

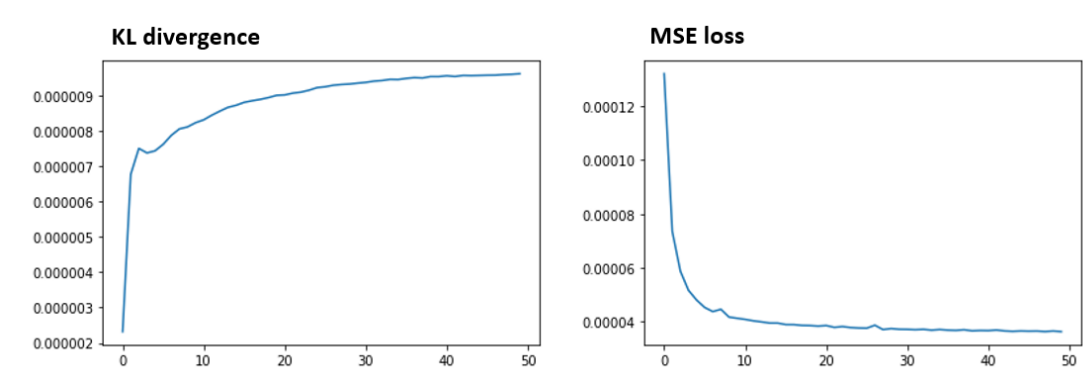
**Problem1**

## 1. model

```
VAE(  
    (encoder): Encoder(  
        (conv1): Conv2d(3, 32, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1))  
        (relu1): ReLU()  
        (conv2): Conv2d(32, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1))  
        (relu2): ReLU()  
        (conv3): Conv2d(128, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1))  
        (relu3): ReLU()  
        (conv4): Conv2d(256, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1))  
        (relu4): ReLU()  
        (fc_mu): Linear(in_features=1024, out_features=256, bias=True)  
        (fc_logvar): Linear(in_features=1024, out_features=256, bias=True)  
    )  
    (decoder): Decoder(  
        (main): Sequential(  
            (0): ConvTranspose2d(256, 512, kernel_size=(4, 4), stride=(1, 1))  
            (1): ReLU(inplace=True)  
            (2): ConvTranspose2d(512, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1))  
            (3): ReLU(inplace=True)  
            (4): ConvTranspose2d(128, 32, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1))  
            (5): ReLU(inplace=True)  
            (6): ConvTranspose2d(32, 16, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1))  
            (7): ReLU(inplace=True)  
            (8): ConvTranspose2d(16, 3, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1))  
            (9): Sigmoid()  
        )  
    )  
)
```

- Training epoch : 50
- Learning rate schedule : 初始為 0.001 之後每 15 個 epoch 乘上 0.6
- Data augmentation : 水平垂直翻轉
- Optimizer : Adam

