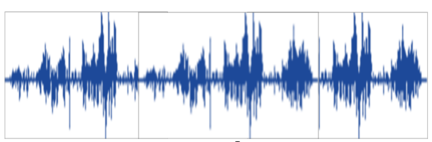
Unsupervised Conditional Generation

Unsupervised Conditional Generation

Domain X  Domain Y

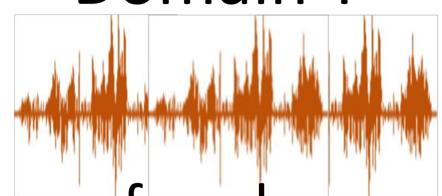
Transform an object from one domain to another ***without paired data*** (e.g. style transfer)

Domain X



male

Domain Y



female

Domain X	Domain Y
It is good.	It is bad.
It's a good day.	It's a bad day.
I love you.	I don't love you.

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

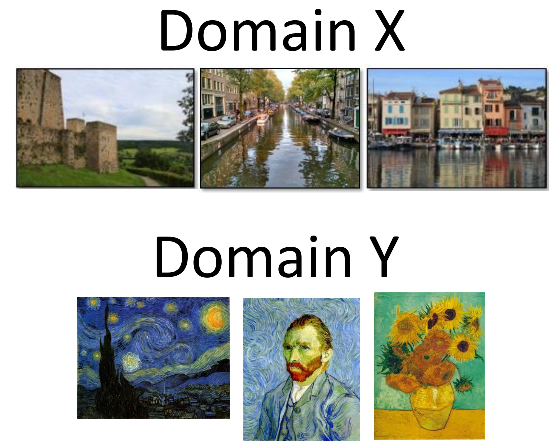
DE_Y

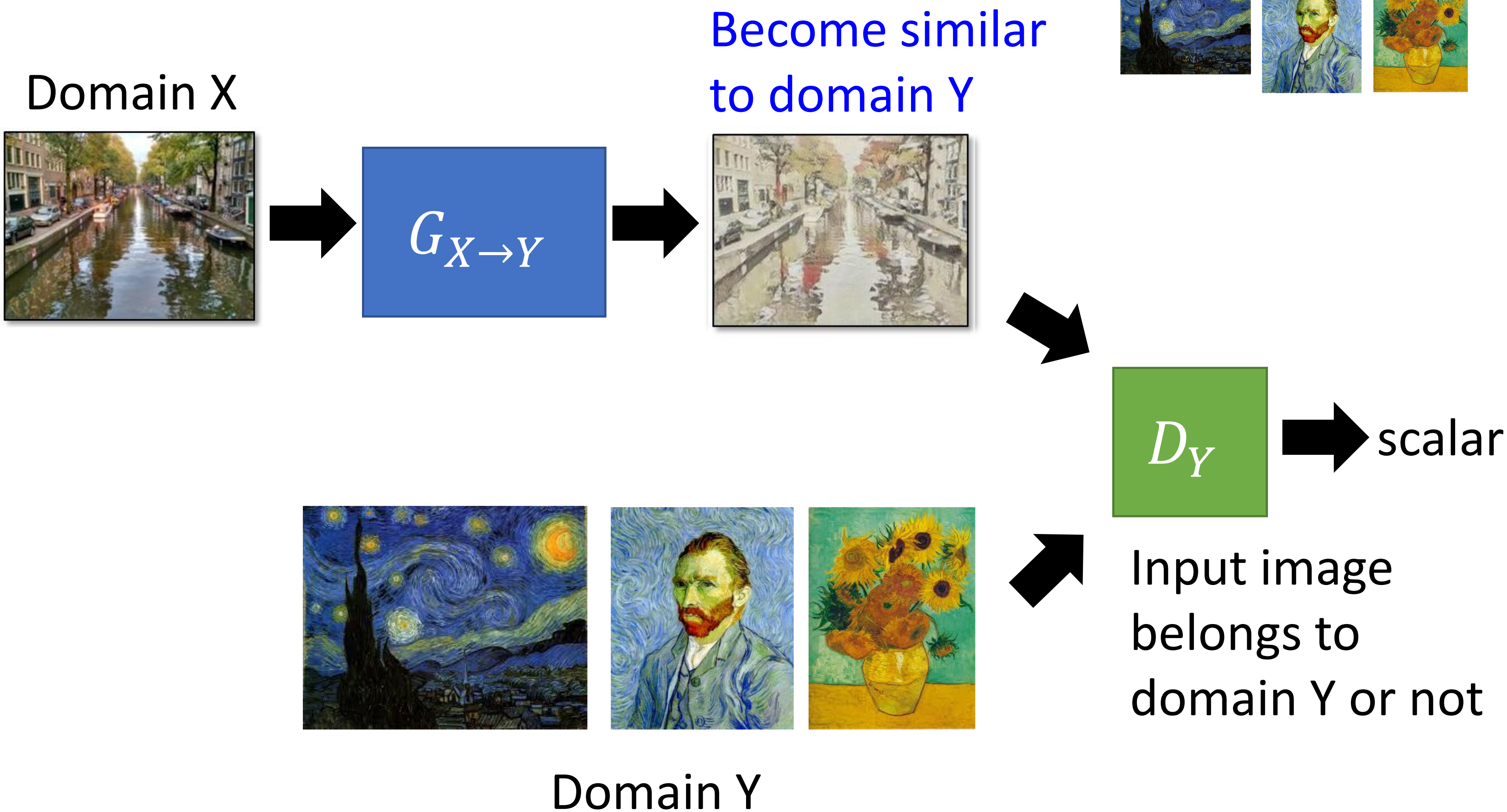
Decoder of domain Y

Domain Y

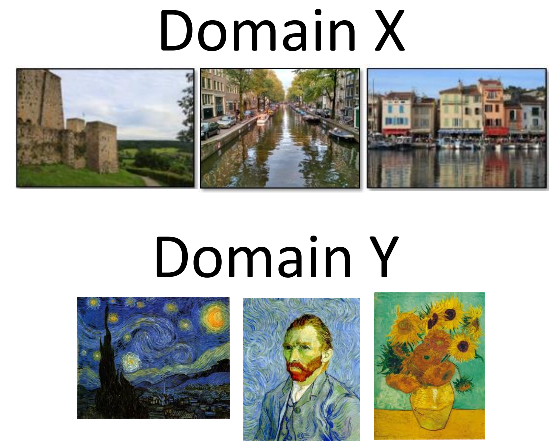
Larger change, only keep the semantics

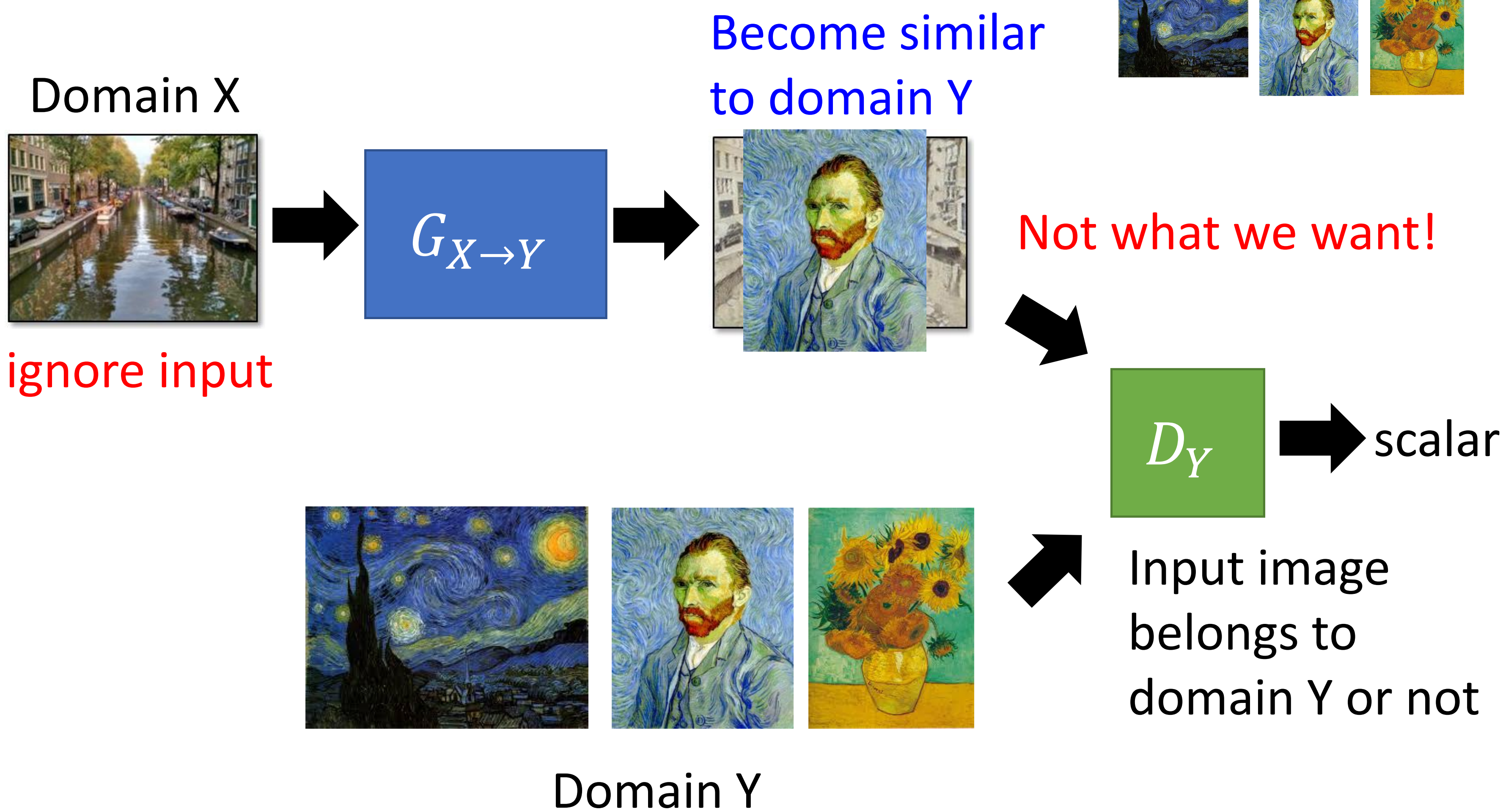
Direct Transformation





Direct Transformation





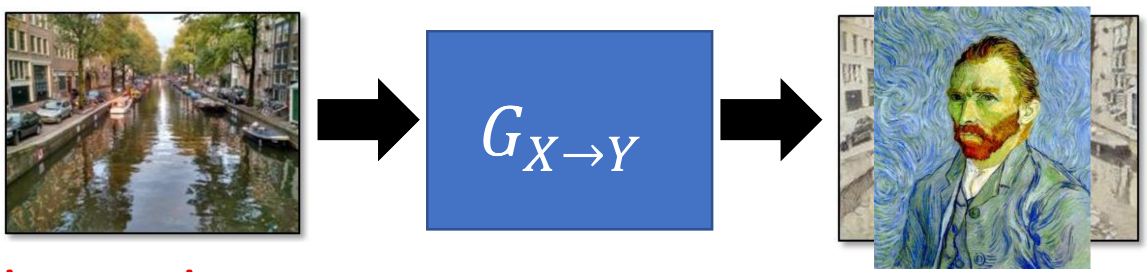
Direct Transformation

Domain X

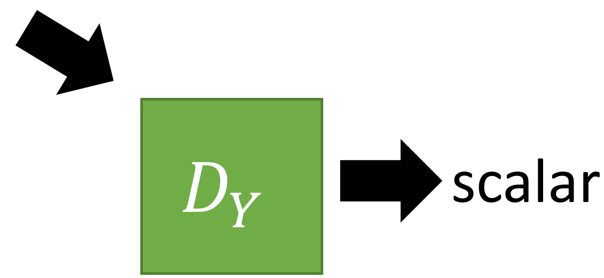
Domain Y

Become similar to domain Y

Domain X



Not what we want!



ignore input

仅仅准备两个域的图像，经过 generator 可能生成与输入完全不相关的输出

The issue can be avoided by network design.

