DRIT:
Diverse Image-to-Image Translation via Disentangled Representations

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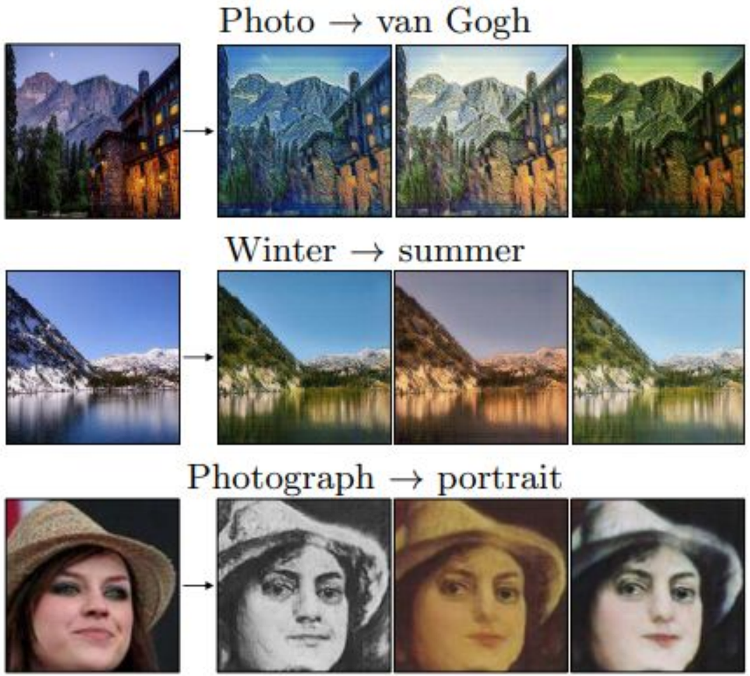
ECCV 2018

Sungman Cho

Introduction

Introduction



"Generate diverse outputs with unpaired training data."

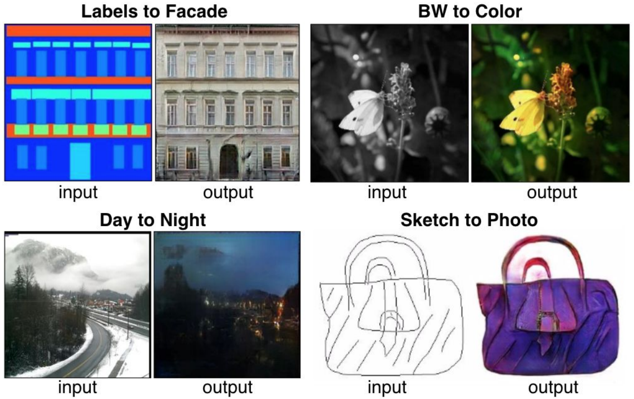
Challenges

- Aligned training image pairs are either difficult to collect or do not exist. (Pix2Pix)

Not unpair

- Many such mappings are inherently multimodal.
  A single input may correspond to multiple possible outputs.
  (CycleGAN, DiscoGAN, UNIT)

Not diverse



Pix2Pix


CycleGAN

Challenges

- **Aligned training image pairs are either difficult to collect or do not exist. (Pix2Pix)**

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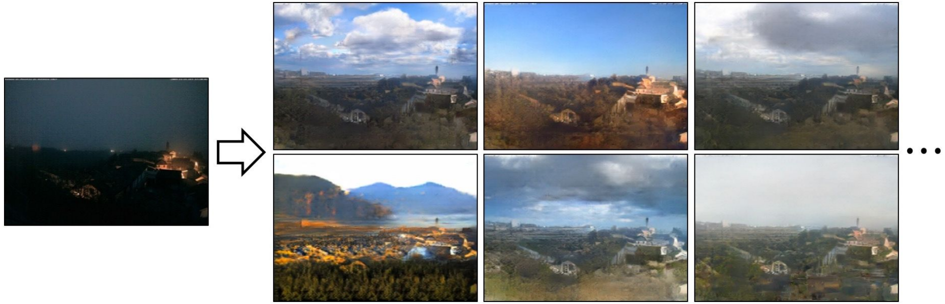
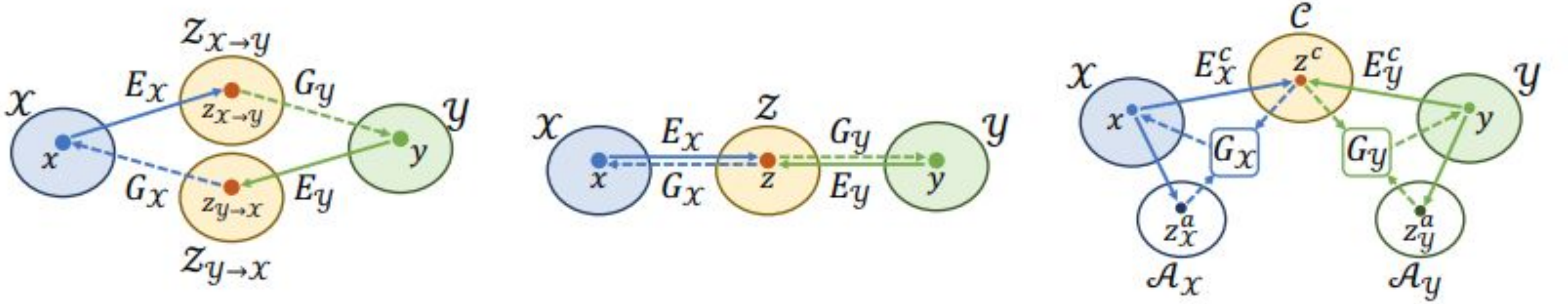


BicycleGAN

CycleGAN

Related Works

Method	Pix2Pix [18]	CycleGAN [46]	UNIT [26]	BicycleGAN [47]	Ours
Unpaired	-	✓	✓	-	✓
Multimodal	-	-	-	✓	✓



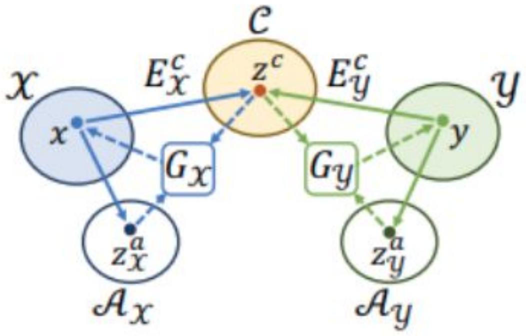
(a) CycleGAN [46] (b) UNIT [26] (c) Ours

Introduction

- We propose to **embed images onto two spaces**:

  1) A domain-invariant content space

  2) A domain-specific attribute space



(c) Ours

“Generate diverse outputs with unpaired training data.”

