Learning and forgetting in image classification and generation

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Universitat Autònoma de Barcelona

MARIE CURIE ACTIONS

Horizon 2020

About me

ETS Ing. Telecomunicación
Universidad Politécnica de Madrid (Spain)

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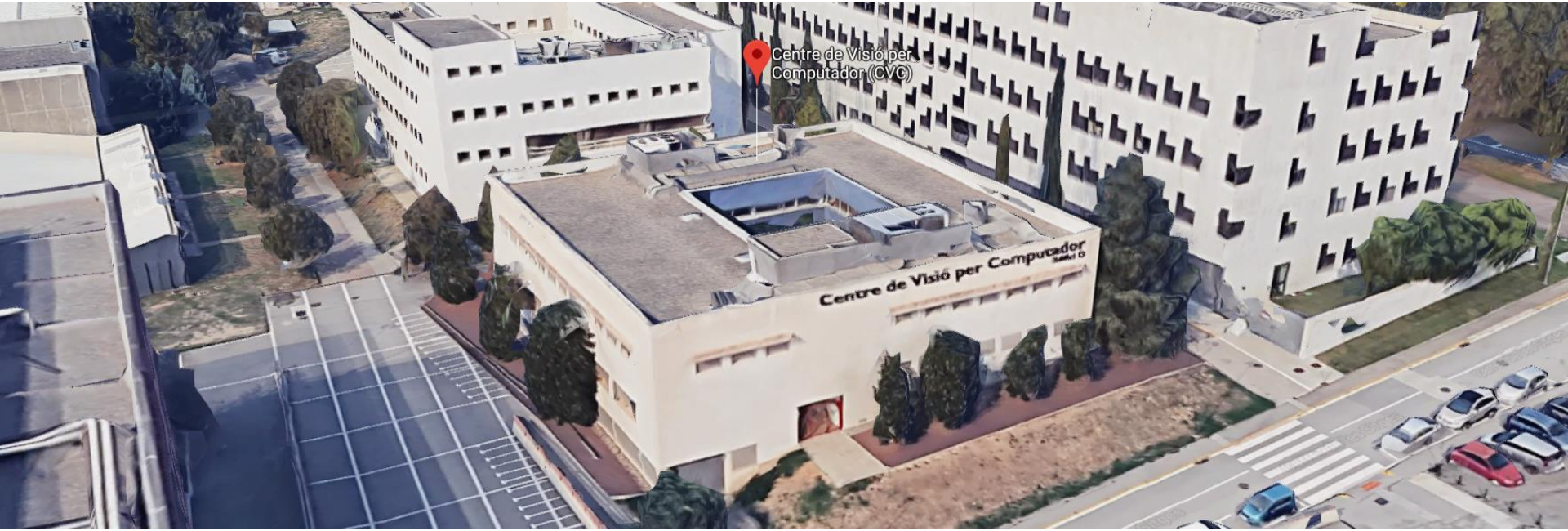
Institute of Computing Technology,
Chinese Academy of Sciences (China)

Computer Vision Center,
Universitat Autònoma de Barcelona (Spain)

Research interests:
Multimedia
Computer vision
Deep learning
Multimodal representations
Lifelong learning

Computer Vision Center (UAB campus)



Only Center in Europe fully devoted to Computer Vision

23 Years

+130 Staff

+20 Nationalities

M€2,3 Income / year

8 PhD thesis /year

+100 Intl publications / year

Learning and Machine Perception (LAMP) group

Joost van de Weijer
Leader

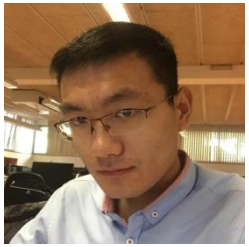
Senior PhDs



Postdocs


PhD students











Outline

- Introduction
- Transferring GANs (ECCV 2018)
- Rotated elastic weight consolidation (ICPR 2018)
- Memory Replay GANs (NIPS 2018)
- Mix and match networks (CVPR 2018)

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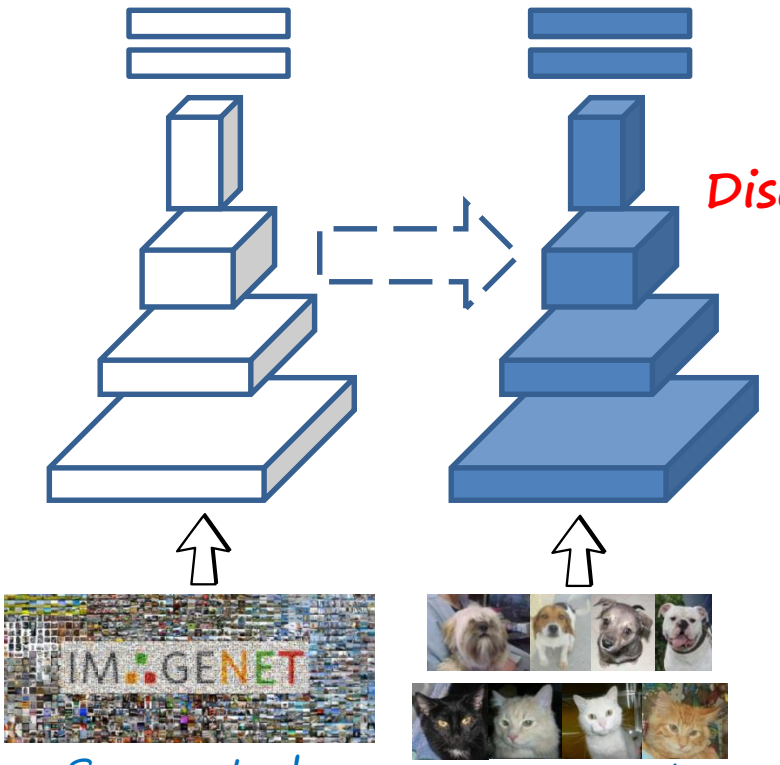
Transfer learning and lifelong learning

Forgets source task, i.e. catastrophic forgetting **(who cares?)**

Forgets task 1 **(big deal!!)**

Transfer+adaptation

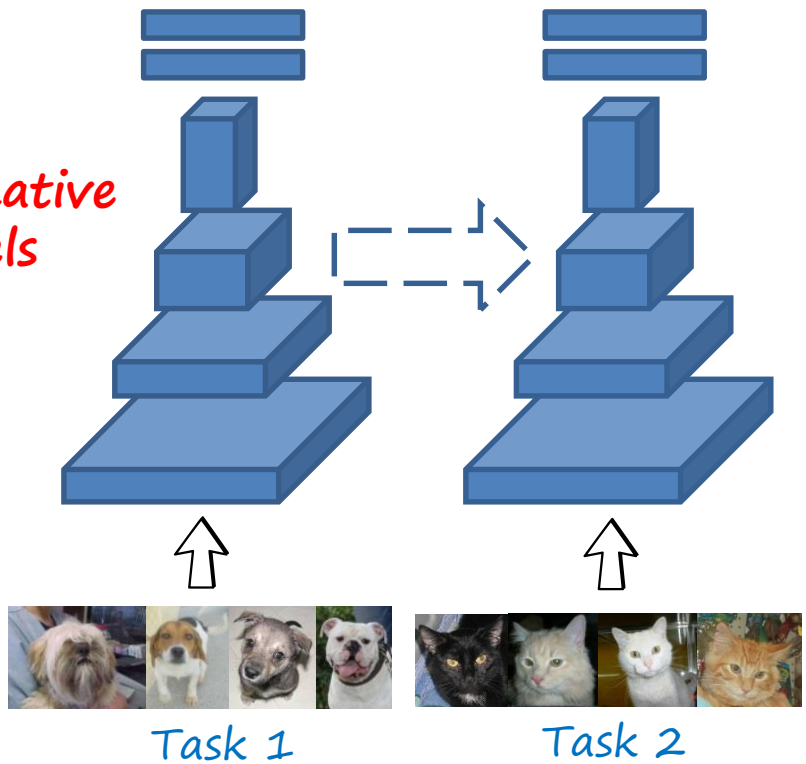
Lifelong learning



Source task

Target task

Discriminative models



Task 1

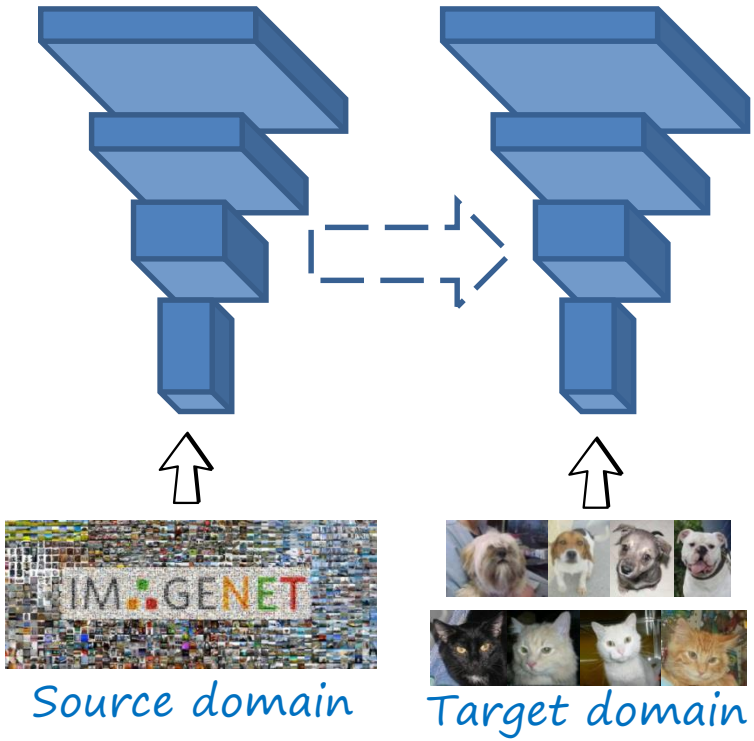
Task 2

Rotated elastic weight consolidation (ICPR 2018)

Liu et al., Rotate your Networks: Better Weight Consolidation and Less Catastrophic Forgetting, ICPR 2018

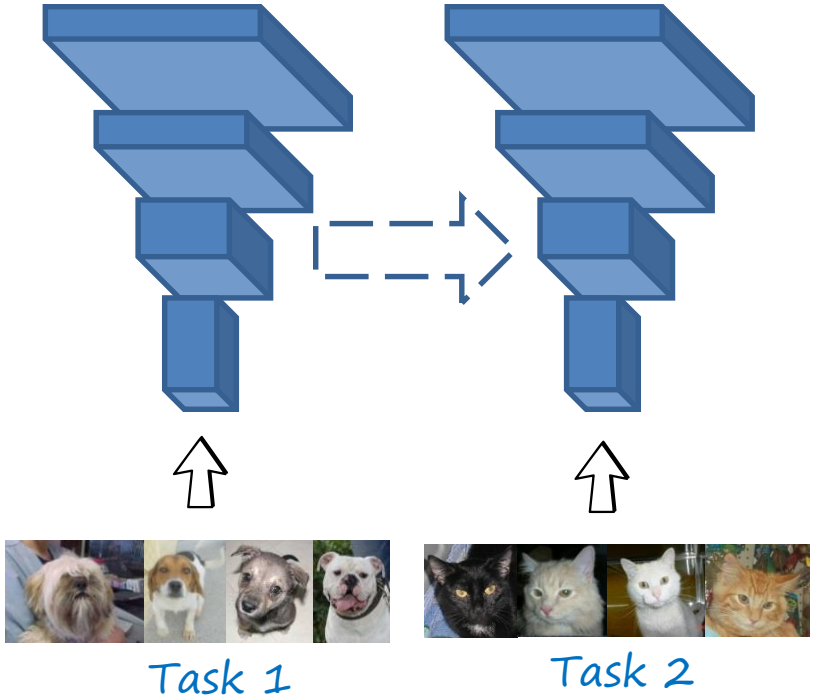
Transfer learning and lifelong learning (now with GANs for image generation)

Transfer+adaptation (generative)



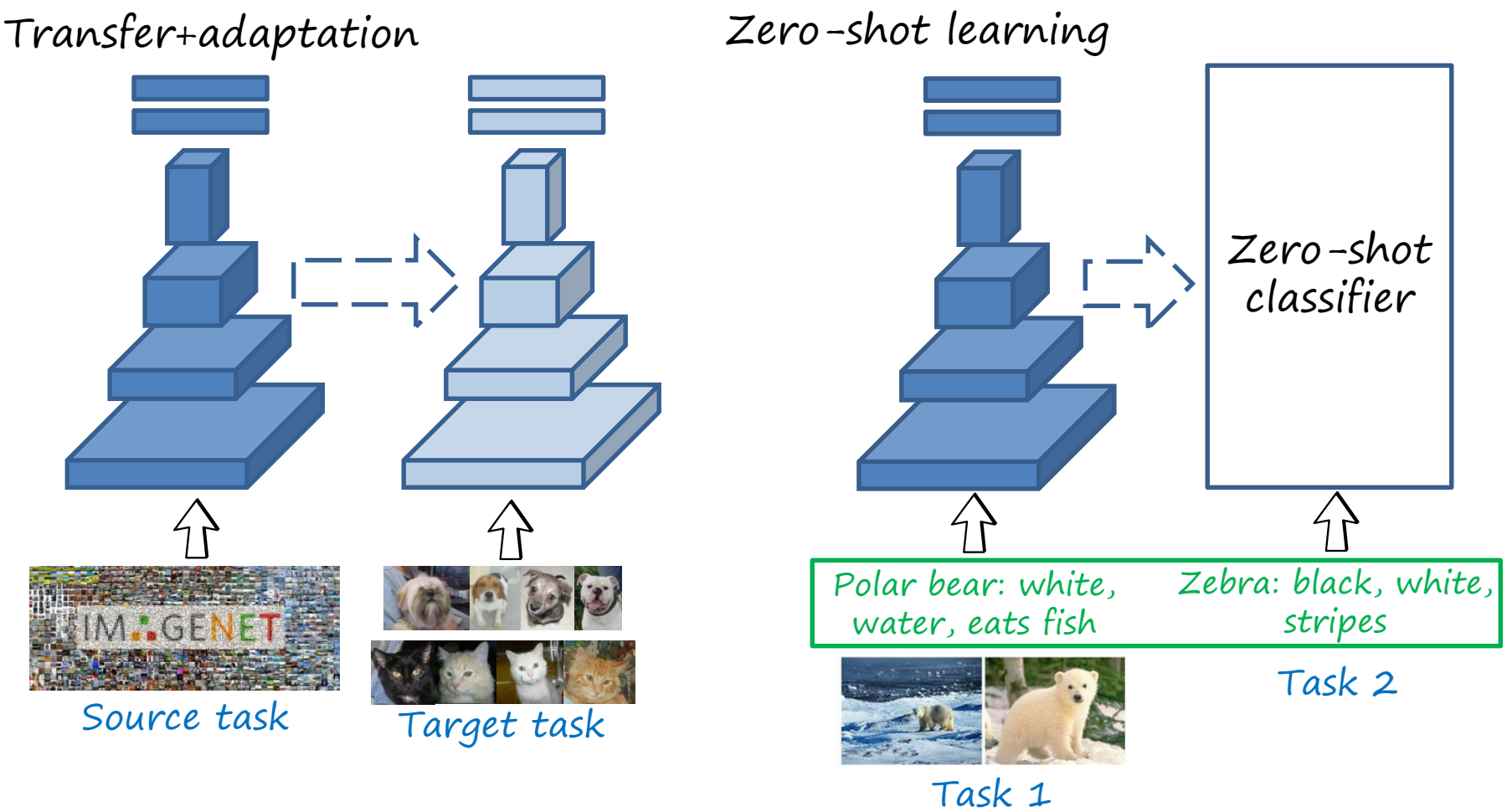
Transferring GANs (ECCV 2018)

Lifelong learning (generative)



Memory Replay GANs (NIPS 2018)

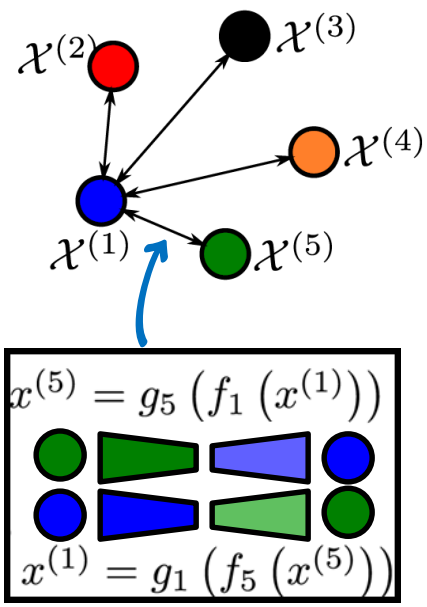
Transfer learning and zero-shot learning



Zero-pair image-to-image translations

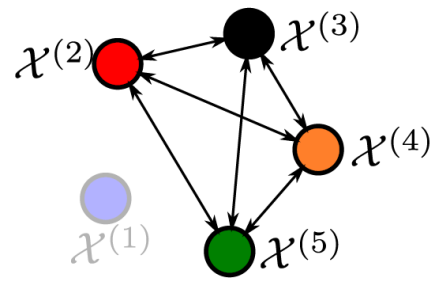
*Only these translations are trained (**seen**)*

Train



*Evaluate on these **unseen** translations (no training pairs)*

Test



Mix and match networks (CVPR 2018)

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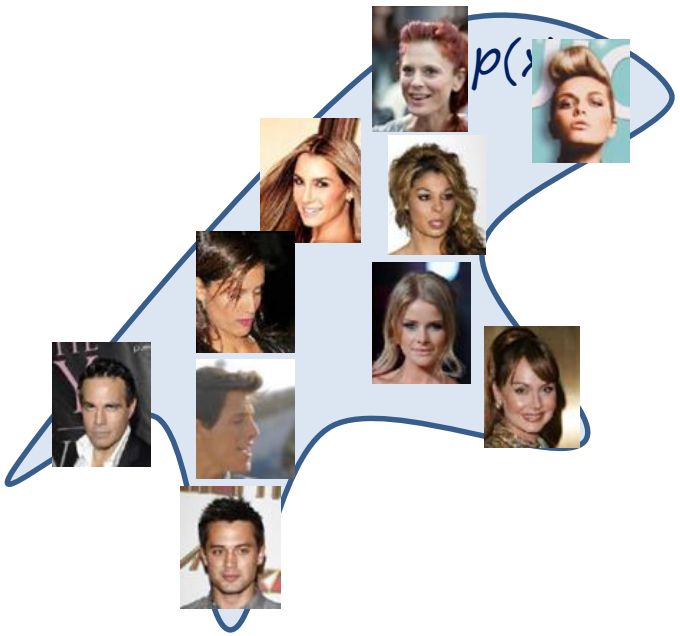
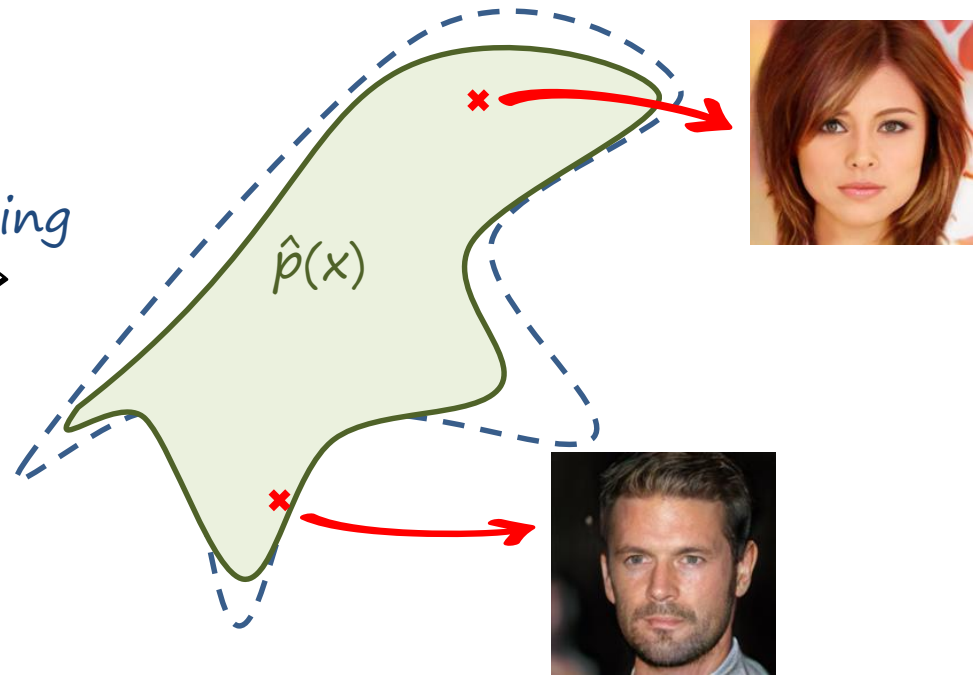
Generative models: networks that imagine

Training data
(e.g. 64x64x3≈12K dims)



