Generative Adversarial Network

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- Generative Adversarial Network
- Conditional GAN
- Example Code

Generative Adversarial Network

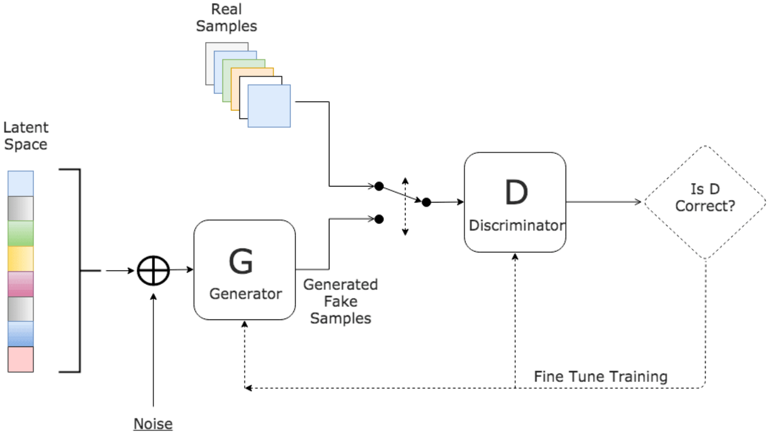
- Motivation: if deep neural network is so expressive, how about put two in competition?

- Goodfellow et al., Generative Adversarial Nets, 2014
- Generate synthetic data: images, sentences, ...
- "the most interesting idea in the last 10 years in Machine Learning" – Yann LeCun, Turing Award winner (2018)

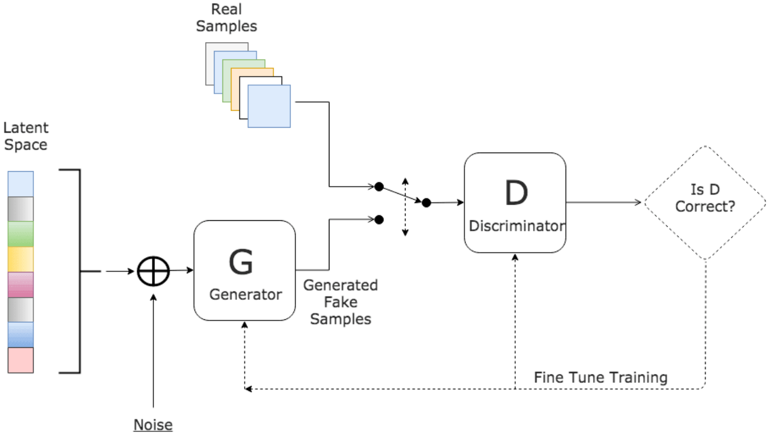
- Karras et al., A Style-Based Generator Architecture for Generative Adversarial Networks, 2019

Architecture of GAN

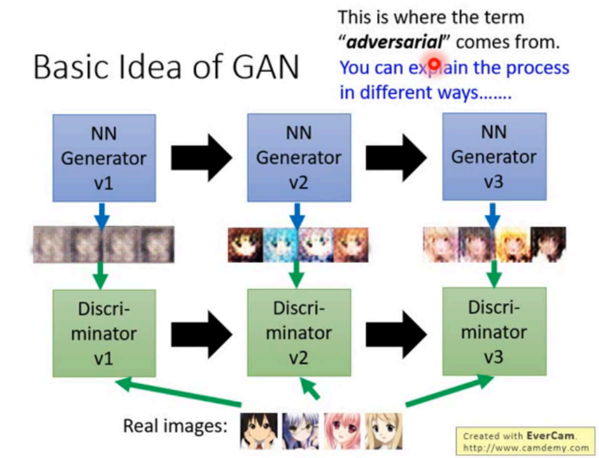
- Generator (G): latent space $\rightarrow$ synthetic data
- Each element in the latent space can represent a characteristic of the synthetic data



