Wasserstein GAN (WGAN)

Arjovsky, M., Chintala, S., & Bottou, L. (2017, July). Wasserstein generative adversarial networks. In *International conference on machine learning* (pp. 214-223). PMLR.

- The *Total Variation* (TV) distance

$$\delta(\mathbb{P}_r, \mathbb{P}_g) = \sup_{A \in \Sigma} |\mathbb{P}_r(A) - \mathbb{P}_g(A)| \, .$$

- The *Kullback-Leibler* (KL) divergence

$$KL(\mathbb{P}_r \| \mathbb{P}_g) = \int \log \left(\frac{P_r(x)}{P_g(x)} \right) P_r(x) d\mu(x) \, ,$$

where both $\mathbb{P}_r$ and $\mathbb{P}_g$ are assumed to admit densities with respect to a same measure μ defined on $\mathcal{X}$.[2] The KL divergence is famously assymetric and possibly infinite when there are points such that $P_g(x) = 0$ and $P_r(x) > 0$.

- The *Jensen-Shannon* (JS) divergence

$$JS(\mathbb{P}_r, \mathbb{P}_g) = KL(\mathbb{P}_r \| \mathbb{P}_m) + KL(\mathbb{P}_g \| \mathbb{P}_m) \, ,$$

where $\mathbb{P}_m$ is the mixture $(\mathbb{P}_r + \mathbb{P}_g)/2$. This divergence is symmetrical and always defined because we can choose $\mu = \mathbb{P}_m$.

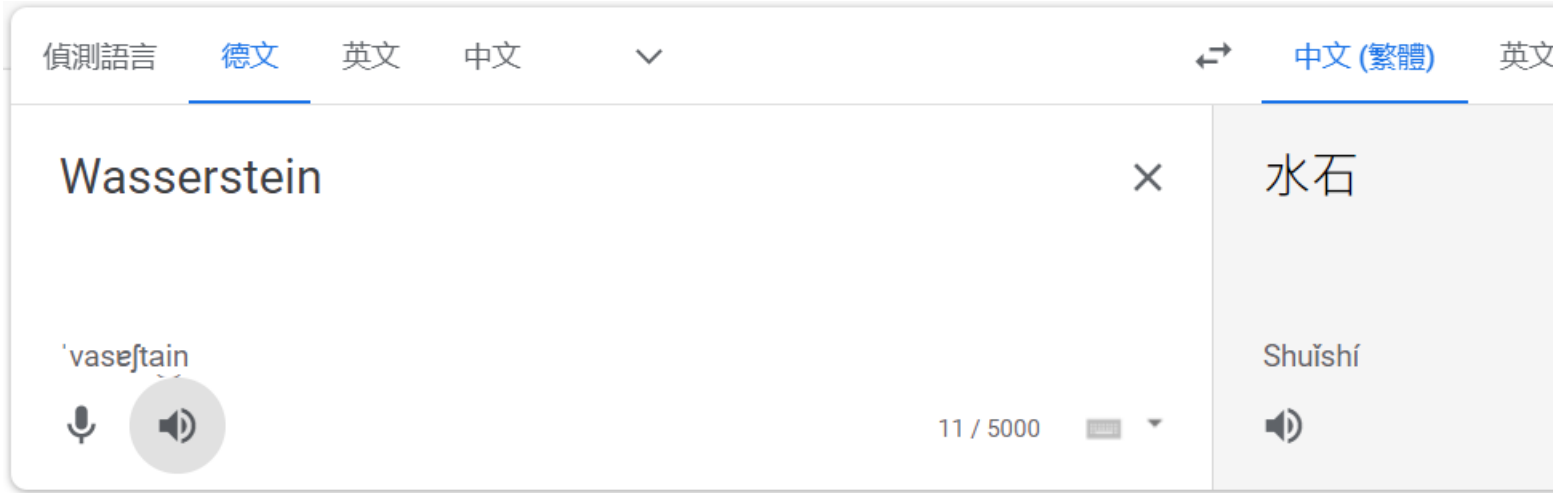
- The *Earth-Mover* (EM) distance or Wasserstein-1

$$W(\mathbb{P}_r, \mathbb{P}_g) = \inf_{\gamma \in \Pi(\mathbb{P}_r, \mathbb{P}_g)} \mathbb{E}_{(x,y) \sim \gamma} \big[\, \|x - y\| \, \big] \, , \quad (1)$$

where $\Pi(\mathbb{P}_r, \mathbb{P}_g)$ is the set of all joint distributions $\gamma(x, y)$ whose marginals are respectively $\mathbb{P}_r$ and $\mathbb{P}_g$. Intuitively, $\gamma(x, y)$ indicates how much "mass" must be transported from x to y in order to transform the distributions $\mathbb{P}_r$ into the distribution $\mathbb{P}_g$. The EM distance then is the "cost" of the optimal transport plan.

Arjovsky, M., Chintala, S., & Bottou, L. (2017, July). Wasserstein generative adversarial networks. In *International conference on machine learning* (pp. 214-223). PMLR.

The name "Wasserstein distance" was coined by R. L. Dobrushin in 1970, after learning of it in the work of Russian mathematician Leonid Vaserštein 1969, however the metric was first defined by Leonid Kantorovich in The Mathematical Method of Production Planning and Organization (Russian original 1939) in the context of optimal transport planning of goods and materials. Some scholars thus encourage use of the terms "Kantorovich metric" and "Kantorovich distance". Most English-language publications use the German spelling "Wasserstein" (attributed to the name "Vaserštein" being of German origin).



https://en.wikipedia.org/wiki/Wasserstein_metric

JS divergence is not suitable

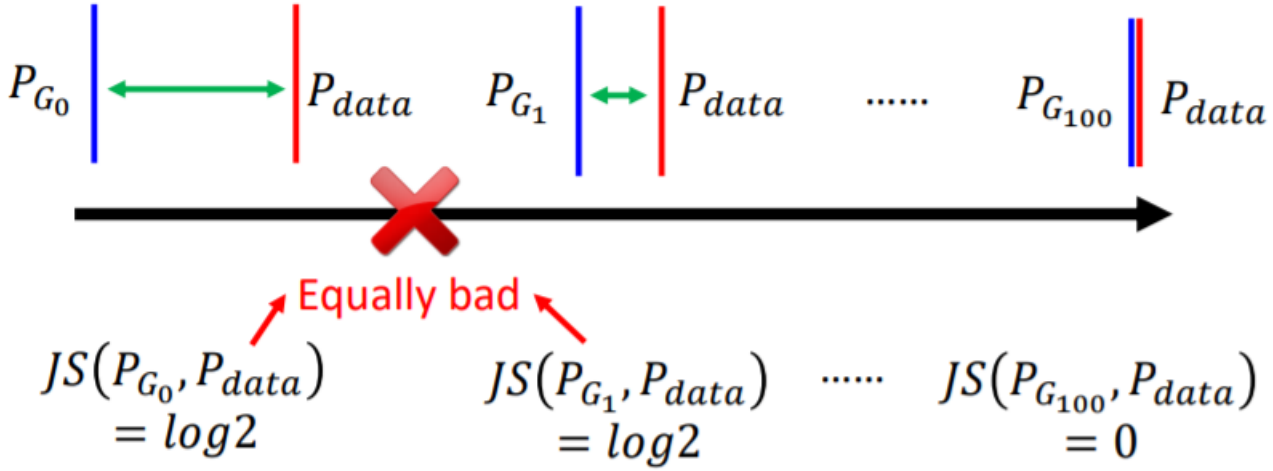
- In most cases, P_G and P_{data} are not overlapped.

JS divergence is log2 if two distributions do not overlap.

Intuition: If two distributions do not overlap, binary classifier achieves 100% accuracy

$$KL\left(P_{data}||\frac{P_{data}+P_G}{2}\right)+KL\left(P_G||\frac{P_{data}+P_G}{2}\right)$$

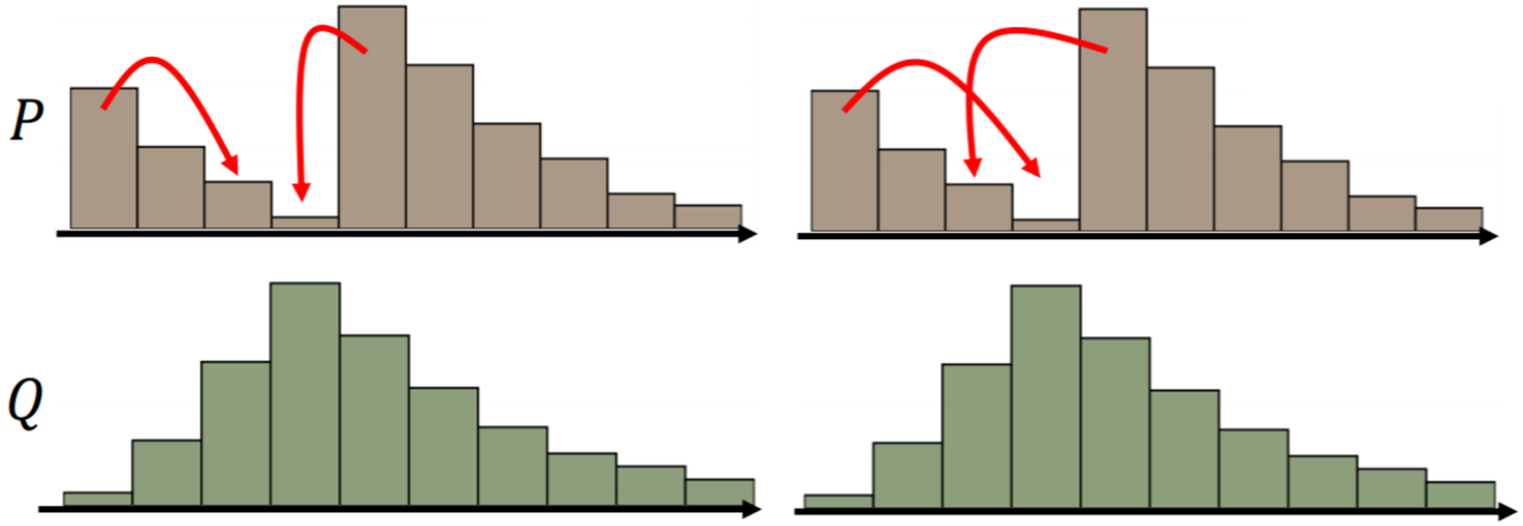
$2JSD(P_{data}||P_G)$ Jensen-Shannon divergence



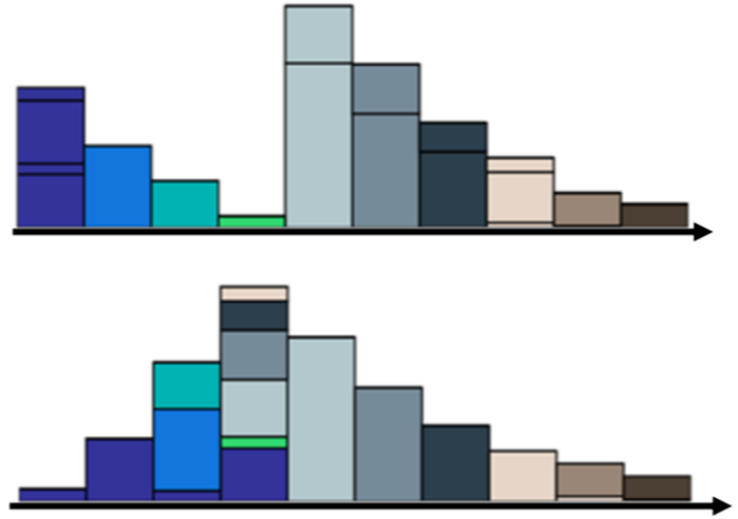
Reference: 李弘毅 GAN Lecture 6 (2018) https://youtu.be/3JP-xuBJsyc

W-GAN: Earth move's distance

- Considering one distribution P as a pile of earth, and another distribution Q as the target
- The average distance the earth mover has to move the earth.



Best “moving plans” of this example

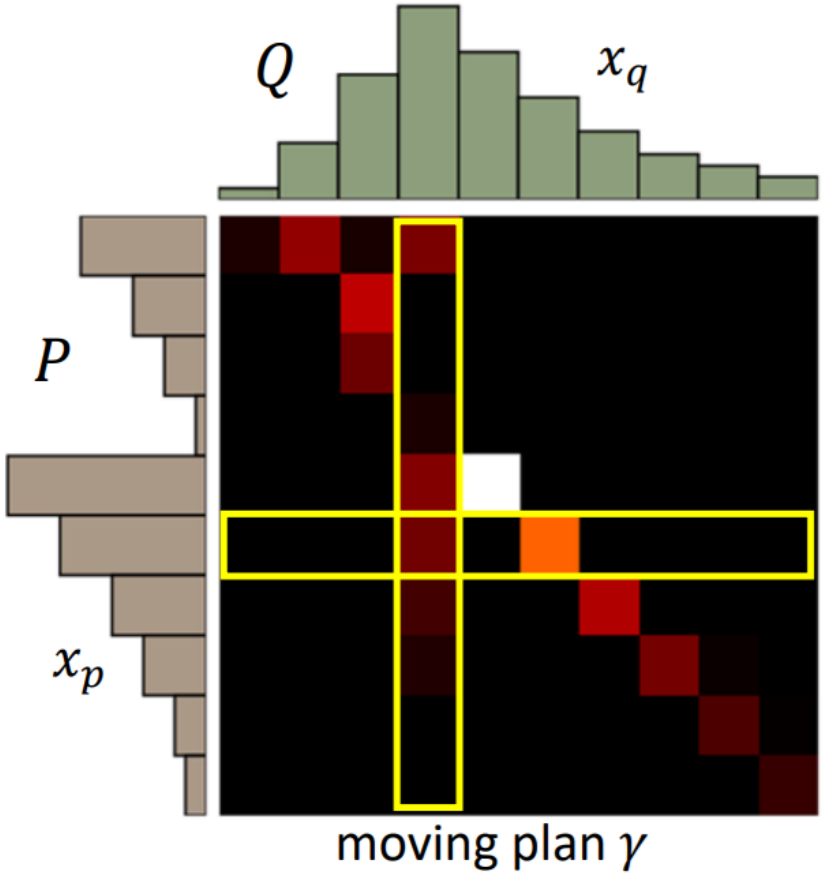


Reference: 李弘毅 GAN Lecture 6 (2018) https://youtu.be/3JP-xuBJsyc

W-GAN: Earth move's distance

A "moving plan" is a matrix

The value of the element is the amount of earth from one position to another.



Average distance of a plan γ:

$$B(\gamma) = \sum_{x_p, x_q} \gamma(x_p, x_q) \|x_p - x_q\|$$

Earth Mover's Distance:

$$W(P, Q) = \min_{\gamma \in \Pi} B(\gamma)$$

Reference: 李弘毅 GAN Lecture 6 (2018) https://youtu.be/3JP-xuBJsyc

The discriminator that measures Wasserstein distance can be trained by adding Lipschitz continuity constraint to the objective function

GAN

$$D^* = arg \max_D V(D, G)$$

$$V(D, G) = E_{x \sim P_{data}}[logD(x)] + E_{x \sim P_G}[\log(1 - D(x))]$$

WGAN

$$D^* = arg \max_{D \in 1-Lipschitz} V(D, G)$$

$$V(D, G) = E_{x \sim P_{data}}[D(x)] + E_{x \sim P_G}[D(x)]$$

The discriminator that measures Wasserstein distance can be trained by adding Lipschitz continuity constraint to the objective function

Lipschitz continuity

From Wikipedia, the free encyclopedia

In mathematical analysis, **Lipschitz continuity**, named after Rudolf Lipschitz, is a strong form of uniform continuity for functions. Intuitively, a Lipschitz continuous function is limited in how fast it can change: there exists a real number such that, for every pair of points on the graph of this function, the absolute value of the slope of the line connecting them is not greater than this real number; the smallest such bound is called the *Lipschitz constant* of the function (or *modulus of uniform continuity*). For instance, every function that has bounded first derivatives is Lipschitz continuous.[1]

https://en.wikipedia.org/wiki/Lipschitz_continuity

The discriminator that measures Wasserstein distance can be trained by adding Lipschitz continuity constraint to the objective function

Evaluate wasserstein distance between P_{data} and P_G

$$V(G,D) = \max_{D \in 1-Lipschitz} \{E_{x \sim P_{data}}[D(x)] - E_{x \sim P_G}[D(x)]\}$$

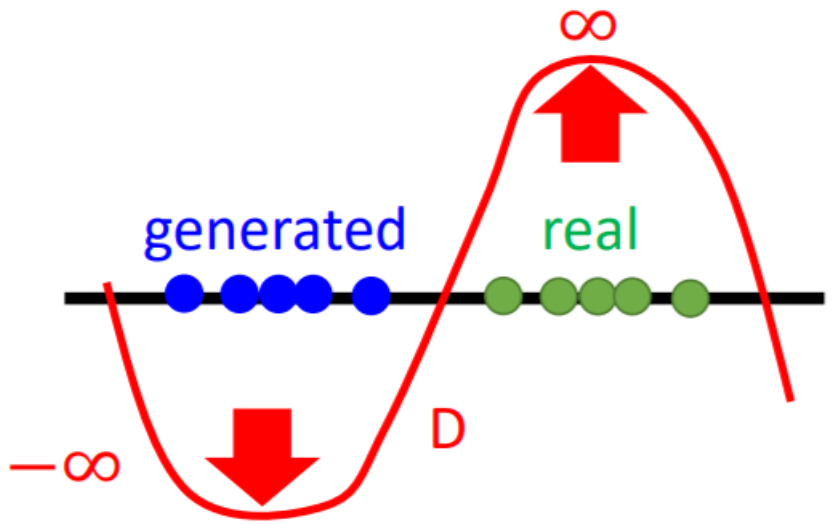
D has to be smooth enough.

