

شبکه‌های مولد تخصصی Generative Adversarial Networks (GAN)



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Agenda

- Simple GAN
- Transposed convolution & DCGAN
- TF2 for researchers! (pre-requirement)
- Auto-Encoders
- U-Net & Segmentation
- GAN overriding Model.train_step
- Pix2pix
- Cycle-GAN



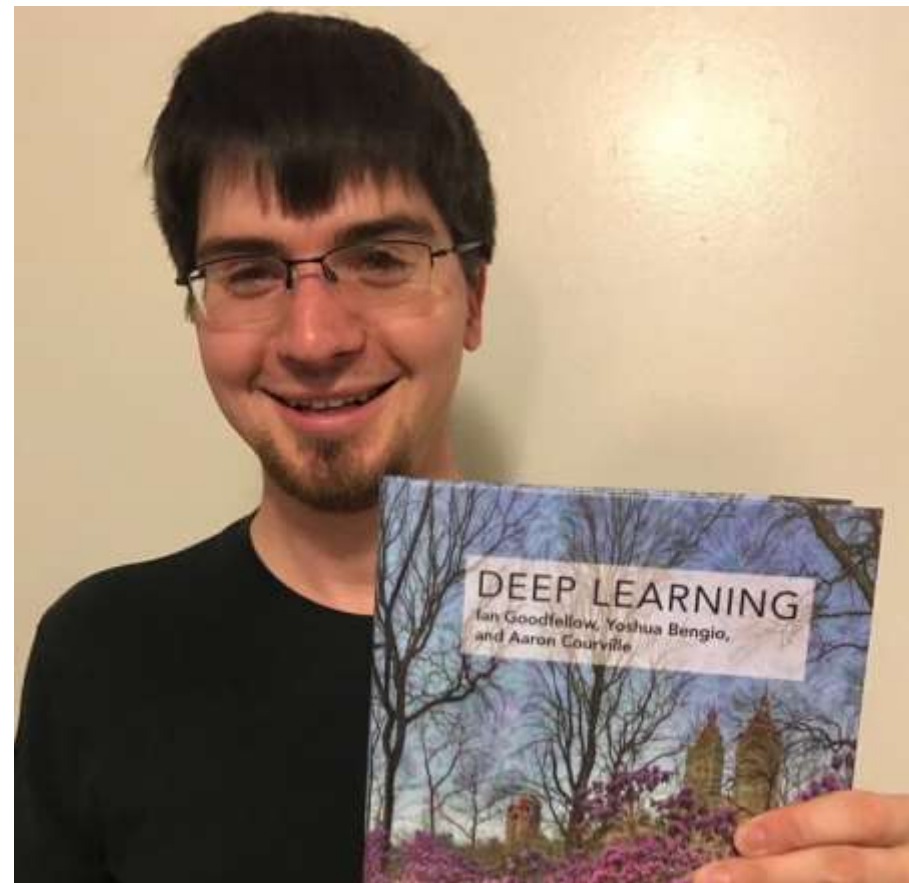
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What is GAN?

- They were first introduced by [Ian Goodfellow](#) *et al.* in 2014.
- Can learn to draw samples from a model that is similar to data that we give them.



They have achieved some incredible results:

after 5 epochs



after 100 epochs



Some the latest results from NVIDIA



https://research.nvidia.com/sites/default/files/pubs/2017-10_Progressive-Growing-of/karras2018iclr-paper.pdf

GANs

شبکه های مولد

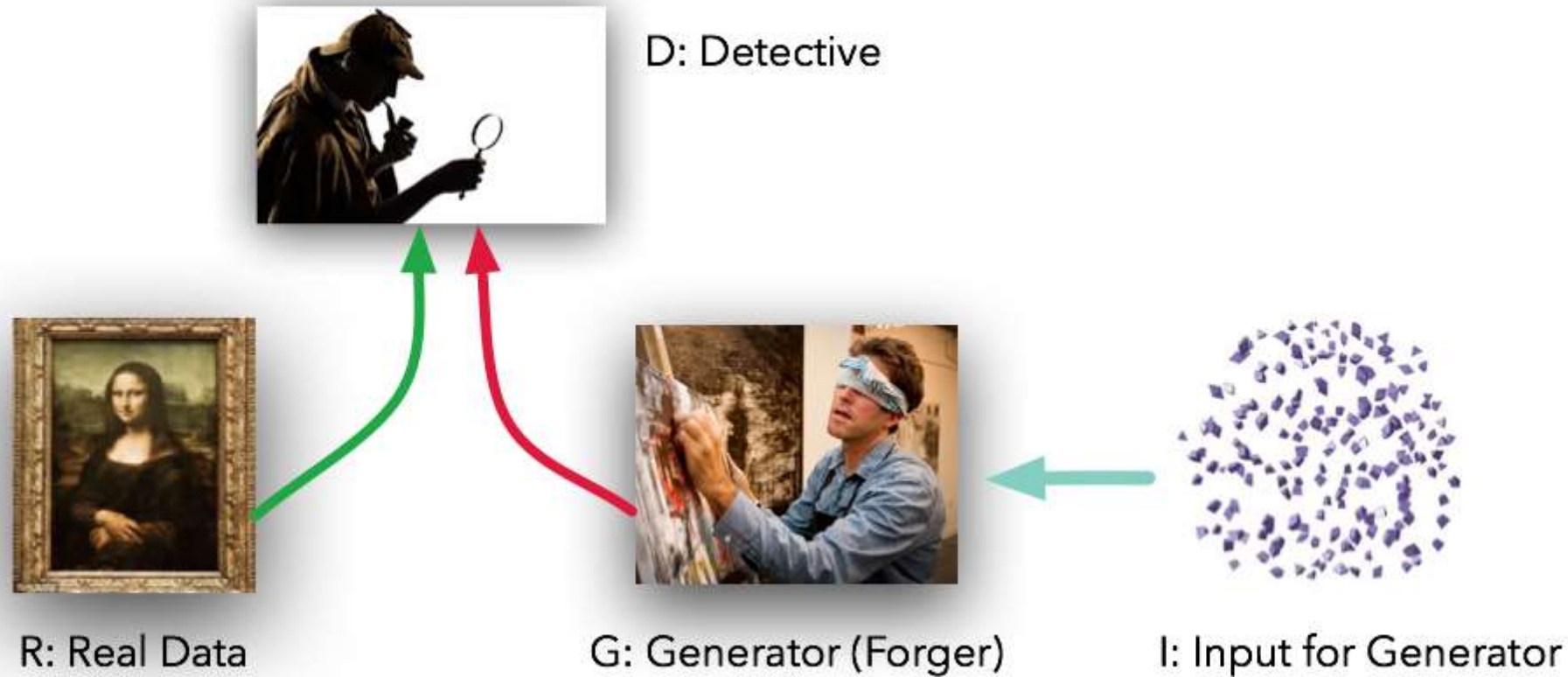
Alireza Akhavanpour

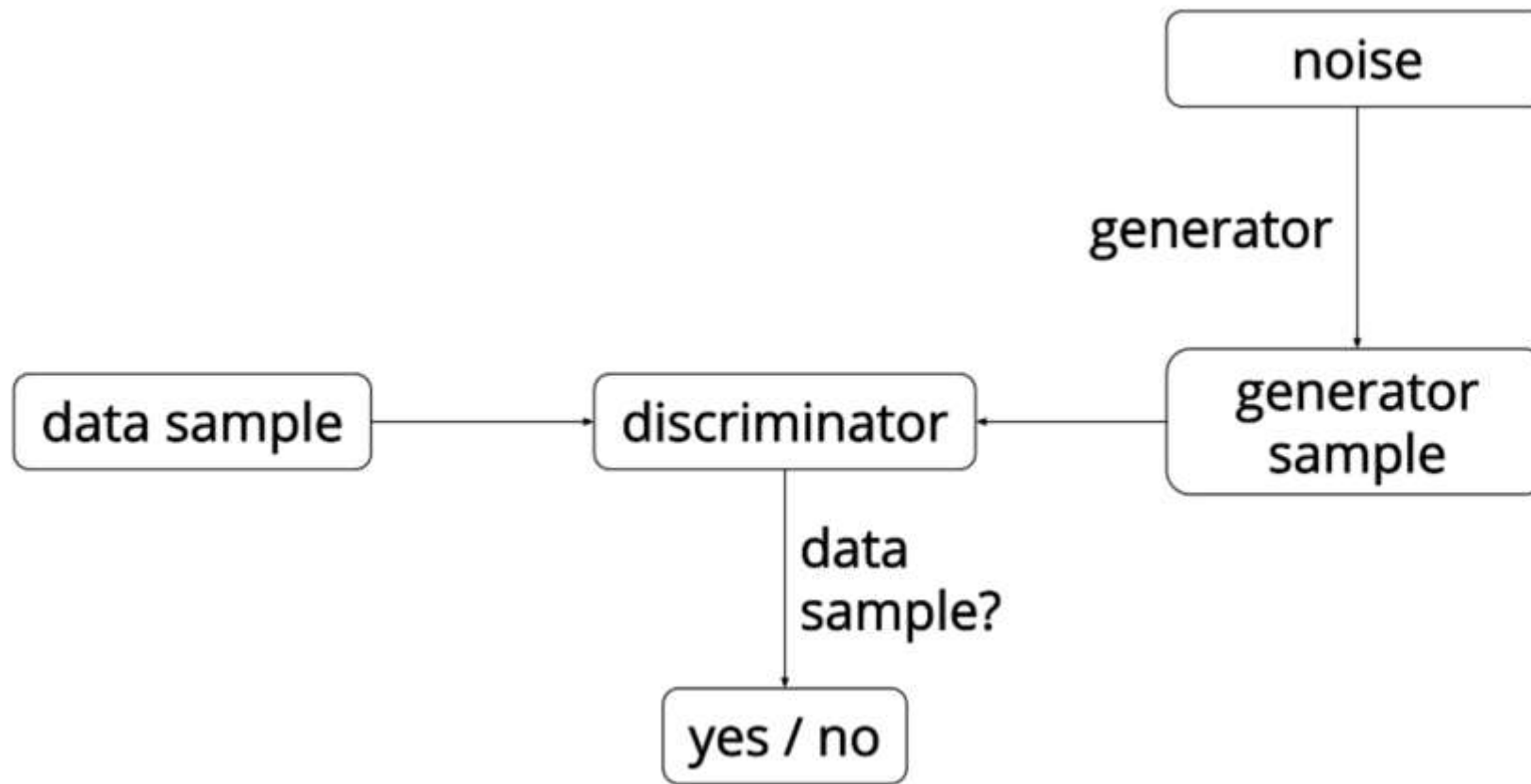
علیرضا اخوان پور



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Generative Adversarial Networks





Source: <https://ishmaelbelghazi.github.io/ALI>





Reza Zadeh @Reza_Zadeh · 15m

GANs in nature: Cuckoos (Generator) lay eggs in Warbler (Discriminator) bird's nests, tricking warblers to raise cuckoo chicks. Warblers are evolving to recognize cuckoo eggs to destroy them. Simultaneously, cuckoos evolve to produce more warbler-like eggs [cam.ac.uk/research/featu...](https://www.cam.ac.uk/research/features/the-reed-warbler-and-the-cuckoo-an-escalating-game-of-trickery-and-defence)



<https://www.cam.ac.uk/research/features/the-reed-warbler-and-the-cuckoo-an-escalating-game-of-trickery-and-defence>

GANs

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GAN Lab

<https://poloclub.github.io/ganlab/>



پیاده سازی ۱

<http://nbviewer.jupyter.org/github/alireza-akhavan/class.vision/blob/master/55-simple-GAN.ipynb>