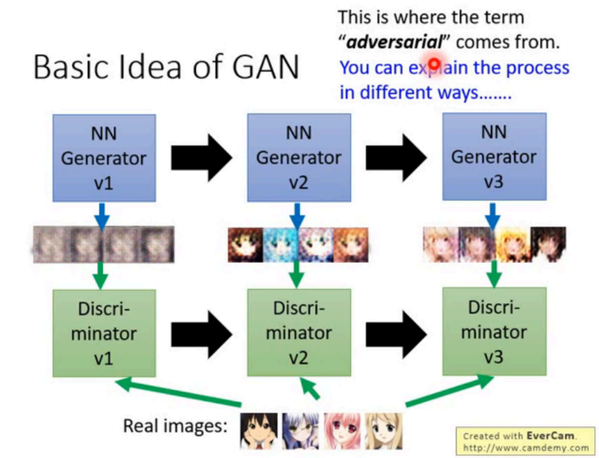
- Discriminator (D): synthetic data $\rightarrow$ score (scalar)
- The score is used to judge whether the synthetic data is "realistic" or not



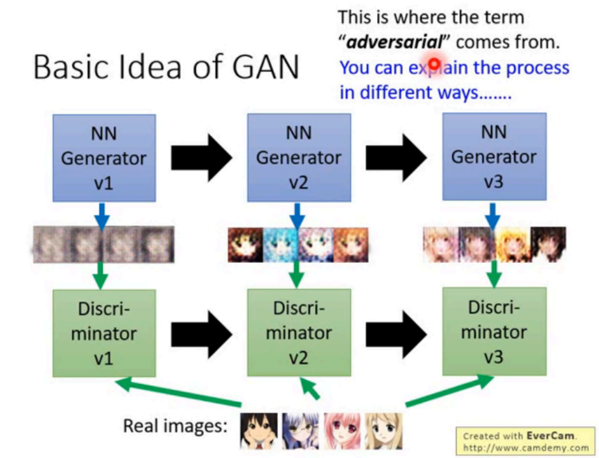
- To start: Generator v1 generates some synthetic data and Discriminator v1 tries to differentiate real and synthetic



- Generator v2's goal is to fool Discriminator v1 by improving synthetic data quality

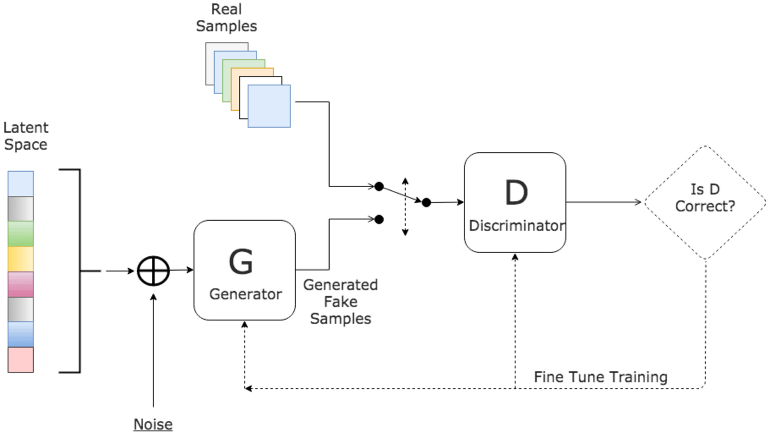


- Discriminator v2's goal is to defeat Generator v2 by identifying what is real and what is synthetic



- Step 1: initialize the parameters of generator and discriminator
- Step 2: fix generator, use it to generate synthetic data
- Step 3: sample real data from training set
- Step 4: **update** discriminator so that it can differentiate real and synthetic
- Step 5: fix discriminator, **update** generator till the current discriminator can no longer differentiate real and synthetic
- Step 6: go to Step 2

- During training, generator and discriminator are combined to form a large network with one hidden layer in the middle representing the generated data



