AutoEncoder

AILAB
Hanyang Univ.

오늘 실습 내용

1. AutoEncoder 구현
2. Denoising AutoEncoder 구현
3. Stacked AutoEncoder 구현

- 1 데이터 전처리
- 2 모델 및 optimizer 정의
- 3 학습
- 4 학습 결과 확인

오늘 실습 내용

1. AutoEncoder 구현
2. Denoising AutoEncoder 구현
3. Stacked AutoEncoder 구현

AutoEncoder

- Data Compression
  - 데이터 압축

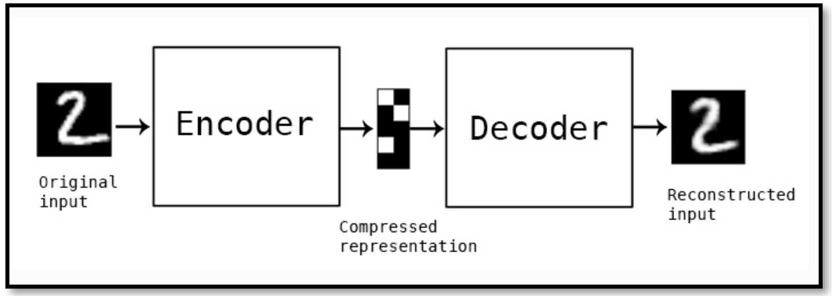
- Data Visualization
  - 데이터 가시화

- Curse of dimensionality
  - 차원의 저주 해결

- Discovering most important features
  - 가장 중요한 피쳐 찾기

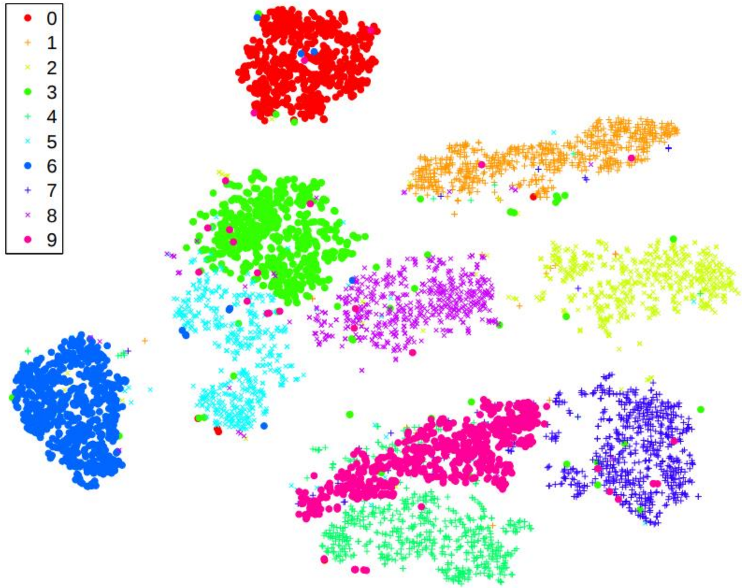
Why AutoEncoder?

- Data Compression
  - 데이터 압축
- Data Visualization
  - 데이터 가시화
- Curse of dimensionality
  - 차원의 저주 해결
- Discovering most important features
  - 가장 중요한 피쳐 찾기



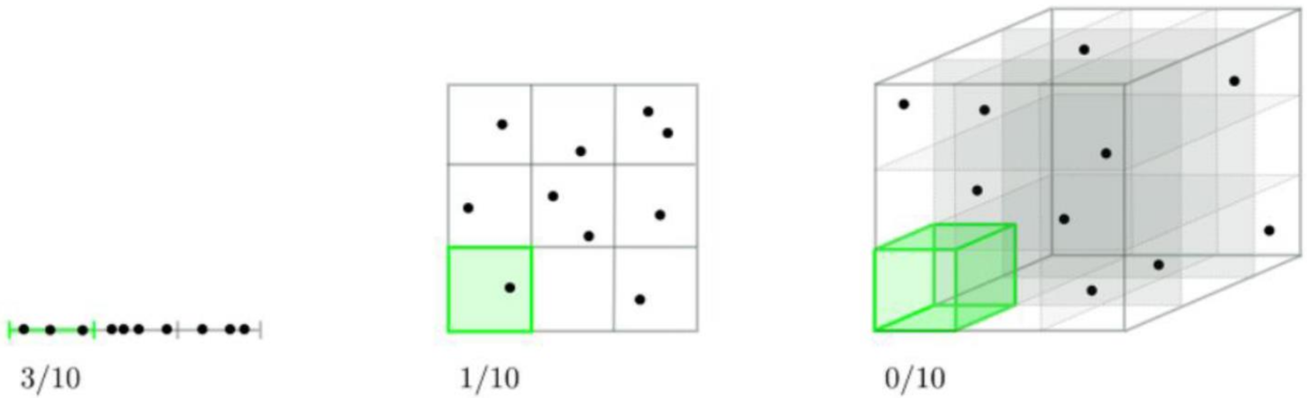
Why AutoEncoder?

- Data Compression
  - 데이터 압축
- Data Visualization
  - 데이터 가시화
- Curse of dimensionality
  - 차원의 저주 해결
- Discovering most important features
  - 가장 중요한 피쳐 찾기



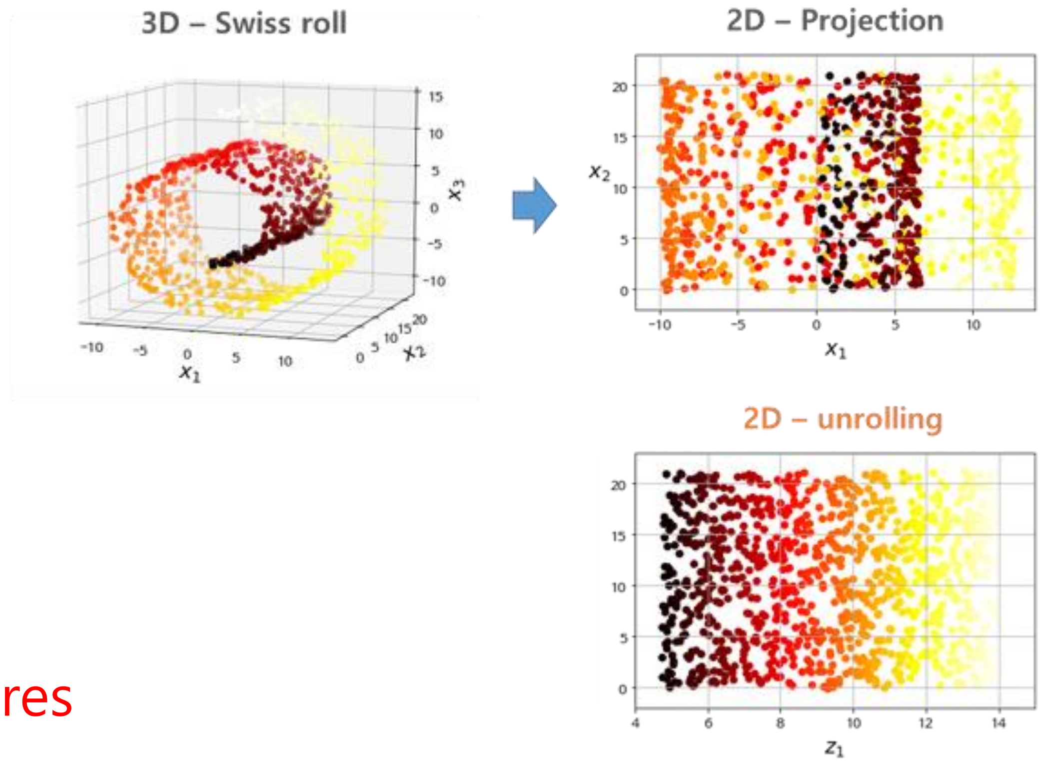
Why AutoEncoder?

