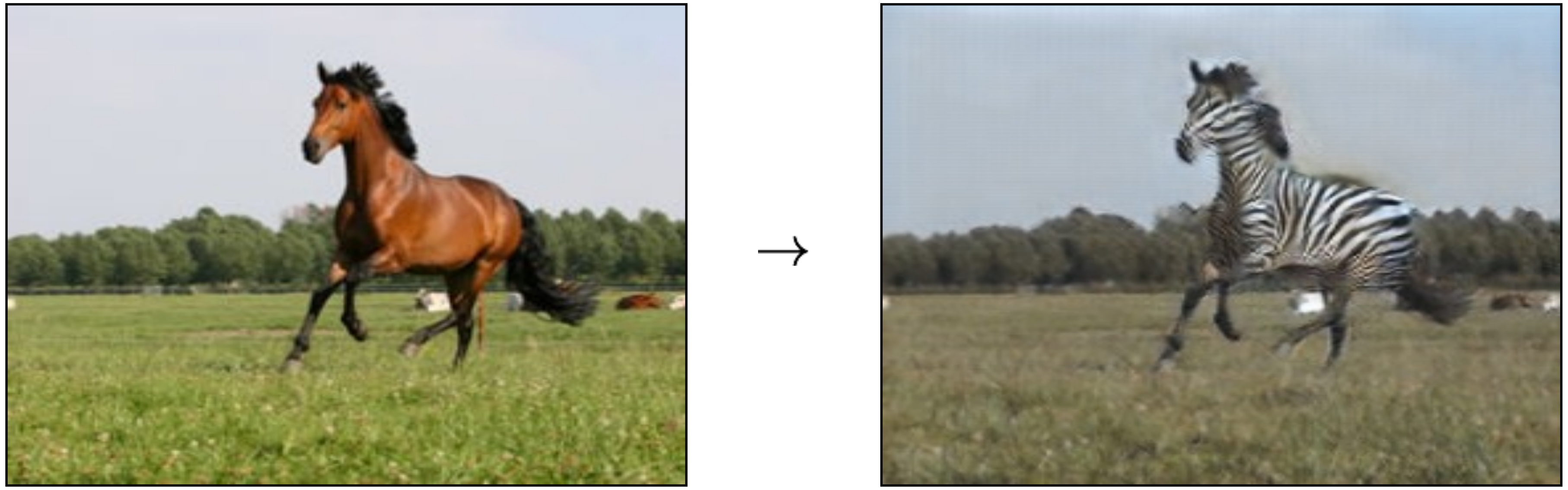
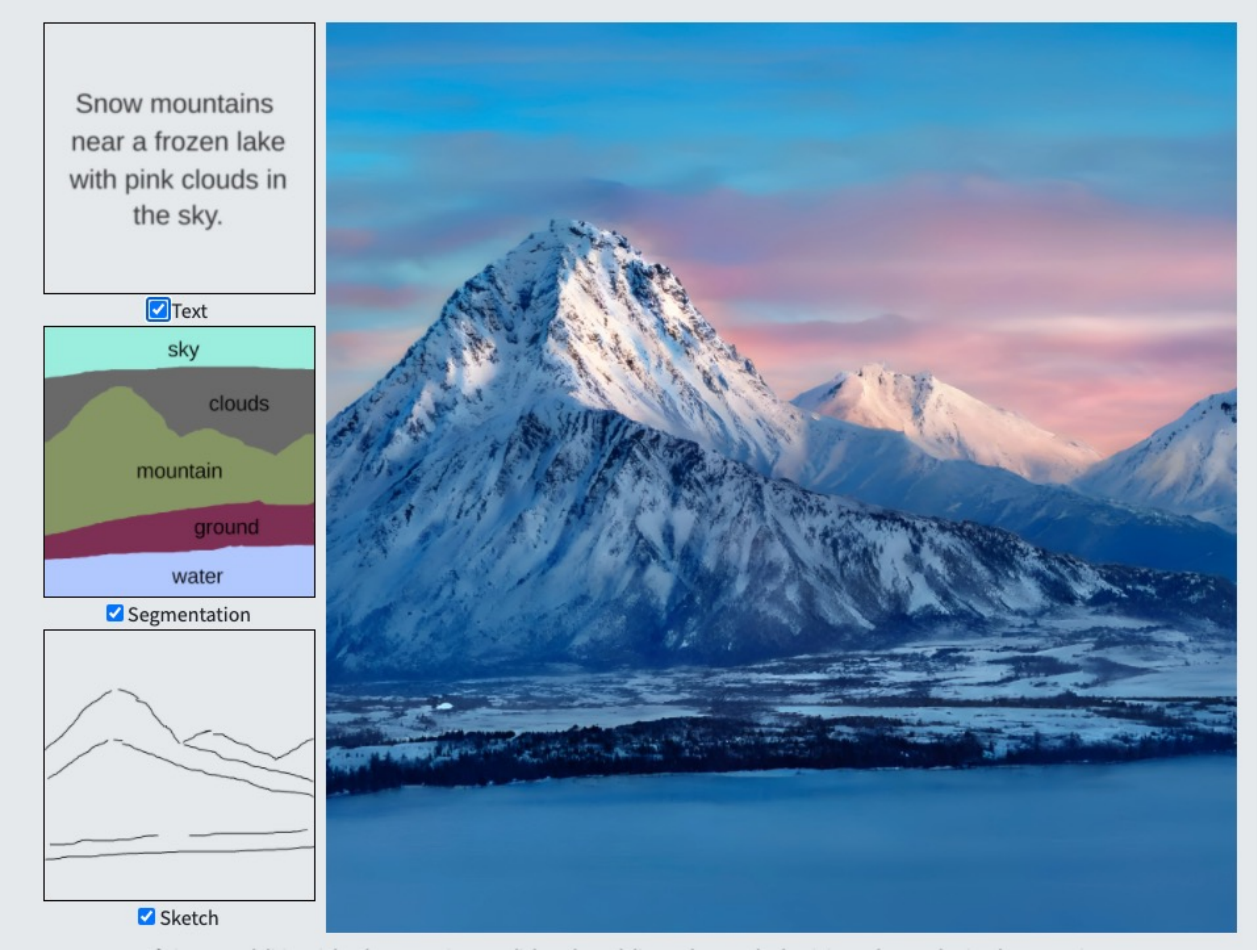


Image-to-Image Translation and Conditional Generative Models (part II)

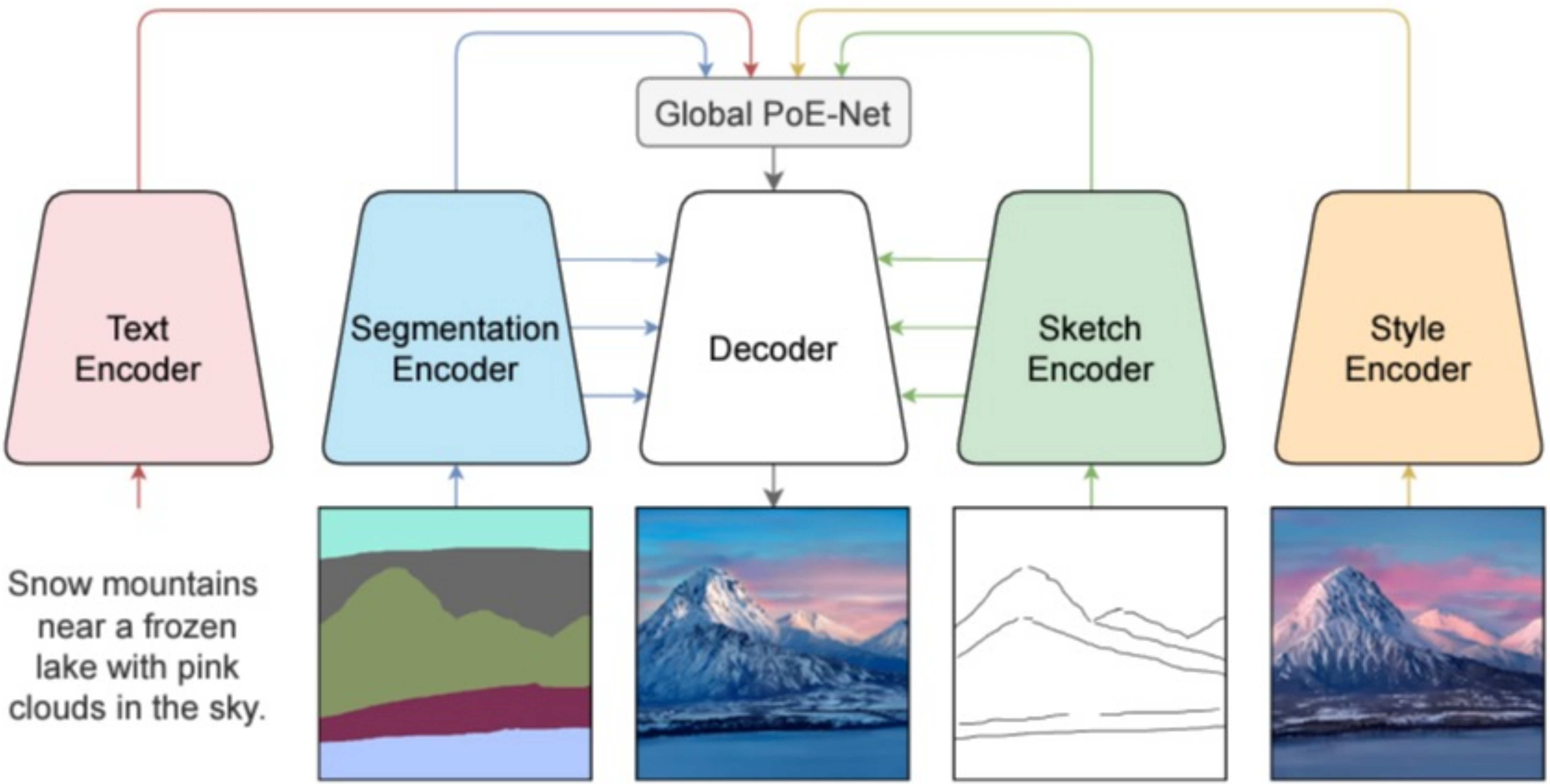
Jun-Yan Zhu

16-726, Spring 2025

Many slides from Phillip Isola, Ming-Yu Liu, Xun Huang, etc.



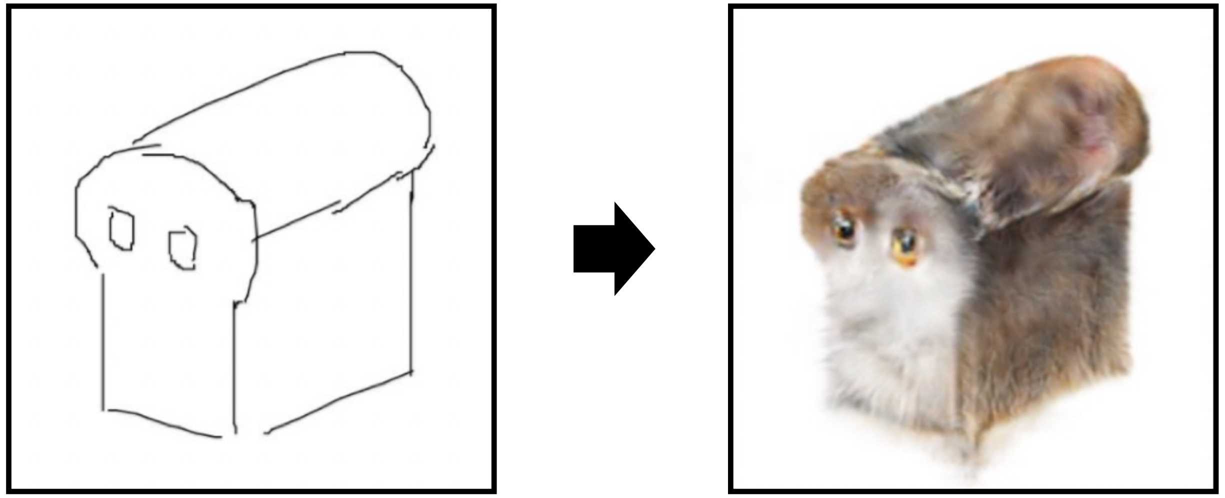
Multimodal Conditional Image Synthesis with Product-of-Experts GANs [Huang et al., 2021]



Multimodal Conditional Image Synthesis with Product-of-Experts GANs [Huang et al., 2021]


NVIDIA
GauGAN2
Paint Me a Picture

Supervised Learning Approach



Edges2cats

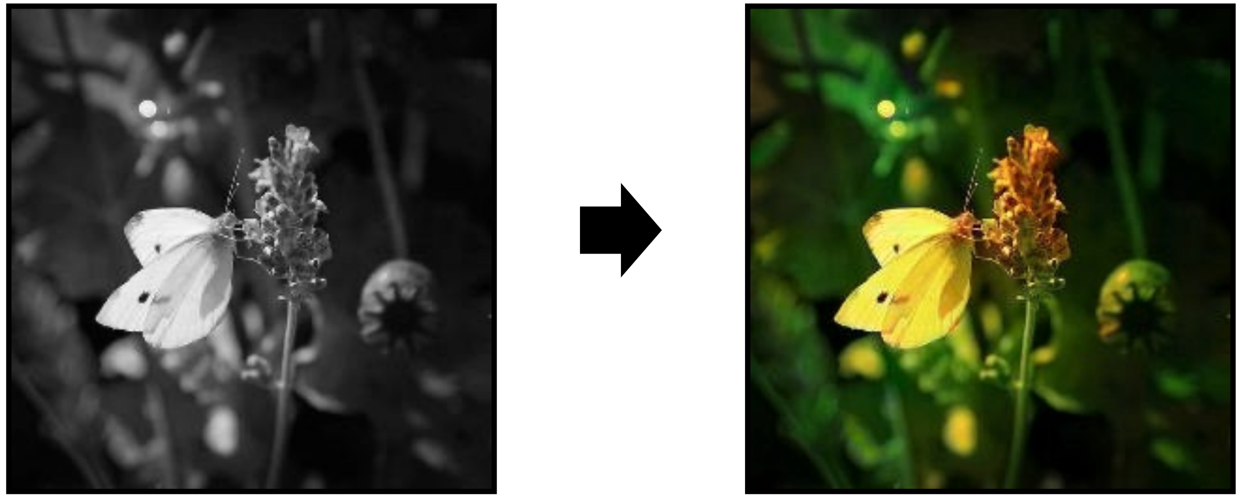
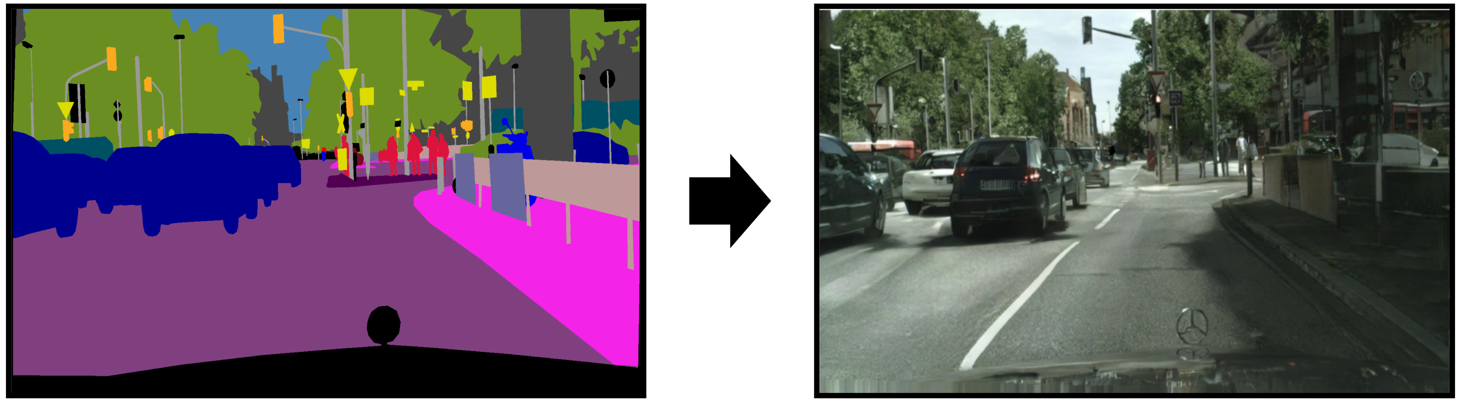
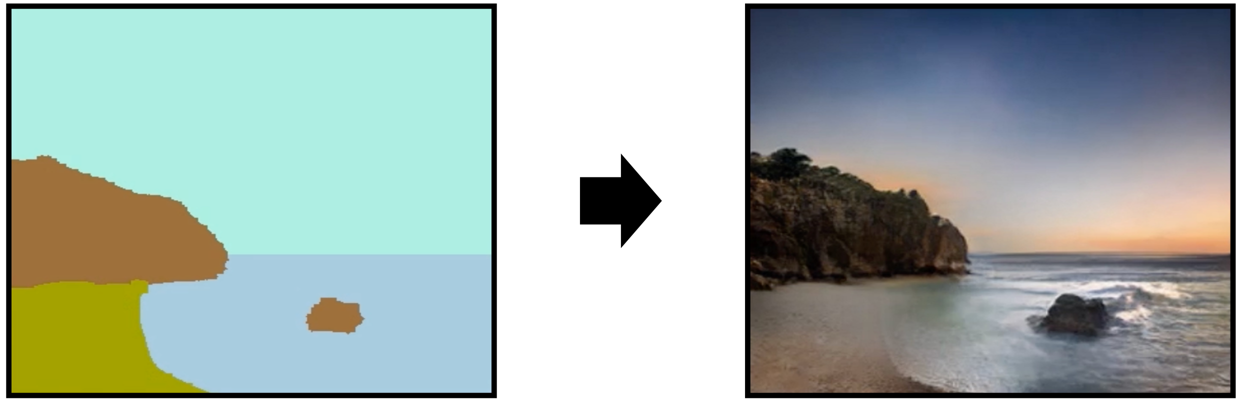


