### Copyright Notice

These slides are distributed under the Creative Commons License.

<u>DeepLearning.Al</u> makes these slides available for educational purposes. You may not use or distribute these slides for commercial purposes. You may make copies of these slides and use or distribute them for educational purposes as long as you cite <u>DeepLearning.Al</u> as the source of the slides.

For the rest of the details of the license, see <a href="https://creativecommons.org/licenses/by-sa/2.0/legalcode">https://creativecommons.org/licenses/by-sa/2.0/legalcode</a>

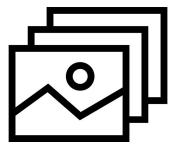


deeplearning.ai

# Unpaired Image-to-Image Translation

#### Outline

- Paired vs. unpaired image-to-image translation
- Unpaired image-to-image translation
  - Mapping between two piles of image styles
  - Finding commonalities and differences



Edges to photo



Paired images

Edges to photo

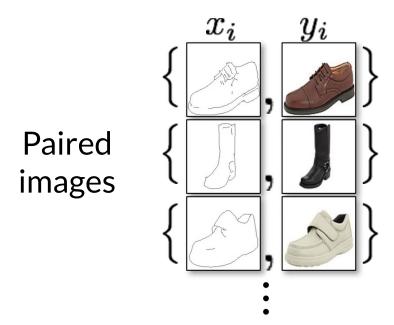


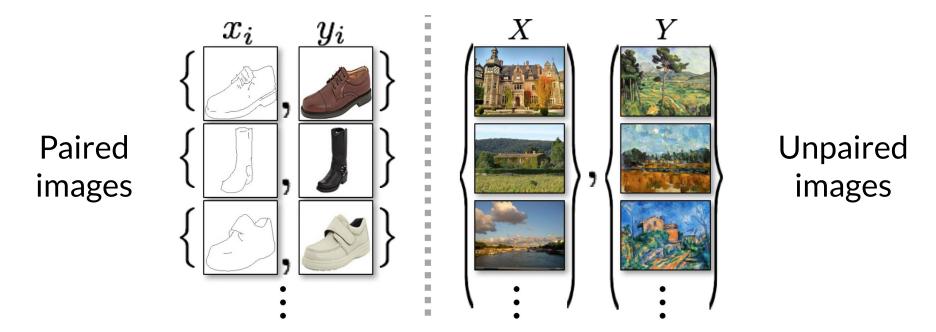
Paired images

Monet to photo



**Unpaired** images

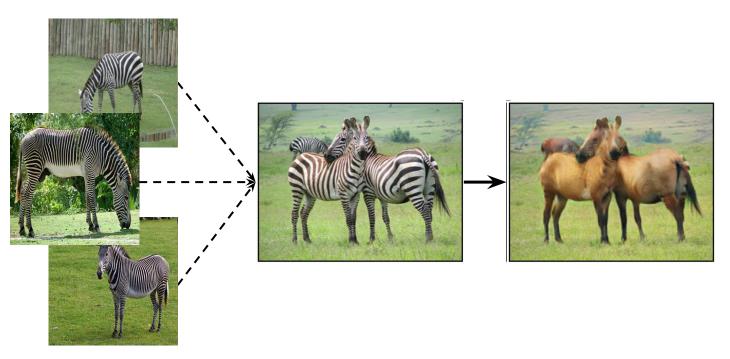




#### **Unpaired Image-to-Image Translation**

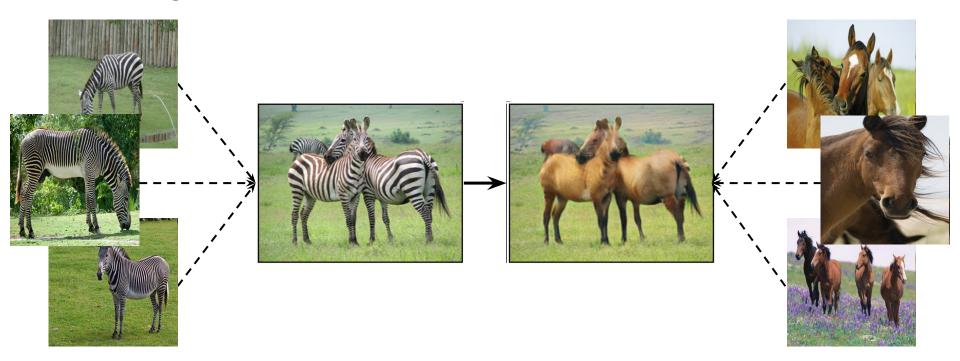


#### Mapping Between Two Piles



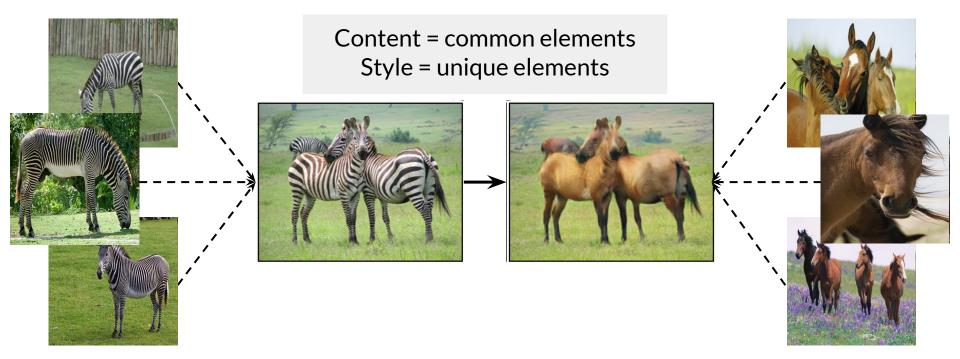
(Center) Images available from: https://arxiv.org/abs/1703.10593 (Side) Images available from: https://github.com/togheppi/CycleGAN

#### Mapping Between Two Piles



(Center) Images available from: https://arxiv.org/abs/1703.10593 (Sides) Images available from: https://github.com/togheppi/CycleGAN

#### Mapping Between Two Piles



(Center) Images available from: https://arxiv.org/abs/1703.10593 (Sides) Images available from: https://github.com/togheppi/CycleGAN

#### Summary

- Unpaired image-to-image translation:
  - Learns a mapping between two piles of images
  - Examines common elements of the two piles (content) and unique elements of each pile (style)
- Unlike paired image-to-image translation, this method is unsupervised



