In [1]:

```
import numpy as np
import matplotlib.pyplot as plt
import torch
import torchvision
import torchvision.datasets as datasets
from torchvision import transforms
import torchvision.transforms as transforms
from torch import nn
import math
import random
```

In [2]:

```
transform = transforms.ToTensor()
batch_size = 200


train_data = datasets.MNIST(
    root = 'data',
    train = True,
    transform = transform,
    download = True,
)
test_data = datasets.MNIST(
    root = 'data',
    train = False,
    transform = transform
)
val_data, test_data = torch.utils.data.random_split(test_data, [int(0.9 * len(test_data
)), int(0.1 * len(test_data))])
from torch.utils.data import DataLoader
loaders = {
    'train' : torch.utils.data.DataLoader(train_data,
                                          batch_size=batch_size,
                                          shuffle=True,
                                          num_workers=1),

    'test'  : torch.utils.data.DataLoader(test_data,
                                          batch_size=batch_size,
                                          shuffle=False,
                                          num_workers=1),
    'validate' : torch.utils.data.DataLoader(val_data,
                                          batch_size=batch_size,
                                          shuffle=False,
                                          num_workers=1)
}
```

In [3]:

```
#get image set with 10 image label each
imageset=np.zeros((10,28,28))
imageset=torch.from_numpy(imageset)
imageset=imageset.float()
complabel=0
while(complabel<10):
  for images,labels in loaders['test']:
    for i in range(labels.size(0)):
      if(labels[i]==complabel):
        imageset[complabel]=images[i].clone()
        complabel+=1
```

Comparing PCA and Autoencoders

PCA: Implementation and reconstruction visualisation

In [4]:

```
#function for standardizing image
def Standardize(X):
    mu = np.mean(X, axis = 0)
    X = X - mu
    std = np.std(X, axis = 0)
    std_filled = std.copy()
    std_filled[std == 0] = 1.0
    Xbar = (X-mu) / std_filled
    return Xbar, mu, std
```

In [5]:

```
#function for calculating eigen values and eigen vectors
def eig(S):
    eig_val, eig_vec = np.linalg.eigh(S)
    sorted_eig  = np.argsort(-eig_val)
    eig_val = eig_val[sorted_eig]
    eig_vec = eig_vec[:, sorted_eig]
    return (eig_val, eig_vec)
```

In [6]:

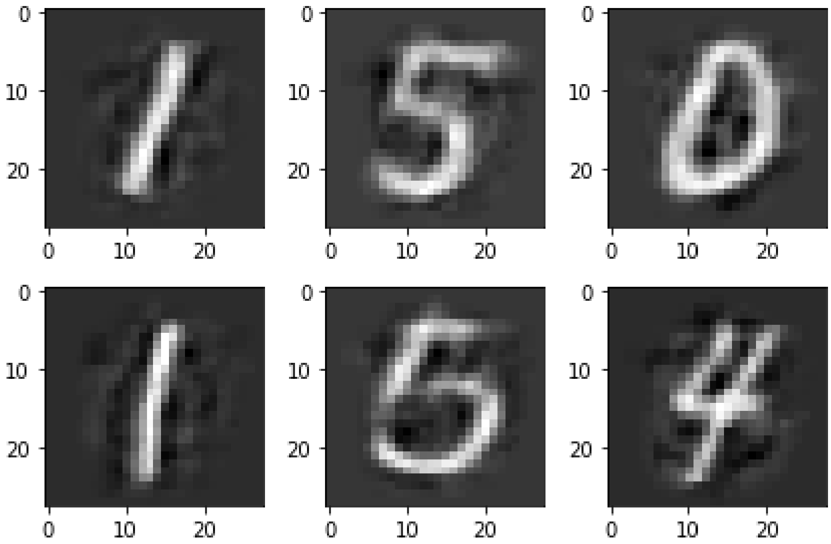
```
#implementing PCA
def PCA(X, num_components):
    #calculate the data covariance matrix S
    S = np.cov(X)
    #calculate eig values and eig vectors
    eig_vals, eig_vecs = eig(S)
    #select eigen vectors
    U = eig_vecs[:, range(num_components)]
    #to reconstruct, we first compute the projection
    #matrix
    P = U@U.T # projection matrix
    return P
```

In [7]:

```
def compute_projection(X,k):
    X = X.detach().numpy()
    Xbar, mu, std = Standardize(X)
    projection = PCA(Xbar.T, k)
    return projection
```

In [8]:

```
k = 30 #number of components
for itr, (images, labels) in enumerate(loaders['test']):
    image = images.reshape(images.shape[0], -1) #flatten images
    projection = compute_projection(image.T,k)
    image = image.detach().numpy().T
    Xbar, mu, std = Standardize(image)
    output = Xbar@projection
    output = output.reshape(28,28,batch_size)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[:,:,0],cmap='gray')
    ax2.imshow(output[:,:,1],cmap='gray')
    ax3.imshow(output[:,:,2],cmap='gray')
    ax4.imshow(output[:,:,3],cmap='gray')
    ax5.imshow(output[:,:,4],cmap='gray')
    ax6.imshow(output[:,:,5],cmap='gray')
    fig.tight_layout()
    break
```



Autoencoder

Model definition

In [9]:

```
class AE(nn.Module):
  def __init__(self):
    super(AE, self).__init__()
    self.encoder = nn.Sequential(
        nn.Linear(784,512),
        nn.ReLU(),
        nn.Linear(512,256),
        nn.ReLU(),
        nn.Linear(256,128),
        nn.ReLU(),
        nn.Linear(128,30),
        nn.ReLU())
    self.decoder =nn.Sequential(
        nn.Linear(30,128),
        nn.ReLU(),
        nn.Linear(128,256),
        nn.ReLU(),
        nn.Linear(256,784),
        nn.ReLU())

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

Training

In [10]:

```
# AE initializations
epochs = 10
model = AE()
loss_func = nn.MSELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
```

In [11]:

```
def train(no_epochs, model, loss_func, loaders):
    train_loss = list()
    val_loss = list()
    pred_accuracy = list()
    best_val_loss = 1
    for epoch in range(no_epochs):
        total_train_loss = 0
        total_val_loss = 0

        model.train()
        # training
        for itr, (images, labels) in enumerate(loaders['train']):

            # Forward pass
            images = images.reshape(-1,784)
            outputs = model(images.float())
            loss = loss_func(outputs, images)
            # Backward and optimize
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
            total_train_loss += loss.item()

        total_train_loss = total_train_loss / (itr + 1)
        train_loss.append(total_train_loss)

        # validation
        model.eval()
        total = 0
        for itr, (images, labels) in enumerate(loaders['validate']):
            images = images.reshape(-1,784)
            outputs = model(images.float())

            loss = loss_func(outputs, images)
            total_val_loss += loss.item()

            pred = torch.nn.functional.softmax(outputs, dim=1)
            for i, p in enumerate(pred):
                if labels[i] == torch.max(p.data, 0)[1]:
                    total = total + 1

        accuracy = total / len(val_data)
        pred_accuracy.append(accuracy)

        total_val_loss = total_val_loss / (itr + 1)
        val_loss.append(total_val_loss)

        print('\nEpoch: {}/{}, Train Loss: {:.8f}, Val Loss: {:.8f}'.format(epoch + 1,
no_epochs, total_train_loss, total_val_loss))

        if total_val_loss < best_val_loss:
            best_val_loss = total_val_loss
            print("Saving the model state dictionary for Epoch: {} with Validation los
s: {:.8f}".format(epoch + 1, total_val_loss))
            model_state = model.state_dict()

    plt.figure(figsize=(4, 4))
    plt.plot(np.arange(1, no_epochs+1), train_loss, label="Train loss")
    plt.plot(np.arange(1, no_epochs+1), val_loss, label="Validation loss")
```

```
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.title("Loss Plot")
    plt.legend(loc='upper right')
    return model_state
```

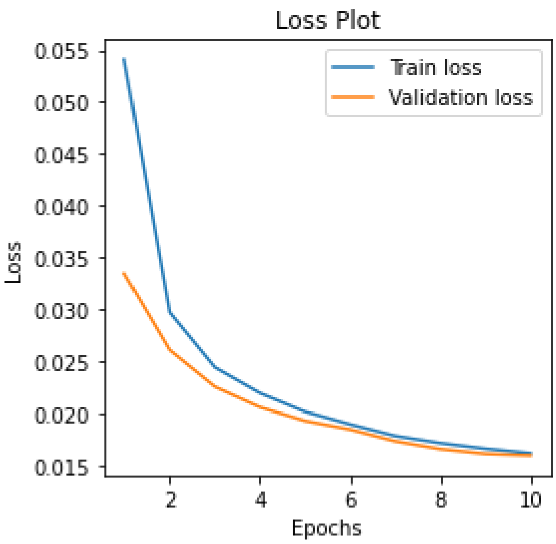
In [12]:

```
def evaluate(model, loss_func, loaders):

    model.eval()
    total_test_loss = 0
    total = 0

    with torch.no_grad():

        for itr, (images, labels) in enumerate(loaders['test']):
            images = images.reshape(-1,784)
            outputs = model(images.float())

            loss = loss_func(outputs, images)
            total_test_loss += loss.item()

            pred = torch.nn.functional.softmax(outputs, dim=1)
            for i, p in enumerate(pred):
                if labels[i] == torch.max(p.data, 0)[1]:
                    total = total + 1

        accuracy = total / len(test_data)
        total_test_loss = total_test_loss / (itr + 1)

    return loss, accuracy
```

In [13]:

```
# train and evaluate model
model_state = train(epochs, model, loss_func, loaders)
torch.save(model_state, 'AE.pt')
model.load_state_dict(torch.load('AE.pt'))

test_loss, test_acc = evaluate(model, loss_func, loaders)

print('AE model results')
print(f'Test Loss: {test_loss:.3f}%')
```

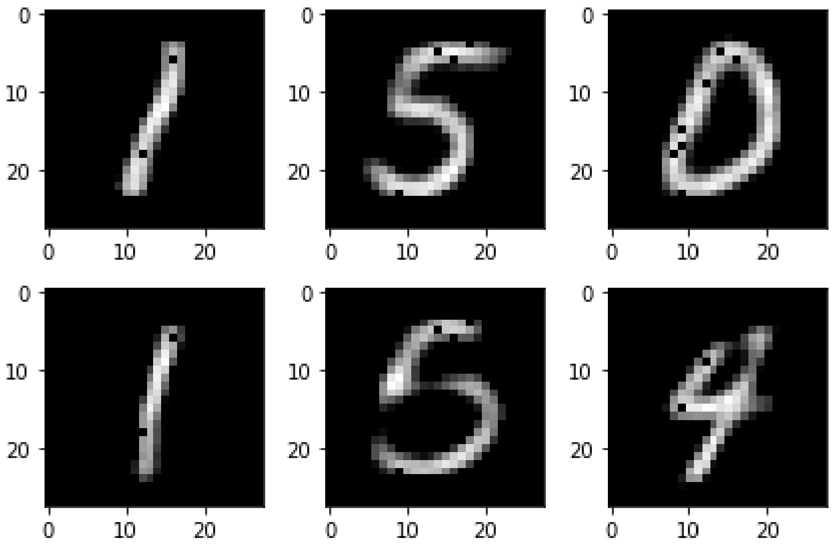
```
Epoch: 1/10, Train Loss: 0.05408907, Val Loss: 0.03346715
Saving the model state dictionary for Epoch: 1 with Validation loss: 0.033
46715

Epoch: 2/10, Train Loss: 0.02975160, Val Loss: 0.02612659
Saving the model state dictionary for Epoch: 2 with Validation loss: 0.026
12659

Epoch: 3/10, Train Loss: 0.02446097, Val Loss: 0.02260237
Saving the model state dictionary for Epoch: 3 with Validation loss: 0.022
60237

Epoch: 4/10, Train Loss: 0.02199433, Val Loss: 0.02064100
Saving the model state dictionary for Epoch: 4 with Validation loss: 0.020
64100

Epoch: 5/10, Train Loss: 0.02020628, Val Loss: 0.01932137
Saving the model state dictionary for Epoch: 5 with Validation loss: 0.019
32137

Epoch: 6/10, Train Loss: 0.01899472, Val Loss: 0.01849526
Saving the model state dictionary for Epoch: 6 with Validation loss: 0.018
49526

Epoch: 7/10, Train Loss: 0.01788276, Val Loss: 0.01737667
Saving the model state dictionary for Epoch: 7 with Validation loss: 0.017
37667

Epoch: 8/10, Train Loss: 0.01719269, Val Loss: 0.01662175
Saving the model state dictionary for Epoch: 8 with Validation loss: 0.016
62175

Epoch: 9/10, Train Loss: 0.01665720, Val Loss: 0.01616471
Saving the model state dictionary for Epoch: 9 with Validation loss: 0.016
16471

Epoch: 10/10, Train Loss: 0.01622295, Val Loss: 0.01601806
Saving the model state dictionary for Epoch: 10 with Validation loss: 0.01
601806
AE model results
Test Loss: 0.017%
```



Reconstruction visualisation

In [14]:

```
for itr, (images, labels) in enumerate(loaders['test']):
    images = images.reshape(-1,784)
    output = model(images.float())
    output = output.detach().numpy().reshape(-1,28,28)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[0],cmap='gray')
    ax2.imshow(output[1],cmap='gray')
    ax3.imshow(output[2],cmap='gray')
    ax4.imshow(output[3],cmap='gray')
    ax5.imshow(output[4],cmap='gray')
    ax6.imshow(output[5],cmap='gray')
    fig.tight_layout()
    break
```



Experimenting with hidden units of varying sizes

Model definition

In [15]:

```
class AE_x(nn.Module):
  def __init__(self,hidsize):
    super(AE_x, self).__init__()
    self.hidsize=hidsize
    self.encoder = nn.Sequential(
        nn.Linear(784,hidsize),
        nn.ReLU())
    self.decoder =nn.Sequential(
        nn.Linear(hidsize,784),
        nn.ReLU())