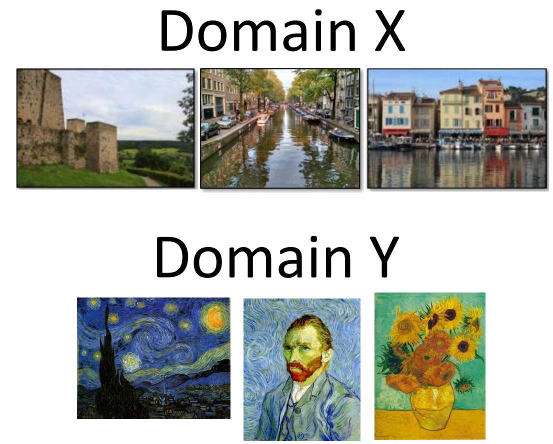
Simpler generator makes the input and output more closely related.

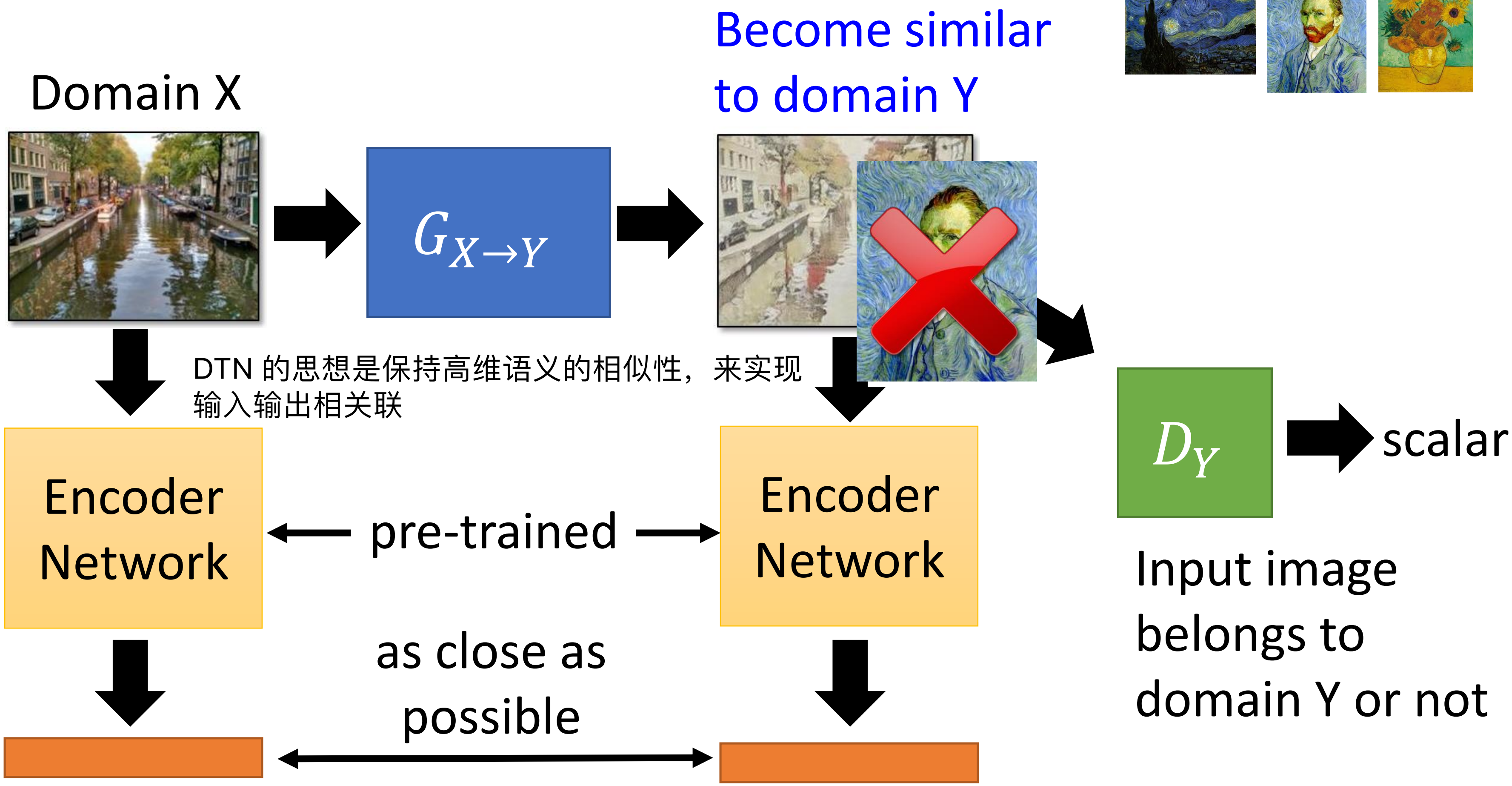
浅层网络相关性更强，深层网络则相反

Input image belongs to domain Y or not

[Tomer Galanti, et al. ICLR, 2018]

Direct Transformation



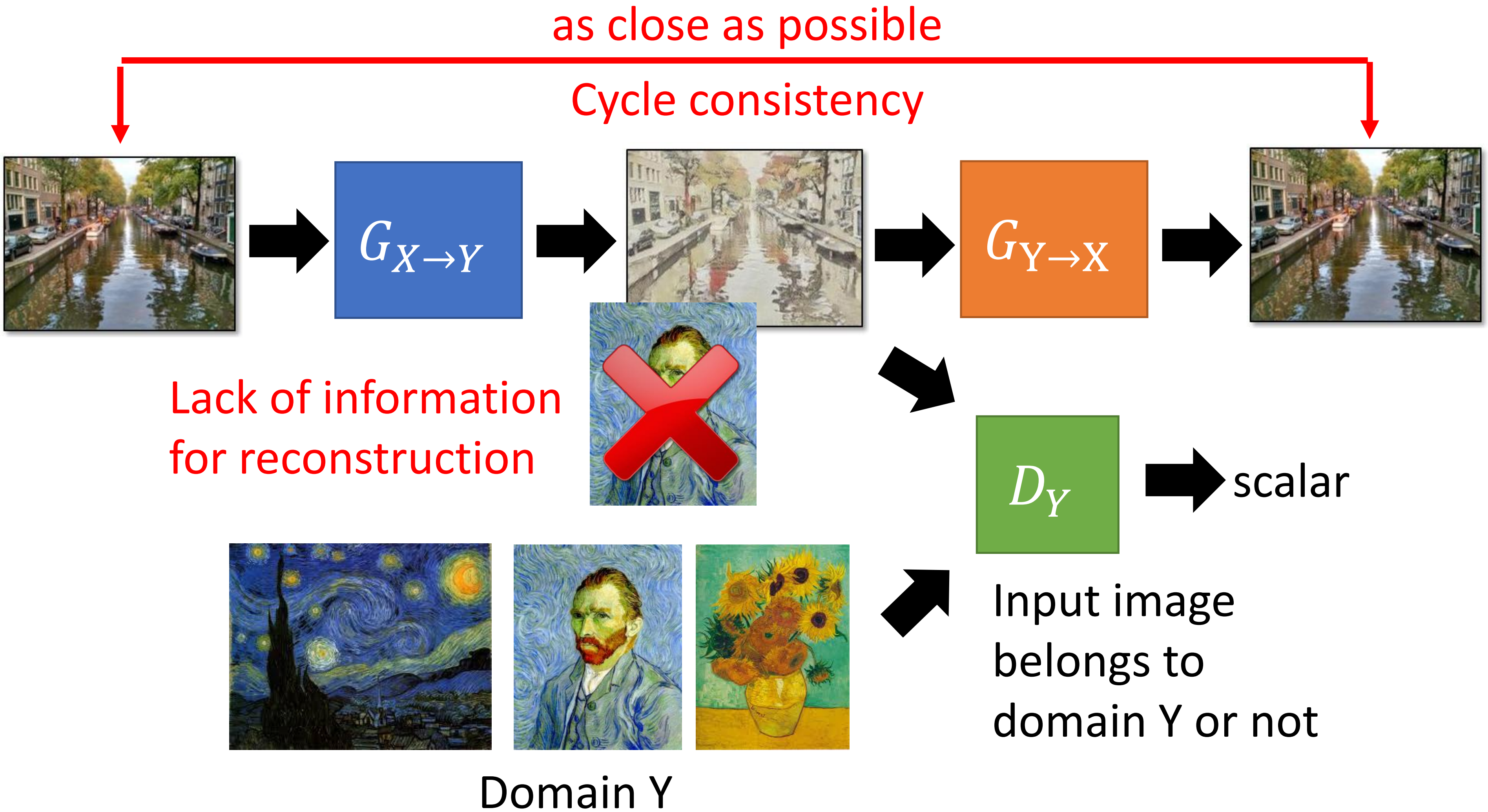


Baseline of DTN [Yaniv Taigman, et al., ICLR, 2017]

