Technische Hochschule Rosenheim

Deep Learning

Unsupervised Learning – Generative Adversarial Networks (GANs)

Technische Hochschule Rosenheim
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Acknowledgements

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https://lme.tf.fau.de/

Overview

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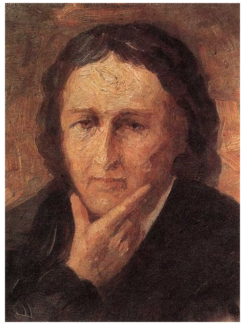
- GAN basics
- Conditional GANs
- Deep Convolutional GANs

GAN Basics

Let’s Play a Game (or the Principle of GANs)

Discriminator



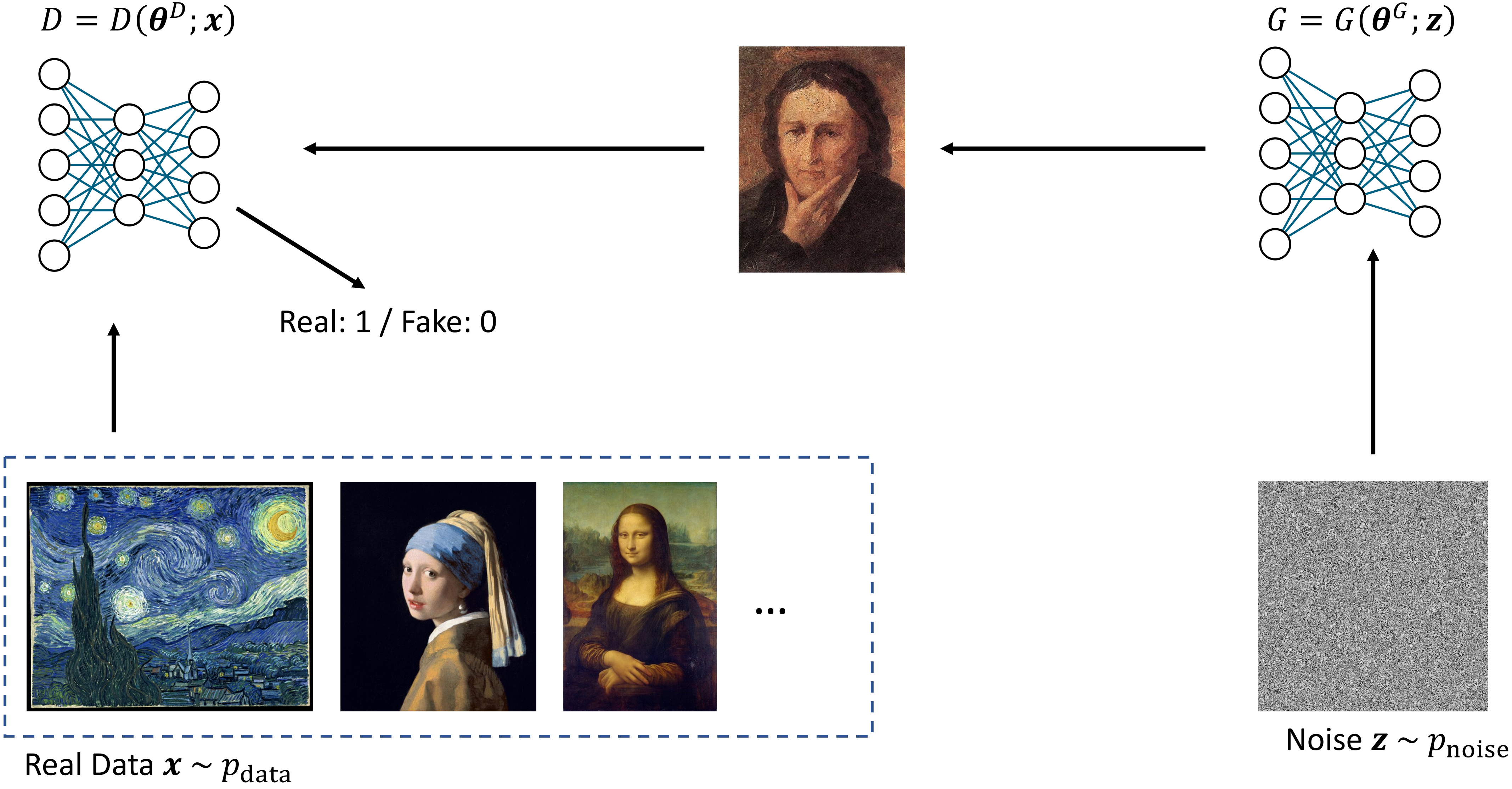
Generator

Real or Fake?

…

Real Data

Let’s Play a Game (or the Principle of GANs)



GANs – A Two Player Game (Minimax)

