* Mao, Xudong, et al. "Least squares generative adversarial networks." Proceedings of the IEEE International Conference on Computer Vision. 2017.

SIMPLe : Simple Idea Meaningful Performance Level up*

ISL Lab Seminar

Hansol Kang

Image System Laboratory

Contents

Image System Laboratory

Introduction

Research Trend, Review(Concept, Vanilla GAN, DCGAN, InfoGAN)

Image System Laboratory

Introduction

- Research Trend

Image System Laboratory

Introduction

- Research Trend

Flickr-Faces-HQ (FFHQ)

- **70,000** high-quality PNG images at **1024×1024** resolution
- Considerable variation in terms of **age, ethnicity and image background**
- Good coverage of accessories such as **eyeglasses, sunglasses, hats, etc**.

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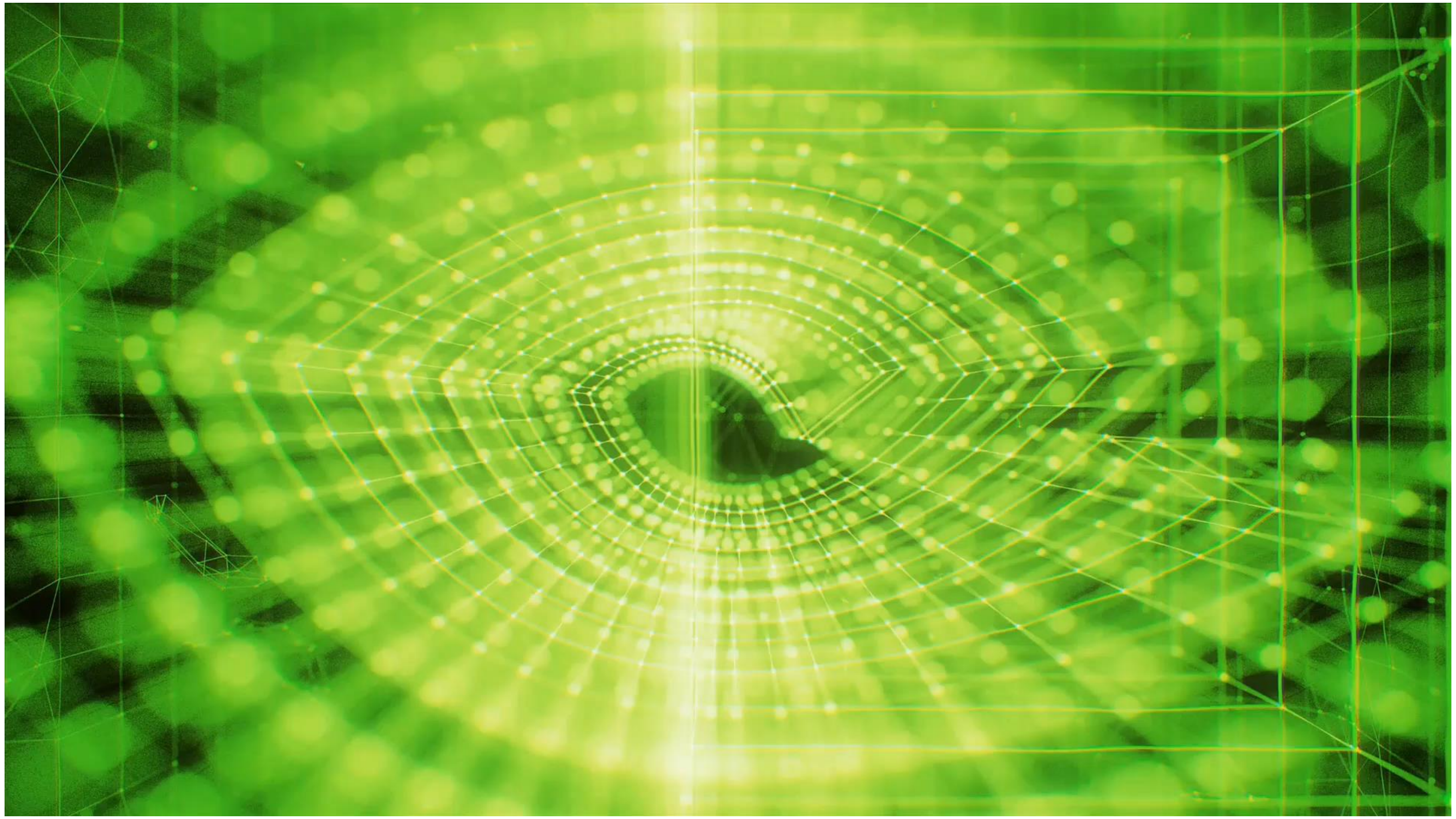
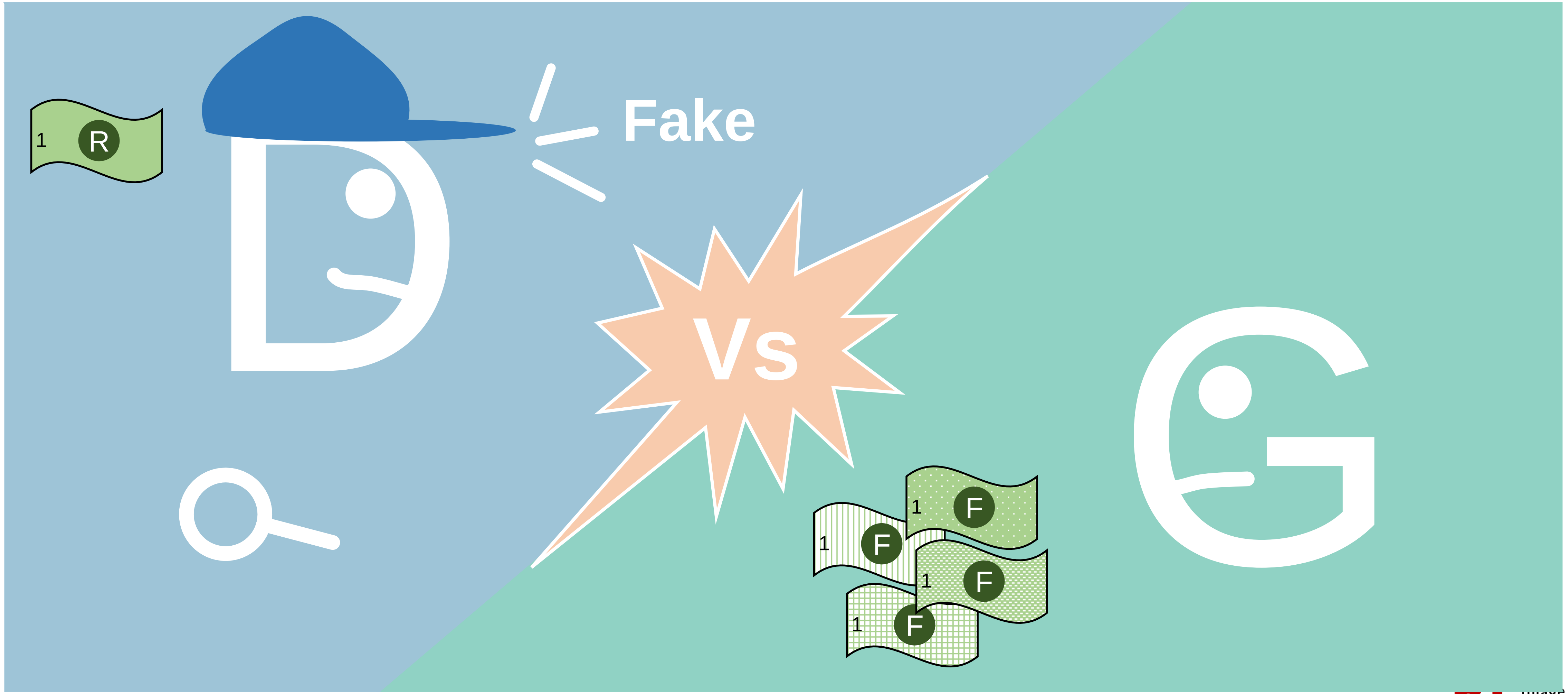
Introduction