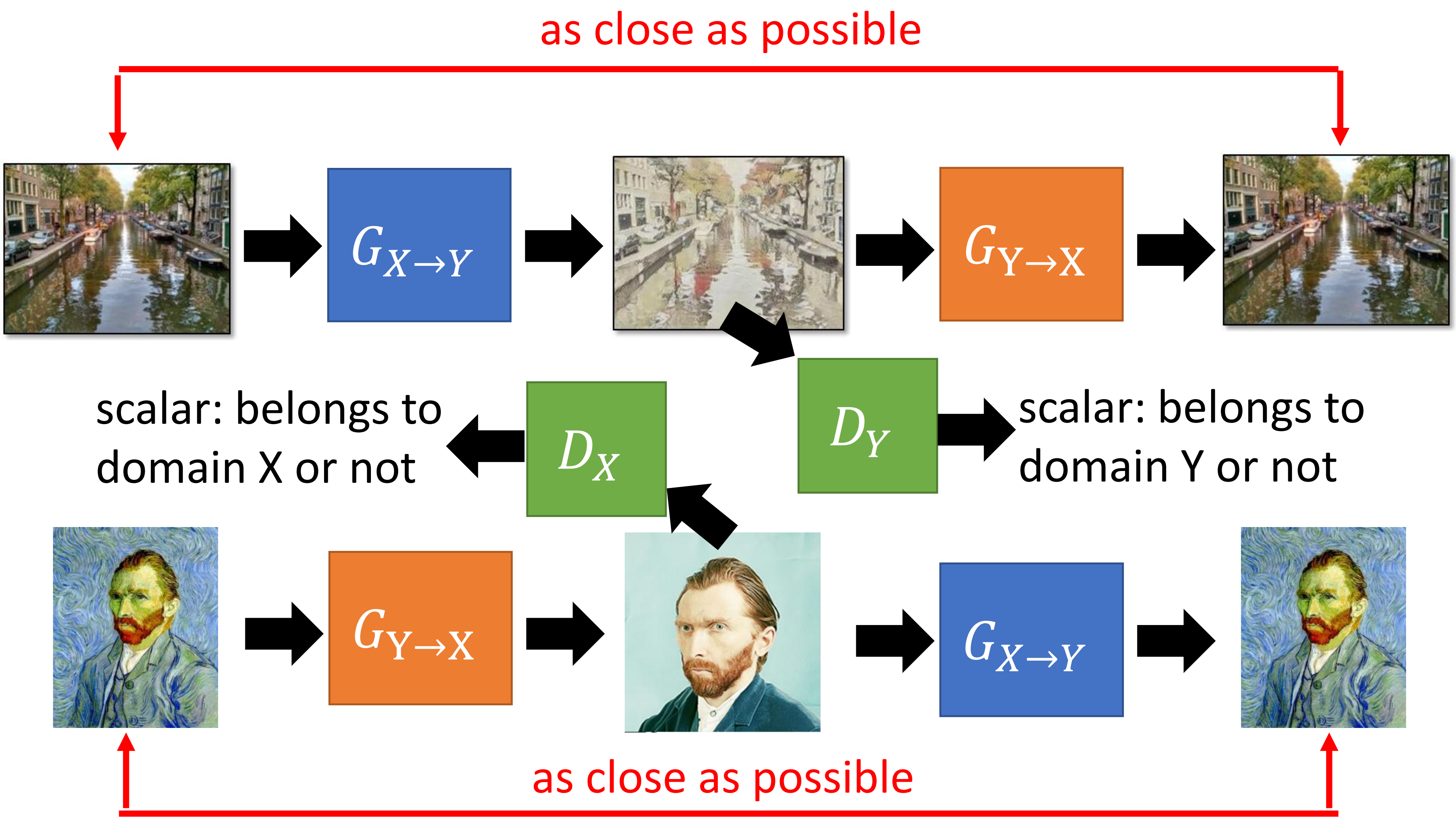
[Jun-Yan Zhu, et al., ICCV, 2017]

Direct Transformation

构建两个生成器，实现循环一致性

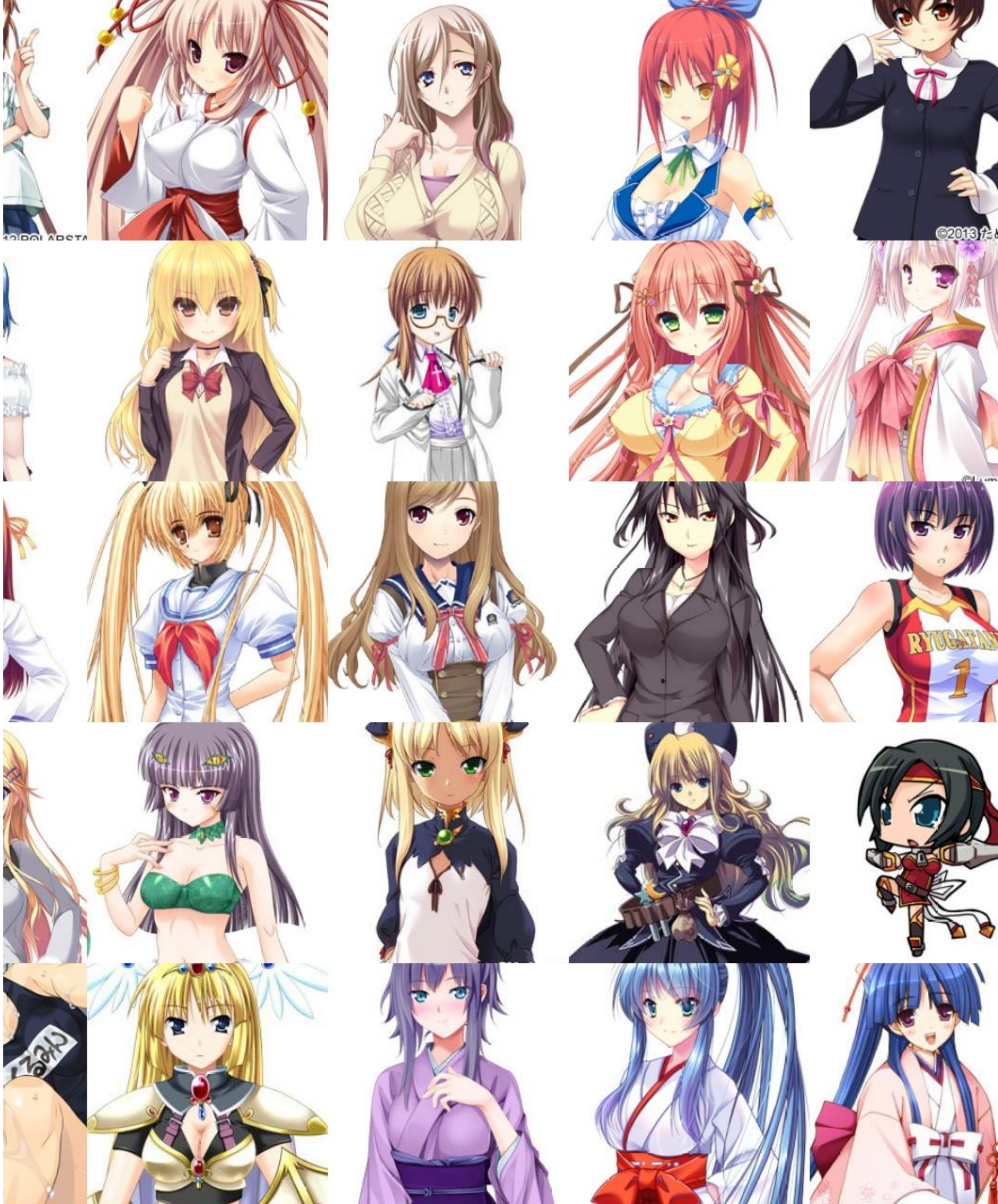


Direct Transformation



Cycle GAN – Silver Hair

- https://github.com/Aixile/chainer-cyclegan



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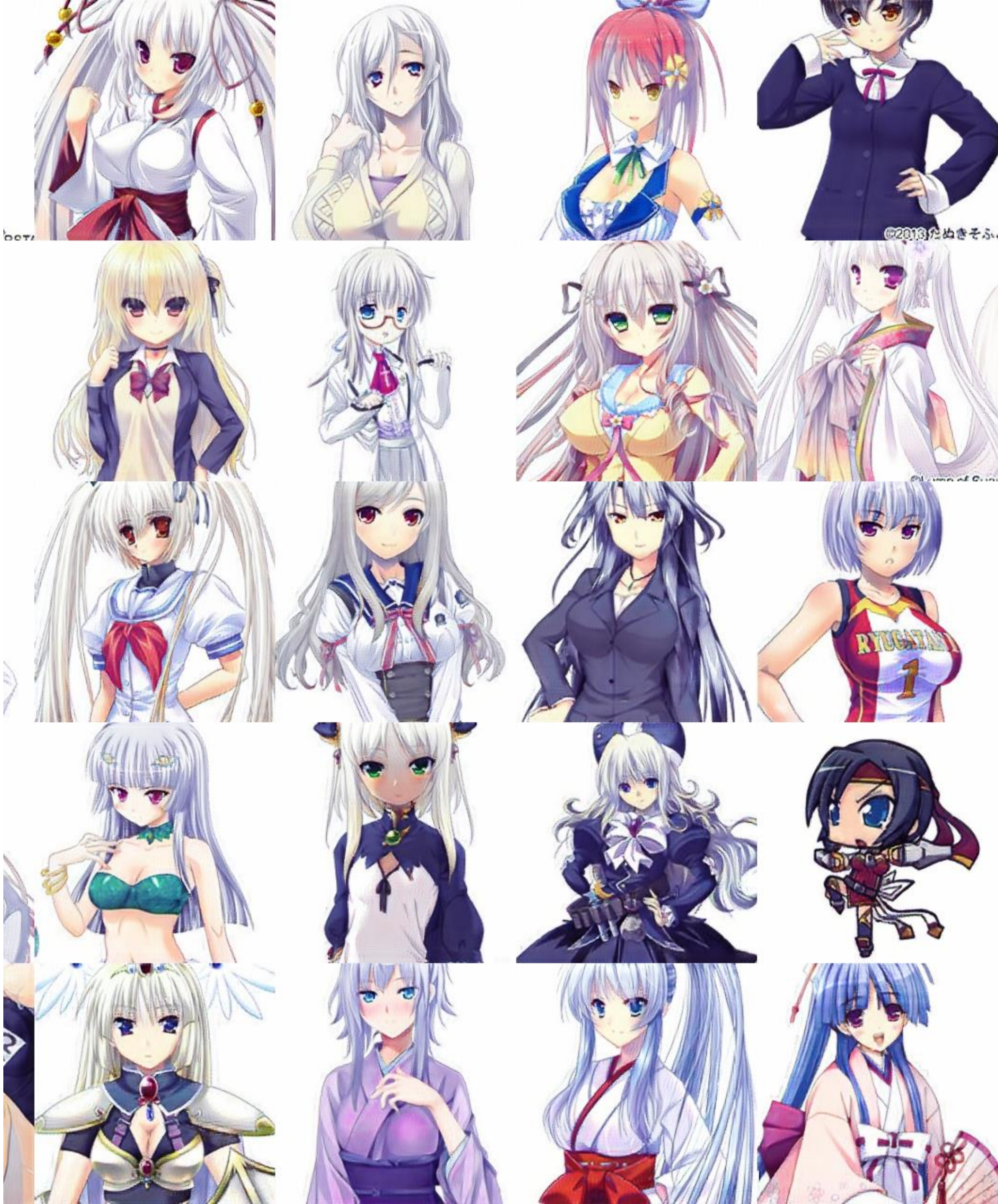
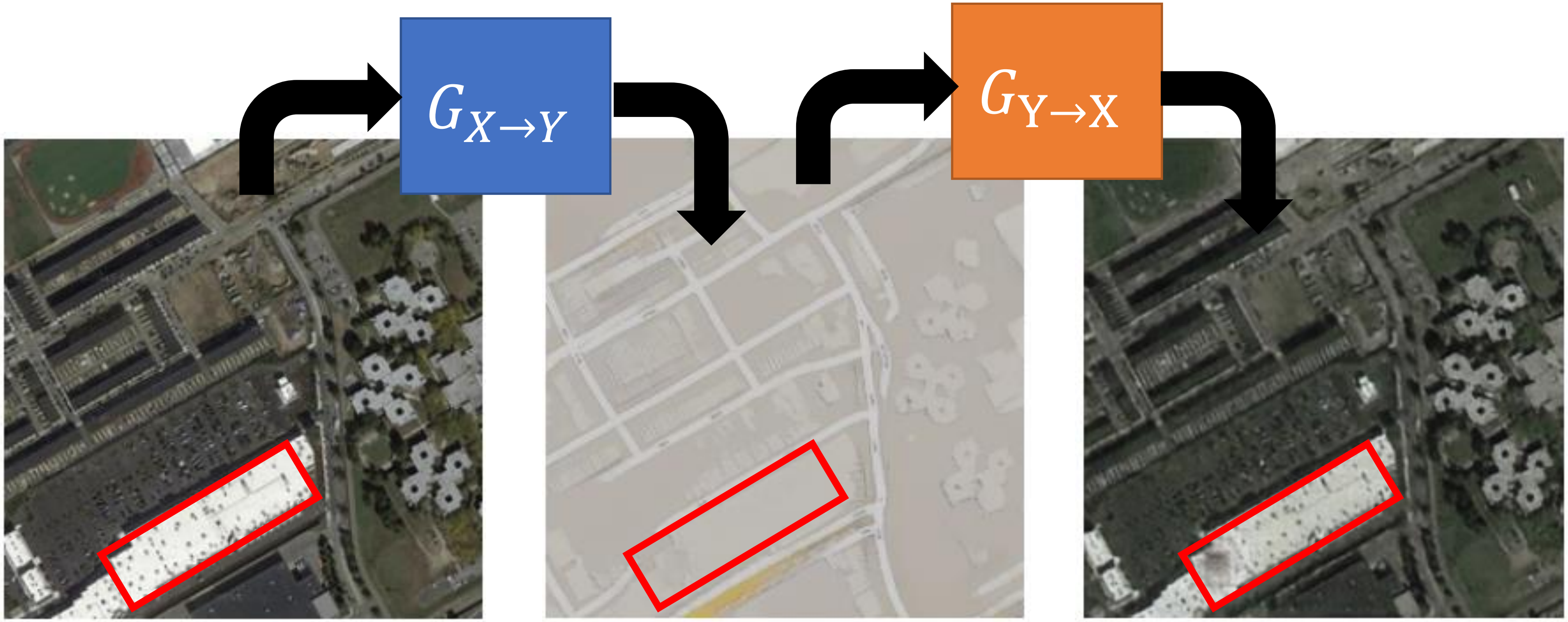


