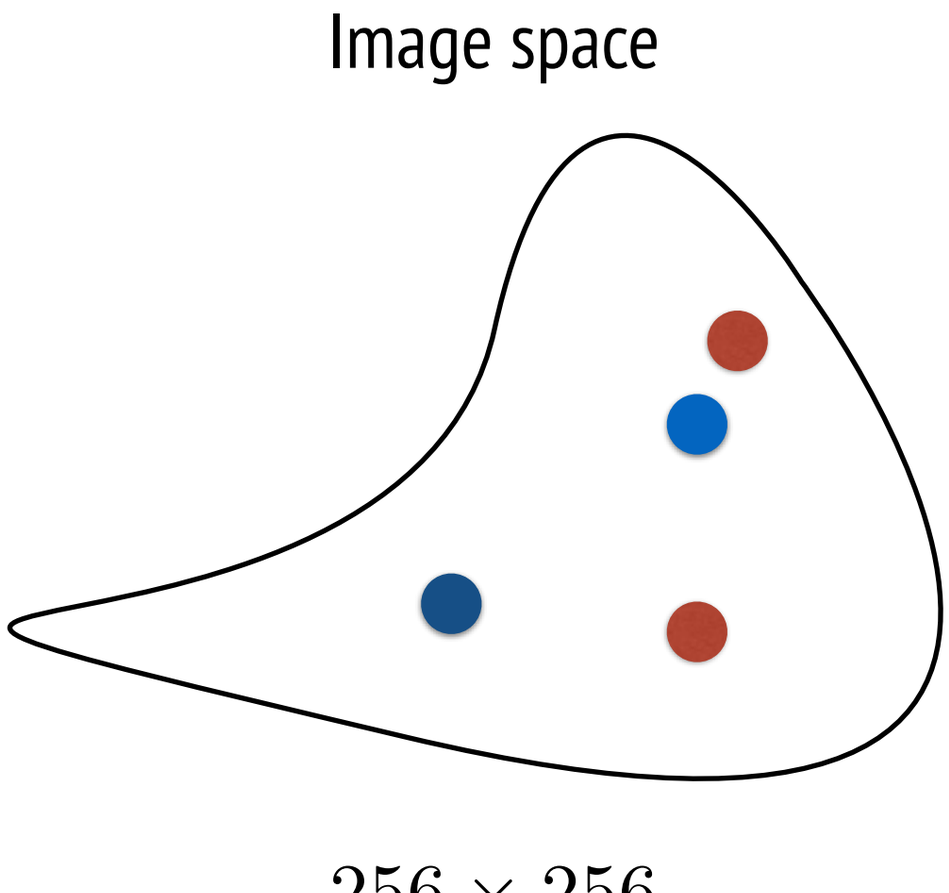
Image-to-image Translation

Sergey Tulyakov

Today

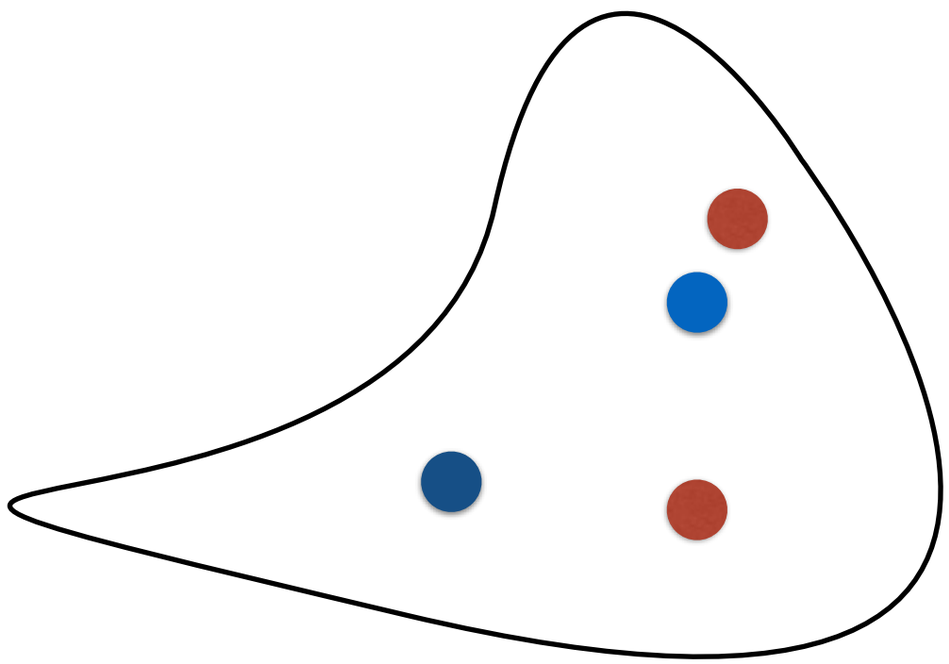
- Image-to-image translation
  - Paired
  - Unpaired
  - Multimodal
- Stacked architectures
- Normalization layers
- Applications

VAE: Interpolation



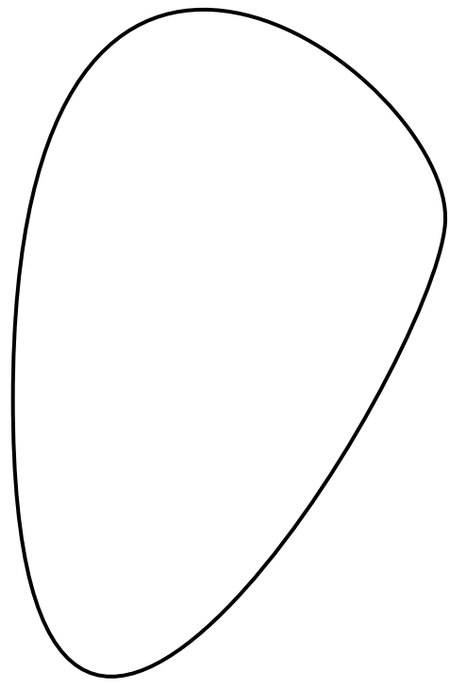
VAE: Interpolation

Image space



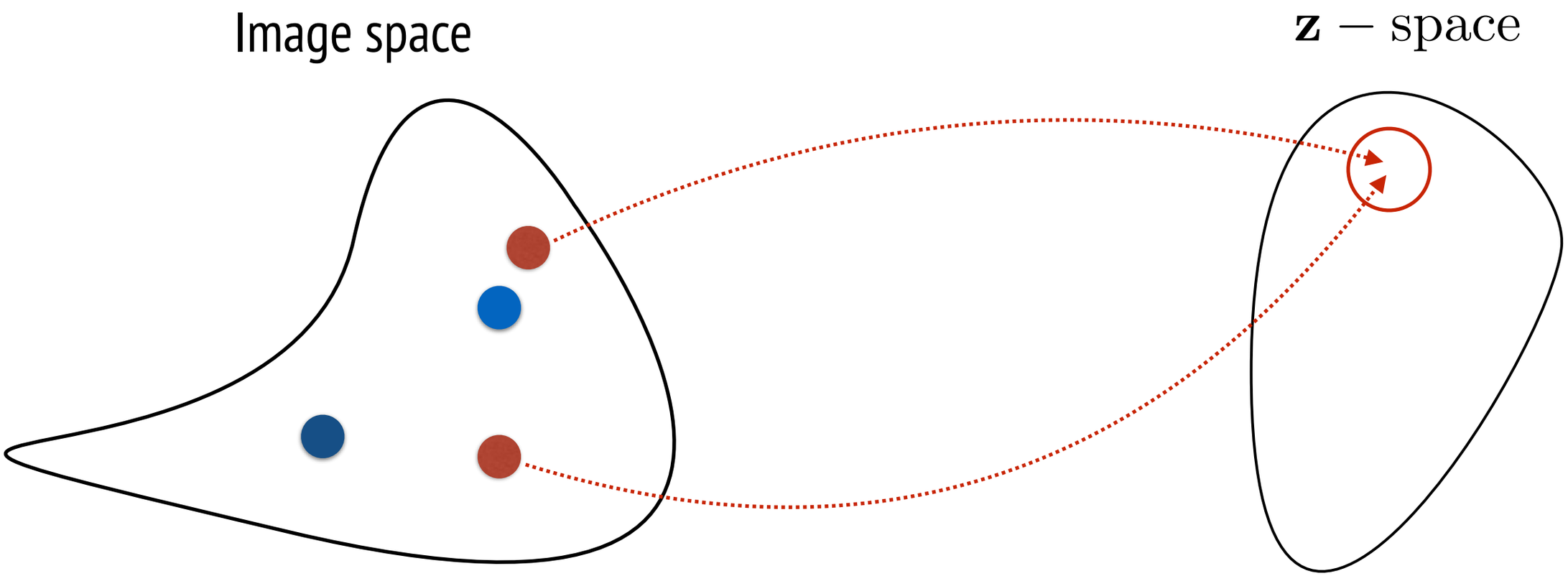
256×256

$\mathbf{z}-$ space

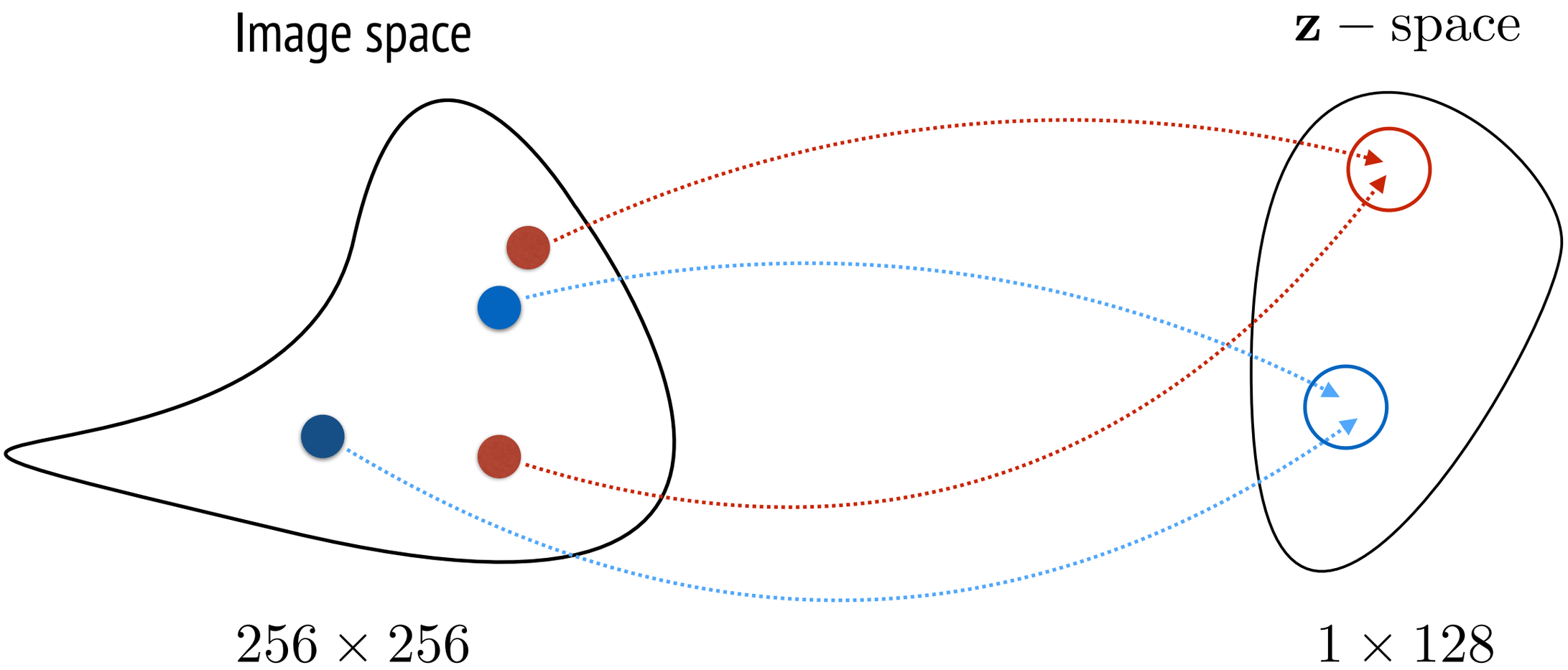


1×128

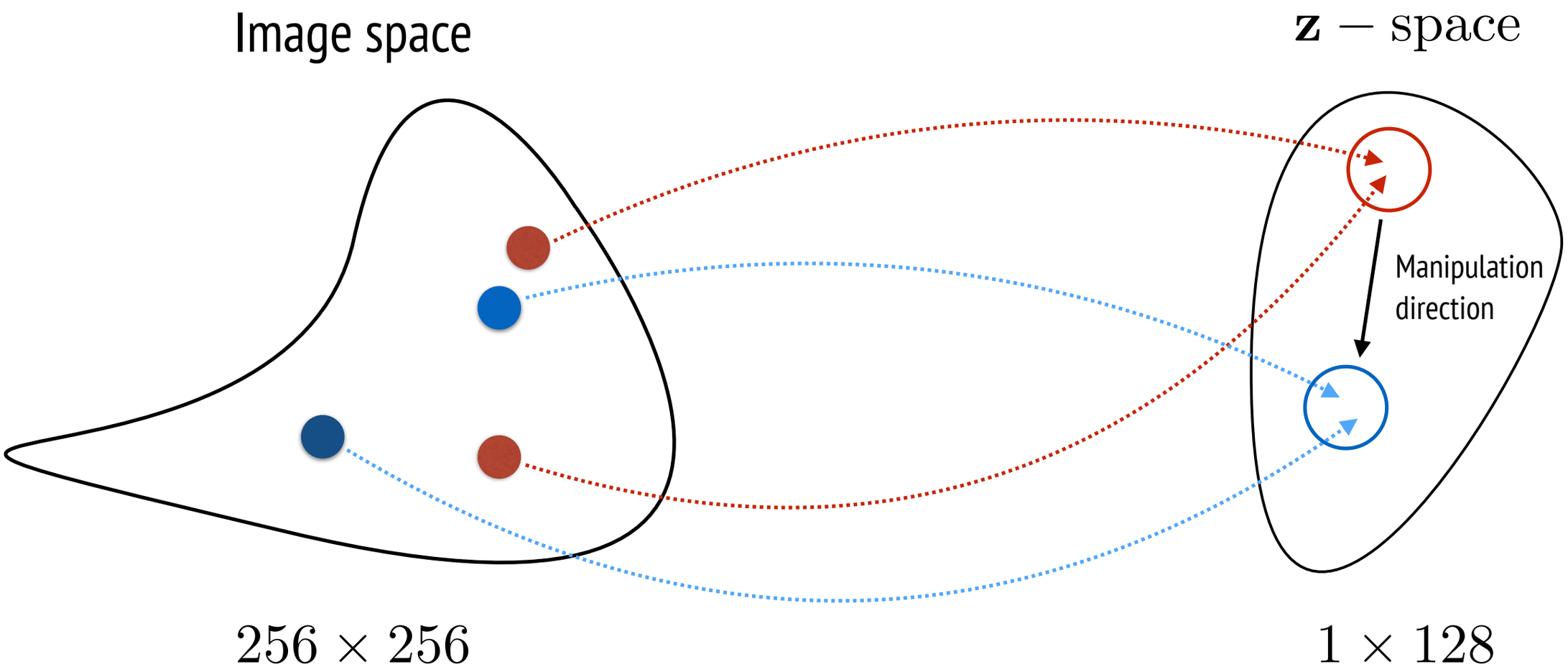
VAE: Interpolation



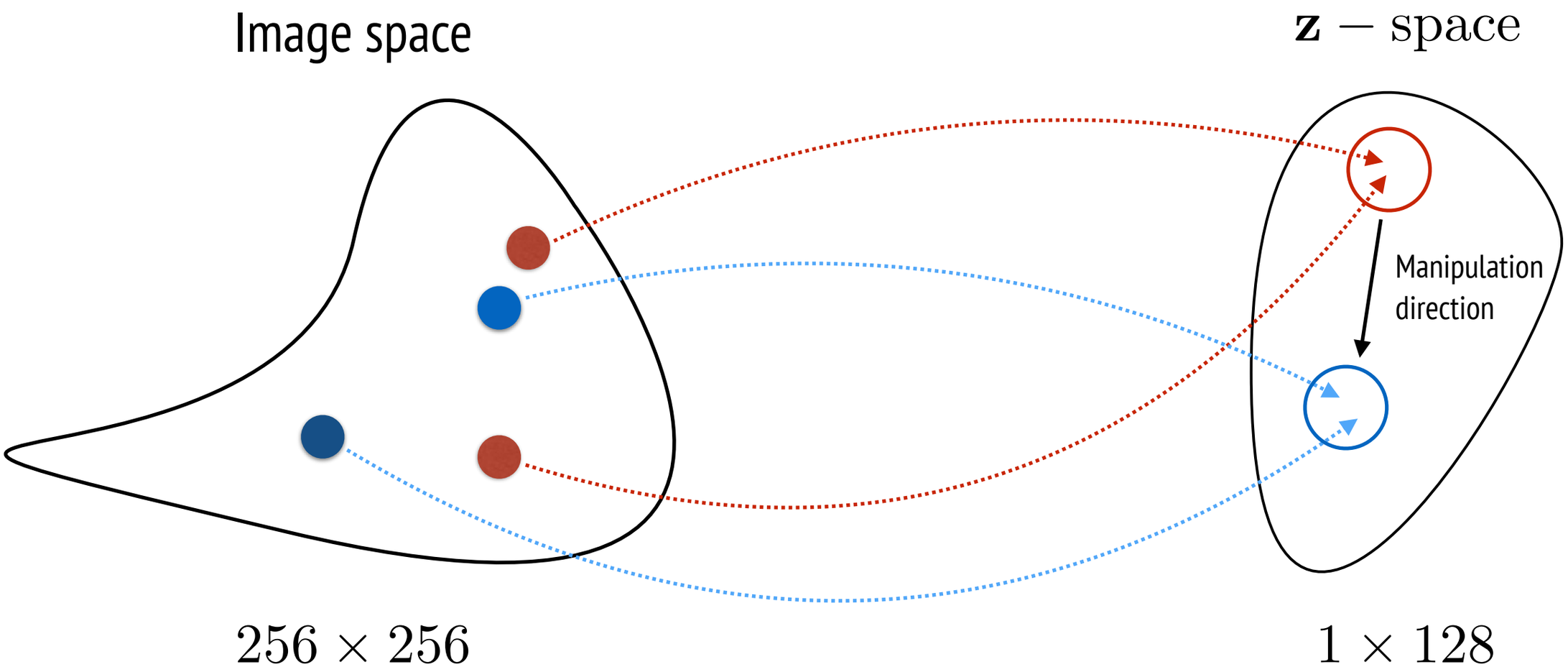
VAE: Interpolation



VAE: Interpolation



VAE: Interpolation



Not smiling

Smiling

No beard

Has beard

CVAE-GAN: Interpolation

More advanced VAEs can be used but:

- How to pick the right direction?
- How to know where to stop?
- How to change only a single attribute?

Source

Target

Image-to-image Translation

Given two domain the goal is to translate image from one possible representation to another.

$$\mathbf{x} \sim p(\mathbf{x}|\mathbf{y})$$
$$\mathbf{y} \sim p(\mathbf{y}|\mathbf{x})$$

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

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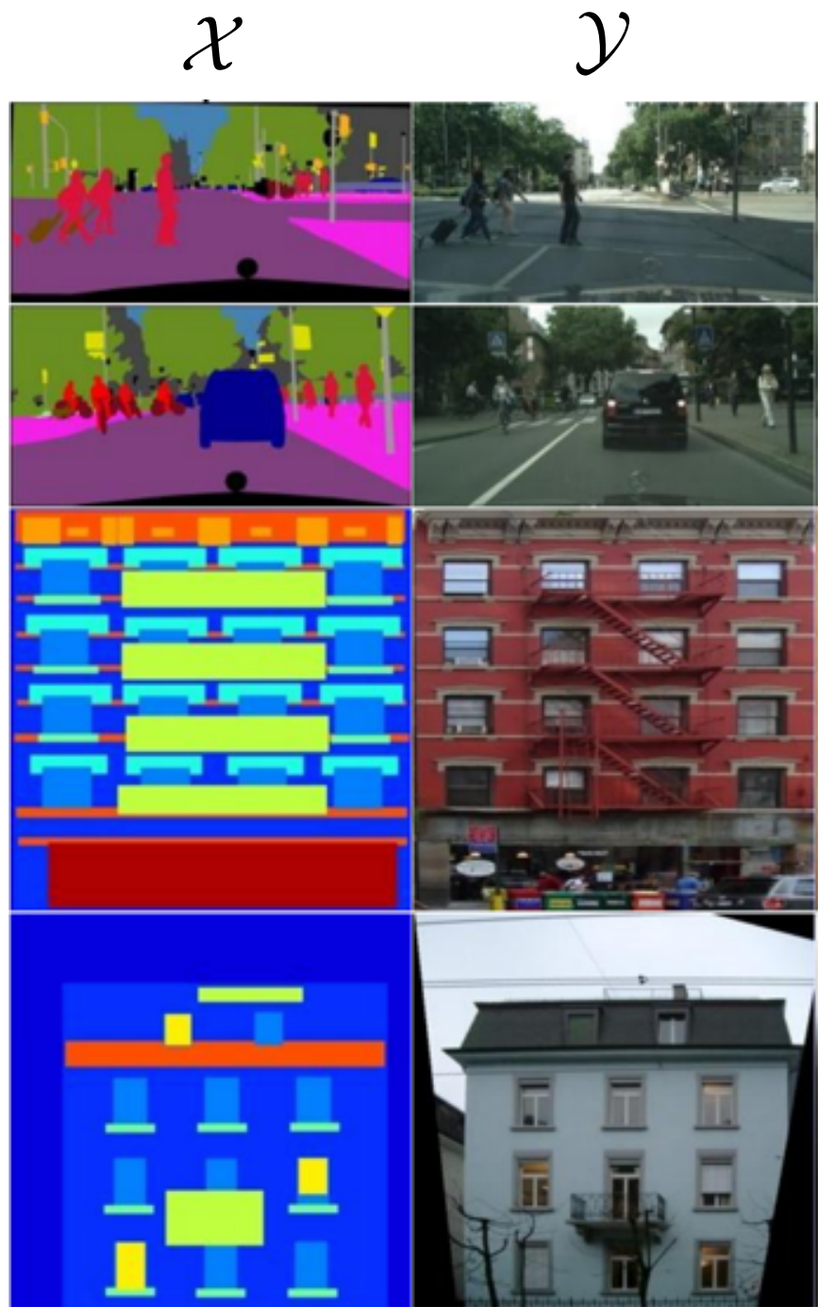
Paired image-to-image translation

$$\mathbf{x}, \mathbf{y} \sim p(\mathbf{x}, \mathbf{y})$$



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Unpaired

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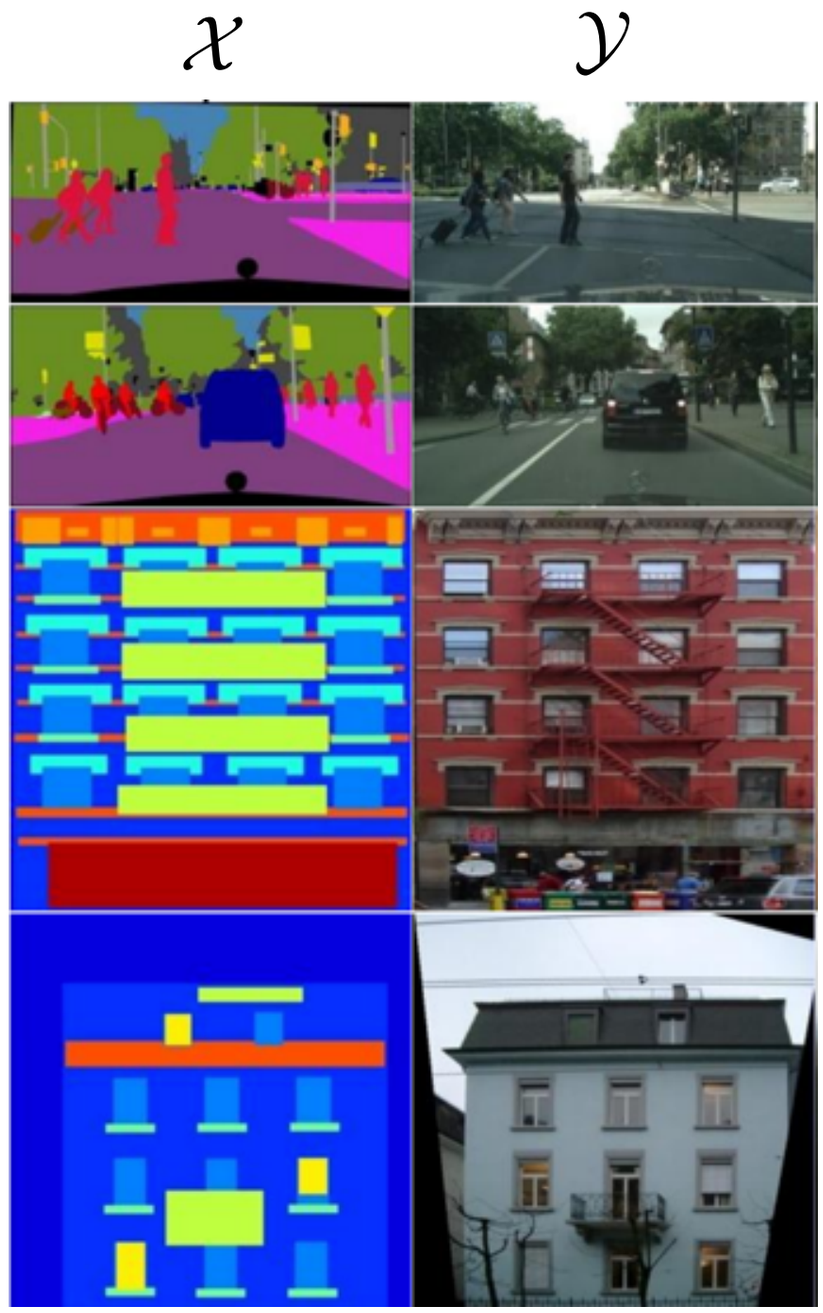
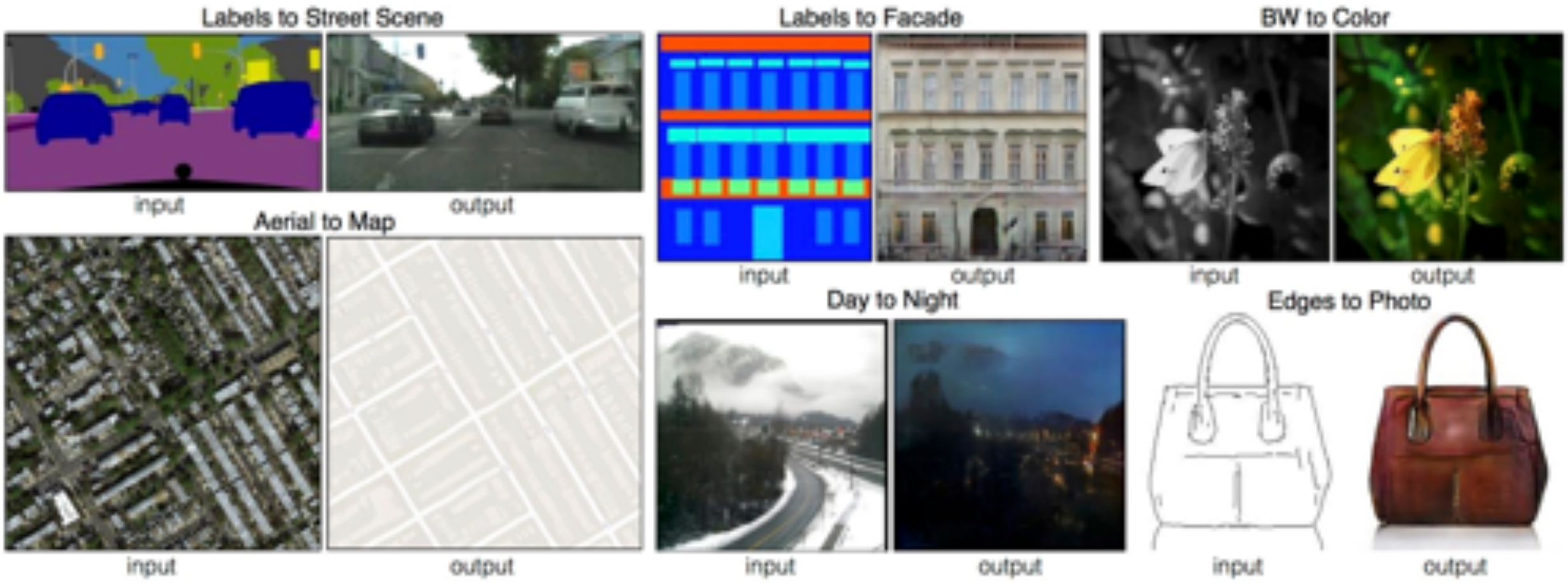


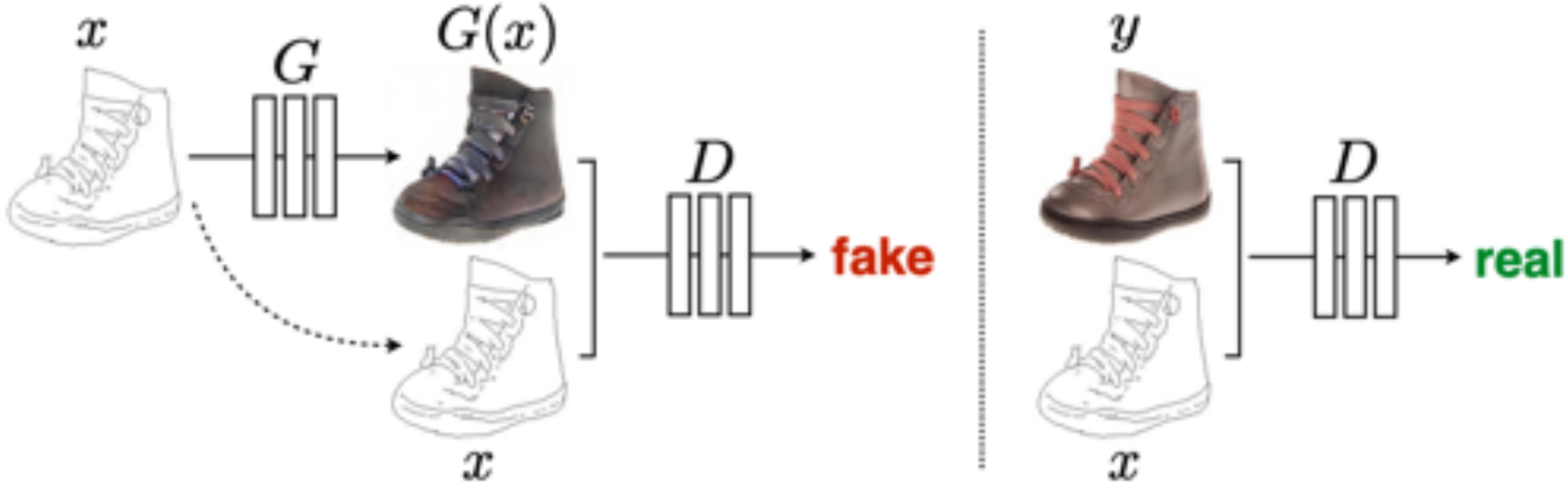
Isola, Phillip, et al. "Image-to-image translation with conditional adversarial networks." CVPR'2017

Pix2Pix: Motivation



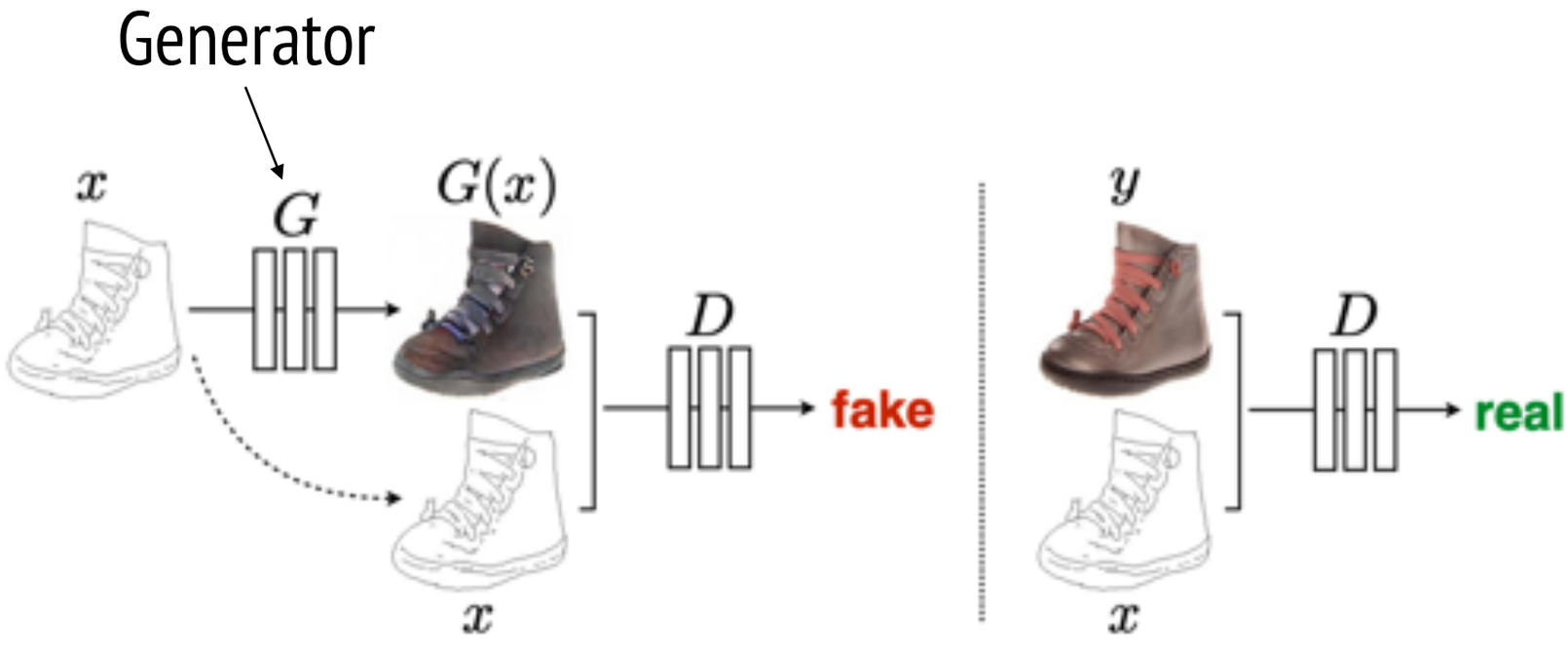
Isola, Phillip, et al. "Image-to-image translation with conditional adversarial networks." CVPR'2017

Pix2Pix: Conditional Architecture



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

Pix2Pix: Conditional Architecture



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

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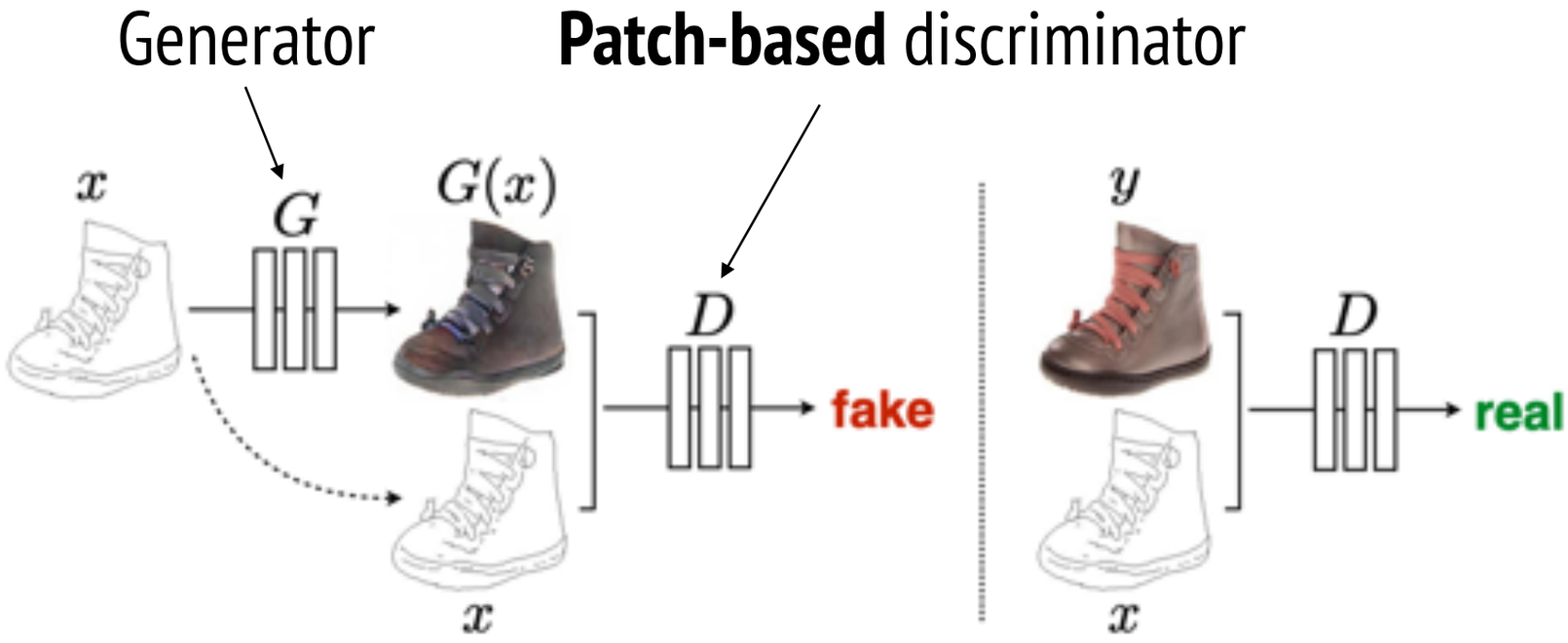

