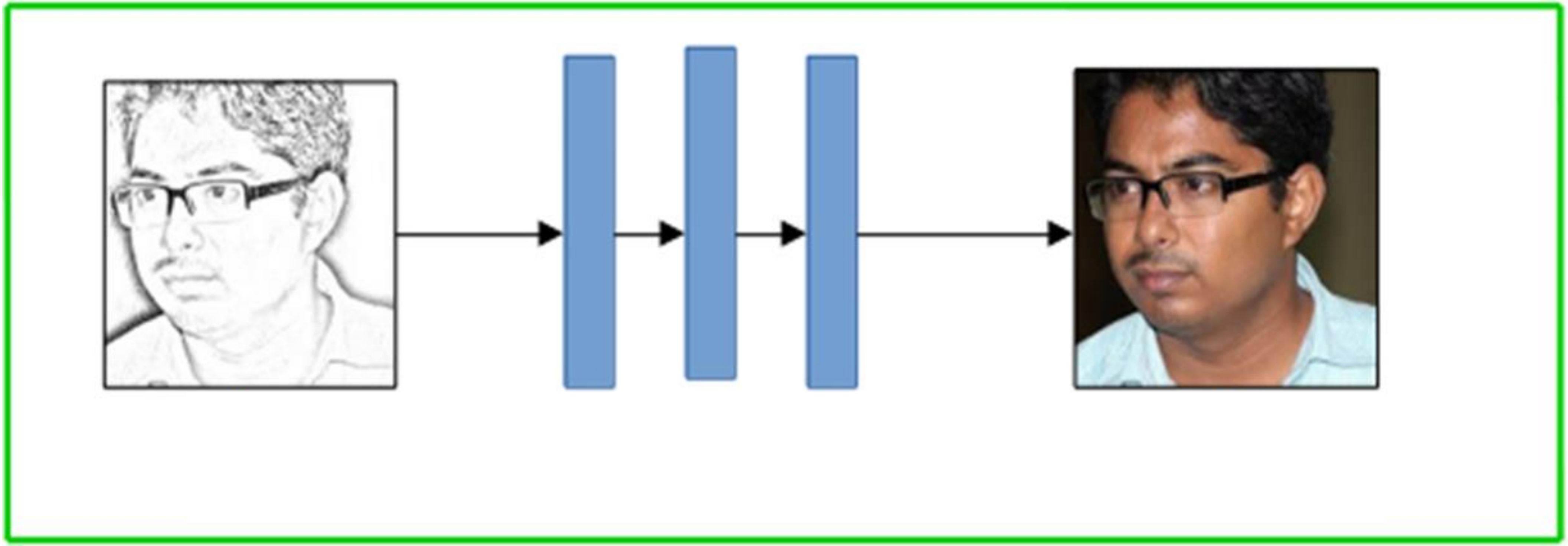
Conditional GANs

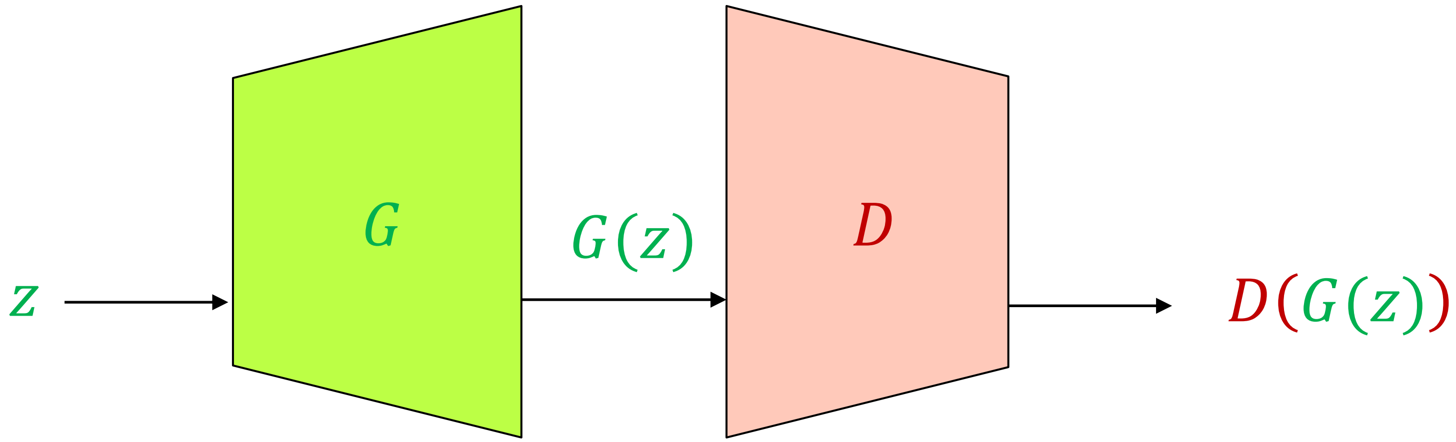


Outline

- Introduction
- Generation conditioned on class
  - Self-attention GAN
  - BigGAN
- Generation conditioned on image
  - Paired image-to-image translation: pix2pix
  - Unpaired image-to-image translation: CycleGAN
- Recent trends

Conditional generation

- Suppose we want to condition the generation of samples on discrete side information (label) y
  - How do we add y to the basic GAN framework?



Conditional generation

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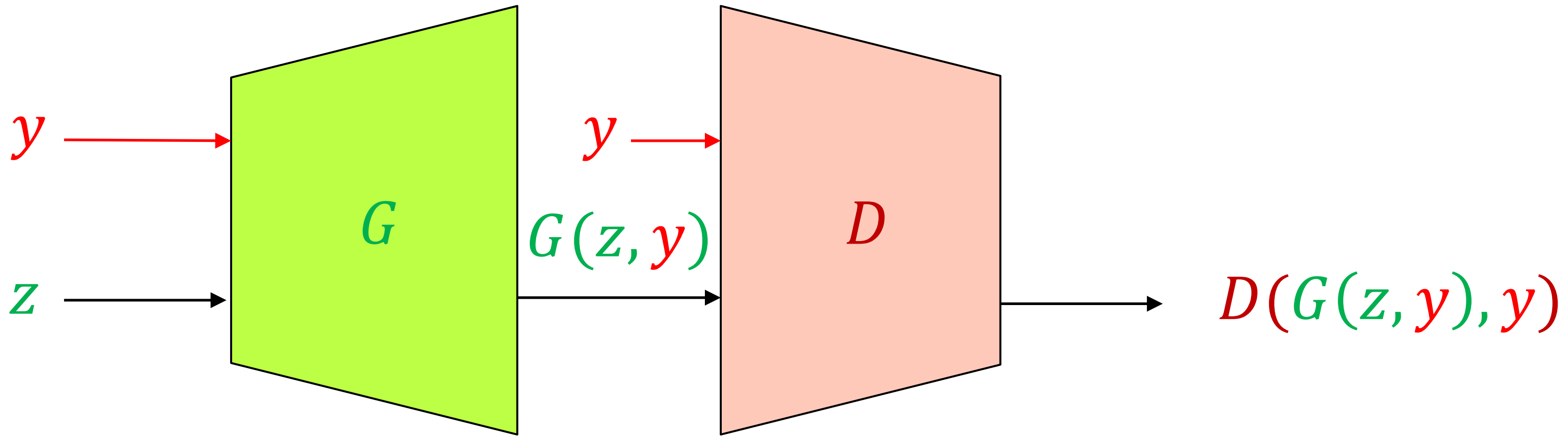


Conditional generation

- Example: simple network for generating 28 x 28 MNIST digits

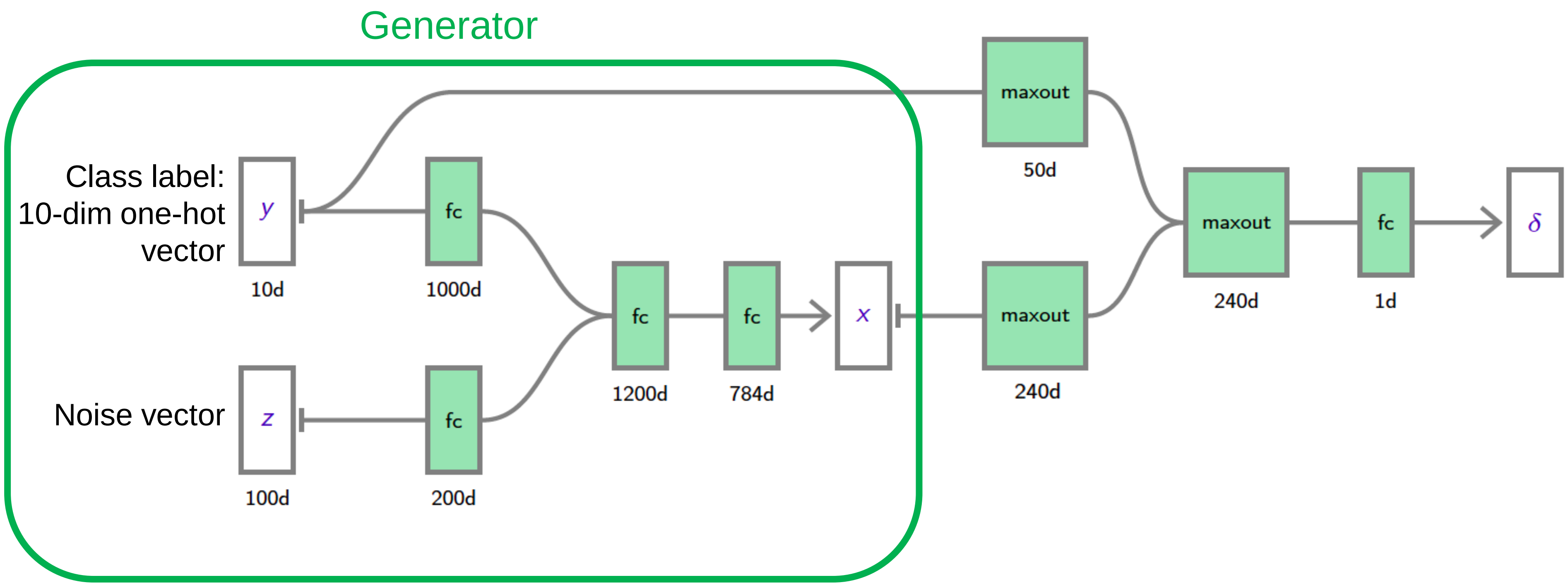


Figure source:
[F. Fleuret]

M. Mirza and S. Osindero, [Conditional Generative Adversarial Nets], arXiv 2014

Conditional generation

- Example: simple network for generating 28 x 28 MNIST digits

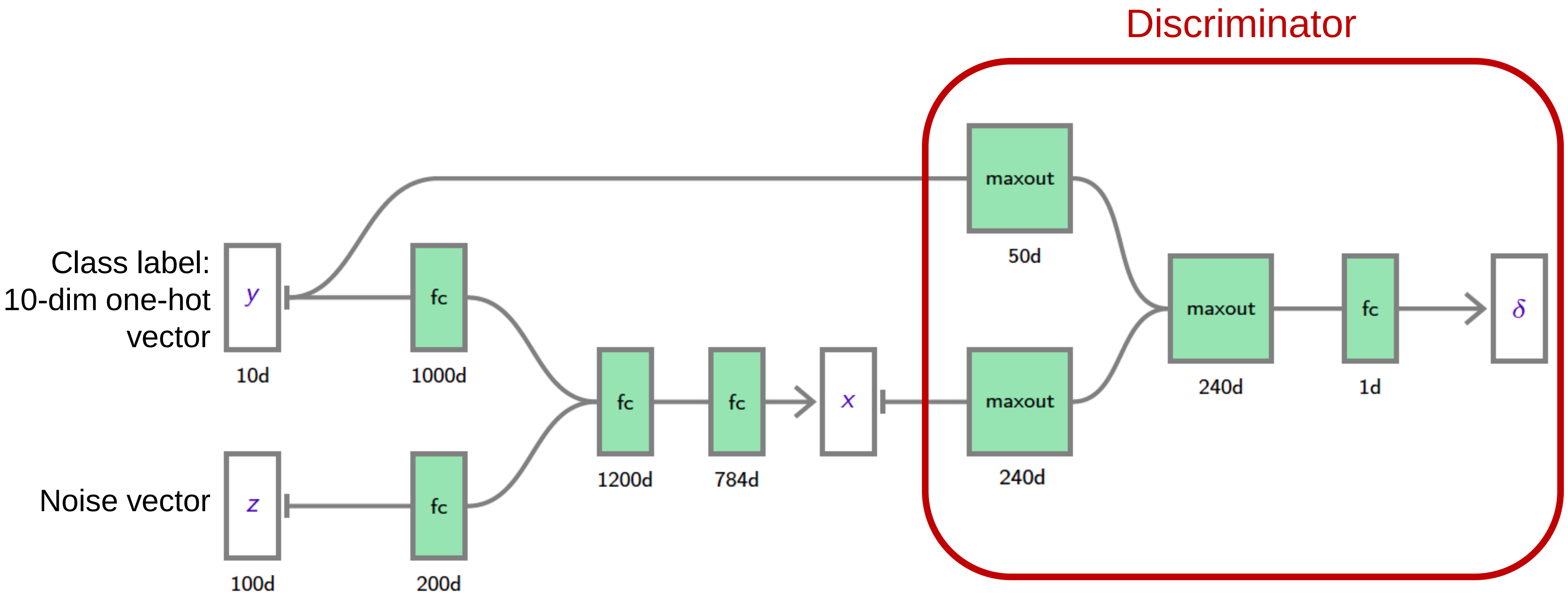
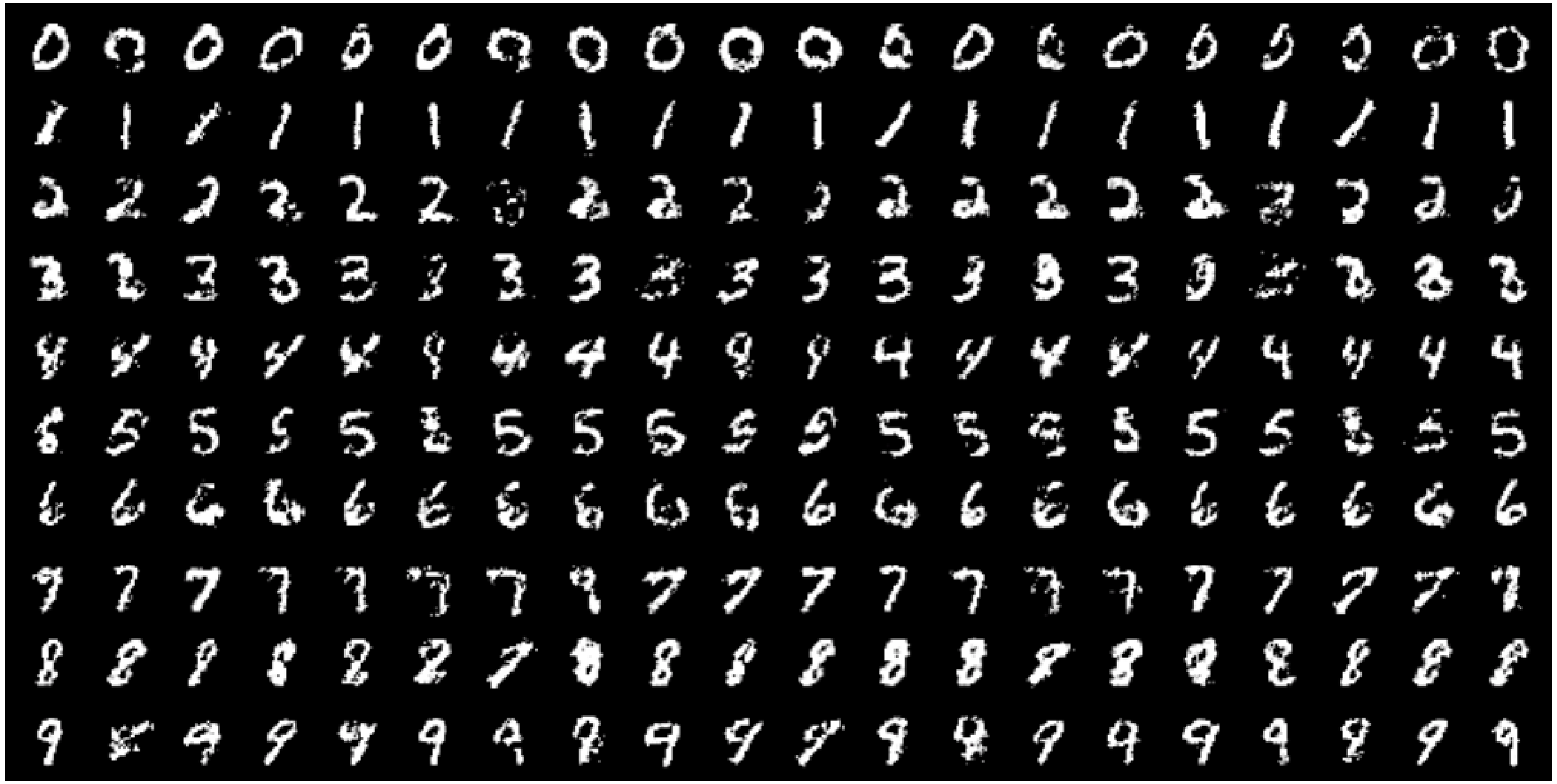


Figure source:
F. Fleuret

M. Mirza and S. Osindero, Conditional Generative Adversarial Nets, arXiv 2014

Conditional generation

- Example: simple network for generating 28 x 28 MNIST digits



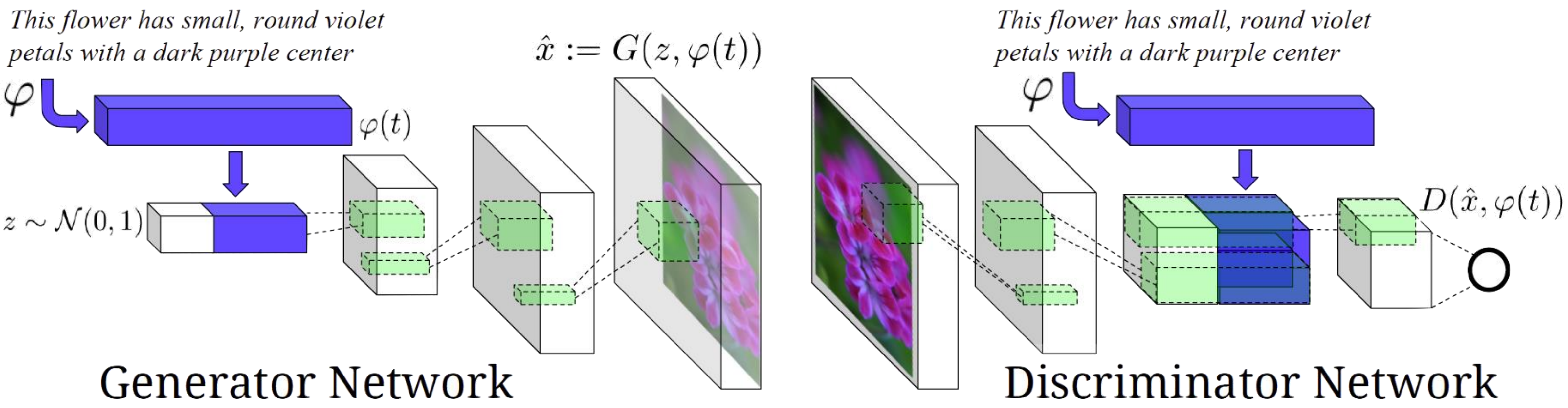
M. Mirza and S. Osindero, [Conditional Generative Adversarial Nets](), arXiv 2014

