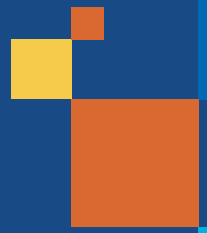
Intel Summer Camp 2021

Introduction to Generative Adversarial Networks

IOTG Computer Vision Algo R&D
Vladislav Sovrasov



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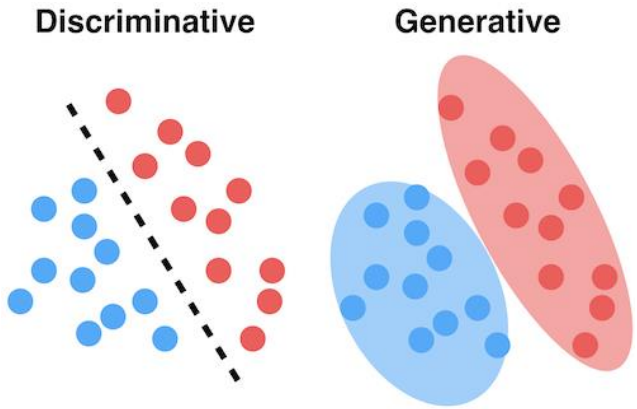
Agenda

- What is a generative model?
- When do we need to generate new data?
- Overview of the GAN learning framework
- How to evaluate GANs?
- Problems and limitations of the approach
- Examples of practical applications

Discriminative and generative learning

- Discriminative model tries to establish a boundary between classes. It learns a conditional distribution *p(y|x)*.
- Generative models can generate new data instances. They learn the joint distribution *p(x,y)* or *p(x)* if there are no labels.



When do we need to generate new data?

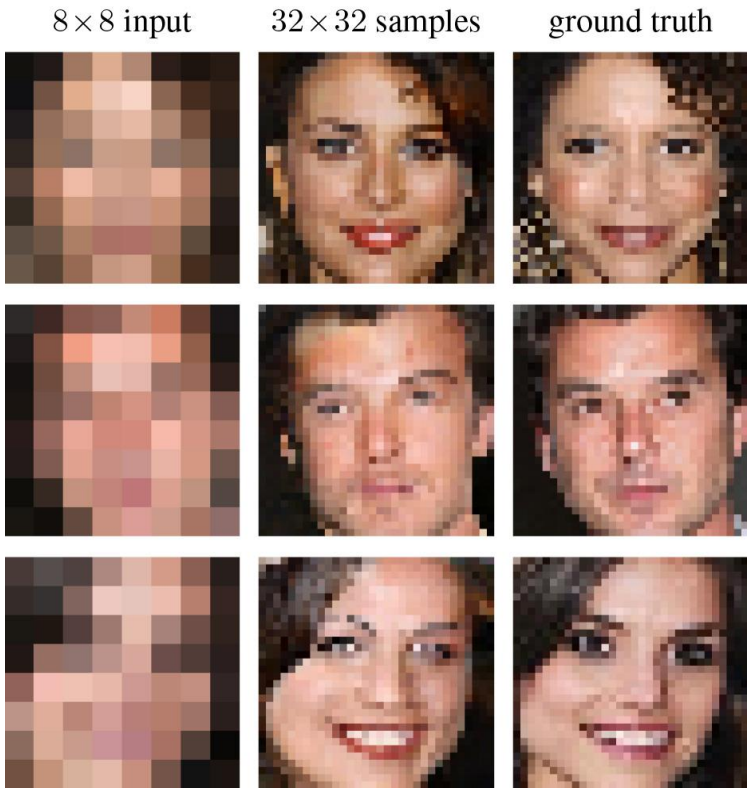
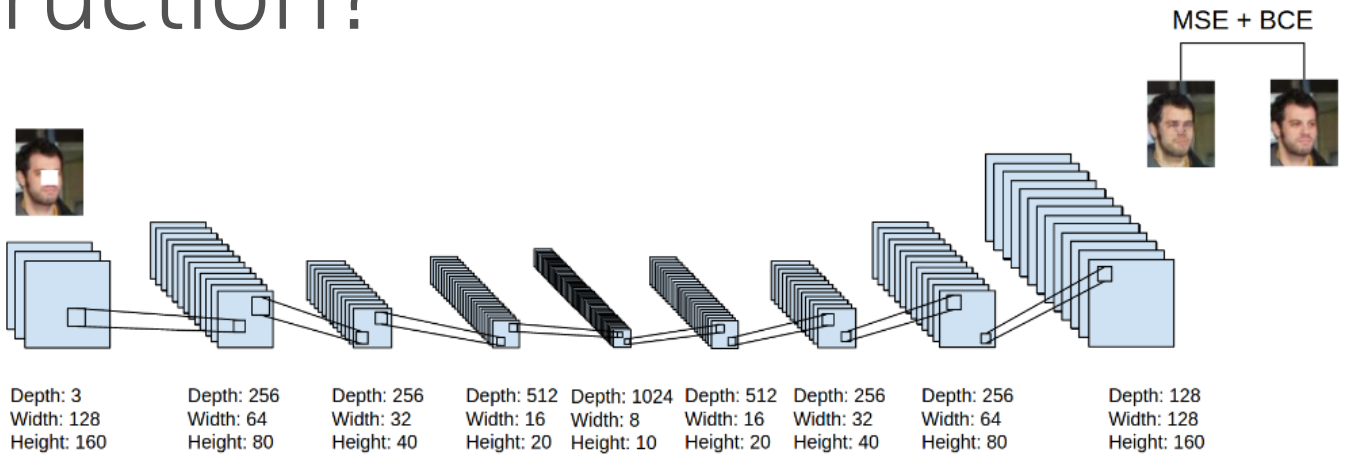
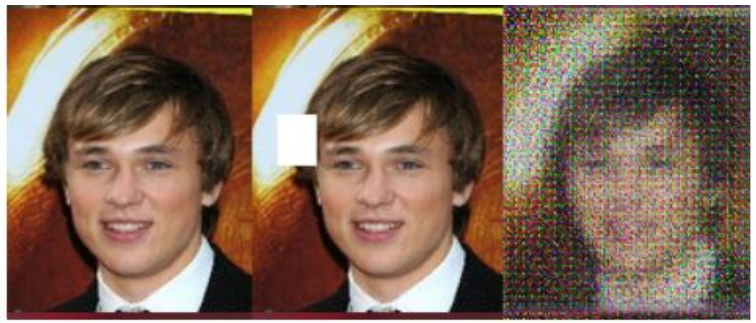


