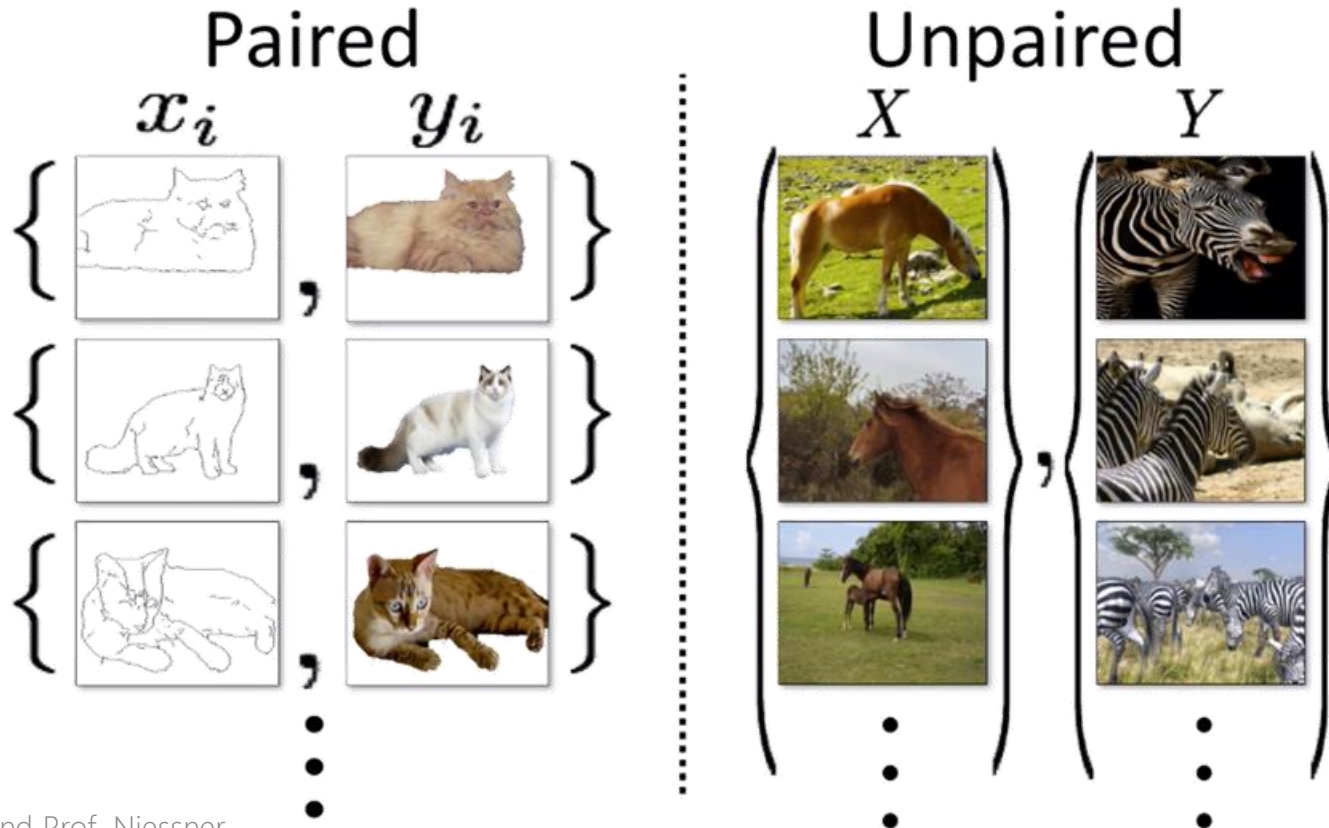


Conditional Generative Adversarial Networks (cGANs) continued!

