Autoencoder &
Transposed Convolution

2018.02.28

최건호

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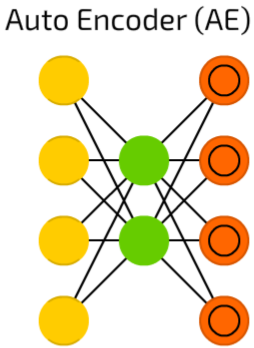
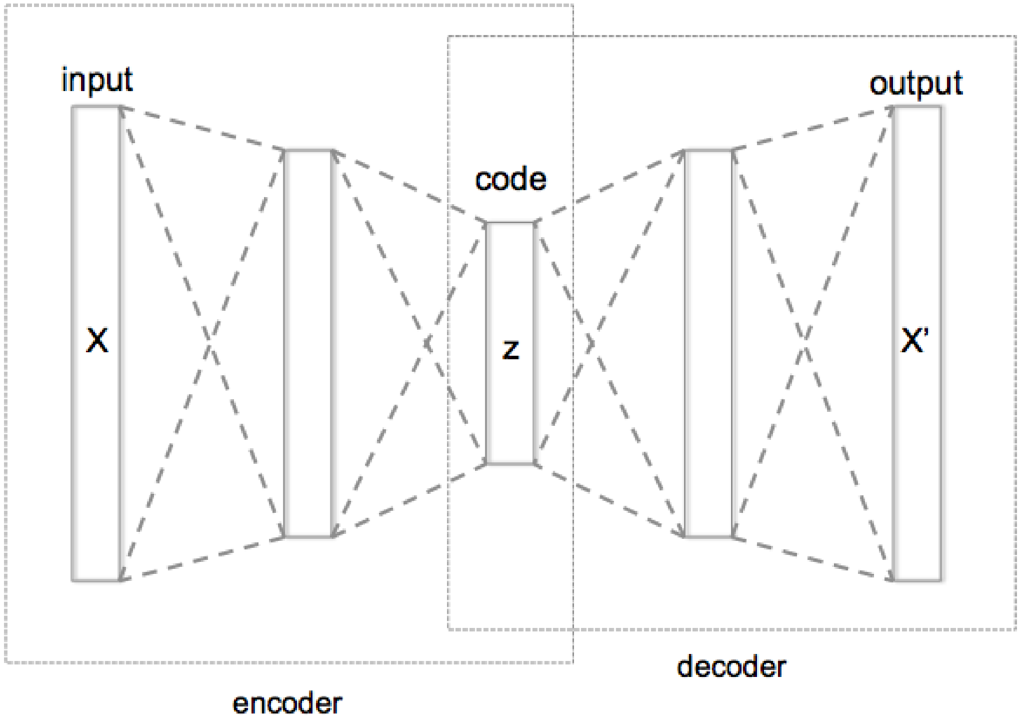
Autoencoder



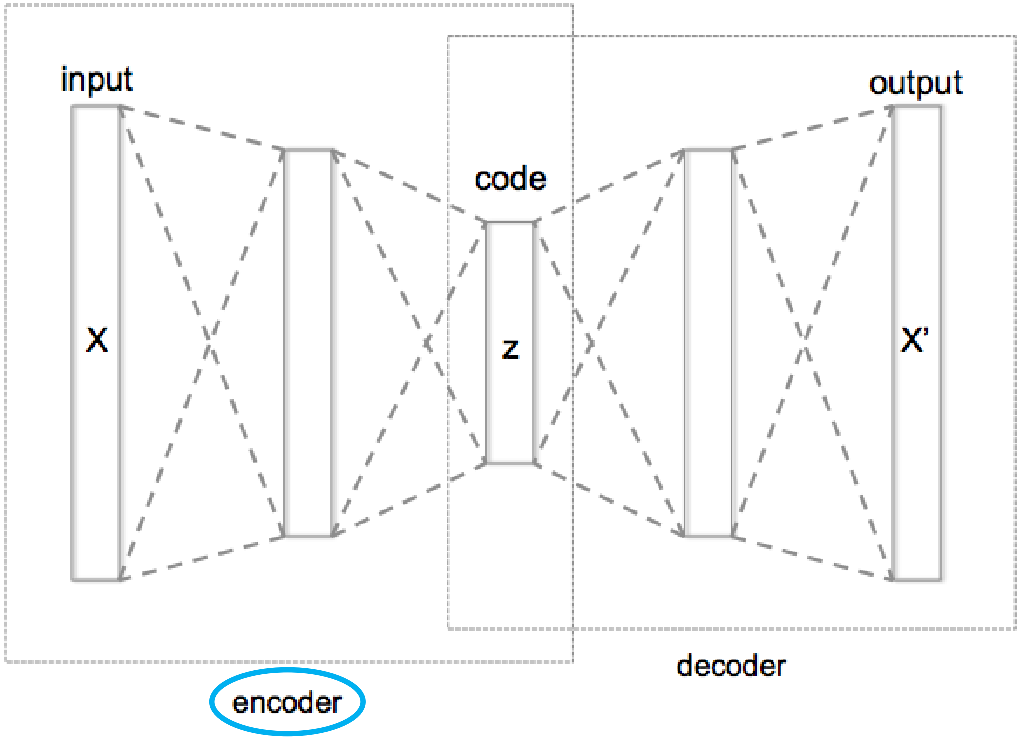
- Unsupervised Learning
- Feature Learning
- Representation Learning
- Efficient Coding
- Dimensionality Reduction

(출처: http://www.asimovinstitute.org/neural-network-zoo/)

