Structure-Aware Manipulation of Images and Videos

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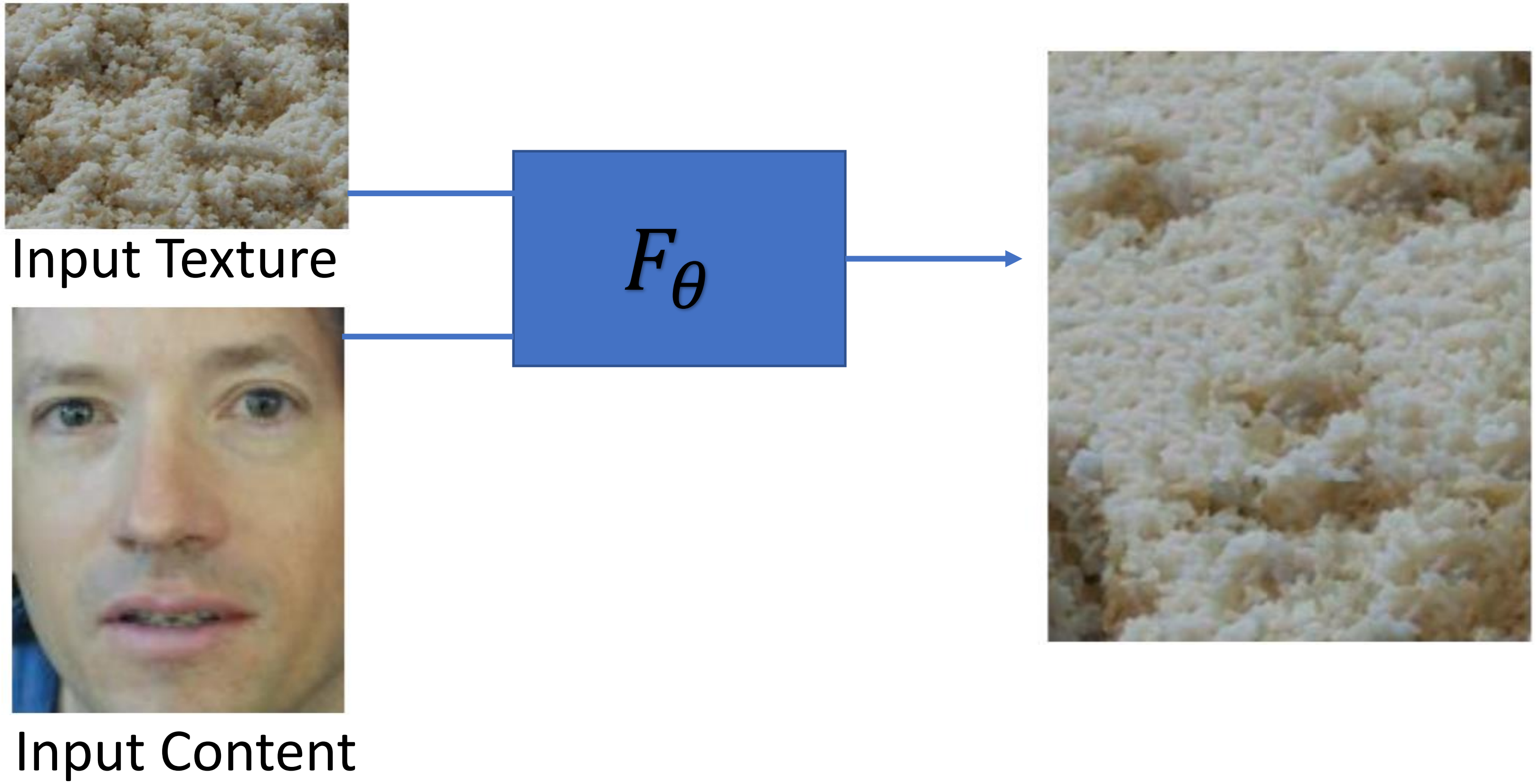
What is a natural image?

Intelligent machines must **understand** perceived content

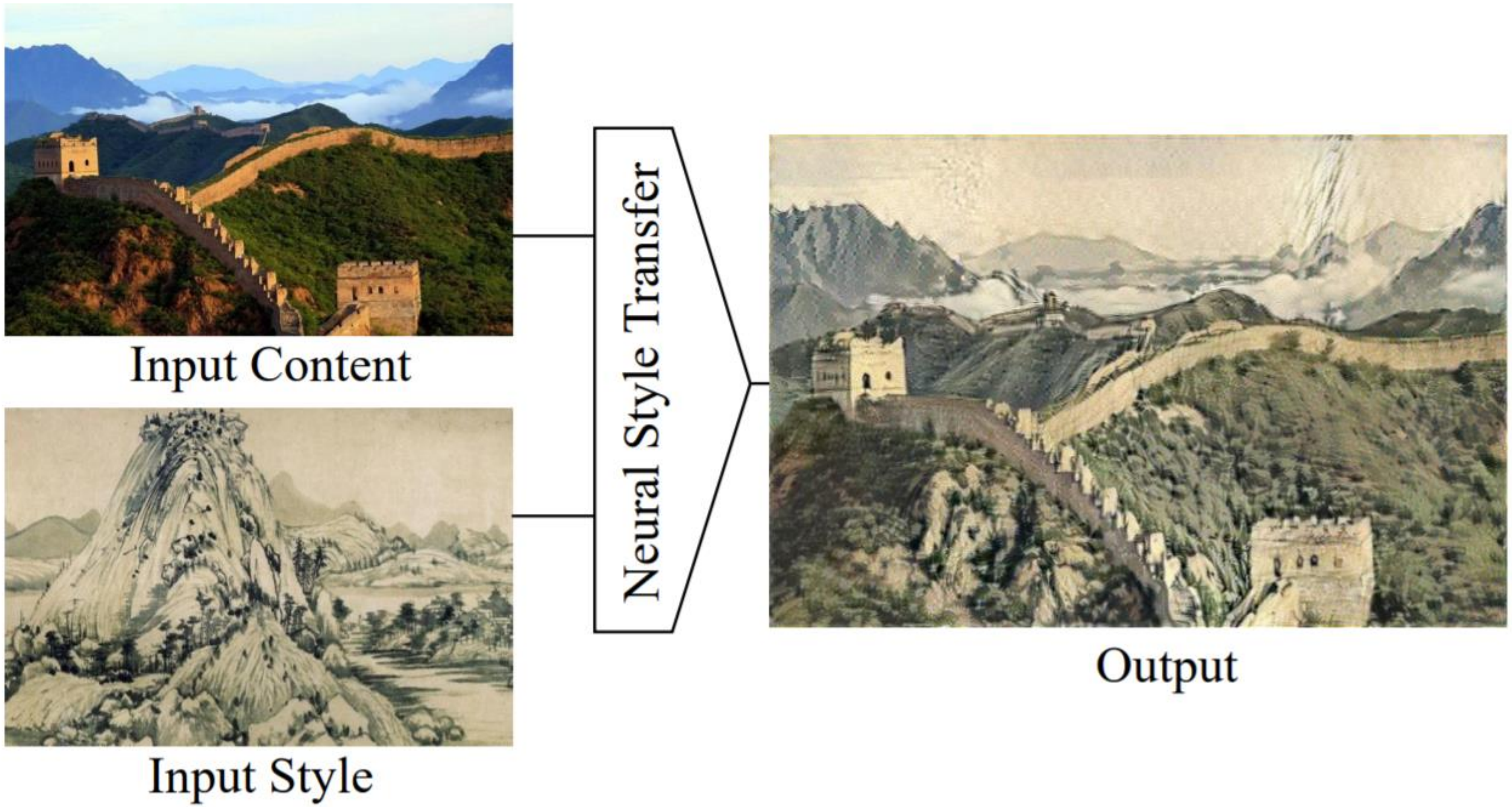
Understanding by creating/manipulating: "What I cannot create, I do not understand" (Richard Feynman)