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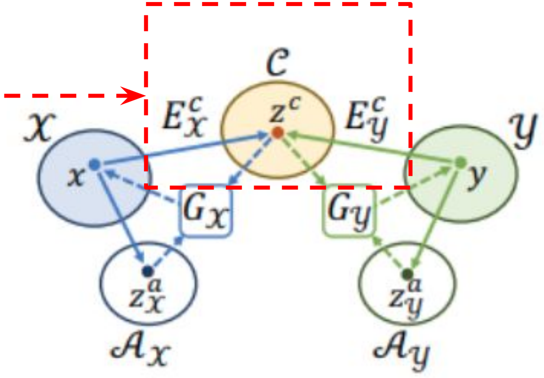

(c) Ours

“Generate diverse outputs with unpaired training data.”

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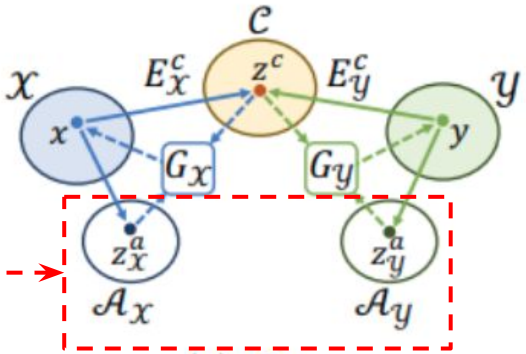
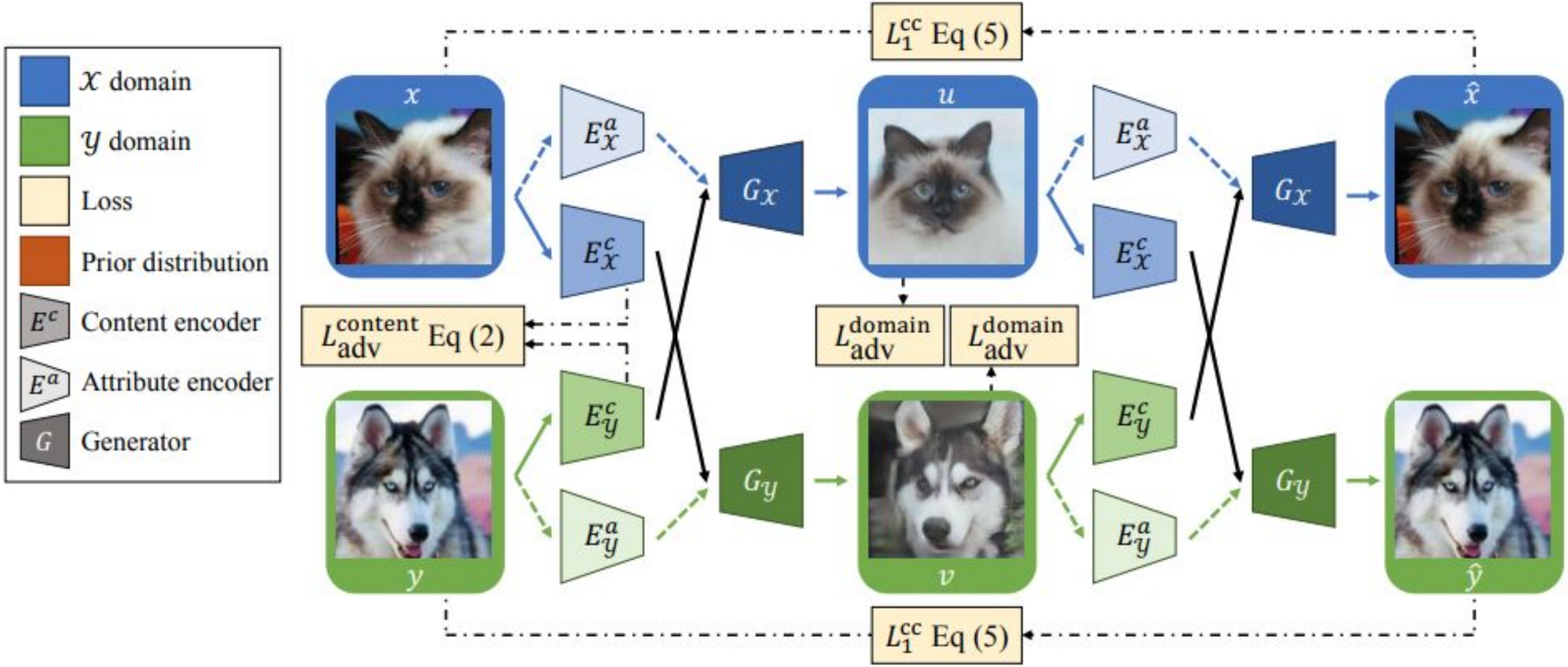


(c) Ours

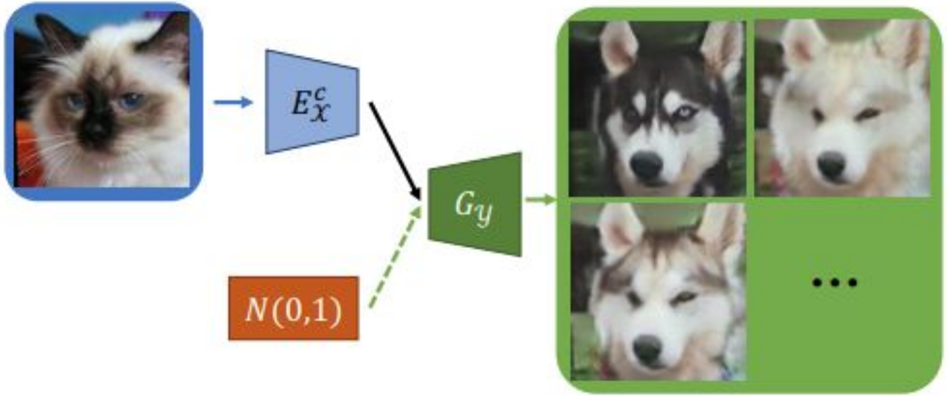
“Generate diverse outputs with unpaired training data.”