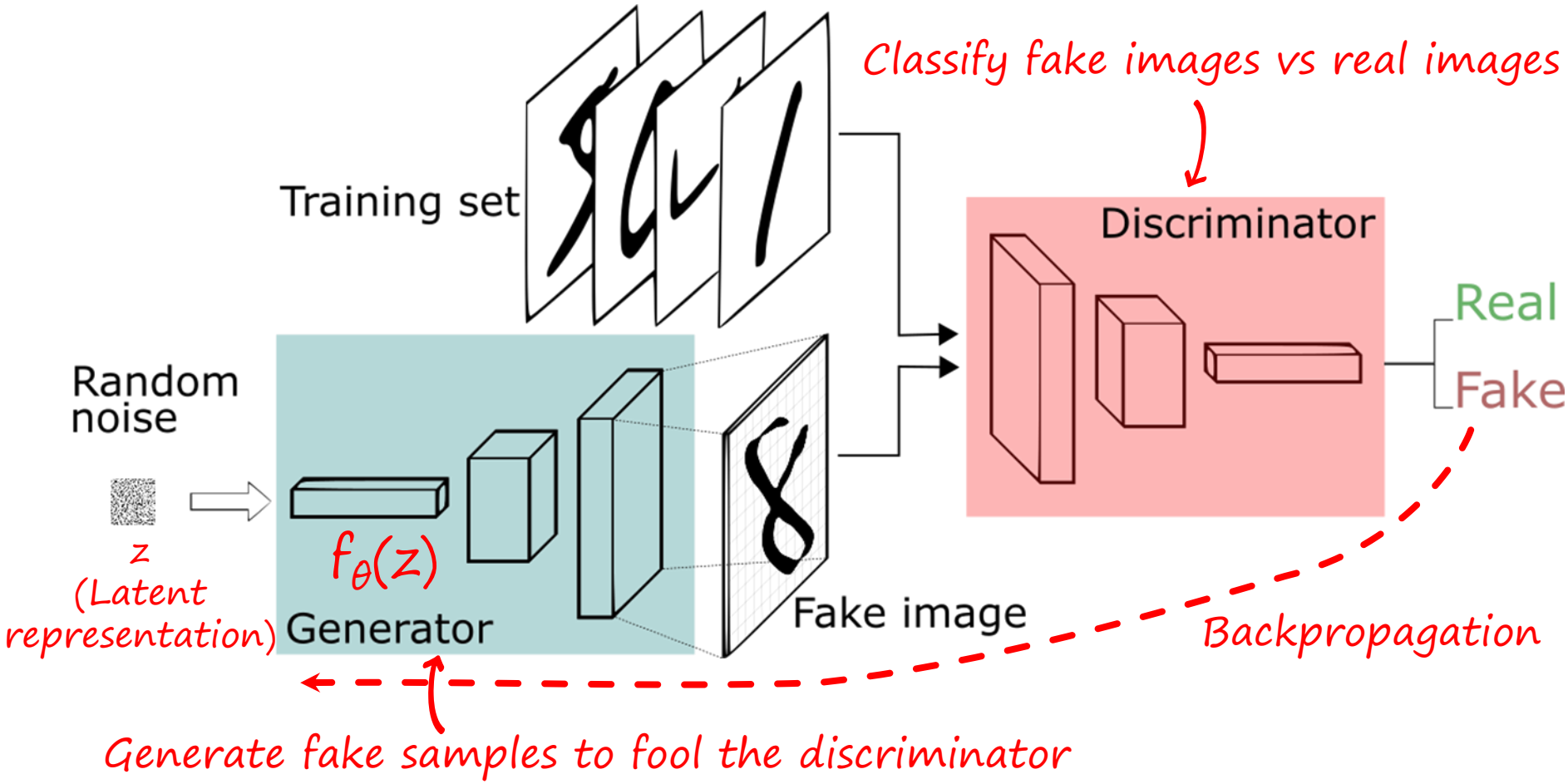
Learning

Sampling



Different approaches
- Density estimation
- Variational autoencoders
- Autoregressive models
- Generative adversarial networks (GANs)

Generative Adversarial Networks (GANs)

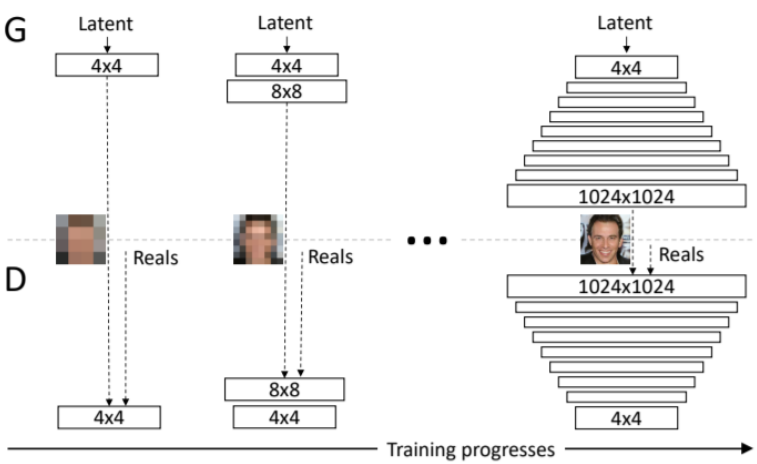


Goodfellow et al., "Generative Adversarial Networks", NIPS 2014
Figure from https://deeplearning4j.org/generative-adversarial-network

Generative Adversarial Networks

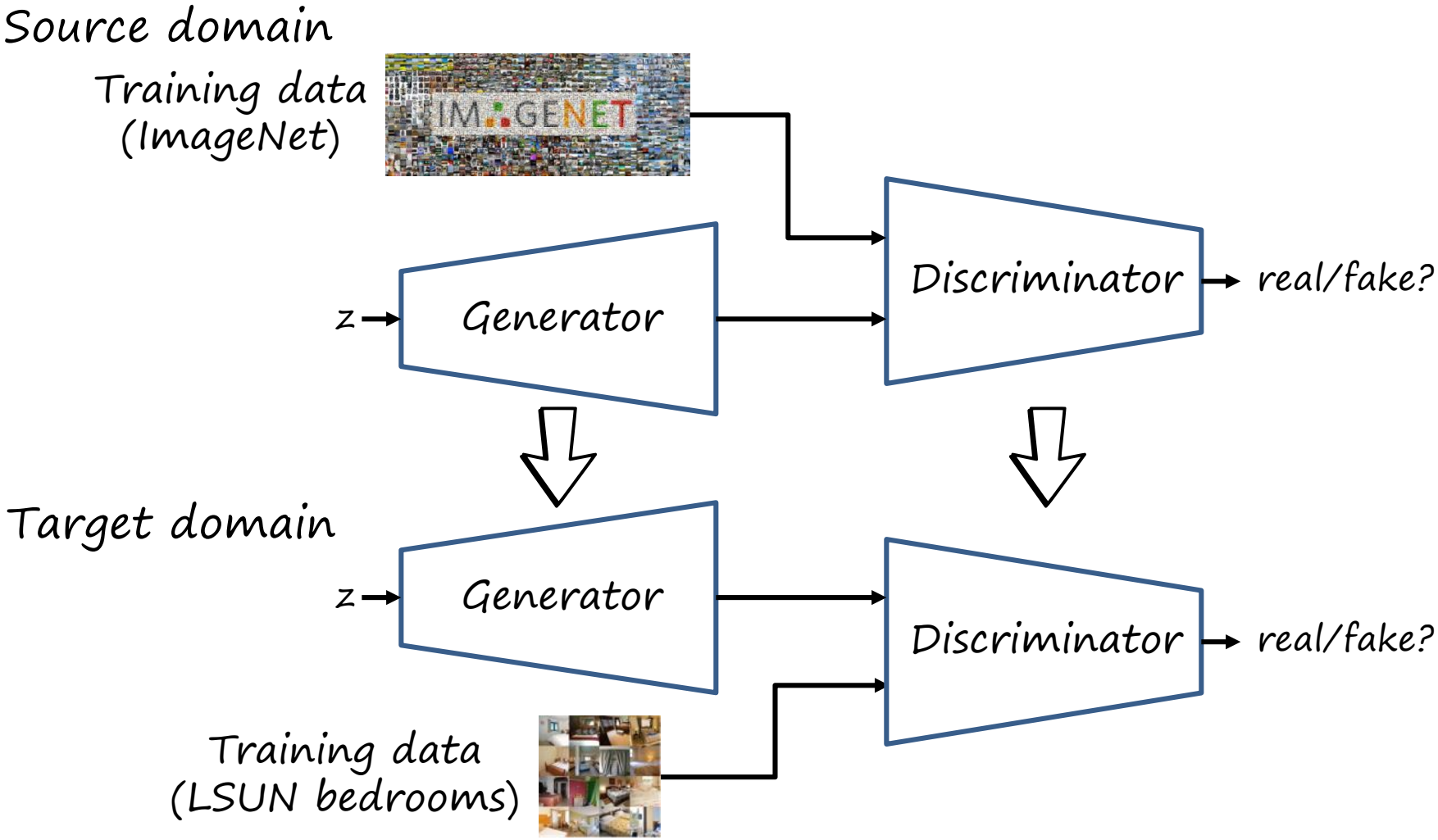
Wasserstein GAN (WGAN-GP)

Progressive growing of GANs



and many more…

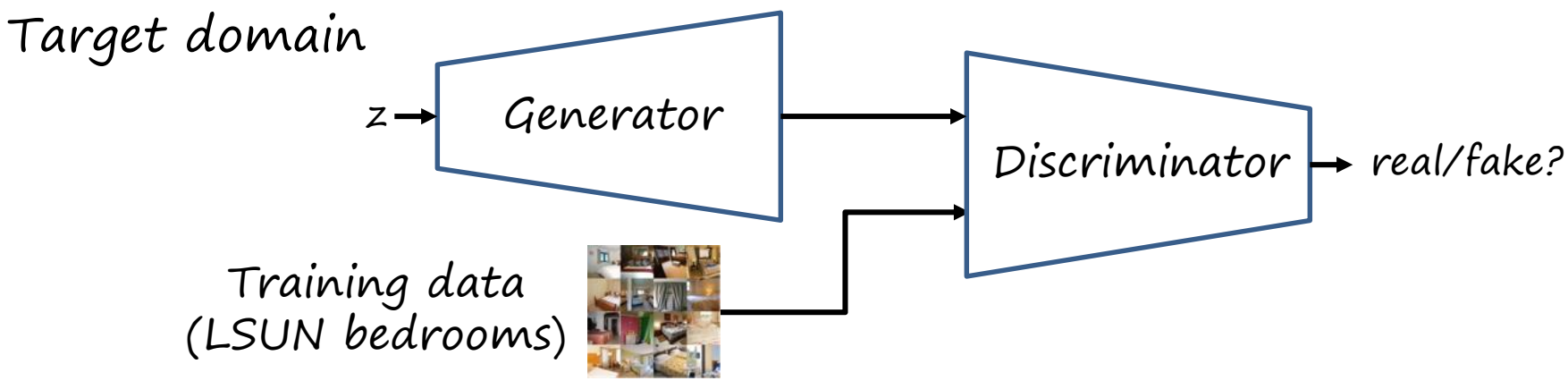
Transferring GAN representations



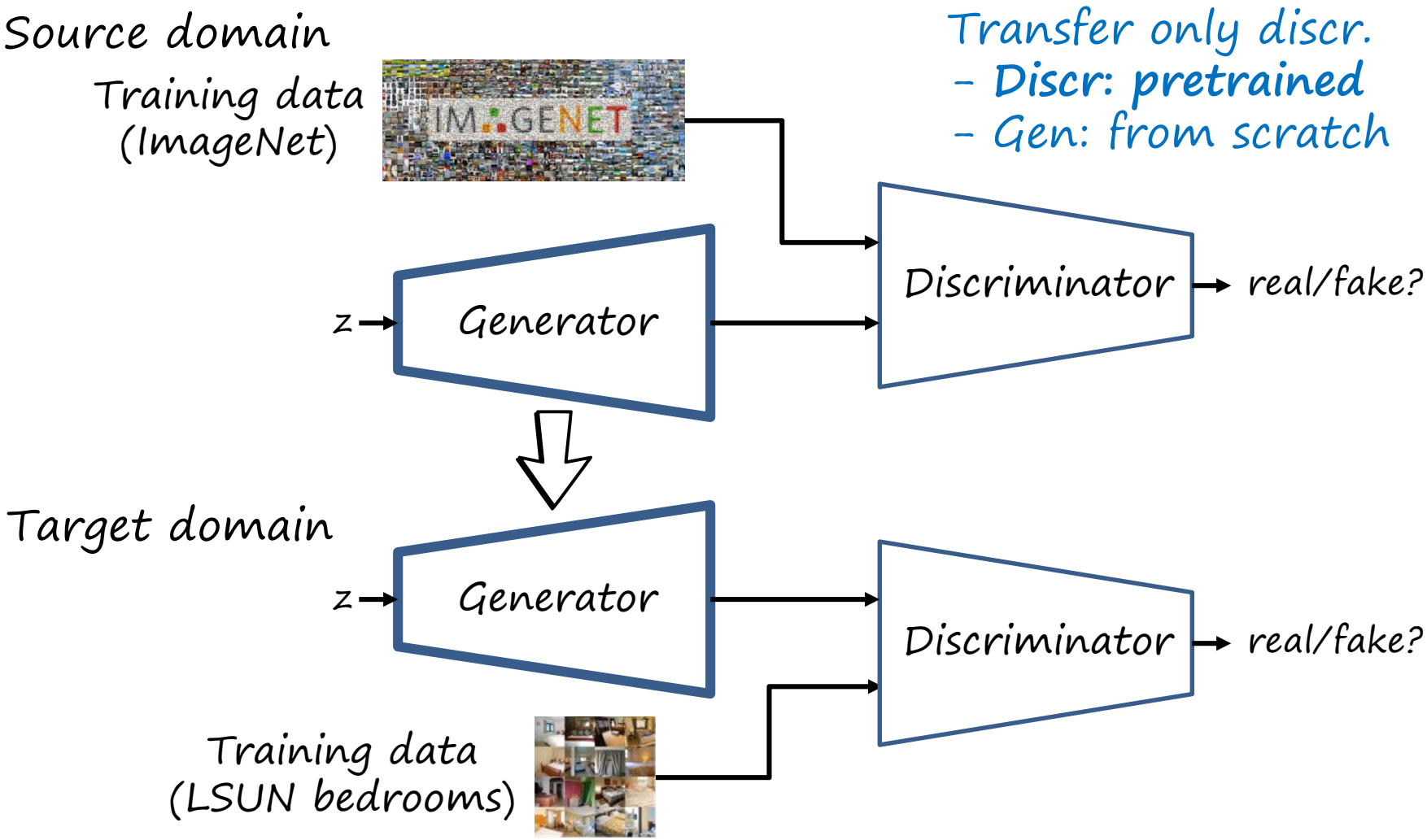
Wang *et al.*, "Transferring GANs: generating images from limited data", ECCV 2018

Transfer configuration

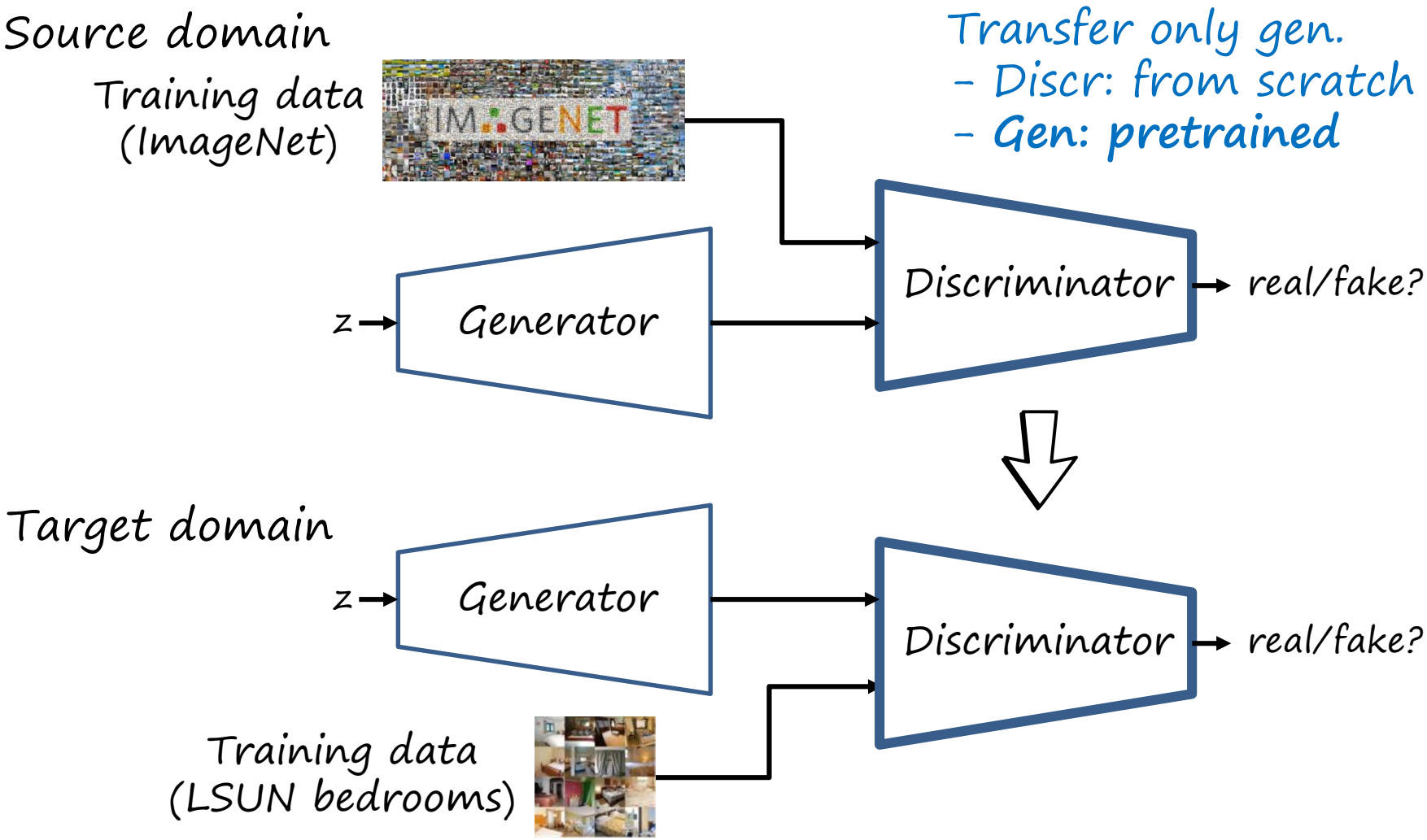
Training from scratch
- Discr: from scratch
- Gen: from scratch



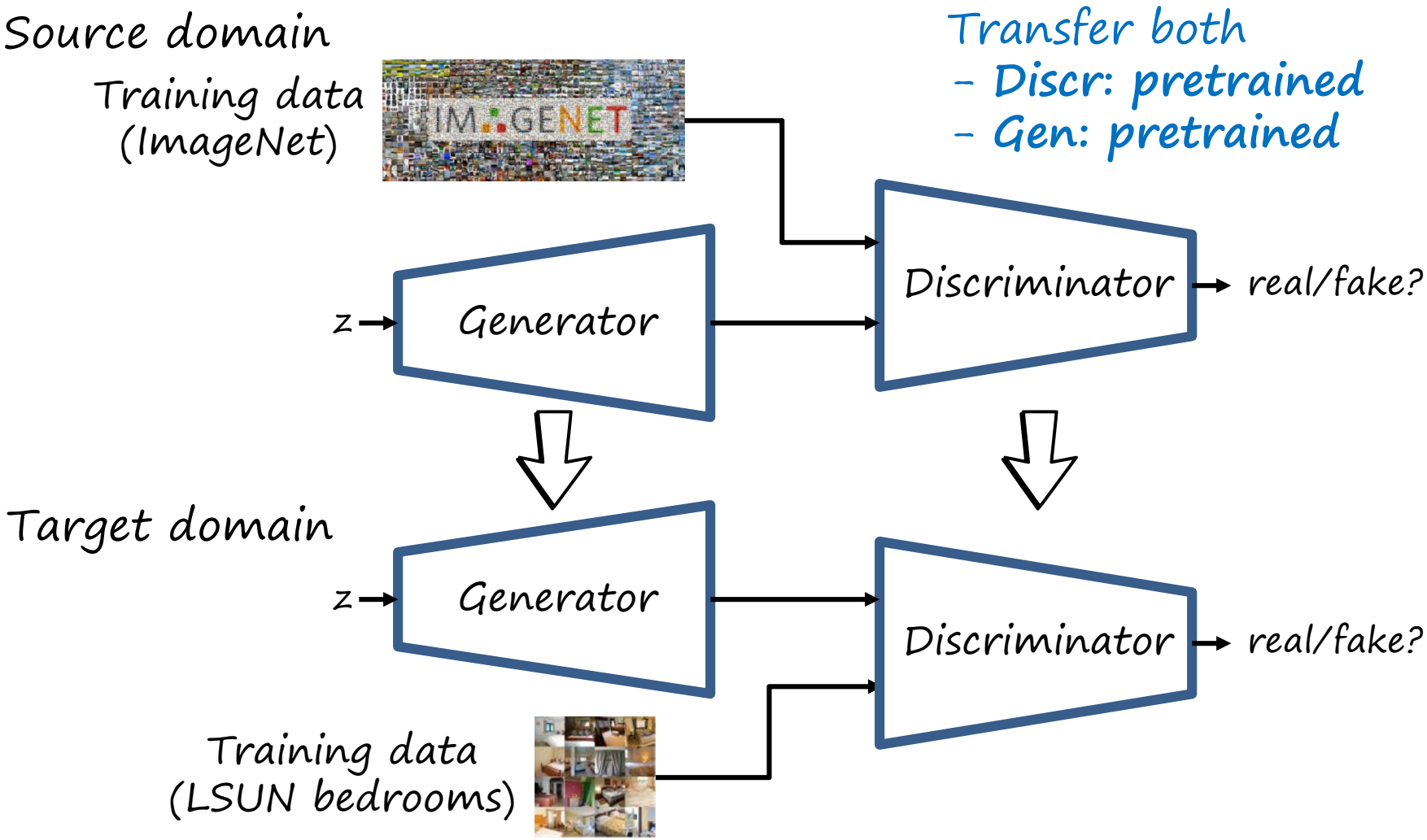
Transfer configuration



Transfer configuration



Transfer configuration

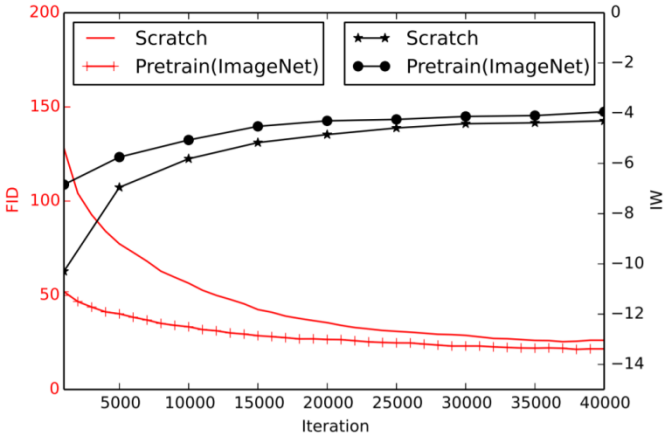


Transfer configuration

- What should I transfer?
  - Experiment: ImageNet to Bedrooms (100K images)