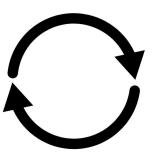


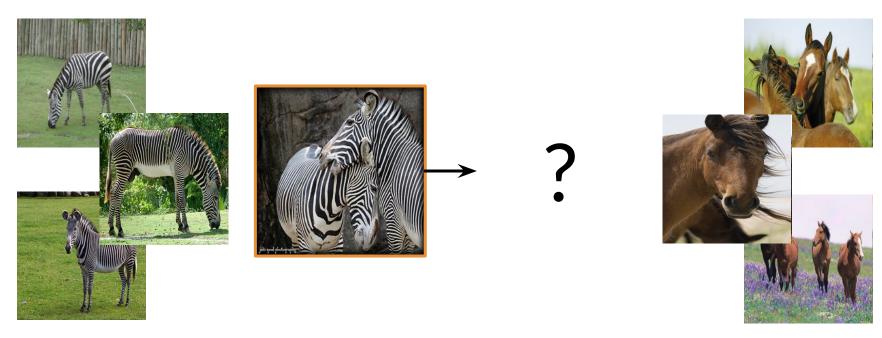
deeplearning.ai

## CycleGAN Overview

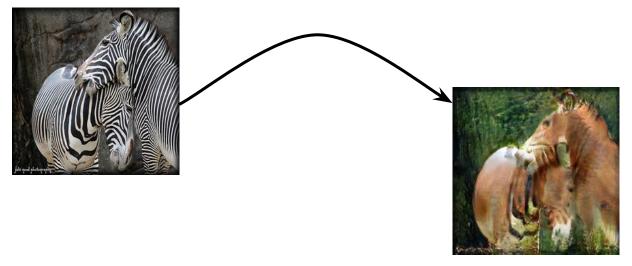
#### Outline

- Overview of CycleGAN
  - The "Cycle" in CycleGAN
  - o Two GANs!



