, 3, 1).squeeze()
   img +- 1
   img /= 2
   return img
if __name__ == '__main__' :
   noise_A_np - np.load('/home/DL/assn5/p1/result/gimages/26.npy')
   noise_A = torch.from_numpy(noise_A_np).to('cuda')
   image_A - netG(noise_A)
   A_image = preprocess_img(image_A)
   plt.imshow(A_image)
   plt.savefig('A_image.png')
   plt.cla()
   noise_B_np = np.load('/home/DL/assn5/p1/result/gimages/464.npy')
   noise_B = torch.from_numpy(noise_B_np).to('cuda')
   image_B = netG(noise_B)
   B_image = preprocess_img(image_B)
   plt.imshow(B_image)
   plt.savefig('B_image.png')
   plt.cla()
   noise_C_np = np.load('/home/DL/assn5/p1/result/gimages/14.npy')
   noise_C = torch.from_numpy(noise_C_np).to('cuda')
   image_C = netG(noise_C)
   C_image = preprocess_img(image_C)
   plt.imshow(C_image)
   plt.savefig('C_image.png')
   plt.cla()
   final_noise = noise_A - noise_B + noise_C
   final_image = netG(final_noise)
   final_im = preprocess_img(final_image)
   plt.axis('off')
   plt.title('withMaskman - withoutMaskMan + Woman')
   plt.imshow(final_im)
   plt.savefig('A_B_C.png')
   plt.show()
```

1.2. Some result images including generated images using DC-GAN.



Generated Images Using DC-GAN



Example Image 1 : With Mask Man



Example Image 2 : Without Mask Man



Example Image 3 : Woman



-



+





With Mask Man – Without Mask Man + Woman = Arithmetic Result Image

1.3. What did you learn through this problem #1.

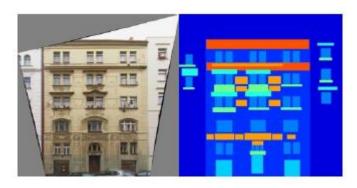
While doing Problem #1, I was able to learn about the model structure and learning method of DC-GAN. And through arithmetic, I learned how to use DC-GAN's latent z. And I learned that the role of noise is important when generating images using DC-GAN. Also, I learned that arithmetic doesn't work well as I expected and how to make a code using source code.

1.4. Discuss about the experimental results, network architecture, and training techniques.

From the results, it was found that the arithmetical process was not easy. And it was not easy to create an image from the noise vector. Perhaps the dataset is small in size, so the result is not perfect. And if you use the loud noise value, the result seems to be better. In particular, for hyperparameter nz at first test, we thought that we could create three characteristic features if we set nz to 3, but there was a problem that the image could not be generated well. This is thought to be because DC-GAN itself cannot define the exact condition, so if the information is too condensed during encoding by reducing nz, decoding is not good.

2. [Problem #2] Training and Testing Paired Image-to-Image Translation

Problem #2 is about training Pix2pix model. We can read and understand the pix2pix using generator and discriminator network. And we can implement the pix2pix model from github repository. We should train and test the pix2pix network with "Façade Dataset". We can download the data set from github repository, too. The following figure shows an example of Facades Dataset.



GitHub - junyanz/pytorch-CycleGAN-and-pix2pix: Image-to-Image Translation in PyTorch

2.1. Try the efforts to improve the performance on your network. For example, your hyperparameter setting or collecting dataset or your network improvements that are not provided by the basic codes.

To use the source code downloaded from github, we first built an environment.

```
(p2) user@7ffe62bf4ffe:/home/DL/assn5/p2$ conda env create -f environment.yml
Collecting package metadata (repodata.json): done
Solving environment: done
```

The conda environment was constructed as follows using the "environment.yml" file.

Dataset download to be used for pix2pix model was carried out using shell script as follows.

```
(pytorch-CycleGAN-and-pix2pix) user@7ffe62bf4ffe:/home/DL/assn5/p2$ ./datasets/download_pix2pix_dataset.sh facades
Specified [facades]
WARNING: timestamping does nothing in combination with -O. See the manual
for details.
 -2022-05-25 04:24:34-- http://efrosgans.eecs.berkeley.edu/pix2pix/datasets/facades.tar.gz
Resolving efrosgans.eecs.berkeley.edu (efrosgans.eecs.berkeley.edu)... 128.32.244.190
Connecting to efrosgans.eecs.berkeley.edu (efrosgans.eecs.berkeley.edu)|128.32.244.190|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 30168306 (29M) [application/x-gzip]
Saving to: './datasets/facades.tar.gz'
 ./datasets/facades.tar.gz
                                                                                100%[======
2022-05-25 04:25:19 (649 KB/s) - './datasets/facades.tar.gz' saved [30168306/30168306]
facades/test/
facades/test/27.jpg
facades/test/5.jpg
facades/test/72.jpg
facades/test/1.jpg
facades/test/10.jpg
facades/test/100.jpg
facades/test/101.jpg
facades/test/102.jpg
```

For training, the hyperparameter was set using "train_options.py" and "base_options.py" as follows.