- Data Compression
  - 데이터 압축
- Data Visualization
  - 데이터 가시화
- Curse of dimensionality
  - 차원의 저주 해결
- Discovering most important features
  - 가장 중요한 피쳐 찾기



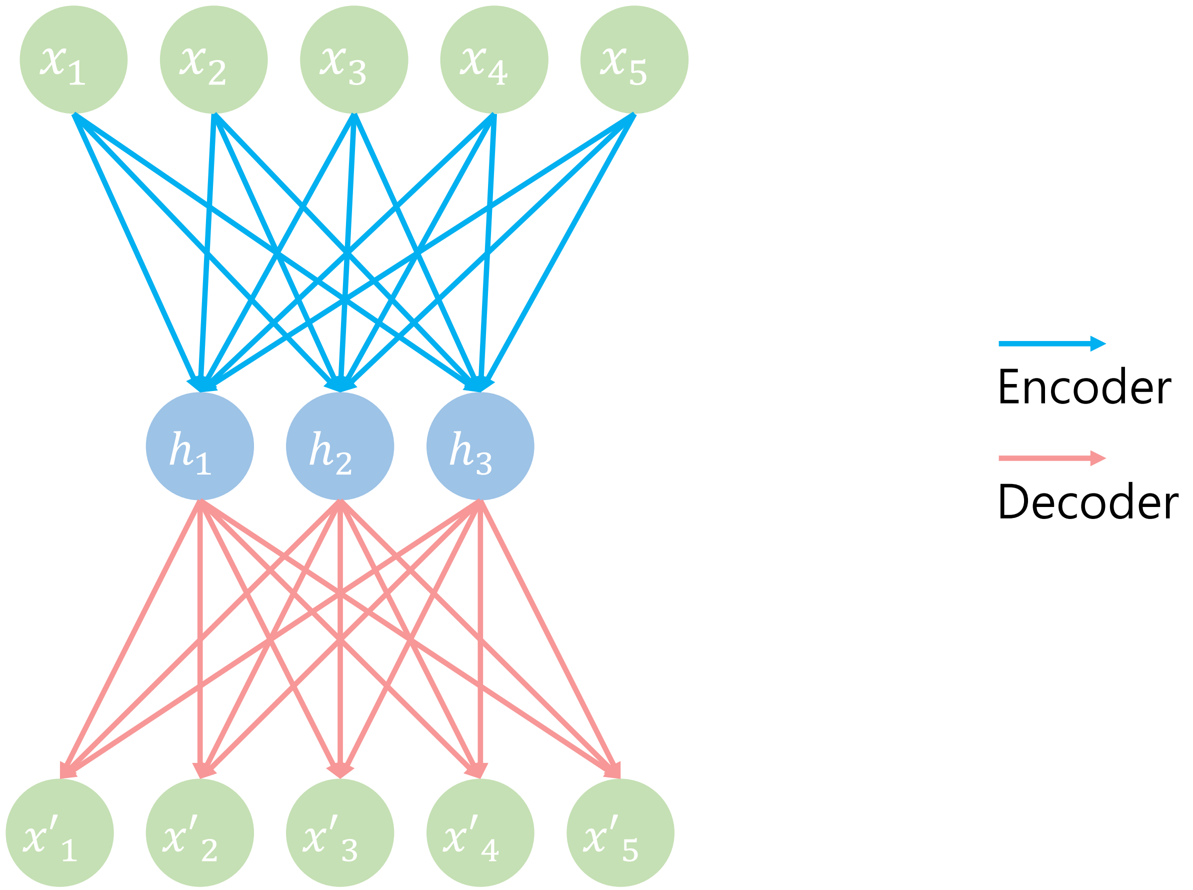
Why AutoEncoder?

- Data Compression
  - 데이터 압축
- Data Visualization
  - 데이터 가시화
- Curse of dimensionality
  - 차원의 저주 해결
- Discovering most important features
  - 가장 중요한 feature 찾기



AutoEncoder

- 모델 아키텍쳐



AutoEncoder

- 모델 코드

```
[ ] import torch
    import torch.nn as nn
    import torch.optim as optim
    import matplotlib.pyplot as plt
    import numpy as np
```

```
[ ] torch.manual_seed(0)
    torch.cuda.manual_seed(0)
    torch.cuda.manual_seed_all(0)
```

```
[ ] if torch.cuda.is_available():
        device = torch.device('cuda')
    else:
        device = torch.device('cpu')
```

```
[ ] import torchvision
    import torchvision.transforms as transforms

    train_dataset = torchvision.datasets.MNIST(root="MNIST_data/",
                                        train=True,
                                        transform=transforms.ToTensor(),
                                        download=True)
    test_dataset = torchvision.datasets.MNIST(root="MNIST_data/",
                                        train=False,
                                        transform=transforms.ToTensor(),
                                        download=True)
```

```
[ ] batch_size = 128

    train_dataloader = torch.utils.data.DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
    test_dataloader = torch.utils.data.DataLoader(test_dataset, batch_size=batch_size)
```

AutoEncoder

- 모델 코드


```
[ ] class Encoder(nn.Module):
        def __init__(self):
          super(Encoder, self).__init__()
          self.linear = nn.Linear(784, 256)
          self.activation = nn.Sigmoid()

        def forward(self, x):
          x = self.linear(x)
          x = self.activation(x)
          return x

    class Decoder(nn.Module):
        def __init__(self):
          super(Decoder, self).__init__()
          self.linear = nn.Linear(256, 784)
          self.activation = nn.Sigmoid()

        def forward(self, x):
          x = self.linear(x)
          x = self.activation(x)
          return x

    class AutoEncoder(nn.Module):
      def __init__(self):
        super(AutoEncoder, self).__init__()
        self.encoder = Encoder()
        self.decoder = Decoder()

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

```
[ ] model = AutoEncoder().to(device)
```

```
[ ] optimizer = optim.Adam(model.parameters(), lr=0.001) # set optimize
```

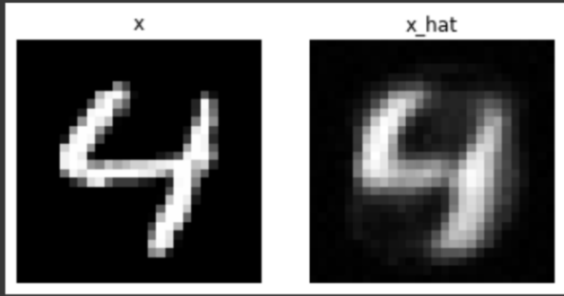
```
[ ] criterion = nn.MSELoss()
```

