Convolutional Neural Networks – Part 5 Generative Adversarial Networks

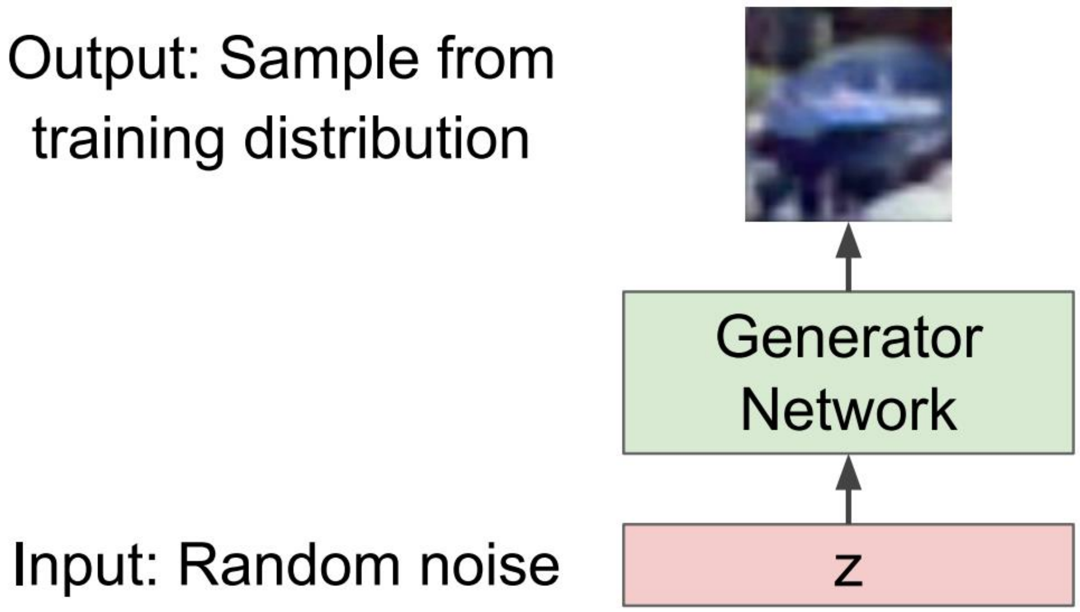
ECE 449

Content

- GAN
- Conditional GAN
- CycleGAN
- Domain Adaptation

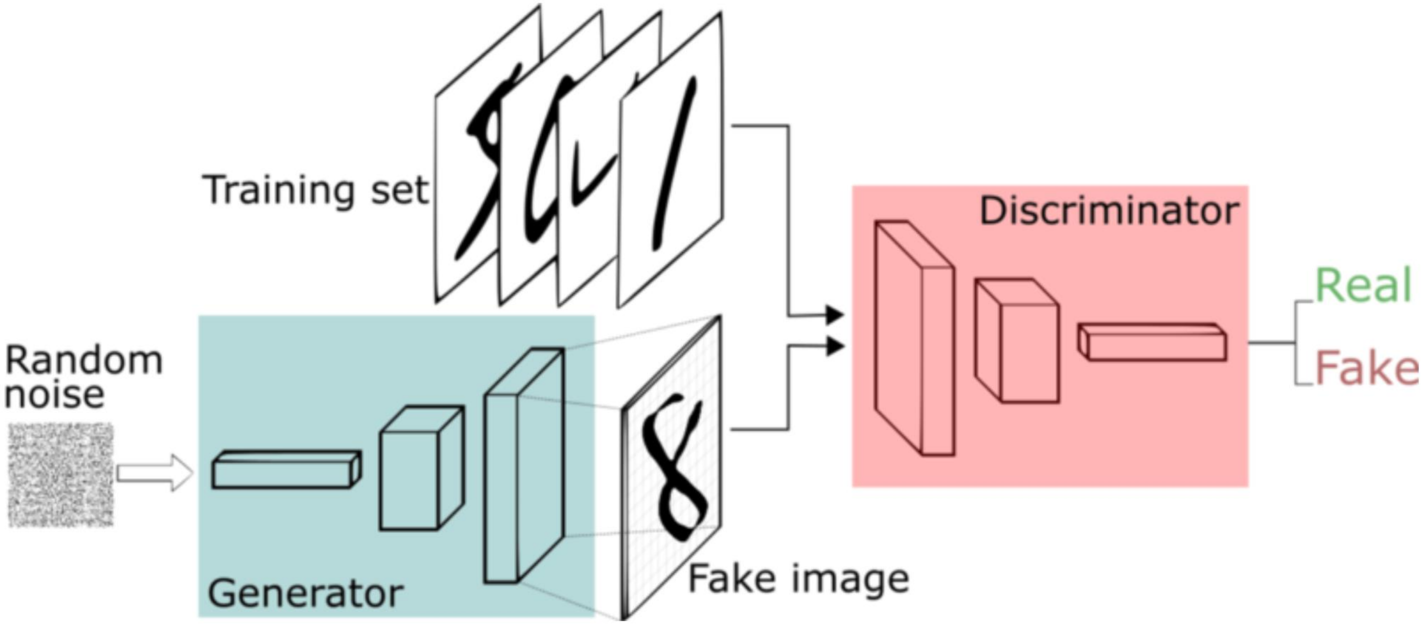
Generative Adversarial Networks (GAN)