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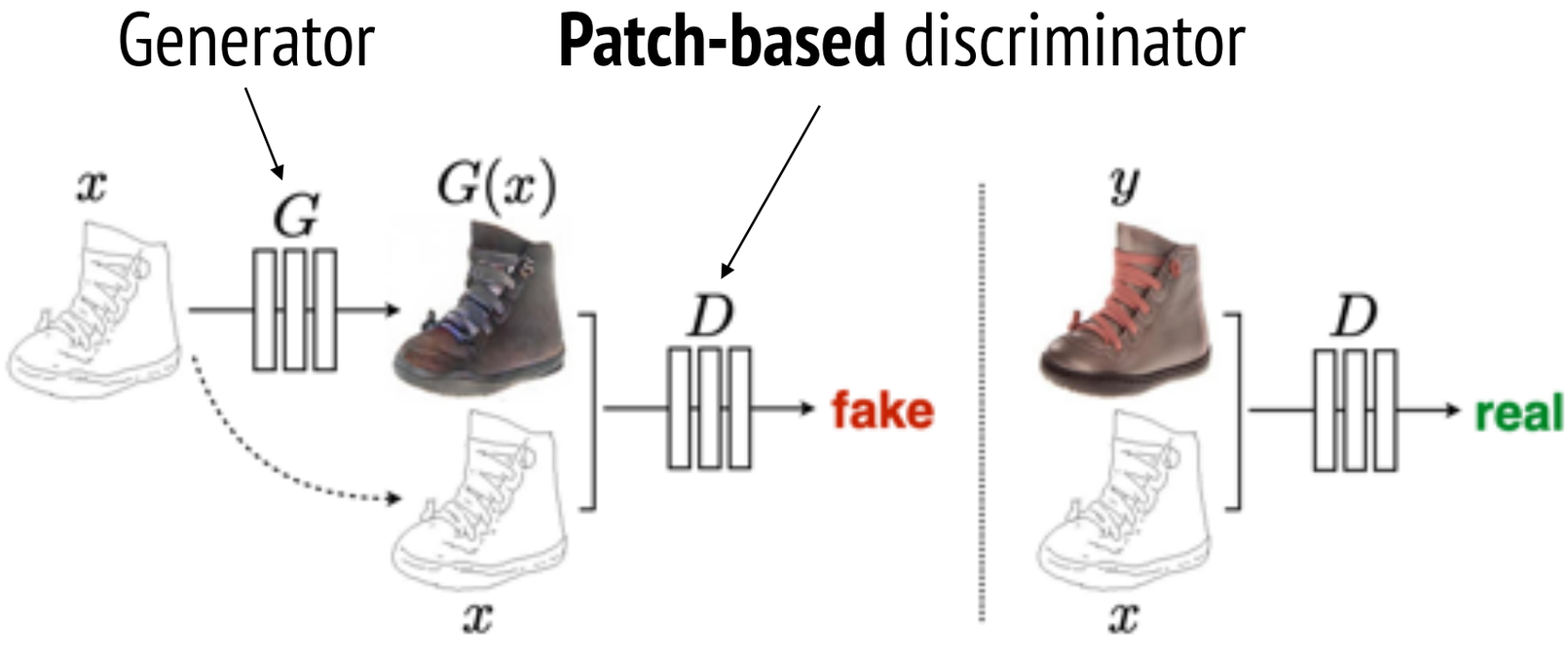

Combined GAN-loss and reconstruction loss:

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

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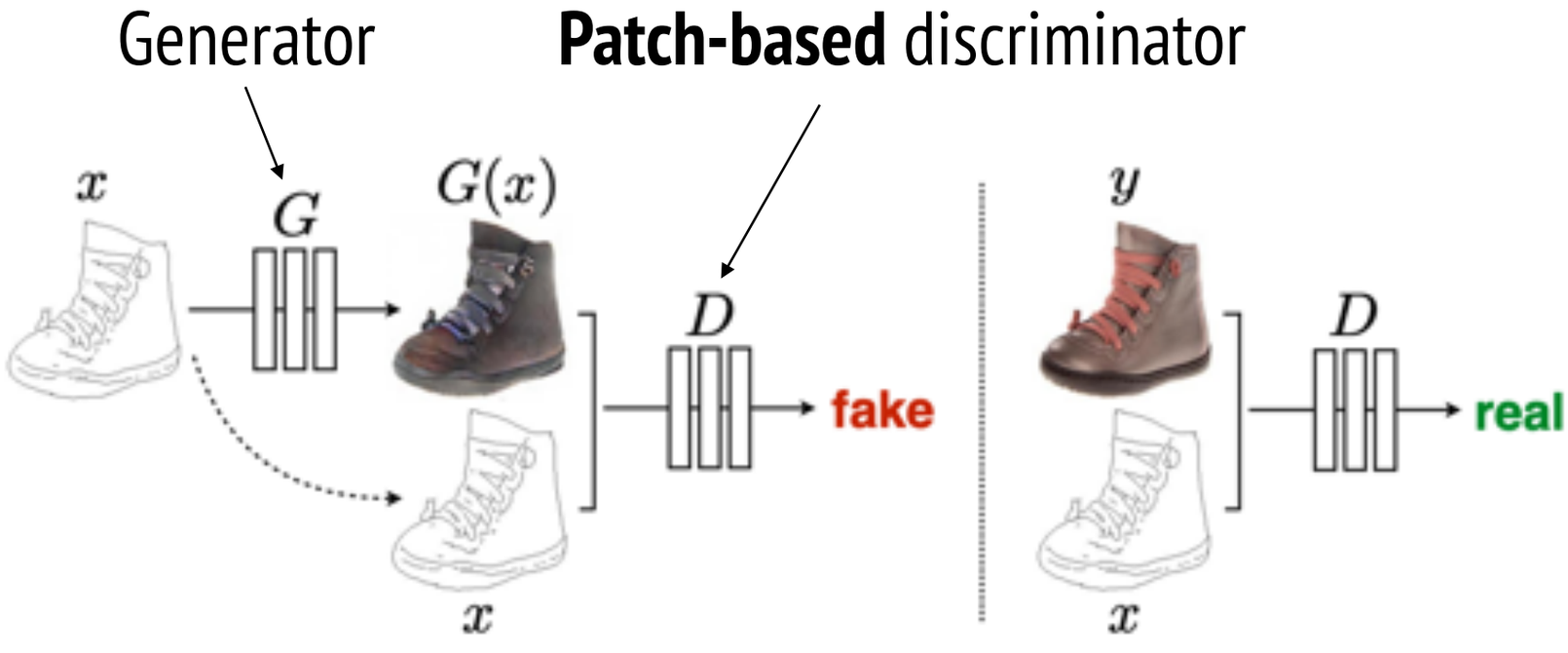

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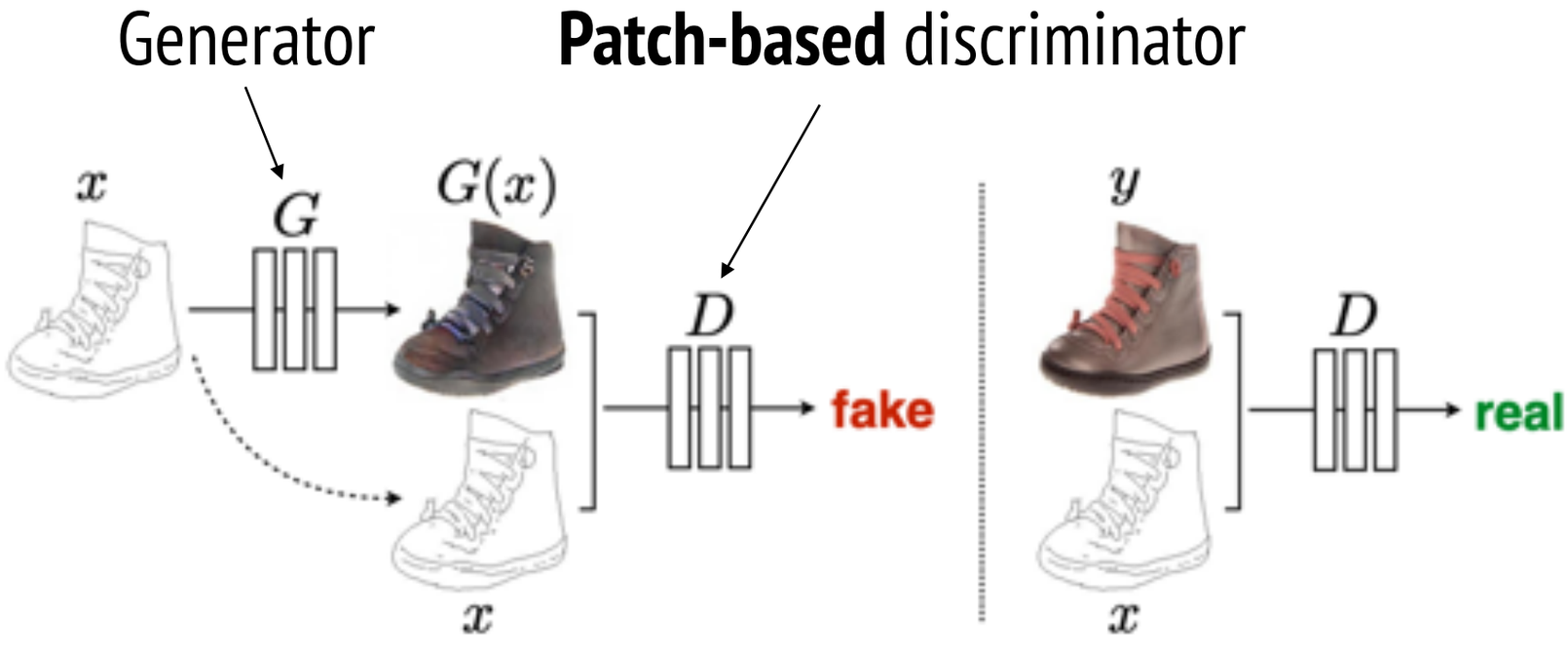
$$\mathcal{L}_{cGAN}(G, D) = \mathbb{E}_{x,y}[\log D(x, y)] + \mathbb{E}_{x,z}[\log(1 - D(x, G(x, z))]$$

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

Pix2Pix: Conditional Architecture



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

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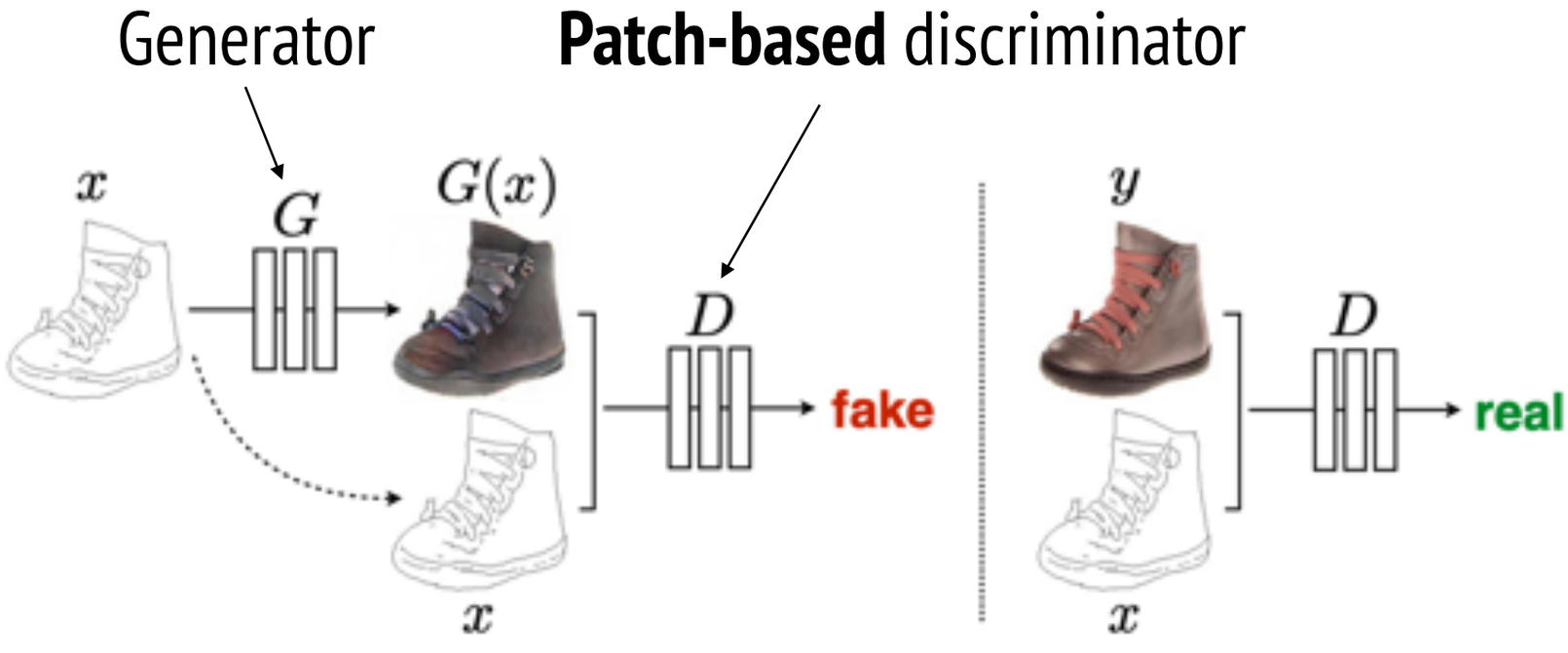
Pix2Pix: Conditional Architecture



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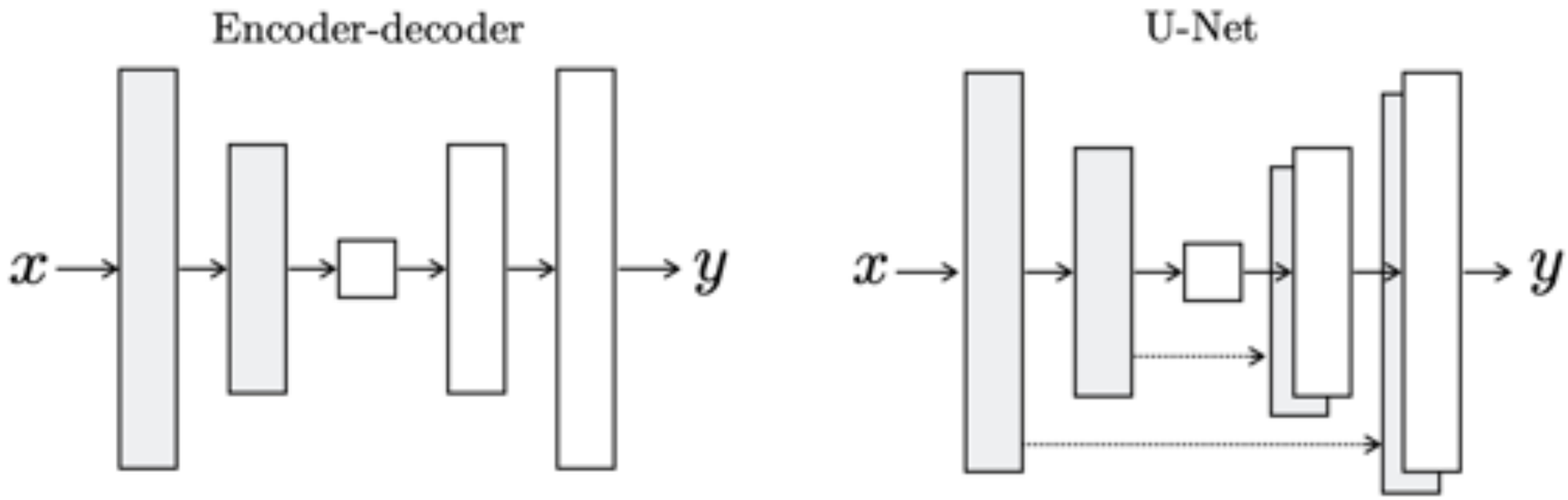
$$G^* = \arg\min_G \max_D \mathcal{L}_{cGAN}(G,D) + \lambda \mathcal{L}_{L1}(G)$$

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

Pix2Pix: Generator

Skip connections in generator



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Pix2Pix: Ablations

Loss	Per-pixel acc.	Per-class acc.	Class IOU
L1	0.42	0.15	0.11
GAN	0.22	0.05	0.01
cGAN	0.57	0.22	0.16
L1+GAN	0.64	0.20	0.15
L1+cGAN	**0.66**	**0.23**	**0.17**
Ground truth	0.80	0.26	0.21

Table 1: FCN-scores for different losses, evaluated on Cityscapes labels↔photos.

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Pix2Pix: Ablations

Loss	Per-pixel acc.	Per-class acc.	Class IOU
Encoder-decoder (L1)	0.35	0.12	0.08
Encoder-decoder (L1+cGAN)	0.29	0.09	0.05
U-net (L1)	0.48	0.18	0.13
U-net (L1+cGAN)	**0.55**	**0.20**	**0.14**

Table 2: FCN-scores for different generator architectures (and objectives), evaluated on Cityscapes labels↔photos. (U-net (L1-cGAN) scores differ from those reported in other tables since batch size was 10 for this experiment and 1 for other tables, and random variation between training runs.)

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Pix2Pix: Ablations

Discriminator receptive field	Per-pixel acc.	Per-class acc.	Class IOU
1×1	0.39	0.15	0.10
16×16	0.65	0.21	**0.17**
70×70	**0.66**	**0.23**	**0.17**
286×286	0.42	0.16	0.11

Table 3: FCN-scores for different receptive field sizes of the discriminator, evaluated on Cityscapes labels→photos. Note that input images are 256 × 256 pixels and larger receptive fields are padded with zeros.

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Pix2Pix: Results and Applications

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

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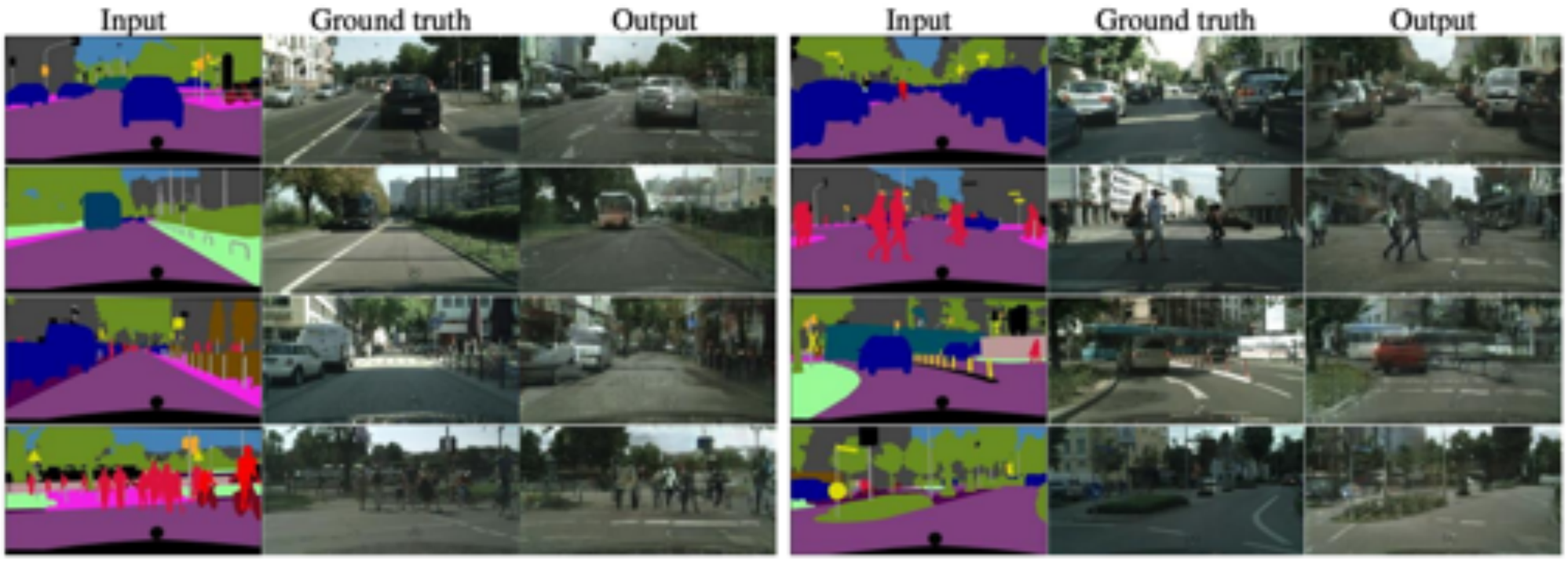

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Pix2Pix: Results and Applications

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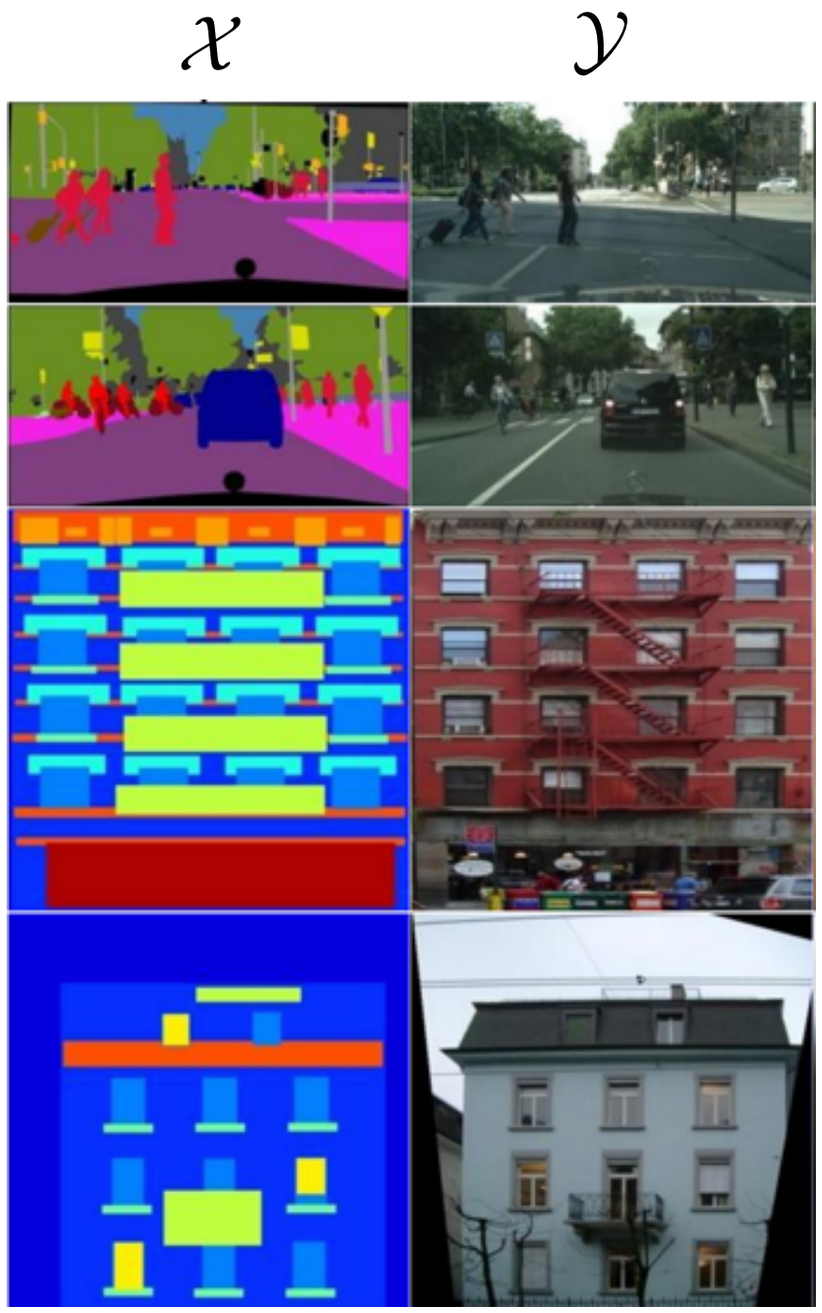

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Unpaired Image-to-image Translation

Given inability to sample from joint distribution (i.e. observe paired data), learning conditional distribution (i.e. translation) is an ill-posed problem.

Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." ICCV'2017.

Unpaired Image-to-image Translation

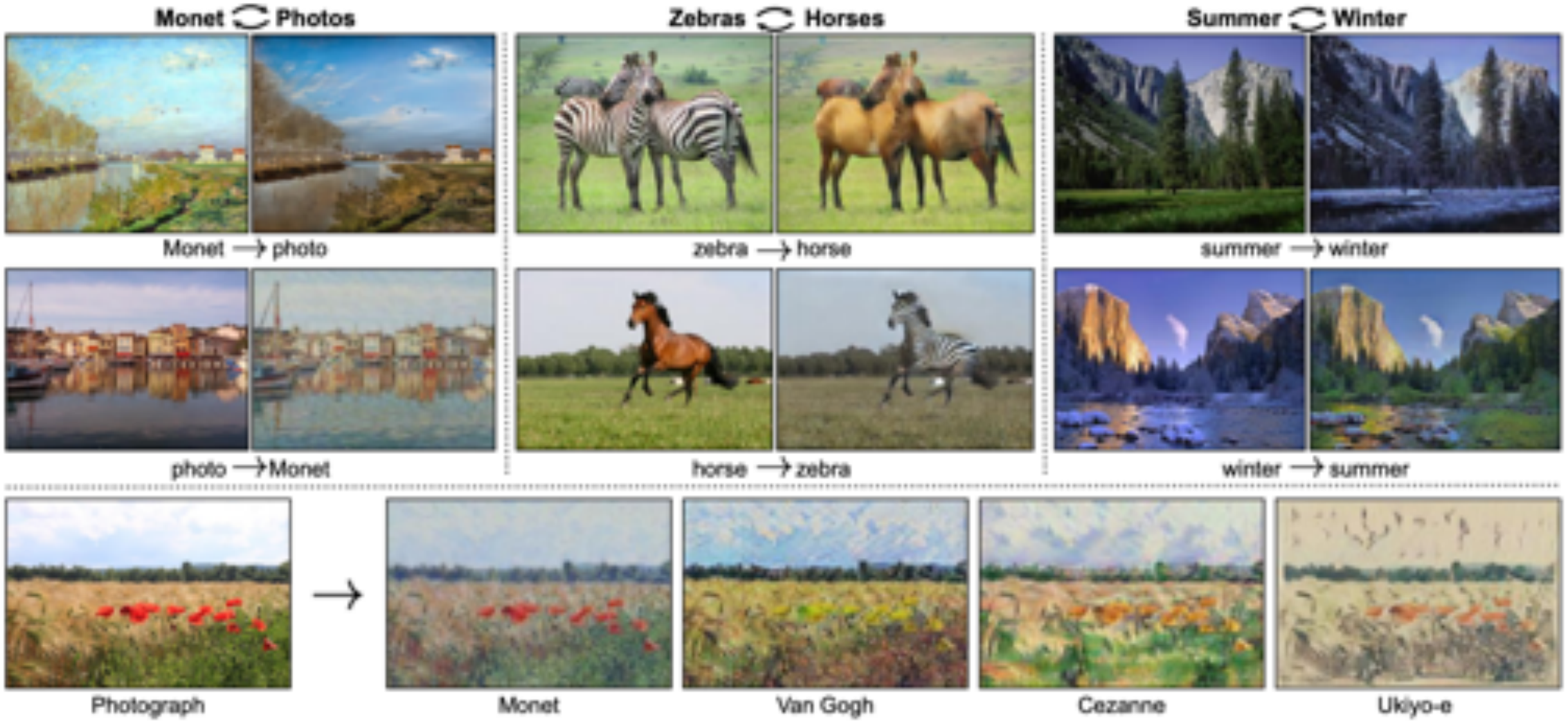
Given inability to sample from joint distribution (i.e. observe paired data), learning conditional distribution (i.e. translation) is an ill-posed problem.

To solve it, constraints are necessary:

- Cycle-consistency constraint
- Weight-sharing constraint
- Equivariance constraint

Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." ICCV'2017.

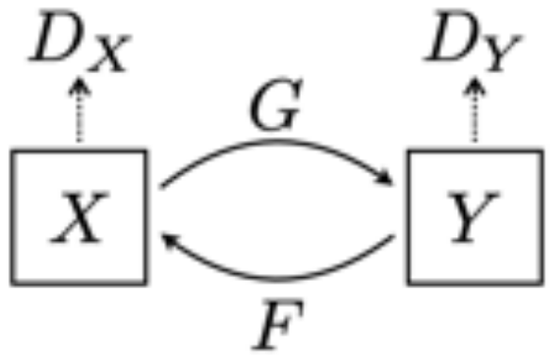
CycleGAN



It is sometimes impossible to get the same image in a different representation

Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." ICCV'2017.

CycleGAN: Overview



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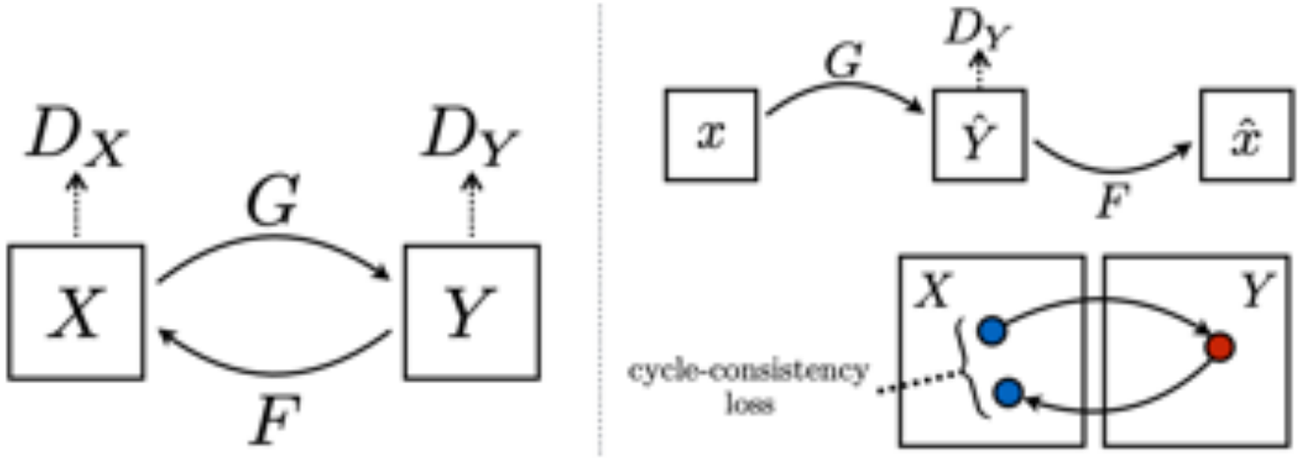

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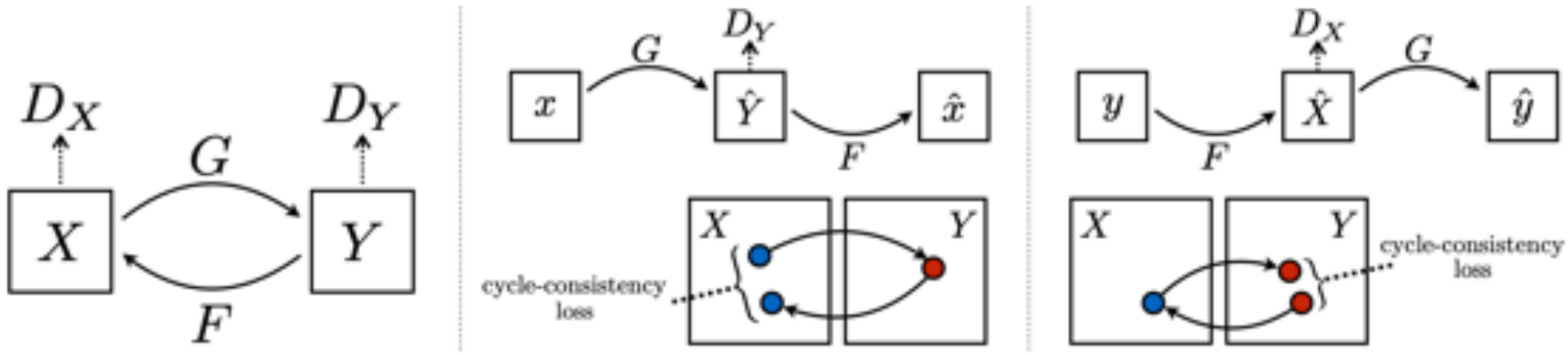

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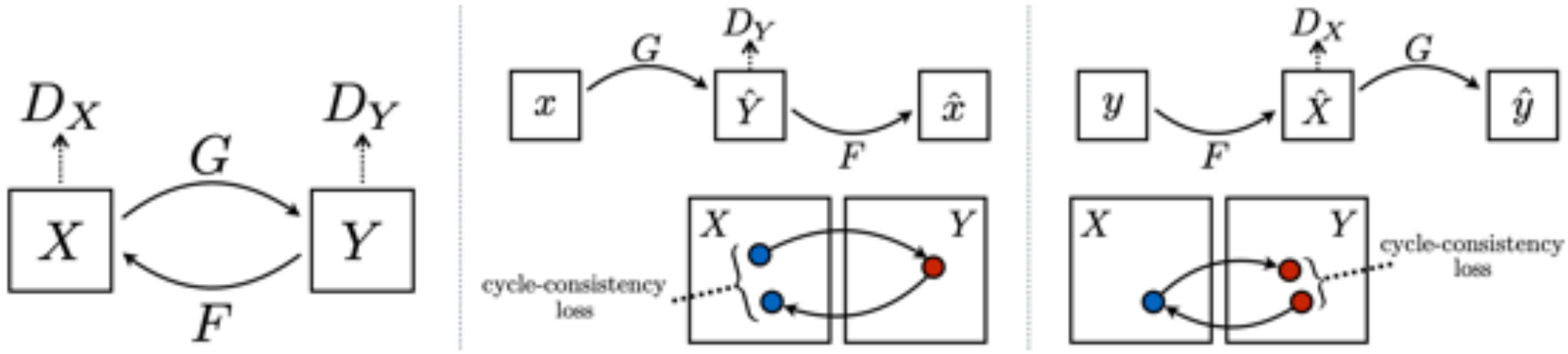

Adversarial loss:

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

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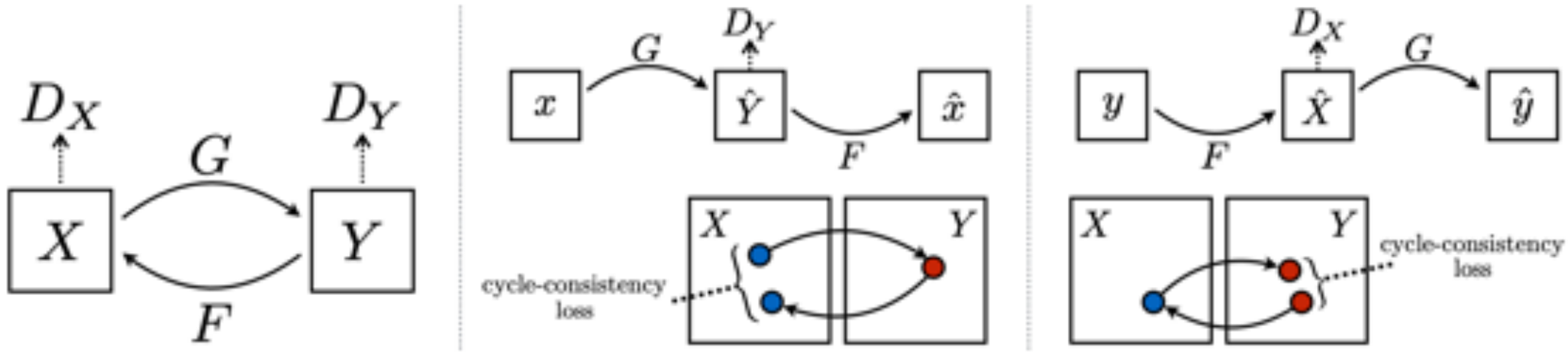

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Cycle-consistency loss:

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

Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." ICCV'2017.

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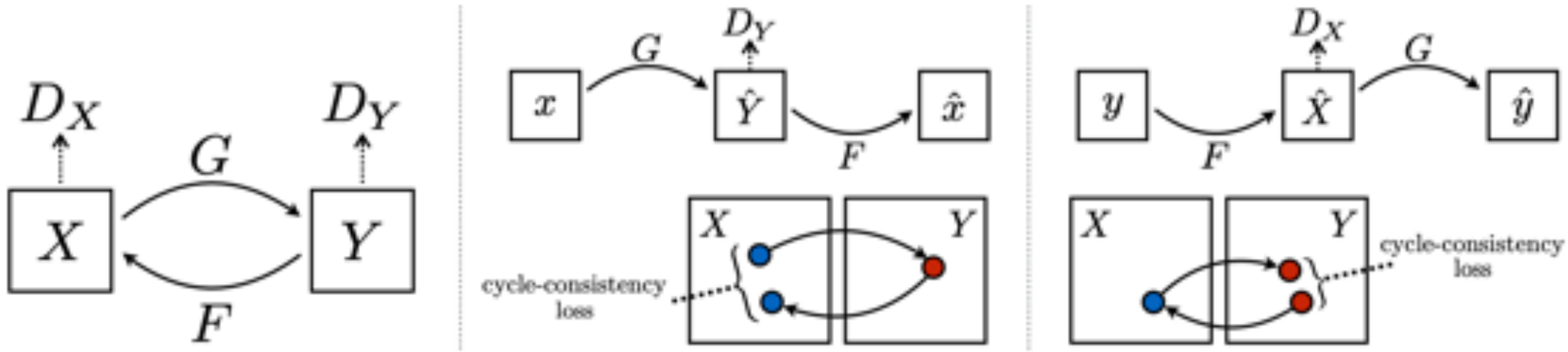

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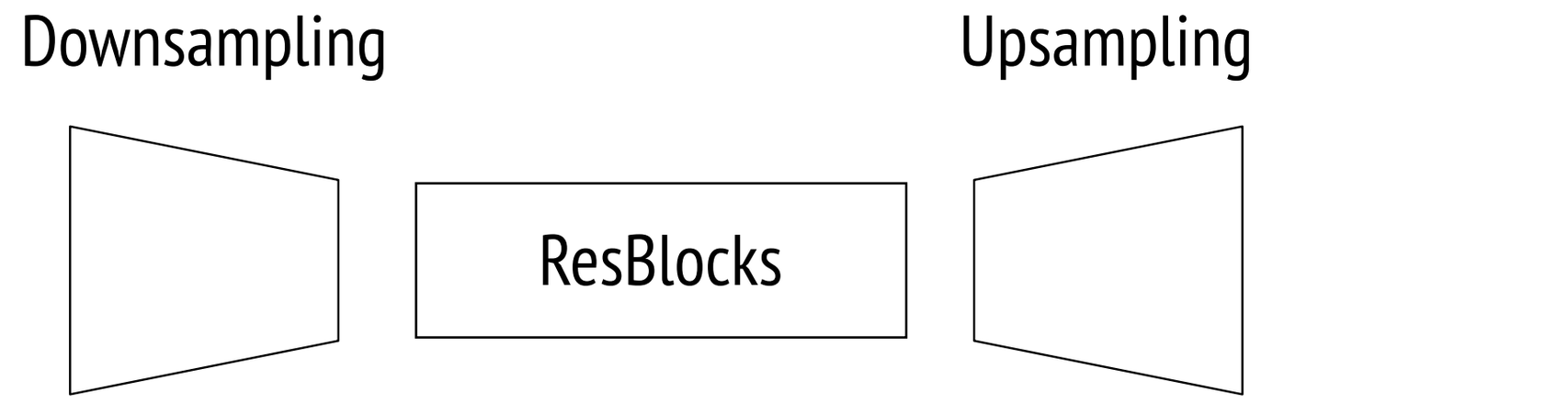
Full objective:

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

Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." ICCV'2017.

CycleGAN: Architecture



Johnson, Justin, Alexandre Alahi, and Li Fei-Fei. "Perceptual losses for real-time style transfer and super-resolution." ECCV'2016.

