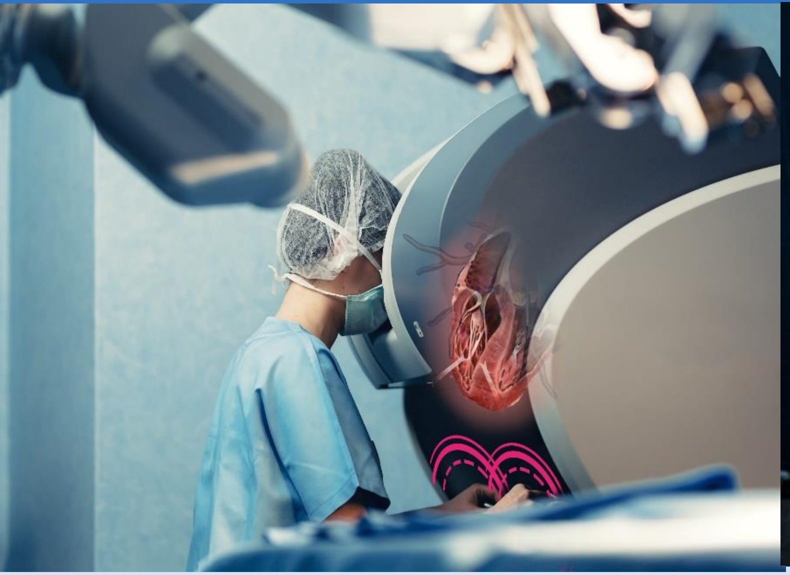
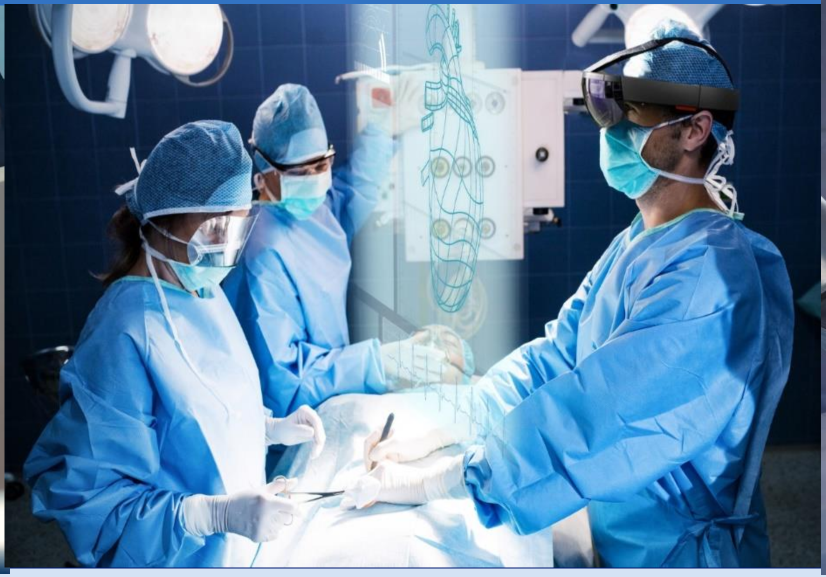
Synthesizing realistic surgical images with sim2real GANs


Sebastian Bodenstedt
Translational Surgical Oncology

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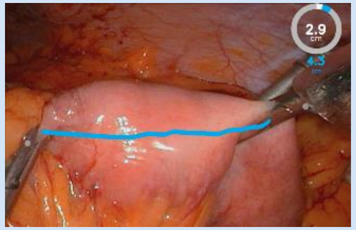
Deutsches Krebsforschungszentrum
Universitätsklinikum Carl Gustav Carus Dresden
Medizinische Fakultät Carl Gustav Carus, TU Dresden
Helmholtz-Zentrum Dresden-Rossendorf

Motivation: Example applications of ML in surgery

Robotics

Surgical Training

Data Analysis



Human-Machine Interaction

Navigation

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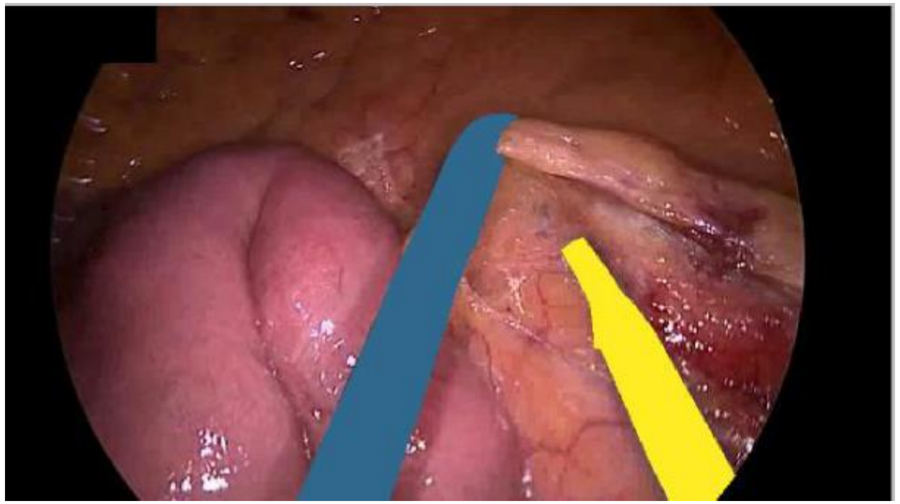
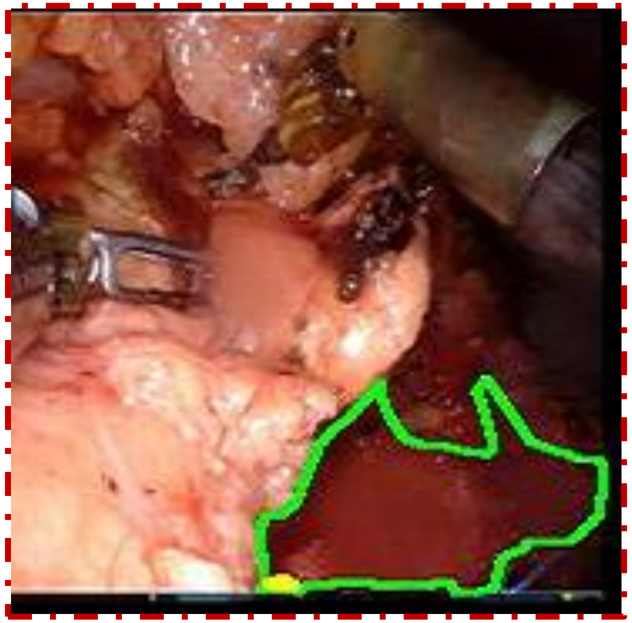
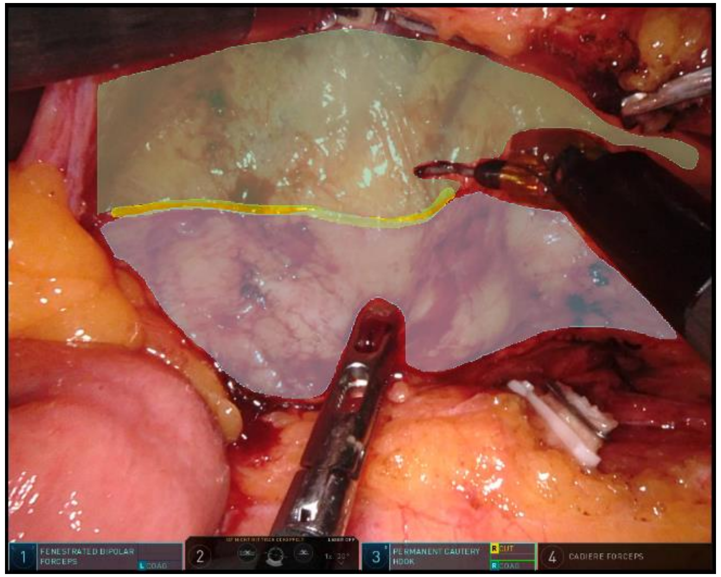
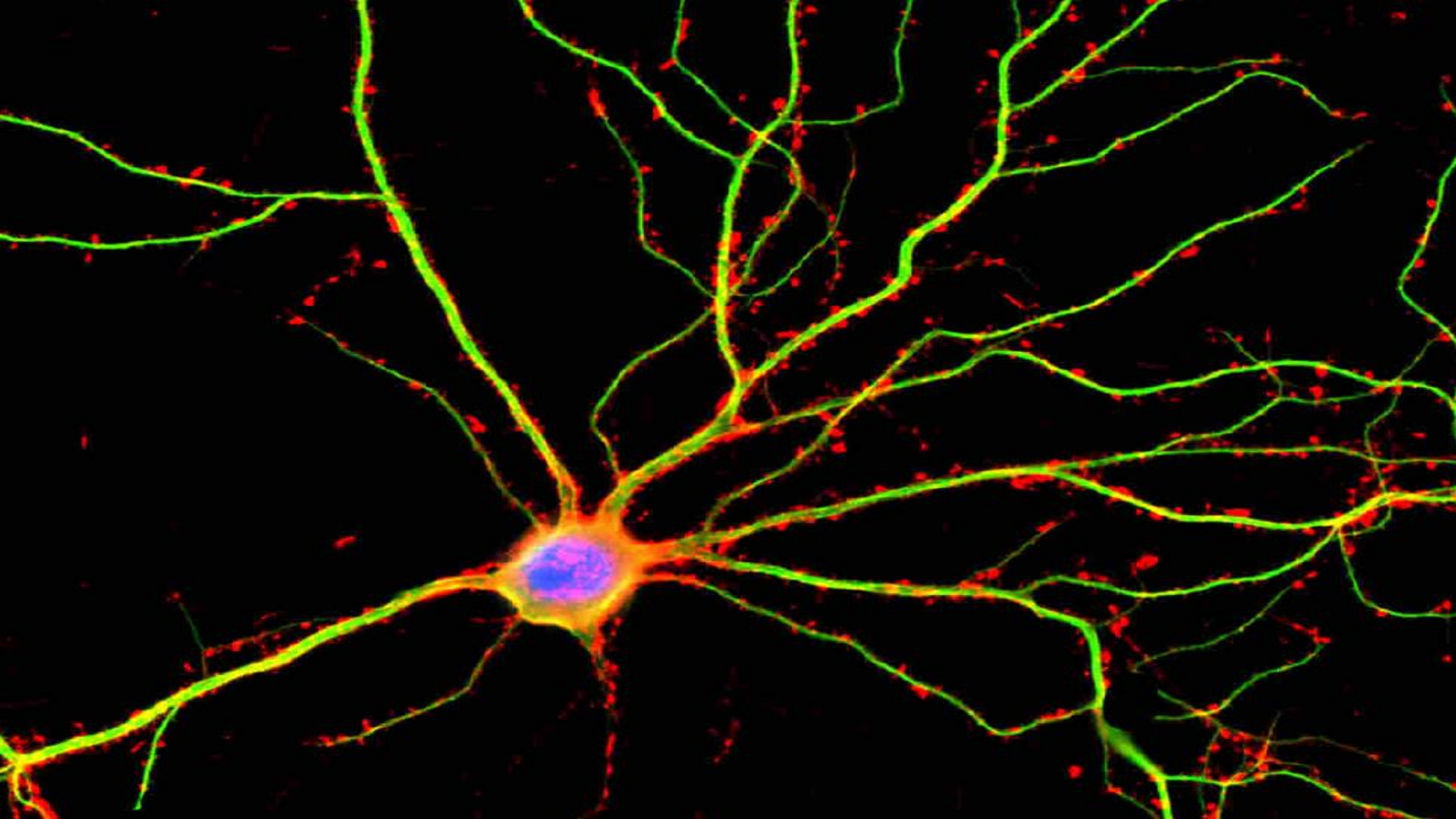
Motivation: Annotation of data

- Machine learning relies on large amounts of annotated training examples
- Annotation often requires expert knowledge is time consuming