DRIT (Training Phase)

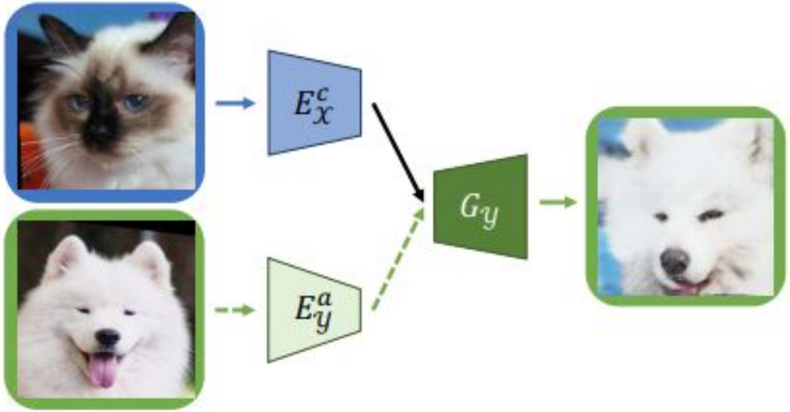


(a) Training with unpaired images

DRIT (Test Phase)



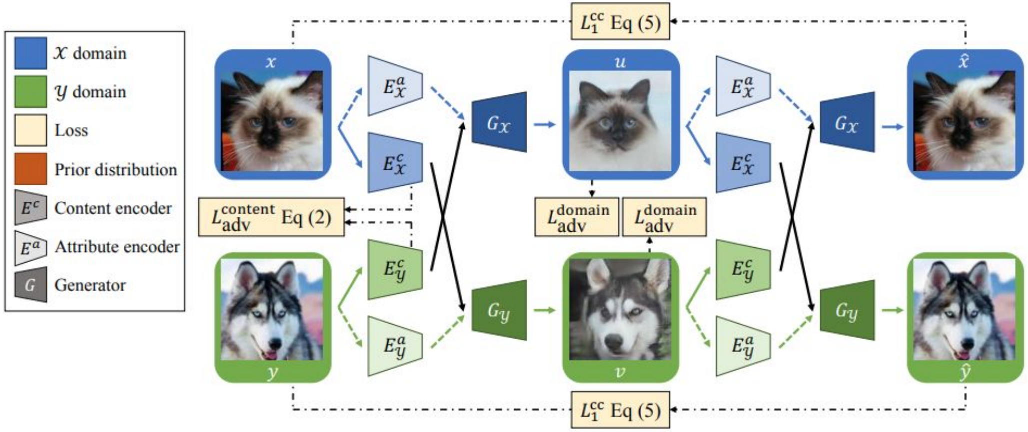
(b) Testing with random attributes



(c) Testing with a given attribute

Methods

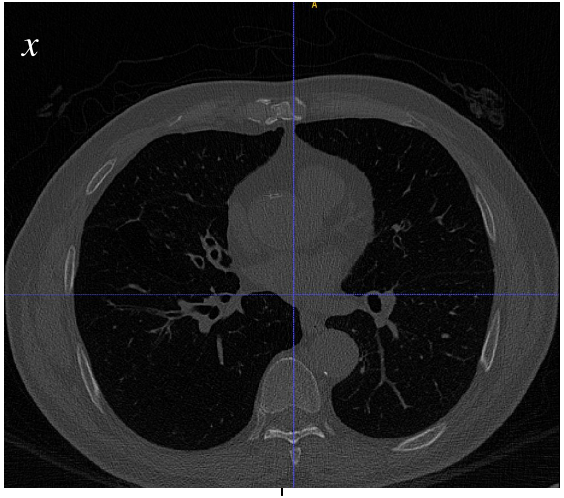
DRIT with Losses

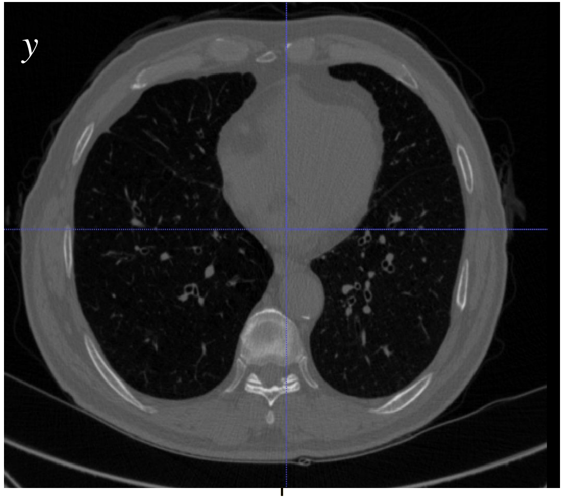


$$\min_{G,E^c,E^a} \max_{D,D^c} \quad \lambda_{adv}^{content} L_{adv}^{c} + \lambda_1^{cc} L_1^{cc} + \lambda_{adv}^{domain} L_{adv}^{domain} + \lambda_1^{recon} L_1^{recon}$$
$$+\lambda_1^{latent} L_1^{latent} + \lambda_{KL} L_{KL}$$

- **Content adversarial loss**
- **Cross-cycle consistency loss**
- **Domain adversarial loss**
- **Self-reconstruction loss**
- **KL loss**
- **Latent regression loss**

In our case ?





