InfoGAN : Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets

: Mutual Information

ISL Lab Seminar

Hansol Kang

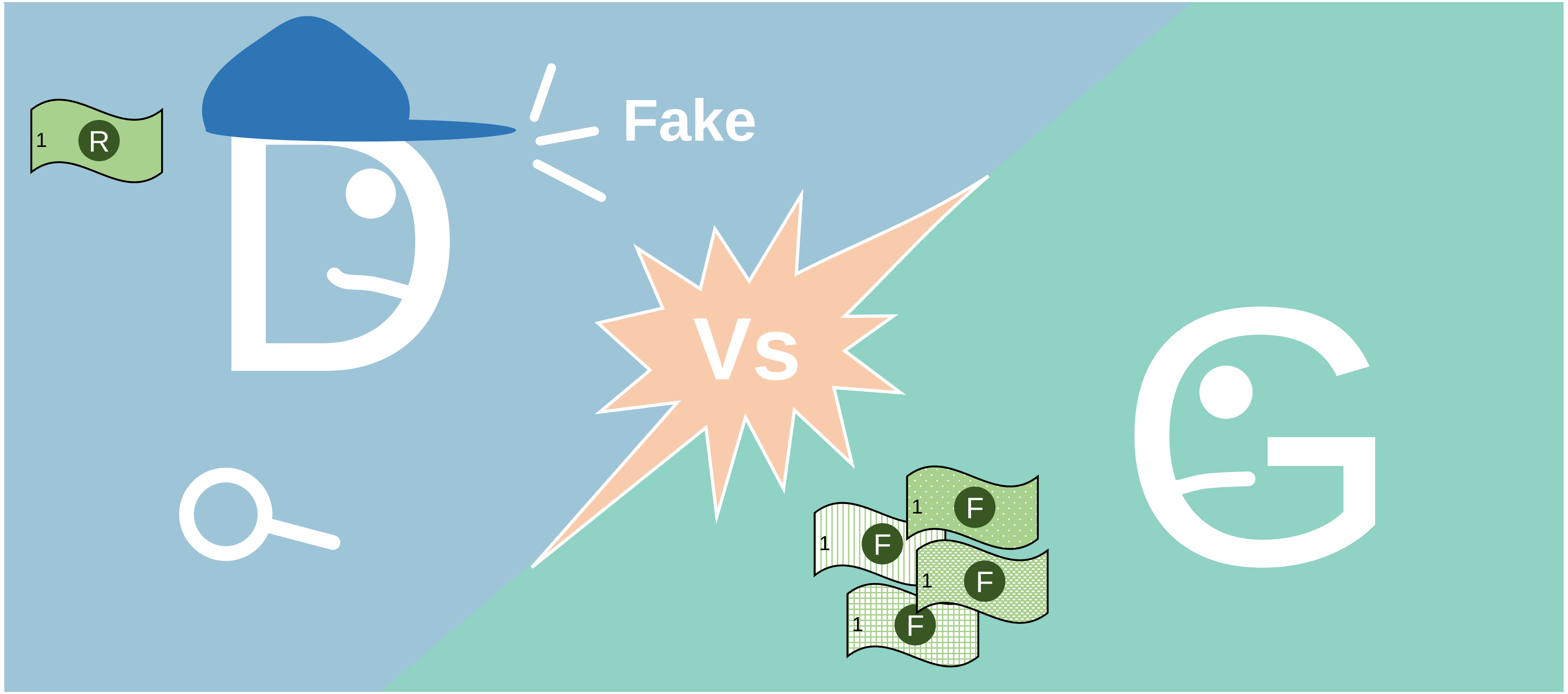
Contents

Review

Vanilla GAN, DCGAN

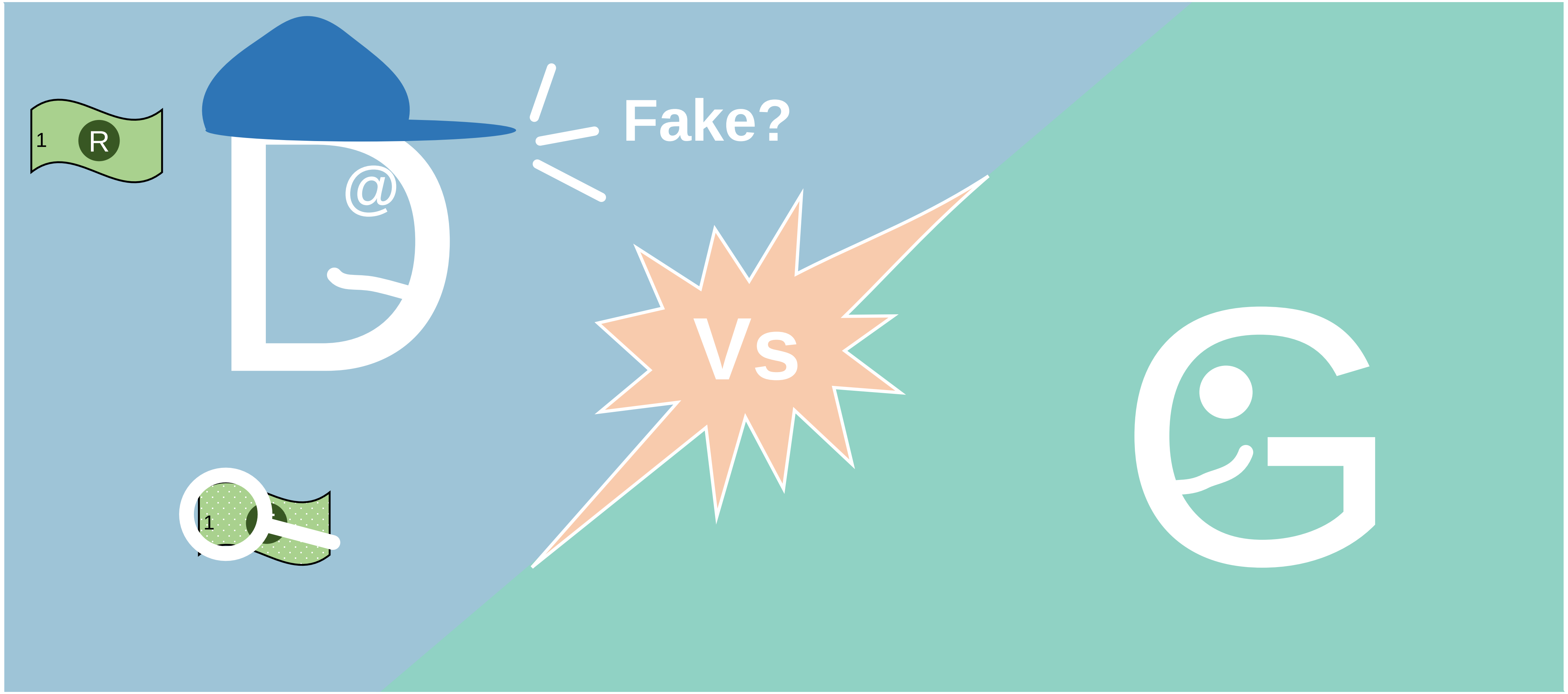
Review

- Concept of GAN



Review

- Concept of GAN



Review

- Adversarial nets

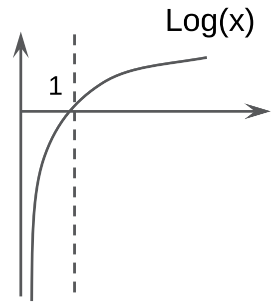
$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_z(z)}[\log(1-D(G(z)))]$$

Smart D

Real case $E_{x\sim p_{data}(x)}[\log \underbrace{D(x)}_{1}] + E_{z\sim p_z(z)}[\log(1-D(G(z)))]$ should be 0

Fake case $E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_z(z)}[\log(1-\underbrace{D(G(z))}_{0})]$ should be 0

cf.



Stupid D

Real case $E_{x\sim p_{data}(x)}[\log \underbrace{D(x)}_{0}] + E_{z\sim p_z(z)}[\log(1-D(G(z)))]$ should be negative infinity

Fake case $E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_z(z)}[\log(1-\underbrace{D(G(z))}_{1})]$ should be negative infinity

**D perspective,
it should be maximum.**

Review

- Adversarial nets

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

Generator

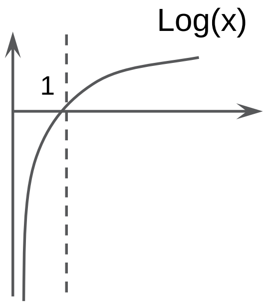
Smart G $\quad E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_{z}(z)}[\log(1-D(G(z)))]$ should be negative infinity

1

Stupid G $\quad E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_{z}(z)}[\log(1-D(G(z)))]$ should be 0

0

cf.



G perspective,
it should be minimum.