2. learning curve

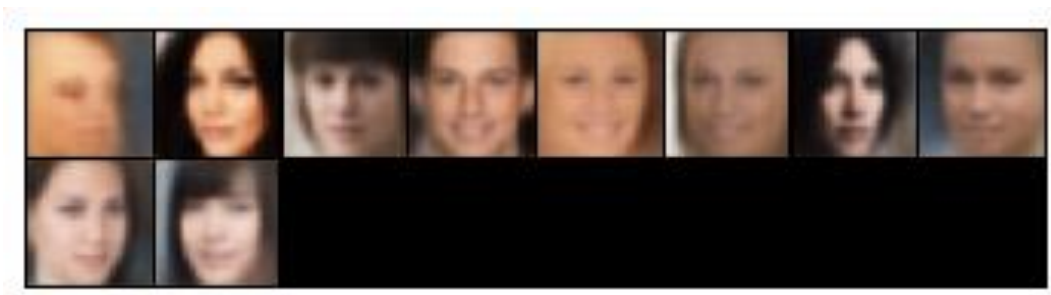


3. Reconstruct testing image

Testing image



Reconstructed image

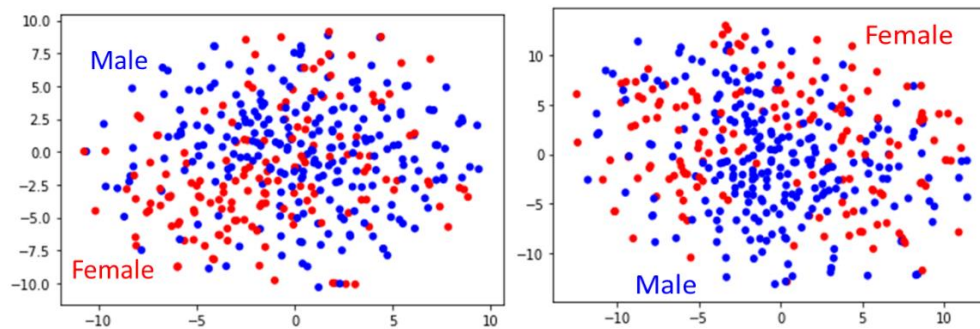


MSE							
0.148	0.107	0.096	0.082	0.068	0.081	0.092	0.085
0.077	0.092						

#### 4. Randomly generate images



#### 5. tSNE visualize



#### 6.

VAE 在訓練時收斂速度非常快，但其重建結果較難達到很好的還原效果，還原出來的影像共同特徵較多，也較為模糊，而這樣的結果也可以在進行 tSNE 可視化時看到，VAE 模型可能因為對於特徵提去能力較差，因此難以良好區分不同類別。

### Problem2

#### 1.

```
Generator(  
  (main): Sequential(  
    (0): ConvTranspose2d(64, 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()
)
)
Discriminator(
  (main): Sequential(
    (0): Conv2d(3, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (1): LeakyReLU(negative_slope=0.2, inplace=True)
    (2): Conv2d(64, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (3): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (4): LeakyReLU(negative_slope=0.2, inplace=True)
    (5): Conv2d(128, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (6): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (7): LeakyReLU(negative_slope=0.2, inplace=True)
    (8): Conv2d(256, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
    (9): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (10): LeakyReLU(negative_slope=0.2, inplace=True)
    (11): Conv2d(512, 1, kernel_size=(4, 4), stride=(1, 1), bias=False)
    (12): Sigmoid()
  )
)

```

- Training epoch : 100
- Learning rate schedule : 初始為 0.001 之後每 15 個 epoch 乘上 0.6
- Data augmentation : 水平垂直翻轉、標準化、亮度對比隨機調整
- Optimizer : Adam

## 2.Randomly generate images



3.

在 GAN 訓練過程中因為難以用數值及時驗證訓練情形，必須將各階段訓練結果生成圖像。此外在 generator 與 discriminator 分別訓練的過程中要將另一項輸出先進行 detach 避免更新權重時同時更新到另一項。而訓練時放入的雜訊總類中，隨機雜訊訓練結果要比高斯雜訊來的好。最後生成的圖像可以看到會受到一開始訓練資料的變換影響，像是有對比亮度調整、圖片旋轉等。

4.

GAN 在訓練中加入了 discriminator 因此相較於 VAE 訓練過程複雜許多，但也使得 GAN 的訓練結過更佳，在圖片生成的結果中就可看到，VAE 的結果較為模糊，不同影像間共同點也比較多，而 GAN 生成的圖片影像輪廓與差異較為分明。

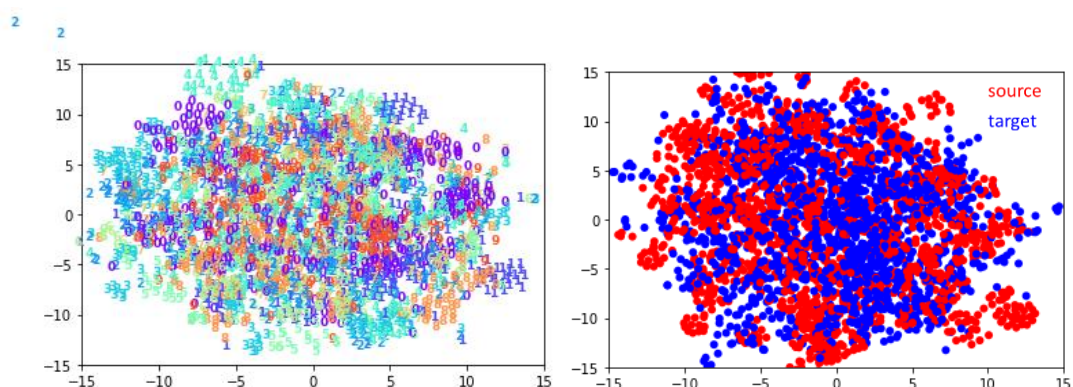
### Problem3

1~3.

