FastCampus Pytorch

Ch10. Generative Adversarial Netowkrs

HARRY KIM

Lecture Content

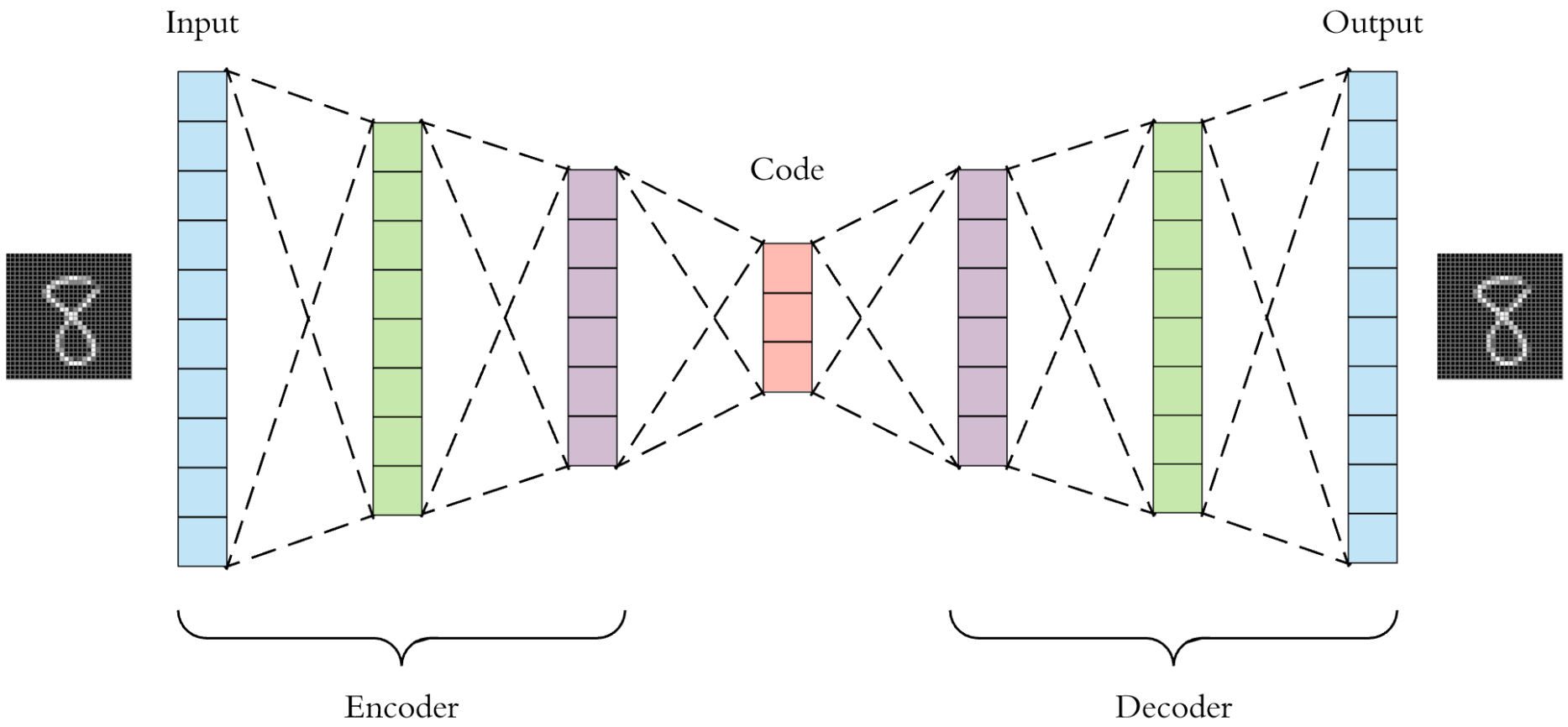
1. Limit of Auto-Encoder
2. Adversarial Networks
3. DCGAN
4. cGAN
5. Recent Works

- 강의 자료
  - Online
    - NIPS 2016 Tutorial: Generative Adversarial Networks [https://arxiv.org/pdf/1701.00160.pdf]
    - UNSUPERVISED REPRESENTATION LEARNING WITH DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS [https://arxiv.org/pdf/1511.06434.pdf]
    - Conditional Generative Adversarial Nets [https://arxiv.org/pdf/1411.1784.pdf]
    - Pix2Pix [https://arxiv.org/pdf/1611.07004.pdf]
    - Progressive Growing of GANs for Improved Quality, Stability, and Variation [https://arxiv.org/pdf/1710.10196.pdf]
    - UVA DEEP LEARNING COURSE [University of Amsterdam, 2018]

1. Limit of Auto-Encoder

Limit of Auto-Encoder

- **Auto-Encoder**



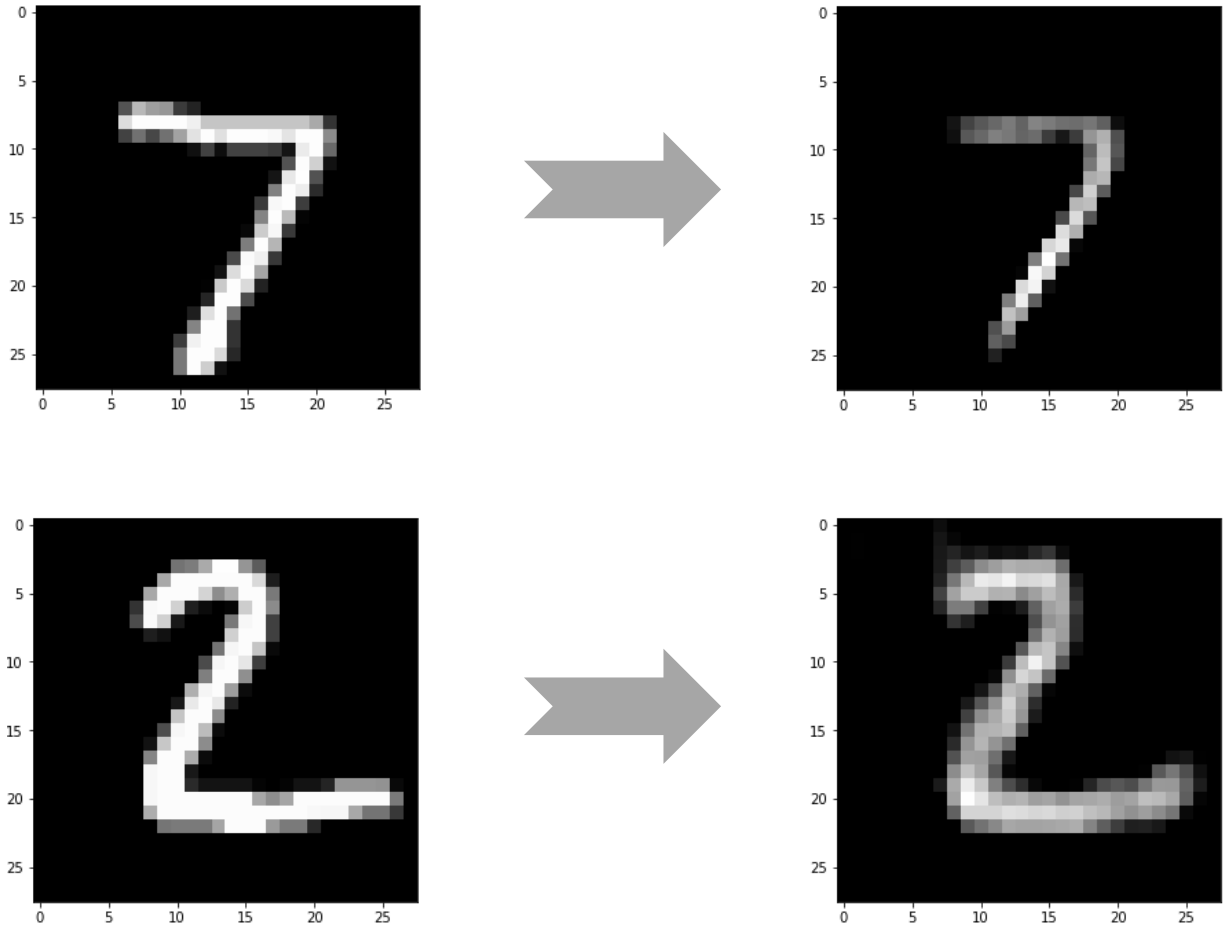
https://towardsdatascience.com/applied-deep-learning-part-3-autoencoders-1c083af4d798

Limit of Auto-Encoder

- **Variational Auto-Encoder**
  - **Variational Inference**
  - $q_\phi(z|x) \sim N(\mu_q(x), \Sigma_q(x))$
  - **Reparameterization trick**
  - $z = \mu(x) + \sigma(x) * \varepsilon, \quad \varepsilon \sim N(0,1)$
  - **Z가 zero-mean Gaussian일 때,**
  - $D_{KL}(q_\phi(z|x)||p_\theta(z)) = D_{KL}[N(\mu_q(x), \Sigma_q(x))||N(0,1)]$

Limit of Auto-Encoder

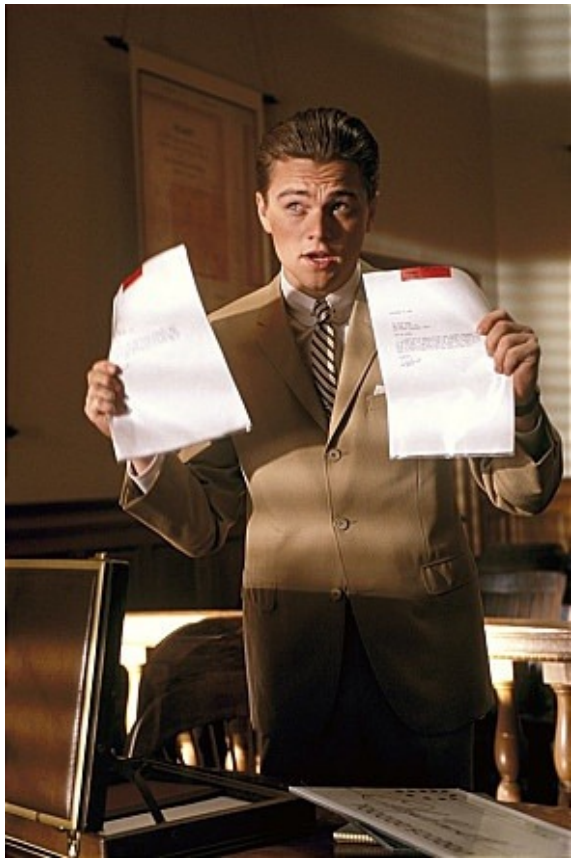
- **Other limitation**
  - 그림이 Blur하게 출력됨



2. GAN(Generative Adversarial Networks)

GAN(Generative Adversarial Network)

- **적대적 생성(Adversarial Networks)**
  - 생성을 '적대적'으로 하겠다



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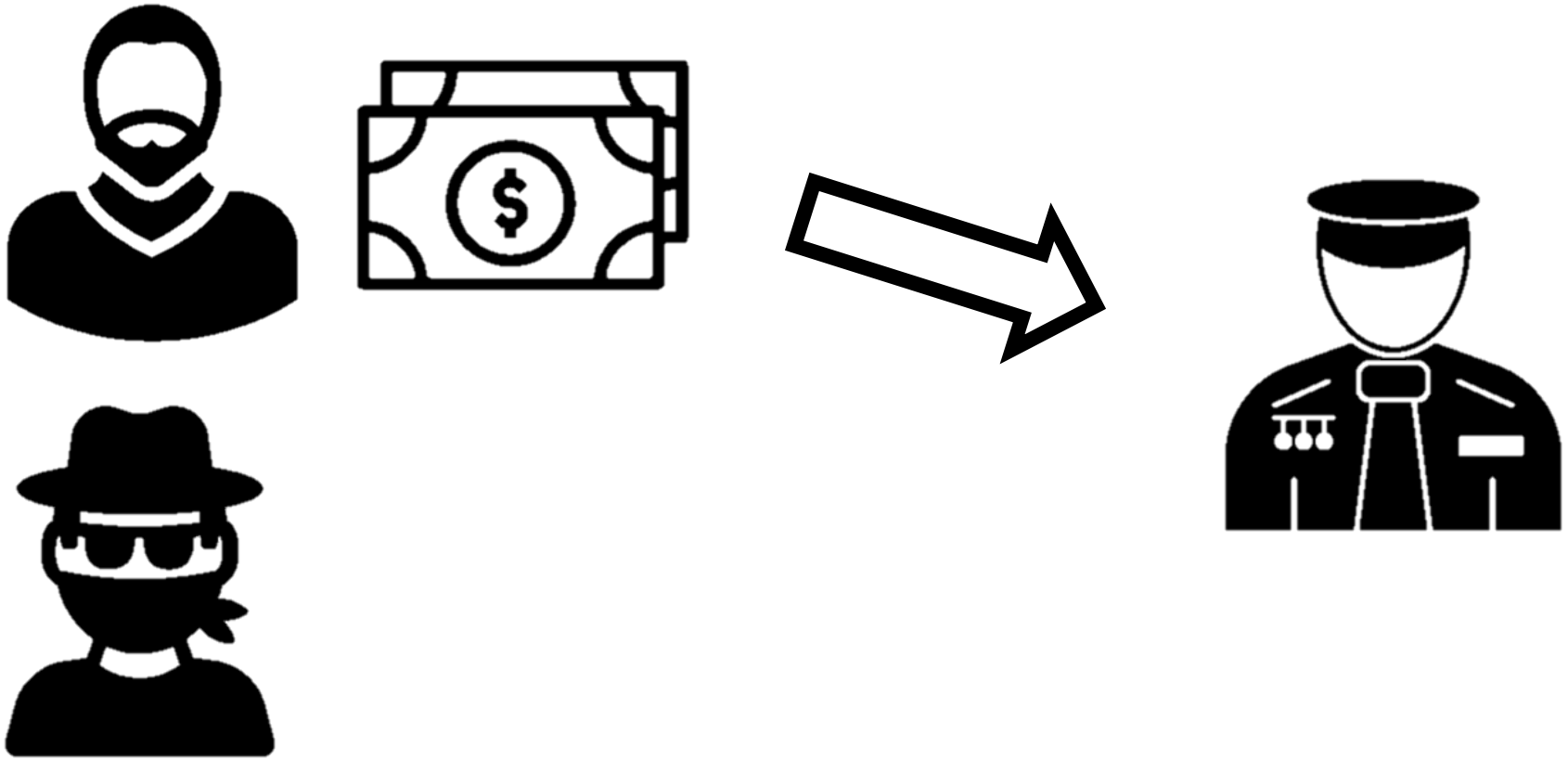

