DLCV Fall 2021 HW2

Problem 1

```
1. Model Architecture
```

```
Generator(
  (l1): Sequential(
    (0): Linear(in_features=100, out_features=8192, bias=False)
    (1): BatchNorm1d(8192, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (2): LeakyReLU(negative_slope=0.2, inplace=True)
  )
  (l2_5): Sequential(
    (0): Sequential(
      (0): ConvTranspose2d(512, 256, kernel_size=(5, 5), stride=(2, 2), padding=(2, 2), output_padding=(1, 1), bias=False)
      (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): LeakyReLU(negative_slope=0.2, inplace=True)
    )
    (1): Sequential(
      (0): ConvTranspose2d(256, 128, kernel_size=(5, 5), stride=(2, 2), padding=(2, 2), output_padding=(1, 1), bias=False)
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): LeakyReLU(negative_slope=0.2, inplace=True)
    )
    (2): Sequential(
      (0): ConvTranspose2d(128, 64, kernel_size=(5, 5), stride=(2, 2), padding=(2, 2), output_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): ConvTranspose2d(64, 3, kernel_size=(5, 5), stride=(2, 2), padding=(2, 2), output_padding=(1, 1))
    (4): Tanh()
  )
)
Discriminator(
  (ls): Sequential(
    (0): Conv2d(3, 64, kernel_size=(5, 5), stride=(2, 2), padding=(2, 2))
    (1): LeakyReLU(negative_slope=0.2)
    (2): Sequential(
      (0): Conv2d(64, 128, kernel_size=(5, 5), stride=(2, 2), padding=(2, 2))
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): LeakyReLU(negative_slope=0.2)
    )
    (3): Sequential(
      (0): Conv2d(128, 256, kernel_size=(5, 5), stride=(2, 2), padding=(2, 2))
      (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): LeakyReLU(negative_slope=0.2)