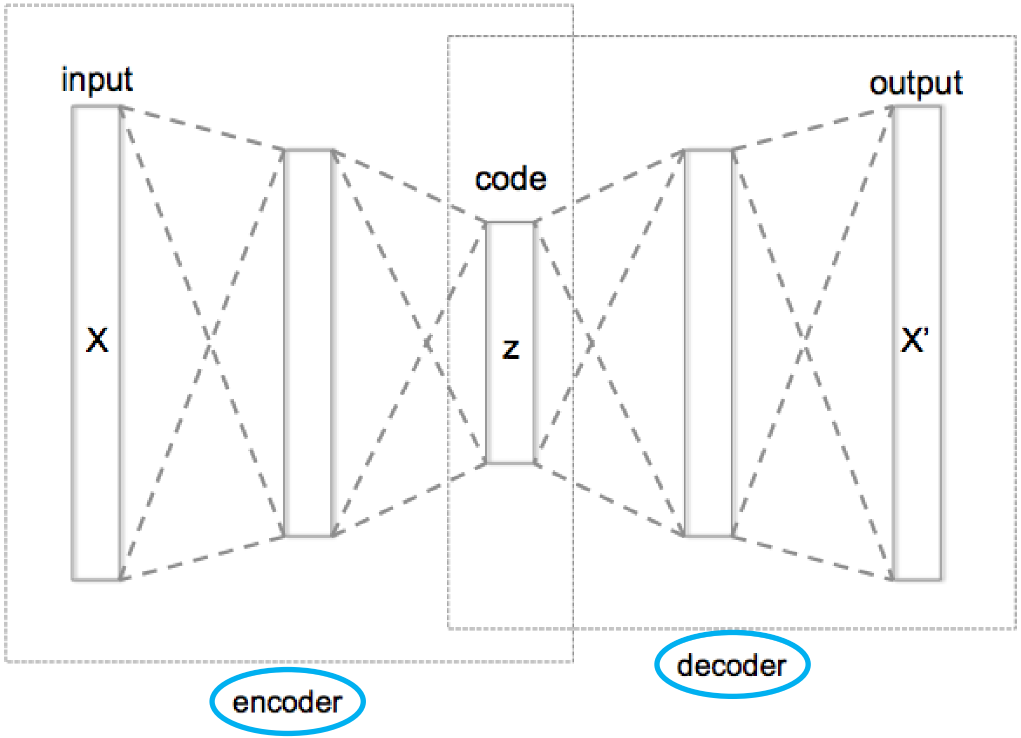
Autoencoder



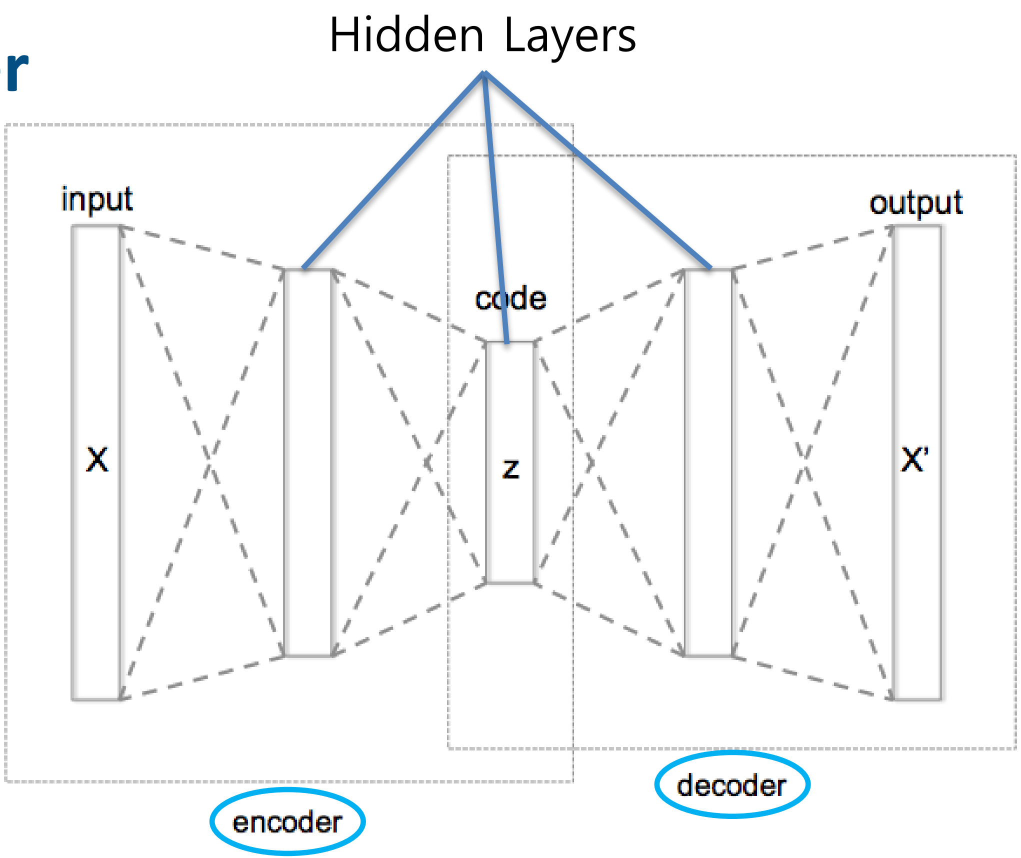
Autoencoder



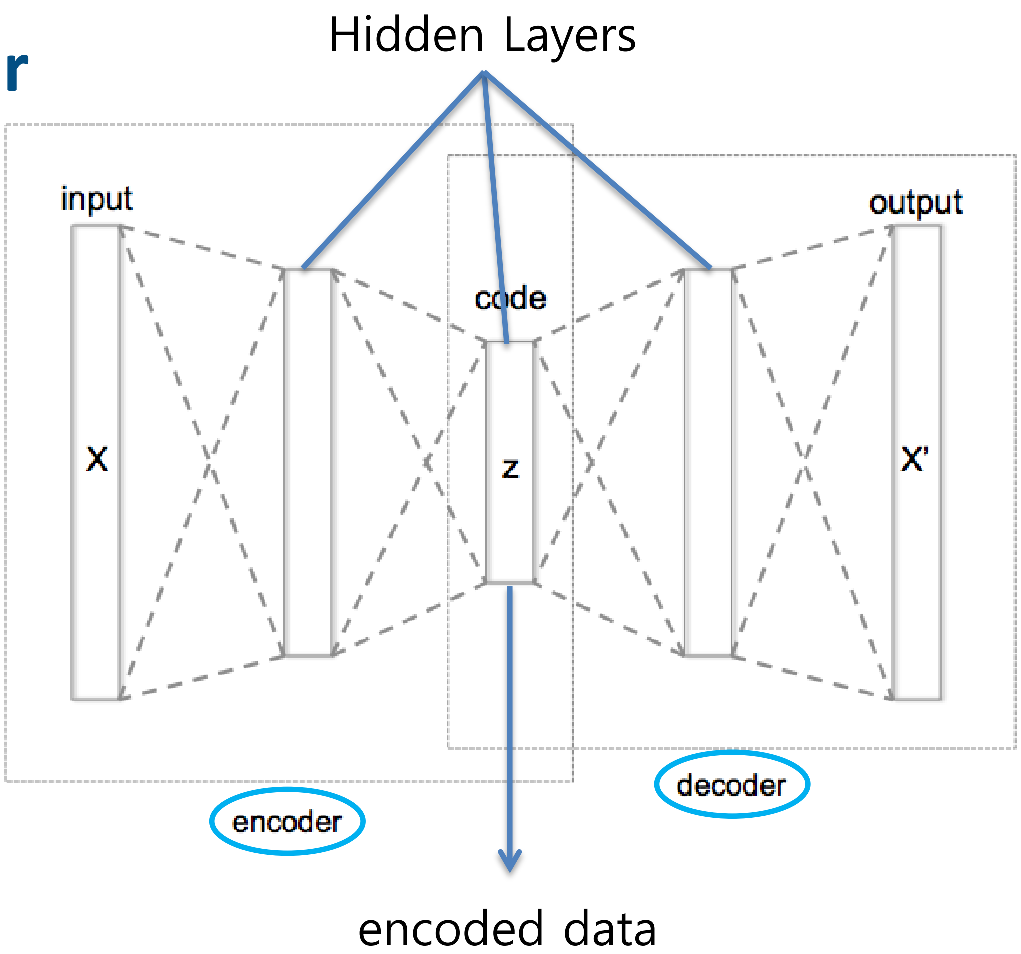
Autoencoder



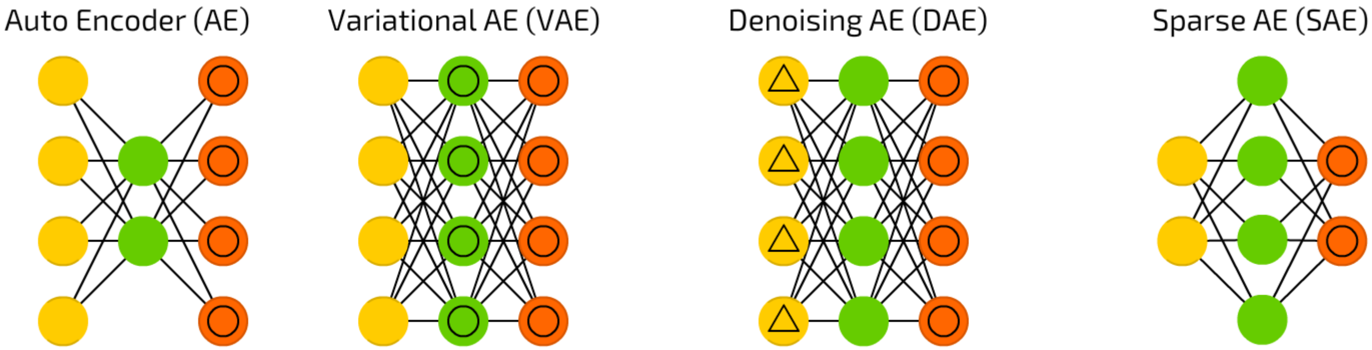
Autoencoder



Autoencoder



Autoencoder



다양한 형태가 있음

(출처: http://www.asimovinstitute.org/neural-network-zoo/)

Autoencoder

Loss는 어떻게 계산할까?

Autoencoder

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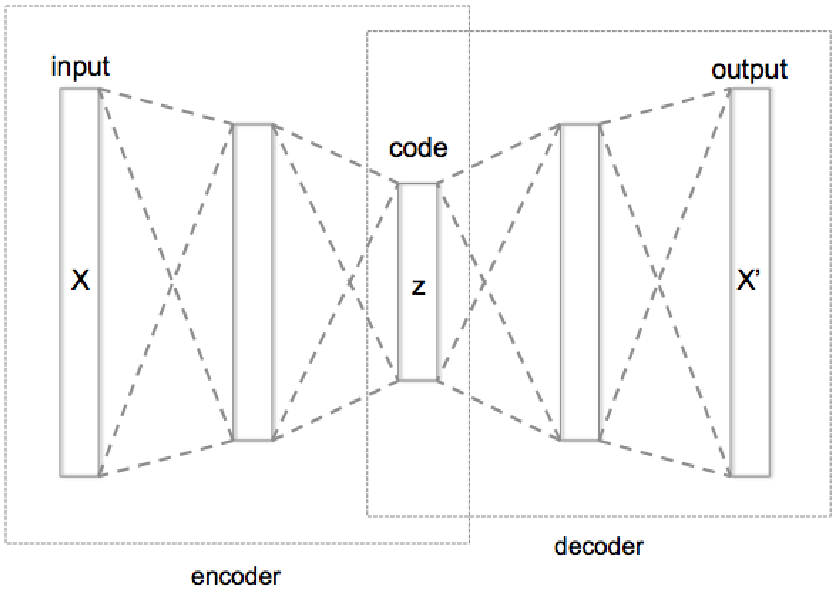