Image colorization



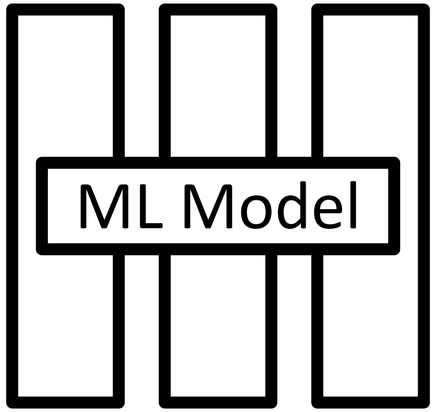
Street view images



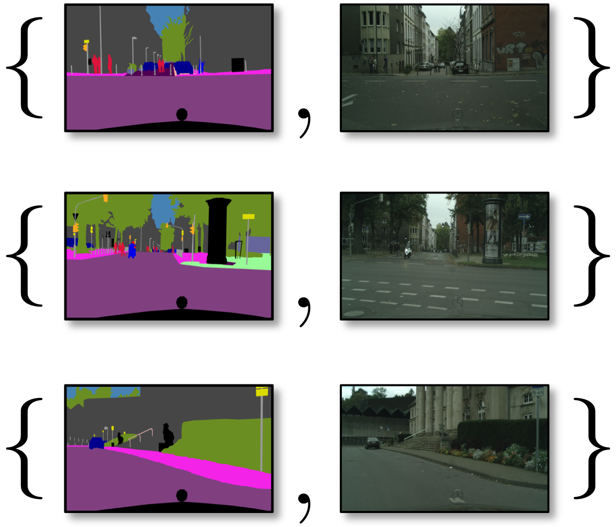
Natural outdoor images

Supervised Learning Approach

User Input

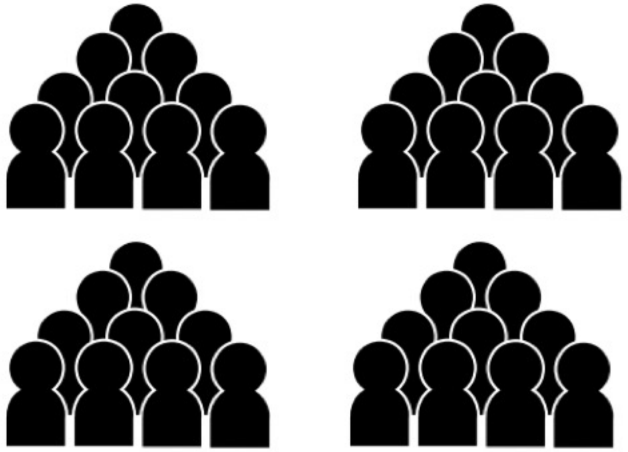


Learning algorithm

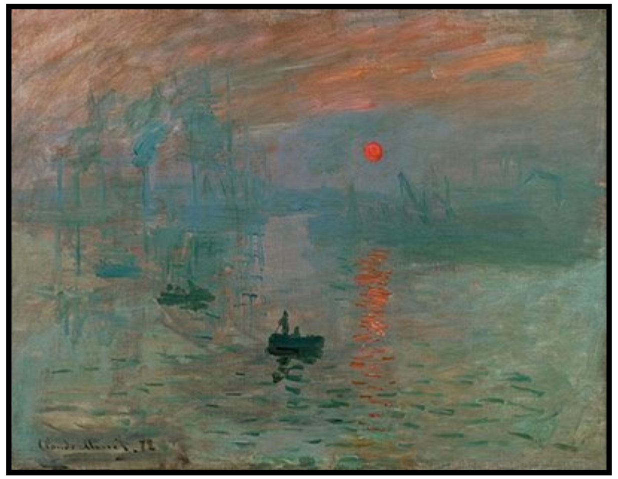


Labeled data

Visual Content



Expensive labor



Artistic authoring

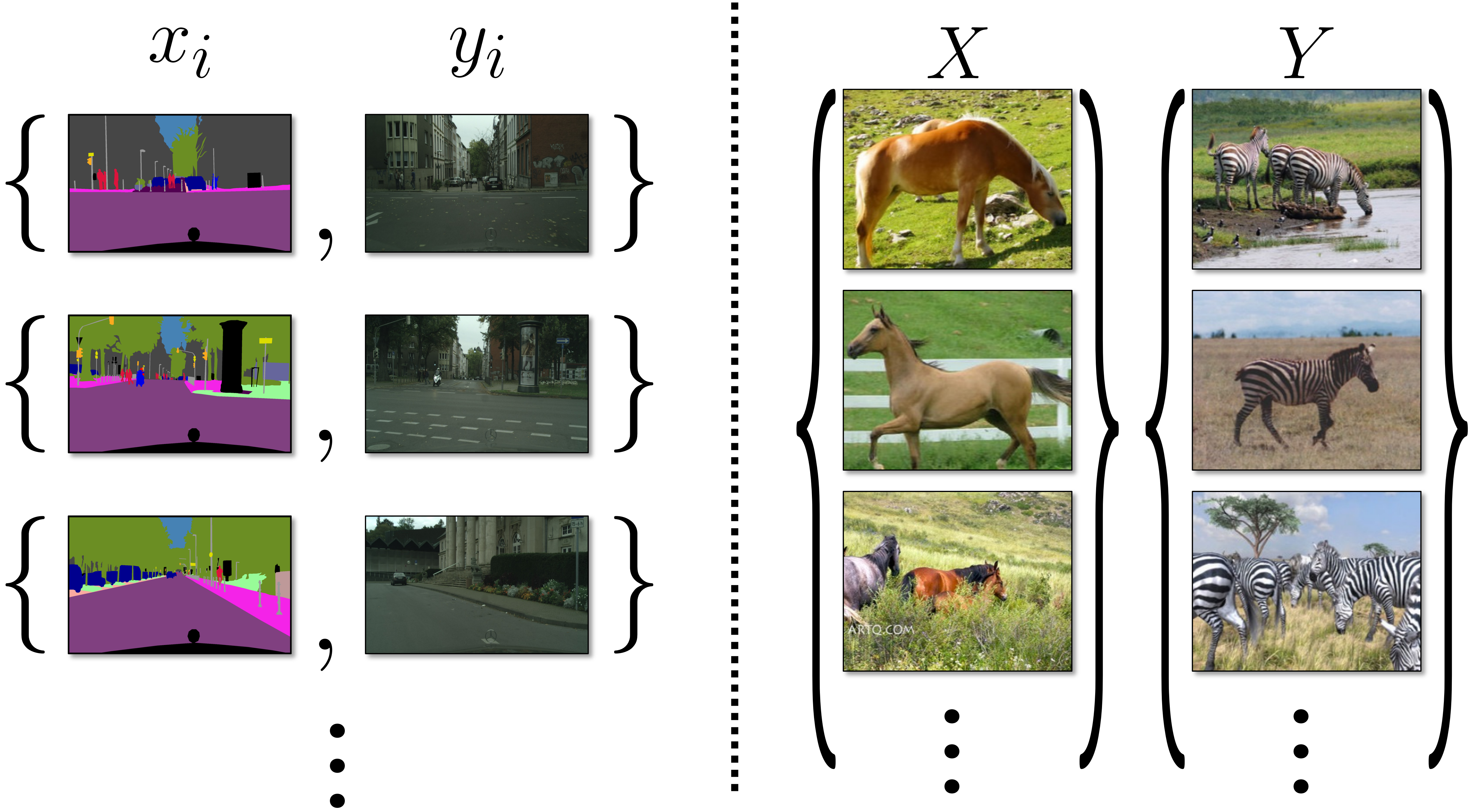
horse

zebra

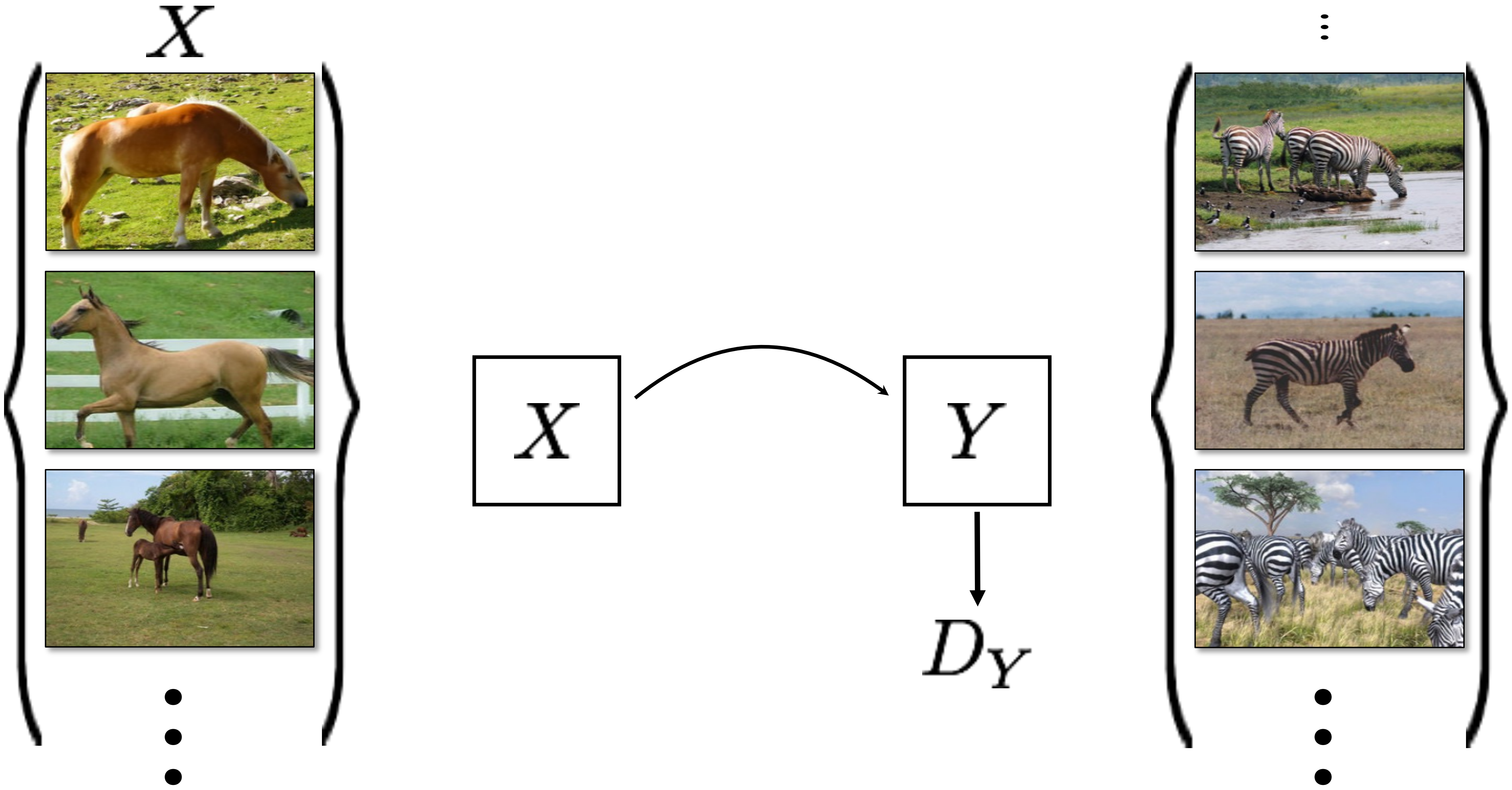
Infeasible

Supervised

Unsupervised



Unsupervised Learning of $p(y \mid x)$

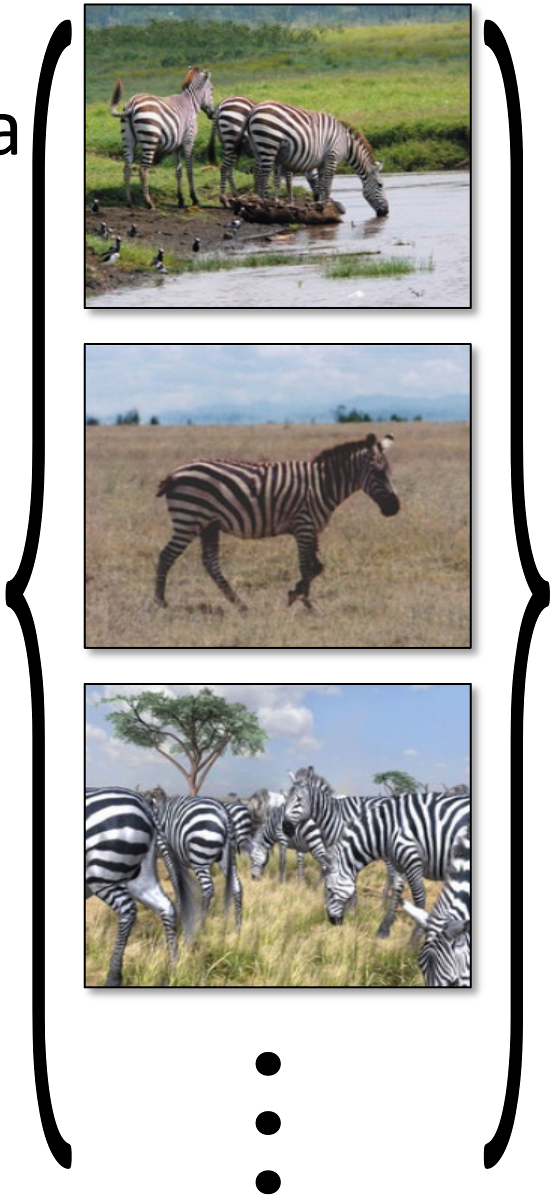


[Zhu*, Park*, Isola, and Efros, 2017]

