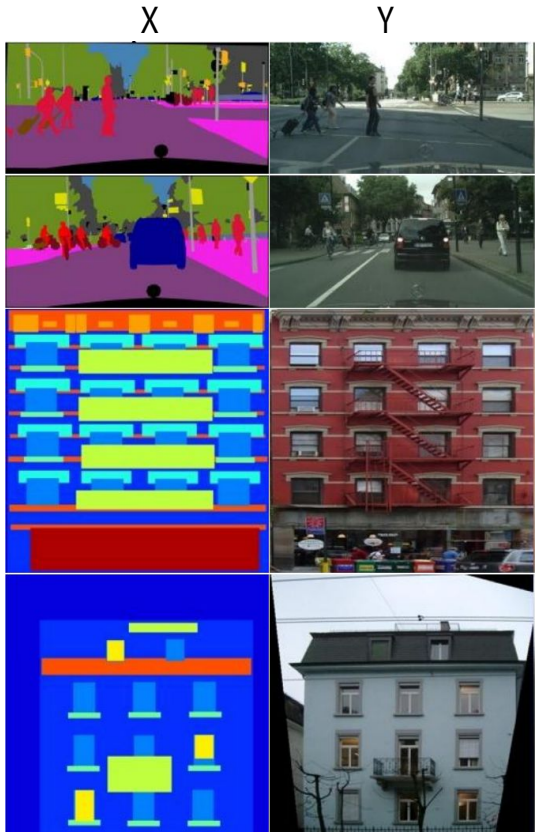
# Image-to-image Translation

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

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

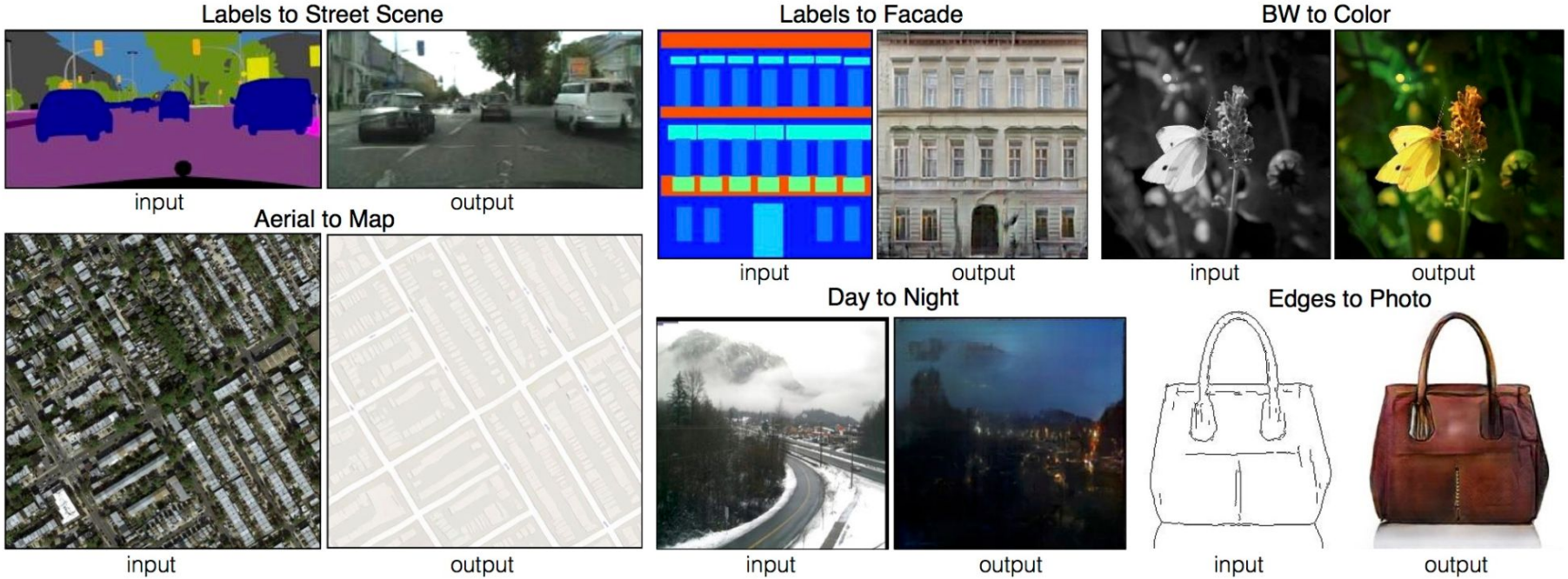
Paired image-to-image translation

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



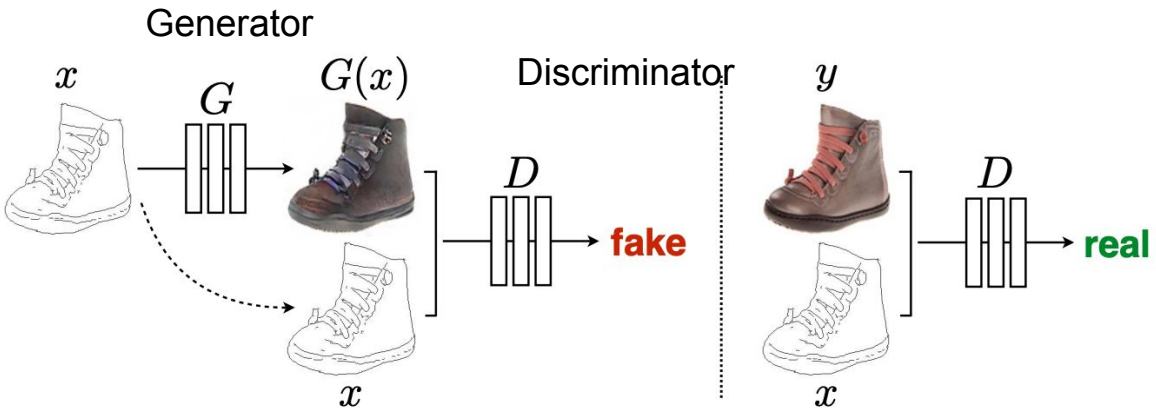

Isola, Phillip, et al. "Image-to-image translation with conditional adversarial networks." CVPR'2017

# Image-to-image Translation




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

# Image-to-image Translation: Pix2Pix




Combined GAN-loss and reconstruction loss:

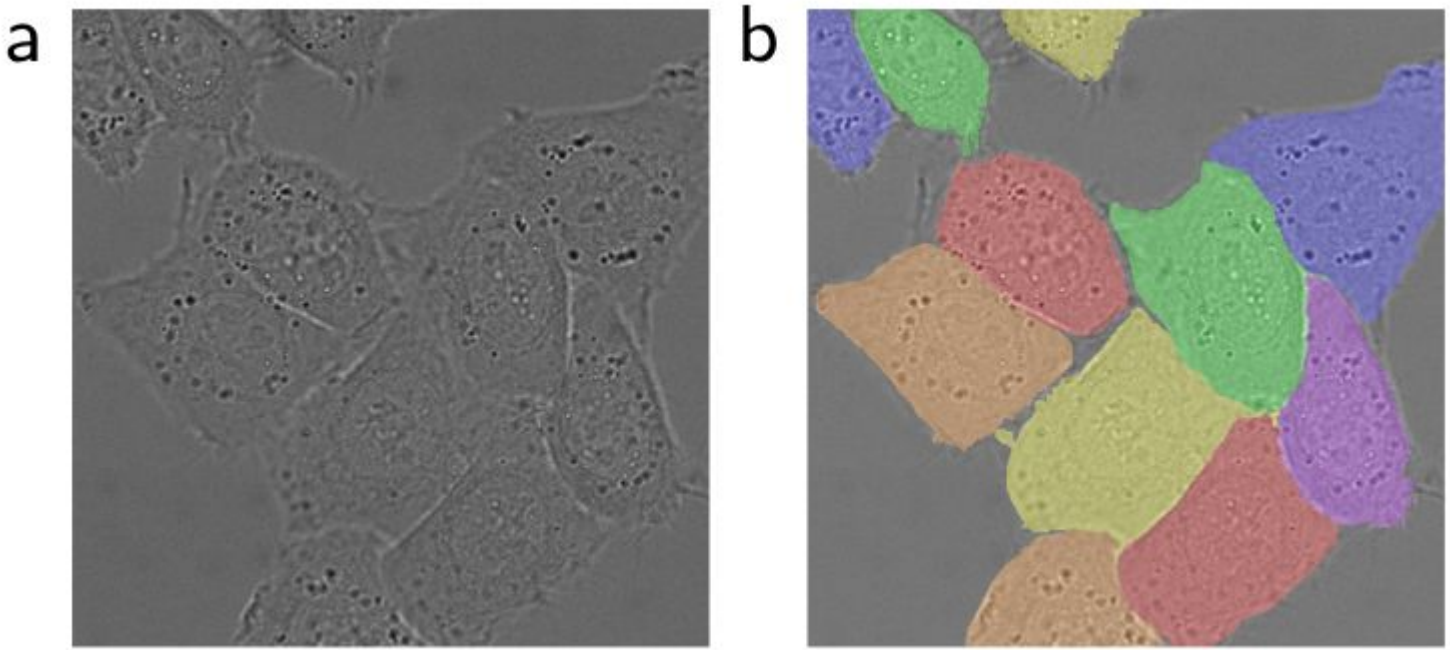
$$\mathcal{L}_{cGAN}(G,D) = \mathbb{E}_{x,y}[\log D(x,y)] + \mathbb{E}_{x,z}[\log(1 - D(x, G(x,z))]$$

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

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

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

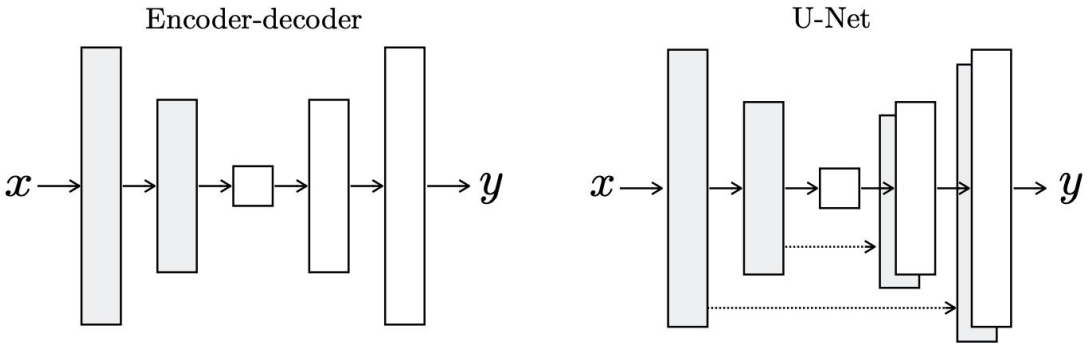
# Image-to-image Translation: Pix2Pix




U-Net: Convolutional Networks for Biomedical Image Segmentation Olaf Ronneberger, Philipp Fischer, Thomas Brox MICCAI 2015

# Image-to-image Translation: Pix2Pix

Skip connections in generator

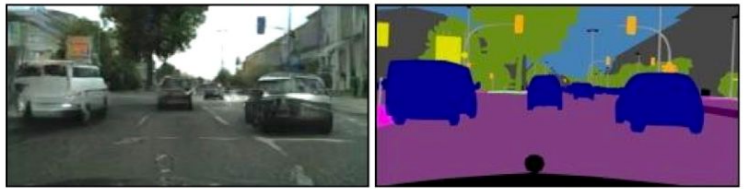



U-Net: Convolutional Networks for Biomedical Image Segmentation Olaf Ronneberger, Philipp Fischer, Thomas Brox MICCAI 2015

# 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.)



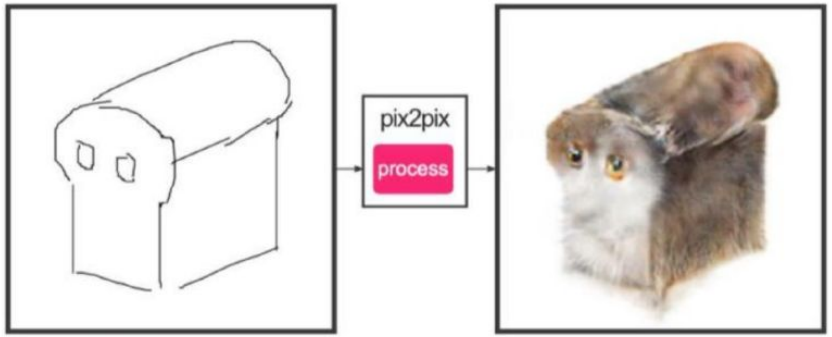
# Pix2Pix: Ablations

| 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.

# Pix2Pix: Applications

#edges2cats *by Christopher Hesse*




*sketch by Ivy Tsai*

Background removal

*by Kaihu Chen*

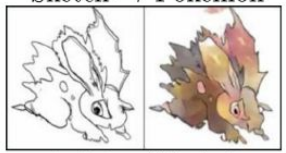
Palette generation

*by Jack Qiao*

Sketch→ Portrait

*by Mario Klingemann*

Sketch → Pokemon

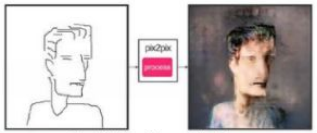


*by Bertrand Gondouin*

"Do as I do"

*by Brannon Dorsey*

#fotogenerator



*sketch by Yann LeCun*

# Unpaired Image-to-image Translation

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

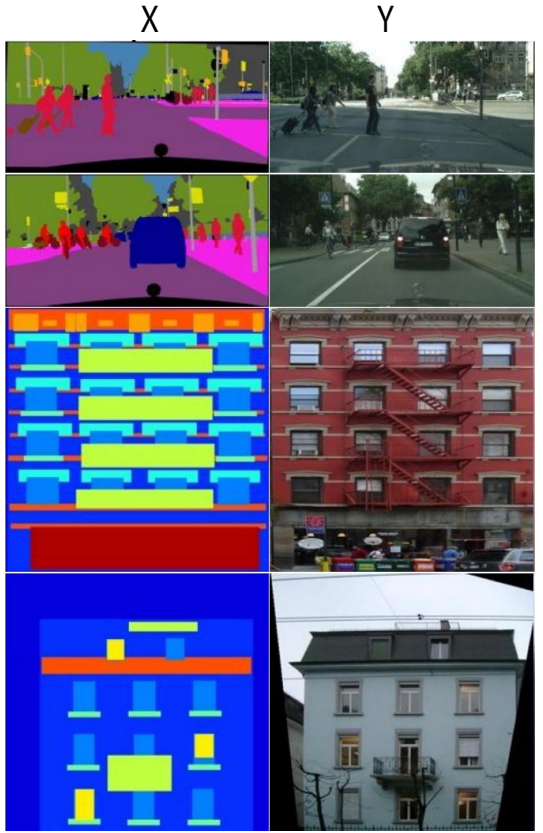
$$\mathbf{x} \sim p(\mathbf{x}|\mathbf{y})$$
$$\mathbf{y} \sim p(\mathbf{y}|\mathbf{x})$$