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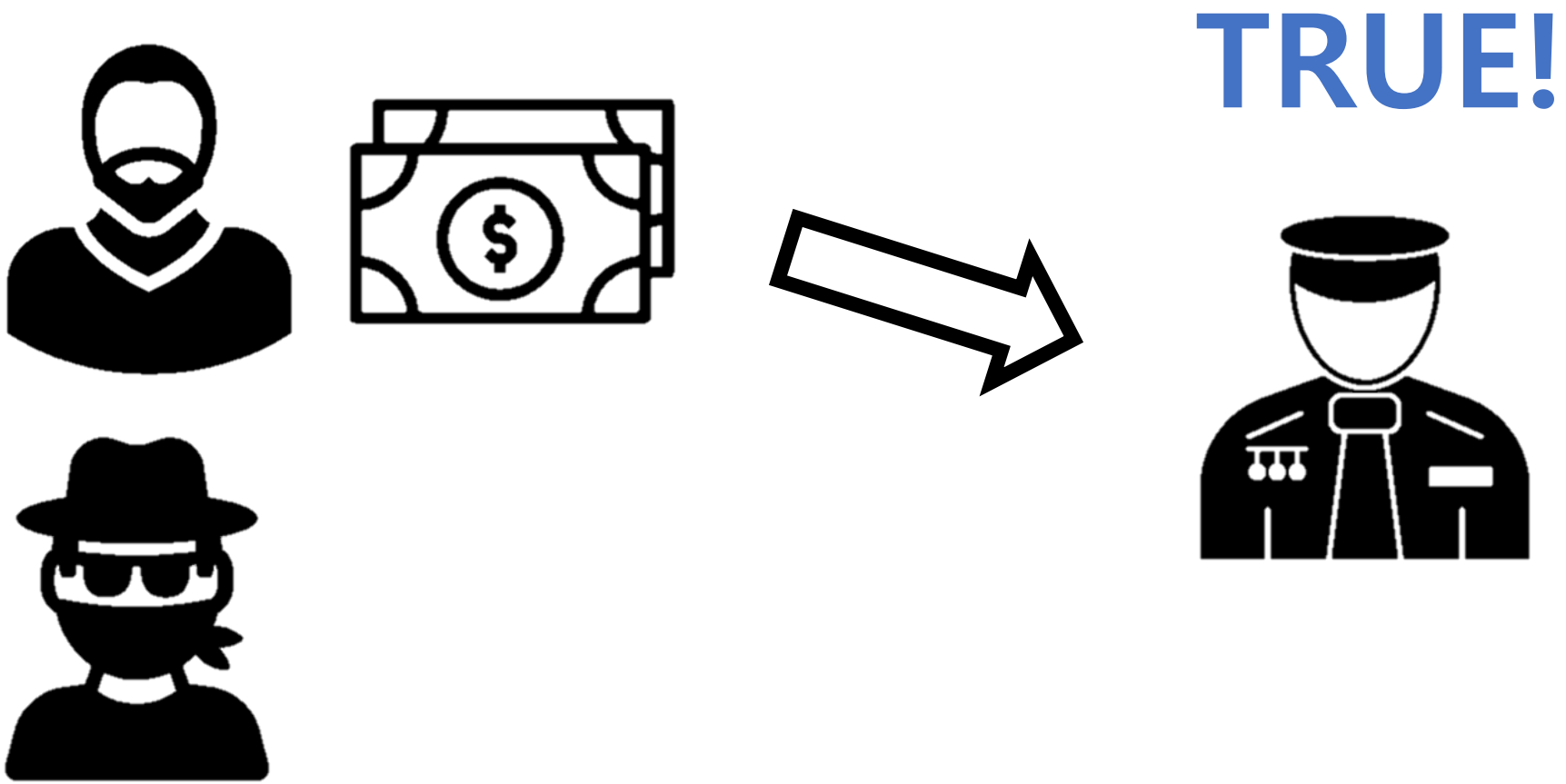

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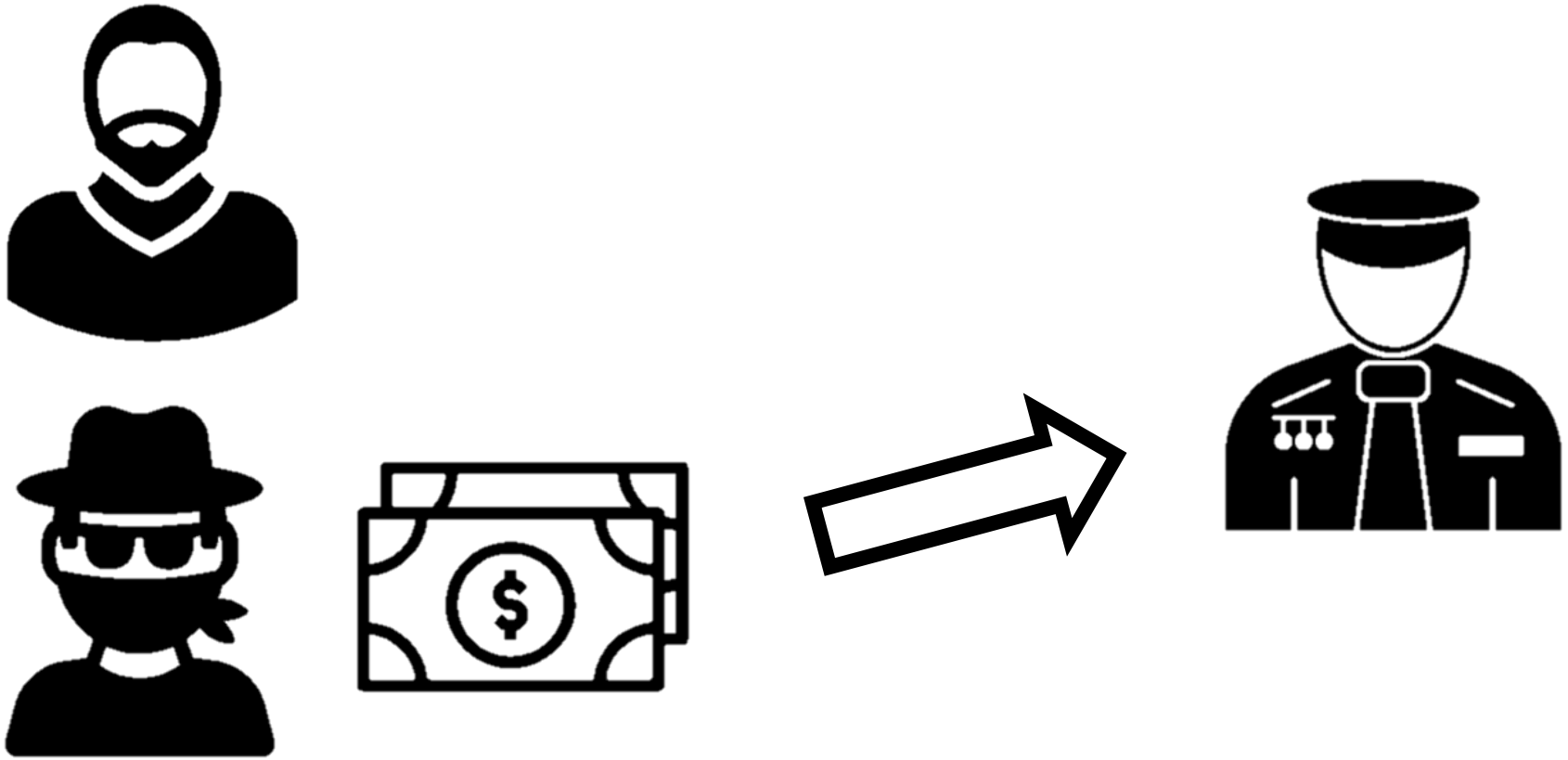

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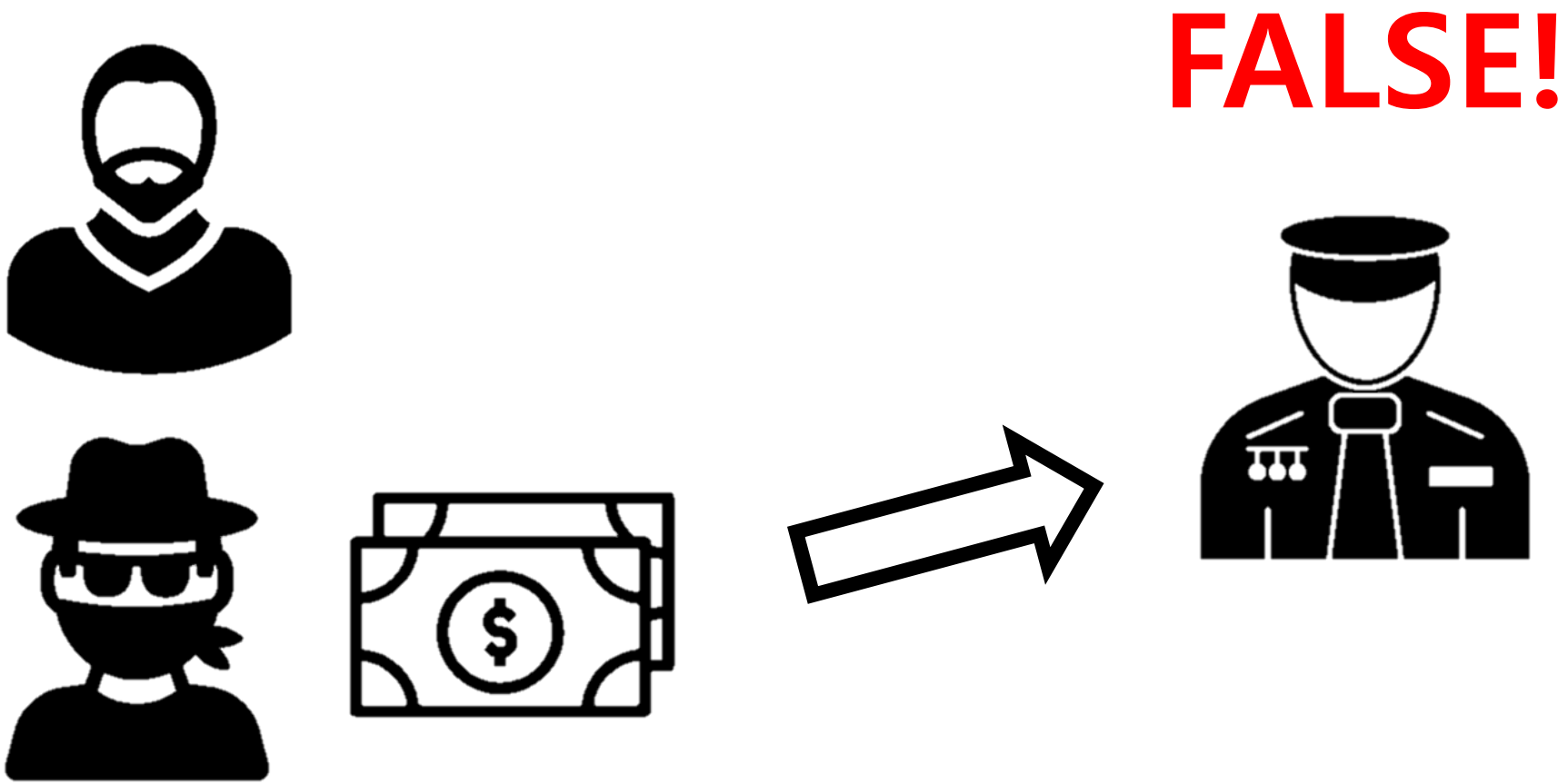

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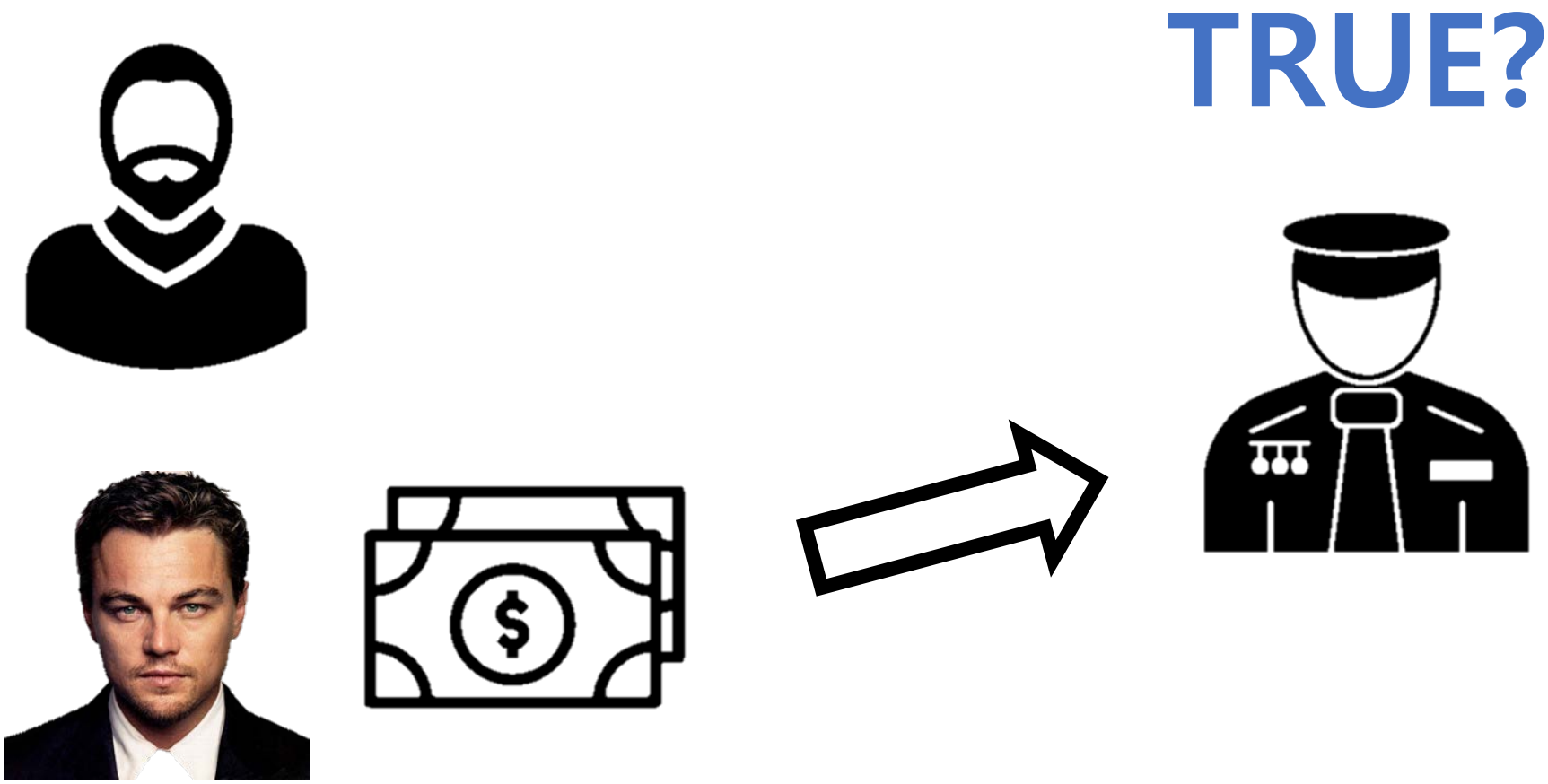