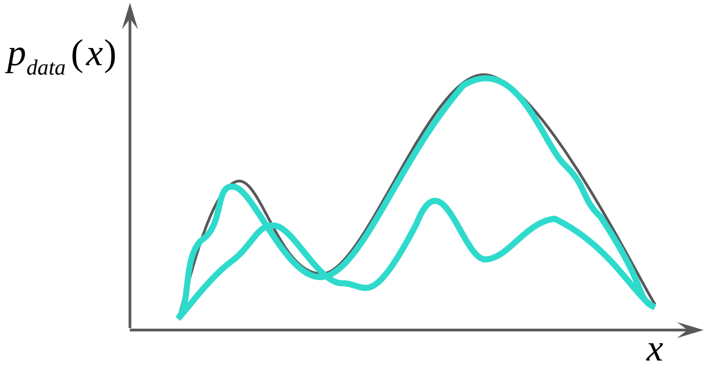
Review

- GAN

"Generative Adversarial Networks"

Goal Method

Vs

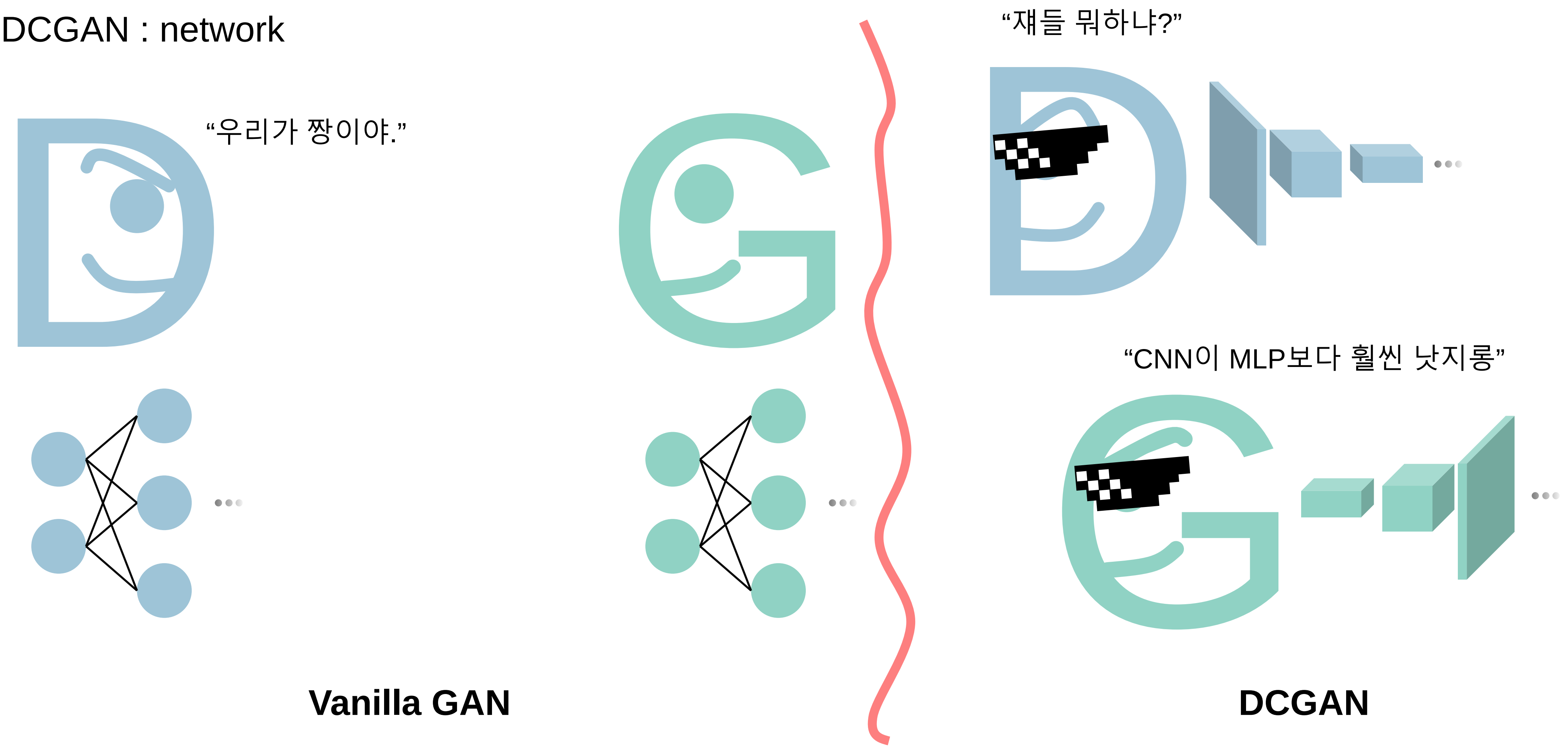


1) Global Optimality of $p_g = p_{data}$

2) Convergence of Algorithm

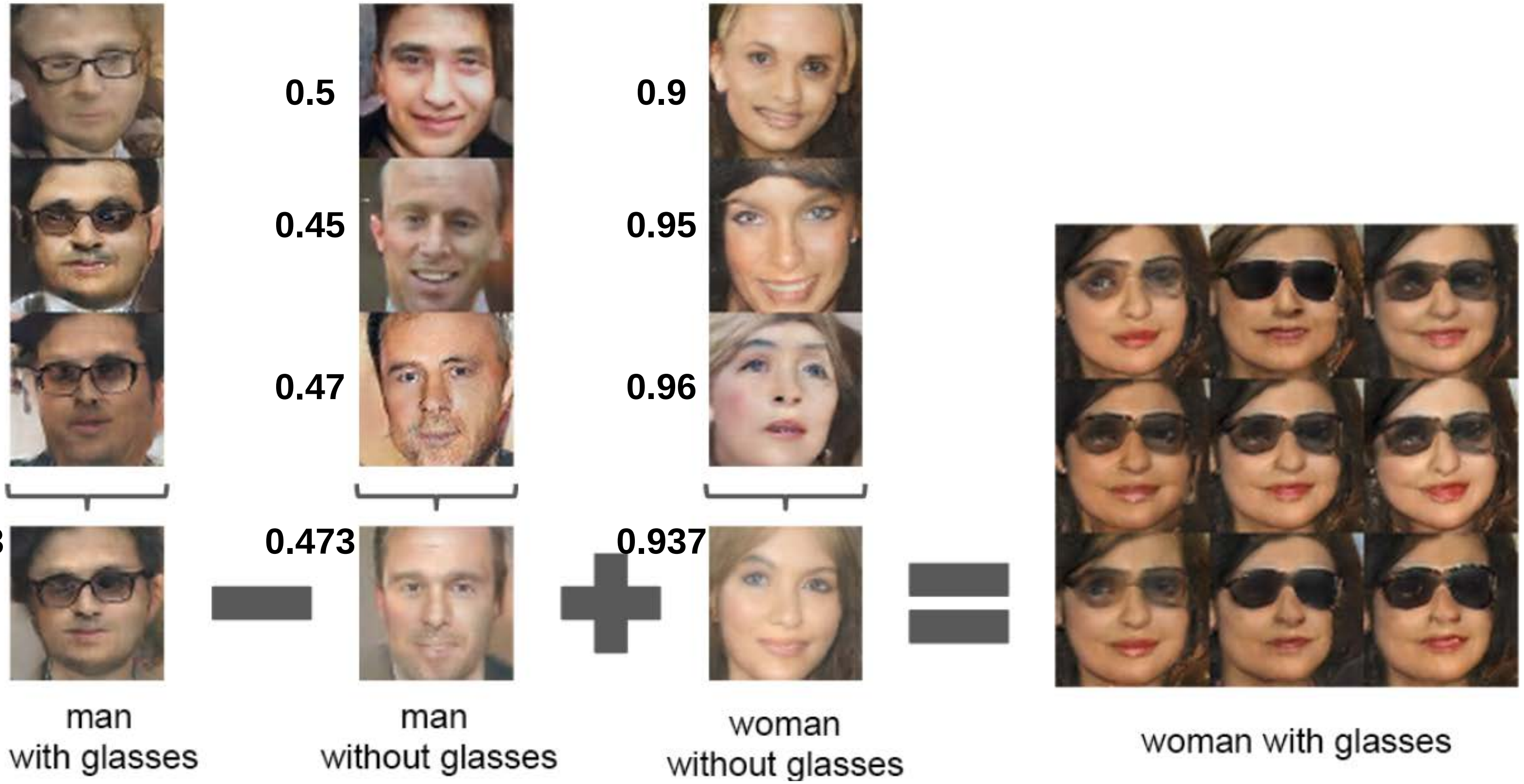
Review

- DCGAN : network



Review

- DCGAN : latent space



I. Review

II. InfoGAN

III. Experiment

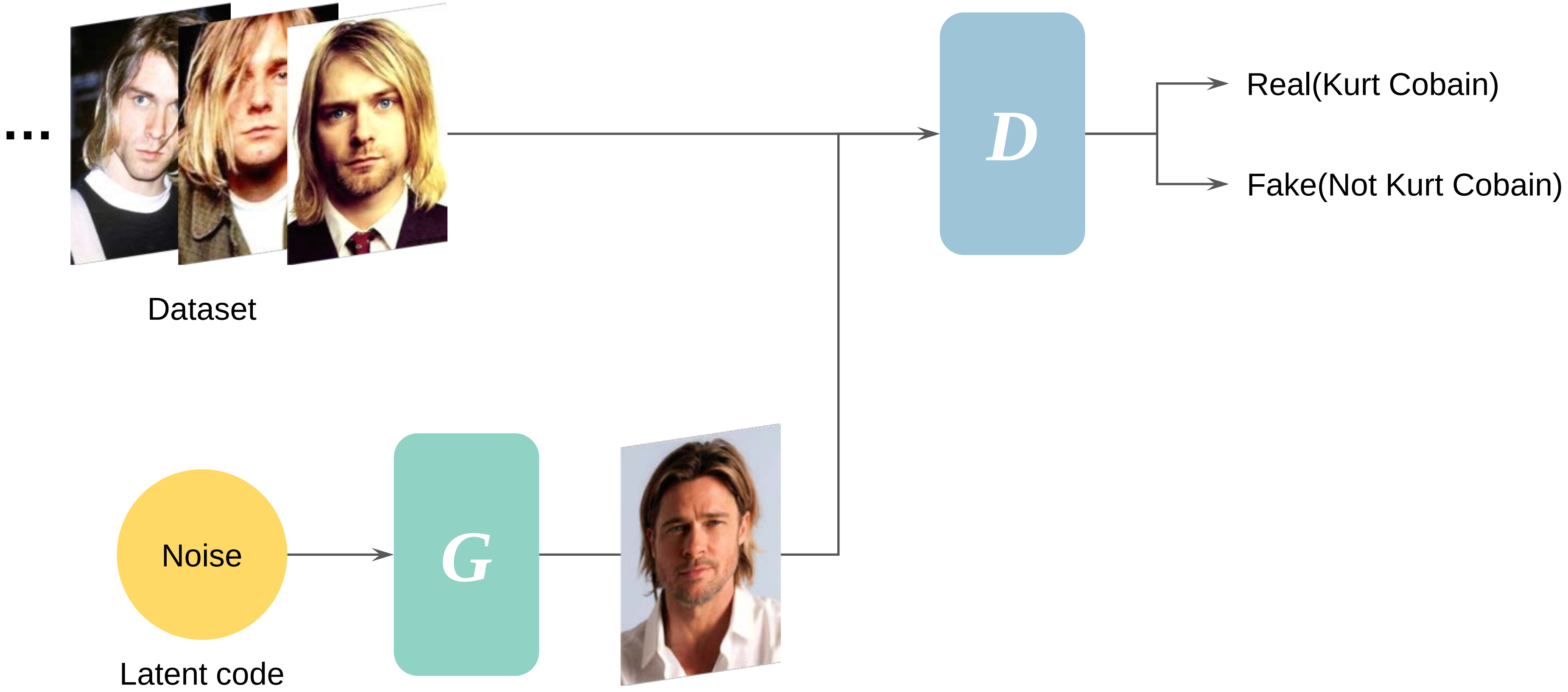
IV. Summary

InfoGAN

