Image-to-image translation

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Learning and machine perception (LAMP) group
Computer Vision Center (Barcelona)

Outline

- M2CR project framework
- Paired image-to-image translation (pix2pix)
- Unpaired image-to-image translation (cycleGAN)
- Unseen translations (mix&match networks)

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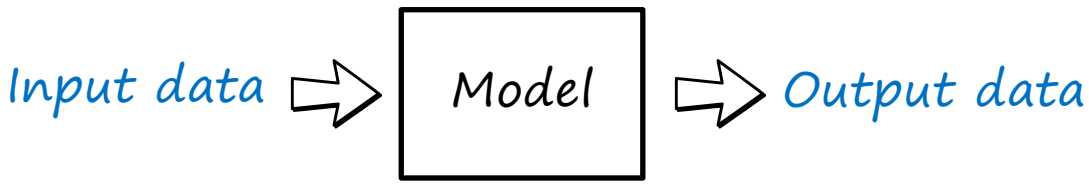
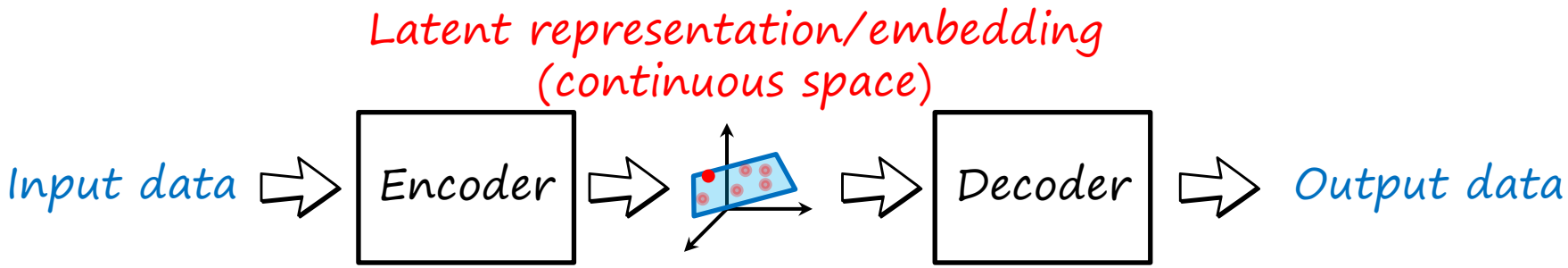
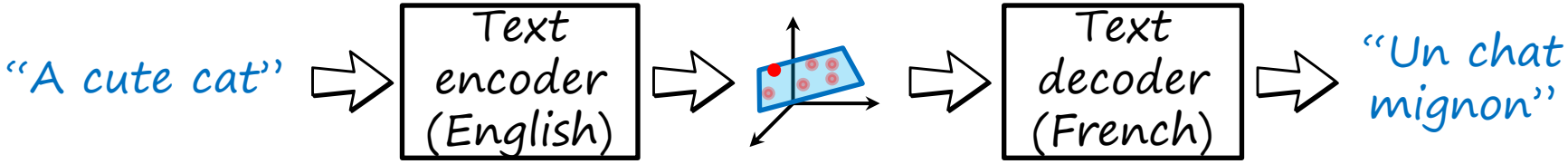
Encoder-decoder framework



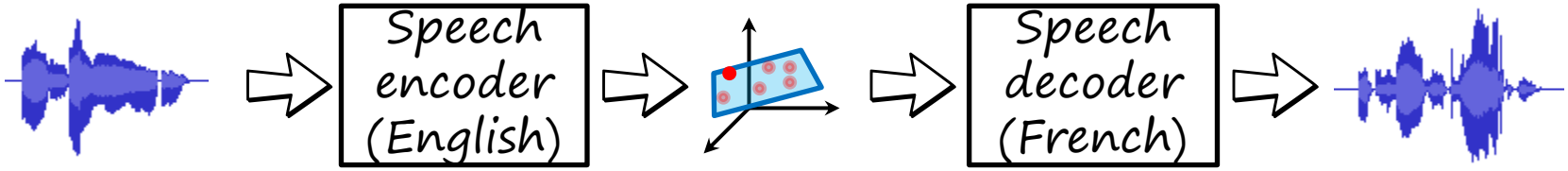


M2CR partners

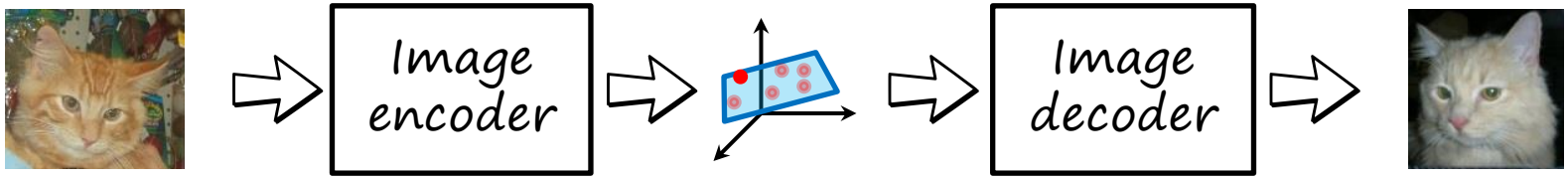
Natural language processing (LIUM- University of Maine)



Speech processing (MILA- University of Montreal)

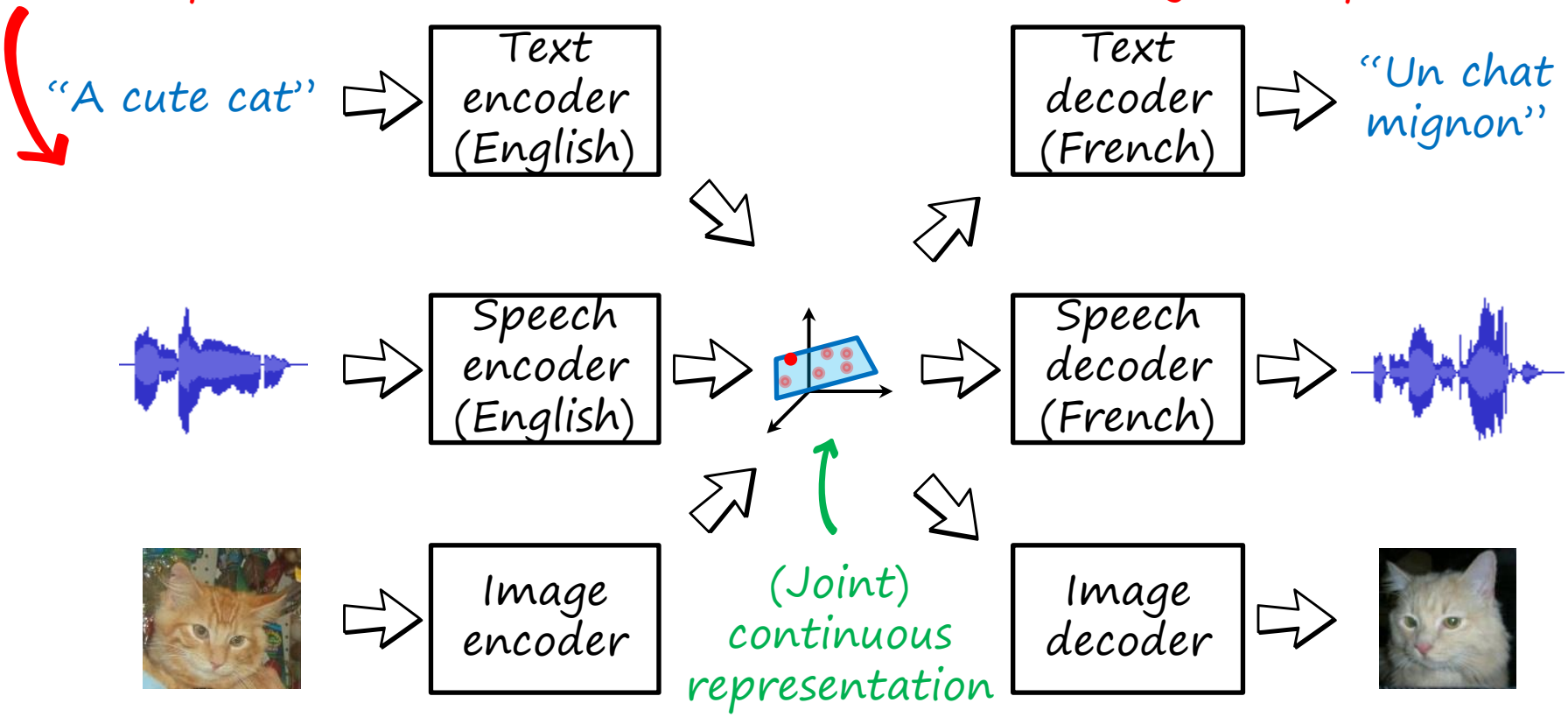


Computer vision (CVC- Autonomous University of Barcelona)

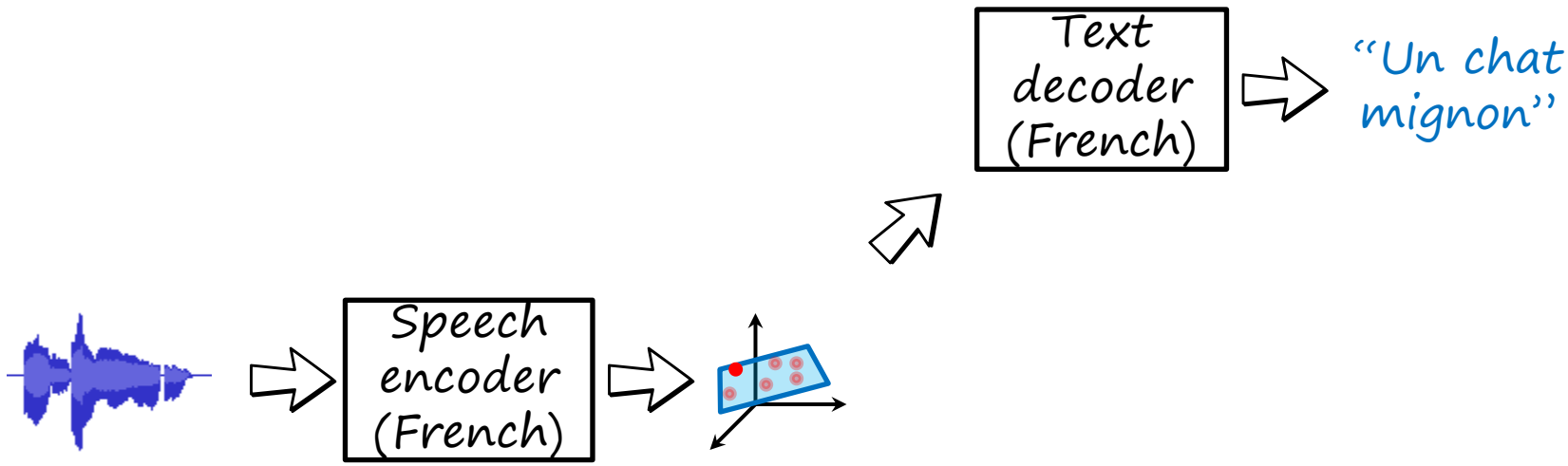


M2CR: multilingual multimodal continuous representations

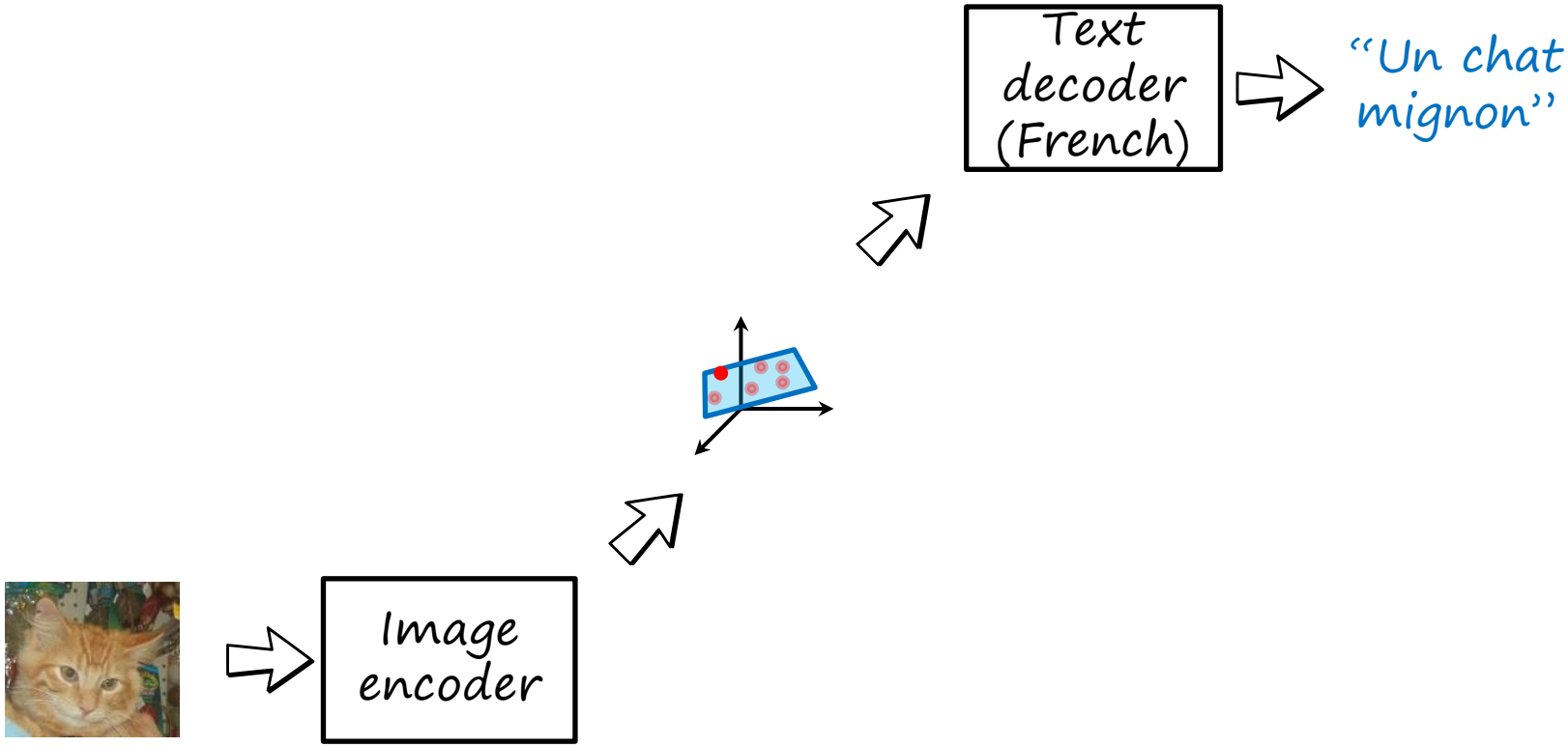
Humans perceive, understand and communicate through multiple ***modalities***



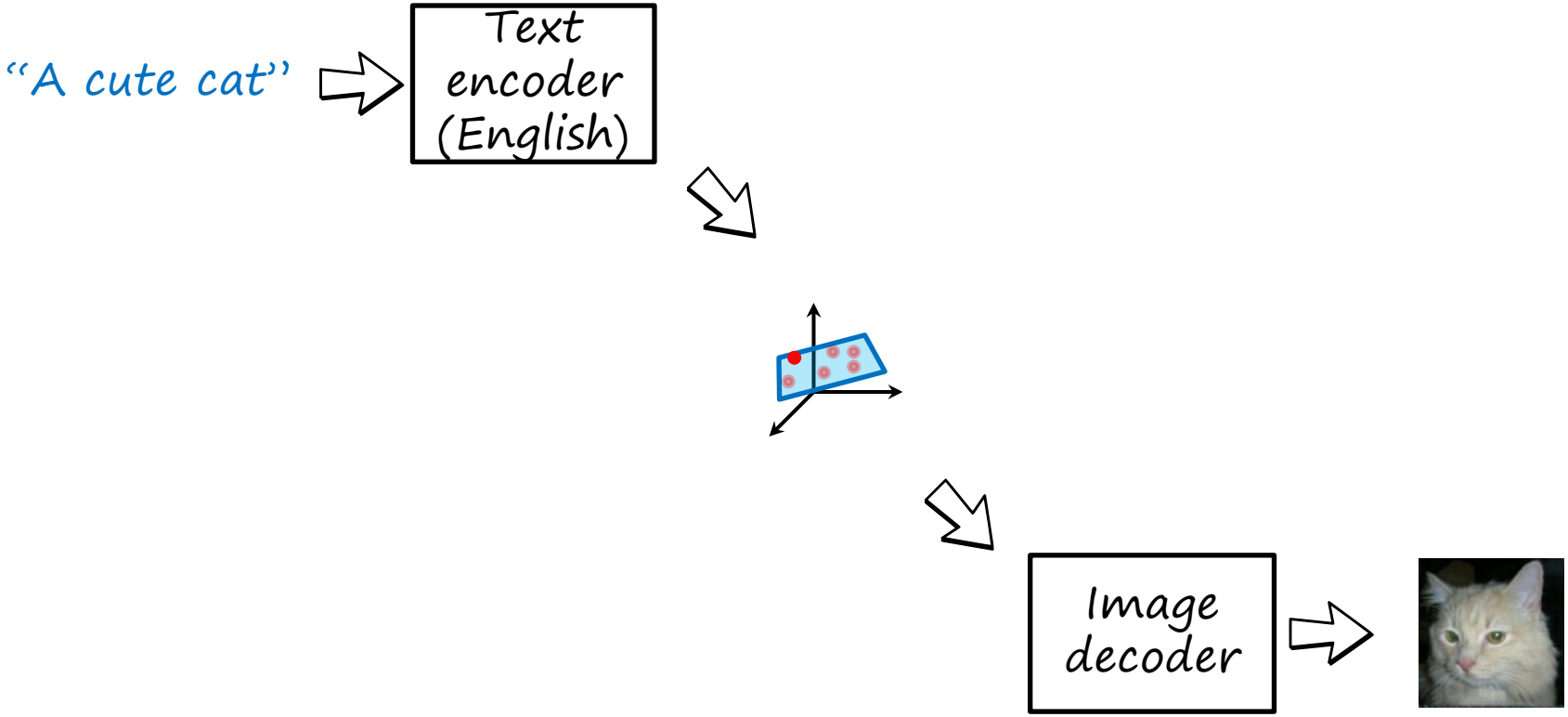
Cross-modal translation
Example: speech recognition



