

# Generative Adversarial Network (Intro)

2018/05/06

강준하

# Reference

- [Taehun Kim] 지적 대화를 위한 깊고 넓은 딥러닝
  - <https://www.slideshare.net/carpedm20/pycon-korea-2016?qid=0b8383ce-826d-4451-ae10-9cf323842145&v=&b>
- [Jaejun Yoo] PR12와 함께 이해하는 GANs
  - <https://www.slideshare.net/thinkingfactory/pr12-intro-to-gans-jaejun-yoo>
- [Yunjey Choi] 1시간만에 GAN(Generative Adversarial Network) 완전 정복하기
  - <https://www.slideshare.net/NaverEngineering/1-gangenerative-adversarial-network>
- 오일석, 기계학습, 2017, 한빛미디어

# Index

1. Generative Model Introduction
2. About GAN

# 1. Generative Model Introduction

# Motivation



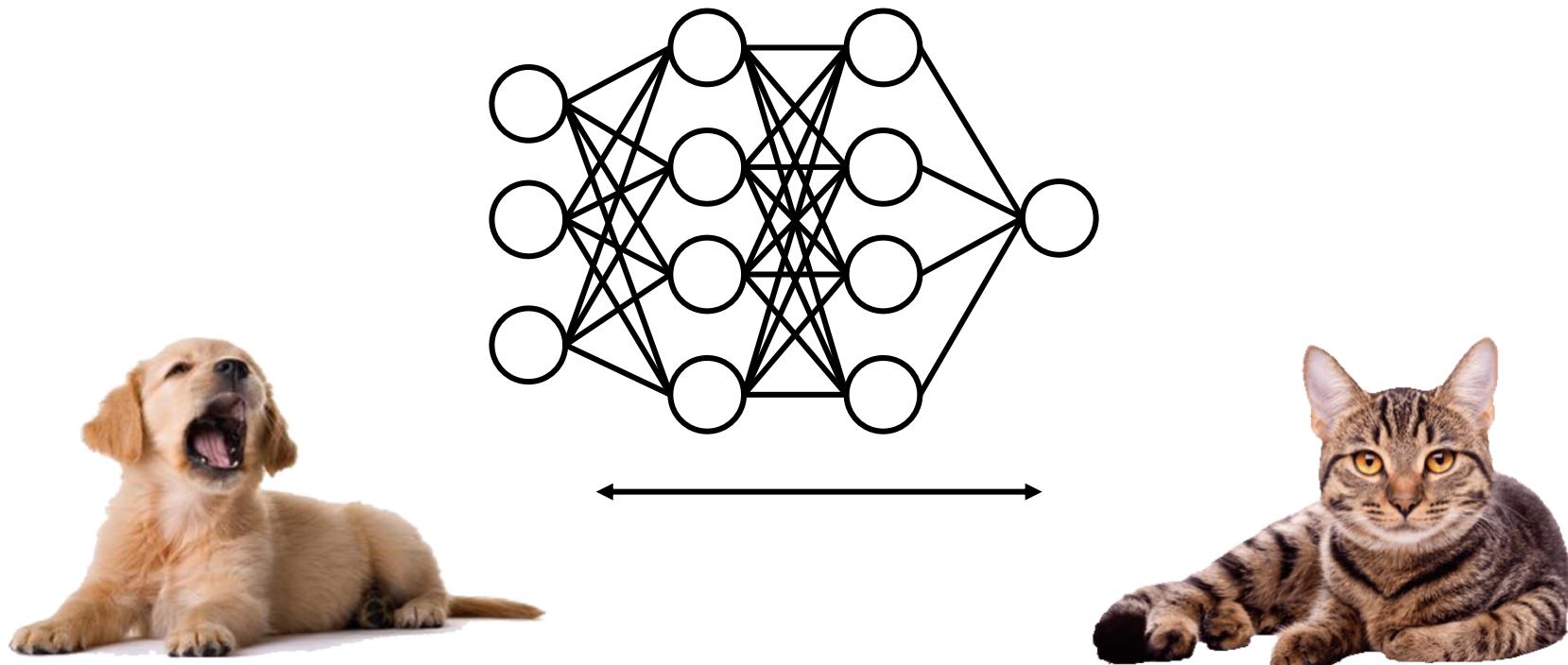
**“Generated Images by Neural Network”**

\* Figure adopted from BEGAN paper released at 31. Mar. 2017 David Berthelot et al. Google ([link](#))

# What is 'Generative Model'?

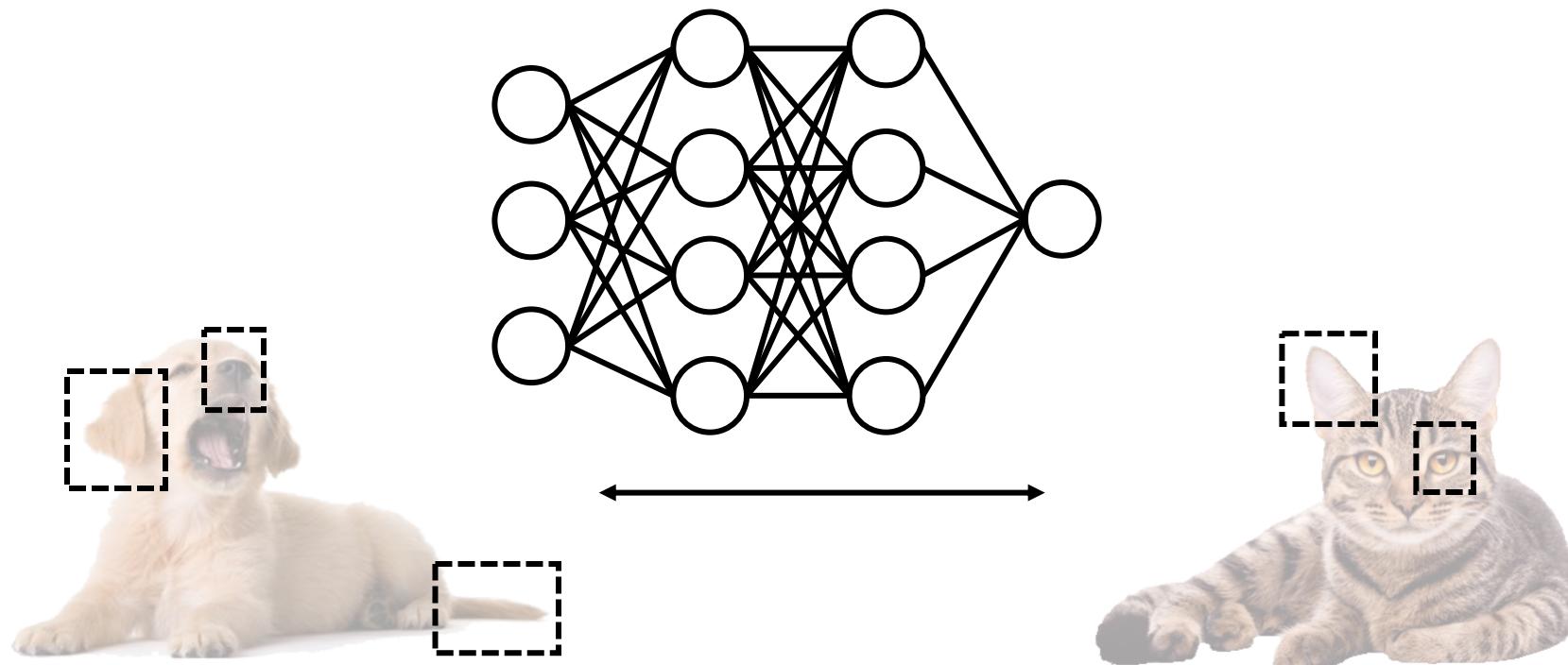
- Richard Feynman
  - “What I cannot create, I do not understand.”  
(내가 만들어낼 수 없다면, 난 그것을 이해하지 못한 것이다.)
- 이제까지 우리가 공부해왔던 내용 : 분별 모델

