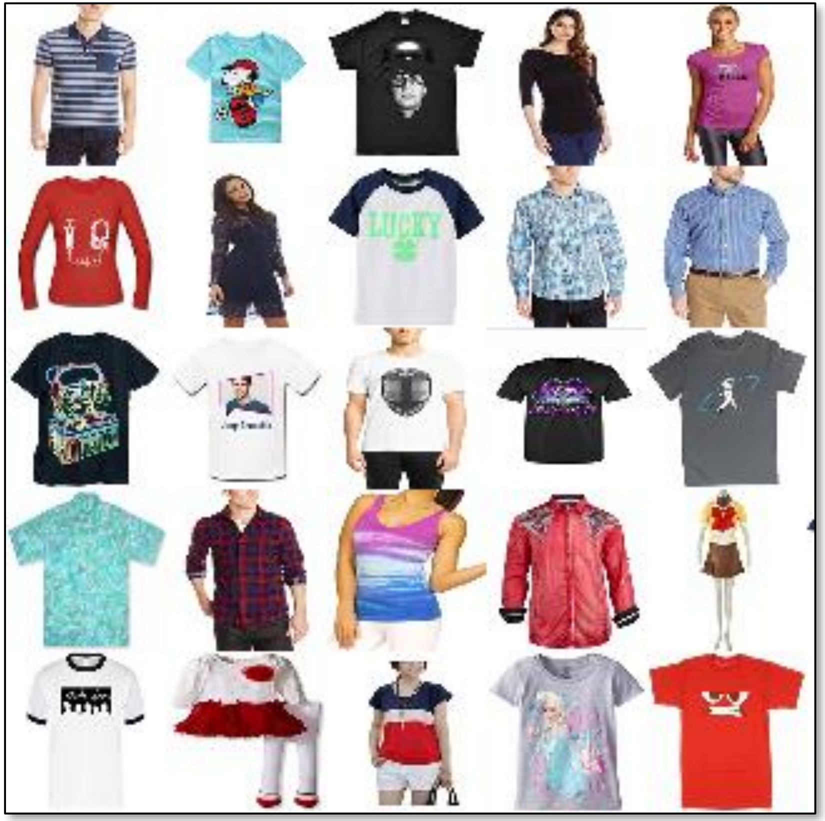
Conditional Generative Adversarial Networks (cGANs)

Conditional GANs (cGANs)

- Gain control of output
- Modeling (e.g., sketch-based modeling, etc.)
  - Add semantic meaning to latent space manifold
- Domain transfer
  - Labels on A -> transfer to B, train network on 'B', test on B
  - More later

GAN Manifold



Train Data

Sampled Data -> G(z)

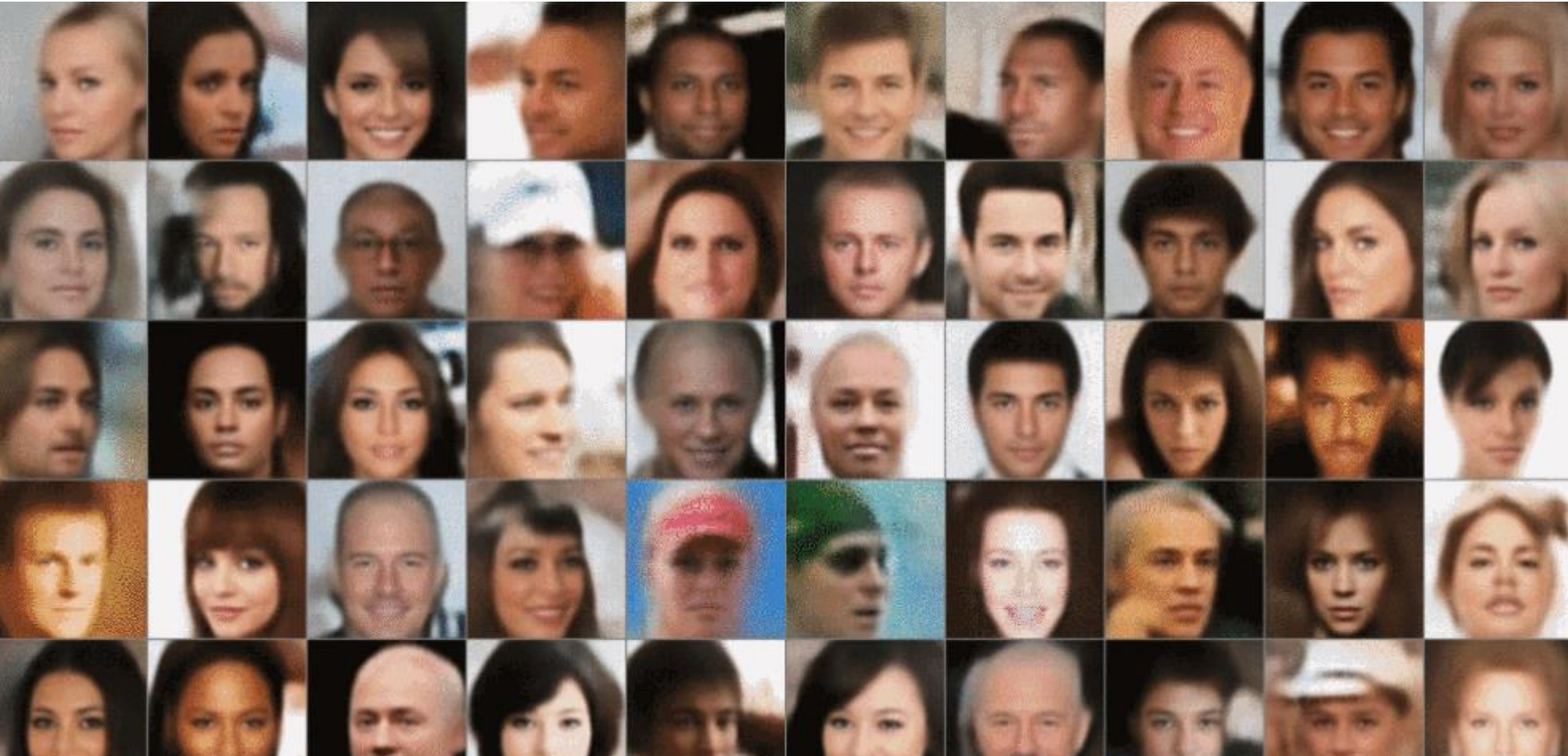
[Radford et al. 15]

GAN Manifold

a - b + c

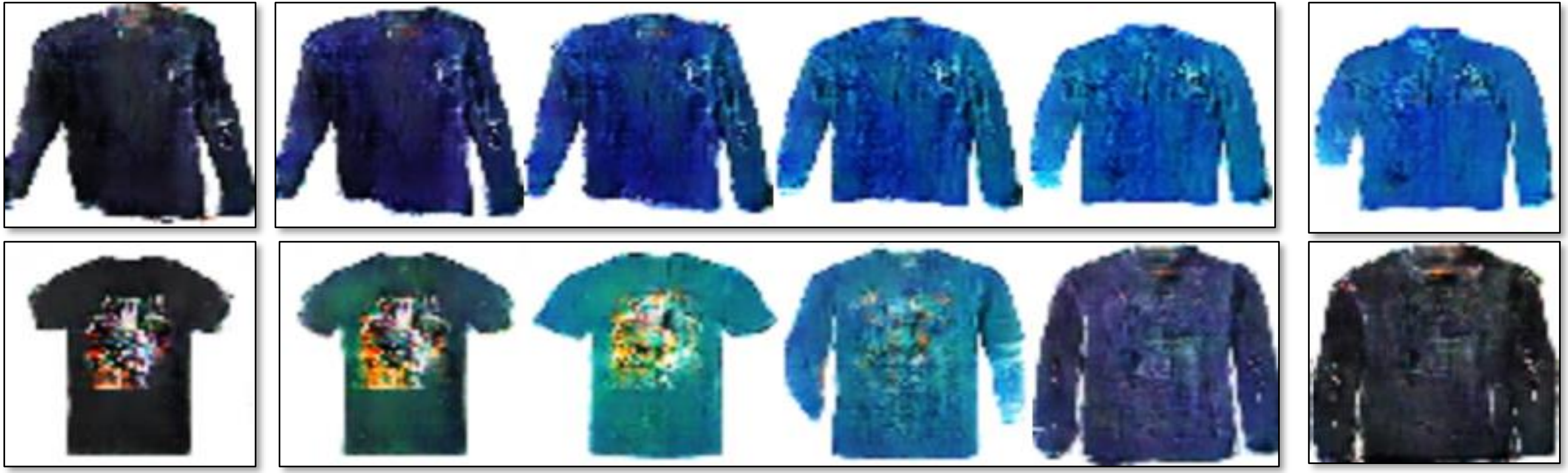
[Bojanowski et al 17]

GAN Manifold



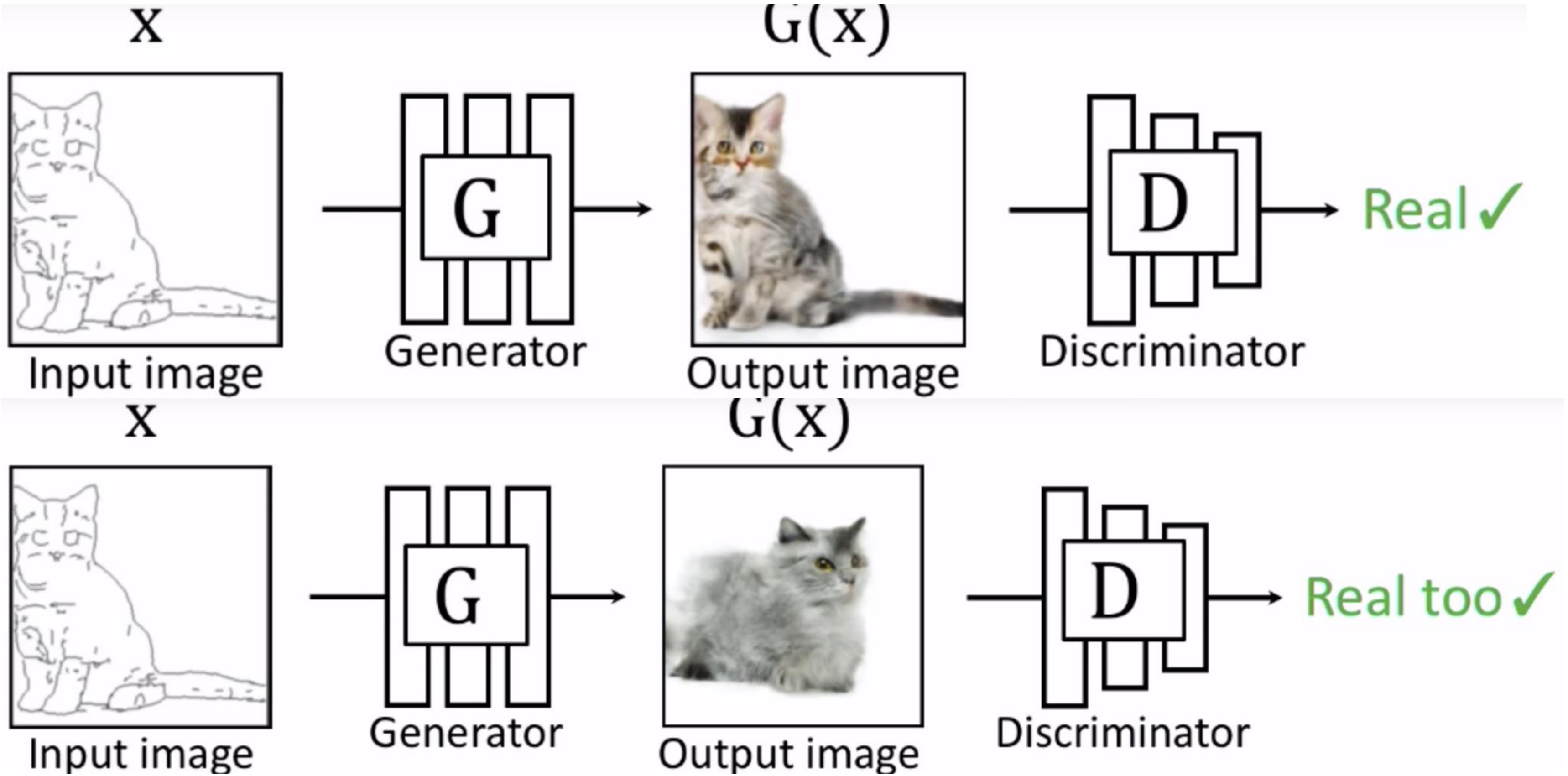
GAN Manifold

$G(z_0)$ Linear interpolation in z space: $G(z_0 + t \cdot (z_1 - z_0))$ $G(z_1)$



