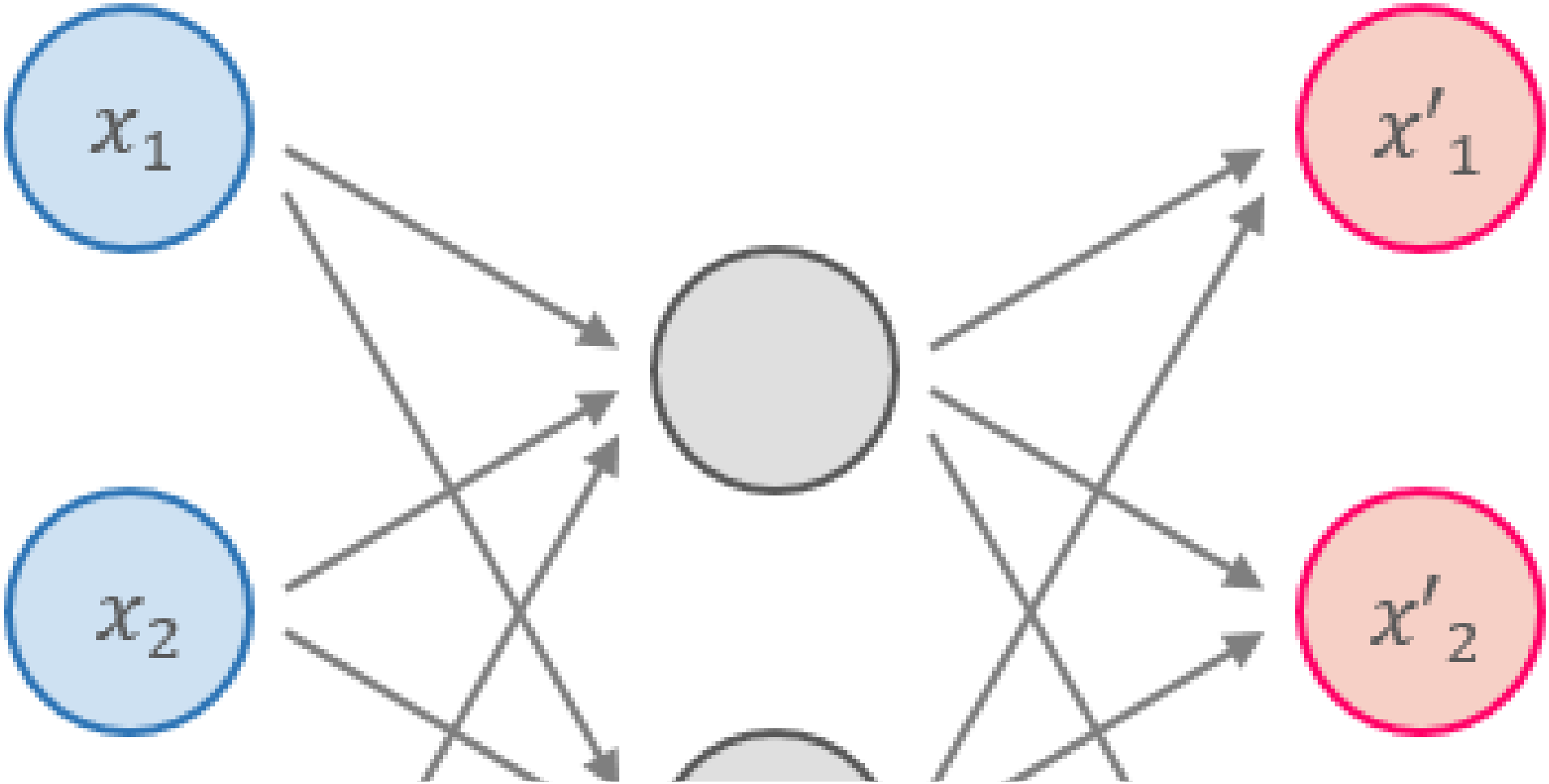
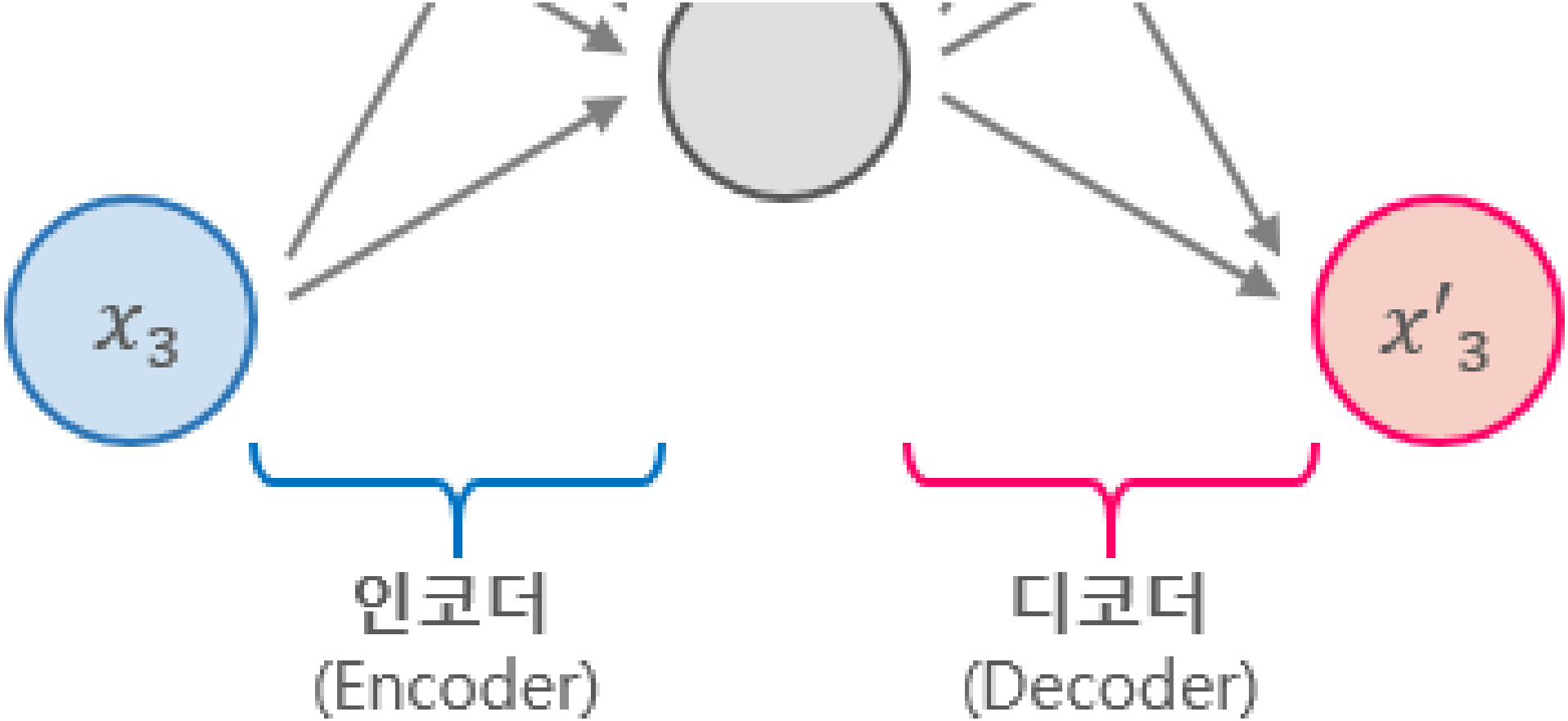
Auto Encoder