# Discriminative vs Generative



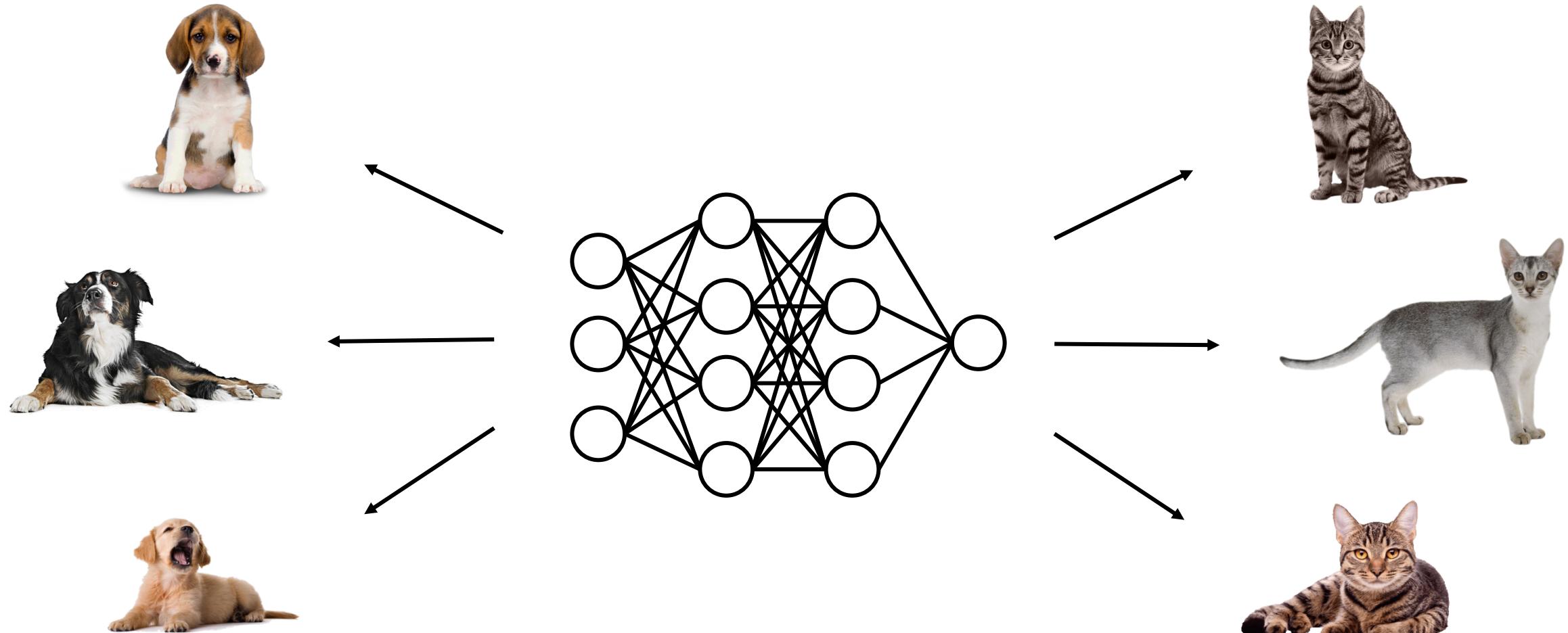
개와 고양이를 구분하는 모델

# Discriminative vs Generative



단순히 특징을 배운 것에 불과

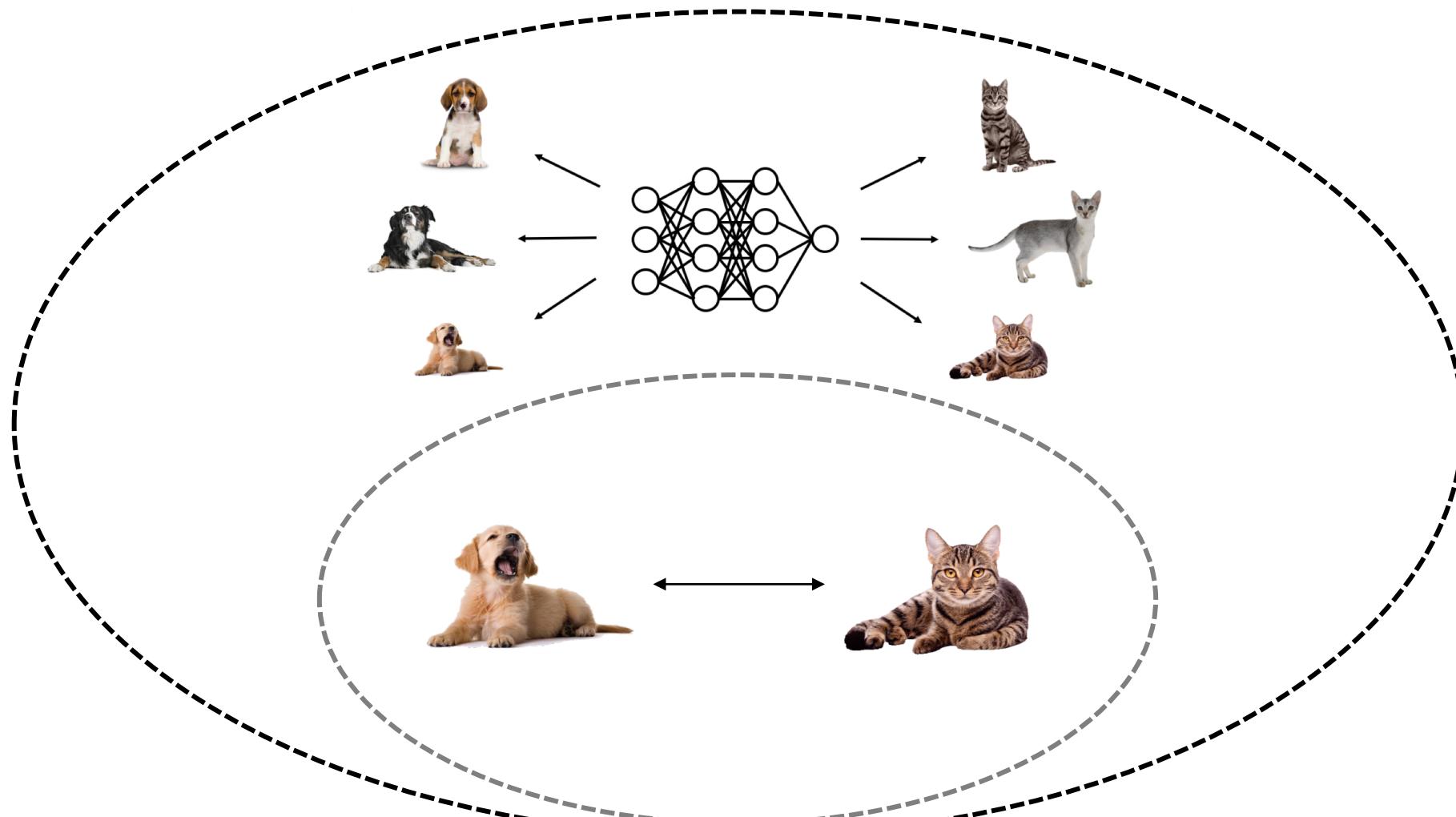
# Discriminative vs Generative



개와 고양이 사진을 만들 수 있는 모델?

→ 분류 모델보다는 개와 고양이를 제대로 이해하고 있다!

# Discriminative vs Generative



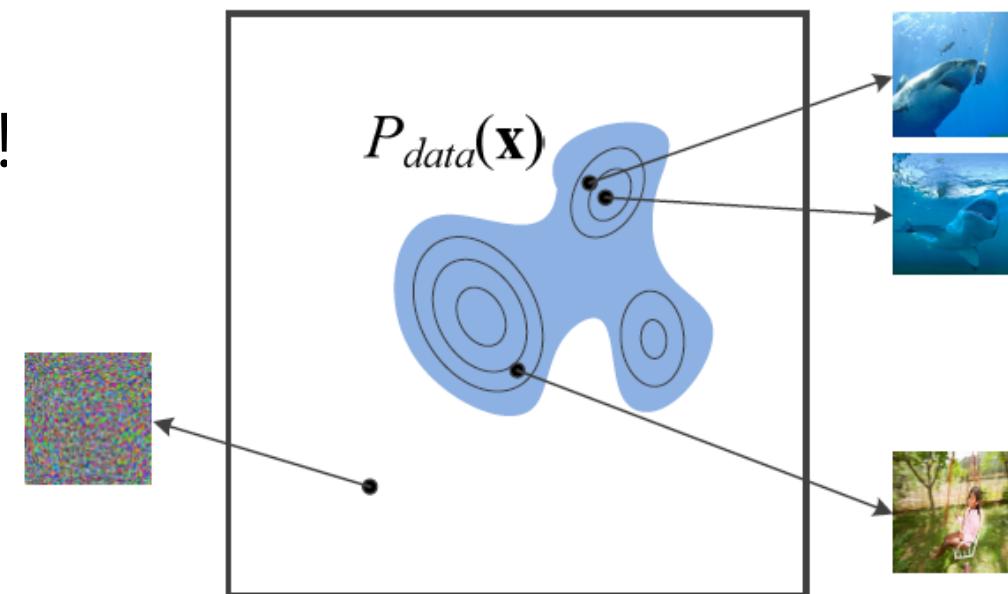
제대로 이해하고 있다면, 개와 고양이의 분류는 쉬운 문제

# Discriminative vs Generative

모델	학습 단계가 할 일	예측 단계가 할 일	지도 여부
분별 모델	$P(y x)$ 추정	$f: x \mapsto y$	지도 학습