CycleGAN: Results

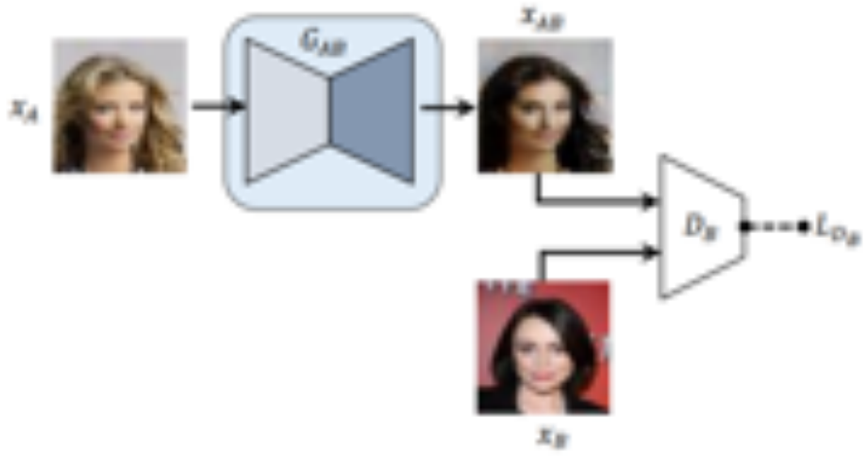
CycleGAN: Results

DiscoGAN

Kim, Taeksoo, et al. "Learning to discover cross-domain relations with generative adversarial networks." ICML'2017.

DiscoGAN

Standard GAN



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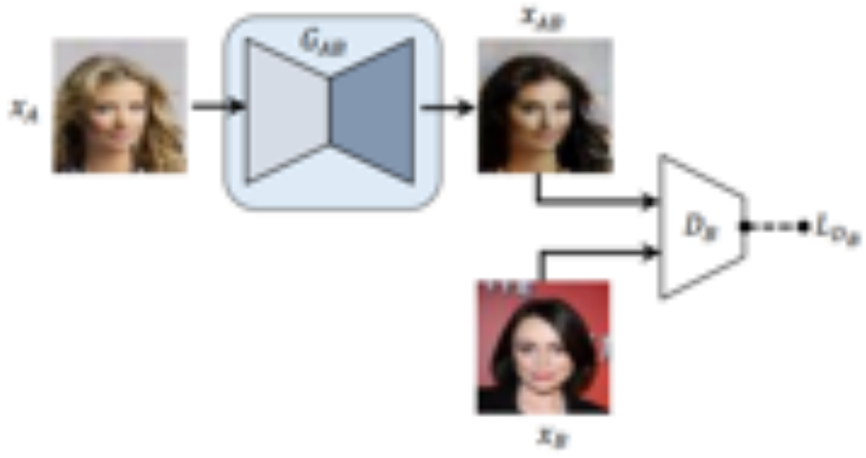
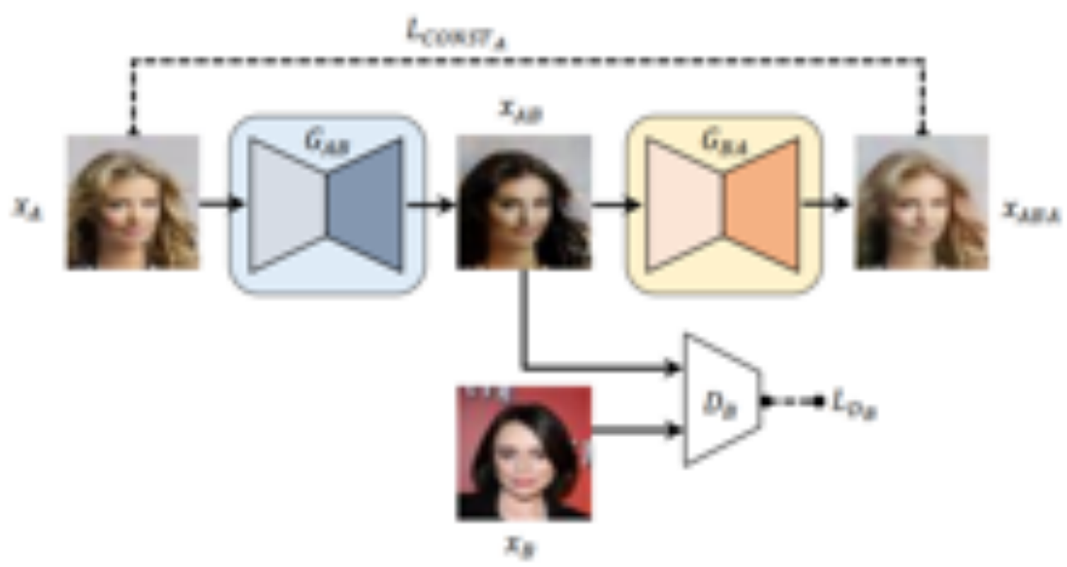
DiscoGAN

Standard GAN



Gan w/ reconstruction loss



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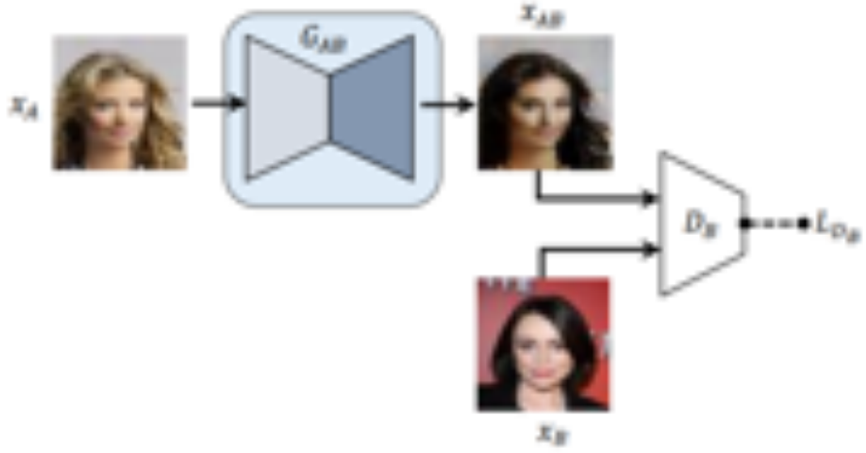

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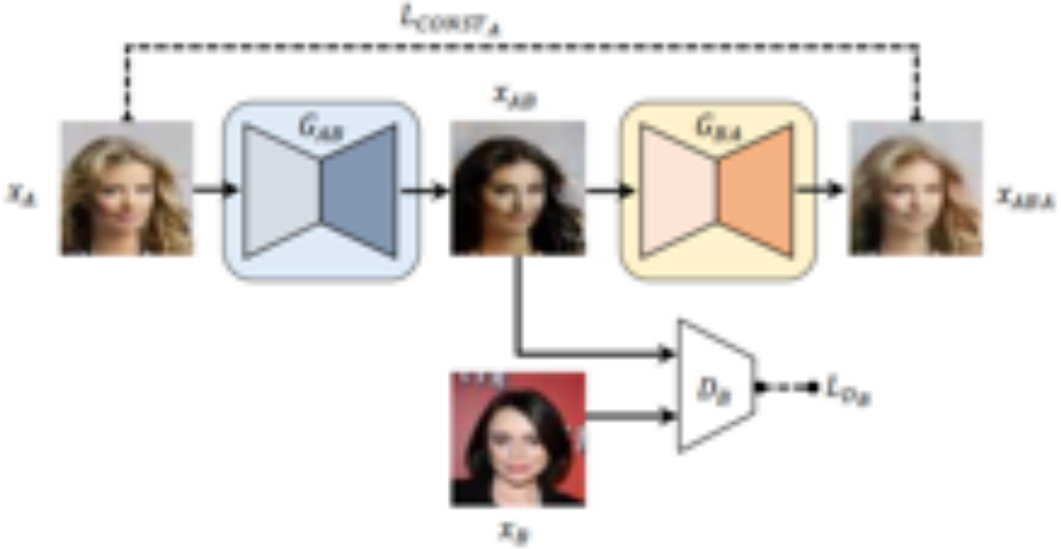
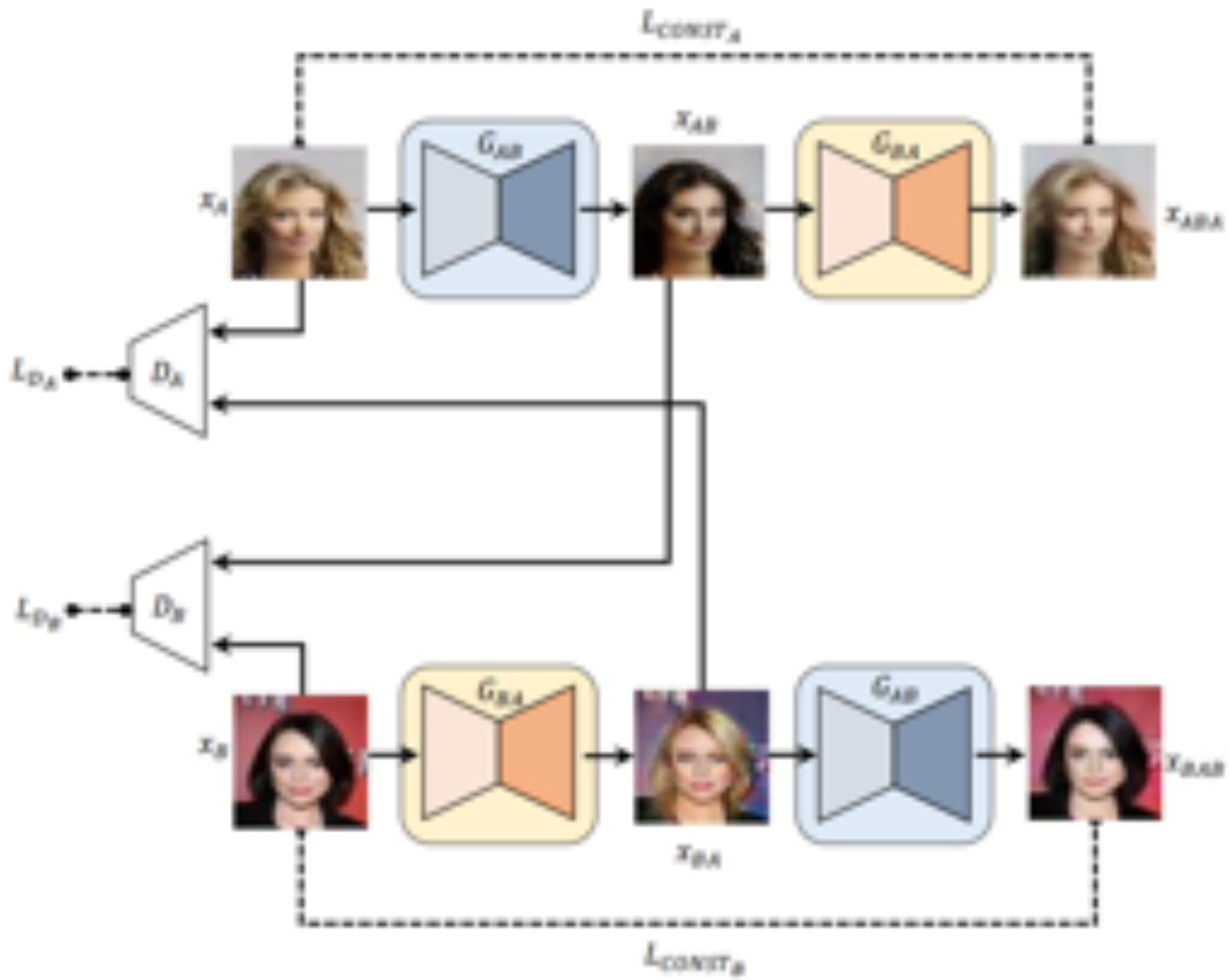


DiscoGAN



Kim, Taeksoo, et al. "Learning to discover cross-domain relations with generative adversarial networks." ICML'2017.

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Image-to-image Translation

Given inability to sample from joint distribution (i.e. observe paired data), learning conditional distribution (i.e. translation) is an ill-posed problem.

To solve it, constraints are necessary:

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- Weight-sharing constraint
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CoGAN: Coupled Generative Adversarial Networks

Liu, Ming-Yu, and Oncel Tuzel. "Coupled generative adversarial networks." NIPS'2016

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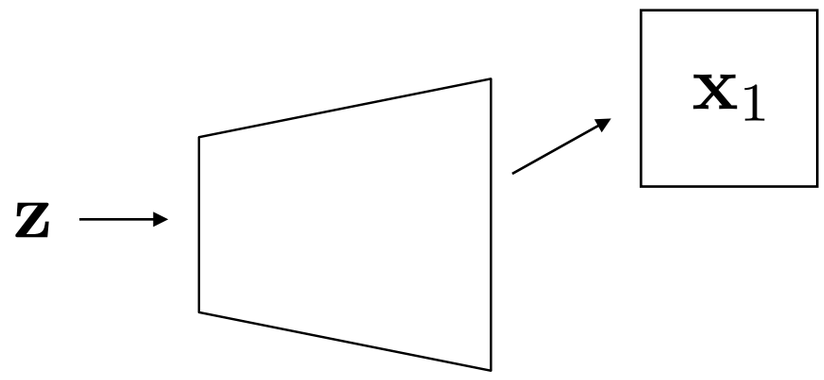

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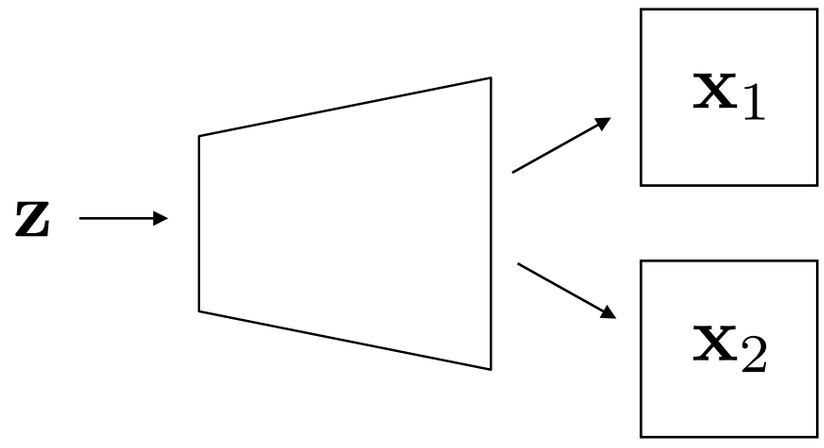

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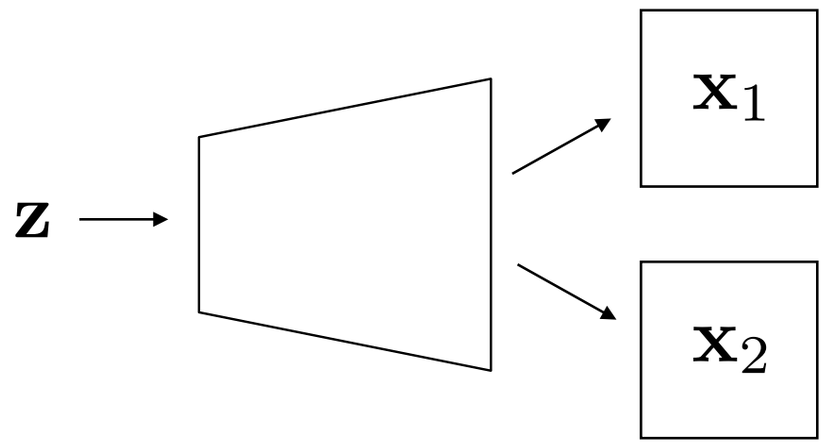

Observation: images in both domain share structure but not the style

Liu, Ming-Yu, and Oncel Tuzel. "Coupled generative adversarial networks." NIPS'2016

Constraint: Shared Latent Space

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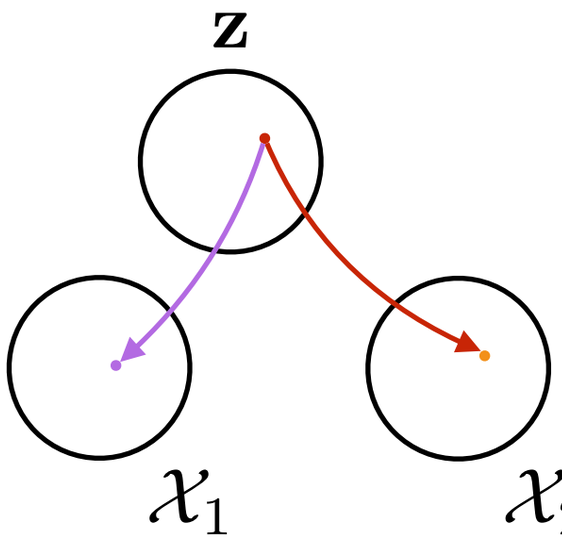

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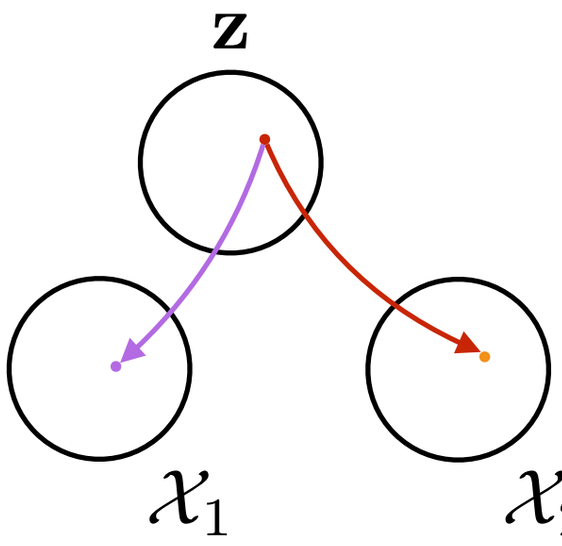

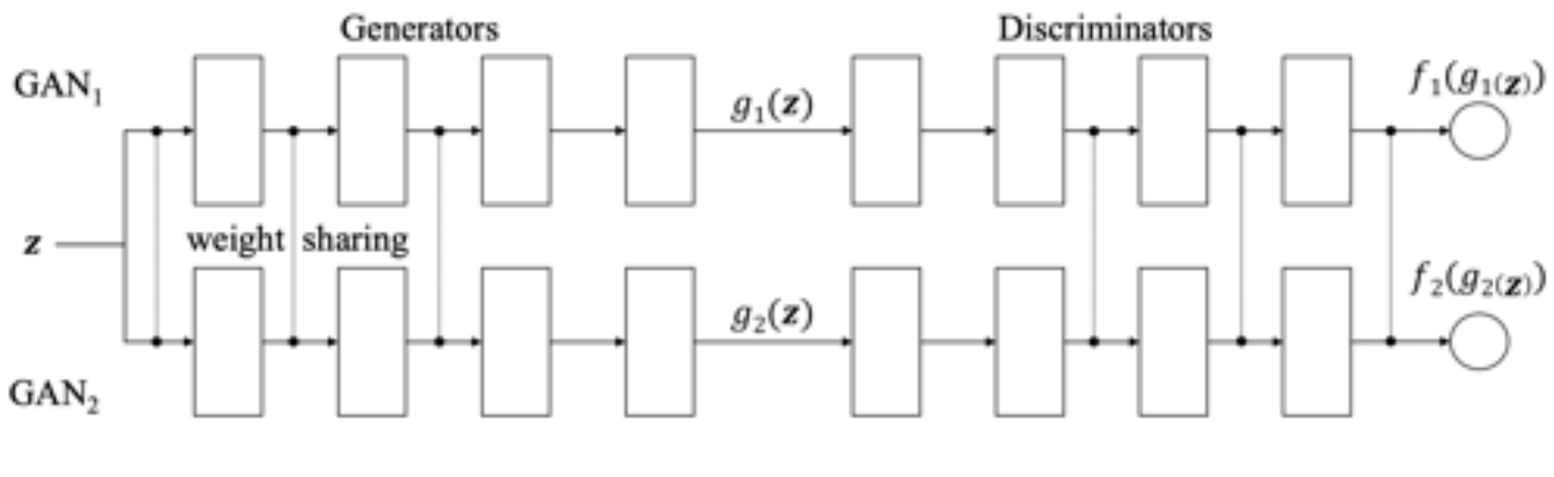

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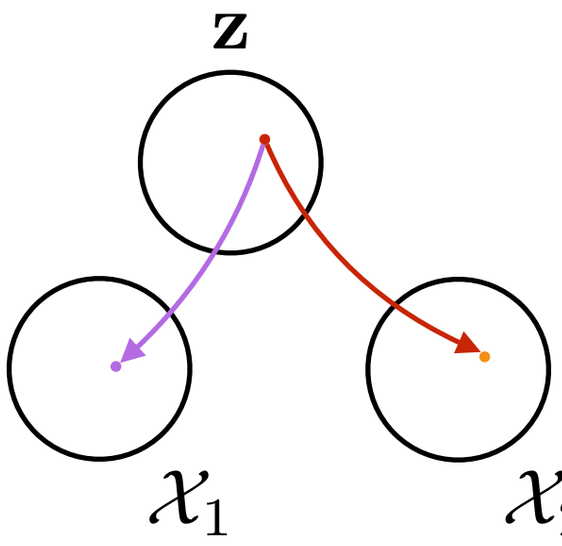
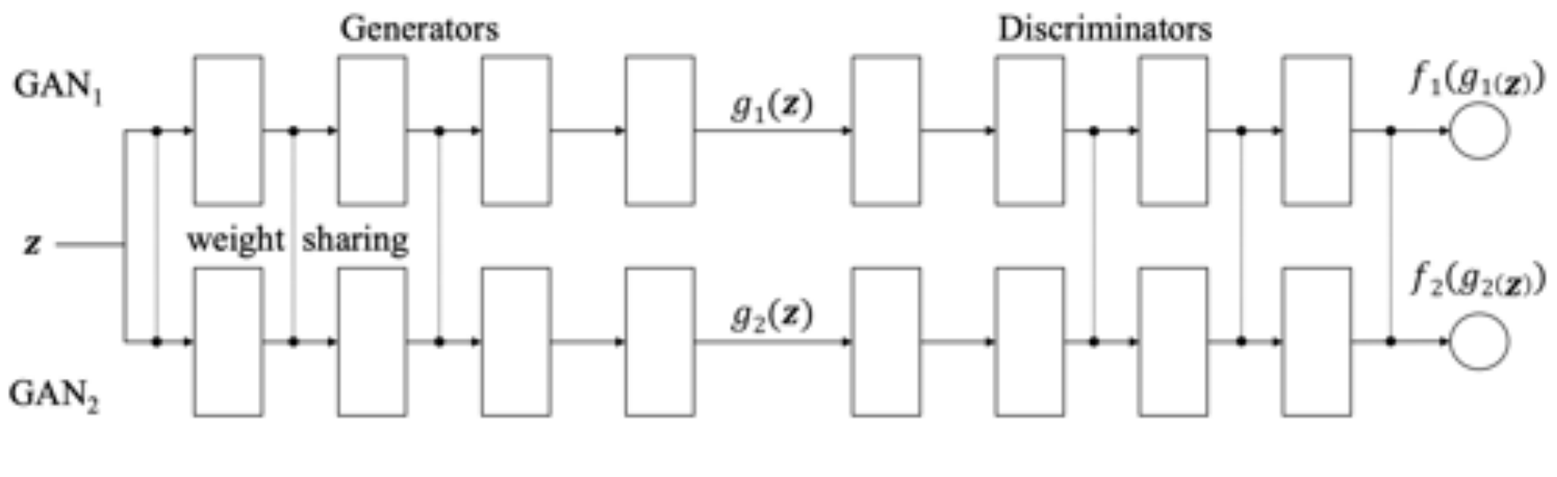
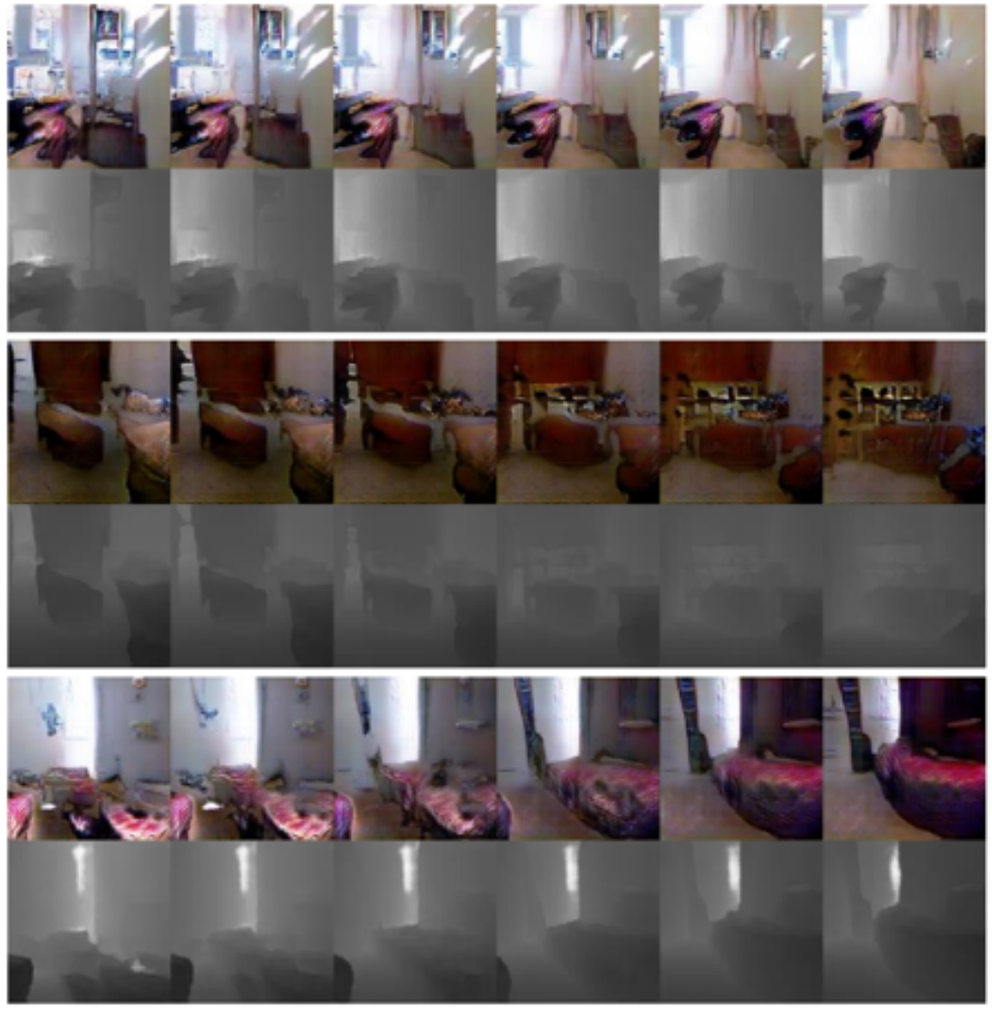




Implementation: shared latent space via weights sharing. Initial layers render low-frequency structure, while last layers encode the style

Liu, Ming-Yu, and Oncel Tuzel. "Coupled generative adversarial networks." NIPS'2016

CoGAN: Results



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Extending CoGAN: MUNIT

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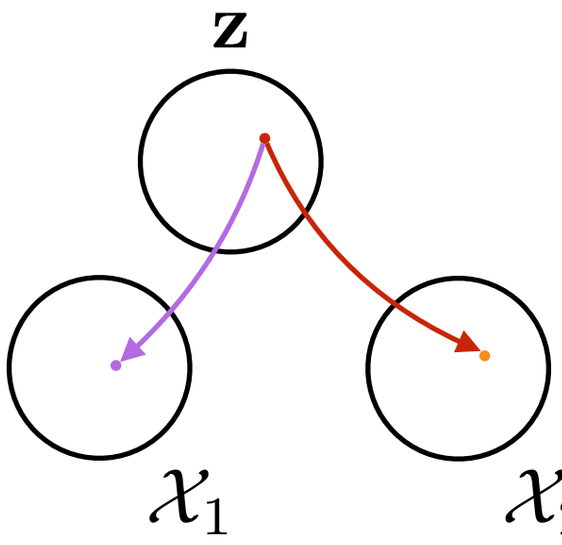

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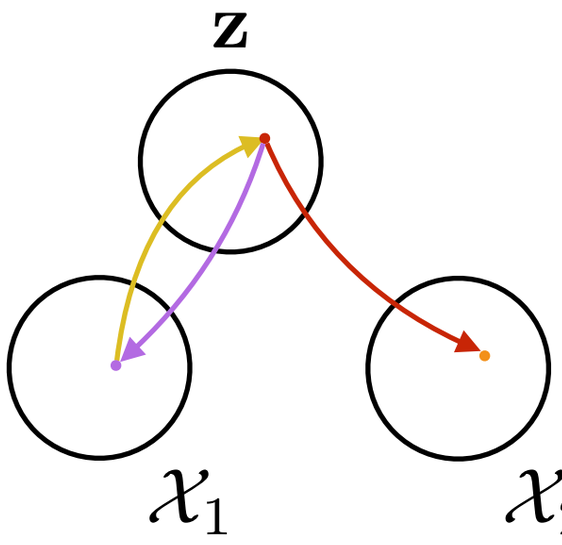

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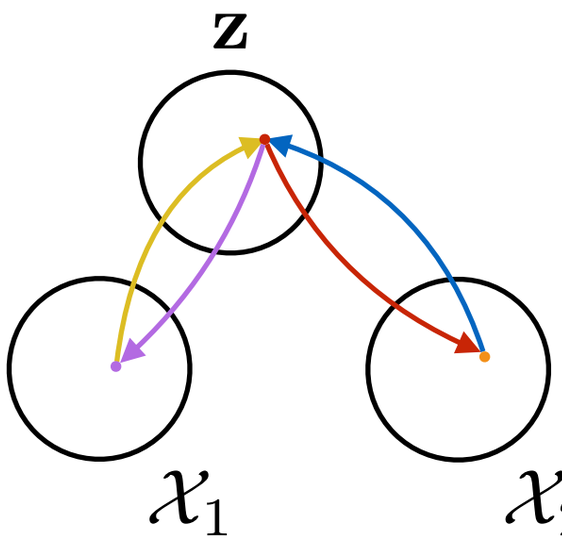

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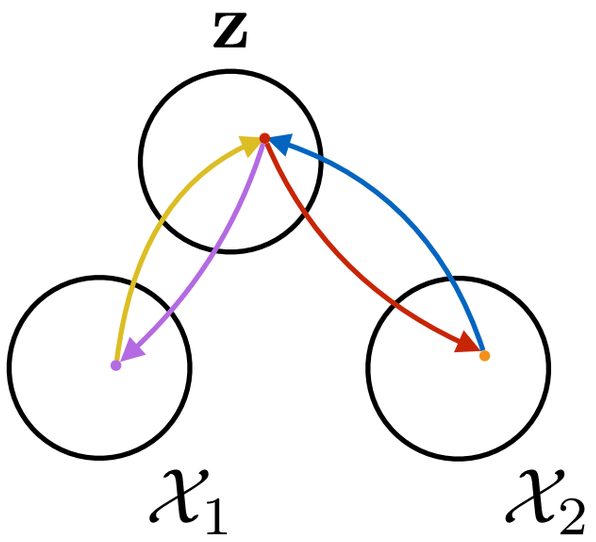

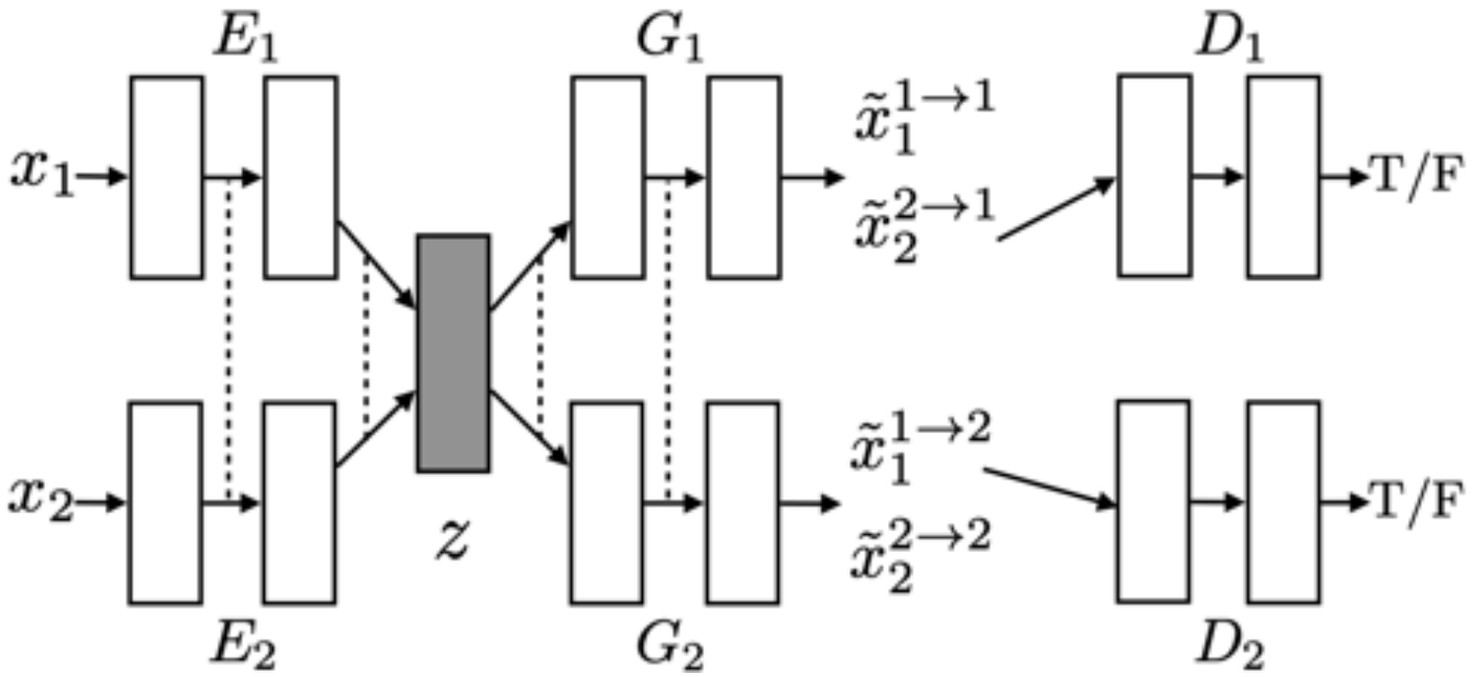

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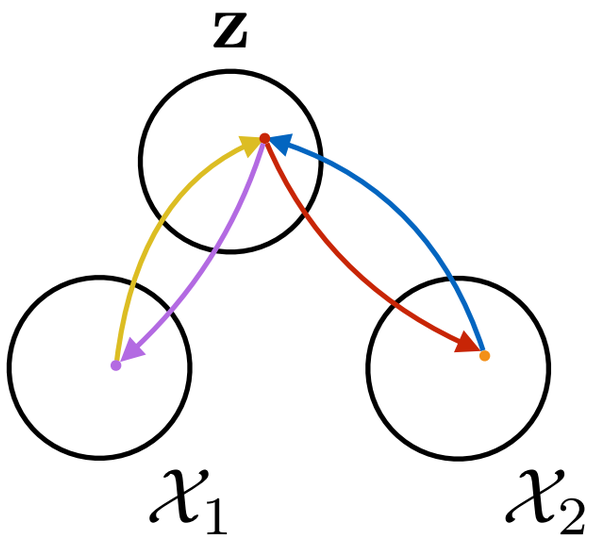

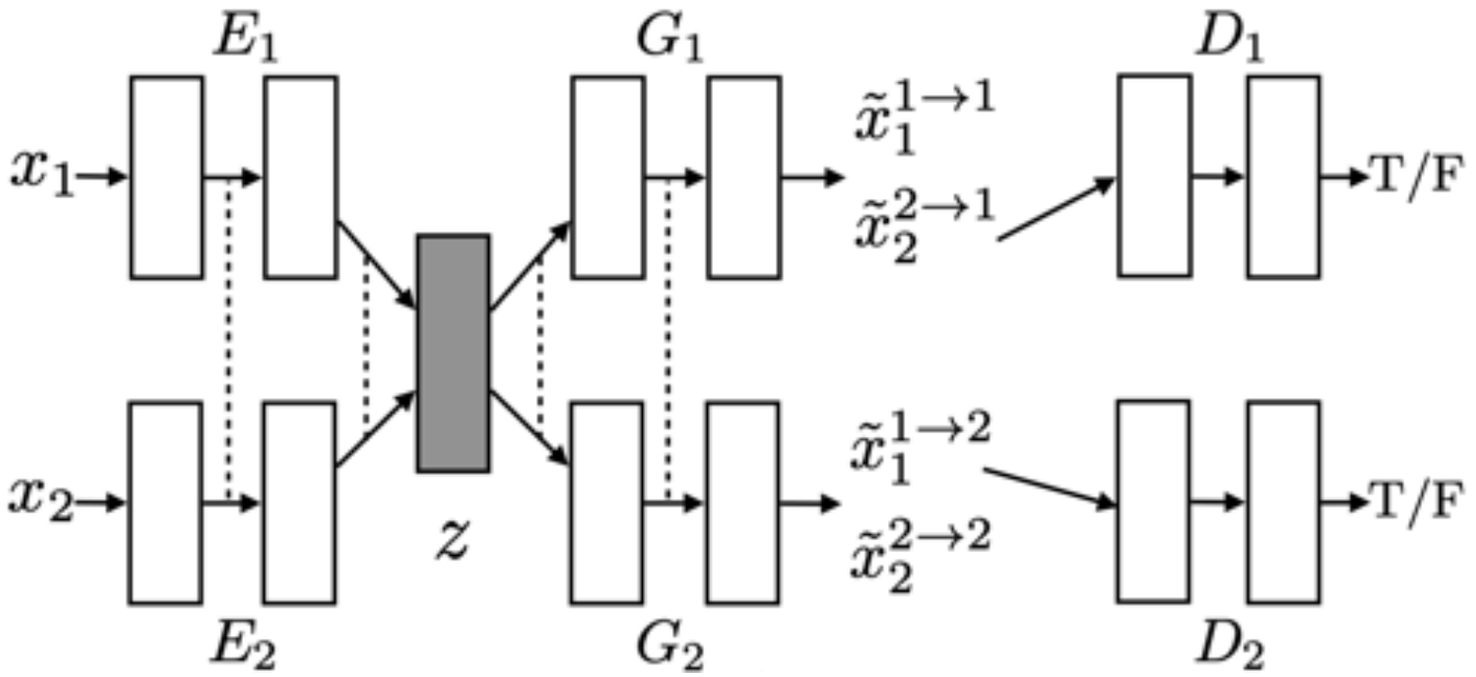

VAE

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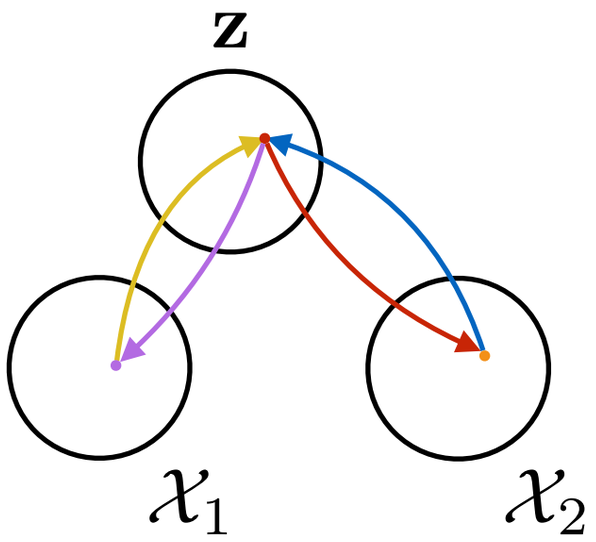

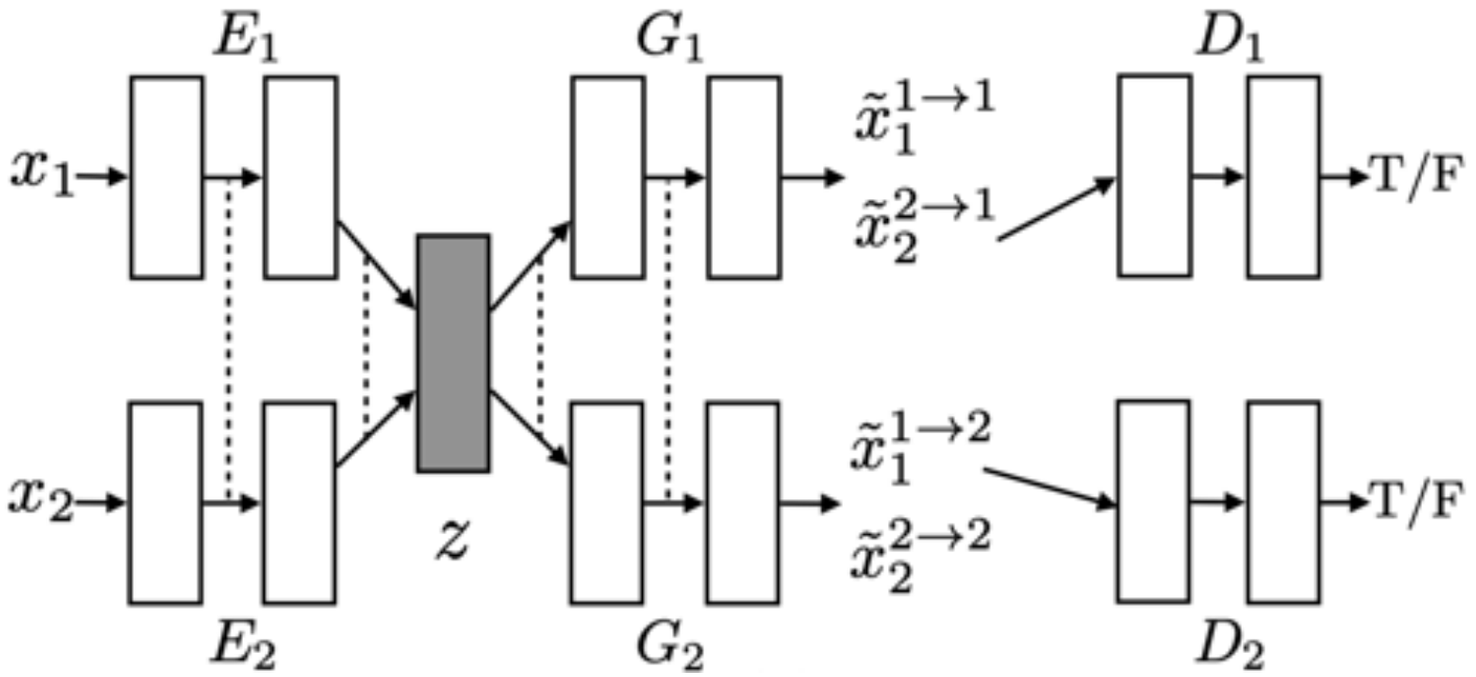

VAE

Implementation: train encoders with shared weights to go from image space to shared latent space

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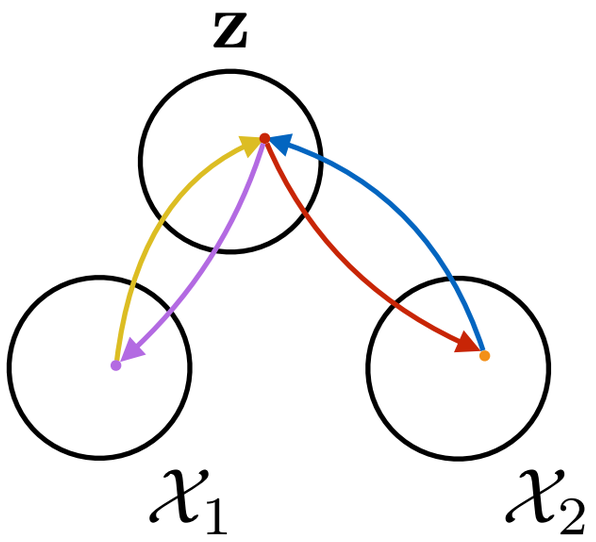

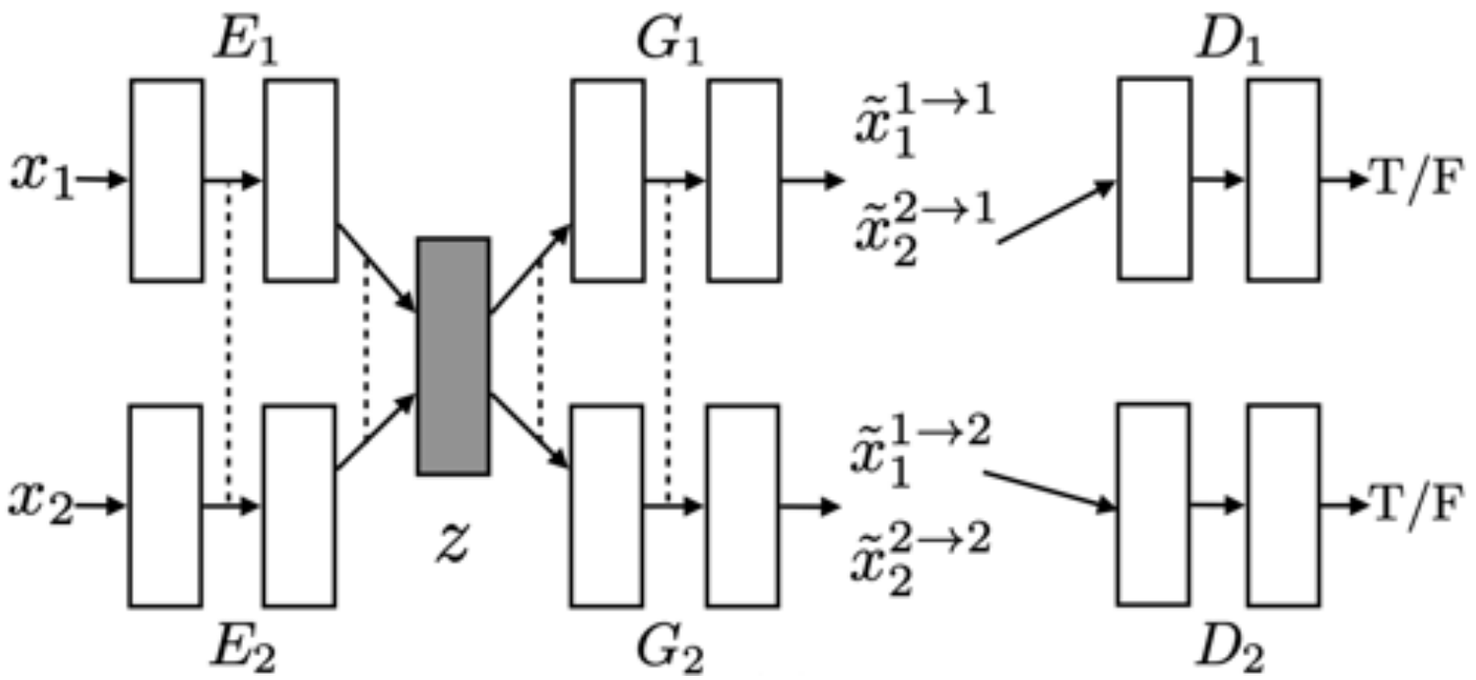

VAE

Issue: it is not a VAE, since it doesn't support sampling and cannot compute likelihood. Latent representation is a tensor, not a vector

Liu, Ming-Yu, Thomas Breuel, and Jan Kautz. "Unsupervised image-to-image translation networks." NIPS'2017

MUNIT: Results

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Given inability to sample from joint distribution (i.e. observe paired data), learning conditional distribution (i.e. translation) is an ill-posed problem.

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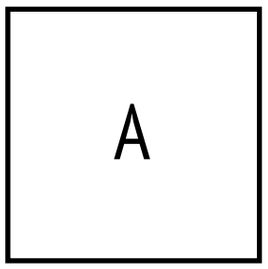

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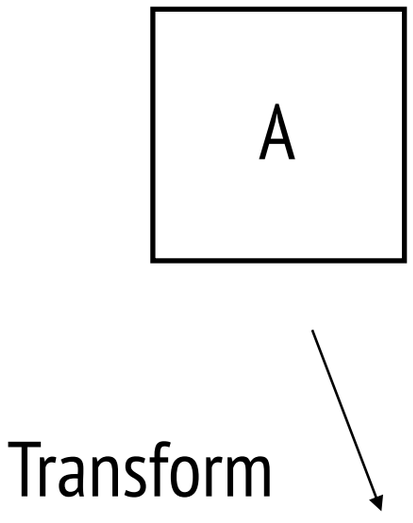

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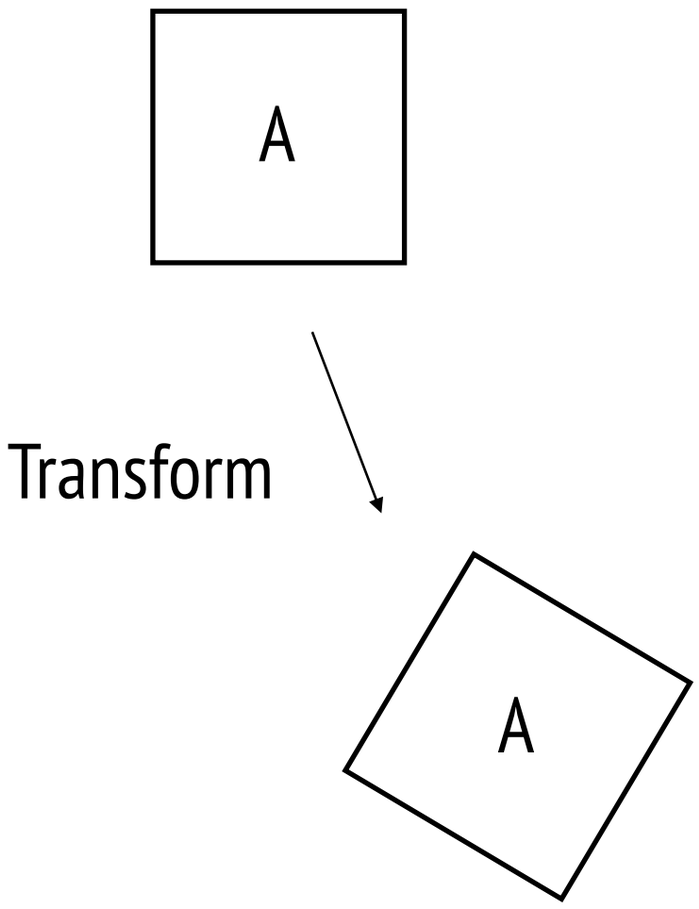

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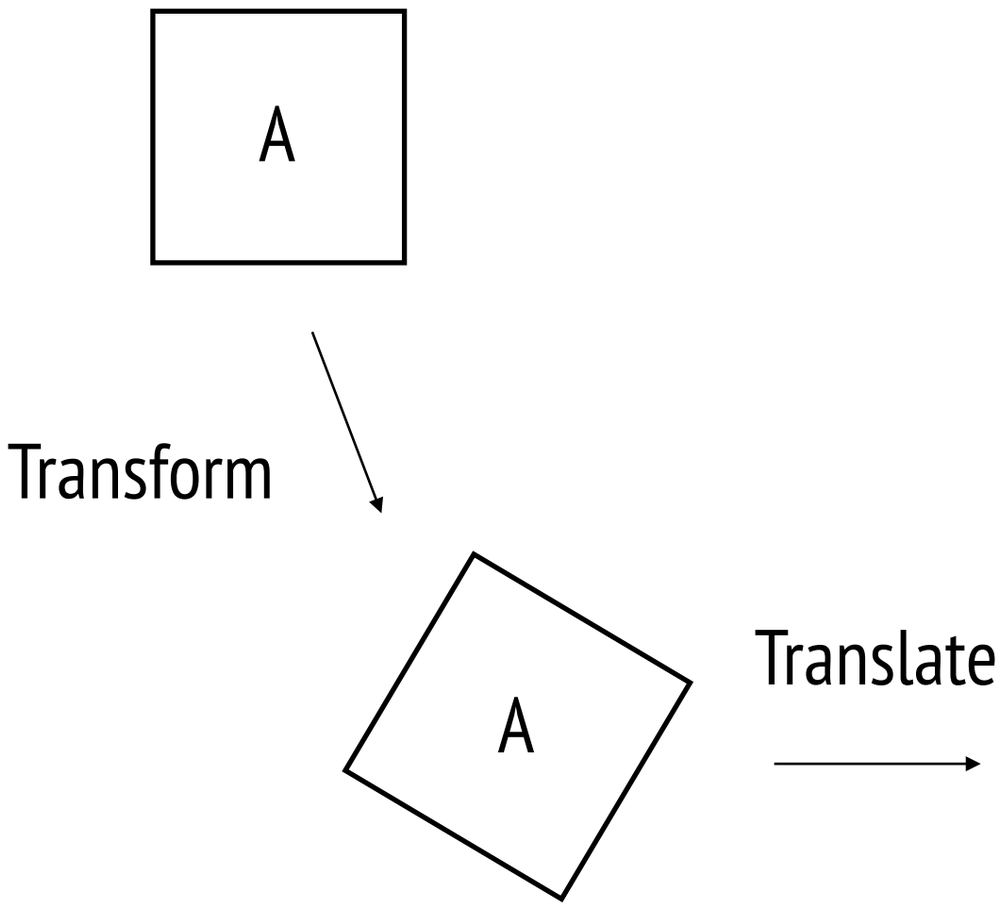

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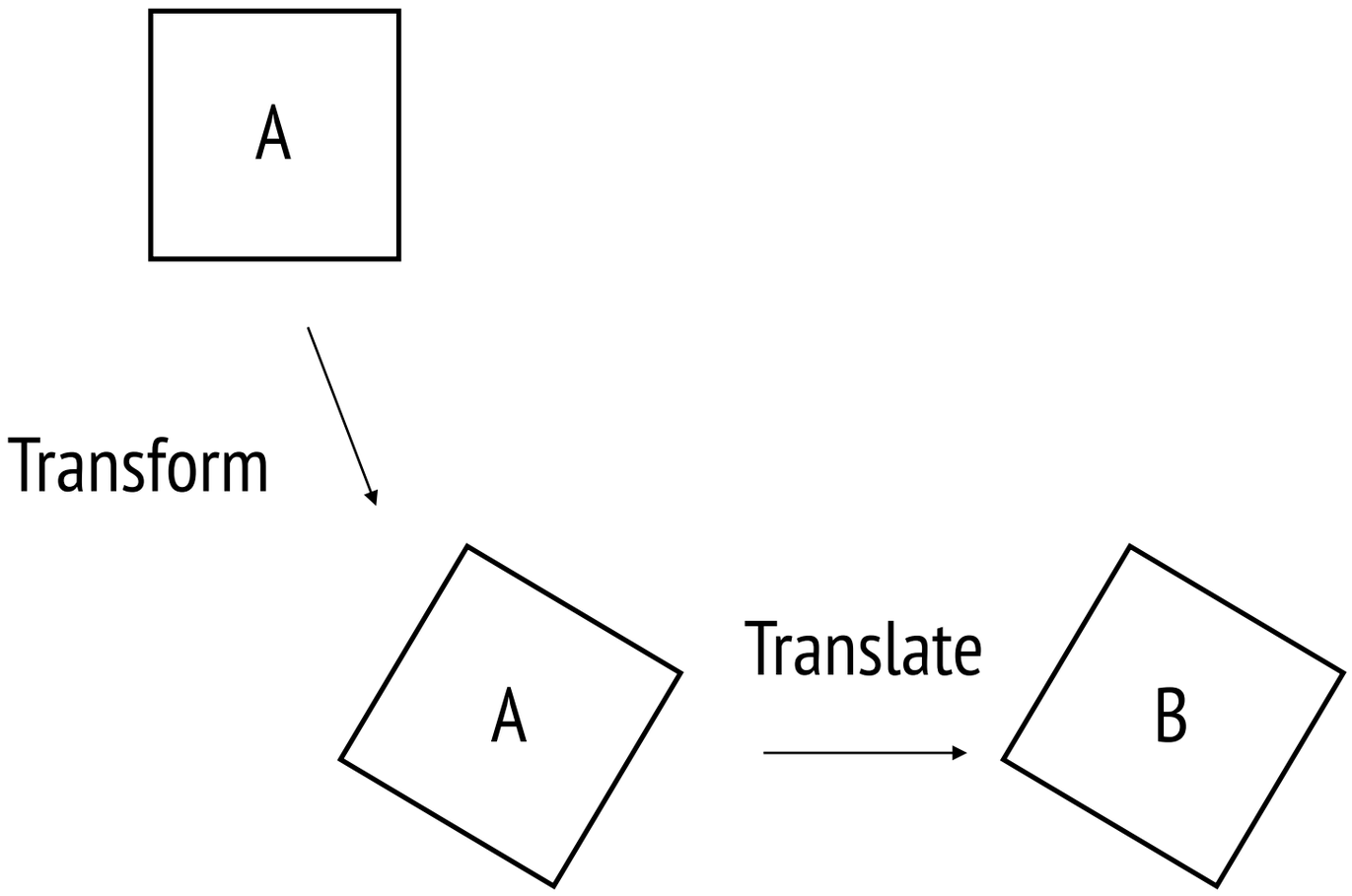

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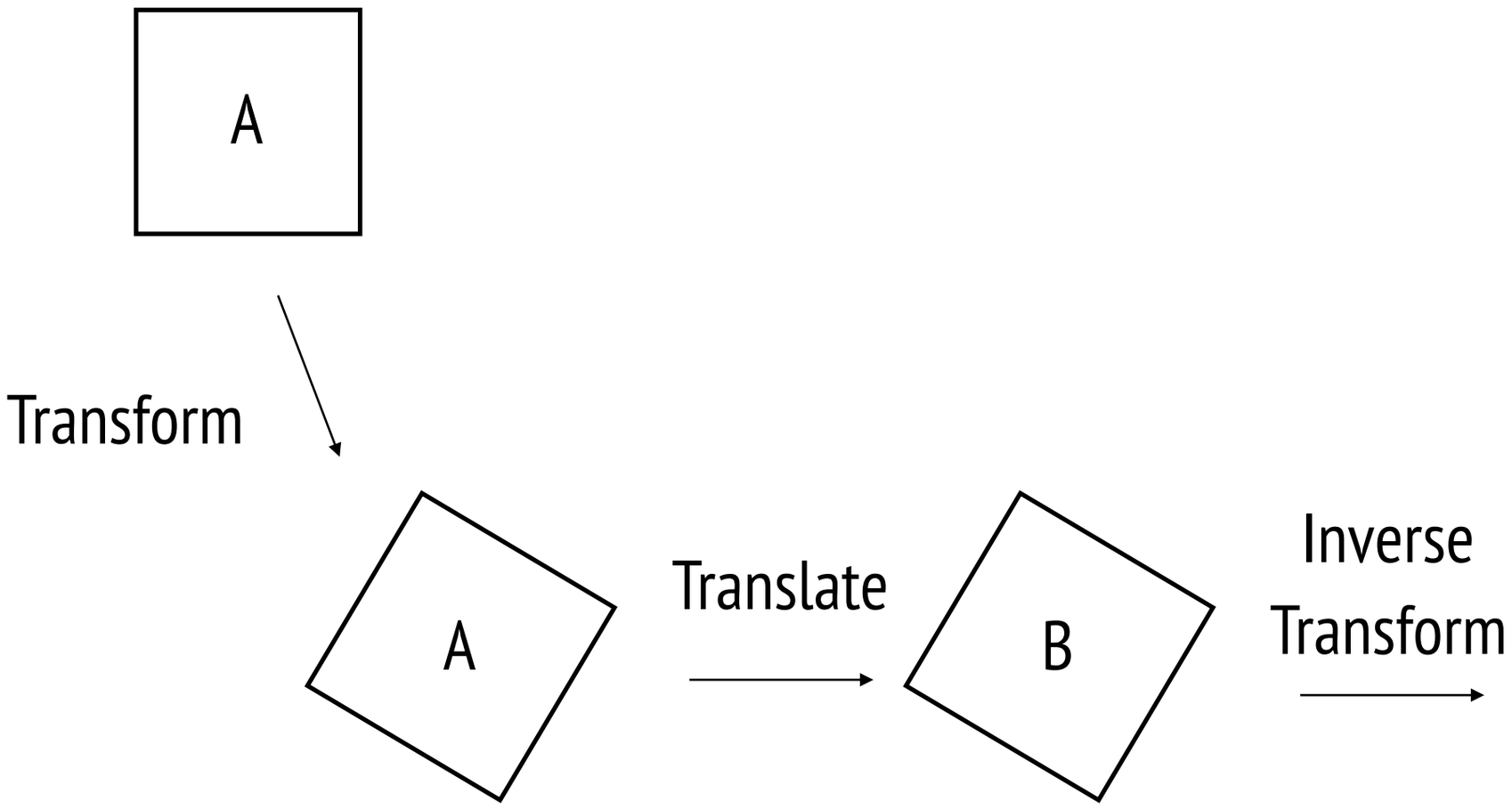

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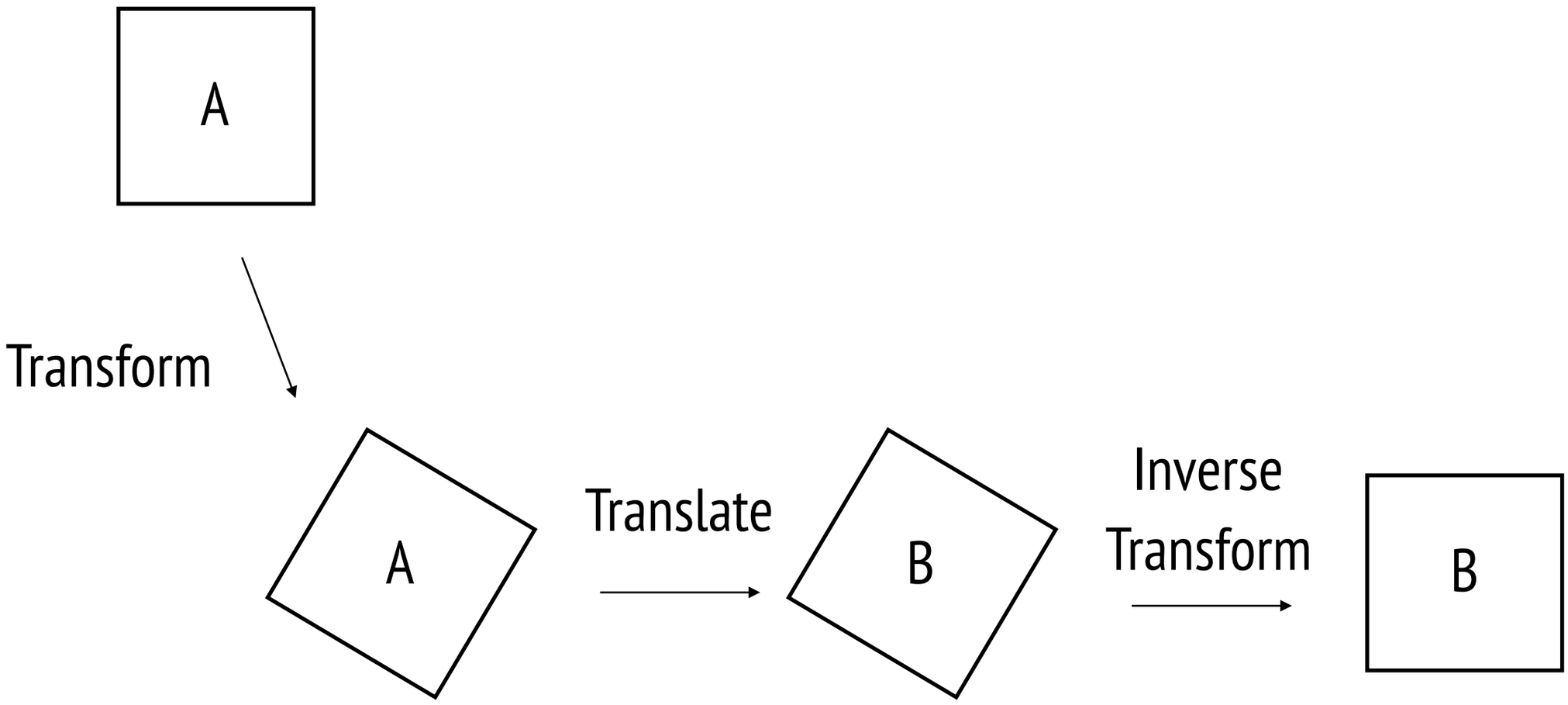

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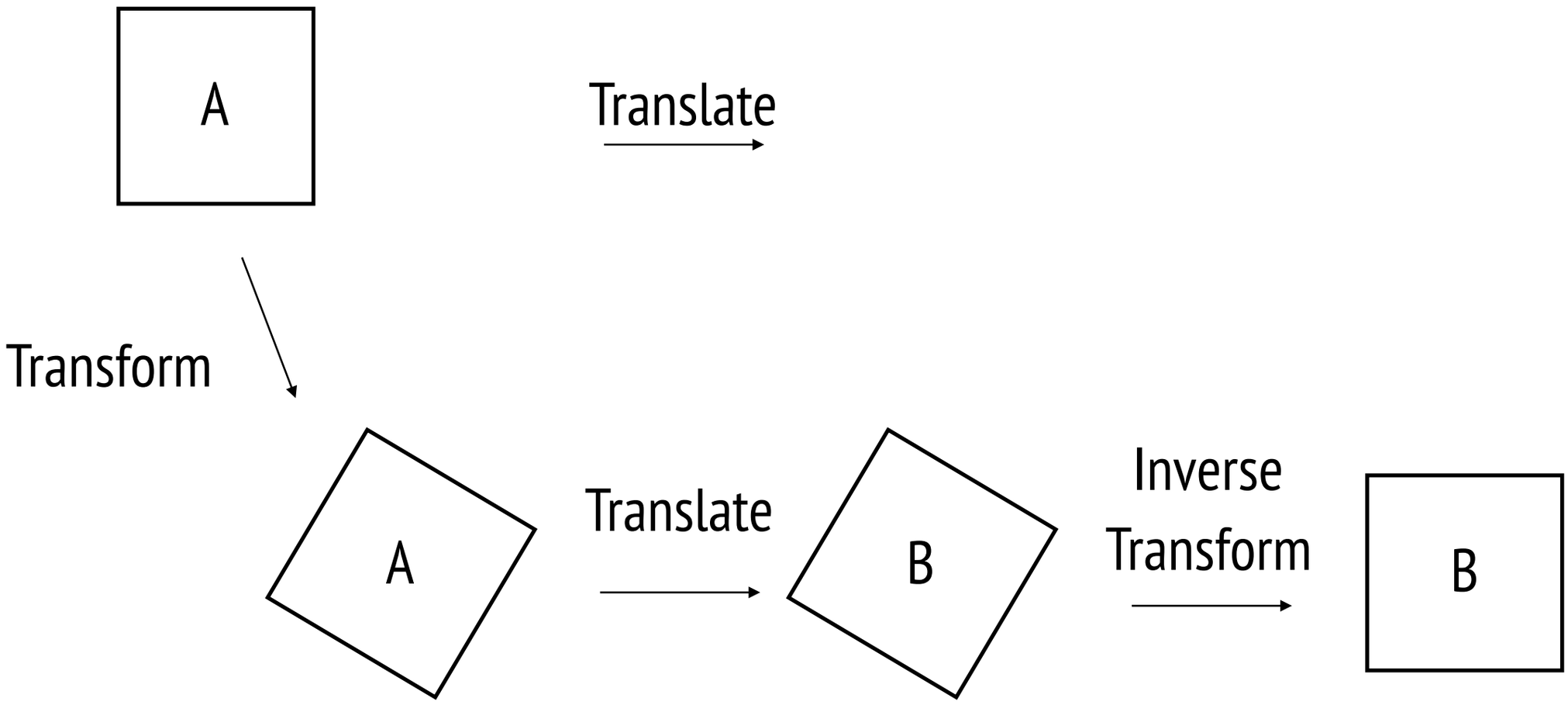

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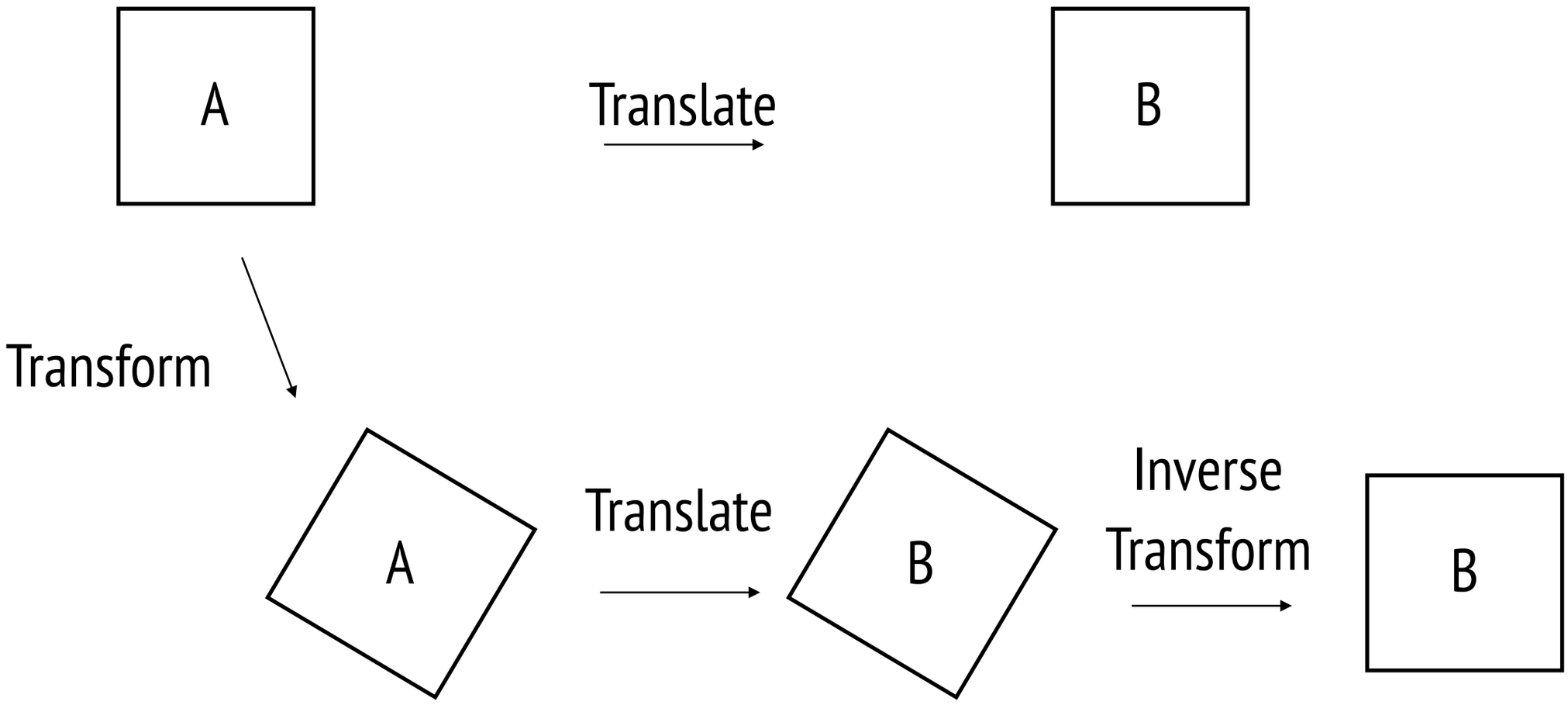

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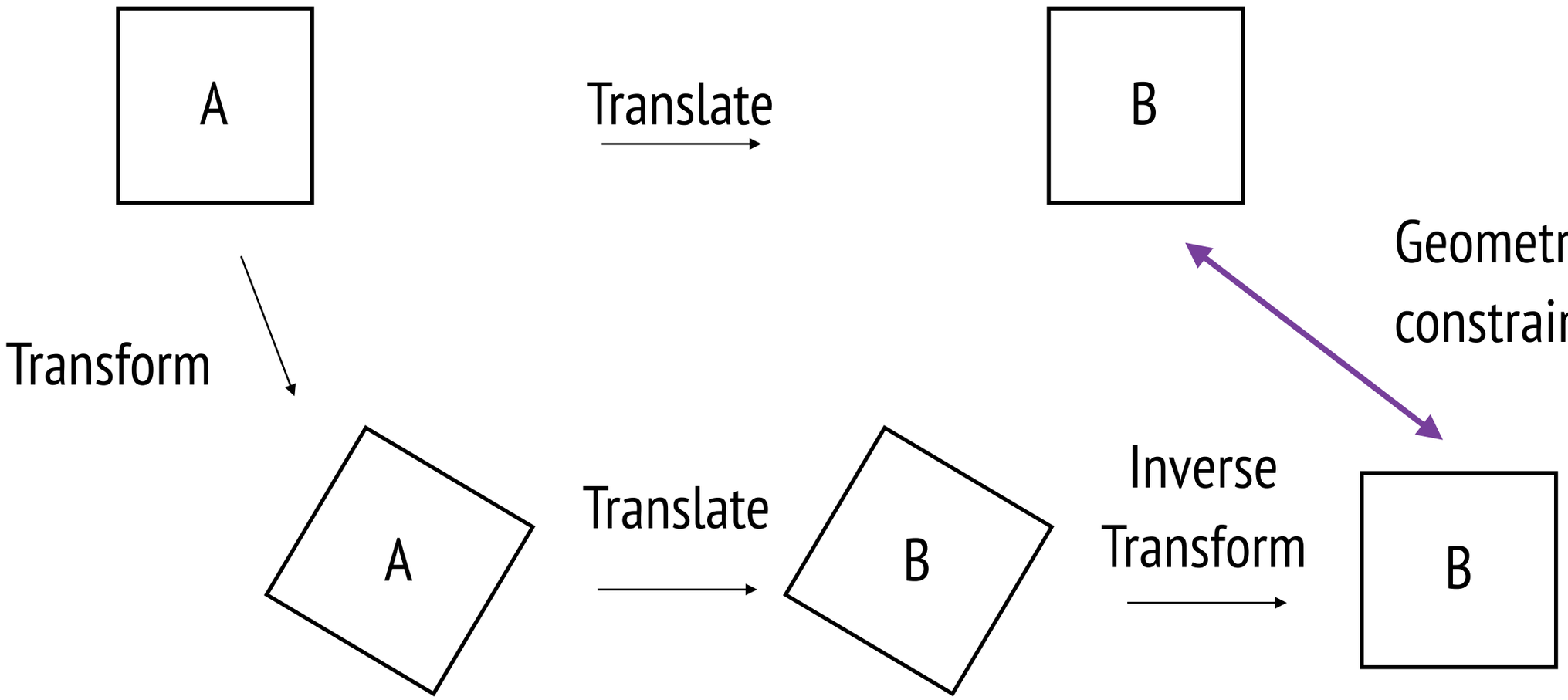

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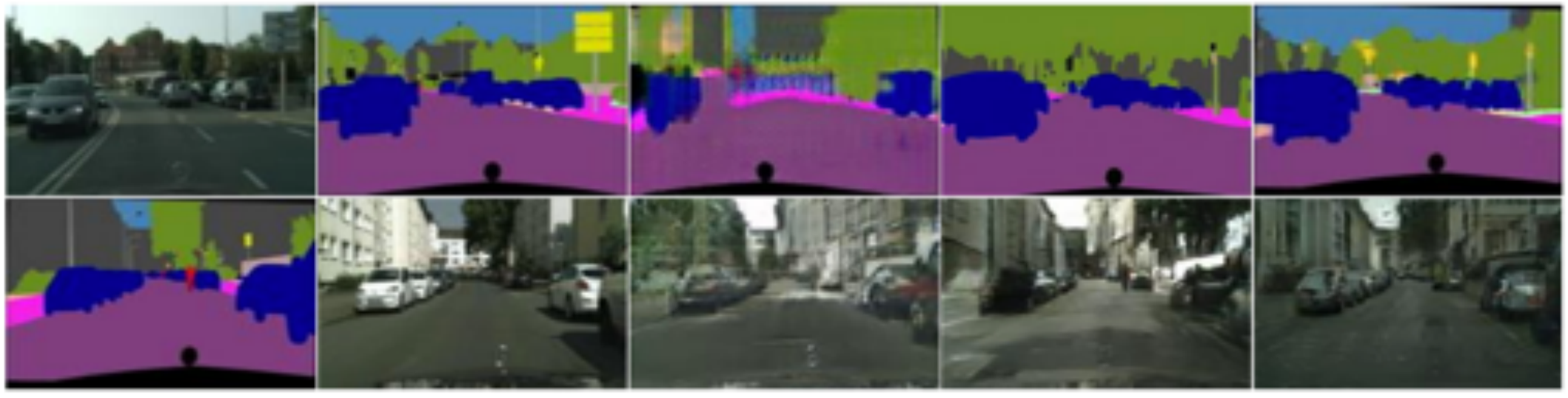

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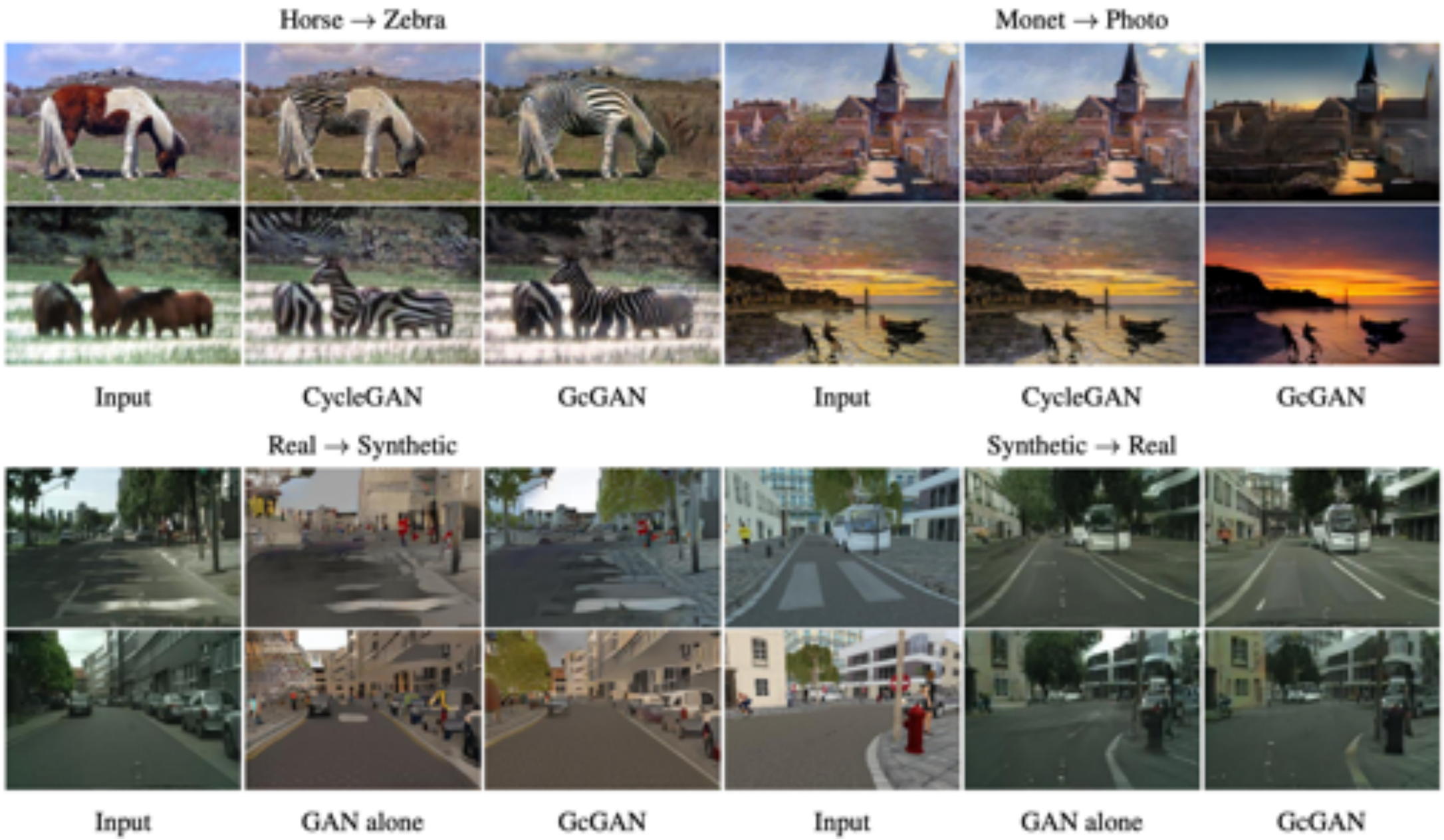
Geometry-consistency Constraint: Results



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Paired Image-to-image Translation

Given two domains the goal is to translate image from one possible representation to another.

$$\mathbf{x} \sim p(\mathbf{x}|\mathbf{y})$$

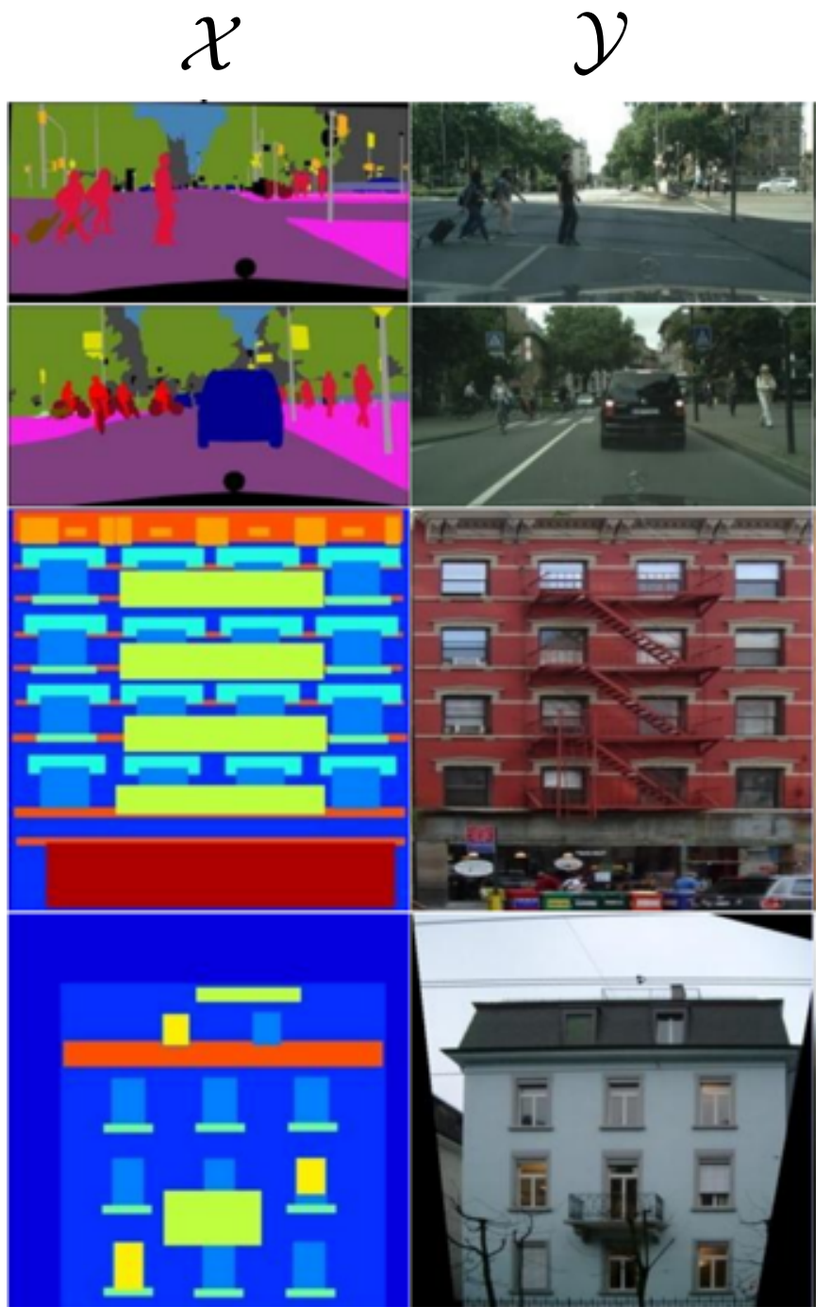
$$\mathbf{y} \sim p(\mathbf{y}|\mathbf{x})$$

Paired image-to-image translation

$$\mathbf{x}, \mathbf{y} \sim p(\mathbf{x}, \mathbf{y})$$

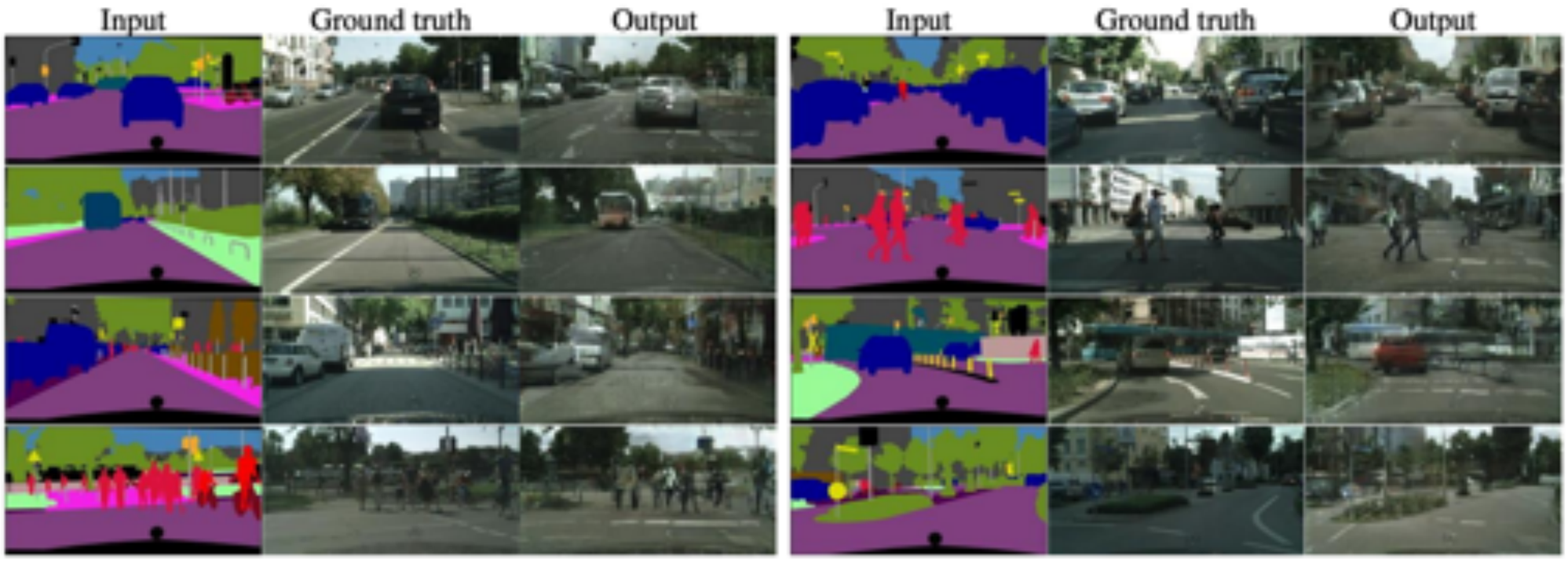
Unpaired

$$\mathbf{x} \sim p(\mathbf{x}), \ \mathbf{y} \sim p(\mathbf{y})$$



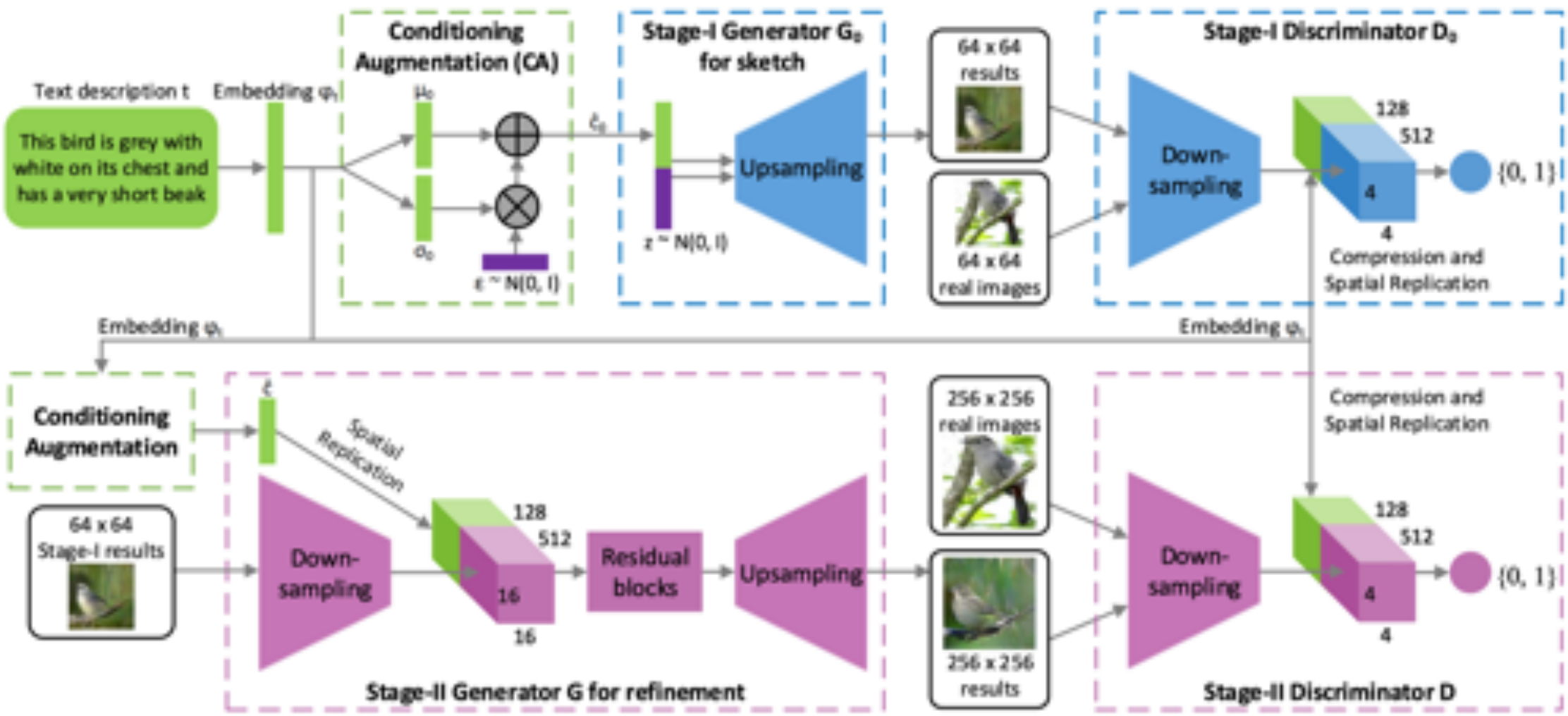
Isola, Phillip, et al. "Image-to-image translation with conditional adversarial networks." CVPR'2017

Pix2Pix: Results and Applications



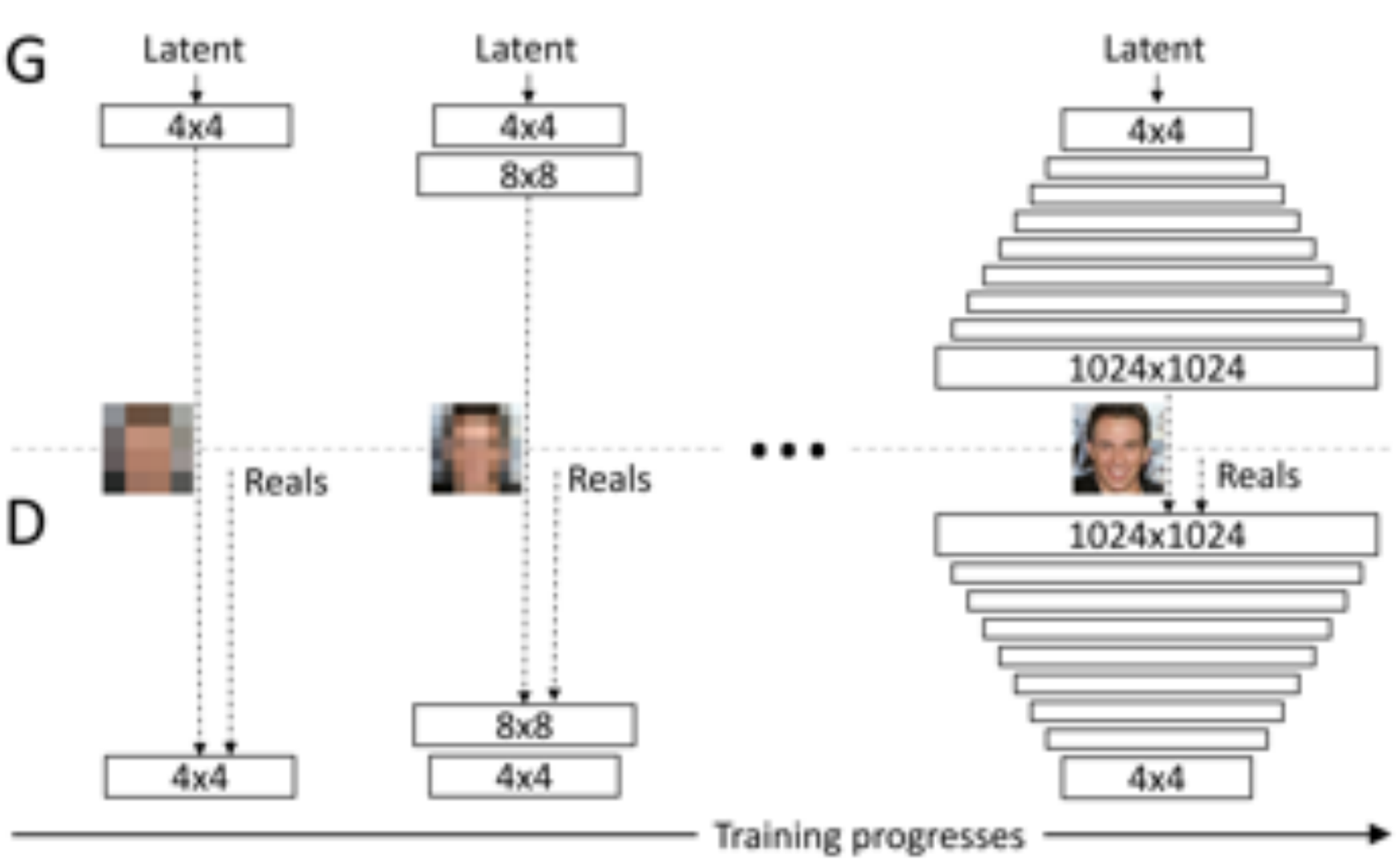
Isola, Phillip, et al. "Image-to-image translation with conditional adversarial networks." CVPR'2017

Multi-stage Architectures: StackGAN



Zhang, Han, et al. "Stackgan: Text to photo-realistic image synthesis with stacked generative adversarial networks." ICCV'2017

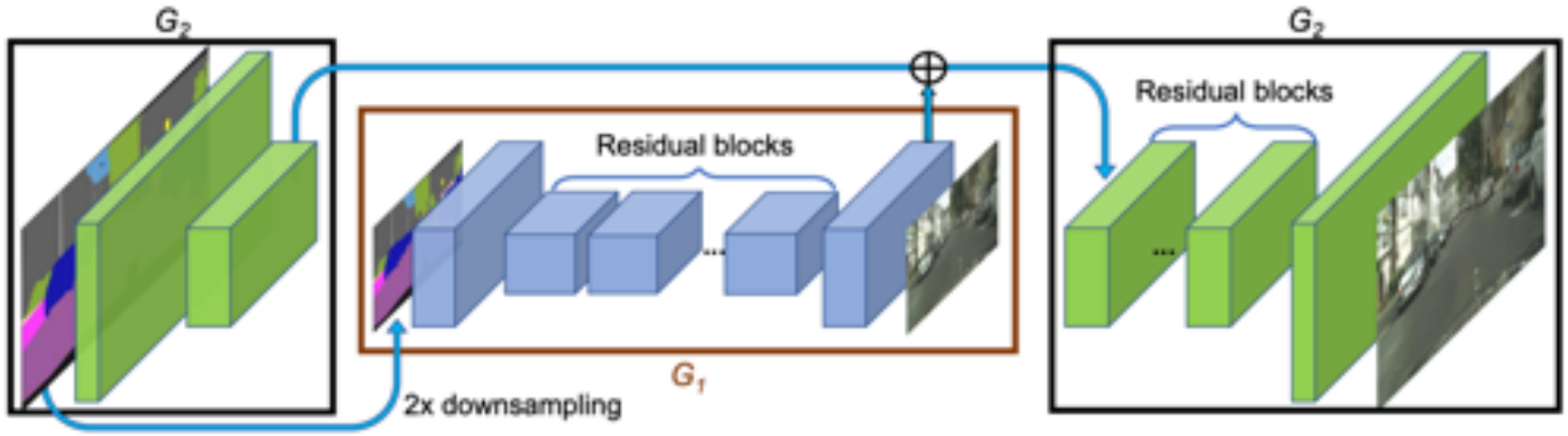
Multi-stage Architectures: ProgressiveGAN



Karras, Tero, et al. "Progressive growing of gans for improved quality, stability, and variation." ICLR'2017

Pix2PixHD: Multi-stage for I2I-translation

Idea: two-stage coarse-to-fine generation of HD images



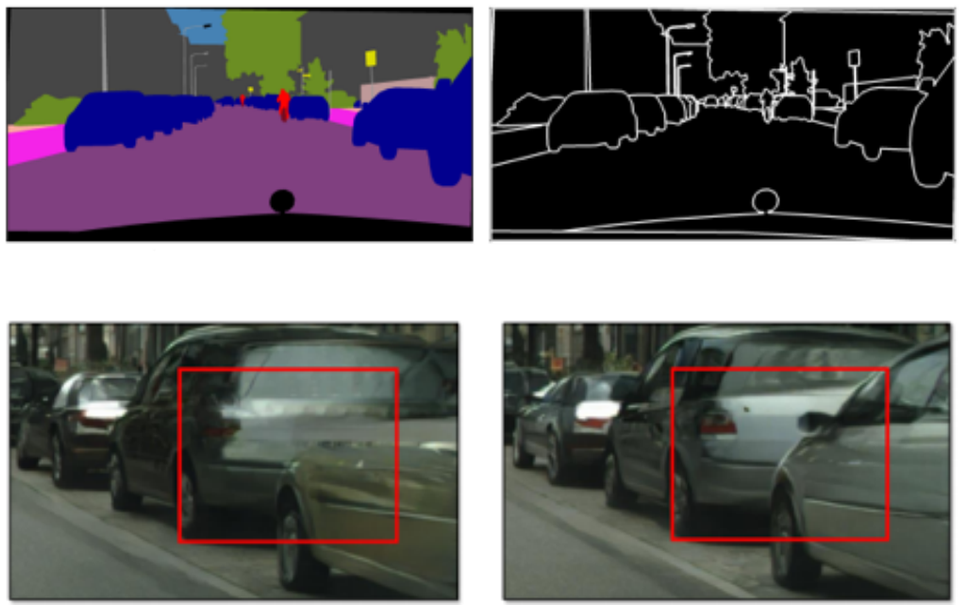
Other contributions:

- Instance segmentation information
- Instance-wise feature embeddings

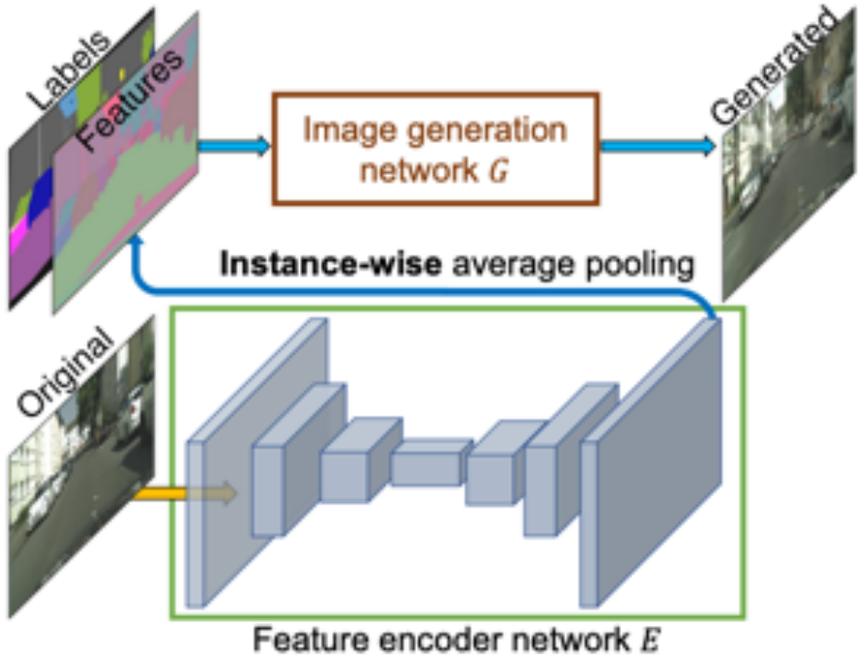
Wang, Ting-Chun, et al. "Pix2pixHD: High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs." CVPR'2018

Pix2PixHD: Multi-stage for I2I-translation

Instance segmentation



Instance-wise features



Features are then average-pooled for each instance

Wang, Ting-Chun, et al. "Pix2pixHD: High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs." CVPR'2018

Pix2PixHD: Results

Input labels

Synthesized image

Wang, Ting-Chun, et al. "Pix2pixHD: High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs." CVPR'2018

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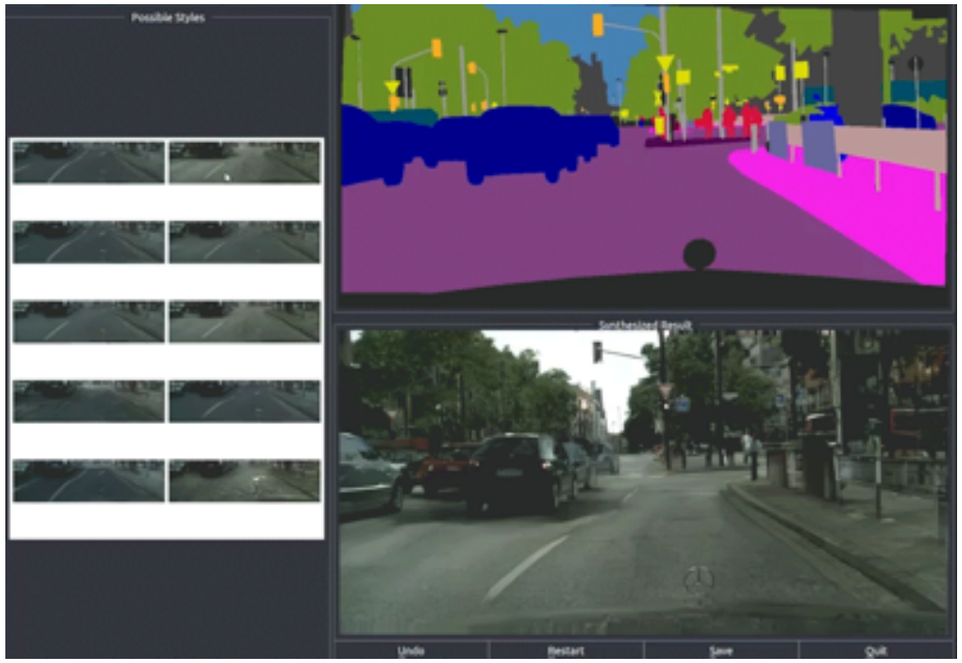

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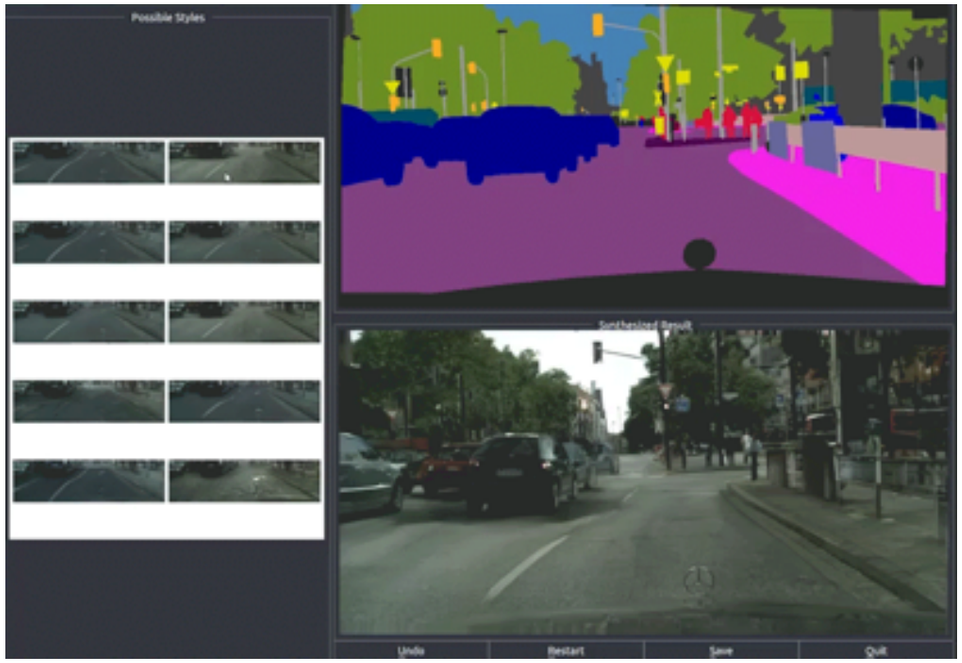

Wang, Ting-Chun, et al. "Pix2pixHD: High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs." CVPR'2018

Normalization Layers

We will cover the following:

- Batch Normalization (BN)
- Instance Normalization (IN)
- Adaptive Instance Normalization (AdaIN)
- SPatially Adaptive DEnormalization (SPADE)

There are many, many more….

Batch Normalization

Problem: small changes in the initial layers result in significant changes in the deeper layers. This way deeper layers have to learn to adapt to different distributions of their inputs.

Ioffe, and Szegedy. "Batch normalization: Accelerating deep network training by reducing internal covariate shift." 2015

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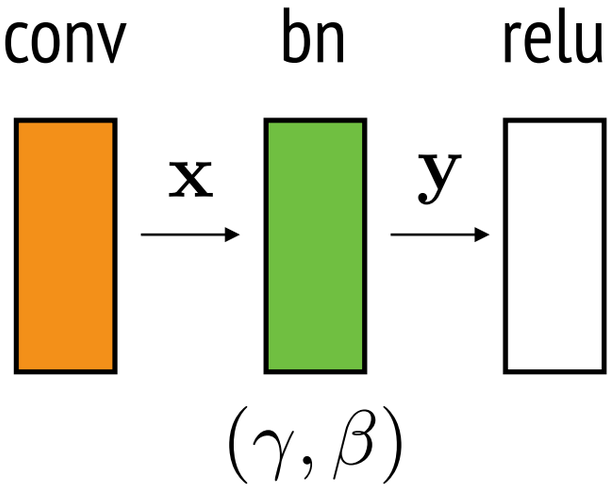

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Batch Normalization

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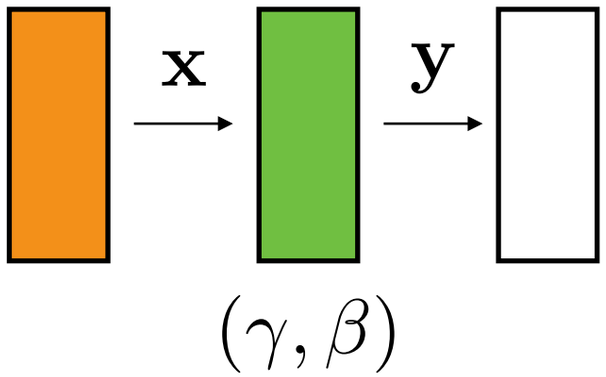
Compute:

$$\mu_B = \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \sigma_B^2 = \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_B)^2$$



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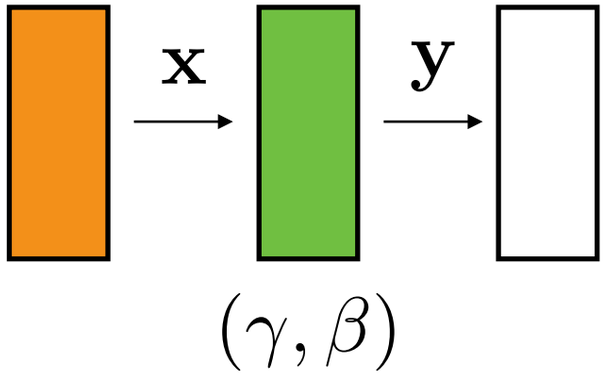

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Normalize:

$$\hat{x}_i^{(k)} = \frac{x_i^{(k)} - \mu_B^{(k)}}{\sqrt{\sigma_B^{(k)^2} + \epsilon}}$$

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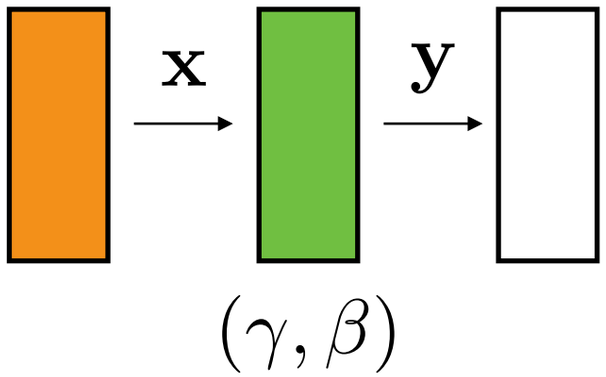

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For stability

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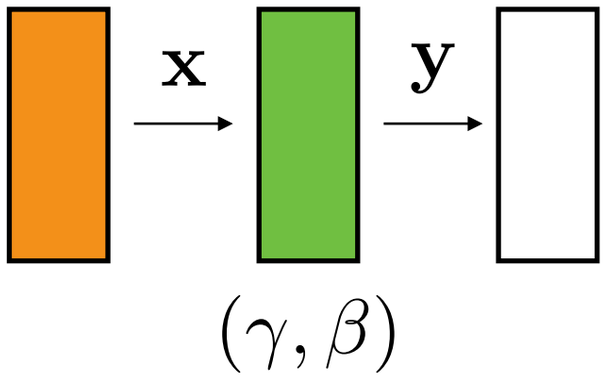

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Normalize:

$$\hat{x}_i^{(k)} = \frac{x_i^{(k)} - \mu_B^{(k)}}{\sqrt{\sigma_B^{(k)^2} + \epsilon}}$$

For stability

Transform:

$$y_i^{(k)} = \gamma^{(k)}\hat{x}_i^{(k)} + \beta^{(k)}$$

Ioffe, and Szegedy. "Batch normalization: Accelerating deep network training by reducing internal covariate shift." 2015

Batch Normalization

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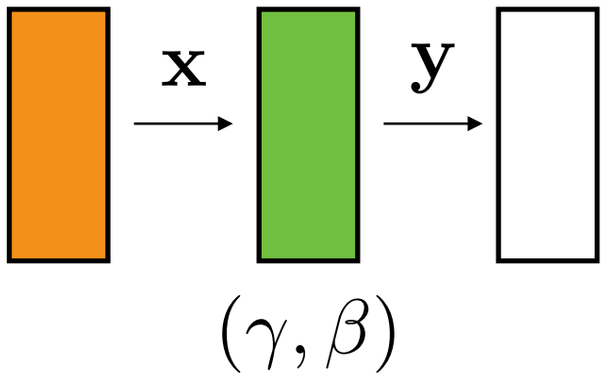

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Normalize:

$$\hat{x}_i^{(k)} = \frac{x_i^{(k)} - \mu_B^{(k)}}{\sqrt{\sigma_B^{(k)^2} + \epsilon}}$$

For stability

Learned

Transform:

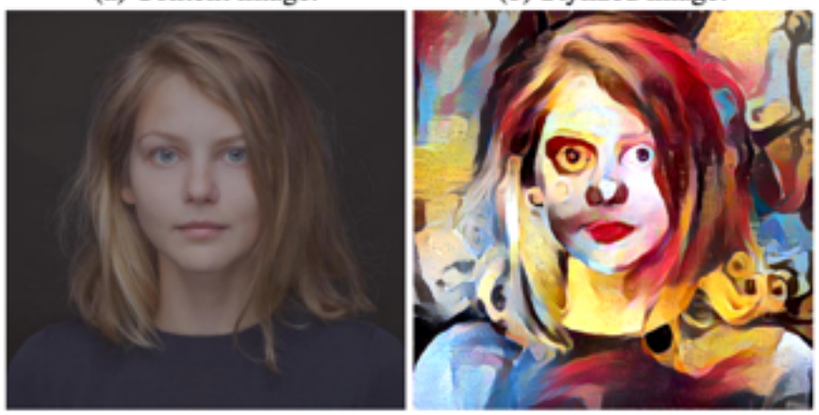
$$y_i^{(k)} = \gamma^{(k)}\hat{x}_i^{(k)} + \beta^{(k)}$$

Ioffe, and Szegedy. "Batch normalization: Accelerating deep network training by reducing internal covariate shift." 2015

Instance Normalization

Problem: Contrast of a stylized image does not depend on the contrast of content image

(a) Content image. (b) Stylized image.



(c) Low contrast content image. (d) Stylized low contrast image.

Compute:

$$\mu_{ti} = \frac{1}{HW} \sum_{l=1}^{W} \sum_{m=1}^{H} x_{tilm}$$

$$\sigma_{ti}^2 = \frac{1}{HW} \sum_{l=1}^{W} \sum_{m=1}^{H} (x_{tilm} - mu_{ti})^2$$

Ulyanov, Vedaldi, and Lempitsky. "Instance normalization: The missing ingredient for fast stylization." 2016

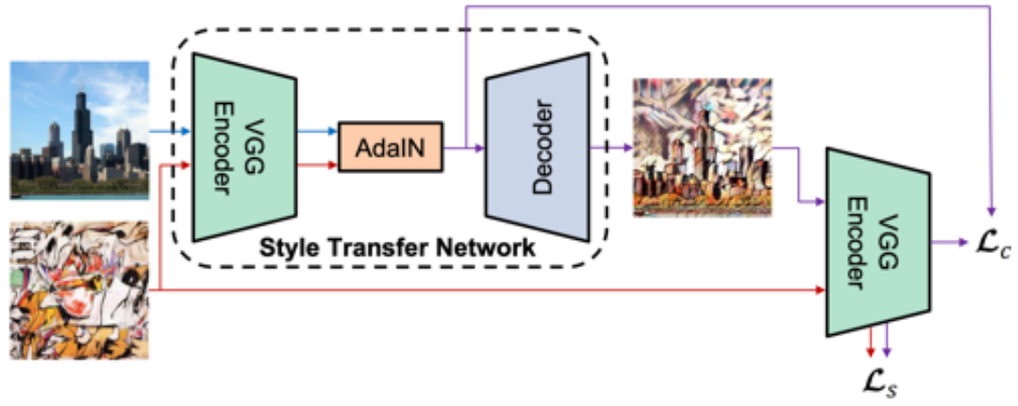
Adaptive Instance Normalization

Idea: If IN normalizes the input to a single style specified by the affine parameters, is it possible to adapt it to arbitrarily given styles by using adaptive affine transformations?

