台灣人工智慧學校技術領袖培訓班

Transfer Learning:
Part 4. Transfer Learning for Visual Synthesis

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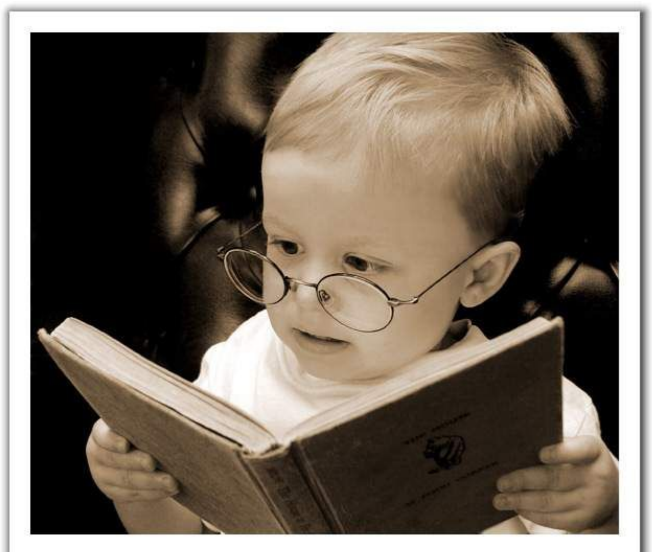
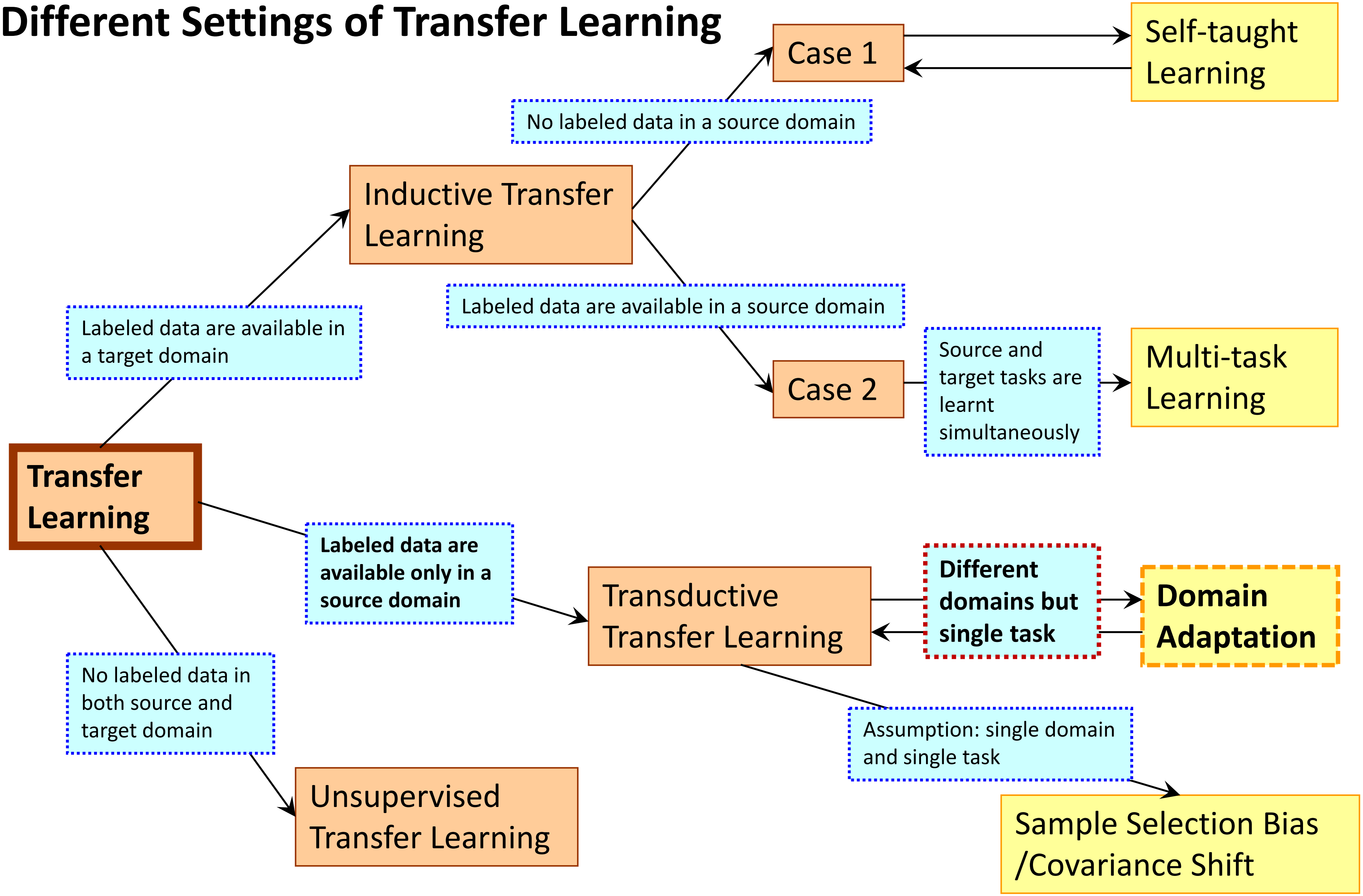
Topic #4 (15:20~17:00)

- Transfer Learning
  - Introduction to Transfer Learning (TL)
  - Challenges in Transfer Learning
  - Transfer Learning for Visual Analysis
  - Transfer Learning for Visual Synthesis



Different Settings of Transfer Learning

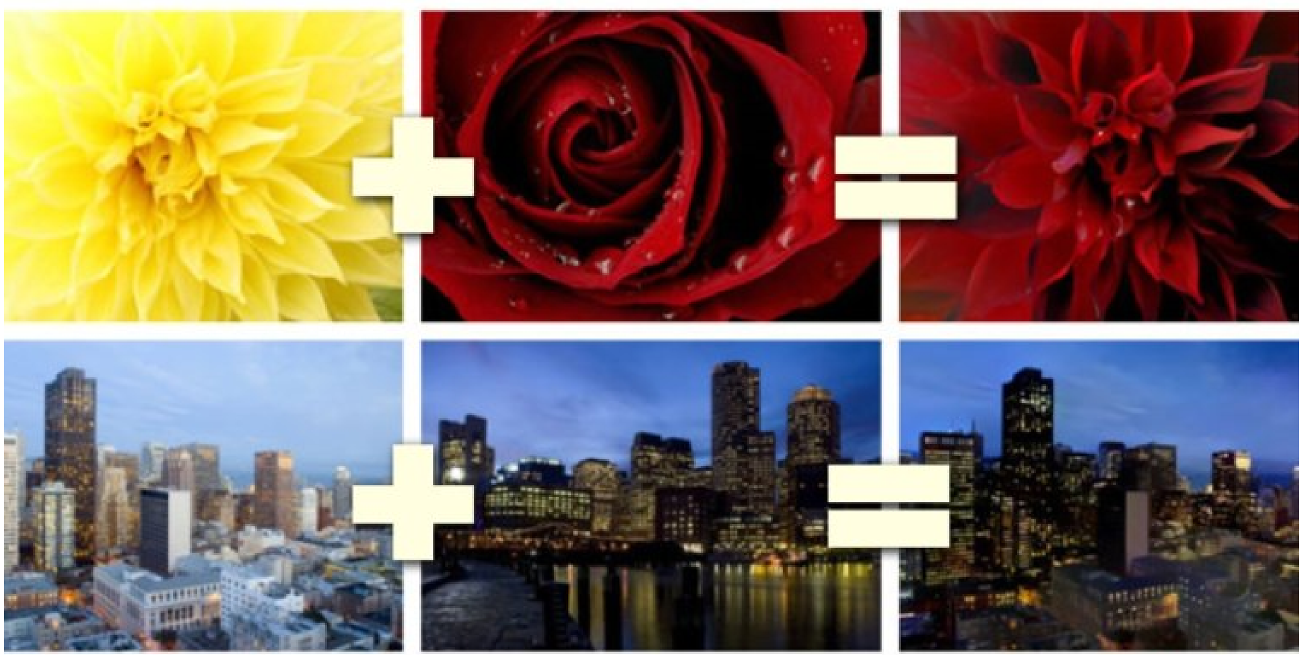


S. J. Pan and Q. Yang, “A survey on transfer learning,” IEEE TKDE, 2010.

Transfer Learning for Manipulating Data?

- TL not only addresses cross-domain classification tasks.
- Let's see how we can synthesize and manipulate data across domains.
- As a computer vision guy, let's focus on visual data in this lecture…

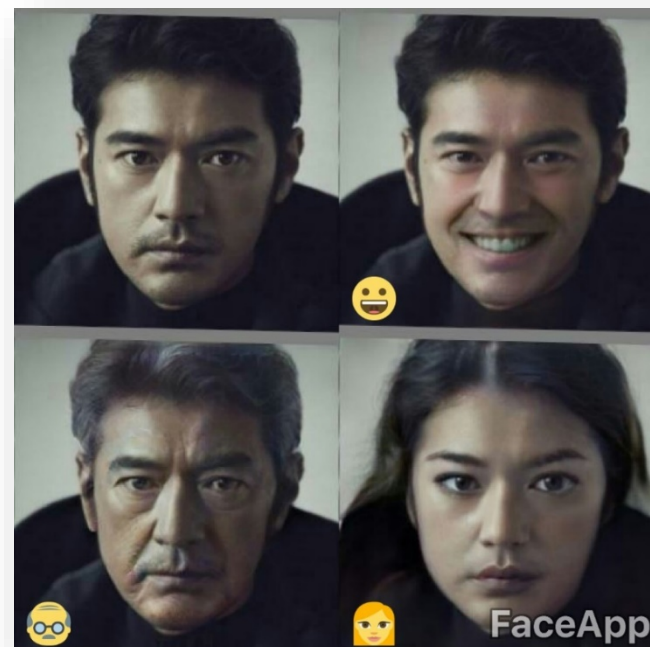
Source Domain



Target Domain

What to Cover in Part 4?

- Cross-Domain Image Translation
    - Pix2pix (CVPR’17)
    - CycleGAN (ICCV’17), DualGAN (ICCV’17), DiscoGAN (ICML’17)
    - UNIT (NIPS’17)
    - DTN (ICLR’17)
    - Beyond image translation
- Representation Disentanglement
    - InfoGAN (NIPS’16) & AC-GAN (ICML’17)
    - StarGAN (CVPR’18)
    - CDRD (CVPR’18)
- Final Remarks



What to Cover in Part 4?

- Cross-Domain Image Translation
  - Pix2pix (CVPR’17): Pairwise cross-domain training data
  - CycleGAN/DualGAN/DiscoGAN: Unpaired cross-domain training data
  - UNIT (NIPS’17): Learning cross-domain image representation (with unpaired training data)
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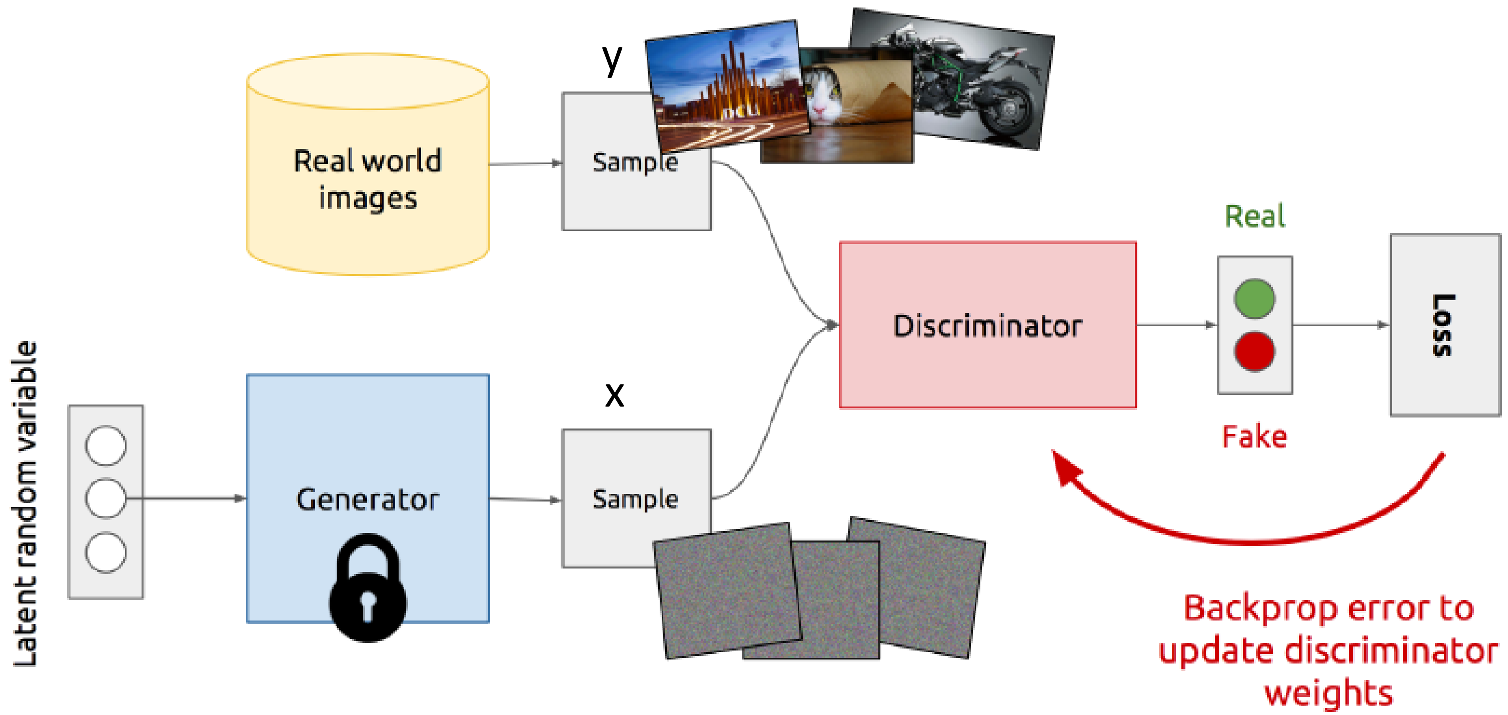
A Super Brief Review for Generative Adversarial Networks (GAN)

- Architecture of GAN
  - Loss $\mathcal{L}_{GAN}(G, D) = \mathbb{E}[\log(1 - D\ (G(x)))] + \mathbb{E}[\log D(y)]$



Goodfellow et al., Generative Adversarial Nets, NIPS, 2014

Pix2pix

- Image-to-image translation with conditional adversarial networks (CVPR’17)
    - Can be viewed as image style transfer

Sketch

Photo

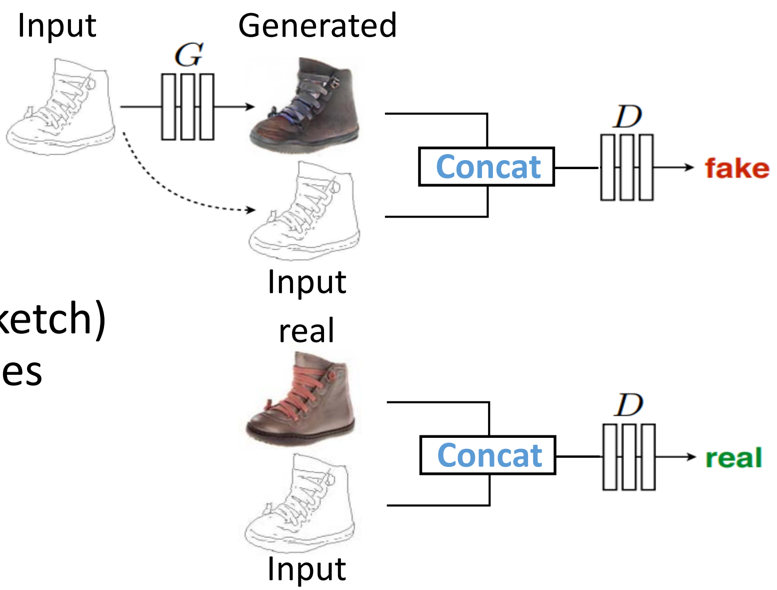
Isola et al. " Image-to-image translation with conditional adversarial networks." *CVPR* 2017.

Pix2pix

Testing Phase

- **Goal / Problem Setting**
  - Image translation across two distinct domains (e.g., sketch v.s. photo)
  - Pairwise training data
- Method: Conditional GAN
  - Example: Sketch to Photo
    - Generator
      Input: Sketch
      Output: Photo
    - Discriminator
      Input: Concatenation of Input(Sketch) & Synthesized/Real(Photo) images
      Output: Real or Fake

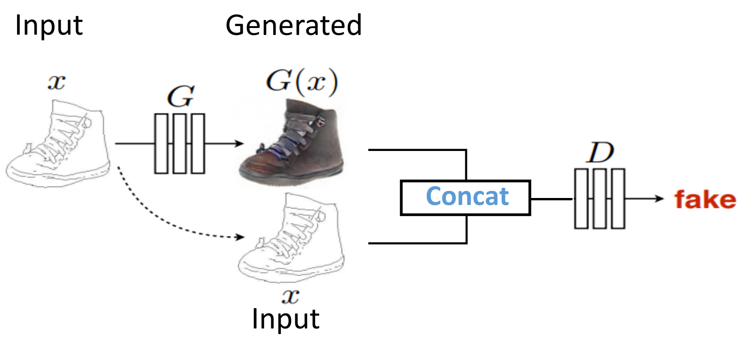
Training Phase

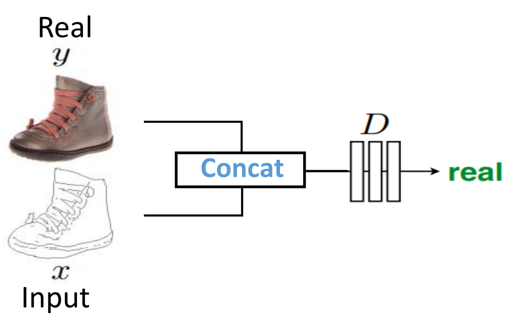


Pix2pix

- ***Learning the model***

Training Phase





Overall objective function

$$G^* = \arg\min_{G}\max_{D} \mathcal{L}_{cGAN}(G, D) + \mathcal{L}_{L1}(G)$$

Conditional GAN loss

$$\mathcal{L}_{cGAN}(G, D) = \mathbb{E}_{x}\underbrace{[\log(1 - D(\overbrace{x, G(x)}^{\text{Concatenate}}))]}_{\text{Fake (Generated)}} + \mathbb{E}_{x,y}\underbrace{[\log D(\overbrace{x, y}^{\text{Concatenate}})]}_{\text{Real}}$$

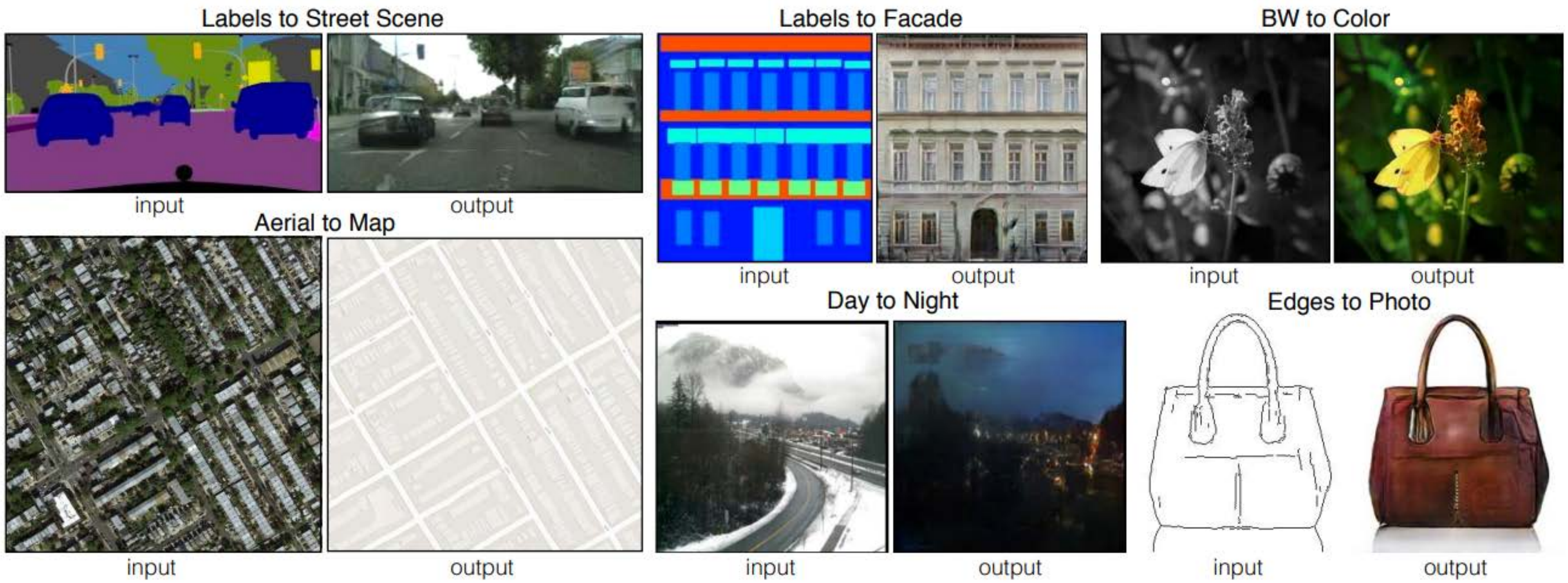
Reconstruction Loss

$$\mathcal{L}_{L1}(G) = \mathbb{E}_{x,y}[\|y - G(x)\|_1]$$

Isola et al. " Image-to-image translation with conditional adversarial networks." *CVPR* 2017.

Pix2pix

- ***Experiment results***



Demo page: https://affinelayer.com/pixsrv/

Isola et al. " Image-to-image translation with conditional adversarial networks." *CVPR* 2017.

What to Cover in Part 4?