- Research Trend



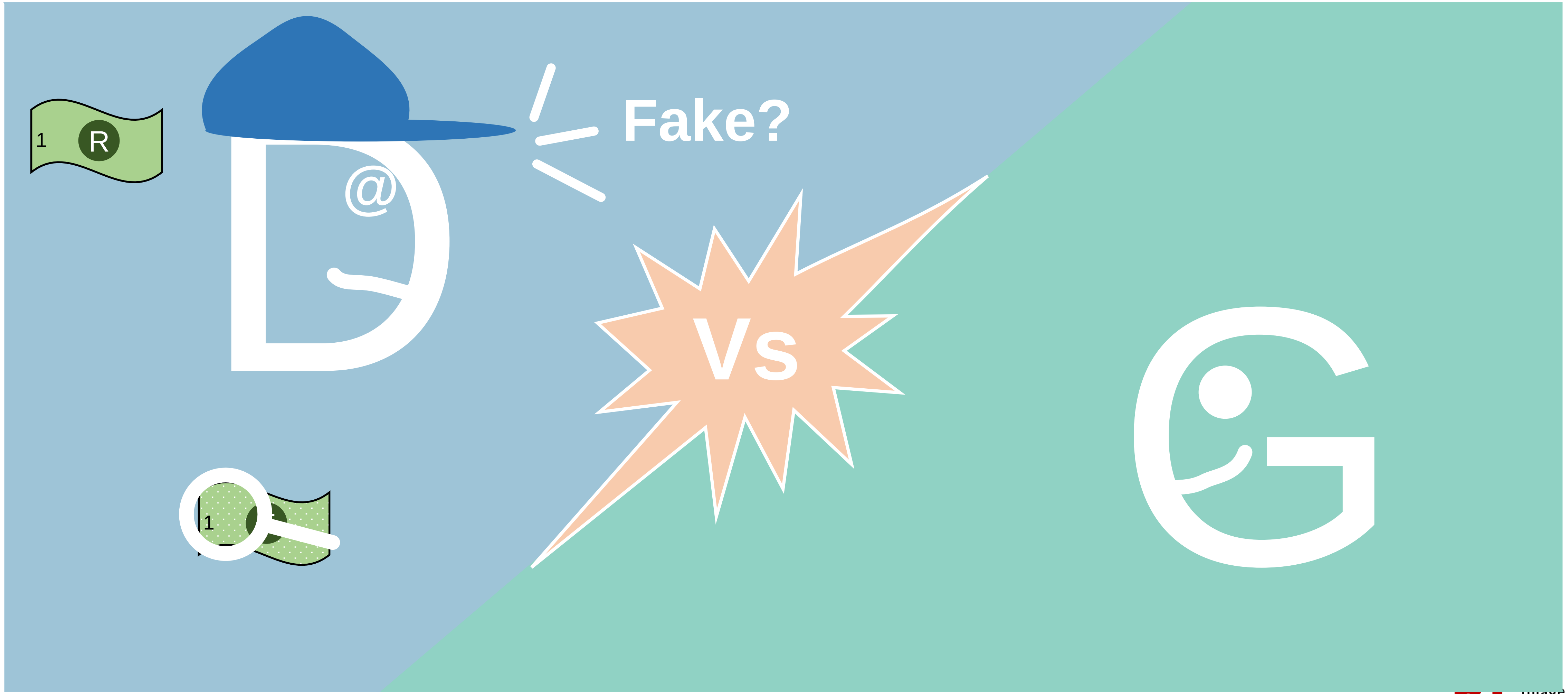
Introduction

- Concept of GAN



Introduction

- Concept of GAN



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Introduction

- Vanilla GAN : Adversarial Nets

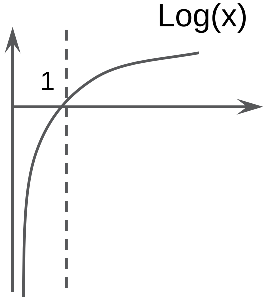
$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}[\log D(x)] + E_{z\sim p_z(z)}[\log(1-D(G(z)))]$$

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.

Image System Laboratory

Introduction

- Vanilla GAN : Adversarial Nets

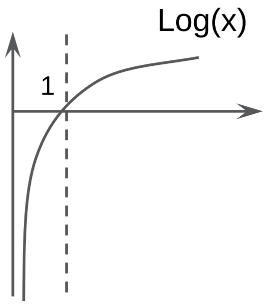
$$\min_G \max_D V(D,G) = E_{x \sim p_{data}(x)}[\log D(x)] + E_{z \sim p_z(z)}[\log(1 - D(G(z)))]$$

Generator

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

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

cf.



G perspective,
it should be minimum.

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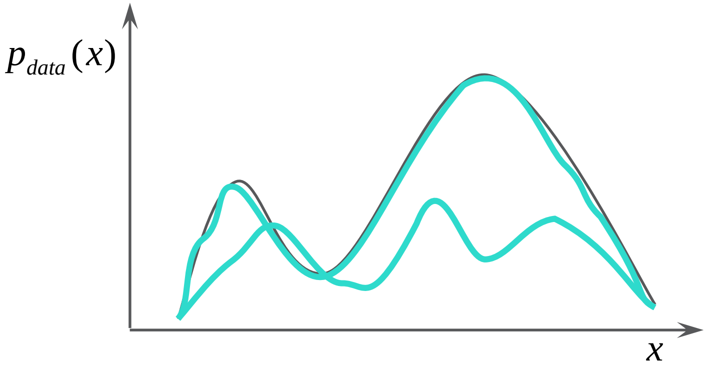
Introduction

- Vanilla GAN : Mathematical Proof

“Generative Adversarial Networks”

