In this attempt I tried reducing the convolution filters size and increased the latent space to 16 dimensions, the results were better than the previous model as they were sharp as well as they were able to correctly decode the input, it was successful in decoding very hard samples like the ones in 12th and 14th column

This model has better results than compared to the previous model even though it has just 200k params and the earlier model had 300k params.

Imports

```
import torch
import torch.nn as nn
import matplotlib.pyplot as plt
```

Import utility functions

```
from helper_data import get_dataloaders_mnist
from helper_train import train_autoencoder_v1
from helper_utils import set_deterministic, set_all_seeds
from helper_plotting import plot_training_loss
from helper_plotting import plot_generated_images
from helper_plotting import plot_latent_space_with_labels
```

```
##########################
### SETTINGS
##########################

# Device
CUDA_DEVICE_NUM = 3
NUM_CLASSES = 10
DEVICE = torch.device(f'cuda:{0}' if torch.cuda.is_available() else 'cpu')
print('Device:', DEVICE)

# Hyperparameters
RANDOM_SEED = 123
LEARNING_RATE = 0.0005
BATCH_SIZE = 32
NUM_EPOCHS = 10
```

```
Device: cuda:0
```

```
set_deterministic
set_all_seeds(RANDOM_SEED)
```

Dataset

```
##########################
### Dataset
##########################

train_loader, valid_loader, test_loader = get_dataloaders_mnist(
    batch_size=BATCH_SIZE,
    num_workers=2,
    validation_fraction=0.)
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz to data/MNIST/raw/train-images-idx3-ubyte.gz
100%  9912422/9912422 [00:00<00:00, 17765435.55it/s]
Extracting data/MNIST/raw/train-images-idx3-ubyte.gz to data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to data/MNIST/raw/train-labels-idx1-ubyte.gz
100%  28881/28881 [00:00<00:00, 833074.48it/s]
Extracting data/MNIST/raw/train-labels-idx1-ubyte.gz to data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to data/MNIST/raw/t10k-images-idx3-ubyte.gz
100%  1648877/1648877 [00:00<00:00, 16612479.24it/s]
Extracting data/MNIST/raw/t10k-images-idx3-ubyte.gz to data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to data/MNIST/raw/t10k-labels-idx1-ubyte.gz
100%  4542/4542 [00:00<00:00, 149262.55it/s]
Extracting data/MNIST/raw/t10k-labels-idx1-ubyte.gz to data/MNIST/raw
```

```
# Checking the dataset
print('Training Set:\n')
for images, labels in train_loader:
    print('Image batch dimensions:', images.size())
    print('Image label dimensions:', labels.size())
    print(labels[:10])
    break

# Checking the dataset
print('\nValidation Set:')
for images, labels in valid_loader:
    print('Image batch dimensions:', images.size())
    print('Image label dimensions:', labels.size())
    print(labels[:10])
    break

# Checking the dataset
print('\nTesting Set:')
for images, labels in test_loader:
    print('Image batch dimensions:', images.size())
    print('Image label dimensions:', labels.size())
    print(labels[:10])
    break
```

```
Training Set:

Image batch dimensions: torch.Size([32, 1, 28, 28])
Image label dimensions: torch.Size([32])
tensor([1, 2, 1, 9, 0, 6, 9, 8, 0, 1])

Validation Set:

Testing Set:
Image batch dimensions: torch.Size([32, 1, 28, 28])
Image label dimensions: torch.Size([32])
tensor([7, 2, 1, 0, 4, 1, 4, 9, 5, 9])
```