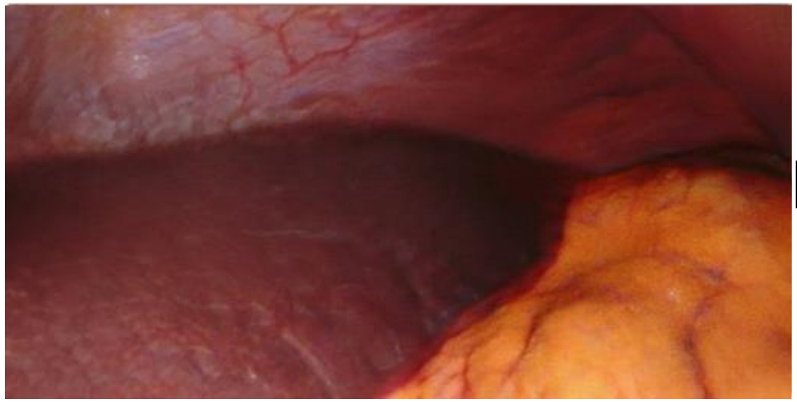


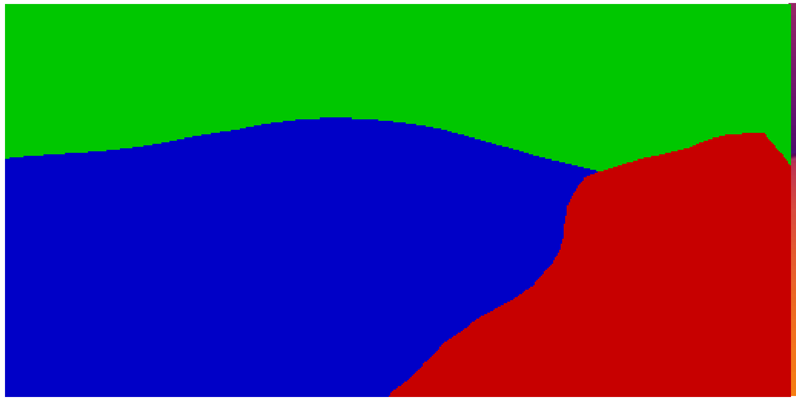




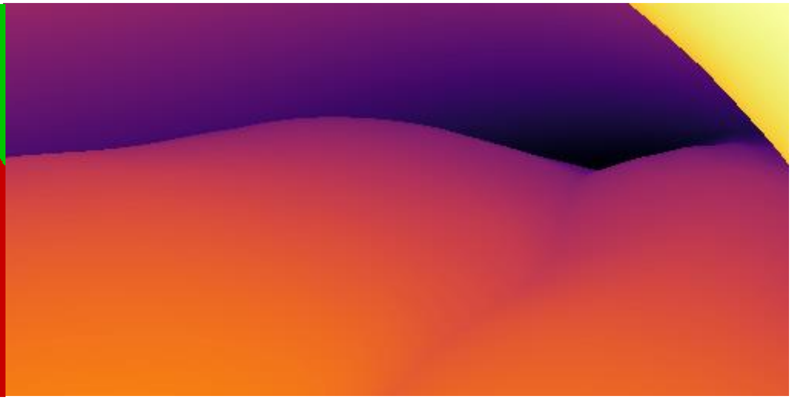
Motivation: Synthetic Data Generation

- Generating ground truth data for synthetic scenes is trivial
- Apply realistic textures to synthetic scenes





Segmentation



Depth

Optical Flow

Pfeiffer,..,Weitz, Speidel MICCAI 2019: „Generating large labeled data sets for laparoscopic image processing tasks using unpaired image-to-image translation"
Rivoir,..,Weitz, Speidel ICCV 2021: „Long-Term Temporally Consistent Unpaired Video Translation from Simulated Surgical 3D Data"

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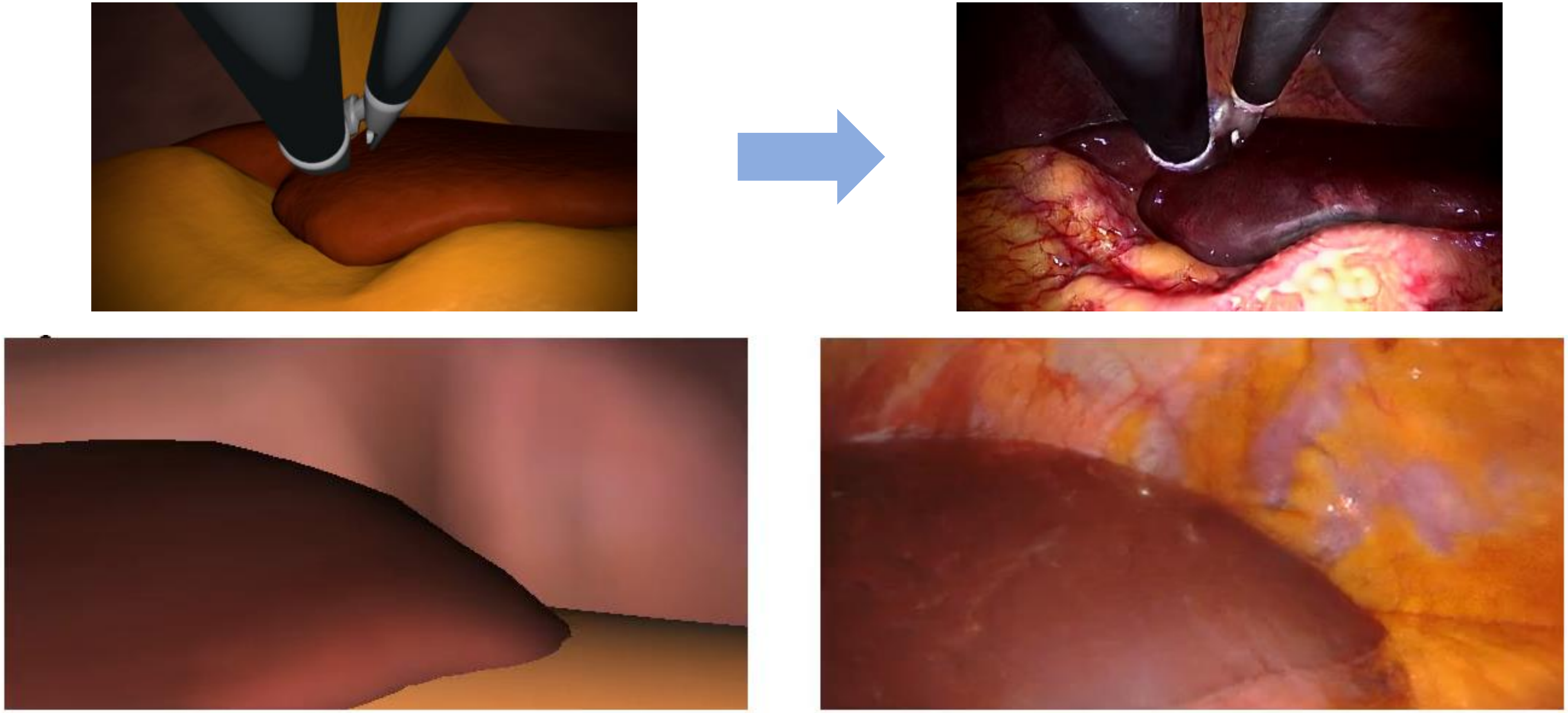

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Example Deep Fakes

Image: https://github.com/iperov/DeepFaceLive

Image: Chris Ume

Image: https://this-person-does-not-exist.com

Image: https://thenextweb.com

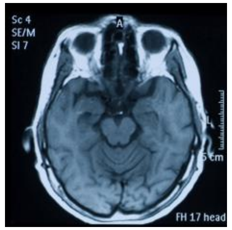
Overview lecture

- Introduction to Generative Adversarial Networks (GANs)
  - What are generative models
  - Different modes of learning
  - Components of GANs
- Example usages of GANs
  - Image2Image translation

Supervised vs unsupervised learning

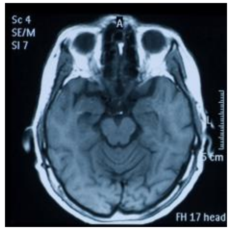
Supervised learning (concept learning)

- Learning by labeled example, i.e. we “tell” the algorithm what to learn
- Two forms of output
  - **Symbolic (classification)**
    - Output is a discrete value/category, e.g. “tumor”/“no tumor”



“no tumor”

  - **Subsymbolic/regression**
    - Output is continuous value, e.g. age or temperature

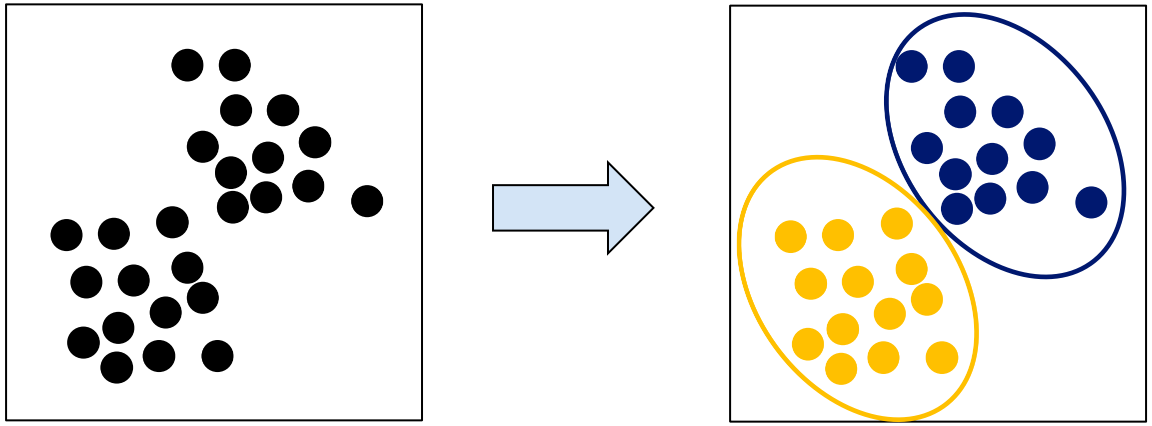


“42.0 years old”

Supervised vs unsupervised learning

Unsupervised learning

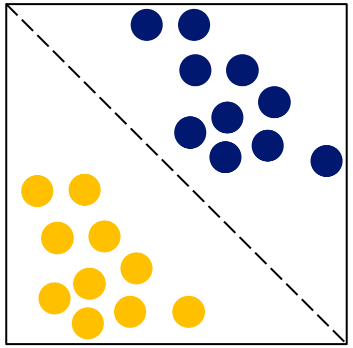
- Detect previously unknown patterns in unlabeled data
  - No desired output!
- Example applications
  - Find anomalies in data, e.g. credit card usage
  - Find clusters, e.g. grouping pictures



Discriminative vs generative learning

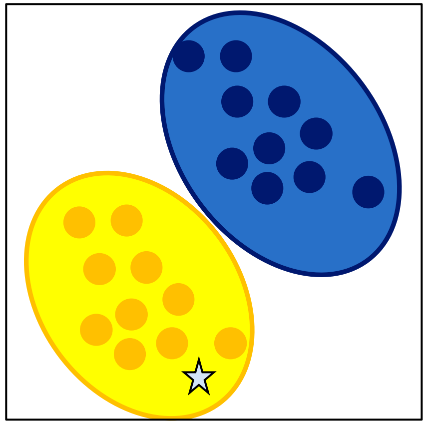
Discriminative learning a.k.a classification

- Supervised learning problem
- A class label is assigned to an input
- => can be used to **discriminate** between given examples



Generative Learning

- Unsupervised learning problem
- A model learns the distribution of input data
- => can be used to **generate** new examples of that distribution



