```
In [1]: from platform import python version
        print('Notebook was originally ran with Python version:')
        print(python_version())
        Notebook was originally ran with Python version:
        3.6.6
In [2]:
        import numpy as np
        import matplotlib.pyplot as plt
        import torch
        import torch.nn as nn
        import torch.optim as optim
        from torch.utils.data import TensorDataset
        from torch.utils.data import DataLoader
        from DataPreparation.dataset preparation import get SVHN dataset
        from sklearn.model selection import train test split
        import warnings
        warnings.filterwarnings('ignore')
        %matplotlib inline
        %load ext autoreload
        %autoreload 2
```

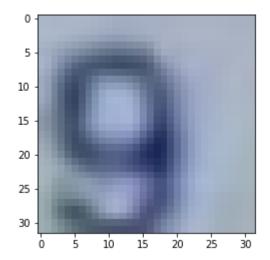
## A. Load the Dataset

Set the data directory to the path where the following files exist: train 32x32.mat, test 32x32.mat

```
In [3]: data dir = 'Dataset/SVHN/'
        validation_split = 0.2
        seed = 6135
In [4]: X_train, y_train, X_val, y_val, X_test, y_test, X_train_max = get_SVHN_dataset(da
        scale = lambda img: X train max * ((img / 2) + 0.5)
        print('X_train shape: ', X_train.shape)
        print('y_train shape: ', y_train.shape)
        print('X_val shape: ', X_test.shape)
        print('y_val shape: ', y_test.shape)
        print('X_test shape: ', X_test.shape)
        print('y test shape: ', y test.shape)
        Generating numpy dataset from existing .mat files in Dataset/SVHN/
        X_train shape: (58606, 3, 32, 32)
        y train shape:
                        (58606,)
        X val shape: (26032, 3, 32, 32)
        y val shape:
                      (26032,)
        X test shape: (26032, 3, 32, 32)
        y test shape: (26032,)
```

### Visualization sanity check

```
In [5]: plt.imshow(np.transpose(scale(X_test[250]), (1, 2, 0)).astype('uint8'))
   plt.show()
```



```
In [6]: batch_size = 256
    X_train_ = TensorDataset(torch.from_numpy(X_train))
    loader_train = DataLoader(X_train_, batch_size=batch_size, shuffle=True)

    X_val_ = TensorDataset(torch.from_numpy(X_val))
    loader_val = DataLoader(X_val_, batch_size=batch_size, shuffle=False)

    X_test_ = TensorDataset(torch.from_numpy(X_test))
    loader_test = DataLoader(X_test_, batch_size=batch_size, shuffle=False)
```

### **B.** Train the Model

#### Select device

```
In [7]: # CUDA for PyTorch
    use_cuda = torch.cuda.is_available()
    device = torch.device("cuda:0" if use_cuda else "cpu")
    print('Using device=GPU') if use_cuda else print('Using device=CPU')

Using device=GPU
```

#### VAE

```
In [8]: from models.vae import VAE
    num_latent = 100
    model = VAE(num_latent).to(device)
```

```
In [9]: # Hyperparameters
learning_rate = 3e-4
num_epochs = 100
```

```
In [10]:
         from utils.train eval utils import train model
         print('~~~ Training with GPU ~~~') if use cuda else print('~~~ Training with CPU
         num params = sum(p.numel() for p in model.parameters() if p.requires grad)
         print('Model has %.2fM trainable parameters.\n' % (num params/1e6))
         optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)
         train history = train model(model, optimizer, loader train,
                                     loader_val, num_epochs,
                                     device)
         LPOCII JO.
         Train: elbo -71.9778, likelihood -39.4060, KL 32.5719
         Validation: elbo -79.8376, likelihood -46.6083, KL 33.2293
         -----
         Epoch 97:
         Train: elbo -71.5037, likelihood -38.9638, KL 32.5399
         Validation: elbo -80.5824, likelihood -47.8544, KL 32.7280
         Epoch 98:
         Train: elbo -71.4471, likelihood -38.8846, KL 32.5625
         Validation: elbo -81.2226, likelihood -48.6840, KL 32.5386
         ______
         Epoch 99:
         Train: elbo -71.7573, likelihood -39.1462, KL 32.6111
         Validation: elbo -80.3220, likelihood -46.8925, KL 33.4295
         Epoch 100:
         Train: elbo -71.4943, likelihood -38.9519, KL 32.5424
         Validation: elbo -80.3651, likelihood -47.8037, KL 32.5614
```

```
In [11]: PATH = 'vae100.pt'
torch.save(model, PATH)
```

