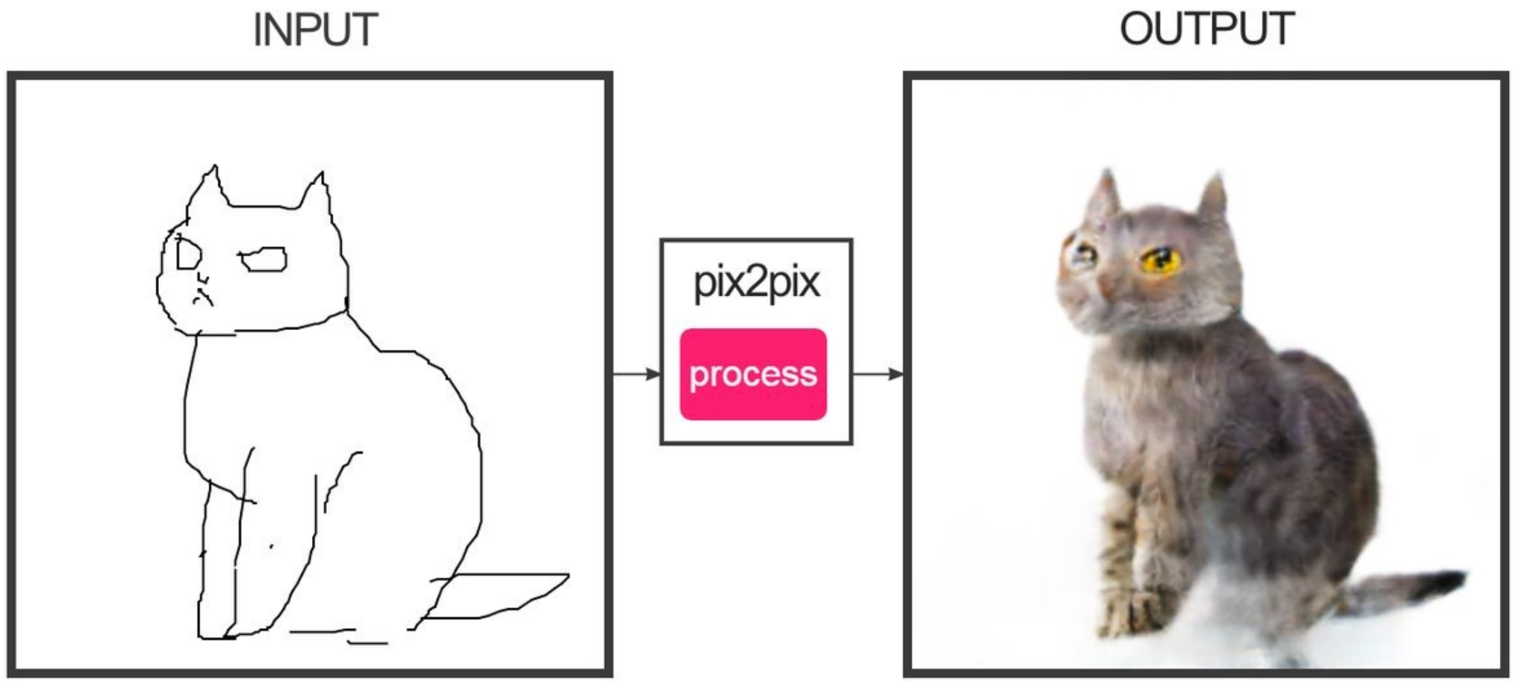


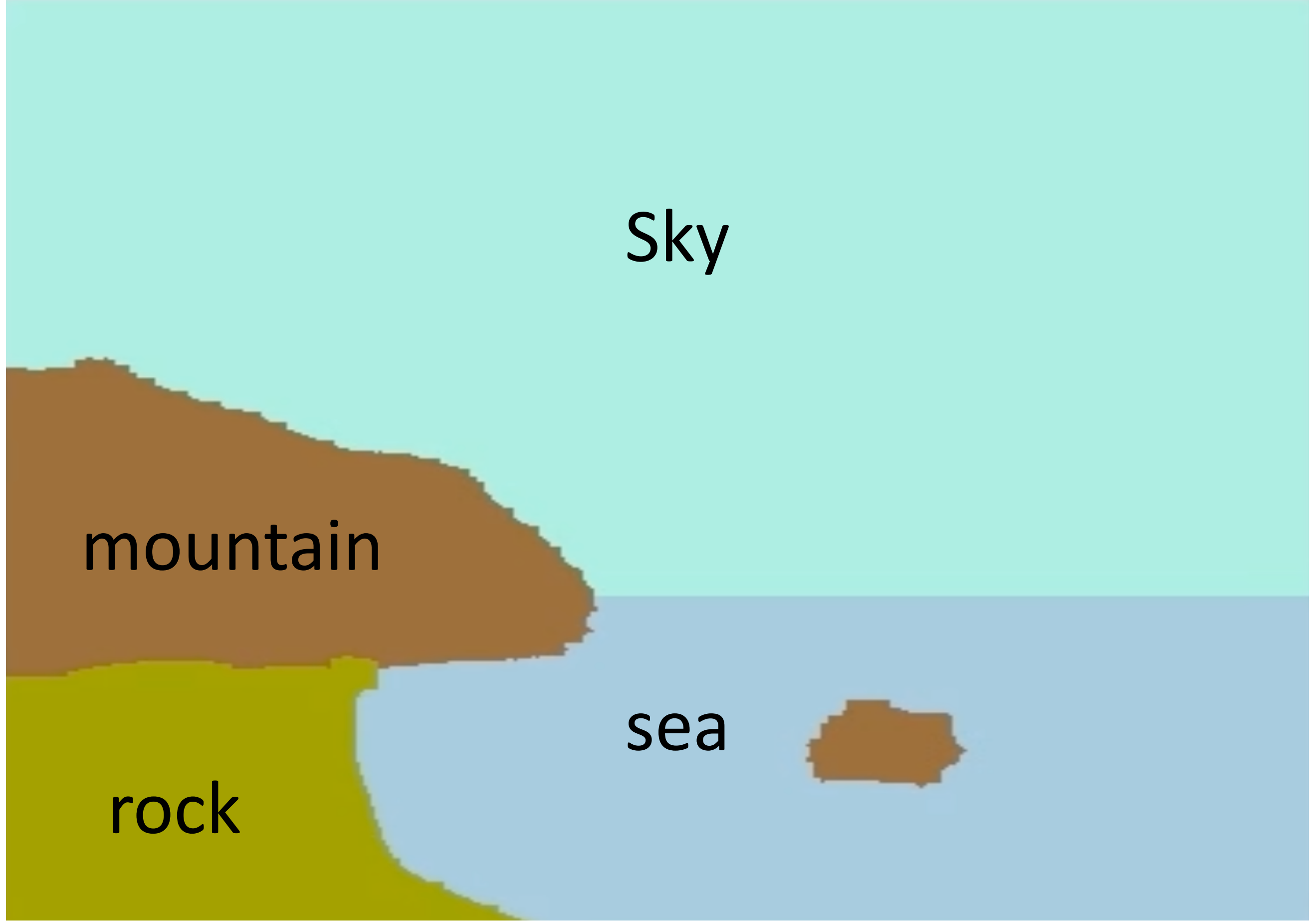
Conditional GANs, Image-to-Image Translation

Jun-Yan Zhu

16-726, Spring 2023

© https://affinelayer.com/pixsrv/, pix2pix [Isola et al., 2016]

Problem Statement

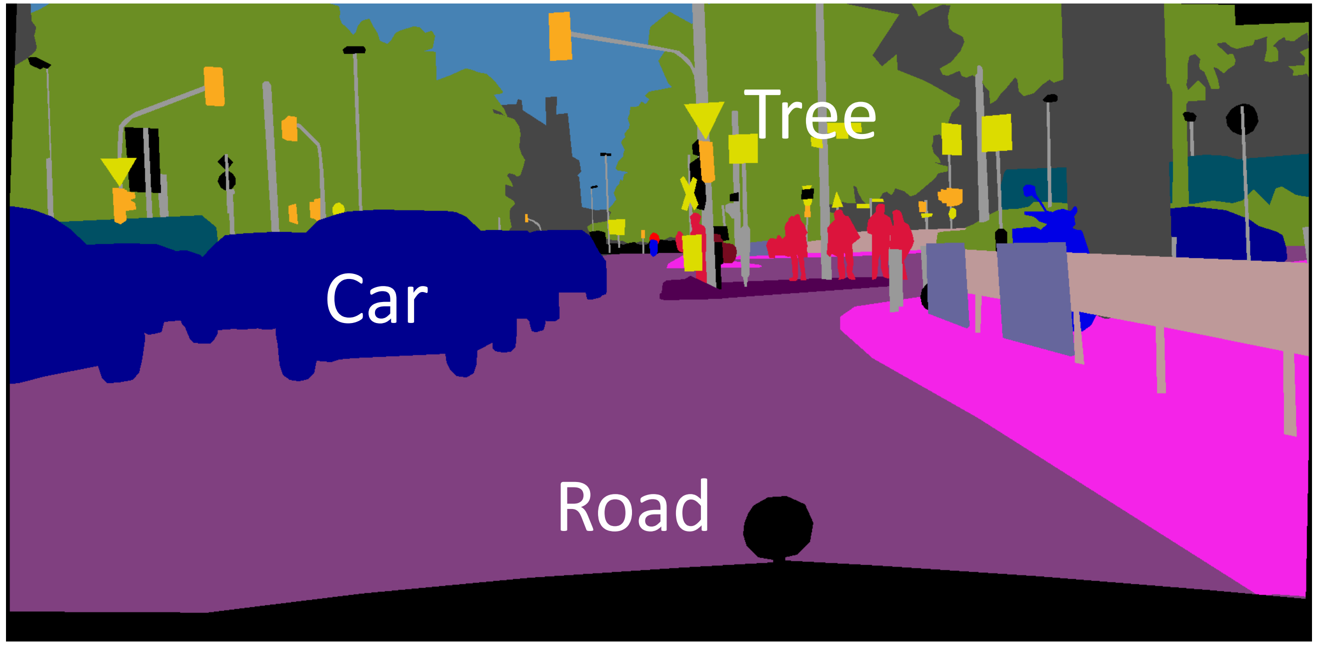


Input


Output

Goal: synthesize a photograph given an input image

Problem Statement



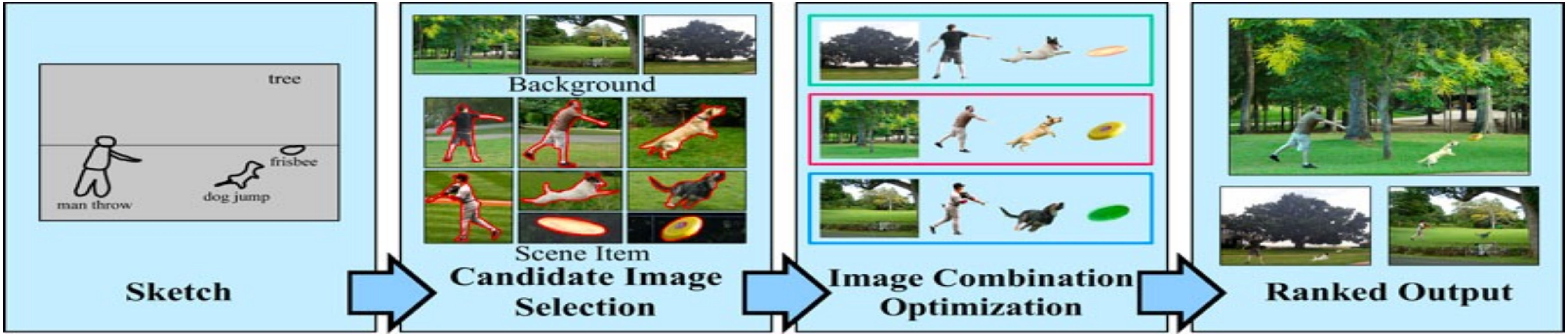
Input

Output

Goal: synthesize a photograph given an input image

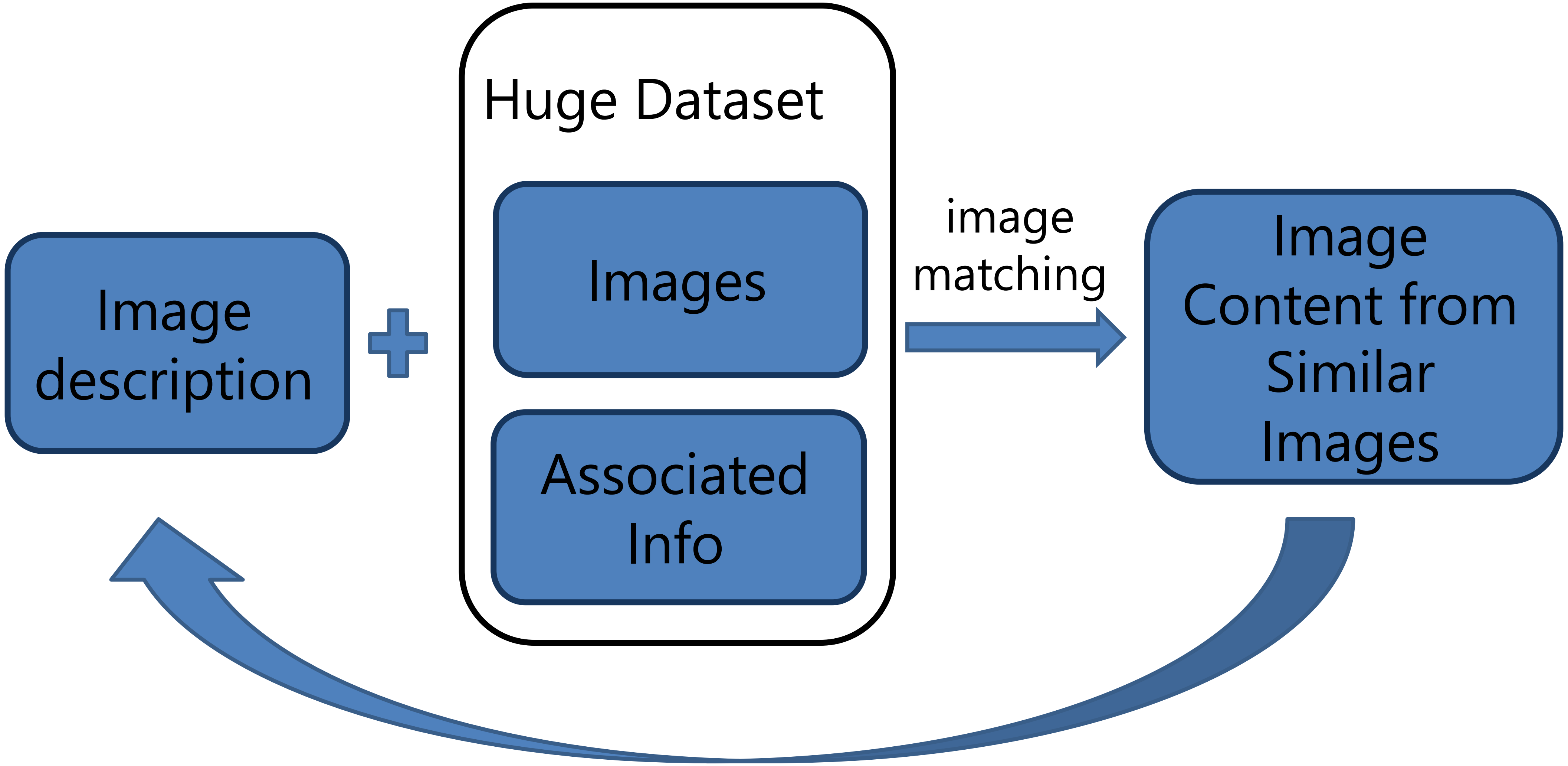
Early work (Example-based)

Semantic Photo Synthesis [Johnson et al., Eurographics 2006]



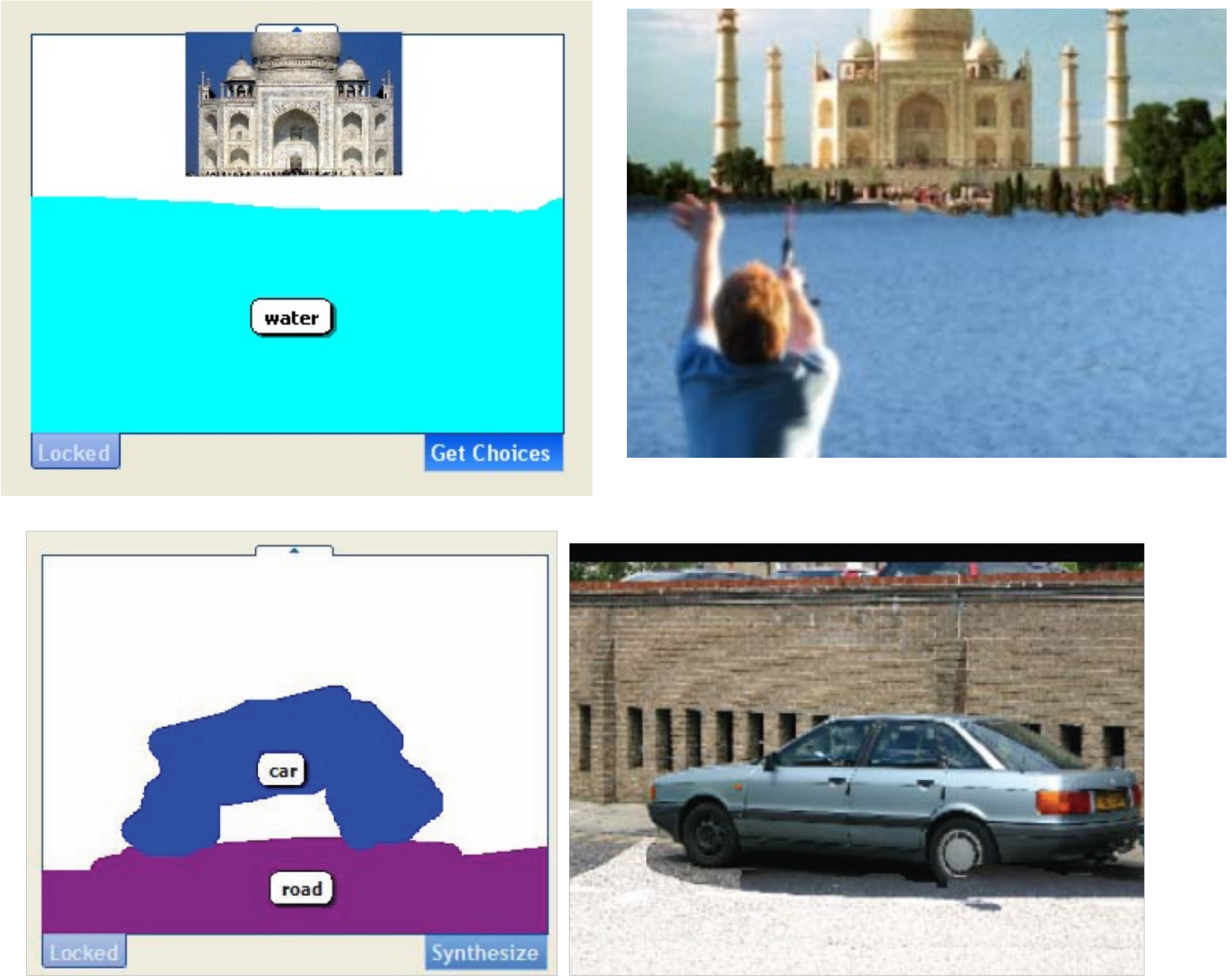
Sketch2Photo [Tao et al., SIGGRAPH Asia 2009]