Paired image-to-image translation

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

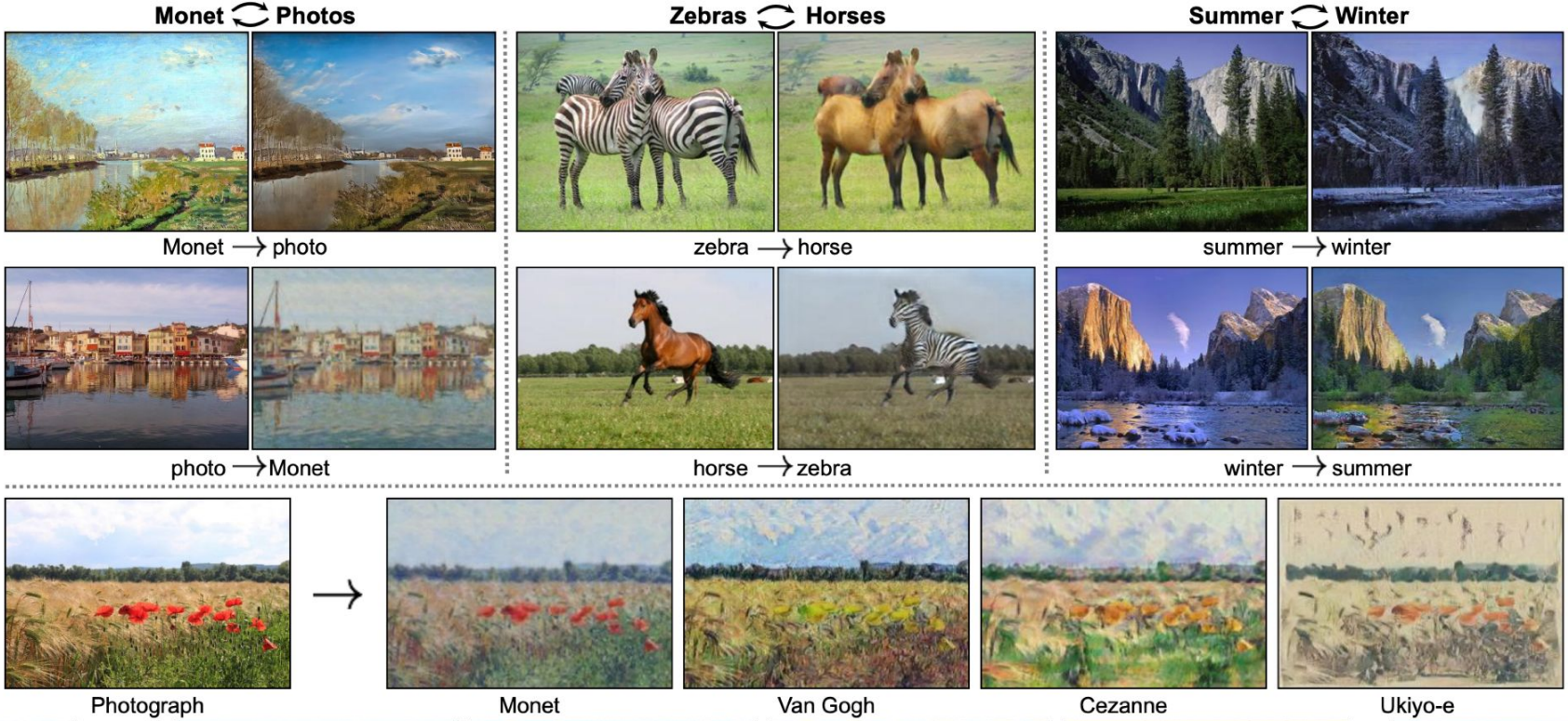
Unpaired

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




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

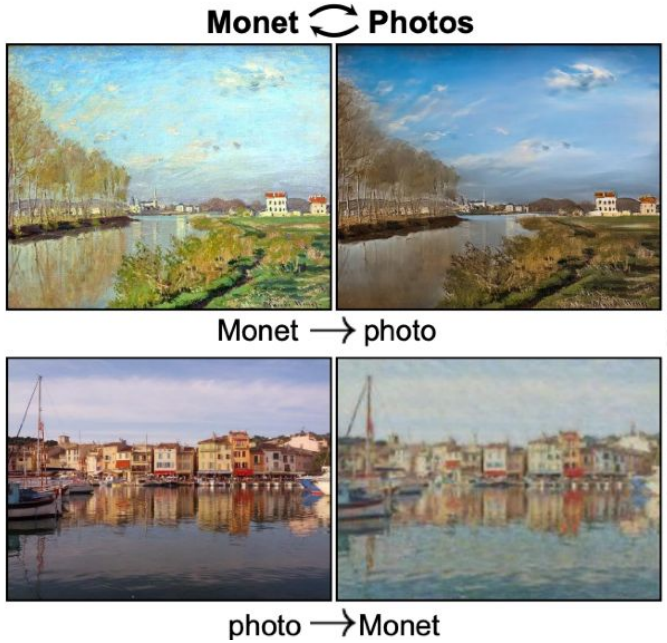
# Unpaired Image-to-image Translation




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

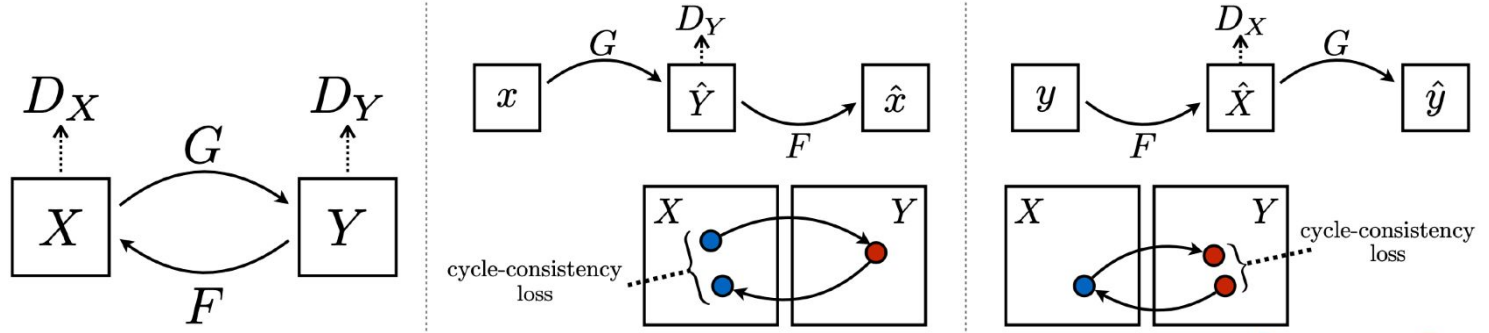
# Unpaired Image-to-image Translation

To solve it, constraints are necessary:
- Cycle-consistency constraint
- Weight-sharing constraint
- Geometry-consistency constraint




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

# CycleGAN




Adversarial loss:

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

Cycle-consistency loss:

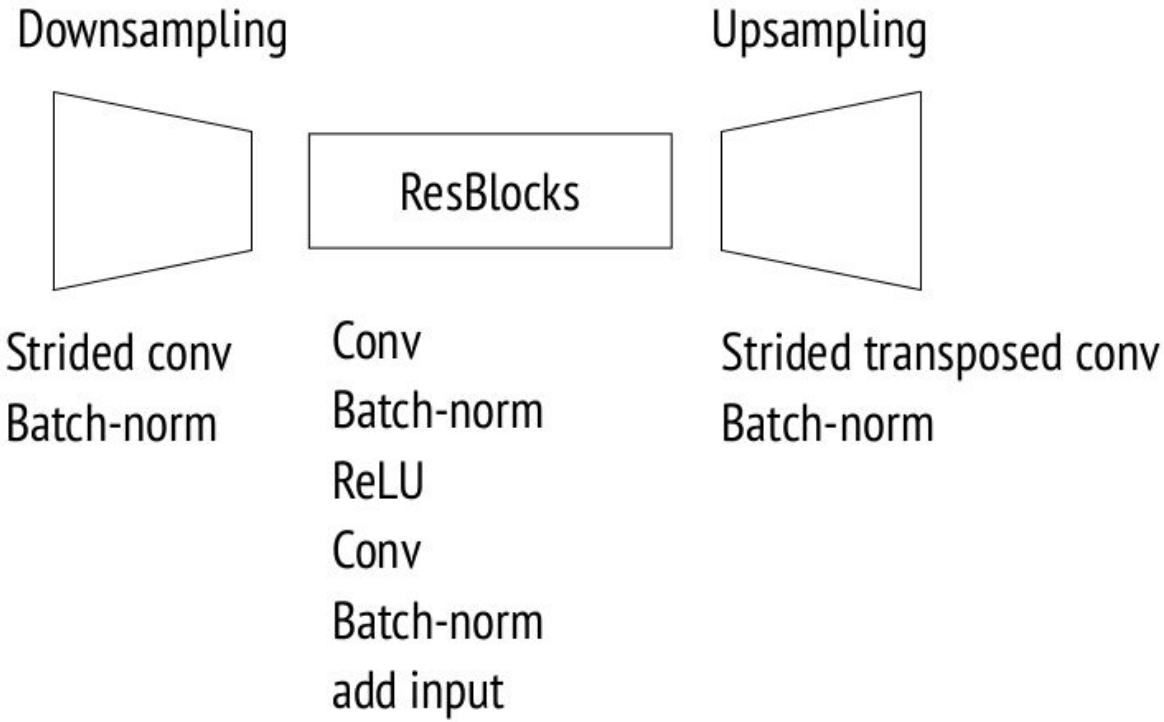
$$\mathcal{L}_{\text{cyc}}(G, F) = \mathbb{E}_{x \sim p_{\text{data}}(x)}[\|F(G(x)) - x\|_1] + \mathbb{E}_{y \sim p_{\text{data}}(y)}[\|G(F(y)) - y\|_1]$$

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

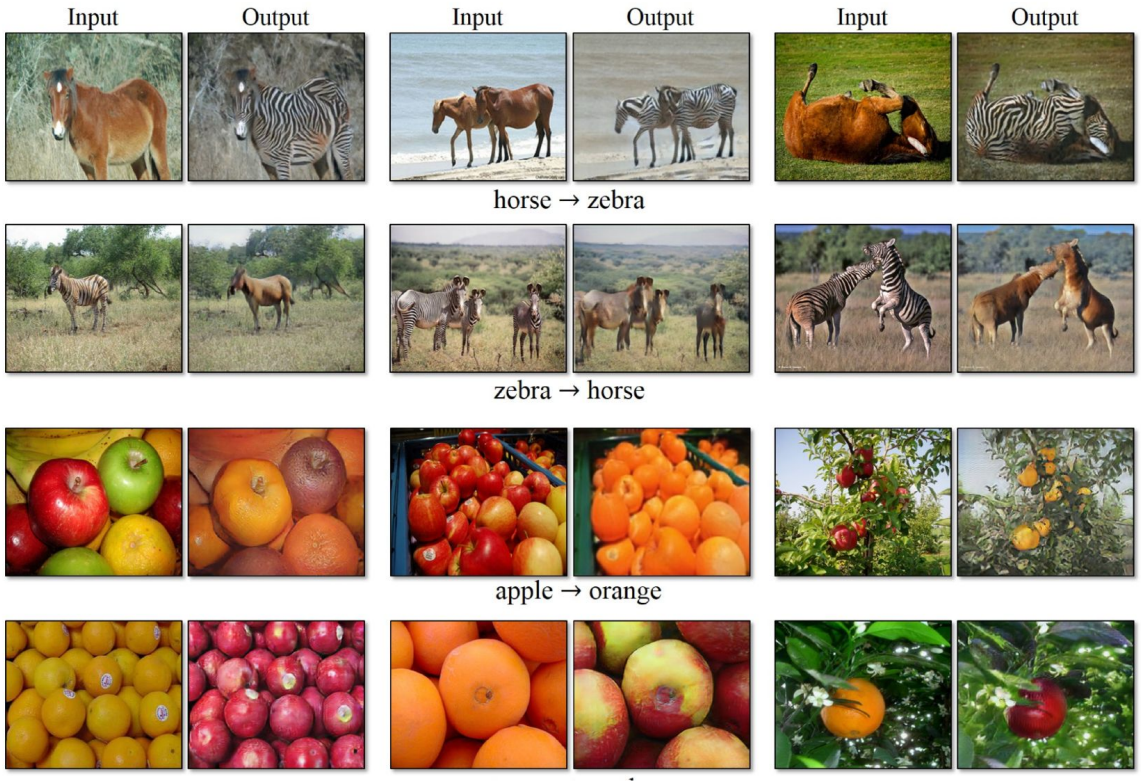



Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." ICCV 2017.

# CycleGAN


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

# CycleGAN

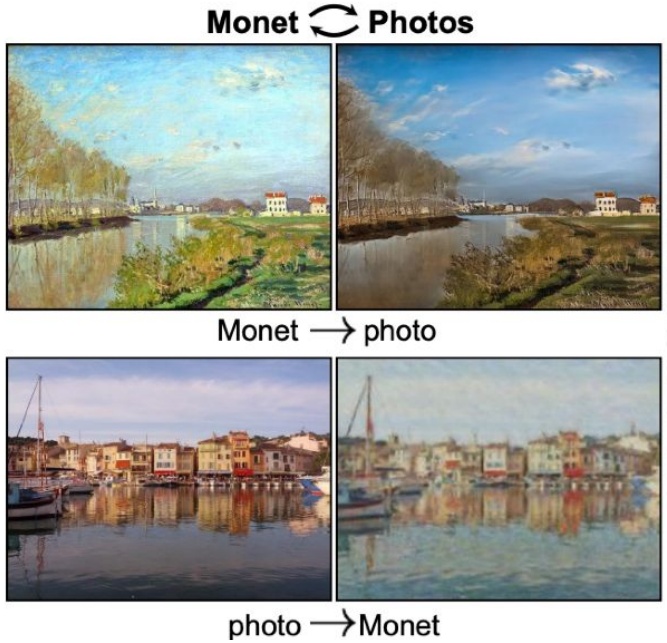



Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." ICCV 2017.

# Unpaired Image-to-image Translation

To solve it, constraints are necessary:

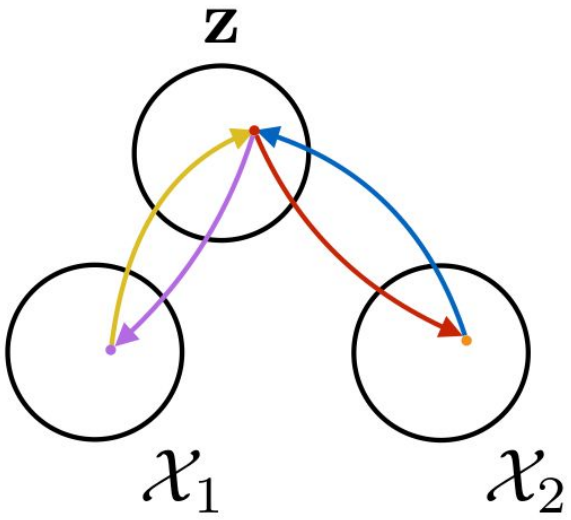
- Cycle-consistency constraint
- **Weight-sharing constraint**
- Geometry-consistency constraint

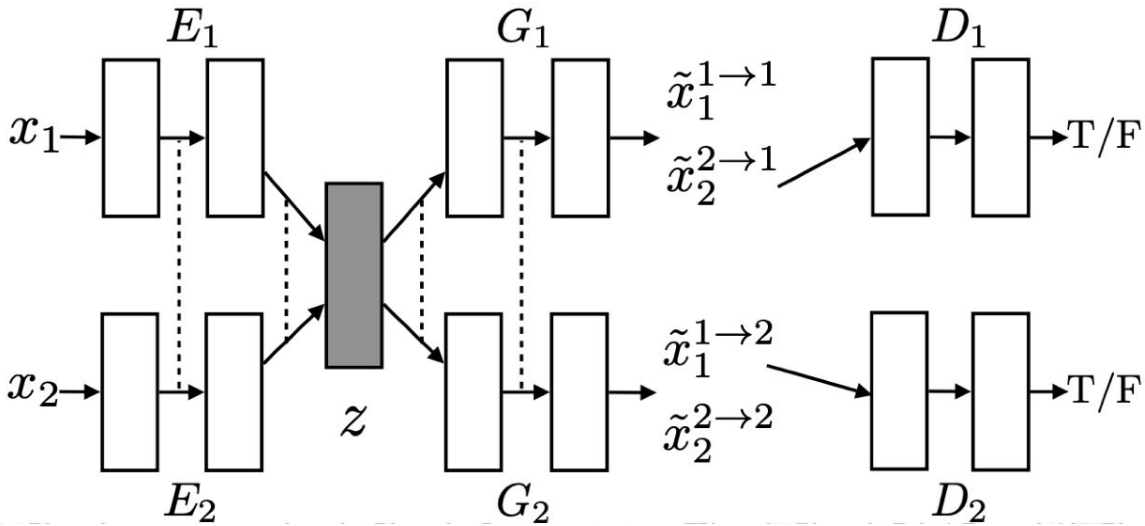



Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." ICCV 2017.

# Unpaired Translation with weight sharing

Train encoders with shared weights to go from image space to shared latent space

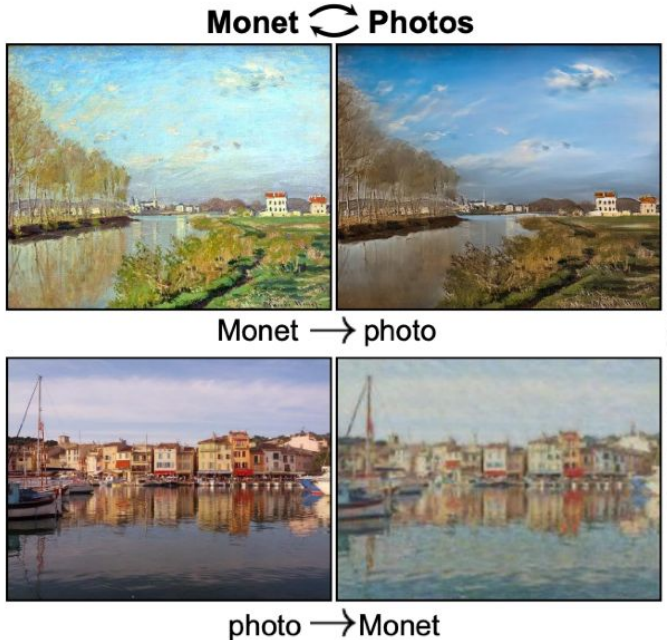



Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." ICCV 2017.

