Deep Learning Course

Assignment Four

Assignment Goals:

- Implementing Fully Connected AutoEncoders
- Implement naive generative model
- Understand VAE and GAN, then implement a classical generative model: VAE-GAN.

DataSet

In this Assignment, you will use the Fashion-MNIST dataset. The dataset is not given in the assignment package, please download/load by yourself. *Hint*: You can use

```
(x_train, _), (x_test, _)  = keras.datasets.fashion_mnist.load_data()
```

to load the dataset.

Requirements

1. **(20 points) Implement a Fully Connected AutoEncoder**

    - Your AutoEncoder should have a bottleneck with two neurons and use Mean Squared Error (MSE) as the objective function. Design the model structure by yourself. Notice that in an AutoEncoder, the layer with the least number of neurons is referred to as a bottleneck.
    - Train your model on MNIST. Plot the train and test loss.
    - Randomly select 10 images from the test set, encode the selected 10 images, visualize the original images and the decoded images.

2. **(30 points) Naive generative model**

    This question is about using an AutoEncoder to generate similar but not identical hand digits. We use a naive approach: Try to see if a trained decoder can map randomly generated inputs (random numbers) to a recognizable hand-written digit.

    A. Start with your Fully Connected AutoEncoder from part 1. Try to generate new images by inputting some random numbers to the decoder (i.e. the bottleneck layer). Visualize 10 generated images. (10 points)

B. Now restrict each neuron of the bottleneck layer to have a distribution with mean zeroes and variance one (i.e. $N(0, 1)$). Retrain the Fully Connected AutoEncoder with the normalized bottleneck. Now randomly generate inputs to the bottleneck layer that are drawn from the multi-variate standard normal distribution, and use the randomly generated inputs to generate new images. Visualize 10 generated images. (15 points)

C. Are the output images different between A) and B)? If so, why do you think this difference occurs? (5 points)

3. **(50 points) Advanced generative model**

In this part, you are asking to implement a VAE-GAN model. A VAE-GAN is a Generative Adversarial Network whose generator is an Variational Autoencoder.Here is the paper which proposed the VAE-GAN: **[PAPER]**. You may need to read this paper before implementing this model.

A. Implement a Variational Autoencoder based on your Fully Connected AutoEncoder from part 1. Use your VAE to randomly generate 10 images. Does the VAE produce a different quality of output image? (30 points)

B. Implement a VAE-GAN based on your implemented VAE. Train the VAE-GAN. (20 points)

- Then use your VAE-GAN to randomly generate 10 images from $p(z)$.
- Randomly select 10 images from the test dataset and reconstruct them using your model, then visualize the original and reconstructed images.

Hint: For the generation and reconstruction tasks, refer to Section 4.1 in the paper.

Submission Notes:

Please use Jupyter Notebook. The notebook should include the final code, results, and answers. You should submit your Notebook in .pdf and .ipynb format. (penalty 10 points).

Notice that your AutoEncoders should have only one bottleneck.

Instructions:

The university policy on academic dishonesty and plagiarism (cheating) will be taken very seriously in this course. Everything submitted should be your writing or coding. You must not let other students copy your work. Spelling and grammar count.

Your implementation

Import Dependencies

In [1]:

```
# import dependencies
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
from torch.utils.data import DataLoader
import torch.nn.functional as F
from tqdm import tqdm
import random
import numpy as np
```

```
c:\Users\mikew\miniconda3\Lib\site-packages\tqdm\auto.py:21: TqdmWarning: IProgress
not found. Please update jupyter and ipywidgets. See https://ipywidgets.readthedocs.
io/en/stable/user_install.html
  from .autonotebook import tqdm as notebook_tqdm
```

hyperparameters

In [2]:

```
# hyperparameters:

epochs = 10
lr = 1e-3
batch_size = 32
bottleneck_num = 2
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print('you are training on: ', device)
```

```
you are training on:  cuda
```

In [3]:

```
bottleneck_num = 2
img_num = 10
```

dataloader

In [4]:

```
# download dataset
transform = transforms.Compose([
    transforms.ToTensor()
])

trainset = torchvision.datasets.FashionMNIST(root='./data', train=True, download=Tr
trainloader = DataLoader(trainset, batch_size=batch_size, shuffle=True)

testset = torchvision.datasets.FashionMNIST(root='./data', train=False, download=Tr
testloader = DataLoader(testset, batch_size=batch_size, shuffle=False)
```

In [5]:
```
# test
for images, labels in trainloader:
    print(images.shape)
    for label in labels:
        print(label)
        break
    break
```

```
torch.Size([32, 1, 28, 28])
tensor(6)
```

helper functions

In [5]:
```
def plot_loss(losses, name = None):
    plt.plot(losses)
    plt.xlabel('epoch')
    plt.ylabel('loss')
    plt.title(name + ' loss graph')
    plt.show()
```

In [45]:
```
def generate_nums(num = 10):
    rand_input = np.random.randn(num,bottleneck_num)
    return rand_input
```

In [46]:
```
def plot_images(images, num_img = 10):
    fig, axs = plt.subplots(1,num_img, figsize = (20,4))
    for i in range(num_img):
        # print(images[i].shape)
        img = images[i].to('cpu')
        img = img.detach().numpy()
        axs[i].imshow(img.squeeze(0), cmap = 'gray')
        # axs[i].set_title('Image ', i)
```

In [33]:
```
# train
def train(model, loss_fn, optimizer, num_epochs , trainloader, testloader):
    train_losses = []
    valid_losses = []

    for epoch in range(num_epochs):
        model.train()
        total_loss = 0
        for images, _ in tqdm(trainloader):
            images = images.to(device)
            output_image = model(images)
            optimizer.zero_grad()
            loss = loss_fn(output_image, images)
            loss.backward()
            optimizer.step()
            total_loss += loss.item()
        avg_loss_train = total_loss / len(trainloader)
        train_losses.append(avg_loss_train)

        # valid loss
```

```
        model.eval()
        valid_loss = 0
        with torch.no_grad():
            for images, _ in tqdm(testloader):
                images = images.to(device)
                valid_output = model(images)
                loss = loss_fn(valid_output,images)
                valid_loss += loss.item()
        avg_loss_valid = valid_loss / len(testloader)
        valid_losses.append(avg_loss_valid)
        print(f'Epoch {epoch+1}/{num_epochs}, Train Loss: {avg_loss_train:.4f}, Tes

    return train_losses,valid_losses, model
```