```
def initialing(self, perser)

""Define the common options that are used in both training and test,""

* bail: parameters

parameter day agreement("-datacout, required-inue, help-'path to images (should have subfolders trainA, trainB, valA, valB, etc)')

parameter day agreement("-datacout, required-inue, help-'path to images (should have subfolders trainA, trainB, valA, valB, etc)')

parameter day agreement("-datacout, required-inue, help-'path to images (should have subfolders trainA, trainB, valA, valB, etc)')

parameter day agreement("-datacout, required-inue, help-'gath in parameter day agreement("-datacout, required-inue, default-s), help-'gath inue, default-s), help-'gath inue, default-s), help-'gath inue, default-s), help-'gath of spout inue, default-s), parameter, day agreement("-metri, spowint, default-shape," of gan filters in the last coun layer')

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```

```
def initialize(self, parser):

parser - Basequitons.initialize(self, parser)

* vision and HDM visualization parameters

parser.add_argament('-display_fered', type-int, default-400, help='frequency of shouding training results on screen')

parser.add_argament('-display_fered', type-int, default-4, help='if positive, display all langes in a single vision web panel with certain number of images per row.')

parser.add_argament('-display_sered', type-int, default-4, help='inindo id of the web display')

parser.add_argament('-display_sered', type-int, default-5, help-'inindo id of the web display')

parser.add_argament('-display_sered', type-int, default-5, help-'inido served of the web display')

parser.add_argament('-display_sered', type-int, default-500, help-'frequency of shouting training results to heal')

parser.add_argament('-print_fered', type-int, default-500, help-'frequency of shouting training results to heal')

parser.add_argament('-print_fered', type-int, default-500, help-'frequency of saving training results to console')

parser.add_argament('-seve_latest_fered', type-int, default-500, help-'frequency of saving the latest results')

parser.add_argament('-seve_latest_fered', type-int, default-500, help-'frequency of saving the latest results')

parser.add_argament('-seve_latest_fered', type-int, default-500, help-'frequency of saving the latest results')

parser.add_argament('-seve_latest_fered', type-int, default-500, help-'frequency of saving the consolate at the end of epochs')

parser.add_argament('-seve_latest_fered', type-int, default-500, help-'frequency of saving the consolate at the end of epochs')

parser.add_argament('-continue_train', action-store_true', help-'continue training: load the latest model')

parser.add_argament('-continue_train', action-istore_true', help-'continue training: load the latest model')

parser.add_argament('-mpoch_seve_type-int, default-100, help-'number of epochs to linearly decay learning rate to zero')

parser.add_argament('-mpoch_seve_type-int, default-100, he
```

To train, I ran the train.py file as follows.

```
(Optorch-tycledow-ond-include) overgittenishifes: //www.flut.resolt/pip python train.py --distancet .//distancet./facades --name facades.picipix --model picipix --model picip
```

As learning progresses, the results are shown for each epoch as follows.

```
(epoch: 200, iters: 100, time: 0.036, data: 0.422) G_GAN: 3.706 G_L1: 17.589 D_real: 0.069 D_fake: 0.051 (epoch: 200, iters: 200, time: 0.037, data: 0.004) G_GAN: 1.446 G_L1: 20.361 D_real: 0.071 D_fake: 0.455 (epoch: 200, iters: 300, time: 0.036, data: 0.003) G_GAN: 2.974 G_L1: 14.946 D_real: 0.034 D_fake: 0.097 (epoch: 200, iters: 400, time: 0.774, data: 0.002) G_GAN: 4.774 G_L1: 19.740 D_real: 0.008 D_fake: 0.018 saving the latest model (epoch 200, total_iters 80000) saving the model at the end of epoch 200, iters 80000 End of epoch 200 / 200 Time Taken: 17 sec (pytorch-CycleGAN-and-pix2pix) user@7ffe62bf4ffe:/home/DL/assn5/p2$
```

In the meantime, weight is saved every five turns of the epoch.