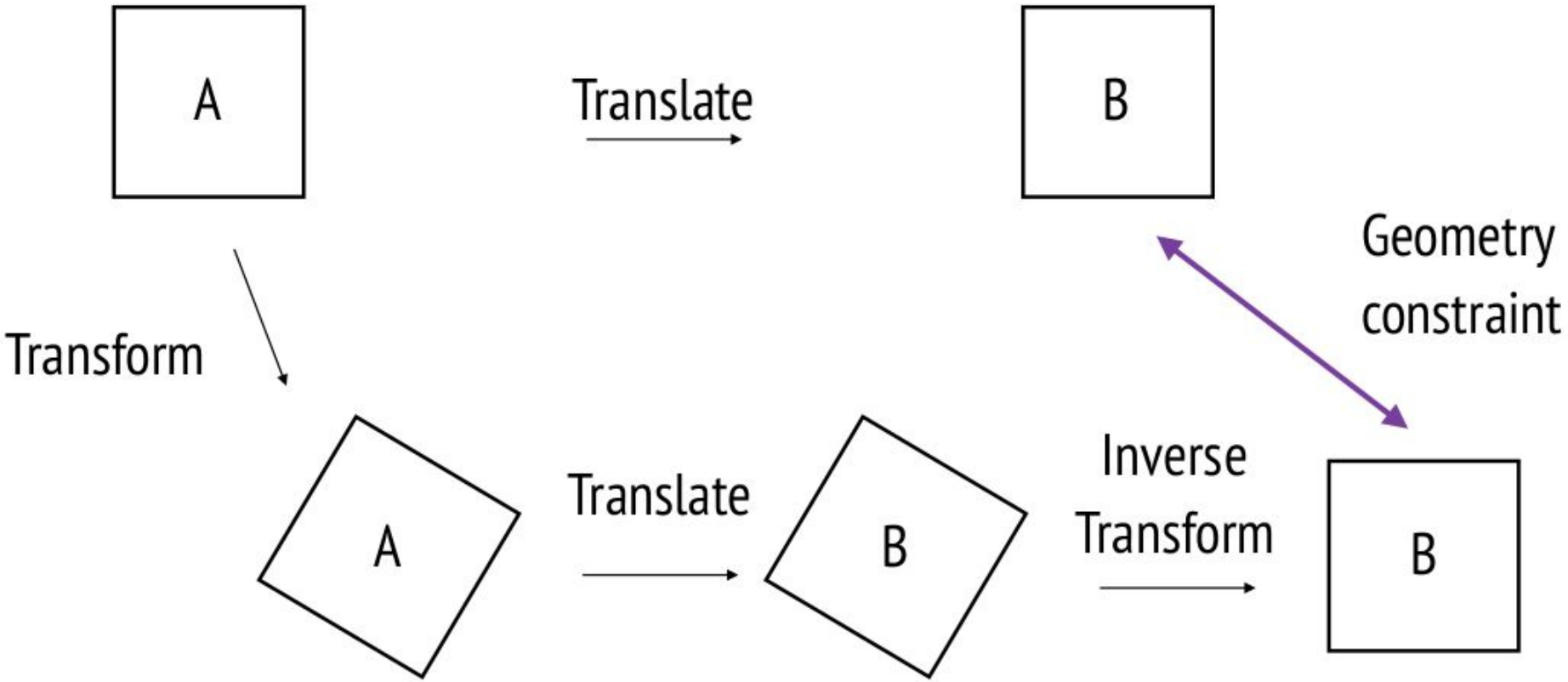
# Unpaired Image-to-image Translation

To solve it, constraints are necessary:
- Cycle-consistency constraint
- Weight-sharing constraint
- **Geometry-consistency constraint**

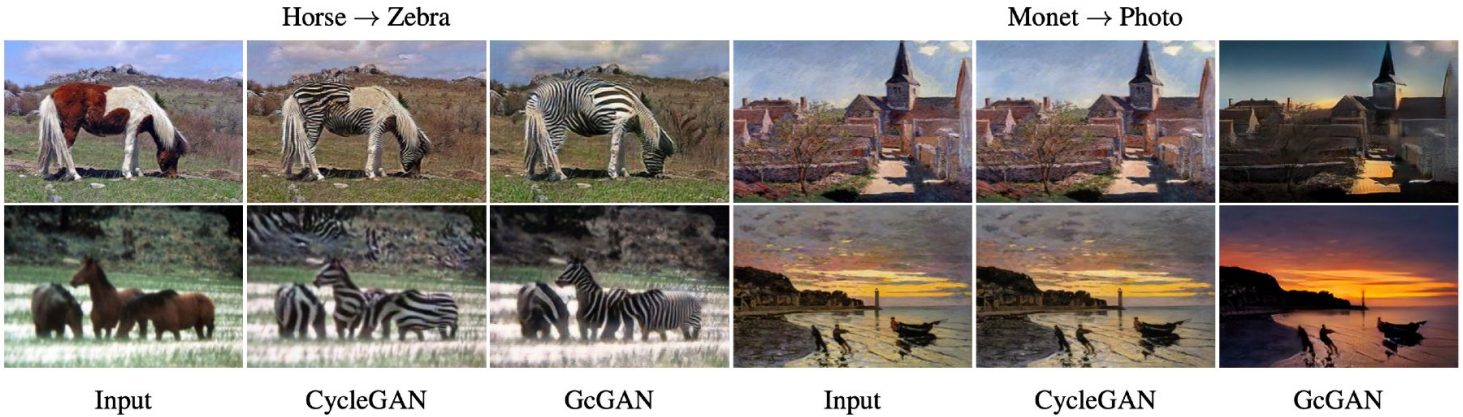



Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." ICCV 2017.

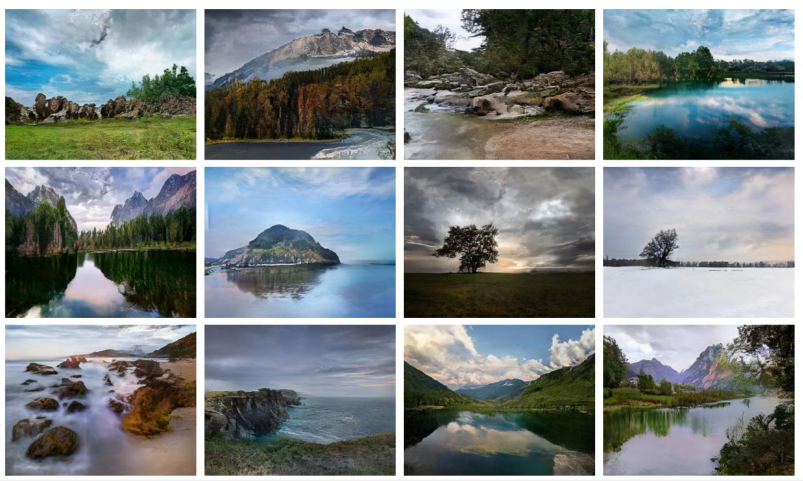
# Geometry-consistency Constraint



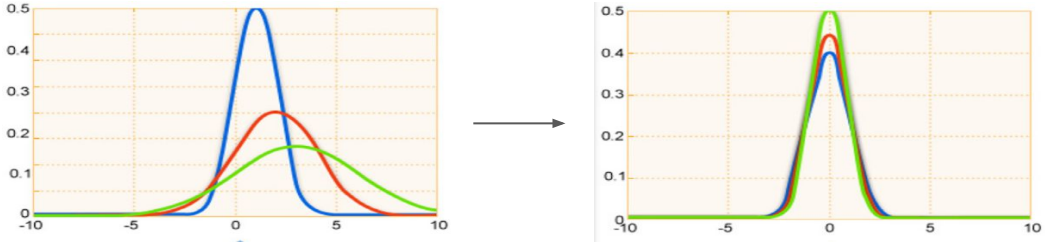
# Geometry-consistency Constraint



# Advanced methods



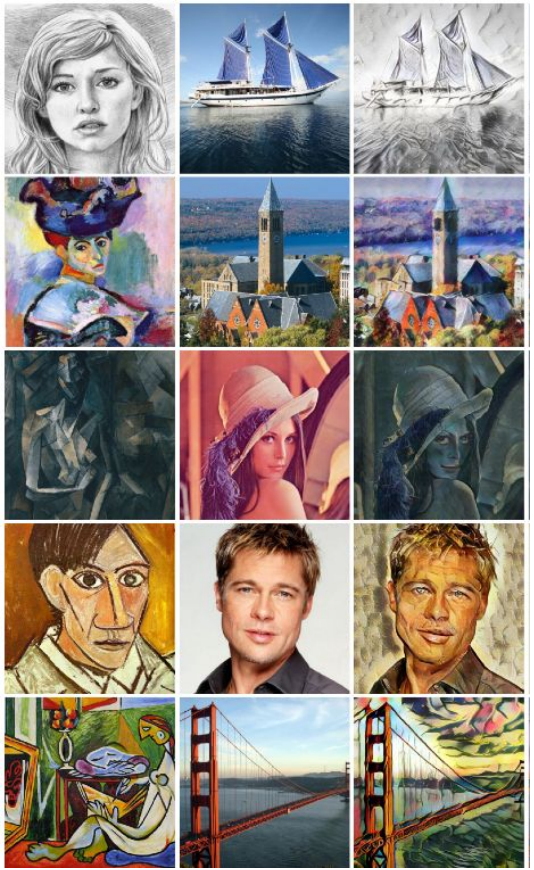
# Style transfer




(a) Content image.

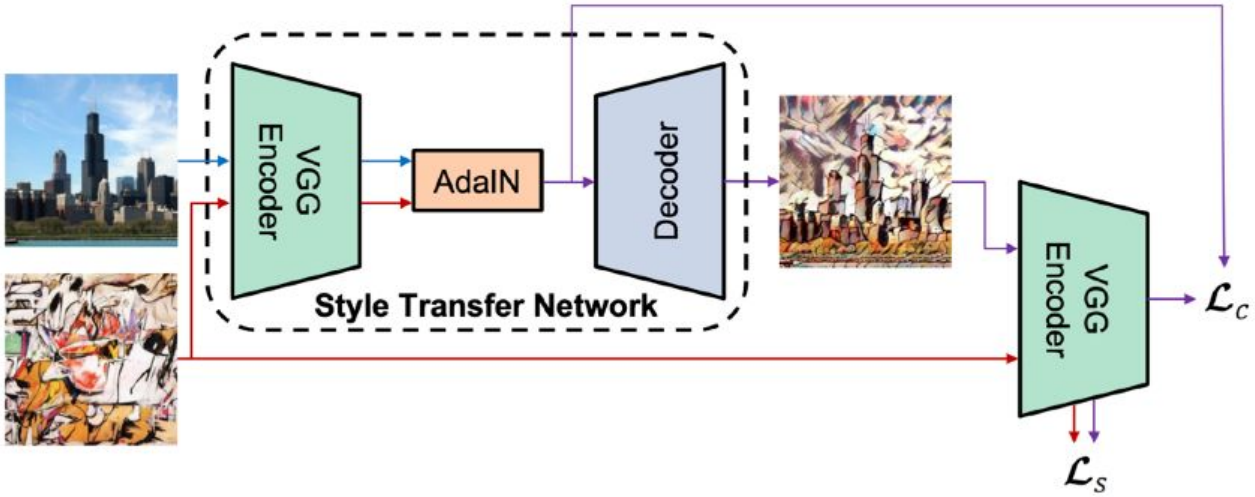
(c) Low contrast content image.

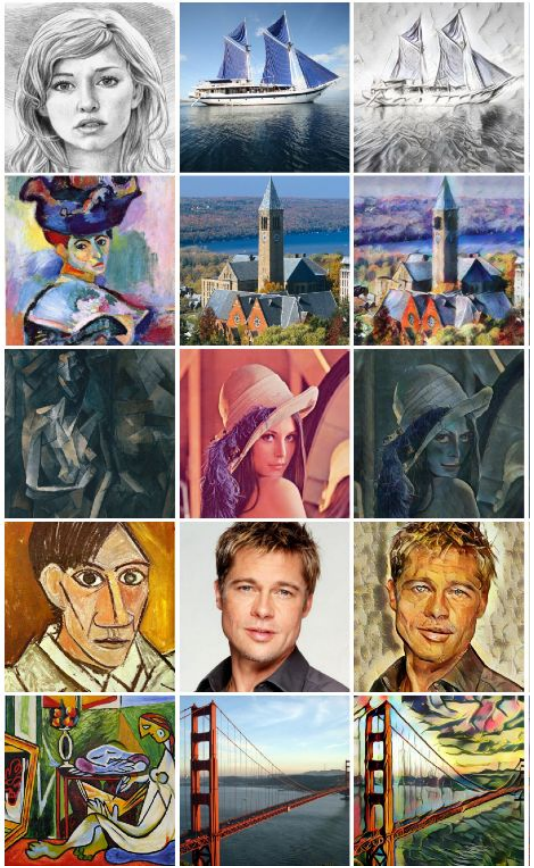
The two images are identical after instance normalization.
We obtain style invariant representations.



Instance Normalization: The Missing Ingredient for Fast Stylization,Dmitry Ulyanov, Andrea Vedaldi, Victor Lempitsky

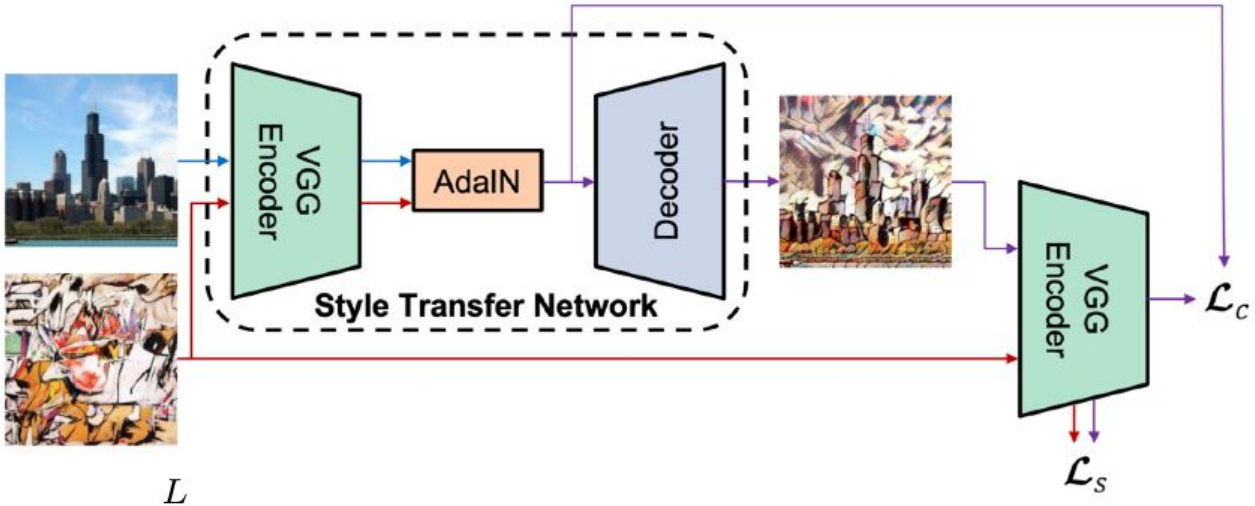
# Style transfer



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

# Style transfer



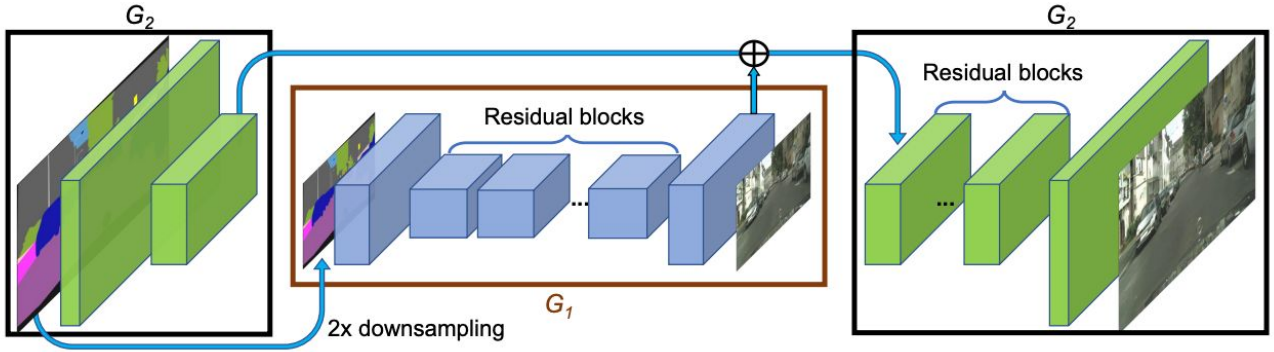

$$\mathcal{L}_c = \|f(g(t)) - t\|_2$$

$$\mathcal{L}_s = \sum_{i=1}^{L} \|\mu(\phi_i(g(t))) - \mu(\phi_i(s))\|_2 \quad + \quad \sum_{i=1}^{L} \|\sigma(\phi_i(g(t))) - \sigma(\phi_i(s))\|_2$$