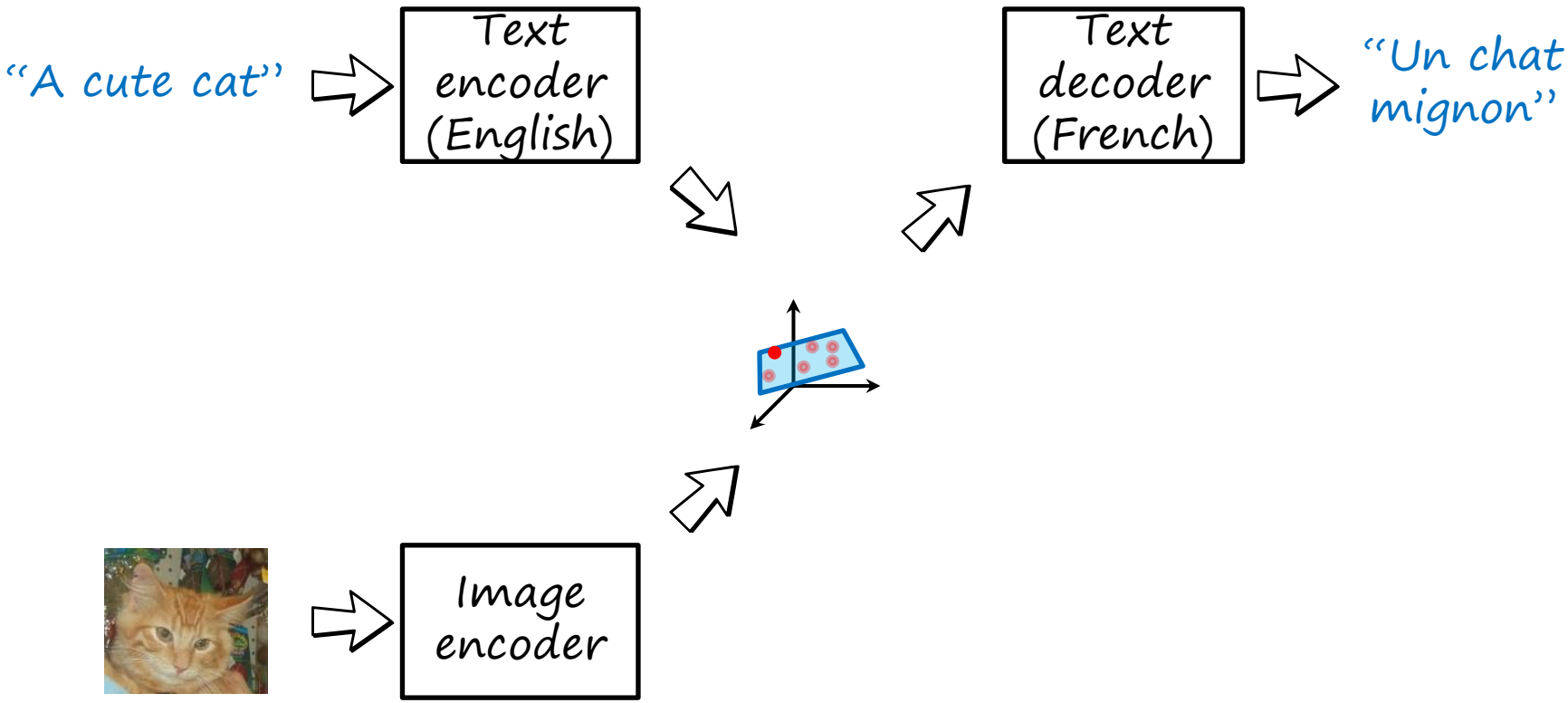
Cross-modal translation
Example: image captioning



M2CR: multilingual multimodal continuous representations



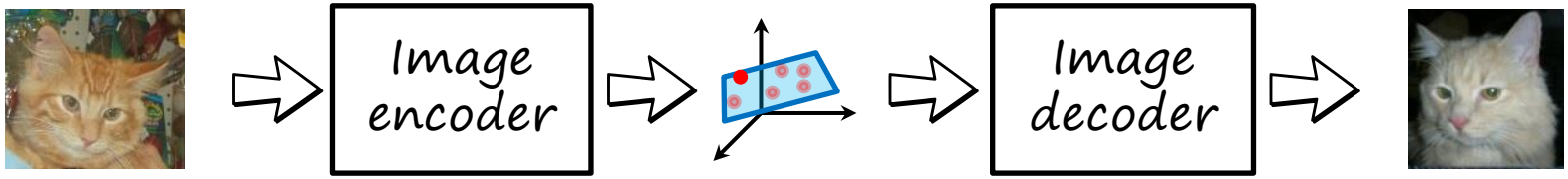
Multimodal translation
Example: text+image to text



Challenges

- Heterogeneous modalities
  - Images: fixed-size 2D data in a continuous space
  - Speech: variable-length 1D in a continuous space
  - Language: variable-length discrete (one-hot) data
- Heterogeneous encoders-decoders
  - Text, speech: recurrent neural networks (RNNs)
  - Images: convolutional neural networks (CNNs)
- How to combine modalities properly
  - Usually depends on the particular task

This talk: image-to-image translation



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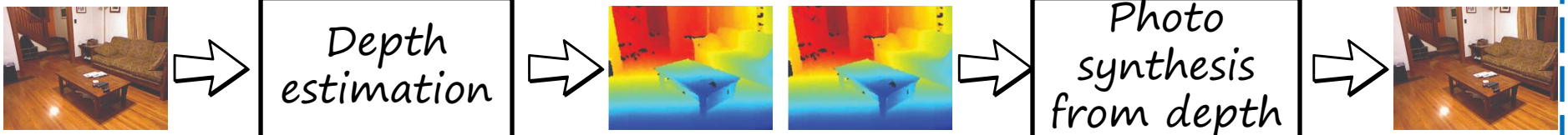
"Easy" problems

"Difficult" problems

Intra-modal problems (i.e. RGB)

Cross-modal problems



How to solve the inverse problem?

- Just signal processing: not possible

- Machine learning: do you have enough **data**?
  - Learn **priors** (e.g. faces)
  - Discover the data **manifold**
  - More realistic approximation

Image-to-image translation

- General purpose
- Learns from image pairs (input, output)

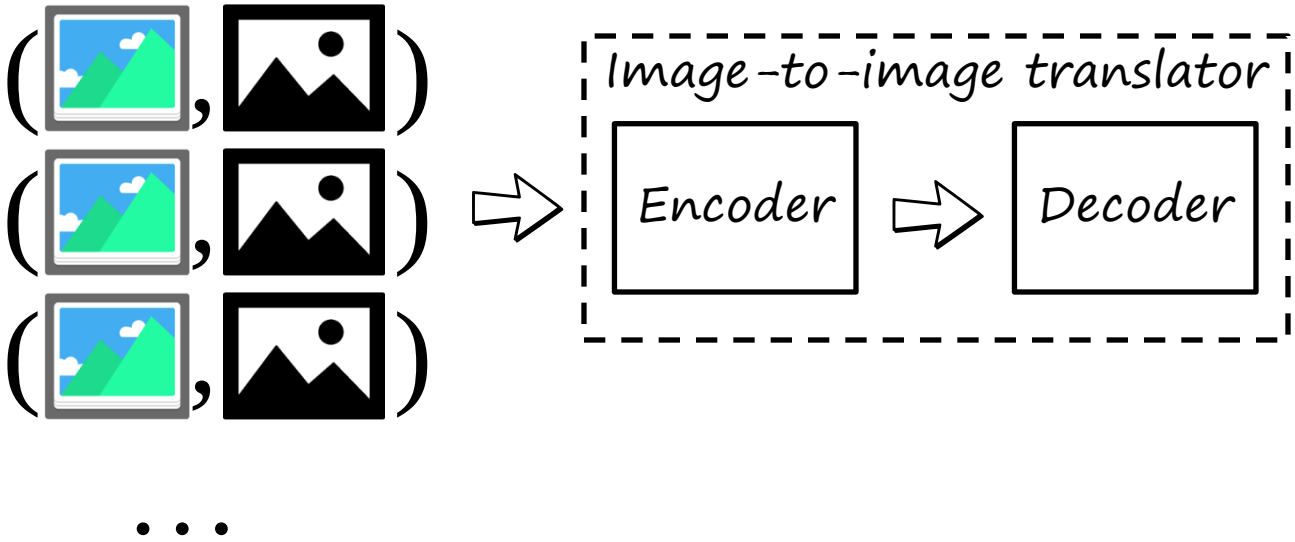
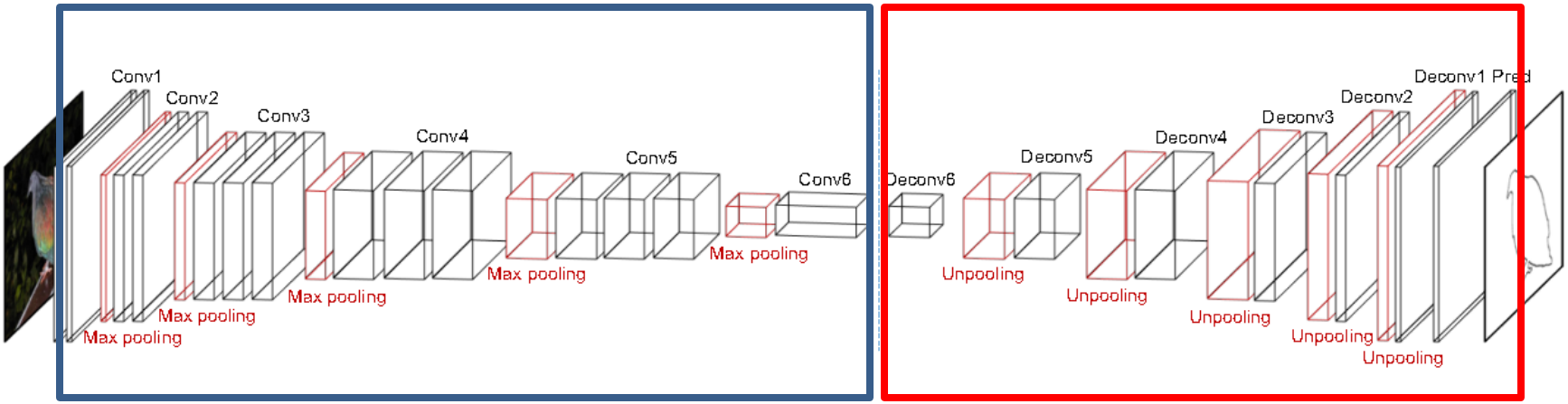
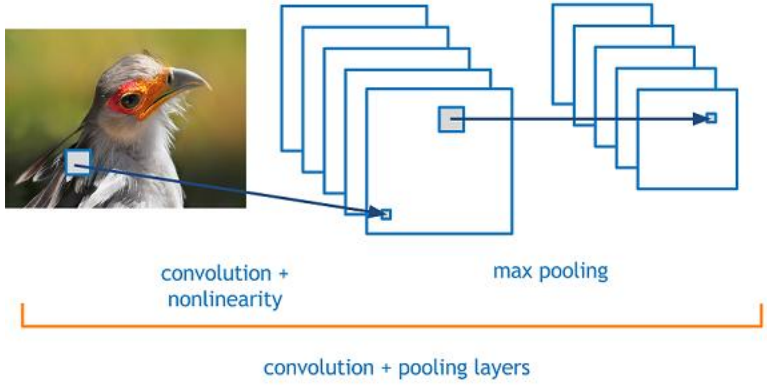


Image encoder-decoder

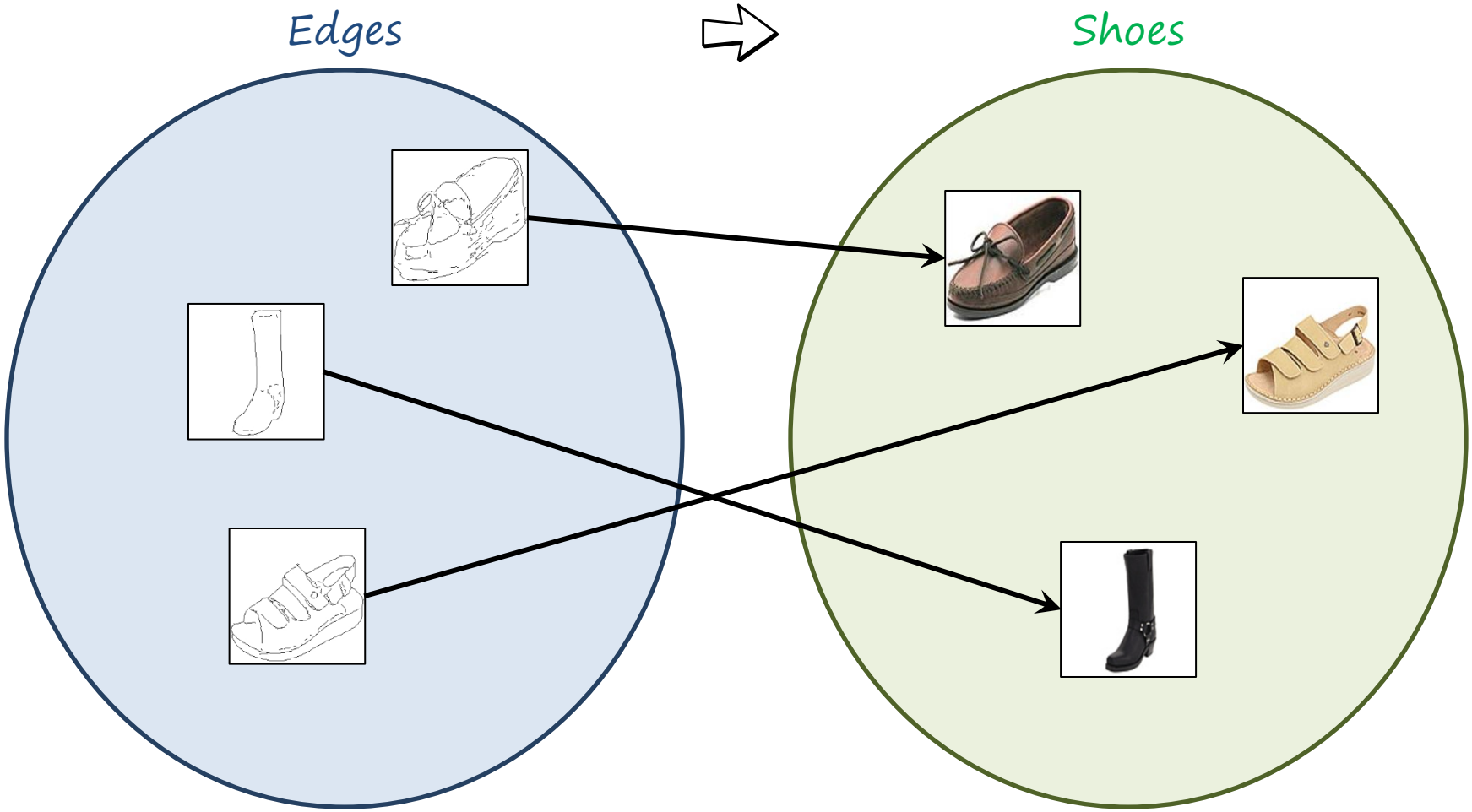
Convolutional encoder

(De)convolutional decoder

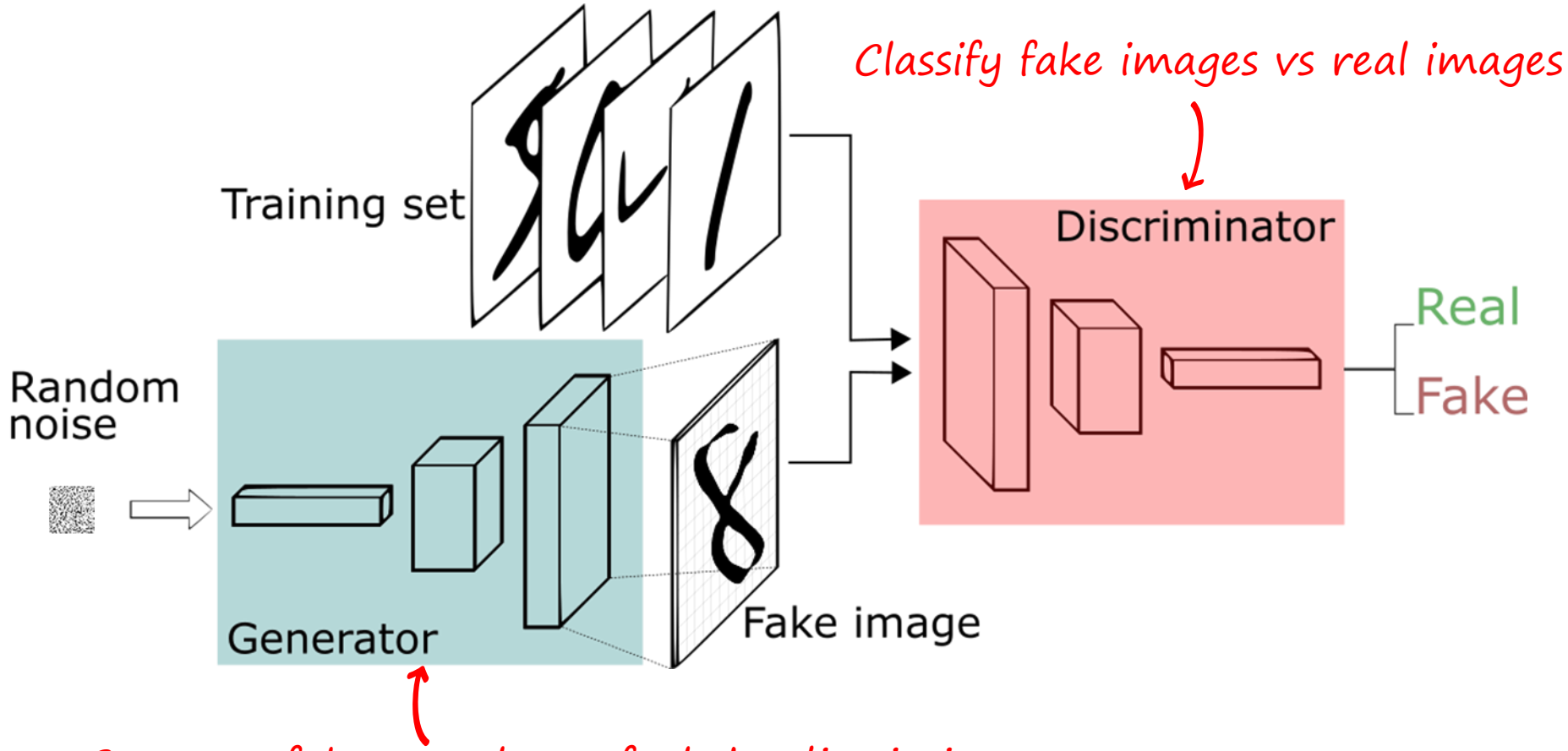




Paired image-to-image translation



Generative Adversarial Networks

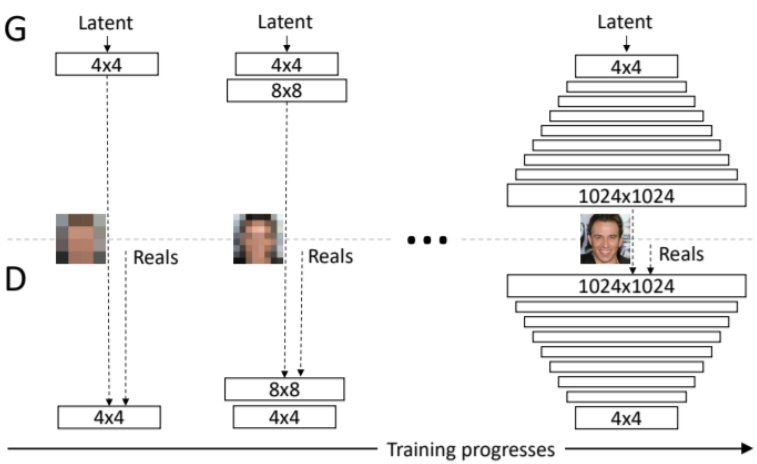


Goodfellow et al., "Generative Adversarial Networks", NIPS 2014
Figure from https://deeplearning4j.org/generative-adversarial-network

Generative Adversarial Networks

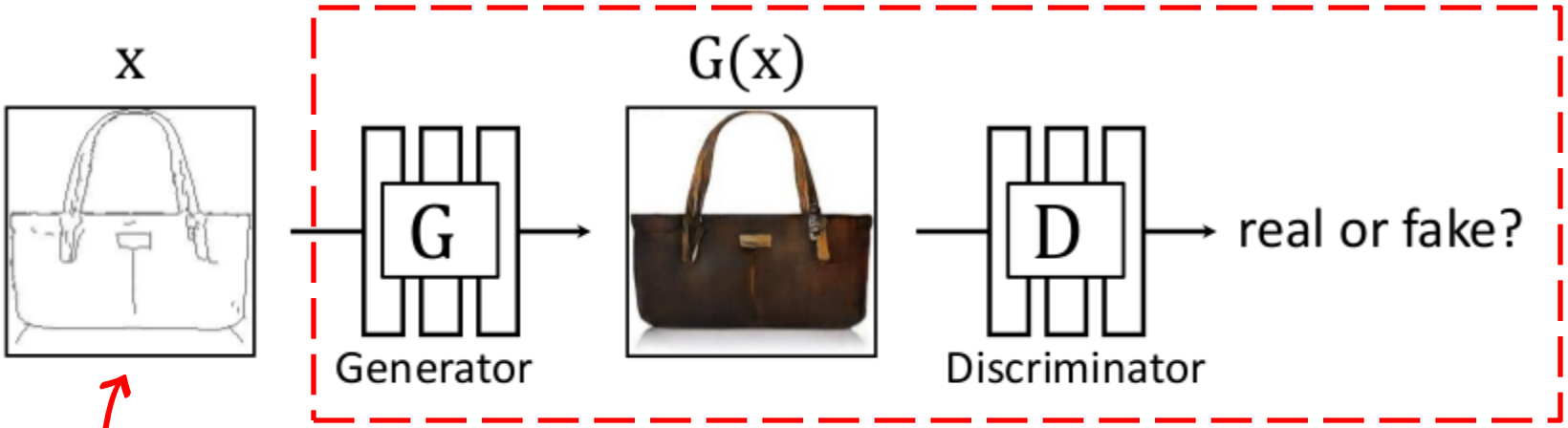
Wasserstein GAN (WGAN-GP)

