CycleGAN

Pattern Recognition & Machine Learning Laboratory
Geon-jun Yang

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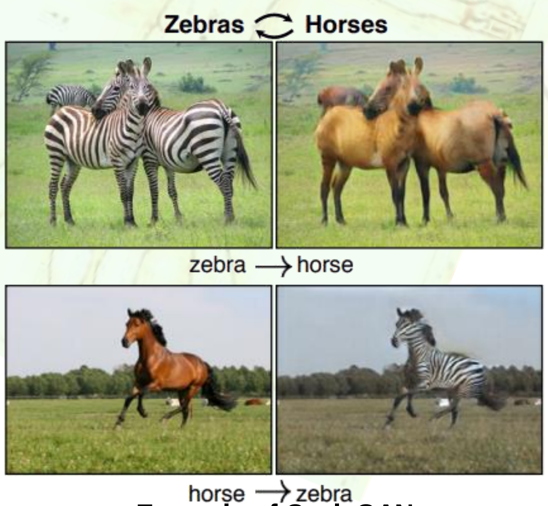
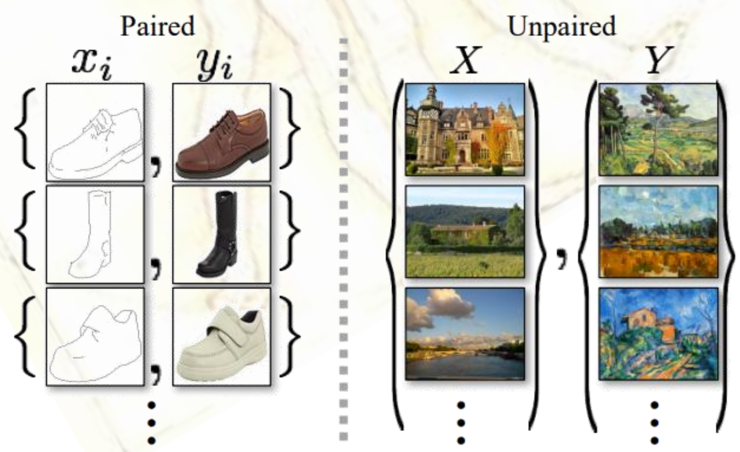
Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks [J. Zhu et al., 2017] (1/5)

- **Goal**
  - Image-to-image translation without paired train data
- **Motivation**
  - Obtaining paired training data is difficult and expensive
  - Assume there is underlying relationship between the domains
- **Method**
  - Translation should be cycle consistent
  - Add a cycle consistency loss
  - Combine with adversarial losses



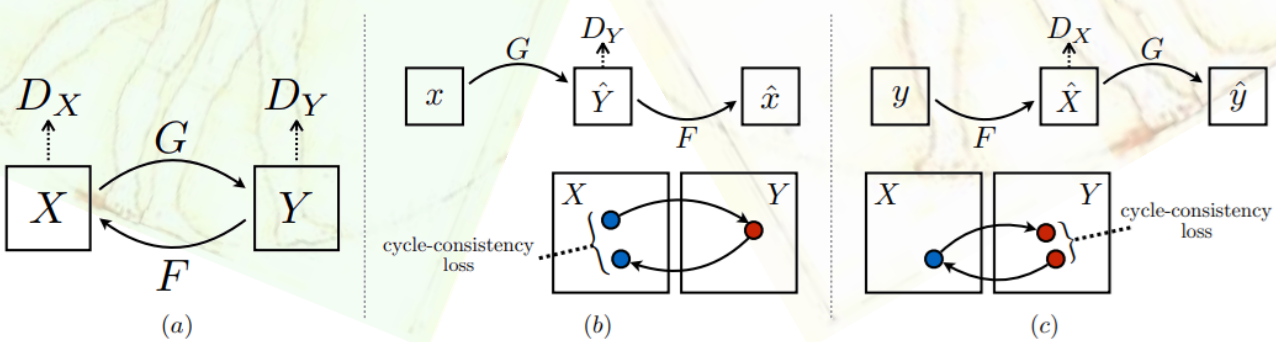
Example of CycleGAN



Types of datasets

Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks [J. Zhu et al., 2017] (2/5)

