Problem1 GAN

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(5%) Please print the model architecture of method A and B.

```
Generator(
  (tconv1): ConvTranspose2d(100, 512, kernel_size=(4, 4), stride=(1, 1), bias=False)
  (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (tconv2): ConvTranspose2d(512, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
  (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (tconv3): ConvTranspose2d(256, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
  (bn3): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (tconv4): ConvTranspose2d(128, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
  (bn4): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (tconv5): ConvTranspose2d(64, 3, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
)
Discriminator(
  (conv1): Conv2d(3, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
  (conv2): Conv2d(64, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
  (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv3): Conv2d(128, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
  (bn3): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv4): Conv2d(256, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
  (bn4): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (conv5): Conv2d(512, 1, kernel_size=(4, 4), stride=(1, 1), bias=False)
)
```

DCGAN

```
WGAN_Discriminator(
  (l1): Sequential(
    (0): Conv2d(3, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1))
    (1): LeakyReLU(negative_slope=0.2)
    (2): Sequential(
      (0): Conv2d(64, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1))
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (2): InstanceNorm2d(128, eps=1e-05, momentum=0.1, affine=False, track_runn
ing_stats=False)
      (3): LeakyReLU(negative_slope=0.2)
    )
    (3): Sequential(
      (0): Conv2d(128, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1))
      (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (2): InstanceNorm2d(256, eps=1e-05, momentum=0.1, affine=False, track_runn
ing_stats=False)
      (3): LeakyReLU(negative_slope=0.2)
    )
    (4): Sequential(
      (0): Conv2d(256, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1))
      (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_
stats=True)
      (2): InstanceNorm2d(512, eps=1e-05, momentum=0.1, affine=False, track_runn
ing_stats=False)
      (3): LeakyReLU(negative_slope=0.2)
    )
    (5): Conv2d(512, 1, kernel_size=(4, 4), stride=(1, 1))
  )
)
```

Model B: WGAN-GP

This WGAN use same generator as DCGAN , with discriminator slightly different.

(5%) Please show the first 32 generated images of both method A and B then discuss the difference between method A and B.

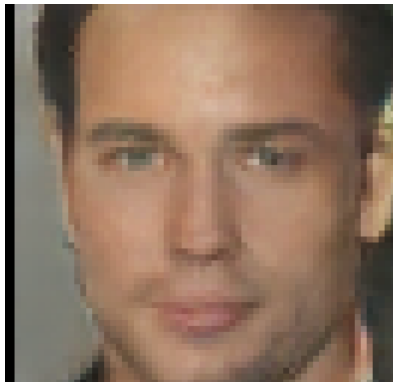
DCGAN

WGAN-GP

- The main difference between DCGAN and WGAN-GP is how to calculate loss. For WGAN-GP, techniques such as weight-clipping and gradient penalty are utilized to prevent discriminator from being too strong, and make sure that the training process is stable.

(5%) Please discuss what you've observed and learned from implementing GAN.

- Hyper-parameters provided by authors of paper are important, it is advised not to modify it.
- Sometimes, discriminator would become too accurate, which leads to "gradient vanish". They key point of training DCGAN and WGAN is to make sure that both discriminator and generator are well-matched.
- The model of discriminator is designed to be shallow, compared to typical classifier. This is intended to weaken discriminator.
- (I think I have generated pictures of Brad Pitt and Mark Zuckerberg lol.)