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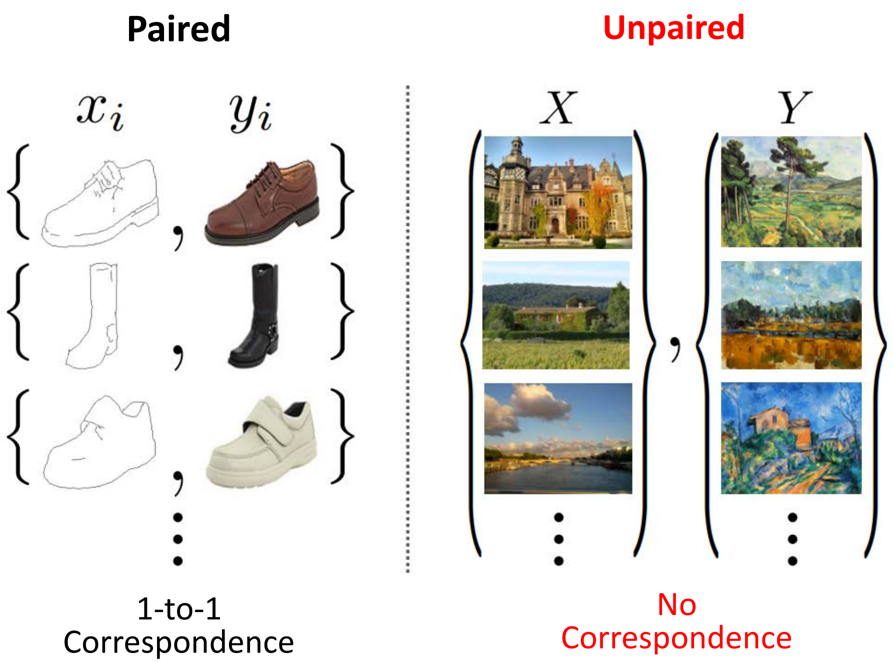
- Final Remarks

CycleGAN/DiscoGAN/DualGAN

- CycleGAN (CVPR'17)
  - Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks -to-image translation with conditional adversarial networks



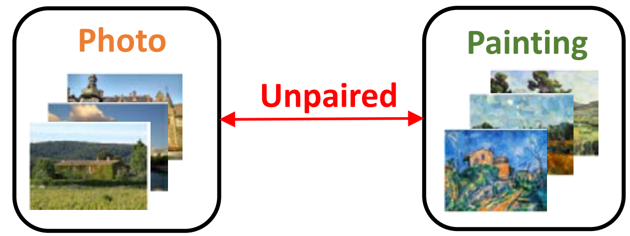
- Easier to collect training data
- More practical

Zhu et al. "Unpaired Image-To-Image Translation Using Cycle-Consistent Adversarial Networks." *CVPR* 2017.

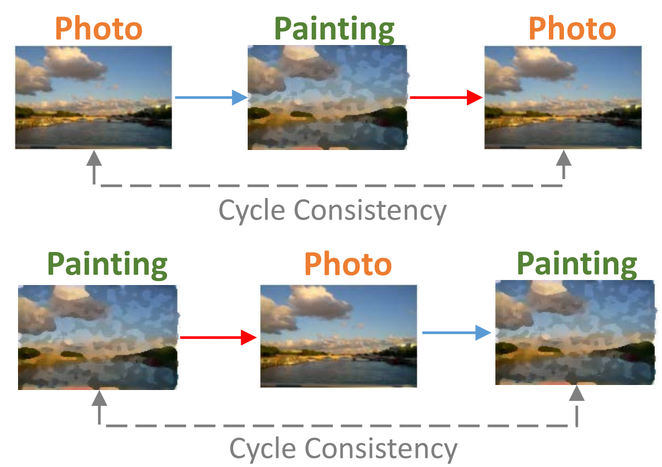
CycleGAN

- **Goal / Problem Setting**
  - Image translation across two distinct domains
  - Unpaired training data

Training data

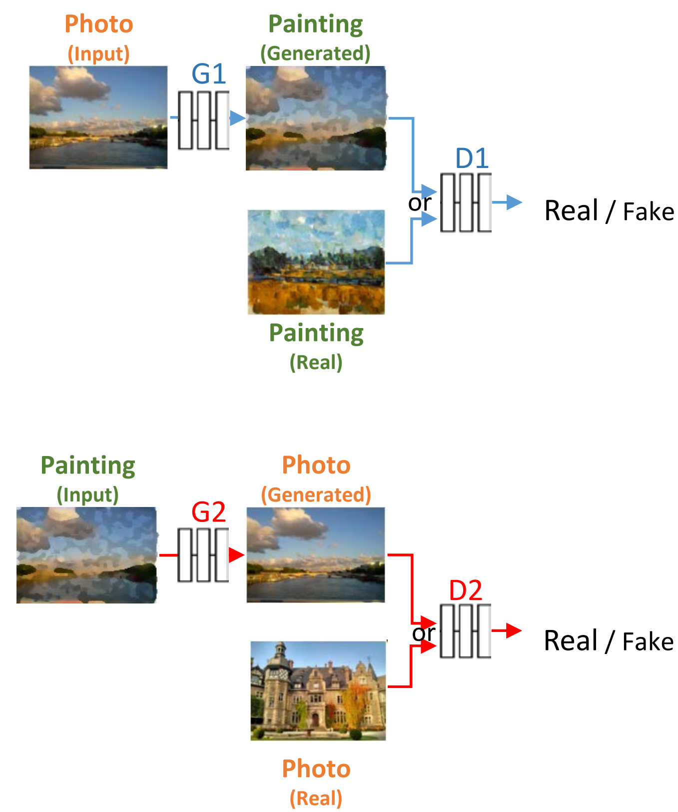


- **Idea**
  - Autoencoding-like image translation
  - Cycle consistency between two domains



CycleGAN

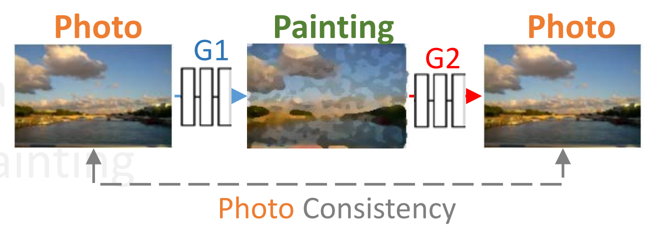
- Method (Example: Photo & Painting)
  - Based on 2 GANs
    - First GAN (G1, D1): Photo to Painting
    - Second GAN (G2, D2): Photo to Painting
  - Cycle Consistency
    - Photo consistency
    - Painting consistency



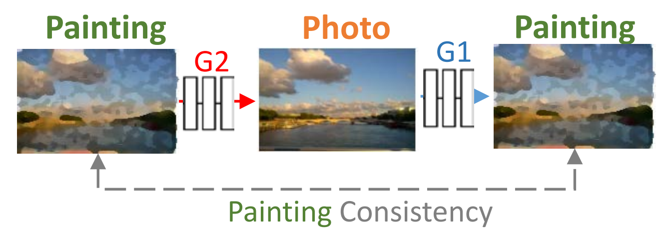
Zhu et al. "Unpaired Image-To-Image Translation Using Cycle-Consistent Adversarial Networks." *CVPR* 2017.

CycleGAN

- Method (Example: Photo vs. Painting)
  - Based on 2 GANs
    - First GAN (G1, D1): Photo to Pa
    - Second GAN (G2, D2): Photo to Painting



  - Cycle Consistency
    - Photo consistency
    - Painting consistency



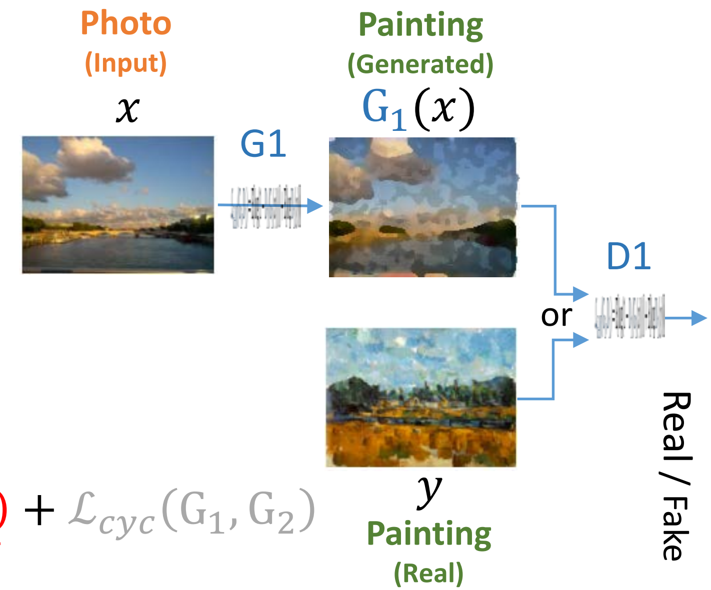
Zhu et al. "Unpaired Image-To-Image Translation Using Cycle-Consistent Adversarial Networks." *CVPR* 2017.

CycleGAN

- **Learning**

Overall objective function

$$G_1^*, G_2^* = \arg\min_{G_1,G_2}\max_{D_1,D_2} \underbrace{\mathcal{L}_{GAN}(G_1, D_1)}_{\text{First GAN}} + \underbrace{\mathcal{L}_{GAN}(G_2, D_2)}_{\text{Second GAN}} + \mathcal{L}_{cyc}(G_1, G_2)$$

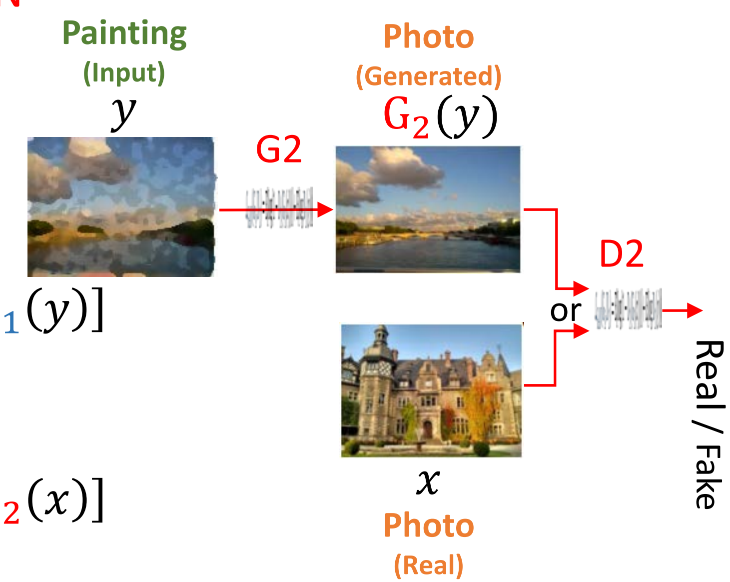


- **Adversarial Loss**
  - First GAN (G1, D1):

$$\mathcal{L}_{GAN}(G_1, D_1) = \mathbb{E}[\log(1 - D_1(G_1(x)))] + \mathbb{E}[\log D_1(y)]$$

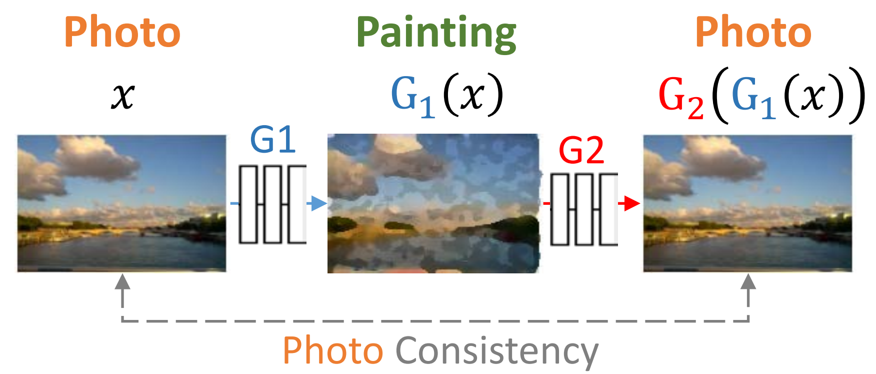
  - Second GAN (G2, D2):

$$\mathcal{L}_{GAN}(G_2, D_2) = \mathbb{E}[\log(1 - D_2(G_2(y)))] + \mathbb{E}[\log D_2(x)]$$



Zhu et al. "Unpaired Image-To-Image Translation Using Cycle-Consistent Adversarial Networks." *CVPR* 2017.

CycleGAN



- **Learning**

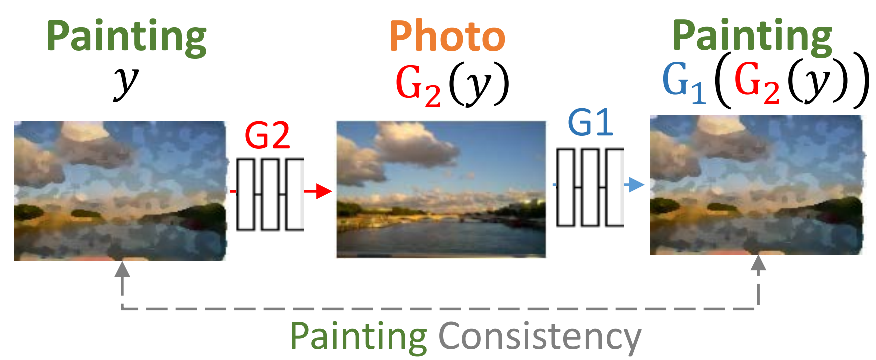
Overall objective function

$$G_1^*, G_2^* = \arg\min_{G_1, G_2}\max_{D_1, D_2} \mathcal{L}_{GAN}(G_1, D_1) + \mathcal{L}_{GAN}(G_2, D_2) + \mathcal{L}_{cyc}(G_1, G_2)$$

Cycle Consistency

- **Consistency Loss**
  - Photo and Painting consistency

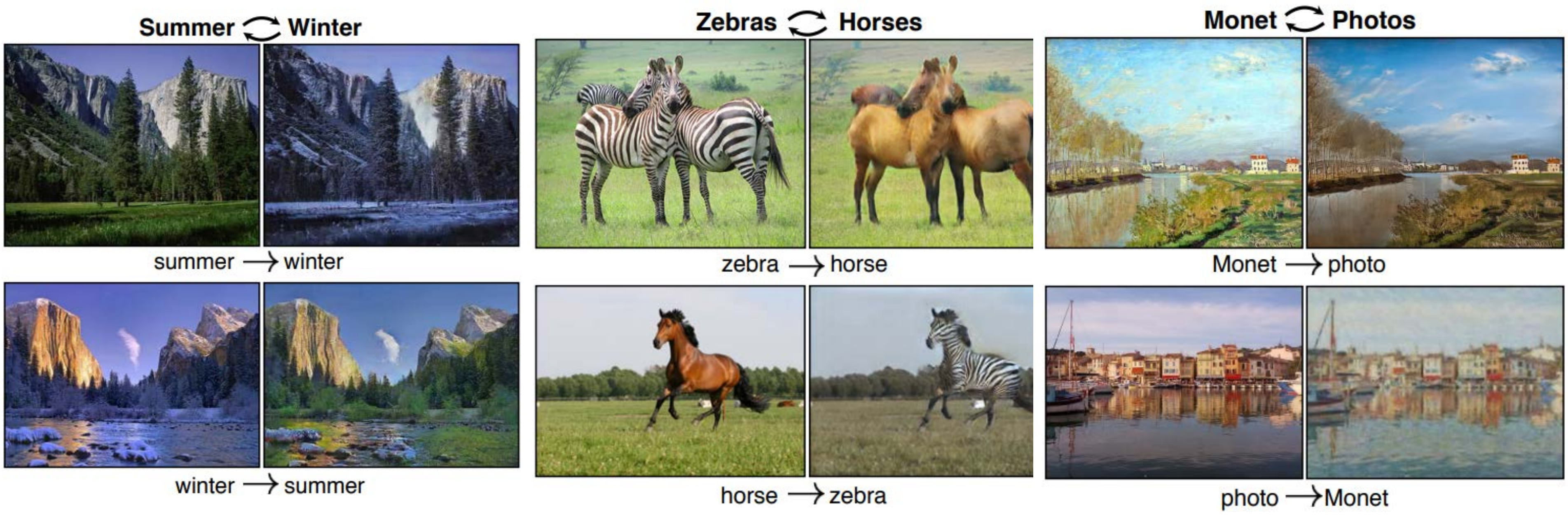
$$\mathcal{L}_{cyc}(G_1, G_2) = \mathbb{E}\left[\left\|G_2(G_1(x)) - x\right\|_1\right] + \left[\left\|G_1(G_2(y)) - y\right\|_1\right]$$



Zhu et al. "Unpaired Image-To-Image Translation Using Cycle-Consistent Adversarial Networks." *CVPR* 2017.

CycleGAN

- Example results

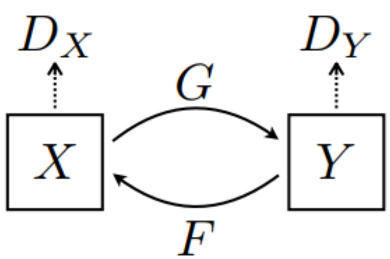


Project Page: https://junyanz.github.io/CycleGAN/

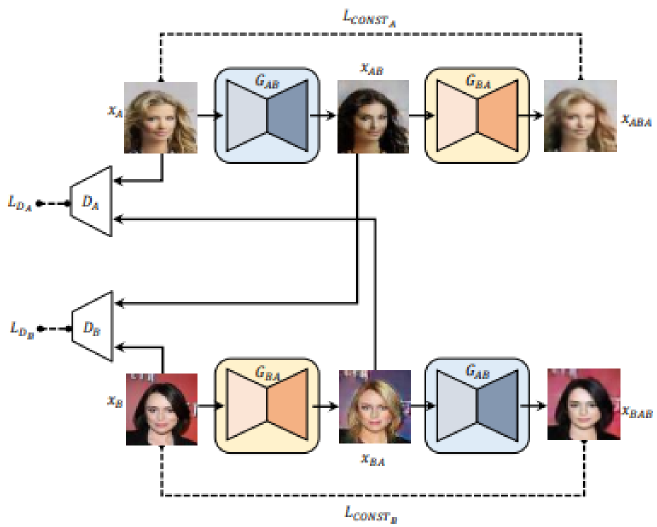
Zhu et al. "Unpaired Image-To-Image Translation Using Cycle-Consistent Adversarial Networks." *CVPR* 2017.

Image Translation Using Unpaired Training Data

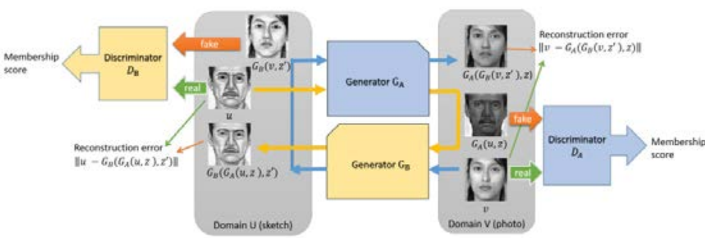
- CycleGAN, DiscoGAN, and DualGAN



CycleGAN
ICCV’17



DiscoGAN
ICML’17



DualGAN
ICCV’17

Zhu et al. "Unpaired Image-To-Image Translation Using Cycle-Consistent Adversarial Networks." *CVPR* 2017.
Kim et al. "Learning to Discover Cross-Domain Relations with Generative Adversarial Networks.“, *ICML 2017*
Yi, Zili, et al. "Dualgan: Unsupervised dual learning for image-to-image translation." *ICCV 2017*

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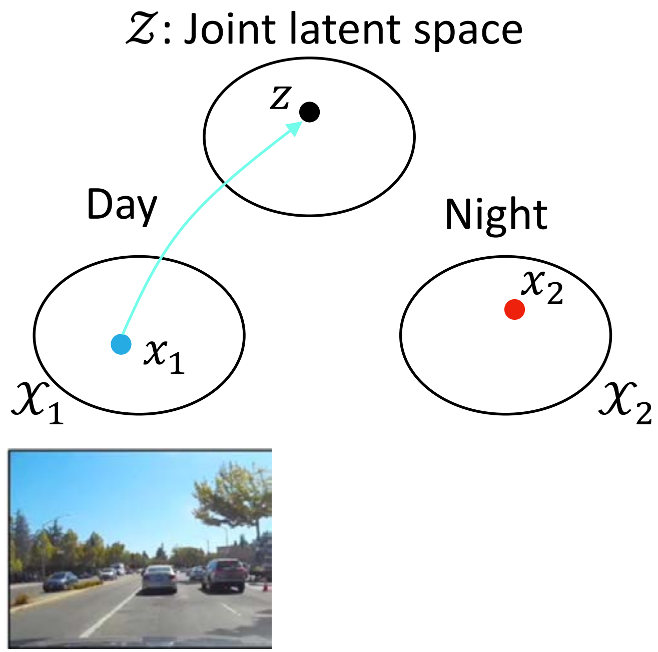
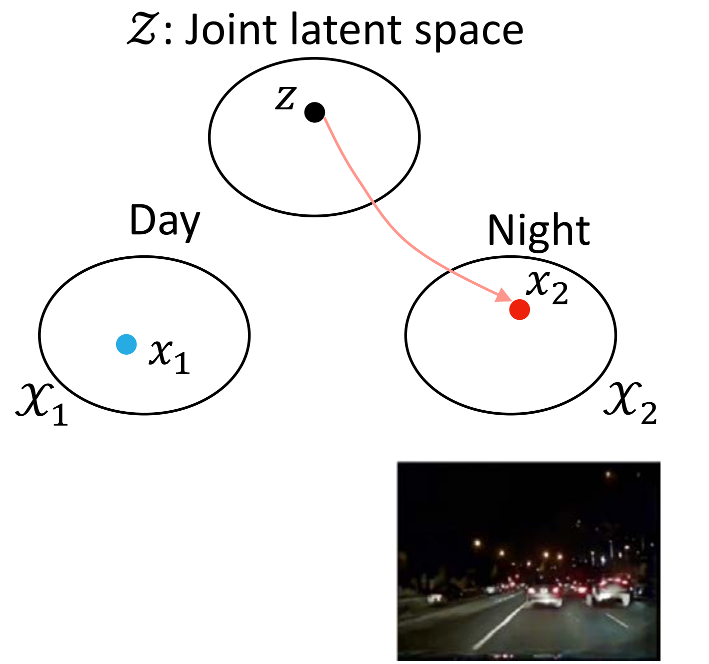
UNIT

- Unsupervised Image-to-Image Translation Networks (NIPS'17)
  - Image translation via learning cross-domain joint representation