Lipschitz Function

$$\|f(x_1) - f(x_2)\| \leq K\|x_1 - x_2\|$$

Output change / Input change

K=1 for "$1-Lipschitz$"



Reference: 李弘毅 GAN Lecture 6 (2018) https://youtu.be/3JP-xuBJsyc

Use weight clipping to solve the constrained optimization

$$D^* = arg \max_{D \in 1-Lipschitz} V(D, G)$$

Weight Clipping [Martin Arjovsky, et al., arXiv, 2017]

Force the parameters w between c and -c

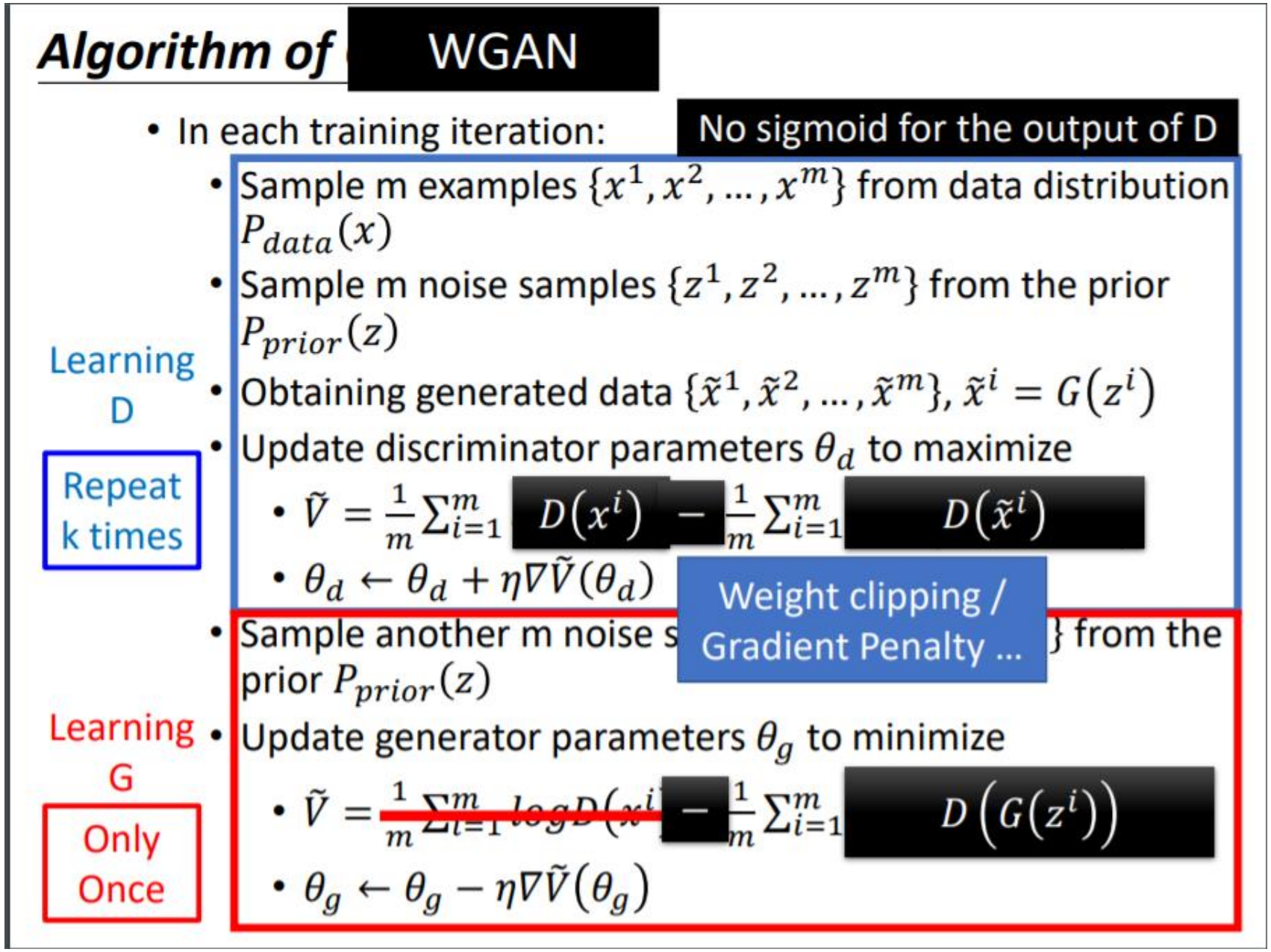
After parameter update, if w > c, w = c;

if w < -c, w = -c

Use weight clipping to solve constrained optimization in PPO

$$J_{PPO2}^{\theta'}(\theta) = \sum_{(s_t, a_t)} min\left(\frac{p_\theta(a_t|s_t)}{p_{\theta'}(a_t|s_t)} A^{\theta'}(s_t, a_t), clip\left(\frac{p_\theta(a_t|s_t)}{p_{\theta'}(a_t|s_t)}, 1-\varepsilon, 1+\varepsilon\right) A^{\theta'}(s_t, a_t)\right)$$

W-GAN



Reference: 李弘毅 GAN Lecture 6 (2018) https://youtu.be/3JP-xuBJsyc

Update discriminator parameters θ_d to maximize

- $\tilde{V} = \frac{1}{m}\sum_{i=1}^{m} D(x^i) - \frac{1}{m}\sum_{i=1}^{m} D(\tilde{x}^i)$
- $\theta_d \leftarrow \theta_d + \eta \nabla \tilde{V}(\theta_d)$

Weight clipping / Gradient Penalty ...

Sample another m noise s } from prior $P_{\ldots}(z)$

GAN

```
[19]: def train_discriminator(real_images, opt_d):
        # Clear discriminator gradients
        opt_d.zero_grad()

        # Pass real images through discriminator
        real_preds = discriminator(real_images)
        real_targets = torch.ones(real_images.size(0), 1, device=device)
        real_loss = F.binary_cross_entropy(real_preds, real_targets)
        real_score = torch.mean(real_preds).item()

        # Generate fake images
        latent = torch.randn(batch_size, latent_size, 1, 1, device=device)
        fake_images = generator(latent.to(device))

        # Pass fake images through discriminator
        fake_targets = torch.zeros(fake_images.size(0), 1, device=device)
        fake_preds = discriminator(fake_images)
        fake_loss = F.binary_cross_entropy(fake_preds, fake_targets)
        fake_score = torch.mean(fake_preds).item()

        # Update discriminator weights
        loss = real_loss + fake_loss
        loss.backward()
        opt_d.step()
        return loss.item(), real_score, fake_score
```

WGAN

```
# Pass real images through discriminator
real_preds = discriminator(real_images)
real_loss = torch.mean(real_preds)
```

```
# Pass fake images through discriminator
fake_preds = discriminator(fake_images)
fake_loss = torch.mean(fake_preds)

# Update discriminator weights
loss = fake_loss - real_loss
```

```
# Parameter(Weight) Clipping for K-Lipshitz constraint
for p in discriminator.parameters():
  p.data.clamp_(-0.01, 0.01)
return loss.item()
```

No sigmoid for the output of D

GAN

[15]:
```
discriminator = nn.Sequential(
    # in: 3 x 128 x 128

    nn.Conv2d(3, 64, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(64),
    nn.LeakyReLU(0.2, inplace=True),
    # out: 64 x 64 x 64

    nn.Conv2d(64, 128, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(128),
    nn.LeakyReLU(0.2, inplace=True),
    # out: 128 x 32 x 32

    nn.Conv2d(128, 256, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(256),
    nn.LeakyReLU(0.2, inplace=True),
    # out: 256 x 16 x 16

    nn.Conv2d(256, 512, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(512),
    nn.LeakyReLU(0.2, inplace=True),
    # out: 512 x 8 x 8

    nn.Conv2d(512, 1024, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(1024),
    nn.LeakyReLU(0.2, inplace=True),
    # out: 1024 x 4 x 4

    nn.Conv2d(1024, 1, kernel_size=4, stride=1, padding=0, bias=False),
    # out: 1 x 1 x 1

    nn.Flatten(),
    nn.Sigmoid())
```

WGAN

```
discriminator = nn.Sequential(
    # in: 3 x 128 x 128

    nn.Conv2d(3, 64, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(64),
    nn.LeakyReLU(0.2, inplace=True),
    # out: 64 x 64 x 64

    nn.Conv2d(64, 128, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(128),
    nn.LeakyReLU(0.2, inplace=True),
    # out: 128 x 32 x 32

    nn.Conv2d(128, 256, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(256),
    nn.LeakyReLU(0.2, inplace=True),
    # out: 256 x 16 x 16

    nn.Conv2d(256, 512, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(512),
    nn.LeakyReLU(0.2, inplace=True),
    # out: 512 x 8 x 8

    nn.Conv2d(512, 1024, kernel_size=4, stride=2, padding=1, bias=False),
    nn.BatchNorm2d(1024),
    nn.LeakyReLU(0.2, inplace=True),
    # out: 1024 x 4 x 4

    nn.Conv2d(1024, 1, kernel_size=4, stride=1, padding=0, bias=False),
    # out: 1 x 1 x 1

    nn.Flatten(),
    #nn.Sigmoid()
)
```

- $\tilde{V} = \frac{1}{m}\sum_{i=1}^{m} \log D(x^i) - \frac{1}{m}\sum_{i=1}^{m} D\left(G\left(z^i\right)\right)$

GAN

```
[28]: def train_generator(opt_g):
        # Clear generator gradients
        opt_g.zero_grad()

        # Generate fake images
        latent = torch.randn(batch_size, latent_size, 1, 1
        fake_images = generator(latent)

        # Try to fool the discriminator
        preds = discriminator(fake_images)
        targets = torch.ones(batch_size, 1, device=device)
        loss = F.binary_cross_entropy(preds, targets)

        # Update generator weights
        loss.backward()
        opt_g.step()

        return loss.item()
```

WGAN

```
# Try to fool the discriminator
preds = discriminator(fake_images)
loss = -torch.mean(preds)
```

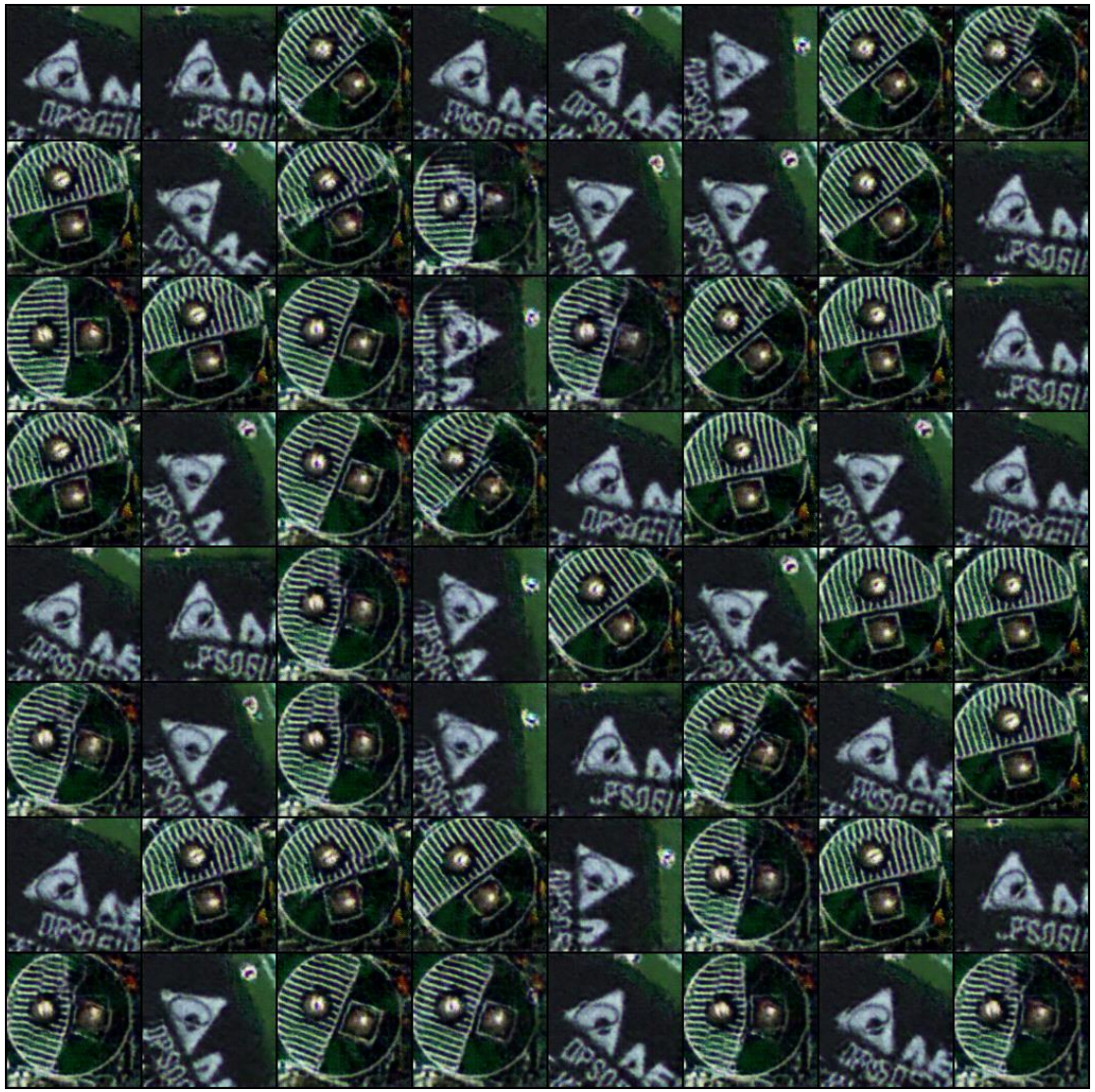
Practice

- Open “8.2. WGAN.ipynb"