Progressive growing of GANs



and many more…

pix2pix: image-to-image translation with conditional GANs



Input condition (instead of random noise)

G: generate fake samples that can fool D

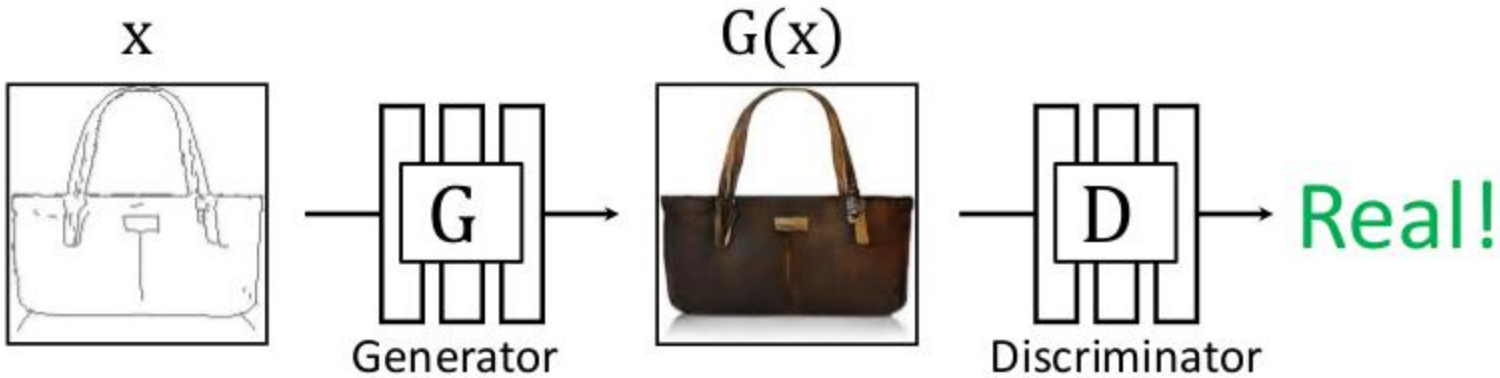
D: classify fake samples vs. real images

This is still a GAN

Isola et al., "Image-to-Image Translation with Conditional Adversarial Networks", CVPR 2017

Slide adapted from Zhu and Isola

pix2pix: image-to-image translation with conditional GANs

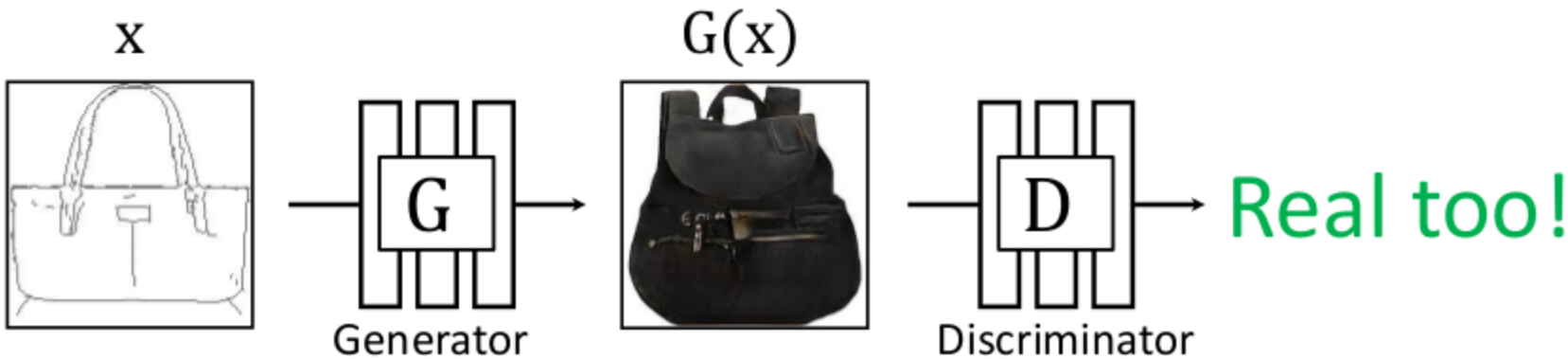


$$\min_G \max_D \mathbb{E}_{x,y}[\log D(G(x)) + \log(1 - D(y))]$$

Optimization problem in a conventional GAN

Isola et al., "Image-to-Image Translation with Conditional Adversarial Networks", CVPR 2017
Slide adapted from Zhu and Isola

pix2pix: image-to-image translation with conditional GANs



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Isola et al., "Image-to-Image Translation with Conditional Adversarial Networks", CVPR 2017
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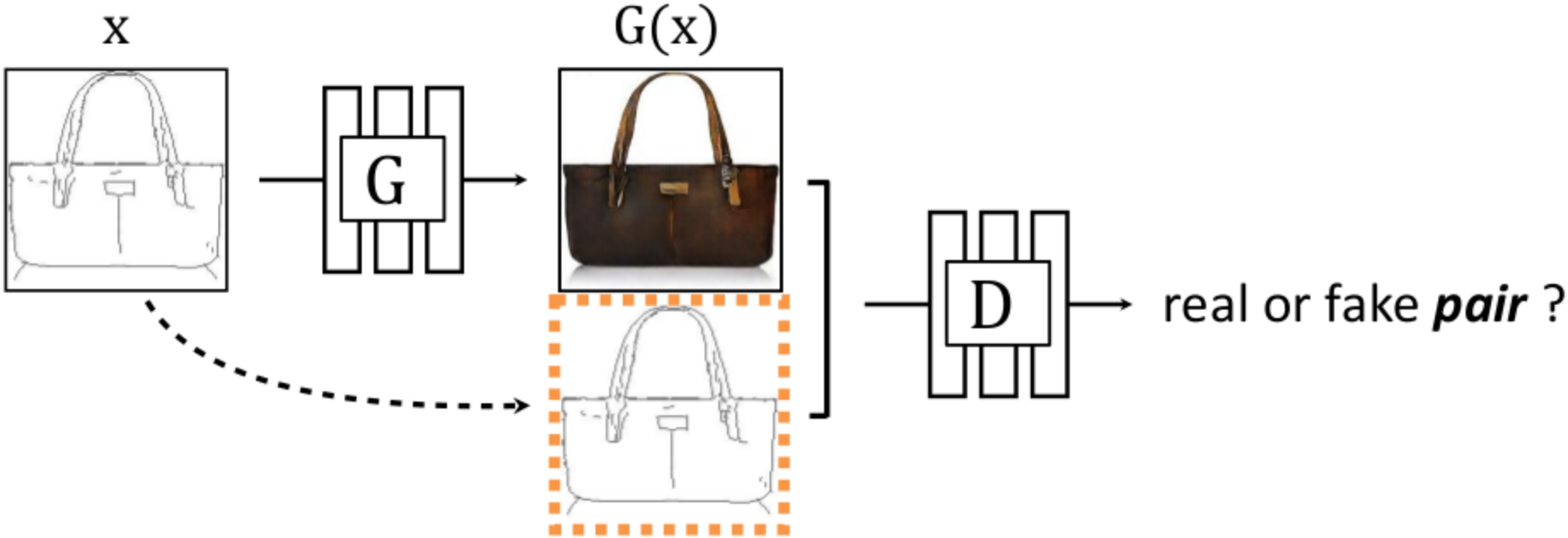
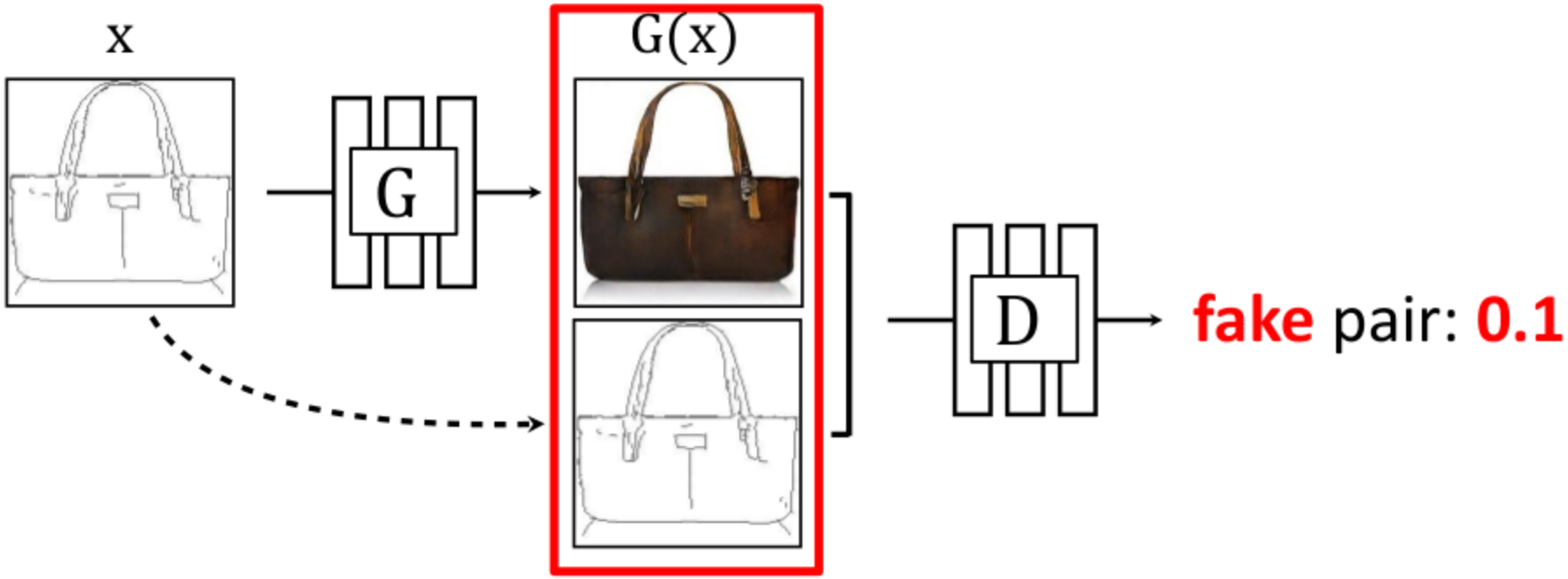


$$\min_G \max_D \mathbb{E}_{x,y}[\log D(x, G(x)) + \log(1 - D(x, y))]$$

Isola et al., "Image-to-Image Translation with Conditional Adversarial Networks", CVPR 2017
Slide adapted from Zhu and Isola

pix2pix: image-to-image translation with conditional GANs



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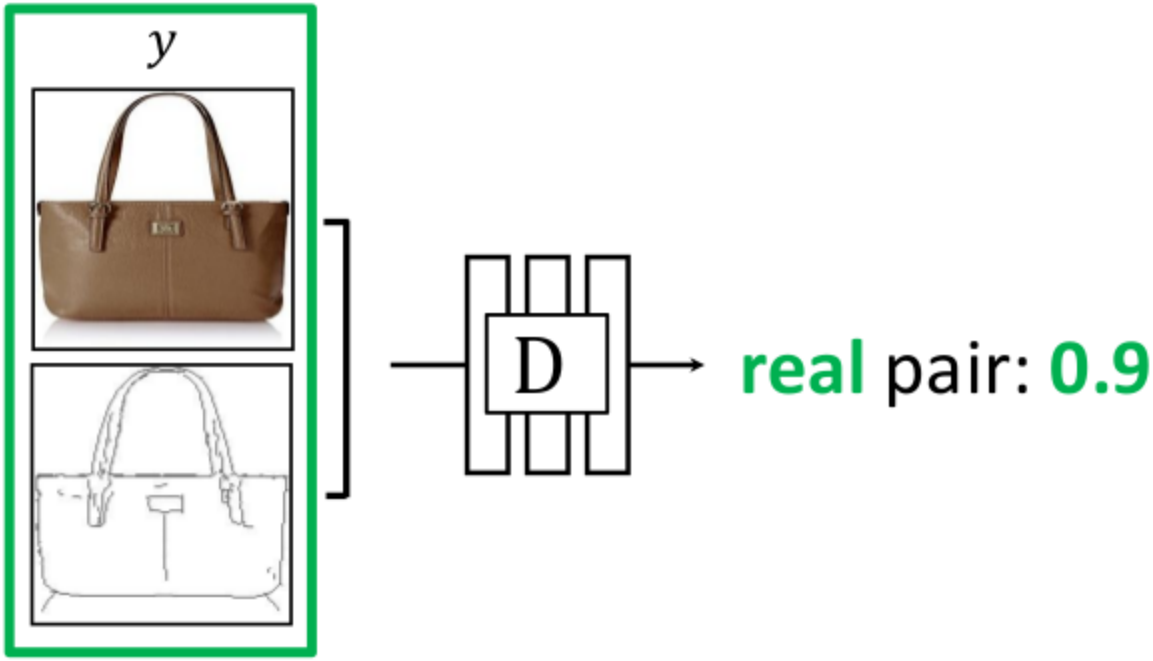

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Isola et al., "Image-to-Image Translation with Conditional Adversarial Networks", CVPR 2017
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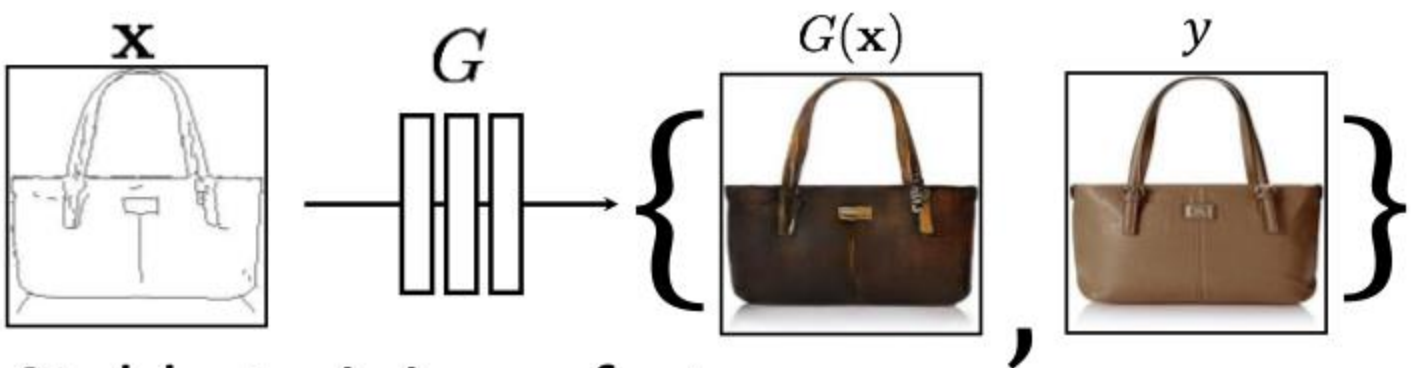
pix2pix: image-to-image translation with conditional GANs

- Training details
  - Conditional GAN + L1

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

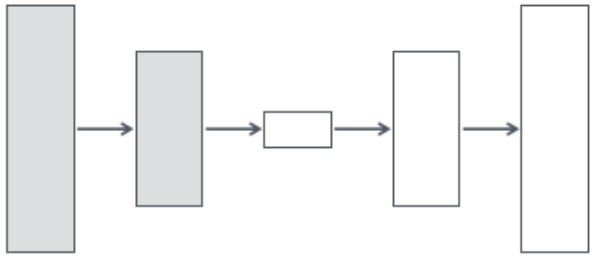


  - Stable training + fast convergence.

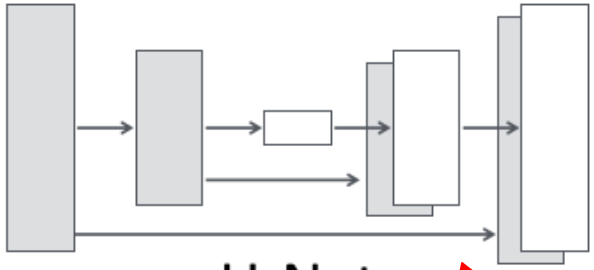
Isola et al., "Image-to-Image Translation with Conditional Adversarial Networks", CVPR 2017
Slide adapted from Zhu and Isola

pix2pix: image-to-image translation with conditional GANs

Generator



Encoder-decoder



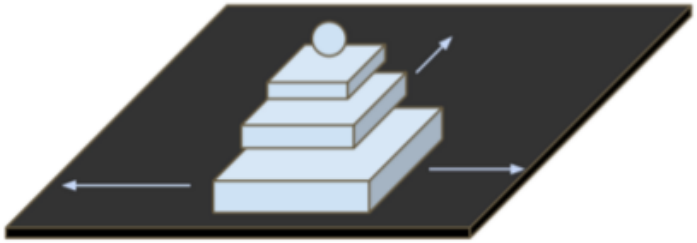
U-Net

[Ronneberger et al.]