	Generator	Scratch		Pretrained	
	Discriminator	Scratch	Pretrained	Scratch	Pretrained
Lower better	FID $(\mathcal{X}^{tgt}_{data}, \mathcal{X}^{tgt}_{gen})$	32.87	30.57	56.16	**24.35**
Higher better	IW $(\mathcal{X}^{tgt}_{val}, \mathcal{X}^{tgt}_{gen})$	-4.27	-4.02	-6.35	**-3.88**
		None	Only discr.	Only gen.	Both

- Training is faster and images have better quality
  - Especially when data is limited



Learning with limited data

Target dataset:
Bedroom

From scratch

Pretrained (ImageNet)

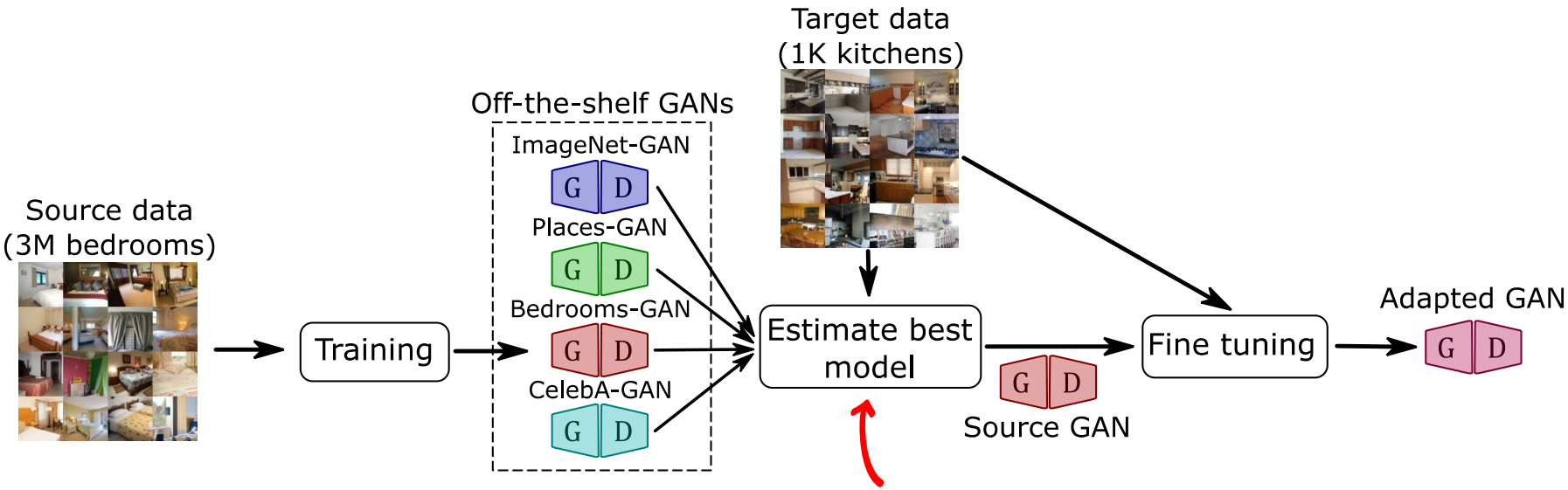
1000 images

10000 images

100000 images

Wang *et al.*, "Transferring GANs: generating images from limited data", ECCV 2018

Pretrain model selection



Estimated as
$\min_k$ FID(generated by GAN_k, target real)

Wang *et al.*, "Transferring GANs: generating images from limited data", ECCV 2018

Good/bad source datasets

Source

Places
(205 classes
~10K img/class)

Target

Kitchen
(50K)

Bedrooms
(1 class
3M images)

Kitchen
(50K)

Generative: very **dense**, diversity not so important (e.g. LSUN Bedrooms)

Discriminative: very **diverse**, medium density (e.g. ImageNet, Places)

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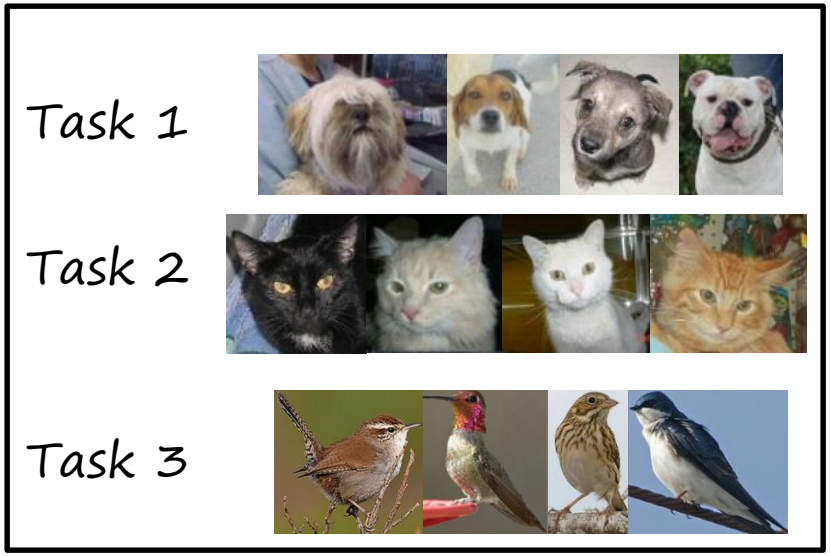
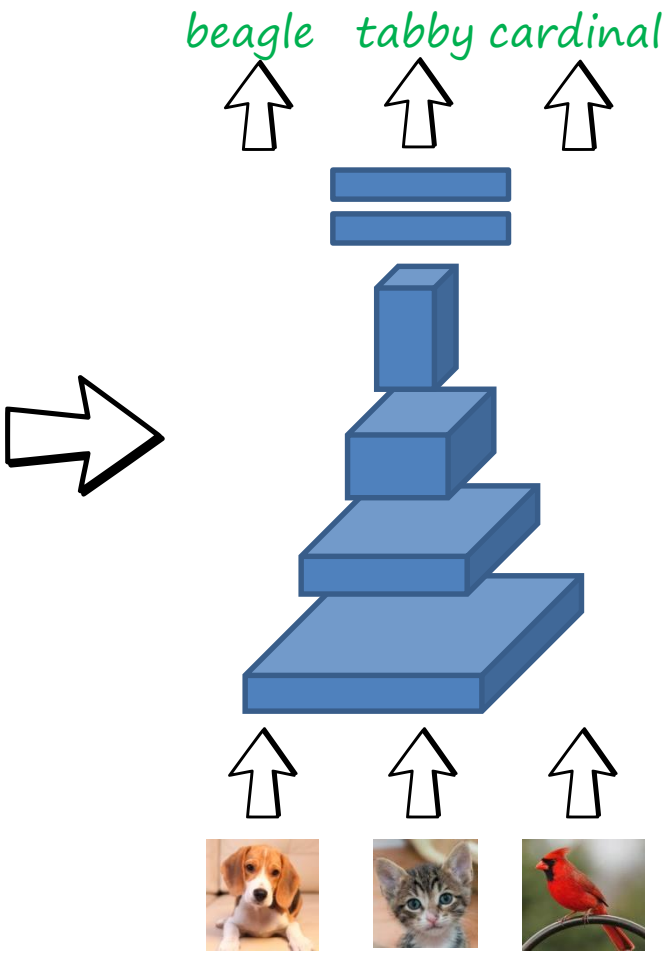
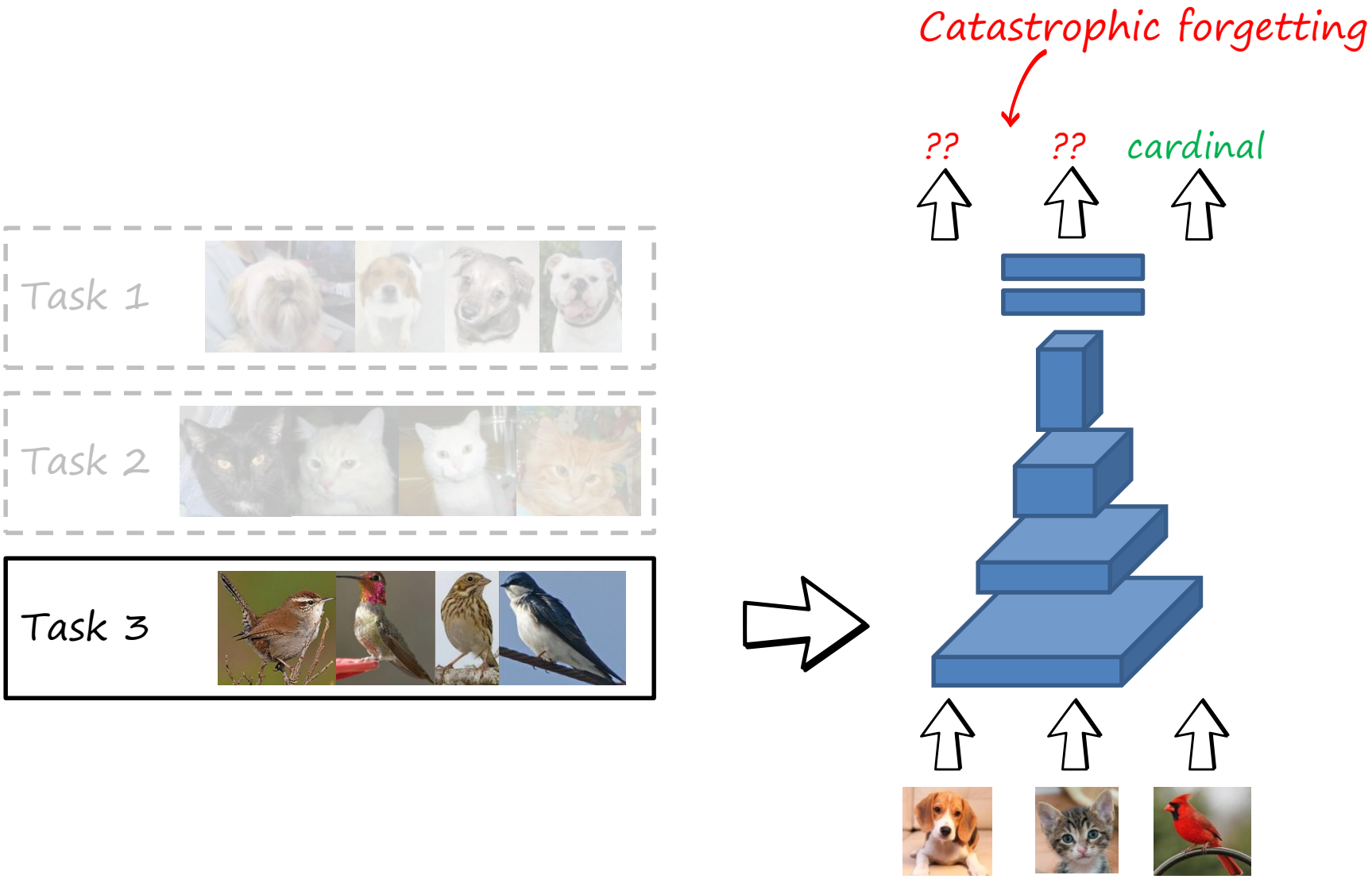
When are neural networks good?

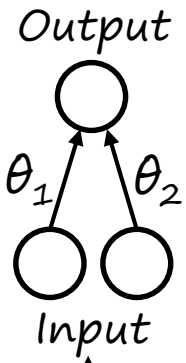




Sequential learning

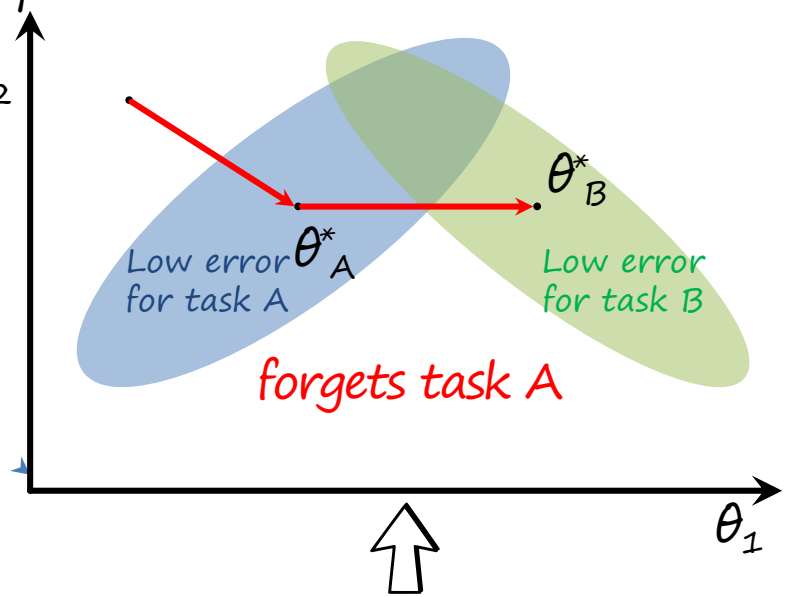


Catastrophic interference and forgetting



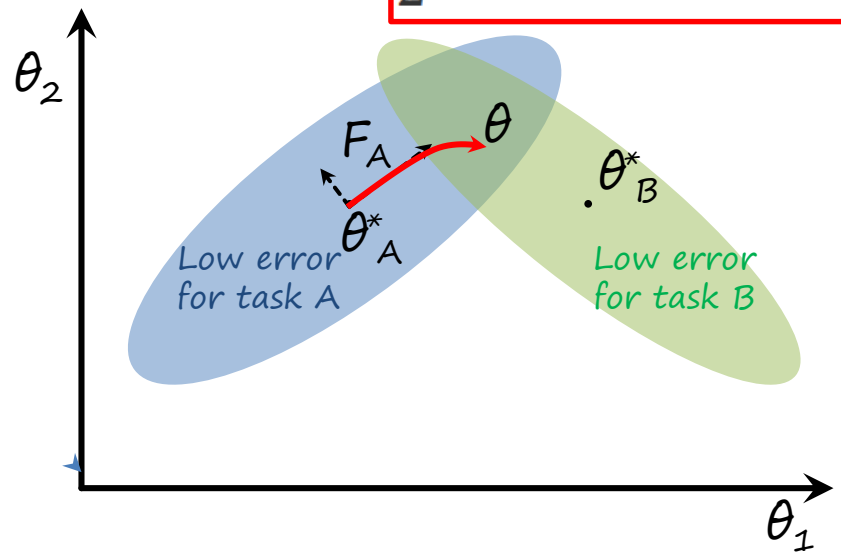
Training/fine tuning

$$\mathcal{L}(\theta) = \mathcal{L}_B(\theta)$$



Elastic weight consolidation (EWC)

$$\mathcal{L}(\theta) = \mathcal{L}_B(\theta) + \boxed{\frac{\lambda}{2}(\theta - \theta^*_A)^\intercal F_A (\theta - \theta^*_A)}$$



Problem: size of F_A is $(\#\theta)^2$!!!

Task B

Kirkpatric et al., Overcoming catastrophic forgetting in neural networks, PNAS, 2017

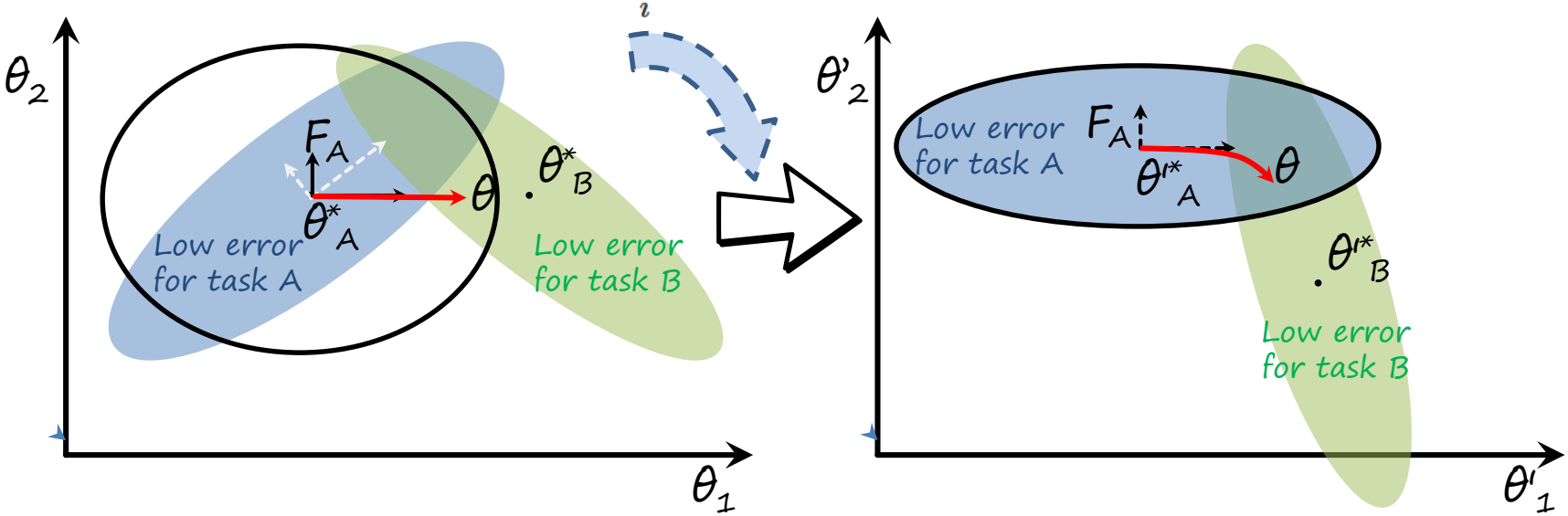
Rotated elastic weight consolidation

Size of the diagonal of F_A is $\#\theta$

Elastic weight consolidation in practice
(with diagonal approx. of F_A)

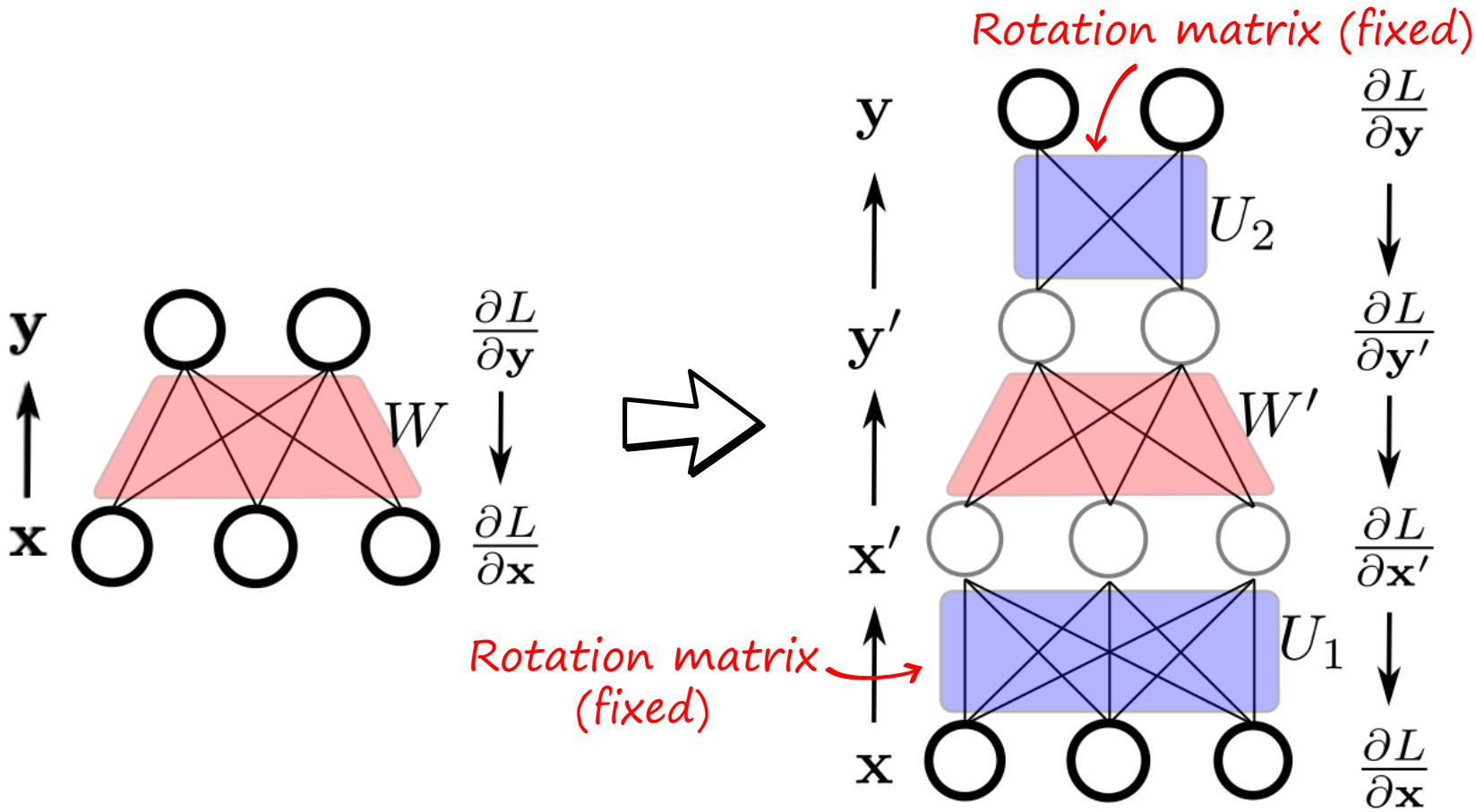
Rotated elastic weight consolidation (R-EWC)

$$\mathcal{L}(\theta) = \mathcal{L}_B(\theta) + \frac{\lambda}{2}\sum_i (F_A)_i \left(\theta_i - (\theta^*_A)_i\right)^2$$