- 출처 : https://github.com/wjddyd66/Pytorch/blob/master/Autoencoder.ipynb

Autoencoder

AutoEncoder 은 아래의 그림과 같이 단순히 입력을 출력으로 복사하는 신경 망(비지도 학습) 이다.





아래 링크는 AutoEncoder에 관한 개념 설명이 나와있다.
[Auto Encoder]

1. Settings

1) Import required libraries

```
import numpy as np
import torch
```

```
import torch.nn as nn
import torch.optim as optim
import torch.nn.init as init
import torchvision.datasets as dset
import torchvision.transforms as transforms
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
```

2) Set hyperparameters

```
batch_size = 256
learning_rate = 0.0002
num_epoch = 5
```

2. Data

1) Download Data

```
mnist_train = dset.MNIST("./", train=True, transform=transforms.ToTensor(), target_transform=None, download=True)
mnist_test = dset.MNIST("./", train=False, transform=transforms.ToTensor(), target_transform=None, download=True)
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Failed to download (trying next):
HTTP Error 503: Service Unavailable

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-images-idx3-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-images-idx3-ubyte.gz to ./MNIST/r
```

9913344/? [00:13<00:00, 716383.75it/s]

```
Extracting ./MNIST/raw/train-images-idx3-ubyte.gz to ./MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Failed to download (trying next):
HTTP Error 503: Service Unavailable

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-labels-idx1-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-labels-idx1-ubyte.gz to ./MNIST/r
```