Semantic Photo Synthesis



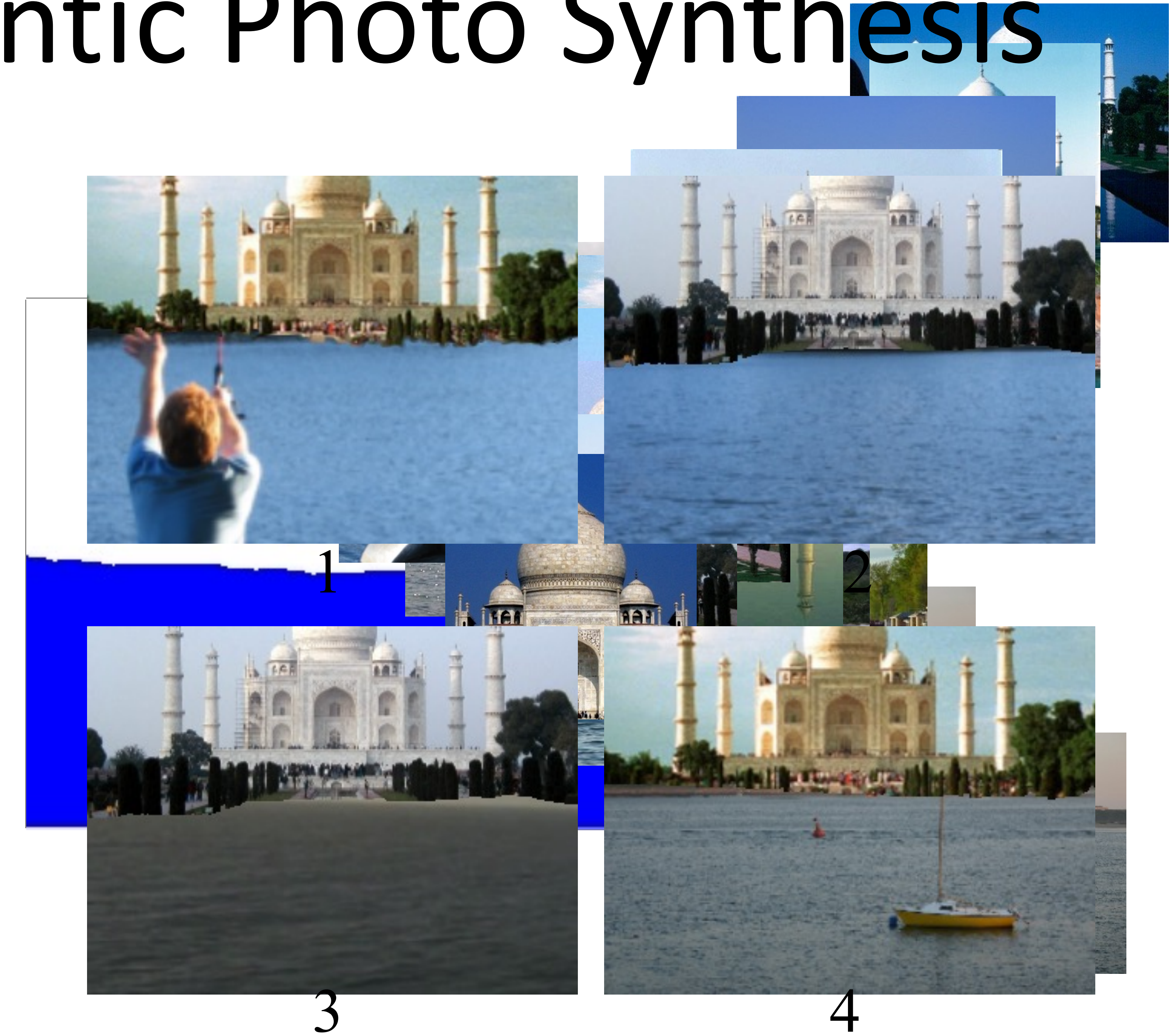
M. Johnson, G. Brostow, J. Shotton, O. A. c, and R. Cipolla, “Semantic Photo Synthesis,” Eurographics 2006

Semantic Photo Synthesis [EG'06]

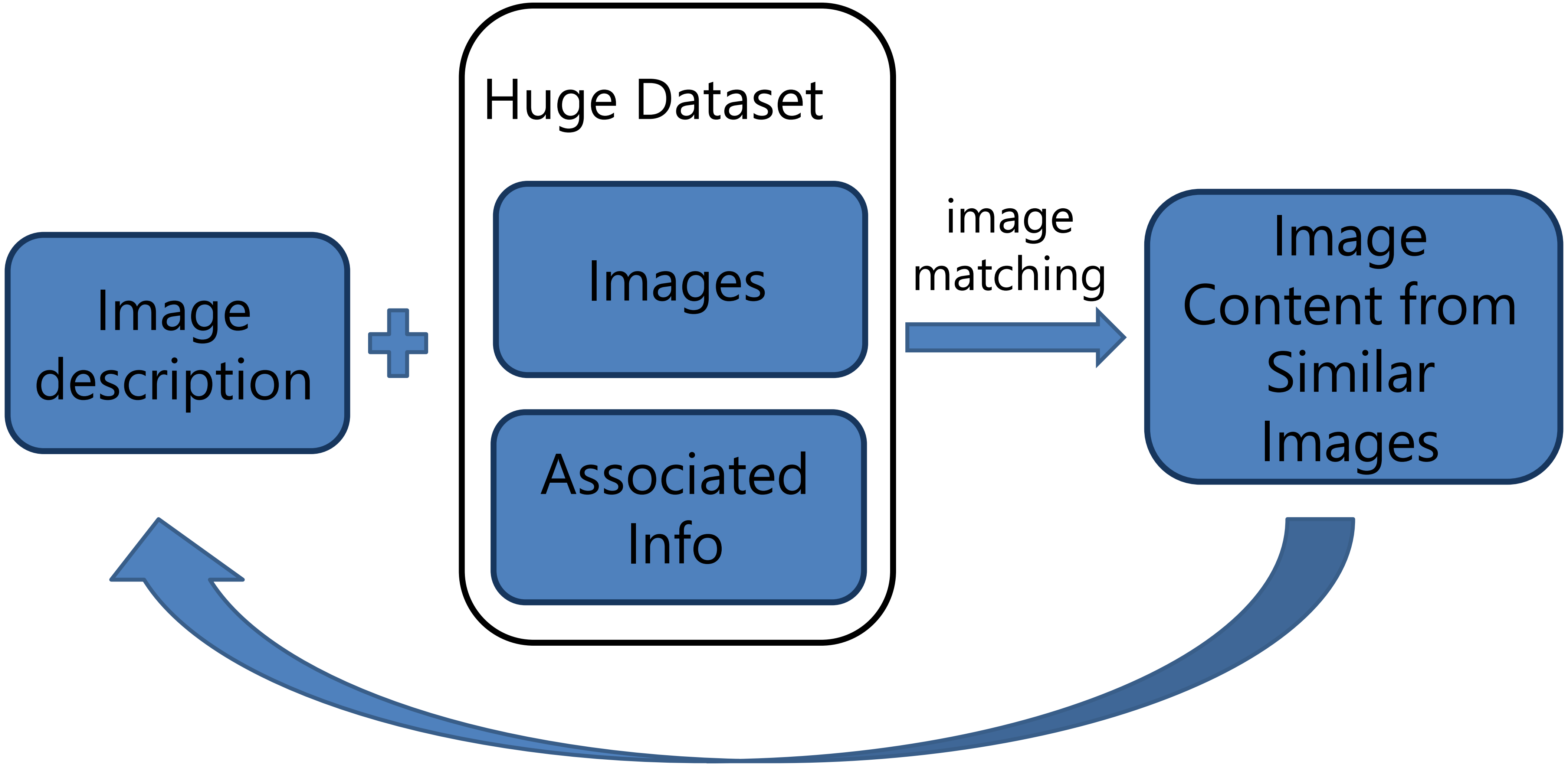


M. Johnson, G. Brostow, J. Shotton, O. A. c, and R. Cipolla, "Semantic Photo Synthesis," Eurographics 2006

Semantic Photo Synthesis



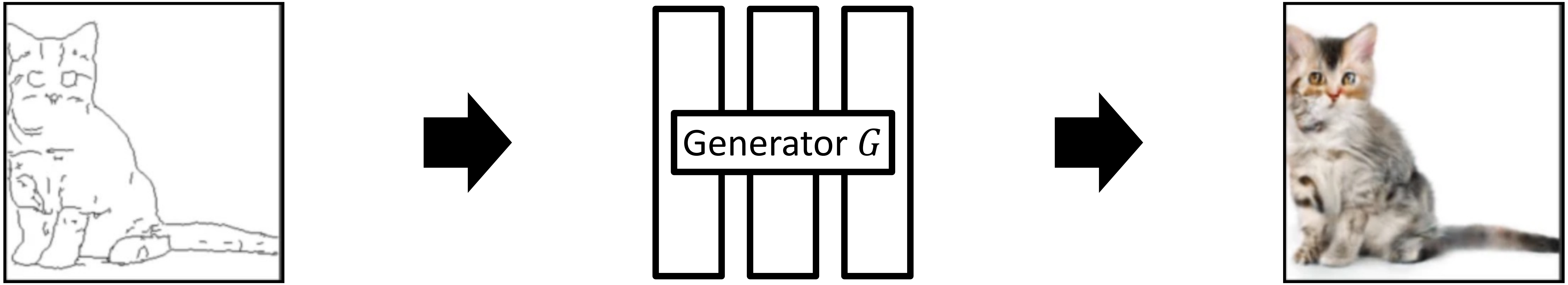
Semantic Photo Synthesis



M. Johnson, G. Brostow, J. Shotton, O. A. c, and R. Cipolla, "Semantic Photo Synthesis," Computer Graphics Forum Journal (Eurographics 2006), vol. 25, no. 3, 2006.

Learning-based methods

Loss functions for Image Synthesis



Input x | Learnable rendering | Output Image $\mathrm{G}(x)$

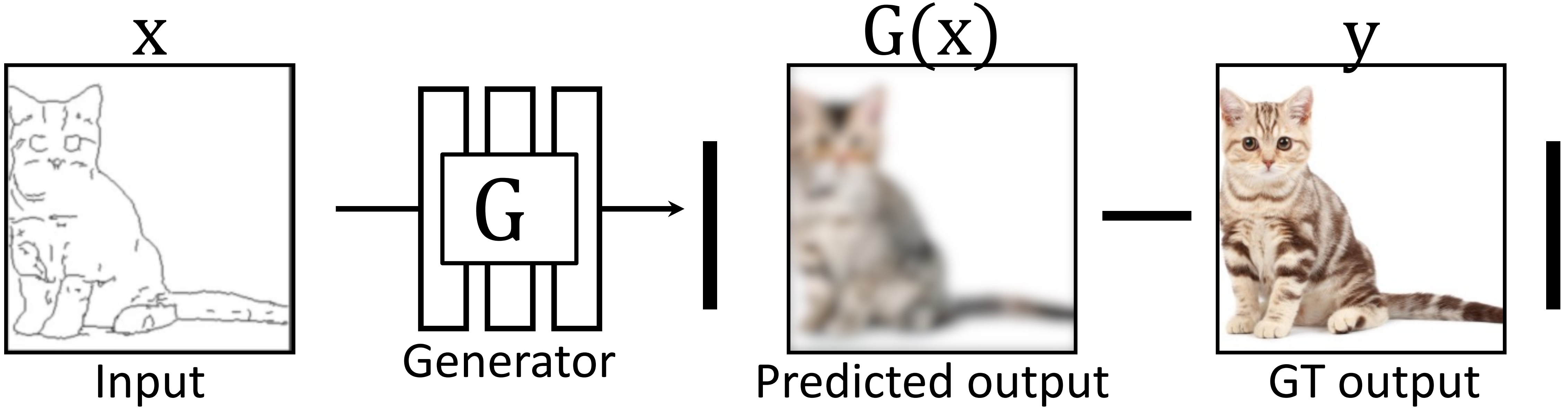
What is a good objective $\mathcal{L}$?

- What is a good loss?
- How to calculate it efficiently?
- How to collect data (x, y)?

Problem Statement

$$\arg\min_{G} \overset{\text{Loss function}}{\underline{\mathcal{L}}}(\underbrace{G}_{\text{Generator}}(\underbrace{x}_{\text{Input Info}}), \underbrace{y}_{\text{Output image}})$$

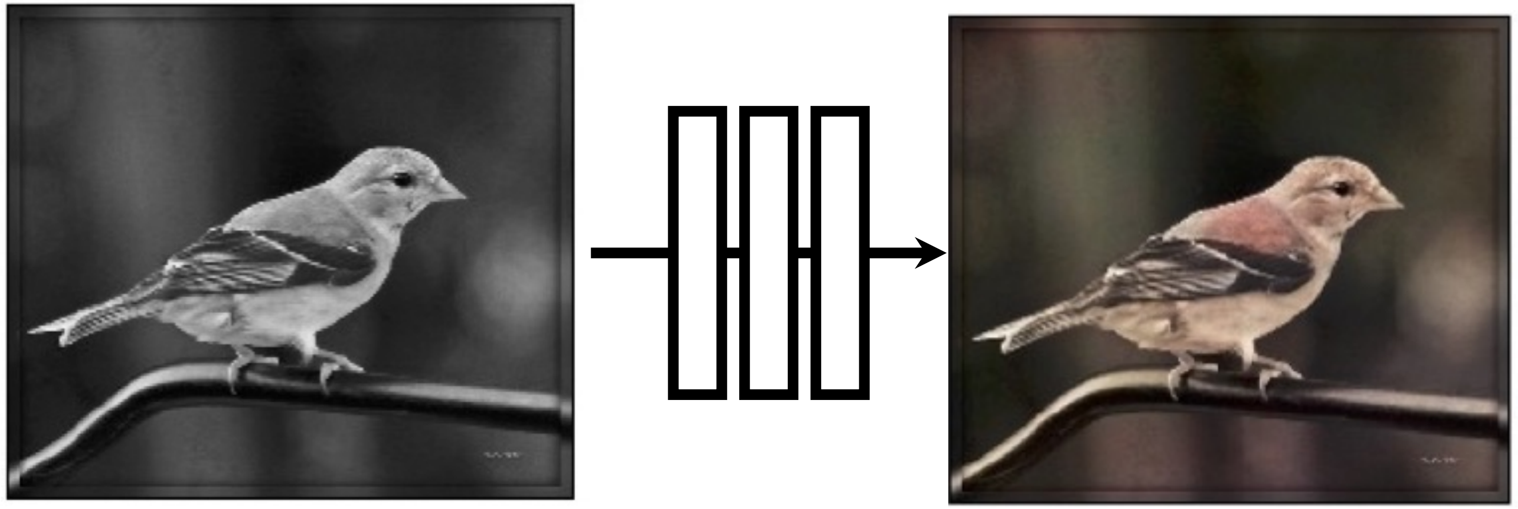
Designing Loss Functions



L2 regression $\arg\min_{G} \mathbb{E}[\,||G(x) - y||\,]$

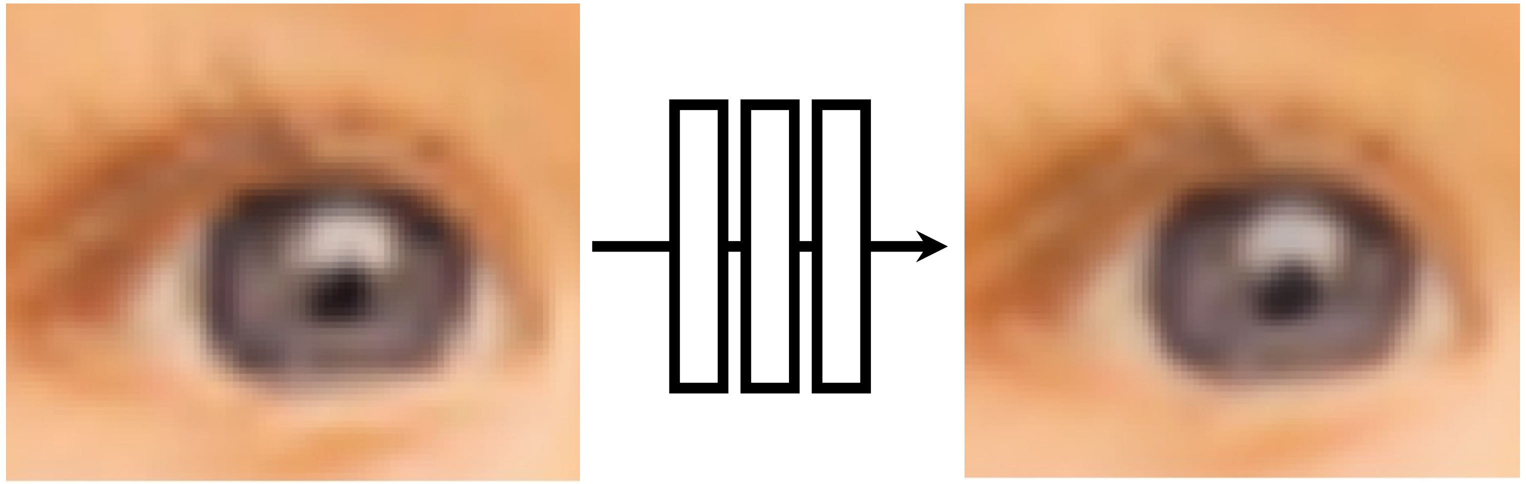
Designing Loss Functions

Image colorization



L2 regression

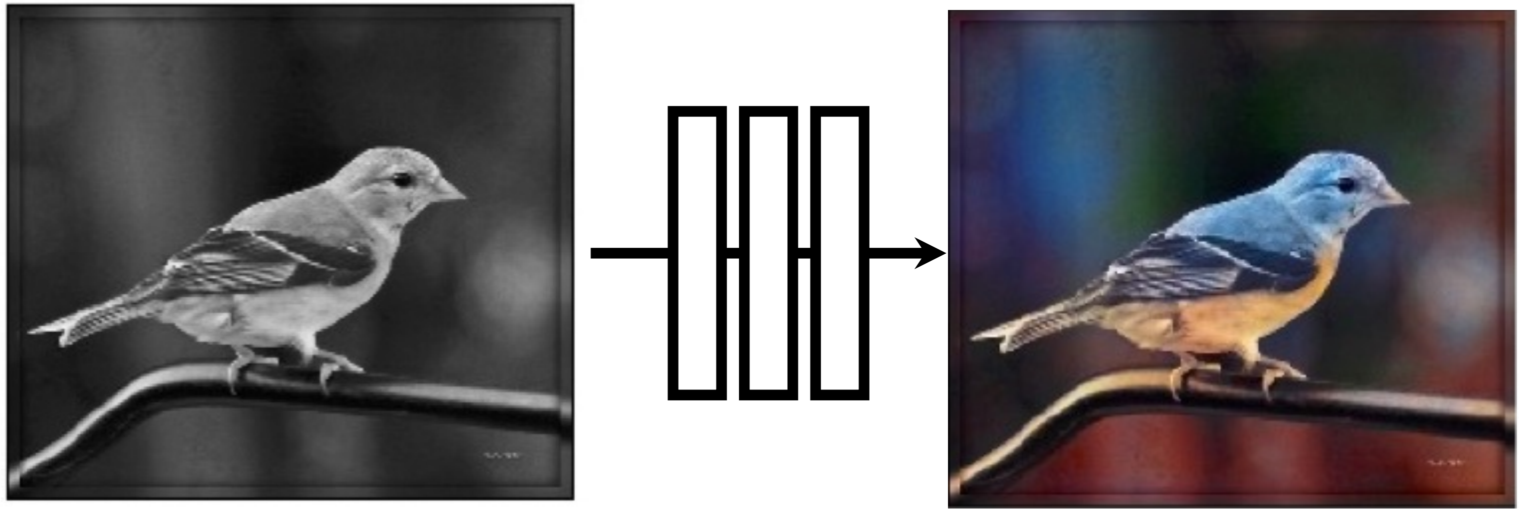
Super-resolution



L2 regression

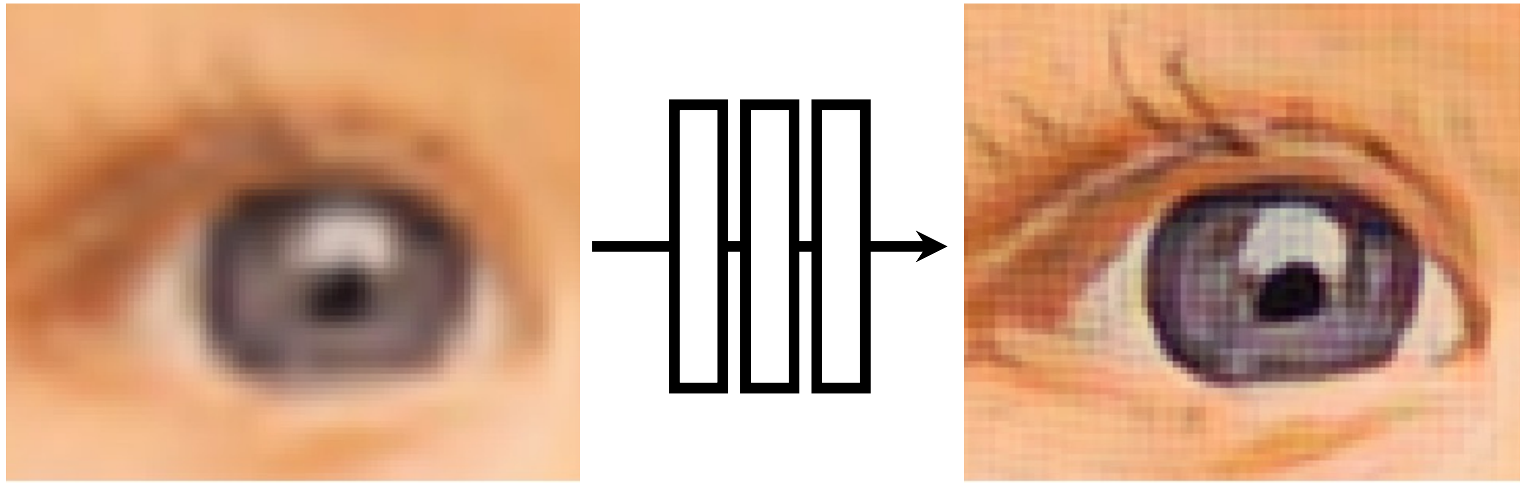
Designing Loss Functions

Image colorization



[Zhang et al. 2016]

Super-resolution

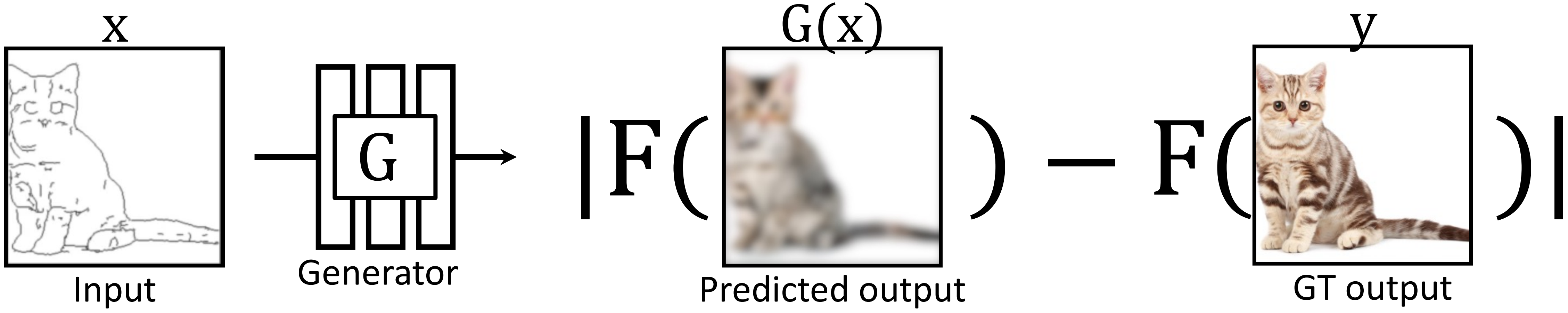


[Gatys et al., 2016], [Johnson et al. 2016], [Dosovitskiy and Brox. 2016]

<u>Classification Loss:</u>
Cross entropy objective,
with colorfulness term

<u>Feature/Perceptual loss</u>
Deep feature matching
objective

CNNs as a Perceptual Metric



F is a deep network (e.g., ImageNet classifier)

Perceptual Loss

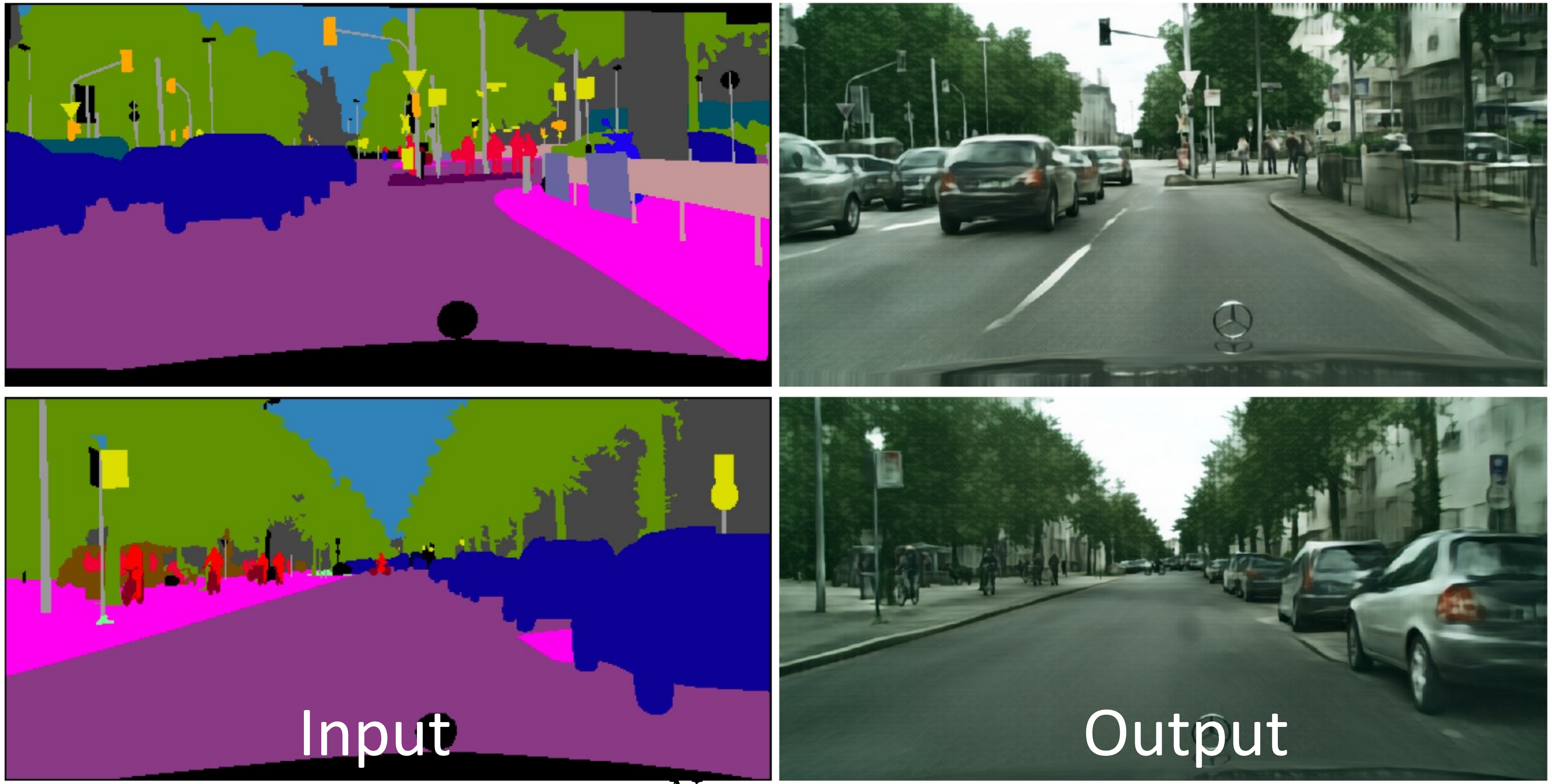
weight

(i)-th layer

$$\arg\min_G \mathbb{E}_{(x,y)} \sum_{i=1}^{N} \lambda_i \frac{1}{M_i} ||F^{(i)}(G(x)) - F^{(i)}(y))||_2^2$$

The number of elements in the (i)-th layer

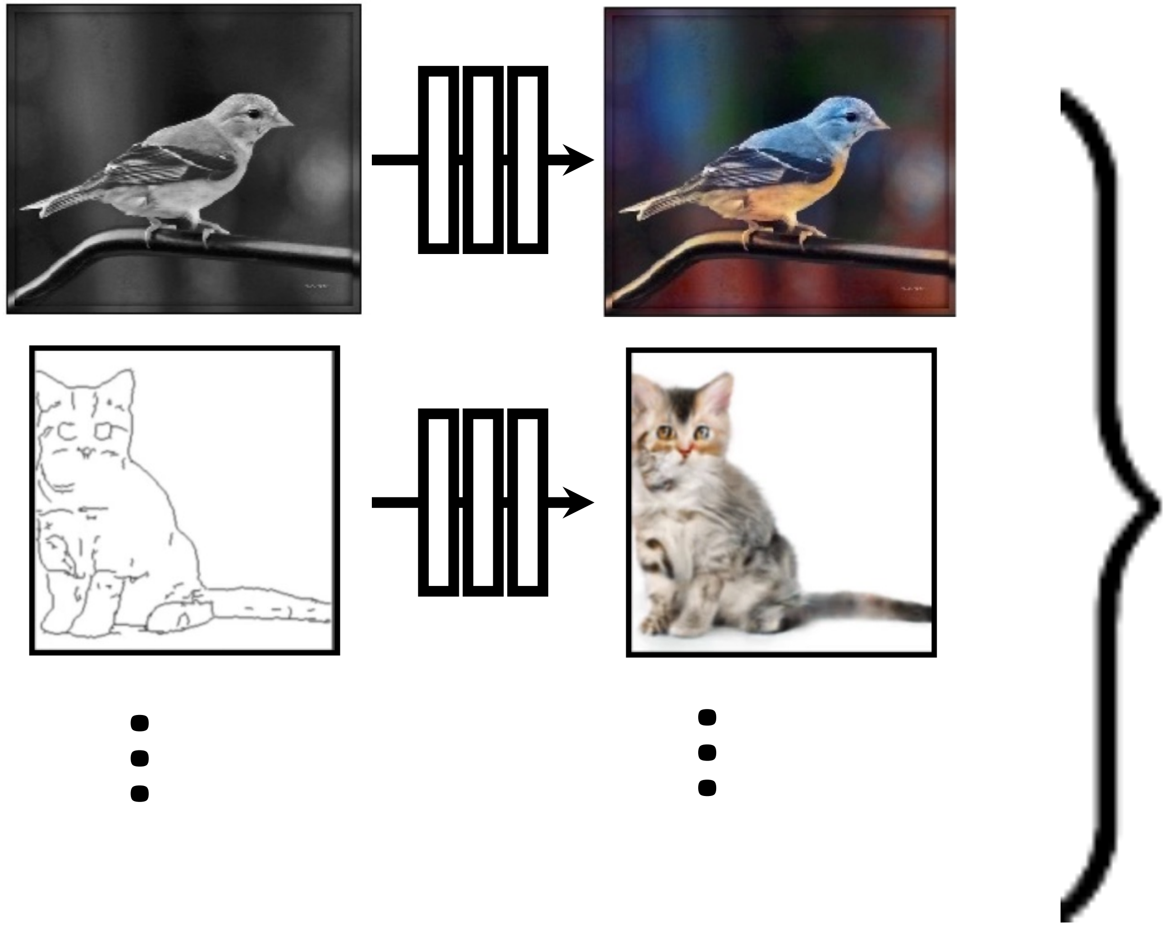
Learning with Perceptual Loss



Training objective: $\arg\min_{G} \mathbb{E}_{(x,y)} \sum_{i=1}^{N} \lambda_i \frac{1}{M_i} ||F^{(i)}(G(x)) - F^{(i)}(y)||_2^2$

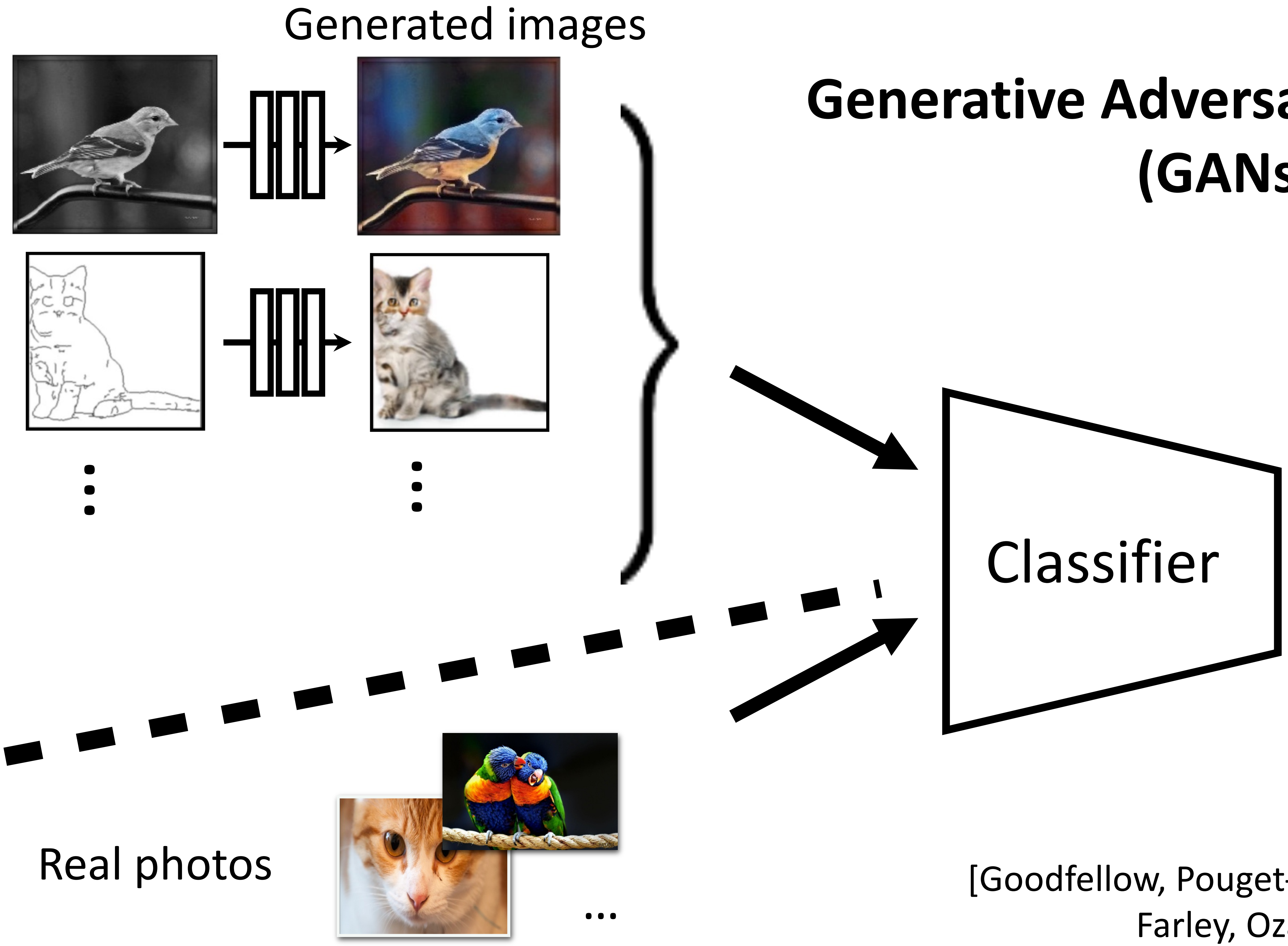
CRN [Chen and Koltun, 2017]

Generated images

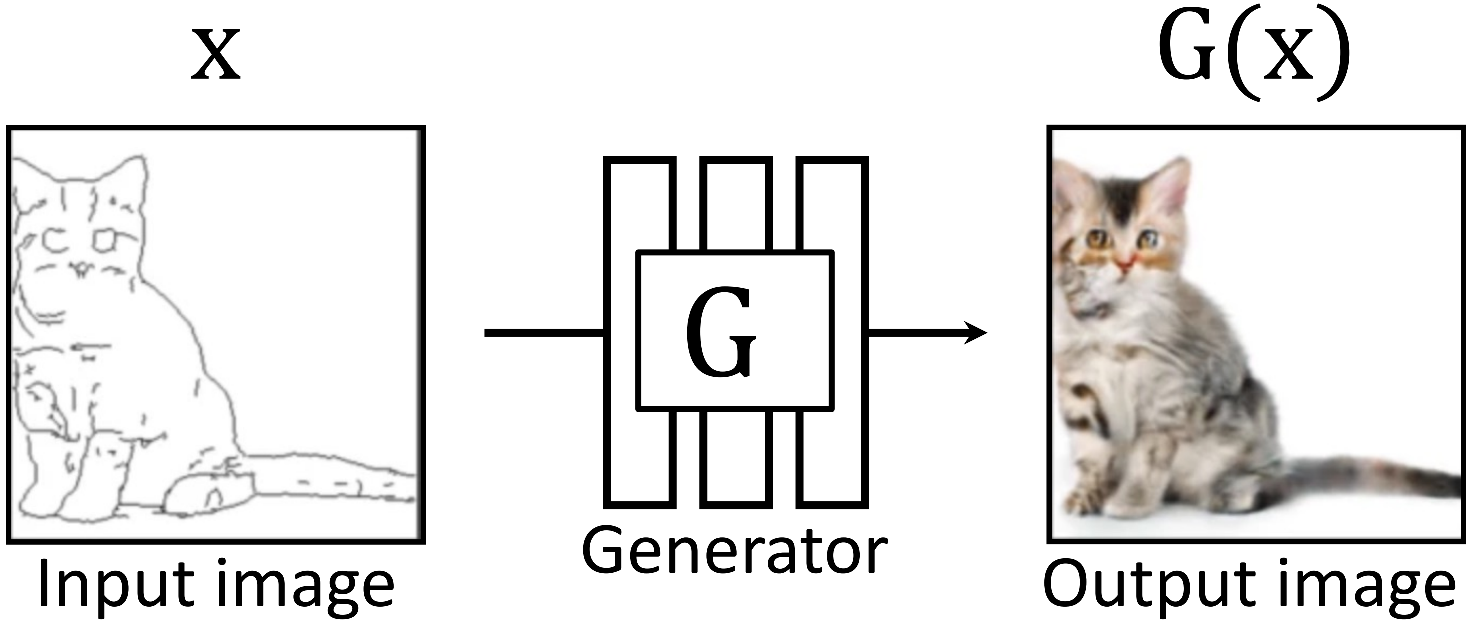


Universal loss?

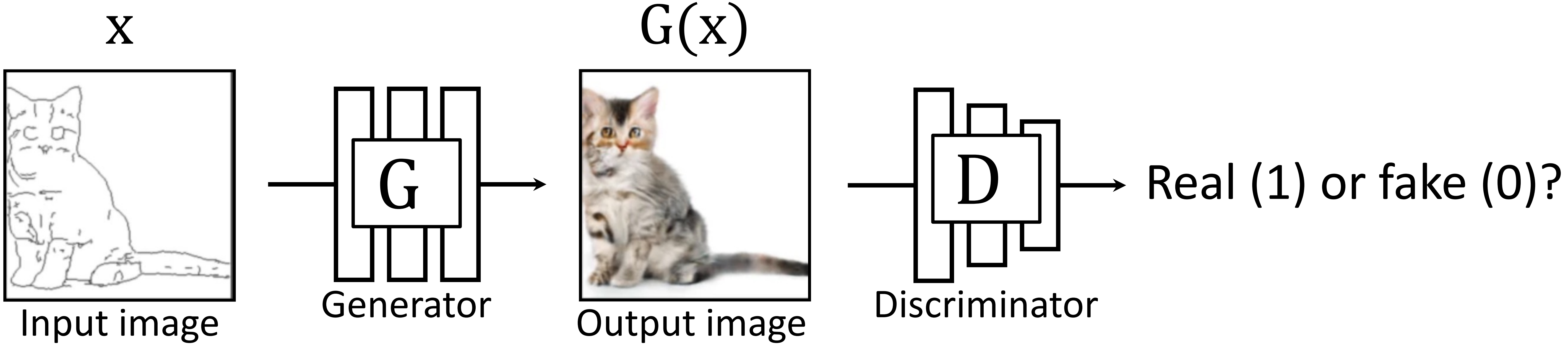
Generative Adversarial Network (GANs)



[Goodfellow, Pouget-Abadie, Mirza, Xu, Warde-Farley, Ozair, Courville, Bengio 2014]



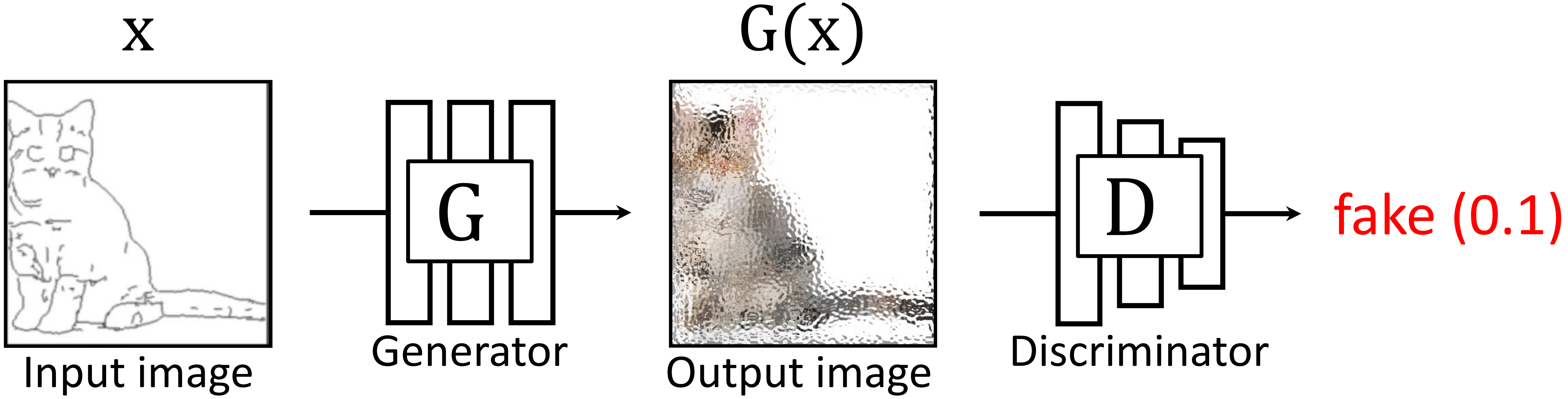
[Goodfellow et al. 2014]



A two-player game:

- G tries to generate fake images that can fool D.
- D tries to detect fake images.

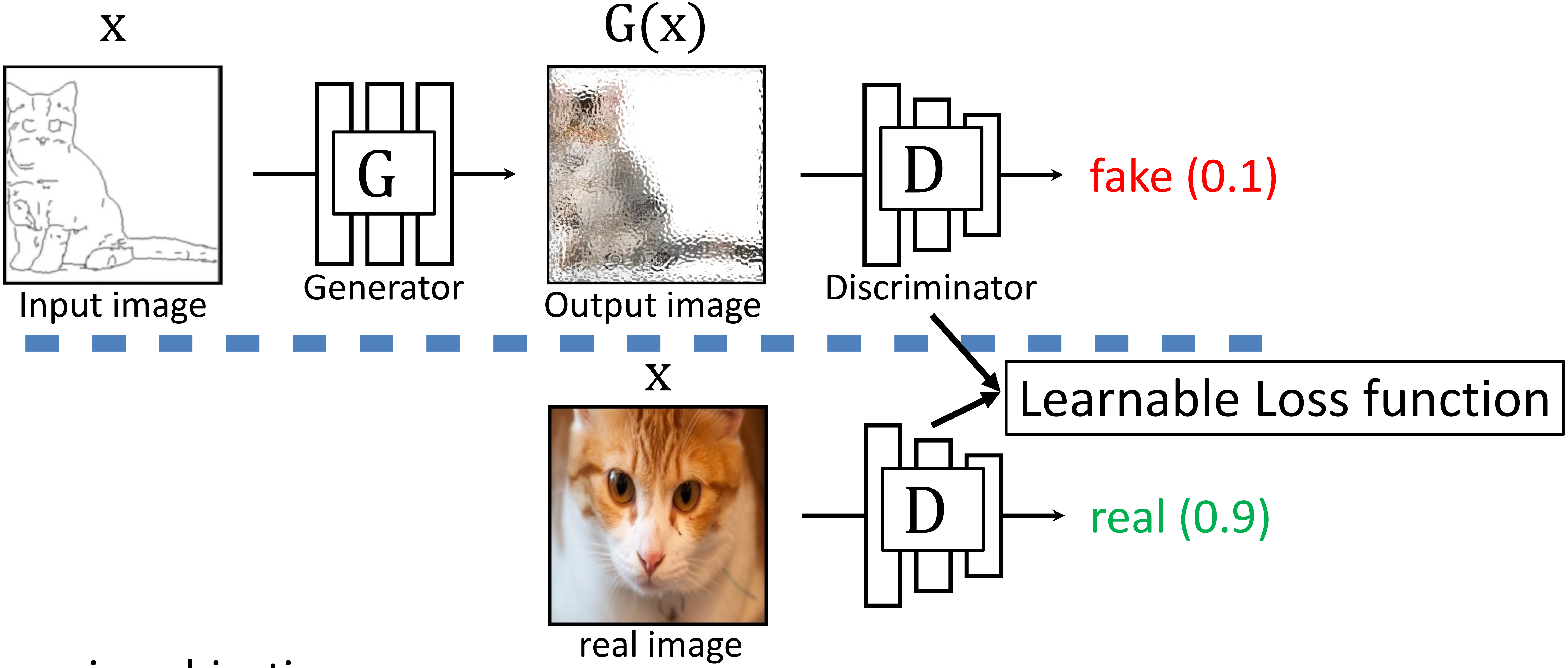
[Goodfellow et al. 2014]



Learning objective

$$\min_{G} \max_{\boxed{D}} \mathbb{E}_x \boxed{[\log(1 - D(G(x)))]} + \mathbb{E}_y [\log D(y)]$$

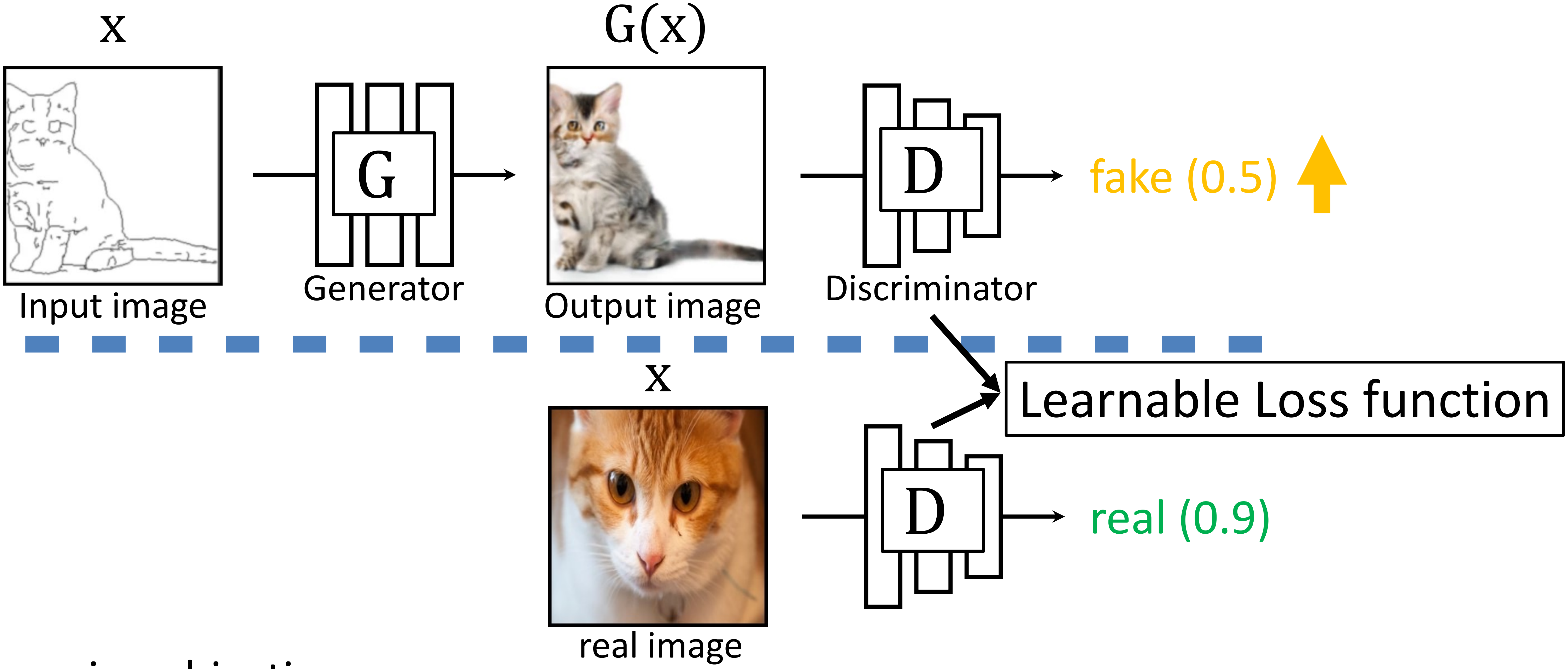
[Goodfellow et al. 2014]



Learning objective

$$\min_{G} \max_{\boxed{D}} \mathbb{E}_x \boxed{[\log(1 - D(G(x)))]} + \mathbb{E}_y \boxed{[\log D(y)]}$$

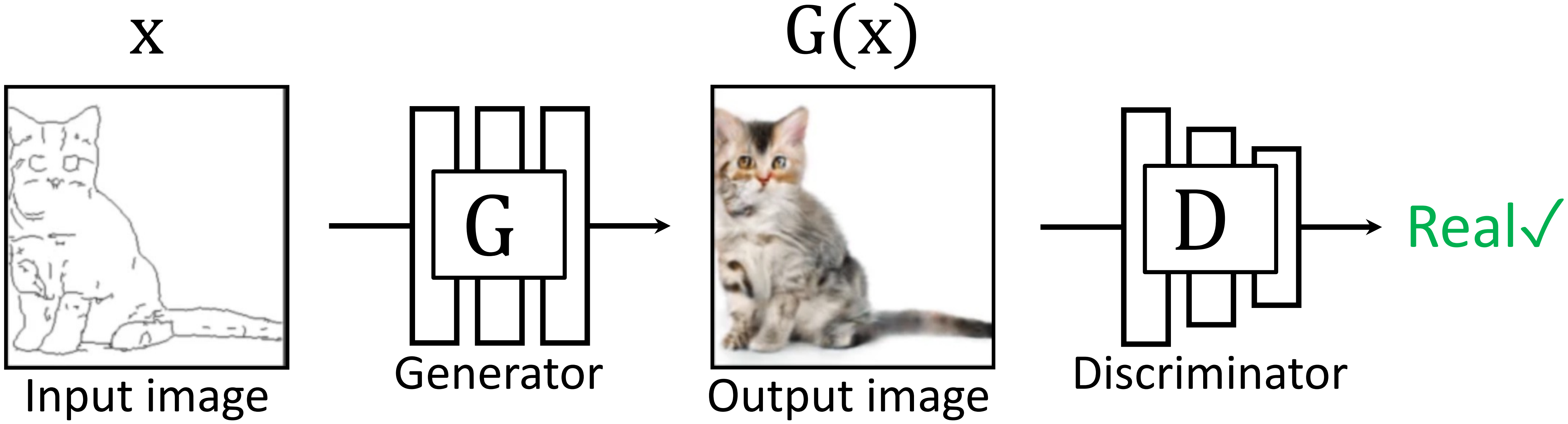
[Goodfellow et al. 2014]



Learning objective

$$\min_{\boxed{G}}\max_{D}\mathbb{E}_x[\log(1-\boxed{D(G(x))]}+\mathbb{E}_y[\log D(y)]$$

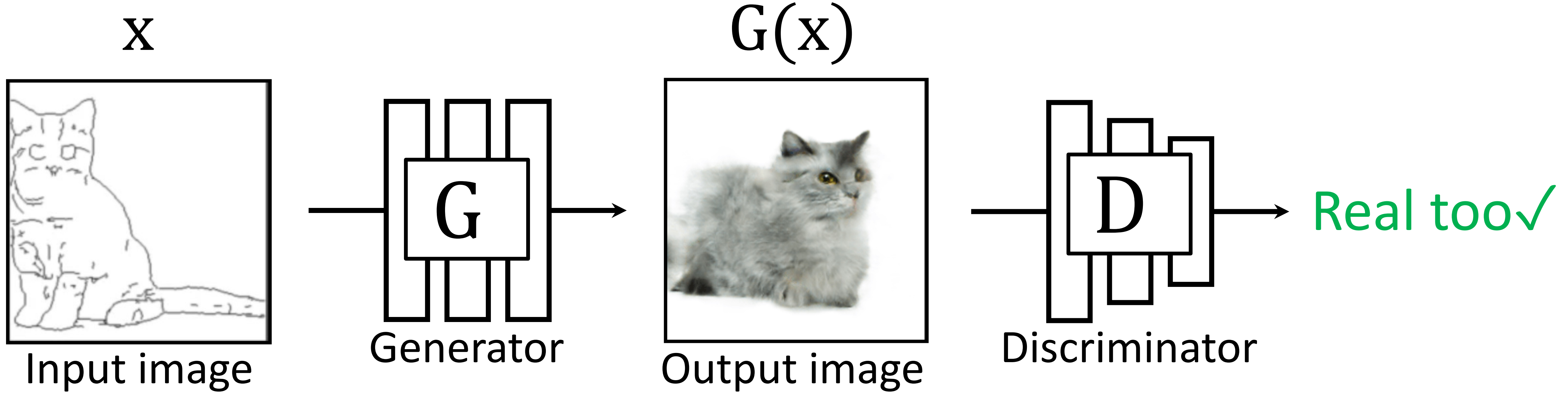
[Goodfellow et al. 2014]



Learning objective

$$\min_G \max_D \mathbb{E}_x[\log(1 - D(G(x))] + \mathbb{E}_y[\log D(y)]$$

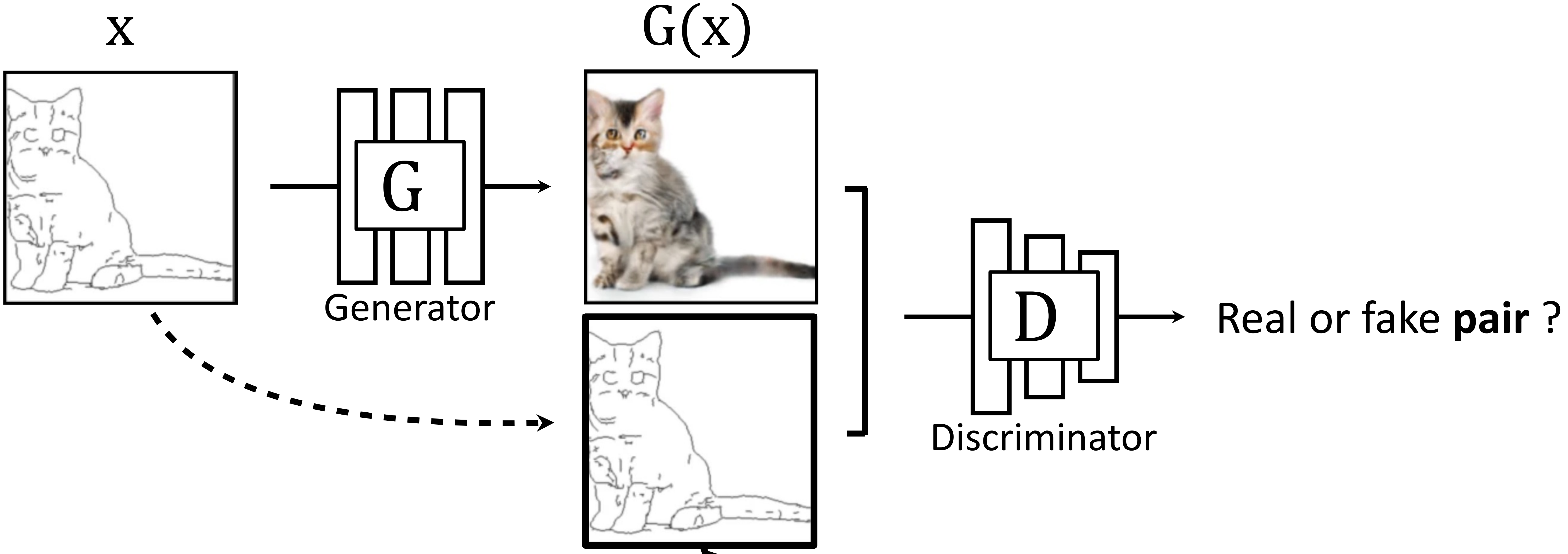
Pix2pix [Isola et al., 2016]



Learning objective

$$\min_G \max_D \mathbb{E}_x[\log(1 - D(G(x))] + \mathbb{E}_y[\log D(y)]$$

Pix2pix [Isola et al., 2016]

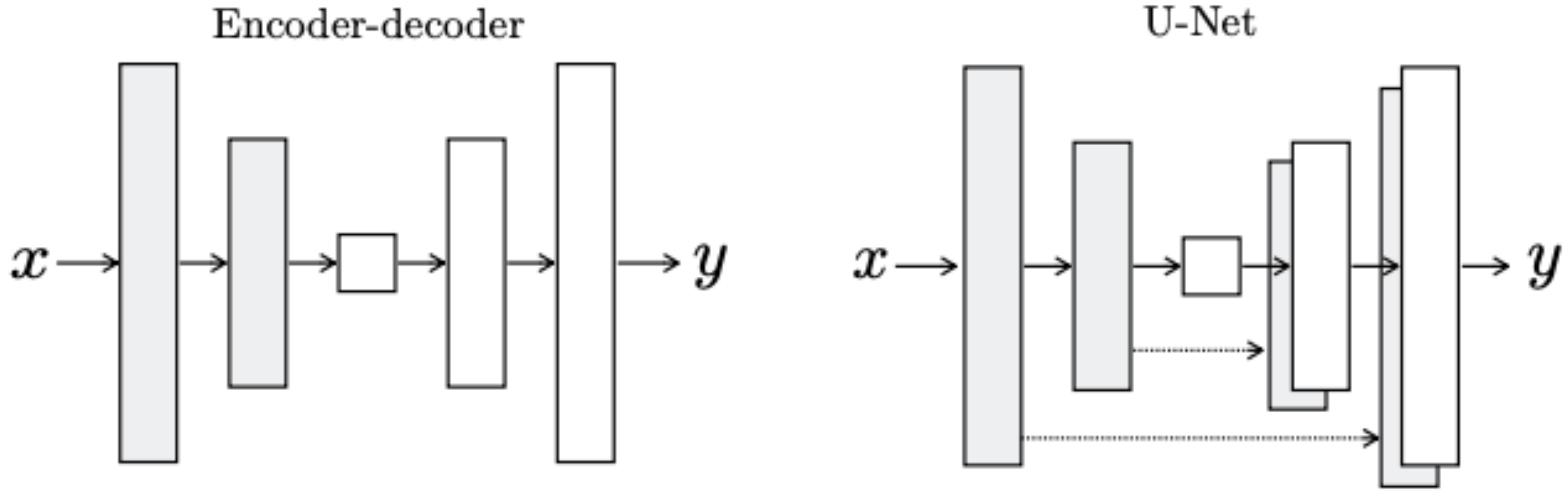


Learning objective

$$\min_G \max_D \mathbb{E}_x[\log(1-D(\boxed{x}, G(x))] + \mathbb{E}_{x,y}[\log D(\boxed{x}, y)]$$

Pix2pix [Isola et al., 2016]

pix2pix Generator (U-Net)

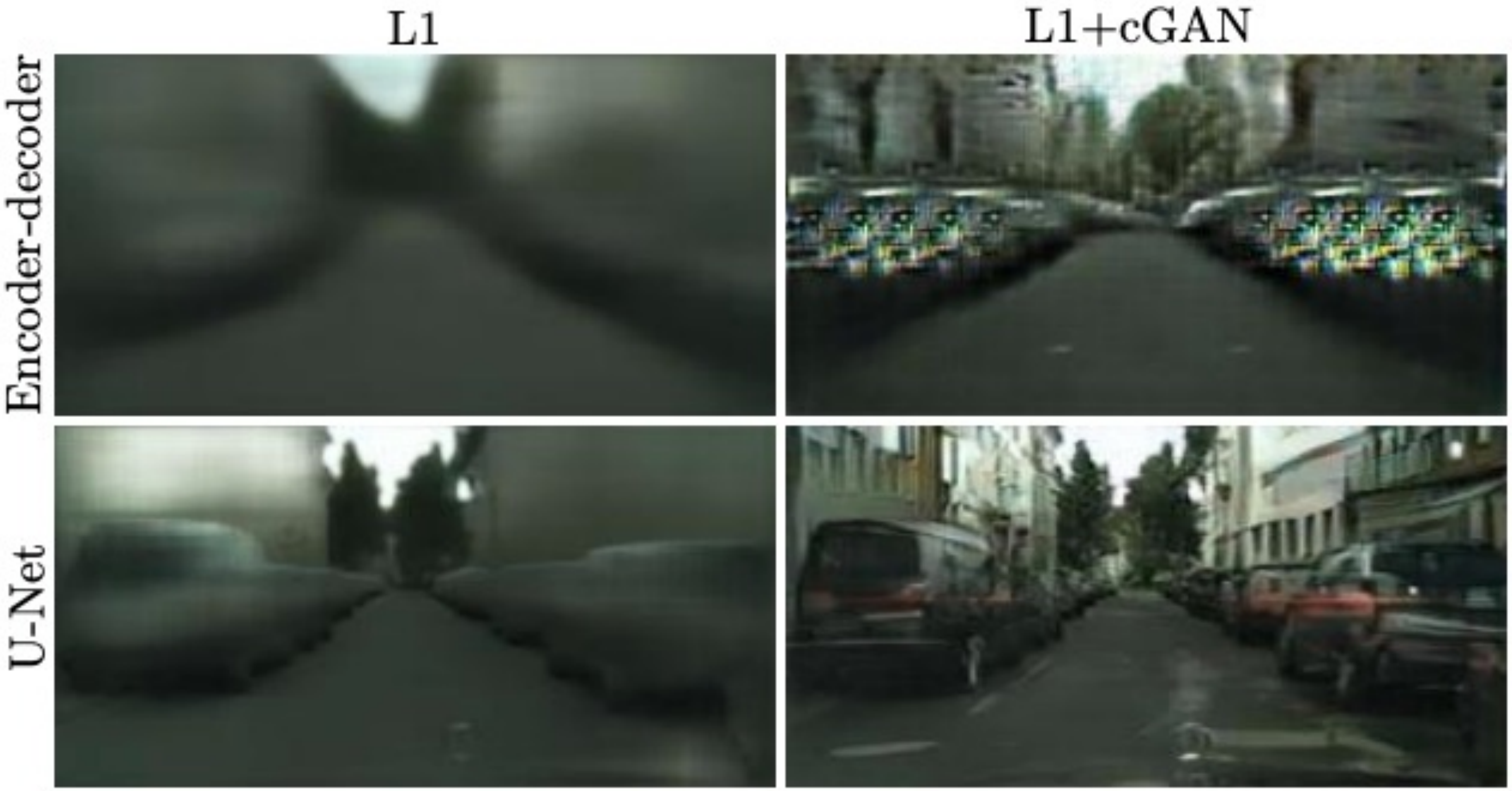


<u>U-Net</u> [Ronneberger et al.]: popular CNN backbone for biomedical image segmentation

<u>U-Net</u>: preserve high-frequency information (e.g., edge) of the input image.

<u>Encoder-decoder</u>: lose high-frequency details due to the information bottleneck

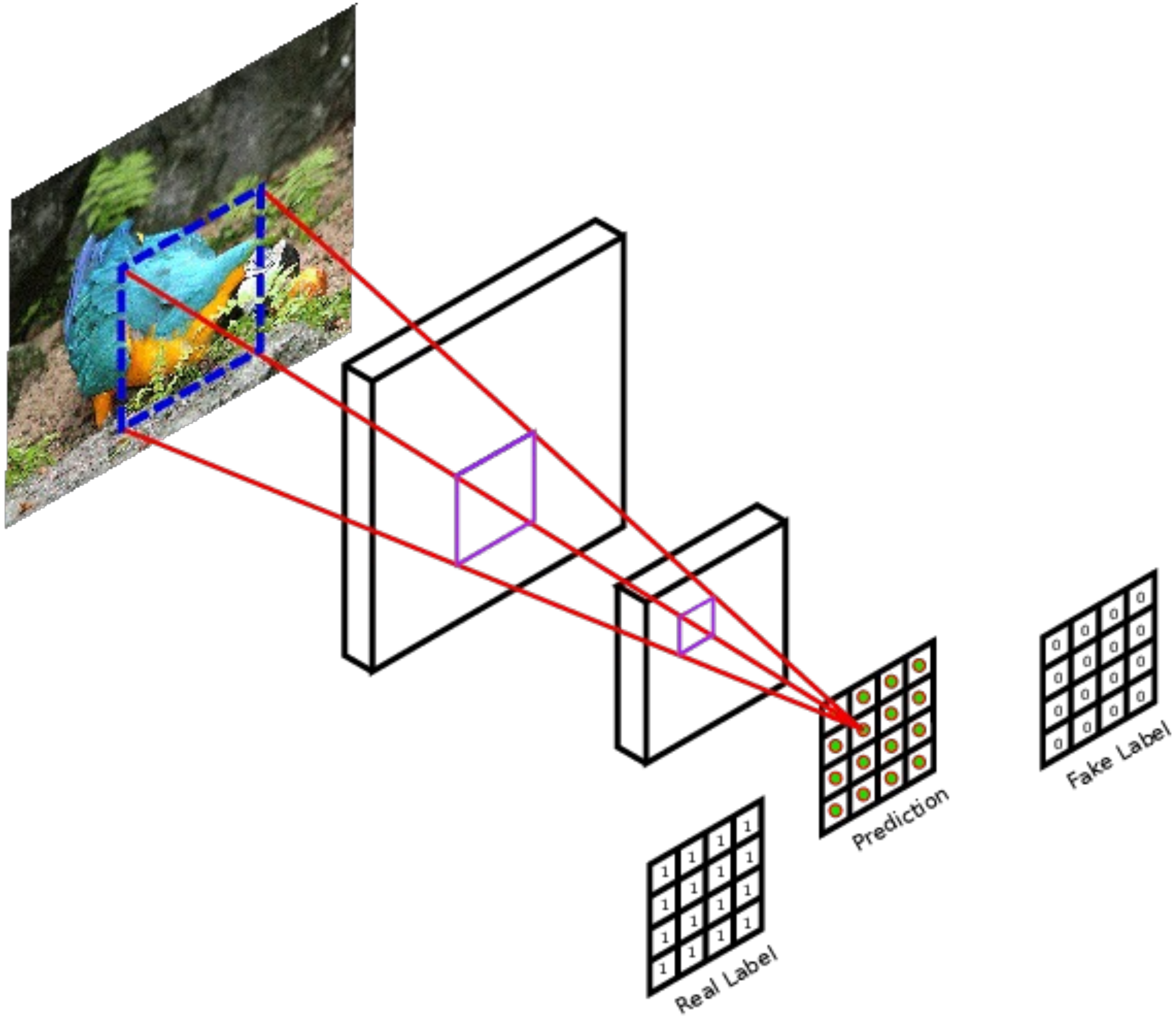
pix2pix Generator (U-Net)



Generator design is critical for image quality.

cGAN (conditional GANs) loss: capture realism. L1 loss stabilizes training (faster convergence)

pix2pix Discriminator (PatchGAN)

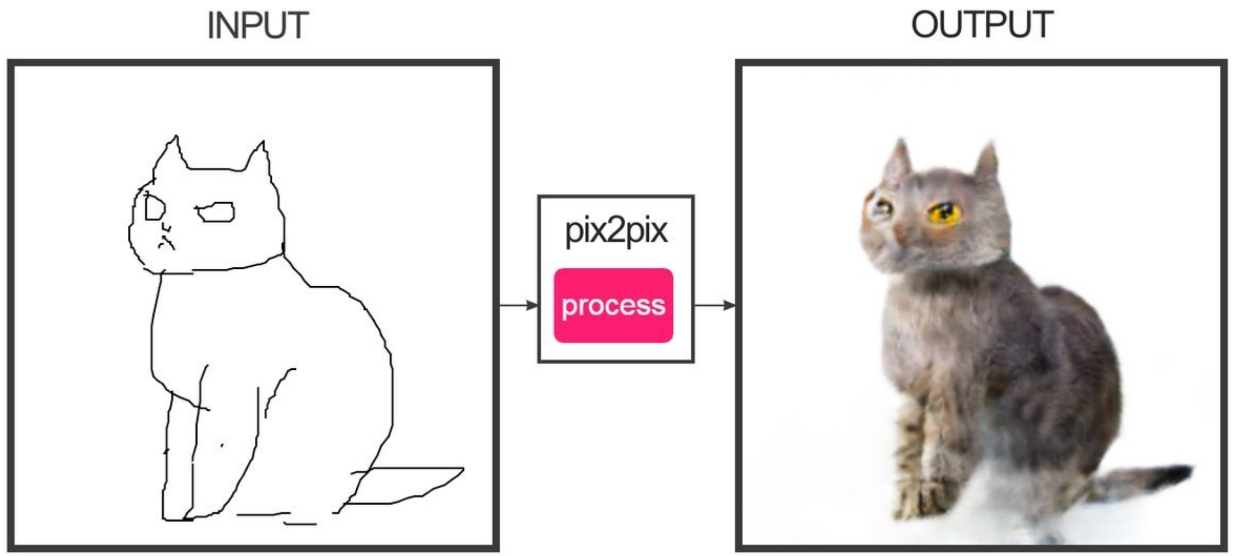


- Rather than penalizing if output *image* looks fake, penalize if each overlapping *patches* looks fake
- Focus on <u>local</u> visual cues (color, textures).
- <u>Global</u> structure: the input image has already encoded global structure. L1 loss can help as well.

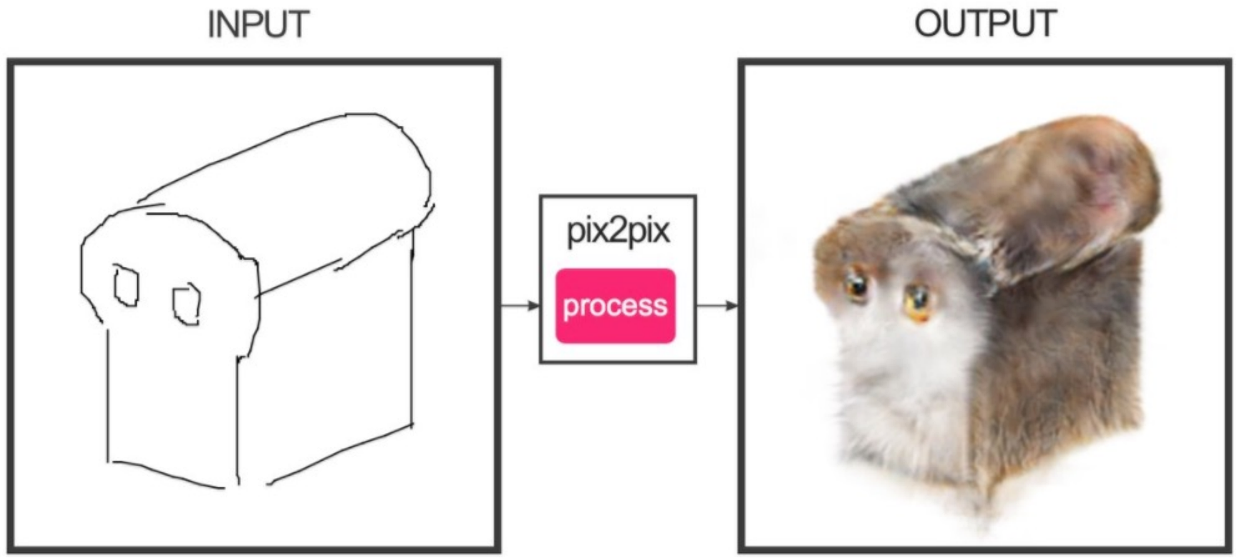
Advantages

- Faster, fewer parameters
- More supervised observations
- Applies to arbitrarily large images

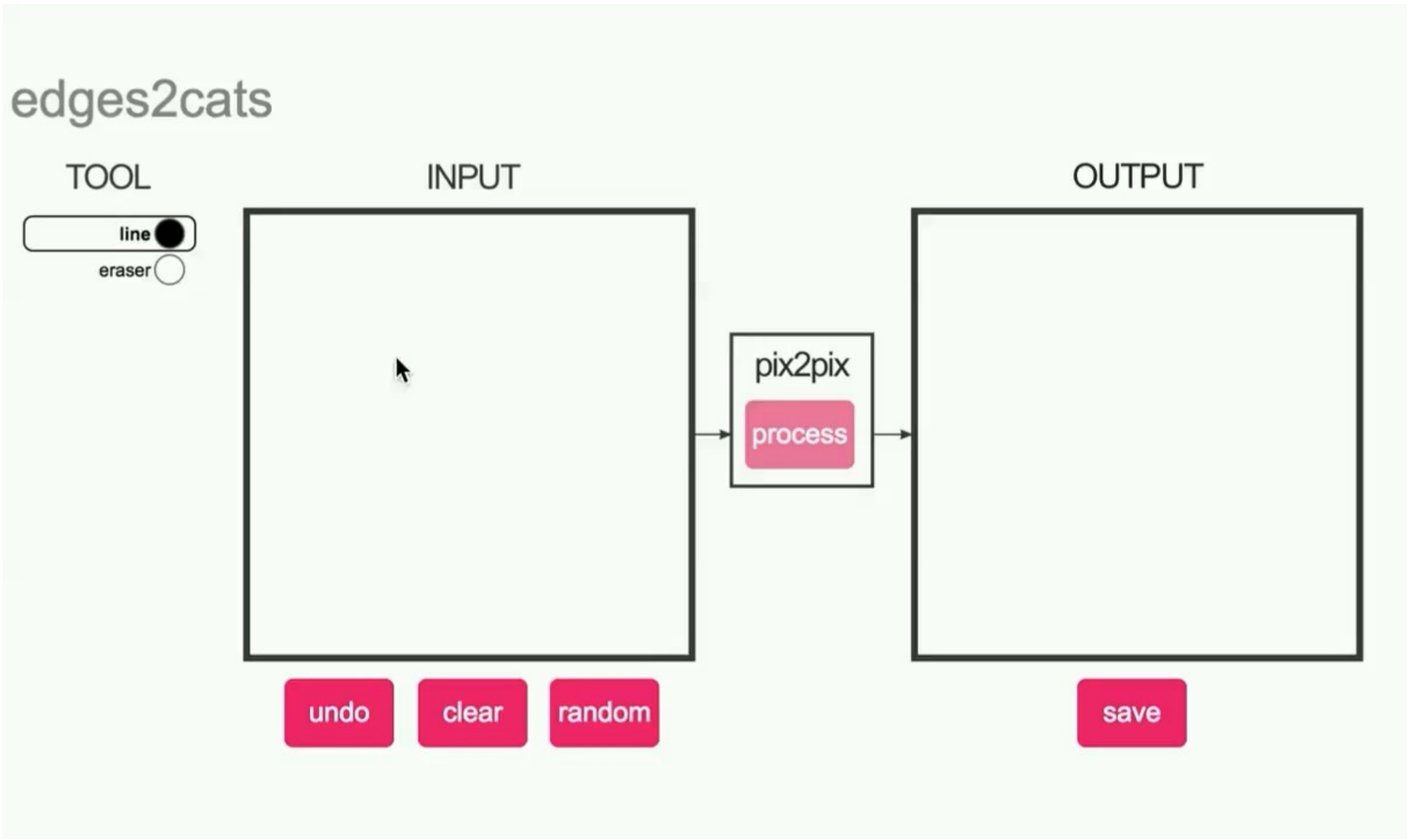
#edges2cats [Christopher Hesse]



@gods_tail



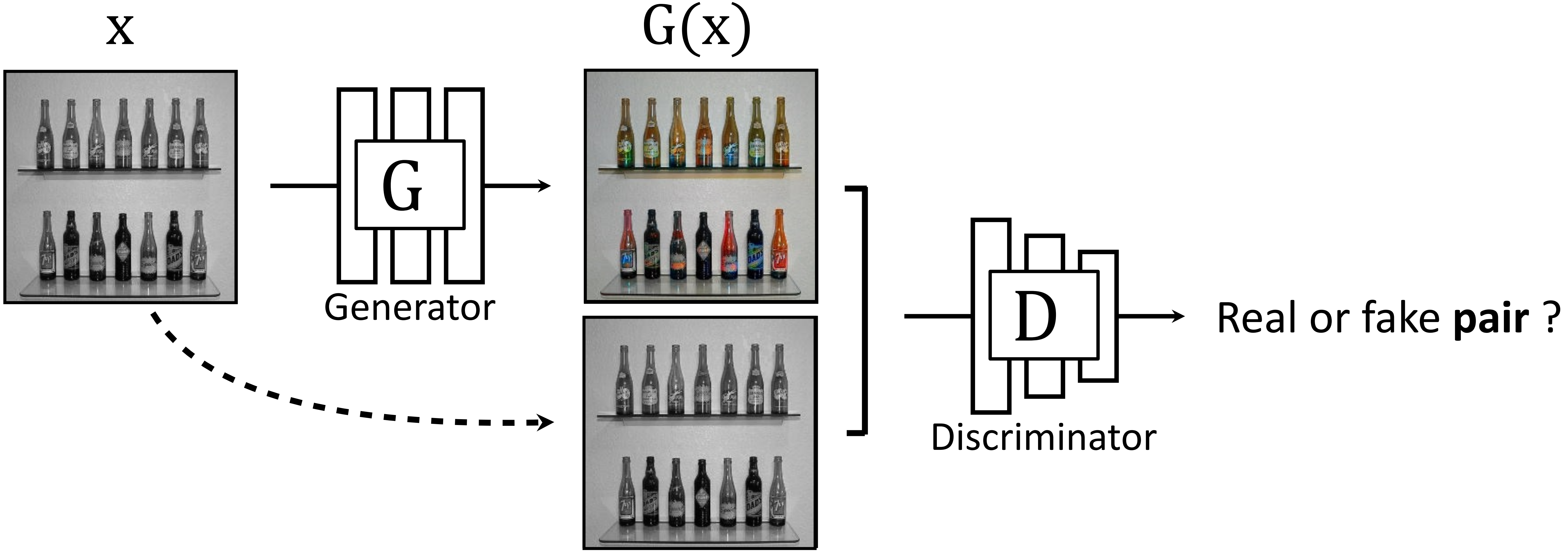
Ivy Tasi @ivymyt



@matthematician

Vitaly Vidmirov @vvid

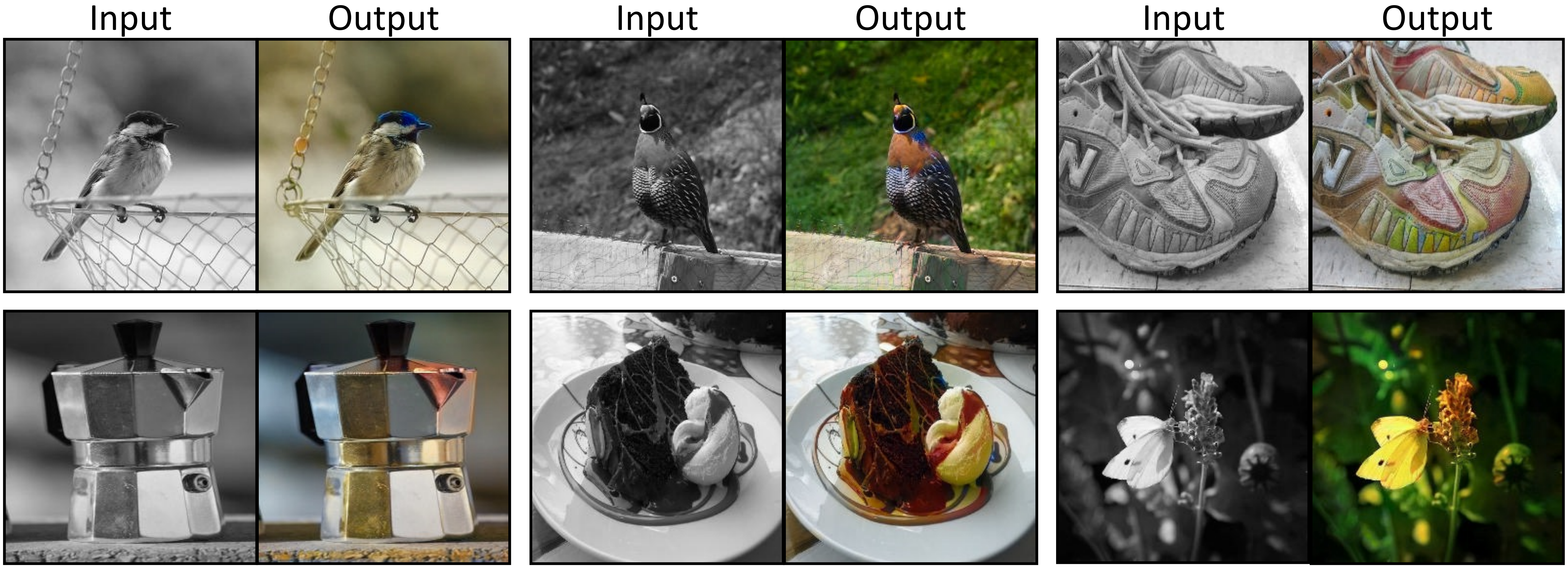
https://affinelayer.com/pixsrv/



Input: **Grayscale** → Output: **Color**

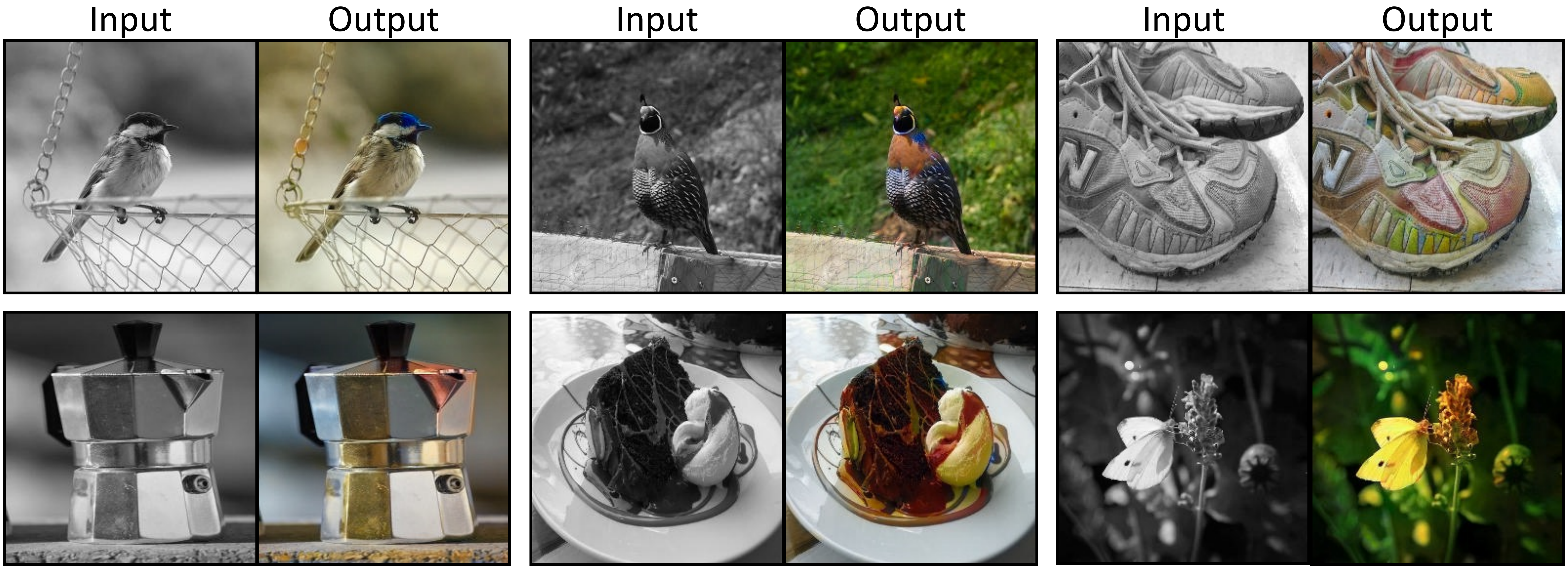
Input: **Sketch** → Output: **Photo**

Automatic Colorization with pix2pix

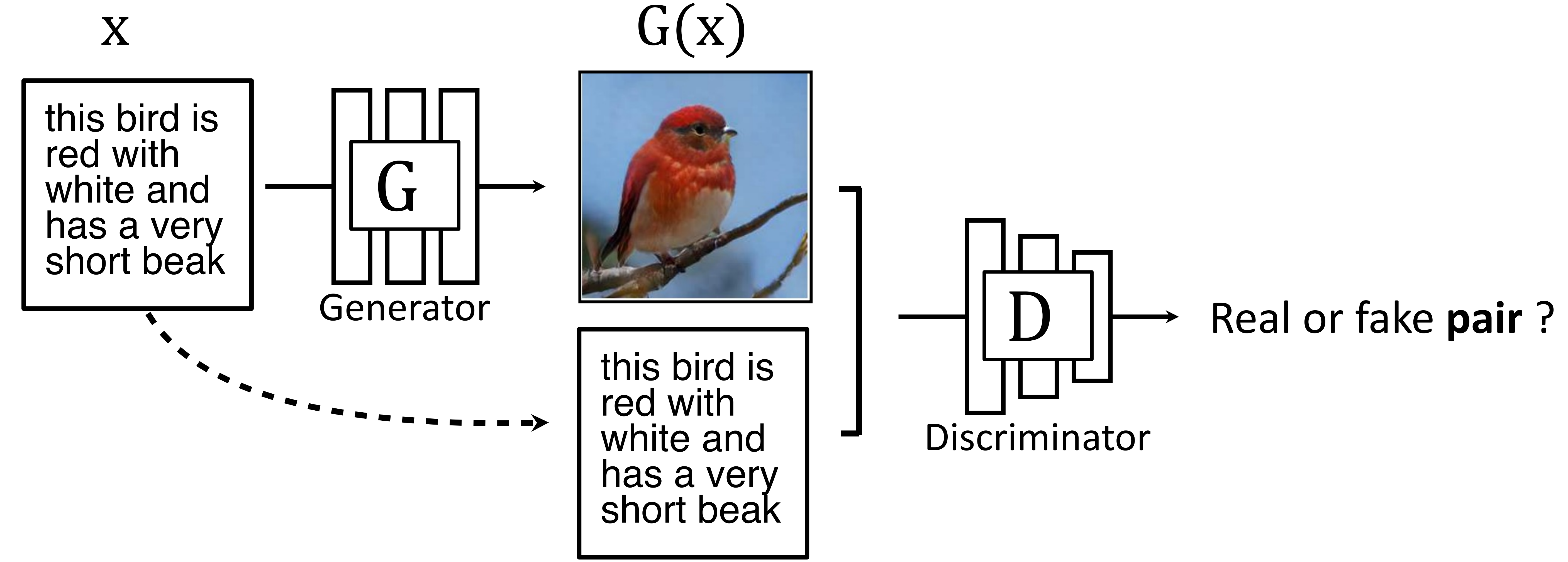


Data from [Russakovsky et al. 2015]

Automatic Colorization with pix2pix



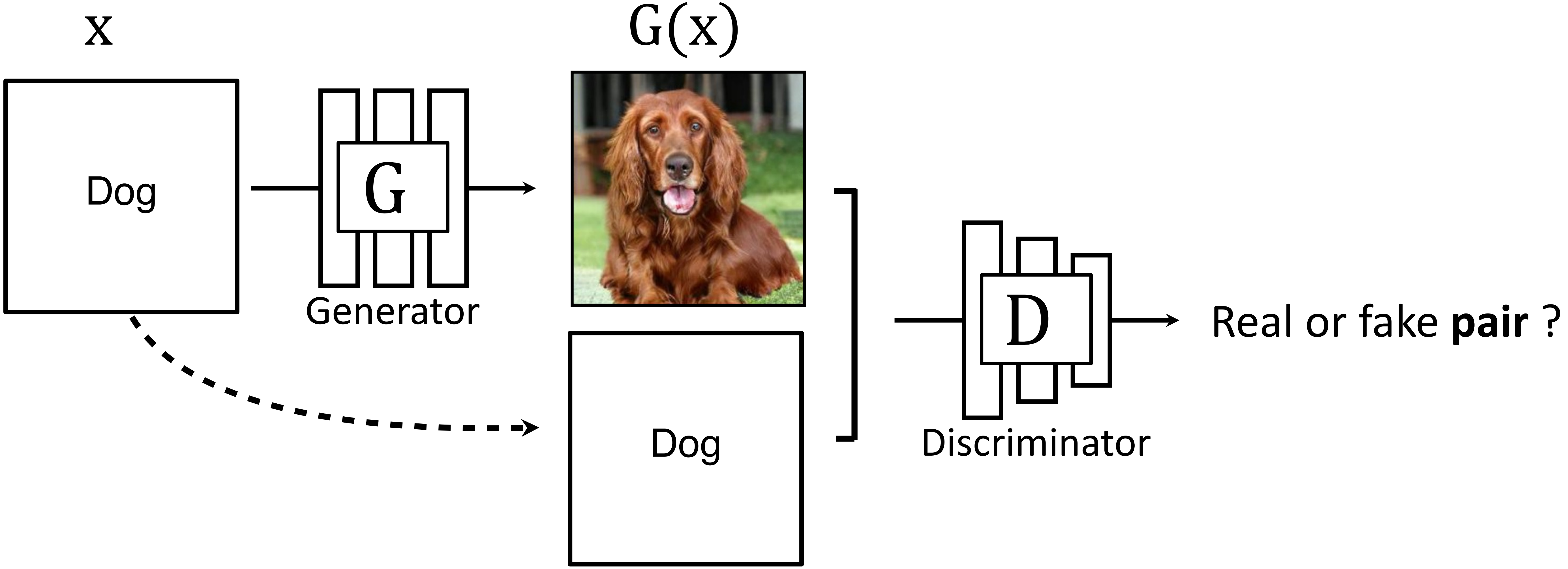
Data from [Russakovsky et al. 2015]



Input: **Text** → Output: **Photo**

<u>Text-to-Image Synthesis</u>

StackGAN, StackGAN++ [Zhang et al., 2016 and 2017], AttnGAN [Xu et al., 2018]



Input: **Class** → Output: **Photo**

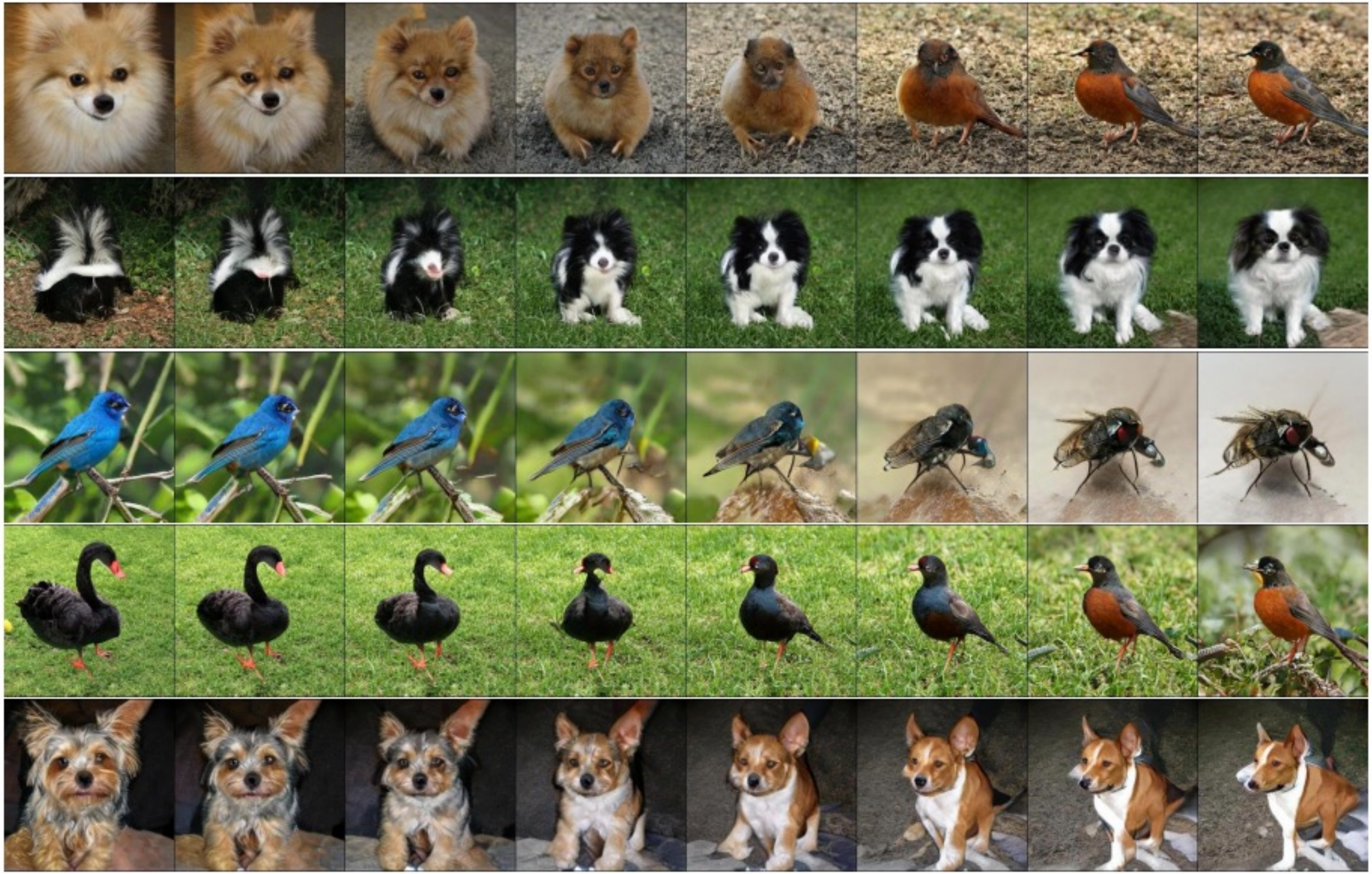
Class-conditional GANs

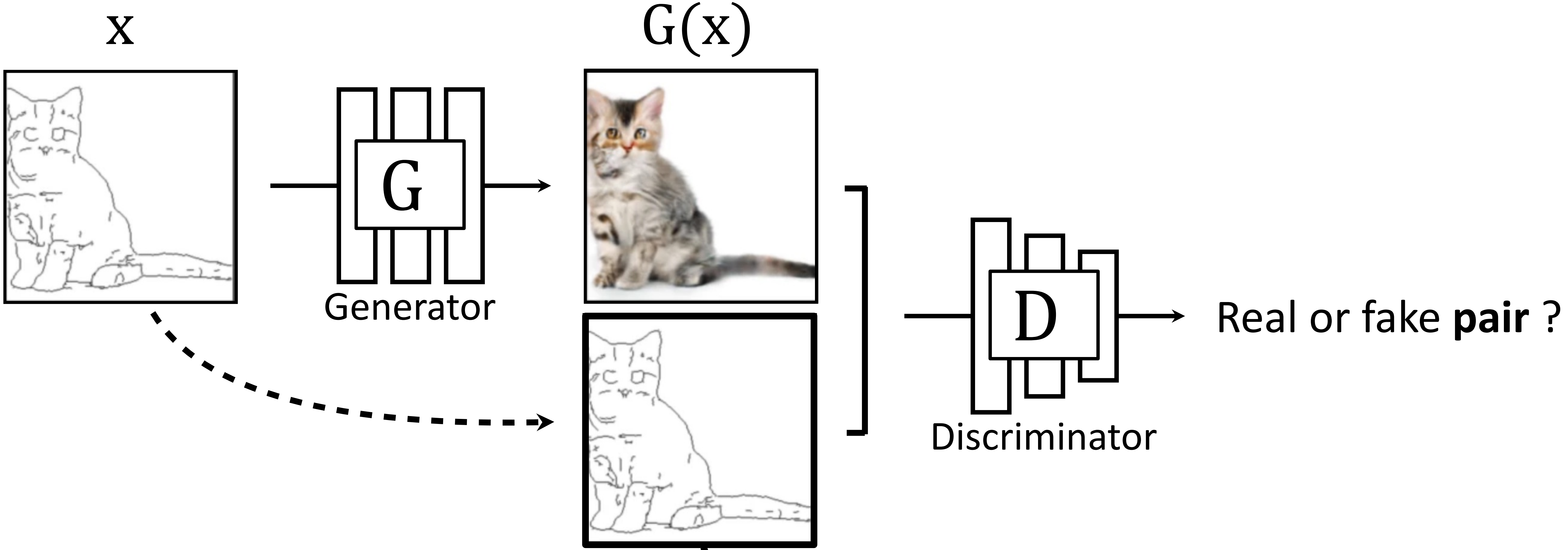
cGANs [Mirza and Osindero. 2014], SAGAN [Zhang et al., 2018], BigGAN [Brock et al., 2019]

StyleGAN-XL [Sauer et al., 2022]

BigGAN

(a) 128×128 (b) 256×256 (c) 512×512 (d)





Learning objective

$$\min_{G} \max_{D} \mathbb{E}_x[\log(1-D(\boxed{x}, G(x))]+\mathbb{E}_{x,y}[\log D(\boxed{x}, y)]$$

Pix2pix [Isola et al., 2016]

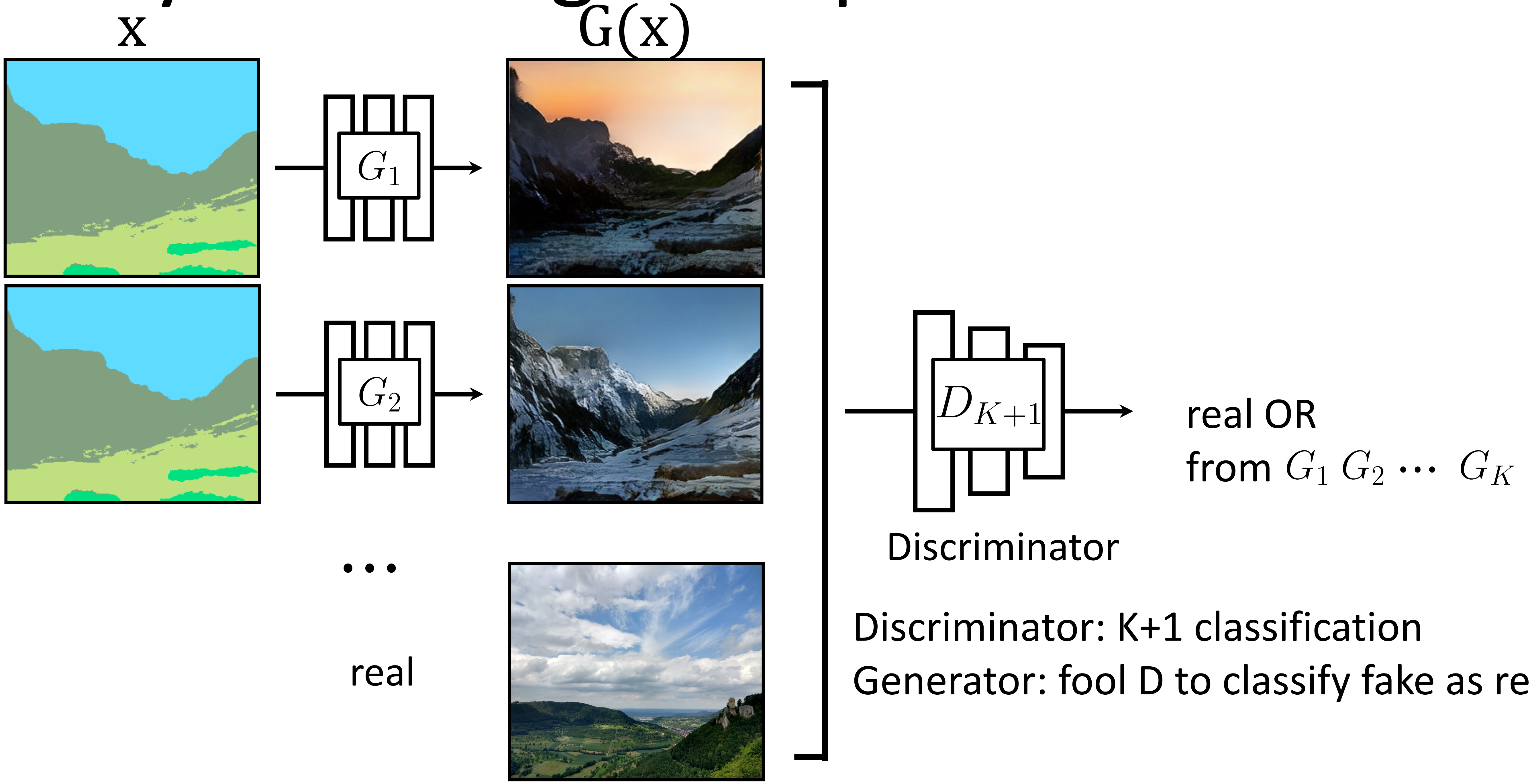
Limitations

- One-to-one mapping.
- Low-resolution output.
- Requires paired training data

Improving Conditional GANs

- **Multimodal synthesis.**
- High-resolution synthesis.
- Model training without pairs (next lecture)

Synthesizing Multiple Results



Discriminator: K+1 classification

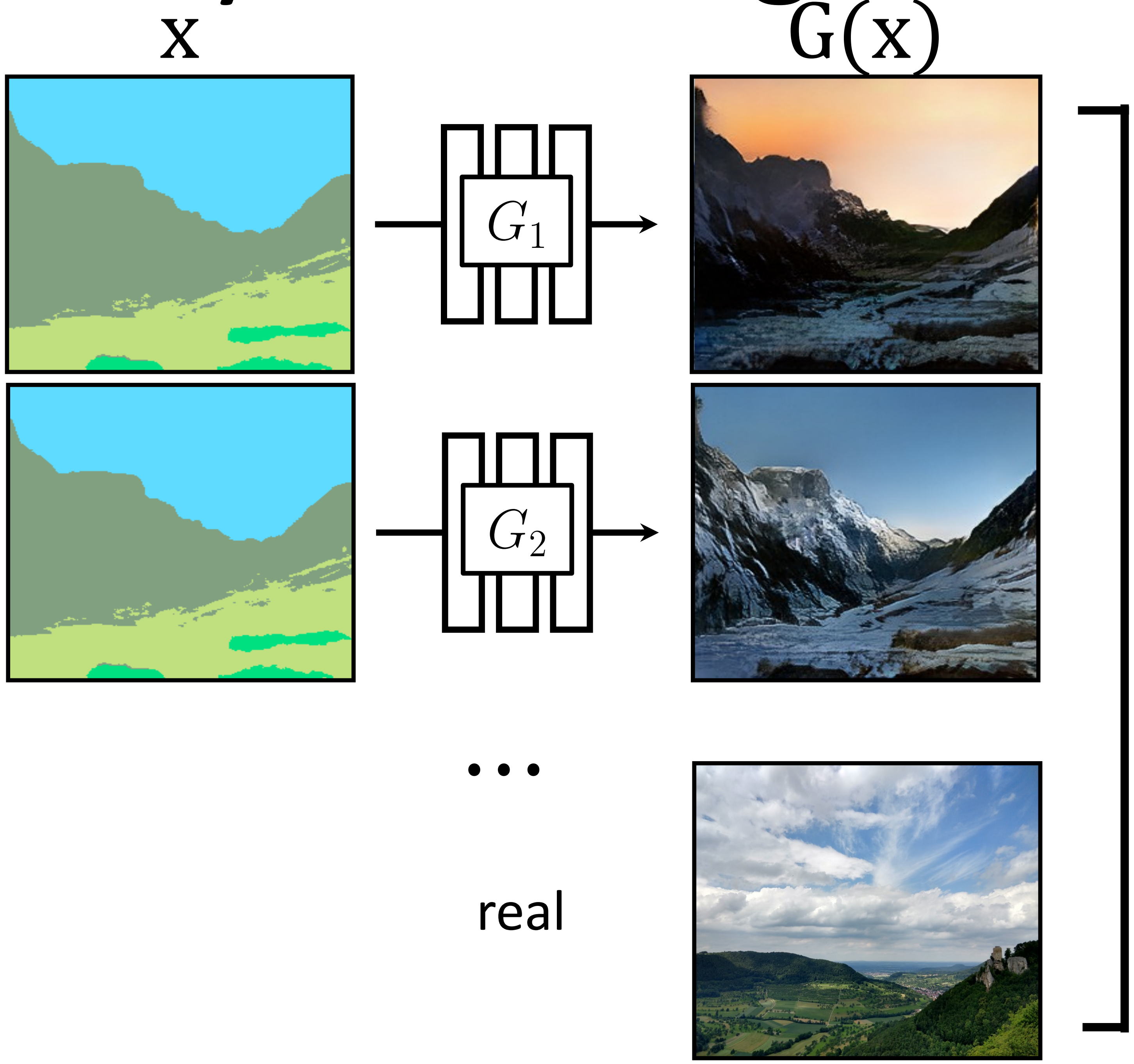
Generator: fool D to classify fake as real

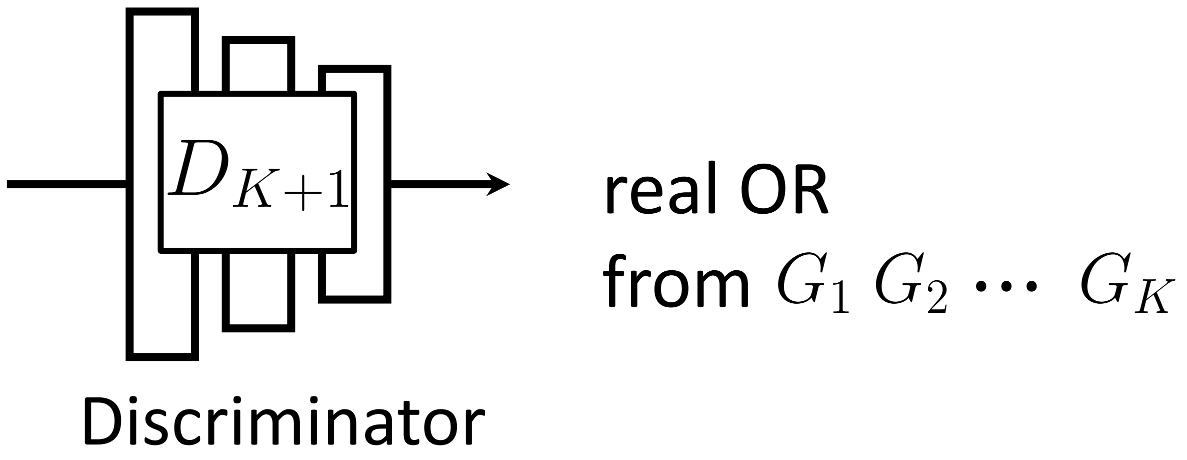
Multi-agent Diverse GANs [Ghosh et al., CVPR 2018]

Synthesizing Multiple Results

Multi-agent Diverse GANs [Ghosh et al., CVPR 2018]

Synthesizing Multiple Results





Discriminator: K+1 classification

Generator: fool D to classify fake as real

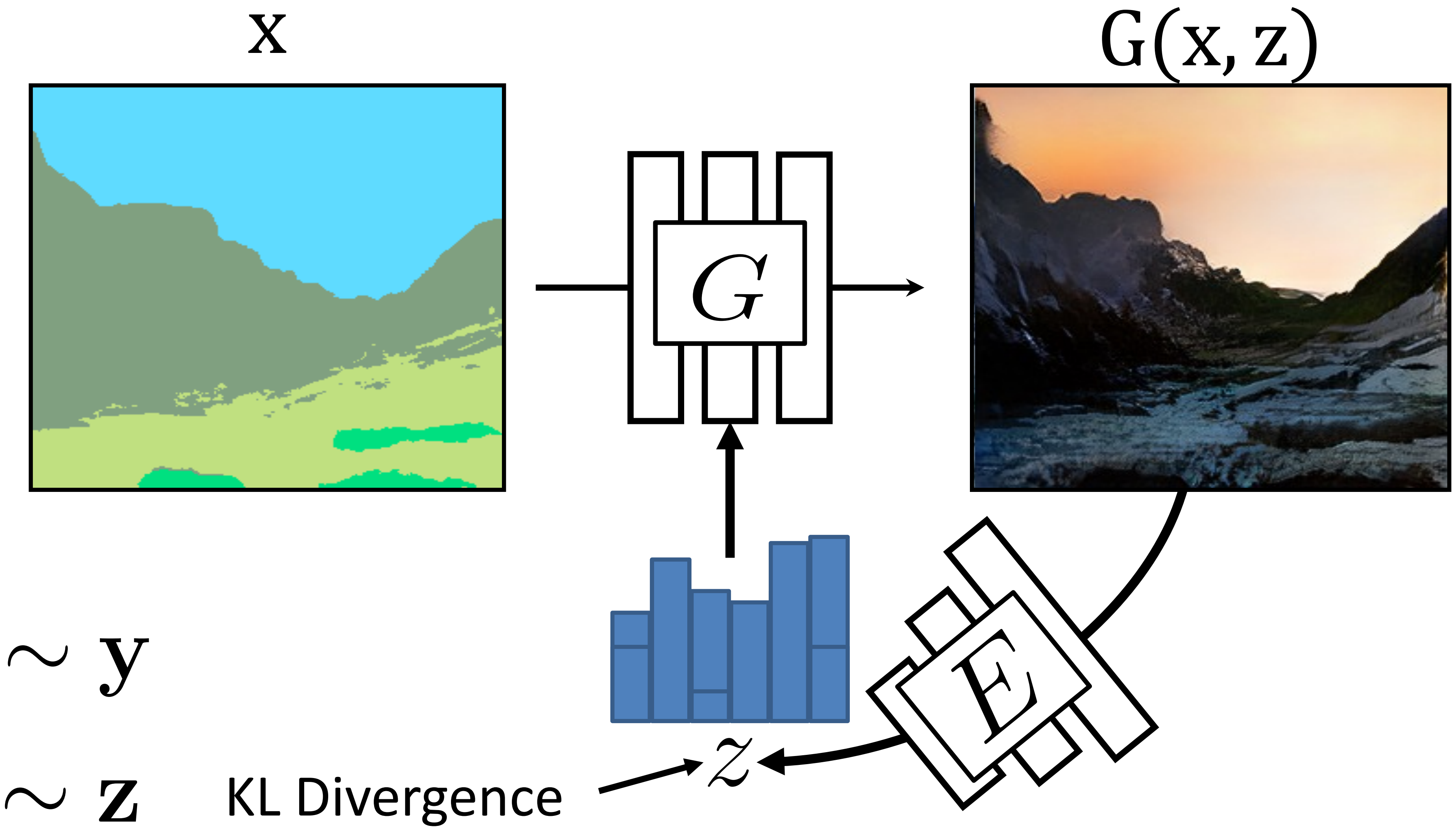
Multi-agent Diverse GANs [Ghosh et al., CVPR 2018]

Synthesizing Multiple Results

Night input | Day output 1 | Day output 2 | Day output 3

Multi-agent Diverse GANs [Ghosh et al., CVPR 2018]

Synthesizing Multiple Results



$$G(\mathbf{x}, E(\mathbf{y})) \sim \mathbf{y}$$

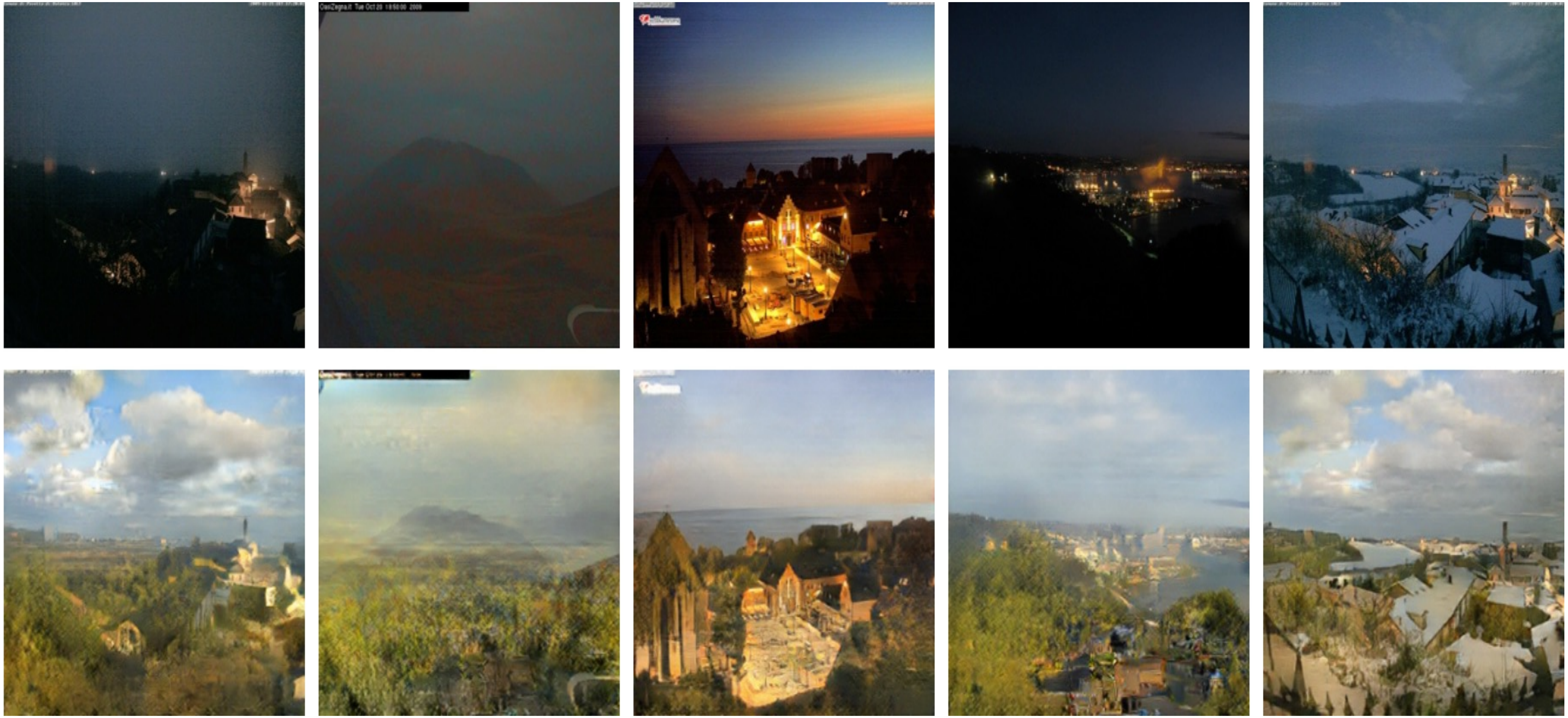
$$E(G(\mathbf{x}, \mathbf{z})) \sim \mathbf{z}$$

VAE-GAN [Larsen et al., 2016], BicycleGAN [Zhu et al., 2017]

Synthesizing Multiple Results

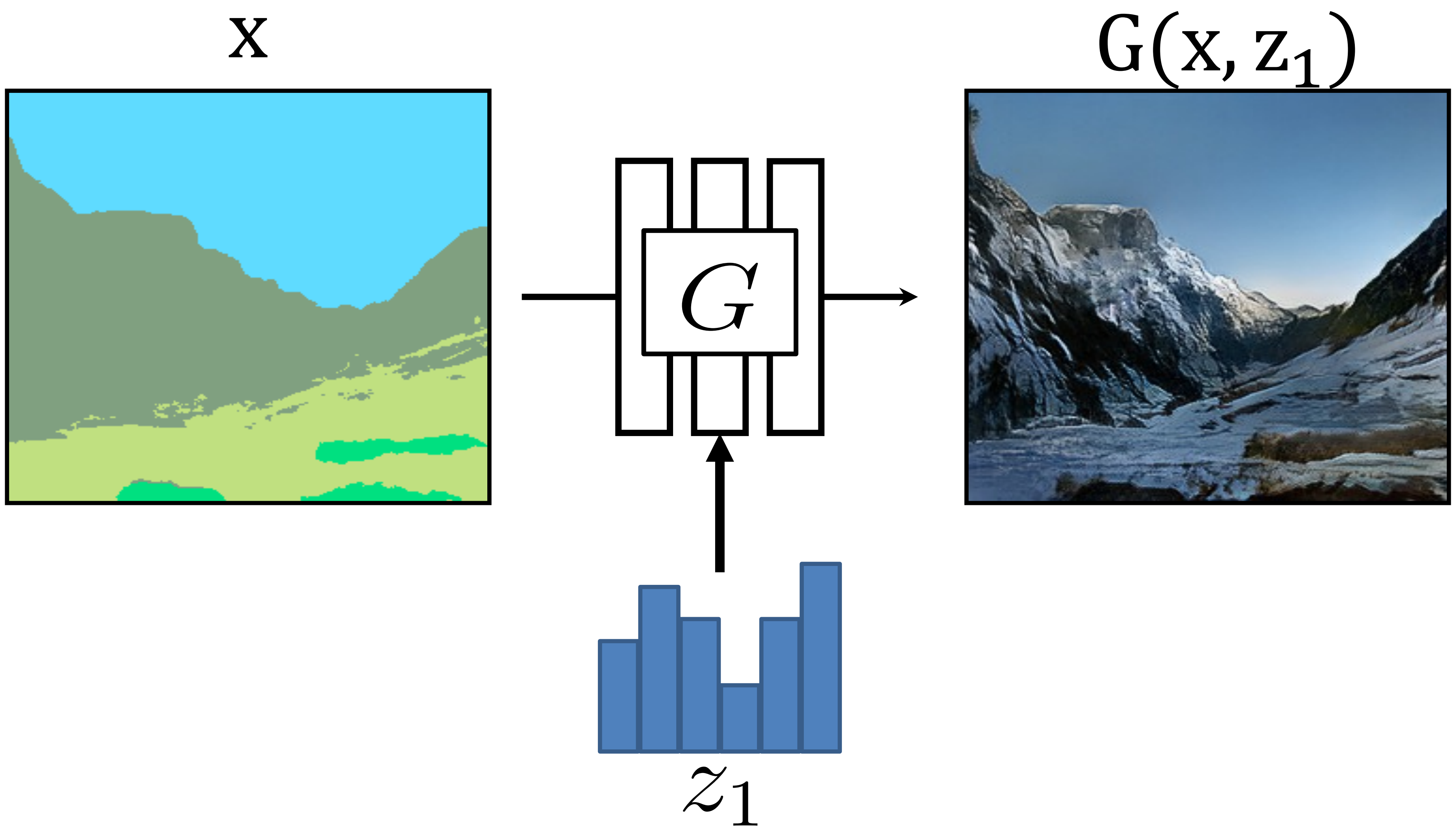
BicycleGAN [Zhu et al., 2017]

Synthesizing Multiple Results



BicycleGAN [Zhu et al., 2017]

Synthesizing Multiple Results

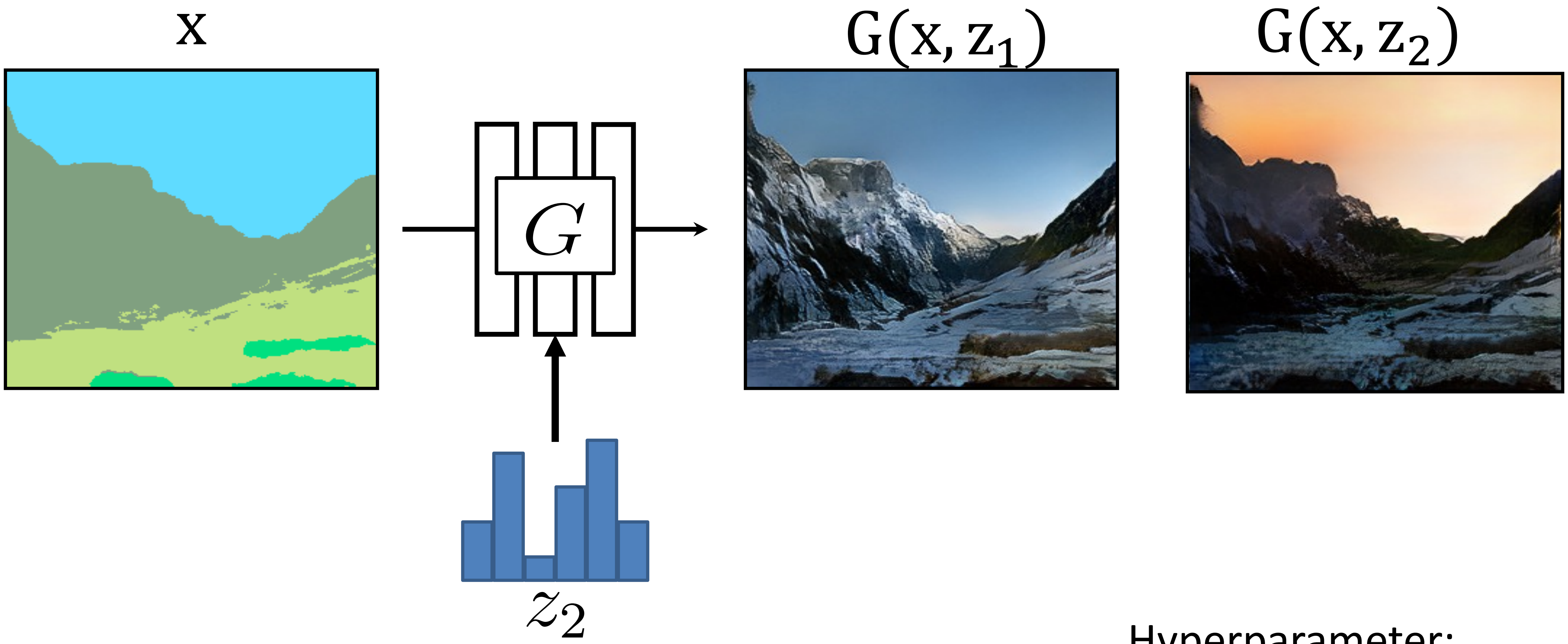


Hyperparameter:
Degree of diversity

$$\max_{G} \; \mathcal{L}_{\boldsymbol{z}}(G) = \mathbb{E}_{\boldsymbol{z}_1, \boldsymbol{z}_2}\left[\min\left(\frac{\|G(\boldsymbol{x}, \boldsymbol{z}_1) - G(\boldsymbol{x}, \boldsymbol{z}_2)\|}{\|\boldsymbol{z}_1 - \boldsymbol{z}_2\|}, \tau\right)\right],$$

Diversity-Sensitive GAN [Yang et al., 2019]

Synthesizing Multiple Results




$$\max_{G} \mathcal{L}_{\boldsymbol{z}}(G) = \mathbb{E}_{\boldsymbol{z}_1, \boldsymbol{z}_2}\left[\min\left(\frac{\| \quad - \quad \|}{\|\boldsymbol{z}_1 - \boldsymbol{z}_2\|}, \tau\right)\right]$$

Hyperparameter:
Degree of diversity

Diversity-Sensitive GAN [Yang et al., 2019]

Synthesizing Multiple Results

Hyperparameter:
Degree of diversity

$$\max_{G} \mathcal{L}_{\boldsymbol{z}}(G) = \mathbb{E}_{\boldsymbol{z}_1, \boldsymbol{z}_2}\left[\min\left(\frac{\|G(\boldsymbol{x}, \boldsymbol{z}_1) - G(\boldsymbol{x}, \boldsymbol{z}_2)\|}{\|\boldsymbol{z}_1 - \boldsymbol{z}_2\|}, \tau\right)\right]$$

Diversity-Sensitive GAN [Yang et al., 2019]