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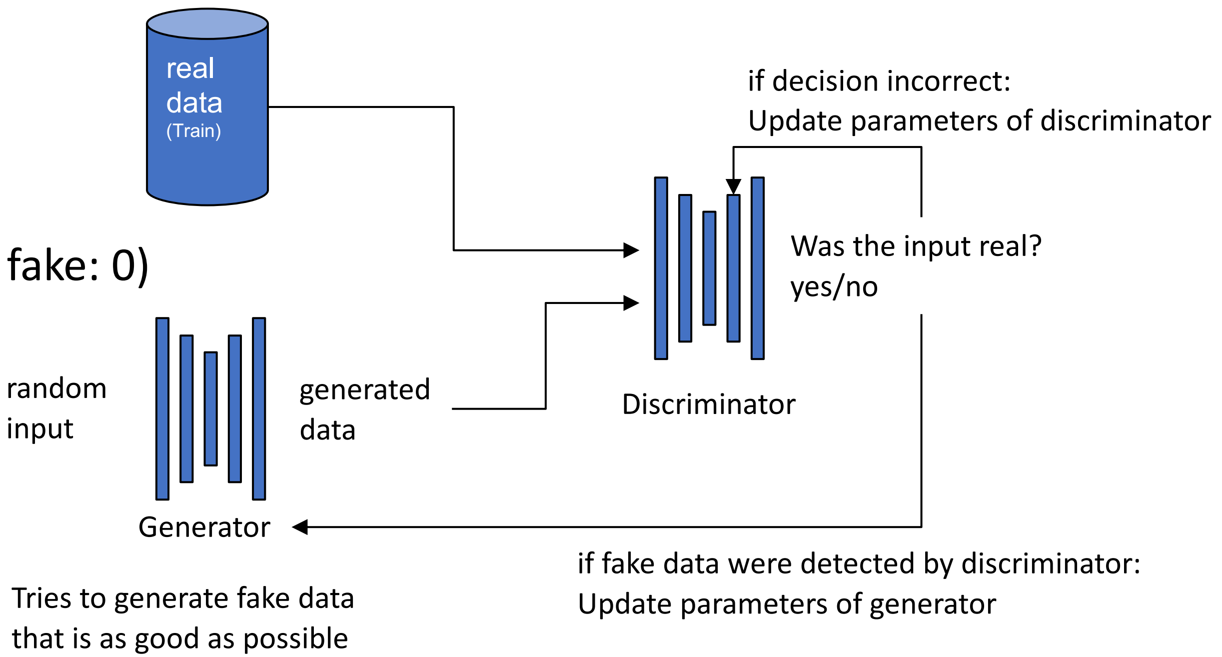
- Objectives
  - **Discriminator** tries to distinguish real from fake data
  - **Generator** tries to generate data such that discriminator is fooled

- **Training**: Alternate between
  1. Training of **discriminator**
     - use real as well as fake data with labels (real: 1, fake: 0)
     - train using cross entropy
     - keep generator weights frozen
  2. Training of **generator**
     - update weights if fake was not good enough
     - keep discriminator weights frozen



Training GANs – Minimax

Alternate between

1. Train D: Maximize $$E_{\boldsymbol{x}\sim p_{\text{data}}} \log \overbrace{D(\boldsymbol{x})}^{\text{prop. real data}} + E_{\boldsymbol{z}\sim p_{\text{noise}}} \log \overbrace{\left(1 - D\left(G(\boldsymbol{z})\right)\right)}^{\text{prop. fake data}}$$

   $\longrightarrow$ Minimize $$L^D(\boldsymbol{\theta}^D, \boldsymbol{\theta}^G) = -E_{\boldsymbol{x}\sim p_{\text{data}}} \log D(\boldsymbol{x}) - E_{\boldsymbol{z}\sim p_{\text{noise}}} \log\left(1 - D\left(G(\boldsymbol{z})\right)\right)$$

   $\longrightarrow$ Trained to distinguish real data samples from fake ones

2. Train G: Maximize L^D $\longrightarrow$ Minimize $L^G = -L^D$

   Generator minimizes log-probability of the discriminator being correct
   $\longrightarrow$ Trained to generate data domain images and fool D

- Optional: run *k* steps of one player for every step of the other player
- Equilibrium is a saddle point of the discriminator loss

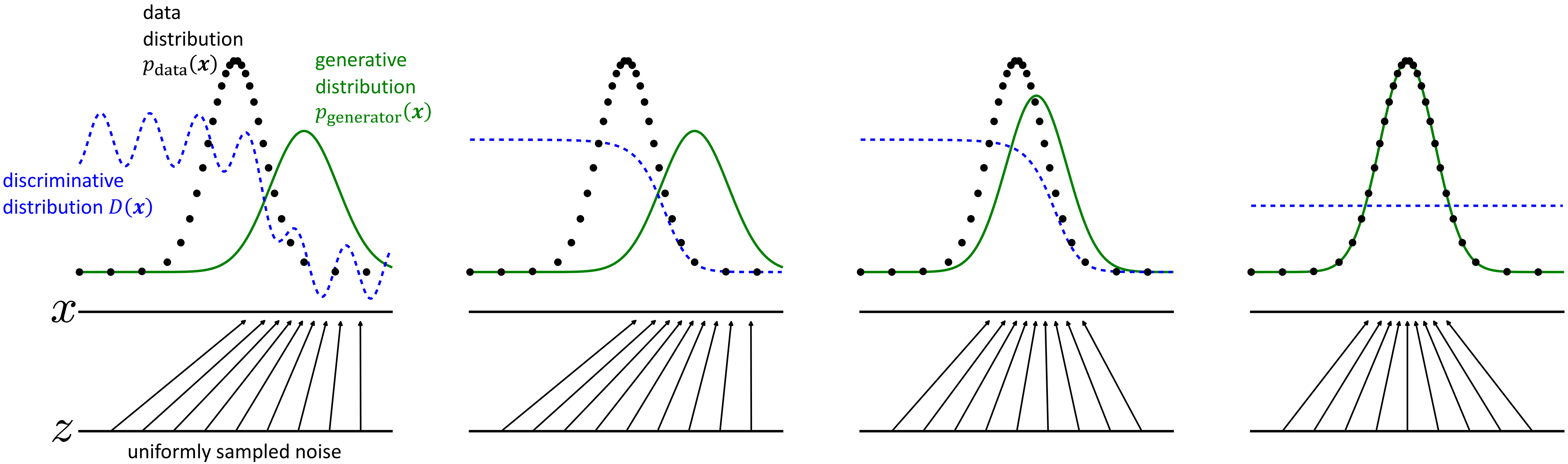
Training GANs – Optimal Discriminator

- Assumption: both densities are nonzero everywhere
  - Otherwise, some input values are never trained → some $D(\boldsymbol{x})$ have undetermined behavior
- For fixed generator, solve for $\frac{\partial L^D}{\partial D(\boldsymbol{x})} = 0$
- Optimal $D^*(\boldsymbol{x})$ for any $p_{\text{data}}(\boldsymbol{x})$ and $p_{\text{generator}}(\boldsymbol{x})$:

$$D^*(\boldsymbol{x}) = \frac{p_{\text{data}}(\boldsymbol{x})}{p_{\text{data}}(\boldsymbol{x}) + p_{\text{generator}}(\boldsymbol{x})}$$

