ECE 570 Assignment 6 Exercise

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Exercise 1: Creating an image denoiser using a CNN autoencoder. (30 points)

In this exercise you are trying to build a autoencoder with CNN layers that can denoise images.

Task 1: Create additive noise transform

1. Add code to `AddGaussianNoise` transform class that will:
   - Add additive Gaussian noise to the batch of input images (i.e add noise with gaussian distribution on each pixel). The noise for every pixel should have mean value 0 and standard deviation of 0.3, i.e $\epsilon \sim N(0, 0.3)$.
   - Clip the values to be between 0 and 1 again as they may be outside the range for pixel values after adding Gaussian noise.
2. Plot the first 3 training images and their noisy counterparts in a 2x3 subplot with appropriate titles, figure size, label, etc.

In this task, we concatenate the original dataset and noisy dataset and get a single dataloader. You should be careful with what you load at each iteration. In a more general case, there are many ways of dealing with multiple datasets. For example, you can create separate dataloaders and use `zip` to load samples from them. Here is a post discussing how to use `zip` https://discuss.pytorch.org/t/two-dataloaders-from-two-different-datasets-within-the-same-loop/87766/1 (https://discuss.pytorch.org/t/two-dataloaders-from-two-different-datasets-within-the-same-loop/87766/1).

In [2]:
```
# Import and load MNIST data
import torchvision
import numpy as np
import torch
import matplotlib.pyplot as plt


class AddGaussianNoise(object):
  ###########################   <YOUR CODE>  ############################


    def __init__(self, mean, std):
        self.mean = mean
        self.std = std


    def __call__(self, tensor):
        tn_size = tensor.size()
        image_noise = tensor + self.mean+ torch.randn(tn_size) * self.std
        y = torch.clamp(image_noise,min=0,max = 1)
        return y



  #########################  <END YOUR CODE>  ############################


transform_noisy = torchvision.transforms.Compose([torchvision.transforms.ToTenso
transform_original = torchvision.transforms.Compose([torchvision.transforms.ToTe

train_dataset_noisy = torchvision.datasets.MNIST('data', train=True, download=Tr
train_dataset_original = torchvision.datasets.MNIST('data', train=True, download
test_dataset_noisy = torchvision.datasets.MNIST('data', train=False, download=Tr
test_dataset_original = torchvision.datasets.MNIST('data', train=False, download

print(torch.max(train_dataset_noisy.__getitem__(0)[0]).item())
print(torch.min(train_dataset_noisy.__getitem__(0)[0]).item())
```

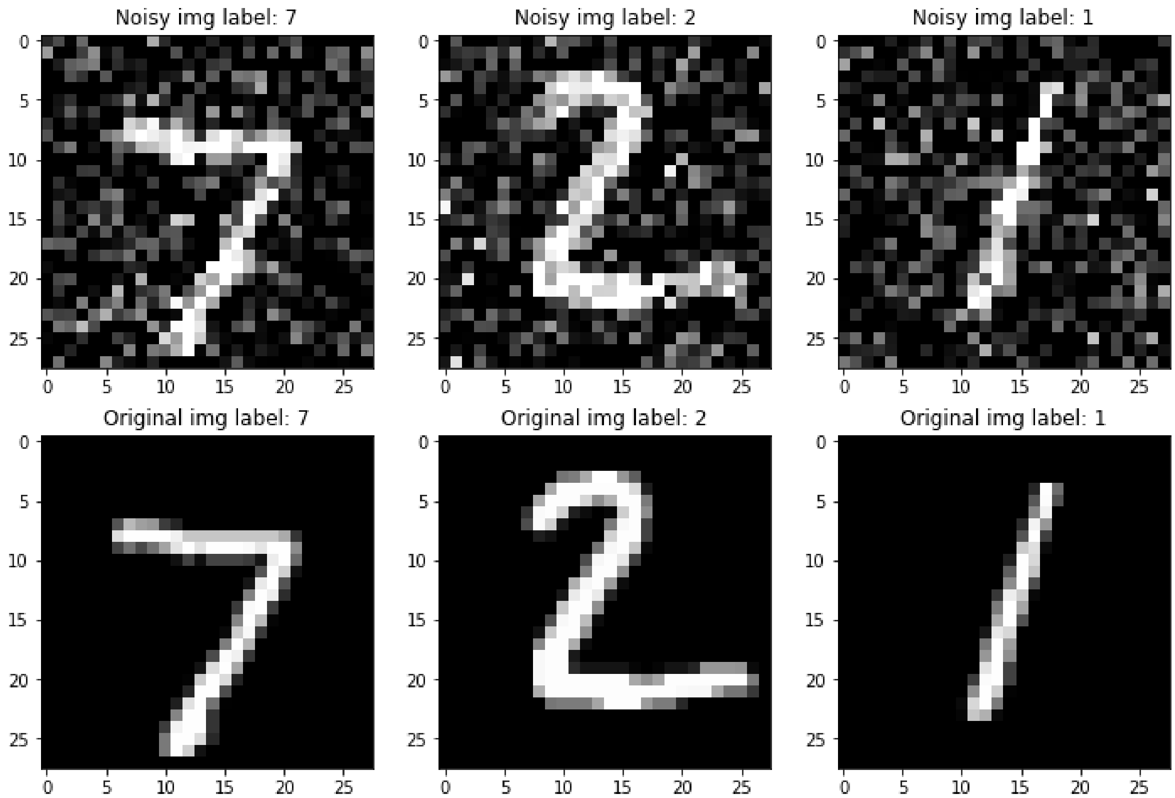
```
1.0
0.0
```

In [3]:
```
device = 'cuda' if torch.cuda.is_available()==True else 'cpu'
device = torch.device(device)
print(f'We are using device name "{device}"')
print(f'Device name {torch.cuda.get_device_name(0)}')
```

```
We are using device name "cuda"
Device name NVIDIA GeForce GTX 1060 with Max-Q Design
```

In [353]:
```
class ConcatDataset(torch.utils.data.Dataset):
    def __init__(self, *datasets):
        self.datasets = datasets

    def __getitem__(self, i):
        return tuple(d[i] for d in self.datasets)

    def __len__(self):
        return min(len(d) for d in self.datasets)


batch_size_train, batch_size_test = 64, 1000
train_loader = torch.utils.data.DataLoader(ConcatDataset(train_dataset_noisy, tra
                      batch_size=batch_size_train, shuffle=True)
test_loader = torch.utils.data.DataLoader(ConcatDataset(test_dataset_noisy, test_
                      batch_size=batch_size_test, shuffle=False)
###########################   <YOUR CODE>  ############################
# Plot the first 3 training images with corresponding noisy images


batch_idx, (images, _) = next(enumerate(test_loader))
#images = images.to(device).cpu().detach()
#images = images.cpu()

#print(images.size(), output.size())

fig, ax = plt.subplots(2,3)
fig.set_size_inches(12,8)

for idx in range(3):
    ax[0,idx].imshow(images[0][idx][0], cmap='gray')
    ax[0,idx].set_title(f'Noisy img label: {images[1][idx]}')
    ax[1,idx].imshow(_[0][idx][0], cmap='gray')
    ax[1,idx].set_title(f'Original img label: {_[1][idx]}')

fig.show()




#########################  <END YOUR CODE>  ############################
```

```
D:\Anaconda3\lib\site-packages\ipykernel_launcher.py:36: UserWarning: Matplotli
b is currently using module://ipykernel.pylab.backend_inline, which is a non-GU
I backend, so cannot show the figure.
```



Task 2: Create and train a denoising autoencoder

1. Build an autoencoder neural network structure with encoders and decoders that is a little more complicated than in the instructions. You can also create the network to have convolutional or transpose convolutional layers. (You can follow the instructions code skeleton with a key difference of using convolutional layers).
2. Move your model to GPU so that you can train your model with GPU. (This step can be simultaneously implemented in the above step)
3. Train your denoising autoencoder model with appropriate optimizer and **MSE** loss function. The loss function should be computed between the output of the noisy images and the clean images, i.e., $L(x, g(f(\tilde{x})))$, where $\tilde{x} = x + \epsilon$ is the noisy image and ϵ is the Gaussian niose. You should train your model with enough epochs so that your loss reaches a relatively steady value. **Note: Your loss on the test data should be lower than 20.** You may have to experiment with various model architectures to achieve this test loss.
4. Visualize your result with a 3 x 3 grid of subplots. You should show 3 test images, 3 test images with noise added, and 3 test images reconstructed after passing your noisy test images through the DAE.

In [402]:

In [ ]:

In [640]:
```
batch_size_train, batch_size_test = 64, 1000
train_loader = torch.utils.data.DataLoader(ConcatDataset(train_dataset_noisy, tra
                      batch_size=batch_size_train, shuffle=True)
test_loader = torch.utils.data.DataLoader(ConcatDataset(test_dataset_noisy, test_
                      batch_size=batch_size_test, shuffle=False)
```

In [534]:
```
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim

latent_feature = 16

class our_AE(nn.Module):
    def __init__(self):
        super(our_AE, self).__init__()

    # encoder
        self.en_fc1 = nn.Linear(in_features=784, out_features=512)
        self.en_fc2 = nn.Linear(in_features=512, out_features=latent_feature)

        # decoder
        self.de_fc1 = nn.Linear(in_features=latent_feature, out_features=512)
        self.de_fc2 = nn.Linear(in_features=512, out_features=784)


    def forward(self, x):

        # encoding layers
        x = x.view(-1, 784)
        x = F.relu(self.en_fc1(x))
        x = F.relu(self.en_fc2(x))

        # decoding layers
        x = F.relu(self.de_fc1(x))
        x = torch.sigmoid(self.de_fc2(x))
        x = x.view(-1, 1, 28, 28)
        return x


AE = our_AE().to(device)
optimizer = optim.Adam(AE.parameters(), lr=1e-4)
loss_fn = nn.MSELoss(reduction='sum')
```

