## **Autoencoder & Anomaly Detection**

### **Namwoo Kang**

Smart Design Lab
CCS Graduate School of Green Transportation
KAIST



### Reference

### □ 강의 슬라이드 및 실습코드는 아래의 링크에서 받으실 수 있습니다

- http://www.smartdesignlab.org/dl\_aischool\_2021.html
- Contributors: 김성신, 유소영, 이성희, 김은지

### □ 강의 소스

- Andrew Ng O ML Class (www.holehouse.org/mlclass/)
- Fei-Fei Li & Justin Johnson & Serena Yeung, CS231n: Convolutional Neural Networks for Visual Recognition, Stanford (<a href="http://cs231n.stanford.edu/">http://cs231n.stanford.edu/</a>)
- Stefano Ermon & Aditya Grover, CS 236: Deep Generative Models , Stanford (<a href="https://deepgenerativemodels.github.io/">https://deepgenerativemodels.github.io/</a>)
- 모두를 위한 딥러닝 (https://hunkim.github.io/ml/)
- 모두를 위한 딥러닝 시즌 2 (https://deeplearningzerotoall.github.io/season2/lec\_tensorflow.html)
- 이활석, Autoencoders (https://www.slideshare.net/NaverEngineering/ss-96581209)
- 최윤제, 1시간만에 GAN(Generative Adversarial Network) 완전 정복하기 (<a href="https://www.slideshare.net/NaverEngineering/1-gangenerative-adversarial-network?gid=c53ce33f-6643-4437-8e93-88776c9cebb1&v=&b=&from\_search=5">search=5</a>)
- 김성범, [핵심 머신러닝] Principal Component Analysis (PCA, 주성분 분석) (https://youtu.be/FhQm2Tc8Kic)



### **Contents**

- Ch1: Introduction to Unsupervised Learning Part I
- → Probability & Maximum Likelihood
- Ch2: Introduction to Unsupervised Learning Part II
- → Generative Model & Dimensionality Reduction

Ch3: Principal Component Analysis (PCA)

→ Machine Learning Model

Ch4: Autoencoder & Anomaly Detection

Ch5: Variational AutoEncoder (VAE)

**Ch6: Generative Adversarial Network (GAN)** 

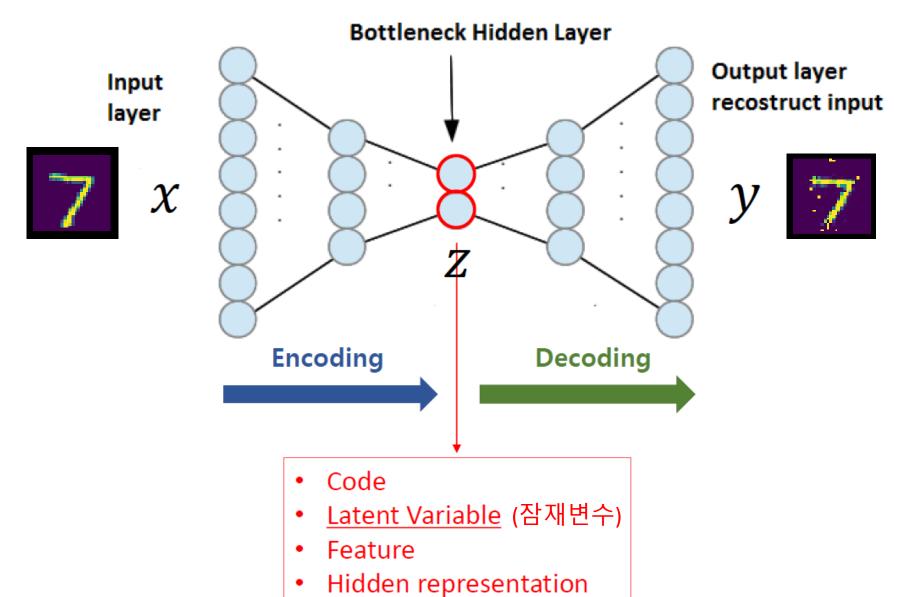
Ch7: Application: Mechanical Design + Al

