Problem 1

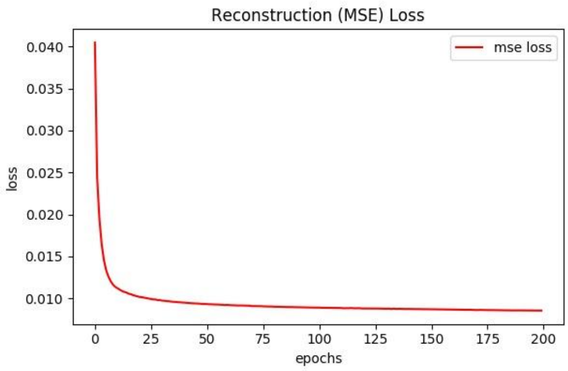
1-1: VAE model

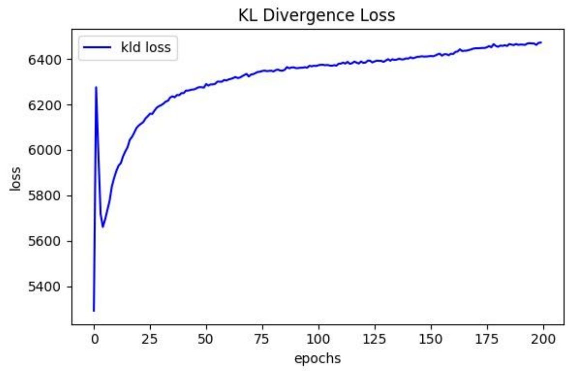
```
VAE(
  (encoder): Sequential(
    (0): Conv2d(3, 32, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (1): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): LeakyReLU(negative_slope=0.005, inplace=True)
    (3): Conv2d(32, 32, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (4): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (5): LeakyReLU(negative_slope=0.005, inplace=True)
    (6): Conv2d(32, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (7): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (8): LeakyReLU(negative_slope=0.005, inplace=True)
    (9): Conv2d(64, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (10): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (11): LeakyReLU(negative_slope=0.005, inplace=True)
  )
  (z_mean): Linear(in_features=2048, out_features=512, bias=True)
  (z_logvar): Linear(in_features=2048, out_features=512, bias=True)
  (z_decode): Linear(in_features=512, out_features=2048, bias=True)
  (decoder): Sequential(
    (0): ConvTranspose2d(128, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): LeakyReLU(negative_slope=0.01, inplace=True)
    (3): ConvTranspose2d(64, 32, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (4): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (5): LeakyReLU(negative_slope=0.01, inplace=True)
    (6): ConvTranspose2d(32, 32, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (7): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (8): LeakyReLU(negative_slope=0.01, inplace=True)
    (9): ConvTranspose2d(32, 3, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (10): BatchNorm2d(3, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (tanh): Tanh()
)
```

Epoch:200 learning rate: 0.0001 optimizer: Adam

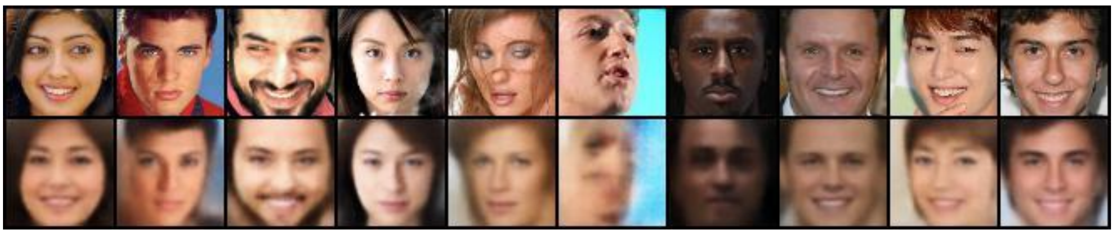
Activation: tanh function latent space: 512