In [550]:
```
###########################   <YOUR CODE>   ############################
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim

latent_feature = 16

class our_AE(nn.Module):
    def __init__(self):
        super(our_AE, self).__init__()
        self.en_fc1 = nn.Linear(in_features=288, out_features=128)
        self.en_fc2 = nn.Linear(in_features=128, out_features=16)

        self.de_fc1 = nn.Linear(in_features=latent_feature, out_features=128)
        self.de_fc2 = nn.Linear(in_features=128, out_features=288)


        self.en1 = nn.Conv2d(1, 8, 3, stride=2, padding=1)
        self.en2 = nn.Conv2d(8, 16, 3, stride=2, padding=1)
        self.en3 = nn.Conv2d(16, 32, 3, stride=2, padding=0)
        self.batch = nn.BatchNorm2d(latent_feature)
        self.flat = nn.Flatten(start_dim=1)

        self.deflat = nn.Unflatten(dim=1, unflattened_size=(32, 3, 3))
        self.de1 = nn.ConvTranspose2d(32 , latent_feature, 3, stride=2, output_pa
        self.batch1 = nn.BatchNorm2d(latent_feature)
        self.de2 = nn.ConvTranspose2d(16, 8, 3, stride=2, padding=1, output_padd
        self.batch2 = nn.BatchNorm2d(8)
        self.de3 = nn.ConvTranspose2d(8, 1, 3, stride=2, padding=1, output_paddi




    # encoder
        #self.en_fc1 = nn.Linear(in_features=288, out_features=128)
        #self.en_fc2 = nn.Linear(in_features=128, out_features=latent_feature)
        #self.batch = nn.BatchNorm2d(latent_feature)
        #self.en1 = nn.Conv2d(1,8,3,stride = 2, padding = 1)
        #self.en2 = nn.Conv2d(8,16,3,stride = 2, padding = 1)
        #self.en3 = nn.Conv2d(16,32,3,stride = 2, padding = 1)
        #self.flat = nn.Flatten(start_dim=1)
        # decoder
        #self.de_fc1 = nn.Linear(in_features=latent_feature, out_features=128)
        #self.de_fc2 = nn.Linear(in_features=128, out_features=288)
        #self.de1 = nn.ConvTranspose2d(32,16,3,padding = 1,stride = 2, output_pad
        #self.de2 = nn.ConvTranspose2d(16,8,3,padding = 1,stride = 2, output_padd
        #self.de3 = nn.ConvTranspose2d(8,1,3,padding = 1,stride = 2, output_paddi
        #self.debatch1 = nn.BatchNorm2d(latent_feature)
        #self.debatch2 = nn.BatchNorm2d(8)
        #self.deflat = nn.Unflatten(dim =1, unflattened_size=(32,3,3))

        #self.en_fc1 = nn.Linear(in_features=288, out_features=128)
        #self.en_fc2 = nn.Linear(in_features=128, out_features=latent_feature)

        #self.en1 = nn.Conv2d(1, 8, 3, stride=2, padding=1)
        #self.en2 = nn.Conv2d(8, 16, 3, stride=2, padding=1)
```

```
        #self.en3 = nn.Conv2d(16, 32, 3, stride=2, padding=0)
       # self.batch = nn.BatchNorm2d(latent_feature)
        #self.en1 = nn.Conv2d(1, 8, 3, padding=1, stride=2)
        #self.en2 = nn.Conv2d(8, 16, 3, padding=1, stride=2)
        #self.en3 = nn.Conv2d(16, 32, 3, stride=2, padding=0)
        #self.en_fc1 = nn.Linear(in_features=288, out_features=128)
        #self.en_fc2 = nn.Linear(in_features=128, out_features=latent_feature)
        #self.flat = nn.Flatten(start_dim=1)
        #self.en_batch = nn.BatchNorm2d(latent_feature)



        #self.de_fc1 = nn.Linear(in_features=16, out_features=128)
        #self.de_fc2 = nn.Linear(in_features=128, out_features=288)

        #self.debatch1 = nn.BatchNorm2d(latent_feature)
        #self.debatch2 = nn.BatchNorm2d(8)
        #self.deflat = nn.Unflatten(dim=1, unflattened_size=(32, 3, 3))
        #self.de1 = nn.ConvTranspose2d(32 , 16, 3, stride=2, output_padding=0)
        #self.de2 = nn.ConvTranspose2d(16, 8, 3, stride=2, padding=1, output_pad
        #self.de3 = nn.ConvTranspose2d(8, 1, 3, stride=2, padding=1, output_padd


        #self.de_fc1 = nn.Linear(in_features=latent_feature, out_features=128)
        #self.de_fc2 = nn.Linear(in_features=128, out_features=288)
        #self.de1 = nn.ConvTranspose2d(32 , 16, 3, stride=2, output_padding=1)
        #self.debatch1 = nn.BatchNorm2d(latent_feature)
        #self.de2 = nn.ConvTranspose2d(16, 8, 3, stride=2, padding=1, output_pad
        #self.deflat = nn.Unflatten(dim=1, unflattened_size=(16, 3, 3))
        #self.debatch2 = nn.BatchNorm2d(8)
       # self.de3 = nn.ConvTranspose2d(8, 1, 3, stride=2, padding=1, output_padd


    def forward(self, x):


        x = F.relu(self.en1(x))
        x = F.relu(self.batch(self.en2(x)))
        x = F.relu(self.en3(x))
        x = self.flat(x)
        x = F.relu(self.en_fc1(x))
        x = self.en_fc2(x)

        x = F.relu(self.de_fc1(x))
        x = F.relu(self.de_fc2(x))

        x = self.deflat(x)
        x = F.relu(self.batch1(self.de1(x)))
        x = F.relu(self.batch2(self.de2(x)))
        x = self.de3(x)
        x = torch.sigmoid(x)

        #x = F.relu(self.en1(x))
        #x = F.relu(self.batch(self.en2(x)))
        #x = F.relu(self.en3(x))
        #x = x.view(-1, 288)
        #x = F.relu(self.en_fc1(x))
```

```
        #x = self.en_fc2(x)

        #x = F.relu(self.en1(x))
        #x = self.en2(x)
        #print(x.size())
        #x = F.relu(self.en_batch(x))
        #print(x.size())
        #x = F.relu(self.en3(x))
        ##print(x.size())
        #x = x.view(-1, 288)
        #print(x.size())
        #x = F.relu(self.en_fc1(x))
        #print(x.size())
        #x = F.relu(self.en_fc2(x))
        #print(x.size())

        # encoding layers
        #x = F.relu(self.en1(x))

        #x = F.relu(self.batch(self.en2(x)))
        #x = F.relu(self.en3(x))
        #x = x.view(-1,32768)
        #x = x.view(-1, 784)
        #x = F.relu(self.en_fc1(x))
        #x = self.en_fc2(x)

        # decoding layers
        #x = F.relu(self.de_fc1(x))
        #x = F.relu(self.de_fc2(x))
        #x = self.deflat(x)
        #x = self.de1(x)
        #x = F.relu(self.debatch1(self.de1(x)))
        #x = self.de2(x)
        #x = F.relu(self.debatch2(self.de2(x)))
        #x = self.de3(x)
        #x = torch.sigmoid((x))
        #x = torch.sigmoid(self.de_fc2(x))
        #x = x.view(-1, 1, 28, 28)
        #x = F.relu(self.de1(x))
        #x = F.relu(x)
        #x = F.relu(self.de2(x))
        #x = self.deflat(x)
        #x = self.de_conv1(x)
        #x = F.relu(self.debatch1(x))
        #x = F.relu(self.debatch2(self.de_conv2(x)))
        #x = self.de_conv3(x)

        #x = F.relu(self.de_fc1(x))
        #x = F.relu(self.de_fc2(x))
        #x = self.deflat(x)
        #x = F.relu(self.debatch1(self.de1(x)))
        #x = F.relu(self.debatch2(self.de2(x)))
       # x = F.relu(self.de3(x))
       # x = torch.sigmoid(x)
        return x
```

```
AE = our_AE().to(device)
optimizer = optim.Adam(AE.parameters(), lr=1e-4)
loss_fn = nn.MSELoss(reduction='sum')


########################  <END YOUR CODE>  ############################
```

In [553]:

```
def train(epoch, device):

    AE.train()

    for batch_idx, (images, _) in enumerate(train_loader):

        images,orig = images[0], _[0]
        optimizer.zero_grad()
        images,orig = images.float(), orig.float()
        images = images.to(device)
        orig = orig.to(device)
        output = AE(images)
        loss = loss_fn(output,orig)
        loss.backward()
        optimizer.step()

        if batch_idx % 10 == 0:
            train_losses.append(loss.item()/batch_size_train)
            train_counter.append(
            (batch_idx*64) + ((epoch-1)*len(train_loader.dataset)))
        if batch_idx % 100 == 0:
            print(f'Epoch {epoch}: [{batch_idx*len(images)}/{len(train_loader.da


def test(epoch, device):

    AE.eval()

    test_loss = 0
    correct = 0

    with torch.no_grad():
        for images, _ in test_loader:
            images = images[0]
            _ = _[0].float()
            images = images.to(device)
            _ = _.to(device)
            output = AE(images)
            test_loss += loss_fn(output, _).item()

        test_loss /= len(test_loader.dataset)
        test_losses.append(test_loss)
        test_counter.append(len(train_loader.dataset)*epoch)

    print(f'Test result on epoch {epoch}: Avg loss is {test_loss}')
```

In [ ]:

In [554]:
```
train_losses = []
train_counter = []
test_losses = []
test_counter = []
max_epoch = 10

for epoch in range(1, max_epoch+1):
    train(epoch, device=device)
    test(epoch, device=device)
```