- **Formulation**
  - **Learn mapping functions between two domains**
    - $G : X \rightarrow Y$
    - $F : Y \rightarrow X$
  - **Adversarial loss**
    - G: generator, D_Y: discriminator
    - $L_{GAN}(G, D_Y, X, Y) = E_{y\sim P_{data}(y)}[\log D_Y(y)] + E_{x\sim P_{data}(x)}[\log(1 - D_Y(G(x)))]$
    - G tries to minimize the function, while D_Y tries to maximize it
  - **Cycle consistency loss**
    - Adversarial losses alone can't guarantee a desired output
    - Learned mapping functions should be cycle-consistent
    - $L_{GAN}(G, F) = E_{y\sim P_{data}(y)}\left[\left\|F(G(x)) - x\right\|_1\right] + E_{x\sim P_{data}(x)}\left[\left\|G(F(y)) - y\right\|_1\right]$



formulations

Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks [J. Zhu et al., 2017] (3/5)

- **Implementation**
  - **Network architecture**
    - **Three conv layers, several residual blocks, two conv layer with stride ½**
    - **Instance normalization, PatchGANs**
- **Results**
  - **Amazon Mechanical Turk (AMT)**
    - **Real vs fake test on maps↔aerial photos**
    - **CycleGAN fooled participants on around quarter of trials**
    - **All other methods almost never fooled participants**
  - **Fully Convolutional Network (FCN) score**
    - **Cityscapes labels→photos**
    - **CycleGAN outperforms the baselines**

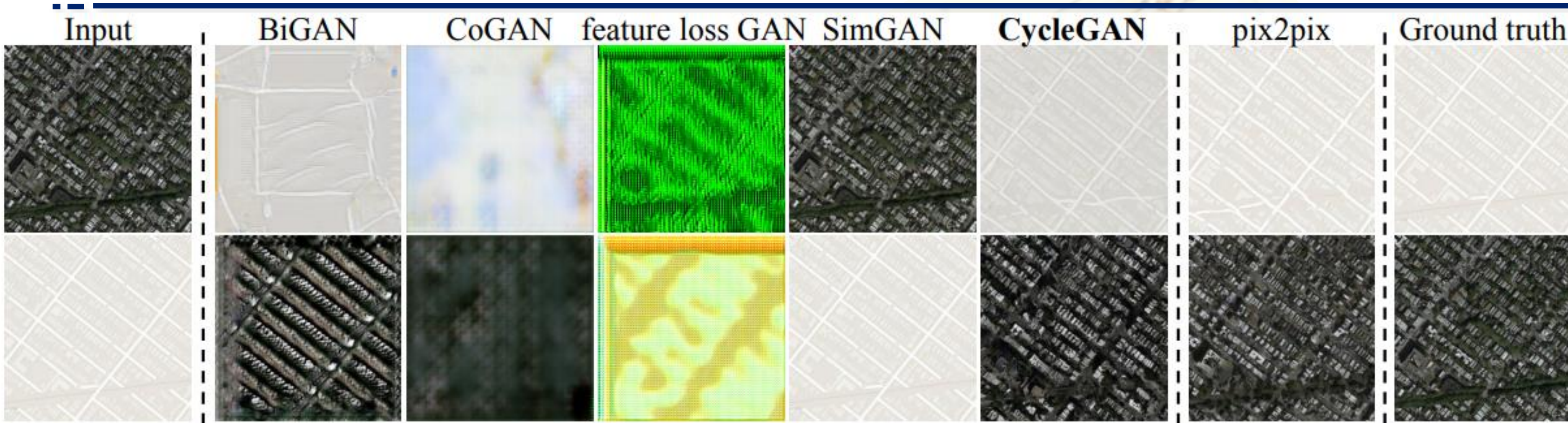
Table 1 Real vs fake test

Loss	Map → Photo % Turkers labeled *real*	Photo → Map % Turkers labeled *real*
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 2 FCN-scores on cityscapes