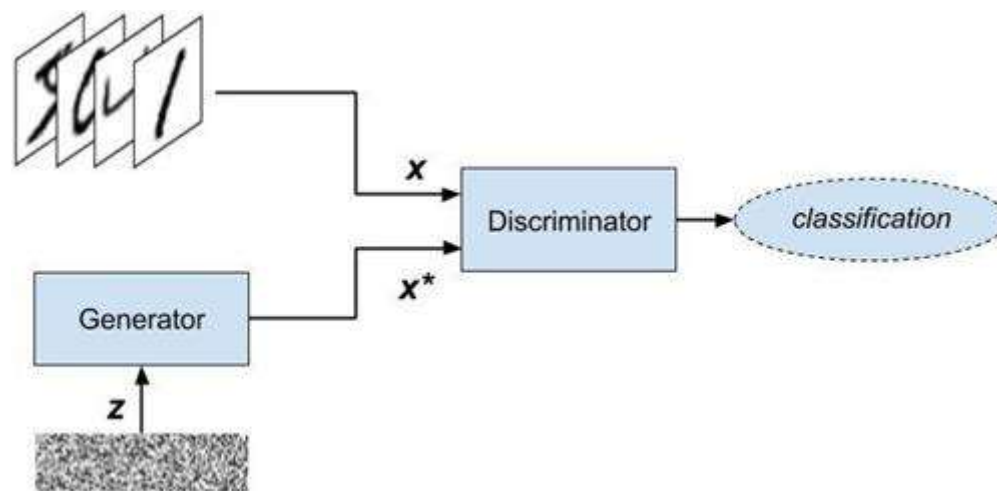


Agenda

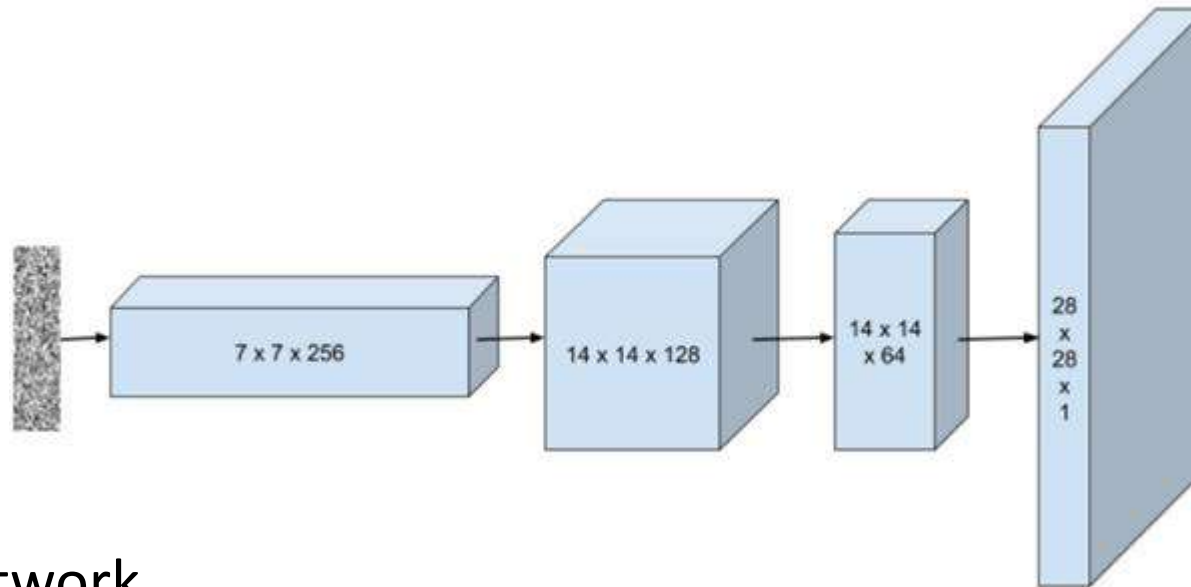
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Deep Convolutional GAN

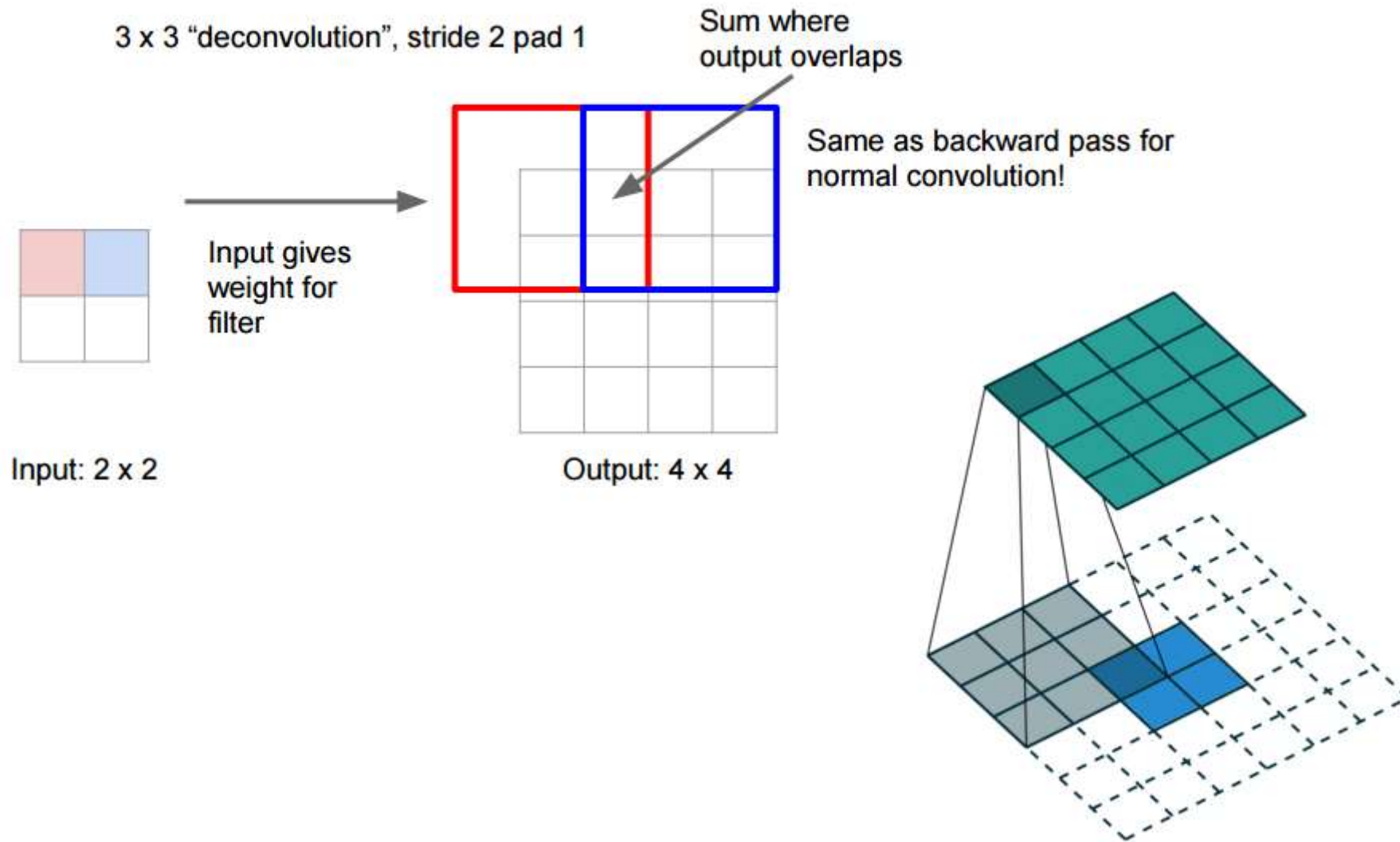


The Generator Network with Transposed convolutions



The Generator Network.

The Generator takes in a random noise vector as input and produces a $28 \times 28 \times 1$ image. It does so by multiple layers of transposed convolutions. In between the convolutional layers, we apply batch normalization to stabilize the training process. (Image is not to scale.)



Transposed convolution

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1																						
2			<u>Input</u>							<u>Kernel</u>							<u>Output</u>					
3																						
4																	1	2	3	3	2	1
5			1	1	1	1				1	1	1					2	4	6	6	4	2
6			1	1	1	1				1	1	1					3	6	9	9	6	3
7			1	1	1	1				1	1	1					3	6	9	9	6	3
8			1	1	1	1											2	4	6	6	4	2
9																	1	2	3	3	2	1
10																						

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About Keras

Getting started

Introduction to Keras for engineers

Introduction to Keras for researchers

The Keras ecosystem

Learning resources

Frequently Asked Questions

Developer guides

Search Keras documentation...



» Getting started

Getting started

Are you an engineer or data scientist? Do you ship reliable and performant applied machine learning solutions? Check out our **Introduction to Keras for engineers**.

Are you a machine learning researcher? Do you publish at NeurIPS and push the state-of-the-art in CV and NLP? Check out our **Introduction to Keras for researchers**.

Are you a beginner looking for both an introduction to machine learning and an introduction to Keras and TensorFlow? You're going to need more than a one-pager. And you're in luck: **we've got just the book for you.**

https://keras.io/getting_started/intro_to_keras_for_researchers

GANs

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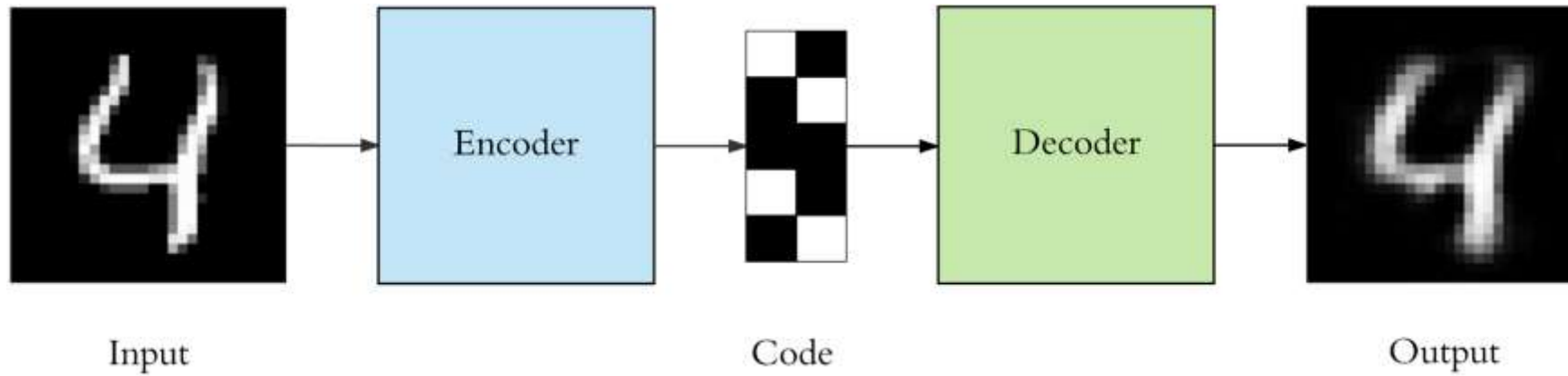
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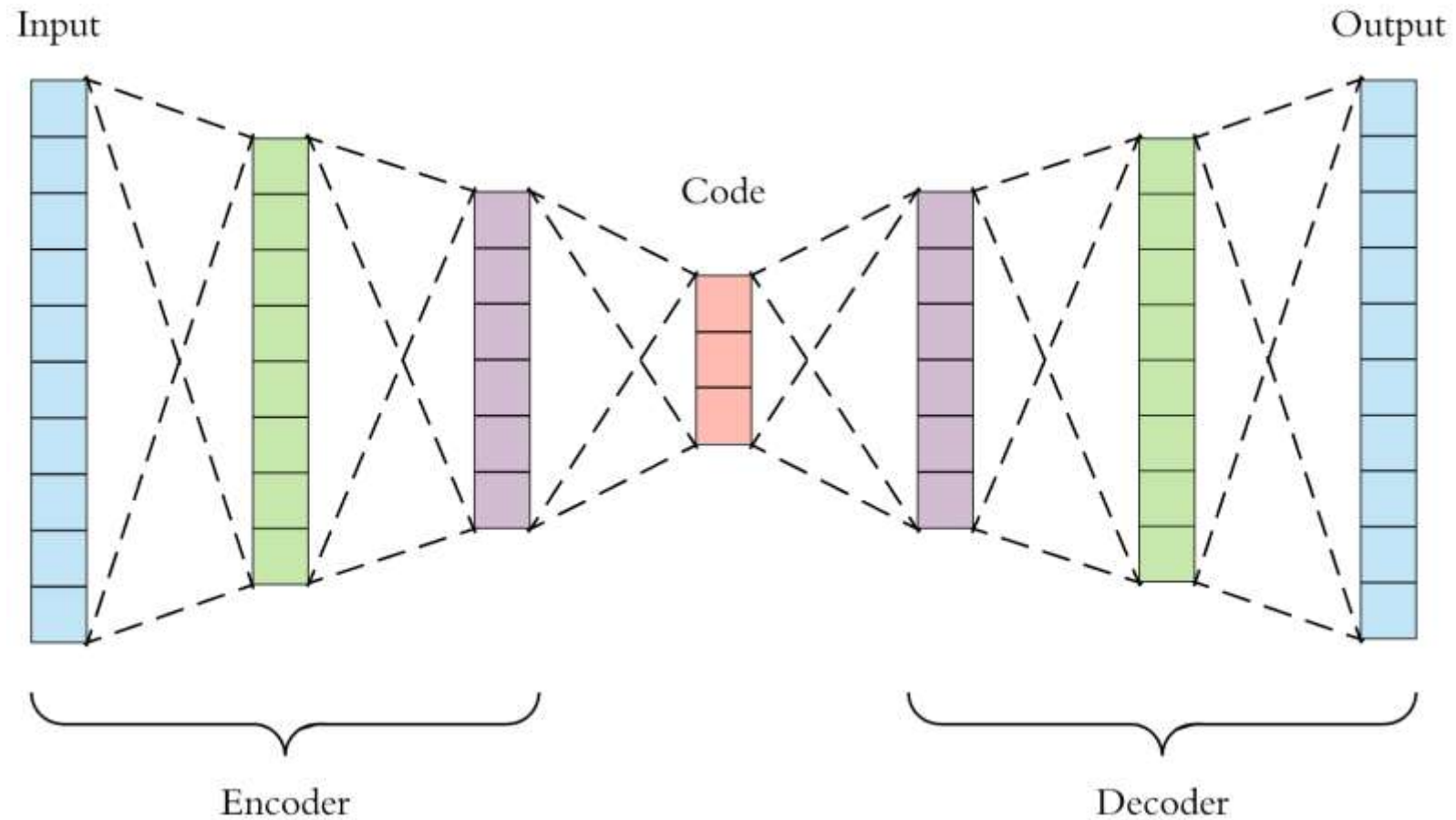
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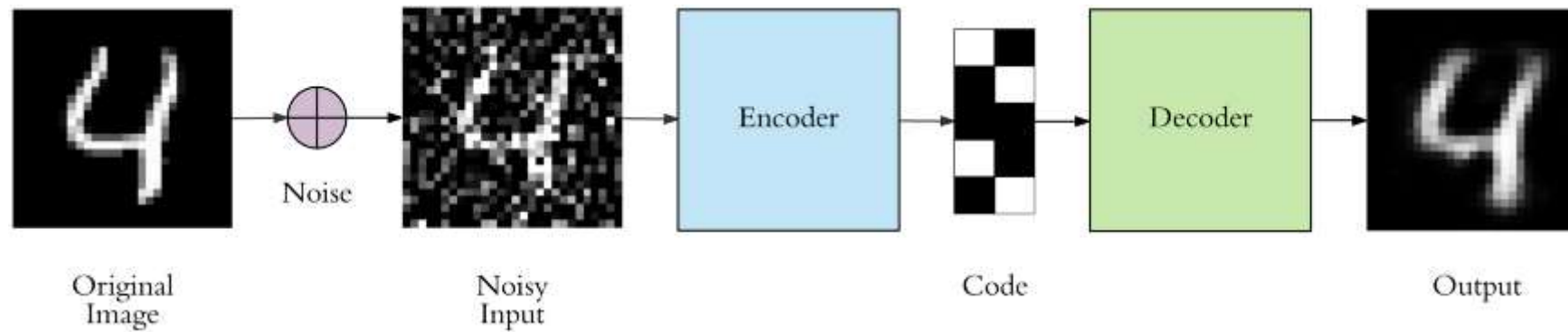
What is auto encoder?