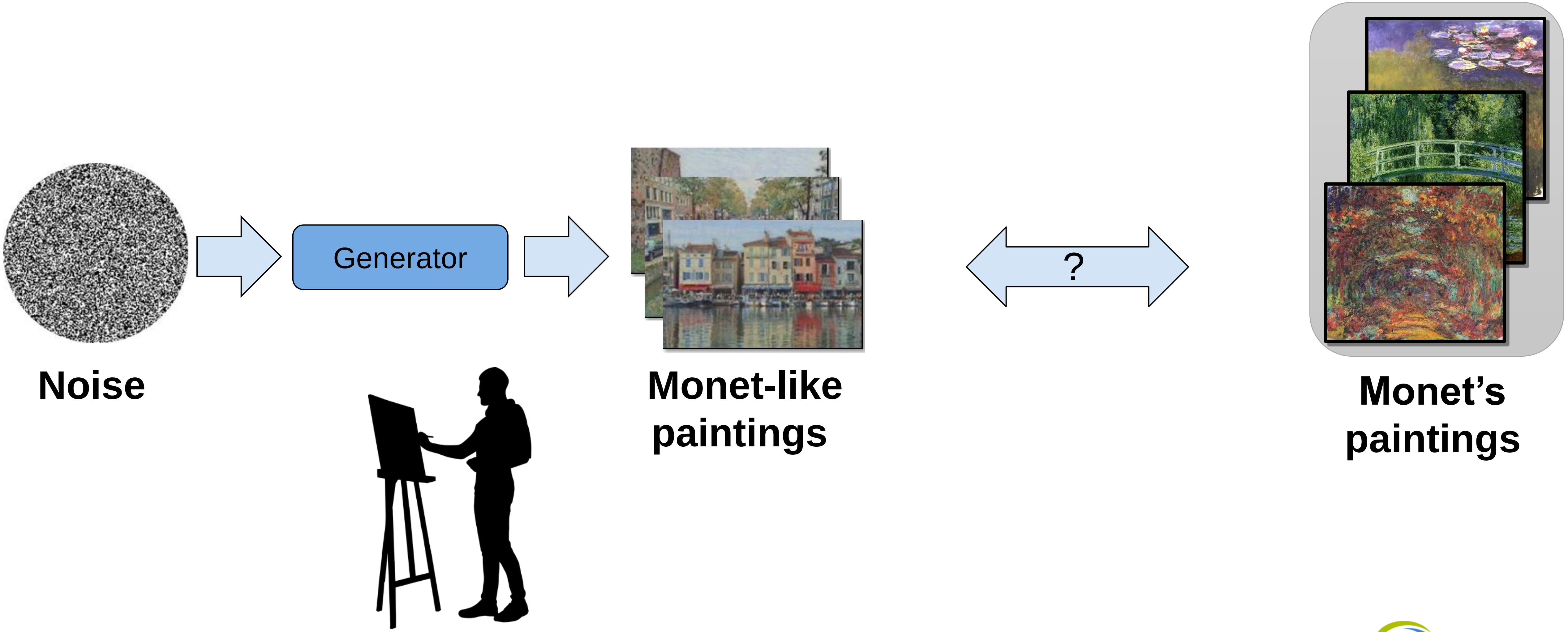
Both play a role in Generative Adversarial Networks!

Generative Adversarial Networks (GANs)

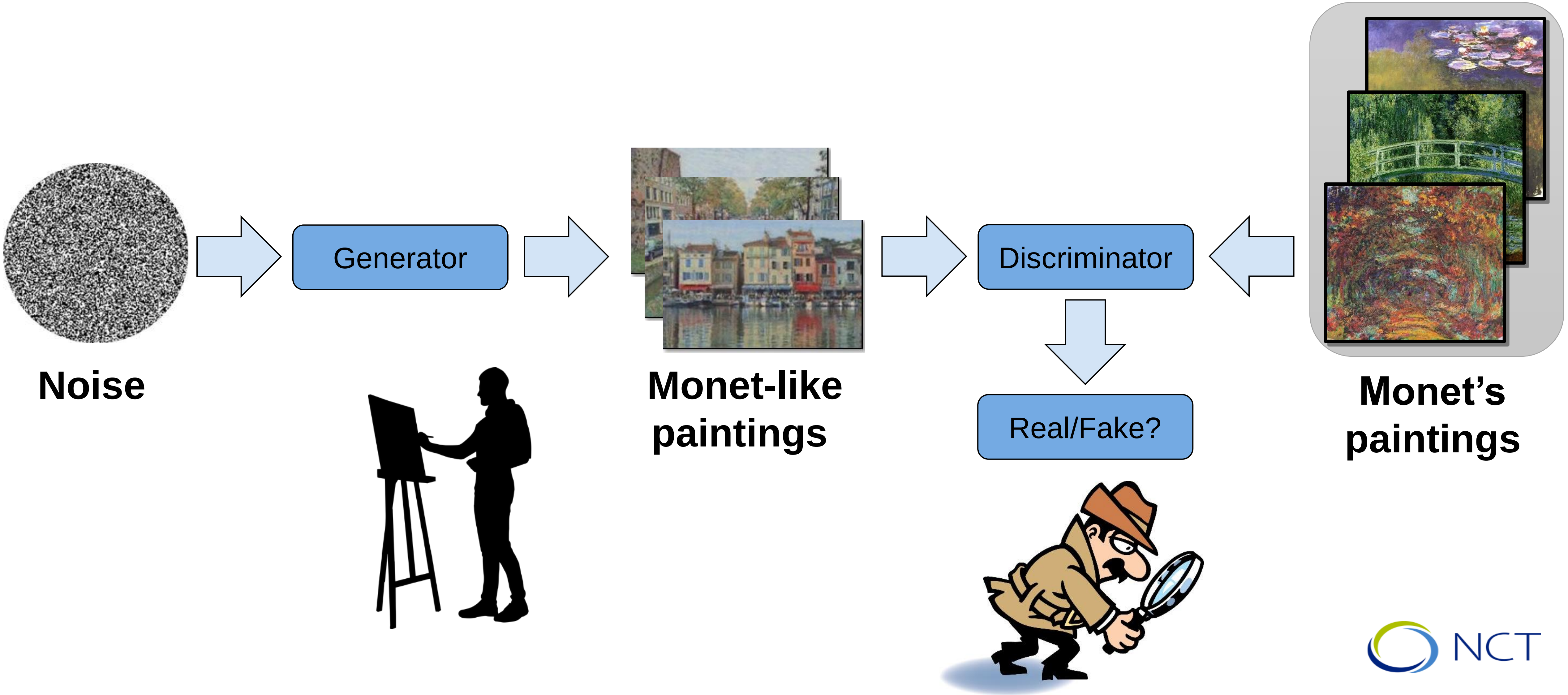
Generative models based on Deep Neural Networks

- An approach for training generative models
  - Introduced by Goodfellow et al. *Generative Adversarial Networks*
- Generally consists of two separate models
  - **Generator**: generates new samples from a target domain
  - **Discriminator:** determines whether a sample is real (from domain) or generated
- Training a GAN is comparable to an arms race between the separate models
  - Example: art forger vs. detective

Example: Teaching an art style

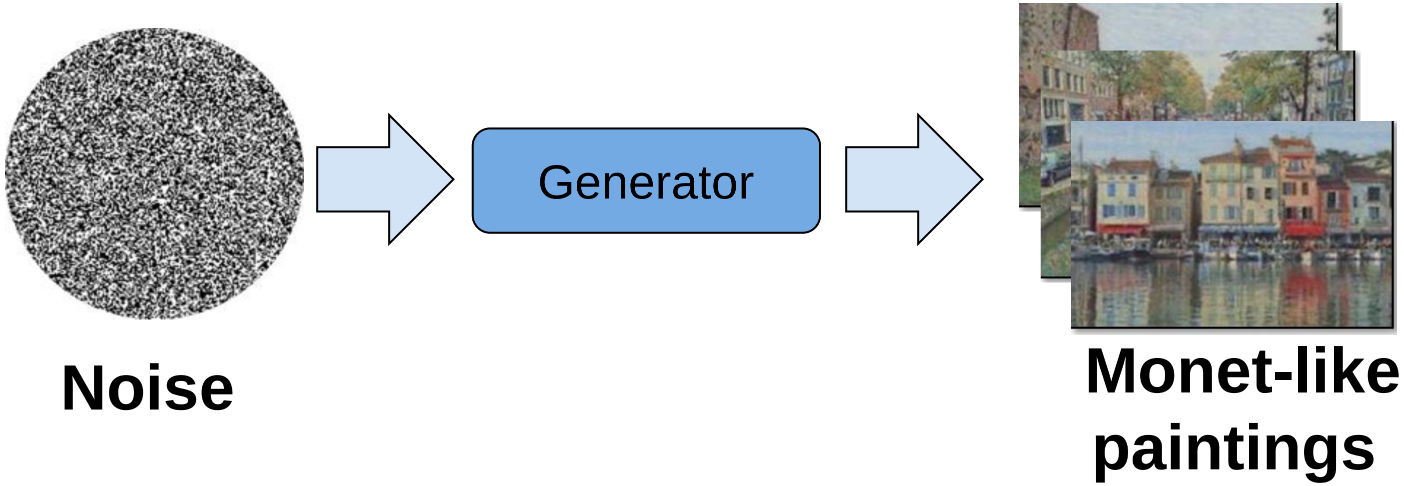


Example: Teaching an art style



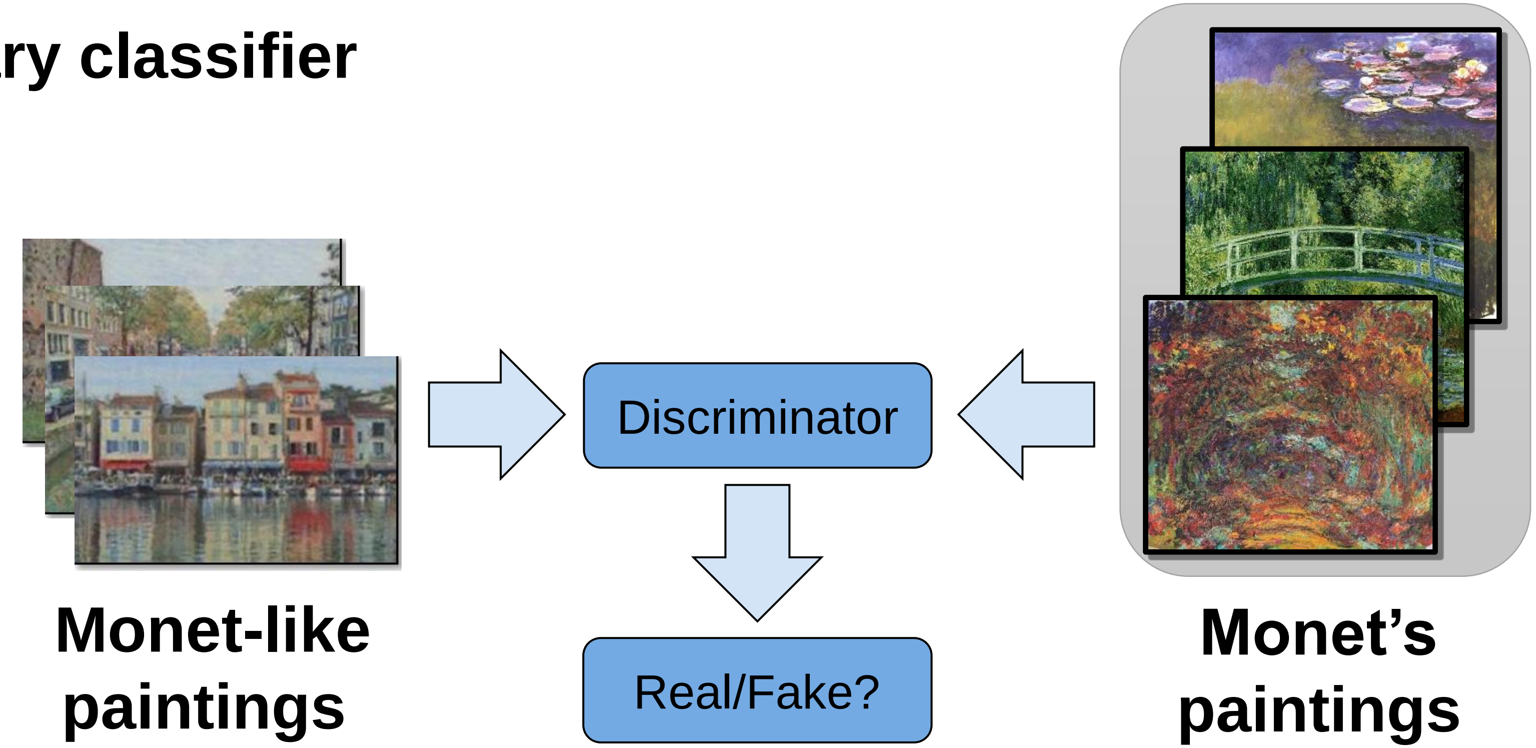
Generator

- Learns **distribution** of **a target domain**
  - Given a random input vector, generates a sample
    - Points in vector (latent) space correspond to points in target domain
  - **Latent space** => compression of the target domain
  - Often a Convolutional Neural Network (CNN)