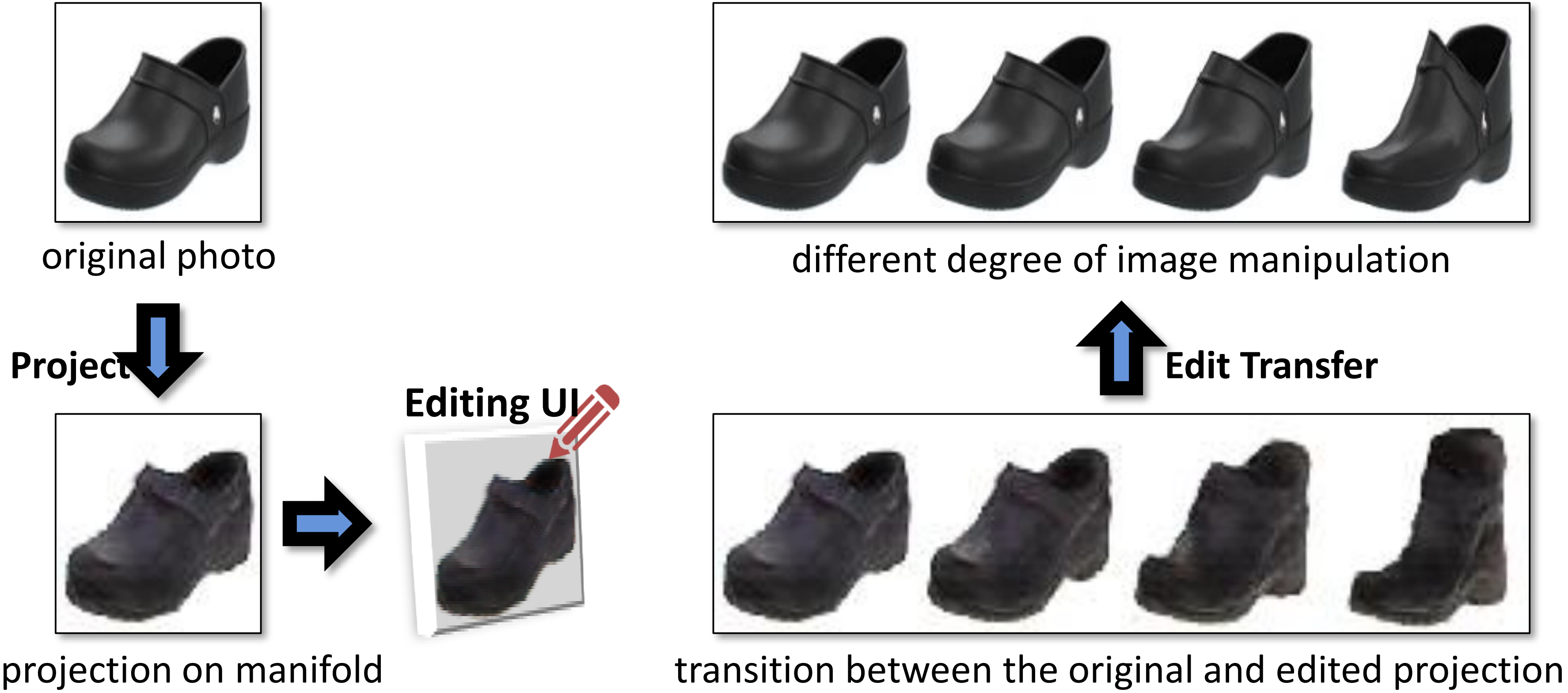
[Radford et al. 15]

Conditional GANs (cGANs)



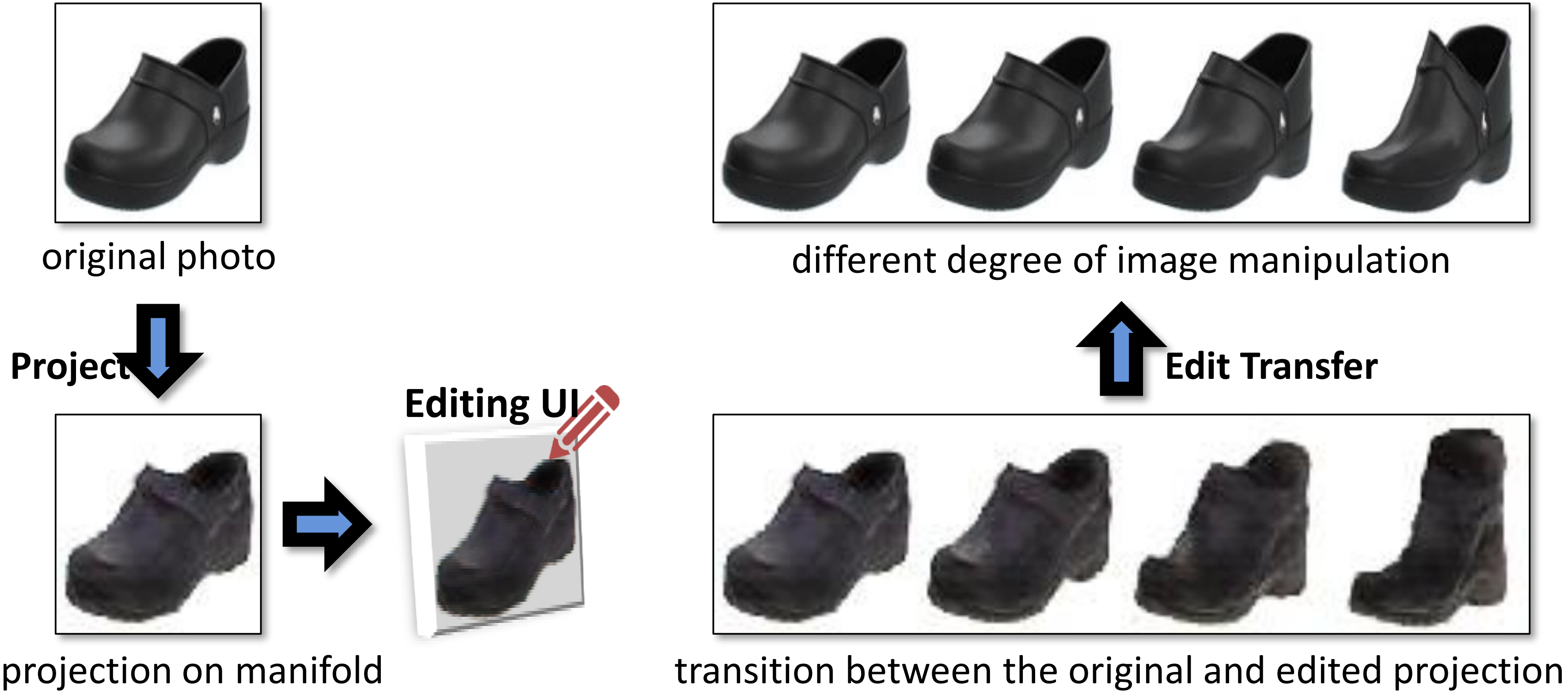
Slide credit Zhu

iGANs: Overview



Slide credit Zhu / [Zhu et al. 16]

iGANs: Overview



Slide credit Zhu / [Zhu et al. 16]

iGANs: Projecting an Image onto the Manifold

Input: real image x^R

Output: latent vector z

Optimization

$$z^* = \arg\min \mathcal{L}(G(z), x^R)$$

Reconstruction loss L

Generative model $G(z)$

Slide credit Zhu / [Zhu et al. 16]

iGANs: Projecting an Image onto the Manifold

Input: real image x^R
Output: latent vector z

Optimization

$$z^* = \arg\min \mathcal{L}(G(z), x^R)$$

Inverting Network $\mathrm{z} = P(x)$

$$\theta_P^* = \arg\min_{\theta_P} \sum_{x_n^R} \mathcal{L}(\underbrace{G(P(x^R; \theta_P))}_{\text{Auto-encoder}}, x^R)$$

with a fixed decoder G

Slide credit Zhu / [Zhu et al. 16]

iGANs: Projecting an Image onto the Manifold

Input: real image x^R

Output: latent vector z

Optimization

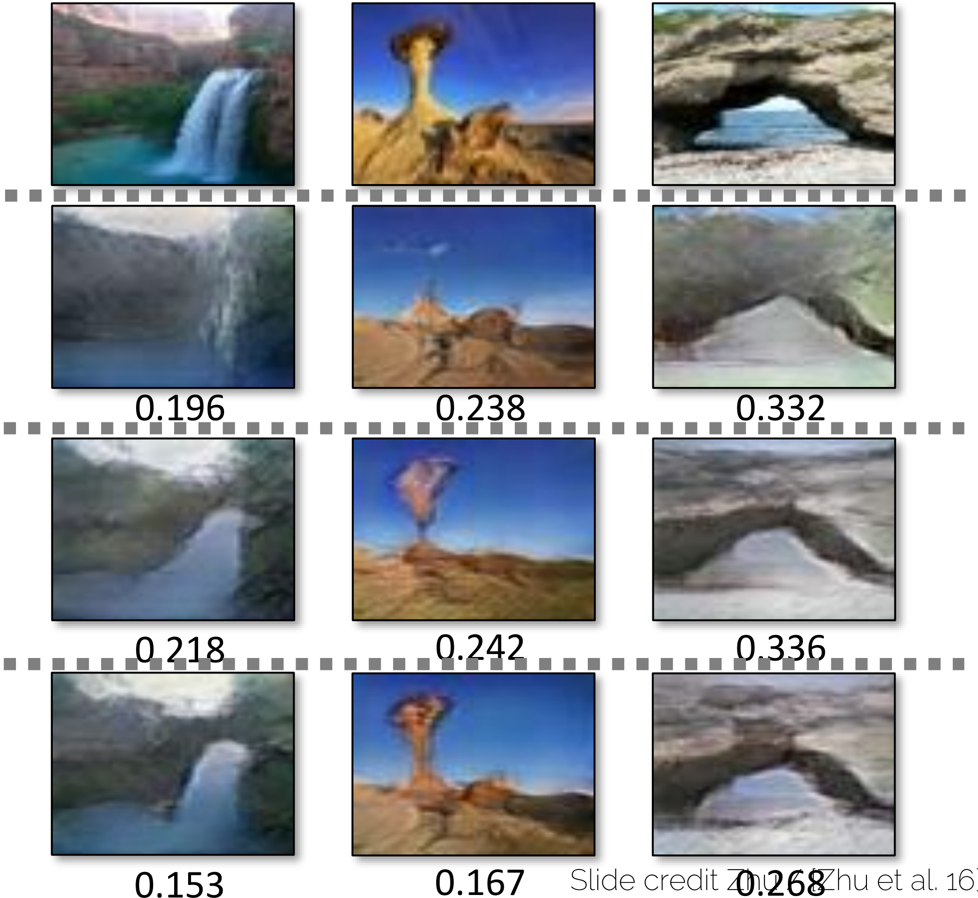
$$z^* = \arg\min \mathcal{L}(G(z), x^R)$$

Inverting Network $\mathrm{z} = P(x)$

$$\theta_P^* = \arg\min_{\theta_P} \sum_{x_n^R} \mathcal{L}(G(P(x^R;\theta_P)), x^R)$$

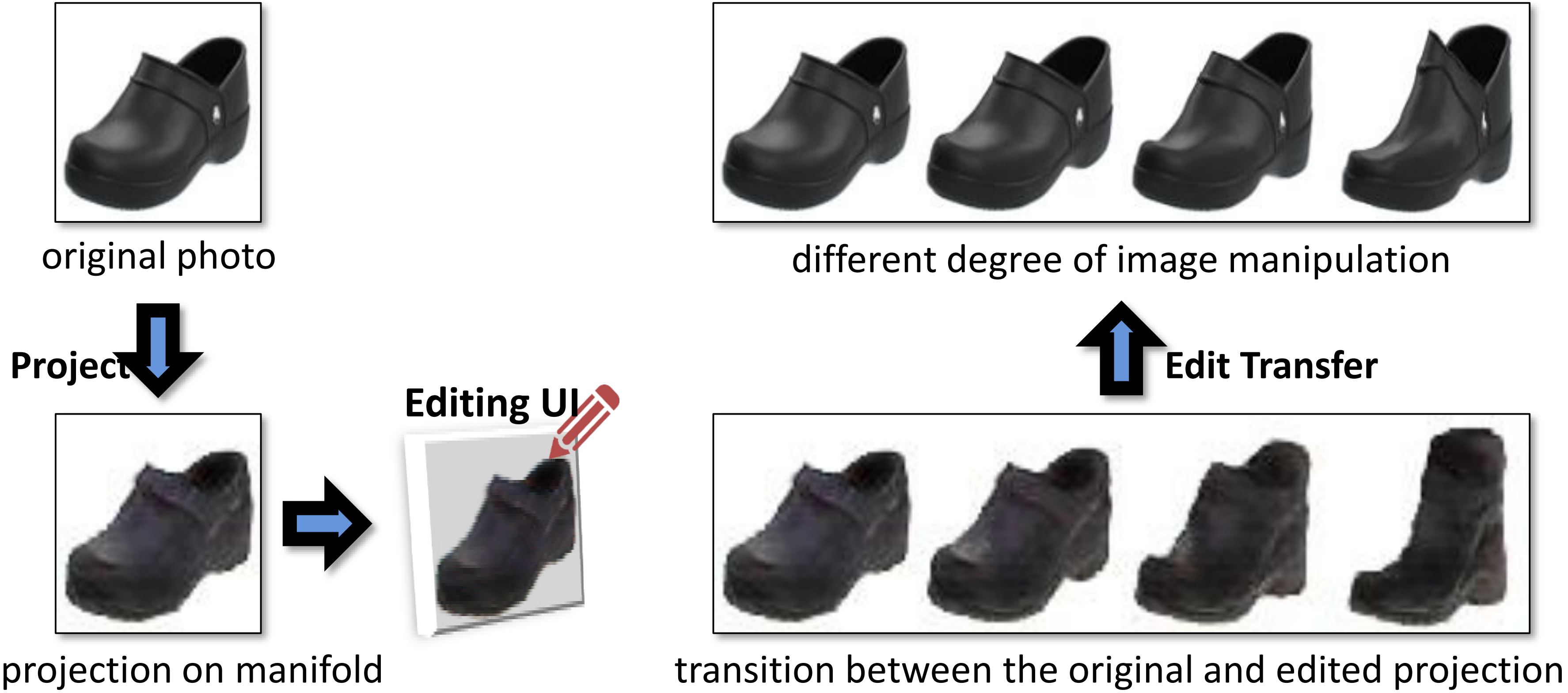
Hybrid Method

Use the network as initialization for the optimization problem



Slide credit Zhu [Zhu et al. 16]

iGANs: Overview



Slide credit Zhu / [Zhu et al. 16]

iGANs: Manipulating the Latent Vector

constraint violation loss L_g

user guidance image

Objective:

$$z^* = \arg\min_{z\in\mathbb{Z}} \Big\{ \underbrace{\sum_g (\mathcal{L}_g(G(z), v_g)}_{\text{data term}} + \underbrace{\lambda_s \cdot \|z - z_0\|_2^2}_{\text{manifold smoothness}} \Big\}.$$