where each $\varphi_i$ denotes a layer in VGG-19

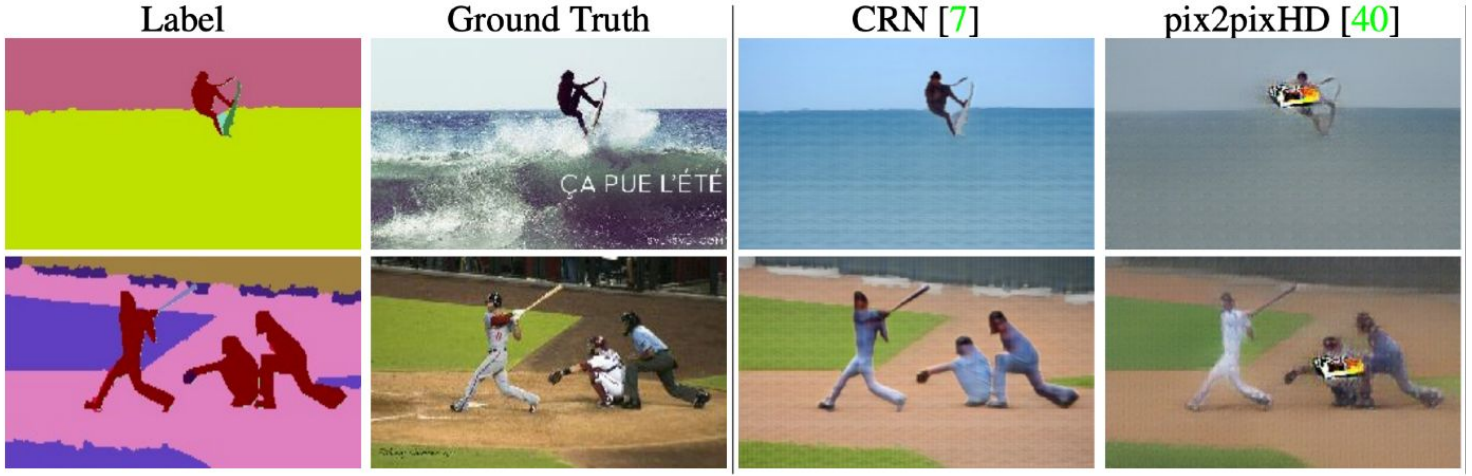
# Pix2PixHD

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

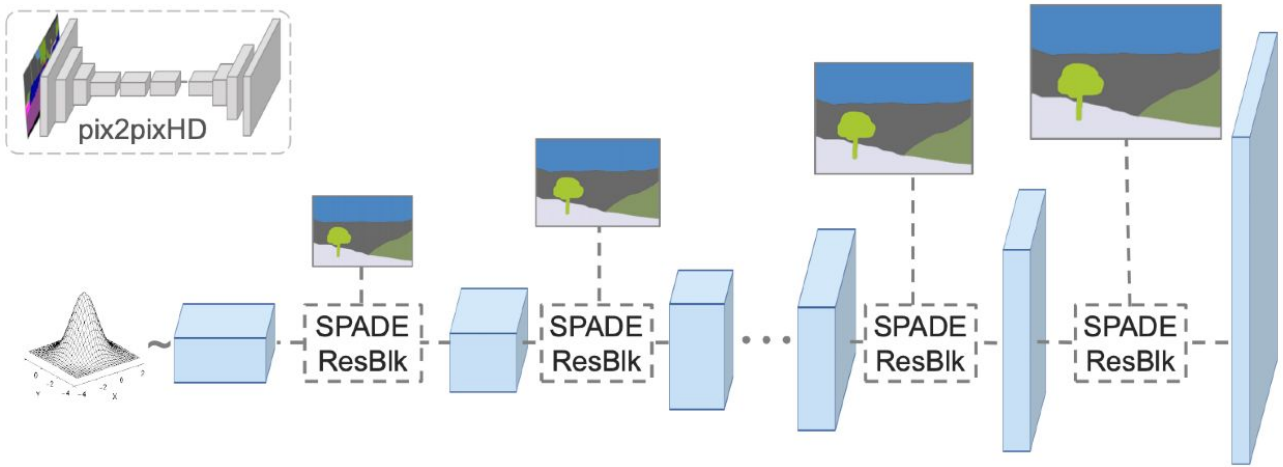



Input labels

# Pix2PixHD

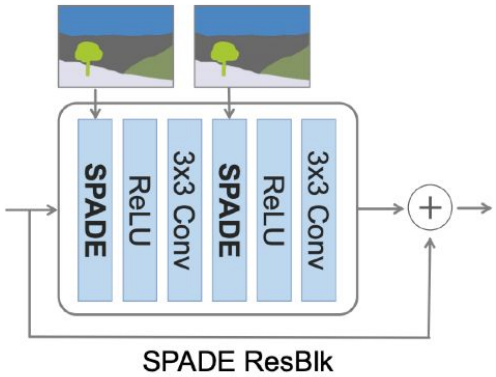


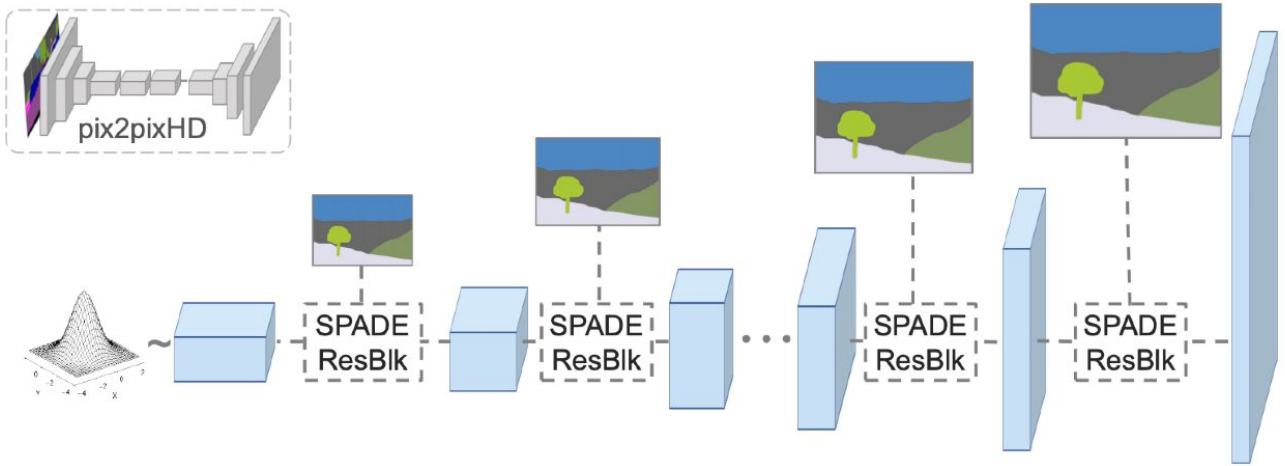
# Spade

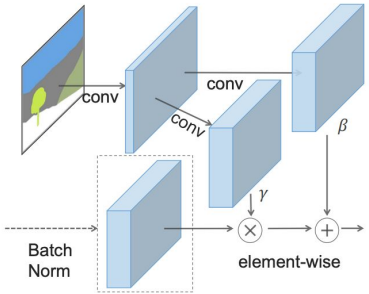



Park, Taesung, et al. "Semantic image synthesis with spatially-adaptive normalization." CVPR'2019

# Spade

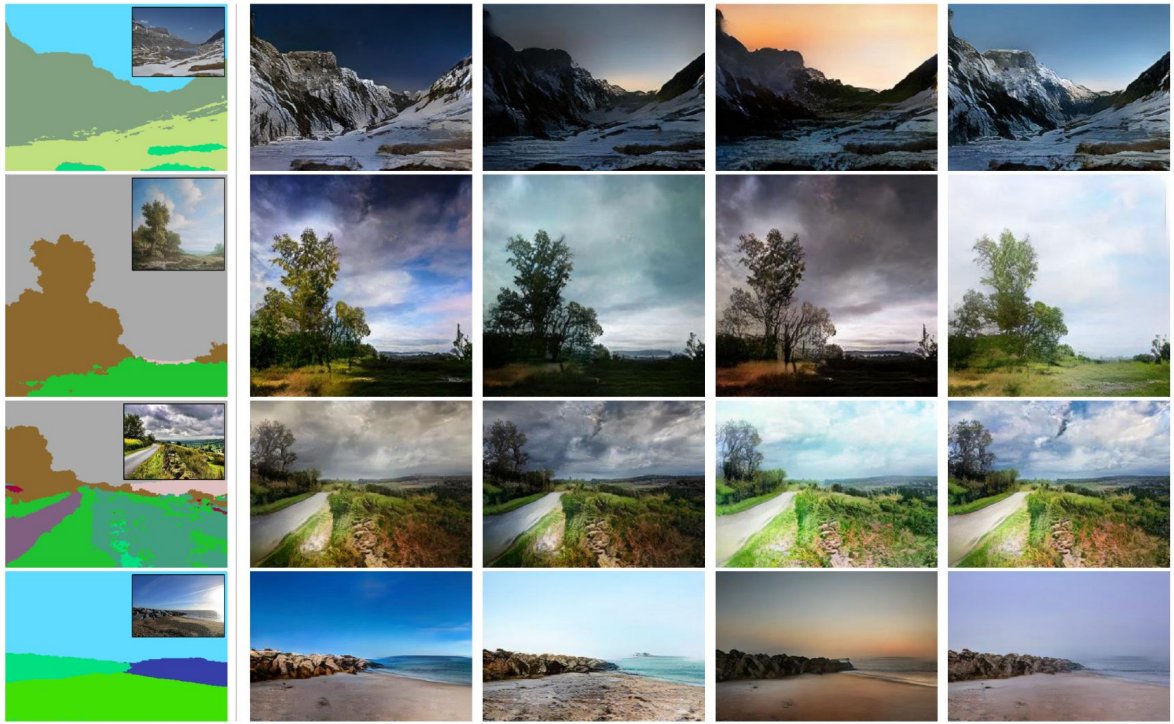



Park, Taesung, et al. "Semantic image synthesis with spatially-adaptive normalization." CVPR'2019

# Spade



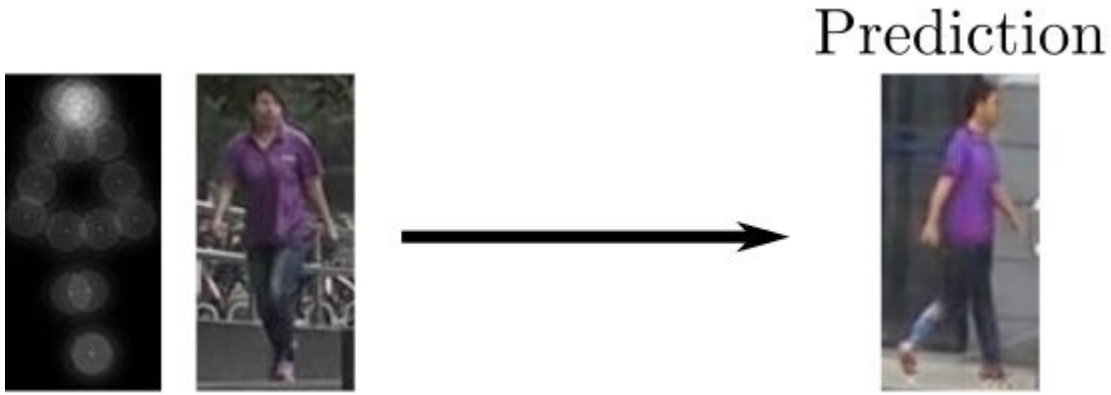
Live demo

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

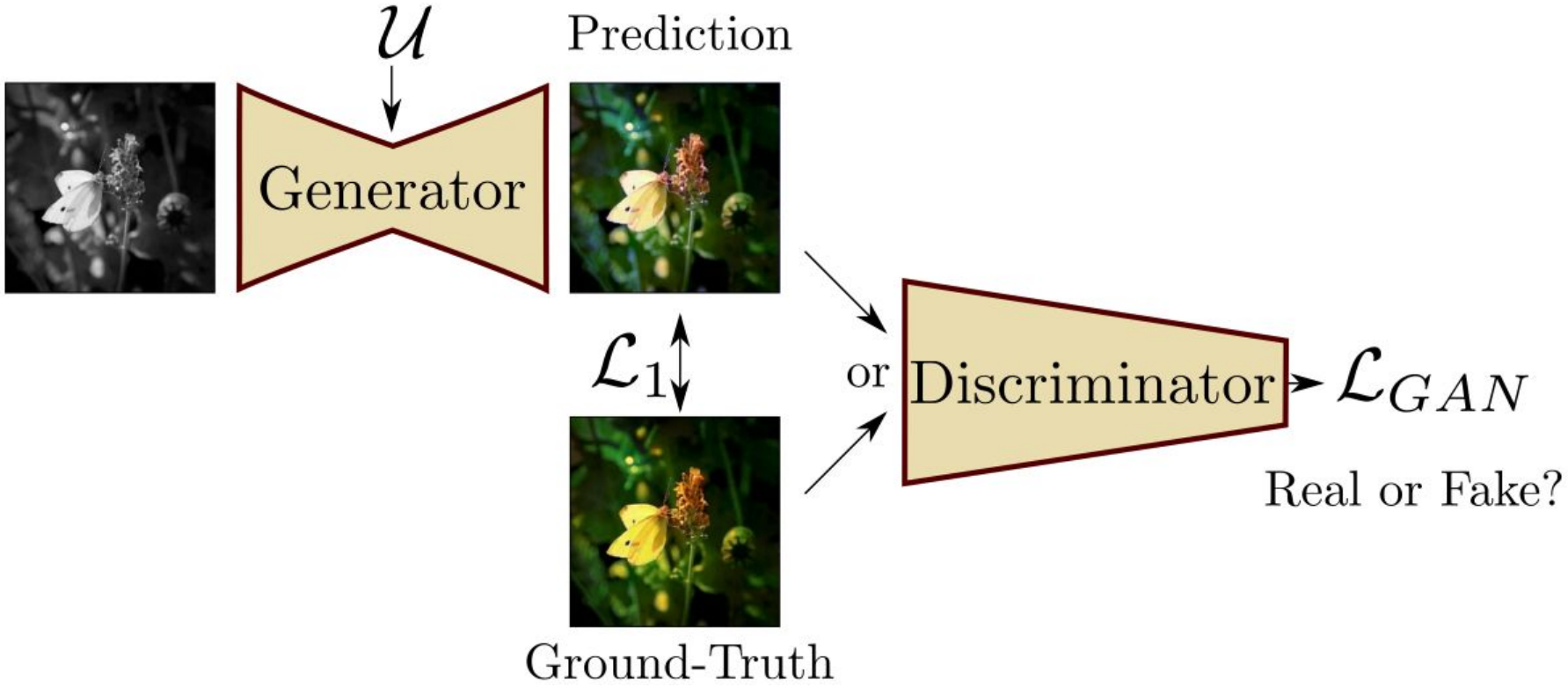
# Pose-guided Image Generation

Stéphane Lathuilière

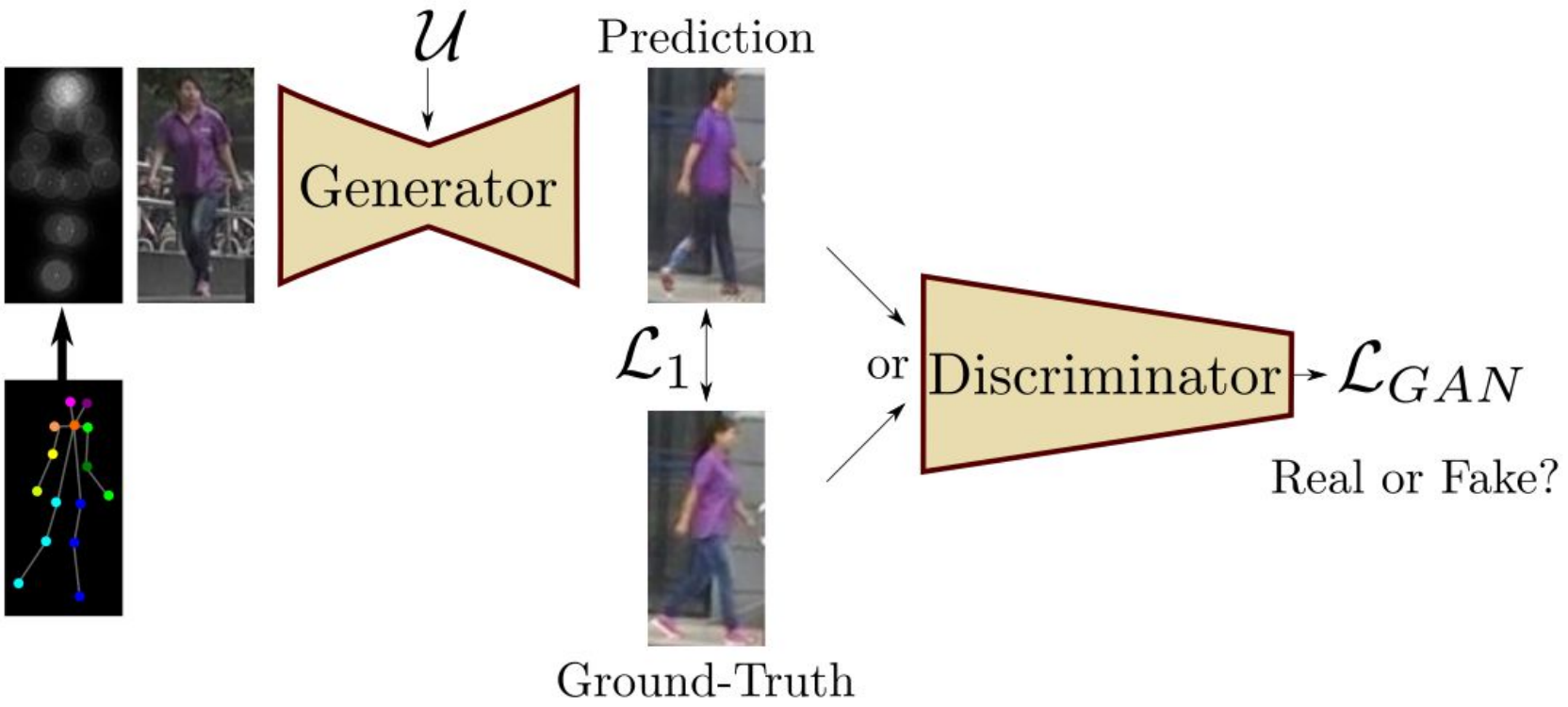
# Introduction



# Pix2Pix


$\mathcal{U}$
Prediction
Generator
$\mathcal{L}_1$
or
Discriminator
$\mathcal{L}_{GAN}$
Real or Fake?
Ground-Truth

# Pix2Pix for pose guided



# Pix2Pix for pose guided

# Pose guided

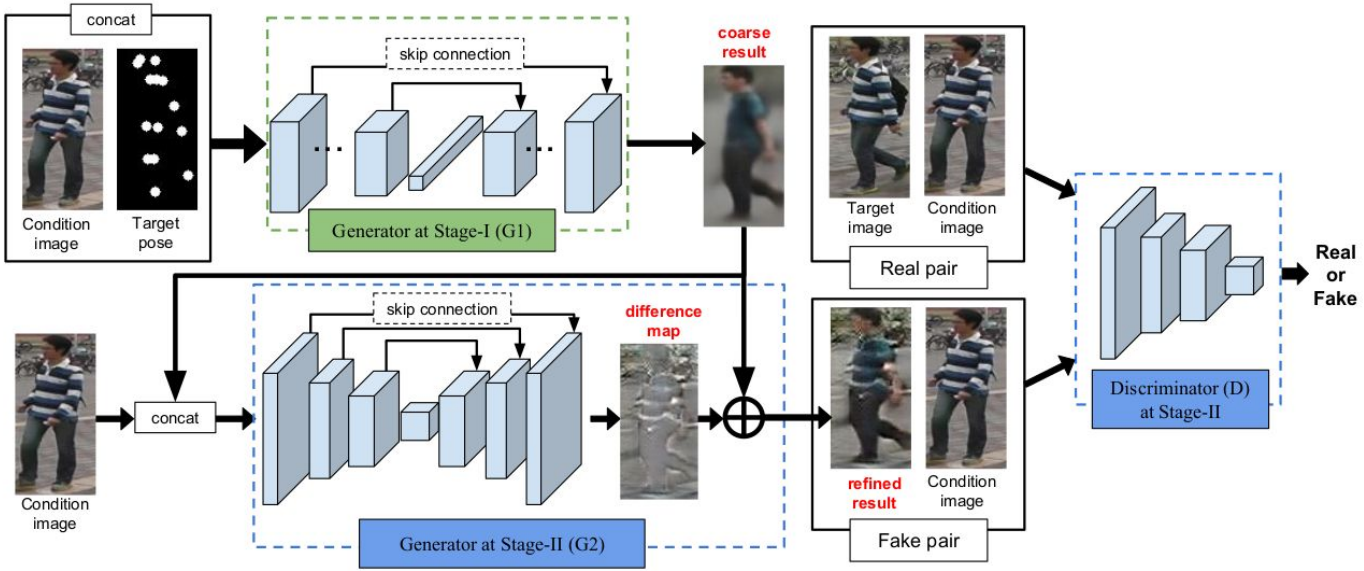
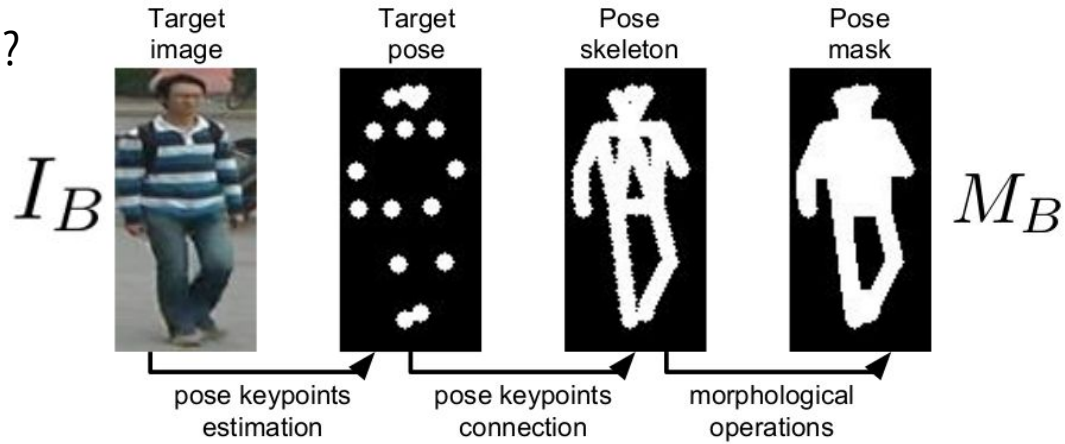



Figure 2: The overall framework of our Pose Guided Person Generation Network (PG$^2$). It contains two stages. Stage-I focuses on pose integration and generates an initial result that captures the global structure of the human. Stage-II focuses on refining the initial result via adversarial training and generates sharper images.