What is auto encoder?



Denoising Autoencoders



پیاده سازی

- **Intro to Autoencoders**

- <https://www.tensorflow.org/tutorials/generative/autoencoder>
- <https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/generative/autoencoder.ipynb>

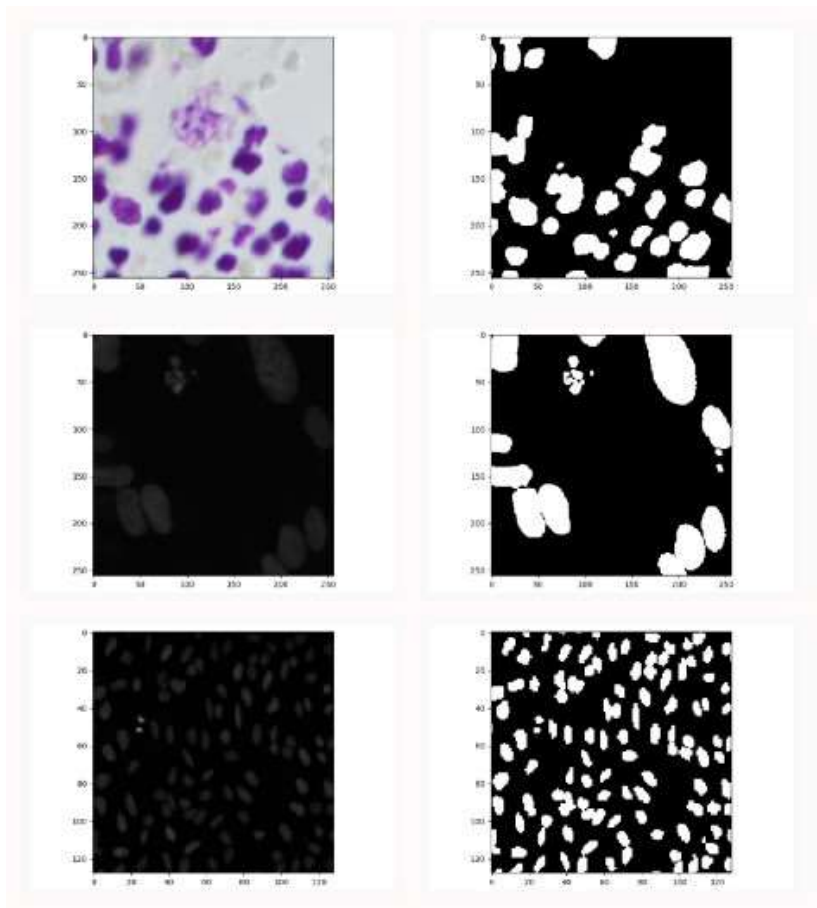


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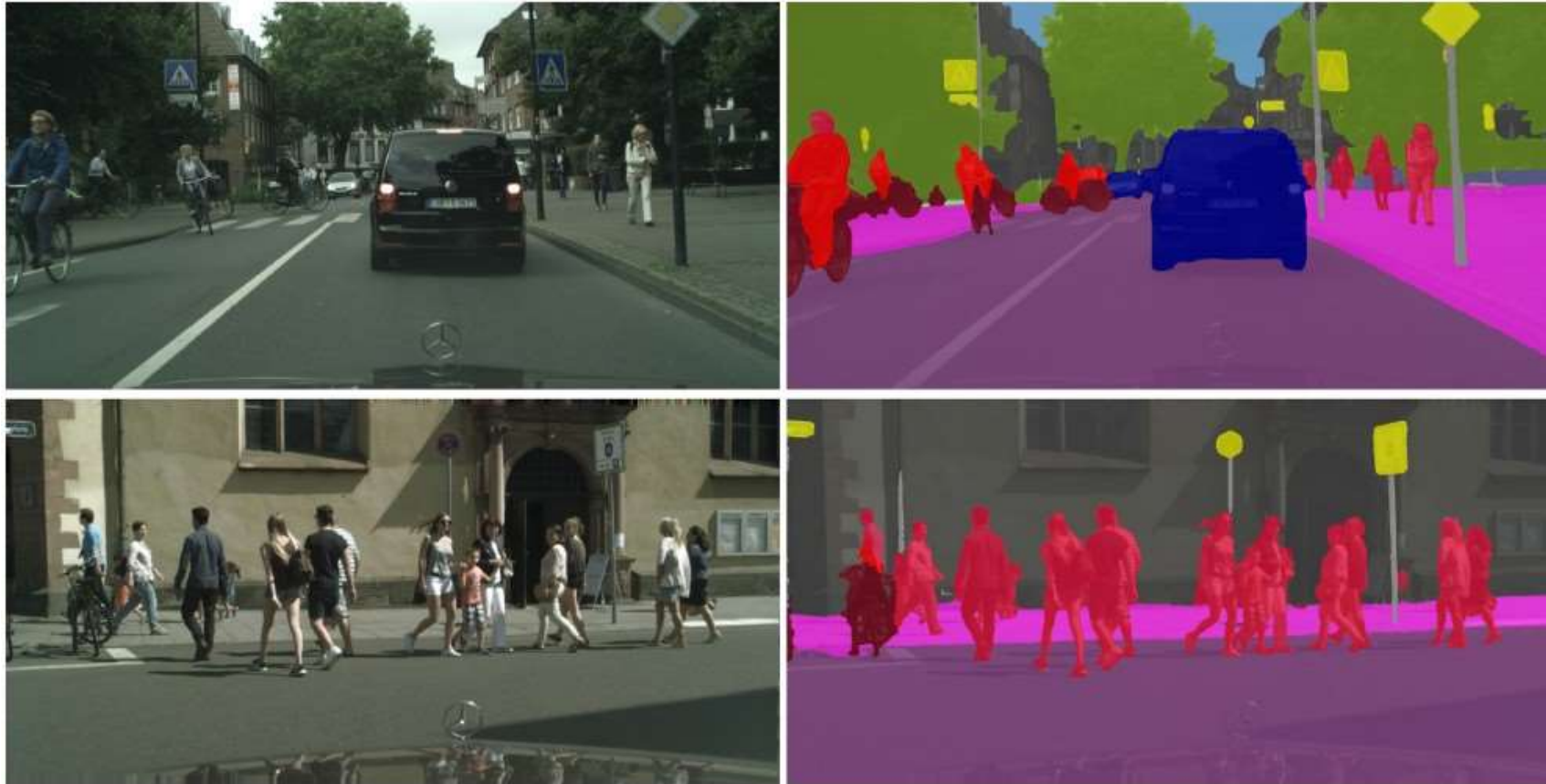
Segmentation



Human Segmentation



Semantic segmentation



Semantic segmentation of Cityscapes, with input on left and output on right. ([source](#))

128x128x3

```
inputs = Input((IMG_HEIGHT, IMG_WIDTH, IMG_CHANNELS))  
s = Lambda(lambda x: x / 255)(inputs)
```



128x128x3

128x128x16

```
inputs = Input((IMG_HEIGHT, IMG_WIDTH, IMG_CHANNELS))  
s = Lambda(lambda x: x / 255) (inputs)
```

```
c1 = Conv2D(16, (3, 3), activation='relu', padding='same') (s)  
c1 = Dropout(0.1) (c1)  
c1 = Conv2D(16, (3, 3), activation='relu', padding='same') (c1)
```



128x128x3

128x128x16

64x64x16

```
inputs = Input((IMG_HEIGHT, IMG_WIDTH, IMG_CHANNELS))  
s = Lambda(lambda x: x / 255) (inputs)  
  
c1 = Conv2D(16, (3, 3), activation='relu', padding='same') (s)  
c1 = Dropout(0.1) (c1)  
c1 = Conv2D(16, (3, 3), activation='relu', padding='same') (c1)  
p1 = MaxPooling2D((2, 2)) (c1)
```



128x128x3

128x128x16

64x64x16

64x64x32

32x32x32

```
inputs = Input((IMG_HEIGHT, IMG_WIDTH, IMG_CHANNELS))  
s = Lambda(lambda x: x / 255) (inputs)
```

```
c1 = Conv2D(16, (3, 3), activation='relu', padding='same') (s)  
c1 = Dropout(0.1) (c1)  
c1 = Conv2D(16, (3, 3), activation='relu', padding='same') (c1)  
p1 = MaxPooling2D((2, 2)) (c1)
```

```
c2 = Conv2D(32, (3, 3), activation='relu', padding='same') (p1)  
c2 = Dropout(0.1) (c2)  
c2 = Conv2D(32, (3, 3), activation='relu', padding='same') (c2)  
p2 = MaxPooling2D((2, 2)) (c2)
```