    )
    (4): Sequential(
      (0): Conv2d(256, 512, kernel_size=(5, 5), stride=(2, 2), padding=(2, 2))
      (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): LeakyReLU(negative_slope=0.2)
    )
    (5): Conv2d(512, 1, kernel_size=(4, 4), stride=(1, 1))
    (6): Sigmoid()
  )
)
```

```
2. Result images
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3. Performance
    a. FID: 28.97234688597007
    b. IS: 2.130328565811233

4. Discuss what you’ve observed and learned from implementing GAN.
    a. GAN isn't stable, and need lots of time to try.
    b. The batch size shouldn't be too large, probably 128 is the maximum.
        Otherwise the model will collapse.
    c. Since the task is to generate image, many transforms could be tried.
```

Problem 2

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1. Model Archetecture
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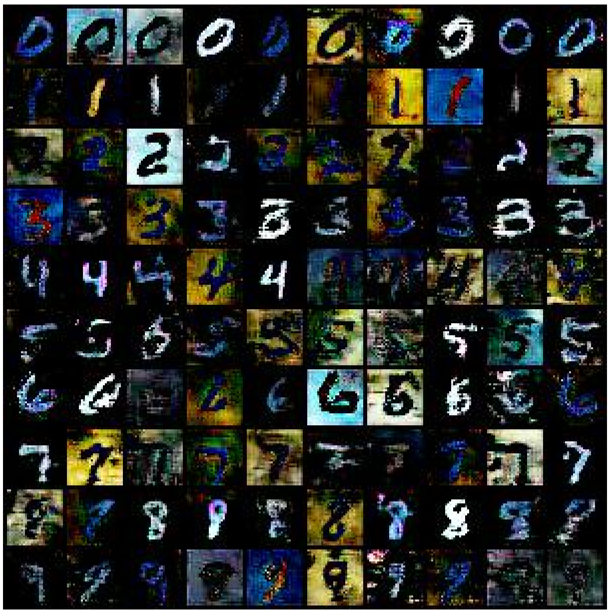
```
Generator(
  (label_emb): Embedding(10, 100)
  (l1): Sequential(
    (0): Linear(in_features=100, out_features=6272, bias=True)
  )
  (conv_blocks): Sequential(
    (0): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (1): Upsample(scale_factor=2.0, mode=nearest)
    (2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (4): LeakyReLU(negative_slope=0.2, inplace=True)
    (5): Upsample(scale_factor=2.0, mode=nearest)
    (6): Conv2d(128, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (7): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (8): LeakyReLU(negative_slope=0.2, inplace=True)
    (9): Conv2d(64, 3, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (10): Tanh()
  )