Concept, Mutual Information, Variational method, Results

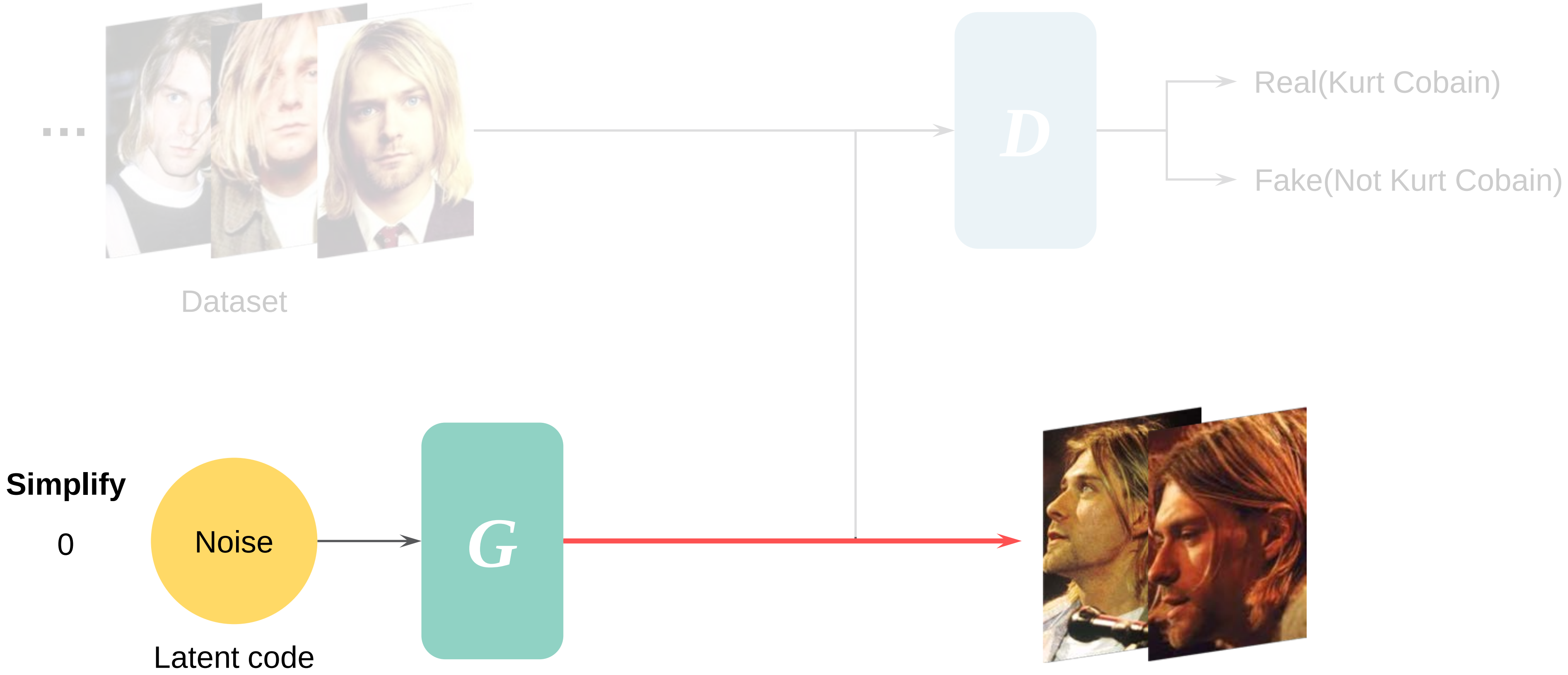
InfoGAN

- Concept



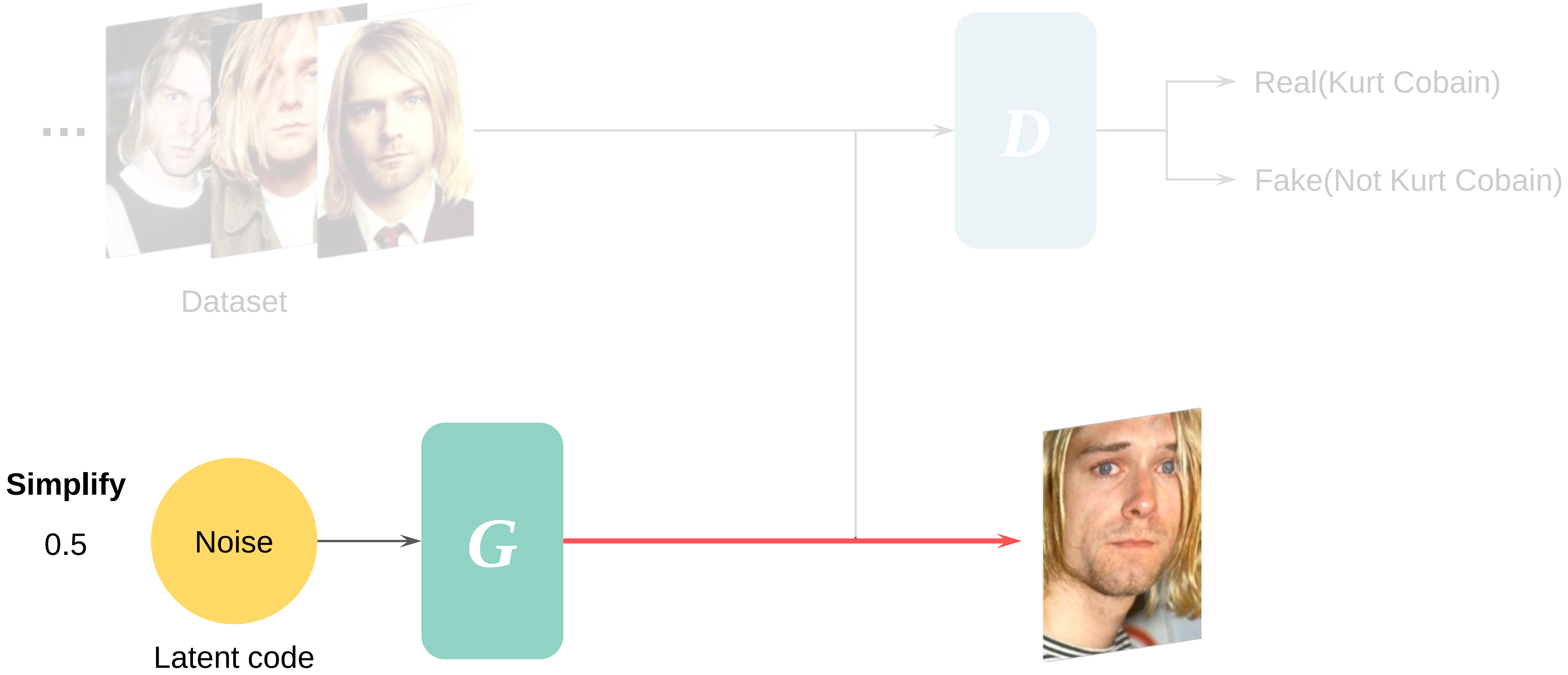
InfoGAN

- Concept



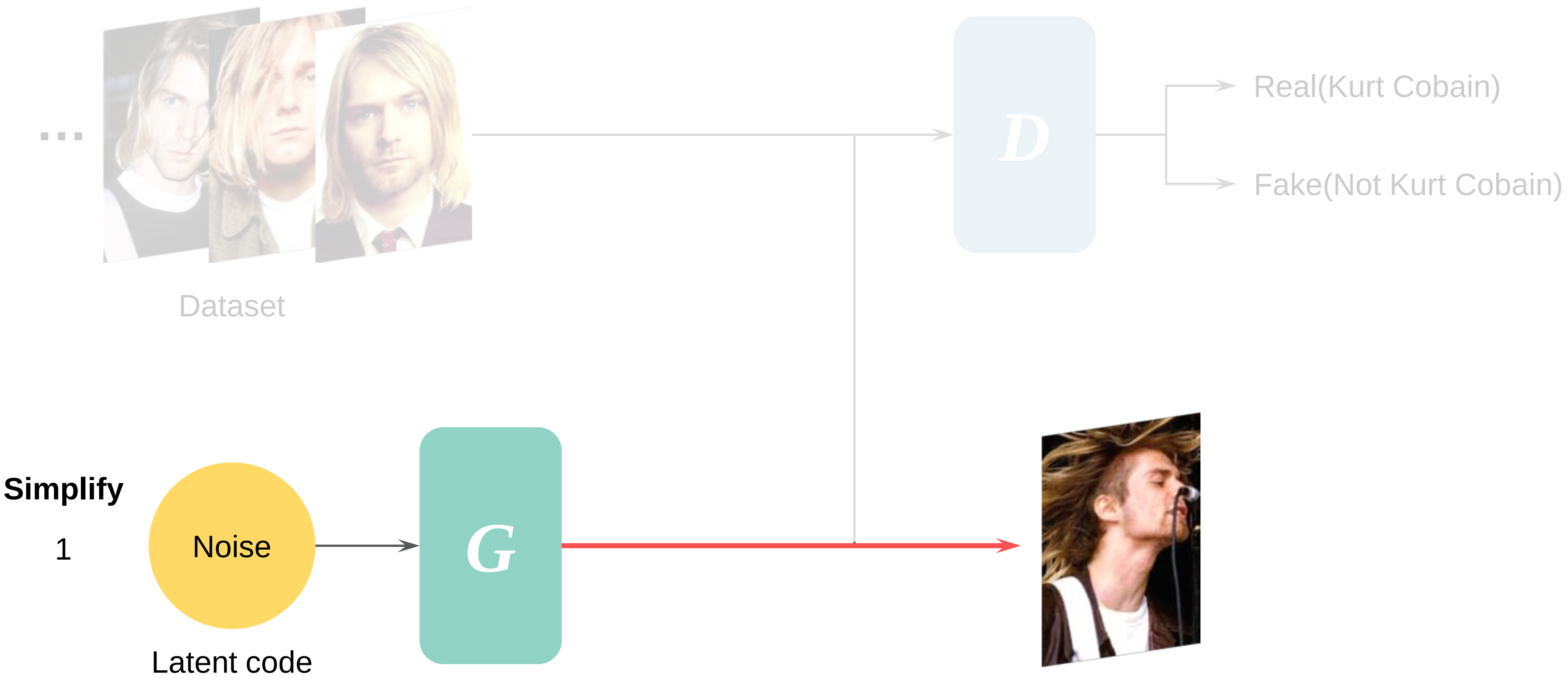
InfoGAN

- Concept



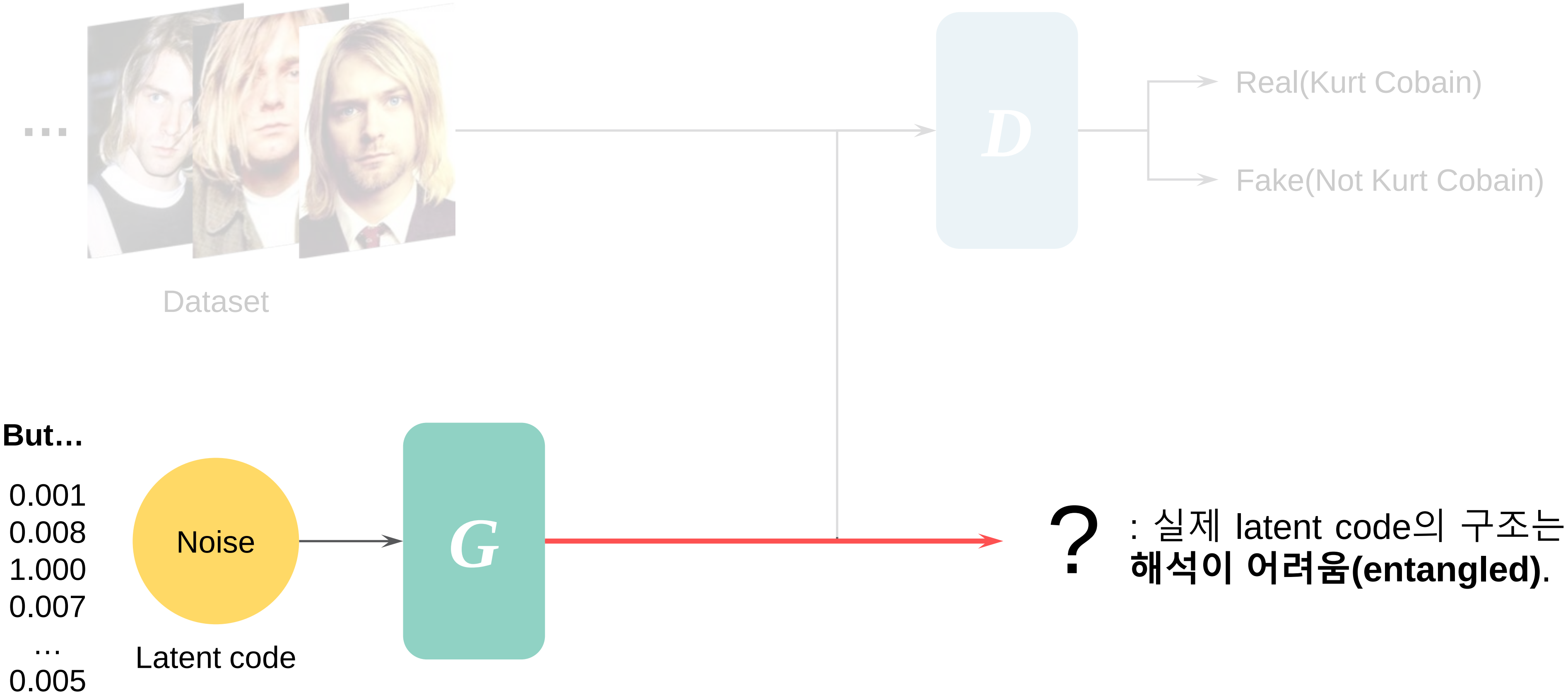
InfoGAN

- Concept



InfoGAN

- Concept



: 실제 latent code의 구조는 복잡하여 **해석이 어려움(entangled)**.

InfoGAN

- Concept

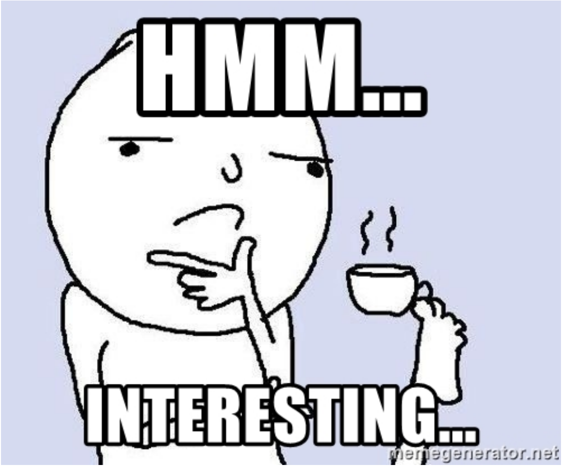
0.001
0.008
1.000
0.007
…
0.005

Noise

Latent code

G

? : 실제 latent code의 구조는 복잡하여 **해석이 어려움(entangled)**.



Let's make the latent code simple.

[0.001, 0.008, …, 005] ⟶ [005]

The proper generation is difficult.

Idea

How about adding latent code?

Z	C
0.001	0
0.008	0
1.000	0
0.007	0
…	…
0.005	1

Z C

Latent code

C : Condition

InfoGAN

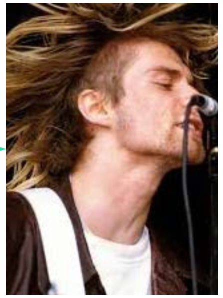
- Concept

"뭐야? 그러면 C를 Z 옆에 바로 붙이면 되는 거야?"