Pose Guided Person Image Generation, Ma et. al. Nips 2017

# Pose guided

What about the background?

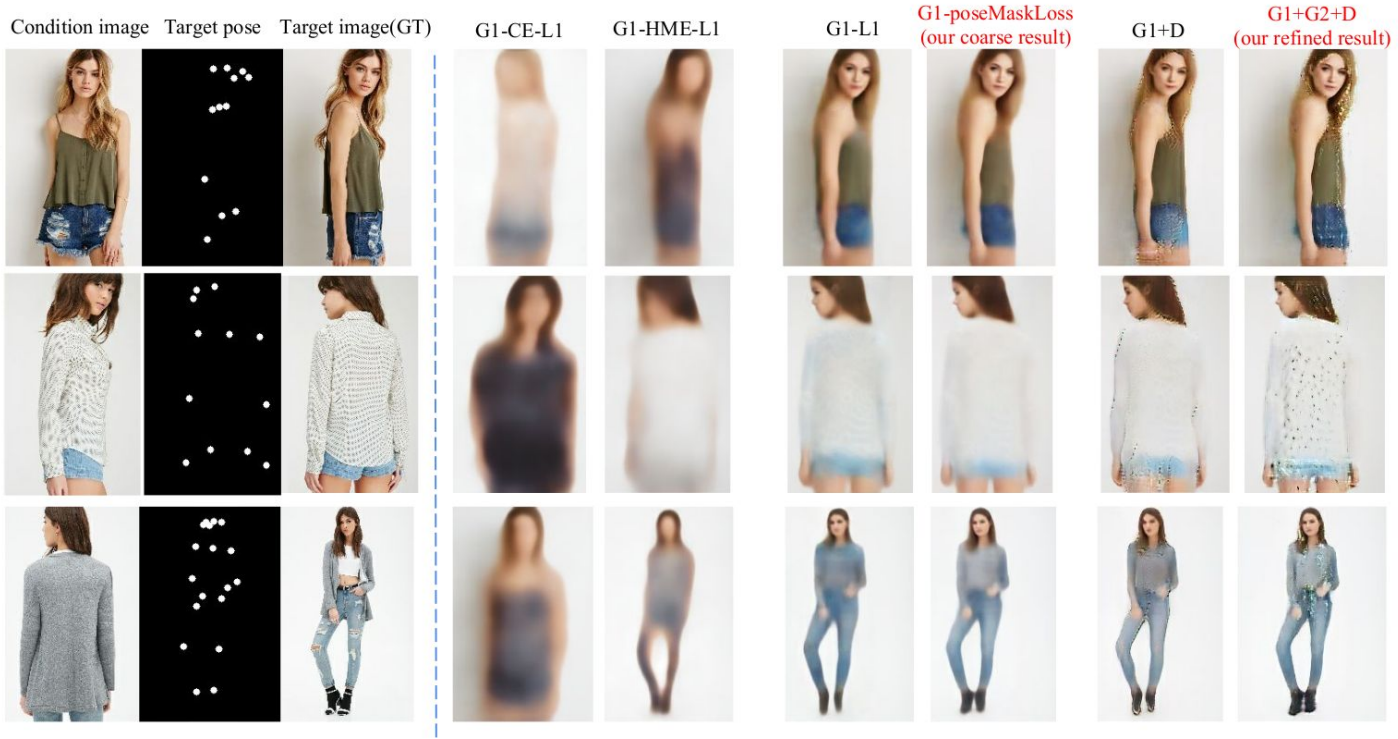



They give more weight to the foreground:

$$\mathcal{L}_{\mathrm{G1}} = \|(\mathrm{G1}(I_A, P_B) - I_B) \odot (1 + M_B)\|_1$$

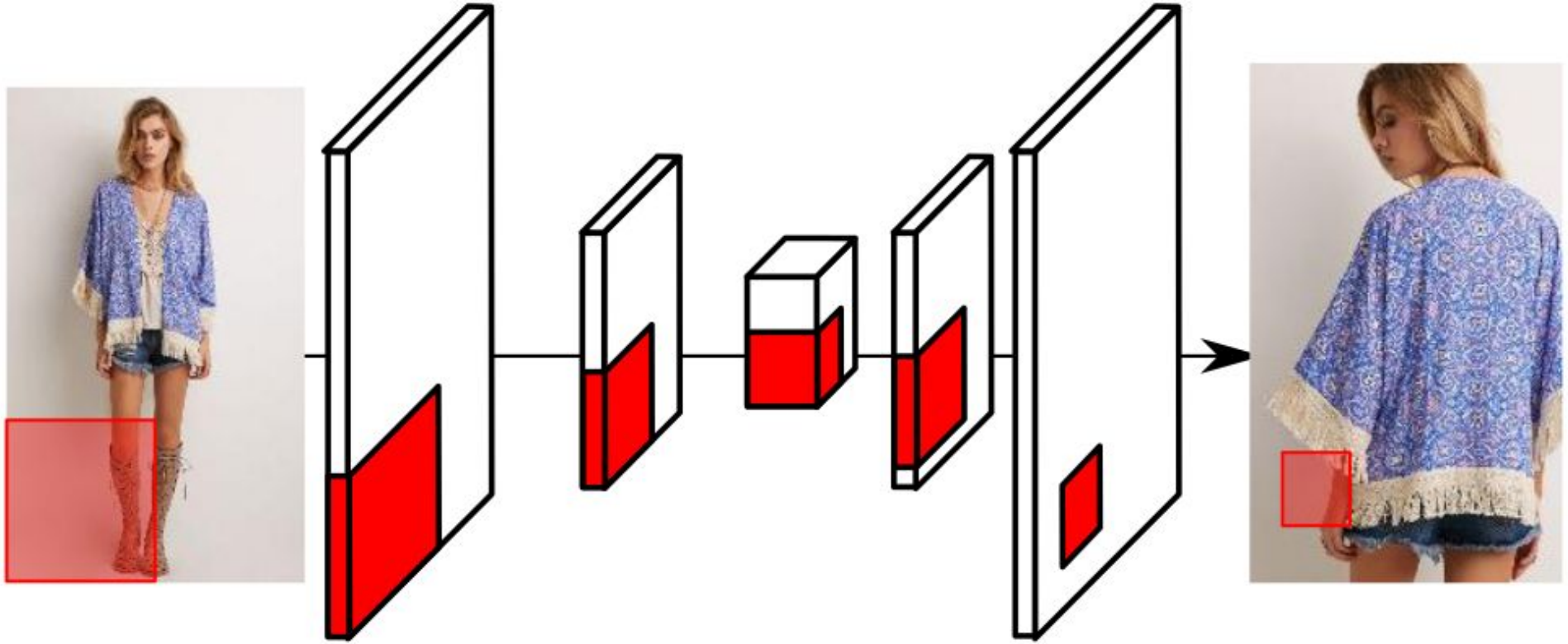
Pose Guided Person Image Generation, Ma et. al. Nips 2017

# Pose guided




Pose Guided Person Image Generation, Ma et. al. Nips 2017

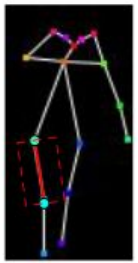
# Pix2Pix for pose guided: problem



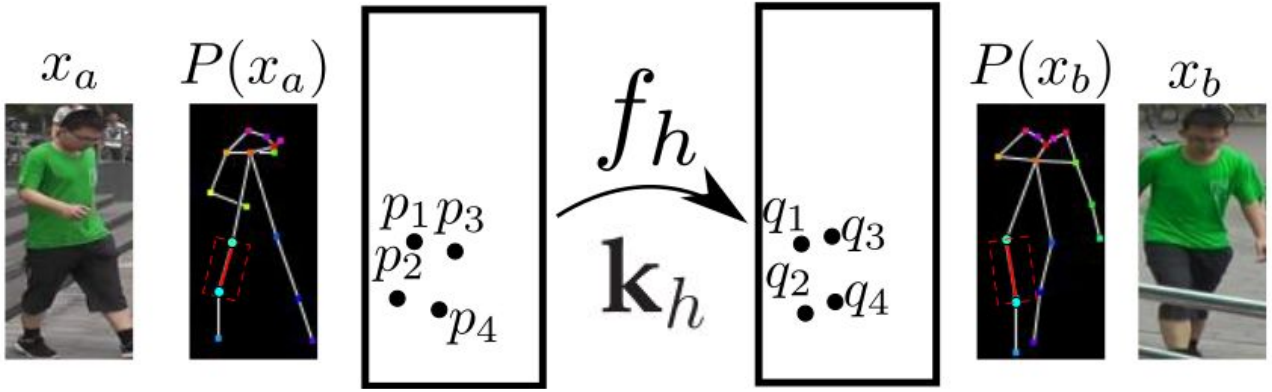
# Pose guided: deformable GAN

$x_a$ $P(x_a)$

$P(x_b)$ $x_b$

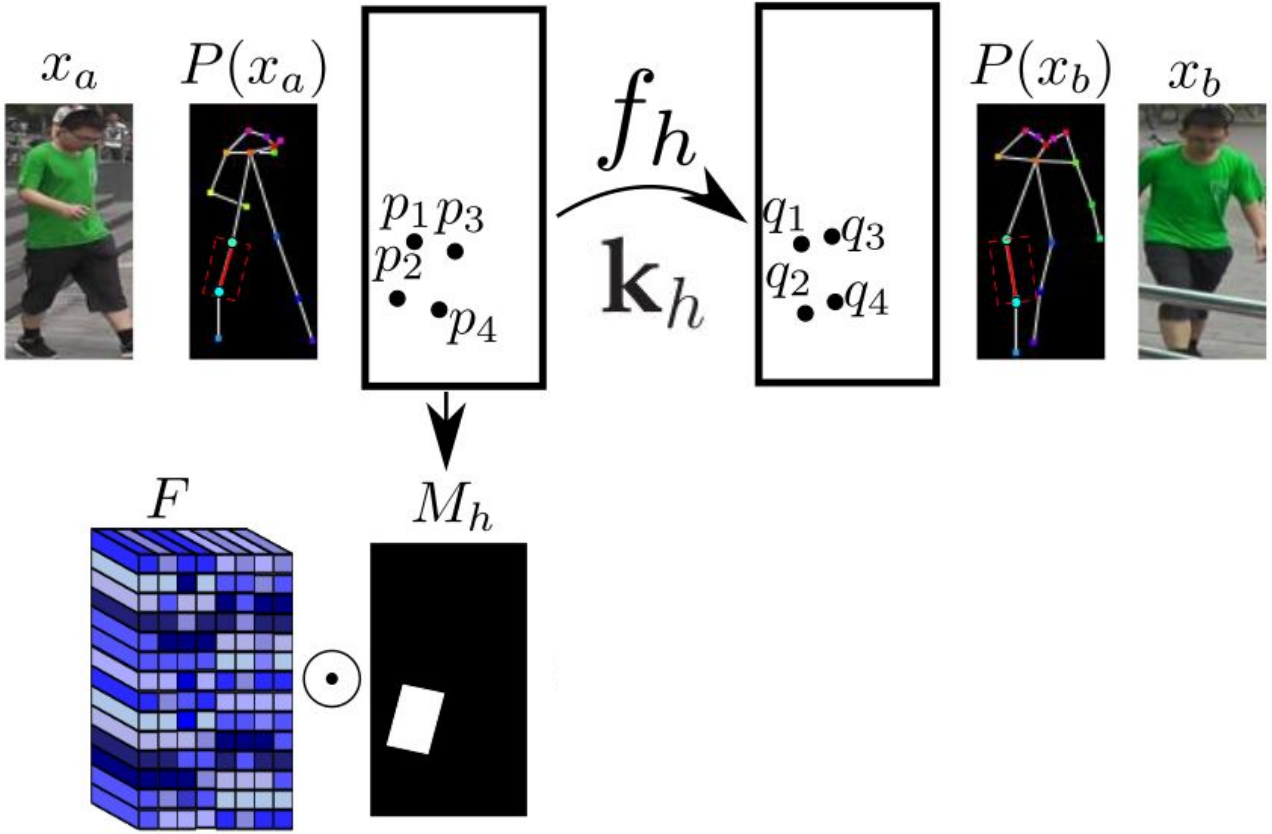


# Pose guided: deformable GAN

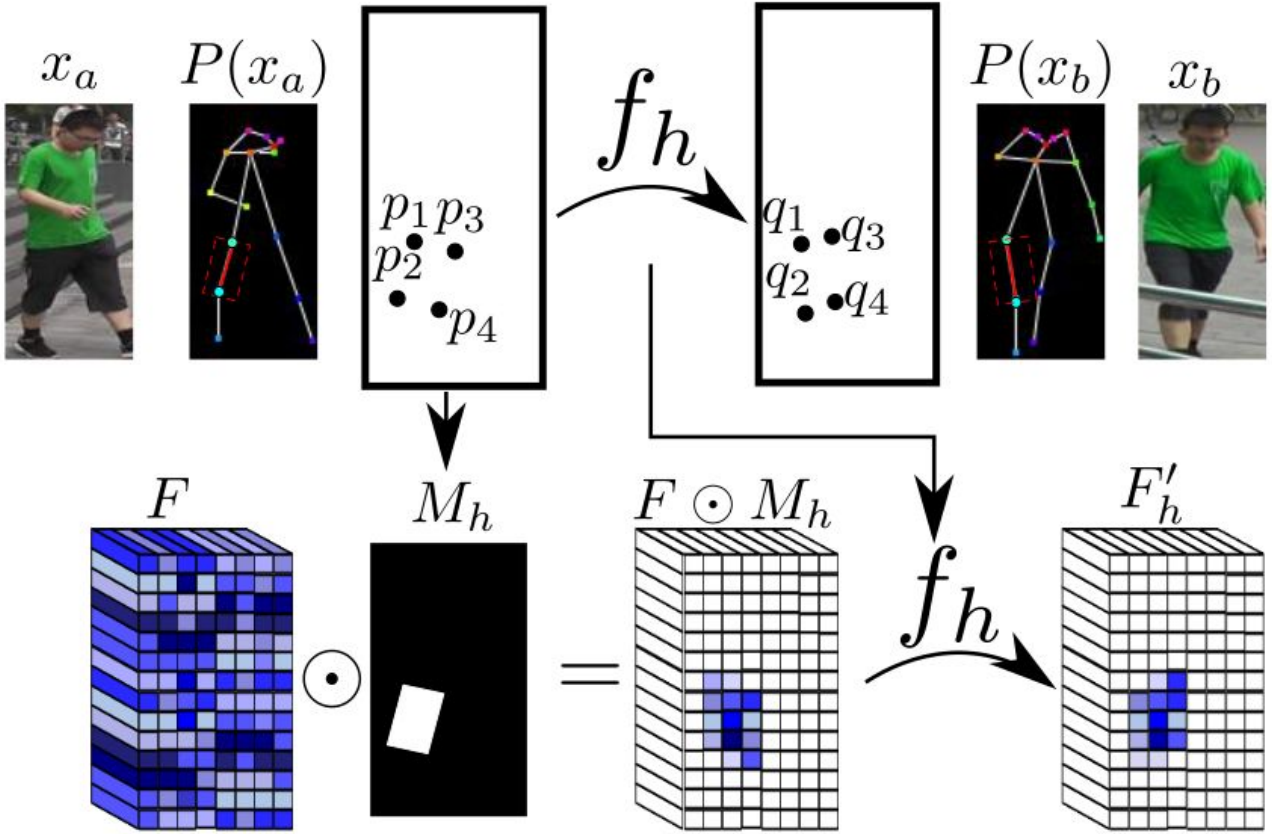



$$\min_{\mathbf{k}_h} \sum_{\mathbf{p}_j \in R_h^a, \mathbf{q}_j \in R_h^b} ||\mathbf{q}_j - f_h(\mathbf{p}_j; \mathbf{k}_h)||_2^2.$$