Autoencoder

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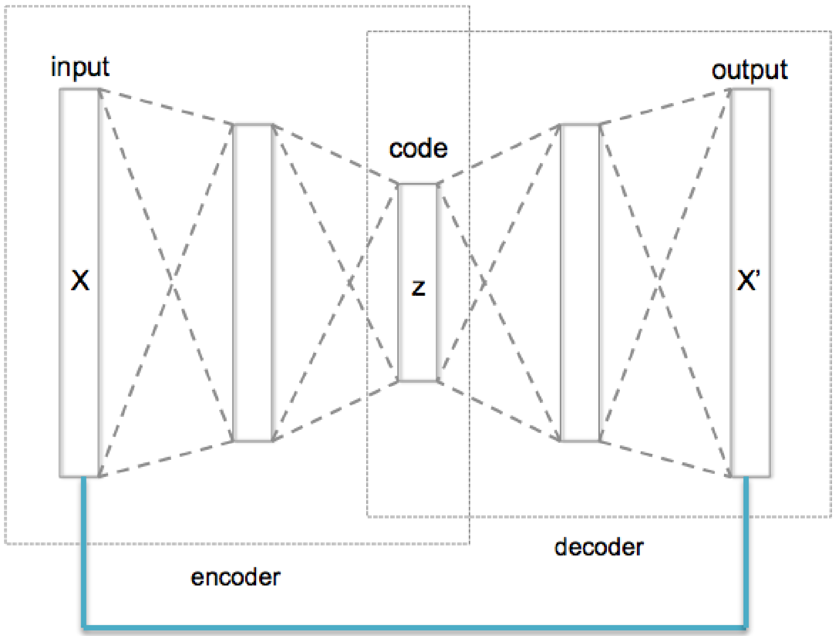
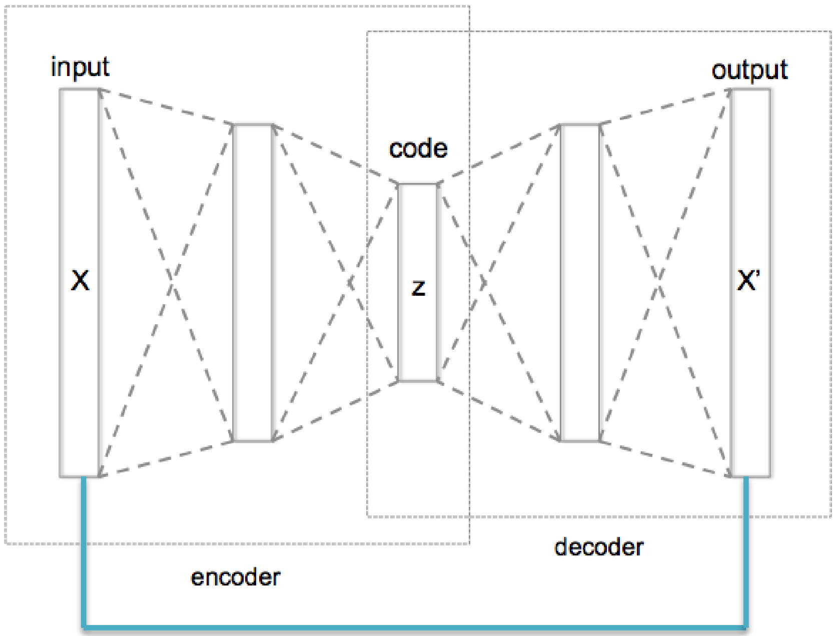


$$\|x - x'\|$$

Autoencoder

Loss는 어떻게 계산할까?

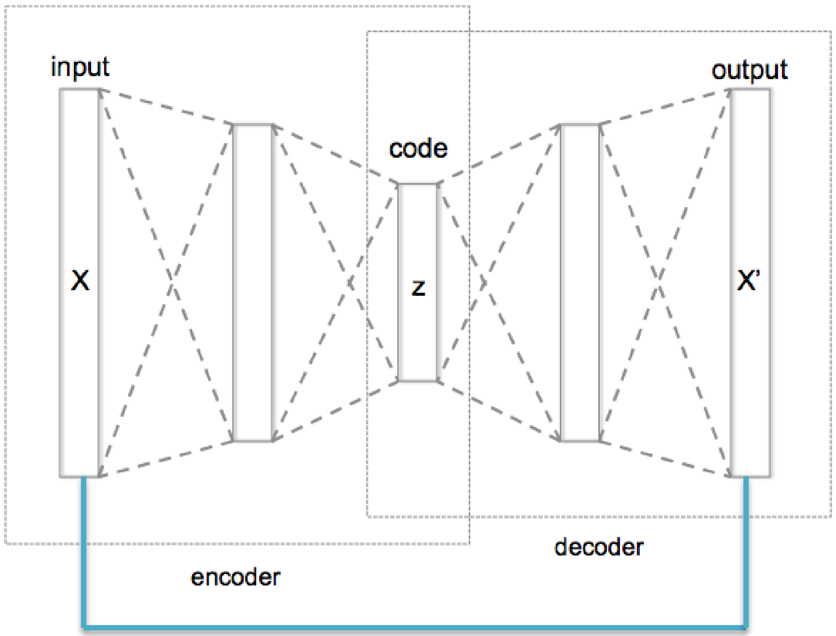


$$\|x - x'\|$$

원본 데이터 x 자체가 라벨의 역할을 하여 reconstructed 된 데이터 또는 decoded 데이터와의 차이로 loss를 계산.

Autoencoder

Loss는 어떻게 계산할까?



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L1 loss나 L2 loss를 많이 사용함

Autoencoder

MNIST data

```
class Autoencoder(nn.Module):
    def __init__(self):
        super(Autoencoder,self).__init__()
        self.encoder = nn.Linear(28*28,50)
        self.decoder = nn.Linear(50,28*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

model = Autoencoder().cuda()
```

Autoencoder

MNIST 데이터는 28x28 이기 때문에 784개의 숫자를 50짜리 latent feature로 encode

```python
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Autoencoder

MNIST data

MNIST 데이터는 28x28 이기 때문에 784개의 숫자를 50짜리 latent feature로 encode

50개의 latent feature에서 다시 784개로 decode

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        out = self.decoder(encoded).view(batch_size,1,28,28)

        return out

model = Autoencoder().cuda()
```

50개의 latent feature에서 다시 784개로 decode

모델 구조에 알맞게 데이터를 reshape하여 전달

Autoencoder

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

loss_arr =[]

for i in range(num_epoch):
    for j,[image,label] in enumerate(train_loader):
        x = Variable(image).cuda()

        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])
```

Autoencoder

Loss function은 Mean Squared Error

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

loss_arr =[]

for i in range(num_epoch):
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        loss.backward()
        optimizer.step()

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

Autoencoder

Loss function은 Mean Squared Error

원본 데이터 x와 모델의 output간의 차이를 통해 loss를 구하고 Back Prop.

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

loss_arr =[]

for i in range(num_epoch):
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        x = Variable(image).cuda()

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

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        print(loss)
        loss_arr.append(loss.cpu().data.numpy()[0])
```

Convolution Transposed

이미지 데이터를 사용할 때는 Encoding, Decoding을 Fully connected layer 말고 Convolution으로 할 수는 없을까?

Convolution Transposed

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⇩

Encoding 부분은 기존의 convolution 연산으로 가능한데 Decoding 부분은 어떻게 하지?

Convolution Transposed

이미지 데이터를 사용할 때는 Encoding, Decoding을 Fully connected layer 말고 Convolution으로 할 수는 없을까?

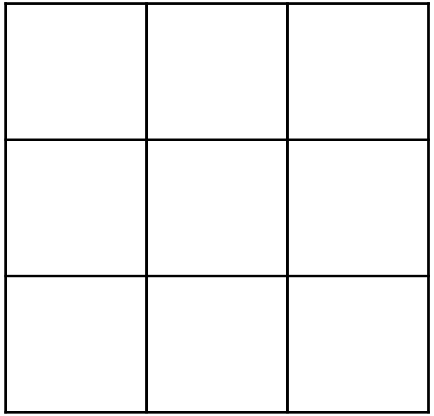
⇩

Encoding 부분은 기존의 convolution 연산으로 가능한데 Decoding 부분은 어떻게 하지?

⇩

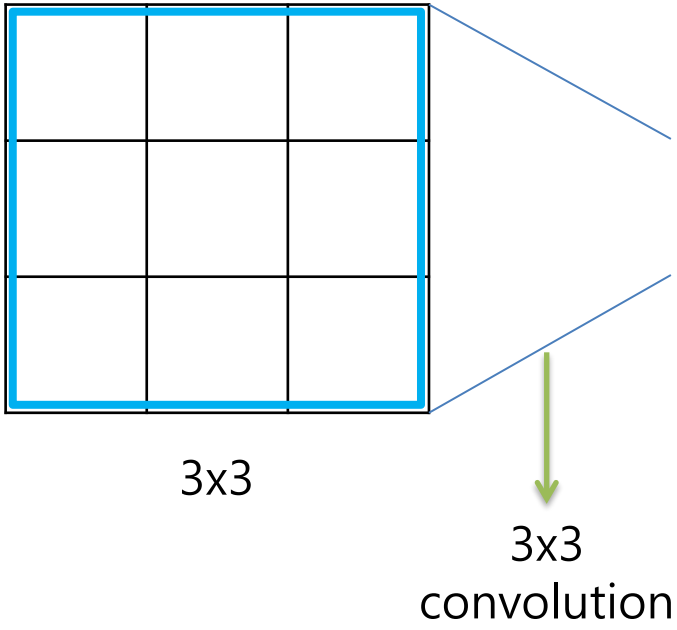
Transposed Convolution!!