Model

```
##########################
### MODEL
##########################


class Reshape(nn.Module):
    def __init__(self, *args):
        super().__init__()
        self.shape = args

    def forward(self, x):
        return x.view(self.shape)
```

```
class Trim(nn.Module):
    def __init__(self, *args):
        super().__init__()

    def forward(self, x):
        return x[:, :, :28, :28]


class AutoEncoder(nn.Module):
    def __init__(self):
        super().__init__()

        self.encoder = nn.Sequential( #784
                nn.Conv2d(1, 16, stride=(1, 1), kernel_size=(3, 3), padding=1),
                nn.LeakyReLU(0.01),
                nn.Conv2d(16, 32, stride=(2, 2), kernel_size=(3, 3), padding=1),
                nn.LeakyReLU(0.01),
                nn.Conv2d(32, 64, stride=(2, 2), kernel_size=(3, 3), padding=1),
                nn.LeakyReLU(0.01),
                nn.Conv2d(64, 64, stride=(1, 1), kernel_size=(3, 3), padding=1),
                nn.Flatten(),
                nn.Linear(64 * 7 * 7, 16)
        )
        self.decoder = nn.Sequential(
                torch.nn.Linear(16, 64 * 7 * 7),
                Reshape(-1, 64, 7, 7),
                nn.ConvTranspose2d(64, 64, stride=(1, 1), kernel_size=(3, 3), padding=1),
                nn.LeakyReLU(0.01),
                nn.ConvTranspose2d(64, 32, stride=(2, 2), kernel_size=(3, 3), padding=1),
                nn.LeakyReLU(0.01),
                nn.ConvTranspose2d(32, 16, stride=(2, 2), kernel_size=(3, 3), padding=0),
                nn.LeakyReLU(0.01),
                nn.ConvTranspose2d(16, 1, stride=(1, 1), kernel_size=(3, 3), padding=0),
                Trim(),  # 1x29x29 -> 1x28x28
                nn.Sigmoid()
                )

    def forward(self, x):
        x = self.encoder(x)
        x = self.decoder(x)
        return x
```

```
set_all_seeds(RANDOM_SEED)


model = AutoEncoder()
model.to(DEVICE)

optimizer = torch.optim.Adam(model.parameters(), lr=LEARNING_RATE)
```

```
sum(p.numel() for p in model.parameters() if p.requires_grad)
```

```
223889
```