Goal Method

Vs

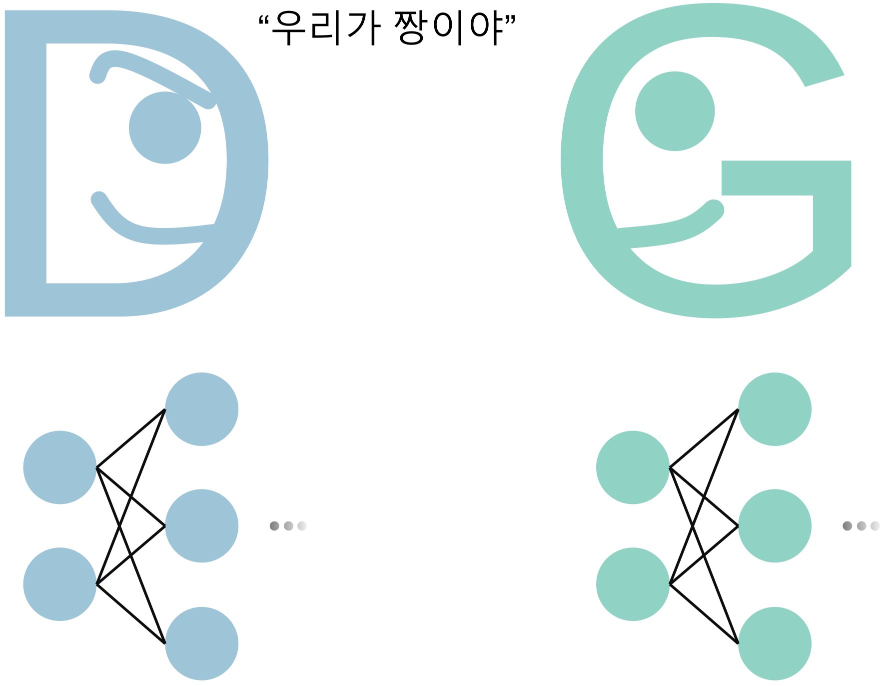


1) Global Optimality of $p_g = p_{data}$

2) Convergence of Algorithm

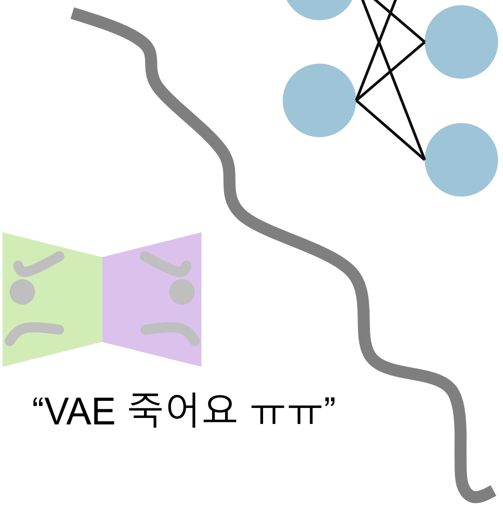
Introduction

- DCGAN : Network



Vanilla GAN

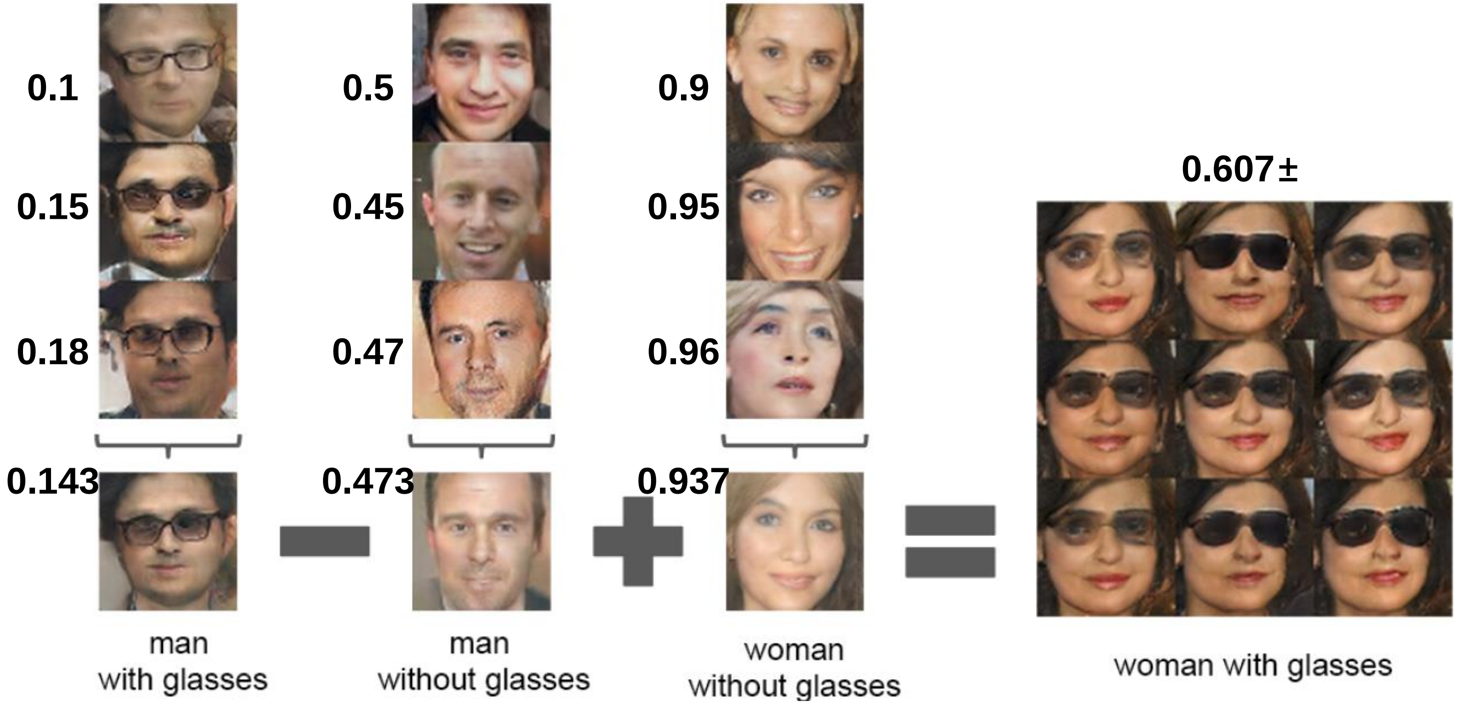
DCGAN



Introduction

- DCGAN : Latent Space

0 1



고차원(Image)에서 의미 x
저차원(Latent code)에서 의미 o

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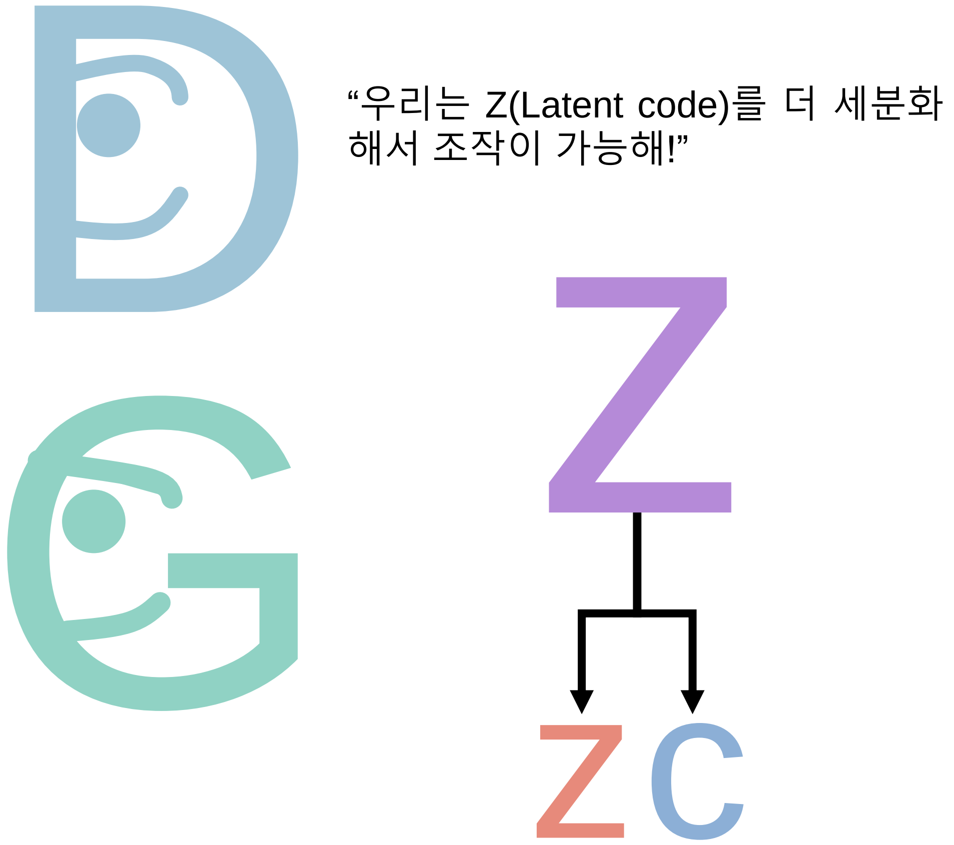
Introduction

- InfoGAN - Network

DCGAN



InfoGAN

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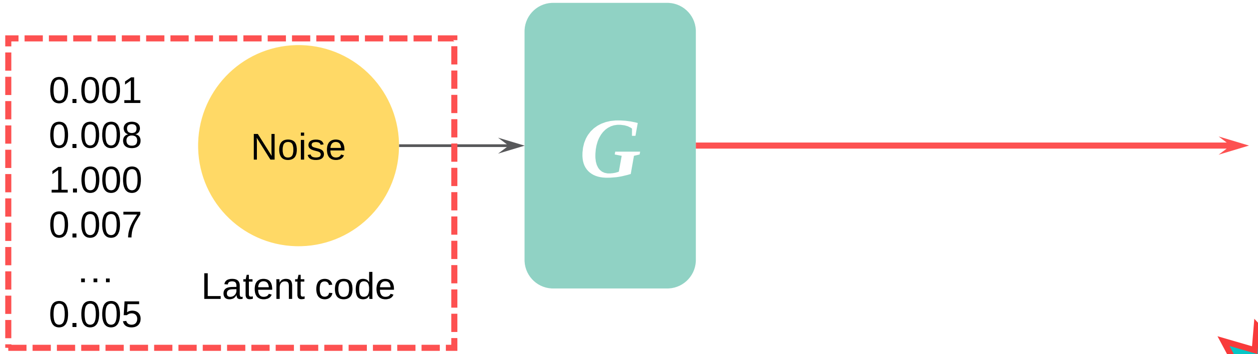
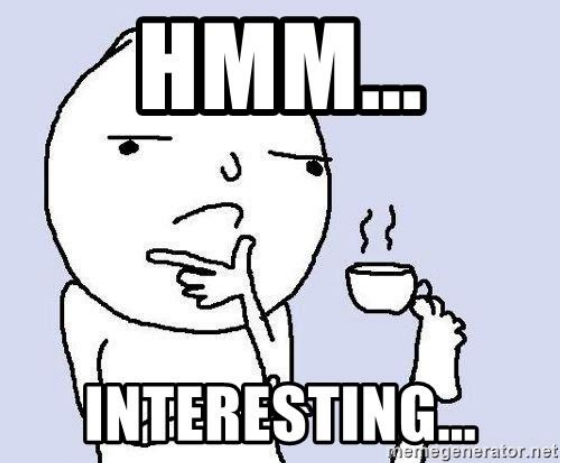
Introduction

- InfoGAN - Latent Code



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



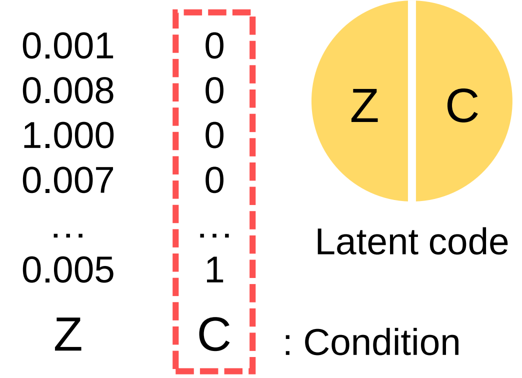
Let's make the latent code simple.

[0.001, 0.008, …, 0.005] ⟶ c

The proper generation is difficult.

Idea

How about adding latent code?



: Condition

해석이 가능한 Condition을 제공.

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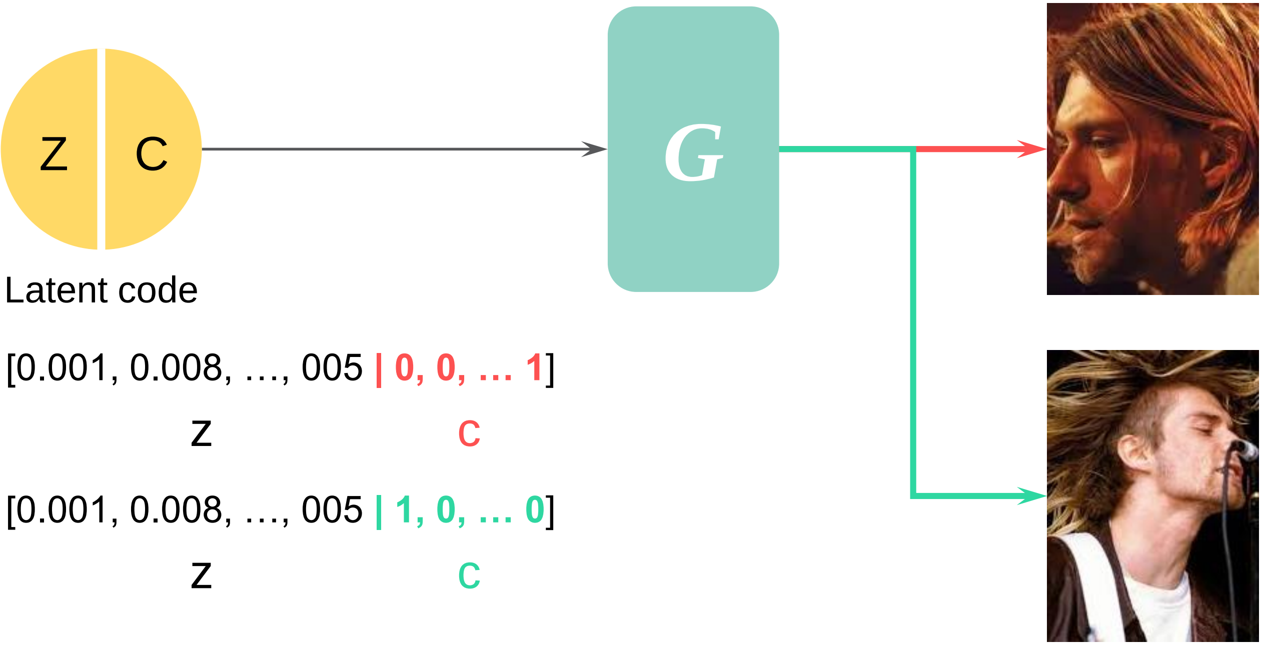
Introduction

- InfoGAN - Latent Code

“뭐야? 그러면 C를 Z 옆에 바로 붙이면 되는 거야?”



