

# Introduction



# Image-to-Image Translation

Learn the mapping between an input image and an output image using a training set of aligned image pairs.



### Unpaired Image-to-Image Translation

Learn the mapping G between two data domains X and Y without having paired examples such that G(X) is indistinguishable from Y.

# Introduction



#### **GANs**

Adopt an adversarial loss to learn the mapping such that the translated images cannot be distinguished from the images in the target domain.



### **Cycle Consistency**

As adversary loss is not enough to find the right mapping, Cycle consistency Loss is adopted to prevent collapse.

#### Monet C Photos



Monet  $\rightarrow$  photo

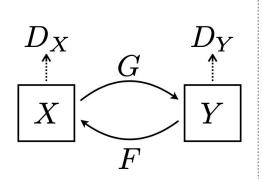


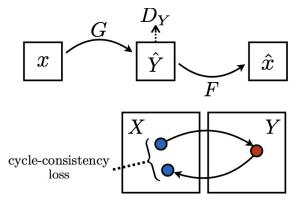
photo  $\rightarrow$  Monet

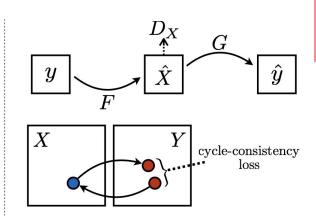
# **CycleGAN**

- Captures the characteristics of the input collection and learns to translate them into a target collection without being trained on image pairs
- Implemented by GANs and Cycle consistency loss.

# **Formulation**







- Two mappings  $G: X \rightarrow Y \text{ and } F: Y \rightarrow X$
- Dx and Dy are discriminators
- G and F are generators

Forward
 cycle-consistency loss:
 x → G(x) → F (G(x)) ≈ x

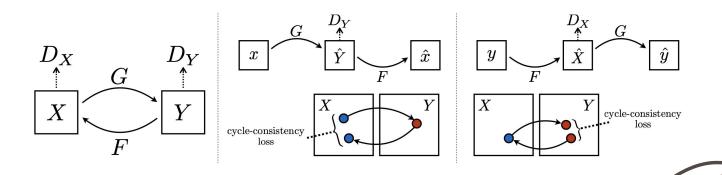
Backward
 cycle-consistency loss:
 y → F (y) → G(F (y)) ≈ y

# **Formulation**

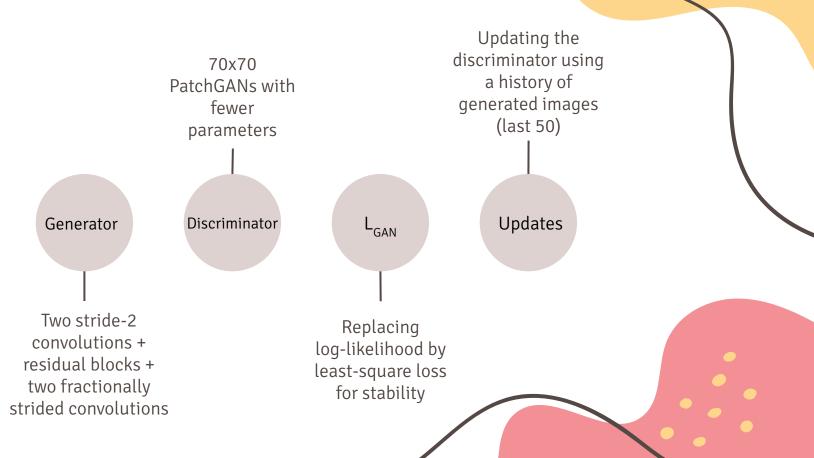
$$\mathcal{L}_{GAN}(G, D_Y, X, Y) = \mathbb{E}_{y \sim p_{\text{data}}(y)}[\log D_Y(y)] + \mathbb{E}_{x \sim p_{\text{data}}(x)}[\log(1 - D_Y(G(x)))]$$

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

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



# **Implementation**



# **Evaluation**



# **Qualitative Evaluation**

25 participants per algorithm using Amazon Mechanical Turk



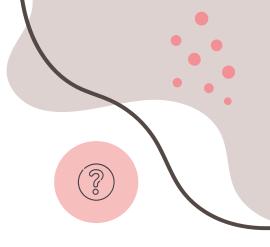
# **Quantitative Evaluation**

FCN Score used in predicting a label for a generated image and comparing it with the original label



#### **Baselines**

CoGAN SimGAN BiGAN/ALI Pix2pix

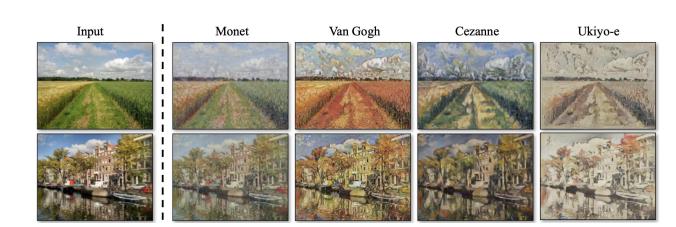


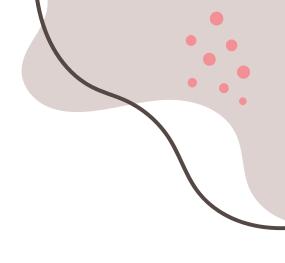
#### **Ablations**

Both cycle loss and GAN losses are necessary to achieve the best possible results

# **Application: Collection Style Transfer**

Mimic the style of of an entire collection of artworks rather than the style of a single image





# Application: Object Transfiguration and Season

Translate one object into another object of the same category.

**Transfer** 













zebra → horse





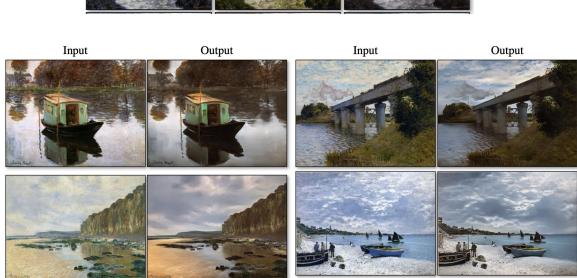




winter Yosemite → summer Yosemite

# Application: Photo generation from paintings

Painting to photo translation using an additive loss L<sub>identity</sub>to to preserve the coloring



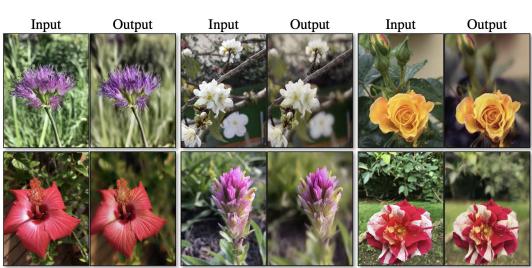
CycleGAN

Input

CycleGAN+Lidentity

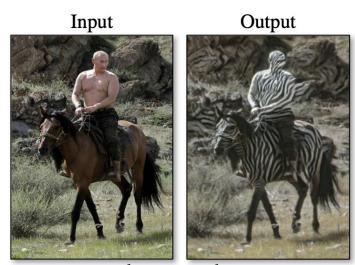
# **Application: Photo enhancement**

Decreasing the depth of field in photos taken by smartphones



# Conclusion

- CycleGAN is the first GAN-based unpaired image-to-image translator
- Models the mapping in a cycle with GAN Loss and cycle-consistency loss
- Limitations in geometric changes and failures due to distribution characteristics of the training set



horse → zebra



# Thanks!

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