Attribute x

Low Dose

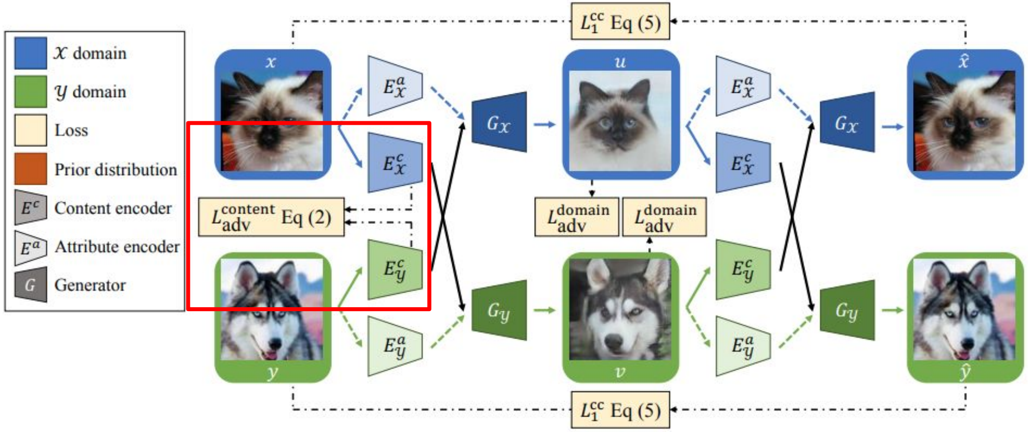
Attribute y

Standard Dose

Shared Content c

CT

DRIT : Content adversarial loss



$$\min_{G,E^c,E^a} \max_{D,D^c} \boxed{\lambda_{\text{adv}}^{\text{content}} L_{\text{adv}}^{c}} + \lambda_1^{\text{cc}} L_1^{\text{cc}} + \lambda_{\text{adv}}^{\text{domain}} L_{\text{adv}}^{\text{domain}} + \lambda_1^{\text{recon}} L_1^{\text{recon}}$$
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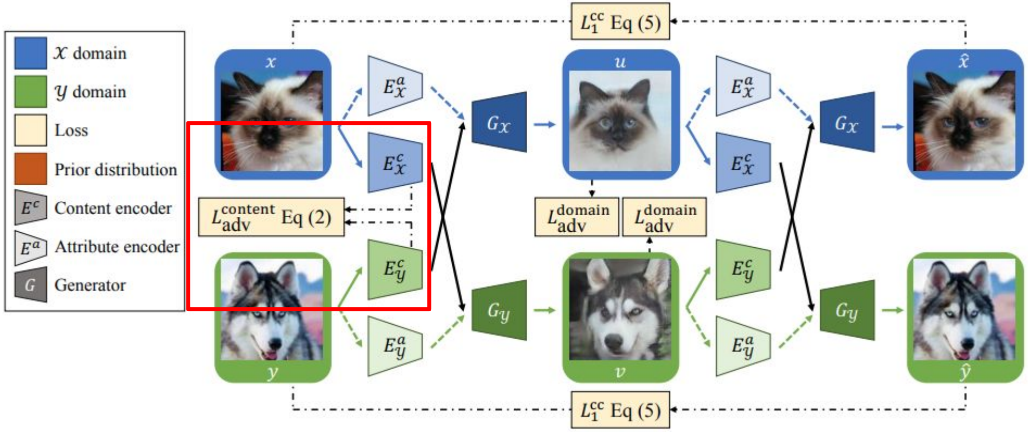
“Disentangle Content and Attribute Representations”

DRIT : Content adversarial loss



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$$+\lambda_1^{\text{latent}} L_1^{\text{latent}} + \lambda_{\text{KL}} L_{\text{KL}}$$

$$L_{\text{adv}}^{\text{content}}(E_{\mathcal{X}}^c, E_{\mathcal{Y}}^c, D^c) = \mathbb{E}_x[\frac{1}{2}\log D^c(E_{\mathcal{X}}^c(x)) + \frac{1}{2}\log(1 - D^c(E_{\mathcal{X}}^c(x)))]$$
$$+ \mathbb{E}_y[\frac{1}{2}\log D^c(E_{\mathcal{Y}}^c(y)) + \frac{1}{2}\log(1 - D^c(E_{\mathcal{Y}}^c(y)))]$$

DRIT : Content adversarial loss

- **Content Discriminator**

  aims to distinguish the domain of the encoded features

- **Content Encoder**

  learn to produce encoded content whose domain can't be distinguished by discriminator

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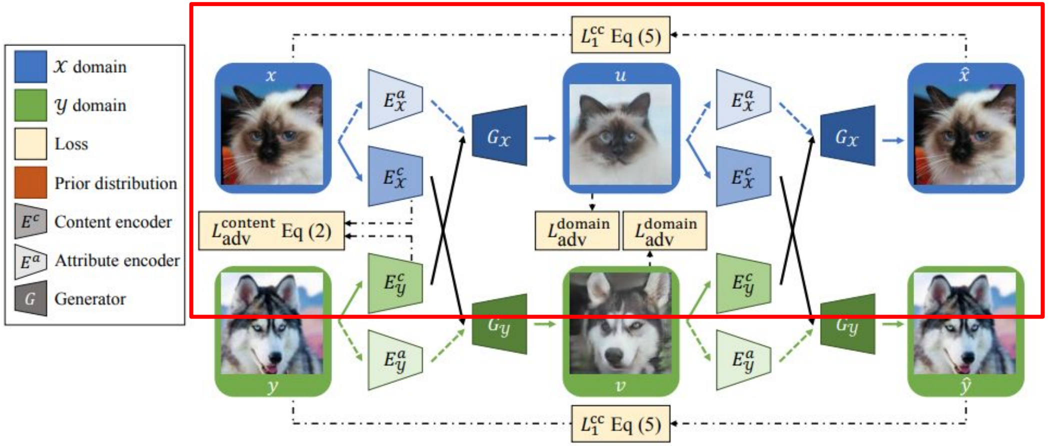
$$
\begin{aligned}
L_{\text{adv}}^{\text{content}}(E_{\mathcal{X}}^c, E_{\mathcal{Y}}^c, D^c) = \mathbb{E}_x[\frac{1}{2}\log D^c(E_{\mathcal{X}}^c(x)) + \frac{1}{2}\log(1 - D^c(E_{\mathcal{X}}^c(x)))] \\
+ \mathbb{E}_y[\frac{1}{2}\log D^c(E_{\mathcal{Y}}^c(y)) + \frac{1}{2}\log(1 - D^c(E_{\mathcal{Y}}^c(y)))]
\end{aligned}
$$

DRIT : Cross-cycle Consistency Loss



$$\min_{G,E^c,E^a} \max_{D,D^c} \; \lambda_{adv}^{content} L_{adv}^{c} + \boxed{\lambda_1^{cc} L_1^{cc}} + \lambda_{adv}^{domain} L_{adv}^{domain} + \lambda_1^{recon} L_1^{recon} + \lambda_1^{latent} L_1^{latent} + \lambda_{KL} L_{KL}$$

- **Content adversarial loss**
- **Cross-cycle consistency loss**
- **Domain adversarial loss**
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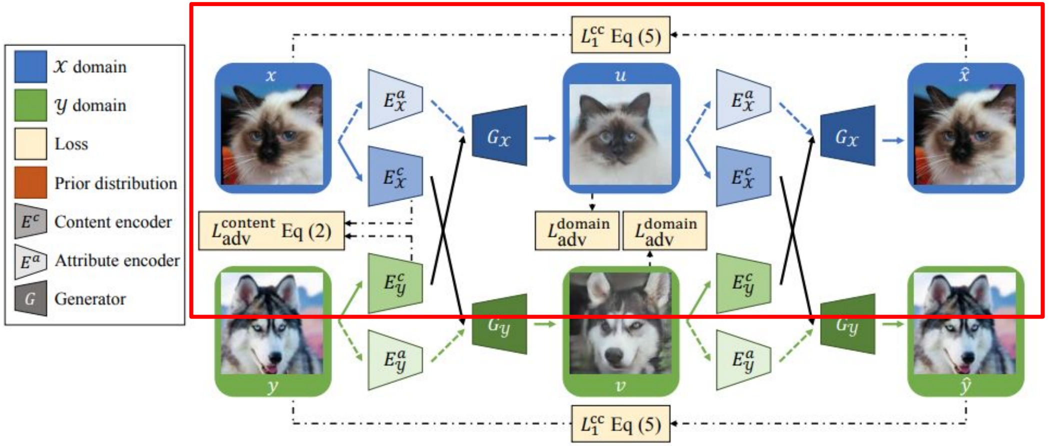
“Combining a content representation from an arbitrary image and an attribute representation from an image of target domain”

DRIT : Cross-cycle Consistency Loss



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$$\begin{aligned} L_1^{cc}(G_{\mathcal{X}}, G_{\mathcal{Y}}, E_{\mathcal{X}}^c, E_{\mathcal{Y}}^c, E_{\mathcal{X}}^a, E_{\mathcal{Y}}^a) = \mathbb{E}_{x,y}[&\|G_{\mathcal{X}}(E_{\mathcal{Y}}^c(v), E_{\mathcal{X}}^a(u)) - x\|_1 \\ &+\|G_{\mathcal{Y}}(E_{\mathcal{X}}^c(u), E_{\mathcal{Y}}^a(v)) - y\|_1], \end{aligned}$$

where $u = G_{\mathcal{X}}(E_{\mathcal{Y}}^c(y)), E_{\mathcal{X}}^a(x))$ and $v = G_{\mathcal{Y}}(E_{\mathcal{X}}^c(x)), E_{\mathcal{Y}}^a(y))$.