1-2: loss plot





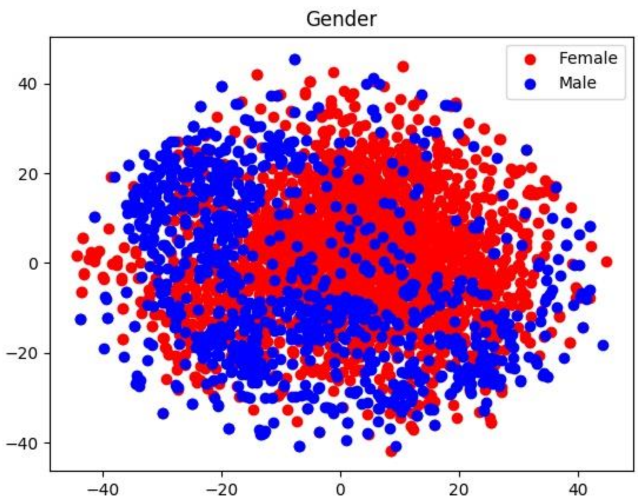
1-3: mse table



0.0058 0.0142 0.0195 0.0092 0.0109 0.0150 0.0035 0.0051 0.0093 0.0065

1-4: 32 random face

1-5 Gender t-SNE



1-6: Discussion

(1)輸出結果

VAE 的原理是先透過 encoder 將 input image 投影到 latent space 用 decoder 還原出圖片，或許是 latent space 只能保留局部的重要資訊，導致 output 的影像清晰度有些不足，但人臉輪廓及五官尚能辨識。

(2)hyperparameter

一開始對 VAE 的 training 特性不了解，直接沿用上次作業的 hyperparameter，20epoch 以及 0.00002 的 learning rate。從 1-2 的 loss plot 來看，就可以解釋為什麼一開始訓練出來的 generator 長出來的人臉非常不像人，畢竟 20 epoch 只是後來訓練成功的 1/10，而且是用較低的 learning rate。後來 hyperparameter 是參考這個 work: https://github.com/podgorskiy/VAE。

Problem 2

2-1 GAN model

```
Generator(
  (decoder): Sequential(
    (0): ConvTranspose2d(100, 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)
  )
  (output): Sequential(
    (0): ConvTranspose2d(64, 3, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (1): Tanh()
  )
)
```

```
Discriminator(
  (main): Sequential(
    (0): Conv2d(3, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): LeakyReLU(negative_slope=0.2, inplace=True)
    (3): Conv2d(64, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (4): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (5): LeakyReLU(negative_slope=0.2, inplace=True)
    (6): Conv2d(128, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (7): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (8): LeakyReLU(negative_slope=0.2, inplace=True)
    (9): Conv2d(256, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (10): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (11): LeakyReLU(negative_slope=0.2, inplace=True)
  )
  (output): Sequential(
    (0): Conv2d(512, 1, kernel_size=(4, 4), stride=(1, 1), bias=False)
    (1): Sigmoid()
  )
)
```

Epoch:200 learning rate: 0.0002 optimizer: Adam

Activation: tanh function latent space: 100

2-2: random 32 faces

2-3 Discussion

有了 VAE 的經驗，GAN 的實作架構以及 Training 的設定就上手許多。與 VAE 本質上的差異是 GAN 是利用 generator 和 discriminator 來交叉訓練，如果有一方明顯有較強的 performance，GAN 便會訓練不起來，所以 G,D 架構的差異不能太大，確保持續的勢均力敵。

2-4 VAE/GAN face comparison

和 VAE 相比，GAN 可以生成較豐富且多樣性的圖片，雖然在 random 32 faces 裡有 1-2 張圖片不是那麼理想，但其他張圖片都能產生更多元的表情以及五官細節。我認為原因可能有二，由於 GAN 是對抗式訓練，generator 可以藉由 discriminator 的對抗來提升合成細節的能力。另外是 VAE 必須在 reconstruction loss 與 KL-divergence loss 取最佳平衡，因此訓練到一定程度後，loss 便無法有效的提升 encoding 的能力，導致細節臉部細節表現不如 GAN。

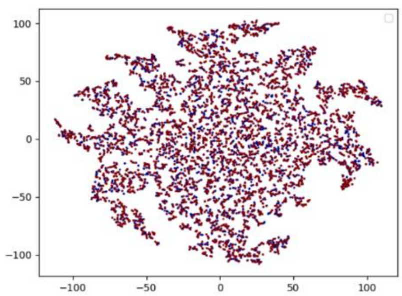
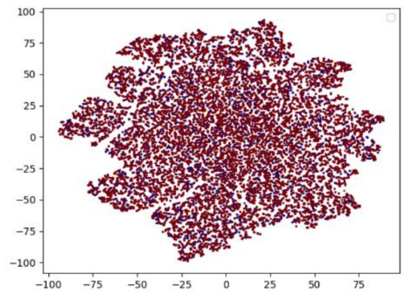
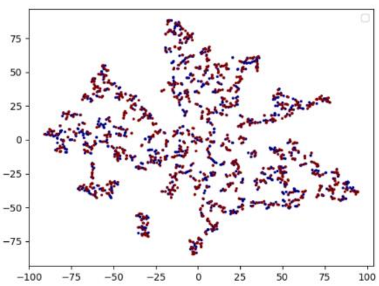
Problem 3