Image credit: https://arxiv.org/pdf/1702.00783.pdf

Image credit : https://github.com/csxmli2016/SymmFCNet

Why not L2 reconstruction?





Avery Allen, Wenchen Li - Generative Adversarial Denoising Autoencoder for Face Completion (2016)

Pioneering works

- Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio - Generative Adversarial Networks (2014)
- Mehdi Mirza, Simon Osindero - Conditional Generative Adversarial Nets (2014)
- Alec Radford, Luke Metz, Soumith Chintala - Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks (2015)

Dynamics of research on the GANs topic

*"**Generative Adversarial Networks is the most interesting idea in the last 10 years in Machine Learning**." — Yann LeCun, Chief AI scientist at Facebook*

Cumulative number of paper publications/journals related to GANs per year since its introduction in 2014:

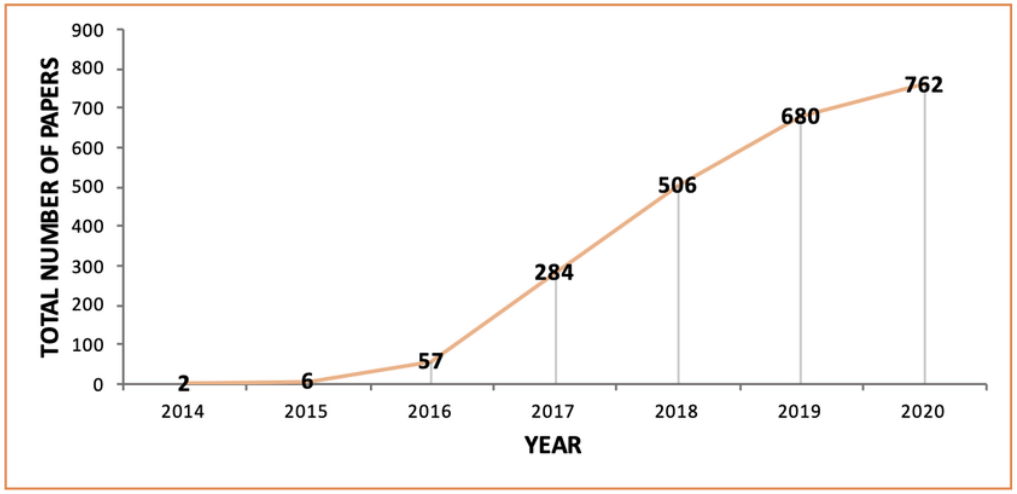


Image credit: Farou, Zakarya & Mouhoub, Noureddine & Horvath, Tomas. (2020). Data Generation Using Gene Expression Generator.