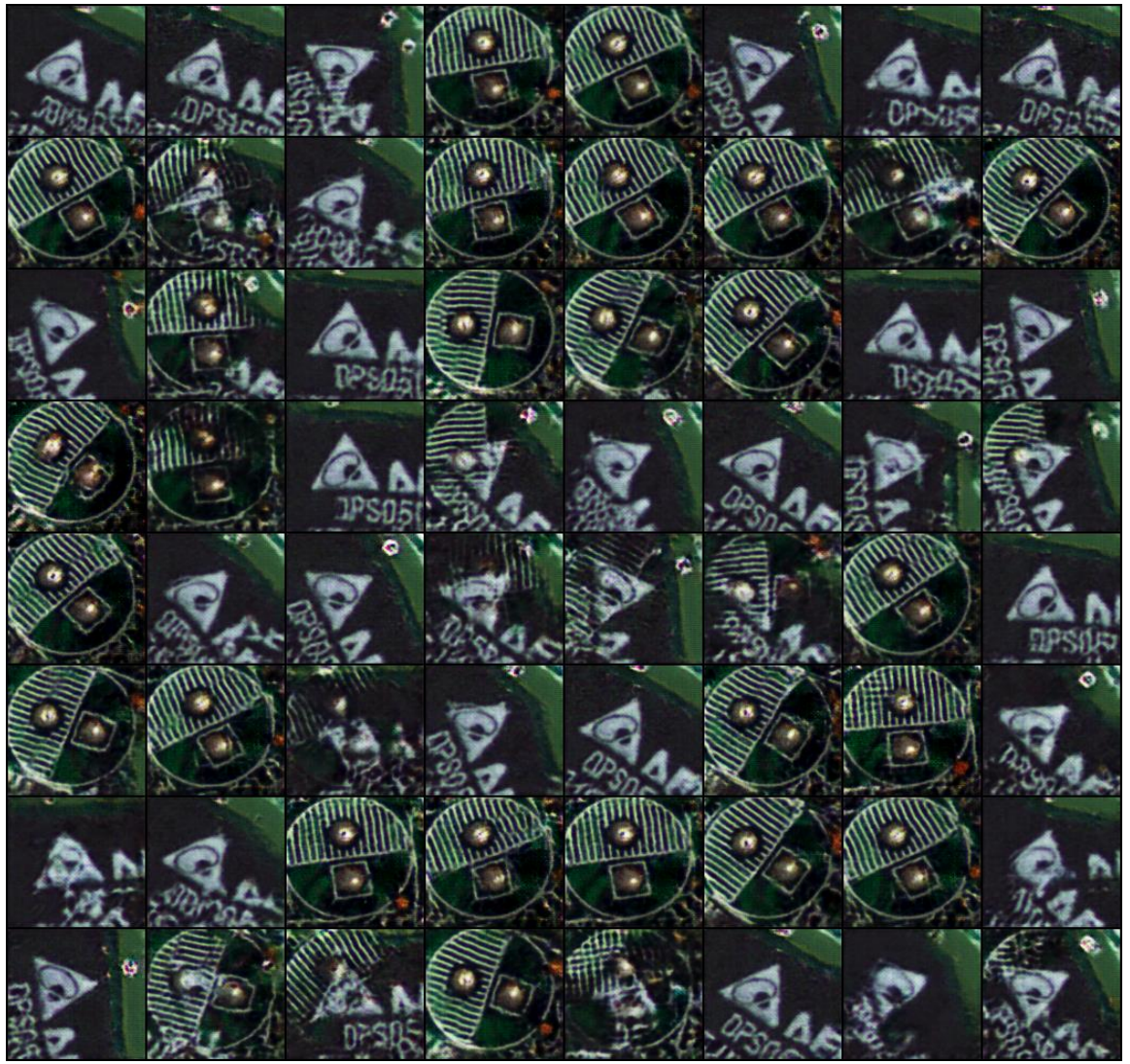
HW7 (2)

- Use your own images, e.g., facial expression to train a WGAN.
- Show the generated images.
- Try latent vectors like (all 1), (all 0.5), (all 0.3), (0, 0, 1, 0, ….), (one dimension goes from 0 to 1 and other dimensions fixed), … to see the generated images.

GAN, 5.6K



WGAN, 4K



GAN, 5.6K

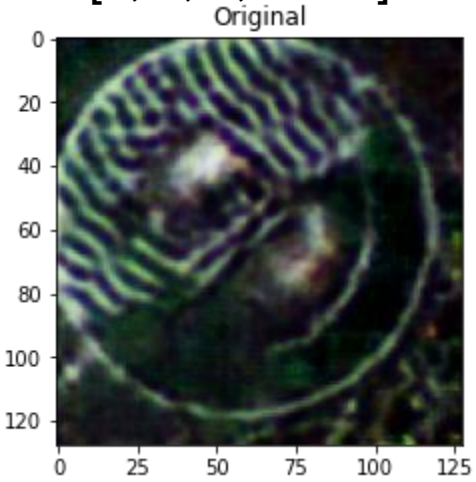
[0, 0, 0...0]

[1, 1, 1...1]

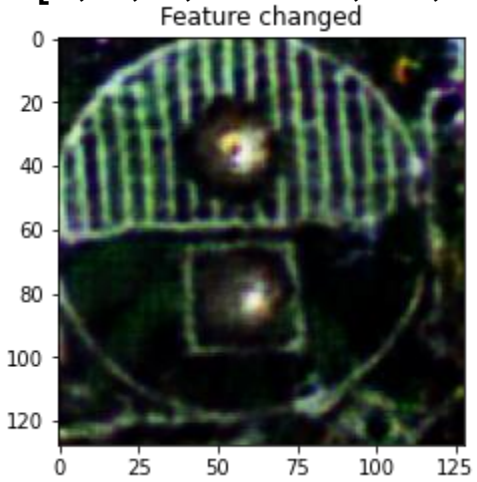
[-1, -1, -1...-1]

WGAN, 4K

[1, 1, 1, 1… 1]



[1, 1, 1, 1… 10, 10, 1… 1]

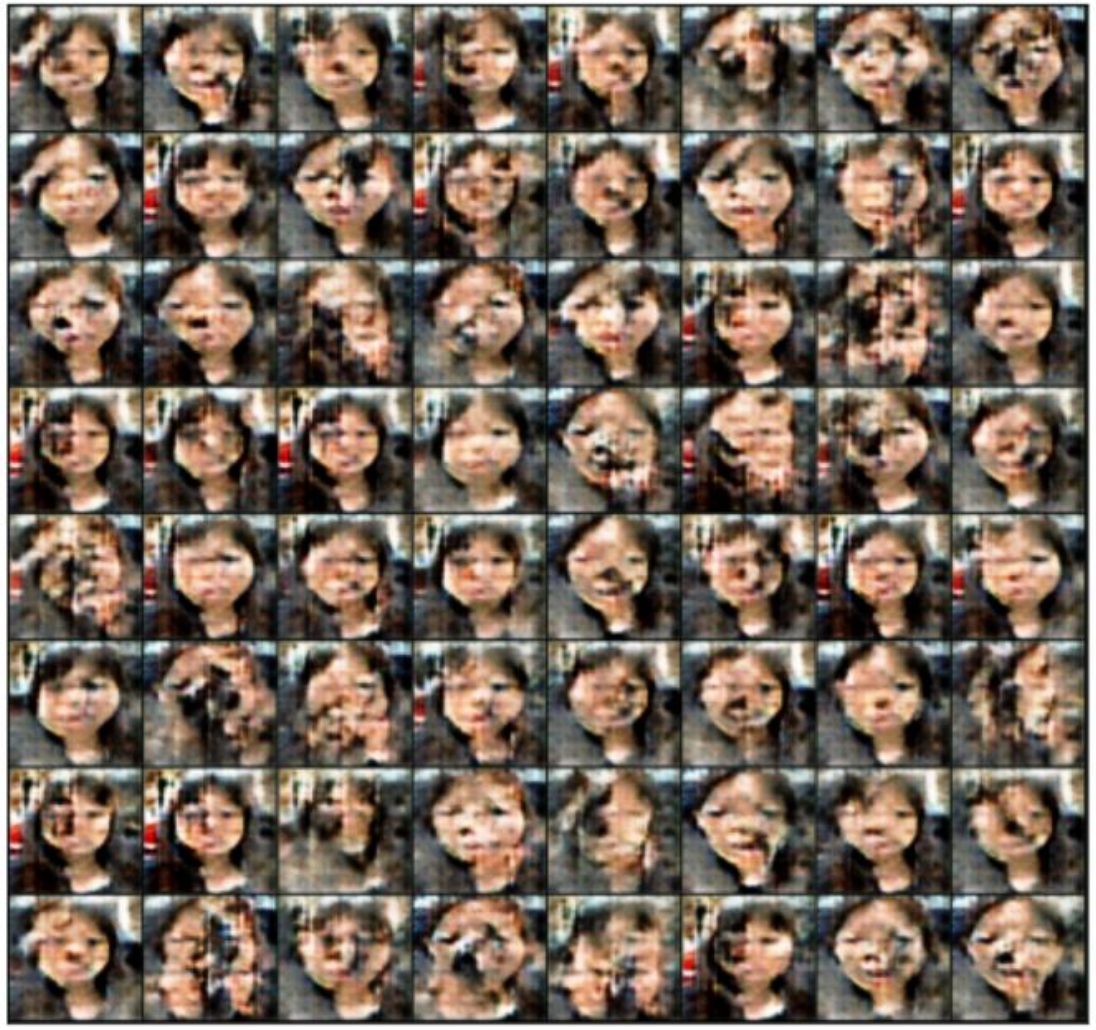


Features 50, 51 = 10

Epoch =560

1060

torch.Size([128, 3, 128, 128])



torch.Size([128, 3, 128, 128])

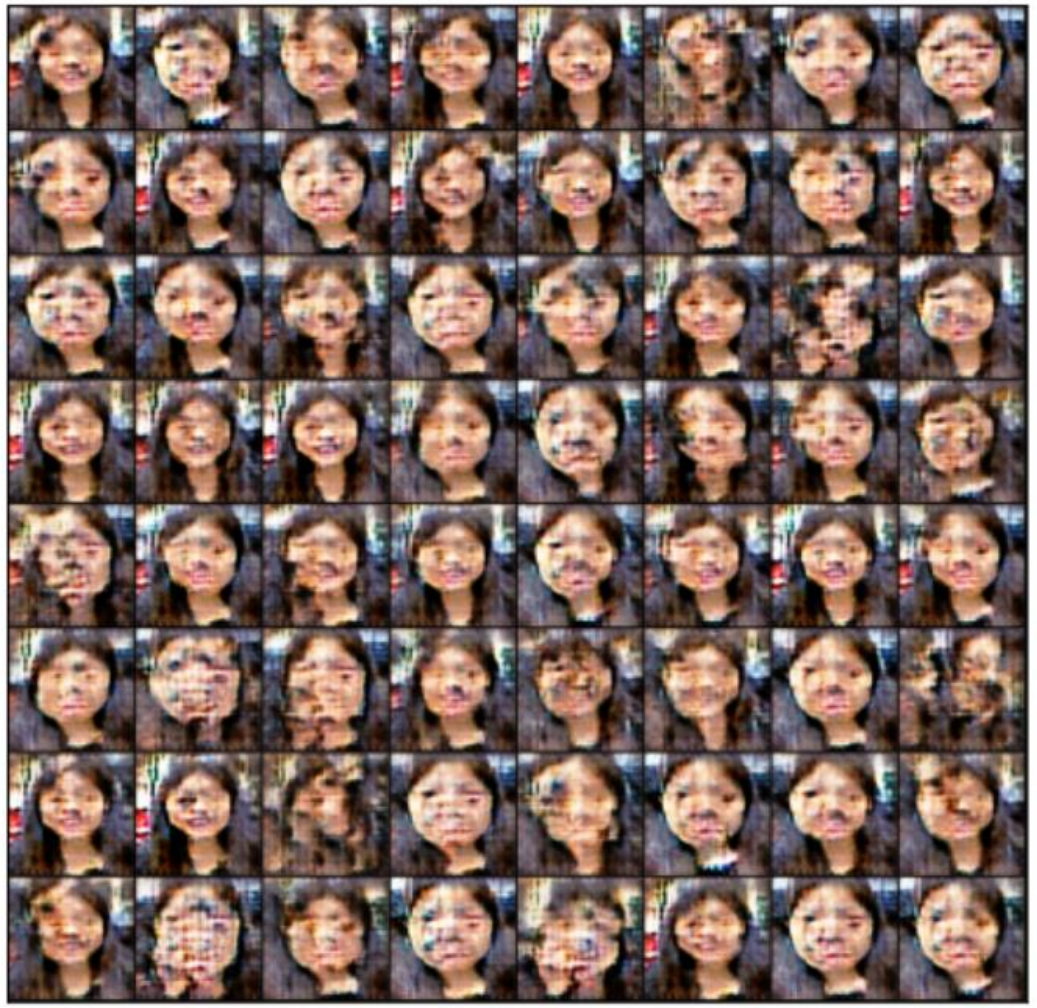
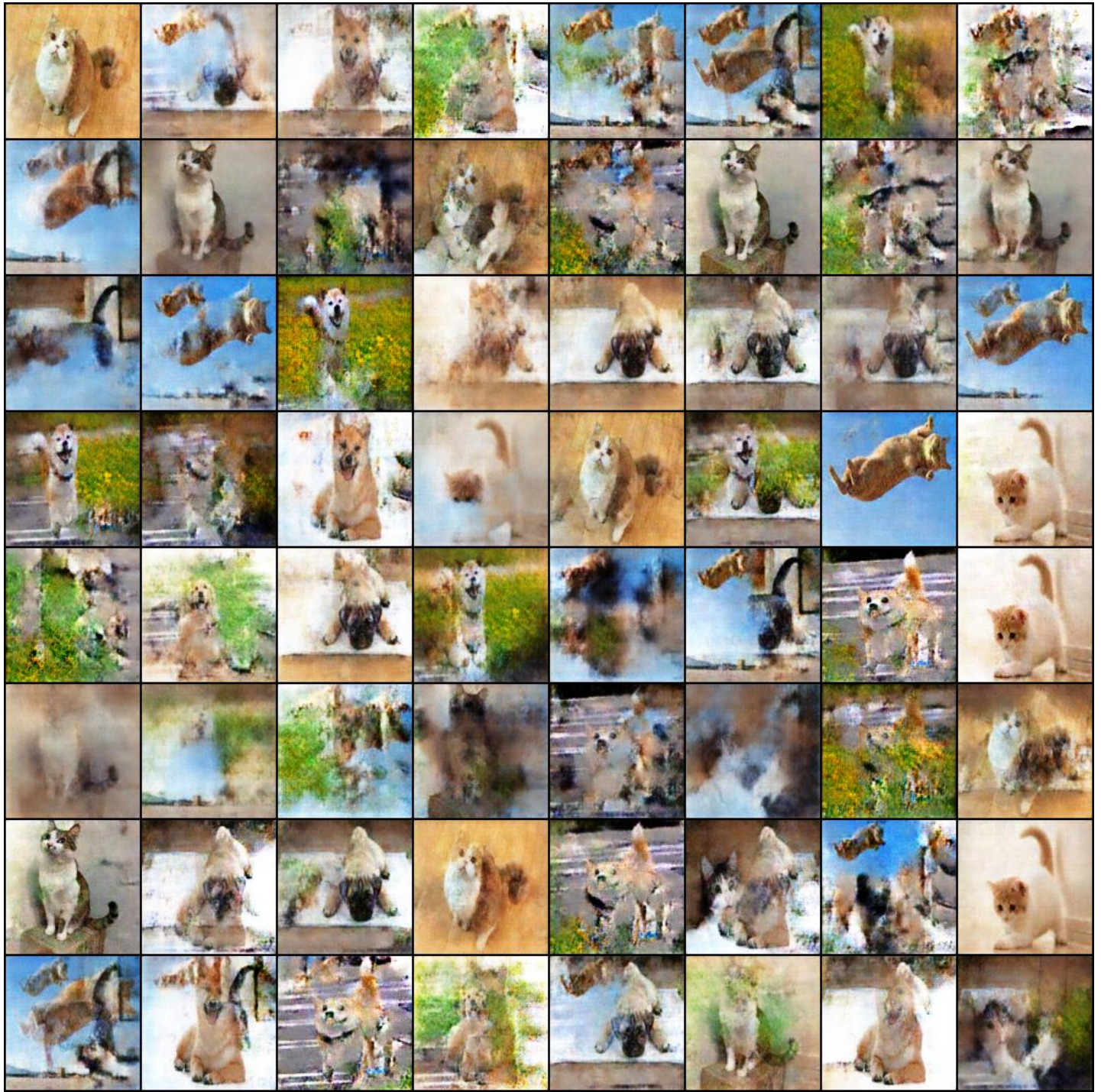
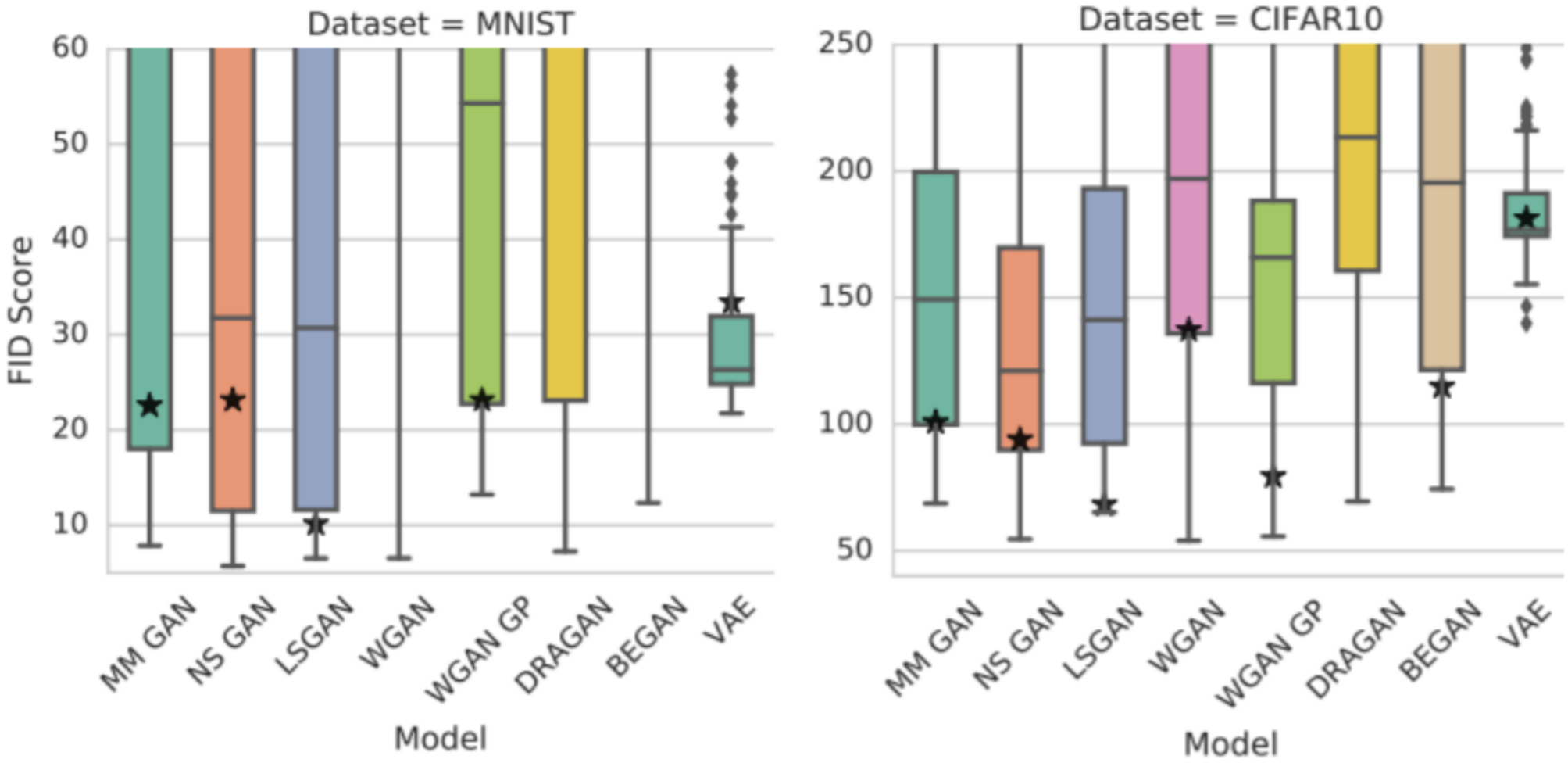