1. Auto-Encoder

In [8]:

```
# define model
class AutoEncoder(nn.Module):
    def __init__(self, bottle_dim=2):
        super(AutoEncoder, self).__init__()
        # Encoder
        self.encoder = nn.Sequential(
            nn.Linear(28*28, 64),
            nn.ReLU(),
            nn.Linear(64, 32),
            nn.ReLU(),
            nn.Linear(32, bottle_dim), # Bottleneck with two neurons
        )
        # Decoder
        self.decoder = nn.Sequential(
            nn.Linear(bottle_dim, 32),
            nn.ReLU(),
            nn.Linear(32, 64),
            nn.ReLU(),
            nn.Linear(64, 28*28),
            nn.Sigmoid() # Output is normalized to [0, 1]
        )

    def forward(self, x):
        x_shape = x.shape
        x = torch.flatten(x, start_dim=1)
        # print(x.shape)
        encoded = self.encoder(x)
        decoded = self.decoder(encoded)

        return decoded.reshape(x_shape)
```

In [7]:

```
model = AutoEncoder().to(device)
loss_fn = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr = lr)
```

In [8]:

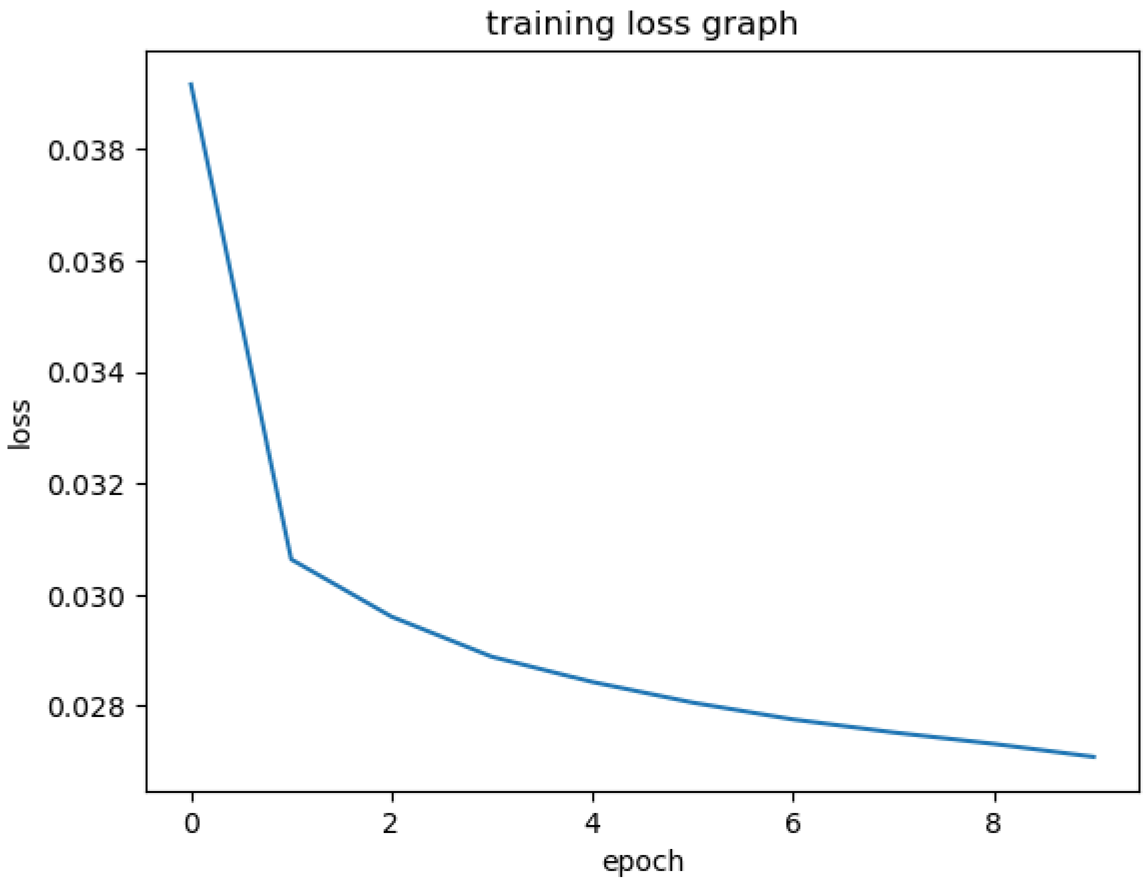
```
train_losses, valid_losses, trained_model = train(model, loss_fn, optimizer, epochs
```