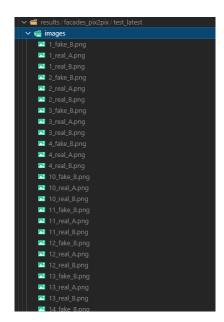
```
| 135_net_G.pth
| 140_net_D.pth
| 140_net_G.pth
| 145_net_D.pth
| 145_net_G.pth
| 150_net_D.pth
| 150_net_G.pth
| latest_net_D.pth
| latest_net_G.pth
| latest_net_G.pth
| latest_net_G.pth
```

```
(pytorch-CycleGAN-and-pix2pix) user@7ffe62bf4ffe:/home/DL/assn5/p2$ python train.py --dataroo
t ./datasets/facades --name facades_pix2pix_AtoB --model pix2pix --direction AtoB --gpu_ids 1
Warning: wandb package cannot be found. The option "--use_wandb" will result in error.
----- Options
              batch_size: 1
                   beta1: 0.5
         checkpoints_dir: ./checkpoints
continue_train: False
              crop size: 256
            dataroot: ./datasets/facades
dataset_mode: aligned
                                                                 [default: None]
               direction: AtoB
                                                                 [default: BtoA]
             display_env: main
            display_freq: 400
display_id: 1
           display_ncols: 4
            display_port: 8097
          display_server: http://localhost
          display_winsize: 256
                   epoch: latest
             epoch_count: 1
                gan_mode: vanilla
                 gpu_ids: 1
                                                                  [default: 0]
               init_gain: 0.02
               init_type: normal
                input_nc: 3
                 isTrain: True
                                                                  [default: None]
               lambda_L1: 100.0
                load_iter: 0
                                                                  [default: 0]
               load_size: 286
                      lr: 0.0002
          lr_decay_iters: 50
               lr_policy: linear
        max_dataset_size: inf
                   model: pix2pix
                n_epochs: 100
          n_epochs_decay: 100
              n_layers_D: 3
                     name: facades_pix2pix_AtoB
                                                                [default: facades_pix2pix]
                    ndf: 64
                    netD: basic
                    netG: unet 256
                     ngf: 64
              no_dropout: False
                 no_flip: False
                 no_html: False
                    norm: batch
              num_threads: 4
               output_nc: 3
                   phase: train
               pool_size: 0
              preprocess: resize_and_crop
              print_freq: 100
            save_by_iter: False
         save_epoch_freq: 5
         save_latest_freq: 5000
          serial_batches: False
                  suffix:
        update_html_freq: 1000
               use_wandb: False
                verbose: False
  ---- End ---
dataset [AlignedDataset] was created
The number of training images = 400
initialize network with normal
initialize network with normal
model [Pix2PixModel] was created
----- Networks initialized -----
[Network G] Total number of parameters : 54.414 M
[Network D] Total number of parameters : 2.769 M
```

To test, I ran the test.py file as follows.

```
Option-in-cyclecite.and pictopic) acceptifice.nintific./haseline/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/acception/a
```

Images are then created in the result folder as follows.

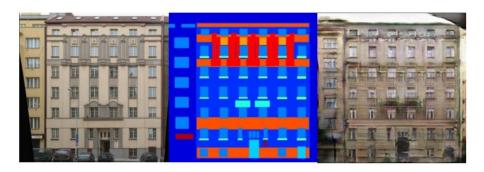


2.2. Some result images including generated images using pix2pix.

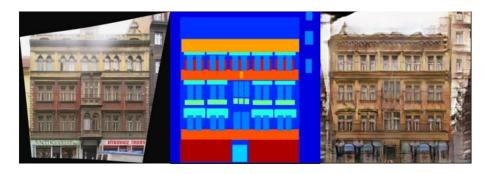
The training data set has the following image structure.



Train A Train B



Real A Real B Fake A



Real A Real B Fake A



Real B Real A Fake B

2.3. What did you learn through this problem #2.

I learned pix2pix structure and learning method for paired image-to-image translation. And I learned how to configure the paired image set for paired image-to-image translation learning. I learned about reflecting learning changes according to paired image characteristics.

2.4. Discuss about the experimental results, network architecture, and training techniques.

In the case of facades dataset, the processing image B and A characterizing the window and door of the real image are translated into B, so it can be confirmed that the actual image A is converted to B well according to the characteristics of the window and door. However, it was confirmed that the image generated during the opposite conversion was similar to image B in terms of the number of windows, doors, and appearance structure, but the texture and color of the exterior of the building were not learned as similar to A. In this case, the characteristics of the paired images are well learned in the pix2pix learning structure. In other words, train B set is an image that structures the characteristics of windows and doors well, so if we convert it to A->B, I think I can clearly express the characteristics, but when converting to B->A, the train A data can be used as a whole. The characteristics of a building and its exterior structure, windows, doors, etc. are well learned and expressed, but the color and texture of the building. It was confirmed that it was not learned up to the characteristics that were difficult to learn

2.5. Create your own idea and show the implementation results.

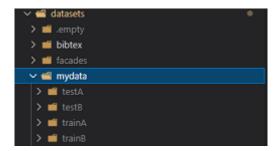
Collect the dataset for your idea.

I collected data through googling to use pokemon which is from animation and animals as dataset. I prepared 500 training data and 150 test data.



Implement the code that realizes your idea.

Mydata folder was created in ./datasets as follows to organize training data and test data.



