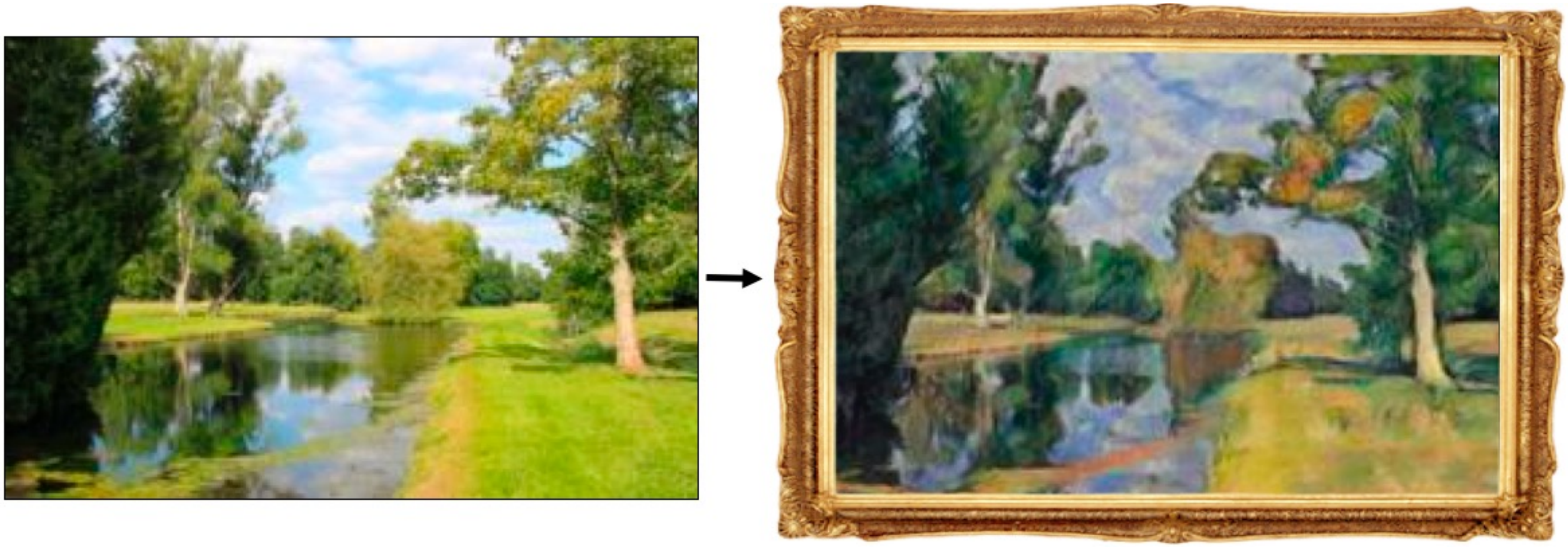
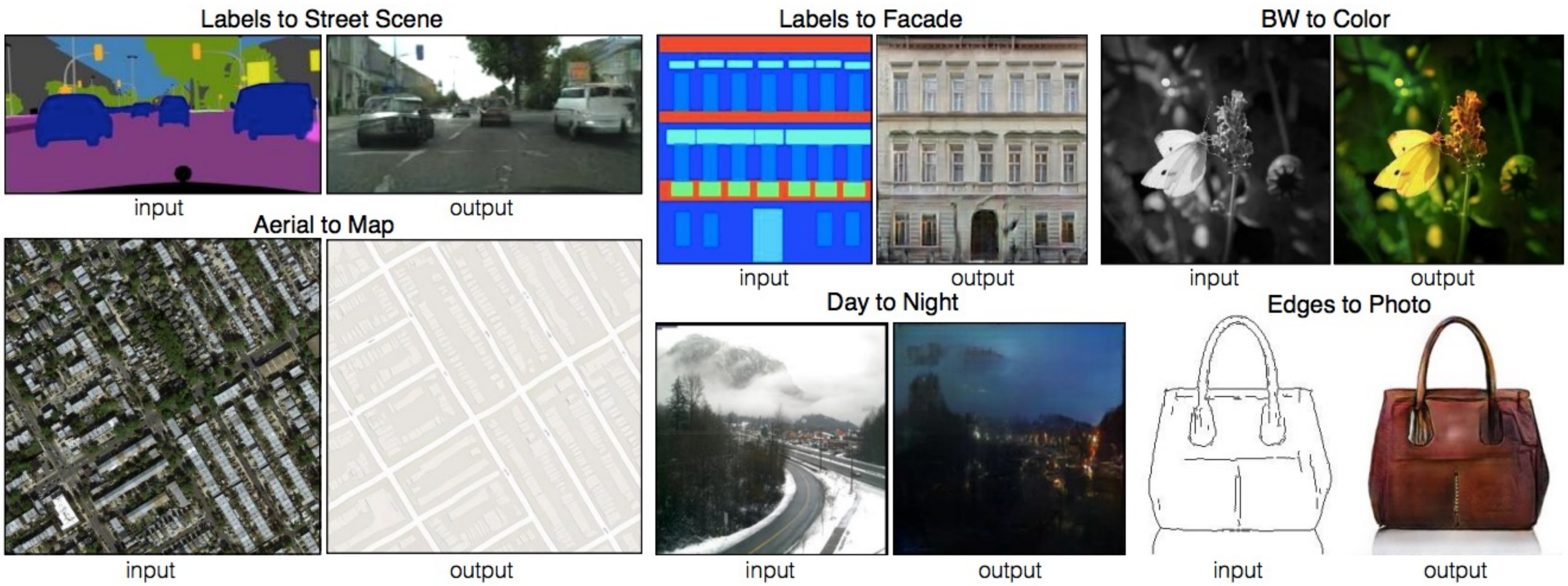
Image-to-image translation



Outline

- Paired image-to-image translation: pix2pix
- Unpaired image-to-image translation: CycleGAN
- Extensions, applications

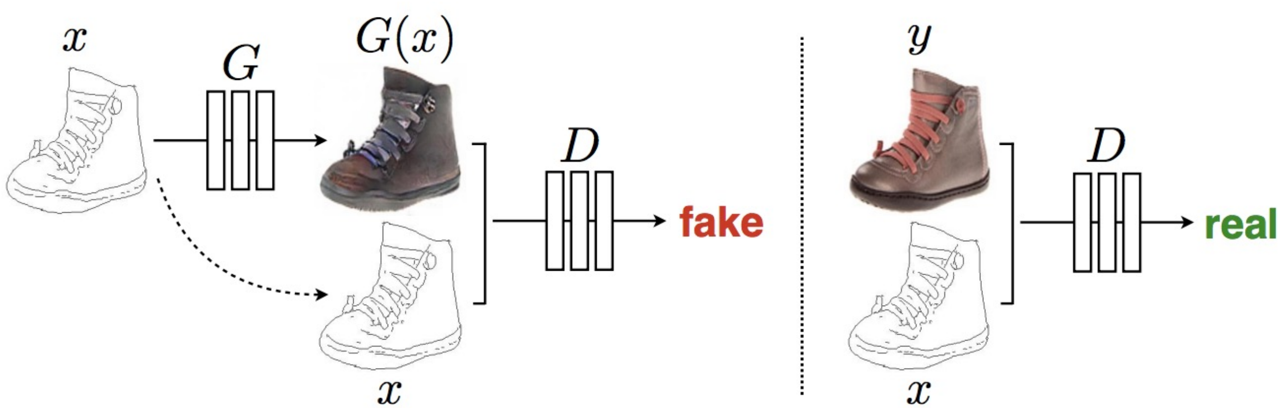
Paired image-to-image translation



P. Isola, J.-Y. Zhu, T. Zhou, A. Efros, [Image-to-Image Translation with Conditional Adversarial Networks,]() CVPR 2017

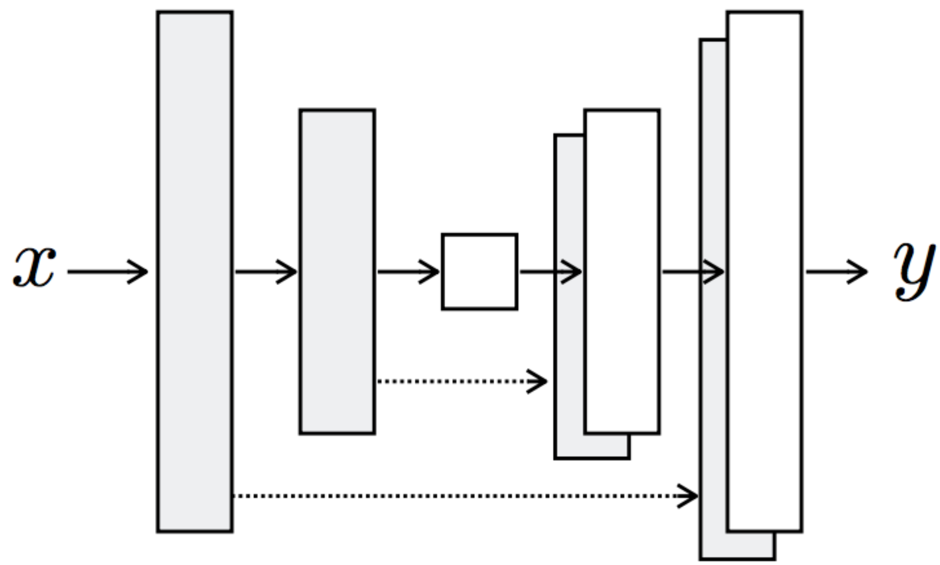
Pix2pix

- Produce modified image y conditioned on input image x (note change of notation)
  - Generator receives x as input
  - Discriminator receives an x, y pair and has to decide whether it is real or fake