- The optimum is reached for $p_{\text{generator}} = p_{\text{data}}$, i.e., $D^*(\boldsymbol{x}) = \frac{1}{2}$
- GANs use supervised learning to estimate this ratio
  - Underfitting / Overfitting

Training GANs – Illustration



Source: [Goo14]

Non-Saturating Games – Modify Generator's Loss

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$$L^D = -E_{\boldsymbol{x}\sim p_{\text{data}}} \log \underbrace{D(\boldsymbol{x})}_{\text{prop. real data}} - E_{\boldsymbol{z}\sim p_{\text{noise}}} \log \Big(\underbrace{1 - D\big(G(\boldsymbol{z})\big)}_{\text{prop. fake data}}\Big)$$

(same as before)

$$L^G = -E_{\boldsymbol{z}\sim p_{\text{noise}}} \log D\big(G(\boldsymbol{z})\big)$$

(new)

- Objective: Improve generator when sample is recognized as being fake
- Particularly in the beginning, the discriminator will usually be better than the generator
  - leads to vanishing gradient of G for original loss (G minimizes log-probability of D being correct)
  - model cannot be trained, saturation
  - generator has lost the game before it really started
- Now: G maximizes log-probability of D being mistaken
  - Disadvantage: Equilibrium no longer describable with single loss

Other Losses: Feature Matching Loss / Perceptual Loss

- G trained to match expected value of features $f(\boldsymbol{x})$ of intermediate layer of D:

$$L^G = \left\| E_{\boldsymbol{x} \sim p_{\mathrm{data}}} f(\boldsymbol{x}) - E_{\boldsymbol{z} \sim p_{\mathrm{noise}}} f\big(G(\boldsymbol{z})\big) \right\|_2^2$$

- prevents “overtraining” of G on current D

- Many more loss functions exist, e.g.,
  - Wasserstein Loss (helps to counter vanishing gradients in D)
  - KL divergence
- But: the approximation strategy matters more than the loss

How to Evaluate GANs – Inception Score

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- Objectives:
  1. Generated images should be recognizable
     - feed image $\boldsymbol{x}$ through neural network for classification to obtain probabilities for labels y
       - standard: Inception v-3 pre-trained on Imagenet
       - results in conditional label distribution $p(y \mid \boldsymbol{x})$
     - meaningful images have a distribution where one class dominates, i.e.,
     - image-wise class distribution $p(y \mid \boldsymbol{x})$ should have low entropy
  2. Generated images should be diverse
     - Class distribution over all generated images $p(y) = \int p(y \mid \boldsymbol{x} = G(z))\, dz$ should be close to uniform, i.e.,
     - entropy should be high

- Based on KL divergence between distributions (higher = better):

$$\exp\left(E_x(KL(p(y \mid \boldsymbol{x}), p(y)))\right)$$

- see [Sal16] for details

How to Evaluate GANs – Fréchet Inception Distance (FID)

- Use intermediate layer (last pooling layer of Inception-v3 pre-trained on ImageNet)
- Model data distribution by multivariate Gaussians ($\boldsymbol{\mu}, \boldsymbol{\Sigma}$)
- FID score between real images $\boldsymbol{x}$ and generated images $\boldsymbol{g}$ (lower = better):

$$\left\|\boldsymbol{\mu}_x - \boldsymbol{\mu}_g\right\|_2^2 + \operatorname{tr}\left(\boldsymbol{\Sigma}_x + \boldsymbol{\Sigma}_g - 2\sqrt{\boldsymbol{\Sigma}_x \boldsymbol{\Sigma}_g}\right)$$

  - More robust to noise than Inception Score
  - No class concept needed

- see [Heu17] for details

GANs in Comparison to Other Generative Models

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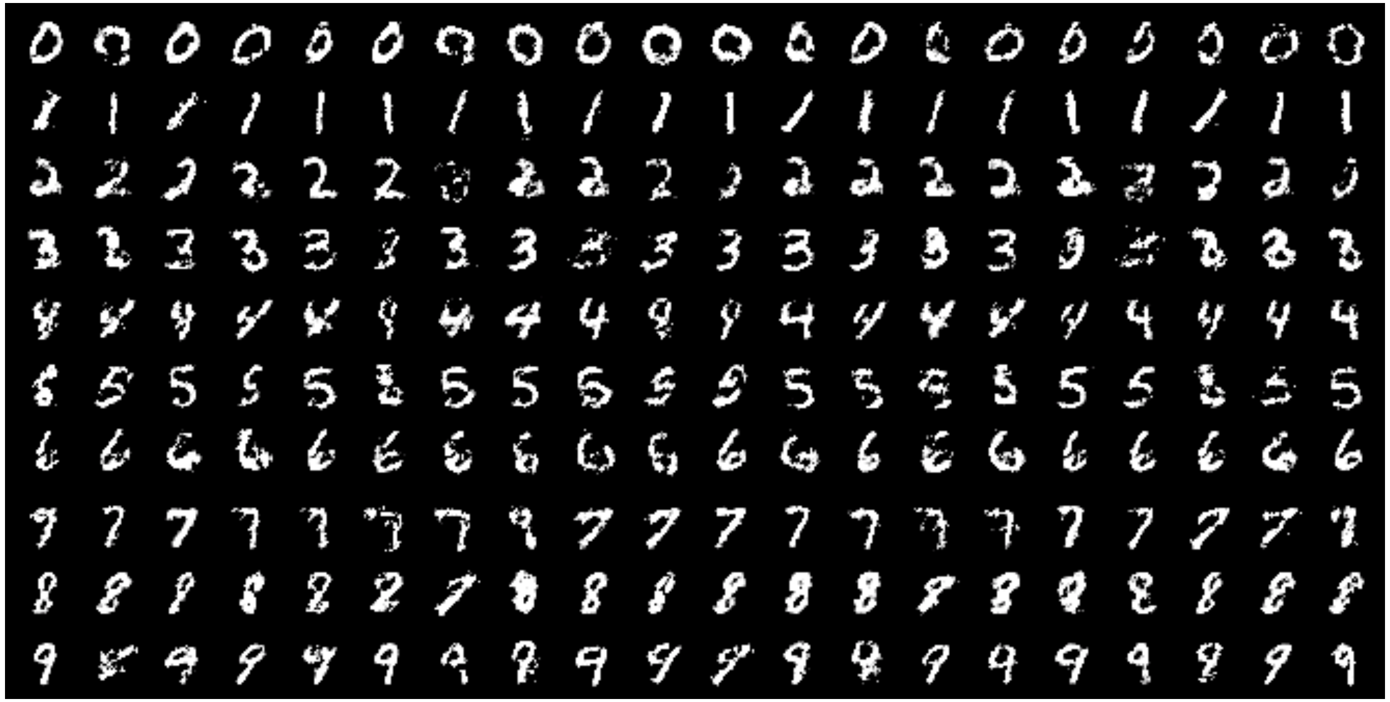
- Ability to generate samples in parallel
- Very few restrictions (e.g., compared to Boltzmann machines)
  - No Markov chain needed!
- No variational bound is needed
  - GANs known to be asymptotically consistent since the model families are universal function approximators