Conditional generation

- Another example: text-to-image synthesis

LSTM text encoder

Spatial replication,
depth concatenation

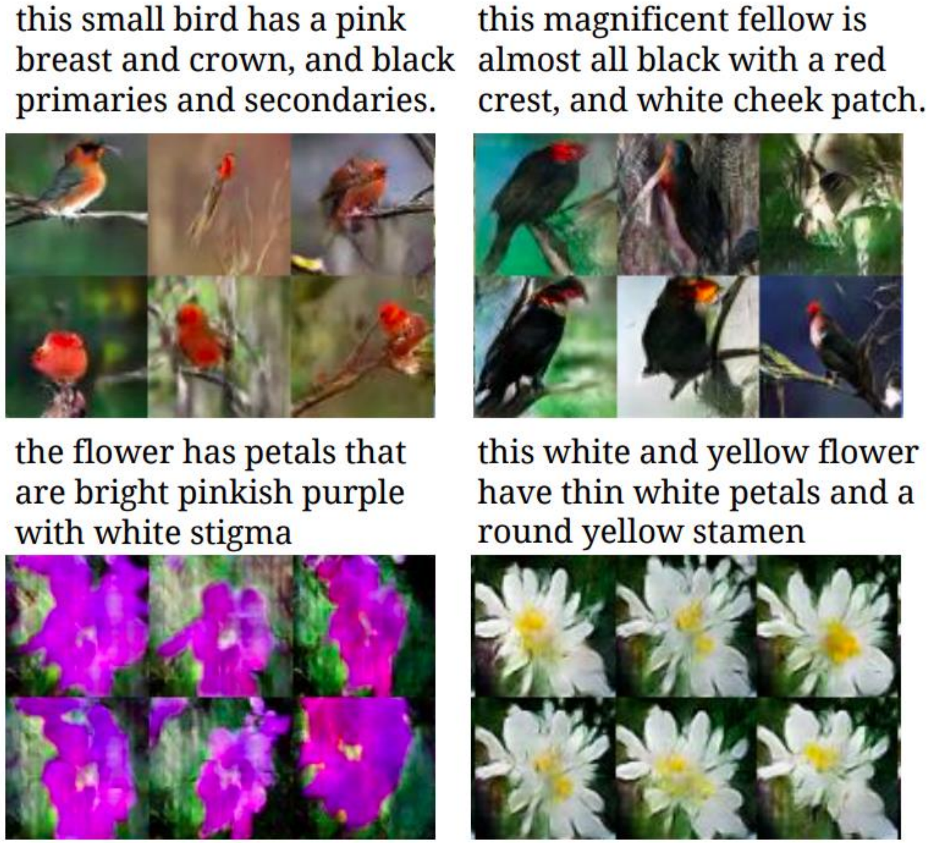


S. Reed, Z. Akata, X. Yan, L. Logeswaran, B. Schiele, H. Lee, [Generative adversarial text to image synthesis](), ICML 2016

Conditional generation

- Another example: text-to-image synthesis

Previously unseen captions (*zero-shot* setting)



Captions seen in the training set

S. Reed, Z. Akata, X. Yan, L. Logeswaran, B. Schiele, H. Lee, [Generative adversarial text to image synthesis](), ICML 2016

Outline

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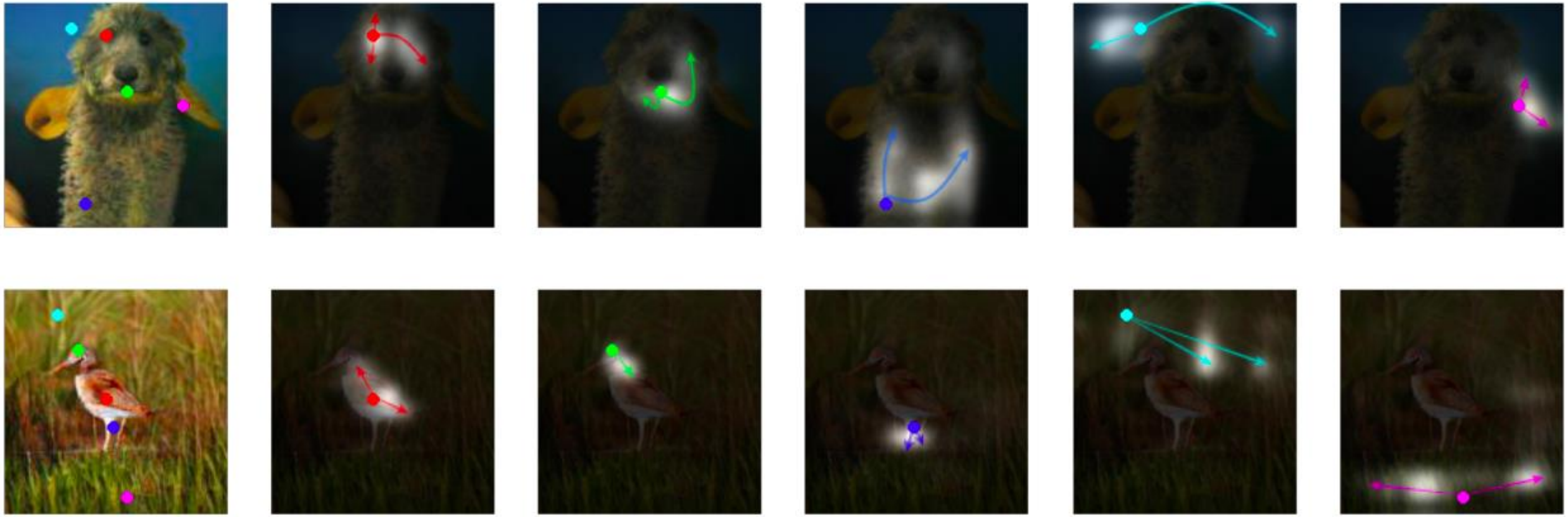
  - BigGAN

Self-attention GAN (SAGAN)

- Adaptive receptive fields to capture non-local structure

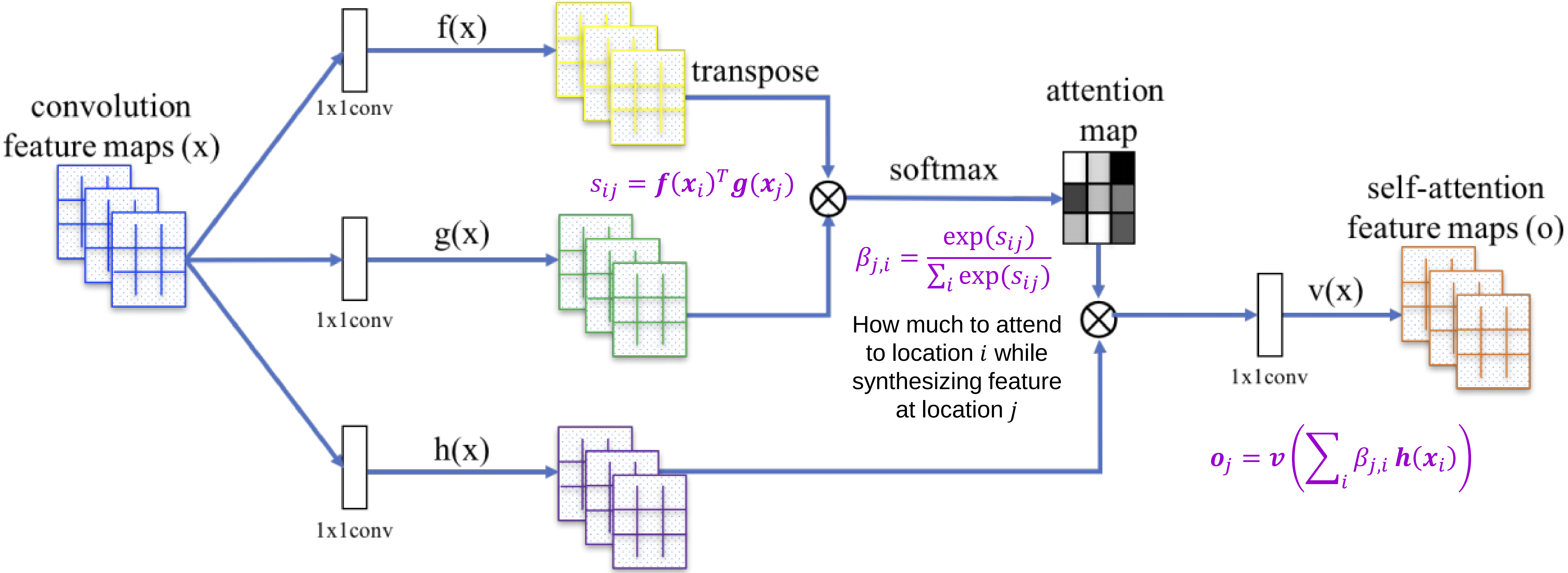


SAGAN generates images by leveraging complementary features in distant portions of the image rather than local regions of fixed shape to generate consistent objects/scenarios. In each row, the first image shows five representative query locations with color coded dots. The other five images are attention maps for those query locations, with corresponding color coded arrows summarizing the most-attended regions.

H. Zhang, I. Goodfellow, D. Metaxas, A. Odena. [Self-Attention Generative Adversarial Networks](). ICML 2019

Self-attention GAN

- Adaptive receptive fields to capture non-local structure (based on Wang et al., 2018)



Self-attention GAN: Implementation details

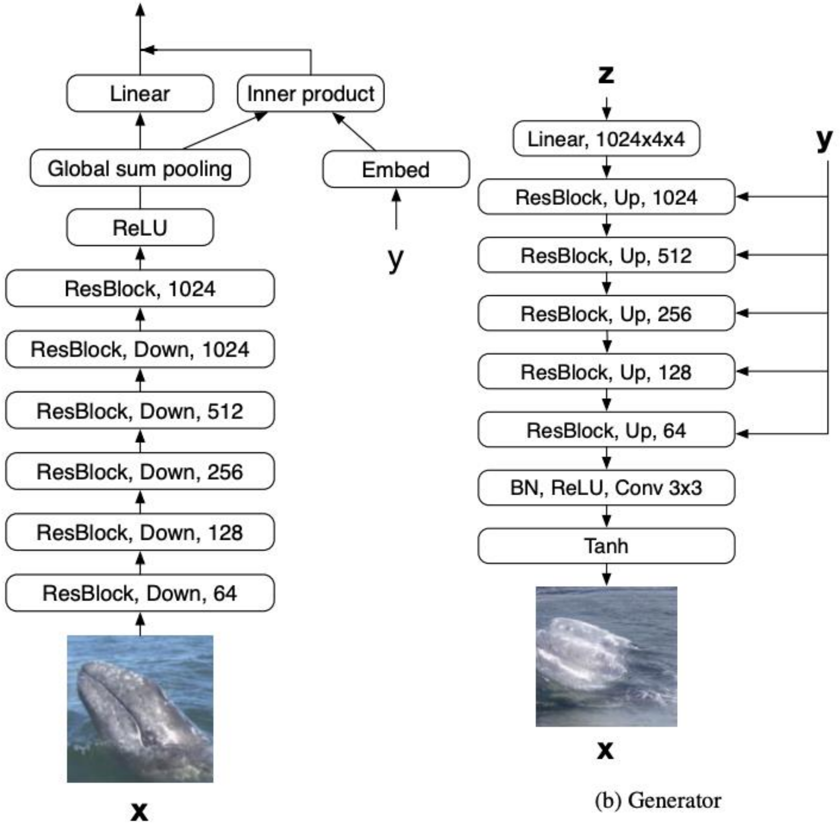
- Hinge loss formulation:

$$L_D = -\mathbb{E}_{(x,y)\sim p_{\text{data}}}[\min(0, D(x,y) - 1)] \\ -\mathbb{E}_{z\sim p_z, y\sim p_{\text{data}}}[\min(0, -D(G(z,y),y) - 1)]$$

$$L_G = -\mathbb{E}_{z\sim p_z, y\sim p_{\text{data}}} D(G(z,y),y)$$

Self-attention GAN: Implementation details

- Hinge loss formulation
- Conditioning the discriminator: *projection* (Miyato & Koyama, 2018)
- Conditioning the generator: *conditional batch norm*



(a) Discriminator

(b) Generator

Figure source

Self-attention GAN: Implementation details

- Hinge loss formulation
- Conditioning the discriminator: *projection* (Miyato & Koyama, 2018)
- Conditioning the generator: *conditional batch norm*
- *Spectral normalization* for generator and discriminator (Miyato et al., 2018) – divide weight matrices by largest singular value (estimated)
- Different learning rates for generator and discriminator (TTUR – Heusel et al., 2017)

Self-attention GAN: Results

- 128 x 128 ImageNet

goldfish

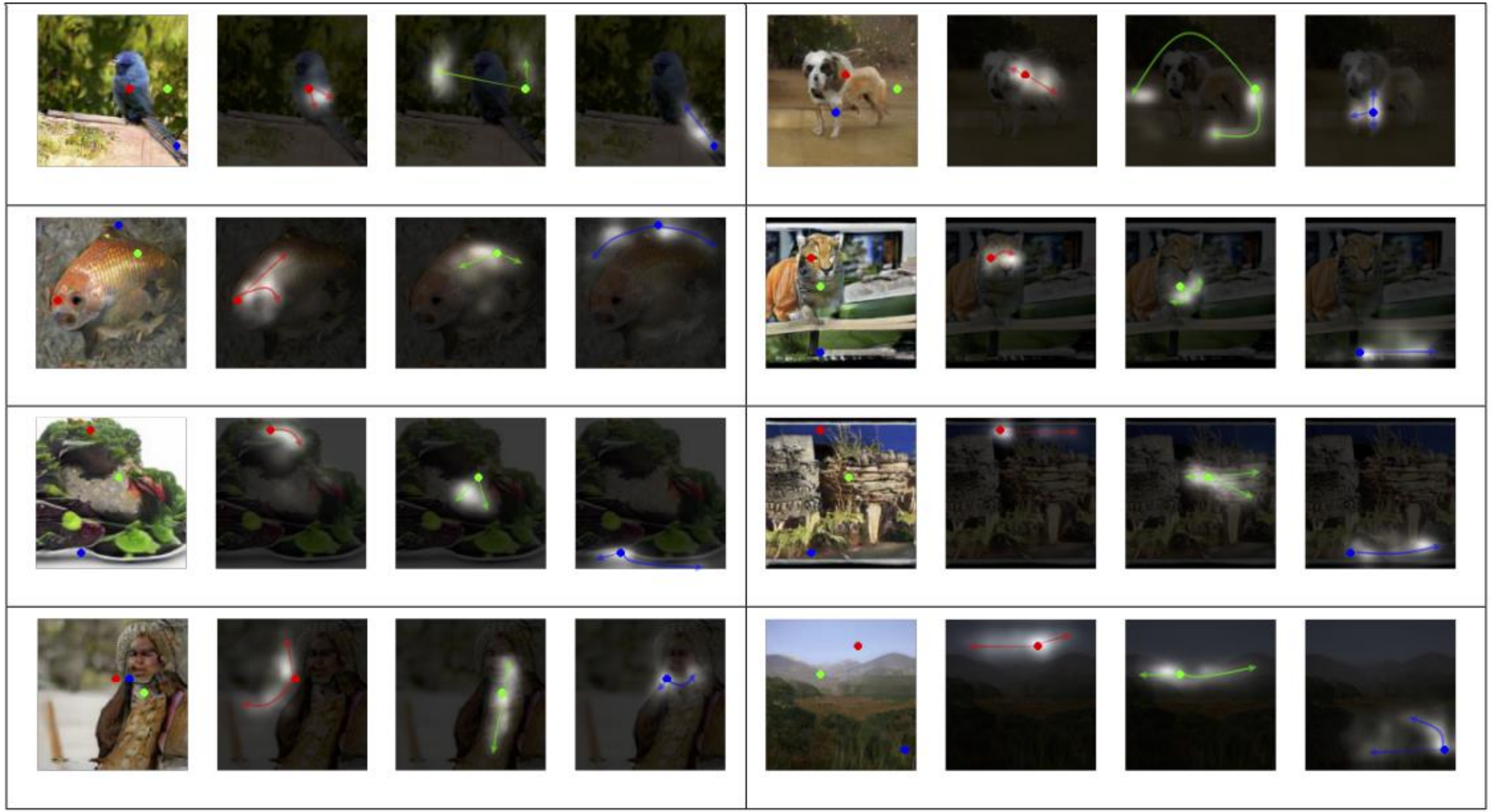
indigo bunting

redshank

Saint Bernard

Self-attention GAN: Results

- Attention map visualization



BigGAN

- Scale up SA-GAN to generate ImageNet images up to 512 x 512 resolution

A. Brock, J. Donahue, K. Simonyan, Large scale GAN training for high fidelity natural image synthesis, ICLR 2019

BigGAN: Implementation details

- 8x larger batch size, 50% more channels (2x more parameters) than baseline SA-GAN
- Hierarchical latent space: feed (transformations of) z vector into multiple layers of the generator

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- Hierarchical latent space: feed (transformations of) z vector into multiple layers of the generator
- Truncation trick: at test time, resample the values of the z vector with magnitude above a chosen threshold
  - Trade off diversity for image quality

"The effects of increasing truncation. From left to right, the threshold is set to 2, 1, 0.5, 0.04."