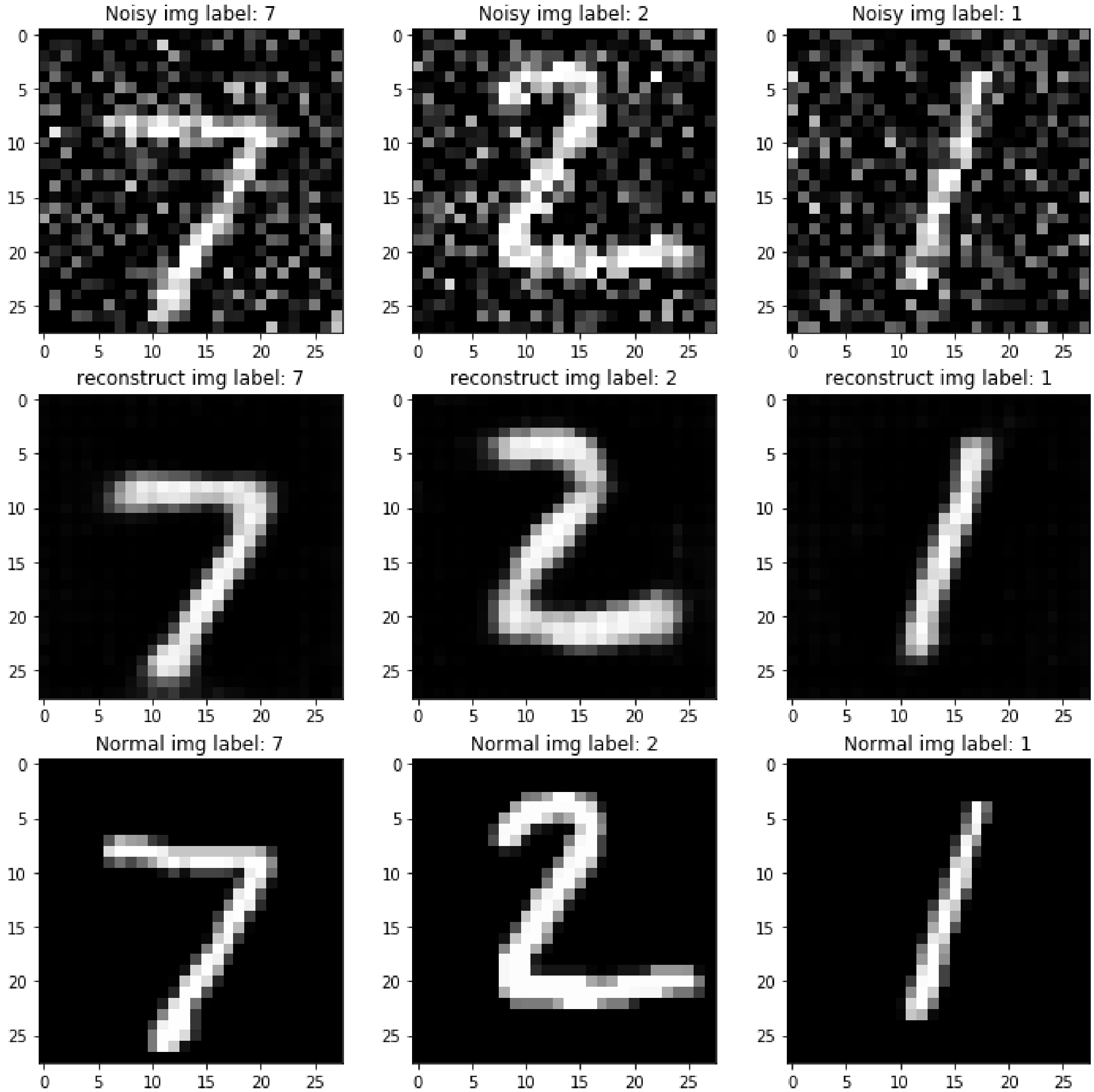
```
Epoch 1: [0/60000] Loss: 61.79195022583008
Epoch 1: [6400/60000] Loss: 56.15406036376953
Epoch 1: [12800/60000] Loss: 53.14657211303711
Epoch 1: [19200/60000] Loss: 49.01898193359375
Epoch 1: [25600/60000] Loss: 46.82391357421875
Epoch 1: [32000/60000] Loss: 45.55665588378906
Epoch 1: [38400/60000] Loss: 41.394287109375
Epoch 1: [44800/60000] Loss: 39.03569412231445
Epoch 1: [51200/60000] Loss: 37.21958923339844
Epoch 1: [57600/60000] Loss: 35.88697814941406
Test result on epoch 1: Avg loss is 35.5519265625
Epoch 2: [0/60000] Loss: 35.91407012939453
Epoch 2: [6400/60000] Loss: 33.92999267578125
Epoch 2: [12800/60000] Loss: 32.342926025390625
Epoch 2: [19200/60000] Loss: 31.150474548339844
Epoch 2: [25600/60000] Loss: 28.60101318359375
Epoch 2: [32000/60000] Loss: 29.60930061340332
Epoch 2: [38400/60000] Loss: 28.64295768737793
Epoch 2: [44800/60000] Loss: 26.983196258544922
Epoch 2: [51200/60000] Loss: 26.862001419067383
Epoch 2: [57600/60000] Loss: 26.96673583984375
Test result on epoch 2: Avg loss is 24.81240703125
Epoch 3: [0/60000] Loss: 26.1354923248291
Epoch 3: [6400/60000] Loss: 24.051523208618164
Epoch 3: [12800/60000] Loss: 22.581462860107422
Epoch 3: [19200/60000] Loss: 23.86558723449707
Epoch 3: [25600/60000] Loss: 23.17548370361328
Epoch 3: [32000/60000] Loss: 21.35110855102539
Epoch 3: [38400/60000] Loss: 22.90218162536621
Epoch 3: [44800/60000] Loss: 21.081008911132812
Epoch 3: [51200/60000] Loss: 20.620534896850586
Epoch 3: [57600/60000] Loss: 20.8162899017334
Test result on epoch 3: Avg loss is 19.735333984375
Epoch 4: [0/60000] Loss: 20.17789077758789
Epoch 4: [6400/60000] Loss: 18.638526916503906
Epoch 4: [12800/60000] Loss: 19.68832015991211
Epoch 4: [19200/60000] Loss: 18.127243041992188
Epoch 4: [25600/60000] Loss: 17.06698226928711
Epoch 4: [32000/60000] Loss: 18.117088317871094
Epoch 4: [38400/60000] Loss: 17.960147857666016
Epoch 4: [44800/60000] Loss: 17.01280975341797
Epoch 4: [51200/60000] Loss: 17.758037567138672
Epoch 4: [57600/60000] Loss: 16.173904418945312
Test result on epoch 4: Avg loss is 16.8565416015625
Epoch 5: [0/60000] Loss: 18.47439193725586
Epoch 5: [6400/60000] Loss: 16.64104461669922
Epoch 5: [12800/60000] Loss: 17.136985778808594
```

```
Epoch 5: [19200/60000] Loss: 16.0782470703125
Epoch 5: [25600/60000] Loss: 15.557445526123047
Epoch 5: [32000/60000] Loss: 16.043121337890625
Epoch 5: [38400/60000] Loss: 15.081007957458496
Epoch 5: [44800/60000] Loss: 14.619203567504883
Epoch 5: [51200/60000] Loss: 16.444189071655273
Epoch 5: [57600/60000] Loss: 13.933531761169434
Test result on epoch 5: Avg loss is 14.95315888671875
Epoch 6: [0/60000] Loss: 14.442033767700195
Epoch 6: [6400/60000] Loss: 16.401737213134766
Epoch 6: [12800/60000] Loss: 13.787269592285156
Epoch 6: [19200/60000] Loss: 15.23563003540039
Epoch 6: [25600/60000] Loss: 15.302131652832031
Epoch 6: [32000/60000] Loss: 14.844217300415039
Epoch 6: [38400/60000] Loss: 14.218480110168457
Epoch 6: [44800/60000] Loss: 14.280085563659668
Epoch 6: [51200/60000] Loss: 13.021913528442383
Epoch 6: [57600/60000] Loss: 13.730072021484375
Test result on epoch 6: Avg loss is 13.87830380859375
Epoch 7: [0/60000] Loss: 14.344173431396484
Epoch 7: [6400/60000] Loss: 14.286958694458008
Epoch 7: [12800/60000] Loss: 14.586257934570312
Epoch 7: [19200/60000] Loss: 15.08311653137207
Epoch 7: [25600/60000] Loss: 14.23099422454834
Epoch 7: [32000/60000] Loss: 14.66063117980957
Epoch 7: [38400/60000] Loss: 13.309335708618164
Epoch 7: [44800/60000] Loss: 13.489328384399414
Epoch 7: [51200/60000] Loss: 13.659099578857422
Epoch 7: [57600/60000] Loss: 13.732620239257812
Test result on epoch 7: Avg loss is 13.123766796875
Epoch 8: [0/60000] Loss: 13.03959846496582
Epoch 8: [6400/60000] Loss: 14.46481704711914
Epoch 8: [12800/60000] Loss: 13.08922290802002
Epoch 8: [19200/60000] Loss: 13.485458374023438
Epoch 8: [25600/60000] Loss: 12.40336799621582
Epoch 8: [32000/60000] Loss: 13.776098251342773
Epoch 8: [38400/60000] Loss: 12.446738243103027
Epoch 8: [44800/60000] Loss: 14.180386543273926
Epoch 8: [51200/60000] Loss: 13.072967529296875
Epoch 8: [57600/60000] Loss: 13.024934768676758
Test result on epoch 8: Avg loss is 12.65623603515625
Epoch 9: [0/60000] Loss: 12.641887664794922
Epoch 9: [6400/60000] Loss: 12.734647750854492
Epoch 9: [12800/60000] Loss: 11.126644134521484
Epoch 9: [19200/60000] Loss: 14.229244232177734
Epoch 9: [25600/60000] Loss: 11.967765808105469
Epoch 9: [32000/60000] Loss: 12.803081512451172
Epoch 9: [38400/60000] Loss: 12.280834197998047
Epoch 9: [44800/60000] Loss: 13.864828109741211
Epoch 9: [51200/60000] Loss: 13.11871337890625
Epoch 9: [57600/60000] Loss: 13.390953063964844
Test result on epoch 9: Avg loss is 12.29120185546875
Epoch 10: [0/60000] Loss: 10.749900817871094
Epoch 10: [6400/60000] Loss: 13.59035873413086
Epoch 10: [12800/60000] Loss: 13.02316951751709
Epoch 10: [19200/60000] Loss: 11.145601272583008
Epoch 10: [25600/60000] Loss: 13.381590843200684
```

```
Epoch 10: [32000/60000] Loss: 12.83629035949707
Epoch 10: [38400/60000] Loss: 14.020696640014648
Epoch 10: [44800/60000] Loss: 12.35506534576416
Epoch 10: [51200/60000] Loss: 11.513629913330078
Epoch 10: [57600/60000] Loss: 12.051469802856445
Test result on epoch 10: Avg loss is 11.8816705078125
```