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

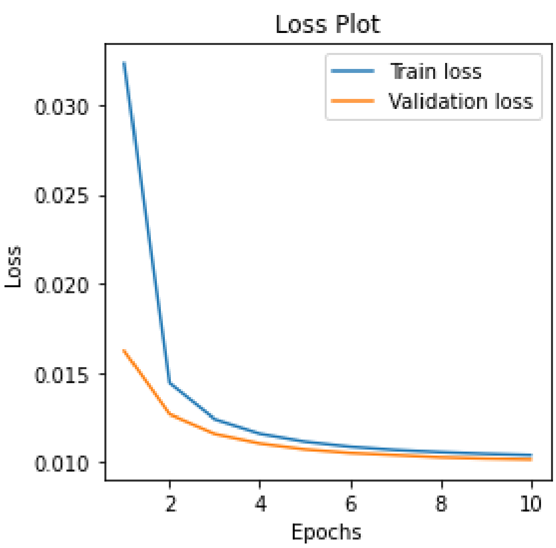
Training and reconstruction visualisation

Hidden size = 64

In [16]:

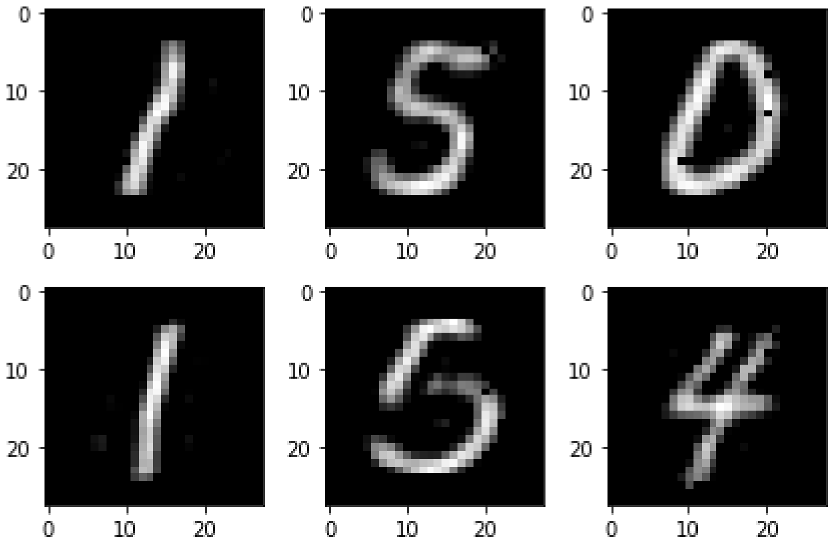
```
# Experiments on hidden size = 64
model = AE_x(64)
optimizer = torch.optim.Adam(model.parameters(), lr = 0.001)
model_state = train(epochs, model, loss_func, loaders)
torch.save(model_state, 'AE_64.pt')
model.load_state_dict(torch.load('AE_64.pt'))

test_loss, test_acc = evaluate(model, loss_func, loaders)

print('AE with hidden layer size = 64')
print(f'Test Loss: {test_loss:.3f}%')
```

```
Epoch: 1/10, Train Loss: 0.03232032, Val Loss: 0.01621916
Saving the model state dictionary for Epoch: 1 with Validation loss: 0.016
21916

Epoch: 2/10, Train Loss: 0.01442780, Val Loss: 0.01268214
Saving the model state dictionary for Epoch: 2 with Validation loss: 0.012
68214

Epoch: 3/10, Train Loss: 0.01240985, Val Loss: 0.01159057
Saving the model state dictionary for Epoch: 3 with Validation loss: 0.011
59057

Epoch: 4/10, Train Loss: 0.01160351, Val Loss: 0.01105583
Saving the model state dictionary for Epoch: 4 with Validation loss: 0.011
05583

Epoch: 5/10, Train Loss: 0.01115701, Val Loss: 0.01072387
Saving the model state dictionary for Epoch: 5 with Validation loss: 0.010
72387

Epoch: 6/10, Train Loss: 0.01087598, Val Loss: 0.01052397
Saving the model state dictionary for Epoch: 6 with Validation loss: 0.010
52397

Epoch: 7/10, Train Loss: 0.01069338, Val Loss: 0.01040627
Saving the model state dictionary for Epoch: 7 with Validation loss: 0.010
40627

Epoch: 8/10, Train Loss: 0.01056986, Val Loss: 0.01027946
Saving the model state dictionary for Epoch: 8 with Validation loss: 0.010
27946

Epoch: 9/10, Train Loss: 0.01047729, Val Loss: 0.01020947
Saving the model state dictionary for Epoch: 9 with Validation loss: 0.010
20947

Epoch: 10/10, Train Loss: 0.01040670, Val Loss: 0.01016248
Saving the model state dictionary for Epoch: 10 with Validation loss: 0.01
016248
AE with hidden layer size = 64
Test Loss: 0.011%
```



In [17]:

```
for itr, (images, labels) in enumerate(loaders['test']):
    images = images.reshape(-1,784)
    output = model(images.float())
    output = output.detach().numpy().reshape(-1,28,28)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[0],cmap='gray')
    ax2.imshow(output[1],cmap='gray')
    ax3.imshow(output[2],cmap='gray')
    ax4.imshow(output[3],cmap='gray')
    ax5.imshow(output[4],cmap='gray')
    ax6.imshow(output[5],cmap='gray')
    fig.tight_layout()
    break
```

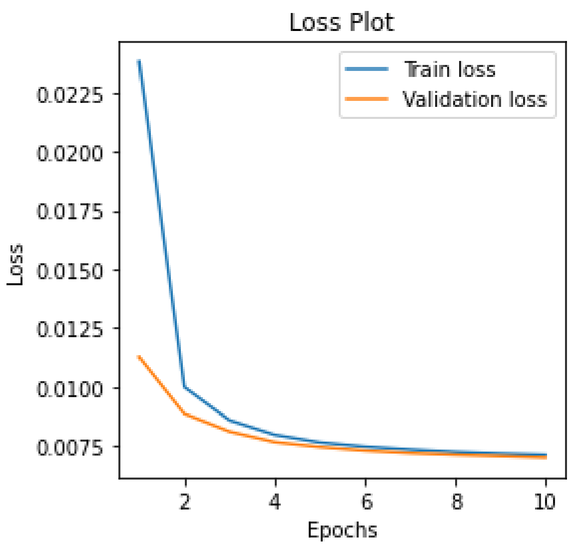


Hidden size = 128

In [18]:

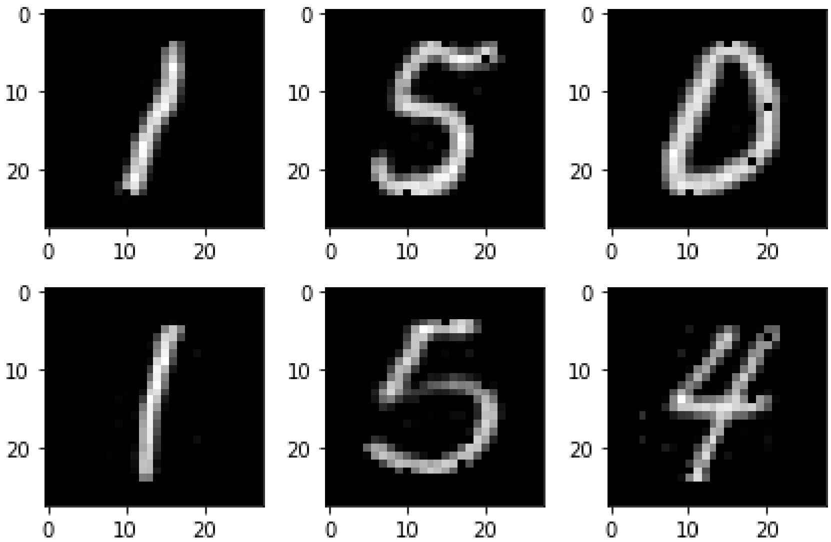
```
model = AE_x(128)
optimizer = torch.optim.Adam(model.parameters(), lr = 0.001)
model_state = train(epochs, model, loss_func, loaders)
torch.save(model_state, 'AE_128.pt')
model.load_state_dict(torch.load('AE_128.pt'))

test_loss, test_acc = evaluate(model, loss_func, loaders)

print('AE with hidden layer size = 128')
print(f'Test Loss: {test_loss:.3f}%')
```

```
Epoch: 1/10, Train Loss: 0.02382906, Val Loss: 0.01126040
Saving the model state dictionary for Epoch: 1 with Validation loss: 0.011
26040

Epoch: 2/10, Train Loss: 0.00999279, Val Loss: 0.00885473
Saving the model state dictionary for Epoch: 2 with Validation loss: 0.008
85473

Epoch: 3/10, Train Loss: 0.00857938, Val Loss: 0.00810194
Saving the model state dictionary for Epoch: 3 with Validation loss: 0.008
10194

Epoch: 4/10, Train Loss: 0.00796535, Val Loss: 0.00765706
Saving the model state dictionary for Epoch: 4 with Validation loss: 0.007
65706

Epoch: 5/10, Train Loss: 0.00764392, Val Loss: 0.00745174
Saving the model state dictionary for Epoch: 5 with Validation loss: 0.007
45174

Epoch: 6/10, Train Loss: 0.00746546, Val Loss: 0.00729962
Saving the model state dictionary for Epoch: 6 with Validation loss: 0.007
29962

Epoch: 7/10, Train Loss: 0.00734449, Val Loss: 0.00719674
Saving the model state dictionary for Epoch: 7 with Validation loss: 0.007
19674

Epoch: 8/10, Train Loss: 0.00724182, Val Loss: 0.00712549
Saving the model state dictionary for Epoch: 8 with Validation loss: 0.007
12549

Epoch: 9/10, Train Loss: 0.00717185, Val Loss: 0.00706930
Saving the model state dictionary for Epoch: 9 with Validation loss: 0.007
06930

Epoch: 10/10, Train Loss: 0.00712128, Val Loss: 0.00700865
Saving the model state dictionary for Epoch: 10 with Validation loss: 0.00
700865
AE with hidden layer size = 128
Test Loss: 0.007%
```



In [19]:

```
for itr, (images, labels) in enumerate(loaders['test']):
    images = images.reshape(-1,784)
    output = model(images.float())
    output = output.detach().numpy().reshape(-1,28,28)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[0],cmap='gray')
    ax2.imshow(output[1],cmap='gray')
    ax3.imshow(output[2],cmap='gray')
    ax4.imshow(output[3],cmap='gray')
    ax5.imshow(output[4],cmap='gray')
    ax6.imshow(output[5],cmap='gray')
    fig.tight_layout()
    break
```

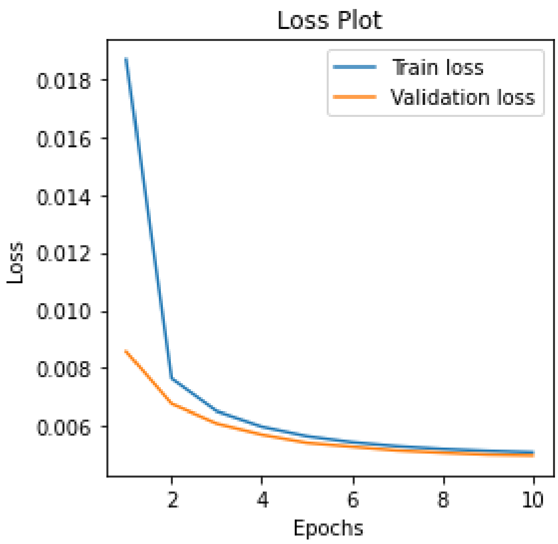


Hidden size = 256

In [20]:

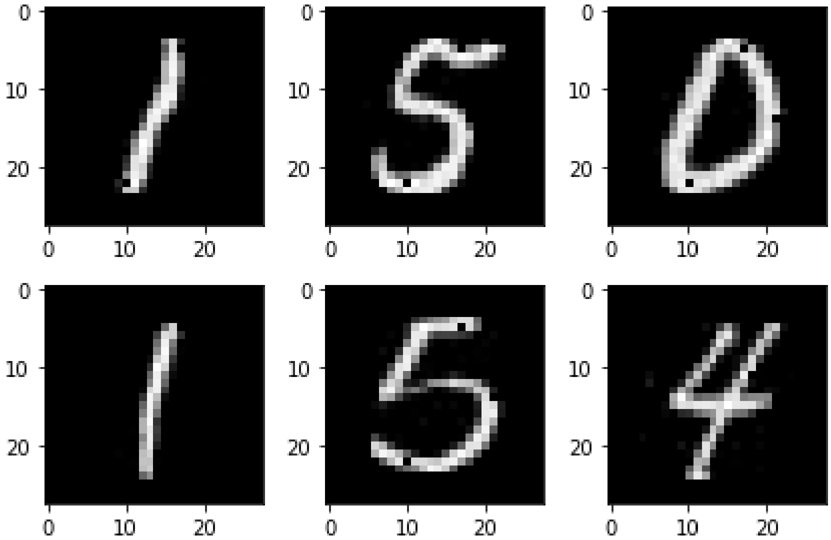
```
model = AE_x(256)
optimizer = torch.optim.Adam(model.parameters(), lr = 0.001)
model_state = train(epochs, model, loss_func, loaders)
torch.save(model_state, 'AE_256.pt')
model.load_state_dict(torch.load('AE_256.pt'))

test_loss, test_acc = evaluate(model, loss_func, loaders)

print('AE with hidden layer size = 256')
print(f'Test Loss: {test_loss:.3f}%')
```

```
Epoch: 1/10, Train Loss: 0.01866487, Val Loss: 0.00856984
Saving the model state dictionary for Epoch: 1 with Validation loss: 0.008
56984

Epoch: 2/10, Train Loss: 0.00764408, Val Loss: 0.00677048
Saving the model state dictionary for Epoch: 2 with Validation loss: 0.006
77048

Epoch: 3/10, Train Loss: 0.00651548, Val Loss: 0.00609346
Saving the model state dictionary for Epoch: 3 with Validation loss: 0.006
09346

Epoch: 4/10, Train Loss: 0.00598584, Val Loss: 0.00570942
Saving the model state dictionary for Epoch: 4 with Validation loss: 0.005
70942

Epoch: 5/10, Train Loss: 0.00565790, Val Loss: 0.00542882
Saving the model state dictionary for Epoch: 5 with Validation loss: 0.005
42882

Epoch: 6/10, Train Loss: 0.00545160, Val Loss: 0.00529532
Saving the model state dictionary for Epoch: 6 with Validation loss: 0.005
29532

Epoch: 7/10, Train Loss: 0.00531264, Val Loss: 0.00516408
Saving the model state dictionary for Epoch: 7 with Validation loss: 0.005
16408

Epoch: 8/10, Train Loss: 0.00521577, Val Loss: 0.00508598
Saving the model state dictionary for Epoch: 8 with Validation loss: 0.005
08598

Epoch: 9/10, Train Loss: 0.00515088, Val Loss: 0.00502145
Saving the model state dictionary for Epoch: 9 with Validation loss: 0.005
02145

Epoch: 10/10, Train Loss: 0.00510258, Val Loss: 0.00499387
Saving the model state dictionary for Epoch: 10 with Validation loss: 0.00
499387
AE with hidden layer size = 256
Test Loss: 0.006%
```