Discriminator

- Distinguishes real from fake (generated) examples
  - Real examples come from training set
  - Generated examples come from generator
  - Indirectly **connects** generator to target domain
  - Often a Convolutional Neural Network (CNN)
    - **Binary classifier**



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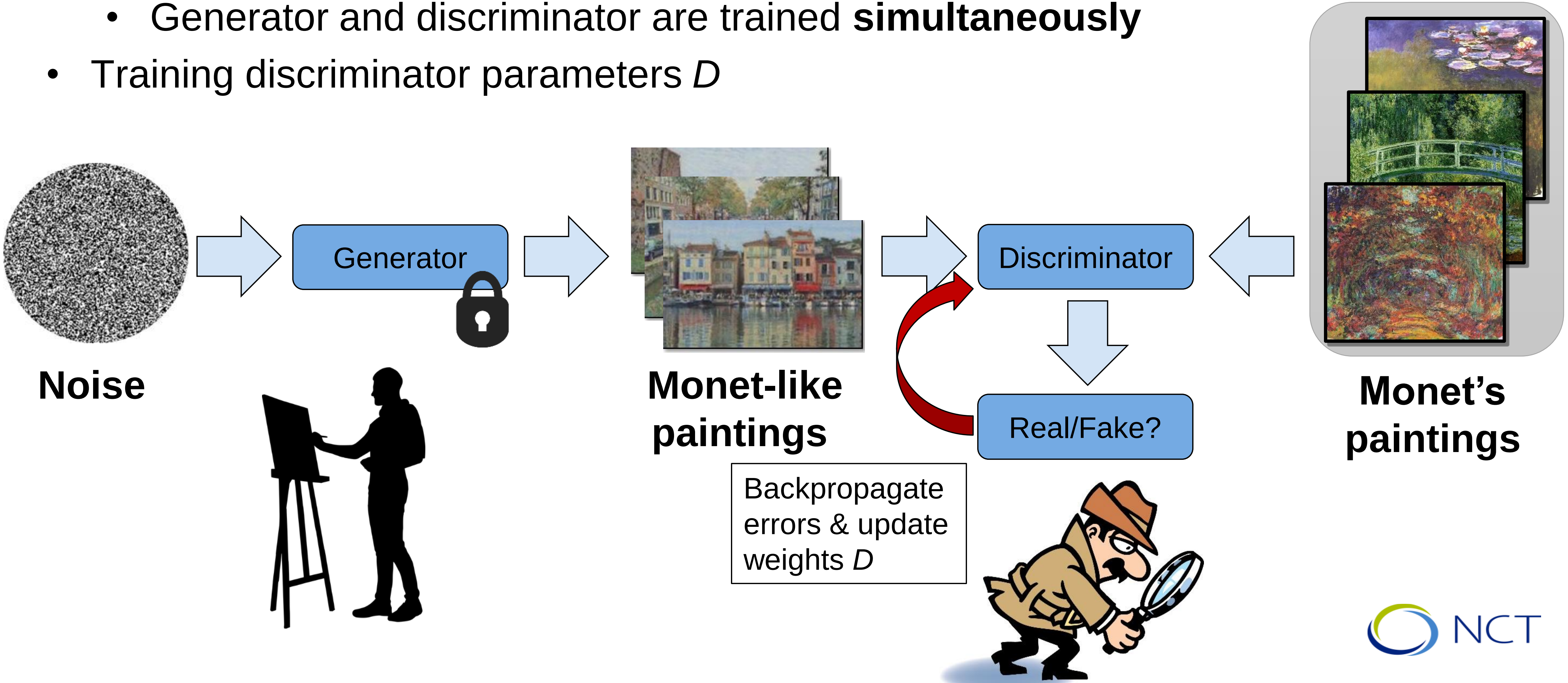
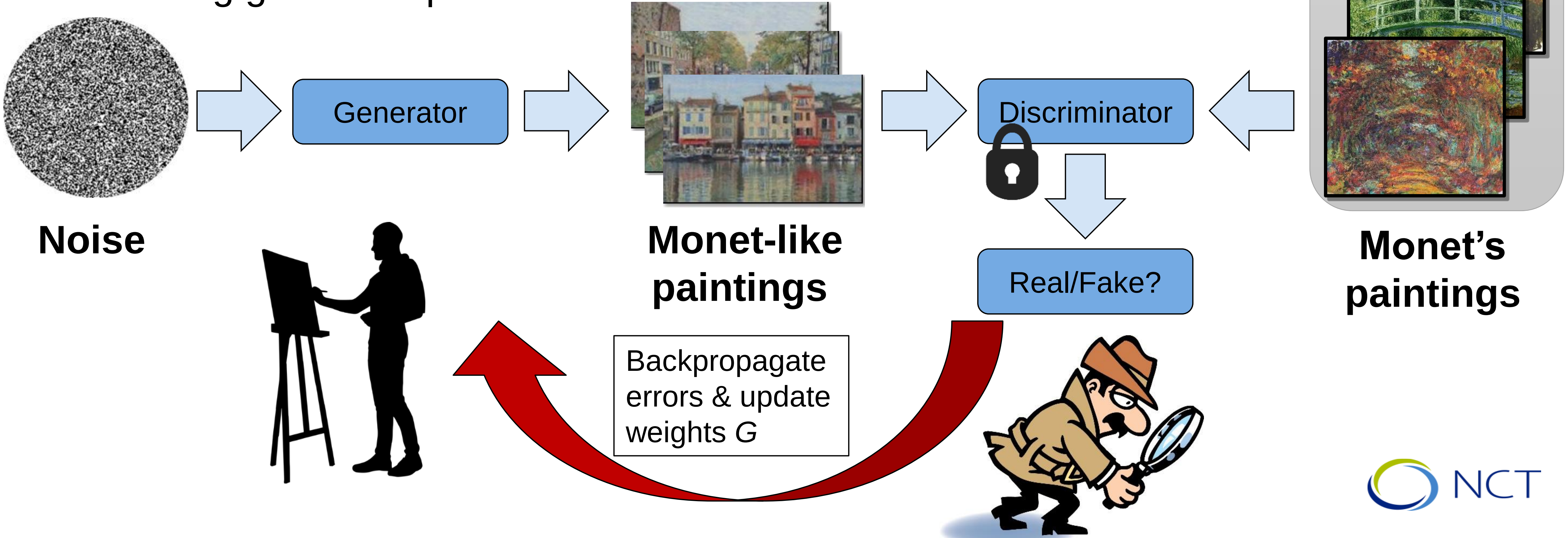
Training a GAN

- Two step process
  - Generator and discriminator are trained **simultaneously**
- Training discriminator parameters *D*



Training a GAN

- Two step process
  - Generator and discriminator are trained simultaneously
- Training discriminator parameters *D*
- Training generator parameters *G*



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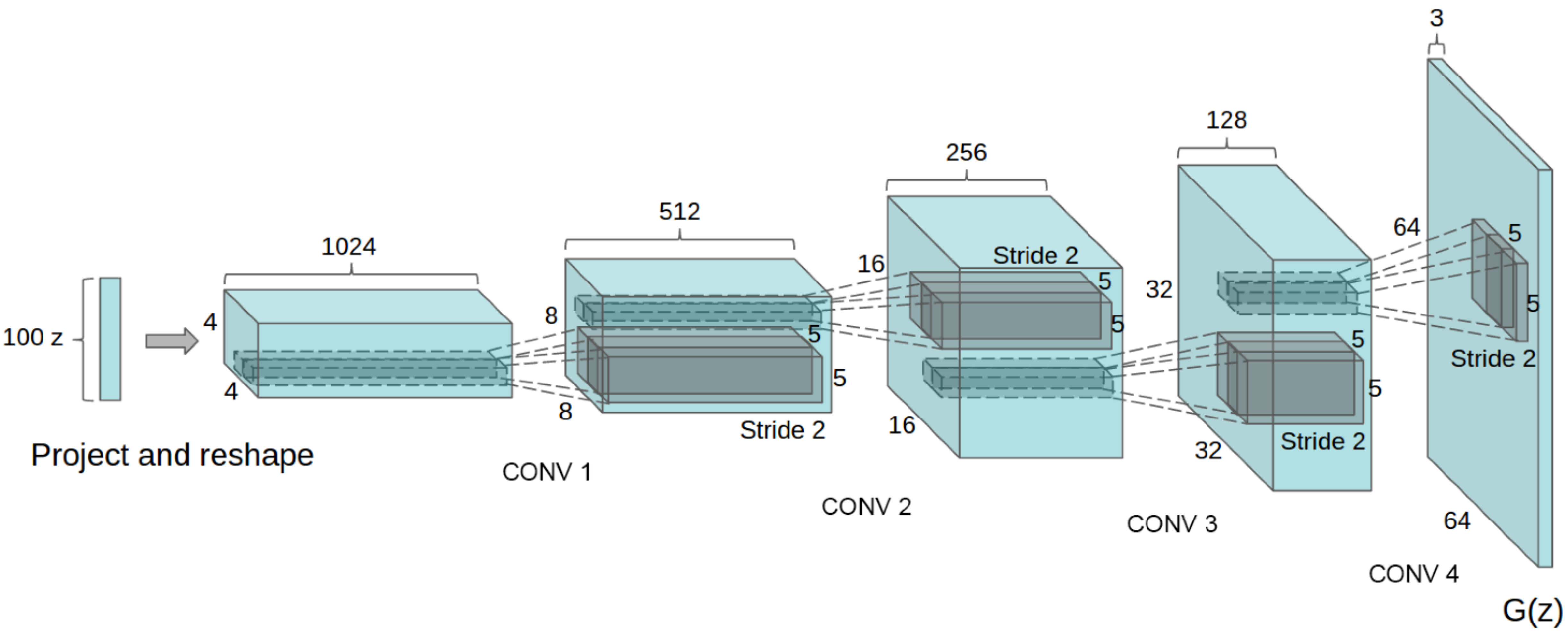
Training a GAN

- Two step process
  - Generator and discriminator are trained simultaneously
- Training discriminator parameters *D*
- Training generator parameters *G*
- Formulated as a **minimax** game
  - The discriminator aims to maximize its reward, i.e. its fake/real accuracy
  - The generator aims to minimize the reward of the discriminator

Some examples



Radford, A., Metz, L., & Chintala, S. (2015). Unsupervised representation learning with deep convolutional generative adversarial networks. *arXiv preprint arXiv:1511.06434*.