In [565]:
```
batch_idx, (images, _) = next(enumerate(test_loader))
images = images[0].to(device)
output = AE(images).cpu().detach()
images = images.cpu()

print(images.size(), output.size())

fig, ax = plt.subplots(3,3)
fig.set_size_inches(12,12)
#batch_idx, (images, _) = next(enumerate(test_loader))


for idx in range(3):
    ax[0,idx].imshow(images[idx][0], cmap='gray')
    ax[0,idx].set_title(f'Noisy img label: {_[1][idx]}')
    ax[1,idx].imshow(output[idx][0], cmap='gray')
    ax[1,idx].set_title(f'reconstruct img label: {_[1][idx]}')
    ax[2,idx].imshow(_[0][idx][0], cmap='gray')
    ax[2,idx].set_title(f'Normal img label: {_[1][idx]}')
fig.show()
```

```
torch.Size([1000, 1, 28, 28]) torch.Size([1000, 1, 28, 28])

D:\Anaconda3\lib\site-packages\ipykernel_launcher.py:20: UserWarning: Matplotli
b is currently using module://ipykernel.pylab.backend_inline, which is a non-GU
I backend, so cannot show the figure.
```



Exercise 2: Build a variational autoencoder(VAE) that can generate MNIST images (70 points)

Task 0: Setup

1. Import necessary packages
2. Load the MNIST data as above.
3. Specify the device.

In [4]:
```
############################   <YOUR CODE>   ############################

import torchvision
import torch
import torch.optim as optim

transform = torchvision.transforms.Compose([torchvision.transforms.ToTensor()]) #

train_dataset = torchvision.datasets.MNIST('data', train=True, download=True, tra
test_dataset = torchvision.datasets.MNIST('data', train=False, download=True, tra


device = 'cuda' if torch.cuda.is_available()==True else 'cpu'
device = torch.device(device)
print(f'We are using device name "{device}"')
print(f'Device name {torch.cuda.get_device_name(0)}')
#########################  <END YOUR CODE>  ############################
```

```
We are using device name "cuda"
Device name NVIDIA GeForce GTX 1060 with Max-Q Design
```

In [5]:
```
transform = torchvision.transforms.Compose([torchvision.transforms.ToTensor()])

batch_size_train, batch_size_test = 64, 1000

train_dataset = torchvision.datasets.MNIST('data', train=True, download=True, tra
test_dataset = torchvision.datasets.MNIST('data', train=False, download=True, tra

train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=batch_size_t
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=batch_size_tes
```

Task 1: VAE Loss function

Construct your loss function. The loss function for VAE is a little bit difficult:

$$\begin{aligned}\textbf{NegativeELBO}(x, g, f) &= \mathbb{E}_{q_f}[-\log p_g(x|z)] + KL(q_f(z|x), p_g(z)) \\ &= \text{ReconstructionLoss} + \text{Regularizer}\end{aligned}$$

In this exercise, you will build the VAE (variational autoencoder) model satisfying following conditions which simplifies the computation of loss function:

1. $p_g(z)$ is a standard normal distribution.
2. $q_f(z|x)$ is a multivariate Gaussian with trainable mean and variance along each dimension.
3. The output distribution of the decoder is an independent Bernoulli distribution for every pixel value since the values are between 0 and 1.

While we discussed the Gaussian distribution in class, here we assume the output distribution of the decoder is an independent Bernoulli distribution for every pixel value since the values are between 0 and 1. The value of the pixel corresponds to the average of the Bernoulli distribution. This loss can be seen in Appendix C.1 of the original VAE paper: [https://arxiv.org/pdf/1312.6114.pdf (https://arxiv.org/pdf/1312.6114.pdf)](https://arxiv.org/pdf/1312.6114.pdf). With such assumption, the reconstruction loss can be calculated using the binary-cross-entropy loss between the original images and the output of the VAE. See [torch.nn.functional.binary_cross_entropy (https://pytorch.org/docs/stable/nn.functional.html#binary-cross-entropy)](https://pytorch.org/docs/stable/nn.functional.html#binary-cross-entropy). You should use the sum reduction of the loss to sum the loss over all the pixels.

The second part is the KL-Divergence between your model's approximate posterier $q_f(z|x)$ and the model prior $p_g(z)$. If we assume $p_g(z)$ is a standard normal distribution and $q_f(z|x)$ is a Gaussian with unknown mean and variance, then this KL divergence can be computed in closed form (see Appendix B of original VAE paper above):
$KL(q_f(z|x), p_g(z)) = -\frac{1}{2}\sum_{j=1}^{d}(1 + \log(\sigma_j^2) - \mu_j^2 - \sigma_j^2)$.

Your task here is to write a function `vae_loss` that takes the value of your model's output, the original images, mu, and log_var (i.e., the $\log(\sigma_j^2)$ term), and returns the the reconstruction loss and the KL loss terms **separately** (i.e., the function should return two loss arrays). To visualize these losses separately in a later task, you will need the reconstruction loss and KL loss separated.

In [6]:
```
def vae_loss(output, mu, log_var, images):


  ###########################   <YOUR CODE>  ############################
    regu = 1 + log_var - mu.pow(2) - log_var.exp()
    regu_sum = -0.5 * torch.sum(regu)
    Loss_reco = F.binary_cross_entropy(input=output.view(-1, 28*28), target=imag

    return Loss_reco, regu_sum

  #########################  <END YOUR CODE>  ############################
```

Task 2: VAE model

Build the VAE (variational autoencoder) model based on the instructions given below and in the comments.

- Inside the `reparameterize` function you job is to output a latent vector. You should first calculate the standard deviation `std` from the log variance variable `log_var` (i.e., compute σ from $\log(\sigma^2)$, then generate the vector in Gaussian distribution with `mu` and `std`. **Importantly**, this should use the reparametrization trick so that we can backpropagate through this random step.
- Inside the `forward` function you should extract the `mu` and `log_var` from the latent representation after the encoder. The output of encoder should be in the dimension `[batch_size x 2 x latent_feature]`, which includes a mean and log variance for each latent feature and for each instance in the batch. Remember that in VAEs, the encoder outputs the parameters of the latent distribution. Note that the second dimension has value 2, so you need to split this tensor into two components, one called `mu` and the other called `log_var` ---which will be fed into reparameterize.

In [7]:
```
import torch.nn as nn
import torch.nn.functional as F


class our_VAE(nn.Module):
    def __init__(self, latent_feature = 16): # you can use any number of latent j
        super(our_VAE, self).__init__()

        self.latent_feature = latent_feature


        self.en_input1 = nn.Linear(in_features=784, out_features=500)
        self.en_hidden1 = nn.Linear(in_features=500, out_features=latent_feature

        self.en_hidden2 = nn.Linear(in_features=500, out_features=latent_feature
        #    self.en_hidden2 = nn.Linear(in_features=500, out_features=latent_fec

        self.de_hidden = nn.Linear(in_features=500, out_features=784)
        self.de_latent = nn.Linear(in_features=latent_feature, out_features=500)


    def reparameterize(self, mu, log_var):


        sample = torch.randn_like(torch.exp(log_var/2))*torch.exp(log_var/2) + mu

        return sample
    def encoder(self, x):

        #forword
        x = x.view(-1, 784)

        x = self.en_input1(x)
        x = F.relu(x)

        mu = self.en_hidden1(x)
        log_var =  self.en_hidden2(x)

        z = self.reparameterize(mu,log_var)


        return mu, log_var, z

    def decoder(self, z):


        #forword
        z = self.de_latent(z)
        x = F.relu(z)

        x = torch.sigmoid((self.de_hidden(x)))
        return x



    def forward(self, x):
```

```
        mu = self.encoder(x)[0]
        log_var = self.encoder(x)[1]
        z = self.encoder(x)[2]
        #decode
        x = self.decoder(z)


        return x, mu, log_var
```

Task 3: Train and visualize output

1. Train your model with an appropriate optimizer and the above loss function. You should train your model with enough epochs so that your loss reaches a relatively steady value.
2. Visualize your result. You should **show three pairs of images** where each pair consists of an original test image and its VAE reconstructed version.
3. Keep track of the loss. You should save the negative ELBO, Reconstruction Loss and KL Divergence Loss after every 10 batches in the trainining and **create a plot with three curves** using [matplotlib.pyplot.plot (https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.plot.html)](https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.plot.html). Each curve should correpond to one of the losses. The x-axis will be the number of batches divided by 10 and the y-axis will be the loss. **Make sure you clearly specify the legend, x-label and y-label.**

Note: It is always a good idea to keep track of the loss in the process of training to help you understand what is happening during training.

In [8]:

```
###########################    <YOUR CODE>   ############################
device = 'cuda' if torch.cuda.is_available()==True else 'cpu'
device = torch.device(device)
learning_rate = 0.0001
batch_size_train, batch_size_test = 64, 1000
epochs = 1

VAE = our_VAE().to(device)

optimizer = optim.Adam(params=VAE.parameters(), lr=learning_rate)

#########################  <END YOUR CODE>  ###########################
```