Algorithm Initialize θ_d for D and θ_g for G

- In each training iteration:

Learning D

- Sample m examples $\{x^1, x^2, \ldots, x^m\}$ from database
- Sample m noise samples $\{z^1, z^2, \ldots, z^m\}$ from a distribution
- Obtaining generated data $\{\tilde{x}^1, \tilde{x}^2, \ldots, \tilde{x}^m\}$, $\tilde{x}^i = G(z^i)$
- Update discriminator parameters θ_d to maximize
  - $\tilde{V} = \frac{1}{m}\sum_{i=1}^{m} logD(x^i) + \frac{1}{m}\sum_{i=1}^{m} log\left(1 - D(\tilde{x}^i)\right)$
  - $\theta_d \leftarrow \theta_d + \eta \nabla \tilde{V}(\theta_d)$

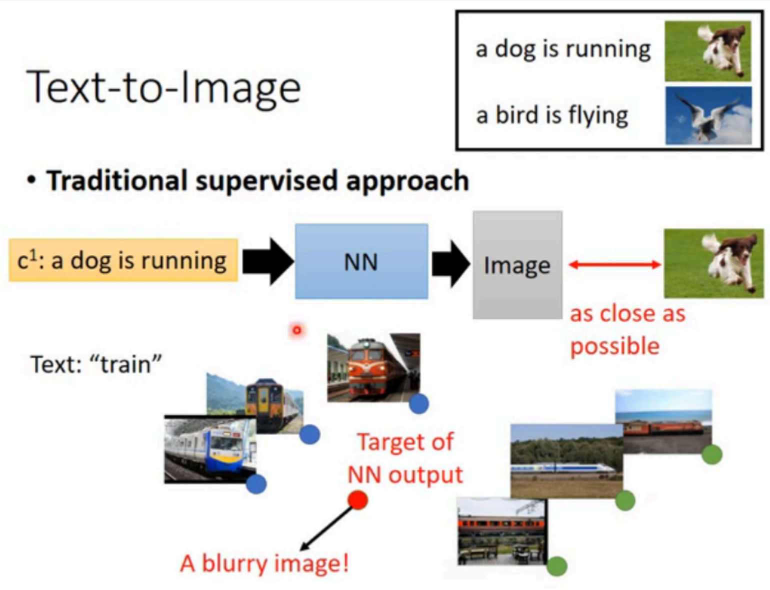
Learning G

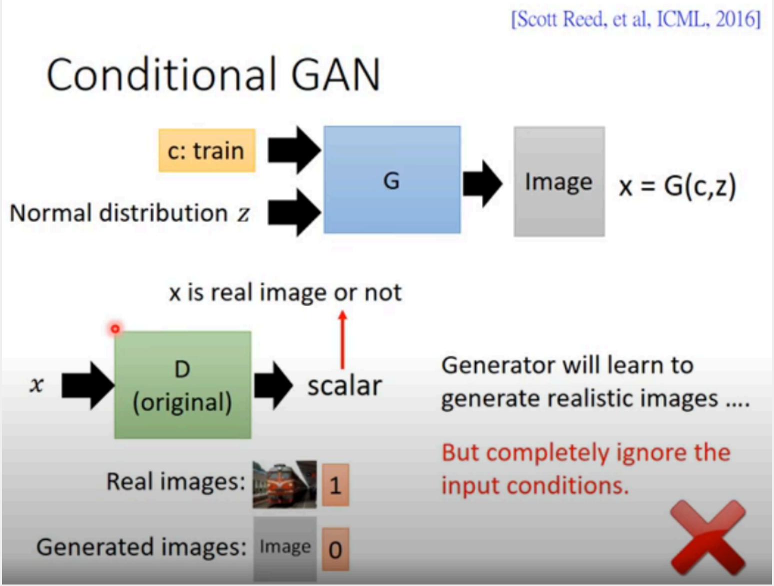
- Sample m noise samples $\{z^1, z^2, \ldots, z^m\}$ from a distribution
- Update generator parameters θ_g to maximize
  - $\tilde{V} = \frac{1}{m}\sum_{i=1}^{m} log\left(D\left(G(z^i)\right)\right)$
  - $\theta_g \leftarrow \theta_g + \eta \nabla \tilde{V}(\theta_g)$