- Problem: Want to sample from complex, high-dimensional training distribution. No direct way to do this
- Solution: Sample from a simple distribution, e.g. random noise. Learn transformation to training distribution.



Training GANs: Two-Player Game

- Generator network: try to fool the discriminator by generating real-looking images
- Discriminator network: try to distinguish between real and fake images



Training GANs: Two-Player Game

- Generator network: try to fool the discriminator by generating real-looking images
- Discriminator network: try to distinguish between real and fake images
- Train jointly in **minimax game**
- Minimax objective function

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

Training GANs: Two-Player Game

- Train jointly in **minimax game**
- Minimax objective function

Discriminator outputs likelihood in (0,1) of real image

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

Discriminator output for real data x

Discriminator output for generated fake data G(z)

  - **Discriminator** (θ_d) wants to maximize objective such that D(x) is close to 1 (real) and D(G(z)) is close to 0 (fake)
  - **Generator** (θ_g) wants to minimize objective such that D(G(z)) is close to 1 (discriminator is fooled into thinking generated G(z) is real)

Training GANs: Two-Player Game

- Minimax objective function

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

- Alternate between
  - 1. Gradient ascent on discriminator

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

  - 2. Gradient descent on generator

$$\min_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$

GAN Training Algorithm

for number of training iterations **do**

for k steps **do**

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D_{\theta_d}(x^{(i)}) + \log(1 - D_{\theta_d}(G_{\theta_g}(z^{(i)}))) \right]$$

end for

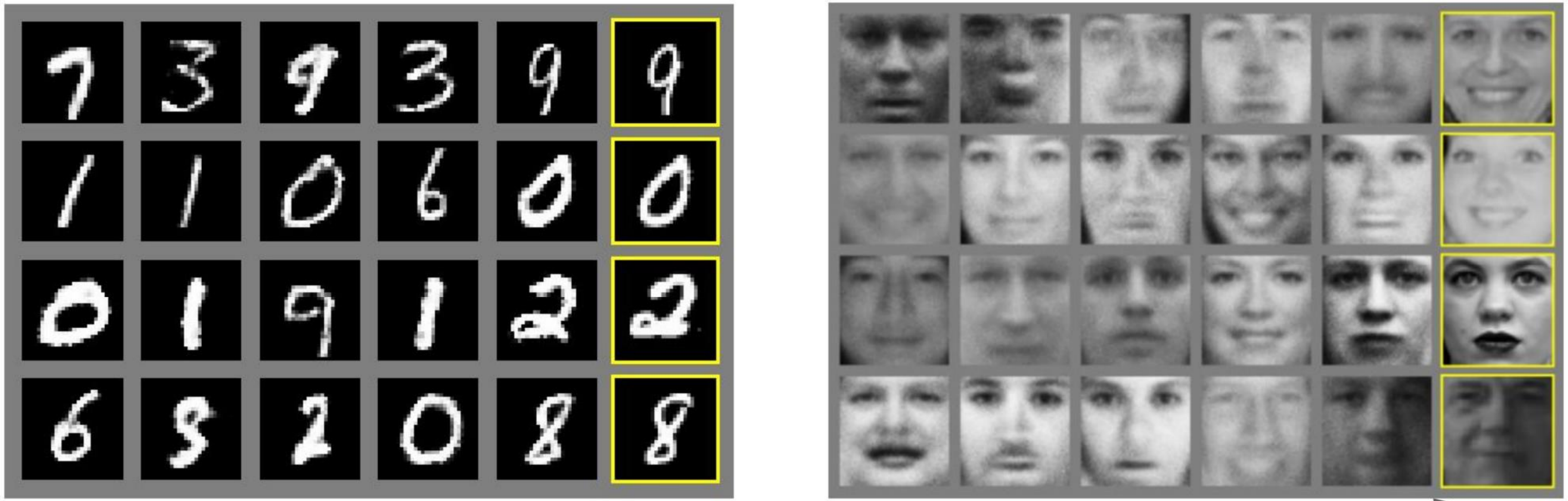
- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by ascending its stochastic gradient (improved objective):