128x128x3

128x128x16

64x64x16

64x64x32

32x32x32

32x32x64

16x16x64

```
inputs = Input((IMG_HEIGHT, IMG_WIDTH, IMG_CHANNELS))  
s = Lambda(lambda x: x / 255) (inputs)
```

```
c1 = Conv2D(16, (3, 3), activation='relu', padding='same') (s)  
c1 = Dropout(0.1) (c1)  
c1 = Conv2D(16, (3, 3), activation='relu', padding='same') (c1)  
p1 = MaxPooling2D((2, 2)) (c1)
```

```
c2 = Conv2D(32, (3, 3), activation='relu', padding='same') (p1)  
c2 = Dropout(0.1) (c2)  
c2 = Conv2D(32, (3, 3), activation='relu', padding='same') (c2)  
p2 = MaxPooling2D((2, 2)) (c2)
```

```
c3 = Conv2D(64, (3, 3), activation='relu', padding='same') (p2)  
c3 = Dropout(0.2) (c3)  
c3 = Conv2D(64, (3, 3), activation='relu', padding='same') (c3)  
p3 = MaxPooling2D((2, 2)) (c3)
```



128x128x3

128x128x16

64x64x16

64x64x32

32x32x32

32x32x64

16x16x64

16x16x128

8x8x128

```
inputs = Input((IMG_HEIGHT, IMG_WIDTH, IMG_CHANNELS))
s = Lambda(lambda x: x / 255)(inputs)

c1 = Conv2D(16, (3, 3), activation='relu', padding='same')(s)
c1 = Dropout(0.1)(c1)
c1 = Conv2D(16, (3, 3), activation='relu', padding='same')(c1)
p1 = MaxPooling2D((2, 2))(c1)

c2 = Conv2D(32, (3, 3), activation='relu', padding='same')(p1)
c2 = Dropout(0.1)(c2)
c2 = Conv2D(32, (3, 3), activation='relu', padding='same')(c2)
p2 = MaxPooling2D((2, 2))(c2)

c3 = Conv2D(64, (3, 3), activation='relu', padding='same')(p2)
c3 = Dropout(0.2)(c3)
c3 = Conv2D(64, (3, 3), activation='relu', padding='same')(c3)
p3 = MaxPooling2D((2, 2))(c3)

c4 = Conv2D(128, (3, 3), activation='relu', padding='same')(p3)
c4 = Dropout(0.2)(c4)
c4 = Conv2D(128, (3, 3), activation='relu', padding='same')(c4)
p4 = MaxPooling2D(pool_size=(2, 2))(c4)
```



128x128x3

128x128x16

64x64x16

64x64x32

32x32x32

32x32x64

16x16x64

16x16x128

8x8x128

8x8x256

```
inputs = Input((IMG_HEIGHT, IMG_WIDTH, IMG_CHANNELS))
s = Lambda(lambda x: x / 255)(inputs)

c1 = Conv2D(16, (3, 3), activation='relu', padding='same')(s)
c1 = Dropout(0.1)(c1)
c1 = Conv2D(16, (3, 3), activation='relu', padding='same')(c1)
p1 = MaxPooling2D((2, 2))(c1)

c2 = Conv2D(32, (3, 3), activation='relu', padding='same')(p1)
c2 = Dropout(0.1)(c2)
c2 = Conv2D(32, (3, 3), activation='relu', padding='same')(c2)
p2 = MaxPooling2D((2, 2))(c2)

c3 = Conv2D(64, (3, 3), activation='relu', padding='same')(p2)
c3 = Dropout(0.2)(c3)
c3 = Conv2D(64, (3, 3), activation='relu', padding='same')(c3)
p3 = MaxPooling2D((2, 2))(c3)

c4 = Conv2D(128, (3, 3), activation='relu', padding='same')(p3)
c4 = Dropout(0.2)(c4)
c4 = Conv2D(128, (3, 3), activation='relu', padding='same')(c4)
p4 = MaxPooling2D(pool_size=(2, 2))(c4)

c5 = Conv2D(256, (3, 3), activation='relu', padding='same')(p4)
c5 = Dropout(0.3)(c5)
c5 = Conv2D(256, (3, 3), activation='relu', padding='same')(c5)
```



128x128x3

128x128x16

64x64x16

64x64x32

32x32x32

32x32x64

16x16x64

16x16x128

8x8x128

8x8x256

```
inputs = Input((IMG_HEIGHT, IMG_WIDTH, IMG_CHANNELS))
s = Lambda(lambda x: x / 255)(inputs)

c1 = Conv2D(16, (3, 3), activation='relu', padding='same')(s)
c1 = Dropout(0.1)(c1)
c1 = Conv2D(16, (3, 3), activation='relu', padding='same')(c1)
p1 = MaxPooling2D((2, 2))(c1)

c2 = Conv2D(32, (3, 3), activation='relu', padding='same')(p1)
c2 = Dropout(0.1)(c2)
c2 = Conv2D(32, (3, 3), activation='relu', padding='same')(c2)
p2 = MaxPooling2D((2, 2))(c2)

c3 = Conv2D(64, (3, 3), activation='relu', padding='same')(p2)
c3 = Dropout(0.2)(c3)
c3 = Conv2D(64, (3, 3), activation='relu', padding='same')(c3)
p3 = MaxPooling2D((2, 2))(c3)

c4 = Conv2D(128, (3, 3), activation='relu', padding='same')(p3)
c4 = Dropout(0.2)(c4)
c4 = Conv2D(128, (3, 3), activation='relu', padding='same')(c4)
p4 = MaxPooling2D(pool_size=(2, 2))(c4)

c5 = Conv2D(256, (3, 3), activation='relu', padding='same')(p4)
c5 = Dropout(0.3)(c5)
c5 = Conv2D(256, (3, 3), activation='relu', padding='same')(c5)
```



128x128x3

128x128x16

64x64x16

64x64x32

32x32x32

32x32x64

16x16x64

16x16x128

8x8x128

8x8x256

16x16x128

```
c4 = Conv2D(128, (3, 3), activation='relu', padding='same') (p3)
c4 = Dropout(0.2) (c4)
c4 = Conv2D(128, (3, 3), activation='relu', padding='same') (c4)
p4 = MaxPooling2D(pool_size=(2, 2)) (c4)

c5 = Conv2D(256, (3, 3), activation='relu', padding='same') (p4)
c5 = Dropout(0.3) (c5)
c5 = Conv2D(256, (3, 3), activation='relu', padding='same') (c5)

u6 = Conv2DTranspose(128, (2, 2), strides=(2, 2), padding='same') (c5)
```



128x128x3

128x128x16

64x64x16

64x64x32

32x32x32

32x32x64

16x16x64

16x16x128

8x8x128

8x8x256

16x16x128

16x16x256

```
c4 = Conv2D(128, (3, 3), activation='relu', padding='same') (p3)
c4 = Dropout(0.2) (c4)
c4 = Conv2D(128, (3, 3), activation='relu', padding='same') (c4)
p4 = MaxPooling2D(pool_size=(2, 2)) (c4)

c5 = Conv2D(256, (3, 3), activation='relu', padding='same') (p4)
c5 = Dropout(0.3) (c5)
c5 = Conv2D(256, (3, 3), activation='relu', padding='same') (c5)

u6 = Conv2DTranspose(128, (2, 2), strides=(2, 2), padding='same') (c5)
u6 = concatenate([u6, c4])
```



128x128x3

128x128x16

64x64x16

64x64x32

32x32x32

32x32x64

16x16x64

16x16x128

8x8x128

8x8x256

16x16x128

16x16x256

16x16x128

```
c4 = Conv2D(128, (3, 3), activation='relu', padding='same') (p3)
c4 = Dropout(0.2) (c4)
c4 = Conv2D(128, (3, 3), activation='relu', padding='same') (c4)
p4 = MaxPooling2D(pool_size=(2, 2)) (c4)

c5 = Conv2D(256, (3, 3), activation='relu', padding='same') (p4)
c5 = Dropout(0.3) (c5)
c5 = Conv2D(256, (3, 3), activation='relu', padding='same') (c5)

u6 = Conv2DTranspose(128, (2, 2), strides=(2, 2), padding='same') (c5)
u6 = concatenate([u6, c4])
c6 = Conv2D(128, (3, 3), activation='relu', padding='same') (u6)
c6 = Dropout(0.2) (c6)
c6 = Conv2D(128, (3, 3), activation='relu', padding='same') (c6)
```



128x128x3

128x128x16

64x64x16

64x64x32

32x32x32

32x32x64

16x16x64

16x16x128

8x8x128

8x8x256

16x16x128

16x16x256

16x16x128

32x32x64

32x32x128

32x32x64

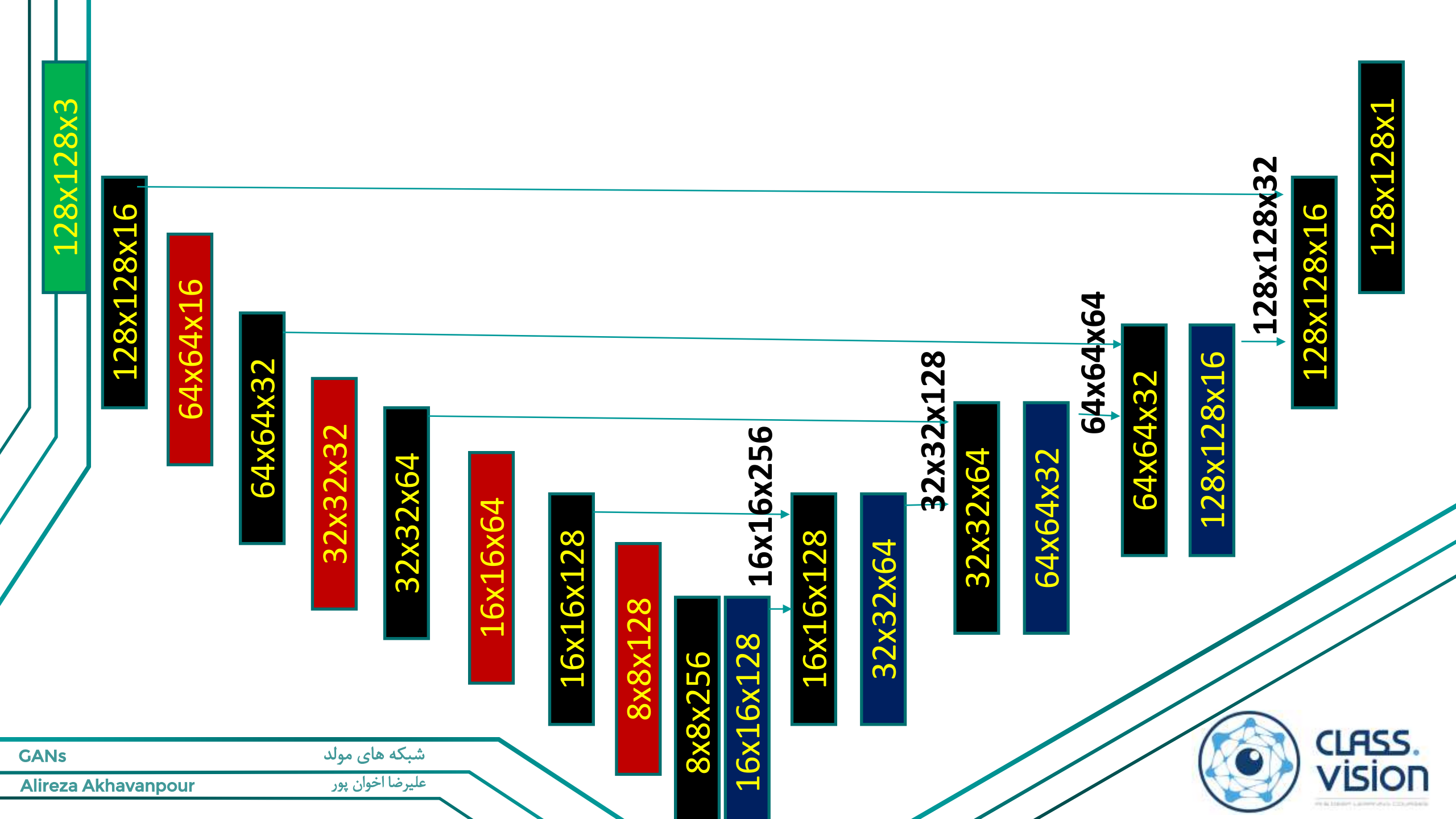
```
c4 = Conv2D(128, (3, 3), activation='relu', padding='same') (p3)
c4 = Dropout(0.2) (c4)
c4 = Conv2D(128, (3, 3), activation='relu', padding='same') (c4)
p4 = MaxPooling2D(pool_size=(2, 2)) (c4)
```

```
c5 = Conv2D(256, (3, 3), activation='relu', padding='same') (p4)
c5 = Dropout(0.3) (c5)
c5 = Conv2D(256, (3, 3), activation='relu', padding='same') (c5)
```

```
u6 = Conv2DTranspose(128, (2, 2), strides=(2, 2), padding='same') (c5)
u6 = concatenate([u6, c4])
c6 = Conv2D(128, (3, 3), activation='relu', padding='same') (u6)
c6 = Dropout(0.2) (c6)
c6 = Conv2D(128, (3, 3), activation='relu', padding='same') (c6)
```

```
u7 = Conv2DTranspose(64, (2, 2), strides=(2, 2), padding='same') (c6)
u7 = concatenate([u7, c3])
c7 = Conv2D(64, (3, 3), activation='relu', padding='same') (u7)
c7 = Dropout(0.2) (c7)
c7 = Conv2D(64, (3, 3), activation='relu', padding='same') (c7)
```