Issue of Cycle Consistency

循环一致性的潜在问题是 输入输出的很多细节被隐藏的
隐变量空间，语义不够丰富

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

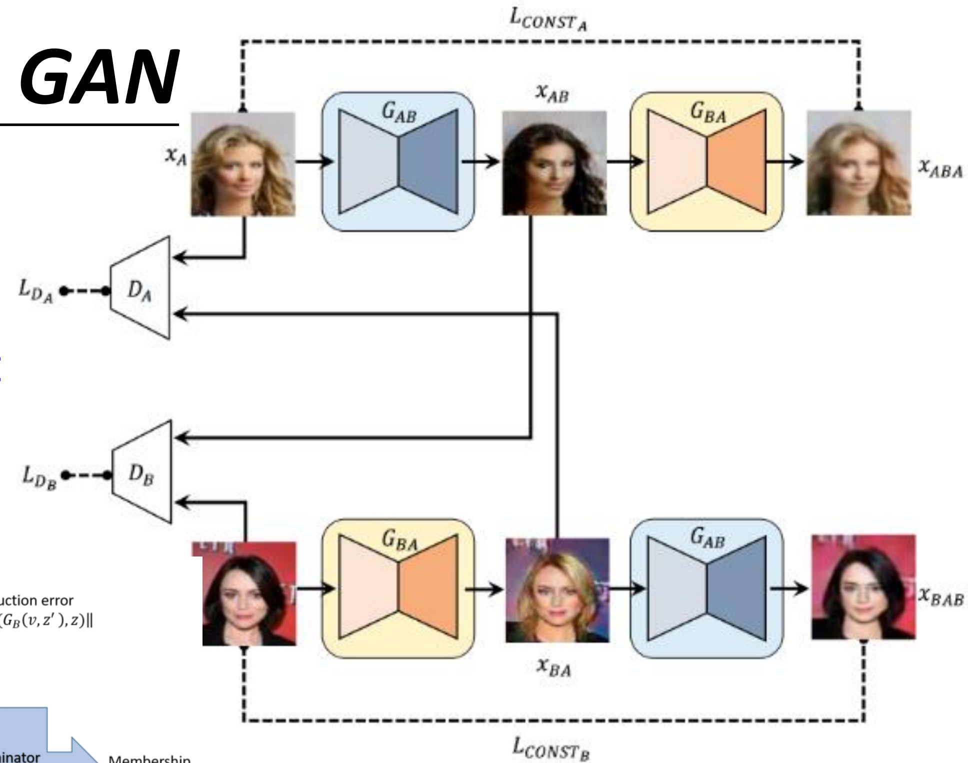
[Casey Chu, et al., NIPS workshop, 2017]



The information is hidden.

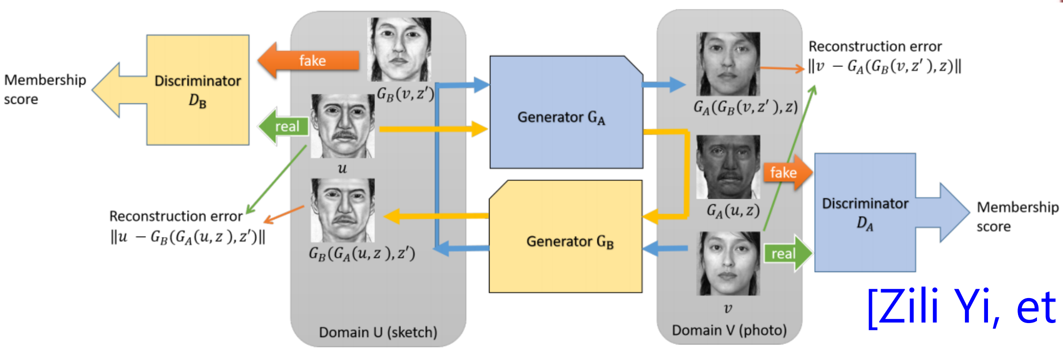
三种思路一致的网络

Disco GAN



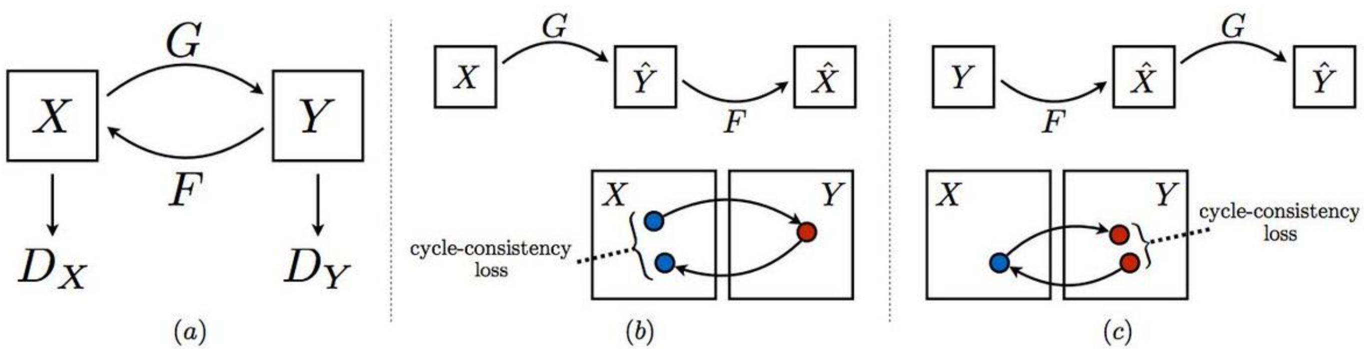
[Taeksoo Kim, et al., ICML, 2017]

Dual GAN



[Zili Yi, et al., ICCV, 2017]

Cycle GAN

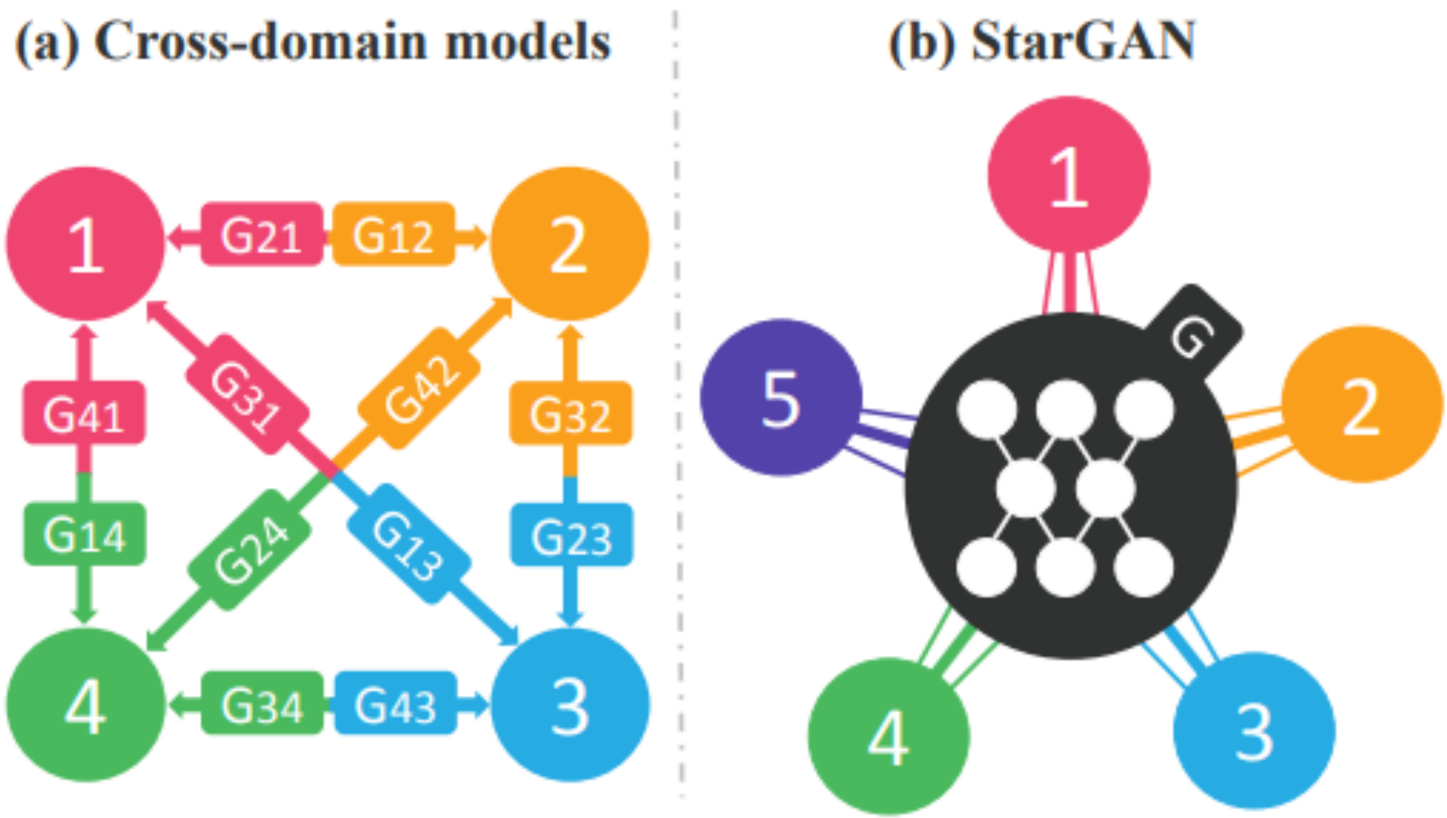


[Jun-Yan Zhu, et al., ICCV, 2017]