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log(D_{\theta_d}(G_{\theta_g}(z^{(i)})))$$

end for

Examples

Generated samples



Nearest neighbor from training set

Examples

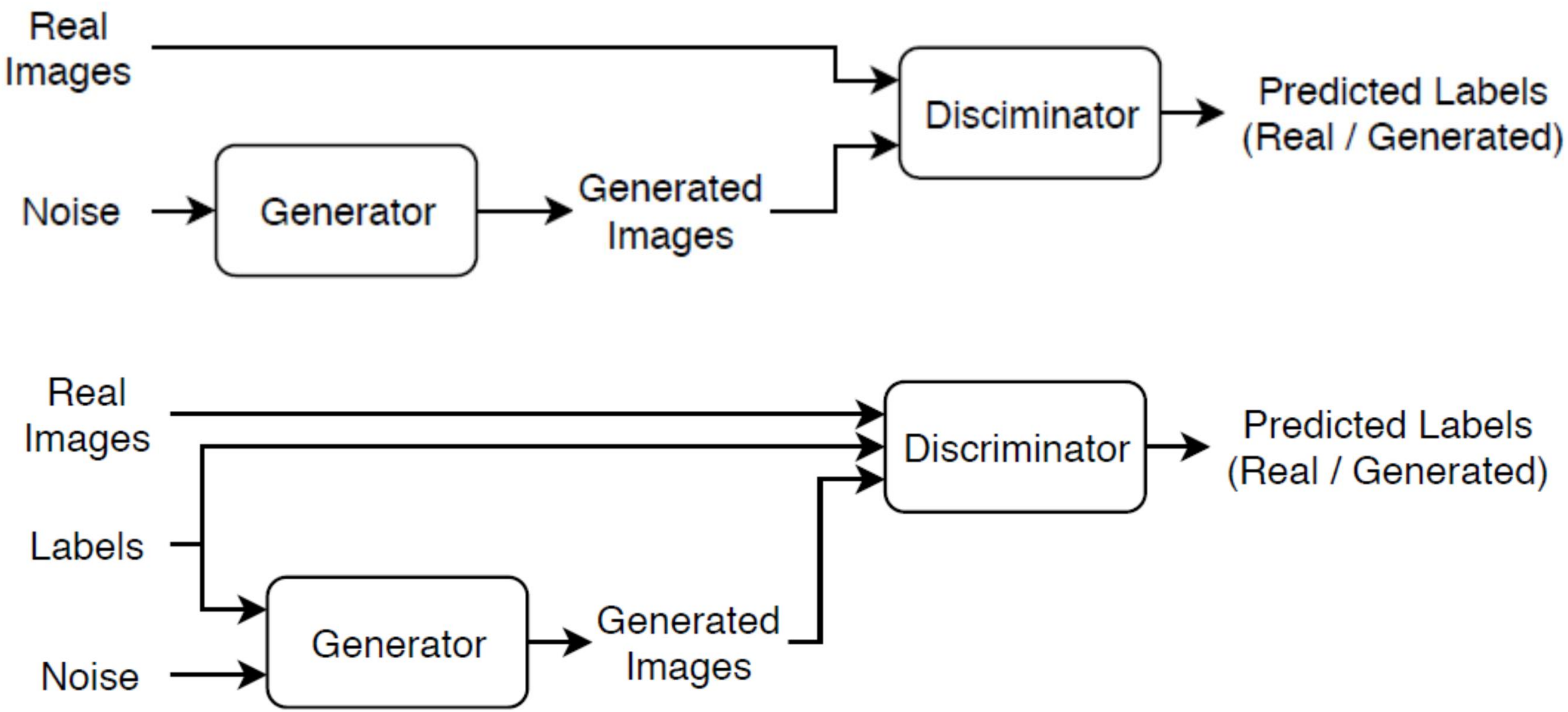
Generated samples (CIFAR-10)