Manipulating Texture



A.A.Efros, W.T.Freeman. “Image Quilting for Texture Synthesis and Transfer”. SIGGRAPH01

Manipulating Style

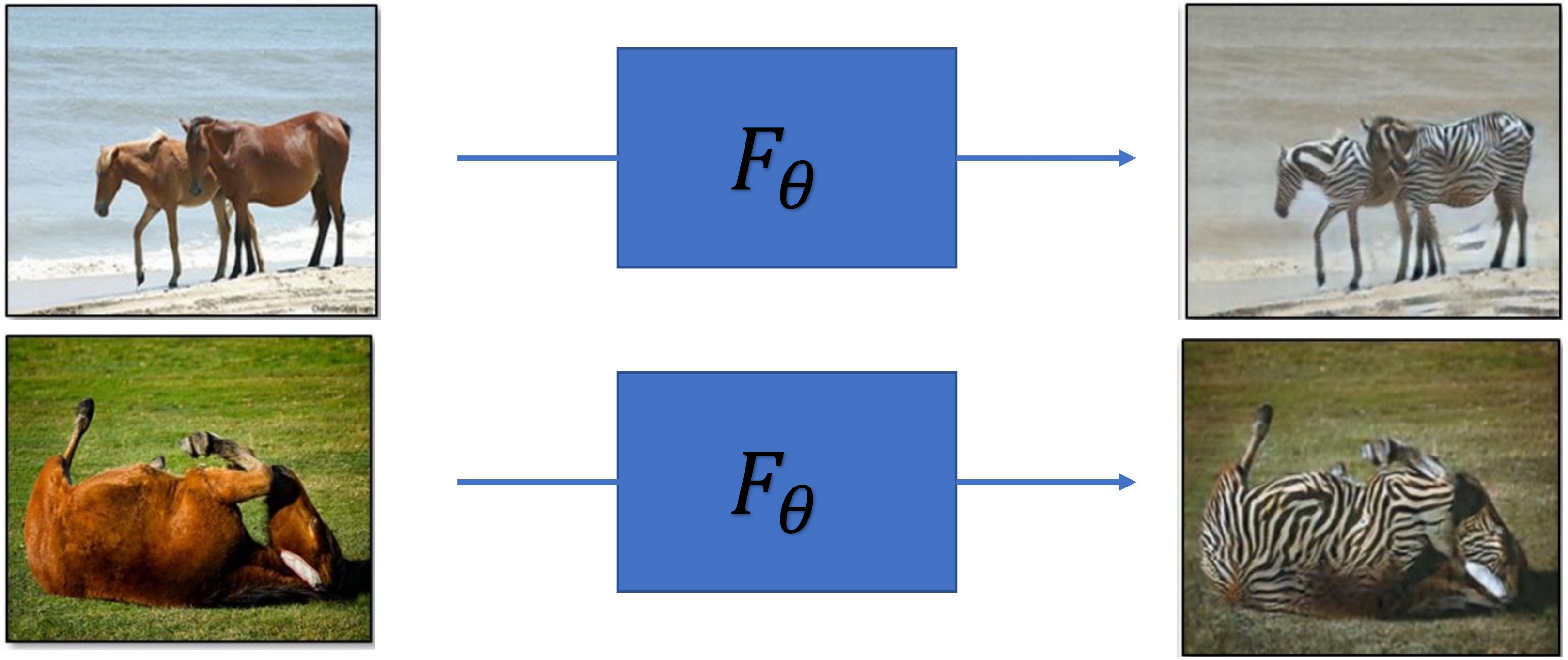


L. A. Gatys, A. S. Ecker, and M. Bethge. “A neural algorithm of artistic style”. 2015.

Image to Image Translation

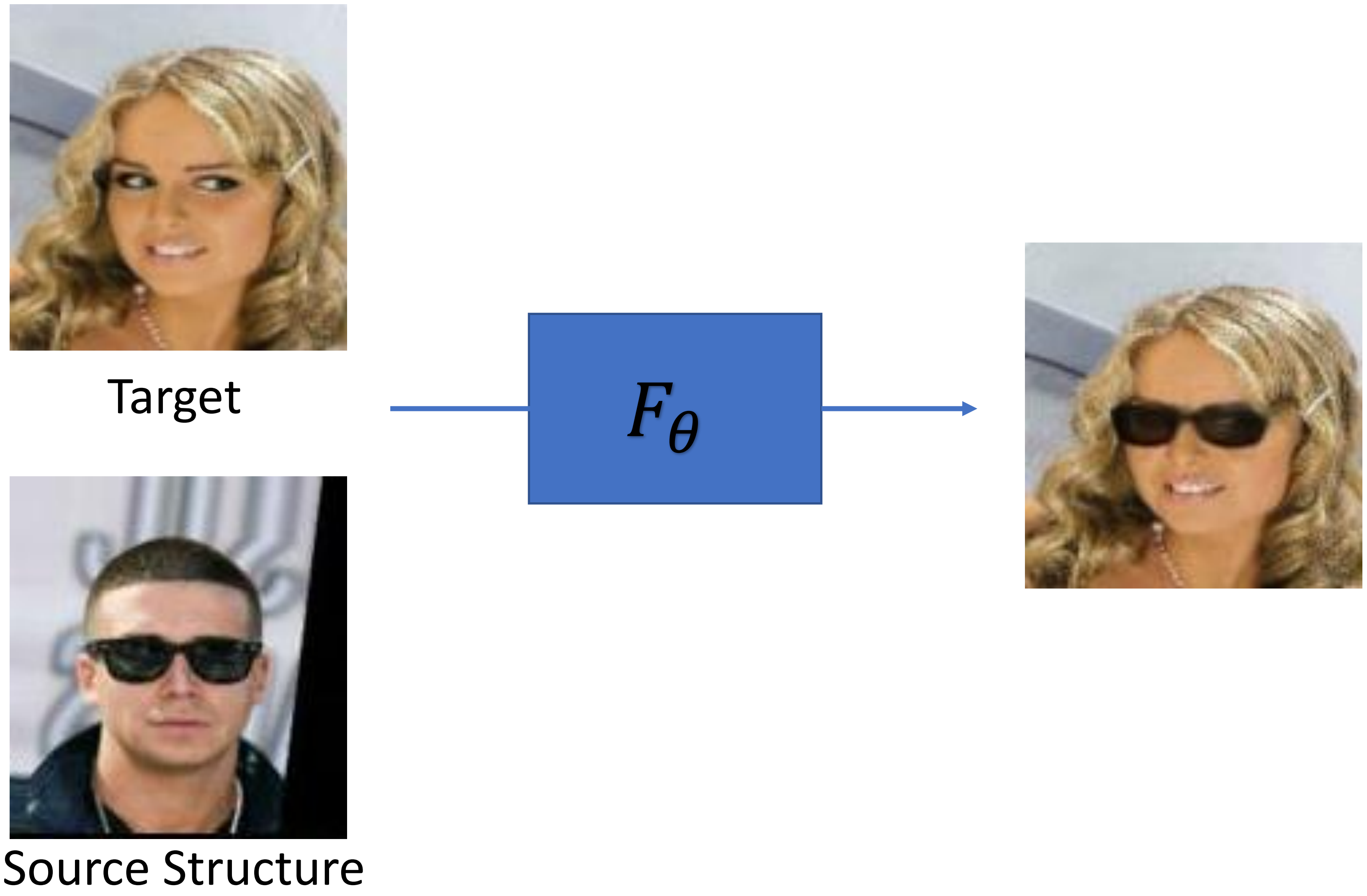
1. $\mathrm{F}_{\theta}(\mathrm{x})$ preserves the **structure** of objects of x
2. $\mathrm{F}_{\theta}(\mathrm{x})$ belongs to Y's distribution (changes **style**)