DRIT : Cross-cycle Consistency Loss

- **Forward Translation & Backward translation.**

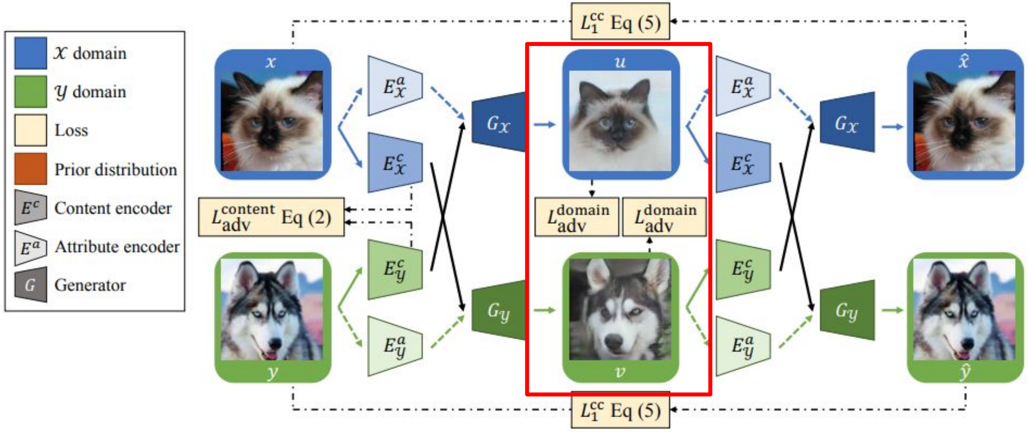
  Exploit the disentangled content and attribute representation

---

$$L_1^{cc}(G_{\mathcal{X}}, G_{\mathcal{Y}}, E_{\mathcal{X}}^c, E_{\mathcal{Y}}^c, E_{\mathcal{X}}^a, E_{\mathcal{Y}}^a) = \mathbb{E}_{x,y}[\|G_{\mathcal{X}}(E_{\mathcal{Y}}^c(v), E_{\mathcal{X}}^a(u)) - x\|_1 + \|G_{\mathcal{Y}}(E_{\mathcal{X}}^c(u), E_{\mathcal{Y}}^a(v)) - y\|_1],$$

where $u = G_{\mathcal{X}}(E_{\mathcal{Y}}^c(y)), E_{\mathcal{X}}^a(x))$ and $v = G_{\mathcal{Y}}(E_{\mathcal{X}}^c(x)), E_{\mathcal{Y}}^a(y))$.

DRIT : Others



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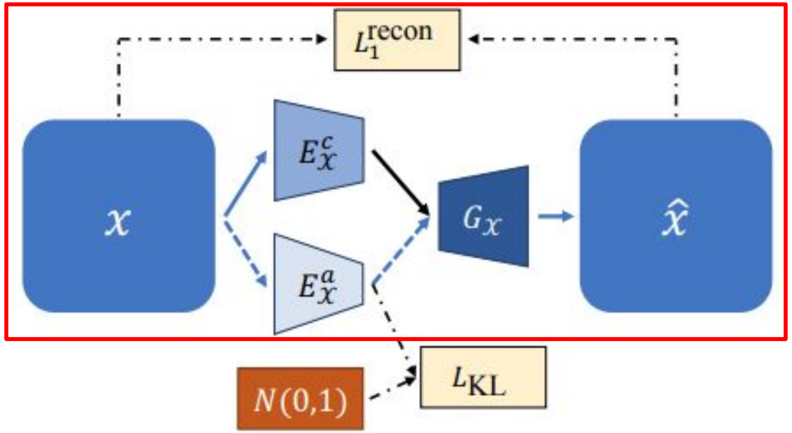
“Generator attempt to generate realistic images”

DRIT : Others



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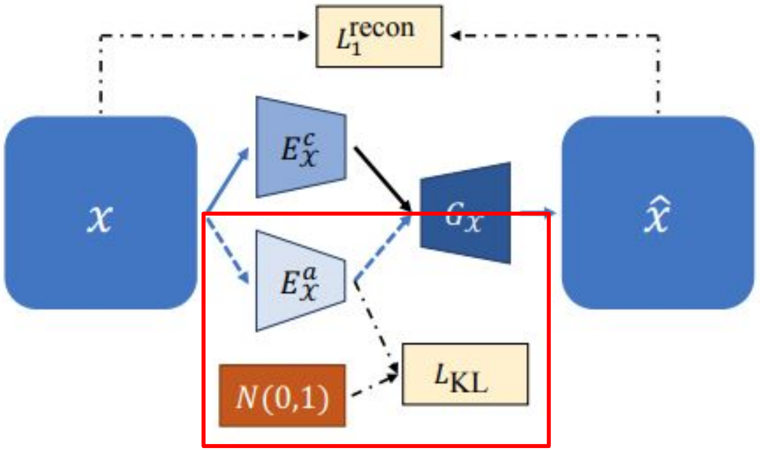
“With encoded content/attribute features,
the decoders should decode them back to original inputs”

DRIT : Others



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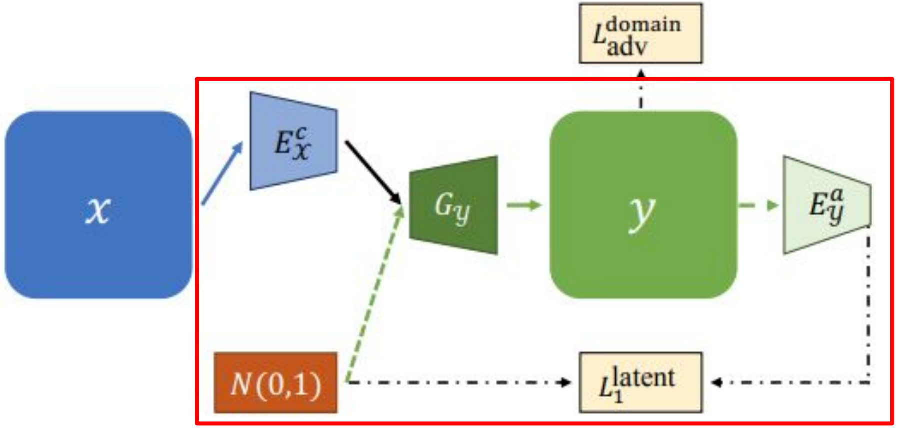
**"In order to perform stochastic sampling at test time,
we encourage the attribute to be as close to a prior Gaussian distribution."**