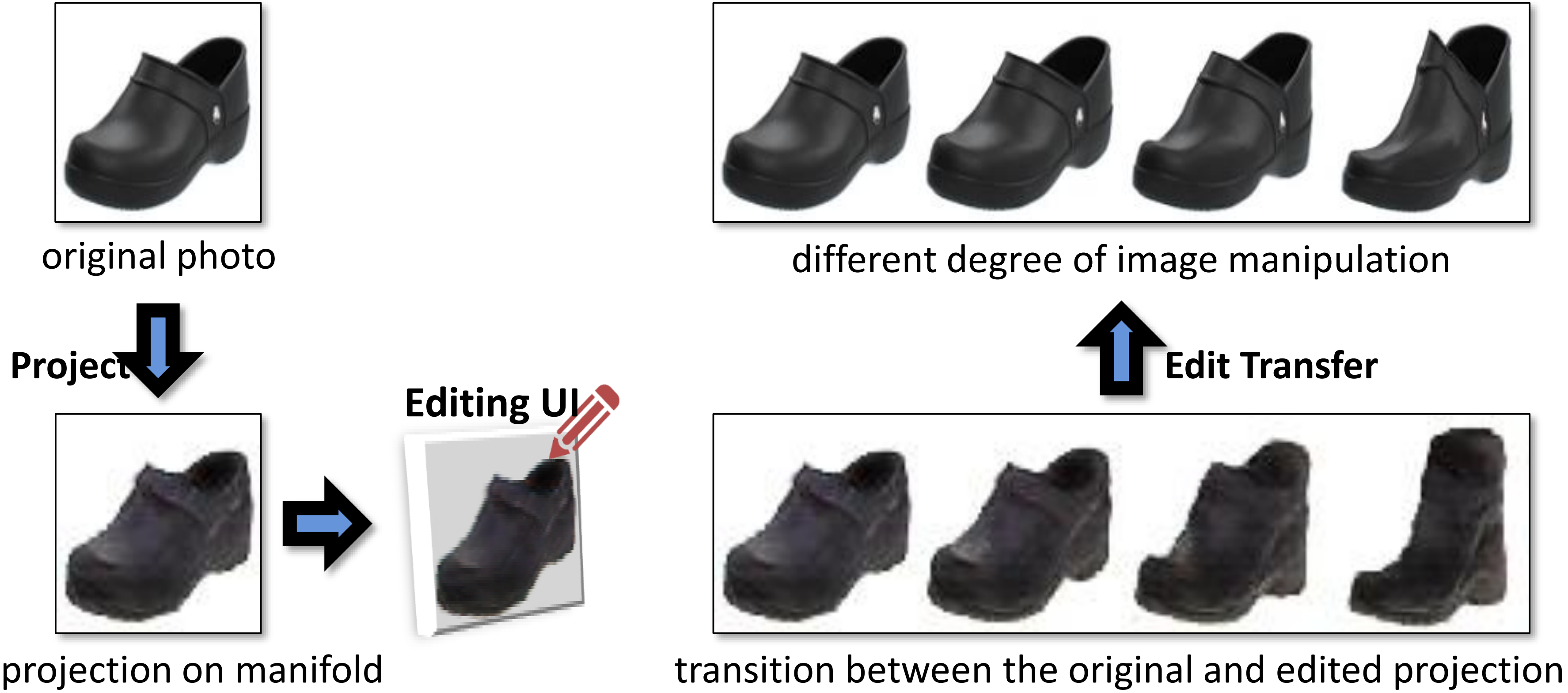
Guidance v_g

$G(z)$

z_0

Slide credit Zhu / [Zhu et al. 16]

iGANs: Overview

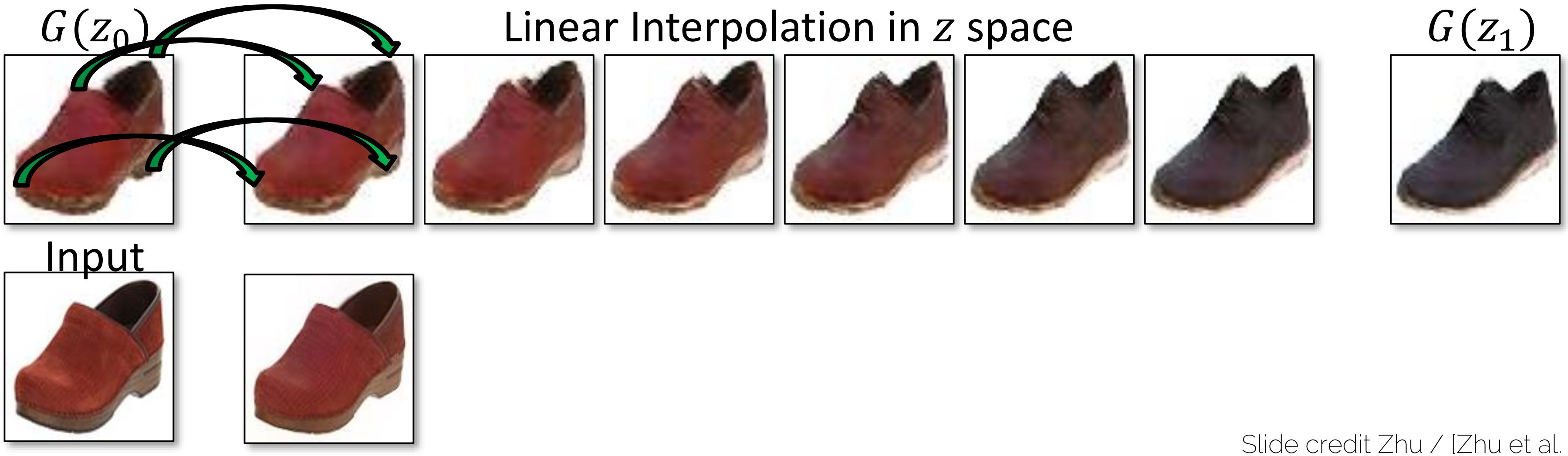


Slide credit Zhu / [Zhu et al. 16]

iGANs: Edit Transfer

Motion **(u, v)+** **Color** **($A_{3\times4}$):** estimate per-pixel geometric and color variation

$$\iint \underbrace{\|I(x,y,t)-\boxed{A}\cdot I(x+\boxed{u},y+\boxed{v},t+1)\|^2}_{\text{data term}}+\underbrace{\sigma_s(\|\nabla u\|^2+\|\nabla v\|^2)}_{\text{spatial reg}}+\underbrace{\sigma_c\|\nabla A\|^2}_{\text{color reg}}dxdy$$

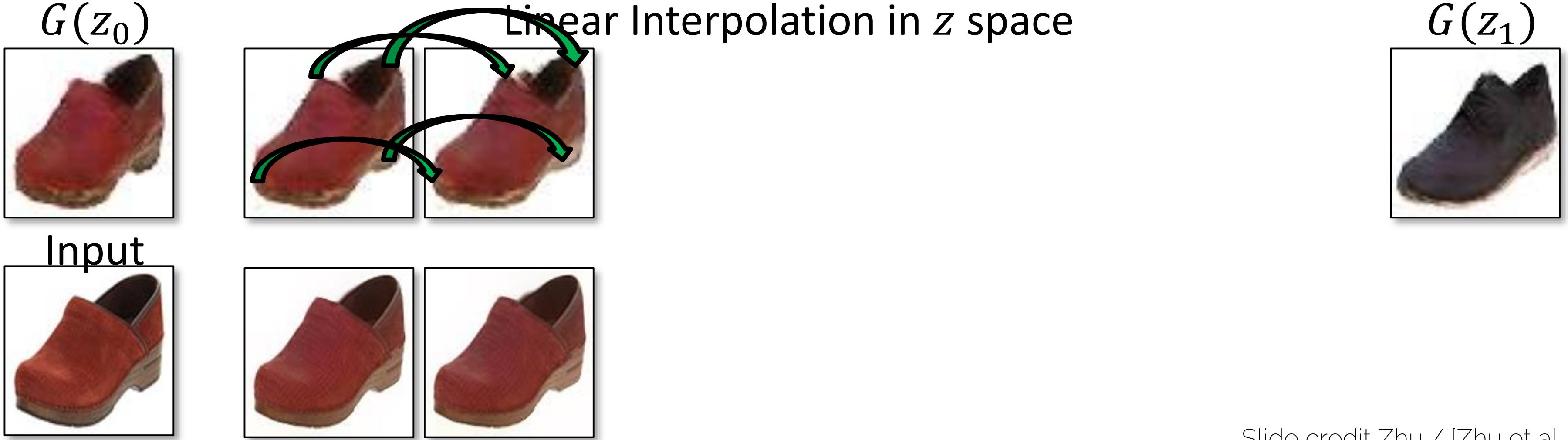


Slide credit Zhu / [Zhu et al. 16]

iGANs: Edit Transfer

Motion (u, v)+ Color ($A_{3\times4}$): estimate per-pixel geometric and color variation

$$\iint \underbrace{\|I(x,y,t) - \boxed{A} \cdot I(x+\boxed{u}, y+\boxed{v}, t+1)\|^2}_{\text{data term}} + \underbrace{\sigma_s(\|\nabla u\|^2 + \|\nabla v\|^2)}_{\text{spatial reg}} + \underbrace{\sigma_c \|\nabla A\|^2}_{\text{color reg}} dxdy$$



Slide credit Zhu / [Zhu et al. 16]

iGANs: Edit Transfer

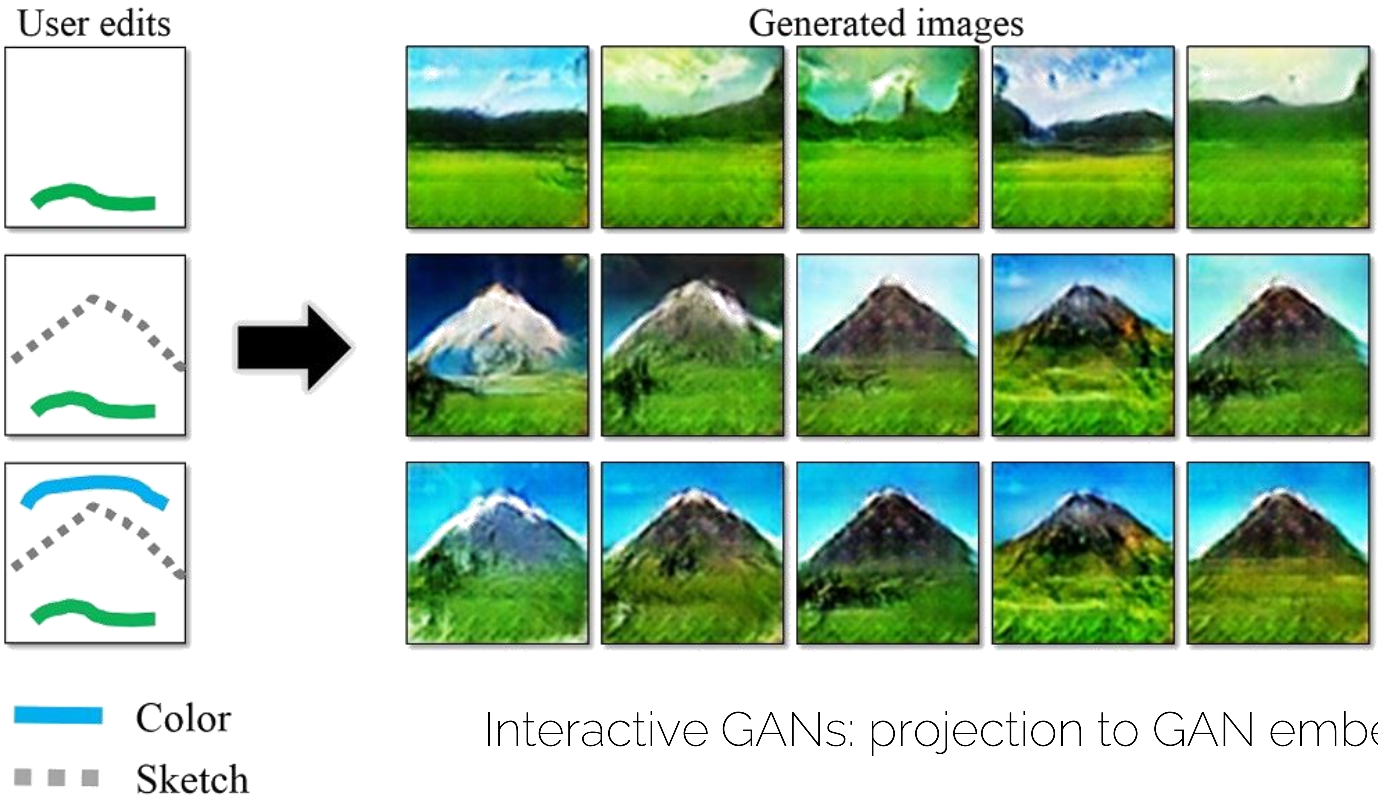
Motion (u, v)+ Color ($A_{3\times4}$): estimate per-pixel geometric and color variation

$$\iint \underbrace{\|I(x,y,t) - \boxed{A} \cdot I(x+\boxed{u}, y+\boxed{v}, t+1)\|^2}_{\text{data term}} + \underbrace{\sigma_s(\|\nabla u\|^2 + \|\nabla v\|^2)}_{\text{spatial reg}} + \underbrace{\sigma_c \|\nabla A\|^2}_{\text{color reg}} dxdy$$