Unsupervised Learning of $p(y \mid x)$

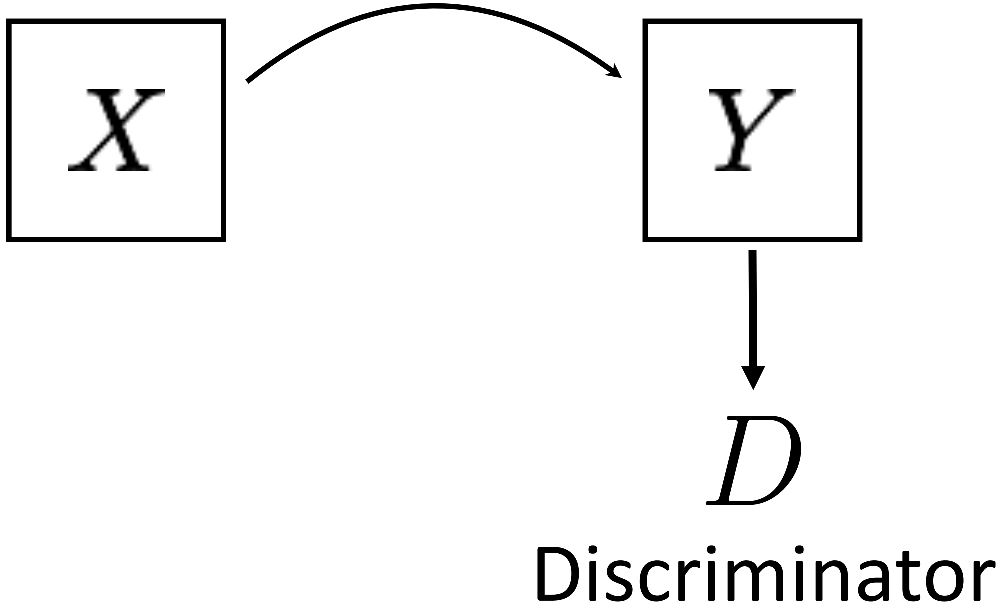
X

Y

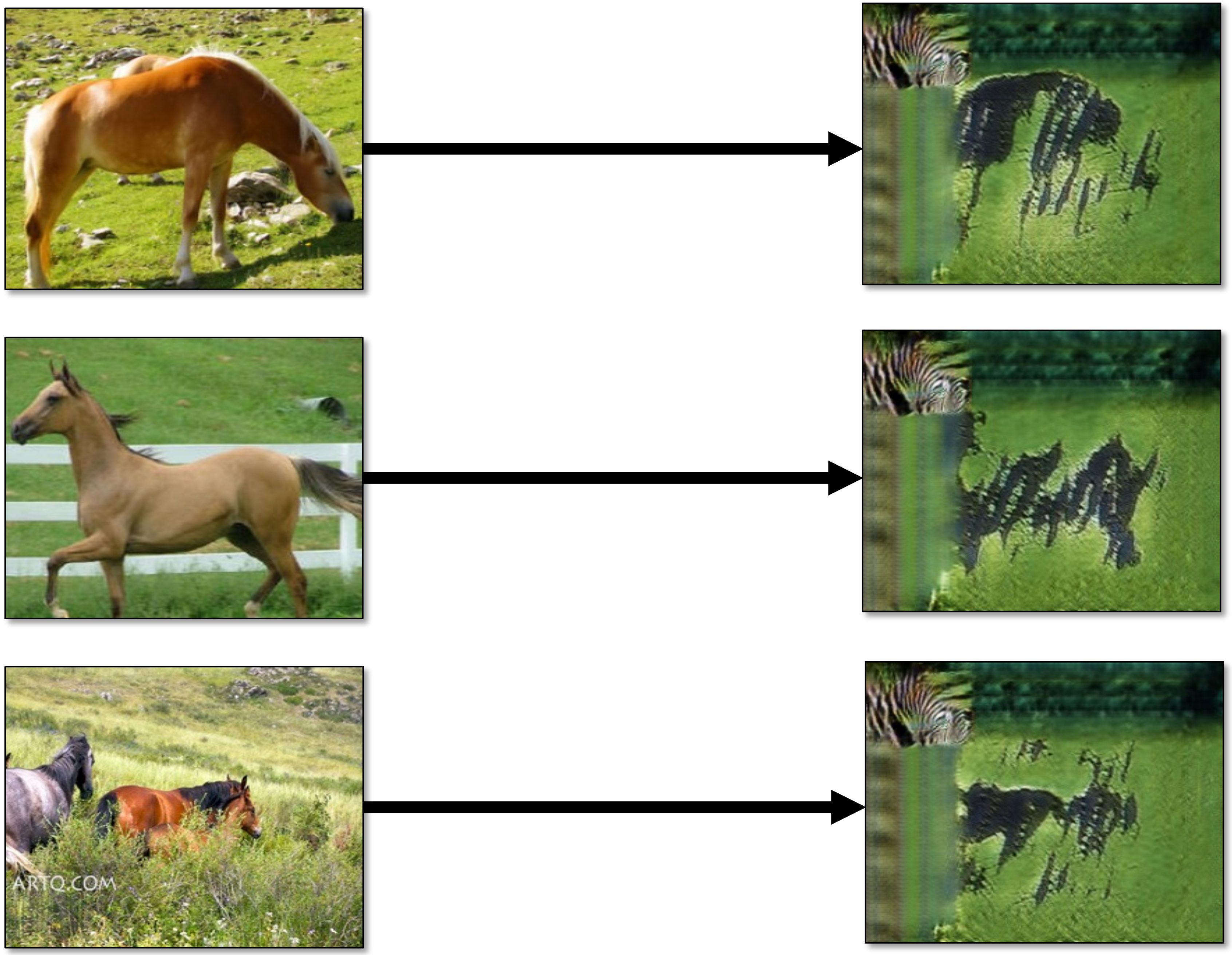


fake zebra real zebra

$$\mathbb{E}_x \log(1-D(\underline{G(x)}))+\mathbb{E}_y \log D(\underline{y})$$



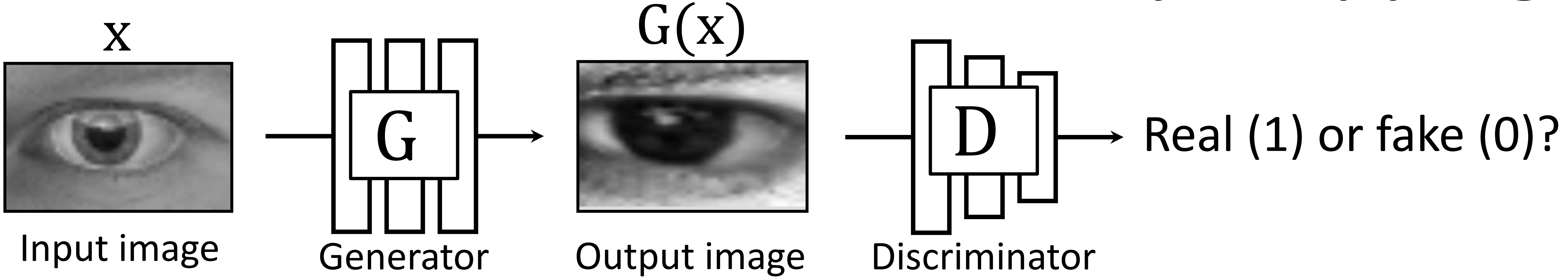
Unsupervised Learning of $p(y \mid x)$



- artifacts
- ignore inputs

[Goodfellow et al. 2014]

Additional Constraint: Identity Mapping

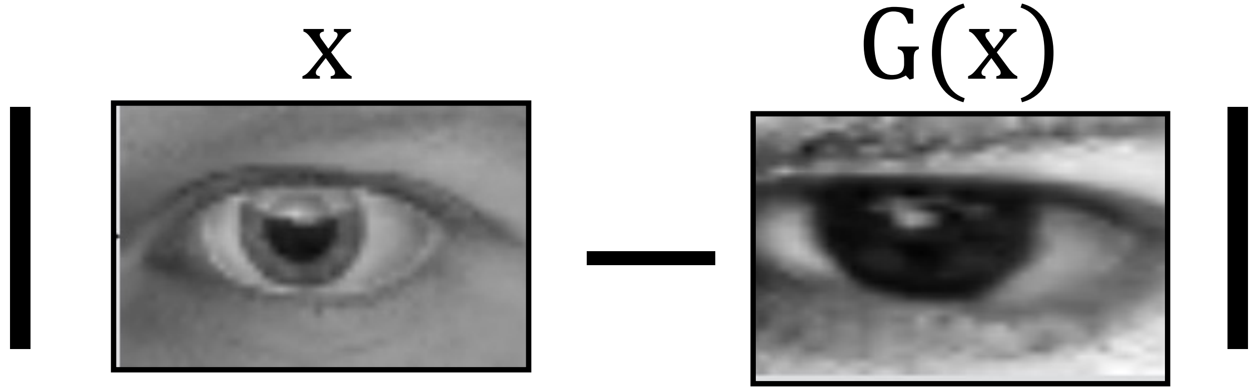


Adversarial loss

$$\mathbb{E}_x \log(1 - D_Y(G(x))) + \mathbb{E}_y \log D_Y(y)$$

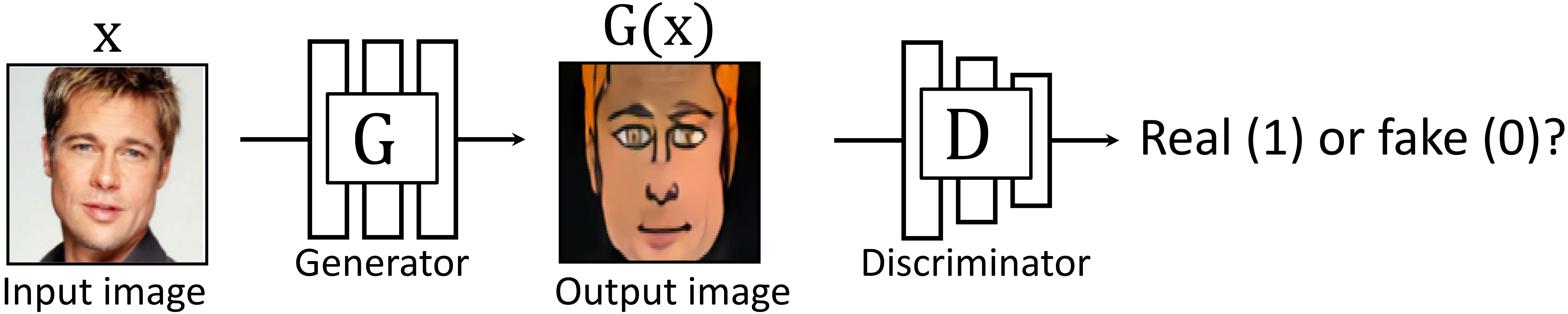
Self-Regularization loss

$$\mathbb{E}_x ||G(x) - x||_1$$



SimGAN [Shrivastava et al., 2017]

Additional Constraint: Feature Loss

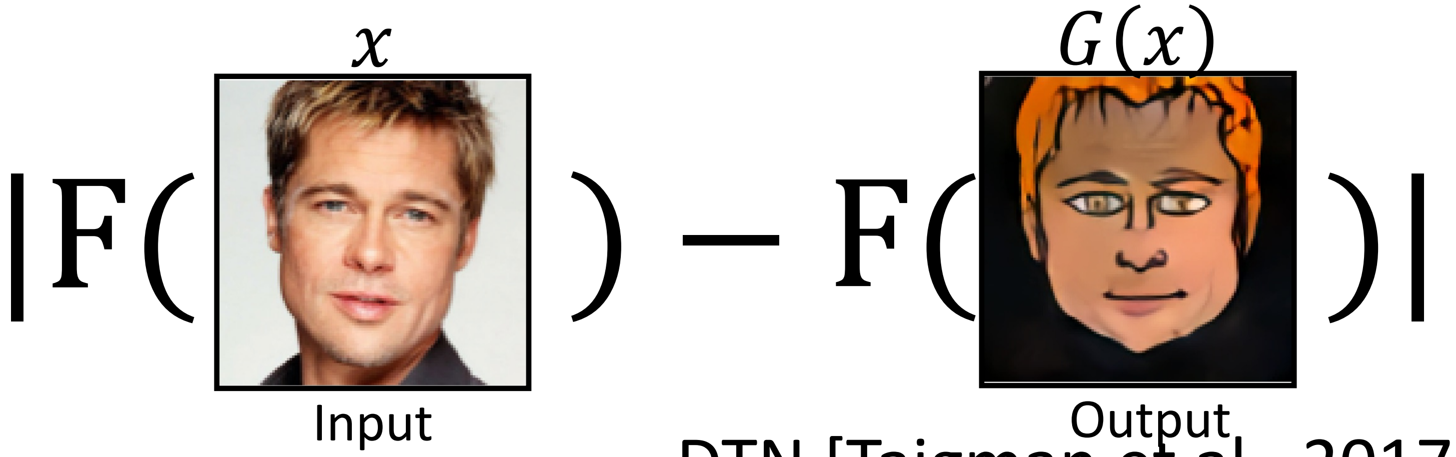


Adversarial loss

$$\mathbb{E}_x \log(1 - D_Y(G(x))) + \mathbb{E}_y \log D_Y(y)$$

Feature loss

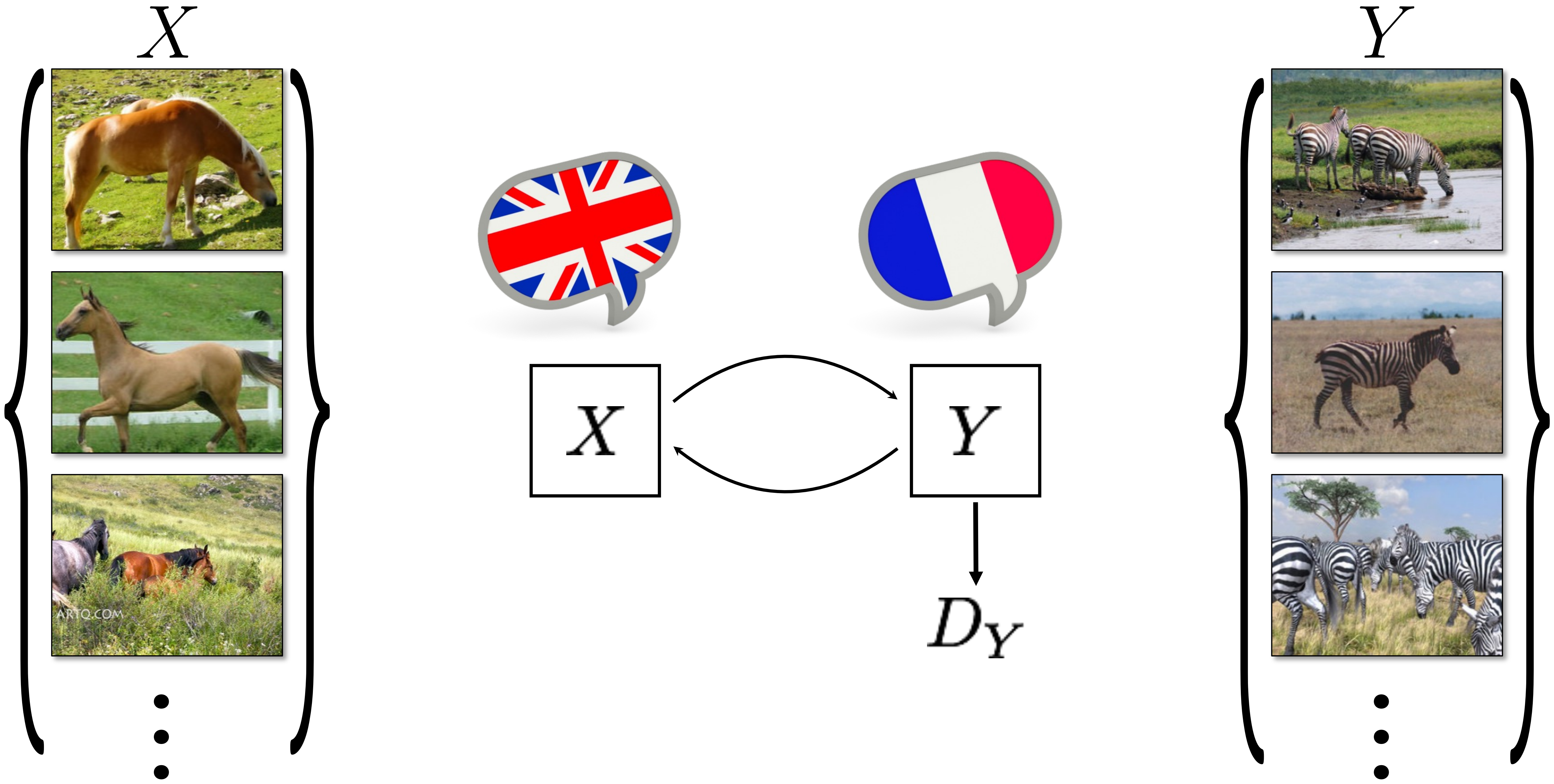
$$\mathbb{E}_x ||F(G(x)) - F(x)||$$



Requires F to work across two domains

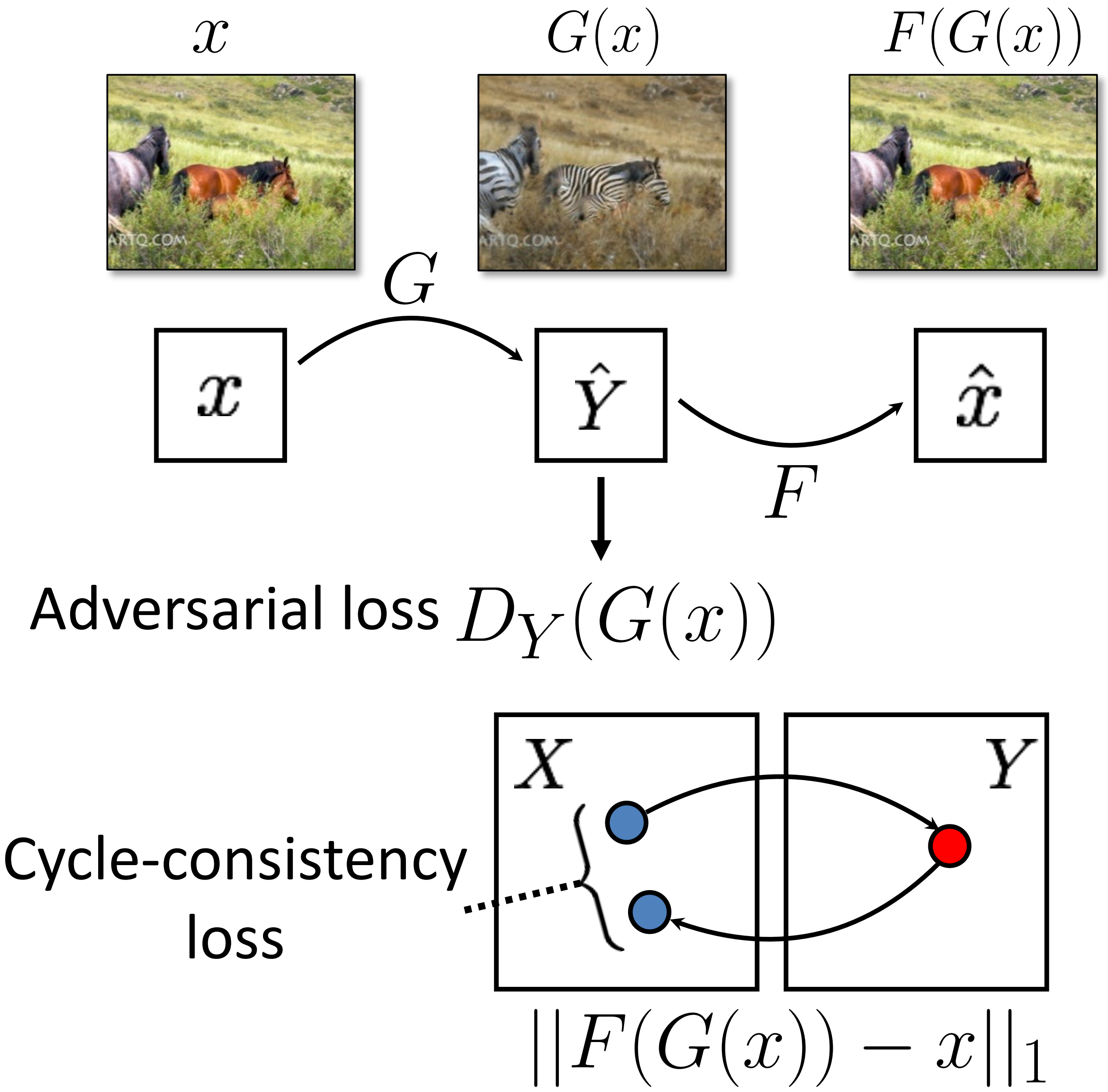
DTN [Taigman et al., 2017]