Stage1: Encode to the joint space



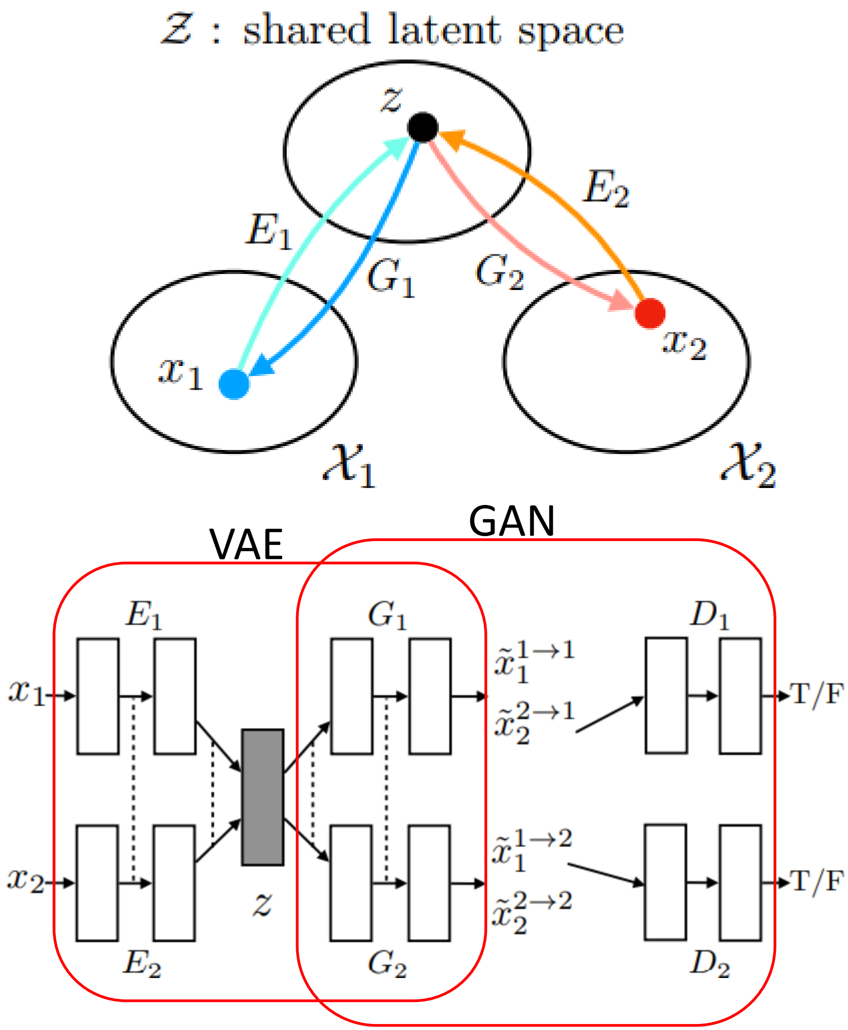
Stage2: Generate cross-domain images



Liu et al., "Unsupervised image-to-image translation networks.", NIPS 2017

UNIT

- Goal/Problem Setting
  - Image translation
    across two distinct domains
  - Unpaired training image data
- Idea
  - Based on two parallel VAE-GAN models



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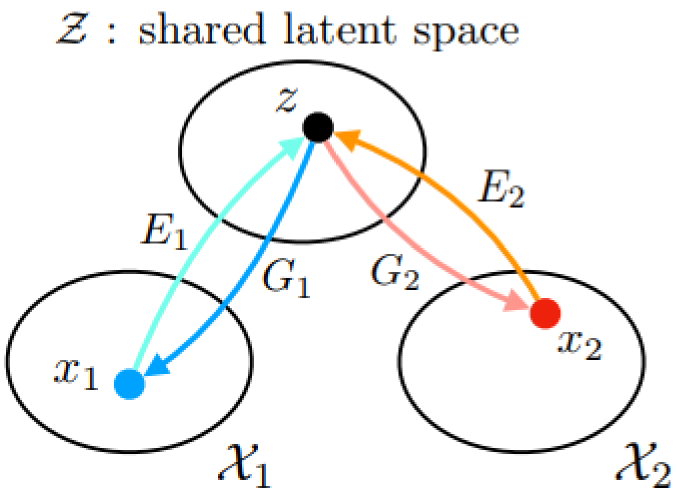
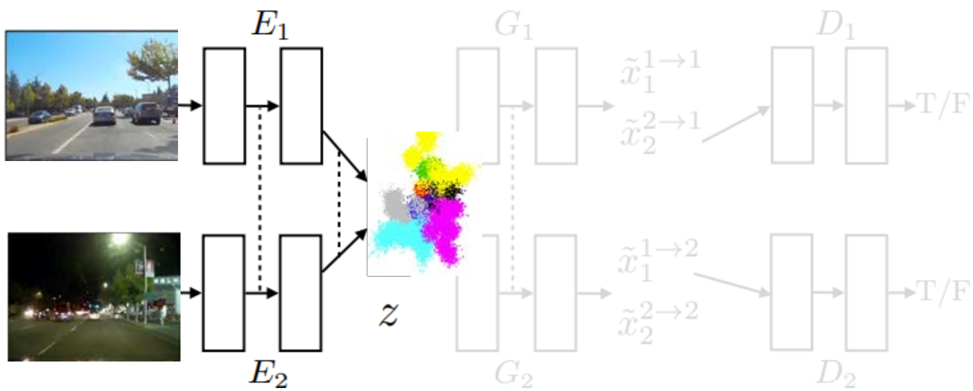
UNIT

- Goal/Problem Setting
  - Image translation across two distinct domains
  - Unpaired training image data
- Idea
  - Based on two parallel VAE-GAN models
  - Learning of joint representation across image domains

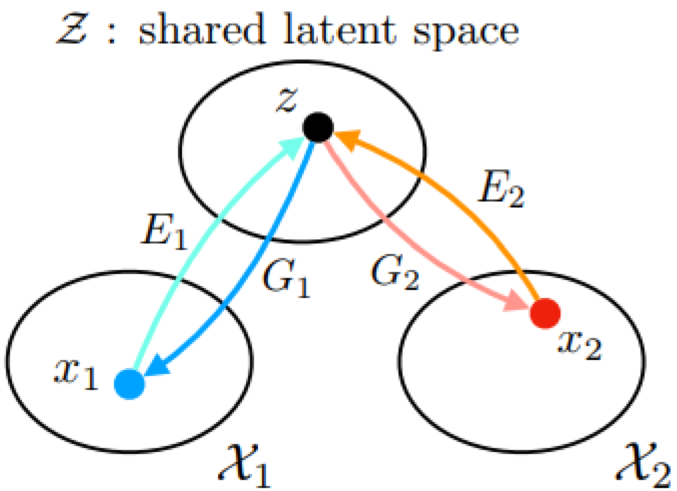


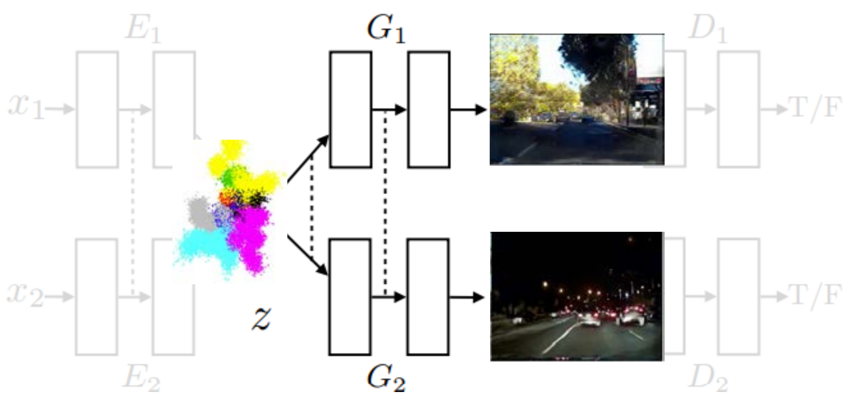


Liu et al., "Unsupervised image-to-image translation networks.", NIPS 2017

UNIT

- Goal/Problem Setting
  - Image translation
    across two distinct domains
  - Unpaired training image data
- Idea
  - Based on two parallel VAE-GAN models
  - Learning of joint representation
    across image domains
  - Generate cross-domain images
    from joint representation





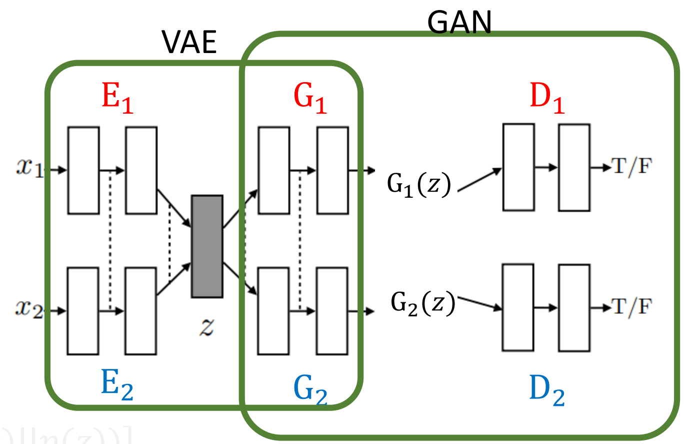
Liu et al., "Unsupervised image-to-image translation networks.“, NIPS 2017

UNIT

- ***Learning***

Overall objective function

$$\mathrm{G}^* = \arg\min_{\mathrm{G}}\max_{\mathrm{D}} \underbrace{\mathcal{L}_{VAE}(\mathrm{E}_1,\mathrm{G}_1,\mathrm{E}_2,\mathrm{G}_2)}_{\textbf{Variation Autoencoder}} + \underbrace{\mathcal{L}_{GAN}(\mathrm{G}_1,\mathrm{D}_1,\mathrm{G}_2,\mathrm{D}_2)}_{\textbf{Adversarial}}$$



Variation Autoencoder Loss

$$\mathcal{L}_{VAE}(\mathrm{E}_1,\mathrm{G}_1,\mathrm{E}_2,\mathrm{G}_2) = \mathbb{E}[\|\mathrm{G}_1(\mathrm{E}_1(x_1)) - x_1\|_2] + \mathbb{E}[\mathcal{KL}(q_1(z)\|p(z))]$$
$$\mathbb{E}[\|\mathrm{G}_2(\mathrm{E}_2(x_2)) - x_2\|_2] + \mathbb{E}[\mathcal{KL}(q_2(z)\|p(z))]$$

Adversarial Loss

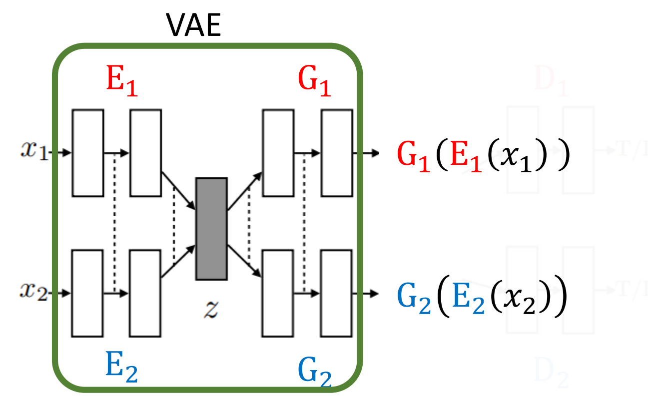
$$\mathcal{L}_{GAN}(\mathrm{G}_1,\mathrm{D}_1,\mathrm{G}_2,\mathrm{D}_2) = \mathbb{E}[\log(1 - \mathrm{D}_1(\mathrm{G}_1(z))] + \mathbb{E}[\log \mathrm{D}_1(y_1)]$$
$$\mathbb{E}[\log(1 - \mathrm{D}_2(\mathrm{G}_2(z))] + \mathbb{E}[\log \mathrm{D}_2(y_2)]$$

UNIT

- ***Learning***

Overall objective function

$$G = \arg\min_{G}\max_{D} \mathcal{L}_{VAE}(\mathrm{E}_1, \mathrm{G}_1, \mathrm{E}_2, \mathrm{G}_2) + \mathcal{L}_{GAN}(\mathrm{G}_1, \mathrm{D}_1, \mathrm{G}_2, \mathrm{D}_2)$$



Variation Autoencoder Loss

$$\begin{aligned}\mathcal{L}_{VAE}(\mathrm{E}_1, \mathrm{G}_1, \mathrm{E}_2, \mathrm{G}_2) = {} & \mathbb{E}\left[\left\|\mathrm{G}_1\left(\mathrm{E}_1(x_1)\right) - x_1\right\|_2\right] + \mathbb{E}[\mathcal{KL}(q_1(z)||p(z))] \\ & \mathbb{E}\left[\left\|\mathrm{G}_2\left(\mathrm{E}_2(x_2)\right) - x_2\right\|_2\right] + \mathbb{E}[\mathcal{KL}(q_2(z)||p(z))]\end{aligned}$$

Reconstruction

Adversarial Loss

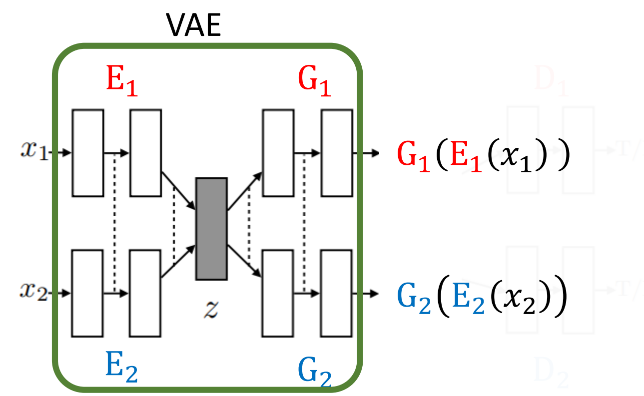
$$\begin{aligned}\mathcal{L}_{GAN}(\mathrm{G}_1, \mathrm{D}_1, \mathrm{G}_2, \mathrm{D}_2) = {} & \mathbb{E}[\log(1 - \mathrm{D}_1(\mathrm{G}_1(z))] + \mathbb{E}[\log \mathrm{D}_1(y_1)] \\ & \mathbb{E}[\log(1 - \mathrm{D}_2(\mathrm{G}_2(z))] + \mathbb{E}[\log \mathrm{D}_2(y_2)]\end{aligned}$$

UNIT

- ***Learning***

Overall objective function

$$G = \arg\min_{G}\max_{D} \mathcal{L}_{VAE}(E_1, G_1, E_2, G_2) + \mathcal{L}_{GAN}(G_1, D_1, G_2, D_2)$$



Variation Autoencoder Loss

$$\mathcal{L}_{VAE}(E_1, G_1, E_2, G_2) = \mathbb{E}\left[\left\|G_1\left(E_1(x_1)\right) - x_1\right\|_2\right] + \mathbb{E}[\mathcal{KL}(q_1(z)||p(z))]$$
$$\mathbb{E}\left[\left\|G_2\left(E_2(x_2)\right) - x_2\right\|_2\right] + \mathbb{E}[\mathcal{KL}(q_2(z)||p(z))]$$

Prior Loss

Adversarial Loss

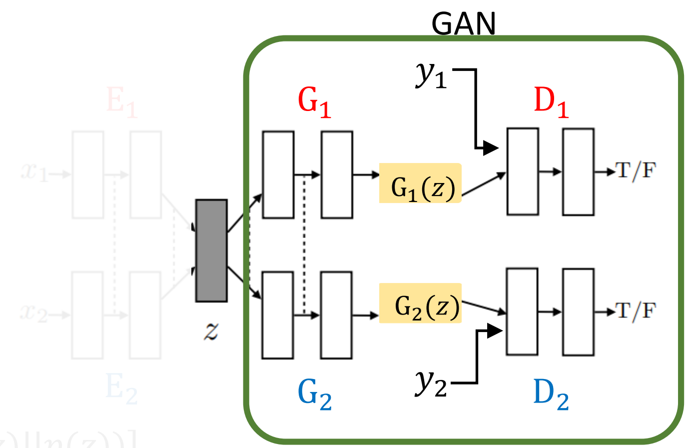
$$\mathcal{L}_{GAN}(G_1, D_1, G_2, D_2) = \mathbb{E}[\log(1 - D_1(G_1(z))] + \mathbb{E}[\log D_1(y_1)]$$
$$\mathbb{E}[\log(1 - D_2(G_2(z))] + \mathbb{E}[\log D_2(y_2)]$$

UNIT

- ***Learning***

Overall objective function

$$\mathrm{G} = \arg\min_{\mathrm{G}}\max_{\mathrm{D}} \mathcal{L}_{VAE}(\mathrm{E}_1, \mathrm{G}_1, \mathrm{E}_2, \mathrm{G}_2) + \mathcal{L}_{GAN}(\mathrm{G}_1, \mathrm{D}_1, \mathrm{G}_2, \mathrm{D}_2$$



Variation Autoencoder Loss

$$\begin{aligned}\mathcal{L}_{VAE}(\mathrm{E}_1, \mathrm{G}_1, \mathrm{E}_2, \mathrm{G}_2) = {} & \mathbb{E}[||\mathrm{G}_1(\mathrm{E}_1(x_1)) - x_1||_2] + \mathbb{E}[\mathcal{KL}(q_1(z)||p(z))] \\ & \mathbb{E}[||\mathrm{G}_2(\mathrm{E}_2(x_2)) - x_2||_2] + \mathbb{E}[\mathcal{KL}(q_2(z)||p(z))]\end{aligned}$$

Adversarial Loss

$$\begin{aligned}\mathcal{L}_{GAN}(\mathrm{G}_1, \mathrm{D}_1, \mathrm{G}_2, \mathrm{D}_2) = {} & \mathbb{E}[\log(1 - \mathrm{D}_1(\mathrm{G}_1(z))] + \mathbb{E}[\log \mathrm{D}_1(y_1)] \\ & \mathbb{E}[\log(1 - \mathrm{D}_2(\mathrm{G}_2(z))] + \mathbb{E}[\log \mathrm{D}_2(y_2)]\end{aligned}$$

Generated

UNIT

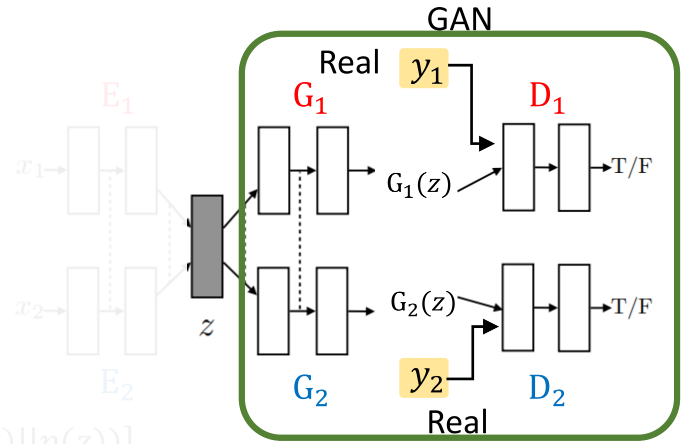
- ***Learning***

Overall objective function

$$G = \arg\min_{G}\max_{D} \mathcal{L}_{VAE}(E_1, G_1, E_2, G_2) + \mathcal{L}_{GAN}(G_1, D_1, G_2, D_2$$

Variation Autoencoder Loss

$$\mathcal{L}_{VAE}(E_1, G_1, E_2, G_2) = \mathbb{E}[||G_1(E_1(x_1)) - x_1||_2] + \mathbb{E}[\mathcal{KL}(q_1(z)||p(z))]$$
$$\mathbb{E}[||G_2(E_2(x_2)) - x_2||_2] + \mathbb{E}[\mathcal{KL}(q_2(z)||p(z))]$$



Adversarial Loss

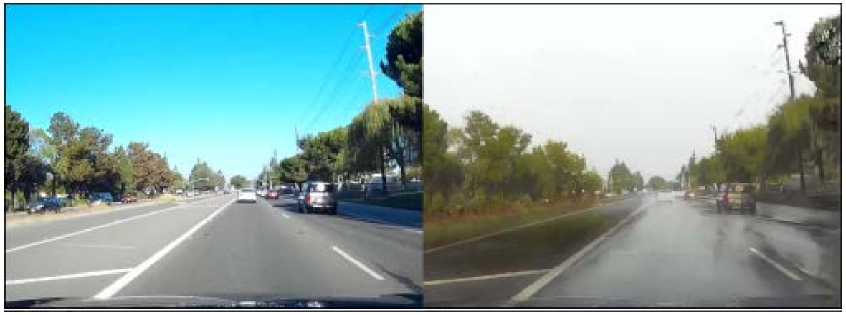
$$\mathcal{L}_{GAN}(G_1, D_1, G_2, D_2) = \mathbb{E}[\log(1 - D_1(G_1(z))] + \mathbb{E}[\log D_1(y_1)]$$
$$\mathbb{E}[\log(1 - D_2(G_2(z))] + \mathbb{E}[\log D_2(y_2)]$$

Real

UNIT

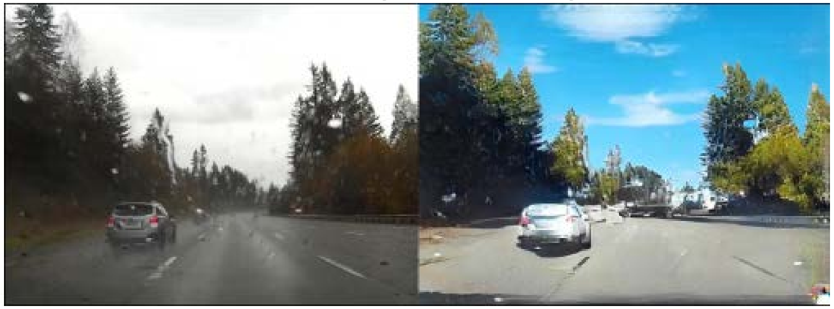
- Example results

Sunny → Rainy



Real Street-view → Synthetic Street-view

Rainy → Sunny



Synthetic Street-view → Real Street-view

Github Page: https://github.com/mingyuliutw/UNIT

Liu et al., "Unsupervised image-to-image translation networks.", NIPS 2017

What to Cover in Part 4?