Conditional GANs (CGANs)

Conditional GANs – Idea

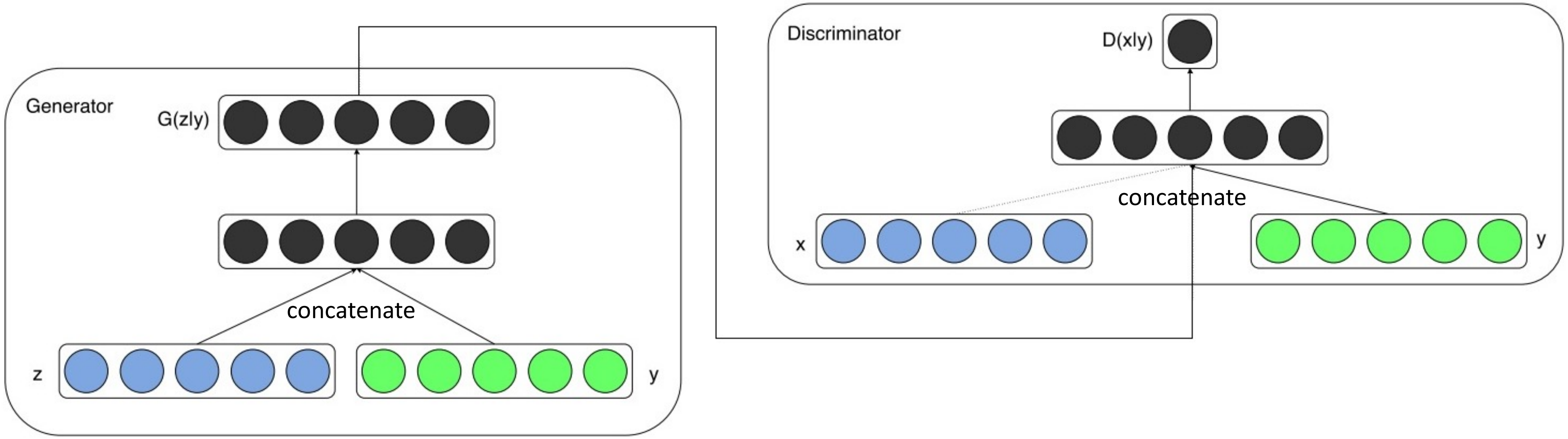
- Problem: Generator creates a “fake” generic image → not specific for a certain condition/characteristic
- Example: **text to image generation** – image should depend on the text
- Idea: Provide additional vector y to networks to encode **conditioning** [Mirza14]

Generated samples conditioned on one label (digit)



Conditional GANs – Overview

Source: [Mirza14]



- Generator G receives the noise vector $\boldsymbol{z}$ as well as a conditioning vector $\boldsymbol{y}$
- Discriminator D receives image $\boldsymbol{x}$ and also $\boldsymbol{y}$
- Loss functions change to

$$L^D = -E_{\boldsymbol{x}\sim p_{\text{data}}} \log D(\boldsymbol{x} \mid \boldsymbol{y}) - E_{\boldsymbol{z}\sim p_{\text{noise}}} \log\Big(1 - D\big(G(\boldsymbol{z} \mid \boldsymbol{y})\big)\Big)$$
$$L^G = -L^D$$

Example: Conditional GANs for Face Generation

- Add conditional feature (e.g., smiling, gender, old age, ...)
- Generator/Discriminator learn to operate in **modes**:
  - Generator learns to generate a face with a certain attribute
  - Discriminator learns to decide whether the face contains attribute