GAN(Generative Adversarial Network)

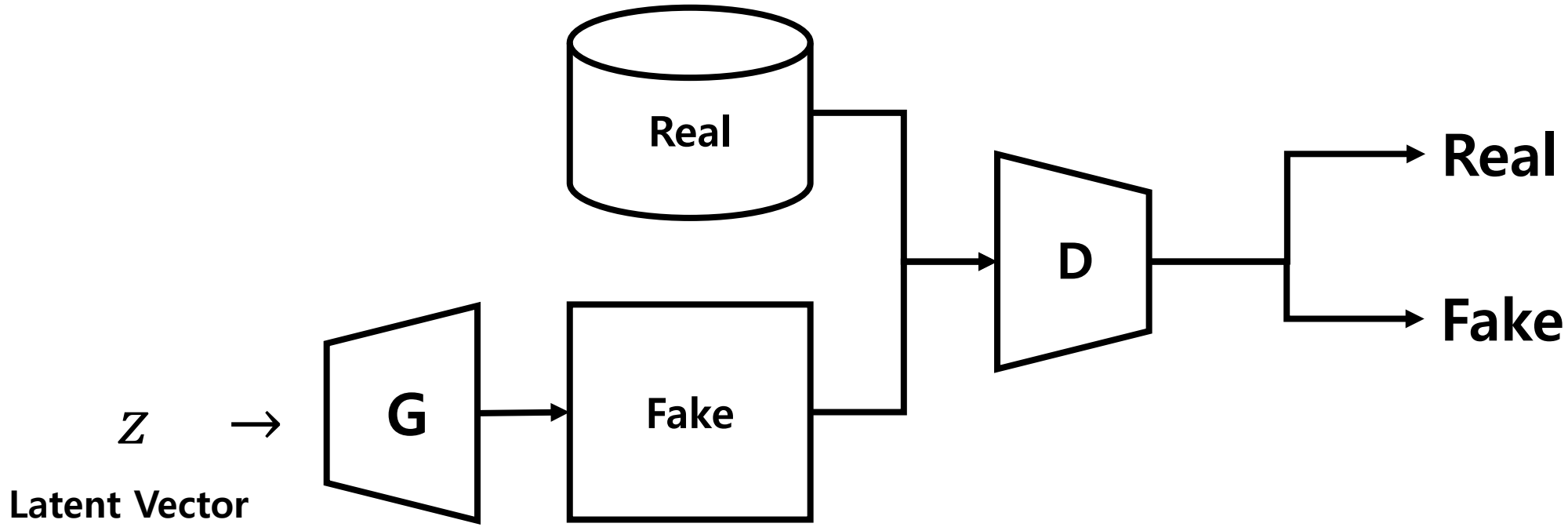
- **적대적 생성(Adversarial Networks)**
  - 위조 지폐범 = Generator
  - 경찰 = Discriminator

“위조 지폐범”을 학습시켜 경찰을 헷갈리게 만듦

GAN(Generative Adversarial Network)

- 적대적 생성(Adversarial Networks)

경찰(Discriminator)은..



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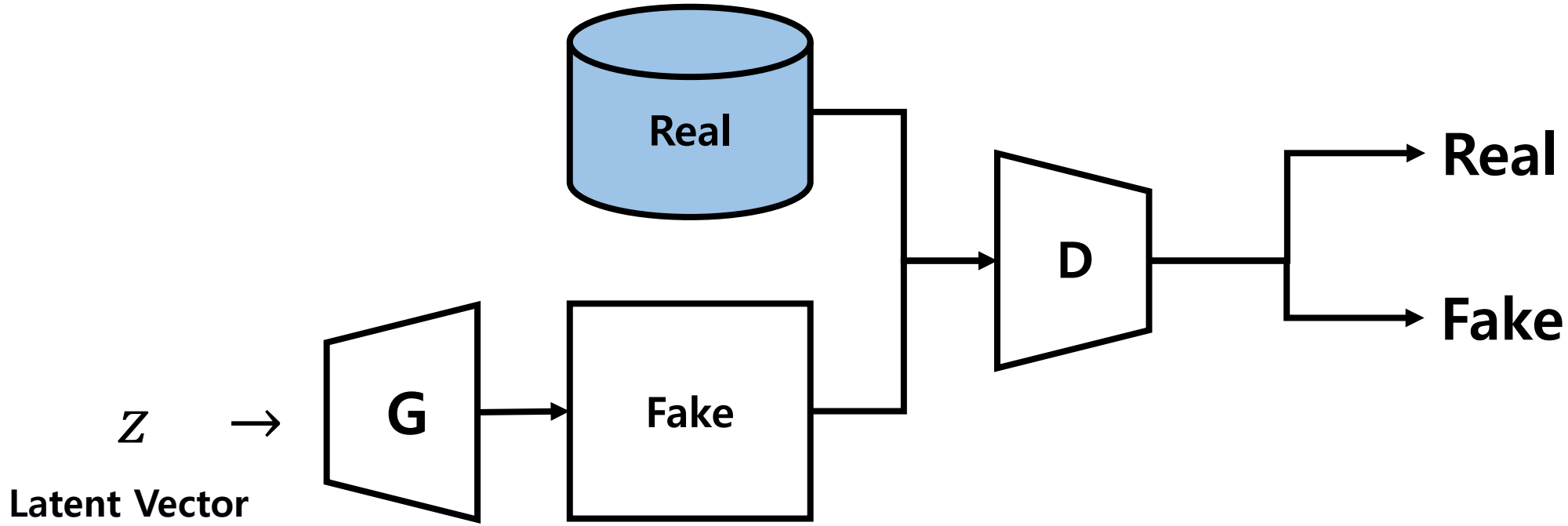

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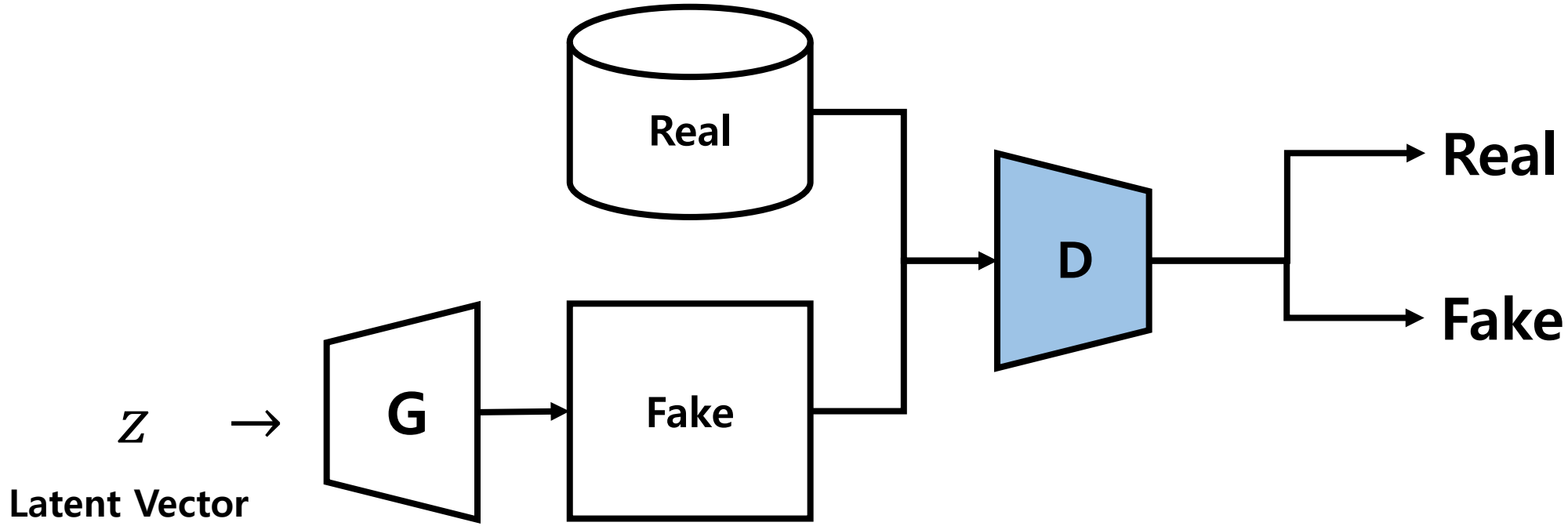

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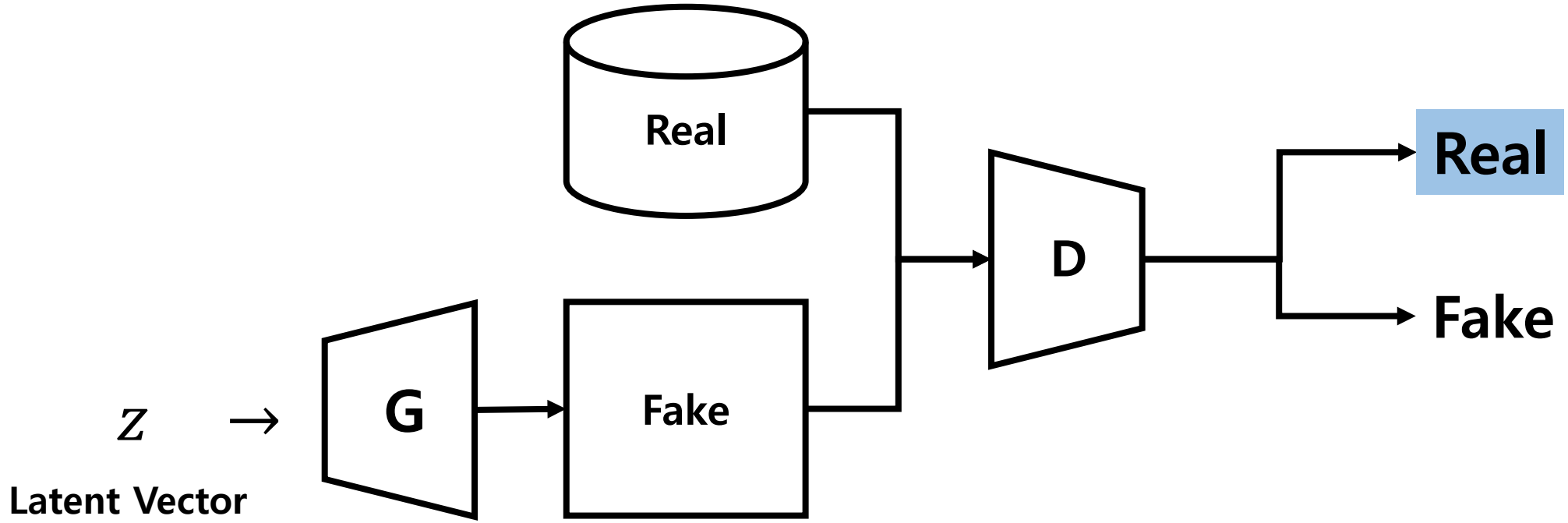

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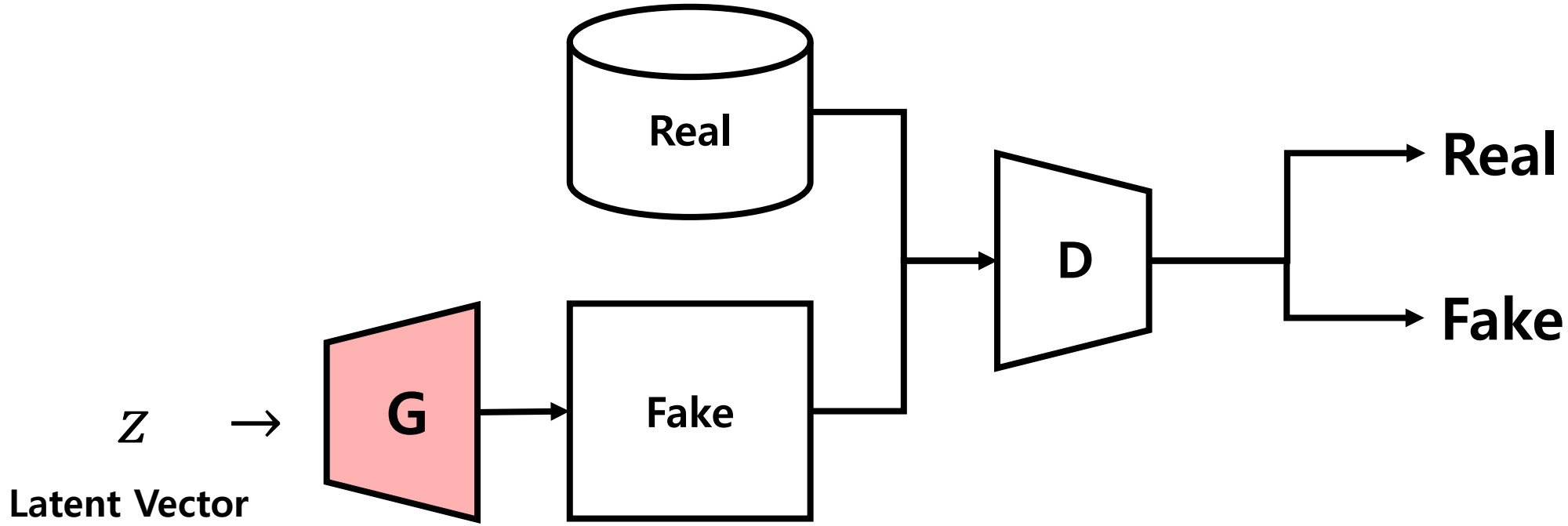