Z | C

Latent code

G



[0.001, 0.008, …, 005 **| 0, 0, … 1**]
Z C

[0.001, 0.008, …, 005 **| 1, 0, … 0**]
Z C

[0.001, 0.008, …, 005 ~~| 0, 0, … 1~~]
Z ~~C~~

[0.001, 0.008, …, 005 ~~| 1, 0, … 0~~]
Z ~~C~~

Ignore the additional latent code c

$$\min_G \max_D V(D,G)$$

Cost function을 수정하여 c의 영향을 만듦.
(Mutual Information)

InfoGAN

- Mutual Information

$$I(X;Y) = H(X) - H(X \mid Y) \qquad I(X;Y) = \frac{P(X \cap Y)}{P(X)P(Y)}$$

ISL Browser

https://isl.cnu.ac.kr

Supervised Learning

검색 결과 약 107,000,000개

Supervised Learning Clustering

검색 결과 약 25,300,000개

Unsupervised Learning

검색 결과 약 13,400,000개

Unsupervised Learning Clustering

검색 결과 약 7,770,000개

Clustering

검색 결과 약 40,900,000개

Deep Learning

검색 결과 약 1,380,000,000개

$$P(SL) = 0.07754 \qquad P(SL \cap C) = 0.01833$$

$$P(UL) = 0.00971 \qquad P(UL \cap C) = 0.00563$$

$$P(C) = 0.02964$$

$$\frac{P(SL \cap C)}{P(SL)P(C)} = \frac{0.01833}{0.07754 \times 0.02964} = 7.97551$$

$$\frac{P(UL \cap C)}{P(UL)P(C)} = \frac{0.00563}{0.00971 \times 0.02964} = 19.56190$$

“두 사건 사이의 연관성 파악”

InfoGAN

- Mutual Information

$$\min_G \max_D V_I(D,G) = V(D,G) - \lambda I(c;G(z,c))$$

: Generator와 c 사이의 연관성을 cost로 정의

Maximize

Hard to maximize directly as it requires access to the posterior $P(c|x)$

VAE Seminar (18.07.23)

$$\min L(\phi,\theta,x)$$

$$L(\phi,\theta,x) = \underbrace{-E_{q_\phi(z|x)}\left[\log\left(p(x|g_\theta(z))\right)\right]}_{\text{Reconstruction Error}} + \underbrace{KL\left(q_\phi(z|x)\,\|\,p(z)\right)}_{\text{Regularization}}$$

InfoGAN

- Variational method

$$P(c|x) \quad \leftsquigarrow \quad Q(c|x)$$

Intractable(Very complicated) **Tractable(e.g Gaussian)**

$$\min_G \max_D V_I(D,G) = V(D,G) - \lambda I\big(c; G(z,c)\big)$$

$$I\big(c; G(z,c)\big) = H(c) - H\big(c \mid G(z,c)\big) \quad \textbf{(1)}$$

$$H\big(c \mid G(z,c)\big) = -\iint P\big(c, G(z,c)\big) \ln P\big(c \mid G(z,c)\big) dc dG(z,c)$$

$$= -\iint P\big(c \mid G(z,c)\big) P\big(G(z,c)\big) \ln P\big(c \mid G(z,c)\big) dc dG(z,c)$$

$$= -\iint P\big(G(z,c)\big) P\big(c \mid G(z,c)\big) \ln P\big(c \mid G(z,c)\big) dc dG(z,c)$$

$$= -\int P\big(G(z,c)\big) E_{c' \sim P(c|x)}\big[\ln P(c' \mid x)\big] dG(z,c)$$

$$= -E_{x \sim G(z,c)}\Big[E_{c' \sim P(c|x)}\big[\ln P(c' \mid x)\big]\Big]$$

c.f Conditional Entropy

$$H\big(y \mid x\big) = -\iint P(y,x) \ln P(y \mid x) dy dx$$

Product rule

$$= -\iint P(y \mid x) P(x) \ln P(y \mid x) dy dx$$

$$I\big(c; G(z,c)\big) = H(c) + E_{x \sim G(z,c)}\Big[E_{c' \sim P(c|x)}\big[\ln P(c' \mid x)\big]\Big] \quad \textbf{(2)}$$

InfoGAN

- Variational method

$Q(c \mid x)$ **Tractable distribution**

$$I\left(c;G(z,c)\right)=H(c)+E_{x\sim G(z,c)}\left[E_{c'\sim P(c|x)}\left[\ln P(c'|x)\right]\right] \quad \textbf{(2)}$$

c.f KL Divergence

$$D_{KL}\left(P \,\|\, Q\right)=E_{x\sim P}\left[\ln\frac{P(x)}{Q(x)}\right]$$

$$D_{KL}\left(P \,\|\, Q\right)=0$$: 동일 분포

$$D_{KL}\left(P(c'|x) \,\|\, Q(c'|x)\right)=E_{c'\sim P(c|x)}\left[\ln\frac{P(c'|x)}{Q(c'x)}\right]$$

$$=E_{c'\sim P(c|x)}\ln P(c'x)-E_{c'\sim P(c|x)}\ln Q(c'|x)$$

$$E_{c'\sim P(c|x)}\ln P(c'x)=D_{KL}\left(P(c'|x) \,\|\, Q(c'|x)\right)+E_{c'\sim P(c|x)}\ln Q(c'|x)$$

$$I\left(c;G(z,c)\right)=H(c)+E_{x\sim G(z,c)}\left[\underbrace{D_{KL}\left(P(c'|x) \,\|\, Q(c'|x)\right)}_{\geq 0}+E_{c'\sim P(c|x)}\ln Q(c'|x)\right] \quad \textbf{(3)}$$

$$\geq H(c)+E_{x\sim G(z,c)}\left[E_{c'\sim P(c|x)}\ln Q(c'|x)\right] \quad \textbf{(4)}$$

InfoGAN

- Variational method

$$I(c;G(z,c)) \geq H(c) + E_{x \sim G(z,c)}\left[E_{c' \sim P(c|x)} \ln Q(c'|x)\right] \quad \textbf{(4)}$$

$P(c|x)$ **: 여전히 남음.**

Lemma

$$E_{x \sim X, y \sim Y|x}\left[f(x,y)\right] = E_{x \sim X, y \sim Y|x, x' \sim X|y}\left[f(x',y)\right]$$

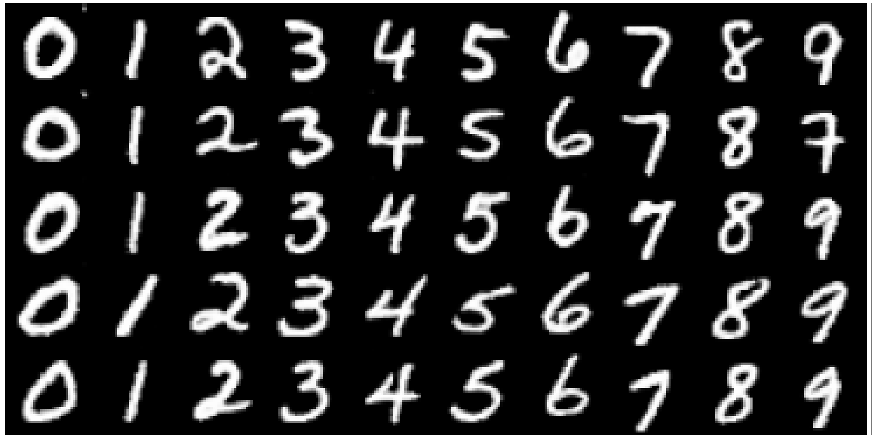
$$L_I(G,Q) = H(c) + E_{c \sim P(c), x \sim G(z,c)}\left[\ln Q(c|x)\right] \quad \textbf{(5)}$$

$$= H(c) + E_{x \sim G(z,c)}\left[E_{c' \sim P(c|x)} \ln Q(c'|x)\right]$$

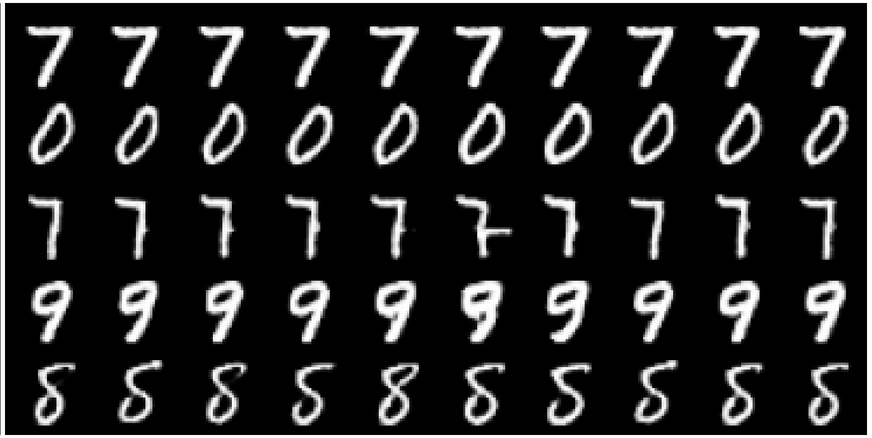
$$\min_G \max_D V_{InfoGAN}(D,G,Q) = V(D,G) - \lambda L_I(G,Q)$$

InfoGAN

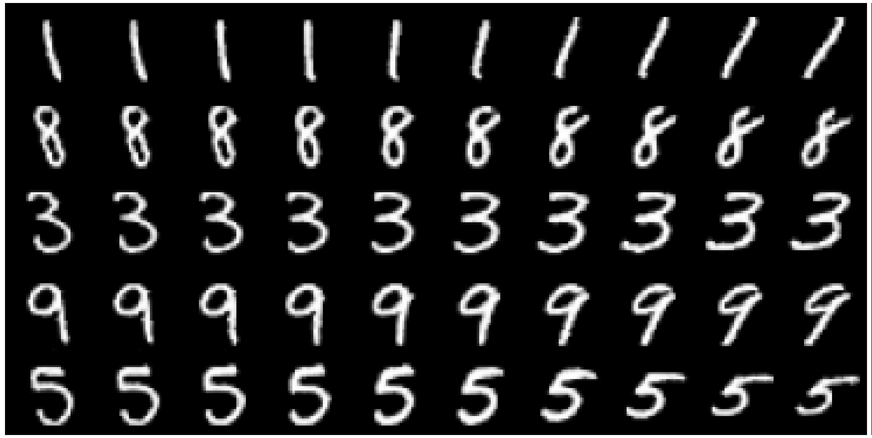
- Results



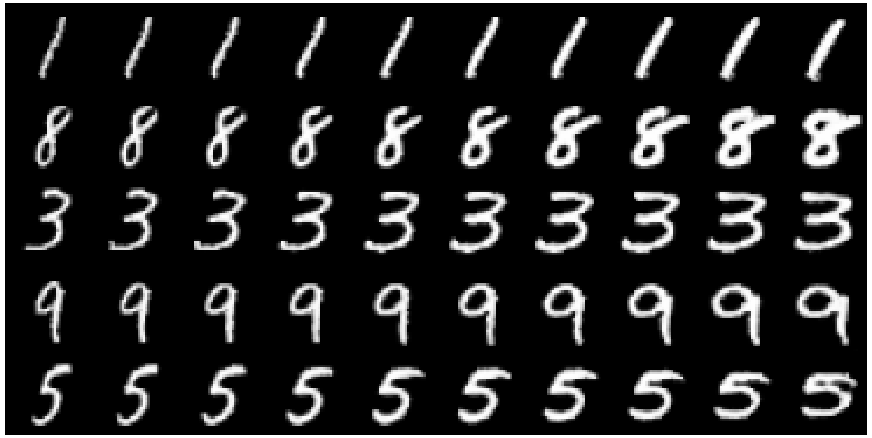
(a) Varying c_1 on InfoGAN (Digit type)