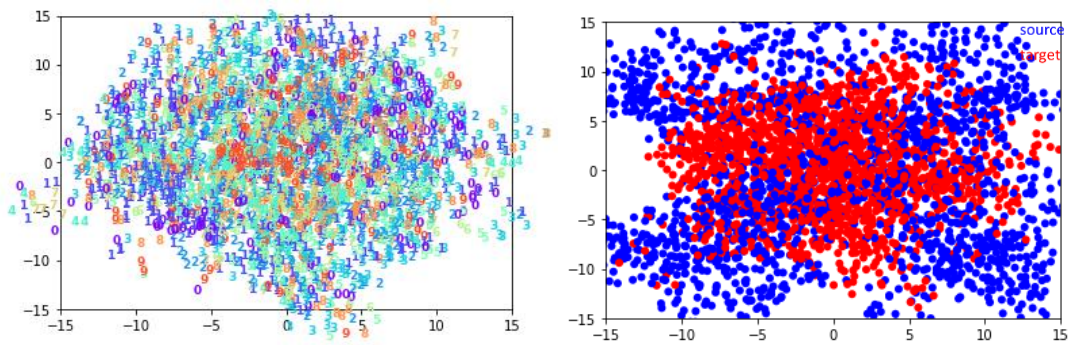
	USPS → MNIST-M	MNIST-M → SVHN	SVHN → USPS
Trained on source	13.67%	19.99%	40.51%
DANN	28.73%	48.2%	51.67%
Trained on target	91.28%	91.49%	96.91%

4.

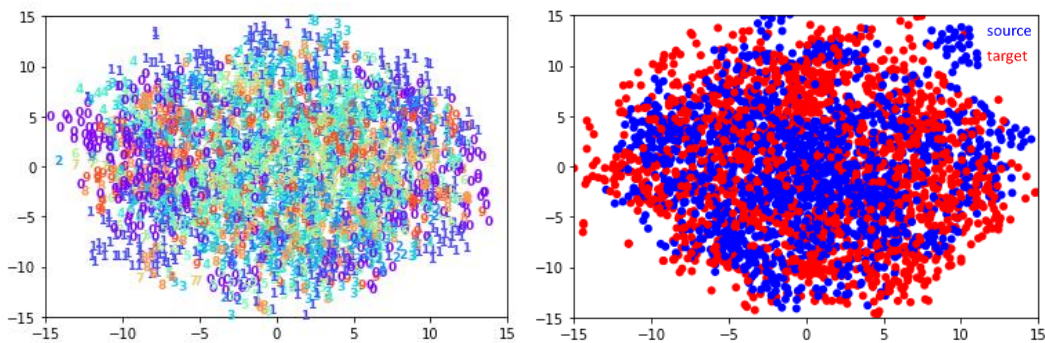
USPS → MNIST-M



MNIST-M→SVHN



SVHN→USPS



5.

```

FeatureExtractor(
  (conv): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): ReLU(inplace=True)
    (3): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (4): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (5): ReLU(inplace=True)
    (6): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (7): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (8): ReLU(inplace=True)
    (9): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (10): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (11): ReLU(inplace=True)
    (12): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (14): ReLU(inplace=True)
    (15): AdaptiveAvgPool2d(output_size=(1, 1))
  )

```



```

    )
) Classifier(
    (linear1): Linear(in_features=512, out_features=256, bias=True)
    (relu1): ReLU(inplace=True)
    (linear2): Linear(in_features=256, out_features=10, bias=True)
) Discriminator(
    (layer): Sequential(
        (0): Linear(in_features=512, out_features=256, bias=True)
        (1): LeakyReLU(negative_slope=0.2)
        (2): Linear(in_features=256, out_features=128, bias=True)
        (3): LeakyReLU(negative_slope=0.2)
        (4): Linear(in_features=128, out_features=1, bias=True)
        (5): Sigmoid()
    )
)

```

- Training epoch : 50
- Learning rate schedule : 0.001
- Data augmentation : 標準化 { transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)) }
- Optimizer : 皆為 Adam
- 三組資料集都以相同模型進行訓練

6.

在訓練之前需要先將影像轉為彩色，若都轉為黑白彩色影像會損失資訊使得無法訓練，而在上述結果中以黑白資料作為 Source 來訓練彩色資料時，結果會較差。

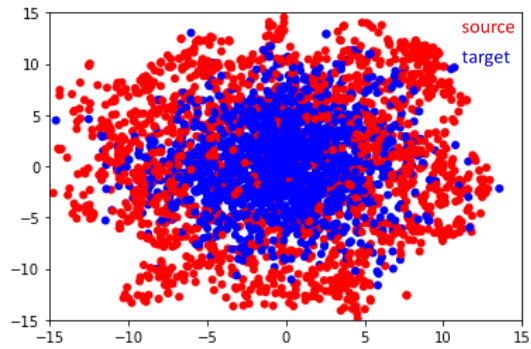
## Problem4

1.