In [21]:

```
for itr, (images, labels) in enumerate(loaders['test']):
    images = images.reshape(-1,784)
    output = model(images.float())
    output = output.detach().numpy().reshape(-1,28,28)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[0],cmap='gray')
    ax2.imshow(output[1],cmap='gray')
    ax3.imshow(output[2],cmap='gray')
    ax4.imshow(output[3],cmap='gray')
    ax5.imshow(output[4],cmap='gray')
    ax6.imshow(output[5],cmap='gray')
    fig.tight_layout()
    break
```



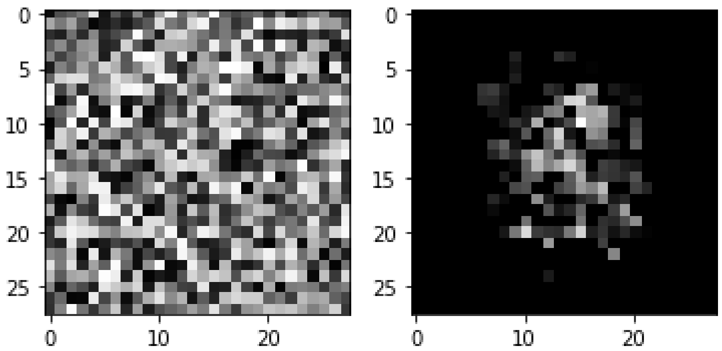
Noise image

In [22]:

```
images = np.random.random((1, 784)).astype(np.float32)
images = torch.tensor(images, dtype=torch.float)
output = model(images)
output = output.detach().numpy().reshape(-1,28,28)
fig, (ax1, ax2) = plt.subplots(1,2)
ax1.imshow(images.reshape(28,28),cmap='gray')
ax2.imshow(output[0],cmap='gray')
```

Out[22]:

```
<matplotlib.image.AxesImage at 0x7f71ebfdf890>
```



Sparse autoencoders

Model definition and train functions

In [23]:

```
class SAE(nn.Module):
  def __init__(self):
    super(SAE, self).__init__()
    self.encoder = nn.Sequential(
        nn.Linear(784,1225),
        nn.ReLU())
    self.decoder =nn.Sequential(
        nn.Linear(1225,784),
        nn.ReLU())

  def forward(self,x):
    x=self.encoder(x)
    l1loss=torch.norm(x,p=1)
    x=self.decoder(x)
    return x,l1loss
```

In [24]:

```
def train_SAE(no_epochs, model, loss_func, loaders, lam):
    train_loss = list()
    val_loss = list()
    pred_accuracy = list()
    best_val_loss = 1
    for epoch in range(no_epochs):
        total_train_loss = 0
        total_val_loss = 0

        model.train()
        # training
        for itr, (images, labels) in enumerate(loaders['train']):

            # Forward pass
            images = images.reshape(-1,784)
            outputs, l1loss = model(images.float())
            loss = loss_func(outputs, images) + lam*l1loss
            # Backward and optimize
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
            total_train_loss += loss.item()

        total_train_loss = total_train_loss / (itr + 1)
        train_loss.append(total_train_loss)

        # validation
        model.eval()
        total = 0
        for itr, (images, labels) in enumerate(loaders['validate']):
            images = images.reshape(-1,784)
            outputs, l1loss = model(images.float())
            loss = loss_func(outputs, images) + lam*l1loss
            total_val_loss += loss.item()

            pred = torch.nn.functional.softmax(outputs, dim=1)
            for i, p in enumerate(pred):
                if labels[i] == torch.max(p.data, 0)[1]:
                    total = total + 1

        accuracy = total / len(val_data)
        pred_accuracy.append(accuracy)

        total_val_loss = total_val_loss / (itr + 1)
        val_loss.append(total_val_loss)

        print('\nEpoch: {}/{}, Train Loss: {:.8f}, Val Loss: {:.8f}'.format(epoch + 1,
no_epochs, total_train_loss, total_val_loss))

        if total_val_loss < best_val_loss:
            best_val_loss = total_val_loss
            print("Saving the model state dictionary for Epoch: {} with Validation los
s: {:.8f}".format(epoch + 1, total_val_loss))
            model_state = model.state_dict()

    plt.figure(figsize=(4, 4))
    plt.plot(np.arange(1, no_epochs+1), train_loss, label="Train loss")
    plt.plot(np.arange(1, no_epochs+1), val_loss, label="Validation loss")
    plt.xlabel('Epochs')
```

```
    plt.ylabel('Loss')
    plt.title("Loss Plot")
    plt.legend(loc='upper right')
    return model_state
```

In [25]:

```
def evaluate_SAE(model, loss_func, loaders, lam):

    model.eval()
    total_test_loss = 0
    total = 0

    with torch.no_grad():

        for itr, (images, labels) in enumerate(loaders['test']):
            images = images.reshape(-1,784)
            outputs, l1loss = model(images.float())
            loss = loss_func(outputs, images) + lam*l1loss
            total_test_loss += loss.item()

            pred = torch.nn.functional.softmax(outputs, dim=1)
            for i, p in enumerate(pred):
                if labels[i] == torch.max(p.data, 0)[1]:
                    total = total + 1

        accuracy = total / len(test_data)
        total_test_loss = total_test_loss / (itr + 1)

    return loss, accuracy
```

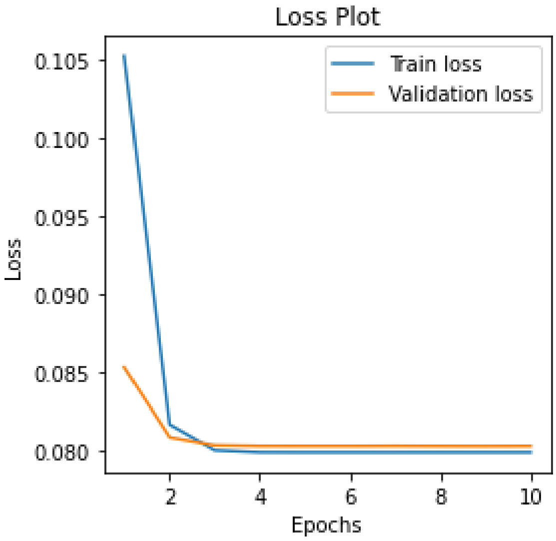
Training, reconstruction visualisation, average activation

Ll1 = 1e-4

In [26]:

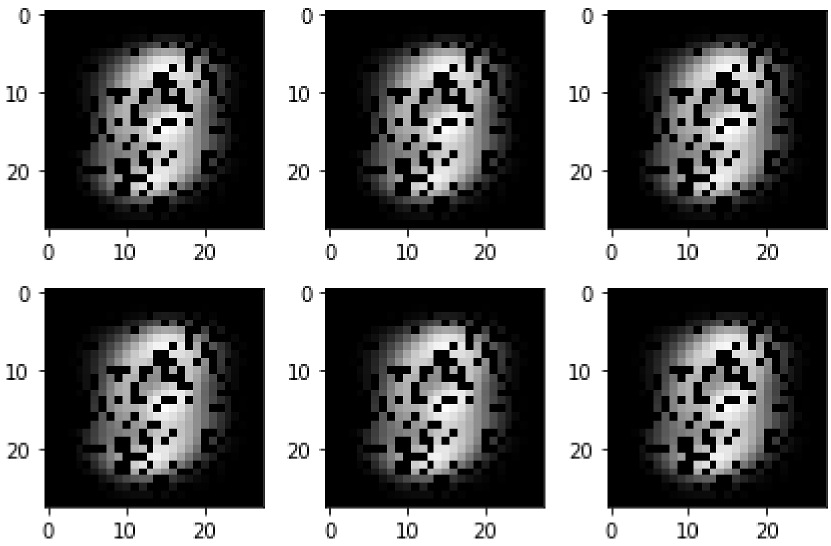
```
lam = 1e-4
model = SAE()
optimizer = torch.optim.Adam(model.parameters(), lr = 0.001)
model_state = train_SAE(epochs, model, loss_func, loaders, lam)
torch.save(model_state, 'SAE.pt')
model.load_state_dict(torch.load('SAE.pt'))

test_loss, test_acc = evaluate_SAE(model, loss_func, loaders, lam)

print('SAE')
print(f'Test Loss: {test_loss:.3f}%')

print("Average hidden layer activations for random 10 images")
sum=0
for i in range(10):
    avg=torch.norm(model.encoder(imageset[i].reshape(1,784)),p=1)/256.0
    print(avg.detach().numpy())
    sum+=avg.detach().numpy()
print("Average of these values",sum/10.0)
```

```
Epoch: 1/10, Train Loss: 0.10526543, Val Loss: 0.08531345
Saving the model state dictionary for Epoch: 1 with Validation loss: 0.085
31345

Epoch: 2/10, Train Loss: 0.08165429, Val Loss: 0.08084103
Saving the model state dictionary for Epoch: 2 with Validation loss: 0.080
84103

Epoch: 3/10, Train Loss: 0.08001549, Val Loss: 0.08033699
Saving the model state dictionary for Epoch: 3 with Validation loss: 0.080
33699

Epoch: 4/10, Train Loss: 0.07988684, Val Loss: 0.08029310
Saving the model state dictionary for Epoch: 4 with Validation loss: 0.080
29310

Epoch: 5/10, Train Loss: 0.07988144, Val Loss: 0.08028978
Saving the model state dictionary for Epoch: 5 with Validation loss: 0.080
28978

Epoch: 6/10, Train Loss: 0.07988175, Val Loss: 0.08028959
Saving the model state dictionary for Epoch: 6 with Validation loss: 0.080
28959

Epoch: 7/10, Train Loss: 0.07988172, Val Loss: 0.08029617

Epoch: 8/10, Train Loss: 0.07988246, Val Loss: 0.08028735
Saving the model state dictionary for Epoch: 8 with Validation loss: 0.080
28735

Epoch: 9/10, Train Loss: 0.07988268, Val Loss: 0.08028223
Saving the model state dictionary for Epoch: 9 with Validation loss: 0.080
28223

Epoch: 10/10, Train Loss: 0.07988263, Val Loss: 0.08028912
SAE
Test Loss: 0.083%
Average hidden layer activations for random 10 images
0.0
0.0
0.0
0.0
0.0
0.0
0.0
0.0
0.0
0.0
Average of these values 0.0
```


Loss Plot
Train loss
Validation loss
0.105
0.100
0.095
0.090
0.085
0.080
Loss
2
4
6
8
10
Epochs

In [27]:

```
for itr, (images, labels) in enumerate(loaders['test']):
    images = images.reshape(-1,784)
    output,l1loss = model(images.float())
    output = output.detach().numpy().reshape(-1,28,28)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[0],cmap='gray')
    ax2.imshow(output[1],cmap='gray')
    ax3.imshow(output[2],cmap='gray')
    ax4.imshow(output[3],cmap='gray')
    ax5.imshow(output[4],cmap='gray')
    ax6.imshow(output[5],cmap='gray')
    fig.tight_layout()
    break
```

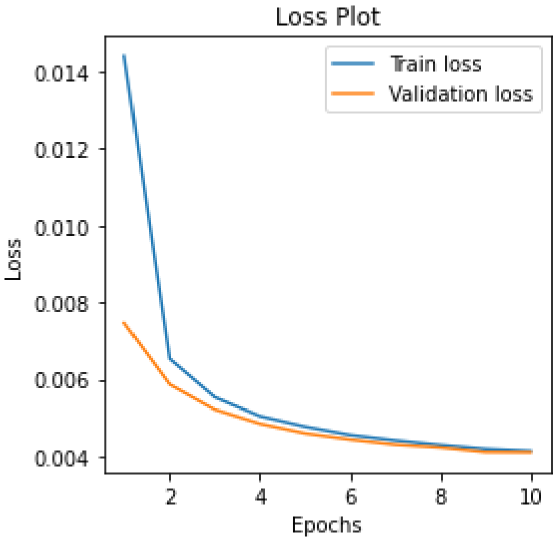


Ll1 = 1e-7

In [28]:

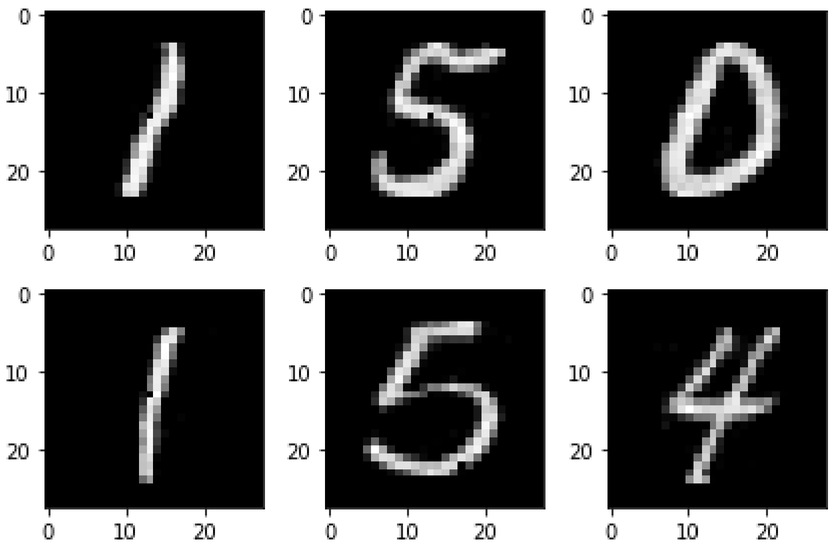
```
lam = 1e-7
model = SAE()
optimizer = torch.optim.Adam(model.parameters(), lr = 0.001)
model_state = train_SAE(epochs, model, loss_func, loaders, lam)
torch.save(model_state, 'SAE.pt')
model.load_state_dict(torch.load('SAE.pt'))

test_loss, test_acc = evaluate_SAE(model, loss_func, loaders, lam)

print('SAE')
print(f'Test Loss: {test_loss:.3f}%')

sum = 0
for i in range(10):
    avg=torch.norm(model.encoder(imageset[i].reshape(1,784)),p=1)/256.0
    print(avg.detach().numpy())
    sum+=avg.detach().numpy()
print("Average of these values",sum/10.0)
```

```
Epoch: 1/10, Train Loss: 0.01440497, Val Loss: 0.00746009
Saving the model state dictionary for Epoch: 1 with Validation loss: 0.007
46009

Epoch: 2/10, Train Loss: 0.00653160, Val Loss: 0.00586821
Saving the model state dictionary for Epoch: 2 with Validation loss: 0.005
86821

Epoch: 3/10, Train Loss: 0.00553560, Val Loss: 0.00520955
Saving the model state dictionary for Epoch: 3 with Validation loss: 0.005
20955

Epoch: 4/10, Train Loss: 0.00503823, Val Loss: 0.00484235
Saving the model state dictionary for Epoch: 4 with Validation loss: 0.004
84235

Epoch: 5/10, Train Loss: 0.00476778, Val Loss: 0.00459411
Saving the model state dictionary for Epoch: 5 with Validation loss: 0.004
59411

Epoch: 6/10, Train Loss: 0.00455334, Val Loss: 0.00443560
Saving the model state dictionary for Epoch: 6 with Validation loss: 0.004
43560

Epoch: 7/10, Train Loss: 0.00441385, Val Loss: 0.00430453
Saving the model state dictionary for Epoch: 7 with Validation loss: 0.004
30453

Epoch: 8/10, Train Loss: 0.00429453, Val Loss: 0.00422959
Saving the model state dictionary for Epoch: 8 with Validation loss: 0.004
22959

Epoch: 9/10, Train Loss: 0.00419192, Val Loss: 0.00411023
Saving the model state dictionary for Epoch: 9 with Validation loss: 0.004
11023

Epoch: 10/10, Train Loss: 0.00413833, Val Loss: 0.00410431
Saving the model state dictionary for Epoch: 10 with Validation loss: 0.00
410431
SAE
Test Loss: 0.005%
0.22294258
0.12105809
0.24480529
0.22813293
0.21950965
0.22135073
0.23372062
0.1735722
0.20082784
0.21301198
Average of these values 0.2078931897878647
```



In [29]:

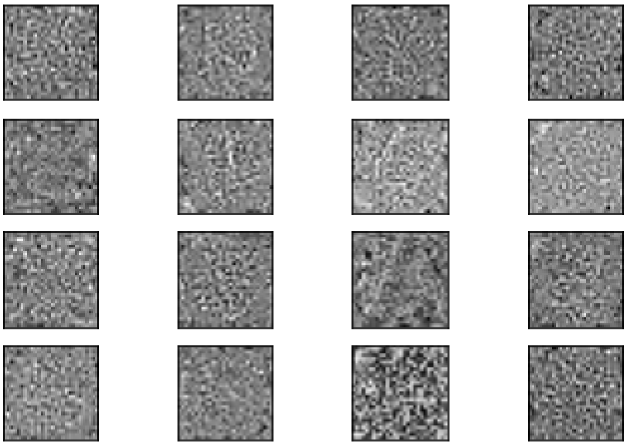
```
for itr, (images, labels) in enumerate(loaders['test']):
    images = images.reshape(-1,784)
    output,l1loss = model(images.float())
    output = output.detach().numpy().reshape(-1,28,28)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[0],cmap='gray')
    ax2.imshow(output[1],cmap='gray')
    ax3.imshow(output[2],cmap='gray')
    ax4.imshow(output[3],cmap='gray')
    ax5.imshow(output[4],cmap='gray')
    ax6.imshow(output[5],cmap='gray')
    fig.tight_layout()
    break
```



Learned filter weights

In [30]:

```
ix=1
fig,ax=plt.subplots()
for i in range(16):
    ax=plt.subplot(4,4,ix)
    ax.set_xticks([])
    ax.set_yticks([])
    im=ax.imshow(model.encoder[0].weight[i].detach().numpy().reshape(28,28),cmap='gray'
)
    ix+=1
```

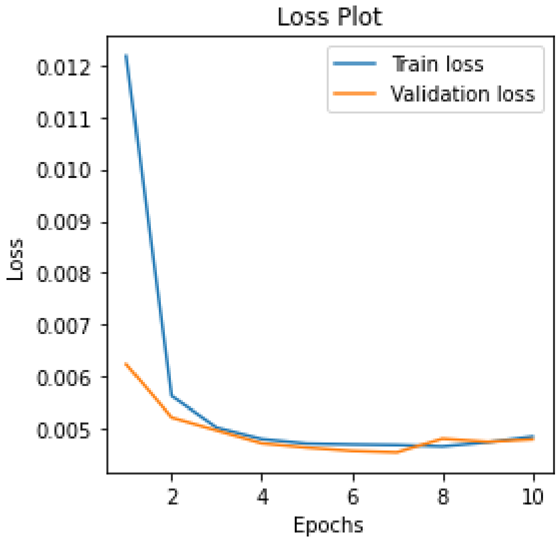


Ll1 = 1e-10

In [31]:

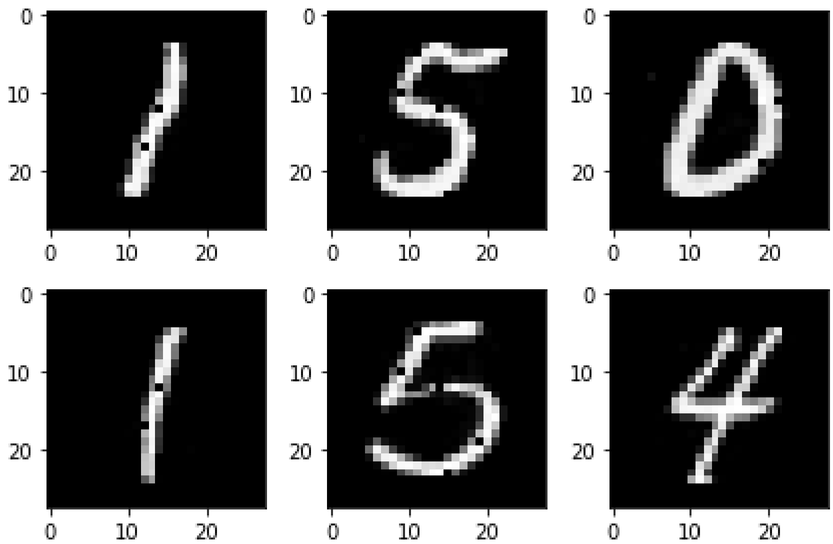
```
lam = 1e-10
model = SAE()
optimizer = torch.optim.Adam(model.parameters(), lr = 0.001)
model_state = train_SAE(epochs, model, loss_func, loaders, lam)
torch.save(model_state, 'SAE.pt')
model.load_state_dict(torch.load('SAE.pt'))

test_loss, test_acc = evaluate_SAE(model, loss_func, loaders, lam)

print('SAE')
print(f'Test Loss: {test_loss:.3f}%')

sum = 0
for i in range(10):
    avg=torch.norm(model.encoder(imageset[i].reshape(1,784)),p=1)/256.0
    print(avg.detach().numpy())
    sum+=avg.detach().numpy()
print("Average of these values",sum/10.0)
```

```
Epoch: 1/10, Train Loss: 0.01217758, Val Loss: 0.00623362
Saving the model state dictionary for Epoch: 1 with Validation loss: 0.006
23362

Epoch: 2/10, Train Loss: 0.00562736, Val Loss: 0.00521313
Saving the model state dictionary for Epoch: 2 with Validation loss: 0.005
21313

Epoch: 3/10, Train Loss: 0.00501873, Val Loss: 0.00496377
Saving the model state dictionary for Epoch: 3 with Validation loss: 0.004
96377

Epoch: 4/10, Train Loss: 0.00479798, Val Loss: 0.00471605
Saving the model state dictionary for Epoch: 4 with Validation loss: 0.004
71605

Epoch: 5/10, Train Loss: 0.00471127, Val Loss: 0.00463341
Saving the model state dictionary for Epoch: 5 with Validation loss: 0.004
63341

Epoch: 6/10, Train Loss: 0.00469491, Val Loss: 0.00457035
Saving the model state dictionary for Epoch: 6 with Validation loss: 0.004
57035

Epoch: 7/10, Train Loss: 0.00468404, Val Loss: 0.00454252
Saving the model state dictionary for Epoch: 7 with Validation loss: 0.004
54252

Epoch: 8/10, Train Loss: 0.00465764, Val Loss: 0.00480575

Epoch: 9/10, Train Loss: 0.00473605, Val Loss: 0.00474531

Epoch: 10/10, Train Loss: 0.00484734, Val Loss: 0.00479318
SAE
Test Loss: 0.005%
1.4414914
0.7546469
1.5121508
1.1029224
1.4302654
1.2466452
1.580469
1.196076
1.283687
1.768665
Average of these values 1.3317019104957581
```



In [32]:

```
for itr, (images, labels) in enumerate(loaders['test']):
    images = images.reshape(-1,784)
    output,l1loss = model(images.float())
    output = output.detach().numpy().reshape(-1,28,28)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[0],cmap='gray')
    ax2.imshow(output[1],cmap='gray')
    ax3.imshow(output[2],cmap='gray')
    ax4.imshow(output[3],cmap='gray')
    ax5.imshow(output[4],cmap='gray')
    ax6.imshow(output[5],cmap='gray')
    fig.tight_layout()
    break
```



Standard AE: reconstruction, average activation and filter weights

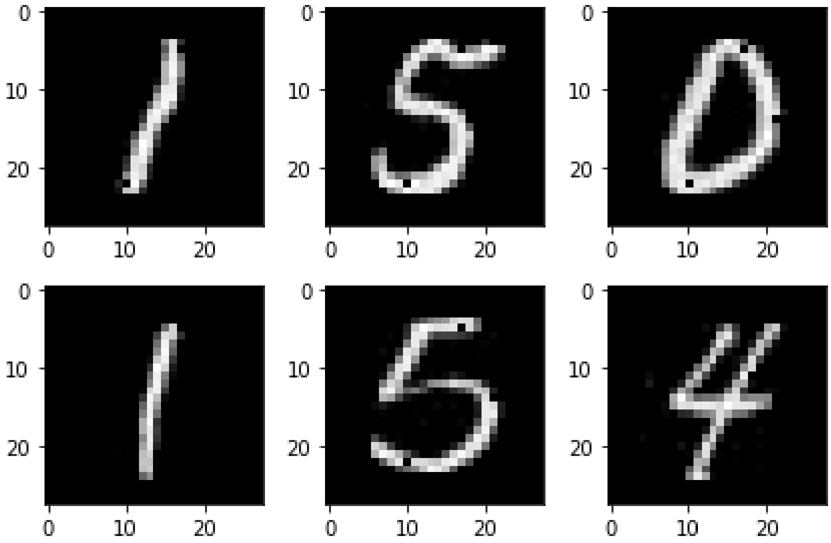
In [33]:

```
model = AE_x(256)
model.load_state_dict(torch.load('AE_256.pt'))
sum = 0
for i in range(10):
    avg=torch.norm(model.encoder(imageset[i].reshape(1,784)),p=1)/256.0
    print(avg.detach().numpy())
    sum+=avg.detach().numpy()
print("Average of these values",sum/10.0)
```

```
0.8476365
0.44866323
0.87702745
0.6128765
0.8592719
0.72487545
0.9427591
0.70593137
0.78175676
1.099273
Average of these values 0.7900071203708648
```

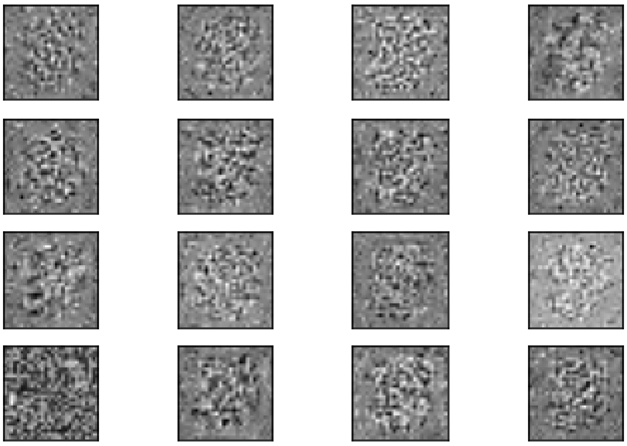
In [34]:

```
for itr, (images, labels) in enumerate(loaders['test']):
    images = images.reshape(-1,784)
    output = model(images.float())
    output = output.detach().numpy().reshape(-1,28,28)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[0],cmap='gray')
    ax2.imshow(output[1],cmap='gray')
    ax3.imshow(output[2],cmap='gray')
    ax4.imshow(output[3],cmap='gray')
    ax5.imshow(output[4],cmap='gray')
    ax6.imshow(output[5],cmap='gray')
    fig.tight_layout()
    break
```



In [35]:

```
ix=1
fig,ax=plt.subplots()
for i in range(16):
    ax=plt.subplot(4,4,ix)
    ax.set_xticks([])
    ax.set_yticks([])
    im=ax.imshow(model.encoder[0].weight[i].detach().numpy().reshape(28,28),cmap='gray'
)
    ix+=1
```



Denoising Autoencoders

Standard AE: Results on noisy image, learned filter weights

In [36]:

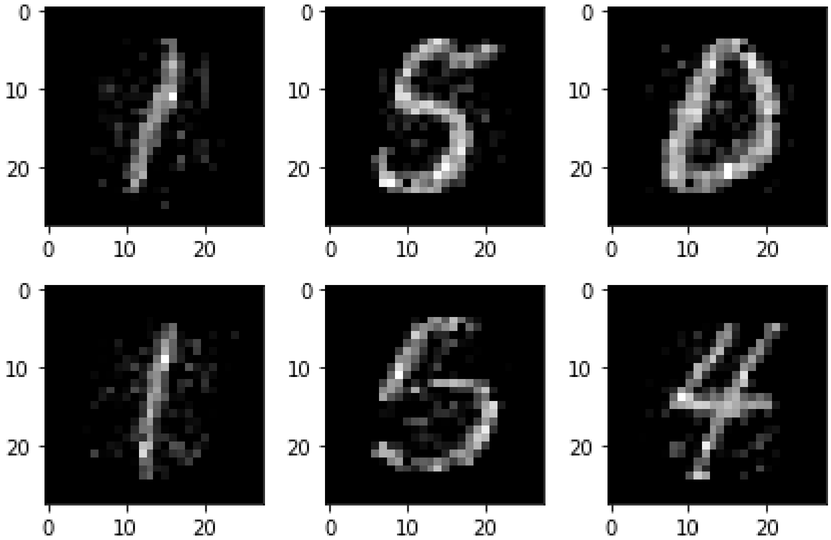
```
model.load_state_dict(torch.load('AE_256.pt'))
```

Out[36]:

```
<All keys matched successfully>
```

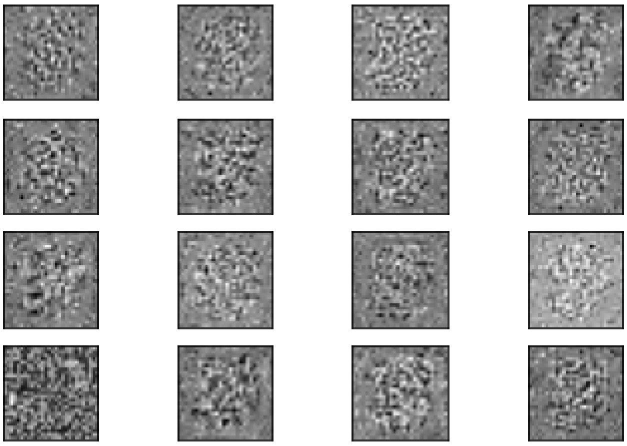
In [37]:

```
for itr, (images, labels) in enumerate(loaders['test']):
    images = images.reshape(-1,784)
    images = images + torch.clip(torch.randn_like(images) * 0.3,0.,1.)
    output = model(images.float())
    output = output.detach().numpy().reshape(-1,28,28)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[0],cmap='gray')
    ax2.imshow(output[1],cmap='gray')
    ax3.imshow(output[2],cmap='gray')
    ax4.imshow(output[3],cmap='gray')
    ax5.imshow(output[4],cmap='gray')
    ax6.imshow(output[5],cmap='gray')
    fig.tight_layout()
    break
```



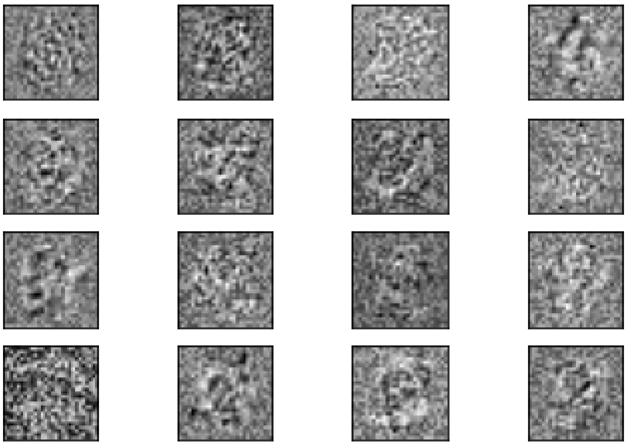
In [38]:

```
ix=1
fig,ax=plt.subplots()
for i in range(16):
    ax=plt.subplot(4,4,ix)
    ax.set_xticks([])
    ax.set_yticks([])
    im=ax.imshow(model.encoder[0].weight[i].detach().numpy().reshape(28,28),cmap='gray'
)
    ix+=1
```



In [39]:

```
ix=1
fig,ax=plt.subplots()
for i in range(16):
    ax=plt.subplot(4,4,ix)
    ax.set_xticks([])
    ax.set_yticks([])
    im=ax.imshow(model.decoder[0].weight[:,i].detach().numpy().reshape(28,28),cmap='gra
y')
    ix+=1
```



DAE: Model definition

In [40]:

```
class DAE(nn.Module):
  def __init__(self,noise):
    super(DAE, self).__init__()
    self.encoder = nn.Sequential(
        nn.Linear(784,256),
        nn.ReLU())
    self.decoder =nn.Sequential(
        nn.Linear(256,784),
        nn.ReLU())
    self.noise = noise

  def forward(self,x):
    x_ = x + torch.randn_like(x) * self.noise
    x_ = torch.clip(x_,0.,1.)
    x_=self.encoder(x_)
    x_=self.decoder(x_)
    return x_
```

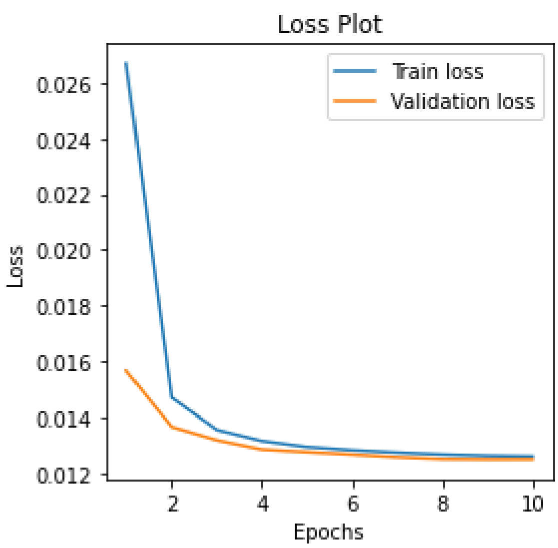
Training, reconstruction visualisation, learned decoder weights

Noise factor = 0.3

In [41]:

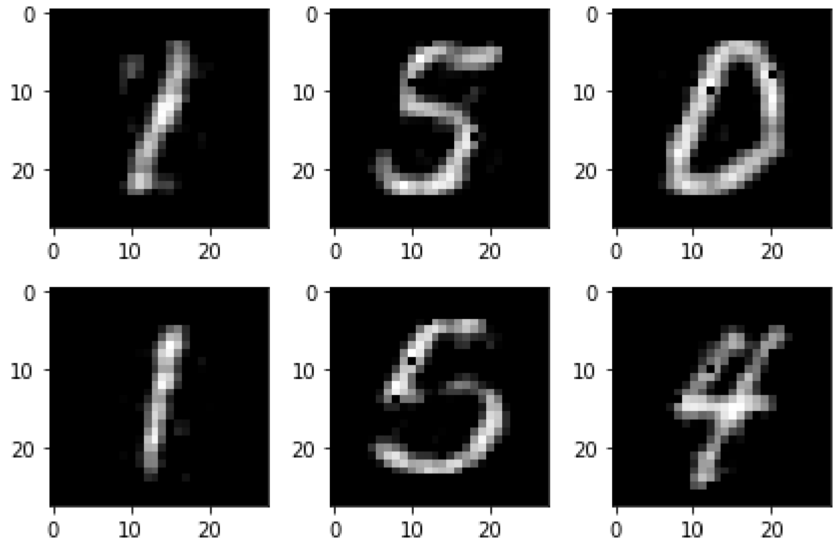
```
noise_factor = 0.3
model = DAE(noise_factor)
optimizer = torch.optim.Adam(model.parameters(), lr = 0.001)
model_state = train(epochs, model, loss_func, loaders)
torch.save(model_state, 'DAE_0.3.pt')
model.load_state_dict(torch.load('DAE_0.3.pt'))

test_loss, test_acc = evaluate(model, loss_func, loaders)

print('DAE with noise factor = ',noise_factor)
print(f'Test Loss: {test_loss:.3f}%')
```

```
Epoch: 1/10, Train Loss: 0.02669187, Val Loss: 0.01565860
Saving the model state dictionary for Epoch: 1 with Validation loss: 0.015
65860

Epoch: 2/10, Train Loss: 0.01470162, Val Loss: 0.01364547
Saving the model state dictionary for Epoch: 2 with Validation loss: 0.013
64547

Epoch: 3/10, Train Loss: 0.01353915, Val Loss: 0.01317017
Saving the model state dictionary for Epoch: 3 with Validation loss: 0.013
17017

Epoch: 4/10, Train Loss: 0.01314202, Val Loss: 0.01283746
Saving the model state dictionary for Epoch: 4 with Validation loss: 0.012
83746

Epoch: 5/10, Train Loss: 0.01292795, Val Loss: 0.01274328
Saving the model state dictionary for Epoch: 5 with Validation loss: 0.012
74328

Epoch: 6/10, Train Loss: 0.01281292, Val Loss: 0.01265650
Saving the model state dictionary for Epoch: 6 with Validation loss: 0.012
65650

Epoch: 7/10, Train Loss: 0.01272666, Val Loss: 0.01256180
Saving the model state dictionary for Epoch: 7 with Validation loss: 0.012
56180

Epoch: 8/10, Train Loss: 0.01265856, Val Loss: 0.01249582
Saving the model state dictionary for Epoch: 8 with Validation loss: 0.012
49582

Epoch: 9/10, Train Loss: 0.01261302, Val Loss: 0.01248529
Saving the model state dictionary for Epoch: 9 with Validation loss: 0.012
48529

Epoch: 10/10, Train Loss: 0.01259181, Val Loss: 0.01248693
DAE with noise factor =  0.3
Test Loss: 0.013%
```



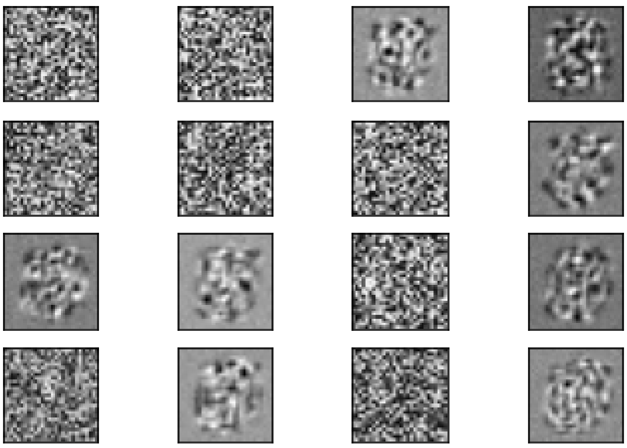
In [42]:

```
for itr, (images, labels) in enumerate(loaders['test']):
    images = images.reshape(-1,784)
    output = model(images.float())
    output = output.detach().numpy().reshape(-1,28,28)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[0],cmap='gray')
    ax2.imshow(output[1],cmap='gray')
    ax3.imshow(output[2],cmap='gray')
    ax4.imshow(output[3],cmap='gray')
    ax5.imshow(output[4],cmap='gray')
    ax6.imshow(output[5],cmap='gray')
    fig.tight_layout()
    break
```



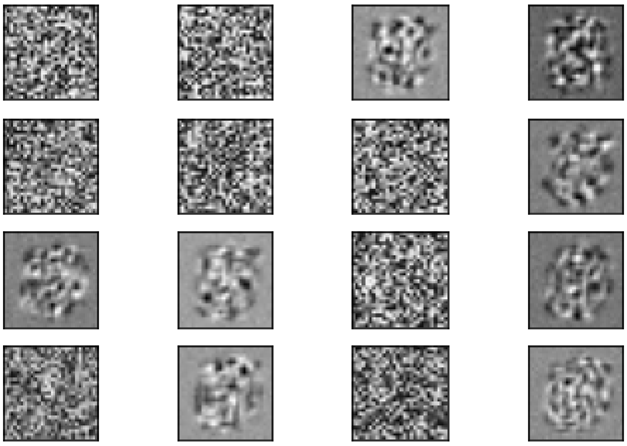
In [43]:

```
ix=1
fig,ax=plt.subplots()
for i in range(16):
    ax=plt.subplot(4,4,ix)
    ax.set_xticks([])
    ax.set_yticks([])
    im=ax.imshow(model.encoder[0].weight[i].detach().numpy().reshape(28,28),cmap='gray'
)
    ix+=1
```



In [44]:

```
ix=1
fig,ax=plt.subplots()
for i in range(16):
    ax=plt.subplot(4,4,ix)
    ax.set_xticks([])
    ax.set_yticks([])
    im=ax.imshow(model.encoder[0].weight[i].detach().numpy().reshape(28,28),cmap='gray'
)
    ix+=1
```

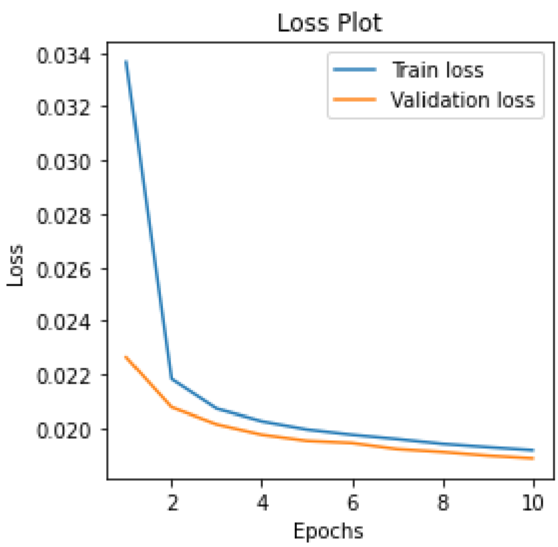


Noise factor = 0.5

In [45]:

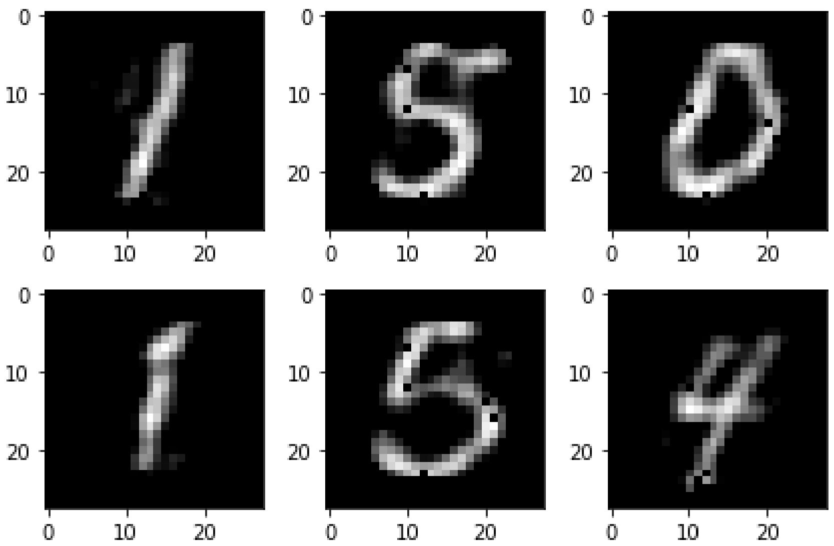
```
noise_factor = 0.5
model = DAE(noise_factor)
optimizer = torch.optim.Adam(model.parameters(), lr = 0.001)
model_state = train(epochs, model, loss_func, loaders)
torch.save(model_state, 'DAE_0.5.pt')
model.load_state_dict(torch.load('DAE_0.5.pt'))

test_loss, test_acc = evaluate(model, loss_func, loaders)

print('DAE with noise factor = ',noise_factor)
print(f'Test Loss: {test_loss:.3f}%')
```

```
Epoch: 1/10, Train Loss: 0.03366244, Val Loss: 0.02263773
Saving the model state dictionary for Epoch: 1 with Validation loss: 0.022
63773

Epoch: 2/10, Train Loss: 0.02183563, Val Loss: 0.02078038
Saving the model state dictionary for Epoch: 2 with Validation loss: 0.020
78038

Epoch: 3/10, Train Loss: 0.02072825, Val Loss: 0.02014695
Saving the model state dictionary for Epoch: 3 with Validation loss: 0.020
14695

Epoch: 4/10, Train Loss: 0.02026154, Val Loss: 0.01976066
Saving the model state dictionary for Epoch: 4 with Validation loss: 0.019
76066

Epoch: 5/10, Train Loss: 0.01995634, Val Loss: 0.01953405
Saving the model state dictionary for Epoch: 5 with Validation loss: 0.019
53405

Epoch: 6/10, Train Loss: 0.01976215, Val Loss: 0.01945415
Saving the model state dictionary for Epoch: 6 with Validation loss: 0.019
45415

Epoch: 7/10, Train Loss: 0.01960220, Val Loss: 0.01922793
Saving the model state dictionary for Epoch: 7 with Validation loss: 0.019
22793

Epoch: 8/10, Train Loss: 0.01942365, Val Loss: 0.01911856
Saving the model state dictionary for Epoch: 8 with Validation loss: 0.019
11856

Epoch: 9/10, Train Loss: 0.01929965, Val Loss: 0.01898268
Saving the model state dictionary for Epoch: 9 with Validation loss: 0.018
98268

Epoch: 10/10, Train Loss: 0.01918737, Val Loss: 0.01888177
Saving the model state dictionary for Epoch: 10 with Validation loss: 0.01
888177
DAE with noise factor =  0.5
Test Loss: 0.020%
```



In [46]:

```
for itr, (images, labels) in enumerate(loaders['test']):
    images = images.reshape(-1,784)
    output = model(images.float())
    output = output.detach().numpy().reshape(-1,28,28)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[0],cmap='gray')
    ax2.imshow(output[1],cmap='gray')
    ax3.imshow(output[2],cmap='gray')
    ax4.imshow(output[3],cmap='gray')
    ax5.imshow(output[4],cmap='gray')
    ax6.imshow(output[5],cmap='gray')
    fig.tight_layout()
    break
```

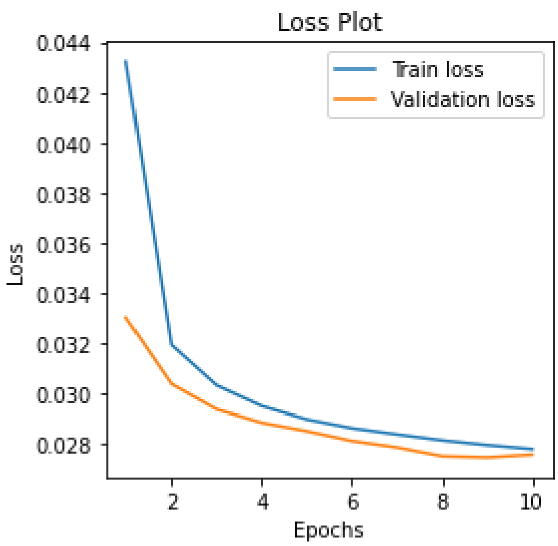


Noise factor = 0.8

In [47]:

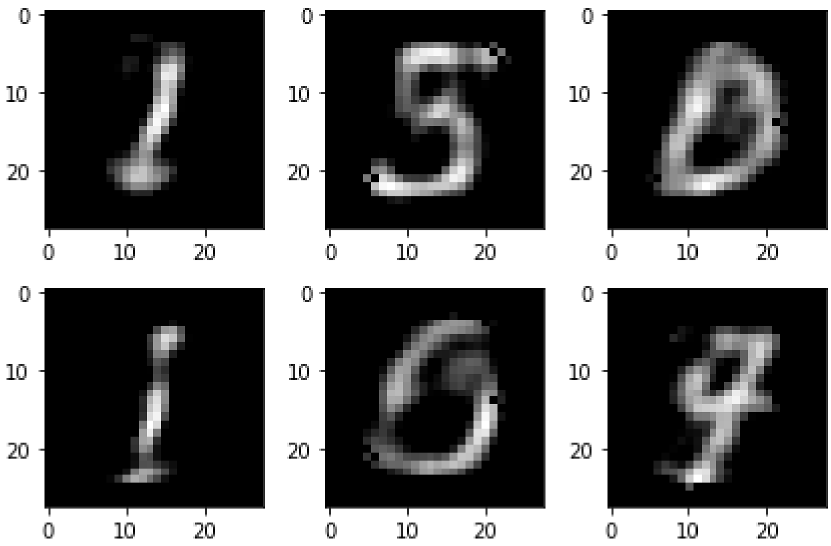
```
noise_factor = 0.8
model = DAE(noise_factor)
optimizer = torch.optim.Adam(model.parameters(), lr = 0.001)
model_state = train(epochs, model, loss_func, loaders)
torch.save(model_state, 'DAE_0.8.pt')
model.load_state_dict(torch.load('DAE_0.8.pt'))

test_loss, test_acc = evaluate(model, loss_func, loaders)

print('DAE with noise factor = ',noise_factor)
print(f'Test Loss: {test_loss:.3f}%')
```

```
Epoch: 1/10, Train Loss: 0.04323547, Val Loss: 0.03302477
Saving the model state dictionary for Epoch: 1 with Validation loss: 0.033
02477

Epoch: 2/10, Train Loss: 0.03195086, Val Loss: 0.03039708
Saving the model state dictionary for Epoch: 2 with Validation loss: 0.030
39708

Epoch: 3/10, Train Loss: 0.03034074, Val Loss: 0.02939121
Saving the model state dictionary for Epoch: 3 with Validation loss: 0.029
39121

Epoch: 4/10, Train Loss: 0.02952303, Val Loss: 0.02885515
Saving the model state dictionary for Epoch: 4 with Validation loss: 0.028
85515

Epoch: 5/10, Train Loss: 0.02898893, Val Loss: 0.02852172
Saving the model state dictionary for Epoch: 5 with Validation loss: 0.028
52172

Epoch: 6/10, Train Loss: 0.02863966, Val Loss: 0.02813355
Saving the model state dictionary for Epoch: 6 with Validation loss: 0.028
13355

Epoch: 7/10, Train Loss: 0.02839463, Val Loss: 0.02787875
Saving the model state dictionary for Epoch: 7 with Validation loss: 0.027
87875

Epoch: 8/10, Train Loss: 0.02815883, Val Loss: 0.02753057
Saving the model state dictionary for Epoch: 8 with Validation loss: 0.027
53057

Epoch: 9/10, Train Loss: 0.02797072, Val Loss: 0.02748147
Saving the model state dictionary for Epoch: 9 with Validation loss: 0.027
48147

Epoch: 10/10, Train Loss: 0.02781271, Val Loss: 0.02758843
DAE with noise factor =  0.8
Test Loss: 0.028%
```



In [48]:

```
for itr, (images, labels) in enumerate(loaders['test']):
    images = images.reshape(-1,784)
    output = model(images.float())
    output = output.detach().numpy().reshape(-1,28,28)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[0],cmap='gray')
    ax2.imshow(output[1],cmap='gray')
    ax3.imshow(output[2],cmap='gray')
    ax4.imshow(output[3],cmap='gray')
    ax5.imshow(output[4],cmap='gray')
    ax6.imshow(output[5],cmap='gray')
    fig.tight_layout()
    break
```

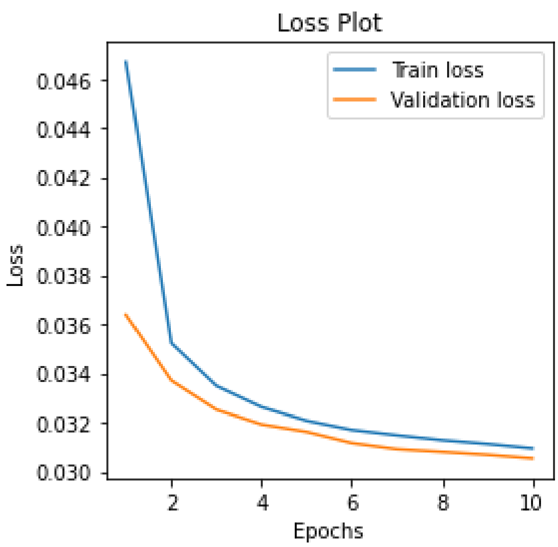


Noise factor = 0.9

In [49]:

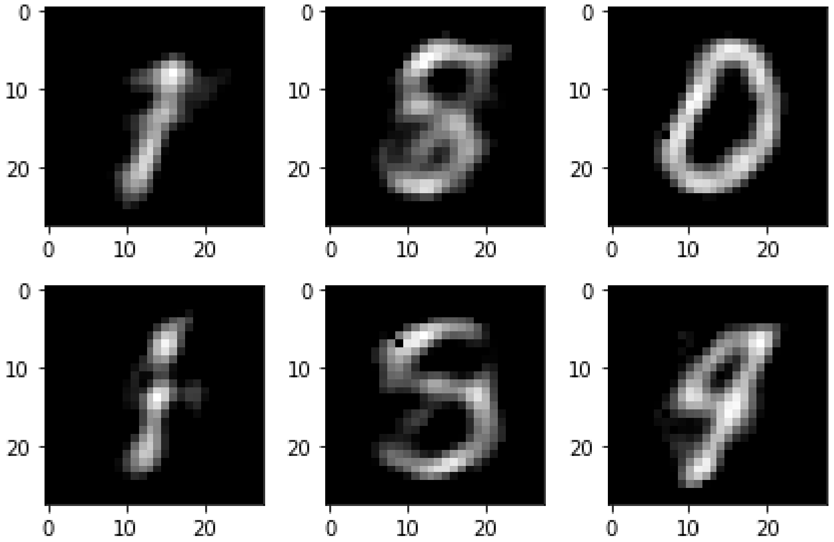
```
noise_factor = 0.9
model = DAE(noise_factor)
optimizer = torch.optim.Adam(model.parameters(), lr = 0.001)
model_state = train(epochs, model, loss_func, loaders)
torch.save(model_state, 'DAE_0.9.pt')
model.load_state_dict(torch.load('DAE_0.9.pt'))

test_loss, test_acc = evaluate(model, loss_func, loaders)

print('DAE with noise factor = ',noise_factor)
print(f'Test Loss: {test_loss:.3f}%')
```

```
Epoch: 1/10, Train Loss: 0.04668936, Val Loss: 0.03637553
Saving the model state dictionary for Epoch: 1 with Validation loss: 0.036
37553

Epoch: 2/10, Train Loss: 0.03523245, Val Loss: 0.03370456
Saving the model state dictionary for Epoch: 2 with Validation loss: 0.033
70456

Epoch: 3/10, Train Loss: 0.03348647, Val Loss: 0.03251853
Saving the model state dictionary for Epoch: 3 with Validation loss: 0.032
51853

Epoch: 4/10, Train Loss: 0.03262801, Val Loss: 0.03191420
Saving the model state dictionary for Epoch: 4 with Validation loss: 0.031
91420

Epoch: 5/10, Train Loss: 0.03206589, Val Loss: 0.03161474
Saving the model state dictionary for Epoch: 5 with Validation loss: 0.031
61474

Epoch: 6/10, Train Loss: 0.03169260, Val Loss: 0.03116177
Saving the model state dictionary for Epoch: 6 with Validation loss: 0.031
16177

Epoch: 7/10, Train Loss: 0.03147703, Val Loss: 0.03091469
Saving the model state dictionary for Epoch: 7 with Validation loss: 0.030
91469

Epoch: 8/10, Train Loss: 0.03127714, Val Loss: 0.03080220
Saving the model state dictionary for Epoch: 8 with Validation loss: 0.030
80220

Epoch: 9/10, Train Loss: 0.03112589, Val Loss: 0.03068558
Saving the model state dictionary for Epoch: 9 with Validation loss: 0.030
68558

Epoch: 10/10, Train Loss: 0.03094704, Val Loss: 0.03053976
Saving the model state dictionary for Epoch: 10 with Validation loss: 0.03
053976
DAE with noise factor =  0.9
Test Loss: 0.032%
```



In [50]:

```
for itr, (images, labels) in enumerate(loaders['test']):
    images = images.reshape(-1,784)
    output = model(images.float())
    output = output.detach().numpy().reshape(-1,28,28)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[0],cmap='gray')
    ax2.imshow(output[1],cmap='gray')
    ax3.imshow(output[2],cmap='gray')
    ax4.imshow(output[3],cmap='gray')
    ax5.imshow(output[4],cmap='gray')
    ax6.imshow(output[5],cmap='gray')
    fig.tight_layout()
    break
```