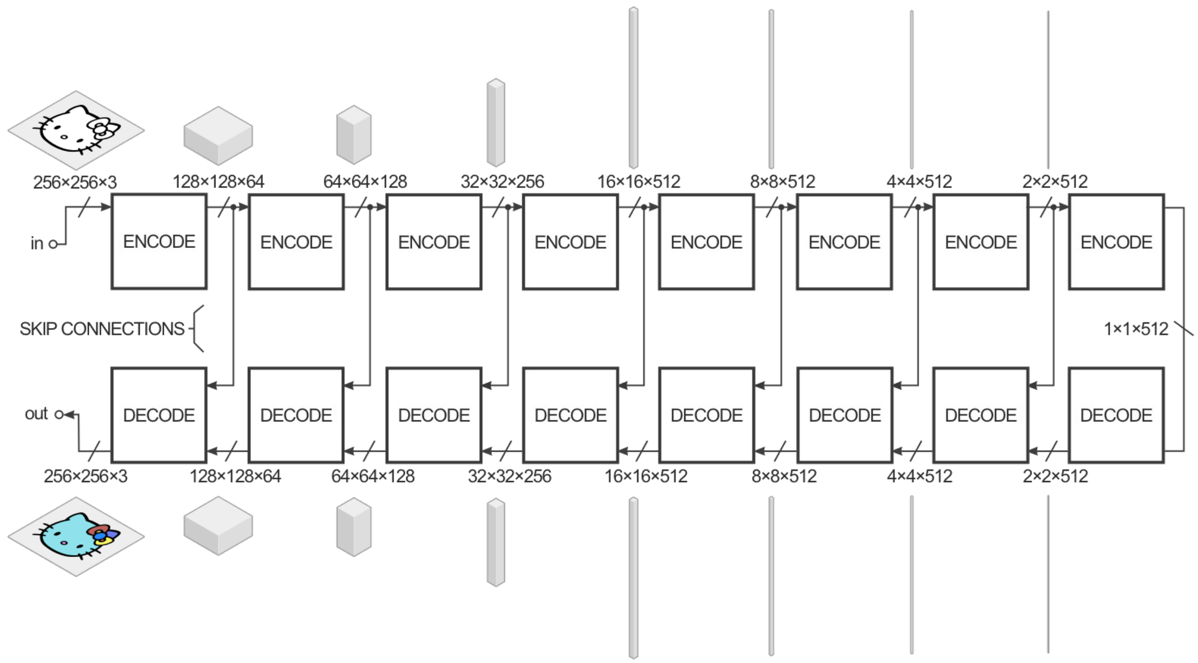
Pix2pix: Generator

- Generator architecture: U-Net (no z used as input)



Pix2pix: Generator

- Generator architecture: U-Net (no z used as input)



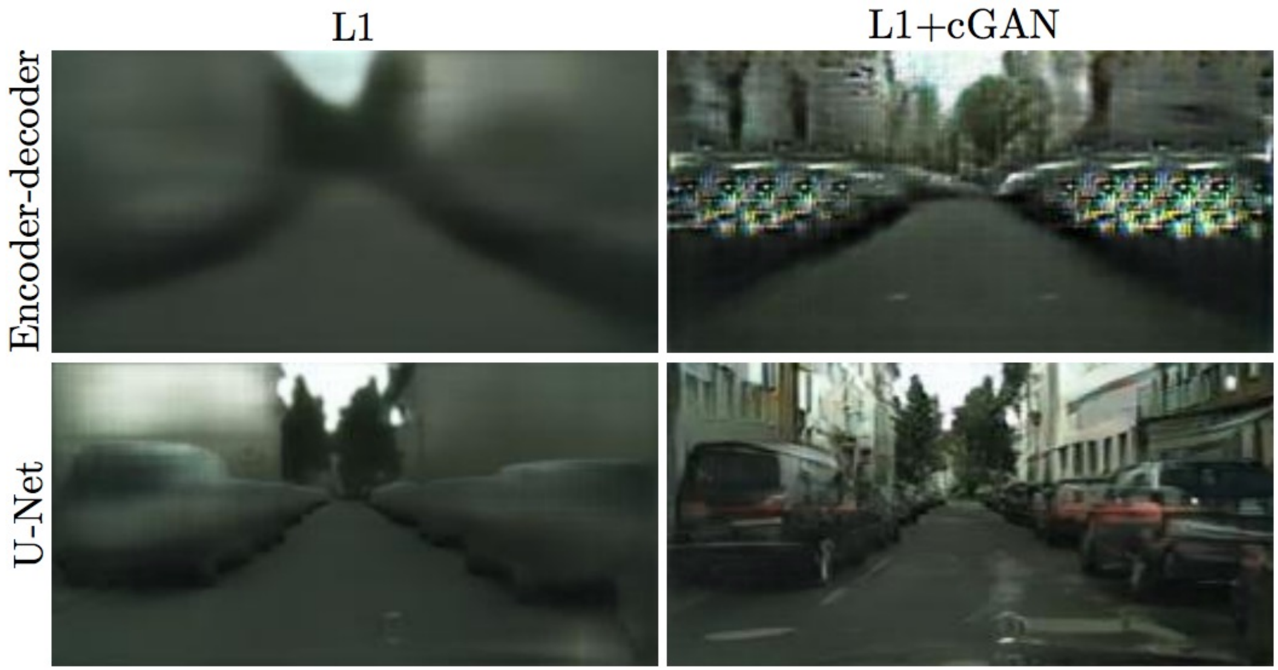
Encode: convolution → BatchNorm → ReLU

Decode: transposed convolution → BatchNorm → ReLU

Figure source

Pix2pix: Generator

Effect of adding skip connections to the generator



Pix2pix: Generator loss

- GAN loss plus L1 reconstruction penalty

$$G^* = \arg\min_G \max_D \mathcal{L}_{GAN}(G, D) + \lambda \sum_i \|y_i - G(x_i)\|_1$$

Generated output $G(x_i)$ should be close to ground truth target y_i

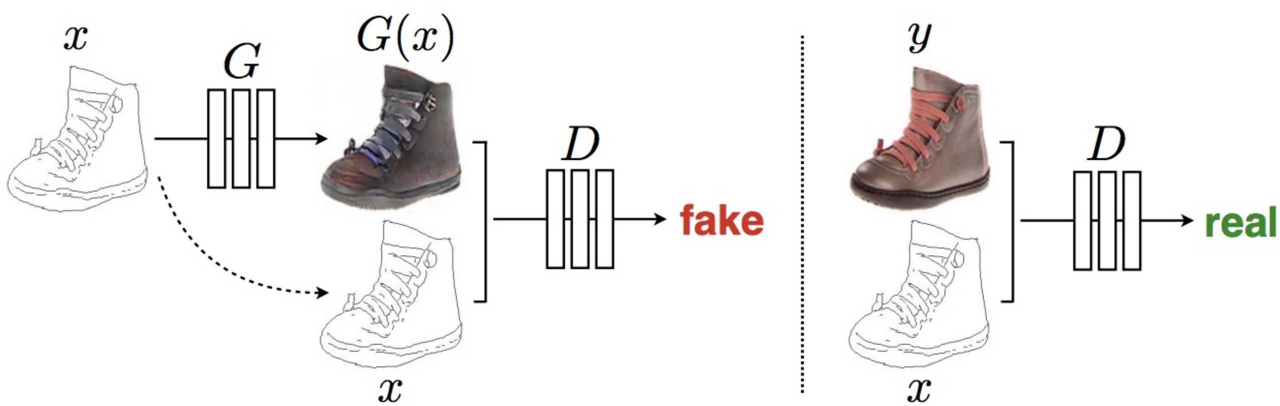
Pix2pix: Generator loss

- GAN loss plus L1 reconstruction penalty

$$G^* = \arg\min_G \max_D \mathcal{L}_{GAN}(G, D) + \lambda \sum_i \|y_i - G(x_i)\|_1$$

Pix2pix: Discriminator

- Given input image x and second image y, decide whether y is a ground truth target or produced by the generator



Pix2pix: Discriminator

- "PatchGAN" architecture: output a 30x30 map where each value (0 to 1) represents the quality of the corresponding section of the output image, average to obtain final discriminator loss
- Implemented as FCN, effective patch size can be increased by increasing the depth

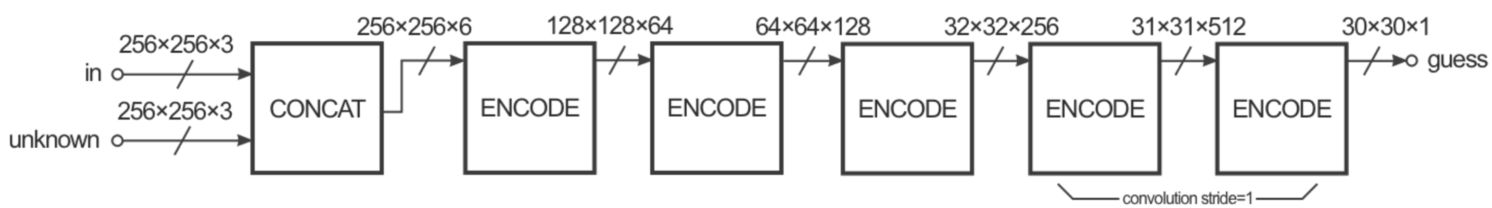


Figure source

Pix2pix: Discriminator

- “PatchGAN” architecture: output a 30x30 map where each value (0 to 1) represents the quality of the corresponding section of the output image, average to obtain final discriminator loss
- Implemented as FCN, effective patch size can be increased by increasing the depth

