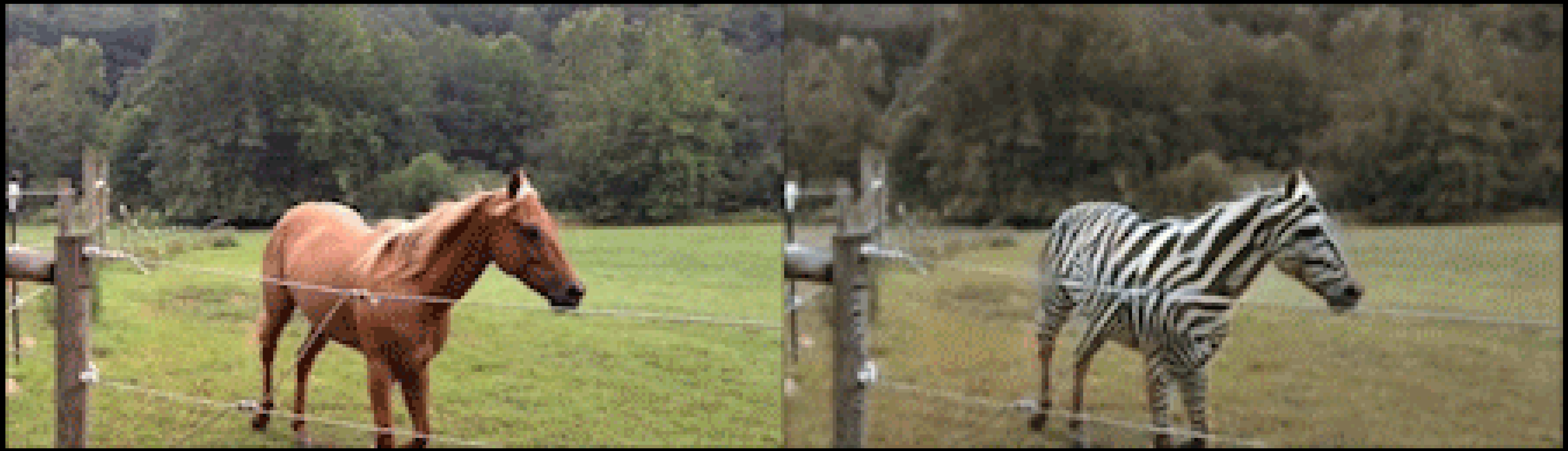
AI for the Media

Week 7, CycleGAN + SuperRes

25.2.2022 / UAL-CCI

~ Vít Růžička

Today we will learn about a model capable of:



Overview

(pre-recorded lecture)

Domain to domain models, CycleGANs and Super resolution:

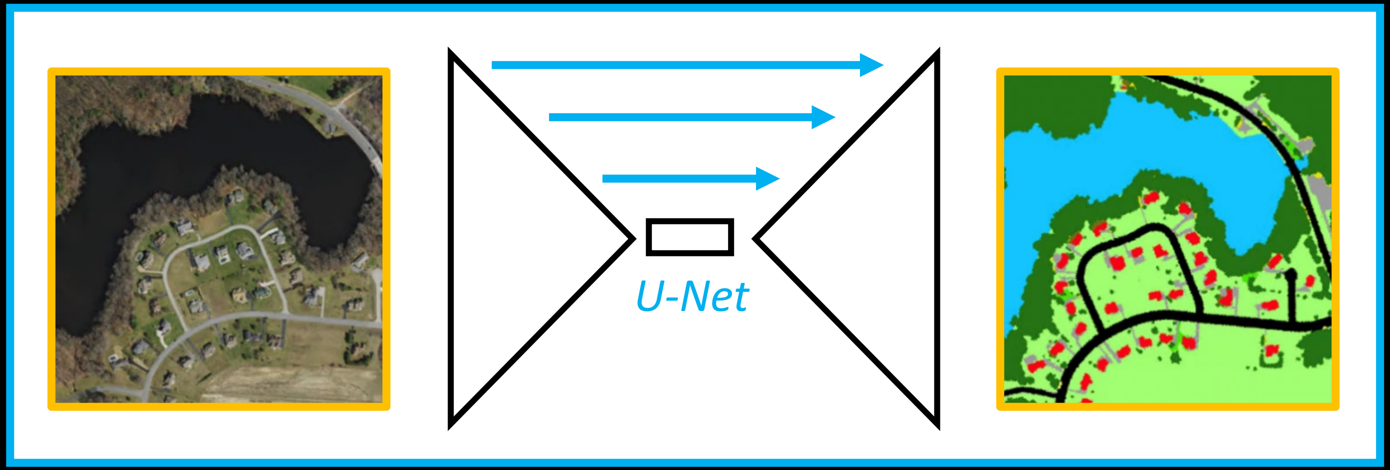
- **CycleGAN** as a simple extension to pix2pix
- **SuperResolution**
  - As a tool to increase quality of generated images with some cost involved
- **Limitations and follow-up readings**

Practical session (*during the live session*):

- **Code**: Trying a CycleGAN model
- **Demo**: Easy SuperResolution tools to use

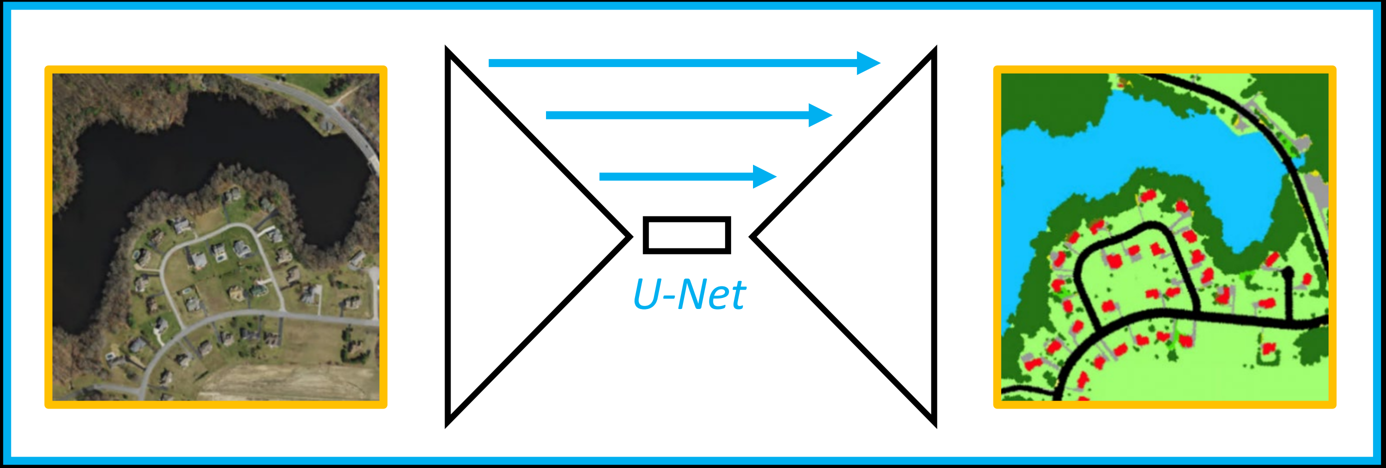
Recap

U-Net



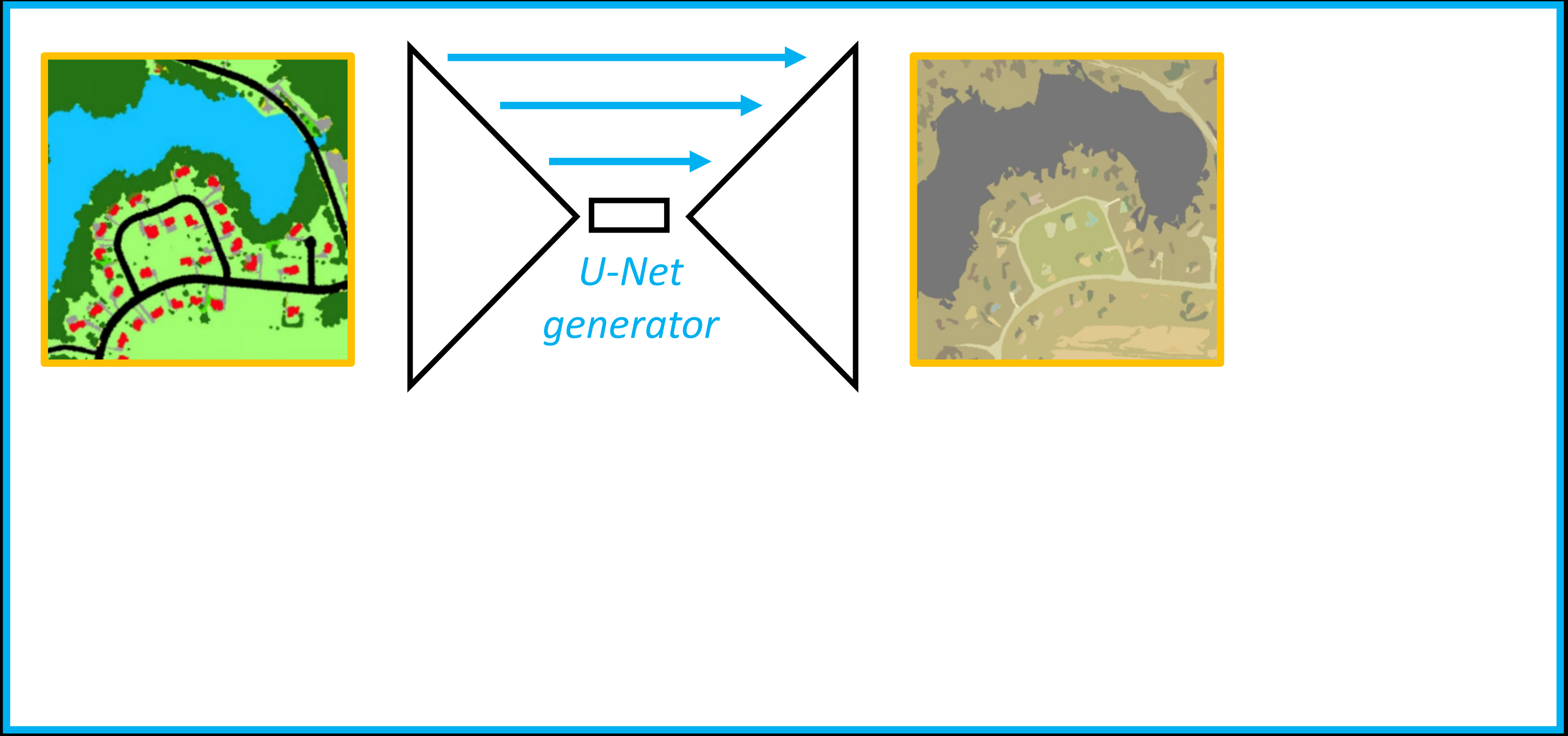
- Typical model for **semantic segmentation**