)
Discriminator(
  (conv_blocks): Sequential(
    (0): Conv2d(3, 16, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
    (1): LeakyReLU(negative_slope=0.2, inplace=True)
    (2): Dropout2d(p=0.25, inplace=False)
    (3): Conv2d(16, 32, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
    (4): LeakyReLU(negative_slope=0.2, inplace=True)
    (5): Dropout2d(p=0.25, inplace=False)
    (6): BatchNorm2d(32, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (7): Conv2d(32, 64, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
    (8): LeakyReLU(negative_slope=0.2, inplace=True)
    (9): Dropout2d(p=0.25, inplace=False)
    (10): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (11): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
    (12): LeakyReLU(negative_slope=0.2, inplace=True)
    (13): Dropout2d(p=0.25, inplace=False)
    (14): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
  (adv_layer): Sequential(
    (0): Linear(in_features=512, out_features=1, bias=True)
    (1): Sigmoid()
  )
  (aux_layer): Sequential(
    (0): Linear(in_features=512, out_features=10, bias=True)
  )
)
[0] 0:[tmux]*
```

```
2. Result images
```



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3. Accuracy
    0.8370
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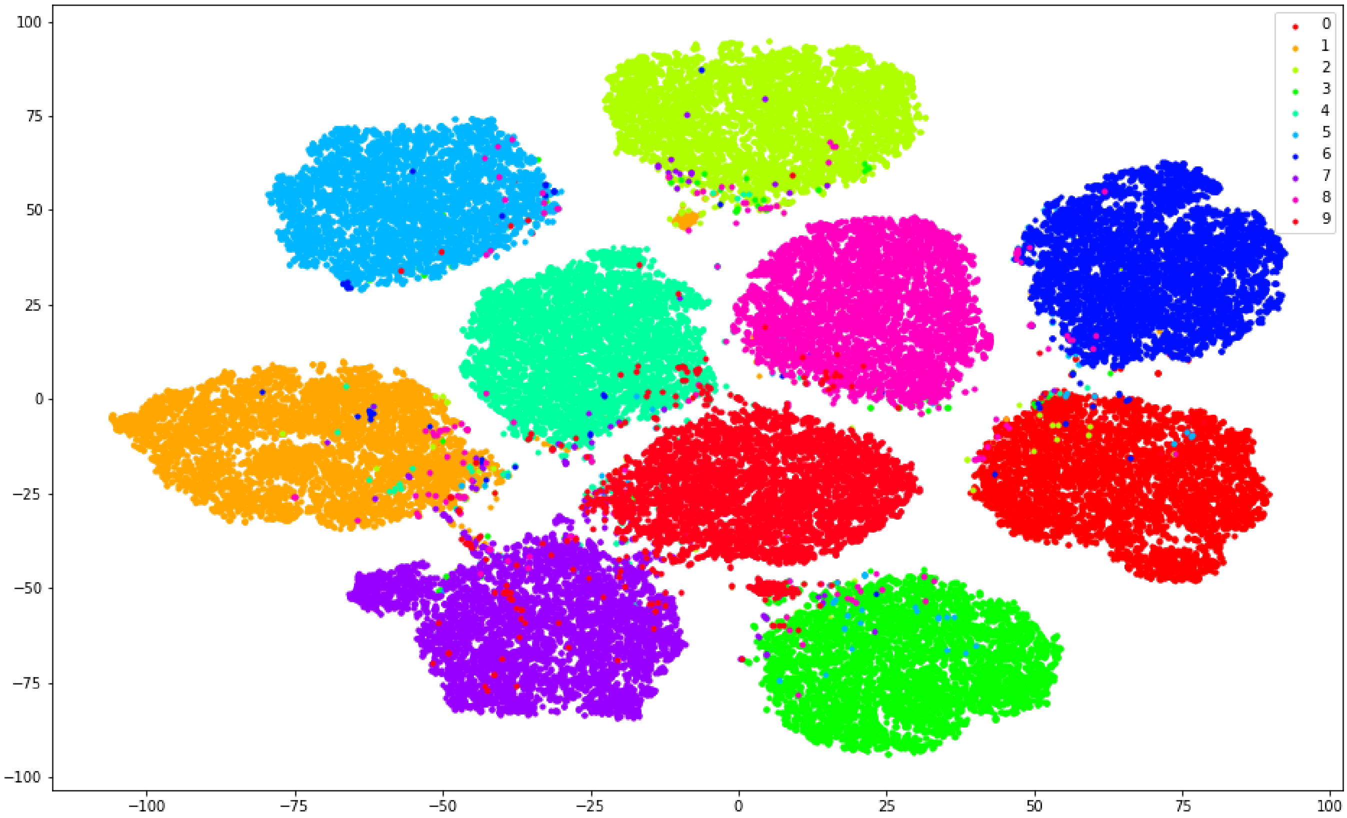
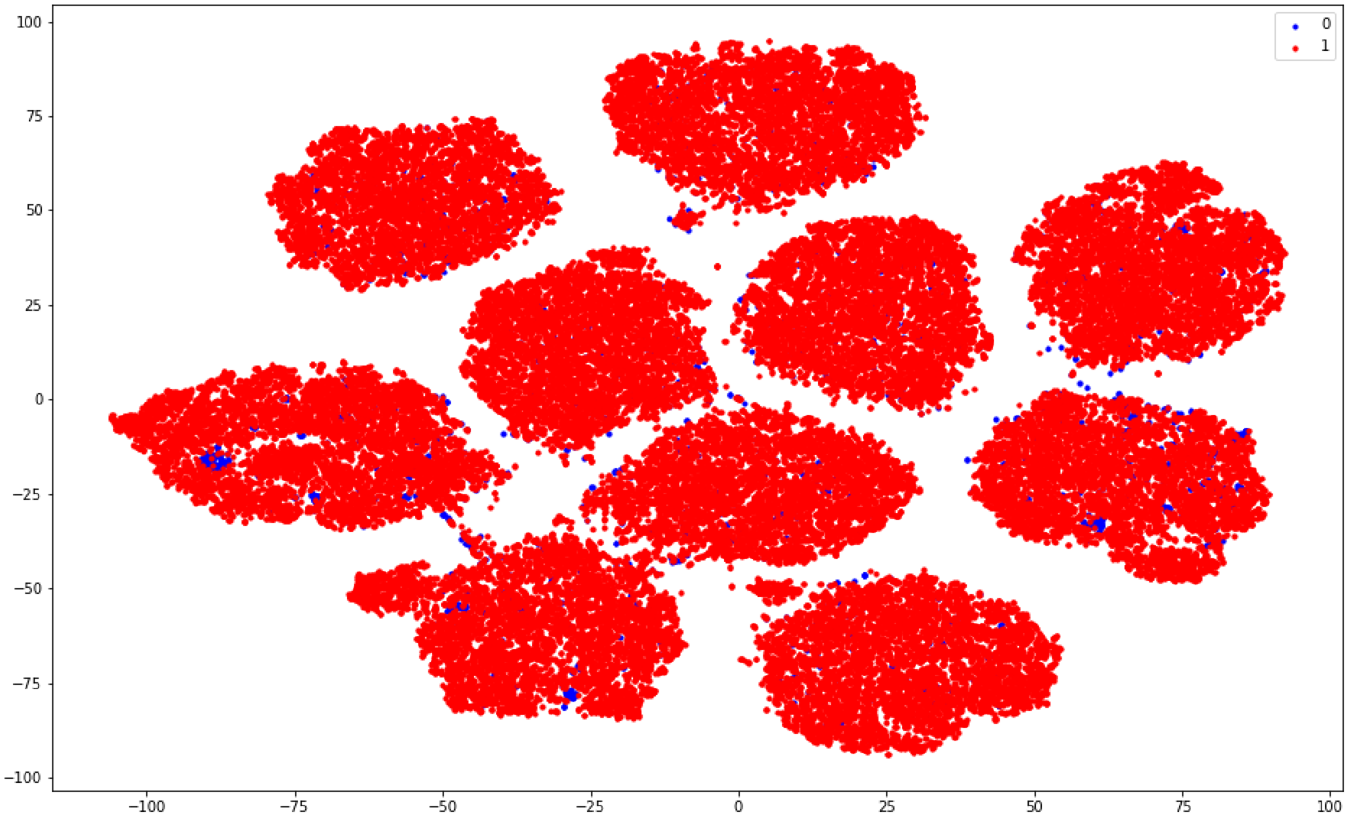
Problem 3

```
1. Table
```

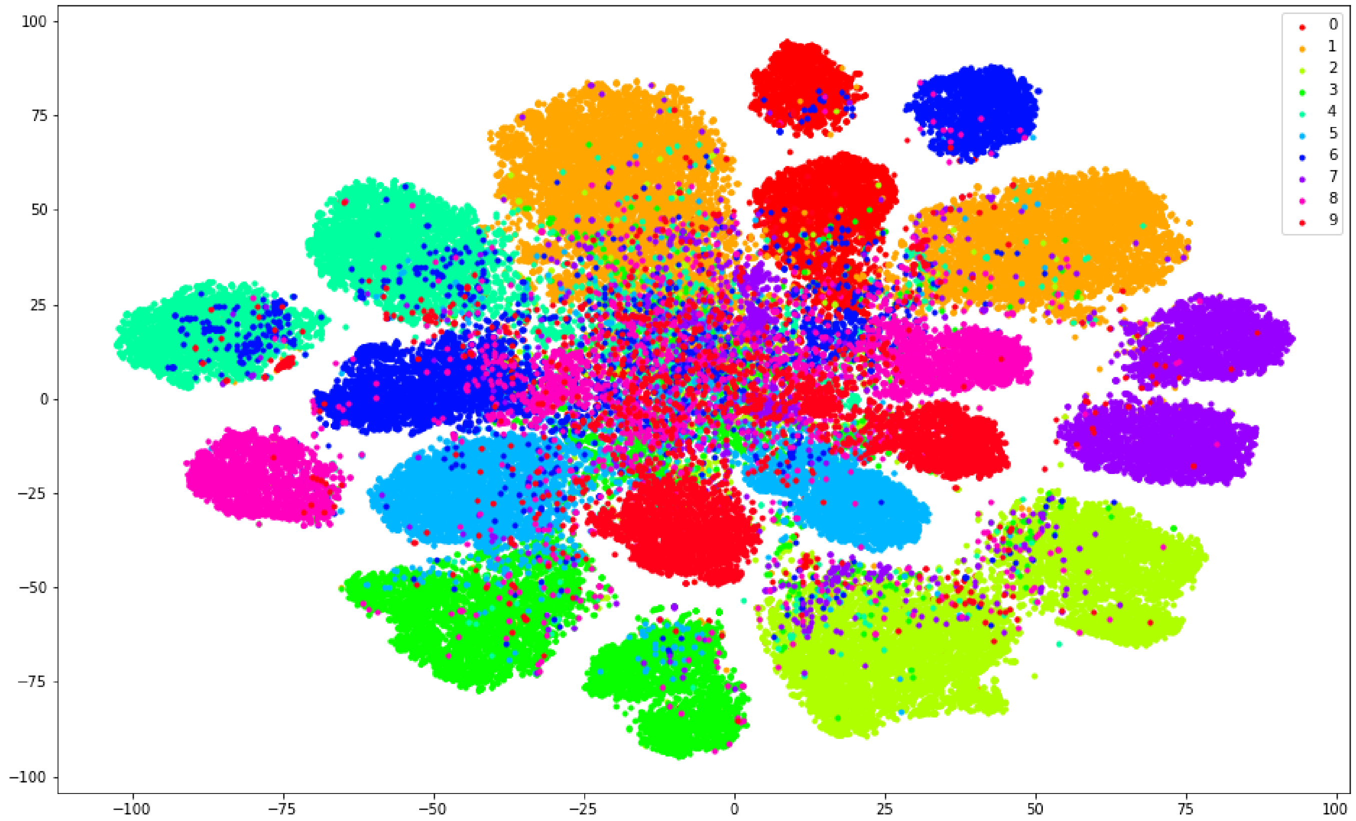
.	mnistm -> usps	svhn -> mnistm	usps -> svhn
Trained on source	0.7433	0.4098	0.2049
Adaption(original)	0.8594	0.4935	0.2995
Adaption(improved)	0.9053	0.6143	XX
Trained on target	0.9601	0.9969	0.9136