Convolution Transposed

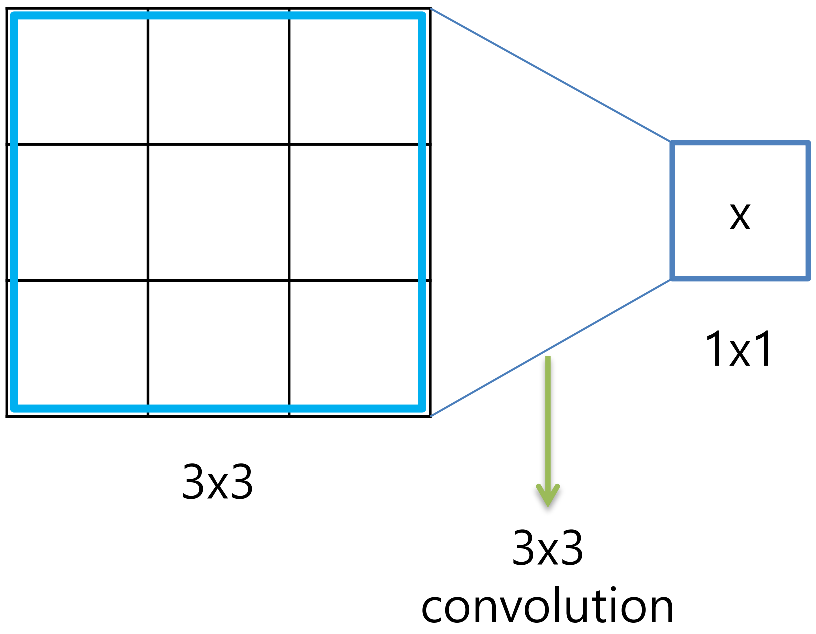


3x3

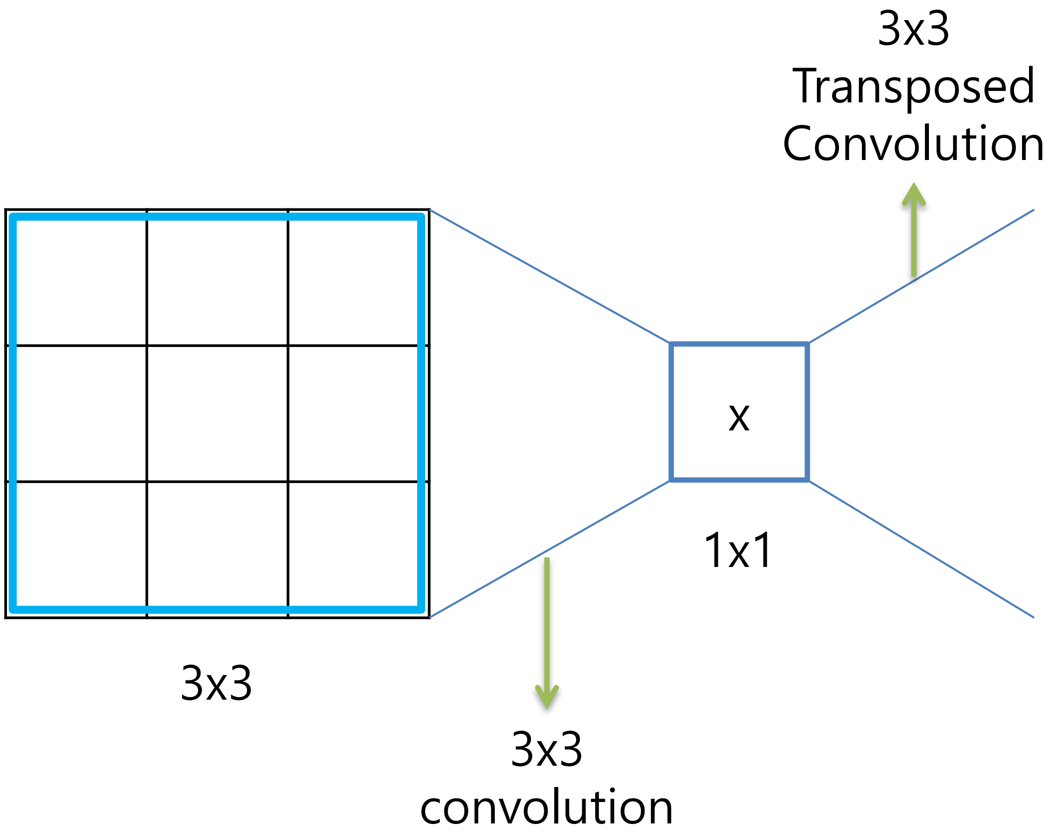
Convolution Transposed



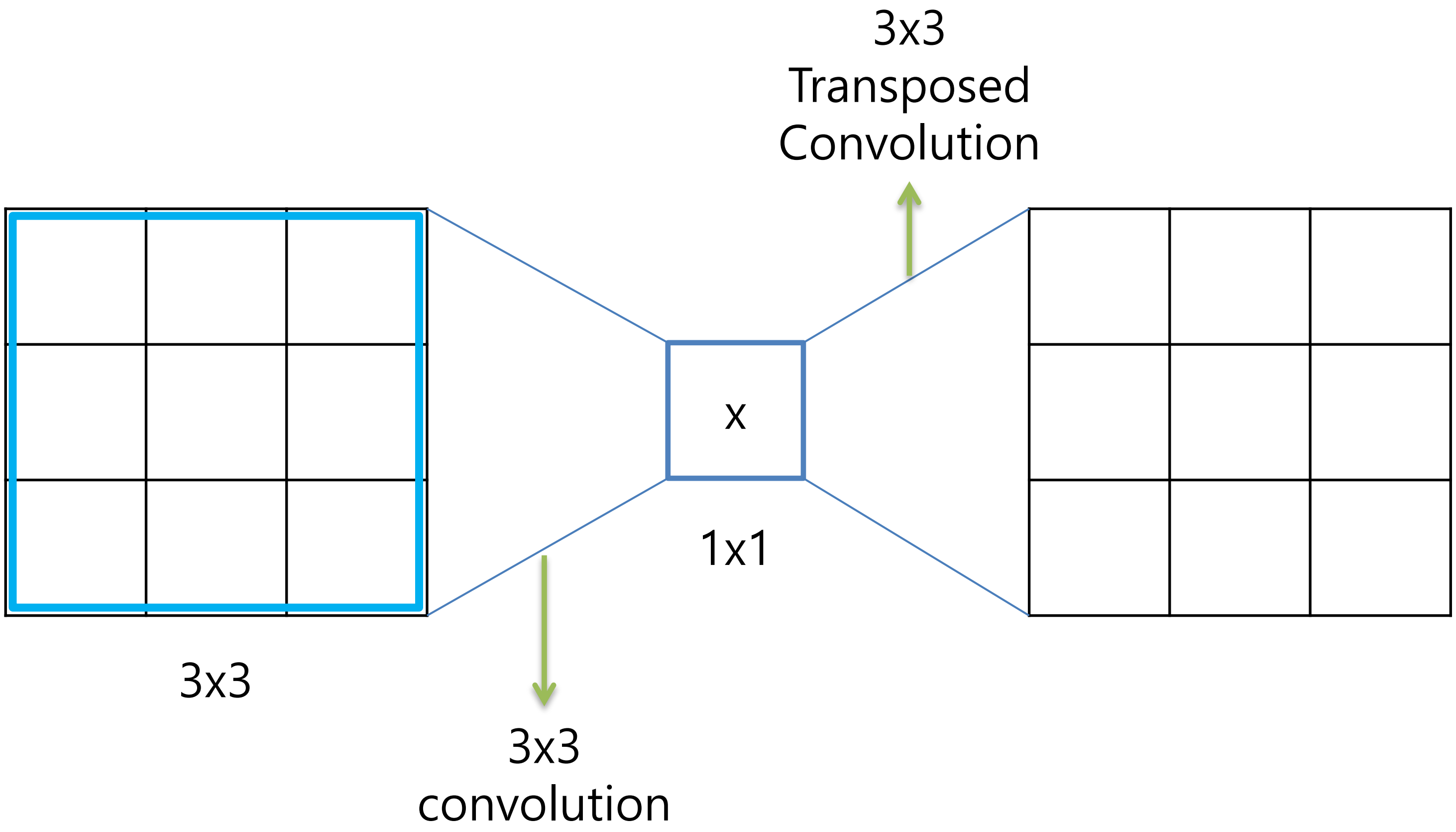
Convolution Transposed



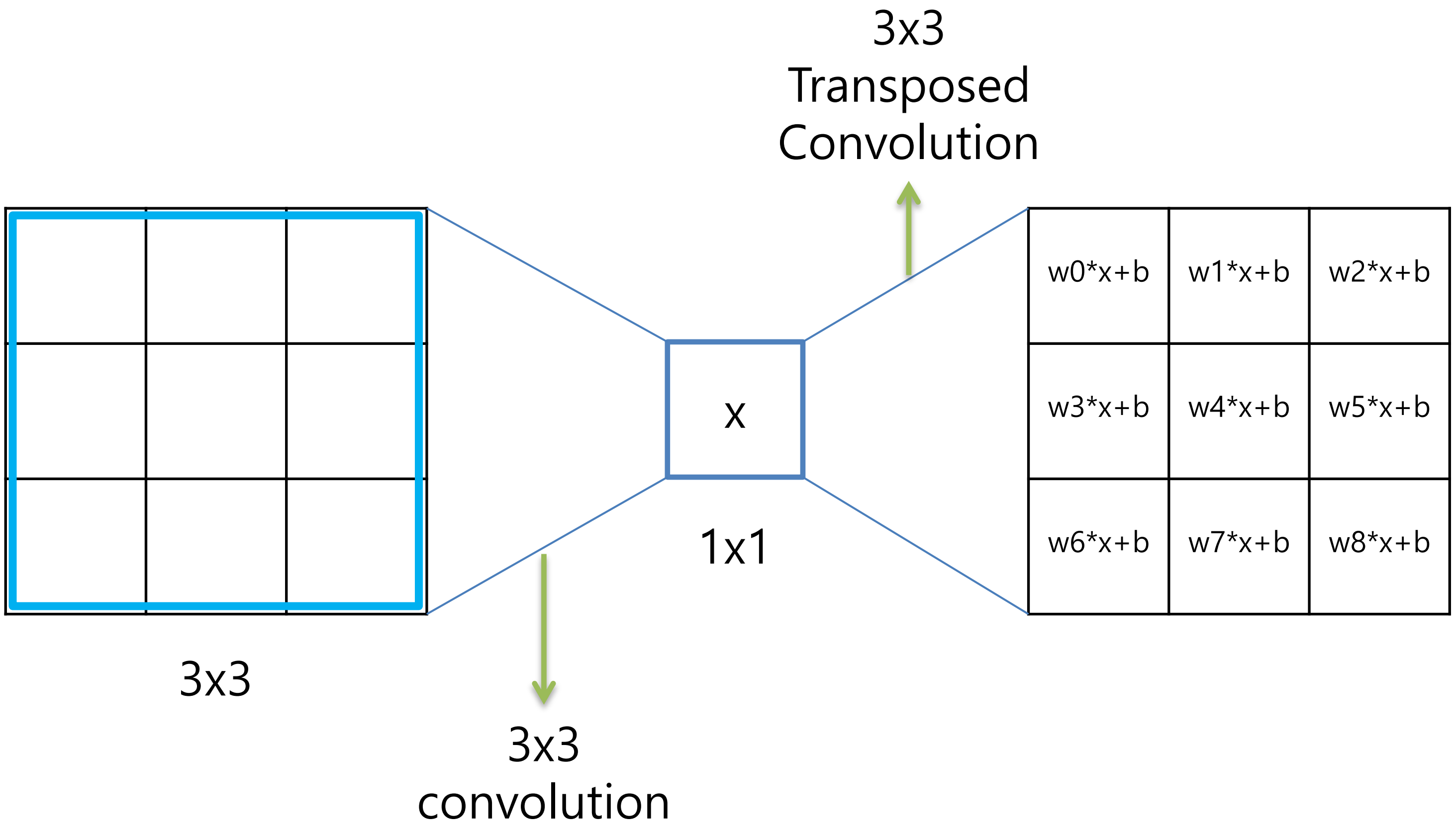
Convolution Transposed



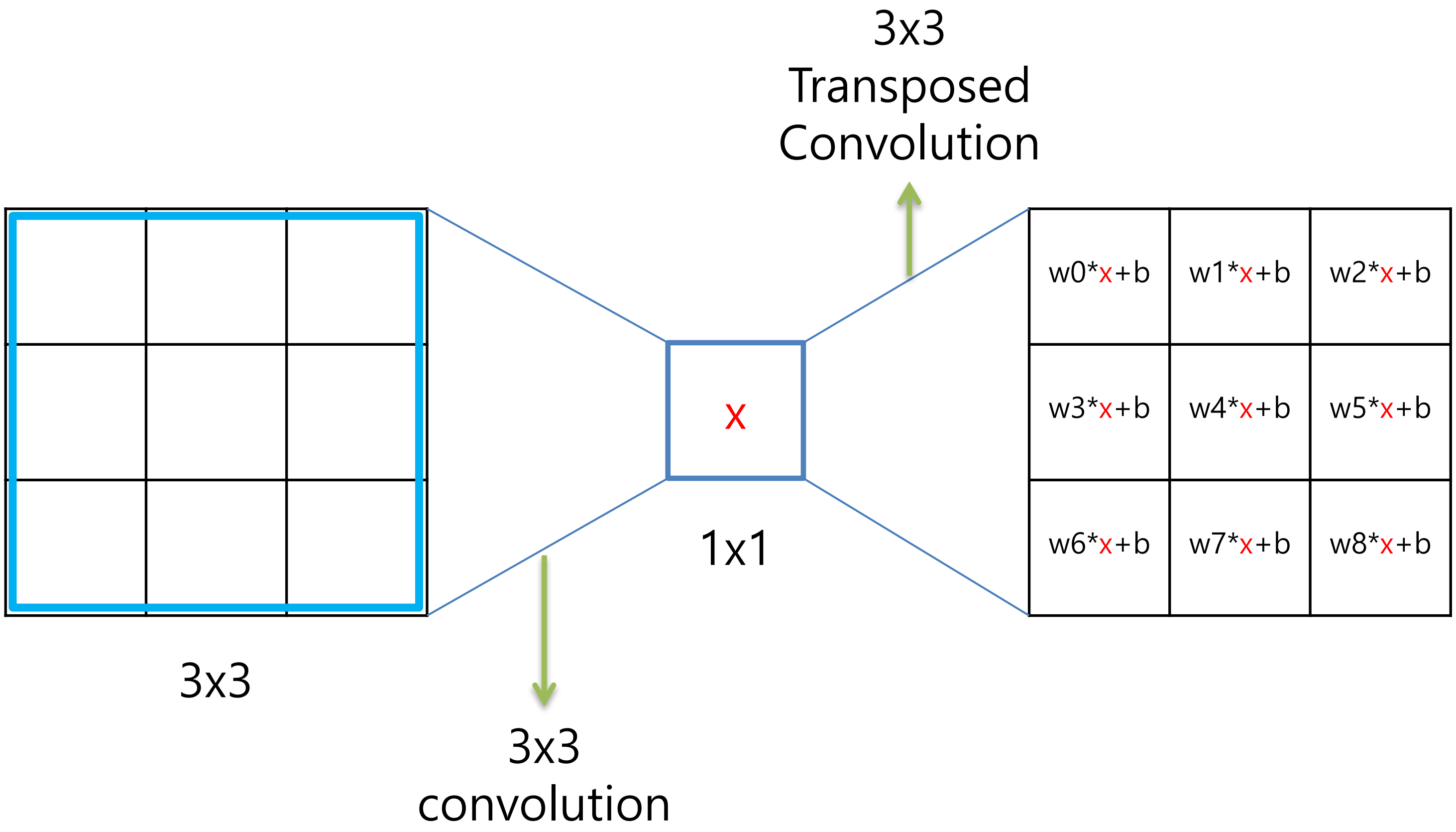
Convolution Transposed



Convolution Transposed

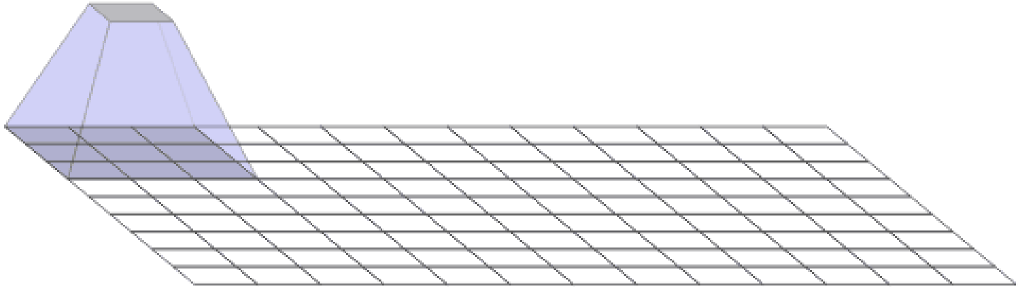


Convolution Transposed



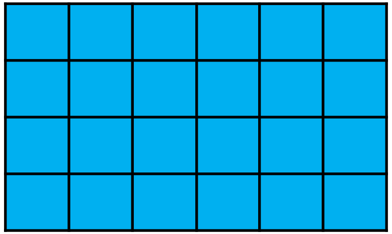
Convolution Transposed

Kernel size 3x3
stride 2



Convolution Transposed

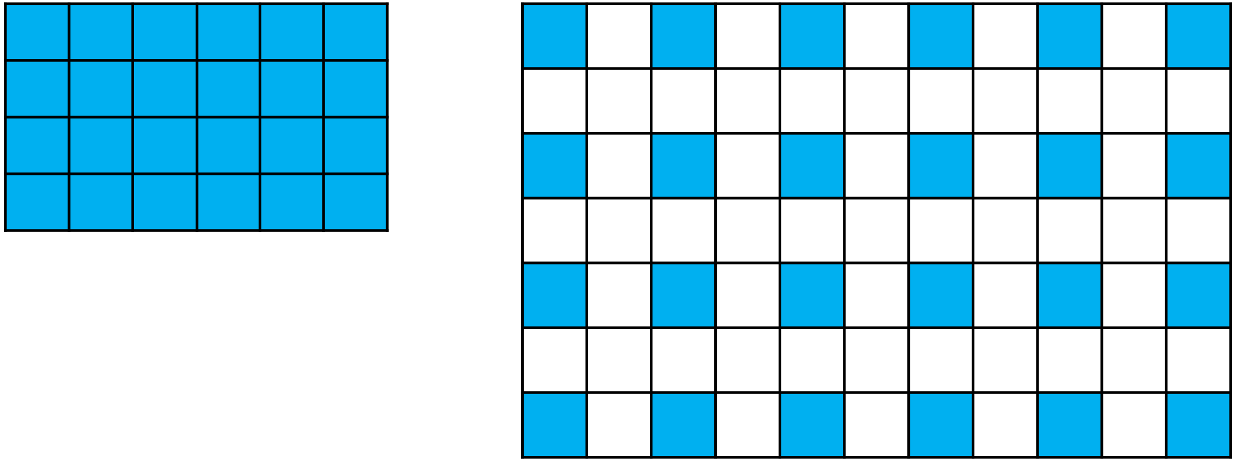
Kernel size 3x3
stride 2



6x4 image

Convolution Transposed

Kernel size 3x3
stride 2



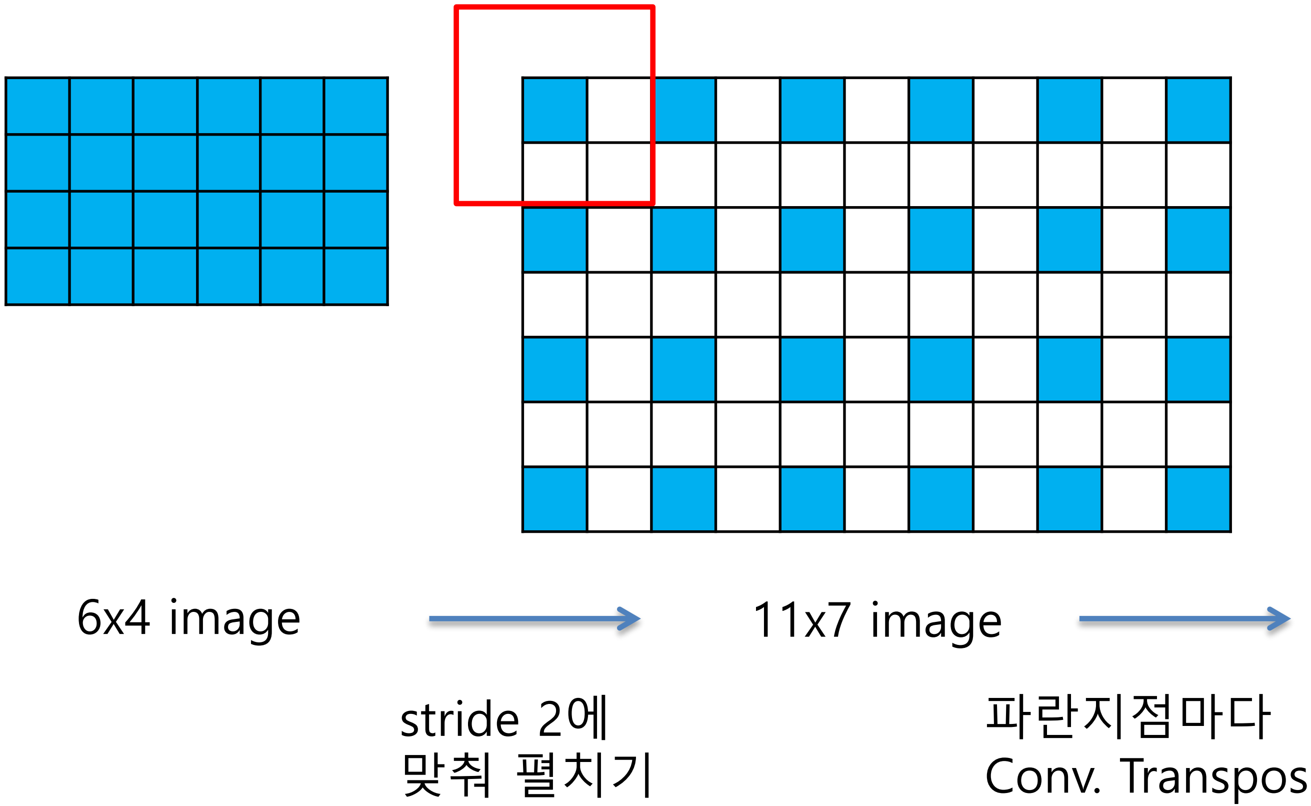
6x4 image

11x7 image

stride 2에
맞춰 펼치기