U-Net

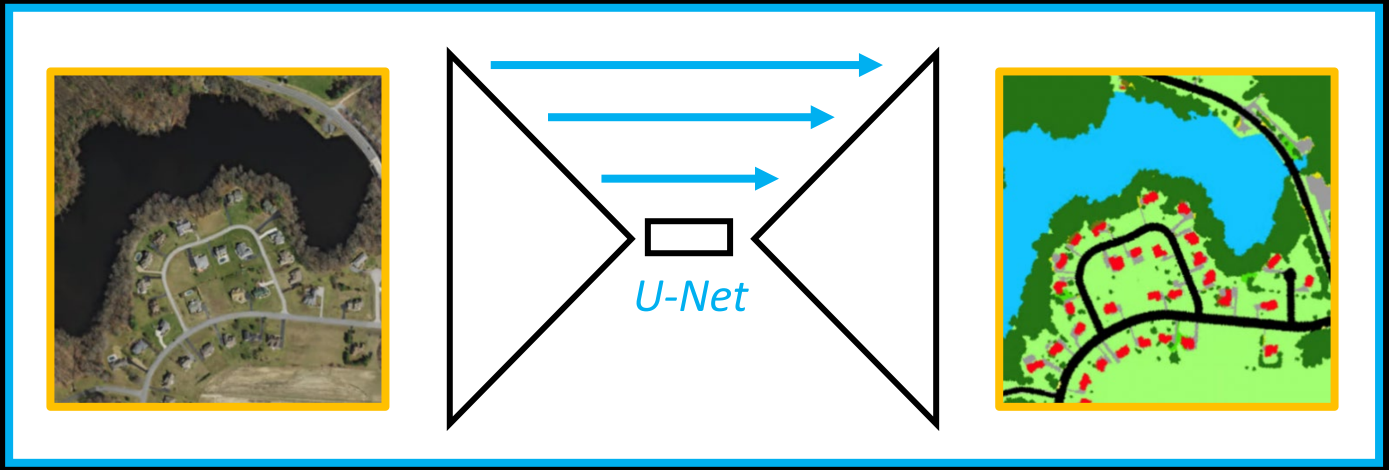


- Typical model for **semantic segmentation**

pix2pix

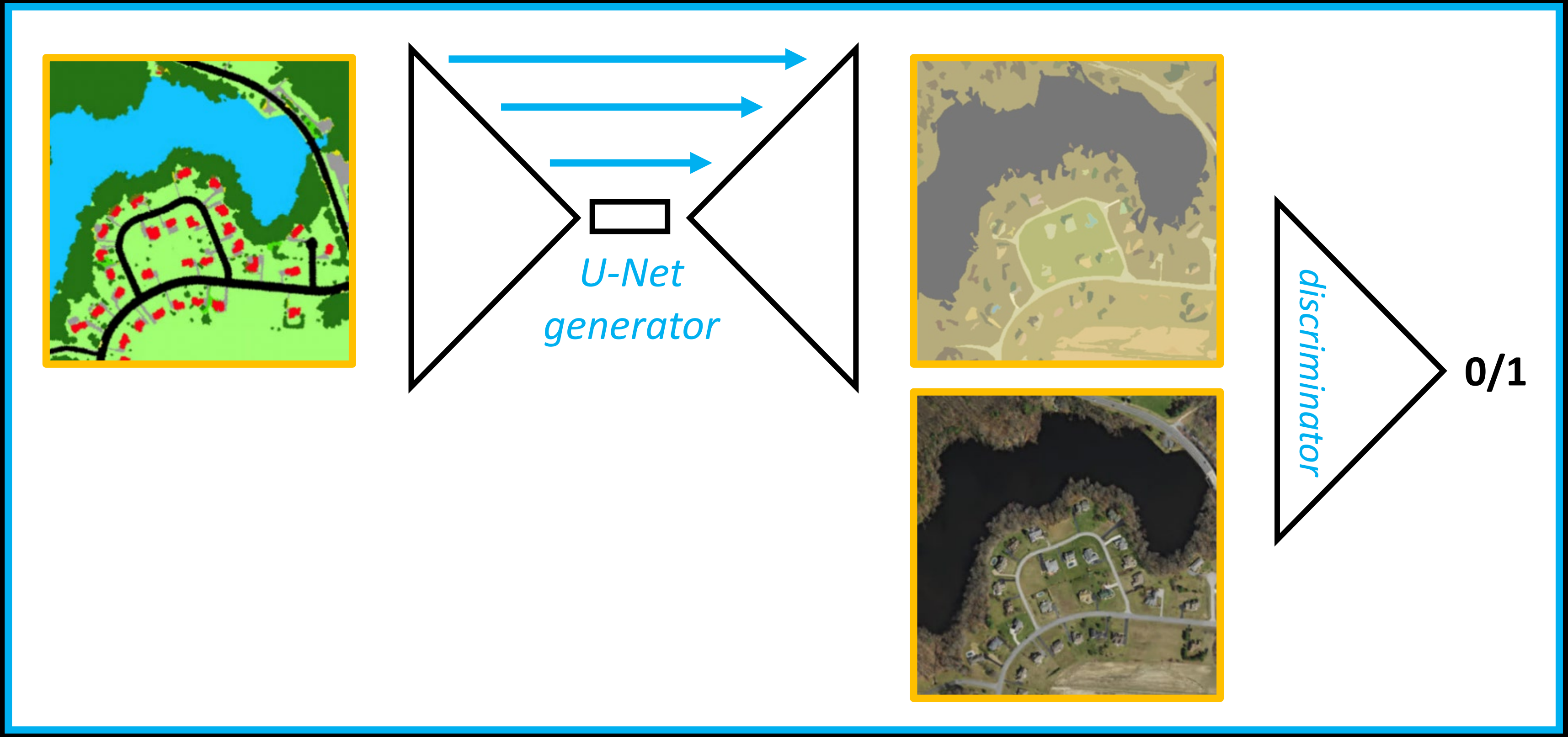


U-Net



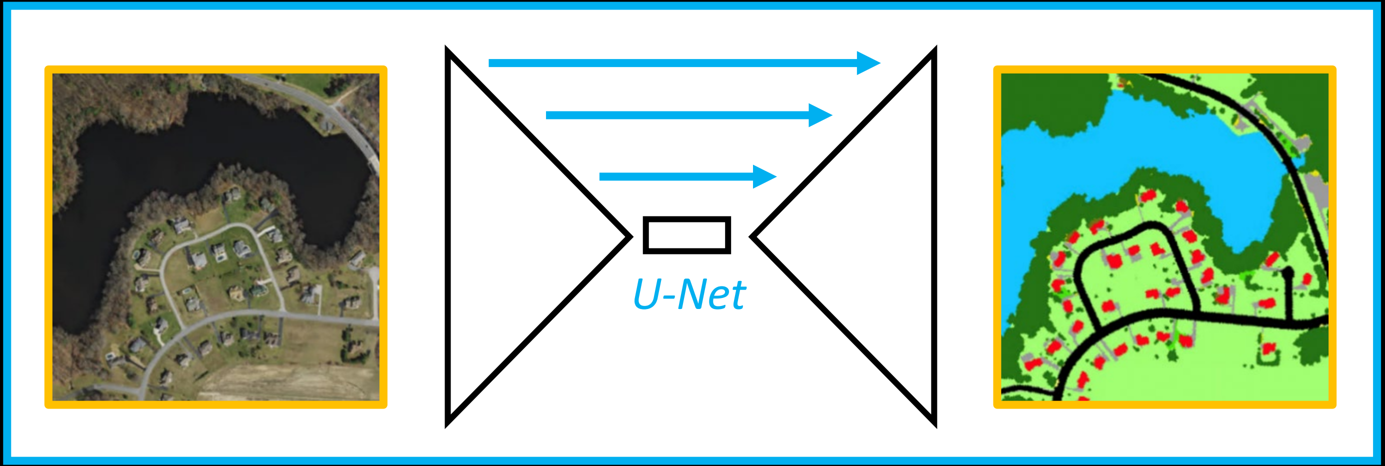
- Typical model for **semantic segmentation**

pix2pix



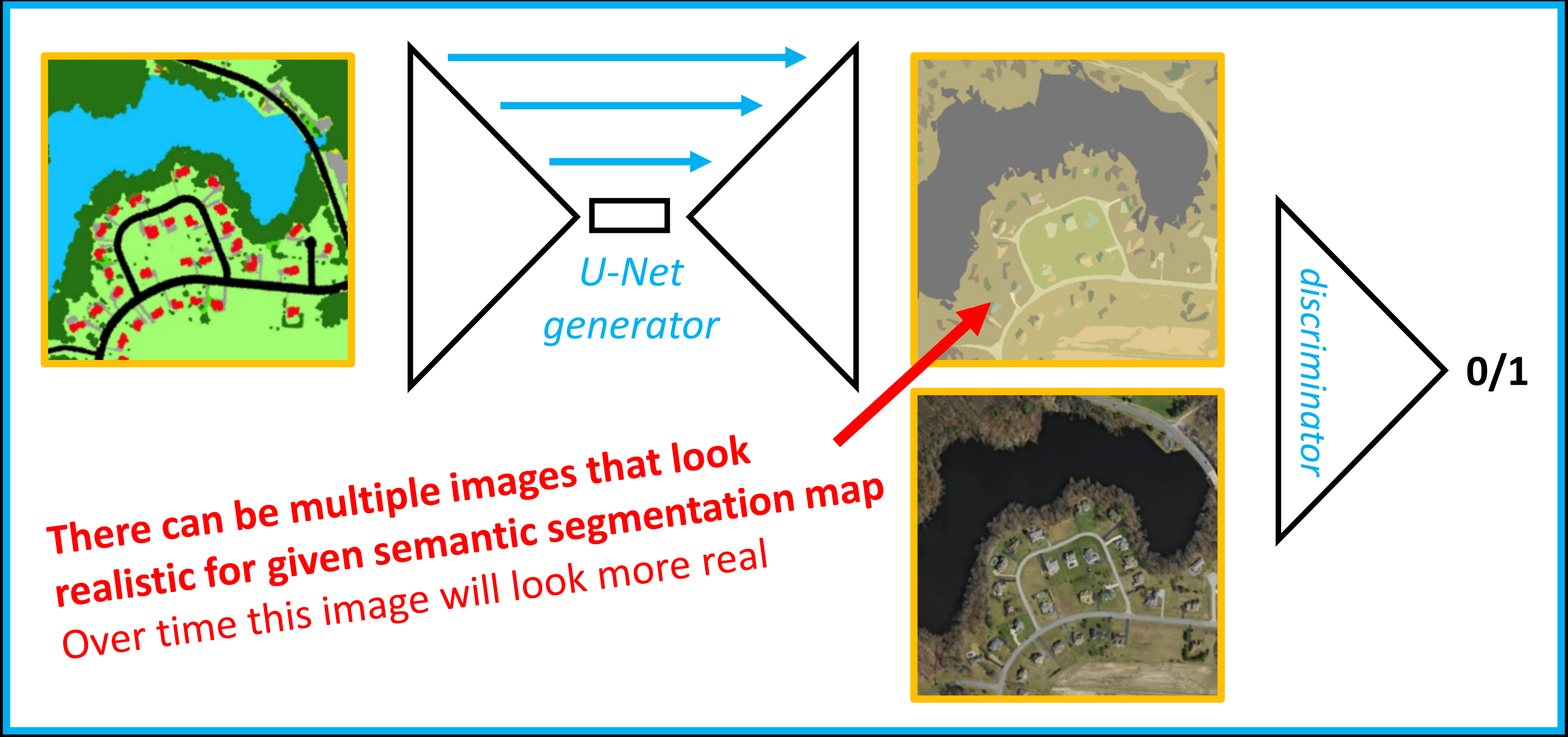
- Typical model when the output has **multiple possible realities**

U-Net



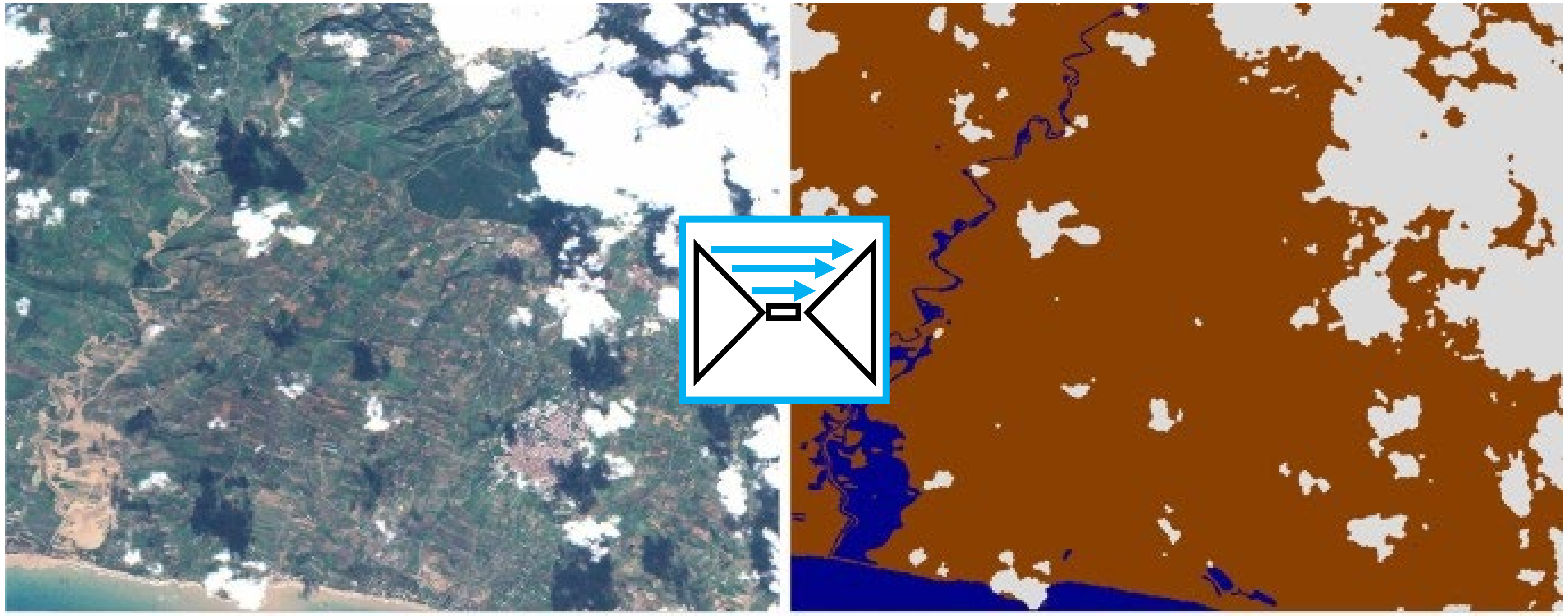
- Typical model for **semantic segmentation**

pix2pix



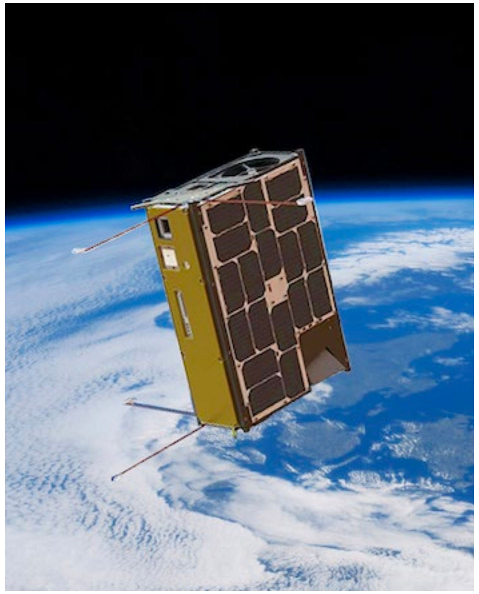
- Typical model when the output has **multiple possible realities**

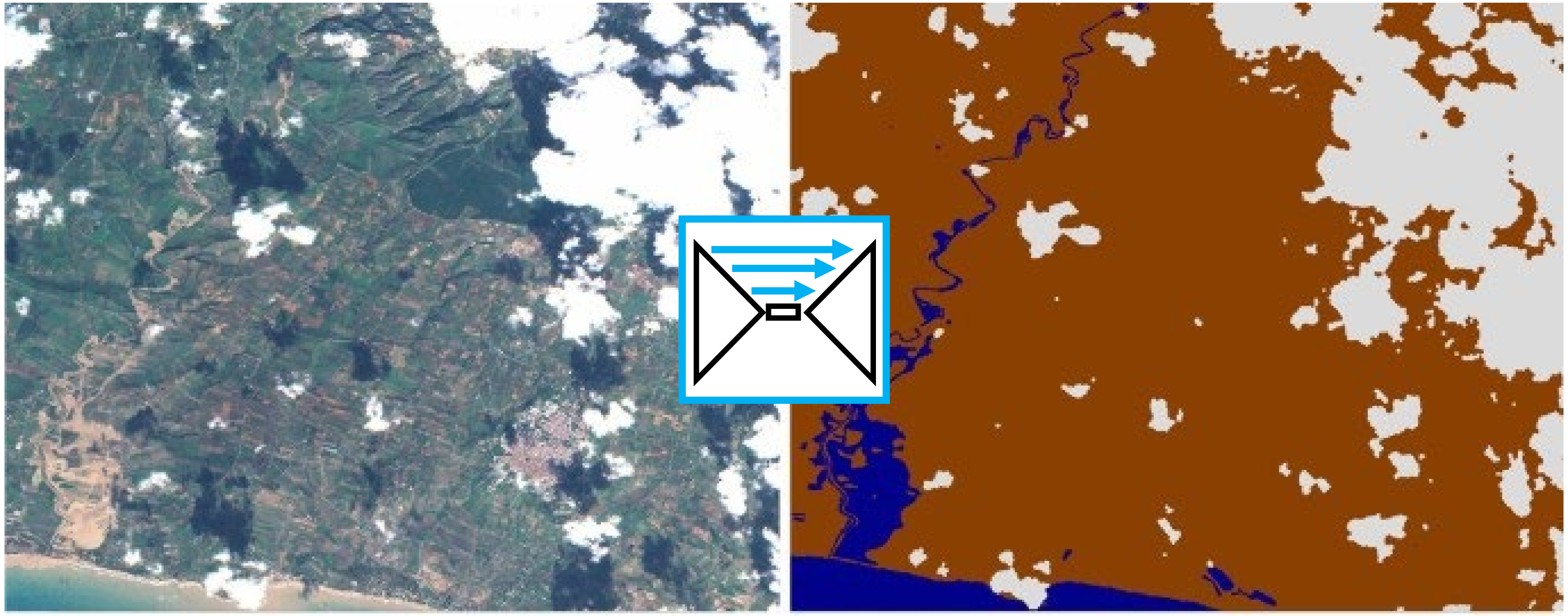
U-Net: Real-world example

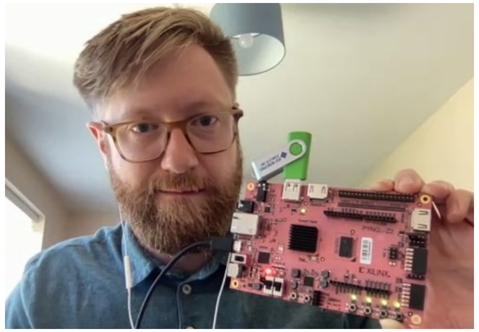


Nature paper: Towards global **flood mapping onboard low cost satellites** with ML

U-Net: Real-world example





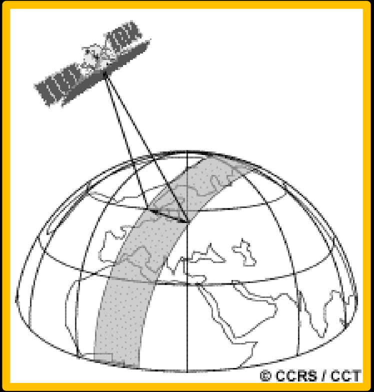


radiation resistant HW

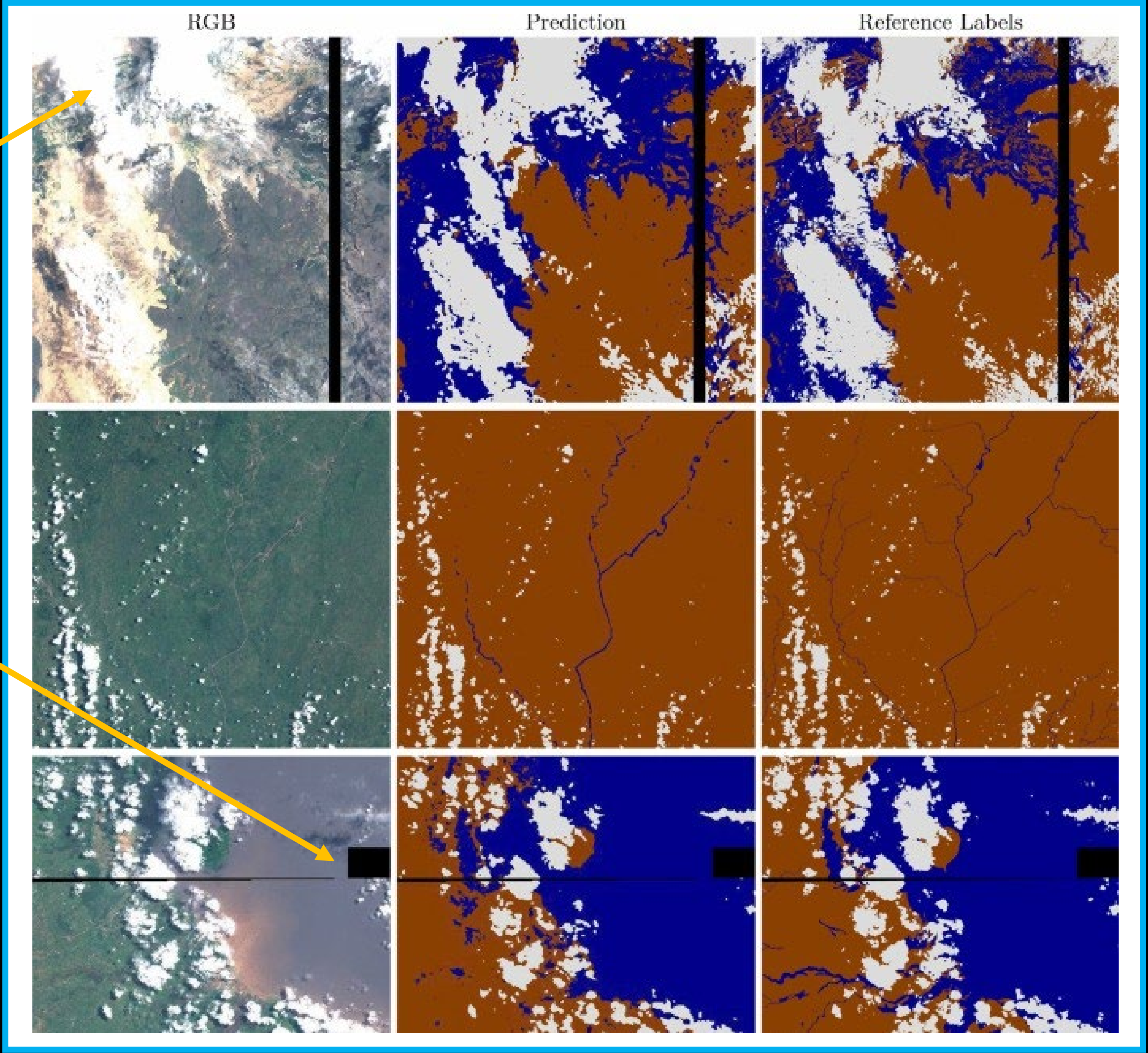
Nature paper: Towards global **flood mapping** **onboard low cost satellites** with ML

Real-world is messy!