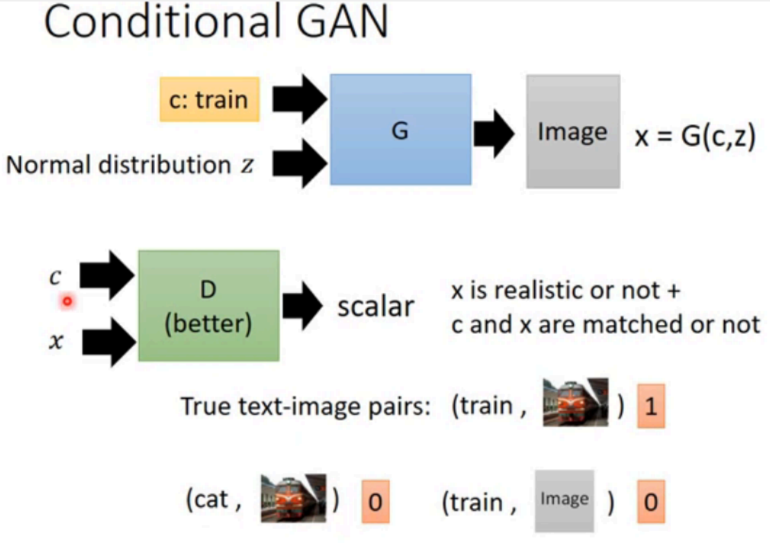
- link

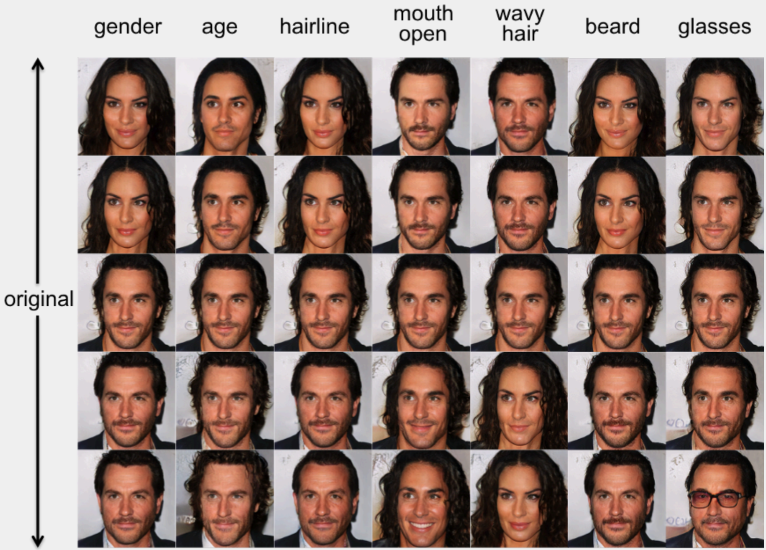
Conditional GAN

- Conditional GAN represents a class of useful GAN variations: supervised, unsupervised


Text-to-Image
a dog is running
a bird is flying
• Traditional supervised approach
c1: a dog is running
NN
Image
as close as possible
Text: "train"
Target of NN output
A blurry image!