Problem2 Diffusion model

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1. (5%) Please print your model architecture and describe your implementation details.

```
ContextUnet(
  (init_conv): ResidualConvBlock(
    (conv1): Sequential(
      (0): Conv2d(3, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): GELU()
    )
    (conv2): Sequential(
      (0): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): GELU()
    )
  )
  (down1): UnetDown(
    (model): Sequential(
      (0): ResidualConvBlock(
        (conv1): Sequential(
          (0): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (2): GELU()
        )
        (conv2): Sequential(
          (0): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (2): GELU()
        )
      )
      (1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    )
  )
  (down2): UnetDown(
    (model): Sequential(
      (0): ResidualConvBlock(
        (conv1): Sequential(
          (0): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
          (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (2): GELU()
        )
        (conv2): Sequential(
          (0): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
          (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (2): GELU()
        )
      )
      (1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    )
  )
```

```
(to_vec): Sequential(
  (0): AvgPool2d(kernel_size=7, stride=7, padding=0)
  (1): GELU()
)
(timeembed1): EmbedFC(
  (model): Sequential(
    (0): Linear(in_features=1, out_features=512, bias=True)
    (1): GELU()
    (2): Linear(in_features=512, out_features=512, bias=True)
  )
)
(timeembed2): EmbedFC(
  (model): Sequential(
    (0): Linear(in_features=1, out_features=256, bias=True)
    (1): GELU()
    (2): Linear(in_features=256, out_features=256, bias=True)
  )
)
(contextembed1): EmbedFC(
  (model): Sequential(
    (0): Linear(in_features=10, out_features=512, bias=True)
    (1): GELU()
    (2): Linear(in_features=512, out_features=512, bias=True)
  )
)
(contextembed2): EmbedFC(
  (model): Sequential(
    (0): Linear(in_features=10, out_features=256, bias=True)
    (1): GELU()
    (2): Linear(in_features=256, out_features=256, bias=True)
  )
)
(up0): Sequential(
  (0): ConvTranspose2d(512, 512, kernel_size=(7, 7), stride=(7, 7))
  (1): GroupNorm(8, 512, eps=1e-05, affine=True)
  (2): ReLU()
)
```

```
,
(up1): UnetUp(
  (model): Sequential(
    (0): ConvTranspose2d(1024, 256, kernel_size=(2, 2), stride=(2, 2))
    (1): ResidualConvBlock(
      (conv1): Sequential(
        (0): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (2): GELU()
      )
      (conv2): Sequential(
        (0): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (2): GELU()
      )
    )
    (2): ResidualConvBlock(
      (conv1): Sequential(
        (0): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (2): GELU()
      )
      (conv2): Sequential(
        (0): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        (2): GELU()
      )
    )
  )
)
```

```
  (up2): UnetUp(
    (model): Sequential(
      (0): ConvTranspose2d(512, 256, kernel_size=(2, 2), stride=(2, 2))
      (1): ResidualConvBlock(
        (conv1): Sequential(
          (0): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (2): GELU()
        )
        (conv2): Sequential(
          (0): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (2): GELU()
        )
      )
      (2): ResidualConvBlock(
        (conv1): Sequential(
          (0): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (2): GELU()
        )
        (conv2): Sequential(
          (0): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
          (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (2): GELU()
        )
      )
    )
  )
  (out): Sequential(
    (0): Conv2d(512, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): GroupNorm(8, 256, eps=1e-05, affine=True)
    (2): ReLU()
    (3): Conv2d(256, 3, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  )
)
```

Reference:
https://github.com/TeaPearce/Conditional_Diffusion_MNIST
https://arxiv.org/abs/2207.12598

Implement details:

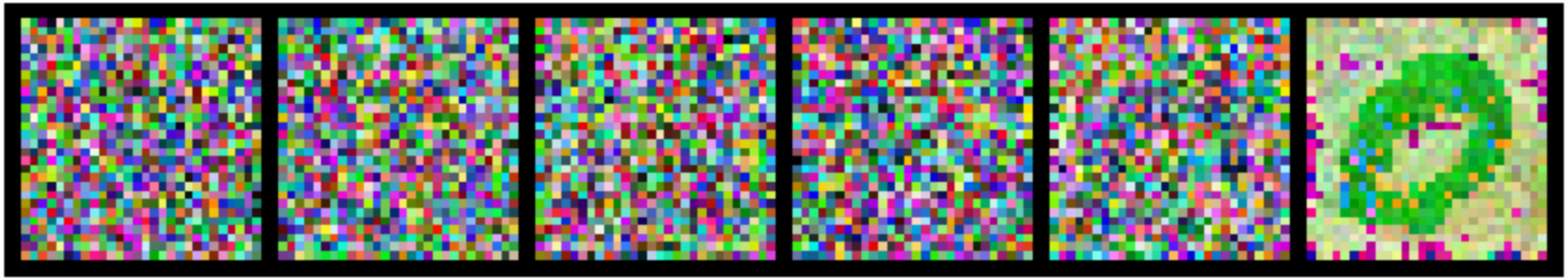
- The neural network architecture is a small U-Net.
- Classifier-Free Diffusion Guidance method is used for conditioning.
- Loss is MSE between added noise and predicted loss
- The context embedding may be dropped with probability of 0.1 during training.

```
config = {
    'data_dir': '../input/hw2-data/h
    'dfname': '../input/hw2-data/hw2
    'lr': 1e-4,
    'num_epochs': 100,
    'batch_size': 256,
    'num_classes': 10,
    'n_T': 300,
    'img_size': 28,
```