- Clouds everywhere
- Erroneous data, Noisy



- Limited viewing capability



Topic I: CycleGANs

Introduction

Motivation

- We can’t always get paired data!

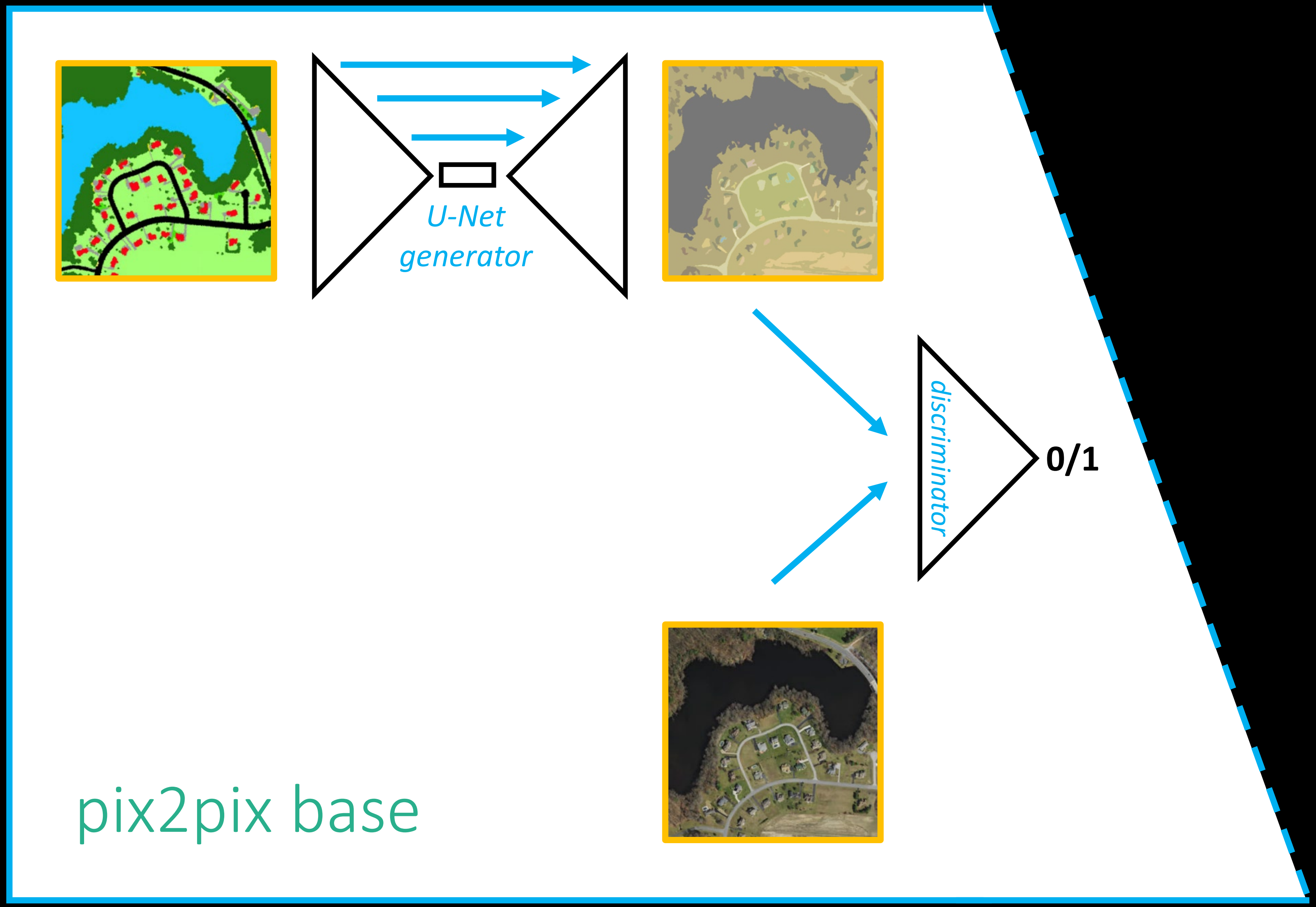
- Hard to collect pairs
    - **horse2zebra**

- We want it to work with new unseen samples
    - **day2night**
    - *(also not exactly pairs)*

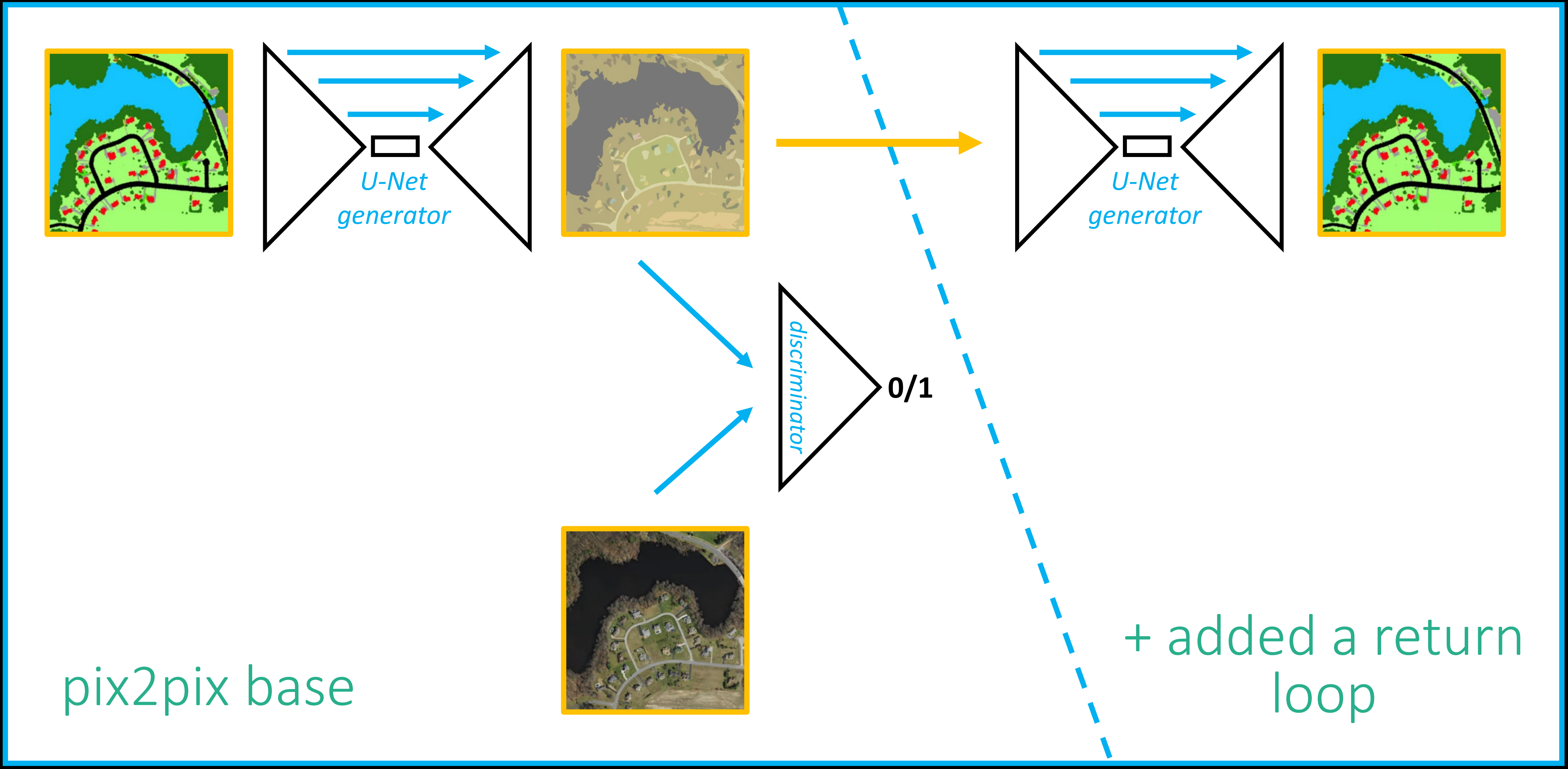
- When accessing archive data, we may have incompatible recordings
    - **Optical2sar**
    - *(same location, but different sensor type)*

13 channels *8 channels*

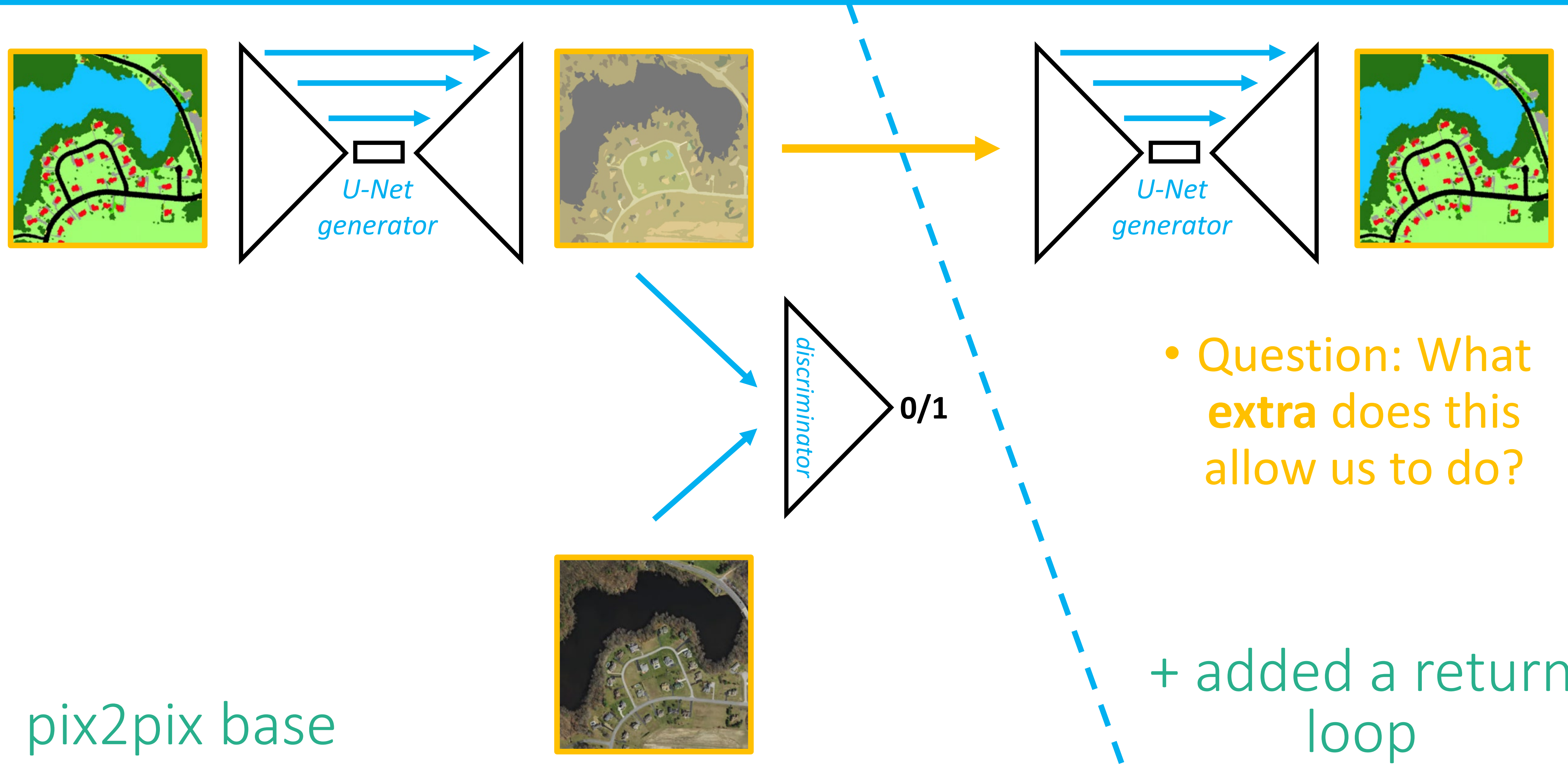
CycleGAN



CycleGAN


U-Net
generator
discriminator
0/1
U-Net
generator
pix2pix base
+ added a return
loop