StarGAN

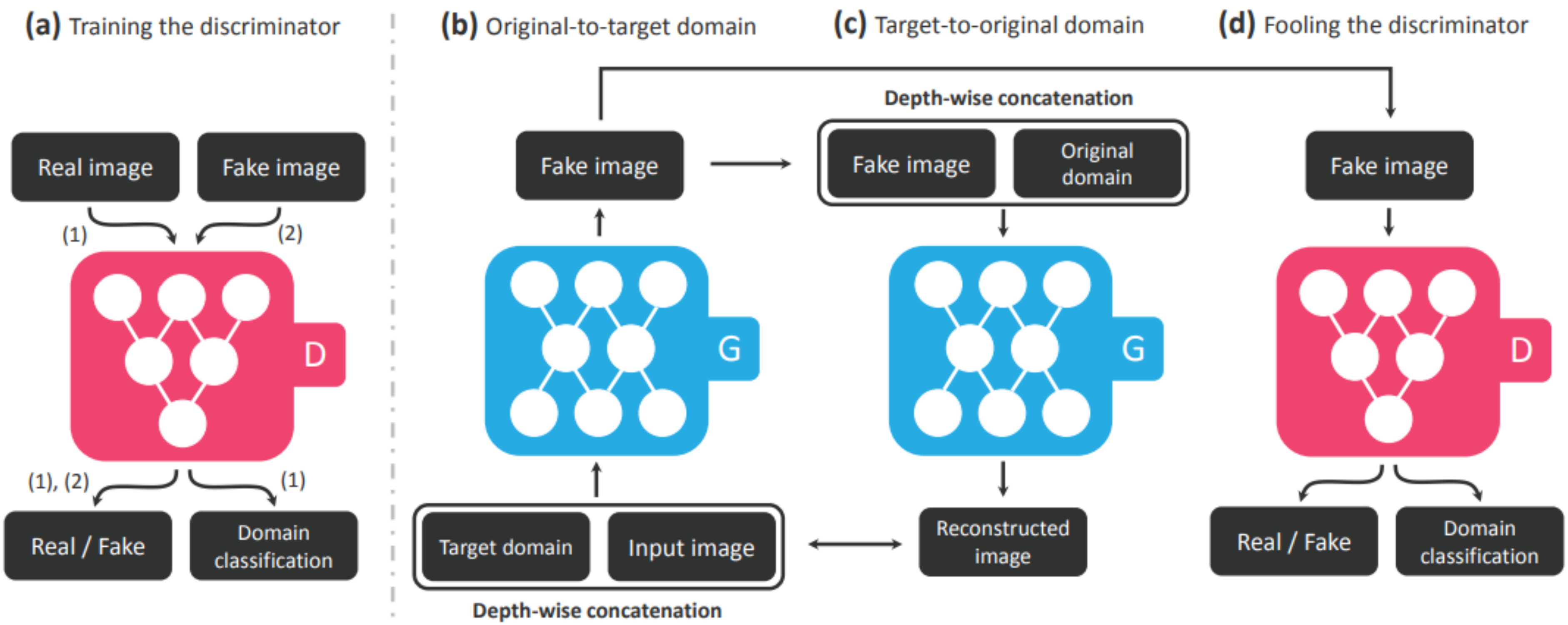
For multiple domains, considering starGAN

[Yunjey Choi, arXiv, 2017]

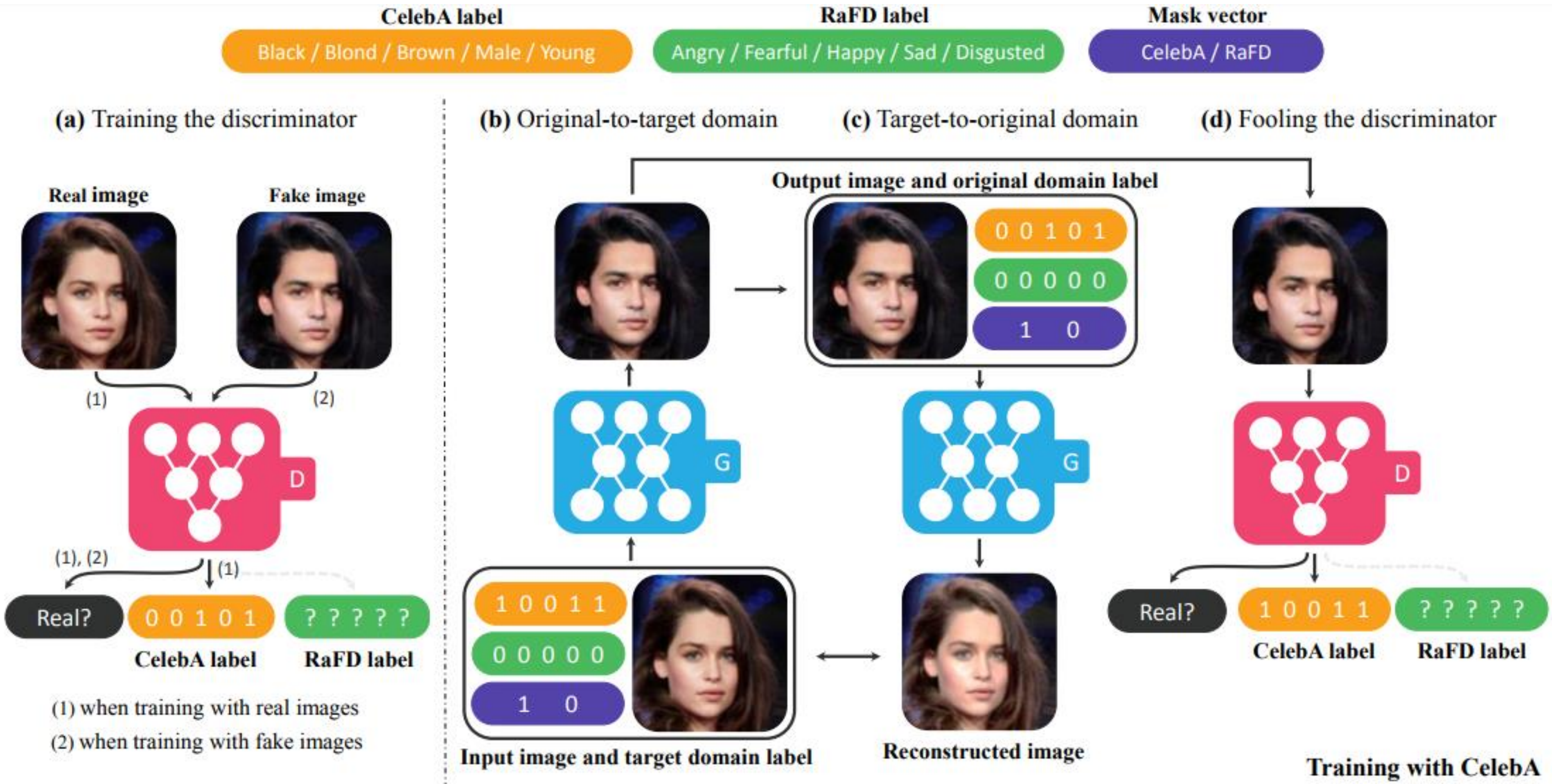


StarGAN

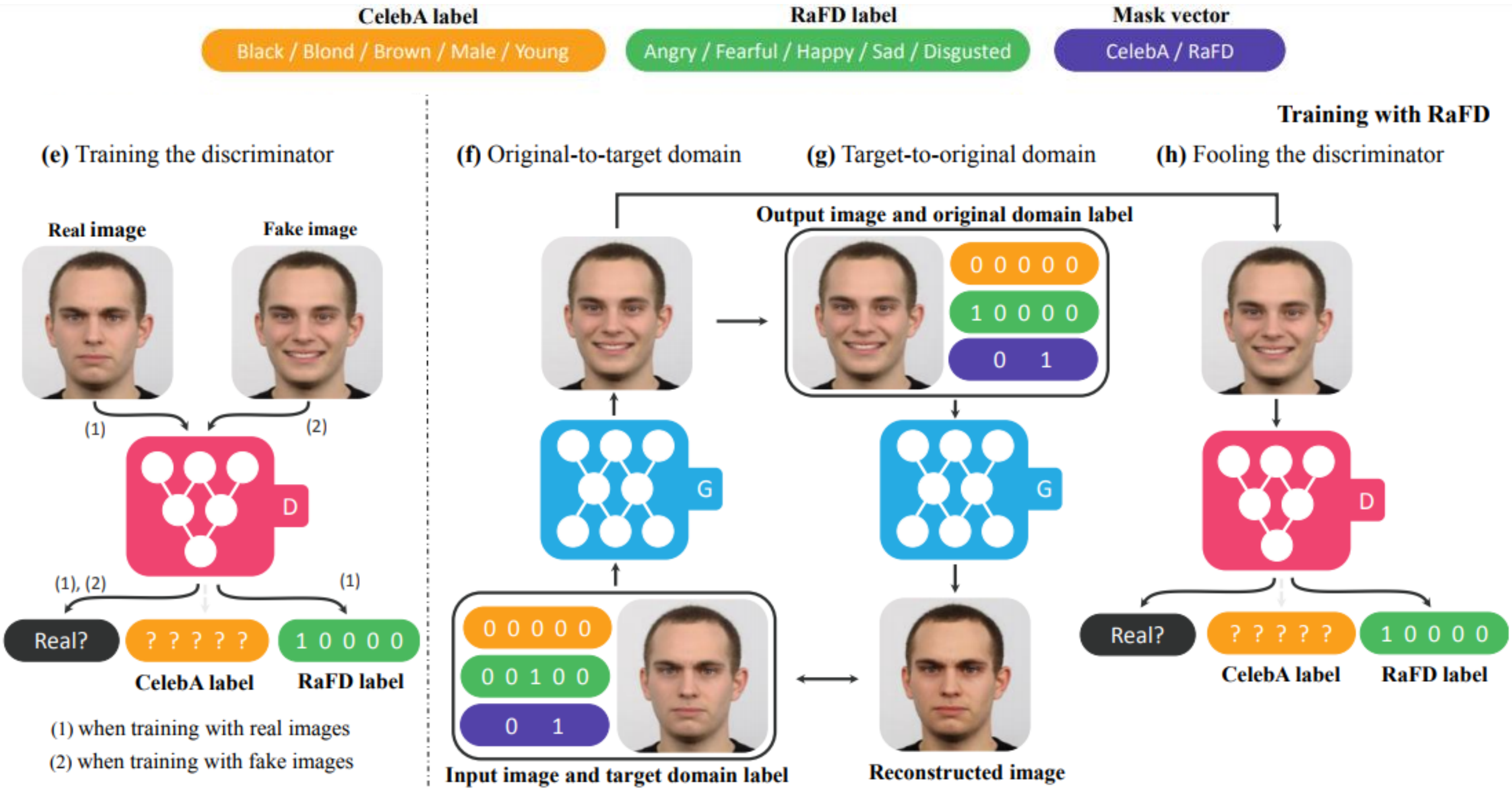
stargan 的核心思想是，将 domain 也作为输入向量，从而实现单个 generator
能够实现多个域的转换，并在基础上增加判别器的判断