[Scott Reed, et al, ICML, 2016]
Conditional GAN
c: train
Normal distribution z
G
Image
x = G(c,z)
x is real image or not
x
D
(original)
scalar
Generator will learn to
generate realistic images ....
But completely ignore the
input conditions.
Real images:
1
Generated images:
Image
0


Conditional GAN
c: train
Normal distribution z
G
Image
x = G(c,z)
c
x
D
(better)
scalar
x is realistic or not +
c and x are matched or not
True text-image pairs: (train ,) 1
(cat ,) 0
(train , Image) 0


gender
age
hairline
mouth open
wavy hair
beard
glasses
original

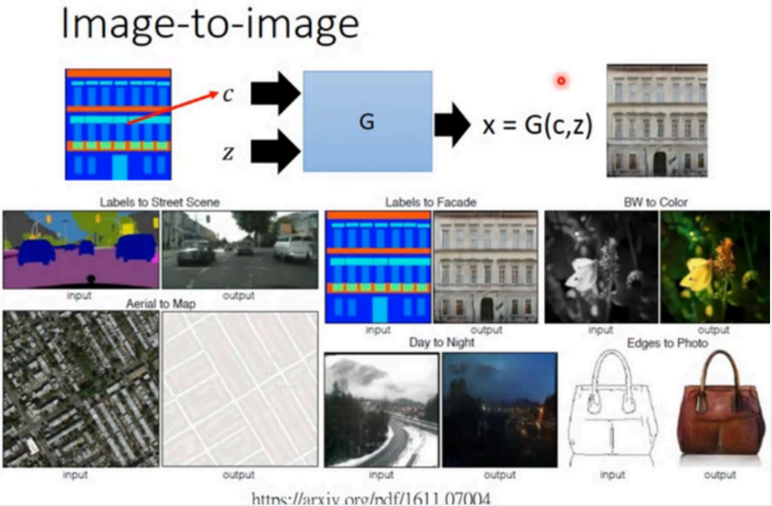


Image-to-image
c
z
G
x = G(c,z)
Labels to Street Scene
input
output
Aerial to Map
input
output
Labels to Facade
input
output
BW to Color
input
output
Day to Night
input
output
Edges to Photo
input
output
https://arxiv.org/pdf/1611.07004

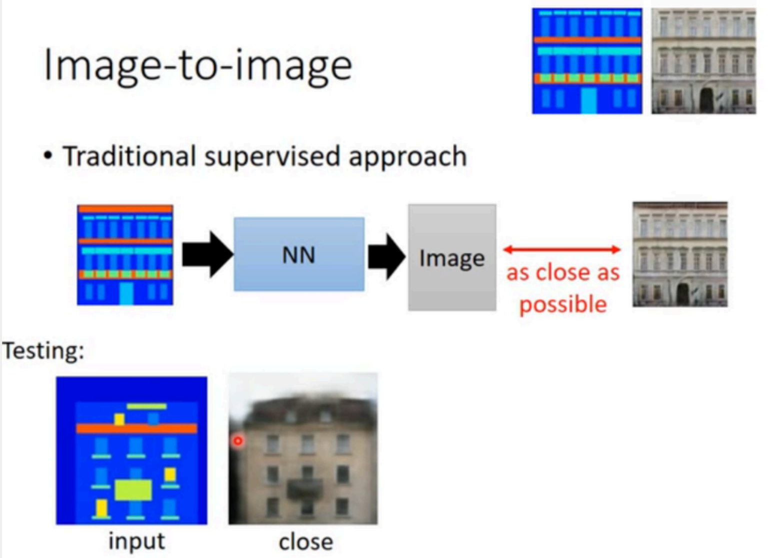


Image-to-image
• Traditional supervised approach
NN
Image
as close as possible
Testing:
input
close