29696/? [00:00<00:00, 38881.80it/s]

```
Extracting ./MNIST/raw/train-labels-idx1-ubyte.gz to ./MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
Failed to download (trying next):
HTTP Error 503: Service Unavailable

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-idx3-ubyte.gz
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-idx3-ubyte.gz to ./MNIST/ra
```

1649664/? [00:00<00:00, 4116924.98it/s]

```
Extracting ./MNIST/raw/t10k-images-idx3-ubyte.gz to ./MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Failed to download (trying next):
HTTP Error 503: Service Unavailable
```

2) Set DataLoader

```
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-idx1-ubyte.gz to ./MNIST/ra
```

```
train_loader = torch.utils.data.DataLoader(mnist_train,batch_size=batch_size, shuffle=True, num_workers=2,drop_last=True)
```

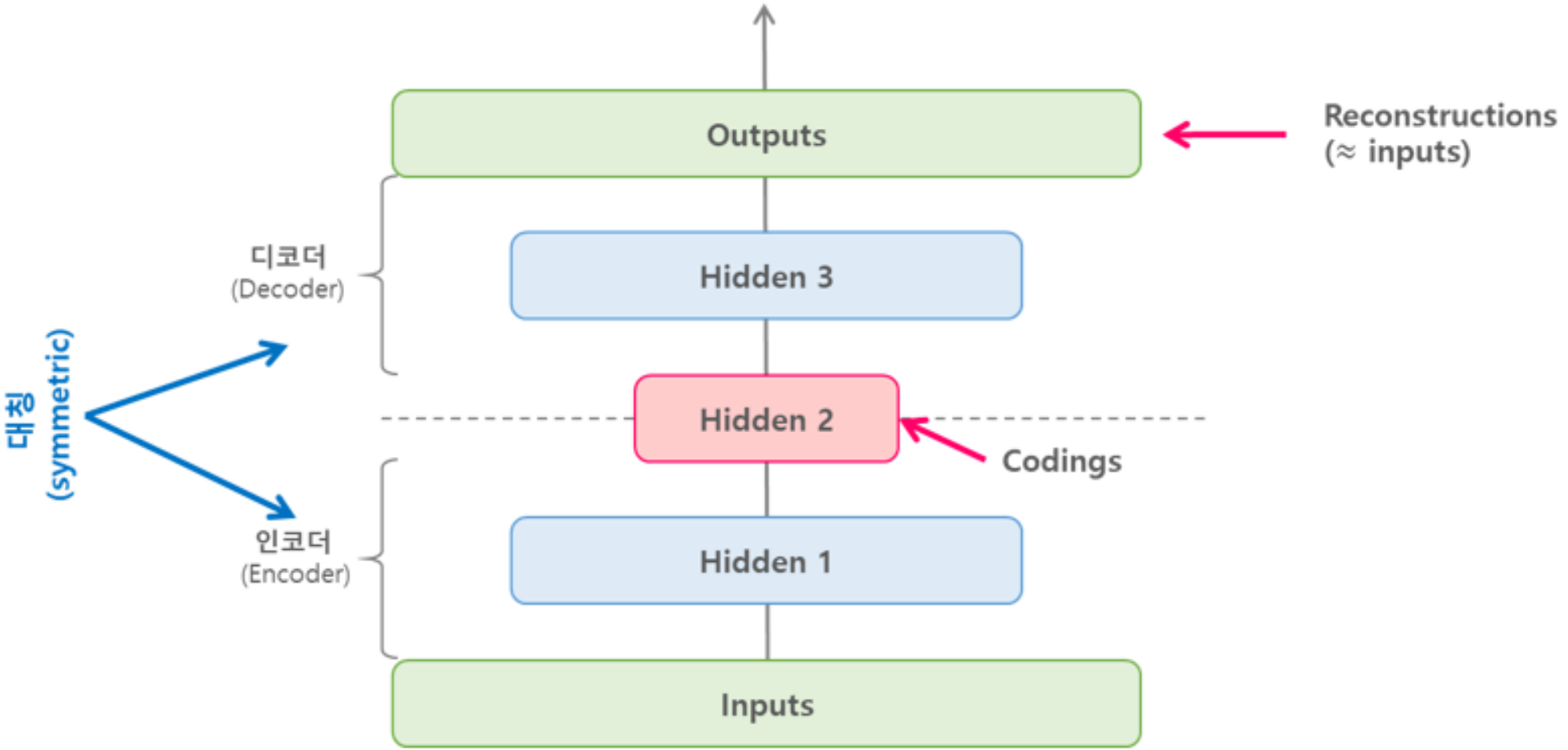
```
train_loader = torch.utils.data.DataLoader(mnist_train,batch_size=batch_size, shuffle=True,num_workers=2,drop_last=True)
test_loader = torch.utils.data.DataLoader(mnist_test,batch_size=batch_size, shuffle=False,num_workers=2,drop_last=True)
```

```
Extracting ./MNIST/raw/t10k-labels-idx1-ubyte.gz to ./MNIST/raw
```

Stacked AutoEncoder

Stacked AutoEncoder는 여러개의 히든 레이어를 가지는 Auto Encoder이며, 레이어를 추가할수록 AutoEncoder가 더 복잡한 코딩을 학습할 수 있다.