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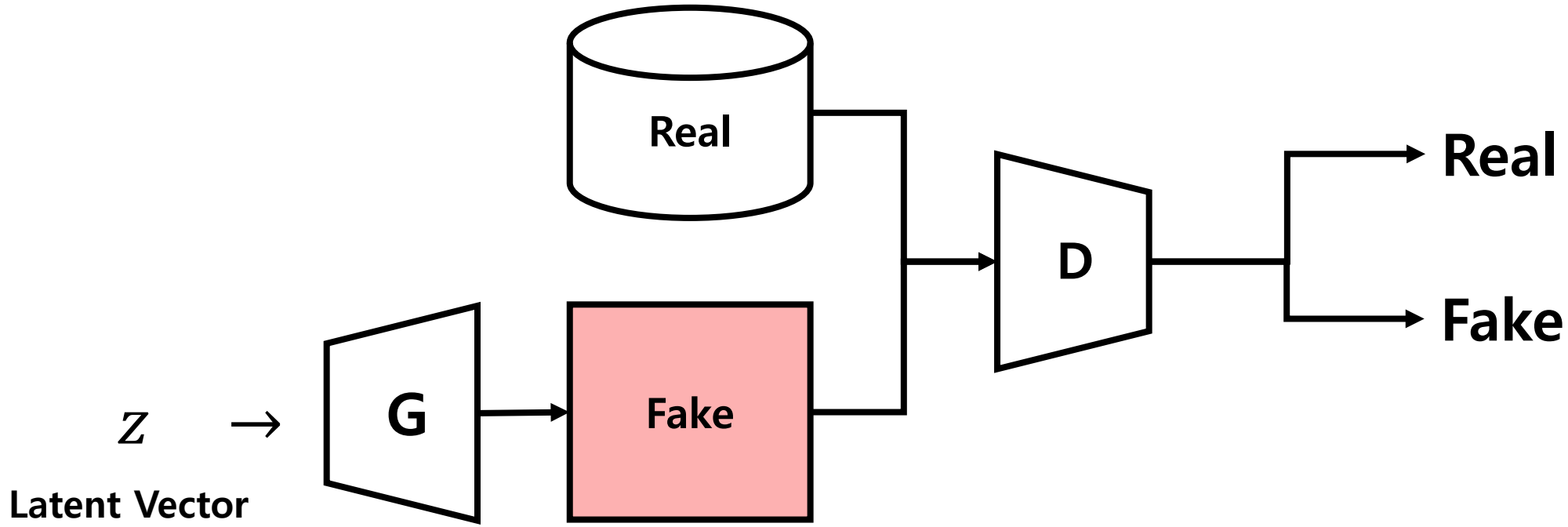

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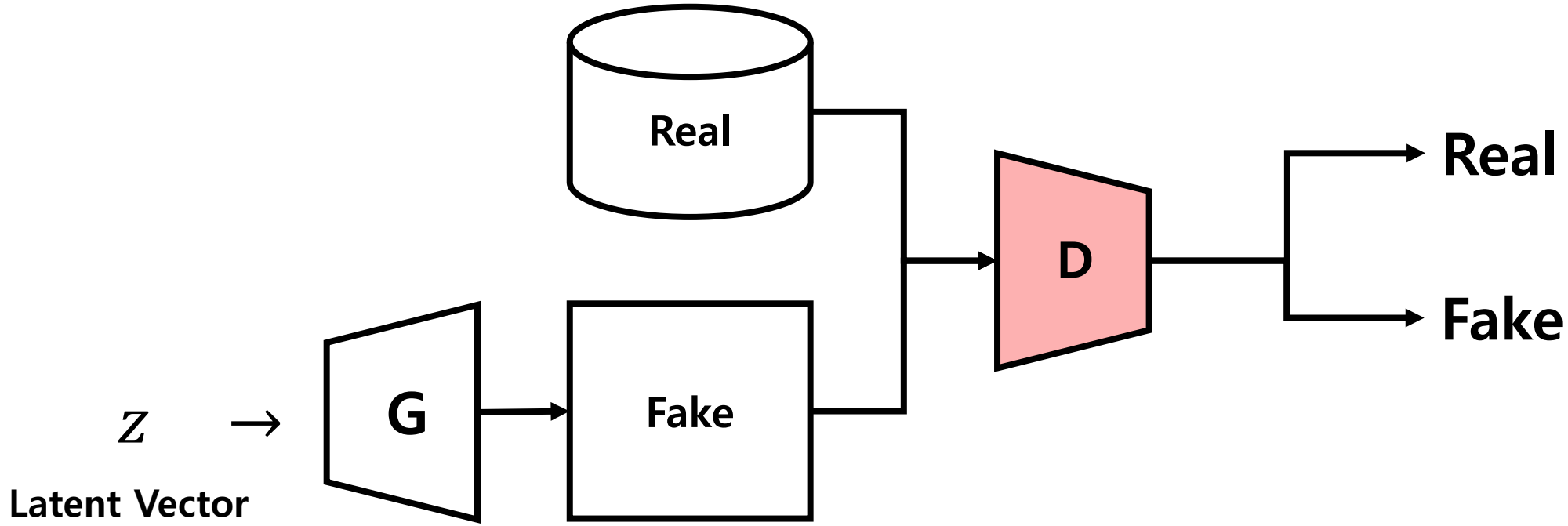

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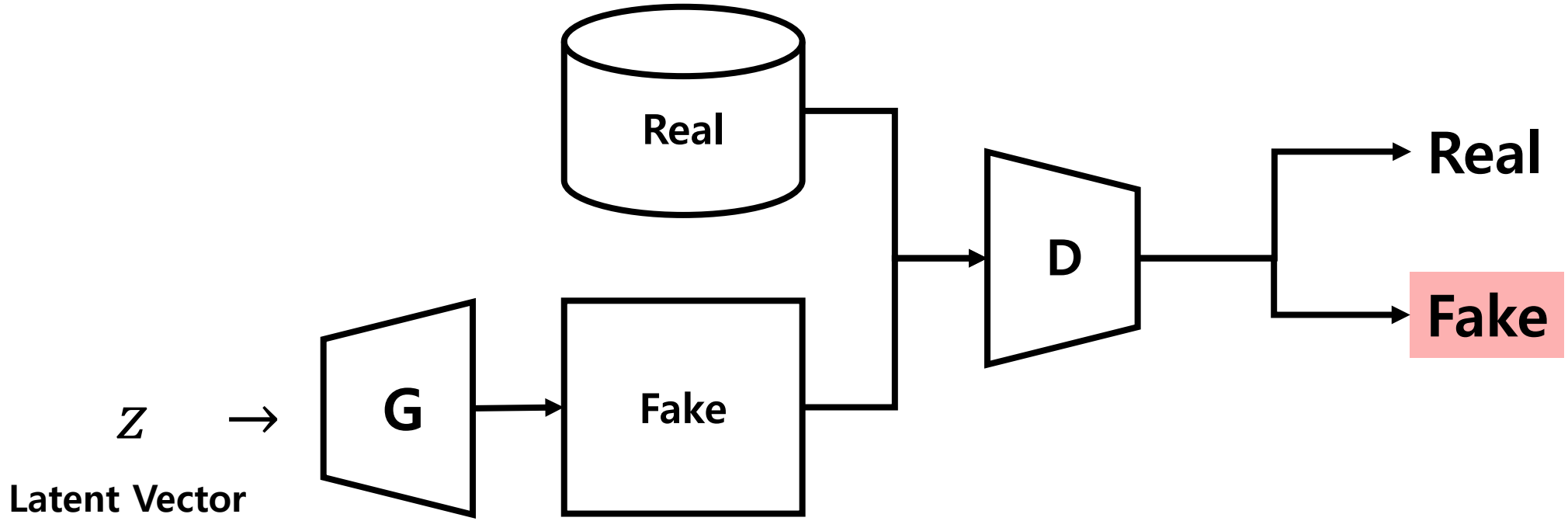

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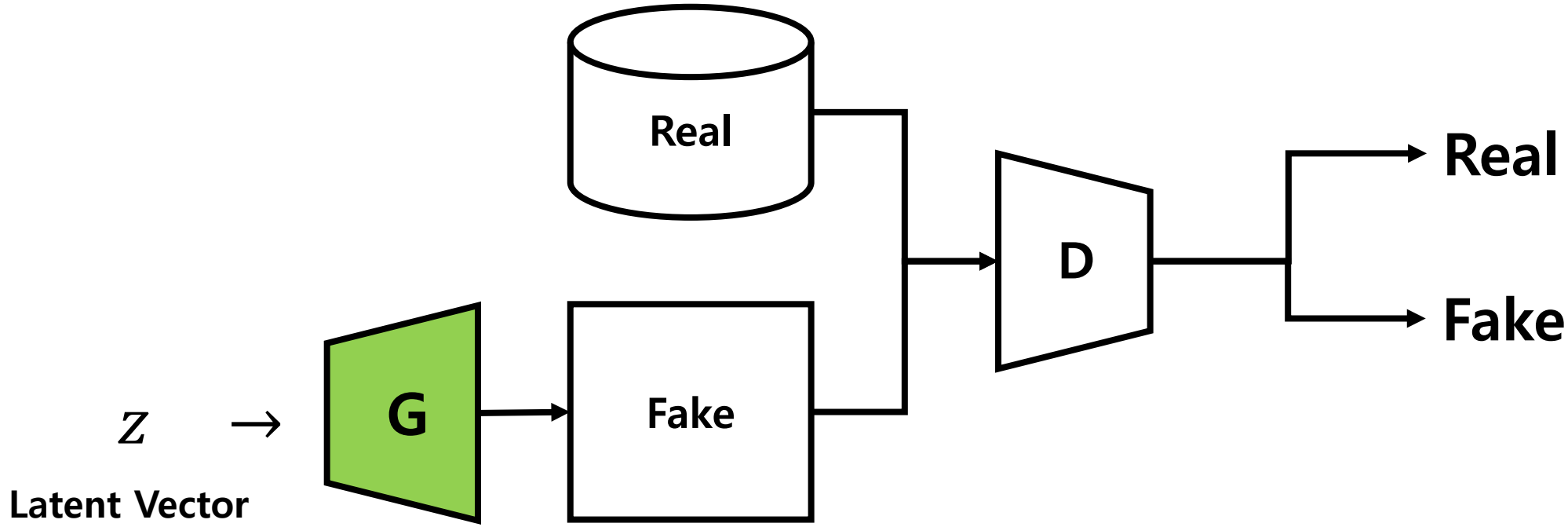

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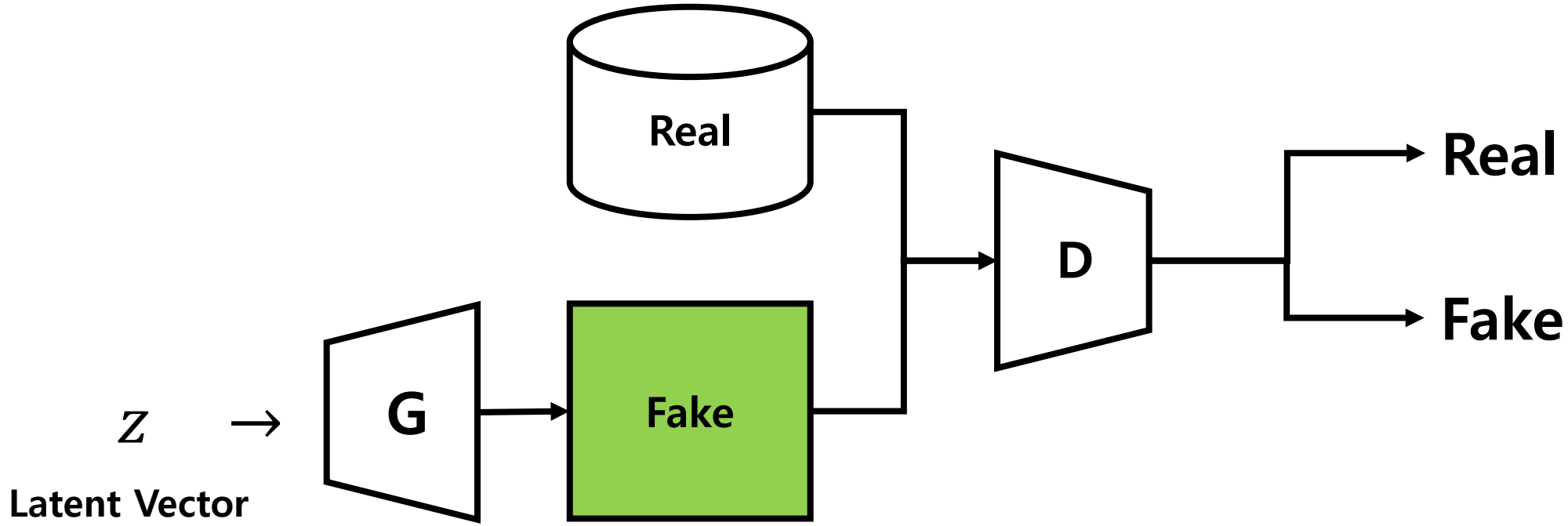

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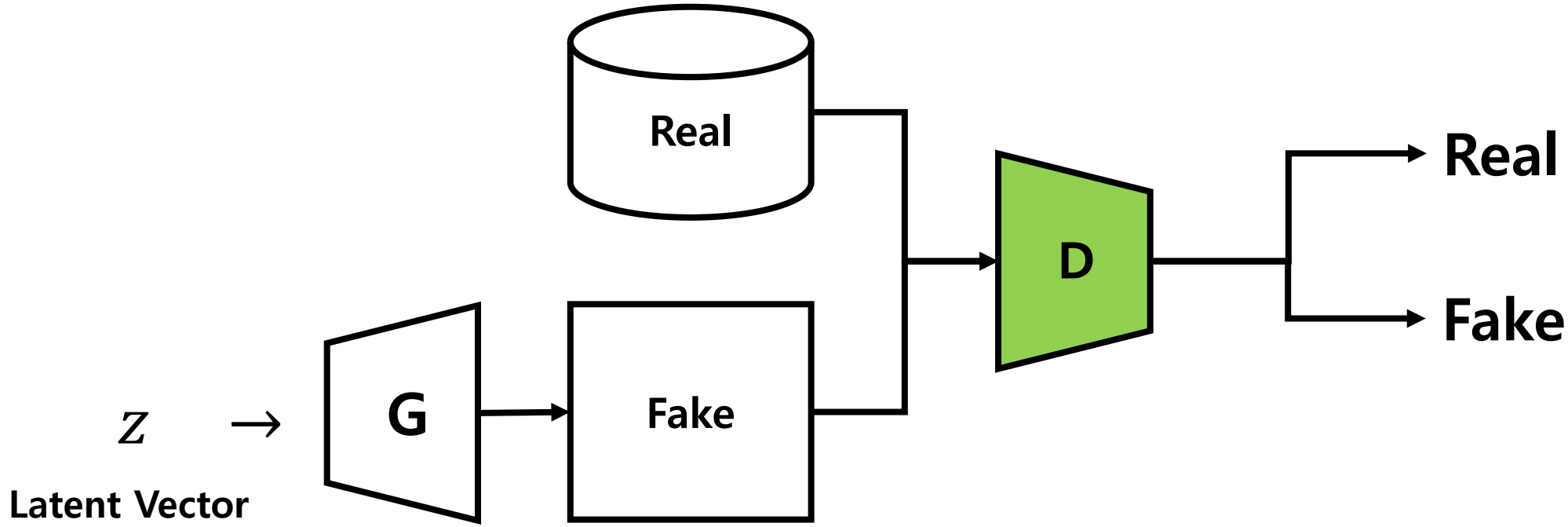