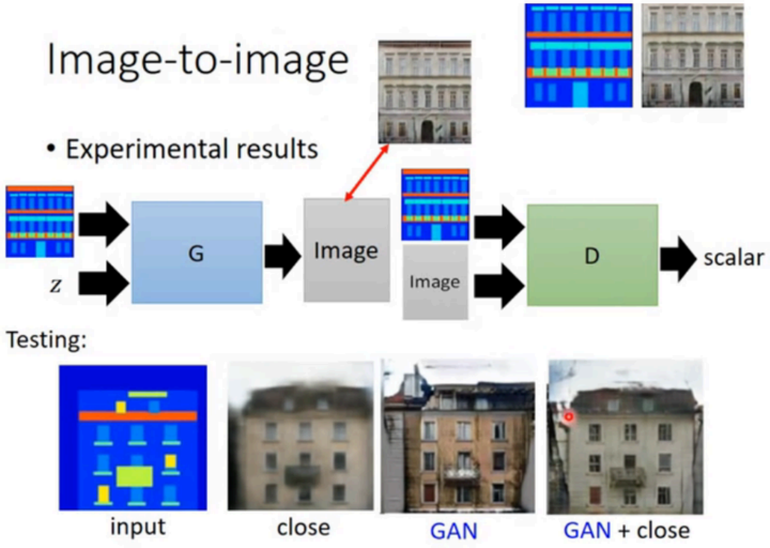
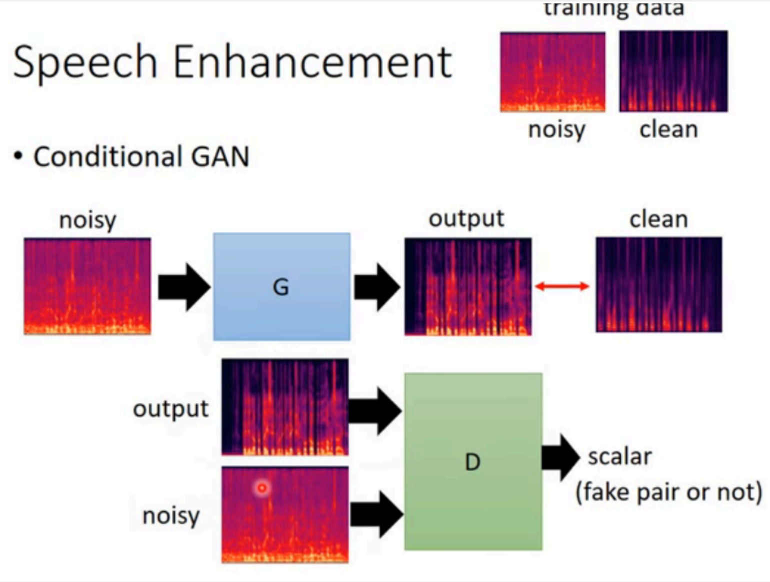
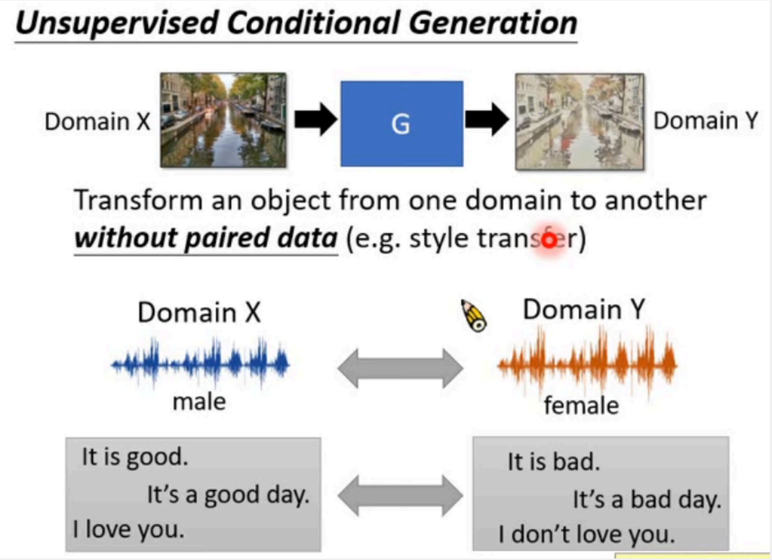