In order to use pix2pix, it is necessary to combine each data into one. Therefore, the process of combining data into one using "combine_A_and_B.py" was carried out as follows.

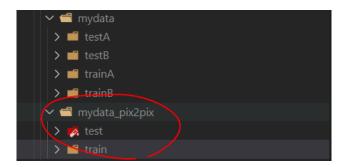
```
parser = argparse.ArgumentParser('create image pairs')
parser.add.argument('--fold,A', dest='fold,A', help='input directory for image A', type=str, default='/home/DL/assn5/p2/datasets/mydata/trainA')
parser.add.argument('--fold,AB', dest='fold,AB', help='input directory', type=str, default='/home/DL/assn5/p2/datasets/mydata/trainB')
parser.add.argument('--fold,AB', dest='fold,AB', help='output directory', type=str, default='/home/DL/assn5/p2/datasets/mydata_pix2pix')
parser.add.argument('--usu,AB', dest='sea,B', help='input directory', type=str, default='/home/DL/assn5/p2/datasets/mydata_pix2pix')
parser.add.argument('--no.multiprocessing', dest='no_multiprocessing', help='If used, chooses single CPU execution instead of parallel execution', action='store_true',default=True)
args = parser.parse_args()

parser.add.argument('--fold,A', dest='fold,A', help='input directory for image A', type=str, default='/home/DL/assn5/p2/datasets/mydata/testA')
parser.add.argument('--fold,A', dest='fold,A', help='input directory for image B', type=str, default='/home/DL/assn5/p2/datasets/mydata/testB')
parser.add.argument('--fold,A', dest='fold,A', help='input directory', type=str, default='/home/DL/assn5/p2/datasets/mydata/testB')
parser.add.argument('--fold,A', dest='fold,A', help='input directory', type=str, default='/home/DL/assn5/p2/datasets/mydata/testB')
parser.add.argument('--fold,A', dest='fold,A', help='input directory', type=str, default='/home/DL/assn5/p2/datasets/mydata/testB')
parser.add.argument('--noum.ings', help='number of images', type=int, default='/home/DL/assn5/p2/datasets/mydata/testB')
parser.add.argument('--noum.ings', dest='no_multiprocessing', help='If used, chooses single CPU execution instead of parallel execution', action='store_true', default=True)
aparser.anda argument('--noum.ings', help='number of images', type=int, default=True)
aparser.anda argument('--noum.ings', dest='no_multiprocessing', help='If used, chooses single CPU execution instead of parallel execution', action='store_true', default
```

The extensions of the data I collected were different from .jpg and .png, so I needed to modify the existing code.

```
img_fold_A = os.path.join(args.fold_A, sp)
     img_fold_B = os.path.join(args.fold_B, sp)
    img_list = os.listdir(img_fold_A)
    if args.use AB:
         img_list = [img_path for img_path in img_list if '_A.' in img_path]
    num_imgs = min(args.num_imgs, len(img_list))
print('split = %s, use %d/%d images' % (sp, num_imgs, len(img_list)))
img_fold_AB = os.path.join(args.fold_AB, sp)
    if not os.path.isdir(img_fold_AB):
    os.makedirs(img_fold_AB)
print('split = %s, number of images = %d' % (sp, num_imgs))
    for n in range(num_imgs):
    name_A = img_list[n]
    path_A = os.path.join(img_fold_A, name_A)
          if args.use_AB:
              name B = name A.replace(' A.', ' B.')
         name_B = name_B[:-4] + '.jpg
         path_B = os.path.join(img_fold_B, name_B)
if os.path.isfile(path_A) and os.path.isfile(path_B):
              name_AB = name_A
              if args.use_AB:
              name_AB = name_AB.replace('_A.', '.') # remove _A
path_AB = os.path.join(img_fold_AB, name_AB)
               if not args.no_multiprocessing:
                   pool.apply_async(image_write, args=(path_A, path_B, path_AB))
                  im_A = cv2.imread(path_A, 1) # python2: cv2.CV_LOAD_IMAGE_COLOR; python3: cv2.IMREAD_COLOR
                   im_B = cv2.imread(path_B, 1) # python2: cv2.CV_LOAD_IMAGE_COLOR; python3: cv2.IMREAD_COLOR
im_B = cv2.resize(im_B, (256, 256))
im_AB = np.concatenate([im_A, im_B], 1)
                   cv2.imwrite(path_AB, im_AB)
if not args.no_multiprocessing:
    pool.close()
```

And when I run "combine_A_and_B.py", the data is combined as follows.



500 training data and 150 test data exist as a pair as follows.