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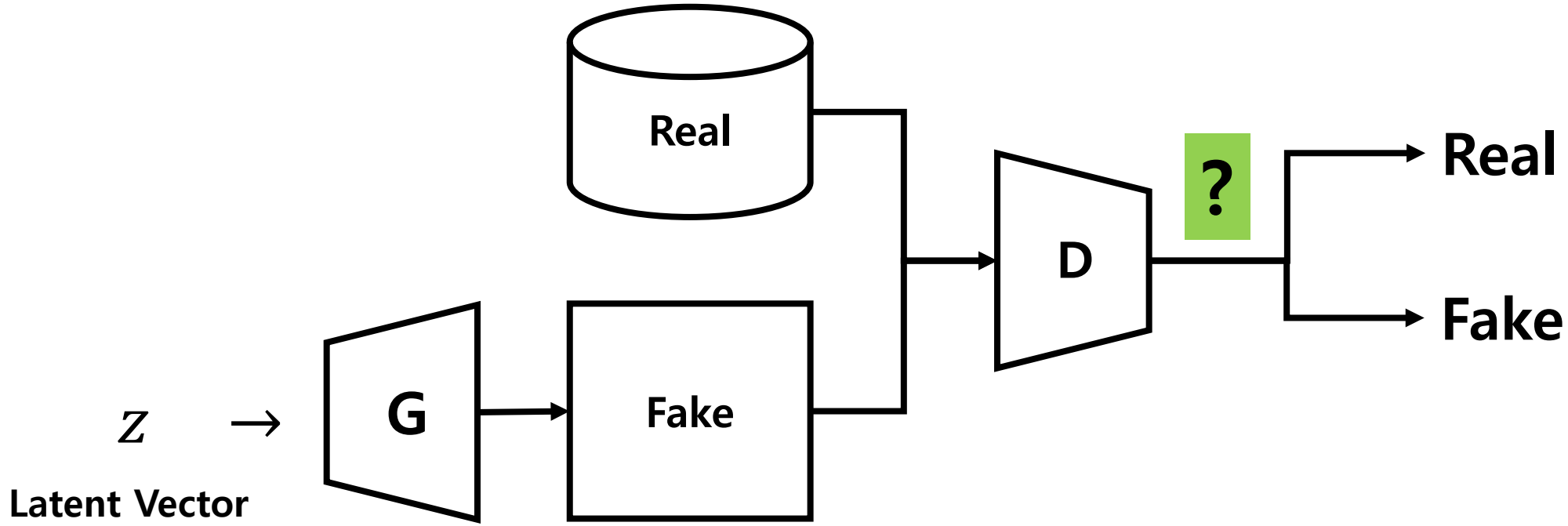

GAN(Generative Adversarial Network)

- **적대적 생성(Adversarial Networks)의 학습**
  - 목적함수는 다음과 같이 설정 가능
    - Generator는 Discriminator를 속이는 그림을 만들고
    - Discriminator는 그림을 완벽히 판별할 줄 알아야함
  - 이를 수학적으로 표현하면,

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

    - $G(z)$: 만든 위조 그림, $D(x)$: 제대로 판별할 확률
    - D를 우선적으로 극대화 시킨 후, G에 대해 학습

GAN(Generative Adversarial Network)

- **적대적 생성(Adversarial Networks)의 학습**
  - $\max D$

$$E_{x\sim p_{data}(x)}\ logD(x) + E_{z\sim p_z(z)} log(1 - D(G(z)))$$

    - $D(x)$: x가 진짜라고 판단되면 1 / 가짜라고 판단되면 0

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  - Discriminator가 완벽히 구분할 수 있다면?

$$logD(x) = log(1) = 0\ \&\ log\left(1 - D\left(G(z)\right)\right) = log(1) = 0$$

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  - Discriminator가 구분 못할 경우?

$$logD(x) = log(\sim 0) = -\infty\ \&\ log\left(1 - D\left(G(z)\right)\right) = log(\sim 0) = -\infty$$

GAN(Generative Adversarial Network)

- **적대적 생성(Adversarial Networks)의 학습**
  - $\min G$

$$E_{x\sim p_{data}(x)}\ logD(x) + E_{z\sim p_z(z)} log(1 - D(G(z)))$$

    - $G(x) : D\big(G(z)\big)$를 1로 만들기 위해 노력

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  - Generator가 완벽히 모방할 수 있다면?

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GAN(Generative Adversarial Network)

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  - $\min G$

$$E_{x\sim p_{data}(x)}\ logD(x) + E_{z\sim p_z(z)} log(1 - D(G(z)))$$

  - $= \min G$

$$E_{z\sim p_z(z)} log(1 - D(G(z)))$$

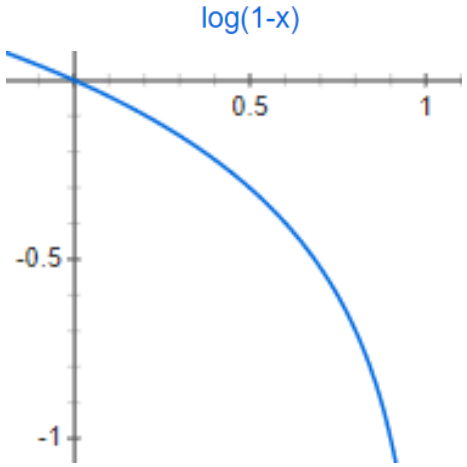
  - $= max\ G$

$$E_{z\sim p_z(z)} log(D(G(z)))$$

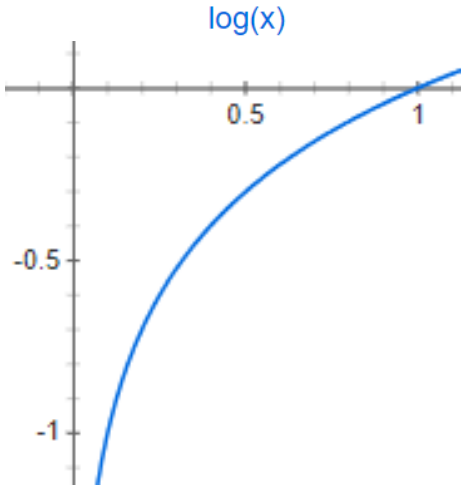
GAN(Generative Adversarial Network)

- **적대적 생성(Adversarial Networks)의 학습**
  - $max\ G$

$$E_{z\sim p_z(z)} log(D(G(z)))$$



  - 처음 D를 학습할 때는 G가 엉뚱한 이미지를 생성
  - 따라서, D가 매우 쉽게 판별 (= $D(G(z))$는 0)
  - 초기 함수의 0 부근에서 움직임 (= 이 때 기울기 작음)
  - 즉, 학습이 더딤



  - 하지만 위와 같이 설정할 경우,
  - 0부근에서의 기울기가 큼
  - 따라서 학습을 빠르게 진행할 수 있음

GAN(Generative Adversarial Network)

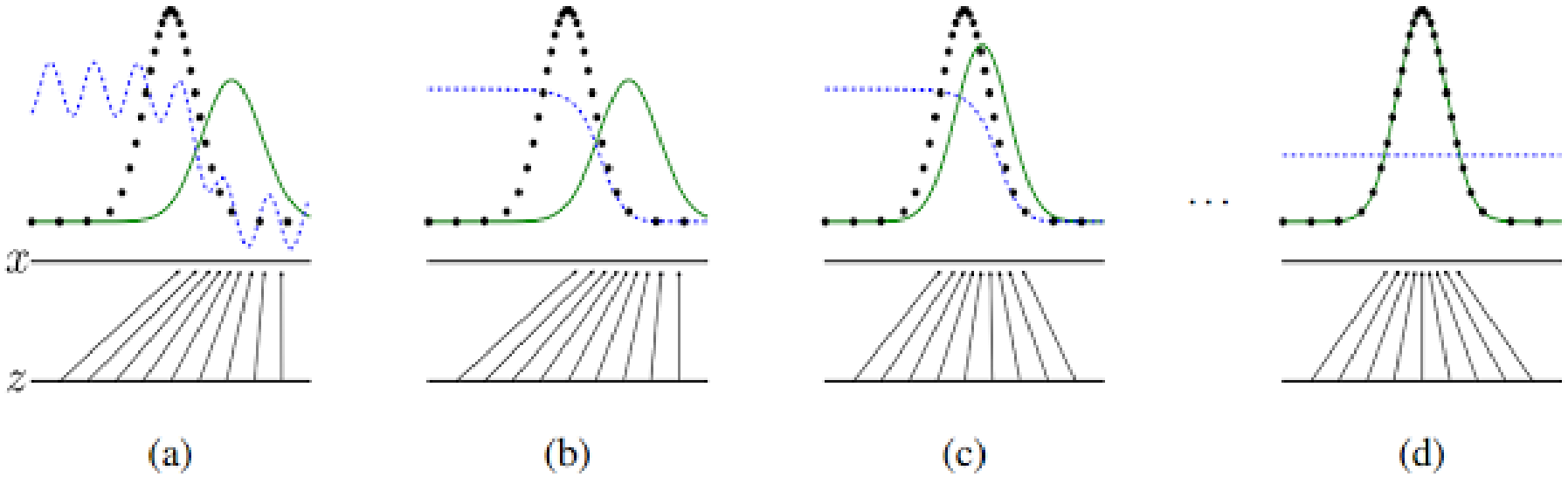
- **적대적 생성(Adversarial Networks)의 학습**
  - 최종 목적함수를 연속적으로 표현하면 아래와 같음

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

$$= \int_x P_{data(x)} logD(x) + P_{g(x)}\left[\log\left(1 - D(x)\right)\right]dx$$

GAN(Generative Adversarial Network)

- **적대적 생성(Adversarial Networks)의 학습**
  - 이를 그림으로 표현하면 아래와 같음
    - 파란선 : Discriminator
    - 녹색선 : Generator
    - 검정선 : Data

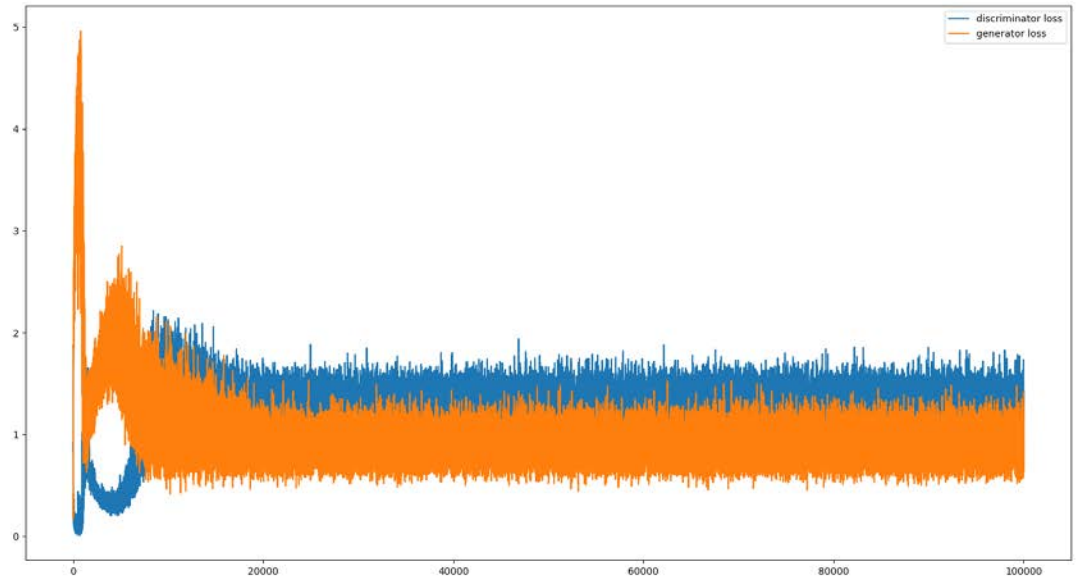


https://arxiv.org/pdf/1701.00160.pdf

3. DCGAN(Deep Convolutional GAN)

DCGAN(Deep Convolution GAN)

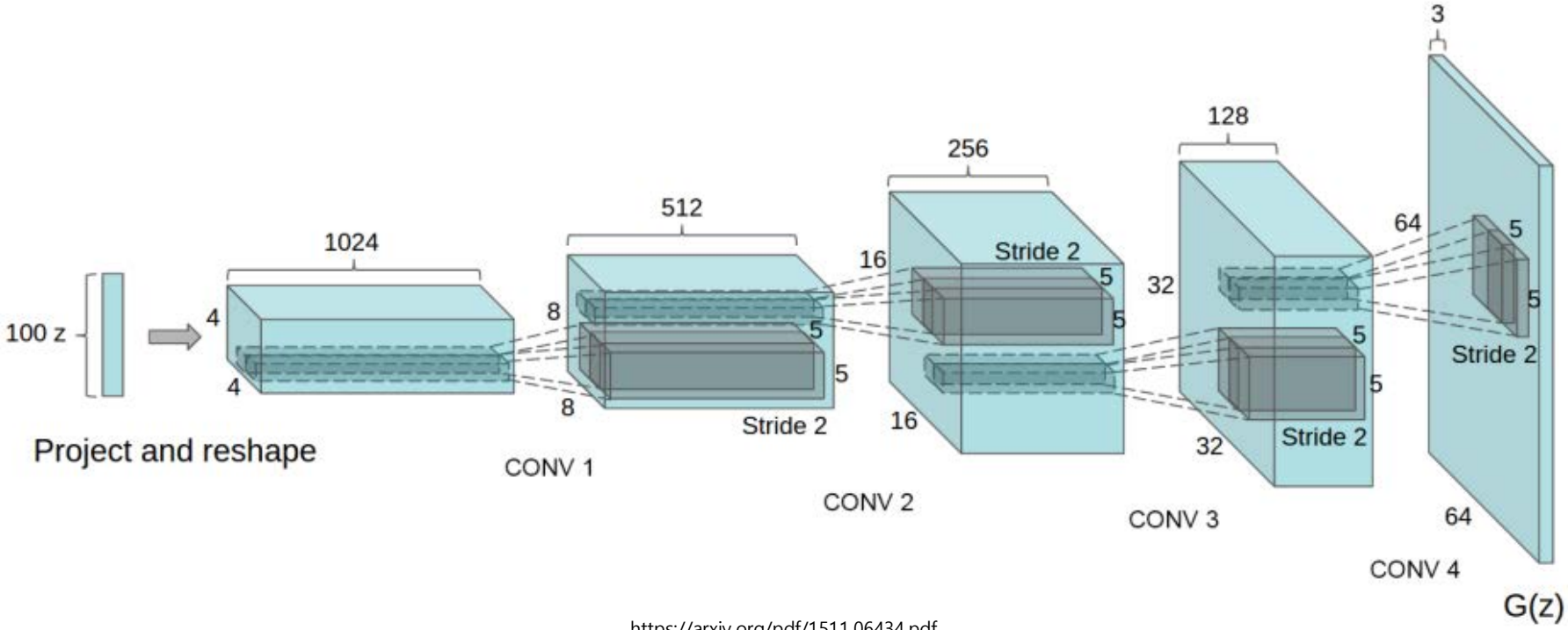
- **GAN의 불안정성**
  - GAN은 Nash Equilibrium을 찾는 것이라 할 수 있는데,
  - 어떨 때는 Gradient Descent를 통해 찾을 수 있는 반면, 찾을 수 없는 때도 많음
  - 즉, Unstable하다고 할 수 있음



https://stats.stackexchange.com/questions/330834/gan-losses-balance-but-quality-of-generated-image-still-bad