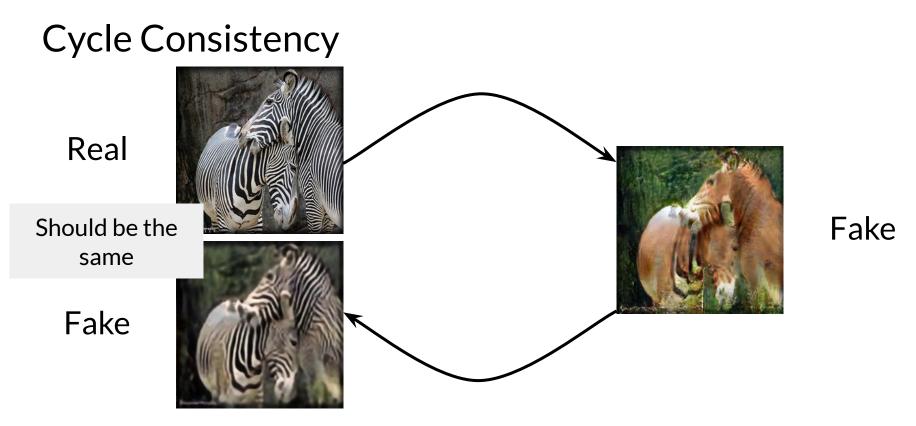


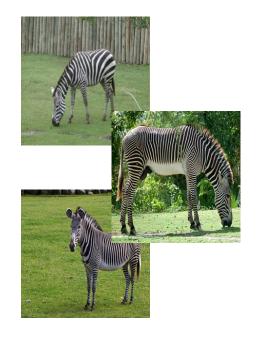
Real

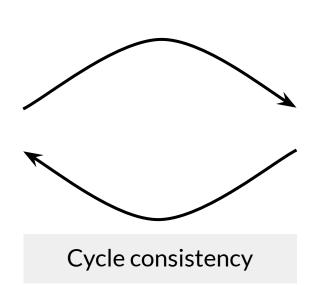


Fake

Real Fake Fake

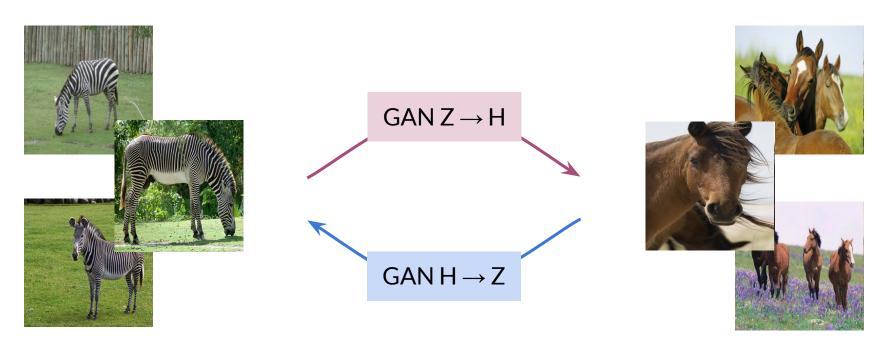




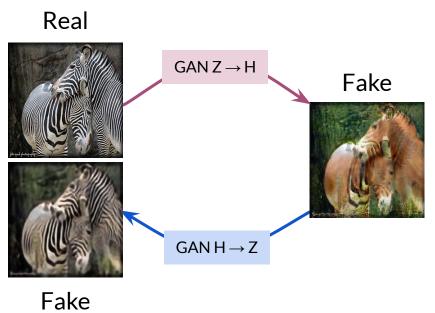




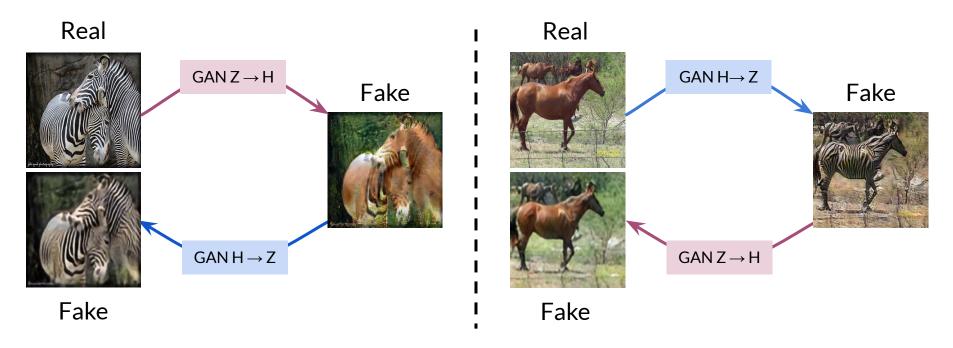
#### Two GANs

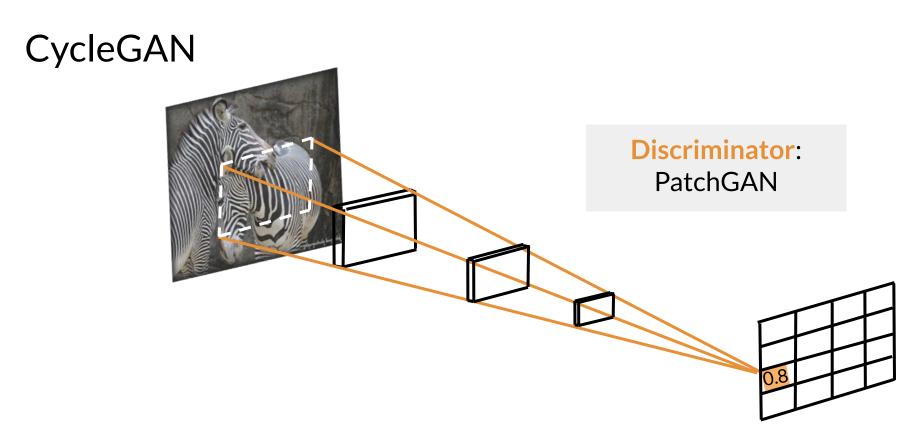


#### Two GANs

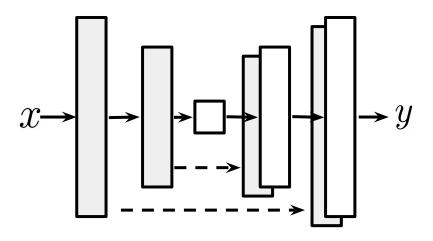


#### Two GANs



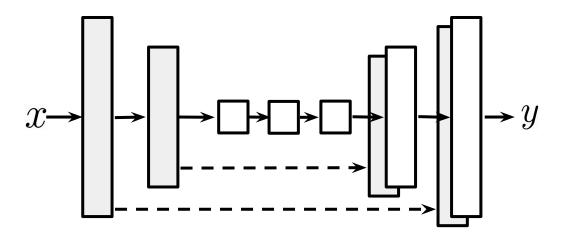


#### CycleGAN



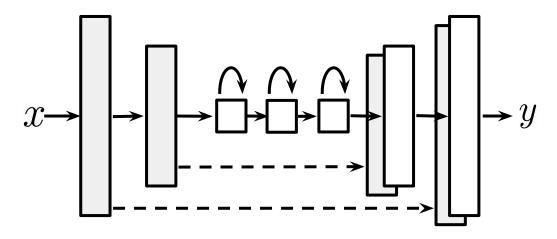
Generator ≈ U-Net

#### CycleGAN



Generator ≈ U-Net + DCGAN generator

#### CycleGAN



Additional skip connections

Generator ≈ U-Net + DCGAN generator

#### Summary

- CycleGAN uses two GANs for unpaired image-to-image translation
- The discriminators are PatchGAN's
- The generators are similar to a U-Net and DCGAN generator with additional skip connections



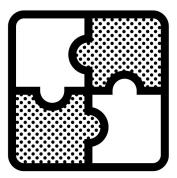


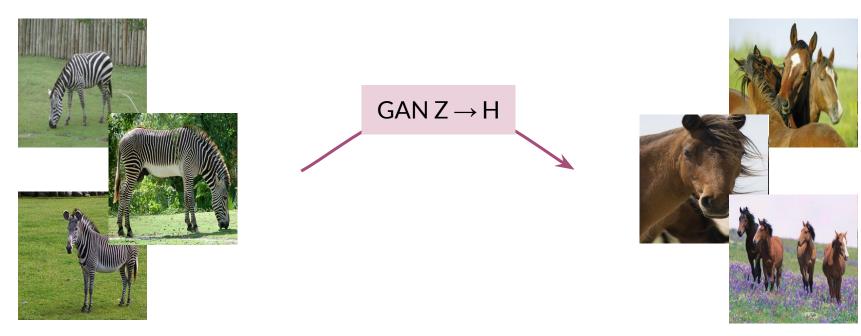
deeplearning.ai

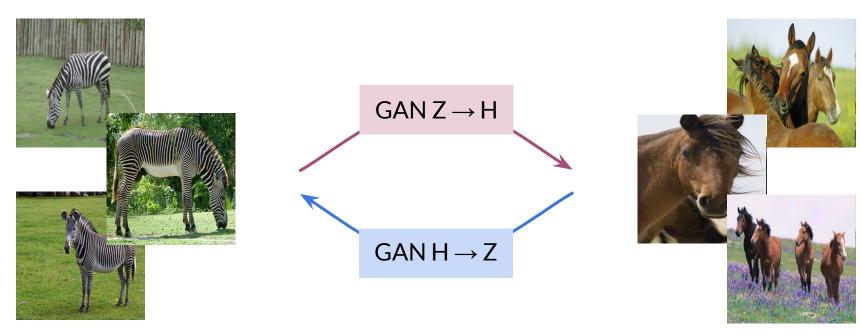
# CycleGAN: Two GANs

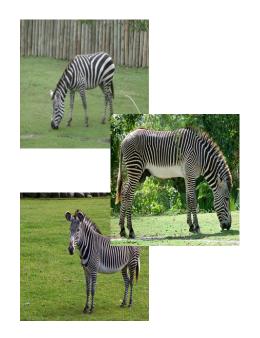
#### Outline

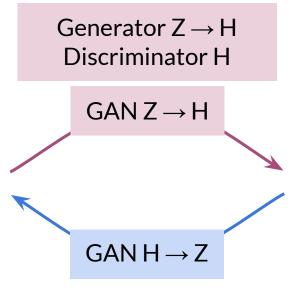
- Two GANs, four components
  - Two generators
  - Two discriminators



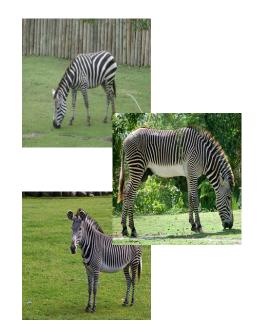








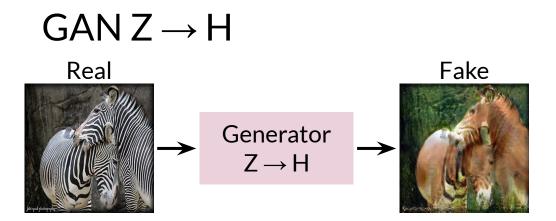


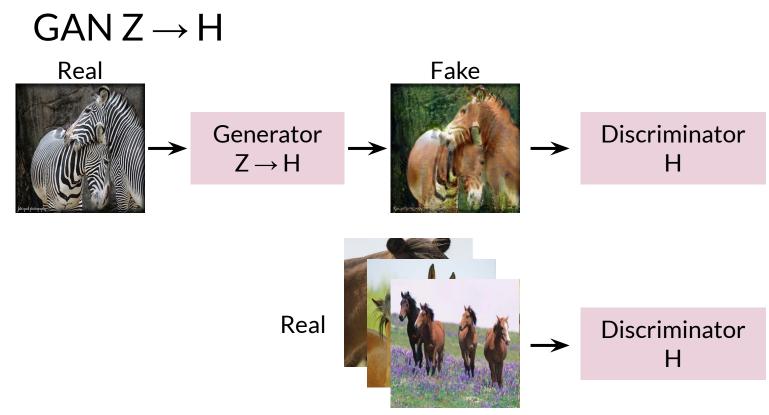


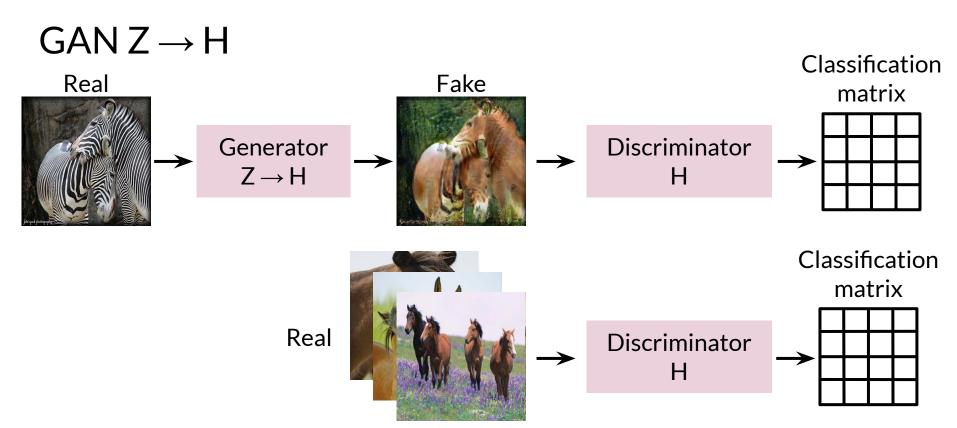
Generator  $Z \rightarrow H$ Discriminator H  $GANZ \rightarrow H$  $\mathsf{GAN}\,\mathsf{H}\to\mathsf{Z}$ Generator  $H \rightarrow Z$ 