Liu, Masana et al., Rotate your Networks: Better Weight Consolidation and Less Catastrophic Forgetting, ICPR 2018

Rotating fully connected layers



Liu , Masana et al., Rotate your Networks: Better Weight Consolidation and Less Catastrophic Forgetting, ICPR 2018

Computing the rotations

$$F_W = \mathbb{E}_{p\sim\pi}\left[\left(\frac{\partial L}{\partial \mathbf{y}}\right)\mathbf{x}\mathbf{x}^\intercal\left(\frac{\partial L}{\partial \mathbf{y}}\right)^\intercal\right]$$

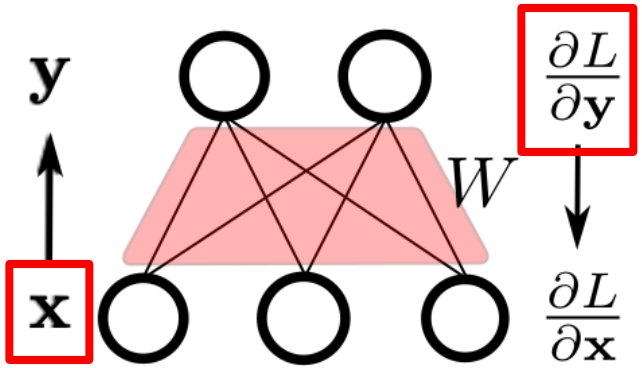
Assuming x and δL/δy independent

$$F_W \approx \mathbb{E}_{\substack{x\sim\pi\\ y\sim p}}\left[\left(\frac{\partial L}{\partial \mathbf{y}}\right)\left(\frac{\partial L}{\partial \mathbf{y}}\right)^\intercal\right]\mathbb{E}_{x\sim\pi}\left[\mathbf{x}\mathbf{x}^\intercal\right]$$

$$\mathbb{E}_{x\sim\pi}\left[\mathbf{x}\mathbf{x}^\intercal\right] = \boxed{U_1}S_1V_1^\intercal$$

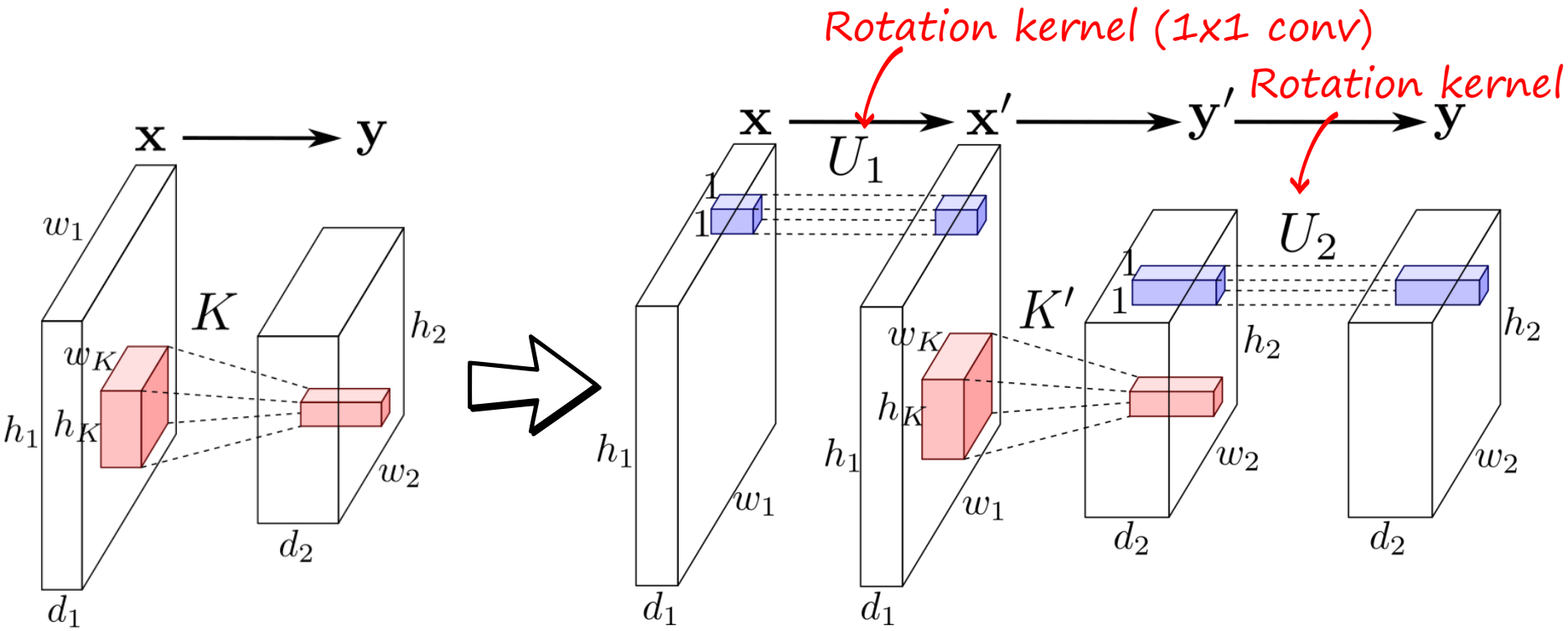
$$\mathbb{E}_{\substack{x\sim\pi\\ y\sim p}}\left[\left(\frac{\partial L}{\partial \mathbf{y}}\right)\left(\frac{\partial L}{\partial \mathbf{y}}\right)^\intercal\right] = \boxed{U_2}S_2V_2^\intercal$$

Using SVD



Liu , Masana et al., Rotate your Networks: Better Weight Consolidation and Less Catastrophic Forgetting, ICPR 2018

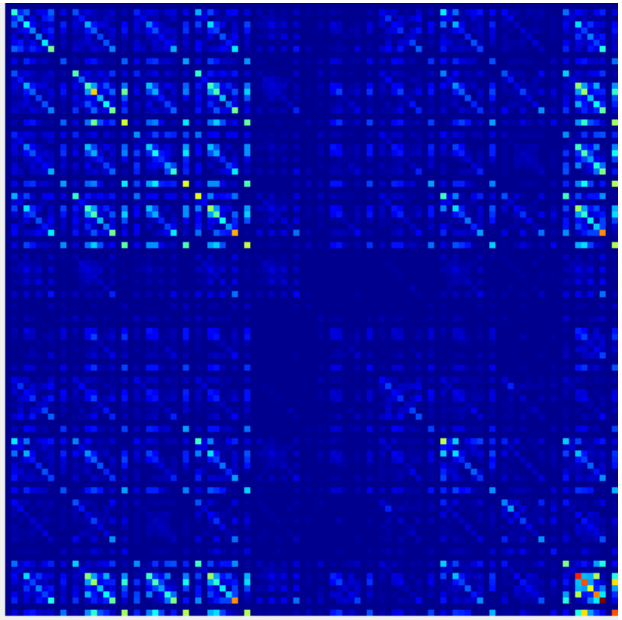
Rotating convolutional layers



Liu et al., Rotate your Networks: Better Weight Consolidation and Less Catastrophic Forgetting, ICPR 2018

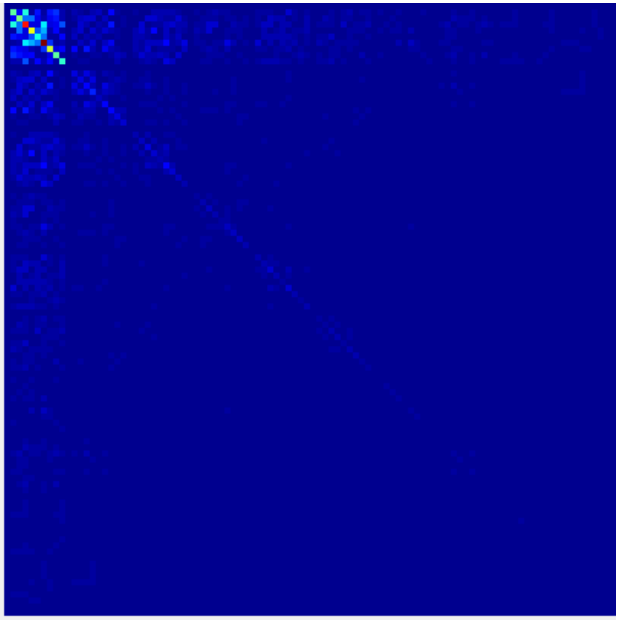
Fisher Information matrix

No rotation (i.e. EWC)



Energy in the diagonal: 40%

After rotation (i.e. R-EWC)



Energy in the diagonal: 74%

Liu , Masana et al., Rotate your Networks: Better Weight Consolidation and Less Catastrophic Forgetting, ICPR 2018

Experimental results (2 tasks)

- MNIST dataset. Two tasks: 0-4 and 5-9

	$\lambda = 1$		$\lambda = 10$		$\lambda = 100$		$\lambda = 1000$		$\lambda = 10000$	
	Task 1	Task 2	Task 1	Task 2	Task 1	Task 2	Task 1	Task 2	Task 1	Task 2
FT	6.1	97.6	6.1	97.6	6.1	97.6	6.1	97.6	6.1	97.6
EWC [5]	66.8	90.9	75.3	95.6	**85.8**	**92.8**	78.4	93.7	81.0	88.8
R-EWC - conv only	62.7	89.2	67.5	96.1	80.4	91.4	**84.7**	**93.1**	75.5	93.7
R-EWC - fc only	78.9	95.3	79.0	95.8	87.4	93.5	93.0	82.3	**94.3**	**88.0**
R-EWC - all	77.2	96.7	**91.7**	**91.2**	86.9	95.9	96.3	81.1	92.1	86.0
R-EWC - all no last	71.5	91.8	84.9	97.0	**91.6**	**94.5**	94.6	88.4	97.9	79.4

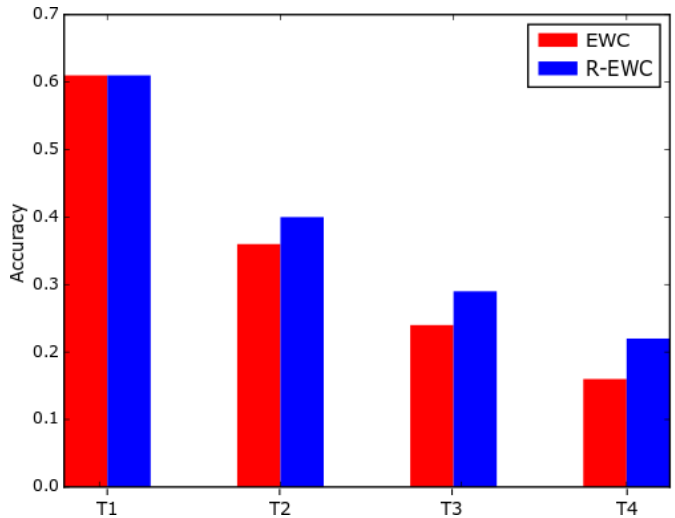
- Several datasets

	EWC [5] (T1 / T2)	R-EWC (T1 / T2)
MNIST	89.3 (85.8 / 92.8)	**93.1** (91.6 / 94.5)
CIFAR-100	37.5 (23.5 / 51.5)	**42.5** (30.2 / 54.7)
CUB-200 Birds	45.3 (42.3 / 48.6)	**48.4** (53.3 / 45.2)
Stanford-40 Actions	50.4 (44.3 / 58.4)	**52.5** (52.3 / 52.6)

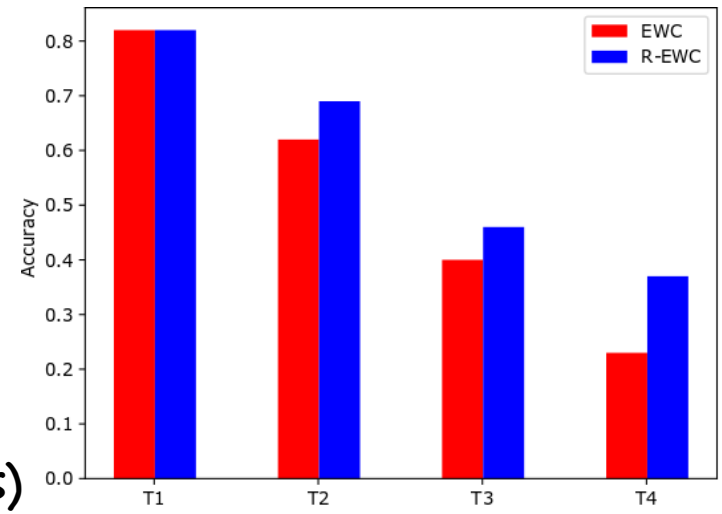
Liu , Masana et al., Rotate your Networks: Better Weight Consolidation and Less Catastrophic Forgetting, ICPR 2018

Experimental results (4 tasks)

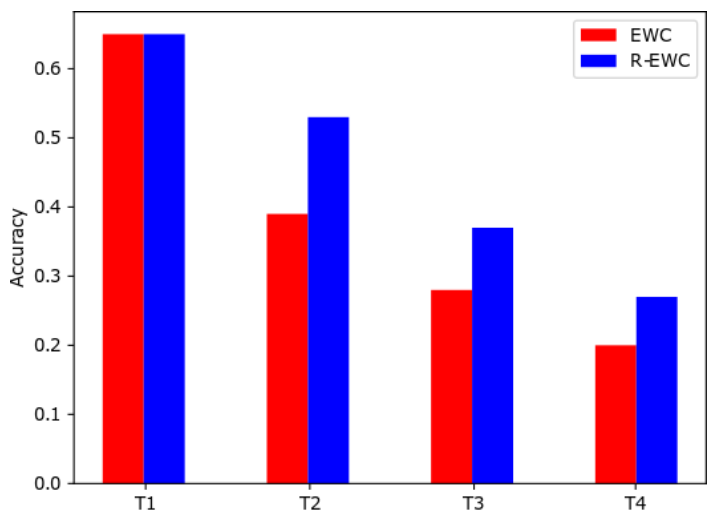
CIFAR 100



Stanford Actions



CUB 200 (birds)



Liu , Masana et al., Rotate your Networks: Better Weight Consolidation and Less Catastrophic Forgetting, ICPR 2018

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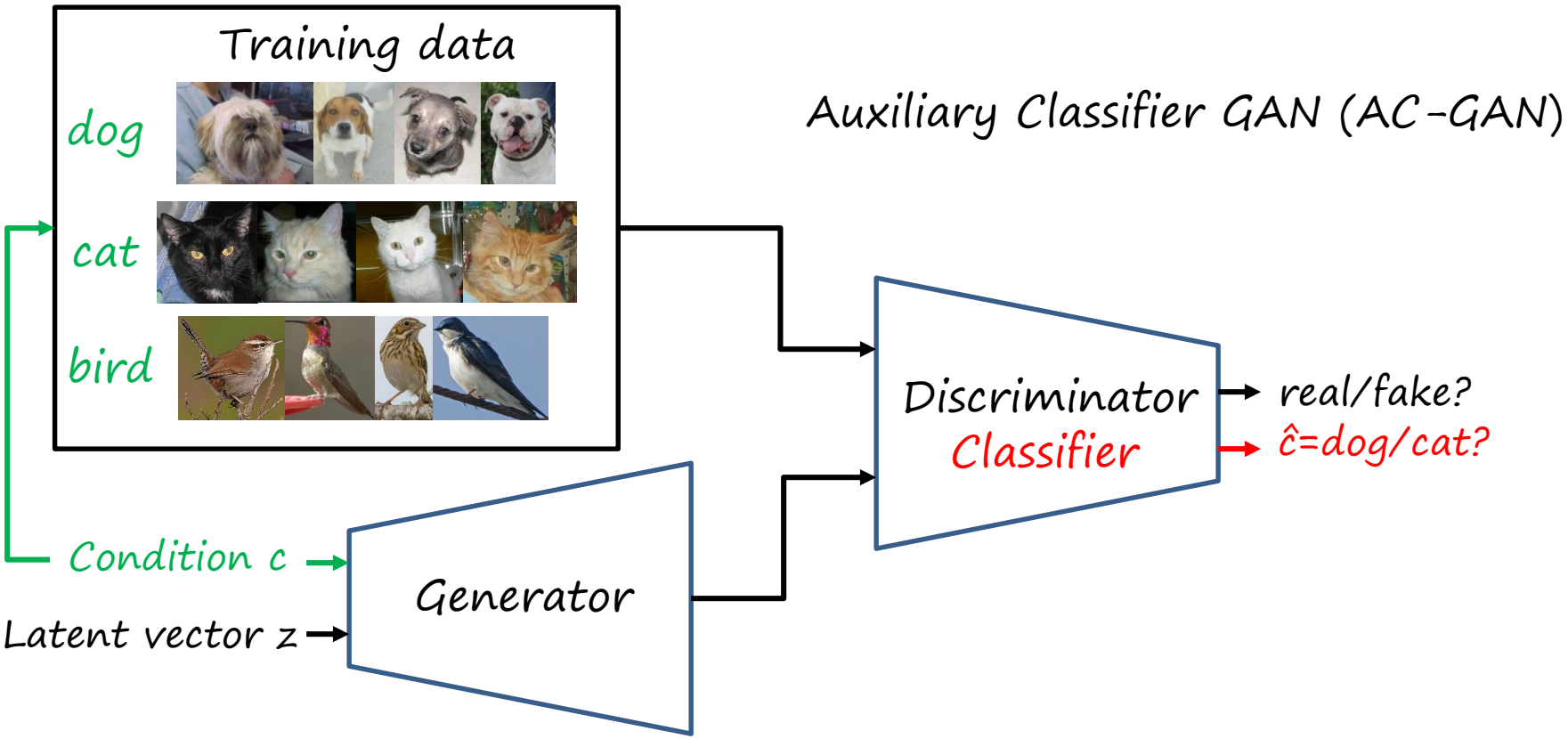
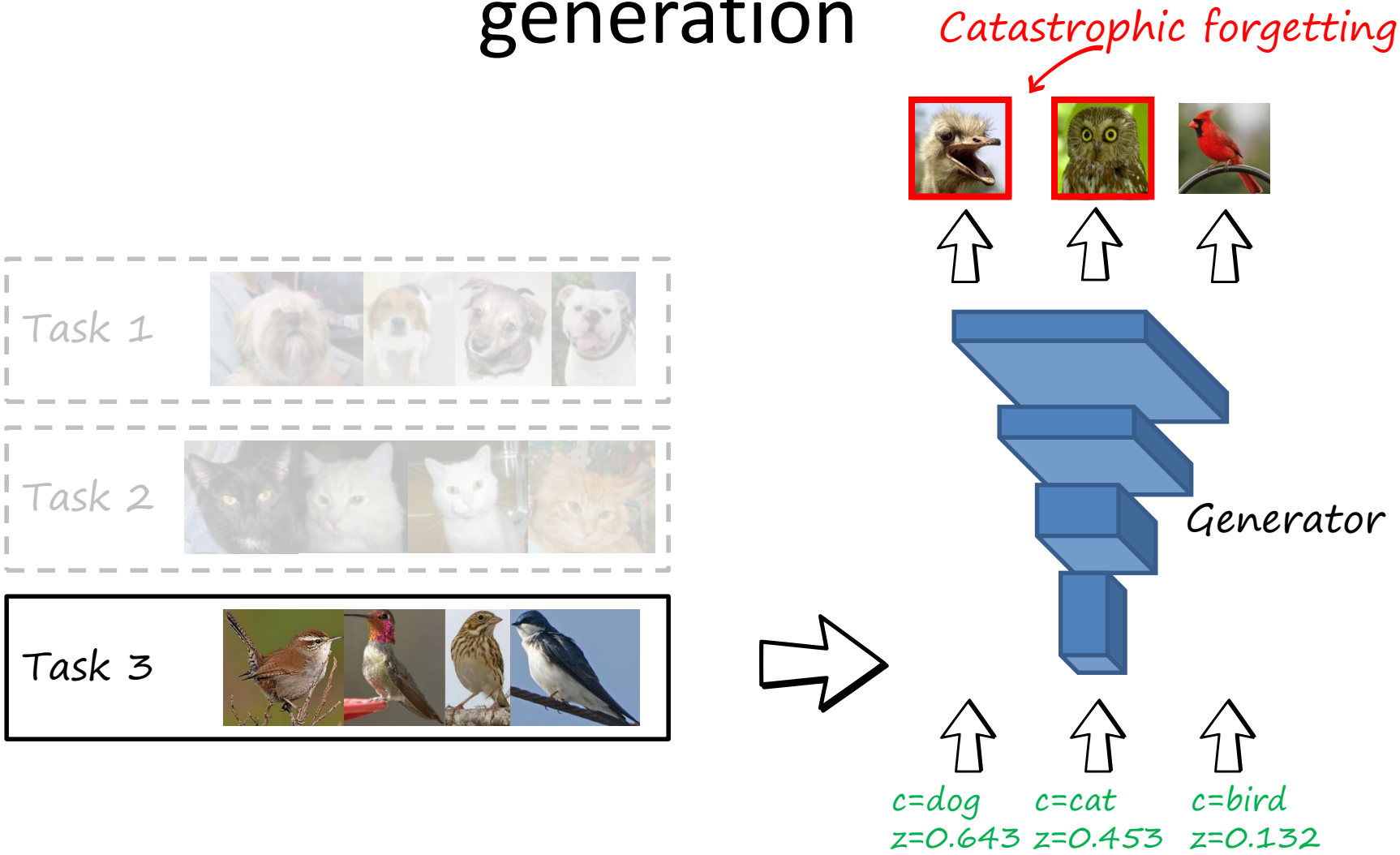
Joint training (non-sequential)