DRIT : Others



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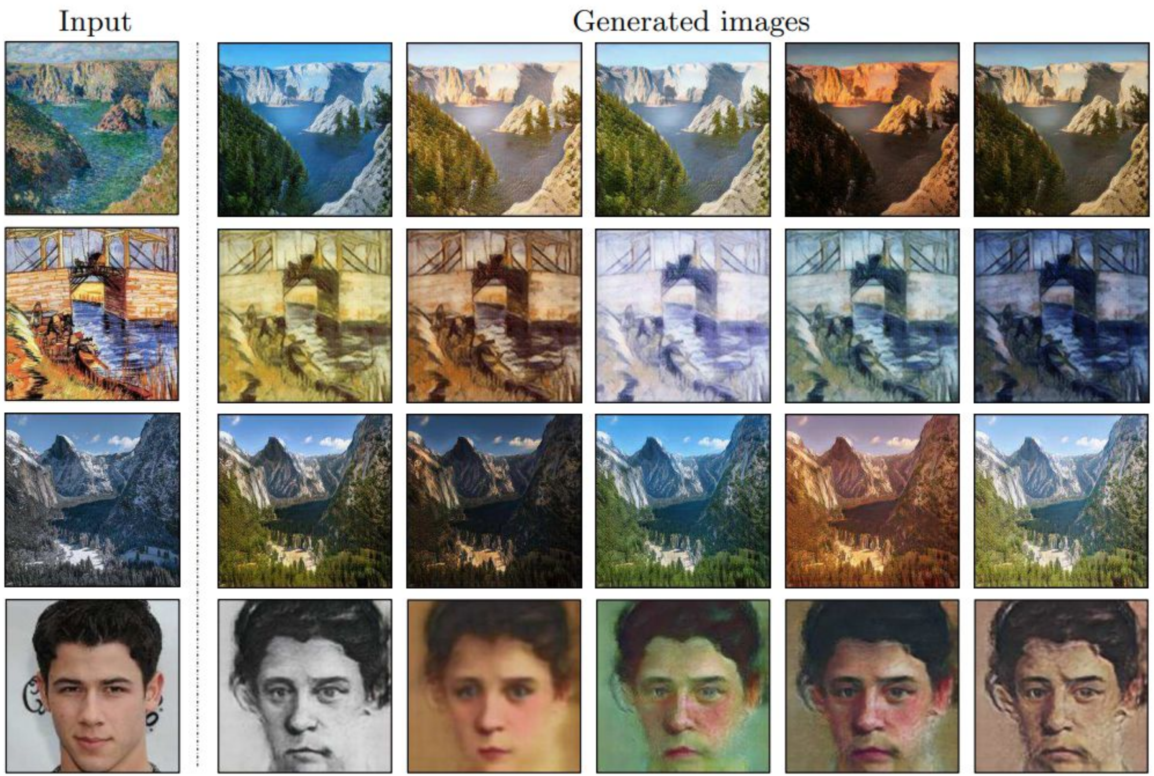
"To encourage invertible mapping between the image and the latent space"