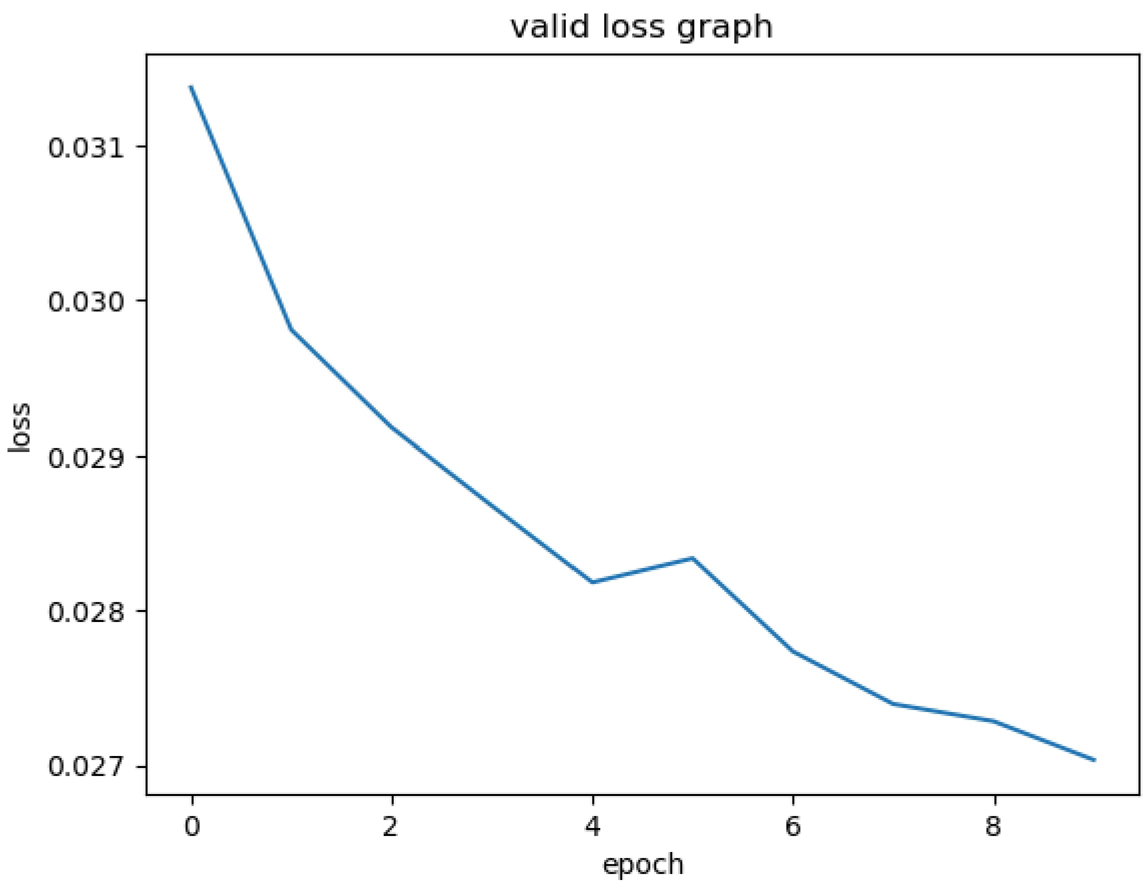
```
100%|██████████| 1875/1875 [00:17<00:00, 105.25it/s]
100%|██████████| 313/313 [00:01<00:00, 166.92it/s]
Epoch 1/10, Train Loss: 0.0392, Test Loss: 0.0314
100%|██████████| 1875/1875 [00:15<00:00, 122.59it/s]
100%|██████████| 313/313 [00:01<00:00, 160.65it/s]
Epoch 2/10, Train Loss: 0.0306, Test Loss: 0.0298
100%|██████████| 1875/1875 [00:14<00:00, 128.82it/s]
100%|██████████| 313/313 [00:01<00:00, 189.48it/s]
Epoch 3/10, Train Loss: 0.0296, Test Loss: 0.0292
100%|██████████| 1875/1875 [00:15<00:00, 122.17it/s]
100%|██████████| 313/313 [00:02<00:00, 140.47it/s]
Epoch 4/10, Train Loss: 0.0289, Test Loss: 0.0287
100%|██████████| 1875/1875 [00:15<00:00, 122.98it/s]
100%|██████████| 313/313 [00:01<00:00, 190.25it/s]
Epoch 5/10, Train Loss: 0.0284, Test Loss: 0.0282
100%|██████████| 1875/1875 [00:14<00:00, 127.46it/s]
100%|██████████| 313/313 [00:01<00:00, 165.59it/s]
Epoch 6/10, Train Loss: 0.0281, Test Loss: 0.0283
100%|██████████| 1875/1875 [00:16<00:00, 113.80it/s]
100%|██████████| 313/313 [00:02<00:00, 132.25it/s]
Epoch 7/10, Train Loss: 0.0278, Test Loss: 0.0277
100%|██████████| 1875/1875 [00:17<00:00, 107.39it/s]
100%|██████████| 313/313 [00:02<00:00, 133.28it/s]
Epoch 8/10, Train Loss: 0.0275, Test Loss: 0.0274
100%|██████████| 1875/1875 [00:17<00:00, 110.21it/s]
100%|██████████| 313/313 [00:01<00:00, 159.87it/s]
Epoch 9/10, Train Loss: 0.0273, Test Loss: 0.0273
100%|██████████| 1875/1875 [00:16<00:00, 111.89it/s]
100%|██████████| 313/313 [00:02<00:00, 148.61it/s]
Epoch 10/10, Train Loss: 0.0271, Test Loss: 0.0270
```

Plot Loss

In [10]:

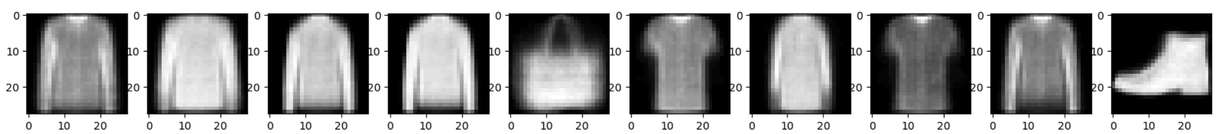
```
plot_loss(train_losses, name = 'training')
plot_loss(valid_losses, name = 'valid')
```


training loss graph
0.038
0.036
0.034
0.032
0.030
0.028
loss
0
2
4
6
8
epoch


valid loss graph
0.031
0.030
0.029
0.028
0.027
loss
0
2
4
6
8
epoch

Visual Evaluation

In [12]:
```
# draw 10 randomly selected images:
output_images = []
trained_model.eval()
with torch.no_grad():
    for i in range(10):
        rand_int = random.randint(0, len(testset)-1)
        selected_image,_ = testset[rand_int]
        selected_image = selected_image.to(device)
        # plt.imshow(selected_image.squeeze(0))
        output_image = trained_model(selected_image)
        output_images.append(output_image)

    plot_images(output_images)
```



2. Naive Generative Net

1. generate randomly

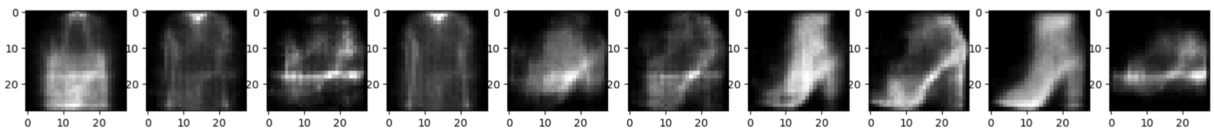
In [17]:
```
# generate images
def generate_image(input, model):
    input = torch.tensor(input, dtype=torch.float32)
    output = model.decoder(input).reshape(1,28,28)
    return output
```

In [50]:
```
def generate_norm_nums(num=10):
    mean = np.array([0, 0])  # Mean vector
    covariance_matrix = np.eye(2)  # Covariance matrix (identity matrix for standar

    # Generate samples
    num_samples = num
    samples = np.random.multivariate_normal(mean, covariance_matrix, num_samples)
    return samples
```

In [21]:
```
rand_input = generate_nums()
print(rand_input)
```

```
[[ 0.59886288  0.33176502]
 [ 0.6857675  -0.13992407]
 [-0.32327146 -0.83554053]
 [ 2.24541164  0.76338554]
 [ 0.32660059 -1.67133497]
 [ 0.39617883  1.83500299]
 [ 0.5744195  -1.4965082 ]
 [-1.4578571   0.4342719 ]
 [ 0.12995407  0.16491713]
 [-0.21136404 -1.40577233]]
```

In [17]:
```python
plot_imgs = []
for i in range(img_num):
    output_img = generate_image(rand_input[i],trained_model.to('cpu'))
    plot_imgs.append(output_img)
plot_images(plot_imgs)
```