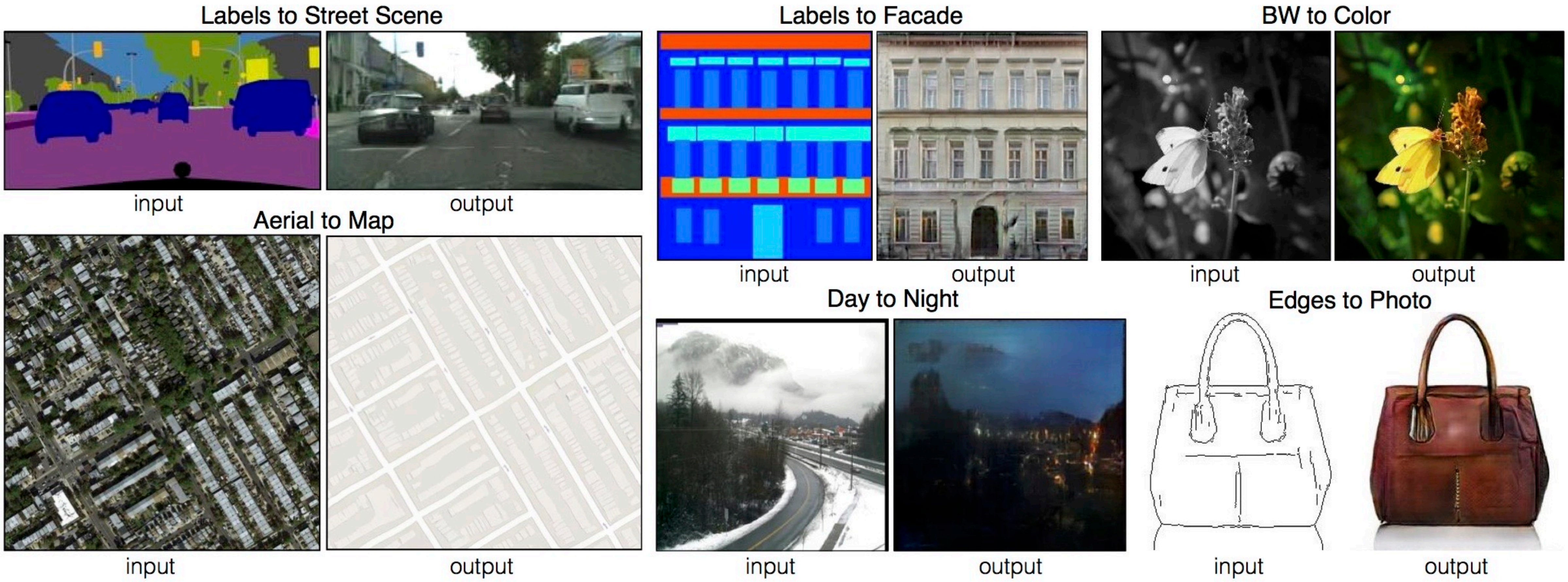
random samples

$\boldsymbol{y} \sim$ old age

$\boldsymbol{y} \sim$ old age + smiling

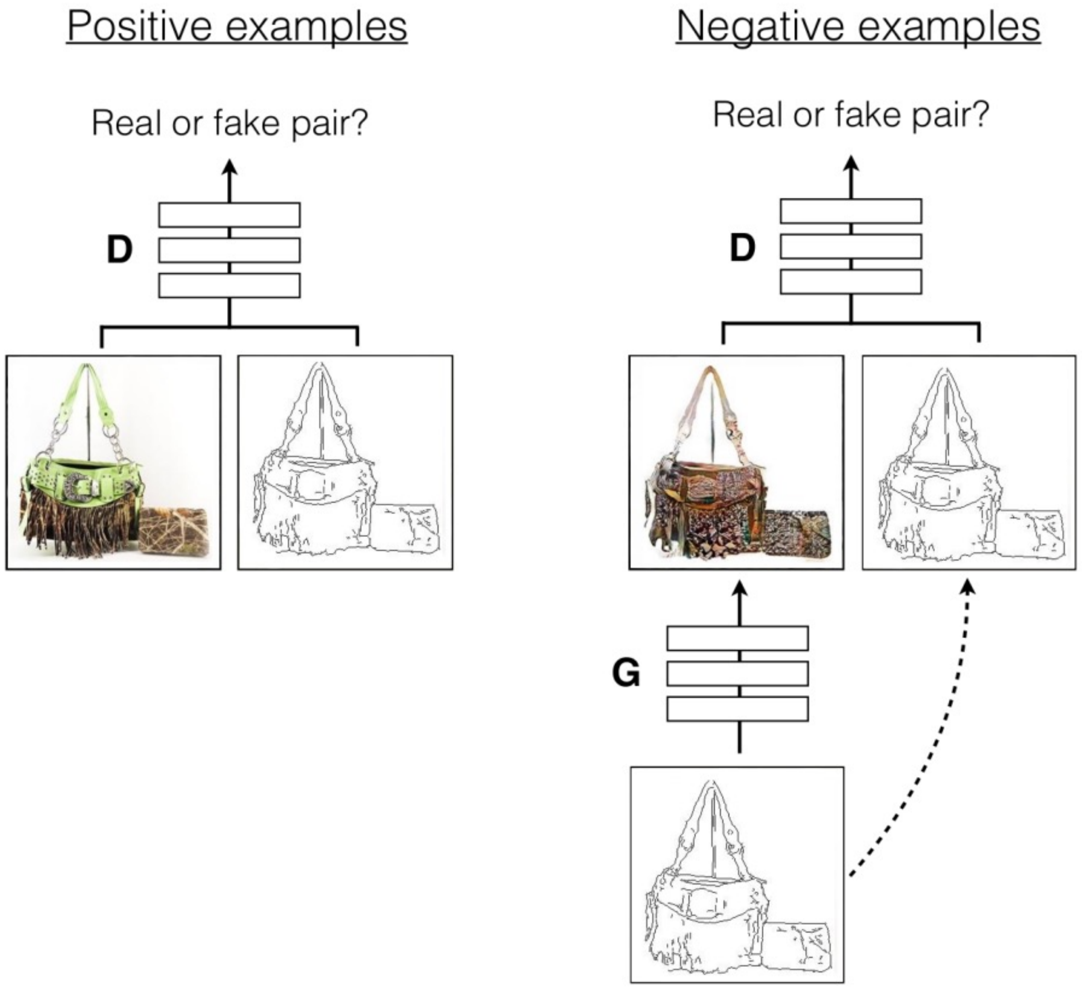
Source: [Gau15]

Image To Image Translation



Source: [Iso16]

Image To Image – Just a Conditional GAN!