생성 모델	$P(x)$ 또는 $P(x y)$ , $P(x, y)$ 추정	$f: \text{씨앗} \mapsto x$ 또는 $f: \text{씨앗 } y \mapsto x$ , $f: \text{씨앗} \mapsto x, y$	비지도 학습

# Generative model

- 자연의 사진 data 또한 어떤 probability distribution model에 의해 생긴 결과일 것이라고 가정
- 그렇다면 이 probability distribution을 알아낼 수 있다면 인위적으로 샘플을 생성 가능
- 진짜처럼 보이는 '가짜' 자료 생성 가능!



# Generative model

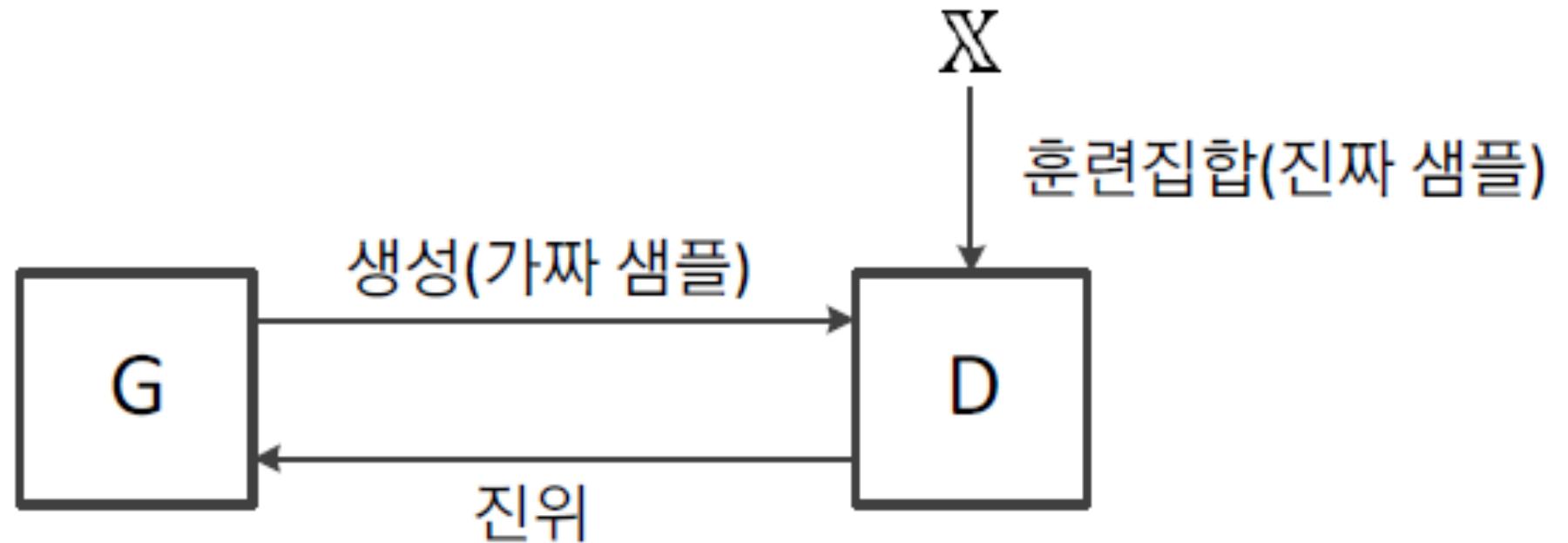
- GAN (Generative Adversarial Network)
- VAE (Variational AutoEncoder)
- RNN
- RBM
- 등의 모델들...
- 현재 GAN이 가장 우월한 성능 보이는 중!