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



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

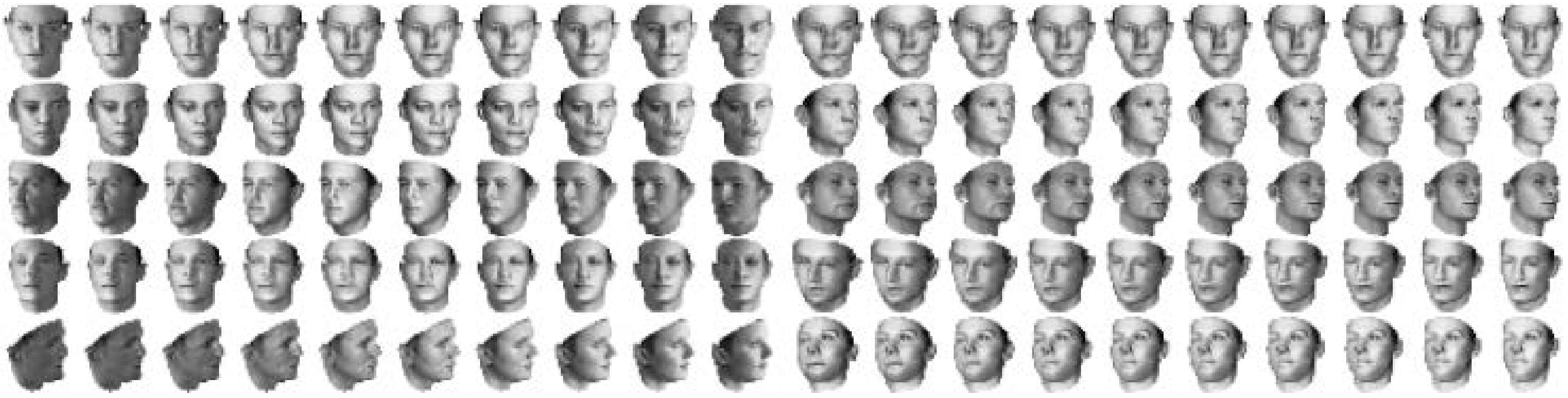


(d) Varying c_3 from -2 to 2 on InfoGAN (Width)

InfoGAN

- Results

(a) Azimuth (pose) (b) Elevation



(c) Lighting (d) Wide or Narrow

InfoGAN

- Results

(a) Rotation (b) Width

InfoGAN

- Results

(a) Azimuth (pose)   (b) Presence or absence of glasses

(c) Hair style   (d) Emotion

Experiment

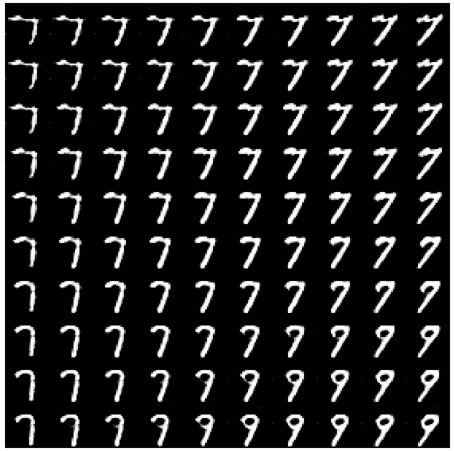
MNIST, FashionMNIST, LSUN

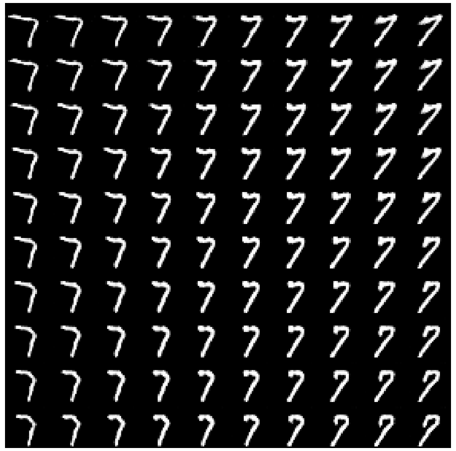
Image System Laboratory

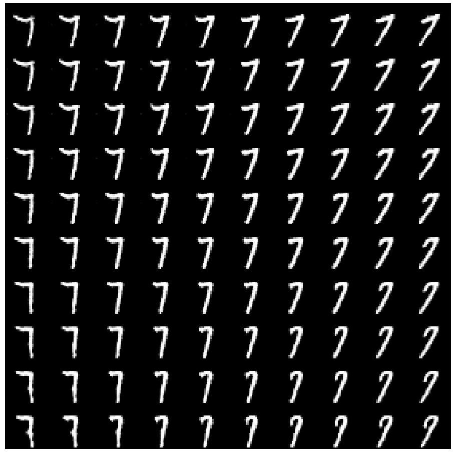
Experiment

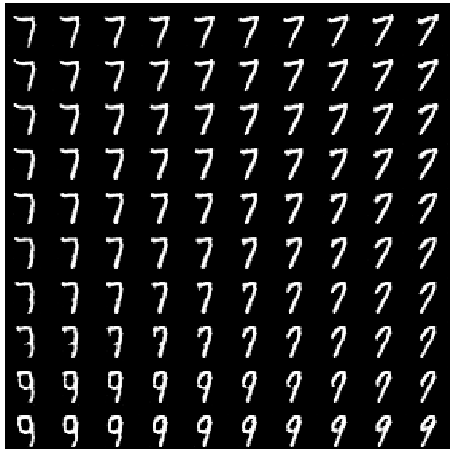
- Results#1 MNIST (continuous)


Epoch 1


Epoch 5


Epoch 10


Epoch 30


Epoch 50

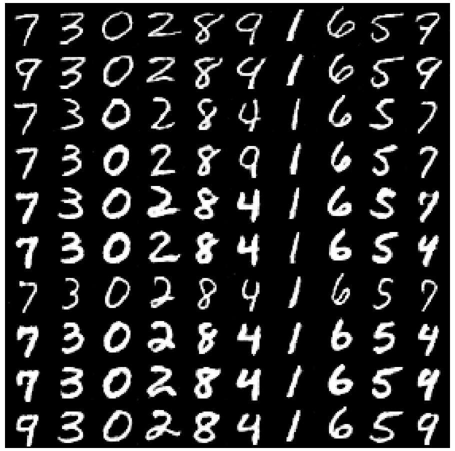

GIF

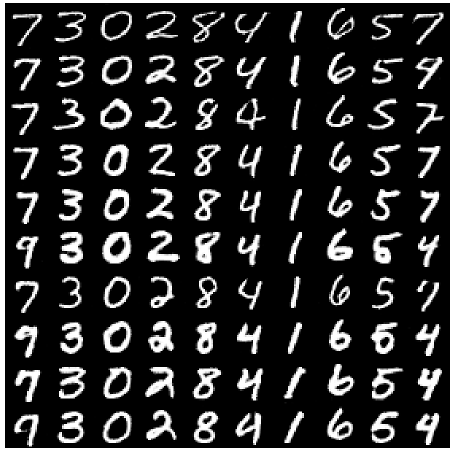
Experiment

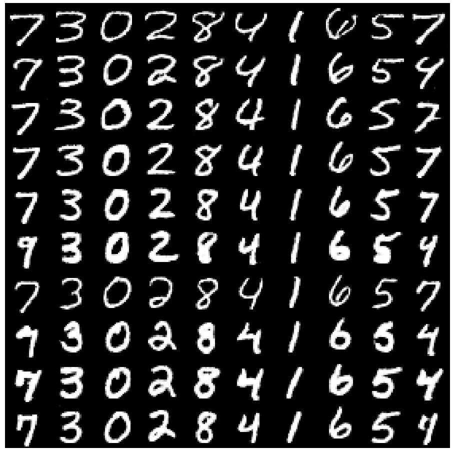
- Results#1 MNIST (categorical)