[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)

Introduction

- InfoGAN - Latent Code

$$\min_G \max_D V_I(D,G) = V(D,G) - \lambda I\big(c; G(z,c)\big)$$: **Generator와 c 사이의 연관성을 cost로 정의**

Maximize

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

VAE Seminar (18.07.23)

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

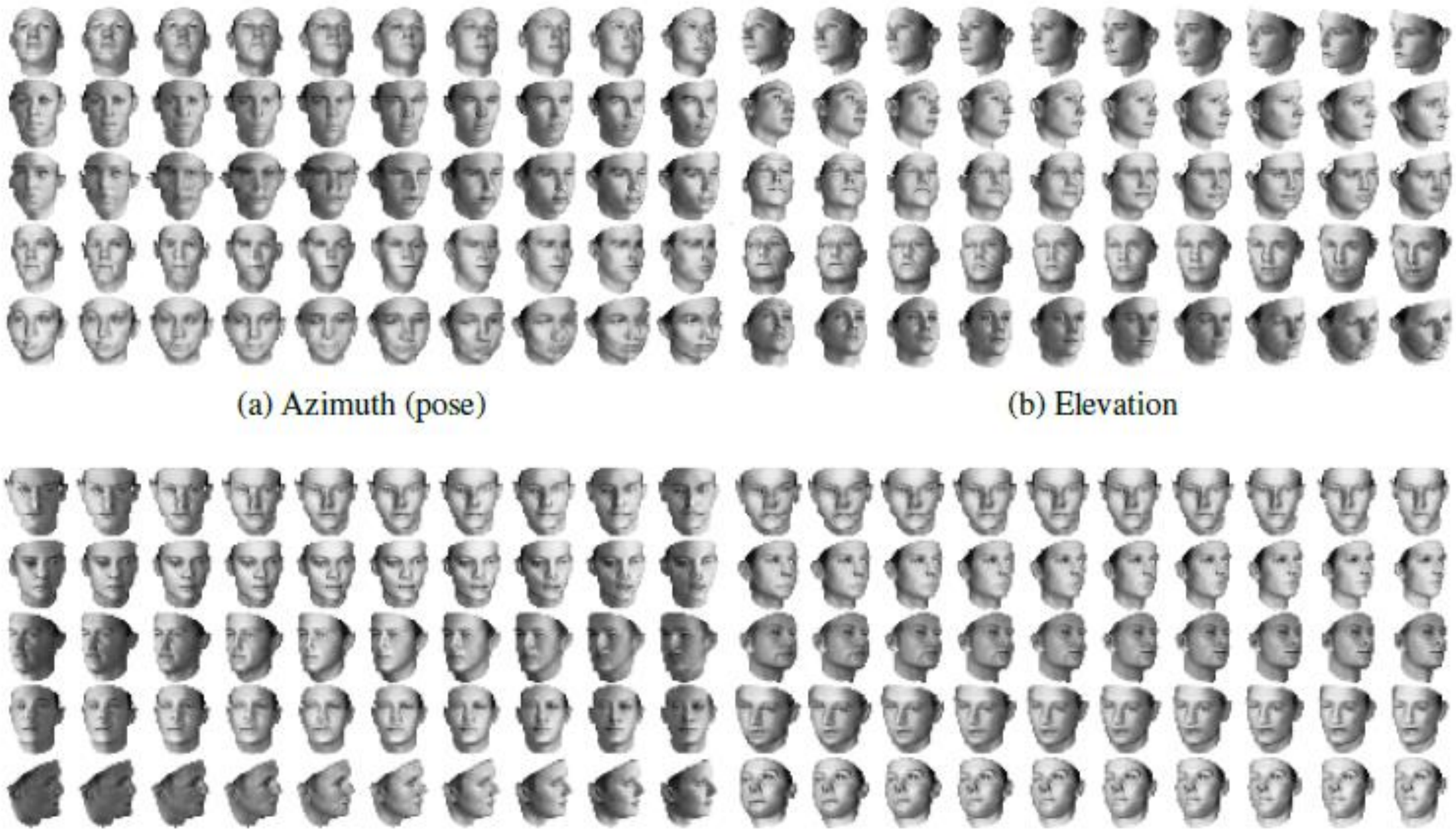
$$L(\phi, \theta, x) = -E_{q_\phi(z|x)}\left[\log\left(p(x \mid g_\theta(z))\right)\right] + KL\left(q_\phi(z \mid x) \,\|\, p(z)\right)$$

Reconstruction Error + Regularization

Image System Laboratory

Introduction

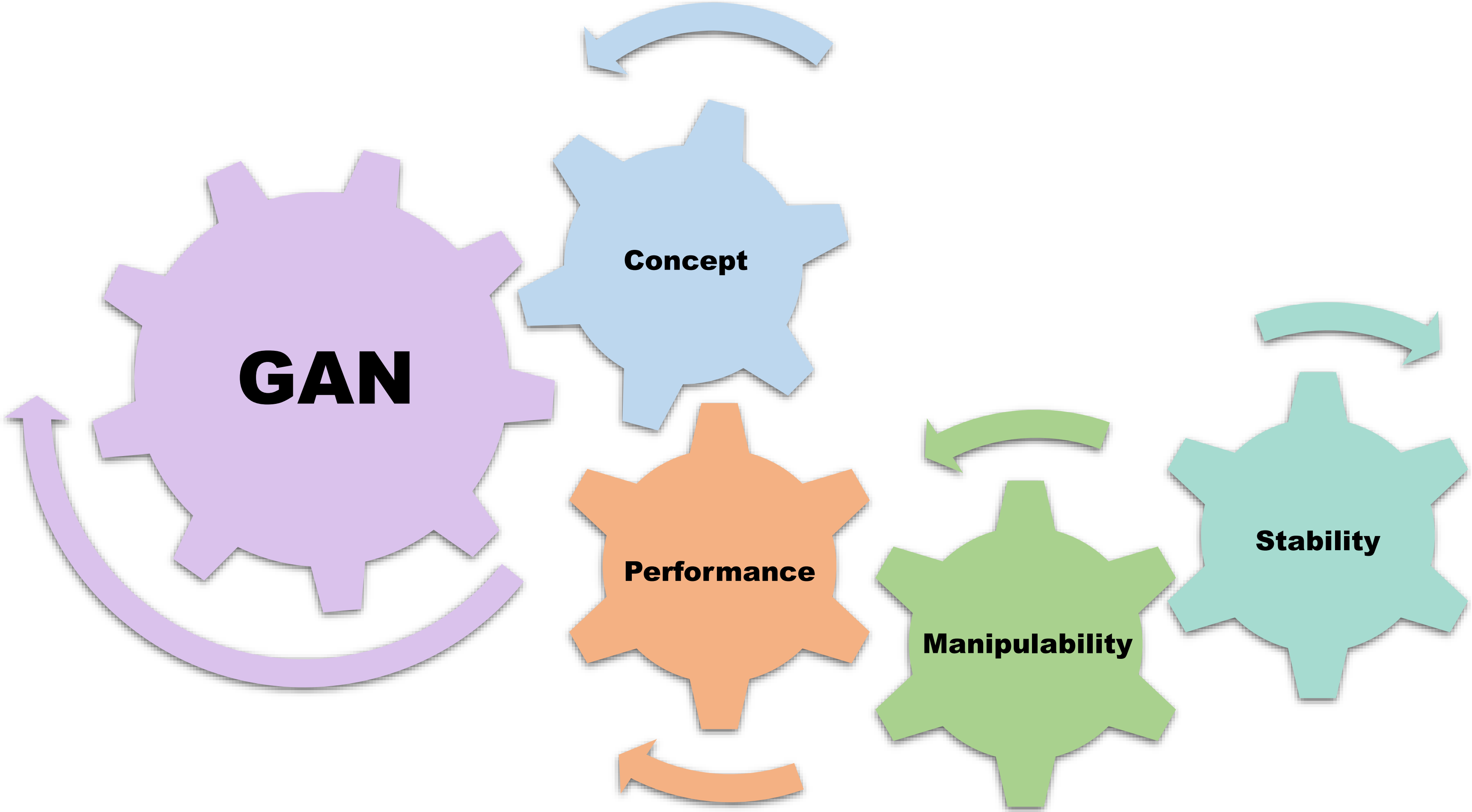
- InfoGAN - Results



(a) Azimuth (pose) (b) Elevation

(c) Lighting (d) Wide or Narrow

Introduction



Concept
- GAN

Performance
- DCGAN, **LSGAN**

Manipulability
- DCGAN, InfoGAN

Stability
- DCGAN, **LSGAN**

LSGAN

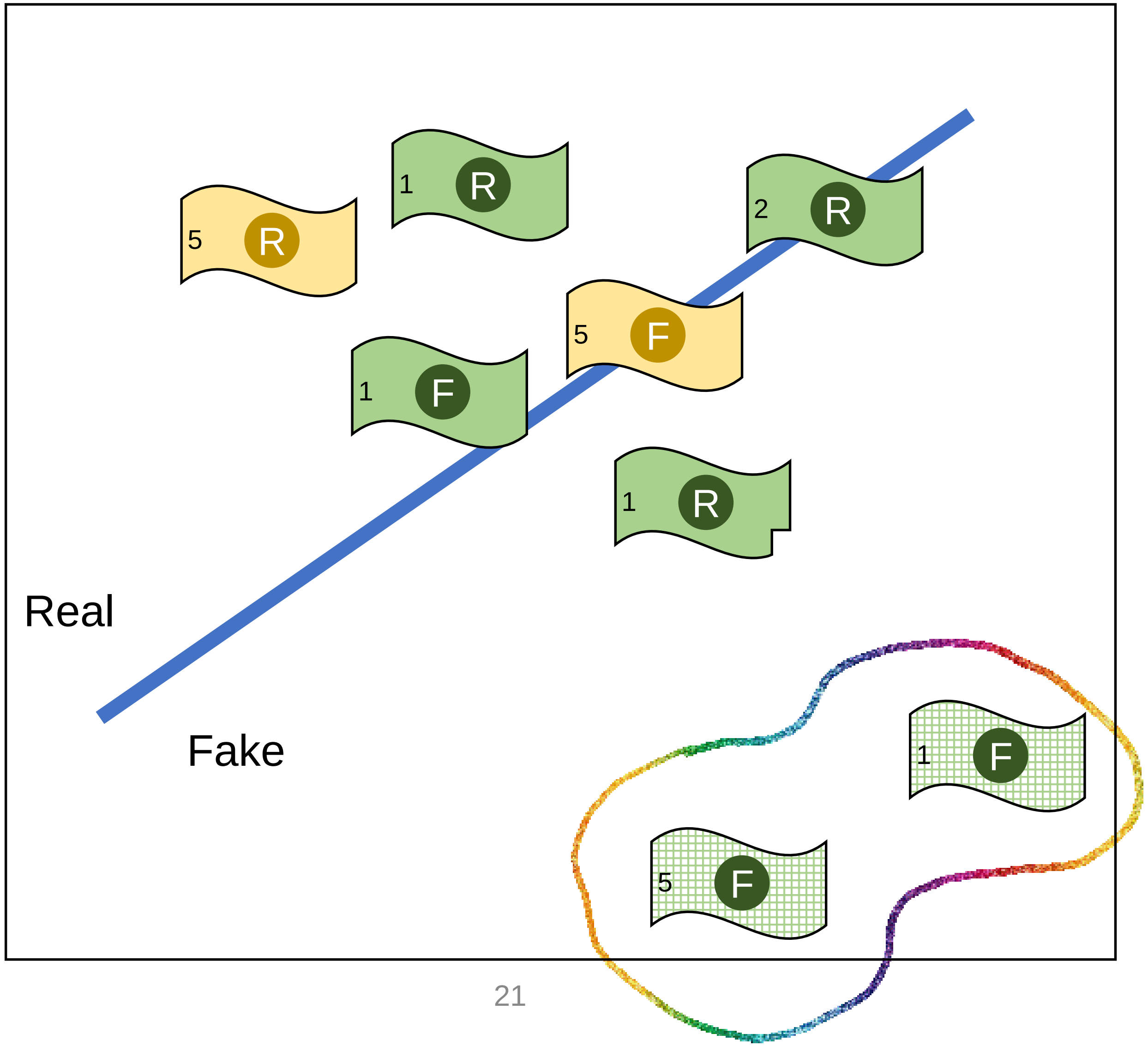
Concept, Objective Function, Global Optimality, Parameter Selection, Results