Paired vs Unpaired Setting



pix2pix: Image-to-Image Translation

Labels to Street Scene

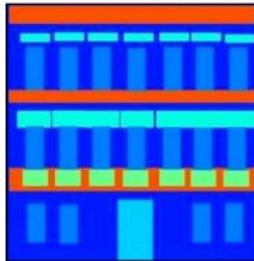


input



output

Labels to Facade



input



output

BW to Color



input



output

Aerial to Map



input

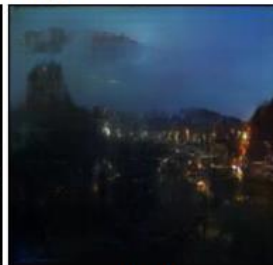


output

Day to Night



input



output

Edges to Photo



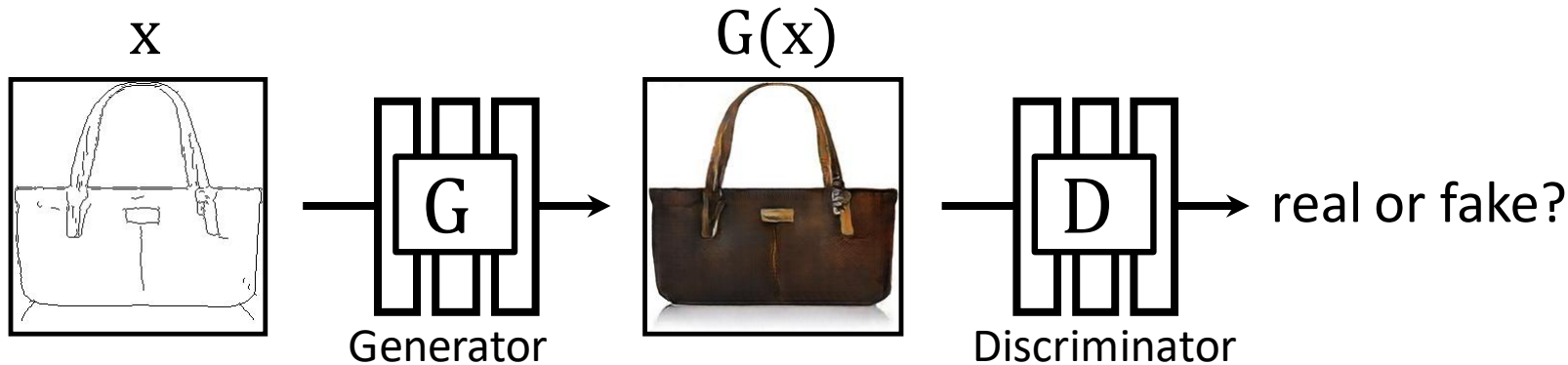
input



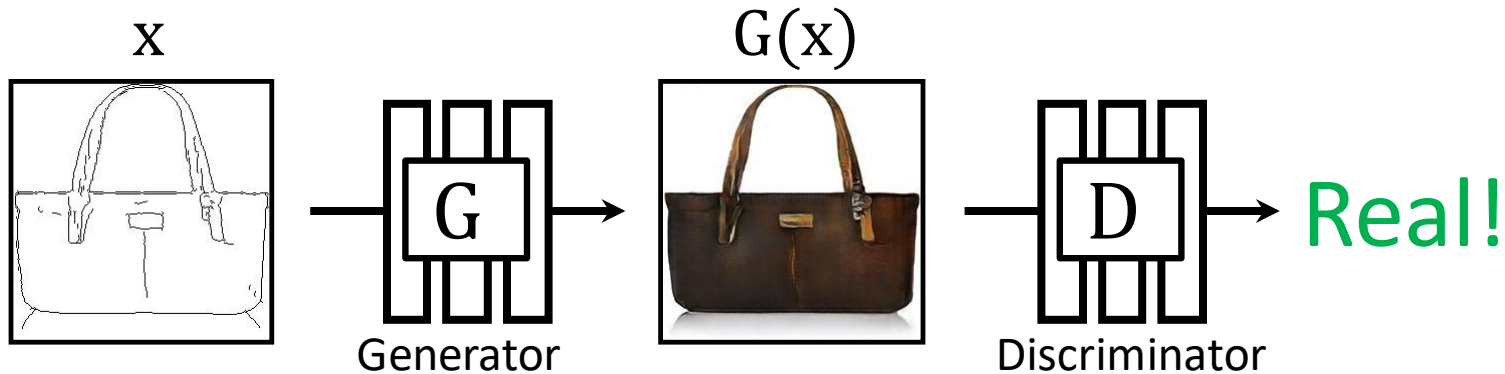
output



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



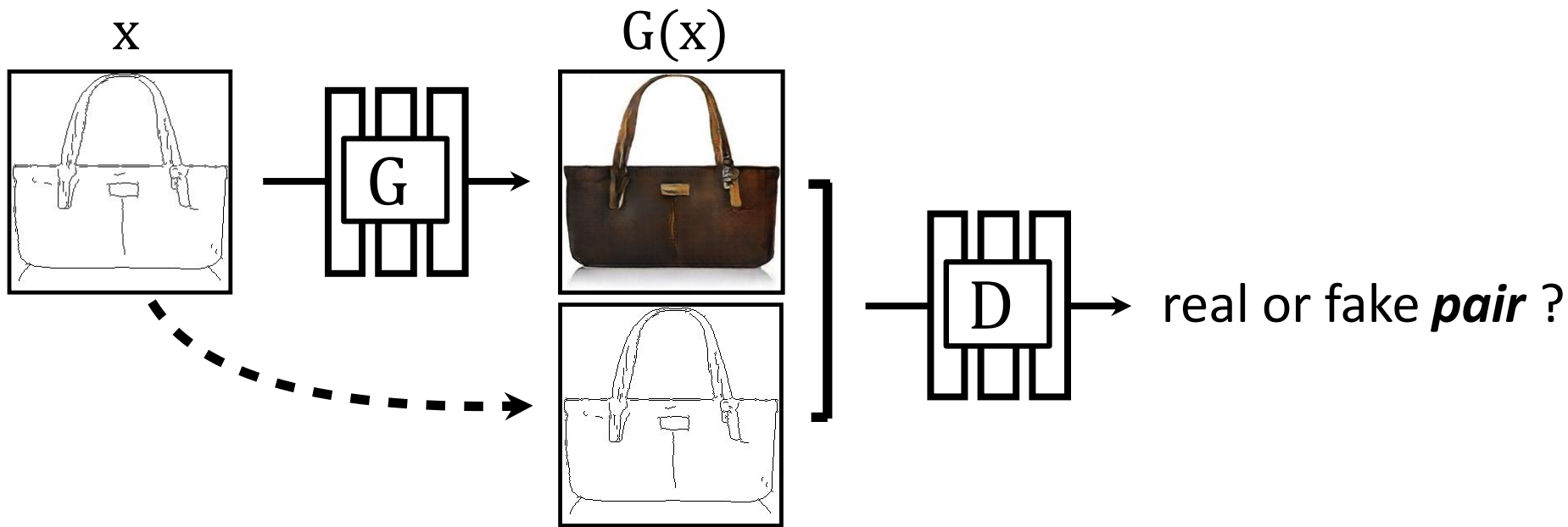
$$\min_G \max_D \mathbb{E}_{x,y} [\log D(G(x)) + \log(1 - D(y))]$$



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



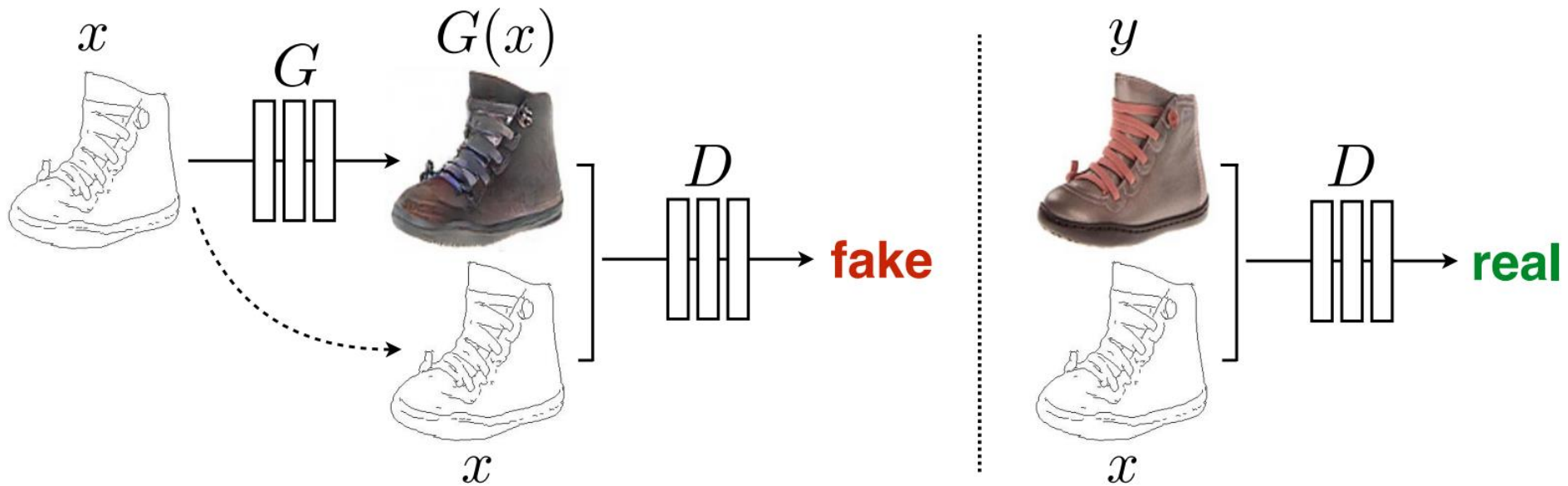
$$\min_G \max_D \mathbb{E}_{x,y} [\log D(G(x)) + \log(1 - D(y))]$$