Image size = 128*128*3
Class 1 = 10, class2 = 10
Latent vector size = 128
Batch = 128
6K



GAN is sensitive to hyper-parameter tuning and its performance range is large. Different GANs' performances are similar

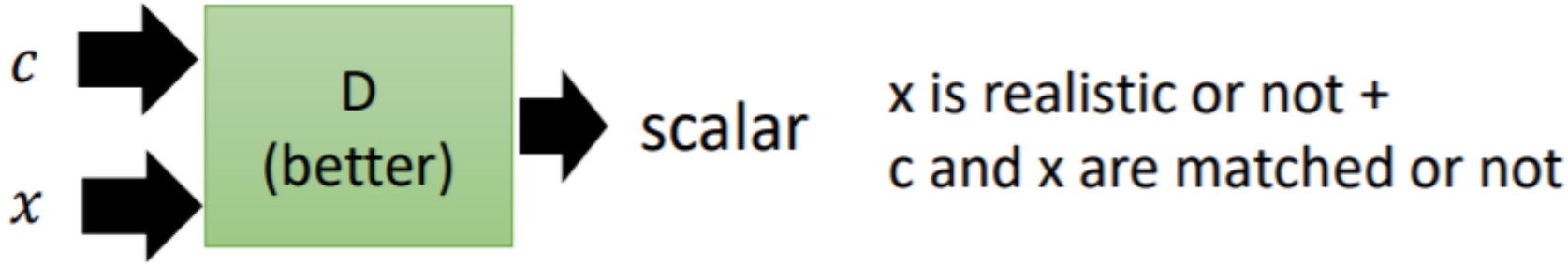


Reference: 李弘毅 GAN Lecture 1 (2018): https://youtu.be/DQNNMiAP5lw

Conditional generation by GAN

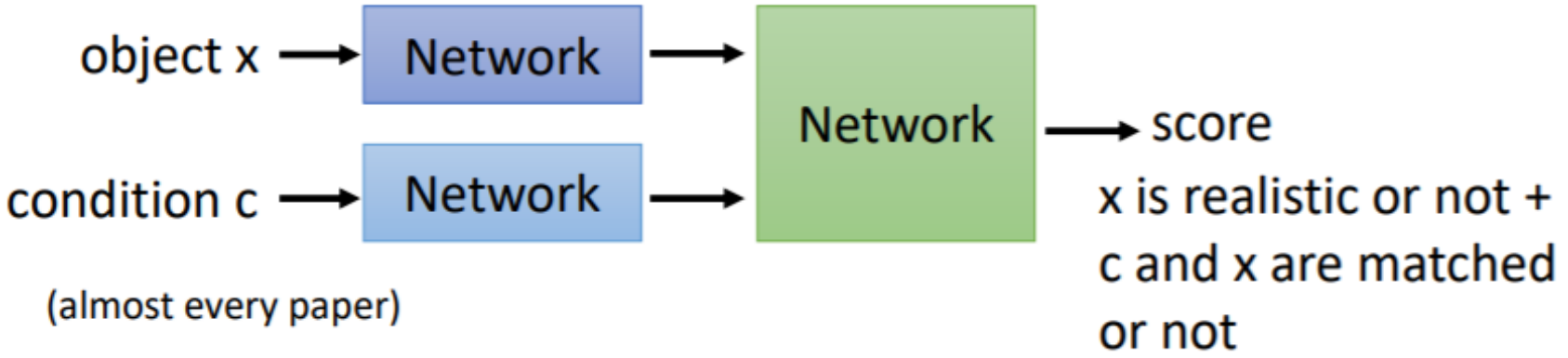
G takes two inputs and *D* checks two conditions

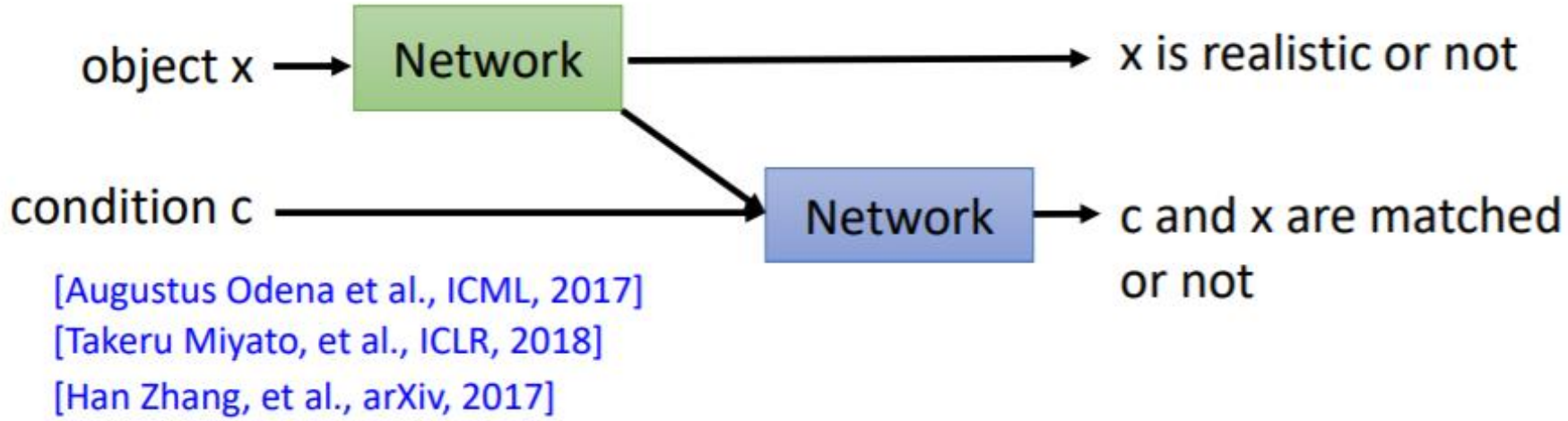
[Scott Reed, et al, ICML, 2016]



Reference: 李弘毅 GAN Lecture 2 (2018): https://youtu.be/LpyL4nZSuqU

Design of *D*





Reference: 李弘毅 GAN Lecture 2 (2018): https://youtu.be/LpyL4nZSuqU

Results of conditional GAN

paired data

blue eyes
red hair
short hair

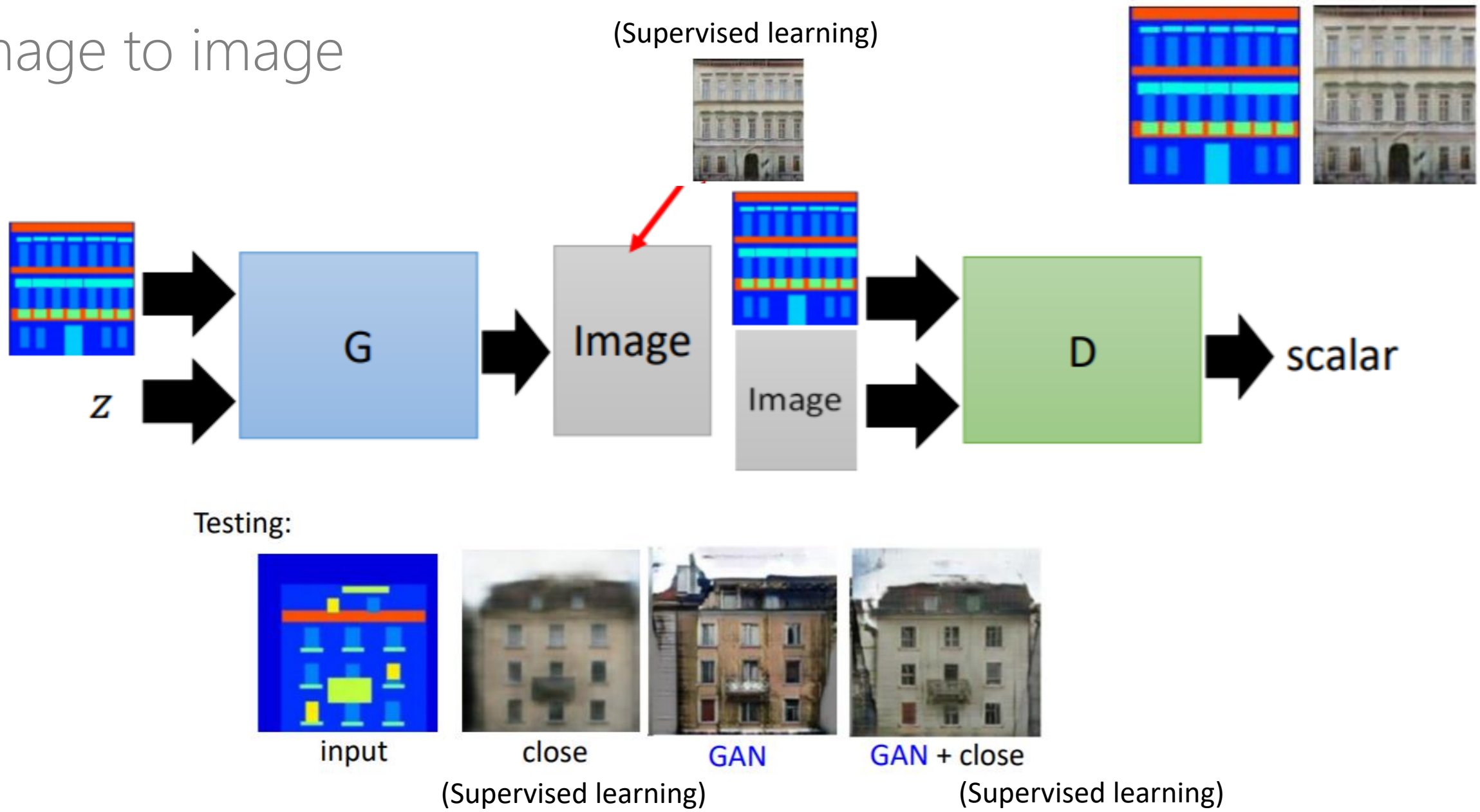
Collecting anime faces and the description of its characteristics

red hair, green eyes

blue hair, red eyes

Reference: 李弘毅 GAN Lecture 2 (2018): https://youtu.be/LpyL4nZSuqU

Image to image



Reference: 李弘毅 GAN Lecture 2 (2018): https://youtu.be/LpyL4nZSuqU

Unsupervised conditional generation

Unsupervised conditional generation

Unsupervised Conditional Generation

Transform an object from one domain to another

without paired data (e.g. style transfer)