In [10]:
```
elbo_n = []
loss_rec = []
KL_loss = []
epochs = 29


for epoch in range(epochs):
    batch_count = 0
    for idx, (images,_) in enumerate(train_loader, 0):

        _ = _.to(device)
        images = images.to(device)


        reconstructions, mu, log_var = VAE(images)

        ReconstructionLoss, Regularizer = vae_loss(reconstructions, mu, log_var,
        loss = ReconstructionLoss + Regularizer

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()



        if (idx % 10) == 0:

            elbo_n.append(loss.item()/batch_size_train)
            loss_rec.append(ReconstructionLoss/batch_size_train)
            KL_loss.append(Regularizer/batch_size_train)


        if (idx % 100) == 0:
            print(f'Epoch {epoch+1}: [{idx*len(images)}/{len(train_loader.datase
```

```
Epoch 1: [0/60000] Loss: 541.614990234375
Epoch 1: [6400/60000] Loss: 265.60626220703125
Epoch 1: [12800/60000] Loss: 224.97598266601562
Epoch 1: [19200/60000] Loss: 226.33551025390625
Epoch 1: [25600/60000] Loss: 208.12464904785156
Epoch 1: [32000/60000] Loss: 184.79495239257812
Epoch 1: [38400/60000] Loss: 180.6696319580078
Epoch 1: [44800/60000] Loss: 181.85986328125
Epoch 1: [51200/60000] Loss: 165.03297424316406
Epoch 1: [57600/60000] Loss: 165.04742431640625
Epoch 2: [0/60000] Loss: 169.83070373535156
Epoch 2: [6400/60000] Loss: 163.33038330078125
Epoch 2: [12800/60000] Loss: 150.0075225830078
Epoch 2: [19200/60000] Loss: 155.22032165527344
Epoch 2: [25600/60000] Loss: 159.76644897460938
Epoch 2: [32000/60000] Loss: 150.3697052001953
Epoch 2: [38400/60000] Loss: 142.97723388671875
Epoch 2: [44800/60000] Loss: 142.7040252685547
Epoch 2: [51200/60000] Loss: 139.32754516601562
```

```
Epoch 2: [57600/60000] Loss: 145.5557861328125
Epoch 3: [0/60000] Loss: 143.24835205078125
Epoch 3: [6400/60000] Loss: 146.56350708007812
Epoch 3: [12800/60000] Loss: 140.36135864257812
Epoch 3: [19200/60000] Loss: 135.13037109375
Epoch 3: [25600/60000] Loss: 142.20370483398438
Epoch 3: [32000/60000] Loss: 132.4593505859375
Epoch 3: [38400/60000] Loss: 134.53012084960938
Epoch 3: [44800/60000] Loss: 134.45941162109375
Epoch 3: [51200/60000] Loss: 133.55247497558594
Epoch 3: [57600/60000] Loss: 137.87088012695312
Epoch 4: [0/60000] Loss: 119.62379455566406
Epoch 4: [6400/60000] Loss: 126.96638488769531
Epoch 4: [12800/60000] Loss: 132.8927459716797
Epoch 4: [19200/60000] Loss: 128.2212677001953
Epoch 4: [25600/60000] Loss: 128.18475341796875
Epoch 4: [32000/60000] Loss: 130.779296875
Epoch 4: [38400/60000] Loss: 127.32376098632812
Epoch 4: [44800/60000] Loss: 124.57012939453125
Epoch 4: [51200/60000] Loss: 121.80685424804688
Epoch 4: [57600/60000] Loss: 124.03004455566406
Epoch 5: [0/60000] Loss: 129.14036560058594
Epoch 5: [6400/60000] Loss: 113.11759948730469
Epoch 5: [12800/60000] Loss: 120.49654388427734
Epoch 5: [19200/60000] Loss: 123.36202239990234
Epoch 5: [25600/60000] Loss: 122.65383911132812
Epoch 5: [32000/60000] Loss: 124.6266860961914
Epoch 5: [38400/60000] Loss: 126.8935775756836
Epoch 5: [44800/60000] Loss: 125.9368896484375
Epoch 5: [51200/60000] Loss: 126.036376953125
Epoch 5: [57600/60000] Loss: 120.81177520751953
Epoch 6: [0/60000] Loss: 127.60289764404297
Epoch 6: [6400/60000] Loss: 121.74482727050781
Epoch 6: [12800/60000] Loss: 124.79853820800781
Epoch 6: [19200/60000] Loss: 117.0324478149414
Epoch 6: [25600/60000] Loss: 119.46788024902344
Epoch 6: [32000/60000] Loss: 121.38280487060547
Epoch 6: [38400/60000] Loss: 123.73699951171875
Epoch 6: [44800/60000] Loss: 114.62242889404297
Epoch 6: [51200/60000] Loss: 116.44264221191406
Epoch 6: [57600/60000] Loss: 119.71424865722656
Epoch 7: [0/60000] Loss: 117.56509399414062
Epoch 7: [6400/60000] Loss: 113.27373504638672
Epoch 7: [12800/60000] Loss: 117.80658721923828
Epoch 7: [19200/60000] Loss: 120.27961730957031
Epoch 7: [25600/60000] Loss: 117.9671859741211
Epoch 7: [32000/60000] Loss: 118.45343017578125
Epoch 7: [38400/60000] Loss: 112.2073745727539
Epoch 7: [44800/60000] Loss: 117.58949279785156
Epoch 7: [51200/60000] Loss: 124.05663299560547
Epoch 7: [57600/60000] Loss: 120.37991333007812
Epoch 8: [0/60000] Loss: 116.50756072998047
Epoch 8: [6400/60000] Loss: 114.43101501464844
Epoch 8: [12800/60000] Loss: 114.31697082519531
Epoch 8: [19200/60000] Loss: 111.72184753417969
Epoch 8: [25600/60000] Loss: 116.67804718017578
Epoch 8: [32000/60000] Loss: 117.05427551269531
```

```
Epoch 8: [38400/60000] Loss: 116.28828430175781
Epoch 8: [44800/60000] Loss: 106.72462463378906
Epoch 8: [51200/60000] Loss: 121.7491226196289
Epoch 8: [57600/60000] Loss: 112.06756591796875
Epoch 9: [0/60000] Loss: 117.65093994140625
Epoch 9: [6400/60000] Loss: 115.95599365234375
Epoch 9: [12800/60000] Loss: 116.32427978515625
Epoch 9: [19200/60000] Loss: 115.98930358886719
Epoch 9: [25600/60000] Loss: 113.64556884765625
Epoch 9: [32000/60000] Loss: 114.58383178710938
Epoch 9: [38400/60000] Loss: 119.94384765625
Epoch 9: [44800/60000] Loss: 113.49661254882812
Epoch 9: [51200/60000] Loss: 120.47146606445312
Epoch 9: [57600/60000] Loss: 109.26859283447266
Epoch 10: [0/60000] Loss: 116.81888580322266
Epoch 10: [6400/60000] Loss: 111.22993469238281
Epoch 10: [12800/60000] Loss: 112.77510833740234
Epoch 10: [19200/60000] Loss: 116.32837677001953
Epoch 10: [25600/60000] Loss: 119.2213134765625
Epoch 10: [32000/60000] Loss: 114.87914276123047
Epoch 10: [38400/60000] Loss: 111.70114135742188
Epoch 10: [44800/60000] Loss: 114.10757446289062
Epoch 10: [51200/60000] Loss: 114.53932189941406
Epoch 10: [57600/60000] Loss: 110.5186996459961
Epoch 11: [0/60000] Loss: 114.95917510986328
Epoch 11: [6400/60000] Loss: 114.23362731933594
Epoch 11: [12800/60000] Loss: 123.74354553222656
Epoch 11: [19200/60000] Loss: 115.09951782226562
Epoch 11: [25600/60000] Loss: 111.32865142822266
Epoch 11: [32000/60000] Loss: 113.57676696777344
Epoch 11: [38400/60000] Loss: 113.54828643798828
Epoch 11: [44800/60000] Loss: 105.96715545654297
Epoch 11: [51200/60000] Loss: 113.33586883544922
Epoch 11: [57600/60000] Loss: 117.92131042480469
Epoch 12: [0/60000] Loss: 111.52523803710938
Epoch 12: [6400/60000] Loss: 113.83534240722656
Epoch 12: [12800/60000] Loss: 112.81007385253906
Epoch 12: [19200/60000] Loss: 112.46443176269531
Epoch 12: [25600/60000] Loss: 117.82553100585938
Epoch 12: [32000/60000] Loss: 117.22862243652344
Epoch 12: [38400/60000] Loss: 117.25086212158203
Epoch 12: [44800/60000] Loss: 112.51124572753906
Epoch 12: [51200/60000] Loss: 111.7439956665039
Epoch 12: [57600/60000] Loss: 110.96453094482422
Epoch 13: [0/60000] Loss: 104.55900573730469
Epoch 13: [6400/60000] Loss: 106.41786193847656
Epoch 13: [12800/60000] Loss: 112.7916030883789
Epoch 13: [19200/60000] Loss: 109.08876037597656
Epoch 13: [25600/60000] Loss: 109.77084350585938
Epoch 13: [32000/60000] Loss: 115.99955749511719
Epoch 13: [38400/60000] Loss: 114.35200500488281
Epoch 13: [44800/60000] Loss: 115.96073913574219
Epoch 13: [51200/60000] Loss: 112.39119720458984
Epoch 13: [57600/60000] Loss: 108.16081237792969
Epoch 14: [0/60000] Loss: 105.07516479492188
Epoch 14: [6400/60000] Loss: 114.81547546386719
Epoch 14: [12800/60000] Loss: 114.135498046875
```

```
Epoch 14: [19200/60000] Loss: 107.96377563476562
Epoch 14: [25600/60000] Loss: 109.44795989990234
Epoch 14: [32000/60000] Loss: 106.8466796875
Epoch 14: [38400/60000] Loss: 109.27615356445312
Epoch 14: [44800/60000] Loss: 110.11396789550781
Epoch 14: [51200/60000] Loss: 111.48529815673828
Epoch 14: [57600/60000] Loss: 108.934326171875
Epoch 15: [0/60000] Loss: 113.64373016357422
Epoch 15: [6400/60000] Loss: 112.14053344726562
Epoch 15: [12800/60000] Loss: 110.89911651611328
Epoch 15: [19200/60000] Loss: 111.36686706542969
Epoch 15: [25600/60000] Loss: 112.04891204833984
Epoch 15: [32000/60000] Loss: 109.81965637207031
Epoch 15: [38400/60000] Loss: 111.38089752197266
Epoch 15: [44800/60000] Loss: 114.00507354736328
Epoch 15: [51200/60000] Loss: 104.90474700927734
Epoch 15: [57600/60000] Loss: 110.19869995117188
Epoch 16: [0/60000] Loss: 111.4589614868164
Epoch 16: [6400/60000] Loss: 117.58454895019531
Epoch 16: [12800/60000] Loss: 103.61521911621094
Epoch 16: [19200/60000] Loss: 107.39073181152344
Epoch 16: [25600/60000] Loss: 110.08524322509766
Epoch 16: [32000/60000] Loss: 109.89796447753906
Epoch 16: [38400/60000] Loss: 112.56758117675781
Epoch 16: [44800/60000] Loss: 117.09356689453125
Epoch 16: [51200/60000] Loss: 112.39229583740234
Epoch 16: [57600/60000] Loss: 110.2315444946289
Epoch 17: [0/60000] Loss: 107.68470764160156
Epoch 17: [6400/60000] Loss: 110.9905776977539
Epoch 17: [12800/60000] Loss: 109.33065795898438
Epoch 17: [19200/60000] Loss: 107.50174713134766
Epoch 17: [25600/60000] Loss: 105.44532775878906
Epoch 17: [32000/60000] Loss: 113.65484619140625
Epoch 17: [38400/60000] Loss: 108.74336242675781
Epoch 17: [44800/60000] Loss: 105.00048828125
Epoch 17: [51200/60000] Loss: 107.22465515136719
Epoch 17: [57600/60000] Loss: 111.87654113769531
Epoch 18: [0/60000] Loss: 115.83758544921875
Epoch 18: [6400/60000] Loss: 106.36834716796875

Epoch 18: [12800/60000] Loss: 109.17564392089844
Epoch 18: [19200/60000] Loss: 107.81333923339844
Epoch 18: [25600/60000] Loss: 109.84882354736328
Epoch 18: [32000/60000] Loss: 114.83026885986328
Epoch 18: [38400/60000] Loss: 112.80632019042969
Epoch 18: [44800/60000] Loss: 105.24431610107422
Epoch 18: [51200/60000] Loss: 106.14044952392578
Epoch 18: [57600/60000] Loss: 106.5606918334961
Epoch 19: [0/60000] Loss: 106.93474578857422
Epoch 19: [6400/60000] Loss: 107.42587280273438
Epoch 19: [12800/60000] Loss: 110.96941375732422
Epoch 19: [19200/60000] Loss: 108.45460510253906
Epoch 19: [25600/60000] Loss: 108.63186645507812
Epoch 19: [32000/60000] Loss: 110.48668670654297
Epoch 19: [38400/60000] Loss: 113.35997772216797
Epoch 19: [44800/60000] Loss: 111.44552612304688
Epoch 19: [51200/60000] Loss: 108.90951538085938
```

```
Epoch 19: [57600/60000] Loss: 101.70510864257812
Epoch 20: [0/60000] Loss: 105.42315673828125
Epoch 20: [6400/60000] Loss: 101.85847473144531
Epoch 20: [12800/60000] Loss: 102.12388610839844
Epoch 20: [19200/60000] Loss: 104.36612701416016
Epoch 20: [25600/60000] Loss: 102.11204528808594
Epoch 20: [32000/60000] Loss: 104.97160339355469
Epoch 20: [38400/60000] Loss: 101.03059387207031
Epoch 20: [44800/60000] Loss: 112.3763427734375
Epoch 20: [51200/60000] Loss: 112.17282104492188
Epoch 20: [57600/60000] Loss: 105.86537170410156
Epoch 21: [0/60000] Loss: 108.57324981689453
Epoch 21: [6400/60000] Loss: 109.39738464355469
Epoch 21: [12800/60000] Loss: 103.2044448852539
Epoch 21: [19200/60000] Loss: 110.90803527832031
Epoch 21: [25600/60000] Loss: 110.16111755371094
Epoch 21: [32000/60000] Loss: 105.50677490234375
Epoch 21: [38400/60000] Loss: 107.64093780517578
Epoch 21: [44800/60000] Loss: 109.41319274902344
Epoch 21: [51200/60000] Loss: 109.54986572265625
Epoch 21: [57600/60000] Loss: 106.1417236328125
Epoch 22: [0/60000] Loss: 114.34379577636719
Epoch 22: [6400/60000] Loss: 109.69964599609375
Epoch 22: [12800/60000] Loss: 109.12013244628906
Epoch 22: [19200/60000] Loss: 113.05963897705078
Epoch 22: [25600/60000] Loss: 105.74330139160156
Epoch 22: [32000/60000] Loss: 107.57171630859375
Epoch 22: [38400/60000] Loss: 105.3431167602539
Epoch 22: [44800/60000] Loss: 108.4130859375
Epoch 22: [51200/60000] Loss: 110.95140075683594
Epoch 22: [57600/60000] Loss: 104.5451889038086
Epoch 23: [0/60000] Loss: 106.25275421142578
Epoch 23: [6400/60000] Loss: 108.04302978515625
Epoch 23: [12800/60000] Loss: 107.1485366821289
Epoch 23: [19200/60000] Loss: 106.62446594238281
Epoch 23: [25600/60000] Loss: 105.88197326660156
Epoch 23: [32000/60000] Loss: 105.25347900390625
Epoch 23: [38400/60000] Loss: 105.27783203125
Epoch 23: [44800/60000] Loss: 107.41853332519531
Epoch 23: [51200/60000] Loss: 113.54322814941406
Epoch 23: [57600/60000] Loss: 104.90532684326172
Epoch 24: [0/60000] Loss: 112.84255981445312
Epoch 24: [6400/60000] Loss: 109.27708435058594
Epoch 24: [12800/60000] Loss: 107.1776351928711
Epoch 24: [19200/60000] Loss: 107.01741027832031
Epoch 24: [25600/60000] Loss: 110.20441436767578
Epoch 24: [32000/60000] Loss: 109.21245574951172
Epoch 24: [38400/60000] Loss: 107.3137435913086
Epoch 24: [44800/60000] Loss: 106.61895751953125
Epoch 24: [51200/60000] Loss: 105.49398803710938
Epoch 24: [57600/60000] Loss: 108.88646697998047
Epoch 25: [0/60000] Loss: 110.7140884399414
Epoch 25: [6400/60000] Loss: 109.99678802490234
Epoch 25: [12800/60000] Loss: 103.19123840332031
Epoch 25: [19200/60000] Loss: 112.1075668334961
Epoch 25: [25600/60000] Loss: 112.43789672851562
Epoch 25: [32000/60000] Loss: 108.65406799316406
```

```
Epoch 25: [38400/60000] Loss: 110.53453826904297
Epoch 25: [44800/60000] Loss: 103.87786865234375
Epoch 25: [51200/60000] Loss: 106.99859619140625
Epoch 25: [57600/60000] Loss: 114.9453125
Epoch 26: [0/60000] Loss: 104.27961730957031
Epoch 26: [6400/60000] Loss: 109.7962875366211
Epoch 26: [12800/60000] Loss: 103.96094512939453
Epoch 26: [19200/60000] Loss: 107.76541137695312
Epoch 26: [25600/60000] Loss: 103.88575744628906
Epoch 26: [32000/60000] Loss: 103.09037780761719
Epoch 26: [38400/60000] Loss: 107.39991760253906
Epoch 26: [44800/60000] Loss: 104.00932312011719
Epoch 26: [51200/60000] Loss: 116.61878967285156
Epoch 26: [57600/60000] Loss: 113.9529037475586
Epoch 27: [0/60000] Loss: 108.46669006347656
Epoch 27: [6400/60000] Loss: 111.04419708251953
Epoch 27: [12800/60000] Loss: 101.6324462890625
Epoch 27: [19200/60000] Loss: 111.98392486572266
Epoch 27: [25600/60000] Loss: 104.98161315917969
Epoch 27: [32000/60000] Loss: 105.76921081542969
Epoch 27: [38400/60000] Loss: 109.53916931152344
Epoch 27: [44800/60000] Loss: 111.39561462402344
Epoch 27: [51200/60000] Loss: 106.7281494140625
Epoch 27: [57600/60000] Loss: 101.11868286132812
Epoch 28: [0/60000] Loss: 104.55828857421875
Epoch 28: [6400/60000] Loss: 109.7392578125
Epoch 28: [12800/60000] Loss: 105.09666442871094
Epoch 28: [19200/60000] Loss: 108.30645751953125
Epoch 28: [25600/60000] Loss: 105.05177307128906
Epoch 28: [32000/60000] Loss: 110.09293365478516
Epoch 28: [38400/60000] Loss: 104.99263000488281
Epoch 28: [44800/60000] Loss: 109.51493835449219
Epoch 28: [51200/60000] Loss: 107.29924011230469
Epoch 28: [57600/60000] Loss: 108.44316864013672
Epoch 29: [0/60000] Loss: 108.96354675292969
Epoch 29: [6400/60000] Loss: 108.33035278320312
Epoch 29: [12800/60000] Loss: 101.68340301513672
Epoch 29: [19200/60000] Loss: 105.0323257446289
Epoch 29: [25600/60000] Loss: 104.2525405883789
Epoch 29: [32000/60000] Loss: 111.99132537841797
Epoch 29: [38400/60000] Loss: 104.01249694824219
Epoch 29: [44800/60000] Loss: 109.0944595336914
Epoch 29: [51200/60000] Loss: 100.80501556396484
Epoch 29: [57600/60000] Loss: 108.34595489501953
```