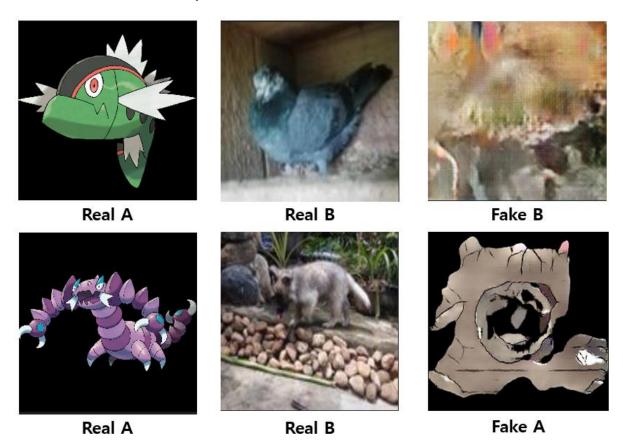
And in order to train, I ran "train.py" in both directions.

```
Sprinch of plotting and plotphysis and plotphysis and protein former through states are supplied as the plot of th
```

For test, I ran "test.py" in both directions.

```
Sports and public amplifications and analysis of price tests and security and price tests are also asked with result in error until good public great in tests the option "-out pushed from the section "-out pushed from the
```

Demonstrate the implementation results.



Discuss about your achievement.

As shown in the above results, in the case of my dataset, it was confirmed that the learned results were not very satisfactory. It was found that even if two pairs of data sets were tried to be well constructed, they could not form a perfectly matched pair, so they could not generate an image that reflected the characteristics of each picture, and slightly produced a general image such as DC-GAN. (Images are created similarly regardless of the input image.) In the case of pix2pix, it was confirmed that the matching pairing similar to the input image had the greatest influence on learning, except for specific parts of the input data and ground truth. In fact, it has been confirmed that many image conversion apps using pix2pix are being developed as mobile apps, and it has been confirmed that the pix2pix model has an excellent effect to apply to certain characteristic values (change to black-and-white, sketch, oil painting, cartoon, etc.).

3. [Problem #3] Training and Testing Paired Text-to-Image Synthesis

Problem #3 is about training paired text-to-image model. We can read and understand the Generative Adversarial Text-to-Image Synthesis using generator and discriminator work. We can implement the text-to-image synthesis model from github repository. Also, we can train and test the text-to-image synthesis model with Flower dataset.



- https://github.com/mirrortower/Text-to-Image-Synthesis

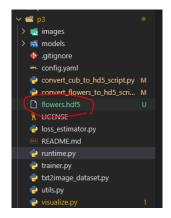
3.1. Try the efforts to improve the performance on your network. For example, your hyperparameter setting or collecting dataset or your network improvements that are not provided by the basic codes.

First, we modified the "convert_flowers_to_hd5_script.py" file to use the flower dataset. The torch that was previously deleted from here. The "torch.utils.serialization.load_lua" module was not available, so the code was modified to use the "torchfile" module.

```
for example, txt_file in zip(sorted(glob(data_path + "/*.t7")), sorted(glob(txt_path + "/*.txt"))):

#example_data = load_lua(example)
example_data = torchfile.load(example)
img_path = example_data['img']
```

In order to use the flowers dataset, it was changed to hd5 format as follows. I downloaded the preconverted hd5 data to eliminate the inconvenience of changing the image to hd5 format.



Hyper-parameter was set through github's argument explanation.

```
Arguments:
 • type : GAN archiecture to use (gan | wgan | vanilla_gan | vanilla_wgan) . default = gan . Vanilla mean not
  • dataset : Dataset to use (birds | flowers) . default = flowers
  • split: An integer indicating which split to use (0: train | 1: valid | 2: test). default = 0
 • 1r : The learning rate. default = 0.0002
 • diter: Only for WGAN, number of iteration for discriminator for each iteration of the generator. default = 5
 • vis_screen : The visdom env name for visualization. default = gan

    save_path : Path for saving the models.

 • 11_coef : L1 loss coefficient in the generator loss fucntion for gan and vanilla_gan. default= 50

    12_coef: Feature matching coefficient in the generator loss fucntion for gan and vanilla_gan. default= 100

 • pre_trained_disc : Discriminator pre-tranined model path used for intializing training.
 • pre_trained_gen Generator pre-tranined model path used for intializing training.
  • batch_size : Batch size. default= 64

    num_workers : Number of dataloader workers used for fetching data. default = 8

  • epochs : Number of training epochs. default= 200
  • cls: Boolean flag to whether train with cls algorithms or not. default= False
```