Overview of the GAN learning framework

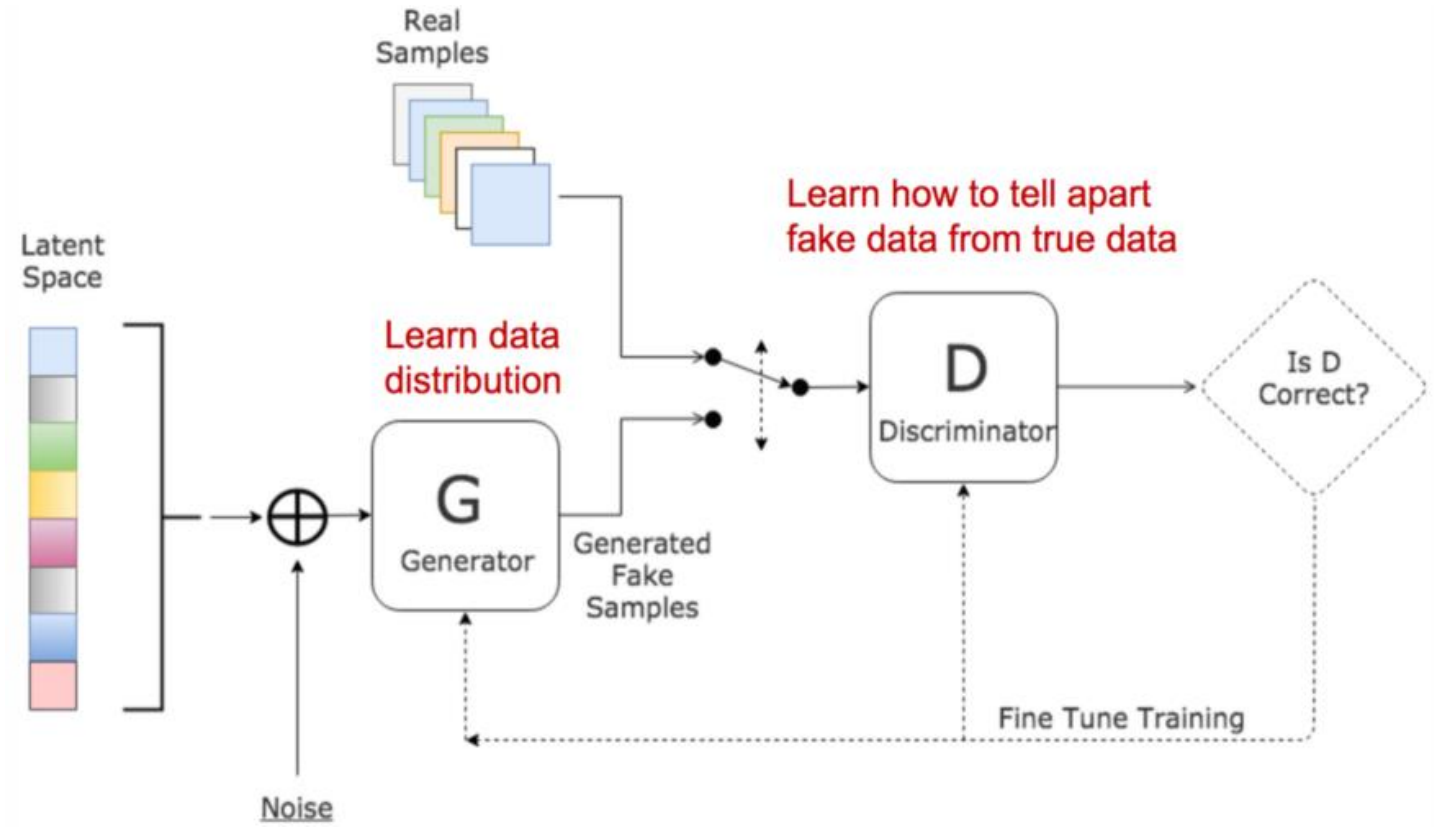


Image credit: https://medium.com/

Adversarial learning technique

x - real data

z - latent variable

D - discriminator

G - generator

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))]$$

How to evaluate GANs?

Example of the Progression in the Capabilities of GANs From 2014 to 2017. Taken from The Malicious Use of Artificial Intelligence: Forecasting, Prevention, and Mitigation, 2018.

How to evaluate GANs?

- Manual Image Inspection
- Birthday paradox test
- Nearest Neighbors test (find the closest image from a set of real images)
- Inception Score:
  - Collect output of the InceptionV3 model on fake images: *p(y|x)*
  - Compute the marginal distribution of labels *p(y)*
  - Compute the average KL-divergence between *p(y|x)* and *p(y)*

$$D_{KL}(p(y|x)||p(y)) = \sum_{y=1}^{C} p(y|x) \log \left(\frac{p(y|x)}{p(y)} \right)$$