BigGAN: Implementation details

- 8x larger batch size, 50% more channels (2x more parameters) than baseline SA-GAN
- Hierarchical latent space: feed (transformations of) z vector into multiple layers of the generator
- Truncation trick: at test time, resample the values of the z vector with magnitude above a chosen threshold
- Lots of other tricks (initialization, training, etc.)
- Training observed to be unstable, but good results are achieved “just before collapse”
- Evidence that discriminator memorizes the training data, but the generator doesn’t

BigGAN: Results

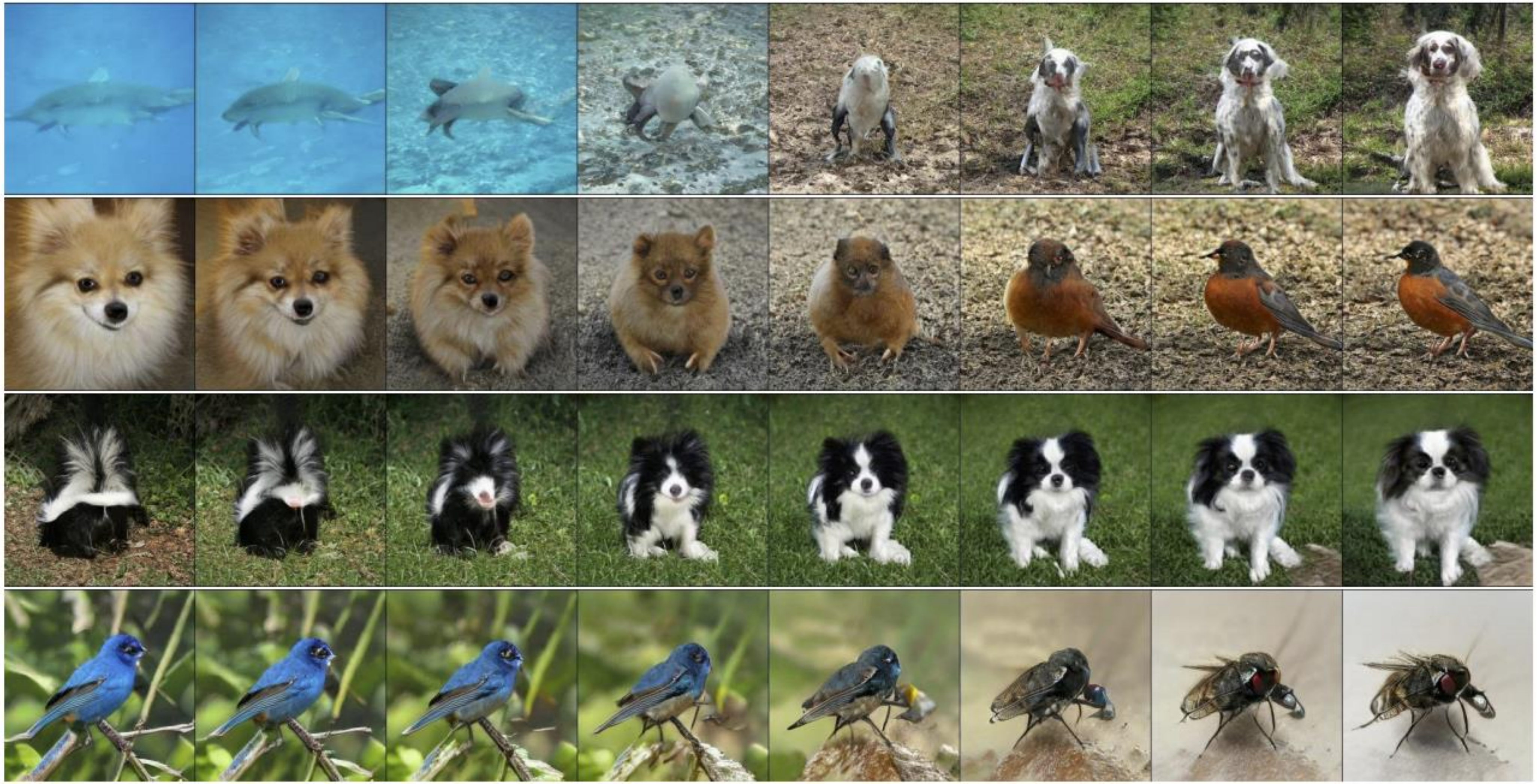
- Samples at 256 x 256 resolution:

BigGAN: Results

- Samples at 512 x 512 resolution:

BigGAN: Results

- Interpolation between c (class embeddings), z (noise vector)



BigGAN: Results

- Difficult classes:

Conditional GANs: Outline

- Introduction
- Generation conditioned on class
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- Generation conditioned on image
  - Paired image-to-image translation: pix2pix
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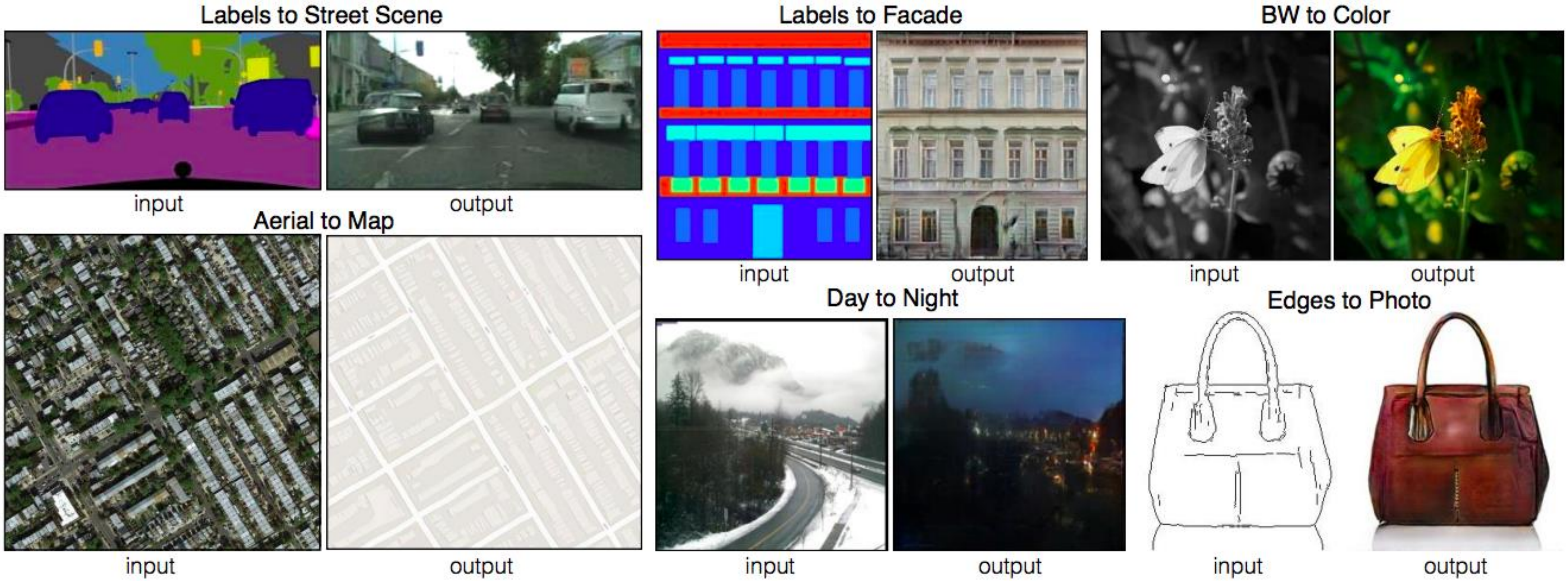
Image-to-image translation



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

Image-to-image translation

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

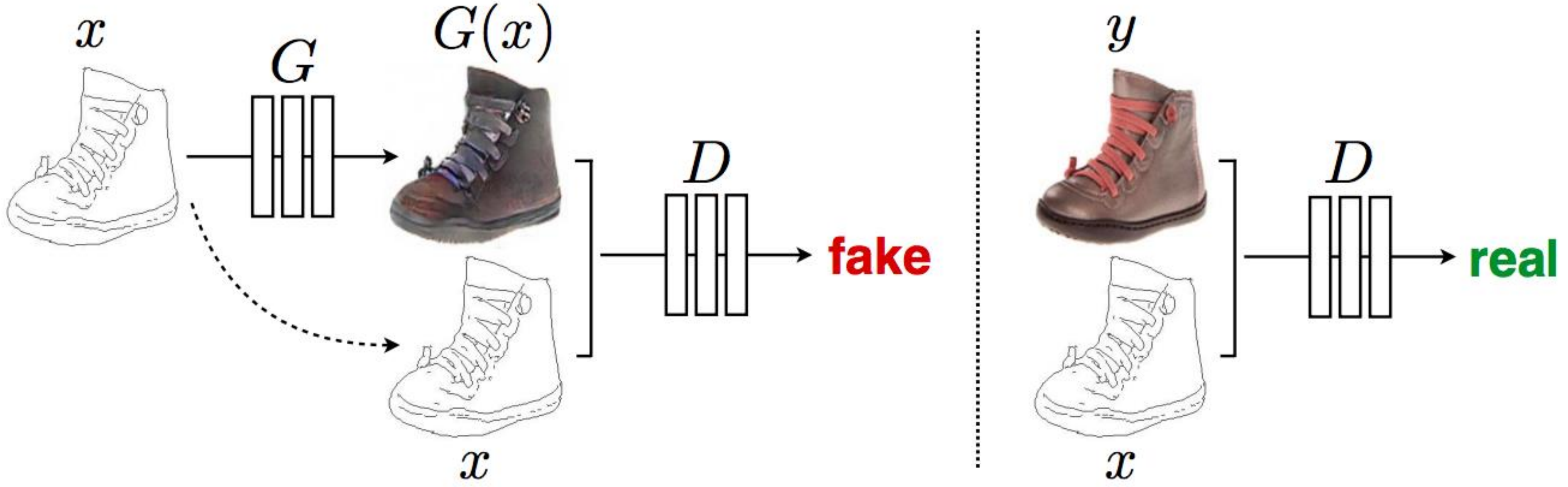
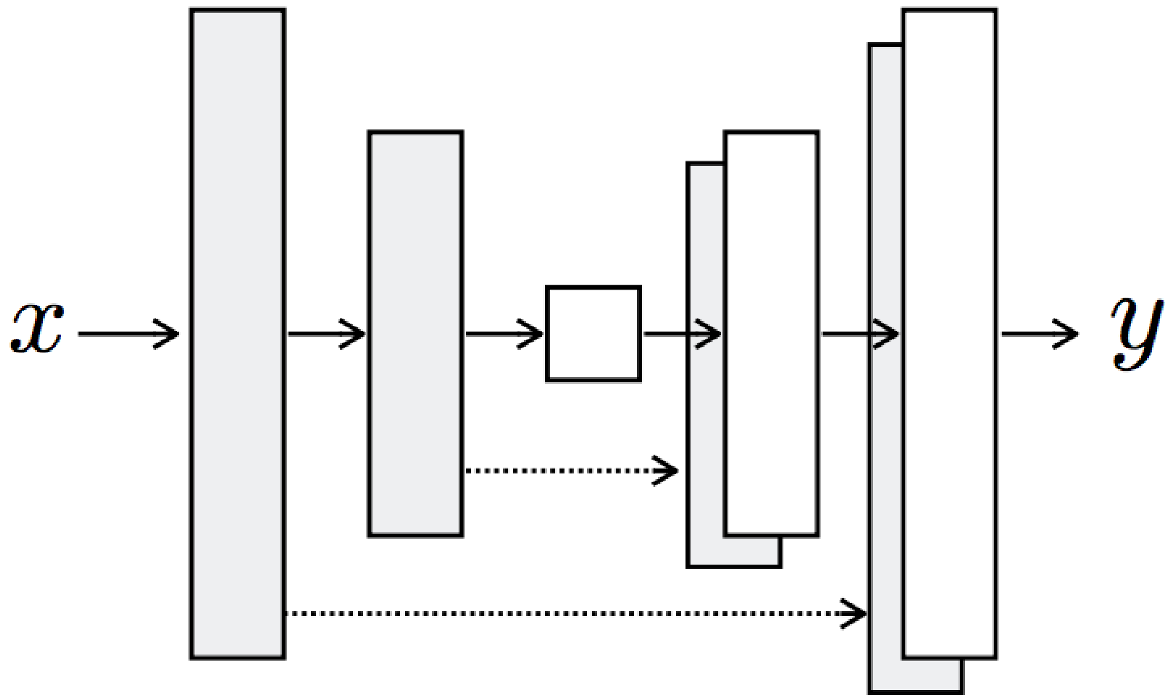


Image-to-image translation

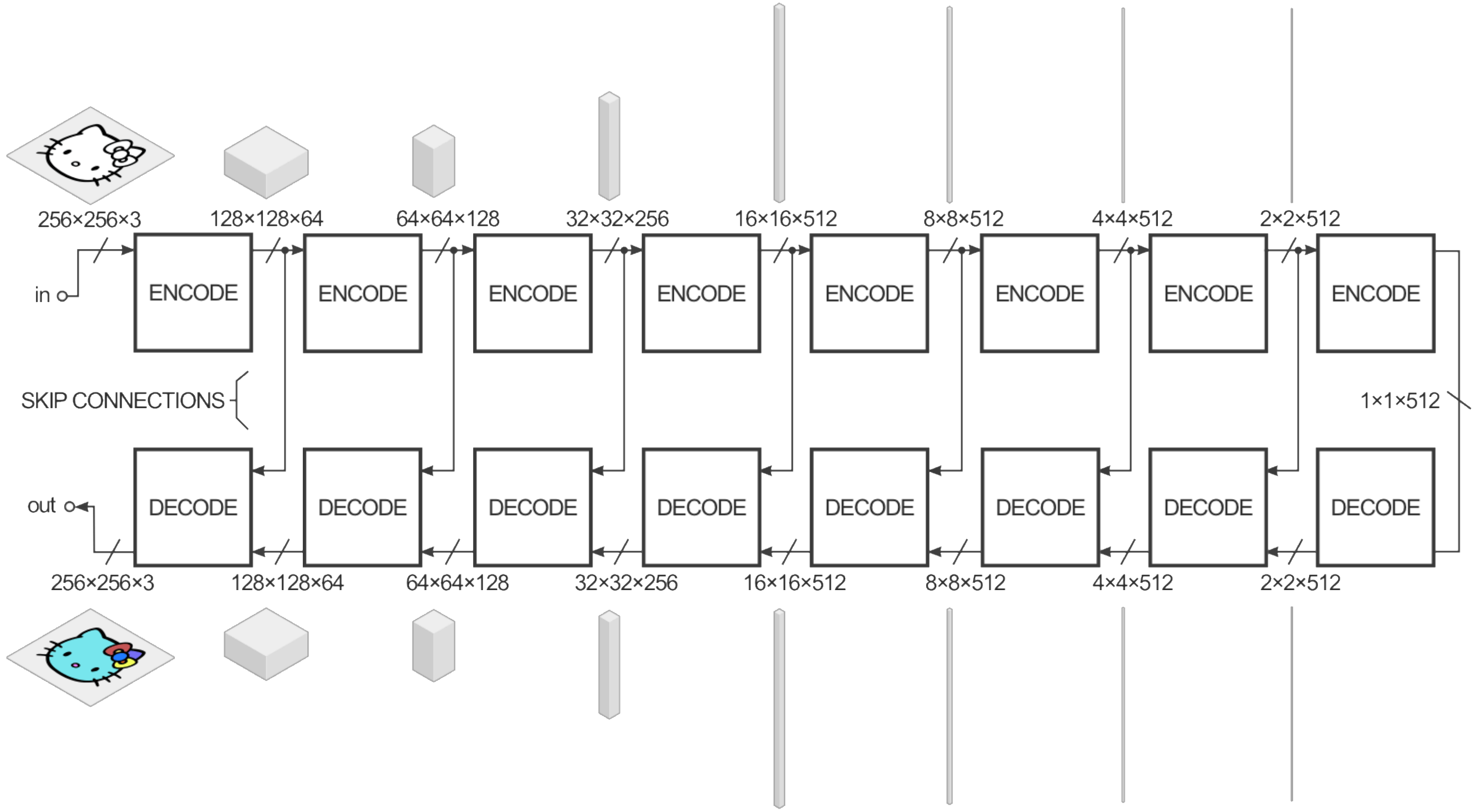
- Generator architecture: U-Net



- Note: z is not used as input, transformation is basically deterministic

Image-to-image translation

- Generator architecture: U-Net



Encode: convolution → BatchNorm → ReLU

Decode: transposed convolution → BatchNorm → ReLU

Figure source

Image-to-image translation

- Generator architecture: U-Net

Effect of adding skip connections to the generator

Image-to-image translation

- 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

Image-to-image translation

- Generator loss: GAN loss plus L1 reconstruction penalty

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

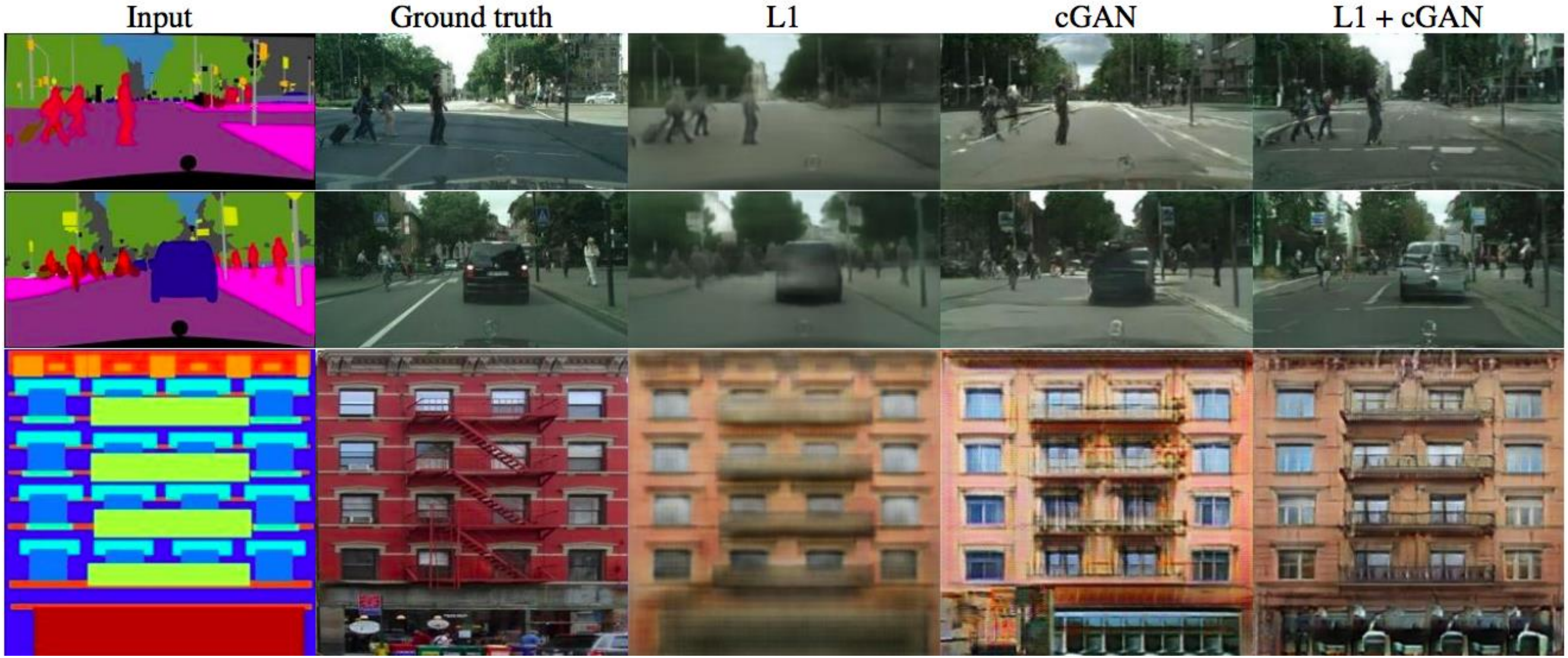


Image-to-image translation

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

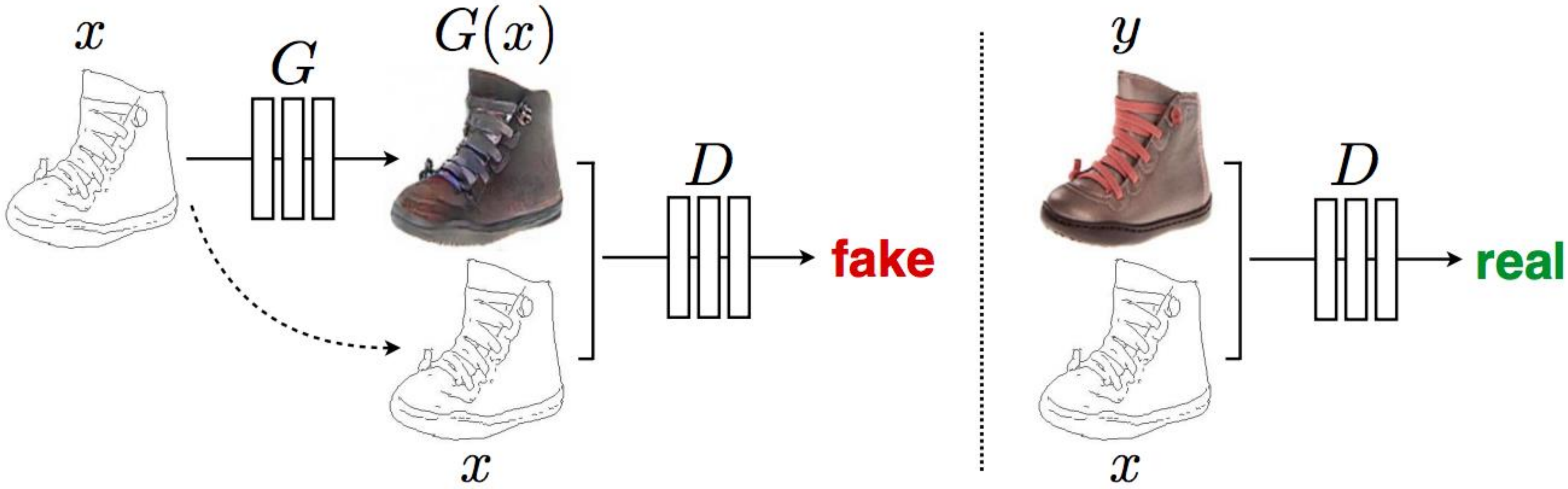


Image-to-image translation

- Discriminator: PatchGAN
  - Given input image x and second image y, decide whether y is a ground truth target or produced by the generator
  - Output is a 30 x 30 map where each value (0 to 1) represents the quality of the corresponding section of the output image, these values are averaged to obtain final discriminator loss
  - Fully convolutional network, effective patch size can be increased by increasing the depth