Additional Constraint: Cycle-Consistency



CycleGAN [Zhu*, Park* et al., ICCV 2017]

Cycle-Consistent Adversarial Networks



Adversarial loss

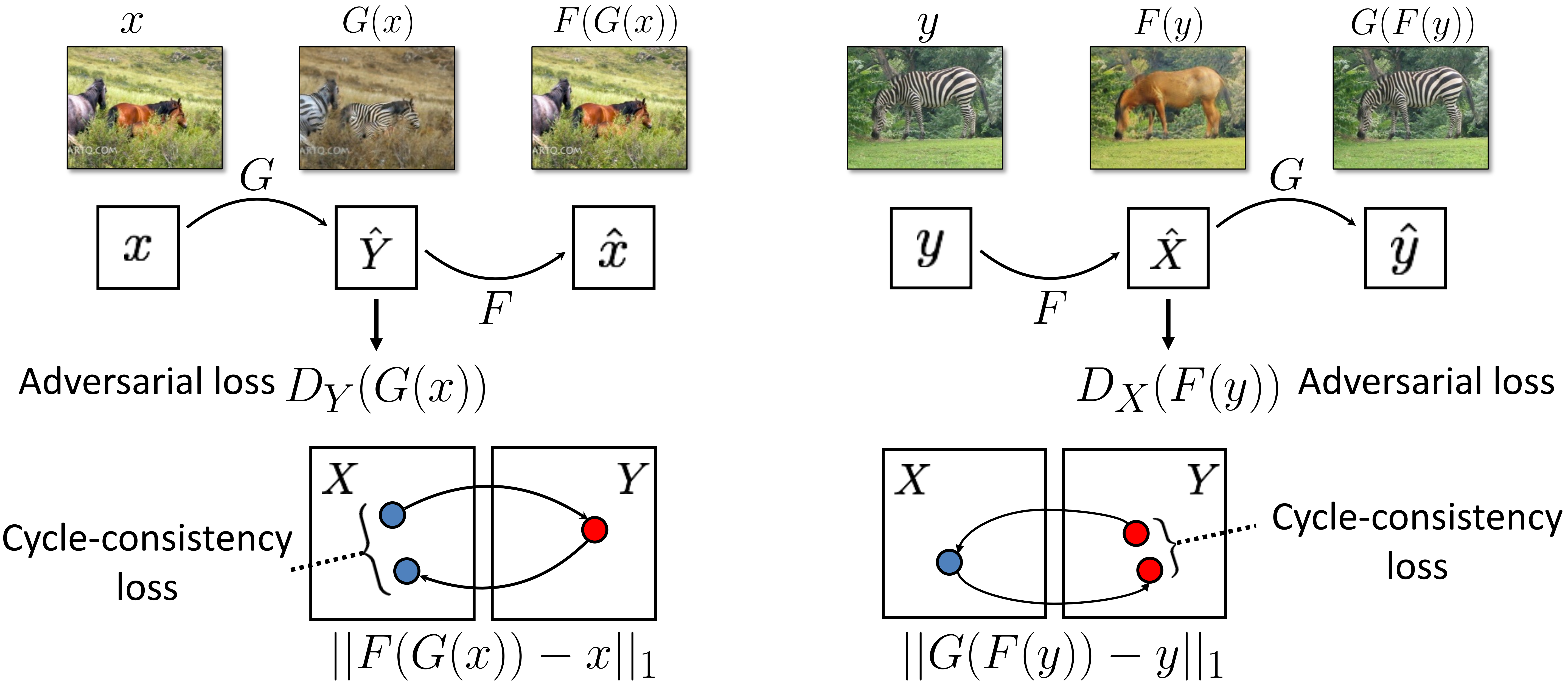
$$\mathbb{E}_x \log(1 - D_Y(G(x))) + \mathbb{E}_y \log D_Y(y)$$

Cycle-consistency loss

$$\mathbb{E}_x ||F(G(x)) - x||_1$$

CycleGAN [Zhu*, Park* et al., ICCV 2017]

Cycle-Consistent Adversarial Networks



CycleGAN [Zhu*, Park* et al., ICCV 2017]

Results

Horse → Zebra

Orange → Apple

Monet's paintings → photographic style

Monet’s paintings → photographic style

Collection Style Transfer

Photograph ©Alexei Efros

Monet

Van Gogh

Cezanne

Ukiyo-e

Improving the Realism of CG Rendering

CG Game: Grand Theft Auto

Street view images in German cities

Data from [Richter et al., 2016], [Cordts et al, 2016]

Improving the Realism of CG Rendering

Output image with German street view style

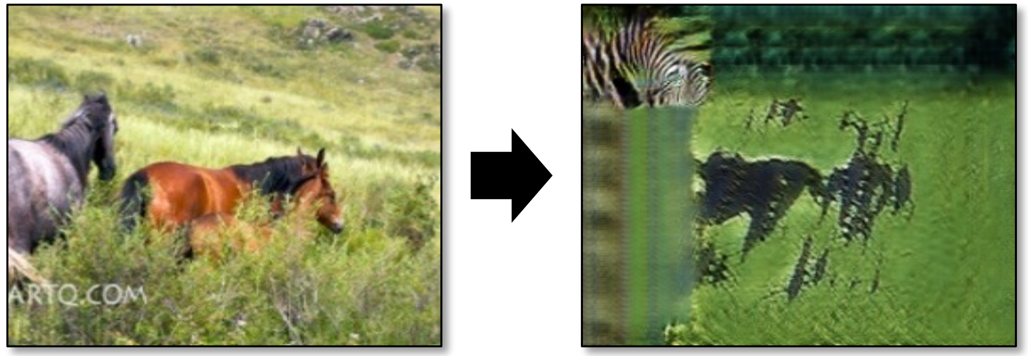
Input CG image

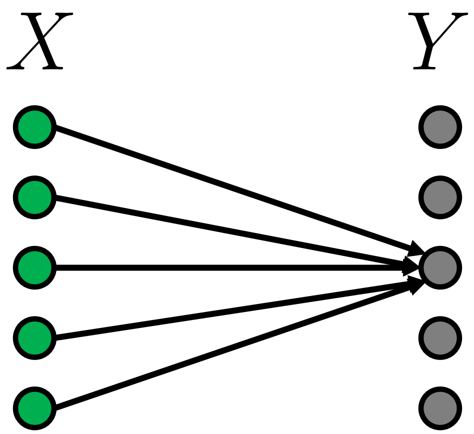
Why CycleGAN works

Why CycleGAN works

Adversarial loss

$$\mathbb{E}_x \log(1 - D_Y(G(x))) + \mathbb{E}_y \log D_Y(y)$$

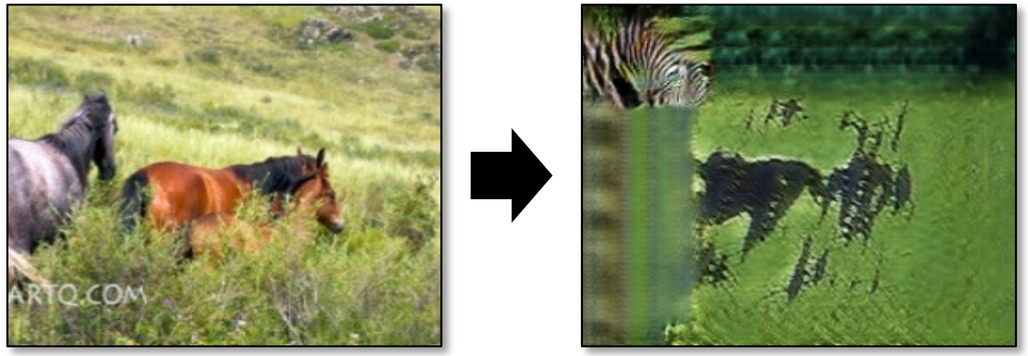




Why CycleGAN works

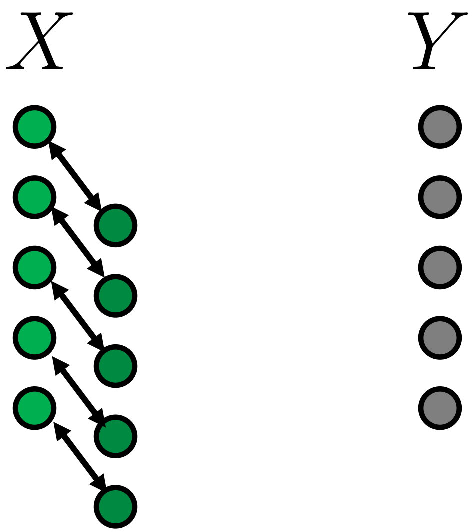
Adversarial loss

$$\mathbb{E}_x \log(1 - D_Y(G(x))) + \mathbb{E}_y \log D_Y(y)$$



Cycle-consistency loss

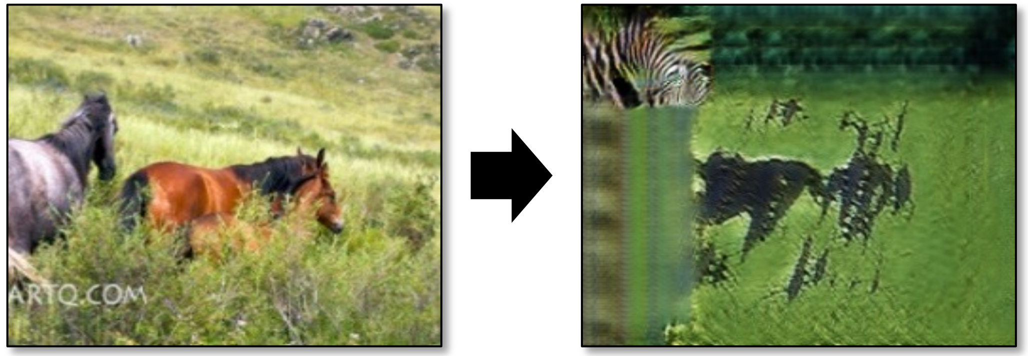
$$\mathbb{E}_x ||F(G(x)) - x||_1$$



Why CycleGAN works

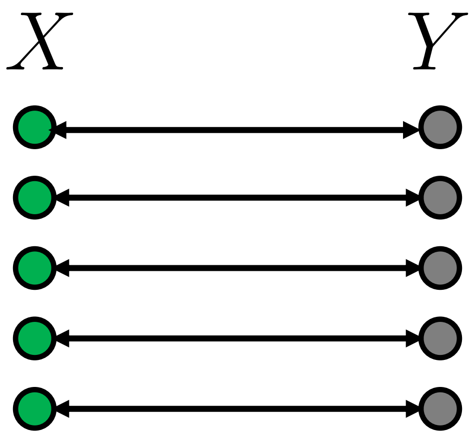
Adversarial loss

$$\mathbb{E}_x \log(1 - D_Y(G(x))) + \mathbb{E}_y \log D_Y(y)$$



Cycle-consistency loss

$$\mathbb{E}_x ||F(G(x)) - x||_1$$



Full objective

Why CycleGAN works

Adversarial loss

$$\mathbb{E}_x \log(1 - D_Y(G(x))) + \mathbb{E}_y \log D_Y(y)$$

Cycle-consistency loss

$$\mathbb{E}_x ||F(G(x)) - x||_1$$

x

$G(x)$

$F(G(x))$

Auto-encoder w/ domain prior

code

$$\boxed{x} \xrightarrow{\text{Encoder } G} \boxed{\hat{Y}} \xrightarrow{\text{Decoder } F} \boxed{\hat{x}}$$

Constraint: $G(x) \sim p_{data}(Y)$

[Hinton and Salakhutdinov. Science 2006]

Why CycleGAN works

Adversarial loss

$$\mathbb{E}_x \log(1 - D_Y(G(x))) + \mathbb{E}_y \log D_Y(y)$$

Under-constrained problem

Cycle-consistency loss

$$\mathbb{E}_x ||F(G(x)) - x||_1$$

Prior of G

<u>A strong regularizer</u>

Assumption: simple invertible function

Probabilistic Interpretation : Upper bound of conditional entropy $H(y|x)$

[Li et al. 2017]

Why CycleGAN works

Adversarial loss

$$\mathbb{E}_x \log(1 - D_Y(G(x))) + \mathbb{E}_y \log D_Y(y)$$

Cycle-consistency loss

$$\mathbb{E}_x ||F(G(x)) - x||_1$$

flip the image

$P \circ G$

$F \circ P^{-1}$

flip the image again

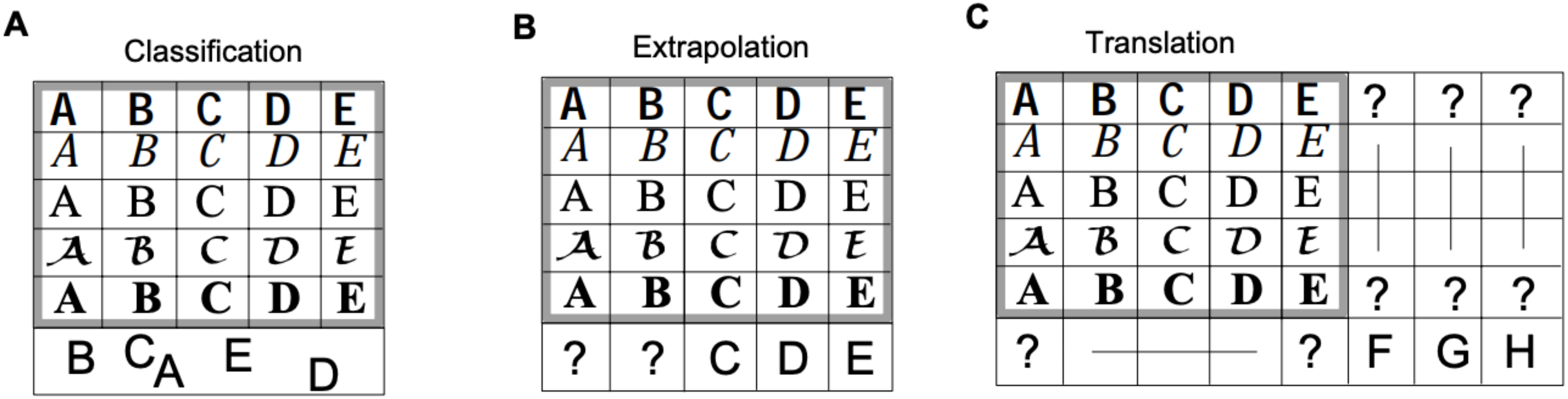
<u>Invertible Perturbation</u>

Adversarial loss: images are horizontally symmetric

Cycle-consistency loss : $||F \circ P^{-1}(P \circ G(x)) - x||$

Style and Content Disentanglement

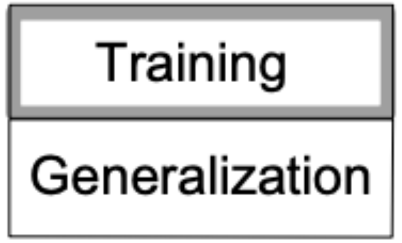
Style and Content Separation



Domain Adaptation

Paired Image-to-Image Translation

Unpaired Image-to-Image Translation



Separating Style and Content
[Tenenbaum and Freeman 1996]

$$y_k^{sc} = \sum_{i=1}^{I} \sum_{j=1}^{J} w_{ijk} a_i^s b_j^c .$$

Style and Content

Adversarial loss

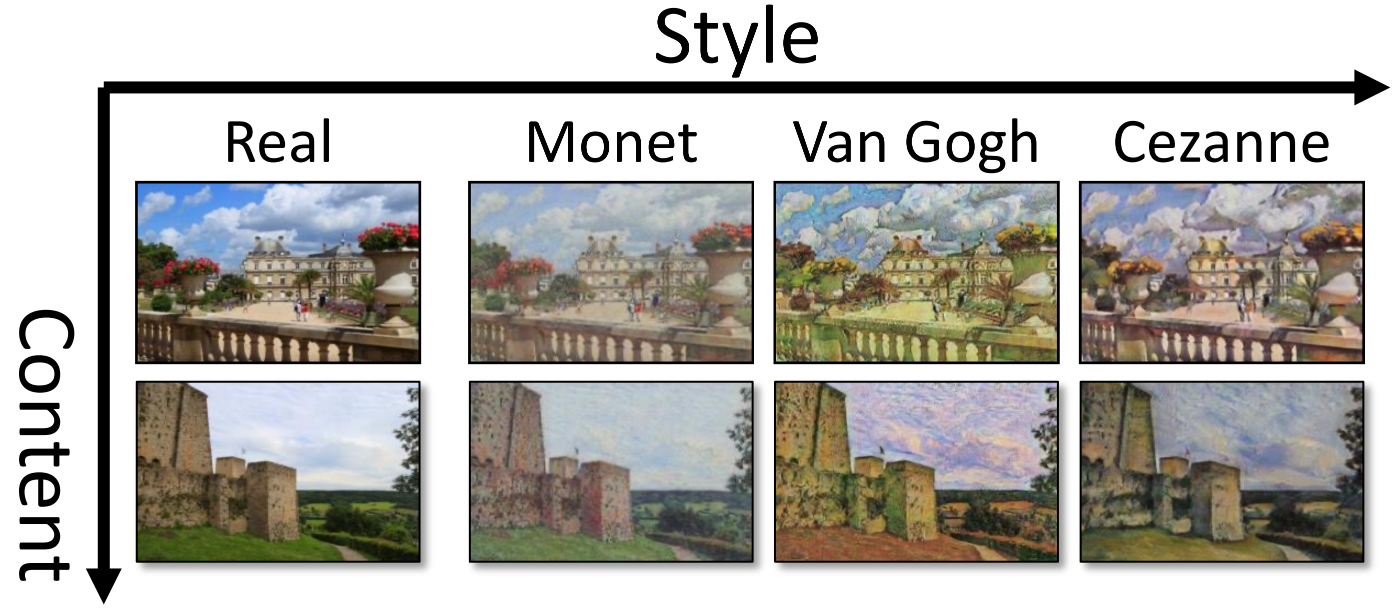
$$\mathbb{E}_x \log(1 - D_Y(G(x))) + \mathbb{E}_y \log D_Y(y)$$