2. normalize bottleneck

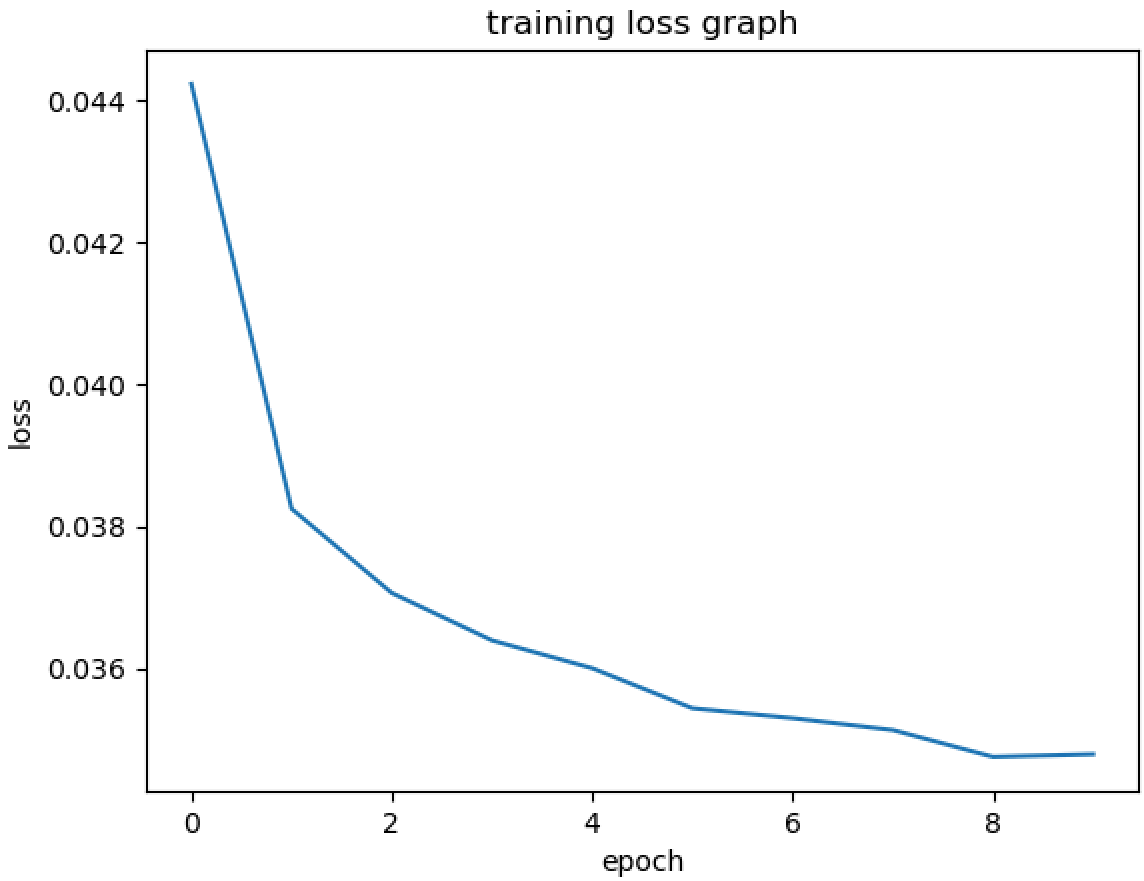
In [12]:
```python
# define model with bottleneck normalization:

class AutoEncoderNorm(nn.Module):
    def __init__(self, bottle_dim=2):
        super(AutoEncoderNorm, self).__init__()
        # Encoder
        self.encoder = nn.Sequential(
            nn.Linear(28*28, 64),
            nn.ReLU(),
            nn.Linear(64, 32),
            nn.ReLU(),
            nn.Linear(32, bottle_dim), # Bottleneck with two neurons
        )
        self.bn = nn.BatchNorm1d(bottle_dim)
        # Decoder
        self.decoder = nn.Sequential(
            nn.Linear(bottle_dim, 32),
            nn.ReLU(),
            nn.Linear(32, 64),
            nn.ReLU(),
            nn.Linear(64, 28*28),
            nn.Sigmoid() # Output is normalized to [0, 1]
        )

    def forward(self, x):
        x_shape = x.shape
        x = torch.flatten(x, start_dim=1)
        # print(x.shape)
        encoded = self.encoder(x)
        batched = self.bn(encoded)
        decoded = self.decoder(batched)
```

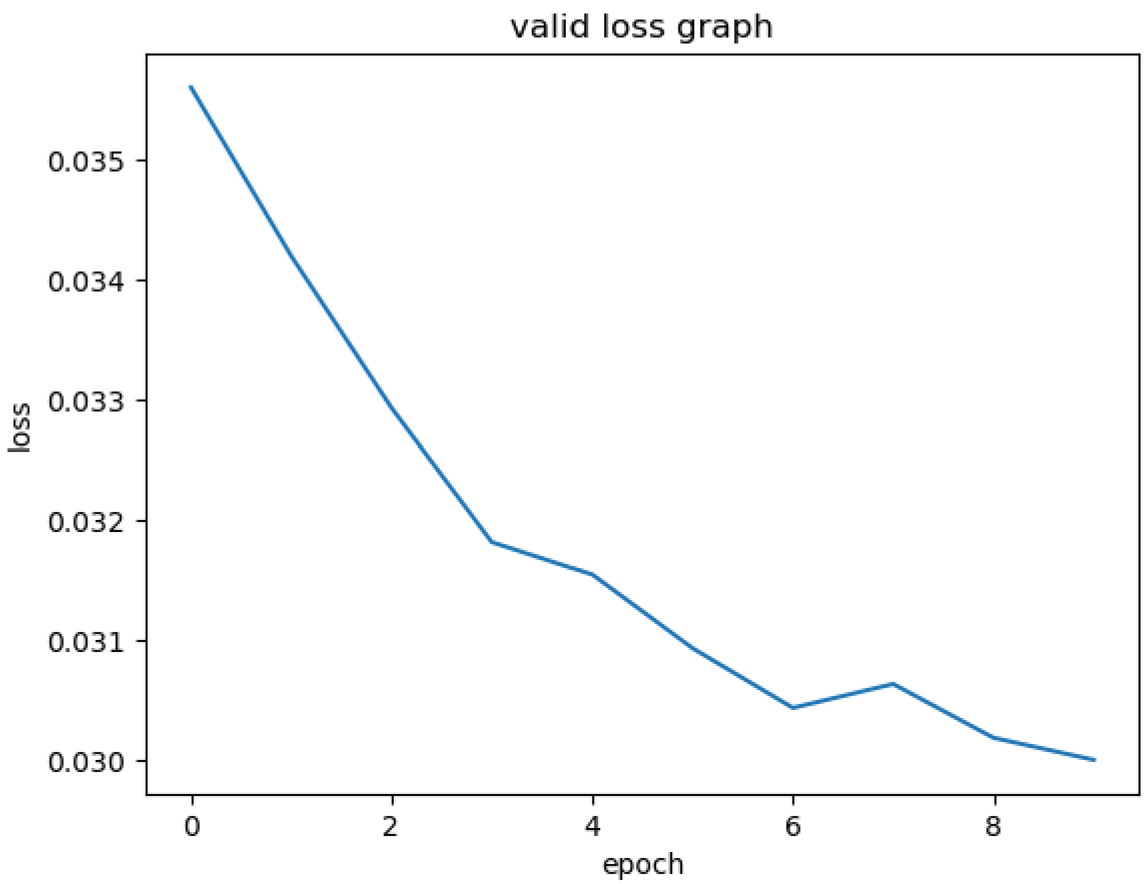
```python
        return decoded.reshape(x_shape)
```