Reference: 李弘毅 GAN Lecture 3 (2018): https://youtu.be/-3LgL3NXLtI

Two approaches for unsupervised conditional generation

- Approach 1: Direct Transformation

Domain X

$G_{X \to Y}$

Domain Y

For texture or color change

- Approach 2: Projection to Common Space

Domain X

EN_X

Encoder of domain X

Face Attribute

DE_Y

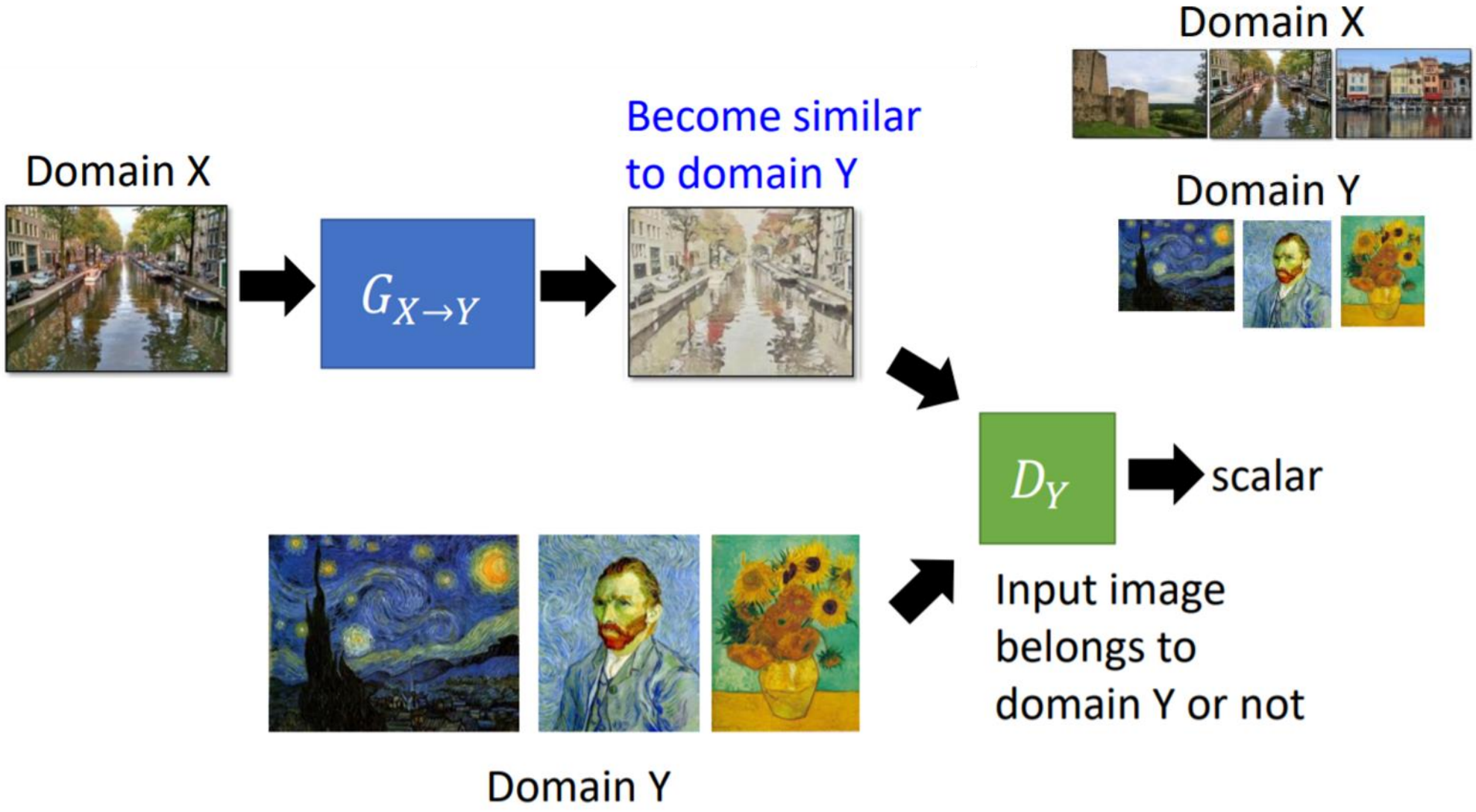
Decoder of domain Y

Domain Y

Larger change, only keep the semantics

Reference: 李弘毅 GAN Lecture 3 (2018): https://youtu.be/-3LgL3NXLtI

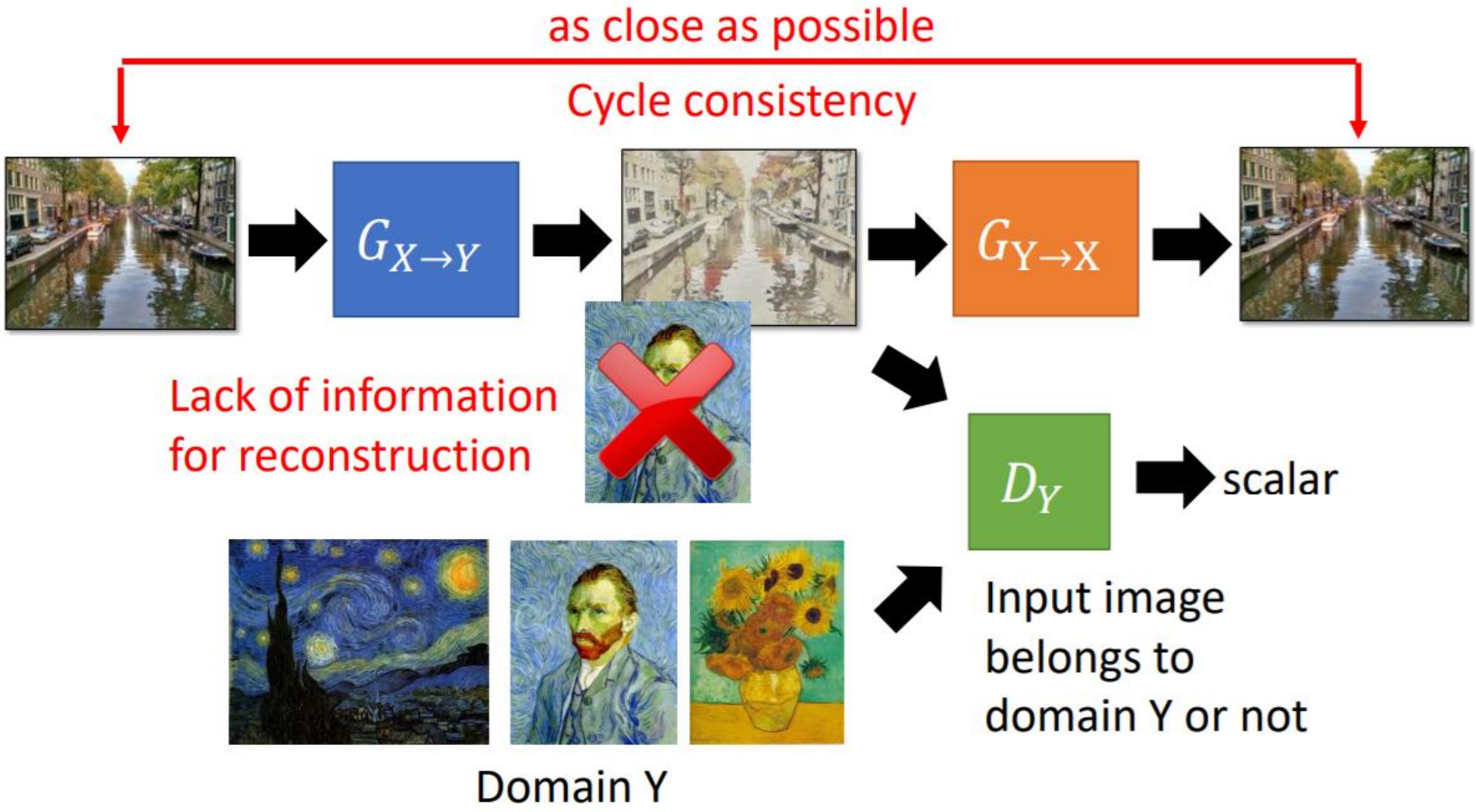
Direct transform



Reference: 李弘毅 GAN Lecture 3 (2018): https://youtu.be/-3LgL3NXLtI

Cycle GAN

[Jun-Yan Zhu, et al., ICCV, 2017]

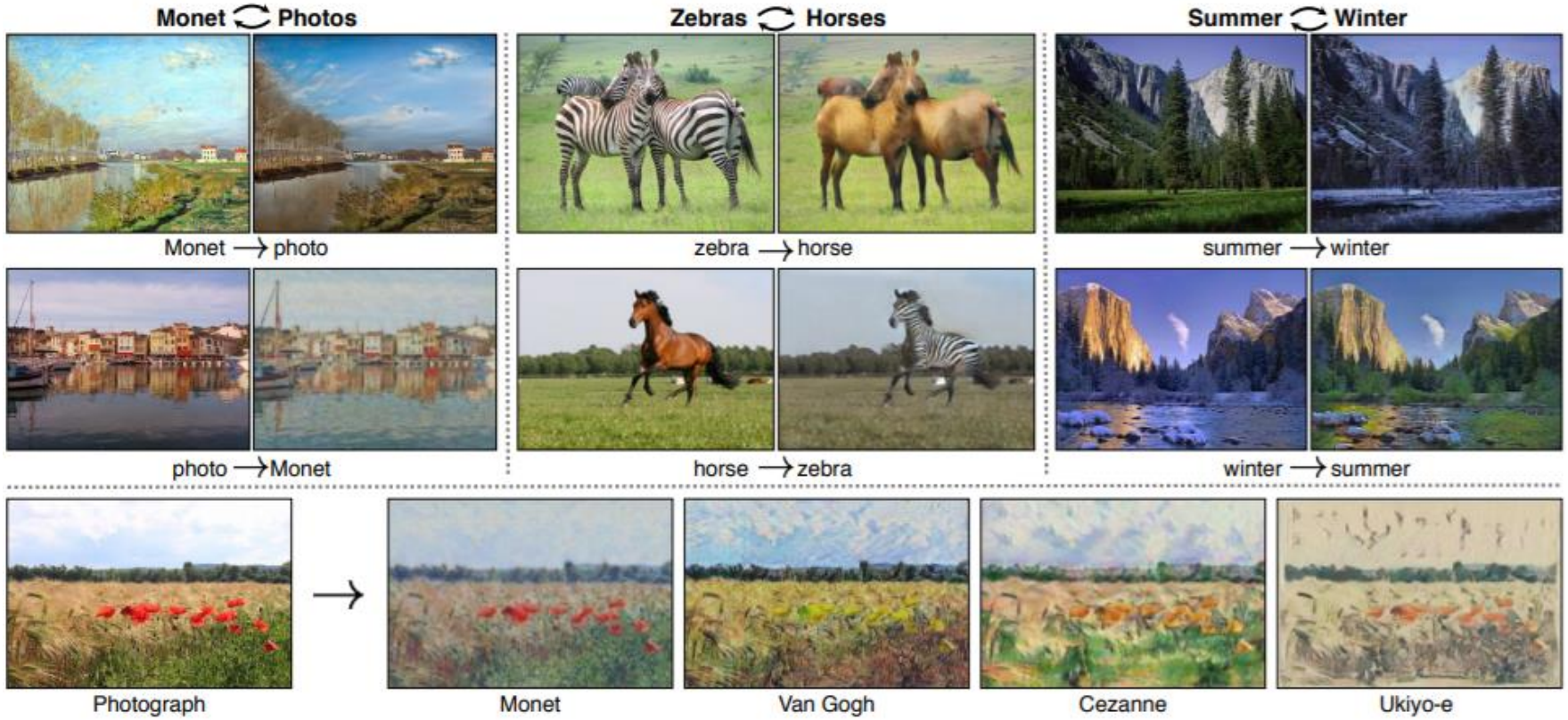


Reference: 李弘毅 GAN Lecture 3 (2018): https://youtu.be/-3LgL3NXLtI

Cycle GAN

Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

Jun-Yan Zhu* Taesung Park* Phillip Isola Alexei A. Efros
Berkeley AI Research (BAIR) laboratory, UC Berkeley



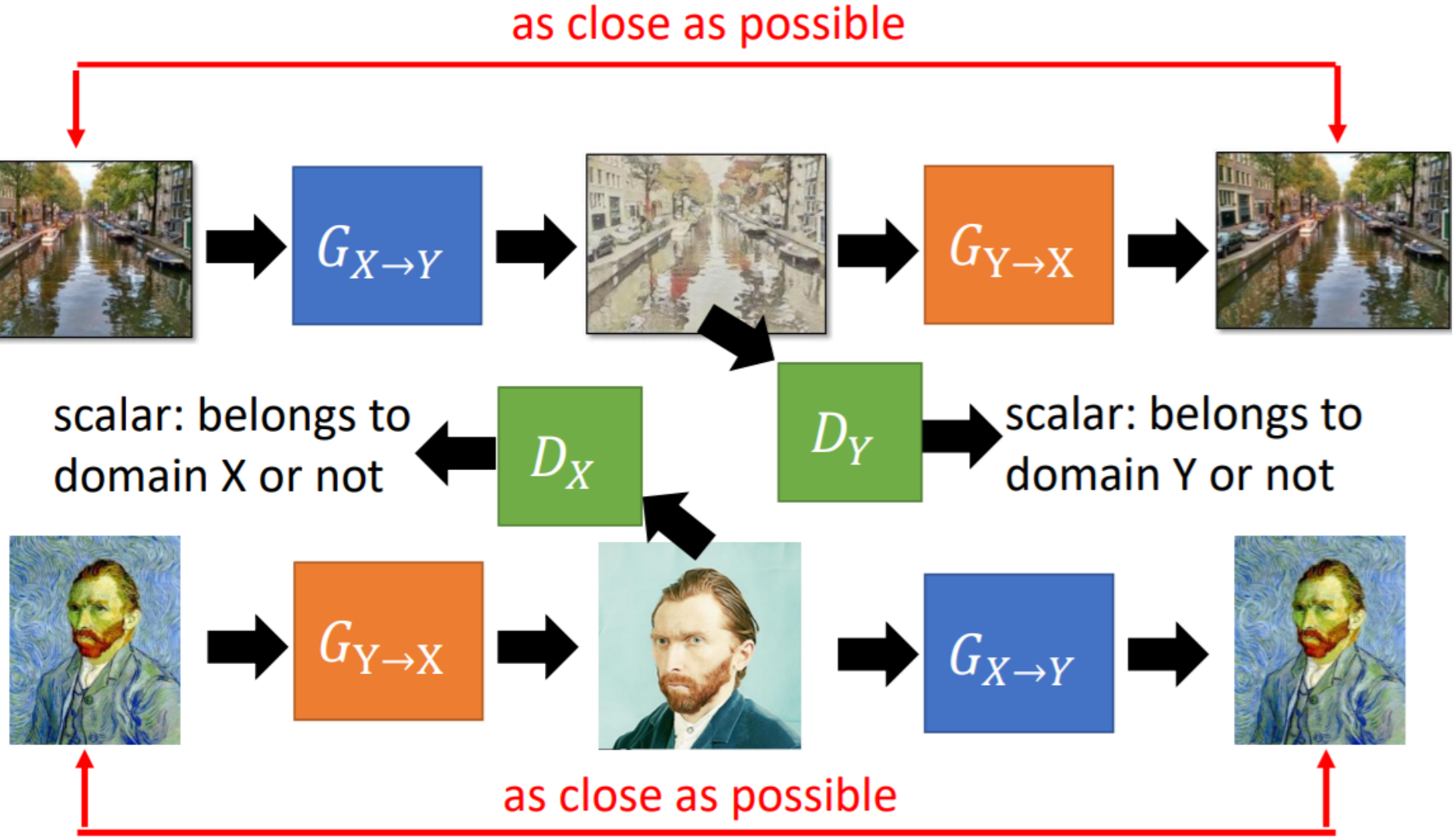
https://arxiv.org/pdf/1703.10593.pdf

Practice

- Open “8.3. CycleGAN.ipynb"

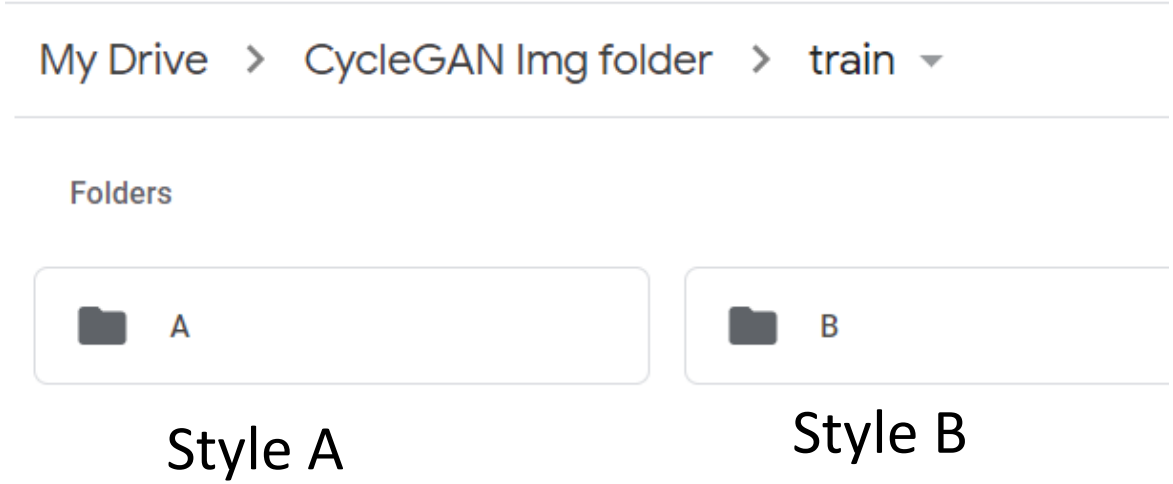
Two-way Cycle GAN training

[Jun-Yan Zhu, et al., ICCV, 2017]