Loss	Per-pixel acc.	Per-class acc.	Class IOU
CoGAN [32]	0.40	0.10	0.06
BiGAN/ALI [9, 7]	0.19	0.06	0.02
SimGAN [46]	0.20	0.10	0.04
Feature loss + GAN	0.06	0.04	0.01
CycleGAN (ours)	**0.52**	**0.17**	**0.11**

Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks [J. Zhu et al., 2017] (4/5)



Photos↔Google Maps

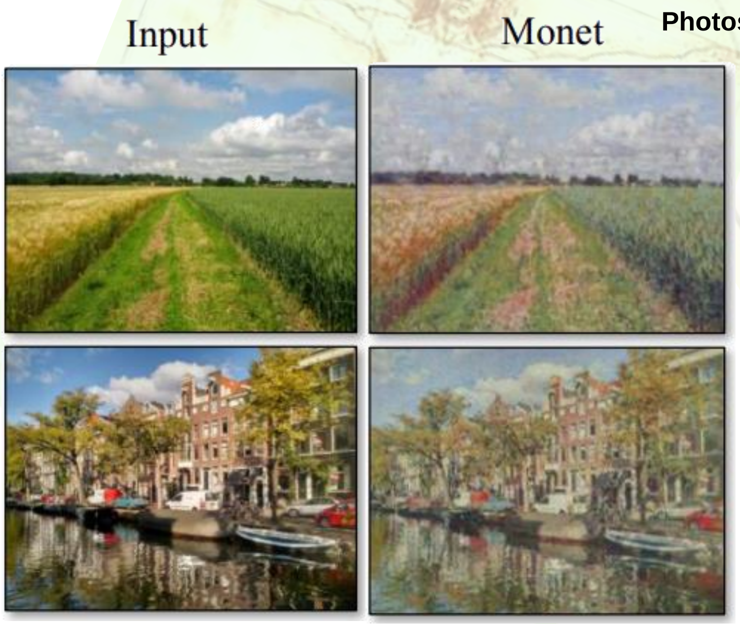
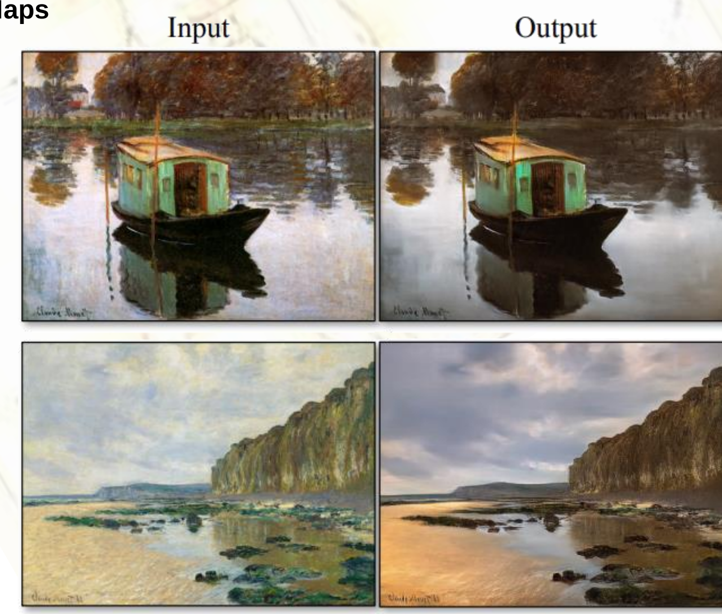


Photo to artistic style of Monet



Paintings to photographic style

J. Zhu, T. Park, P. Isola and A. Efros, “Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks," *ICCV,* 2017.

Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks [J. Zhu et al., 2017] (5/5)

- **Limitations and Discussion**
  - **Tasks that require geometric changes**
    - **dog→cat transfiguration**
    - **Caused by generator architectures**
  - **Distribution characteristics of training datasets**
    - **ImageNet dataset doesn’t contain images of a person riding a horse**
  - **Lingering gap between the results**
    - **Paired training data and unpaired datasets**

dog → cat

winter → summer

horse → zebra