Epoch 1


Epoch 5


Epoch 10


Epoch 30

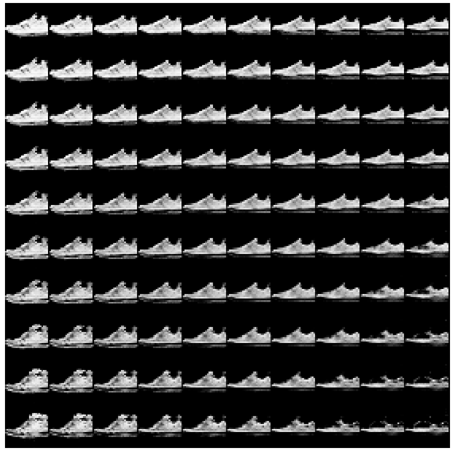

Epoch 50


GIF

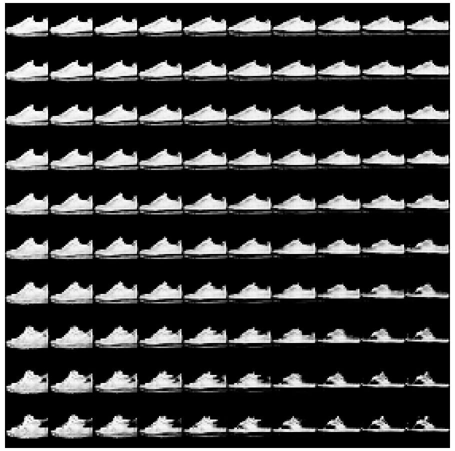
Experiment

- Results#2 Fashion MNIST (continuous)

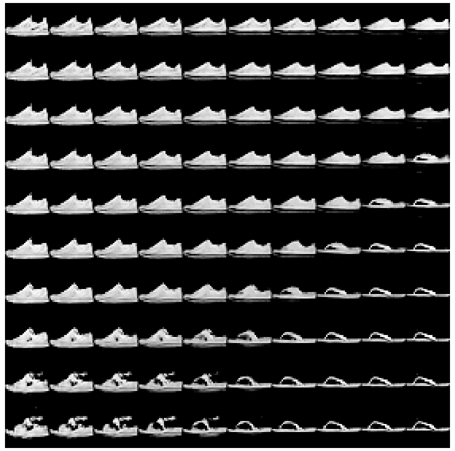
Epoch 1



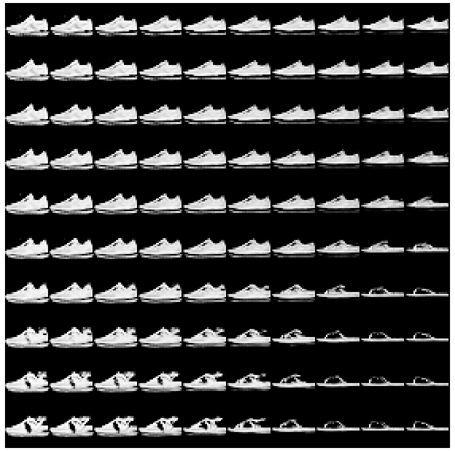
Epoch 5



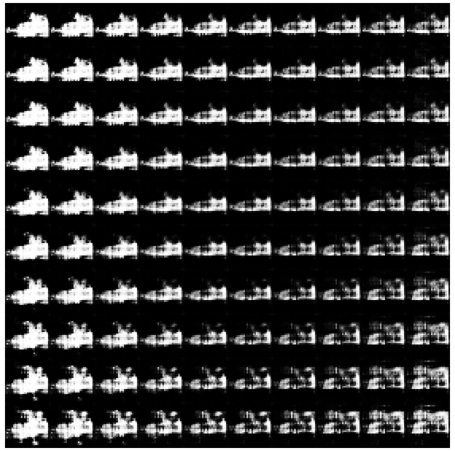
Epoch 10



Epoch 30



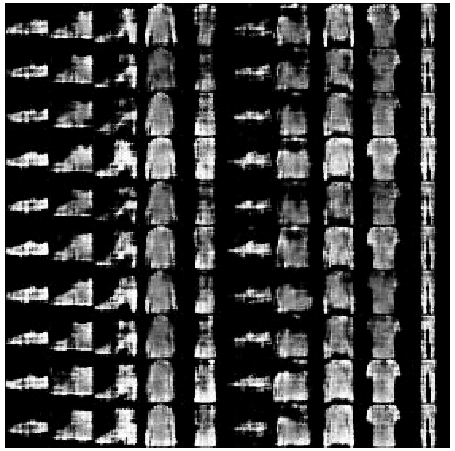
Epoch 50



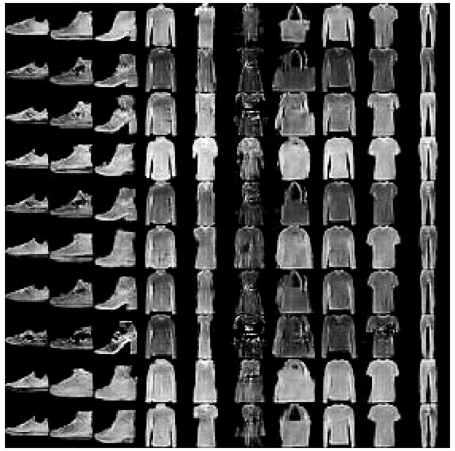
GIF

Experiment

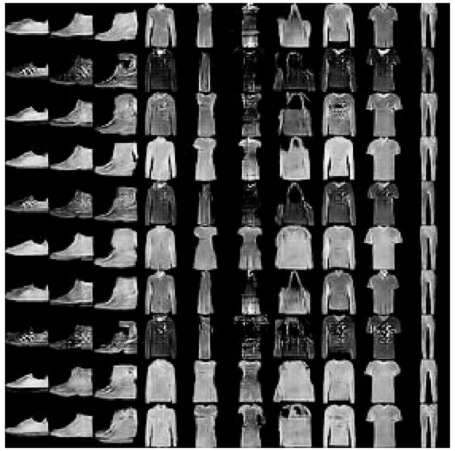
- Results#2 Fashion MNIST (categorical)



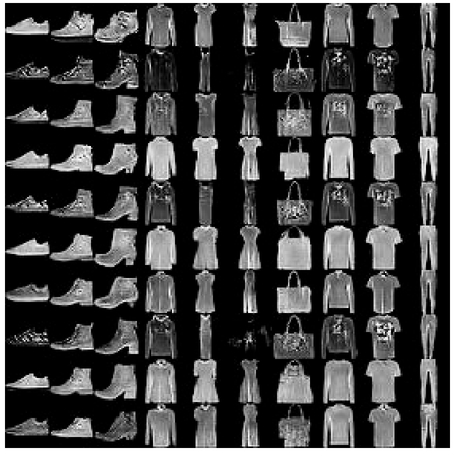
Epoch 1



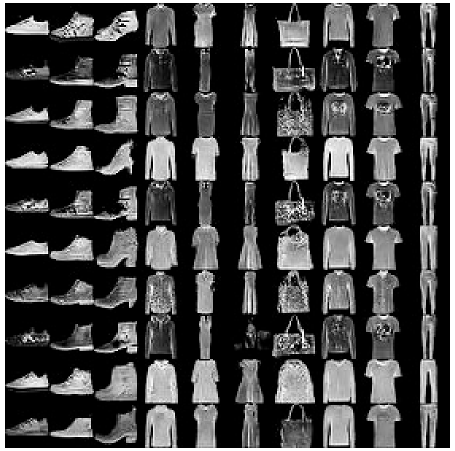
Epoch 5



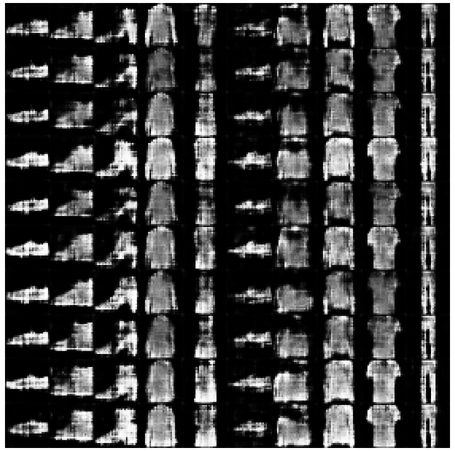
Epoch 10



Epoch 30



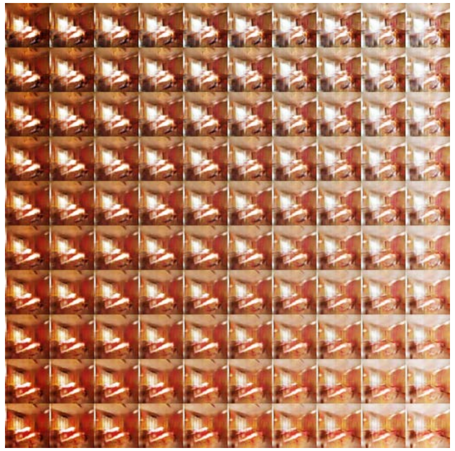
Epoch 50



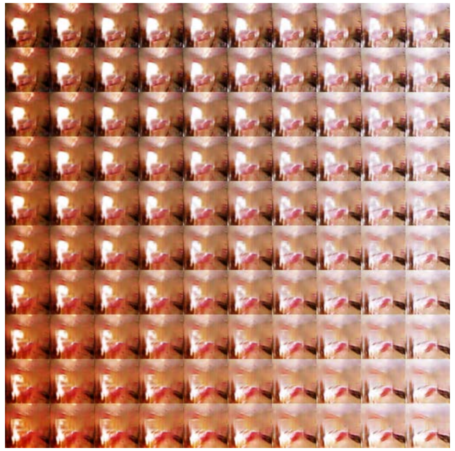
GIF

Experiment

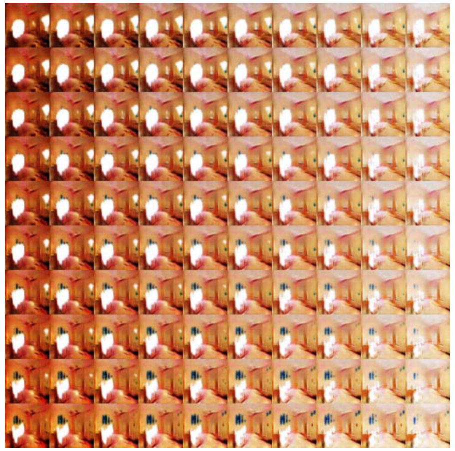
- Results#3 LSUN (continuous)