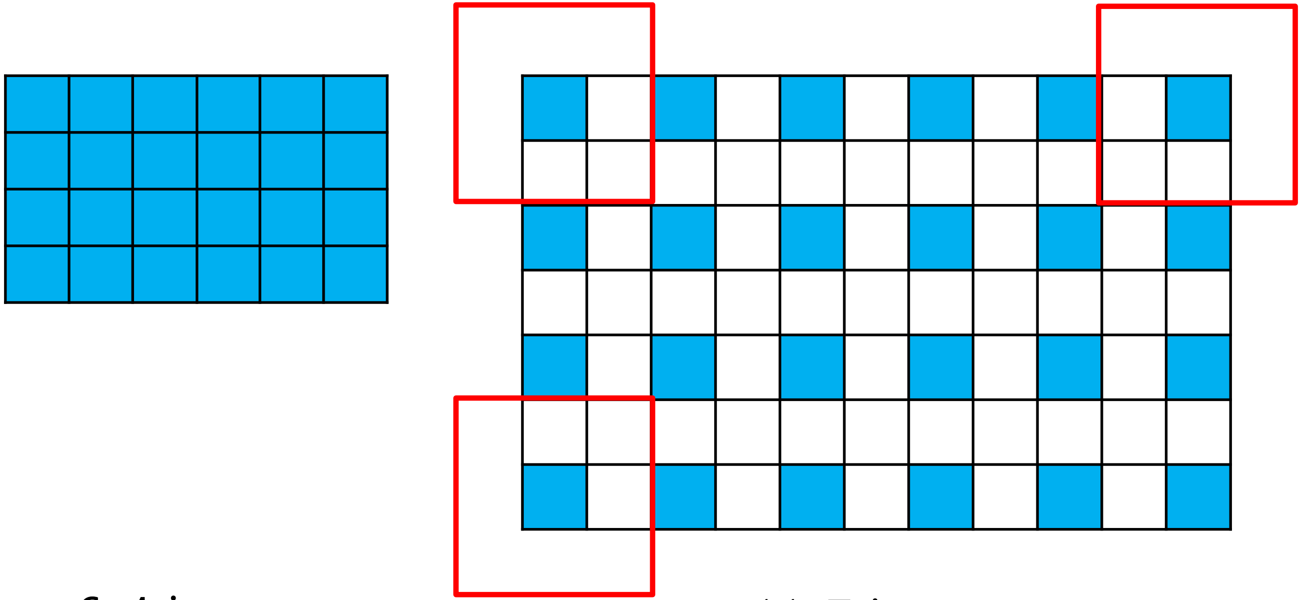
Convolution Transposed

Kernel size 3x3
stride 2



Convolution Transposed

Kernel size 3x3
stride 2



6x4 image → 11x7 image → 13x9 image

stride 2에
맞춰 펼치기

파란지점마다
Conv. Transposed

Convolution Transposed

class `torch.nn.ConvTranspose2d`(*in_channels, out_channels, kernel_size, stride=1, padding=0, output_padding=0, groups=1, bias=True, dilation=1*) [source]

Parameters:

- **in_channels** (*int*) – Number of channels in the input image
- **out_channels** (*int*) – Number of channels produced by the convolution
- **kernel_size** (*int or tuple*) – Size of the convolving kernel
- **stride** (*int or tuple, optional*) – Stride of the convolution
- **padding** (*int or tuple, optional*) – Zero-padding added to both sides of the input
- **output_padding** (*int or tuple, optional*) – Zero-padding added to one side of the output
- **groups** (*int, optional*) – Number of blocked connections from input channels to output channels
- **bias** (*bool, optional*) – If True, adds a learnable bias to the output
- **dilation** (*int or tuple, optional*) – Spacing between kernel elements

Shape:

- Input: $(N, C_{in}, H_{in}, W_{in})$
- Output: $(N, C_{out}, H_{out}, W_{out})$ where

$$H_{out} = (H_{in} - 1) * stride[0] - 2 * padding[0] + kernel\_size[0] + output\_padding[0]$$
$$W_{out} = (W_{in} - 1) * stride[1] - 2 * padding[1] + kernel\_size[1] + output\_padding[1]$$

Convolutional Autoencoder

```python
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

encoder = Encoder().cuda()
```