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

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

pix2pix



pix2pix: Paired Setting

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

Edges → Images

Input

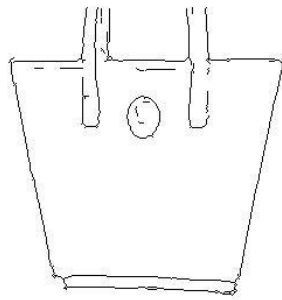
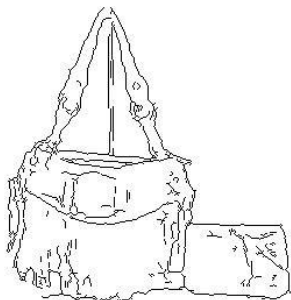
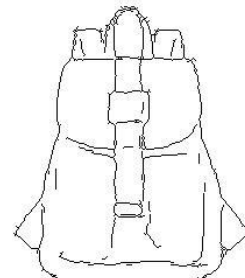
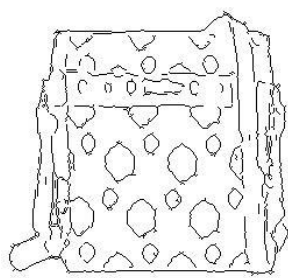
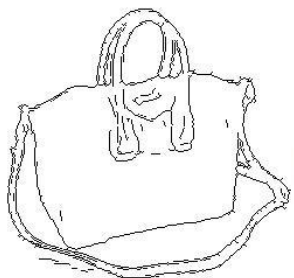
Output

Input

Output

Input

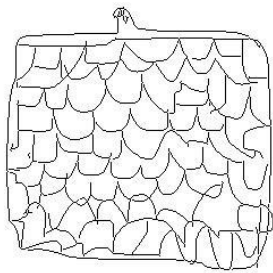
Output



Edges from [Xie & Tu, 2015]

Sketches \rightarrow Images

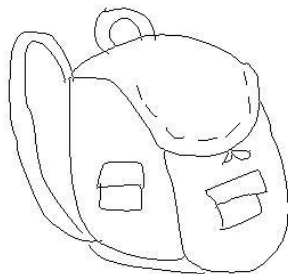
Input



Output



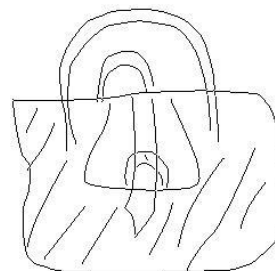
Input



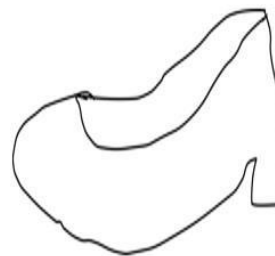
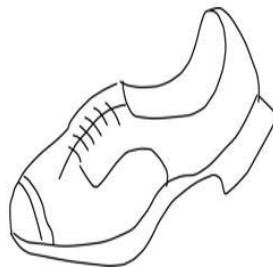
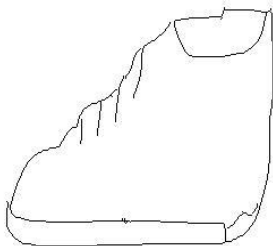
Output



Input



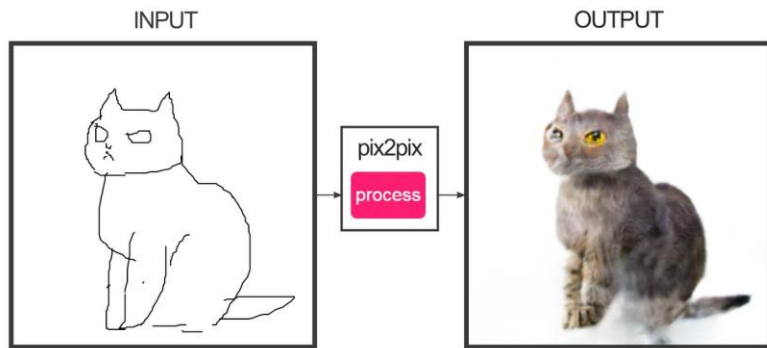
Output



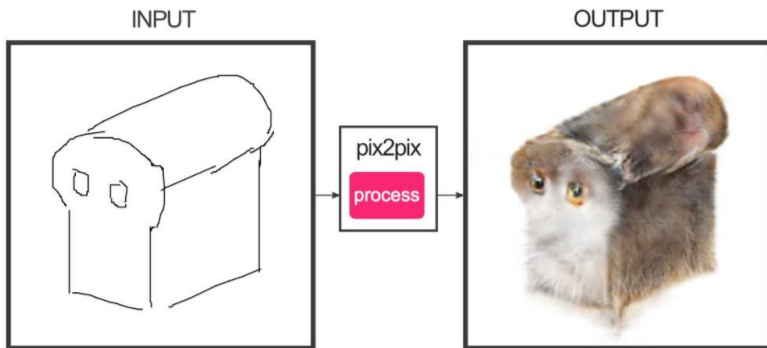
Trained on Edges \rightarrow Images

Data from [Eitz, Hays, Alexa, 2012]

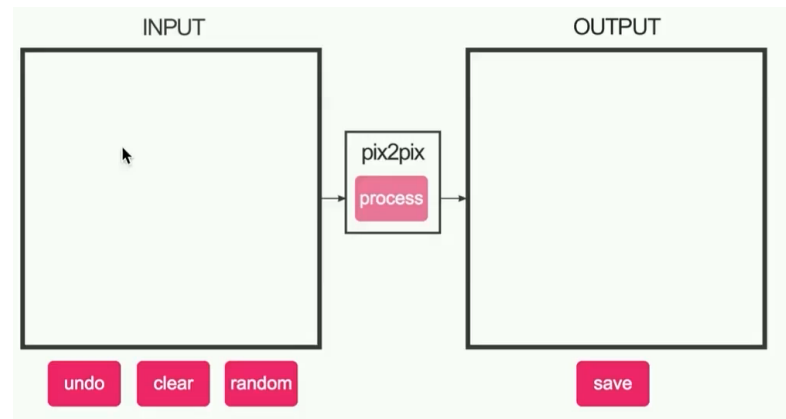
#edges2cats [Christopher Hesse]