## 2. About GAN(Generative Adversarial Network)

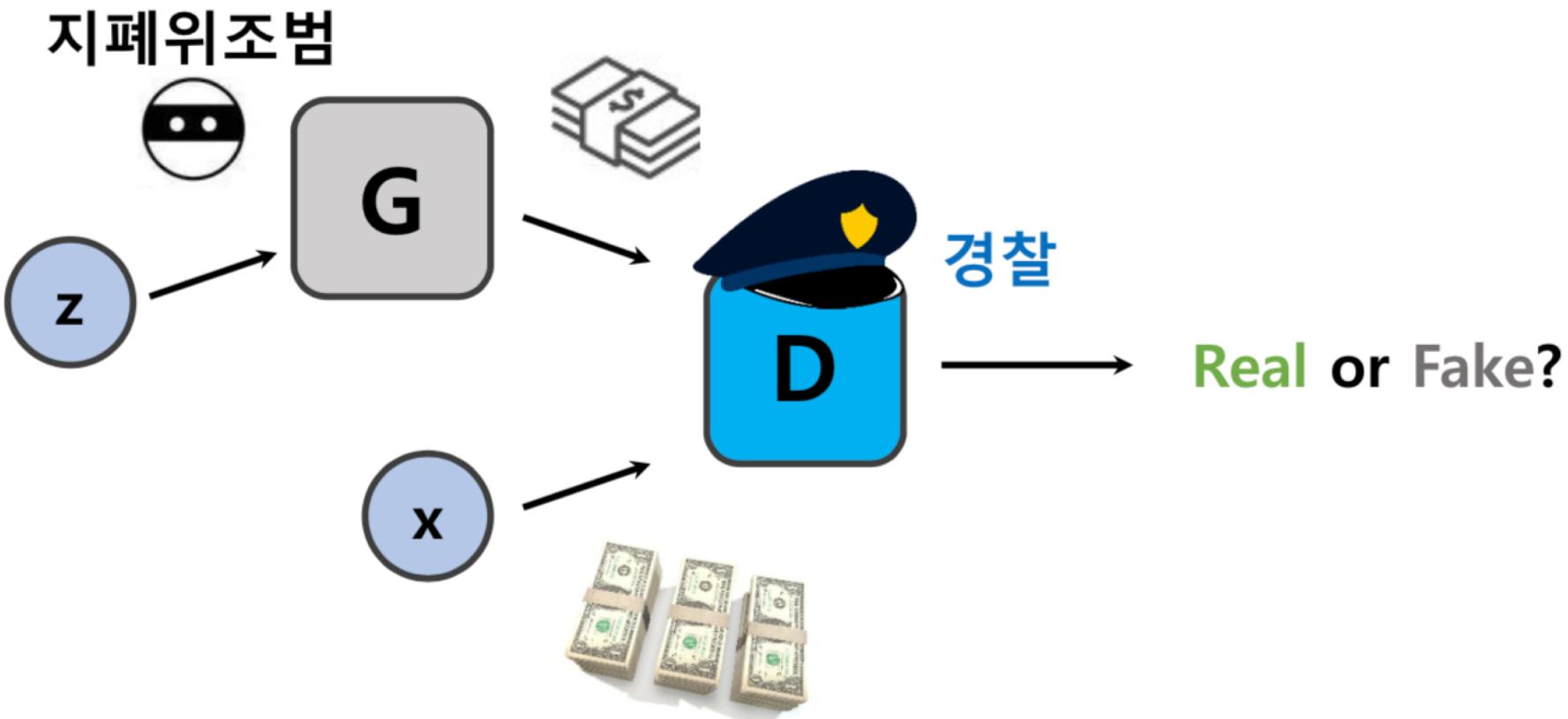
# GAN(Generative Adversarial Network)

- Generative
  - 생성 모델
- Adversarial
  - 서로 대립 관계에 있는, 대립적인
- Network
  - Neural Network 이용해서 구현

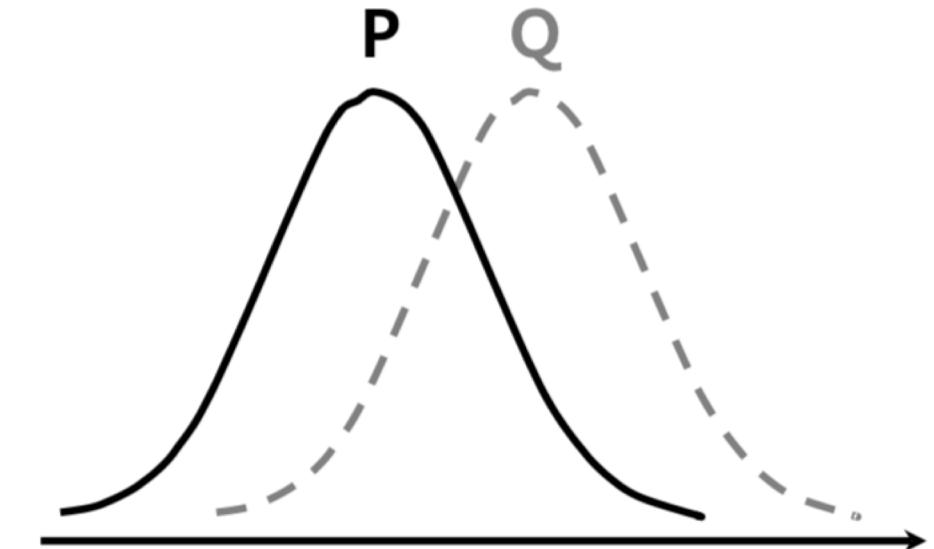
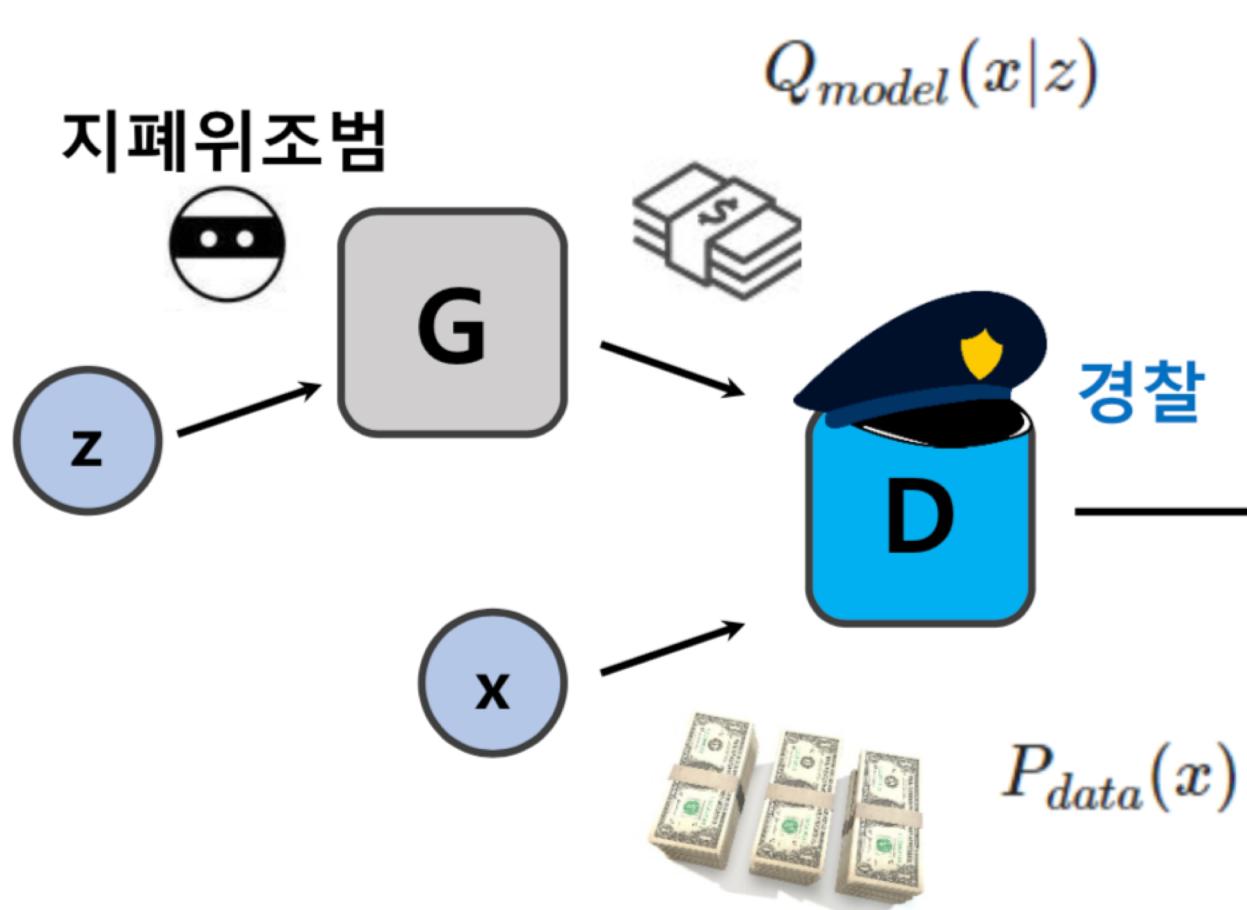
# GAN(Generative Adversarial Network)