StarGAN


CelebA label
Black / Blond / Brown / Male / Young
RaFD label
Angry / Fearful / Happy / Sad / Disgusted
Mask vector
CelebA / RaFD
(a) Training the discriminator
(b) Original-to-target domain
(c) Target-to-original domain
(d) Fooling the discriminator
Real image
Fake image
(1)
(2)
D
(1), (2)
(1)
Real?
0 0 1 0 1
? ? ? ? ?
CelebA label
RaFD label
(1) when training with real images
(2) when training with fake images
Output image and original domain label
0 0 1 0 1
0 0 0 0 0
1 0
G
G
1 0 0 1 1
0 0 0 0 0
1 0
Input image and target domain label
Reconstructed image
D
Real?
1 0 0 1 1
? ? ? ? ?
CelebA label
RaFD label
Training with CelebA

StarGAN



CelebA label
Black / Blond / Brown / Male / Young
RaFD label
Angry / Fearful / Happy / Sad / Disgusted
Mask vector
CelebA / RaFD
Training with RaFD
(e) Training the discriminator
(f) Original-to-target domain
(g) Target-to-original domain
(h) Fooling the discriminator
Real image
Fake image
(1)
(2)
D
(1), (2)
(1)
Real?
? ? ? ? ?
1 0 0 0 0
CelebA label
RaFD label
(1) when training with real images
(2) when training with fake images
Output image and original domain label
0 0 0 0 0
1 0 0 0 0
0 1
G
0 0 0 0 0
0 0 1 0 0
0 1
Input image and target domain label
Reconstructed image