@gods_tail



Ivy Tasi @ivymyt



@matthematician



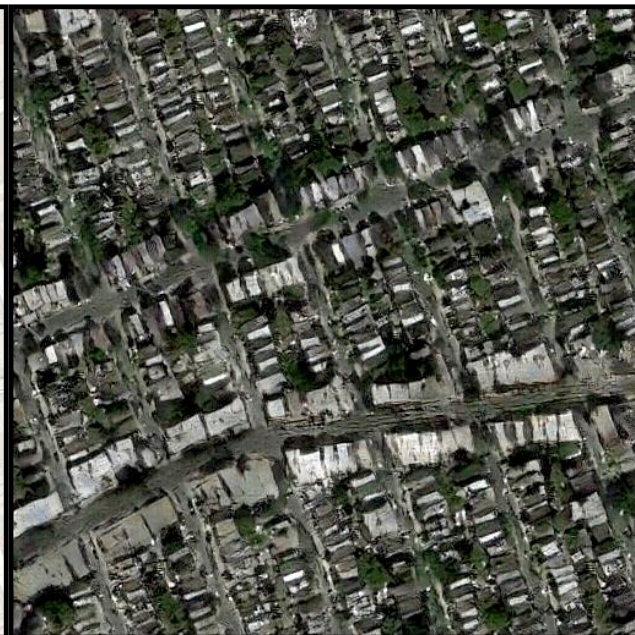
Vitaly Vidmirov @vvid

<https://affinelayer.com/pixsrv/>

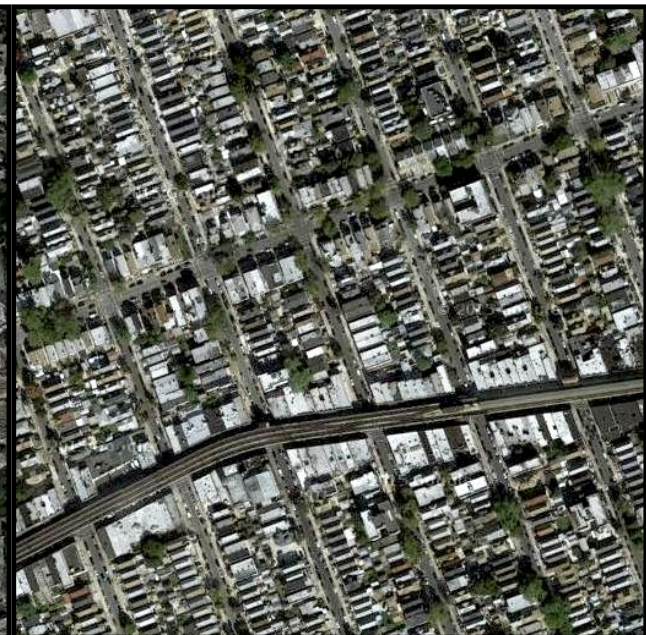
Input



Output



Groundtruth



Data from
[maps.google.com]



slides credit: Isola / Zhu

BW \rightarrow Color

Input

Output



Input

Output



Input

Output



Ideas behind Pix2Pix

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

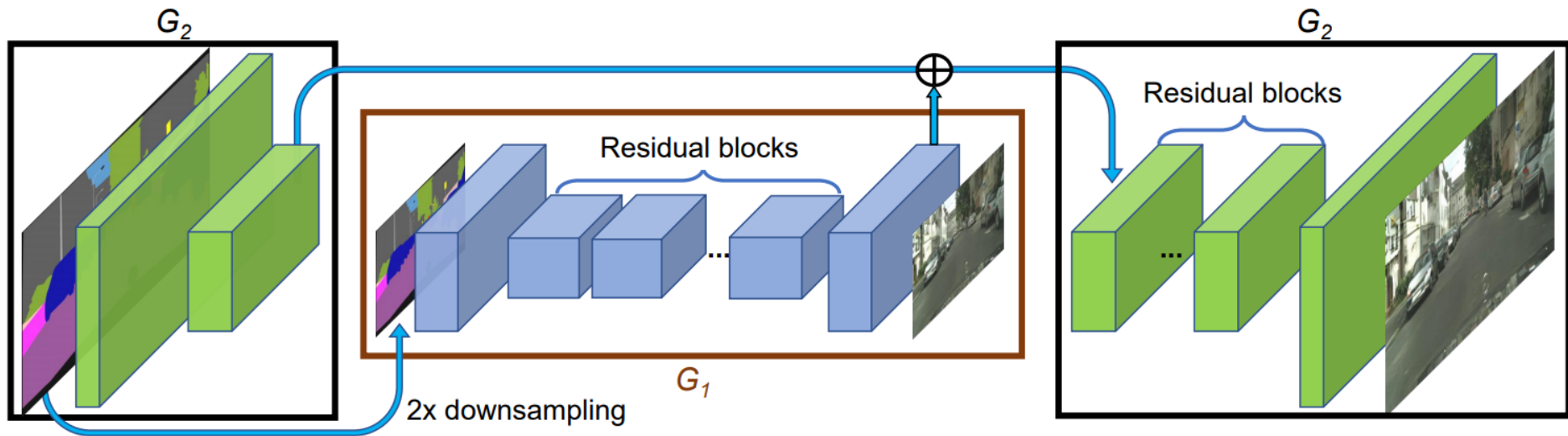
Ideas behind Pix2Pix

- 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

Pix2PixHD



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)

Pix2PixHD

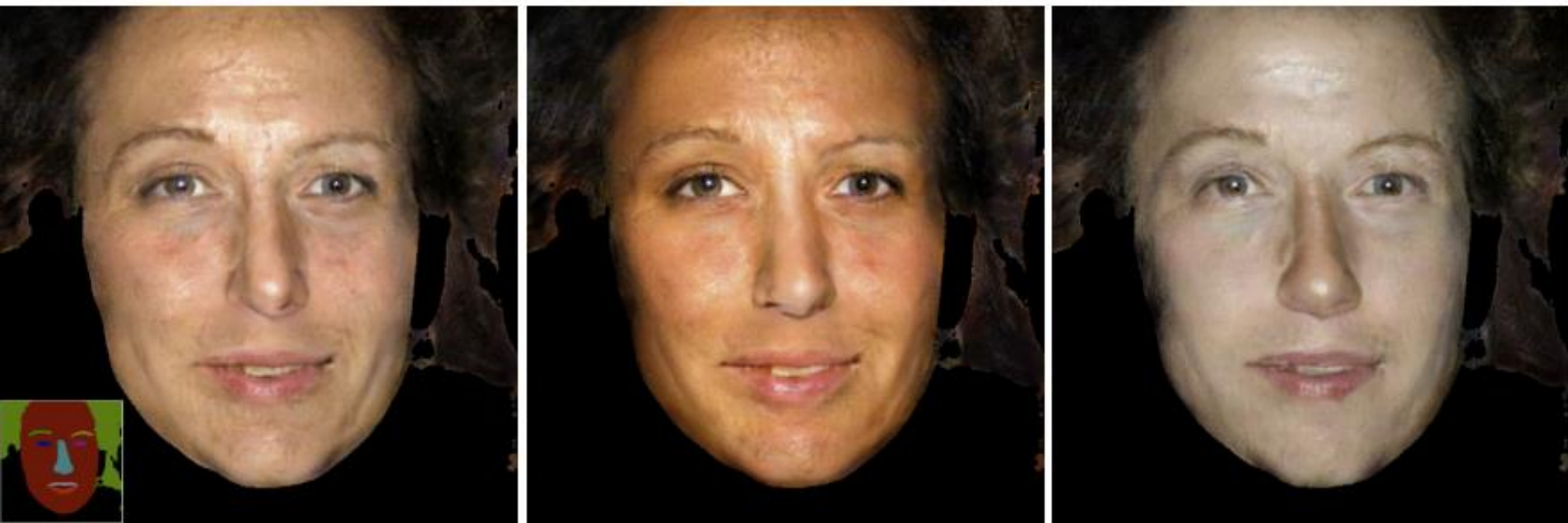
Input labels



Synthesized image



Pix2PixHD



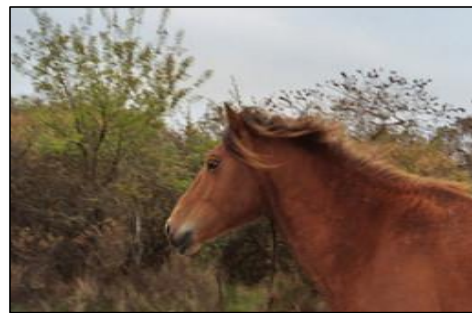
Pix2PixHD (interactive results)