Convolutional Autoencoder

일반적인 CNN model

```
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

encoder = Encoder().cuda()
```

Convolutional Autoencoder

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

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

decoder = Decoder().cuda()
```

Convolutional Autoencoder

```python
class Decoder(nn.Module):
    def __init__(self):
        super(Decoder,self).__init__()
        self.layer1 = nn.Sequential(
                        nn.ConvTranspose2d(256,128,3,2,1,1),
                        nn.ReLU(),
                        nn.BatchNorm2d(128),
                        nn.ConvTranspose2d(128,64,3,1,1),
                        nn.ReLU(),
                        nn.BatchNorm2d(64)
        )
        self.layer2 = nn.Sequential(
                        nn.ConvTranspose2d(64,16,3,1,1),
                        nn.ReLU(),
                        nn.BatchNorm2d(16),
                        nn.ConvTranspose2d(16,1,3,2,1,1),
                        nn.ReLU()
        )

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

decoder = Decoder().cuda()
```

Shape:

- Input: $(N, C_{in}, H_{in}, W_{in})$
- Output: $(N, C_{out}, H_{out}, W_{out})$ where
  $H_{out} = (H_{in} - 1) * stride[0] - 2 * padding[0] + kernel\_size[0] + output\_padding[0]$
  $W_{out} = (W_{in} - 1) * stride[1] - 2 * padding[1] + kernel\_size[1] + output\_padding[1]$

Convolutional Autoencoder

[batch,256,7,7] -> [batch,128,14,14]

```python
class Decoder(nn.Module):
    def __init__(self):
        super(Decoder,self).__init__()
        self.layer1 = nn.Sequential(
                        nn.ConvTranspose2d(256,128,3,2,1,1),
                        nn.ReLU(),
                        nn.BatchNorm2d(128),
                        nn.ConvTranspose2d(128,64,3,1,1),
                        nn.ReLU(),
                        nn.BatchNorm2d(64)
        )
        self.layer2 = nn.Sequential(
                        nn.ConvTranspose2d(64,16,3,1,1),
                        nn.ReLU(),
                        nn.BatchNorm2d(16),
                        nn.ConvTranspose2d(16,1,3,2,1,1),
                        nn.ReLU()
        )

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

decoder = Decoder().cuda()
```

Shape:

- Input: $(N, C_{in}, H_{in}, W_{in})$
- Output: $(N, C_{out}, H_{out}, W_{out})$ where
  $H_{out} = (H_{in} - 1) * stride[0] - 2 * padding[0] + kernel\_size[0] + output\_padding[0]$
  $W_{out} = (W_{in} - 1) * stride[1] - 2 * padding[1] + kernel\_size[1] + output\_padding[1]$

Convolutional Autoencoder

[batch,256,7,7] -> [batch,128,14,14]

[batch,128,14,14] -> [batch,64,14,14]

```python
class Decoder(nn.Module):
    def __init__(self):
        super(Decoder,self).__init__()
        self.layer1 = nn.Sequential(
                        nn.ConvTranspose2d(256,128,3,2,1,1),
                        nn.ReLU(),
                        nn.BatchNorm2d(128),
                        nn.ConvTranspose2d(128,64,3,1,1),
                        nn.ReLU(),
                        nn.BatchNorm2d(64)
        )
        self.layer2 = nn.Sequential(
                        nn.ConvTranspose2d(64,16,3,1,1),
                        nn.ReLU(),
                        nn.BatchNorm2d(16),
                        nn.ConvTranspose2d(16,1,3,2,1,1),
                        nn.ReLU()
        )

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

decoder = Decoder().cuda()
```

Shape:

- Input: $(N, C_{in}, H_{in}, W_{in})$
- Output: $(N, C_{out}, H_{out}, W_{out})$ where
  $H_{out} = (H_{in} - 1) * stride[0] - 2 * padding[0] + kernel\_size[0] + output\_padding[0]$
  $W_{out} = (W_{in} - 1) * stride[1] - 2 * padding[1] + kernel\_size[1] + output\_padding[1]$

Convolutional Autoencoder

[batch,256,7,7] -> [batch,128,14,14]

[batch,128,14,14] -> [batch,64,14,14]

[batch,64,14,14] -> [batch,16,14,14]

```python
class Decoder(nn.Module):
    def __init__(self):
        super(Decoder,self).__init__()
        self.layer1 = nn.Sequential(
                nn.ConvTranspose2d(256,128,3,2,1,1),
                nn.ReLU(),
                nn.BatchNorm2d(128),
                nn.ConvTranspose2d(128,64,3,1,1),
                nn.ReLU(),
                nn.BatchNorm2d(64)
        )
        self.layer2 = nn.Sequential(
                nn.ConvTranspose2d(64,16,3,1,1),
                nn.ReLU(),
                nn.BatchNorm2d(16),
                nn.ConvTranspose2d(16,1,3,2,1,1),
                nn.ReLU()
        )

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

decoder = Decoder().cuda()
```

Shape:

- Input: $(N, C_{in}, H_{in}, W_{in})$
- Output: $(N, C_{out}, H_{out}, W_{out})$ where
  $H_{out} = (H_{in} - 1) * stride[0] - 2 * padding[0] + kernel\_size[0] + output\_padding[0]$
  $W_{out} = (W_{in} - 1) * stride[1] - 2 * padding[1] + kernel\_size[1] + output\_padding[1]$

Convolutional Autoencoder

[batch,256,7,7] -> [batch,128,14,14]

[batch,128,14,14] -> [batch,64,14,14]

[batch,64,14,14] -> [batch,16,14,14]

[batch,16,14,14] -> [batch,1,28,28]

```python
class Decoder(nn.Module):
    def __init__(self):
        super(Decoder,self).__init__()
        self.layer1 = nn.Sequential(
                        nn.ConvTranspose2d(256,128,3,2,1,1),
                        nn.ReLU(),
                        nn.BatchNorm2d(128),
                        nn.ConvTranspose2d(128,64,3,1,1),
                        nn.ReLU(),
                        nn.BatchNorm2d(64)
        )
        self.layer2 = nn.Sequential(
                        nn.ConvTranspose2d(64,16,3,1,1),
                        nn.ReLU(),
                        nn.BatchNorm2d(16),
                        nn.ConvTranspose2d(16,1,3,2,1,1),
                        nn.ReLU()
        )

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

decoder = Decoder().cuda()
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Convolutional Autoencoder

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

# train encoder and decoder

try:
    encoder, decoder = torch.load('./model/autoencoder.pkl')
    print("\n--------model restored--------\n")
except:
    pass

for i in range(epoch):
    for image,label in train_loader:
        image = Variable(image).cuda()
        optimizer.zero_grad()
        output = encoder(image)
        output = decoder(output)
        loss = loss_func(output,image)
        loss.backward()
        optimizer.step()

    if i % 2 == 0:
        torch.save([encoder,decoder],'./model/autoencoder.pkl')
        print(loss)
```

Convolutional Autoencoder

encoder, decoder의 파라미터를 list로 묶어서 학습하도록 전달. loss는 Mean Squared Loss

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기존에 학습시켜 놓은 모델이 있다면 불러오고 아니면 pass

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원본 이미지를 encoding,
decoding하여 결과값과
원본의 차이를 계산

```
for i in range(epoch):
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원본 이미지를 encoding, decoding하여 결과값과 원본의 차이를 계산

일정 기간마다 모델을 저장

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Convolutional Autoencoder

Denoising Autoencoder 같은 경우에는 원본 이미지에 noise를 추가하여 autoencoder를 통과하면 노이즈가 제거된 원본 이미지가 나오도록 학습함.

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이렇게 되면 학습 이후 좀 지저분한 데이터가 들어오더라도 정제할 수 있음

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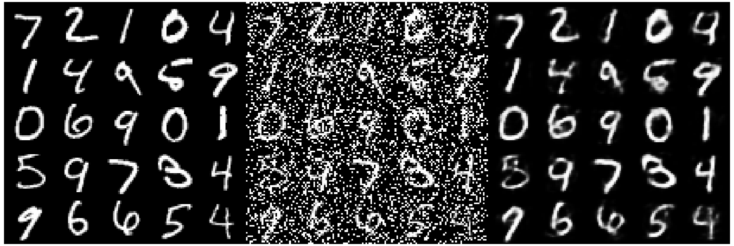