Some examples

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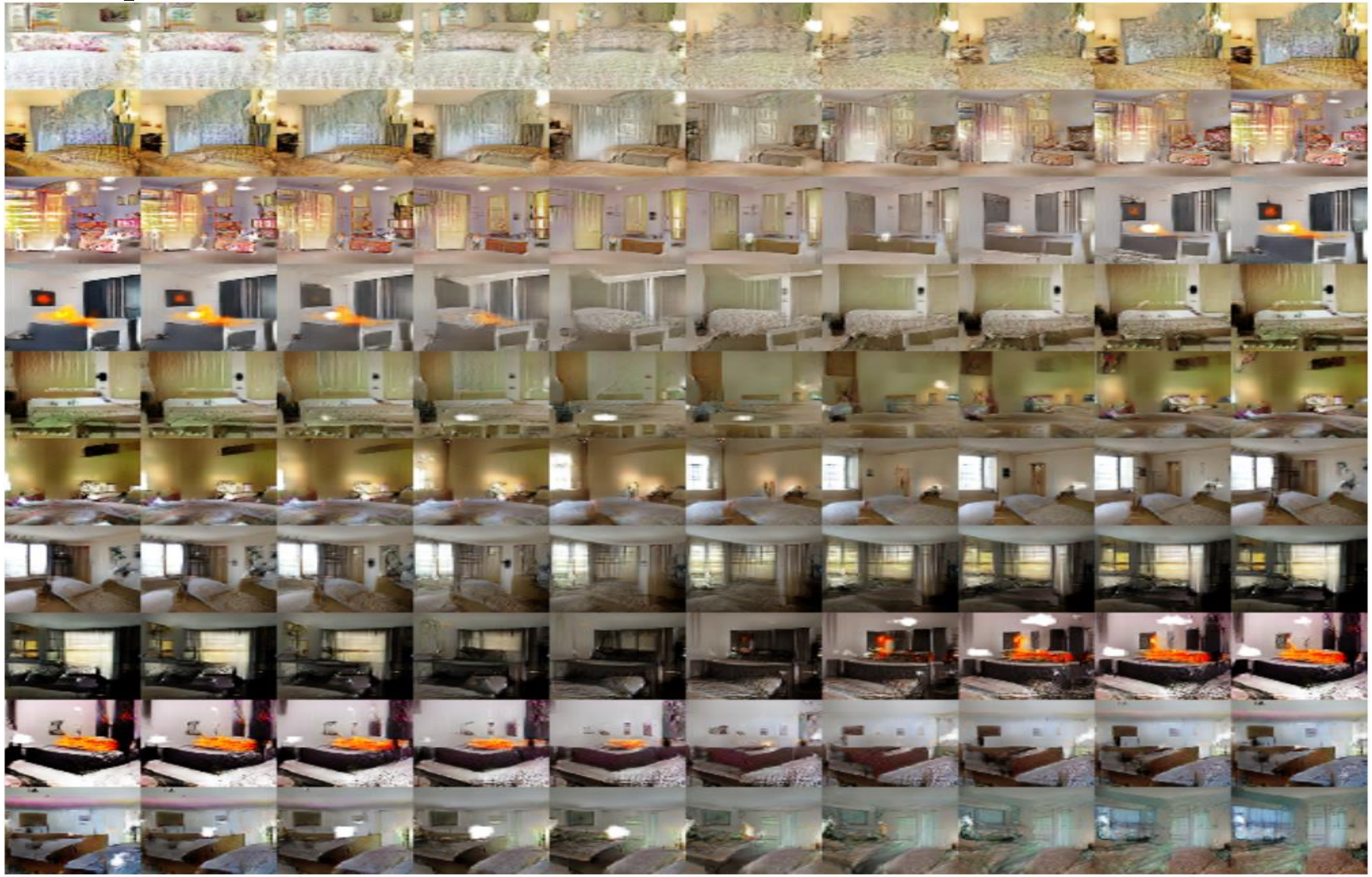
Some examples



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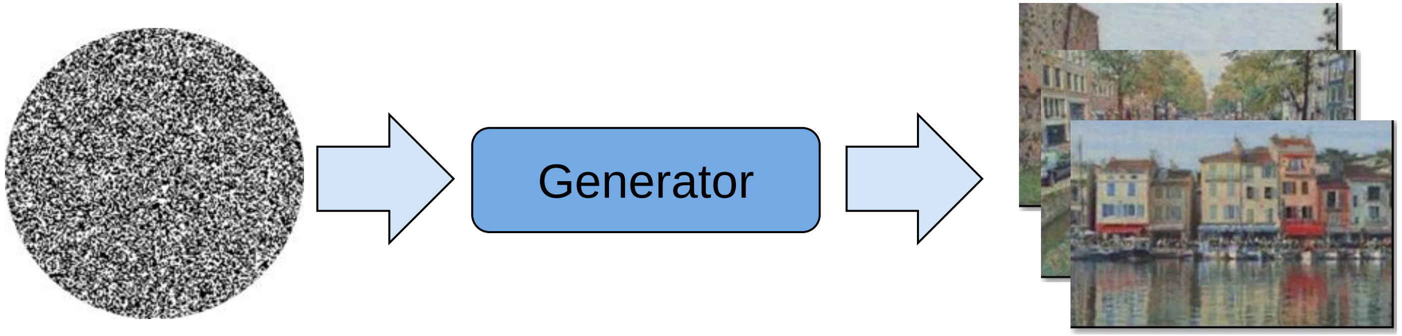
So far

- Image generation from noise



- Next: Image to Image translation

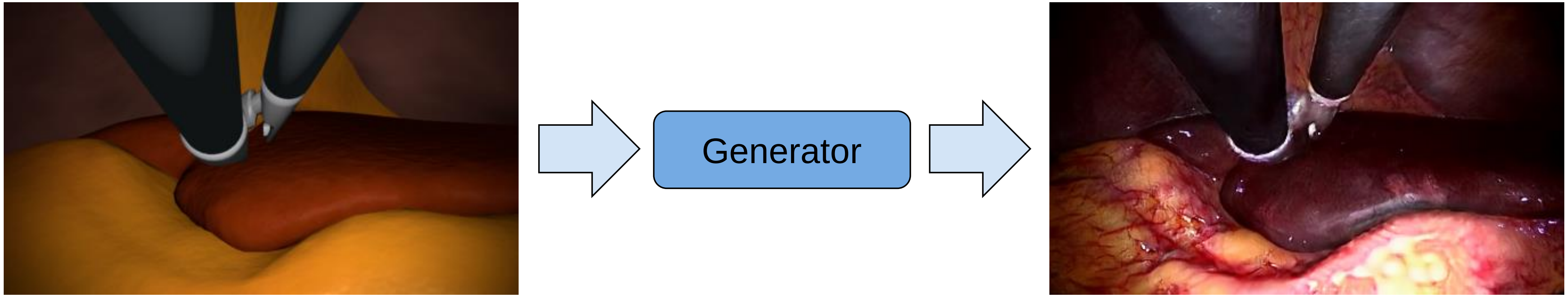
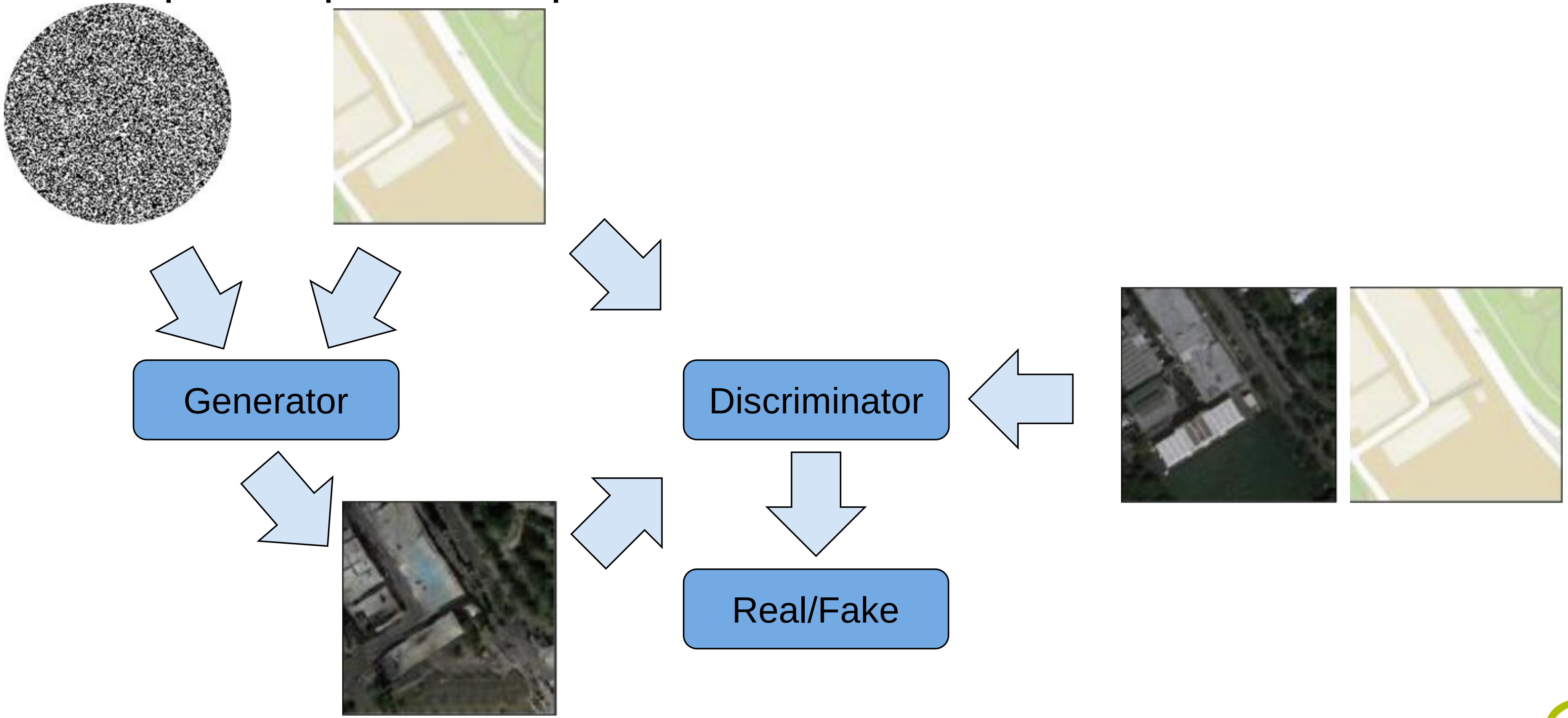


Image to image translation (with paired data)

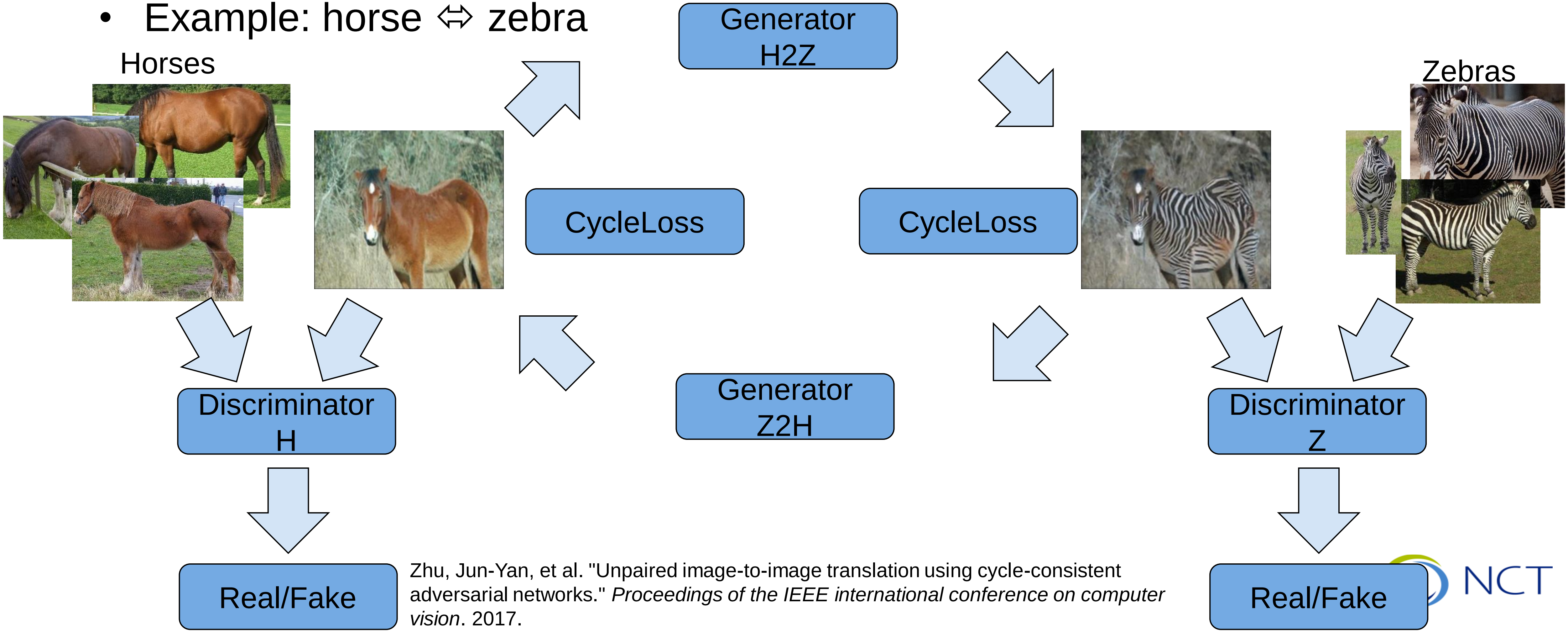
- Generally based on conditional GANs
  - Example: Map to aerial photo