Nearest neighbor from training set

Question

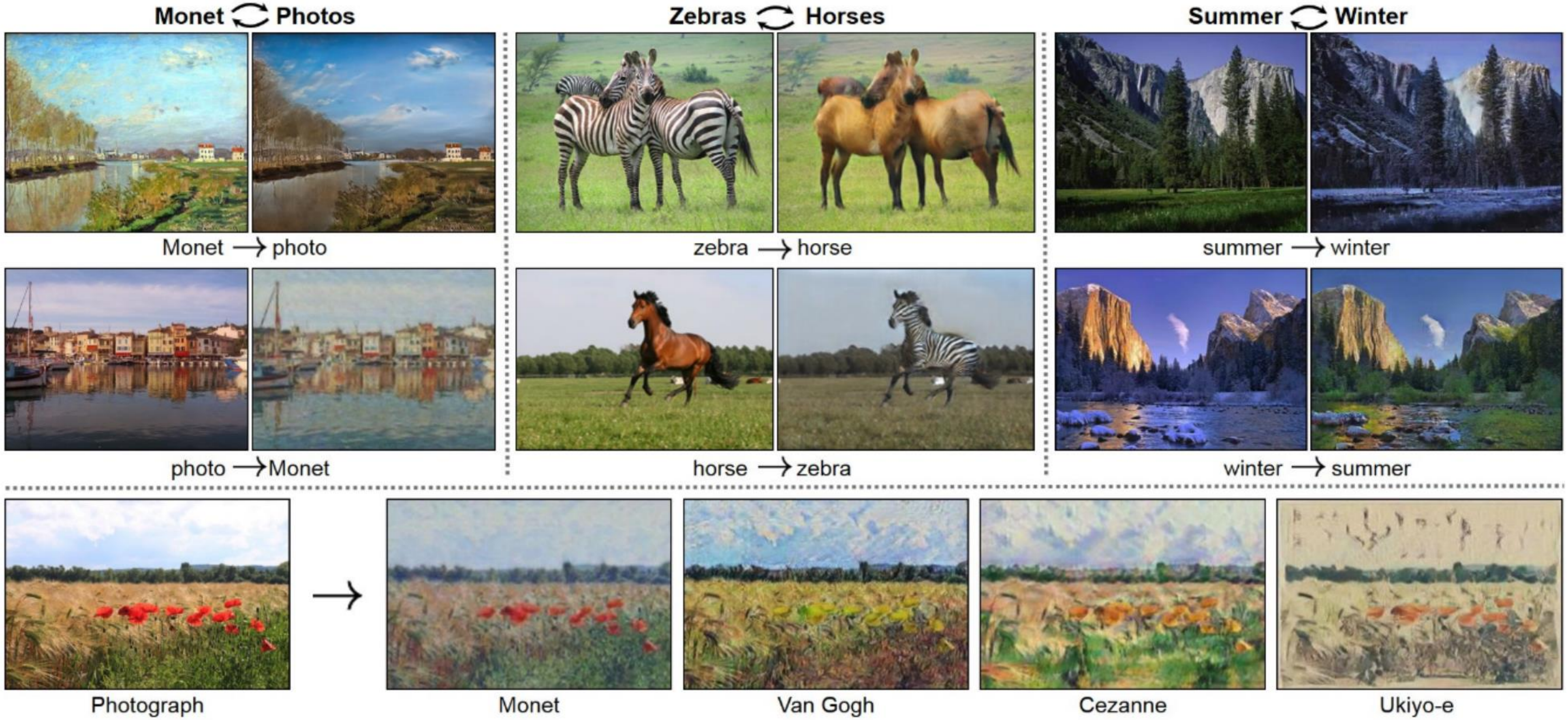
- How to generate an image given a certain label?

Conditional GAN



Style Transfer Problem

- Change the style of an image while preserving the content. How?