$x \in X$ $\qquad\qquad$ $F_{\theta}(x) \in Y$

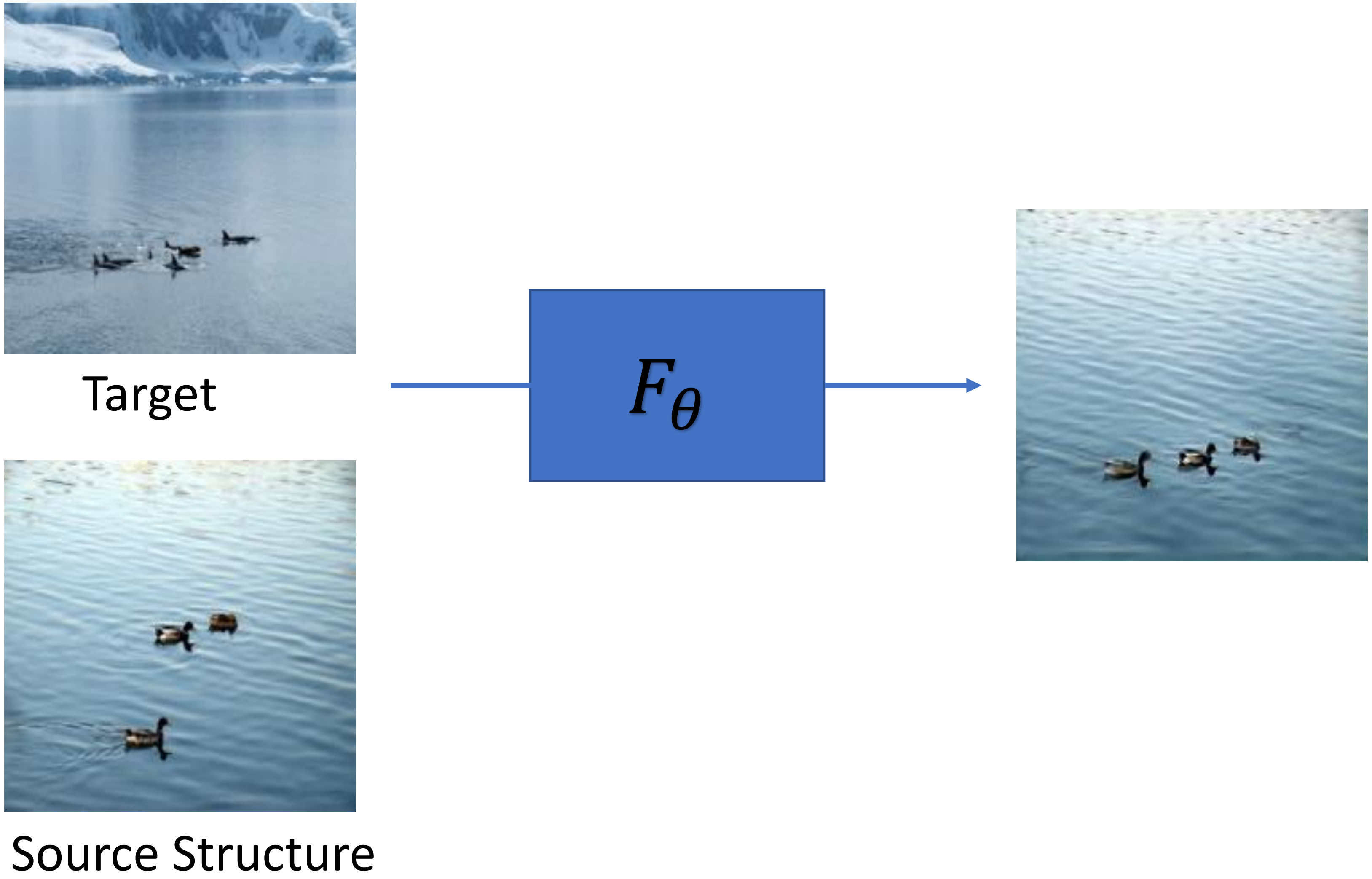


CycleGAN, Zhu et al., ICCV 2017

Manipulating Structure



Manipulating Structure



Applications

Architecture

Video games

Movies

Advertising

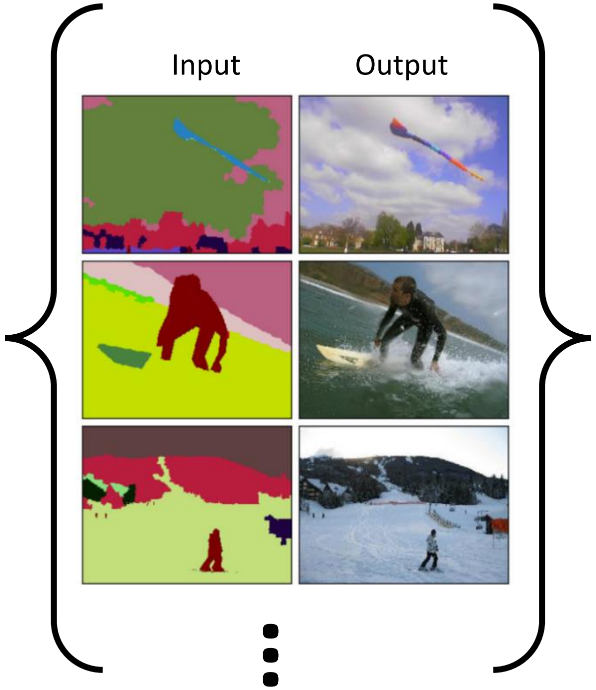
AR/VR

Autonomous Driving Simulations

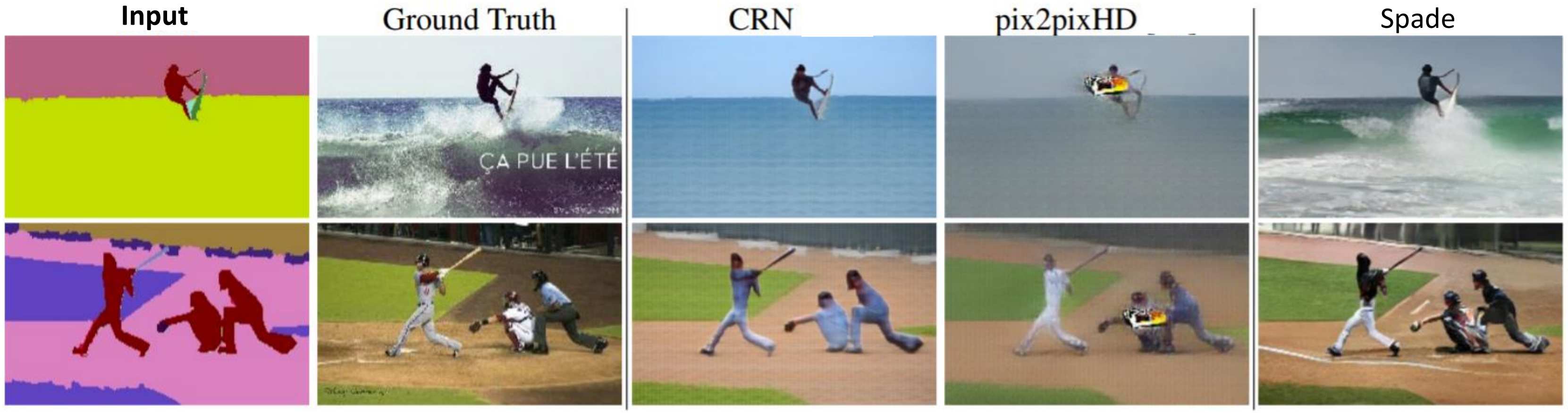
Multi-Image Approaches

Supervised (Paired) Setting

Train



Test



Unsupervised (Unpaired) Setting

A

Faces <u>without</u> glasses

B

Faces with glasses

Control Structure of Generated Faces (Transfer Glasses)

Unsupervised Approaches