Isola, P., Zhu, J. Y., Zhou, T., & Efros, A. A. “Image-to-image translation with conditional adversarial networks”. arXiv preprint arXiv:1611.07004. (2016)

Image to image translation (with unpaired data)

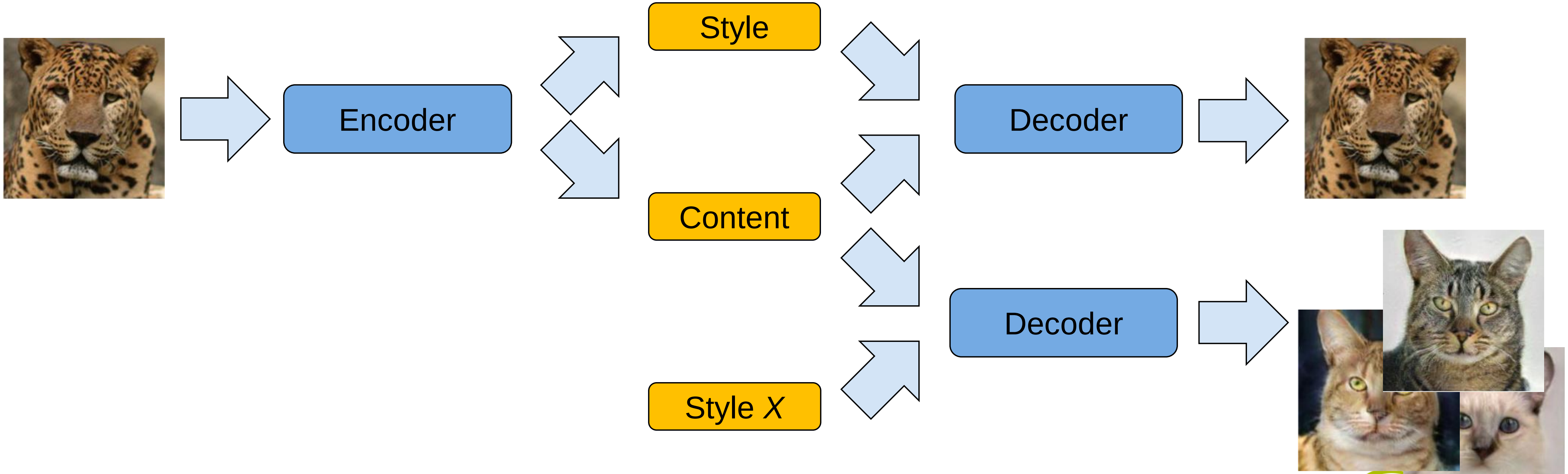
- Dataset with no corresponding classes
- Generally based on Cycle GANs
  - Example: horse ⬄ zebra



Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." *Proceedings of the IEEE international conference on computer vision*. 2017.

Multimodal image to image translation

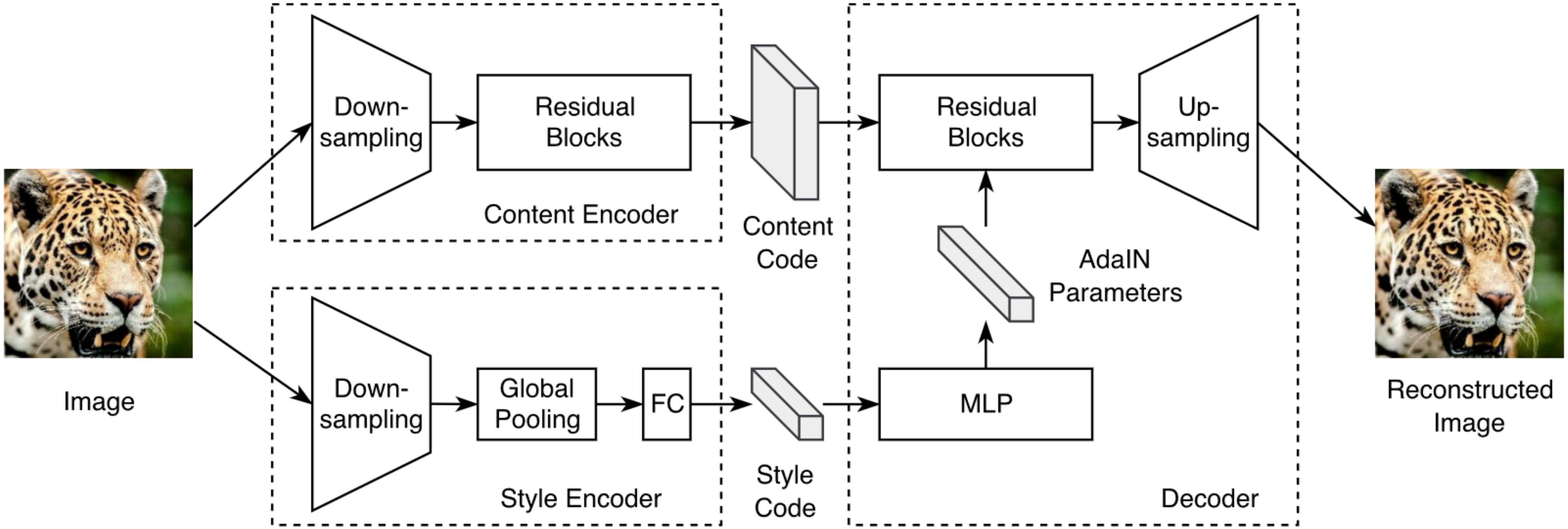
- Assumption:
  - An image can be decomposed into a **content code** and a **style code**
  - Image translation through combining a content code with a different style code



Huang, Xun, et al. "Multimodal unsupervised image-to-image translation." *Proceedings of the European conference on computer vision (ECCV)*. 2018.

Multimodal image to image translation

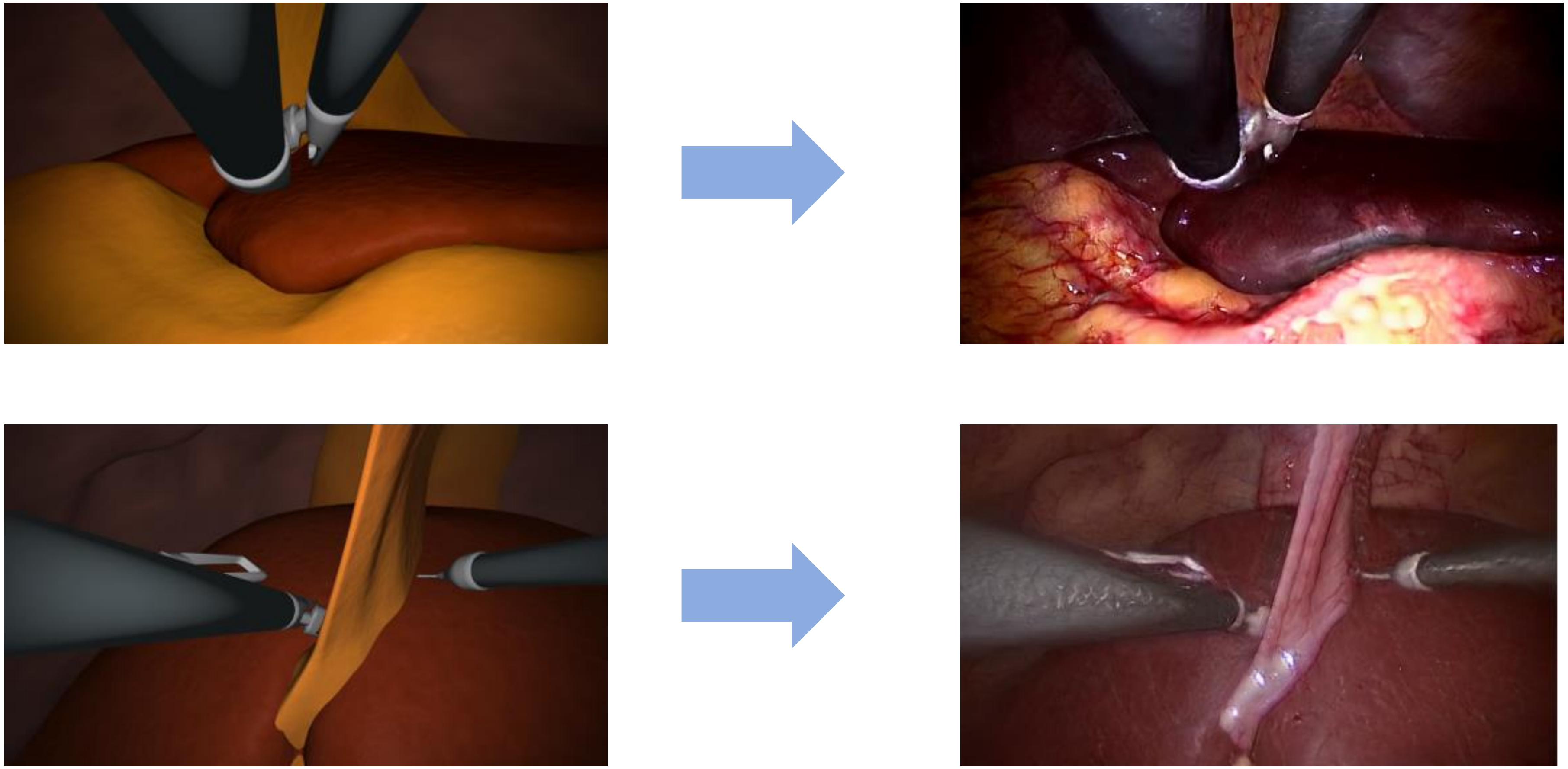
- Trained in similar manner as unpaired image to image
- Additional loss terms for:
  - Reconstruction of images with original codes
  - Reconstruction of codes by decomposing image with know codes



Huang, Xun, et al. "Multimodal unsupervised image-to-image translation." *Proceedings of the European conference on computer vision (ECCV)*. 2018.