$$IS = \exp \left[\mathbb{E}_x D_{KL}(p(y|x)||p(y)) \right]$$

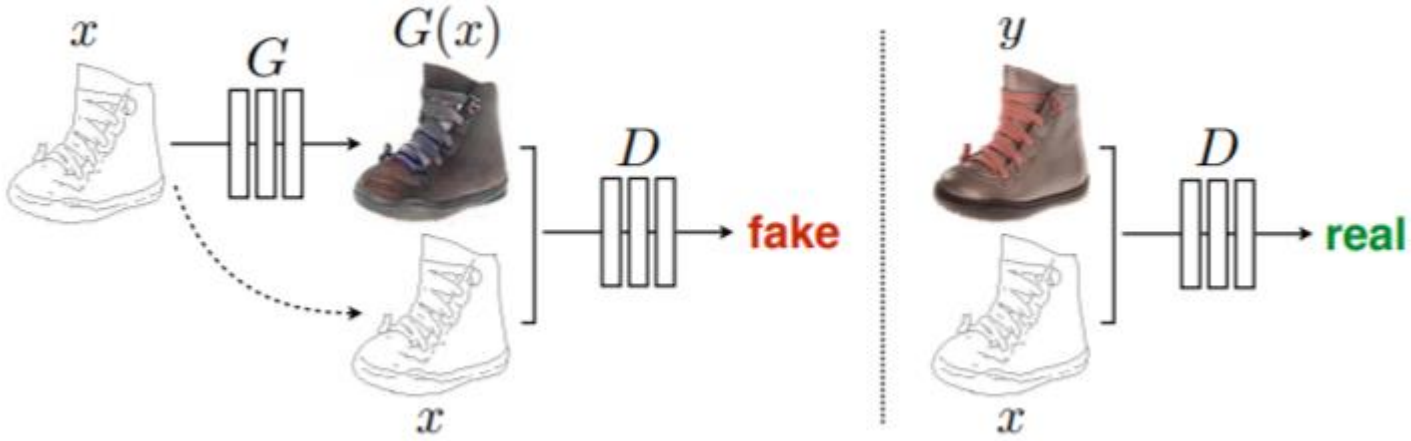
- *Frechet Inception Score*

Problems and limitations of GANs

- Optimization process in not always stable and hard to tune
- Mode collapse
- Inconsistent background
- High-frequency artifacts
- Restricted capacity of the generator and discriminator
- Inconsistency between the learned and actual distribution

Pix2Pix

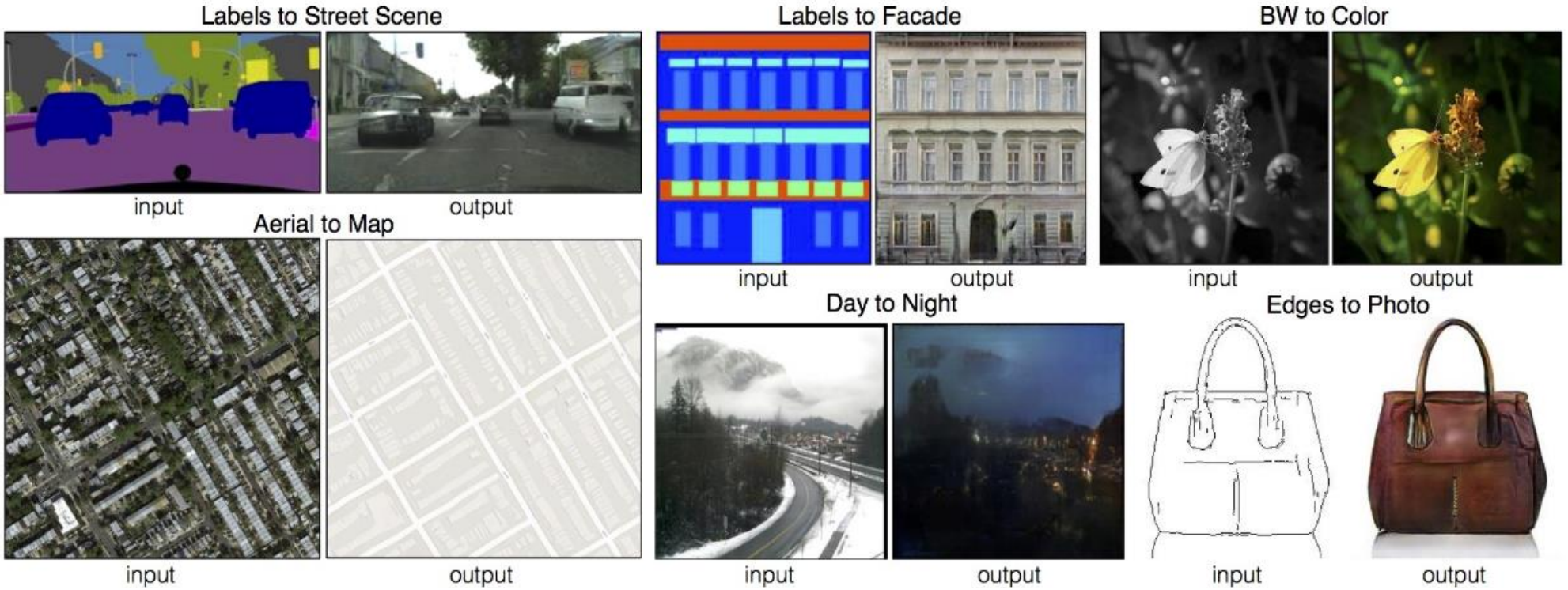
Conditional GAN trained on image pairs.