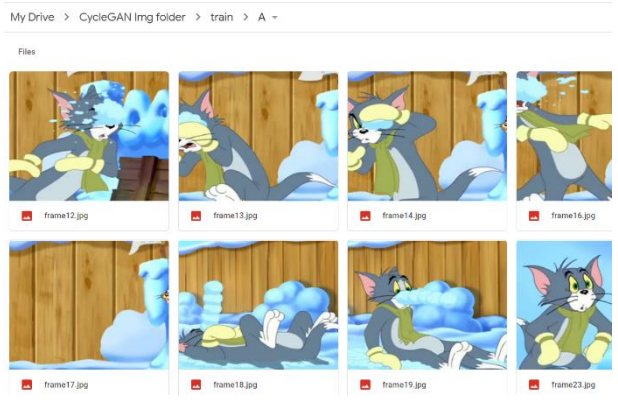
Reference: 李弘毅 GAN Lecture 3 (2018): https://youtu.be/-3LgL3NXLtI

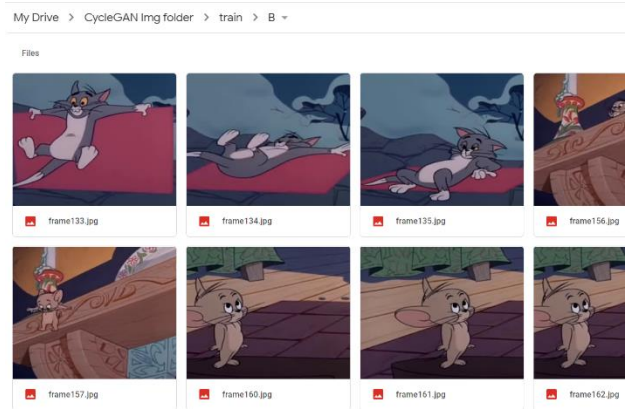
Prepare training images

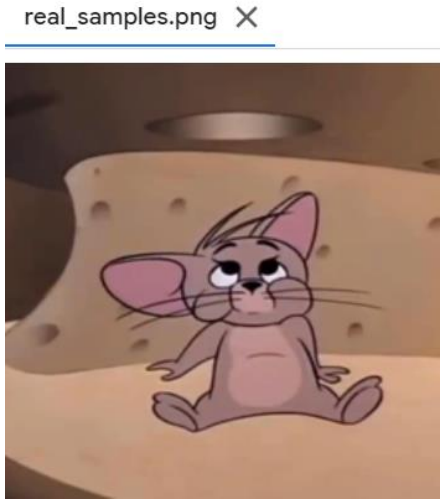


Style A

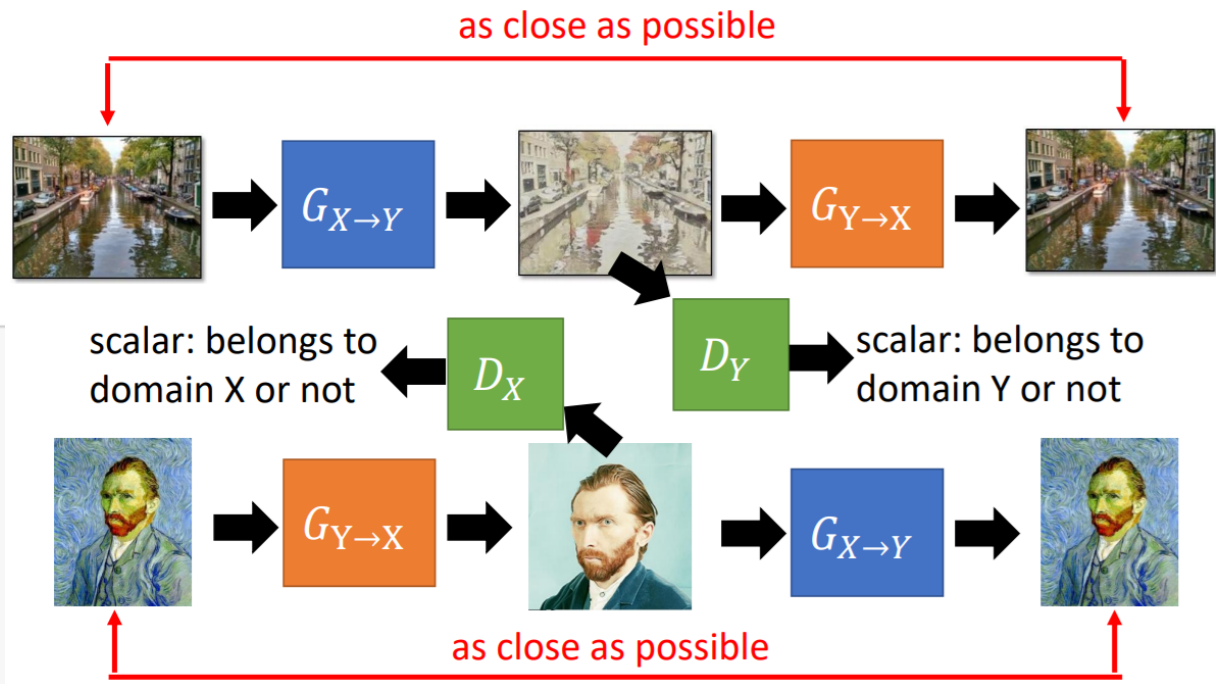
Style B







Training loop



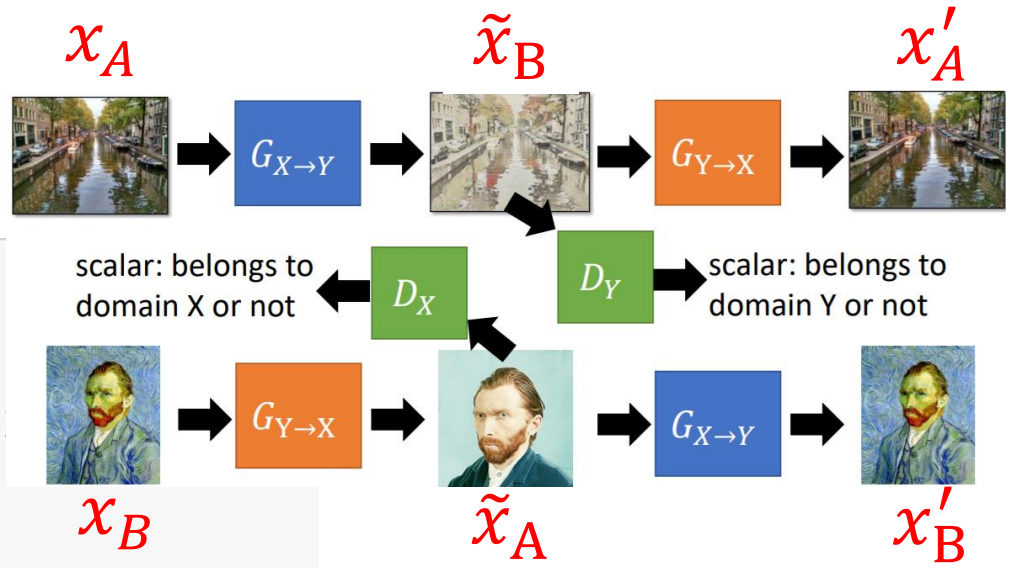
[51]:
```
for epoch in range(0, epochs):
  for i, data in enumerate(dataloader):
    # get batch size data
x_A real_image_A = data["A"].to(device)
x_B real_image_B = data["B"].to(device)
    #batch_size = real_image_A.size(0)

    # real data label is 1, fake data label is 0.
    real_label = torch.full((batch_size, 1), 1, device=device, dtype=torch.float32)
    fake_label = torch.full((batch_size, 1), 0, device=device, dtype=torch.float32)

    # (1) Update G network: Generators A2B and B2A
x̃_A, x̃_B fake_image_A, fake_image_B = UpdateG(real_image_A,real_image_B,real_label,fake_label)

    #(2) Update D network: Discriminator A
    UpdateD_A(fake_image_A)

    #(3) Update D network: Discriminator B
    UpdateD_B(fake_image_B)
```

Train $G_{X\to Y}$ and $G_{Y\to X}$

Train D_X

Train D_Y

Train $G_{X\to Y}$ and $G_{Y\to X}$



[46]:
```
##############################################
# (1) Update G network: Generators A2B and B2A
##############################################
def UpdateG (real_image_A,real_image_B,real_label,fake_labe
  # Set G_A and G_B's gradients to zero
  optimizer_G.zero_grad()
```

Identity loss

```
  # Identity loss
  # G_B2A(A) should equal A if real A is fed
  identity_image_A = netG_B2A(real_image_A)
  loss_identity_A = identity_loss(identity_image_A, real_image_A) * 5.0
  # G_A2B(B) should equal B if real B is fed
  identity_image_B = netG_A2B(real_image_B)
  loss_identity_B = identity_loss(identity_image_B, real_image_B) * 5.0
```

$$\dot{x}_A = G_{Y\to X}(x_A) \quad L(\dot{x}_A, x_A)$$

$$\dot{x}_B = G_{X\to Y}(x_B) \quad L(\dot{x}_B, x_B)$$

GAN loss

```
  # GAN loss
  # GAN loss D_A(G_A(A))
  fake_image_A = netG_B2A(real_image_B)
  fake_output_A = netD_A(fake_image_A)
  loss_GAN_B2A = adversarial_loss(fake_output_A, real_label)
  # GAN loss D_B(G_B(B))
  fake_image_B = netG_A2B(real_image_A)
  fake_output_B = netD_B(fake_image_B)
  loss_GAN_A2B = adversarial_loss(fake_output_B, real_label)
```

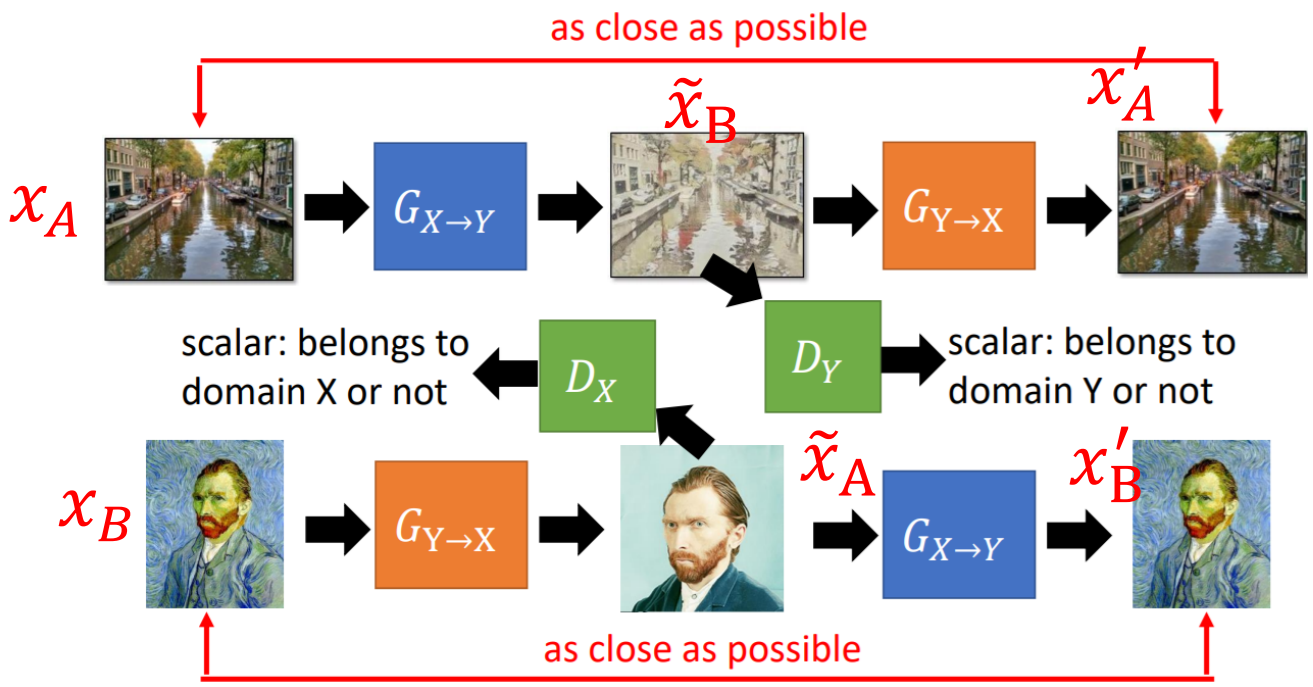
$$\tilde{x}_A = G_{Y\to X}(x_B)$$

$$d_A = D_X(\tilde{x}_A) \quad L(d_A, 1)$$

$$\tilde{x}_B = G_{X\to Y}(x_A)$$

$$d_B = D_Y(\tilde{x}_B) \quad L(d_B, 1)$$

Update $G_{X\to Y}$ and $G_{Y\to X}$



Cycle loss

```
# Cycle loss
recovered_image_A = netG_B2A(fake_image_B)
loss_cycle_ABA = cycle_loss(recovered_image_A, real_image_A) *

recovered_image_B = netG_A2B(fake_image_A)
loss_cycle_BAB = cycle_loss(recovered_image_B, real_image_B) *
```

$$x'_A = G_{Y\to X}(\tilde{x}_B) \qquad L(x_A, x'_A)$$

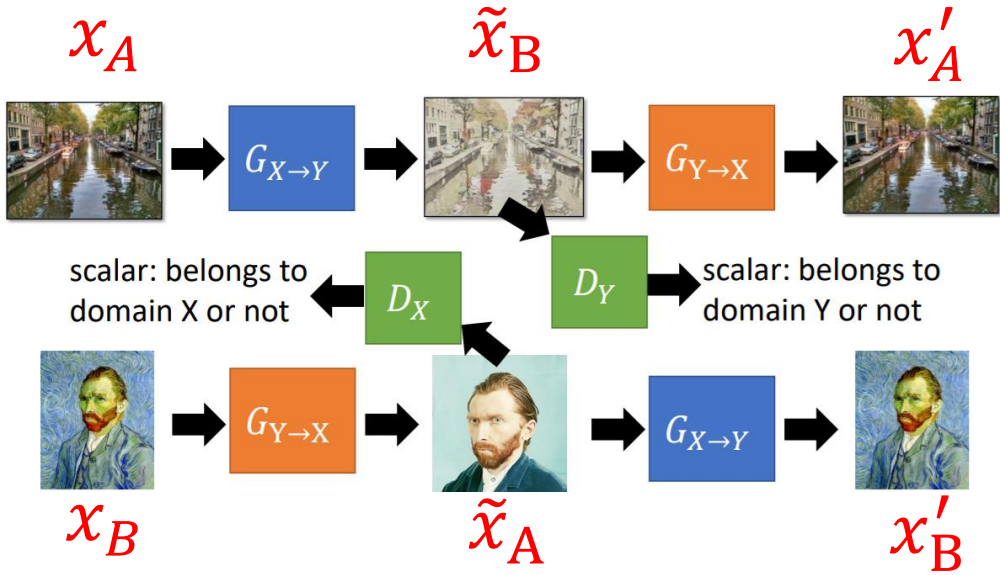
$$x'_B = G_{X\to Y}(\tilde{x}_A) \qquad L(x_B, x'_B)$$

```
# Combined loss and calculate gradients
errG = loss_identity_A + loss_identity_B + loss_GAN_A2B + loss
```

$$L(\dot{x}_A, x_A) + L(\dot{x}_B, x_B) + L(d_A, 1)$$
$$L(d_B, 1) + L(x_A, x'_A) + L(x_B, x'_B)$$

Total loss = Identity loss + GAN loss + Cycle loss

Update D_X



[47]:
```
##############################################
# (2) Update D network: Discriminator A
##############################################
def UpdateD_A (fake_image_A):
  # Set D_A gradients to zero
  optimizer_D_A.zero_grad()

  # Real A image loss
  real_output_A = netD_A(real_image_A)
  errD_real_A = adversarial_loss(real_output_A, real_label)

  # Fake A image loss
  fake_image_A = fake_A_buffer.push_and_pop(fake_image_A)
  fake_output_A = netD_A(fake_image_A.detach())
  errD_fake_A = adversarial_loss(fake_output_A, fake_label)

  # Combined loss and calculate gradients
  errD_A = (errD_real_A + errD_fake_A) / 2
```