Odena et al., Conditional Image Synthesis With Auxiliary Classifier GANs, ICML 2017

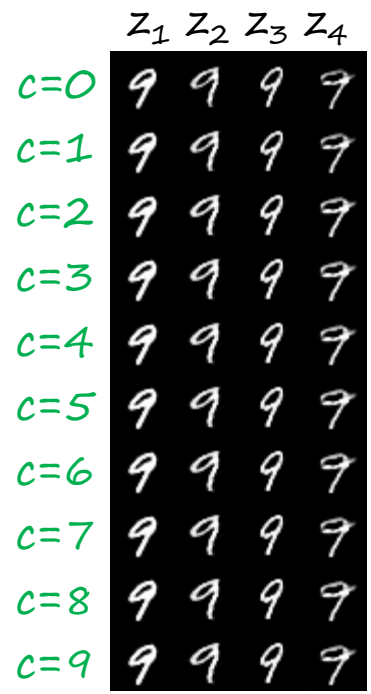
Sequential learning for image generation



Sequential fine tuning and forgetting

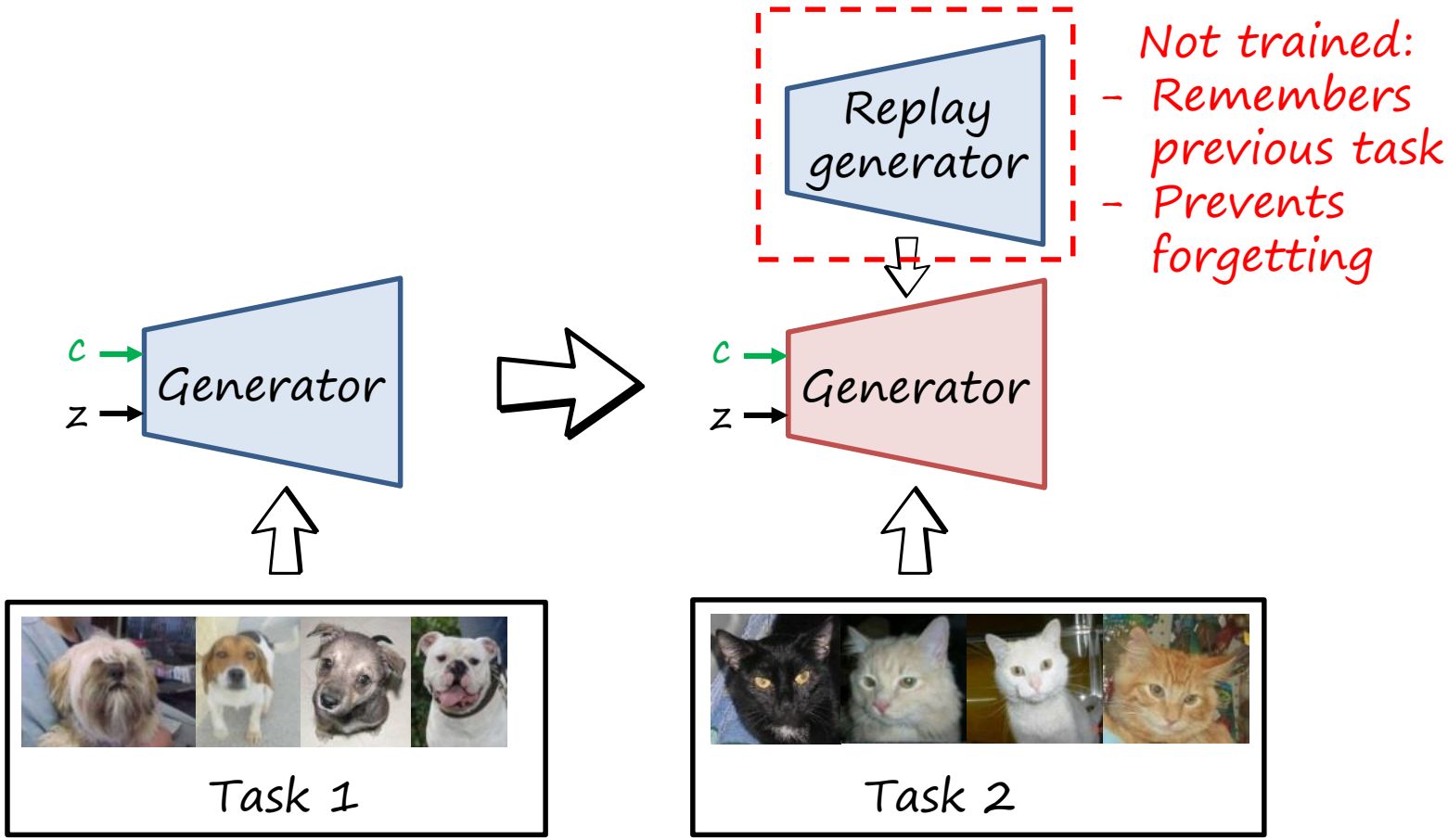
LSUN 4 categories (4 tasks)

MNIST 10 categories (10 tasks)

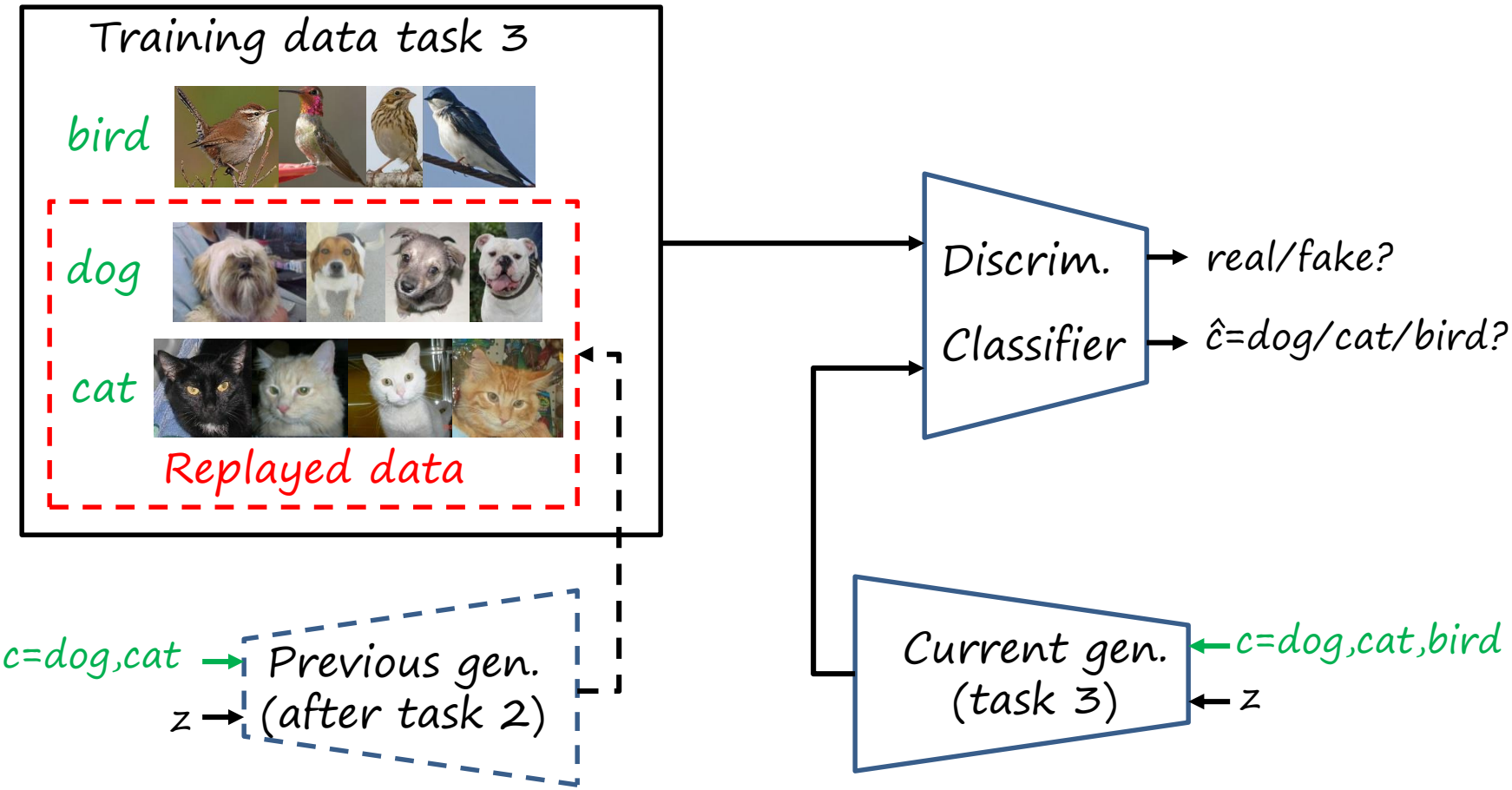


After task 10

Memory Replay GANs (MeRGANs)



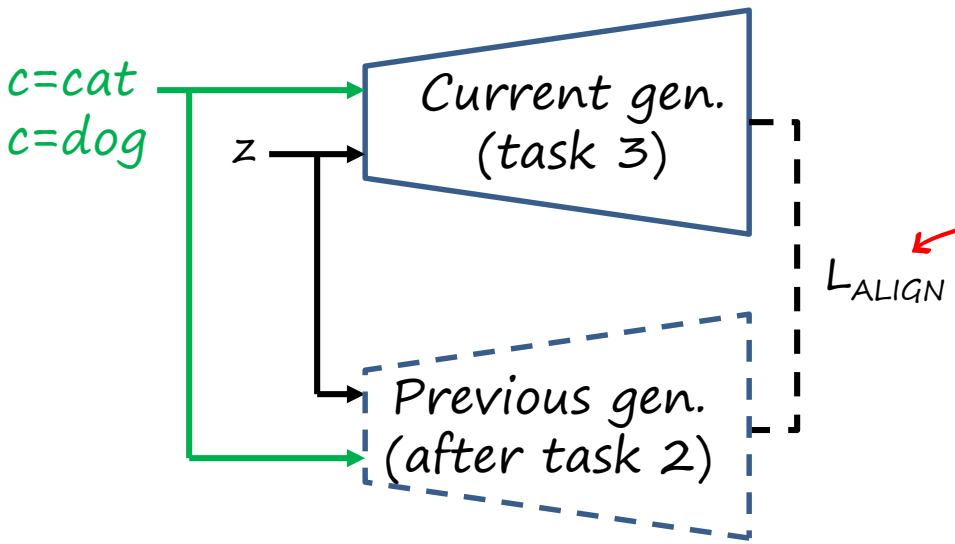
MeRGAN-JTR: joint training w/ replay



Step 1: replay previous tasks

Step 2: joint training

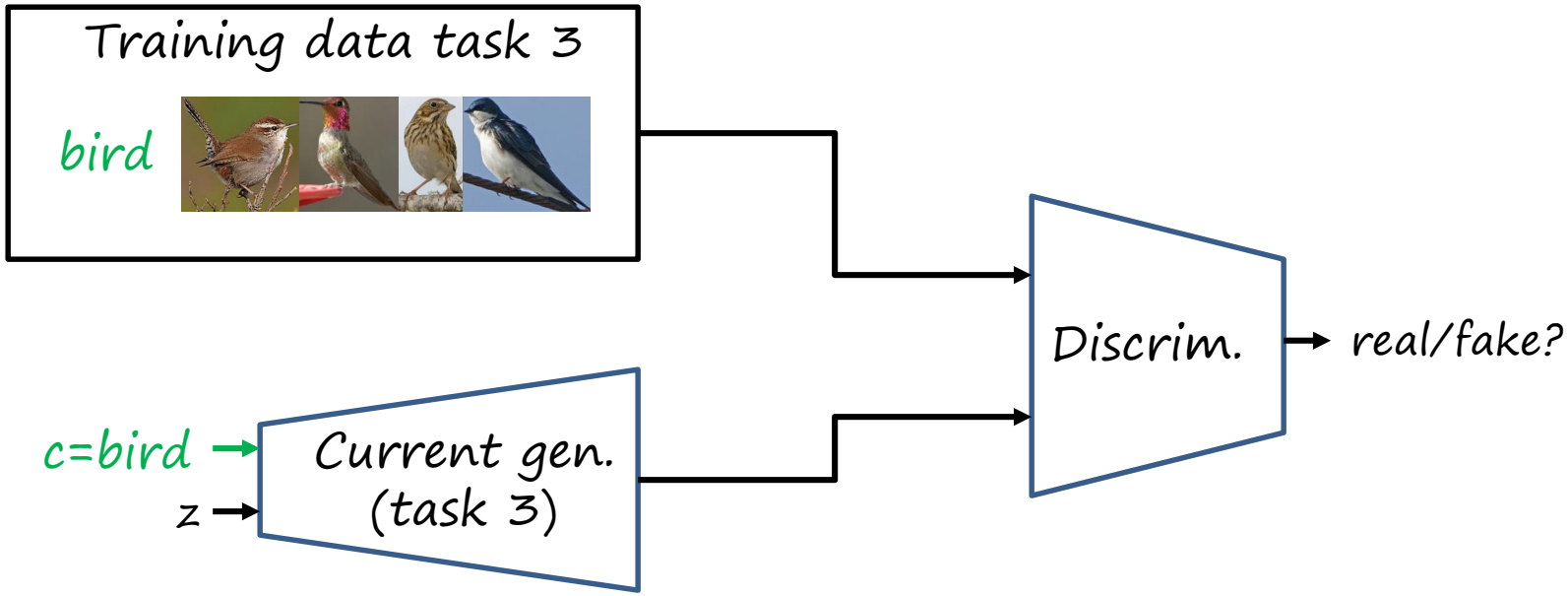
MeRGAN-RA: replay alignment



We can do pixelwise alignment because for given z and c output is deterministic (thanks conditional GAN)

Step 1: replay previous tasks and align

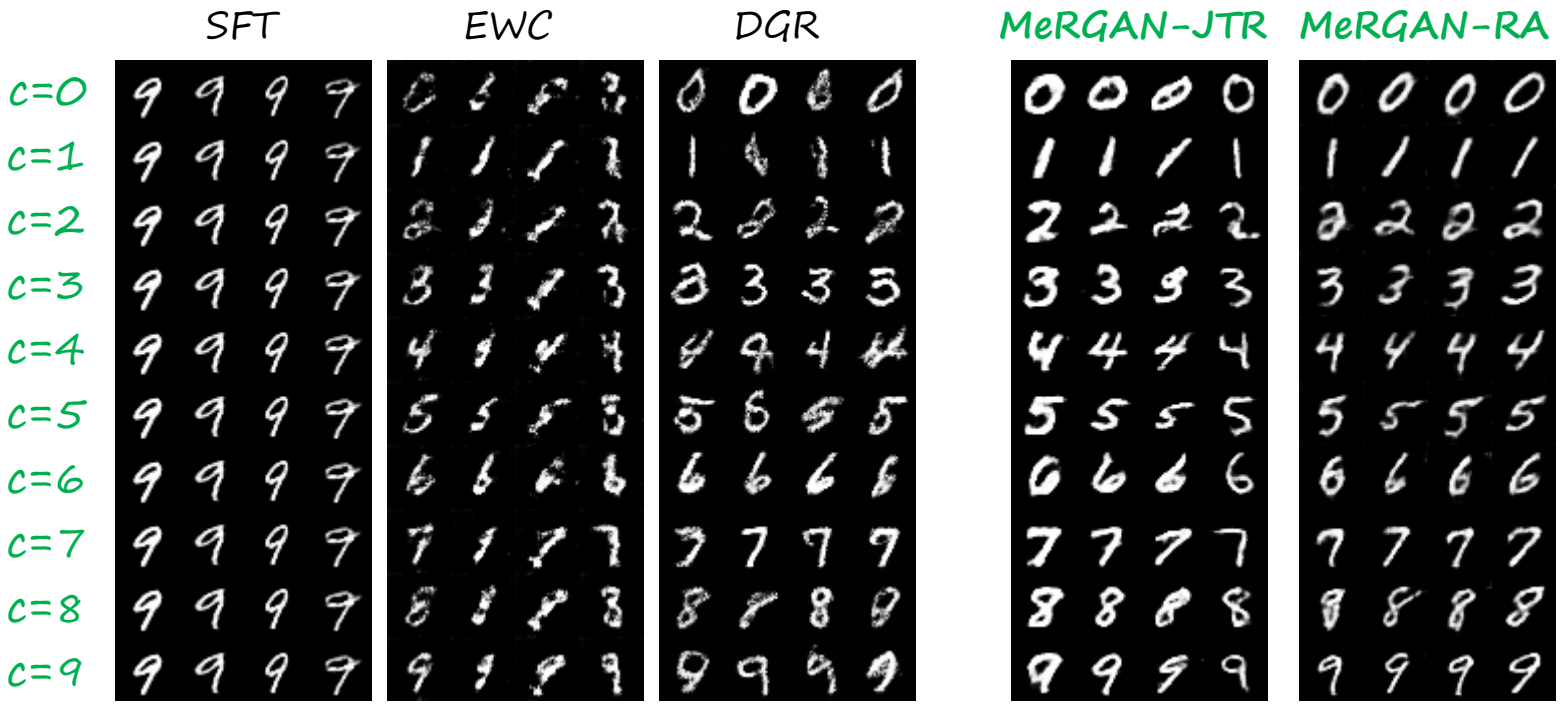
MeRGAN-RA: replay alignment



Step 2: learning new task

Digit generation (MNIST)

10 tasks (10 categories) 3 layers generator



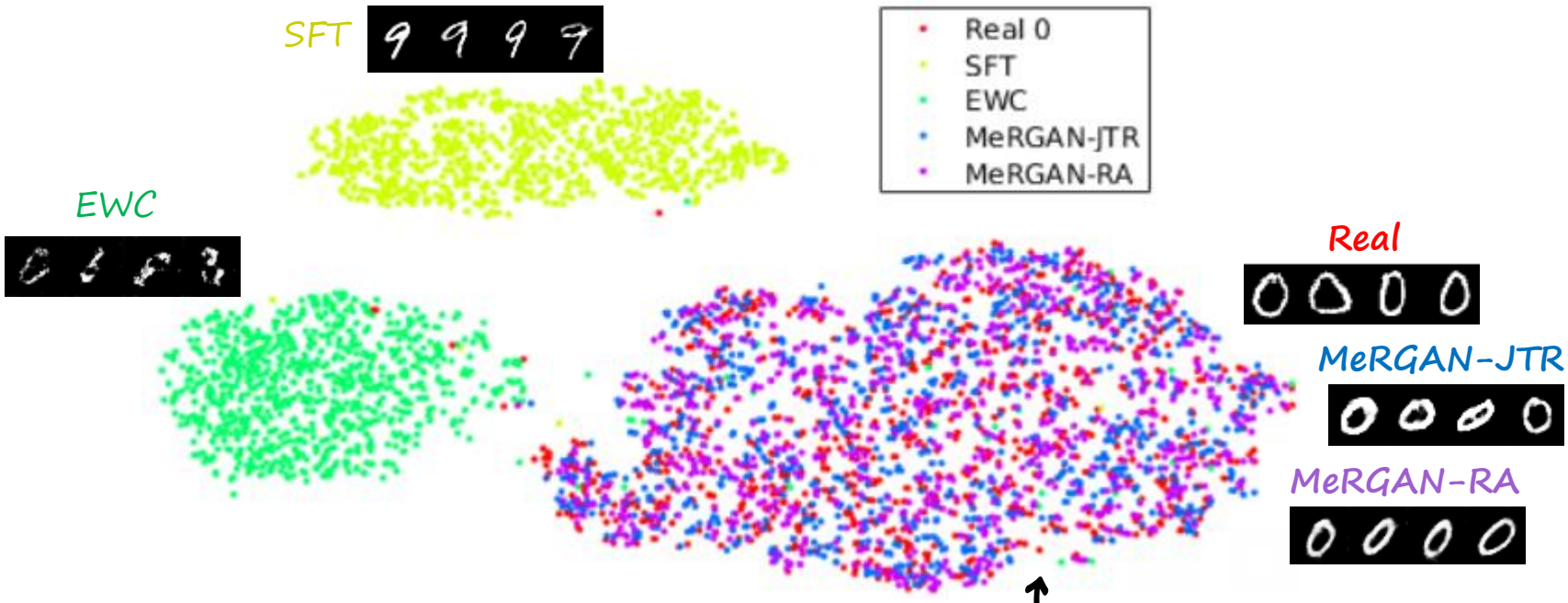
SFT: Sequential fine tuning **EWC**: GAN with EWC [arxiv17] **DGR**: Deep generative replay [NIPS17]