Unsupervised Conditional Generation

- Approach 1: Direct Transformation

Domain X

$G_{X \rightarrow Y}$

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

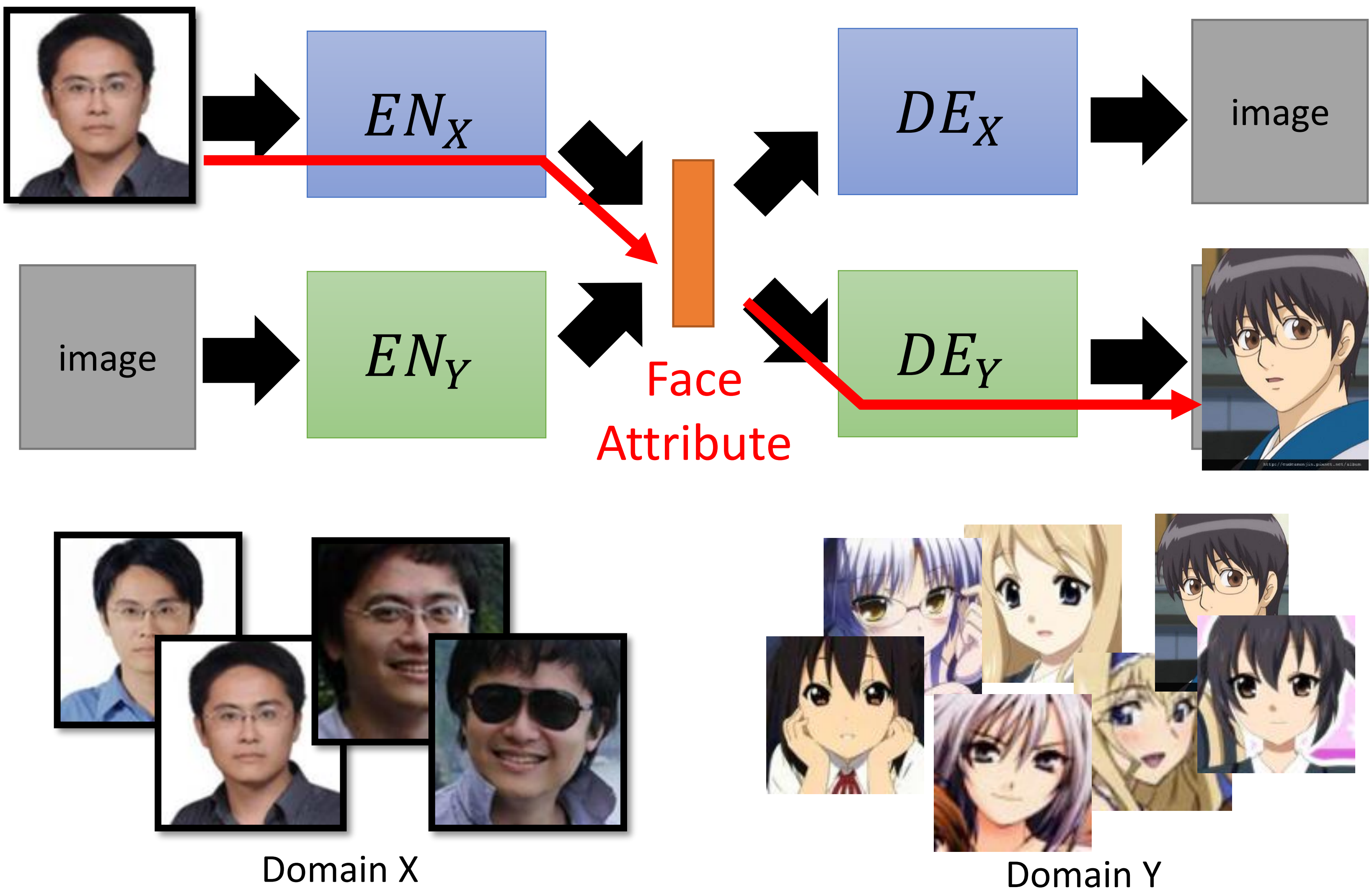
Decoder of domain Y

Domain Y

Larger change, only keep the semantics

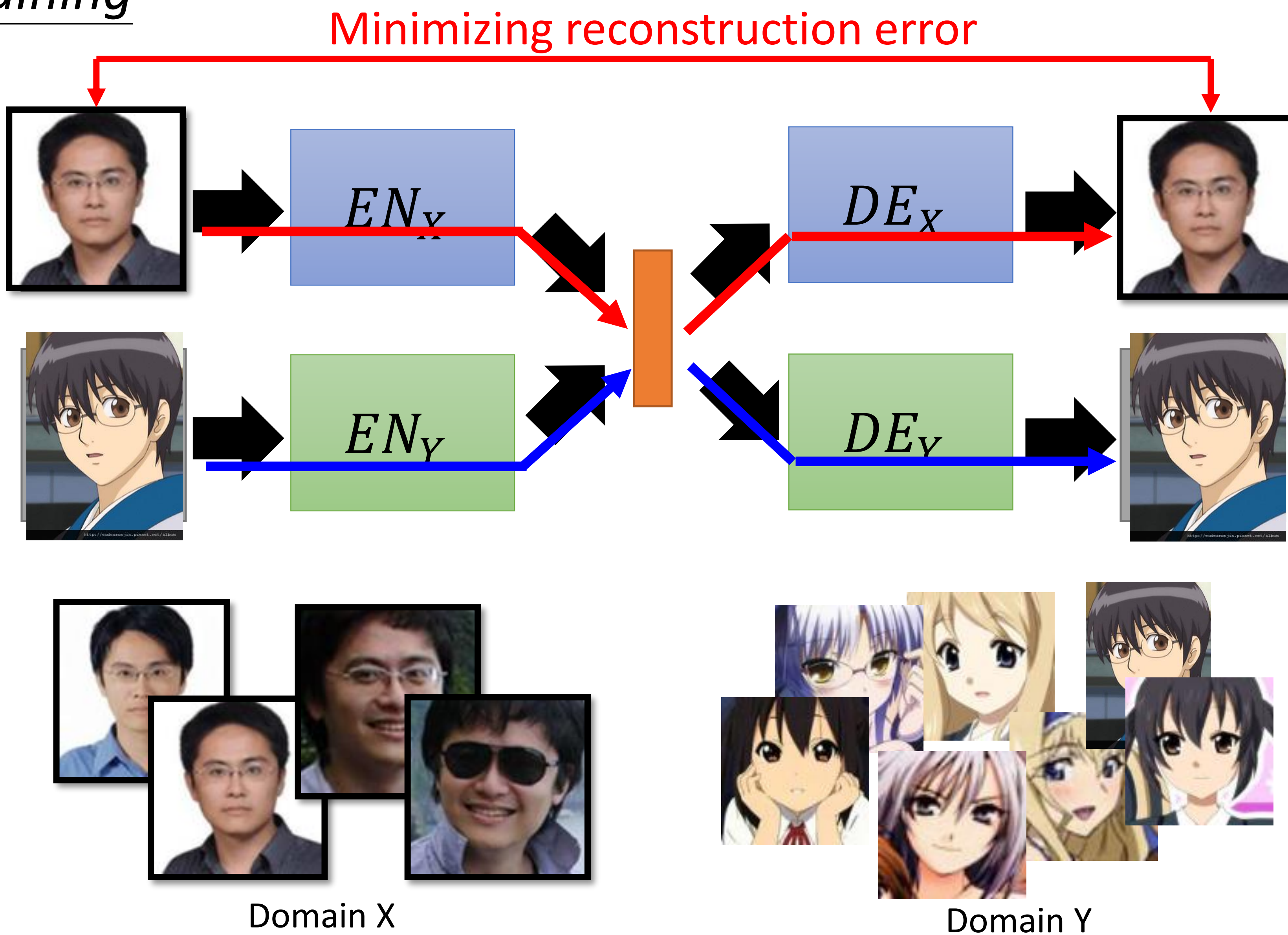
Projection to Common Space

Target



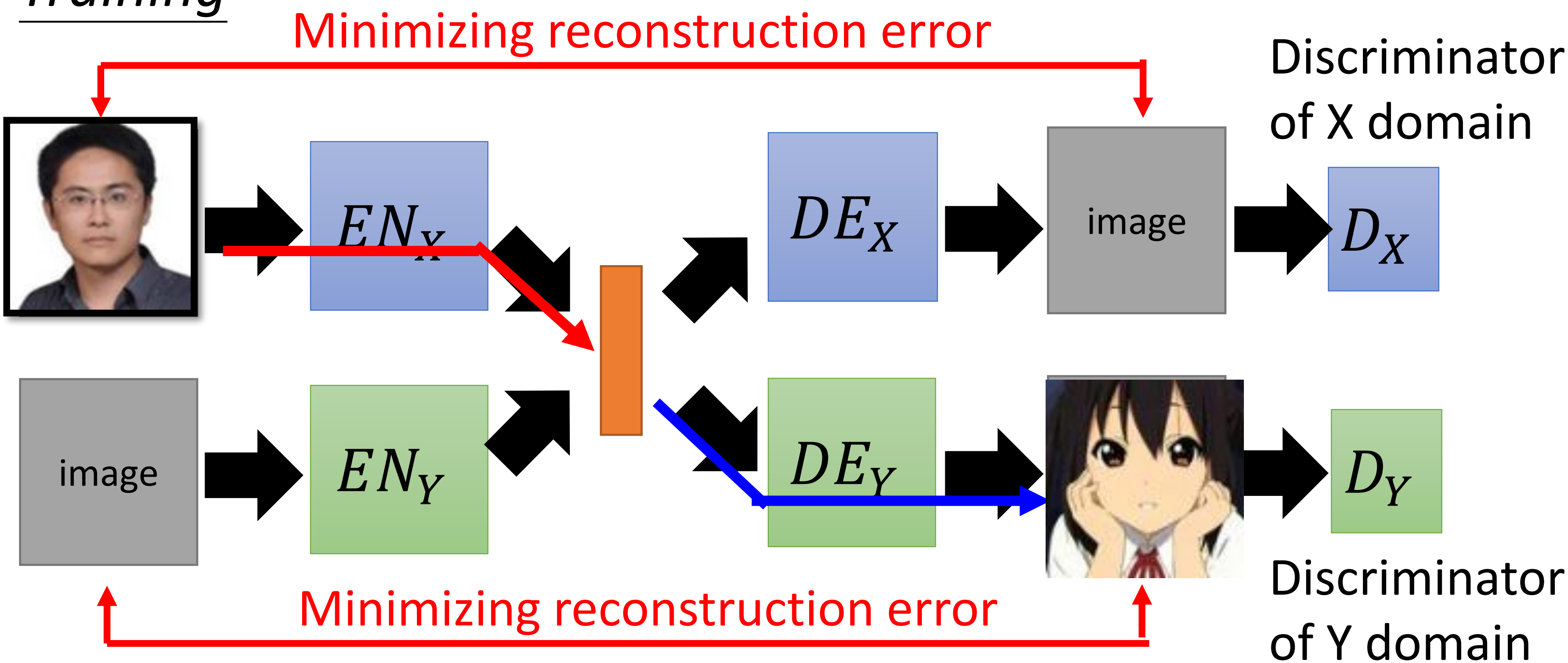
Projection to Common Space

Training



Projection to Common Space

Training

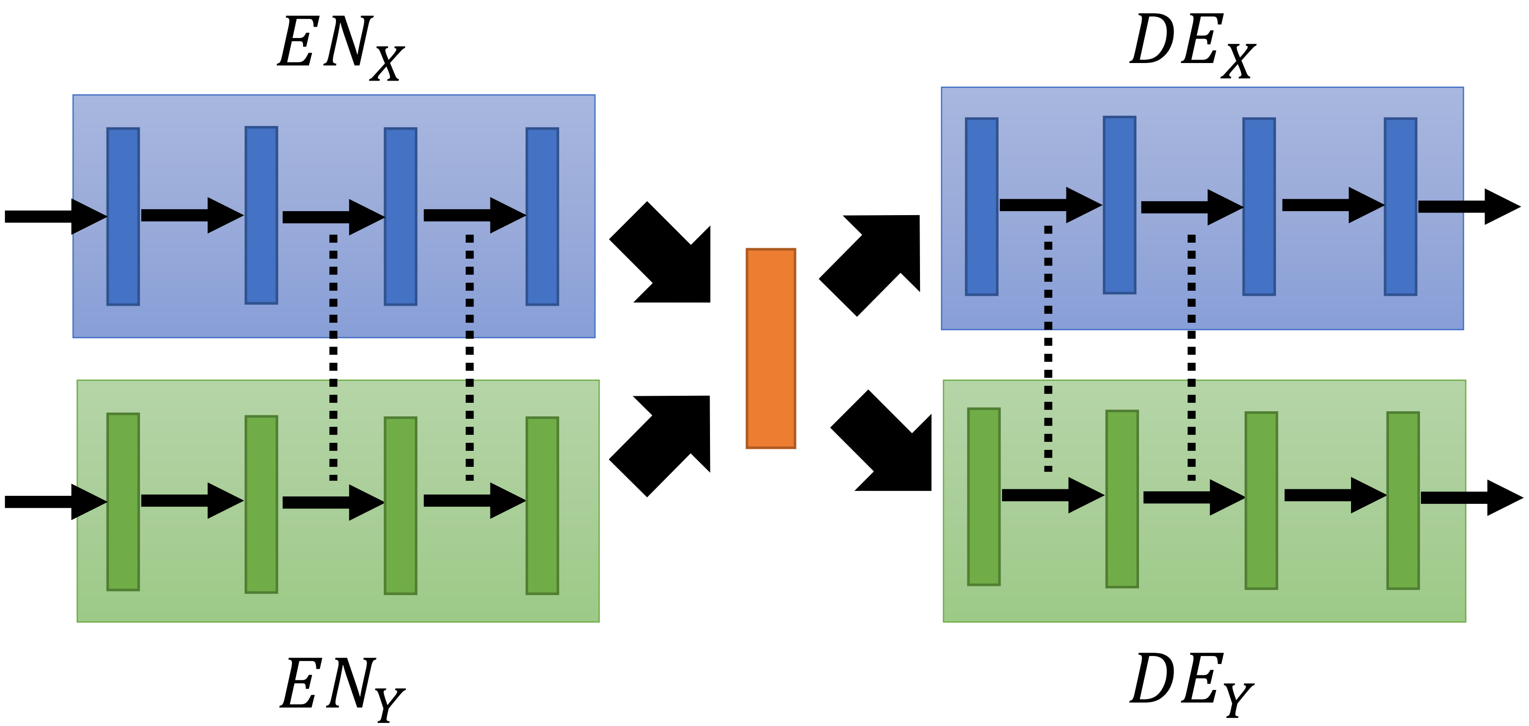


Because we train two auto-encoders separately …

The images with the same attribute may not project to the same position in the latent space.

Projection to Common Space

Training



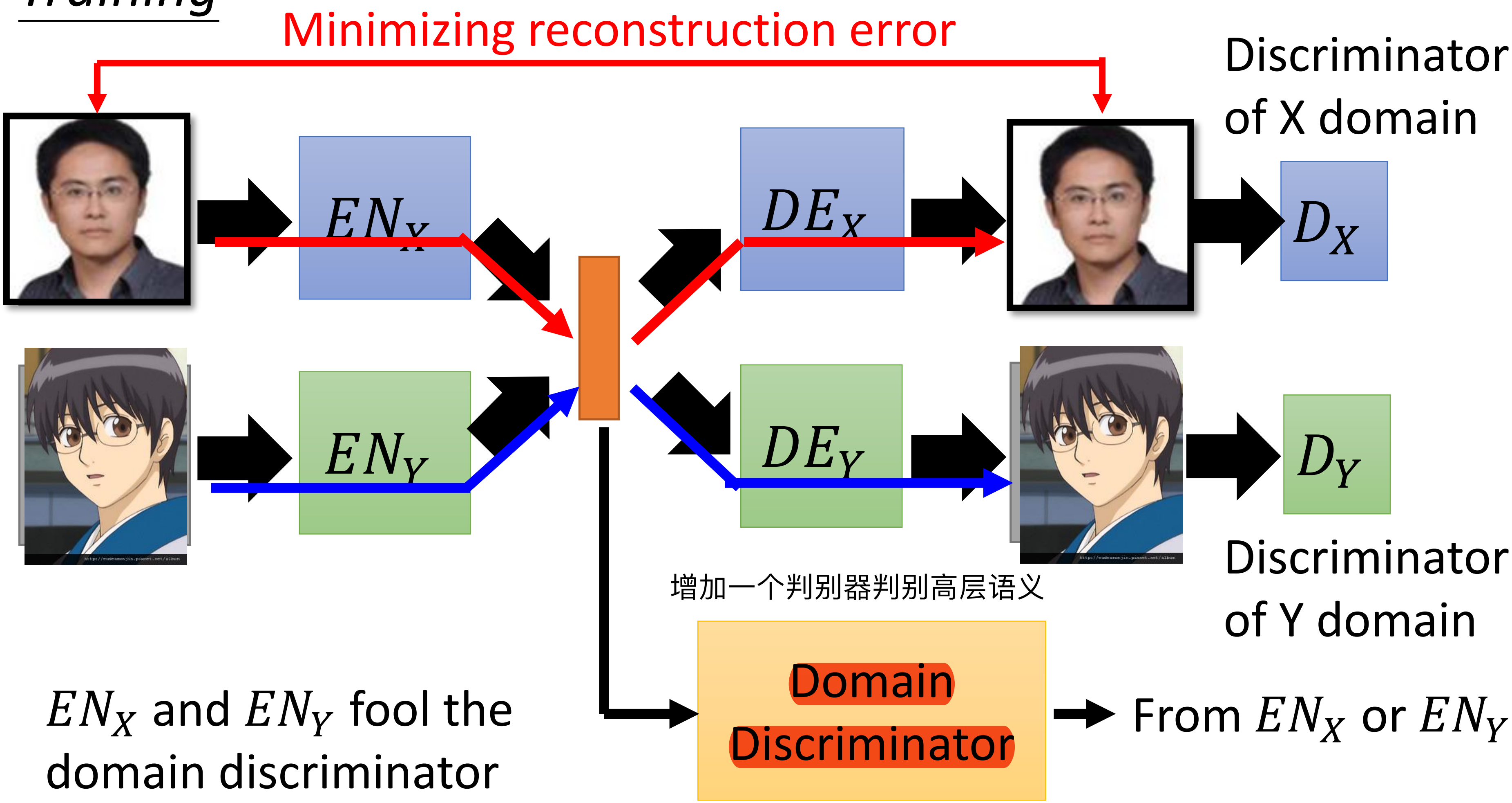
Sharing the parameters of encoders and decoders