CycleGAN

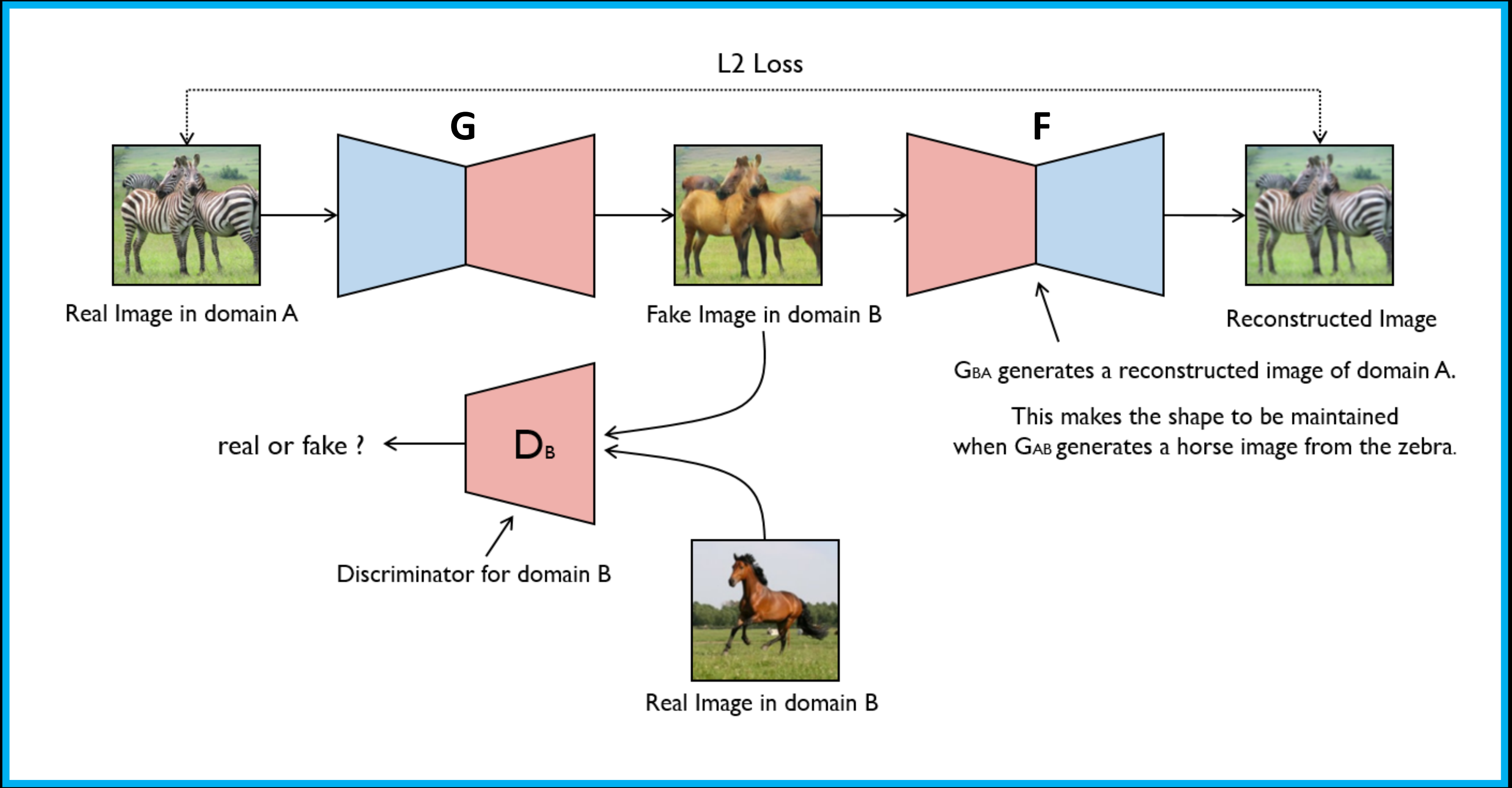


- Question: What **extra** does this allow us to do?

pix2pix base

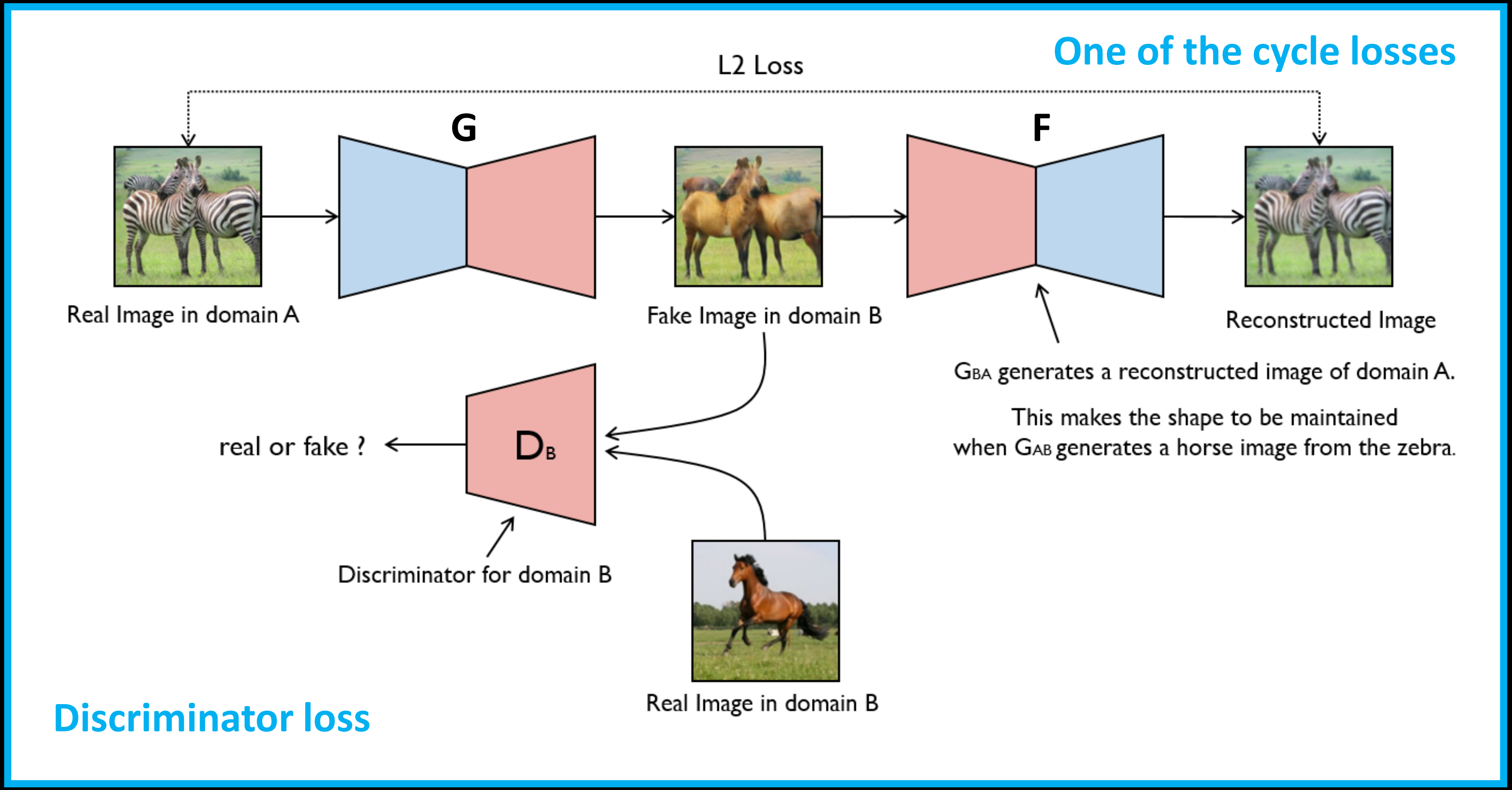
+ added a return loop

CycleGAN, two generators



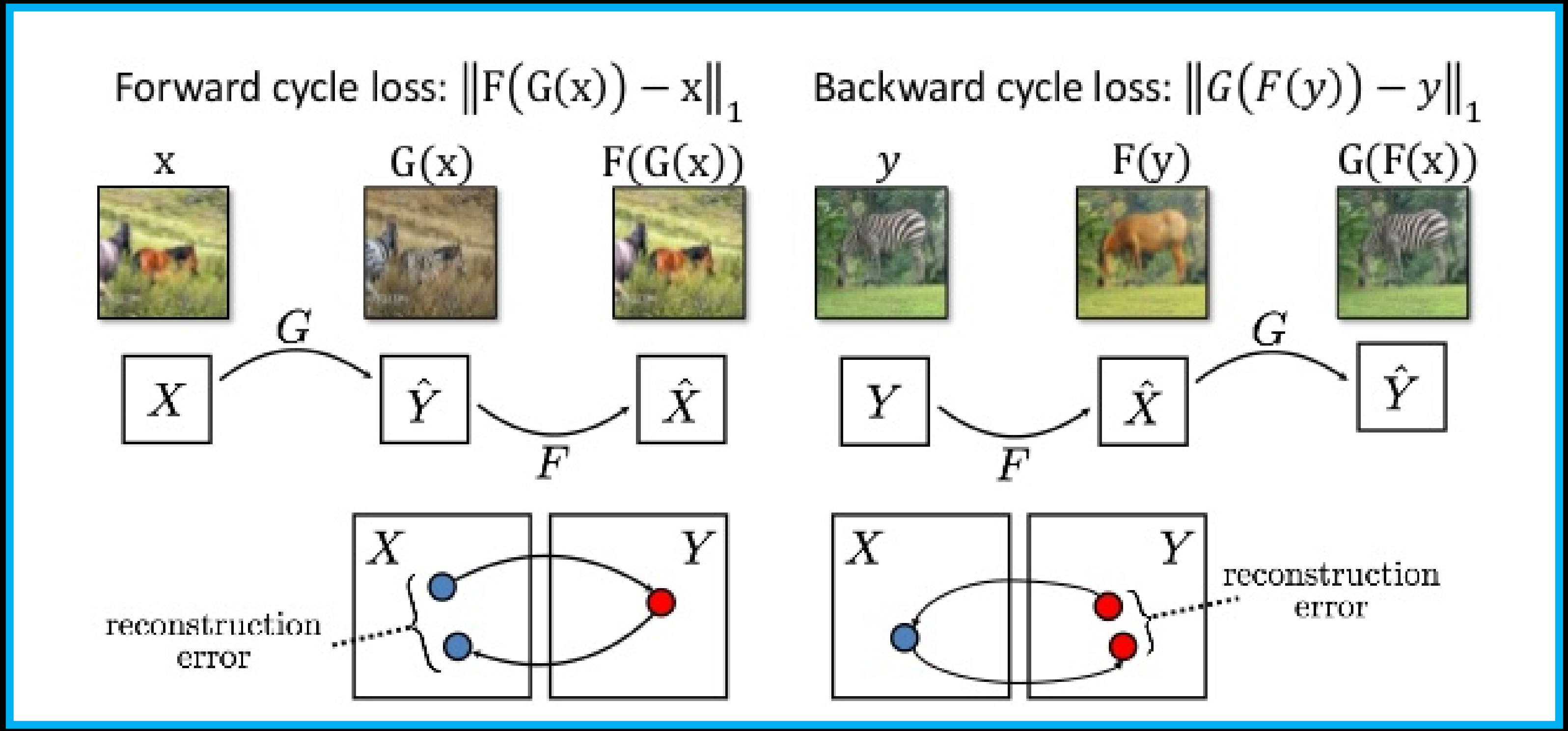
- Setup with two generators going between two domains (**G** and **F**) and a special cyclic loss function. This model **doesn’t require paired data** in the training datasets.

CycleGAN, two generators

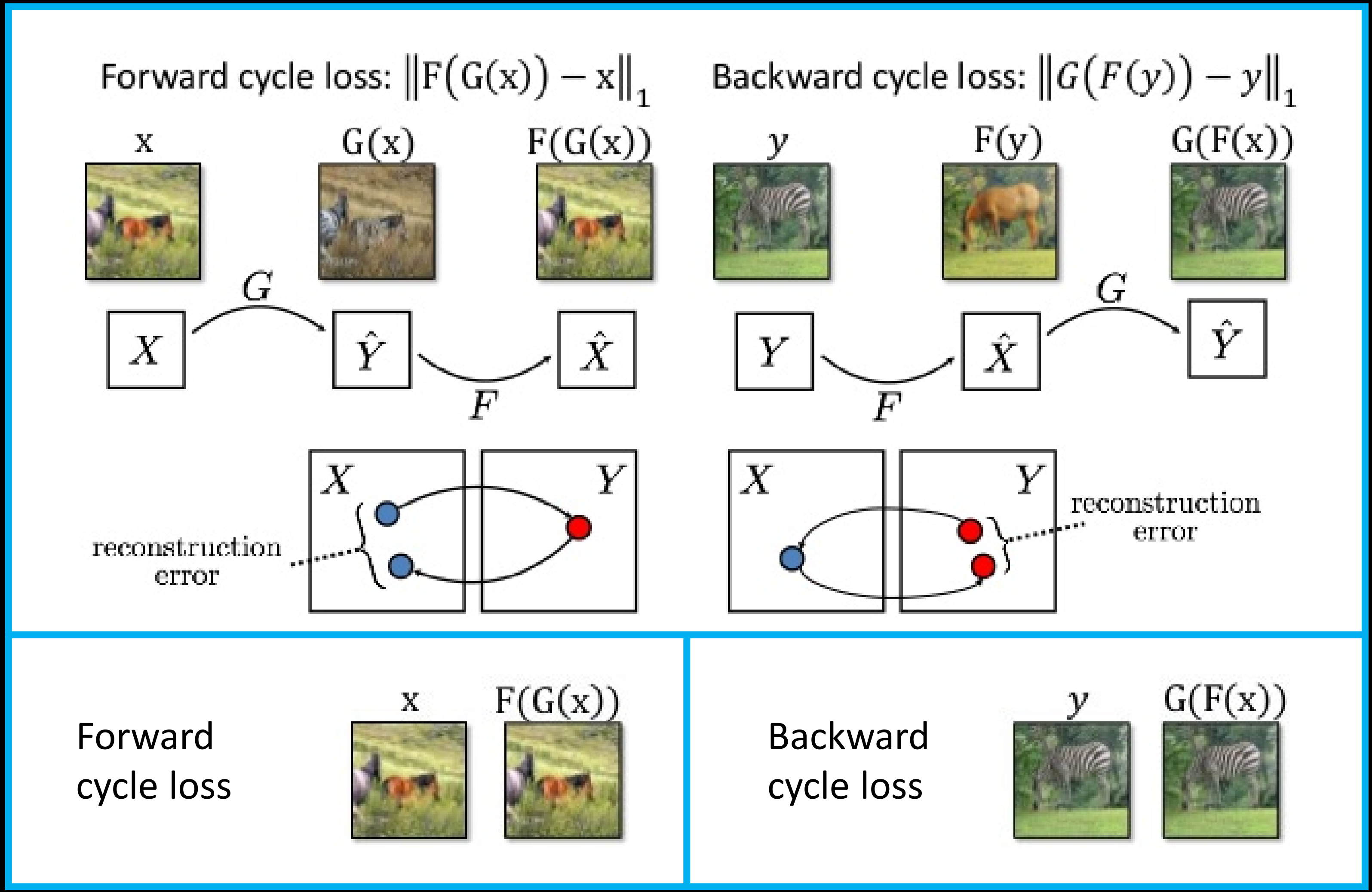


- Setup with two generators going between two domains (**G** and **F**) and a special cyclic loss function. This model **doesn't require paired data** in the training datasets.