پیاده سازی

- <https://nbviewer.jupyter.org/github/Alireza-Akhavan/class.vision/blob/master/U-Net.ipynb>



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Official documentation

- https://keras.io/examples/generative/dcgan_overriding_train_step/

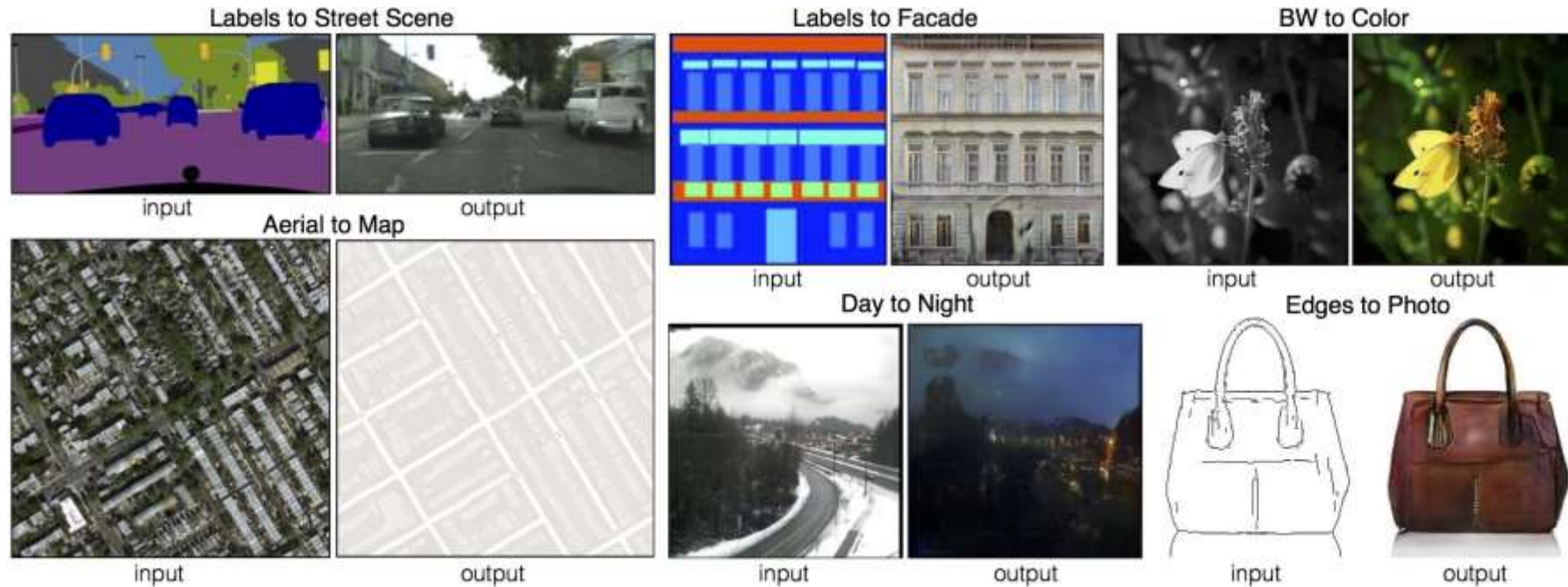


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pix2pix by Isola et al.



Try Online: <https://affinelayer.com/pixsrv/>

Isola, Phillip, et al. "Image-to-image translation with conditional adversarial networks." (2017).

GANs

شبکه های مولد

Alireza Akhavanpour

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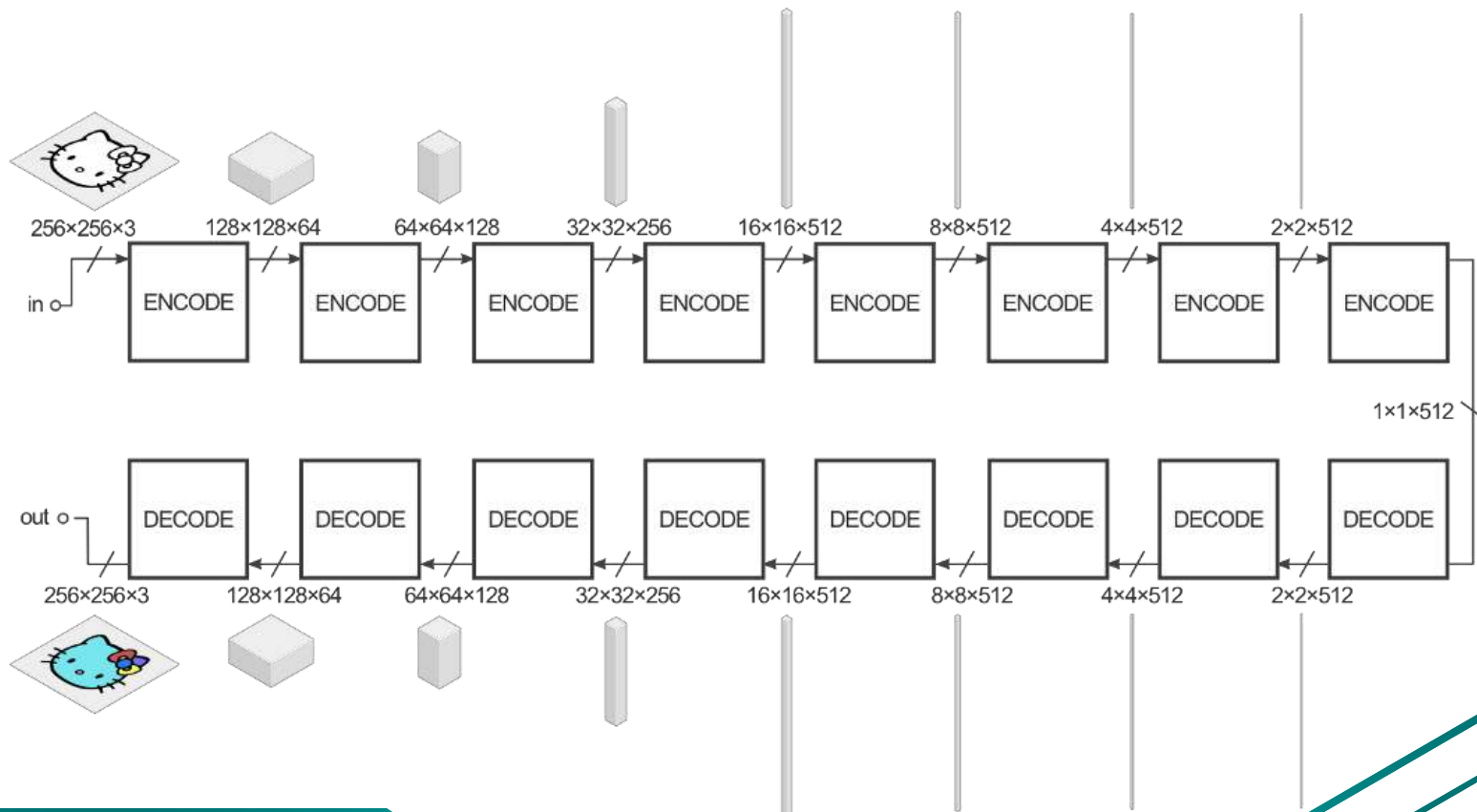
Pix2Pix

- pix2pix uses a **conditional** generative adversarial network (**cGAN**) to learn a mapping from an input image to an output image.



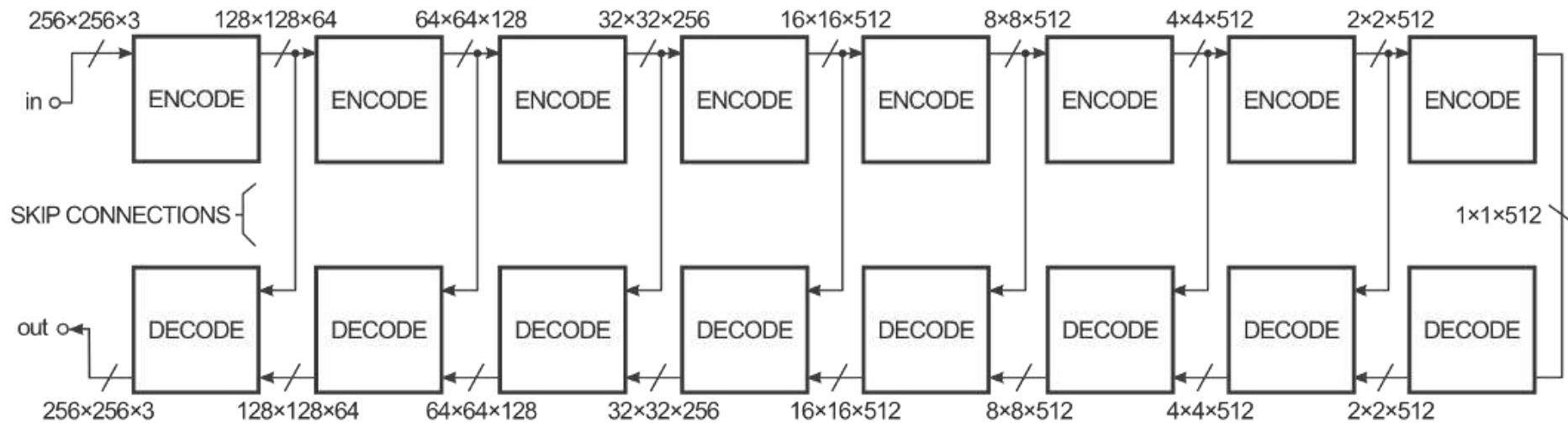
Generator

- The structure of the **generator** is called an “**encoder-decoder**” and in pix2pix the encoder-decoder looks more or less like this:



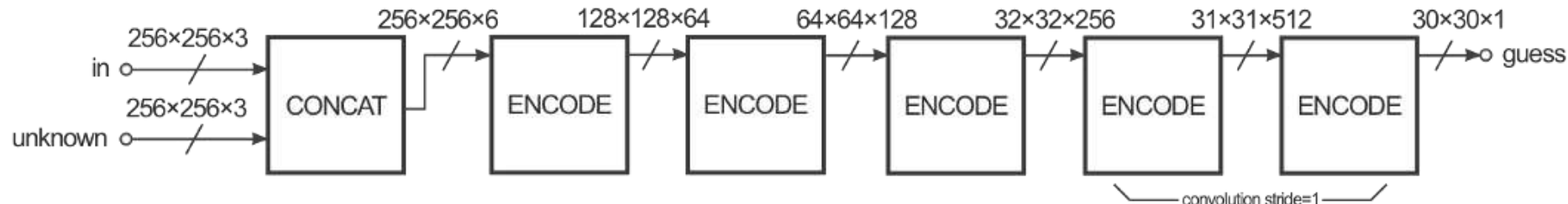
Generator: U-Net

- The authors used a “U-Net” instead of an encoder-decoder.
- skip connections



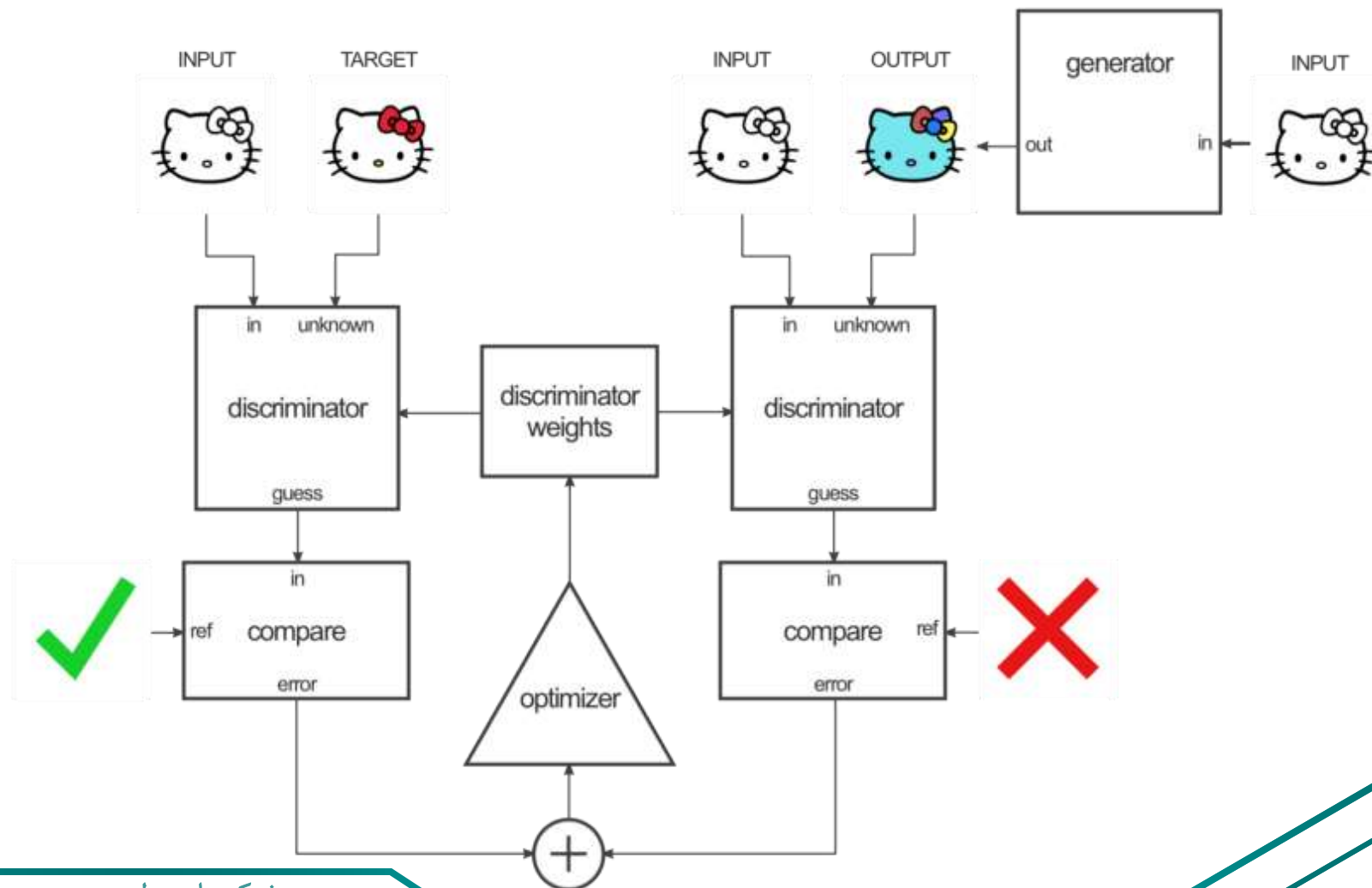
Discriminator - PatchGAN

The Discriminator has the job of **taking two images**, an **input image** and an **unknown image** (which will be either a **target or output image from the generator**), and deciding if the second image was produced by the generator or not.

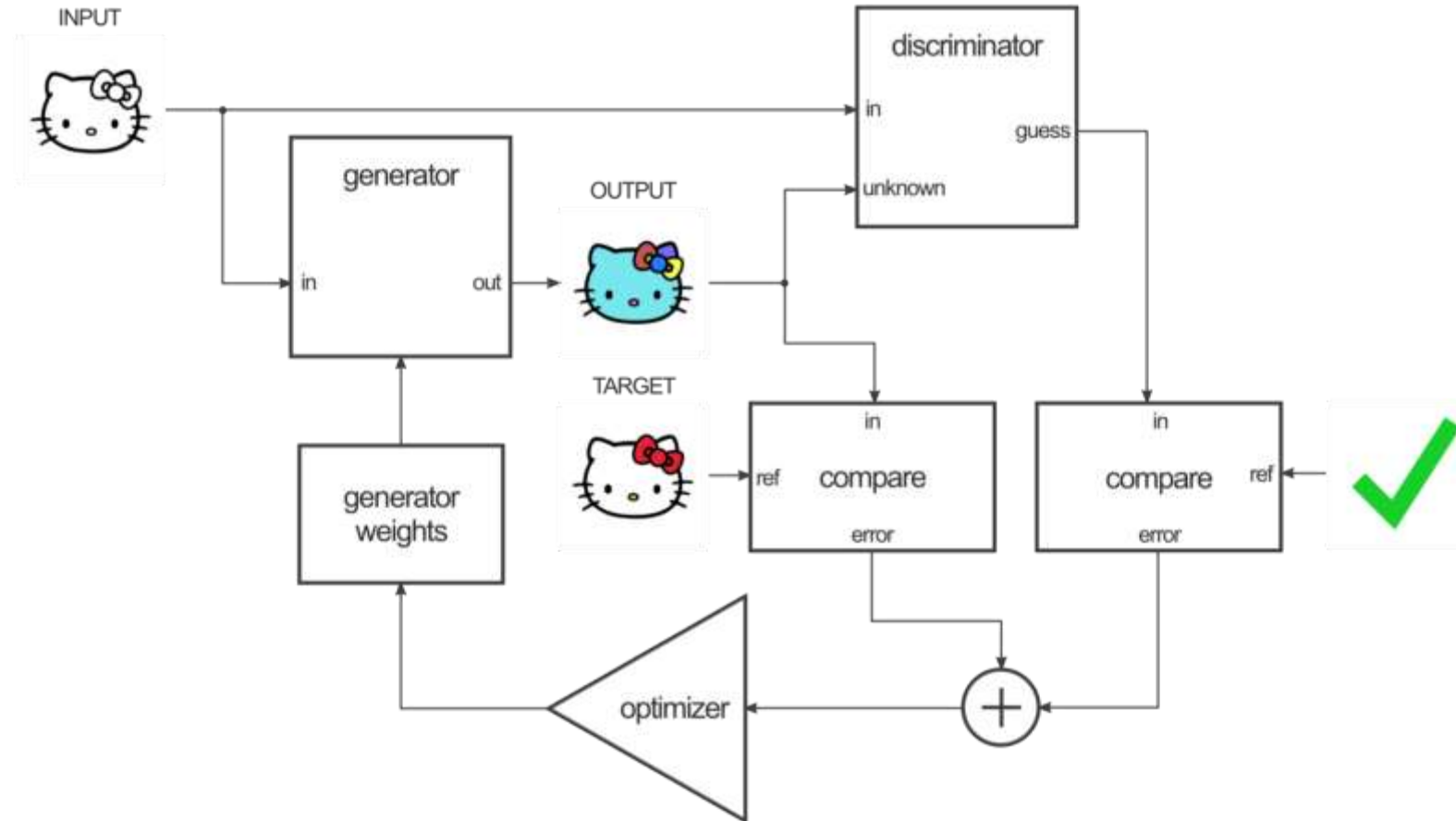


The **output** is a **30x30** image where each pixel value (0 to 1) represents how believable the corresponding section of the unknown image is. In the pix2pix implementation, each pixel from this 30x30 image corresponds to **the believability of a 70x70 patch** of the input image (the **patches overlap** a lot since the input images are 256x256)

Training - D



Training - G



Tutorial

- <https://www.tensorflow.org/tutorials/generative/pix2pix>
- <https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/generative/pix2pix.ipynb>



Agenda

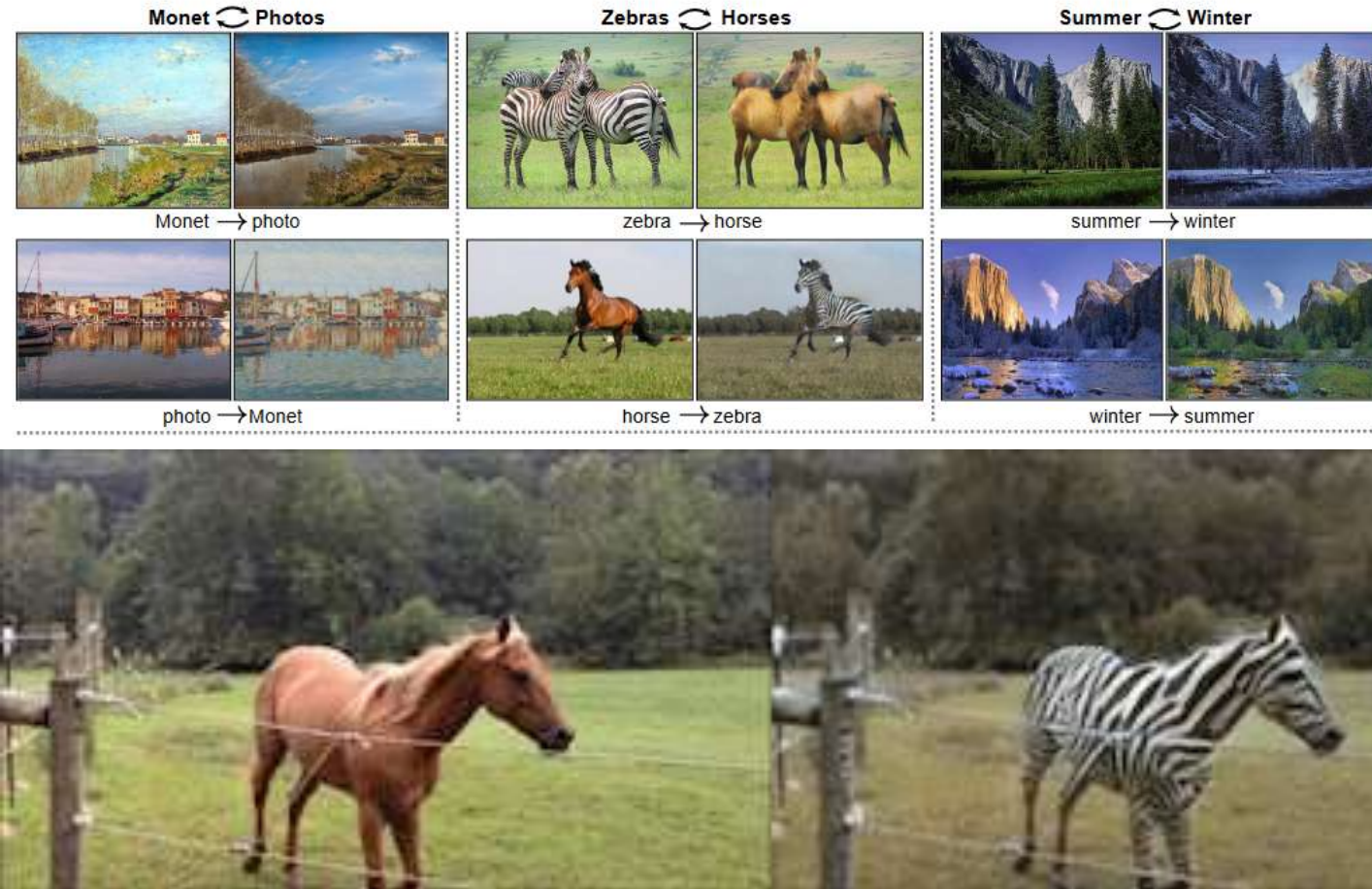
- Simple GAN
- Transposed convolution & DCGAN
- TF2 for researchers! (pre-requirement)
- Auto-Encoders
- U-Net & Segmentation
- GAN overriding Model.train_step
- Pix2pix
- **Cycle-GAN**





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

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Berkeley AI Research (BAIR) laboratory, UC Berkeley