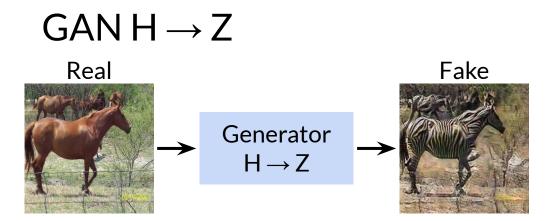
Images available from: https://github.com/togheppi/CycleGAN

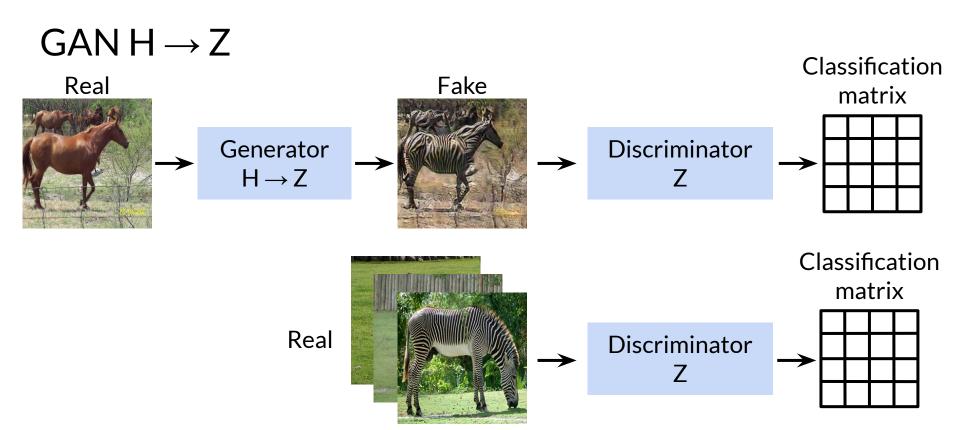
Discriminator Z





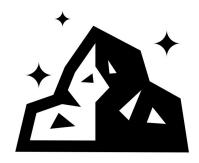






# Summary

- CycleGAN has four components:
  - Two generators
  - Two discriminators
- The inputs to the generators and discriminators are similar to Pix2Pix, except:
  - There are no real target outputs
  - Each discriminator is in charge of one pile of images



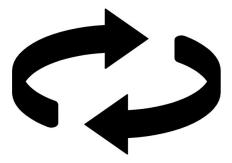


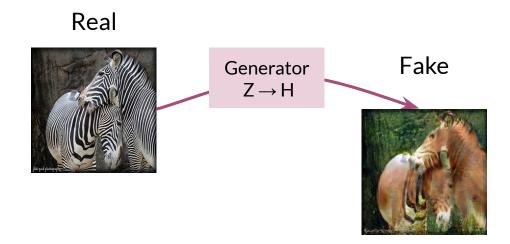
deeplearning.ai

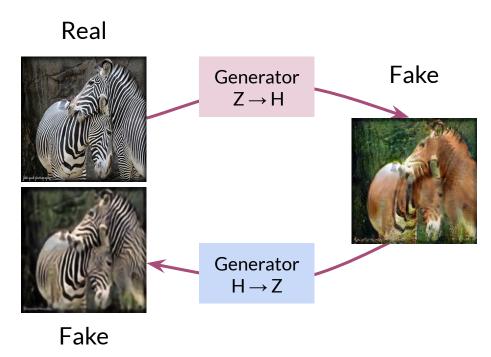
# CycleGAN: Cycle Cycle Consistency

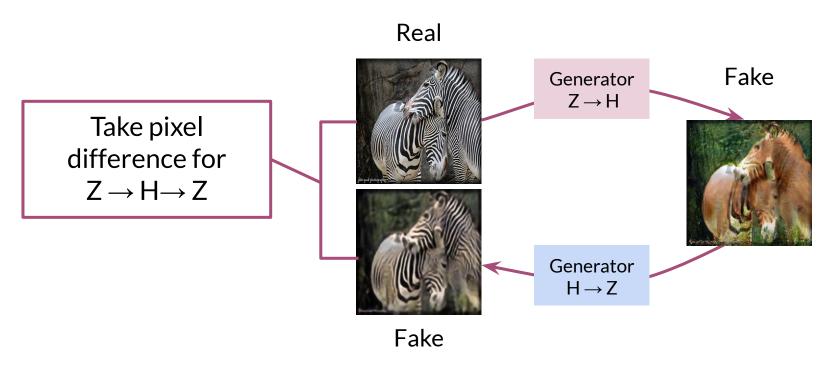
#### **Outline**

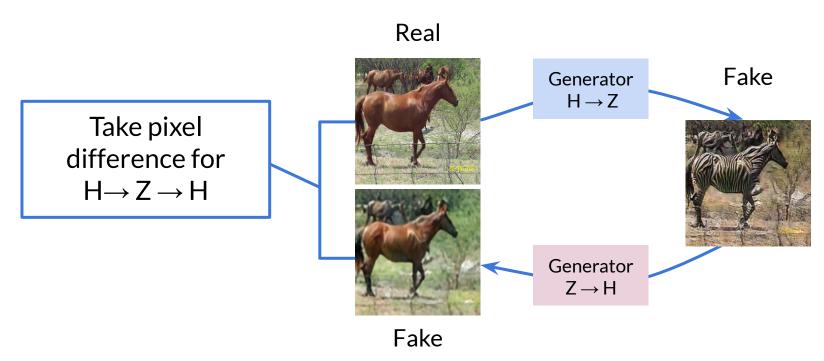
- Encouraging cycle consistency
  - Cycle Consistency Loss term
- Loss with cycle consistency for each of two GANs
- How cycle consistency helps