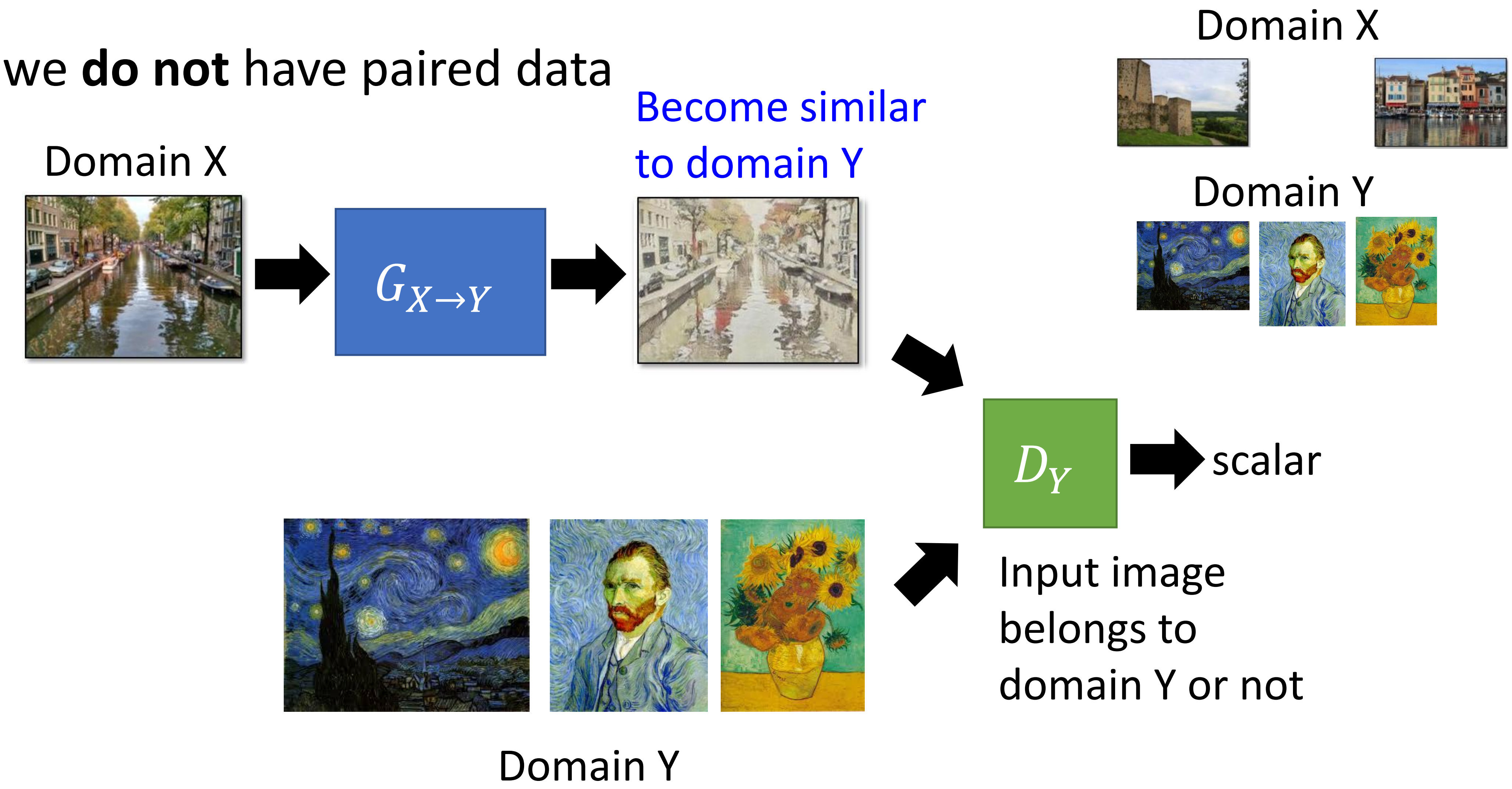


Style Transfer

- If we have paired data
  - Supervised approach

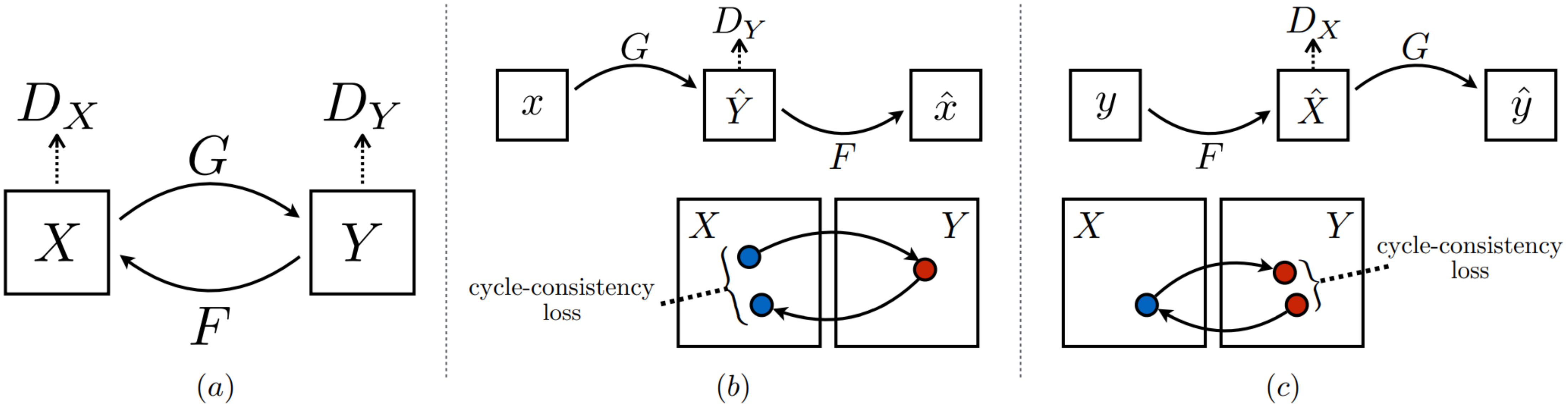
Style Transfer

- If we **do not** have paired data



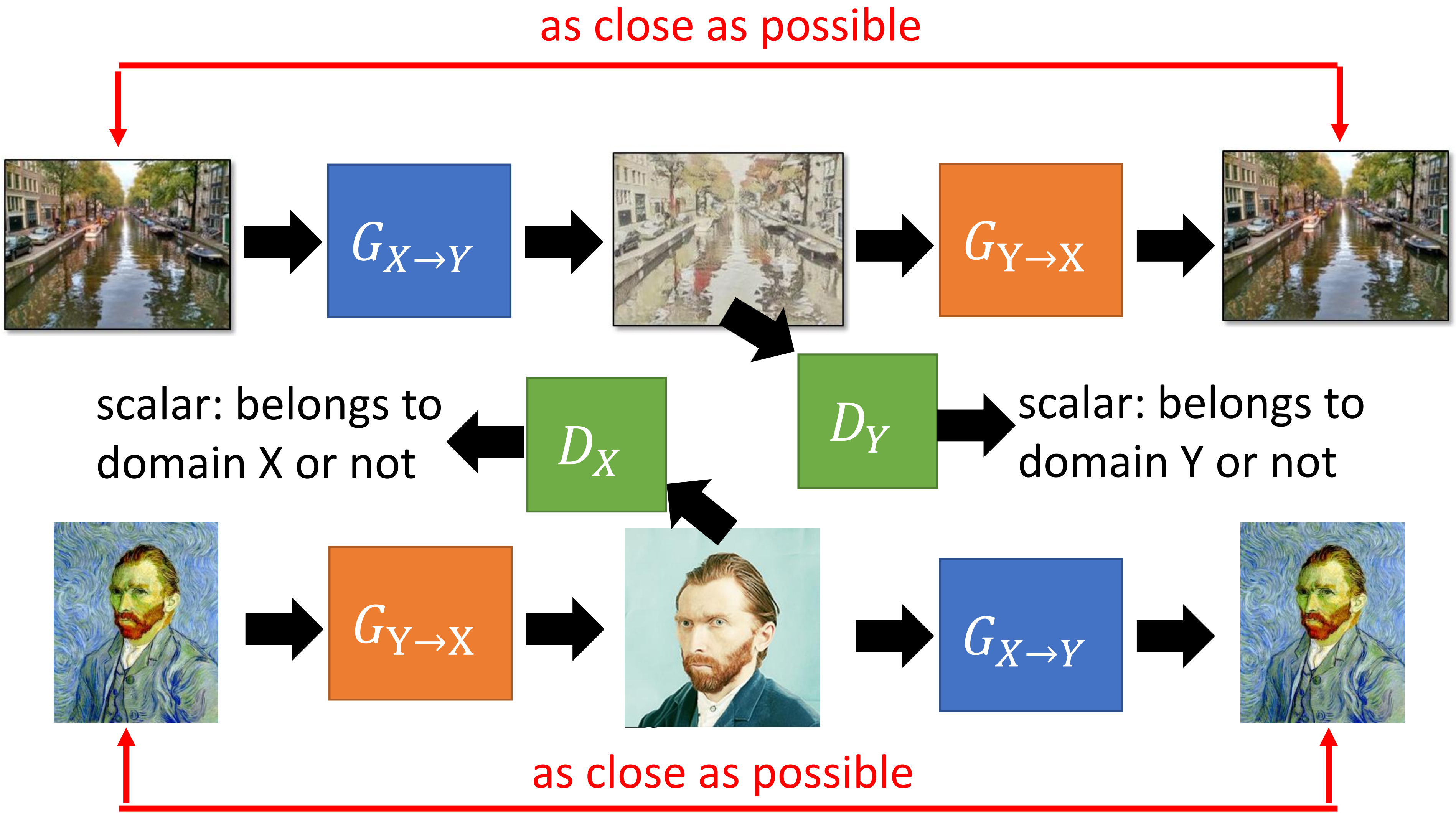
CycleGAN

- Cycle-consistency



Zhu, J. Y., Park, T., Isola, P., & Efros, A. A. (2017). Unpaired image-to-image translation using cycle-consistent adversarial networks. In *Proceedings of the IEEE international conference on computer vision* (pp. 2223-2232).