$G(z_0)$ Linear Interpolation in z space $G(z_1)$

Input Result

cGANs: Interactive GANs



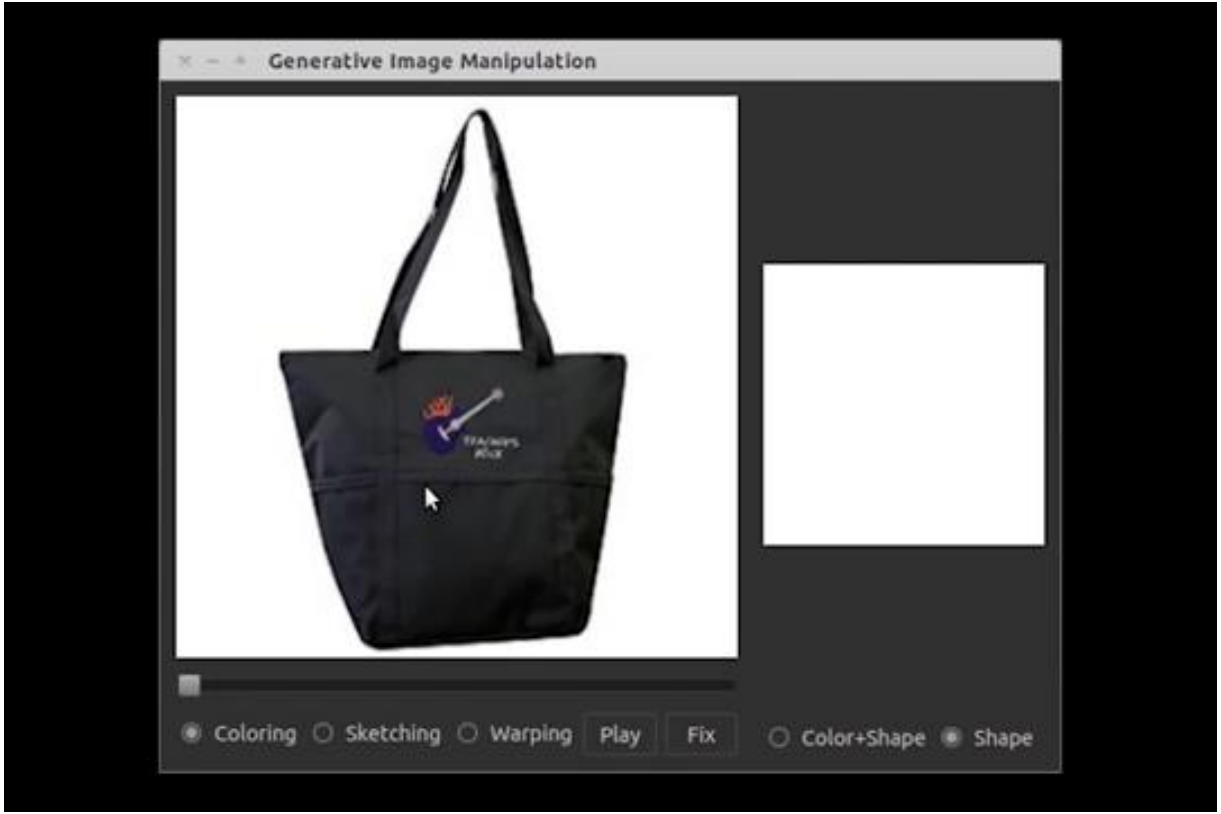
Interactive GANs: projection to GAN embedding

https://github.com/junyanz/iGAN [Zhu et al. 16.]

cGANs: Interactive GANs

https://github.com/junyanz/iGAN [Zhu et al. 16.]

cGANs: Interactive GANs



https://github.com/junyanz/iGAN [Zhu et al. 16.]

Mapping in Latent Space is Difficult!

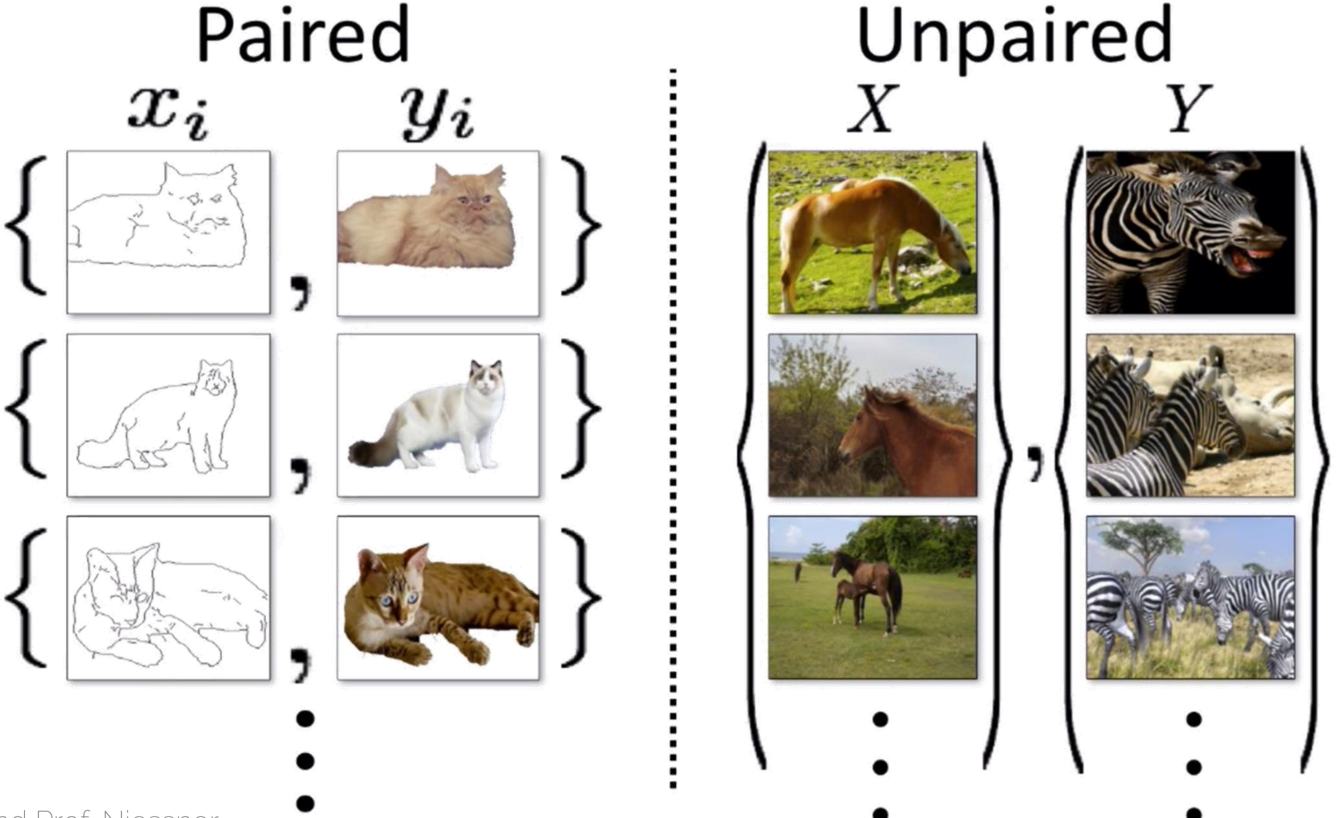
- Semantics are missing
- In most cases, no labels available
- Ideally, need some unsupervised disentangled rep.

(a) Azimuth (pose)

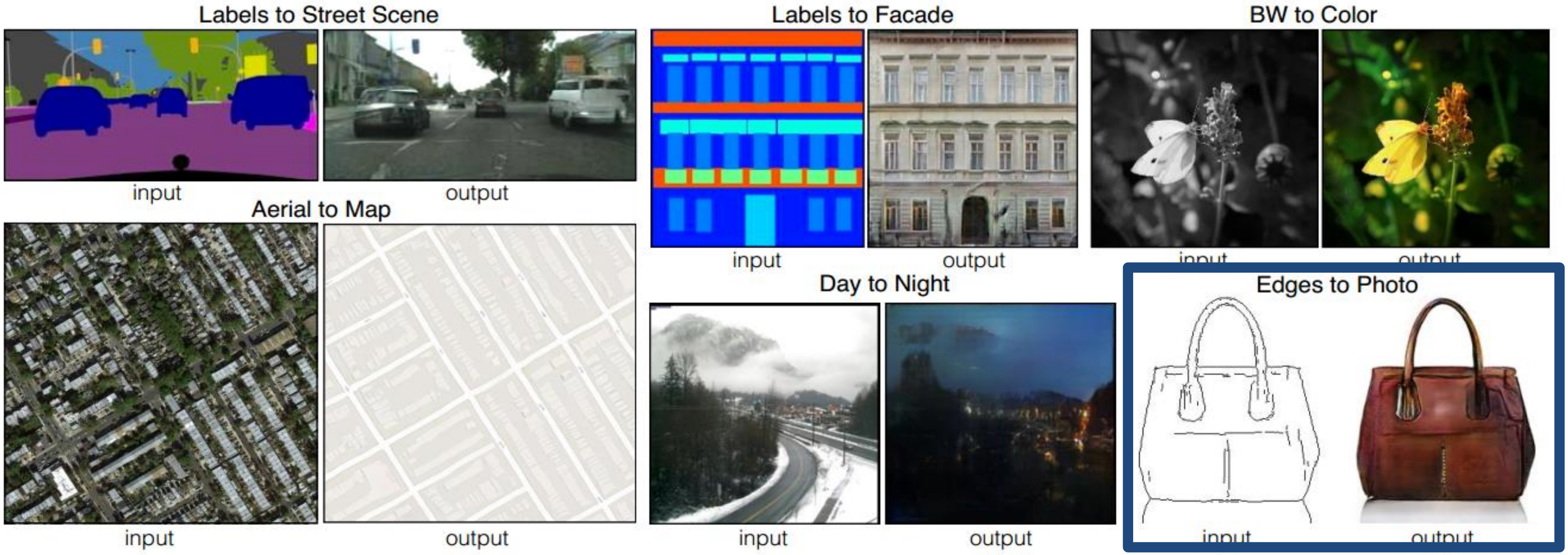
(b) Presence or absence of glasses

InfoGAN [Chen et al. 16]

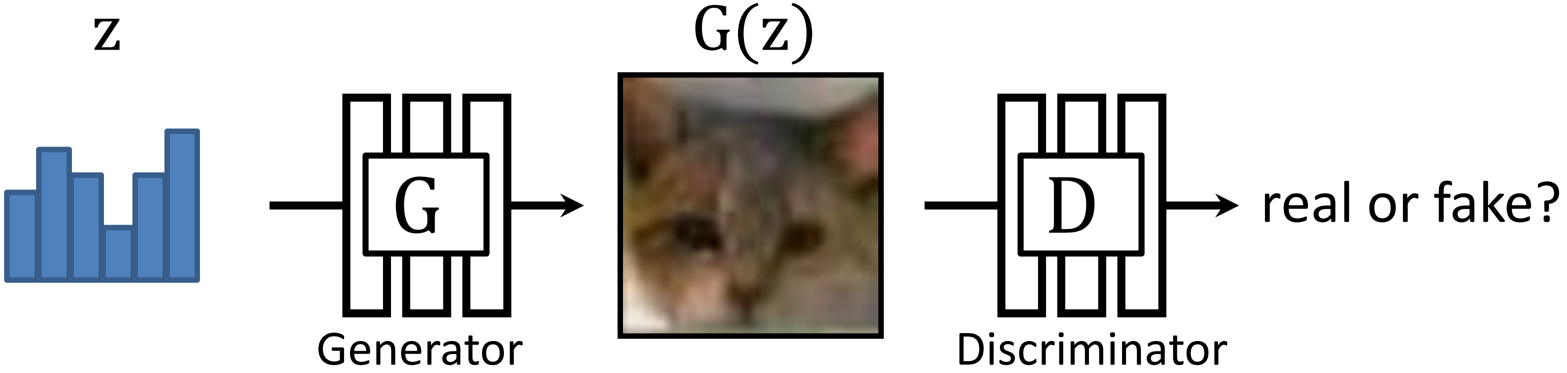
Paired vs Unpaired Setting



pix2pix: Image-to-Image Translation



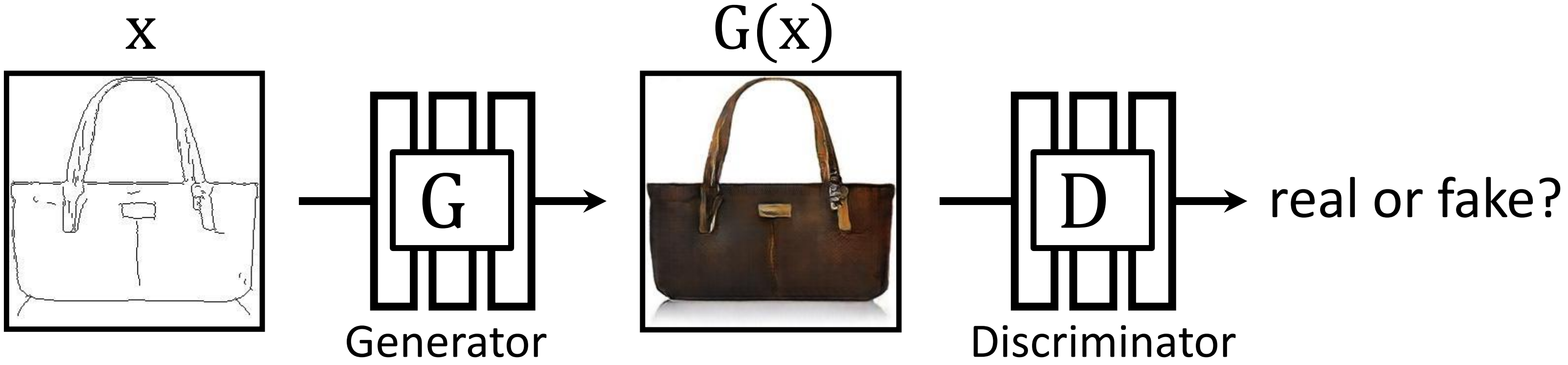
slides credit: Isola / Zhu



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

slides credit: Isola / Zhu

[Goodfellow et al. 2014]

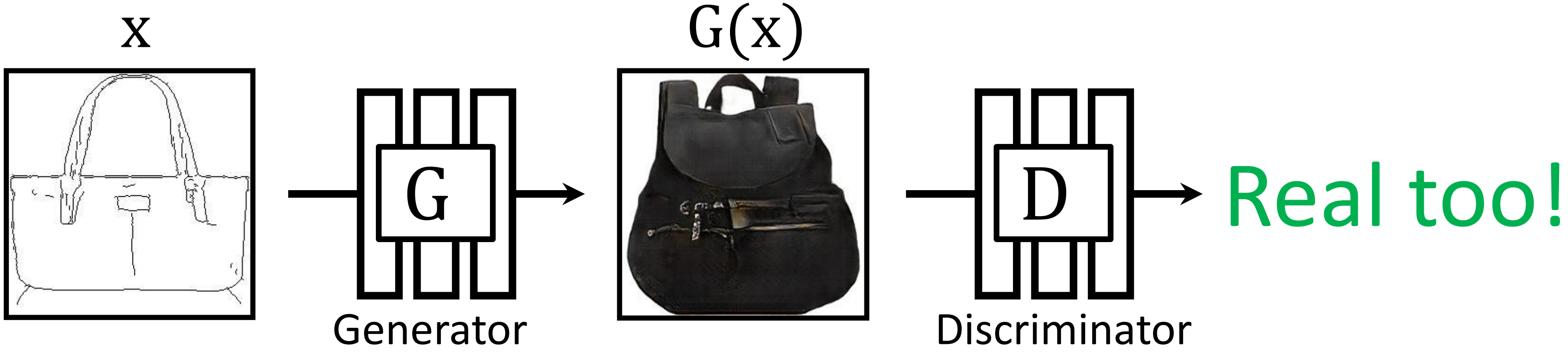


$$\min_{G} \max_{D} \mathbb{E}_{x,y}[\log D(G(x)) + \log(1 - D(y))]$$

slides credit: Isola / Zhu

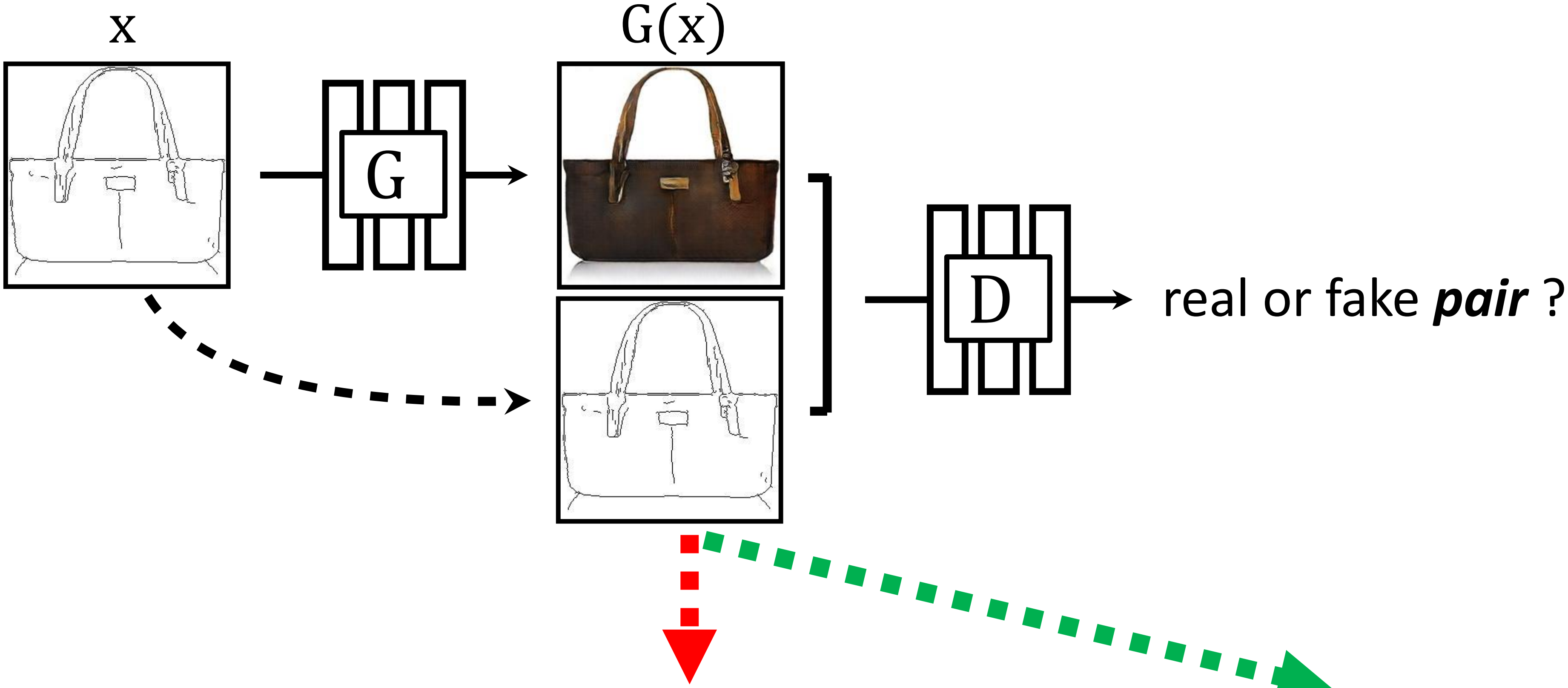
$$\min_{G} \max_{D} \mathbb{E}_{x,y}[\log D(G(x)) + \log(1 - D(y))]$$

slides credit: Isola / Zhu



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

slides credit: Isola / Zhu



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

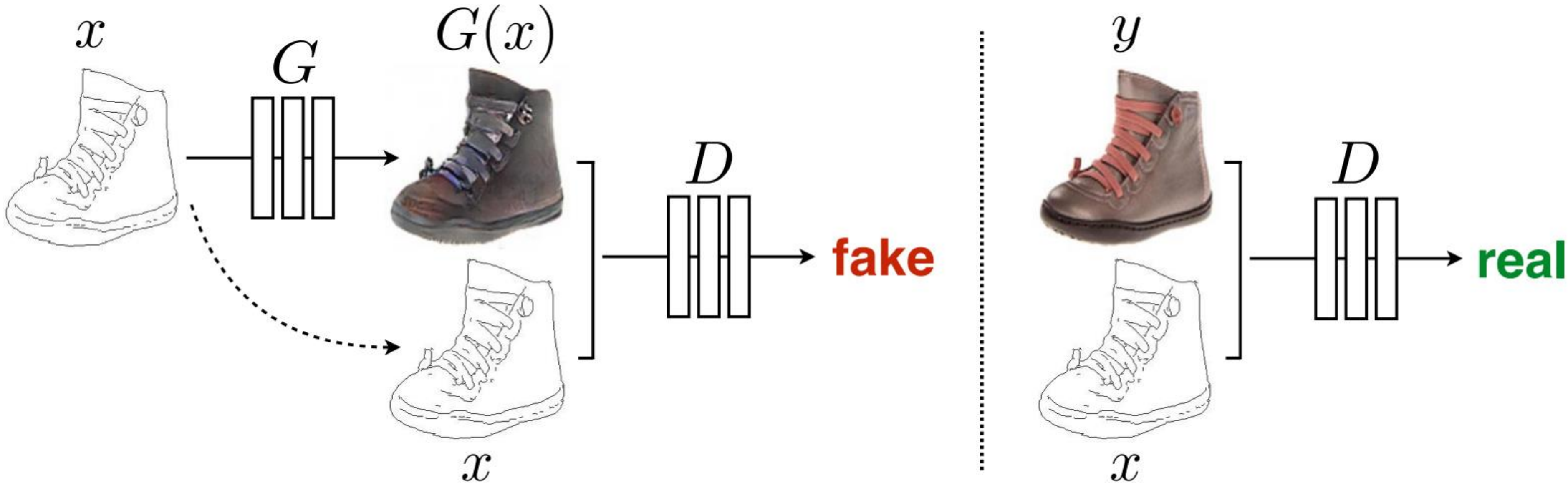
fake pair

real pair

match joint distribution $p(G(x), y) \sim p(x, y)$

slides credit: Isola / Zhu

pix2pix



Edges → Images

Input | Output | Input | Output | Input | Output

Edges from [Xie & Tu, 2015]

slides credit: Isola / Zhu

pix2pix: Paired Setting

- Great when we have 'free' training data
- Often called self-supervised
- Think about these settings ☺

Sketches → Images

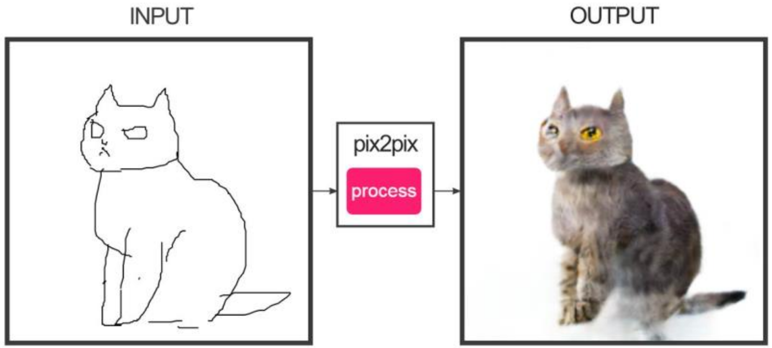
Input	Output	Input	Output	Input	Output

Trained on Edges → Images

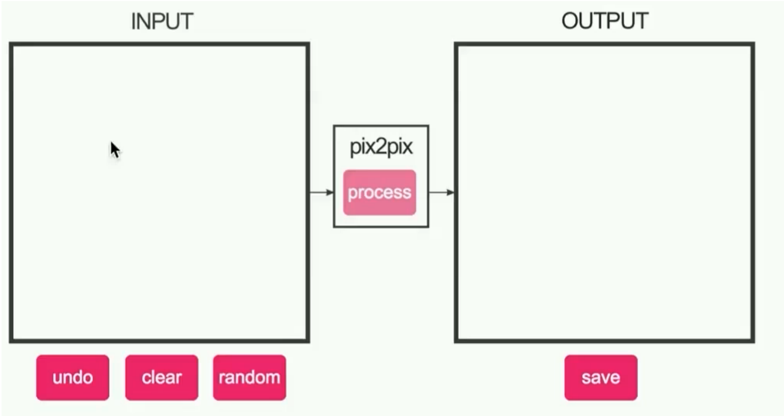
Data from [Eitz, Hays, Alexa, 2012]

slides credit: Isola / Zhu

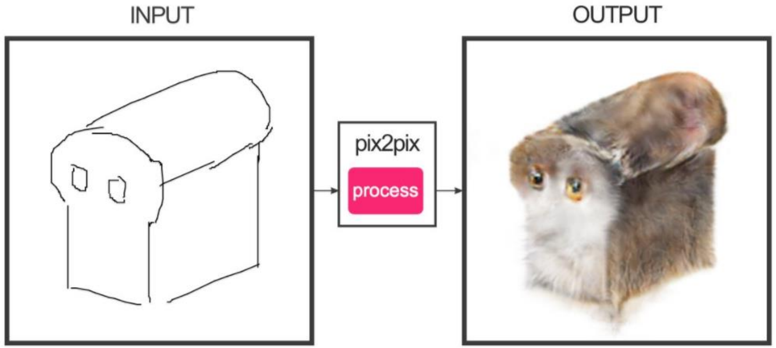
#edges2cats [Christopher Hesse]



@gods_tail



@matthematician



Ivy Tasi @ivymyt

Vitaly Vidmirov @vvid

https://affinelayer.com/pixsrv/

slides credit: Isola / Zhu

Input Output Groundtruth

Data from
[maps.google.com]

slides credit: Isola / Zhu

BW → Color

Input Output Input Output Input Output

slides credit: Isola / Zhu

Data from [Russakovsky et al. 2015]

Ideas behind Pix2Pix

- $L = L_{GAN} + \lambda L_1$ (makes it more constraint)
- Unet / skip connections for preserving structure
- Noise only through dropout
  - cGANs tend to learn to ignore the random vector z
  - Still want probabilistic model

Ideas behind Pix2Pix

- L1 or L2 loss for low frequency details

- GAN discriminator for high frequency details

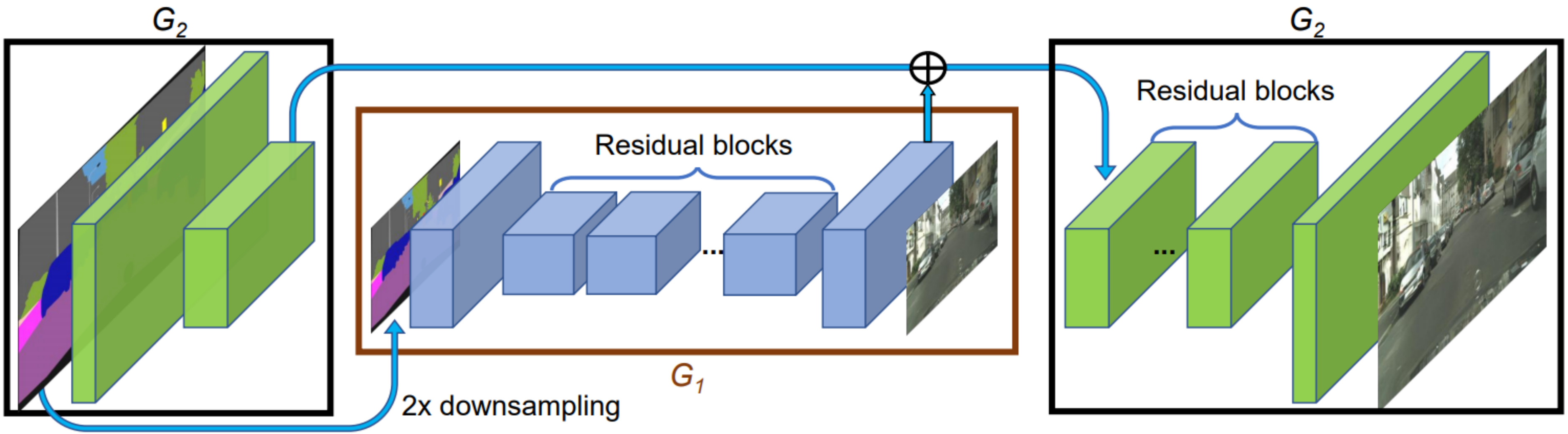
-> PatchGAN
  - GAN discriminator applied only to local patches
  - It's fully-convolutional; i.e., can run on arbitrary image sizes

Pix2PixHD

- Expand the pix2pix idea to multi-scale
- Coarse-to-fine generator + discriminator
- G's and D's are the same but since they operate on different resolutions, they have effectively a larger receptive field

[Wang et al. 18]

Pix2PixHD



[Wang et al. 18]

Pix2PixHD

- Use of multi-scale discriminators

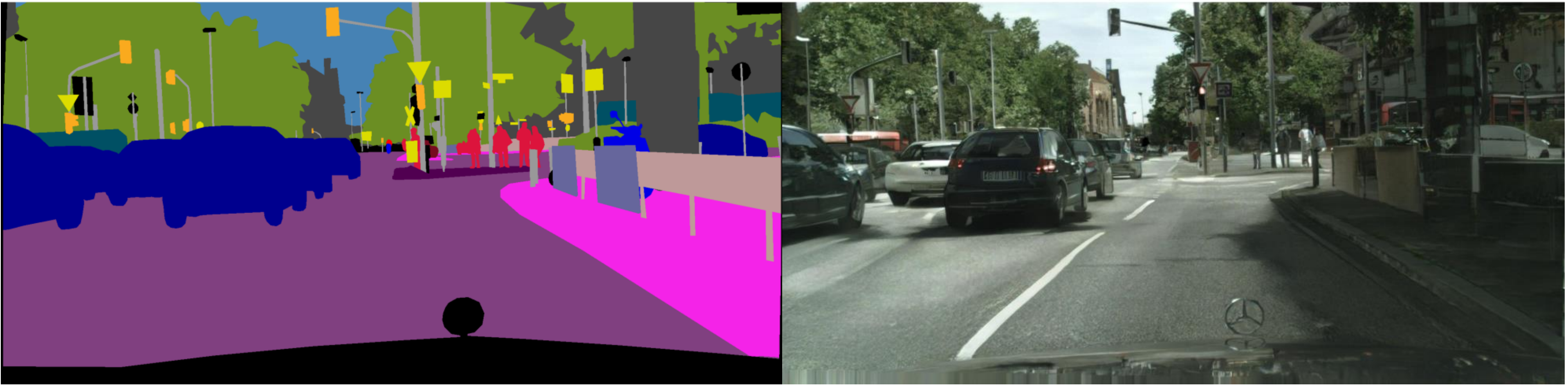
- $\min_{G} \max_{D_1,D_2,D_3} \sum_{k=1,2,3} L_{GAN}(G, D_k)$

- Can make various combinations of stacking discriminator and generator
  - E.g., have a single G and downsample generated and real images – or have intermediate real images (cf. ProGAN)

[Wang et al. 18]

Pix2PixHD

Input labels Synthesized image



[Wang et al. 18]

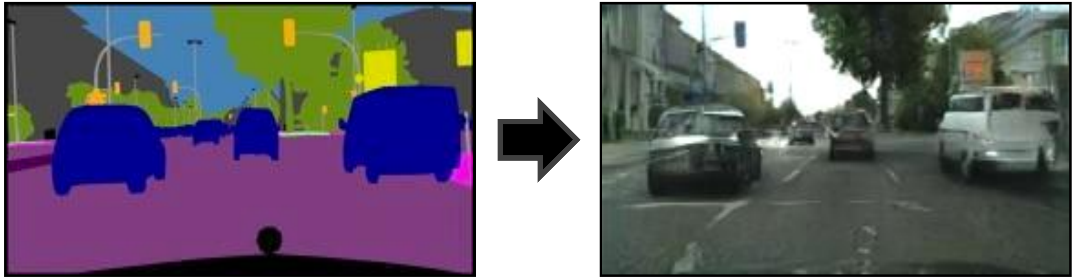
Pix2PixHD

[Wang et al. 18]

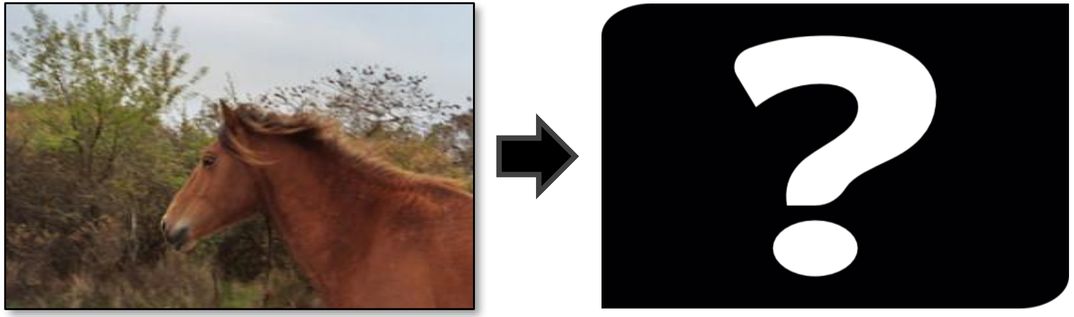
Pix2PixHD (interactive results)

[Wang et al. 18]

Paired



Label ↔ photo: per-pixel labeling

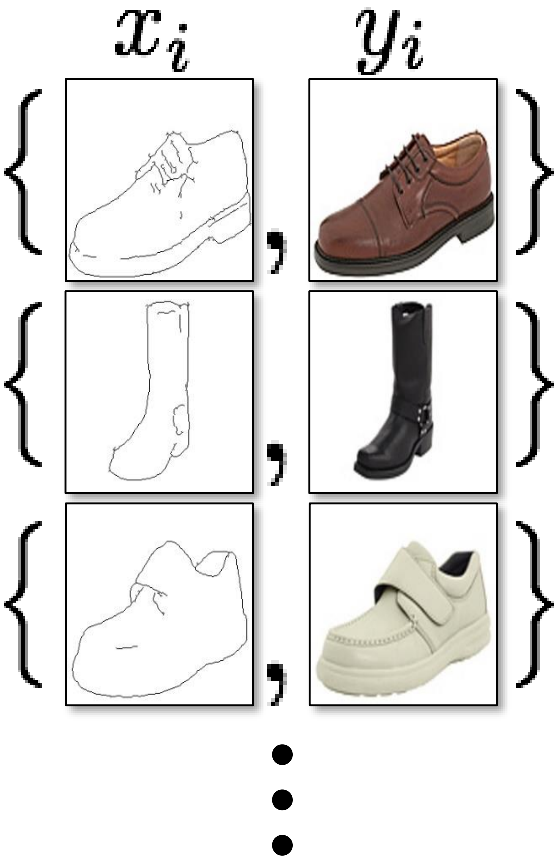


Horse ↔ zebra: how to get zebras?

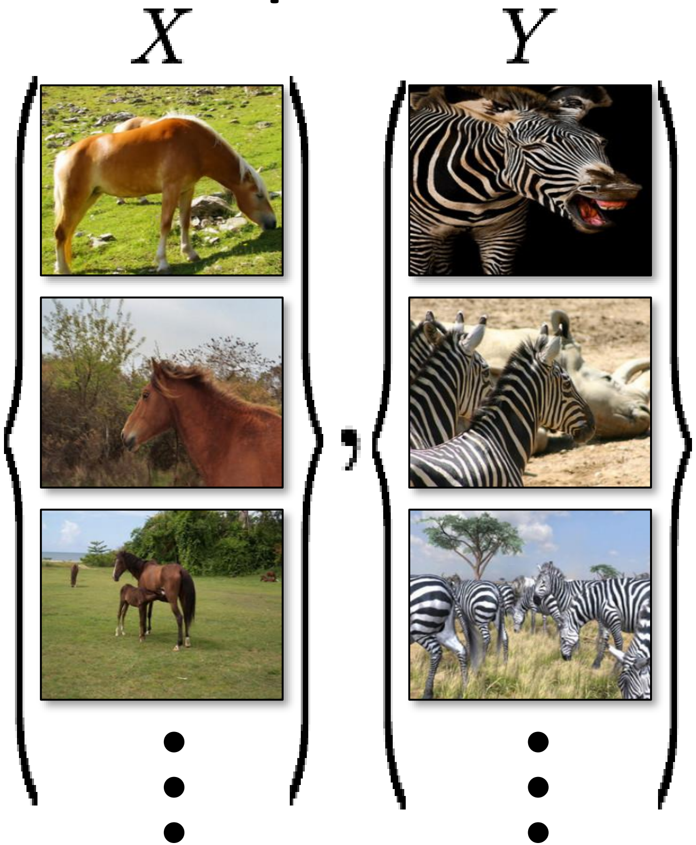
- Expensive to collect pairs.
- Impossible in many scenarios.

slides credit: Isola / Zhu

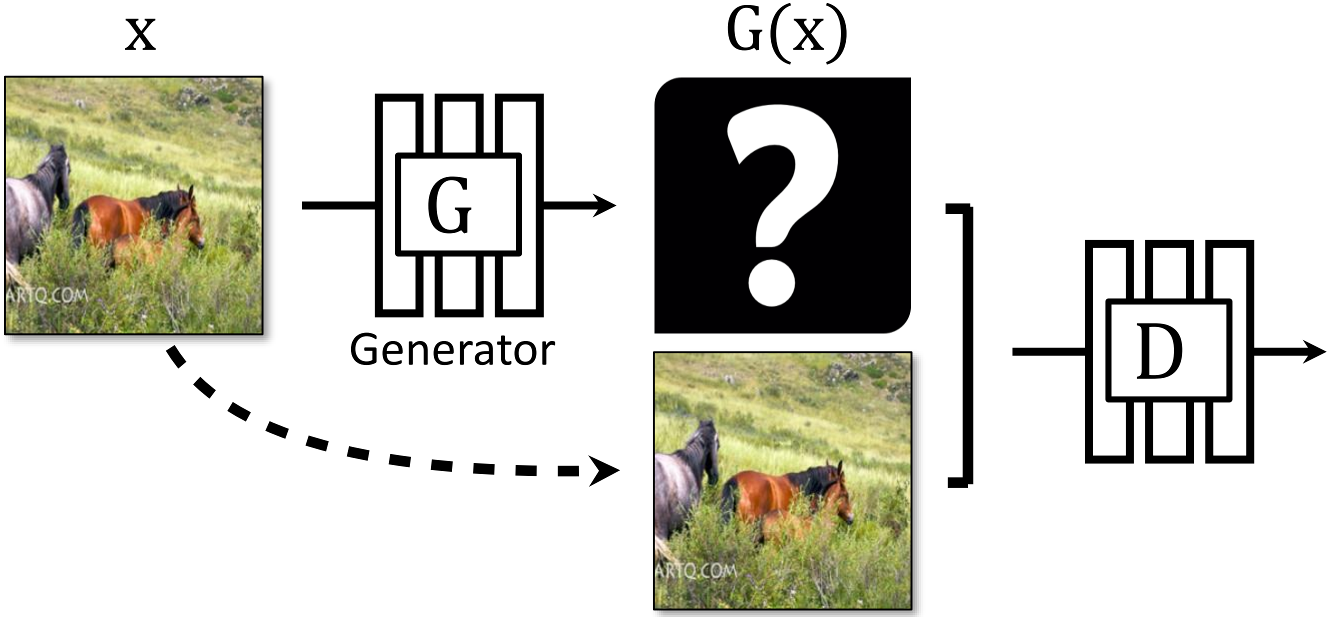
Paired



Unpaired

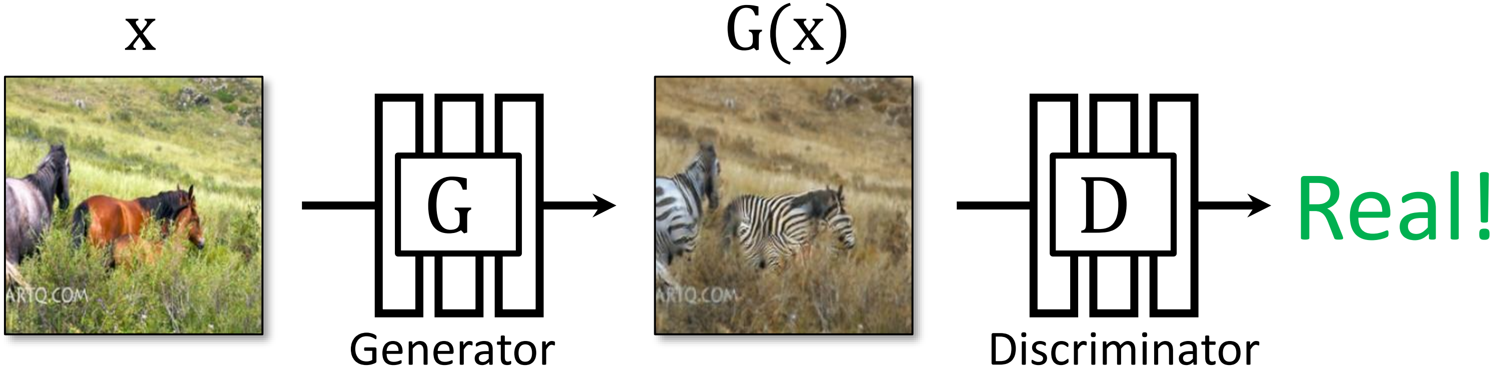


slides credit: Isola / Zhu

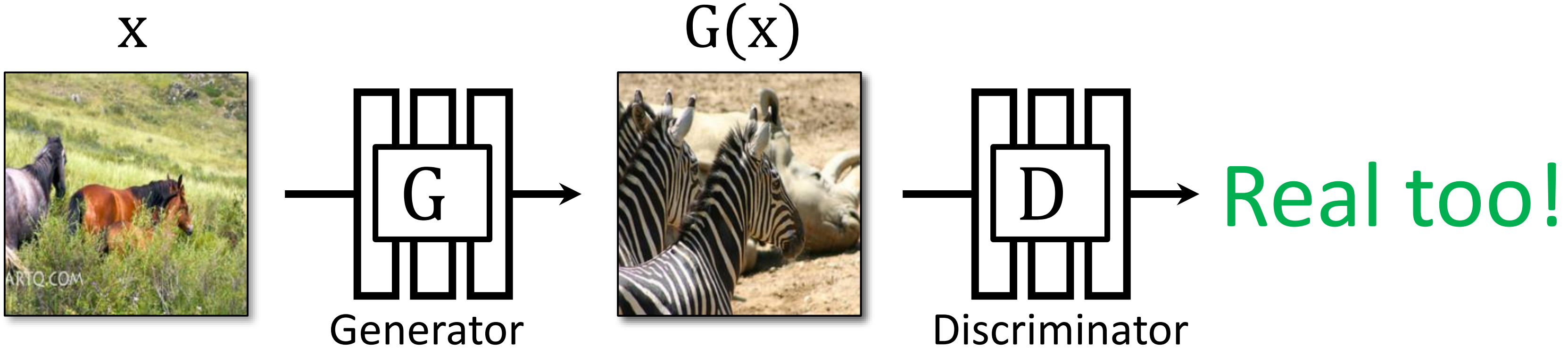


No input-output pairs!

slides credit: Isola / Zhu

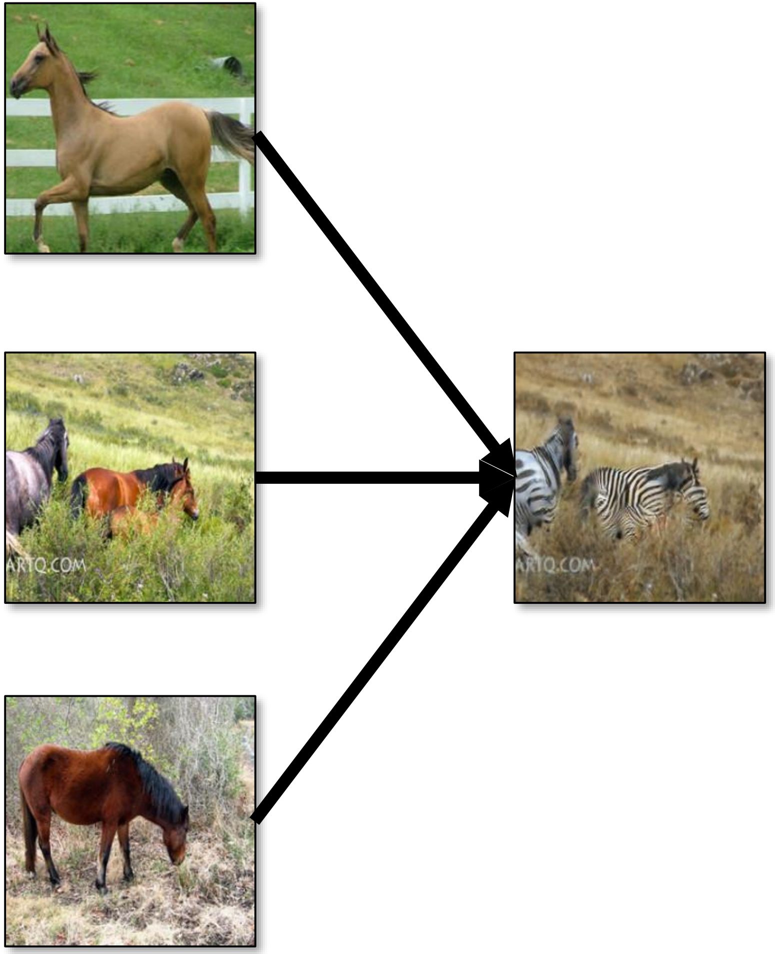


slides credit: Isola / Zhu



GANs doesn't force output to correspond to input

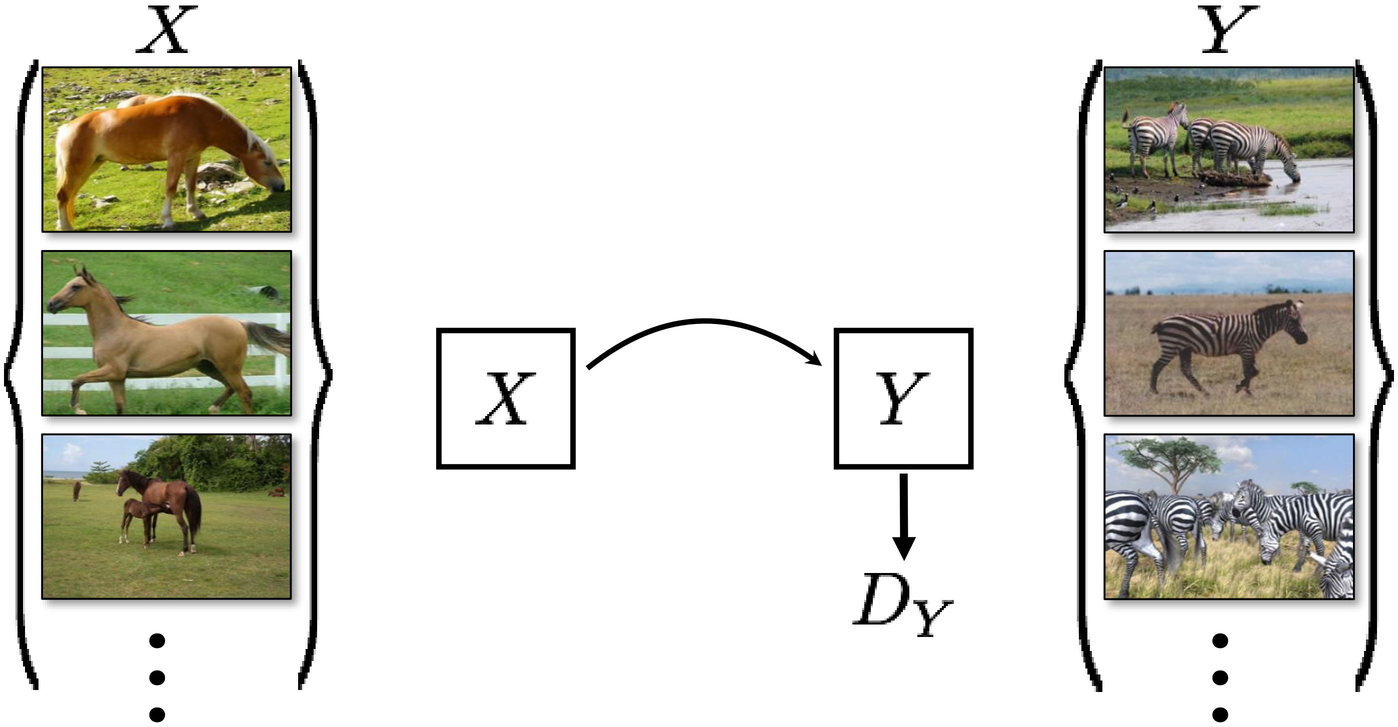
slides credit: Isola / Zhu



mode collapse!

slides credit: Isola / Zhu

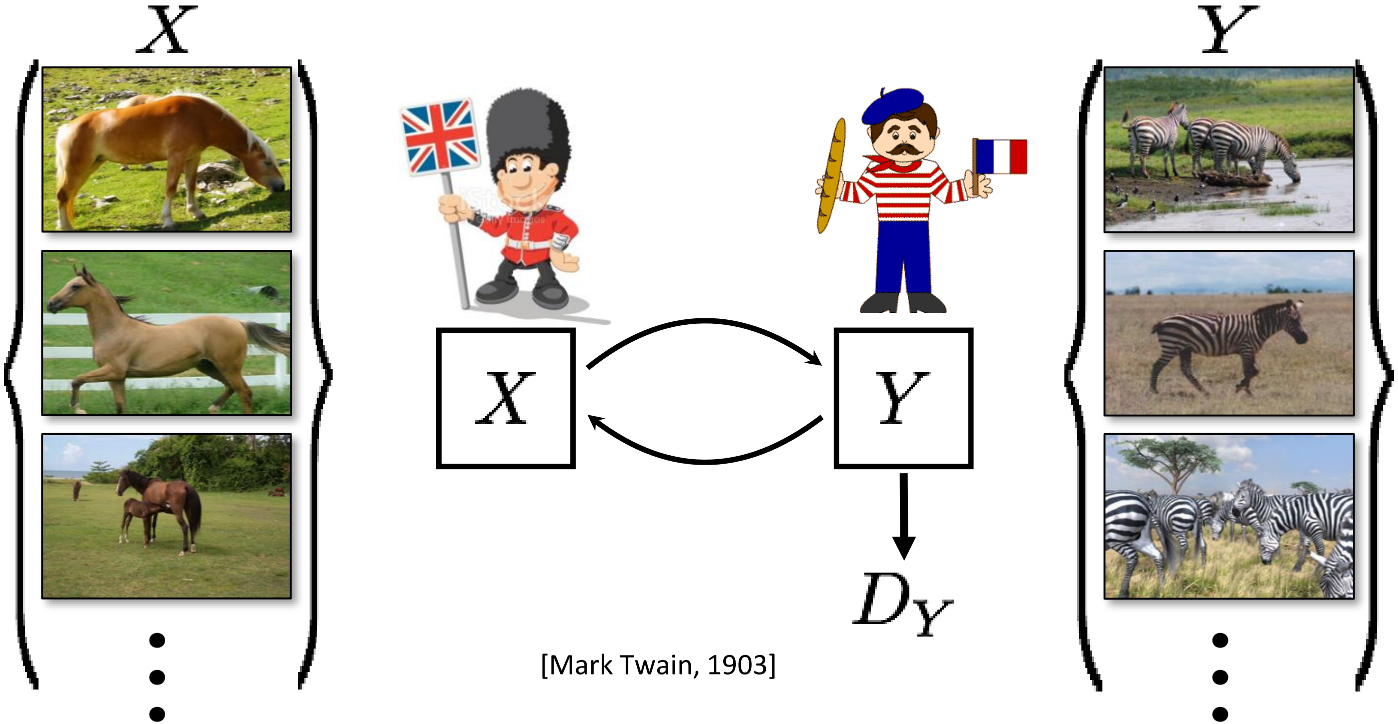
Cycle-Consistent Adversarial Networks



slides credit: Isola / Zhu

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

Cycle-Consistent Adversarial Networks

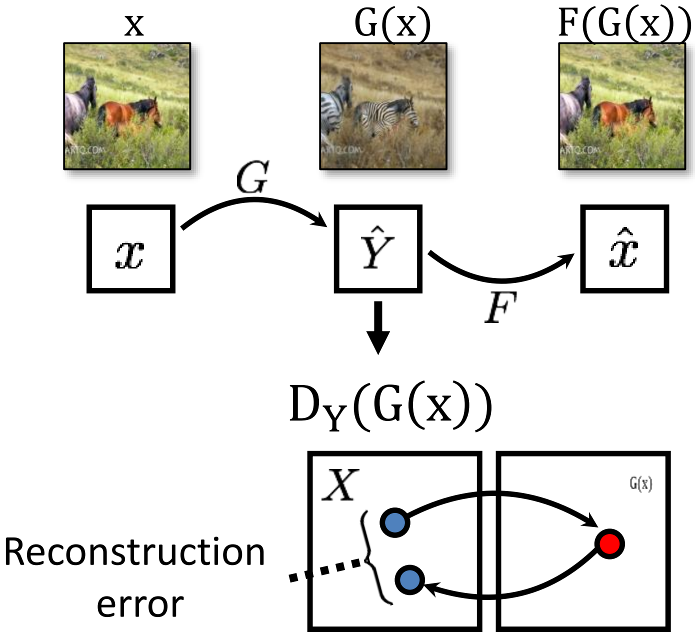


[Mark Twain, 1903]

slides credit: Isola / Zhu

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

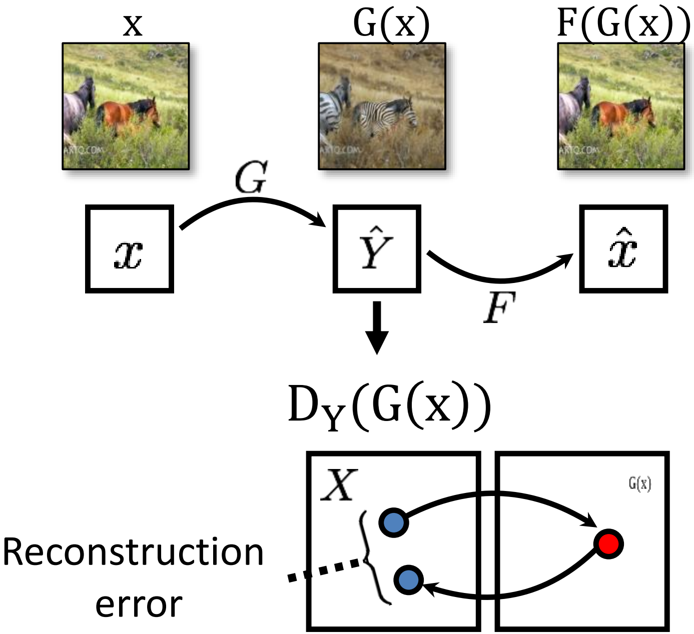
Cycle Consistency Loss



$$\left\|F\big(G(x)\big) - x\right\|_1$$

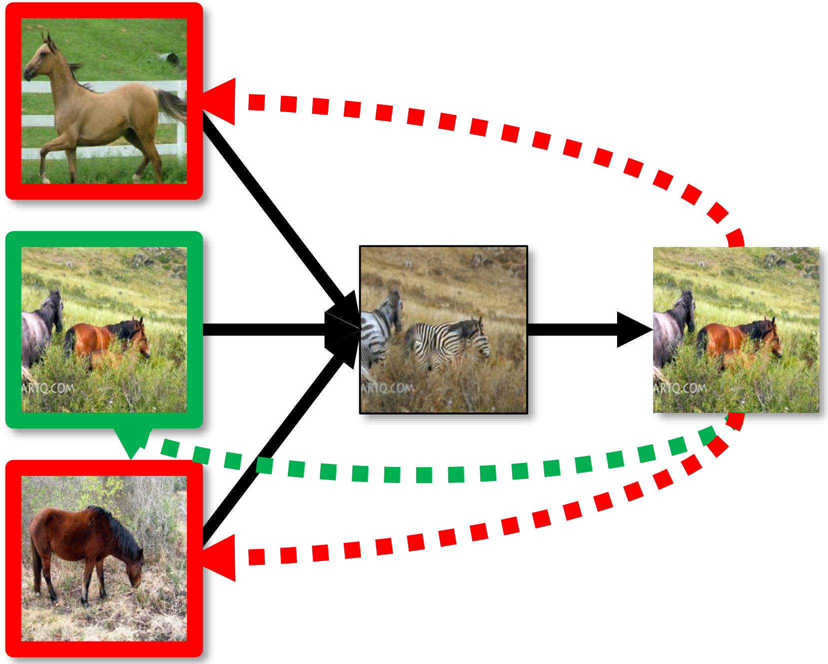
[Zhu*, Park*, Isola, and Efros, ICCV 2017]

Cycle Consistency Loss



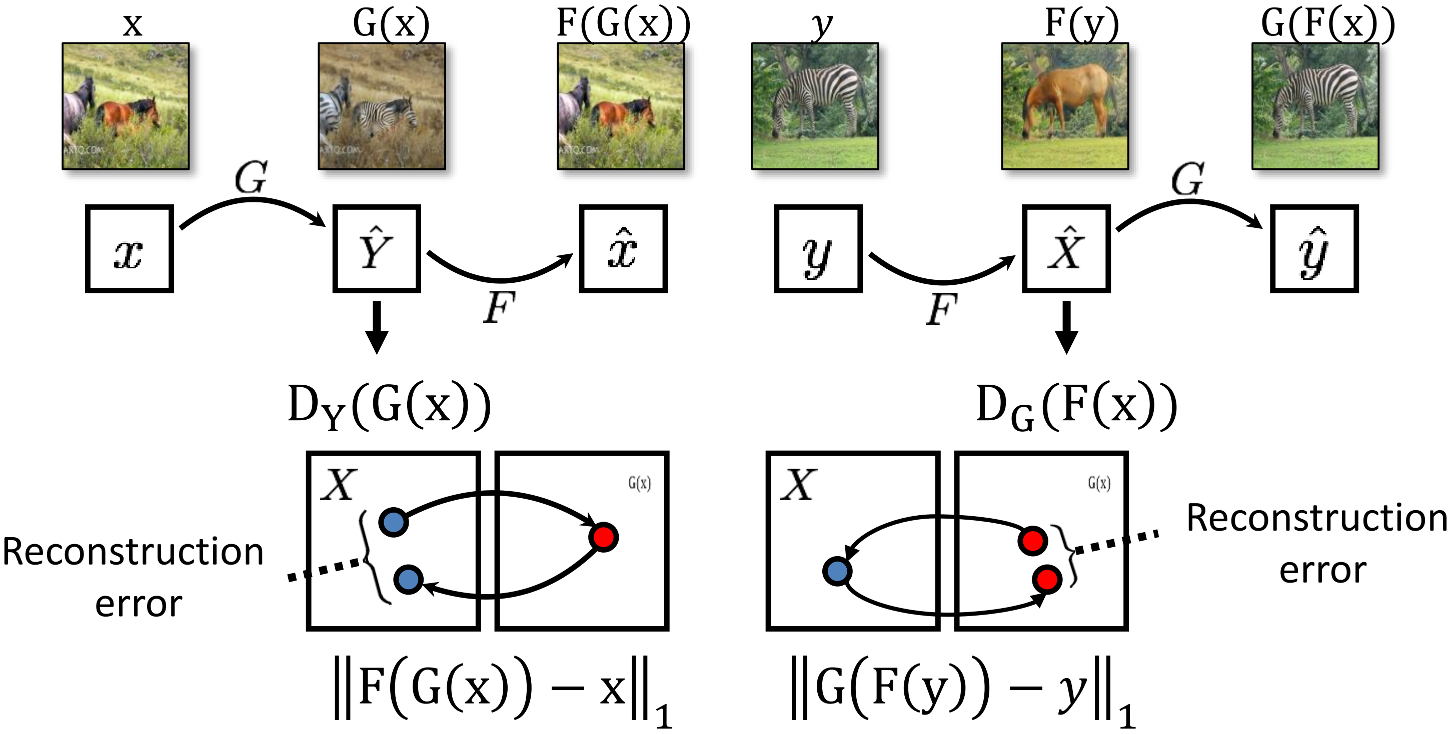
$$\left\| F(G(x)) - x \right\|_1$$

Small / Large cycle loss



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

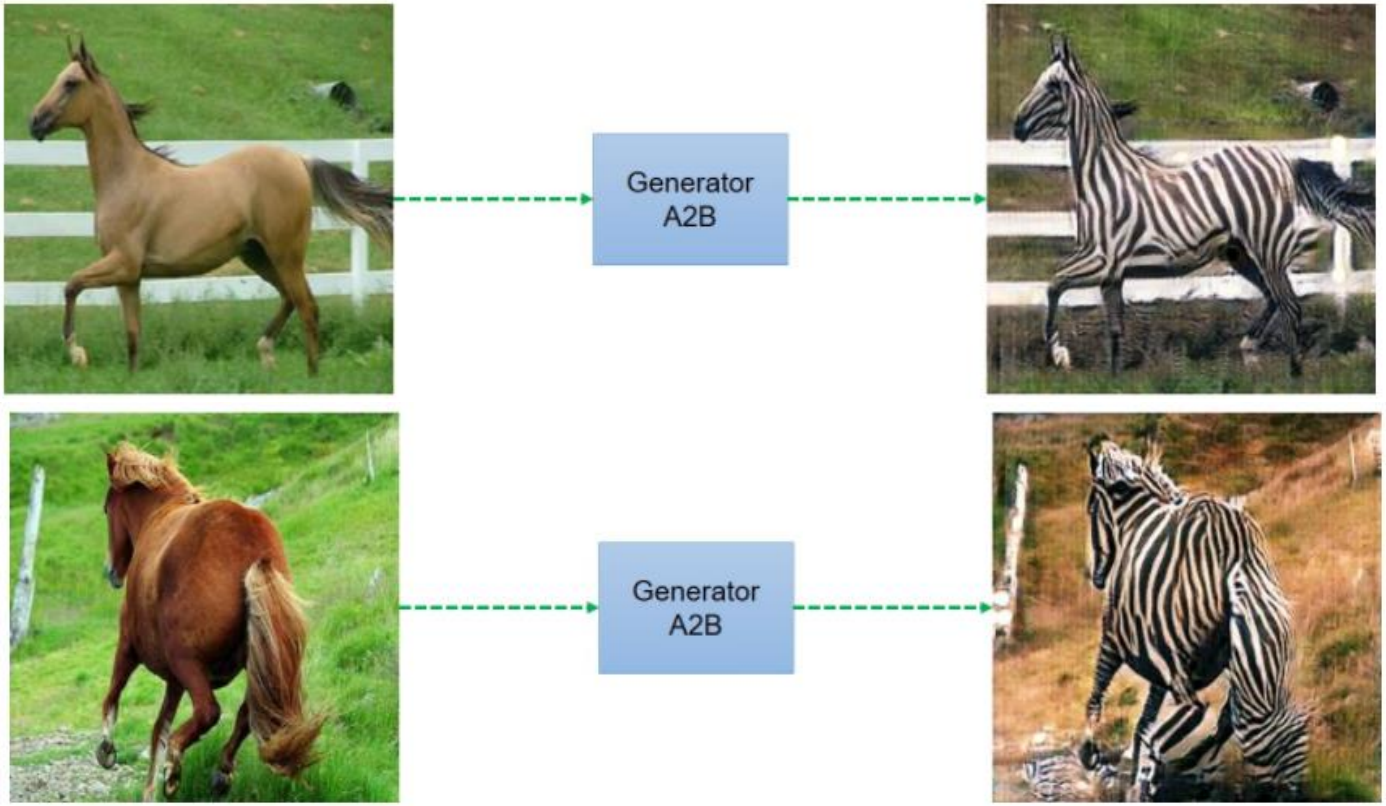
Cycle Consistency Loss



slides credit: Isola / Zhu

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

Cycle GAN - Overview



https://junyanz.github.io/CycleGAN/ [Zhu et al. 17.]

Monet's paintings → photos

slides credit: Isola / Zhu




slides credit: Isola / Zhu

slides credit: Isola / Zhu

Next Lectures

- Next Monday 23rd,
  - Xmas GANs
  - No Lecture

- Next Lecture -> Jan 13th

- Keep working on the projects!

See you next year ☺