#### GAN

```
In [12]: from models.gan import Generator, Discriminator
    num_latent = 100
    generator = Generator(num_latent).to(device)
    discriminator = Discriminator().to(device)
```

```
In [13]: # Hyperparameters
    learning_rate = 1e-4
    b1 = 0.5
    b2 = 0.999
    num_iterations = 20000
    d_iterations = 5
```

```
In [14]:
         from utils.train eval utils gan import train model
         print('~~~ Training with GPU ~~~') if use_cuda else print('~~~ Training with CPU
         num params = sum(p.numel() for p in generator.parameters() if p.requires grad)
         print('Generator has %.2fM trainable parameters.' % (num params/1e6))
         num_params = sum(p.numel() for p in discriminator.parameters() if p.requires_grad
         print('Discriminator has %.2fM trainable parameters.\n' % (num params/1e6))
         optimizer d = torch.optim.Adam(discriminator.parameters(), lr=learning rate, beta
         optimizer g = torch.optim.Adam(generator.parameters(), lr=learning rate, betas=(b
         train_model(discriminator, generator, optimizer_d, optimizer_g,
                     loader train, loader val, num iterations, d iterations, device, use c
                                GAN SVHN generations
```

In [15]: PATH = 'generator%d.pt' % num\_iterations
 torch.save(generator, PATH)
 PATH = 'discriminator%d.pt' % num\_iterations
 torch.save(discriminator, PATH)

## C. Qualitative Evaluation

## C.1. Generate Samples

```
In [16]: num_generations = 64
```

#### VAE

```
In [17]: z = torch.randn(num_generations, num_latent).to(device)
    model.eval()
    with torch.no_grad():
        vae_generations = model.sample(z).cpu().numpy()
    vae_generations = np.transpose(scale(vae_generations), (0, 2, 3, 1)).astype('uinterest)
```

```
In [18]: from utils.plotter import plot_and_save_images
    plot_and_save_images(vae_generations, 'VAE')
```

VAE SVHN generations



#### **GAN**

```
In [19]: z = torch.randn(num_generations, num_latent).to(device)
    generator.eval()
    with torch.no_grad():
        gan_generations = generator.sample(z).cpu().numpy()
    gan_generations = np.transpose(scale(gan_generations), (0, 2, 3, 1)).astype('uint')
```

```
In [20]: from utils.plotter import plot_and_save_images
    plot_and_save_images(gan_generations, 'GAN_')
```

GAN\_ SVHN generations



# C.2. Disentanglement

### **VAE**

```
In [188]: epsilon = 1.5
    top_n = 15
    num_interp = 9
    z = torch.randn((1, num_latent)).to(device)
```

```
# Find dimensions that result in the most change:
          vae disentanglement = np.zeros((num latent, 3, 32, 32))
          model.eval()
          with torch.no_grad():
              original = model.sample(z).cpu().numpy()
              for i in range(num latent):
                   z = z.clone().detach()
                   z [0, i] += epsilon
                  vae_disentanglement[i] = model.sample(z_).cpu().numpy()
          diff = np.sum((vae_disentanglement - original)**2, axis=(1,2,3))
          topn_features = diff.argsort()[-top_n:][::-1]
          print('Most effective latent dimensions:')
          print(topn_features)
          Most effective latent dimensions:
          [36 48 78 90 32 12 37 56 59 49 47 82 42 35 10]
In [190]: # Traverse along those dimensions:
          vae disentanglement = np.zeros((top n, num interp, 3, 32, 32))
          with torch.no grad():
              for i, feature in enumerate(topn_features):
                   z_ = z.clone().detach()
                   z_[0, feature] -= epsilon * np.floor(float(num_interp) / 2)
                  for j in range(num_interp):
                      if j != 0: z [0, feature] += epsilon
                      vae_disentanglement[i, j] = model.sample(z_).cpu().numpy()
```

vae disentanglement = np.transpose(scale(vae disentanglement), (0, 1, 3, 4, 2)).a