- Cross-Domain Image Translation
  - Pix2pix (CVPR'17): Pairwise cross-domain training data
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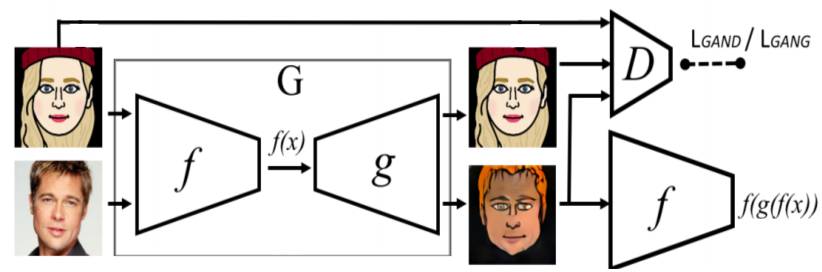
Domain Transfer Networks

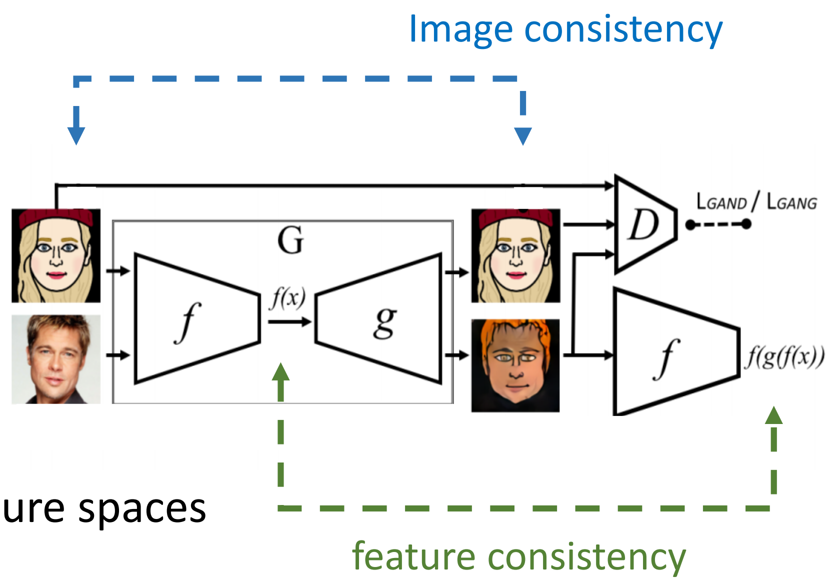
- Unsupervised Cross-Domain Image Generation (ICLR'17)
- Goal/Problem Setting
  - Image translation across two domains
  - One-way only translation
  - Unpaired training data
- Idea
  - Apply unified model to learn joint representation across domains.



Taigman et al., "Unsupervised cross-domain image generation.", ICLR 2016

Domain Transfer Networks

- Unsupervised Cross-Domain Image Generation (ICLR'17)
- Goal/Problem Setting
  - Image translation across two domains
  - One-way only translation
  - Unpaired training data
- Idea
  - Apply unified model to learn joint representation across domains.
  - Consistency observed in image and feature spaces

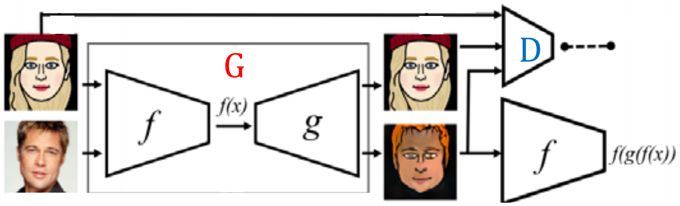


Taigman et al., "Unsupervised cross-domain image generation.", ICLR 2016

Domain Transfer Networks

- ***Learning***
  - **Unified model** to translate across domains

$$G^* = \arg\min_{G}\max_{D} \mathcal{L}_{img}(G) + \mathcal{L}_{feat}(G) + \mathcal{L}_{GAN}(G, D)$$



  - Consistency of feature and image space

$$\mathcal{L}_{img}(G) = \mathbb{E}\left[\left\|g(f(y)) - y\right\|_2\right]$$

$$\mathcal{L}_{feat}(G) = \mathbb{E}\left[\left\|f(g(f(x))) - f(x)\right\|_2\right]$$

  - Adversarial loss

$$\mathcal{L}_{GAN}(G, D) = \mathbb{E}[\log(1 - D(G(x)))] + \mathbb{E}[\log(1 - D(G(y)))] + \mathbb{E}[\log D(y)]$$

Domain Transfer Networks

- ***Learning***
  - **Unified model** to translate across domains

$$G^* = \arg\min_{G}\max_{D} \mathcal{L}_{img}(G) + \mathcal{L}_{feat}(G) + \mathcal{L}_{GAN}(G, D)$$

  - **Consistency of image and feature space**

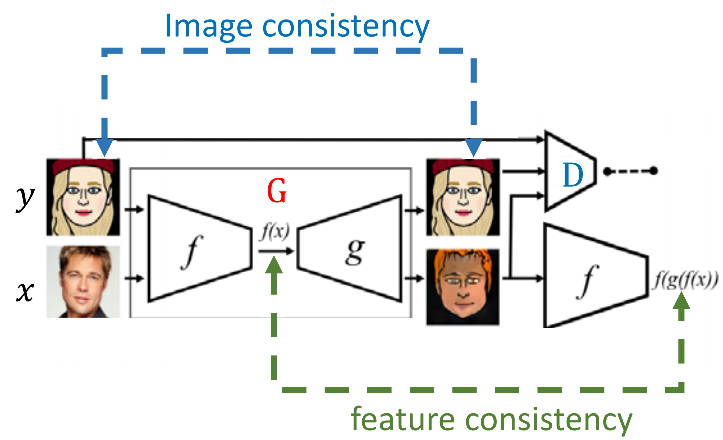
$$\mathcal{L}_{img}(G) = \mathbb{E}\left[\left\|g\left(f(y)\right) - y\right\|_2\right]$$

$$\mathcal{L}_{feat}(G) = \mathbb{E}\left[\left\|f\left(g\left(f(x)\right)\right) - f(x)\right\|_2\right]$$

$$G = \{f, g\}$$

  - Adversarial loss

$$\mathcal{L}_{GAN}(G, D) = \mathbb{E}[\log(1 - D(G(x))] + \mathbb{E}[\log(1 - D(G(y))] + \mathbb{E}[\log D(y)]$$



Domain Transfer Networks

- ***Learning***
  - **Unified model** to translate across domains

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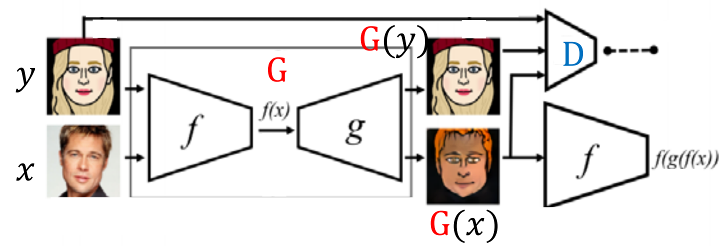

  - Consistency of feature and image space

    $$\mathcal{L}_{img}(G) = \mathbb{E}\left[\left\|g(f(y)) - y\right\|_2\right]$$

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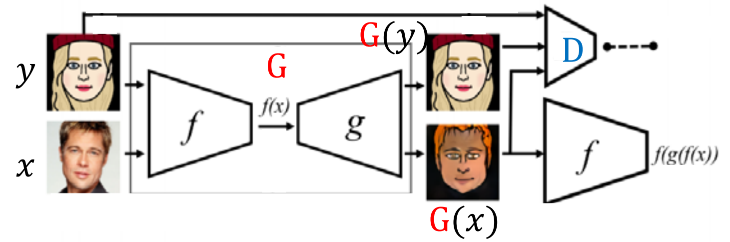
  - **Adversarial loss**

    $$\mathcal{L}_{GAN}(G, D) = \mathbb{E}[\log(1 - D(G(x))] + \mathbb{E}[\log(1 - D(G(y))] + \mathbb{E}[\log D(y)]$$

Domain Transfer Networks

- ***Learning***
  - **Unified model** to translate across domains

$$G^* = \arg\min_{G}\max_{D} \mathcal{L}_{img}(G) + \mathcal{L}_{feat}(G) + \mathcal{L}_{GAN}(G, D)$$



  - Consistency of feature and image space

$$\mathcal{L}_{img}(G) = \mathbb{E}\left[\left\| g(f(y)) - y \right\|_2\right]$$

$$\mathcal{L}_{feat}(G) = \mathbb{E}\left[\left\| f(g(f(x))) - f(x) \right\|_2\right]$$

  - Adversarial loss

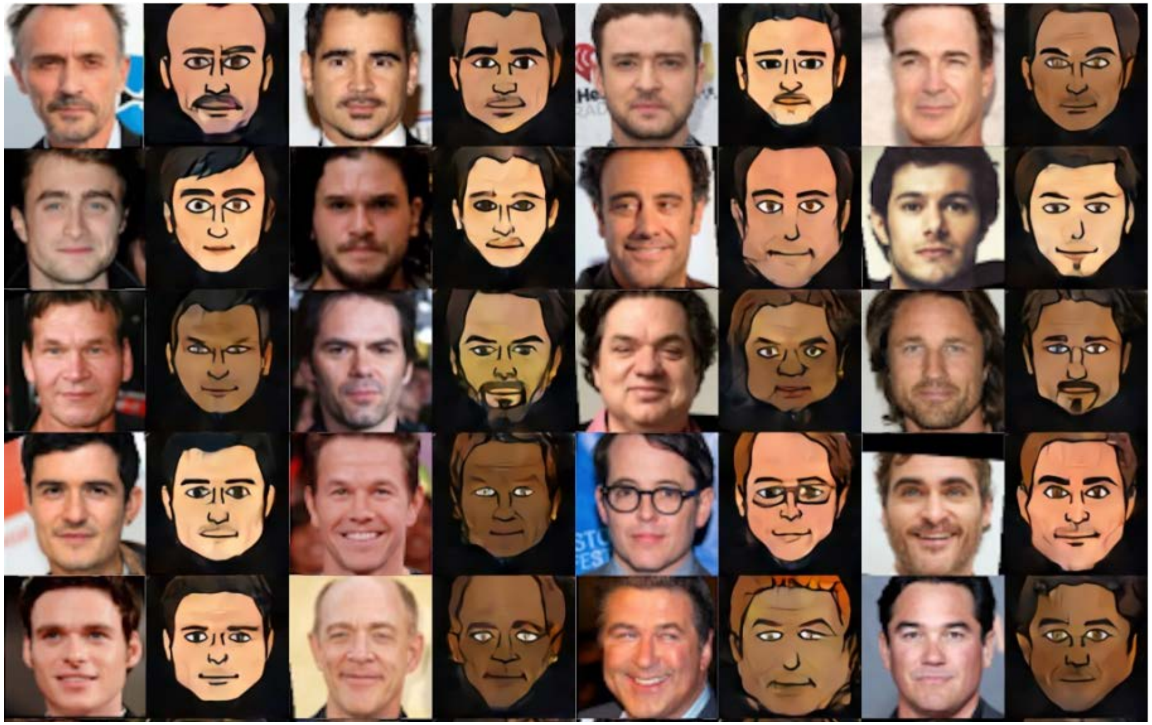
$$\mathcal{L}_{GAN}(G, D) = \mathbb{E}[\log(1 - D(G(x))] + \mathbb{E}[\log(1 - D(G(y))] + \mathbb{E}[\log D(y)]$$

DTN

- Example results

SVHN 2 MNIST

Photo 2 Emoji



Taigman et al., "Unsupervised cross-domain image generation.“, ICLR 2016

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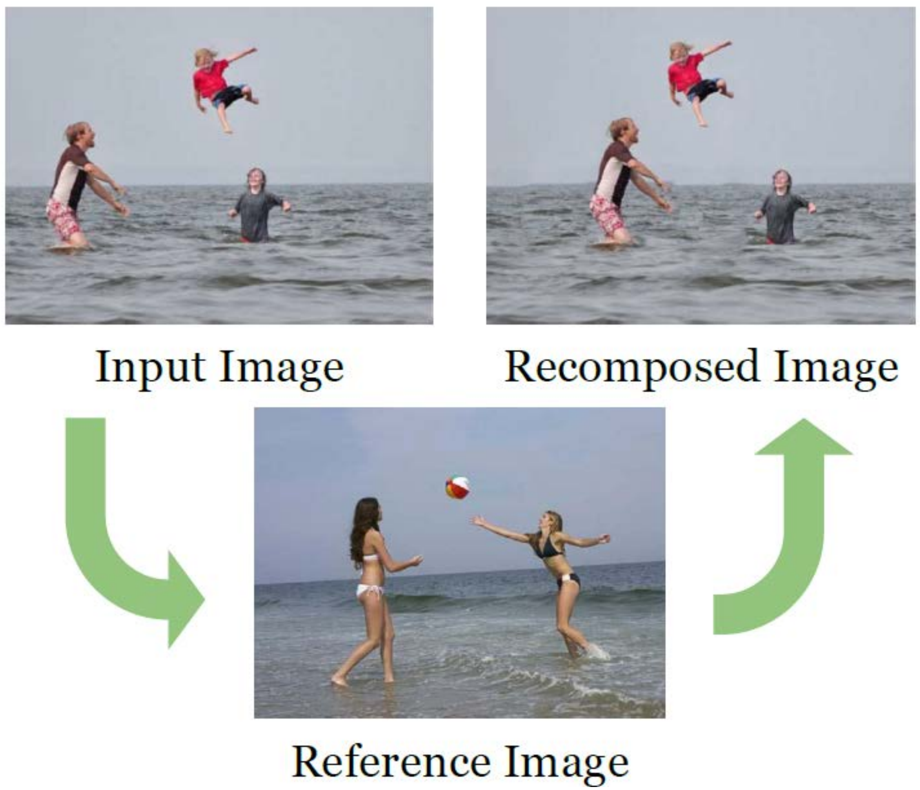
- Final Remarks

Transfer in Photography Composition

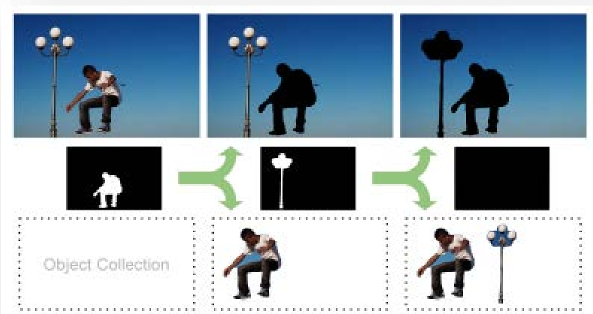
- Photography Recomposition



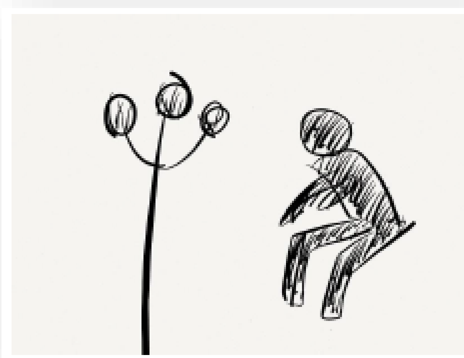
H.-T. Chang, Y.-C. F. Wang, and M.-S. Chen, ACM Multimedia, 2014.
H.-T. Chang, Y.-C. F. Wang, and M.-S. Chen, ACM Multimedia, 2015.

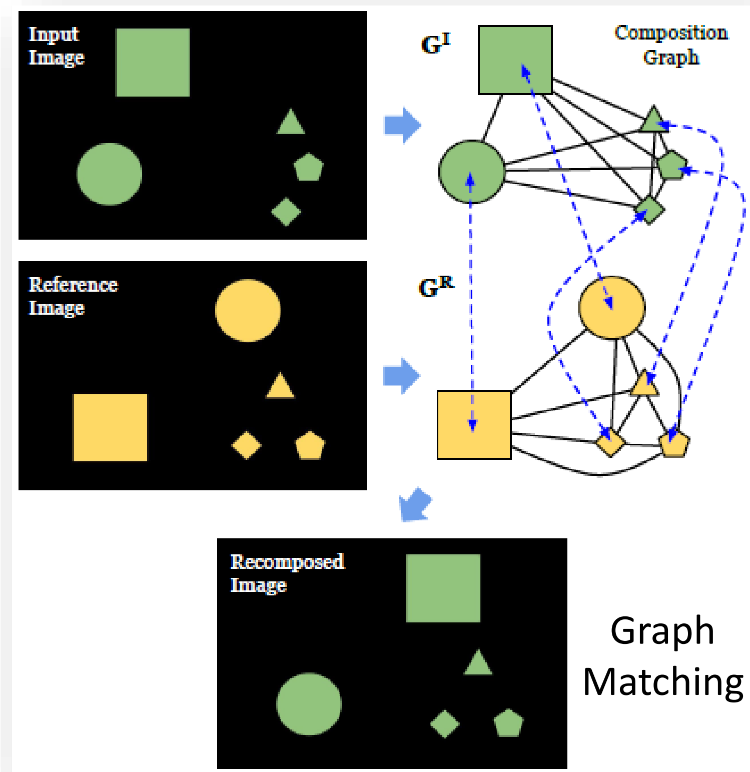
- Our Ideas
  - Foreground object discovery + Graph matching

Input Image



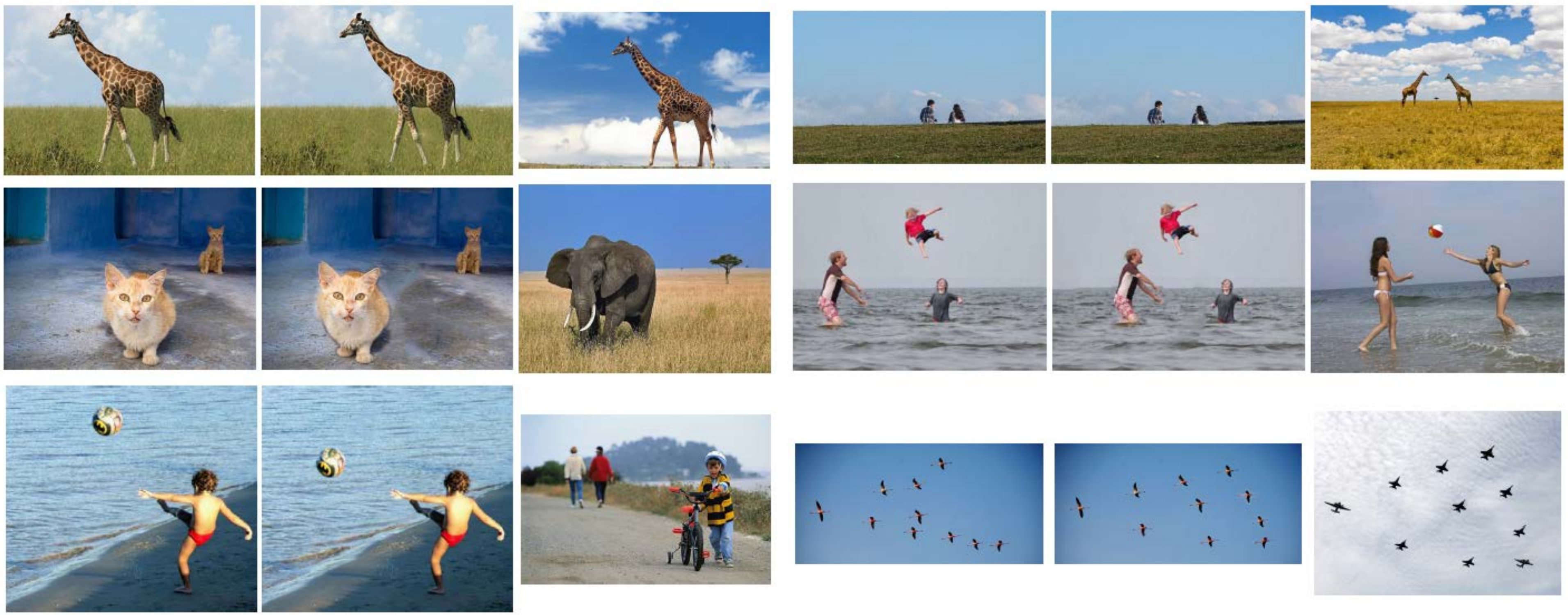
Reference Image





H.-T. Chang, Y.-C. F. Wang, and M.-S. Chen, ACM Multimedia, 2014.