DCGAN(Deep Convolution GAN)

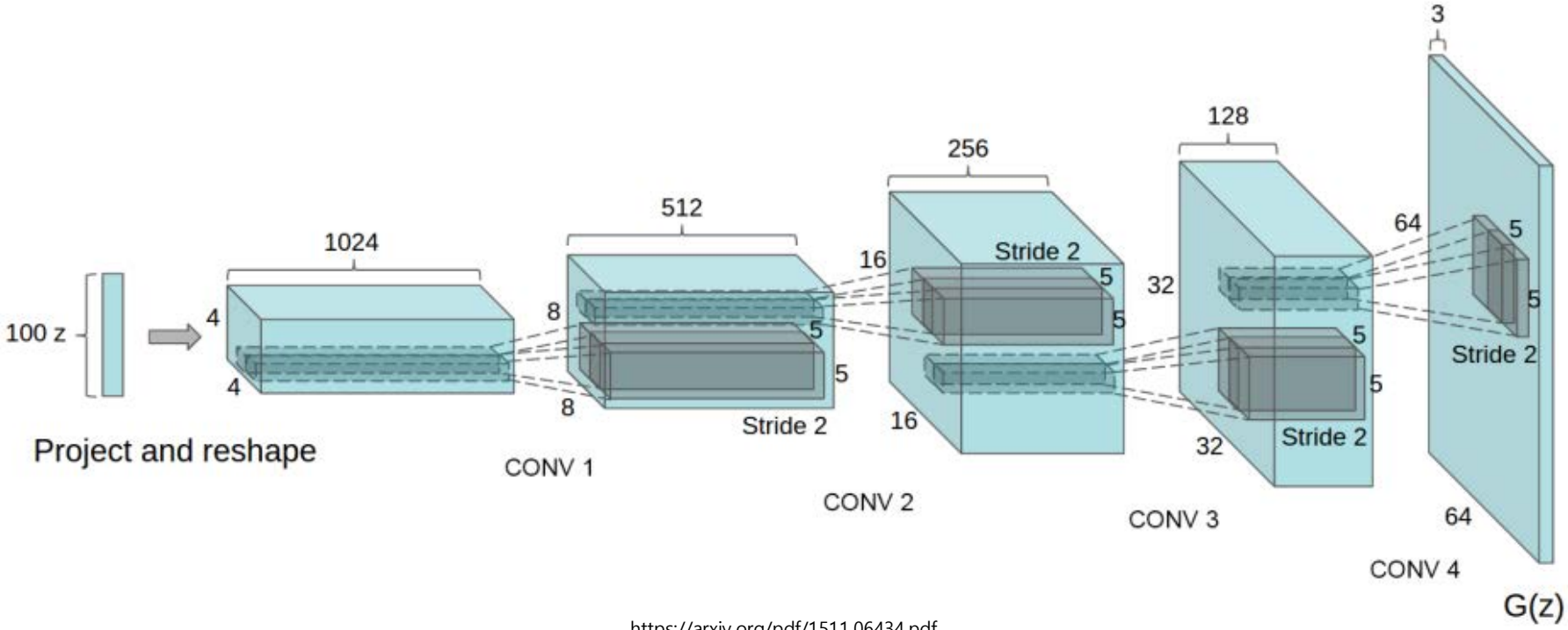
- **GAN의 불안정성 해결 방법**
  - Convolution을 활용한 GAN의 탄생
    - 불필요한 정보를 버리고 중요한 Feature를 가지고 학습
    - 이미지 생성에 최적화



https://arxiv.org/pdf/1511.06434.pdf

DCGAN(Deep Convolution GAN)

- **GAN의 불안정성 해결 방법**
  - Batch Normalization을 추가
  - 단, Generator의 Input과 Discriminator의 Input에는 도입 안 함
  - 하지만 모든 딥러닝 학습이 그렇듯이, 항상 좋은 결과를 보장하지는 않음



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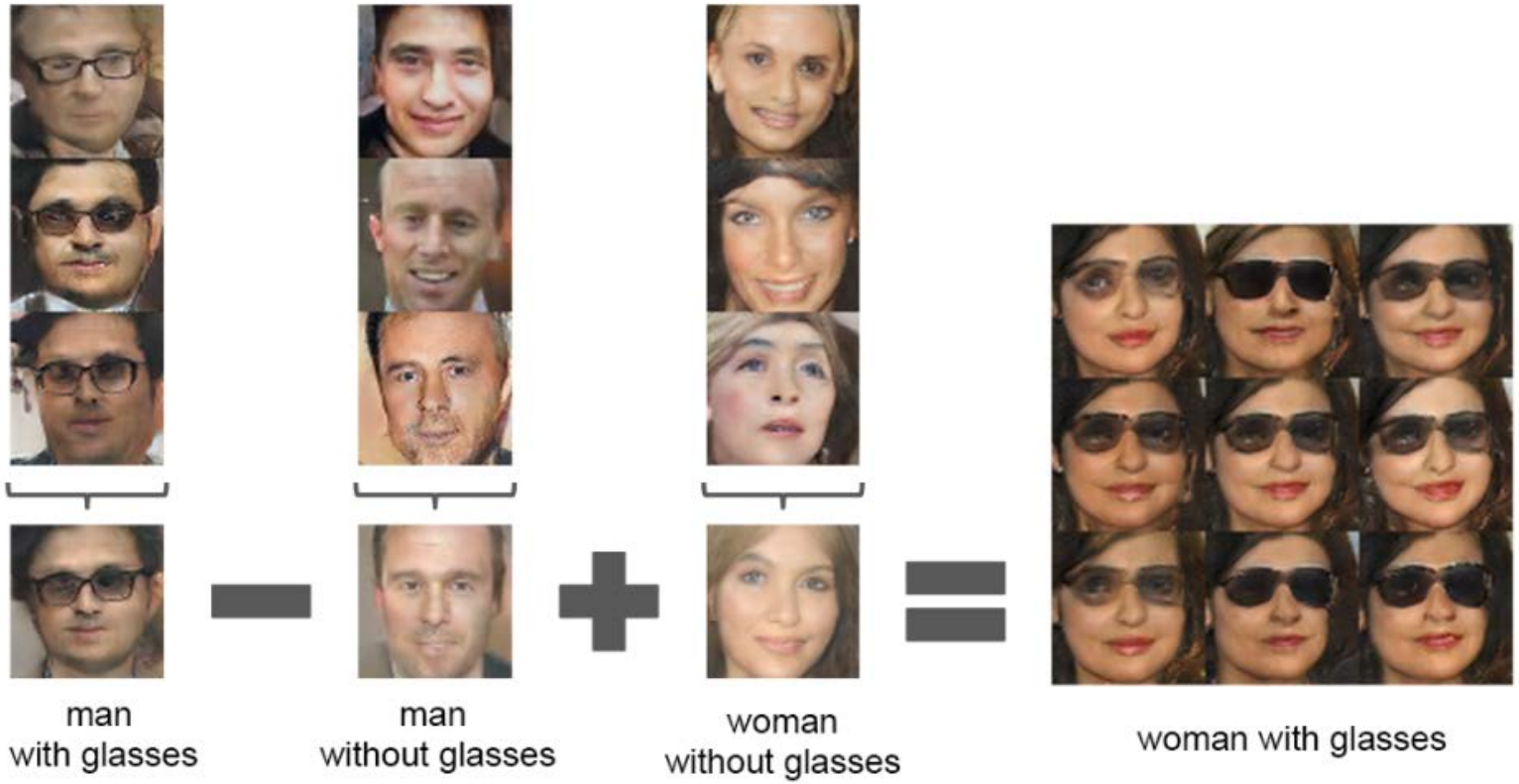
DCGAN(Deep Convolution GAN)

- **DCGAN의 도입**
  - GAN에 비해 훨씬 안정적
  - Vector 연산이 가능 (Latent Vector z의 의미 부여)



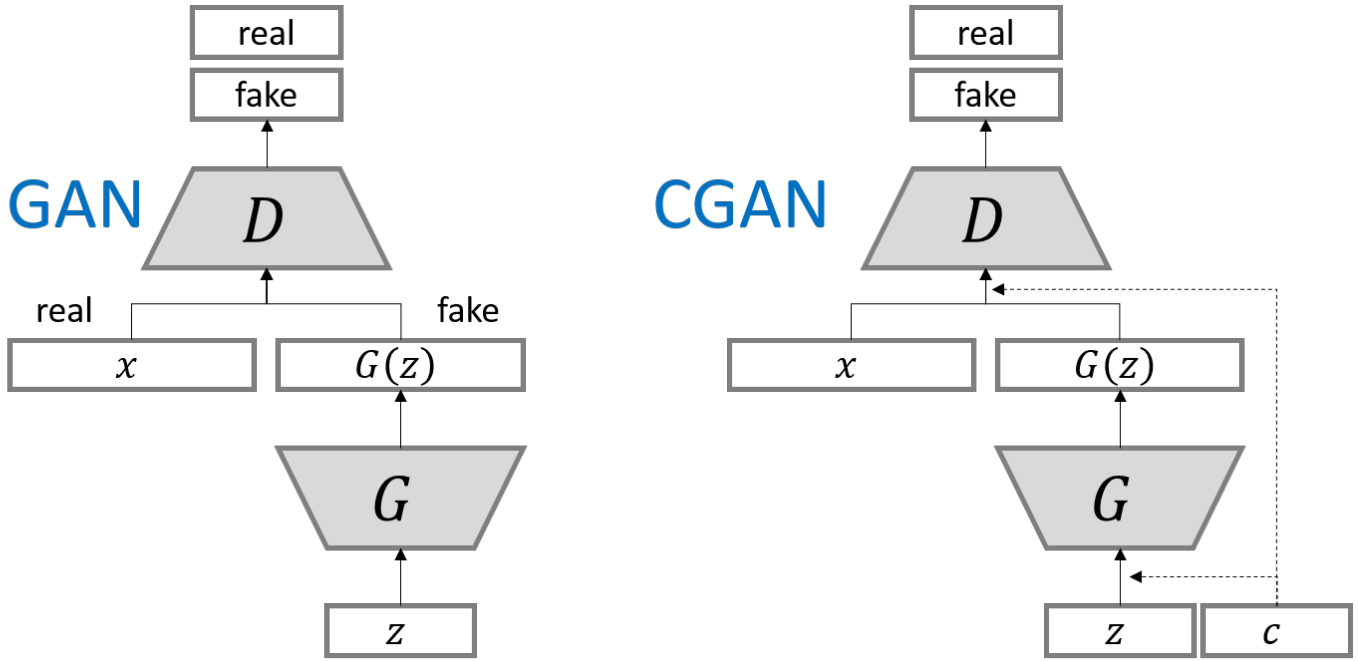
DCGAN(Deep Convolution GAN)

- DCGAN의 결과

4. cGAN(Conditional GAN)

cGAN(Conditional GAN)

- **cGAN**
  - GAN으로부터 특정 이미지를 생성해내고 싶다면?
  - Label(c)을 입력해주자



https://github.com/hwalsuklee/tensorflow-generative-model-collections/blob/master/assets/etc/GAN_structure.png

cGAN(Conditional GAN)

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  - GAN으로부터 특정 이미지를 생성해내고 싶다면?
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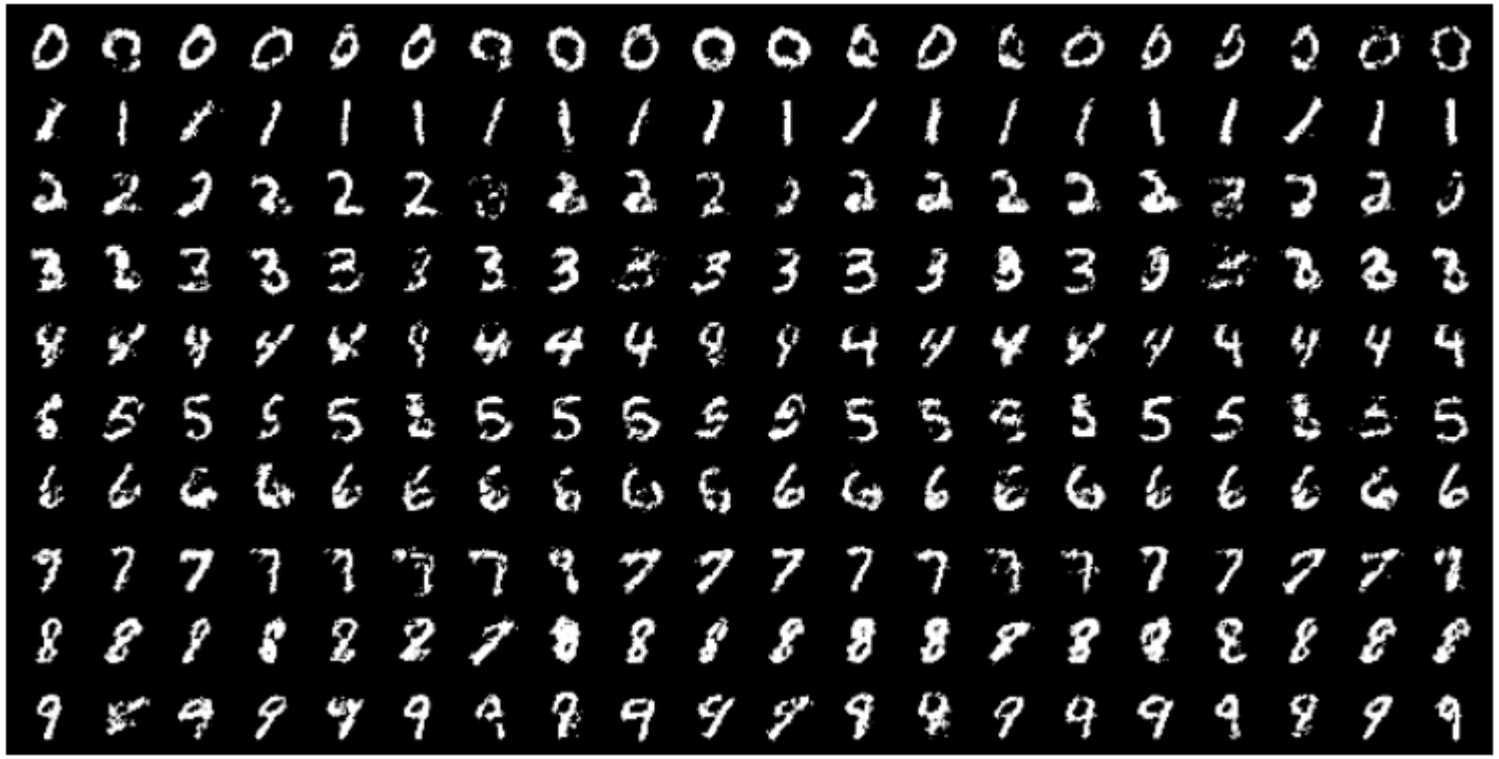
$$\min_G \max_D V(G,D) = E_{x\sim p_{data}(x)} logD(x,c) + E_{z\sim p_Z(z)} log(1 - D(G(z,c),c))$$

cGAN(Conditional GAN)