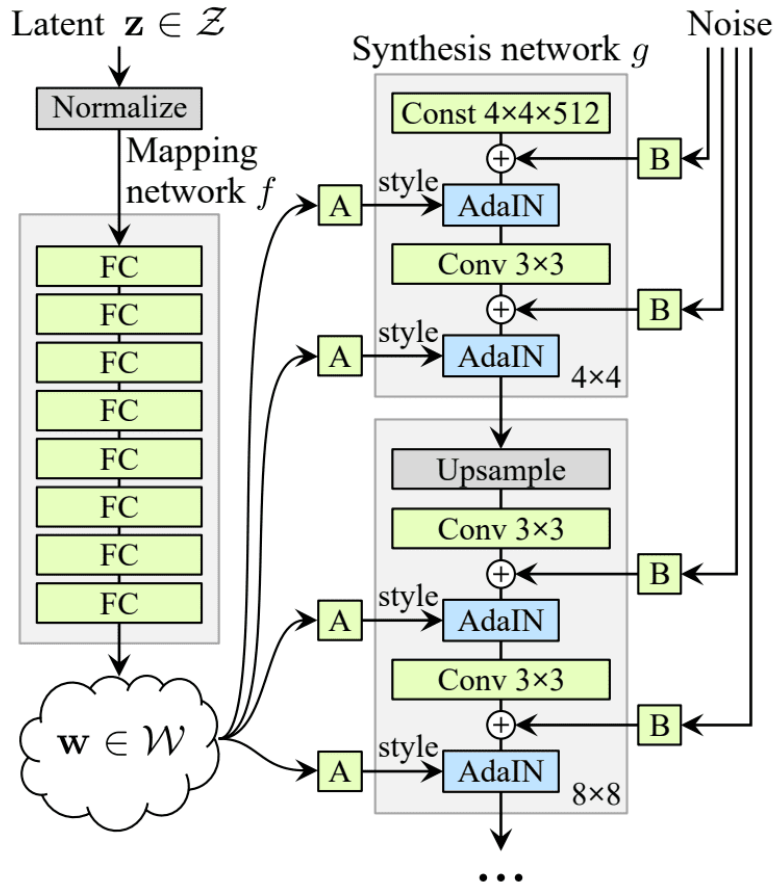
Note: the generator has no additional random input

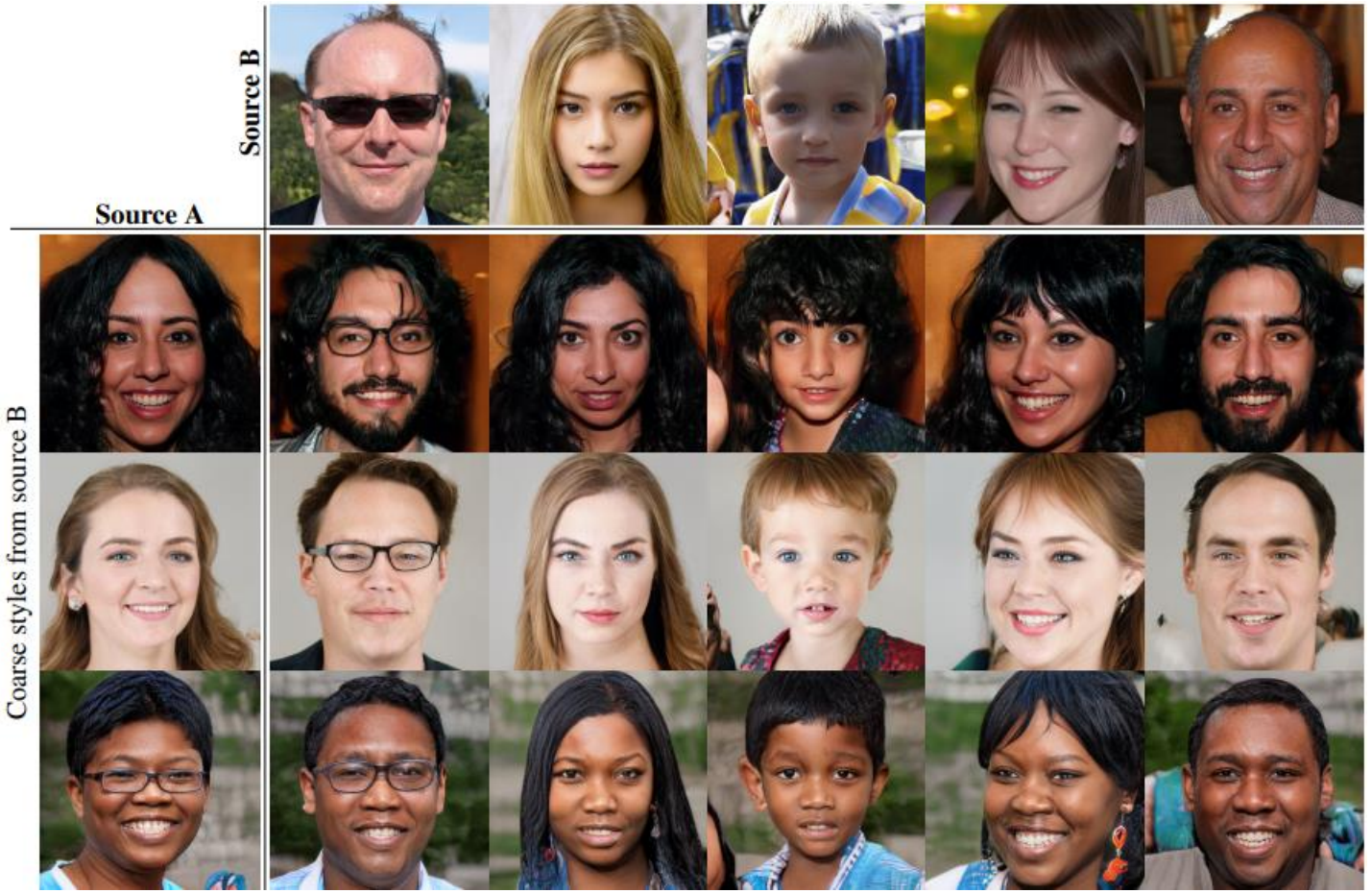
Phillip Isola et al.: Image-to-Image Translation with Conditional Adversarial Nets, CVPR`2017