<https://arxiv.org/pdf/1703.10593.pdf>

GANs

شبکه های مولد

Alireza Akhavanpour

علیرضا اخوان پور



CLASS.
VISION



<https://t.me/cvision/349>

<https://youtu.be/Fea4kZq0oFQ>

GANs

شبکه های مولد

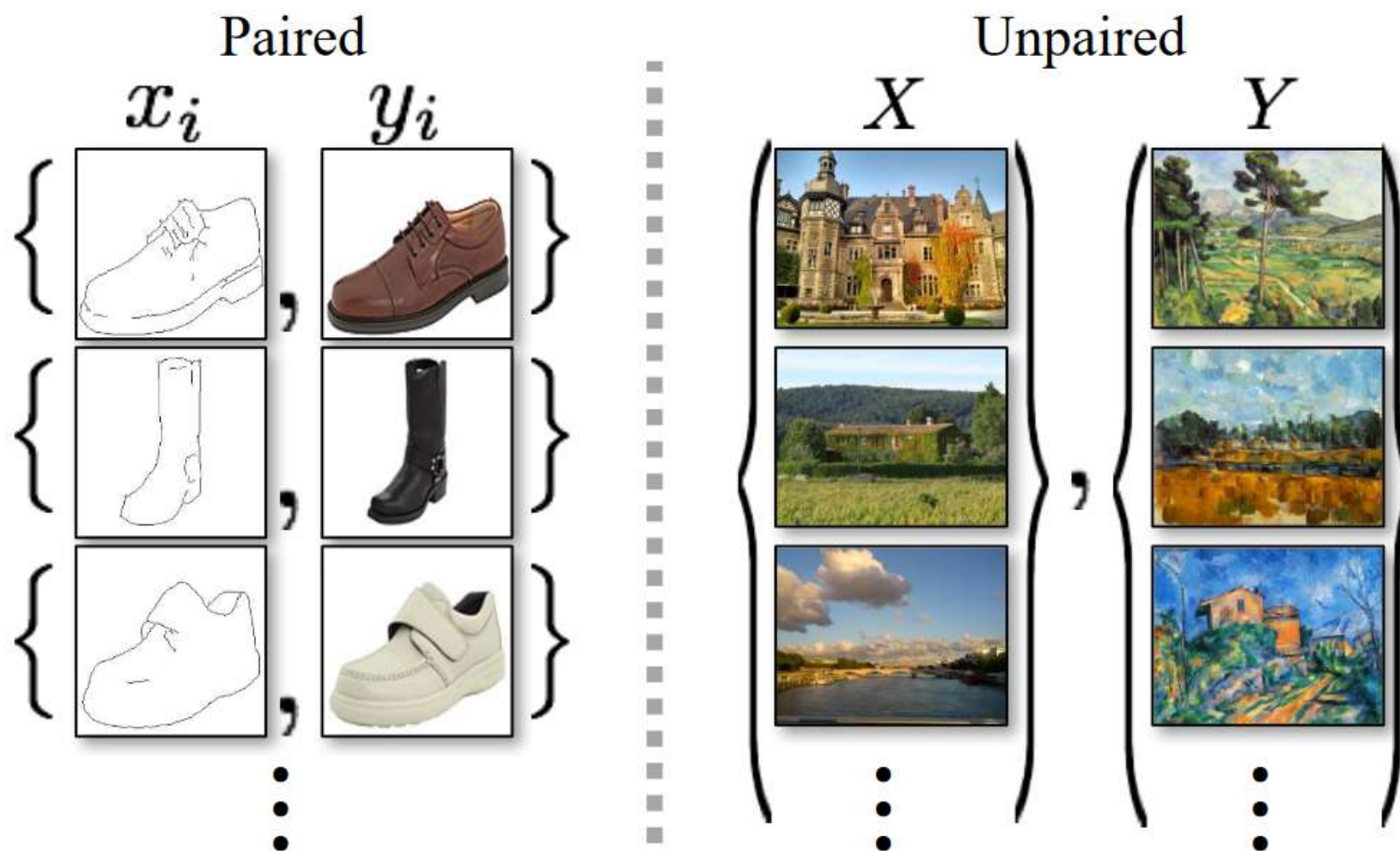
Alireza Akhavanpour

علیرضا اخوان پور

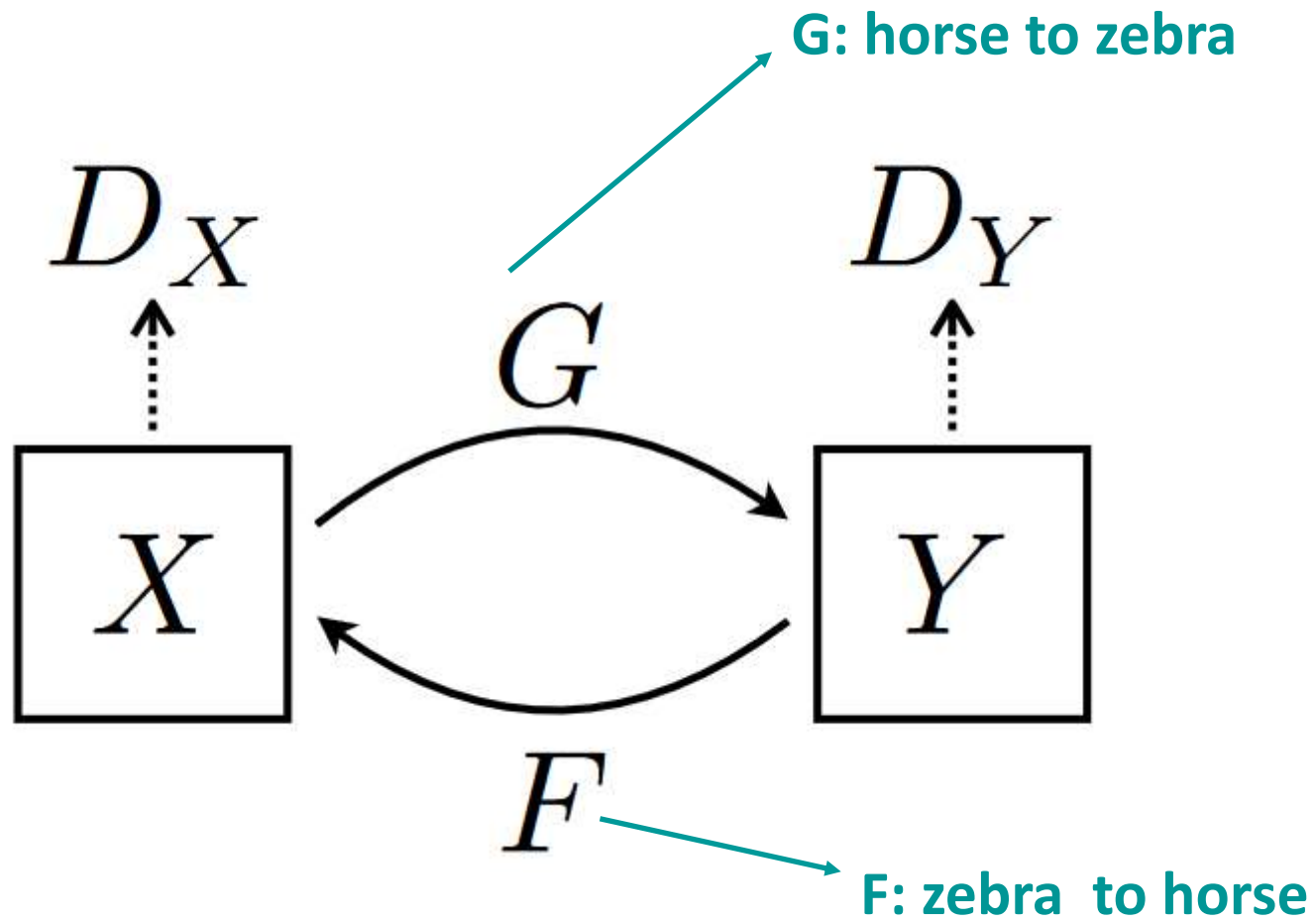


CLASS.
vision
WE & EYESEE LABORATORY COURSEWARE

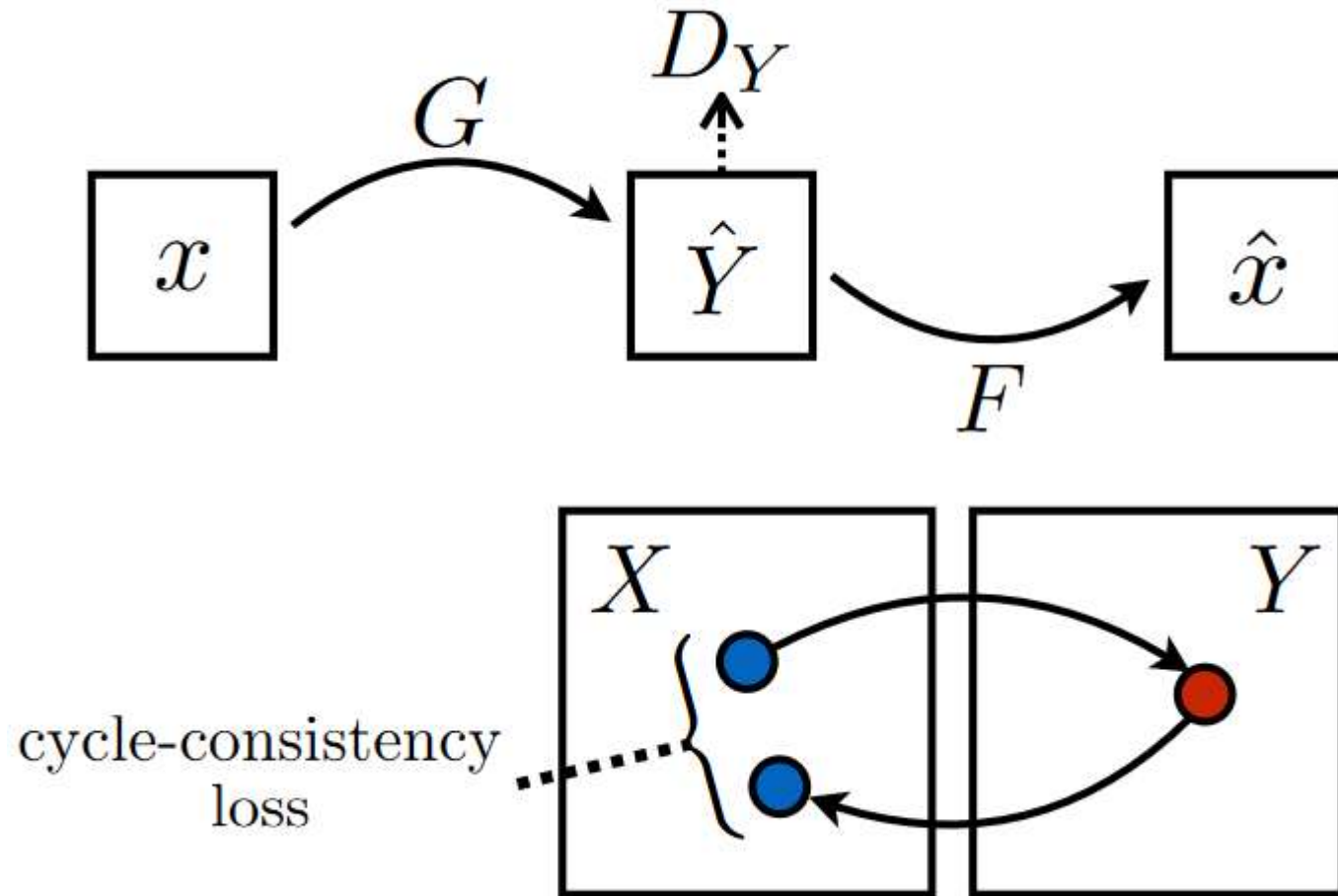
The challenge



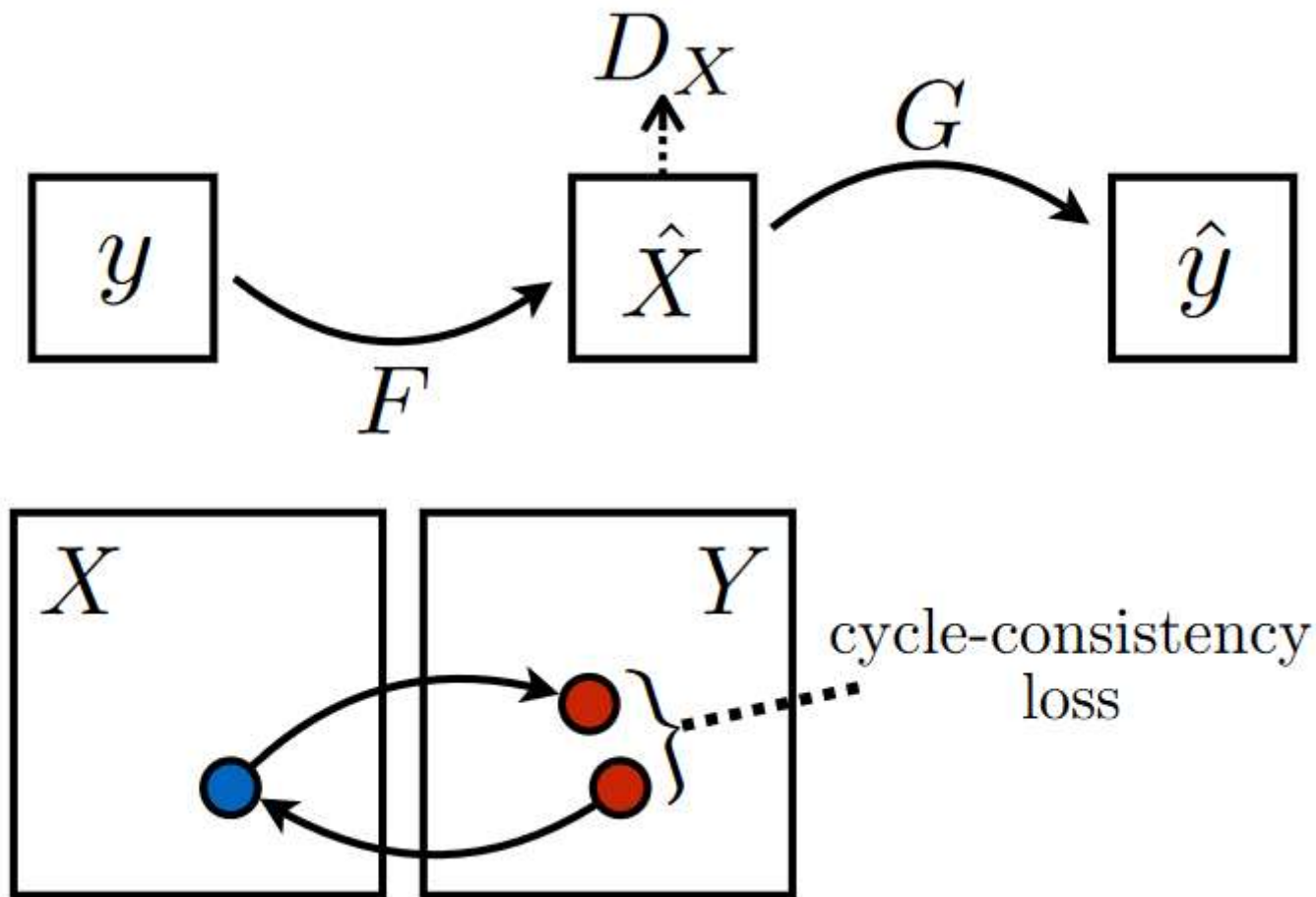
Full translation cycle



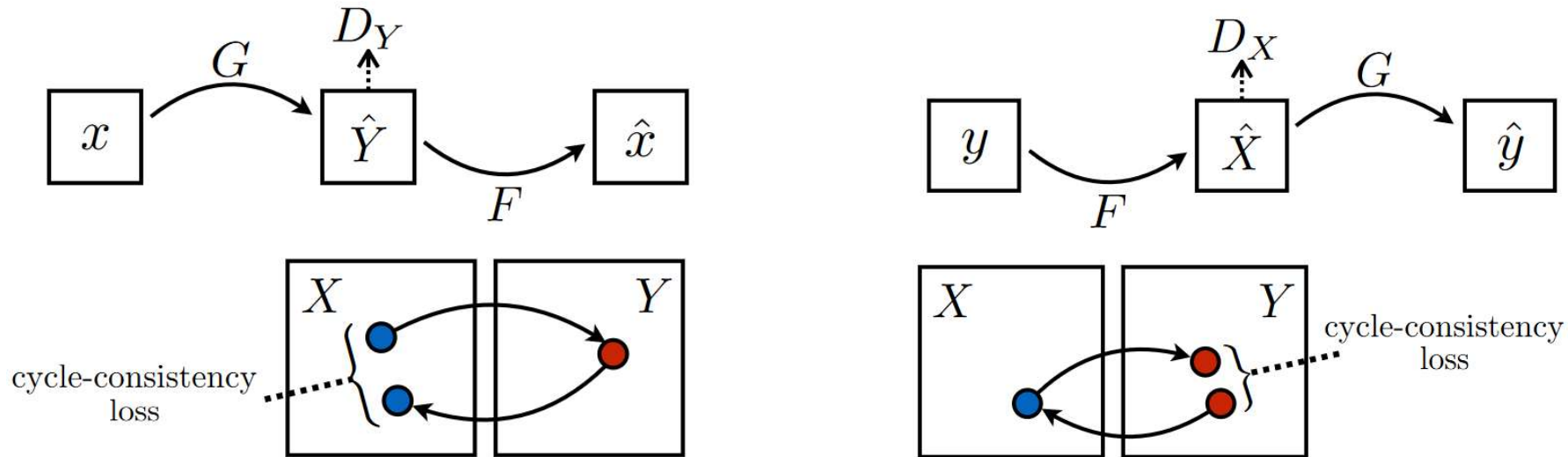
Cycle consistency losses



Cycle consistency losses



Cycle Loss Formulation



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

Full objective

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

$$G^*, F^* = \arg \min_{G, F} \max_{D_X, D_Y} \mathcal{L}(G, F, D_X, D_Y).$$





winter Yosemite → summer Yosemite



summer Yosemite → winter Yosemite





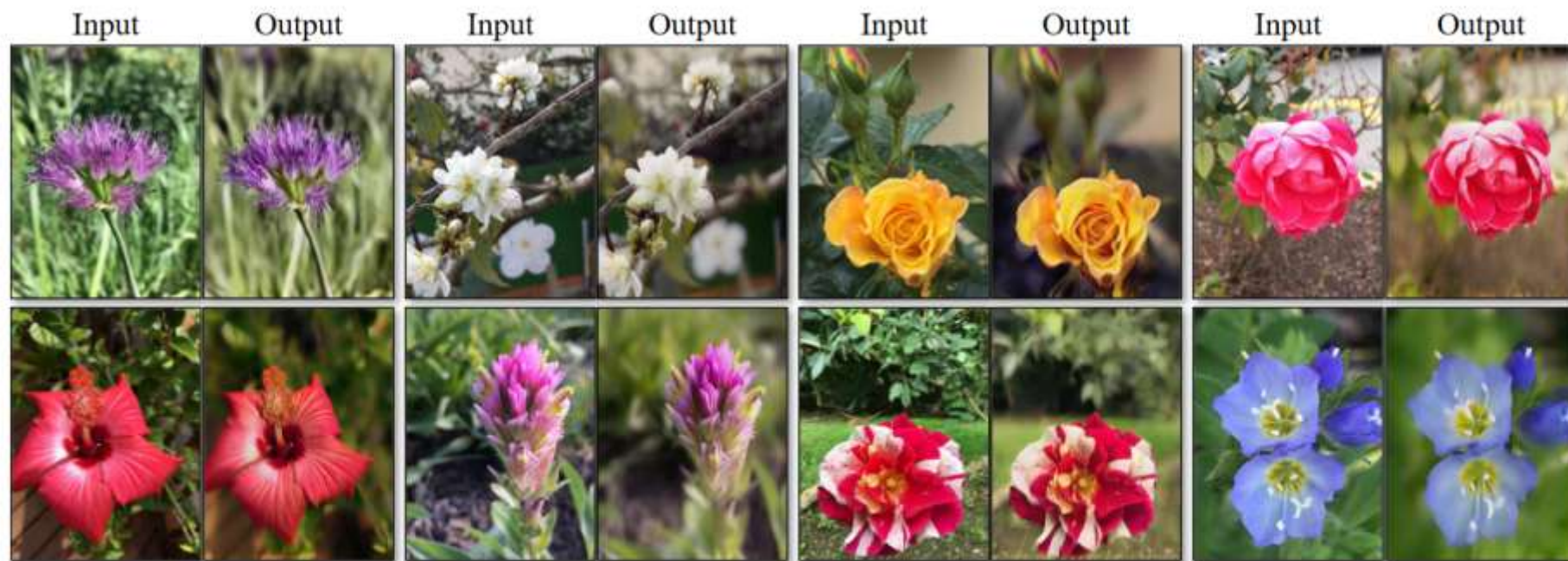
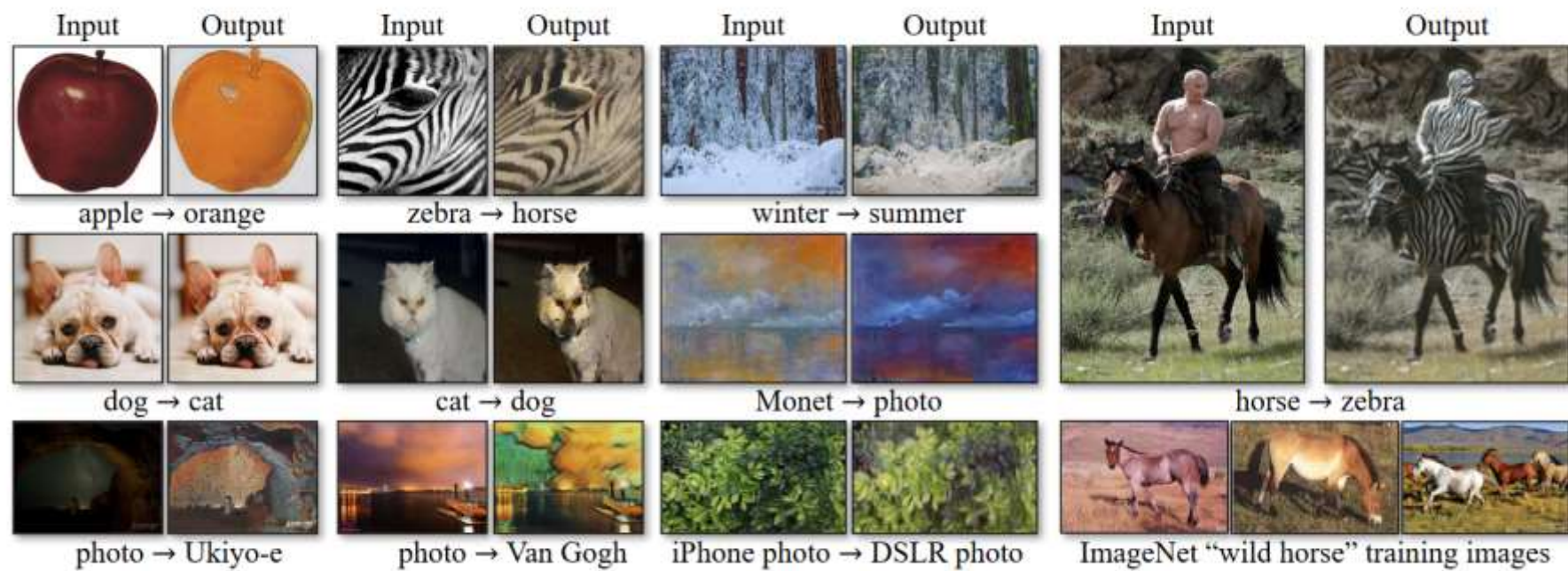