Stacked AutoEncoder는 아래의 그림과 같이 가운데 히든레이어를 기준으로 대칭인 구조를 가진다.



이번 Model은 MNIST를 분류하는 Stacked AutoEncoder를 구현하는 것 이다.

Encoder: [batch_size,1,28,28] -> x.view(batch_size,-1) -> [batch_size,784] -> nn.Linear(28 * 28, 20) -> [batch_size,20]

Decoder: [batch_size,20] -> nn.Linear(20 , 28 * 28) -> [batch_size,784] -> self.decoder(encoded).view(batch_size,1,28,28) -> [batch_size,1,28,28]

1) Model

```
class Autoencoder(nn.Module):
    def __init__(self):
        super(Autoencoder,self).__init__()
        self.encoder = nn.Linear(28*28,20)
        self.decoder = nn.Linear(20,28*28)

    def forward(self,x):
        x = x.view(batch_size,-1)
        encoded = self.encoder(x)
        out = self.decoder(encoded).view(batch_size,1,28,28)
        return out
```

2) Loss func & Optimizer

```
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print(device)

model = Autoencoder().to(device)
loss_func = nn.MSELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)
```

```
cuda:0
```

3) Train

```
loss_arr =[]
for i in range(num_epoch):
```

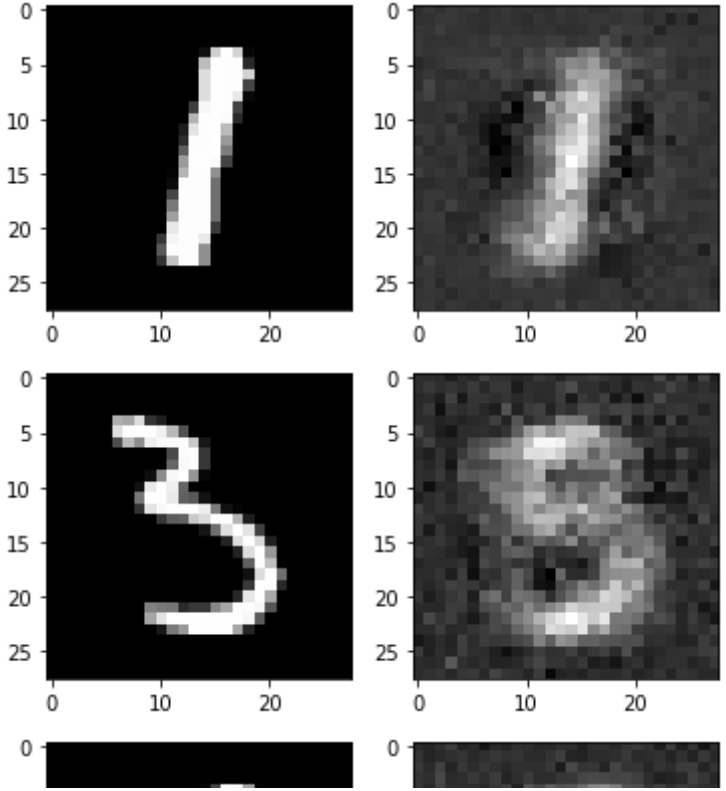
```
    for j,[image,label] in enumerate(train_loader):
        x = image.to(device)

        optimizer.zero_grad()
        output = model.forward(x)
        loss = loss_func(output,x)
        loss.backward()
        optimizer.step()

    if j % 1000 == 0:
        print(loss)
        loss_arr.append(loss.cpu().data.numpy()[0])
```

4) Check with Train Image

AutoEncoder의 Stacked AutoEncoder는 입력과 출력이 같기 때문에 Input Data만으로도 Model의 성능을 판단할 수 있다.

```
out_img = torch.squeeze(output.cpu().data)
print(out_img.size())

for i in range(3):
    plt.subplot(1,2,1)
    plt.imshow(torch.squeeze(image[i]).numpy(),cmap='gray')
    plt.subplot(1,2,2)
    plt.imshow(out_img[i].numpy(),cmap='gray')
    plt.show()
```

```
torch.Size([256, 28, 28])
```