CycleGAN, loss functions

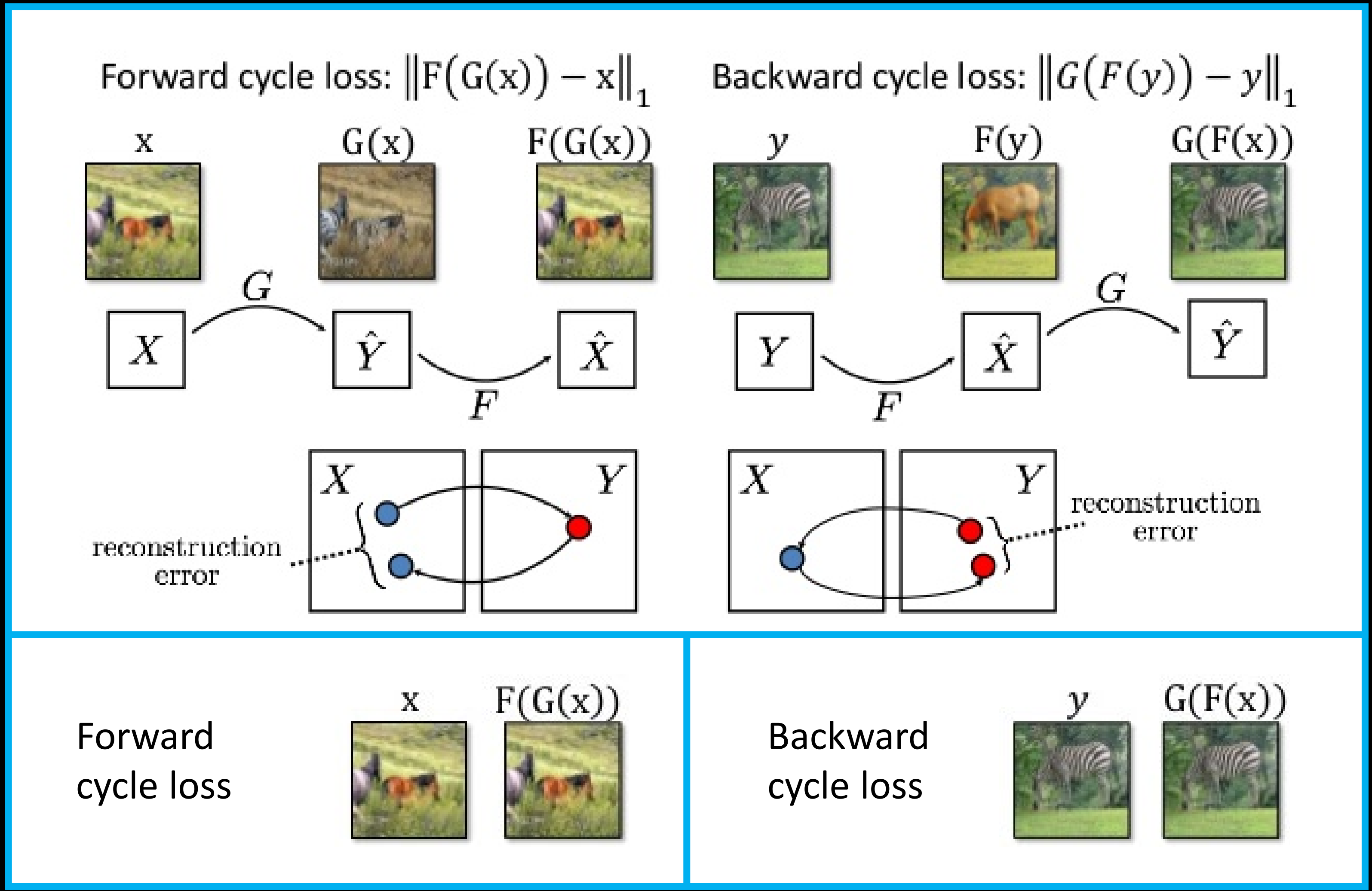


CycleGAN, loss functions



- We call these **cyclic loss functions**

CycleGAN, loss functions



- We call these **cyclic loss functions**

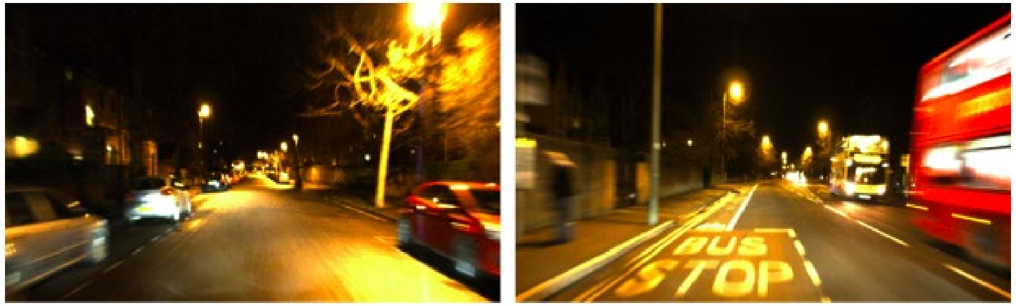
- Alongside the original **discriminator loss functions** (to prevent just learning identity)

Topic I: CycleGANs

Examples

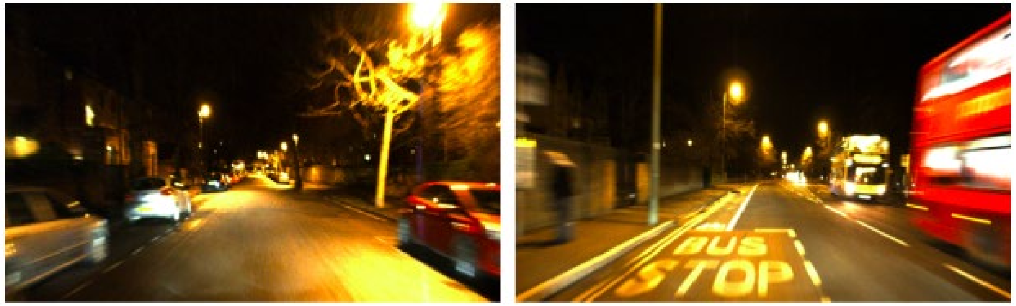
CycleGAN: Real-world example

- Models on autonomous cars usually trained on clean data
- When they encounter night images, the accuracy goes down!



CycleGAN: Real-world example

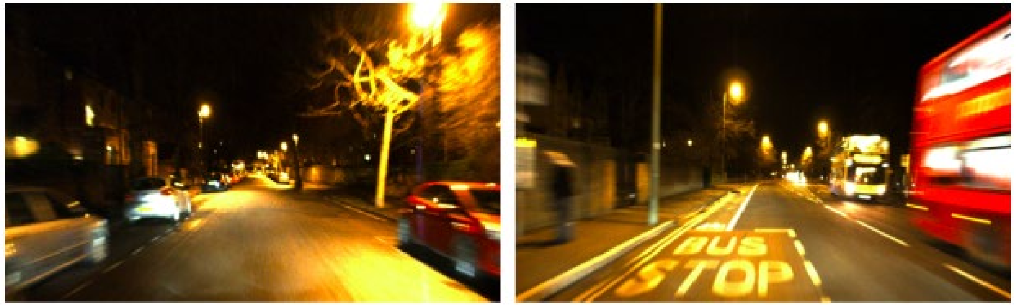
- Models on autonomous cars usually trained on clean data
- When they encounter night images, the accuracy goes down!

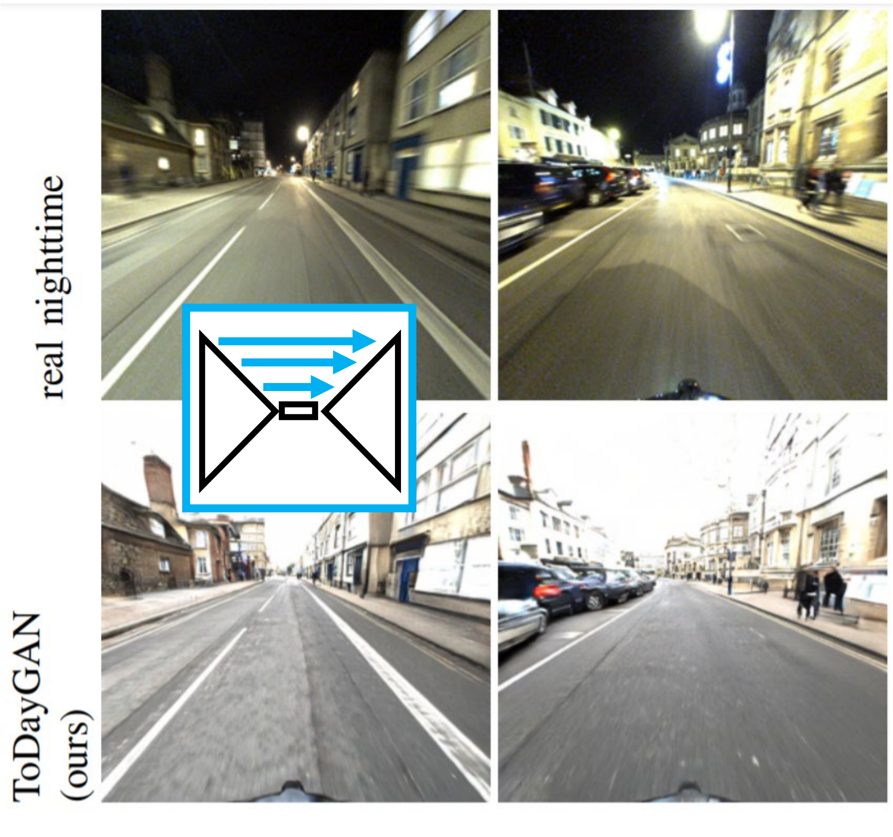


- We want something like a **night2day model**
- We **can't collect** photos from everywhere from as {day, night} **pairs**

CycleGAN: Real-world example

- Models on autonomous cars usually trained on clean data
- When they encounter night images, the accuracy goes down!



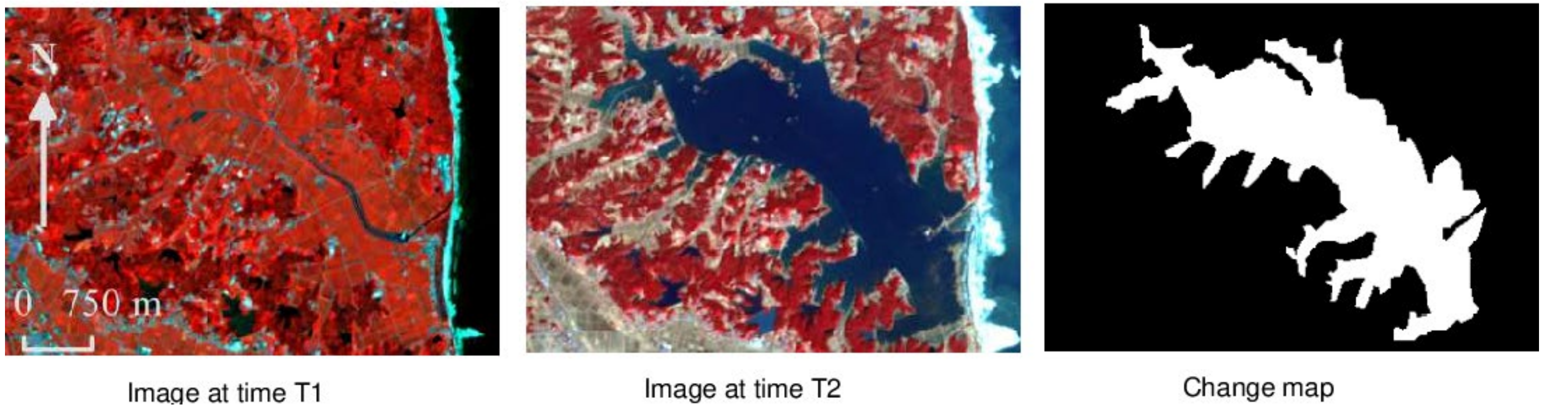


Night 2 Day, followed by more tasks

Night-to-Day Image Translation for Retrieval-based Localization (arxiv.org/abs/1809.09767)

CycleGAN: Real-world example

- **Change detection** with remote sensing images:

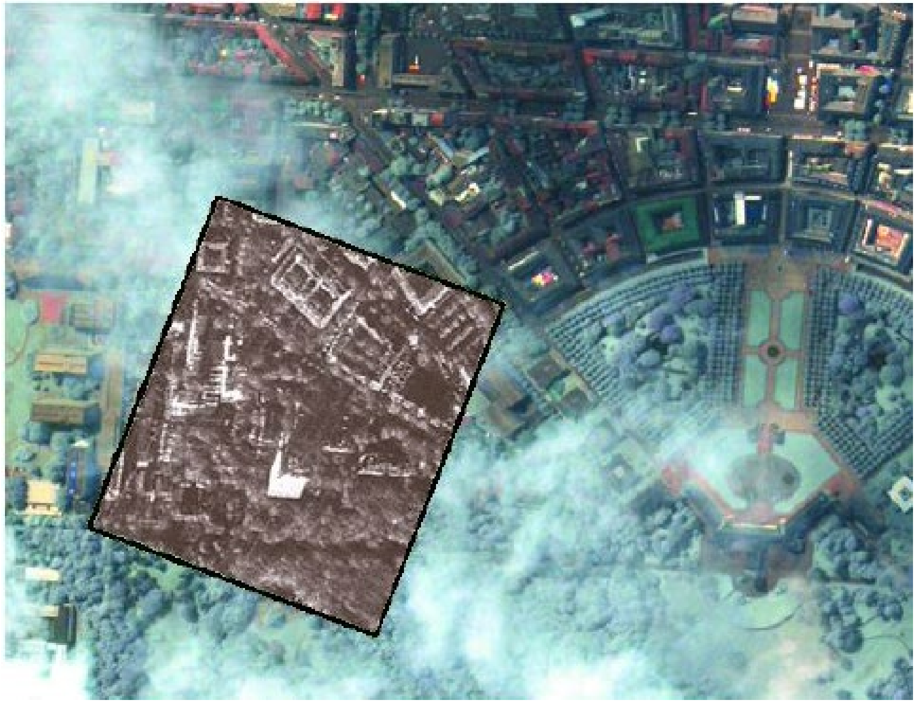


difference image = image at T2 – image at T1

- But what if these two images come from different types of satellites?

CycleGAN: Real-world example

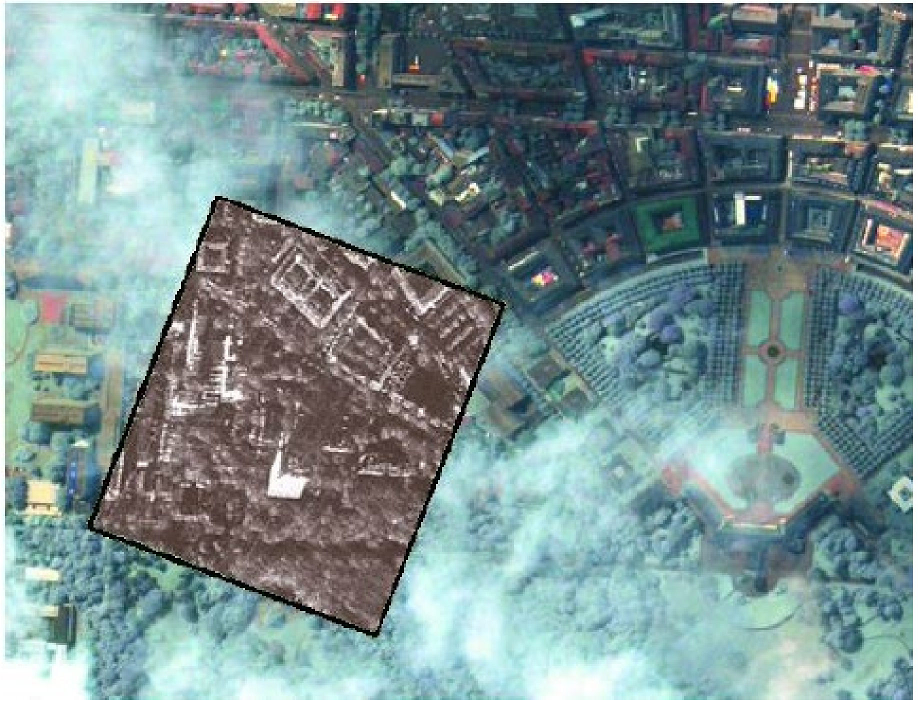
- If the location is covered by clouds, only so-called SAR satellites can see through:



Q: Can we still compare with these?

CycleGAN: Real-world example

- If the location is covered by clouds, only so-called SAR satellites can see through:



Q: Can we still compare with these?

Image at T1

Hard to compare between these

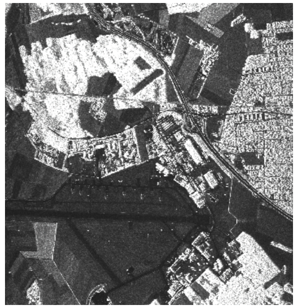
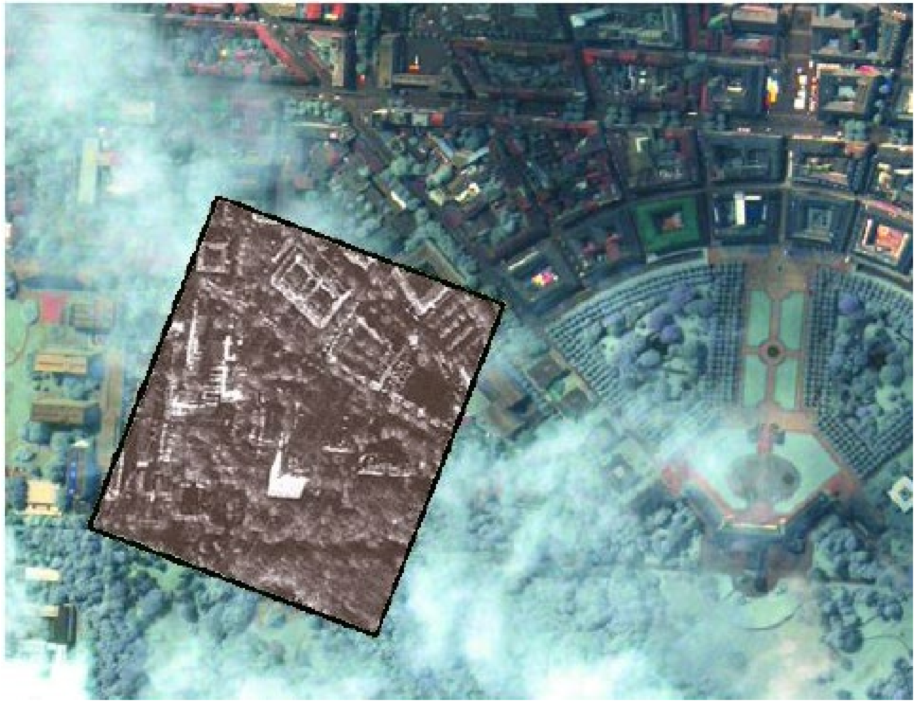


Image at T2

CycleGAN: Real-world example

- If the location is covered by clouds, only so-called SAR satellites can see through:



Q: Can we still compare with these?