Scene generation (LSUN)

4 tasks (4 categories) 18-layer ResNet generator

t-SNE visualizations (MNIST)

Generating digit 0 (i.e. first task) after learning 10 tasks

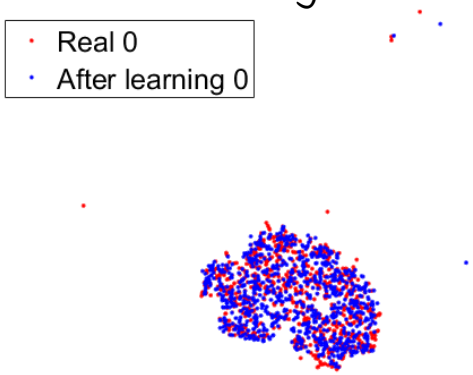


Samples from MeRGANs overlap with real data

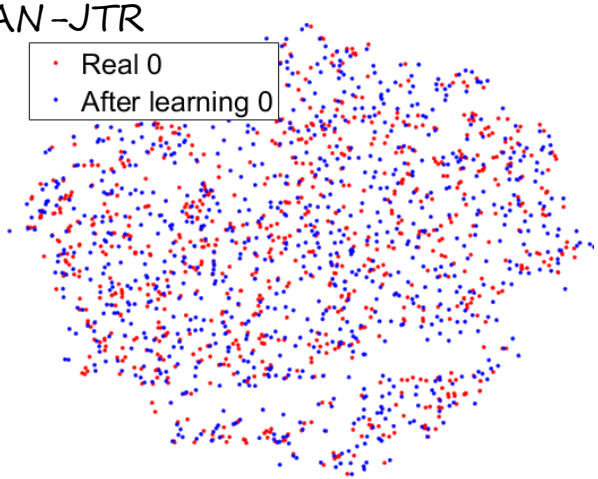
Learning and forgetting in t-SNE (MNIST)

Generating digit 0 (i.e. task 1)

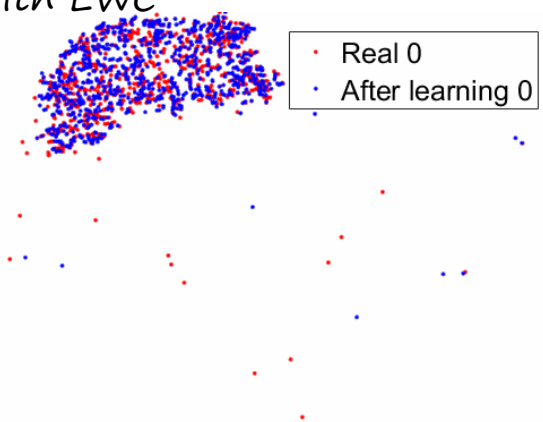
Sequential fine tuning



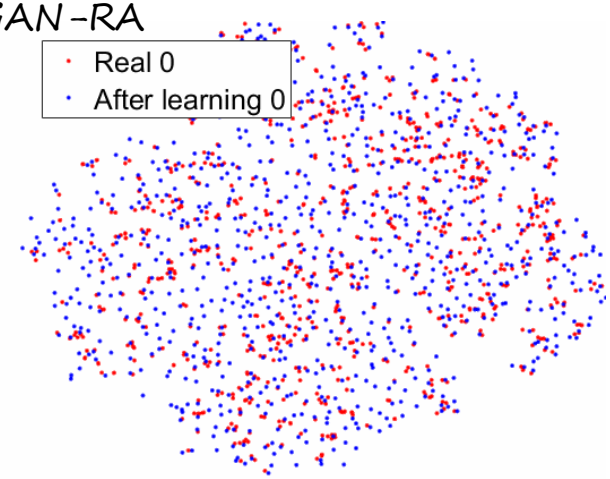
MeRGAN-JTR



GAN with EWC



MeRGAN-RA



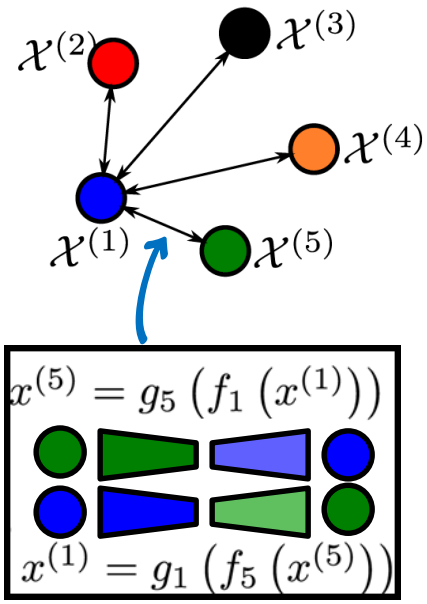
Outline

- Introduction
- Transferring GANs (ECCV 2018)
- Rotated elastic weight consolidation (ICPR 2018)
- Memory Replay GANs (NIPS 2018)
- Mix and match networks (CVPR 2018)

Unseen image-to-image translations

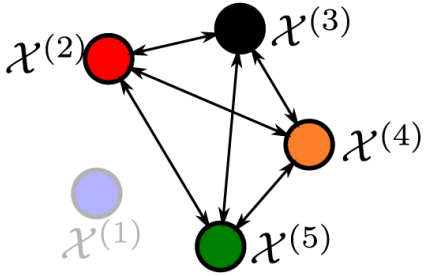
Only these translations are trained (seen)

Train



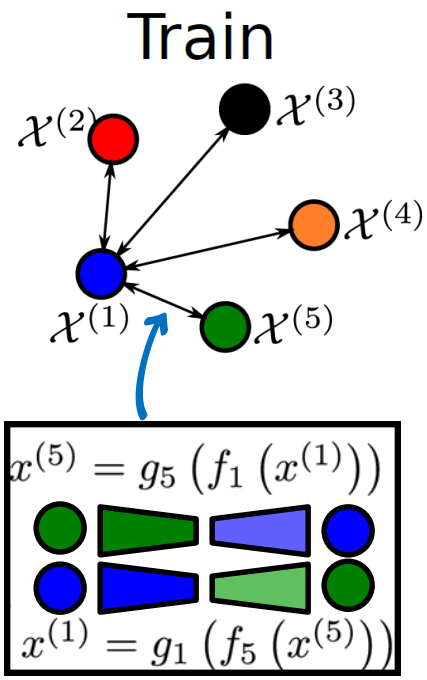
*Evaluate on these **unseen** translations*

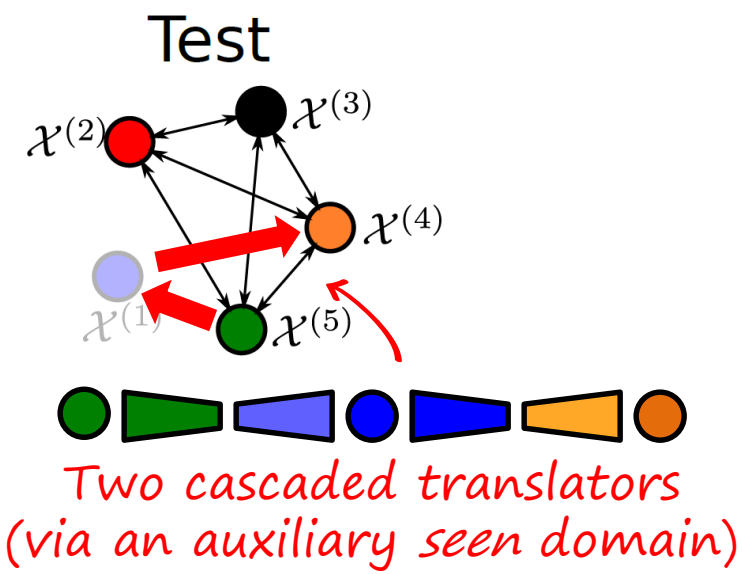
Test



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

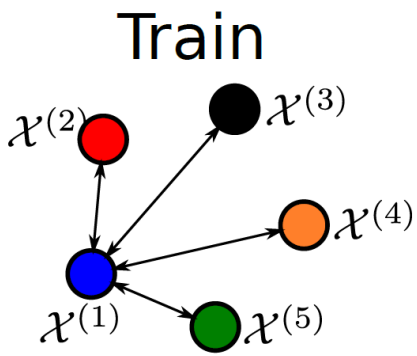
Cascading image-to-image translators

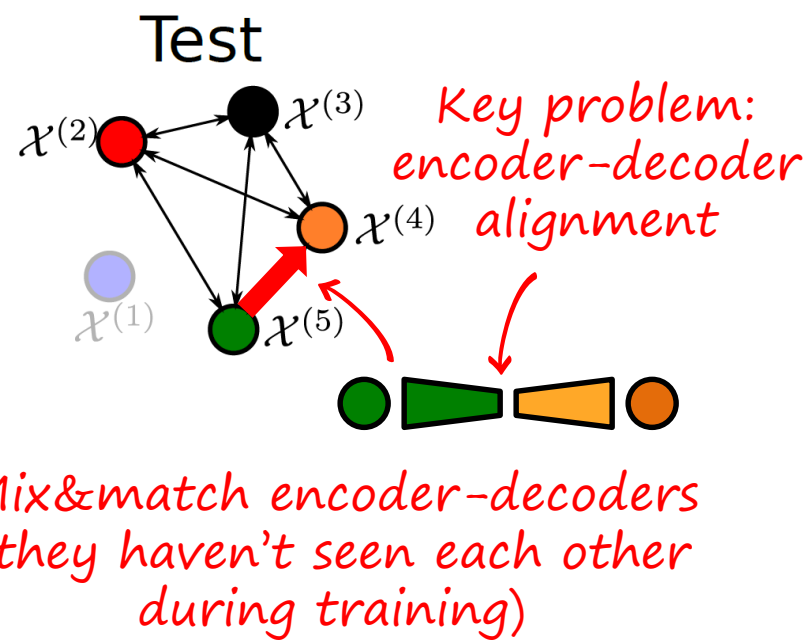




Wang, van de Weijer, Herranz, “Encoder-decoder alignment for zero-pair image-to-image translation”, CVPR 2018

Mix and match networks

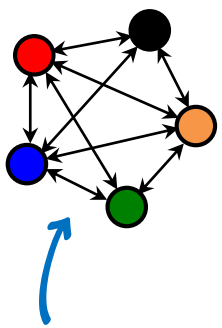


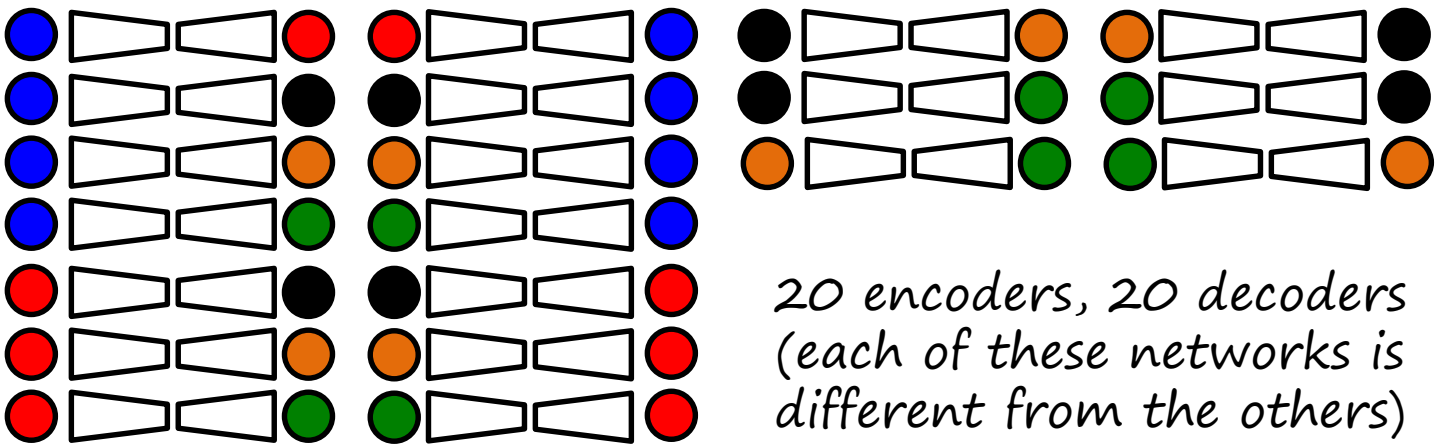


Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

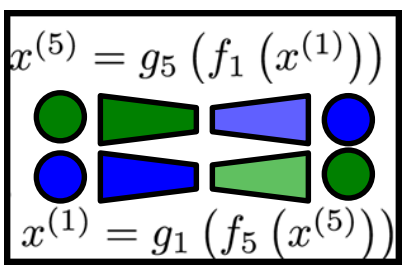
Application: many-to-many translations

We could train all possible translators
Problems:
- No sharing
- Poor scalability: number of networks $O(N^2)$





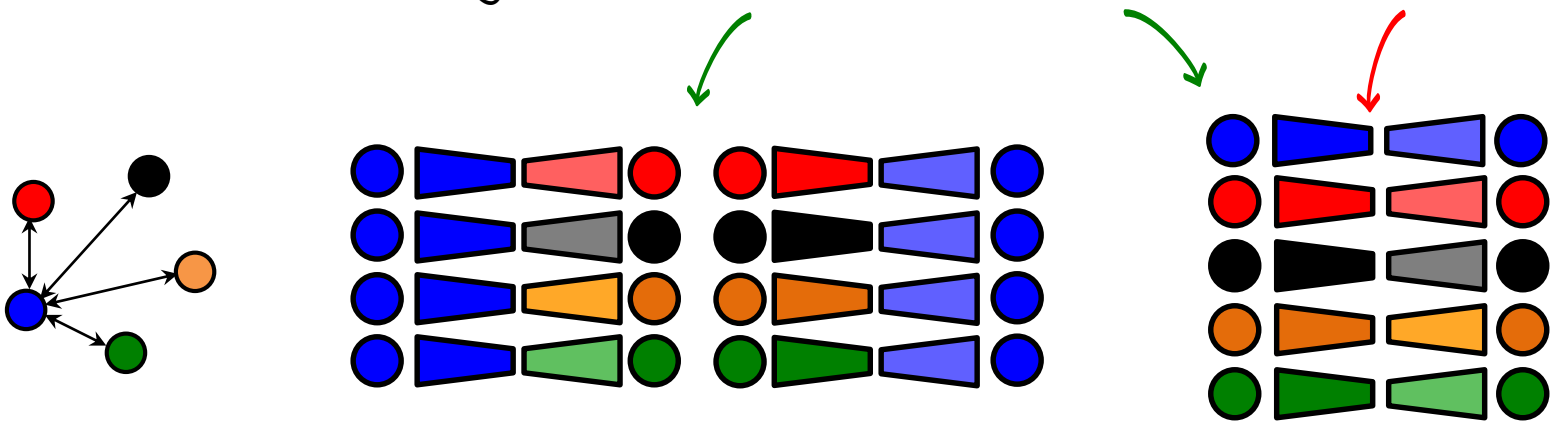
20 encoders, 20 decoders
(each of these networks is different from the others)



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
- Latent representation should be domain-independent
- Achieved using shared encoder/decoders and autoencoders



5 encoders, 5 decoders

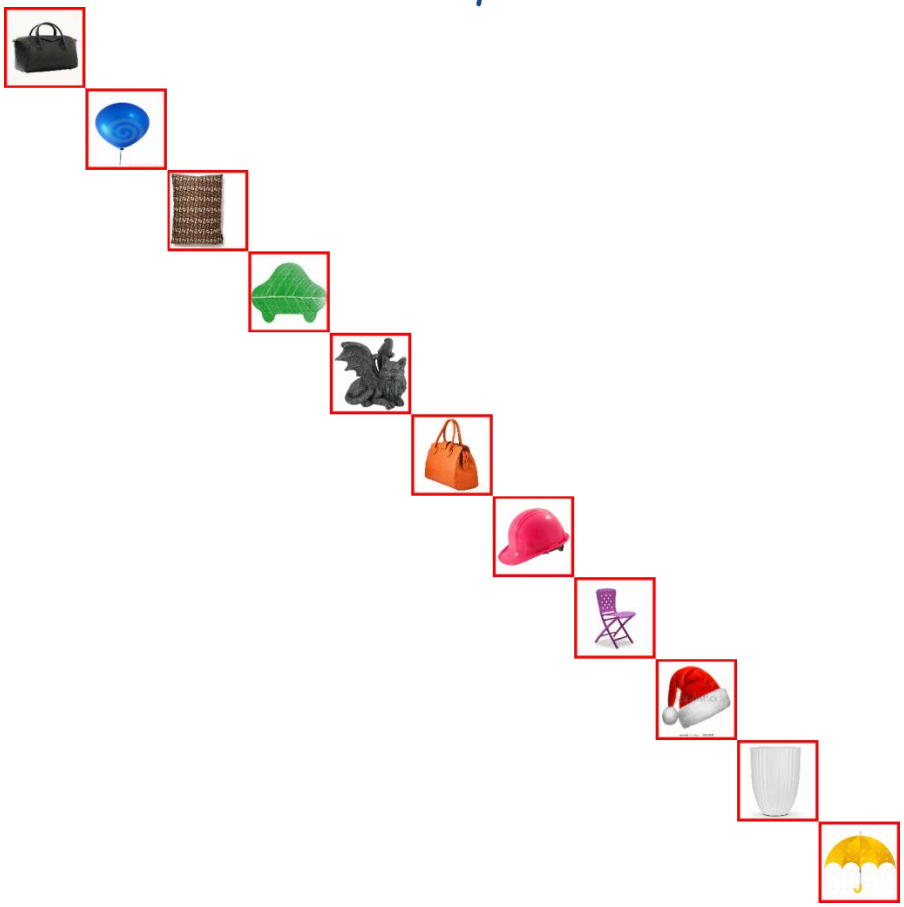
- Scalable: number of networks O(N)

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

Example: scalable recolorization

Input

Unpaired translation
11 colors (i.e. 11 domains)

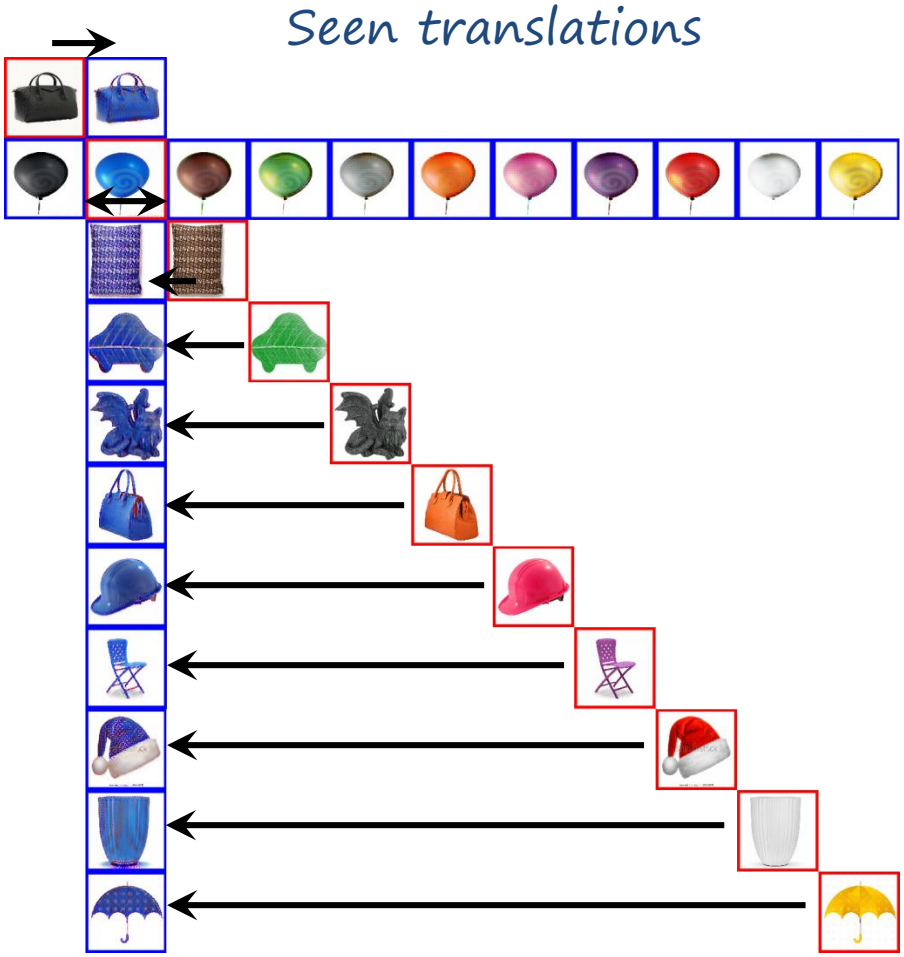


Wang, van de Weijer, Herranz, “Encoder-decoder alignment for zero-pair image-to-image translation”, CVPR 2018

Example: scalable recolorization

Unpaired translation
11 colors (i.e. 11 domains)

Requires training 11 encoders and 11 decoders



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

Example: scalable recolorization

Unpaired translation
11 colors (i.e. 11 domains)