$p(x) \rightarrow p(y)$ change **style**

Cycle-consistency loss

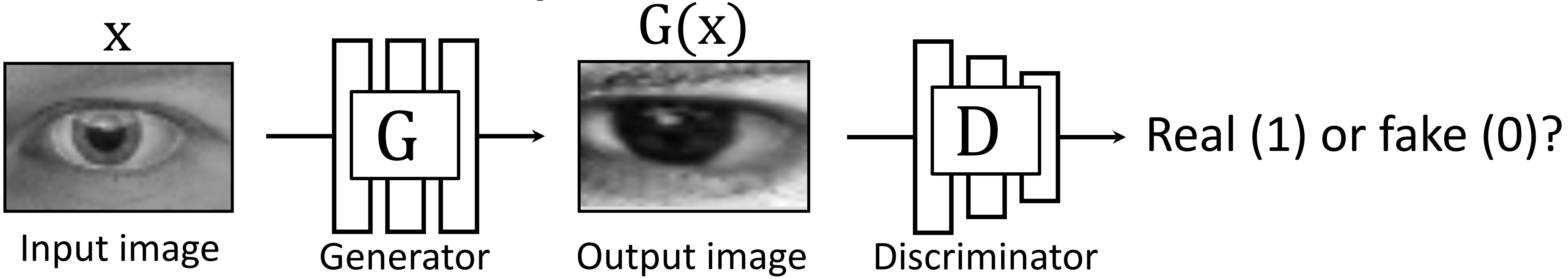
$$\mathbb{E}_x ||F(G(x)) - x||_1$$

Bidirectional: preserve **content**



Separating Style and Content
[Tenenbaum and Freeman 1996]

Style and Content

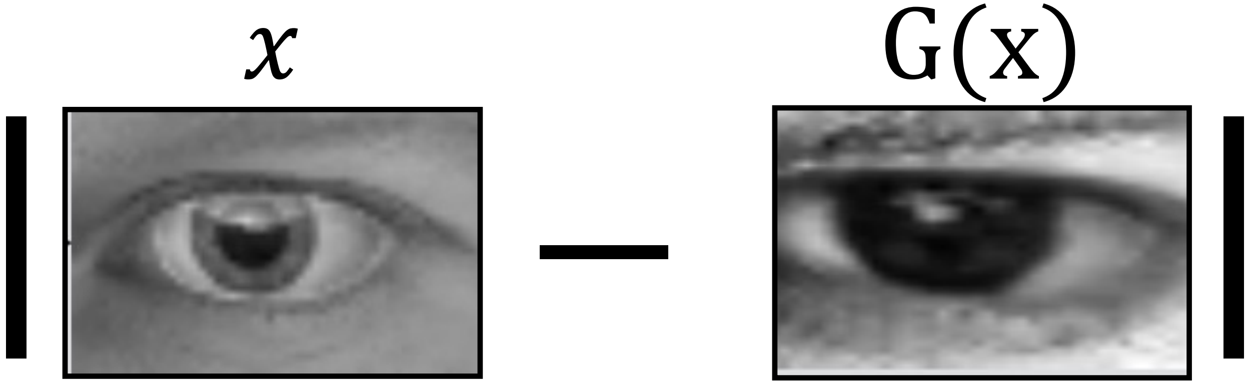


Adversarial loss (change style)

$$\mathbb{E}_x \log(1 - D_Y(G(x))) + \mathbb{E}_y \log D_Y(y)$$

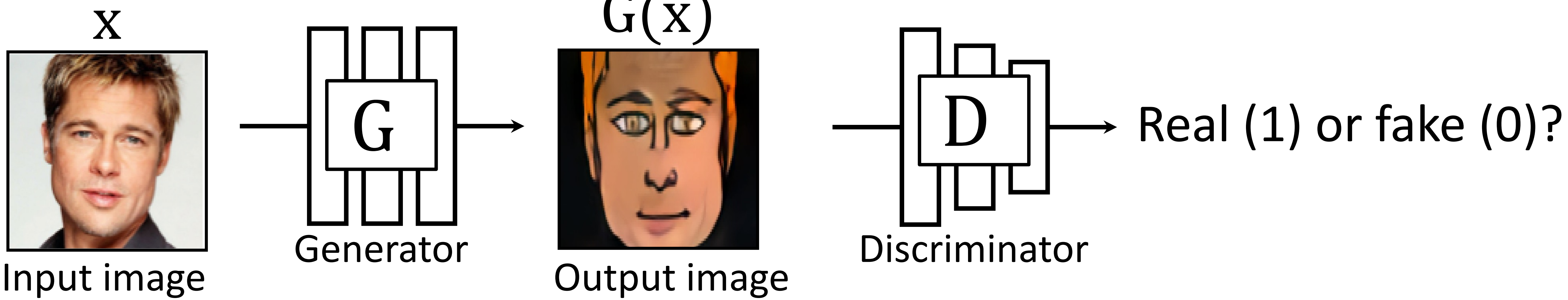
L1 loss (preserve content in pixel space)

$$\mathbb{E}_x ||G(x) - x||_1$$



SimGAN [Shrivastava et al., 2017]

Style and Content

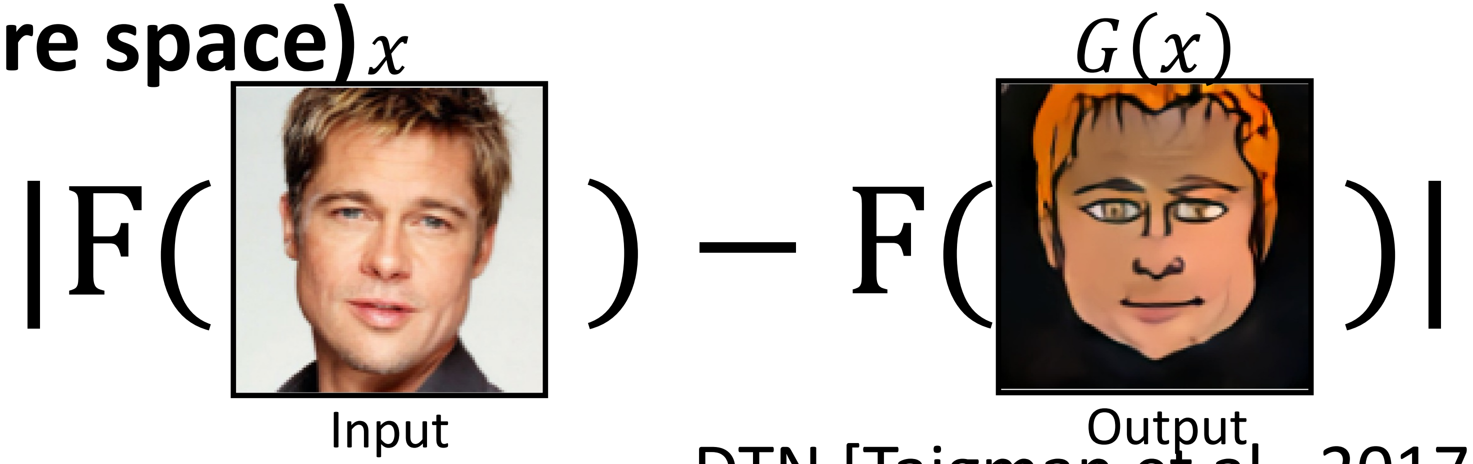


Adversarial loss (change style)

$$\mathbb{E}_x \log(1 - D_Y(G(x))) + \mathbb{E}_y \log D_Y(y)$$

Feature loss (Preserve content in feature space)

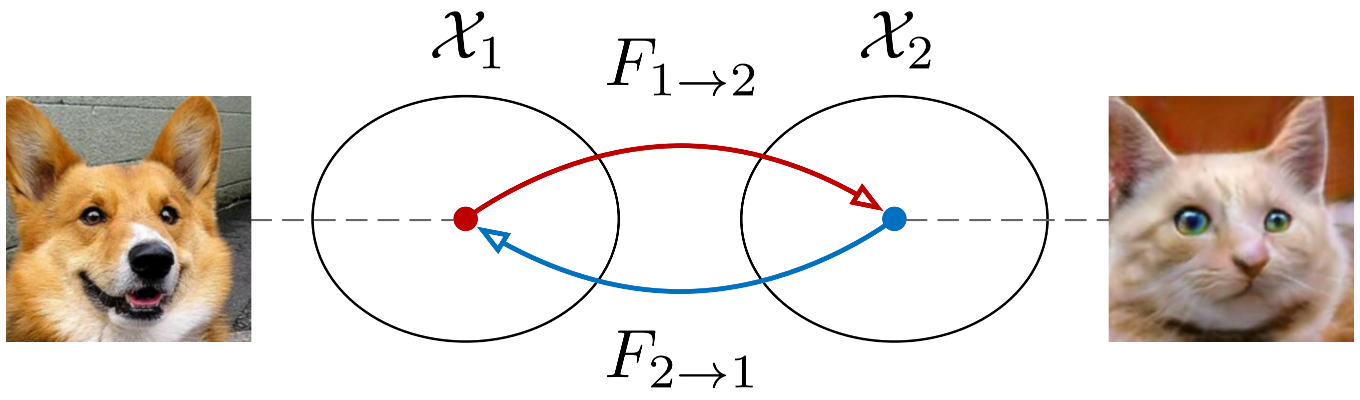
$$\mathbb{E}_x ||F(G(x)) - F(x)||$$

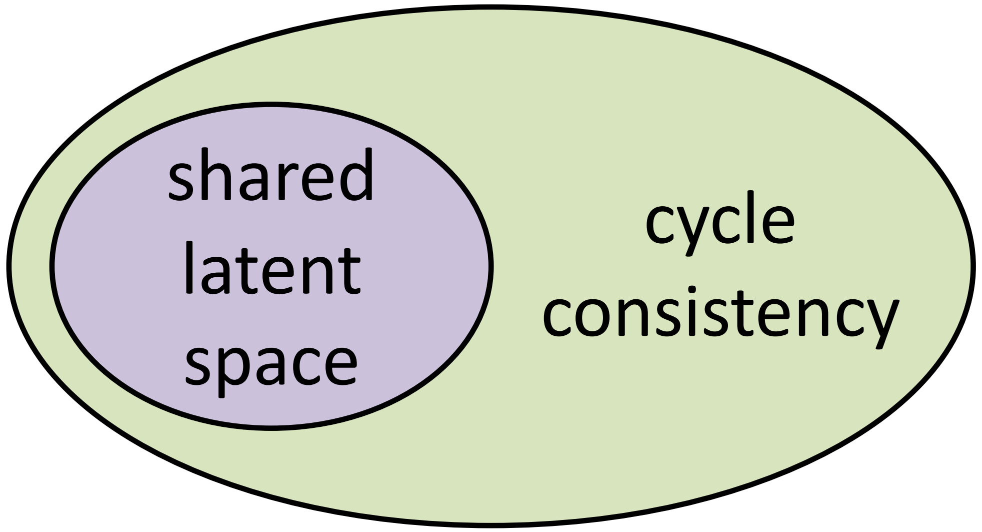


DTN [Taigman et al., 2017]

CycleGAN and UNIT

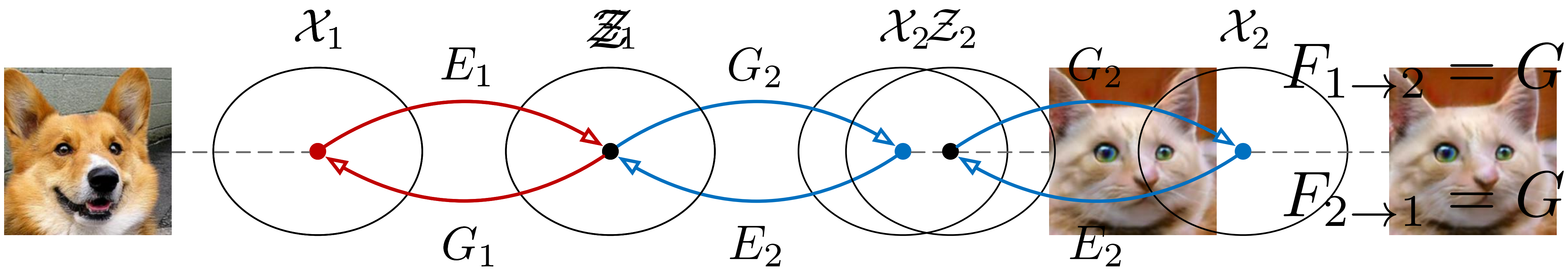
- CycleGAN (**cycle consistency**)





- UNIT (**shared latent space**) [Liu et al. 2017]