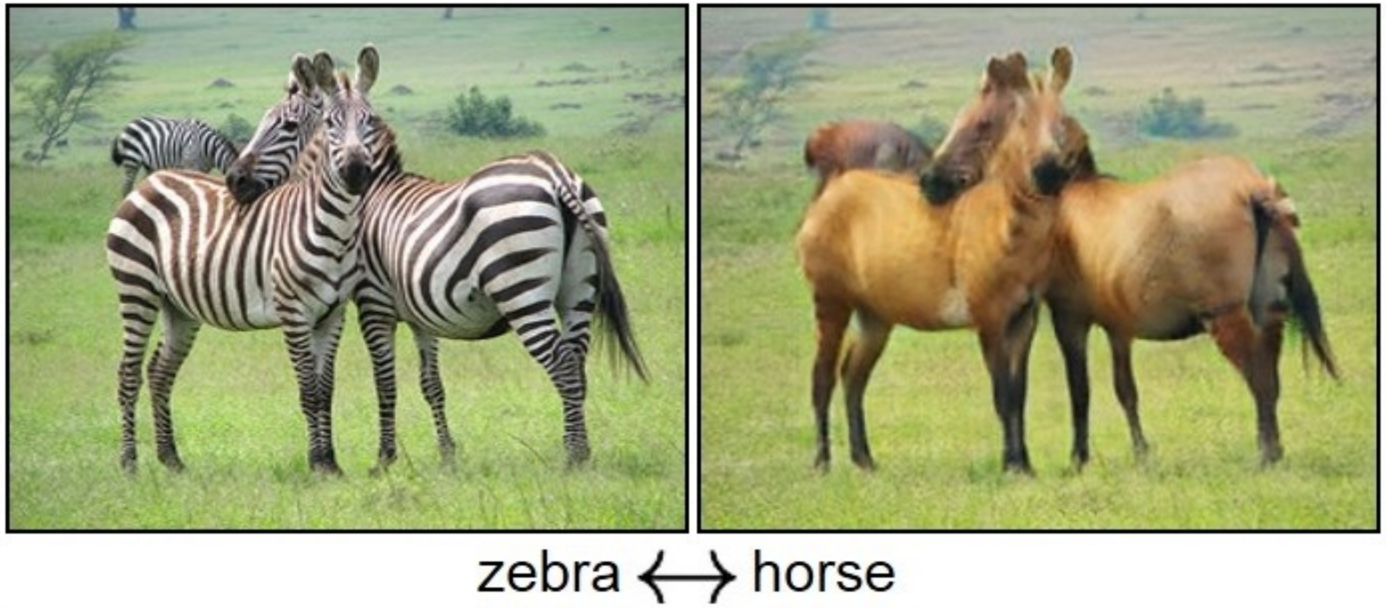


Source: [Iso16]

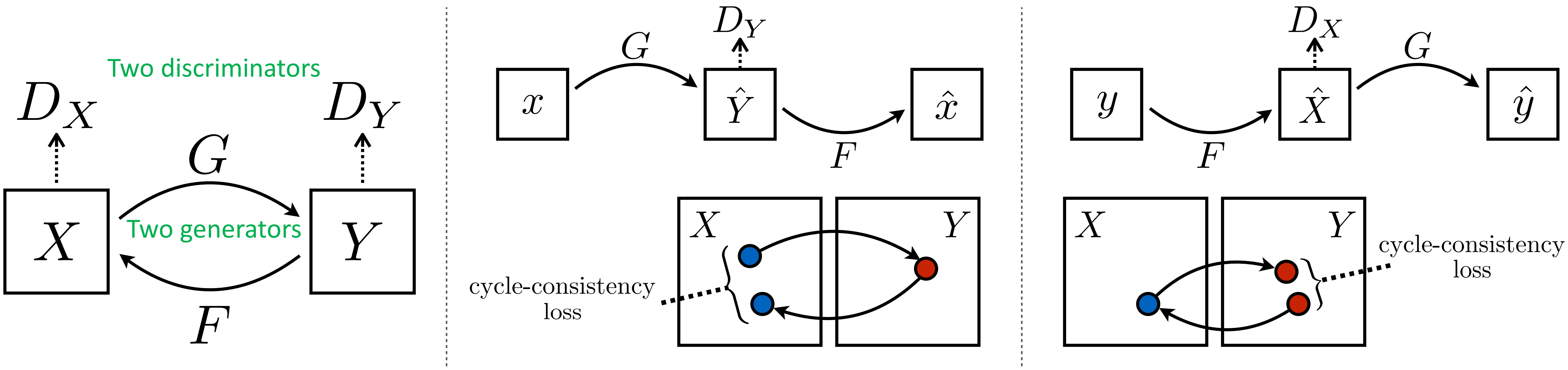
Cycle Consistent GANs

- Image to Image GAN should generate plausible results w.r.t. input
- **Paired data** difficult/impossible to obtain
- Cycle consistency loss [Zhu17]: Couple GAN with trainable **inverse** mapping F such that

$$F\big(G(\boldsymbol{x})\big) \approx \boldsymbol{x} \quad \text{and} \quad G\big(F(\boldsymbol{y})\big) \approx \boldsymbol{y}$$



Cycle Consistency Loss



- Two discriminators D_X and D_Y
- Cycle consistency loss for two generators G, F:

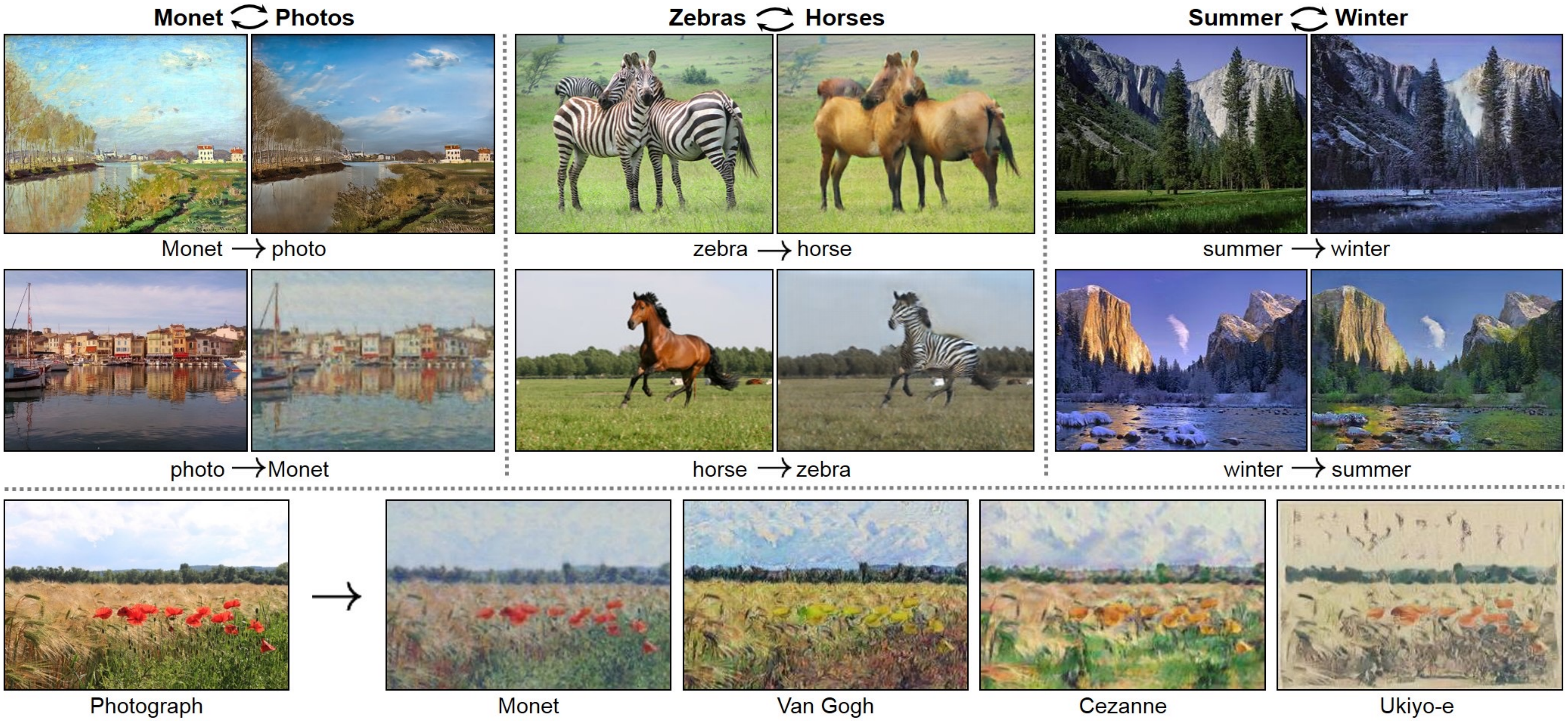
$$L_{\text{cyc}} = E_{\boldsymbol{x} \sim p_{\text{data}}(\boldsymbol{x})}\left(\left\|F(G(\boldsymbol{x})) - \boldsymbol{x}\right\|_1\right) + E_{\boldsymbol{y} \sim p_{\text{data}}(\boldsymbol{y})}\left(\left\|F(G(\boldsymbol{y})) - \boldsymbol{y}\right\|_1\right)$$

- Total loss:

$$L = L_{\text{GAN}}(G, D_X, X, Y) + L_{\text{GAN}}(F, D_Y, X, Y) + \lambda L_{\text{cyc}}(G, F)$$

adapted from [Zhu17]

CycleGAN – Examples



Source: [Zhu17]

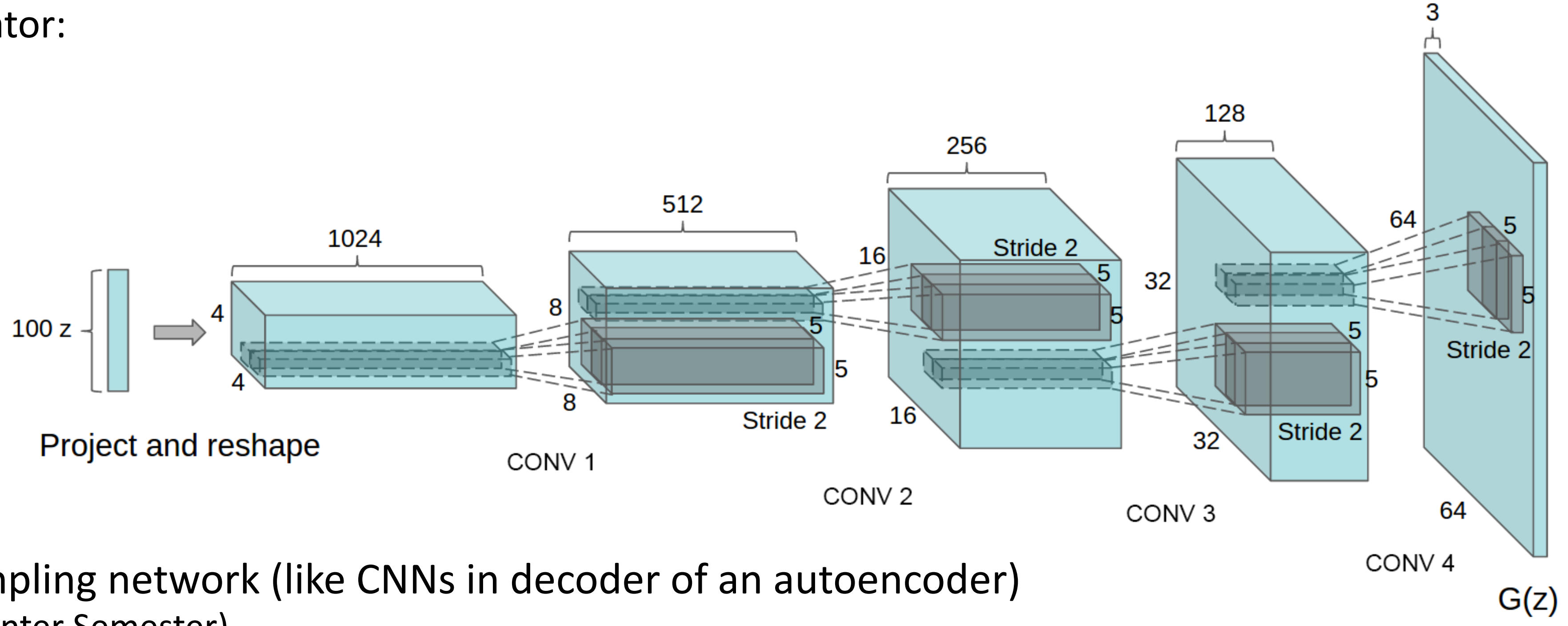
CycleGAN – Examples

Source: [Zhu17]