O. Press, T. Galanti, **S. Benaim,** L. Wolf.
Emerging Disentanglement in Auto-Encoder Based Unsupervised Image Content Transfer.
In **ICLR 2019.**

S. Benaim, M. Khaitov, T. Galanti, L. Wolf.

In **ICCV, 2019.**

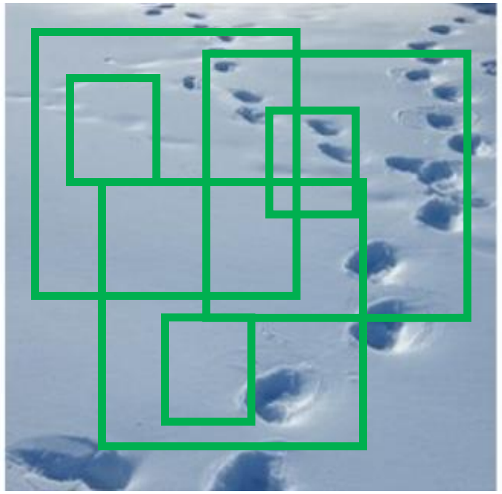
R. Mokady, **S. Benaim**, L. Wolf, A. Bermano.
Mask Based Unsupervised Content Transfer.
In **ICLR, 2020.**

Require a large collection of images from both domains

Patch-Based Approaches

Multi-Image Distribution

Multi-Scale Patch Distribution

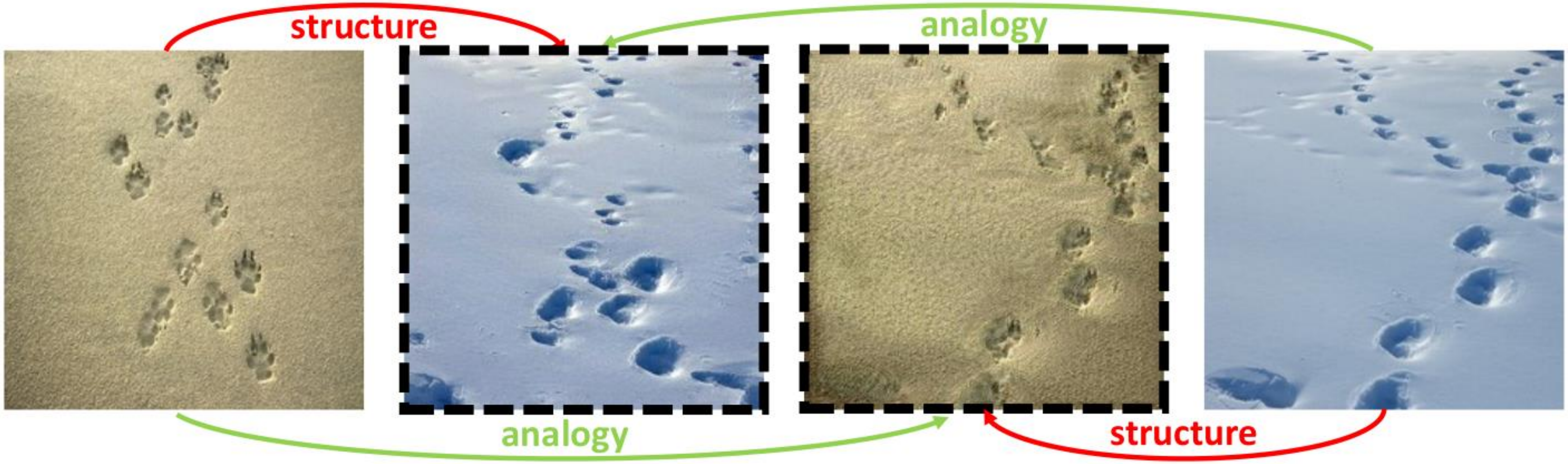


Brock et al., Large Scale GAN Training for High Fidelity Natural Image Synthesis. ICLR 2019