DRIT : Results



Monet → Photo

Van Gogh → Monet

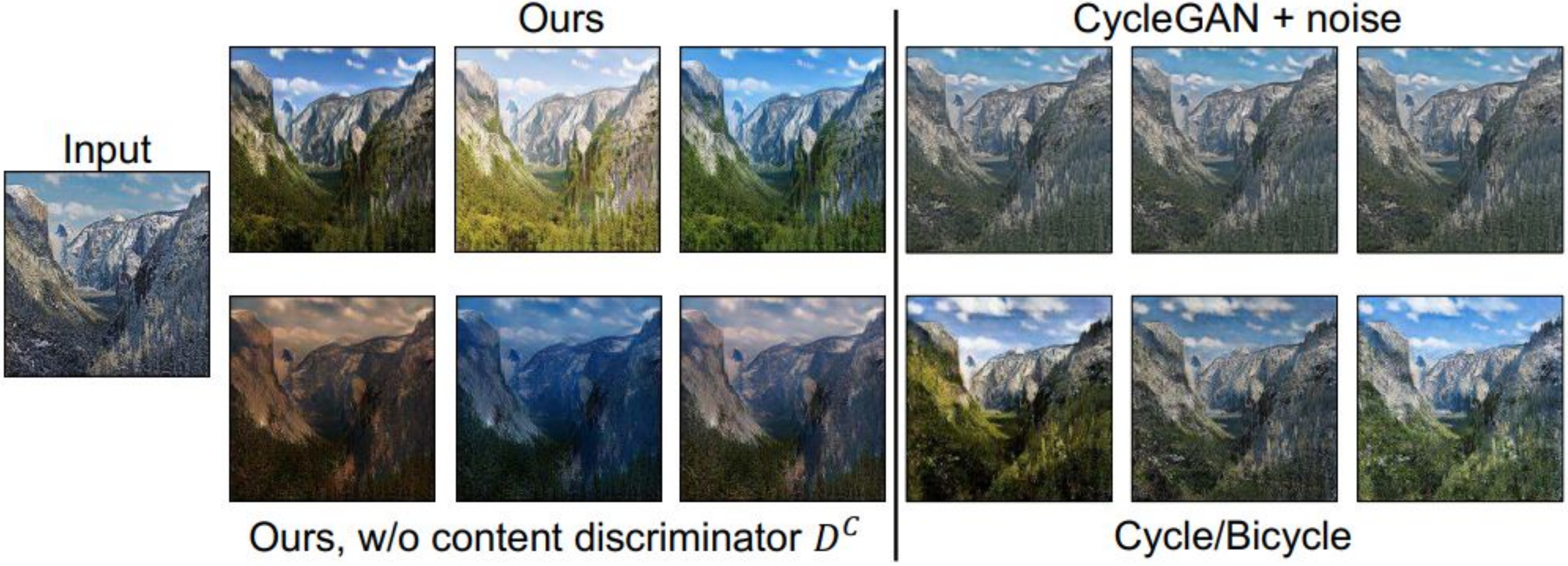
Winter → Summer

Photo → Portrait

Experiments

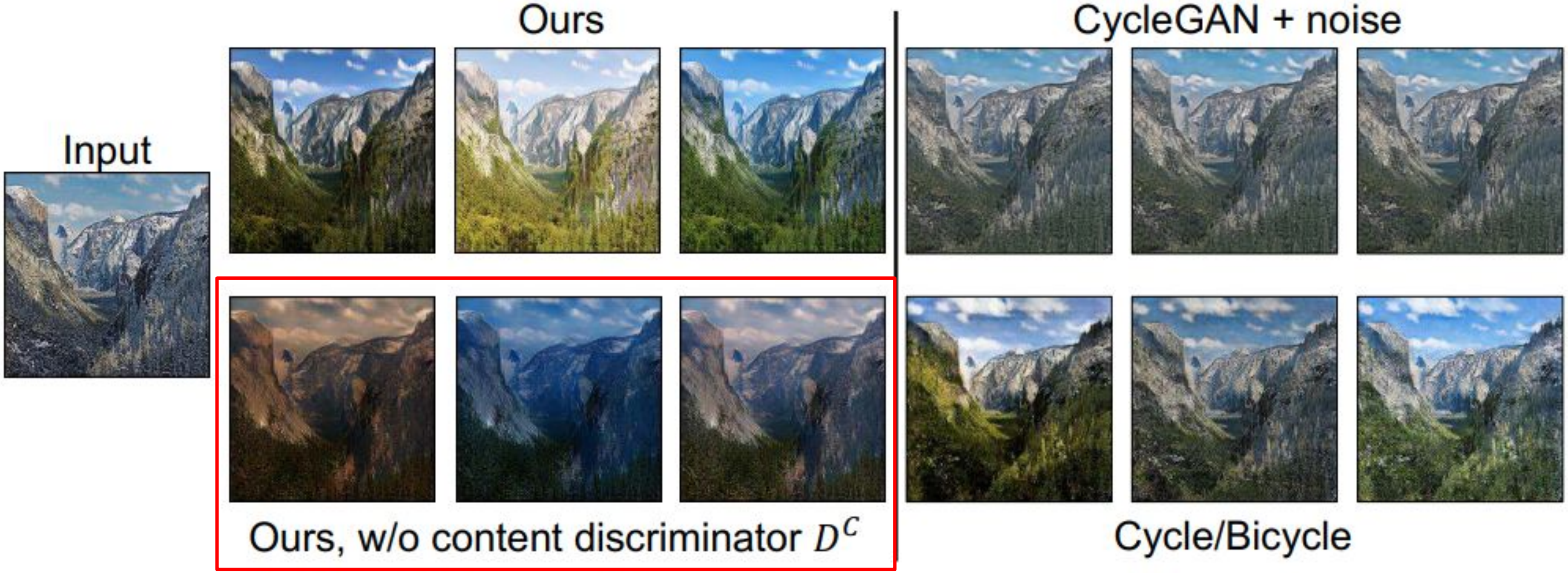
- Diversity
- Unpaired
- Disentangle: Content, Attribute

Qualitative: diversity



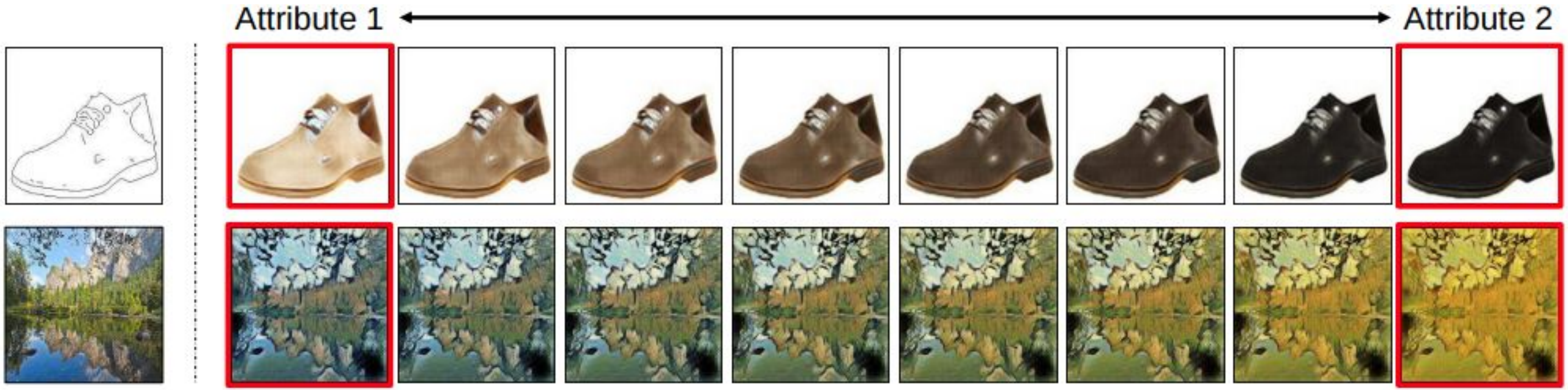
“Winter → Summer”

Qualitative: diversity



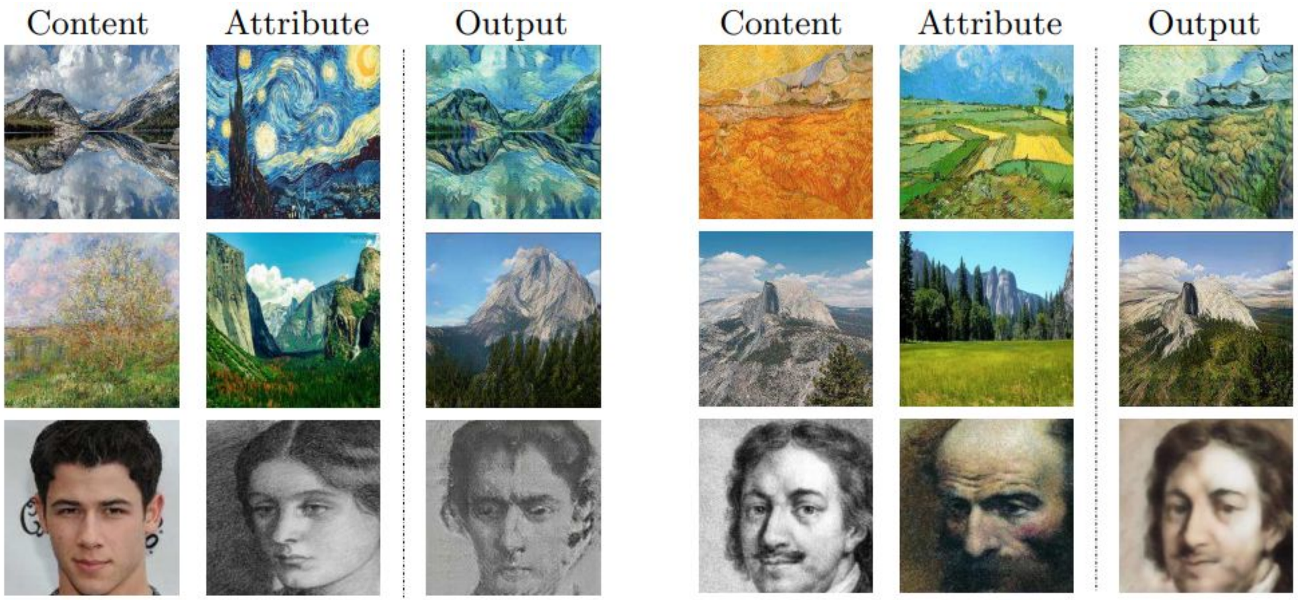
Without the content discriminator,
model fails to capture domain-related details (e.g., the color of tree and sky)