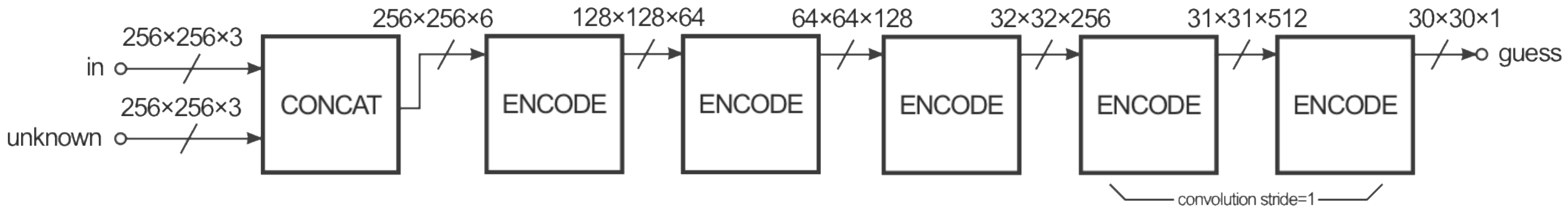


Figure source

Image-to-image translation

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Effect of discriminator patch size on generator output

Image-to-image translation: Results

- Translating between maps and aerial photos

Image-to-image translation: Results

- Translating between maps and aerial photos
- Human study:

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

Image-to-image translation: Results

- Semantic labels to scenes

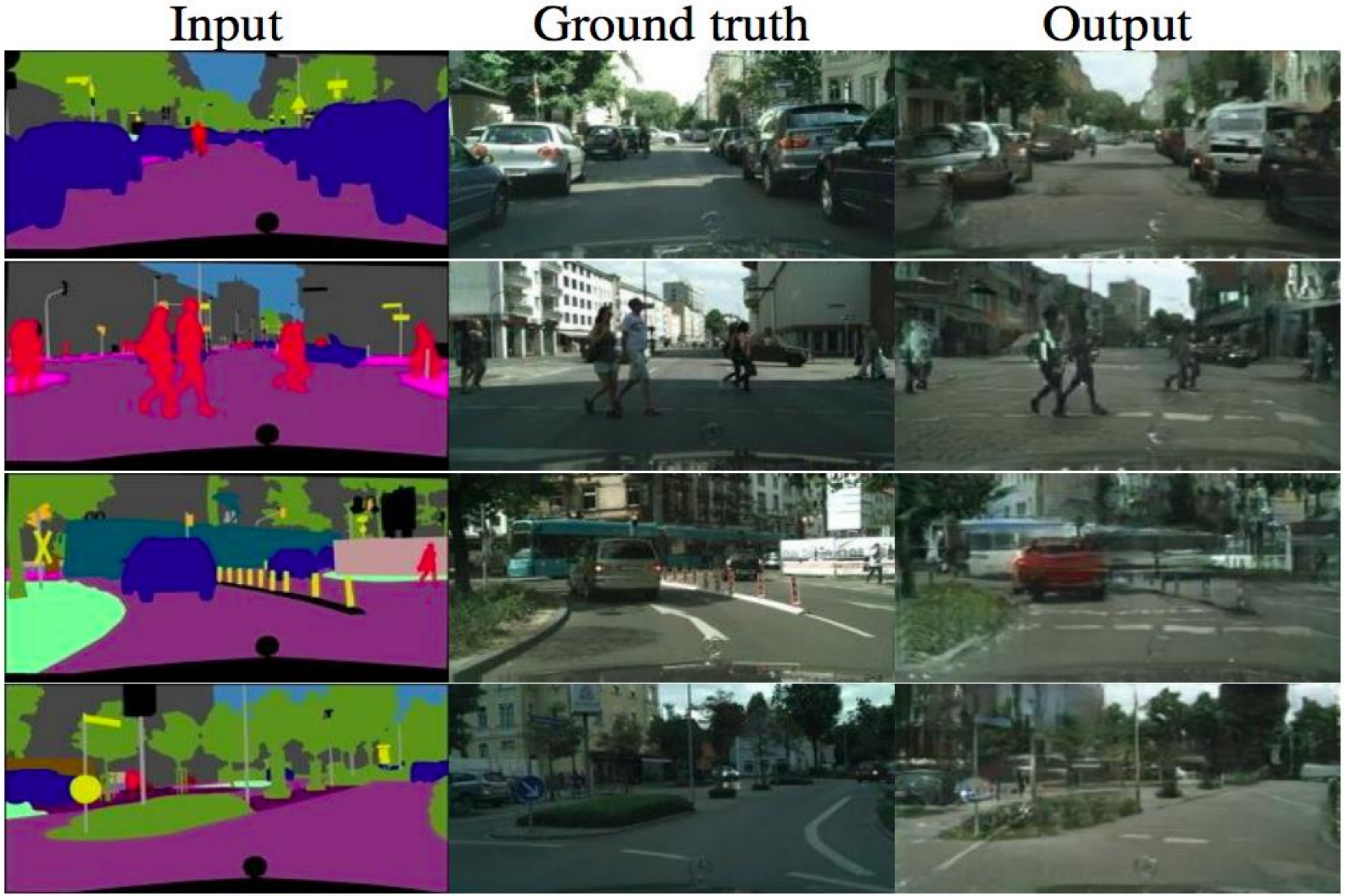


Image-to-image translation: Results

FCN — Fully Convolutional Network

- 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

Image-to-image translation: Results

- Scenes to semantic labels

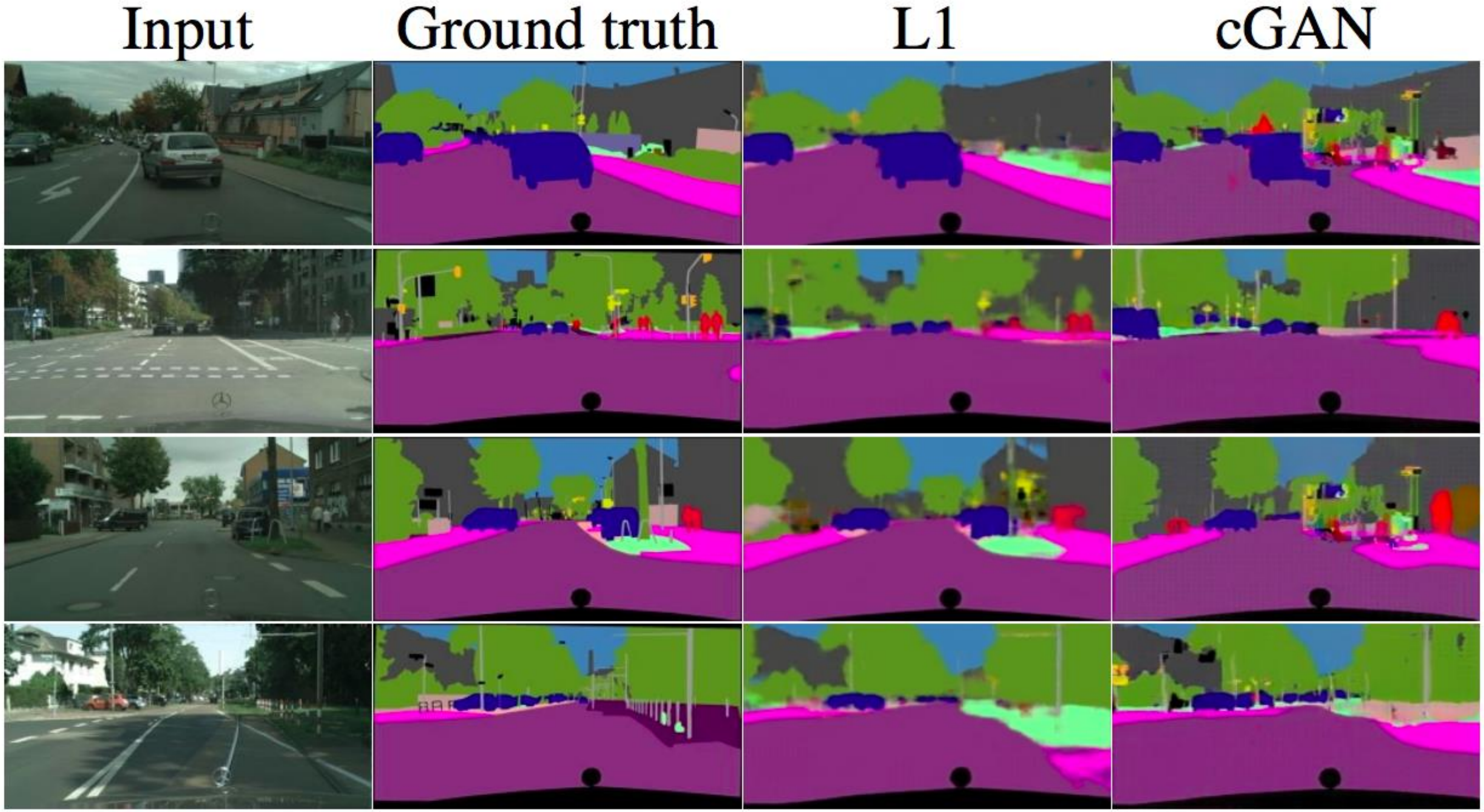


Image-to-image translation: Results

- 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

Image-to-image translation: Results

- Semantic labels to facades

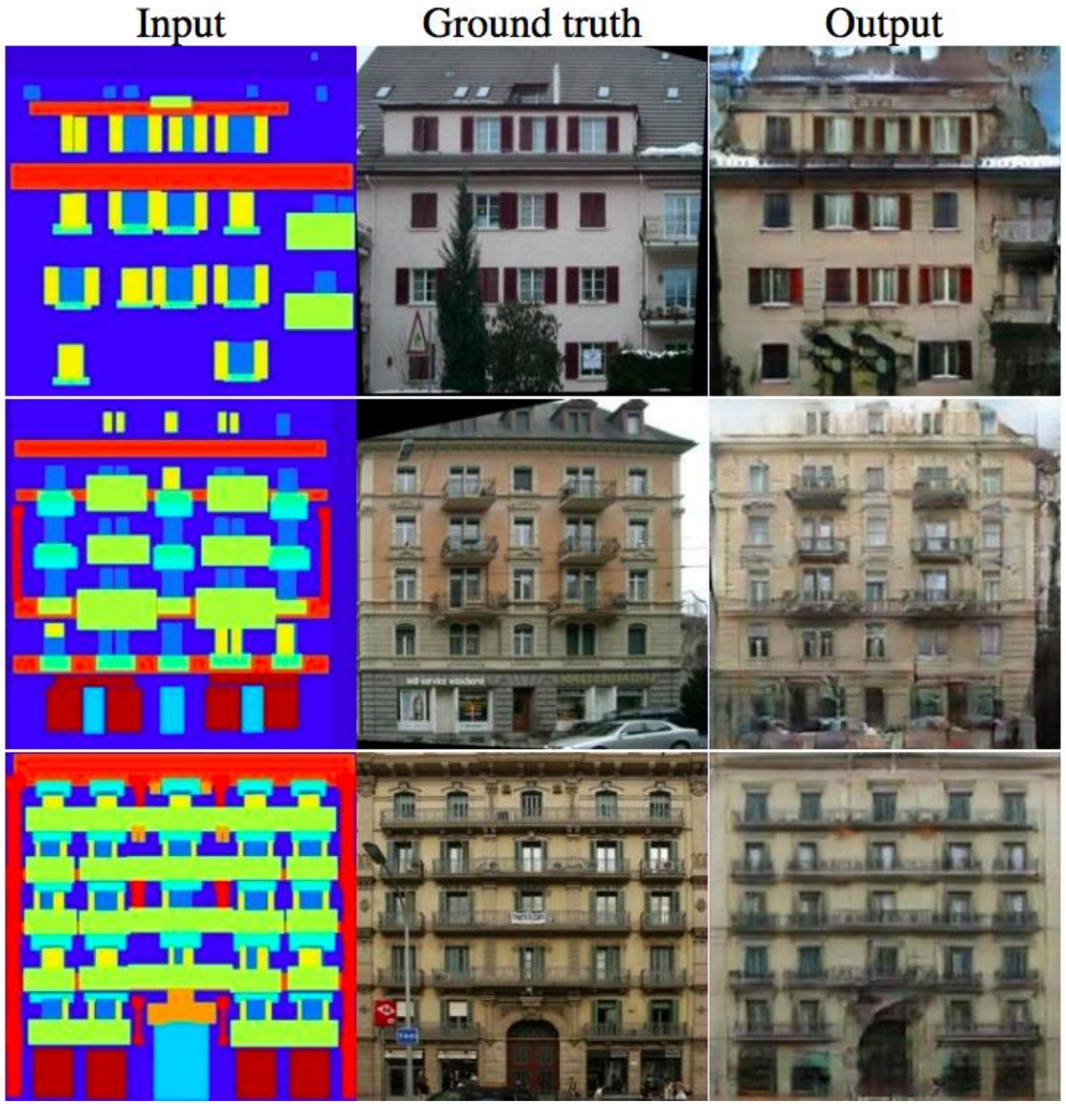


Image-to-image translation: Results

- Day to night

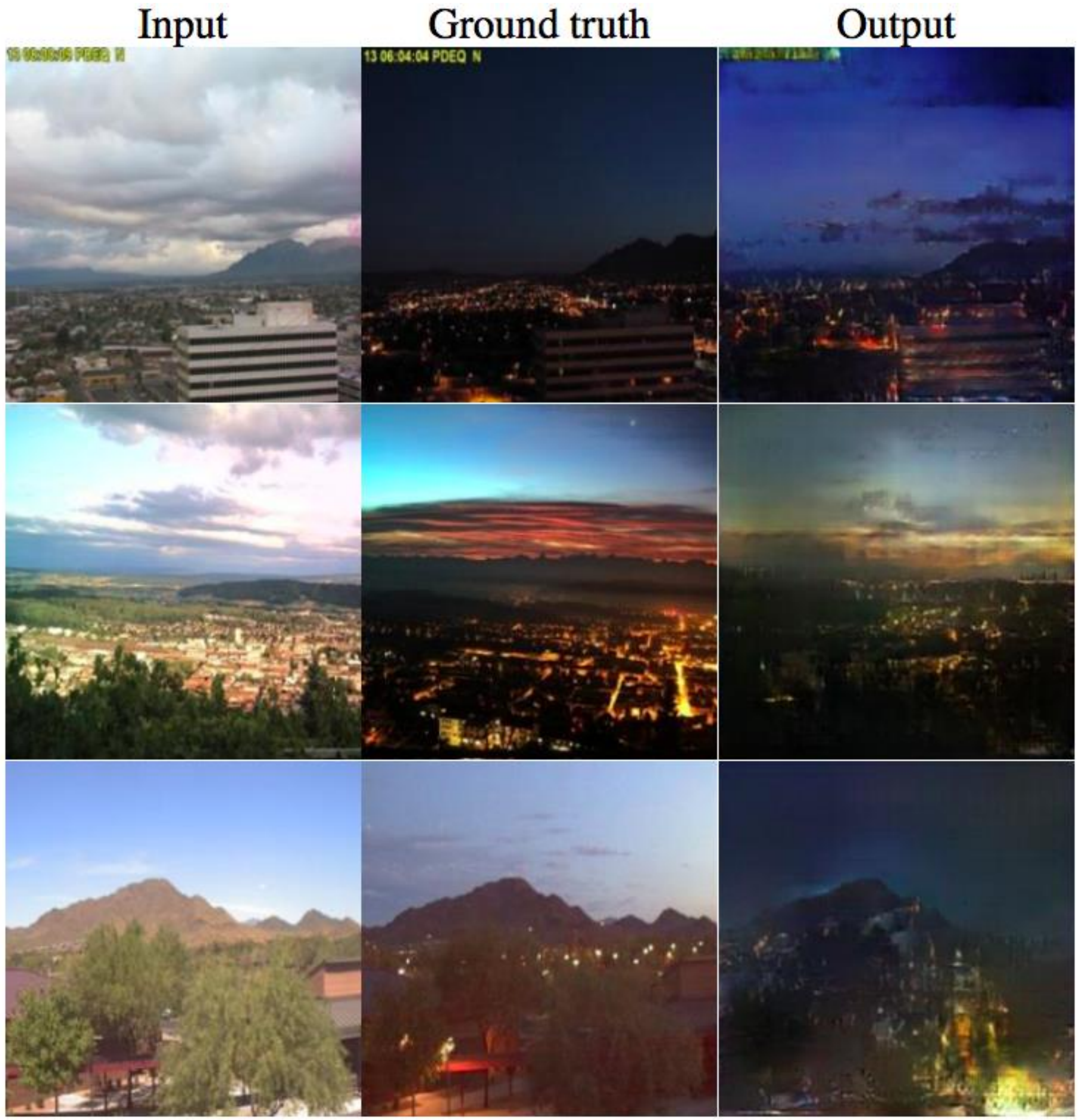


Image-to-image translation: Results

- Edges to photos

Image-to-image translation: Results

- pix2pix demo

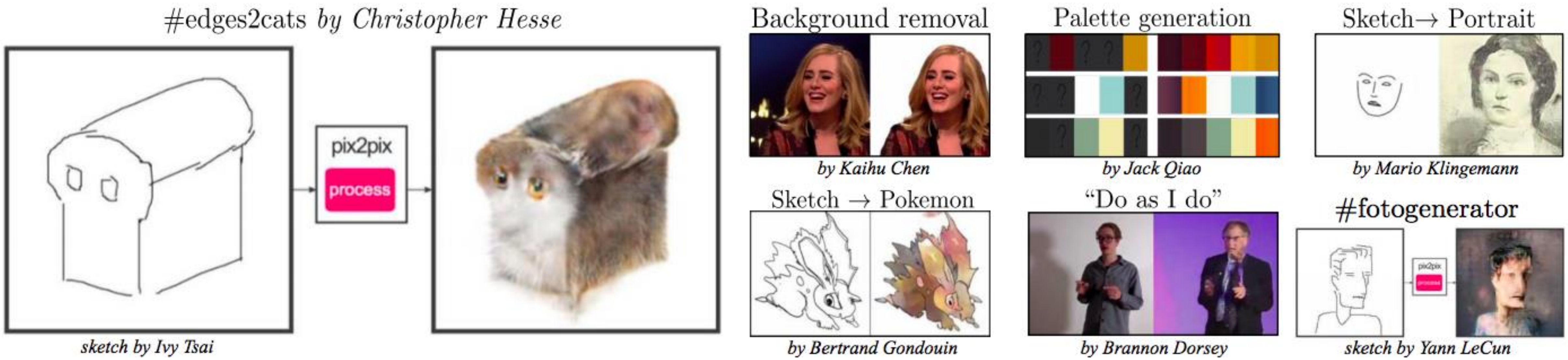
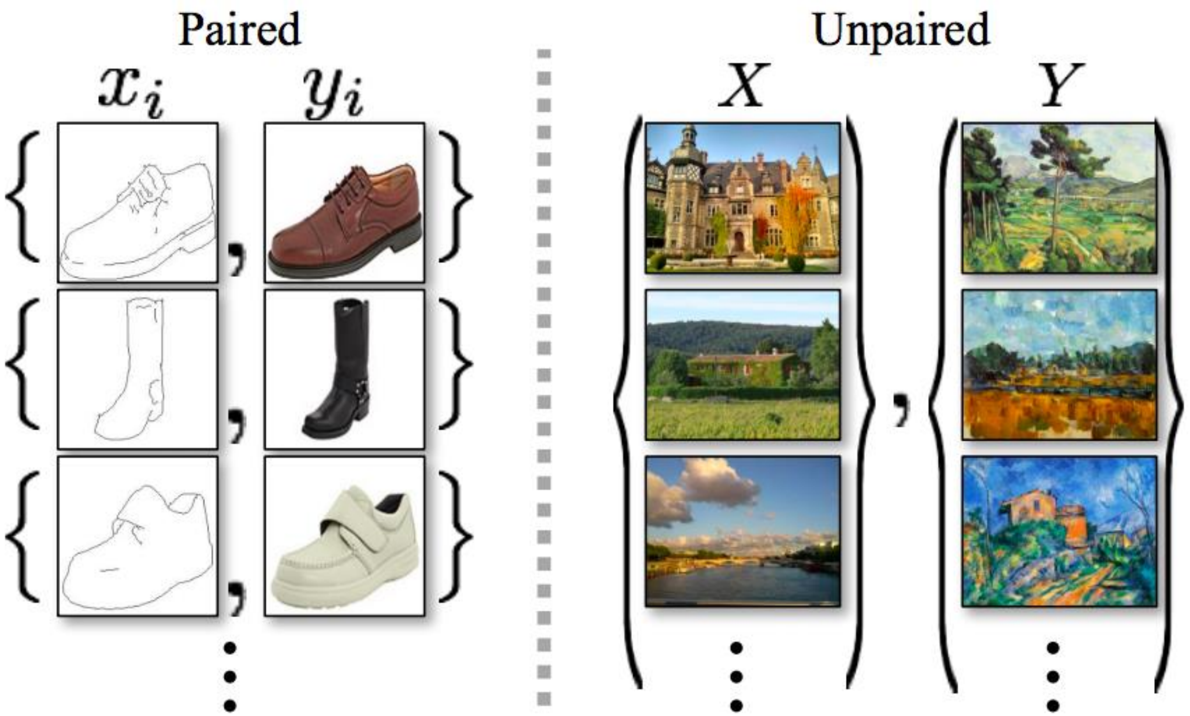