Paired



Label \leftrightarrow photo: per-pixel labeling



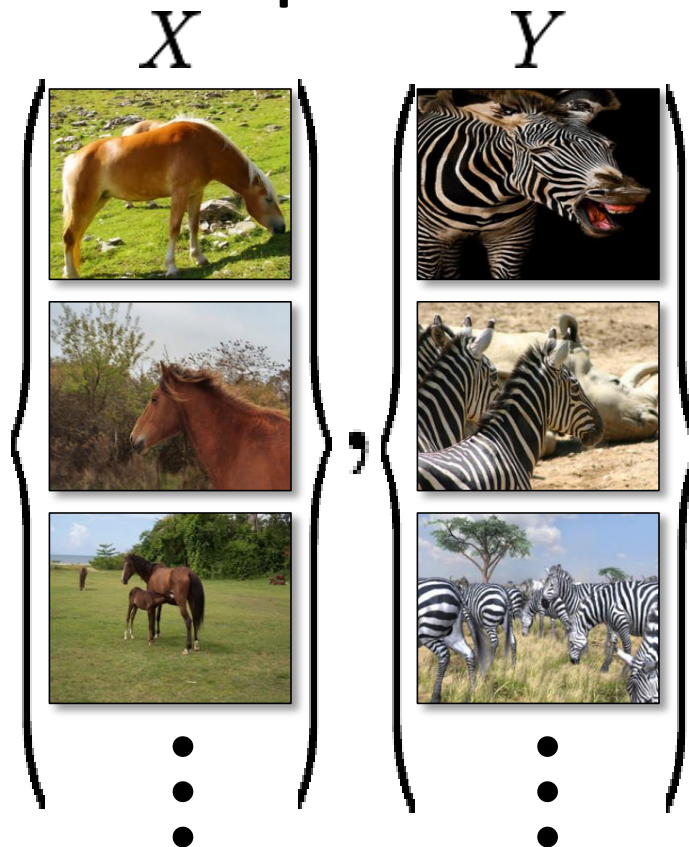
Horse \leftrightarrow zebra: how to get zebras?

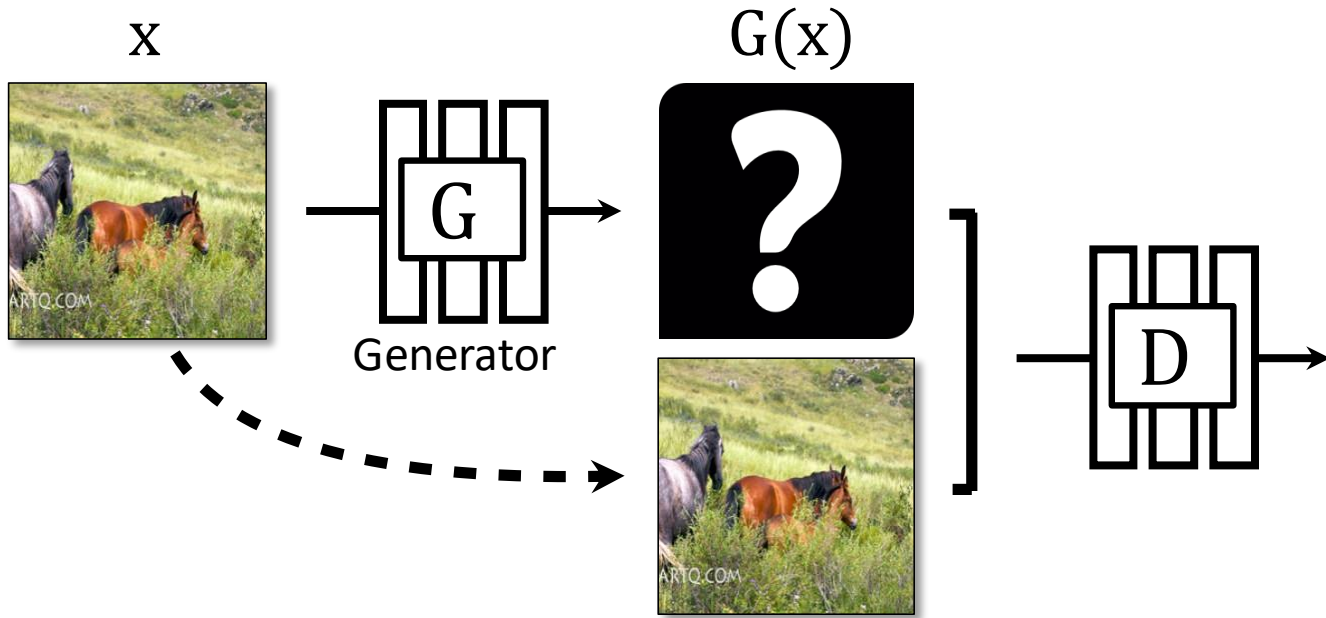
- Expensive to collect pairs.
- Impossible in many scenarios

Paired



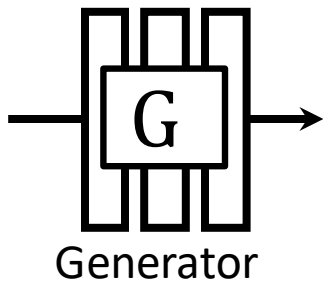
Unpaired



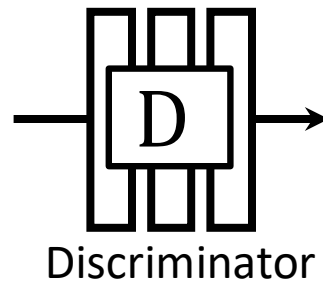


No input-output pairs!

X

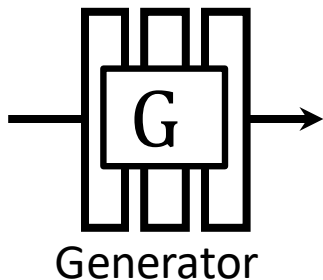


$G(X)$

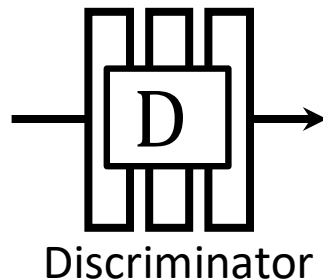


Real!