In [13]:
```python
model = AutoEncoderNorm().to(device)
loss_fn = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr = lr)
train_losses, valid_losses, trained_model = train(model, loss_fn, optimizer, epochs
```

```
100%|██████████| 1875/1875 [00:12<00:00, 151.81it/s]
100%|██████████| 313/313 [00:01<00:00, 200.26it/s]
Epoch 1/10, Train Loss: 0.0442, Test Loss: 0.0356
100%|██████████| 1875/1875 [00:14<00:00, 132.23it/s]
100%|██████████| 313/313 [00:01<00:00, 199.73it/s]
Epoch 2/10, Train Loss: 0.0383, Test Loss: 0.0342
100%|██████████| 1875/1875 [00:14<00:00, 133.38it/s]
100%|██████████| 313/313 [00:01<00:00, 197.18it/s]
Epoch 3/10, Train Loss: 0.0371, Test Loss: 0.0329
100%|██████████| 1875/1875 [00:14<00:00, 130.92it/s]
100%|██████████| 313/313 [00:01<00:00, 196.76it/s]
Epoch 4/10, Train Loss: 0.0364, Test Loss: 0.0318
100%|██████████| 1875/1875 [00:14<00:00, 131.38it/s]
100%|██████████| 313/313 [00:01<00:00, 201.67it/s]
Epoch 5/10, Train Loss: 0.0360, Test Loss: 0.0316
100%|██████████| 1875/1875 [00:14<00:00, 131.84it/s]
100%|██████████| 313/313 [00:01<00:00, 197.40it/s]
Epoch 6/10, Train Loss: 0.0354, Test Loss: 0.0309
100%|██████████| 1875/1875 [00:14<00:00, 133.05it/s]
100%|██████████| 313/313 [00:01<00:00, 200.02it/s]
Epoch 7/10, Train Loss: 0.0353, Test Loss: 0.0304
100%|██████████| 1875/1875 [00:14<00:00, 132.88it/s]
100%|██████████| 313/313 [00:01<00:00, 199.41it/s]
Epoch 8/10, Train Loss: 0.0351, Test Loss: 0.0306
100%|██████████| 1875/1875 [00:14<00:00, 131.00it/s]
100%|██████████| 313/313 [00:01<00:00, 171.86it/s]
Epoch 9/10, Train Loss: 0.0347, Test Loss: 0.0302
100%|██████████| 1875/1875 [00:14<00:00, 128.35it/s]
100%|██████████| 313/313 [00:01<00:00, 193.27it/s]
Epoch 10/10, Train Loss: 0.0348, Test Loss: 0.0300
```

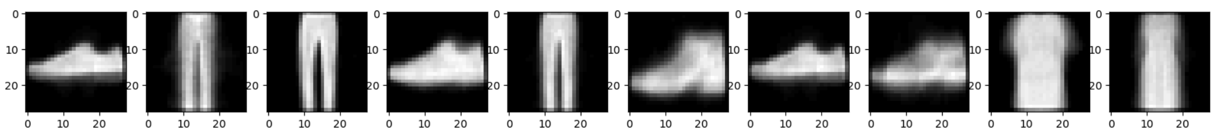
In [14]:
```python
plot_loss(train_losses, name = 'training')
plot_loss(valid_losses, name = 'valid')
```


training loss graph
0.044
0.042
0.040
0.038
0.036
loss
0
2
4
6
8
epoch


valid loss graph
0.035
0.034
0.033
0.032
0.031
0.030
loss
0
2
4
6
8
epoch

In [15]:

```
output_images = []
trained_model.eval()
with torch.no_grad():
    for i in range(10):
        rand_int = random.randint(0, len(testset)-1)
        selected_image,_ = testset[rand_int]
        selected_image = selected_image.to(device)
        # plt.imshow(selected_image.squeeze(0))
        output_image = trained_model(selected_image)
        output_images.append(output_image)

    plot_images(output_images)
```



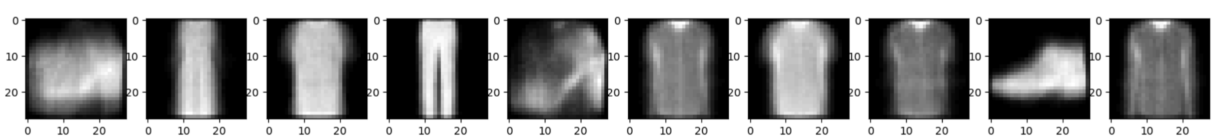
In [21]:

```
# generate numbers:

norm_input = generate_norm_nums()
print(norm_input)
```

```
[[ 1.4640431  -0.31822465]
 [ 0.859052   -0.95344357]
 [ 0.08278221 -0.26002204]
 [-0.62640952 -0.85359865]
 [-2.0814755  -0.65916293]
 [-0.89019548 -0.88384216]
 [-0.0990918   0.27822857]
 [-0.29251342  1.11379447]
 [ 1.65781526  2.10009257]
 [ 1.51241575 -0.27160369]]
```

In [22]:

```
plot_imgs = []
for i in range(img_num):
    output_img = generate_image(rand_input[i],trained_model.to('cpu'))
    plot_imgs.append(output_img)
plot_images(plot_imgs)
```



3. A) and B) are different. images generated from B) is more clear than A). This is because the addition of normaliztion layer. When adding the normalization layer, the decoder is restricted to get input from 2-d vectors drawn from multi-variate standard normal distribution. Therefore, when randomly generate a 2-d vector drawn from the same distribution and pass it to the decoder, the decoder will perform better.