LSGAN

- Concept

학습이 잘되었다
(=50:50)

If 60:40 then stupid G
If 40:60 then stupid D



학습이 잘되었다
(=Good representation)

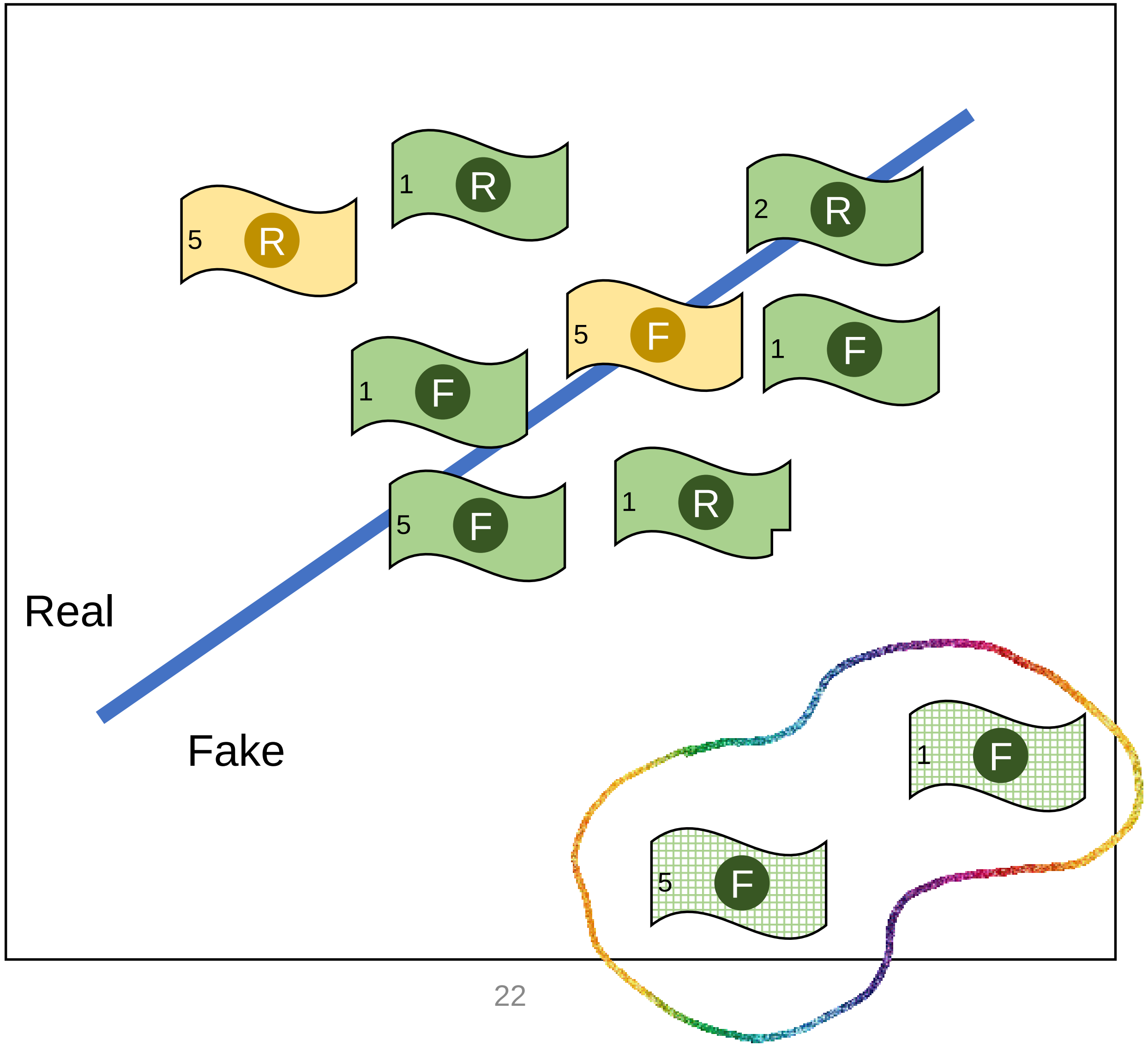
여전히 너무나도 가짜 같은 데이터가 존재

LSGAN

- Concept

경계 근처 ≈ Real? Fake?

Fake -> 경계 근처



훨씬 헷갈리는(Real에 가까운) 데이터 생성

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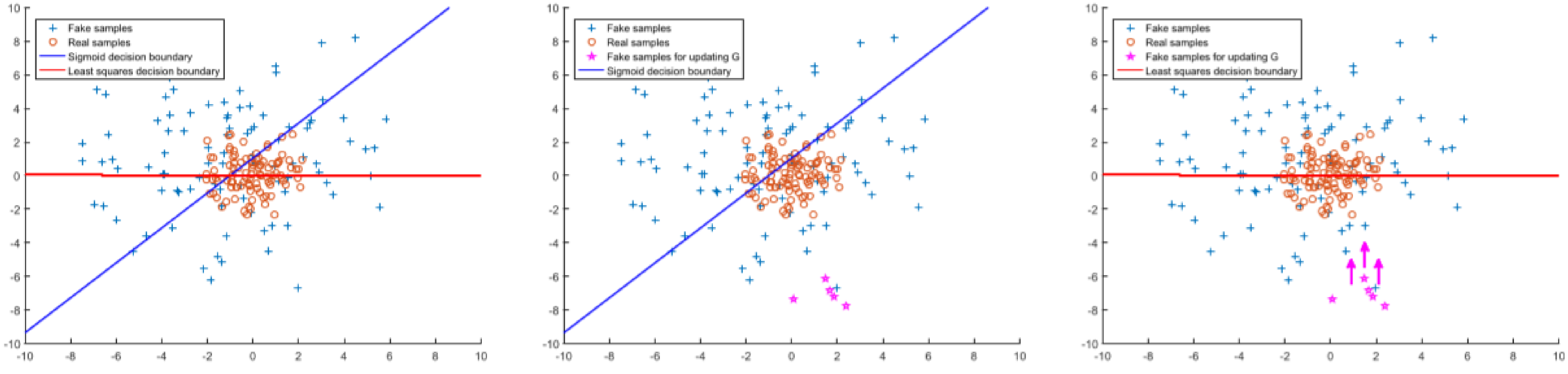
LSGAN

- Concept



(a) (b) (c)

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LSGAN

- Objective function

a : fake label.
b : real label.
c : G wants to make D believe for fake data

$$\boxed{\min_D V_{LSGAN}(D) = \frac{1}{2} E_{x\sim p_{data(x)}}\left[(D(x)-b)^2\right] + \frac{1}{2} E_{x\sim p_z(z)}\left[(D(G(z))-a)^2\right]}$$

$$\min_G V_{LSGAN}(G) = \frac{1}{2} E_{z\sim p_{z(z)}}\left[(D(G(z))-c)^2\right]$$

Smart D

Real case

$$\frac{1}{2} E_{x\sim p_{data(x)}}\left[(D(x)-b)^2\right] + \frac{1}{2} E_{x\sim p_z(z)}\left[(D(G(z))-a)^2\right]$$

1

(b=1), should be 0

Fake case

$$\frac{1}{2} E_{x\sim p_{data(x)}}\left[(D(x)-b)^2\right] + \frac{1}{2} E_{x\sim p_z(z)}\left[(D(G(z))-a)^2\right]$$

0

(a=0), should be 0

Stupid D

Real case

$$\frac{1}{2} E_{x\sim p_{data(x)}}\left[(D(x)-b)^2\right] + \frac{1}{2} E_{x\sim p_z(z)}\left[(D(G(z))-a)^2\right]$$

0

(b=1), should be 1

1

Fake case

$$\frac{1}{2} E_{x\sim p_{data(x)}}\left[(D(x)-b)^2\right] + \frac{1}{2} E_{x\sim p_z(z)}\left[(D(G(z))-a)^2\right]$$

(a=0), should be 1

D perspective,
it should be minimum.

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LSGAN

- Objective function

a : fake label.
b : real label.
c : G wants to make D believe for fake data

$$\min_D V_{LSGAN}(D) = \frac{1}{2} E_{x\sim p_{data(x)}}\left[(D(x)-b)^2\right] + \frac{1}{2} E_{x\sim p_z(z)}\left[(D(G(z))-a)^2\right]$$

$$\boxed{\min_G V_{LSGAN}(G) = \frac{1}{2} E_{z\sim p_{z(z)}}\left[(D(G(z))-c)^2\right]}$$

Generator

Smart G $\quad \frac{1}{2} E_{z\sim p_{z(z)}}\left[(D(G(z))-c)^2\right]$ $\quad$ (c=1), should be 0

1

Stupid G $\quad \frac{1}{2} E_{z\sim p_{z(z)}}\left[(D(G(z))-c)^2\right]$ $\quad$ (c=1), should be 1

0

G perspective,
it should be minimum.