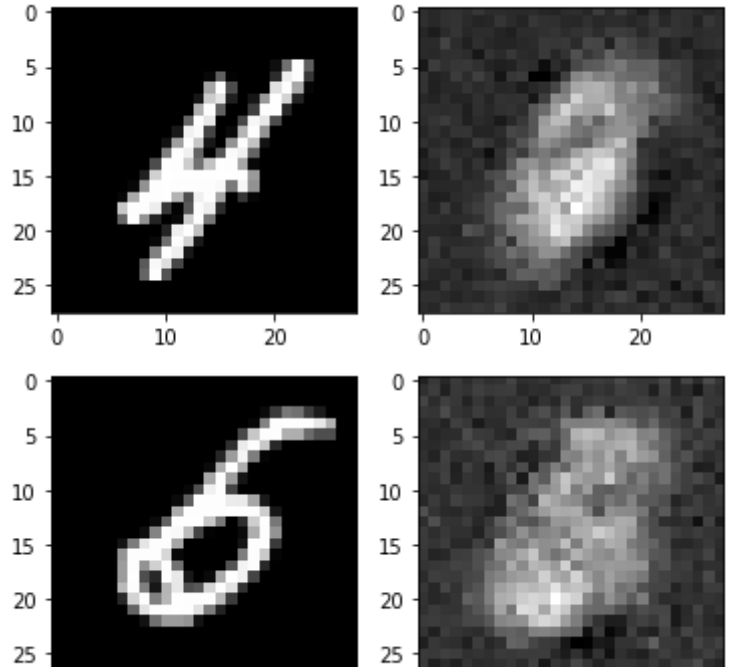


5) Check with Test Image

```
with torch.no_grad():
  for i in range(1):
      for j,[image,label] in enumerate(test_loader):
          x = image.to(device)

          optimizer.zero_grad()
          output = model.forward(x)

      if j % 1000 == 0:
          print(loss)
```

```
out_img = torch.squeeze(output.cpu().data)
print(out_img.size())

for i in range(2):
    plt.subplot(1,2,1)
    plt.imshow(torch.squeeze(image[i]).numpy(),cmap='gray')
    plt.subplot(1,2,2)
    plt.imshow(out_img[i].numpy(),cmap='gray')
    plt.show()
```

```
torch.Size([256, 28, 28])
```



Convolution Stacked AutoEncoder

Stacked AutoEncoder의 Model이 성능이 안좋은 것을 확인하여 Model을 ANN구조가 아닌 CNN의 구조로서 다시 작성한다.

중요한것은 **Convolution Stacked AutoEncoder에서의 Decoder**이다.
결국 줄어든 Feature 특성을 다시 Input Size에 맞게 늘리기 위해서는 Convolution연산과 같은 방법으로서 Data를 늘려야 하기 때문이다.
이러한 Convolution의 역 연산을 **DeConvolution**이라 한다.

Pytorch는 이러한 연산을 **ConvTranspose2d**을 통하여 지원한다.

```
torch.nn.ConvTranspose2d(in_channels, out_channels, kernel_size, stride=1, padding=0, output_padding=0, groups=1, bias=True, dilation=1, padding_mode='zeros')
```

- stride: controls the stride for the cross-correlation.
- padding: controls the amount of implicit zero-paddings on both sides for dilation * (kernel_size - 1) - padding number of points. See note below for details.
- output_padding: controls the additional size added to one side of the output shape. See note below for details.
- dilation: controls the spacing between the kernel points; also known as the à trous algorithm. It is harder to describe, but this link has a nice visualization of what dilation does.
- groups: controls the connections between inputs and outputs

아래와 같은 가정이 있을때 **간단한 수식을 사용하여 Output의 차원의 크기를 쉽게 예측**할 수 있다.

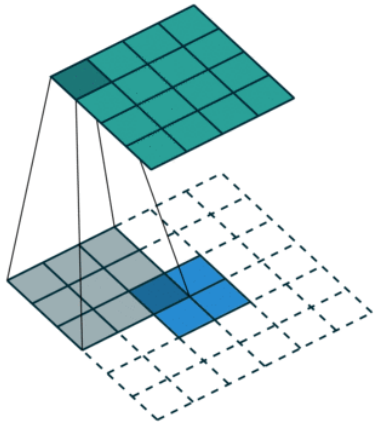
- 입력 크기: (N, C_{in}, H_{in}, W_{in})
- 출력 크기: (N, C_{out}, H_{out}, W_{out})

$$H_{out} = (H_{in} - 1) \times stride[0] - 2 \times padding[0] + dilation[0] \times (kernel_size[0] - 1) + output_padding[0] + 1$$
$$W_{out} = (W_{in} - 1) \times stride[0] - 2 \times padding[0] + dilation[0] \times (kernel_size[0] - 1) + output_padding[0] + 1$$