shared latent space $\Longrightarrow$ cycle consistency

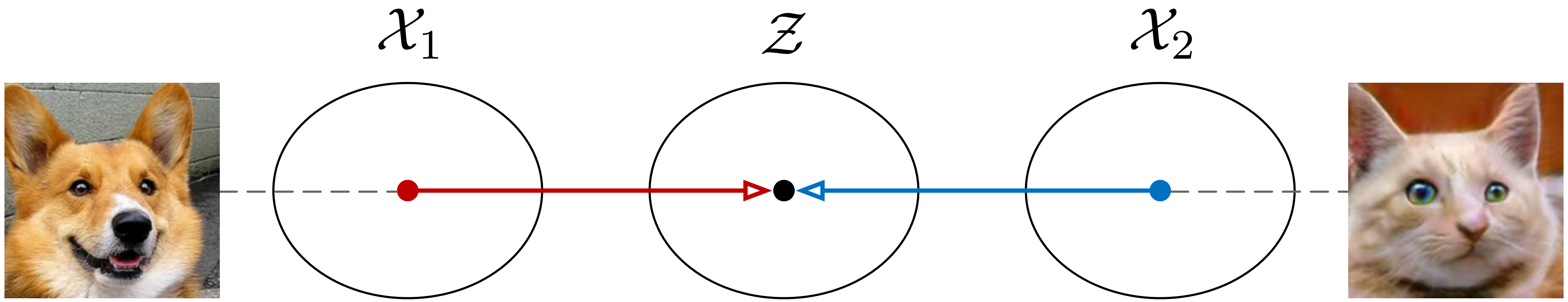


$$F_{1\to 2} = G_2 \circ E_1$$

$$F_{2\to 1} = G_1 \circ E_2$$

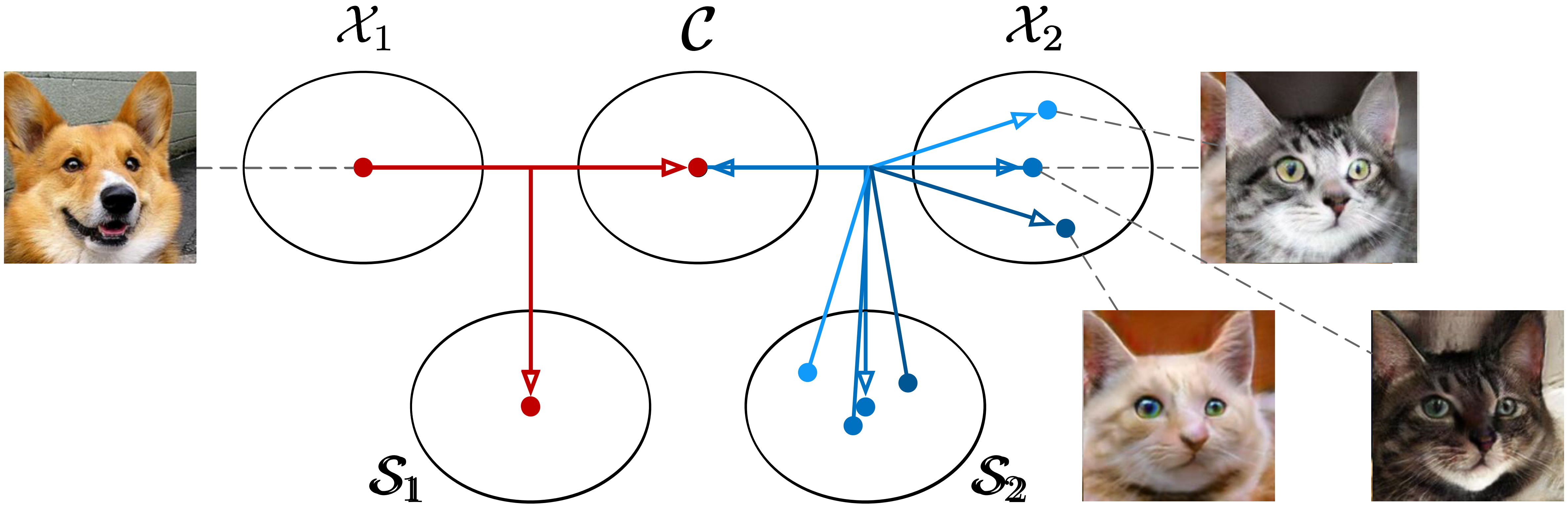
Disentangling the Latent Space

- UNIT
  - A single **shared, domain-invariant** latent space $\mathcal{Z}$

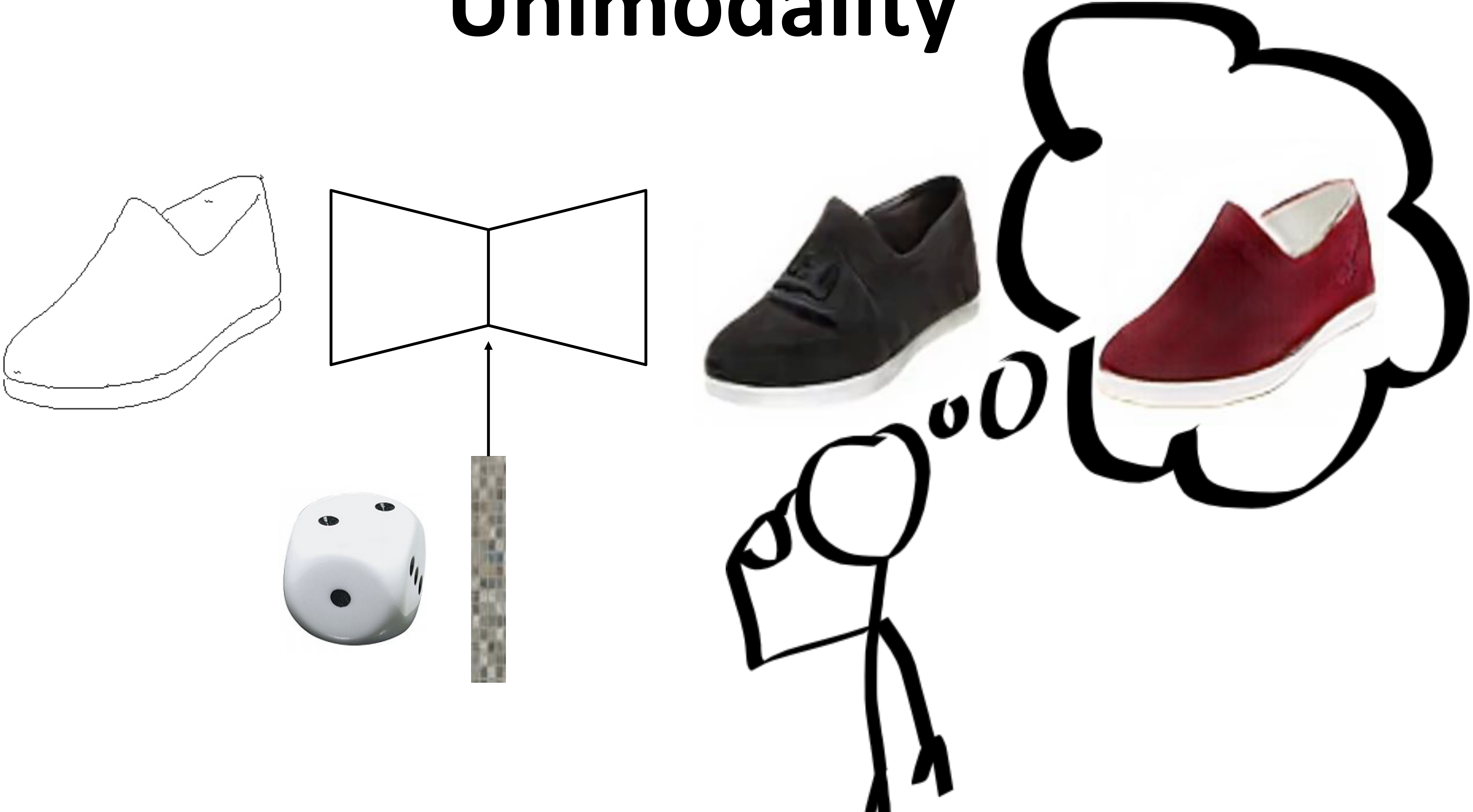


Disentangling the Latent Space

- Multimodal UNIT (MUNIT)
  - A **content** space $\mathcal{C}$ that is **shared, domain-invariant**
  - Two **style** spaces $\mathcal{S}_1, \mathcal{S}_2$ that are **unshared, domain-specific**



Unimodality

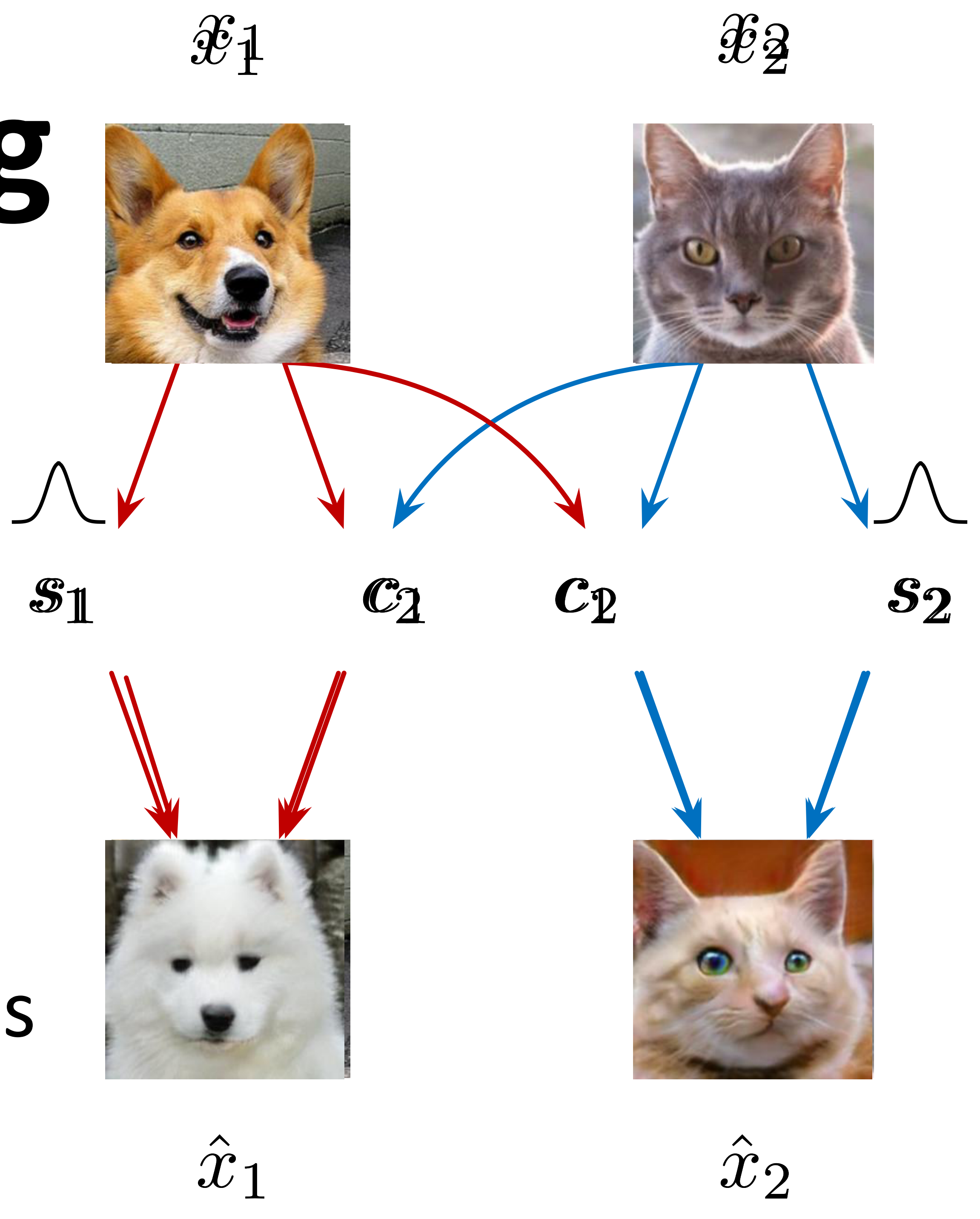


Towards Multimodality

...

Training

- Notations:
  - x: images
  - c: content
  - s: style
- Loss:
  - Bidirectional reconstruction loss
    - Image reconstruction loss
    - Latent reconstruction loss
  - GAN loss

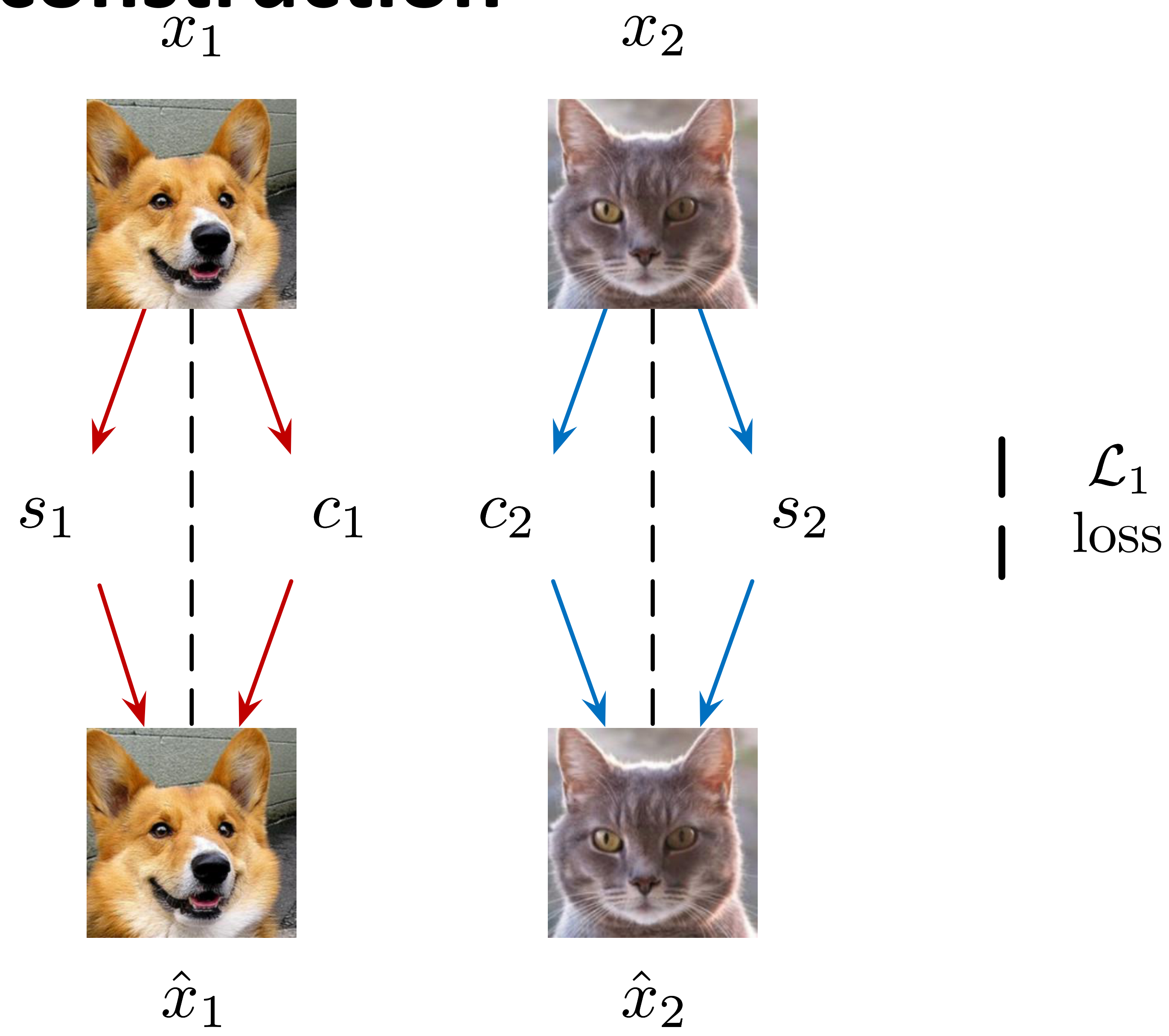


Within-domain reconstruction
Cross-domain translation

Bidirectional Reconstruction Loss: Image Reconstruction

Notations:

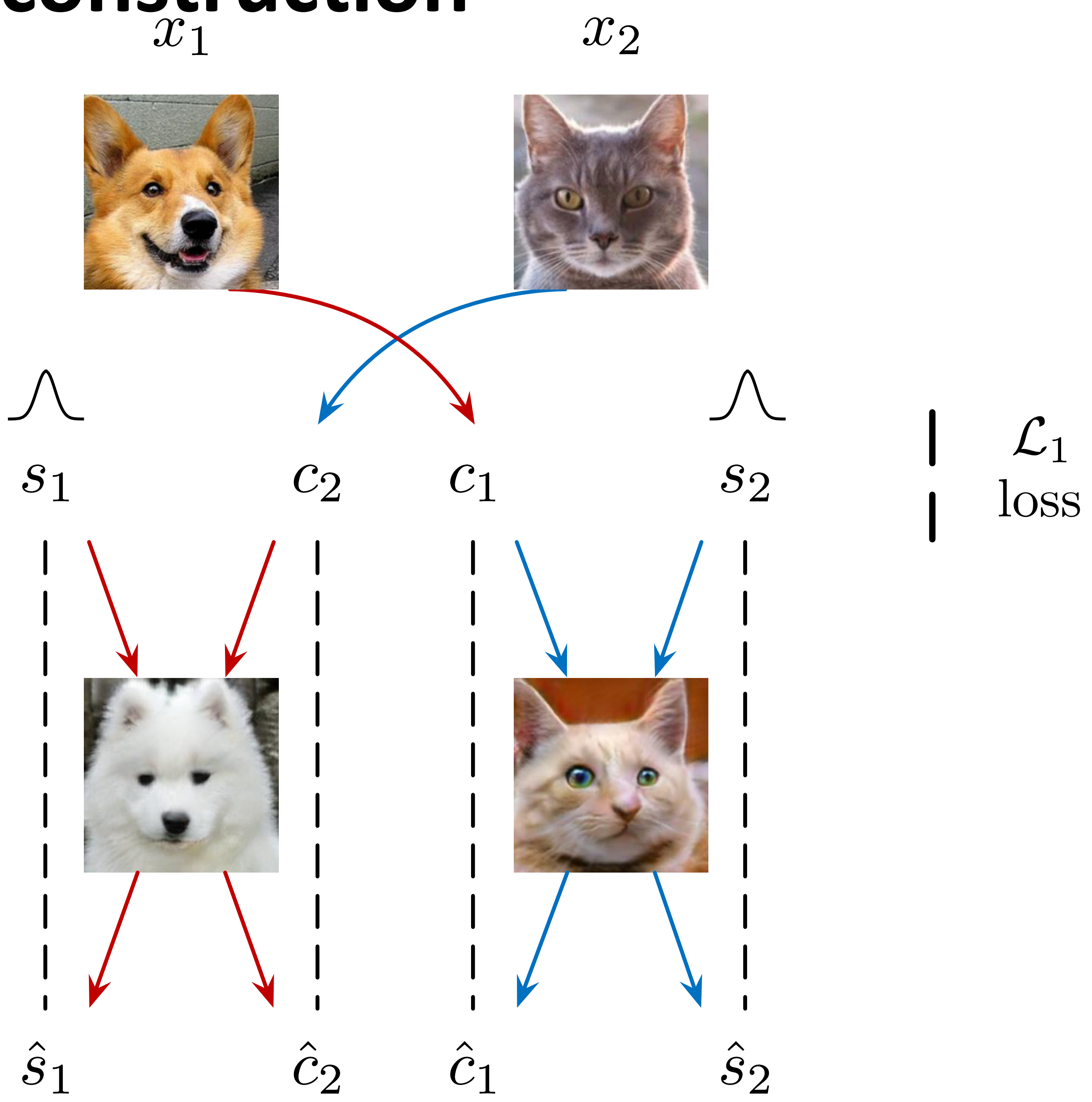
- x: images
- c: content
- s: style



Bidirectional Reconstruction Loss: Image Reconstruction

Notations:

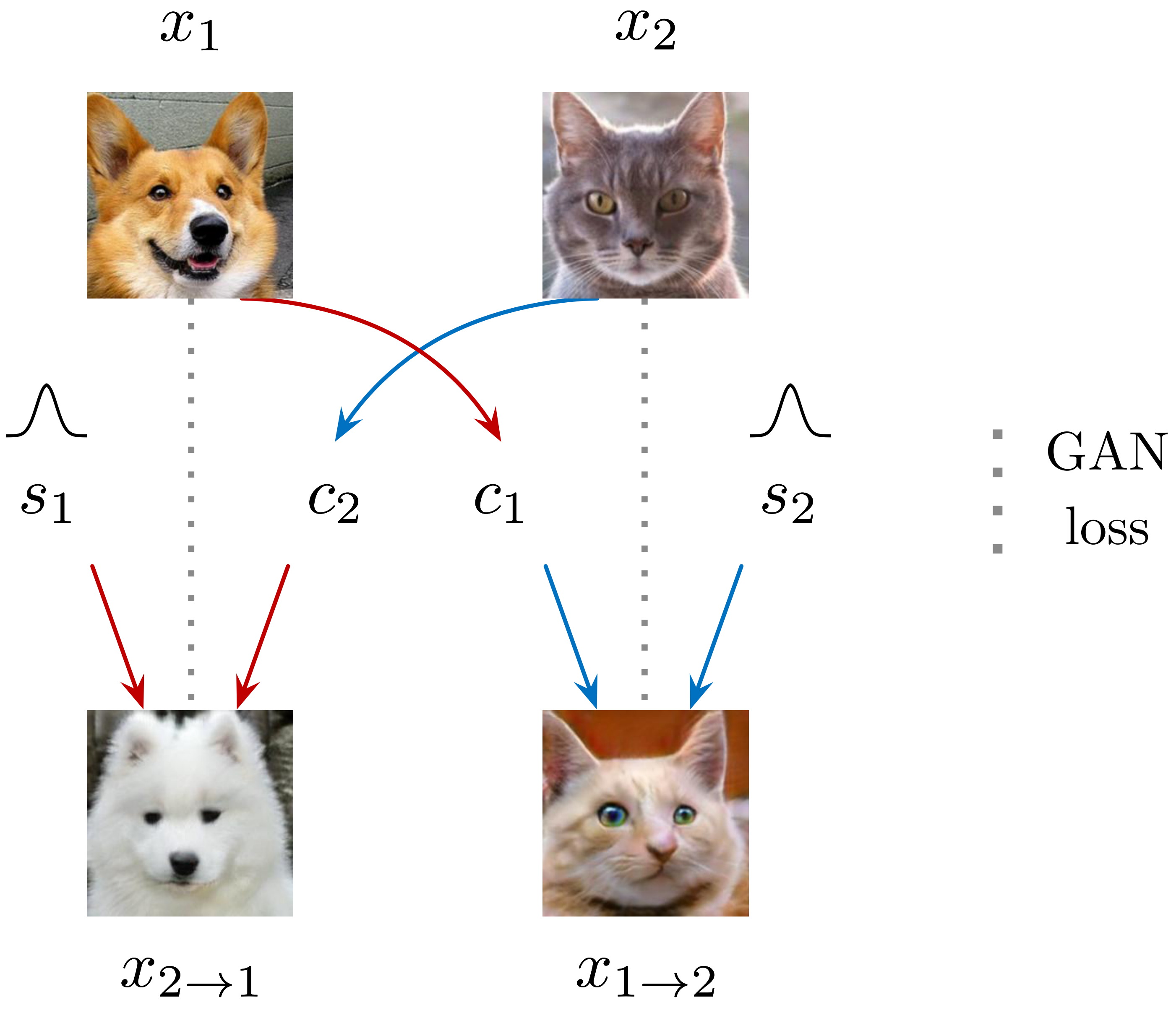
- x: images
- c: content
- s: style



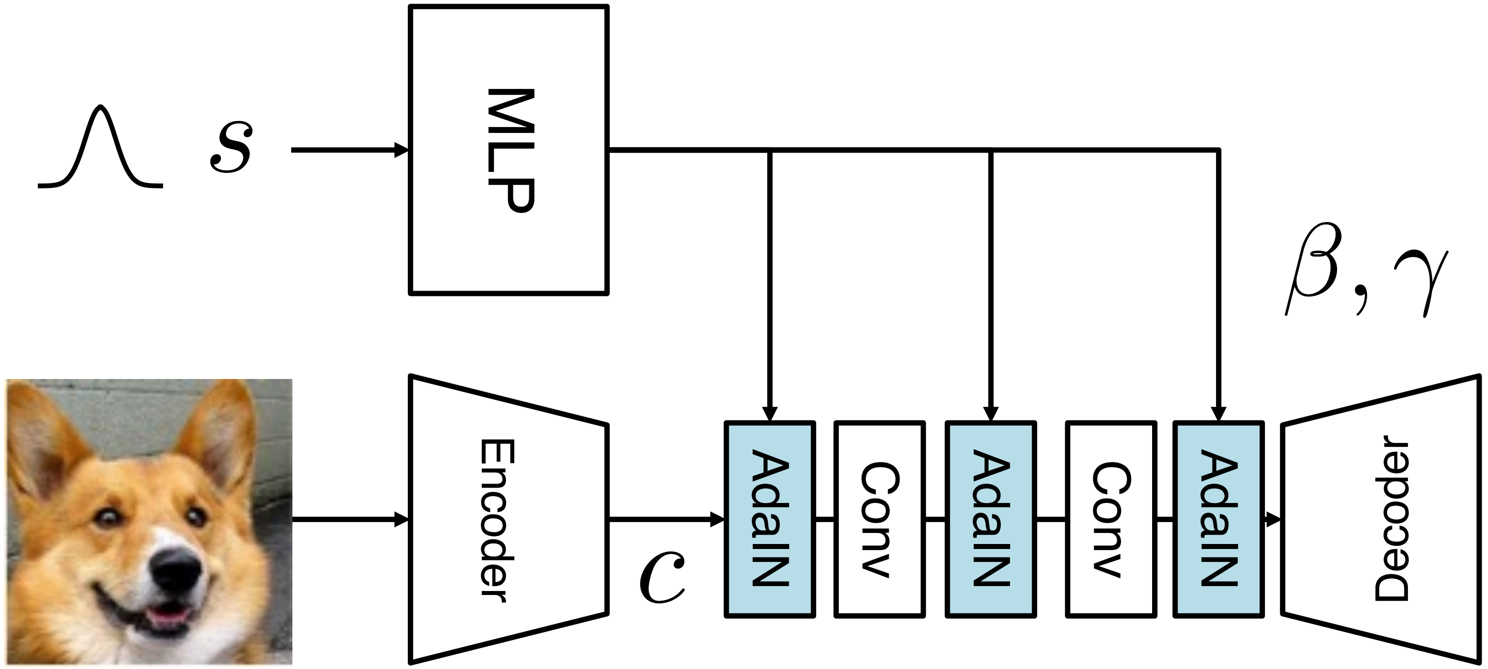
GAN Loss

Notations:

- x: images
- c: content
- s: style



AdaIN in a Generative Network



$$\mathrm{AdaIN}(c, s) = \gamma\left(\frac{c - \mu(c)}{\sigma(c)}\right) + \beta$$

AdaIN in a generative network

Sketches <-> Photo

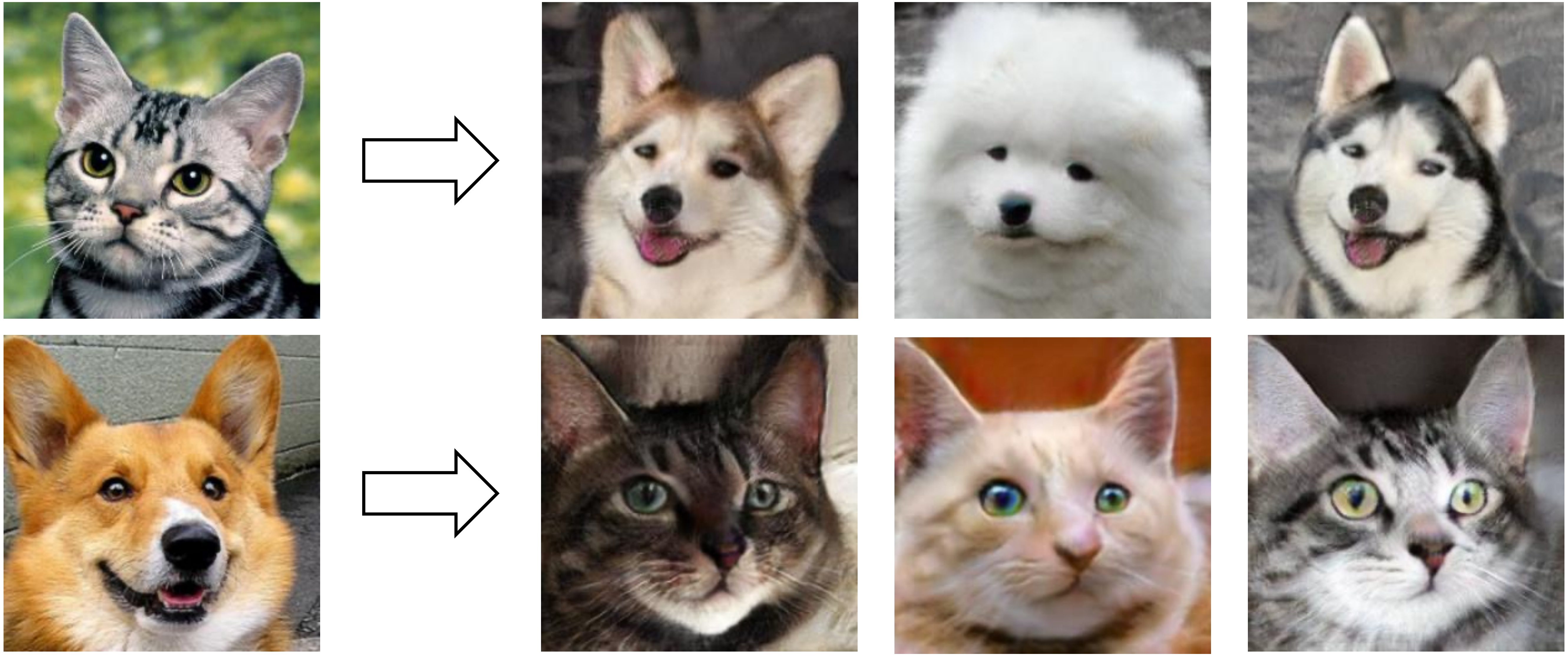
Input

Outputs

Cats ↔ Dogs

Input

Outputs



Synthetic ↔ Real

Input

Outputs

Example-guided Translation

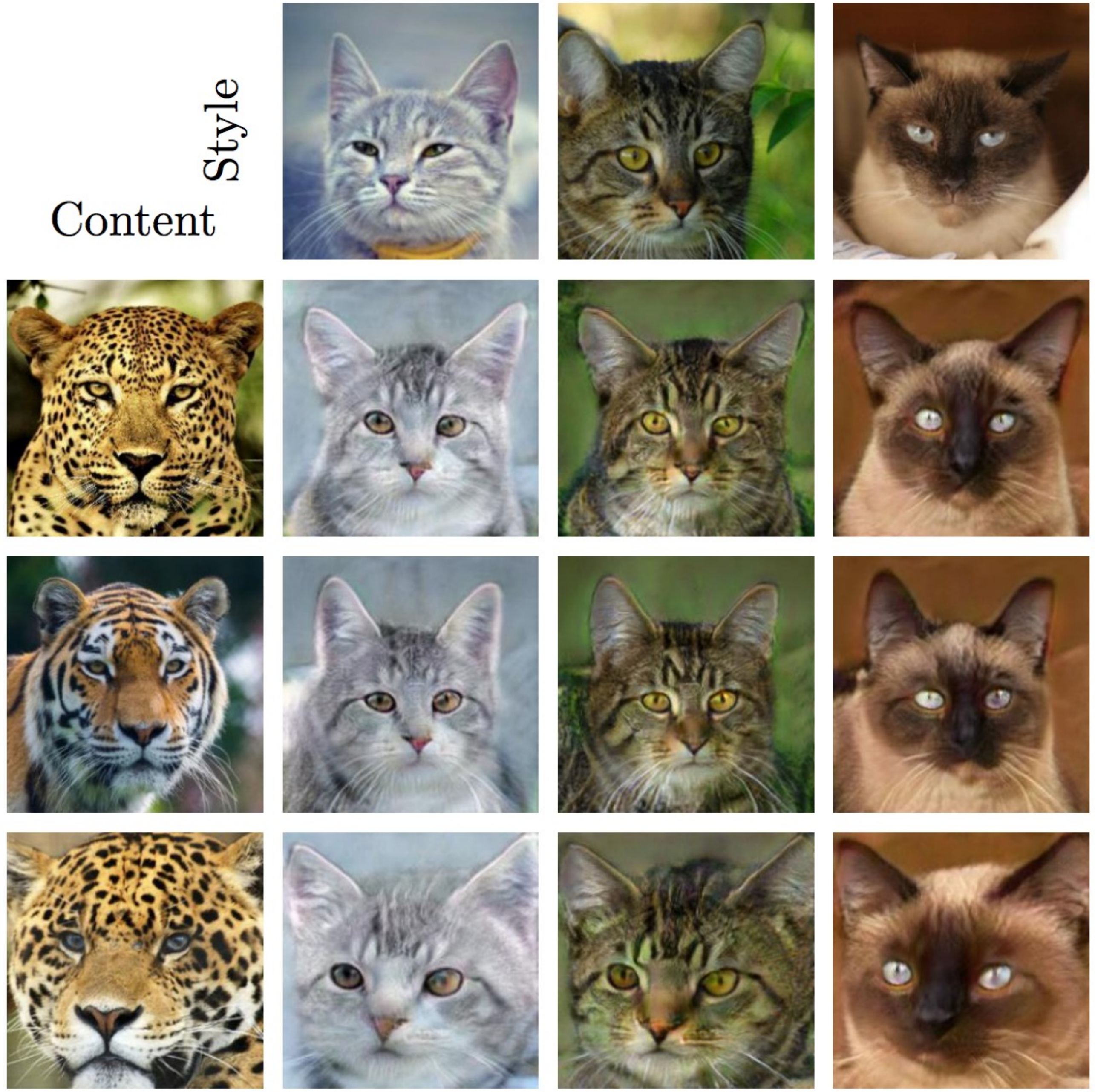
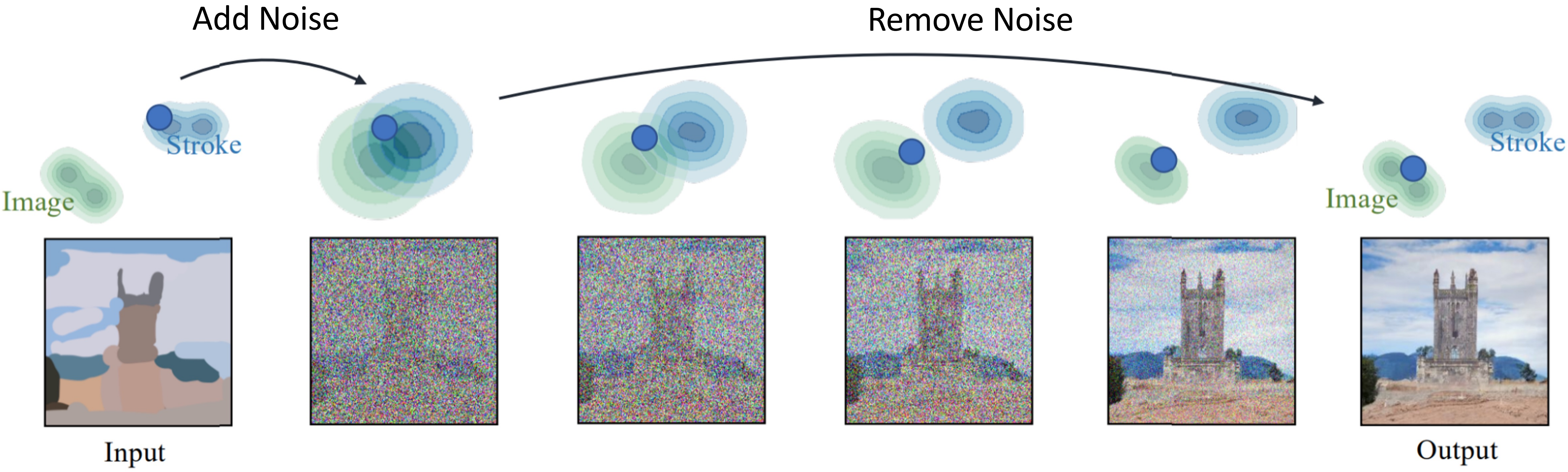