x



$G(x)$



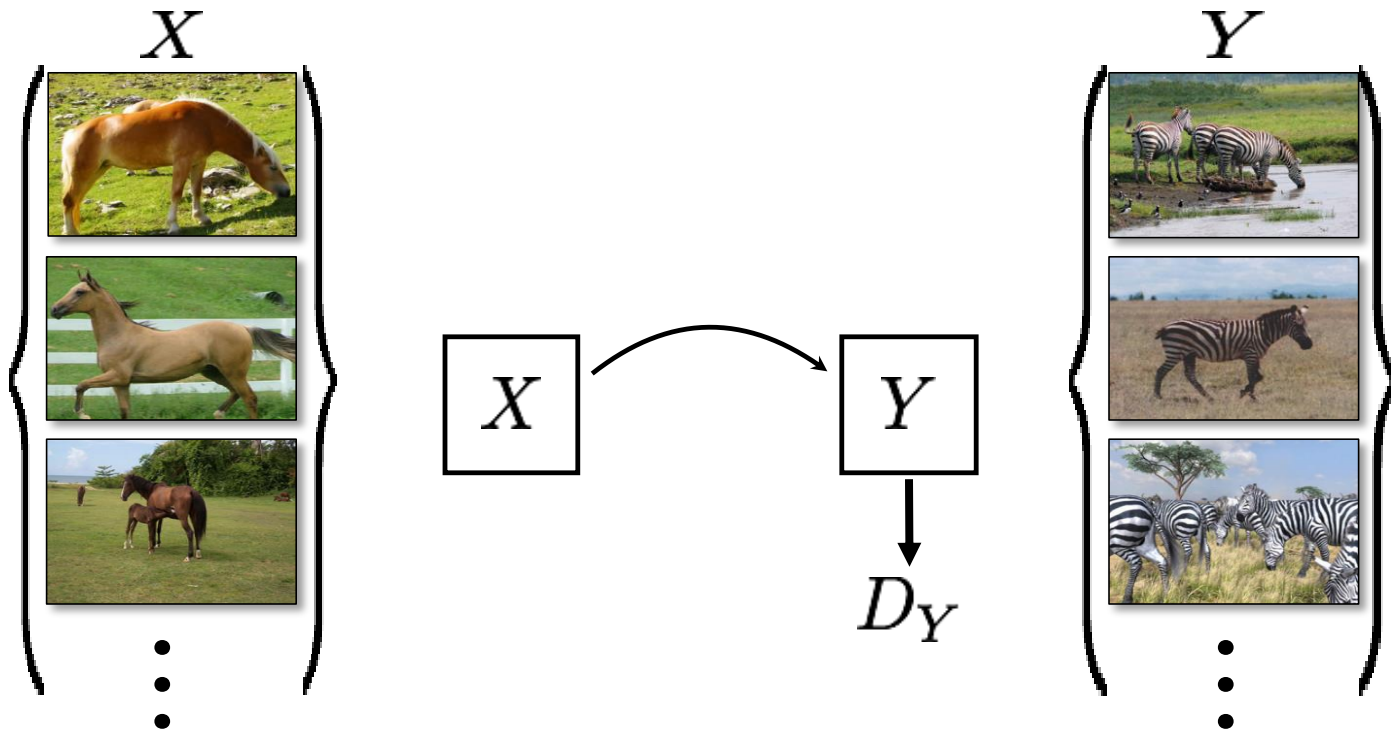
Real too!

GANs doesn't force output to correspond to input

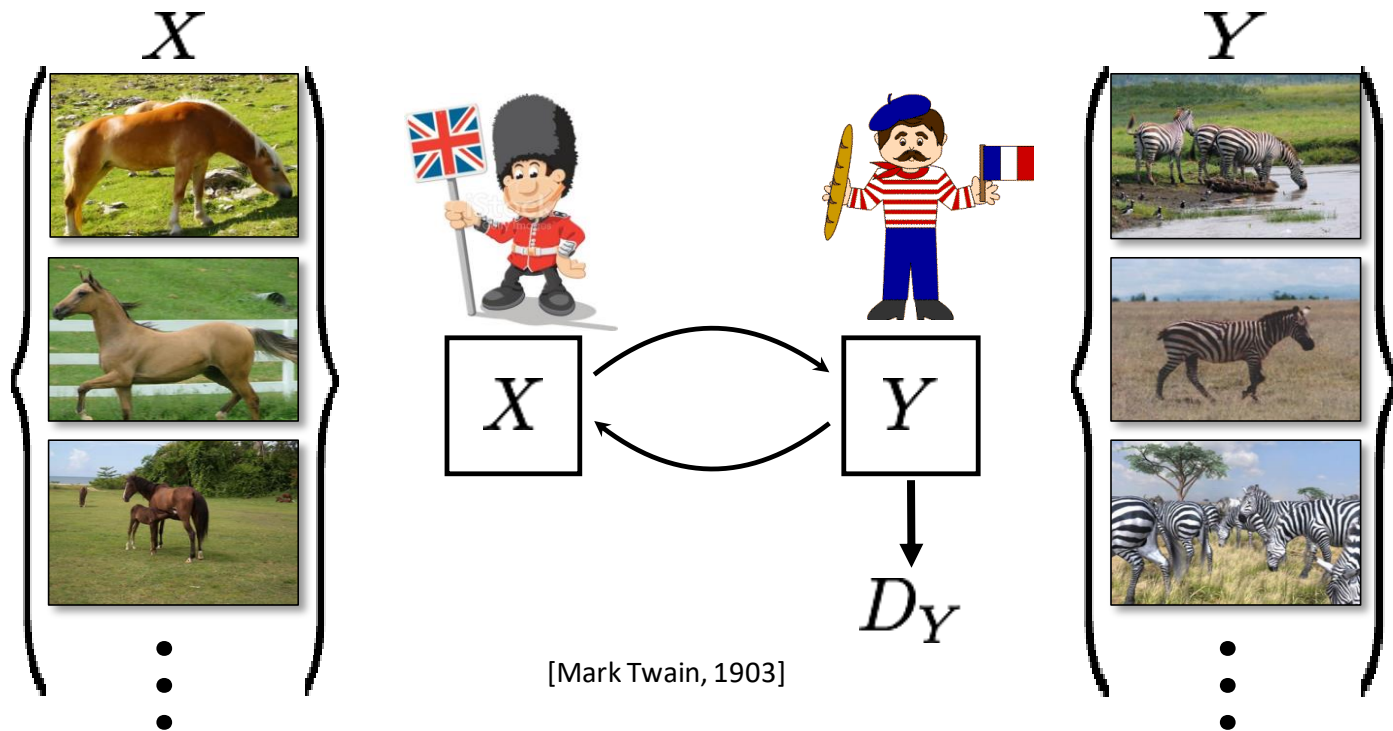


mode collapse!

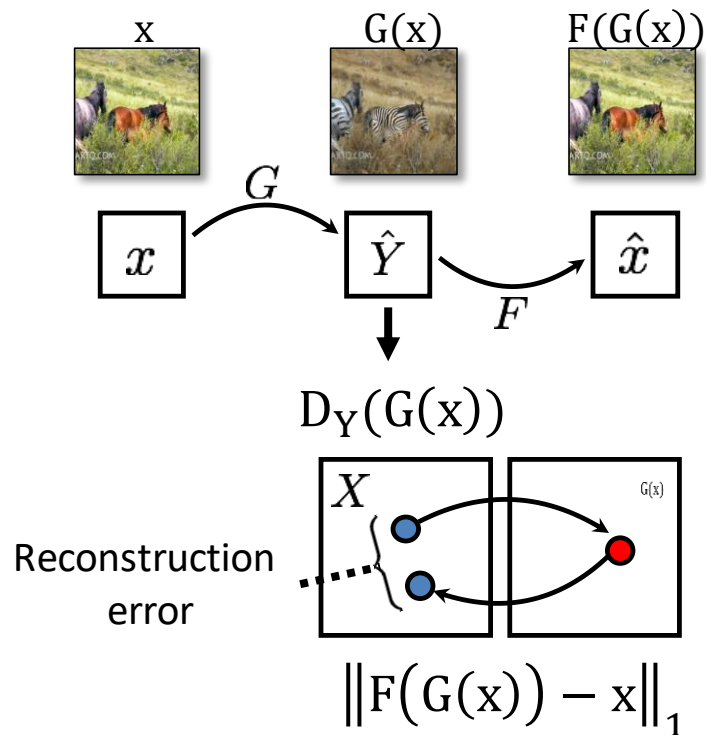
Cycle-Consistent Adversarial Networks



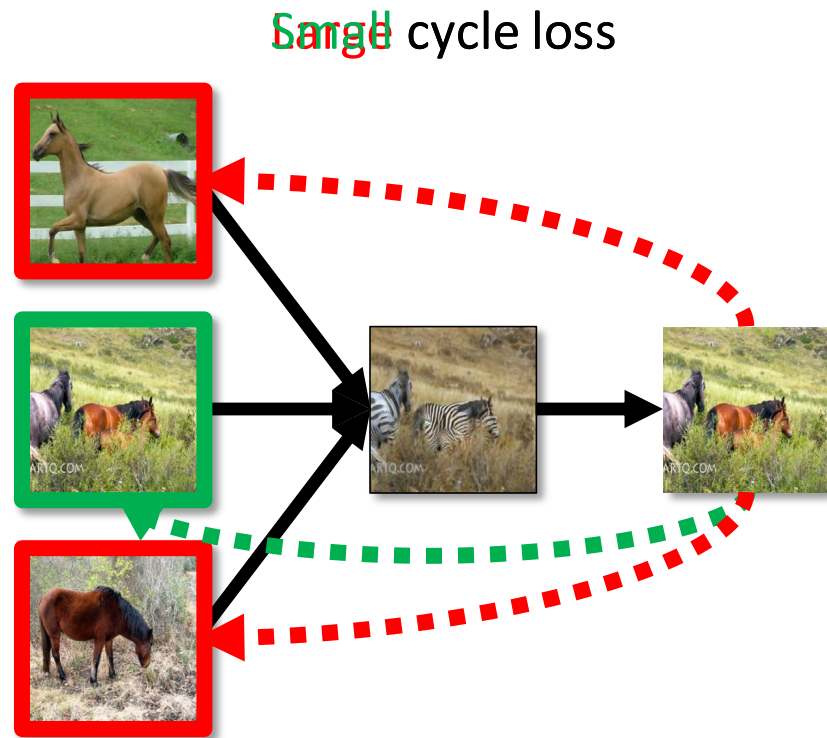
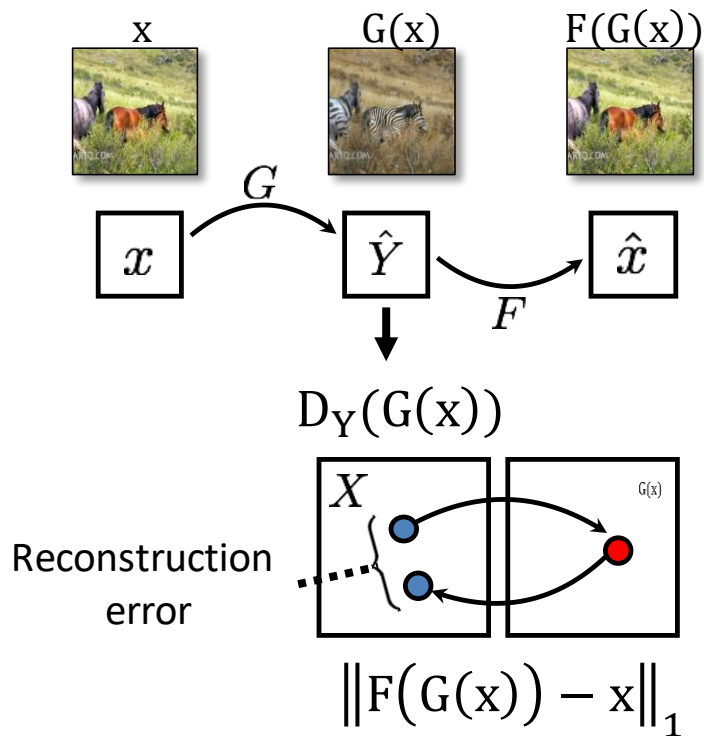
Cycle-Consistent Adversarial Networks