Structural-analogy from a **Single Image Pair**

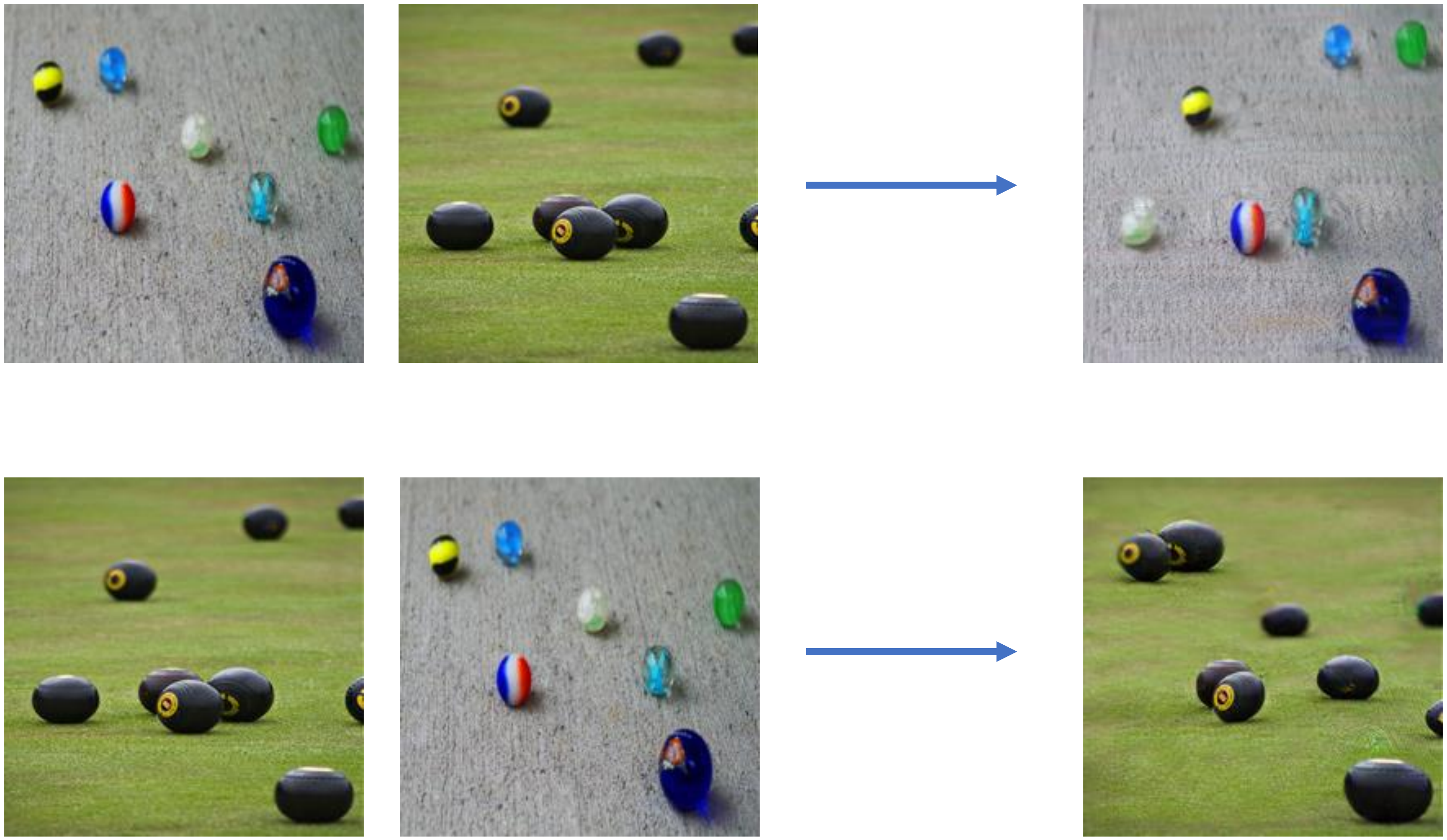
S. Benaim*, R. Mokady*, A. Bermano, D Cohen-Or, L. Wolf. CGF 2020. (*Equal contribution)

Generate an image which is **aligned to the source image** but depicts **structure from a target image**