3-1 ~ 3-3 Accuracy Table

	usps → mnistm	mnistm → svhn	svhn → usps
Train on source	34.41%	35.27%	36.95%
dann	48.68%	51.64%	54.01%
Train on target	90.43%	88.56%	91.52%

3-4:t-SNE separated domain

usps → mnistm　　mnistm → svhn　　svhn → usps

3-5: Model

這個 model 的 backbone 是一個 CNN 架構，意即利用 CNN module 來取 image 的 feature，以及作為兩個輸出的 pipeline。一個是用來預測輸入的資料屬於哪個 domain，另一個是用來預測影像資料屬於 0-9 哪一個類別。

- **gradient:** applied batch norm, leaky Relu
- **loss function:** negative log likilyhood loss
- **training detail:** 100 epoch, 128 batch size, 0.001 learning rate

```
DANN(
  (cnn_layer): Sequential(
    (f_conv1): Conv2d(3, 64, kernel_size=(5, 5), stride=(1, 1))
    (f_bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (f_pool1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (f_relu1): ReLU(inplace=True)
    (f_conv2): Conv2d(64, 50, kernel_size=(5, 5), stride=(1, 1))
    (f_bn2): BatchNorm2d(50, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (f_drop1): Dropout2d(p=0.5, inplace=False)
    (f_pool2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (f_relu2): ReLU(inplace=True)
  )
  (classify_class): Sequential(
    (c_fc1): Linear(in_features=800, out_features=100, bias=True)
    (c_bn1): BatchNorm1d(100, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (c_relu1): ReLU(inplace=True)
    (c_drop1): Dropout2d(p=0.5, inplace=False)
    (c_fc2): Linear(in_features=100, out_features=100, bias=True)
    (c_bn2): BatchNorm1d(100, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (c_relu2): ReLU(inplace=True)
    (c_fc3): Linear(in_features=100, out_features=10, bias=True)
    (c_softmax): LogSoftmax()
  )
  (classify_domain): Sequential(
    (d_fc1): Linear(in_features=800, out_features=100, bias=True)
    (d_bn1): BatchNorm1d(100, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (d_relu1): ReLU(inplace=True)
    (d_fc2): Linear(in_features=100, out_features=2, bias=True)
    (d_softmax): LogSoftmax()
  )
)
```

3-6: Discussion

從 accuracy 前兩組來看(usps → mnistm, mnistm → svhn)，發現雖然兩組的 target 都是彩色的，但後者有顯著較高的辨識率。因此我原先的結論是雖然使用 DANN 可以幫助提升辨識率，但是 source 的資料型態與 target 的資料型態越接近，會有更好的訓練效果。然而，觀察第三組之後，雖然 target 與 source 資料型態前者為彩色，後者為黑白，辨識率卻更高。因此我最後得到的結論是：如果 source data 豐富度或完整性比 target data 高，就能訓練出最好的結果。

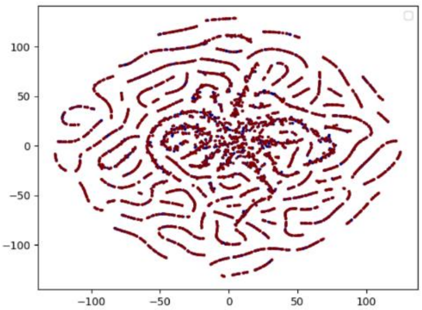
Problem 4

4-1

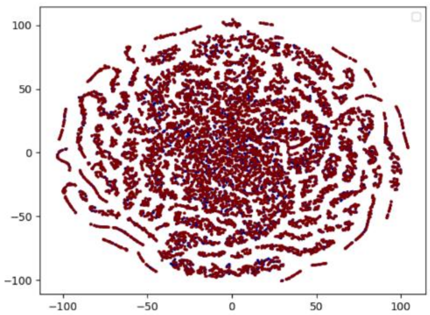
	usps → mnistm	mnistm → svhn	svhn → usps
uda	46.21%	55.79%	69.26%