In [697]:

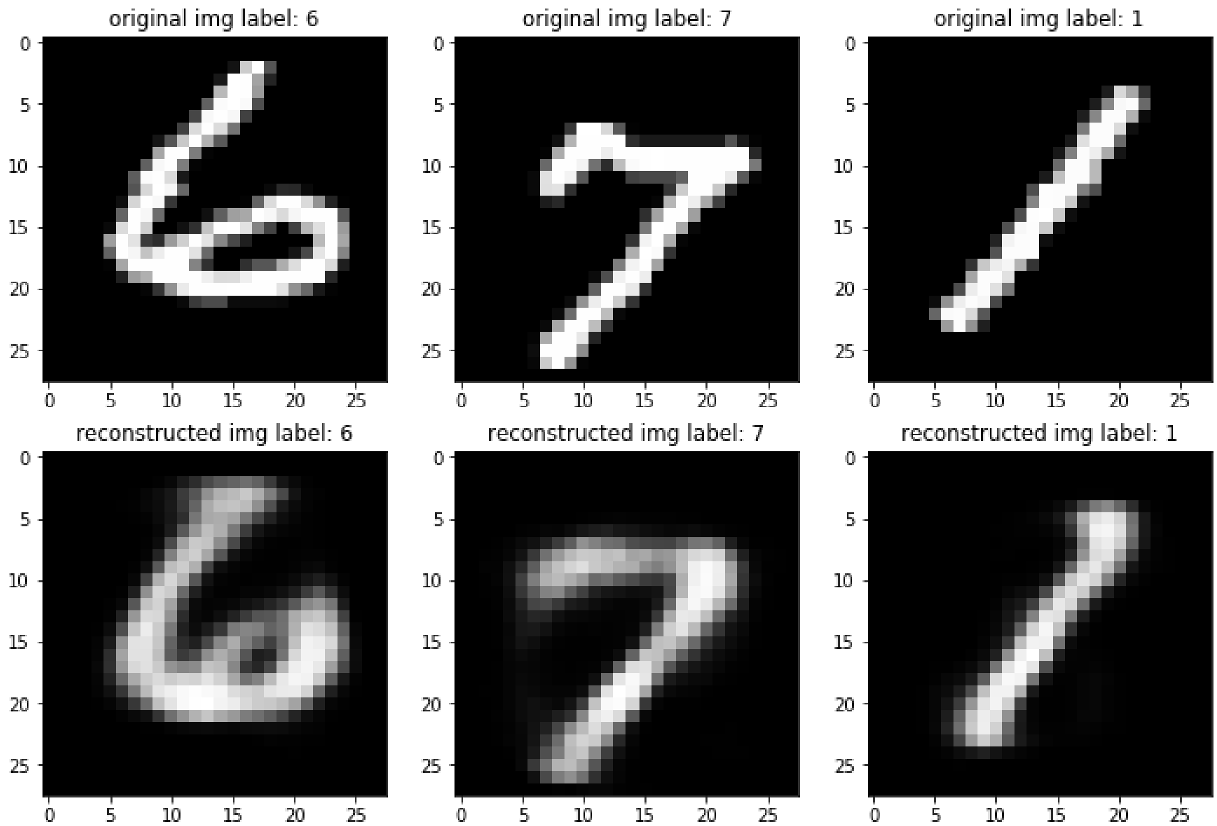
```
import random

with torch.no_grad():


    data = random.sample(list(test_loader), 1)
    for (images, label) in random.sample(list(test_loader), 1):
        images = images.to(device)
        images_0 = np.transpose(imgs[0].cpu().numpy(), [1,2,0])
        images_1 = np.transpose(imgs[1].cpu().numpy(), [1,2,0])
        images_2 = np.transpose(imgs[2].cpu().numpy(), [1,2,0])

        out0 = out[0]
        img1 = out0.cpu().reshape(28,28)
        out1 = out[1]
        img2 = out1.cpu().reshape(28,28)
        out2 = out[2]
        img3 = out2.cpu().reshape(28,28)

        #fig, ax = plt.subplots(2,3)
        #fig.set_size_inches(12,8)
        fig,ax = plt.subplots(2,3)
        fig.set_size_inches(12,8)


        ax[0,0].imshow(np.squeeze(img_1),cmap='gray')
        ax[0,0].set_title(f'original img label: {label[1]}')
        ax[1,0].imshow(img2, cmap='gray')
        ax[1,0].set_title(f'reconstructed img label: {label[1]}')

        ax[0,1].imshow(np.squeeze(img_0),cmap='gray')
        ax[0,1].set_title(f'original img label: {label[0]}')
        ax[1,1].imshow(img1, cmap='gray')
        ax[1,1].set_title(f'reconstructed img label: {label[0]}')

        ax[0,2].imshow(np.squeeze(img_2),cmap='gray')
        ax[0,2].set_title(f'original img label: {label[2]}')
        ax[1,2].imshow(img3, cmap='gray')
        ax[1,2].set_title(f'reconstructed img label: {label[2]}')

    fig.show()


i = 0
VAE.eval()
```

```
D:\Anaconda3\lib\site-packages\ipykernel_launcher.py:46: UserWarning: Matplotli
b is currently using module://ipykernel.pylab.backend_inline, which is a non-GU
I backend, so cannot show the figure.
```