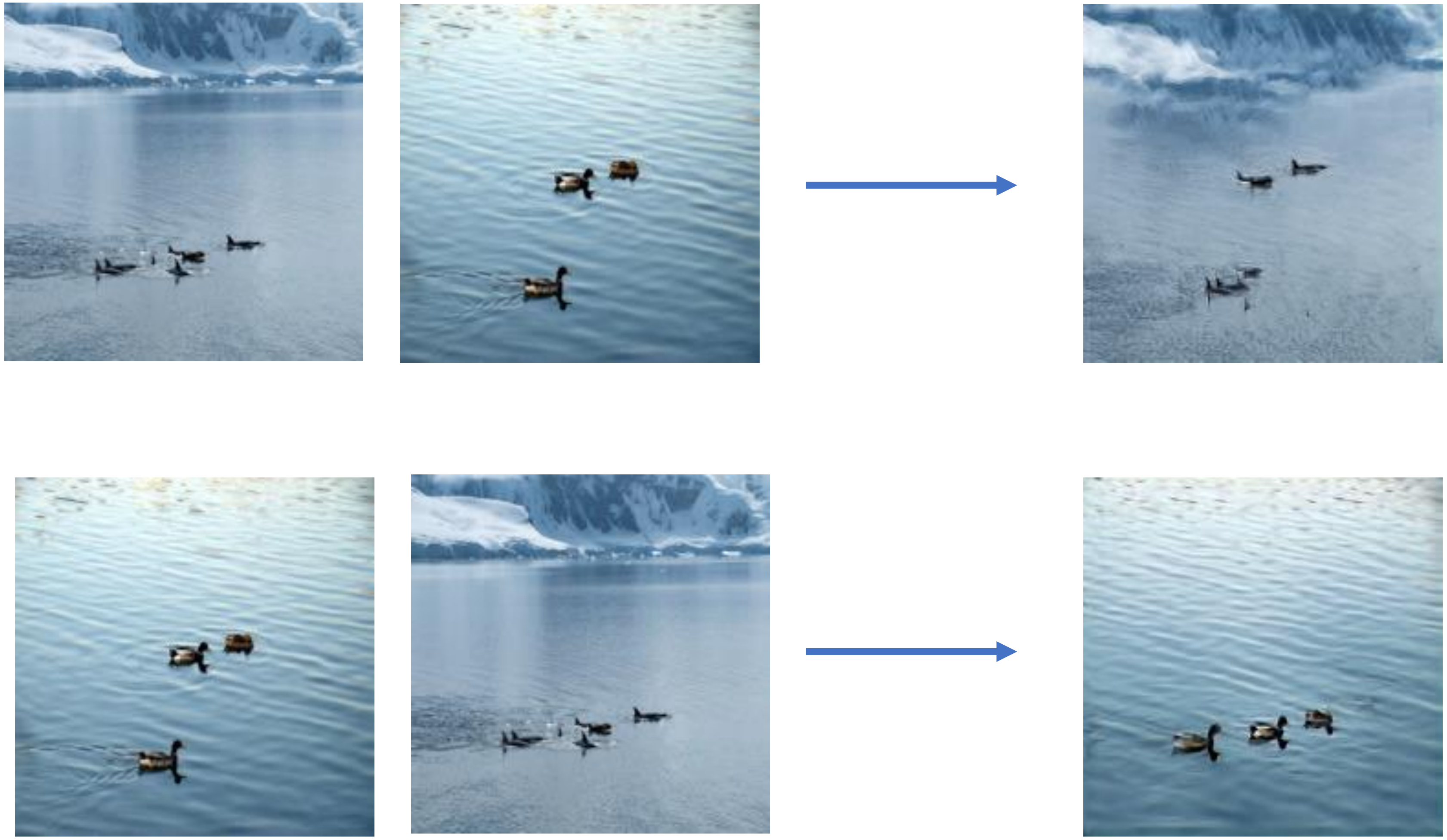
Structural Analogy

Target Source Output



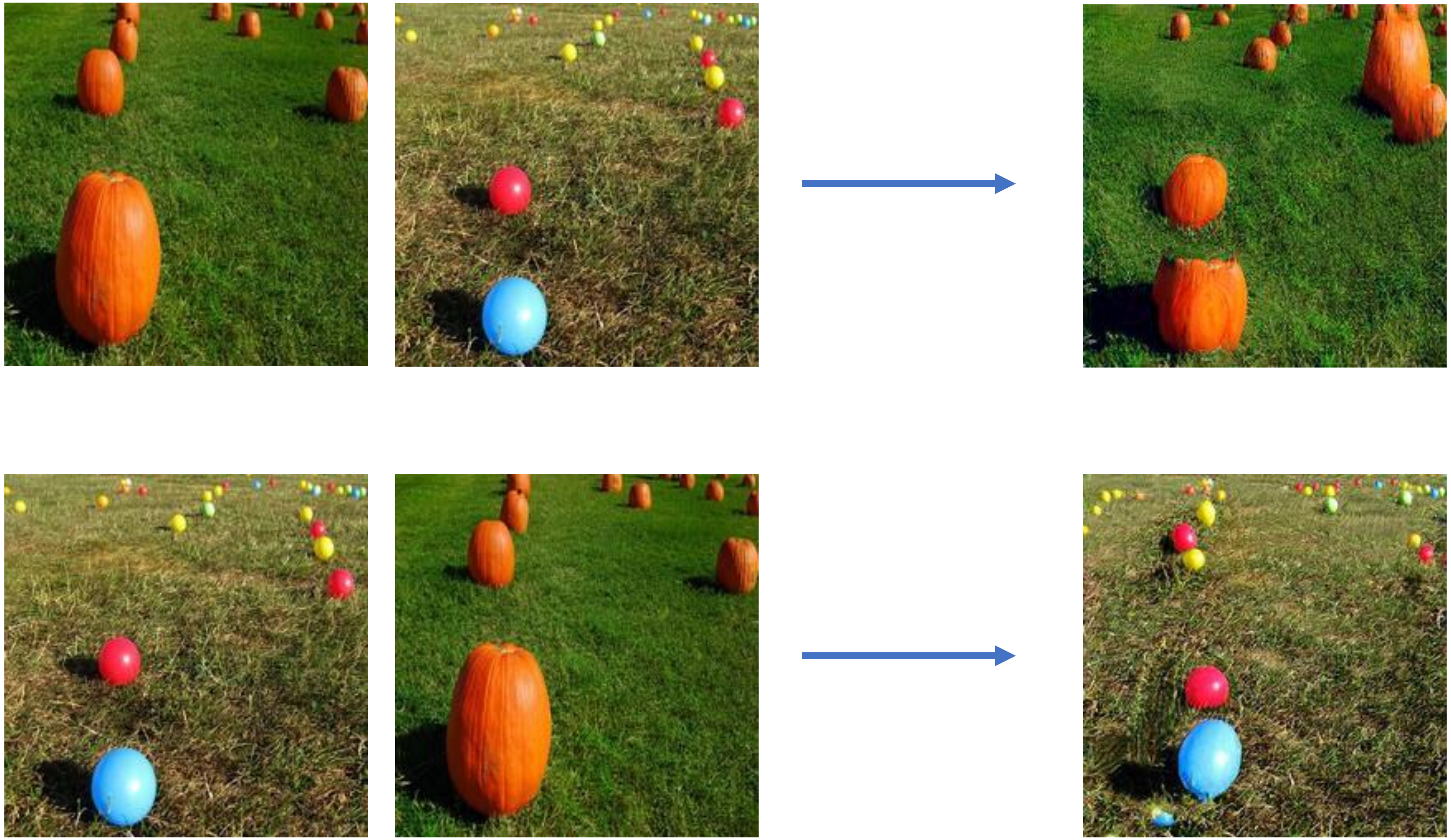
Structural Analogy

Target Source Output



Structural Analogy

Target | Source | Output



Style Transfer

Style

Content

Result

Deep Image Analogy