Qualitative: attribute



Translation results with linear-interpolated attribute vectors between attributes

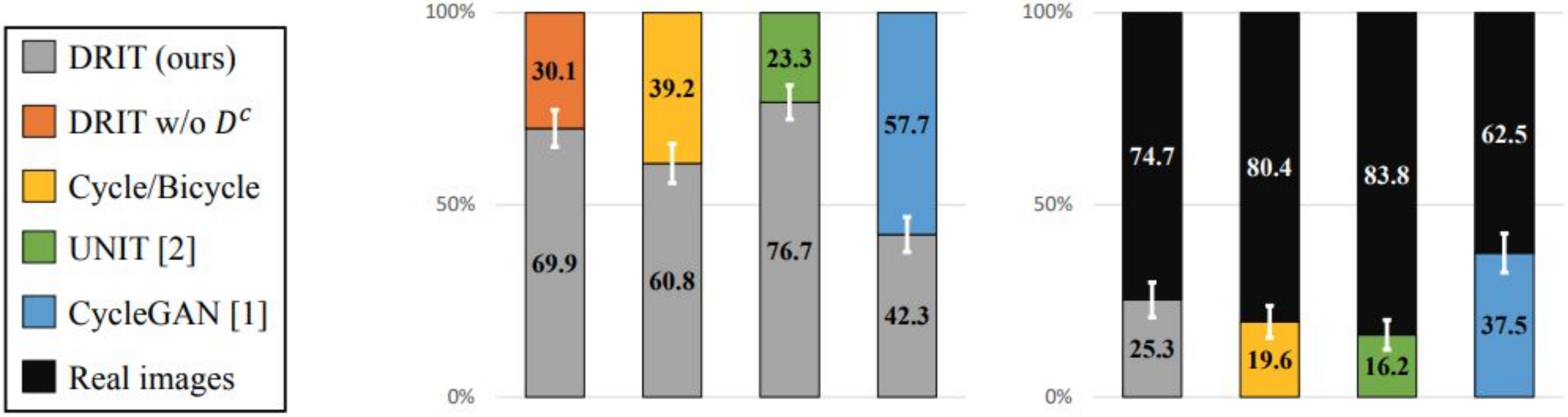
Qualitative: disentangle



(a) Inter-domain attribute transfer (b) Intra-domain attribute transfer

Translation results with linear-interpolated attribute vectors between attributes

Quantitative: realism preference results



Quantitative: diversity, reconstruction err

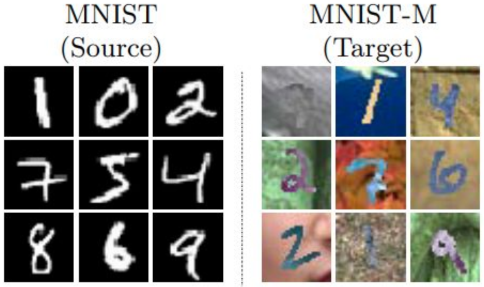
Table 2: **Diversity.** We use the LPIPS metric [45] to measure the diversity of generated images on the Yosemite dataset.

Method	Diversity
real images	.448 ± .012
DRIT	**.424** ± .010
DRIT w/o D^c	.410 ± .016
UNIT [26]	.406 ± .022
CycleGAN [46]	.413 ± .008
Cycle/Bicycle	.399 ± .009

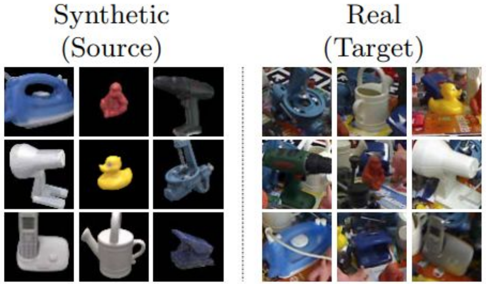
Table 3: **Reconstruct error**. We use the edge-to-shoes dataset to measure the quality of our attribute encoding. The reconstruction error is $\|y - G_{\mathcal{Y}}(E^c_{\mathcal{X}}(x), E^a_{\mathcal{Y}}(y))\|_1$. * BicycleGAN uses *paired* data for training.

Method	Reconstruct error
BicycleGAN [47]*	**0.0945**
DRIT	0.1347
DRIT, w/o D^c	0.2076

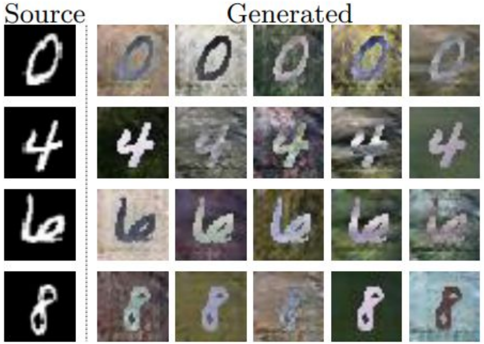
Domain adaptation



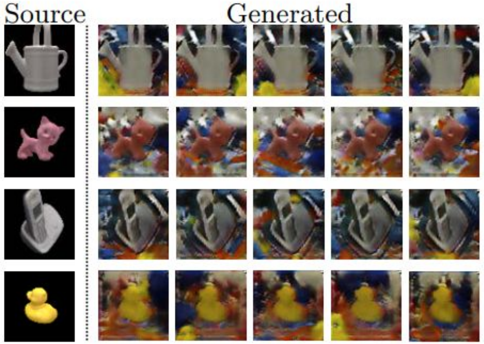
(a) Examples from MNIST/MNIST-M



(b) Examples from Cropped Linemod



(c) MNIST → MNIST-M



(d) Synthetic → Real Cropped LineMod

(a) MNIST-M

Model	Classification Accuracy (%)
Source-only	56.6
CycleGAN [46]	74.5
Ours, ×1	86.93
Ours, ×3	90.21
Ours, ×5	**91.54**
DANN [13]	77.4
DSN [4]	83.2
PixelDA [3]	**95.9**
Target-only	96.5

(b) Cropped LineMod

Model	Classification Accuracy (%)	Mean Angle Error (°)
Source-only	42.9 (47.33)	73.7 (89.2)
CycleGAN [46]	68.18	47.45
Ours, ×1	95.91	42.06
Ours, ×3	97.04	37.35
Ours, ×5	**98.12**	**34.4**
DANN [13]	99.9	56.58
DSN [4]	**100**	53.27
PixelDA [3]	99.98	**23.5**
Target-only	100	12.3 (6.47)

Thank You.