3. Advanced Generative Net

In [6]:

```
# define loss function for part 3:
def loss_fn_VAE(recon_x, x, mu, log_var):
    criterion = nn.MSELoss()
    MSE = criterion(recon_x, x)
    KLD = -0.5 * torch.sum(1 + log_var - mu.pow(2) - log_var.exp())
    KLD/=batch_size*784
    return MSE + KLD
```

In [42]:

```
def generate_VAE_image(input, model, device = 'cpu'):
    input = torch.tensor(input, dtype=torch.float32).to(device)
    hidden = model.fc2(input.unsqueeze(0))
    hidden = hidden.view(-1,128,7,7)
    output = model.conv_decoder(hidden)
    return output
```

1. VAE

In [25]:

```
# define model
class VAE(nn.Module):
    def __init__(self, in_channels = 1, bottle_dim=2):
        super(VAE, self).__init__()
        # define encoder:
        self.conv_encoder = nn.Sequential(
            nn.Conv2d(in_channels, 32, 3, padding=1), # dim: 28 -> 28
            nn.BatchNorm2d(32,momentum=0.9),
            nn.ReLU(),
            nn.Conv2d(32, 64, 3,2,padding=1), # dim: 28->14
            nn.BatchNorm2d(64,momentum=0.9),
            nn.ReLU(),
            nn.Conv2d(64, 128, 3, 2, padding=1), # dim: 14->7
            nn.BatchNorm2d(128,momentum=0.9),
            nn.ReLU(),
            )
        self.fc1 = nn.Sequential(
            nn.Linear(7*7*128, 256),
            nn.BatchNorm1d(256,momentum=0.9),
            nn.ReLU(),

        )
        self.fc2 = nn.Sequential(
            nn.Linear(bottle_dim, 7*7*128),
            nn.BatchNorm1d(7*7*128,momentum=0.9),
            nn.ReLU(),

        )
        self.conv_decoder = nn.Sequential(
            nn.ConvTranspose2d(128,64,3,2,padding=1, output_padding=1),
            nn.BatchNorm2d(64,momentum=0.9),
            nn.ReLU(),
            nn.ConvTranspose2d(64,32,3,2,padding=1, output_padding=1),
            nn.BatchNorm2d(32,momentum=0.9),
            nn.ReLU(),
```

```
            nn.ConvTranspose2d(32, in_channels, 3,padding=1),
            nn.Sigmoid()
        )
        self.mu = nn.Linear(256, bottle_dim)
        self.log_var = nn.Linear(256,bottle_dim)
    def reparameterize(self, mu, log_var):
        std = torch.exp(0.5 * log_var)
        random_noise = torch.randn_like(std)
        return mu + random_noise * std
    def forward(self,x):
        batch_s = x.size()[0]
        encoded = self.conv_encoder(x) # dim: 7*7*256
        # encoded_shape = encoded.shape
        latent = encoded.view(batch_s,-1)
        latent = self.fc1(latent)
        # output dimension: batch * 256
        mu = self.mu(latent)
        log_var = self.log_var(latent)
        hidden = self.reparameterize(mu, log_var)
        # output dim: batch*bottle_dim
        hidden = self.fc2(hidden)
        hidden = hidden.view(-1,128,7,7)
        decoded = self.conv_decoder(hidden)
        return decoded, mu, log_var #, encoded_shape
```

In [33]:

```
# define training function for part 3:
def train_VAE(model, optimizer, trainloader, testloader, num_epochs=20):
    train_losses = []
    valid_losses = []

    for epoch in range(num_epochs):
        model.train()
        total_loss = 0
        for images, _ in tqdm(trainloader):
            images = images.to(device)
            decoded, mu, log_var= model(images)
            loss = loss_fn_VAE(decoded, images, mu, log_var)
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
            total_loss += loss.item()
        avg_loss_train = total_loss / len(trainloader)
        train_losses.append(avg_loss_train)

        # valid loss

        model.eval()
        valid_loss = 0
        with torch.no_grad():
            for images, _ in tqdm(testloader):
                images = images.to(device)
                decoded, mu, log_var = model(images)
                loss = loss_fn_VAE(decoded,images, mu, log_var)
                valid_loss += loss.item()
        avg_loss_valid = valid_loss / len(testloader)
```

```python
        valid_losses.append(avg_loss_valid)
        print(f'Epoch {epoch+1}/{num_epochs}, Train Loss: {avg_loss_train:.4f}, Tes

    return train_losses,valid_losses, model
```

In [34]:
```python
# defince model and configs
model_VAE = VAE().to(device)
optimizer = optim.Adam(model_VAE.parameters(), lr = 1e-5)
train_losses, valid_losses, trained_model = train_VAE(model_VAE, optimizer, trainlo
```

```
  0%|          | 0/1875 [00:00<?, ?it/s]
100%|██████████| 1875/1875 [00:23<00:00, 81.14it/s]
100%|██████████| 313/313 [00:02<00:00, 139.27it/s]
Epoch 1/20, Train Loss: 0.0901, Test Loss: 0.0539
100%|██████████| 1875/1875 [00:22<00:00, 84.92it/s]
100%|██████████| 313/313 [00:02<00:00, 156.13it/s]
Epoch 2/20, Train Loss: 0.0507, Test Loss: 0.0476
100%|██████████| 1875/1875 [00:20<00:00, 90.09it/s]
100%|██████████| 313/313 [00:02<00:00, 151.76it/s]
Epoch 3/20, Train Loss: 0.0461, Test Loss: 0.0478
100%|██████████| 1875/1875 [00:27<00:00, 68.37it/s]
100%|██████████| 313/313 [00:03<00:00, 91.43it/s]
Epoch 4/20, Train Loss: 0.0443, Test Loss: 0.0422
100%|██████████| 1875/1875 [00:27<00:00, 67.02it/s]
100%|██████████| 313/313 [00:01<00:00, 173.02it/s]
Epoch 5/20, Train Loss: 0.0432, Test Loss: 0.0455
100%|██████████| 1875/1875 [00:18<00:00, 98.91it/s]
100%|██████████| 313/313 [00:01<00:00, 170.39it/s]
Epoch 6/20, Train Loss: 0.0427, Test Loss: 0.0410
100%|██████████| 1875/1875 [00:19<00:00, 95.00it/s]
100%|██████████| 313/313 [00:01<00:00, 161.58it/s]
Epoch 7/20, Train Loss: 0.0423, Test Loss: 0.0447
100%|██████████| 1875/1875 [00:18<00:00, 98.85it/s]
100%|██████████| 313/313 [00:01<00:00, 169.19it/s]
Epoch 8/20, Train Loss: 0.0418, Test Loss: 0.0456
100%|██████████| 1875/1875 [00:19<00:00, 94.18it/s]
100%|██████████| 313/313 [00:02<00:00, 147.87it/s]
Epoch 9/20, Train Loss: 0.0414, Test Loss: 0.0417
100%|██████████| 1875/1875 [00:20<00:00, 93.23it/s]
100%|██████████| 313/313 [00:01<00:00, 171.09it/s]
Epoch 10/20, Train Loss: 0.0412, Test Loss: 0.0395
100%|██████████| 1875/1875 [00:18<00:00, 98.96it/s]
100%|██████████| 313/313 [00:01<00:00, 166.44it/s]
Epoch 11/20, Train Loss: 0.0407, Test Loss: 0.0425
100%|██████████| 1875/1875 [00:19<00:00, 96.73it/s]
100%|██████████| 313/313 [00:01<00:00, 160.90it/s]
Epoch 12/20, Train Loss: 0.0406, Test Loss: 0.0406
100%|██████████| 1875/1875 [00:19<00:00, 95.02it/s]
100%|██████████| 313/313 [00:01<00:00, 161.47it/s]
Epoch 13/20, Train Loss: 0.0403, Test Loss: 0.0381
```

```
100%|██████████| 1875/1875 [00:19<00:00, 95.59it/s]
100%|██████████| 313/313 [00:01<00:00, 157.42it/s]
Epoch 14/20, Train Loss: 0.0401, Test Loss: 0.0387
100%|██████████| 1875/1875 [00:21<00:00, 88.64it/s]
100%|██████████| 313/313 [00:02<00:00, 151.78it/s]
Epoch 15/20, Train Loss: 0.0399, Test Loss: 0.0376
100%|██████████| 1875/1875 [00:21<00:00, 86.10it/s]
100%|██████████| 313/313 [00:02<00:00, 136.16it/s]
Epoch 16/20, Train Loss: 0.0397, Test Loss: 0.0389
100%|██████████| 1875/1875 [00:21<00:00, 86.72it/s]
100%|██████████| 313/313 [00:02<00:00, 138.95it/s]
Epoch 17/20, Train Loss: 0.0397, Test Loss: 0.0393
100%|██████████| 1875/1875 [00:22<00:00, 82.99it/s]
100%|██████████| 313/313 [00:02<00:00, 133.59it/s]
Epoch 18/20, Train Loss: 0.0396, Test Loss: 0.0421
100%|██████████| 1875/1875 [00:21<00:00, 87.22it/s]
100%|██████████| 313/313 [00:02<00:00, 155.30it/s]
Epoch 19/20, Train Loss: 0.0394, Test Loss: 0.0374
100%|██████████| 1875/1875 [00:20<00:00, 92.92it/s]
100%|██████████| 313/313 [00:02<00:00, 155.48it/s]
Epoch 20/20, Train Loss: 0.0393, Test Loss: 0.0375
```