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

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

Projection to Common Space

Training



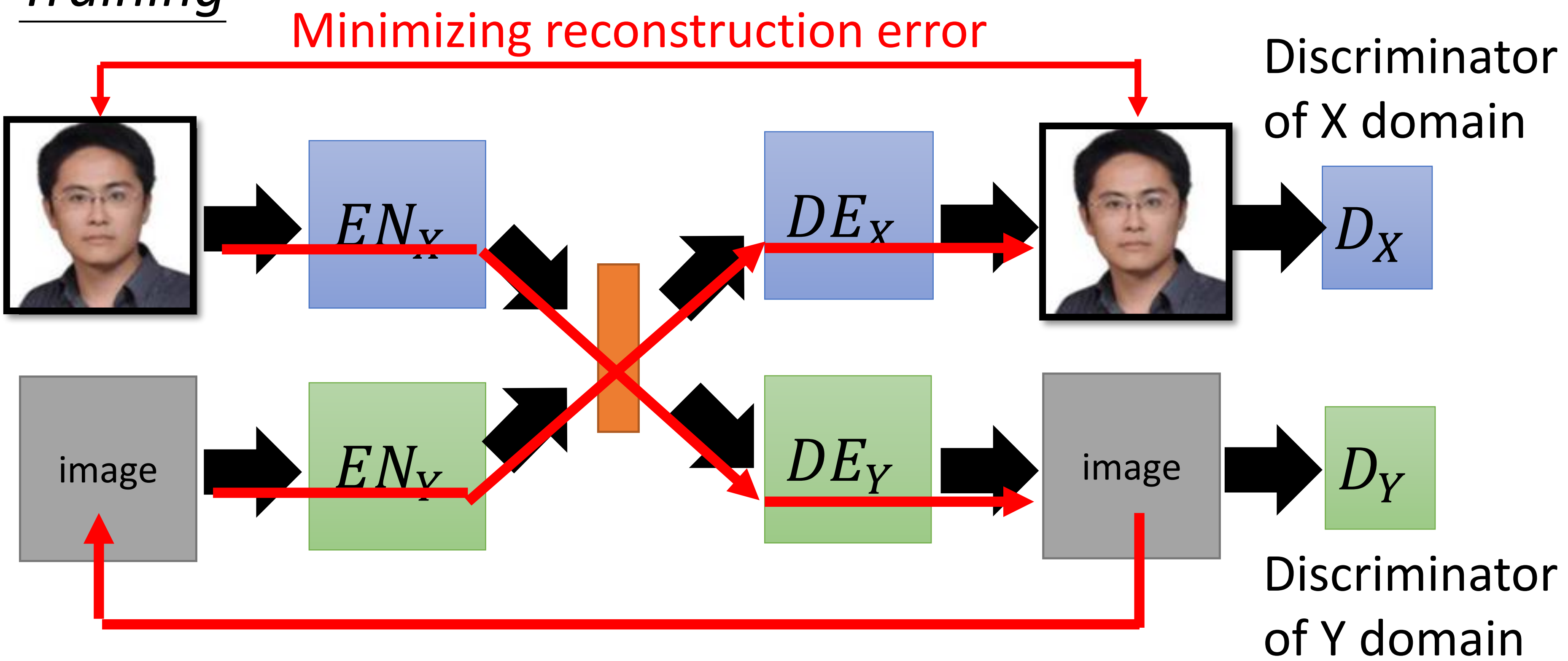
EN_X and EN_Y fool the domain discriminator

The domain discriminator forces the output of EN_X and EN_Y have the same distribution.

[Guillaume Lample, et al., NIPS, 2017]

Projection to Common Space

Training

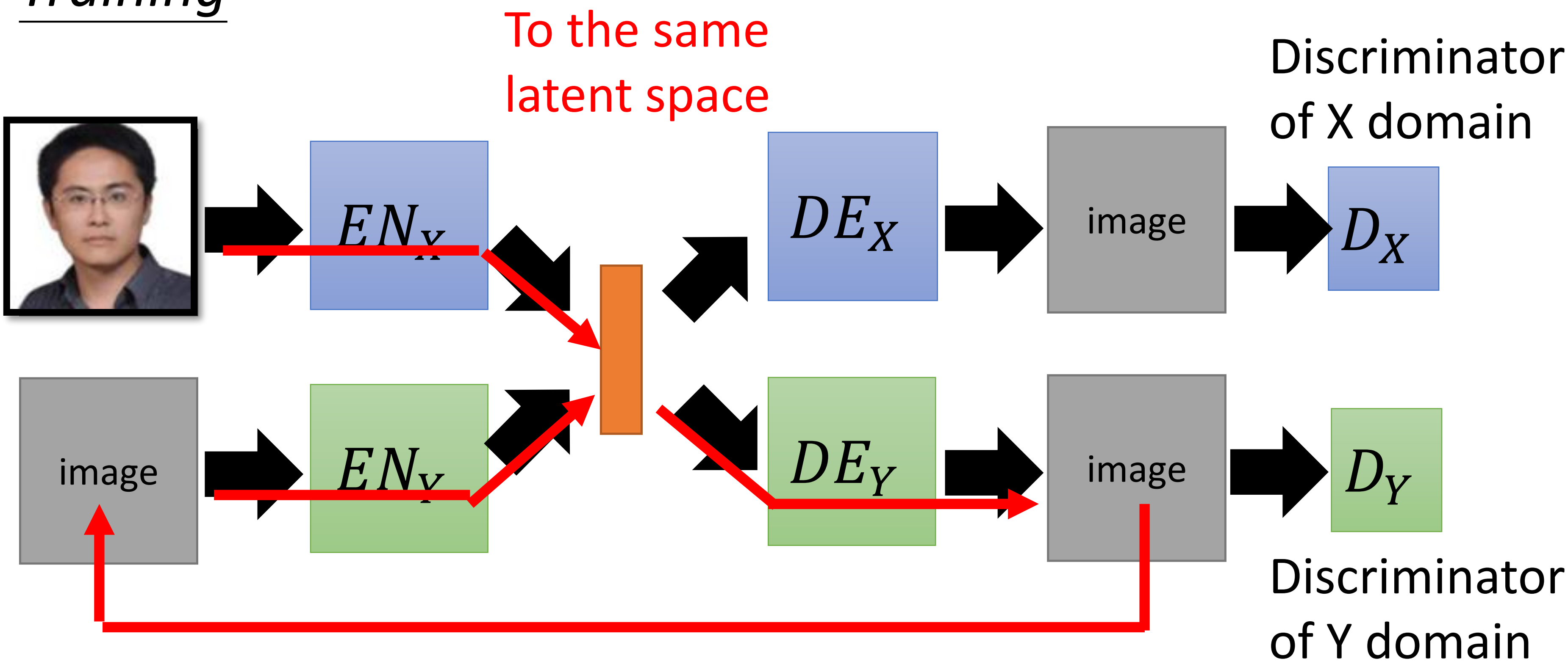


Cycle Consistency:

Used in ComboGAN [Asha Anoosheh, et al., arXiv, 017]

Projection to Common Space

Training



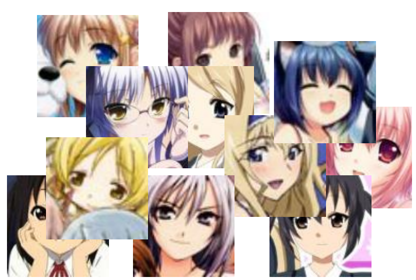
Semantic Consistency:

Used in DTN [Yaniv Taigman, et al., ICLR, 2017] and XGAN [Amélie Royer, et al., arXiv, 2017]

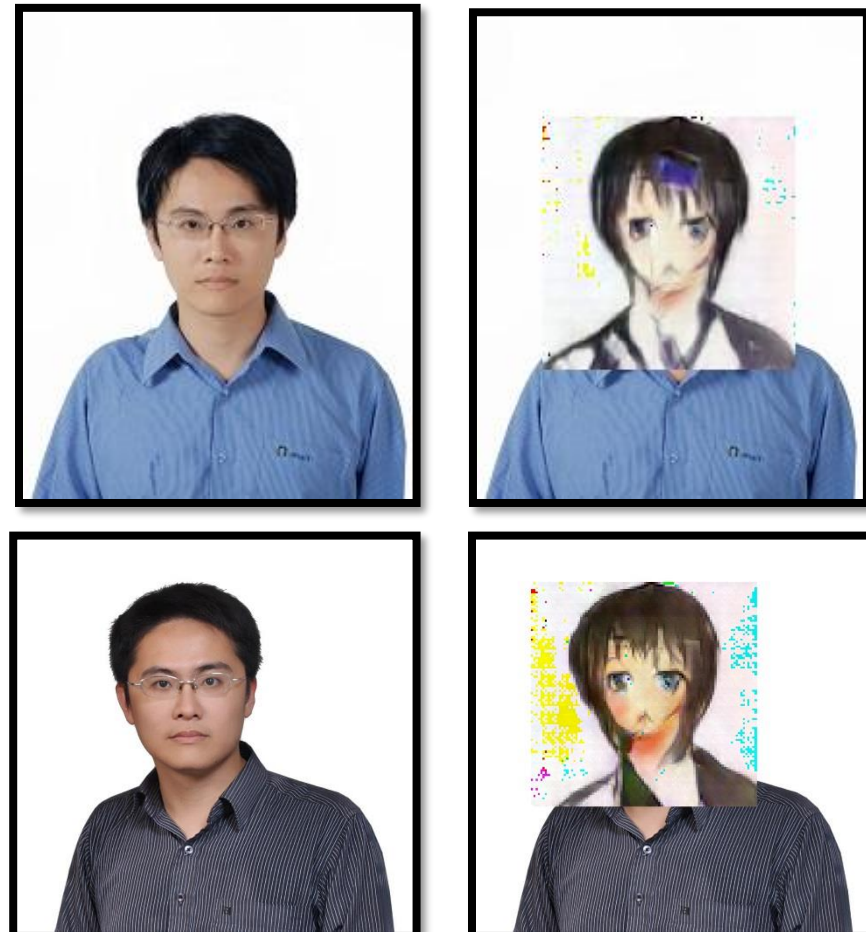
世界二次元化

- Using the code: https://github.com/Hi-king/kawaii_creator
- It is not cycle GAN, Disco GAN

input

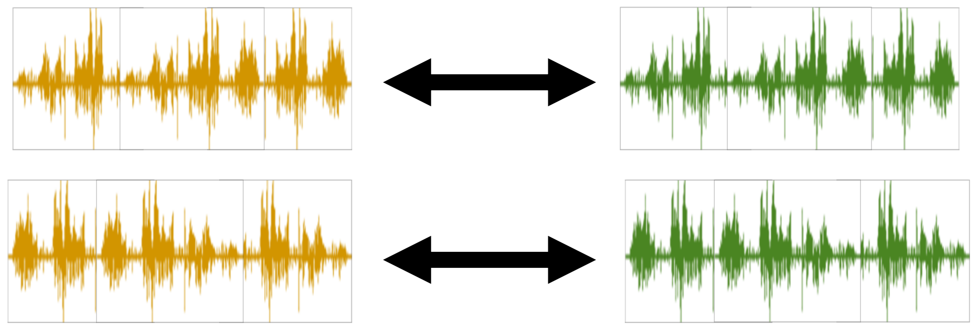


output ***domain***

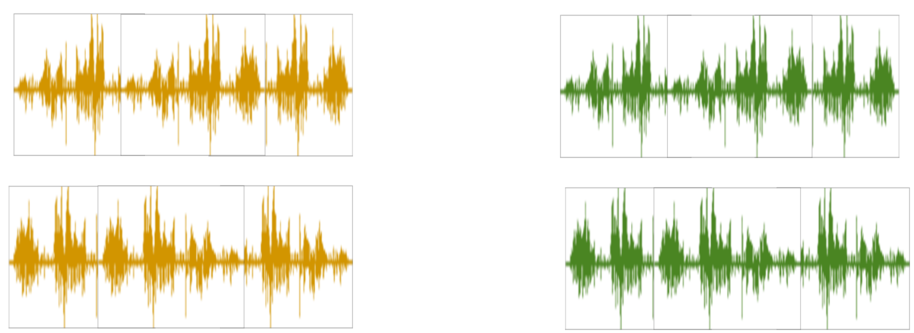


Voice Conversion

In the past



Today



Speakers A and B are talking about completely different things.

Speaker A	Speaker B
我	

感謝周儒杰同學提供實驗結果

Reference

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