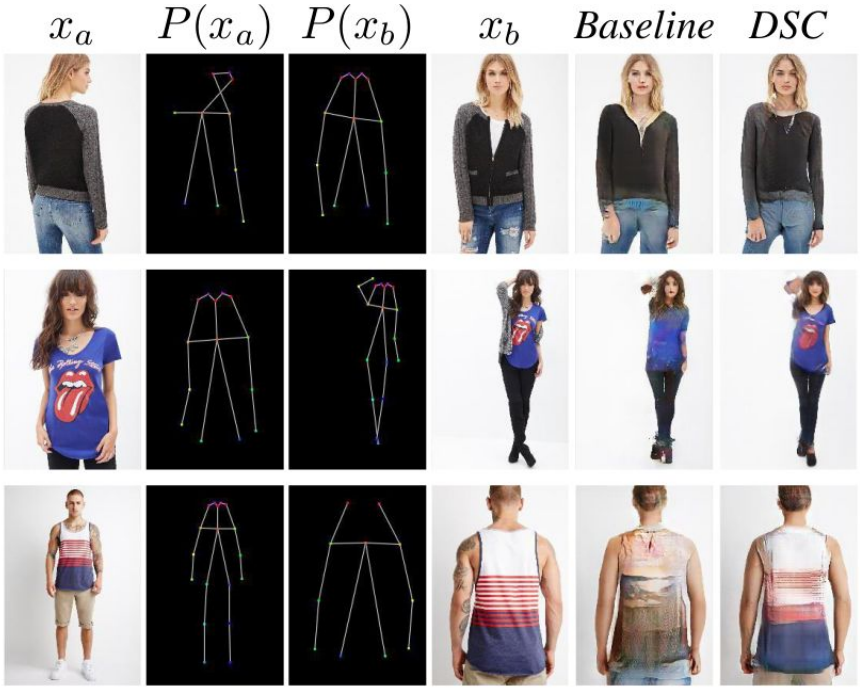
# Pose guided: deformable GAN



# Pose guided: deformable GAN



# Pose guided: deformable GAN

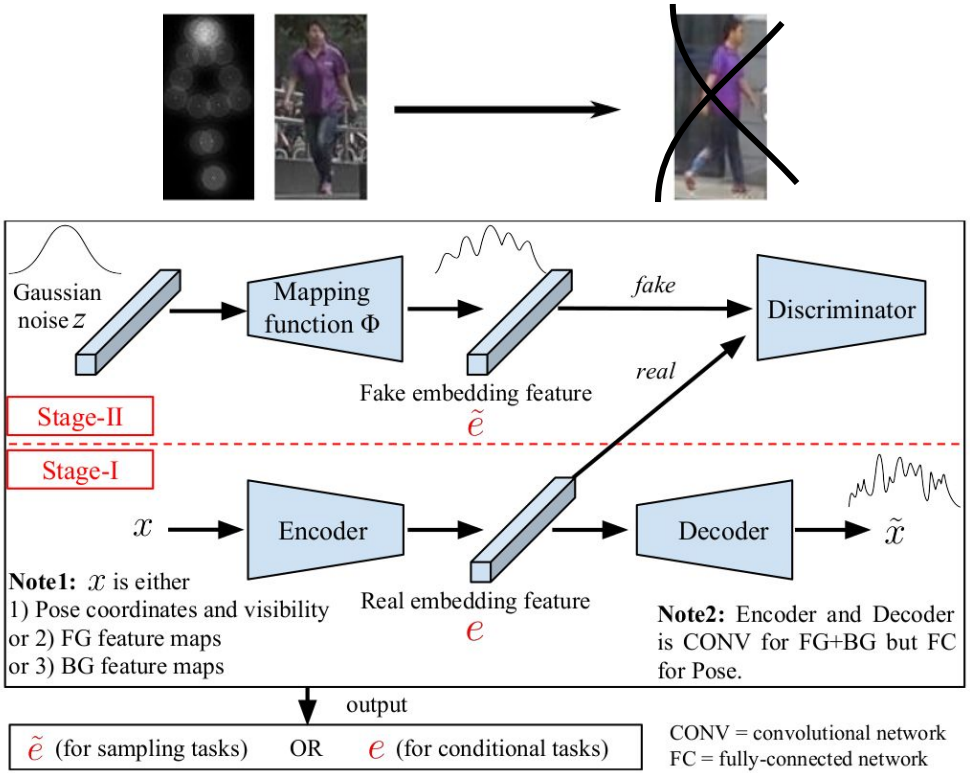


# Pose guided: reconstruction vs GAN

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

| | Market-1501 | | | | |
|---|---|---|---|---|---|
| $\lambda$ | *SSIM* | *IS* | *mask-SSIM* | *mask-IS* | *DS* |
| 0.1 | **0.292** | 2.621 | **0.808** | 3.168 | 0.697 |
| 0.01 | 0.290 | 3.185 | 0.805 | 3.502 | **0.720** |
| 0.001 | 0.245 | **3.566** | 0.779 | **3.634** | 0.609 |

# Pose guided: Disentangled Generation




Disentangled Person Image Generation, Ma et. al., CVPR 2018

# Pose guided: Disentangled Generation

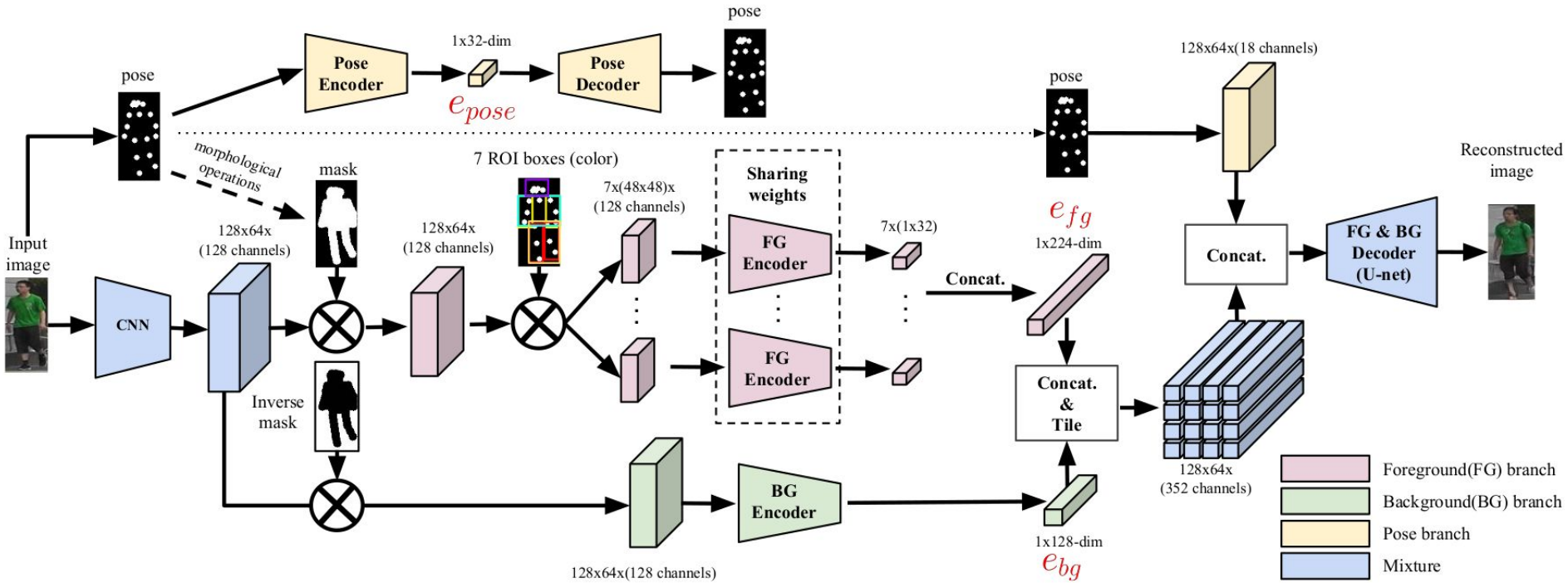



Figure 3: Stage-I: disentangled image reconstruction. This framework is composed of three branches: foreground, background and pose. Note that we use a fully-connected auto-encoder network to reconstruct the pose (incl. keypoint coordinates and visibility), so that we can decode the embedded pose features to obtain the heatmaps at the sampling phase.

# Pose guided: Disentangled Generation

Foreground (FG) sampling (fixed BG and Pose)

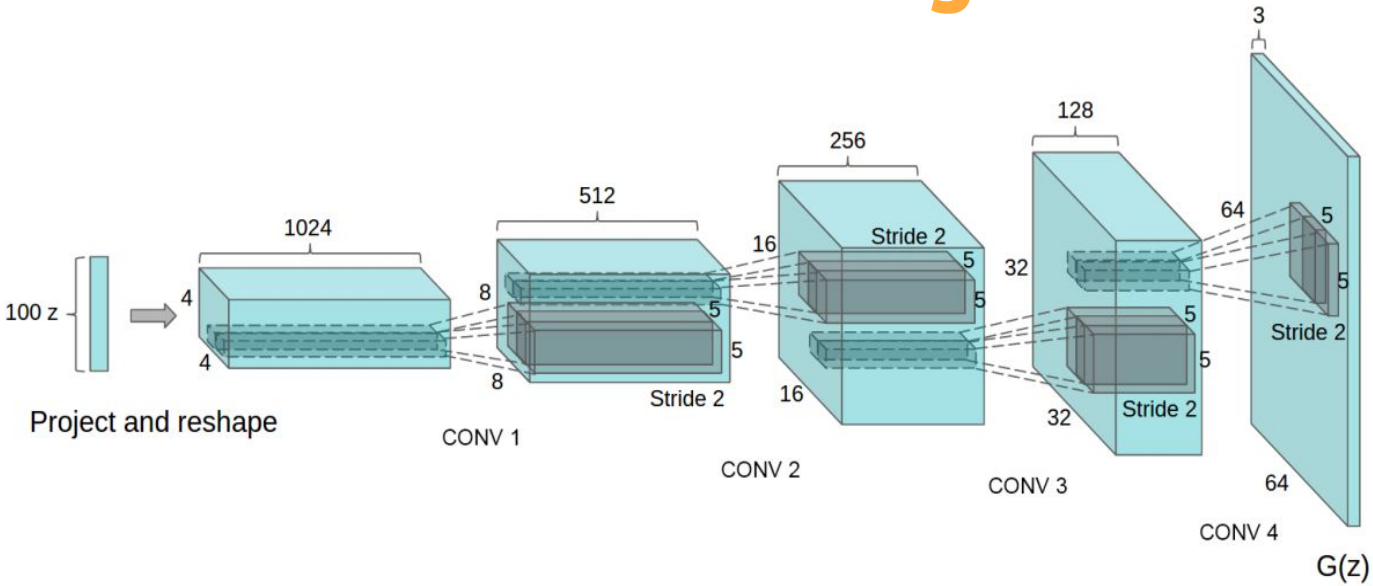
Background (BG) sampling (fixed FG and Pose)

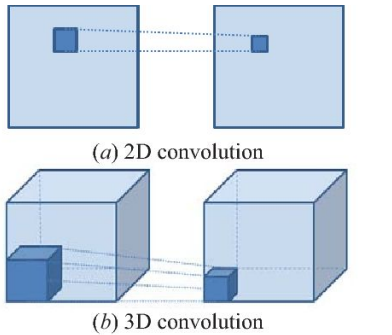
Pose sampling (fixed FG and BG)

FG, BG and Pose sampling

# Video generation

# From DCGAN to video generation

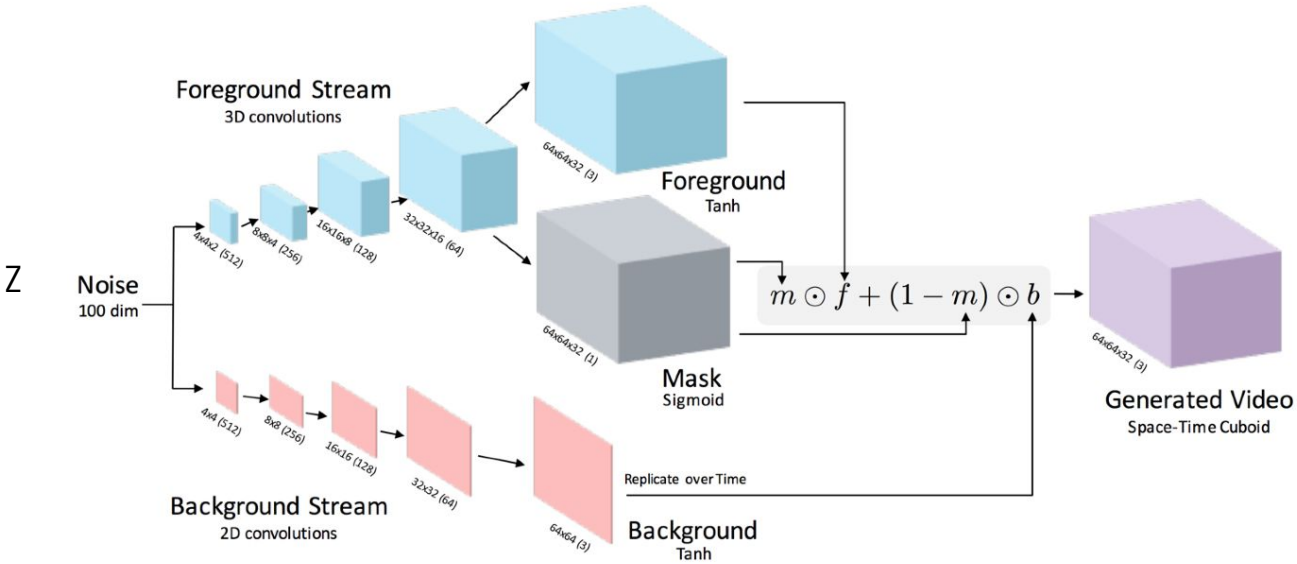



3. Comparison of (a) 2D convolution and (b)

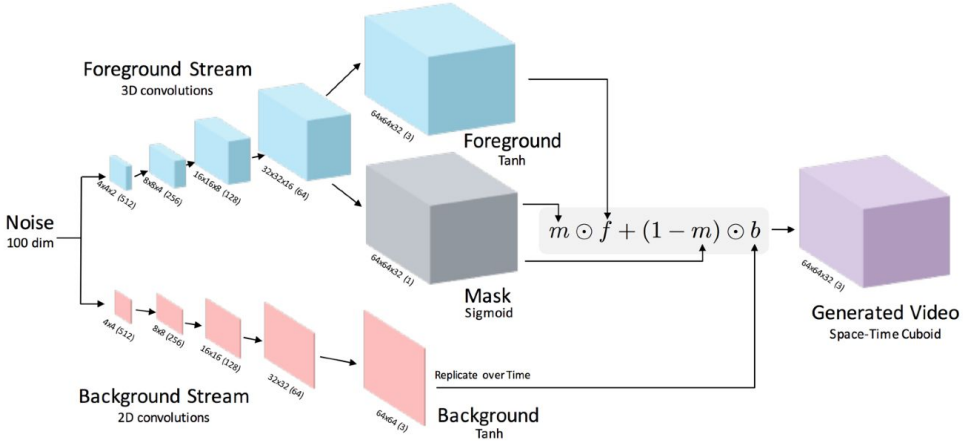
A. Radford, L. Metz, S. Chintala, Unsupervised representation learning with deep convolutional generative adversarial networks, ICLR 2016
Figure from Lung nodule detection based on 3D convolutional neural networks Lei Fan et al.

# Video Generation




Saito, Matsumoto, and Saito. "Temporal generative adversarial nets with singular value clipping." ICCV'2017.

# Video Generation





Saito, Matsumoto, and Saito. "Temporal generative adversarial nets with singular value clipping." ICCV'2017.