Real image loss

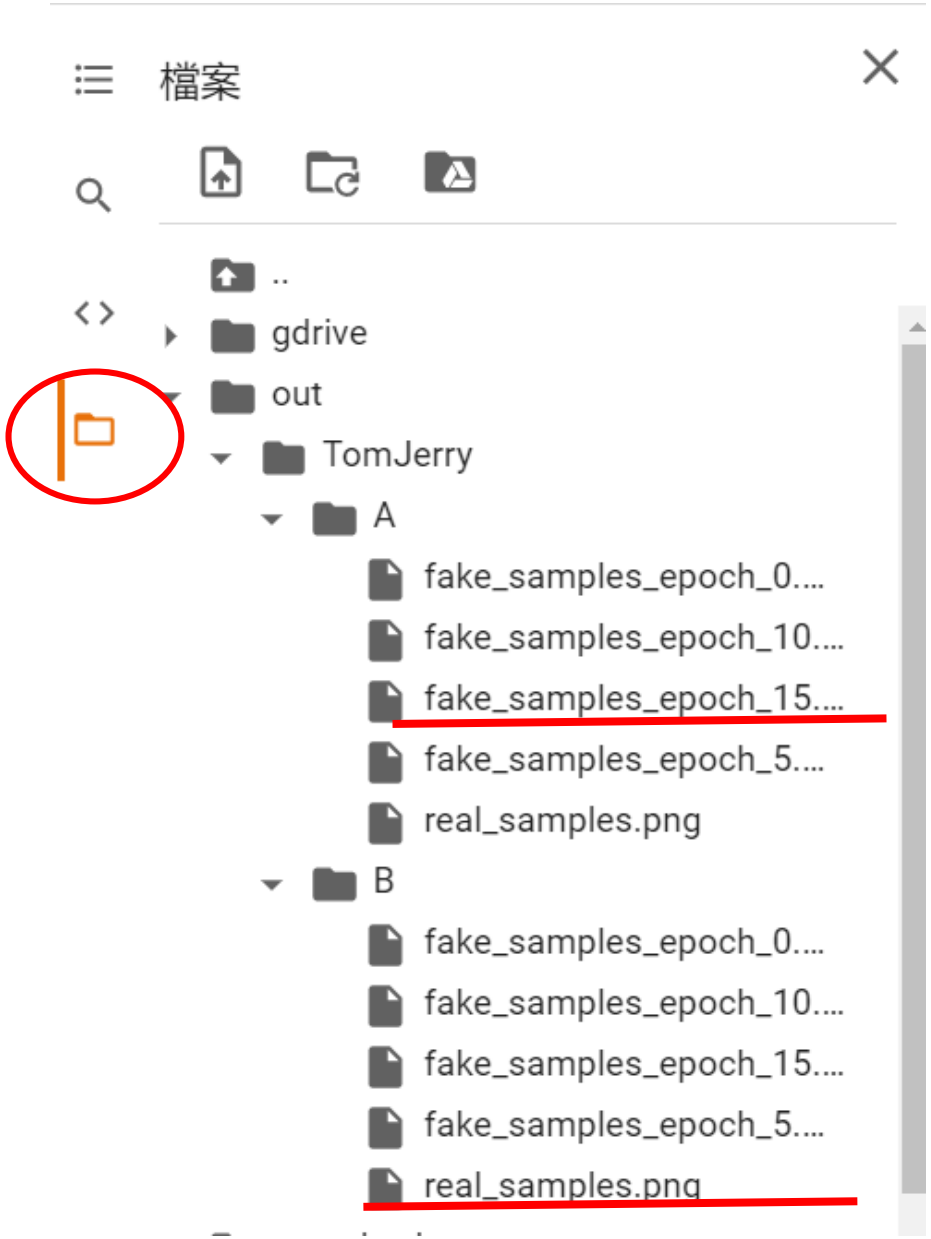
$$d_{AR} = D_{\mathrm{X}}(x_{\mathrm{A}}) \quad L(d_{AR}, 1)$$

Fake image loss

$$d_{AF} = D_{\mathrm{X}}(\tilde{x}_{\mathrm{A}}) \quad L(d_{AF}, 0)$$

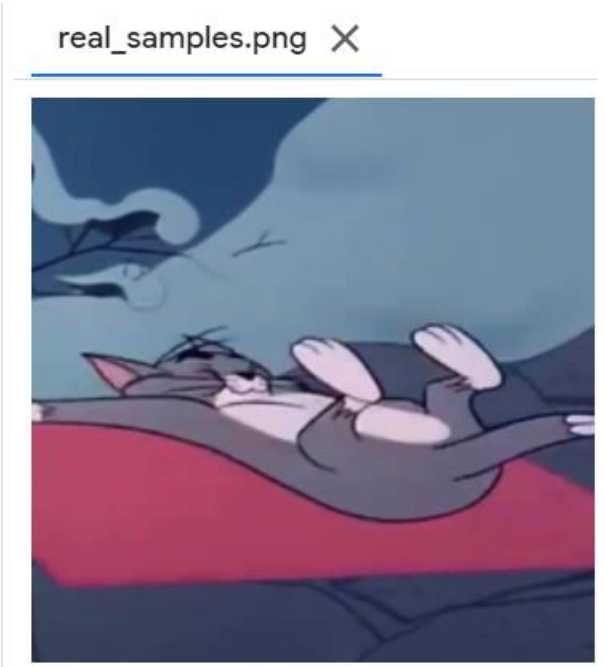
Total loss = Real image loss + Fake image loss

Fake A images generated from real B images

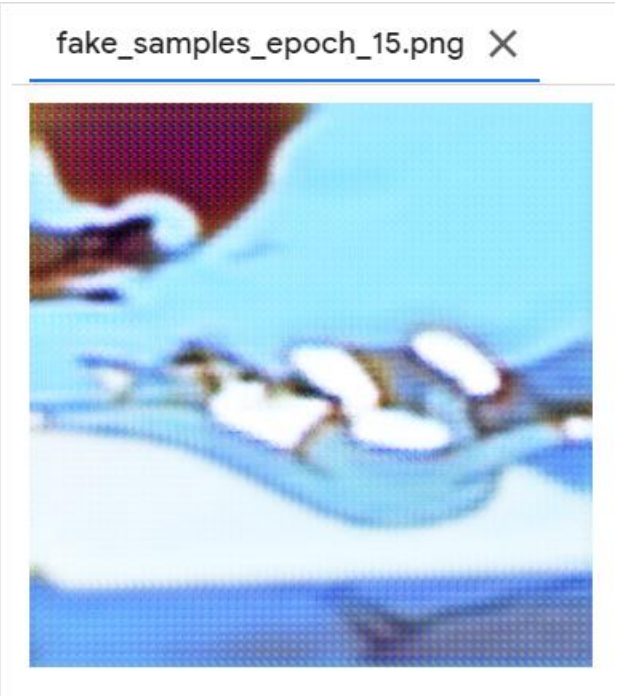


$$\tilde{x}_{\mathrm{A}} = G_{\mathrm{Y}\to\mathrm{X}}(x_B)$$

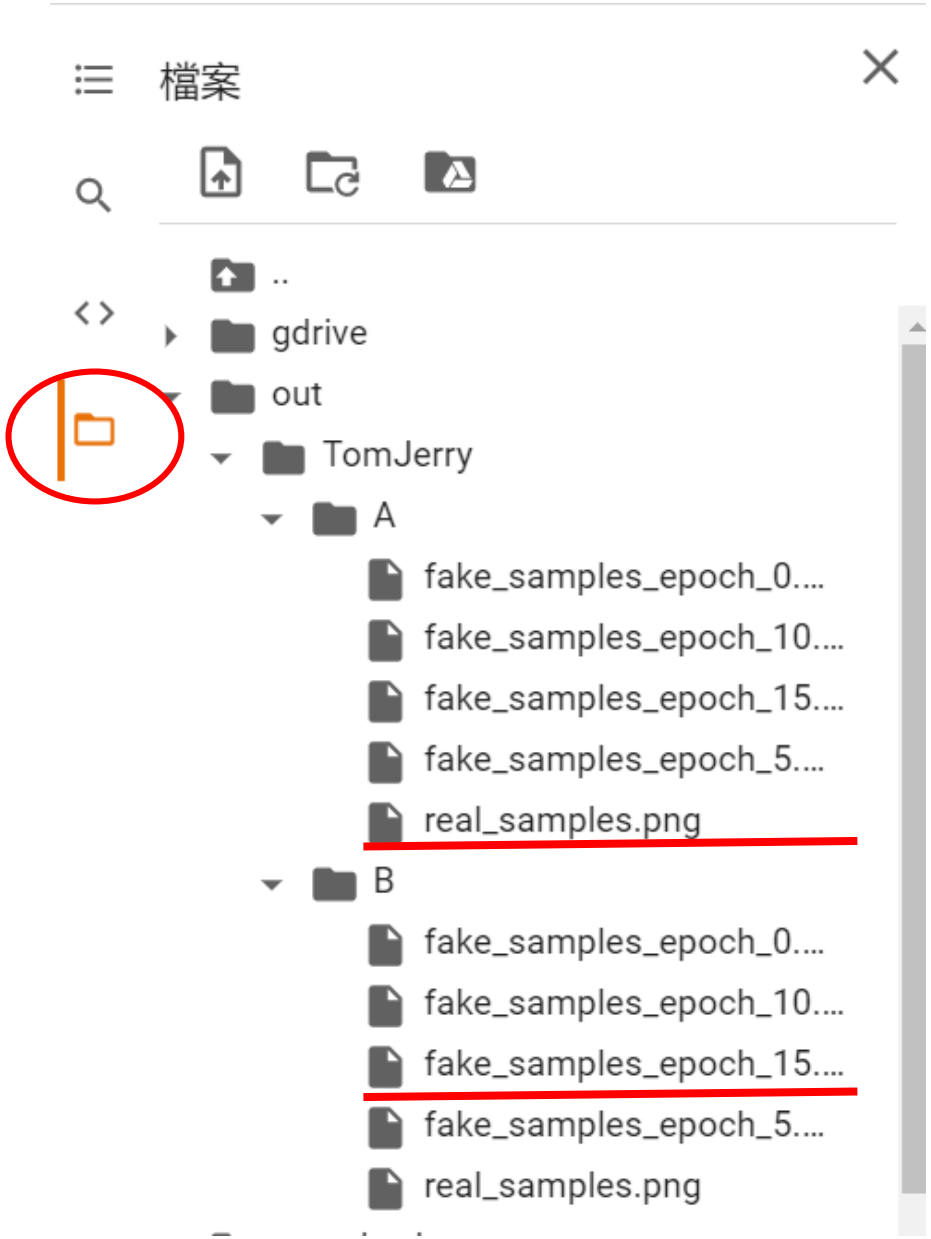
Real B image



Fake A image, epoch 15

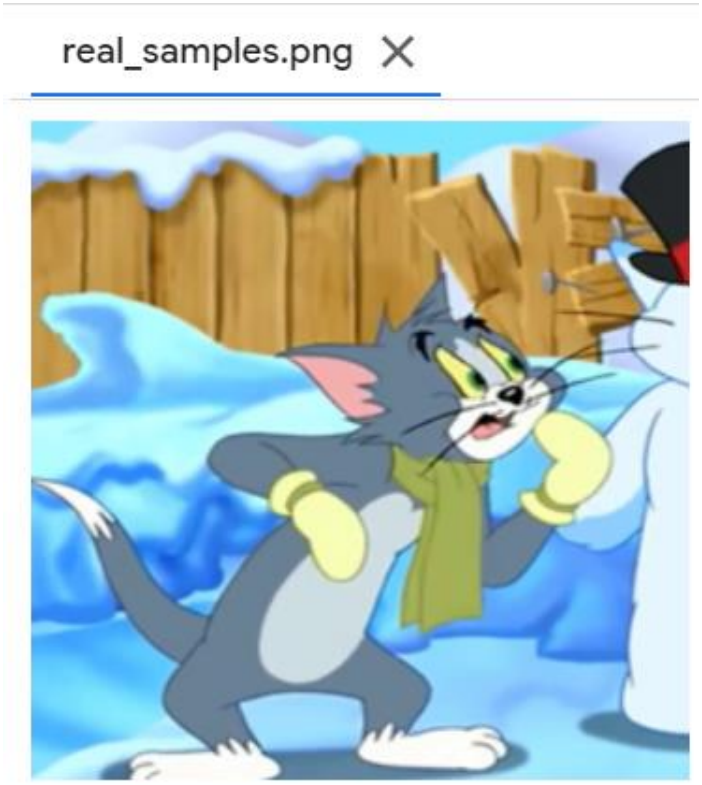


Fake B images generated from real A images



$$\tilde{x}_B = G_{X \to Y}(x_A)$$

Real A image



Fake B image, epoch 20

real_samples.png

fake_samples_epoch_35.png

real_samples.png

fake_samples_epoch_40.png

real_samples.png

fake_samples_epoch_45.png

real_samples.png

fake_samples_epoch_45.png

real_samples.png

fake_samples_epoch_75.png

real_samples.png

fake_samples_epoch_95.png

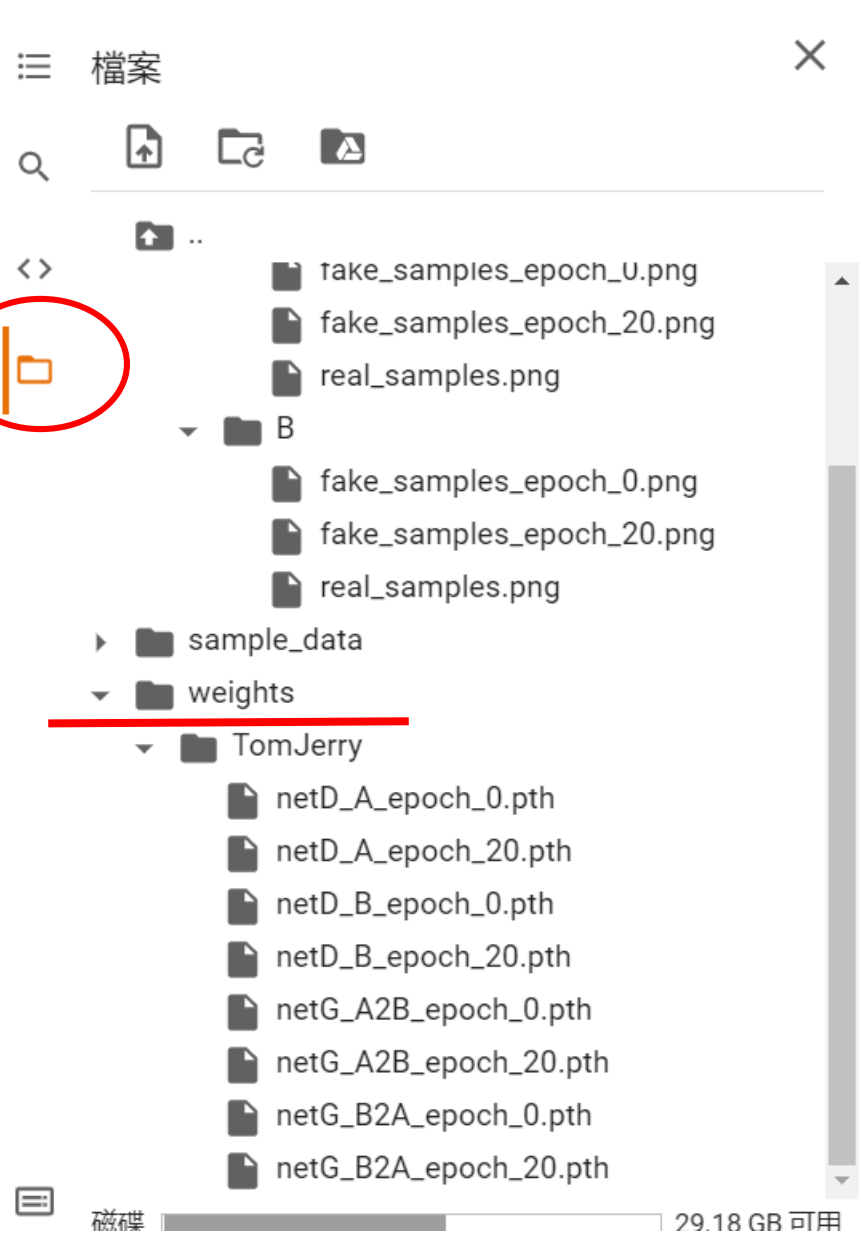
real_samples.png

fake_samples_epoch_80.png

real_samples.png

fake_samples_epoch_95.png

Saved NN




```
        #(2) Update D network: Discriminator A
        UpdateD_A(fake_image_A)

        #(3) Update D network: Discriminator B
        UpdateD_B(fake_image_B)

    if(epoch % print_freq ==0):
        vutils.save_image(real_image_A, f"{outf}/{dataset}/A/real_s
        vutils.save_image(real_image_B, f"{outf}/{dataset}/B/real_s
        fake_image_A = 0.5 * (netG_B2A(real_image_B).data + 1.
        fake_image_B = 0.5 * (netG_A2B(real_image_A).data + 1.
        vutils.save_image(fake_image_A.detach(), f"{outf}/{dataset}
        vutils.save_image(fake_image_B.detach(),f"{outf}/{dataset}/B

        torch.save(netG_A2B.state_dict(), f"weights/{dataset}/netG_
        torch.save(netG_B2A.state_dict(), f"weights/{dataset}/netG_
        torch.save(netD_A.state_dict(), f"weights/{dataset}/netD_A_
        torch.save(netD_B.state_dict(), f"weights/{dataset}/netD_B_

    # Update learning rates
    lr_scheduler_G.step()
    lr_scheduler_D_A.step()
    lr_scheduler_D_B.step()

# save last check pointing
torch.save(netG_A2B.state_dict(), f"weights/{dataset}/netG_A2B.pth"
```