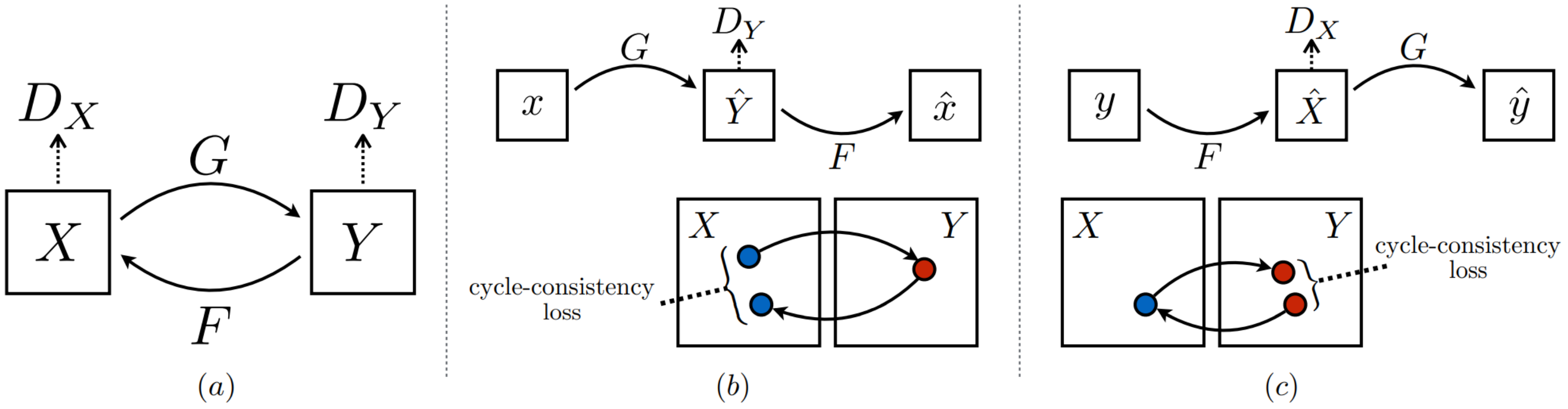
CycleGAN



as close as possible
$G_{X \to Y}$
$G_{Y \to X}$
D_Y
scalar: belongs to domain Y or not
D_X
scalar: belongs to domain X or not
$G_{Y \to X}$
$G_{X \to Y}$
as close as possible

CycleGAN

- Cycle-consistency



$$\begin{aligned}\mathcal{L}(G, F, D_X, D_Y) =& \mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) \\ &+ \mathcal{L}_{\text{GAN}}(F, D_X, Y, X) \\ &+ \lambda \mathcal{L}_{\text{cyc}}(G, F),\end{aligned}$$

$$\begin{aligned}\mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) &= \mathbb{E}_{y \sim p_{\text{data}}(y)}[\log D_Y(y)] \\ &+ \mathbb{E}_{x \sim p_{\text{data}}(x)}[\log(1 - D_Y(G(x))]\end{aligned}$$

$$\begin{aligned}\mathcal{L}_{\text{cyc}}(G, F) &= \mathbb{E}_{x \sim p_{\text{data}}(x)}[\|F(G(x)) - x\|_1] \\ &+ \mathbb{E}_{y \sim p_{\text{data}}(y)}[\|G(F(y)) - y\|_1]\end{aligned}$$

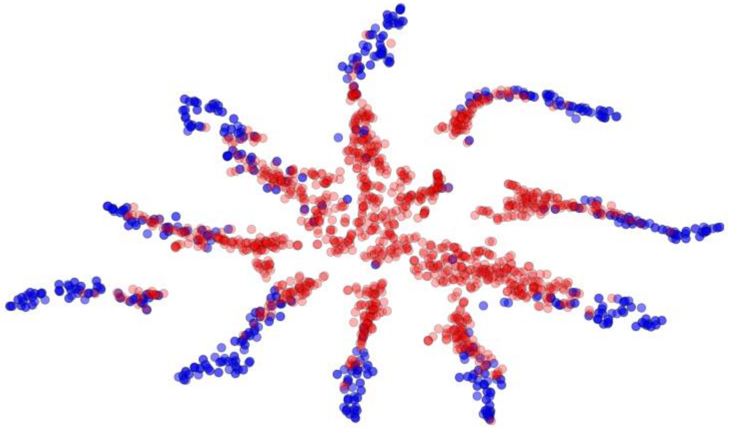
Domain Adaptation

- What would be the embedding space for two domains?