In [191]: # Plot and save results

from utils.plotter import plot\_and\_save\_disentanglement
plot\_and\_save\_disentanglement(vae\_disentanglement, num\_rows=top\_n, num\_cols=num\_i

VAE SVHN disentanglement





#### **GAN**

```
In [115]:
          epsilon = 1.5
          top n = 15
          num_interp = 9
          z = torch.randn((1, num_latent)).to(device)
In [116]: # Find dimensions that result in the most change:
          gan_disentanglement = np.zeros((num_latent, 3, 32, 32))
          generator.eval()
          with torch.no grad():
              original = generator.sample(z).cpu().numpy()
              for i in range(num_latent):
                  z_ = z.clone().detach()
                   z_{0}, i] += epsilon
                  gan_disentanglement[i] = generator.sample(z_).cpu().numpy()
          diff = np.sum((gan_disentanglement - original)**2, axis=(1,2,3))
          topn_features = diff.argsort()[-top_n:][::-1]
          print('Most effective latent dimensions:')
          print(topn features)
          Most effective latent dimensions:
```

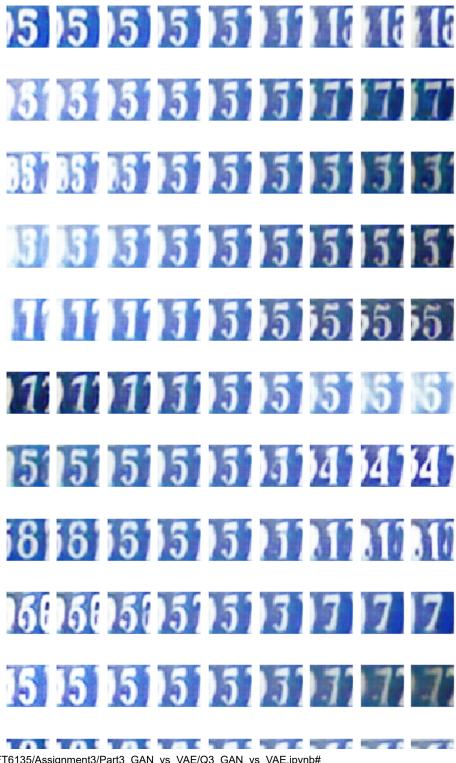
localhost:8888/notebooks/IFT6135/Assignment3/Part3\_GAN\_vs\_VAE/Q3\_GAN\_vs\_VAE.ipynb#

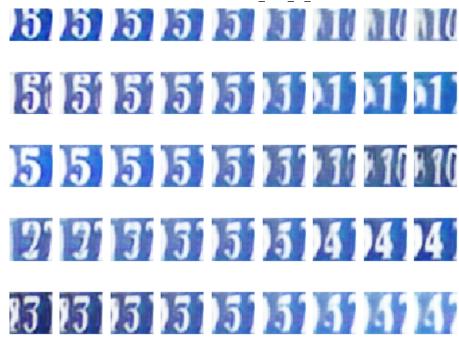
[32 48 90 82 14 8 53 9 42 18 78 3 80 85 16]

In [118]: # Plot and save results

from utils.plotter import plot\_and\_save\_disentanglement plot\_and\_save\_disentanglement(gan\_disentanglement, num\_rows=top\_n, num\_cols=num\_i

GAN SVHN disentanglement





## C.3. Interpolation

#### **VAE latent**

In [88]: from utils.plotter import plot\_and\_save\_interpolation
 plot\_and\_save\_interpolation(vae\_latent, num\_cols=num\_interp, spacename='latent',