Pix2Pix


Labels to Street Scene
input
output
Labels to Facade
input
output
BW to Color
input
output
Aerial to Map
input
output
Day to Night
input
output
Edges to Photo
input
output

Style GAN

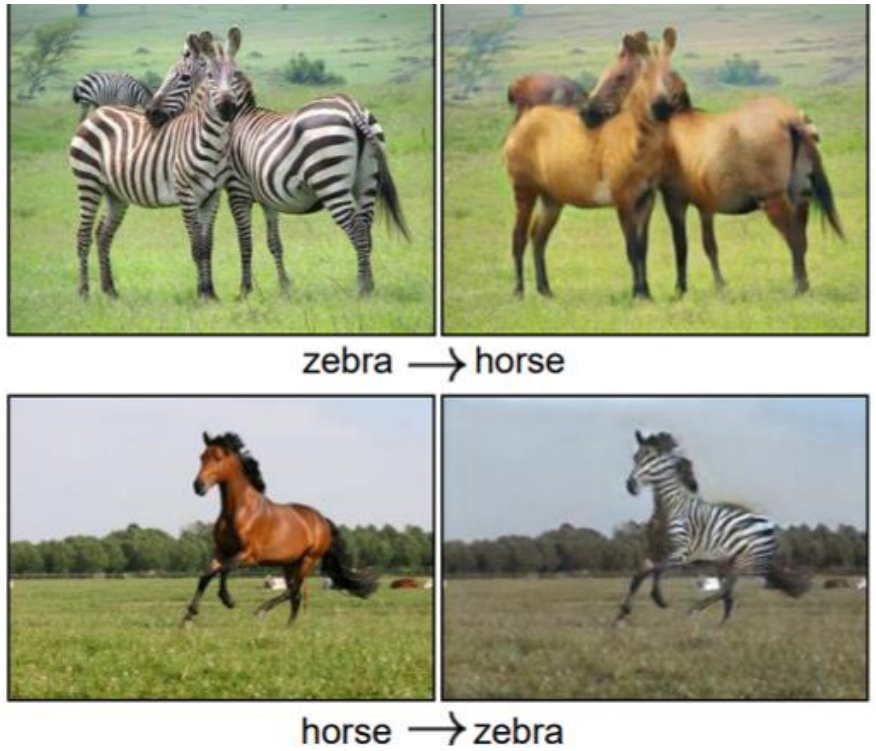




Tero Karras et al.: A Style-Based Generator Architecture for Generative Adversarial Networks (2018)