Skip connections (decoder conditioned on encoder activations)

Discriminator

PatchGAN (FCN)

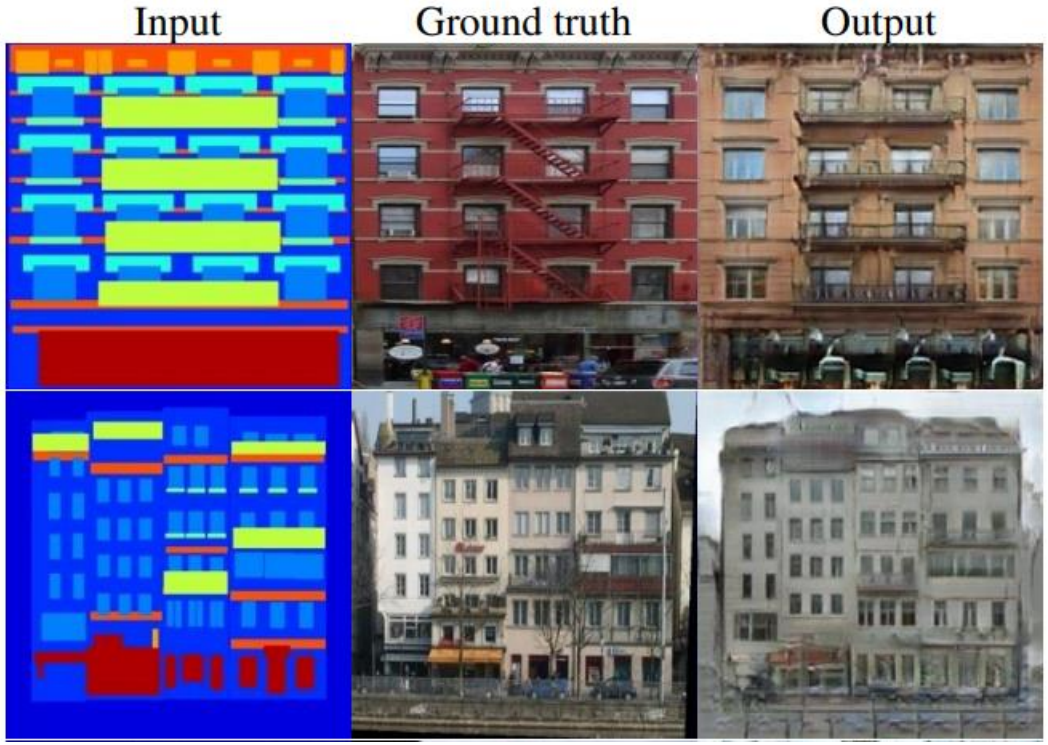


Isola et al., "Image-to-Image Translation with Conditional Adversarial Networks", CVPR 2017

Slide adapted from Zhu and Isola

pix2pix: image-to-image translation with conditional GANs

- Examples



Isola et al, "Image-to-Image Translation with Conditional Adversarial Networks", CVPR 2017
Figures from https://affinelayer.com/pix2pix/

pix2pix: image-to-image translation with conditional GANs

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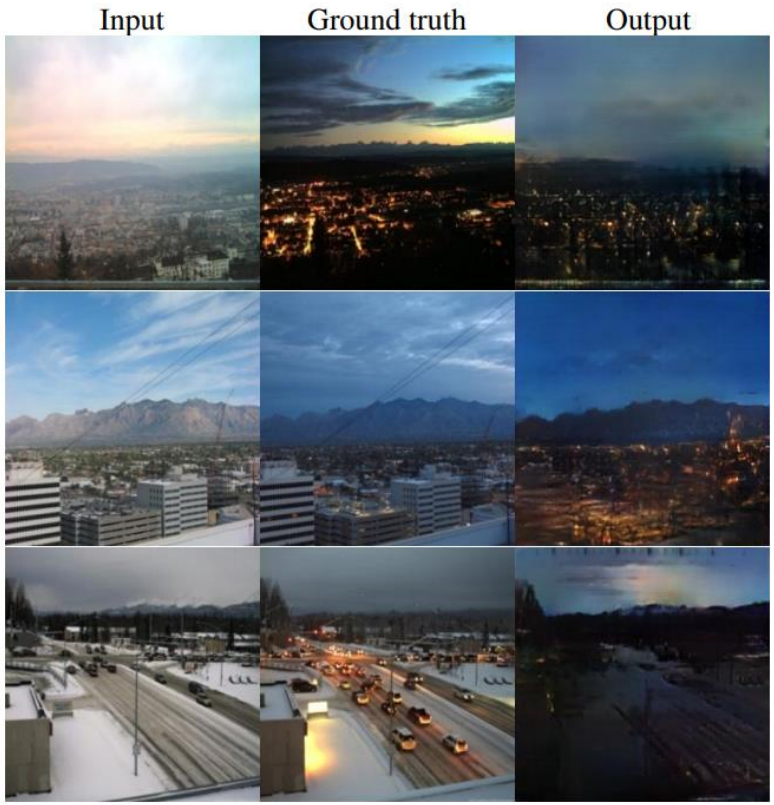
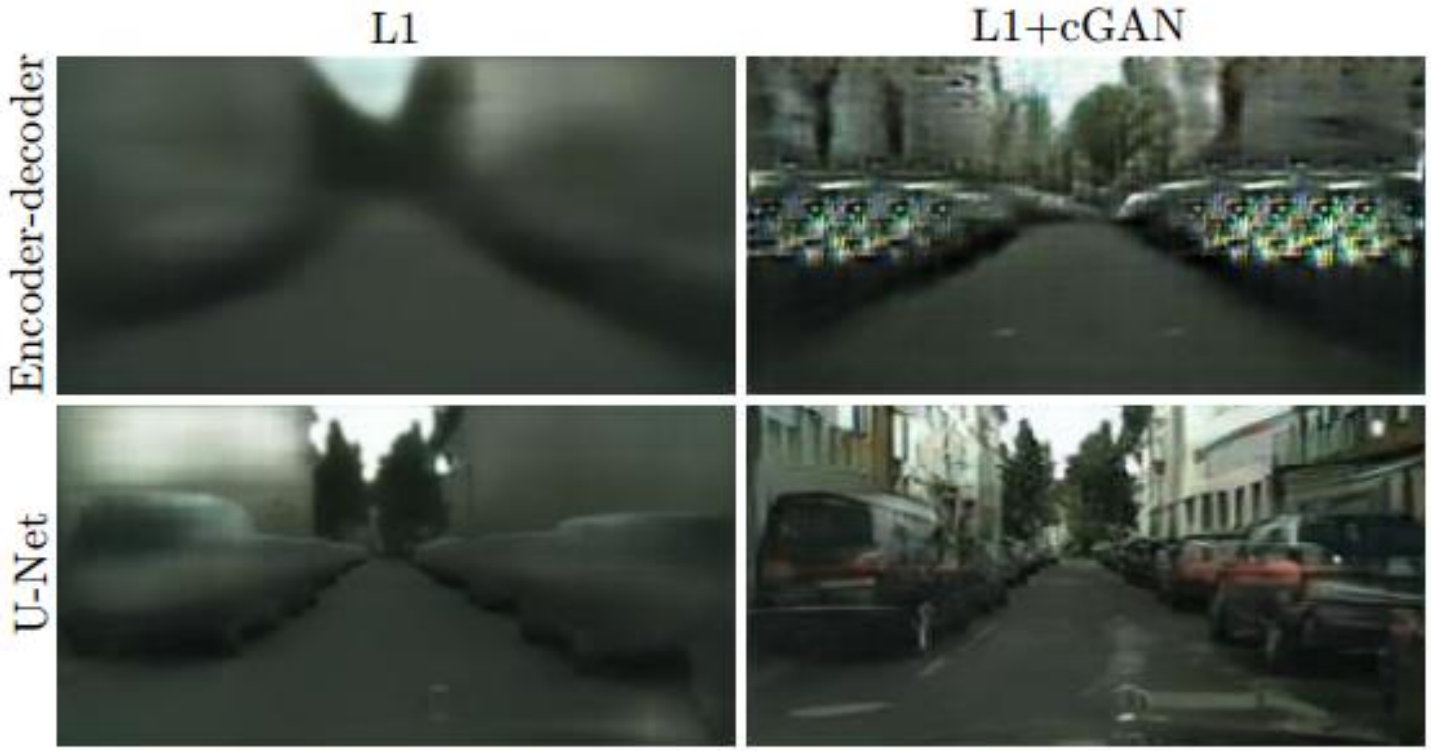
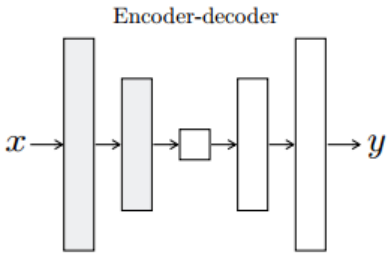


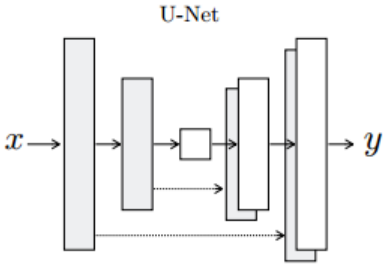
Isola et al, "Image-to-Image Translation with Conditional Adversarial Networks", CVPR 2017
Figures from https://affinelayer.com/pix2pix/

pix2pix: image-to-image translation with conditional GANs

- Encoder-decoder (w/o skip) vs UNet (w/ skip)
- Loss: L1 vs L1+cGAN

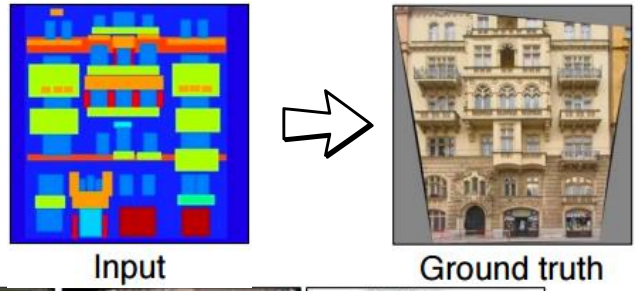


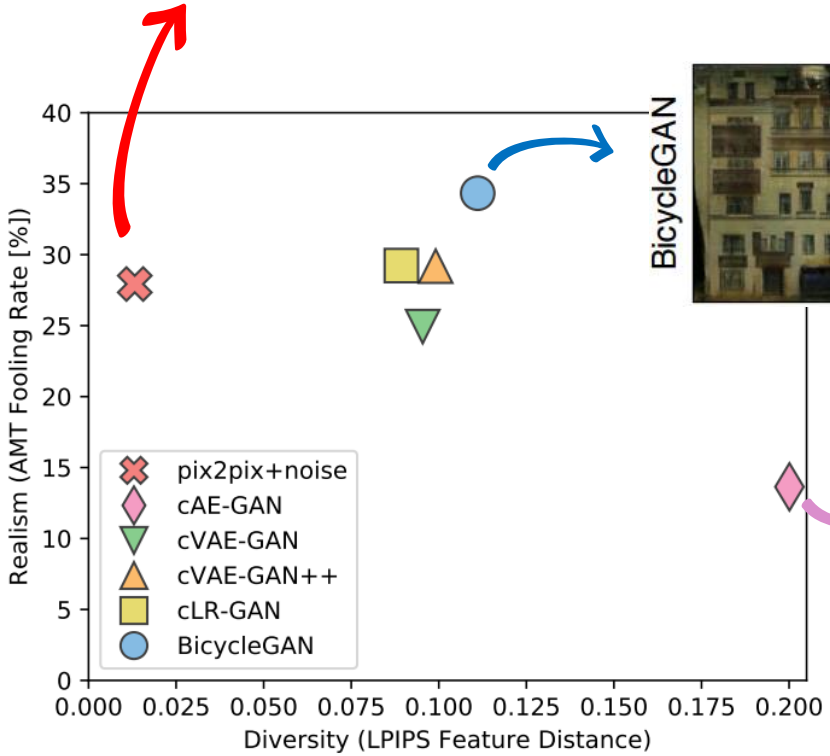




Chen et al, "VGAN-Based Image Representation Learning for Privacy-Preserving Facial Expression Recognition", arxiv 2018

Diversity in image-to-image translation

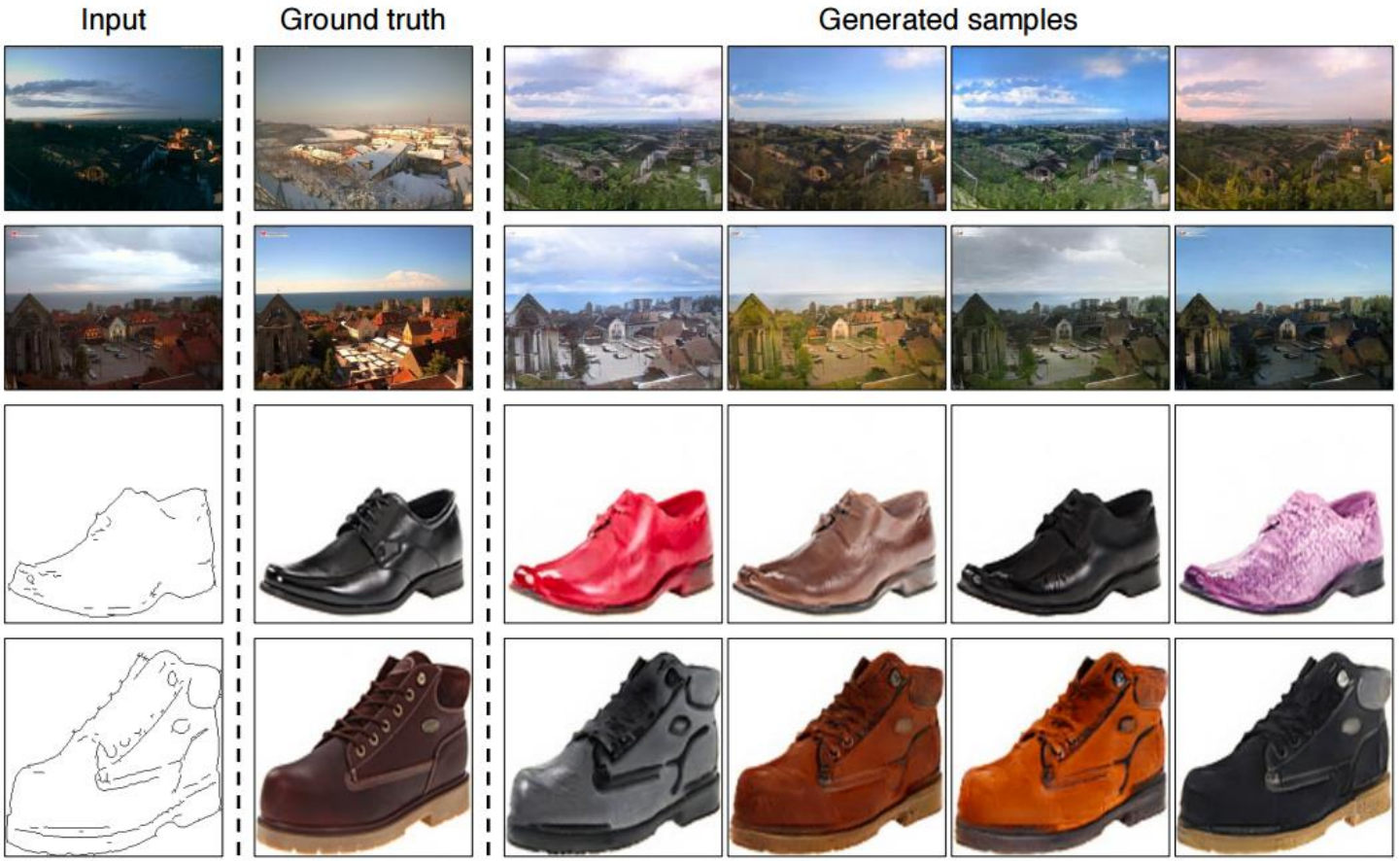




Zhu et al. "Toward Multimodal Image-to-Image Translation", NIPS 2017

Diversity in image-to-image translation

- More results. Bicycle GAN



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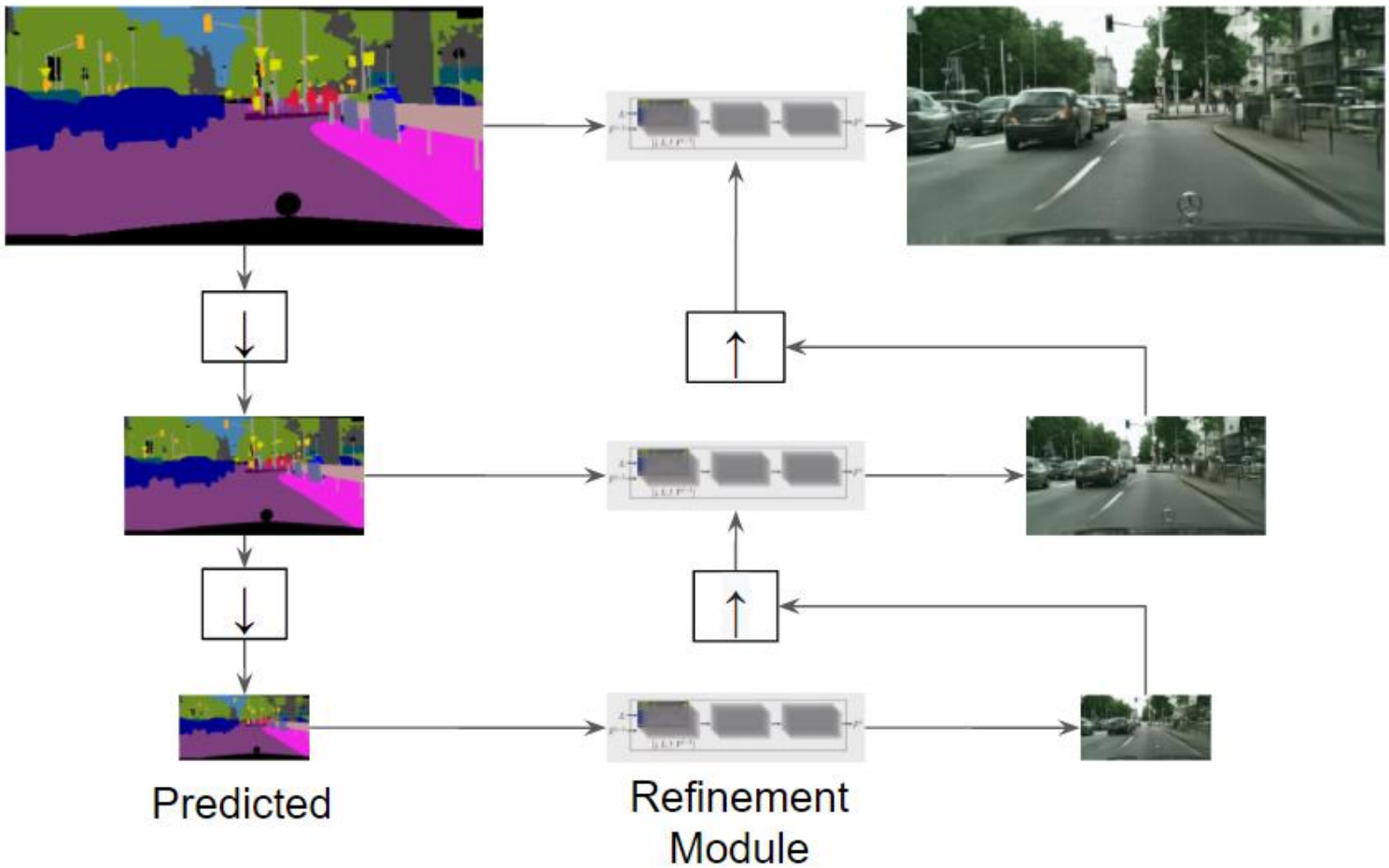
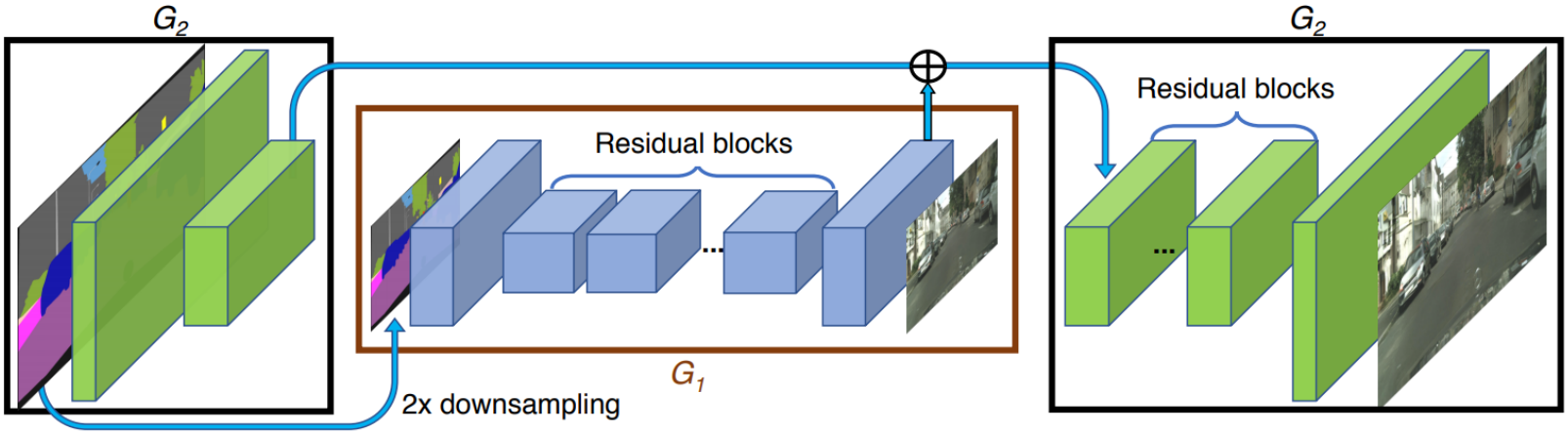
Cascade refinement networks