Requires training 11 encoders and 11 decoders

CycleGANs for all combinations would require 55 encoders and 55 decoders

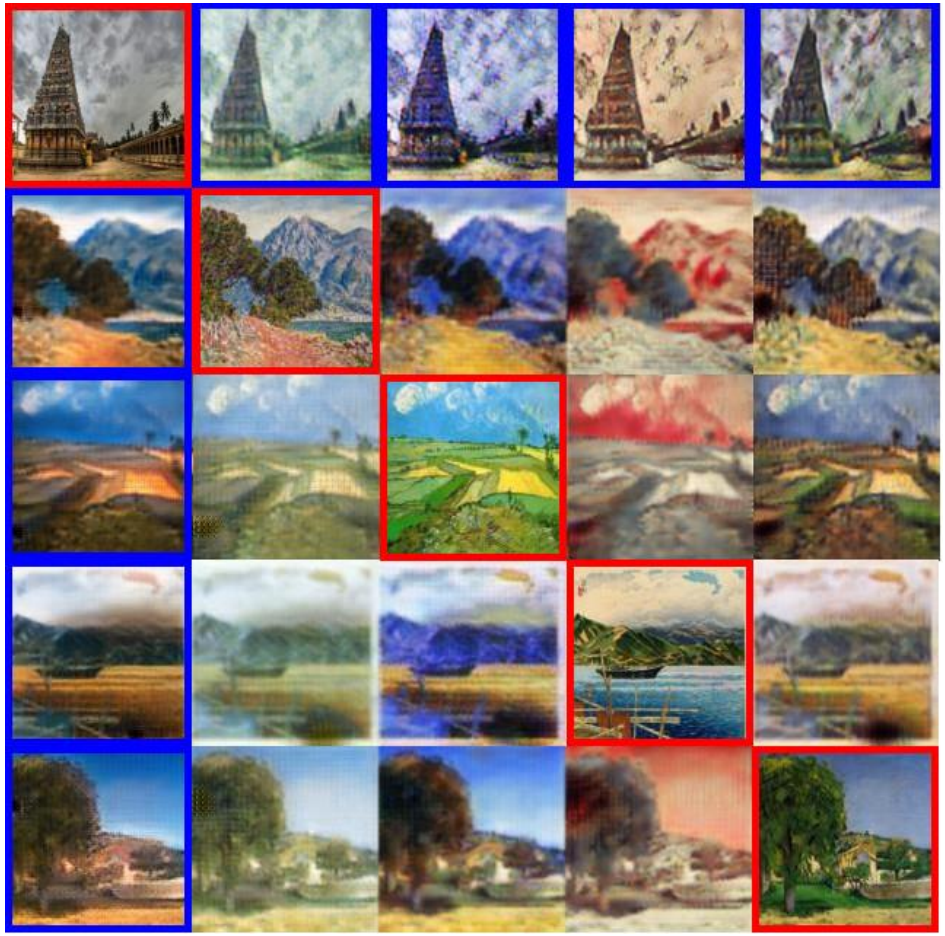
Seen+unseen translations

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)

(5 encoders and 5 decoders)



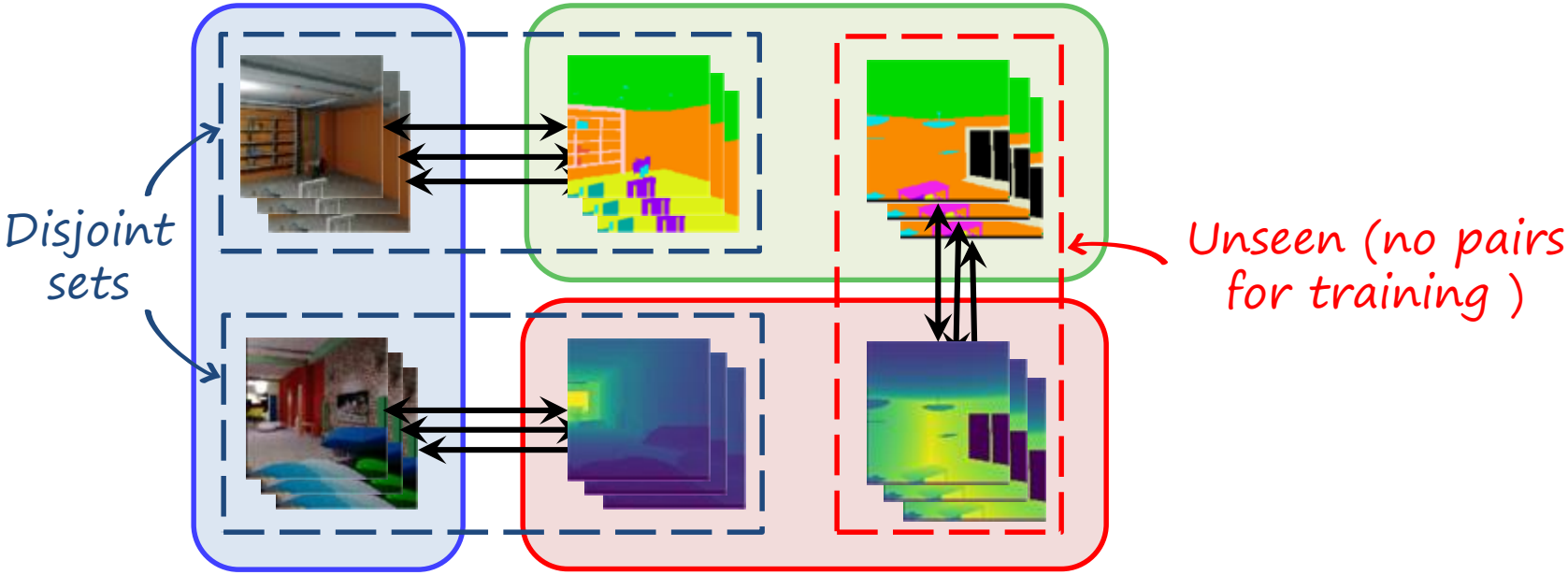
Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

Application: zero-pair translation

Cross-modal translation setting (RGB, segmentation and depth)

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

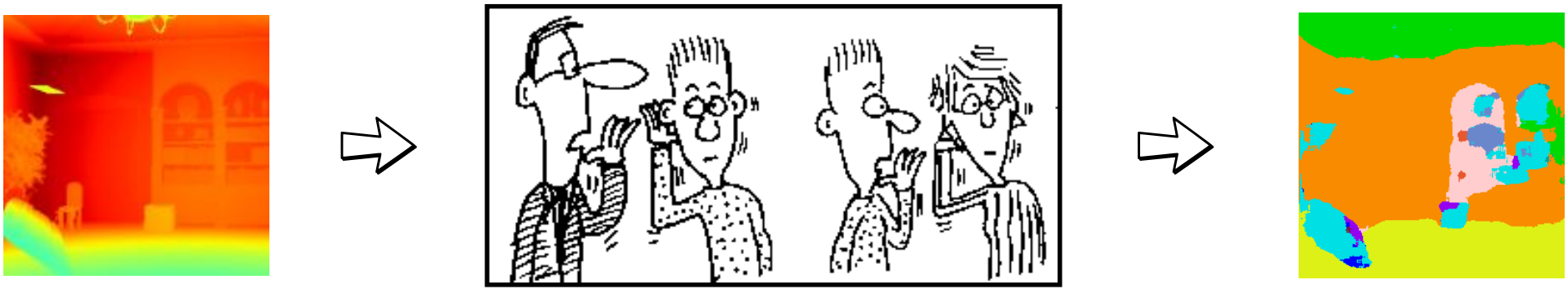
Evaluate on the **unseen zero-pair translations** (depth, segm.)



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)

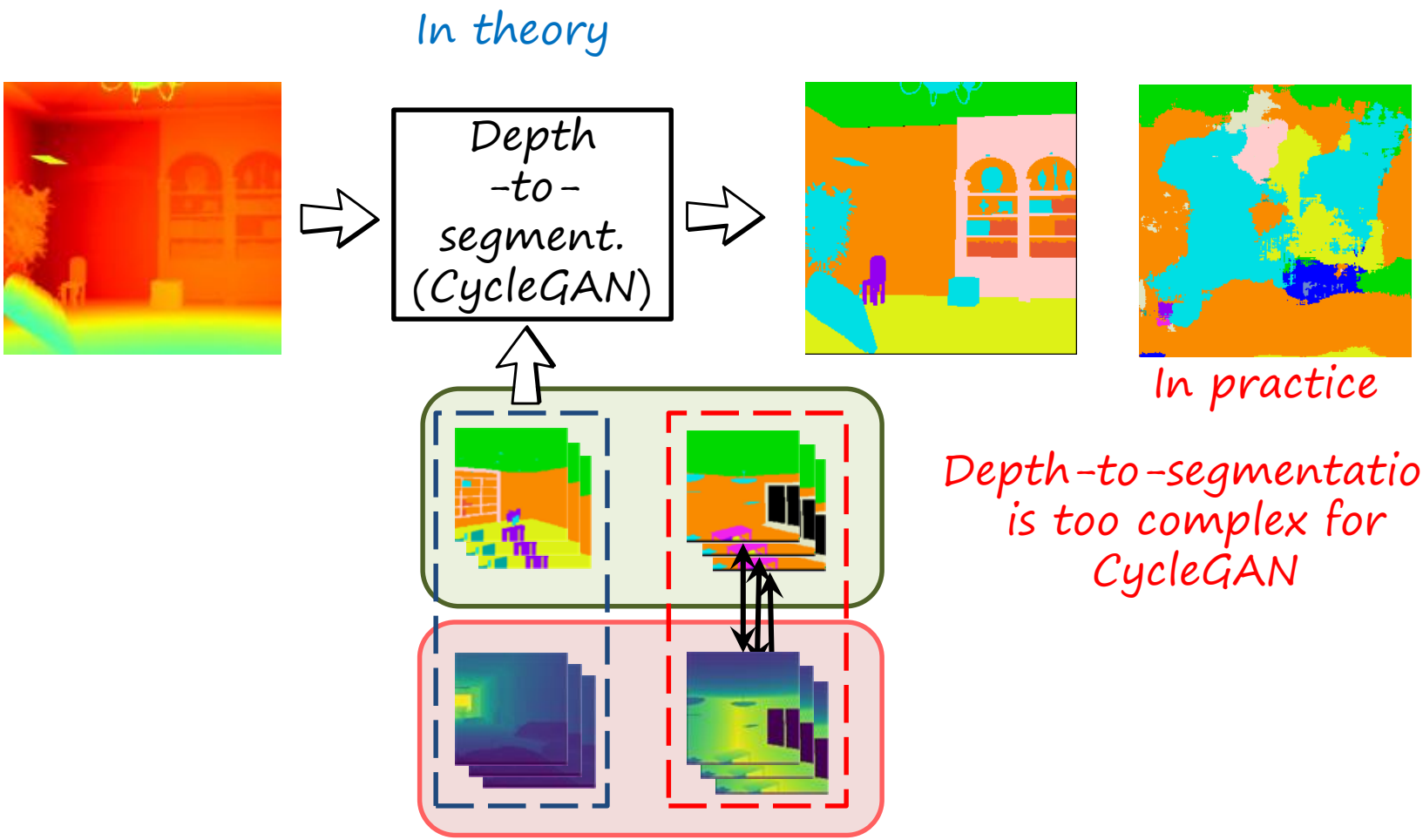
In theory



In practice

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

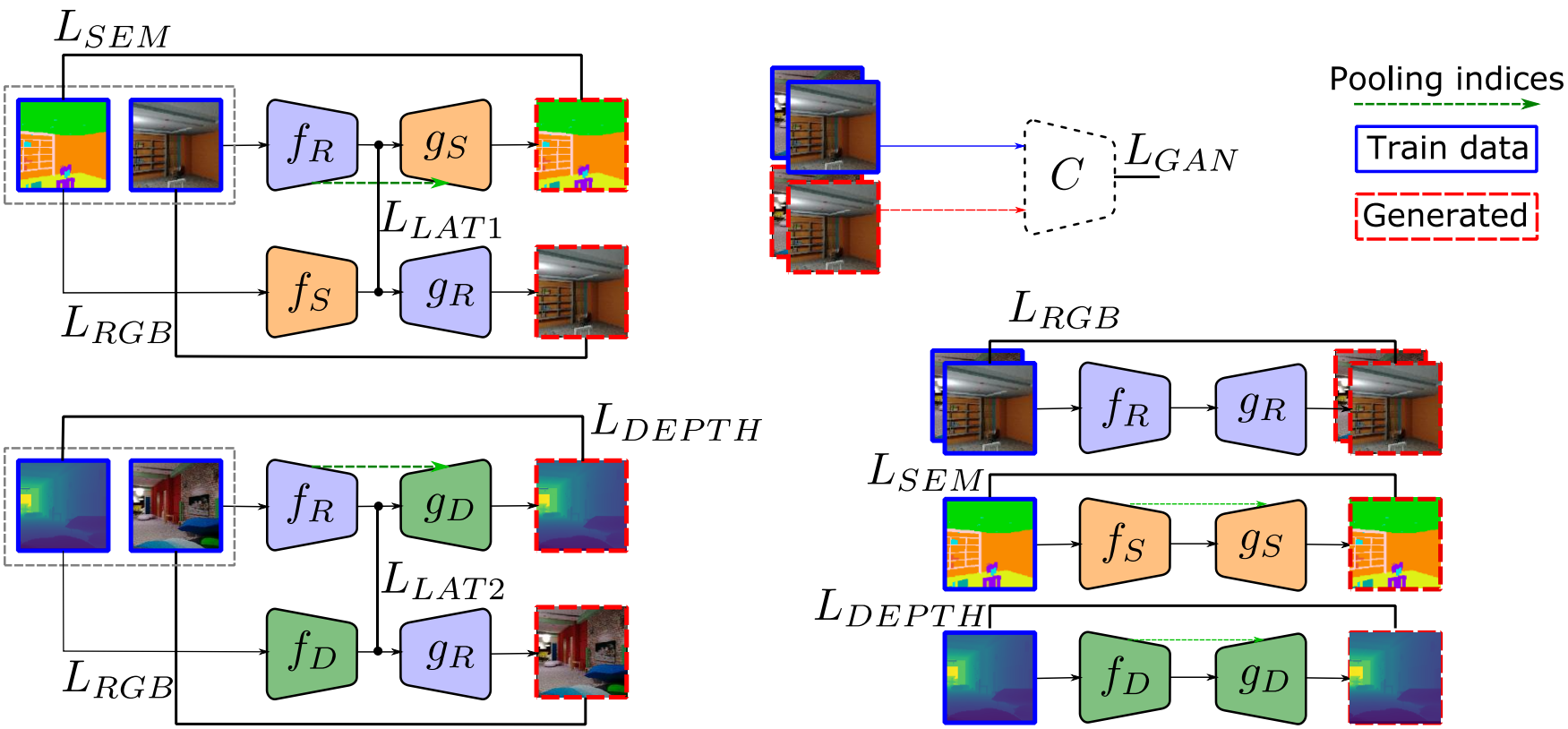
Zero-pair translation with CycleGAN (unpaired translation)



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

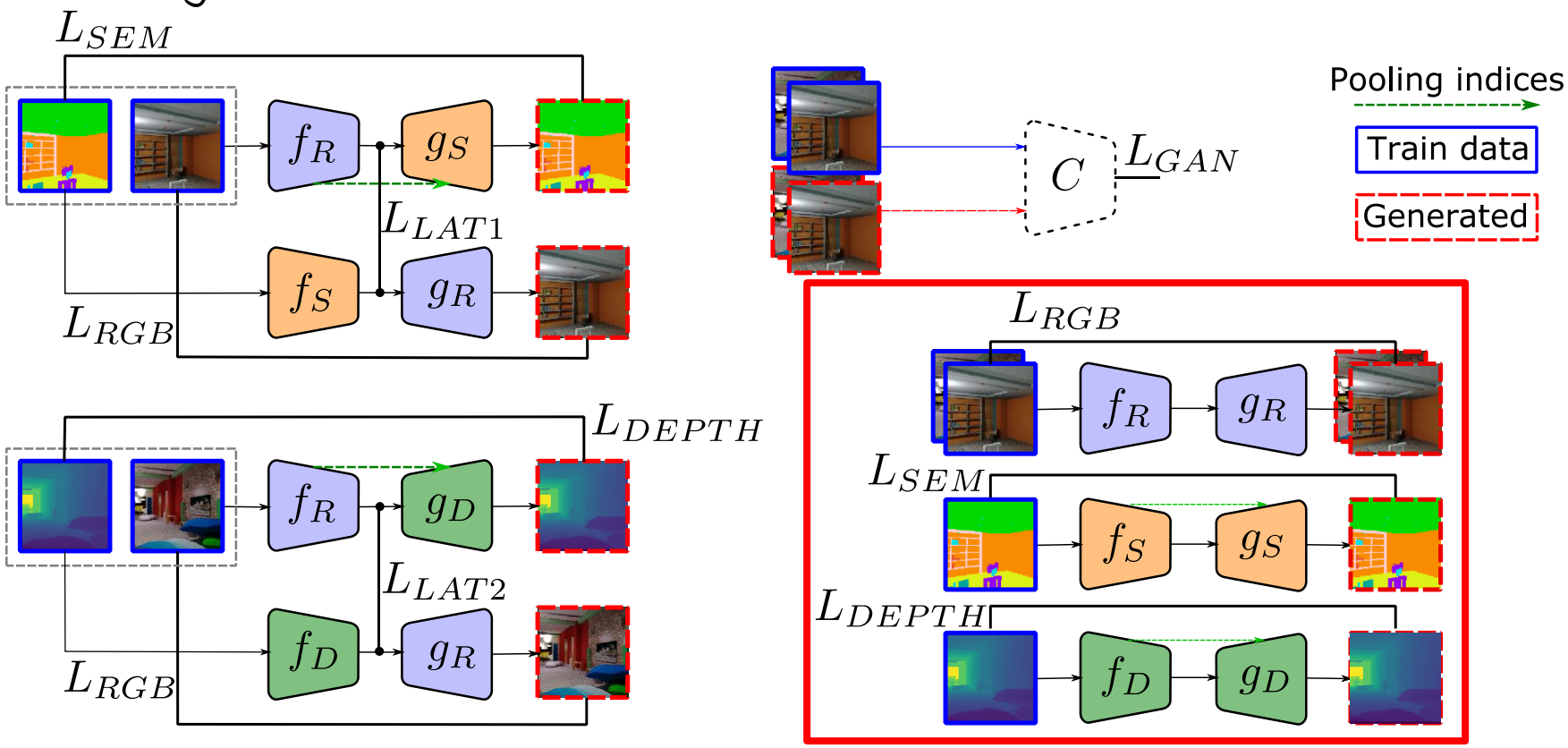


Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

Zero-pair translation with mix and match networks

Training for encoder-decoder alignment:

Autoencoders



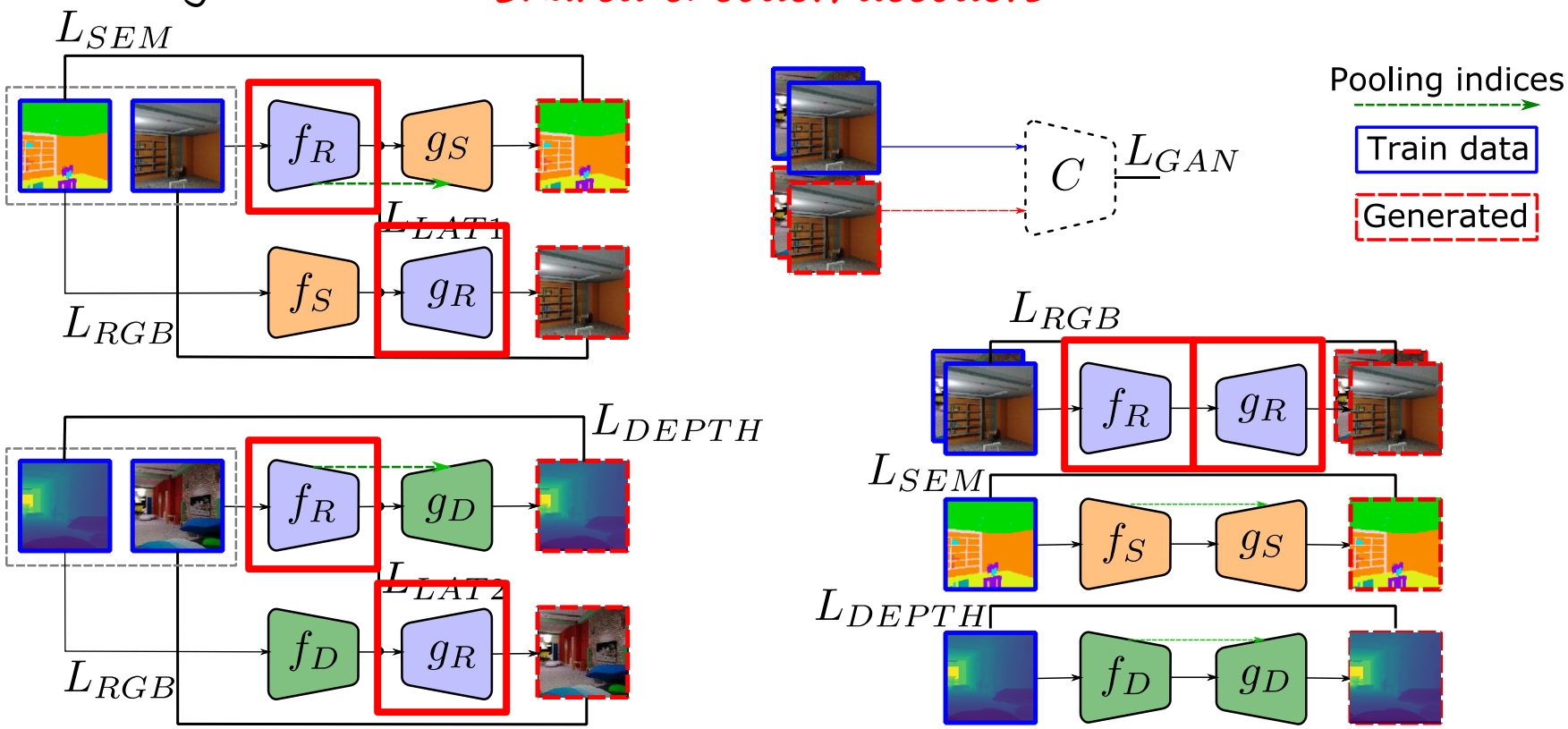
Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