Image at T1

Then we can compare them:

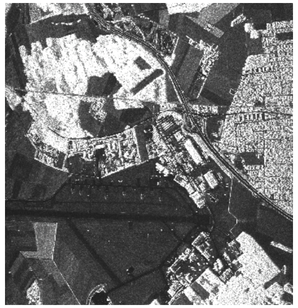


Image at T2

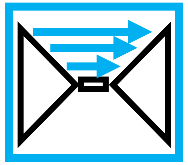
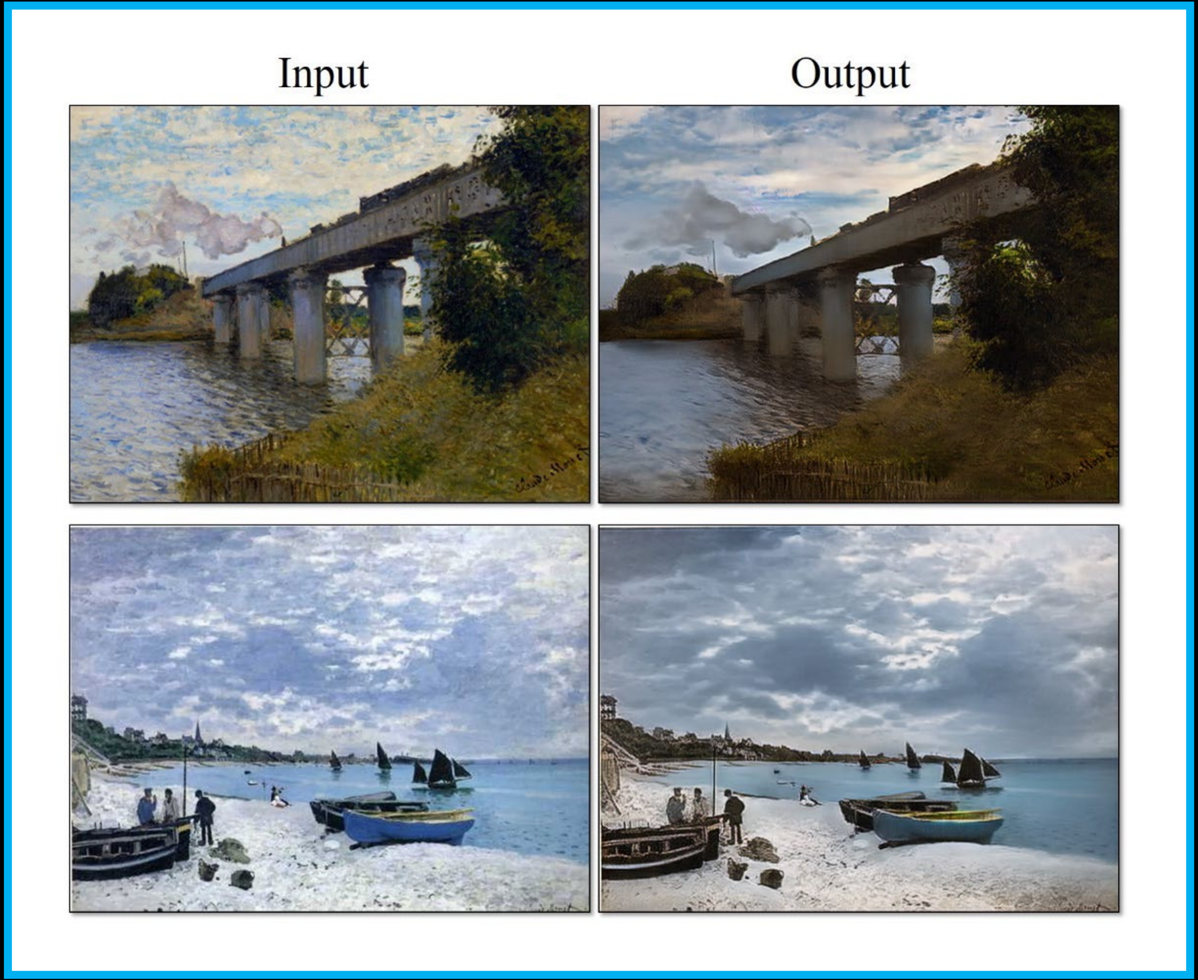


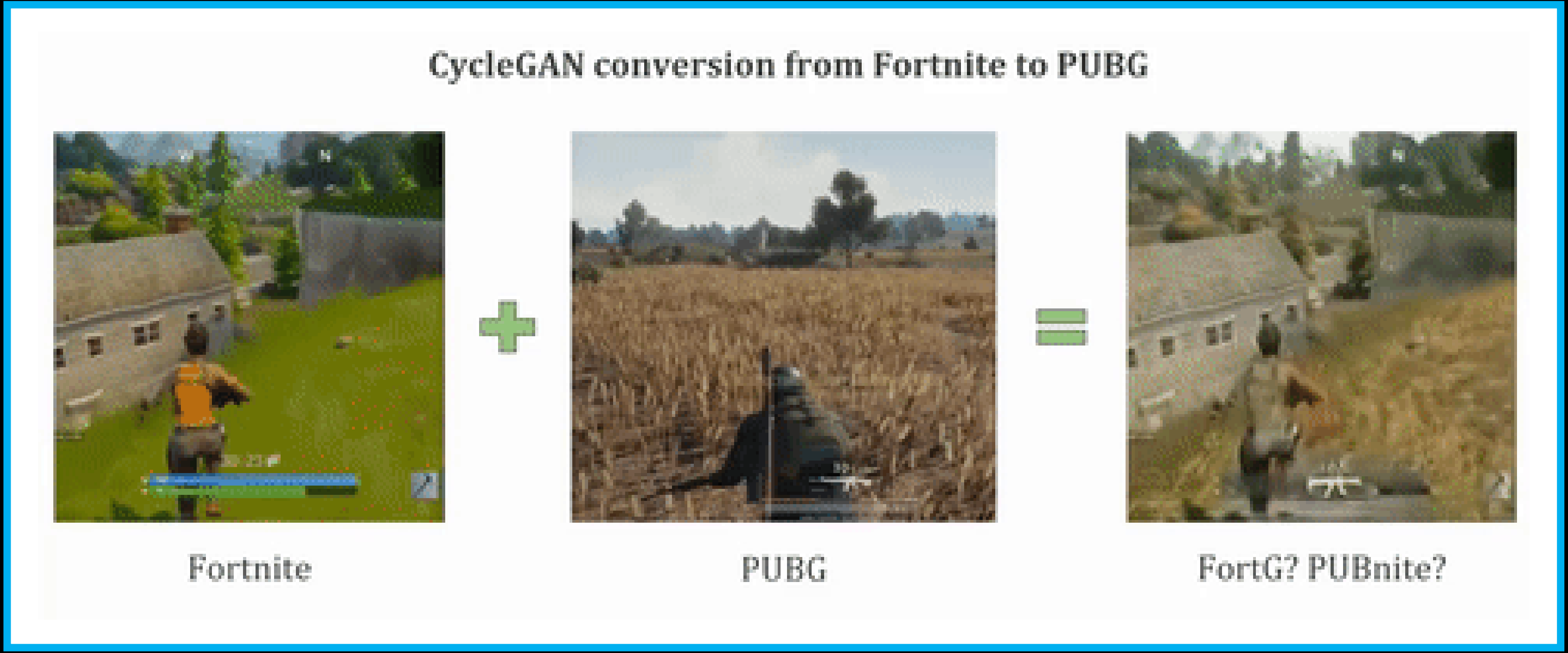
Image at T2
CycleGANed

CycleGAN: Art examples

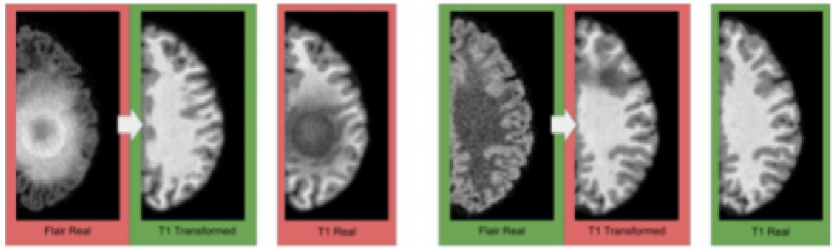
Monet 2 Real,
and more examples at
junyanz.github.io/CycleGAN/



CycleGAN: Art examples



Game 2 Game, Fortnite Into PUBG
youtu.be/xkLtgwWxrec



(a) A translation removing tumors (b) A translation adding tumors

How to interpret CycleGAN results: CycleGAN, as well as any GAN-based method, is fundamentally hallucinating part of the content it creates. Its outputs are predictions of "what might it look like if ..." and the predictions, thought plausible, may largely differ from the ground truth. CycleGAN should only be used with great care and calibration in domains where critical decisions are to be taken based on its output. This is especially true in medical applications, such as translating MRI to CT data. Just as CycleGAN may add fanciful clouds to a sky to make it look like it was painted by Van Gogh, it may add tumors in medical images where none exist, or remove those that do. More information on dangers like this can be found in **Cohen et al**.

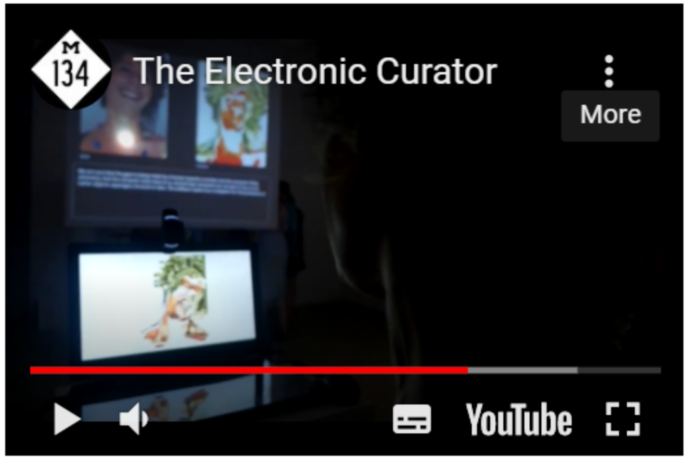
Resurrecting Ancient Cities

Jack Clark used our code to convert ancient maps of **Babylon**, **Jerusalem** and **London** into modern Google Maps and satellite views.

Face ↔ Ramen

Takuya Kato performed a magical and hilarious Face ↔ Ramen translation with CycleGAN. Check out more results **here**

The Electronic Curator



Eran Hadas and Eyal Gruss used CycleGAN to convert human faces into vegetable portraits. They built a real-time art demo which allows users to interact with the model with their own faces.

Source official page: https://junyanz.github.io/CycleGAN/

Topic I: CycleGANs

Limitations

Less control

... on which data gets transferred between the two domains >

Meet the Authors of CycleGAN

Failure Cases

Our model does not work well when a test image looks unusual compared to training images, as shown in the left figure. See more typical failure cases [here]. On translation tasks that involve color and texture changes, as many of those reported above, the method often succeeds. We have also explored tasks that require geometric changes, with little success. For example, on the task of dog ↔ cat transfiguration, the learned translation degenerates into making minimal changes to the input. Handling more varied and extreme transformations, especially geometric changes, is an important problem for future work. We also observe a lingering gap between the results achievable with paired training data and those achieved by our unpaired method. In some cases, this gap may be very hard -- or even impossible -- to close: for example, our method sometimes permutes the labels for tree and building in the output of the cityscapes photos → labels task. Resolving this ambiguity may require some form of weak semantic supervision. Integrating weak or semi-supervised data may lead to substantially more powerful translators, still at a fraction of the annotation cost of the fully-supervised systems.

Source official page: https://junyanz.github.io/CycleGAN/

Steganography

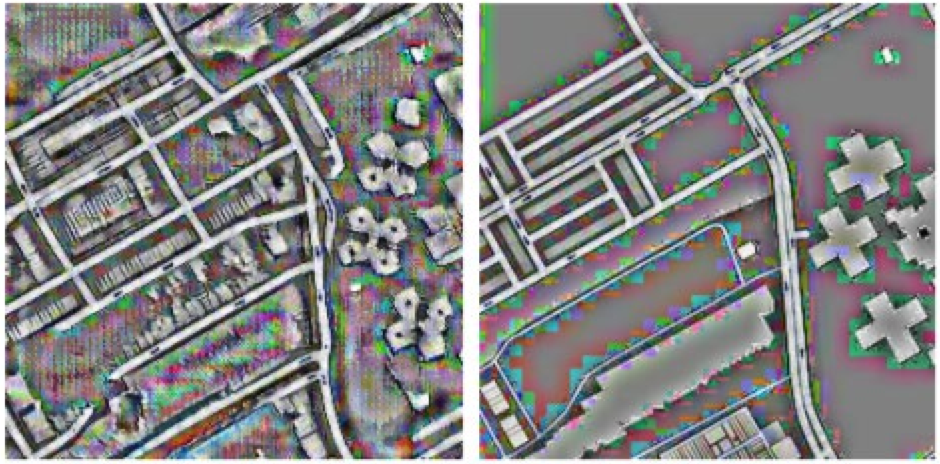
No message

Eagle has landed!

Steganography = encoding secret information into an image

(a) Aerial photograph: x. (b) Generated map: Fx. (c) Aerial reconstruction: GFx.

Figure 1: Details in x are reconstructed in GFx, despite not appearing in the intermediate map Fx.



(a) Generated map. (b) Training map, for comparison.

Figure 2: Maps with details amplified by adaptive histogram equalization. Information is present in the generated map even in regions that appear empty to the naked eye.

CycleGAN steganography

- Beware of what we are actually learning with the two generators …
  - **Steganography** = encoding secret information into an image (*such as the recipe of what to reconstruct*)

CycleGAN, a Master of Steganography - arxiv.org/abs/1712.02950

***)** PS: now it’s a good time to take a pause

Topic II: SuperResolution

Introduction

SuperResolution

- **Task motivation**
  - We saw that we can transfer from one domain to another domain, even if the data isn't paired …
  - **Intuition**: Could we consider *low resolution images* and *high resolution images* as two domains?
    - Would we benefit from having them paired (converting HQ image into LQ is easy!)

