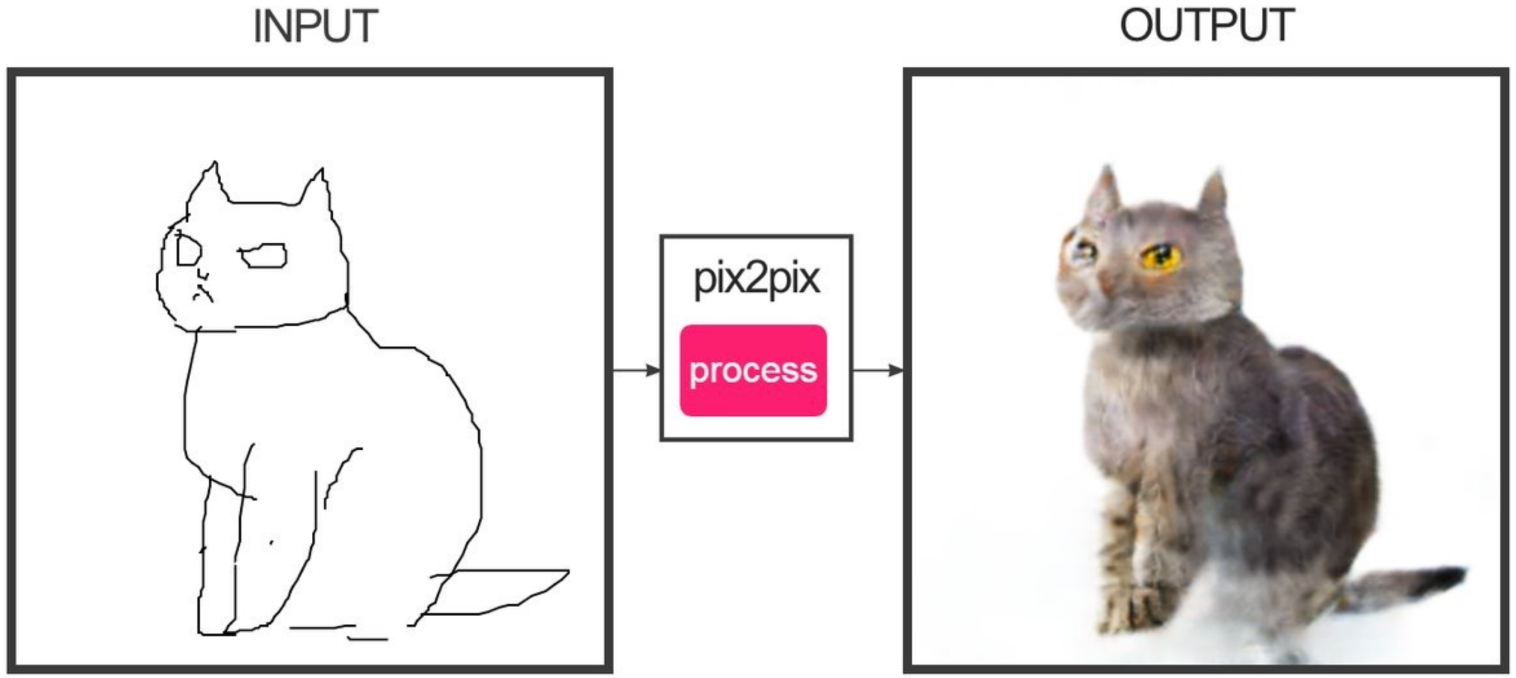


Conditional GANs, Image-to-Image Translation

Jun-Yan Zhu

16-726, Spring 2022

Ideal models (Dream)

Pros: good sample, fast sample, Exact/fast likelihoods
good coverage, easy to training, learn low-dimensional latent representation.

Autoregressive models

Pros: Exact likelihoods, good coverage
Cons: Slow to evaluate or sample

VAEs

Pros: fast to sample, fast to train, good coverage

Cons: Blurry samples (in practice)

GANs

Pros: fast to sample, fast to train, good samples

Cons: No likelihoods (density), bad coverage (mode collapse)

Flow-based models

Pros: fast to sample, exact likelihoods

Cons: memory-intensive; slow training; limited choices for generators,
high-dimensional codes

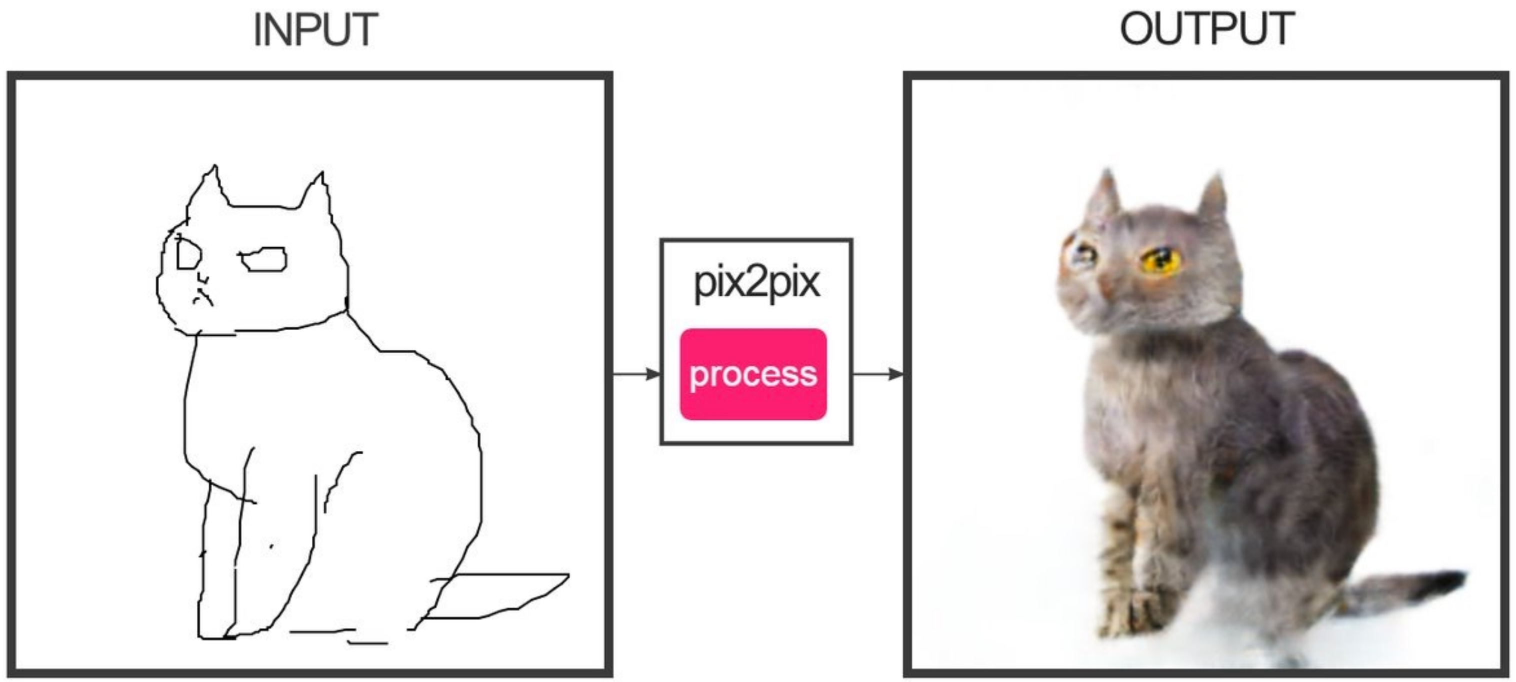
Diffusion models

Pros: good samples, good coverage

Cons: slow training, slow sampling

Which model is better?

- It depends on your applications
  - Synthesis
  - Classification
  - Density estimation
- Which model is easier to train?
- Which model is faster (training & inference)?

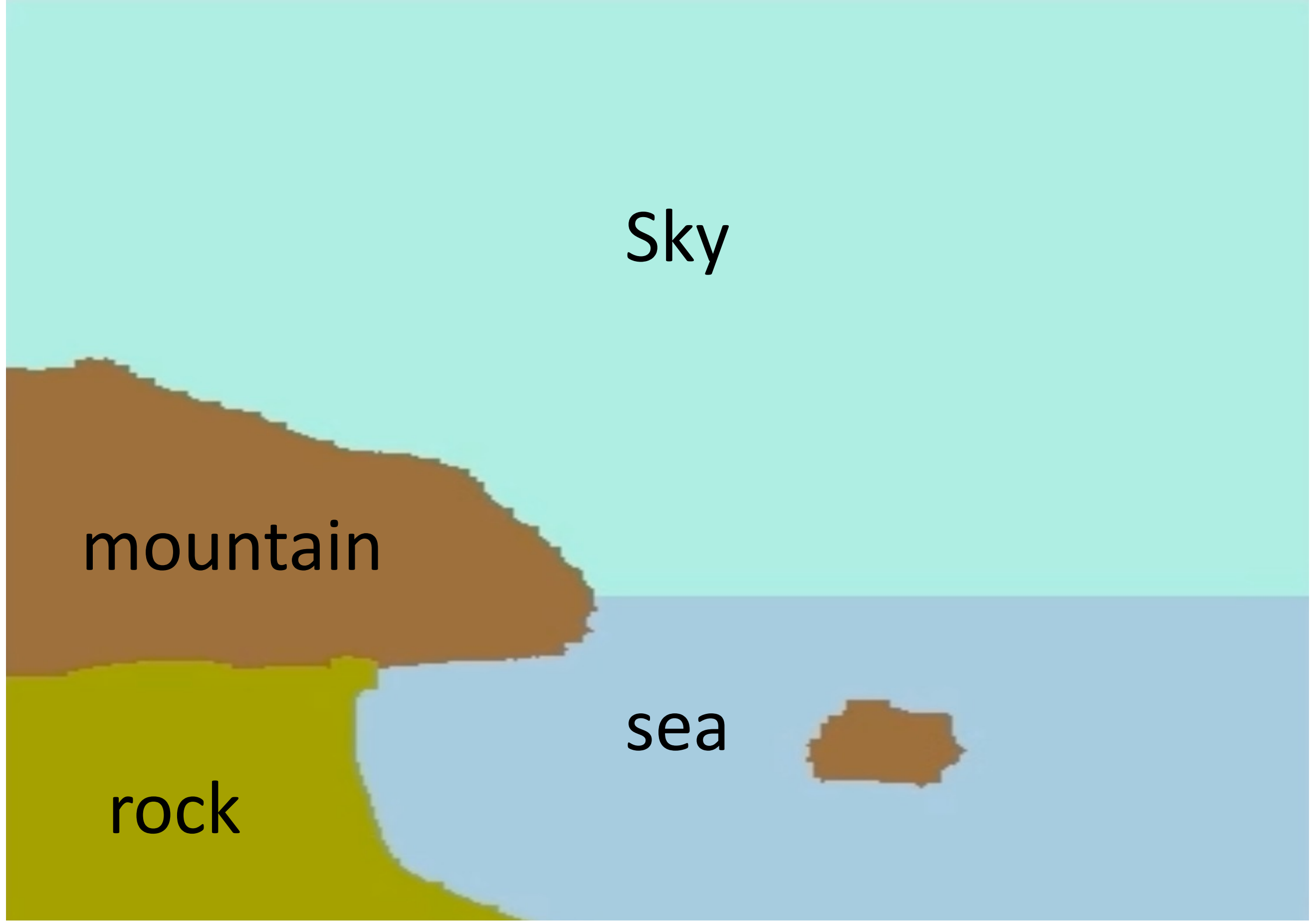


Conditional GANs, Image-to-Image Translation

Jun-Yan Zhu

16-726, Spring 2021

Problem Statement

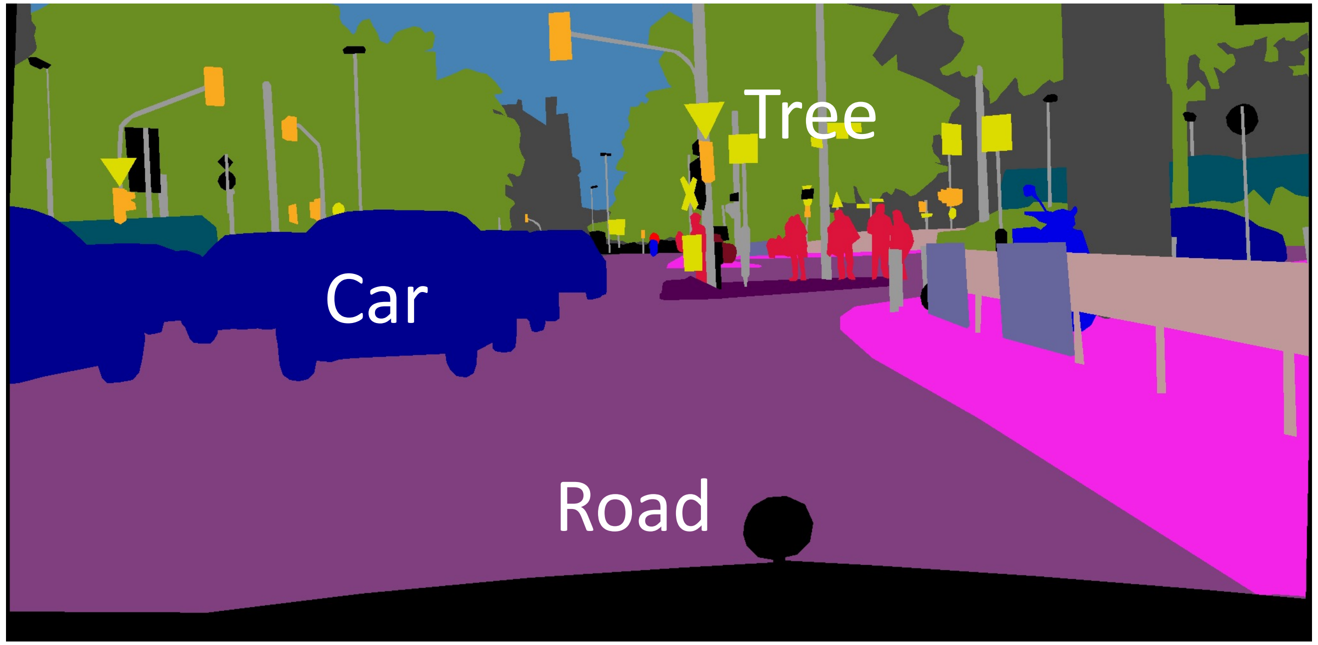


Input

Output

Goal: synthesize a photograph given an input image

Problem Statement



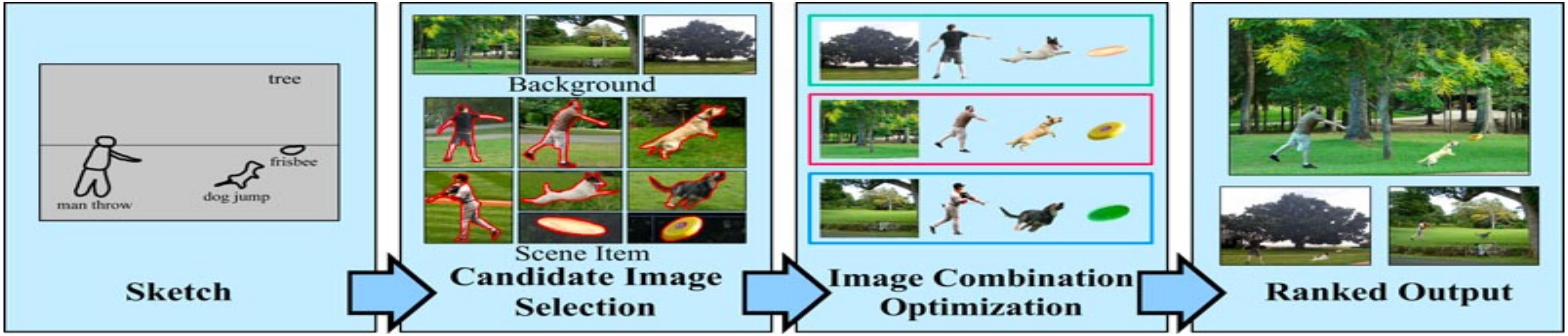
Input

Output

Goal: synthesize a photograph given an input image

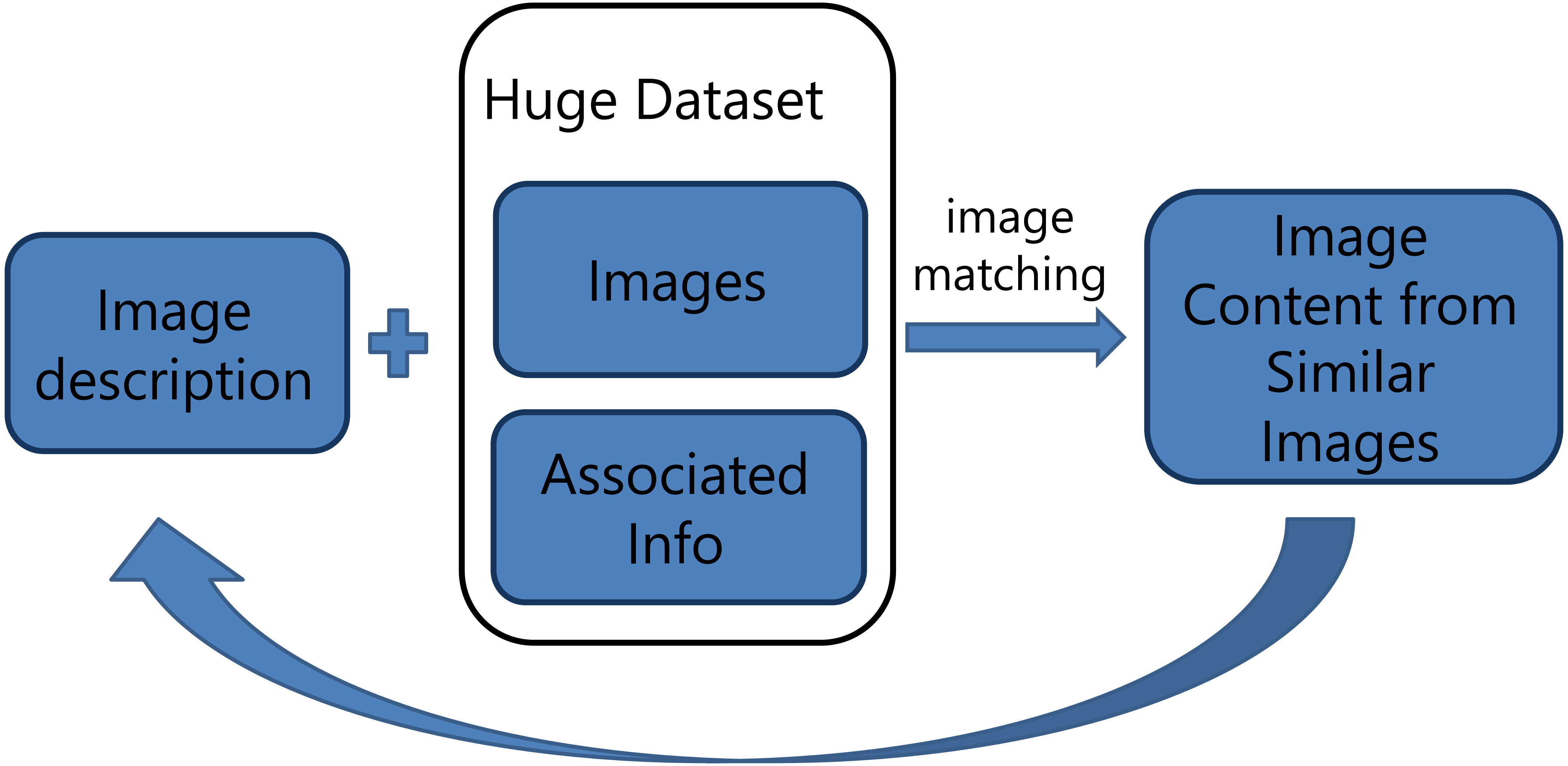
Early work (Example-based)

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



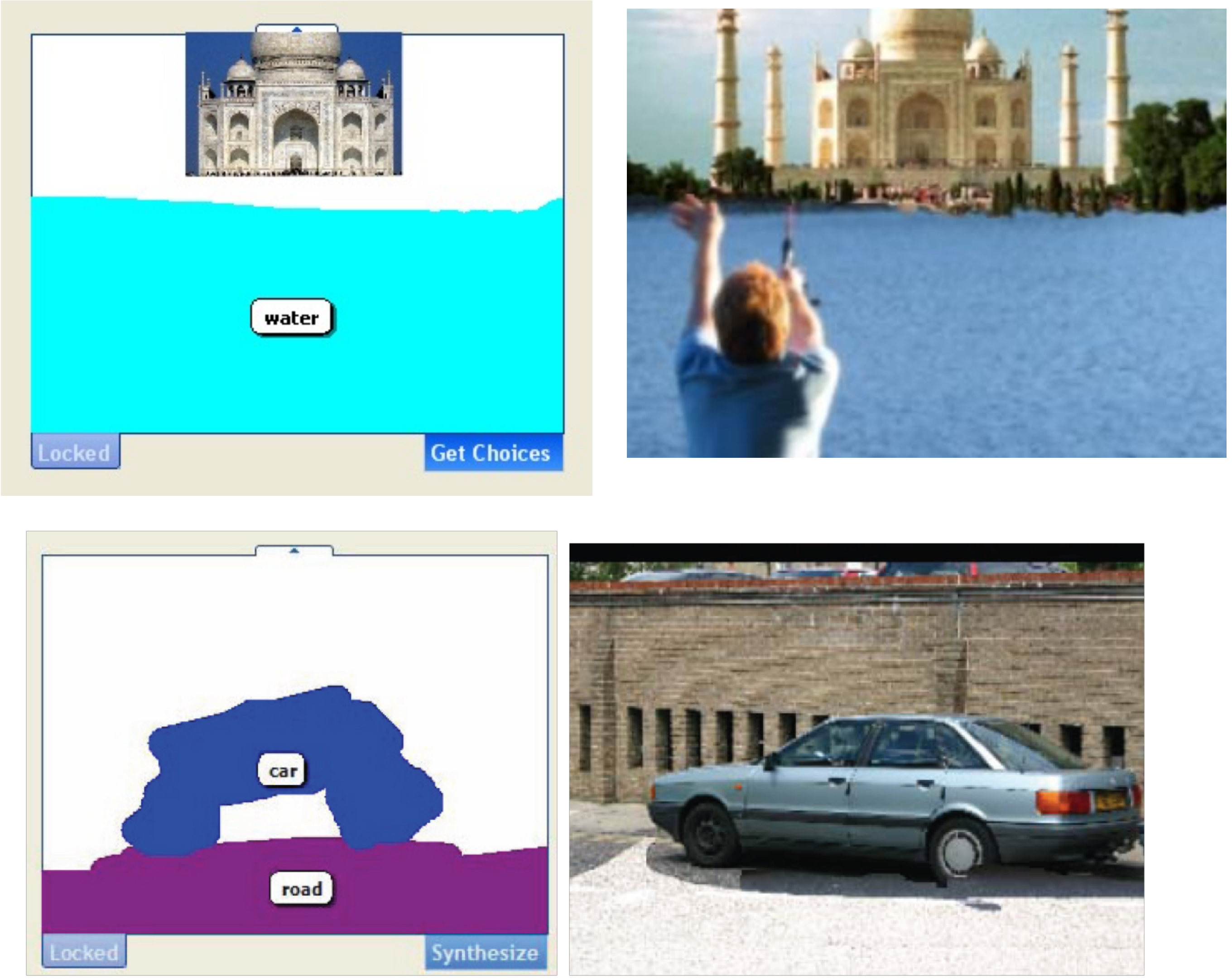
Sketch2Photo [Tao et al., SIGGRAPH Asia 2009]

Semantic Photo Synthesis



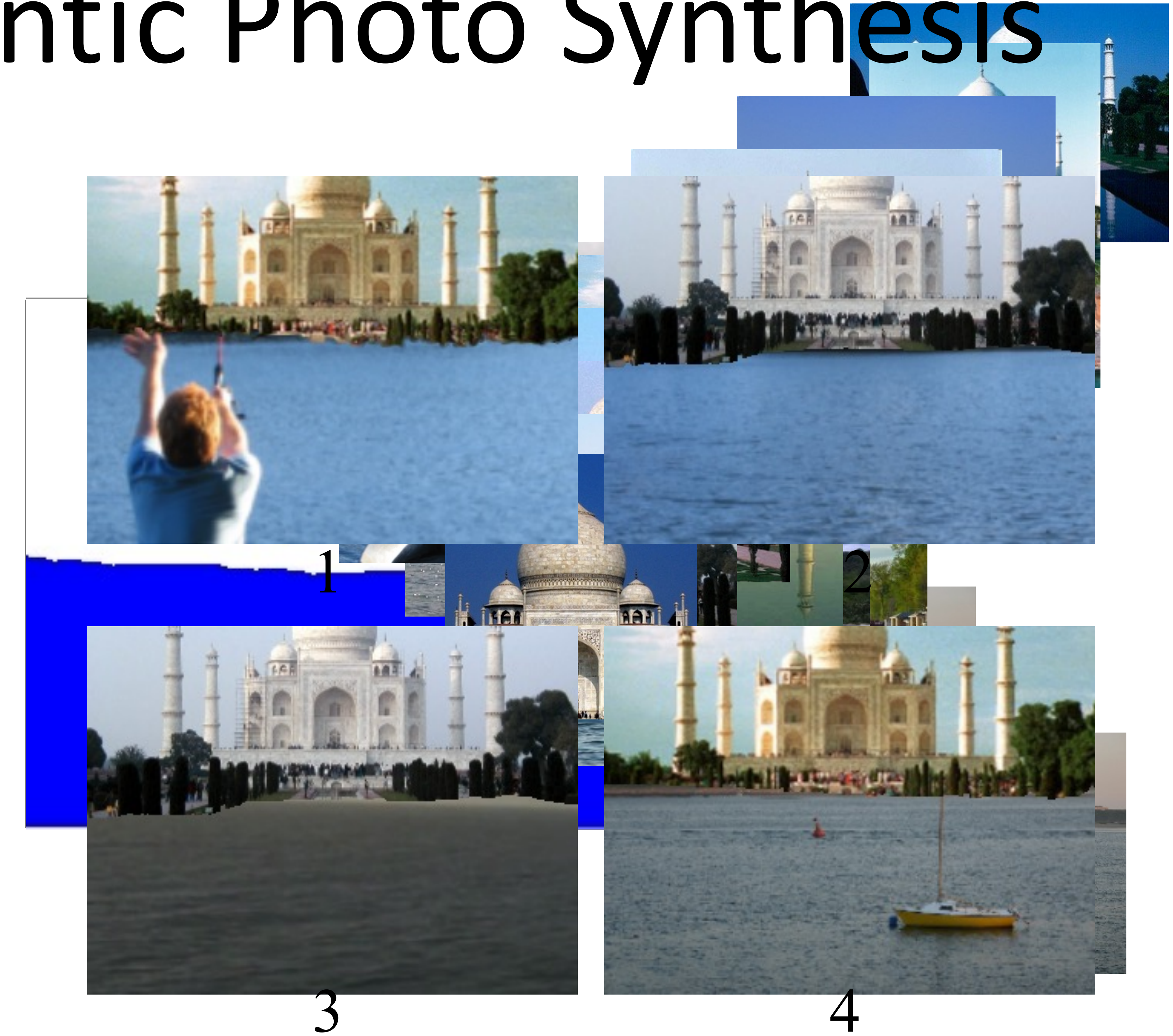
M. Johnson, G. Brostow, J. Shotton, O. A. c, and R. Cipolla, “Semantic Photo Synthesis,” Eurographics 2006

Semantic Photo Synthesis [EG’06]

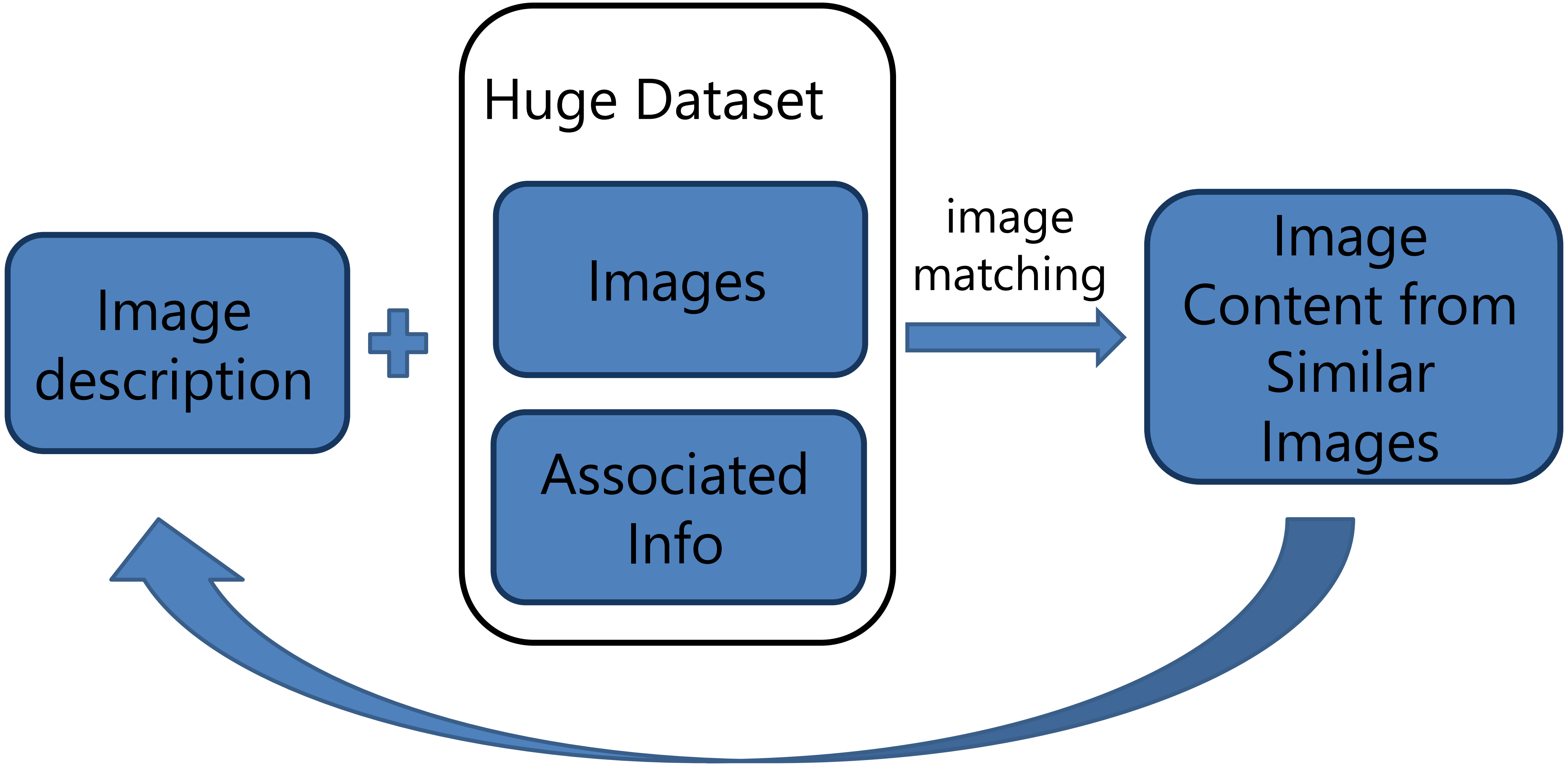


M. Johnson, G. Brostow, J. Shotton, O. A. c, and R. Cipolla, “Semantic Photo Synthesis,” Eurographics 2006

Semantic Photo Synthesis



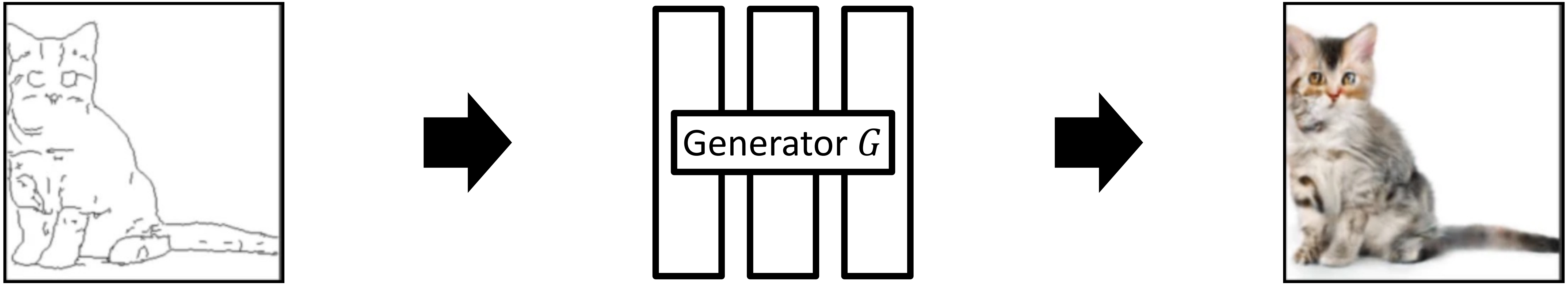
Semantic Photo Synthesis



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)?

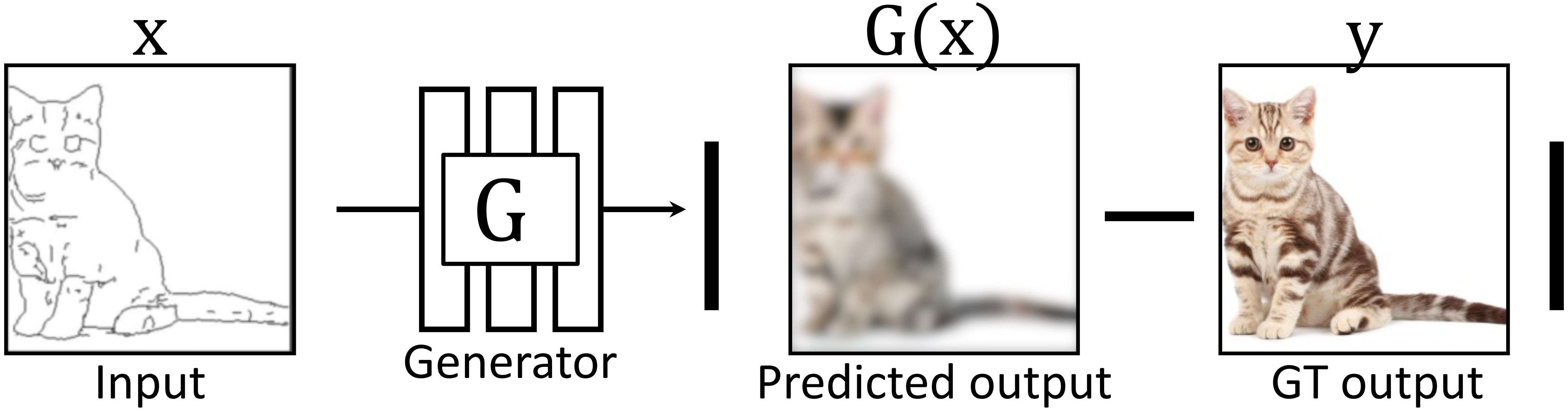
Problem Statement

Loss function

$$\arg\min_{G} \mathcal{L}(G(x), y)$$

Generator | Input Info | Output image

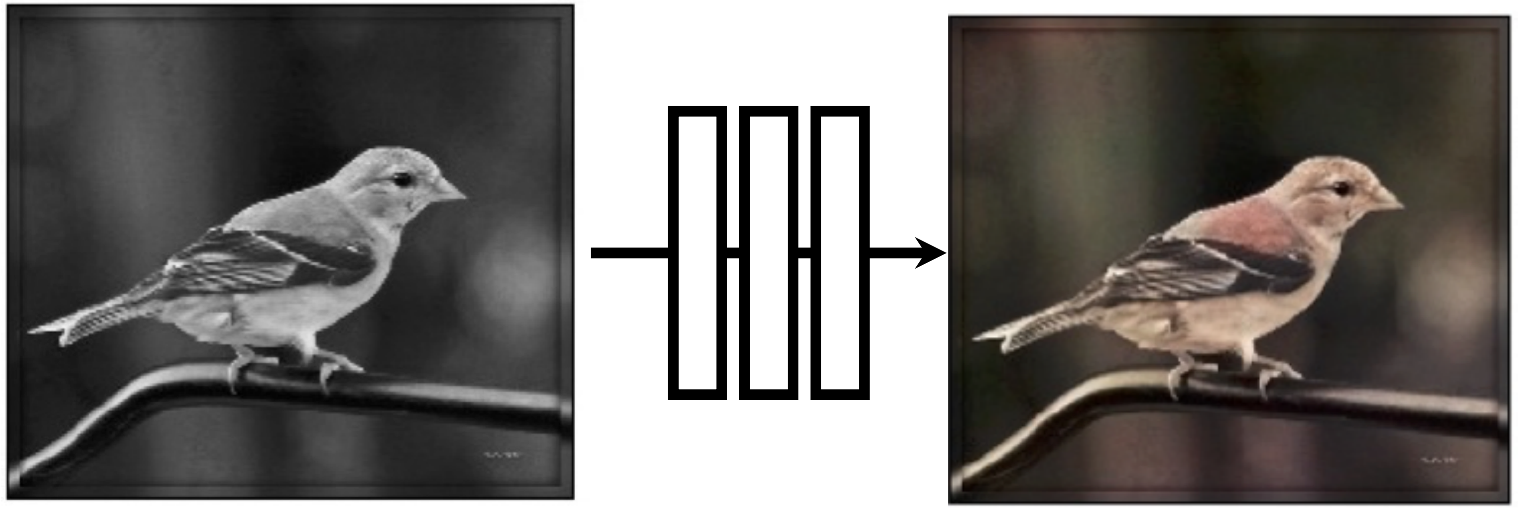
Designing Loss Functions



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

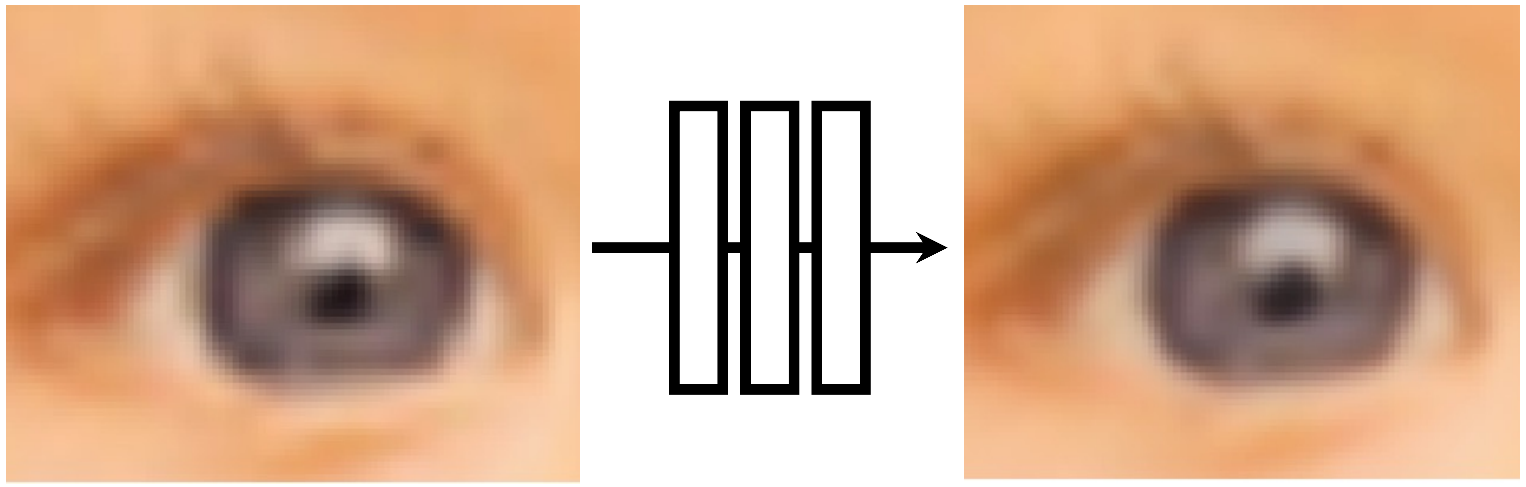
Designing Loss Functions

Image colorization



L2 regression

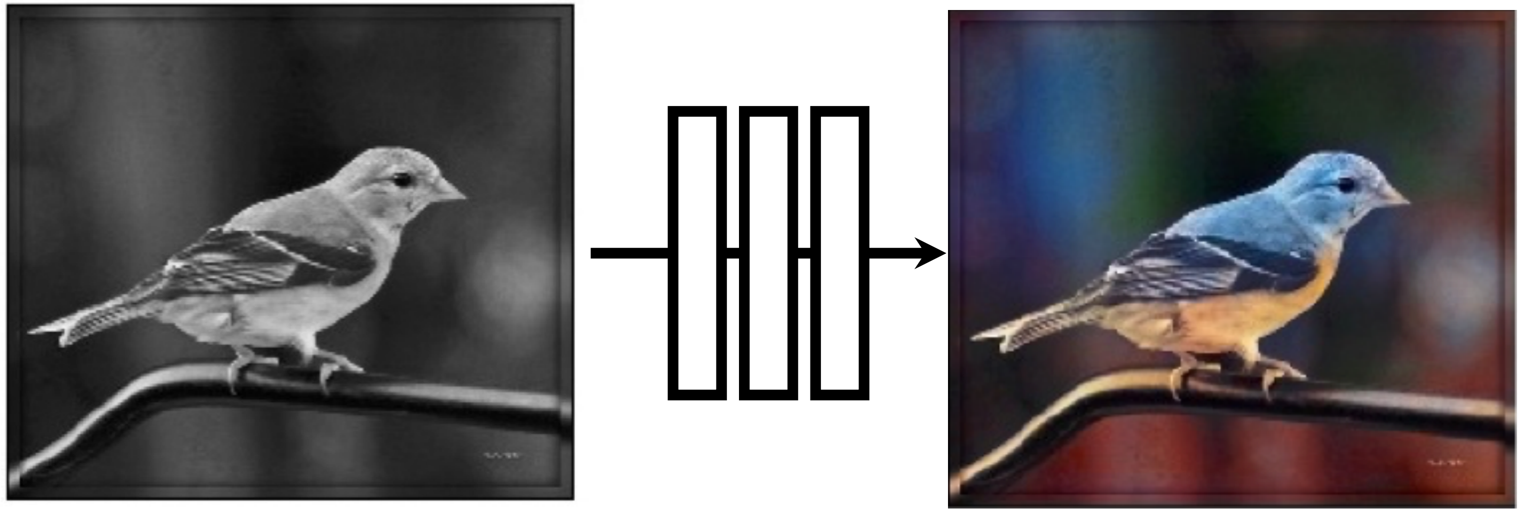
Super-resolution



L2 regression

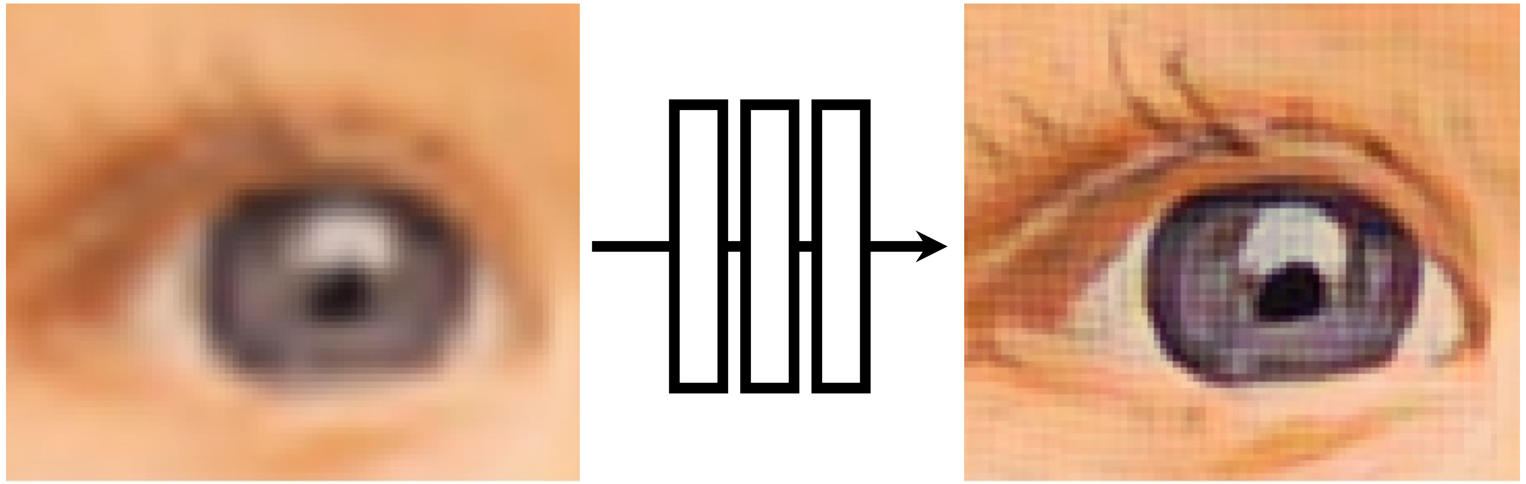
Designing Loss Functions

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

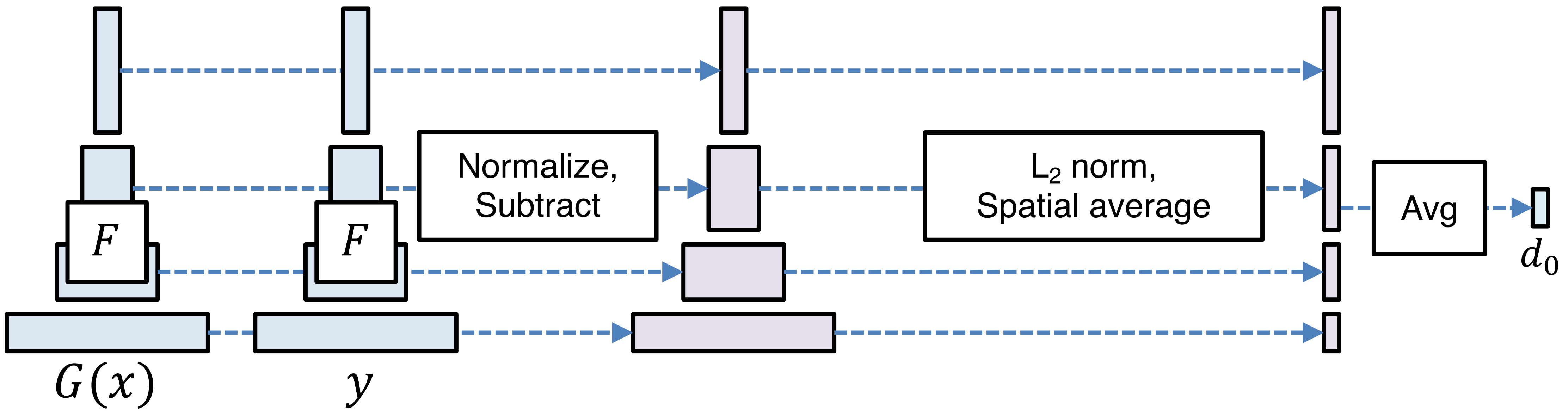
<u>Feature/Perceptual loss</u>
Deep feature matching
objective

“Perceptual Loss”

Gatys et al. In CVPR, 2016.
Johnson et al. In ECCV, 2016.
Dosovitskiy and Brox. In NIPS, 2016.

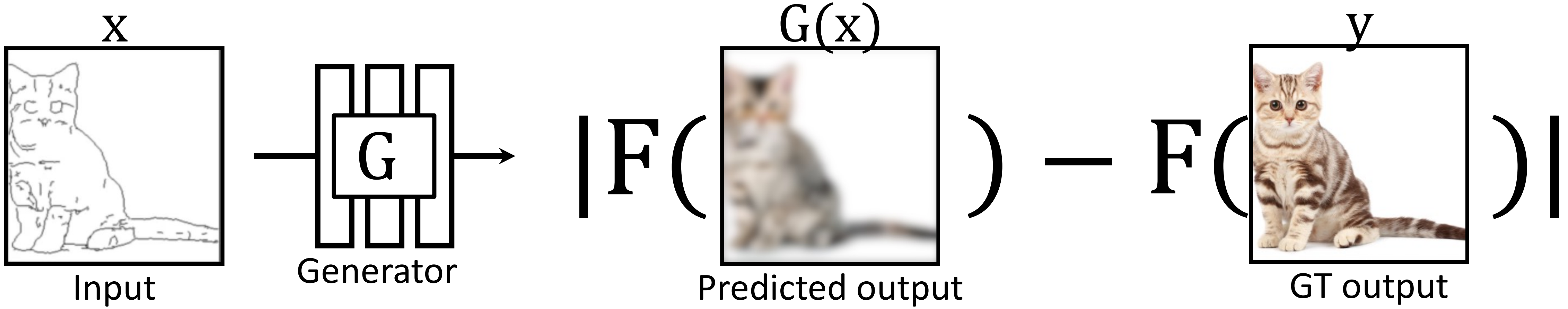
Chen and Koltun. In ICCV, 2017.

CNNs as a Perceptual Metric



c.f. Gatys et al. CVPR 2016. Johnson et al. ECCV 2016. Dosovitskiy and Brox. NIPS 2016.

CNNs as a Perceptual Metric



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

Perceptual Loss

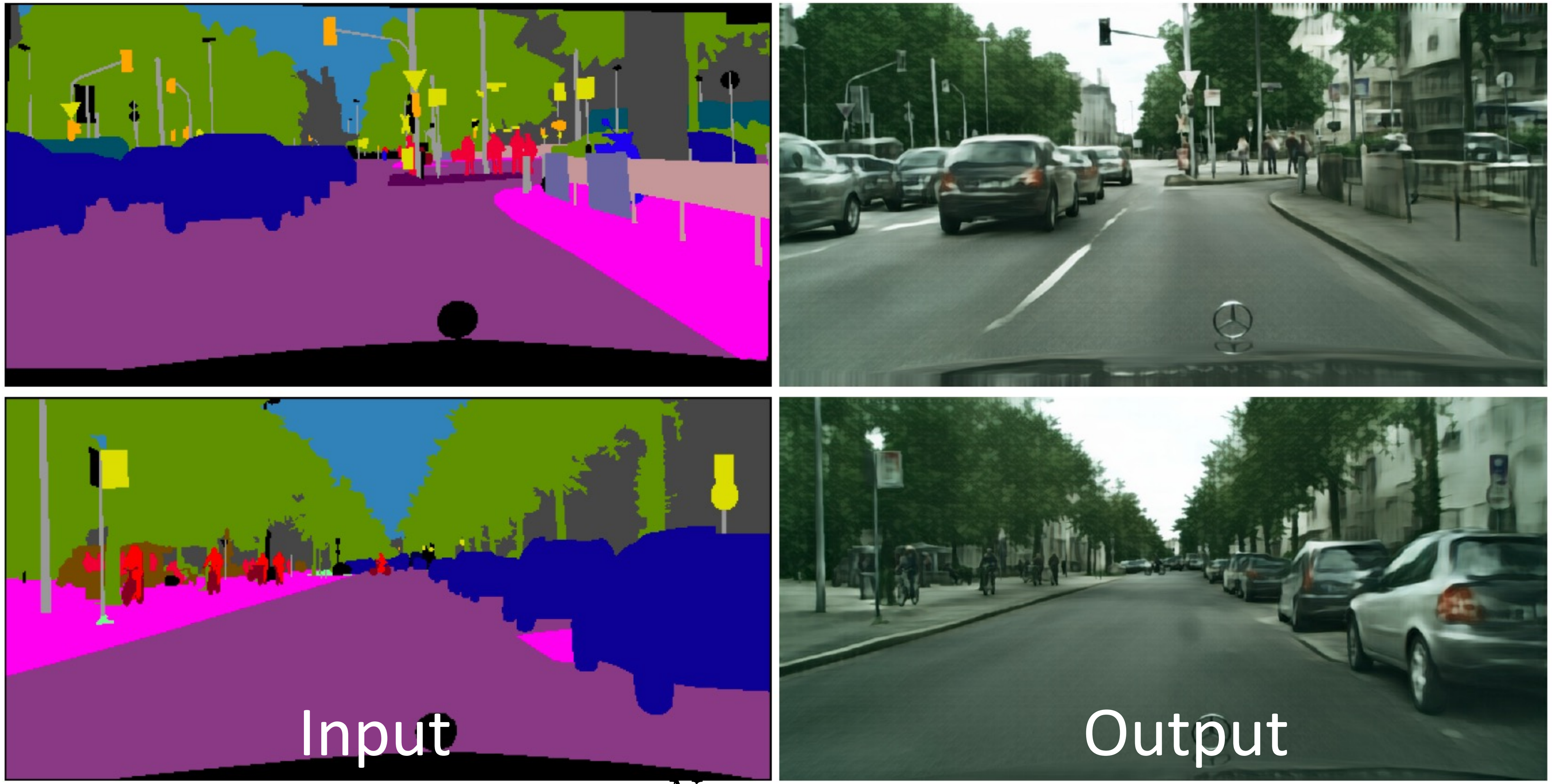
weight

(i)-th layer

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

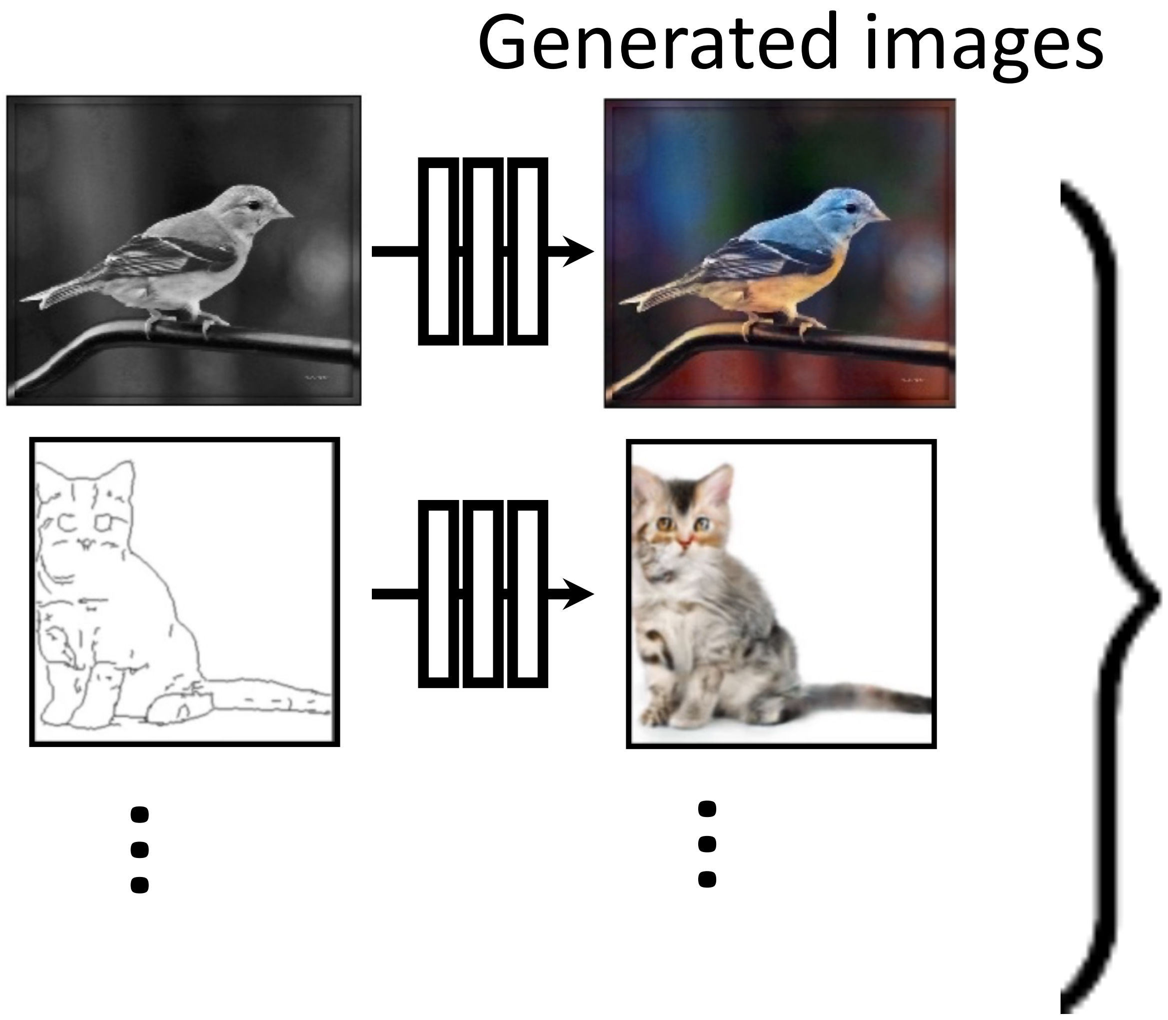
The number of elements in the (i)-th layer

Learning with Perceptual Loss



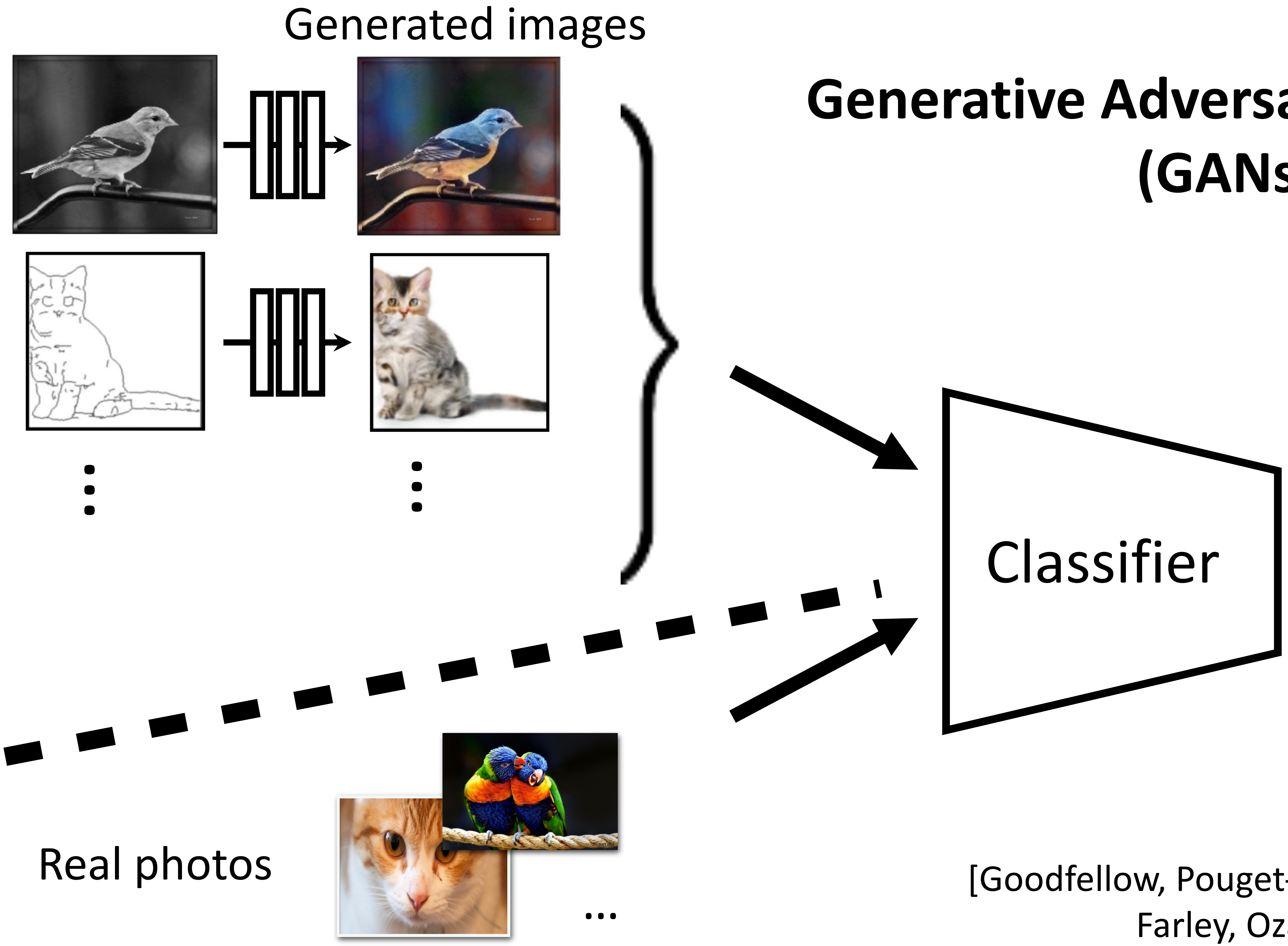
Training objective: $\arg\min_G \mathbb{E}_{(x,y)} \sum_{i=1}^{N} \lambda_i \frac{1}{M_i} ||F^{(i)}(G(x)) - F^{(i)}(y))||_2^2$

CRN [Chen and Koltun, 2017]



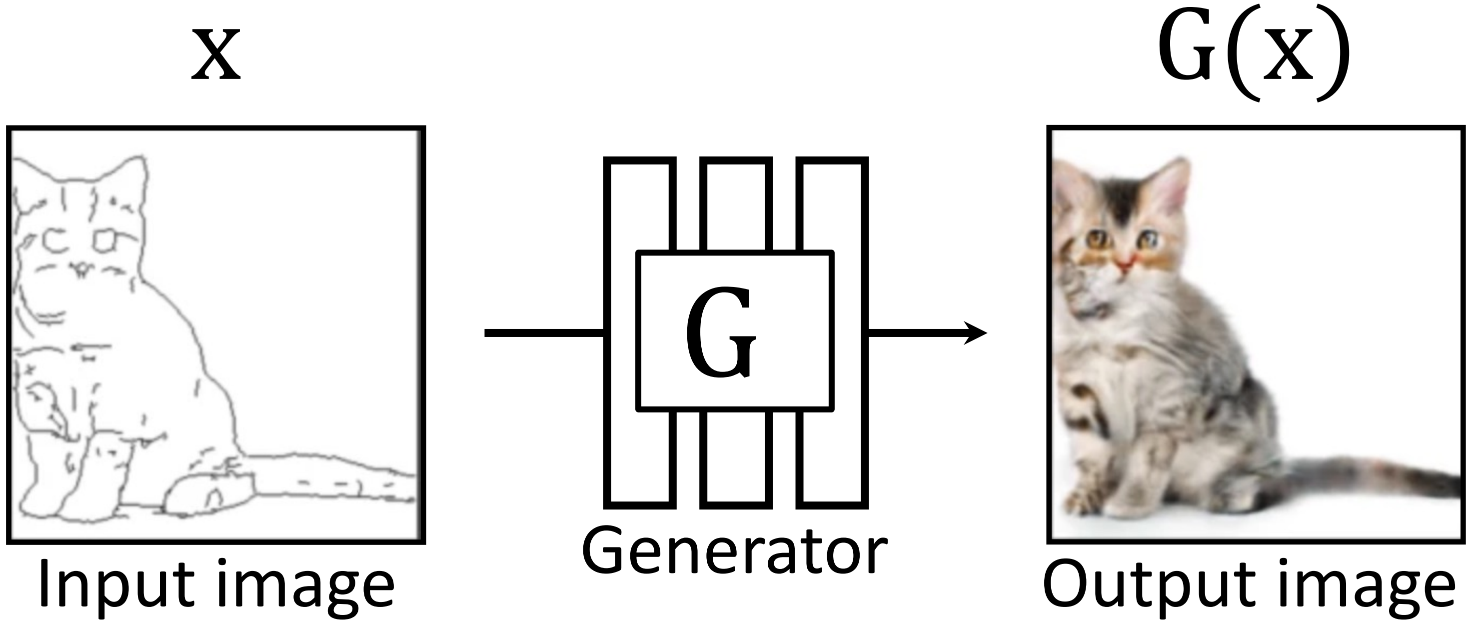
Universal loss?

Generative Adversarial Network (GANs)

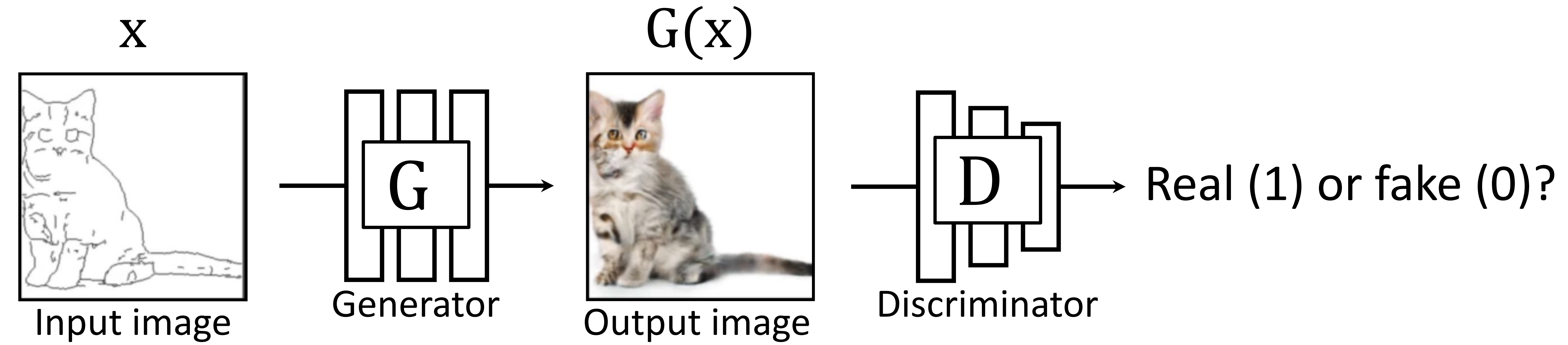


Real vs. Fake

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



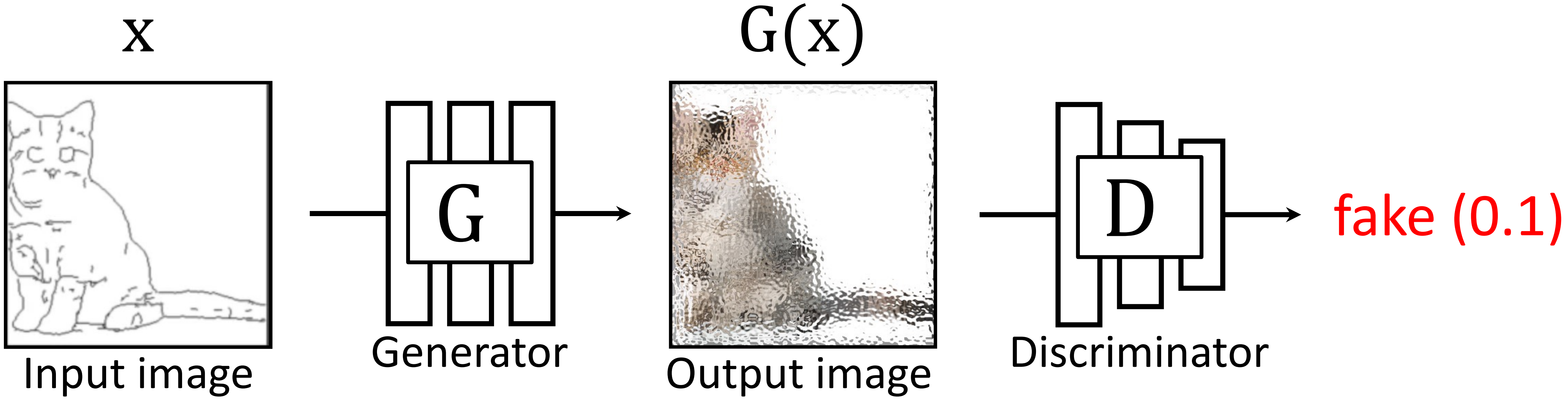
[Goodfellow et al. 2014]



A two-player game:

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

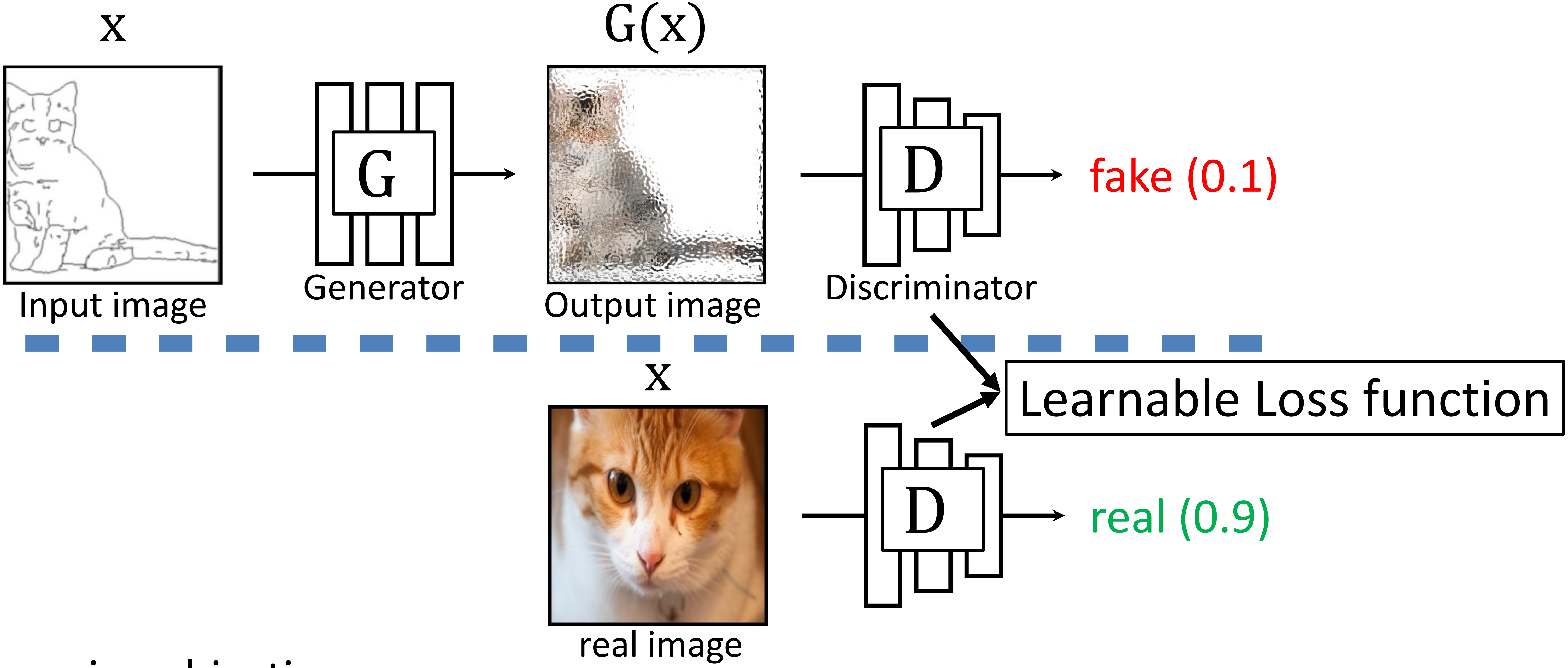
[Goodfellow et al. 2014]



Learning objective

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

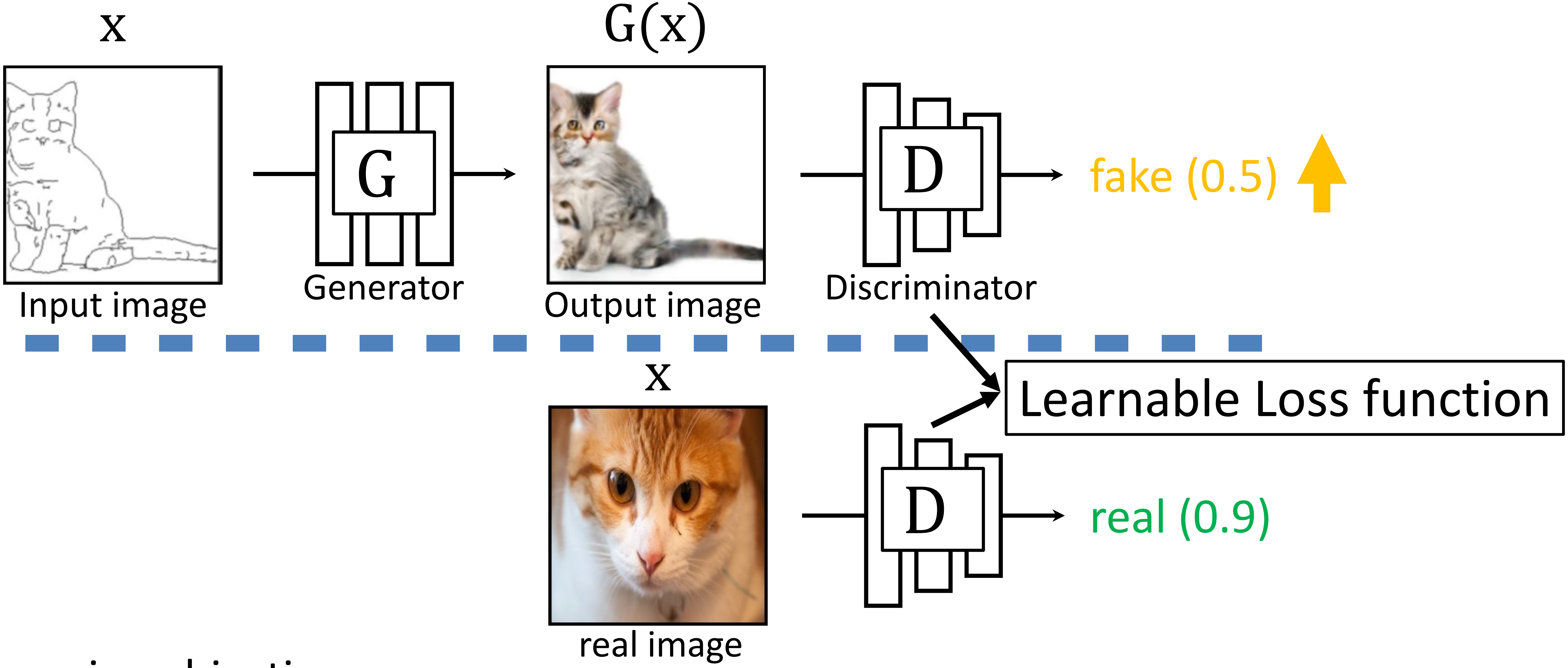
[Goodfellow et al. 2014]



Learning objective

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

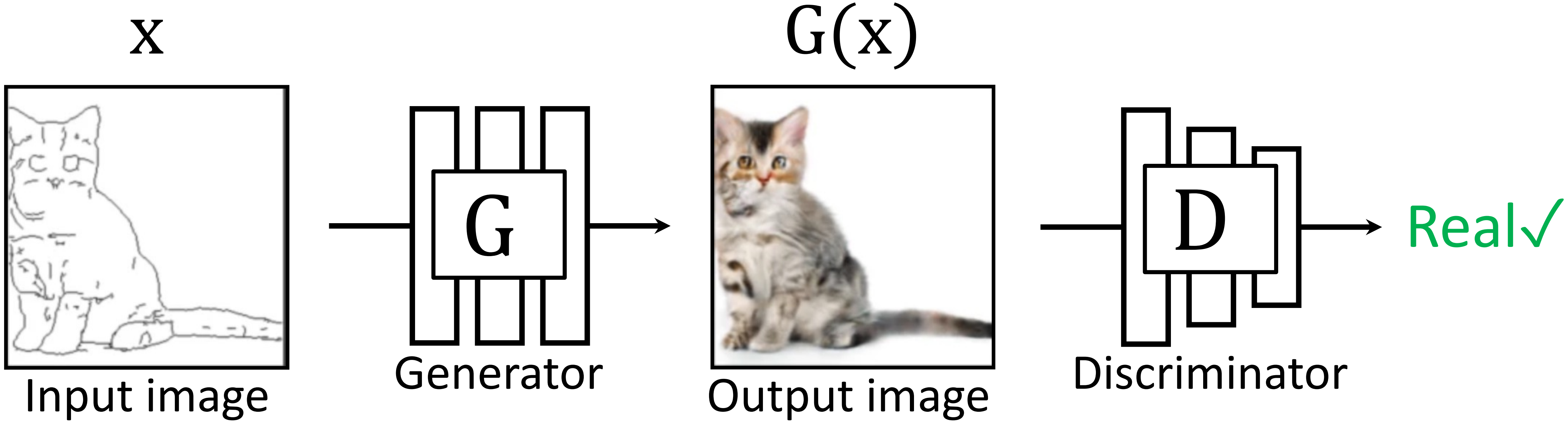
[Goodfellow et al. 2014]



Learning objective

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

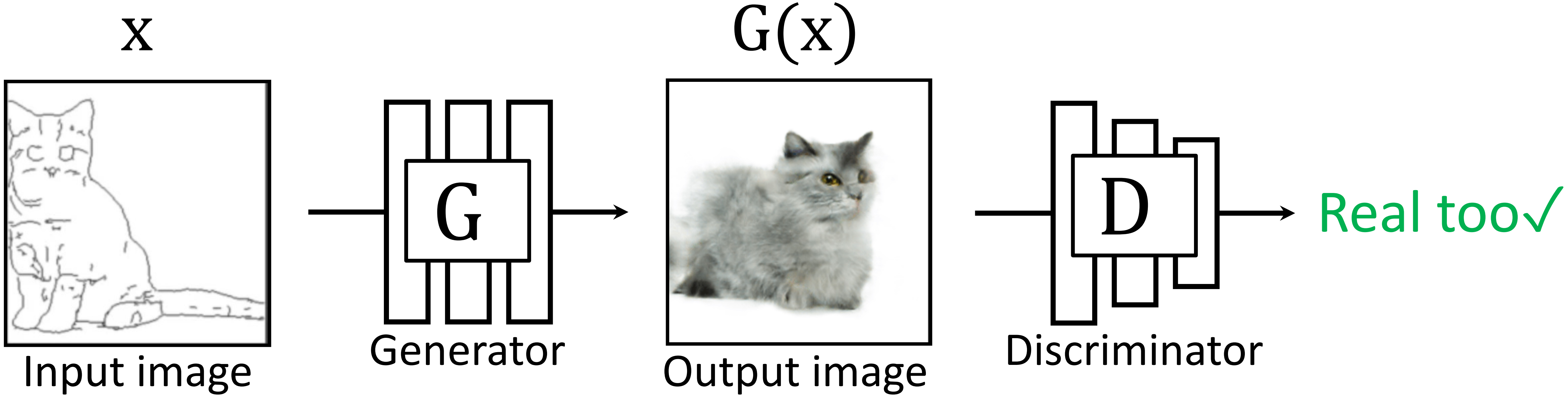
[Goodfellow et al. 2014]



Learning objective

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

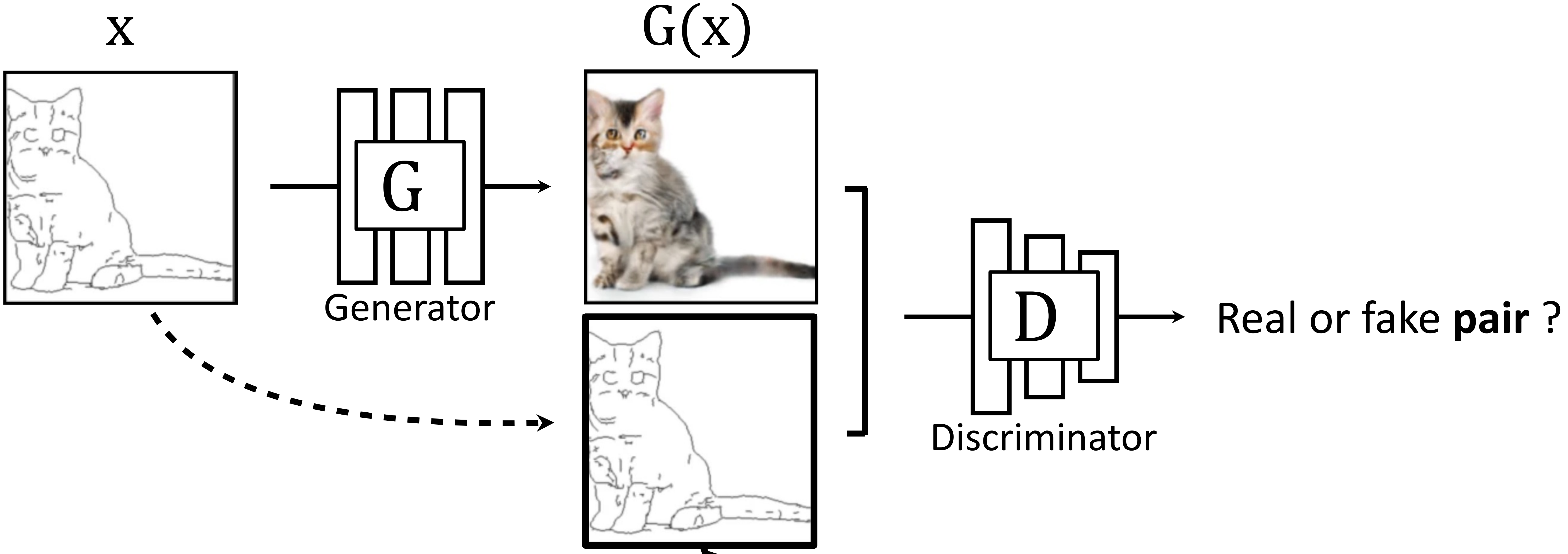
Pix2pix [Isola et al., 2016]



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]

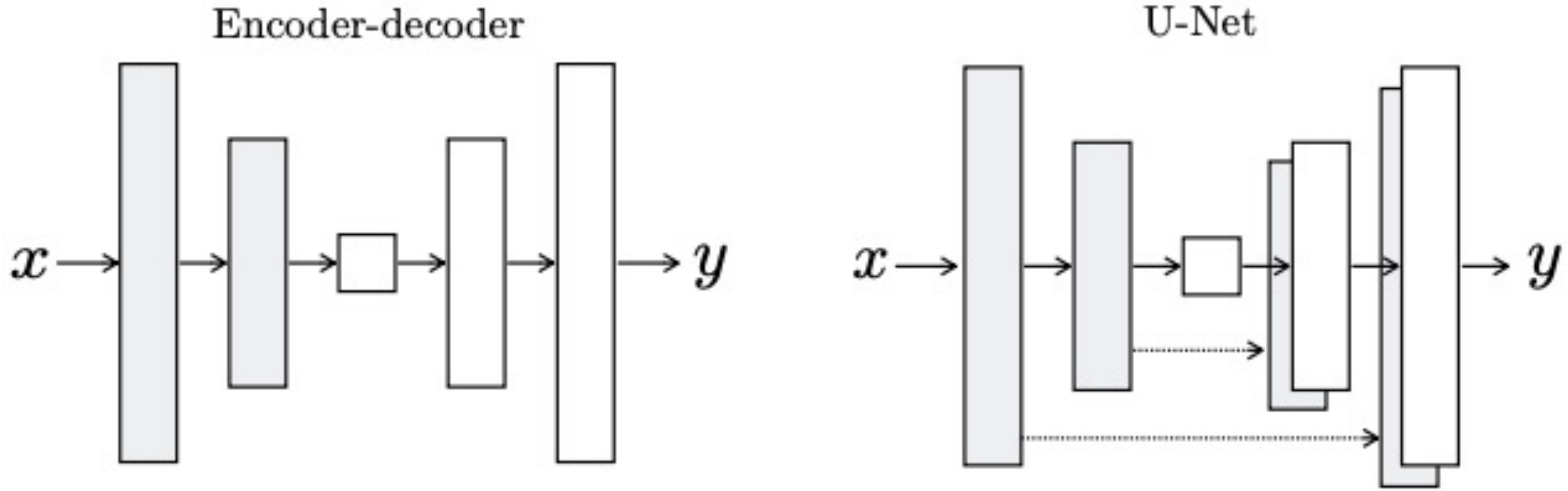


Learning objective

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

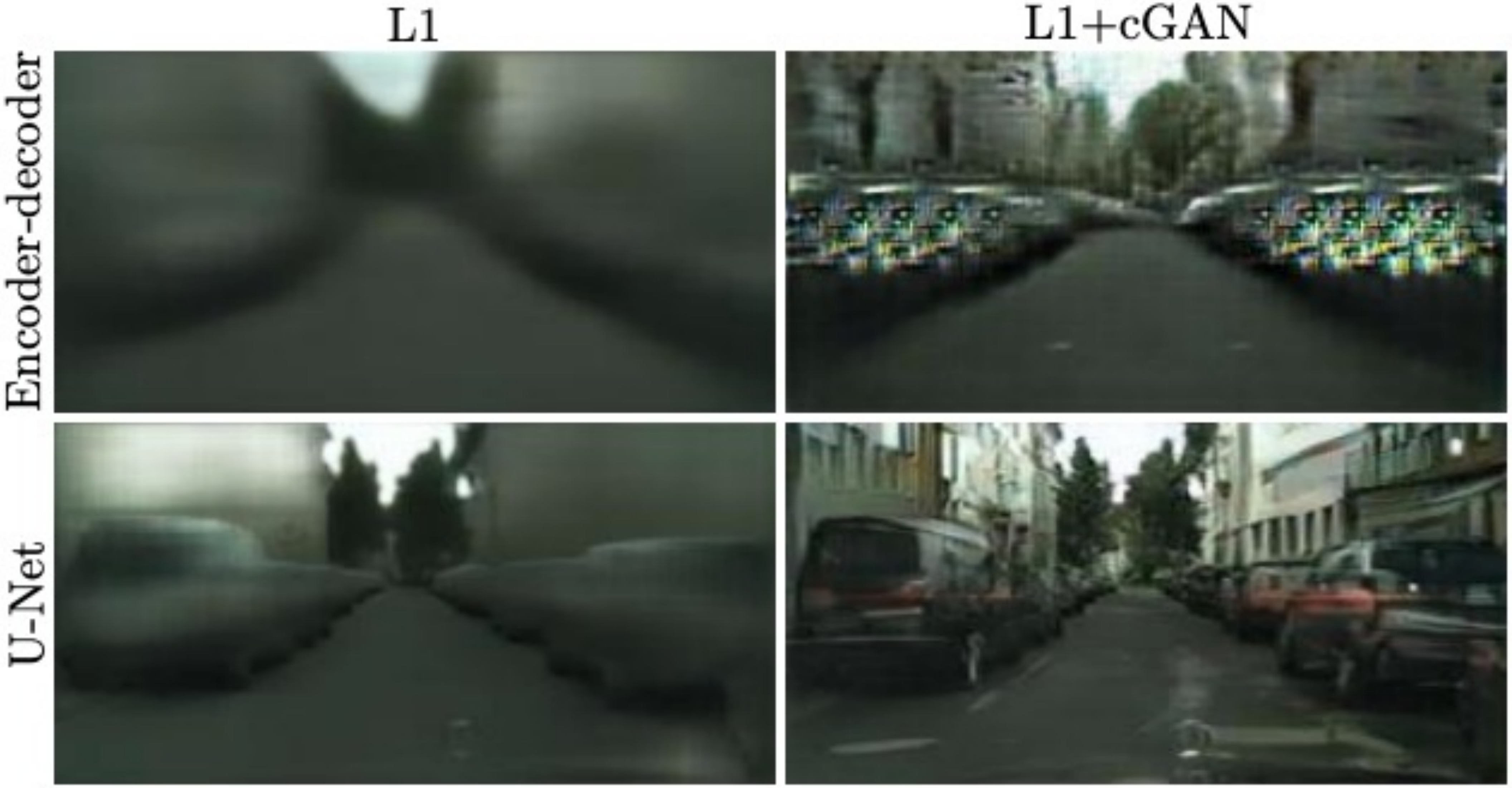
Pix2pix [Isola et al., 2016]

pix2pix Generator (U-Net)



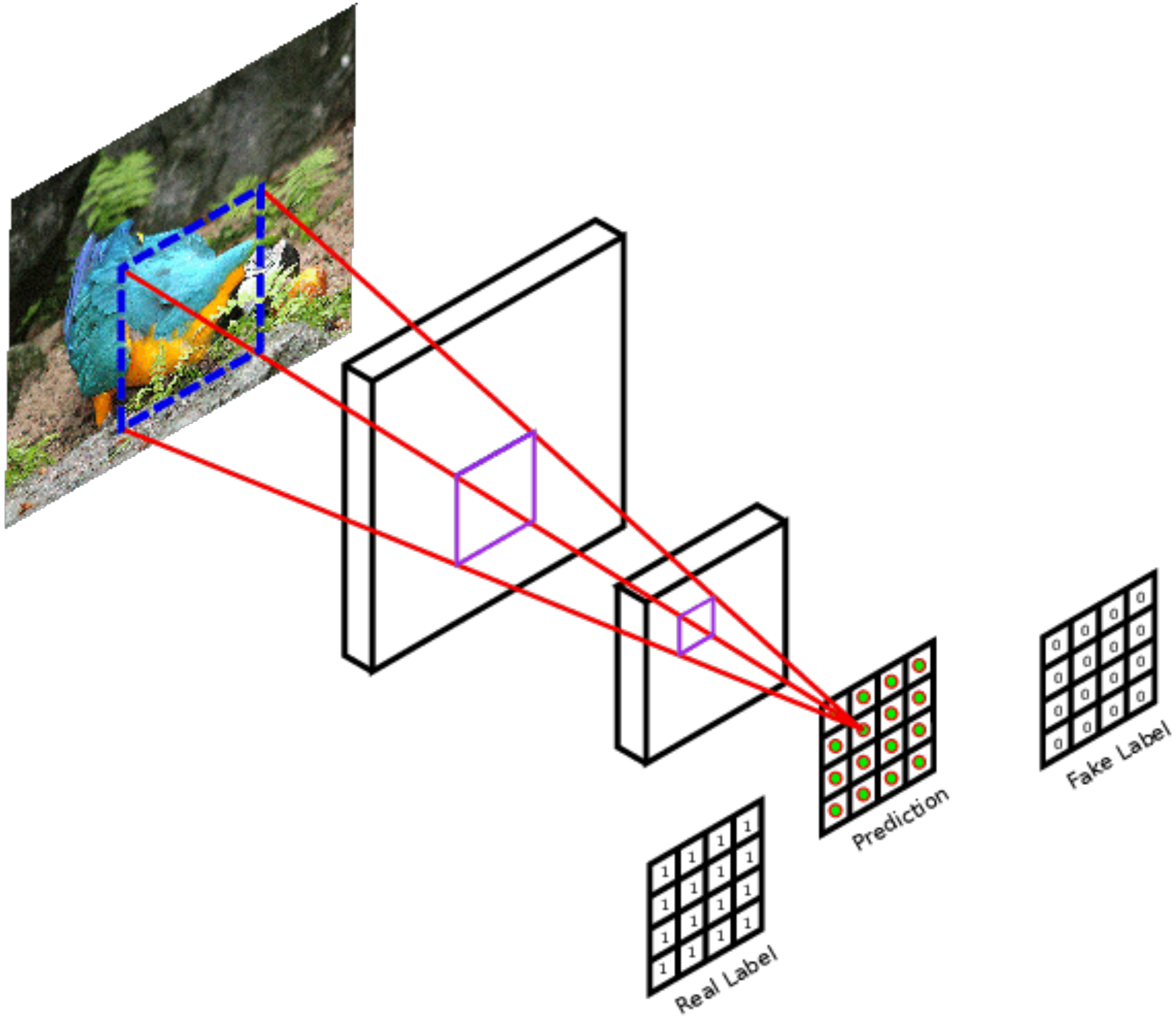
U-Net [Ronneberger et al.]: popular CNN backbone for biomedical image segmentation
U-Net: preserve high-frequency information (e.g., edge) of the input image.
Encoder-decoder: lose high-frequency details due to the information bottleneck

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)

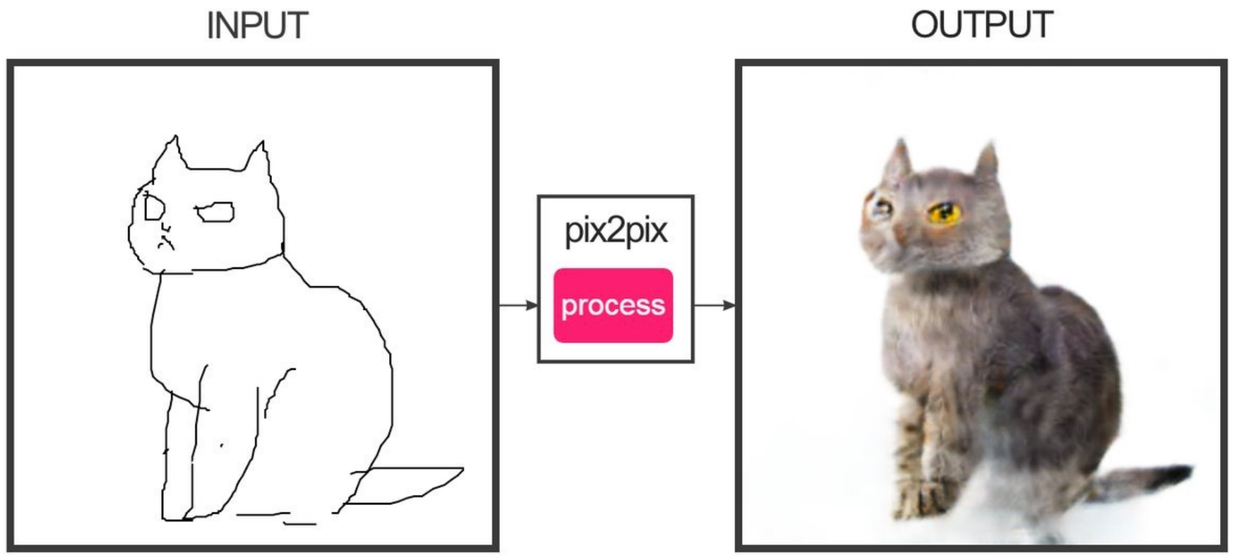


- Rather than penalizing if output *image* looks fake, penalize if each overlapping *patches* looks fake
- Focus on <u>local</u> visual cues (color, textures).
- <u>Global</u> structure: the input image has already encoded global structure. L1 loss can help as well.

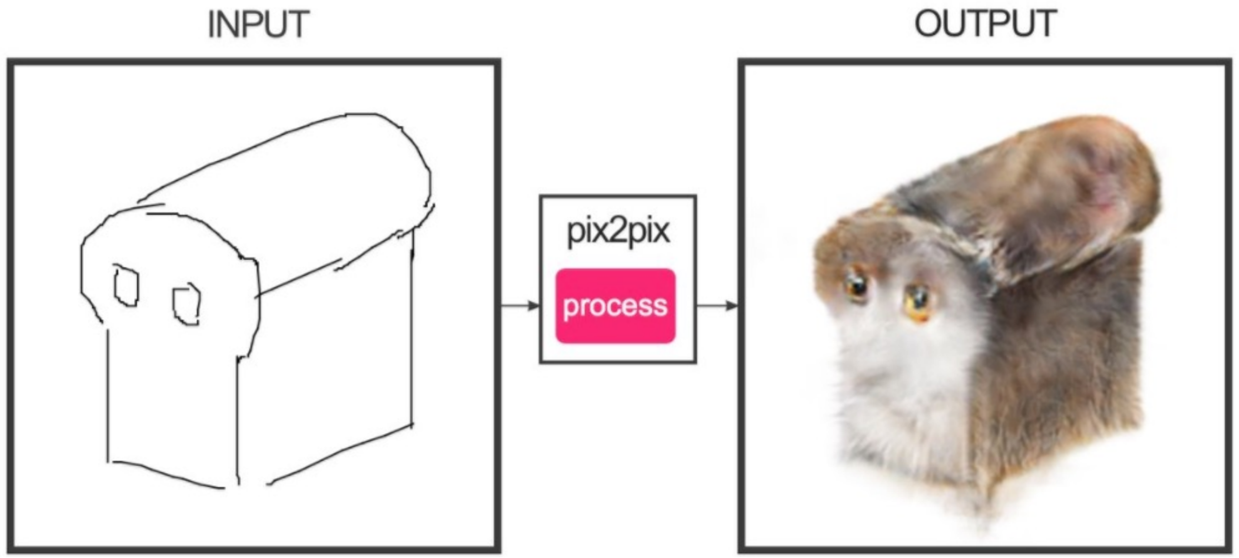
Advantages

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

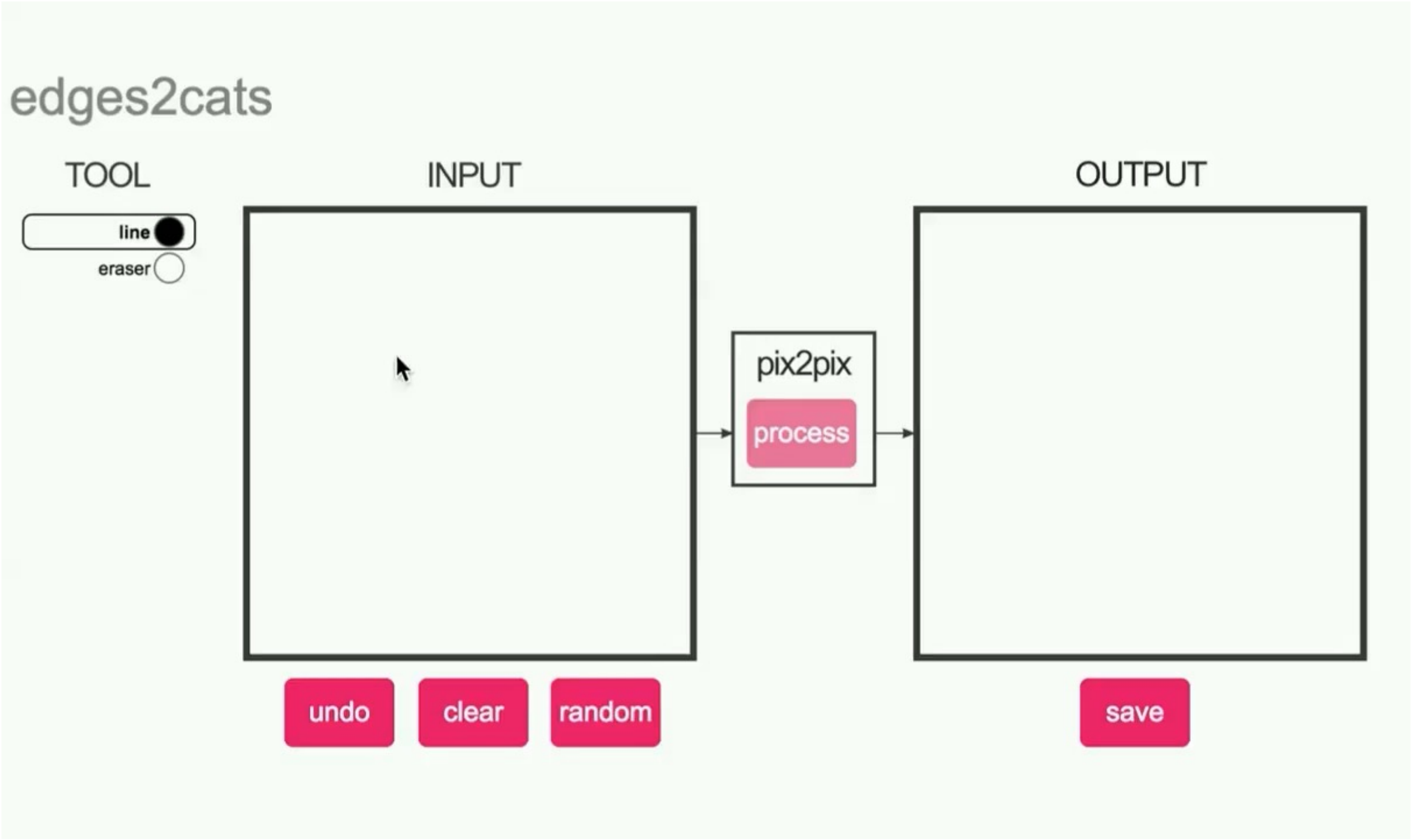
#edges2cats [Christopher Hesse]



@gods_tail



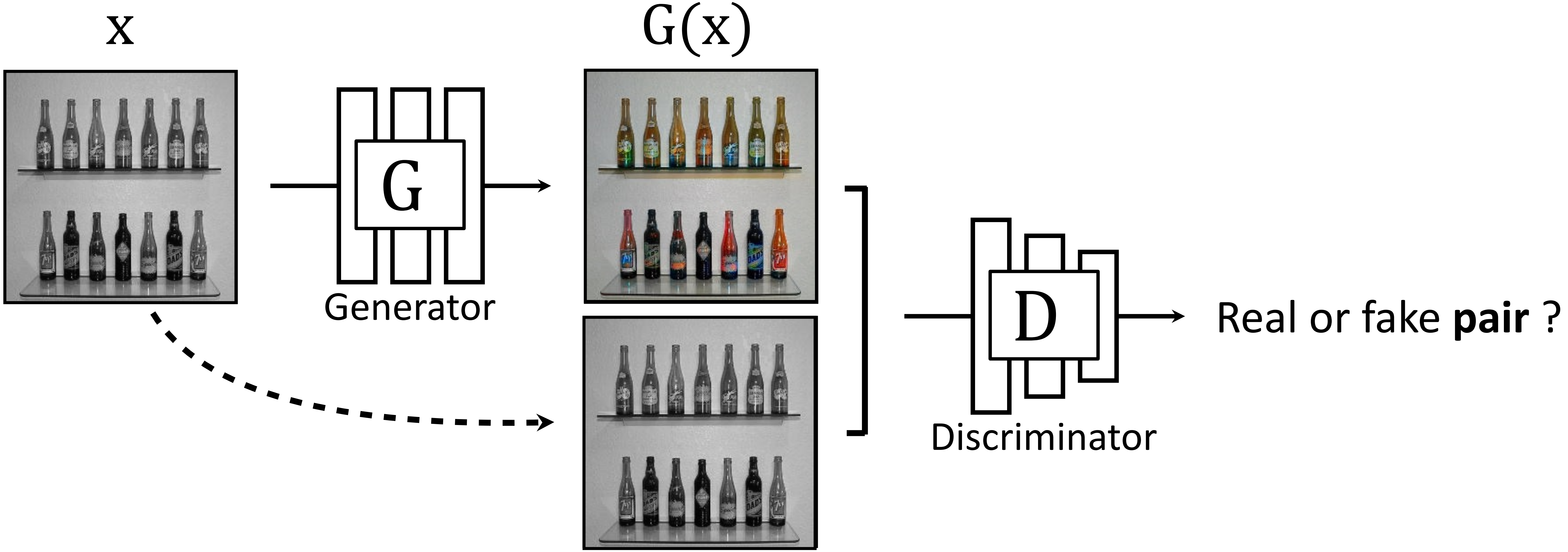
Ivy Tasi @ivymyt



@matthematician

Vitaly Vidmirov @vvid

https://affinelayer.com/pixsrv/



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

Input: **Sketch** → Output: **Photo**

Automatic Colorization with pix2pix

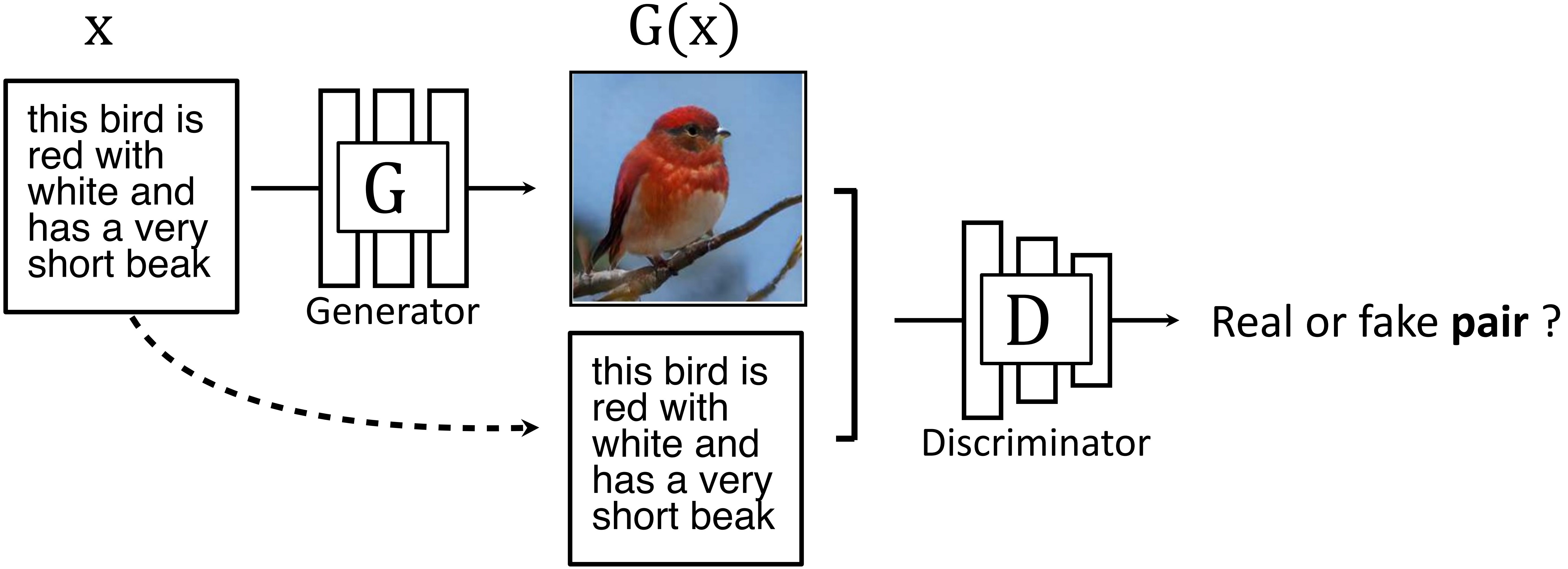
Input Output Input Output Input Output

Data from [Russakovsky et al. 2015]

Automatic Colorization with pix2pix

Input Output Input Output Input Output

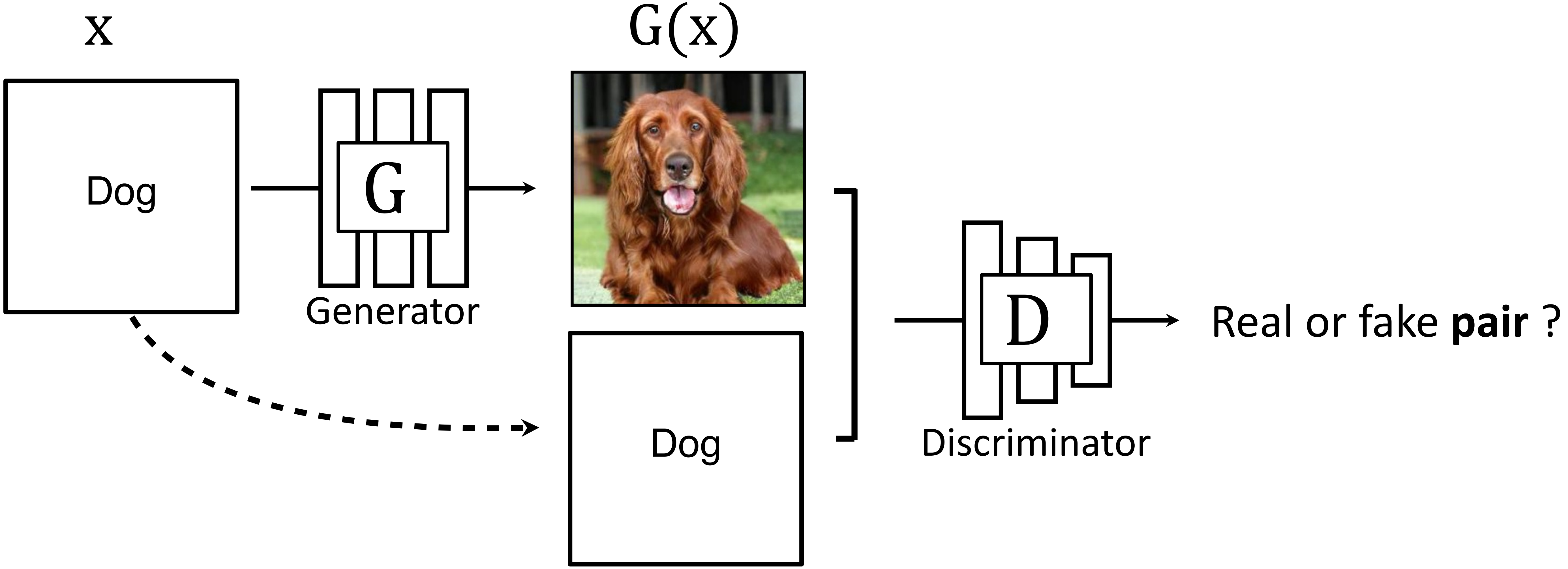
Data from [Russakovsky et al. 2015]



Input: **Text** $\rightarrow$ Output: **Photo**

Text-to-Image Synthesis

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



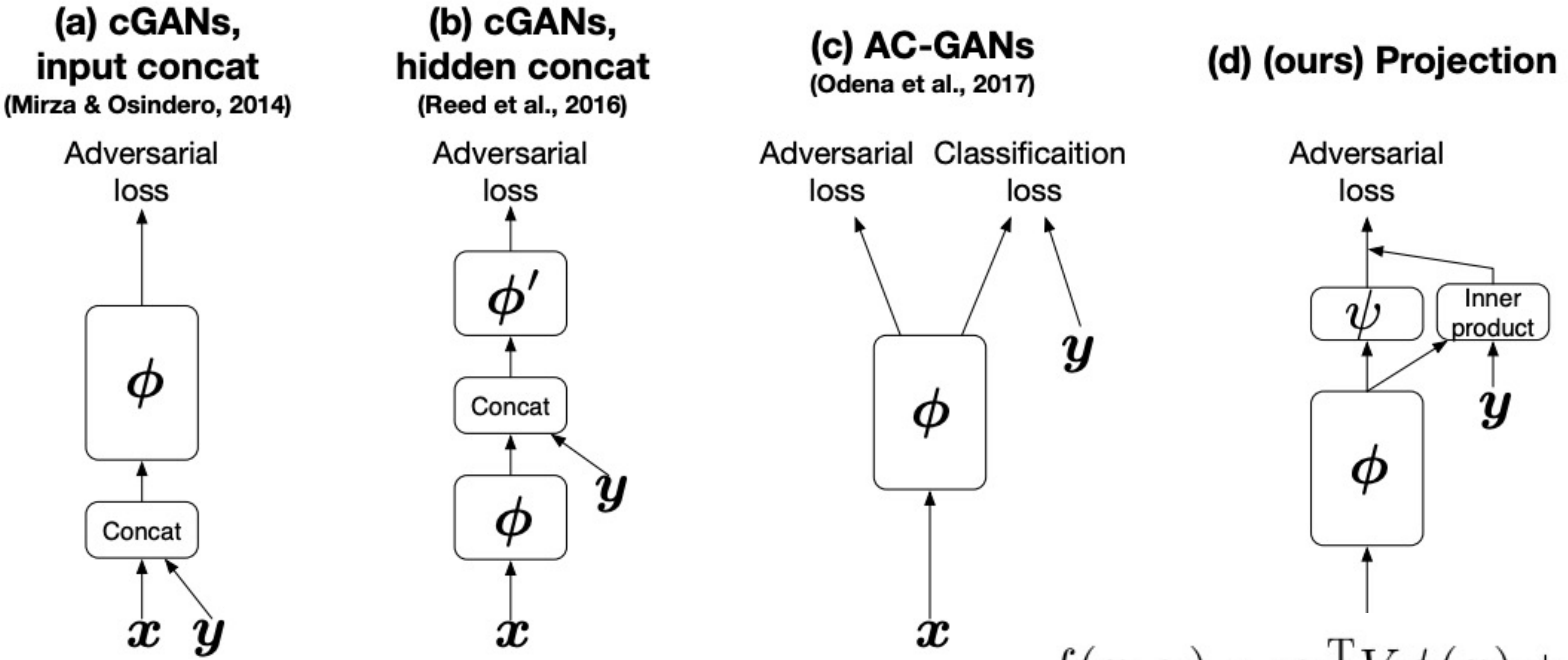
Input: **Class** $\rightarrow$ Output: **Photo**

<u>Class-conditional GANs</u>

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

StyleGAN-XL [Sauer et al., 2022]

Class-conditional Discriminator



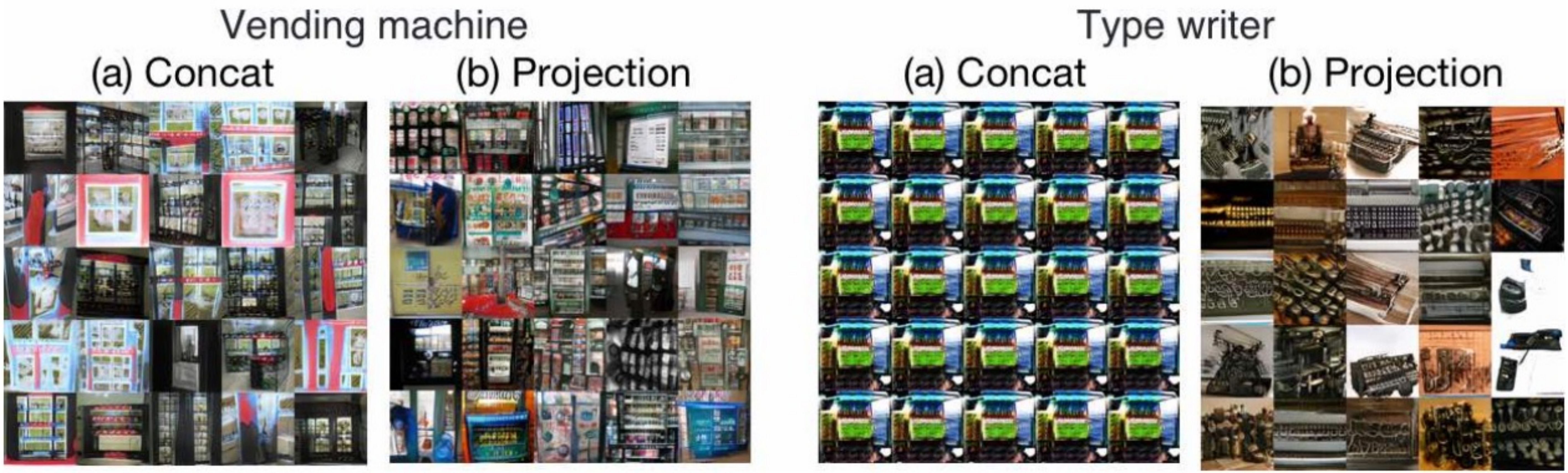
$$f(\boldsymbol{x}, \boldsymbol{y}) := \boldsymbol{y}^{\mathrm{T}} V \boldsymbol{\phi}(\boldsymbol{x}) + \psi(\boldsymbol{\phi}(\boldsymbol{x}))$$

Learnable matrix

x: image, y: class labels (one-hot vector), ϕ, ϕ', ψ : neural networks

Projection Discriminator [Miyato and Koyama, ICLR 2018]

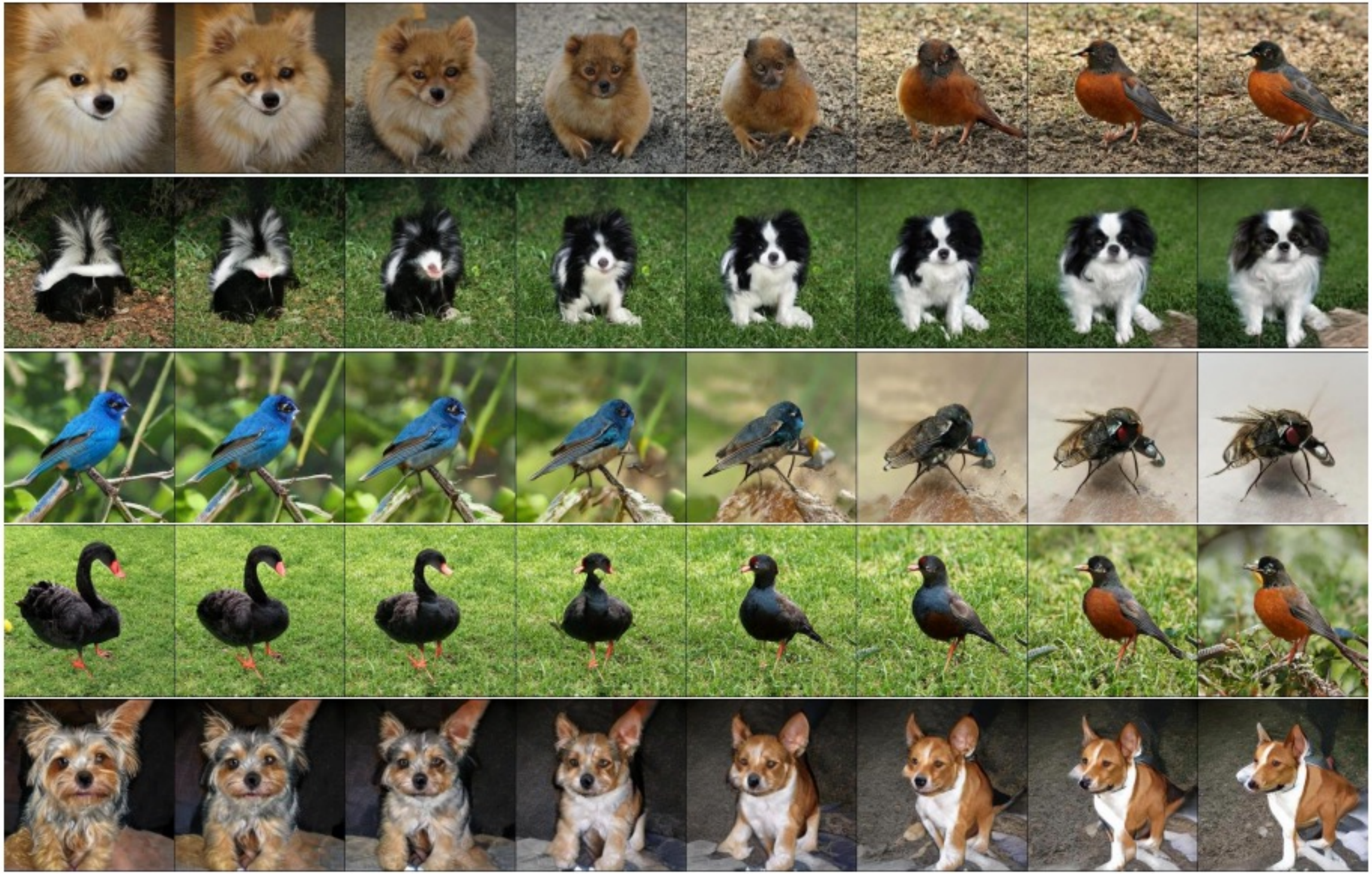
Class-conditional Discriminator

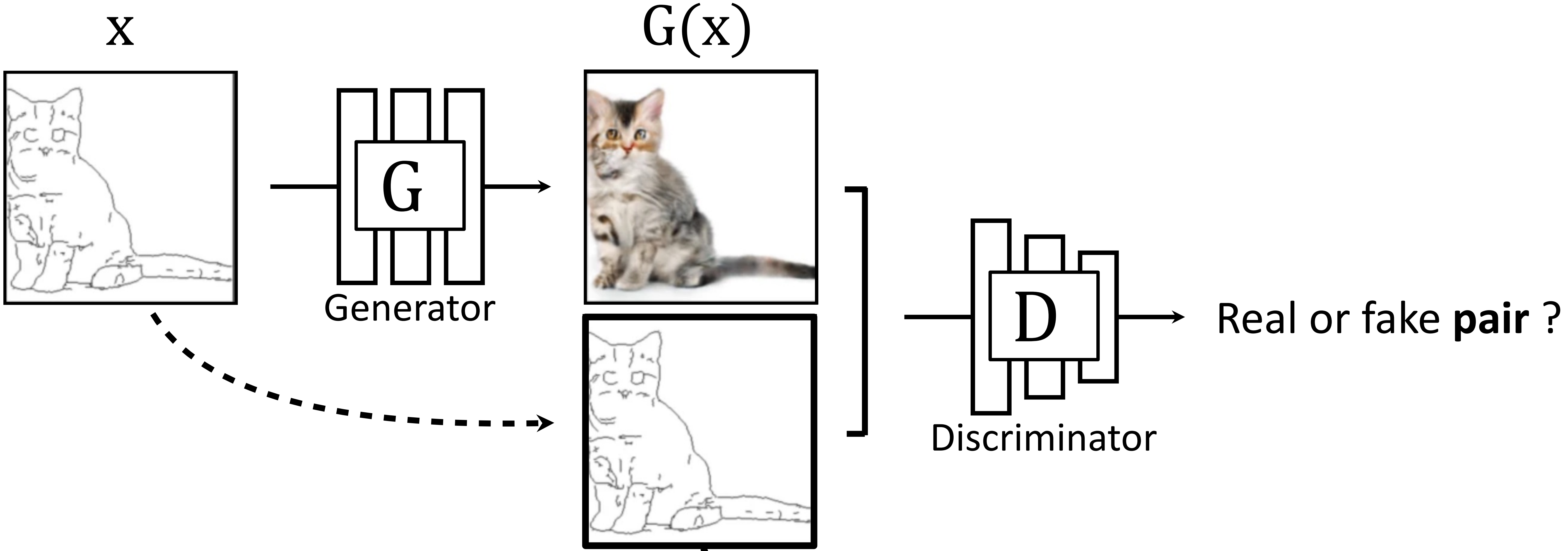


Projection Discriminator [Miyato and Koyama, ICLR 2018]

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]

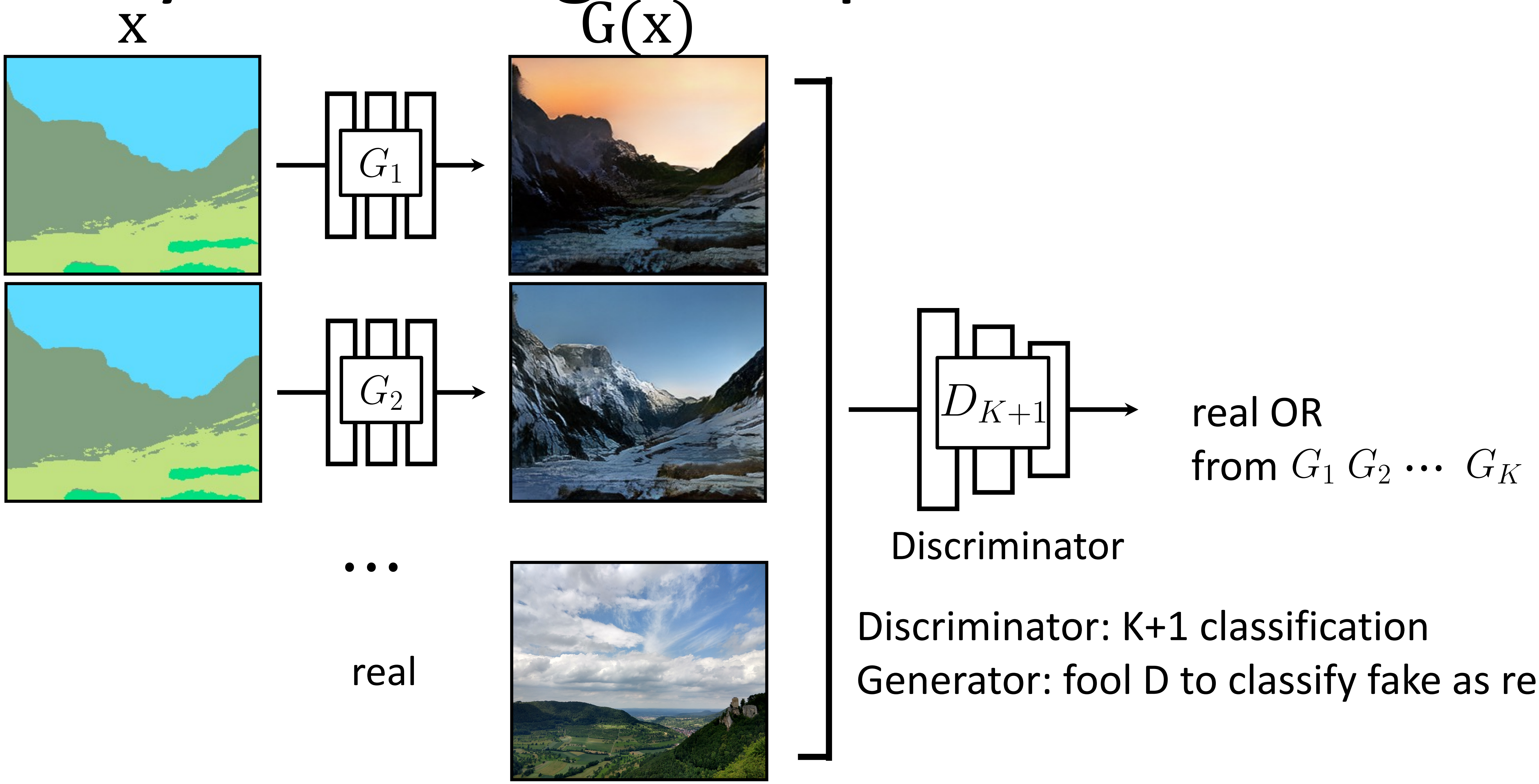
Limitations

- 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

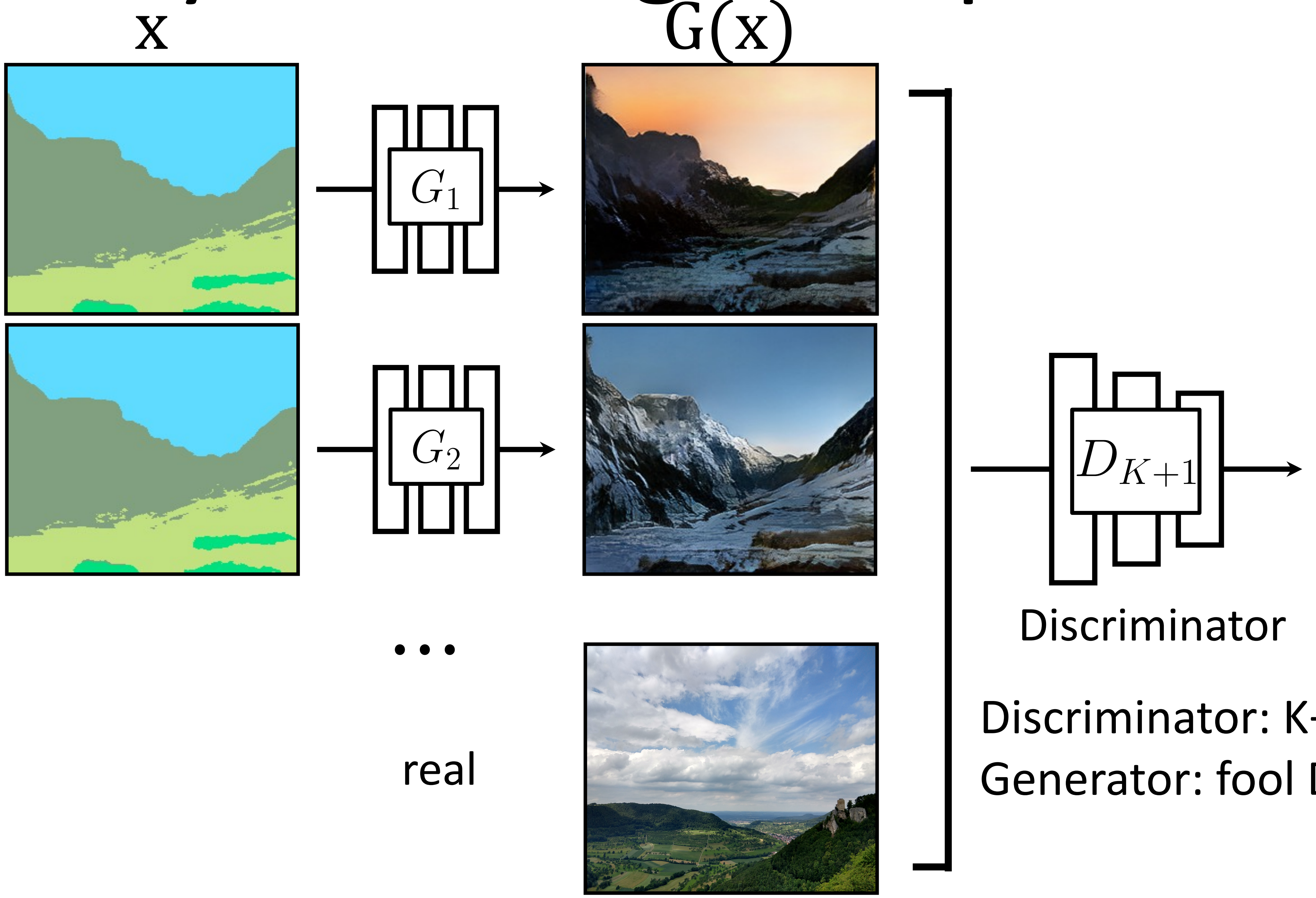
Multi-agent Diverse GANs [Ghosh et al., CVPR 2018]

Synthesizing Multiple Results

Night input Day output 1 Day output 2 Day output 3

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

Synthesizing Multiple Results



real OR
from G_1 G_2 $\cdots$ G_K

Discriminator: K+1 classification

Generator: fool D to classify fake as real

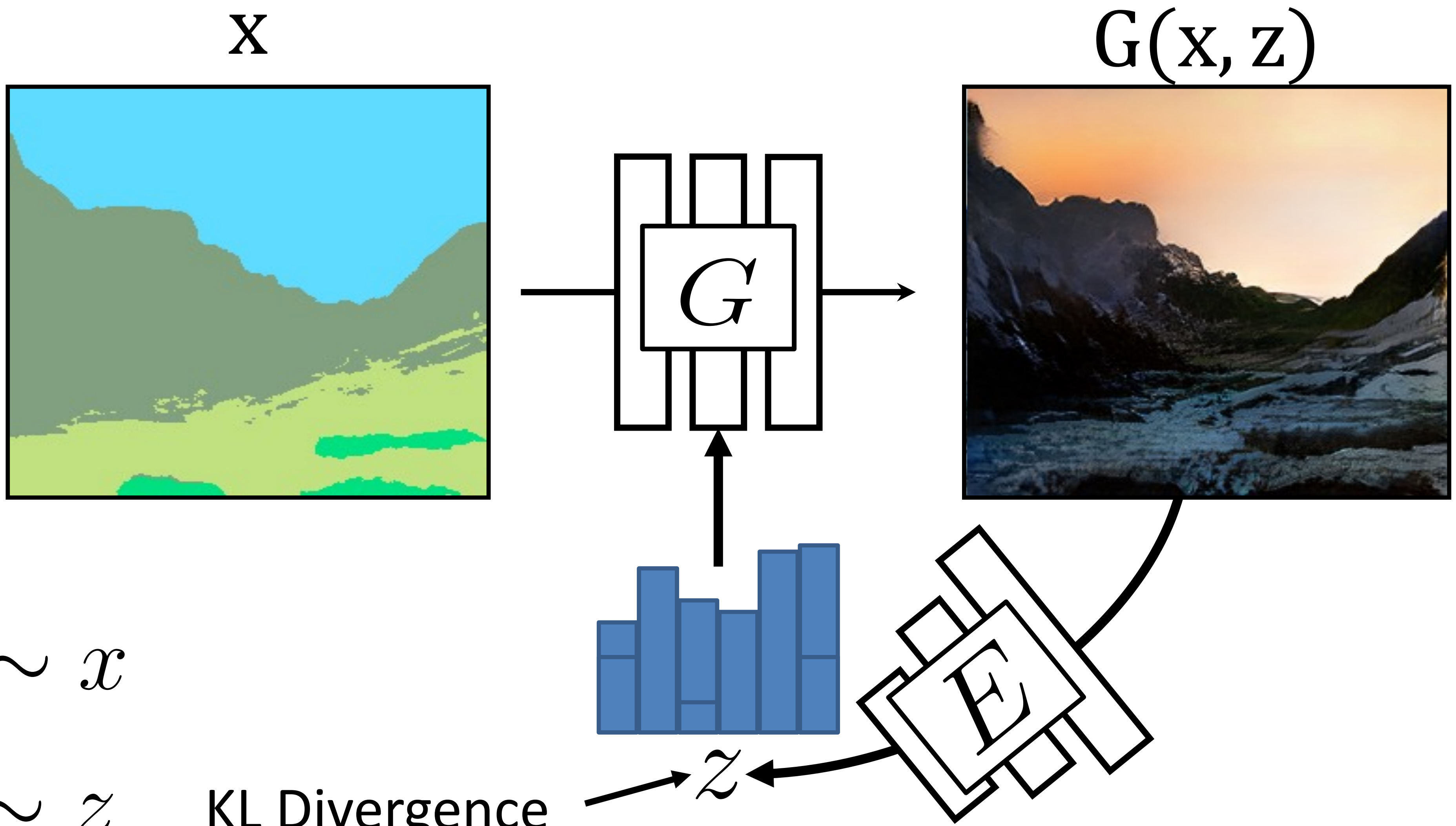
Multi-agent Diverse GANs [Ghosh et al., CVPR 2018]

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



$$G(x, E(x)) \sim x$$

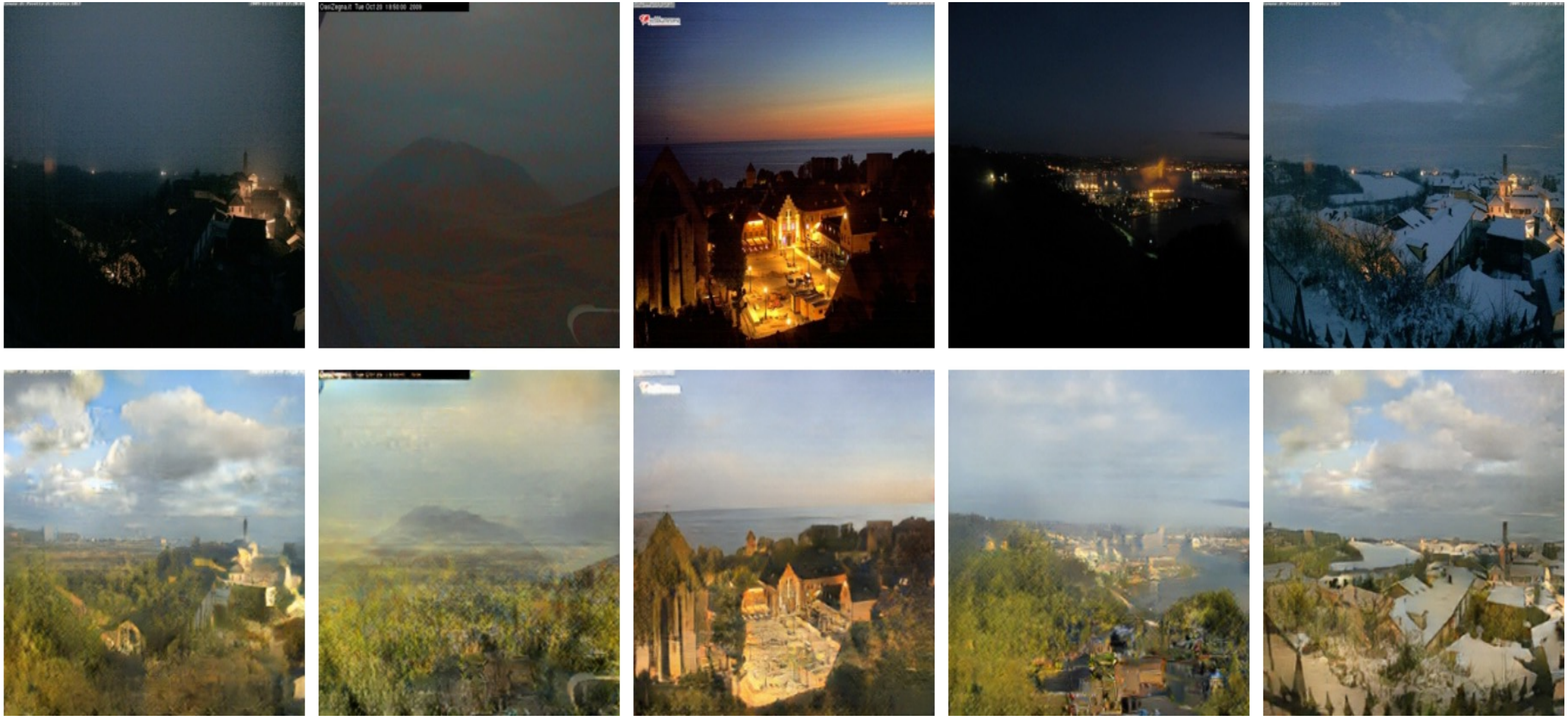
$$E(G(x, z)) \sim z$$

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

Synthesizing Multiple Results

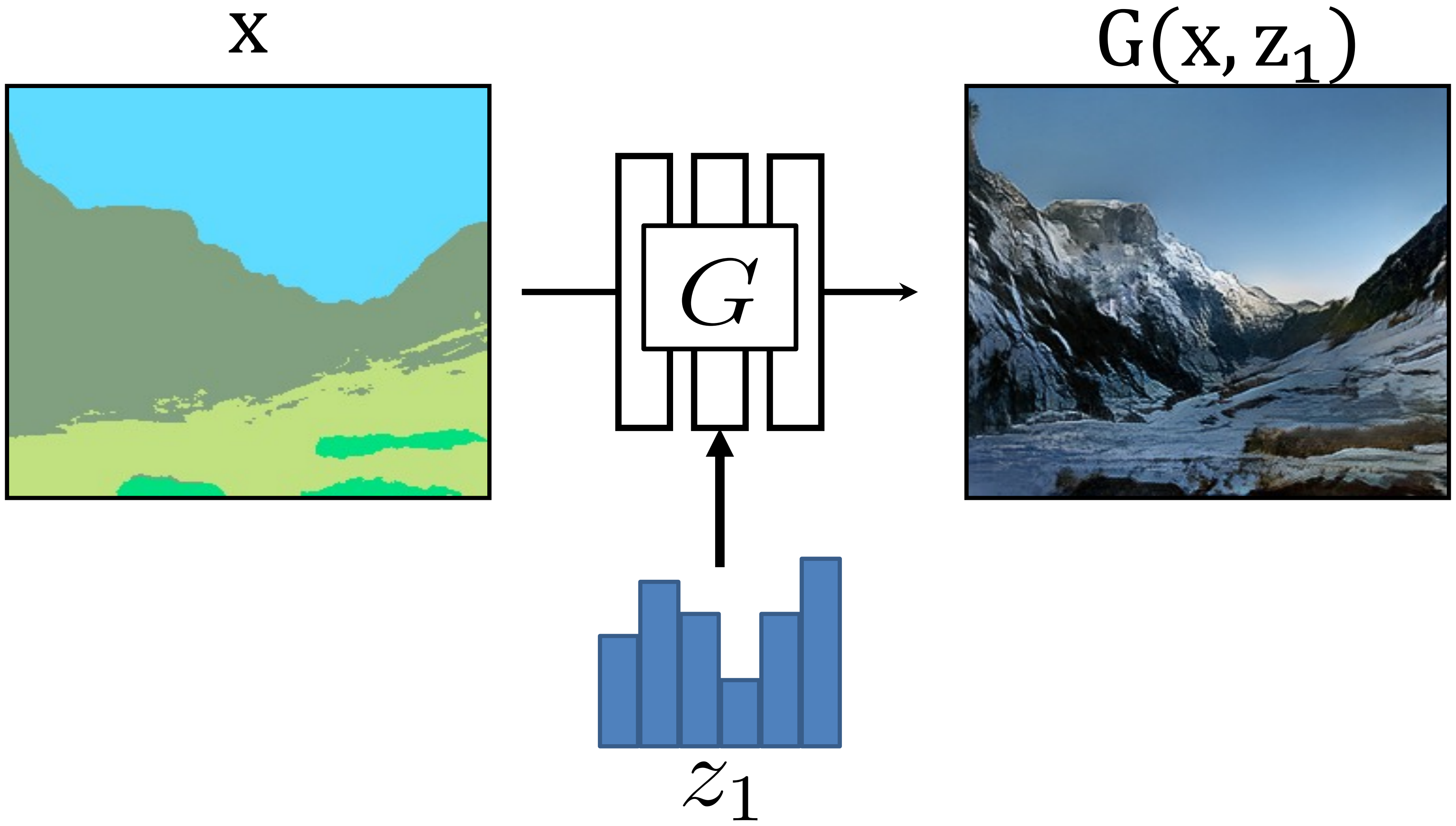
BicycleGAN [Zhu et al., 2017]

Synthesizing Multiple Results



BicycleGAN [Zhu et al., 2017]

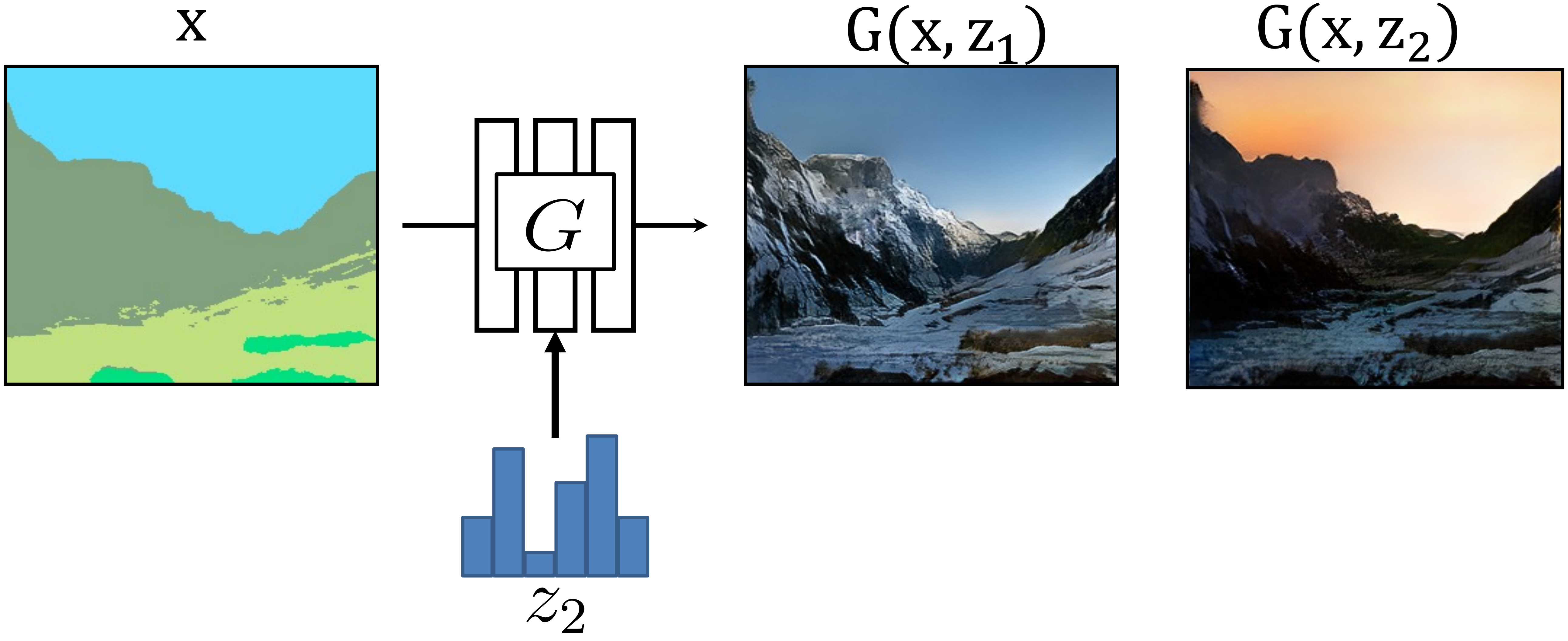
Synthesizing Multiple Results



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

DSGAN [Zhu et al., 2017]

Synthesizing Multiple Results



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

DSGAN [Yang et al., 2019]

Synthesizing Multiple Results

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

DSGAN [Yang et al., 2019]

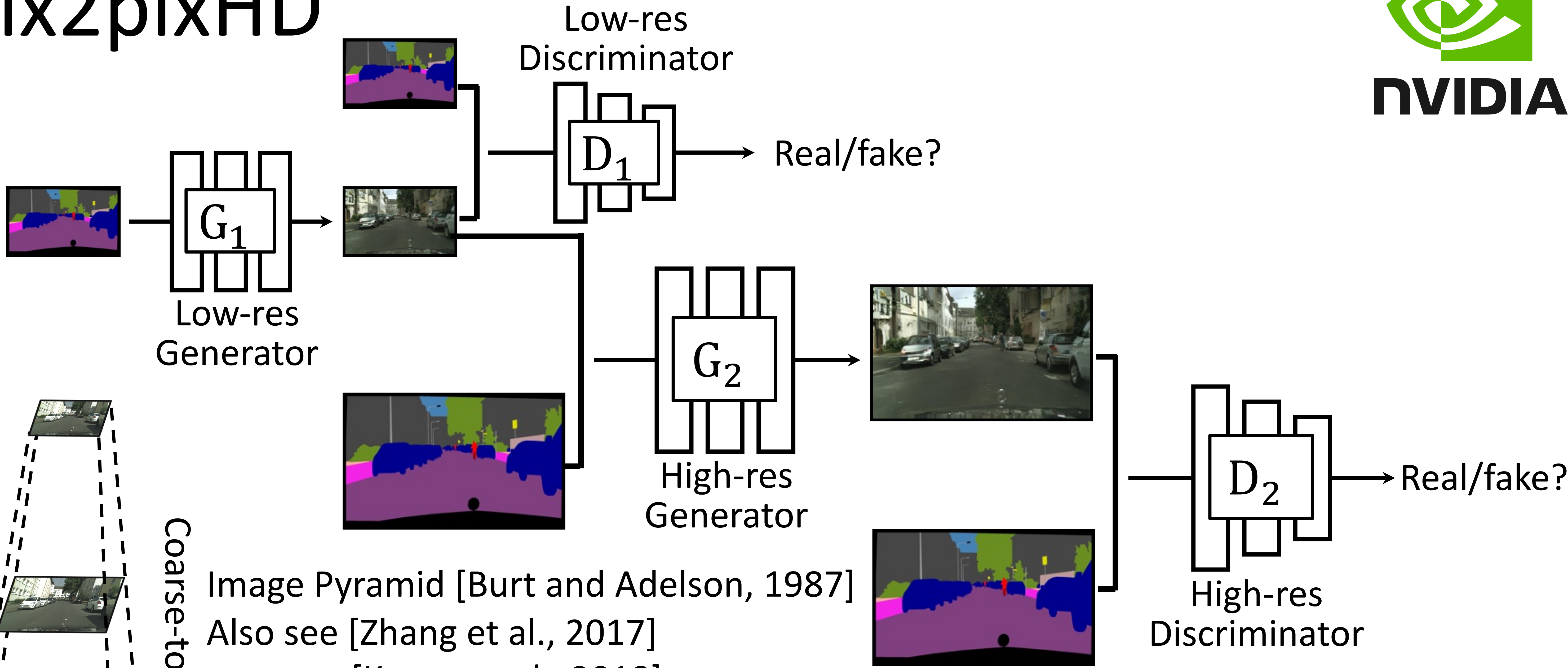
Improving Conditional GANs

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

The Curse of Dimensionality

Pix2pix output

pix2pixHD



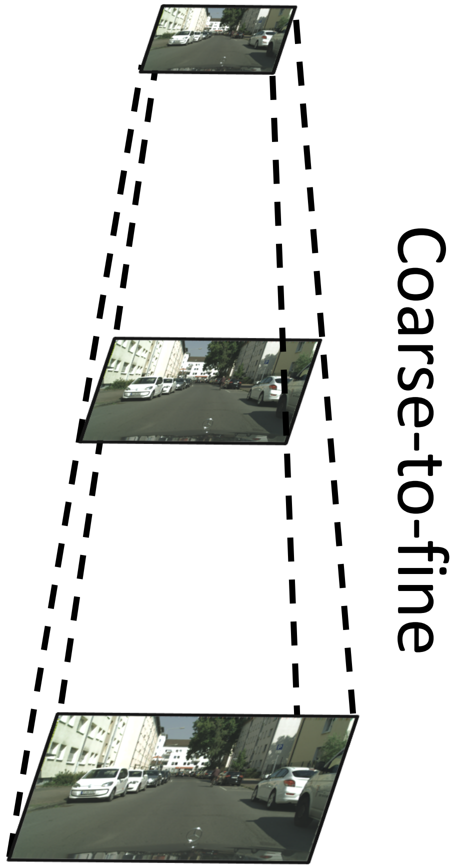
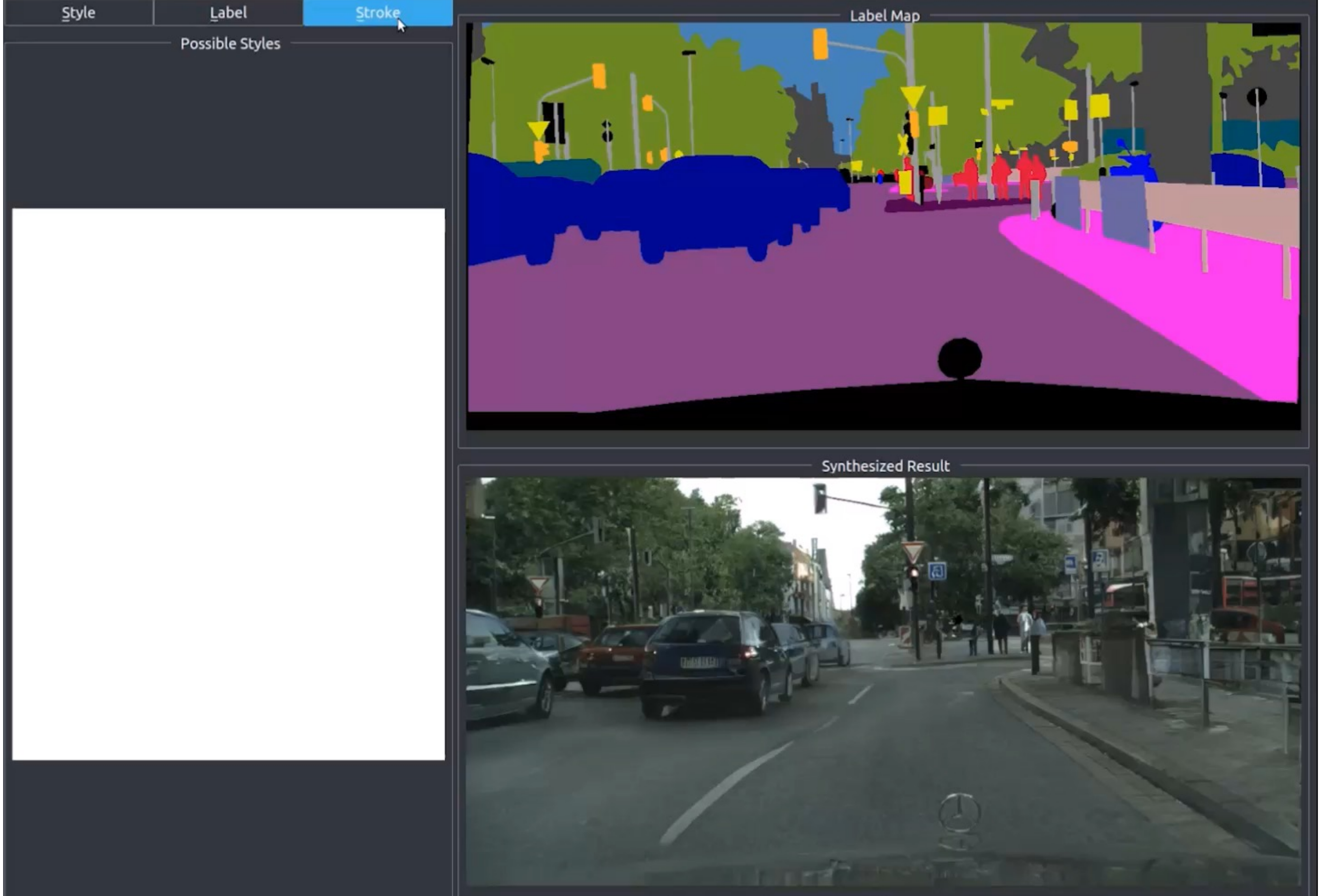


Image Pyramid [Burt and Adelson, 1987]
Also see [Zhang et al., 2017]
[Karras et al., 2018]

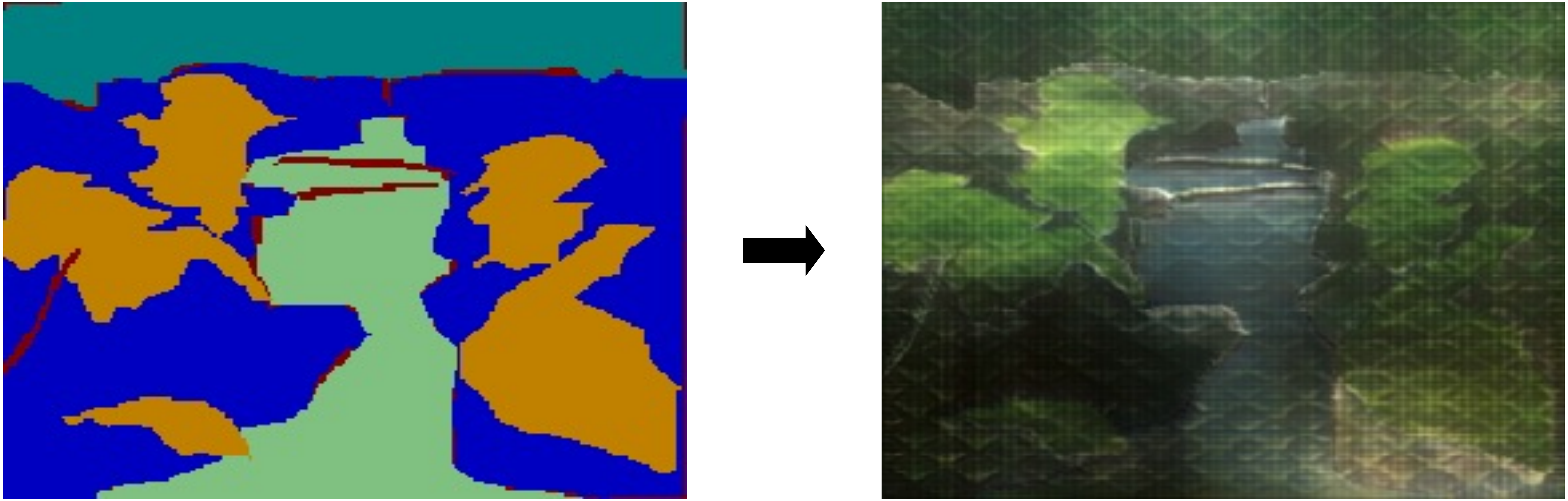
Objective: Multi-scale GANs loss + Perceptual Loss
+ Feature Matching Loss (with Discriminator's features)

pix2pixHD [Wang et al., 2018]

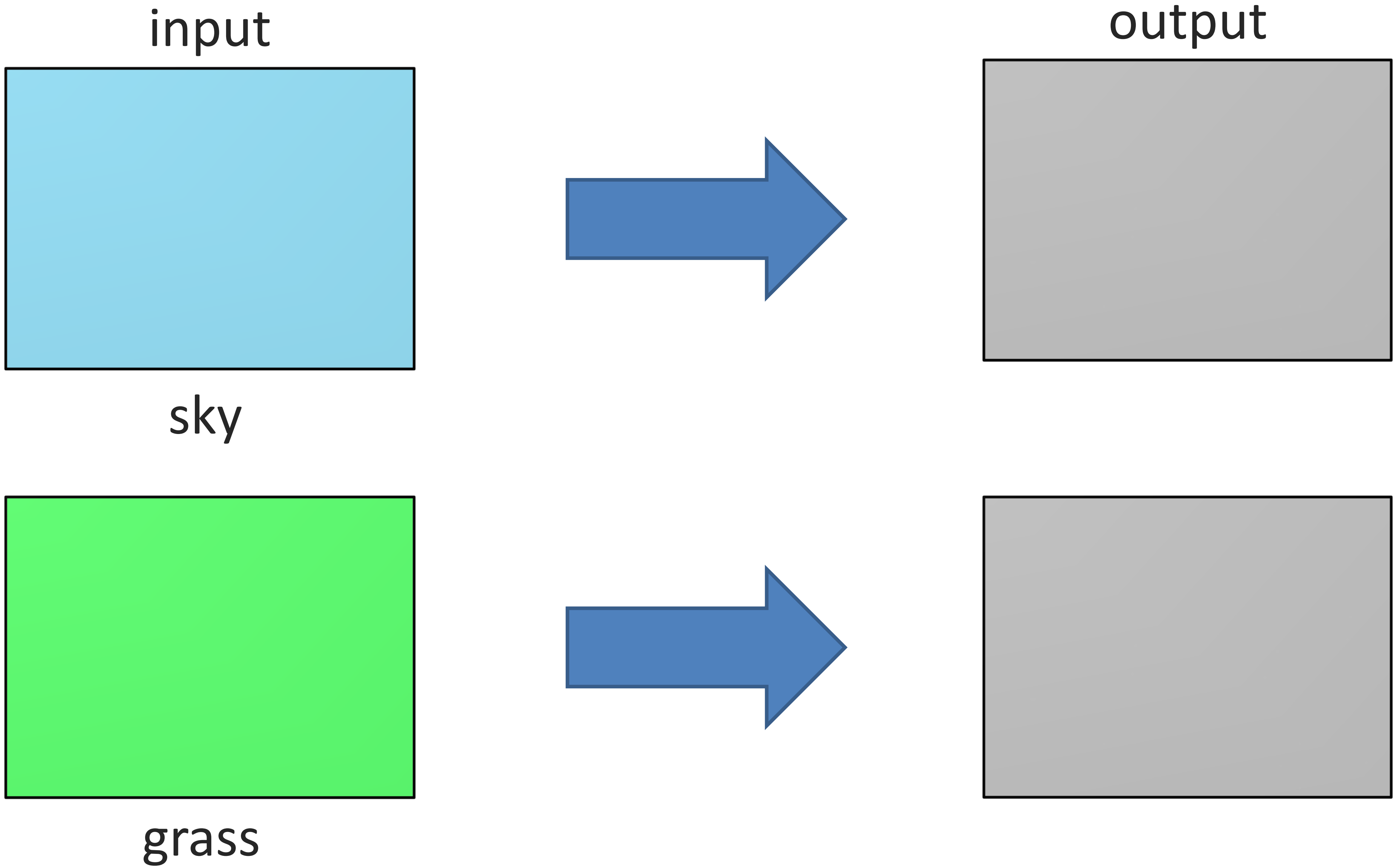
pix2pixHD: 2048×1024


Style
Label
Stroke
Possible Styles
Label Map
Synthesized Result

Conditional Image Synthesis in the Wild

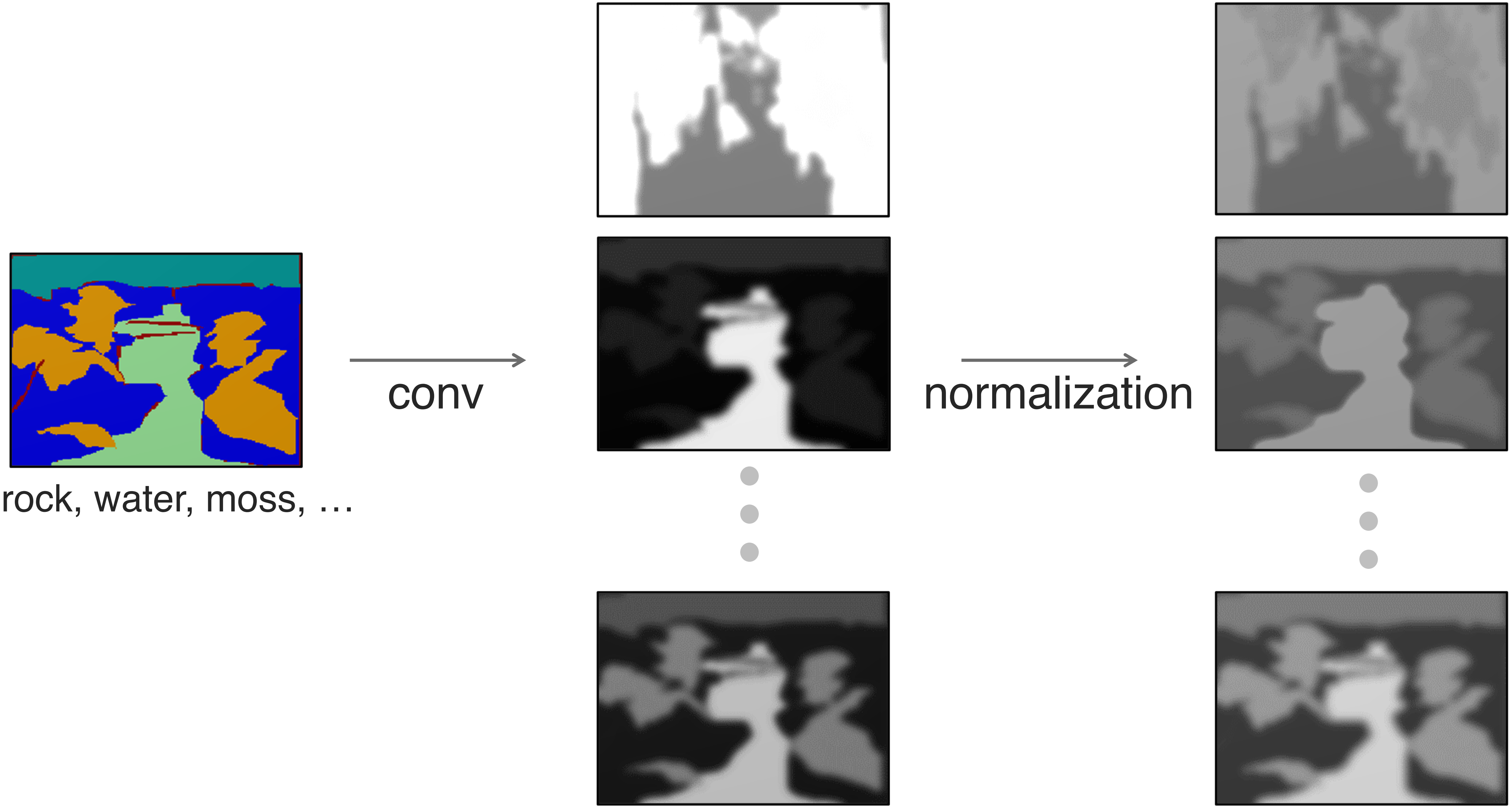


pix2pixHD [Wang et al., 2018]

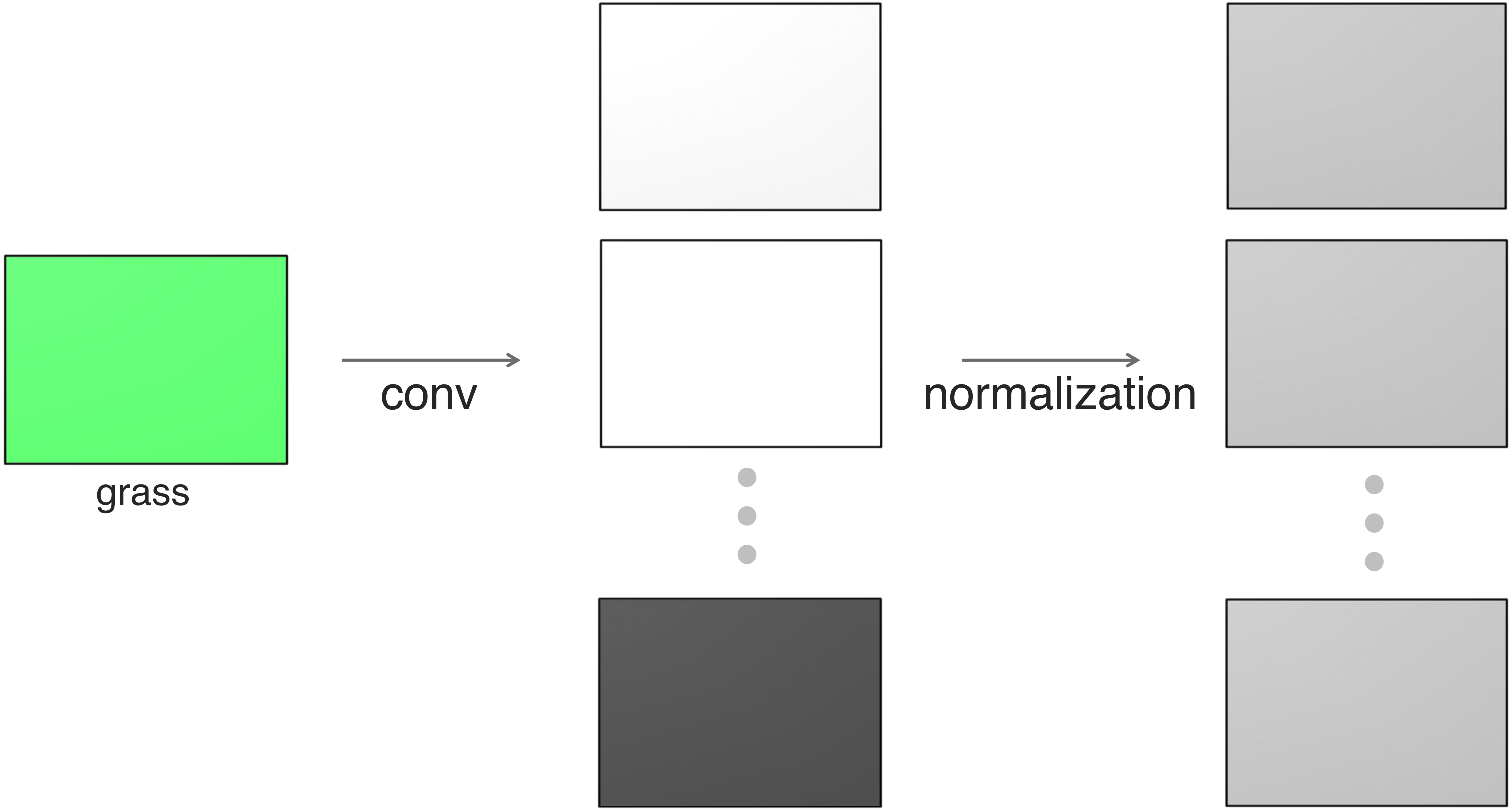


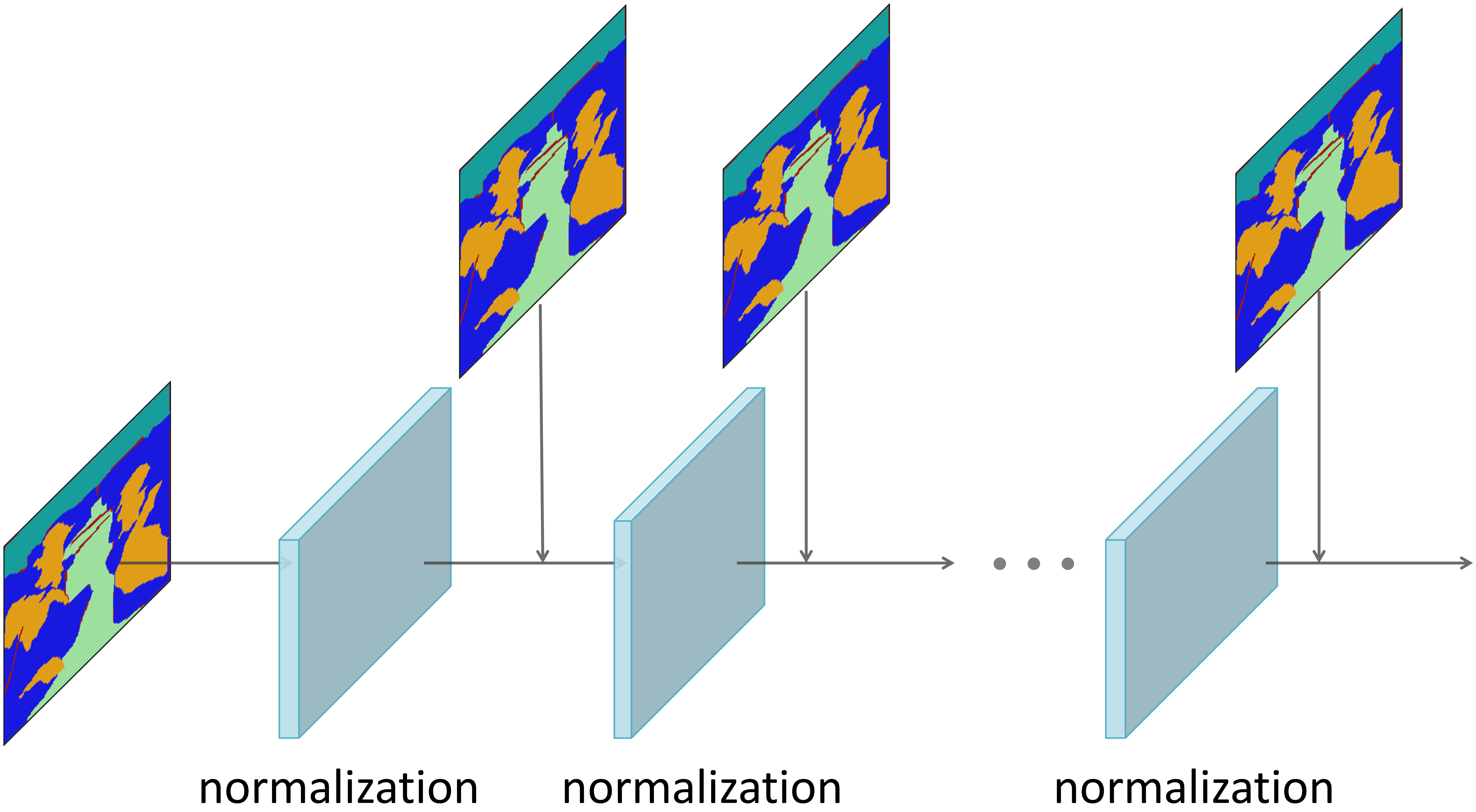
pix2pixHD [Wang et al., 2018]

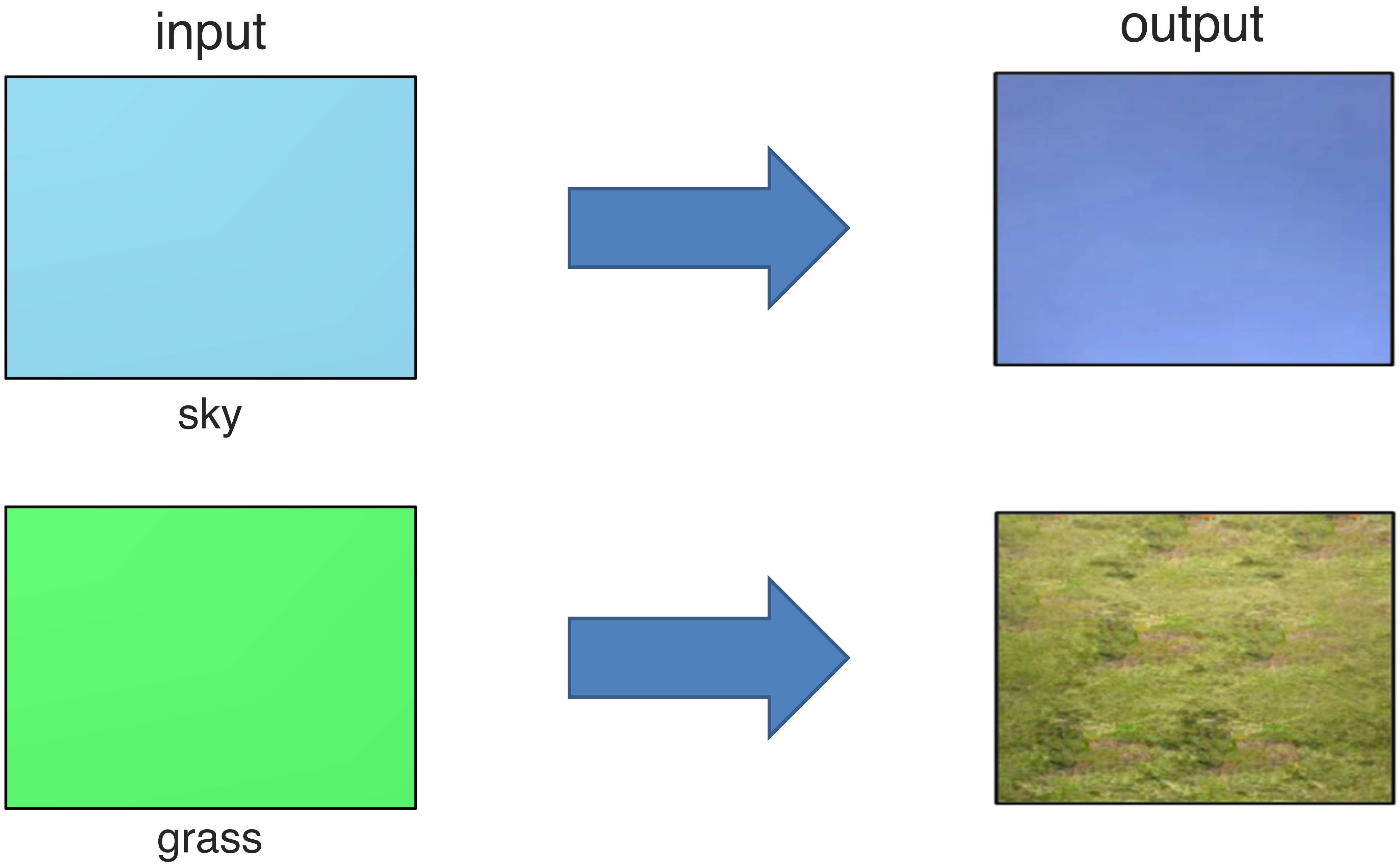
Problem with standard networks



Problem with standard networks

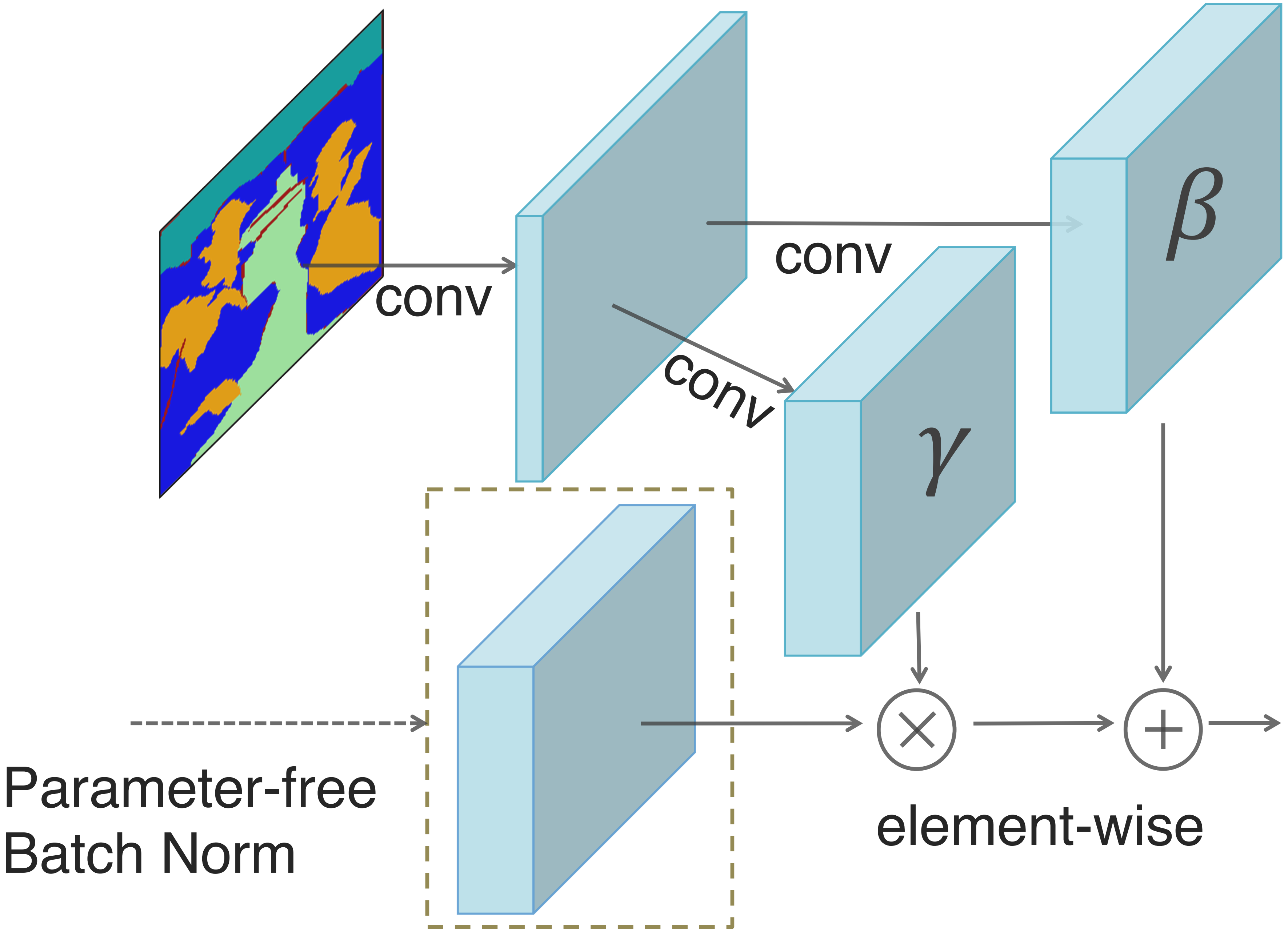



normalization
normalization
normalization



SPADE (ours)

SPADE (SPAtially ADaptive DEnormalization)



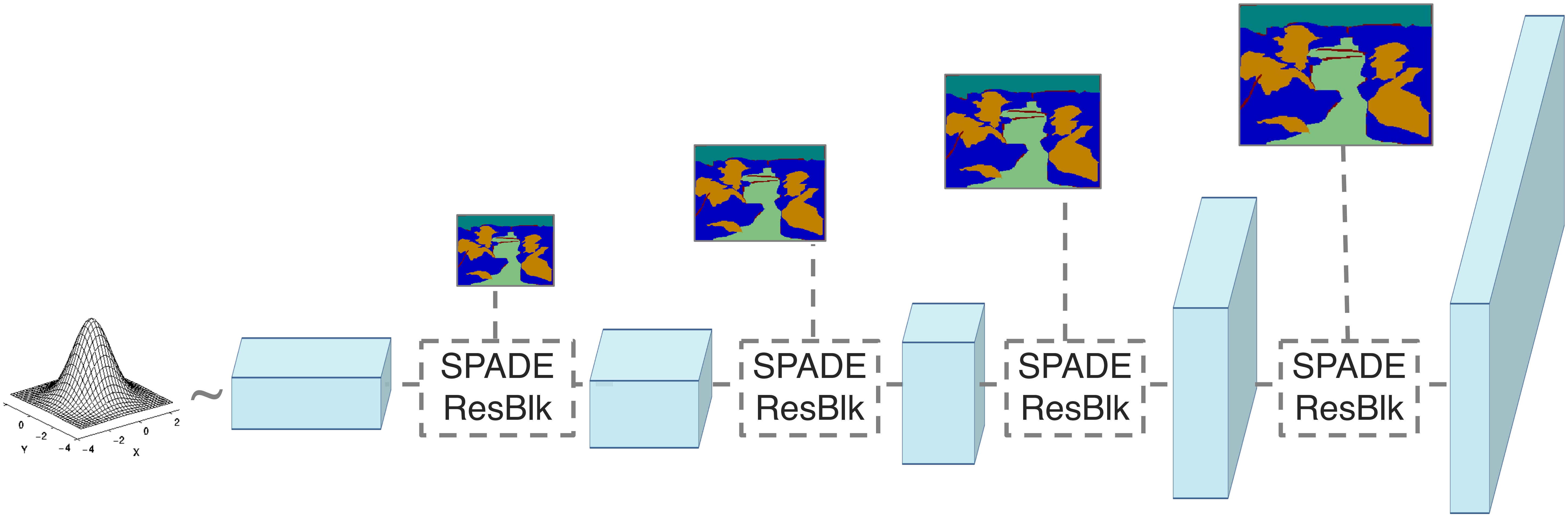
SPADE (SPAtially ADaptive DEnormalization)

Batch Norm (Ioffe et al. 2015)

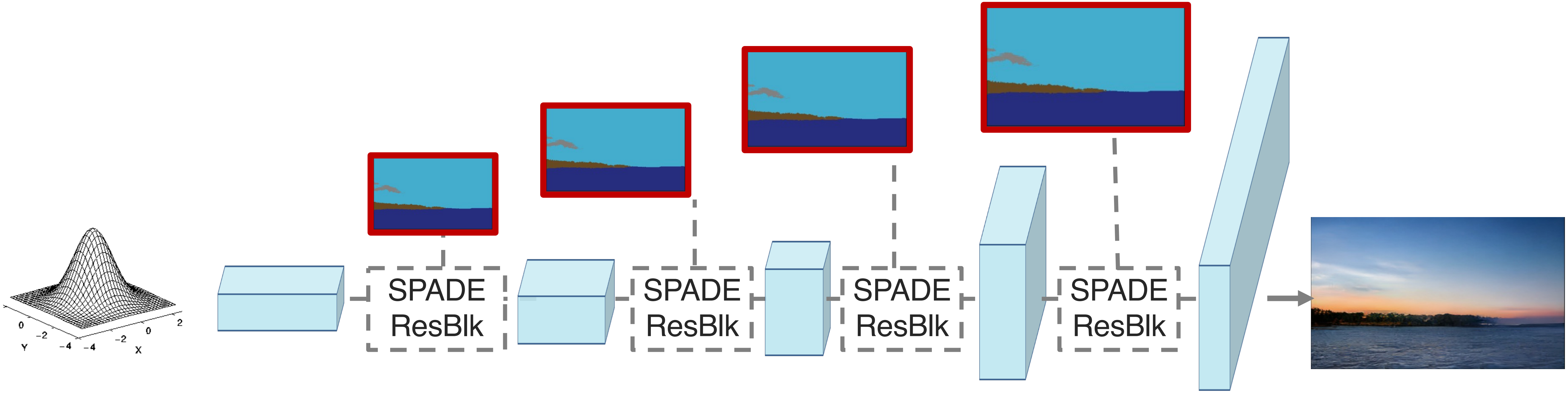
$$y = \underbrace{\frac{x-\mu}{\sigma}}_{\text{normalization}} \cdot \underbrace{\gamma + \beta}_{\text{affine transform}}$$

See other adaptive/conditional normalization: conditional BN (Dumoulin et al.), AdaIN (Huang and Belongie), SFT (Wang et al.)

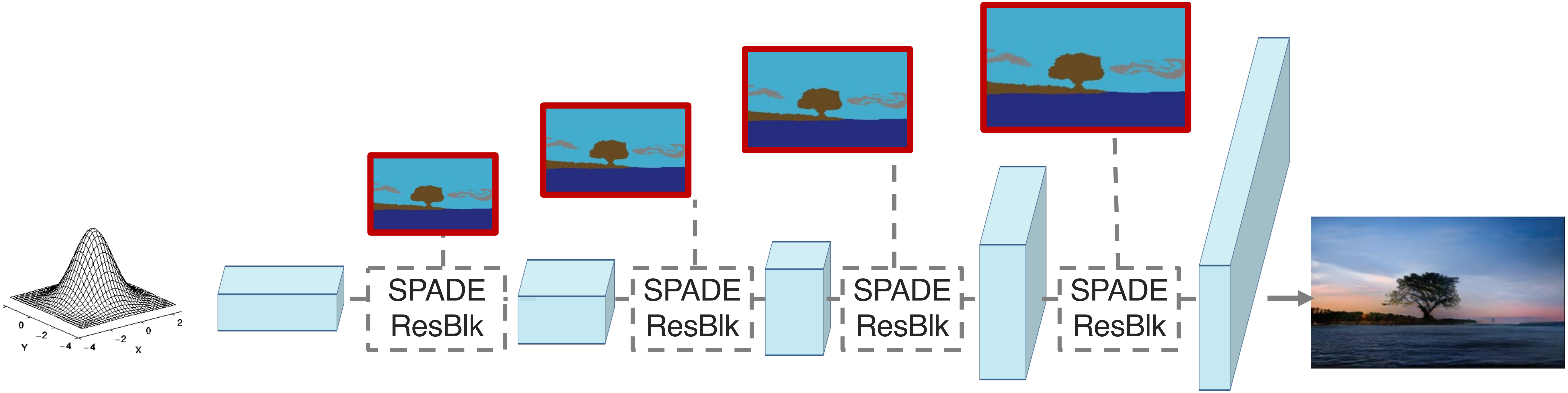
Generator



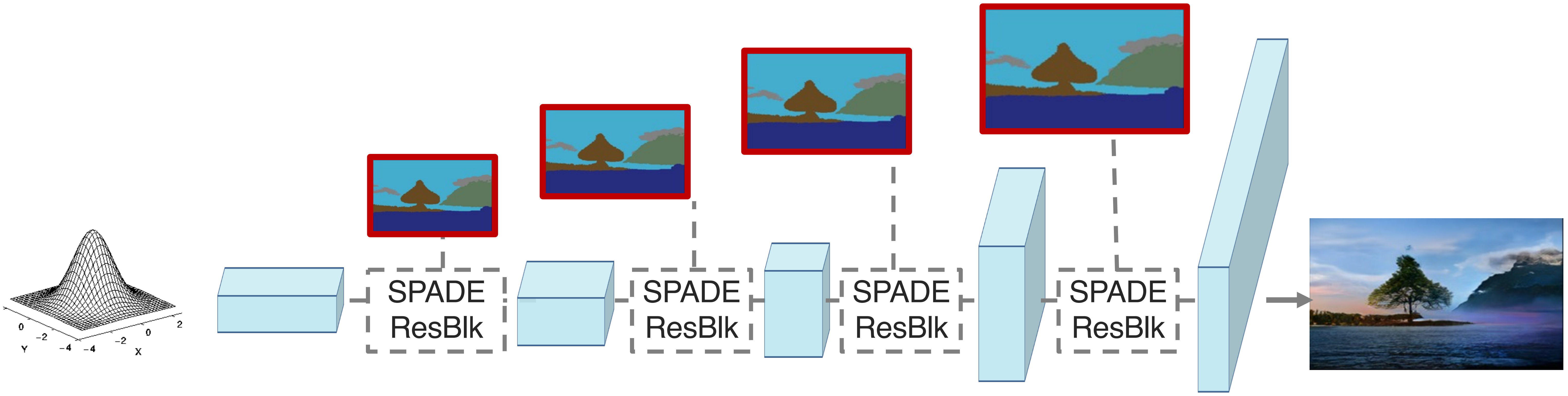
Semantic Control



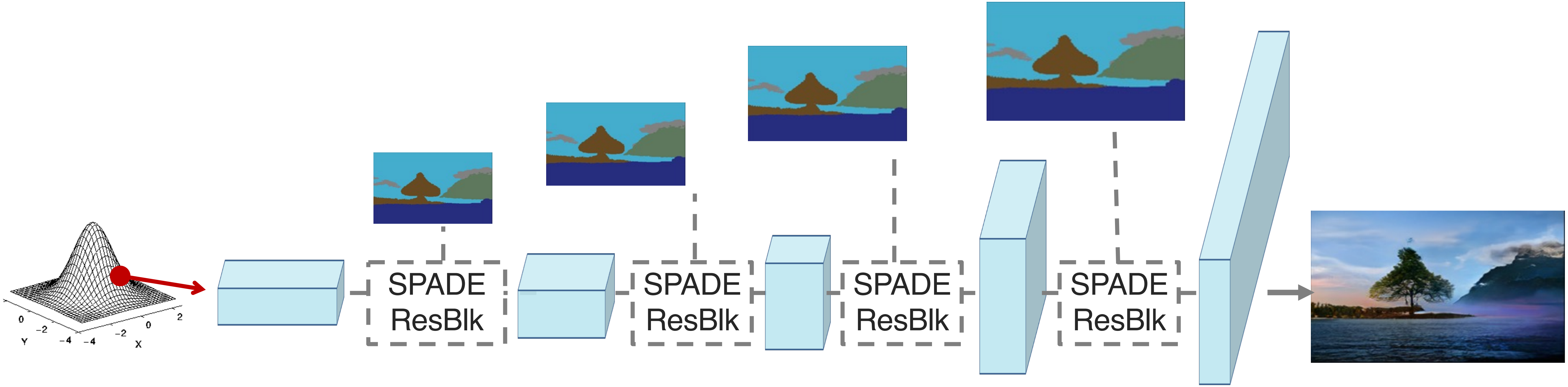
Semantic Control



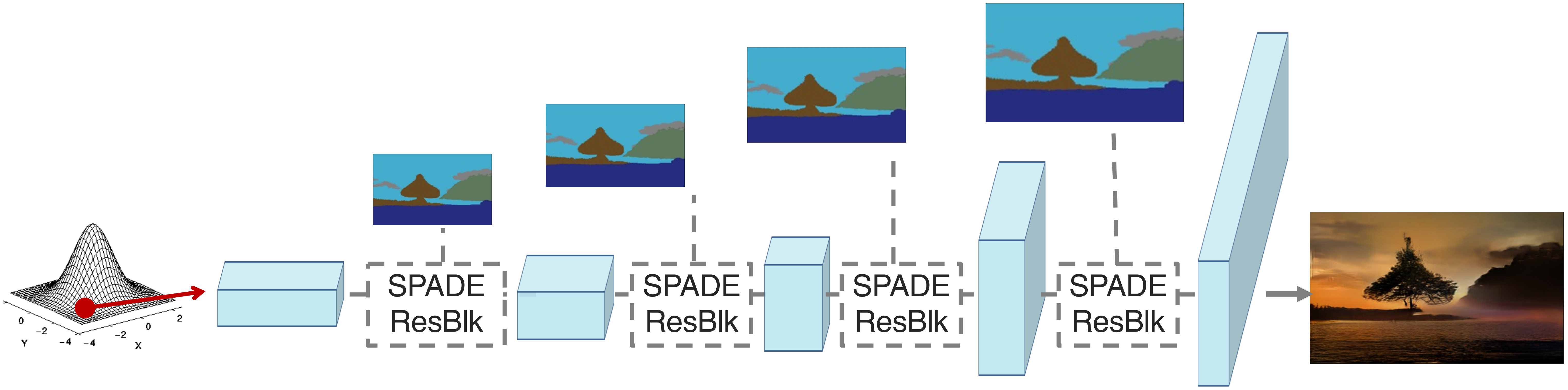
Semantic Control



Style Control

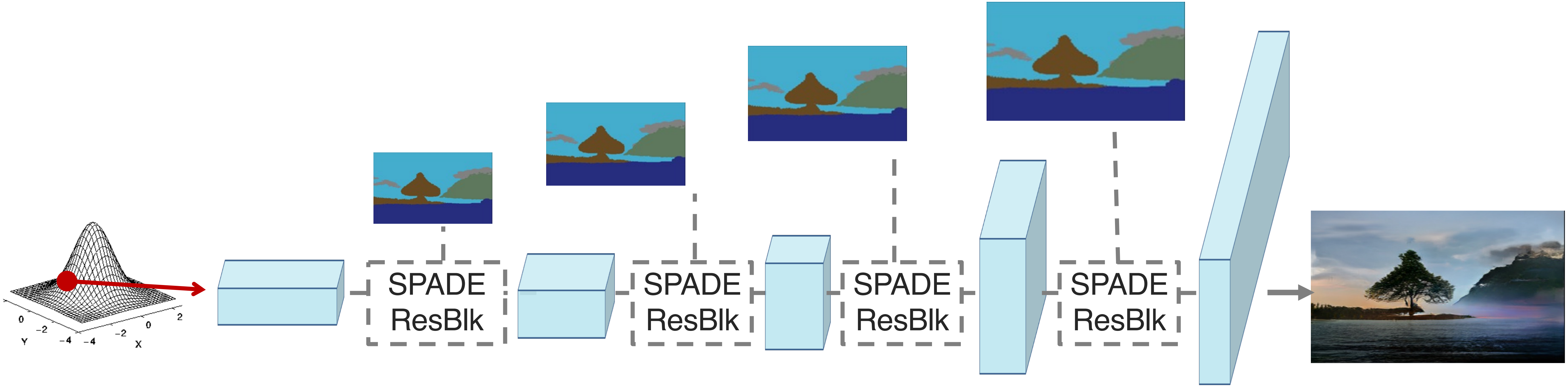


Style Control

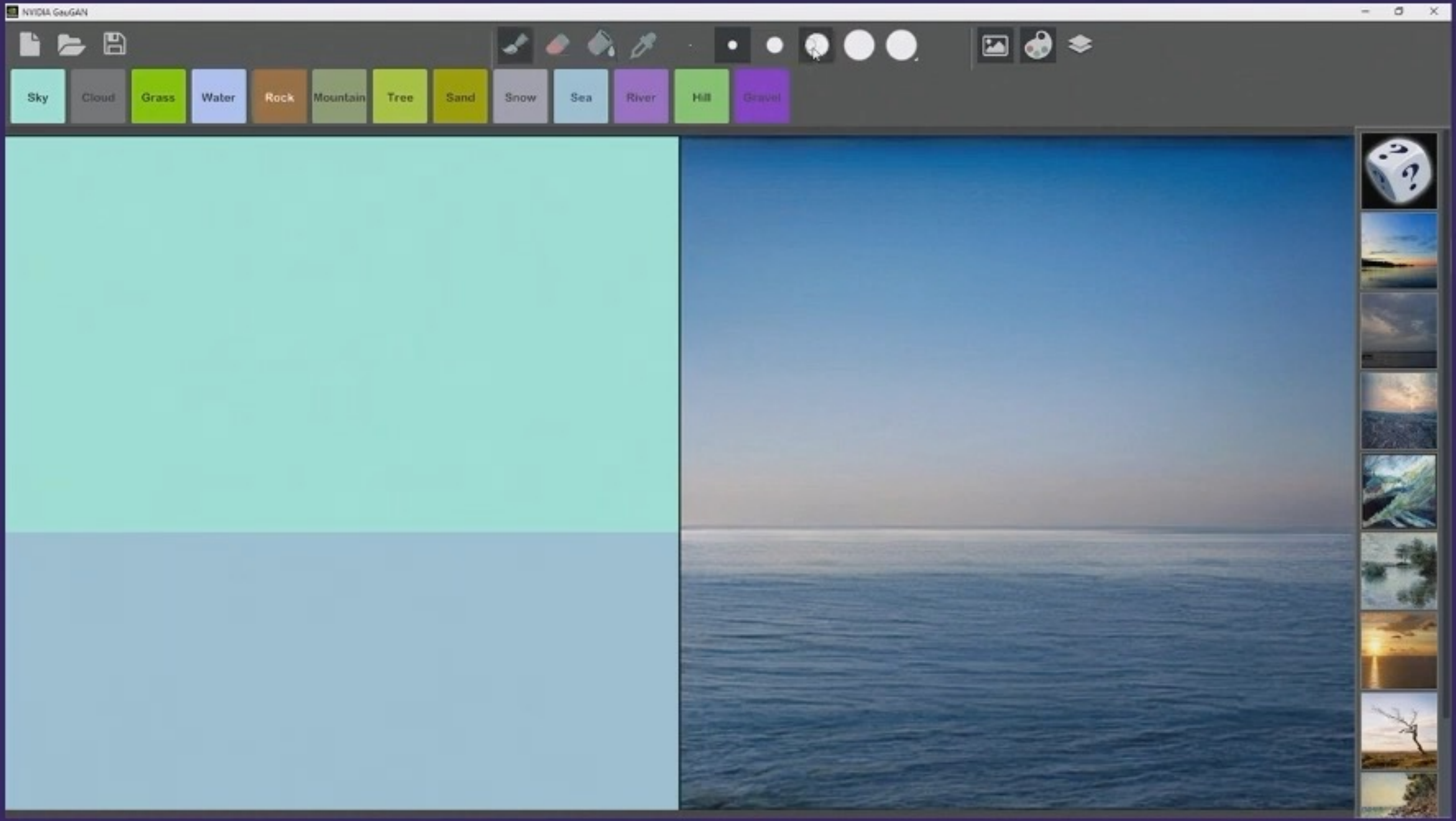


Style Manipulation

Style Control



Style Manipulation



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By Darek Zabrocki, Concept Designer and Illustrator

Thank You!

16-726, Spring 2022