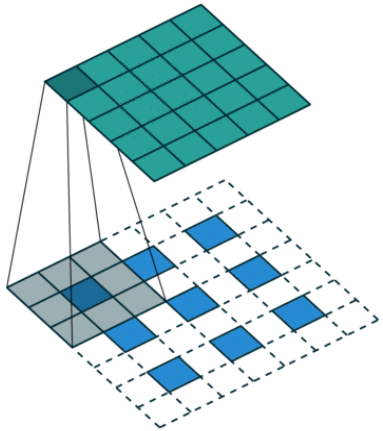
좀 더 명확히 알아보기 위하여 그림으로서 알아보자.
아래 그림의 Parameter는 다음과 같다.

- input size: 2 x 2
- output size: 4 x 4
- kernel size: 3 x 3
- stride: 1
- padding: 0

- out_padding: 0



위와 같은 조건에서 Parameter의 Stride를 2로 증가시키고 Padding을 넣었을 경우의 Deconvolution의 결과이다.



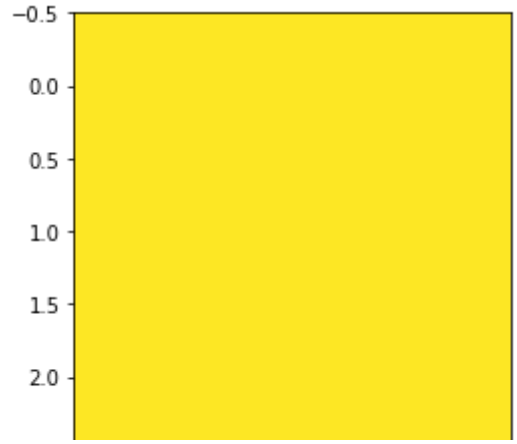
위의 두 그림에서 이해하기 힘든 **Deconvolution에서의 Padding과 Out_padding**에 대해서 좀 더 살펴보자.

Input data

```
# 입력으로 1로 채워진 텐서를 생성합니다.
img = torch.ones(1,1,3,3)
print(img)
```

```
plt.imshow(img.numpy()[0,0,...],vmin=0)

transpose = nn.ConvTranspose2d(in_channels=1, out_channels=1, kernel_size=3, stride=1, padding=0, output_padding=0, bias=False)
# 결과를 확인하기 쉽게 전치 컨볼루션 연산의 가중치를 1로 초기화합니다.
init.constant_(transpose.weight.data,1)
```

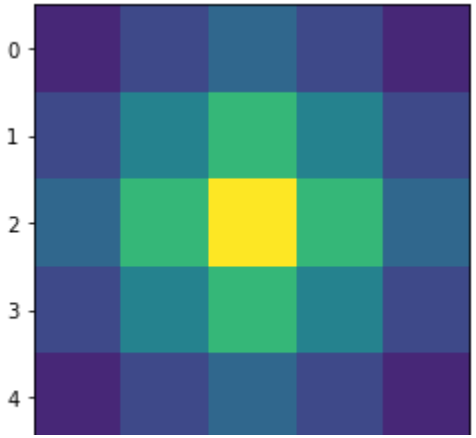
```
tensor([[[[1., 1., 1.],
          [1., 1., 1.],
          [1., 1., 1.]]]])
tensor([[[[1., 1., 1.],
          [1., 1., 1.],
          [1., 1., 1.]]]])
```



Kernel Size=3, stride=1, padding=0, output_padding=0

```
out = transpose(img)
print(out,out.size())

plt.imshow(out.detach().numpy()[0,0,...],vmin=0)
plt.show()
```

```
tensor([[[[1., 2., 3., 2., 1.],
          [2., 4., 6., 4., 2.],
          [3., 6., 9., 6., 3.],
          [2., 4., 6., 4., 2.],
          [1., 2., 3., 2., 1.]]]], grad_fn=<SlowConvTranspose2DBackward>) torch.Size([1, 1, 5, 5
```



Kernel Size=3, stride=2, padding=0, output_padding=0

Stride증가시 Output Size 커짐

```
transpose = nn.ConvTranspose2d(in_channels=1, out_channels=1, kernel_size=3, stride=2, padding=0, output_padding=0, bias=False)
init.constant_(transpose.weight.data,1)
out = transpose(img)

print(out,out.size())
plt.imshow(out.detach().numpy()[0,0,...],vmin=0)
```

```
tensor([[[[1., 1., 2., 1., 2., 1., 1.],
          [1., 1., 2., 1., 2., 1., 1.],
          [2., 2., 4., 2., 4., 2., 2.],
          [1., 1., 2., 1., 2., 1., 1.],
          [2., 2., 4., 2., 4., 2., 2.],
          [1., 1., 2., 1., 2., 1., 1.],
          [1., 1., 2., 1., 2., 1., 1.]]]],
       grad_fn=<SlowConvTranspose2DBackward>) torch.Size([1, 1, 7, 7])
<matplotlib.image.AxesImage at 0x7fbaa65fb550>
```

