# 인공지능 기반 설계 이론 및 사례 연구 8차) Autoencoder와 Anomaly Detection

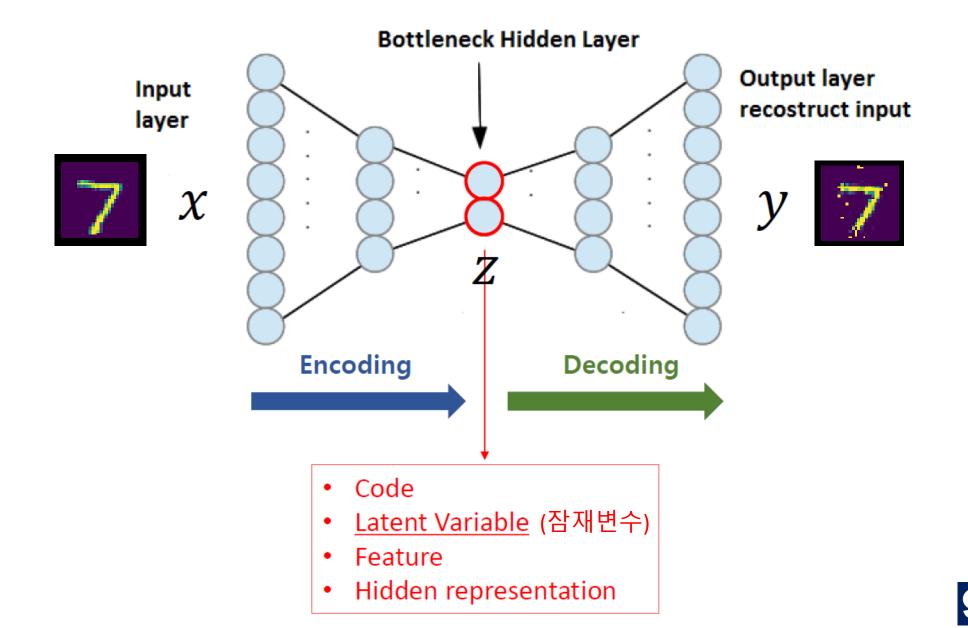
2020년 10월

강남우

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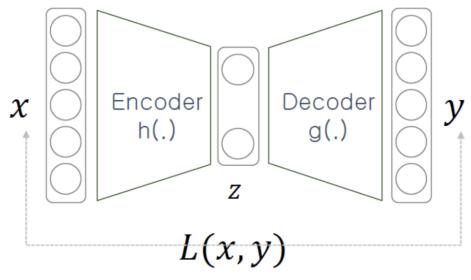


# Autoencoder – How to work





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$$z = h(x) \in \mathbb{R}^{d_z}$$

$$y = g(z) = g(h(x))$$

$$L_{AE} = \sum_{x \in D} L(x, y)$$



MSE or cross-entropy  $L_{AE} = ||x - y||^2$ 

Make output layer same size as input layer  $x, y \in \mathbb{R}^d$ 

Loss encourages output to be close input

입출력이 동일한 네트워크

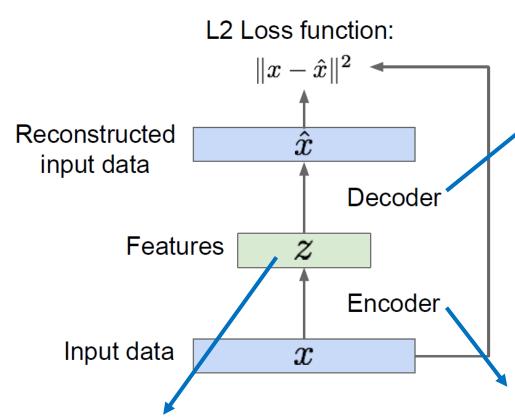
Unsupervised Learning → Supervised Learning

비지도학습문제를 지도학습문제로 바꾸어서 해결

- Decoder가 최소한 학습 데이터는 생성해 낼 수 있게 된다.
  - → 생성된 데이터가 학습 데이터를 좀 닮아있다.
- Encoder가 최소한 학습 데이터는 잘 latent vector로 표현 할 수 있게 된다.
  - → 데이터의 추상화를 위해 많이 사용된다.



## Autoencoder – How to work



z usually smaller than x(dimensionality reduction)

Originally: Linear +

nonlinearity (sigmoid)

Later: Deep, fully-connected

Later: ReLU CNN (upconv)

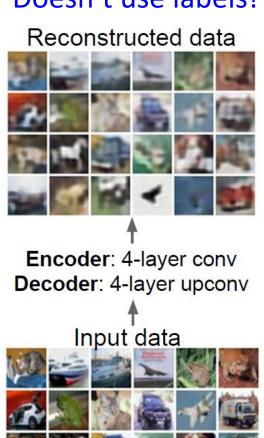
Originally: Linear +

nonlinearity (sigmoid)