labeled

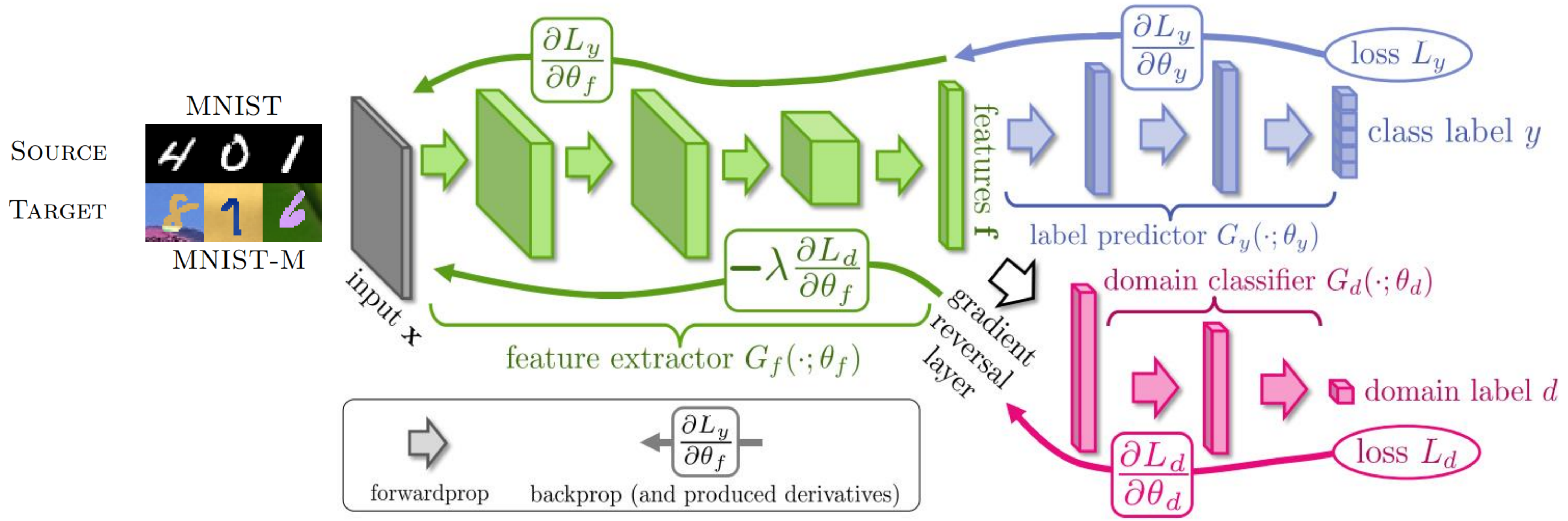
unlabeled

Embedding



Ganin, Y., & Lempitsky, V. (2015, June). Unsupervised domain adaptation by backpropagation. In *International conference on machine learning* (pp. 1180-1189).

Gradient Reversal Layers

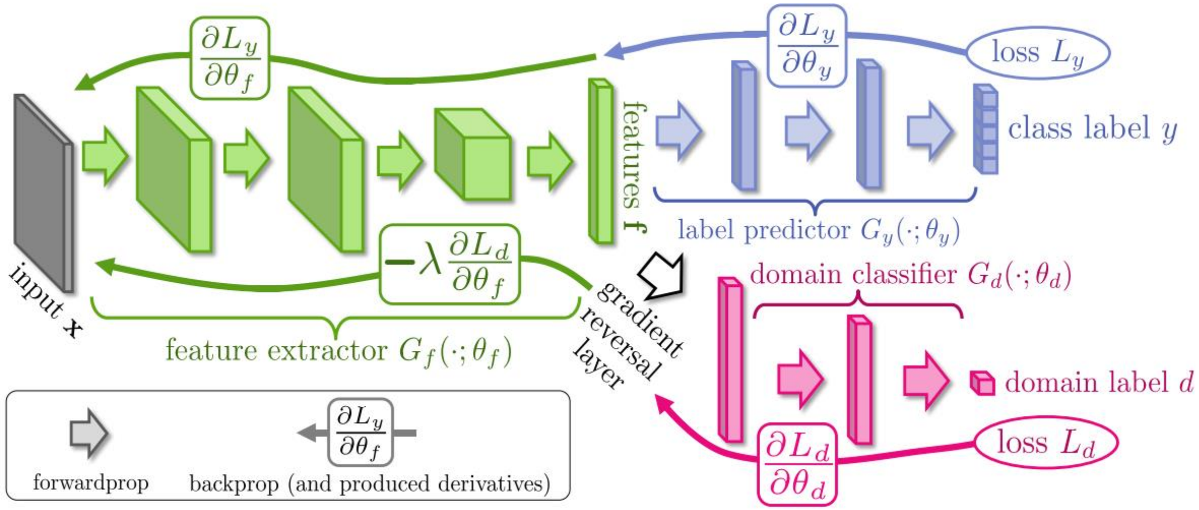


Gradient Reversal Layers

$$E(\theta_f, \theta_y, \theta_d) = \sum_{\substack{i=1..N \\ d_i=0}} L_y\left(G_y(G_f(\mathbf{x}_i;\theta_f);\theta_y), y_i\right) -$$

$$\lambda \sum_{i=1..N} L_d\left(G_d(G_f(\mathbf{x}_i;\theta_f);\theta_d), y_i\right) =$$

$$= \sum_{\substack{i=1..N \\ d_i=0}} L_y^i(\theta_f, \theta_y) - \lambda \sum_{i=1..N} L_d^i(\theta_f, \theta_d)$$



$$(\hat{\theta}_f, \hat{\theta}_y) = \arg\min_{\theta_f, \theta_y} E(\theta_f, \theta_y, \hat{\theta}_d)$$

$$\hat{\theta}_d = \arg\max_{\theta_d} E(\hat{\theta}_f, \hat{\theta}_y, \theta_d)\,.$$

Gradient Reversal Layers

- Example