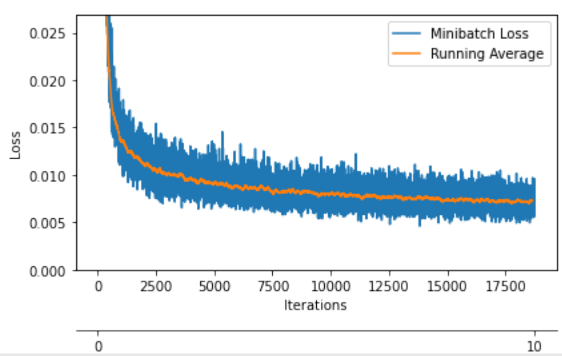
Training

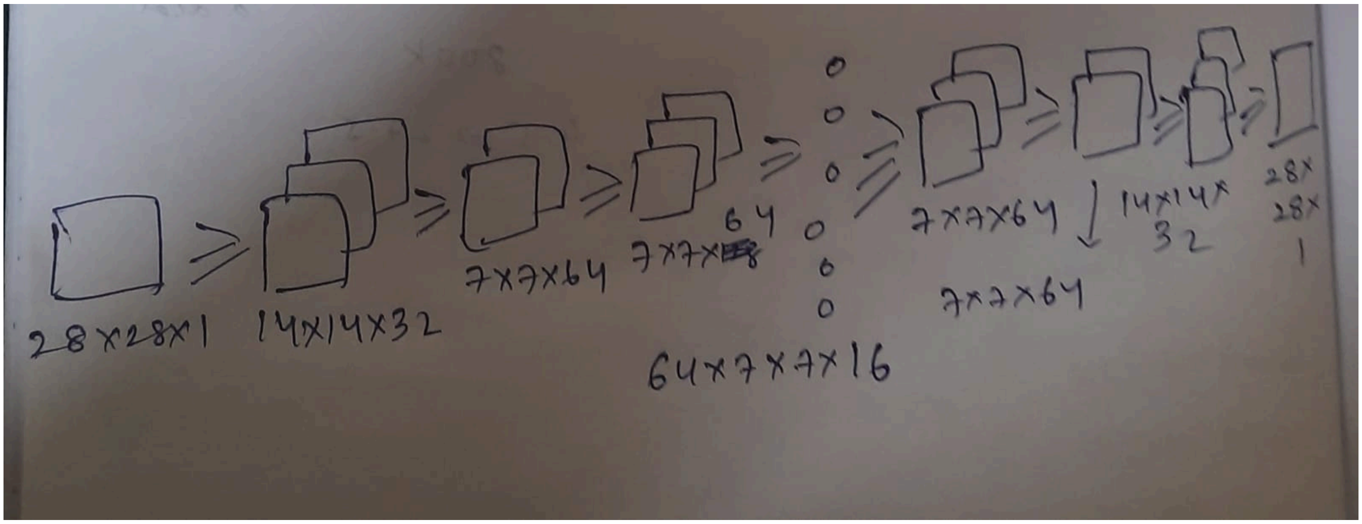
```
log_dict = train_autoencoder_v1(num_epochs=NUM_EPOCHS, model=model,
                                optimizer=optimizer, device=DEVICE,
                                train_loader=train_loader,
                                skip_epoch_stats=True,
                                logging_interval=250)
```

```
Time elapsed: 4.08 min
Epoch: 006/010 | Batch 0000/1875 | Loss: 0.0061
Epoch: 006/010 | Batch 0250/1875 | Loss: 0.0081
Epoch: 006/010 | Batch 0500/1875 | Loss: 0.0083
Epoch: 006/010 | Batch 0750/1875 | Loss: 0.0098
Epoch: 006/010 | Batch 1000/1875 | Loss: 0.0063
Epoch: 006/010 | Batch 1250/1875 | Loss: 0.0071
Epoch: 006/010 | Batch 1500/1875 | Loss: 0.0086
Epoch: 006/010 | Batch 1750/1875 | Loss: 0.0066
Time elapsed: 4.86 min
Epoch: 007/010 | Batch 0000/1875 | Loss: 0.0069
Epoch: 007/010 | Batch 0250/1875 | Loss: 0.0082
Epoch: 007/010 | Batch 0500/1875 | Loss: 0.0073
Epoch: 007/010 | Batch 0750/1875 | Loss: 0.0078
Epoch: 007/010 | Batch 1000/1875 | Loss: 0.0072
Epoch: 007/010 | Batch 1250/1875 | Loss: 0.0081
Epoch: 007/010 | Batch 1500/1875 | Loss: 0.0081
Epoch: 007/010 | Batch 1750/1875 | Loss: 0.0075
Time elapsed: 5.64 min
Epoch: 008/010 | Batch 0000/1875 | Loss: 0.0072
Epoch: 008/010 | Batch 0250/1875 | Loss: 0.0071
Epoch: 008/010 | Batch 0500/1875 | Loss: 0.0068
Epoch: 008/010 | Batch 0750/1875 | Loss: 0.0065
Epoch: 008/010 | Batch 1000/1875 | Loss: 0.0070
Epoch: 008/010 | Batch 1250/1875 | Loss: 0.0066
Epoch: 008/010 | Batch 1500/1875 | Loss: 0.0092
Epoch: 008/010 | Batch 1750/1875 | Loss: 0.0089
Time elapsed: 6.45 min
Epoch: 009/010 | Batch 0000/1875 | Loss: 0.0074
Epoch: 009/010 | Batch 0250/1875 | Loss: 0.0083
Epoch: 009/010 | Batch 0500/1875 | Loss: 0.0068
Epoch: 009/010 | Batch 0750/1875 | Loss: 0.0069
Epoch: 009/010 | Batch 1000/1875 | Loss: 0.0086
Epoch: 009/010 | Batch 1250/1875 | Loss: 0.0070
Epoch: 009/010 | Batch 1500/1875 | Loss: 0.0079
Epoch: 009/010 | Batch 1750/1875 | Loss: 0.0064
Time elapsed: 7.23 min
Epoch: 010/010 | Batch 0000/1875 | Loss: 0.0080
Epoch: 010/010 | Batch 0250/1875 | Loss: 0.0072
Epoch: 010/010 | Batch 0500/1875 | Loss: 0.0074
Epoch: 010/010 | Batch 0750/1875 | Loss: 0.0083
Epoch: 010/010 | Batch 1000/1875 | Loss: 0.0075
Epoch: 010/010 | Batch 1250/1875 | Loss: 0.0082
Epoch: 010/010 | Batch 1500/1875 | Loss: 0.0068
Epoch: 010/010 | Batch 1750/1875 | Loss: 0.0068
Time elapsed: 8.01 min
Total Training Time: 8.01 min
```