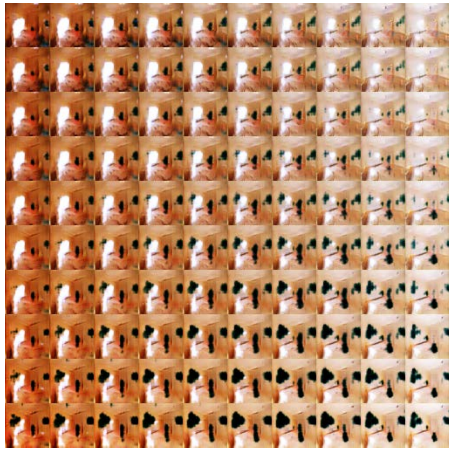
Epoch 1



Epoch 2



Epoch 3



Epoch 4

Epoch 5

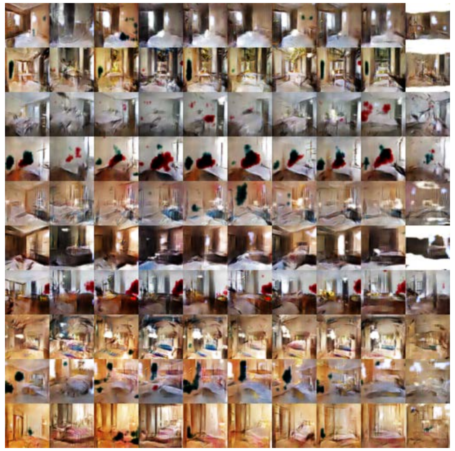
Experiment

- Results#3 LSUN (categorical)

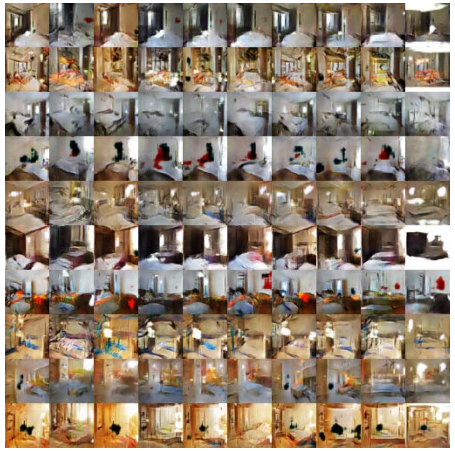
Epoch 1

Epoch 2

Epoch 3



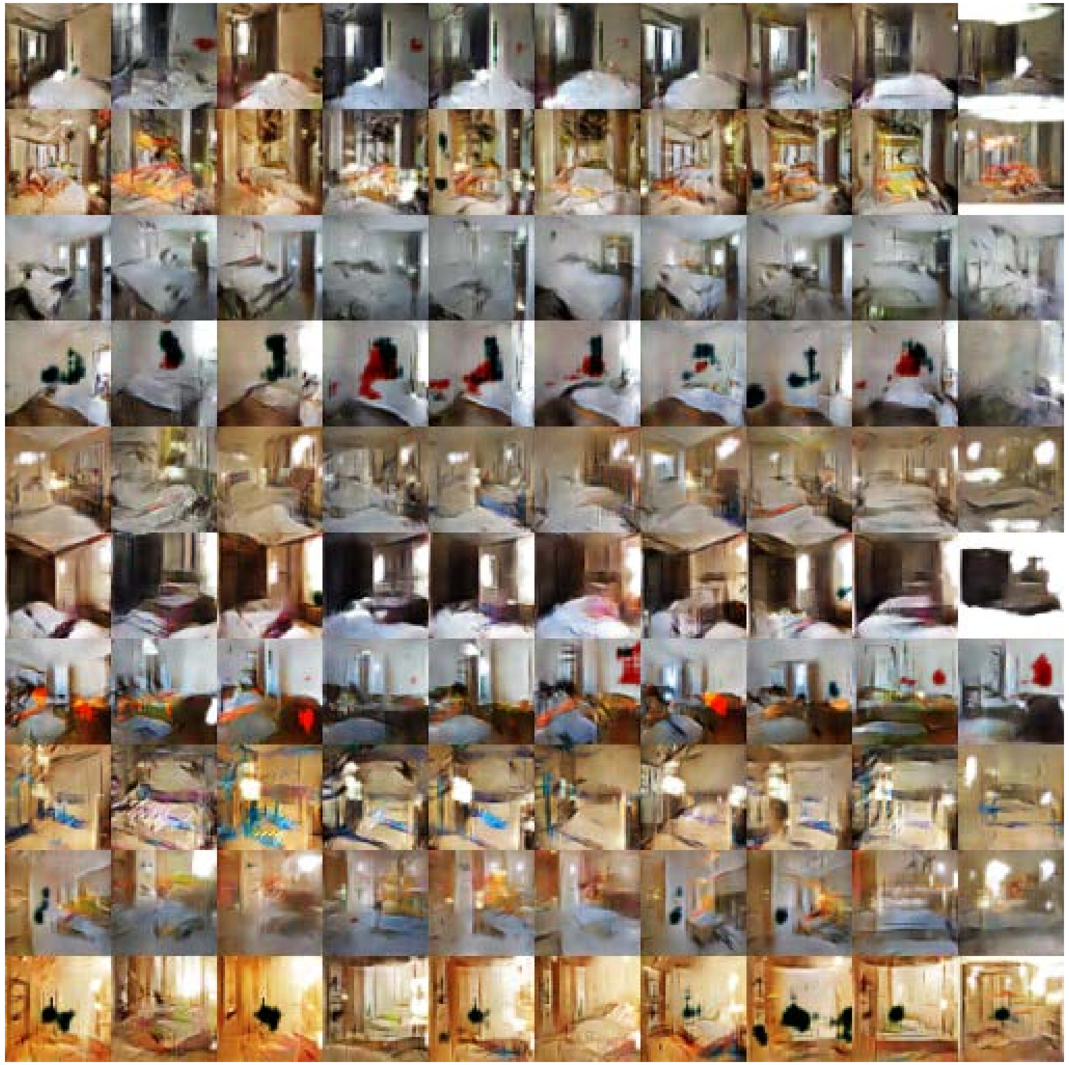
Epoch 4



Epoch 5

Experiment

- Results#3 LSUN (categorical, ep 5)

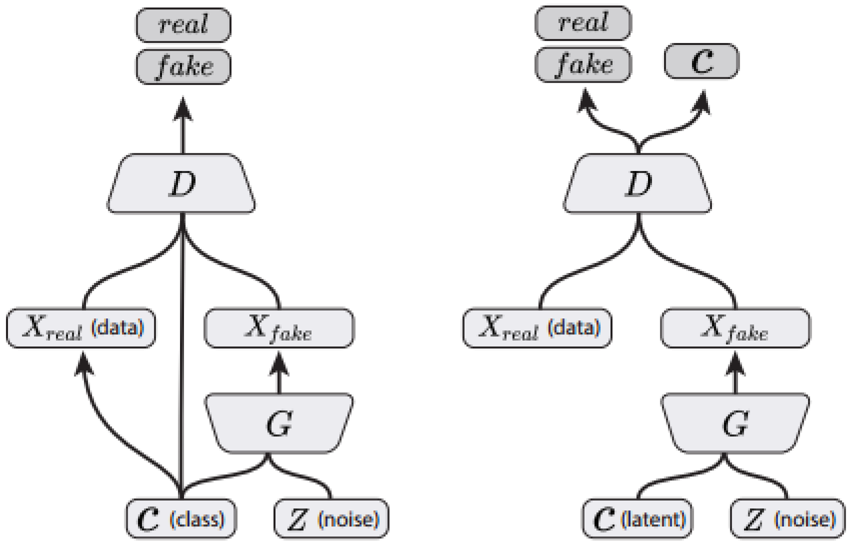


Summary

Summary, Future Work

Summary

- Latent code에 추가적인 code를 할당하여 학습함. **(cGAN과 비슷한 접근법)**
- 기존의 GAN 학습법으로는 추가된 code를 무시하기에 새로운 학습 방법이 필요함.
- Mutual information을 통해 추가된 code와 네트워크 간의 상호 연관성을 부여함.
- 주어진 code는 그 형태에 따라 categorical(discrete)or continuous로 구분되며, 실제 실험을 통해 적절히 학습되는 것을 확인함.



Conditional GAN
(Mirza & Osindero, 2014)

InfoGAN
(Chen, et al., 2016)

Future work

GAN Research

- [x] ~~Vanilla GAN~~
- [x] ~~DCGAN~~
- [x] ~~InfoGAN~~
- [ ] LS GAN
- [ ] BEGAN
- [ ] ~~Pix2Pix~~
- [ ] Cycle GAN
- [ ] Novel GAN(about depth)

Tools

- [x] ~~Document~~
- [x] ~~Programming~~
- [x] ~~PyTorch~~
- [ ] Python executable & UI

I Know What You Did Last Faculty

- [x] ~~C++ Coding Standard~~
- [ ] Mathematical theory
- [ ] LSM applications

Other Research

- [x] ~~Level Processor~~
- [ ] Ice Propagation

Q & A

Thank you for your attention