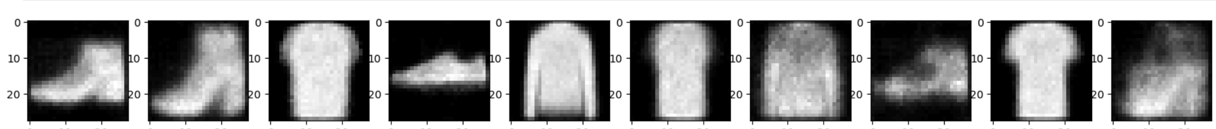
In [56]:

```
rand_input = generate_norm_nums()
print(rand_input)
```

```
[[-0.69723777 -0.42427265]
 [-0.30523351 -0.87435817]
 [ 1.7809977   0.54332961]
 [-1.59168617  0.74610887]
 [ 1.15505797 -0.51771755]
 [ 0.57965833  0.76277957]
 [ 0.30876477 -0.60766888]
 [-0.43013751 -0.08981339]
 [ 1.00790122  0.88548555]
 [-0.04089743 -0.68661904]]
```

In [57]:

```
plot_imgs = []
for i in range(img_num):
    output_img = generate_VAE_image(rand_input[i],trained_model.to('cpu'))
    plot_imgs.append(output_img.squeeze(0))
plot_images(plot_imgs)
```



2. VAE-GAN

In [6]:

```
class Discriminator(nn.Module):
    def __init__(self, in_channels=1, class_num=1):
        super(Discriminator, self).__init__()
        self.conv_layer = nn.Sequential(
            nn.Conv2d(in_channels, 32,kernel_size=5, padding=2, stride=1),
```

```python
            nn.ReLU(),
            nn.Conv2d(32, 128, kernel_size=5,stride=2, padding=2), # 28->14
            nn.BatchNorm2d(128,momentum=0.9),
            nn.ReLU(),
            nn.Conv2d(128, 256, kernel_size=5, padding=2, stride=2), # 14->7
            nn.BatchNorm2d(256,momentum=0.9),
            nn.ReLU(),
            nn.Conv2d(256,256, 5,stride=1,padding=2),
            nn.BatchNorm2d(256),
            nn.ReLU()
            # output dim: 7*7*256
        )
        self.fc_layer = nn.Sequential(
            nn.Linear(7*7*256, 512),
            nn.BatchNorm1d(512,momentum=0.9),
            nn.ReLU(),
            nn.Linear(512,class_num)
        )
        self.sigmoid = nn.Sigmoid()
    def forward(self, x):
        x = self.conv_layer(x) # dim: 7*7*256
        x = x.view(-1, 7*7*256)
        x1 = x
        x = self.fc_layer(x)
        x = self.sigmoid(x)
        return x,x1
```

In [7]:
```python
class Encoder(nn.Module):
    def __init__(self, in_channels=1, bottle_dim=2):
        super(Encoder,self).__init__()
        self.conv1=nn.Conv2d(in_channels, 32, 3, padding=1)   #in_channels=1
        self.bn1=nn.BatchNorm2d(32,momentum=0.9)
        self.conv2=nn.Conv2d(32, 64, 3,2,padding=1)
        self.bn2=nn.BatchNorm2d(64,momentum=0.9)
        self.conv3=nn.Conv2d(64, 128, 3, 2, padding=1)
        self.bn3=nn.BatchNorm2d(128,momentum=0.9)
        self.relu=nn.ReLU()
        self.fc1=nn.Linear(128*7*7,256)
        self.bn4=nn.BatchNorm1d(256,momentum=0.9)
        self.fc_mean=nn.Linear(256,bottle_dim)
        self.fc_logvar=nn.Linear(256,bottle_dim)   #latent dim=2
    def forward(self,x):
        batch_size=x.size()[0]
        out=self.relu(self.bn1(self.conv1(x)))
        out=self.relu(self.bn2(self.conv2(out)))
        out=self.relu(self.bn3(self.conv3(out)))
        out=out.view(batch_size,-1)
        out=self.relu(self.bn4(self.fc1(out)))
        mean=self.fc_mean(out)
        logvar=self.fc_logvar(out)

        return mean,logvar
```