Evaluation

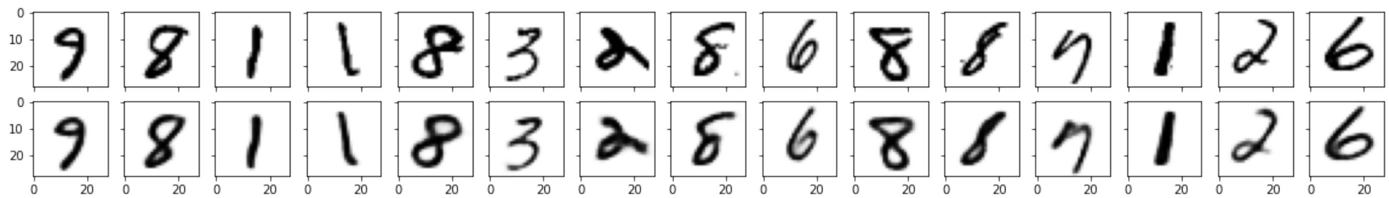
```
plot_training_loss(log_dict['train_loss_per_batch'], NUM_EPOCHS)
plt.show()
```



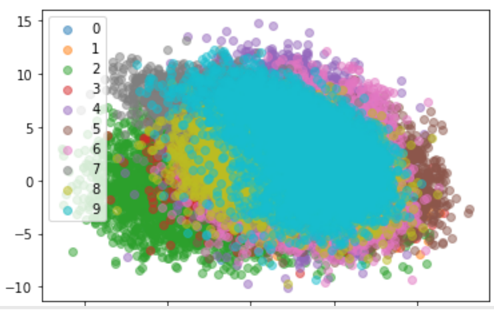


This model with 16 dimension latent space

```
plot_generated_images(data_loader=train_loader, model=model, device=DEVICE)
```



```
plot_latent_space_with_labels(
    num_classes=NUM_CLASSES,
    data_loader=train_loader,
    model=model,
    device=DEVICE)

plt.legend()
plt.show()
```



Decoding one particular image and a new image (Not part of exercise)

```
sample_img = None
sample_labels = None
for images, labels in train_loader:
    sample_img = images
    sample_labels = labels
    break


sample_img = sample_img.to(DEVICE)
encoded_sample =  model.encoder(sample_img)
```

```
len(encoded_sample)
```

```
32
```

```
len(encoded_sample[7])
```

```
16
```

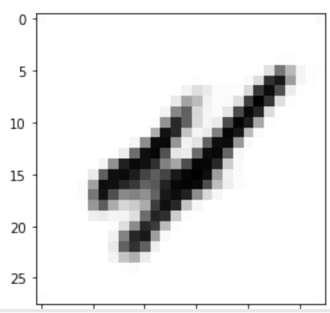
```
sample_labels[7]
```

```
tensor(4)
```

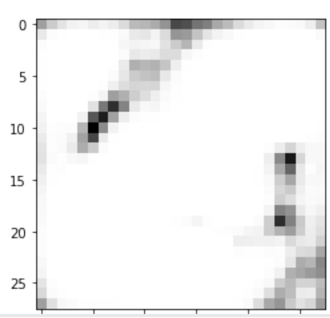
```
encoded_sample[7]
```

```
tensor([ 2.0732,  6.0997,  2.0306,  0.4322,  3.8104,  3.7257,  7.4104, -2.4846,
         5.6626, -1.5646, -7.7405,  7.4450,  2.5906, -1.8175, -4.4246, -3.3760],
       device='cuda:0', grad_fn=<SelectBackward0>)
```

```
with torch.no_grad():
    new_image = model.decoder(encoded_sample[7].to(DEVICE))
    new_image.squeeze_(0)
    new_image.squeeze_(0)
plt.imshow(new_image.to('cpu').numpy(), cmap='binary')
plt.show()
```




```
with torch.no_grad():
    new_image = model.decoder(torch.tensor([-0.9530,  4.7536, -1.7579,  2.1931,  1.6892,  0.1474, -0.9897, -0.8492,
        -5.8476, -2.1962,  5.0543, -7.7104, -8.0243,  0.0736,  5.2480,  7.1616]).to(DEVICE))
    new_image.squeeze_(0)
    new_image.squeeze_(0)
plt.imshow(new_image.to('cpu').numpy(), cmap='binary')
plt.show()
```



Final thoughts - I feel the more number of convoluted paremeters the worse becomes the performance of the autoencoder and the more the nerons in latent space the better the performance gets.