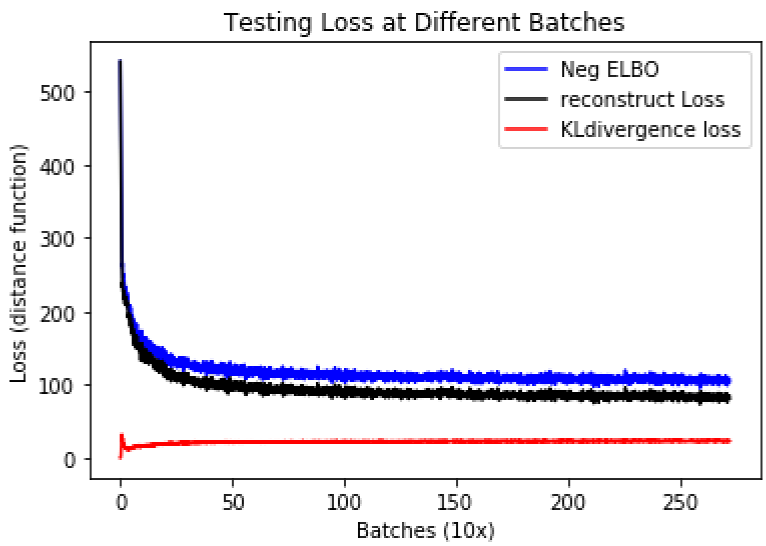
Out[697]:

```
our_VAE(
  (en_input1): Linear(in_features=784, out_features=500, bias=True)
  (en_hidden1): Linear(in_features=500, out_features=16, bias=True)
  (en_hidden2): Linear(in_features=500, out_features=16, bias=True)
  (de_hidden): Linear(in_features=500, out_features=784, bias=True)
```

```
  (de_latent): Linear(in_features=16, out_features=500, bias=True)
)
```



In [11]:
```
losses = plt.figure(2)
#fig, ax = plt.subplots(1,3)
#fig.set_size_inches(12,8)

plt.plot(np.arange(len(elbo_n))/10, elbo_n, 'b')
plt.plot(np.arange(len(loss_rec))/10, loss_rec,'k')
plt.plot(np.arange(len(KL_loss))/10, KL_loss,'r')

plt. title ('Testing Loss at Different Batches')
plt. ylabel ('Loss (distance function)')
plt.xlabel ('Batches (10x)')
legend1 = ['Neg ELBO', 'reconstruct Loss', 'KLdivergence loss']
plt. legend(legend1)


plt.show()
```



In [ ]:

Task 4.1: Latent space of VAE

The latent space will change over time during training as the networks learn which features of the input are most important. In the beginning, the reconstruction error will be poor and the latent space will be mixed up (i.e., it has not identified good features for dimensionality reduction and then reconstruction). However, as it continues to train, the space will begin to show some structure (similar to in PCA) as it finds features that enable good reconstruction even after adding a little noise. Therefore, to get some intuition about this process, in this task, you will visualize how latent space changes in the process of training with the given function `plot_latent`.

1. For better visualization, create a VAE with `latent_features=2`.
2. Similar to task 3, train the VAE for a few epochs. But you will need to plot the latent distribution using the provided `plot_latent` function below at initialization (so you can see what the

latent space looks like at initialization) AND after **each** epoch. You should use the **test** data for plotting this visualization task.

In [681]:
```
def plot_latent(vae, data_loader, num_batches=2):
    with torch.no_grad():
        for ibx, (images,label) in enumerate(data_loader):
            _,_,z = vae.encoder(images.to(device))
            z = z.to('cpu').detach().numpy()
            plt.scatter(z[:, 0], z[:, 1], c=label, cmap='tab10',s=1)
            if ibx > num_batches:
                break
    plt.colorbar()
    plt.show()
```

In [686]:
```
##########################   <YOUR CODE>   ###########################
class our_VAE2(nn.Module):
    def __init__(self, latent_feature = 2): # you can use any number of latent fe
        super(our_VAE2, self).__init__()

        self.latent_feature = latent_feature

    # define the transformations for your encoder and decoder

        self.en_input1 = nn.Linear(in_features=784, out_features=500)
        self.en_hidden1 = nn.Linear(in_features=500, out_features=latent_feature

        self.en_hidden2 = nn.Linear(in_features=500, out_features=latent_feature
        #    self.en_hidden2 = nn.Linear(in_features=500, out_features=latent_fea

        self.de_hidden = nn.Linear(in_features=500, out_features=784)
        self.de_latent = nn.Linear(in_features=latent_feature, out_features=500)


    def reparameterize(self, mu, log_var):


        sample = torch.randn_like(torch.exp(log_var/2))*torch.exp(log_var/2) + mu

        return sample
    def encoder(self, x):

        #forword
        x = x.view(-1, 784)

        x = self.en_input1(x)
        x = F.relu(x)

        mu = self.en_hidden1(x)
        log_var =  self.en_hidden2(x)

        z = self.reparameterize(mu,log_var)


        return mu, log_var, z

    def decoder(self, z):


        #forword
        z = self.de_latent(z)
        x = F.relu(z)

        x = torch.sigmoid((self.de_hidden(x)))
        return x



    def forward(self, x):
```

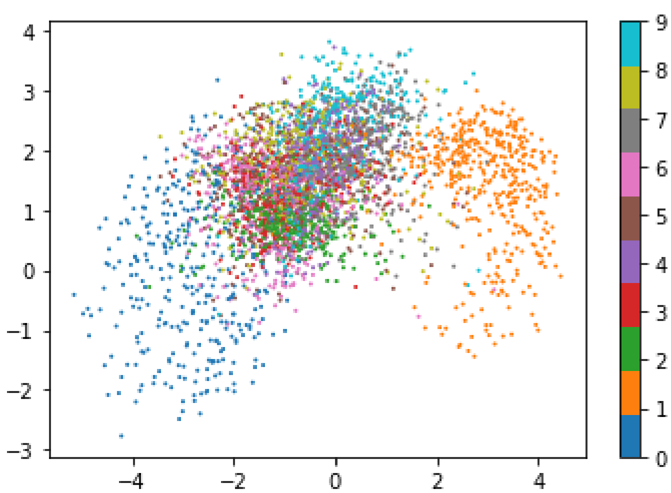
```
        mu = self.encoder(x)[0]
        log_var = self.encoder(x)[1]
        z = self.encoder(x)[2]
        #decode
        x = self.decoder(z)


        return x, mu, log_var
```

In [687]:
```
device = 'cuda' if torch.cuda.is_available()==True else 'cpu'
device = torch.device(device)
learning_rate = 0.0001
batch_size_train, batch_size_test = 64, 1000
epochs = 1

VAE = our_VAE2().to(device)
optimizer = optim.Adam(params=VAE.parameters(), lr=learning_rate)
```

In [688]:
```
def train(epoch, device):

    VAE.train()

    for batch_idx, (images, orig) in enumerate(train_loader):

        optimizer.zero_grad()
        images = images.to(device)
        orig = orig.to(device)
        output, mu, log_var = VAE(images)
        loss, KLD = vae_loss(output, mu, log_var, images)
        elbo = loss + KLD
        elbo.backward()
        optimizer.step()

        if batch_idx % 10 == 0:
            train_elbo.append(elbo.item()/batch_size_train)
            train_loss.append(loss.item()/batch_size_train)
            train_kld.append(KLD.item()/batch_size_train)
            train_idx.append(batch_idx / 10)
            train_counter.append(
                (batch_idx*64) + ((epoch-1)*len(train_loader.dataset)))
        if batch_idx % 100 == 0:
            print(f'Epoch {epoch}: [{batch_idx*len(images)}/{len(train_loader.da


def test(epoch, device):

    VAE.eval()

    test_loss = 0
    correct = 0

    with torch.no_grad():
        for images, orig in test_loader:
            #images = images.()
            images = images.to(device)
            orig = orig.to(device)
            output, mu, log_var = VAE(images)
            loss, kld = vae_loss(output, mu, log_var, images)
            elbo = loss + kld
            test_loss += elbo

    test_loss /= len(test_loader.dataset)
    test_losses.append(test_loss)
    test_counter.append(len(train_loader.dataset)*epoch)

    print(f'Test result on epoch {epoch}: Avg loss is {test_loss}')
```