Effect of discriminator patch size on generator output

Pix2pix: Results

- Translating between maps and aerial photos

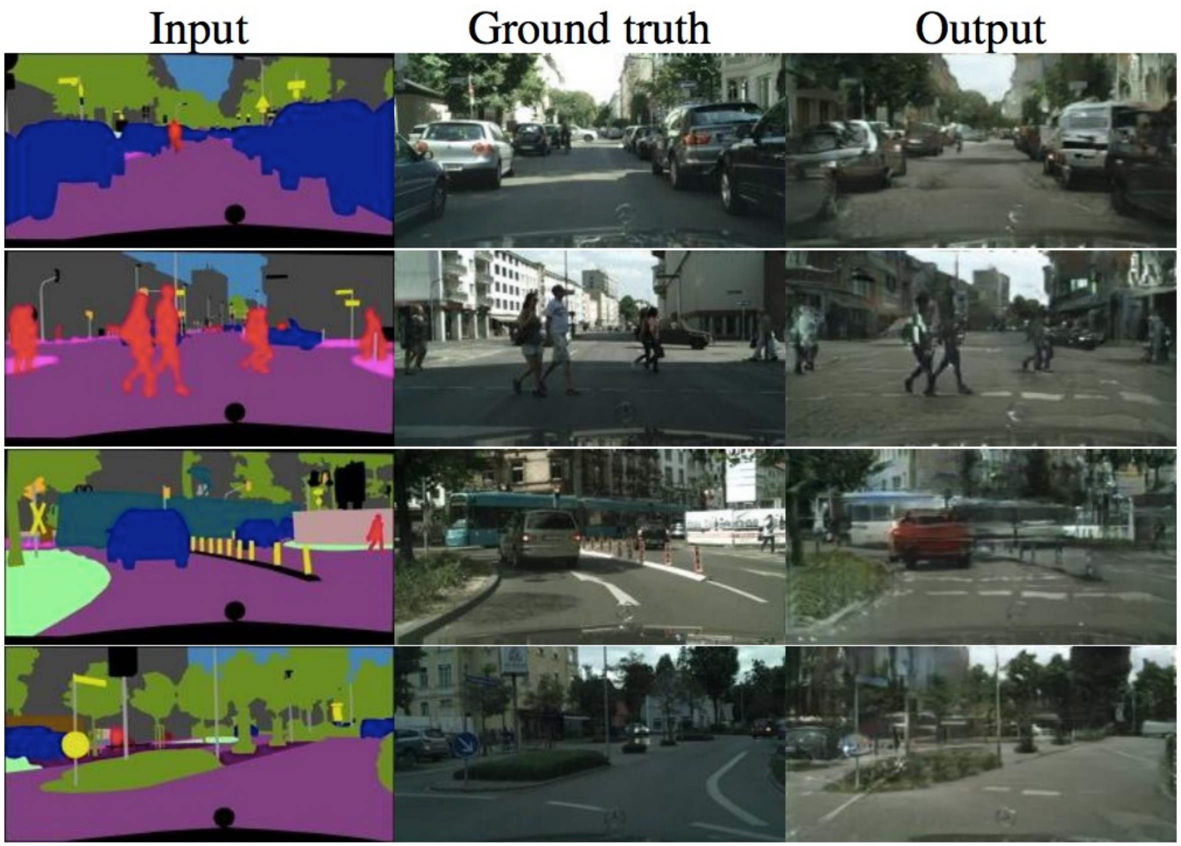
Pix2pix: Results

- Translating between maps and aerial photos
- Human study:

	Photo → Map	**Map → Photo**
Loss	% Turkers labeled *real*	% Turkers labeled *real*
L1	$2.8\% \pm 1.0\%$	$0.8\% \pm 0.3\%$
L1+cGAN	$6.1\% \pm 1.3\%$	$\mathbf{18.9\%} \pm \mathbf{2.5\%}$

Pix2pix: Results

- Semantic labels to scenes



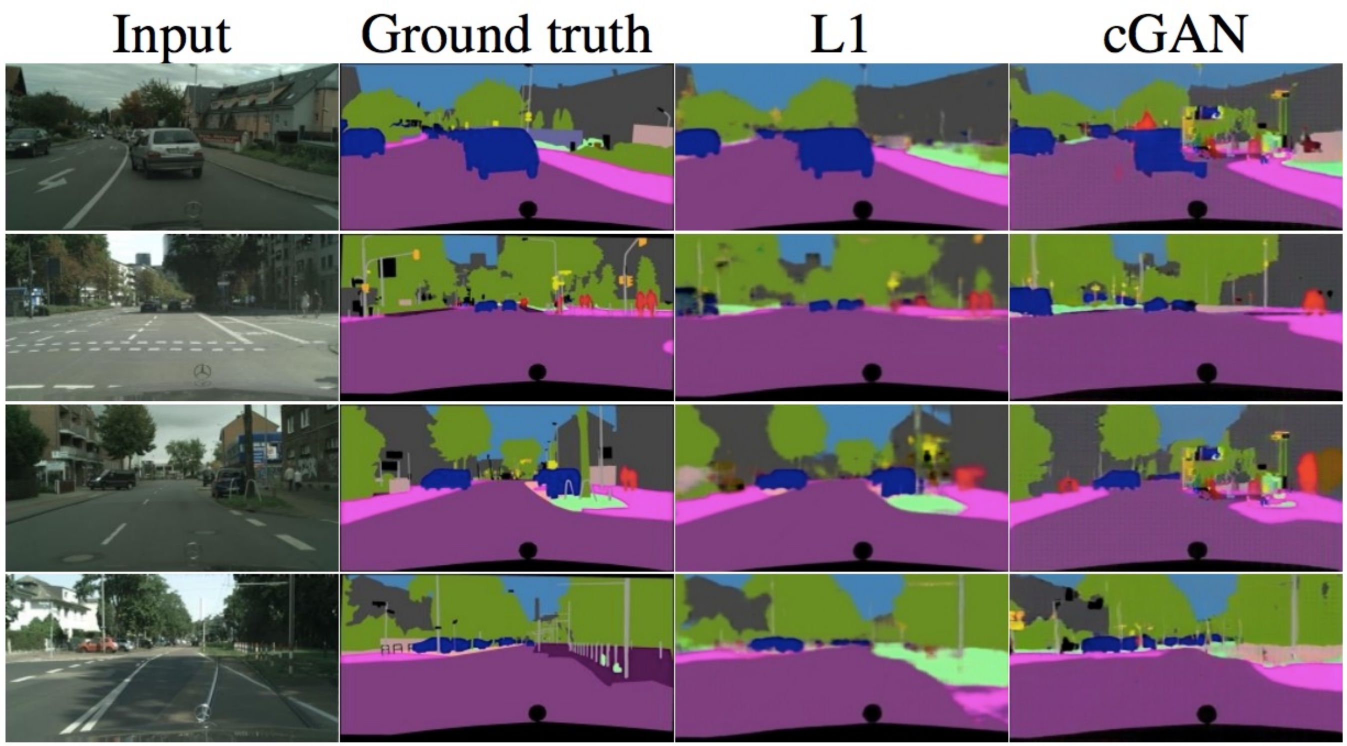
Pix2pix: Results

- Semantic labels to scenes
  - Evaluation: FCN score – the higher the quality of the output, the better the FCN should do at recovering the original semantic labels

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

Pix2pix: Results

- Scenes to semantic labels



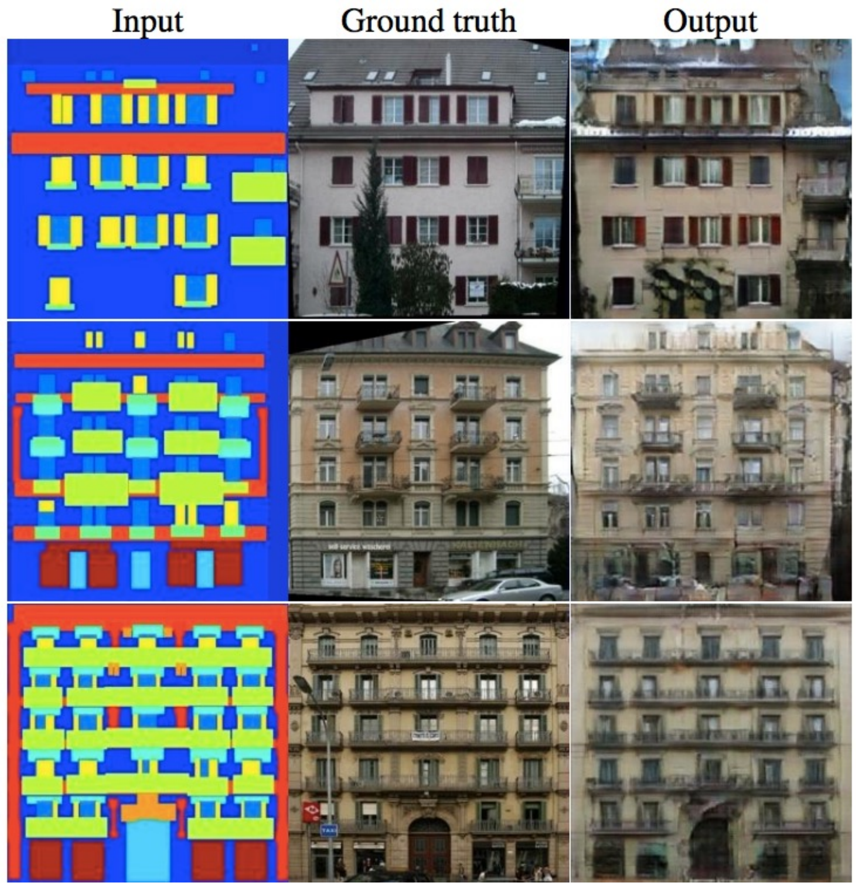
Pix2pix: Results

- Scenes to semantic labels
  - Accuracy is worse than that of regular FCNs or generator with L1 loss

Loss	Per-pixel acc.	Per-class acc.	Class IOU
L1	**0.86**	**0.42**	**0.35**
cGAN	0.74	0.28	0.22
L1+cGAN	0.83	0.36	0.29