- Example Results



Input Image Recomposed Image Reference Image Input Image Recomposed Image Reference Image

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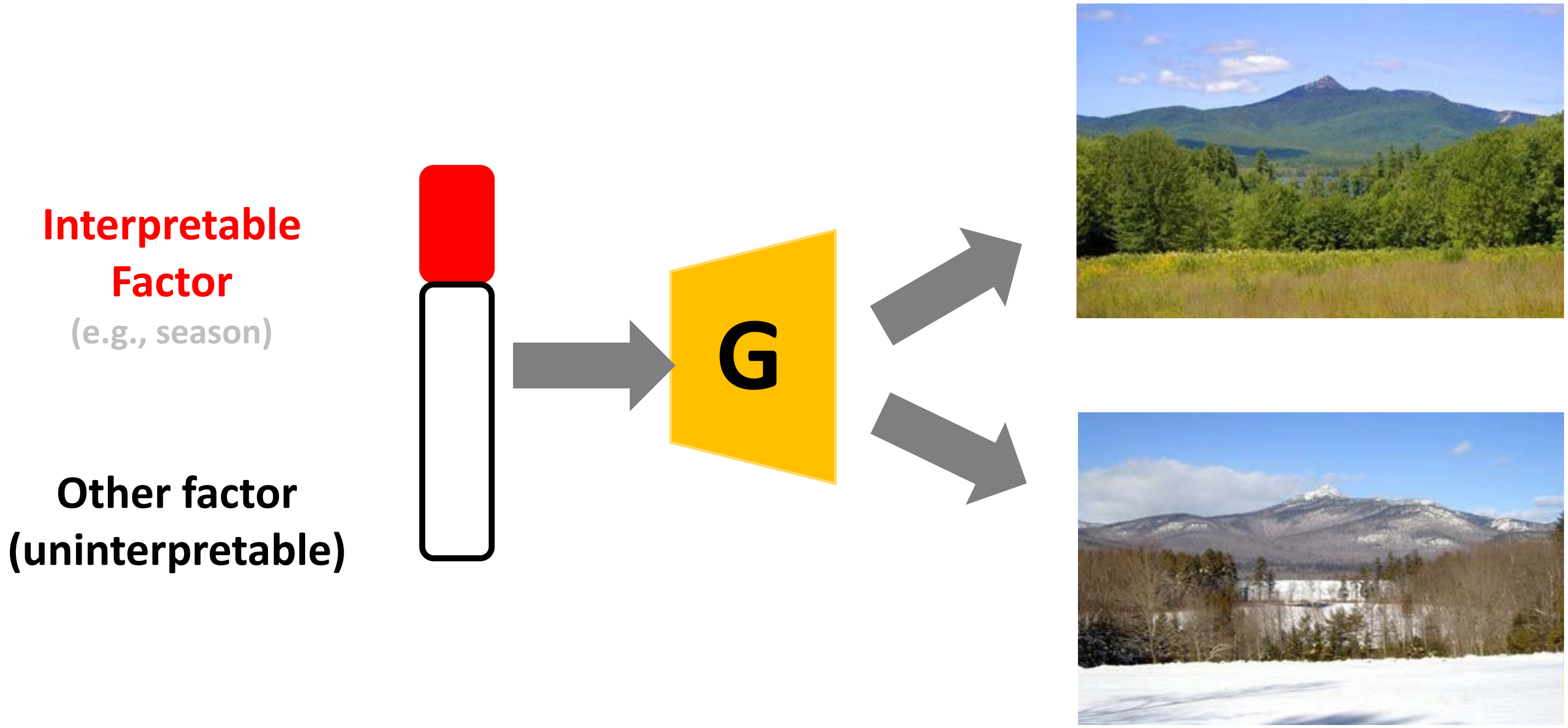
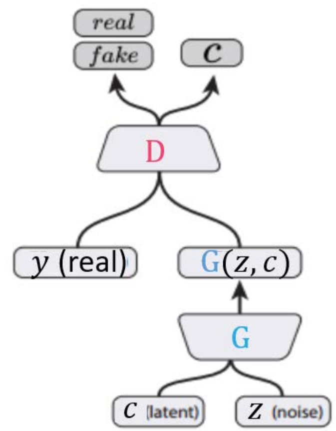
Representation Disentanglement

- Goal
  - Interpretable deep feature representation
  - Disentangle attribute of interest from the derived latent representation



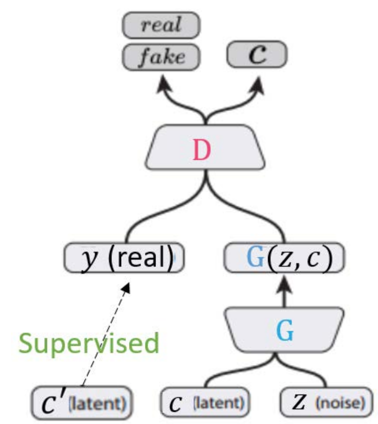
Representation Disentanglement

- Goal
  - Interpretable deep feature representation
  - Disentangle attribute of interest from the derived latent representation
    - Unsupervised: InfoGAN
    - Supervised: AC-GAN



InfoGAN

Chen et al.
NIPS ’16



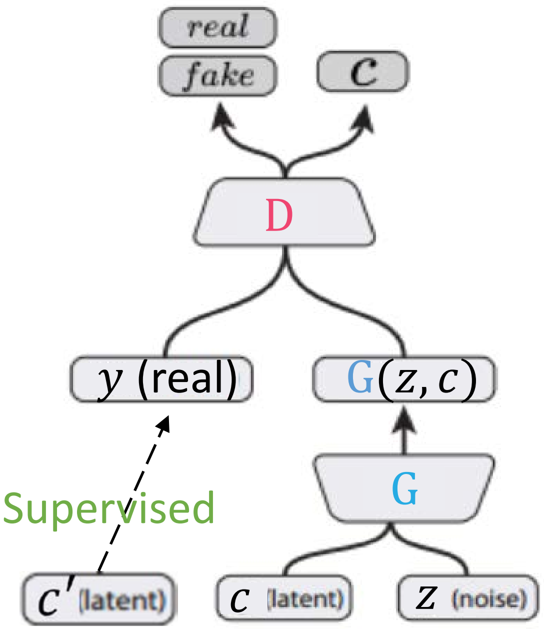
ACGAN

Odena et al.
ICML ’17

Chen et al., InfoGAN: Interpretable representation learning by information maximizing generative adversarial nets., NIPS 2016.
Odena et al., Conditional image synthesis with auxiliary classifier GANs. ICML’17

AC-GAN

- Supervised Disentanglement



- **Learning**
  - **Overall objective function**

$$G^* = \arg\min_{G}\max_{D} \mathcal{L}_{GAN}(G, D) + \mathcal{L}_{cls}(G, D)$$

  - **Adversarial Loss**

$$\mathcal{L}_{GAN}(G, D) = \mathbb{E}[\log(1 - D(G(z, c)))] + \mathbb{E}[\log D(y)]$$

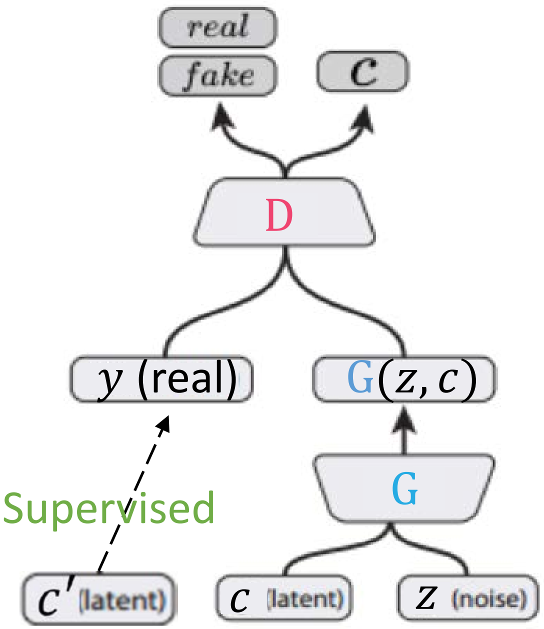
  - **Disentanglement loss**

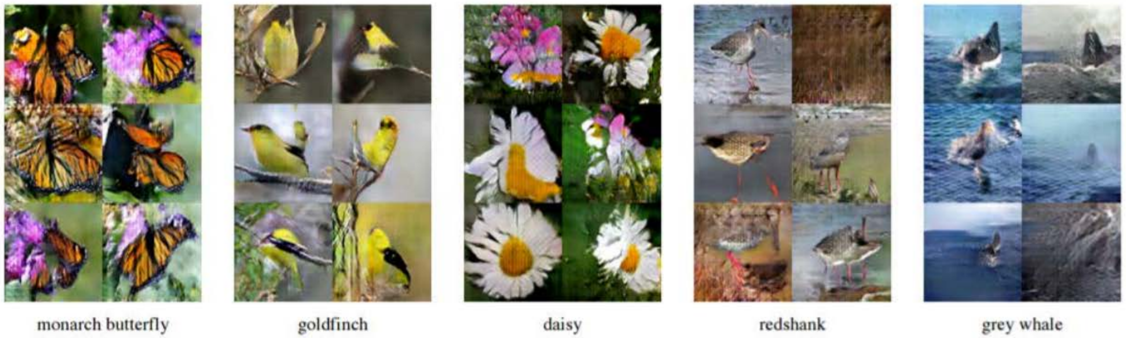
$$\mathcal{L}_{cls}(G, D) = \underbrace{\mathbb{E}[-\log D_{cls}(c'|y)]}_{\text{Real data w.r.t. its domain label}} + \underbrace{\mathbb{E}[-\log D_{cls}(c|G(x, c))]}_{\text{Generated data w.r.t. assigned label}}$$

Odena et al., Conditional image synthesis with auxiliary classifier GANs. ICML'17

AC-GAN

- Supervised Disentanglement



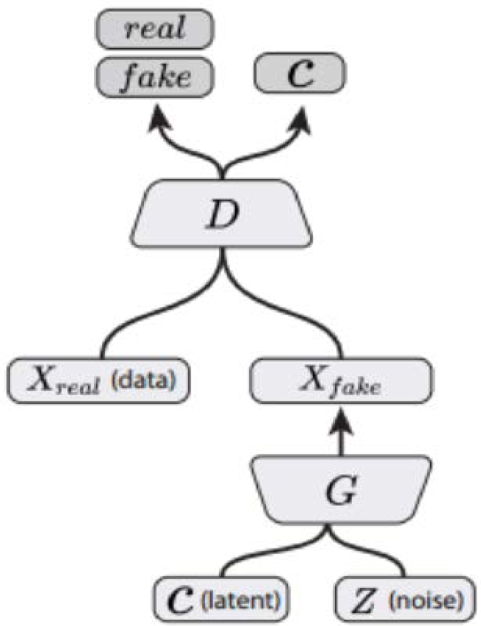


Different c values

Odena et al., Conditional image synthesis with auxiliary classifier GANs. ICML'17

InfoGAN

- Unsupervised Disentanglement



- Learning
  - **Overall objective function**

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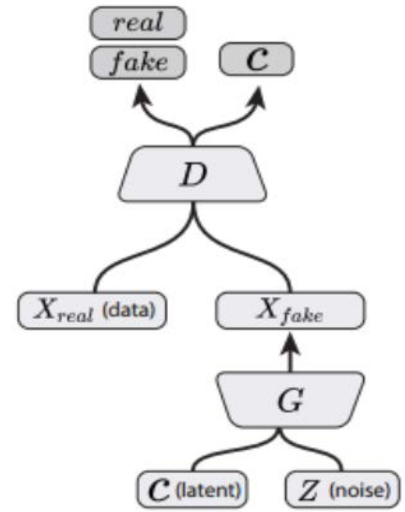
Chen et al., InfoGAN: Interpretable representation learning by information maximizing generative adversarial nets., NIPS 2016.

InfoGAN

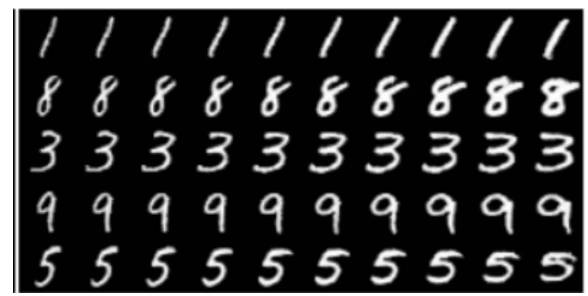


- Unsupervised Disentanglement
  - No guarantee in disentangling particular semantics

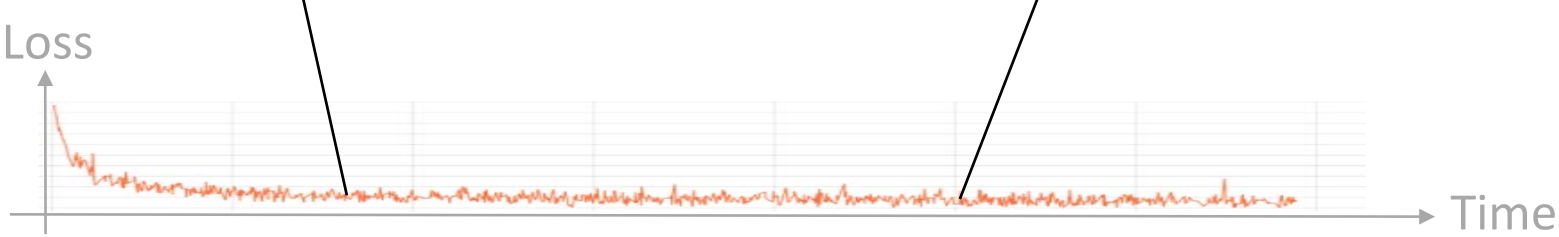
Different c

Rotation Angle

Different c



Width



Training process

Chen et al., InfoGAN: Interpretable representation learning by information maximizing generative adversarial nets., NIPS 2016.

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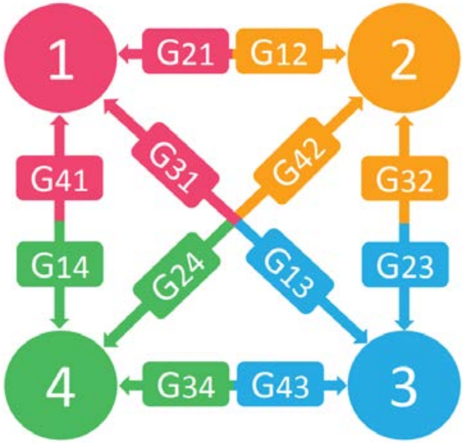
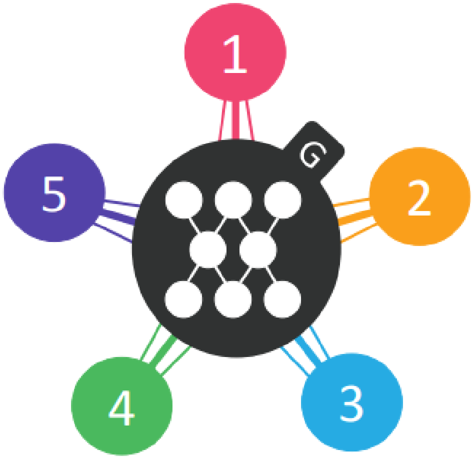
StarGAN

- Goal
  - Unified GAN for multi-domain image-to-image translation

Traditional Cross-Domain Models



Unified Multi-Domain Model (StarGAN)

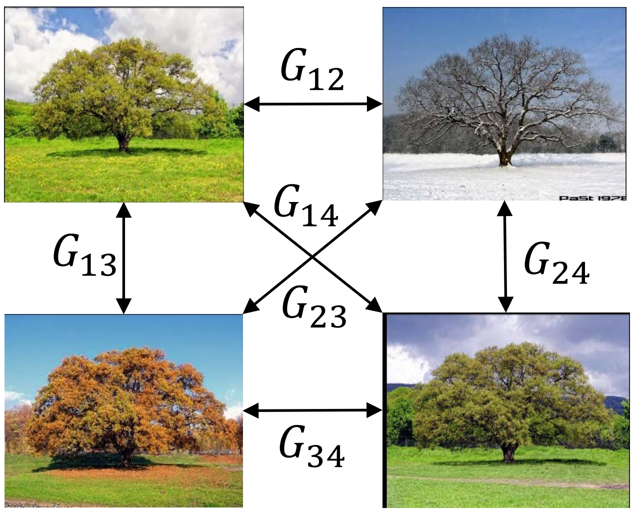


Choi et al. "StarGAN: Unified Generative Adversarial Networks for Multi-Domain Image-to-Image Translation." CVPR 2018

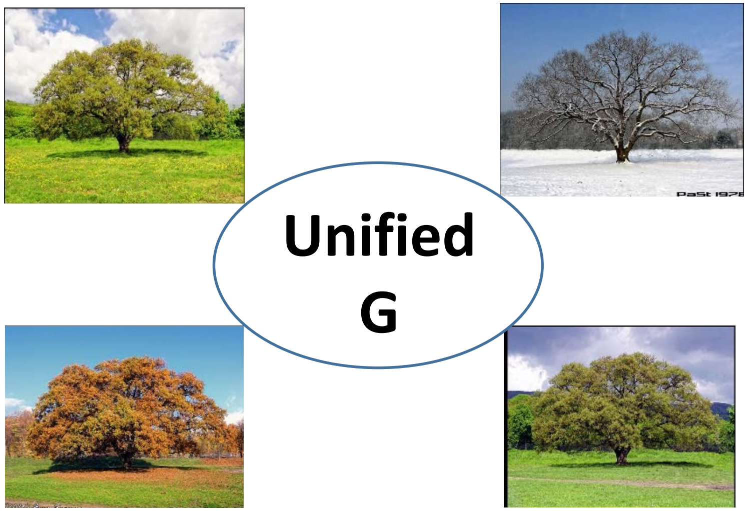
StarGAN

- Goal
  - Unified GAN for multi-domain image-to-image translation

Traditional Cross-Domain Models

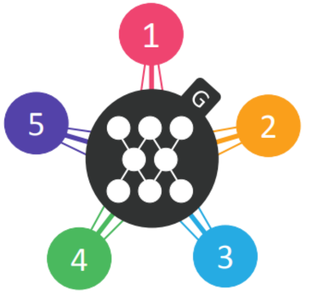


Unified Multi-Domain Model (StarGAN)



StarGAN

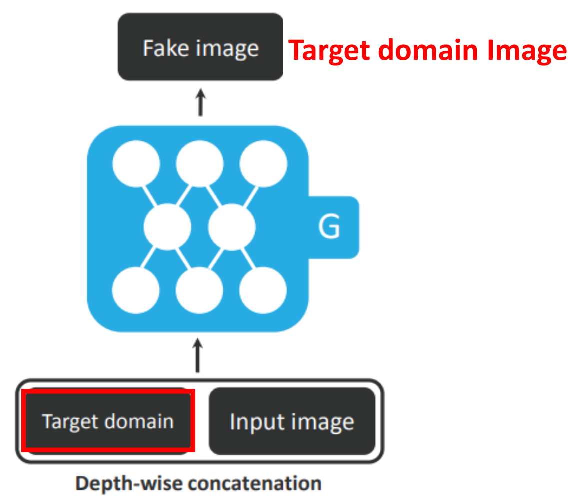
- ***Goal / Problem Setting***
  - **Single** image translation model across **multiple** domains
  - Unpaired training data



StarGAN

- ***Goal / Problem Setting***
  - **Single** Image translation model across **multiple** domains
  - Unpaired training data

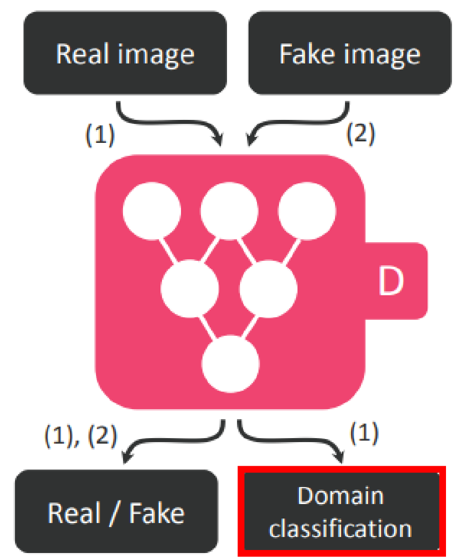
- ***Idea***
  - Concatenate image and target domain label as input of generator
  - Auxiliary domain classifier on Discriminator



StarGAN

- ***Goal / Problem Setting***
  - **Single** Image translation model across **multiple** domains
  - Unpaired training data

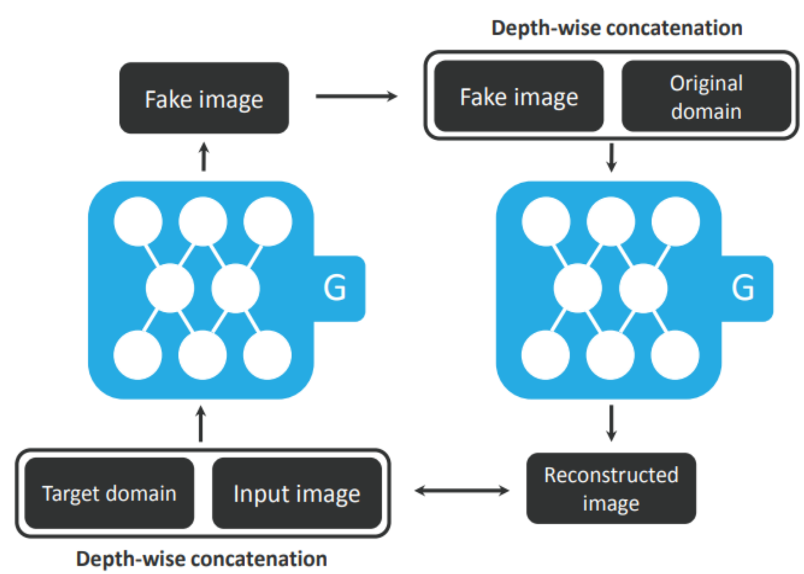
- ***Idea***
  - Concatenate image and target domain label as input of Generator
  - Auxiliary domain classifier as discriminator too



StarGAN

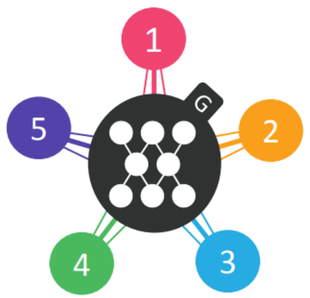
- ***Goal / Problem Setting***
  - **Single** Image translation model across **multiple** domains
  - Unpaired training data

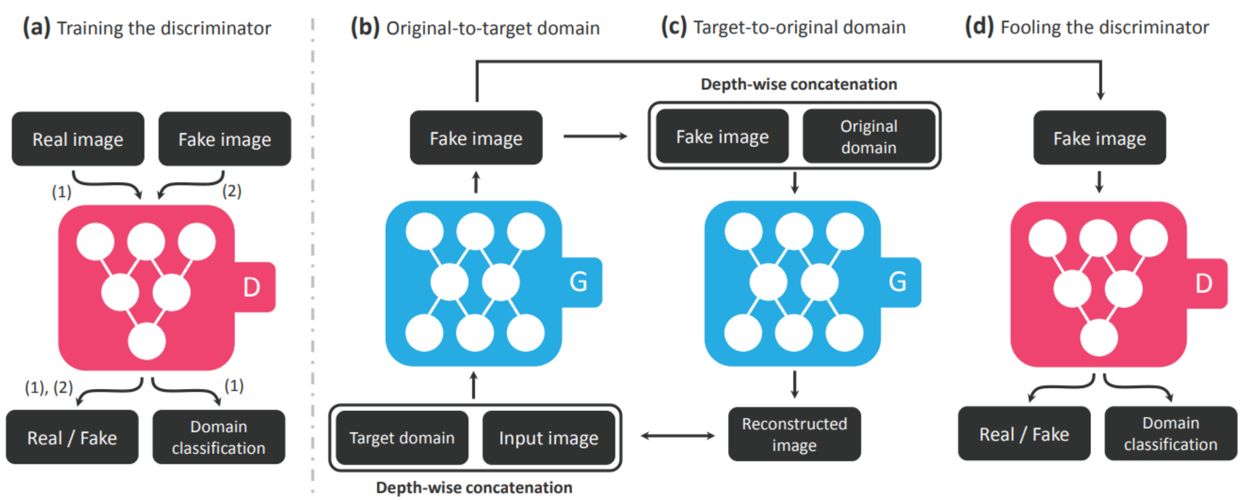
- ***Idea***
  - Concatenate image and target domain label as in
    Generator
  - Auxiliary domain classifier on Discriminator
  - Cycle consistency across domains