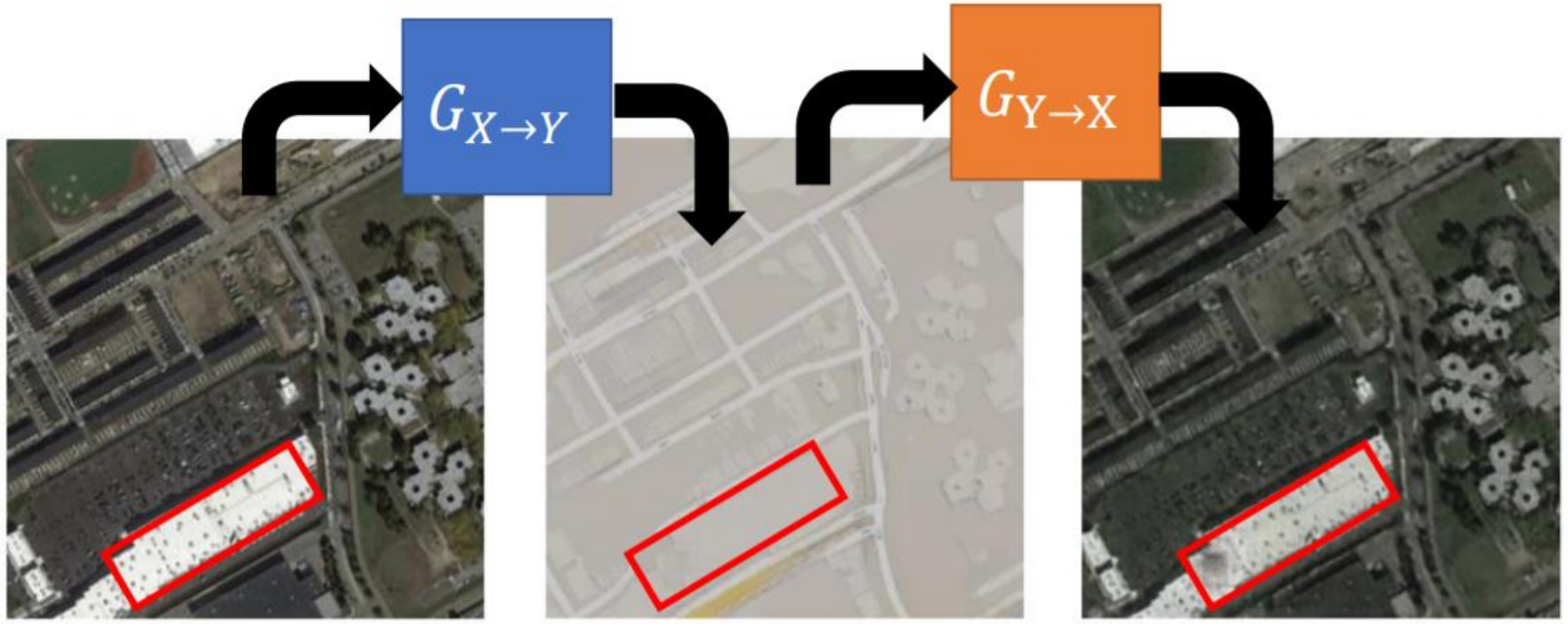
HW7 (3)

- Train a CycleGAN to convert your own images from style A, e.g., facial expression to style B, e.g.,. cartoon style.

Cycle GAN will hide information in the input and display it again in the output

- **CycleGAN: a Master of Steganography (隱寫術)**

[Casey Chu, et al., NIPS workshop, 2017]



The information is hidden.

Reference: 李弘毅 GAN Lecture 3 (2018): https://youtu.be/-3LgL3NXLtI

Projection to common space

- Approach 1: Direct Transformation

Domain X

$G_{X \to Y}$

Domain Y

For texture or color change

- Approach 2: Projection to Common Space

Domain X

EN_X

Encoder of domain X

Face Attribute

DE_Y

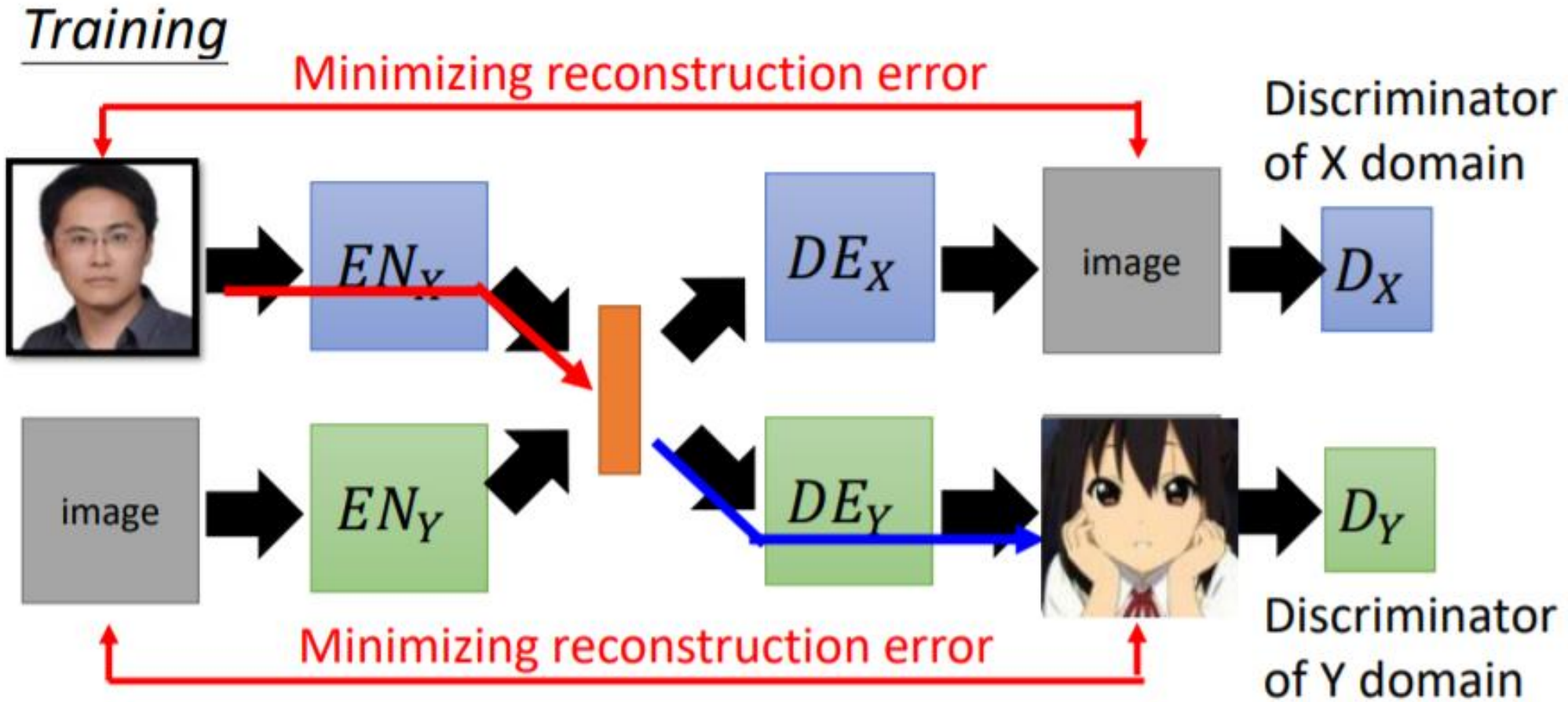
Decoder of domain Y

Domain Y

Larger change, only keep the semantics

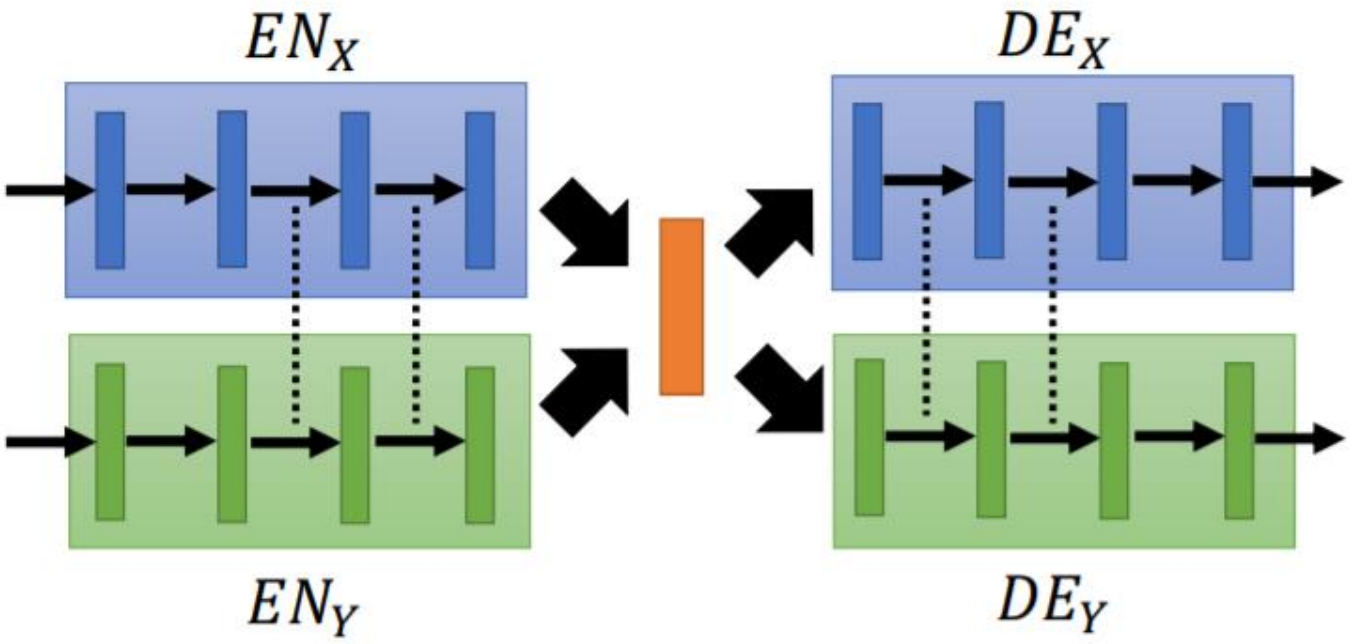
Reference: 李弘毅 GAN Lecture 3 (2018): https://youtu.be/-3LgL3NXLtI

VAE enhanced GAN



Reference: 李弘毅 GAN Lecture 3 (2018): https://youtu.be/-3LgL3NXLtI

Approach 1 – Sharing parameters to tie them together



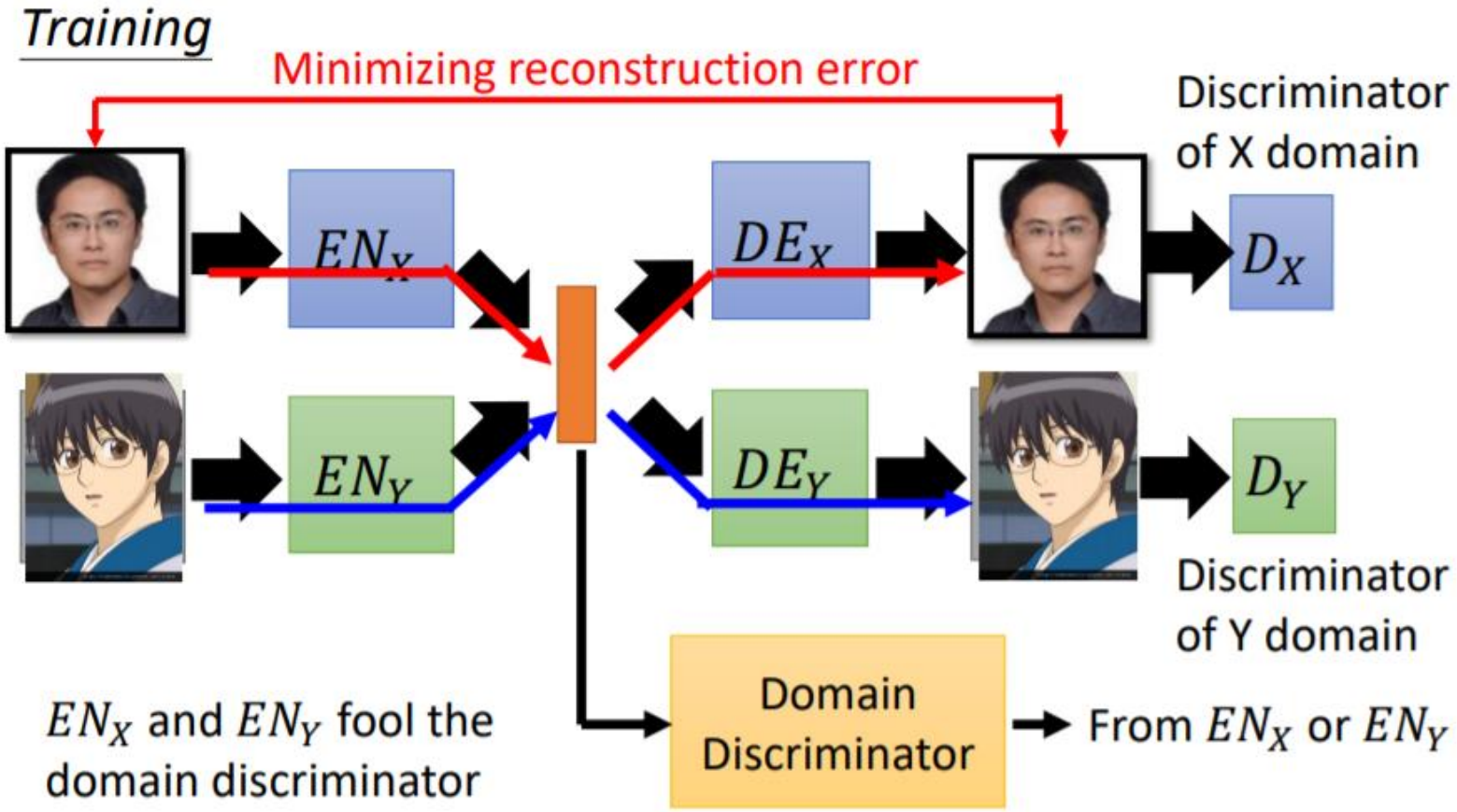
Sharing the parameters of encoders and decoders

Couple GAN [Ming-Yu Liu, et al., NIPS, 2016]

UNIT [Ming-Yu Liu, et al., NIPS, 2017]

Reference: 李弘毅 GAN Lecture 3 (2018): https://youtu.be/-3LgL3NXLtI

Approach 2 – domain discriminator



The domain discriminator forces the output of EN_X and EN_Y have the same distribution. [Guillaume Lample, et al., NIPS, 2017]

Reference: 李弘毅 GAN Lecture 3 (2018): https://youtu.be/-3LgL3NXLtI