```
[ ] sample = test_dataset[1051][0].view(-1, 784).to(device)
```

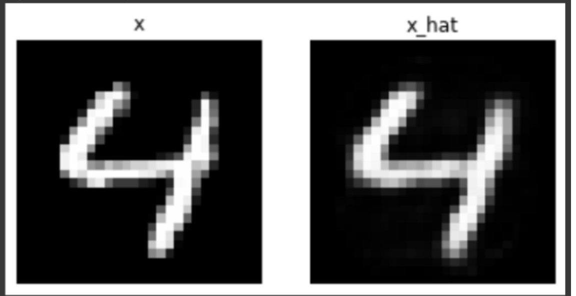
AutoEncoder

- 모델 코드

```
Epoch : 1 / 30, cost : 0.045592669397592545
```




```
Epoch : 2 / 30, cost : 0.018965791910886765
Epoch : 3 / 30, cost : 0.01132714282721281
Epoch : 4 / 30, cost : 0.007959334179759026
Epoch : 5 / 30, cost : 0.006132069043815136
Epoch : 6 / 30, cost : 0.004992660600692034
```




```
Epoch : 7 / 30, cost : 0.004214531742036343
Epoch : 8 / 30, cost : 0.0036551854573190212
Epoch : 9 / 30, cost : 0.003237406723201275
Epoch : 10 / 30, cost : 0.002908063121140003
Epoch : 11 / 30, cost : 0.0026430850848555565
```



```python
epochs = 30

model.train()
for epoch in range(epochs):
    model.train()
    avg_cost = 0
    total_batch_num = len(train_dataloader)

    for b_x, b_y in train_dataloader:
      b_x = b_x.view(-1, 784).to(device)
      z, b_x_hat = model(b_x)  # forward propagation
      loss = criterion(b_x_hat, b_x) # get cost

      avg_cost += loss / total_batch_num
      optimizer.zero_grad()
      loss.backward() # backward propagation
      optimizer.step() # update parameters
    print('Epoch : {} / {}, cost : {}'.format(epoch+1, epochs, avg_cost))

    # observe differences
    if epoch % 5 == 0:
      model.eval()
      fig, ax = plt.subplots(1,2)
      with torch.no_grad():
        test_z, test_output = model(sample)
      ax[0].set_title('x')
      ax[1].set_title('x_hat')

      ax[0].set_axis_off()
      ax[1].set_axis_off()
      ax[0].imshow(np.reshape(sample.detach().cpu(),(28,28)), cmap='gray')
      ax[1].imshow(np.reshape(test_output.detach().cpu(),(28,28)), cmap='gray')
      plt.show()
```

AutoEncoder

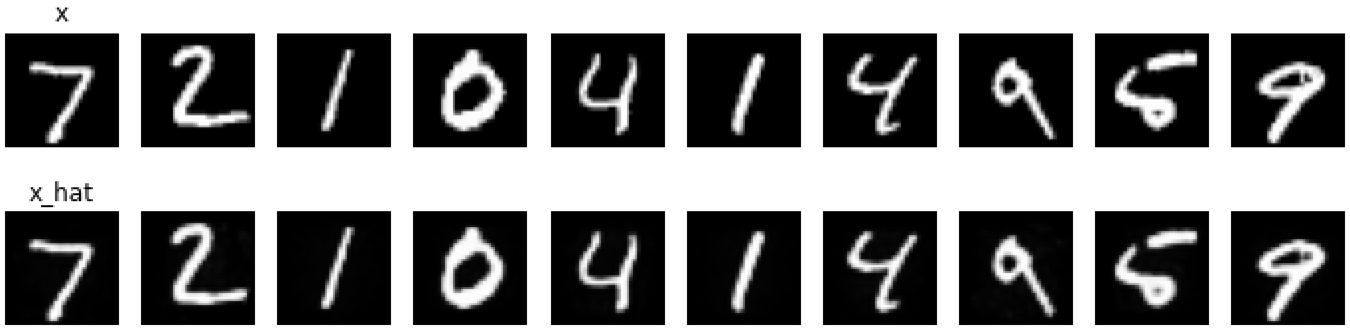
- 학습 결과 확인

4

```
[ ]  import matplotlib.pyplot as plt
     import numpy as np

     model.eval()
     test_samples = torch.zeros((10,28,28))
     for i in range(10):
       test_samples[i] = test_dataset[i][0]
     test_samples = test_samples.view(-1, 784).to(device)
     z, test_output = model(test_samples)

     fig, ax = plt.subplots(2,10,figsize=(12,3))
     ax[0][0].set_title('x')
     ax[1][0].set_title('x_hat')
     for i in range(10):
         ax[0][i].set_axis_off()
         ax[1][i].set_axis_off()
         ax[0][i].imshow(np.reshape(test_samples[i].detach().cpu(),(28,28)), cmap='gray')
         ax[1][i].imshow(np.reshape(test_output[i].detach().cpu(),(28,28)), cmap='gray')
     plt.show()
```

AutoEncoder

- 학습 결과



AutoEncoder

- 다양한 Encoder와 Decoder 학습 방법
  1. Encoder, Decoder class 각각 나눠서 생성 후 하나의 모델로 만들기 (이전 코드)
  2. nn.Sequential 을 사용해 한 모델에서 autoencoder 작성하기
  3. Encoder, Decoder class 각각 나눠서 하나씩 부르기

  등등

AutoEncoder

- 다양한 Encoder와 Decoder 학습 방법
  1. Encoder, Decoder class 각각 나눠서 생성 후 하나의 모델로 만들기 (이전 코드)
  2. **nn.Sequential 을 사용해 한 모델에서 autoencoder 작성하기**
  3. Encoder, Decoder class 각각 나눠서 하나씩 부르기

2

```
[ ] class AutoEncoder(nn.Module):
      def __init__(self):
        super(AutoEncoder, self).__init__()
        self.encoder = nn.Sequential(nn.Linear(784, 256),
                                     nn.Sigmoid(),
                                     )
        self.decoder = nn.Sequential(nn.Linear(256, 784),
                                     nn.Sigmoid(),
                                     )
      def forward(self, x):
        z = self.encoder(x)
        x_hat = self.decoder(z)
        return z, x_hat
```

AutoEncoder

- 다양한 Encoder와 Decoder 학습 방법
  1. Encoder, Decoder class 각각 나눠서 생성 후 하나의 모델로 만들기 (이전 코드)
  2. nn.Sequential 을 사용해 한 모델에서 autoencoder 작성하기
  3. **Encoder, Decoder class 각각 나눠서 하나씩 부르기 1) Parameter List** 2) Parameter group

2

```
class Encoder(nn.Module):
    def __init__(self):
      super(Encoder, self).__init__()
      self.linear = nn.Linear(784, 256)
      self.activation = nn.Sigmoid()
    def forward(self, x):
      return self.activation(self.linear(x))

class Decoder(nn.Module):
    def __init__(self):
      super(Decoder, self).__init__()
      self.linear = nn.Linear(256, 784)
      self.activation = nn.Sigmoid()
    def forward(self, x):
      return self.activation(self.linear(x))
```

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