The following are arguments in "runtime.py".

```
p3 > runtime.py > ...

2   import argparse
3   from PIL import Image
4   import os

5   

6   parser = argparse.ArgumentParser()
7   parser.add_argument("--type", default='gan')
8   parser.add_argument("--lr", default=0.0002, type=float)
9   parser.add_argument("--l1_coef", default=50, type=float)
10   parser.add_argument("--l2_coef", default=100, type=float)
11   parser.add_argument("--cls", default=5, type=int)
12   parser.add_argument("--cls", default=False, action='store_true')
13   parser.add_argument("--vis_screen", default='gan')
14   iv parser.add_argument("--save_path", default='./checkpoints/')
15   parser.add_argument('--inference", default=False, action='store_true')
16   parser.add_argument('--pre_trained_disc', default=None)
17   parser.add_argument('--retrained_gen', default=None)
18   parser.add_argument('--dataset', default=0, type=int)
19   parser.add_argument('--batch_size', default=64, type=int)
20   parser.add_argument('--num_workers', default=8, type=int)
21   parser.add_argument('--num_workers', default=200, type=int)
22   args = parser.parse_args()
23   trainer = Trainer(type=args.type.
```

The path was modified in "config.yaml" to use the downloaded "flowers.hdf5".

```
#flowers_dataset_path: '/scratch/aelnouby/text2image/flowers.hdf5'
flowers_dataset_path: './flowers.hdf5'
```

The code received from the git clone is an old code, so the updateTrace() function of visdom

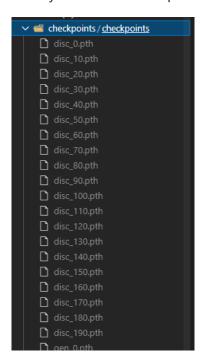
disappeared, so the code was modified as follows.

```
25 else:
26 #self.viz.updateTrace(X=np.array([x]), Y=np.array([y]), env=self.env, win=self.plots[var_name], name=split_name)
27 self.viz.scatter(X=np.array([x]), Y=np.array([y]), env=self.env, win=self.plots[var_name], name=split_name, update='append')
```

Now, we can use "runtime.py" to learn.

```
(hhh) user@7ffe62bf4ffe:/home/DL/assn5/p3$ python runtime.py
/home/DL/assn5/p3/trainer.py:17: YAMLLoadWarning: calling yaml.load() without Loader=... is deprecated, as the default Loader is unsafe. Please reaconfig = yaml.load(f)
Setting up a new session...
Epoch: 0, d_loss= 1.794668, g_loss= 37.672554, D(X)= 0.659038, D(G(X))= 0.525757
Epoch: 0, d_loss= 1.942220, g_loss= 32.695656, D(X)= 0.265561, D(G(X))= 0.083352
Epoch: 0, d_loss= 2.308926, g_loss= 34.753044, D(X)= 0.218201, D(G(X))= 0.0924300
Epoch: 0, d_loss= 1.155093, g_loss= 35.283421, D(X)= 0.522767, D(G(X))= 0.016589
Epoch: 0, d_loss= 1.048615, g_loss= 37.287331, D(X)= 0.687467, D(G(X))= 0.285874
Epoch: 0, d_loss= 1.356555, g_loss= 35.514931, D(X)= 0.458255, D(G(X))= 0.014313
Epoch: 0, d_loss= 1.3771866 g_loss= 36.05829 g_loss= 35.514931, D(X)= 0.88275, D(G(X))= 0.348073
```

In the meantime, weights are saved every ten turns of the epoch.



In order to test, the interference mode was changed to true and pretrained weights.

```
parser = argparse.ArgumentParser()
parser.add_argument("--type", default='gan')
parser.add_argument("--lr", default=0.0002, type=float)
parser.add_argument("--l1_coef", default=50, type=float)
parser.add_argument("--l2_coef", default=100, type=float)
parser.add_argument("--diter", default=5, type=int)
parser.add_argument("--cls", default=False, action='store_true')
parser.add_argument("--vis_screen", default='gan')
parser.add_argument("--save_path", default='./checkpoints/')
parser.add_argument("--pre_trained_disc', default='./checkpoints/checkpoints/disc_190.pth')
parser.add_argument('--pre_trained_gen', default='./checkpoints/checkpoints/ger_190.pth')
parser.add_argument('--batch_size', default=64, type=int)
parser.add_argument('--batch_size', default=8, type=int)
parser.add_argument('--num_workers', default=8, type=int)
parser.add_argument('--pochs', default=200, type=int)
args = parser.parse_args()
```

Then, the model will read the following text to generate images.

this flower has six thick and long white petals with dark purple spots.

this flower has petals that are white and has yellow stamen

the beautiful small flower has yellow petals that are soft, smooth and has white stamen sticking out from the centre

the dark pink petals with smaller white flowers as the center has yellow stamens, and green pedicel.

this flower has petals that are orange with shades of yellow

the bright pink petals have dark pink spots and ruffled edges and the stamen have brown anther.

vibrant petals that extend forward and fold ever so slightly, the yellow is very bright.

pedicel are dark purple in color, petals are oval in shape and are light purple in color

this flower is yellow and brown in color, with petals that are wrinkled,.

this flower has petals that are yellow and are ruffled together

the flower has a brightly colored yellow set of petals.

this flower has petals that are red and has yellow stamen

the flower has pink petals which have a veining pattern and a pink pistil.

the petals on this flower are small and purple in color

the flower has petals that are bell shaped and bright pink with purple and white spots.

this flower has several rounded red petals with orange tips and accents.