Layer:

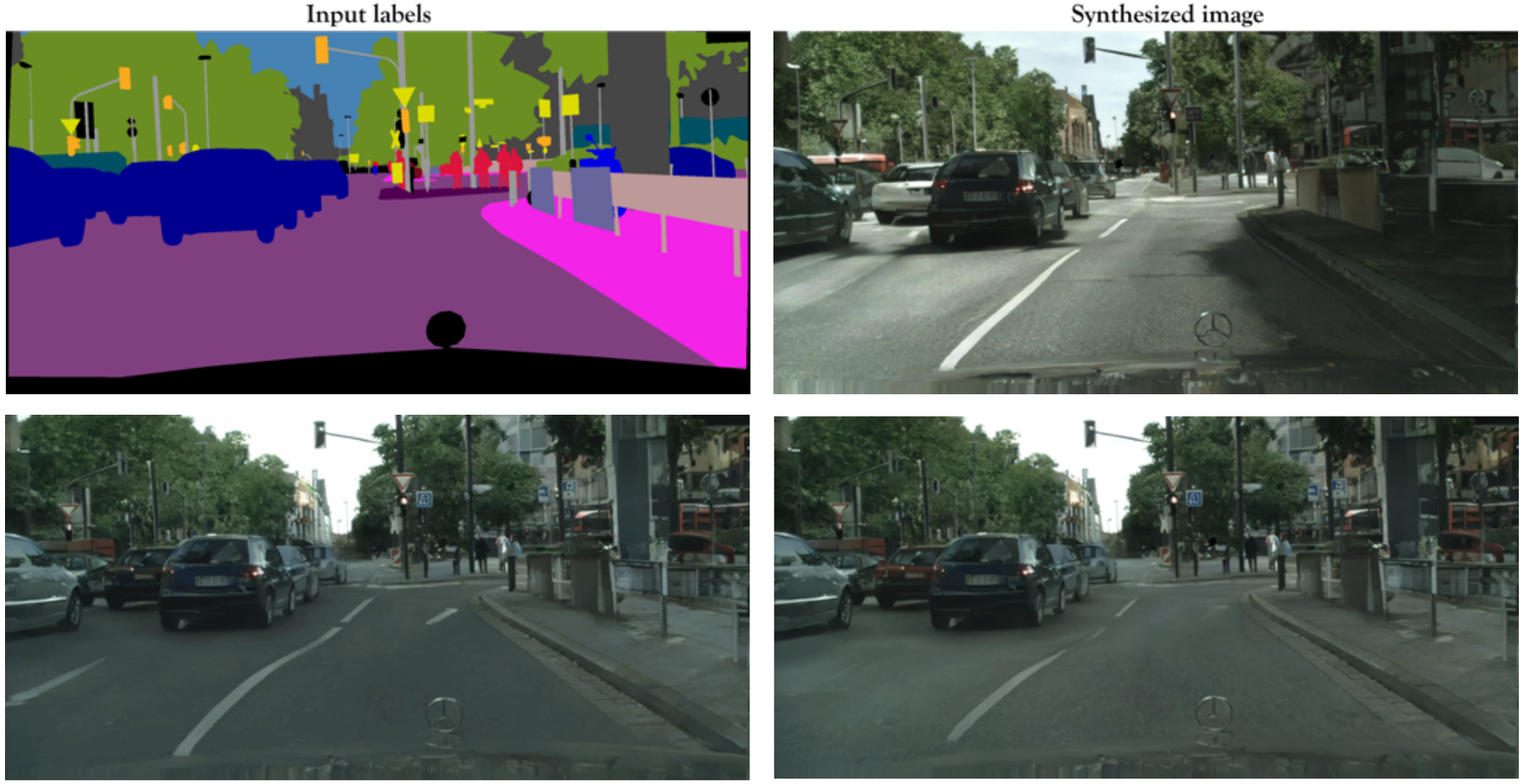
$$\text{AdaIN}(x, y) = \sigma(y)\left(\frac{x - \mu(x)}{\sigma(x)}\right) + \mu(y)$$

Style transfer framework:



Huang, Xun, and Serge Belongie. "Arbitrary style transfer in real-time with adaptive instance normalization." ICCV'2017.

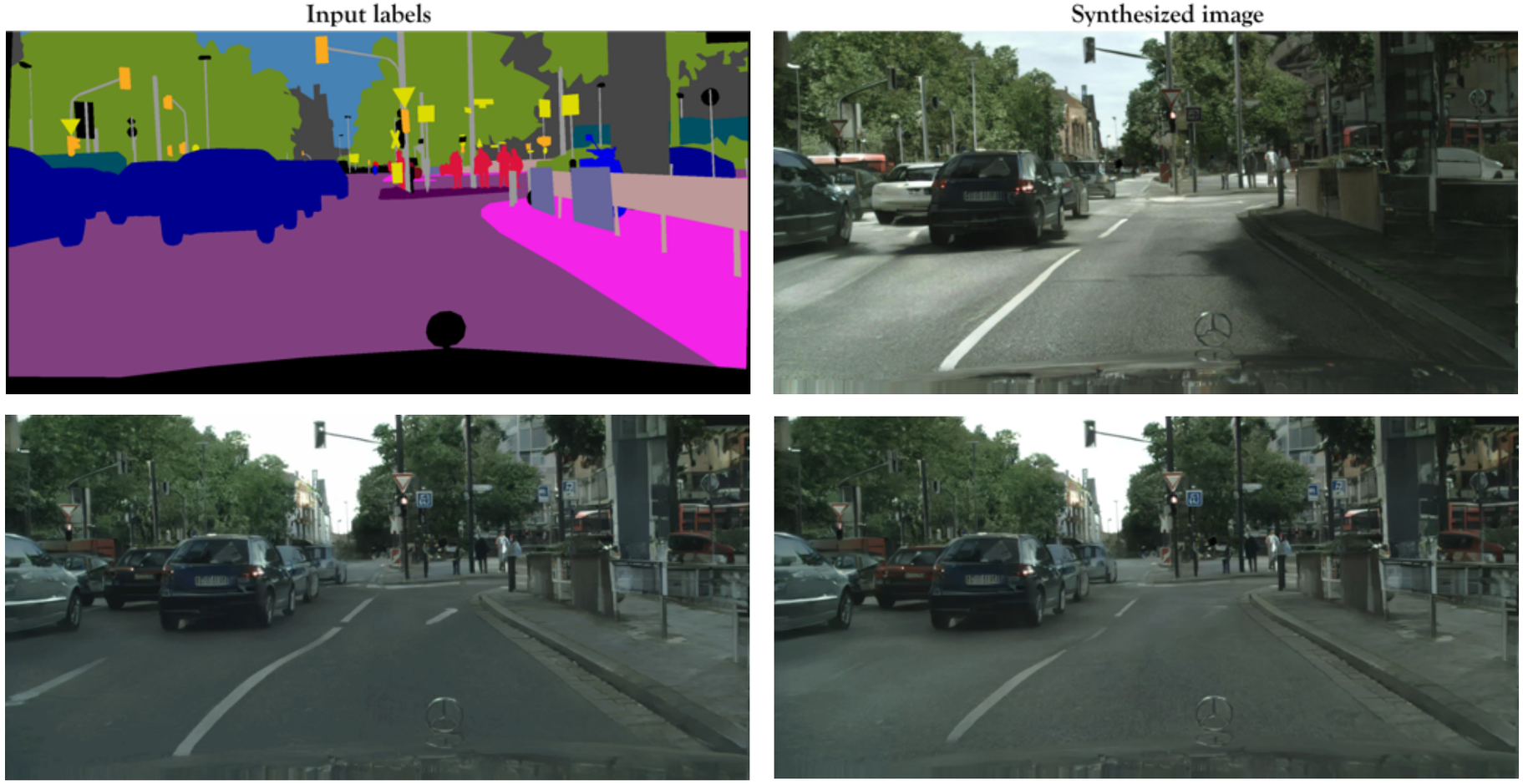
Pix2PixHD: Results



There are many diverse and complex segments

Wang, Ting-Chun, et al. "Pix2pixHD: High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs." CVPR'2018

Pix2PixHD: Results



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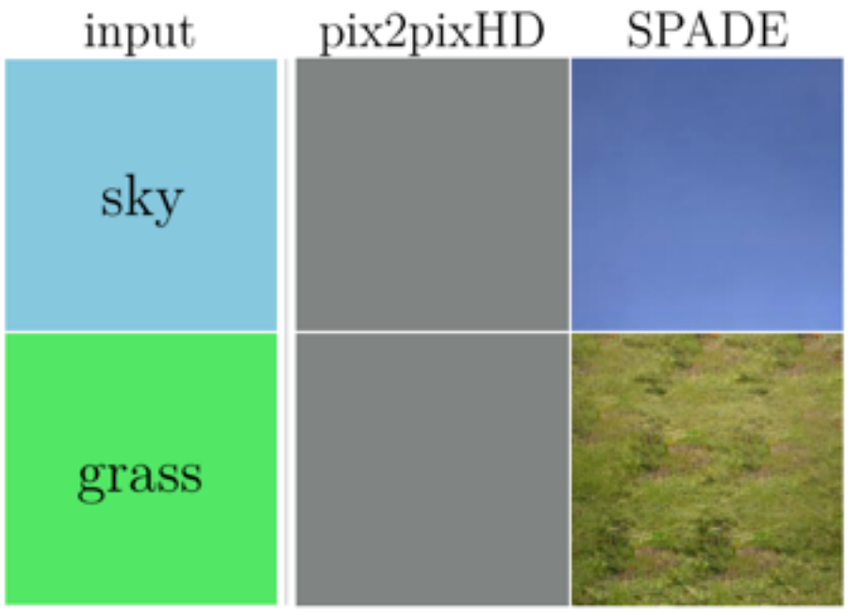
Pix2PixHD: Results

Problem: when segments are large normalization hurts performance

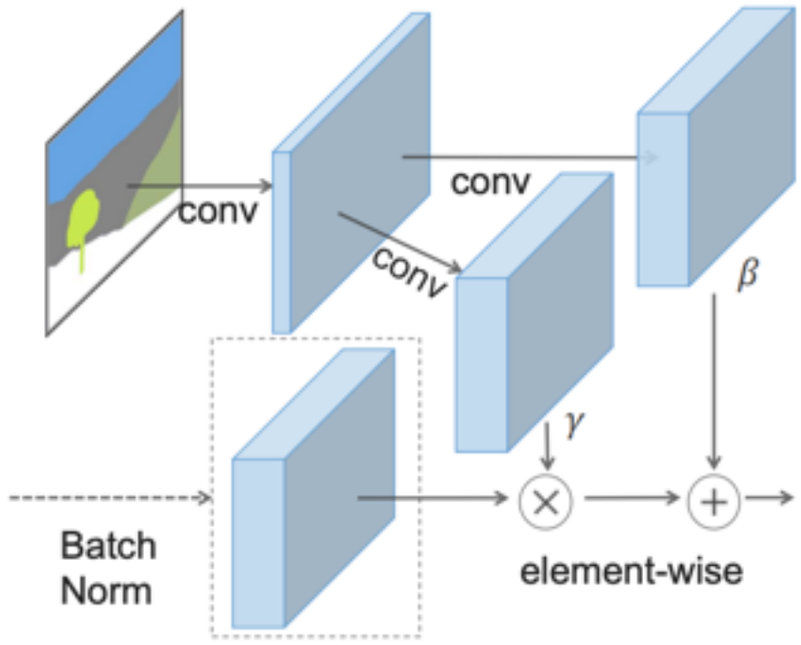
Park, Taesung, et al. "Semantic image synthesis with spatially-adaptive normalization." CVPR'2019

SPatially Adaptive DEnormalization (SPADE)

Problem: when segments are large normalization hurts performance



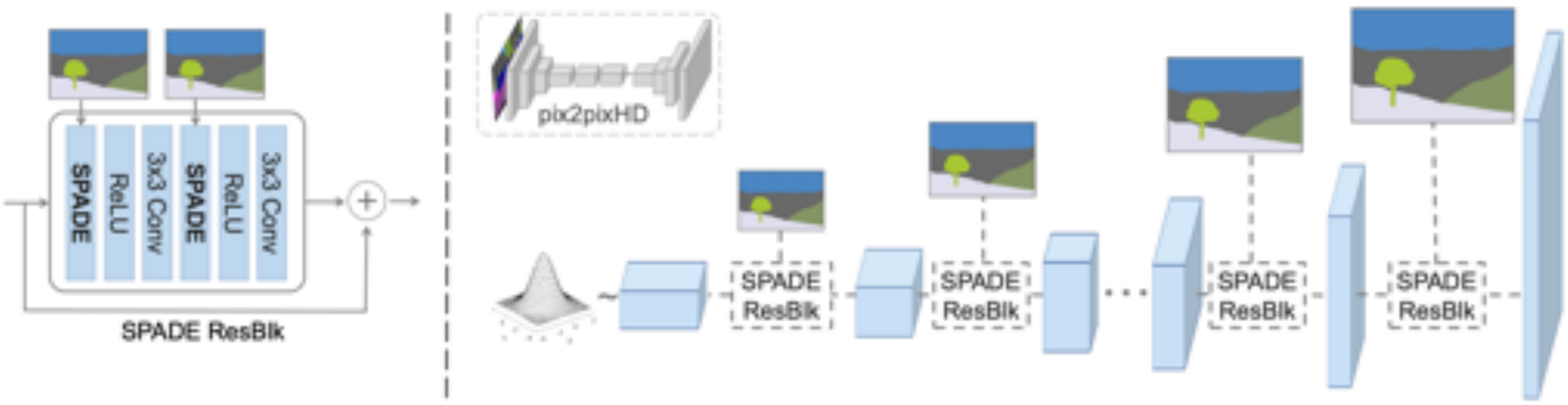
SPADE Block:



Park, Taesung, et al. "Semantic image synthesis with spatially-adaptive normalization." CVPR'2019

SPADE Generator

No Encoder is required



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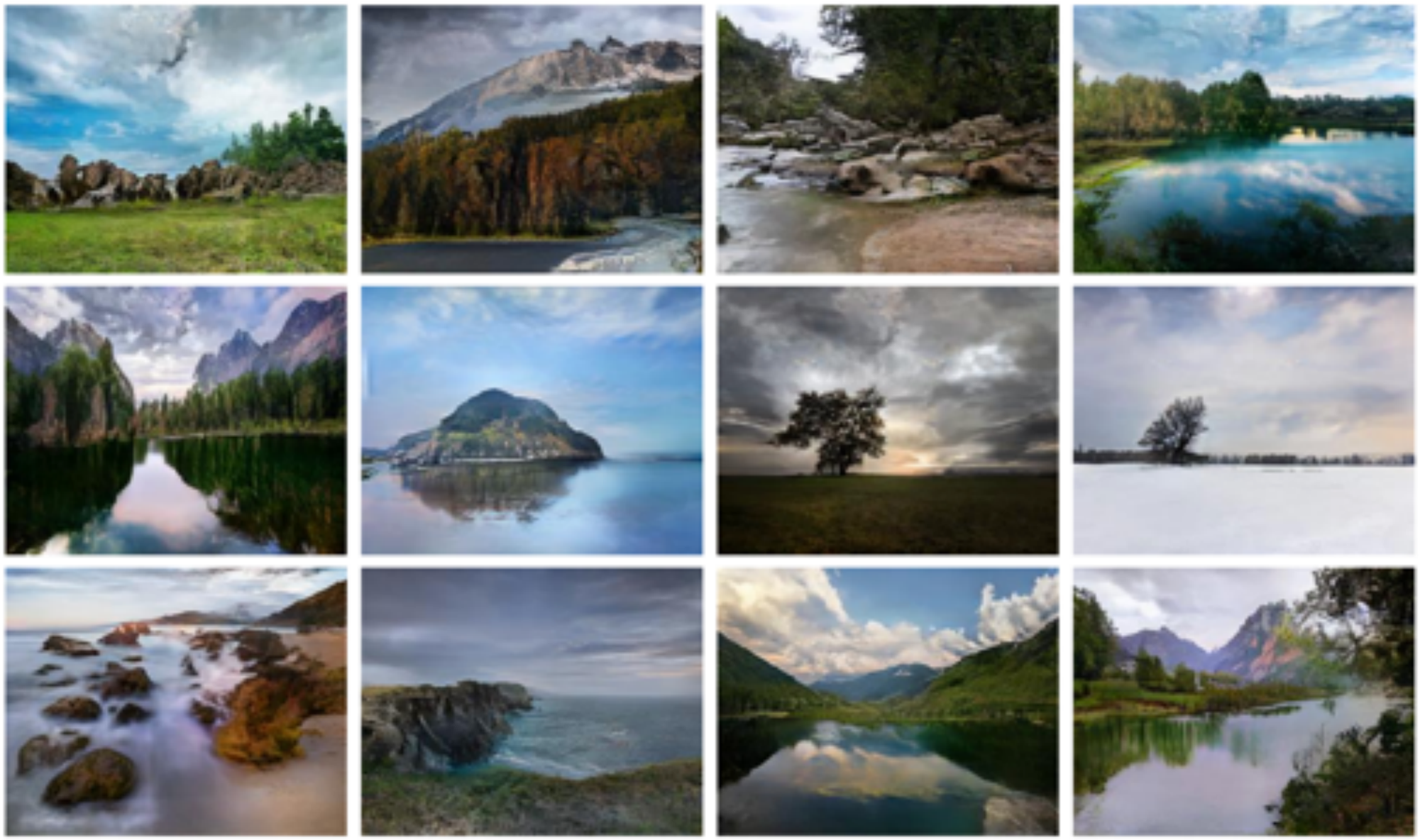
SPADE Results



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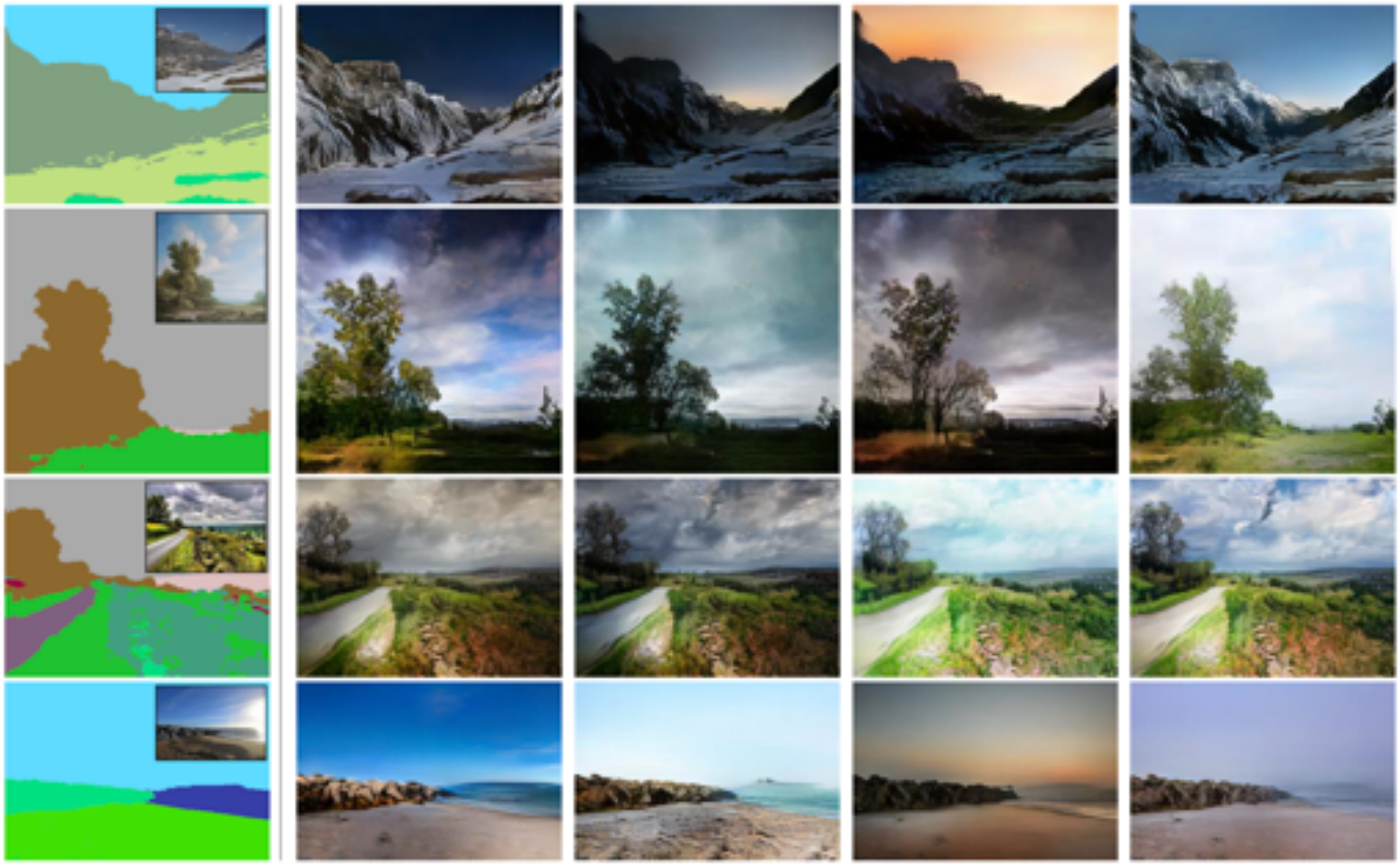

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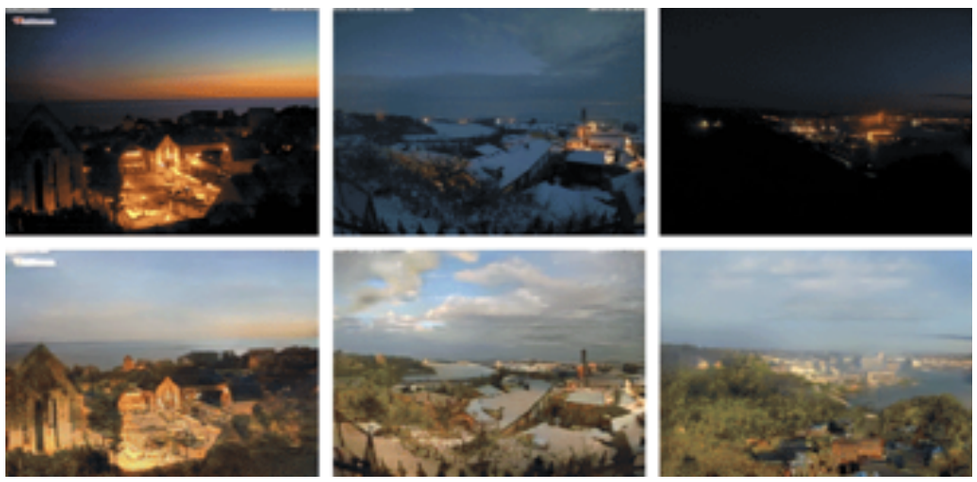
Multimodal Paired Image-to-image Translation

There are many ways of translating an image into another domain

$$\mathbf{x_z} \sim p(\mathbf{x}|\mathbf{y}, \mathbf{z}), \ \mathbf{z} \sim p(\mathbf{z})$$

Paired image-to-image translation

$$\mathbf{x}, \mathbf{y} \sim p(\mathbf{x}, \mathbf{y})$$



Zhu, Jun-Yan, et al. "Toward multimodal image-to-image translation." NIPS'2017

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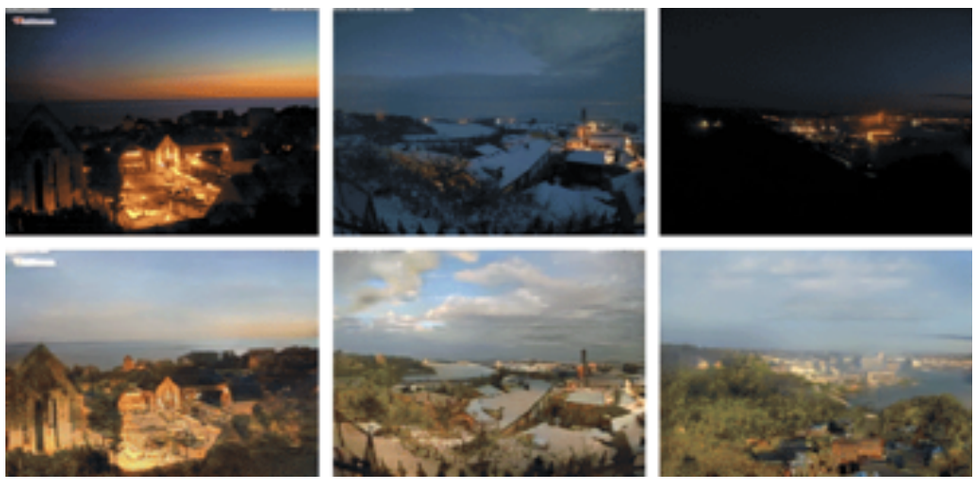


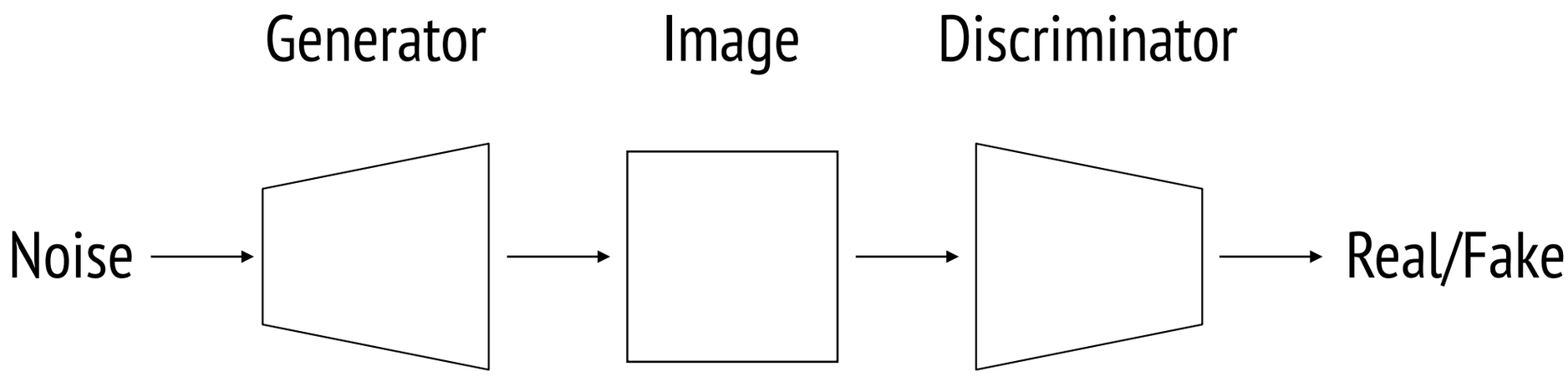
Zhu, Jun-Yan, et al. "Toward multimodal image-to-image translation." NIPS'2017

InfoGAN: Disentangling Modes of Variation

Idea: Can we condition the generative process of GANs to control particular attributes of interest in the generated images?

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

InfoGAN: Disentangling Modes of Variation



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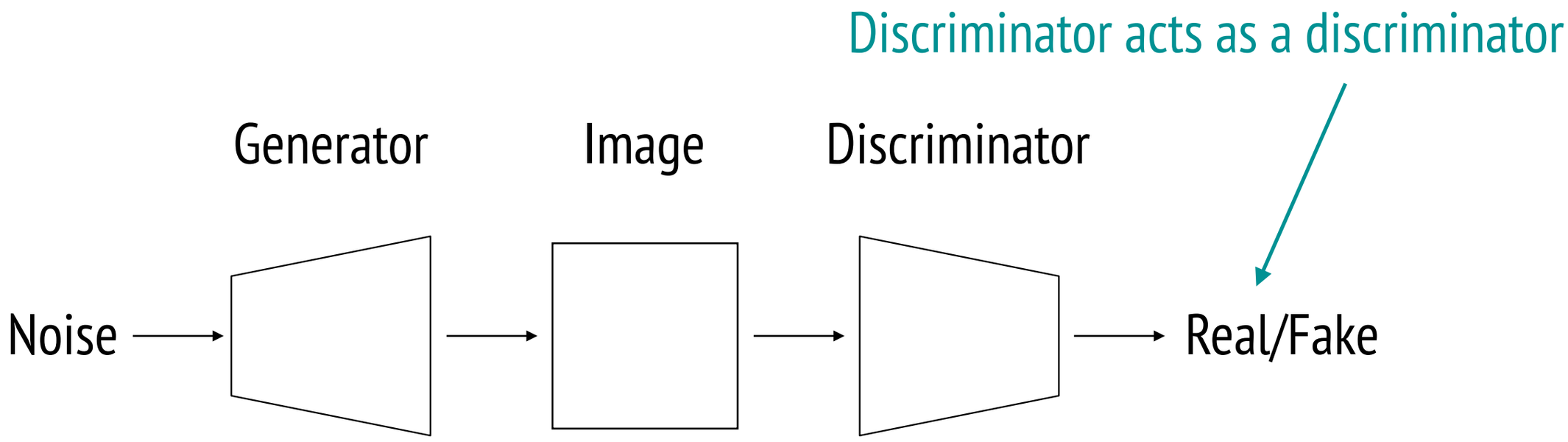

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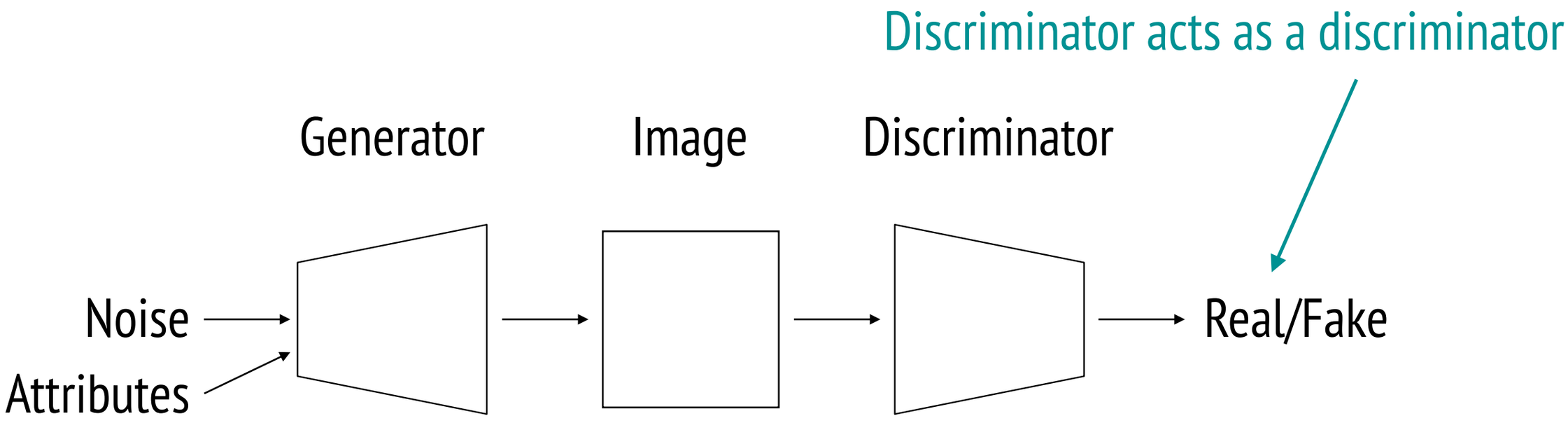

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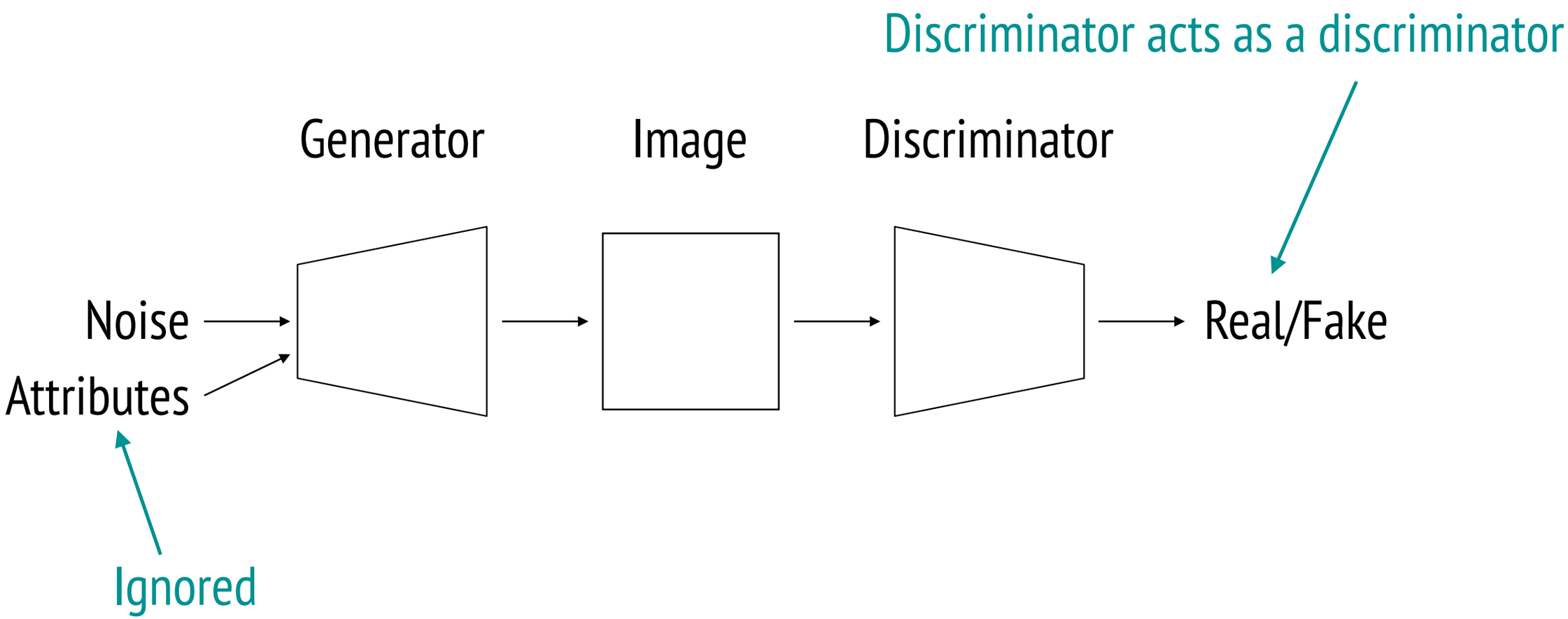

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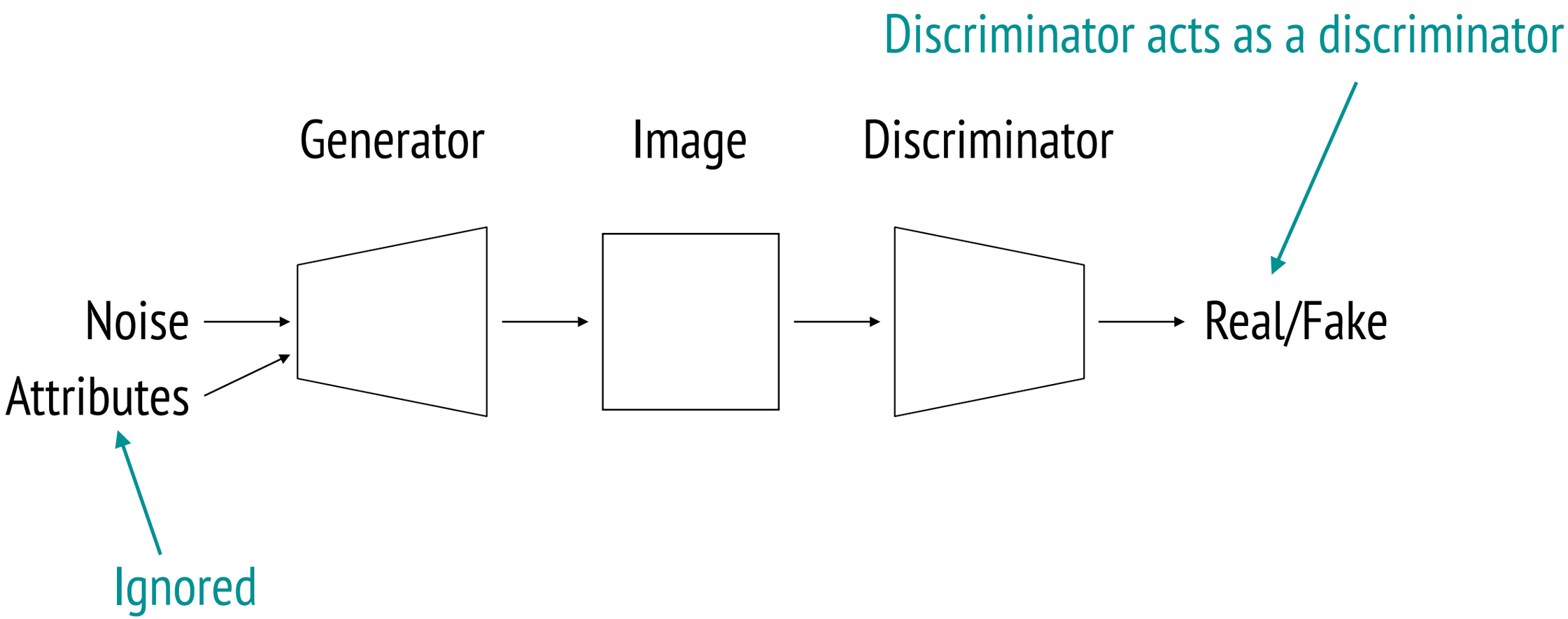

InfoGAN: To enforce the use of the required attributes one has to penalize the Generator if the images do not have this attribute

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

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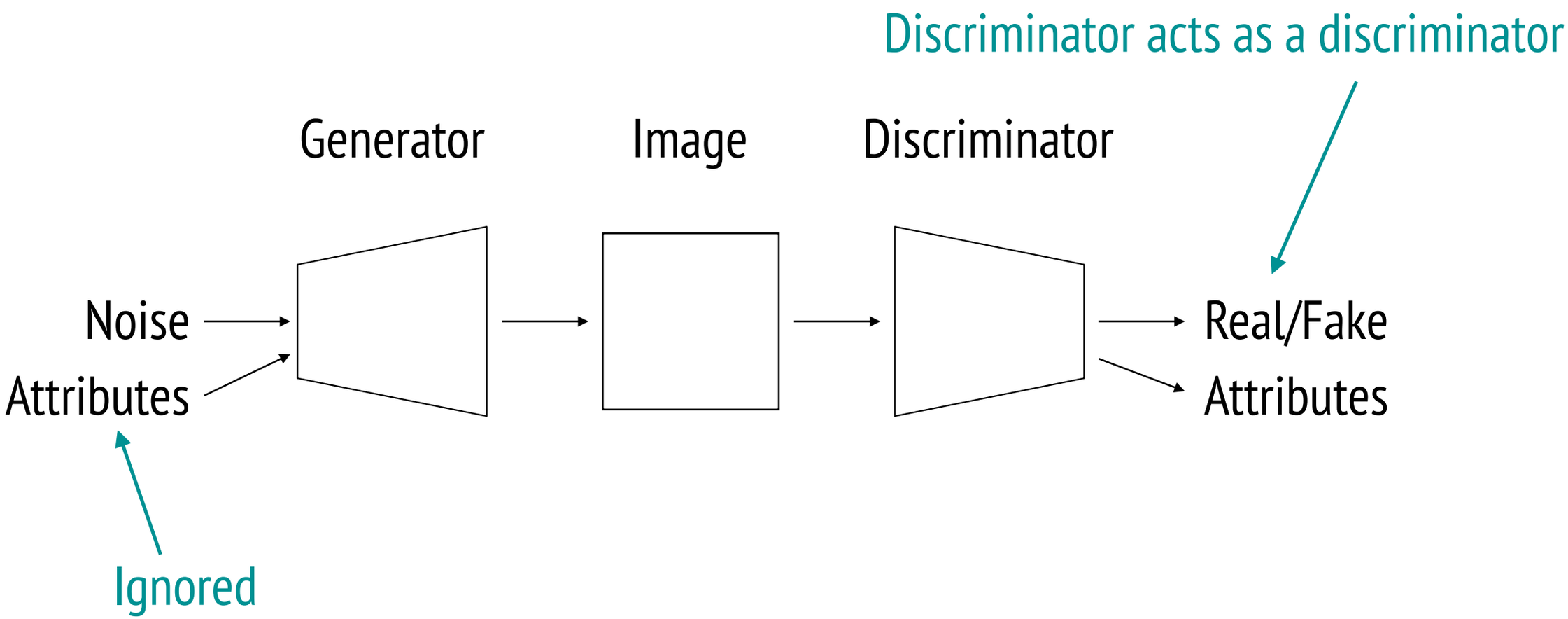

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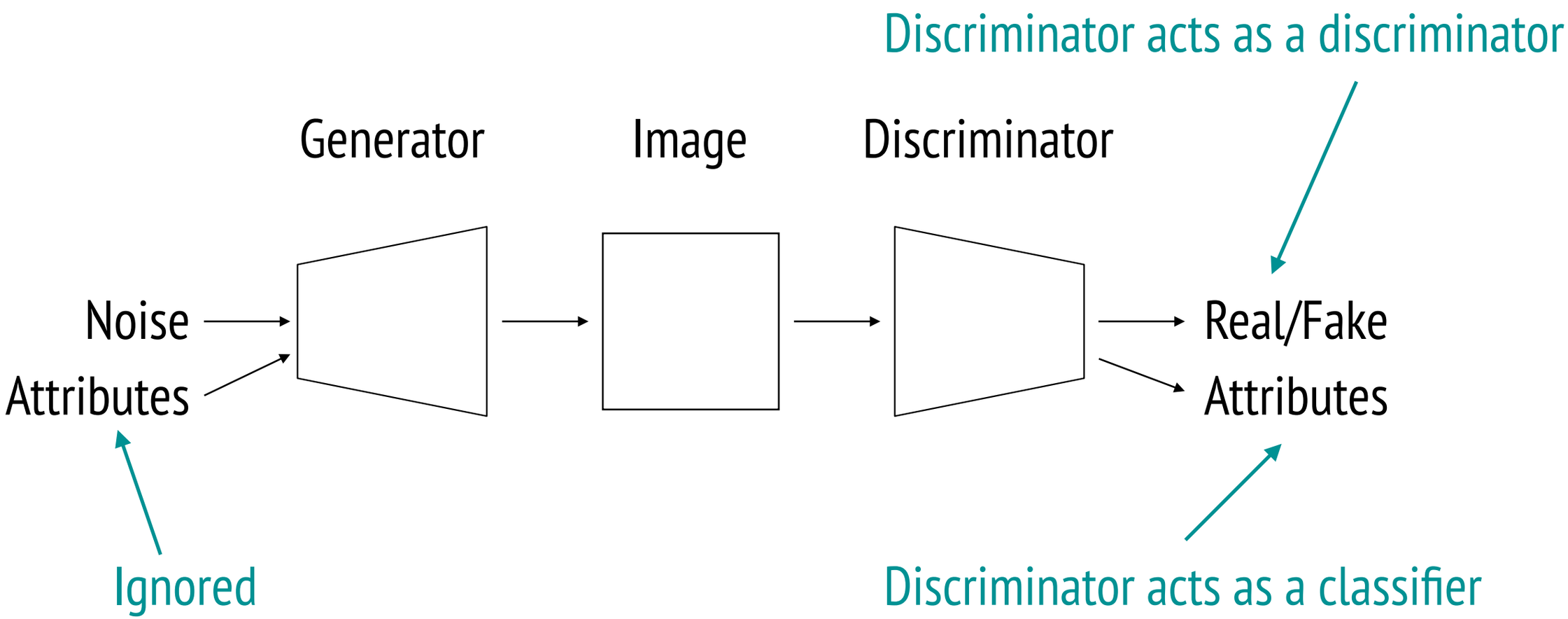

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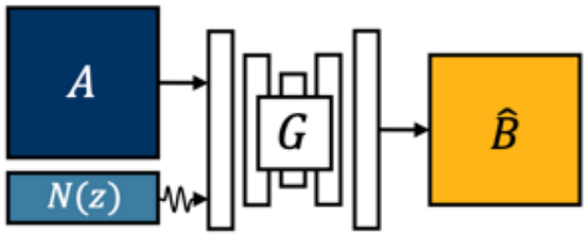
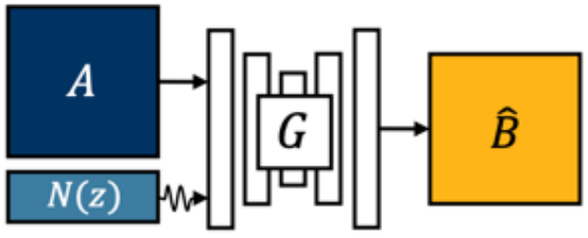
BiCycleGAN: Multimodal Image-to-image



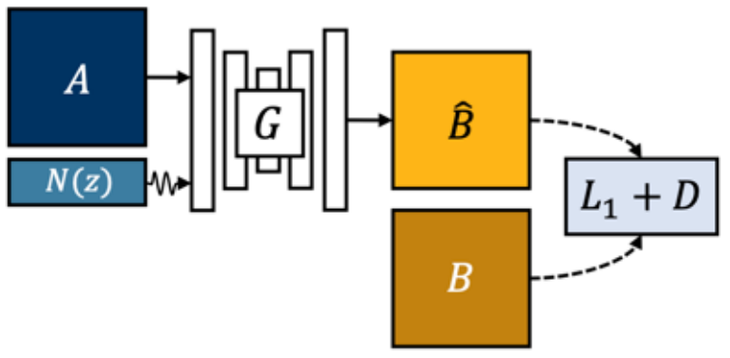
Inference

Zhu, Jun-Yan, et al. "Toward multimodal image-to-image translation." NIPS'2017

BiCycleGAN: Multimodal Image-to-image



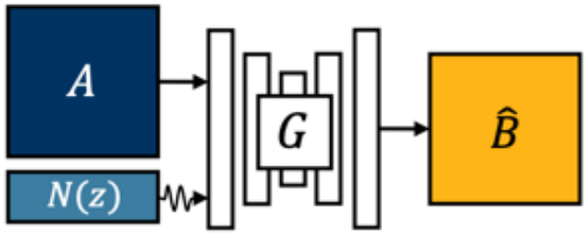
Inference



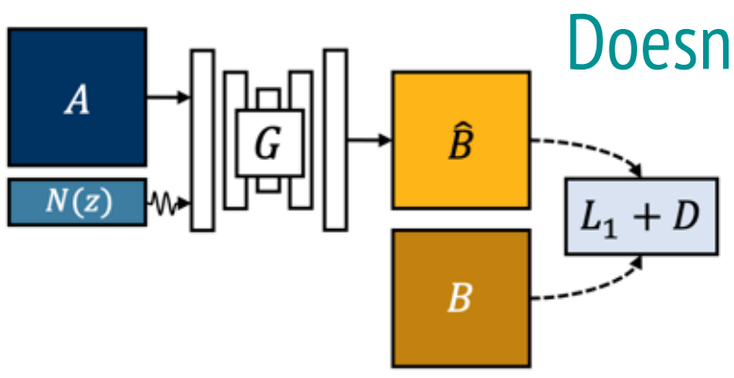
Augmented pix2pix

Zhu, Jun-Yan, et al. "Toward multimodal image-to-image translation." NIPS'2017

BiCycleGAN: Multimodal Image-to-image



Inference



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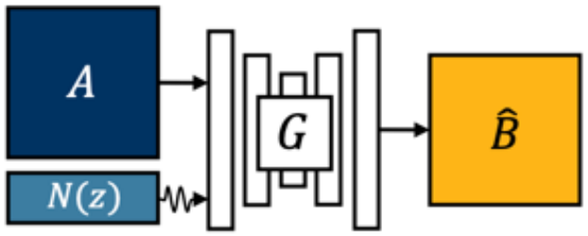
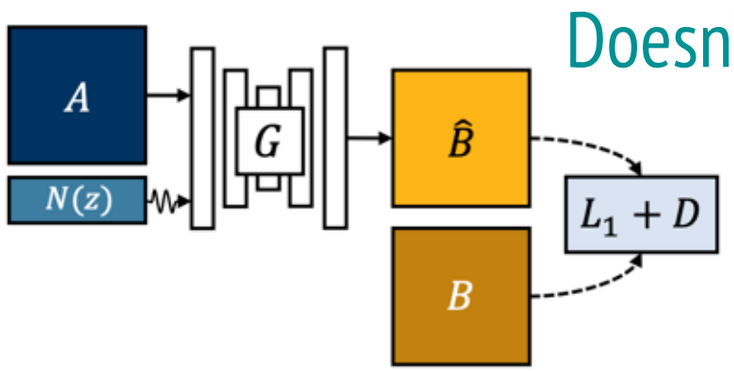
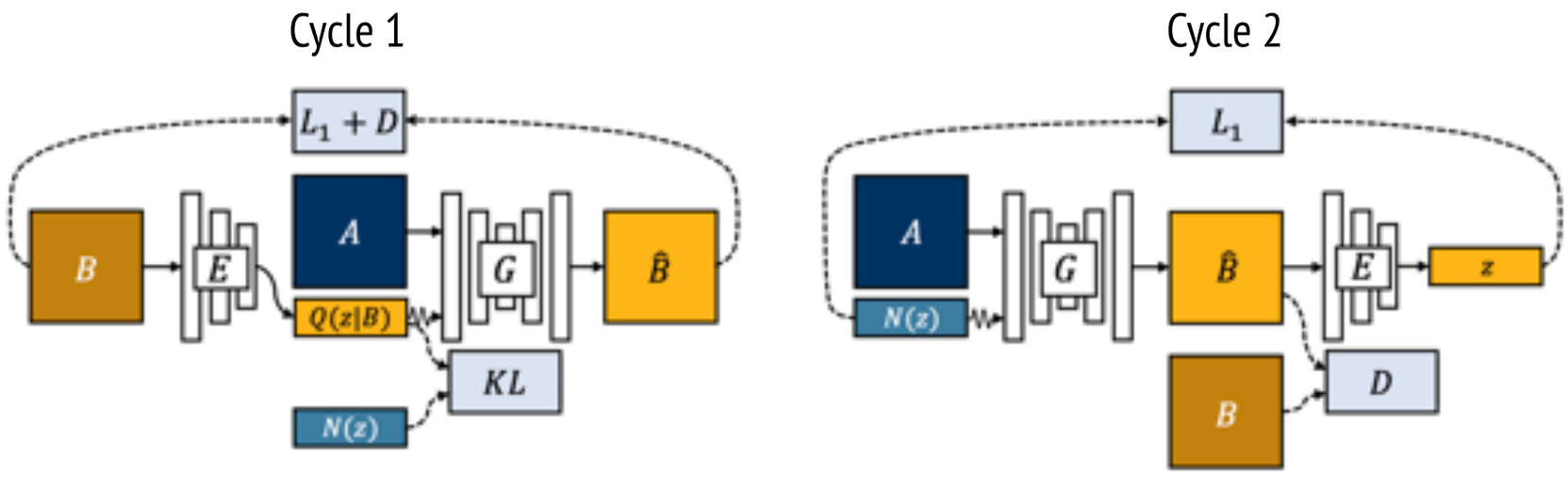
BiCycleGAN: Multimodal Image-to-image



Inference



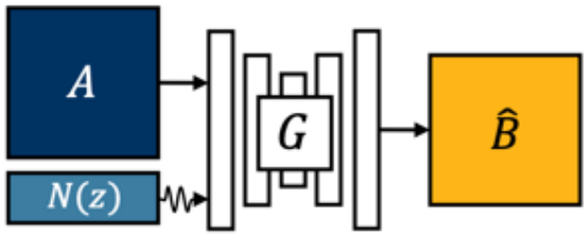
Augmented pix2pix



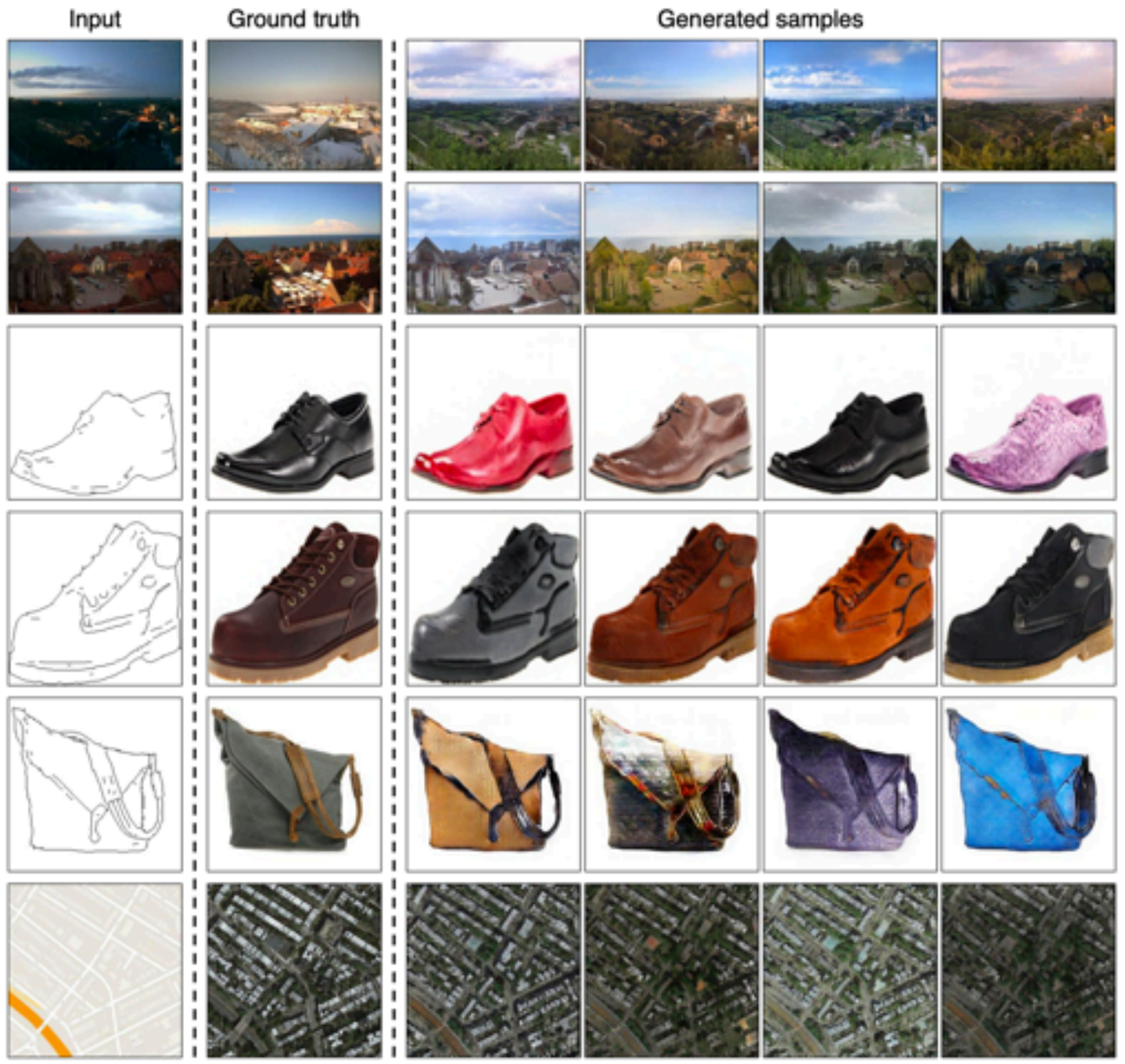
Training BicycleGAN

Zhu, Jun-Yan, et al. "Toward multimodal image-to-image translation." NIPS'2017

BiCycleGAN: Multimodal Image-to-image



Inference



Zhu, Jun-Yan, et al. "Toward multimodal image-to-image translation." NIPS'2017

Multimodal Unpaired Image-to-image Translation

There are many ways of translating an image into another domain

$$\mathbf{x_z} \sim p(\mathbf{x}|\mathbf{y}, \mathbf{z}),\ \mathbf{z} \sim p(\mathbf{z})$$

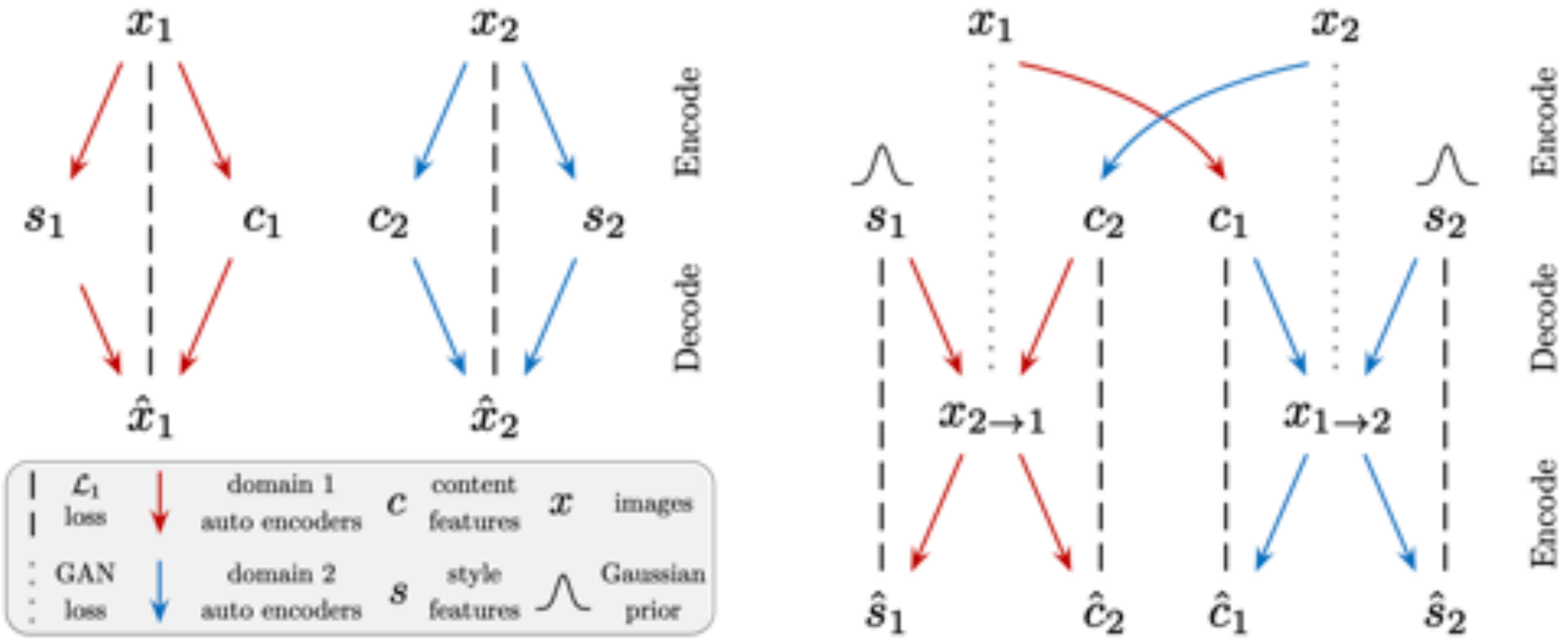
Unpaired

$$\mathbf{x} \sim p(\mathbf{x}),\ \mathbf{y} \sim p(\mathbf{y})$$

Huang, Xun, et al. "Multimodal unsupervised image-to-image translation." ECCV'2018.

Multimodal Unpaired Image-to-image Translation

Assumption: Images can be decomposed into style and content



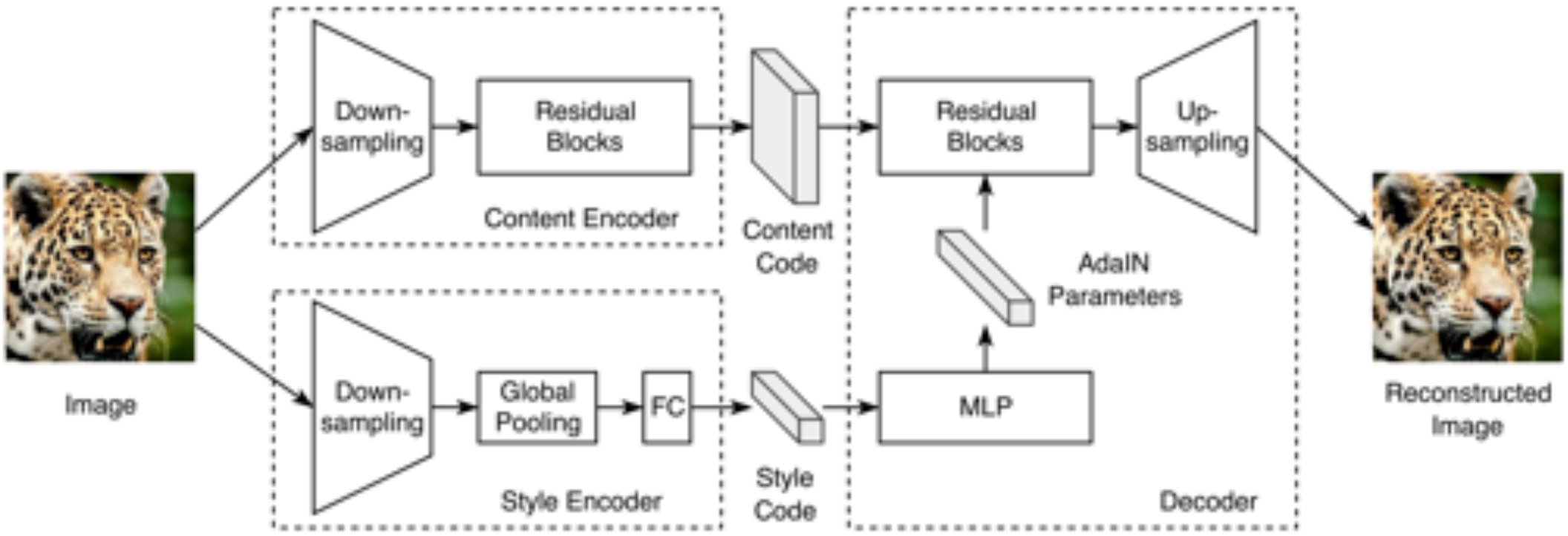
(a) Within-domain reconstruction

(b) Cross-domain translation

Huang, Xun, et al. "Multimodal unsupervised image-to-image translation." ECCV'2018.

Multimodal Unpaired Image-to-image Translation

Assumption: Images can be decomposed into style and content



Huang, Xun, et al. "Multimodal unsupervised image-to-image translation." ECCV'2018.

MUNIT: Results

Assumption: Images can be decomposed into style and content

Huang, Xun, et al. "Multimodal unsupervised image-to-image translation." ECCV'2018.

Other Works

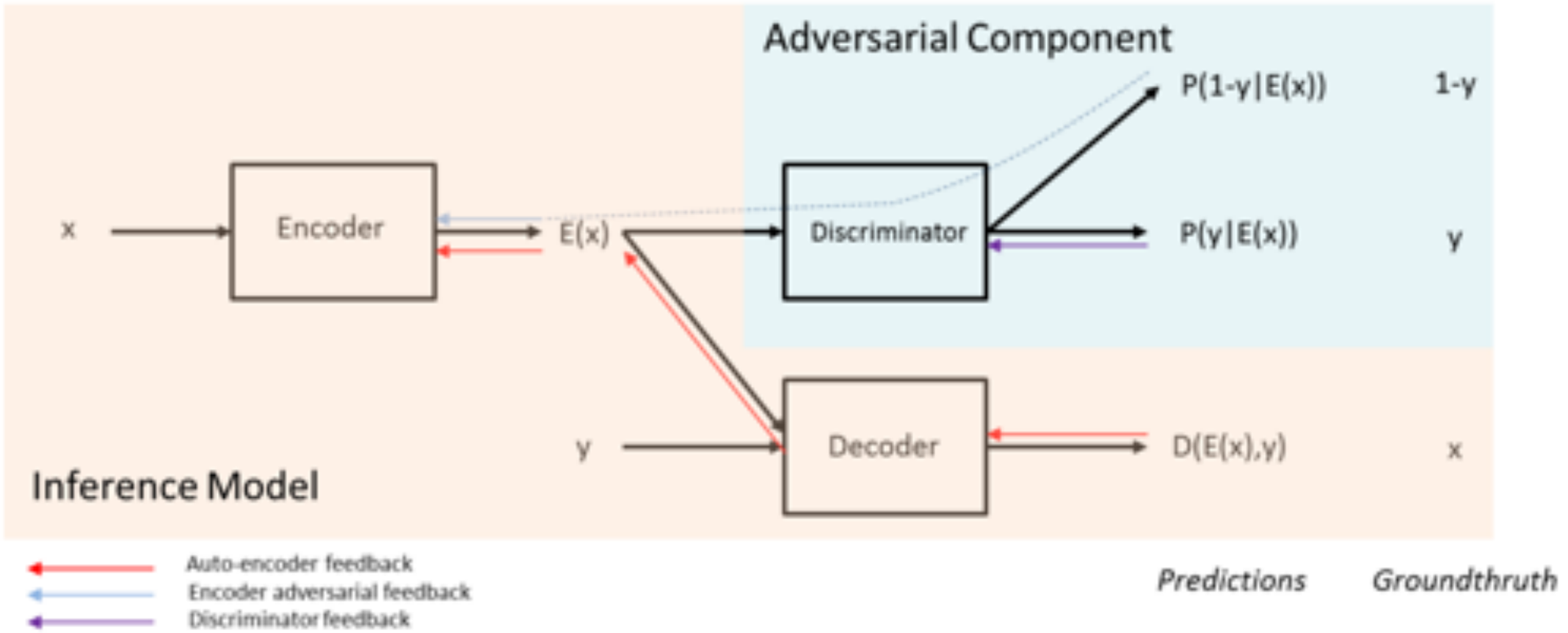
Face-related works:

- Fader Networks
- 3D guided face manipulation

Geometry-based works:

- Transformable Bottleneck Networks
- Volumetric Object Networks

Fader Networks

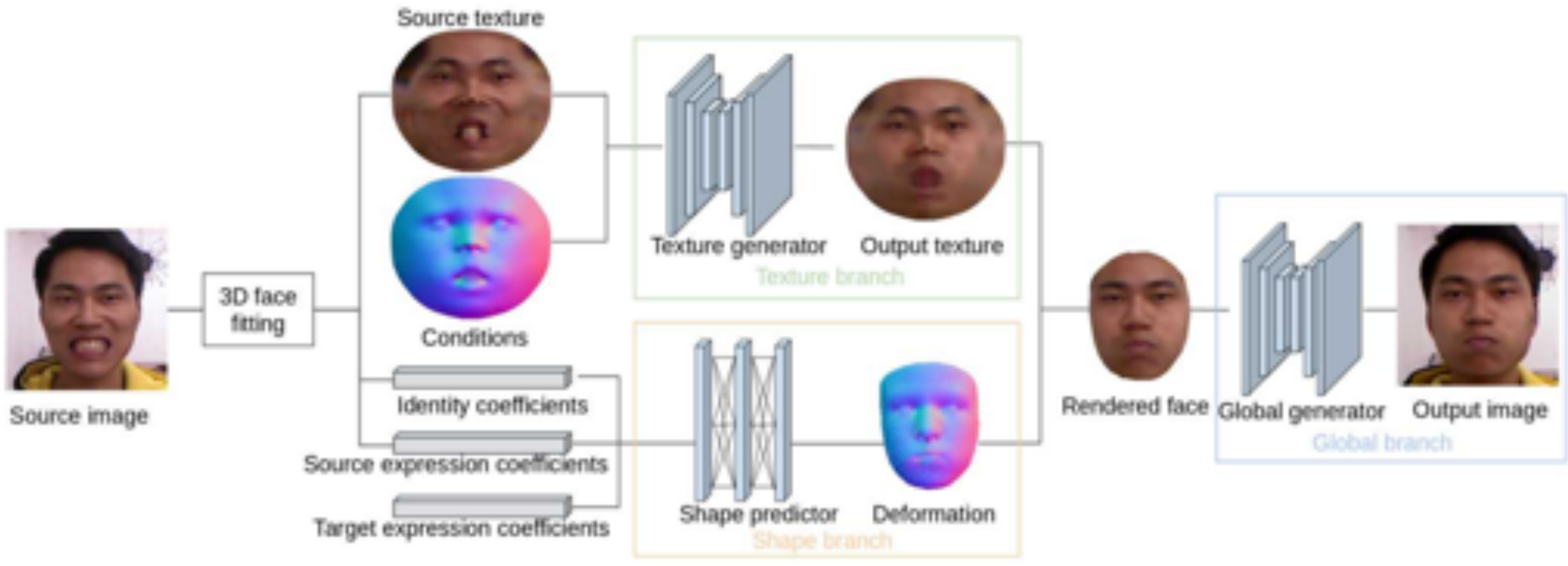


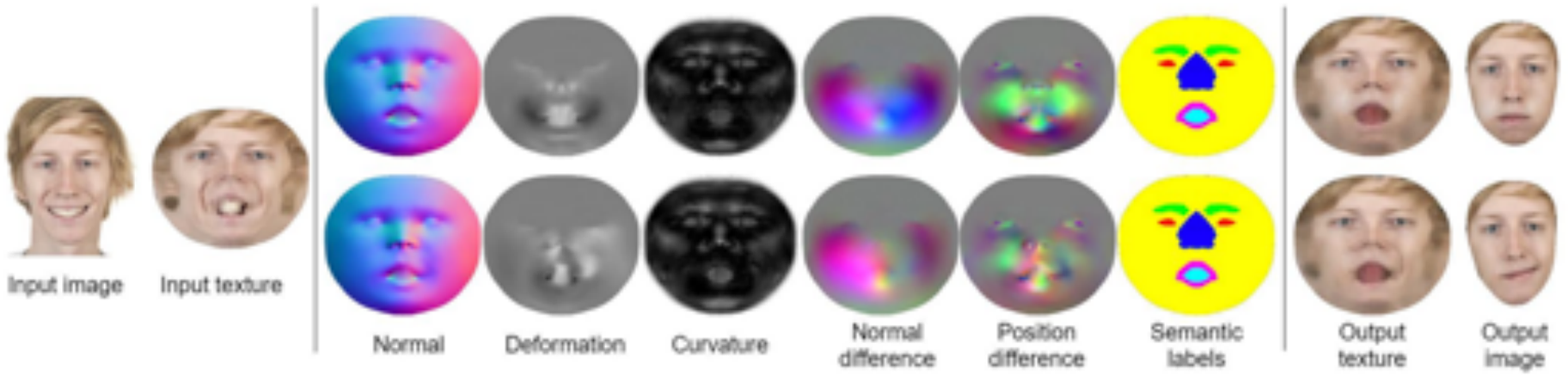
Lample, Guillaume, et al. "Fader networks: Manipulating images by sliding attributes." NIPS'2017

Fader Networks

Lample, Guillaume, et al. "Fader networks: Manipulating images by sliding attributes." NIPS'2017

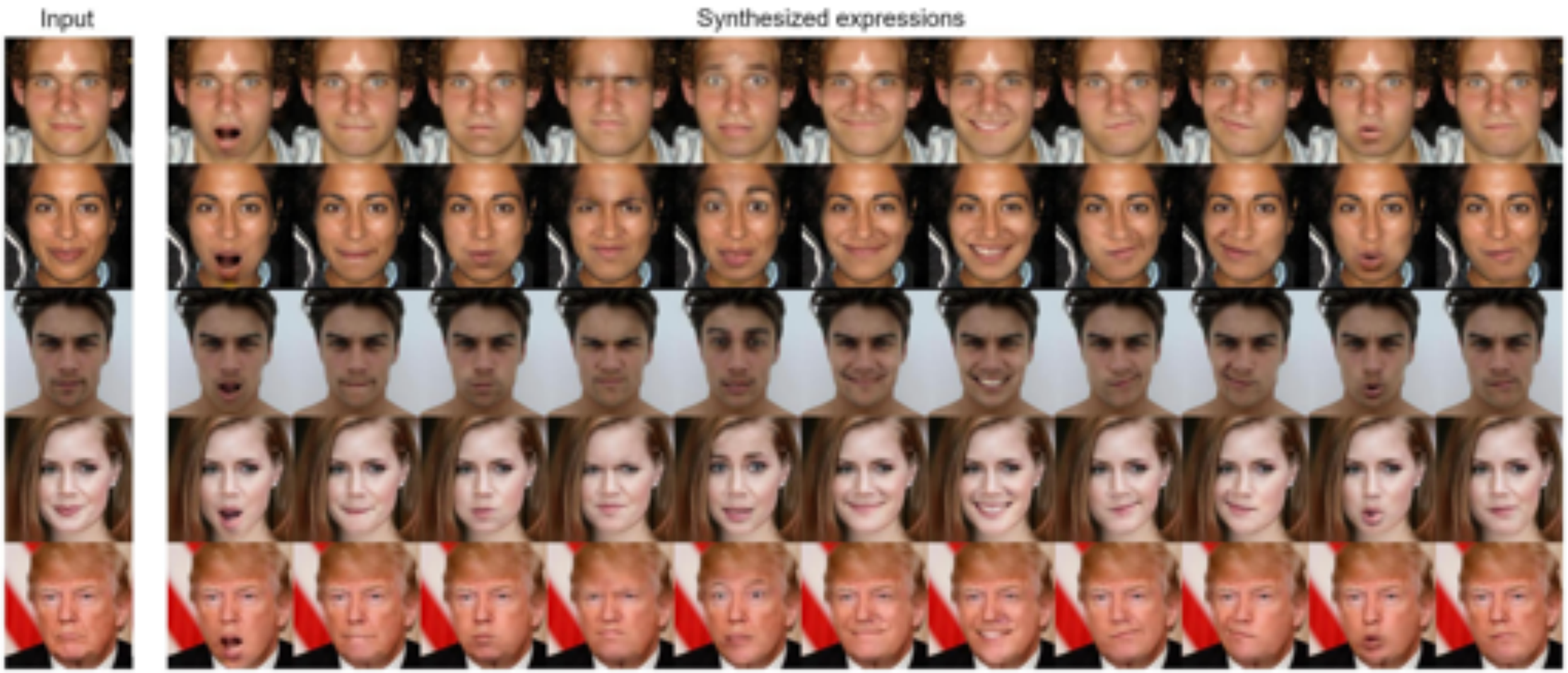
3D Guided Fine-Grained Face Manipulation





Geng, Zhenglin, Chen Cao, and Sergey Tulyakov. "3d guided fine-grained face manipulation." CVPR'2019

3D Guided Fine-Grained Face Manipulation



Geng, Zhenglin, Chen Cao, and Sergey Tulyakov. "3d guided fine-grained face manipulation." CVPR'2019

Other Works

Face-related works:

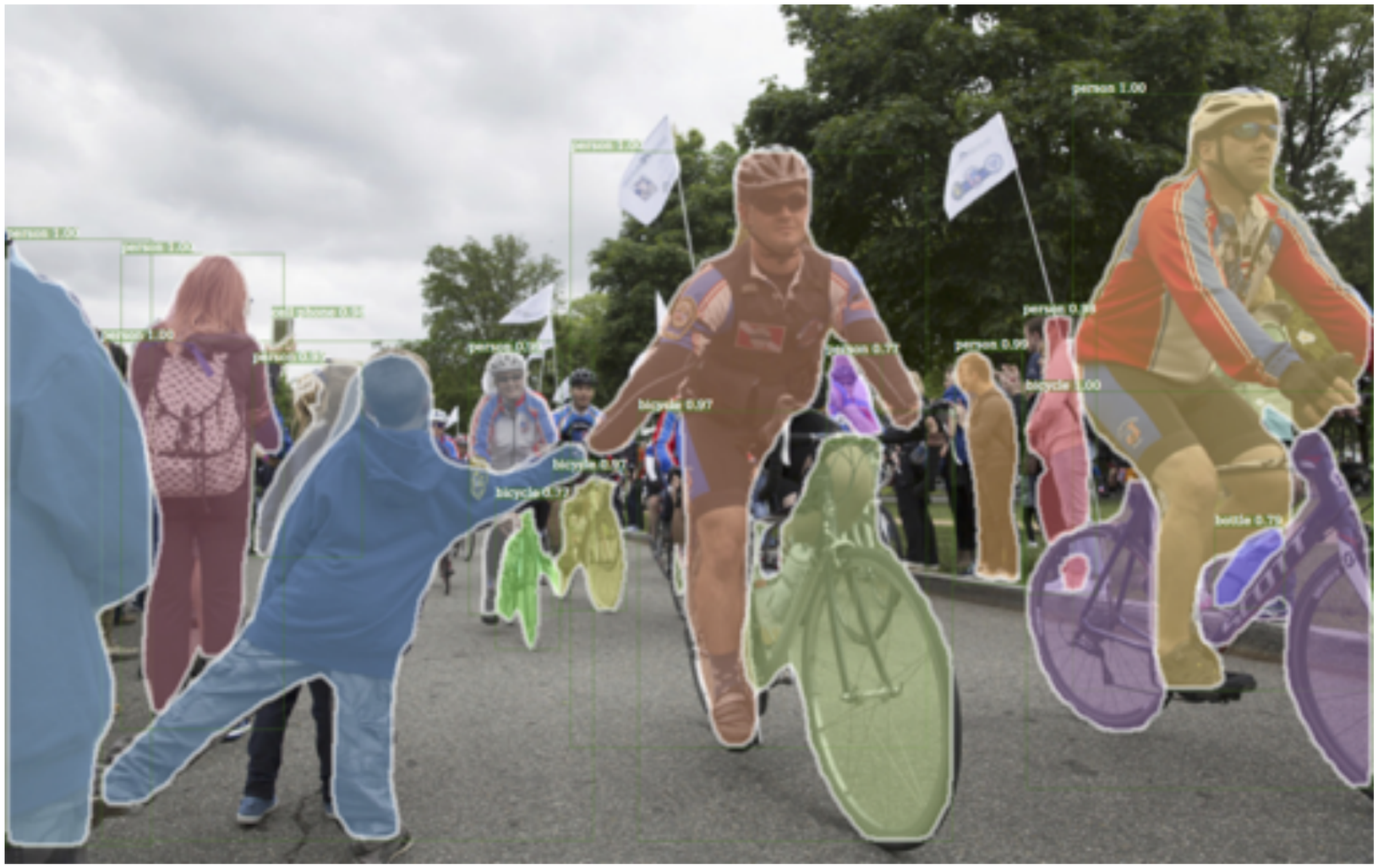
- Fader Networks
- 3D guided face manipulation

Geometry-based works:

- Transformable Bottleneck Networks

Understanding Beyond Pixels

We can understand what object each pixel contains. We get dense semantic maps



What about:

1. Volumetric shape of the object?
2. Back side of the object?
3. Its location in space?

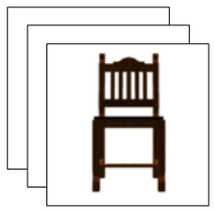
He, Kaiming, et al. "Mask r-cnn." CVPR'2017

Understanding Beyond Pixels

What about volumetric reasoning?