```
params = list(encoder.parameters()) + list(decoder.parameters())
optimizer = optim.Adam(params, lr=0.001)
```

3

```
b_x = b_x.view(-1, 784).to(device)
z = encoder(b_x)  # forward propagation
b_x_hat = decoder(z)  # forward propagation
loss = criterion(b_x_hat, b_x) # get cost

avg_cost += loss / total_batch_num

optimizer.zero_grad()

loss.backward() # backward propagation

optmizer.step() # update parameters
```

AutoEncoder

- 다양한 Encoder와 Decoder 학습 방법
  1. Encoder, Decoder class 각각 나눠서 생성 후 하나의 모델로 만들기 (이전 코드)
  2. nn.Sequential 을 사용해 한 모델에서 autoencoder 작성하기
  3. **Encoder, Decoder class 각각 나눠서 하나씩 부르기** 1) Parameter List **2) 두개의 optimizer**

2

```
class Encoder(nn.Module):
    def __init__(self):
      super(Encoder, self).__init__()
      self.linear = nn.Linear(784, 256)
      self.activation = nn.Sigmoid()
    def forward(self, x):
      return self.activation(self.linear(x))

class Decoder(nn.Module):
    def __init__(self):
      super(Decoder, self).__init__()
      self.linear = nn.Linear(256, 784)
      self.activation = nn.Sigmoid()
    def forward(self, x):
      return self.activation(self.linear(x))
```

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

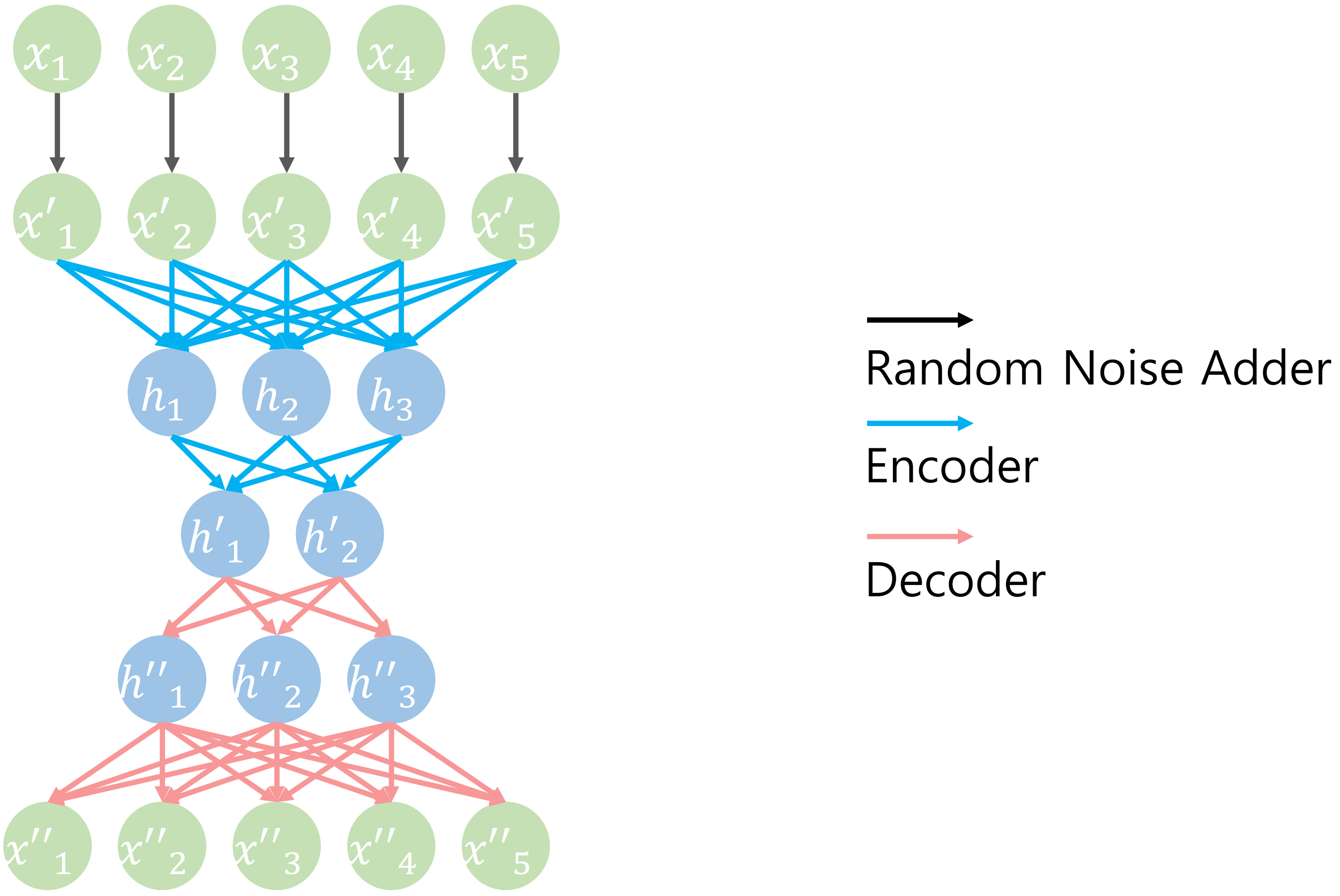
```
optimizer = optim.Adam(
        [
            {"params": encoder.parameters(), "lr": 0.001},
            {"params": decoder.parameters(), "lr": 0.001},
        ])
```

3

```
b_x = b_x.view(-1, 784).to(device)
z = encoder(b_x)  # forward propagation
b_x_hat = decoder(z)  # forward propagation
loss = criterion(b_x_hat, b_x) # get cost

avg_cost += loss / total_batch_num

optimizer.zero_grad()

loss.backward() # backward propagation

optmizer.step() # update parameters
```

Denoising Auto-Encoder model

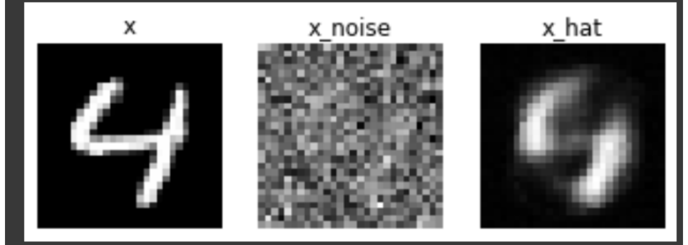
- Denoising AutoEncoder model



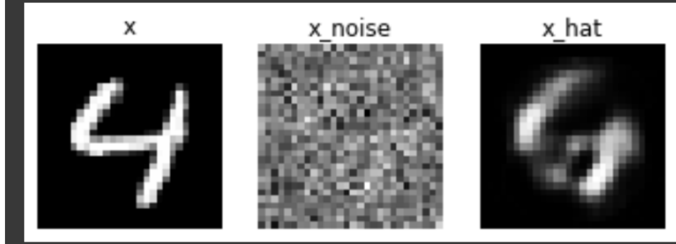
Denoising Auto-Encoder model

- 학습 코드
  - 앞 코드는 이전 autoencoder 코드와 같음