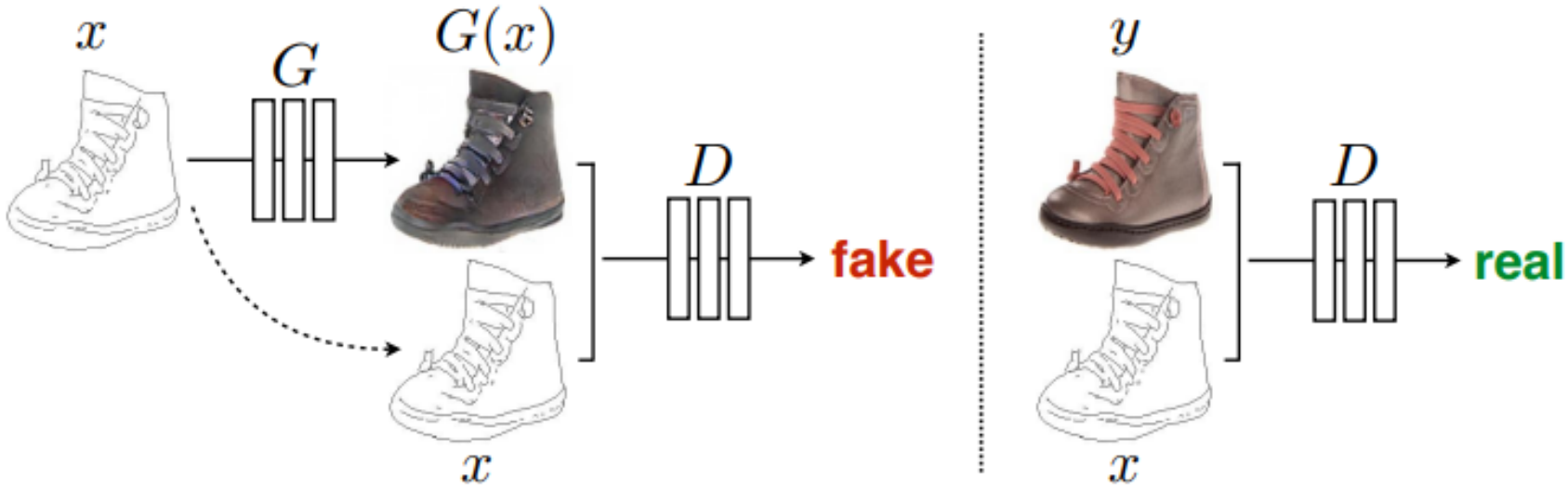
- **cGAN**
  - MNIST에서의 c?
  - c는 0~9의 One-hot-encoding vector



https://arxiv.org/pdf/1411.1784.pdf

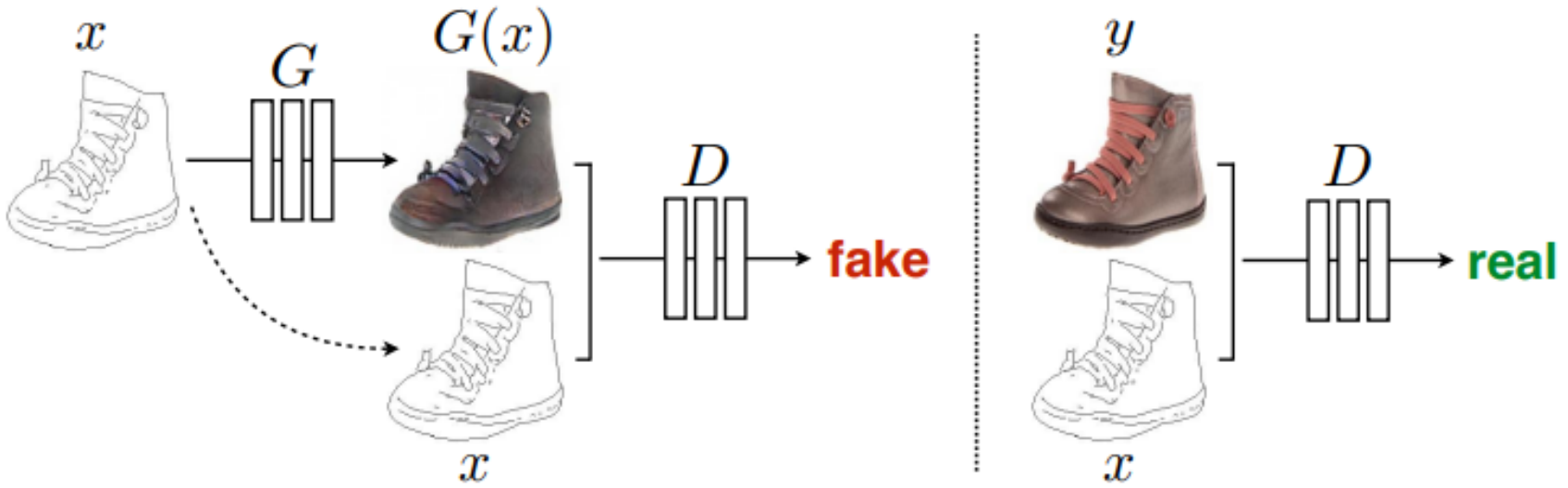
cGAN(Conditional GAN)

- **Pix2pix**
  - cGan을 Image-to-Image Translation으로 활용



cGAN(Conditional GAN)

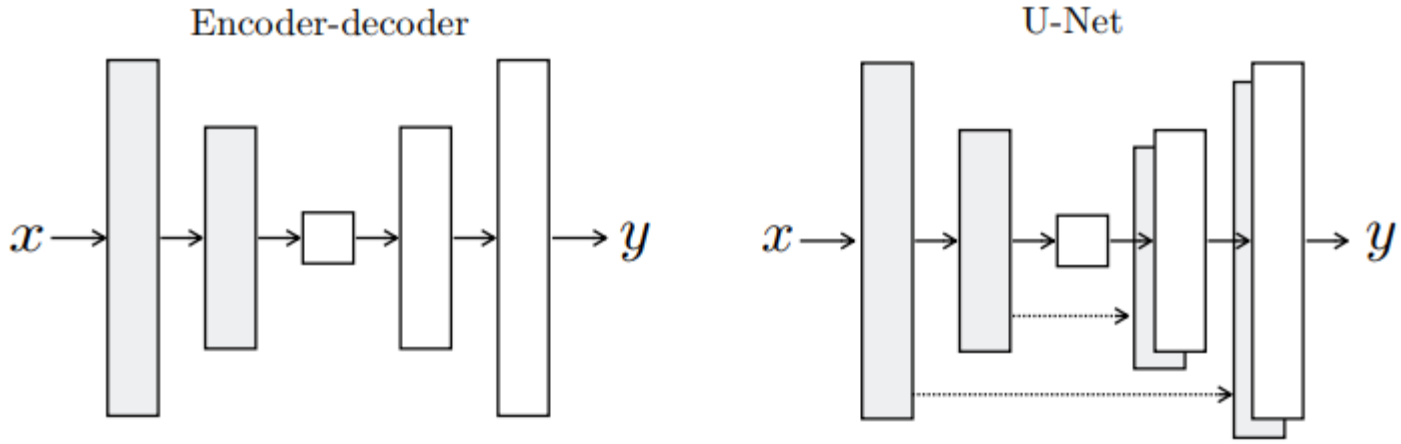
- **Pix2pix**
  - cGan을 Image-to-Image Translation으로 활용
  - 즉, 기존 Label을 주는 것이 아니라 이미지를 전달하여 학습



$$\min_G \max_D V(G,D) = E_{x,y\sim p_{data}(x,y)} logD(x,y) + E_{z\sim p_Z(z)} log(1 - D(x, G(x,z)))$$

cGAN(Conditional GAN)

- **Pix2pix**
  - 이러한 학습을 위해서는 다음과 같은 모델 변경 도입
    - **Loss의 변경 :** L2 loss에서는 Blurry했는데, L1을 사용하여 덜 Blurry하게 만들 수 있음
    - **U-Net 활용** : 입력값(x, z)가 필터를 통해 전달되면서 흐려지지 않게 함



cGAN(Conditional GAN)

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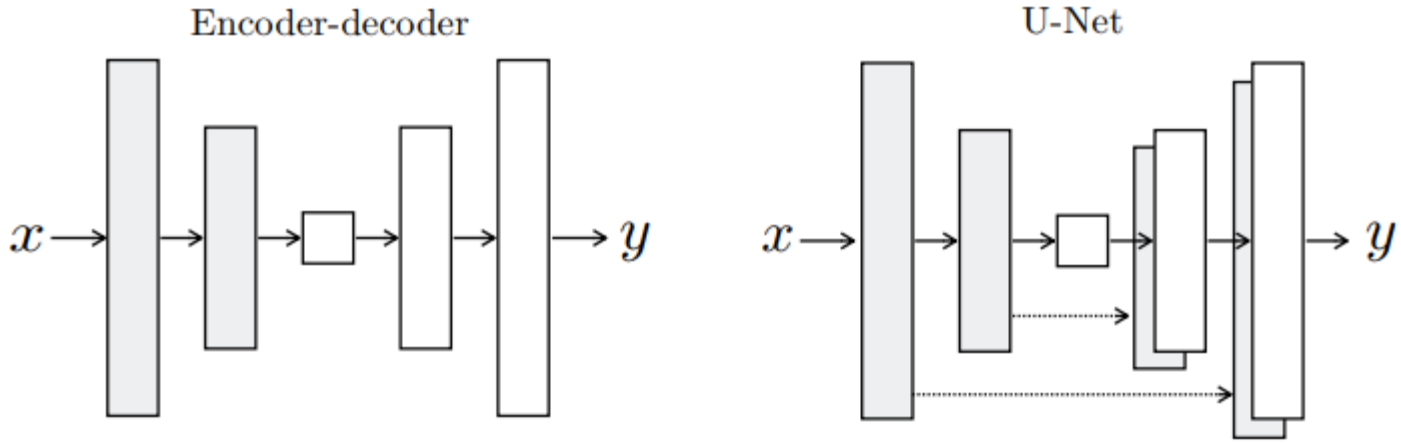
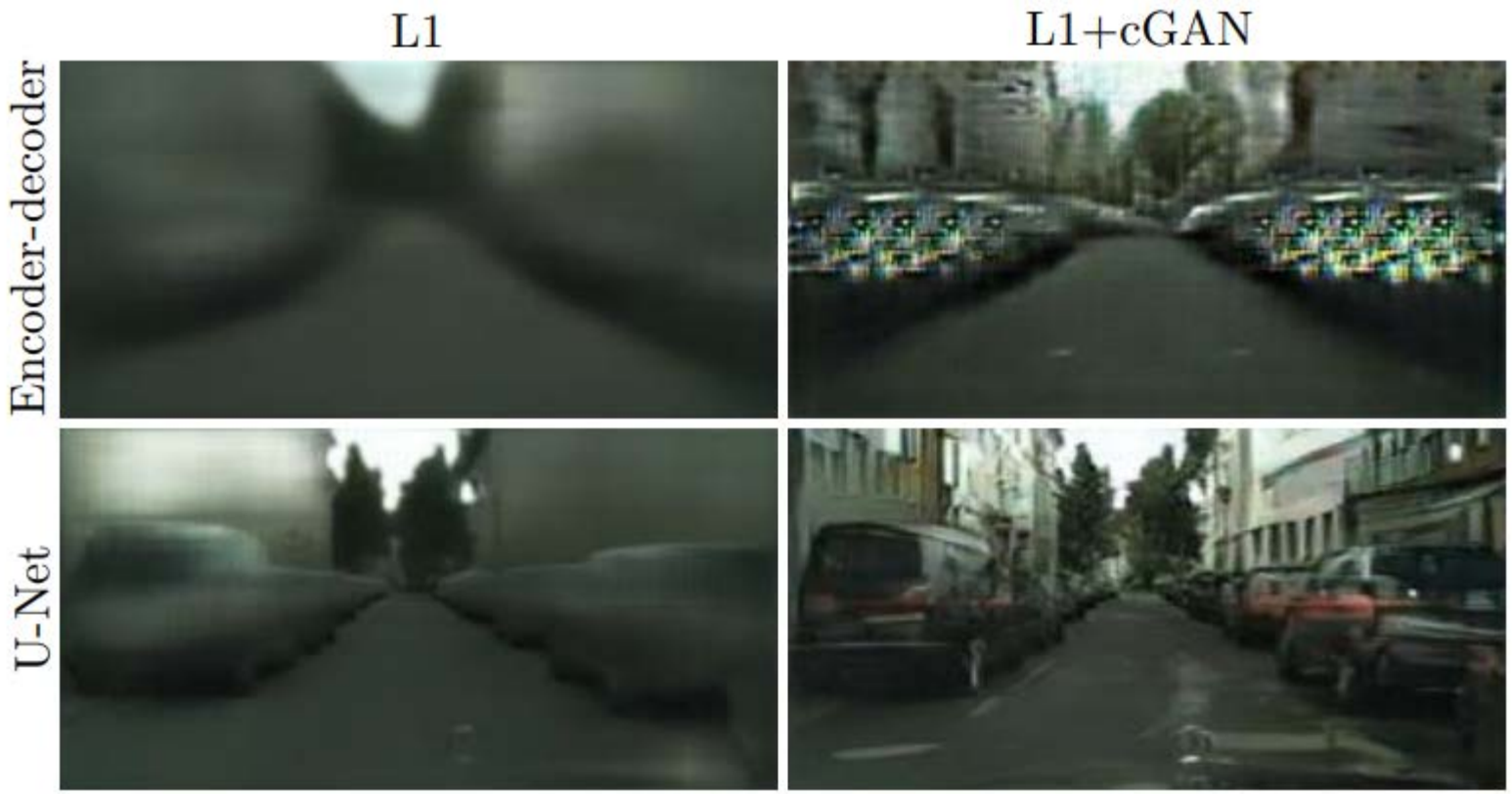