LSGAN

- Objective function

a : fake label.
b : real label.
c : G wants to make D believe for fake data

조금 더 직관적으로 생각해보면,

$$\min_D V_{LSGAN}(D) = \frac{1}{2} E_{x \sim p_{data(x)}} \left[(D(x) - b)^2 \right] + \frac{1}{2} E_{x \sim p_z(z)} \left[(D(G(z)) - a)^2 \right]$$

$$\min_G V_{LSGAN}(G) = \frac{1}{2} E_{z \sim p_{z(z)}} \left[(D(G(z)) - c)^2 \right]$$

D = Classifier

Prediction - Label

LSGAN

- Global Optimality – Vanilla GAN

Vanilla GAN : JSD를 통한 증명

LSGAN : $\chi^2_{Pearson}$ 를 통한 증명

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LSGAN

- Global Optimality – LSGAN

$$\min_D V_{LSGAN}(D) = \frac{1}{2} E_{x \sim p_{data(x)}}\left[(D(x)-b)^2\right] + \frac{1}{2} E_{x \sim p_z(z)}\left[(D(G(z))-a)^2\right]$$

$$\min_G V_{LSGAN}(G) = \frac{1}{2} E_{z \sim p_{z(z)}}\left[(D(G(z))-c)^2\right] \boxed{+\frac{1}{2} E_{x \sim p_{data(x)}}\left[(D(x)-c)^2\right]}$$

This term does not contain parameters of G

$$D^*(x) = \frac{bp_{data}(x) + ap_g(x)}{p_{data}(x) + p_g(x)}$$

$$2C(G) = E_{x \sim p_d}\left[(D^*(x)-c)^2\right] + E_{x \sim p_g}\left[(D^*(x)-c)^2\right]$$

$$= E_{x \sim p_d}\left[\left(\frac{bp_{data}(x) + ap_g(x)}{p_{data}(x) + p_g(x)} - c\right)^2\right] + E_{x \sim p_g}\left[\left(\frac{bp_{data}(x) + ap_g(x)}{p_{data}(x) + p_g(x)} - c\right)^2\right]$$

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2019-04-09

LSGAN

- Global Optimality – LSGAN

$$\boxed{\frac{bp_{data}(x)+ap_g(x)}{p_{data}(x)+p_g(x)}-\frac{cp_{data}(x)+cp_g(x)}{p_{data}(x)+p_g(x)}=\frac{(b-c)p_{data}+(a-c)p_g(x)}{p_{data}+p_g}}$$

$$=E_{x\sim p_d}\left[\left(\frac{bp_{data}(x)+ap_g(x)}{p_{data}(x)+p_g(x)}-c\right)^2\right]+E_{x\sim p_g}\left[\left(\frac{bp_{data}(x)+ap_g(x)}{p_{data}(x)+p_g(x)}-c\right)^2\right]$$

$$=\int_x p_{data}(x)\left(\frac{(b-c)p_{data}(x)+(a-c)p_g(x)}{p_{data}(x)+p_g(x)}\right)^2 dx+\int_x p_g(x)\left(\frac{(b-c)p_{data}(x)+(a-c)p_g(x)}{p_{data}(x)+p_g(x)}\right)^2$$

$$=\int_x \frac{((b-c)p_{data}(x)+(a-c)p_g(x))^2}{p_{data}(x)+p_g(x)}dx$$

$$\boxed{\int_x (p_{data}(x)+p_g(x))\left(\frac{(b-c)p_{data}(x)+(a-c)p_g(x)}{p_{data}(x)+p_g(x)}\right)^2 dx}$$

$$=\int_x \frac{((b-c)(p_{data}(x)+p_g(x))-(b-a)p_g(x))^2}{p_{data}(x)+p_g(x)}dx$$

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LSGAN

- Global Optimality – LSGAN

$$= \int_x \frac{\left((b-c)\left(p_{data}(x)+p_g(x)\right)-(b-a)p_g(x)\right)^2}{p_{data}(x)+p_g(x)}dx$$

If we set $b-c=1 \; and \; b-a=2$

$$2C(G)=\int_x \frac{\left(2p_g(x)-(p_{data}(x)+p_g(x))\right)^2}{p_{data}(x)+p_g(x)}dx$$

$$\boxed{\chi^2_{Pearson}(p_{data}+p_g \,\|\, 2p_g)} \qquad \chi^2_{Pearson} = \frac{\left(q(x)-p(x)\right)^2}{p(x)}$$

If $p_g = p_{data}$ **minimum**

LSGAN

- Parameters Selection

$$\min_D V_{LSGAN}(D) = \frac{1}{2} E_{x \sim p_{data(x)}} \left[(D(x) - b)^2 \right] + \frac{1}{2} E_{x \sim p_z(z)} \left[(D(G(z)) - a)^2 \right] \qquad \min_G V_{LSGAN}(G) = \frac{1}{2} E_{z \sim p_{z(z)}} \left[(D(G(z)) - c)^2 \right]$$

$$b - c = 1 \text{ and } b - a = 2$$

i) $a = -1,\ b = 1 \text{ and } c = 0$

$$\min_D V_{LSGAN}(D) = \frac{1}{2} E_{x \sim p_{data(x)}} \left[(D(x) - 1)^2 \right] + \frac{1}{2} E_{x \sim p_z(z)} \left[(D(G(z)) + 1)^2 \right] \qquad \min_G V_{LSGAN}(G) = \frac{1}{2} E_{z \sim p_{z(z)}} \left[(D(G(z)))^2 \right]$$

ii) $a = 0,\ b = 1 \text{ and } c = b$ ->조건을 따르지 않는 경우

$$\min_D V_{LSGAN}(D) = \frac{1}{2} E_{x \sim p_{data(x)}} \left[(D(x) - 1)^2 \right] + \frac{1}{2} E_{x \sim p_z(z)} \left[(D(G(z)) + 1)^2 \right] \qquad \min_G V_{LSGAN}(G) = \frac{1}{2} E_{z \sim p_{z(z)}} \left[(D(G(z)))^2 \right]$$

성능은 비슷하며, 큰 차이가 없음!

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LSGAN

- Results

Table 1: Statistics of the datasets.

Dataset	#Samples	#Categories
LSUN Bedroom	3,033,042	1
LSUN Church	126,227	1
LSUN Dining	657,571	1
LSUN Kitchen	2,212,277	1
LSUN Conference	229,069	1
HWDB1.0	1,246,991	3,740

(a) Generated by LSGANs.

(b) Generated by DCGANs (Reported in [13]).

LSGAN

- Results

(a) LSGANs.

(b) Regular GANs.

(c) LSGANs.

(d) Regular GANs.

Figure 7: Comparison experiments by excluding batch normalization (BN). (a): LSGANs without BN in G using Adam. (b): Regular GANs without BN in G using Adam. (c): LSGANs without BN in G and D using RMSProp. (d): Regular GANs without BN in G and D using RMSProp.

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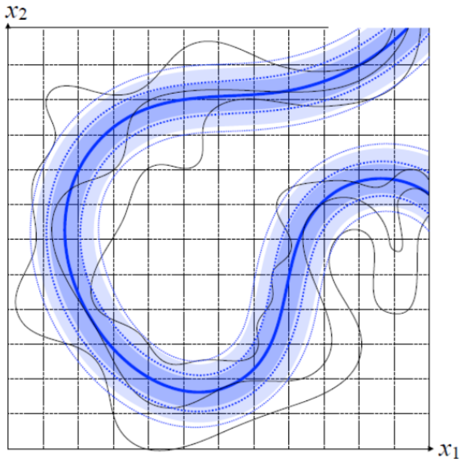
LSGAN

- Results

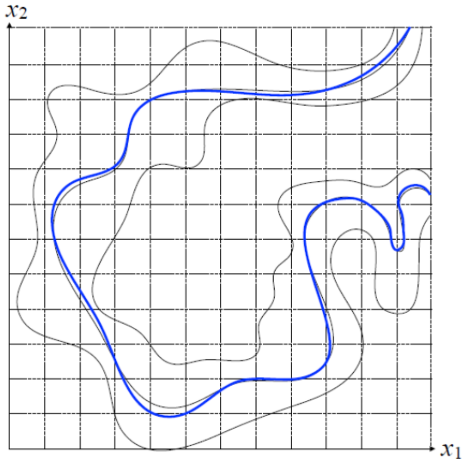
Table 2: Whether the models suffer from model collapse?

Optimizer	BN_G Adam	BN_G RMSProp	BN_{GD} Adam	BN_{GD} RMSProp
Regular GANs	YES	NO	YES	YES
LSGANs	**NO**	NO	YES	**NO**