Pan sharpening

(inspiration from the past)

- Similar situation occurs when we have data of mixed resolutions …

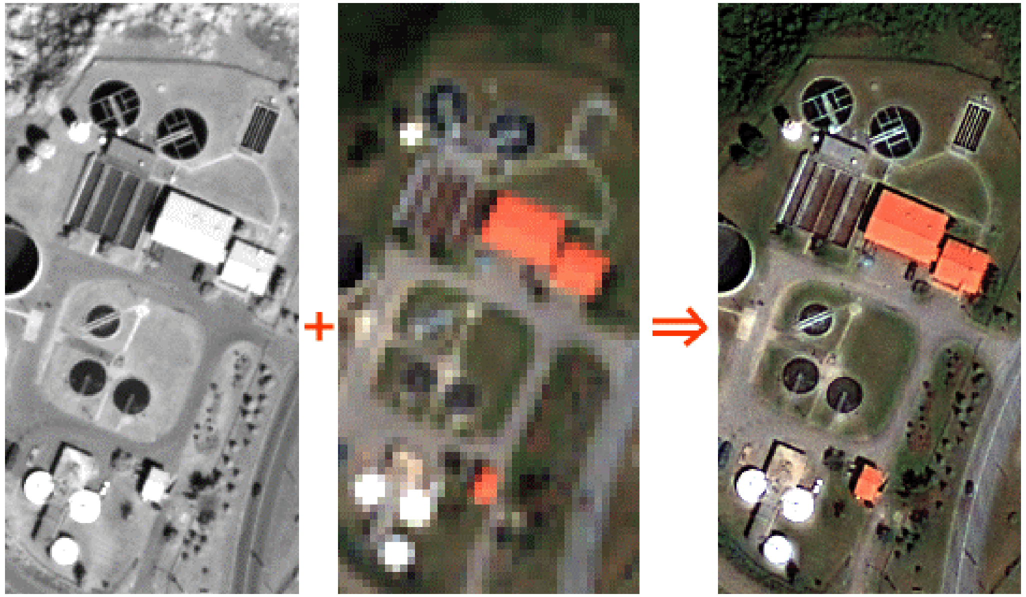
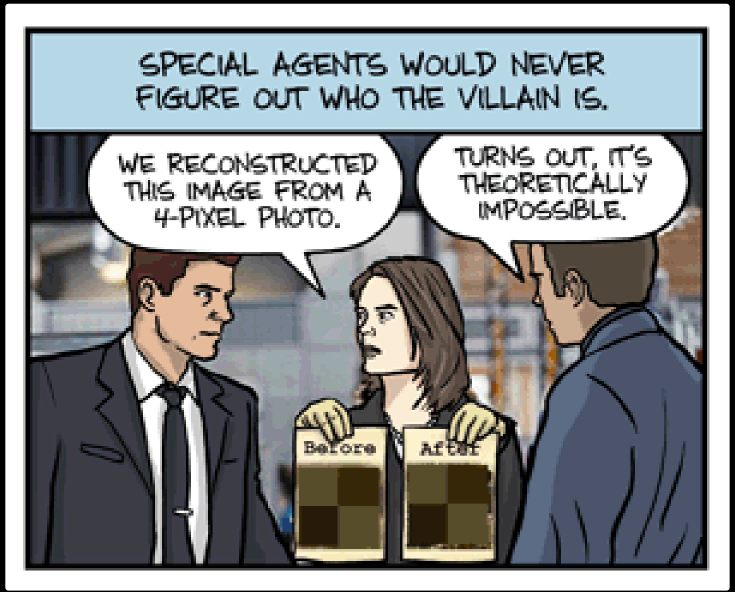


Image source: QuickBird. (C) DigitalGlobe

- High resolution black and white photo + low resolution colour photo
- Pan sharpening is a technique where we combine the detail of the BW photo with additional information of the colour image
- **Old technique: fully manual!**

Zoom and enhance!

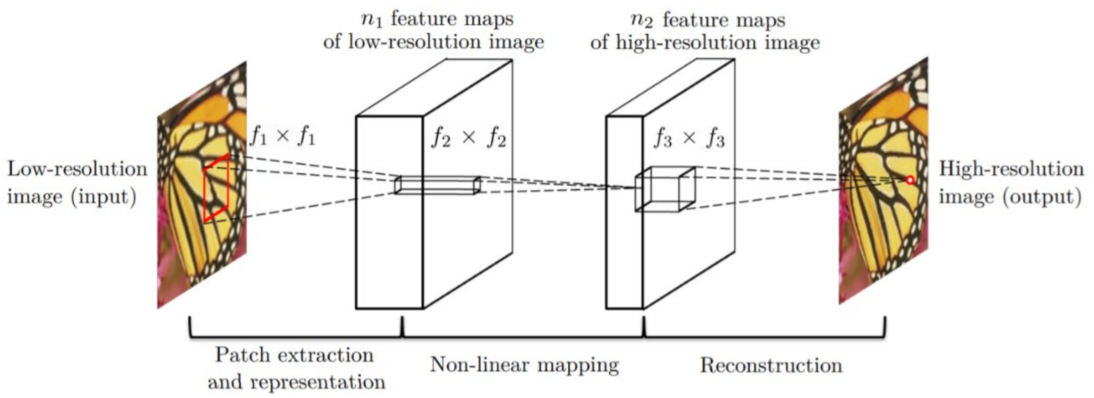


SuperResolution CNN (**SRCNN**)

paper 2015

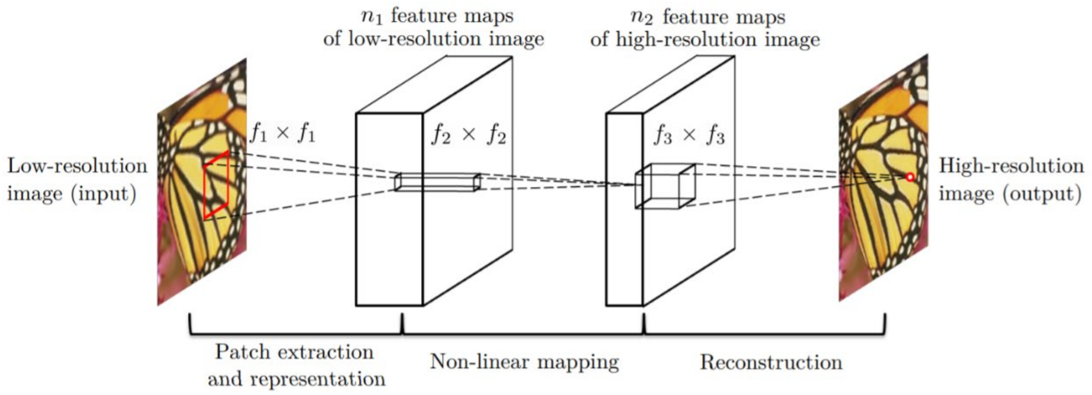
SuperResolution CNN (**SRCNN**)

paper 2015



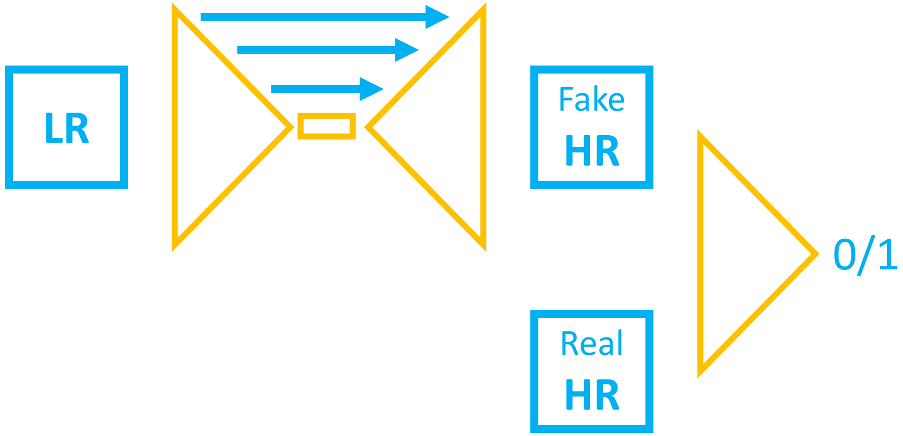
SuperResolution CNN (**SRCNN**)

paper 2015



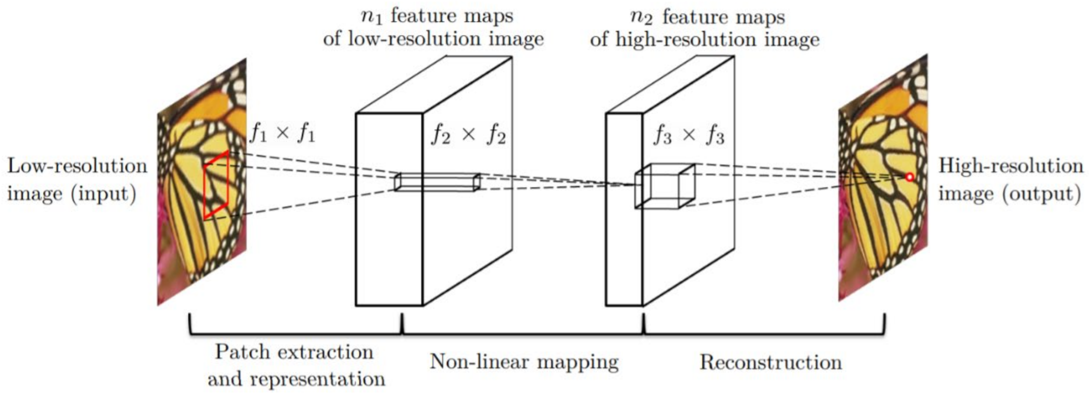
SuperResolution GAN (**SRGAN**)

paper 2017



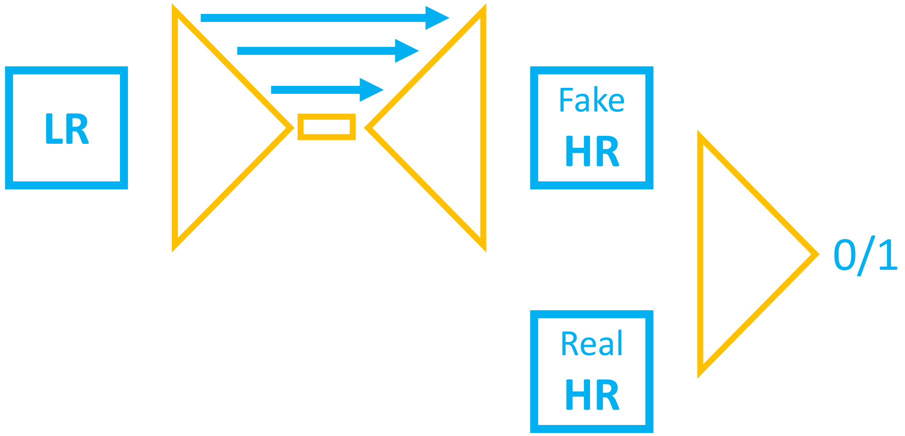
SuperResolution CNN (**SRCNN**)

paper 2015



SuperResolution GAN (**SRGAN**)

paper 2017



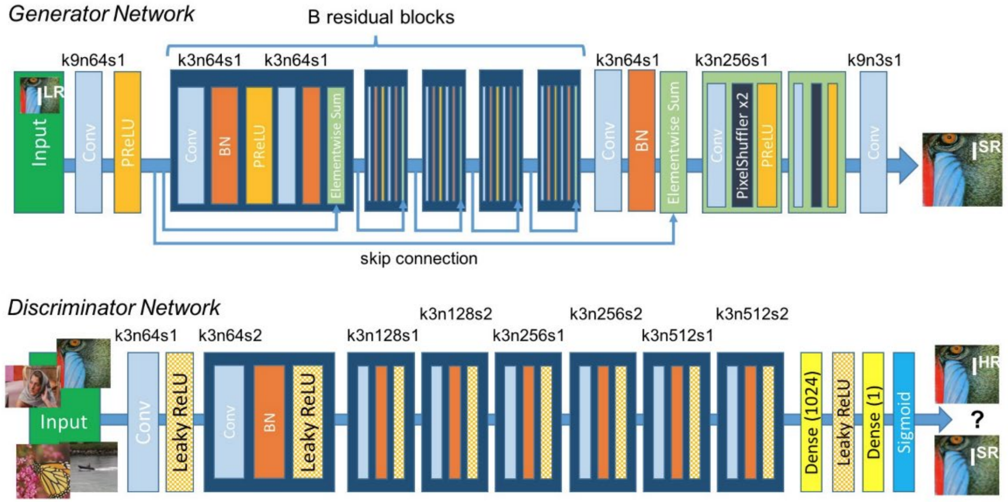
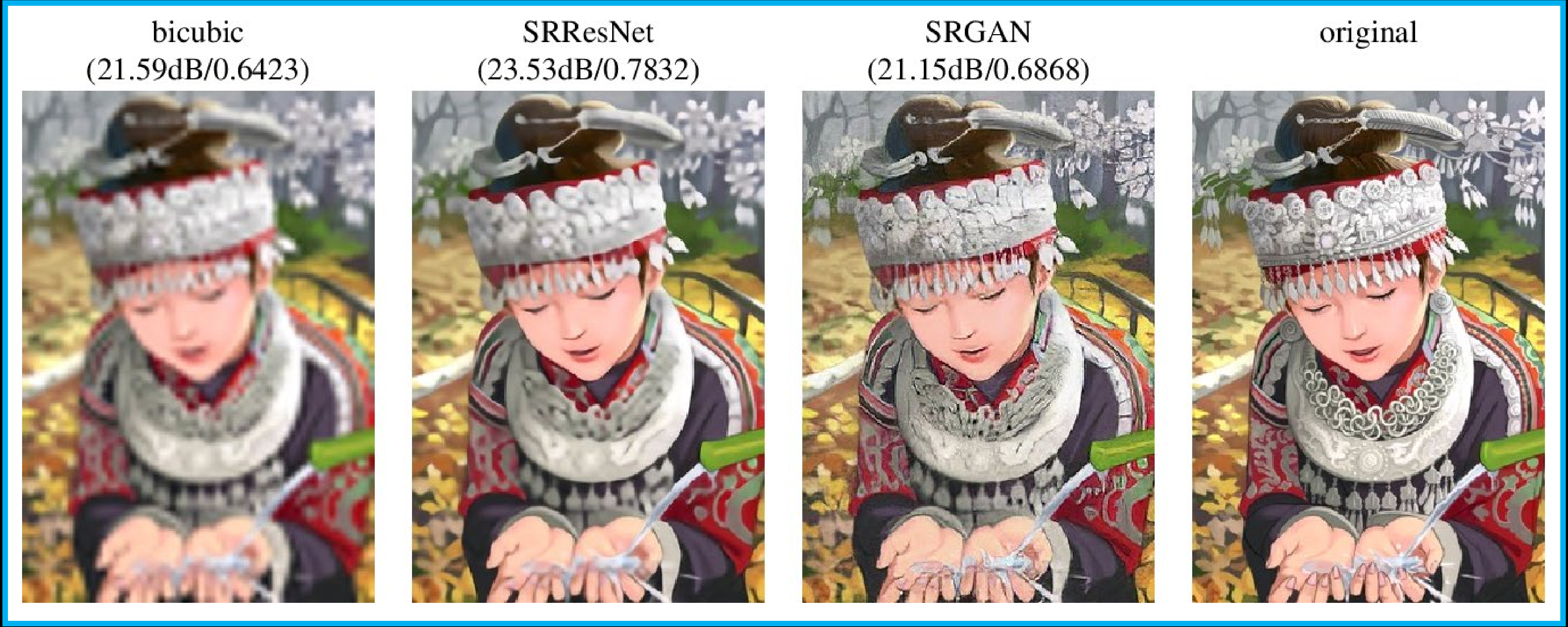


Figure 4: Architecture of Generator and Discriminator Network with corresponding kernel size (k), number of feature maps (n) and stride (s) indicated for each convolutional layer.