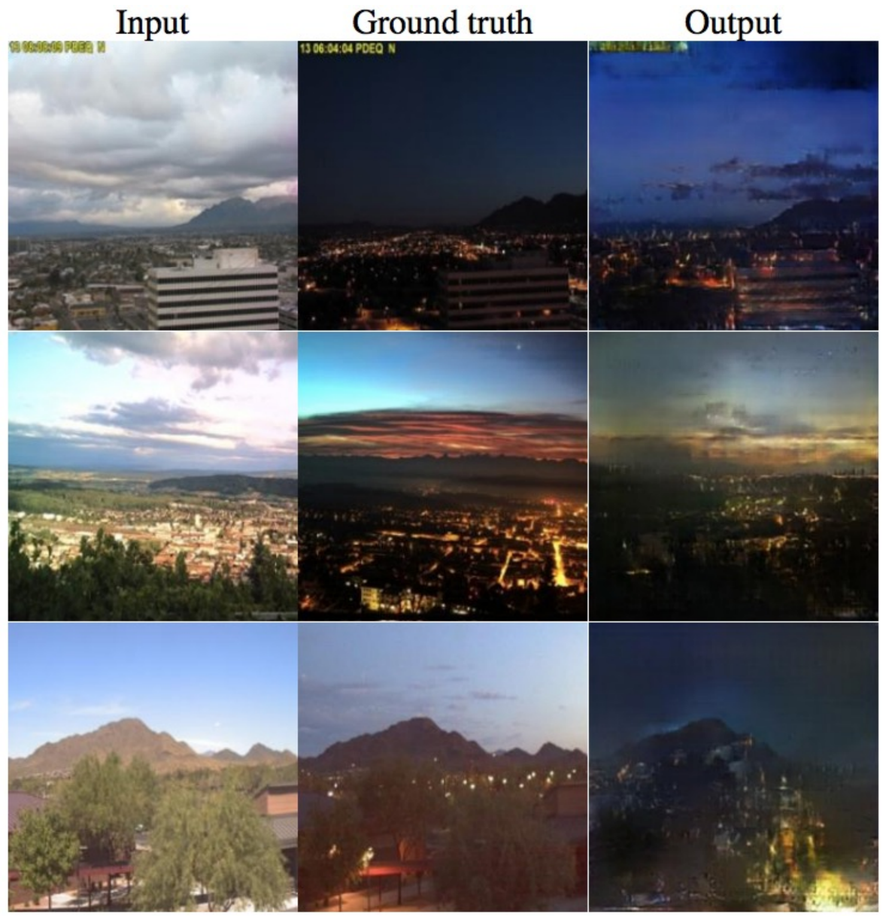
Pix2pix: Results

- Semantic labels to facades



Pix2pix: Results

- Day to night

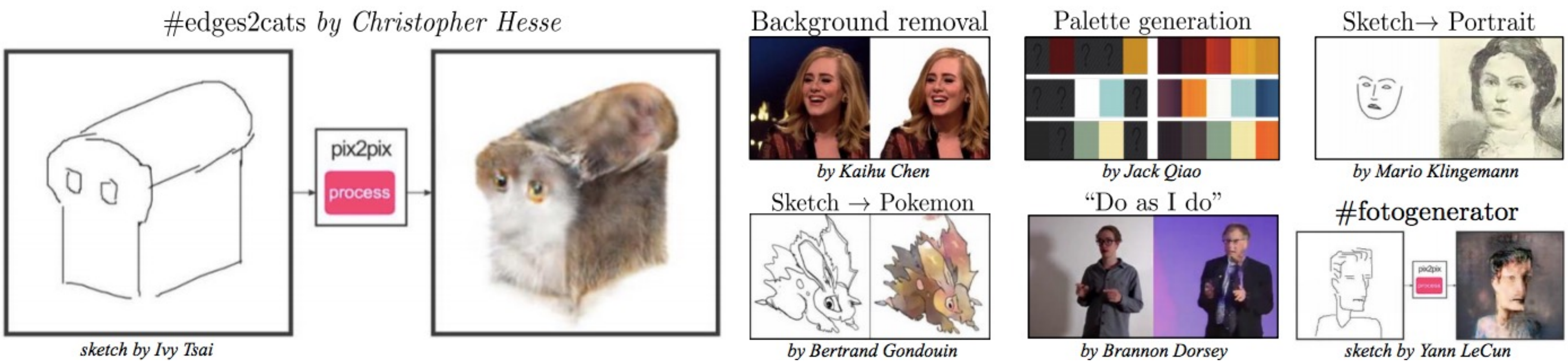


Pix2pix: Results

- Edges to photos

Pix2pix: Results

- [pix2pix demo]



Pix2pix: Limitations

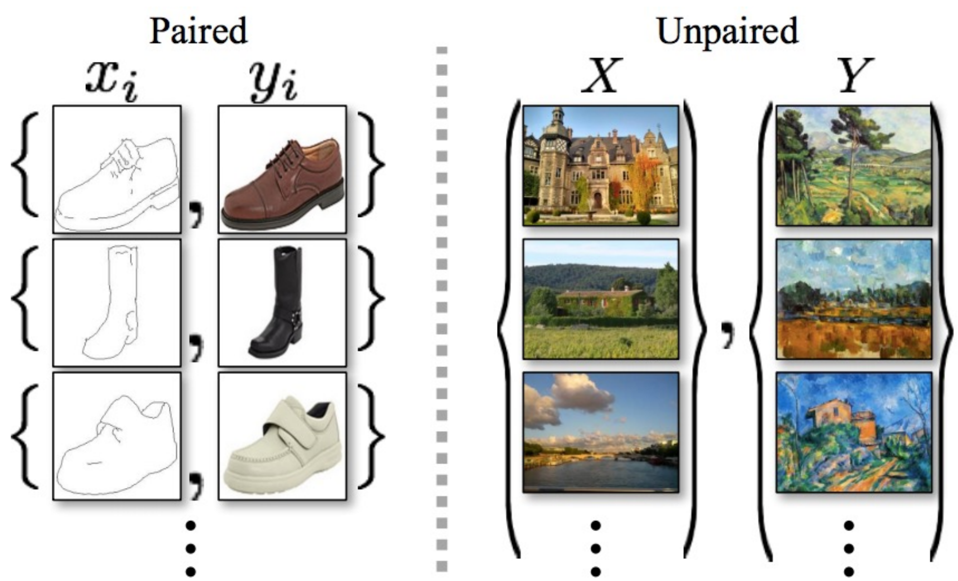
- Visual quality could be improved
- Requires x, y pairs for training
- Does not model conditional distribution $P(y|x)$, returns a single mode instead

Outline

- Paired image-to-image translation: pix2pix
- Unpaired image-to-image translation: CycleGAN

Unpaired image-to-image translation

- Given two unordered image collections X and Y, learn to "translate" an image from one into the other and vice versa



J.-Y. Zhu, T. Park, P. Isola, A. Efros, Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks, ICCV 2017

Unpaired image-to-image translation

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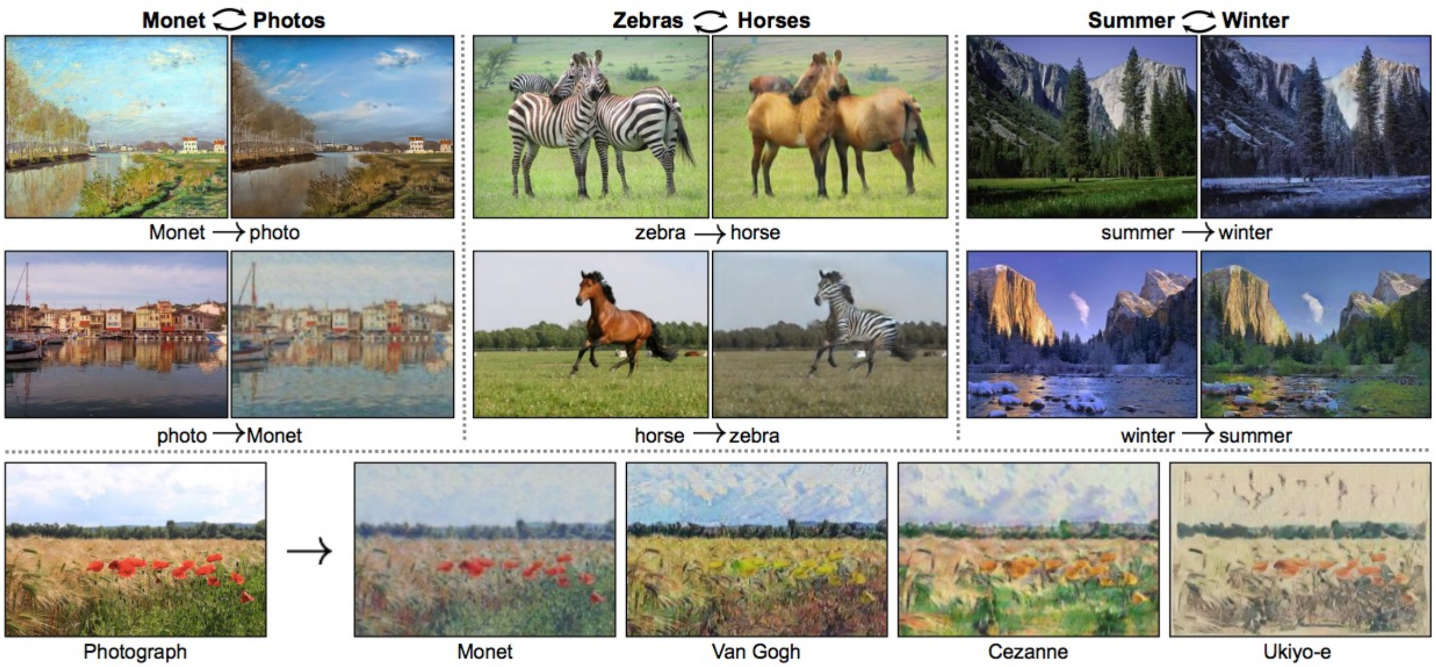
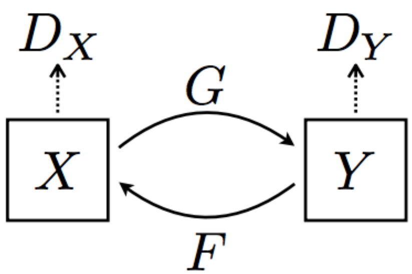