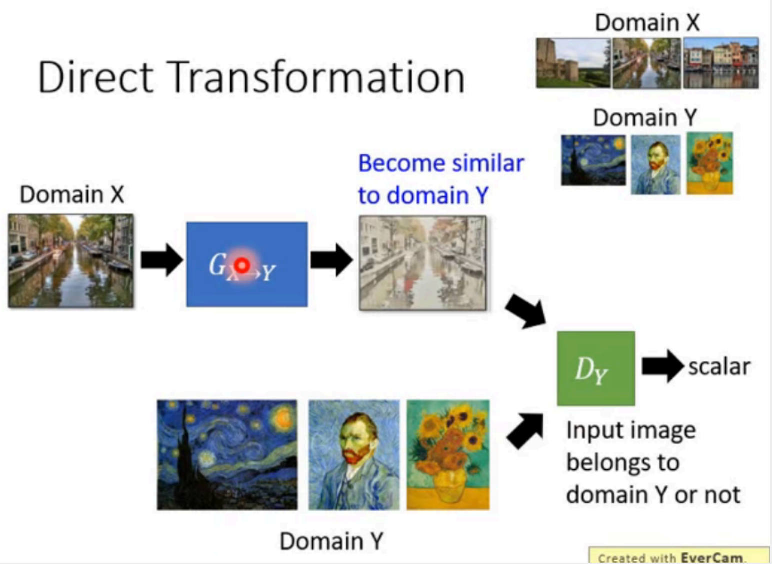
Image-to-image
• Experimental results
z
G
Image
Image
D
scalar
Testing:
input
close
GAN
GAN + close

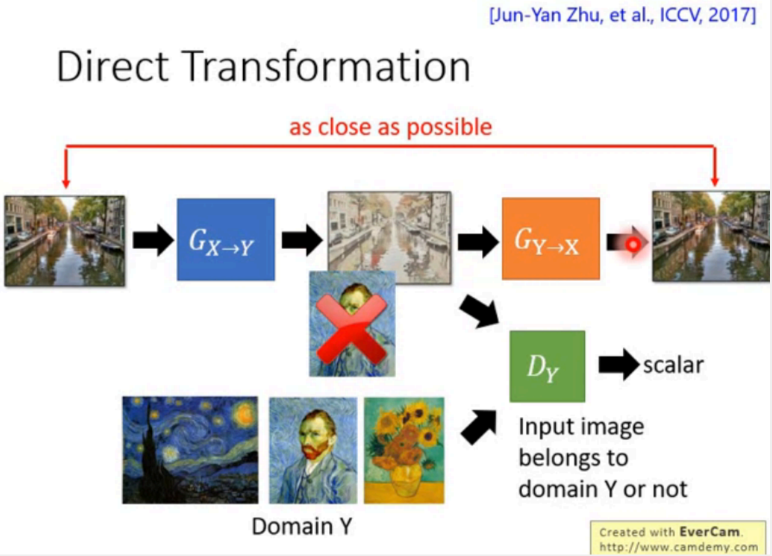

training data
Speech Enhancement
noisy
clean
• Conditional GAN
noisy
G
output
clean
output
D
noisy
scalar
(fake pair or not)

Unsupervised Conditional GAN: style transfer



- Application: voice style transfer
- Past: need speech of the *same content* from two people
- Now: only need speech from two people
- link


Direct Transformation
Domain X
Domain Y
Become similar
to domain Y
Domain X
$G_{X \to Y}$
D_Y
scalar
Input image
belongs to
domain Y or not
Domain Y
Created with EverCam.


[Jun-Yan Zhu, et al., ICCV, 2017]
Direct Transformation
as close as possible
$G_{X \to Y}$
$G_{Y \to X}$
D_Y
scalar
Input image belongs to domain Y or not
Domain Y
Created with EverCam.
http://www.camdemy.com

Example Code

- Conditional GAN: link