Example of mode collapse



VAE : maximum likelihood approach



GAN

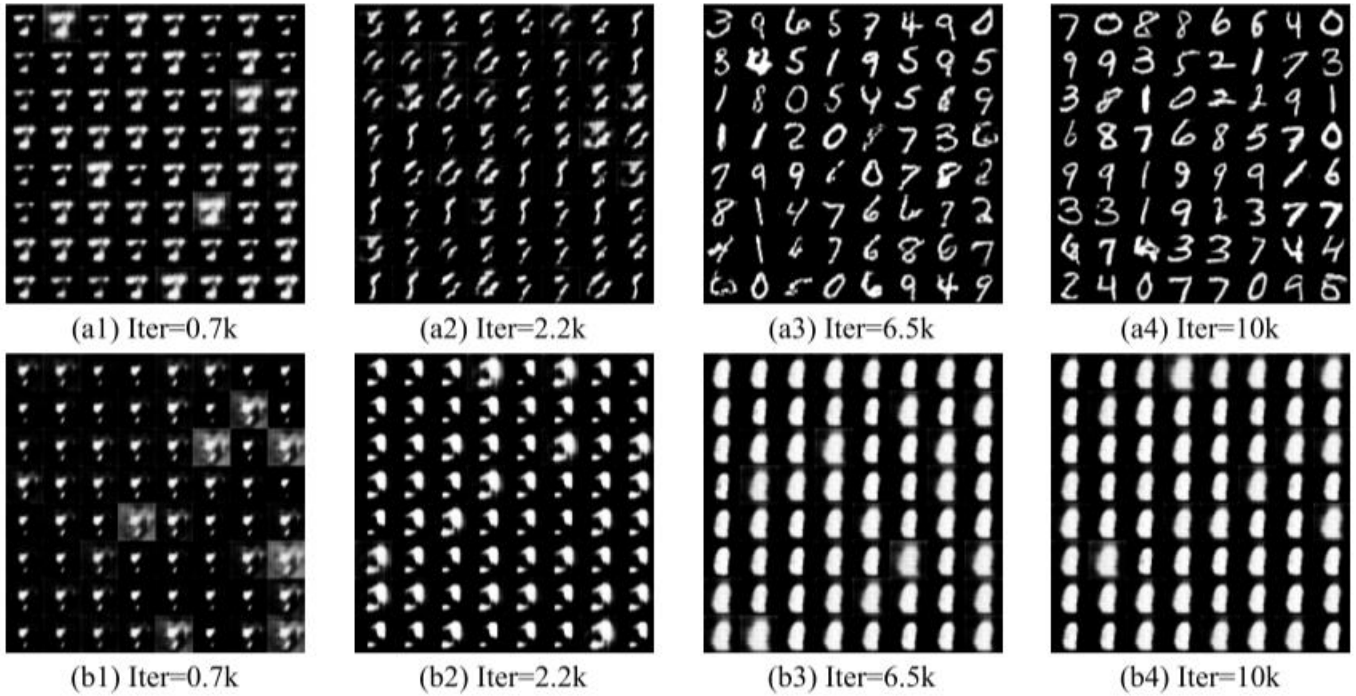


Figure 9: Generated images on MNIST. Upper: Generated by LSGANs. Lower: Generated by regular GANs.

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LSGAN

- Results

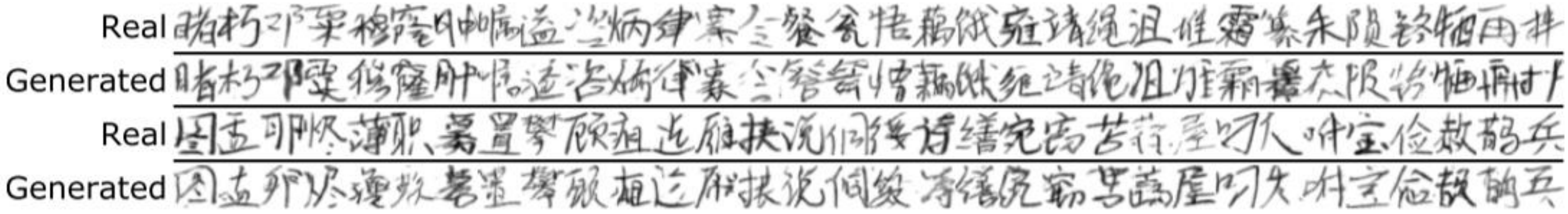

Figure 10: Generated images of handwritten Chinese characters by LSGANs.

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Experiment

Source Code, Celeb-A, Korean Idol

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Experiment

https://github.com/messy-snail/GAN_PyTorch

- Source Code

```python
# loss_func = tc.nn.BCELoss()
loss_func = tc.nn.MSELoss()
g_opt = tc.optim.Adam(G.parameters(), lr=lr, betas=(0.5, 0.999)) #0.999
d_opt = tc.optim.Adam(D.parameters(), lr=lr, betas=(0.5, 0.999))
print("Processing Start")
for ep in range(epoch_sz):
    for step, (images, _) in enumerate(dataloader):
        images = images.to(device)
        mini_batch = images.size()[0]
        z = tc.randn(mini_batch, latent_sz).view(-1, latent_sz, 1, 1).to(device)

        real_label = tc.ones(mini_batch).to(device)
        fake_label = tc.zeros(mini_batch).to(device)

        D_result = D(images).squeeze()
        loss_real = loss_func(D_result, real_label)
        D_result = D(G(z)).squeeze()
        loss_fake = loss_func(D_result, fake_label)

        d_loss = (loss_real+loss_fake)/2
        D.zero_grad()
        d_loss.backward()
        d_opt.step()
```

```python
class Discriminator(nn.Module):
    def __init__(self):
        super(Discriminator, self).__init__()
        self.conv1 = nn.Conv2d(3, 128, 4, 2, 1)
        self.conv2 = nn.Conv2d(128, 256, 4, 2, 1)
        self.conv3 = nn.Conv2d(256, 512, 4, 2, 1)
        self.conv4 = nn.Conv2d(512, 1024, 4, 2, 1)
        self.conv5 = nn.Conv2d(1024, 1, 4, 1, 0)

        self.bn2 = nn.BatchNorm2d(256)
        self.bn3 = nn.BatchNorm2d(512)
        self.bn4 = nn.BatchNorm2d(1024)

    def forward(self, input):
        x = F.leaky_relu(self.conv1(input), 0.2)
        x = F.leaky_relu(self.bn2(self.conv2(x)), 0.2)
        x = F.leaky_relu(self.bn3(self.conv3(x)), 0.2)
        x = F.leaky_relu(self.bn4(self.conv4(x)), 0.2)
        #x = F.sigmoid(self.conv5(x))
        x = self.conv5(x)

        return x
```


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Experiment

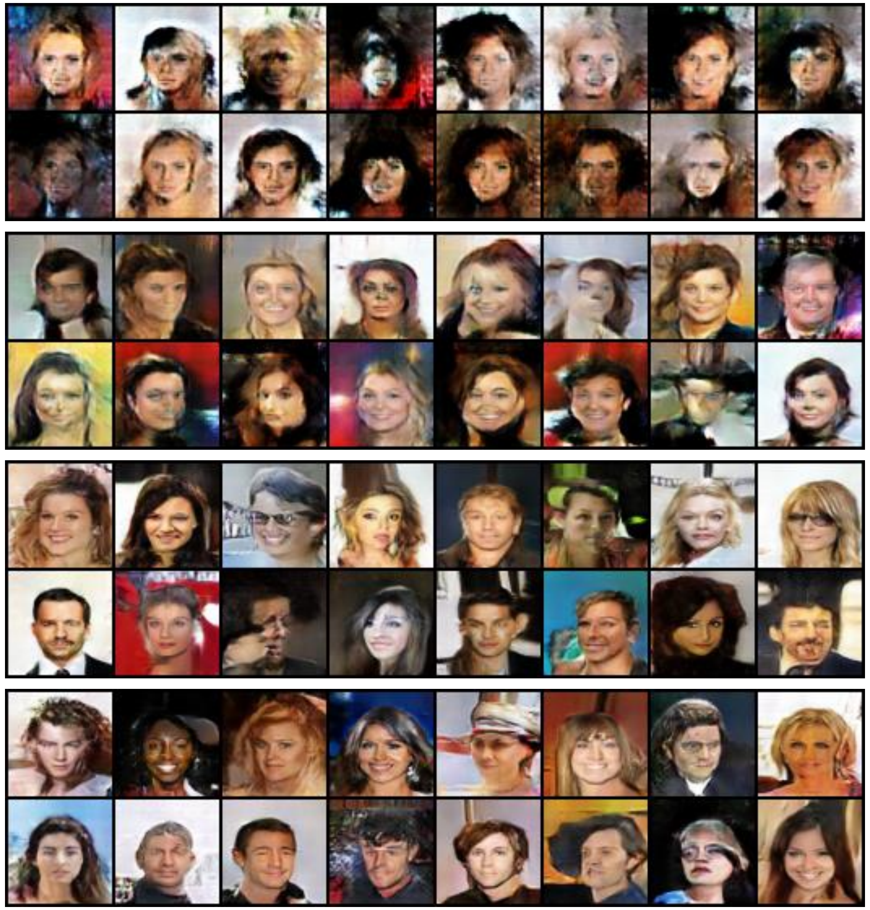
- Celeb-A

ep=1

ep=2

ep=10

ep=16



DCGAN

LSGAN

Experiment

- Celeb-A(without BN)

ep=1

ep=2

ep=3

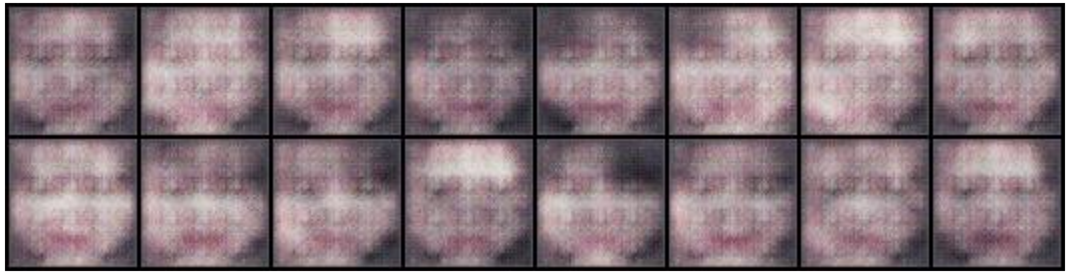
ep=5

DCGAN

LSGAN

Experiment

- Korean Idol(DCGAN)



ep 1

ep 6

ep 21

ep 51

ep 101

ep 201

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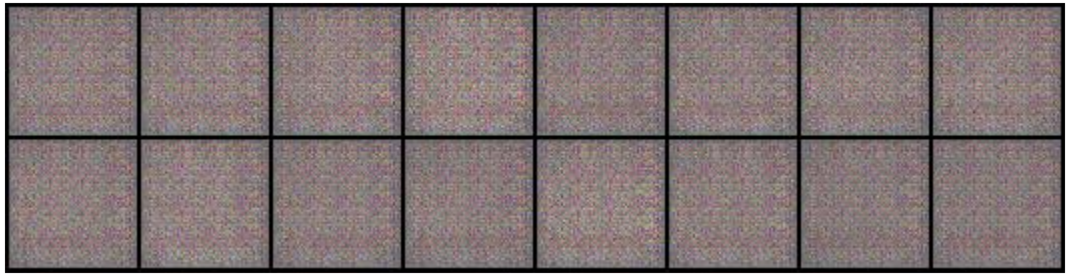
Experiment