Kernel Size=3, stride=2, padding=1, output_padding=0

Padding 추가시 결과값에서 Outline padding크기만큼 제거

```
transpose = nn.ConvTranspose2d(in_channels=1, out_channels=1, kernel_size=3, stride=2, padding=1, output_padding=0, bias=False)
init.constant_(transpose.weight.data,1)
out = transpose(img)

print(out,out.size())
plt.imshow(out.detach().numpy()[0,0,...],vmin=0)
```

```
tensor([[[[1., 2., 1., 2., 1.],
          [2., 4., 2., 4., 2.],
          [1., 2., 1., 2., 1.],
          [2., 4., 2., 4., 2.],
          [1., 2., 1., 2., 1.]]]], grad_fn=<SlowConvTranspose2DBackward>) torch.Size([1, 1, 5, 5
<matplotlib.image.AxesImage at 0x7fbaa6463650>
```

Kernel Size=3, stride=2, padding=0, output_padding=1

out_padding 추가시 out_padding크기만큼 결과값 width, height증가

```
transpose = nn.ConvTranspose2d(in_channels=1, out_channels=1, kernel_size=3, stride=2, padding=0, output_padding=1, bias=False)
init.constant_(transpose.weight.data,1)
out=transpose(img)

print(out,out.size())
plt.imshow(out.detach().numpy()[0,0,...],vmin=0)
```

```
tensor([[[[1., 1., 2., 1., 2., 1., 1., 0.],
          [1., 1., 2., 1., 2., 1., 1., 0.],
          [2., 2., 4., 2., 4., 2., 2., 0.],
          [1., 1., 2., 1., 2., 1., 1., 0.],
          [2., 2., 4., 2., 4., 2., 2., 0.],
          [1., 1., 2., 1., 2., 1., 1., 0.],
          [1., 1., 2., 1., 2., 1., 1., 0.],
          [0., 0., 0., 0., 0., 0., 0., 0.]]]],
```

1) Model

Encoder: 기존에 사용하던 Convolution으로서 Input Size보다 작아지게 구성

Decoder: DeConvolution을 사용하여 Input Size만큼 크기를 키움

```
class Encoder(nn.Module):
    def __init__(self):
        super(Encoder,self).__init__()
        self.layer1 = nn.Sequential(
                        nn.Conv2d(1,16,3,padding=1),                    # batch x 16 x 28 x 28
                        nn.ReLU(),
                        nn.BatchNorm2d(16),
                        nn.Conv2d(16,32,3,padding=1),                   # batch x 32 x 28 x 28
                        nn.ReLU(),
                        nn.BatchNorm2d(32),
                        nn.Conv2d(32,64,3,padding=1),                   # batch x 32 x 28 x 28
                        nn.ReLU(),
                        nn.BatchNorm2d(64),
                        nn.MaxPool2d(2,2)                               # batch x 64 x 14 x 14
        )
        self.layer2 = nn.Sequential(
                        nn.Conv2d(64,128,3,padding=1),                  # batch x 64 x 14 x 14
                        nn.ReLU(),
                        nn.BatchNorm2d(128),
                        nn.MaxPool2d(2,2),
                        nn.Conv2d(128,256,3,padding=1),                 # batch x 64 x 7 x 7
                        nn.ReLU()
        )
```

```
        )

    def forward(self,x):
        out = self.layer1(x)
        out = self.layer2(out)
        out = out.view(batch_size, -1)
        return out



class Decoder(nn.Module):
    def __init__(self):
        super(Decoder,self).__init__()
        self.layer1 = nn.Sequential(
                        nn.ConvTranspose2d(256,128,3,2,1,1),                    # batch x 128 x 14 x 14
                        nn.ReLU(),
                        nn.BatchNorm2d(128),
                        nn.ConvTranspose2d(128,64,3,1,1),                       # batch x 64 x 14 x 14
                        nn.ReLU(),
                        nn.BatchNorm2d(64)
        )
        self.layer2 = nn.Sequential(
                        nn.ConvTranspose2d(64,16,3,1,1),                        # batch x 16 x 14 x 14
                        nn.ReLU(),
                        nn.BatchNorm2d(16),
                        nn.ConvTranspose2d(16,1,3,2,1,1),                       # batch x 1 x 28 x 28
                        nn.ReLU()
        )

    def forward(self,x):
        out = x.view(batch_size,256,7,7)
        out = self.layer1(out)
        out = self.layer2(out)
        return out
```