Later: Deep, fully-connected

Later: ReLU CNN

### Doesn't use labels!





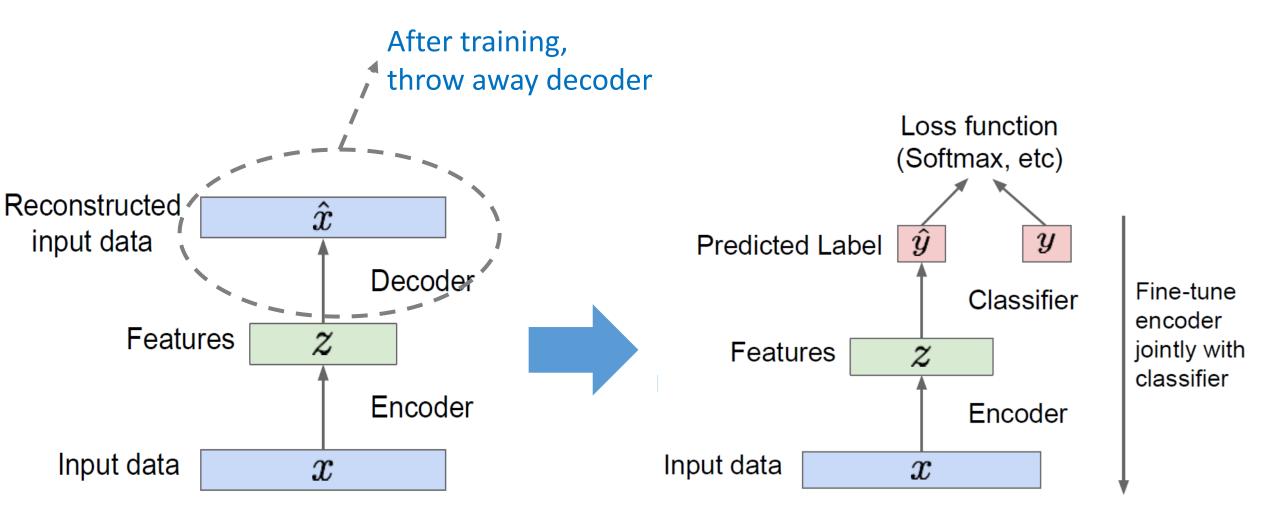
# **Autoencoder Coding**

```
# 모델 호습
hist = model.fit(x_train, x_train, nb_epoch=num_epochs, batch_size=batch_size, shuffle=True, verbose=1)
```

# Reconstructed input data Features Input data L2 Loss function: $\|x - \hat{x}\|^2$ Decoder DecoderEncoder



# **Application 1: Supervised Learning**



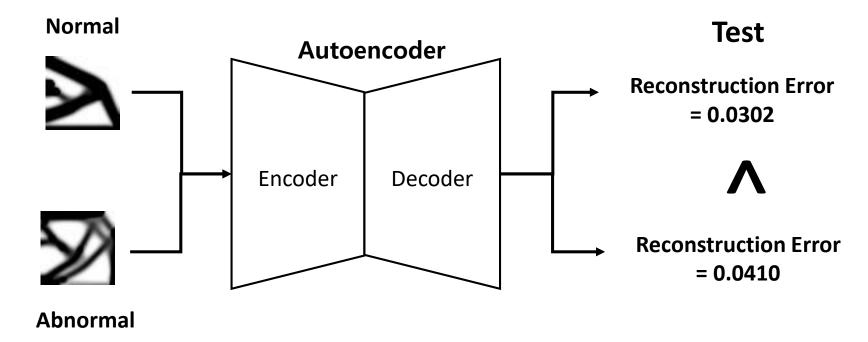
Encoder can be used to initialize a **supervised** model



# **Application 2: Anomaly Detection**

### **Define:**

- Normal: Brackets with *small* compliance → Normal data만 사용해서 AE 학습시키기
- Abnormal: Brackets with *large* compliance



→ Reconstruction Error가 임계치보다 크면 Abnormal로 분류



# **Application 2: Anomaly Detection**

### **Confusion Matrix**

n=165	Predicted: Negative	Predicted: Positive	
Actual: Negative	TN = 50	FP = 10	60
Actual: Positive	FN = 5	TP = 100	105
	55	110	

- true positives (TP): These are cases in which we predicted yes (they have the disease), and they do have the disease.
- true negatives (TN): We predicted no, and they don't have the disease.
- false positives (FP): We predicted yes, but they don't actually have the disease. (Also known as a "Type I error.")
- false negatives (FN): We predicted no, but they actually do have the disease. (Also known as a "Type II error.")



# **Application 2: Anomaly Detection**

### Go to <a href="http://www.smartdesignlab.org/dl.html">http://www.smartdesignlab.org/dl.html</a>

### **Confusion Matrix**

n=165	Predicted: Negative	Predicted: Positive	
Actual: Negative	TN = 50	FP = 10	60
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### 성능지표

- Accuracy (실제 이상/정상인지 맞게 예측한 비율)
  - = (TP+TN)/(TP+FN+FP+TN) = 90.9%
- Precision (이상으로 예측한 것중에 실제 이상인 샘플의 비율)
  - = TP/(TP+FP) = 90.9%
- Recall (실제 이상 샘플중에 이상으로 예측한 비율)

$$= TP/(TP+FN) = 95.20\%$$



# What Questions Do You Have?

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