

# Pix2Pix Overview

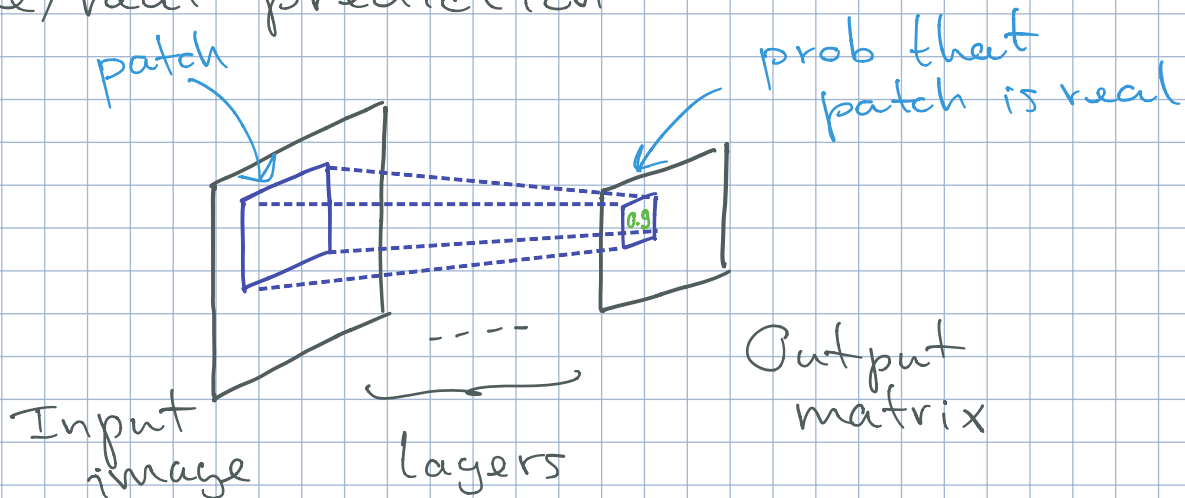
Image to Image translation

$D = \{(x_1^i, x_2^i)\}_{i=1}^n$ , where  $x_1, x_2$  - pair of images

for example  $x_1$  - black & white  
and  $x_2$  - colored version  
OR,  $x_1$  - sketch,  $x_2$  - realistic  
looking object

## Discriminator (aka PatchGAN)

Matrix output instead of single valued  
fake/real prediction



Model can be trained using BCE -  
for fake image output matrix consists of 0's  
and for real - from 1's.

Input to Discriminator:  
 $x_1$  - sketch  
 $x_2$  - real/fake image  
} → concat  
across channels  
dimension

# Generator (U-Net)

Remark : U-Net originally developed to solve image segmentation problem (Encoder-Decoder Architecture) with skip-connections

## Pixel Distance Loss

Addition to BCE loss we can use  $\lambda | \text{real img} - \text{fake img} |$  as a loss function term (for Generator)

$\int$   $L_1$  dist. between pixels

This will enforce generator to build output which even more close to real image.

Generator "sees" real images.

## Unpaired Image-to-Image Translation

### Idea 1

Instead of having dataset of paired images  $\{(x_i^1, x_i^2)\}_{i=1}^n$ , we have two piles of images

$$X = \{x_i\}, Y = \{y_j\}.$$

Goal of model is to find content presented in both piles (common part)

and styles (unique parts of each pic)

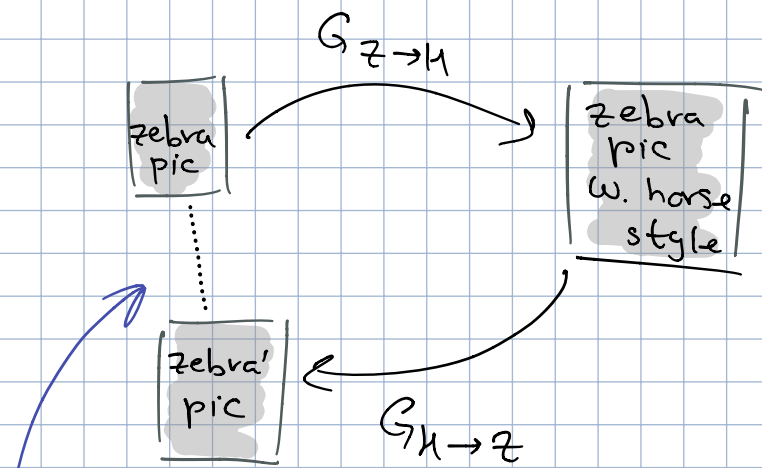
Which will allow us to take content and change its style only.

Example X - pictures of horses, Y - zebras

Model allows us to turn horses on the pic. to zebras and vice versa.

## CycleGAN Overview

Intuition:



Ideally should  
be the same

- 1) Take  $G_{z \rightarrow h}$  and generate horse img from zebra
- 2) Use generated img and  $G_{h \rightarrow z}$  to gen. zebra from fake horse img
- 3) Ideally, zebra' img should closely resemble original real zebra

Remark Repeat the cycle starting from horse picture.

\* Generators : U-Net

\* Discriminator : from PatchGAN

Four components in total:

$$G_{z \rightarrow u}, D_u, G_{u \rightarrow z}, D_z$$

Remark

Unlike Pix2Pix Discriminator takes only an image as input (w/o condition) since dataset is not paired.

### Cycle Consistency Loss

$$\text{Training Loss} = \text{Adversarial} + \lambda \cdot \boxed{\text{Cycle Consist. L}}$$

$$\|X_{\text{zebra}} - X_{\text{zebra}'}\|_1 + \|X_{\text{horse}} - X_{\text{horse}'}\|_1,$$

$$\text{where } X_{\text{zebra}'} = G_{u \rightarrow z}(G_{z \rightarrow u}(X_{\text{zebra}})),$$

$$X_{\text{horse}'} = G_{z \rightarrow u}(G_{u \rightarrow z}(X_{\text{horse}}))$$

Cycles in both directions

Remark

Without Cycle Consist. term Cycle GAN produces poor results.

## Remark

For Adversarial loss instead of using BCE  
Liken  $P_{x \rightarrow z} P_{x \rightarrow x}$ , authors use **LSE**, to prevent  
vanishing gradients problem.

## Identity Loss (Optional Loss term)

Intuition:

$$G_{z \rightarrow u}(x_{\text{horse}}) \approx x_{\text{horse}}$$

since input already a horse,  $G_{z \rightarrow u}$   
should ideally output the same image

We can compute pixel distance between  
 $x_{\text{horse}}$  and  $G_{z \rightarrow u}(x_{\text{horse}})$ .

Similar to  $G_{u \rightarrow z}$ .

! Helps to preserve colors