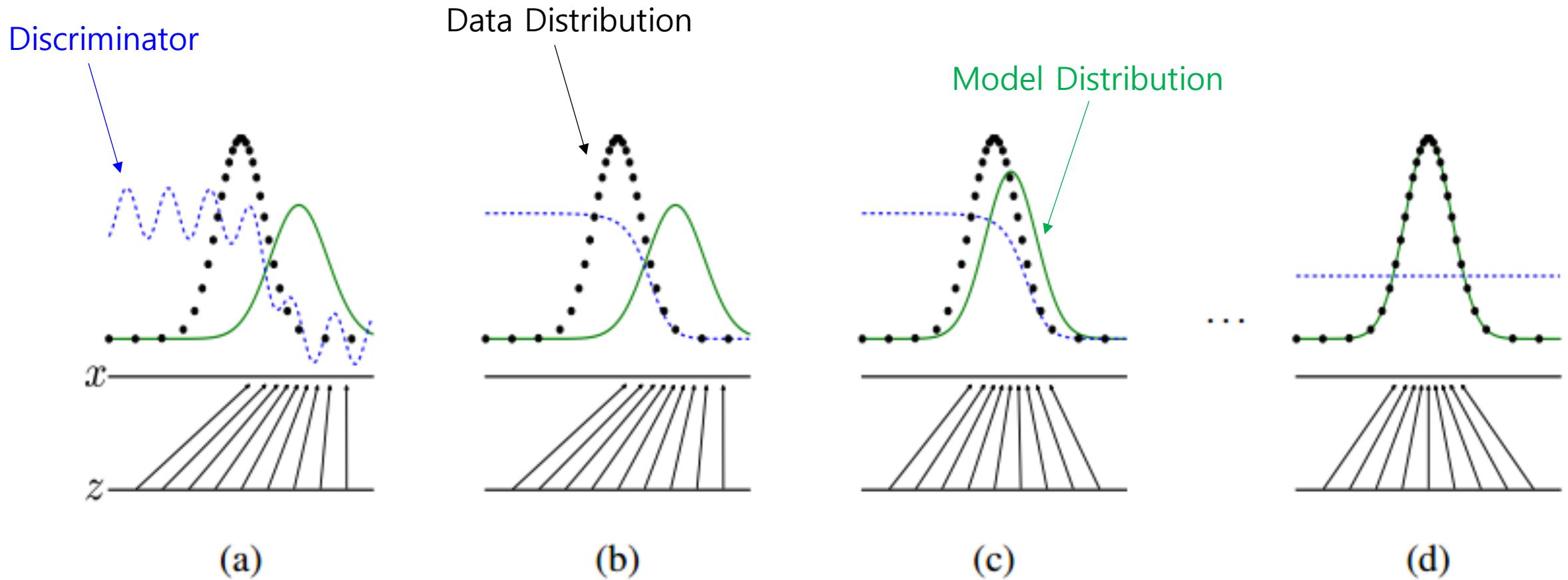
# GAN(Generative Adversarial Network)