```
Epoch : 1 / 30, cost : 0.052579998970031 74
```




```
Epoch : 2 / 30, cost : 0.035839807242155075
Epoch : 3 / 30, cost : 0.032727282494306564
Epoch : 4 / 30, cost : 0.0313720628619194
Epoch : 5 / 30, cost : 0.030546465888619423
Epoch : 6 / 30, cost : 0.030038334429264 07
```




```
Epoch : 7 / 30, cost : 0.029572656378149986
Epoch : 8 / 30, cost : 0.029247337952256203
Epoch : 9 / 30, cost : 0.028981884941458702
Epoch : 10 / 30, cost : 0.028774535283446312
Epoch : 11 / 30, cost : 0.028557226061820984
```

3

```
model.train()
for epoch in range(epochs):
    avg_cost = 0
    total_batch_num = len(train_dataloader)

    for b_x, b_y in train_dataloader:
      b_x = b_x.view(-1, 784).to(device)
      noise = torch.randn(b_x.shape).to(device)
      nosiy_b_x = b_x + noise

      z, b_x_hat = model(nosiy_b_x)  # forward propagation
      loss = criterion(b_x_hat, b_x) # get cost

      avg_cost += loss / total_batch_num
      optimizer.zero_grad()
      loss.backward() # backward propagation
      optimizer.step() # update parameters
    print('Epoch : {} / {}, cost : {}'.format(epoch+1, epochs, avg_cost))

    # observe differences
    model.eval()
    if epoch % 5 == 0:
      fig, ax = plt.subplots(1,3)
      with torch.no_grad():
        noise = torch.randn(sample.shape).to(device)
        noisy_sample = sample + noise
        test_z, test_output = model(noisy_sample)
      ax[0].set_title('x')
      ax[1].set_title('x_noise')
      ax[2].set_title('x_hat')

      ax[0].set_axis_off()
      ax[1].set_axis_off()
      ax[2].set_axis_off()
      ax[0].imshow(np.reshape(sample.detach().cpu(),(28,28)), cmap='gray')
      ax[1].imshow(np.reshape(noisy_sample.detach().cpu(),(28,28)), cmap='gray')
      ax[2].imshow(np.reshape(test_output.detach().cpu(),(28,28)), cmap='gray')
      plt.show()
```

Denoising Auto-Encoder model

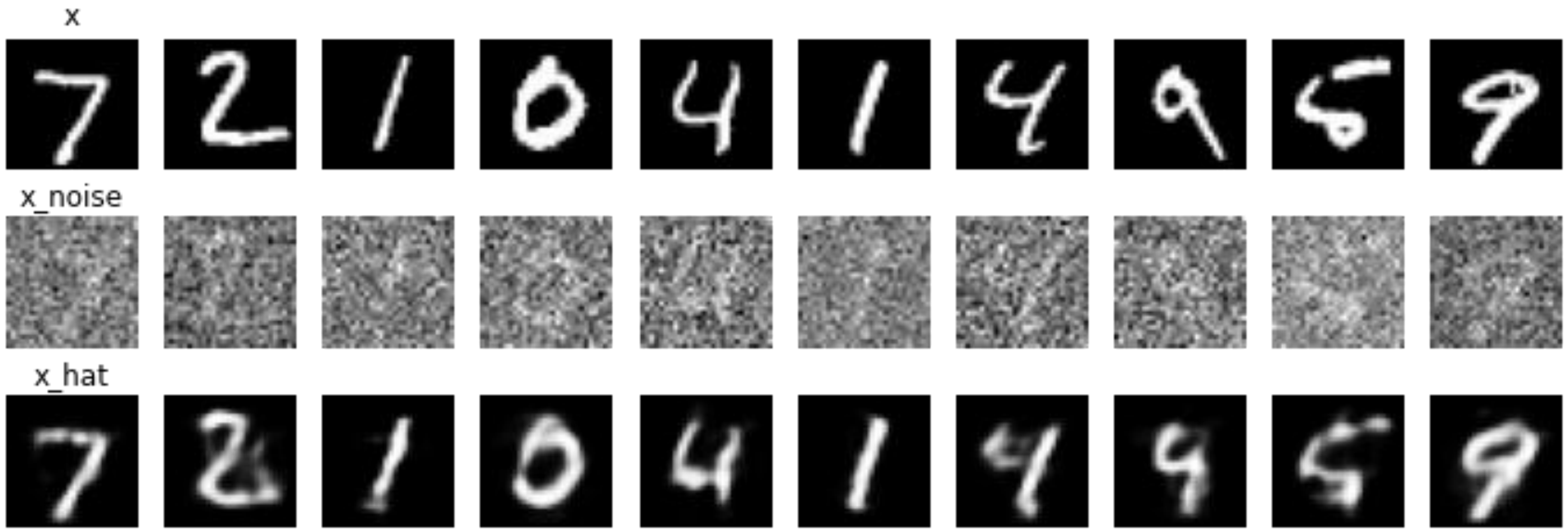
- 학습 결과 확인

4

```
import matplotlib.pyplot as plt
import numpy as np

model.eval()
test_samples = torch.zeros((10,28,28))
for i in range(10):
  test_samples[i] = test_dataset[i][0]

noise = torch.randn(test_samples.shape)
noisy_test_samples = test_samples + noise

noisy_test_samples = noisy_test_samples.view(-1, 784).to(device)

z, test_output = model(noisy_test_samples)

fig, ax = plt.subplots(3,10,figsize=(12,4))

ax[0][0].set_title('x')
ax[1][0].set_title('x_noise')
ax[2][0].set_title('x_hat')

for i in range(10):
    ax[0][i].set_axis_off()
    ax[1][i].set_axis_off()
    ax[2][i].set_axis_off()