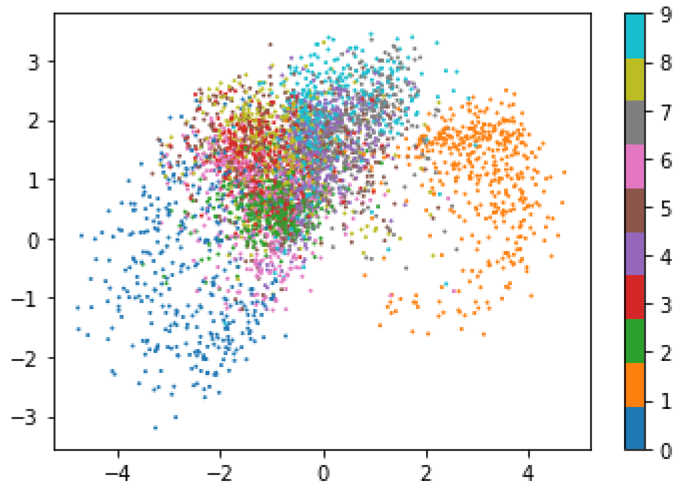
In [691]:
```
train_losses = []
train_counter = []
test_losses = []
test_counter = []
train_elbo = []
train_loss = []
train_kld = []
train_idx = []
train_counter = []

max_epoch = 5
for epoch in range(1, max_epoch+1):
    train(epoch, device=device)
    test(epoch, device=device)
    plot_latent(VAE, test_loader, num_batches=2)
```

```
Epoch 1: [0/60000] Loss: 189.12327575683594
Epoch 1: [6400/60000] Loss: 192.7493133544922
Epoch 1: [12800/60000] Loss: 181.10267639160156
Epoch 1: [19200/60000] Loss: 180.37586975097656
Epoch 1: [25600/60000] Loss: 172.41796875
Epoch 1: [32000/60000] Loss: 178.69703674316406
Epoch 1: [38400/60000] Loss: 175.95465087890625
Epoch 1: [44800/60000] Loss: 180.30374145507812
Epoch 1: [51200/60000] Loss: 179.25967407226562
Epoch 1: [57600/60000] Loss: 187.05014038085938
Test result on epoch 1: Avg loss is 177.90573120117188
```

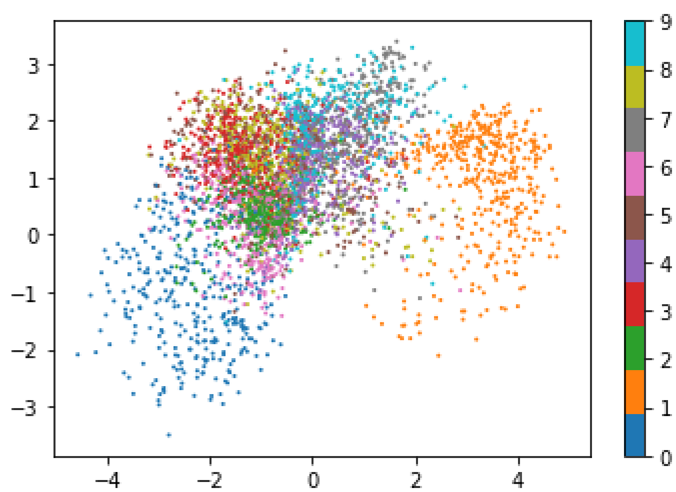



```
Epoch 2: [0/60000] Loss: 173.61524963378906
Epoch 2: [6400/60000] Loss: 174.3282928466797
Epoch 2: [12800/60000] Loss: 168.59487915039062
Epoch 2: [19200/60000] Loss: 181.24362182617188
Epoch 2: [25600/60000] Loss: 173.5217742919922
Epoch 2: [32000/60000] Loss: 167.50035095214844
Epoch 2: [38400/60000] Loss: 184.5255889892578
Epoch 2: [44800/60000] Loss: 180.3052978515625
```

```
Epoch 2: [51200/60000] Loss: 163.1604766845703
Epoch 2: [57600/60000] Loss: 175.9038543701172
Test result on epoch 2: Avg loss is 173.40492248535156
```

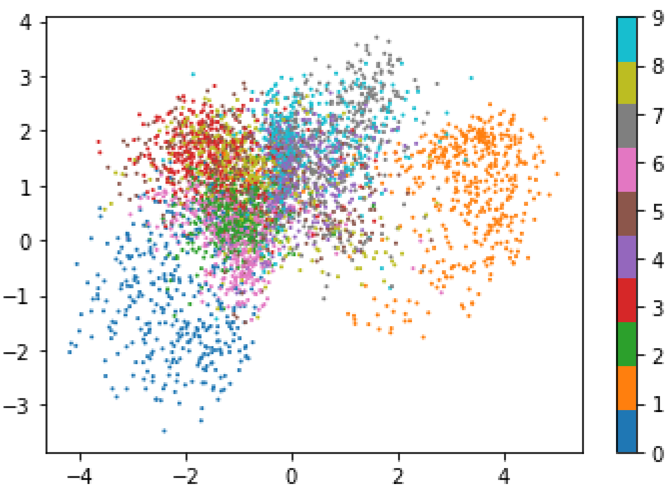



```
Epoch 3: [0/60000] Loss: 175.53697204589844
Epoch 3: [6400/60000] Loss: 179.00067138671875
Epoch 3: [12800/60000] Loss: 167.923095703125
Epoch 3: [19200/60000] Loss: 175.57994079589844
Epoch 3: [25600/60000] Loss: 174.5373992919922
Epoch 3: [32000/60000] Loss: 173.1880340576172
Epoch 3: [38400/60000] Loss: 165.46168518066406
Epoch 3: [44800/60000] Loss: 162.76651000976562
Epoch 3: [51200/60000] Loss: 179.62376403808594
Epoch 3: [57600/60000] Loss: 165.0283660888672
Test result on epoch 3: Avg loss is 169.83641052246094
```

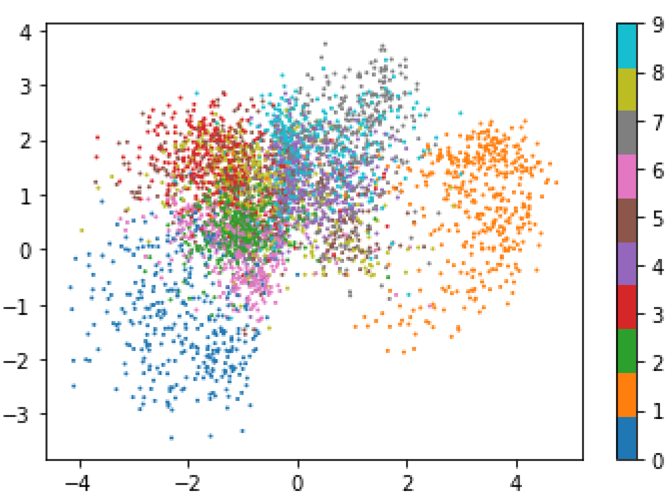



```
Epoch 4: [0/60000] Loss: 166.2953643798828
Epoch 4: [6400/60000] Loss: 166.9381561279297
Epoch 4: [12800/60000] Loss: 183.5512237548828
```

```
Epoch 4: [19200/60000] Loss: 158.77493286132812
Epoch 4: [25600/60000] Loss: 168.7210693359375
Epoch 4: [32000/60000] Loss: 170.55355834960938
Epoch 4: [38400/60000] Loss: 164.44509887695312
Epoch 4: [44800/60000] Loss: 172.88674926757812
Epoch 4: [51200/60000] Loss: 168.10557556152344
Epoch 4: [57600/60000] Loss: 175.9656982421875
Test result on epoch 4: Avg loss is 167.33584594726562
```



```
Epoch 5: [0/60000] Loss: 167.12722778320312
Epoch 5: [6400/60000] Loss: 170.23292541503906
Epoch 5: [12800/60000] Loss: 164.02008056640625
Epoch 5: [19200/60000] Loss: 167.38327026367188
Epoch 5: [25600/60000] Loss: 170.22686767578125
Epoch 5: [32000/60000] Loss: 175.78538513183594
Epoch 5: [38400/60000] Loss: 176.09080505371094
Epoch 5: [44800/60000] Loss: 168.09059143066406
Epoch 5: [51200/60000] Loss: 167.8831329345703
Epoch 5: [57600/60000] Loss: 178.12615966796875
Test result on epoch 5: Avg loss is 165.49884033203125
```



In [ ]:

In [ ]:

Task 4.2 Interpolation of latent space

Interpolation can be quite useful for autoencoder models. For example, by linearly interpolating (or mixing) codes in latent space and decoding the result, the autoencoder can produce a more **semantically meaningful** combination of the corresponding datapoints than linear interpolation in the raw pixel space. Besides, in some cases, interpolation experiments can show that the model has learned a latent space with a particular structure. Specifically, if interpolation between points in the latent space shows a smooth semantic warping in the original image space, then the visualization may suggest that similar points are semantically clustered in the latent space.

In this task, you will do a simple experiment to see the difference between linear interpolation in the latent space and the original data space (raw pixels).

1. With a trained model and test data, sample one $z \sim q(z|x)$ corresponding to label 0 and 1 separately (two samples in total); this can be done by passing test samples (with labels 0 and 1 respectively) through the encoder. These two latent samples will be denoted z_0 and z_1 respectively.
2. Compute the linear interpolation of x_0 and x_1 in the following way: $x' = \alpha x_1 + (1 - \alpha)x_0$ where $\alpha = 0, 0.1, 0.2, \ldots, 0.9, 1.0$. **Plot** all x' images you get in a 1x11 grid.
3. Compute the latent linear interpolation of z_0 and z_1 to get z' in a similar way. Then, reconstruct the x' corresponding to each z' using the decoder. **Plot** all x' images you get in a 1x11 grid.

In [ ]:

```
###########################    <YOUR CODE>    ############################

#########################   <END YOUR CODE>   ###########################
```

In [ ]: