

Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A. Efros. "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks", in IEEE International Conference on Computer Vision (ICCV), 2017.

Presented by Shyamal H. Anadkat

AIPI 540, CV Module

Outline

1. What is **Image-to-Image Translation**?
2. What are **GANs***?
3. What are **CycleGANs**?
4. How does it work?
5. How did they evaluate it?
6. Do they work all the time?
7. Live demo
8. Q/A

Assumption: you know a bit about CNNs.*



Image-to- Image Translation

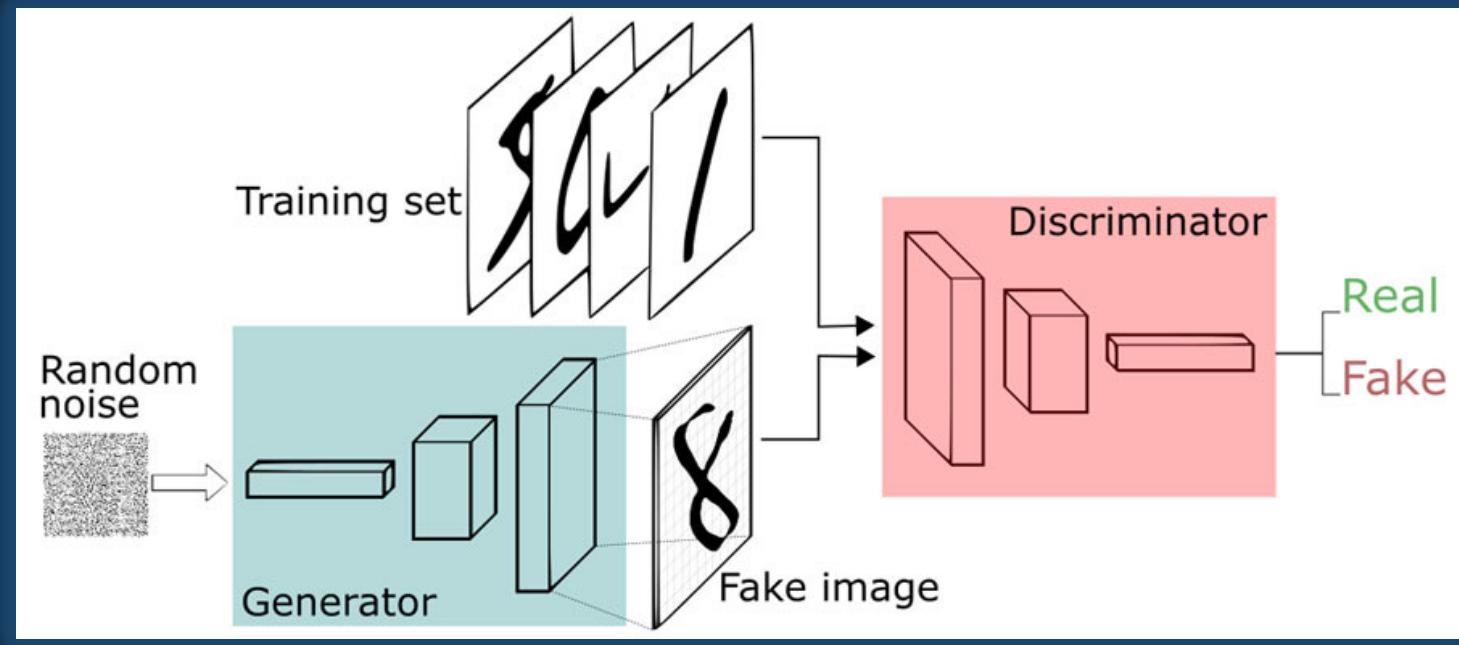
- Class of computer vision problems where goal is to “learn” the mapping between an input image (X) and an output image (Y)
- Wide range of **applications**, such as collection style transfer, object transfiguration, season transfer and photo enhancement.



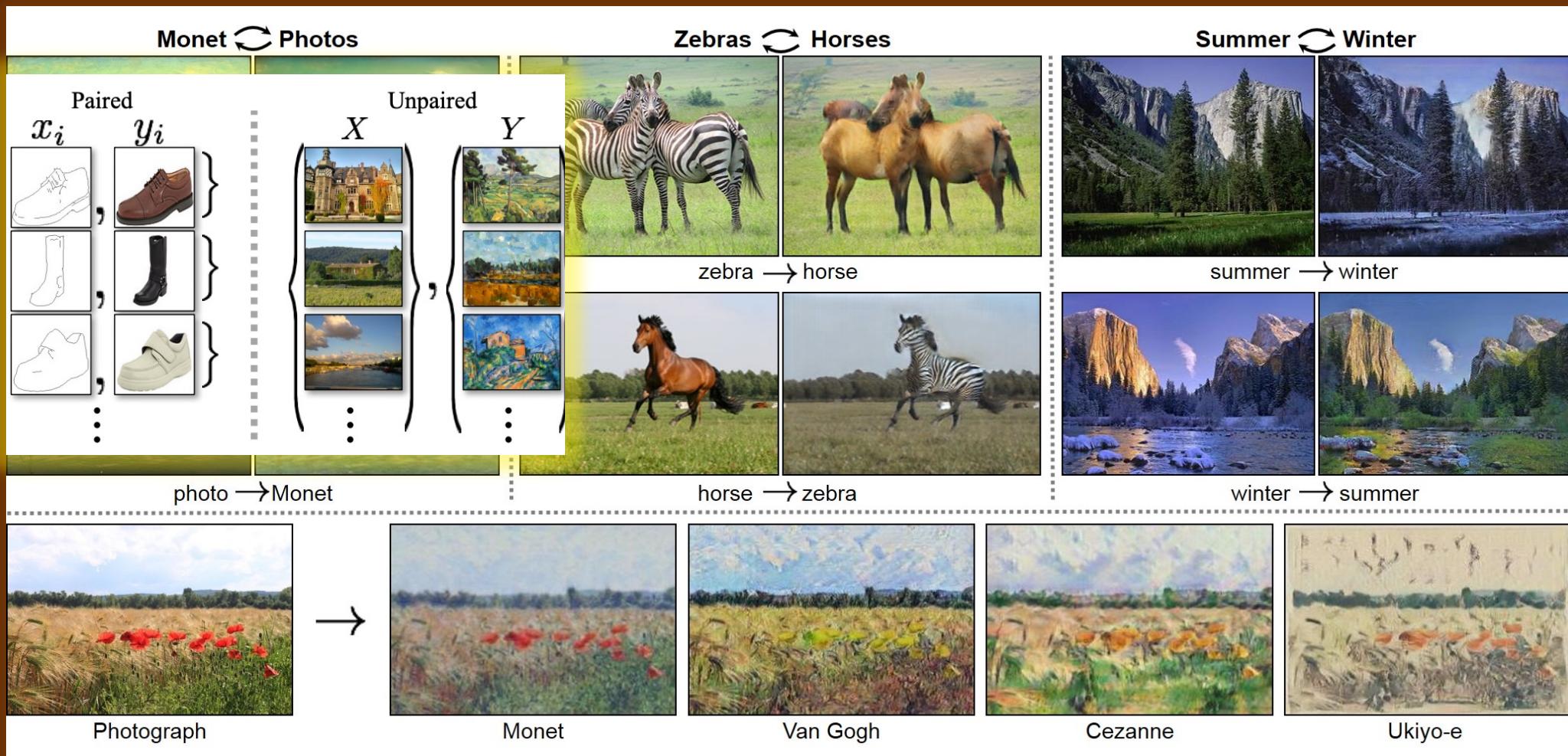
What are GANs?

General Adversarial Networks

- NN architecture introduced by Ian Goodfellow et al., in June '14, in their paper Generative Adversarial Nets
- Generator Network: Produces fake data from random inputs
- Discriminator Network: Separates true data from fake data



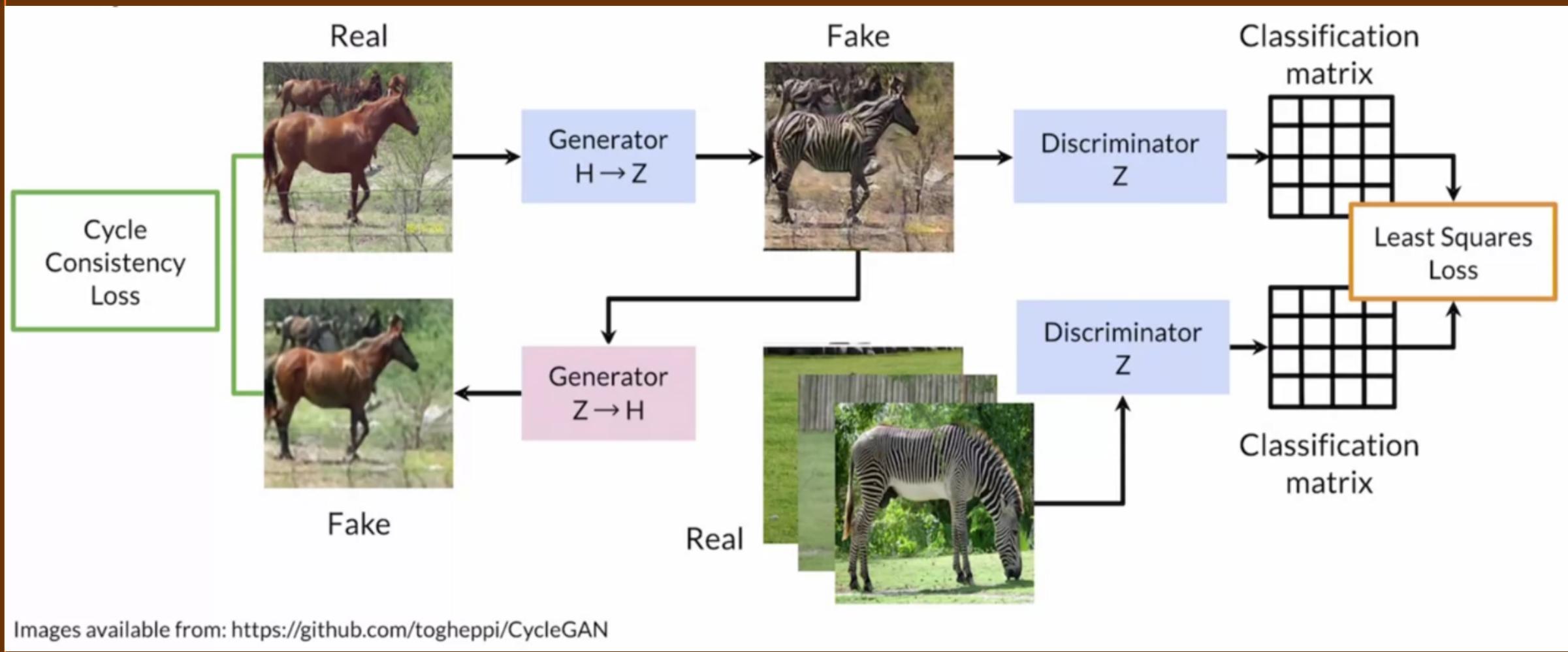
What are CycleGANs?



For two **unpaired** image collections X and Y , CycleGAN learns to “translate” an image from one domain into other and vice versa

Source: <https://junyanz.github.io/CycleGAN/>

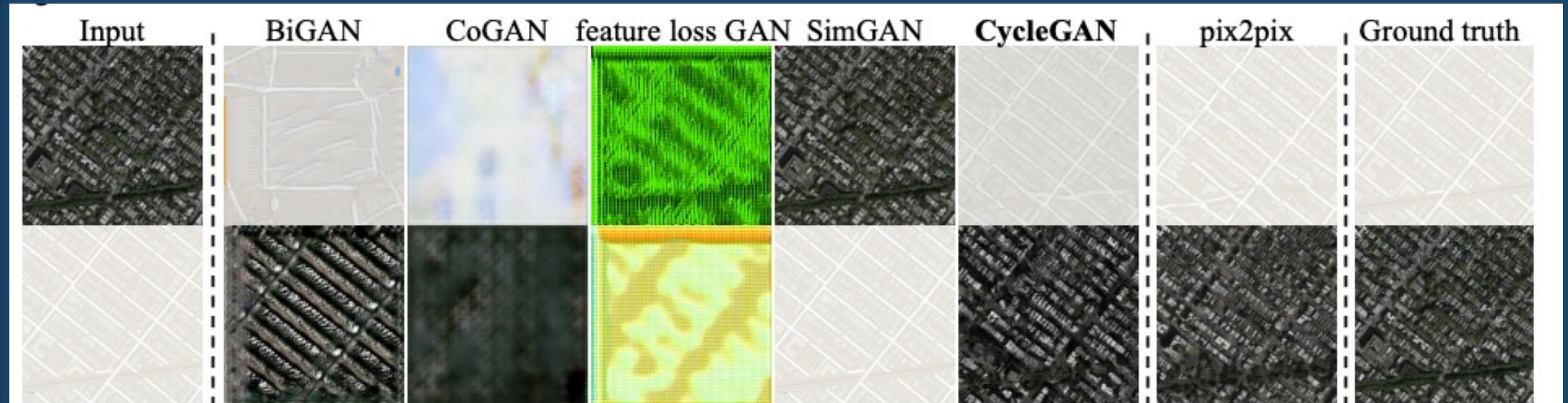
The intuition behind CycleGANs (2 GANs!)



Images available from: <https://github.com/togheppi/CycleGAN>

Source: <https://junyanz.github.io/CycleGAN/>

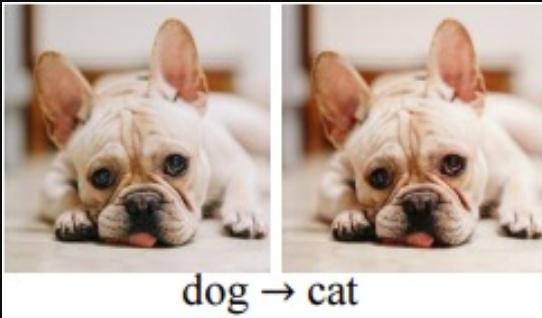
How did the authors evaluate their results?



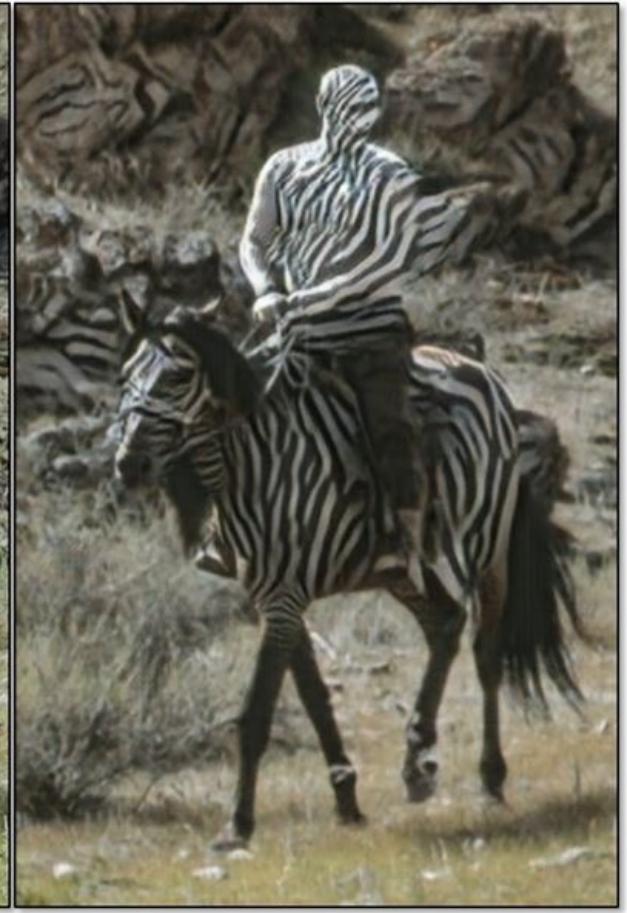
| Loss | Map → Photo | | Photo → Map | |
|--------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|
| | % Turkers labeled <i>real</i> |
| CoGAN [32] | 0.6% ± 0.5% | | 0.9% ± 0.5% | |
| BiGAN/ALI [9, 7] | 2.1% ± 1.0% | | 1.9% ± 0.9% | |
| SimGAN [46] | 0.7% ± 0.5% | | 2.6% ± 1.1% | |
| Feature loss + GAN | 1.2% ± 0.6% | | 0.3% ± 0.2% | |
| CycleGAN (ours) | 26.8% ± 2.8% | | 23.2% ± 3.4% | |

Table 1: AMT “real vs fake” test on maps↔aerial photos at 256×256 resolution.

CycleGAN Limitations



More varied
transformations like
geometric changes



Model does not work well when a test image looks unusual compared to training images

Due to changes in distribution characteristics
(test set vs. training set)

Live Demo

- [Link to Notebook](#)
- Demo notebook: <https://github.com/shyamal-anadkat/cycle-gan-demo/>
- W&B: <https://wandb.ai/shyamal/CycleGAN-and-pix2pix/runs/29q8w844?workspace=user-shyamal>
- Check out their Github Repo: <https://github.com/junyanz/CycleGAN>

Summary



CycleGAN uses two GANs for unpaired image-to-image translation



Cycle consistency loss ensures “realistic” translations and content to be preserved while only changing the styles



Applications in style transfer, object transfiguration etc. (**with some limitations)



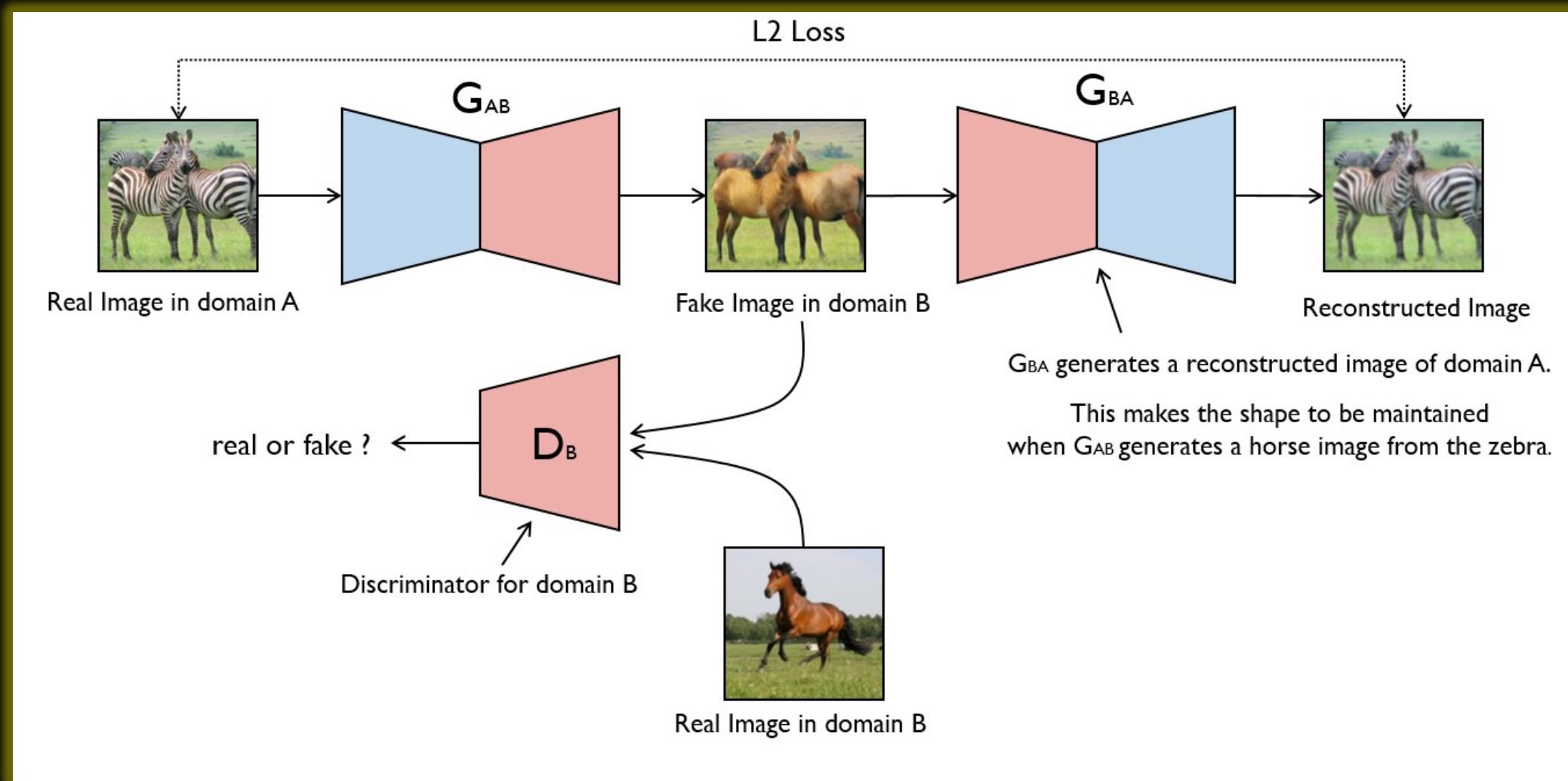
Implementations readily available in PyTorch & TensorFlow

Thank You!

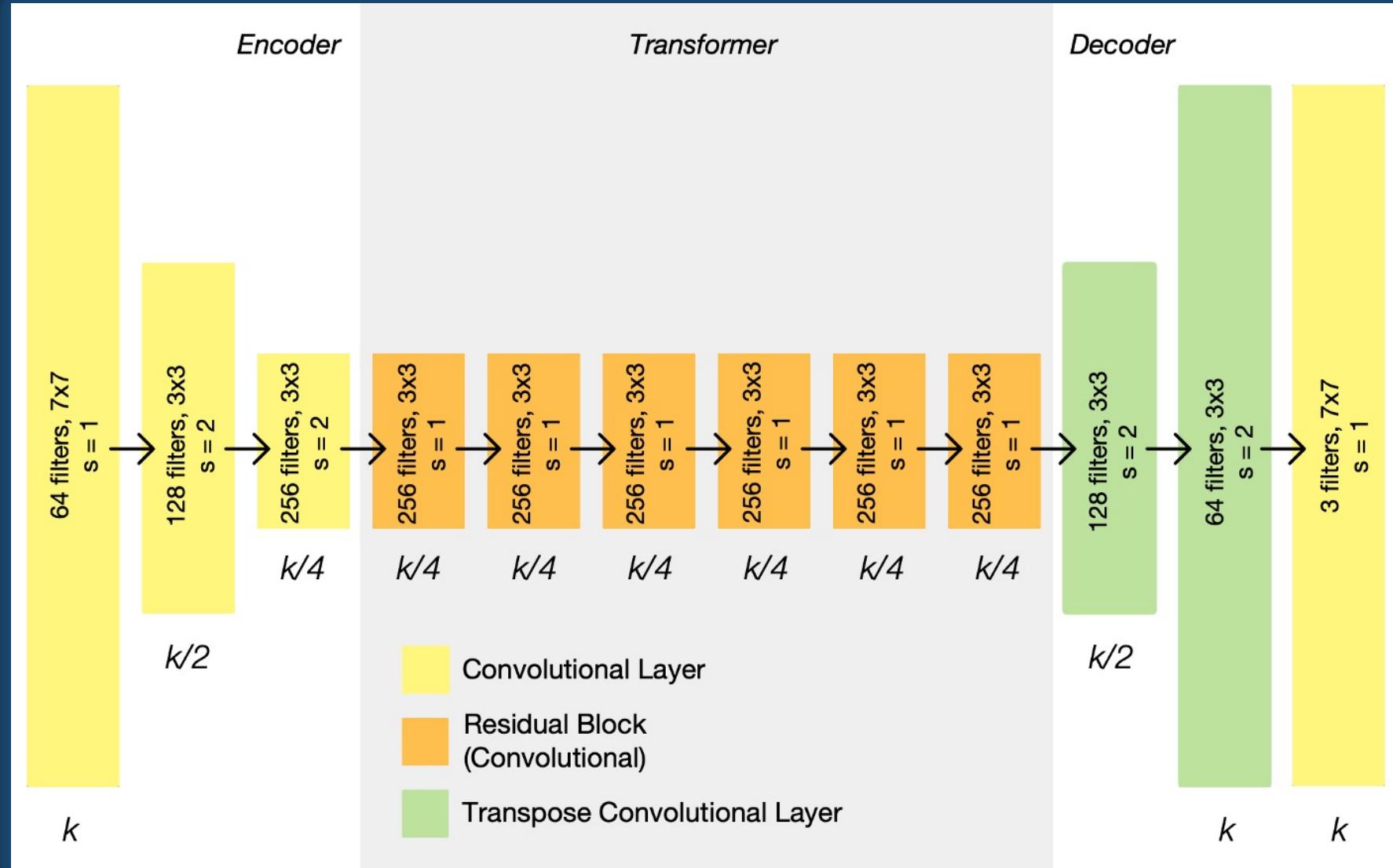
Thanking them:

- The paper! <https://arxiv.org/pdf/1703.10593v7.pdf>
- <https://github.com/junyanz/pytorch-CycleGAN-and-pix2pix>
- <https://junyanz.github.io/CycleGAN/>
- <https://medium.com/analytics-vidhya/>
- <https://github.com/yunjey/mnist-svhn-transfer>

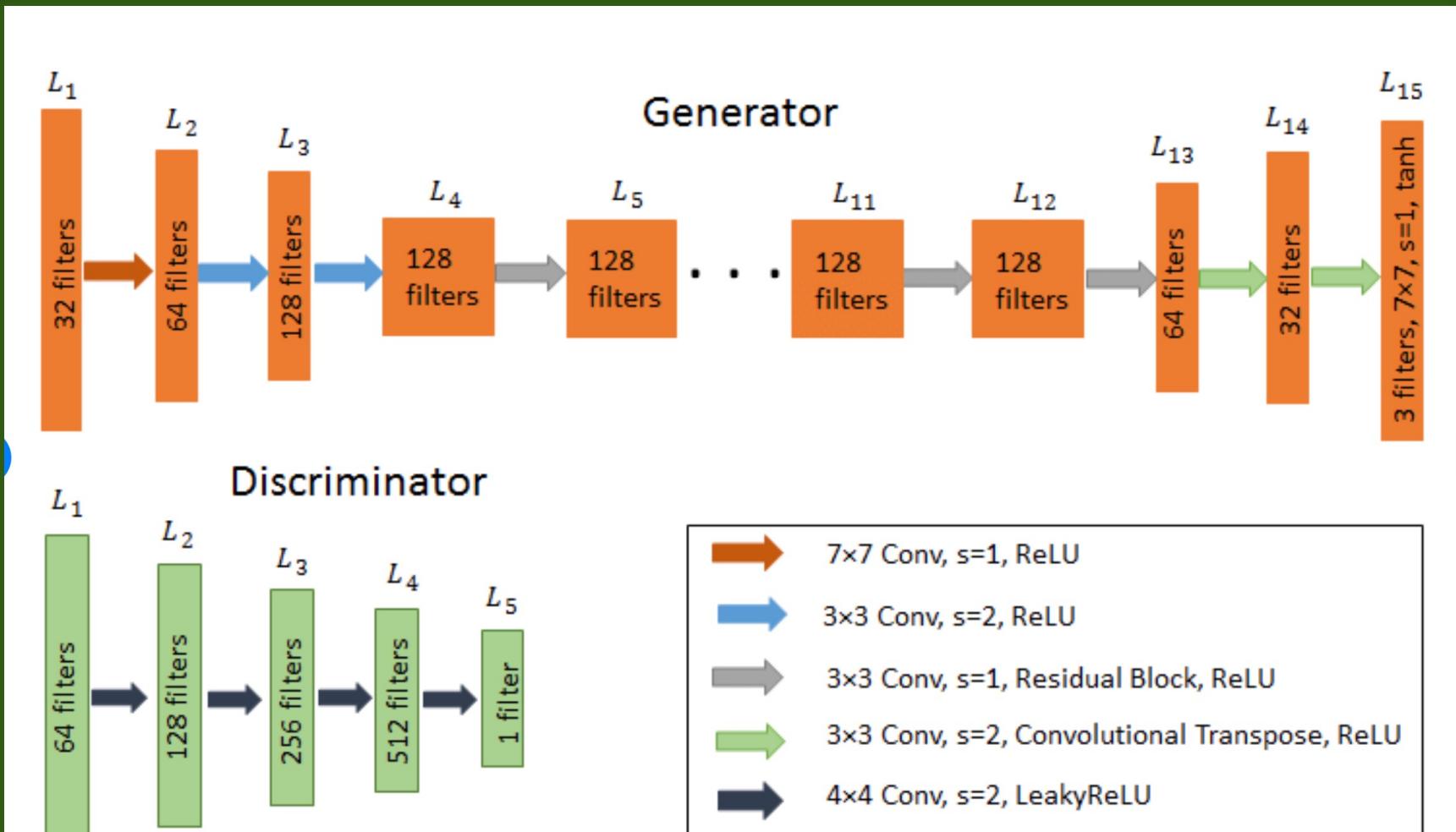
Addendum: Simplified CycleGAN



Addendum: Architecture



Addendum: Architecture



Architecture of the generator and discriminator of unpaired CycleGAN. Conv: 2D Convolutional filter, s: Stride, ReLU: Rectifier linear unit.

Addendum: Mathematical Intuition

- a) Two mapping functions $G: X \rightarrow Y$ and $F: Y \rightarrow X$ and discriminators. D_Y encourages G to translate X into outputs indistinguishable from domain Y , and vice versa for D_X and F .
- b) Forward cycle consistency loss: $x \rightarrow G(x) \rightarrow F(G(x)) \approx x$
- c) Backward cycle consistency loss: $y \rightarrow F(y) \rightarrow G(F(y)) \approx y$