Zero-pair translation with mix and match networks

Training for encoder-decoder alignment:

Autoencoders

Shared encoder/decoders



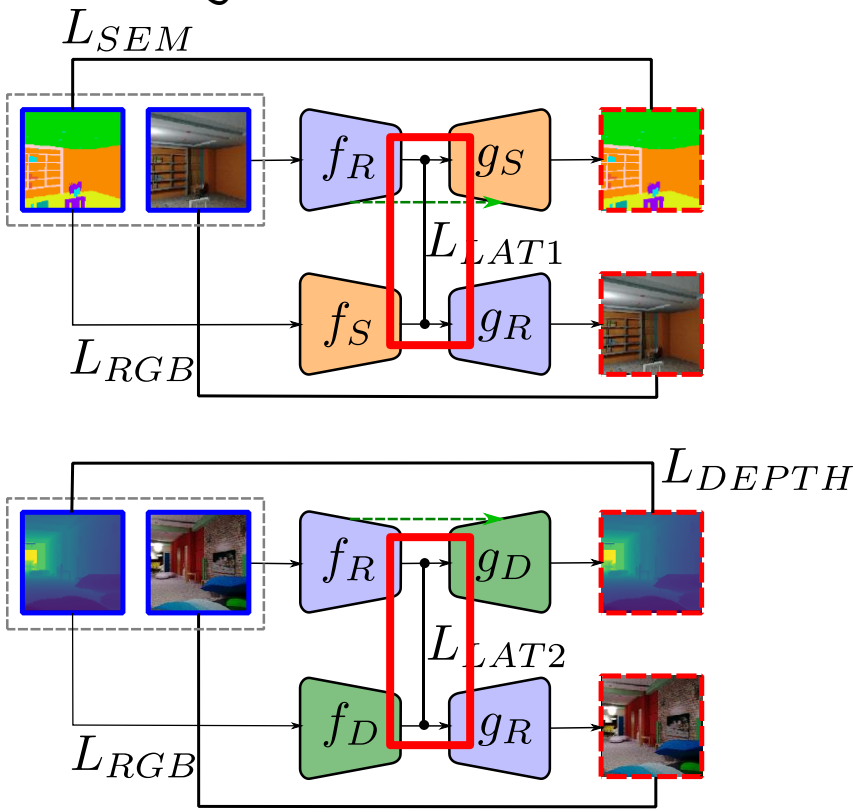
Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

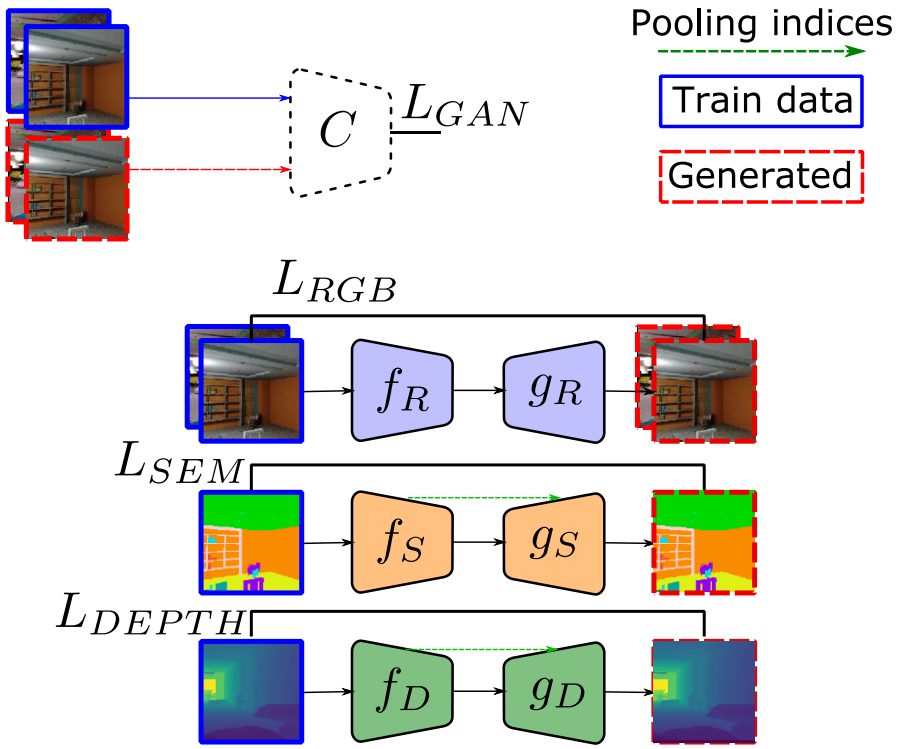
Zero-pair translation with mix and match networks

Training for encoder-decoder alignment:

Autoencoders
Shared encoder/decoders

Latent losses





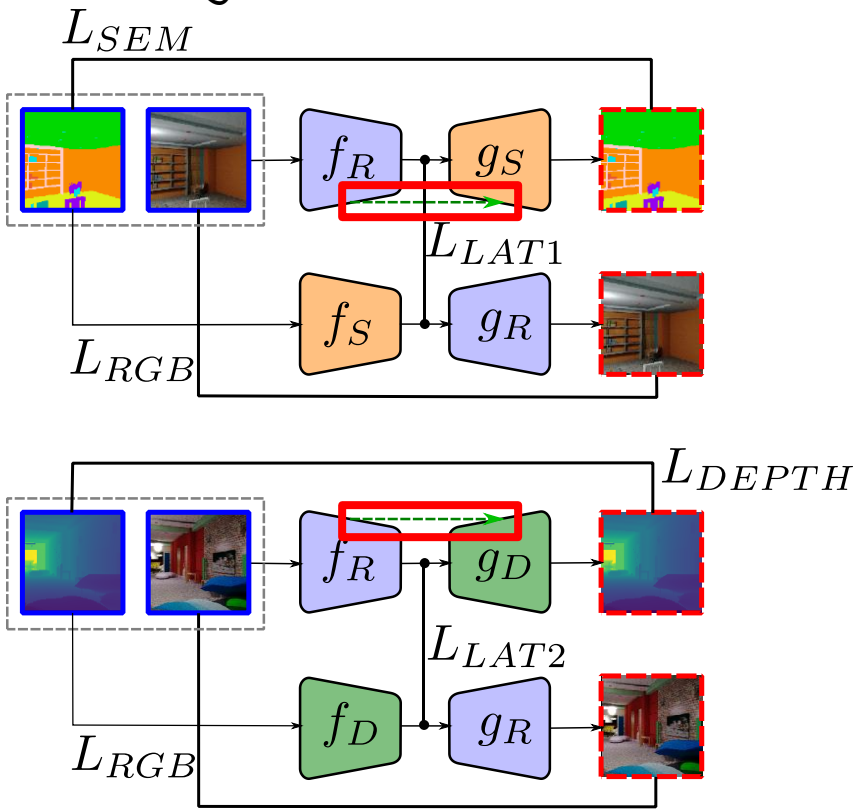
Wang, van de Weijer, Herranz, "Encoder-decoder alignment for zero-pair image-to-image translation", CVPR 2018

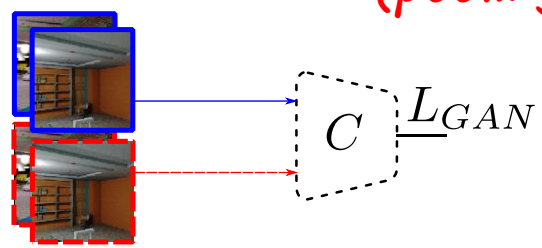
Zero-pair translation with mix and match networks

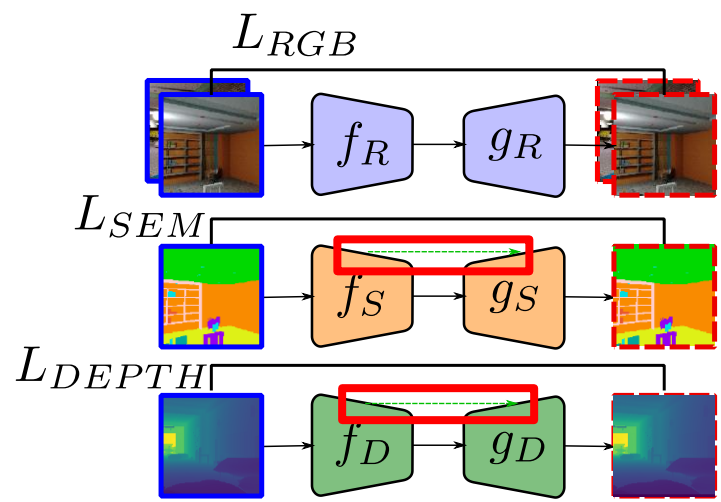
Training for encoder-decoder alignment:

Autoencoders
Shared encoder/decoders

Latent losses
Robust side information (pooling indices)







Pooling indices

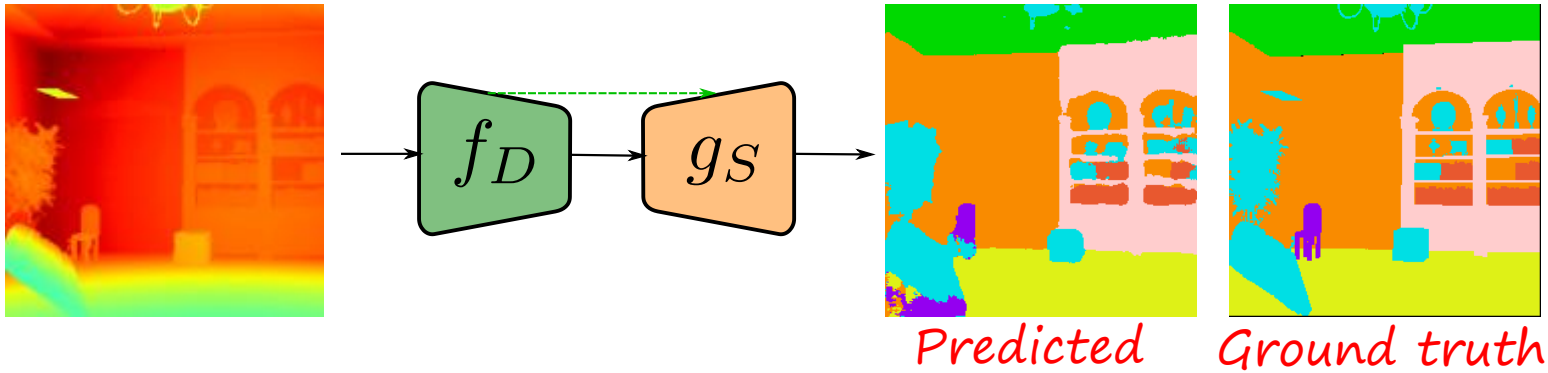
Train data

Generated

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

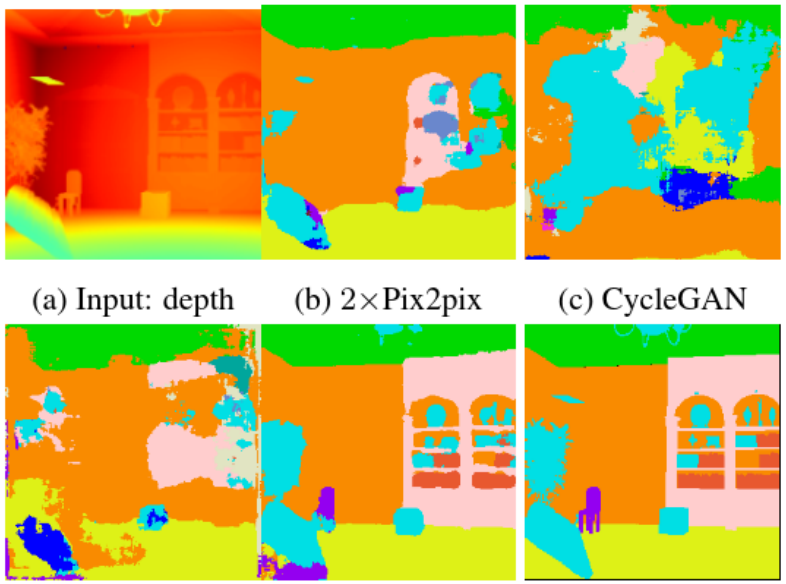
Zero-pair translation with mix and match networks

Test on zero-pair translation depth-to-segmentation



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

Comparison: depth-to-segmentation



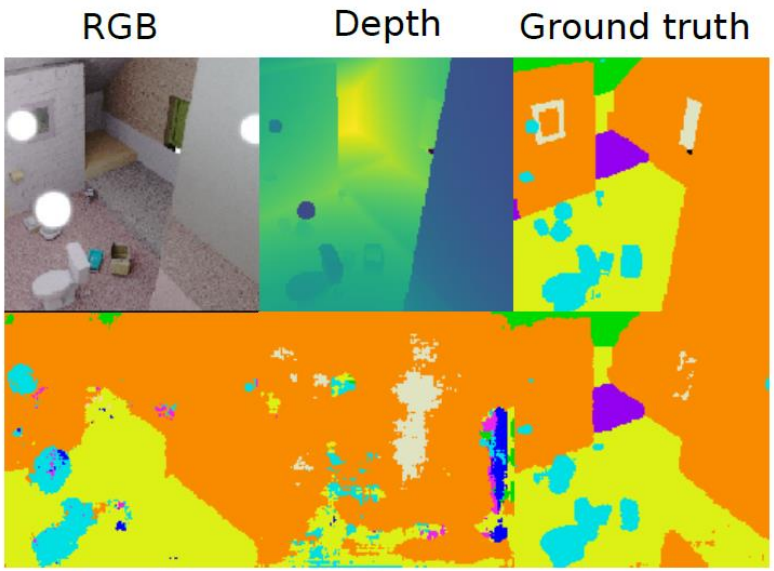
(a) Input: depth (b) 2×Pix2pix (c) CycleGAN

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

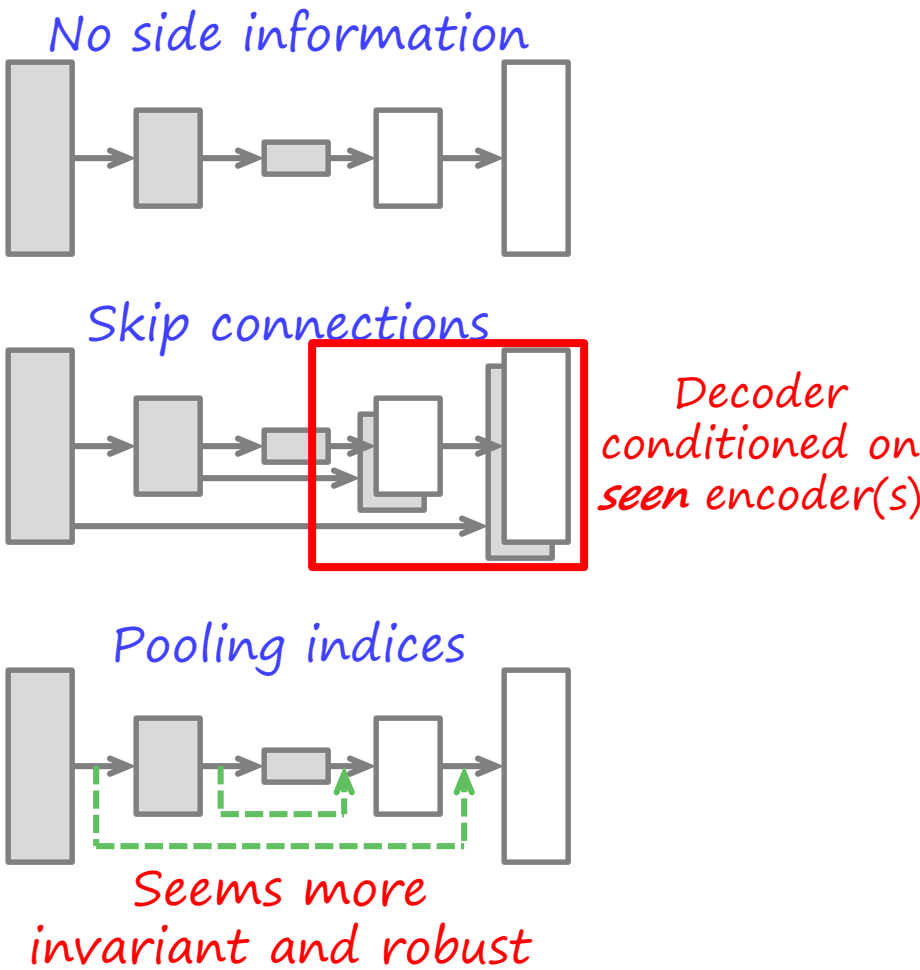
Figure 1: Zero-pair depth→segmentation, trained on (depth,RGB) and (RGB,segmentation).

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

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%



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

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 $D \to R \to S$	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 $D \to R \to S$	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 $D \to S$	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 $(R, D) \to S$	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

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

Outline

- Introduction
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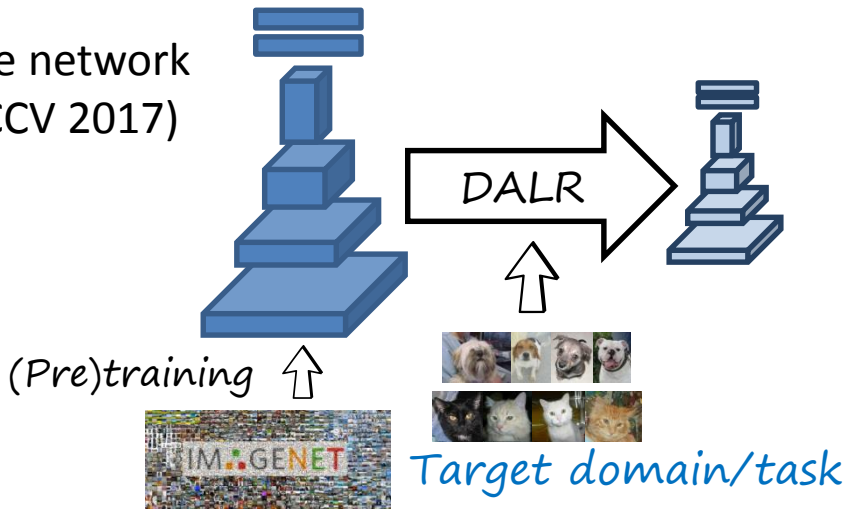
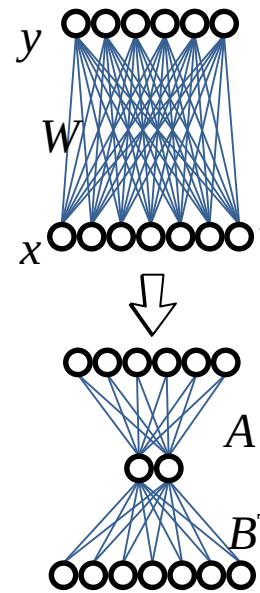
- Rotated elastic weight consolidation (ICPR 2018)
- Memory Replay GANs (NIPS 2018)
- Mix and match networks (CVPR 2018)
- Other works

Other works

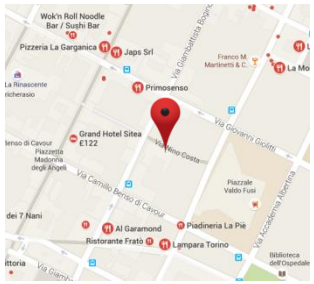
Domain-adaptive network compression (ICCV 2017)



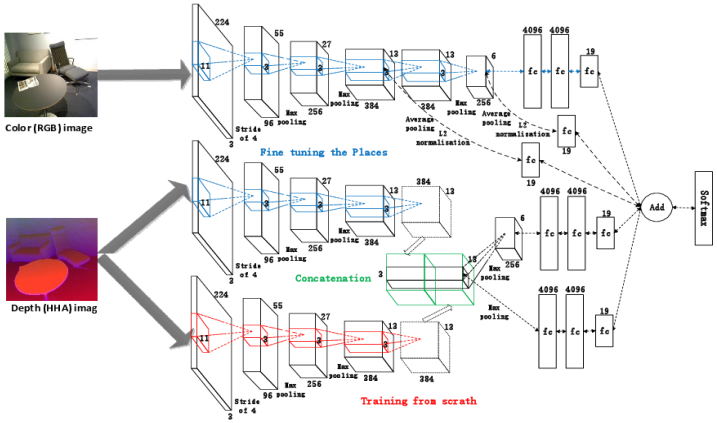


Domain-adaptive low rank (DALR) matrix decomposition

Contextual food recognition and analysis (TMM17,TMM18)



RGB-D deep representations (AAAI17,IJCAI17,TIP18)



THANK YOU!

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www.lherranz.org