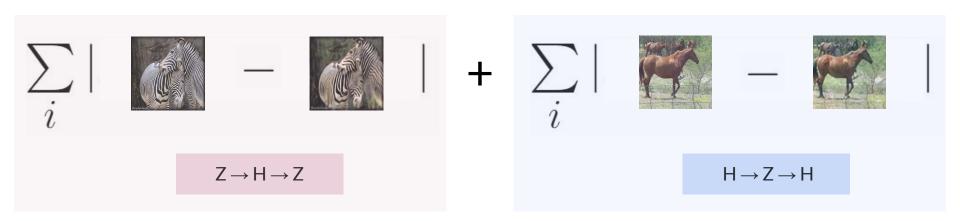






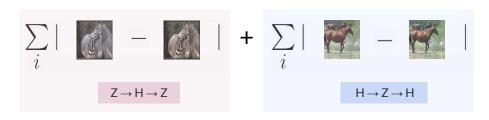






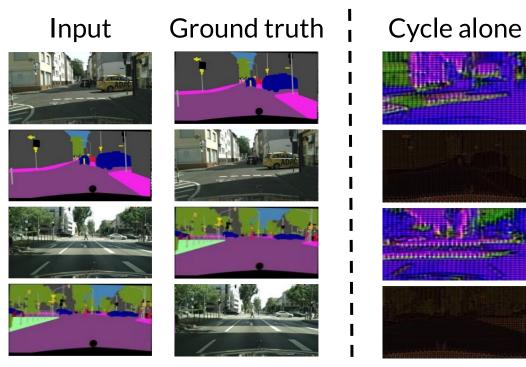
Cycle Consistency Loss is the sum of both directions

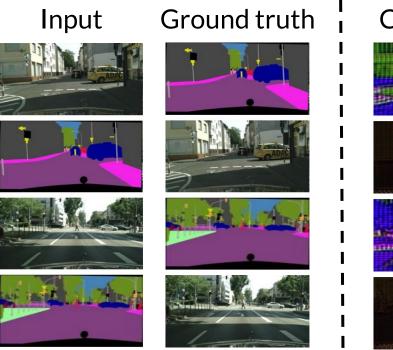
Adversarial Loss +

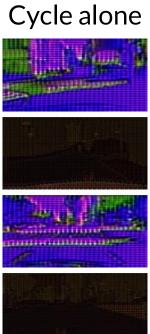


Adversarial Loss + Cycle Consistency Loss

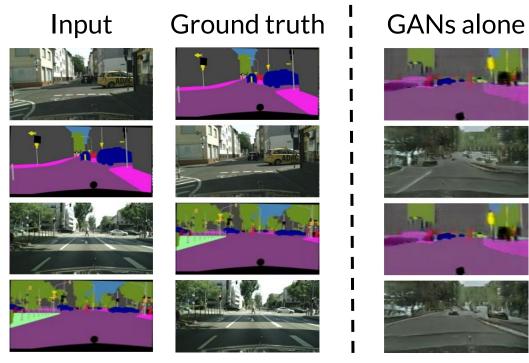
Adversarial Loss + λ \* Cycle Consistency Loss



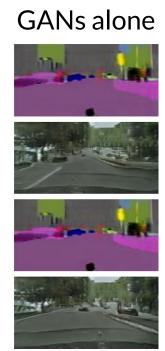




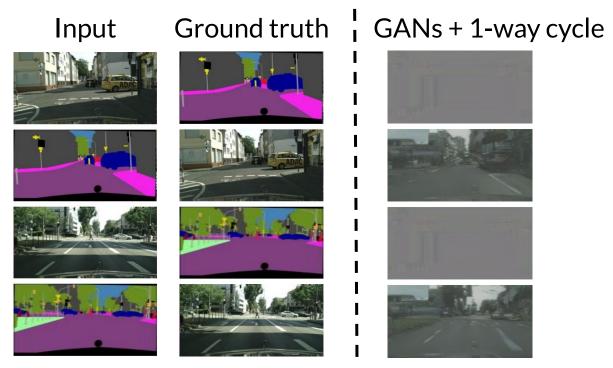
Without Adversarial GAN Loss, outputs are not realistic



# Ground truth Input

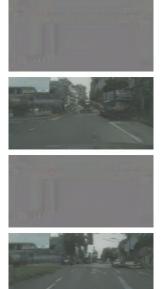


Without Cycle Consistency Loss, outputs show signs of mode collapse

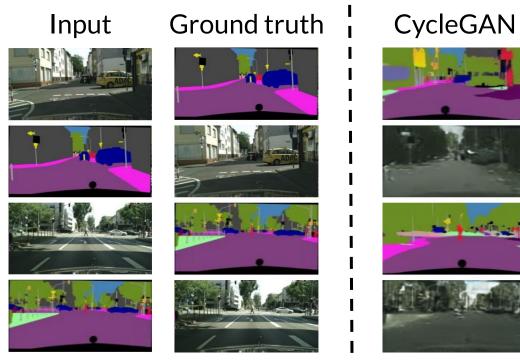


Input

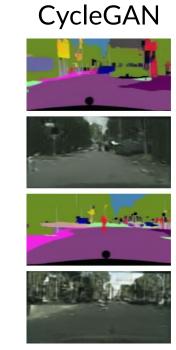
Ground truth GANs + 1-way cycle



Without **full** Cycle Consistency Loss, outputs see mode collapse too



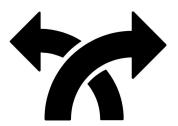
Ground truth Input



CycleGAN uses both
Adversarial Loss and
Cycle Consistency Loss

#### Summary

- Cycle consistency helps transfer uncommon style elements between the two GANs, while maintaining common content
- Add an extra loss term to each generator to softly encourage cycle consistency
- Cycle consistency is used in both directions



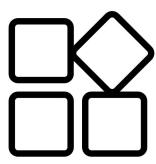


deeplearning.ai

# CycleGAN: Least Squares Loss

#### Outline

- Least squares in statistics
- Least Squares Loss in GANs
  - Discriminator
  - Generator



# Least Squares Loss: Another GAN Loss Function

- Came out when training stability was a big problem in GANS
  - Similar time to WGAN-GP

# Least Squares Loss: Another GAN Loss Function

- Came out when training stability was a big problem in GANS
  - Similar time to WGAN-GP
- Helps with vanishing gradients and mode collapse

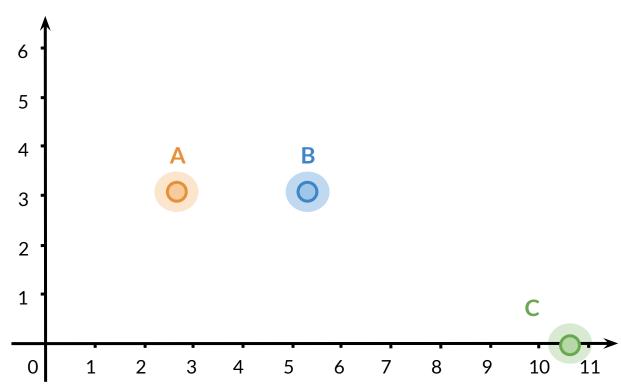


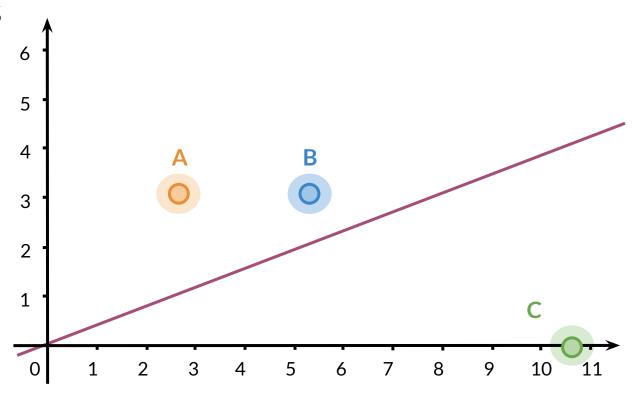
# Least Squares Loss: Another GAN Loss Function