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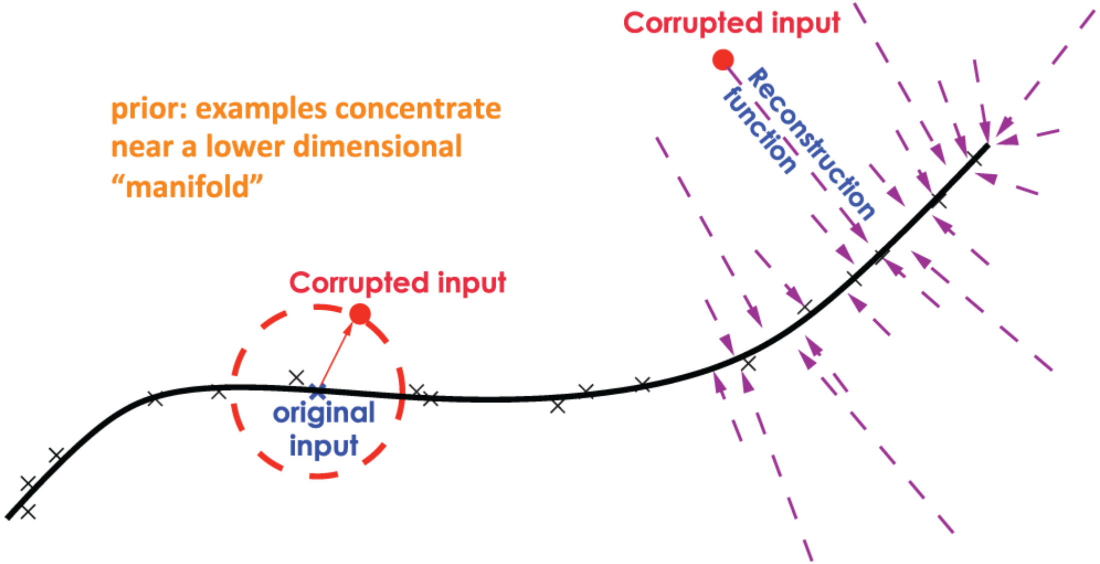
```

Convolutional Autoencoder

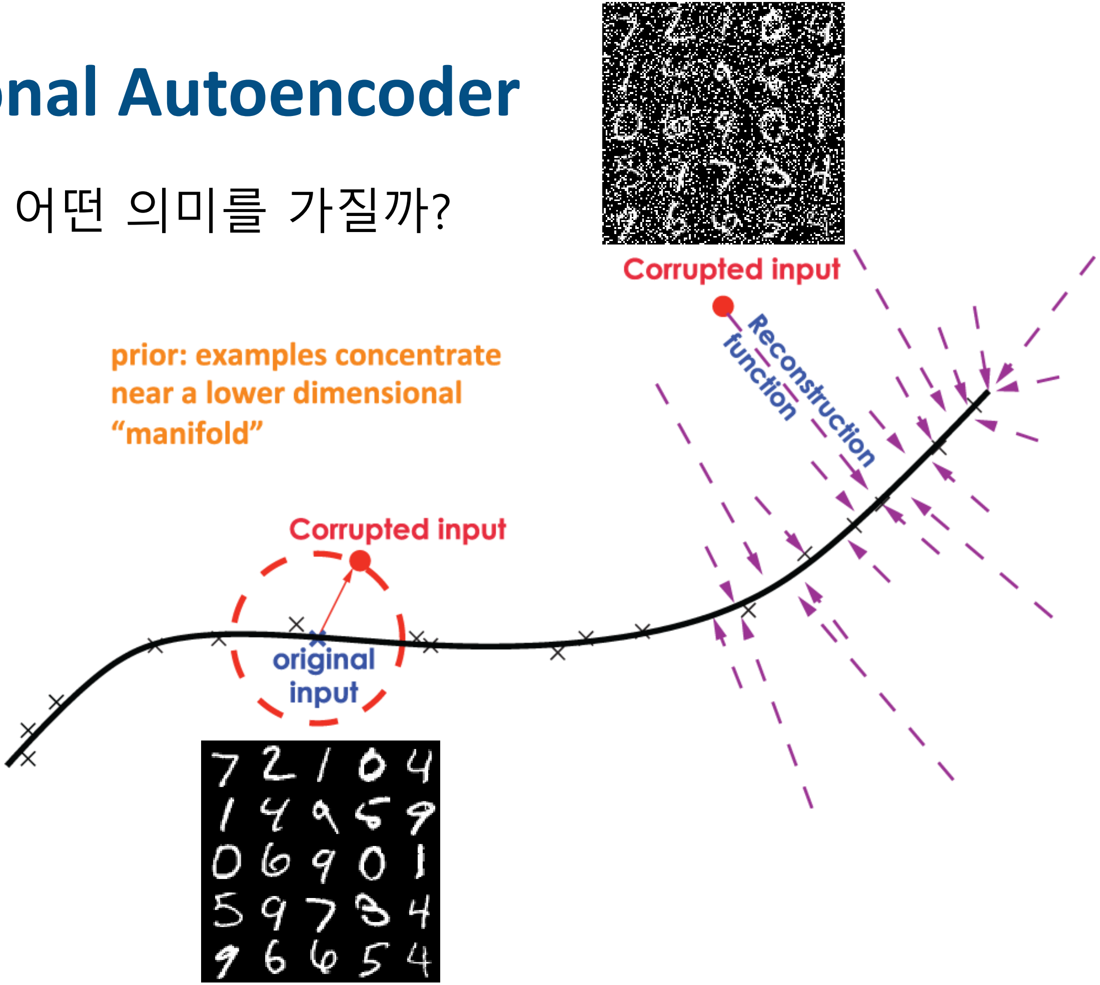
Denoising은 어떤 의미를 가질까?



https://www.slideshare.net/zukun/icml2012-tutorial-representationlearning

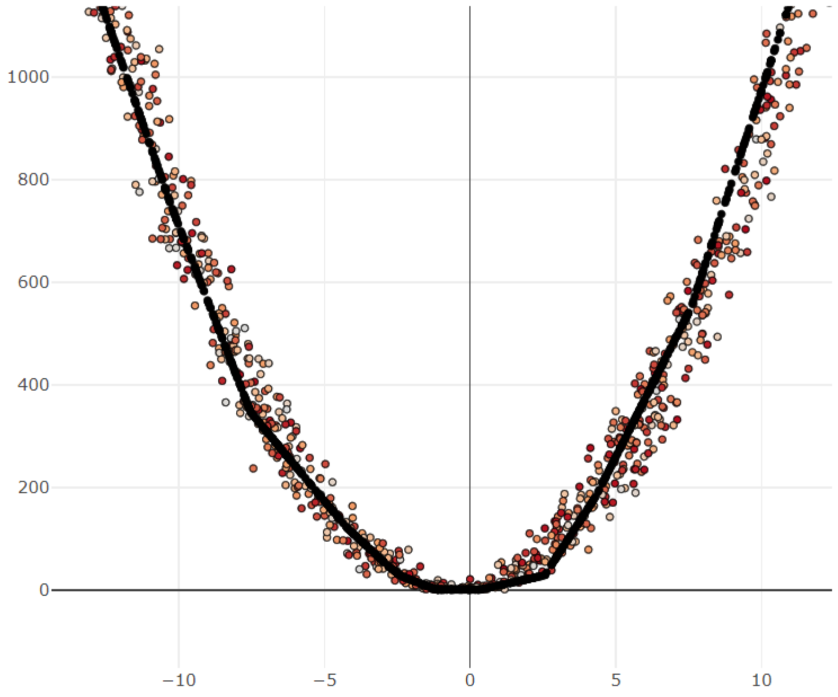
Convolutional Autoencoder

Denoising은 어떤 의미를 가질까?



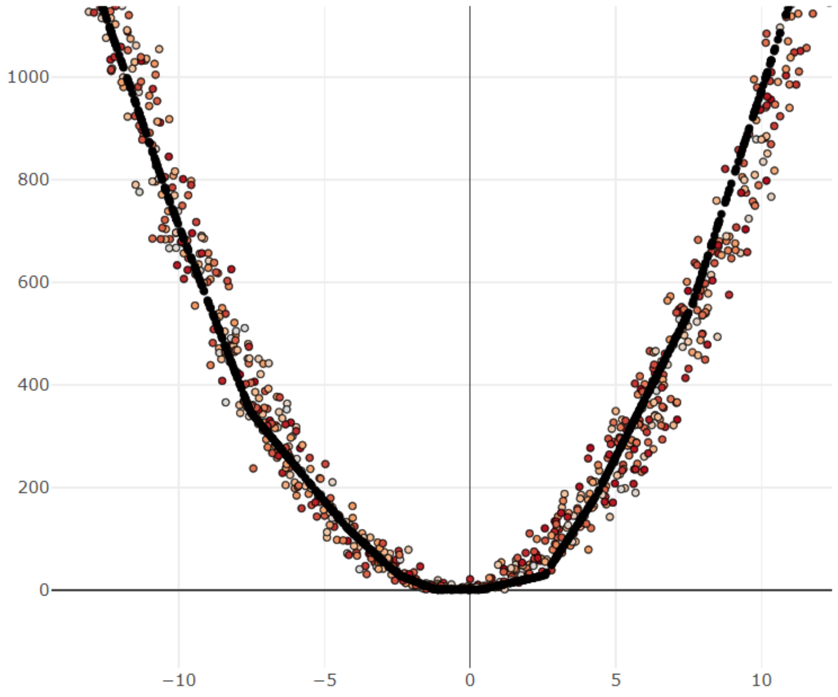
https://www.slideshare.net/zukun/icml2012-tutorial-representationlearning

Convolutional Autoencoder



Convolutional Autoencoder

Noise에 강하게(robust) 학습됨
Filter들도 Clean 데이터보다 더 선명하게 생성됨



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Q&A