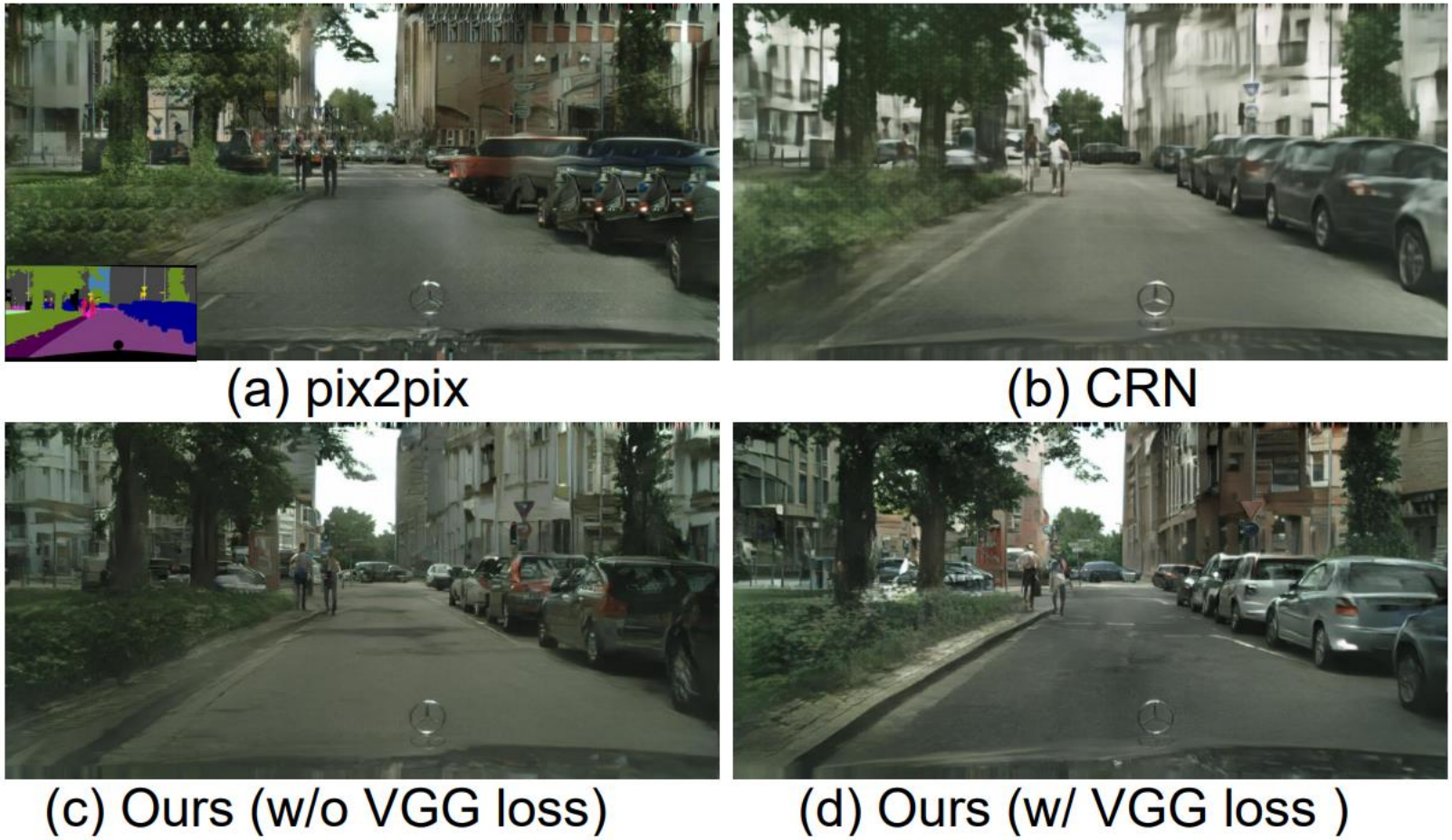
Chen and Koltun, "Photographic Image Synthesis with Cascaded Refinement Networks", ICCV 2017

pix2pixHD



Wang et al, "High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs", arxiv 2017

Comparison image-to-image translation



Wang et al, "High-Resolution Image Synthesis and Semantic Manipulation with Conditional GANs", arxiv 2017

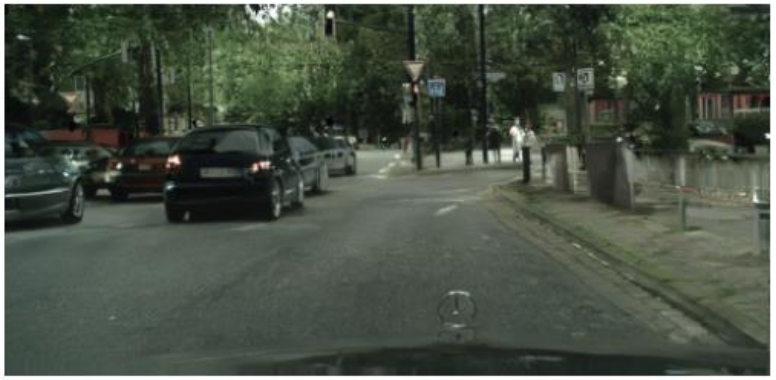
pix2pixHD: interactive image-to-image translation

Semantic labels → Cityscapes street views

Input labels

Synthesized image

Interactive editing results



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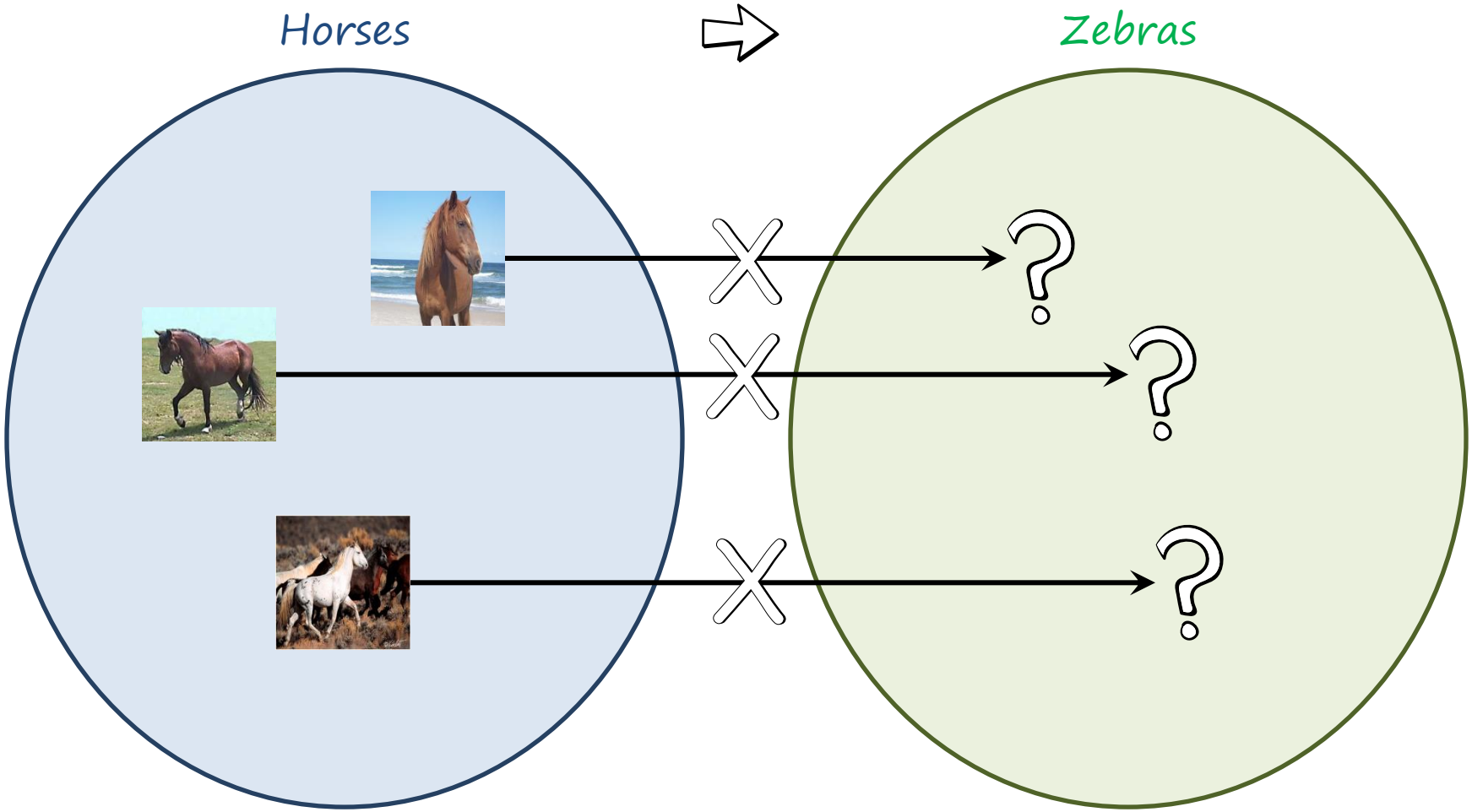
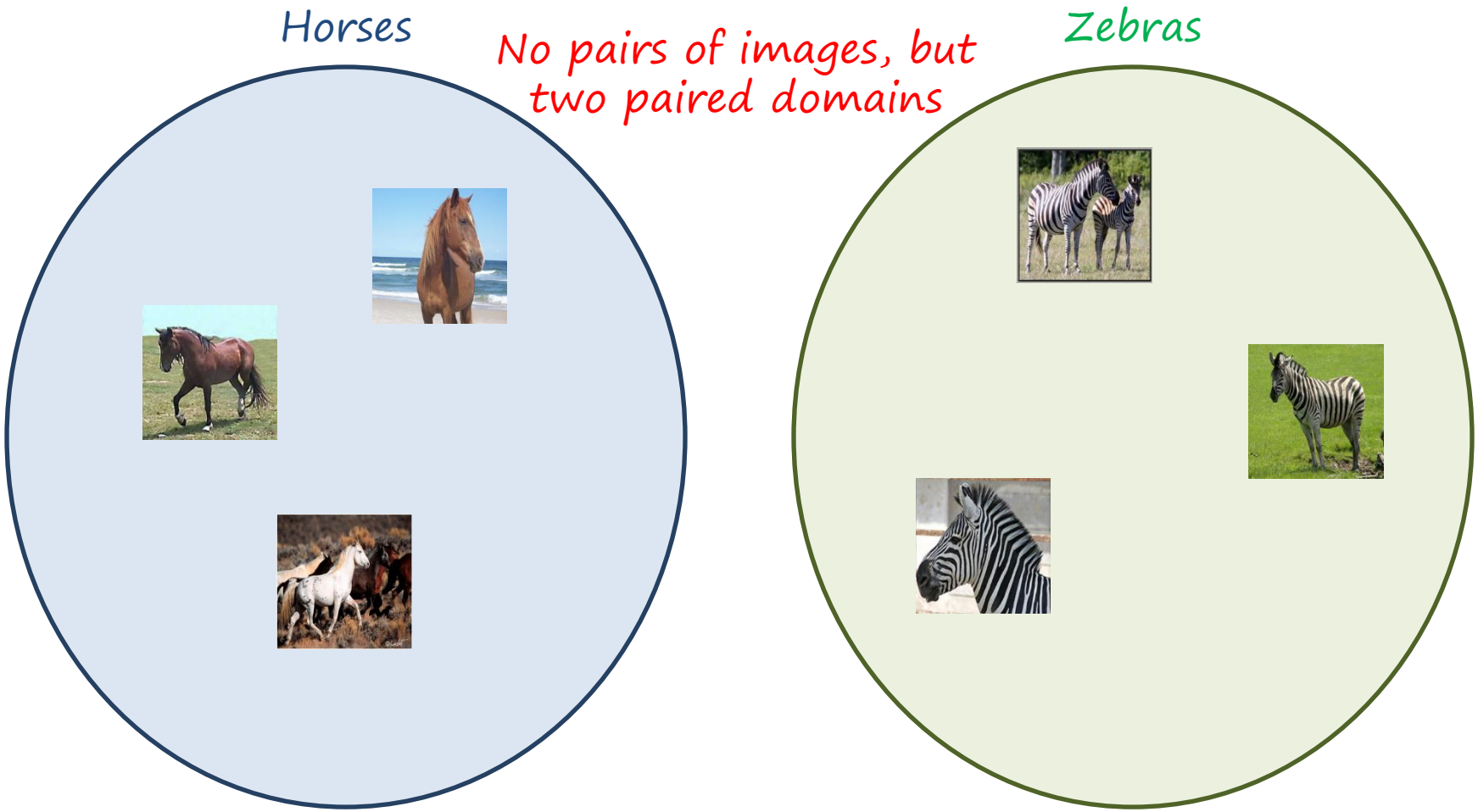
Unpaired image-to-image translation

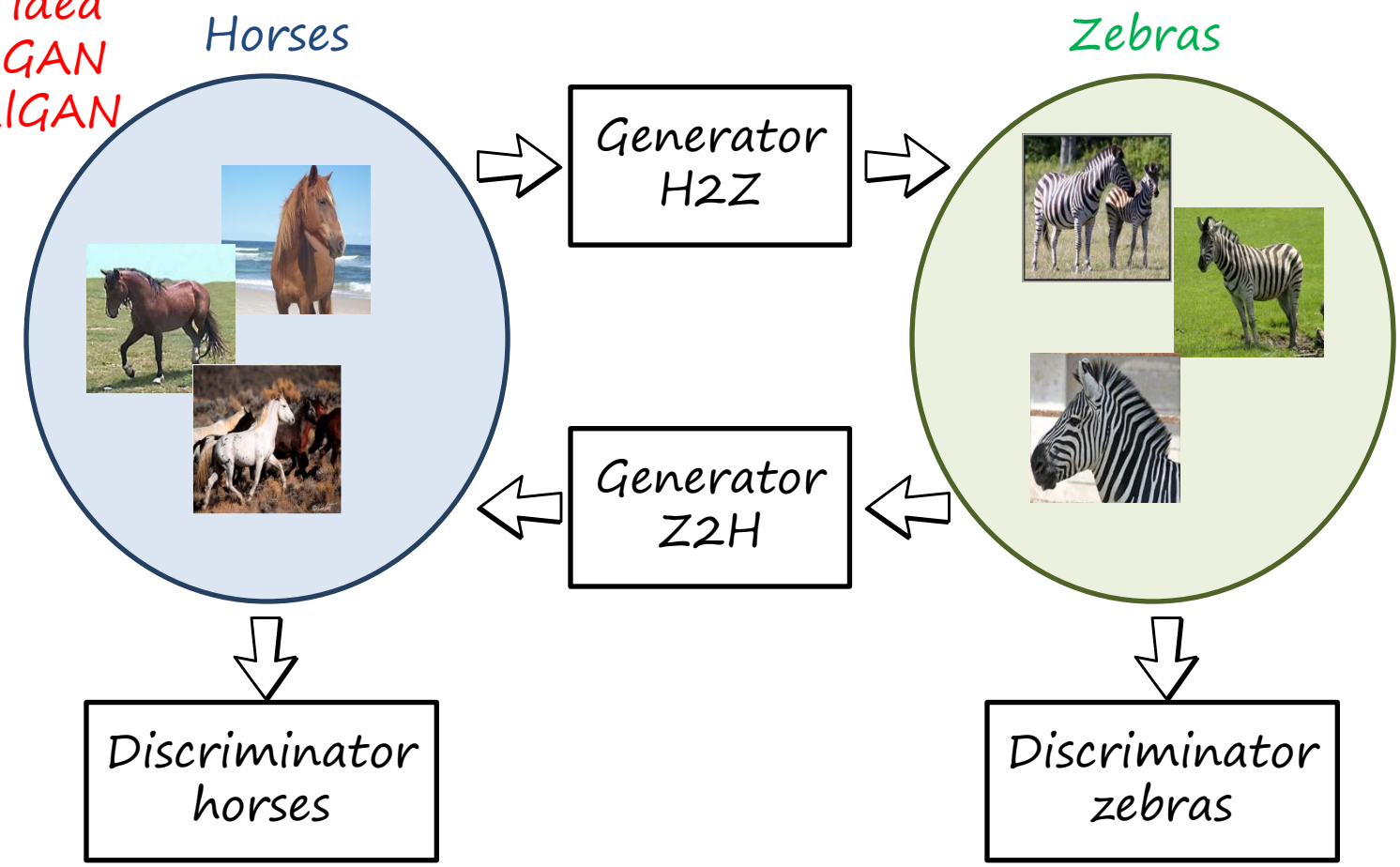


Unpaired image-to-image translation



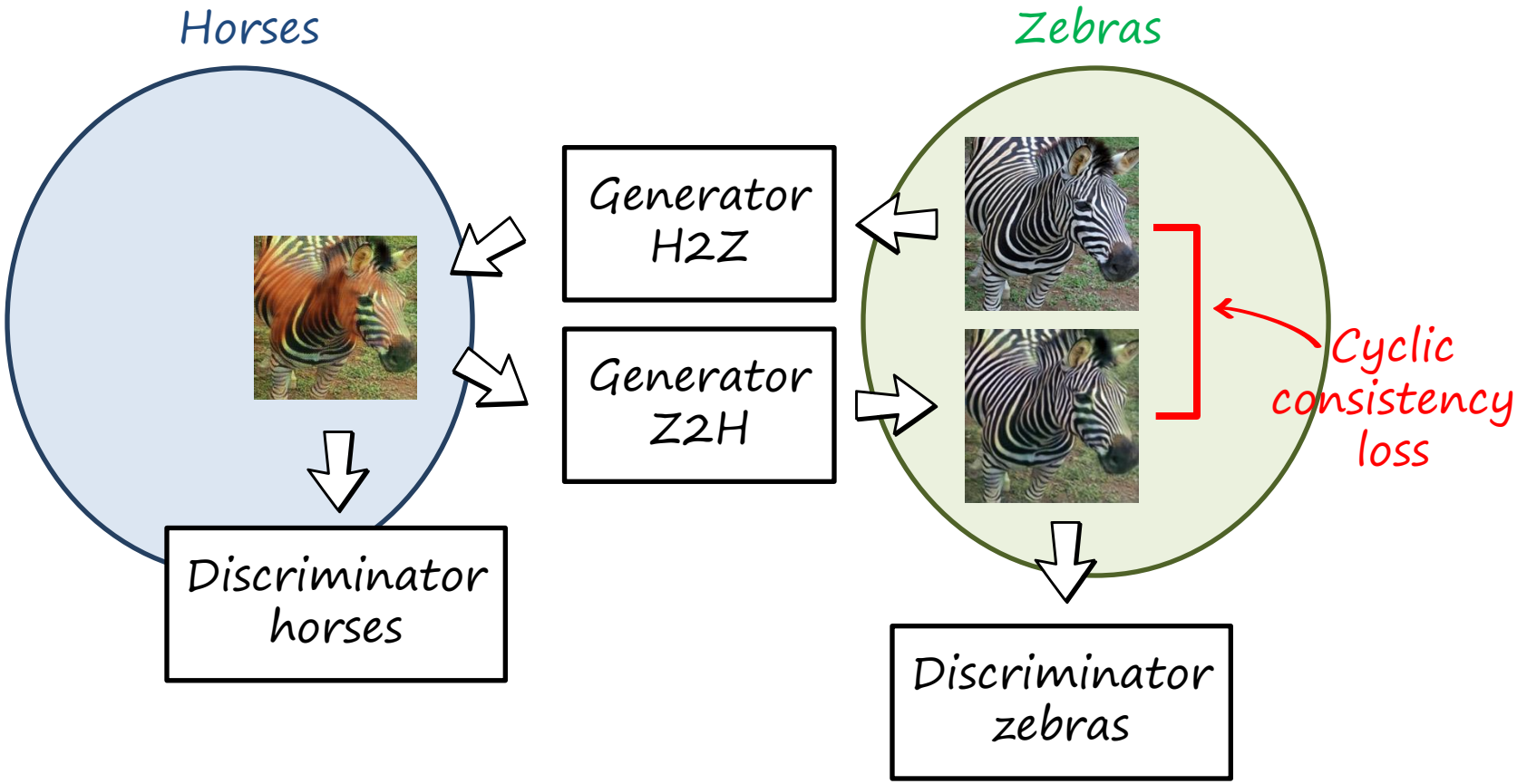
CycleGAN: unpaired image-to-image translation using cycle consistency