Image-to-Image Translation with Diffusion Models

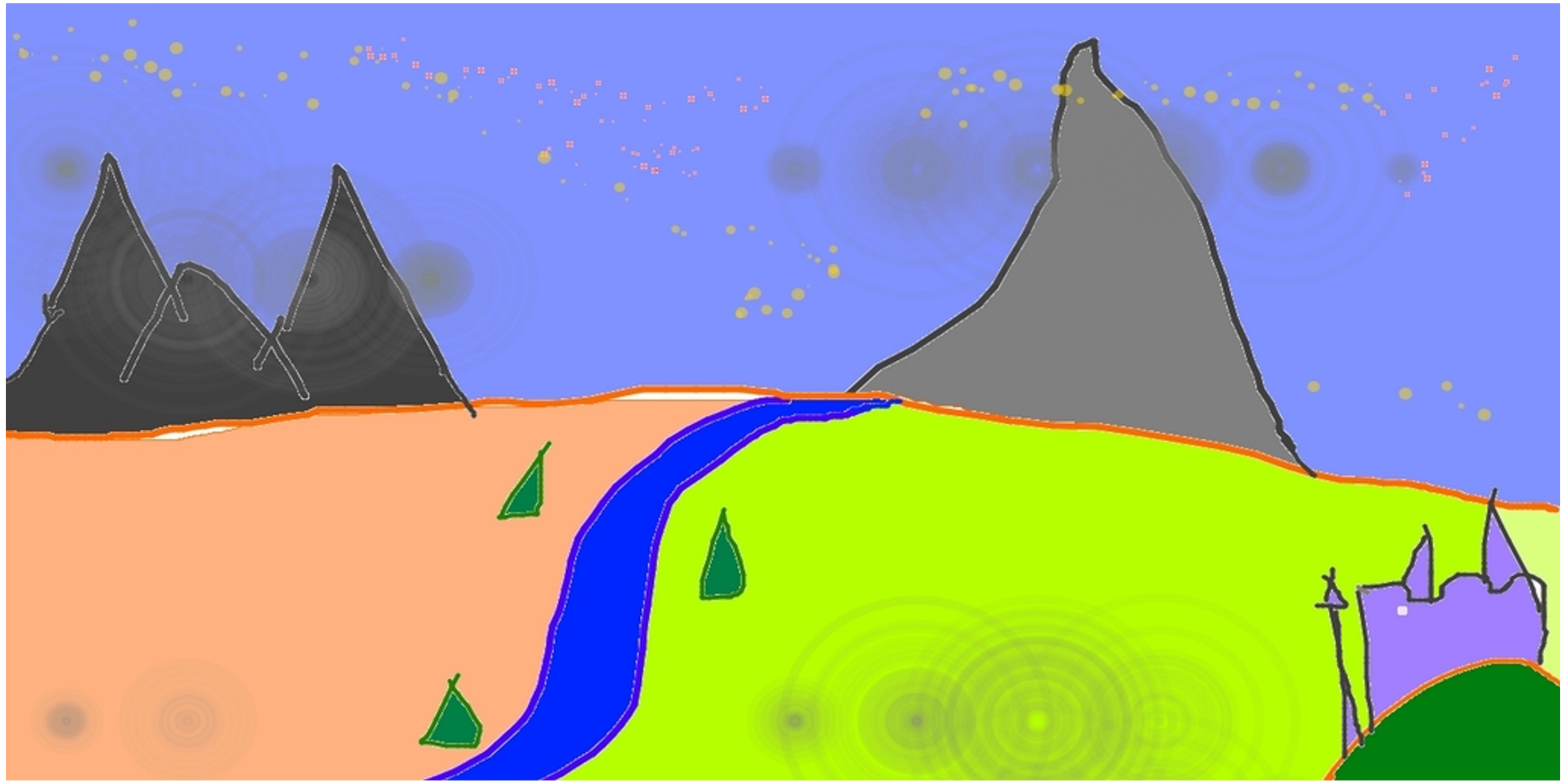
Guided Image Synthesis

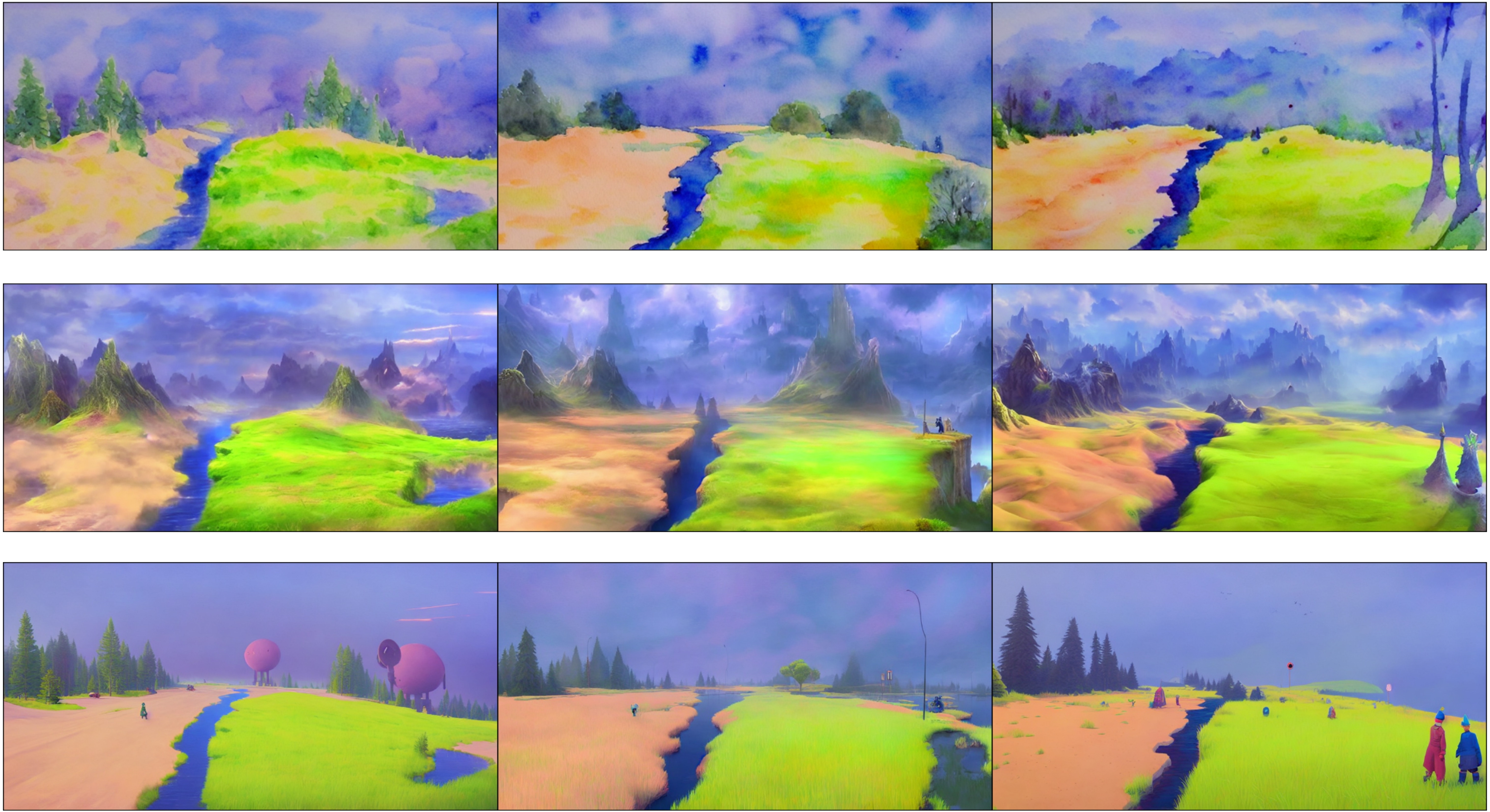
SDEdit (https://arxiv.org/abs/2108.01073) recipe: diffuse → denoise



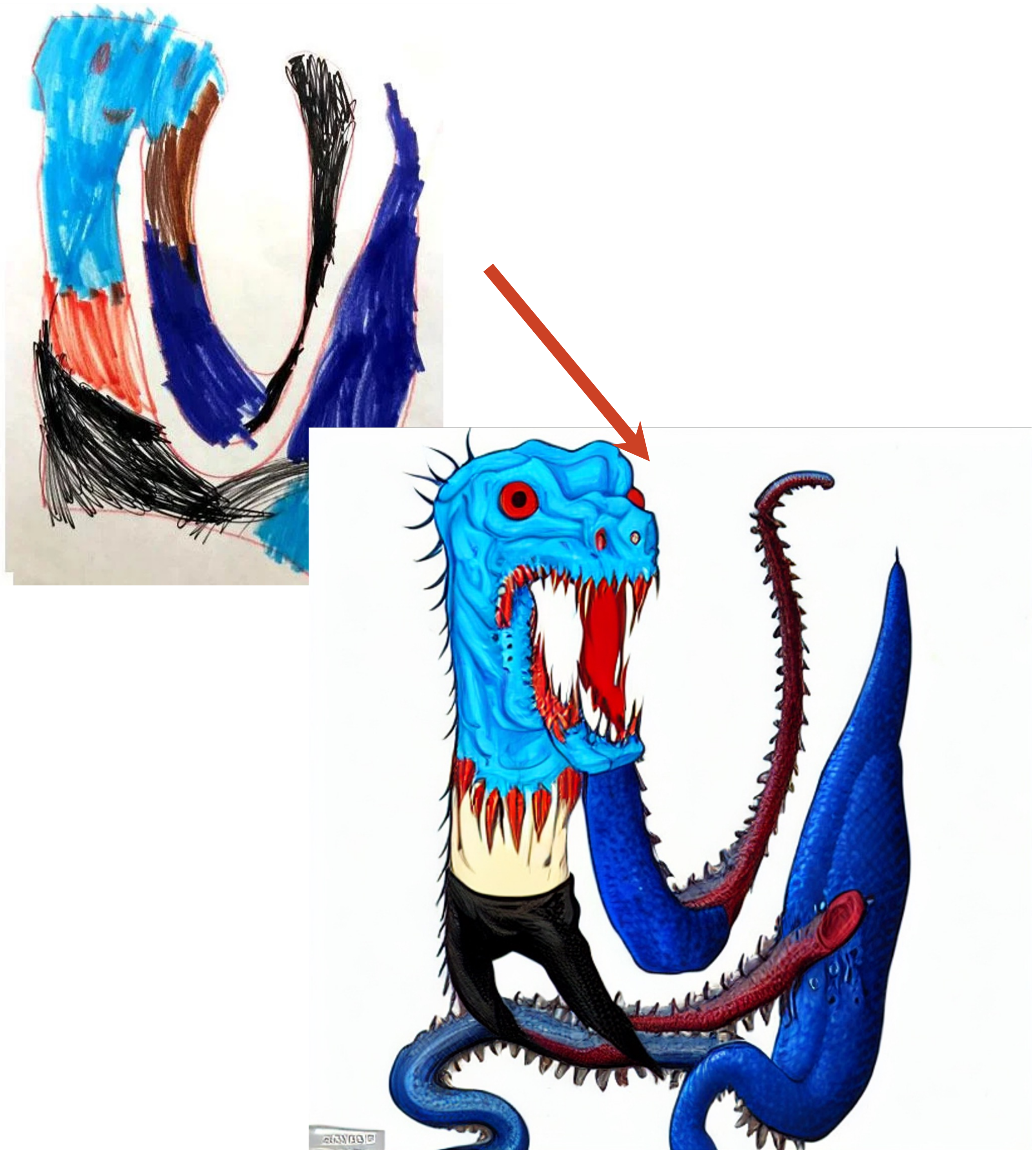
Guided Image Synthesis

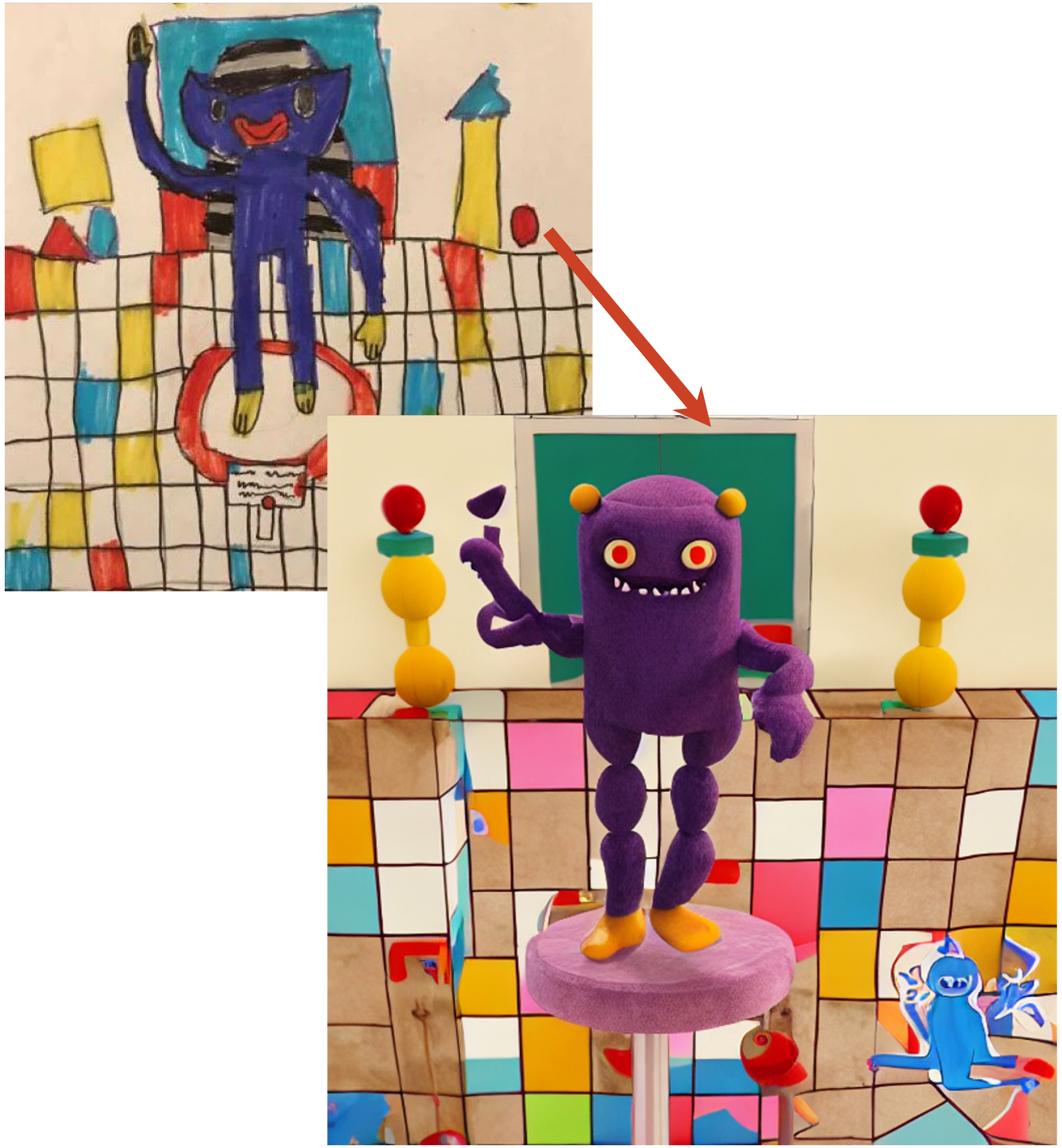
input



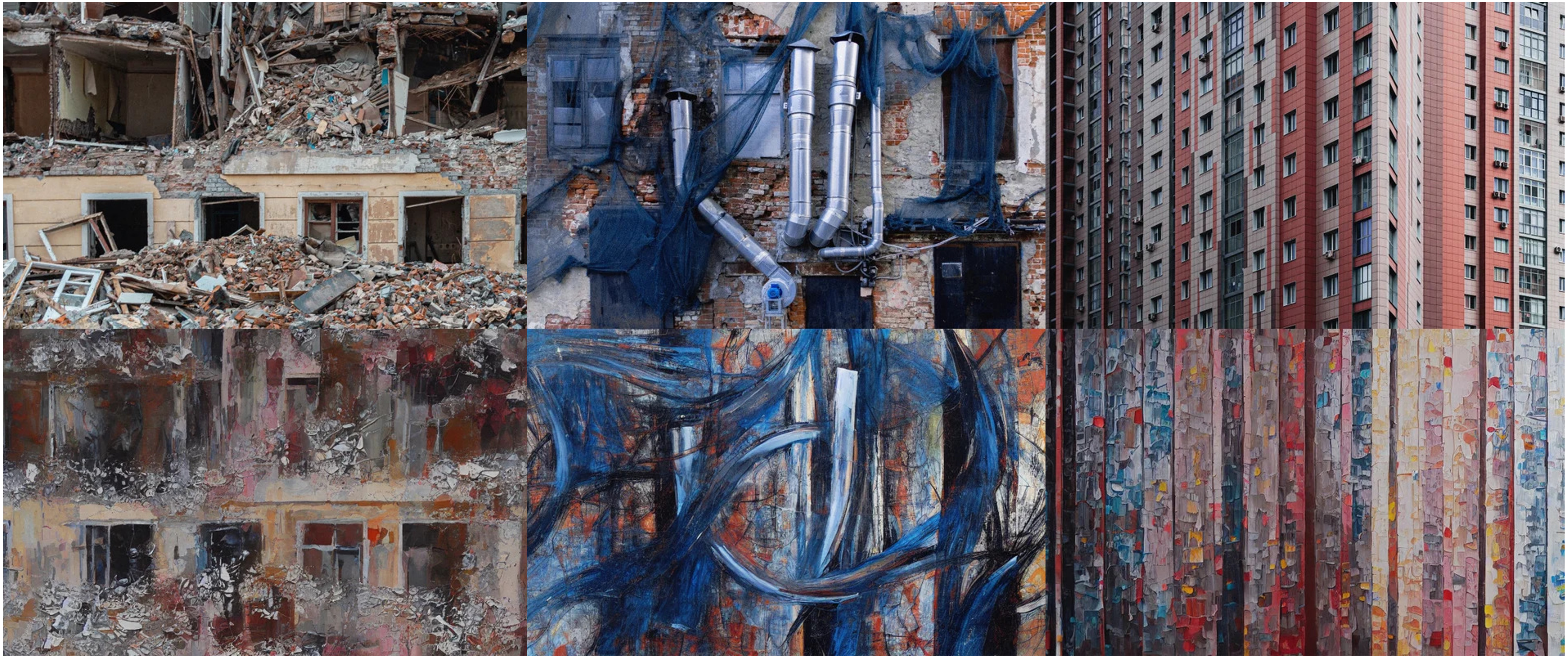


“Upgrade” your child’s artwork





abstract art from photos



original post by u/Pereulkov
https://www.reddit.com/r/StableDiffusion/comments/xhhyad/i_made_abstract_art_from_my_photos/

Thank You!

16-726, Spring 2025

https://learning-image-synthesis.github.io/