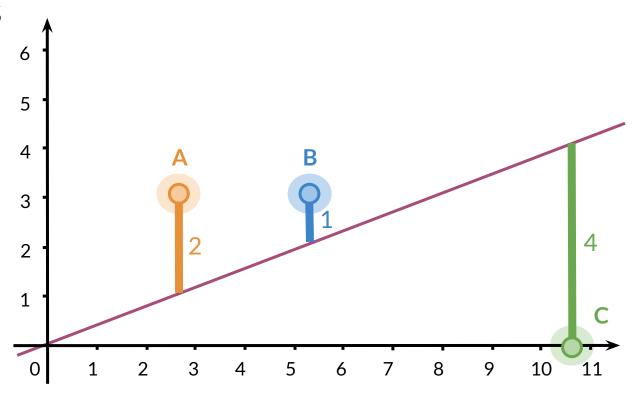
- Came out when training stability was a big problem in GANS
  - Similar time to WGAN-GP
- Helps with vanishing gradients and mode collapse

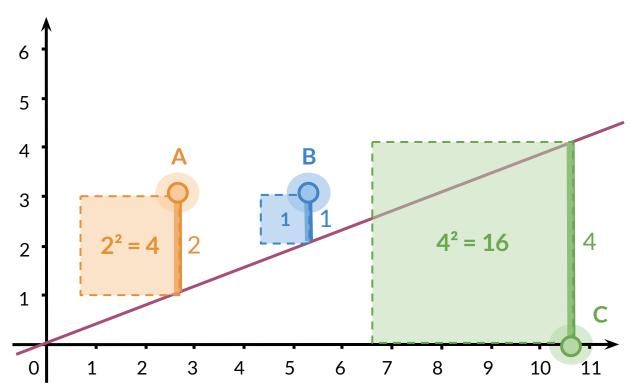


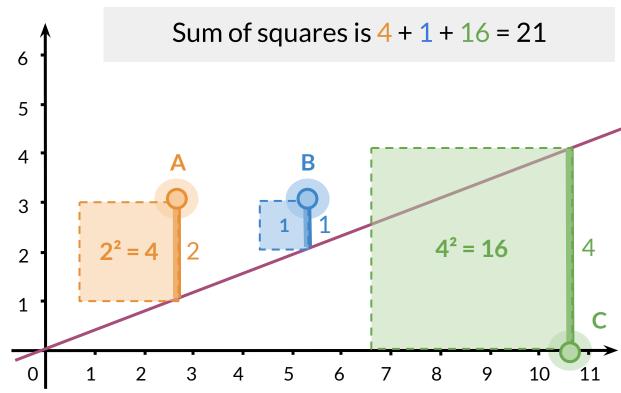
GAN loss functions are chosen empirically



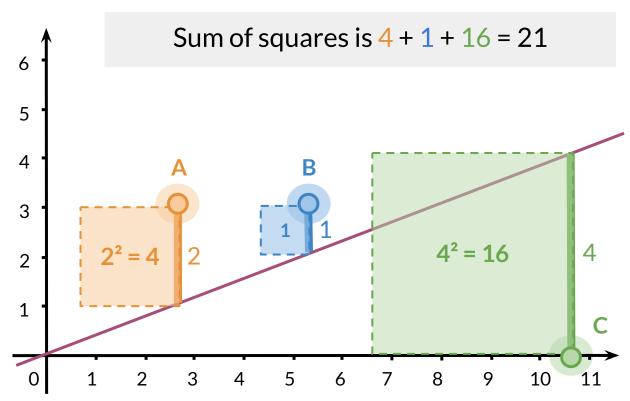








Minimize sum of squares



# **Least Squares Loss: Discriminator**

$$(D(\boldsymbol{x})-1)^2$$

Discriminator classification of real image **x** 

# Least Squares Loss: Discriminator

$$\mathbb{E}_{m{x}}ig[(D(m{x})-1)^2ig]$$

# Least Squares Loss: Discriminator

$$\mathbb{E}_{oldsymbol{x}}ig[(D(oldsymbol{x})-1)^2ig]+ (D(G(oldsymbol{z}))-0)^2$$

Discriminator classification of fake image G(z)

# **Least Squares Loss: Discriminator**

$$\mathbb{E}_{oldsymbol{x}}igl[(D(oldsymbol{x})-1)^2igr]+\mathbb{E}_{oldsymbol{z}}igl[(D(G(oldsymbol{z}))-oldsymbol{0})^2igr]$$

# Least Squares Loss: Discriminator

$$\mathbb{E}_{oldsymbol{x}}ig[(D(oldsymbol{x})-1)^2ig]+\mathbb{E}_{oldsymbol{z}}ig[(D(G(oldsymbol{z})))^2ig]$$

# Least Squares Loss: Generator

$$\mathbb{E}_{oldsymbol{z}}ig[(D(G(oldsymbol{z}))-1)^2ig]$$

Discriminator Loss 
$$\mathbb{E}_{m{x}}ig[(D(m{x})-1)^2ig]+\mathbb{E}_{m{z}}ig[(D(G(m{z})))^2ig]$$

Discriminator Loss 
$$\mathbb{E}_{m{x}}ig[(D(m{x})-1)^2ig]+\mathbb{E}_{m{z}}ig[(D(G(m{z})))^2ig]$$

Generator

$$\mathbb{E}_{oldsymbol{z}}ig[(D(G(oldsymbol{z}))-1)^2ig]$$

Discriminator Loss

$$\mathbb{E}_{oldsymbol{x}}ig[(D(oldsymbol{x})-1)^2ig]+\mathbb{E}_{oldsymbol{z}}ig[(D(G(oldsymbol{z})))^2ig]$$

Generator Loss

$$\mathbb{E}_{oldsymbol{z}}ig[(D(G(oldsymbol{z}))-1)^2ig]$$

Reduces vanishing gradient problem

Discriminator Loss 
$$\mathbb{E}_{m{x}}ig[(D(m{x})-1)^2ig]+\mathbb{E}_{m{z}}ig[(D(G(m{z})))^2ig]$$

Generator

$$\mathbb{E}_{oldsymbol{z}}ig[(D(G(oldsymbol{z}))-1)^2ig]$$

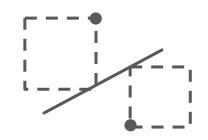
Also known as Mean Squared Error!