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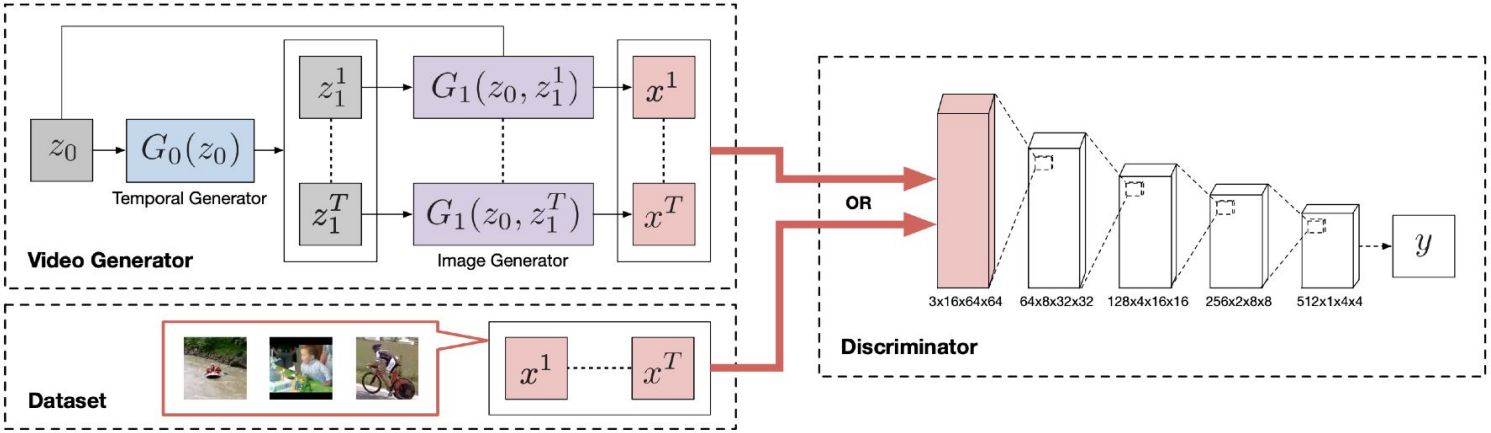
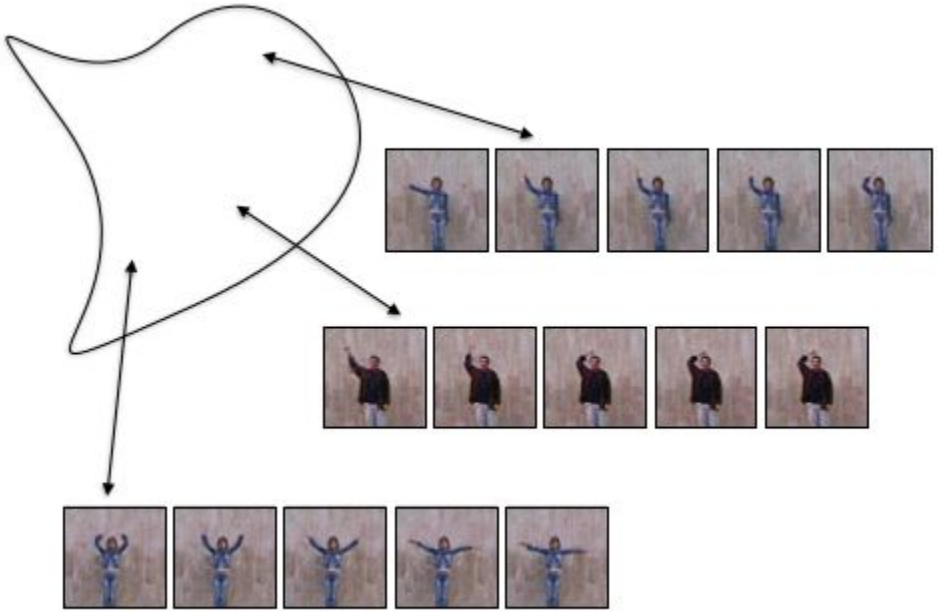



Saito, Matsumoto, and Saito. "Temporal generative adversarial nets with singular value clipping." ICCV'2017.

# Video Generation



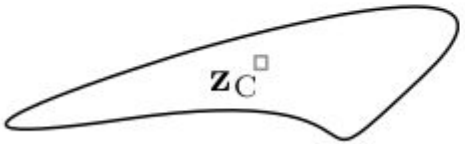
Limitations:

- Fixed length videos only
- No control over motion and content

# Video Generation: MoCoGAN

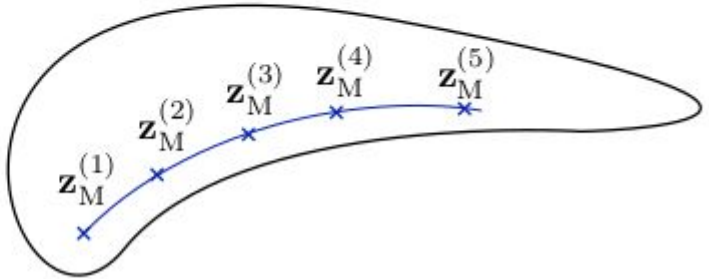
## Sampled content

$$\mathbf{Z}_\mathrm{C} = [\mathbf{z}_\mathrm{C}, \mathbf{z}_\mathrm{C}, ..., \mathbf{z}_\mathrm{C}]$$



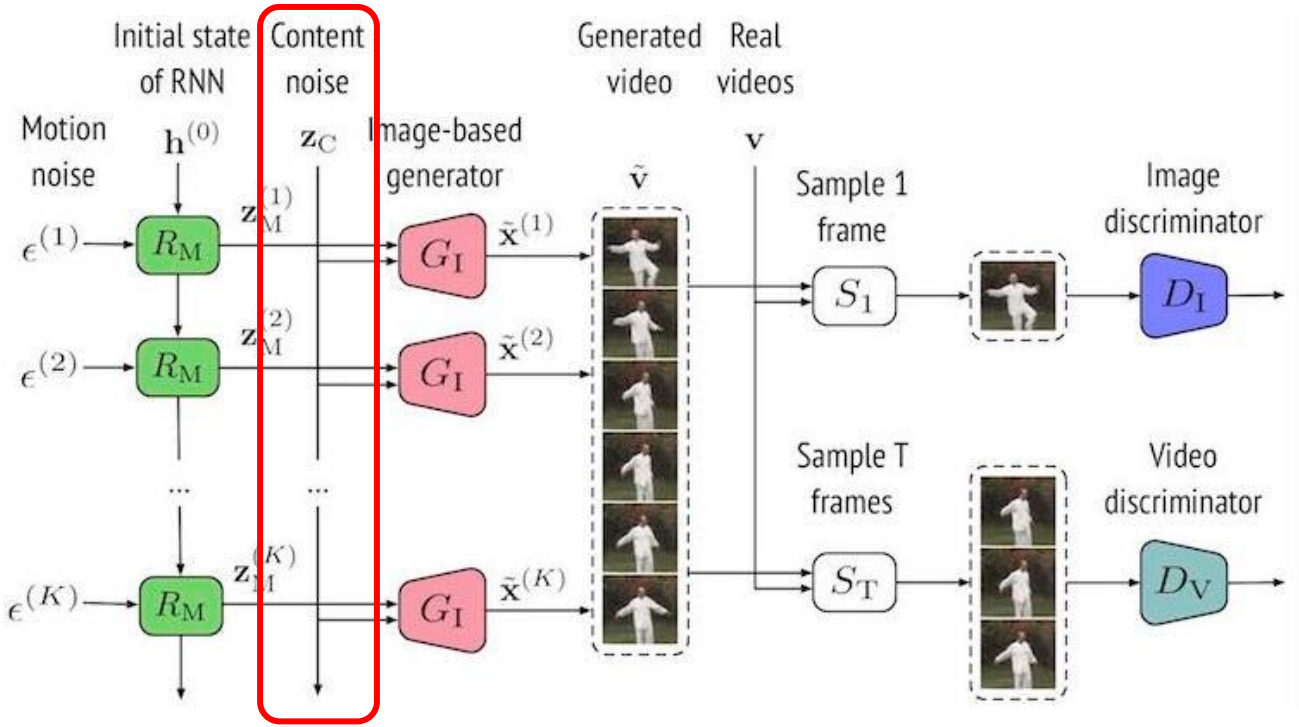

## Motion trajectory

$$\mathbf{Z}_\mathrm{M} = [\mathbf{z}_\mathrm{M}^{(1)}, \mathbf{z}_\mathrm{M}^{(2)}, ..., \mathbf{z}_\mathrm{M}^{(K)}]$$




MoCoGAN: Decomposing Motion and Content for Video Generation Sergey Tulyakov, Ming-Yu Liu, Xiaodong Yang, Jan Kautz CVPR'2018.

# Video Generation: MoCoGAN

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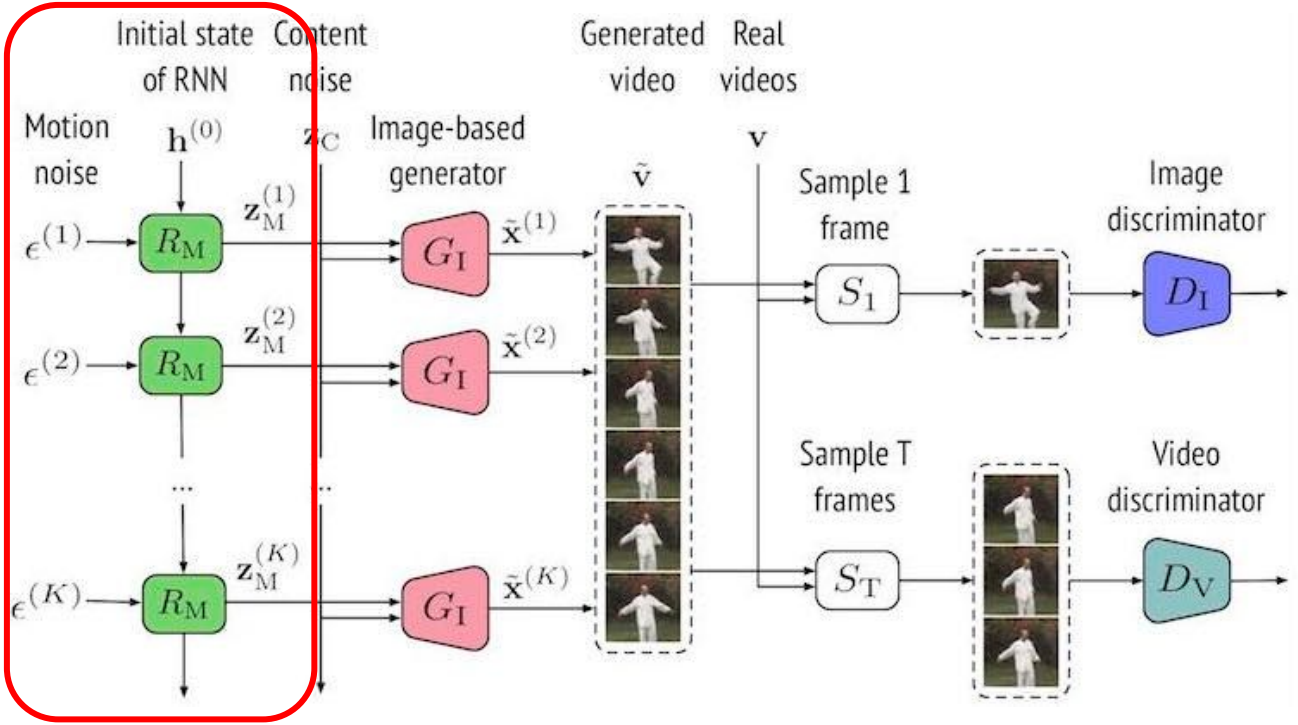


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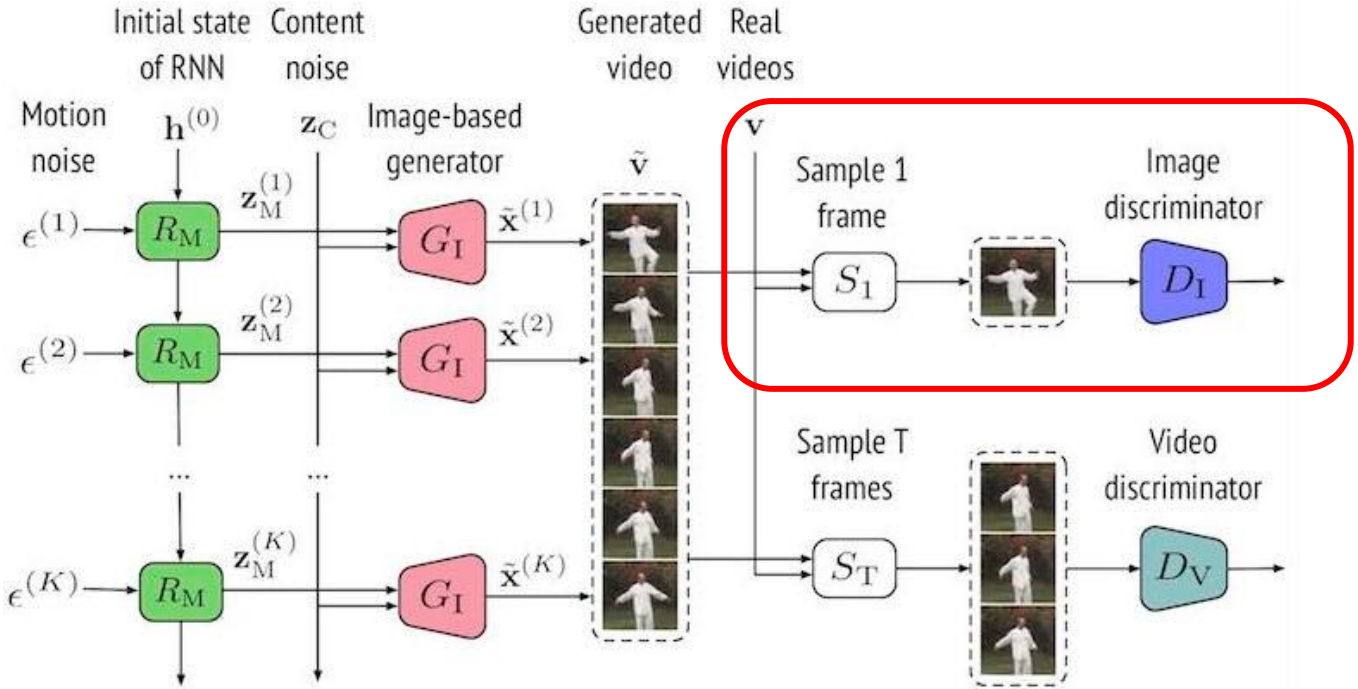


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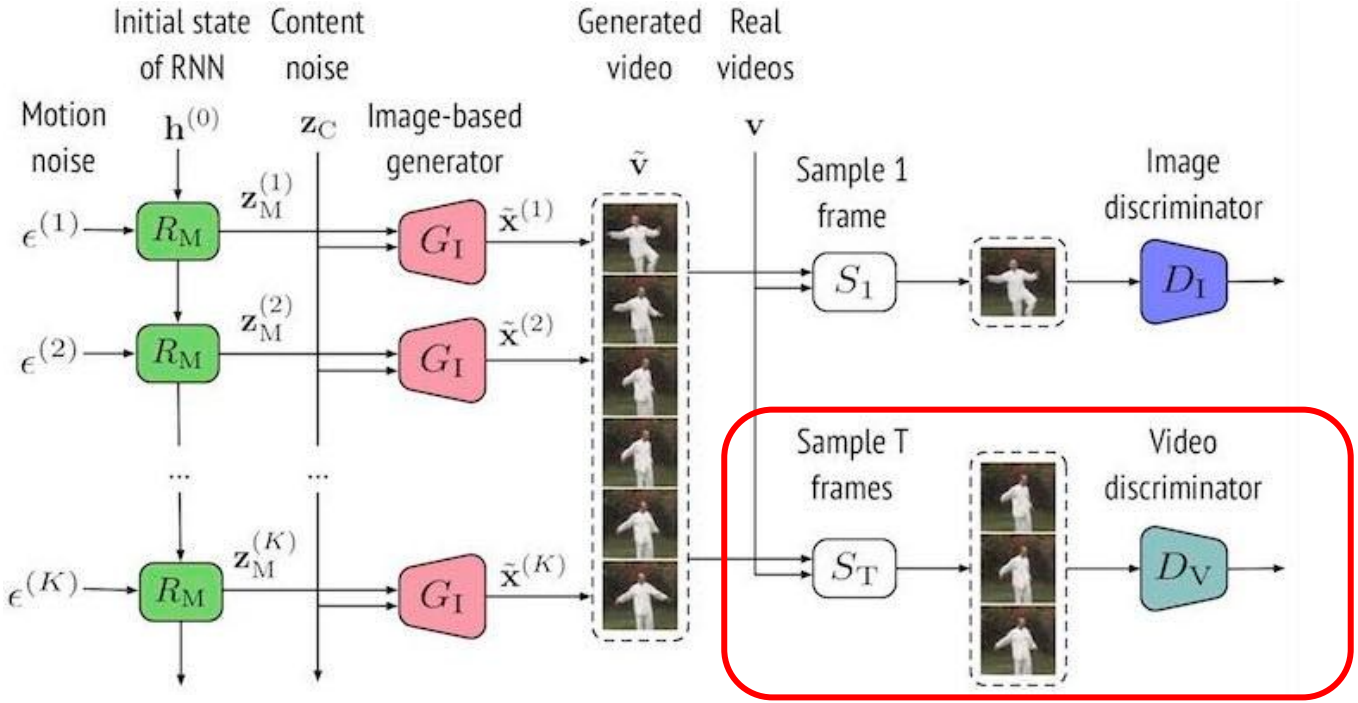


MoCoGAN: Decomposing Motion and Content for Video Generation Sergey Tulyakov, Ming-Yu Liu, Xiaodong Yang, Jan Kautz CVPR'2018.

# Video Generation: MoCoGAN


MoCoGAN: Decomposing Motion and Content for Video Generation Sergey Tulyakov, Ming-Yu Liu, Xiaodong Yang, Jan Kautz CVPR'2018.

# Video Generation: MoCoGAN

We can change the motion without changing the content:

MoCoGAN: Decomposing Motion and Content for Video Generation Sergey Tulyakov, Ming-Yu Liu, Xiaodong Yang, Jan Kautz CVPR'2018.