- (5%) Please show 10 generated images **for each digit (0-9)** in your report. You can put all 100 outputs in one image with columns indicating different noise inputs and rows indicating different digits. [see the below example]

- (5%) Visualize total six images in the reverse process of the **first "0"** in your grid in (2) **with different time steps**. [see the below example]

  T = 0 ,200, 400,600,800,1000



- (5%) Please discuss what you've observed and learned from implementing conditional diffusion model.

  - I learned that the idea behind diffusion model is pretty much similar to VAE but we only have to train network in reverse process. However, it is quite hard to implement.
  - I found that a good classifier is needed to guide the diffusion model.
  - The number of time steps is crucial to training time, but if noise step is too large, it becomes harder for model to reverse the process.

Problem3 Domain Adaption

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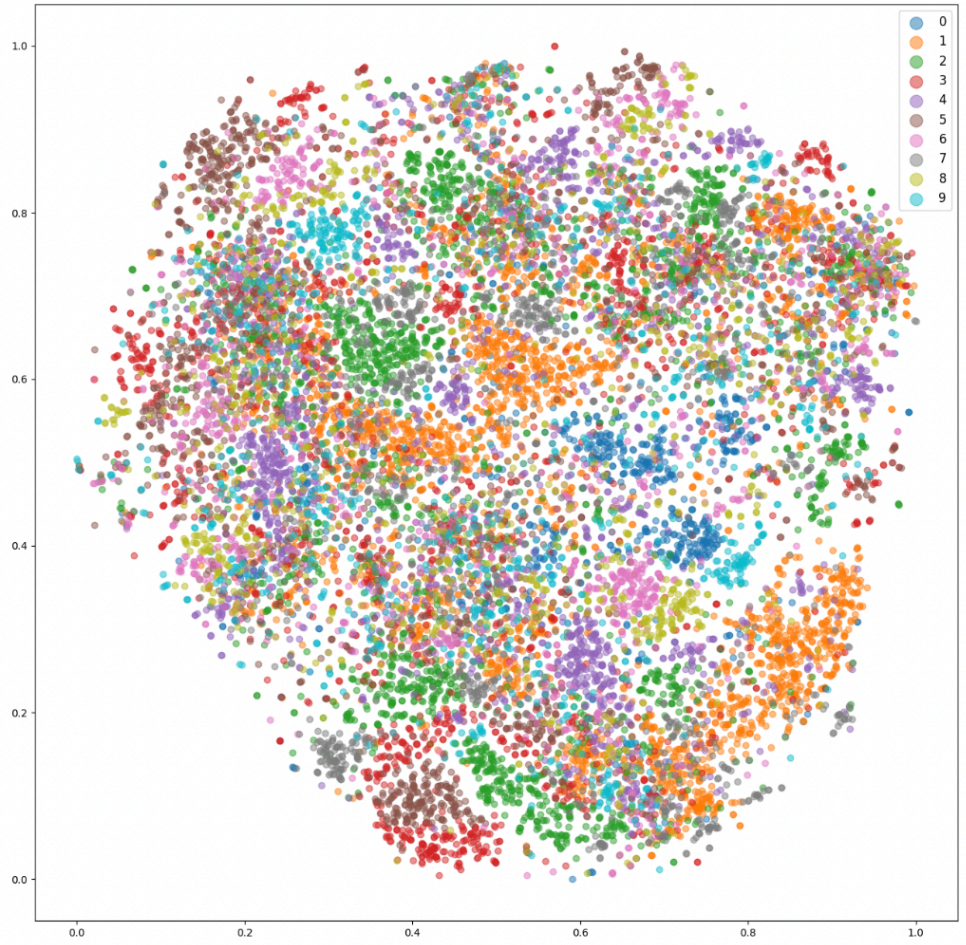
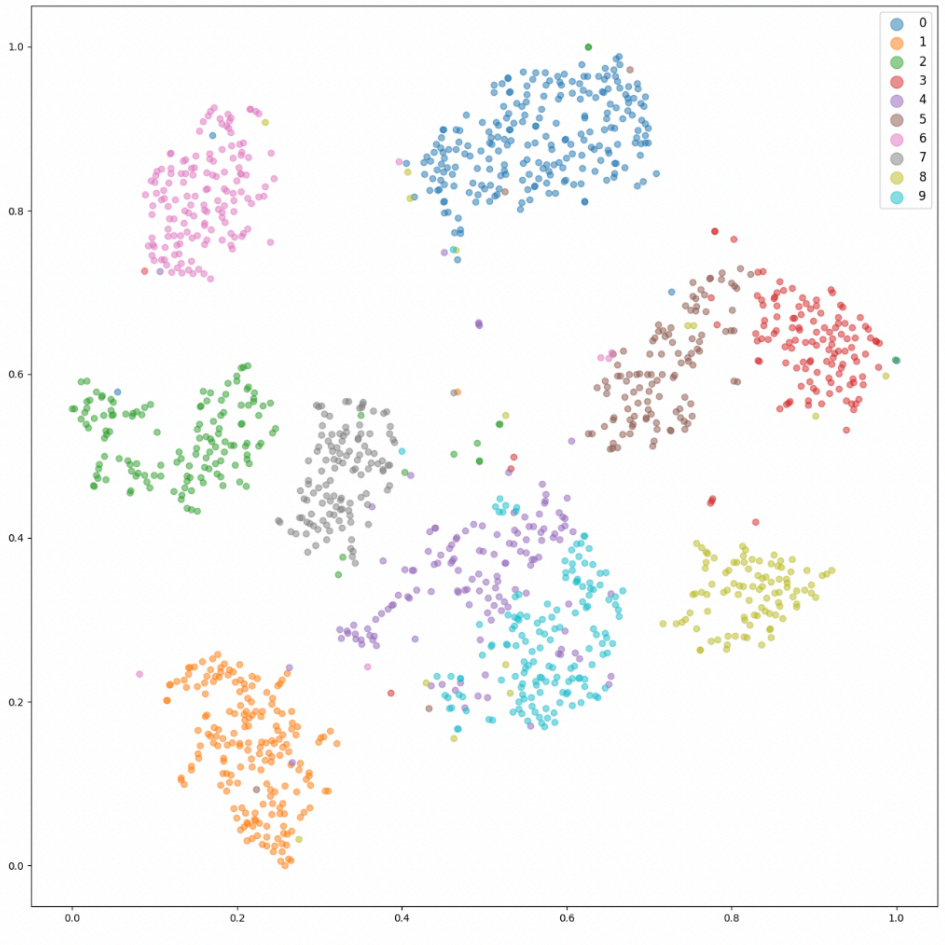
(5%) Please create and fill the table with the following format **in your report**:

	MNIST-M → SVHN	MNIST-M → USPS
Trained on source	0.281	0.732
Adaptation (DANN)	0.48	0.827
Trained on target	0.916	0.948