# GAN(Generative Adversarial Network)

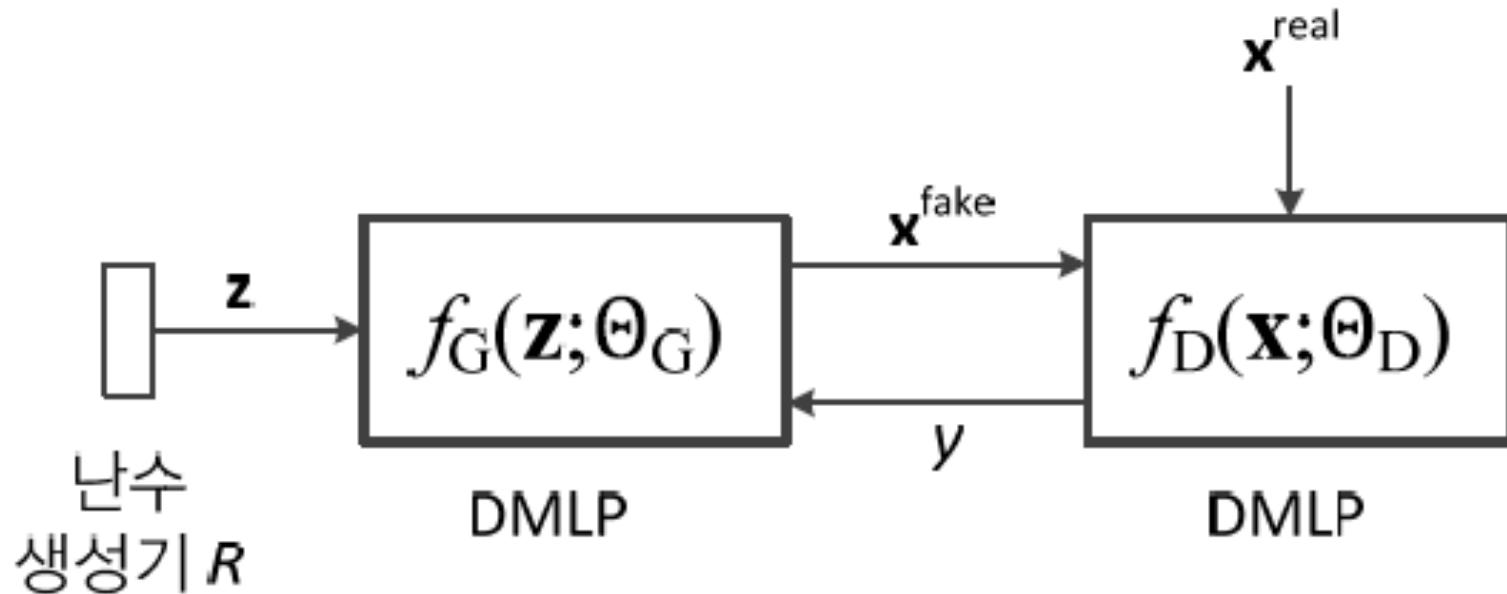


# GAN(Generative Adversarial Network)

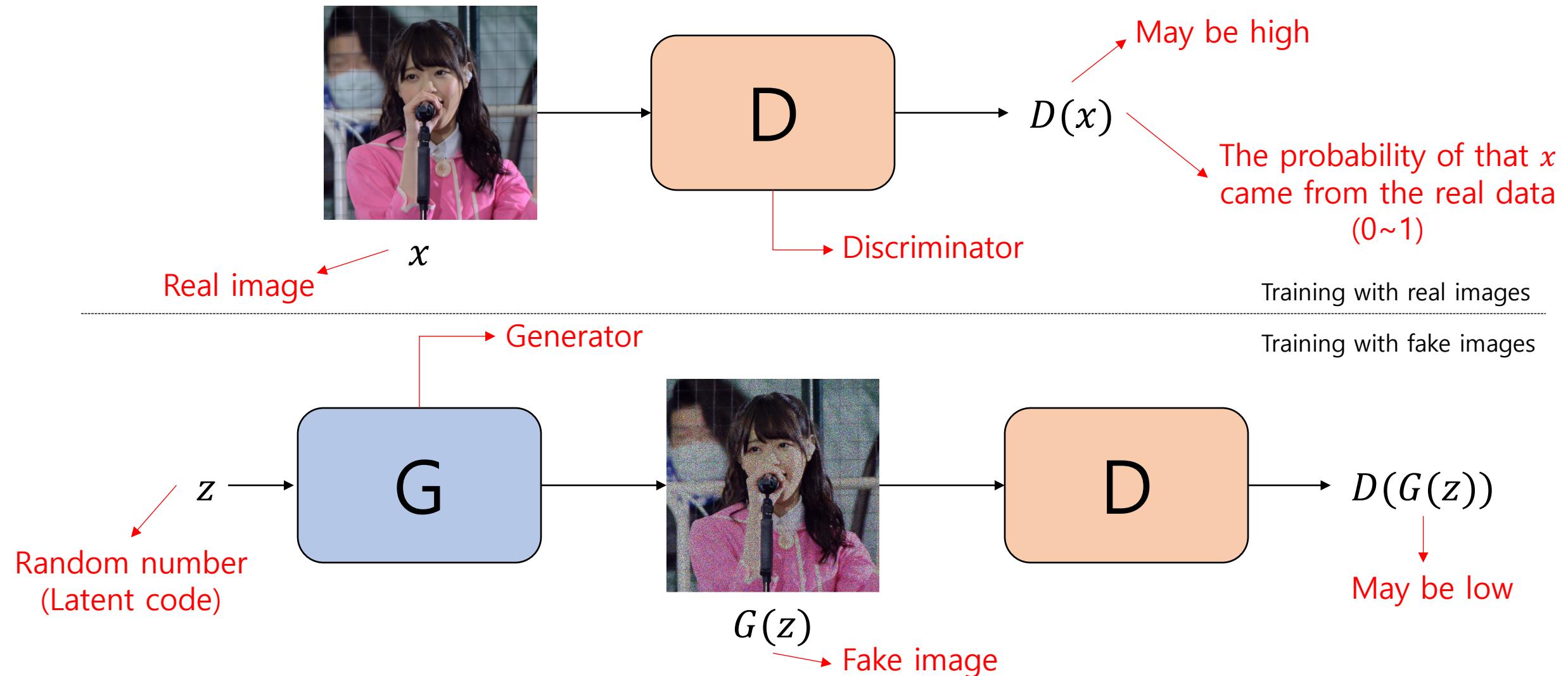


# Structure of GAN

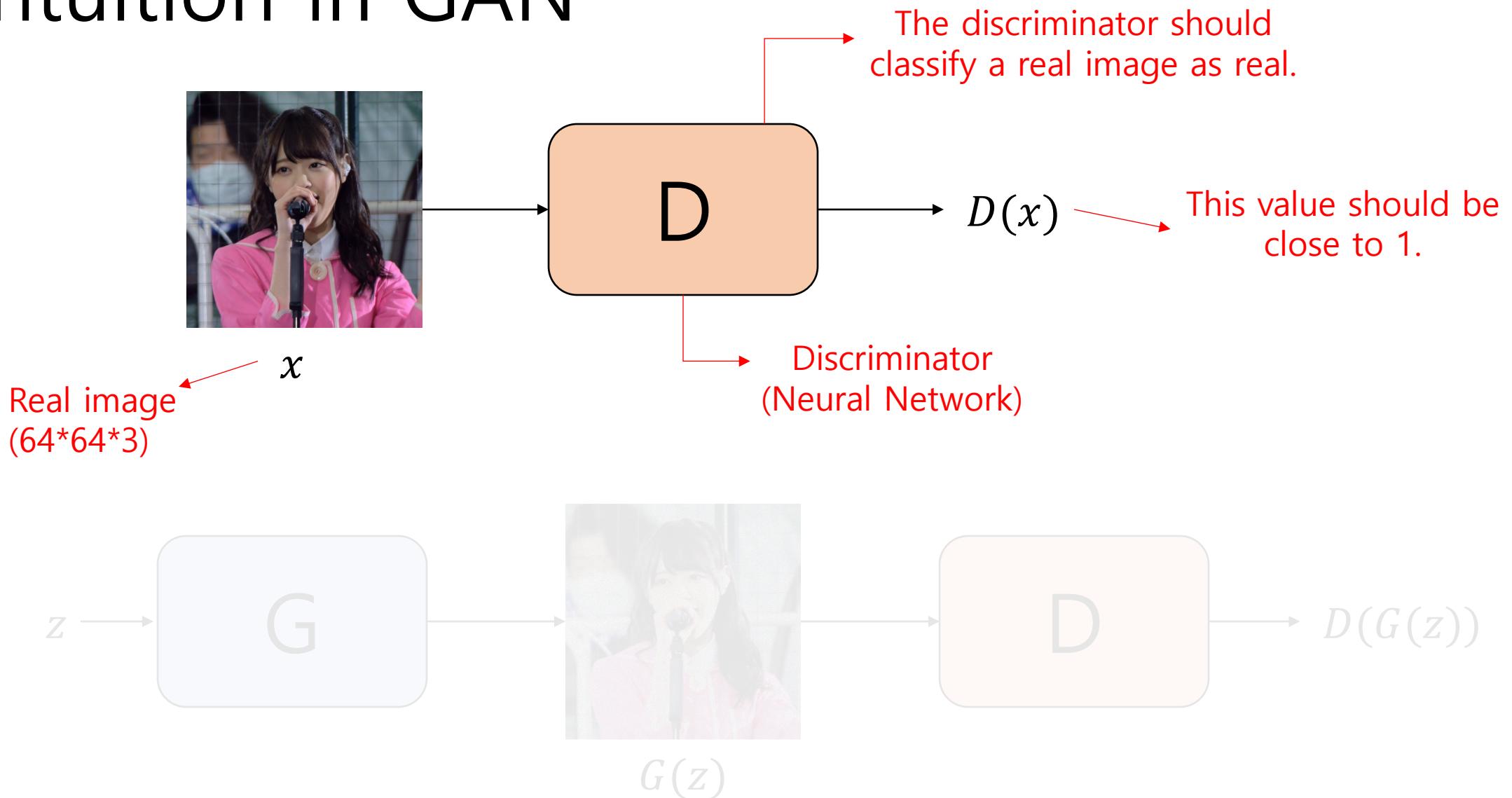
- Generator와 Discriminator를 DMLP(Deep Multi-Layer Perceptron)로 구성