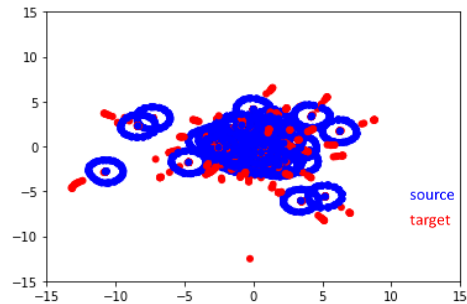
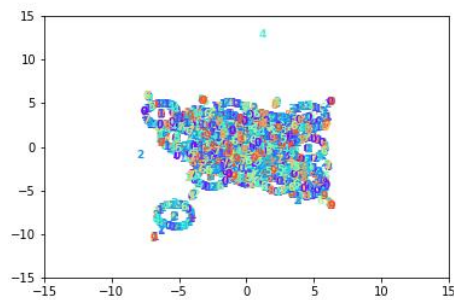
Accuracy on target	USPS → MNIST-M	MNIST-M→SVHN	SVHN→USPS
Improved(??)	10.07	15.938%	13.154

2.

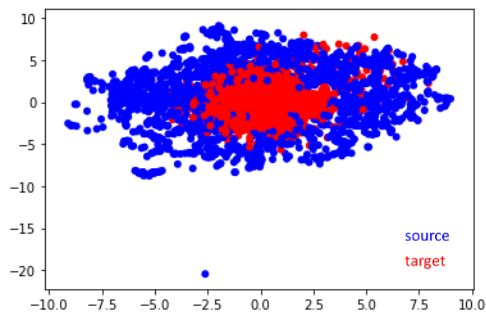
USPS → MNIST-M



MNIST-M→SVHN



SVHN→USPS



3.

```
LeNetEncoder2(
  (encoder): Sequential(
    (0): Conv2d(3, 20, kernel_size=(5, 5), stride=(1, 1))
    (1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (2): ReLU()
    (3): Conv2d(20, 50, kernel_size=(5, 5), stride=(1, 1))
    (4): Dropout2d(p=0.5, inplace=False)
    (5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (6): ReLU()
  )
  (fc1): Linear(in_features=800, out_features=500, bias=True)
)
```

LeNetClassifier(



```

(fc2): Linear(in_features=500, out_features=10, bias=True)
)
Discriminator(
  (layer): Sequential(
    (0): Linear(in_features=500, out_features=200, bias=True)
    (1): ReLU()
    (2): Linear(in_features=200, out_features=200, bias=True)
    (3): ReLU()
    (4): Linear(in_features=200, out_features=2, bias=True)
    (5): LogSoftmax(dim=None)
  )
)

```

此題使用方法為 Adversarial Discriminative Domain Adaptation，且三個資料集也是用同樣模型進行訓練

- Training epoch : discriminator :20 ; classifier : 20
- Learning rate schedule : 0.005
- Optimizer : 皆為 Adam

4.

本題利用 ADDA 來做為不同的 UDA 訓練方式，其主要概念為先利用 source domain 訓練自身的分類器，再將訓練好的 source model 結果與 target domain 一起訓練 discriminator，與 target domain 自身的特徵提取網路，同時在訓練過程中變換 target domain 分類來混淆 discriminator 提升訓練效果，而這樣過程相較於 DANN，ADDA 能夠使得不同來源得資料能有不同的特徵提取能力，同時又能去除兩者的種類差異，來達到更好的自身分類效果，但本題無充裕時間作答，因此訓練效果十分不佳 :(。

參考資料

1. [https://colab.research.google.com/github/smartgeometry-ucl/dl4g/blob/master/variational\\_autoencoder.ipynb#scrollTo=mZaVrj0hX1ry](https://colab.research.google.com/github/smartgeometry-ucl/dl4g/blob/master/variational_autoencoder.ipynb#scrollTo=mZaVrj0hX1ry)
2. [https://github.com/atinghosh/VAE-pytorch/blob/master/VAE\\_celeba.py](https://github.com/atinghosh/VAE-pytorch/blob/master/VAE_celeba.py)
3. [https://pytorch.org/tutorials/beginner/dcgan\\_faces\\_tutorial.html](https://pytorch.org/tutorials/beginner/dcgan_faces_tutorial.html)
4. <https://github.com/Yangyangii/DANN-pytorch/blob/master/DANN.ipynb>
5. <https://github.com/corenel/pytorch-adda>