# Context of Least Squares Loss

Adversarial Loss + λ \* Cycle Consistency Loss

Least Squares Loss

# Summary



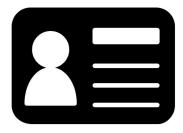
- Least squares fits a line from several points
- Least Squares Loss is used as the Adversarial Loss function in CycleGAN
- More stable than BCELoss, since the gradient is only flat when prediction is exactly correct

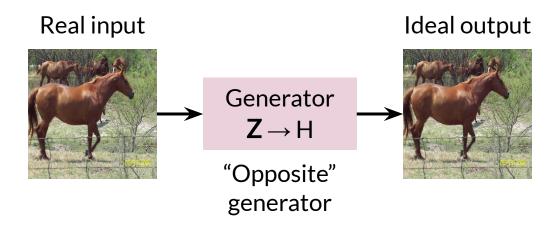


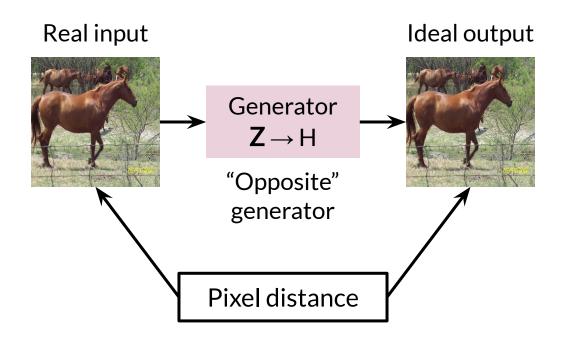
# CycleGAN: Identity Loss

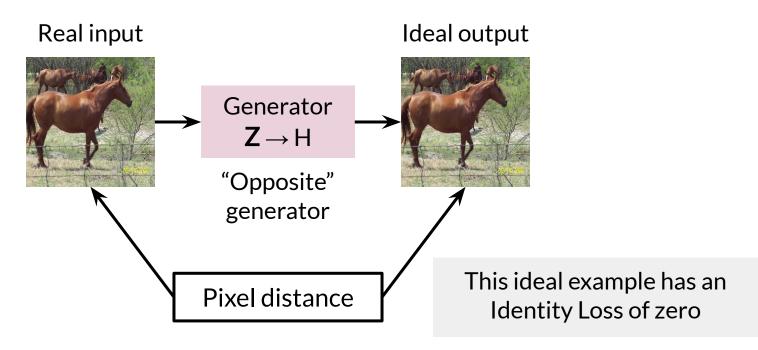
#### Outline

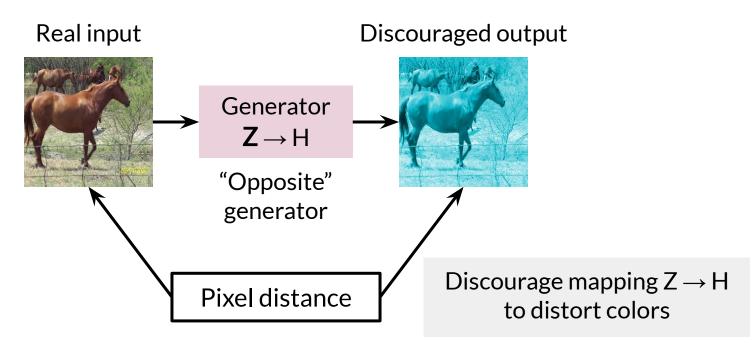
- Identity Loss
  - How it works
  - Impact on outputs





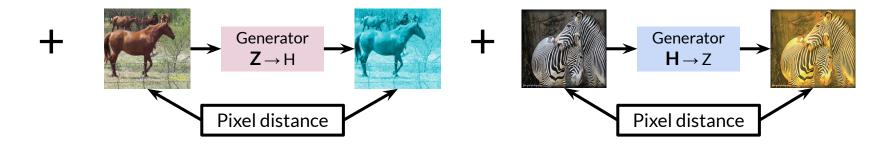






Adversarial Loss + λ \* Cycle Consistency Loss

Adversarial Loss + λ \* Cycle Consistency Loss



Adversarial Loss + λ \* Cycle Consistency Loss

+ Identity Loss

Adversarial Loss +  $\lambda_1^*$  Cycle Consistency Loss

+  $\lambda_2^*$  Identity Loss

# Identity Loss Example: Photo → Monet

Input No Identity Loss With Identity Loss

Identity Loss helps preserve original photo color

Available from: https://arxiv.org/abs/1703.10593

#### Summary

- Identity Loss takes a real image in domain B and inputs it into Generator:
   A → B, expecting an identity mapping
  - An identity mapping means the output is the same as the input
- Pixel distance is used
  - Ideally, no difference between input and output!
- Identity Loss is optionally added to help with color preservation





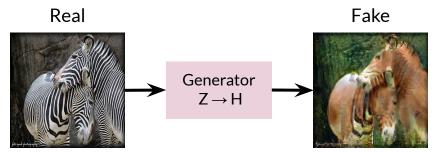
deeplearning.ai

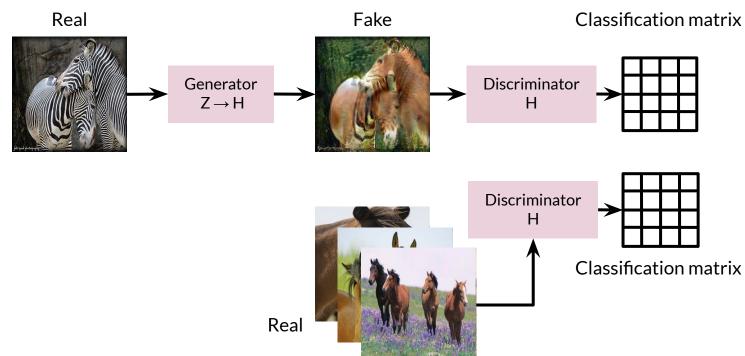
# CycleGAN: Putting It All Together

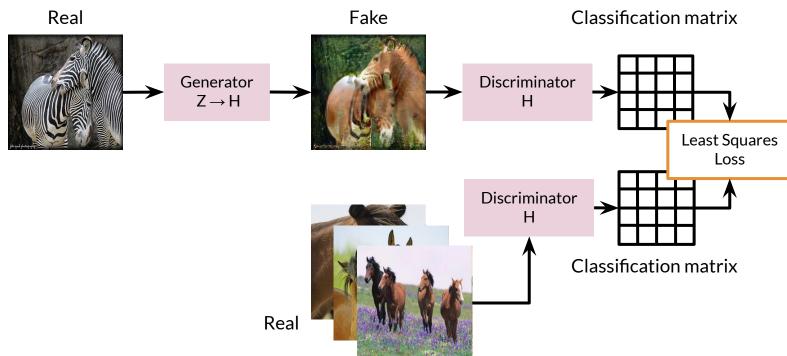
#### Outline

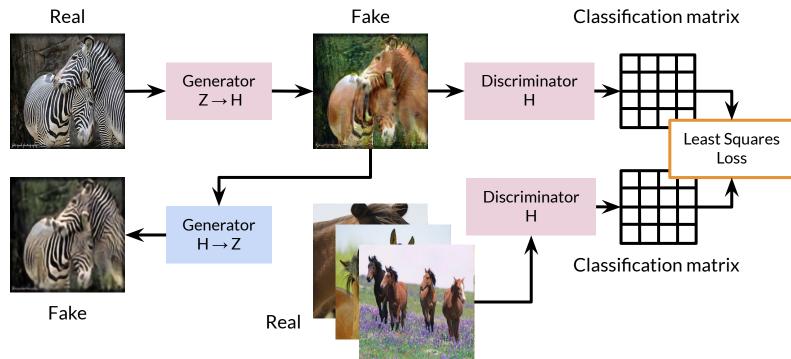
- Putting CycleGAN together!
  - Two GANs
  - Cycle Consistency Loss
  - Least Squares Adversarial Loss
  - Identity Loss (optional)