    ax[0][i].imshow(test_samples[i].detach().cpu(), cmap='gray')
    ax[1][i].imshow(np.reshape(noisy_test_samples[i].detach().cpu(),(28,28)), cmap='gray')
    ax[2][i].imshow(np.reshape(test_output[i].detach().cpu(),(28,28)), cmap='gray')
plt.show()
```

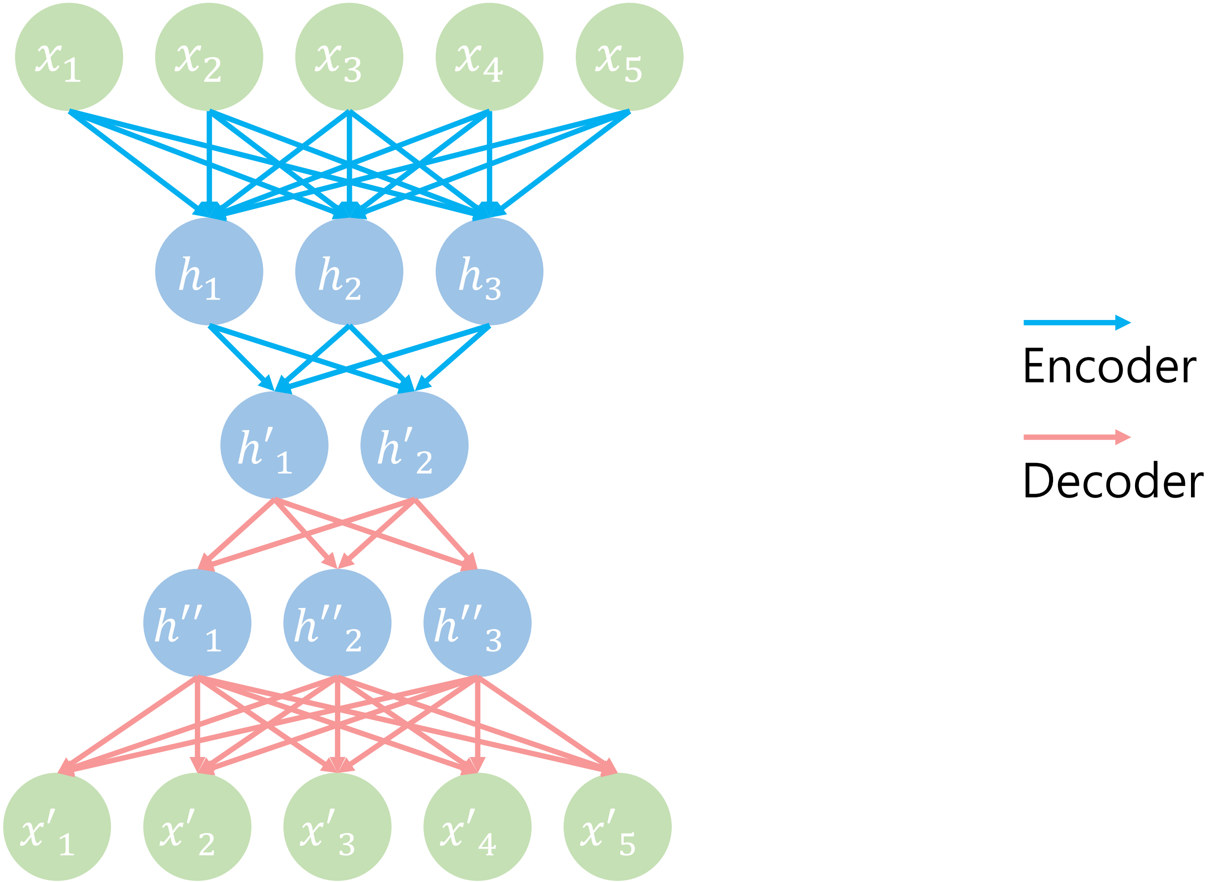
Stacked AutoEncoder and Semi-Supervised Learning

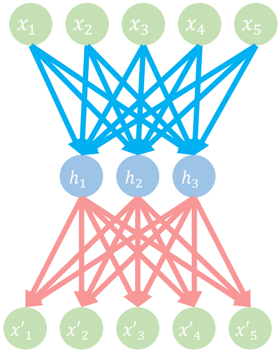
- 학습 결과



Stacked AutoEncoder

- Stacked AutoEncoder

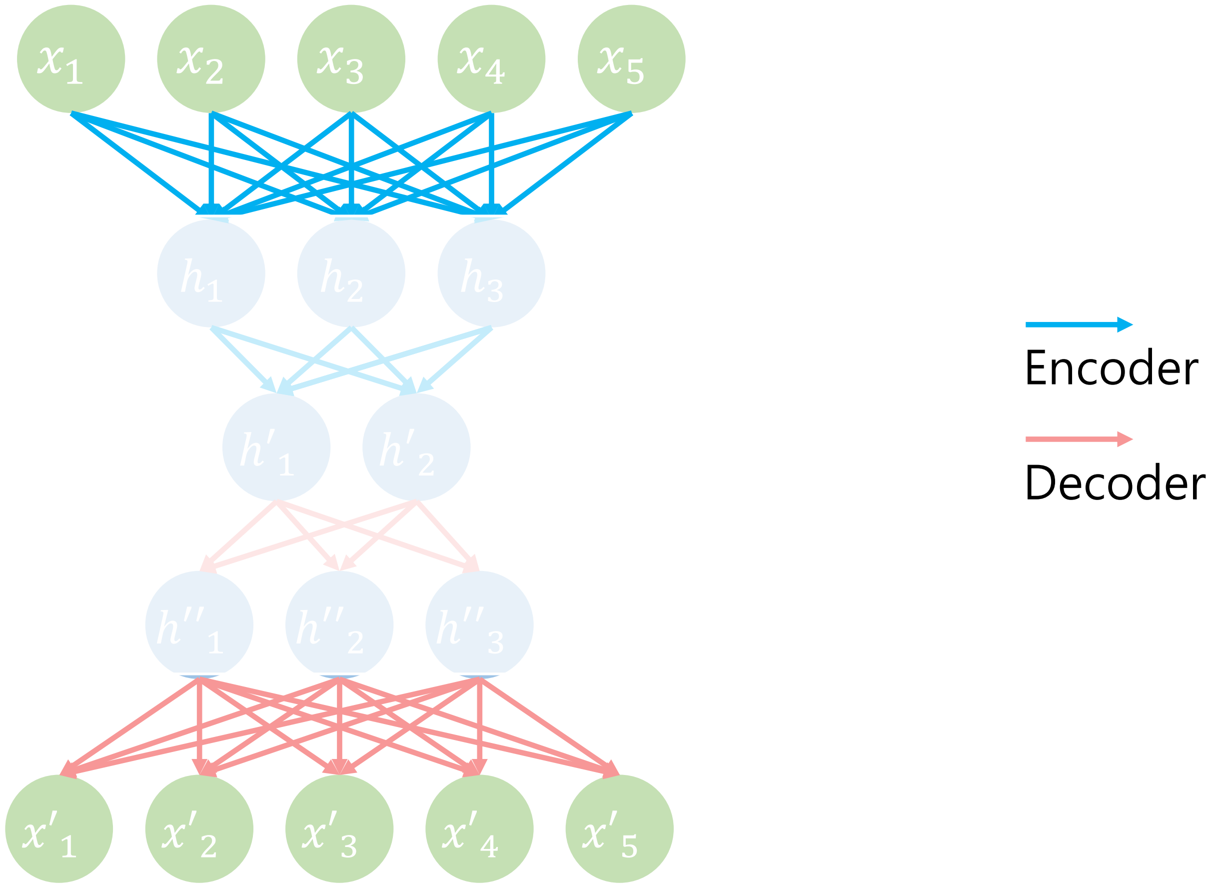


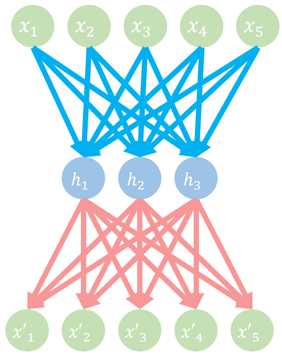


Autoencoder

Stacked AutoEncoder

- Stacked AutoEncoder

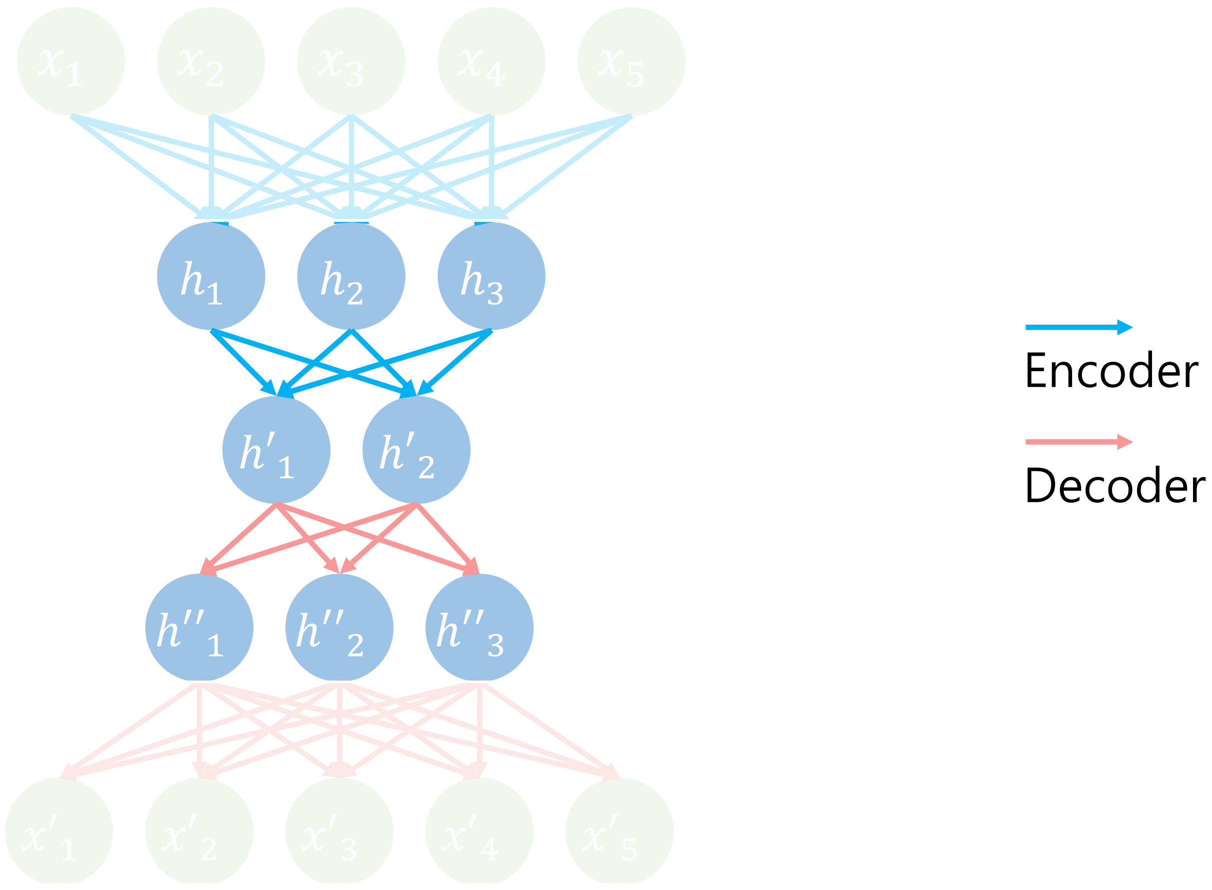


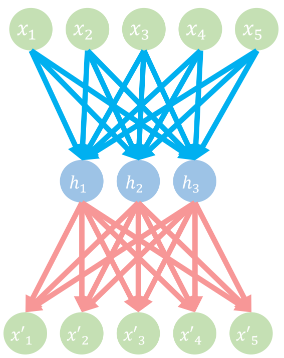


Autoencoder

Stacked AutoEncoder

- Stacked AutoEncoder





Autoencoder

Stacked AutoEncoder

2-1