It can be seen that an image is created in the result folder according to each text.



3.2. Some result images including generated images using Text-to-Image synthesis model.



white petals with a yellow center



this yellow flowers have smooth petals and a bunch of stamens



this white and pale pink flower has a dark pink center



yellow petals little green leaves



violet pointed and vein showing petals with a violet and green pistil



white and yellow ovary flower

3.3. What did you learn through this problem #3.

Through problem #3, I learned about the structure and learning method of the GAN model for text-to-image synthesis. And I learned what dataset should be used and learned for text-to-image synthesis learning. And it was very interesting to be able to create an image using text.

3.4. Discuss about the experimental results, network architecture, and training techniques.

Basically, it seems that it took a long time to learn because of the structure of creating an image from text. It seems that it took about a day to learn 200 epochs. I think I showed good results by setting the hyperparameter and learning the model by referring to the paper. In most cases, good results were produced due to good learning, but there were cases where results were somewhat inconsistent with text. I think this reason is caused by the mode collapse problem. This problem may be solved by improving cycle consistency.

4. [Problem #4] Training and Testing Unpaired Image-to-Image Translation

Problem #4 is about training CycleGAN model. We can read and understand the CycleGAN using the generator and discriminator network. We can implement the CycleGAN from github repository which is same as problem #2. We can train and test the CycleGAN network with horse-to-zebra dataset. We can download horse-to-zebra dataset from that github repository. The following shows example of horse to zebra image translation.



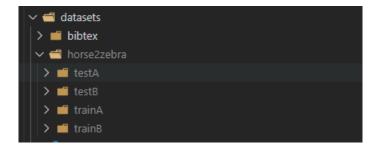


4.1. Try the efforts to improve the performance on your network. For example, your hyperparameter setting or collecting dataset or your network improvements that are not provided by the basic codes.

Dataset download to be used for pix2pix model was carried out using shell script as follows.

(pytorch-CycleGAN-and-pix2pix) user@7ffe62bf4ffe:/home/DL/assn5/p4\$./datasets/download_cyclegan_dataset.sh horse2zebra

Then, the horse2zebra dataset is created as follows.



To train, I ran the train.py file as follows.

```
(pytorch-CycleGAN-and-pix2pix) user@7ffe62bf4ffe:/home/DL/assn5/p4$ python train.py --dataroot ./datasets/horse2zebra --name horse2zebra --model cycle_gar
Warning: wandb package cannot be found. The option "--use_wandb" will result in error.
                         Options
                      batch size: 1
             beta1: 0.5
checkpoints_dir: ./checkpoints
continue_train: False
                     crop_size: 256
                  dataroot: ./datasets/horse2zebra
dataset_mode: unaligned
                                                                                           [default: None]
                 direction: AtoB
display_env: main
display_freq: 400
display_id: 1
                display_ncols: 4
display_port: 8097
             display_server: http://localhost
display_winsize: 256
                    epoch: latest epoch_count: 1
                       gan_mode: lsgan
gpu_ids: 0
                      init_gain: 0.02
init_type: normal
                        input_nc: 3
isTrain: True
                                                                                             [default: None]
                        lambda_A: 10.0
lambda_B: 10.0
              lambda_identity: 0.5
                       load_iter: 0
                                                                                              [default: 0]
                      load_size: 286
lr: 0.0002
               lr_decay_iters: 50
lr_policy: linear
            max_dataset_size: inf
model: cycle_gan
n_epochs: 100
n_epochs_decay: 100
                     n_layers_D: 3
                             name: horse2zebra
                                                                                             [default: experiment name]
                              ndf: 64
                             netG: resnet_9blocks
ngf: 64
                     no_dropout: True
no_flip: False
                         no html: False
                    num threads: 4
                      output_nc: 3
                             phase: train
                      pool_size: 50
                    preprocess: resize_and_crop
print_freq: 100
            save_by_iter: False
save_epoch_freq: 5
save_latest_freq: 5000
               serial_batches: False
                          suffix:
             update_html_freq: 1000
                       use wandb: False
```

As learning progresses, the results are shown for each epoch as follows.