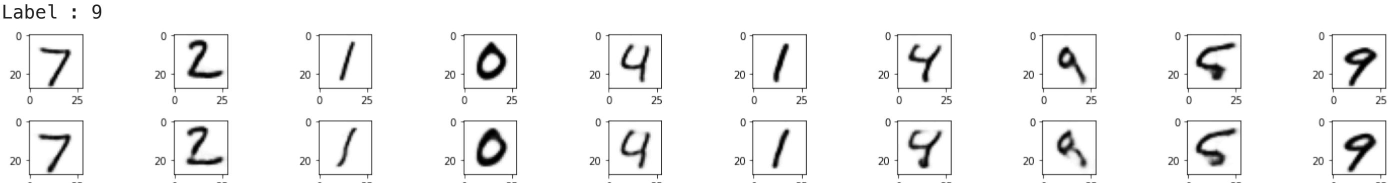
If I had to solve this kind of a problem in the future, I would use fewer Convoluted layers and more neurons in the latent space.

Answer 2 - Adding noise and comparing the output

```
import numpy as np
noise_factor = 0.2


def generate_and_plot_noisy_data(noise_factor=0.2):
  fig, axes = plt.subplots(2, 10,figsize=(20, 2.5))
  fig.tight_layout()
  for images, labels in test_loader:
      sample_test_images = images[:10]
      noisy_imgs = sample_test_images + noise_factor * torch.randn(*sample_test_images.shape)
      noisy_imgs = np.clip(noisy_imgs, 0., 1.)
      labels = labels[:10]

      for idx, label in enumerate(labels):
        print(f"Label : {label}")
        with torch.no_grad():

          sample_test_images = sample_test_images.to(DEVICE)
          encoded_sample_test_images =  model.encoder(sample_test_images)


          new_image = model.decoder(encoded_sample_test_images[idx].to(DEVICE))
          new_image.squeeze_(0)
          new_image.squeeze_(0)
          axes[0][idx].imshow(new_image.to('cpu').numpy(), cmap='binary')

          # ------ Noisy Data -------- #
          noisy_imgs = noisy_imgs.to(DEVICE)
          encoded_noisy_imgs =  model.encoder(noisy_imgs)


          noisy_image = model.decoder(encoded_noisy_imgs[idx].to(DEVICE))
          noisy_image.squeeze_(0)
          noisy_image.squeeze_(0)
          axes[1][idx].imshow(noisy_image.to('cpu').numpy(), cmap='binary')
      break
```

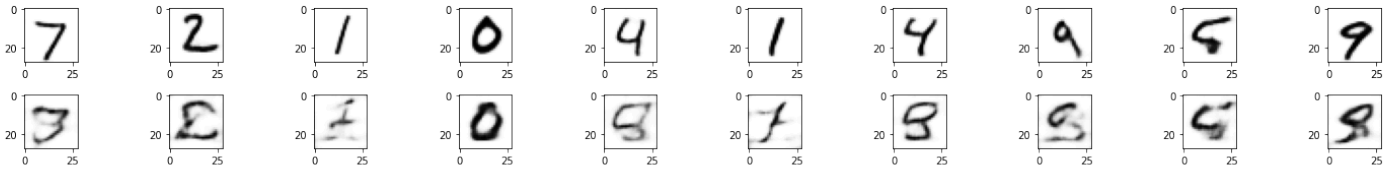
```
generate_and_plot_noisy_data()
```

```
Label : 7
Label : 2
Label : 1
Label : 0
Label : 4
Label : 1
Label : 4
Label : 9
Label : 5
Label : 9
```



```
generate_and_plot_noisy_data(0.4)
```

```
Label : 7
Label : 2
Label : 1
Label : 0
Label : 4
Label : 1
Label : 4
Label : 9
Label : 5
Label : 9
```



We can see that, wight a noise factor of 0.2 the model was able to decode the noisy images fairly efficeintly whereas the with noise factor of 0.4, there were a lot of distortions to the generated images.