Similar idea in DiscoGAN and DualGAN



Zhu et al, "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks", ICCV 2017

CycleGAN: unpaired image-to-image translation using cycle consistency



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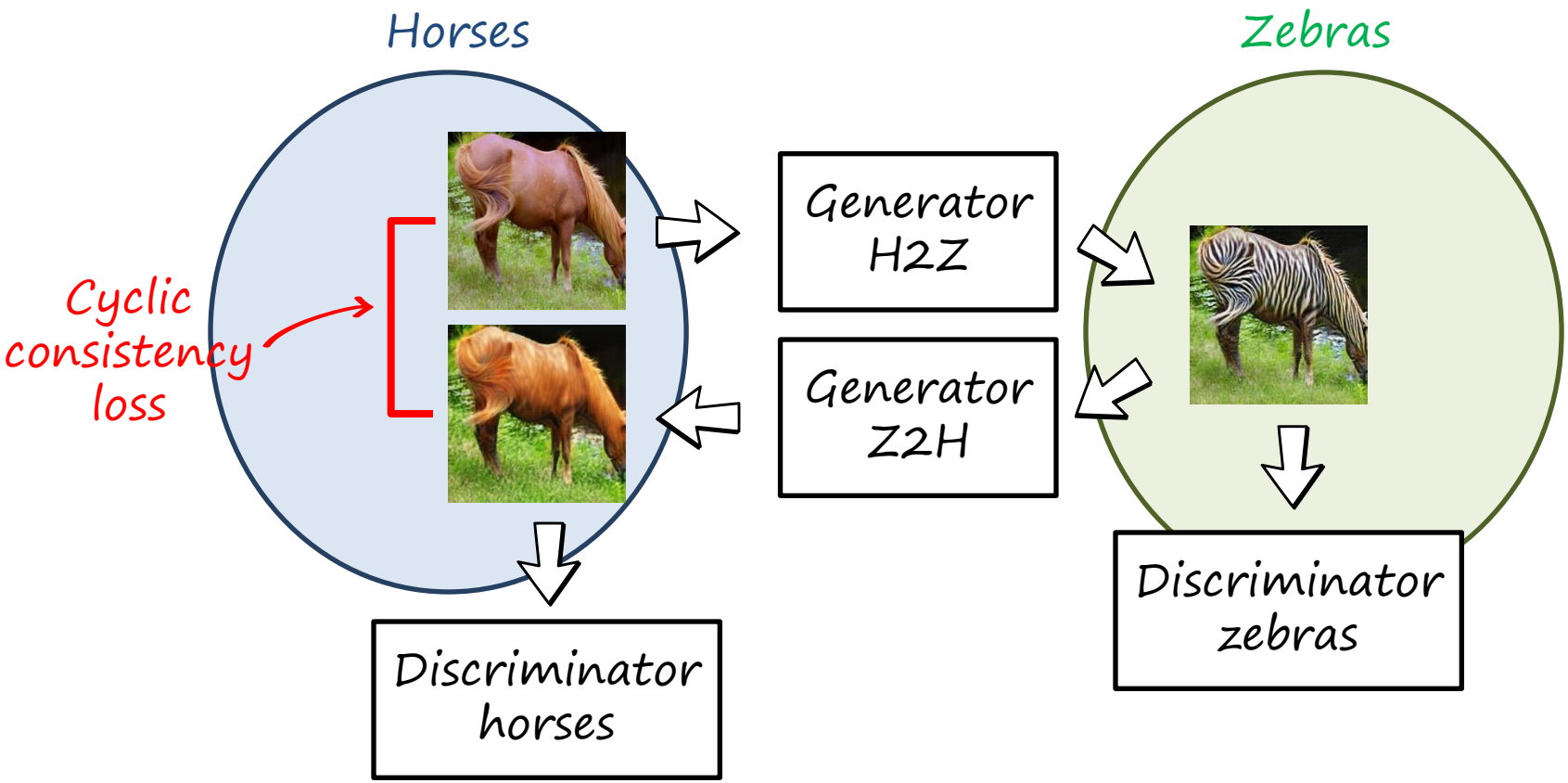
CycleGAN: unpaired image-to-image translation using cycle consistency



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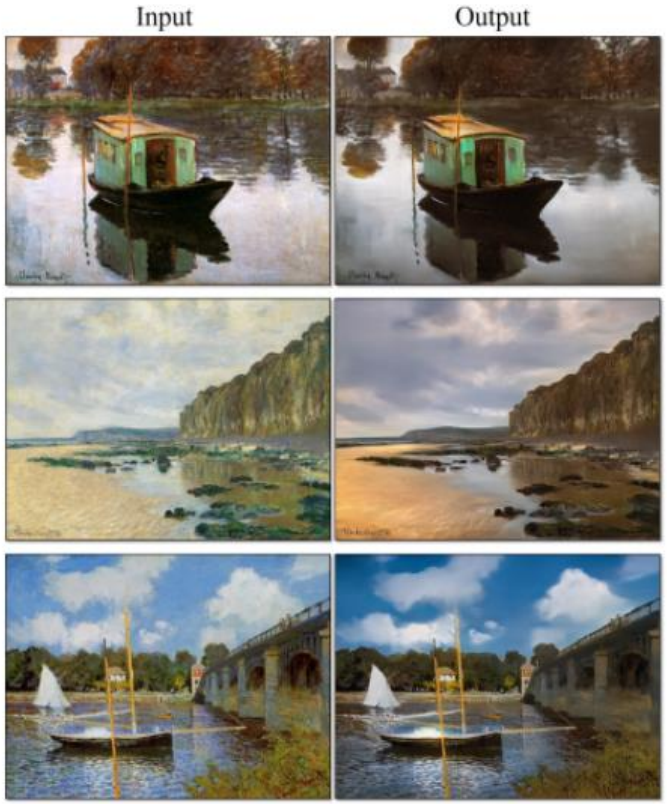
CycleGAN: unpaired image-to-image translation using cycle consistency

- Results

Monet Paintings to Photos

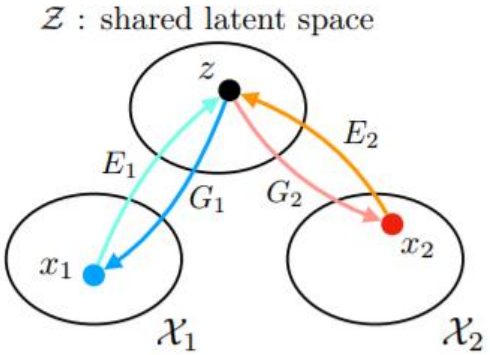


Zhu et al, "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks", ICCV 2017

More unpaired image translation

Domain Transfer Network (DTN)

UNIT



and many more…

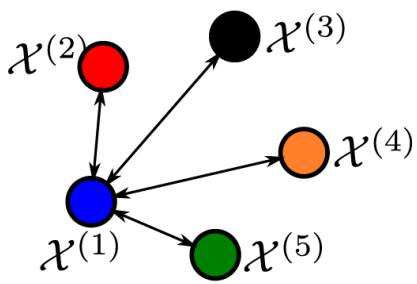
Outline

- M2CR project framework
- Paired image-to-image translation (pix2pix)
- Unpaired image-to-image translation (cycleGAN)
- Unseen translations (mix&match networks)

Unseen translations

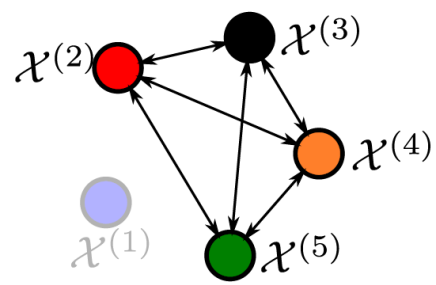
Only these transformations are trained

Train



*Evaluate on these **unseen** translations*

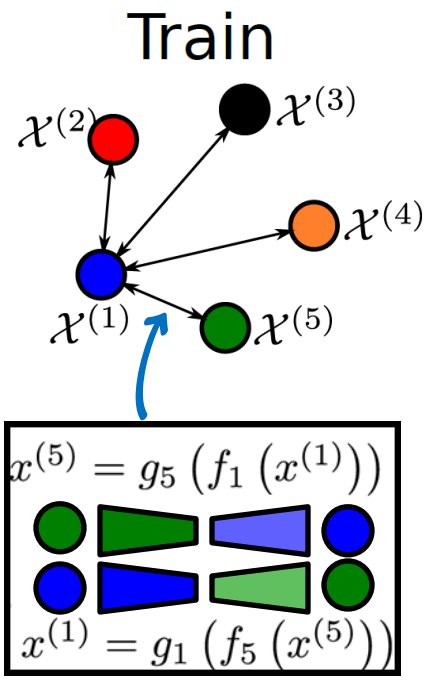
Test

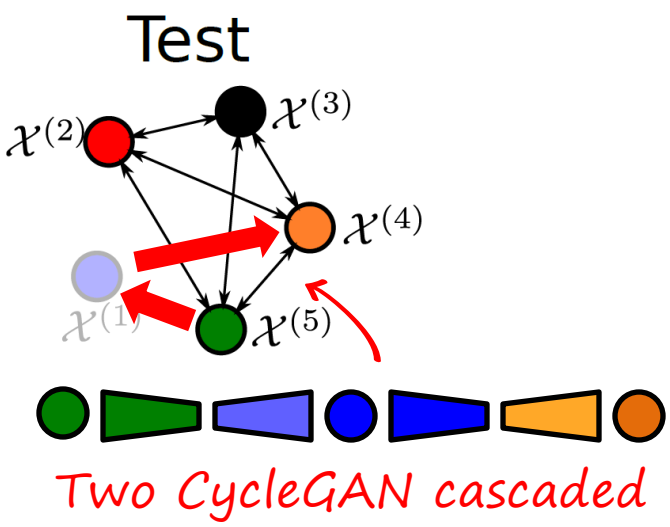


Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

Cascading image-to-image translators

Image-to-image (e.g. CycleGAN)

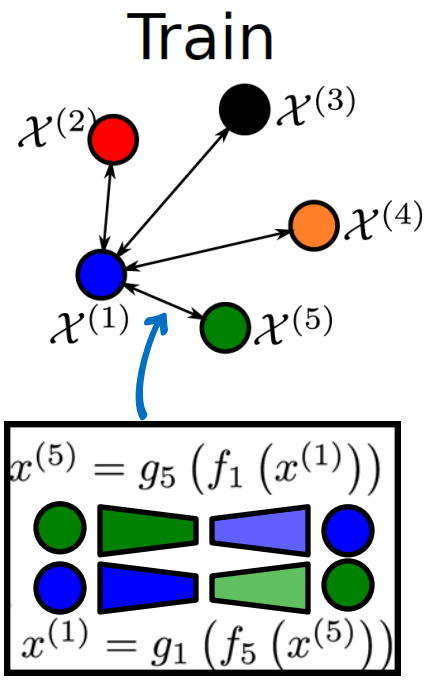


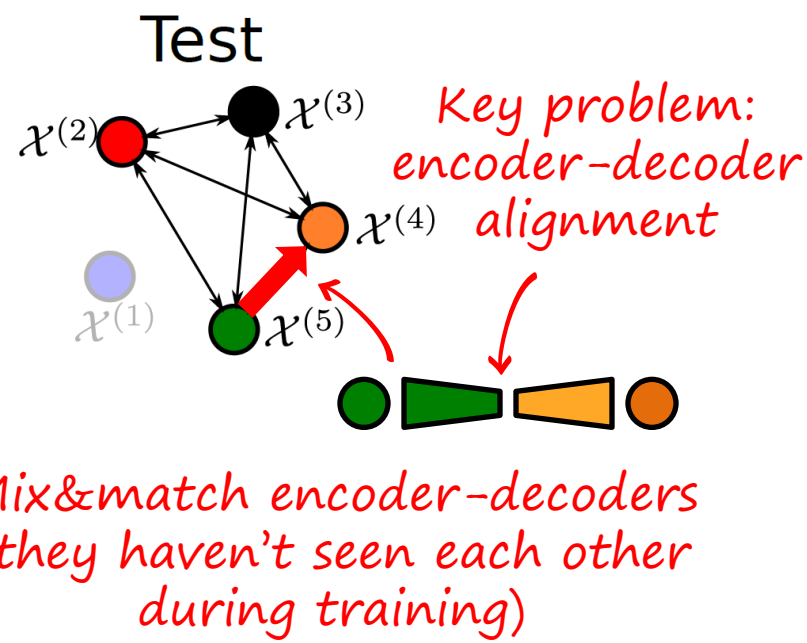


Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

Mix and match networks

Image-to-image (e.g. CycleGAN)

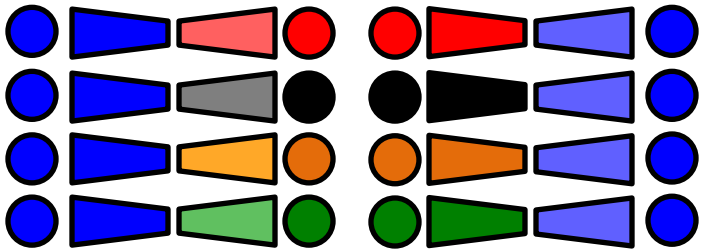




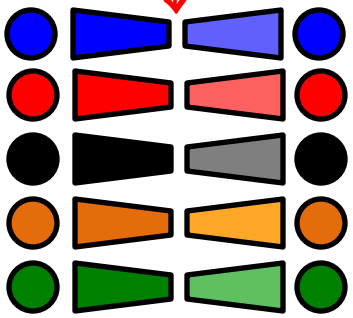
Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

Mix and match networks

Unseen encoder-decoder alignment
- Scalable: number of networks O(N)
- Latent representation should be domain-independent
- Achieved using shared encoder/decoders and autoencoders



5 encoders, 5 decoders



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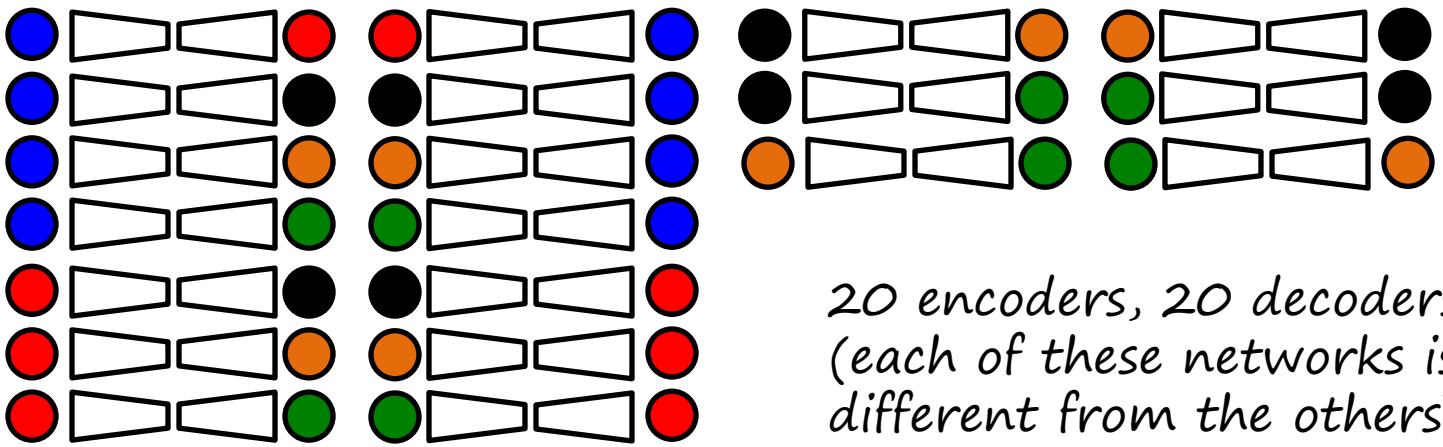
Training all possible translators

Since it is unpaired, we could train all possible translators. Problems:

- No sharing
- Poor scalability: number of networks $O(N^2)$



20 encoders, 20 decoders (each of these networks is different from the others)

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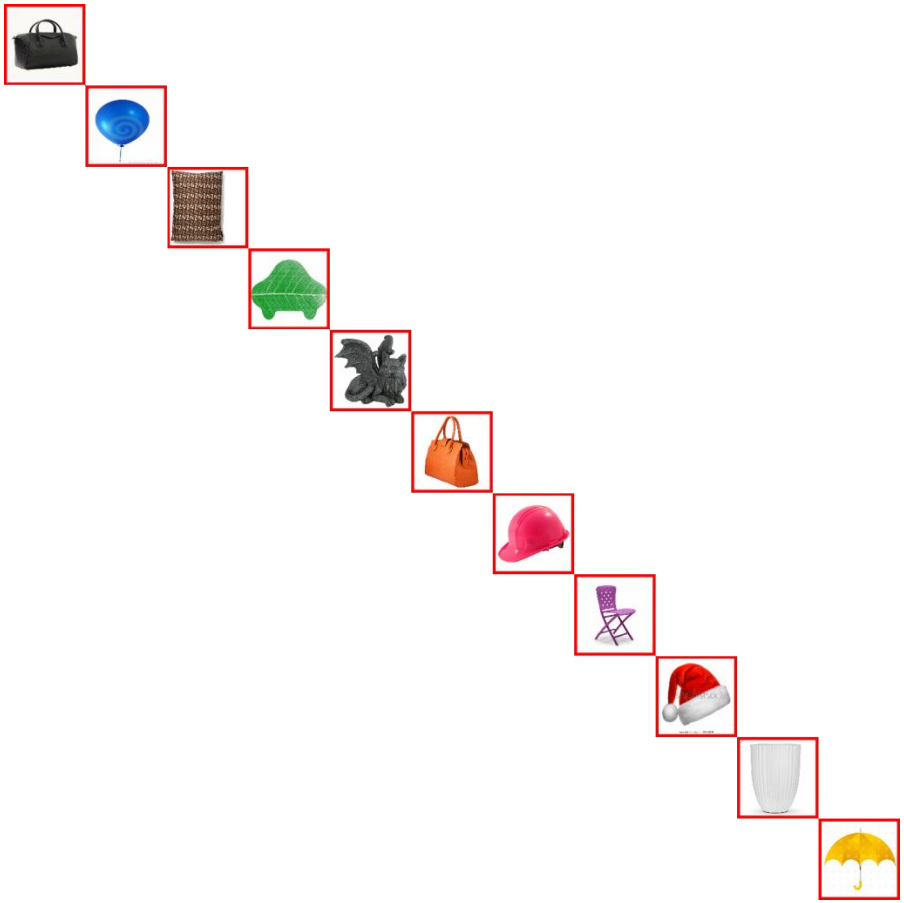
Example: scalable recolorization

Unpaired translation
Eleven colors (i.e. domains)

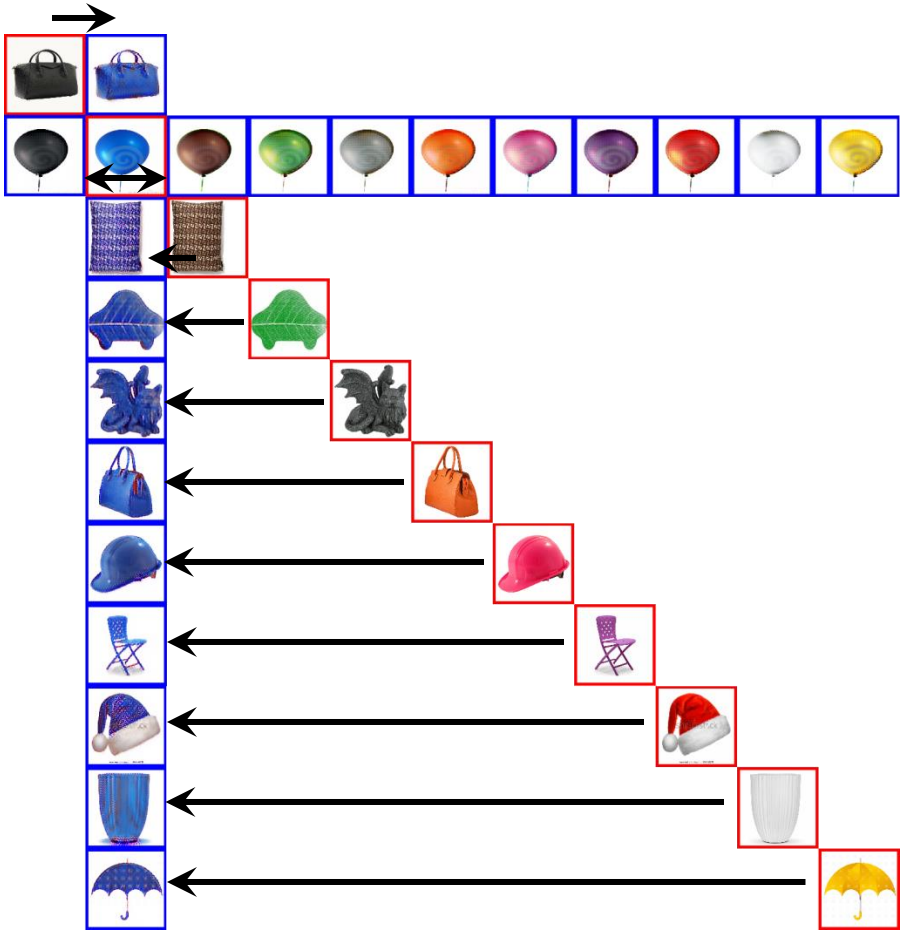


Wang, van de Weijer, Herranz, “Encoder-decoder alignment for zero-pair image-to-image translation”, CVPR 2018