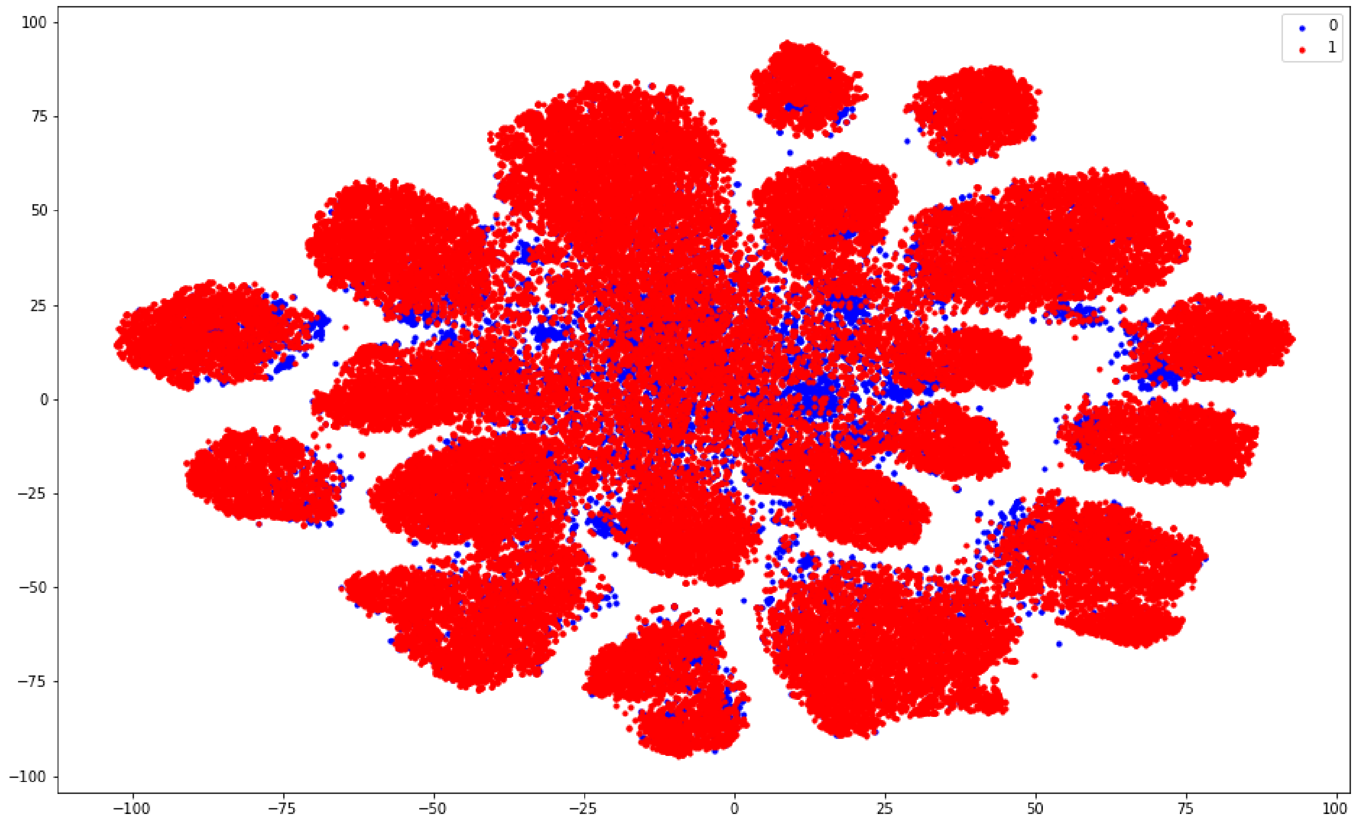
```
2. Visualization
    a. mnistm -> usps
```



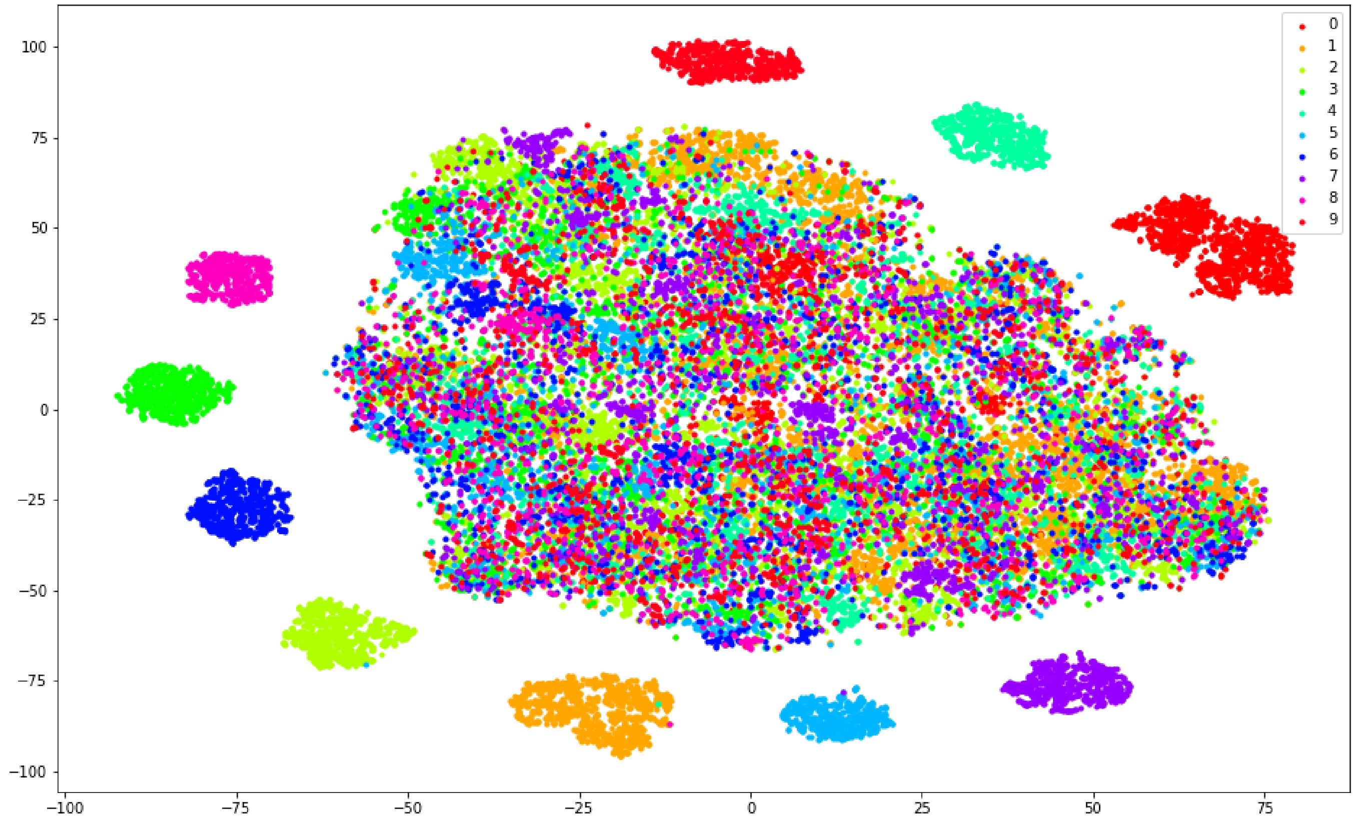


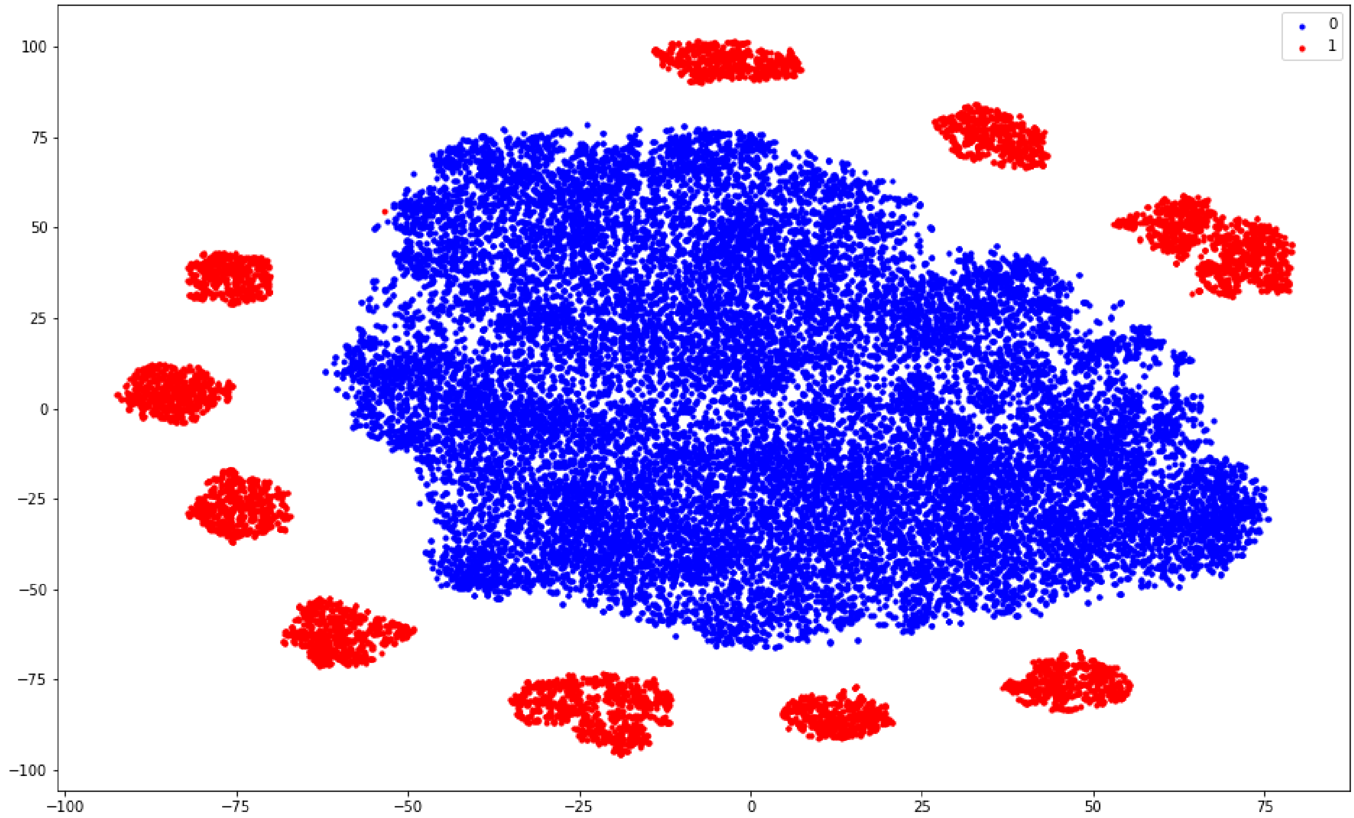

```
b. svhn -> mnistm
```






```
c. usps -> svhn
```



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3. Discussion
    a. Since the numbers of data is quite small for "USPS", compared to the
others, I let the feature dimension down to 256, which is the half of those
in the other two scenarios.
    b. Actually, the task of digit isn't difficult to train. All can be
done in 50 epoch.
    c. Even though the model is modified to the case u -> s, the
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performance still the worst. I think the main reason is the amount of data,
which is always important in deep learning area.
```