Deep Convolutional GANs (DCGAN)

Deep Convolutional GANs (DCGAN)

Generator:



- Discriminator is a CNN
- Generator is an upsampling network (like CNNs in decoder of an autoencoder)
  → Computer Vision (Winter Semester)
- Architecture Guidelines
  - Replace any pooling layer with strided convolutions (D) and transposed convolution (G)
  - Remove fully connected hidden layers for deeper architectures
  - G: Use ReLU activation except for output layer which uses tanh
  - D: Leaky ReLU activation for all layers
  - Use batch normalization

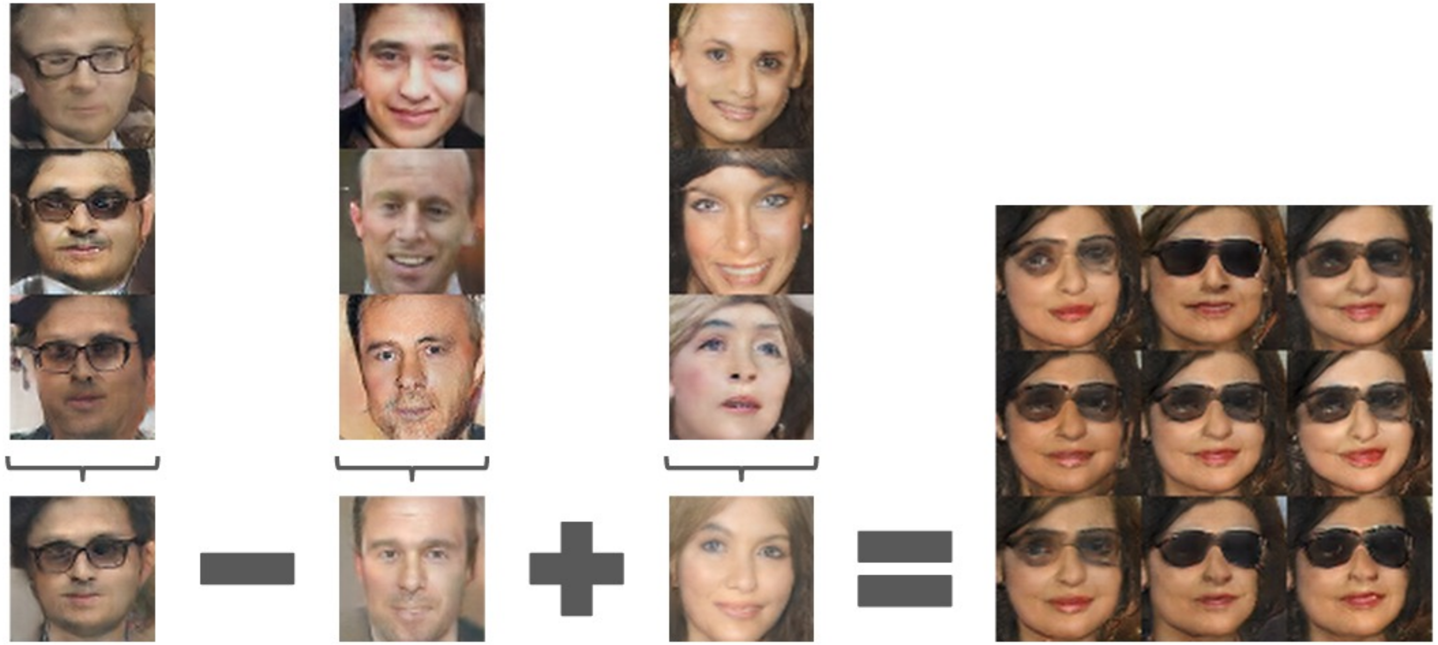
Source: [Rad15]

DCGAN – Examples

Bedrooms after 1 epoch

Source: [Rad15]

Vector Arithmetic



man with glasses | man without glasses | woman without glasses | woman with glasses

- Average three latent z codes and apply operation
  - GANs learn a distributed representation that disentangles the concept of gender from the concept of wearing glasses
- See also “InfoGAN” [Chen16]

Remarks

One-sided Label Smoothing

- Replace targets of the real samples with a smoothed version → replace 1 by 0.9
- Do **not** do the same for fake samples (don’t change 0 label)
  - Otherwise, D will reinforce incorrect behavior
  - G will produce samples that resemble the data or samples it already makes
- Benefits
  - Prevents D from giving very large gradient signal to G
  - Prevents extrapolating to encourage extreme samples

Is Balancing G and D necessary?

No.

- GANs work by estimating ratio of data and model density
  - Ratio estimated correctly only when D is optimal
  - Fine if D overpowers G

But when D gets too good

- G's gradient may vanish → use non-saturating loss
- G's gradient may get too large → use label smoothing

Summary

GANs

- are generative models that use supervised learning to approximate an intractable cost function
- can simulate many cost functions
- hard to find equilibrium between D and G
- cannot generate discrete data
- can also be used for
  - (semi-)supervised classification
  - transfer learning
  - multi-modal outputs
  - ...

- there are many more models out there, e.g.,
  - StackedGANs: Given some text, generate a fitting image [Zha16]
  - Style-Based Generator Architecture (StyleGAN) [Kar18]
    - check out https://www.whichfaceisreal.com/

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