Training was also conducted in the opposite direction.

```
n_layers_D: 3

name: horse2zebra_BtoA

ndf: 64

netD: basic

netG: resnet_9blocks

ngf: 64

no_dropout: True

no_flip: False

no_html: False

no_html: False

no_mm: instance

num_threads: 4

output_nc: 3

phase: train

pool_size: 50

preprocess: resize_and_crop

print_freq: 100

save_by_iter: False

save_by_oter: False
                                                     [default: experiment_name]
```

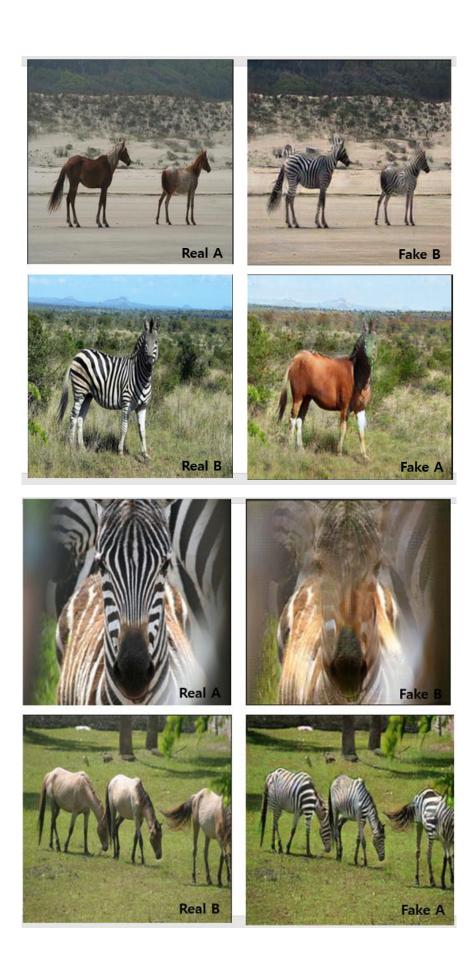
To test, I ran the test.py file as follows.

```
(pycoch cycledW.ead ploppin) usergiffeeddfile; Themana/austrials produced and the control of the
```

4.2. Some result images including generated images using CycleGAN.







4.3. What did you learn through this problem #4.

I learned about CycleGAN structure and learning method for unpaired image to image translation. And I learned how to configure the unpaired image set for unpaired image to image translation learning. Also I learned reflecting of learning change according to unpaired image characteristics.

4.4. Discuss about the experimental results, network architecture, and training techniques.

Unlike pix2pix, which is a paired image to image translation, the CycleGAN uses unpaired data as a learning set, so it was much more free to configure data for training, and it was confirmed that image generation was good regardless of the characteristics of the two paired data during the test. In particular, it is thought that this algorithm, which is much more useful, can be used as it can save considerable time compared to pix2pix in the part of creating the learning data set. However, while pix2pix takes very little time to learn, CycleGAN has a disadvantage that it takes a lot of time to learn If speed is not important, cycle rather than pix2fix. I think it is more useful to use GAN. When learning the same dataset (about 5000 with 200 epochs), pix2pix takes about 3 hours, whereas Cycle GAN takes about 12 hours.

4.5. Create your own idea and show the implementation results.

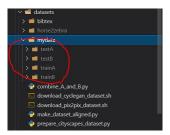
Collect the dataset for your idea.

I collected data through googling to use pokemon which is from animation and animals as dataset. I prepared 500 training data and 150 test data. The same data were prepared to compare the results of Problem #2 with the performance of CycleGAN.



Implement the code that realizes your idea.

However, here, I don't have to pair it up, and I can proceed with training by dividing it into folders as follows.



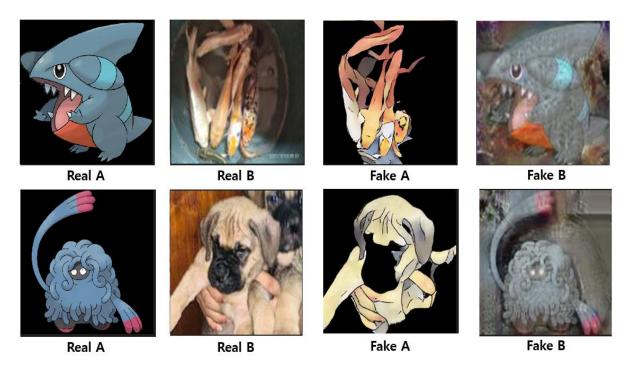
Again, training was conducted in both directions using "train.py".

```
Option of Column and Solicity is semiground in the column and colu
```

And test was conducted in both directions using "test.py"

```
Spring and profession deficiels to semi-deficient formation and place and pl
```

Demonstrate the implementation results.



Discuss about your achievement.

The paired image-to-image translation, pix2pix, is the input image for the unpaired image dataset. Unlike the fact that the characteristics of the input image were not reflected at all when the ground truth was reflected, CycleGAN verified that an image whose characteristics were well reflected by reflecting the characteristics of the input image was generated and that the performance was excellent. In fact, it can be difficult to say that it went completely well because there is a feeling that learning data was made too forcibly. However, I think it was a sufficiently valuable experiment in that it showed better results than the existing pix2pix.