J.-Y. Zhu, T. Park, P. Isola, A. Efros, [Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks](), ICCV 2017

CycleGAN

- Given: domains X and Y
- Train two generators F and G and two discriminators D_X and D_Y
  - G translates from X to Y, F translates from Y to X
  - D_X recognizes images from X, D_Y from Y
  - *Cycle consistency*: we want $F(G(x)) \approx x$ and $G(F(y)) \approx y$



CycleGAN: Architecture

- Generators (based on [Johnson et al.](), 2016):

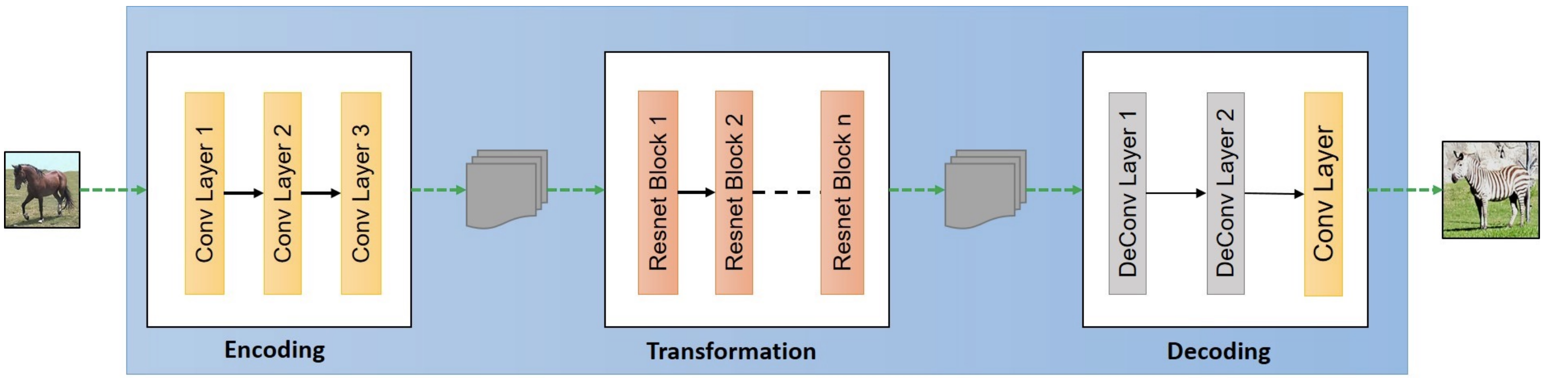


Figure source

- Discriminators: PatchGAN on 70 x 70 patches

CycleGAN: Loss

- Requirements:
  - G translates from X to Y, F translates from Y to X
  - D_X recognizes images from X, D_Y from Y
  - We want $F(G(x)) \approx x$ and $G(F(y)) \approx y$
- CycleGAN discriminator loss: LSGAN

$$\mathcal{L}_{\text{GAN}}(D_Y) = \mathbb{E}_{y\sim p_{\text{data}}(y)}[(D_Y(y)-1)^2] + \mathbb{E}_{x\sim p_{\text{data}}(x)}\left[D_Y\left(G(x)\right)^2\right]$$

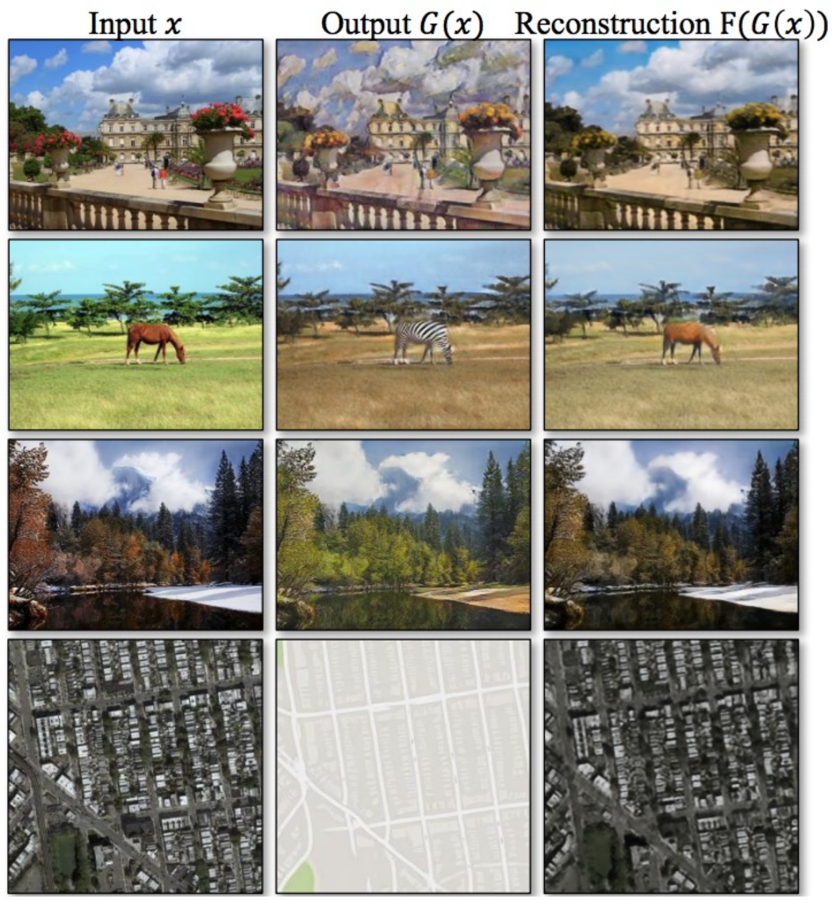
$$\mathcal{L}_{\text{GAN}}(D_X) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[(D_X(x)-1)^2] + \mathbb{E}_{y\sim p_{\text{data}}(y)}\left[D_X\left(F(y)\right)^2\right]$$

- CycleGAN generator loss:

$$\mathcal{L}_{\text{cyc}}(G,F) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[D_Y(G(x)-1)^2] + \mathbb{E}_{y\sim p_{\text{data}}(y)}[D_X(F(y)-1)^2]$$
$$+ \mathbb{E}_{x\sim p_{\text{data}}(x)}\left[\left\|F\left(G(x)\right)-x\right\|_1\right] + \mathbb{E}_{y\sim p_{\text{data}}(y)}\left[\left\|G\left(F(y)\right)-y\right\|_1\right]$$

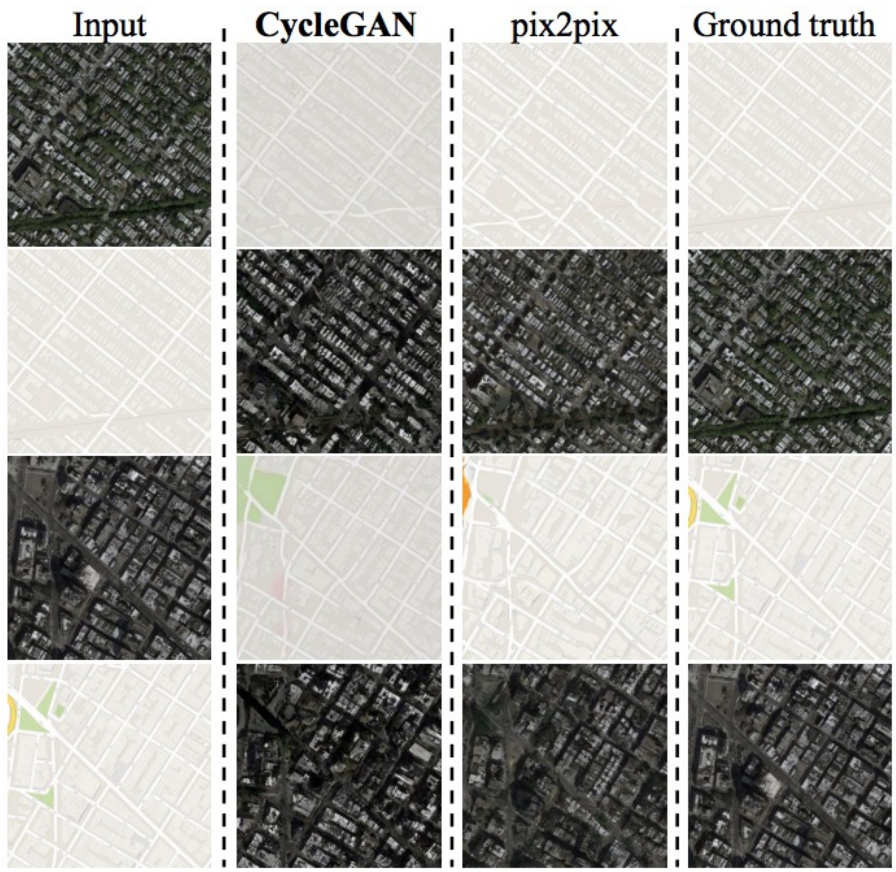
CycleGAN

- Illustration of cycle consistency:



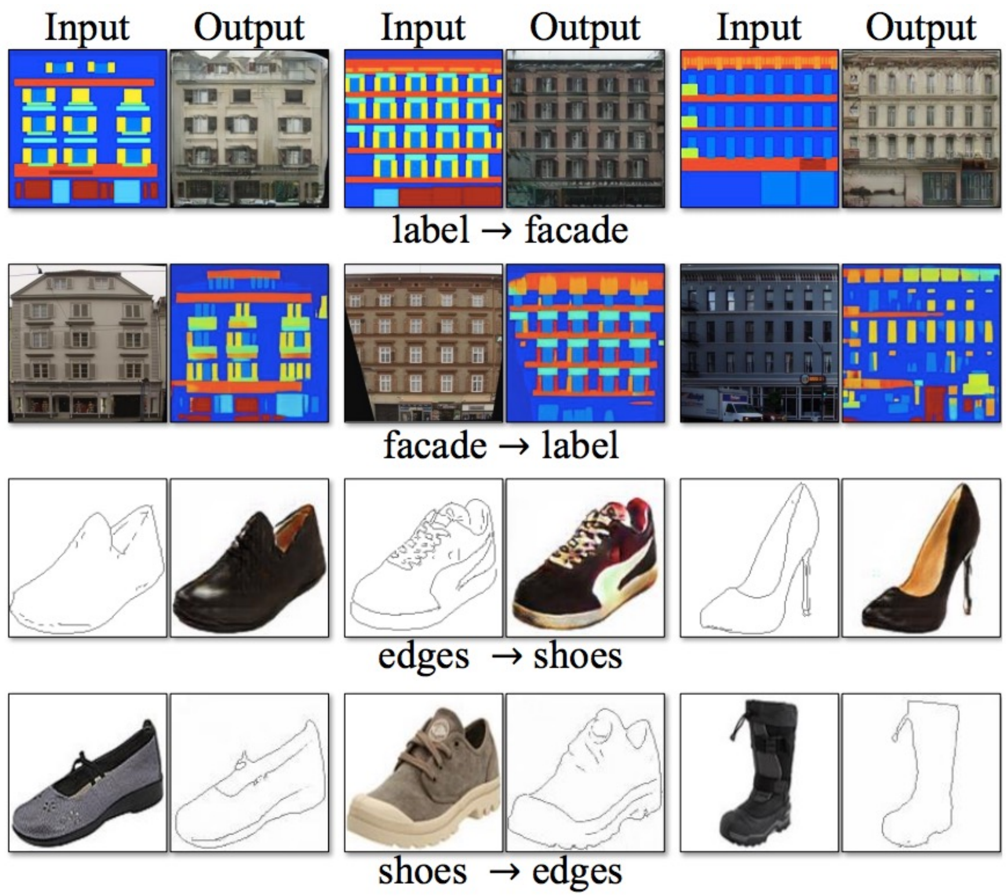
CycleGAN: Results

- Translation between maps and aerial photos



CycleGAN: Results

- Other pix2pix tasks



CycleGAN: Results

- Scene to labels and labels to scene
  - Worse performance than pix2pix due to lack of paired training data

Loss	**Per-pixel acc.**	**Per-class acc.**	**Class IOU**
CoGAN [32]	0.40	0.10	0.06
BiGAN/ALI [9, 7]	0.19	0.06	0.02
SimGAN [46]	0.20	0.10	0.04
Feature loss + GAN	0.06	0.04	0.01
CycleGAN (ours)	**0.52**	**0.17**	**0.11**
pix2pix [22]	0.71	0.25	0.18

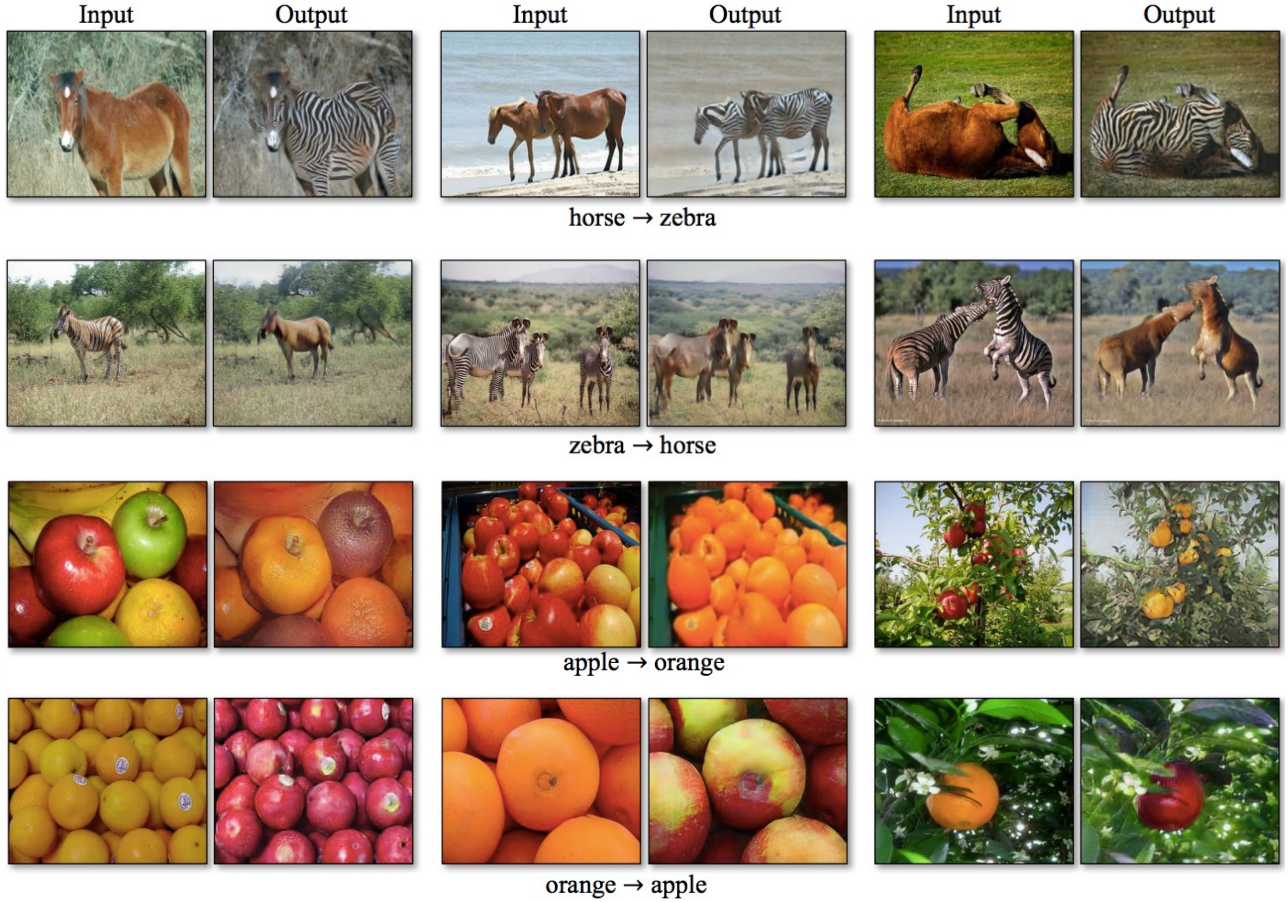
Table 2: FCN-scores for different methods, evaluated on Cityscapes labels→photo.

Loss	**Per-pixel acc.**	**Per-class acc.**	**Class IOU**
CoGAN [32]	0.45	0.11	0.08
BiGAN/ALI [9, 7]	0.41	0.13	0.07
SimGAN [46]	0.47	0.11	0.07
Feature loss + GAN	0.50	0.10	0.06
CycleGAN (ours)	**0.58**	**0.22**	**0.16**
pix2pix [22]	0.85	0.40	0.32

Table 3: Classification performance of photo→labels for different methods on cityscapes.

CycleGAN: Results

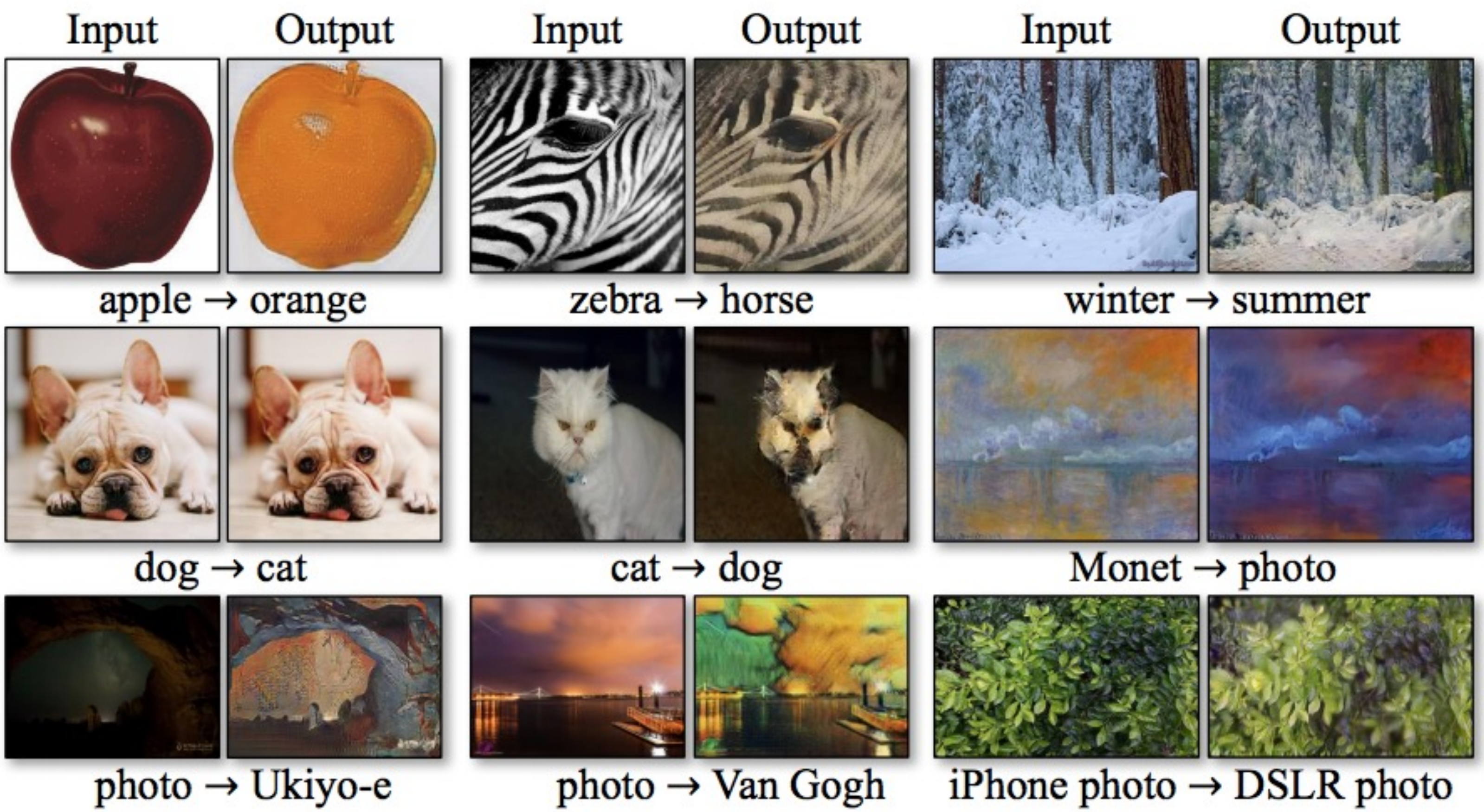
- Tasks for which paired data is unavailable