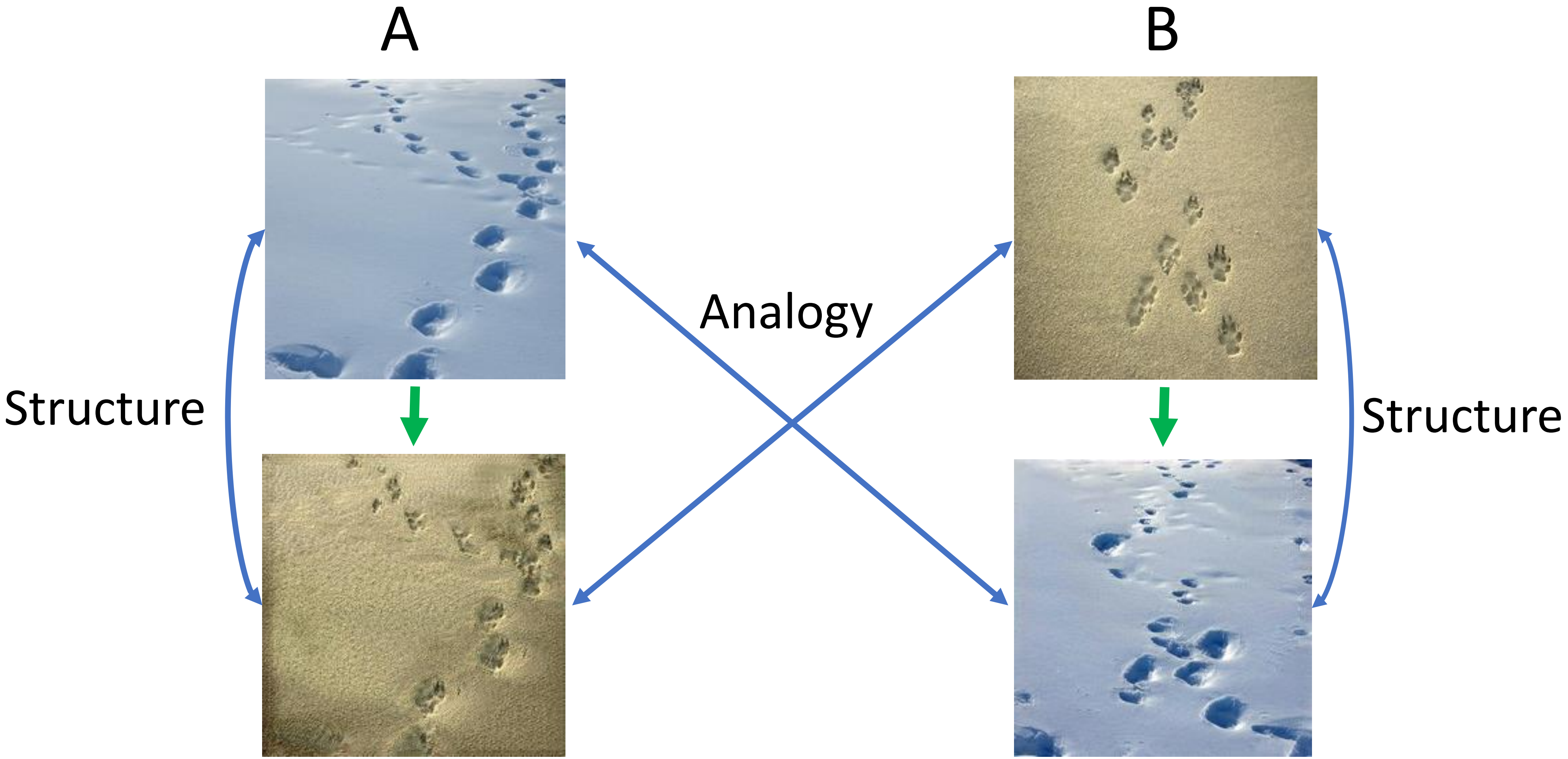
Style

Content

Result

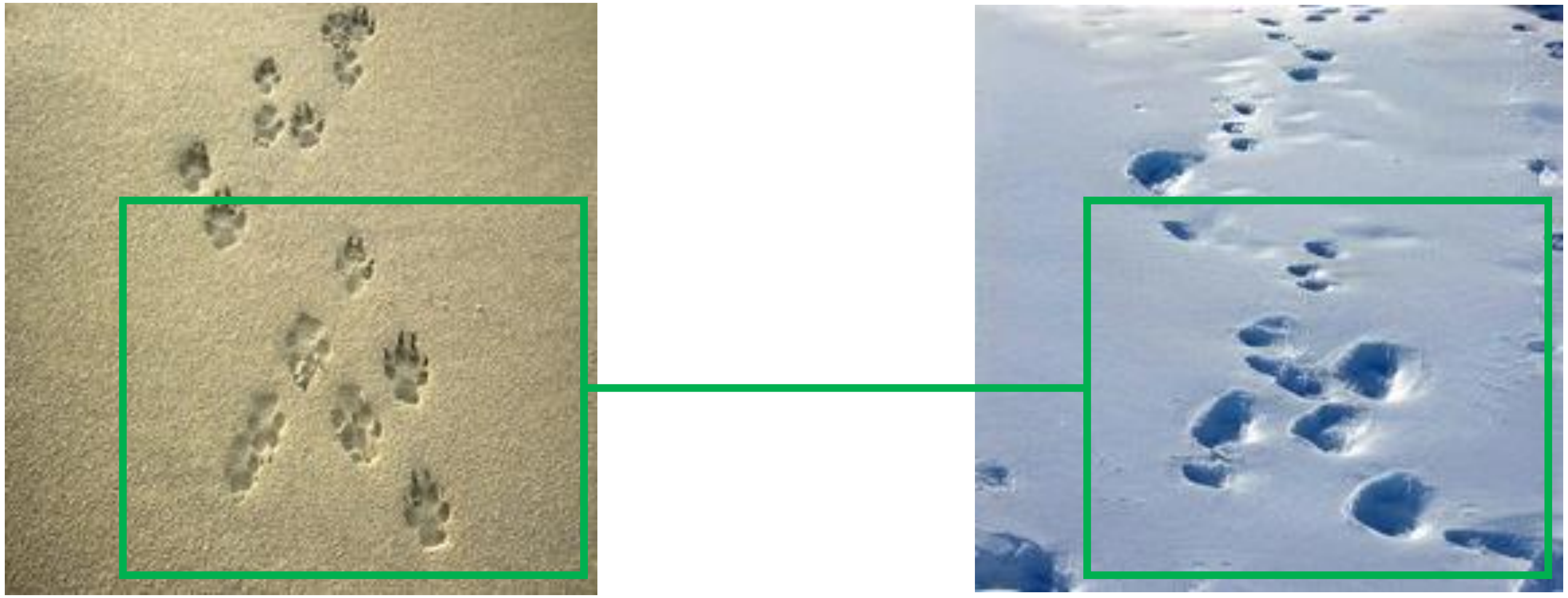
Cannot Change Object Shape

Structural Analogy



Motivation

A B

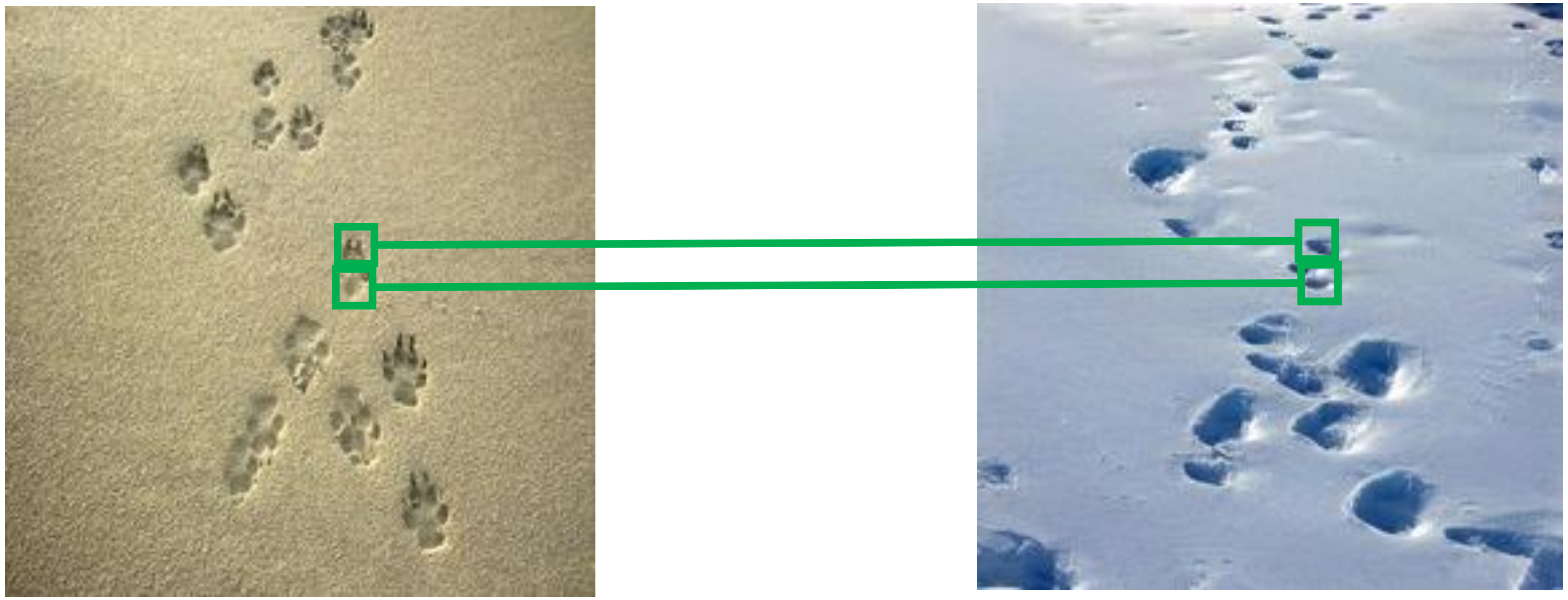


Motivation

A B

Motivation

A B



Proposed Hierarchical Approach