SuperResolution

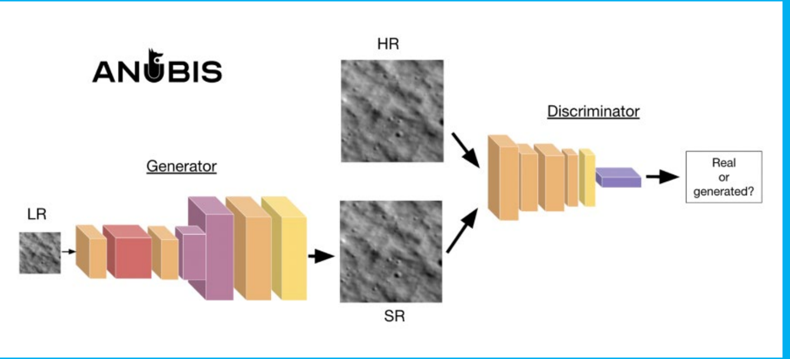


SRGAN from 2017

Topic II: SuperResolution

Examples

Real-world example:
Super resolution of Lunar maps



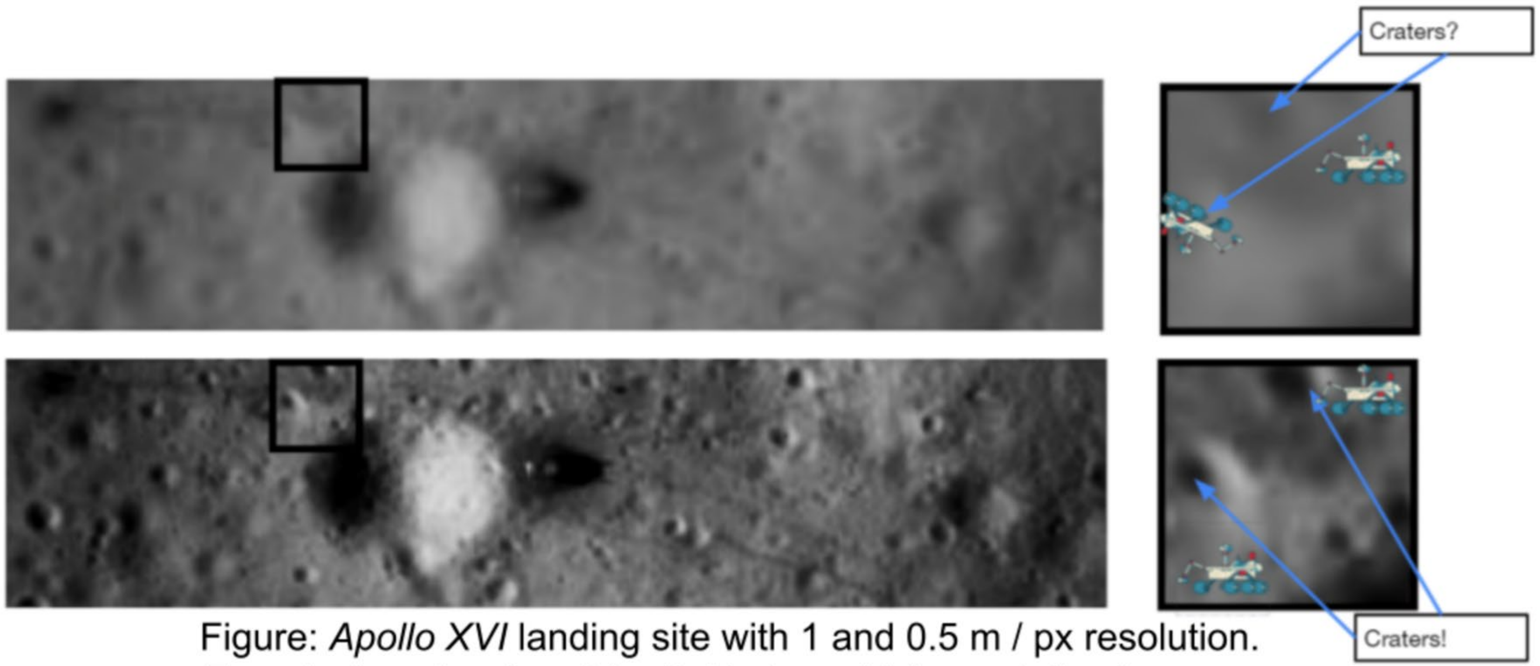


Figure: *Apollo XVI* landing site with 1 and 0.5 m / px resolution.
For mission planning, it is vital to have high resolution images.

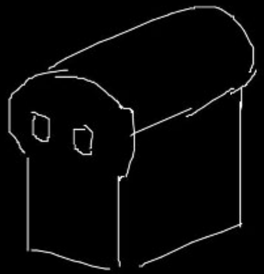
SuperResolution: Art examples

Models such as the Progressive Growing GANs jump between the resolutions of the generated data:

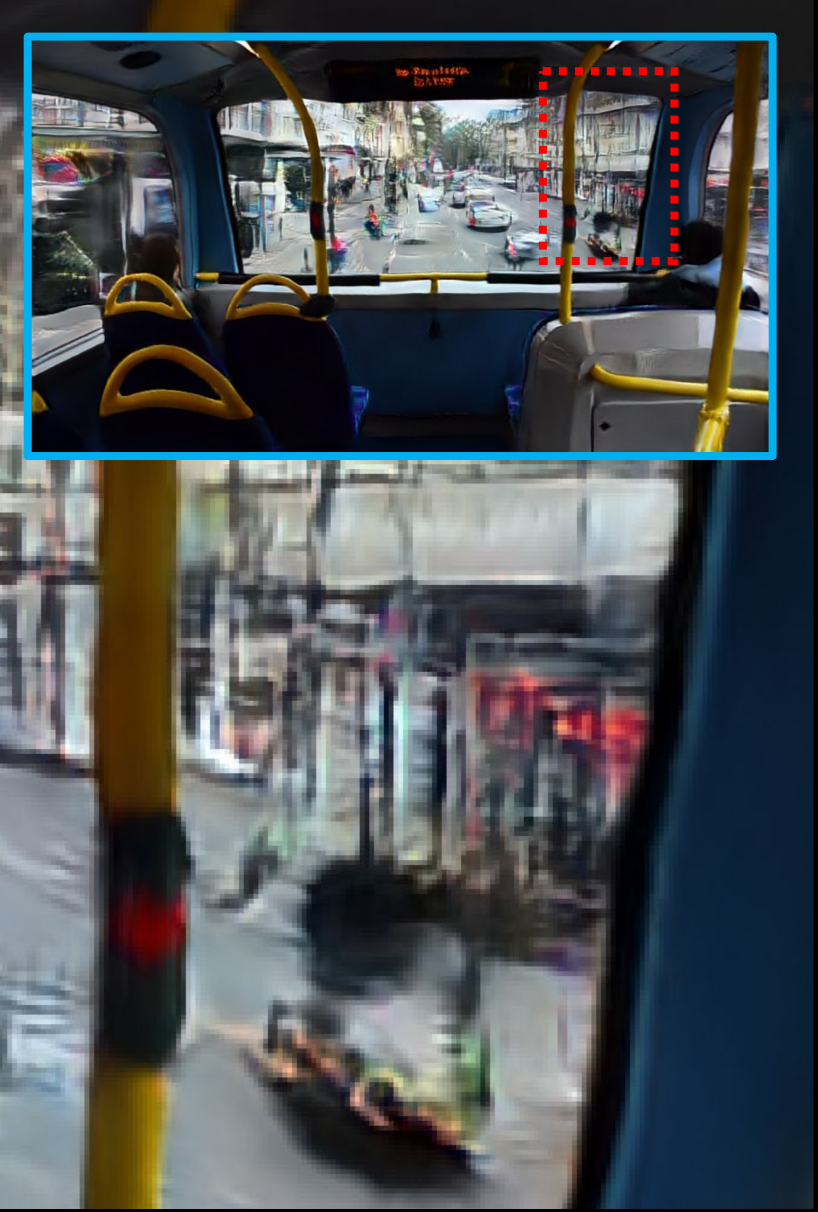
Earlier epochs (while lower res) may look better

Than the model just few iterations after

Instead we can use Super Resolution

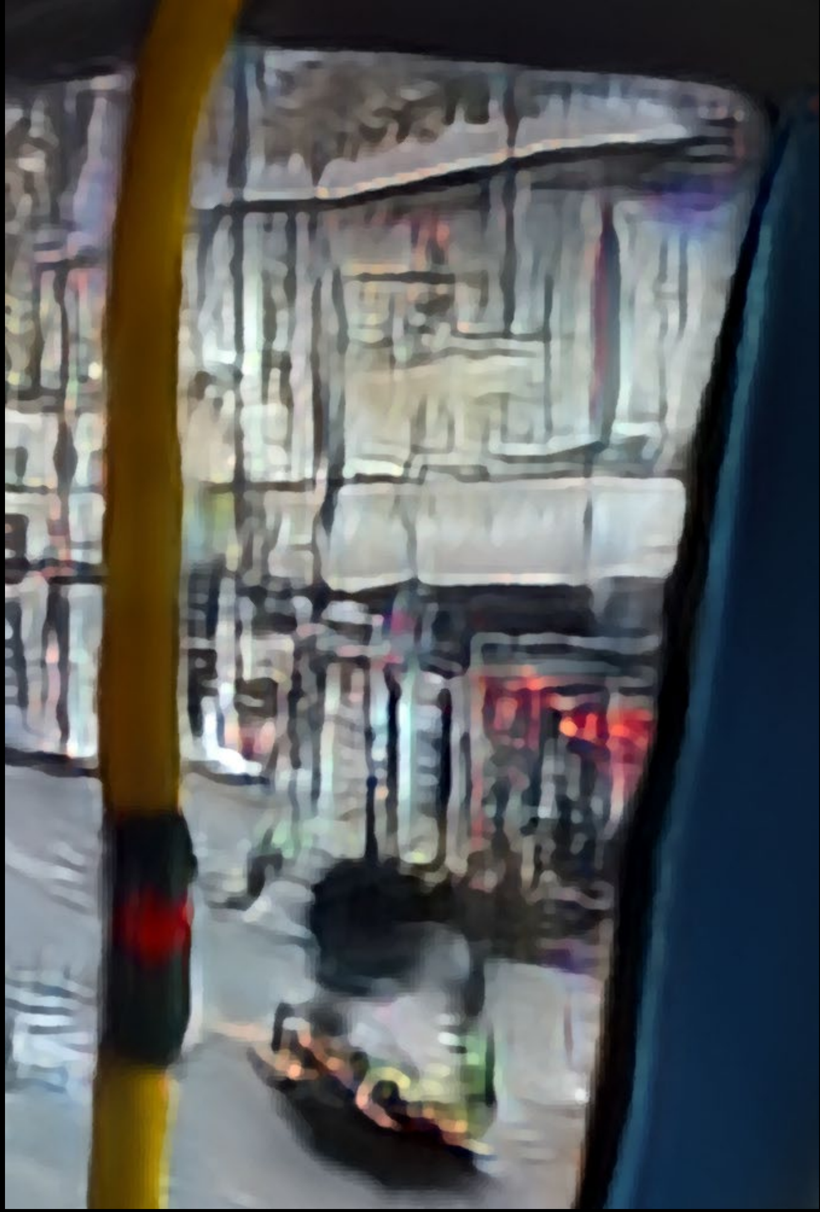


Or some models may produce limited resolution outputs



Original

RealSR (4x)



Anime4k* (4x)

*) Real-time: https://github.com/bloc97/Anime4K / The promise of real-time would mean running SuperRes while playing some low-res video. *Compute > Connection*.

SuperResolution: Art examples

Restoration process:

- Higher **resolution**
- Higher **fps** (interpolate between frames)
- Add **colour** ?

Example DeOldify video:

youtu.be/EqbOhqXHL7E

SuperResolution: Art examples

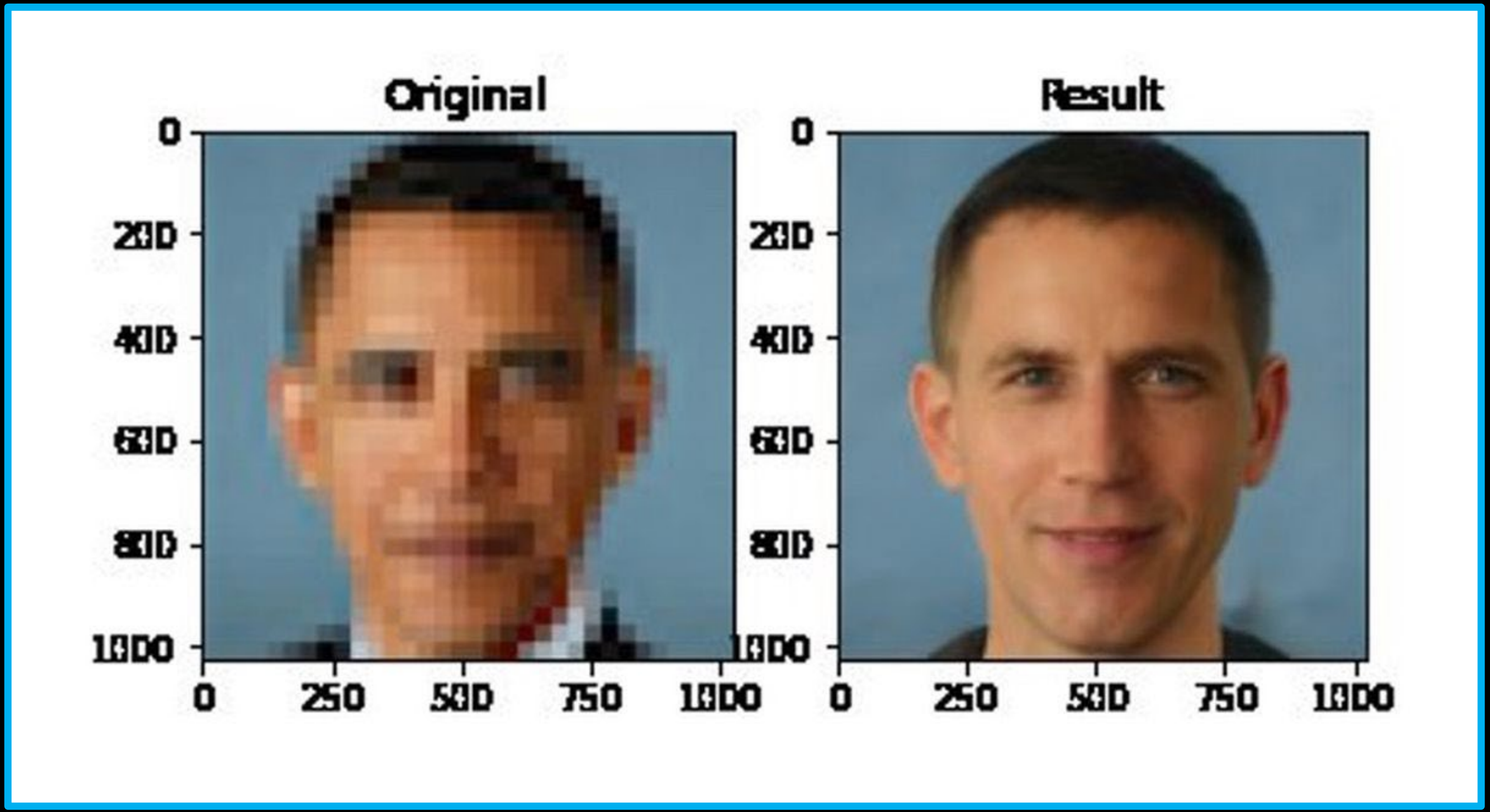
Upscaling game resources

ESRGAN, **X. Wang**, 2018

Mass Effect Legendary Edition: *"We ran all the original, uncompressed source art through an AI up-res program along with some other custom batch tools."* - 2021/02/02/bioware-used-ai-upscaling-to-remaster-mass-effects-original-textures/

Topic II: SuperResolution

Limitations

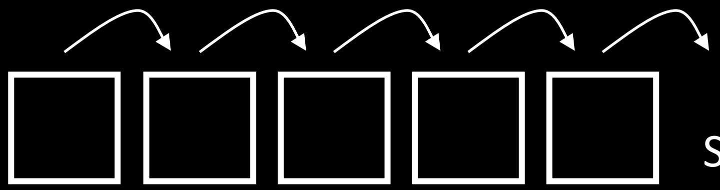


Original
Result
0
200
400
600
800
1000
0
250
500
750
1000

SuperResolution: Limitations

- **Complication:**
  Conceptually we are mixing our data with noise from someone else's datasets

Exploring different SuperResolution models aesthetics: [demo example]



…. 40x!

Show as frames in animation

SuperResolution: Easy tools

- **Applications:**
  - There are some free repositories with access to pre-trained models (video2x)
  - Or these are making it into professional tools (+- expansive usually)
    - Photoshop / Camera raw: helpx.adobe.com/uk/camera-raw/using/enhance.html

- **Video2x** (free application, **repo**)
  - Colab notebooks (link)
  - Windows application (zip)
  - Models: Waifu2X, SRMD, RealSR, Anime4KCPP
  - Input: image / **gif** / **video**

VIDEO2X

Machine learning video/GIF/image upscaling

100x100 px

4x ZOOM

Photoshop Neural Filters

Summary from the lecture

- **CycleGAN**:
  - **Model architecture** with two generators (there and back) and one discriminator
  - **Example** learning between two domains (not paired)
- **Super Resolution**:
  - **Models** as GAN structure
  - **Examples** from research, art and industry … easy to use **Applications**
  - **Limitations** tricky! *(What happens to the reality?)*

Links and additional readings:

- **Papers**:
  - **CycleGAN**: Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks by Jun-Yan Zhu*, Taesung Park*, Phillip Isola, Alexei A. Efros. In ICCV 2017.
  - **pix2pix**: Image-to-Image Translation with Conditional Adversarial Networks by Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, Alexei A. Efros. In CVPR 2017.

  - **SuperResolution** blog post: blog.paperspace.com/image-super-resolution/

End of the lecture

***)** PS: follows material for the practical session …