Convolutional autoencoders

Training functions

In [51]:

```
def train_convAE(no_epochs, model, loss_func, loaders):
    train_loss = list()
    val_loss = list()
    pred_accuracy = list()
    best_val_loss = 1
    for epoch in range(no_epochs):
        total_train_loss = 0
        total_val_loss = 0

        model.train()
        # training
        for itr, (images, labels) in enumerate(loaders['train']):

            # Forward pass
            outputs = model(images.float())
            loss = loss_func(outputs, images)
            # Backward and optimize
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
            total_train_loss += loss.item()

        total_train_loss = total_train_loss / (itr + 1)
        train_loss.append(total_train_loss)

        # validation
        model.eval()
        total = 0
        for itr, (images, labels) in enumerate(loaders['validate']):
            outputs = model(images.float())

            loss = loss_func(outputs, images)
            total_val_loss += loss.item()


        total_val_loss = total_val_loss / (itr + 1)
        val_loss.append(total_val_loss)

        print('\nEpoch: {}/{}, Train Loss: {:.8f}, Val Loss: {:.8f}'.format(epoch + 1,
no_epochs, total_train_loss, total_val_loss))

        if total_val_loss < best_val_loss:
            best_val_loss = total_val_loss
            print("Saving the model state dictionary for Epoch: {} with Validation los
s: {:.8f}".format(epoch + 1, total_val_loss))
            model_state = model.state_dict()

    plt.figure(figsize=(4, 4))
    plt.plot(np.arange(1, no_epochs+1), train_loss, label="Train loss")
    plt.plot(np.arange(1, no_epochs+1), val_loss, label="Validation loss")
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.title("Loss Plot")
    plt.legend(loc='upper right')
    return model_state
```

In [52]:

```
def evaluate_convAE(model, loss_func, loaders):

    model.eval()
    total_test_loss = 0
    total = 0

    with torch.no_grad():

        for itr, (images, labels) in enumerate(loaders['test']):
            outputs = model(images.float())

            loss = loss_func(outputs, images)
            total_test_loss += loss.item()

        total_test_loss = total_test_loss / (itr + 1)

    return loss
```

Decoder: upsample only by unpool

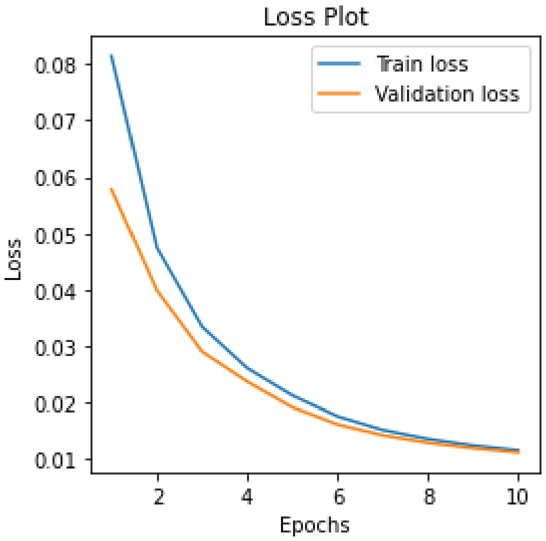
In [53]:

```
class conv_AE_unpool(nn.Module): #define unpooling outside the decoder and separately i
n forward nn.Sequential just takes one input

    def __init__(self): #class constructor
        super(conv_AE_unpool,self).__init__() #calls the parent constructor

        #initializing the encoder module
        self.encoder_conv1 = nn.Sequential(nn.Conv2d(1,8, kernel_size = 3, stride = 1,p
adding= 1),nn.ReLU(),nn.MaxPool2d(kernel_size = (2,2),return_indices = True)) # 28x28x1
to 14x14x8
        self.encoder_conv2 = nn.Sequential(nn.Conv2d(8,16, kernel_size = 3, stride = 1,
padding= 1),nn.ReLU(),nn.MaxPool2d(kernel_size = (2,2),return_indices = True)) #14x14x8
to 7x7x16
        self.encoder_conv3 = nn.Sequential(nn.Conv2d(16,16, kernel_size = 3, stride = 1
,padding= 1),nn.ReLU(),nn.MaxPool2d(kernel_size = (2,2),return_indices = True)) #7x7x16
to 3x3x16

        #initializing the decoder module
        self.decoder_conv1 = nn.Sequential(nn.Identity()) #7x7x16 to 7x7x16
        self.decoder_conv2 = nn.Sequential(nn.Conv2d(16,8, kernel_size = 3, stride = 1,
padding= 1),nn.ReLU()) #14x14x16 to 14x14x8
        self.decoder_conv3 = nn.Sequential(nn.Conv2d(8,1, kernel_size = 3, stride = 1,p
adding= 1),nn.ReLU()) #28x28x8 to 28x28x1

        #defining the unpooling operation
        self.unpool = nn.MaxUnpool2d(kernel_size = (2,2))


    def forward(self,x): #defines the forward pass and also the structure of the networ
k thus helping backprop

        encoded_input,indices1  = self.encoder_conv1(x.float())  # 28x28x1 to 14x14x8
        encoded_input,indices2  = self.encoder_conv2(encoded_input) #14x14x8 to 7x7x16
        encoded_input,indices3  = self.encoder_conv3(encoded_input) #7x7x16 to 3x3x16


        reconstructed_input     = self.unpool(encoded_input,indices3,output_size=torch.
Size([batch_size, 16, 7, 7])) #3x3x16 to 7x7x16
        reconstructed_input     = self.decoder_conv1(reconstructed_input) #7x7x16 to 7x
7x16
        reconstructed_input     = self.unpool(reconstructed_input,indices2) #7x7x16 to
 14x14x16
        reconstructed_input     = self.decoder_conv2(reconstructed_input)#14x14x16 to 1
4x14x8
        reconstructed_input     = self.unpool(reconstructed_input,indices1)#14x14x8 to
 28x28x8
        reconstructed_input     = self.decoder_conv3(reconstructed_input)#28x28x8 to 28
x28x1


        return reconstructed_input
```

In [54]:

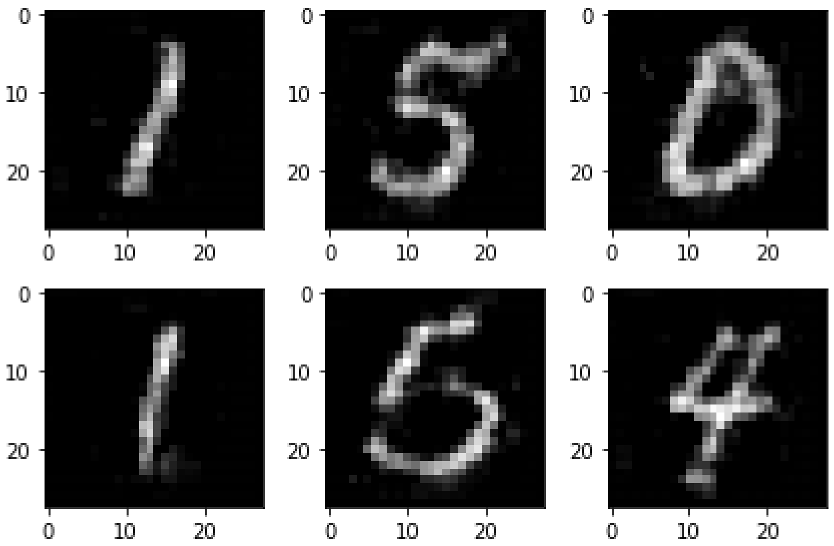
```
model = conv_AE_unpool()
optimizer = torch.optim.Adam(model.parameters(), lr = 0.0001)
model_state = train_convAE(epochs, model, loss_func, loaders)
torch.save(model_state, 'ConvAE_unpool.dth')
model.load_state_dict(torch.load('ConvAE_unpool.dth'))

test_loss = evaluate_convAE(model, loss_func, loaders)

print('Convolutional AE: Decoding by unpooling')
print(f'Test Loss: {test_loss:.3f}%')
```

```
Epoch: 1/10, Train Loss: 0.08146941, Val Loss: 0.05784879
Saving the model state dictionary for Epoch: 1 with Validation loss: 0.057
84879

Epoch: 2/10, Train Loss: 0.04745516, Val Loss: 0.03985545
Saving the model state dictionary for Epoch: 2 with Validation loss: 0.039
85545

Epoch: 3/10, Train Loss: 0.03340785, Val Loss: 0.02897443
Saving the model state dictionary for Epoch: 3 with Validation loss: 0.028
97443

Epoch: 4/10, Train Loss: 0.02605863, Val Loss: 0.02368008
Saving the model state dictionary for Epoch: 4 with Validation loss: 0.023
68008

Epoch: 5/10, Train Loss: 0.02123185, Val Loss: 0.01911809
Saving the model state dictionary for Epoch: 5 with Validation loss: 0.019
11809

Epoch: 6/10, Train Loss: 0.01751559, Val Loss: 0.01608907
Saving the model state dictionary for Epoch: 6 with Validation loss: 0.016
08907

Epoch: 7/10, Train Loss: 0.01511572, Val Loss: 0.01416826
Saving the model state dictionary for Epoch: 7 with Validation loss: 0.014
16826

Epoch: 8/10, Train Loss: 0.01351390, Val Loss: 0.01284182
Saving the model state dictionary for Epoch: 8 with Validation loss: 0.012
84182

Epoch: 9/10, Train Loss: 0.01236237, Val Loss: 0.01188423
Saving the model state dictionary for Epoch: 9 with Validation loss: 0.011
88423

Epoch: 10/10, Train Loss: 0.01151818, Val Loss: 0.01114880
Saving the model state dictionary for Epoch: 10 with Validation loss: 0.01
114880
Convolutional AE: Decoding by unpooling
Test Loss: 0.012%
```


Loss Plot
Train loss
Validation loss
Loss
Epochs
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
2
4
6
8
10

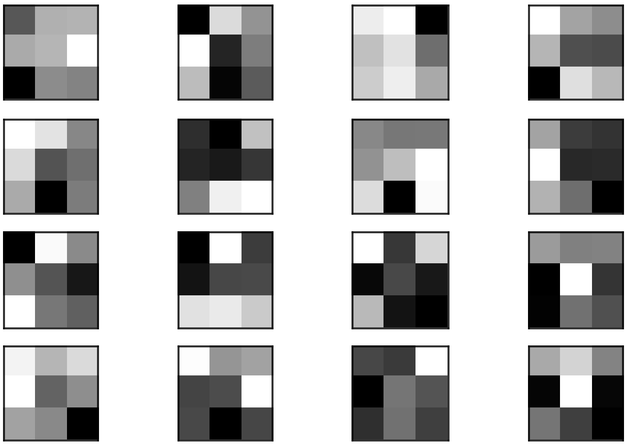
In [55]:

```
for itr, (images, labels) in enumerate(loaders['test']):
    output = model(images.float())
    output = output.detach().numpy().reshape(-1,28,28)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[0],cmap='gray')
    ax2.imshow(output[1],cmap='gray')
    ax3.imshow(output[2],cmap='gray')
    ax4.imshow(output[3],cmap='gray')
    ax5.imshow(output[4],cmap='gray')
    ax6.imshow(output[5],cmap='gray')
    fig.tight_layout()
    break
```



In [56]:

```
ix=1
fig,ax=plt.subplots()
for i in range(16):
    ax=plt.subplot(4,4,ix)
    ax.set_xticks([])
    ax.set_yticks([])
    im=ax.imshow(model.decoder_conv2[0].weight[0,i,:,:].detach().numpy().reshape(3,3),c
map='gray')
    ix+=1
```



Decoder: upsample only by deconvolving

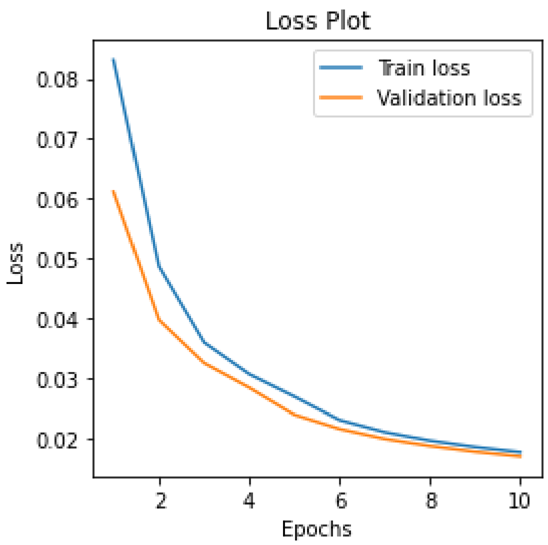
In [57]:

```
class conv_AE_deconv(nn.Module):
    def __init__(self): #class constructor
        super(conv_AE_deconv,self).__init__() #calls the parent constructor

        #initializing the encoder module
        self.encoder_conv1 = nn.Sequential(nn.Conv2d(1,8, kernel_size = 3, stride = 1,p
adding= 1),nn.ReLU(),nn.MaxPool2d(kernel_size = (2,2)))
        self.encoder_conv2 = nn.Sequential(nn.Conv2d(8,16, kernel_size = 3, stride = 1,
padding= 1),nn.ReLU(),nn.MaxPool2d(kernel_size = (2,2)))
        self.encoder_conv3 = nn.Sequential(nn.Conv2d(16,16, kernel_size = 3, stride = 1
,padding= 1),nn.ReLU(),nn.MaxPool2d(kernel_size = (2,2)))

        #initializing the decoder module
        self.decoder_conv1 = nn.Sequential(nn.ConvTranspose2d(16,16, kernel_size = 3, s
tride = 2),nn.ReLU())
        self.decoder_conv2 = nn.Sequential(nn.ConvTranspose2d(16,8, kernel_size = 4, st
ride = 2, padding = 1),nn.ReLU())
        self.decoder_conv3 = nn.Sequential(nn.ConvTranspose2d(8,1, kernel_size = 4, str
ide = 2, padding = 1),nn.ReLU())

    def forward(self,x): #defines the forward pass and also the structure of the networ
k thus helping backprop

        encoded_input  = self.encoder_conv1(x.float())
        encoded_input  = self.encoder_conv2(encoded_input)
        encoded_input  = self.encoder_conv3(encoded_input)

        reconstructed_input     = self.decoder_conv1(encoded_input)
        reconstructed_input     = self.decoder_conv2(reconstructed_input)
        reconstructed_input     = self.decoder_conv3(reconstructed_input)

        return reconstructed_input
```