StarGAN

- ***Goal / Problem Setting***
  - **Single** Image translation model across **multiple** domains
  - Unpaired training data
- ***Idea***
  - Auxiliary domain classifier as discriminator
  - Concatenate image and target domain label as input
  - Cycle consistency across domains



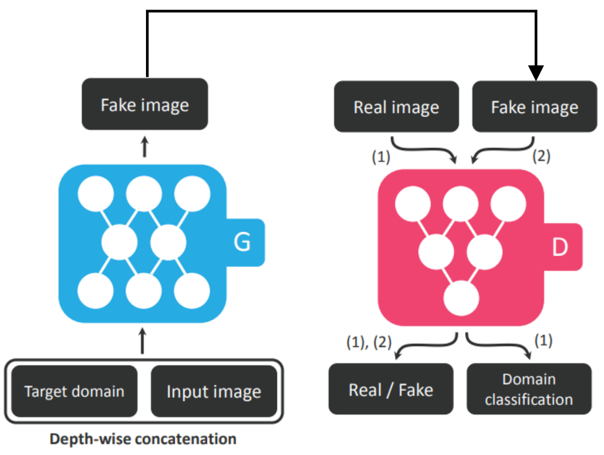


StarGAN

- ***Learning***

Overall objective function

$$G^* = \arg\min_{G}\max_{D} \mathcal{L}_{GAN}(G, D) + \mathcal{L}_{cls}(G, D) + \mathcal{L}_{cyc}(G)$$



StarGAN

- ***Learning***

Overall objective function

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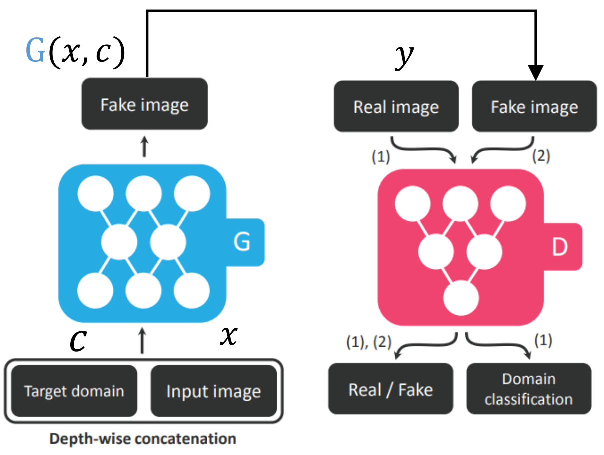
Adversarial Loss



- **Adversarial Loss**

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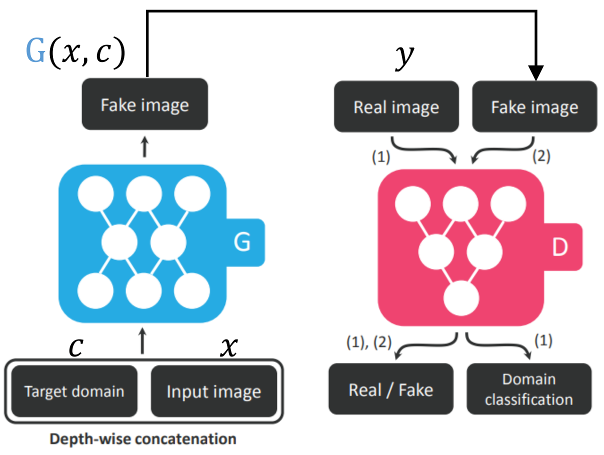
StarGAN

- ***Learning***

Overall objective function

$$G^* = \arg\min_{G}\max_{D} \mathcal{L}_{GAN}(G,D) + \mathcal{L}_{cls}(G,D) + \mathcal{L}_{cyc}(G)$$

Domain Classification Loss



- **Adversarial Loss**

$$\mathcal{L}_{GAN}(G,D) = \mathbb{E}[\log(1 - D(G(x,c)))] + \mathbb{E}[\log D(y)]$$

- **Domain Classification Loss (Disentanglement)**

$$\mathcal{L}_{cls}(G,D) = \mathbb{E}[-\log D_{cls}(c'|y)] + \mathbb{E}[-\log D_{cls}(c|G(x,c))]$$

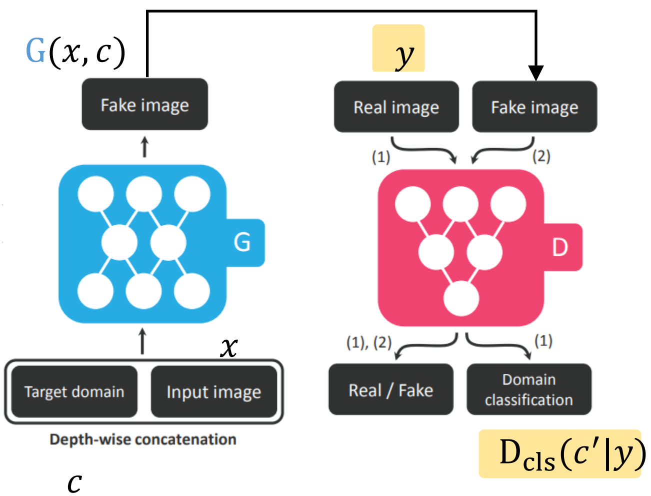
StarGAN

- ***Learning***

Overall objective function

$$G^* = \arg\min_{G}\max_{D} \mathcal{L}_{GAN}(G, D) + \mathcal{L}_{cls}(G, D) + \mathcal{L}_{cyc}(G)$$

Domain Classification Loss



- Adversarial Loss $\mathcal{L}_{GAN}(G, D) = \mathbb{E}[\log(1 - D(G(x, c)))] + \mathbb{E}[\log D(y$

- **Domain Classification Loss** **(Disentanglement)**

$$\mathcal{L}_{cls}(G, D) = \mathbb{E}[\underbrace{-\log D_{\mathrm{cls}}(c'|y)}_{\text{Real data w.r.t. its domain label}}] + \mathbb{E}[-\log D_{\mathrm{cls}}(c|G(x, c))]$$

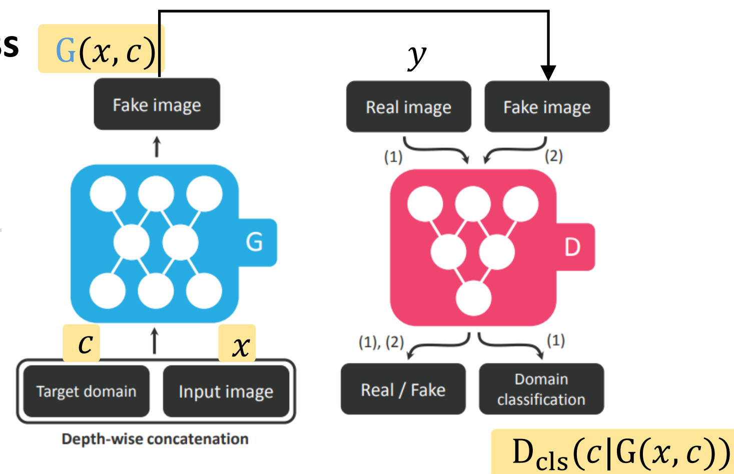
StarGAN

- ***Learning***

Overall objective function

$$G^* = \arg\min_{G}\max_{D} \mathcal{L}_{GAN}(G, D) + \mathcal{L}_{cls}(G, D) + \mathcal{L}_{cyc}(G)$$

Domain Classification Loss



- **Adversarial Loss**

$$\mathcal{L}_{GAN}(G, D) = \mathbb{E}[\log(1 - D(G(x, c)))] +$$

- **Domain Classification Loss (Disentanglement)**

$$\mathcal{L}_{cls}(G, D) = \mathbb{E}[-\log D_{cls}(c'|y)] + \mathbb{E}[-\log \underbrace{D_{cls}(c|G(x, c))}_{\text{Generated data w.r.t. assigned label}}]$$

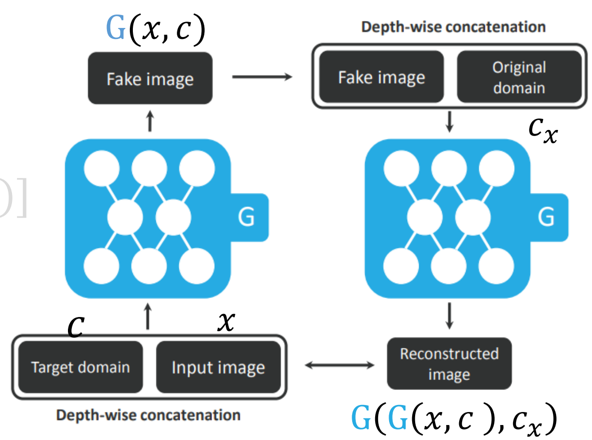
StarGAN

- ***Learning***

Overall objective function

$$G^* = \arg\min_G \max_D \mathcal{L}_{GAN}(G, D) + \mathcal{L}_{cls}(G, D) + \mathcal{L}_{cyc}(G)$$

Consistency Loss



- **Adversarial Loss**

$$\mathcal{L}_{GAN}(G, D) = \mathbb{E}[\log(1 - D(G(x, c)))] + \mathbb{E}[\log D(y)]$$

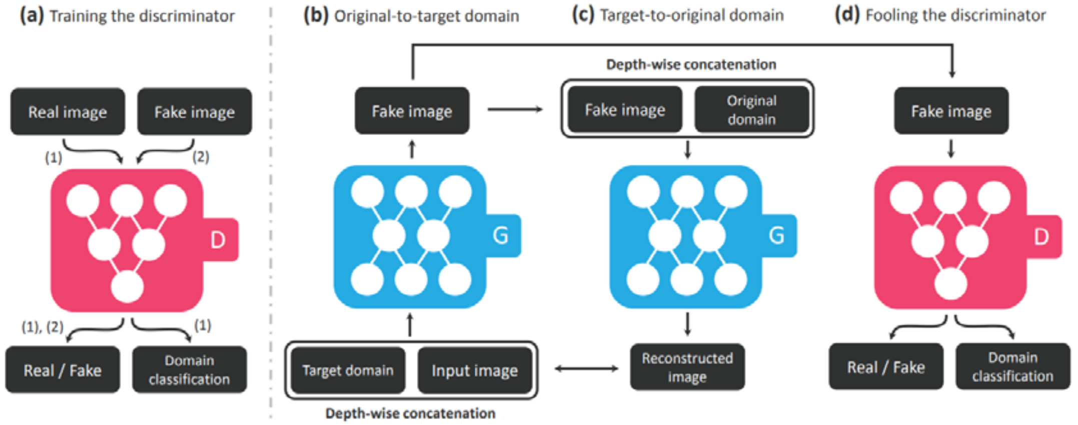
- **Domain Classification Loss (Disentanglement)**

$$\mathcal{L}_{cls}(G, D) = \mathbb{E}[-\log D_{cls}(c'|y)] + \mathbb{E}[-\log D_{cls}(c|G(x, c))]$$

- **Cycle Consistency Loss**

$$\mathcal{L}_{cyc}(G) = \mathbb{E}[\|G(G(x, c), c_x) - x\|_1]$$

StarGAN



- ***Learning***

Overall objective function

$$G^* = \arg\min_{G}\max_{D} \mathcal{L}_{GAN}(G, D) + \mathcal{L}_{cls}(G, D) + \mathcal{L}_{cyc}(G)$$

- **Adversarial Loss**

$$\mathcal{L}_{GAN}(G, D) = \mathbb{E}[\log(1 - D(G(x, c)))] + \mathbb{E}[\log D(y)]$$

- **Domain Classification Loss**

$$\mathcal{L}_{cls}(G, D) = \mathbb{E}[-\log D_{cls}(c'|y)] + \mathbb{E}[-\log D_{cls}(c|G(x, c))]$$

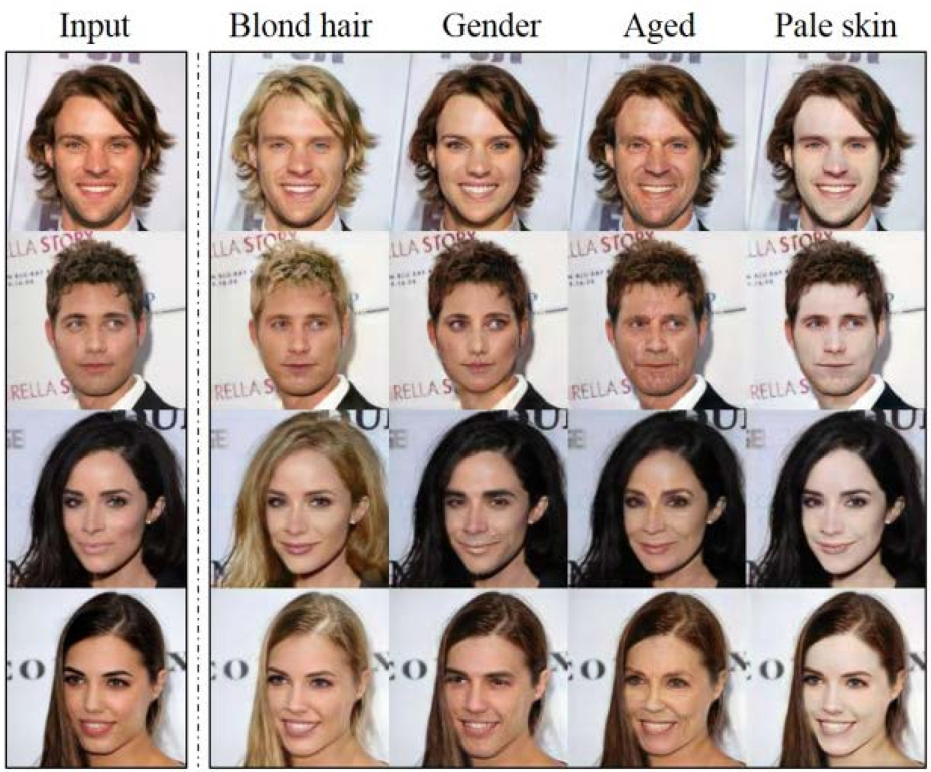
- **Cycle Consistency Loss**

$$\mathcal{L}_{cyc}(G) = \mathbb{E}[\|G(G(x, c\ ), c_x) - x\|_1]$$

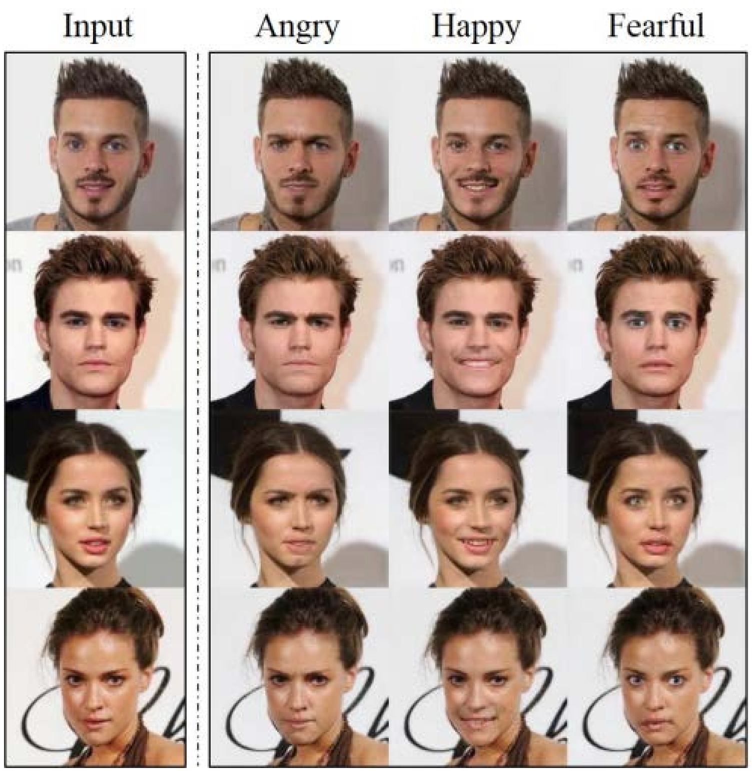
StarGAN

- Example results
  - StarGAN can be viewed as a representation disentanglement model, instead of an image translation one.

Multiple Domains



Multiple Domains



Github Page: https://github.com/yunjey/StarGAN

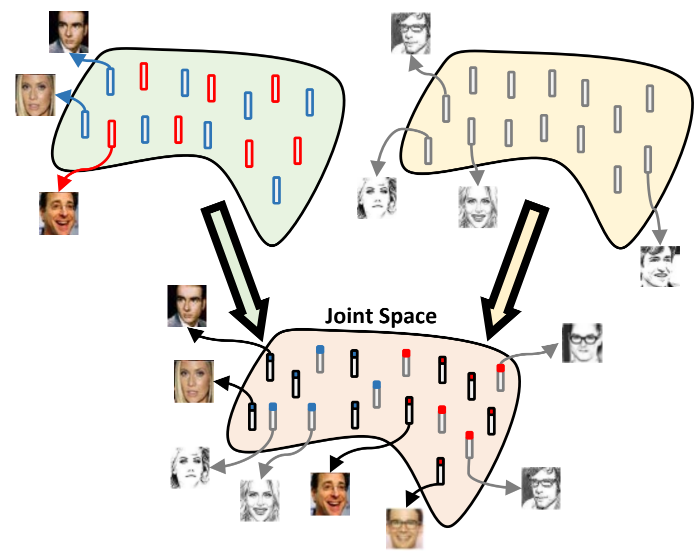
Choi et al. "StarGAN: Unified Generative Adversarial Networks for Multi-Domain Image-to-Image Translation." CVPR 2018

What to Cover in Part 4?

- Cross-Domain Image Translation
  - Pix2pix (CVPR'17): Pairwise cross-domain training data
  - CycleGAN/DualGAN/DiscoGAN: Unpaired cross-domain training data
  - UNIT (NIPS'17): Learning cross-domain image representation (with unpaired training data)
  - DTN (ICLR'17) : Learning cross-domain image representation (with unpaired training data)
  - Beyond image translation
- Representation Disentanglement
  - InfoGAN & AC-GAN: Representation disentanglement in a single domain
  - StarGAN (CVPR'18) : Image translation via representation disentanglement
  - CDRD (CVPR'18) : Cross-domain representation disentanglement and translation
- Final Remarks

Cross-Domain Representation Disnentanglement (CDRD)

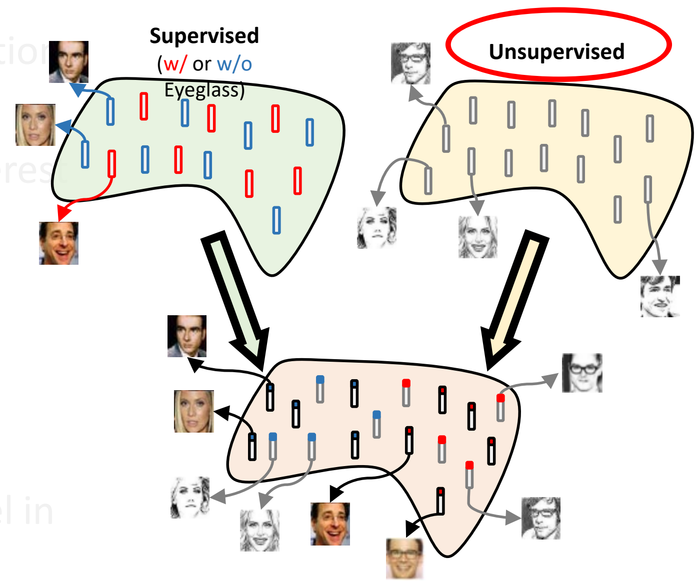
- ***Goal / Problem Setting***
  - Learning cross-domain joint disentangled representation
  - Single domain supervision
  - Cross-domain image translation with attribute of interest
- ***Idea***
  - Bridge the domain gap across domains
  - Auxiliary attribute classifier on Discriminator
  - Semantics of disentangled factor is learned from label in source domain



Wang et al., Detach and Adapt: Learning Cross-Domain Disentangled Deep Representation". *CVPR 2018*

CDRD

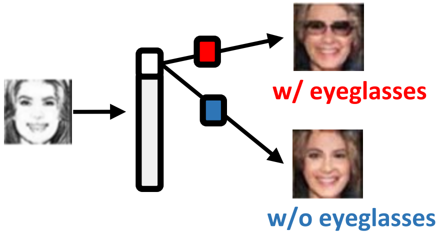
- ***Goal / Problem Setting***
  - Learning cross-domain joint disentangled representatio
  - Single domain supervision
  - Cross-domain image translation with attribute of interes



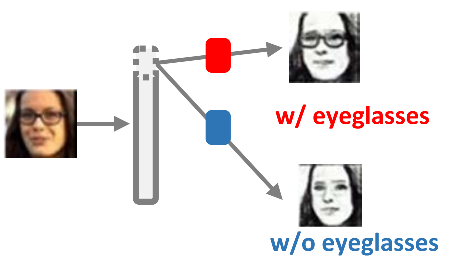
- ***Idea***
  - Bridge the domain gap across domains
  - Auxiliary attribute classifier on Discriminator
  - Semantics of disentangled factor is learned from label in source domain

CDRD

- ***Goal / Problem Setting***
  - Learning cross-domain joint disentangled representation
  - Single domain supervision
  - Cross-domain image translation with attribute of interest