4-2: t-SNE separated domain

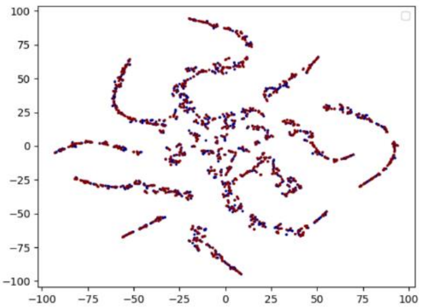
usps → mnistm



mnistm → svhn



svhn → usps



4-3 Model

這個 model 的 backbone 是一個 pre-trained 好的 resnet34 的架構，再加上一個 CNN feature extractor，以及作為兩個輸出的 pipeline。和上一題 DANN 的大架構一樣，一個是用來預測輸入的資料屬於哪個 domain，另一個是用來預測影像資料屬於 0-9 哪一個類別。

- **gradient:** applied batch norm, leaky Relu
- **loss function:** negative log likilyhood loss
- **training detail:** 100 epoch, 128 batch size, 0.001 learning rate

```
DANN_IMPROVED(
  (resnet34): Sequential(
    (0): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU(inplace=True)
    (3): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
    (4): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (1): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (2): BasicBlock(
        (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
```

```
    (5): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (2): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (3): BasicBlock(
        (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
```

```
    (6): Sequential(
      (0): BasicBlock(
        (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (downsample): Sequential(
          (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2), bias=False)
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (1): BasicBlock(
        (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (2): BasicBlock(
        (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (3): BasicBlock(
        (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
        (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
      (4): BasicBlock(
        (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
        (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (relu): ReLU(inplace=True)
```

```
    (5): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (7): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (2): BasicBlock(
      (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
```

```
  )
  (r_convt1): ConvTranspose2d(512, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
  (r_relu1): ReLU(inplace=True)
  (r_convt2): ConvTranspose2d(256, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
  (r_relu2): ReLU(inplace=True)
  (r_convt3): ConvTranspose2d(128, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
  (r_relu3): ReLU(inplace=True)
  (f_conv2): Conv2d(64, 50, kernel_size=(5, 5), stride=(1, 1))
  (f_bn2): BatchNorm2d(50, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (f_drop1): Dropout2d(p=0.5, inplace=False)
  (f_relu2): ReLU(inplace=True)
)
(classify_class): Sequential(
  (c_fc1): Linear(in_features=800, out_features=100, bias=True)
  (c_bn1): BatchNorm1d(100, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (c_relu1): ReLU(inplace=True)
  (c_drop1): Dropout2d(p=0.5, inplace=False)
  (c_fc2): Linear(in_features=100, out_features=100, bias=True)
  (c_bn2): BatchNorm1d(100, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (c_relu2): ReLU(inplace=True)
  (c_fc3): Linear(in_features=100, out_features=10, bias=True)
  (c_softmax): LogSoftmax()
)
(classify_domain): Sequential(
  (d_fc1): Linear(in_features=800, out_features=100, bias=True)
  (d_bn1): BatchNorm1d(100, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (d_relu1): ReLU(inplace=True)
  (d_fc2): Linear(in_features=100, out_features=2, bias=True)
  (d_softmax): LogSoftmax()
)
)
```

4-4: Discussion

從結果來看，發現 usps → mnistm 的辨識率比起 DANN 下降約 2%，但是 mnistm → svhn 上升約 4%，而 svhn → usps 的辨識率提升超過 15%。這個現象可以說明增加深度確實可以幫助 cross domain 的 adaptation，不過 usps → mnistm 反而下降的原因，我猜測是 usps data 本身帶有的 feature 就不如彩色的 mnistm 那麼多，所以深度增加反而提升了 gradient discrimination 的發生。另外，大概訓練 20 個 epoch 後 accuracy 就沒有明顯提升了。

Reference: no collaborator

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. https://github.com/fungtion/DANN-py3

. https://github.com/NaJaeMin92/pytorch-DANN/blob/master/utils.py

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. https://github.com/podgorskiy/VAE