Image to image translation for surgical images

- Unpaired image-to-image translation for generating realistic images



Pfeiffer,..,Weitz, Speidel MICCAI 2019: „Generating large labeled data sets for laparoscopic image processing tasks using unpaired image-to-image translation"

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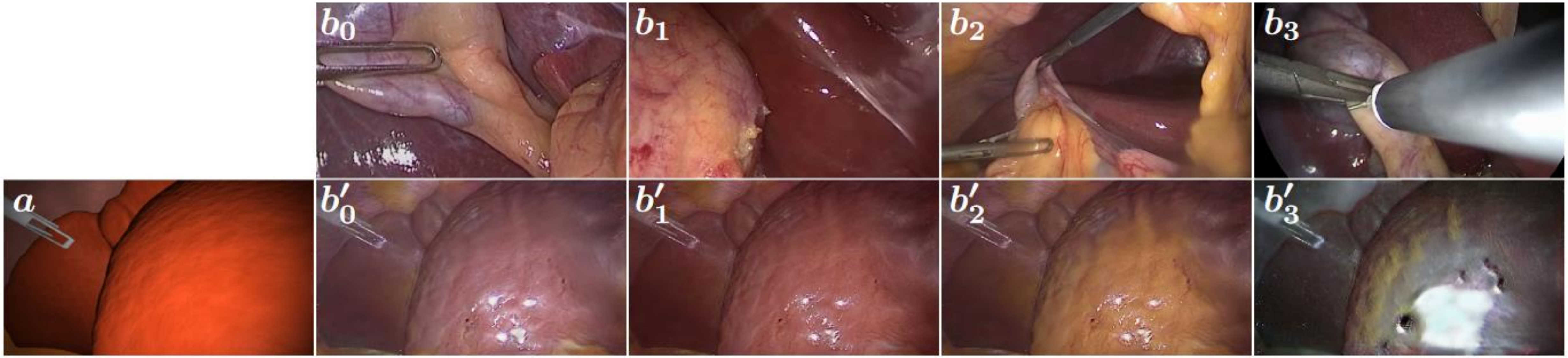
Image to image translation for surgical images

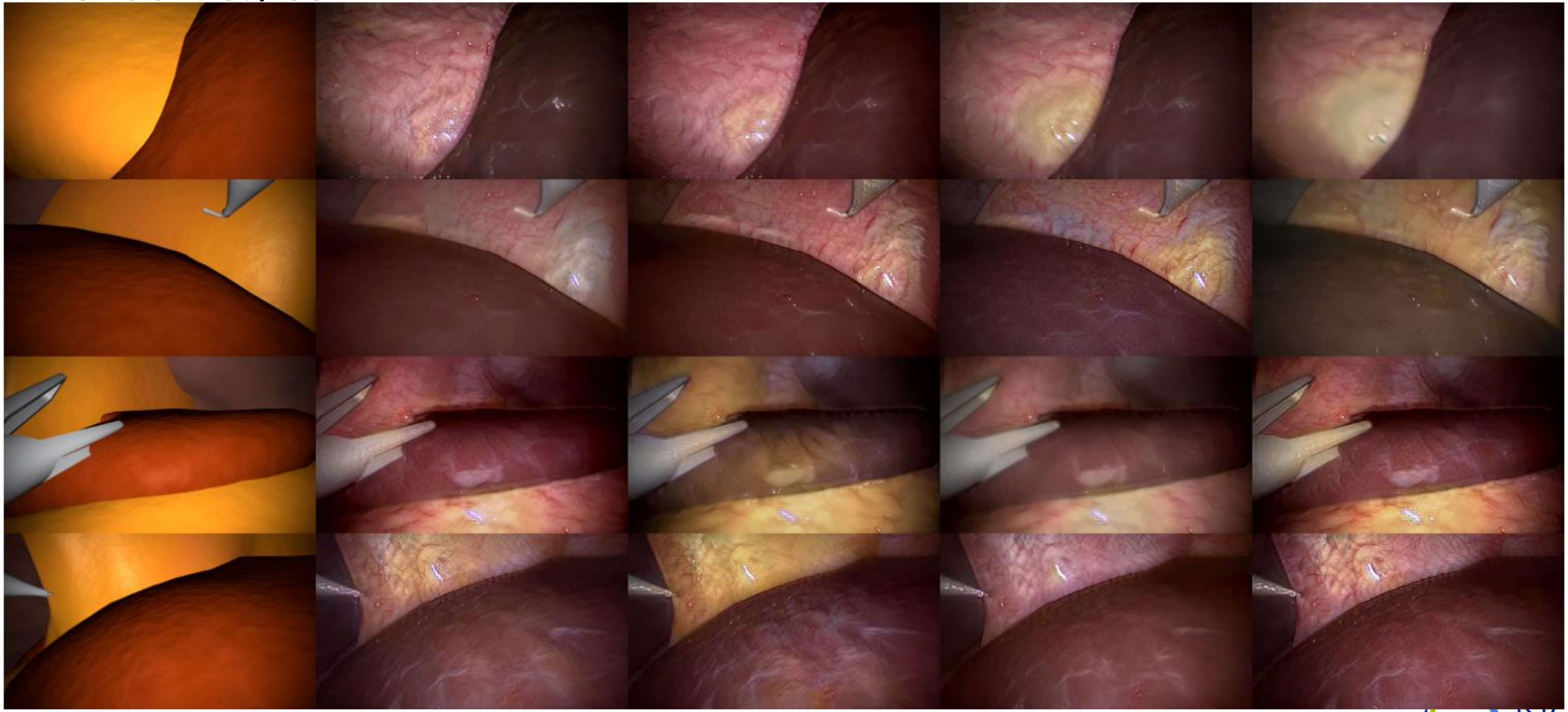
- Different styles extracted from data



Pfeiffer,..,Weitz, Speidel MICCAI 2019: „Generating large labeled data sets for laparoscopic image processing tasks using unpaired image-to-image translation"

Image to image translation for surgical images

- Random styles



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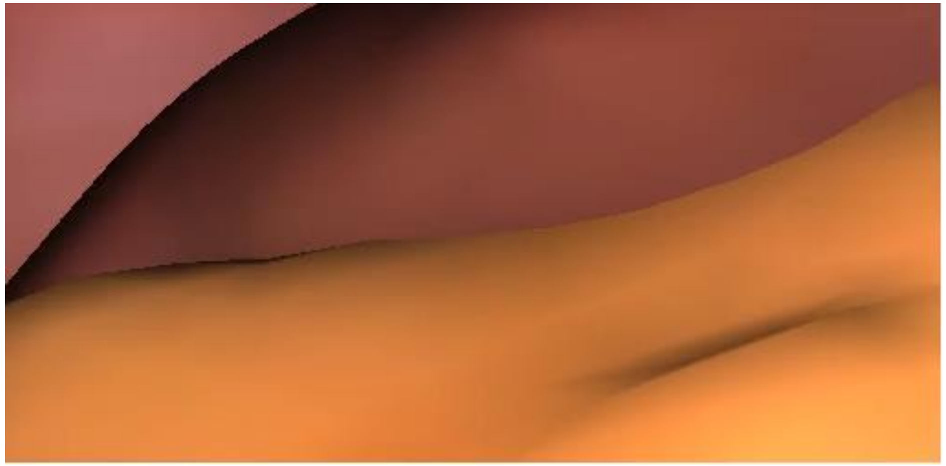
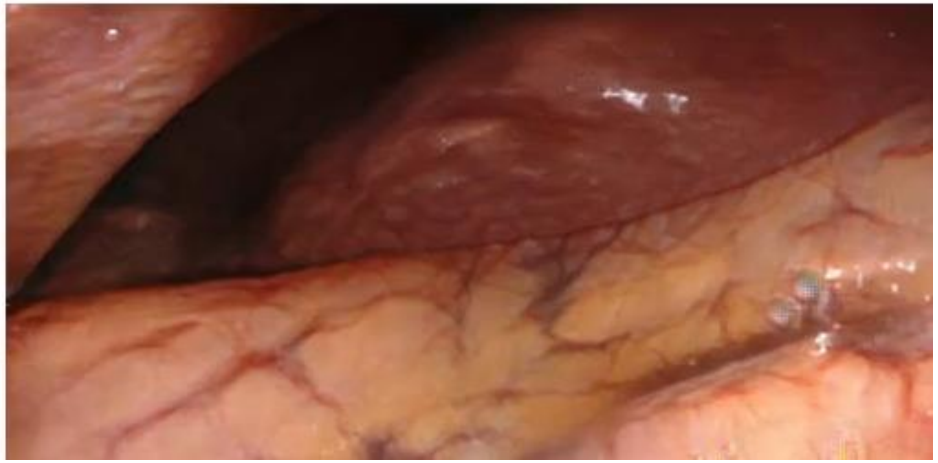
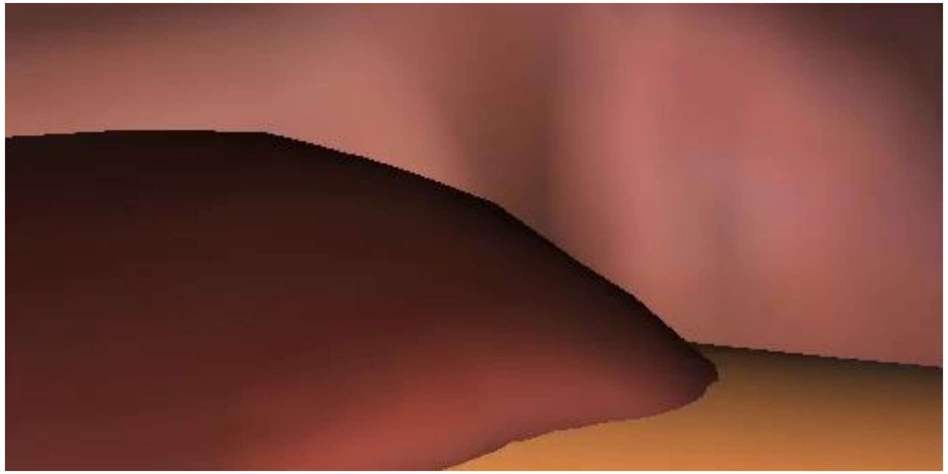
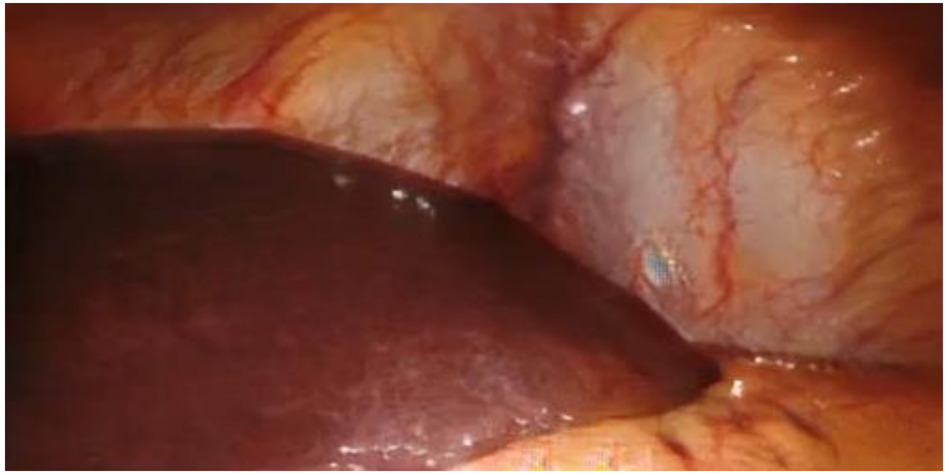
Simulation to video translation for surgical images

- Applying image to image translation to sequences can lead to temporal inconsistencies









Rivoir,..,Weitz, Speidel ICCV 2021: „Long-Term Temporally Consistent Unpaired Video Translation from Simulated Surgical 3D Data"

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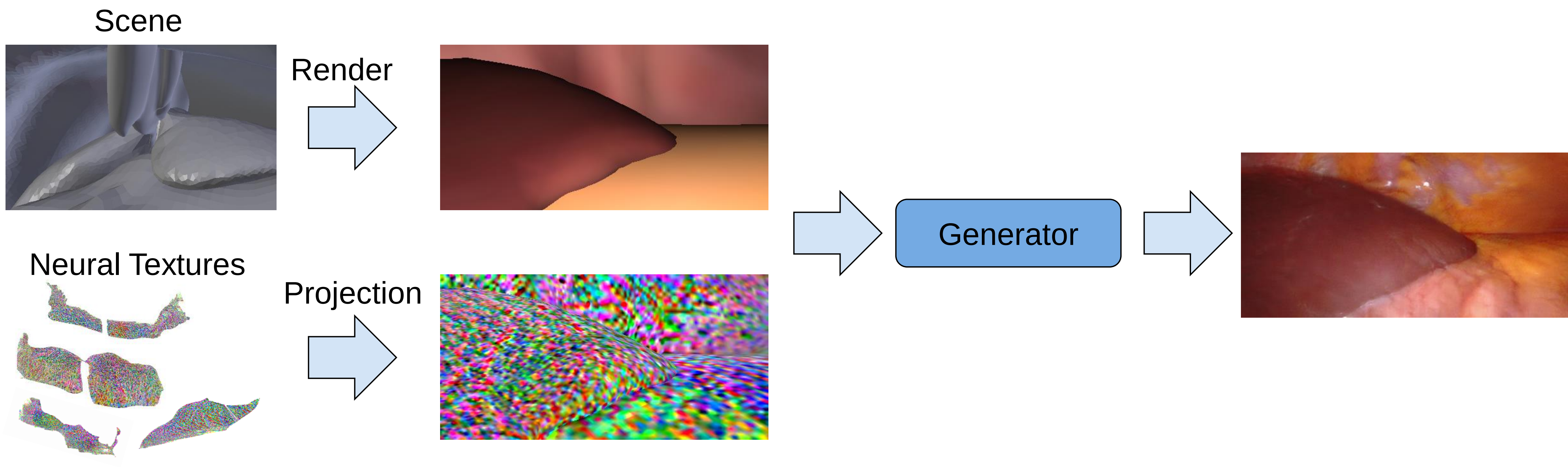
Simulation to video translation for surgical images