2) Loss func & Optimizer

Loss Function에서 중요한 점은 Encoder와 Decoder의 Parameter를 동시에 학습시키기 위해 묶어서 Optimizer에적용시켜야 한다.

```
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print(device)

encoder = Encoder().to(device)
decoder = Decoder().to(device)

# 인코더 디코더의 파라미터를 동시에 학습시키기 위해 이를 묶는 방법입니다.
parameters = list(encoder.parameters())+ list(decoder.parameters())

loss_func = nn.MSELoss()
optimizer = torch.optim.Adam(parameters, lr=learning_rate)
```

```
cuda:0
```

3) Train

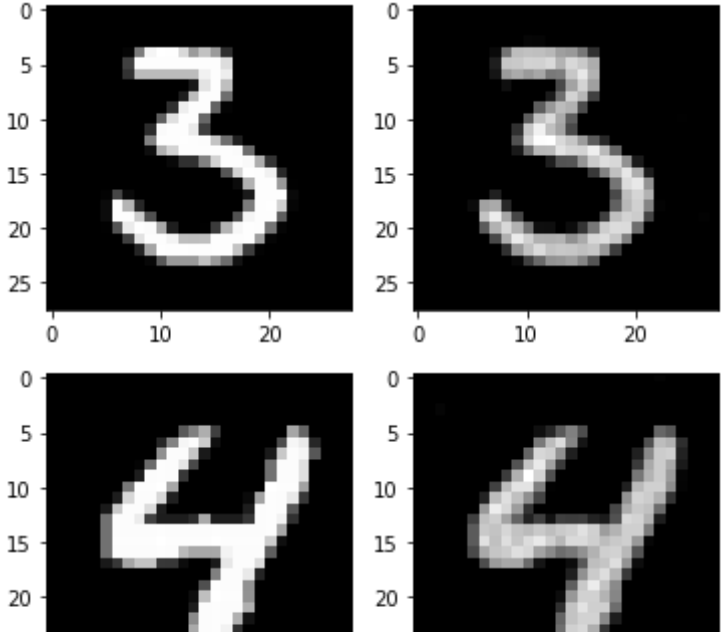
```
# 모델을 불러오는 방법입니다.
# 크게 두가지 방법이 있는데 여기 사용된 방법은 좀 단순한 방법입니다.
# https://pytorch.org/tutorials/beginner/saving_loading_models.html

try:
    encoder, decoder = torch.load('./model/conv_autoencoder.pkl')
    print("\n--------model restored--------\n")
except:
    print("\n--------model not restored--------\n")
    pass

for i in range(num_epoch):
    for j,[image,label] in enumerate(train_loader):
        optimizer.zero_grad()
```

```
            image = image.to(device)

            output = encoder(image)
            output = decoder(output)

            loss = loss_func(output,image)
            loss.backward()
            optimizer.step()

        if j % 10 == 0:
            # 모델 저장하는 방법
            # 이 역시 크게 두가지 방법이 있는데 여기 사용된 방법은 좀 단순한 방법입니다.
            # https://pytorch.org/tutorials/beginner/saving_loading_models.html
            torch.save([encoder,decoder],'./model/conv_autoencoder.pkl')
            print(loss)



        --------model not restored--------
```

4) Check with Train Image

```
out_img = torch.squeeze(output.cpu().data)
print(out_img.size())

for i in range(2):
    plt.subplot(1,2,1)
    plt.imshow(torch.squeeze(image[i]).cpu().numpy(),cmap='gray')
    plt.subplot(1,2,2)
    plt.imshow(out_img[i].numpy(),cmap='gray')
    plt.show()
```

```
torch.Size([256, 28, 28])
```



5) Check with Train Image

```
with torch.no_grad():
    for j,[image,label] in enumerate(test_loader):

        image = image.to(device)
        output = encoder(image)
        output = decoder(output)

    if j % 10 == 0:
        print(loss)


out_img = torch.squeeze(output.cpu().data)
print(out_img.size())

for i in range(2):
    plt.subplot(1,2,1)
```

```
plt.imshow(torch.squeeze(image[i]).cpu().numpy(),cmap='gray')
plt.subplot(1,2,2)
plt.imshow(out_img[i].numpy(),cmap='gray')
plt.show()
```

```
torch.Size([256, 28, 28])
```