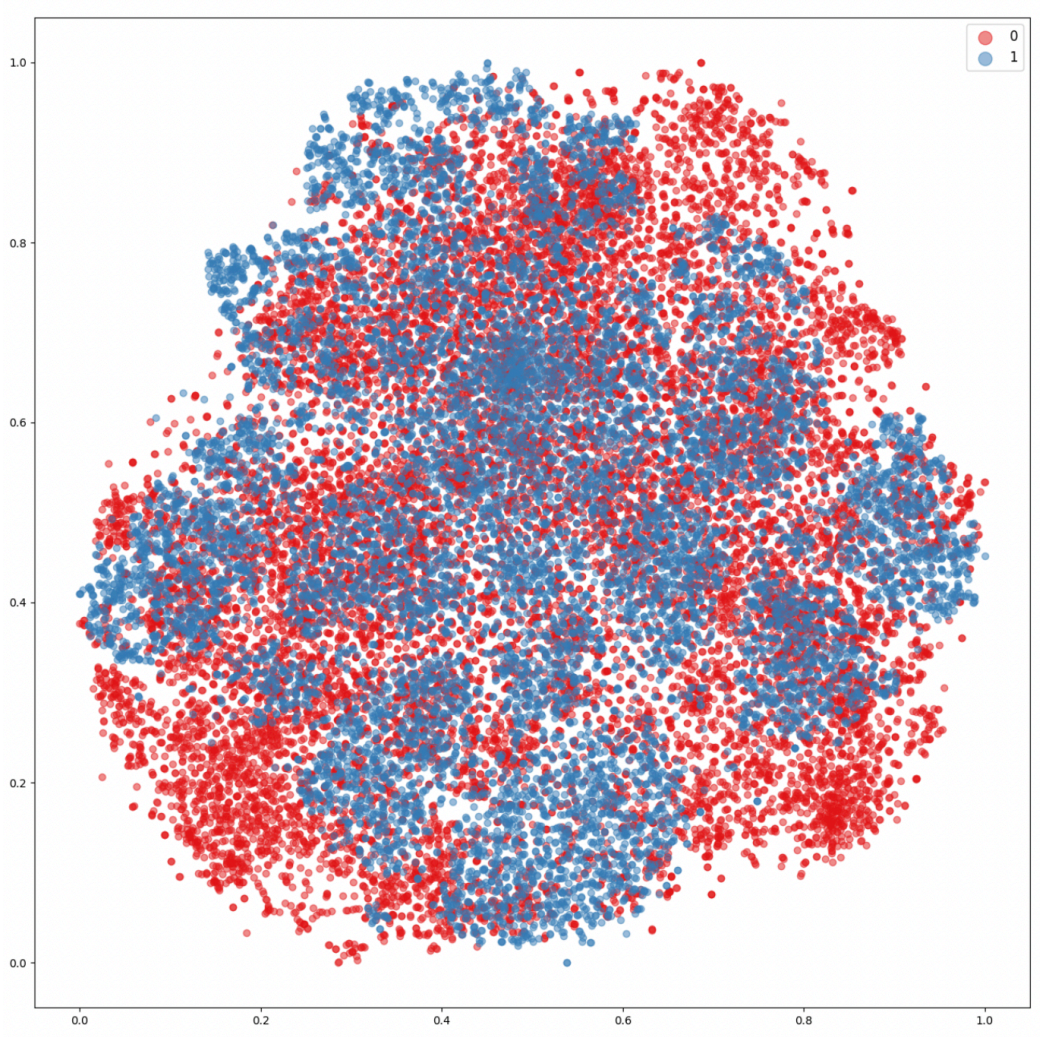
(8%) Please visualize the latent space of DANN by mapping the ***validation*** images to 2D space with t-SNE. For each scenario, you need to plot two figures which are colored **by digit class (0-9)** and **by domain**, respectively.