- Korean Idol(LSGAN)



ep 1

ep 6

ep 21

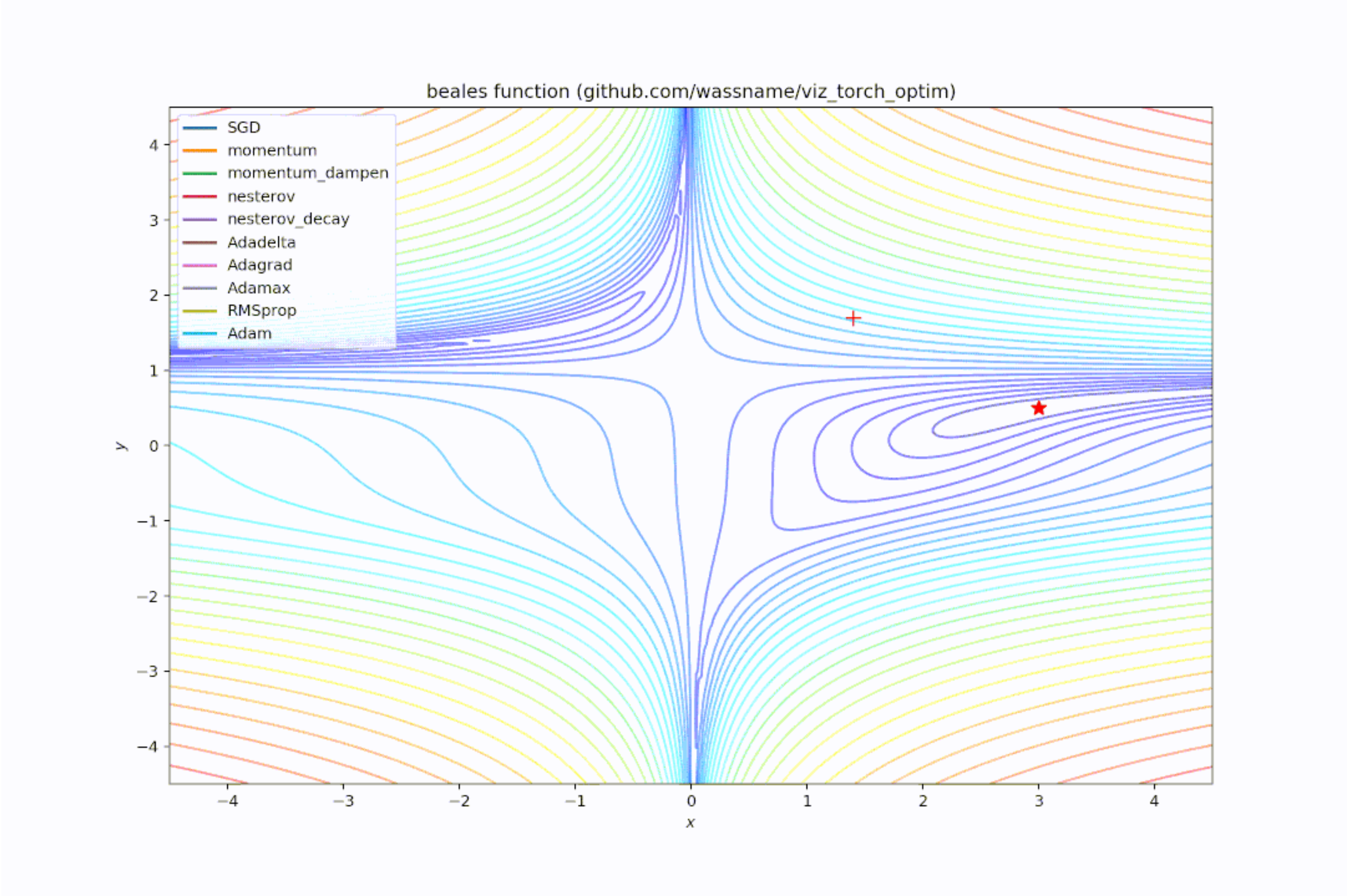
ep 51

ep 101

ep 201

Experiment

- Gueess#1 Optimizer problem?



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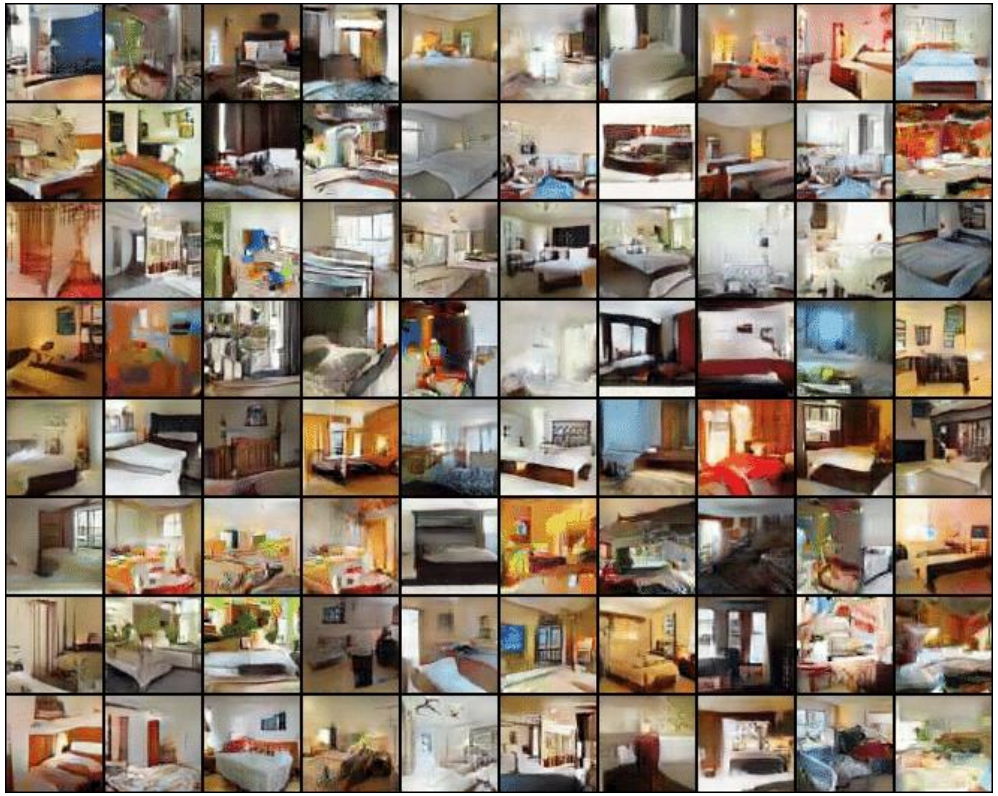
Experiment

- Gueess#2 Domain problem?



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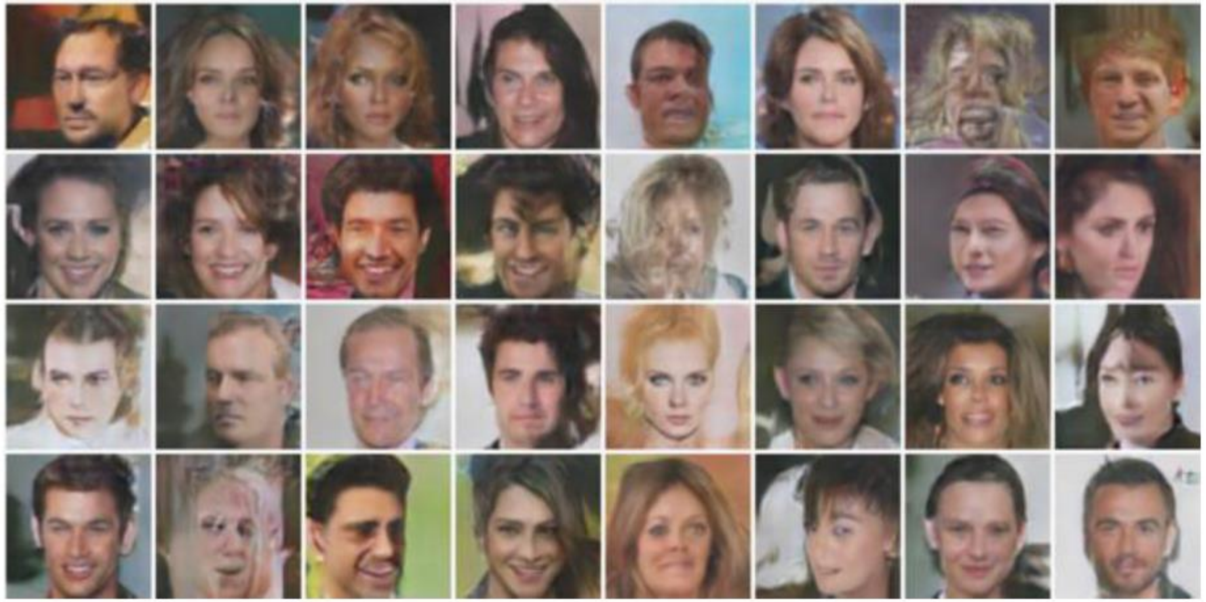
Experiment

- Celeb-A

- Results (CelebA)



https://www.slideshare.net/NaverEngineering/1-gangenerative-adversarial-network

“저자들이 source code를 공개했으면 한다.”

“같은 구조라면, LSGAN이 훨씬 잘 동작한다.”

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Summary

Summary, Future Work

Summary

- 기존의 GAN보다 Real에 가까운 데이터를 생성하고, 안정성도 확보함.
- Pearson Chi square divergence으로 global optimality를 증명함. (기존 GAN은 JSD로 증명)
- 클래스가 많은 데이터에 대해서도 정상적으로 데이터를 생성함.
- 기존의 코드에서 단순히 loss만을 변경하기에 손쉽게 적용이 가능함.

Future work

GAN Research

- [x] ~~Vanilla GAN~~
- [x] ~~DCGAN~~
- [x] ~~InfoGAN~~
- [x] ~~LSGAN~~
- [ ] BEGAN
- [ ] Cycle GAN
- [ ] Style GAN
- [ ] SRGAN

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~~
- [x] ~~Ice Propagation~~

Q & A

Thank you for your attention