- Applying image to image translation to sequences can lead to temporal inconsistencies
- Enforce consistency via neural textures



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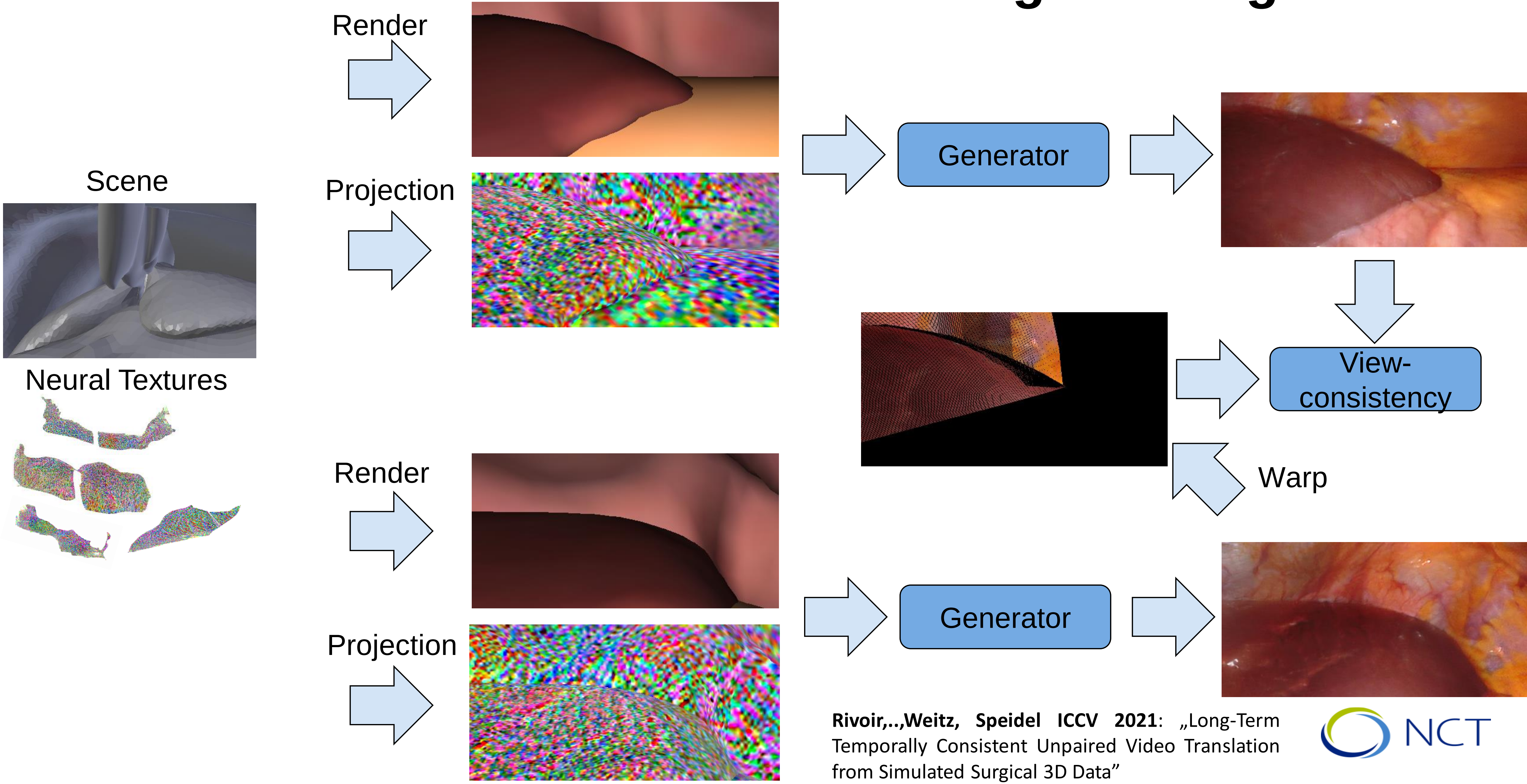
Simulation to video translation for surgical images



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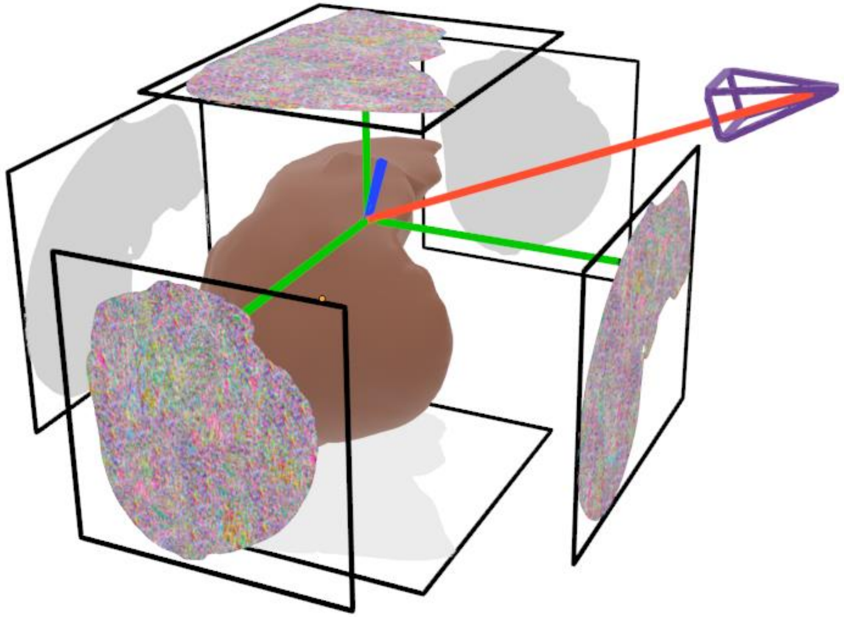
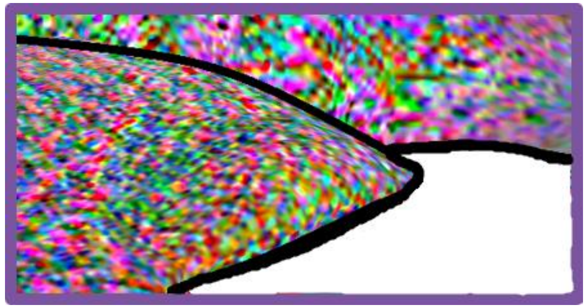
Simulation to video translation for surgical images





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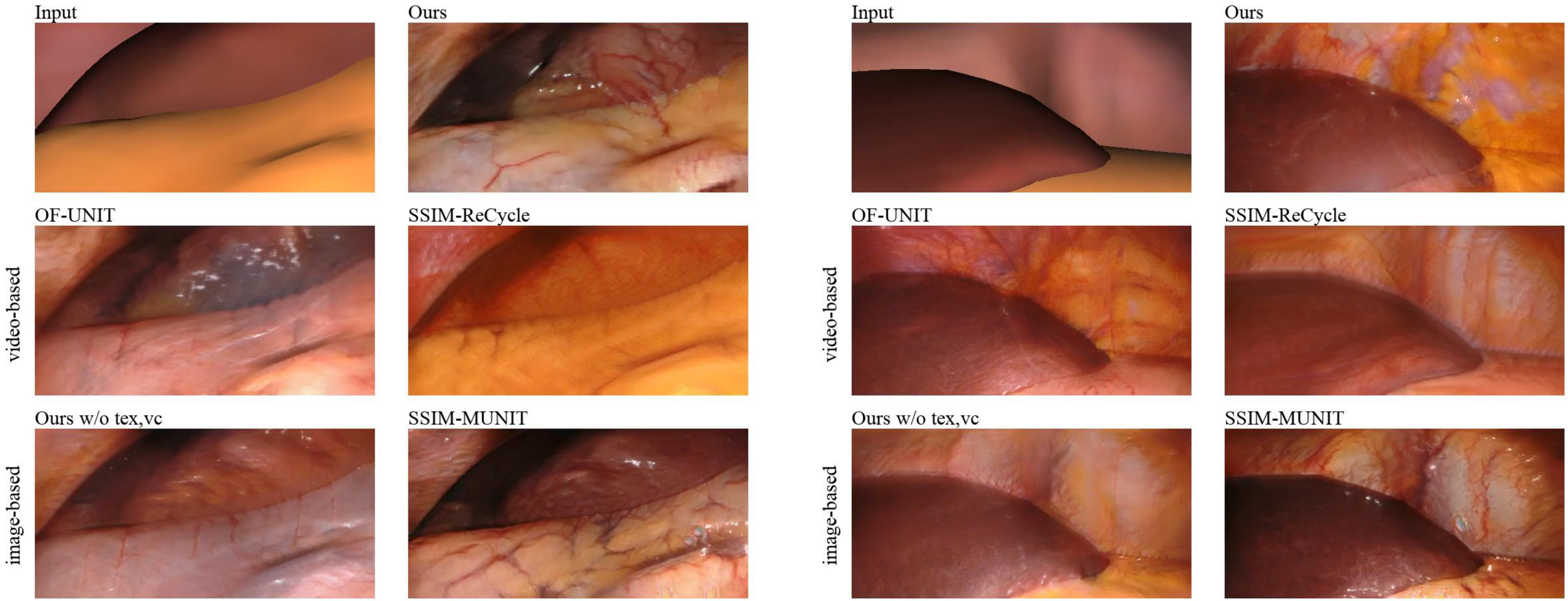
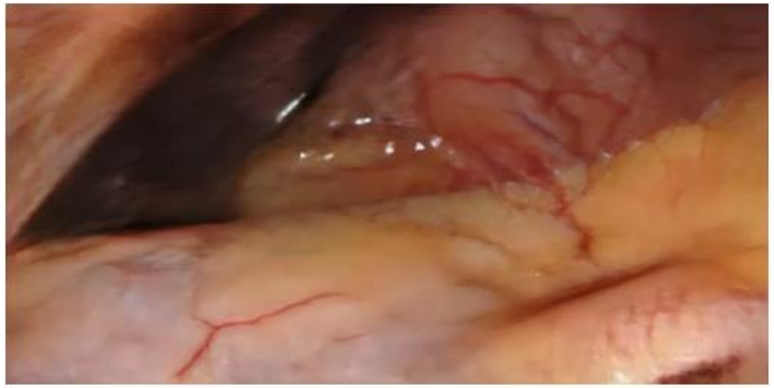
Simulation to video translation for surgical images

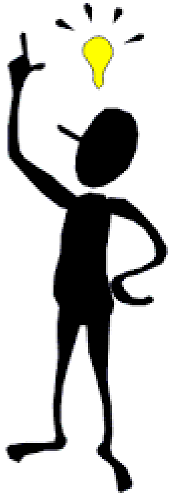


Rivoir,..,Weitz, Speidel ICCV 2021: „Long-Term Temporally Consistent Unpaired Video Translation from Simulated Surgical 3D Data"

Summary

- Introduction into the basics of GANs
  - How to train a GAN to generate images
- GANs for image to image transition
  - Paired
  - Unpaired
- GANs for simulation to video transition
  - Using neural textures





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CeTI Centre for Tactile Internet with Human-in-the-Loop

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