In [8]:
```python
class Decoder(nn.Module):
  def __init__(self, out_channels=1, bottle_dim=2 ):
```

```
    super(Decoder,self).__init__()
    self.fc1=nn.Linear(bottle_dim,7*7*128)
    self.bn1=nn.BatchNorm1d(7*7*128,momentum=0.9)
    self.relu=nn.ReLU()
    self.deconv1=nn.ConvTranspose2d(128,64,6, stride=2, padding=2) # 7->14
    self.bn2=nn.BatchNorm2d(64,momentum=0.9)
    self.deconv2=nn.ConvTranspose2d(64,32,6, stride=2, padding=2) # 14->28
    self.bn3=nn.BatchNorm2d(32,momentum=0.9)
    self.deconv4=nn.ConvTranspose2d(32,out_channels,5, stride=1, padding=2) # 28->2
    self.sigmoid=nn.Sigmoid()

  def forward(self,x):
    x=self.relu(self.bn1(self.fc1(x)))
    x=x.view(-1,128,7,7)
    x=self.relu(self.bn2(self.deconv1(x)))
    x=self.relu(self.bn3(self.deconv2(x)))
    x=self.sigmoid(self.deconv4(x))
    return x
```

In [9]:
```
class VAE_GAN(nn.Module):
    def __init__(self, bottle_dim=2):
        super(VAE_GAN,self).__init__()
        self.bottle_dim = bottle_dim
        self.encoder=Encoder()
        self.decoder=Decoder()
        self.discriminator=Discriminator()


    def forward(self,x):
        batch_size = x.size()[0]
        z_mean, z_logvar=self.encoder(x)
        std = torch.exp(0.5 * z_logvar)

        #sampling epsilon from normal distribution
        epsilon=torch.randn(batch_size,self.bottle_dim).to(device)
        z=z_mean+std*epsilon
        x_tilda=self.decoder(z)

        return z_mean,z_logvar,x_tilda
```

In [18]:
```
gen=VAE_GAN().to(device)
discrim=Discriminator().to(device)
```

In [20]:
```
epochs=5
lr=3e-4
alpha=0.1
gamma=15
batch_size = 32
```

In [11]:
```
len(next(iter(trainloader)))
```

Out[11]: 2

In [21]:
```
criterion=nn.BCELoss().to(device)
optim_E=optim.RMSprop(gen.encoder.parameters(), lr=lr)
```

```
optim_D=optim.RMSprop(gen.decoder.parameters(), lr=lr)
optim_Dis=optim.RMSprop(discrim.parameters(), lr=lr*alpha)
# z_fixed=torch.randn((64,128)).to(device)
# x_fixed=Variable(real_batch[0]).to(device)
```

In [22]:

```
#train
for epoch in range(epochs):
  total_gan_loss = 0
  for image, _ in tqdm(trainloader):
    batch_s=image.size()[0]

    real_label=torch.ones(batch_s,1).to(device)
    fake_label=torch.zeros(batch_s,1).to(device)
    image = image.to(device)
    mean, logvar, generated_img = gen(image)
    z_p = torch.randn(32,bottleneck_num).to(device)
    x_p_tilda = gen.decoder(z_p)

    output = discrim(image)[0]
    errD_real = criterion(output, real_label)
    output= discrim(generated_img)[0]
    errD_rec_enc = criterion(output, fake_label)
    output= discrim(x_p_tilda)[0]
    errD_rec_noise = criterion(output, fake_label)
    gan_loss = errD_real + errD_rec_enc + errD_rec_noise
    optim_Dis.zero_grad()
    gan_loss.backward(retain_graph=True)
    optim_Dis.step()


    output = discrim(image)[0]
    errD_real = criterion(output, real_label)
    output = discrim(generated_img)[0]
    errD_rec_enc = criterion(output, fake_label)
    output = discrim(x_p_tilda)[0]
    errD_rec_noise = criterion(output, fake_label)
    gan_loss = errD_real + errD_rec_enc + errD_rec_noise


    x_l_tilda = discrim(generated_img)[1]
    x_l = discrim(image)[1]
    rec_loss = ((x_l_tilda - x_l) ** 2).mean()
    err_dec = gamma * rec_loss - gan_loss
    optim_D.zero_grad()
    err_dec.backward(retain_graph=True)
    optim_D.step()

    mean, logvar, generated_img = gen(image)
    x_l_tilda = discrim(generated_img)[1]
    x_l = discrim(image)[1]
    rec_loss = ((x_l_tilda - x_l) ** 2).mean()
    prior_loss = 1 + logvar - mean.pow(2) - logvar.exp()
    prior_loss = (-0.5 * torch.sum(prior_loss))/torch.numel(mean.data)
    err_enc = prior_loss + 5*rec_loss

    optim_E.zero_grad()
```

```
    err_enc.backward(retain_graph=True)
    optim_E.step()
    total_gan_loss += gan_loss.item()
  avg_gan_loss = total_gan_loss/len(trainloader)
  print(f'{epoch+1}/{epochs}\tLoss_gan: {avg_gan_loss:.4f}')
```

```
100%|██████████| 1875/1875 [02:08<00:00, 14.54it/s]
1/5	Loss_gan: 0.7249
100%|██████████| 1875/1875 [02:39<00:00, 11.76it/s]
2/5	Loss_gan: 0.1776
100%|██████████| 1875/1875 [03:08<00:00,  9.93it/s]
3/5	Loss_gan: 0.0936
100%|██████████| 1875/1875 [03:13<00:00,  9.68it/s]
4/5	Loss_gan: 0.0647
100%|██████████| 1875/1875 [03:13<00:00,  9.69it/s]
5/5	Loss_gan: 0.0388
```

In [24]:
```
''' visualization:
first row: randomly generated image
second row: original image
third row: corresponding reconstructed image from second row
'''
gen.eval()
indices = random.sample(range(len(testset)),10)
images = torch.stack([testset[i][0] for i in indices]).to(device)
z_p = torch.randn(10,bottleneck_num).to(device)
with torch.no_grad():
    _,_,out_img = gen(images)
    x_p_tilda = gen.decoder(z_p)
images = images.cpu().numpy()
out_img = out_img.cpu().numpy()
x_p_tilda = x_p_tilda.cpu().numpy()

fig, axs = plt.subplots(3, 10, figsize=(20, 4))
for i in range(10):
    axs[0, i].imshow(x_p_tilda[i].squeeze(0), cmap='gray')
    axs[0, i].axis('off')
    axs[1, i].imshow(images[i].squeeze(0), cmap='gray')
    axs[1, i].axis('off')
    axs[2, i].imshow(out_img[i].squeeze(0), cmap='gray')
    axs[2, i].axis('off')

plt.show()
```