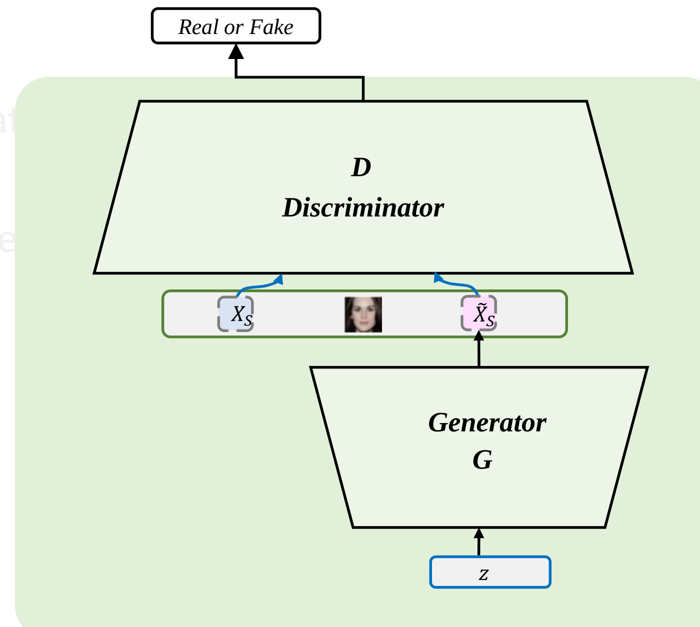


- ***Idea***
  - Bridge the domain gap across domains
  - Auxiliary attribute classifier on Discriminator
  - Semantics of disentangled factor is learned from label in source domain



CDRD

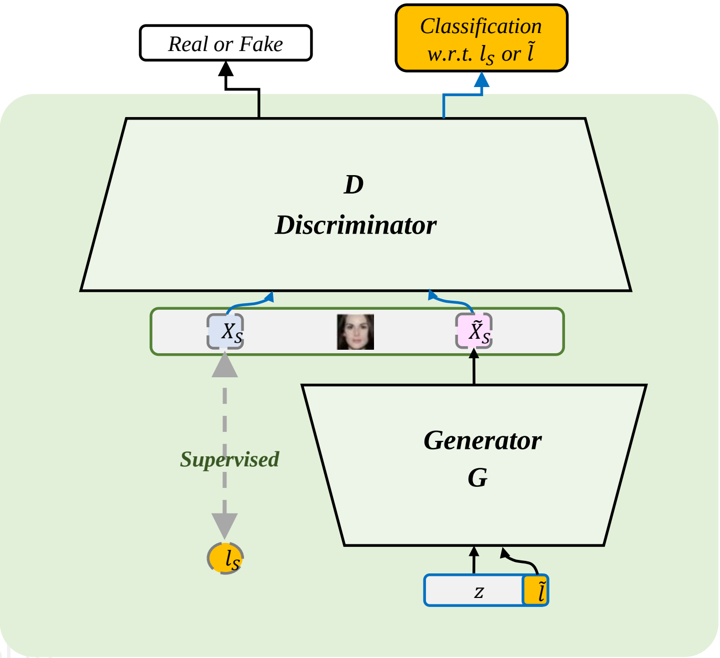
- ***Goal / Problem Setting***
  - Learning cross-domain joint disentangled representat
  - Single domain supervision
  - Cross-domain image translation with attribute of inte



- ***Idea***
  - Based on GAN
  - Auxiliary attribute classifier on Discriminator
  - Bridge the domain gap across domains
  - Semantics of disentangled factor is learned from label in source domain

CDRD

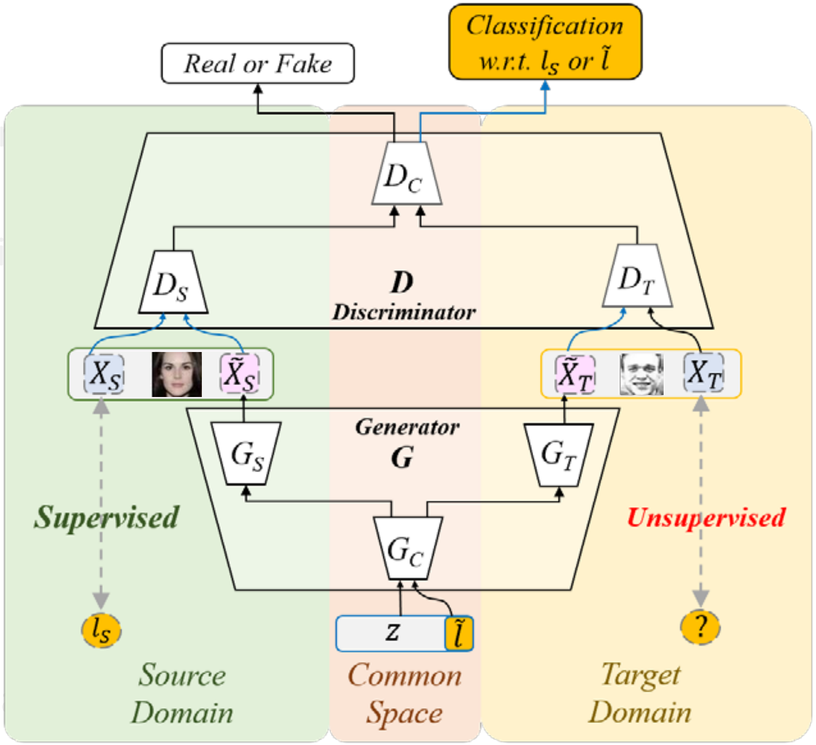
- ***Goal / Problem Setting***
  - Learning cross-domain joint disentangled representat
  - Single domain supervision
  - Cross-domain image translation with attribute of inte



- ***Idea***
  - Based on GAN
  - Auxiliary attribute classifier as Discriminator
  - Bridge the domain gap across domains
  - Semantics of disentangled factor is learned from label in source domain

CDRD

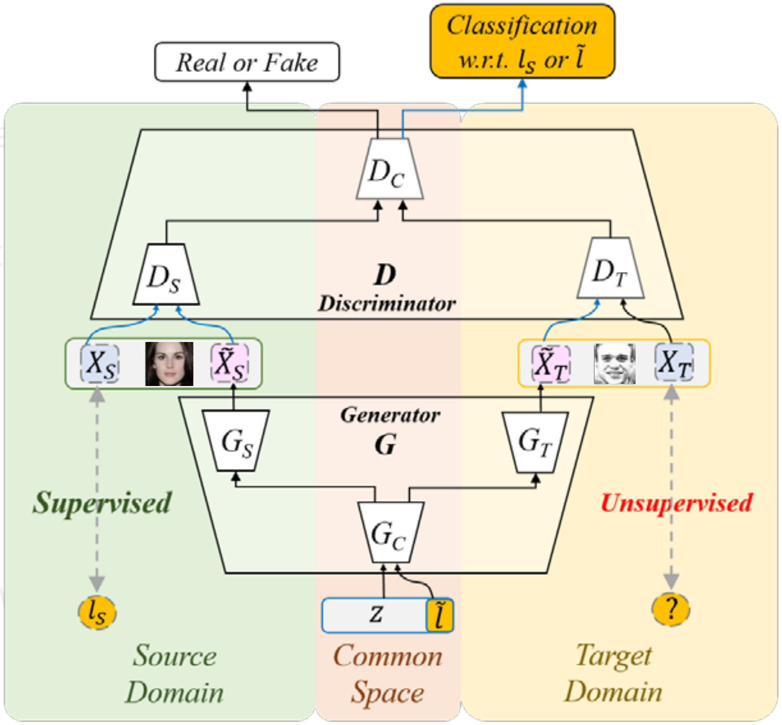
- ***Goal / Problem Setting***
    - Learning cross-domain joint disentangled represe
    - Single domain supervision
    - Cross-domain image translation with attribute of i



- ***Idea***
    - Based on GAN
    - Auxiliary attribute classifier on Discriminator
    - Bridge the domain gap
      with division of high and low-level layers
    - Semantics of disentangled factor is learned from l
      source domain

CDRD

- ***Goal / Problem Setting***
  - Learning cross-domain joint disentangled representa
  - Single domain supervision
  - Cross-domain image translation with attribute of int
- ***Idea***
  - Based on GAN
  - Auxiliary attribute classifier on Discriminator
  - Bridge the domain gap with division of high- and low level layer
  - **Semantics** of disentangled factor is learned from label info in source domain

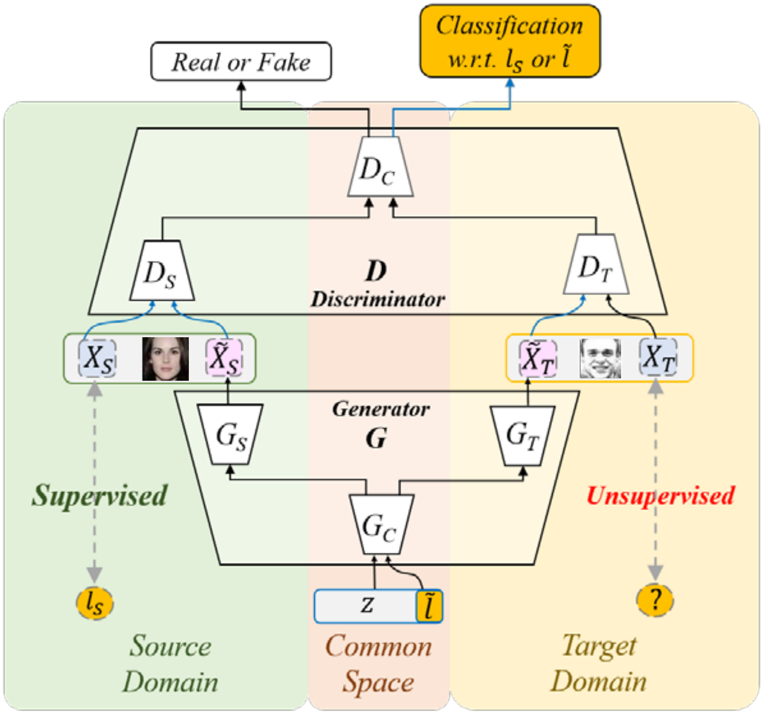


CDRD

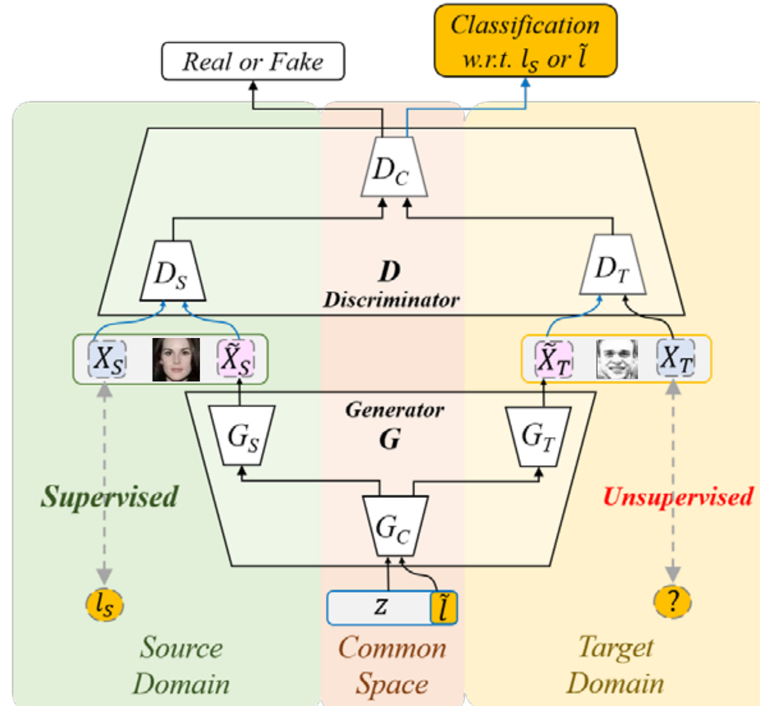
- ***Learning***

  Overall objective function

$$G^* = \arg\min_{G}\max_{D} \mathcal{L}_{GAN}(G, D) + \mathcal{L}_{cls}(G, D)$$



CDRD



- ***Learning***

Overall objective function

$$G^* = \arg\min_{G}\max_{D} \mathcal{L}_{GAN}(G, D) + \mathcal{L}_{cls}(G, D)$$

Adversarial Loss

$$\mathcal{L}_{GAN}(G, D) = \mathcal{L}_{GAN}^{S}(G, D) + \mathcal{L}_{GAN}^{T}(G, D)$$

$$\mathcal{L}_{GAN}^{S}(G, D) = \mathbb{E}[\log(D_C(D_S(X_S)))] + \mathbb{E}\left[\log\left(1 - D_C(D_S(\tilde{X}_S))\right)\right]$$

$$\mathcal{L}_{GAN}^{T}(G, D) = \mathbb{E}[\log(D_C(D_T(X_T)))] + \mathbb{E}\left[\log\left(1 - D_C(D_T(\tilde{X}_T))\right)\right]$$

CDRD

- ***Learning***

Overall objective function

$$G^* = \arg\min_{G}\max_{D} \mathcal{L}_{GAN}(G, D) + \mathcal{L}_{cls}(G, D)$$

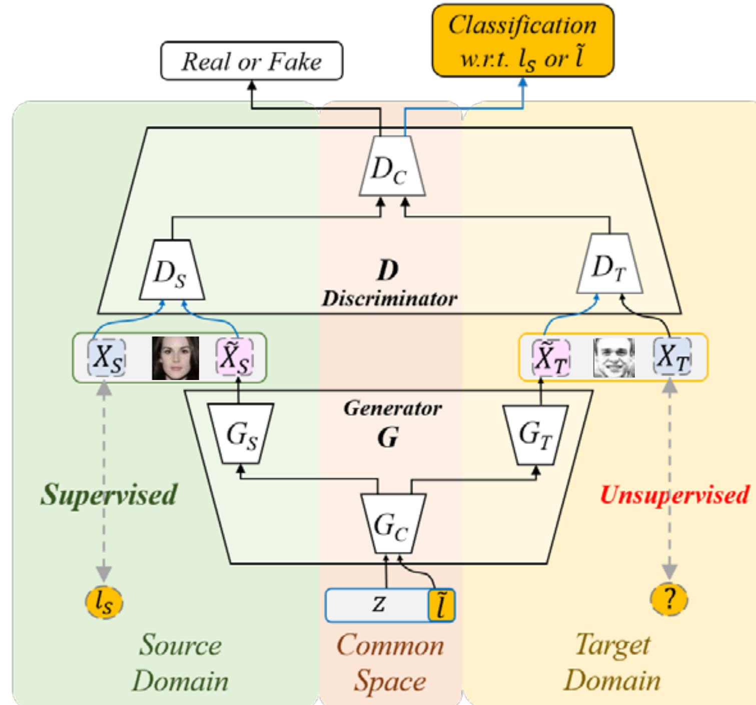
Adversarial Loss

$$\mathcal{L}_{GAN}(G, D) = \mathcal{L}_{GAN}^{S}(G, D) + \mathcal{L}_{GAN}^{T}(G, D)$$

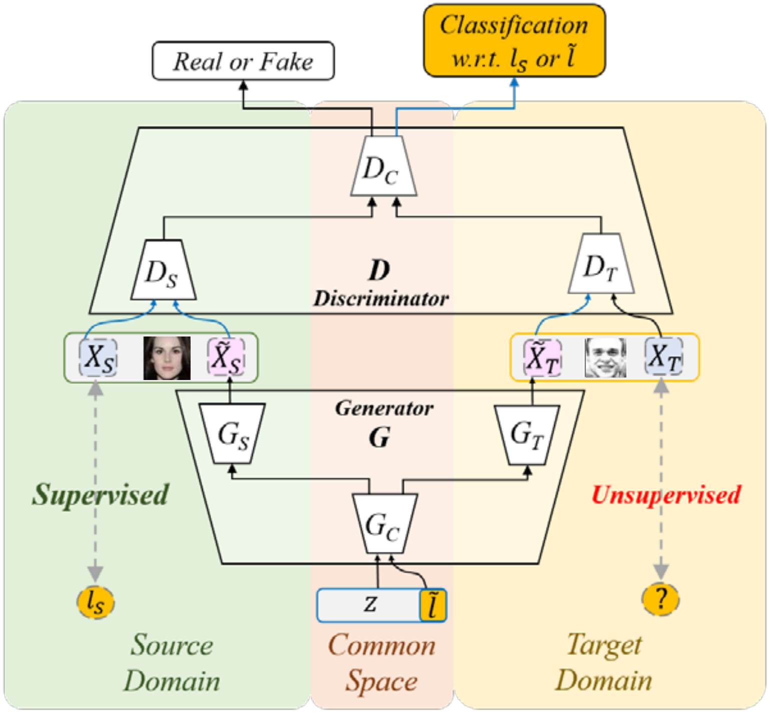
$$\mathcal{L}_{GAN}^{S}(G, D) = \mathbb{E}[\log(D_C(D_S(X_S)))] + \mathbb{E}\left[\log\left(1 - D_C(D_S(\tilde{X}_S))\right)\right]$$

$$\mathcal{L}_{GAN}^{T}(G, D) = \mathbb{E}[\log(D_C(D_T(X_T)))] + \mathbb{E}\left[\log\left(1 - D_C(D_T(\tilde{X}_T))\right)\right]$$

Real



CDRD



- ***Learning***

Overall objective function

$$G^* = \arg\min_G \max_D \mathcal{L}_{GAN}(G, D) + \mathcal{L}_{cls}(G, D)$$

Adversarial Loss

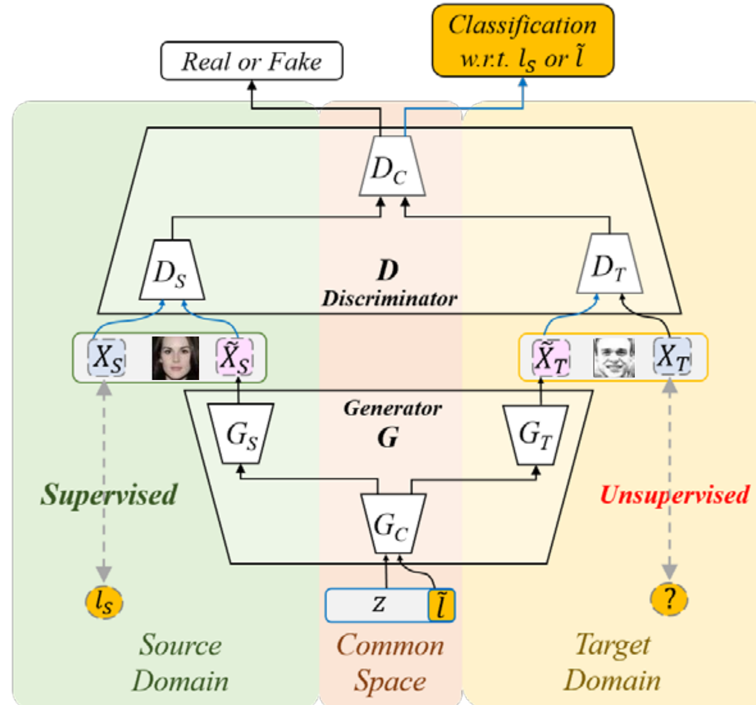
$$\mathcal{L}_{GAN}(G, D) = \mathcal{L}_{GAN}^S(G, D) + \mathcal{L}_{GAN}^T(G, D)$$

$$\mathcal{L}_{GAN}^S(G, D) = \mathbb{E}[\log(D_C(D_S(X_S)))] + \mathbb{E}\left[\log\left(1 - D_C(D_S(\tilde{X}_S))\right)\right]$$

$$\mathcal{L}_{GAN}^T(G, D) = \mathbb{E}[\log(D_C(D_T(X_T)))] + \mathbb{E}\left[\log\left(1 - D_C(D_T(\tilde{X}_T))\right)\right]$$

Generated

CDRD



- ***Learning***

Overall objective function

$$G^* = \arg\min_{G}\max_{D} \mathcal{L}_{GAN}(G, D) + \mathcal{L}_{cls}(G, D)$$

Adversarial Loss

$$\mathcal{L}_{GAN}(G, D) = \mathcal{L}_{GAN}^{S}(G, D) + \mathcal{L}_{GAN}^{T}(G, D)$$

$$\mathcal{L}_{GAN}^{S}(G, D) = \mathbb{E}[\log(D_C(D_S(X_S)))] + \mathbb{E}[\log(1 - D_C(D_S(\tilde{X}_S)))]$$

$$\mathcal{L}_{GAN}^{T}(G, D) = \mathbb{E}[\log(D_C(D_T(X_T)))] + \mathbb{E}[\log(1 - D_C(D_T(\tilde{X}_T)))]$$

Disentangle Loss

$$\mathcal{L}_{cls}(G, D) = \mathcal{L}_{cls}^{S}(G, D) + \mathcal{L}_{cls}^{T}(G, D)$$

$$\mathcal{L}_{cls}^{S}(G, D) = \mathbb{E}[\log P(l = \tilde{l} | \tilde{X}_S)] + \mathbb{E}[\log P(l = l_S | X_S)]$$ **AC-GAN**

$$\mathcal{L}_{cls}^{T}(G, D) = \mathbb{E}[\log P(l = \tilde{l} | \tilde{X}_T)]$$

CDRD

- ***Learning***

Overall objective function

$$G^* = \arg\min_G \max_D \mathcal{L}_{GAN}(G, D) + \mathcal{L}_{cls}(G, D)$$

Adversarial Loss

$$\mathcal{L}_{GAN}(G, D) = \mathcal{L}^S_{GAN}(G, D) + \mathcal{L}^T_{GAN}(G, D)$$

$$\mathcal{L}^S_{GAN}(G, D) = \mathbb{E}[\log(D_C(D_S(X_S)))] + \mathbb{E}\left[\log\left(1 - D_C(D_S(\tilde{X}_S))\right)\right]$$

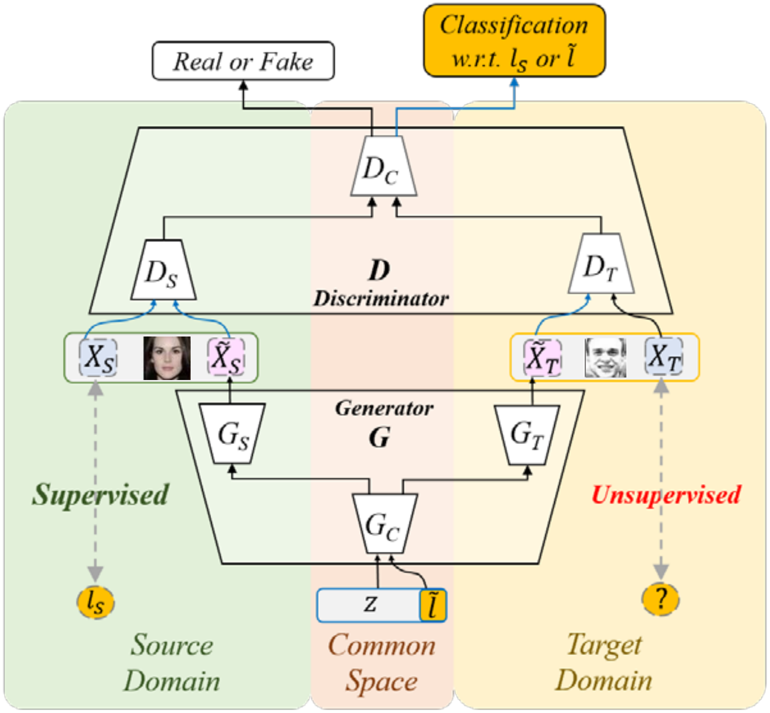
$$\mathcal{L}^T_{GAN}(G, D) = \mathbb{E}[\log(D_C(D_T(X_T)))] + \mathbb{E}\left[\log\left(1 - D_C(D_T(\tilde{X}_T))\right)\right]$$