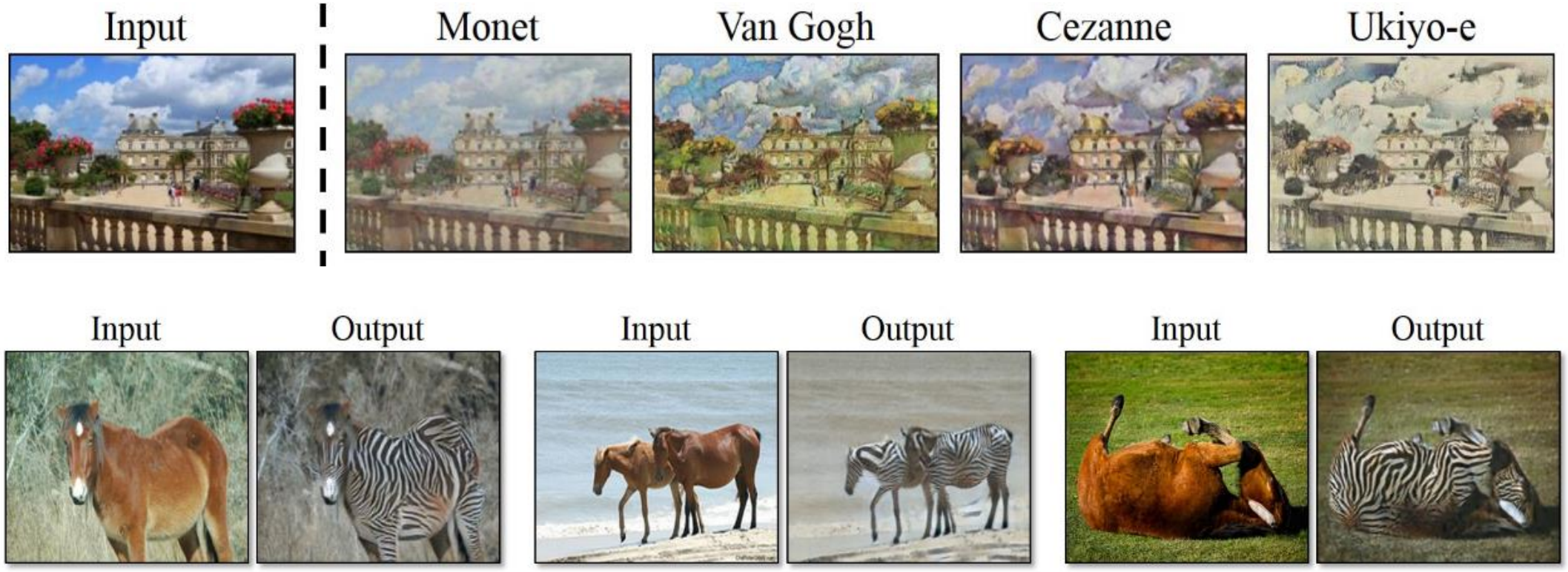
Cycle GAN

Problem formulation: let wee need to learn to transfer images from one domain to another without implicit pairwise annotation

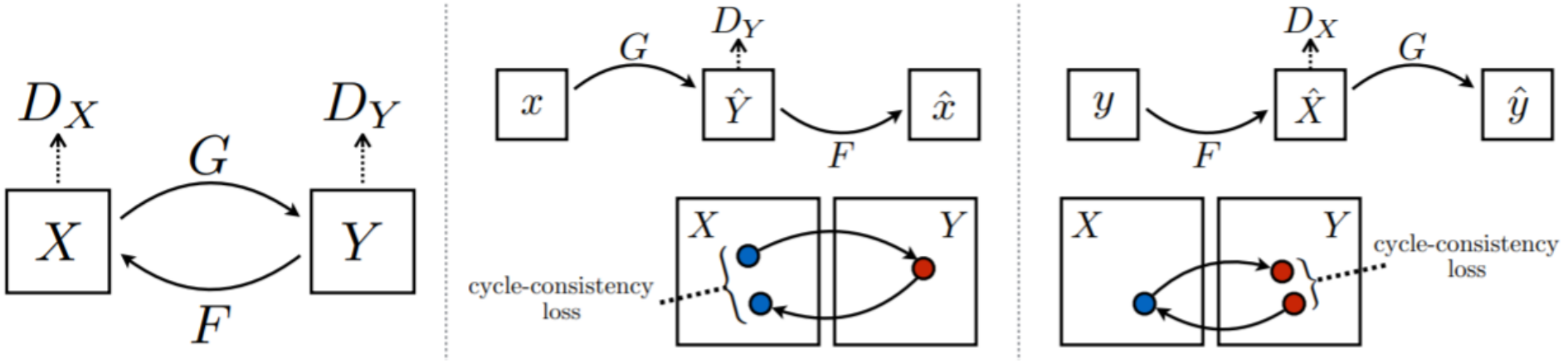


Jun-Yan Zhu et al.: Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks (2017)