Example: scalable recolorization

Unpaired translation
Eleven colors (i.e. domains)

Requires training 10 encoders and 10 decoders



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Example: scalable recolorization

Unpaired translation
Eleven colors (i.e. domains)

Requires training 10 encoders and 10 decoders

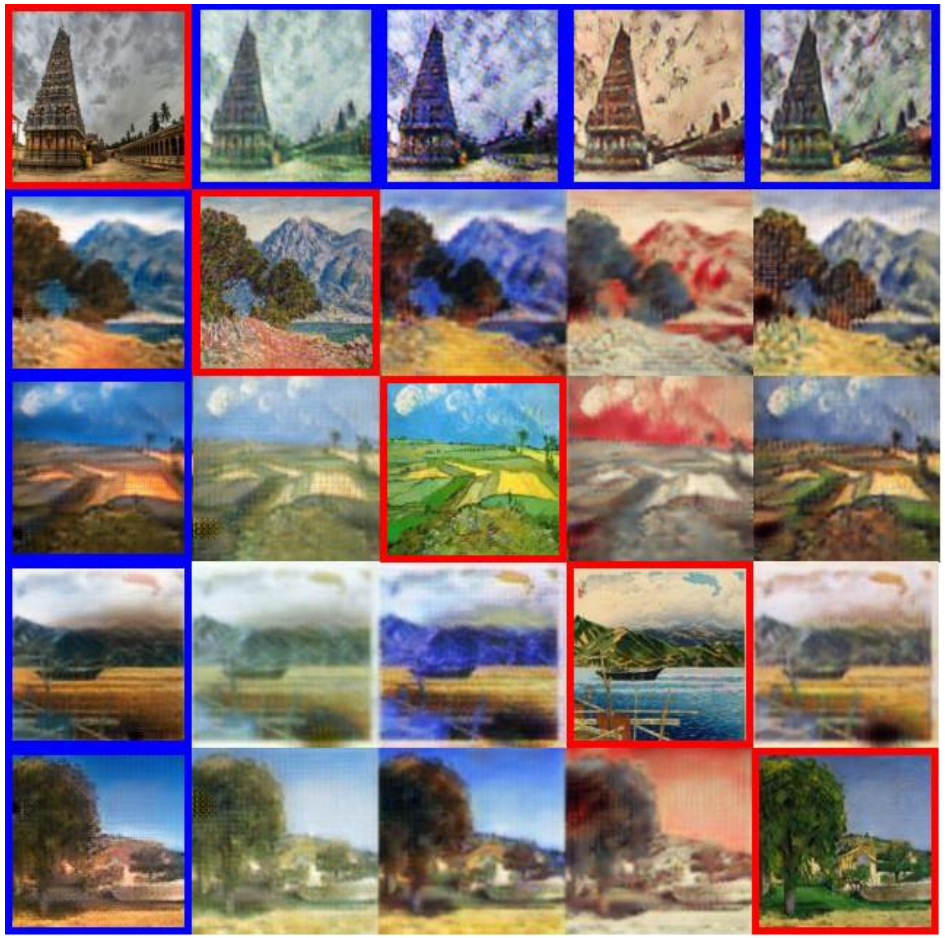
CycleGANs for all combinations would require 55 encoders and 55 decoders

Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

Example: scalable style transfer

Unpaired translation
Five domains
(photo, Monet, van Gogh, Ukiyo-e, Cezanne)

(4 encoders and 4 decoders)



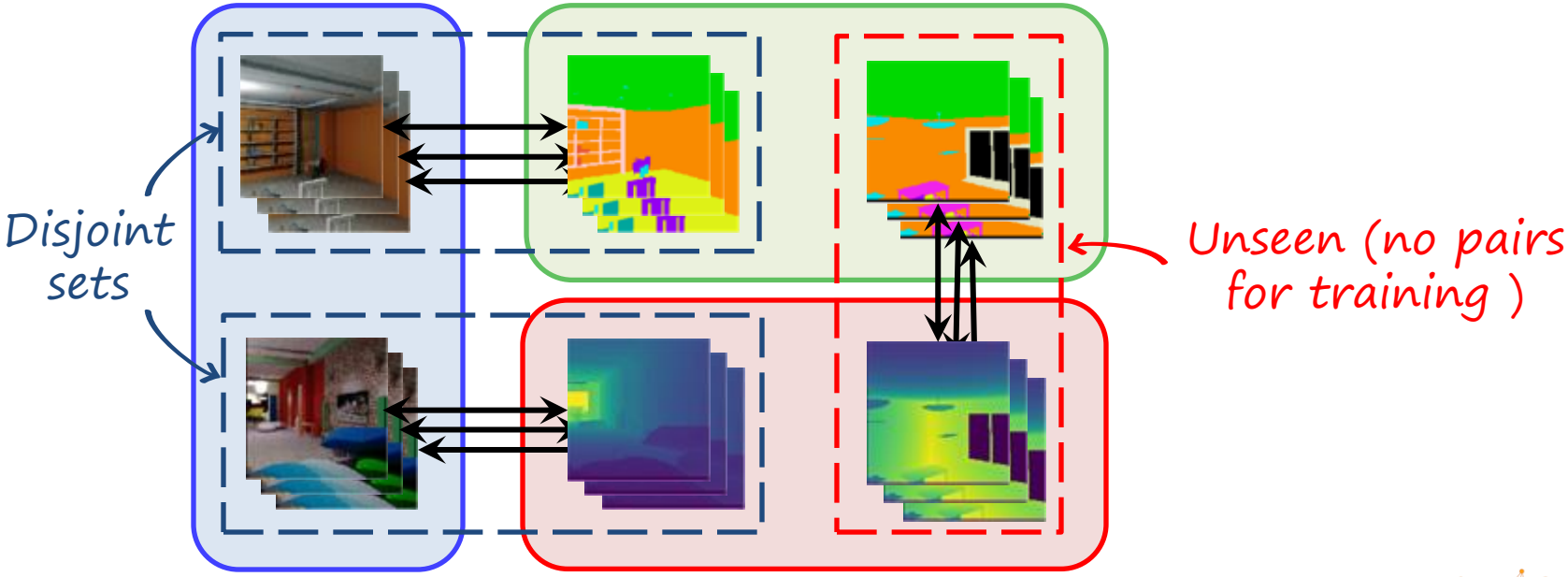
Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

Zero-pair translation

Cross-modal translation setting

Paired data available for (RGB, depth) and (RGB, segm.)

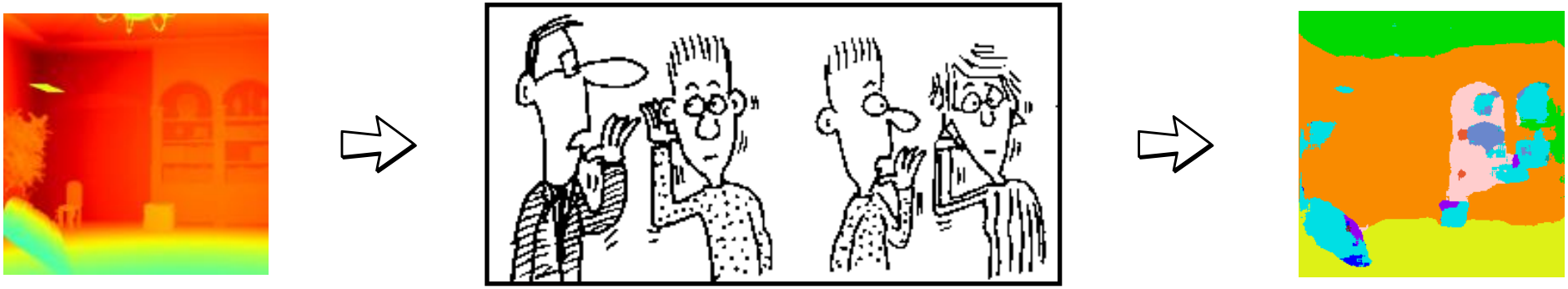
Evaluate on the **unseen zero-pair translations** (depth, segm.)



Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

Zero-pair translation with two cascaded pix2pix (paired translations)

In theory

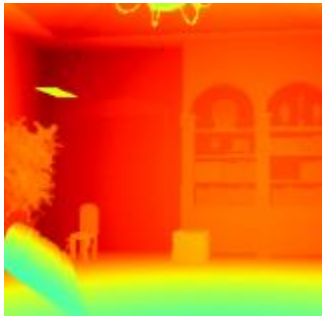


In practice

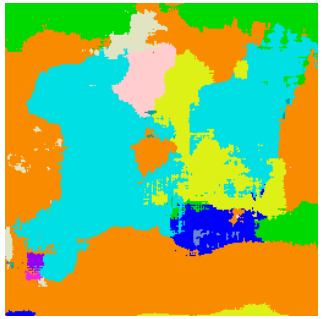
[Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018]

Zero-pair translation with CycleGAN (unpaired translation)

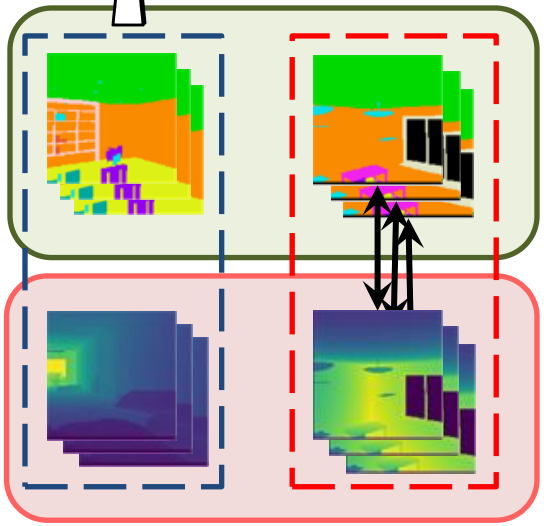
In theory



Depth -to- segment. (CycleGAN)



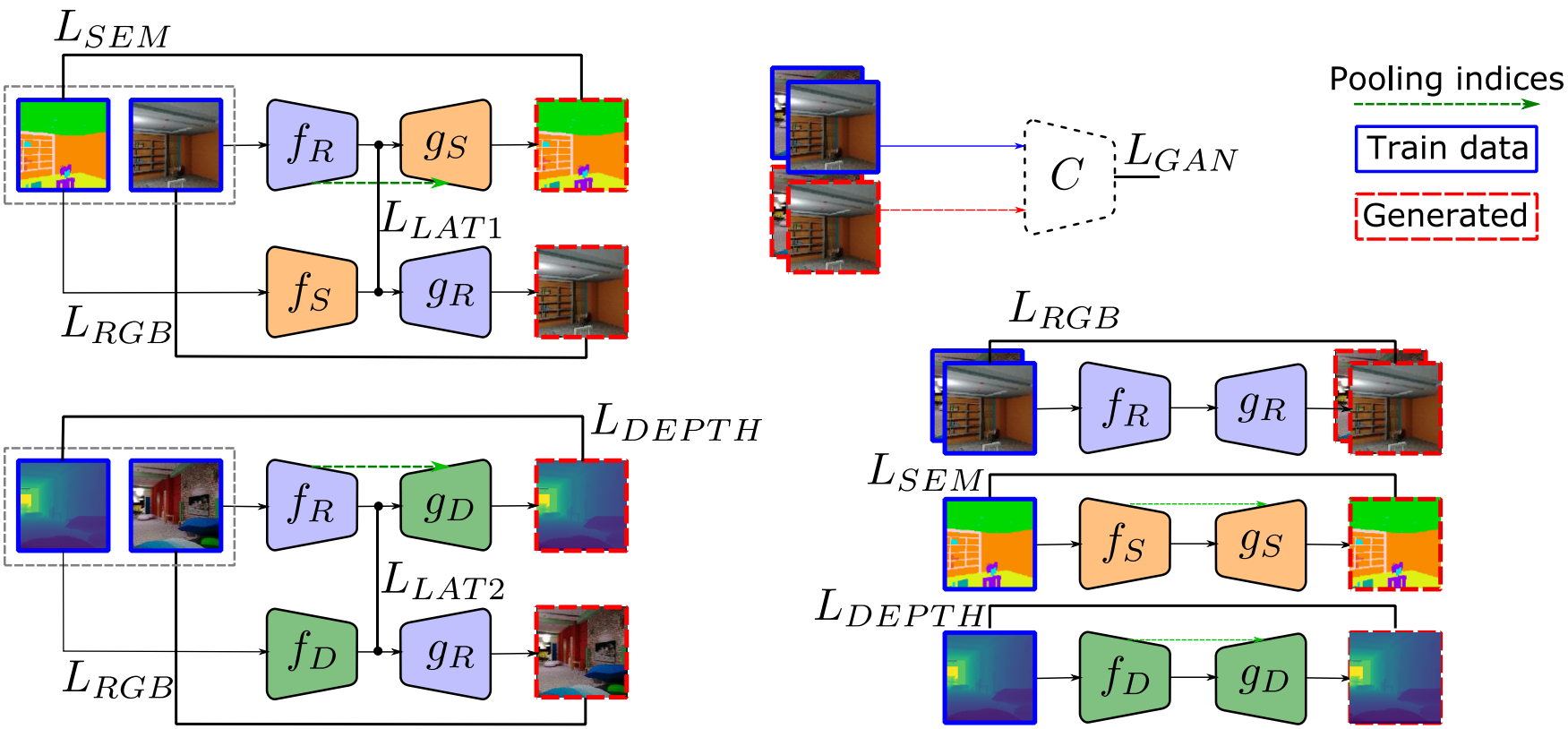
In practice



Depth-to-segmentation is too complex for CycleGAN

Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

Zero-pair translation with mix and match networks

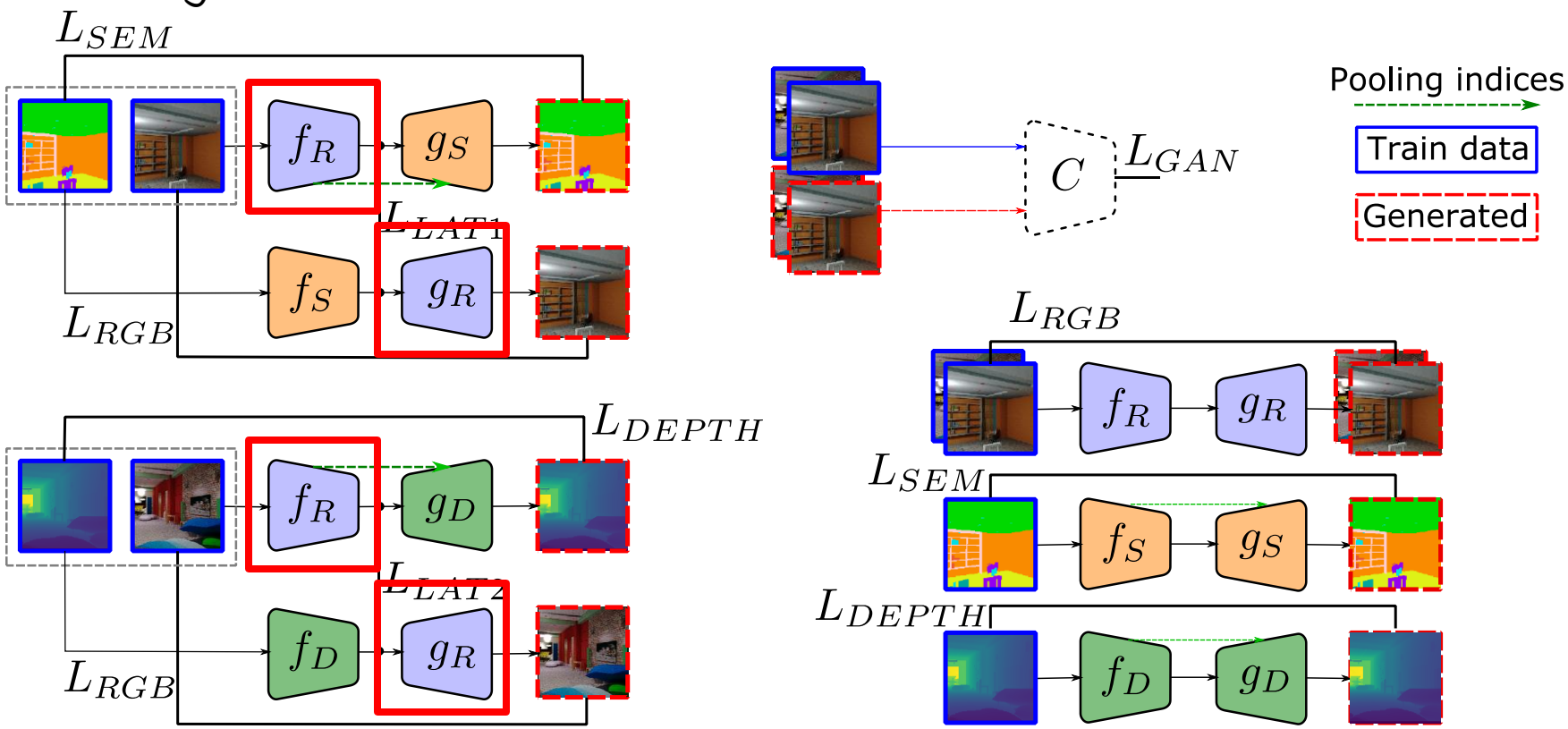


Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

Zero-pair translation with mix and match networks

Training for encoder-decoder alignment:

Shared encoder/decoders



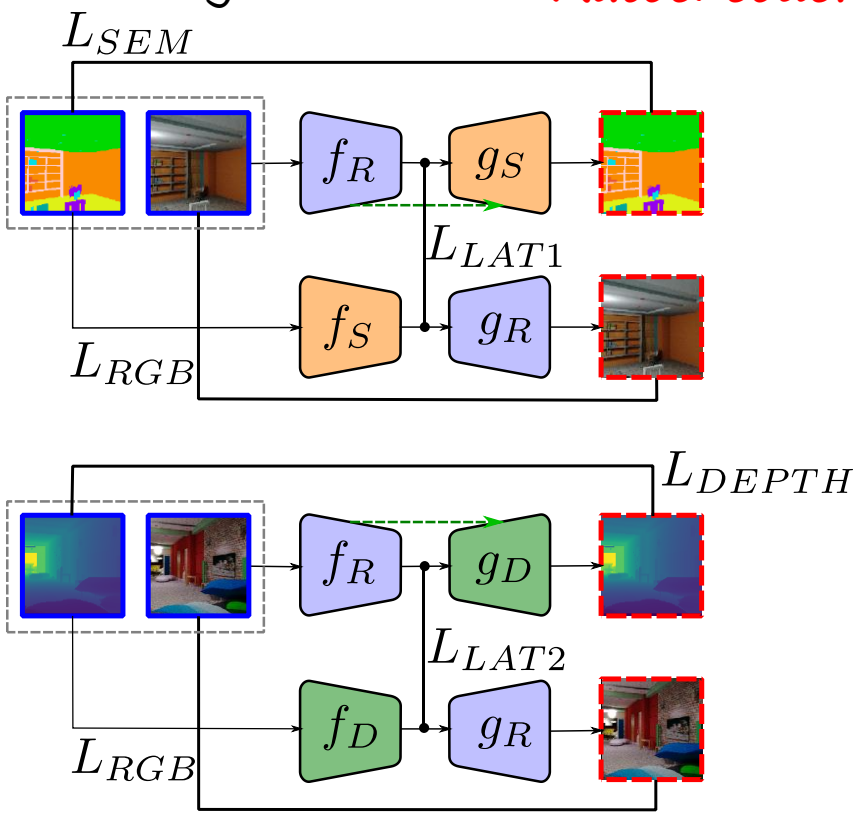
Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