# Video Generation: MoCoGAN

Video prediction:

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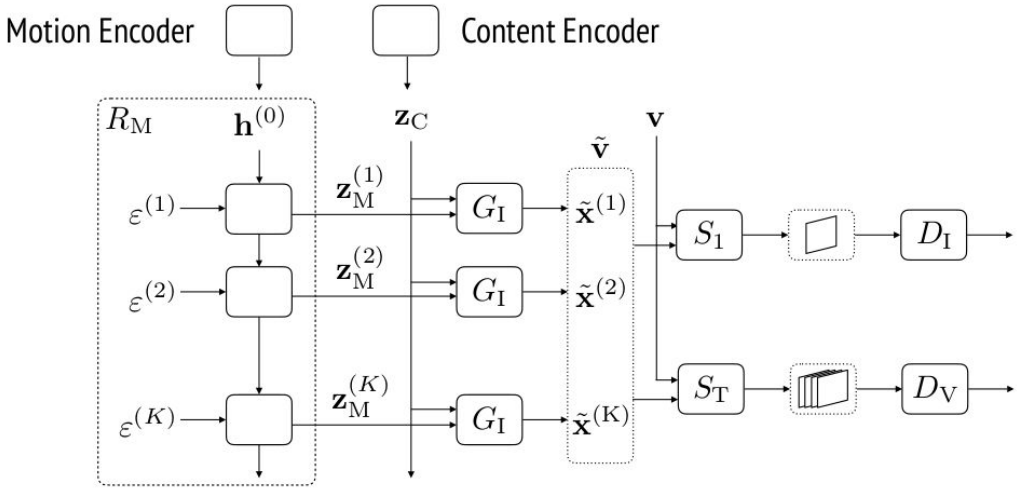
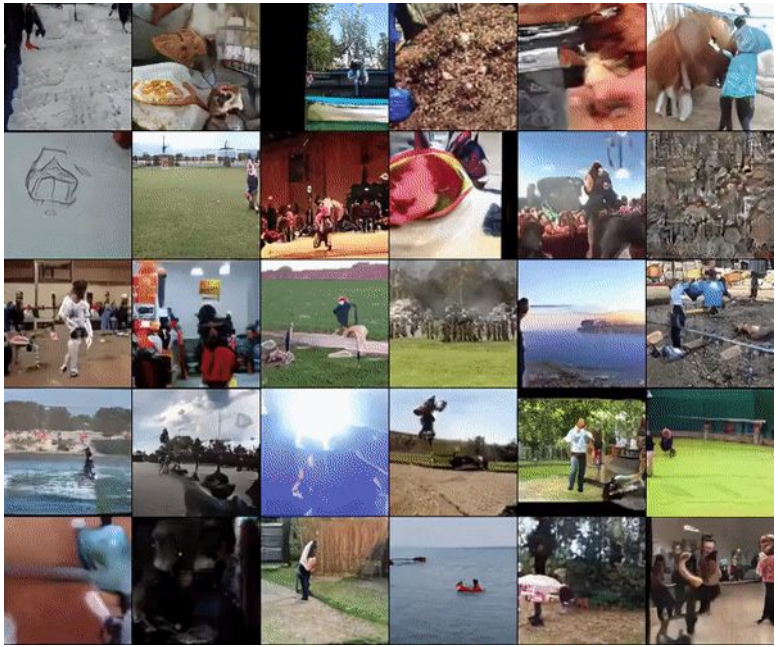
# Video Generation: MoCoGAN

Video prediction:



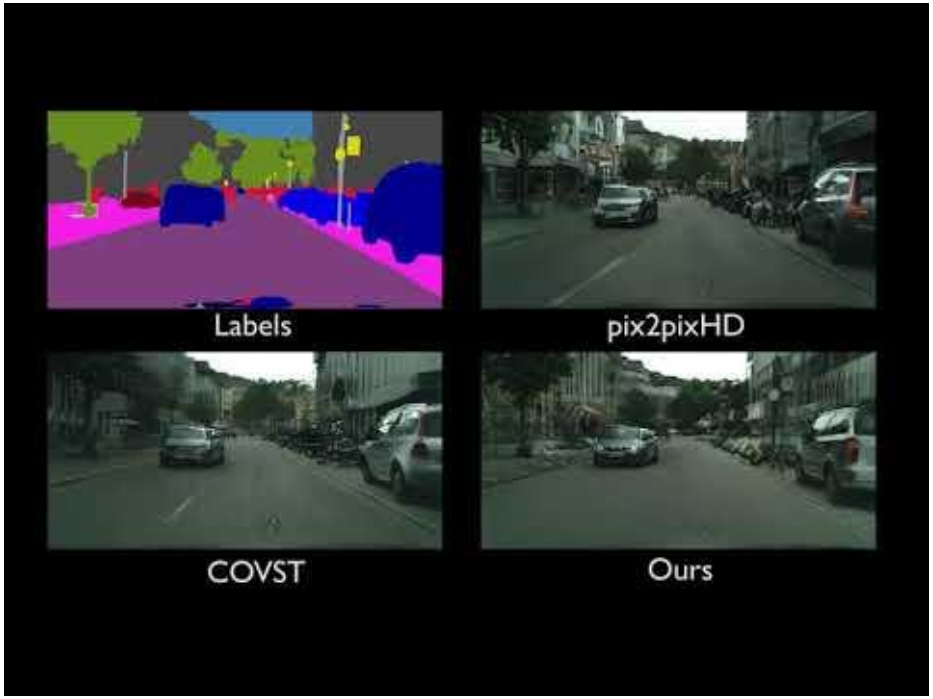

MoCoGAN: Decomposing Motion and Content for Video Generation Sergey Tulyakov, Ming-Yu Liu, Xiaodong Yang, Jan Kautz CVPR'2018.

# Video Generation: DVDGAN



Clark, Aidan, Jeff Donahue, and Karen Simonyan. "Efficient video generation on complex datasets." ArXiv preprint

# Video-to-video translation




Wang, Ting-Chun, et al. "Video-to-video synthesis." NIPS'2018

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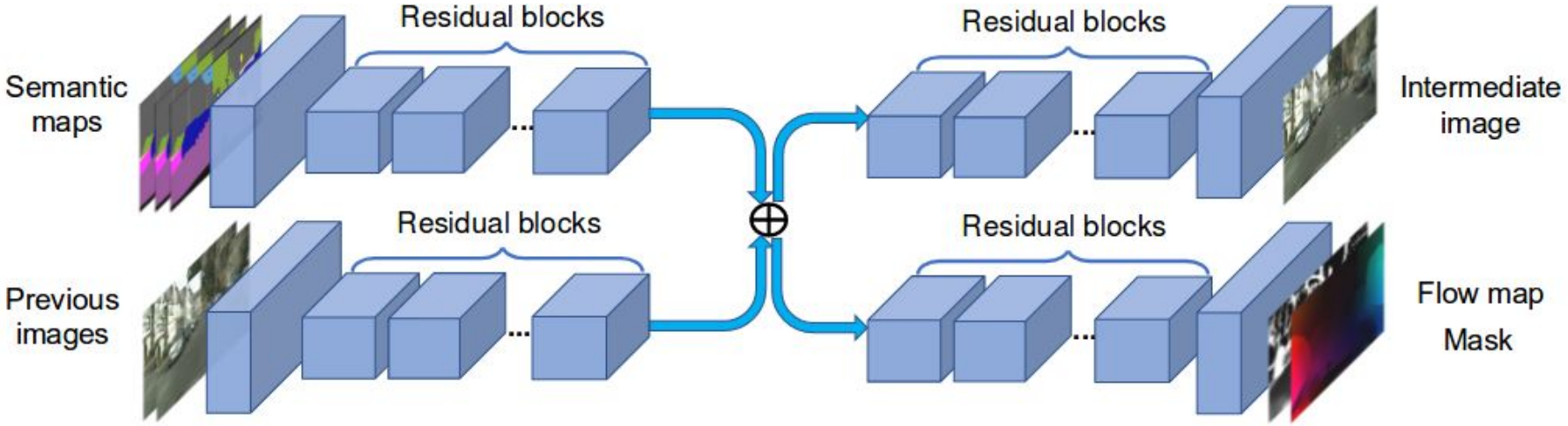
Wang, Ting-Chun, et al. "Video-to-video synthesis." NIPS'2018

# Video-to-video translation




Previous generated frame

$$F(\tilde{\mathbf{x}}_{t-L}^{t-1}, \mathbf{s}_{t-L}^{t}) = (\mathbf{1} - \tilde{\mathbf{m}}_t) \odot \tilde{\mathbf{w}}_{t-1}(\tilde{\mathbf{x}}_{t-1}) + \tilde{\mathbf{m}}_t \odot \tilde{\mathbf{h}}_t$$

Optical flow warping

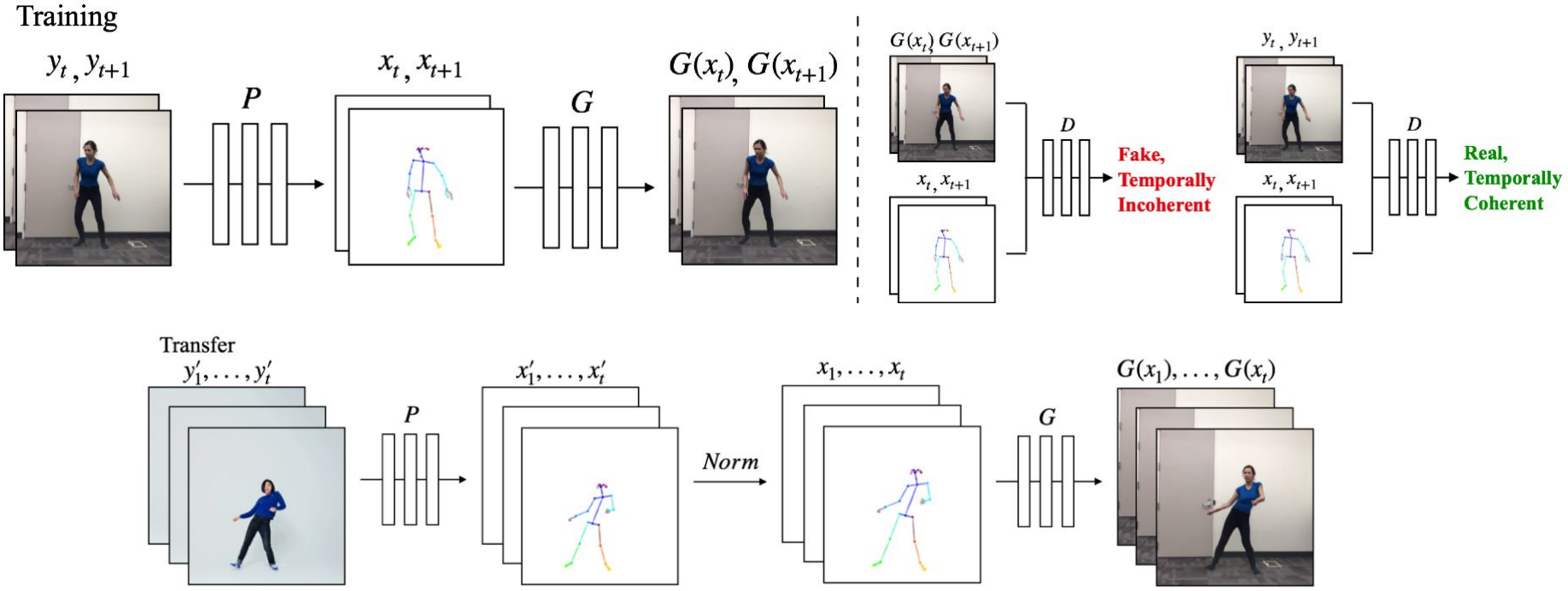
mask

Wang, Ting-Chun, et al. "Video-to-video synthesis." NIPS'2018

# Animating Single Subject

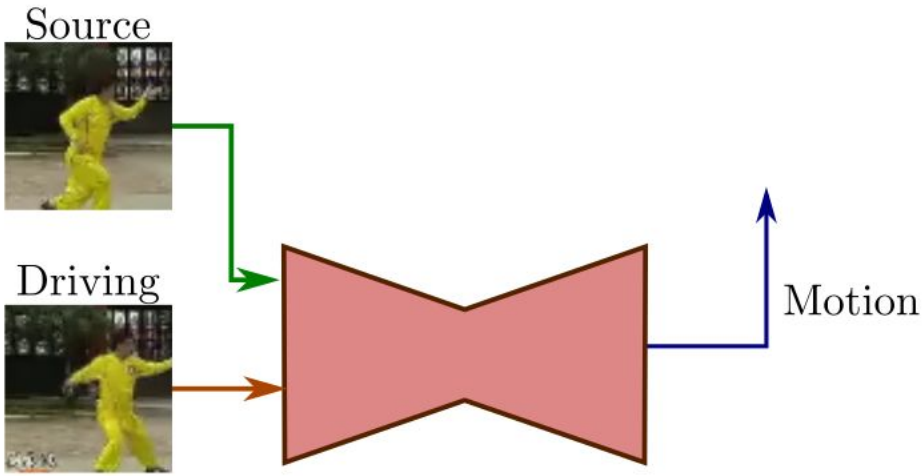

Chan, Caroline, et al. "Everybody dance now." ICCV'2019.

# Animating Single Subject




Chan, Caroline, et al. "Everybody dance now." ICCV'2019.

# Retargeting




A. Siarohin, S. Lathuilière, S. Tulyakov , E. Ricci, N. Sebe, Animating Arbitrary Objects via Deep Motion Transfer , CVPR 2019

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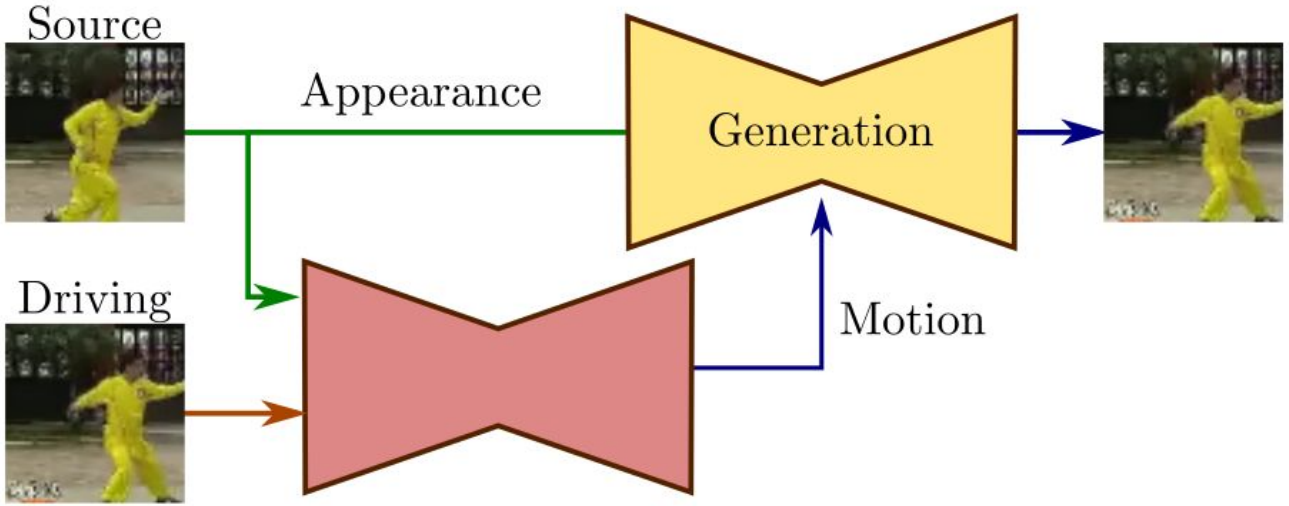


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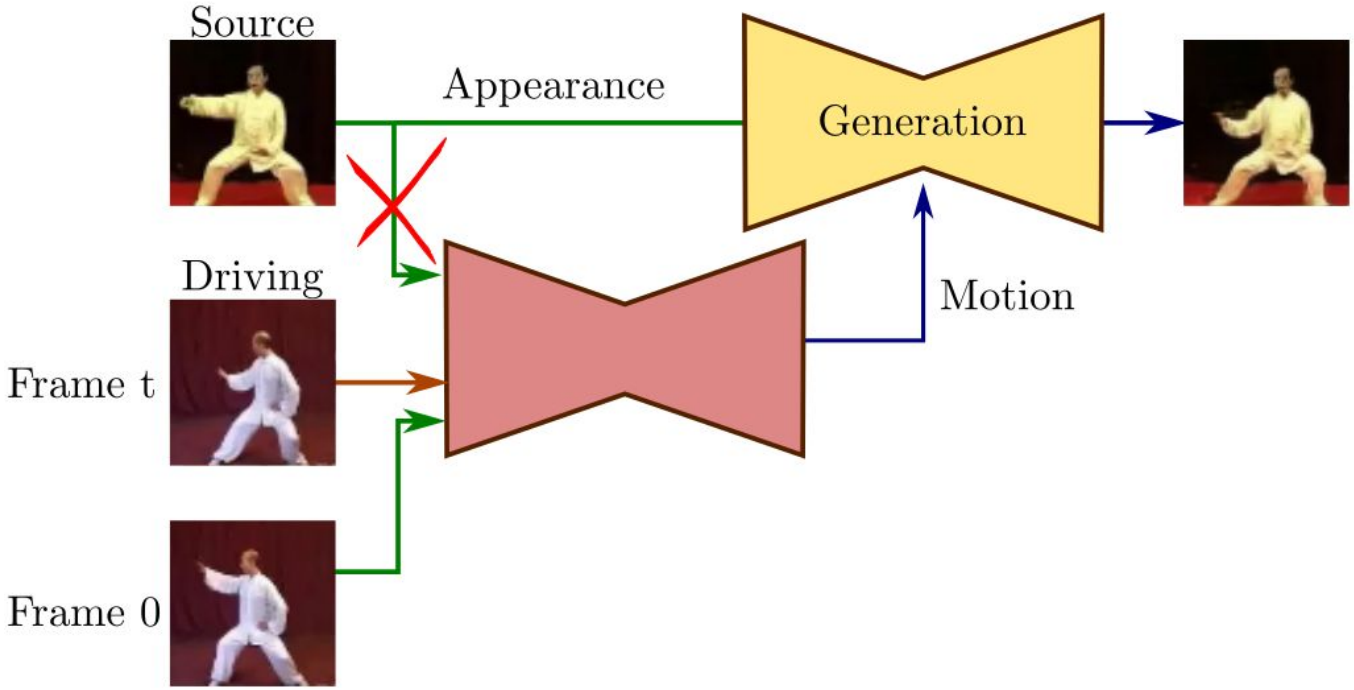


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