Disentangle Loss

$$\mathcal{L}_{cls}(G, D) = \mathcal{L}^S_{cls}(G, D) + \mathcal{L}^T_{cls}(G, D)$$

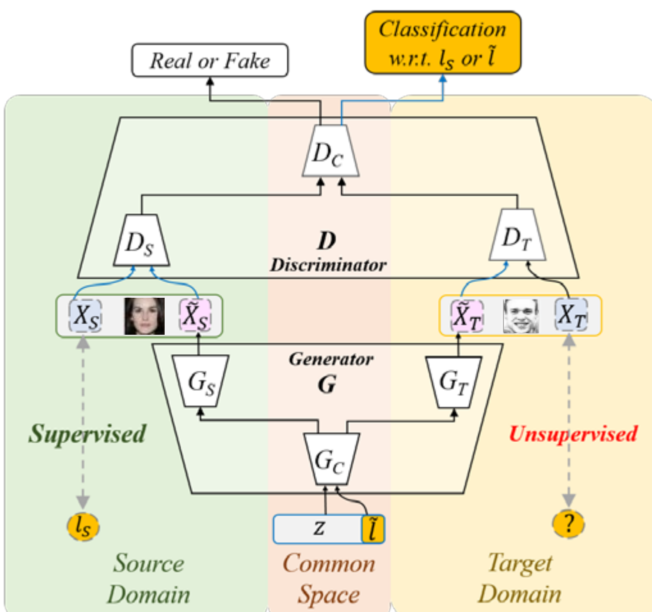
$$\mathcal{L}^S_{cls}(G, D) = \mathbb{E}\left[\log P(l = \tilde{l}|\tilde{X}_S)\right] + \mathbb{E}[\log P(l = l_S|X_S)]$$

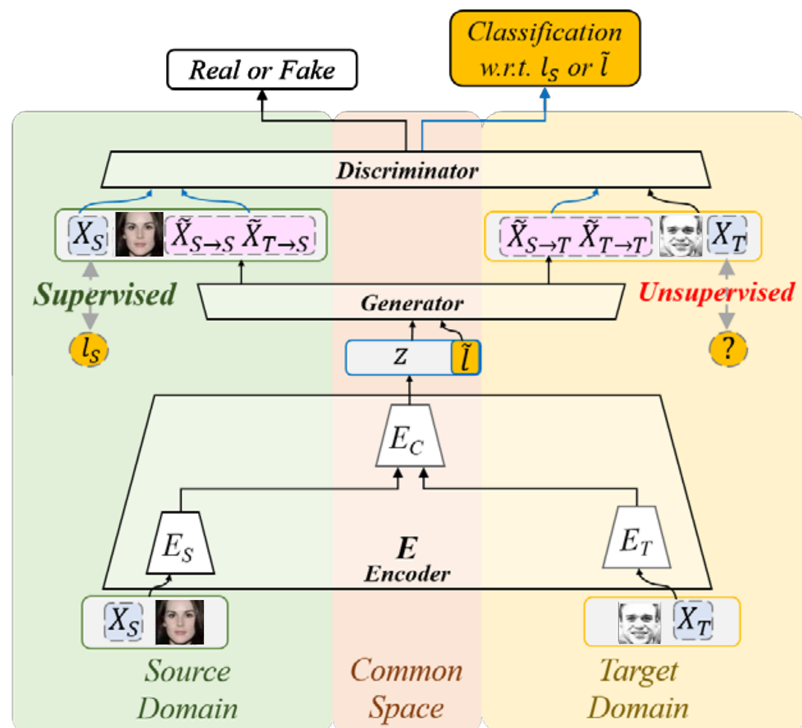
$$\mathcal{L}^T_{cls}(G, D) = \mathbb{E}\left[\log P(l = \tilde{l}|\tilde{X}_T)\right]$$ **InfoGAN**



CDRD

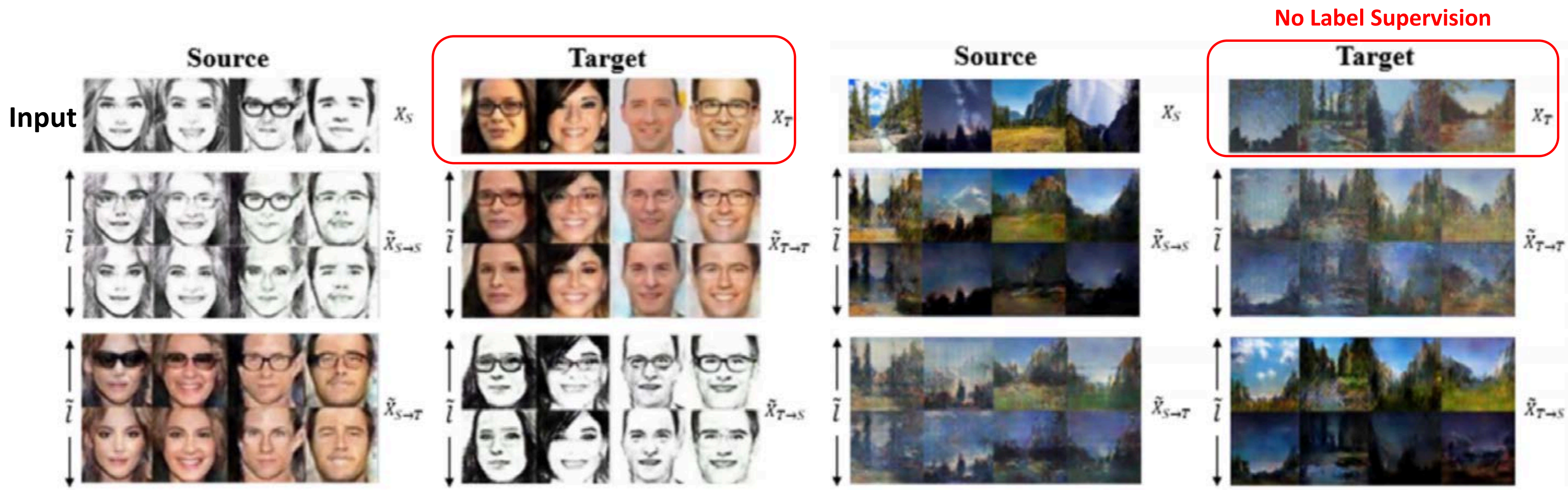
- Add an additional encoder
  - **Input: ~~Gaussian Noise~~** Image
  - Image translation with attribute of interest





CDRD

- ***Experiment results***



Wang et al., Detach and Adapt: Learning Cross-Domain Disentangled Deep Representation". *CVPR 2018*

CDRD

- **Experiment results**

Cross-Domain Classification

Digits

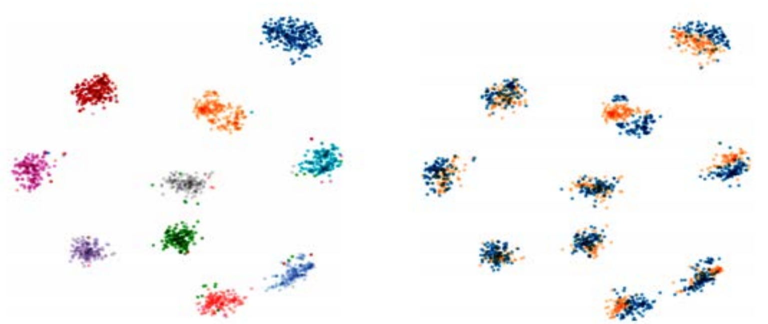
	GFK	JDA	CVPR '13 SA	CVPR '14 TJM	PAMI '17 SCA	CVPR '17 JGSA	ICCV '15 DC	ICML '15 GR	NIPS '16 CoGAN	CVPR '17 ADDA	ECCV '16 DRCN	arXiv '16 ADGAN	CDRD
M → U	67.22	67.28	67.78	63.28	65.11	80.44	79.10	77.10	91.20	89.40	91.80	92.50	**95.05**
U → M	46.45	59.65	48.80	52.25	48.00	68.15	66.50	73.00	89.10	90.10	73.67	90.80	**94.35**
Average	56.84	63.47	58.29	57.77	56.55	74.30	72.80	75.05	90.15	89.75	82.74	91.65	**94.70**

Face

Domain	$\tilde{l}$	NIPS '16 CoGAN	NIPS '17 UNIT	CDRD	E-CDRD
sketch ($\mathcal{S}$)	smiling	89.50	90.10	90.19	90.01
photo ($\mathcal{T}$)	-	78.90	81.04	**87.61**	**88.28**
sketch ($\mathcal{S}$)	glasses	96.63	97.65	97.06	97.19
photo ($\mathcal{T}$)	-	81.01	79.89	**94.49**	**94.84**

Scene

Domain	$\tilde{l}$	NIPS '16 CoGAN	NIPS '17 UNIT	CDRD	E-CDRD
photo ($\mathcal{S}$)	night	98.04	98.49	97.06	97.14
paint ($\mathcal{T}$)	-	65.18	67.81	**84.21**	**85.58**
photo ($\mathcal{S}$)	season	86.74	85.64	86.21	88.92
paint ($\mathcal{T}$)	-	65.94	66.09	**79.87**	**80.03**



(a) Colorize w.r.t. **class 0-9**. (b) Colorize w.r.t. **source/target**.

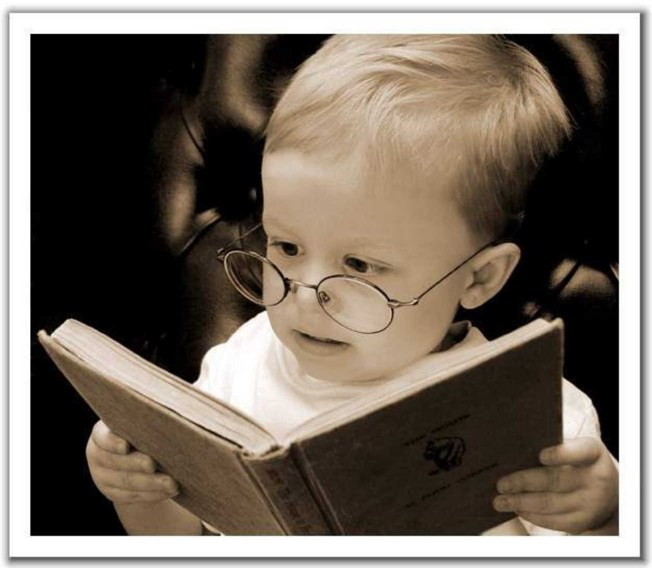
Figure: t-SNE for digit

Comparisons

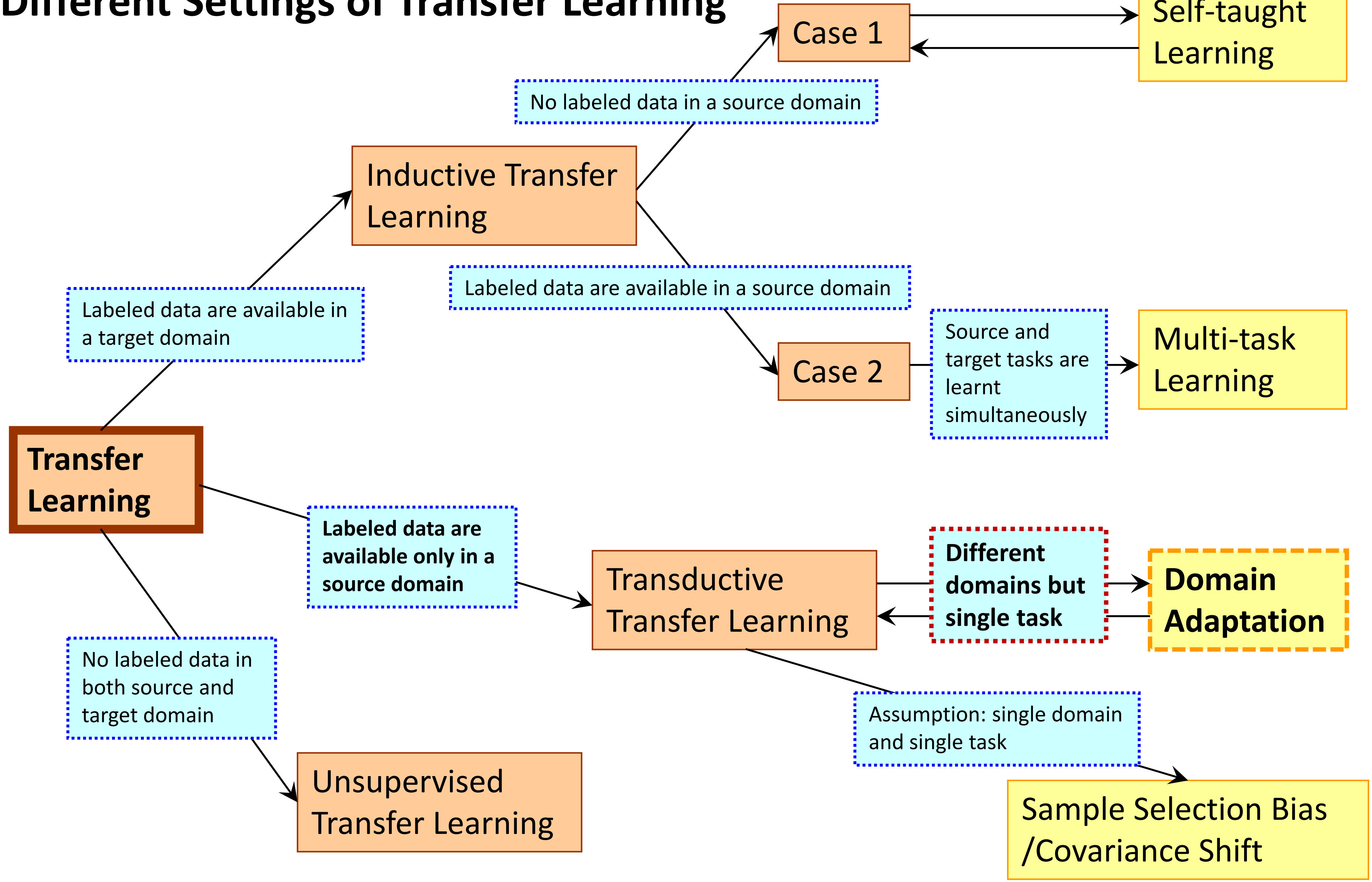
	Cross-Domain Image Translation				Representation Disentanglement	
	Unpaired Training Data	Multi-domains	Bi-direction	Joint Representation	Unsupervised	Interpretability of disentangled factor
Pix2pix	X	X	X	X	Cannot disentangle representation	
CycleGAN	O	X	O	X		
StarGAN	O	O	O	X		
UNIT	O	X	O	O		
DTN	O	X	X	O		
infoGAN	Cannot translate image across domains				O	X
AC-GAN					X	O
CDRD (Ours)	O	O	O	O	Partially	O

What Have We Covered in Today's Lecture?

- Transfer Learning
  - Introduction to Transfer Learning
  - Challenges in Transfer Learning
  - TL for Visual Analysis
  - TL for Visual Synthesis and Manipulation

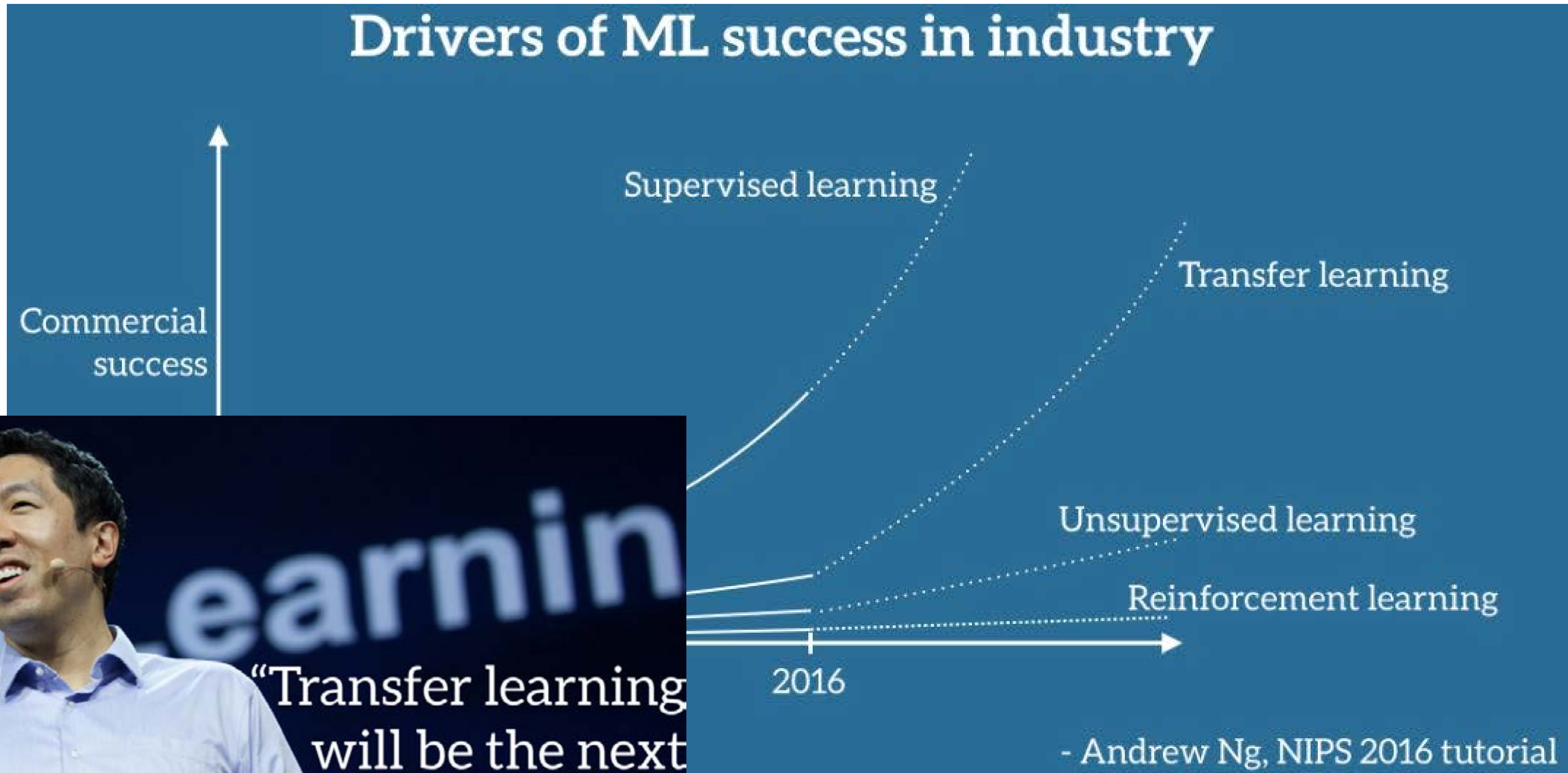


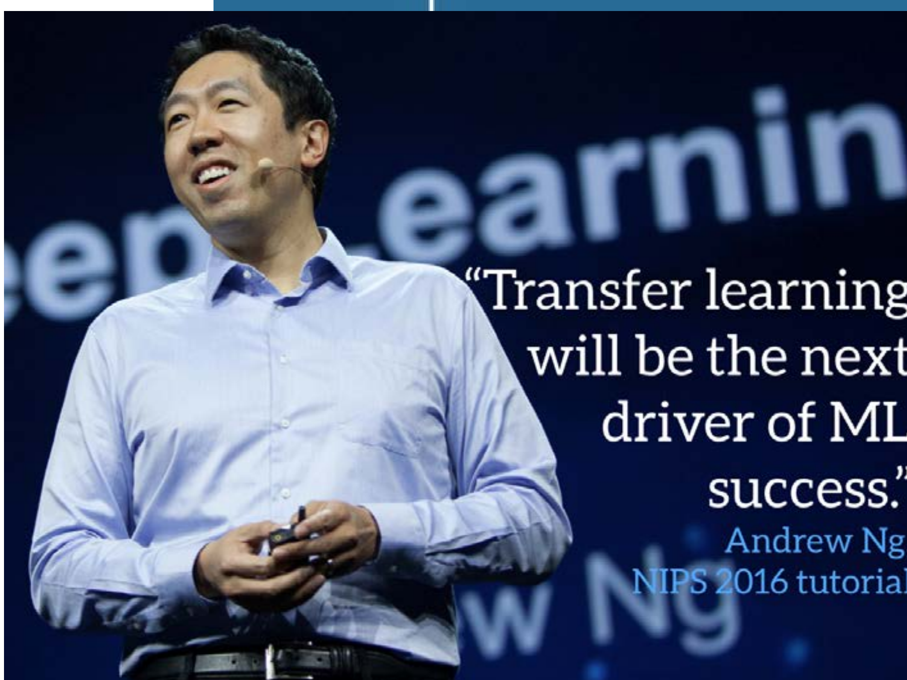
Different Settings of Transfer Learning



S. J. Pan and Q. Yang, "A survey on transfer learning," IEEE TKDE, 2010.

Transfer Learning as a Powerful Solution





Resources – where to learn more

- Awesome Computer Vision, Awesome Deep Vision
  - A curated list of awesome computer vision resources
- Computer Vision Foundation
  - Free access to research materials and CVPR/ICCV papers
- Videolectures and ML&CV Talks
  - Lectures, Keynotes, Panel Discussions
- OpenCV – C++/Python/Java

Vision & Learning Lab at NTU

http://vllab.ee.ntu.edu.tw/

Thank You!