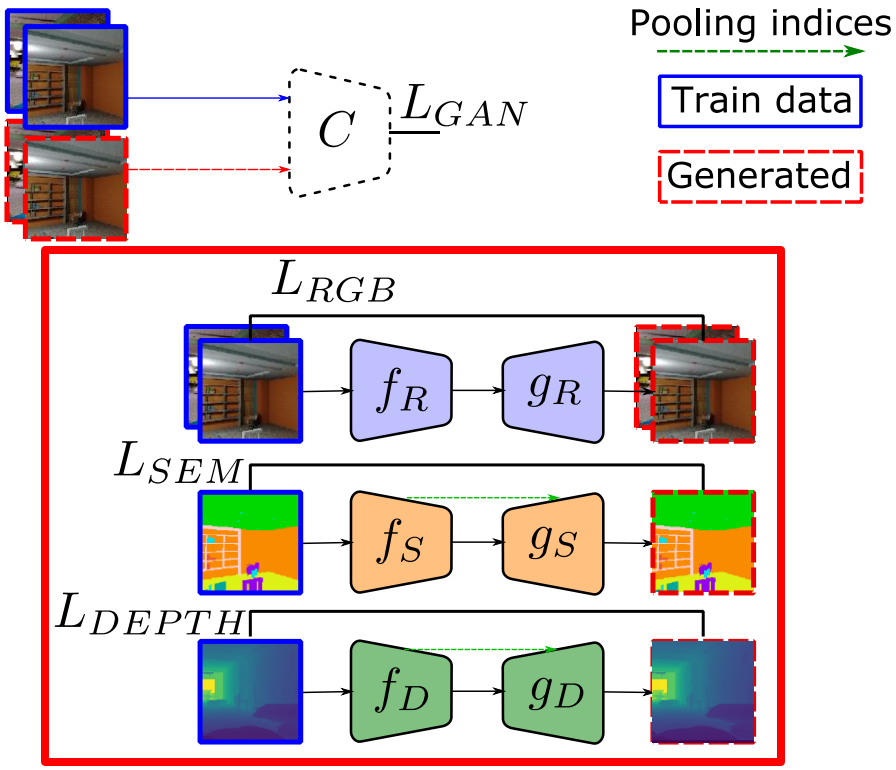
Zero-pair translation with mix and match networks

Training for encoder-decoder alignment:

Shared encoder/decoders

Autoencoders





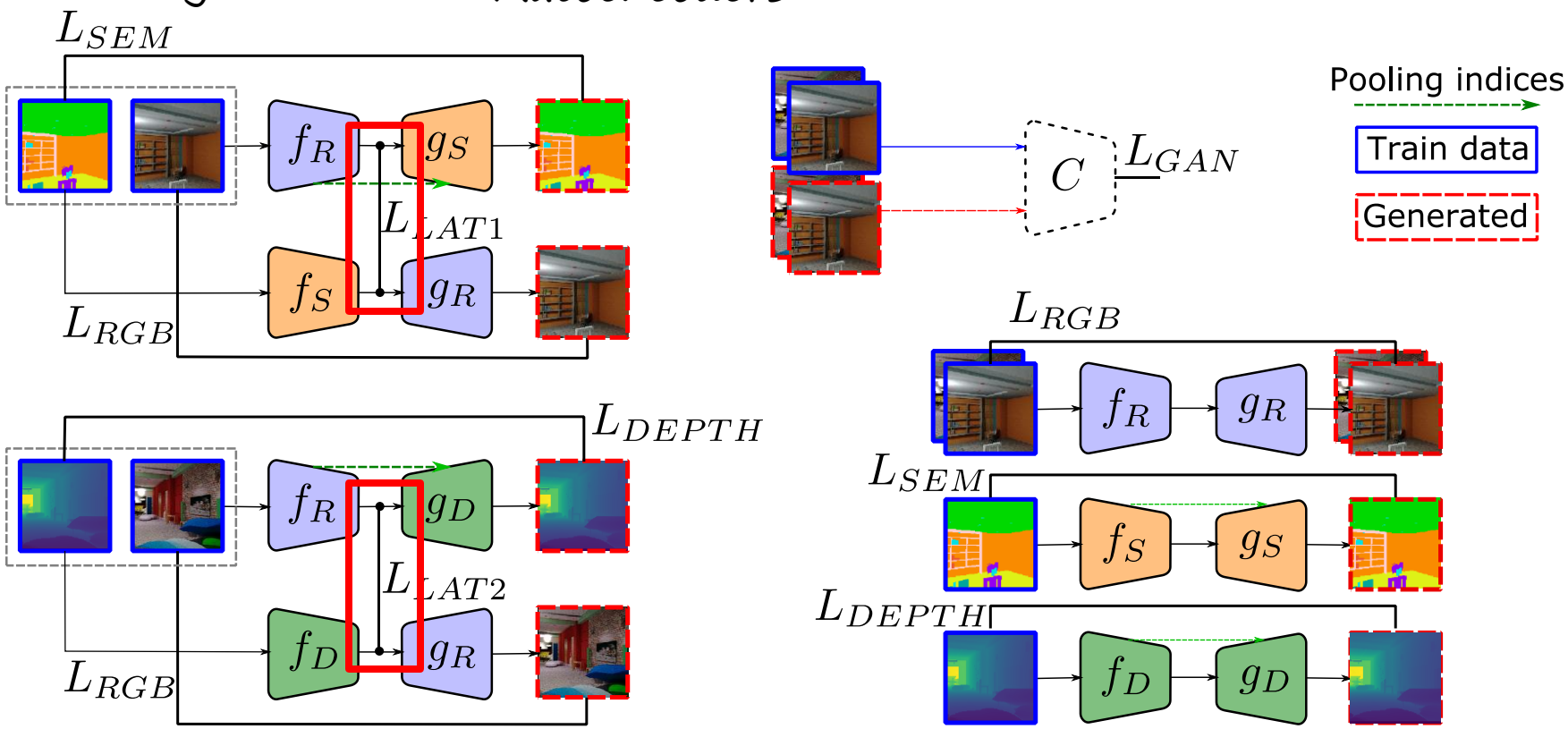
Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

Zero-pair translation with mix and match networks

Training for encoder-decoder alignment:

Shared encoder/decoders
Autoencoders

Latent losses



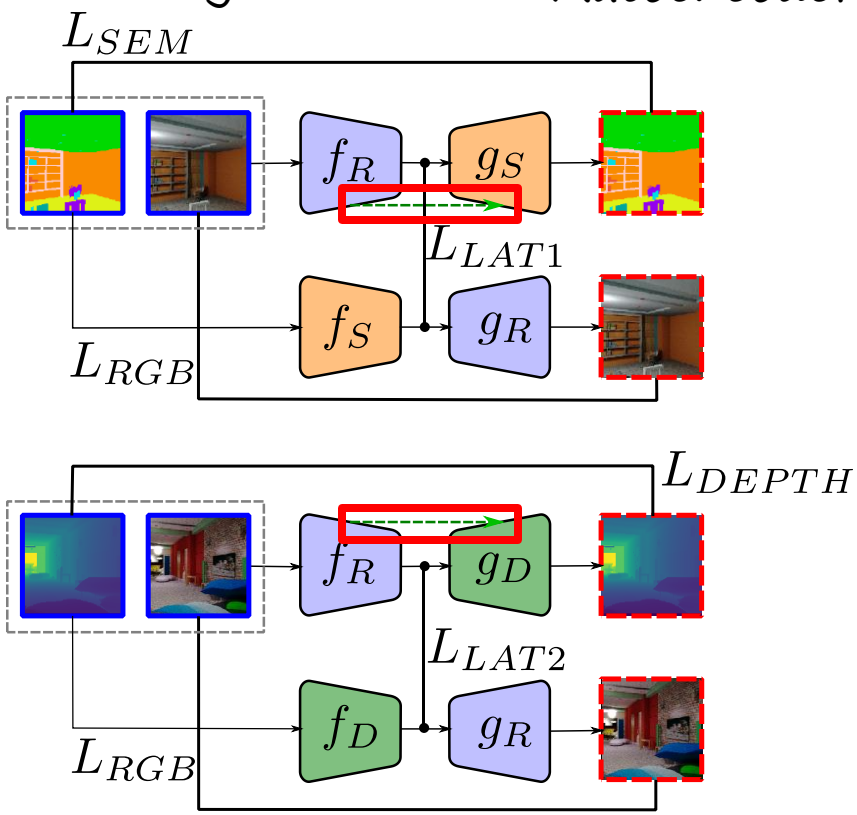
Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

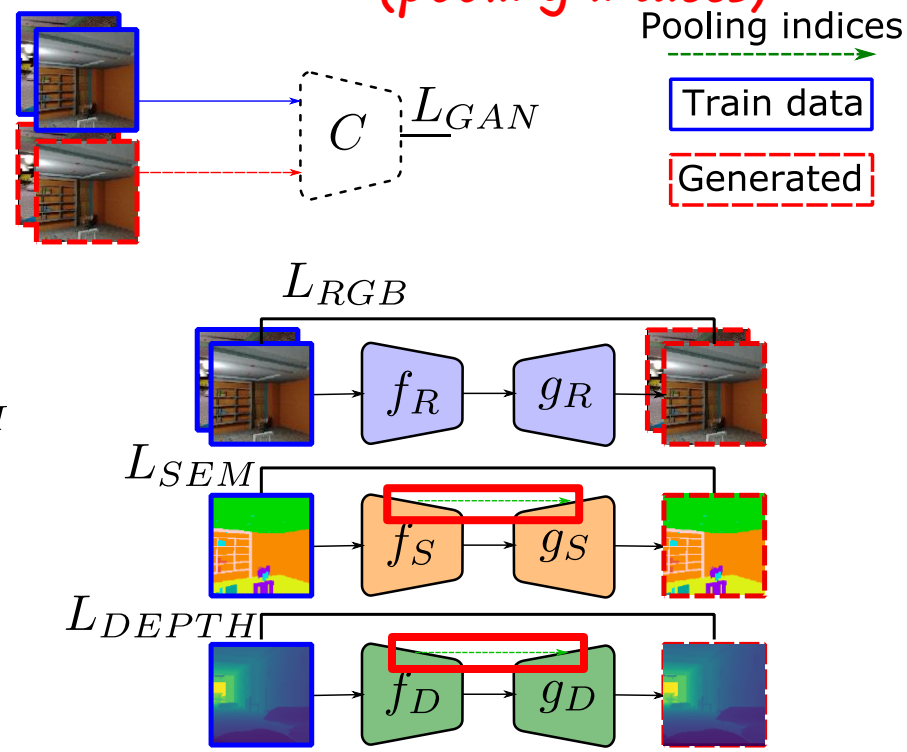
Zero-pair translation with mix and match networks

Training for encoder-decoder alignment:

Shared encoder/decoders
Autoencoders

Latent losses
Robust side information (pooling indices)

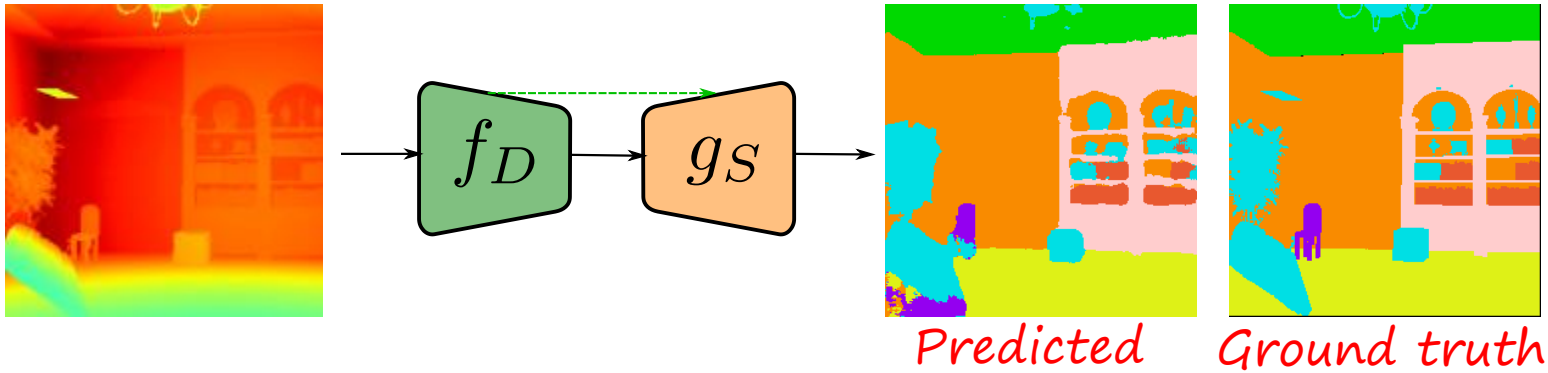




Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

Zero-pair translation with mix and match networks

Test on zero-pair translation depth-to-segmentation



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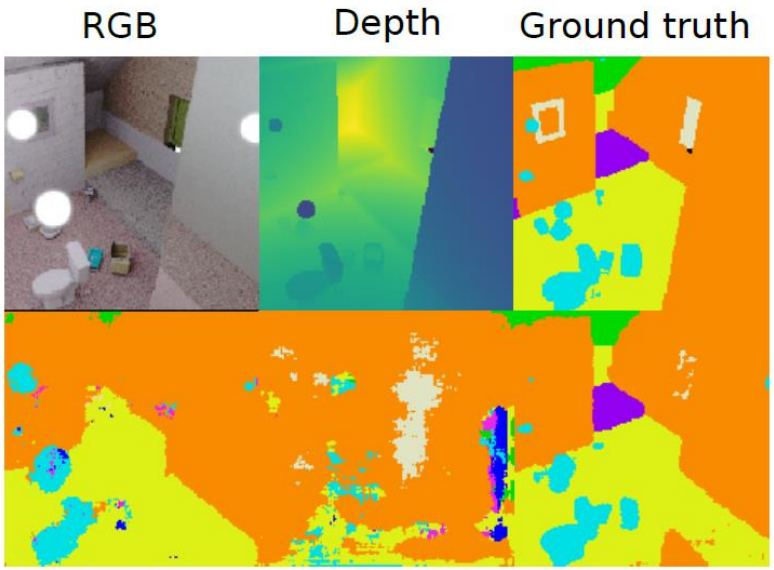
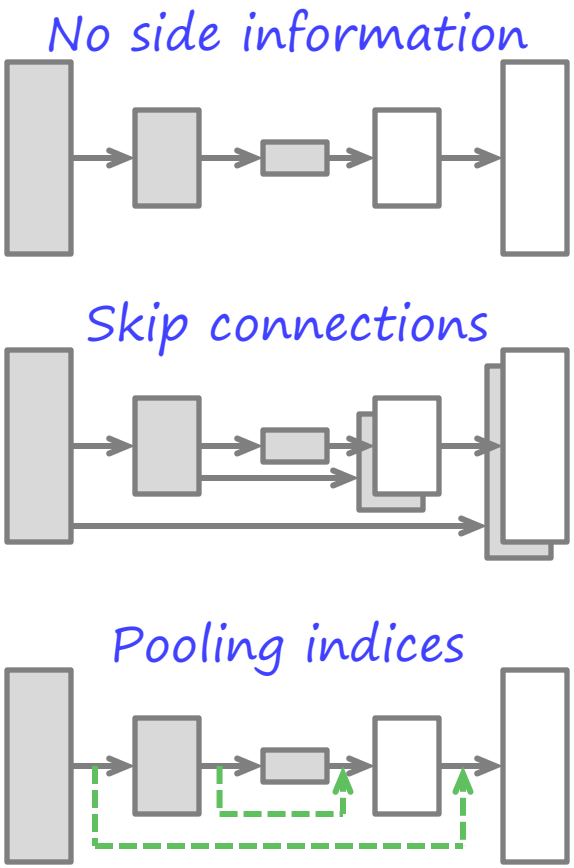
Side information in mix and match networks



Side information	Pretrained	mIoU	Global
-	N	32.2%	63.5%
Skip connections	N	14.1%	52.6%
Pooling indices	N	45.6%	73.4%
Pooling indices	Y	49.5%	80.0%



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Quantitative evaluation

Method	Conn.	L_{SEM}	Bed	Book	Ceiling	Chair	Floor	Furniture	Object	Picture	Sofa	Table	TV	Wall	Window	mIoU	Global
Baselines																	
CycleGAN [34]	SC	CE	2.79	0.00	16.9	6.81	4.48	0.92	7.43	0.57	9.48	0.92	0.31	17.4	15.1	6.34	14.2
2×pix2pix [10]	SC	CE	34.6	1.88	70.9	20.9	63.6	17.6	14.1	0.03	38.4	10.0	4.33	67.7	20.5	25.4	57.6
M&MNet $D \rightarrow R \rightarrow S$	PI	CE	0.02	0.00	8.76	0.10	2.91	2.06	1.65	0.19	0.02	0.28	0.02	58.2	3.3	5.96	32.3
M&MNet $D \rightarrow R \rightarrow S$	SC	CE	25.4	0.26	82.7	0.44	56.6	6.30	23.6	5.42	0.54	21.9	10.0	68.6	19.6	24.7	59.7
Zero-pair																	
M&MNet $D \rightarrow S$	PI	CE	50.8	18.9	89.8	31.6	88.7	48.3	44.9	62.1	17.8	49.9	51.9	86.2	79.2	55.4	80.4
Multi-modal																	
M&MNet $(R, D) \rightarrow S$	PI	CE	49.9	25.5	88.2	31.8	86.8	56.0	45.4	70.5	17.4	46.2	57.3	87.9	79.8	57.1	81.2

Table 3: Zero-pair depth-to-semantic segmentation. **SC**: skip connections, **PI**: pooling indexes, **CE**: cross-entropy

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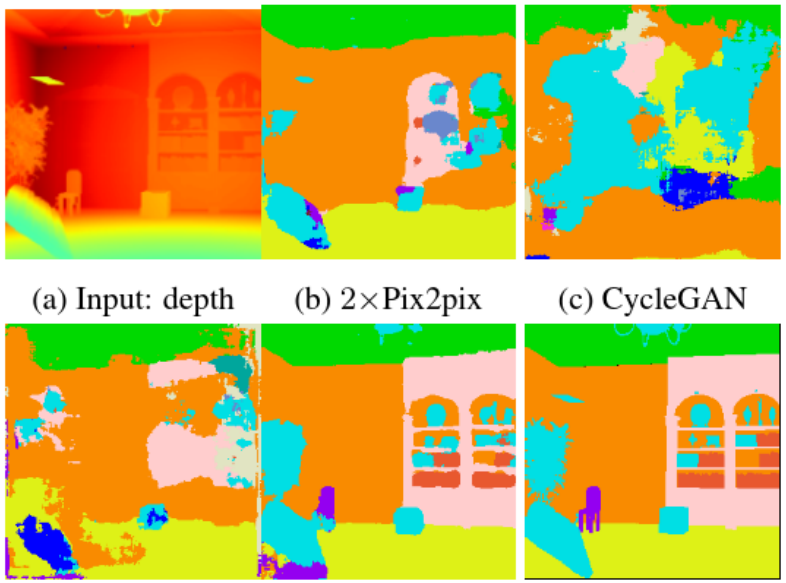
Comparison: depth-to-segmentation



(a) Input: depth (b) 2×Pix2pix (c) CycleGAN

(d) D→R→S (e) Proposed (f) Ground truth

Figure 1: Zero-pair depth→segmentation, trained on (depth,RGB) and (RGB,segmentation).

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Thanks!

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