Cycle GAN

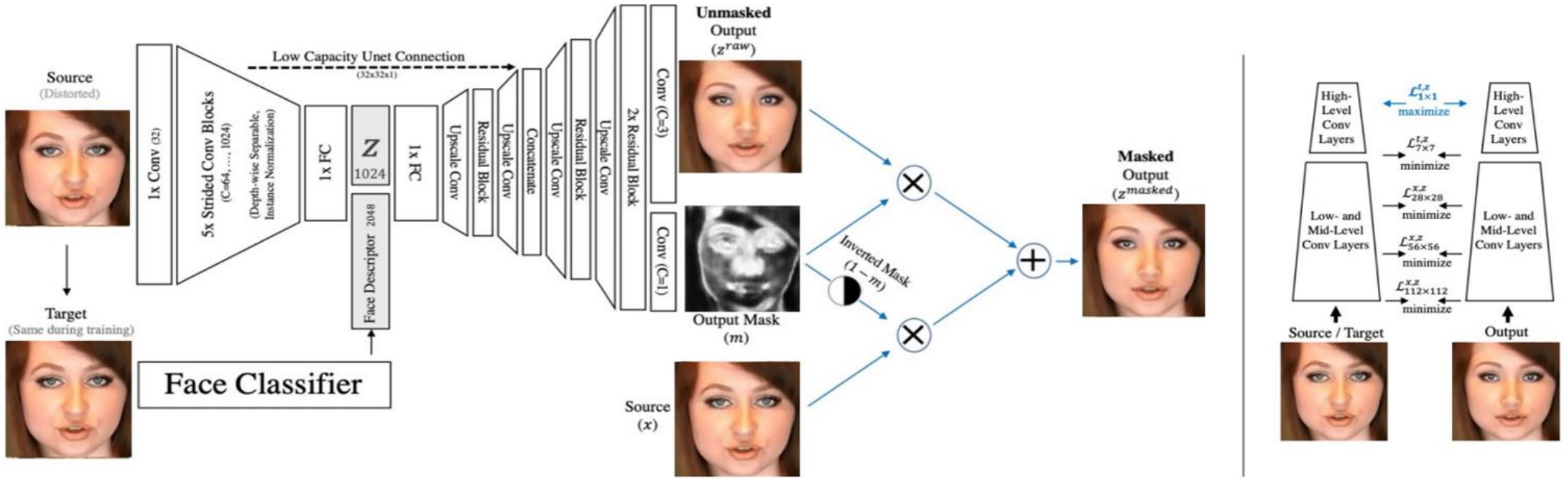

Input
Monet
Van Gogh
Cezanne
Ukiyo-e
Input
Output
Input
Output
Input
Output

Cycle GAN


D_X
D_Y
G
X
Y
F
x
G
D_Y
$\hat{Y}$
$\hat{x}$
F
cycle-consistency loss
X
Y
y
F
D_X
$\hat{X}$
G
$\hat{y}$
X
Y
cycle-consistency loss

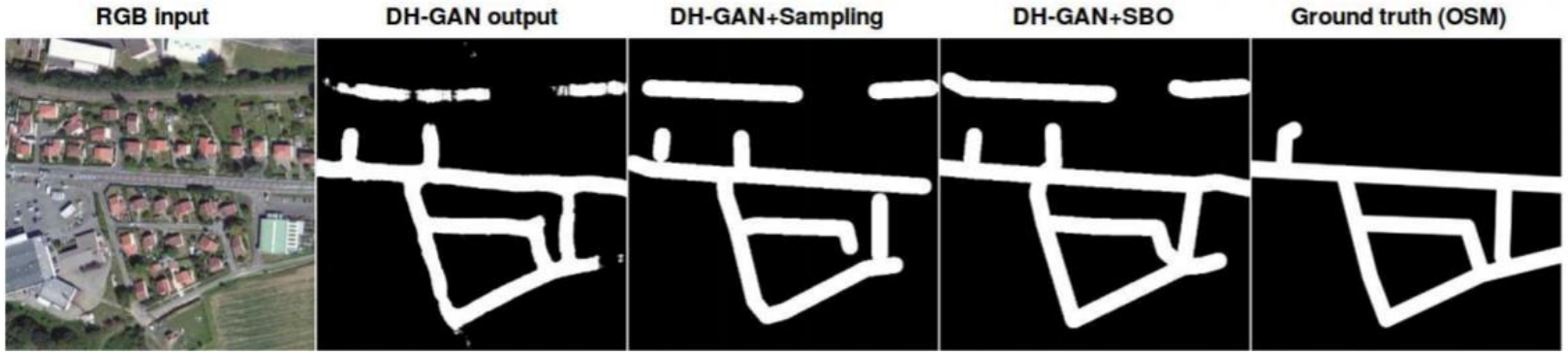
Cycle GAN

Live Face De-Identification in Video

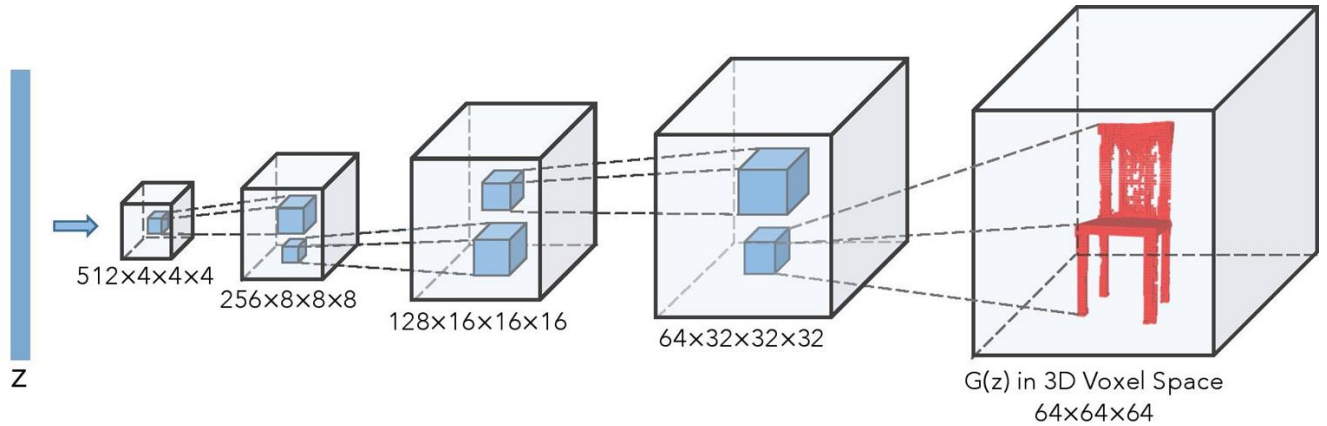


Oran Gafni et al.: Live Face De-Identification in Video, ICCV`2019

Other examples of applications



Dragos Costea et al.: Creating Roadmaps in Aerial Images with Generative Adversarial Networks and Smoothing-based Optimization (2017)



Jiajun Wu et al.: Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling (2016)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