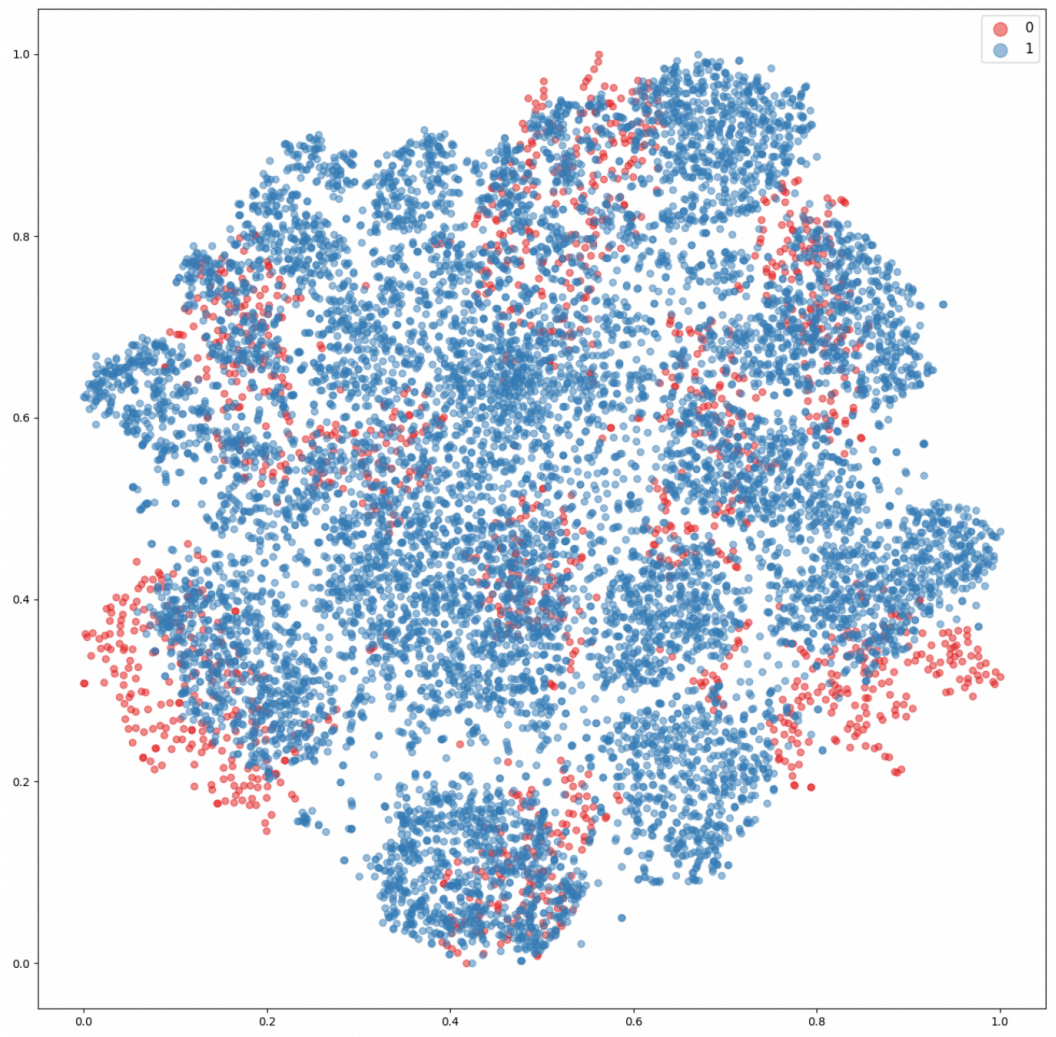
by digit class on SVHN



by digit class on USPS



by domain on SVHN



by domain on USPS

(10%) Please describe the implementation details of your model and discuss what you've observed and learned from implementing DANN.

Implement details:

- For images from SVHN and USPS, different transform and normalize are applied.
- Hyper-parameters :
  - Learning rate = 1e-4
  - batch_size = 256
- Optimizer is Adam, loss is NLLLoss
- The rest training flow basically follows https://arxiv.org/abs/1505.07818

- I've observed the result of t-SNE, and found that USPS dataset is better coherent with MNIST-M on both domain and digit class. The validation accuracy also shows that domain adaption from MNIST-M to USPS is very successful comparing to SVHN.
- I think that it was because images from MNIST-M and USPS are much more similar—they are composed only by digits and colored background, while SHVN contains high variation of format and light and shade.
- Still, the accuracy of DANN on SVHN could reach 0.5m which is a great leap from original. This is really impressive to me.