Image-to-image translation: Limitations

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

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

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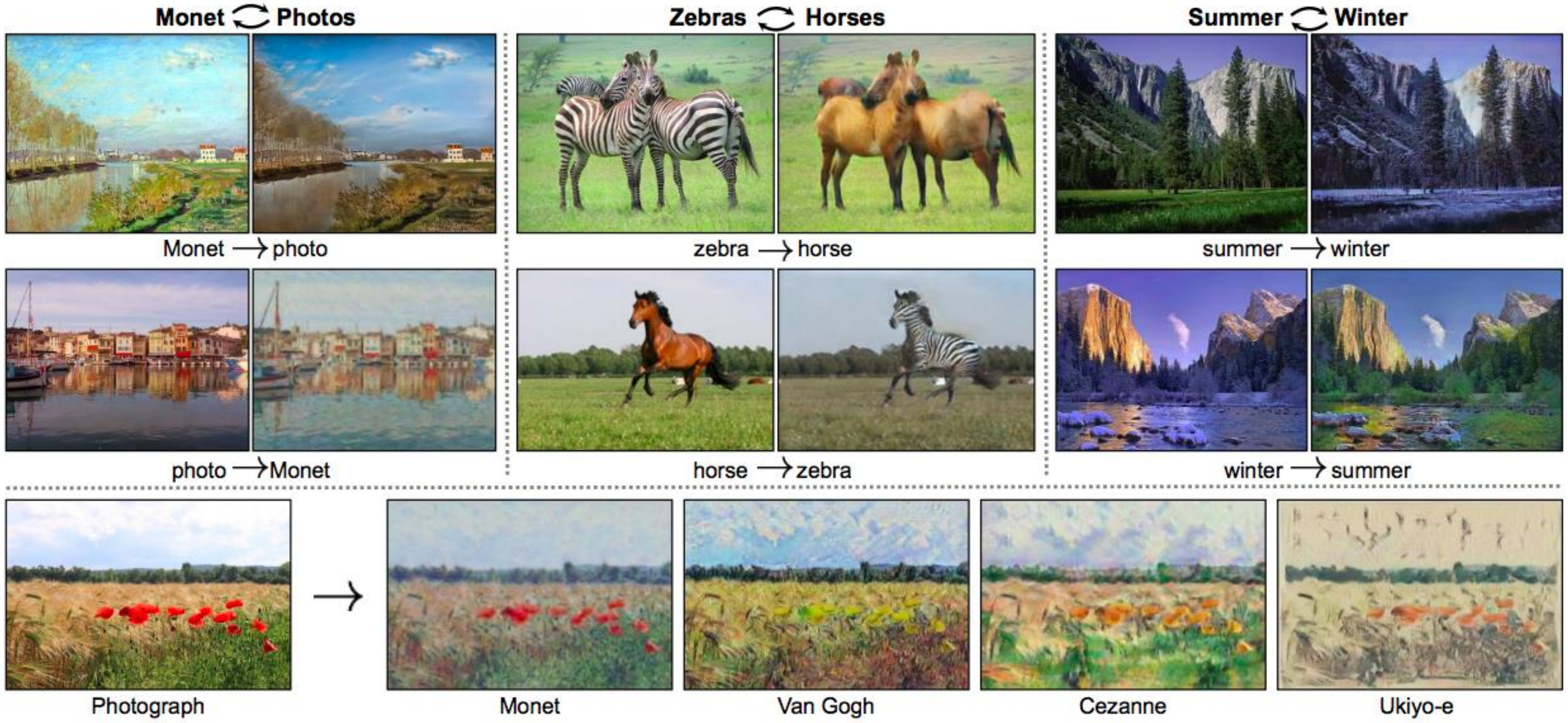
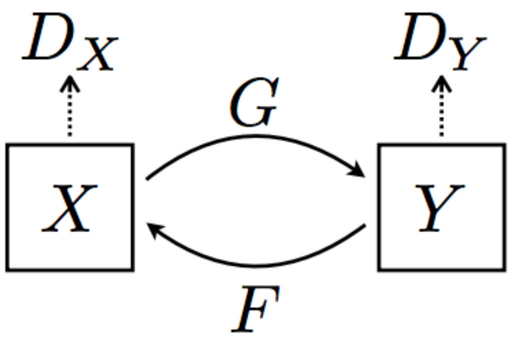


J.-Y. Zhu, T. Park, P. Isola, A. Efros, Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks, ICCV 2017

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):

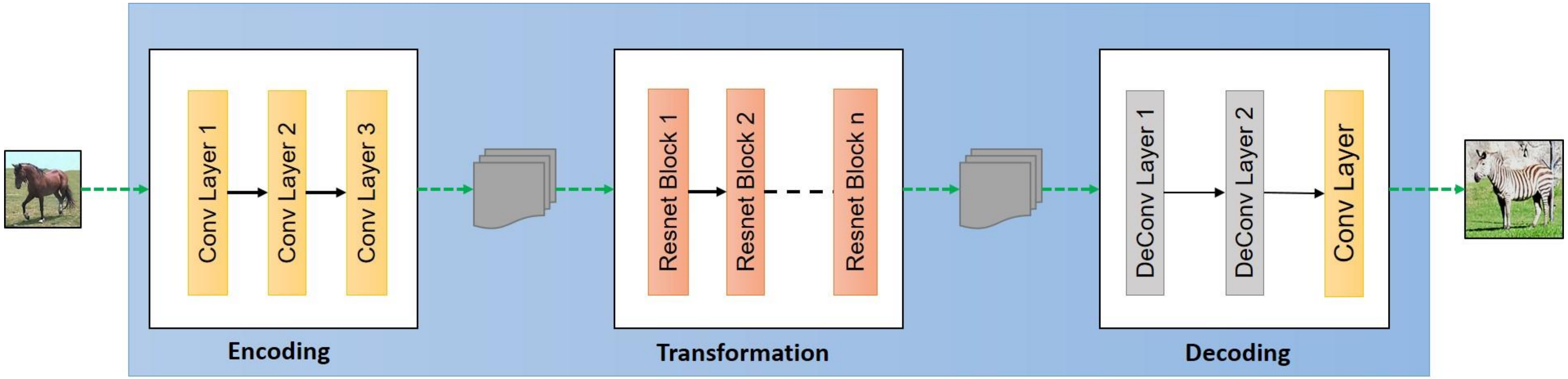


Figure source

- 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

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

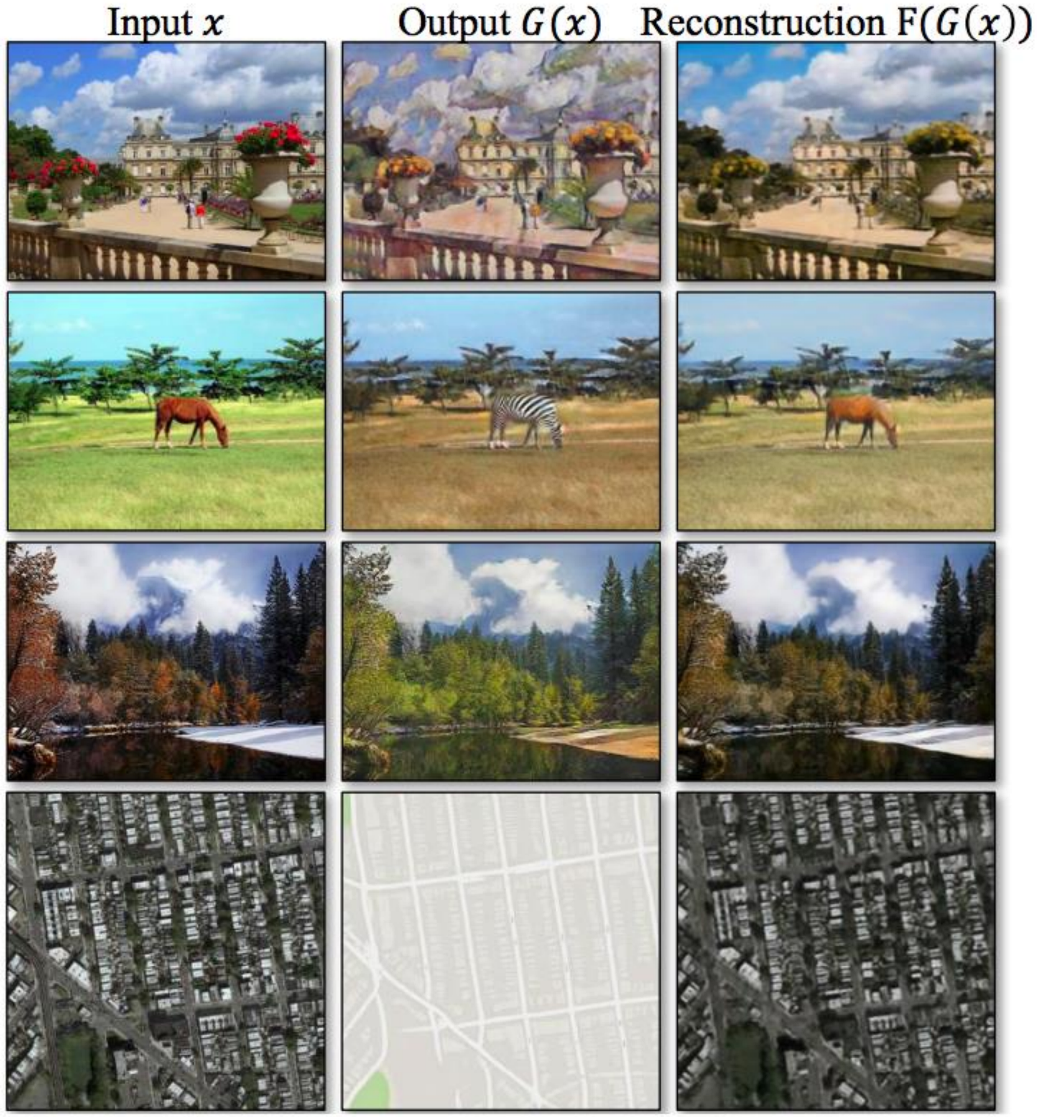
$$\mathcal{L}_{\text{GAN}}(D_X) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[(D_X(x)-1)^2] + \mathbb{E}_{y\sim p_{\text{data}}(y)}\left[D_X\left(F(y)\right)^2\right]$$

- CycleGAN generator loss:

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

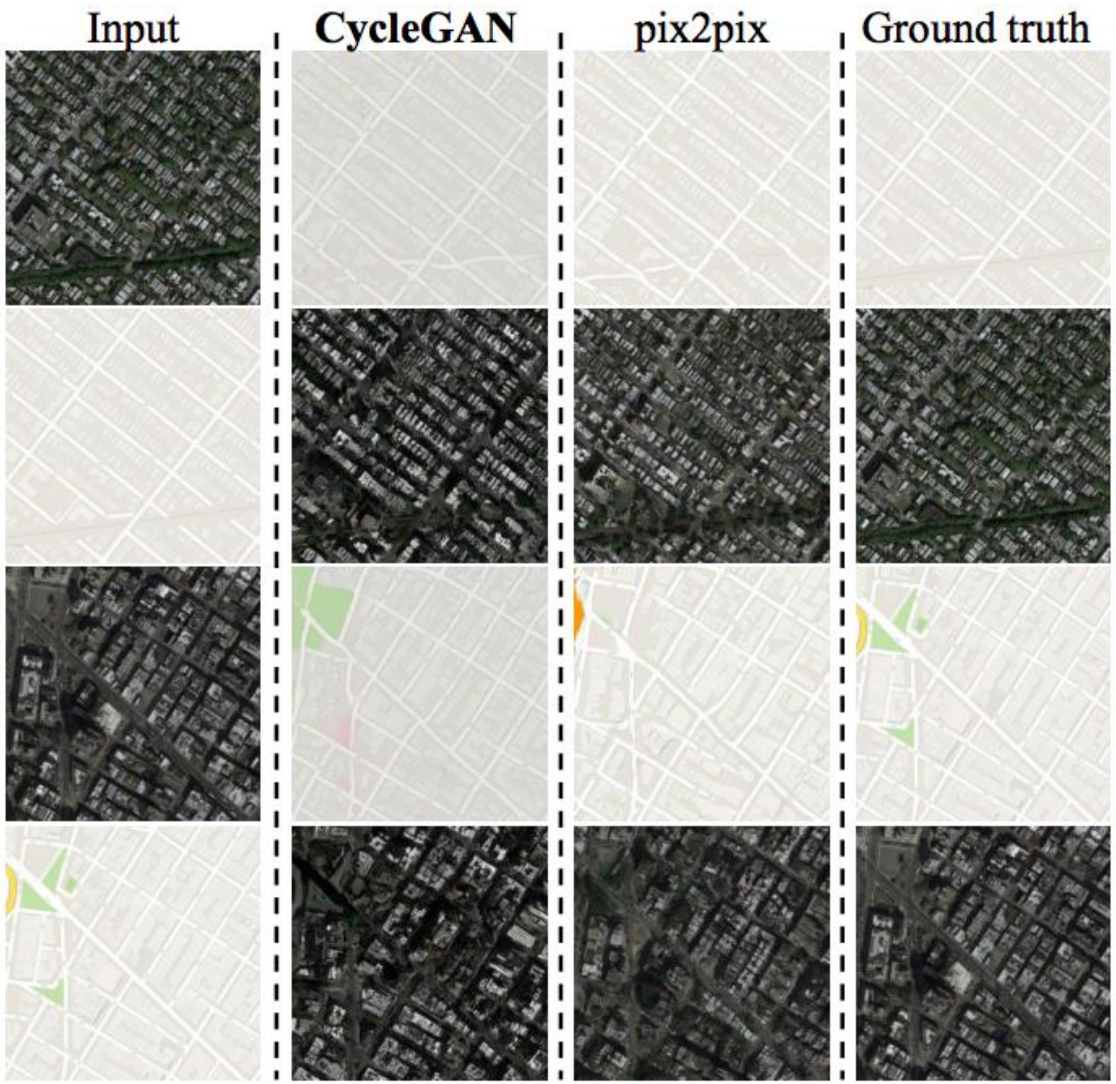
CycleGAN

- Illustration of cycle consistency:



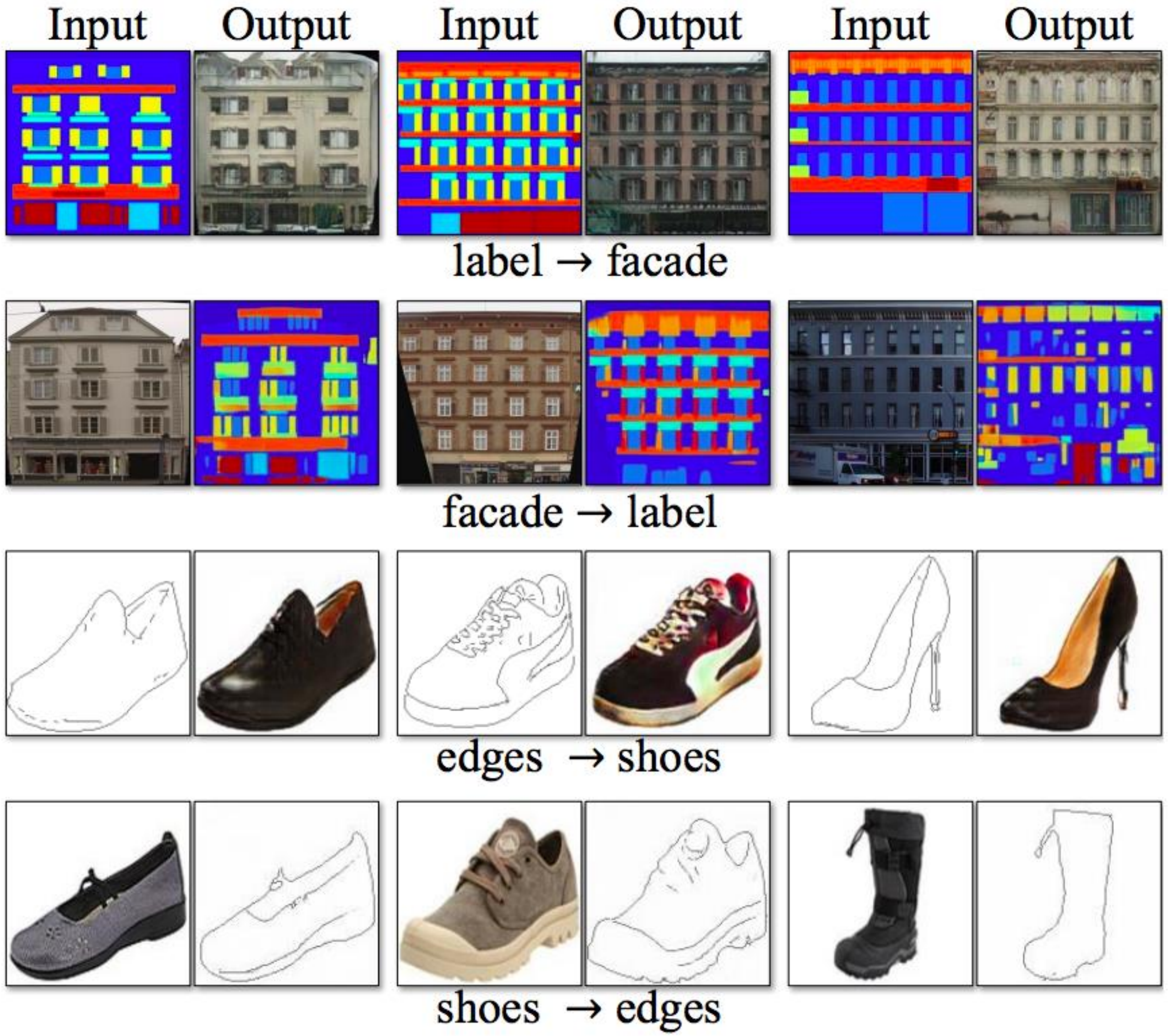
CycleGAN: Results

- 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

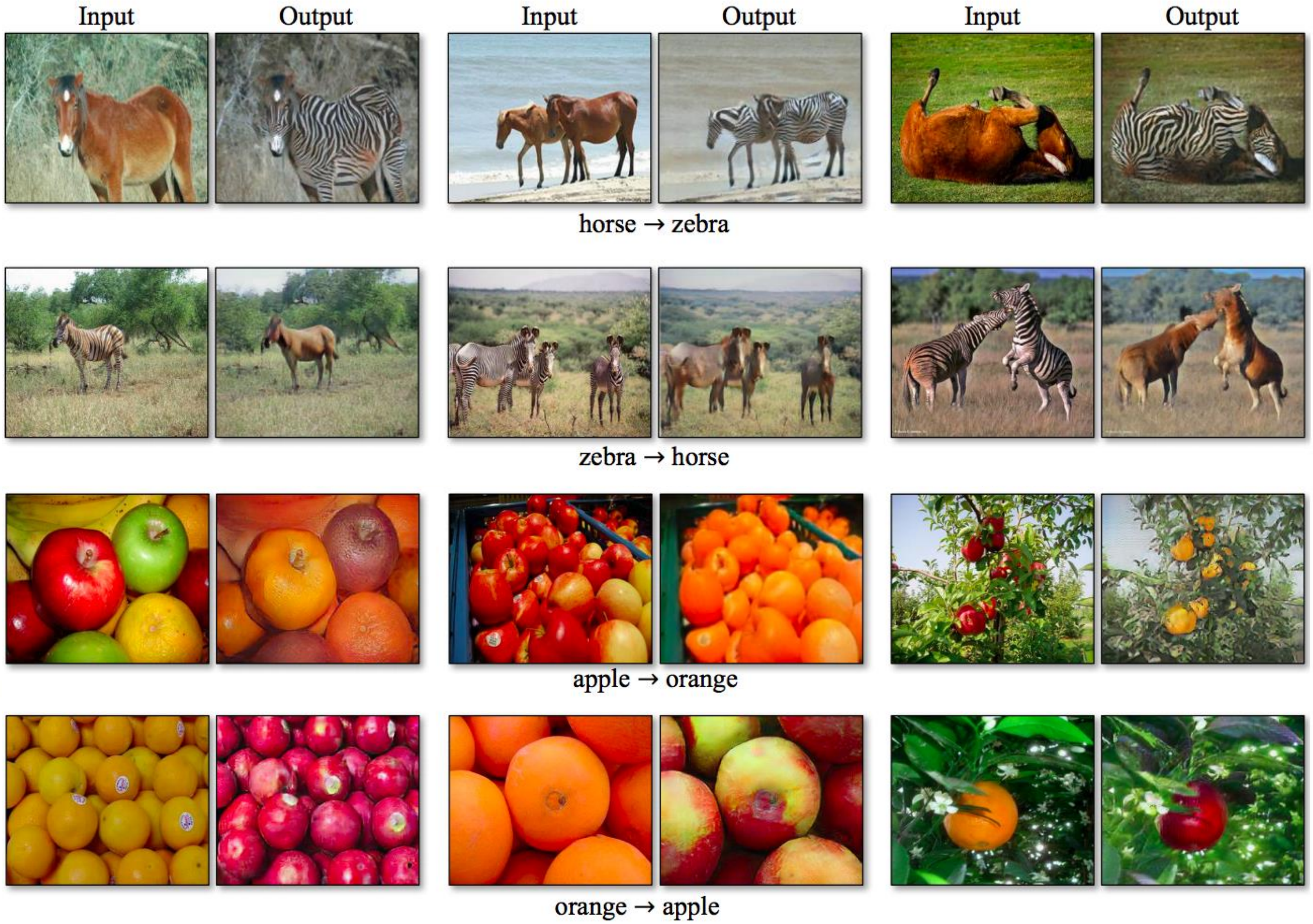
Table 2: FCN-scores for different methods, evaluated on Cityscapes labels→photo.

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.

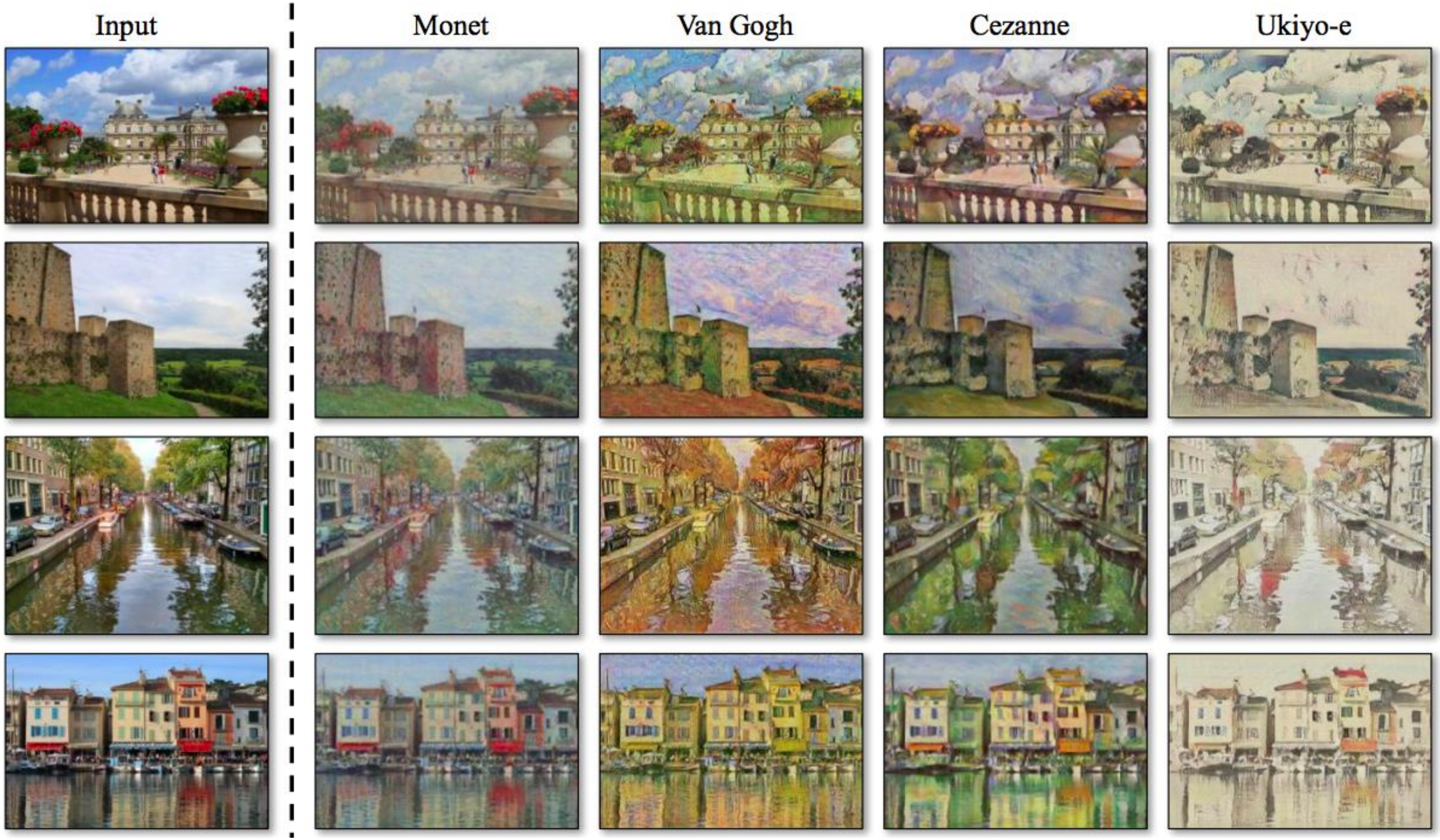
CycleGAN: Results

- Tasks for which paired data is unavailable

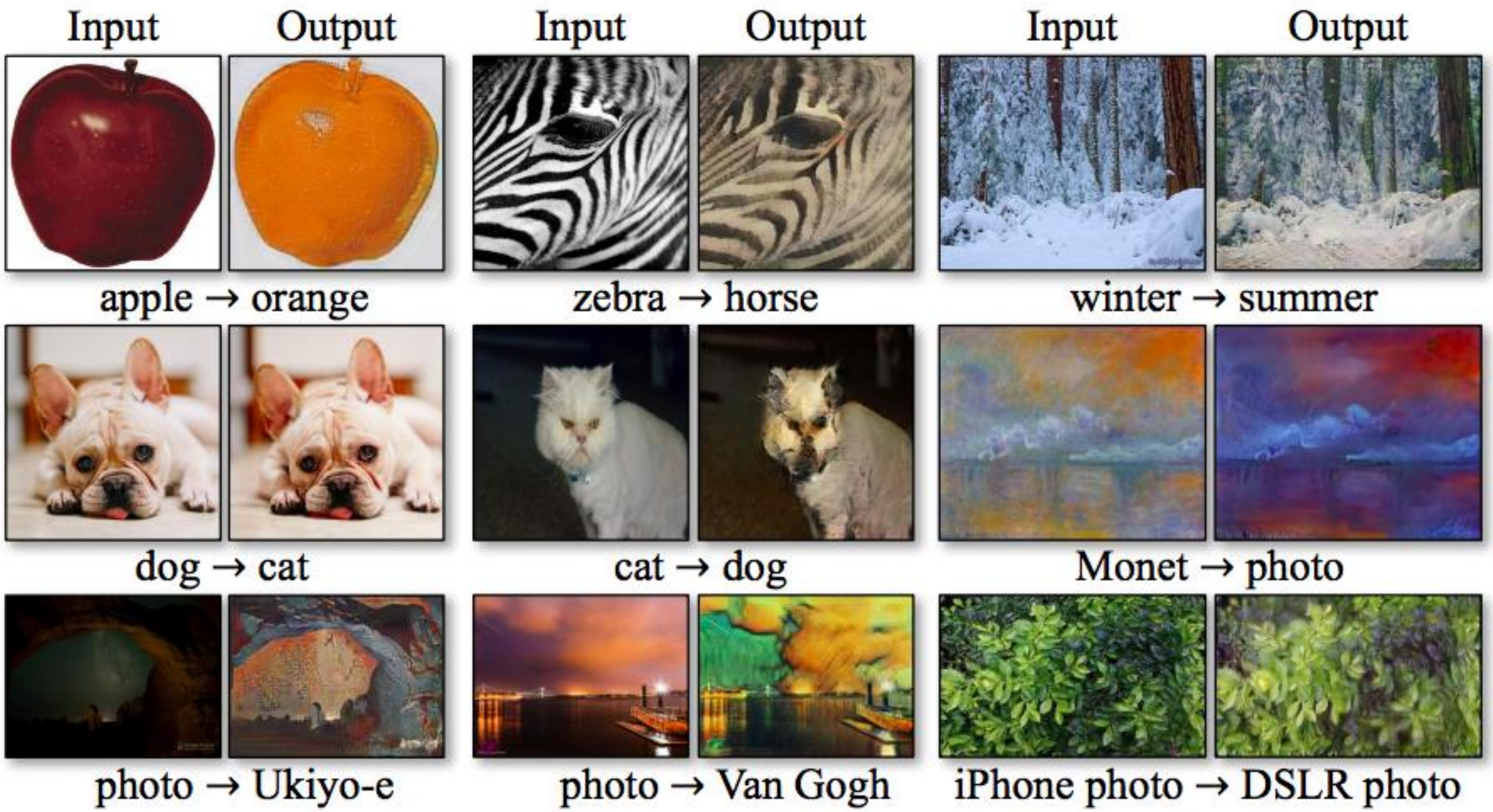


CycleGAN: Results

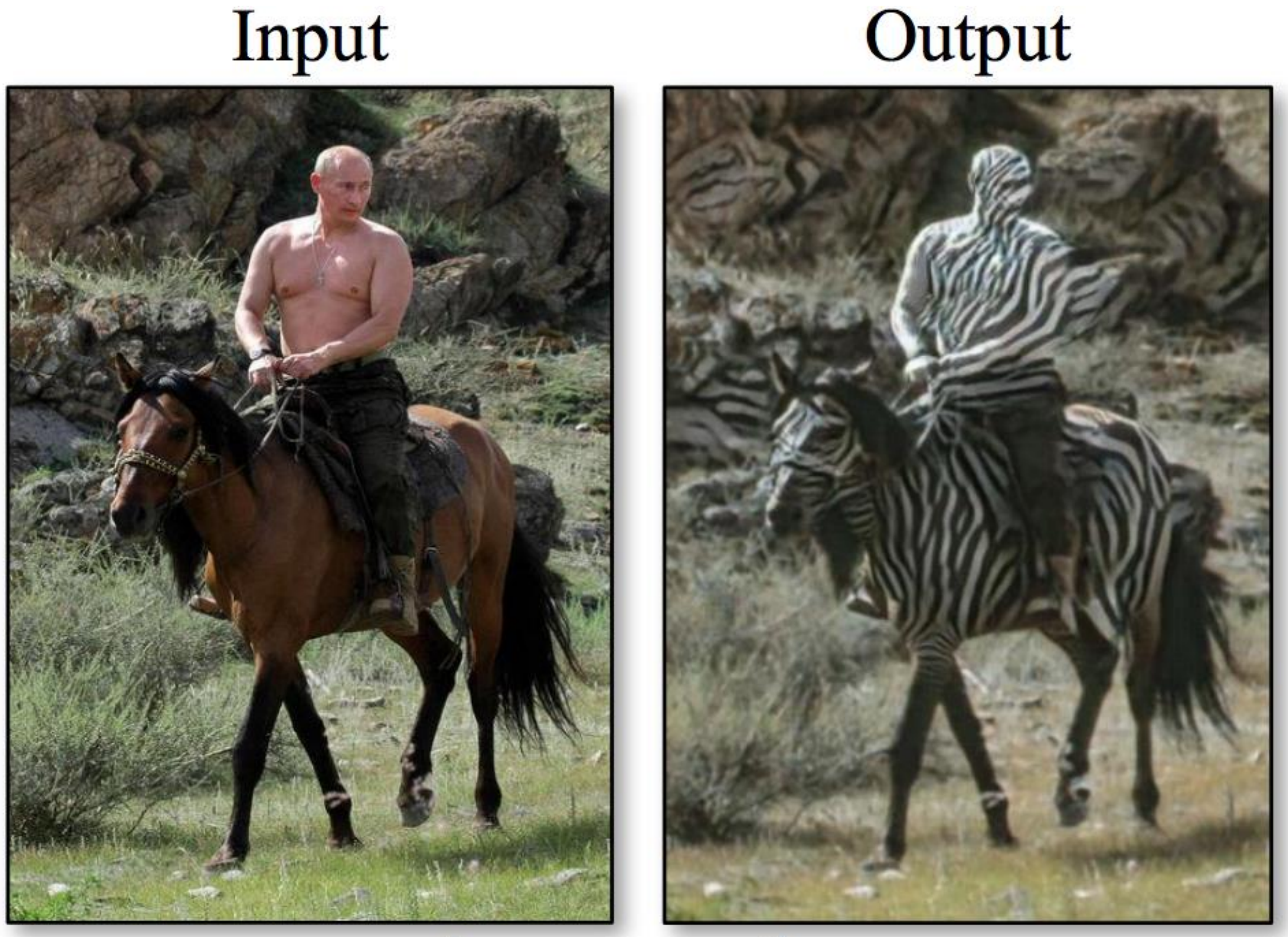
- Style transfer



CycleGAN: Failure cases



CycleGAN: Failure cases



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

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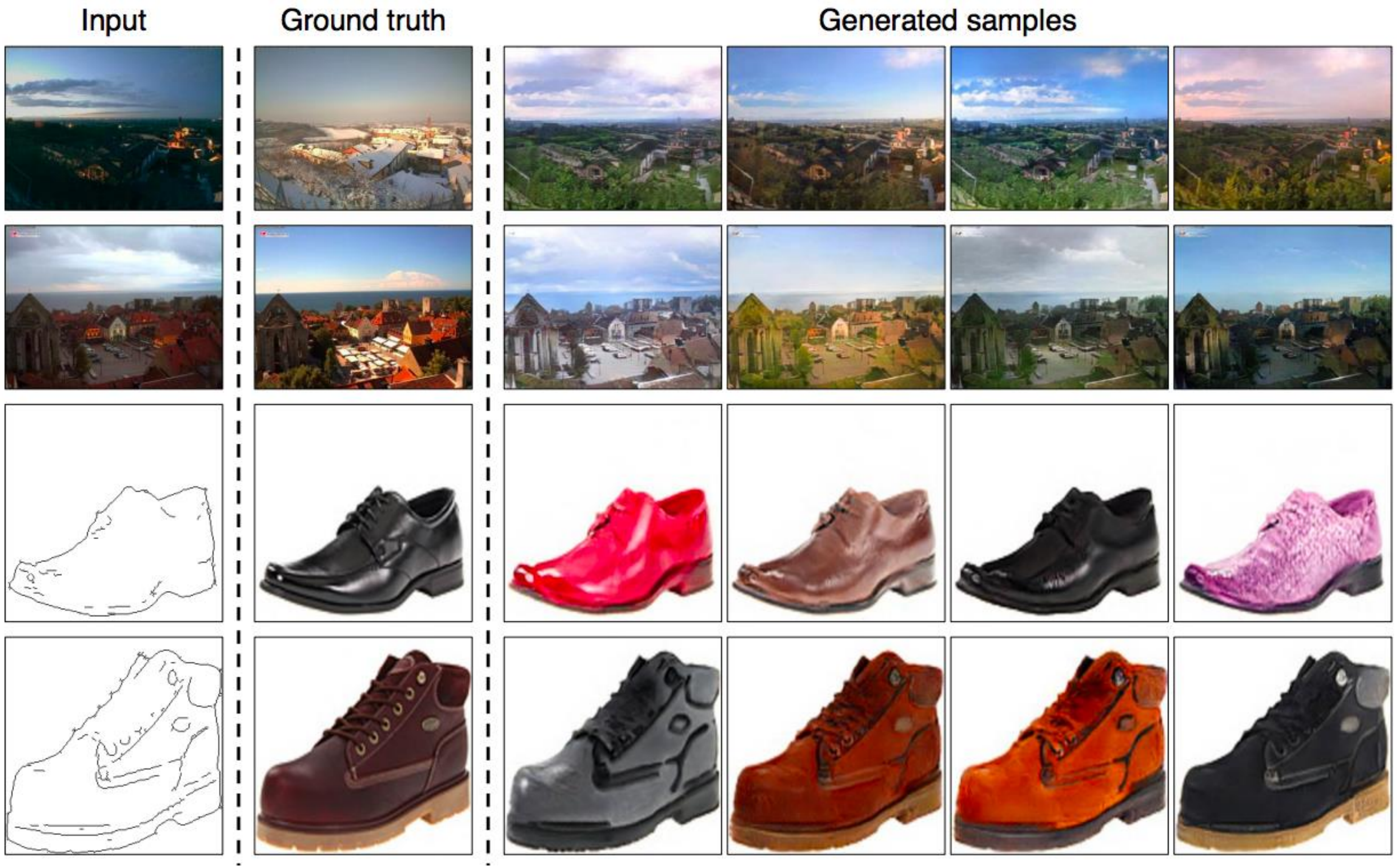
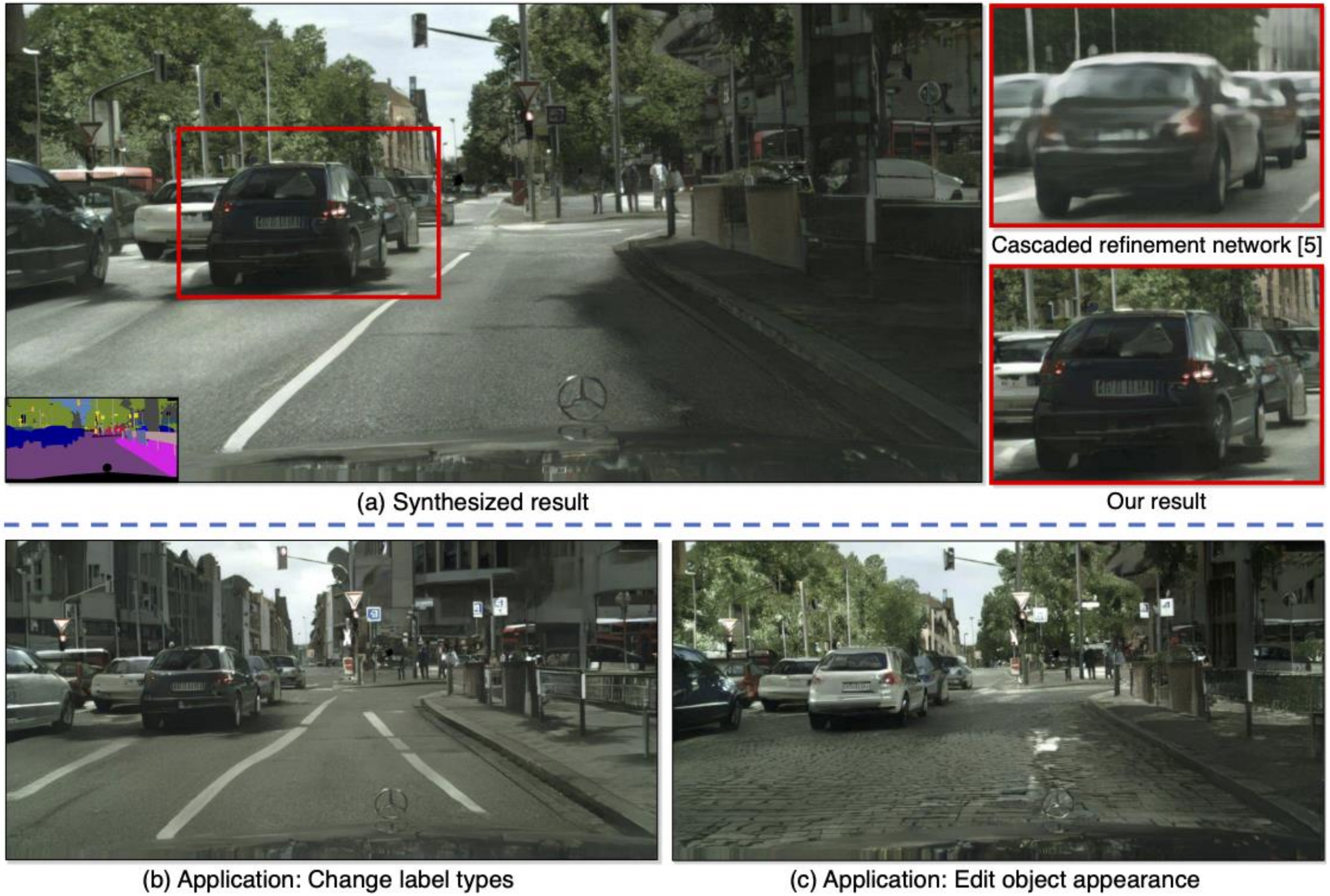
- Generation conditioned on image
  - Paired image-to-image translation: pix2pix
  - Unpaired image-to-image translation: CycleGAN
- Some recent highlights