```
[ ] class Encoder1(nn.Module):
        def __init__(self):
          super(Encoder1, self).__init__()
          self.linear = nn.Linear(784, 256)
          self.activation = nn.Sigmoid()

        def forward(self, x):
          x = self.linear(x)
          x = self.activation(x)
          return x

    class Decoder1(nn.Module):
        def __init__(self):
          super(Decoder1, self).__init__()
          self.linear = nn.Linear(256, 784)
          self.activation = nn.Sigmoid()

        def forward(self, x):
          x = self.linear(x)
          x = self.activation(x)
          return x

    class AutoEncoder1(nn.Module):
      def __init__(self):
        super(AutoEncoder1, self).__init__()
        self.encoder = Encoder1()
        self.decoder = Decoder1()
      def forward(self, x):
        z = self.encoder(x)
        x_hat = self.decoder(z)
        return z, x_hat
```

```
[ ] class Encoder2(nn.Module):
        def __init__(self):
          super(Encoder2, self).__init__()
          self.linear = nn.Linear(256, 64)
          self.activation = nn.Sigmoid()

        def forward(self, x):
          x = self.linear(x)
          x = self.activation(x)
          return x

    class Decoder2(nn.Module):
        def __init__(self):
          super(Decoder2, self).__init__()
          self.linear = nn.Linear(64, 256)
          self.activation = nn.Sigmoid()

        def forward(self, x):
          x = self.linear(x)
          x = self.activation(x)
          return x

    class AutoEncoder2(nn.Module):
      def __init__(self):
        super(AutoEncoder2, self).__init__()
        self.encoder = Encoder2()
        self.decoder = Decoder2()

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

```
[ ] autoencoder1 = AutoEncoder1().to(device).train()
    autoencoder2 = AutoEncoder2().to(device).train()
```

```
[ ] optimizer_1 = optim.Adam(autoencoder1.parameters(), lr=0.001) # set optimizer
    optimizer_2 = optim.Adam(autoencoder2.parameters(), lr=0.001) # set optimizer
```

```
[ ] criterion = nn.MSELoss()
```

Stacked AutoEncoder

- 첫번째 AutoEncoder 학습

3-1

```
[ ]  epochs = 30

     autoencoder1.train()
     for epoch in range(epochs):
         autoencoder1.train()
         avg_cost = 0
         total_batch_num = len(train_dataloader)

         for b_x, b_y in train_dataloader:
           b_x = b_x.view(-1, 784).to(device)
           z, b_x_hat = autoencoder1(b_x)  # forward propagation
           loss = criterion(b_x_hat, b_x) # get cost

           avg_cost += loss / total_batch_num
           optimizer_1.zero_grad()
           loss.backward() # backward propagation
           optimizer_1.step() # update parameters
         print('Epoch : {} / {}, cost : {}'.format(epoch+1, epochs, avg_cost))
```