    - **PatchGAN 도입** : Discriminator가 전체 그림이 아닌 부분적인 이미지들을 보고 판단 (조금 더 Detail)
    - **Classification을 활용한 Loss 추가** : Output의 Label을 판단하여 잘 되었는지 확인

cGAN(Conditional GAN)

- **Pix2pix**

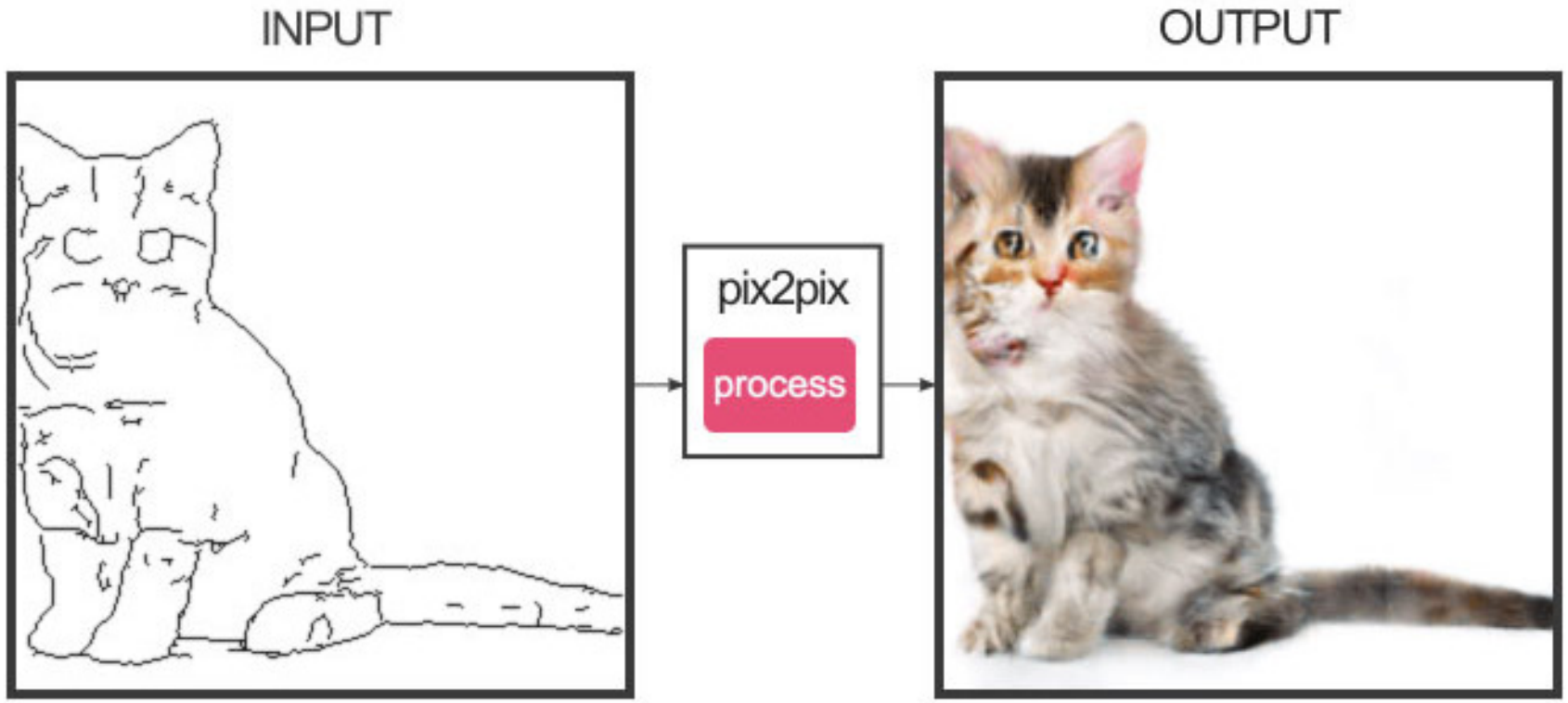


cGAN(Conditional GAN)

- Pix2pix

cGAN(Conditional GAN)

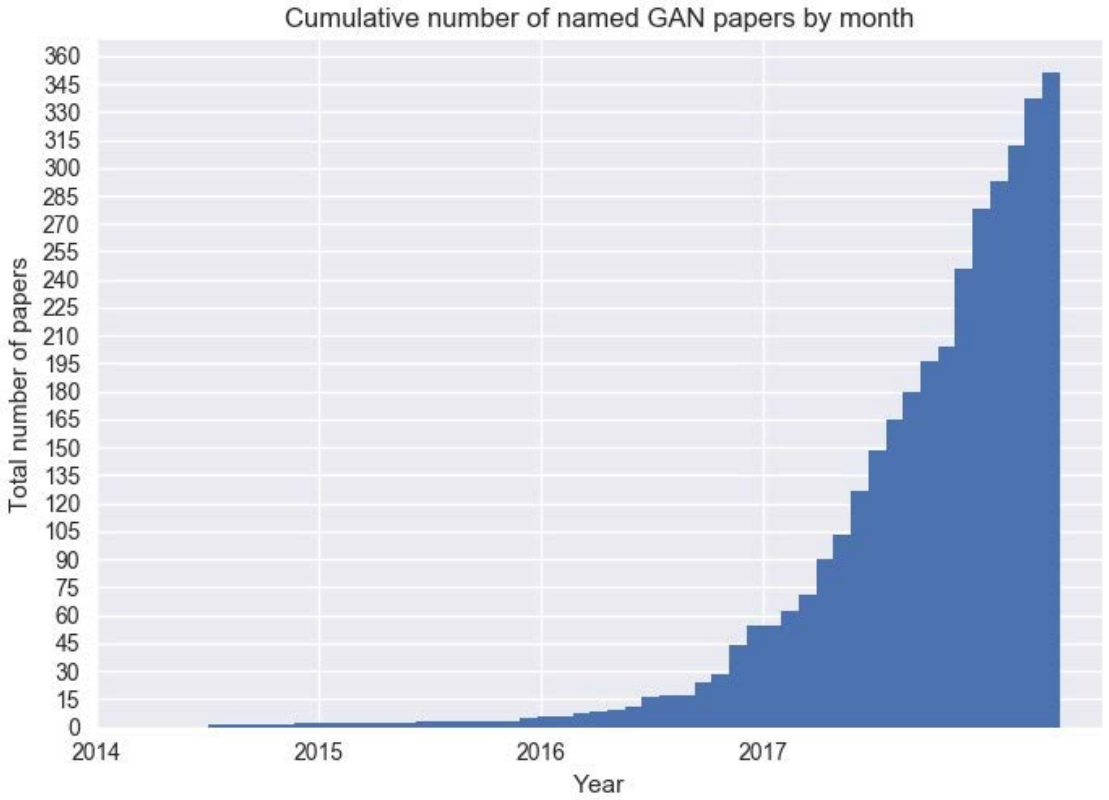
- **Pix2pix**



5. Recent Works

Recent Works

- **Recent Works**
  - GAN은 가장 각광받고 있는 딥러닝 모델이라고 해도 반박불가



https://deephunt.in/the-gan-zoo-79597dc8c347

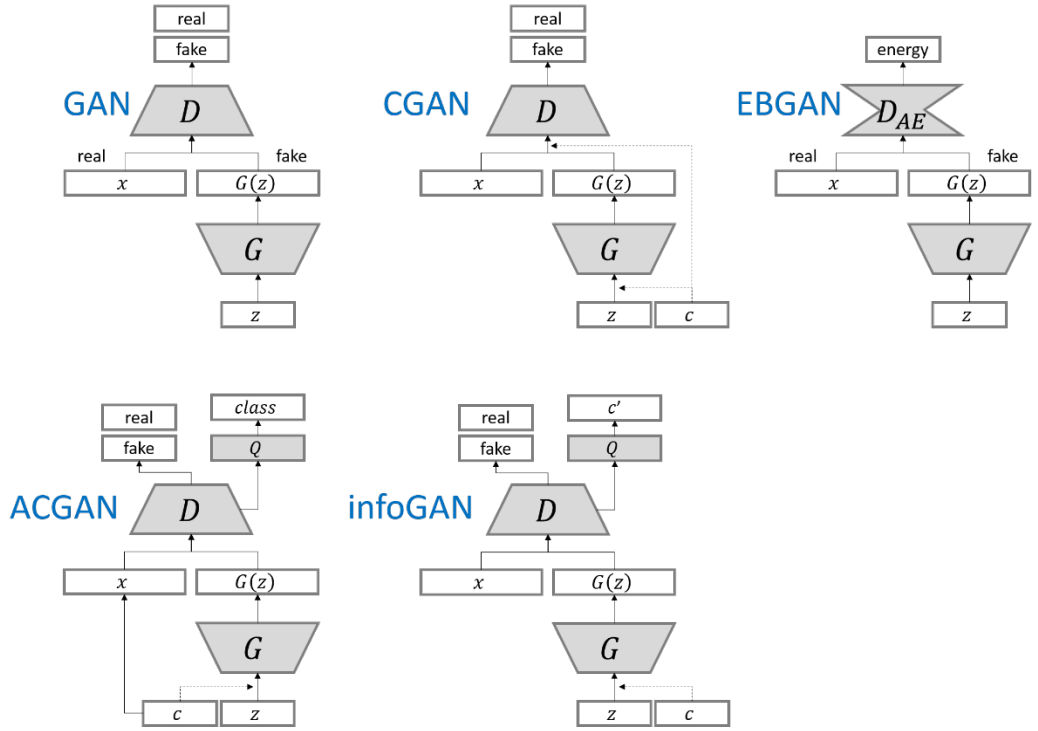
Recent Works

- **Recent Works**
  - InfoGAN
  - ACGAN
  - EBGAN
  - CycleGAN
  - wGAN
  - Progressive GAN
  - ....

Recent Works

- **Recent Works**

Name	*Paper Link*
GAN	Arxiv
LSGAN	Arxiv
WGAN	Arxiv
WGAN_GP	Arxiv
DRAGAN	Arxiv
CGAN	Arxiv
infoGAN	Arxiv
ACGAN	Arxiv
EBGAN	Arxiv
BEGAN	Arxiv



TENSORFLOW : https://github.com/hwalsuklee/tensorflow-generative-model-collections

PYTORCH : https://github.com/eriklindernoren/PyTorch-GAN

Recent Works

- InfoGAN

(a) Varying c_1 on InfoGAN (Digit type)

(b) Varying c_1 on regular GAN (No clear meaning)

(c) Varying c_2 from -2 to 2 on InfoGAN (Rotation)

(d) Varying c_3 from -2 to 2 on InfoGAN (Width)

Recent Works

- **InfoGAN**
  - 라벨 뿐만이 아니라 다양한 특성 학습 가능

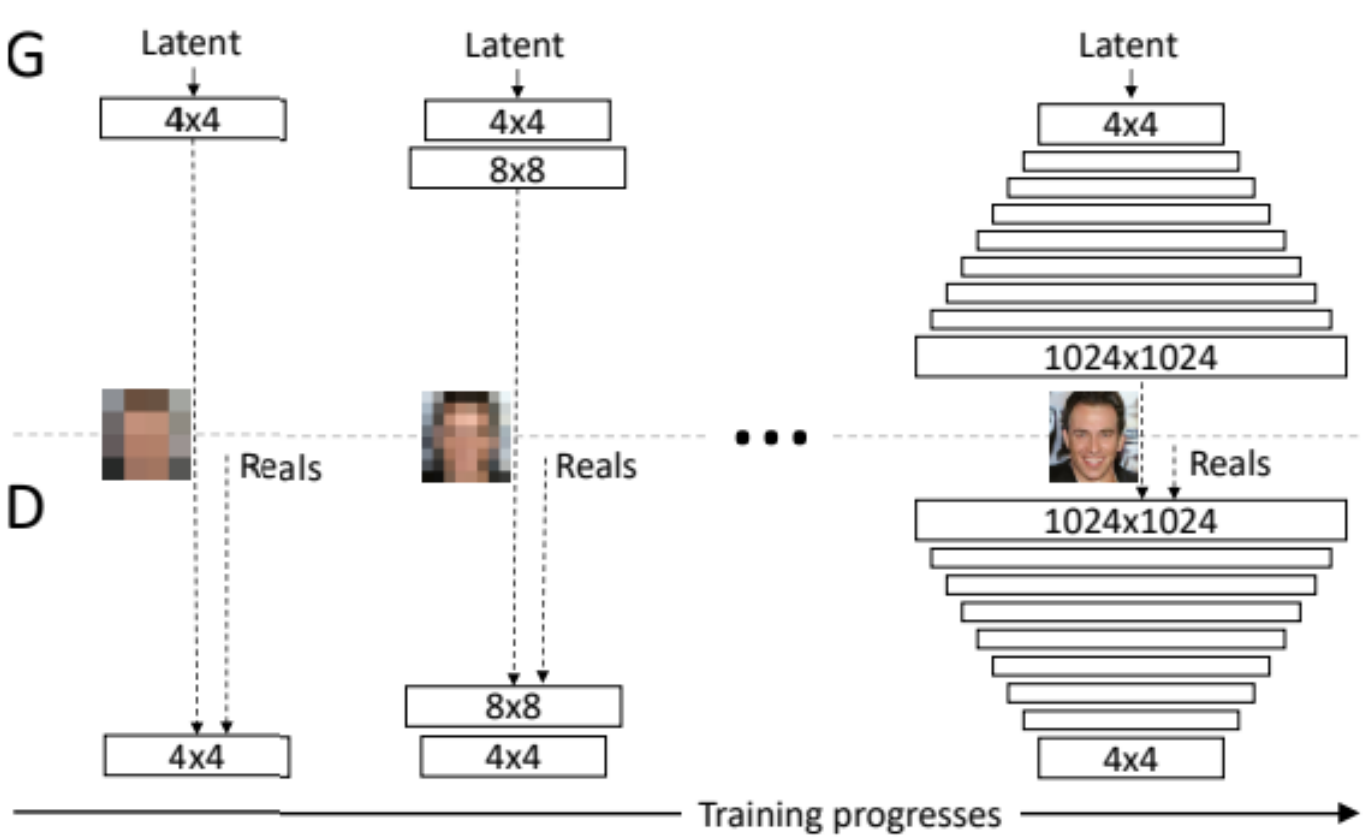
(a) Rotation (b) Width

Recent Works

- Progressive GAN

Recent Works

- Progressive GAN



실 습