Multimodal image-to-image translation (BicycleGAN)



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

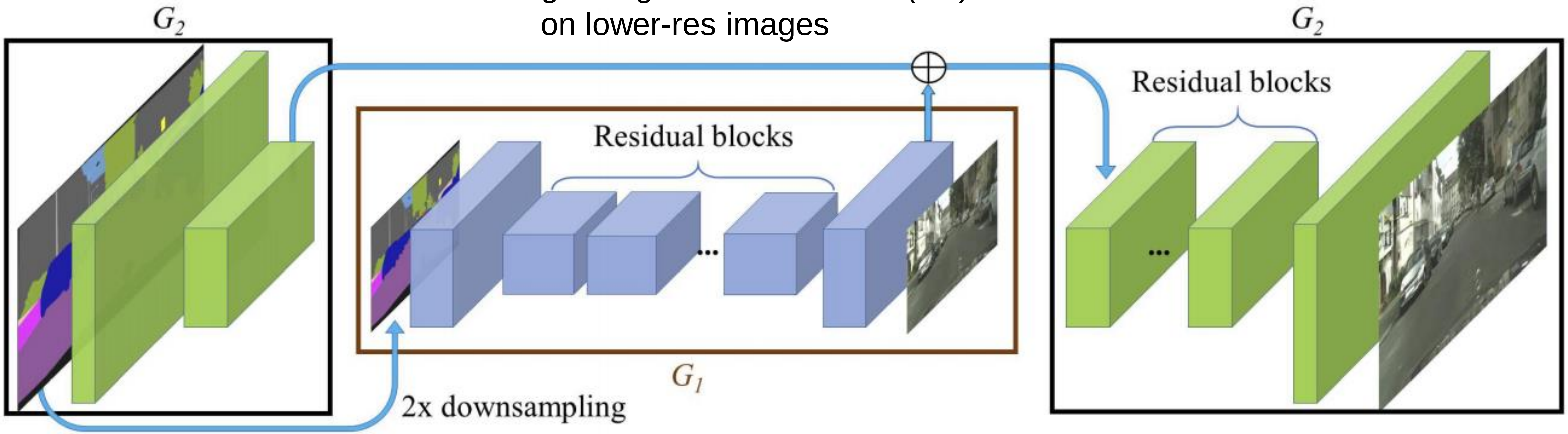


T.-C. Wang et al., [High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs](), CVPR 2018

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



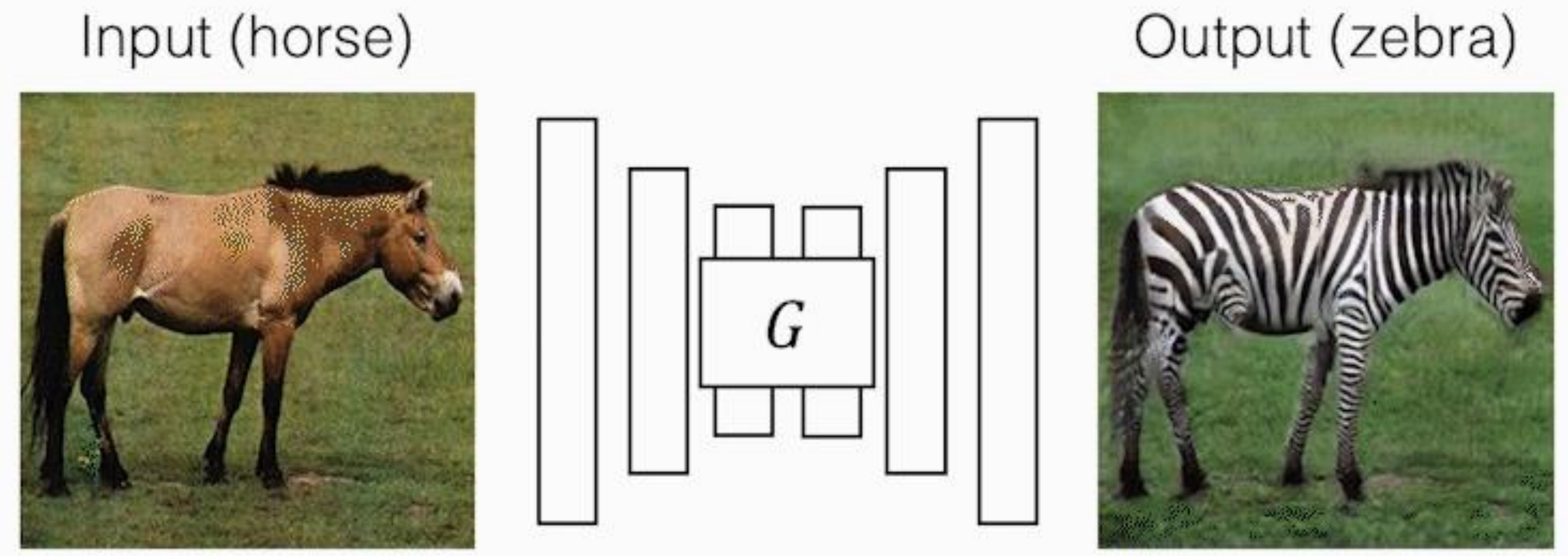
Then append higher-res *enhancer network* (G2) blocks and train G1 and G2 jointly

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

High-resolution, high-quality pix2pix

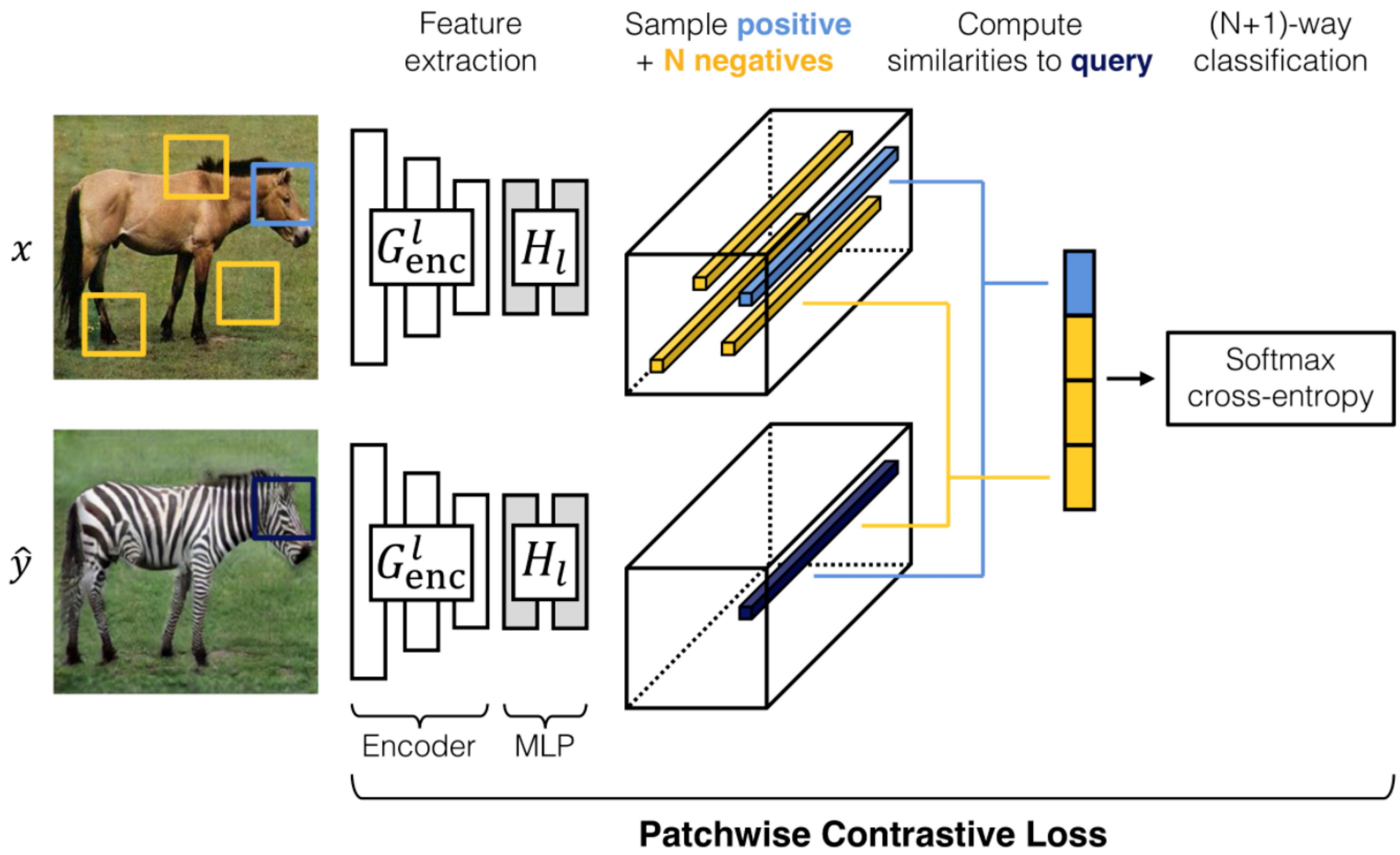
- Two-scale generator architecture (up to 2048 x 1024 resolution)
- Three-scale discriminator architecture (full res, 2x and 4x downsampled)
- Incorporate feature matching loss into discriminator

Contrastive Learning for Unpaired Translation (CUT)



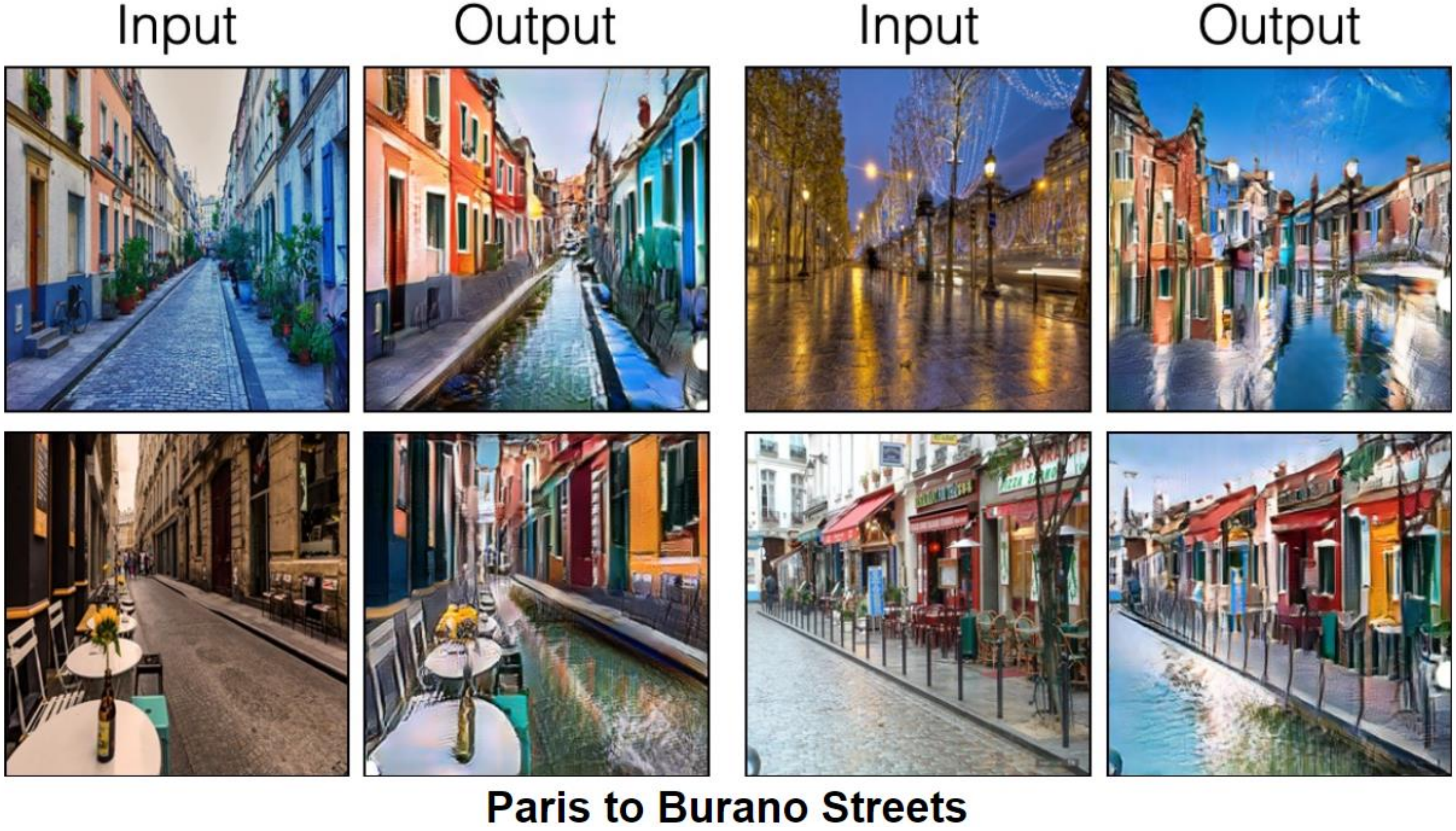
Contrastive Learning for Unpaired Image-to-Image Translation. ECCV 2020

Contrastive Learning for Unpaired Translation (CUT)



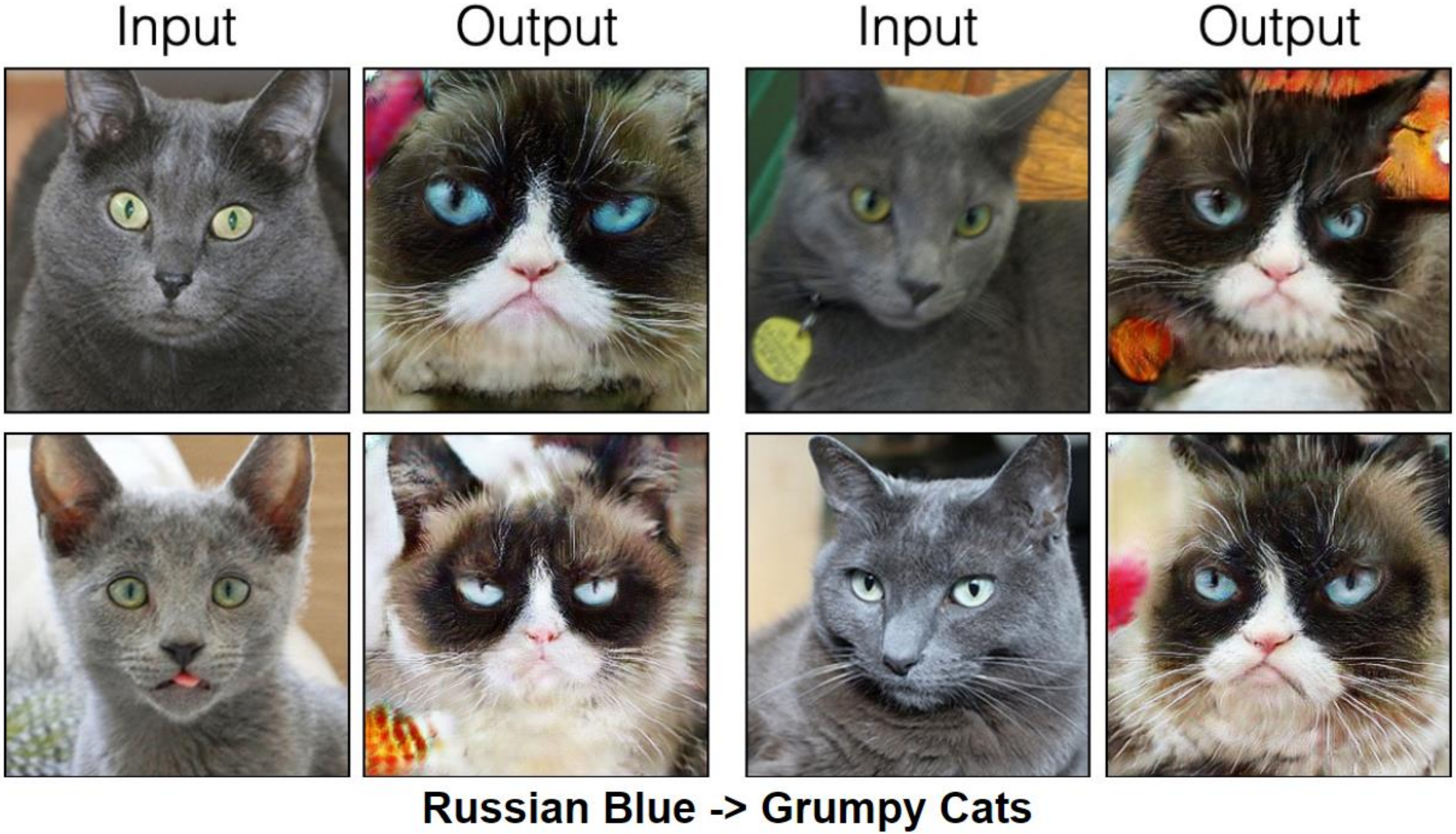
Contrastive Learning for Unpaired Image-to-Image Translation. ECCV 2020