Stacked AutoEncoder

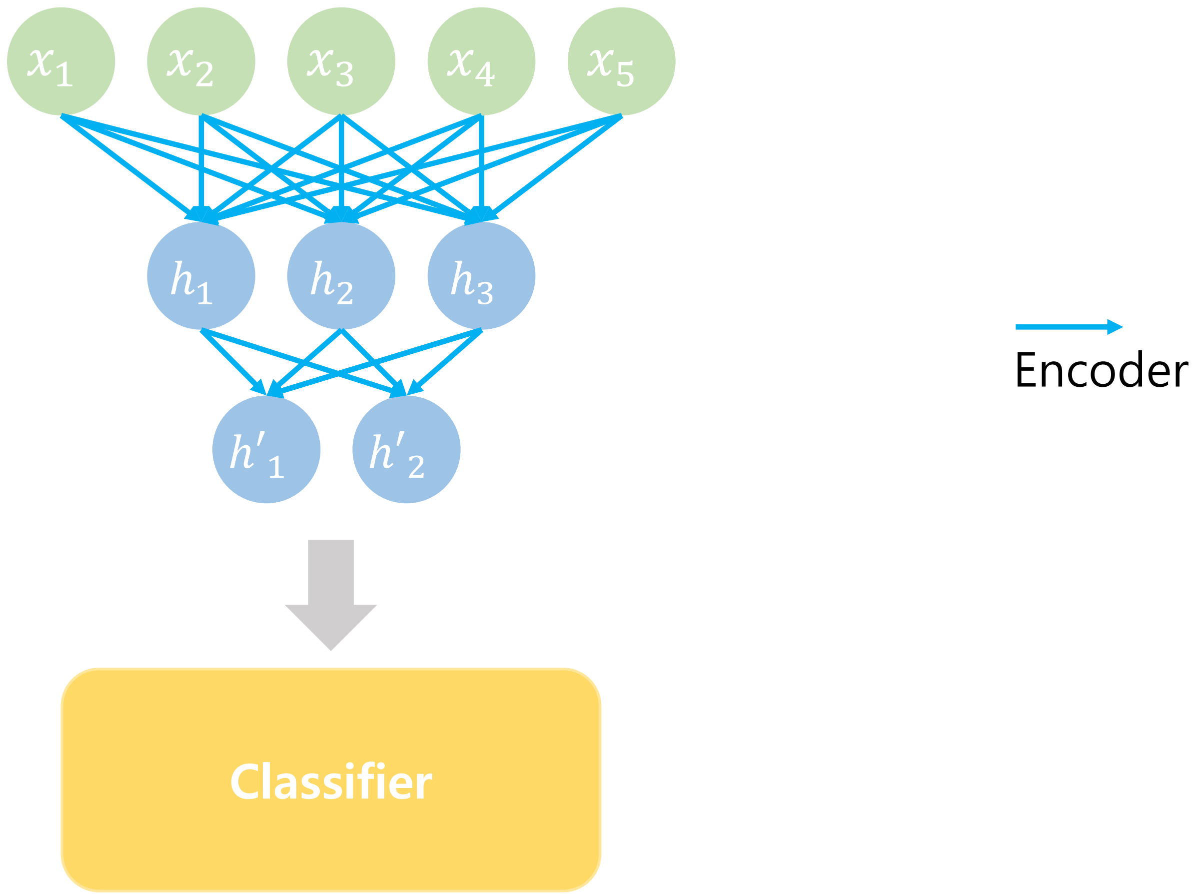
- 두번째 AutoEncoder 학습

3-2

```
[ ]  epochs = 30

     autoencoder1.eval() # freeze first autoencoder
     autoencoder2.train()
     for epoch in range(epochs):
         autoencoder2.train()
         avg_cost = 0
         total_batch_num = len(train_dataloader)

         for b_x, b_y in train_dataloader:
           b_x = b_x.view(-1, 784).to(device)
           with torch.no_grad():
             z1, b_x_hat = autoencoder1(b_x)  # get latent representation from first encoder
           z2, b_x_hat = autoencoder2(z1)
           loss = criterion(b_x_hat, z1) # get cost

           avg_cost += loss / total_batch_num
           optimizer_2.zero_grad()
           loss.backward() # backward propagation
           optimizer_2.step() # update parameters
         print('Epoch : {} / {}, cost : {}'.format(epoch+1, epochs, avg_cost))
```

Stacked AutoEncoder and Semi-Supervised Learning

- Stacked AutoEncoder and Classifier



Stacked AutoEncoder and Semi-Supervised Learning

2-2

```
[ ]  class Classifier(nn.Module):
       def __init__(self):
         super(Classifier, self).__init__()
         self.linear = nn.Linear(64, 32)
         self.activation = nn.Sigmoid()
         self.cls = nn.Linear(32, 10)
       def forward(self, x):
         x = self.linear(x)
         x = self.activation(x)

         x = self.cls(x)
         return x
```

```
[ ]  classifier = Classifier().to(device)
```

```
[ ]  cls_criterion = nn.CrossEntropyLoss()
```

```
[ ]  optimizer = optim.Adam(
             [
                 {"params": autoencoder1.parameters(), "lr": 0.001},
                 {"params": autoencoder2.parameters(), "lr": 0.001},
                 {"params": classifier.parameters(), "lr": 0.001},
             ])
```

Stacked AutoEncoder and Semi-Supervised Learning

- Classifier 학습
  - **Fine-tuning** autoencoder
  - Fine-tune
    - 미리 학습된 weight을 **task**에 맞게 학습하는 것

task : classification, object detection, sentence prediction …

3-3

```
[ ]  autoencoder1.train()
     autoencoder2.train()
     classifier.train()
     total_batch_num = len(train_dataloader)
     epochs=30
     for epoch in range(epochs):
         avg_cost = 0

         for b_x, b_y in train_dataloader:
           b_x = b_x.view(-1, 784).to(device)
           z1, b_x_hat = autoencoder1(b_x) # get latent representation from first encoder
           z2, b_x_hat2 = autoencoder2(z1) # get latent representation from second encoder
           logits = classifier(z2) # classification
           loss = cls_criterion(logits, b_y.to(device)) # get cost

           avg_cost += loss / total_batch_num

           optimizer.zero_grad()

           loss.backward() # backward propagation

           optimizer.step() # update param

         print('Epoch : {} / {}, cost : {}'.format(epoch+1, epochs, avg_cost))
```

Stacked AutoEncoder and Semi-Supervised Learning

4

```
correct = 0
total = 0

classifier.eval()
autoencoder1.eval()
autoencoder2.eval()

for b_x, b_y in test_dataloader:
  b_x = b_x.view(-1, 784).to(device)
  with torch.no_grad():
    z1, b_x_hat = autoencoder1(b_x)
    z2, b_x_hat2 = autoencoder2(z1)
    logits = classifier(z2)

  predicts = torch.argmax(logits, dim=1)

  total += len(b_y)
  correct += (predicts == b_y.to(device)).sum().item()

print(f'Accuracy of the network on test images: {100 * correct / total} %')
```

```
Accuracy of the network on test images: 97.96 %
```

오늘 실습 내용

1. AutoEncoder 구현
2. Denoising AutoEncoder 구현
3. Stacked AutoEncoder 구현

- 각 모델의 Latent Representation에 classifier를 붙여 학습해보고 성능 비교해보기