Transformable Bottleneck Networks

Input



Olszewski, K., Tulyakov, S., Woodford, O., Li, H., & Luo, L. "Transformable Bottleneck Networks." ICCV'2019

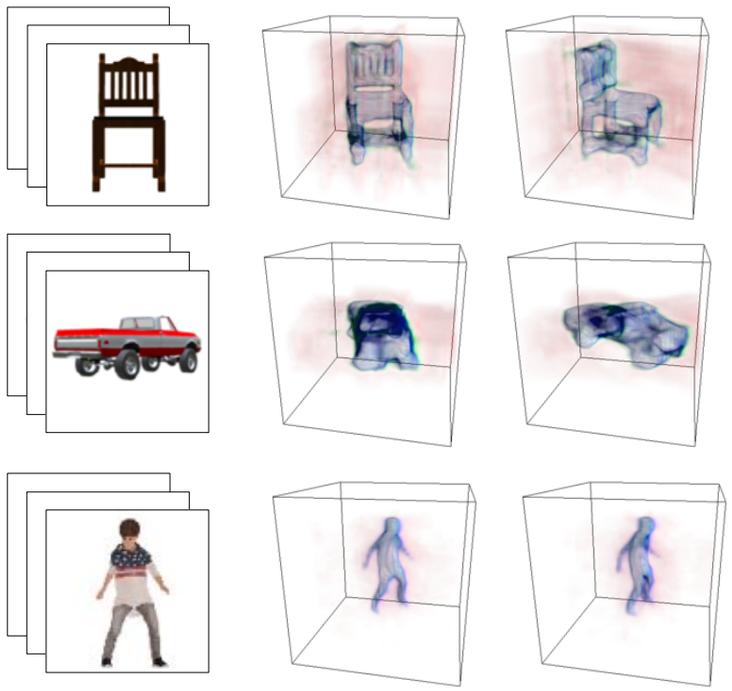
Understanding Beyond Pixels

What about volumetric reasoning?

Transformable Bottleneck Networks

Input

Shape reasoning



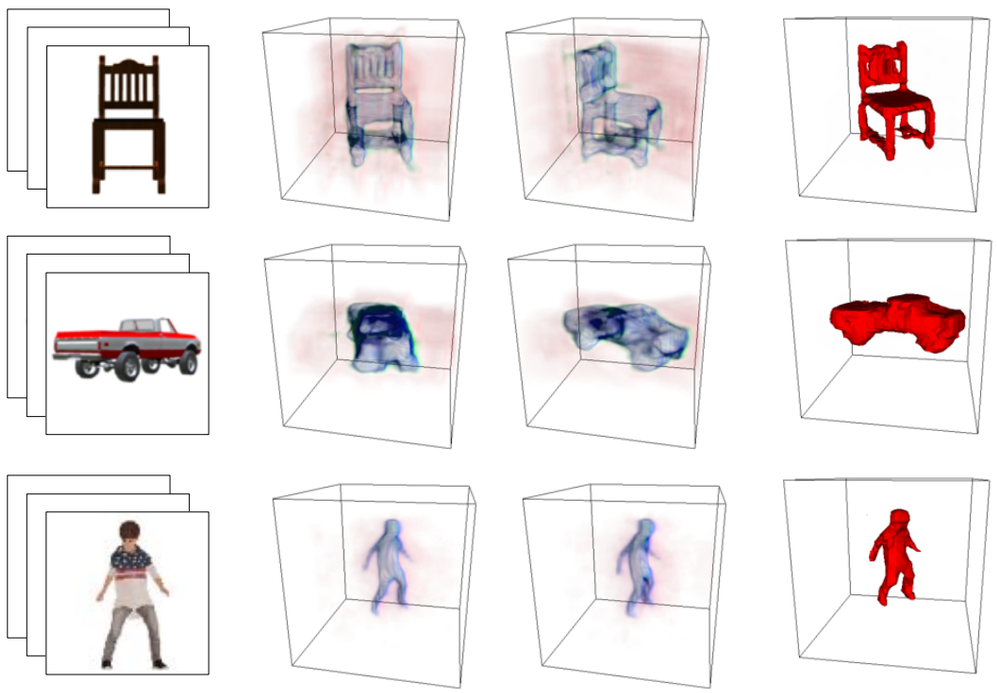
Olszewski, K., Tulyakov, S., Woodford, O., Li, H., & Luo, L. "Transformable Bottleneck Networks." ICCV'2019

Understanding Beyond Pixels

What about volumetric reasoning?

Transformable Bottleneck Networks

Input Shape reasoning Reconstruction

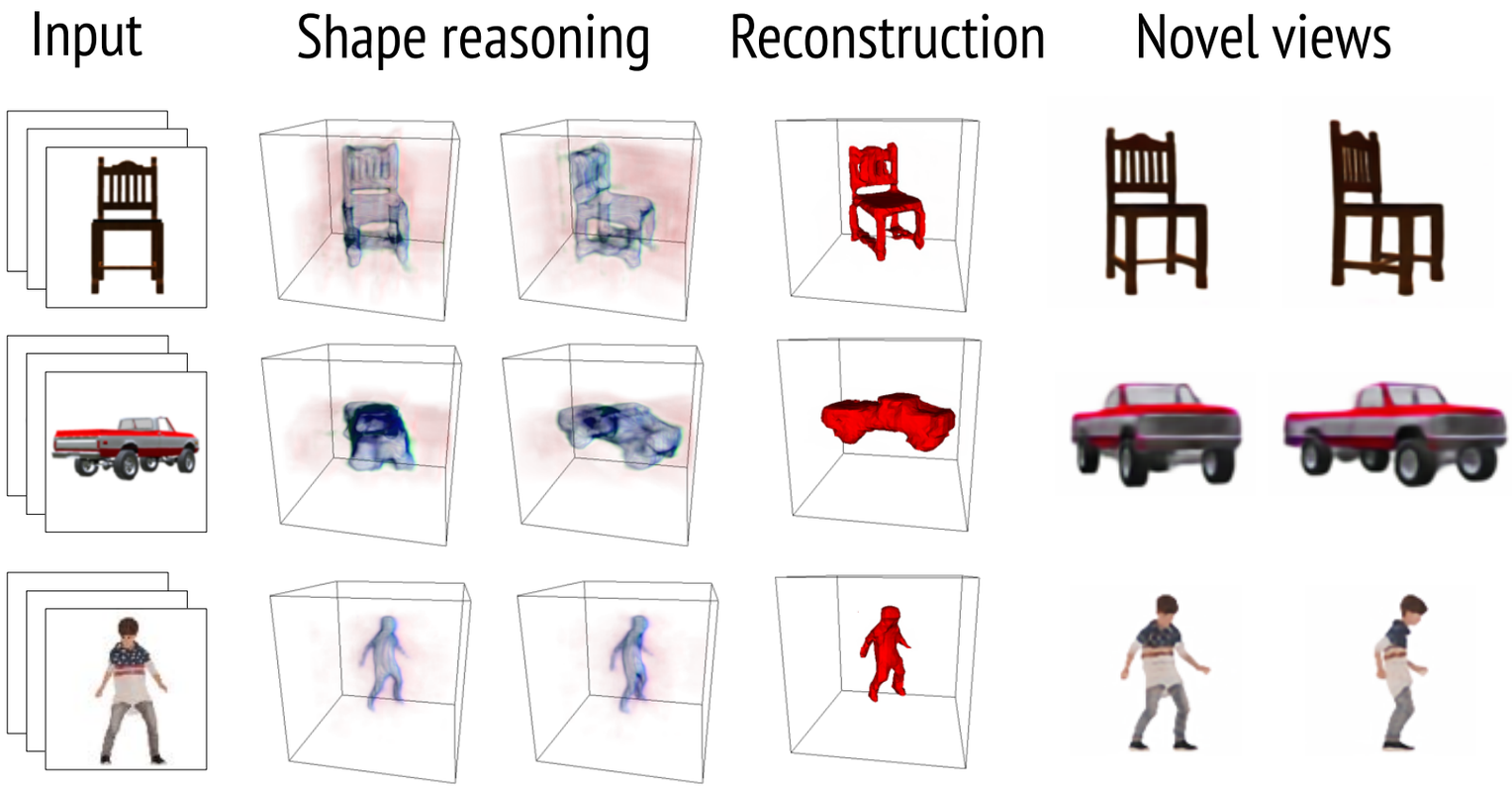


Olszewski, K., Tulyakov, S., Woodford, O., Li, H., & Luo, L. "Transformable Bottleneck Networks." ICCV'2019

Understanding Beyond Pixels

What about volumetric reasoning?

Transformable Bottleneck Networks



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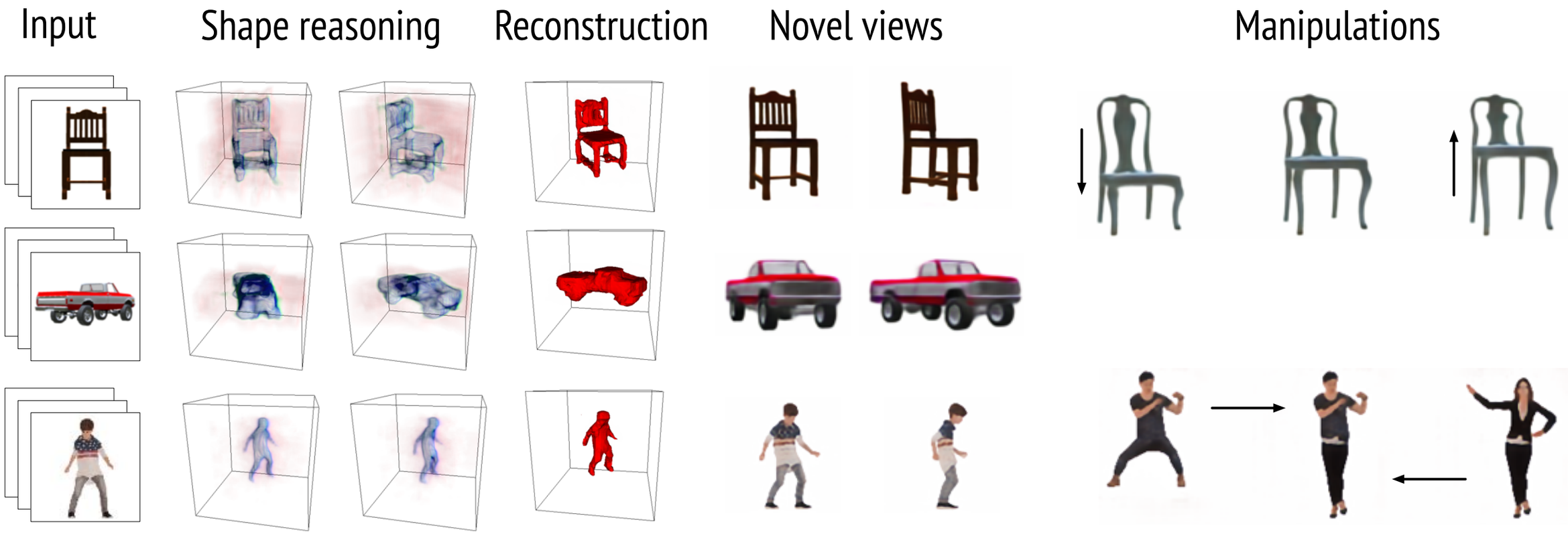
Understanding Beyond Pixels

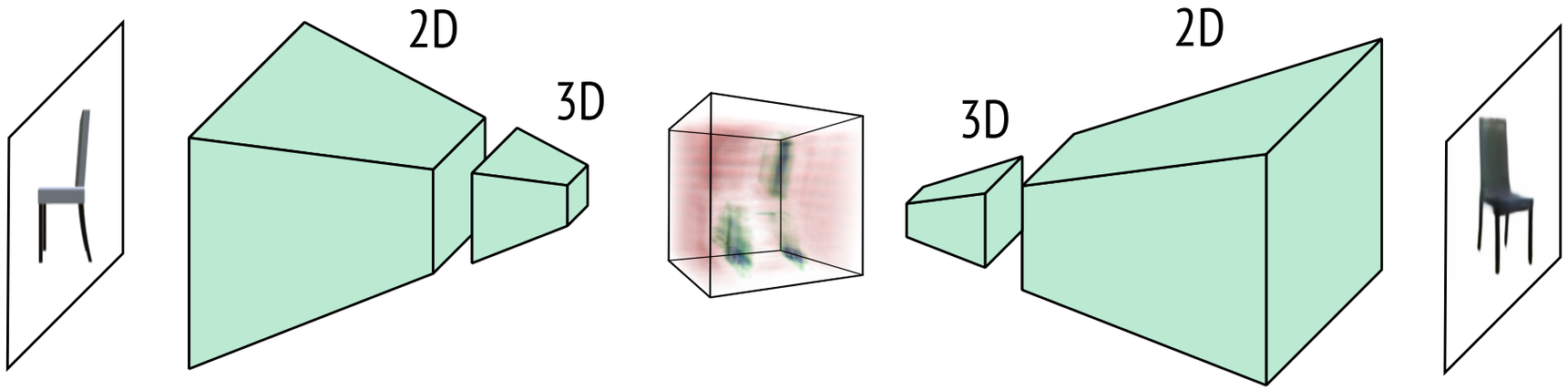
What about volumetric reasoning?

Transformable Bottleneck Networks



Olszewski, K., Tulyakov, S., Woodford, O., Li, H., & Luo, L. "Transformable Bottleneck Networks." ICCV'2019

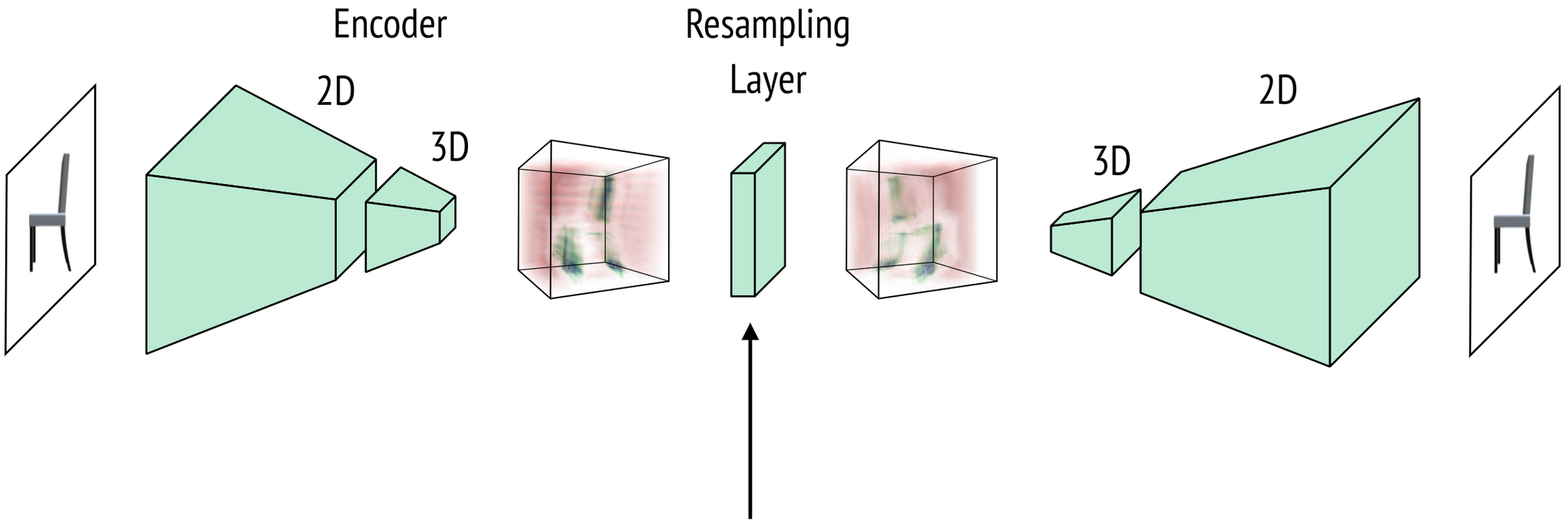
TBNs for Novel View Synthesis



How to specify viewpoint transformation?

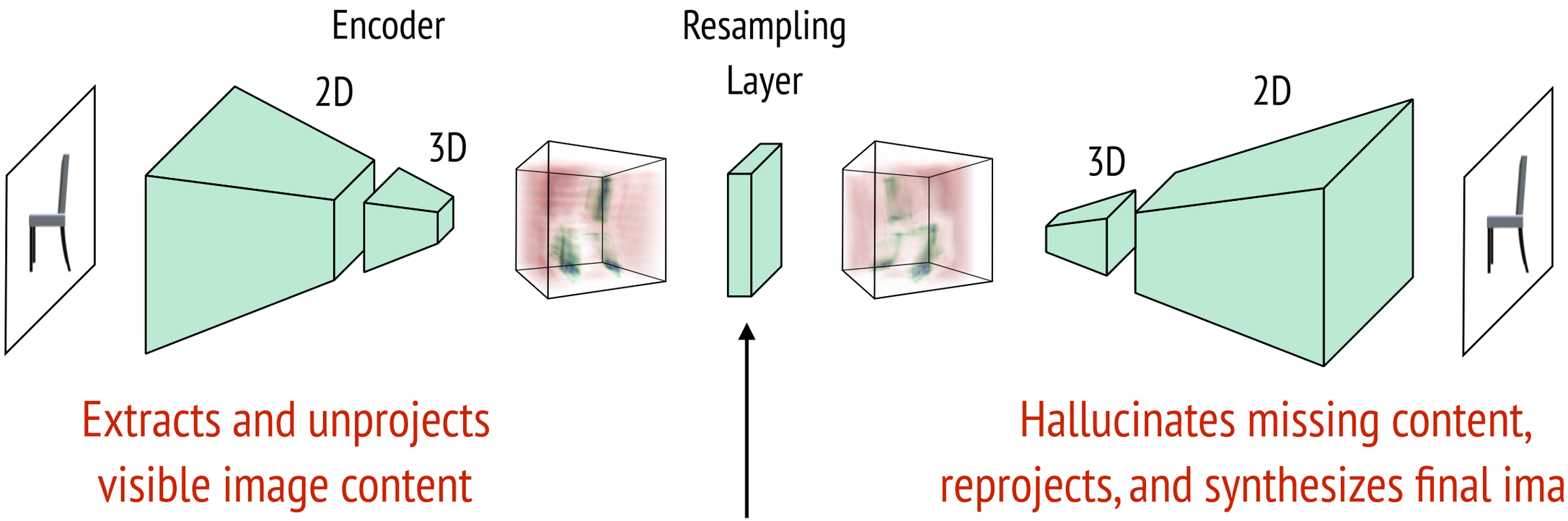
Olszewski, K., Tulyakov, S., Woodford, O., Li, H., & Luo, L. "Transformable Bottleneck Networks." ICCV'2019

TBNs for Novel View Synthesis



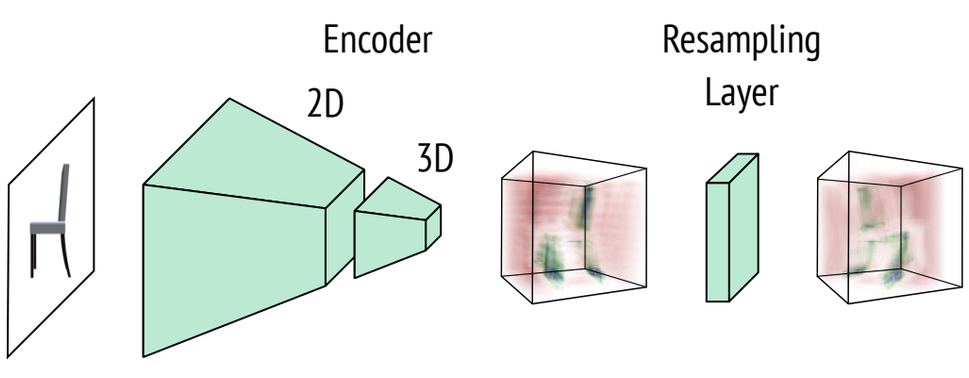
Olszewski, K., Tulyakov, S., Woodford, O., Li, H., & Luo, L. "Transformable Bottleneck Networks." ICCV'2019

TBNs for Novel View Synthesis



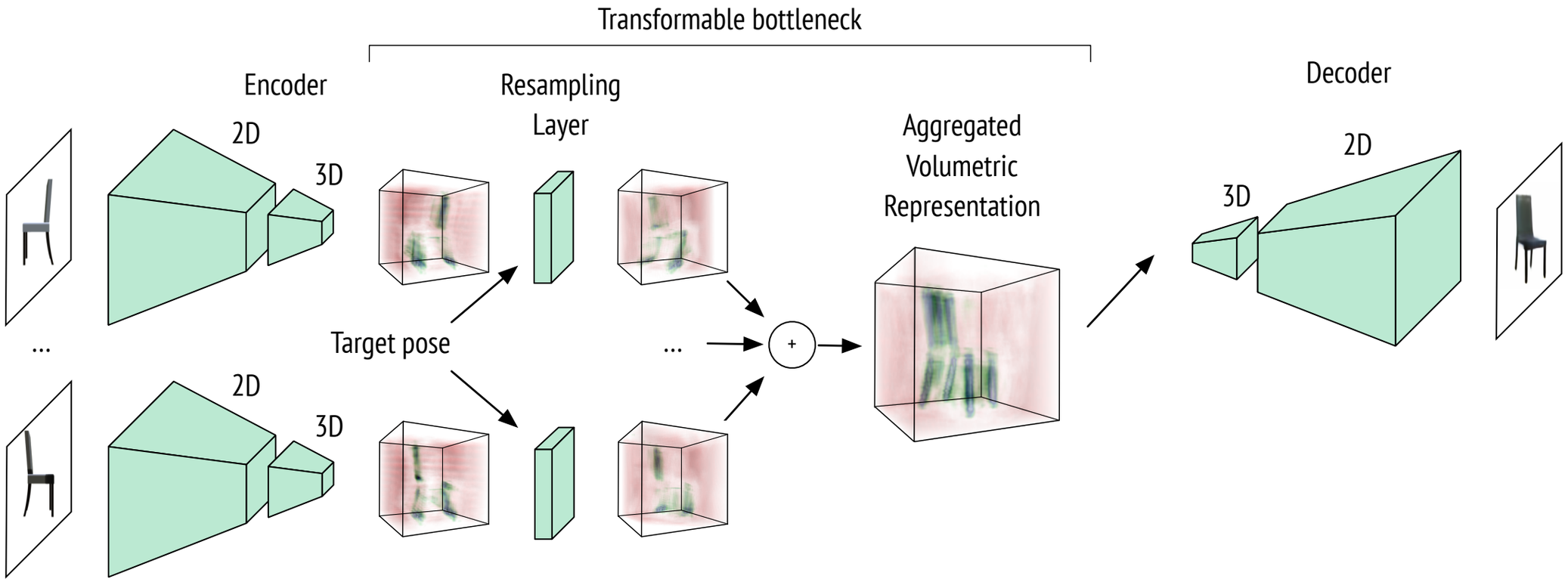
Olszewski, K., Tulyakov, S., Woodford, O., Li, H., & Luo, L. "Transformable Bottleneck Networks." ICCV'2019

Training Using Multiple Views



Olszewski, K., Tulyakov, S., Woodford, O., Li, H., & Luo, L. "Transformable Bottleneck Networks." ICCV'2019

Training Using Multiple Views



Olszewski, K., Tulyakov, S., Woodford, O., Li, H., & Luo, L. "Transformable Bottleneck Networks." ICCV'2019

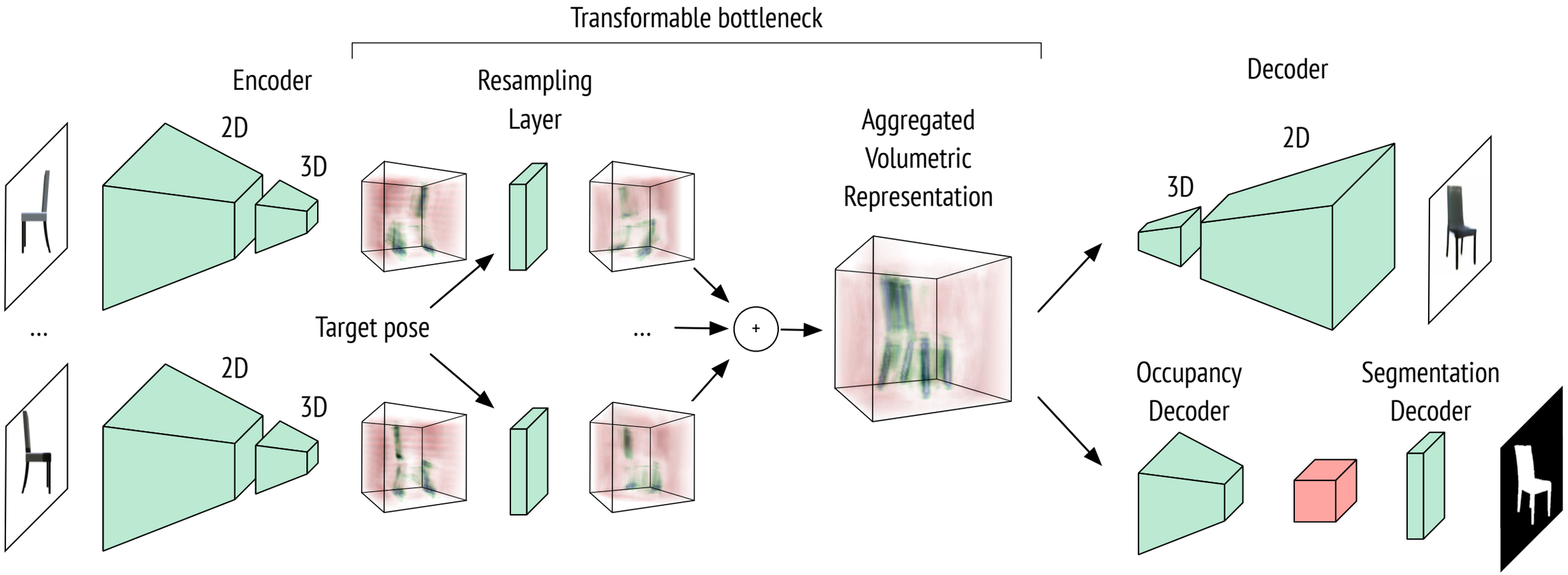
Training Using Multiple Views

Novel view synthesis performed by directly rotating the transformable bottleneck

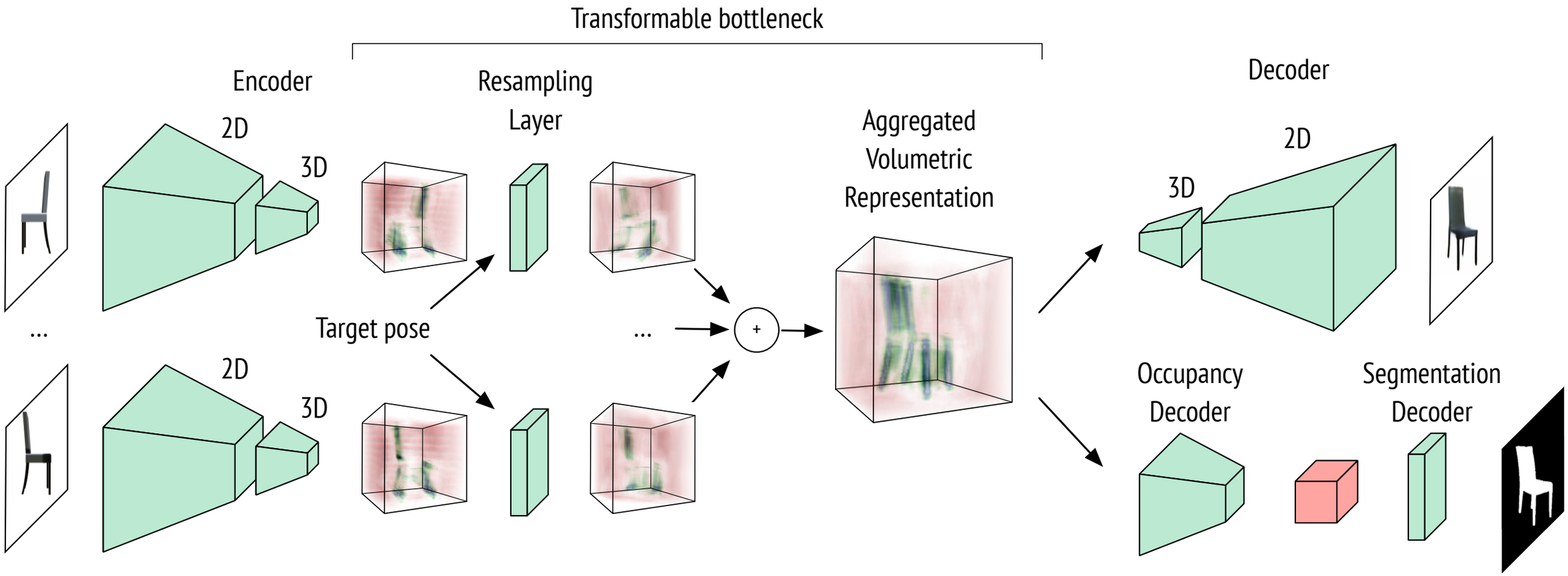
Training Using Multiple Views

Novel view synthesis performed by directly rotating the transformable bottleneck

Volumetric Reconstruction



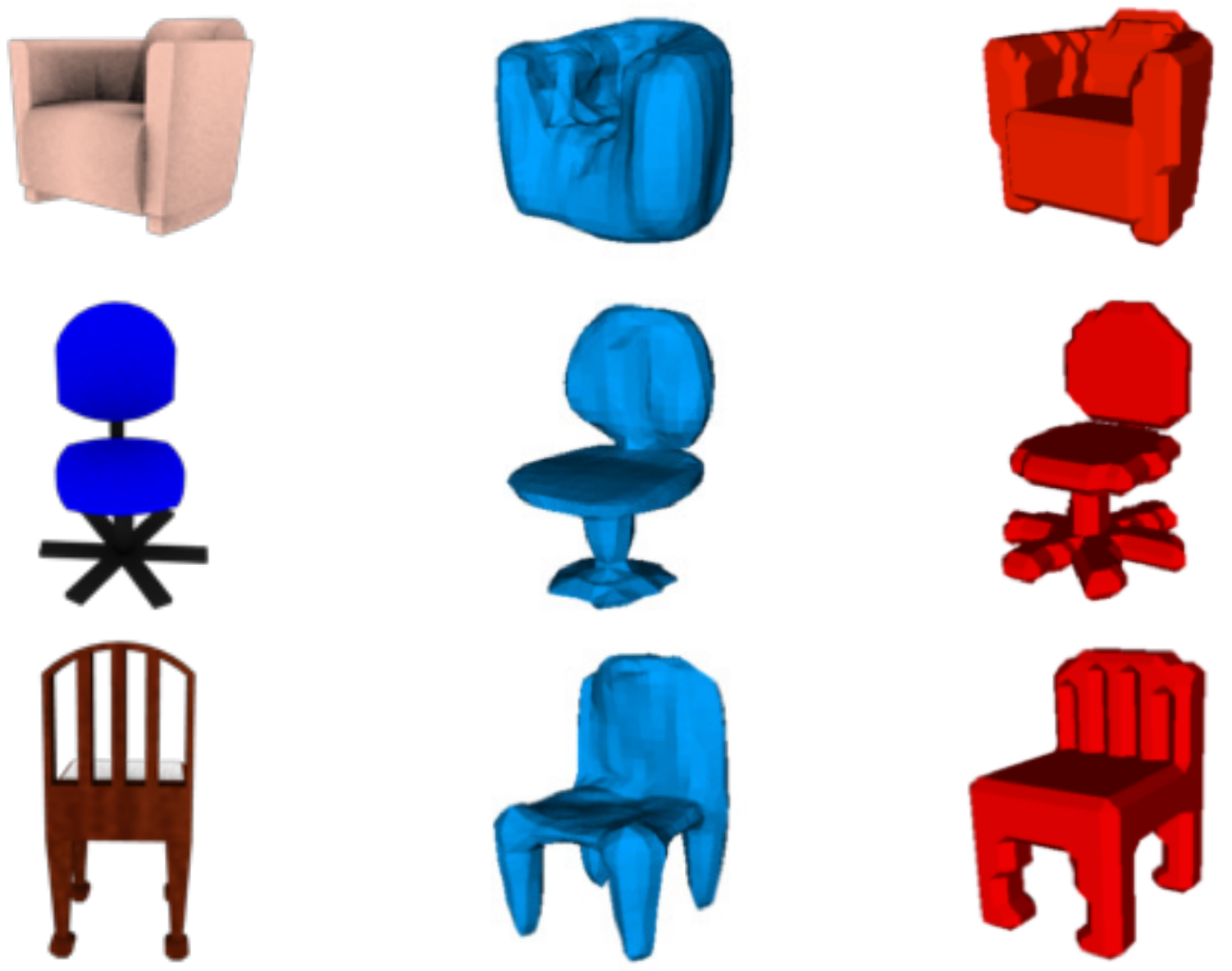
Volumetric Reconstruction



3D ground truth **not** required for training!

Volumetric Reconstruction

Input Image | Inferred Shape | Ground Truth



3D Reconstruction on Real Images

Input Images
(with estimated relative poses)

Extracted meshes
(from 40^3 occupancy volume)

3D Reconstruction on Real Images

Input Images
(with estimated relative poses)

Extracted meshes
(from 40^3 occupancy volume)

3D Printed
Meshes










Image Content Manipulation

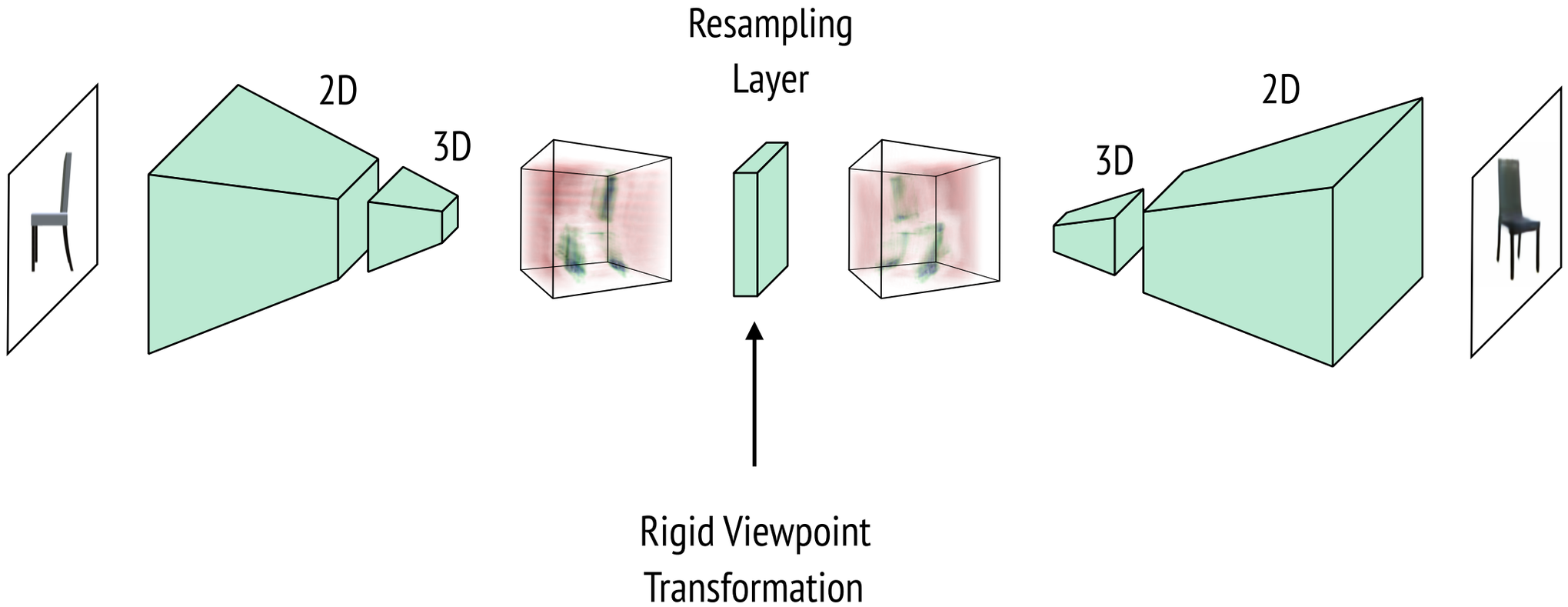


Image Content Manipulation

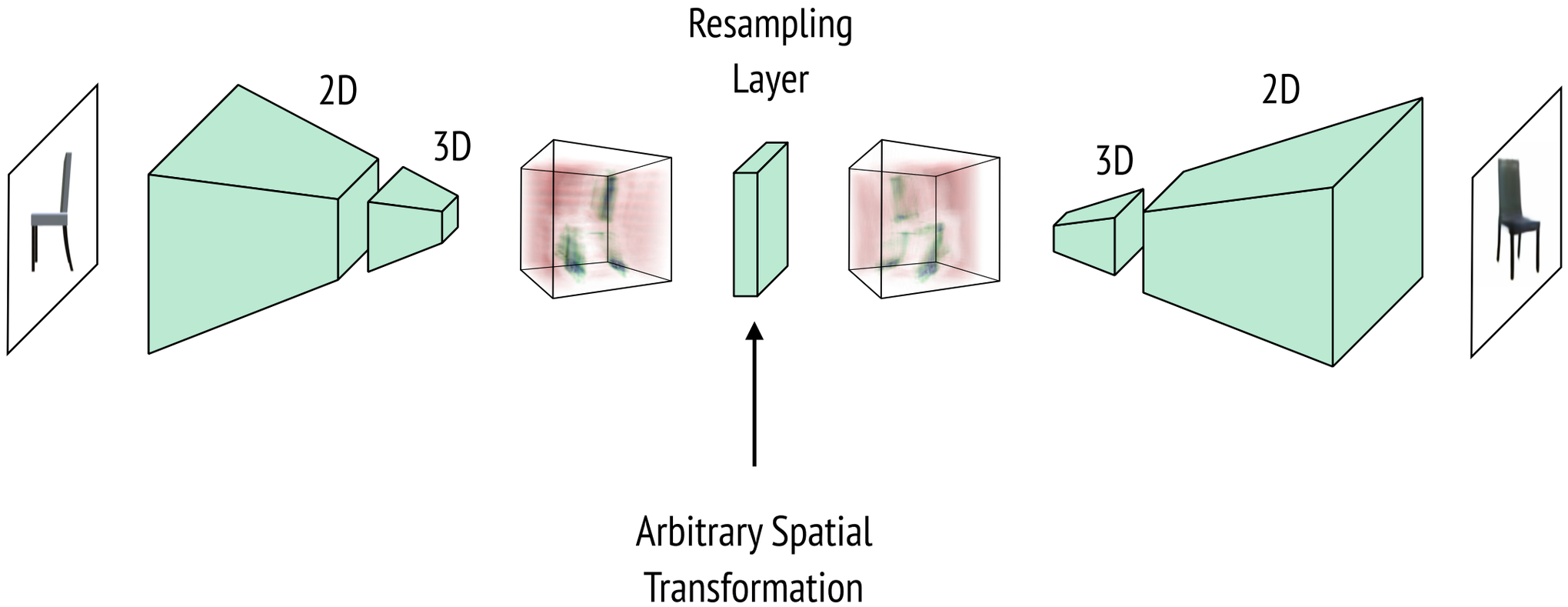


Image Content Manipulation

Vertical Twisting

Vertical Stretching

Nonlinear Inflation

Image Content Manipulation

Vertical Twisting

Vertical Stretching

Nonlinear Inflation

Questions?

- Image-to-image translation
  - Paired
  - Unpaired
  - Multimodal
- Stacked architectures
- Normalization layers
- Applications
- Other works