Contrastive Learning for Unpaired Translation (CUT)



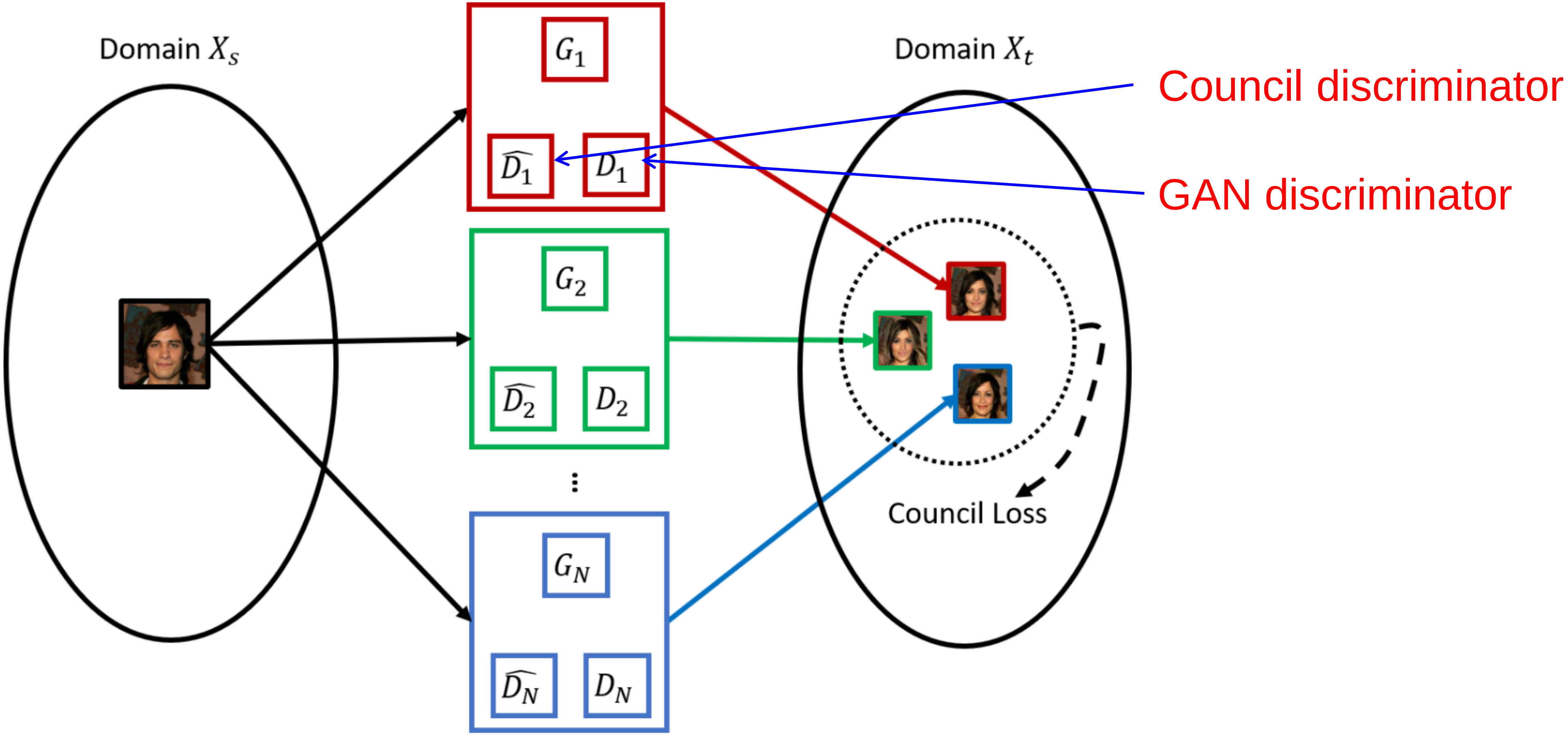
Contrastive Learning for Unpaired Image-to-Image Translation. ECCV 2020

Contrastive Learning for Unpaired Translation (CUT)



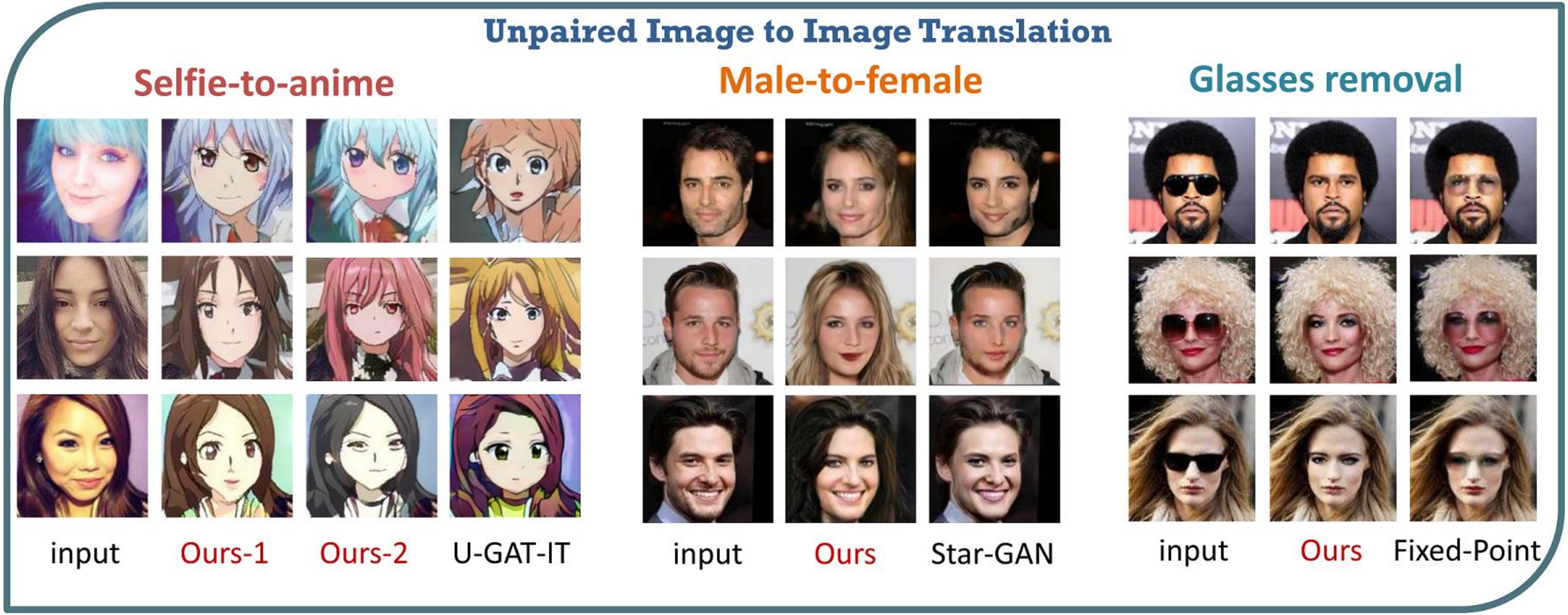
Contrastive Learning for Unpaired Image-to-Image Translation. ECCV 2020

Council-GAN



Breaking the Cycle - Colleagues are all you need. CVPR 2020

Council-GAN



Breaking the Cycle - Colleagues are all you need. CVPR 2020

“The GAN Zoo”

- 3D-ED-GAN - Shape Inpainting using 3D Generative Adversarial Network and Recurrent Convolutional Networks
- 3D-GAN - Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling (github)
- 3D-IWGAN - Improved Adversarial Systems for 3D Object Generation and Reconstruction (github)
- 3D-RecGAN - 3D Object Reconstruction from a Single Depth View with Adversarial Learning (github)
- ABC-GAN - ABC-GAN: Adaptive Blur and Control for improved training stability of Generative Adversarial Networks (github)
- ABC-GAN - GANs for LIFE: Generative Adversarial Networks for Likelihood Free Inference
- AC-GAN - Conditional Image Synthesis With Auxiliary Classifier GANs
- acGAN - Face Aging With Conditional Generative Adversarial Networks
- ACtuAL - ACtuAL: Actor-Critic Under Adversarial Learning
- AdaGAN - AdaGAN: Boosting Generative Models
- AdvGAN - Generating adversarial examples with adversarial networks
- AE-GAN - AE-GAN: adversarial eliminating with GAN
- AEGAN - Learning Inverse Mapping by Autoencoder based Generative Adversarial Nets
- AffGAN - Amortised MAP Inference for Image Super-resolution
- AL-CGAN - Learning to Generate Images of Outdoor Scenes from Attributes and Semantic Layouts
- ALI - Adversarially Learned Inference (github)
- AlignGAN - AlignGAN: Learning to Align Cross-Domain Images with Conditional Generative Adversarial Networks
- AM-GAN - Activation Maximization Generative Adversarial Nets
- AnoGAN - Unsupervised Anomaly Detection with Generative Adversarial Networks to Guide Marker Discovery
- APE-GAN - APE-GAN: Adversarial Perturbation Elimination with GAN
- ARAE - Adversarially Regularized Autoencoders for Generating Discrete Structures (github)
- ARDA - Adversarial Representation Learning for Domain Adaptation
- ARIGAN - ARIGAN: Synthetic Arabidopsis Plants using Generative Adversarial Network
- ArtGAN - ArtGAN: Artwork Synthesis with Conditional Categorial GANs
- AttGAN - Arbitrary Facial Attribute Editing: Only Change What You Want
- AttnGAN - AttnGAN: Fine-Grained Text to Image Generation with Attentional Generative Adversarial Networks
- b-GAN - Generative Adversarial Nets from a Density Ratio Estimation Perspective
- Bayesian GAN - Deep and Hierarchical Implicit Models
- Bayesian GAN - Bayesian GAN (github)
- BCGAN - Bayesian Conditional Generative Adverserial Networks
- BCGAN - Bidirectional Conditional Generative Adversarial networks
- BEGAN - BEGAN: Boundary Equilibrium Generative Adversarial Networks
- BGAN - Binary Generative Adversarial Networks for Image Retrieval (github)
- BicycleGAN - Toward Multimodal Image-to-Image Translation (github)
- BiGAN - Adversarial Feature Learning
- BS-GAN - Boundary-Seeking Generative Adversarial Networks
- C-GAN - Face Aging with Contextual Generative Adversarial Nets
- C-RNN-GAN - C-RNN-GAN: Continuous recurrent neural networks with adversarial training (github)
- CA-GAN - Composition-aided Sketch-realistic Portrait Generation
- CaloGAN - CaloGAN: Simulating 3D High Energy Particle Showers in Multi-Layer Electromagnetic Calorimeters with Generative Adversarial Networks (github)
- CAN - CAN: Creative Adversarial Networks, Generating Art by Learning About Styles and Deviating from Style Norms
- CapsuleGAN - CapsuleGAN: Generative Adversarial Capsule Network
- CatGAN - Unsupervised and Semi-supervised Learning with Categorical Generative Adversarial Networks
- CatGAN - CatGAN: Coupled Adversarial Transfer for Domain Generation
- CausalGAN - CausalGAN: Learning Causal Implicit Generative Models with Adversarial Training
- CC-GAN - Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks (github)
- CDcGAN - Simultaneously Color-Depth Super-Resolution with Conditional Generative Adversarial Network
- CFG-GAN - Composite Functional Gradient Learning of Generative Adversarial Models
- CGAN - Conditional Generative Adversarial Nets
- CGAN - Controllable Generative Adversarial Network
- Chekhov GAN - An Online Learning Approach to Generative Adversarial Networks
- CipherGAN - Unsupervised Cipher Cracking Using Discrete GANs
- CM-GAN - CM-GANs: Cross-modal Generative Adversarial Networks for Common Representation Learning
- CoAtt-GAN - Are You Talking to Me? Reasoned Visual Dialog Generation through Adversarial Learning
- CoGAN - Coupled Generative Adversarial Networks
- ComboGAN - ComboGAN: Unrestrained Scalability for Image Domain Translation (github)

https://github.com/hindupuravinash/the-gan-zoo

“The GAN Zoo”

- ConceptGAN - Learning Compositional Visual Concepts with Mutual Consistency
- Conditional cycleGAN - Conditional CycleGAN for Attribute Guided Face Image Generation
- constrast-GAN - Generative Semantic Manipulation with Contrasting GAN
- Context-RNN-GAN - Contextual RNN-GANs for Abstract Reasoning Diagram Generation
- Coulomb GAN - Coulomb GANs: Provably Optimal Nash Equilibria via Potential Fields
- Cover-GAN - Generative Steganography with Kerckhoffs' Principle based on Generative Adversarial Networks
- Cramèr GAN - The Cramer Distance as a Solution to Biased Wasserstein Gradients
- Cross-GAN - Crossing Generative Adversarial Networks for Cross-View Person Re-identification
- crVAE-GAN - Channel-Recurrent Variational Autoencoders
- CS-GAN - Improving Neural Machine Translation with Conditional Sequence Generative Adversarial Nets
- CVAE-GAN - CVAE-GAN: Fine-Grained Image Generation through Asymmetric Training
- CycleGAN - Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks (github)
- D-GAN - Differential Generative Adversarial Networks: Synthesizing Non-linear Facial Variations with Limited Numl Training Data
- D2GAN - Dual Discriminator Generative Adversarial Nets
- DA-GAN - DA-GAN: Instance-level Image Translation by Deep Attention Generative Adversarial Networks (with Supplementary Materials)
- DAGAN - Data Augmentation Generative Adversarial Networks
- DAN - Distributional Adversarial Networks
- DCGAN - Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks (githut
- DeblurGAN - DeblurGAN: Blind Motion Deblurring Using Conditional Adversarial Networks (github)
- Defense-GAN - Defense-GAN: Protecting Classifiers Against Adversarial Attacks Using Generative Models
- DeliGAN - DeLiGAN : Generative Adversarial Networks for Diverse and Limited Data (github)
- DF-GAN - Learning Disentangling and Fusing Networks for Face Completion Under Structured Occlusions
- DiscoGAN - Learning to Discover Cross-Domain Relations with Generative Adversarial Networks
- DistanceGAN - One-Sided Unsupervised Domain Mapping
- DM-GAN - Dual Motion GAN for Future-Flow Embedded Video Prediction
- DNA-GAN - DNA-GAN: Learning Disentangled Representations from Multi-Attribute Images
- dp-GAN - Differentially Private Releasing via Deep Generative Model
- DP-GAN - DP-GAN: Diversity-Promoting Generative Adversarial Network for Generating Informative and Diversified Text
- DPGAN - Differentially Private Generative Adversarial Network
- DR-GAN - Representation Learning by Rotating Your Faces
- DRAGAN - How to Train Your DRAGAN (github)
- DRPAN - Discriminative Region Proposal Adversarial Networks for High-Quality Image-to-Image Translation
- DSP-GAN - Depth Structure Preserving Scene Image Generation
- DTN - Unsupervised Cross-Domain Image Generation
- DualGAN - DualGAN: Unsupervised Dual Learning for Image-to-Image Translation
- Dualing GAN - Dualing GANs
- Dynamics Transfer GAN - Dynamics Transfer GAN: Generating Video by Transferring Arbitrary Temporal Dynamics from a Source Video to a Single Target Image
- EBGAN - Energy-based Generative Adversarial Network
- ecGAN - eCommerceGAN : A Generative Adversarial Network for E-commerce
- ED//GAN - Stabilizing Training of Generative Adversarial Networks through Regularization
- EGAN - Enhanced Experience Replay Generation for Efficient Reinforcement Learning
- EnergyWGAN - Energy-relaxed Wassertein GANs (EnergyWGAN): Towards More Stable and High Resolution Image Generation
- ExGAN - Eye In-Painting with Exemplar Generative Adversarial Networks
- ExposureGAN - Exposure: A White-Box Photo Post-Processing Framework (github)
- ExprGAN - ExprGAN: Facial Expression Editing with Controllable Expression Intensity
- f-CLSWGAN - Feature Generating Networks for Zero-Shot Learning
- f-GAN - f-GAN: Training Generative Neural Samplers using Variational Divergence Minimization
- FF-GAN - Towards Large-Pose Face Frontalization in the Wild
- FIGAN - Frame Interpolation with Multi-Scale Deep Loss Functions and Generative Adversarial Networks
- Fila-GAN - Synthesizing Filamentary Structured Images with GANs
- First Order GAN - First Order Generative Adversarial Networks
- Fisher GAN - Fisher GAN
- Flow-GAN - Flow-GAN: Bridging implicit and prescribed learning in generative models
- FSEGAN - Exploring Speech Enhancement with Generative Adversarial Networks for Robust Speech Recognition
- FTGAN - Hierarchical Video Generation from Orthogonal Information: Optical Flow and Texture
- FusedGAN - Semi-supervised FusedGAN for Conditional Image Generation

https://github.com/hindupuravinash/the-gan-zoo

“The GAN Zoo”

- FusionGAN - Learning to Fuse Music Genres with Generative Adversarial Dual Learning
- G2-GAN - Geometry Guided Adversarial Facial Expression Synthesis
- GAGAN - GAGAN: Geometry-Aware Generative Adverserial Networks
- GAMN - Generative Adversarial Mapping Networks
- GAN - Generative Adversarial Networks (github)
- GAN-ATV - A Novel Approach to Artistic Textual Visualization via GAN
- GAN-CLS - Generative Adversarial Text to Image Synthesis (github)
- GAN-RS - Towards Qualitative Advancement of Underwater Machine Vision with Generative Adversarial Networks
- GAN-sep - GANs for Biological Image Synthesis (github)
- GAN-VFS - Generative Adversarial Network-based Synthesis of Visible Faces from Polarimetric Thermal Faces
- GANCS - Deep Generative Adversarial Networks for Compressed Sensing Automates MRI
- GANDI - Guiding the search in continuous state-action spaces by learning an action sampling distribution from off-target samples
- GANG - GANGs: Generative Adversarial Network Games
- GANosaic - GANosaic: Mosaic Creation with Generative Texture Manifolds
- GAP - Context-Aware Generative Adversarial Privacy
- GAWWN - Learning What and Where to Draw (github)
- GC-GAN - Geometry-Contrastive Generative Adversarial Network for Facial Expression Synthesis
- GeneGAN - GeneGAN: Learning Object Transfiguration and Attribute Subspace from Unpaired Data (github)
- GeoGAN - Generating Instance Segmentation Annotation by Geometry-guided GAN
- Geometric GAN - Geometric GAN
- GLCA-GAN - Global and Local Consistent Age Generative Adversarial Networks
- GMAN - Generative Multi-Adversarial Networks
- GMM-GAN - Towards Understanding the Dynamics of Generative Adversarial Networks
- GoGAN - Gang of GANs: Generative Adversarial Networks with Maximum Margin Ranking
- GP-GAN - GP-GAN: Towards Realistic High-Resolution Image Blending (github)
- GP-GAN - GP-GAN: Gender Preserving GAN for Synthesizing Faces from Landmarks
- GPU - A generative adversarial framework for positive-unlabeled classification
- GRAN - Generating images with recurrent adversarial networks (github)

And Many More

https://github.com/hindupuravinash/the-gan-zoo

Acknowledgement

Thanks to the following courses and corresponding researchers for making their teaching/research material online

- Deep Learning, Stanford University
- Introduction to Deep Learning, University of Illinois at Urbana-Champaign
- Introduction to Deep Learning, Carnegie Mellon University
- Convolutional Neural Networks for Visual Recognition, Stanford University
- Natural Language Processing with Deep Learning, Stanford University
- And Many More ......