CycleGAN: Results

- Style transfer

CycleGAN: Failure cases



CycleGAN: Failure cases

Input Output

horse → zebra

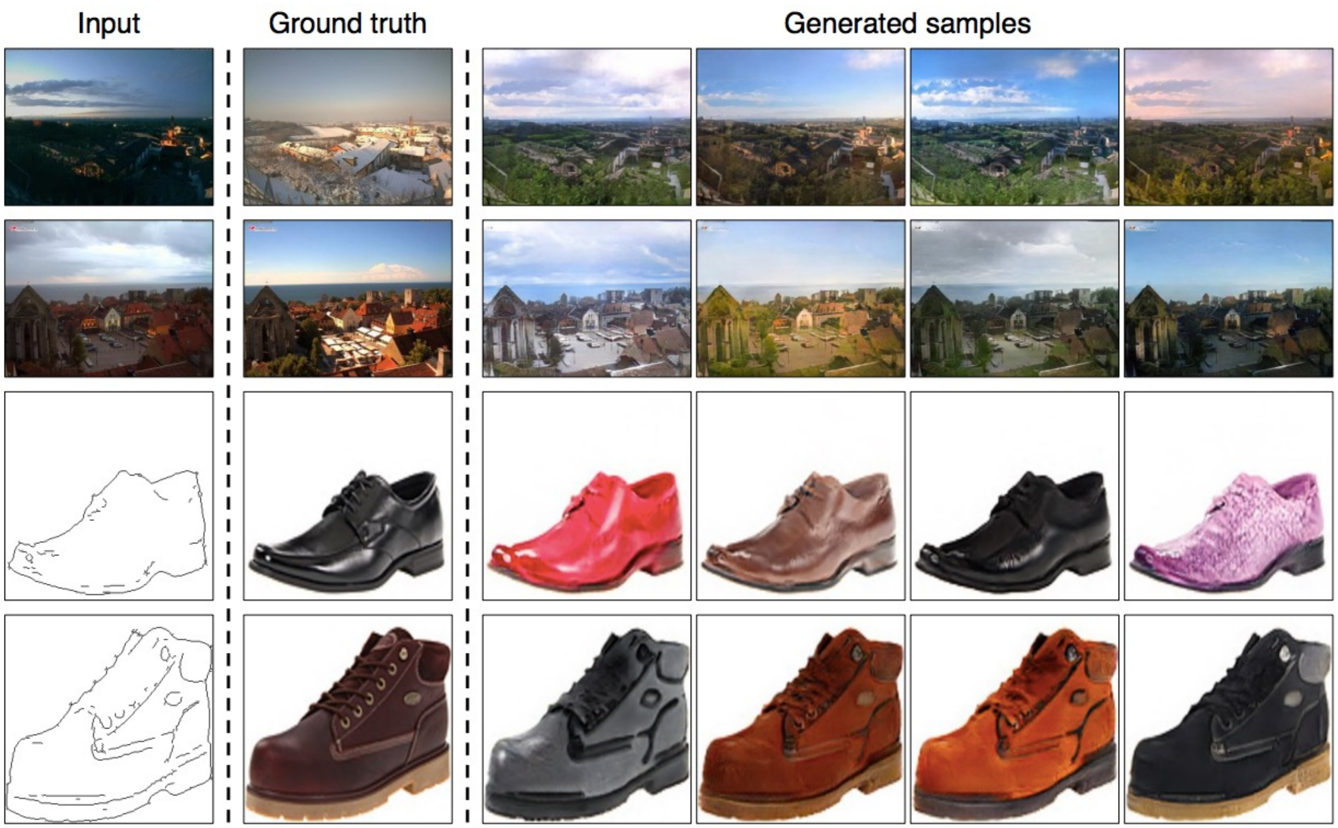
CycleGAN: Limitations

- Cannot handle shape changes (e.g., dog to cat)
- Can get confused on images outside of the training domains (e.g., horse with rider)
- Cannot close the gap with paired translation methods
- Does not account for the fact that one transformation direction may be more challenging than the other

Outline

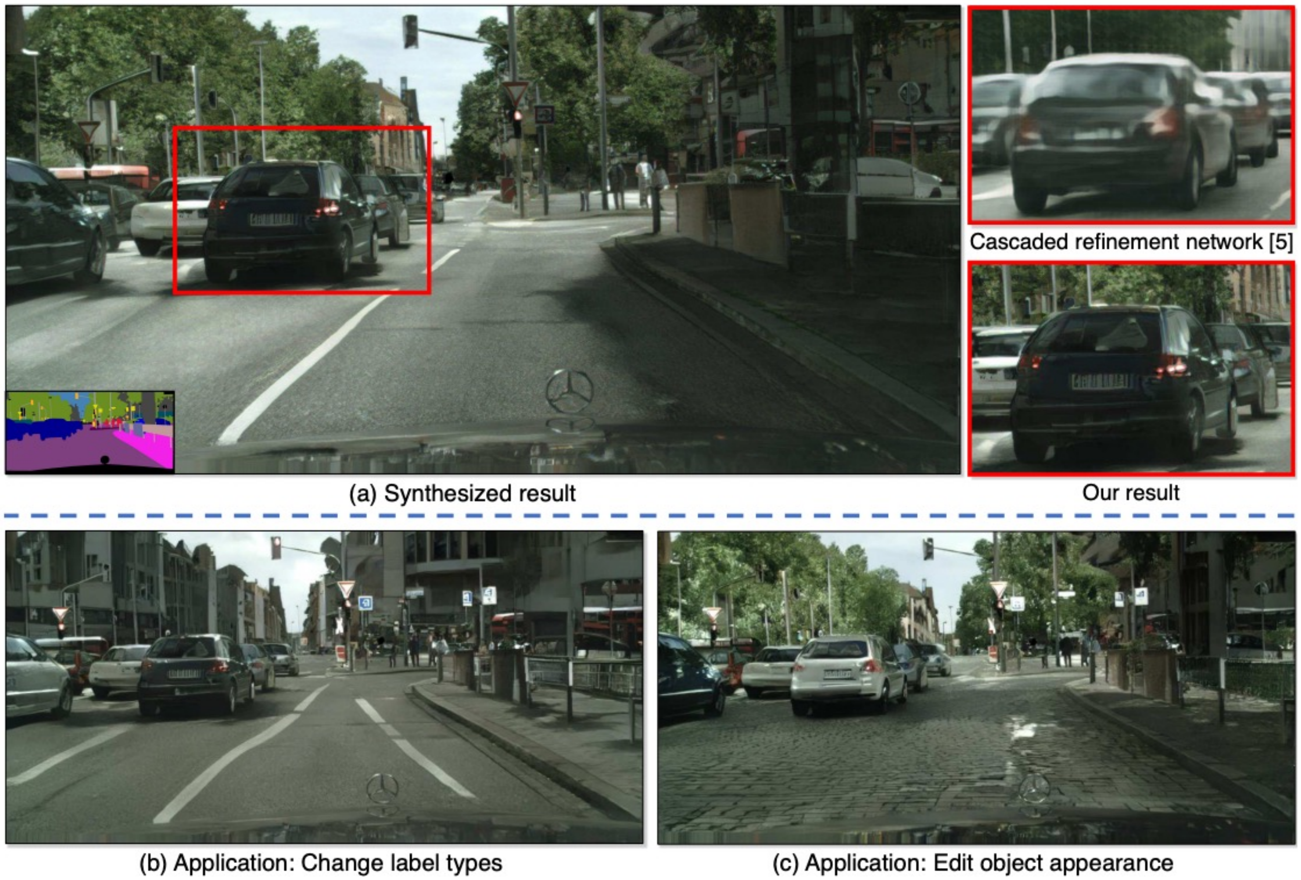
- Paired image-to-image translation: pix2pix
- Unpaired image-to-image translation: CycleGAN
- Extensions, applications

Multimodal image-to-image translation



J.Y. Zhu, R. Zhang, D. Pathak, T. Darrell, A. A. Efros, O. Wang, E. Shechtman, Toward Multimodal Image-to-Image Translation, NIPS 2017