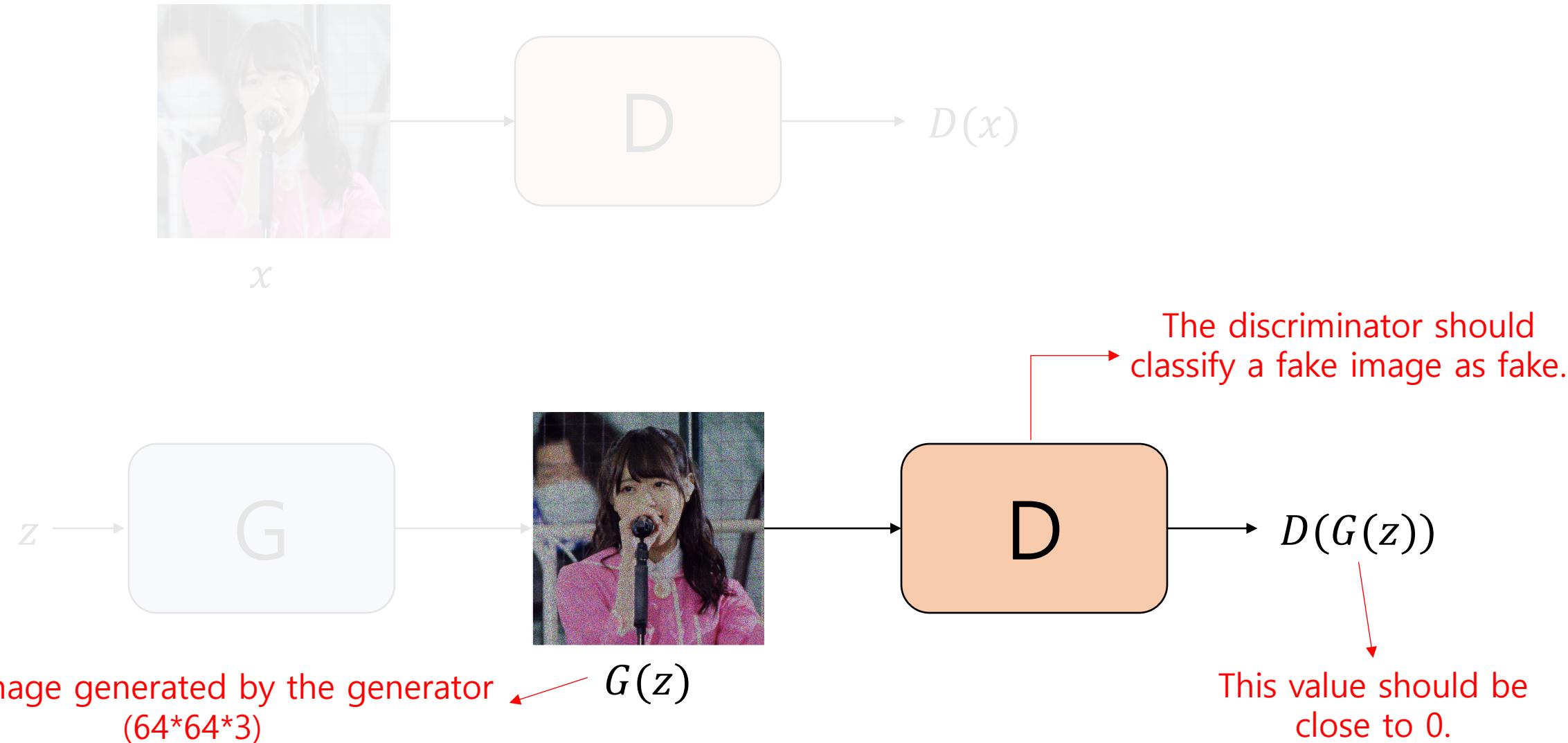
# Intuition in GAN



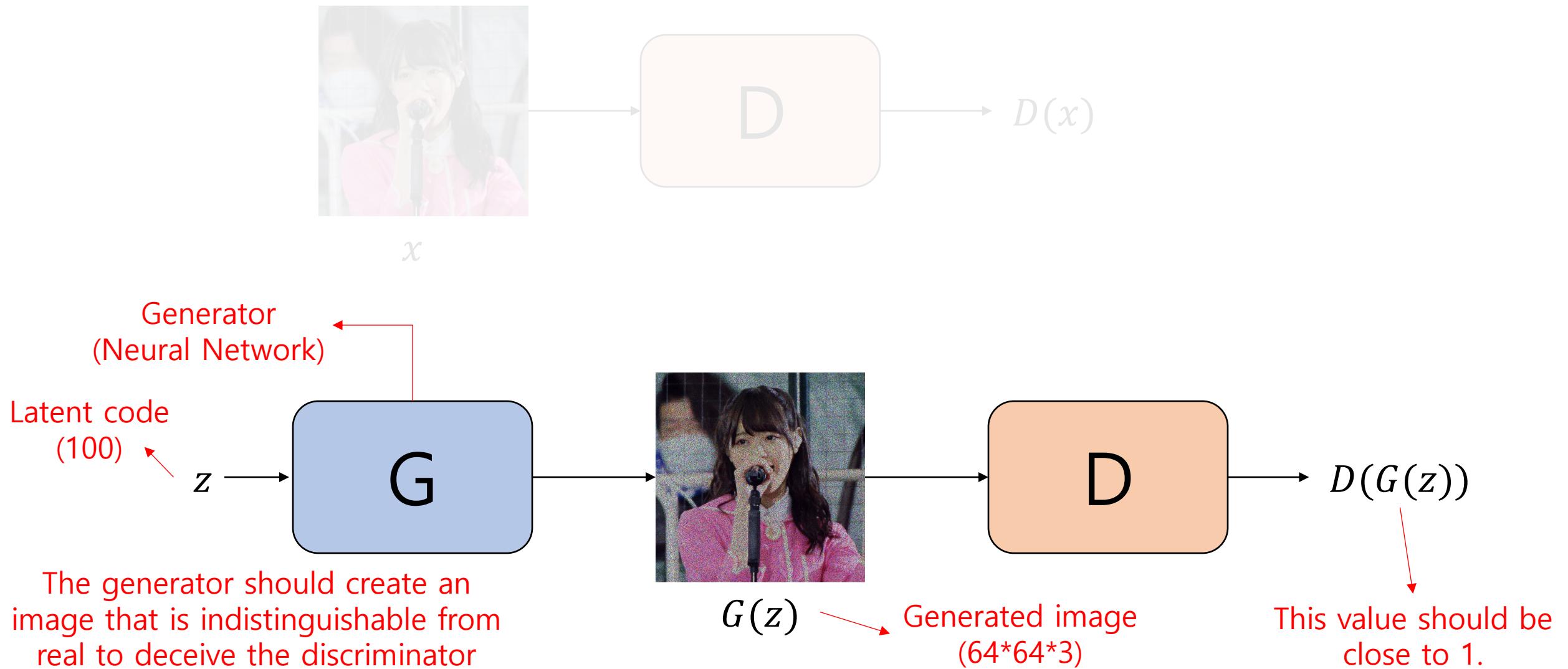
# Intuition in GAN



# Intuition in GAN



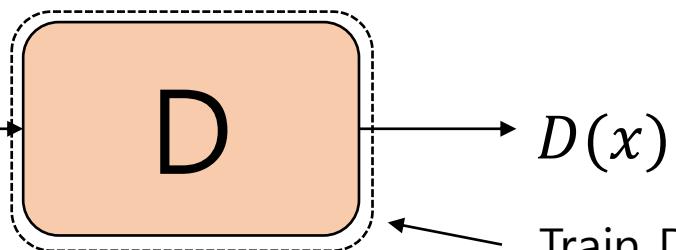
# Intuition in GAN



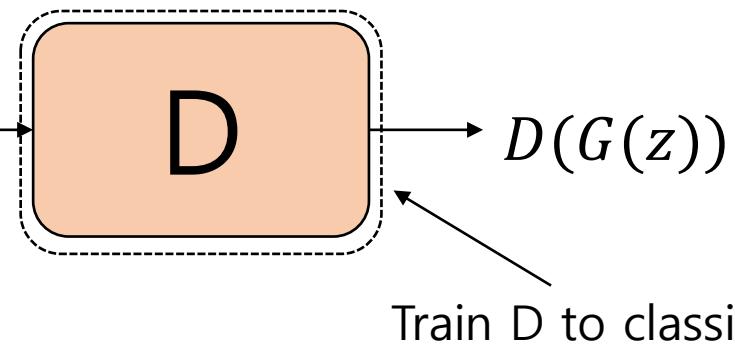
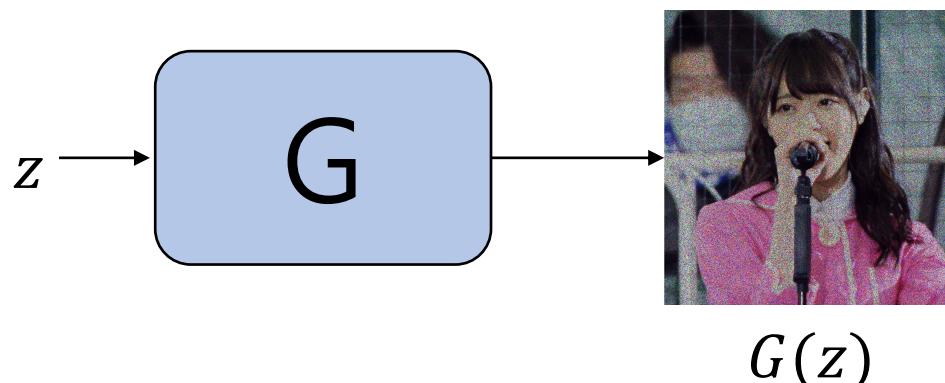
# Objective Function of GAN

$$\min_G \max_D V(D, G) = E_{x \sim p_{data}(x)}[\log D(x)] + E_{z \sim p_z(z)}[\log(1 - D(G(z)))]$$

Sample  $x$  from real data distribution  
Sample latent code  $z$  from Gaussian distribution  
 $D$  should maximize  $V(D, G)$   
Maximum when  $D(x) = 1$   
Maximum when  $D(G(z)) = 0$



Objective function