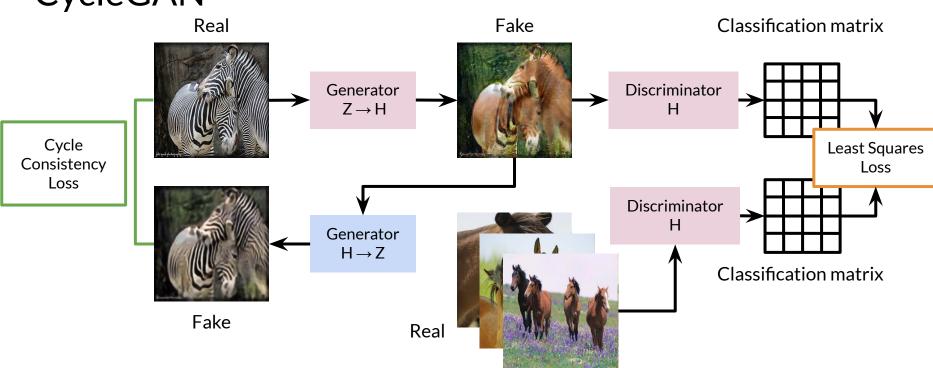


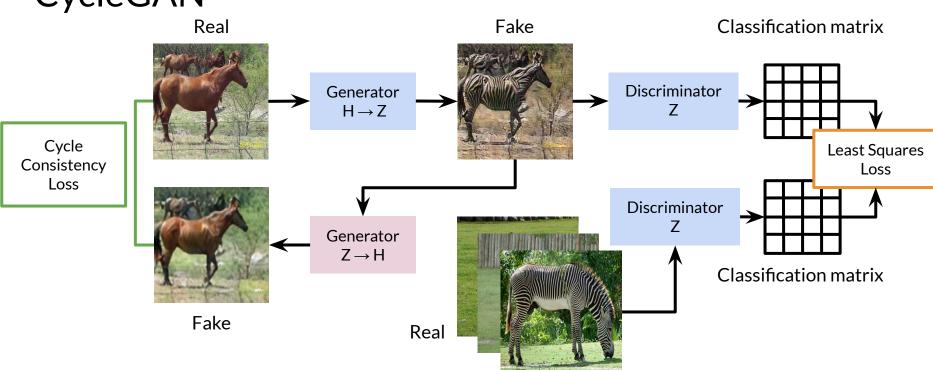


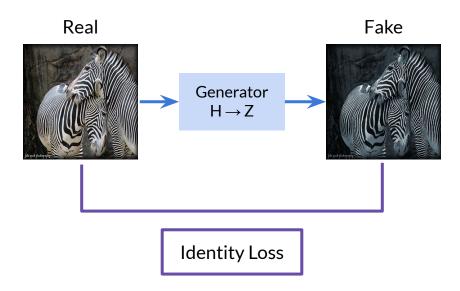


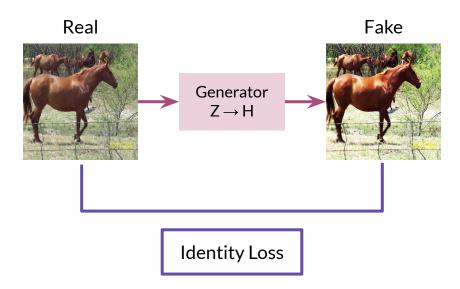




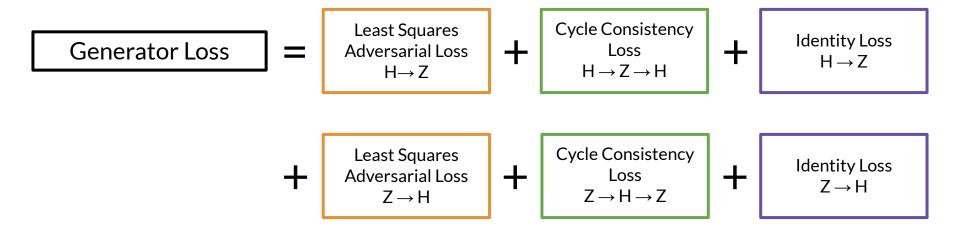






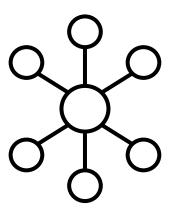


# CycleGAN Loss



## Summary

- CycleGAN is composed of two GANs
- Generators have 6 loss terms in total, 3 each:
  - Least Squares Adversarial Loss
  - Cycle Consistency Loss
  - Identity Loss
- Discriminator is simpler, with BCELoss using PatchGAN





deeplearning.ai

# CycleGAN Applications & Variants

#### Outline

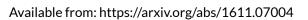
- Overview of some CycleGAN applications
- Some variants of unpaired image-to-image translation



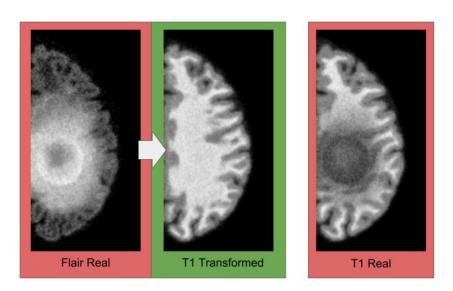
# **Applications**







# **Applications**



Flair Real T1 Transformed T1 Real

(a) A translation removing tumors

(b) A translation adding tumors

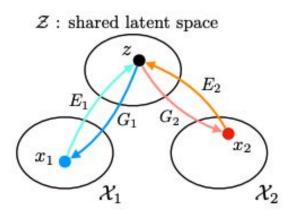
Available from: https://arxiv.org/abs/1805.08841

# **Applications**



Available from: https://www.nature.com/articles/s41598-019-52737-x.pdf

### Variant: UNIT





Available from: https://github.com/mingyuliutw/UNIT

# Variant: Multimodal UNIT (MUNIT)



Available from: https://github.com/NVlabs/MUNIT

# Variant: Multimodal UNIT (MUNIT)



Available from: https://github.com/NVlabs/MUNIT

## Summary

- Various applications of CycleGAN including:
  - Democratized art and style transfer
  - Medical data augmentation
  - Creating paired data
- UNIT and MUNIT are other models for unpaired (unsupervised) image-to-image translation