VAE SVHN latent interpolation



#### **VAE** data

```
In [89]: scales = np.linspace(0, 1, num_interp)
    vae_data = np.zeros((num_interp, 3, 32, 32))
    with torch.no_grad():
        data0 = model.sample(z0).cpu().numpy()
        data1 = model.sample(z1).cpu().numpy()

for i, s in enumerate(scales):
    data = (s * data0) + ((1 - s) * data1)
        vae_data[i] = data

    vae_data = np.transpose(scale(vae_data), (0, 2, 3, 1)).astype('uint8')
```

In [90]: plot\_and\_save\_interpolation(vae\_data, num\_cols=num\_interp, spacename='data', mode

VAE SVHN data interpolation



#### **GAN latent**

```
In [94]: z0 = torch.randn((1, num_latent)).to(device)
z1 = torch.randn((1, num_latent)).to(device)
```

```
In [95]: scales = np.linspace(0, 1, num_interp)
gan_latent = np.zeros((num_interp, 3, 32, 32))
with torch.no_grad():
    for i, s in enumerate(scales):
        z = (s * z0) + ((1 - s) * z1)
        gan_latent[i] = generator.sample(z).cpu().numpy()

gan_latent = np.transpose(scale(gan_latent), (0, 2, 3, 1)).astype('uint8')
```

In [96]: from utils.plotter import plot\_and\_save\_interpolation
 plot\_and\_save\_interpolation(gan\_latent, num\_cols=11, spacename='latent', modelname

GAN SVHN latent interpolation



#### **GAN** data

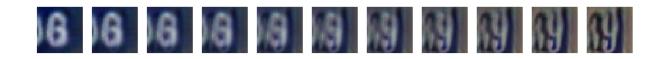
```
In [97]: scales = np.linspace(0, 1, num_interp)
gan_data = np.zeros((num_interp, 3, 32, 32))
with torch.no_grad():
    data0 = generator.sample(z0).cpu().numpy()
    data1 = generator.sample(z1).cpu().numpy()

for i, s in enumerate(scales):
    data = (s * data0) + ((1 - s) * data1)
    gan_data[i] = data

gan_data = np.transpose(scale(gan_data), (0, 2, 3, 1)).astype('uint8')
```

In [98]: plot\_and\_save\_interpolation(gan\_data, num\_cols=num\_interp, spacename='data', mode

GAN SVHN data interpolation



### D. Quantitative Evaluations

```
In [39]: num_generations = 1000
```

### **VAE Generate & Store Samples**

```
In [40]: z = torch.randn(num_generations, num_latent).to(device)
    model.eval()
    with torch.no_grad():
        vae_generations = model.sample(z).cpu().numpy()
    vae_generations = np.transpose(scale(vae_generations), (0, 2, 3, 1)).astype('uintagenerations)
```

```
In [41]: from utils.plotter import sample_saver
    sample_saver(vae_generations, path='samples\\VAE\\subfolder')
```

#### **VAE FID score**

```
In [138]: ! python score_fid.py --model=svhn_classifier.pt samples\VAE

Test
Using downloaded and verified file: Dataset\SVHN\test_32x32.mat
Used epsilon: 1.0E-09
FID score: 31648.761138723774
```

### **GAN Generate & Store Samples**

```
In [43]: z = torch.randn(num_generations, num_latent).to(device)
    generator.eval()
    with torch.no_grad():
        gan_generations = generator.sample(z).cpu().numpy()
        gan_generations = np.transpose(scale(gan_generations), (0, 2, 3, 1)).astype('uinto')
In [44]: from utils.plotter import sample_saver
```

sample\_saver(gan\_generations, path='samples\\GAN\\subfolder')

#### **GAN FID score**

4/22/2019

```
In [139]: ! python score_fid.py --model=svhn_classifier.pt samples\GAN

Test
    Using downloaded and verified file: Dataset\SVHN\test_32x32.mat
    Used epsilon: 1.0E+00
    FID score: 8525.787152984225
In [ ]:
```