Training with real images

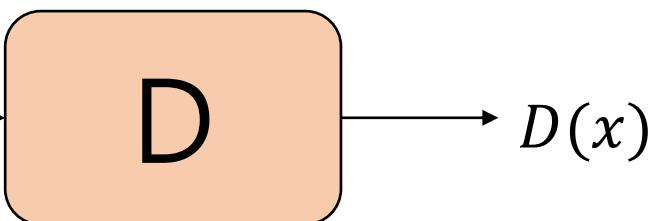
Training with fake images

Train D to classify fake images as fake

# Objective Function of GAN

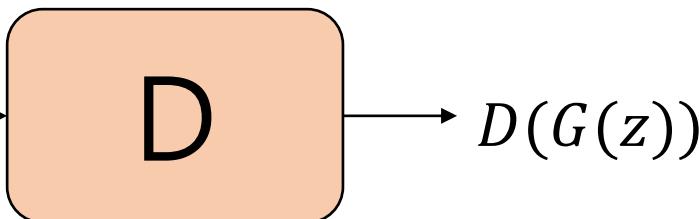
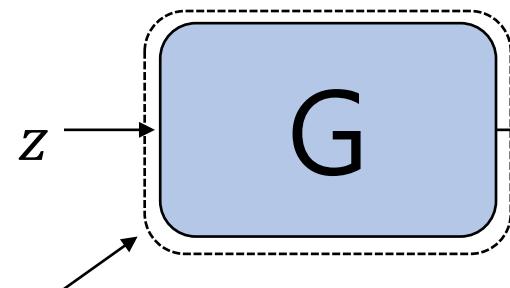
$$\min_G \max_D V(D, G) = E_{x \sim p_{data}(x)} [\log D(x)] + E_{z \sim p_z(z)} [\log(1 - D(G(z)))]$$

*G* is independent of this part  
*G* should minimize  $V(D, G)$   
Minimum when  $D(G(z)) = 1$



Objective function

$x$



Training with real images

Training with fake images

Train  $G$  to deceive  $D$

$G(z)$

# Maybe Next?

- Theory in GAN
- GAN Tensorflow implementation
- Variants of GAN