→ Deep Learning Models

→ CAD/CAM/CAE/Design Optimization + AI

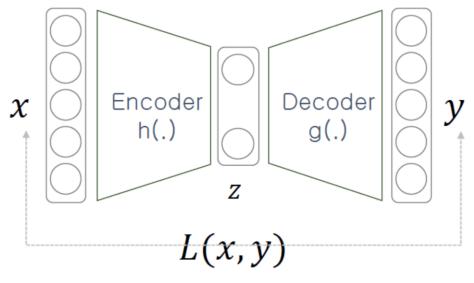


# Autoencoder – How to work





## Autoencoder – How to work



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

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

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



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

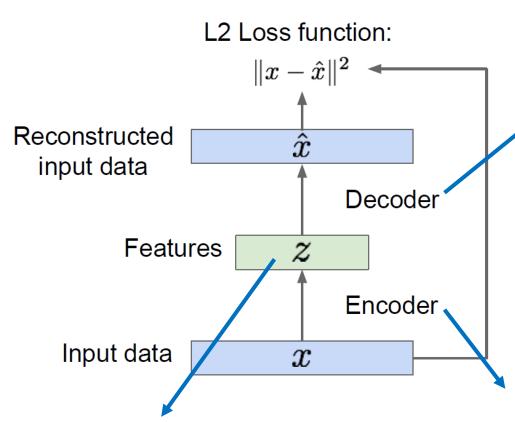
Unsupervised Learning → Supervised Learning

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!





Encoder: 4-layer conv Decoder: 4-layer upconv







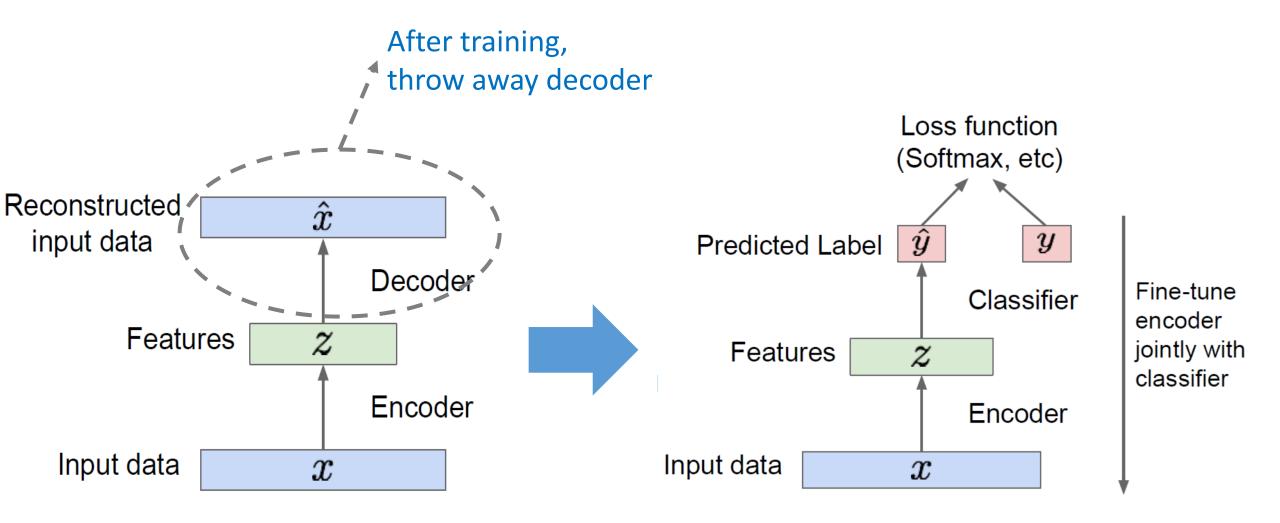
# **Autoencoder Coding**

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

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



# **Application 1: Supervised Learning**

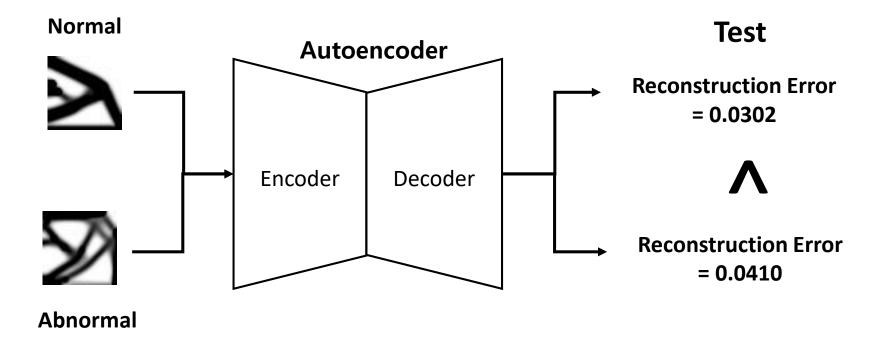


Encoder can be used to initialize a **supervised** model

# **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



# What Questions Do You Have?

nwkang@kaist.ac.kr

www.smartdesignlab.org