High-resolution, high-quality pix2pix

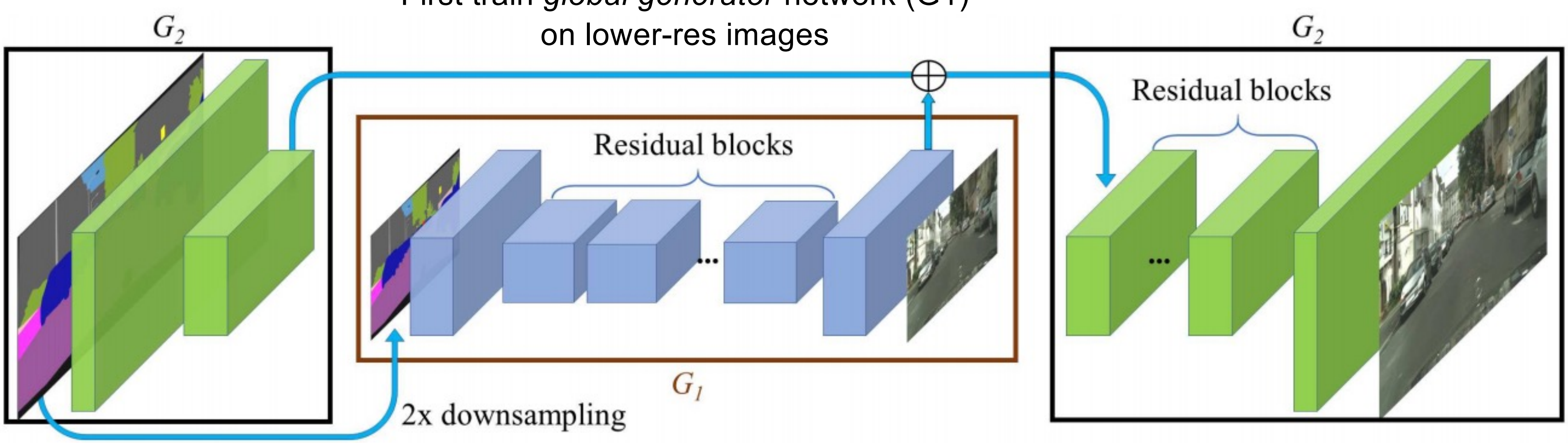


T.-C. Wang et al., [High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs](), CVPR 2018

High-resolution, high-quality pix2pix

- Two-scale generator architecture (up to 2048 x 1024 resolution)

First train *global generator* network (G1)
on lower-res images



Then append higher-res *enhancer network* (G2) blocks and train G1 and G2 jointly

T.-C. Wang et al., [High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs](), CVPR 2018

Human generation conditioned on pose

https://carolineec.github.io/everybody_dance_now/

C. Chan, S. Ginosar, T. Zhou, A. Efros. [Everybody Dance Now.](#) ICCV 2019

Human generation conditioned on pose

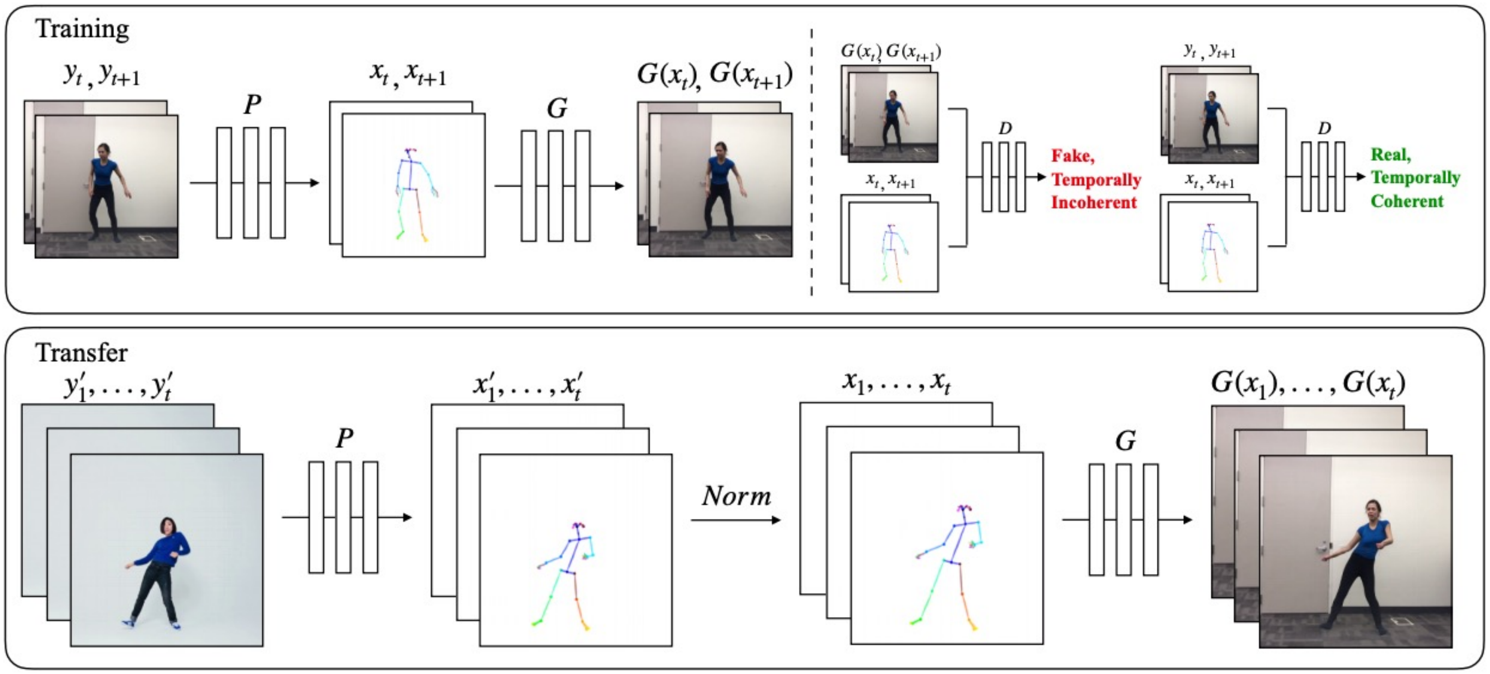
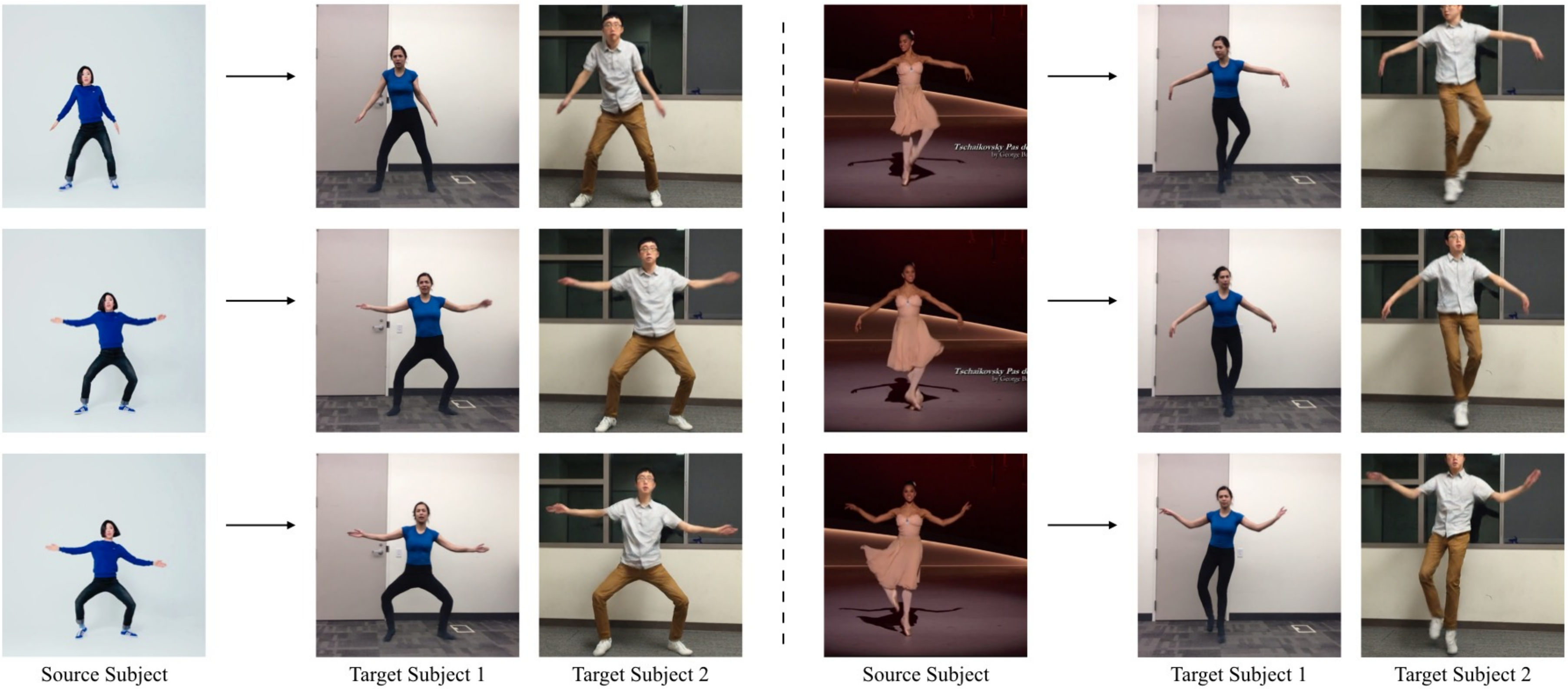


Figure 3: (Top) **Training**: Our model uses a pose detector P to create pose stick figures from video frames of the target subject. We learn the mapping G alongside an adversarial discriminator D which attempts to distinguish between the "real" correspondences $(x_t, x_{t+1}), (y_t, y_{t+1})$ and the "fake" sequence $(x_t, x_{t+1}), (G(x_t), G(x_{t+1}))$. (Bottom) **Transfer**: We use a pose detector P to obtain pose joints for the source person that are transformed by our normalization process $Norm$ into joints for the target person for which pose stick figures are created. Then we apply the trained mapping G.

C. Chan, S. Ginosar, T. Zhou, A. Efros. [Everybody Dance Now.]() ICCV 2019

Human generation conditioned on pose



https://carolineec.github.io/everybody_dance_now/

C. Chan, S. Ginosar, T. Zhou, A. Efros. Everybody Dance Now. ICCV 2019