In [58]:

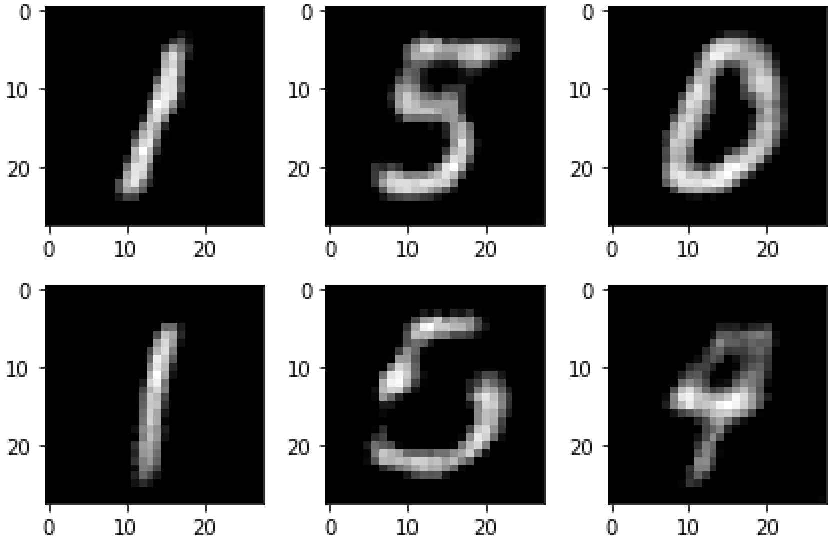
```
model = conv_AE_deconv()
optimizer = torch.optim.Adam(model.parameters(), lr = 0.0001)
model_state = train_convAE(epochs, model, loss_func, loaders)
torch.save(model_state, 'ConvAE_deconv.dth')
model.load_state_dict(torch.load('ConvAE_deconv.dth'))

test_loss = evaluate_convAE(model, loss_func, loaders)

print('Convolutional AE: Decoding by deconvolution')
print(f'Test Loss: {test_loss:.3f}%')
```

```
Epoch: 1/10, Train Loss: 0.08313170, Val Loss: 0.06114338
Saving the model state dictionary for Epoch: 1 with Validation loss: 0.061
14338

Epoch: 2/10, Train Loss: 0.04864719, Val Loss: 0.03968785
Saving the model state dictionary for Epoch: 2 with Validation loss: 0.039
68785

Epoch: 3/10, Train Loss: 0.03592064, Val Loss: 0.03246369
Saving the model state dictionary for Epoch: 3 with Validation loss: 0.032
46369

Epoch: 4/10, Train Loss: 0.03061918, Val Loss: 0.02837561
Saving the model state dictionary for Epoch: 4 with Validation loss: 0.028
37561

Epoch: 5/10, Train Loss: 0.02689574, Val Loss: 0.02383384
Saving the model state dictionary for Epoch: 5 with Validation loss: 0.023
83384

Epoch: 6/10, Train Loss: 0.02296005, Val Loss: 0.02146911
Saving the model state dictionary for Epoch: 6 with Validation loss: 0.021
46911

Epoch: 7/10, Train Loss: 0.02094026, Val Loss: 0.01981629
Saving the model state dictionary for Epoch: 7 with Validation loss: 0.019
81629

Epoch: 8/10, Train Loss: 0.01952578, Val Loss: 0.01863801
Saving the model state dictionary for Epoch: 8 with Validation loss: 0.018
63801

Epoch: 9/10, Train Loss: 0.01847504, Val Loss: 0.01768531
Saving the model state dictionary for Epoch: 9 with Validation loss: 0.017
68531

Epoch: 10/10, Train Loss: 0.01762227, Val Loss: 0.01691854
Saving the model state dictionary for Epoch: 10 with Validation loss: 0.01
691854
Convolutional AE: Decoding by deconvolution
Test Loss: 0.017%
```



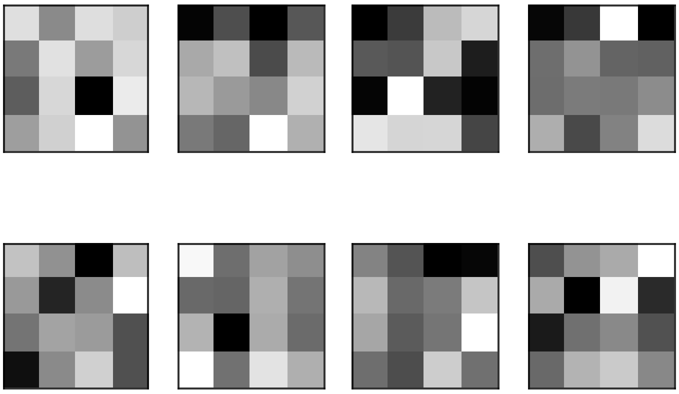
In [59]:

```
for itr, (images, labels) in enumerate(loaders['test']):
    output = model(images.float())
    output = output.detach().numpy().reshape(-1,28,28)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[0],cmap='gray')
    ax2.imshow(output[1],cmap='gray')
    ax3.imshow(output[2],cmap='gray')
    ax4.imshow(output[3],cmap='gray')
    ax5.imshow(output[4],cmap='gray')
    ax6.imshow(output[5],cmap='gray')
    fig.tight_layout()
    break
```



In [60]:

```
ix=1
fig,ax=plt.subplots()
for i in range(8):
    ax=plt.subplot(2,4,ix)
    ax.set_xticks([])
    ax.set_yticks([])
    im=ax.imshow(model.decoder_conv2[0].weight[0,i,:,:].detach().numpy().reshape(4,4),c
map='gray')
    ix+=1
```



Decoder: upsample by unpool and deconvolving

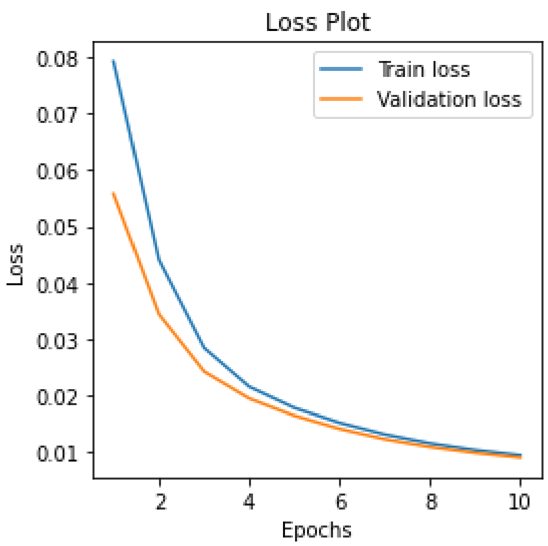
In [61]:

```
class conv_AE_deconv_unpool(nn.Module):
    def __init__(self): #class constructor
        super(conv_AE_deconv_unpool,self).__init__() #calls the parent constructor

         #initializing the encoder module
        self.encoder_conv1 = nn.Sequential(nn.Conv2d(1,8, kernel_size = 3, stride = 1,p
adding= 1),nn.ReLU(),nn.MaxPool2d(kernel_size = (2,2),return_indices = True))
        self.encoder_conv2 = nn.Sequential(nn.Conv2d(8,16, kernel_size = 3, stride = 1,
padding= 1),nn.ReLU(),nn.MaxPool2d(kernel_size = (2,2),return_indices = True))
        self.encoder_conv3 = nn.Sequential(nn.Conv2d(16,16, kernel_size = 3, stride = 1
,padding= 1),nn.ReLU(),nn.MaxPool2d(kernel_size = (2,2),return_indices = True))

        #initializing the decoder module
        self.decoder_conv1 = nn.Sequential(nn.ConvTranspose2d(16,16, kernel_size = 3, s
tride = 1, padding = 1),nn.ReLU())
        self.decoder_conv2 = nn.Sequential(nn.ConvTranspose2d(16,8, kernel_size = 3, st
ride = 1, padding = 1),nn.ReLU())
        self.decoder_conv3 = nn.Sequential(nn.ConvTranspose2d(8,1, kernel_size = 3, str
ide = 1, padding = 1),nn.ReLU())

        #defining the unpooling operation
        self.unpool = nn.MaxUnpool2d(kernel_size = (2,2))

    def forward(self,x): #defines the forward pass and also the structure of the networ
k thus helping backprop

        encoded_input,indices1  = self.encoder_conv1(x.float())
        encoded_input,indices2  = self.encoder_conv2(encoded_input)
        encoded_input,indices3  = self.encoder_conv3(encoded_input)


        reconstructed_input     = self.unpool(encoded_input,indices3,output_size=torch.
Size([batch_size, 16, 7, 7]))
        reconstructed_input     = self.decoder_conv1(reconstructed_input)
        reconstructed_input     = self.unpool(reconstructed_input,indices2)
        reconstructed_input     = self.decoder_conv2(reconstructed_input)
        reconstructed_input     = self.unpool(reconstructed_input,indices1)
        reconstructed_input     = self.decoder_conv3(reconstructed_input)


        return reconstructed_input
```

In [62]:

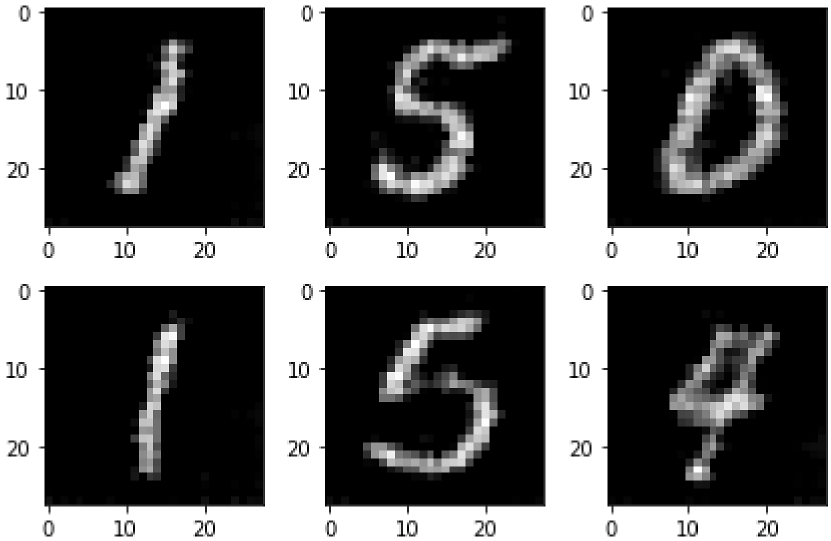
```
model = conv_AE_deconv_unpool()
optimizer = torch.optim.Adam(model.parameters(), lr = 0.0001)
model_state = train_convAE(epochs, model, loss_func, loaders)
torch.save(model_state, 'ConvAE_deconvunpool.dth')
model.load_state_dict(torch.load('ConvAE_deconvunpool.dth'))

test_loss = evaluate_convAE(model, loss_func, loaders)

print('Convolutional AE: Decoding by deconvolution and unpooling')
print(f'Test Loss: {test_loss:.3f}%')
```

```
Epoch: 1/10, Train Loss: 0.07917652, Val Loss: 0.05579346
Saving the model state dictionary for Epoch: 1 with Validation loss: 0.055
79346

Epoch: 2/10, Train Loss: 0.04407337, Val Loss: 0.03443019
Saving the model state dictionary for Epoch: 2 with Validation loss: 0.034
43019

Epoch: 3/10, Train Loss: 0.02847877, Val Loss: 0.02429396
Saving the model state dictionary for Epoch: 3 with Validation loss: 0.024
29396

Epoch: 4/10, Train Loss: 0.02161339, Val Loss: 0.01953368
Saving the model state dictionary for Epoch: 4 with Validation loss: 0.019
53368

Epoch: 5/10, Train Loss: 0.01789357, Val Loss: 0.01649019
Saving the model state dictionary for Epoch: 5 with Validation loss: 0.016
49019

Epoch: 6/10, Train Loss: 0.01523623, Val Loss: 0.01417638
Saving the model state dictionary for Epoch: 6 with Validation loss: 0.014
17638

Epoch: 7/10, Train Loss: 0.01319627, Val Loss: 0.01234486
Saving the model state dictionary for Epoch: 7 with Validation loss: 0.012
34486

Epoch: 8/10, Train Loss: 0.01161702, Val Loss: 0.01098466
Saving the model state dictionary for Epoch: 8 with Validation loss: 0.010
98466

Epoch: 9/10, Train Loss: 0.01043959, Val Loss: 0.00995615
Saving the model state dictionary for Epoch: 9 with Validation loss: 0.009
95615

Epoch: 10/10, Train Loss: 0.00953472, Val Loss: 0.00913176
Saving the model state dictionary for Epoch: 10 with Validation loss: 0.00
913176
Convolutional AE: Decoding by deconvolution and unpooling
Test Loss: 0.009%
```



In [63]:

```
for itr, (images, labels) in enumerate(loaders['test']):
    output = model(images.float())
    output = output.detach().numpy().reshape(-1,28,28)
    fig, ((ax1, ax2, ax3), (ax4, ax5, ax6)) = plt.subplots(2,3)
    ax1.imshow(output[0],cmap='gray')
    ax2.imshow(output[1],cmap='gray')
    ax3.imshow(output[2],cmap='gray')
    ax4.imshow(output[3],cmap='gray')
    ax5.imshow(output[4],cmap='gray')
    ax6.imshow(output[5],cmap='gray')
    fig.tight_layout()
    break
```



In [64]:

```
ix=1
fig,ax=plt.subplots()
for i in range(8):
    ax=plt.subplot(2,4,ix)
    ax.set_xticks([])
    ax.set_yticks([])
    im=ax.imshow(model.decoder_conv2[0].weight[0,i,:,:].detach().numpy().reshape(3,3),c
map='gray')
    ix+=1
```