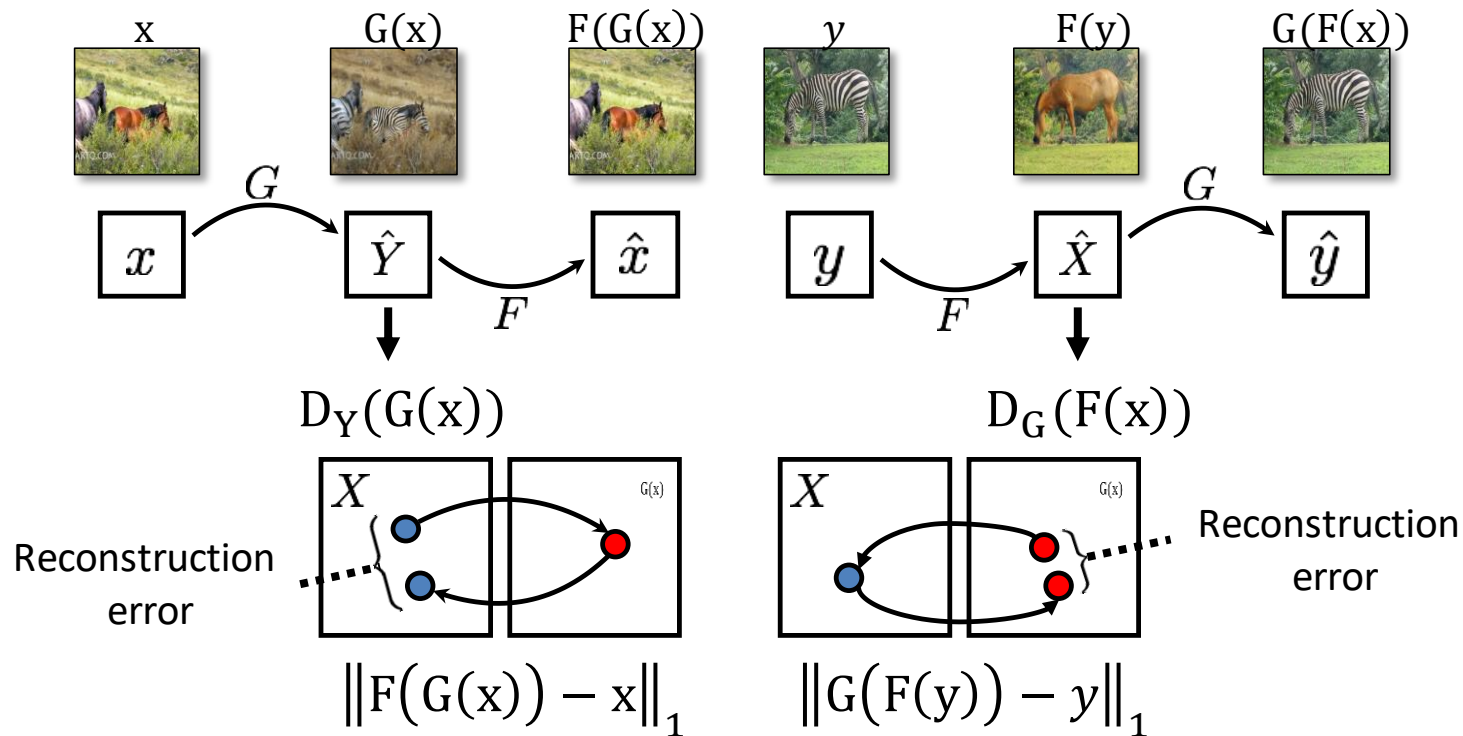
Cycle Consistency Loss



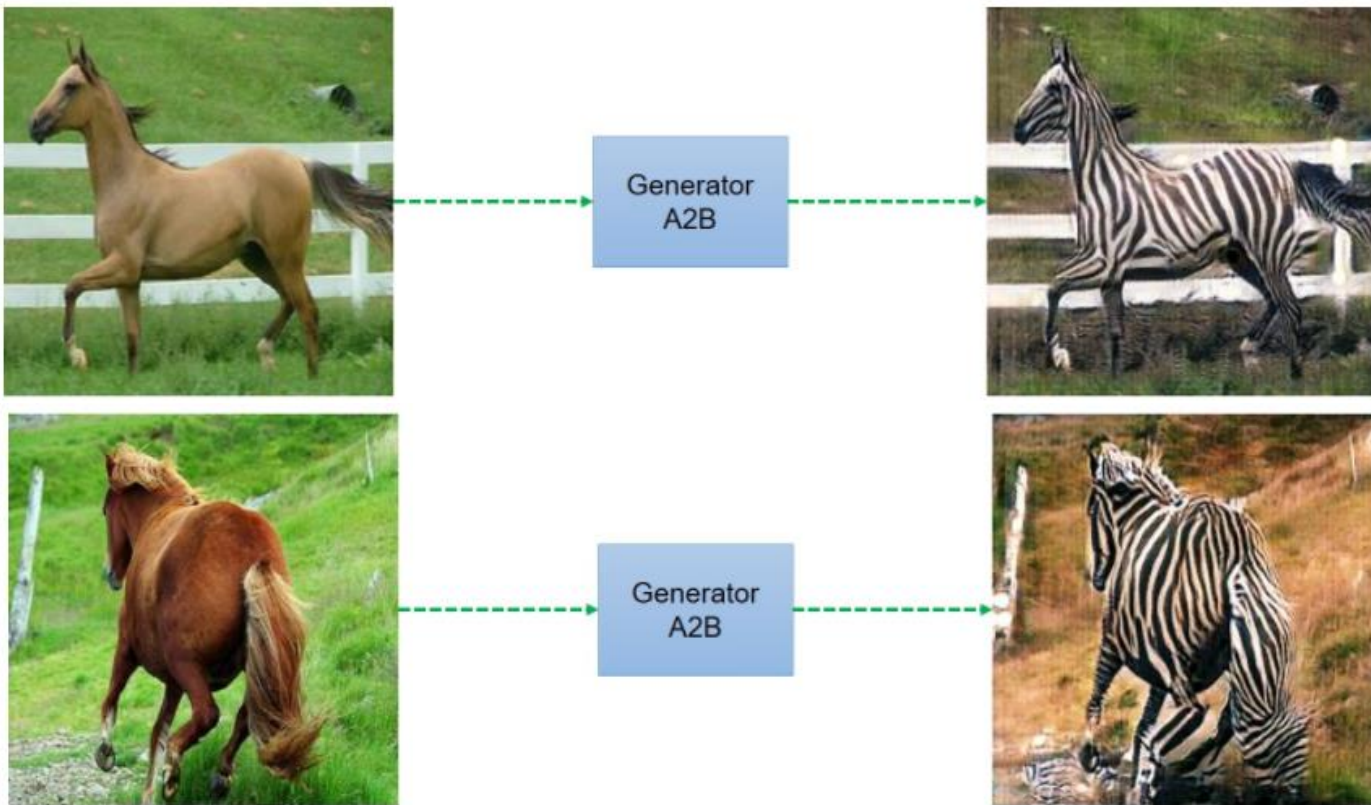
Cycle Consistency Loss



Cycle Consistency Loss



Cycle GAN - Overview



Cycle GAN: Objective

$$\mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) = \mathbb{E}_{y \sim p_{\text{data}}(y)} [\log D_Y(y)] \\ + \mathbb{E}_{x \sim p_{\text{data}}(x)} [\log(1 - D_Y(G(x)))],$$

Domain X

Domain Y

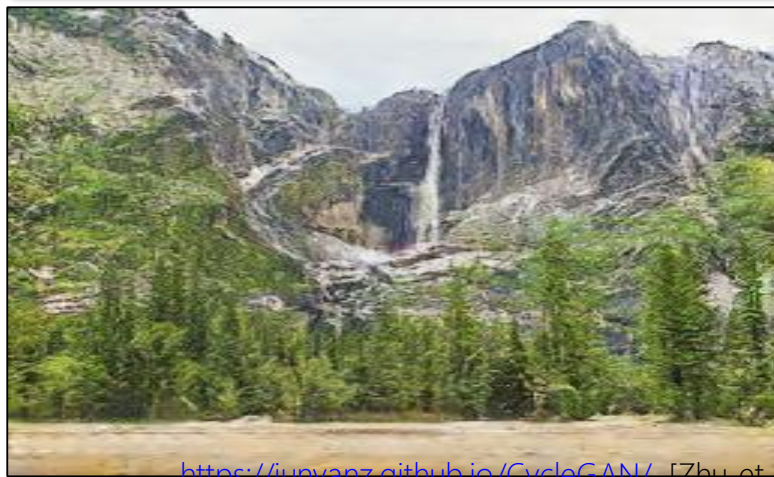
$$\mathcal{L}_{\text{cyc}}(G, F) = \mathbb{E}_{x \sim p_{\text{data}}(x)} [\|F(G(x)) - x\|_1] \\ + \mathbb{E}_{y \sim p_{\text{data}}(y)} [\|G(F(y)) - y\|_1].$$

Cycle consistency

Full Loss: $\mathcal{L}(G, F, D_X, D_Y) = \mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) \\ + \mathcal{L}_{\text{GAN}}(F, D_X, Y, X) \\ + \lambda \mathcal{L}_{\text{cyc}}(G, F),$

Monet's paintings → photos







Administrative

Administrative

- Deadline for final projects
 - Wed Feb 6th, 11:59pm
 - Submission via moodle
 - Submission must contain
 - Code (results must be replicable)
 - 2-3 pages of final report (at most 1 page of text, rest results; i.e., images and tables)
 - Use CVPR templates:
http://cvpr2019.thecvf.com/submission/main_conference/author_guidelines

Administrative

- Poster presentation
 - Friday Feb 8th, 1pm-3pm
 - Location:
 - Magistrale (preliminary – will update if it changes)
 - In the area next to the back entrance (parking lot direction)
 - Poster stands will be provided
 - You need to print posters yourself (poster@in.tum.de)
 - Hang posters 15 mins before presentation session starts

Guest Speakers

- Oriol Vinyals:
 - <https://ai.google/research/people/OriolVinyals>
 - Time: January 31st, 6pm – 8pm
 - Location: HS-1 (CS building – the big one)

Next Lectures

- Next Lecture -> Jan 21st
- Keep working on the projects!

Conditional Generative Adversarial Networks (cGANs) continued!