Figure 14: Photo enhancement: mapping from a set of smartphone snaps to professional DSLR photographs, the system often learns to produce shallow focus. Here we show some of the most successful results in our test set – average performance is considerably worse. Please see our [website](#) for more comprehensive and random examples.

Failure



منابع

<https://livebook.manning.com/#!/book/gans-in-action/chapter-4/v-4/54>
<https://filebox.ece.vt.edu/~jbhuang/teaching/ece6554/sp17/lectures/GAN-topic.pptx>
<https://www.slideshare.net/datamics/slideshare-gan>
<https://mc.ai/conditional%E2%80%8A-%E2%80%8AAdcgan-in-tensorflow/>
<https://medium.com/apache-mxnet/transposed-convolutions-explained-with-ms-excel-52d13030c7e8>
https://leonardoaraujosantos.gitbooks.io/artificial-intelligence/content/image_segmentation.html
<https://towardsdatascience.com/applied-deep-learning-part-3-autoencoders-1c083af4d798>
http://openaccess.thecvf.com/content_cvpr_2017/papers/Isola_Image-To-Image_Translation_With_CVPR_2017_paper.pdf
<https://www.microsoft.com/developerblog/2017/06/12/learning-image-image-translation-cyclegans/>
<https://arxiv.org/pdf/1703.10593.pdf>