Coarsest scale:
Large Patches

Finest scale:
Small Patches

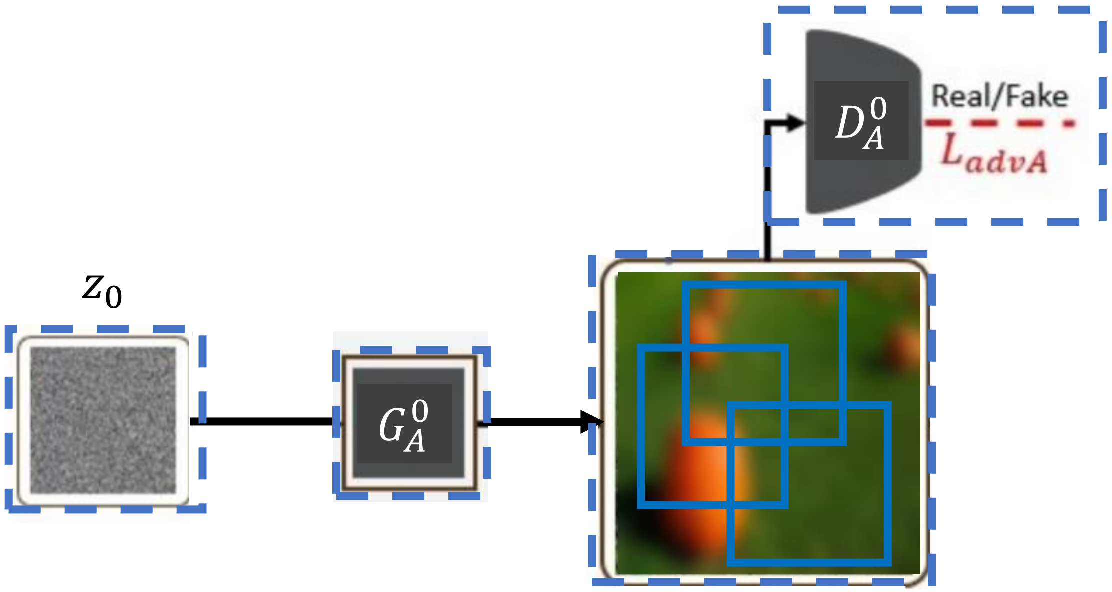
$\bar{a}^0$(Unconditional)
$\overline{ab}^0$(Conditional)

$\bar{a}^N$(Unconditional)
$\overline{ab}^N$(Conditional)

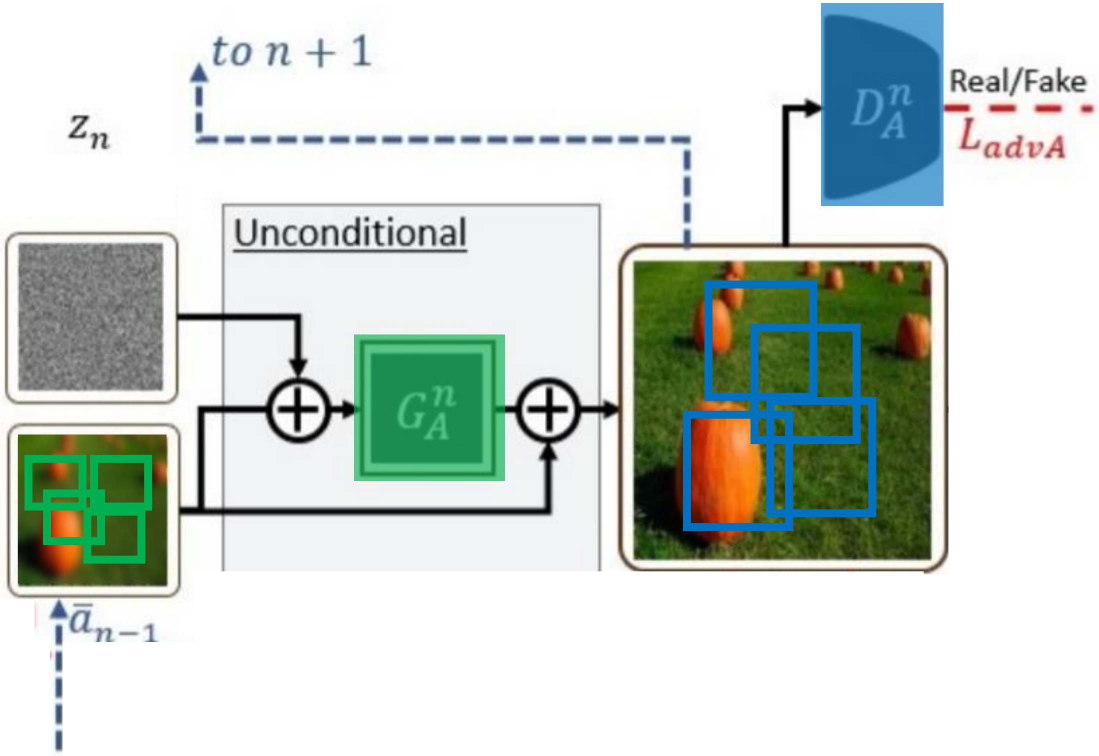
LEVEL $= 0$

LEVEL $= N$

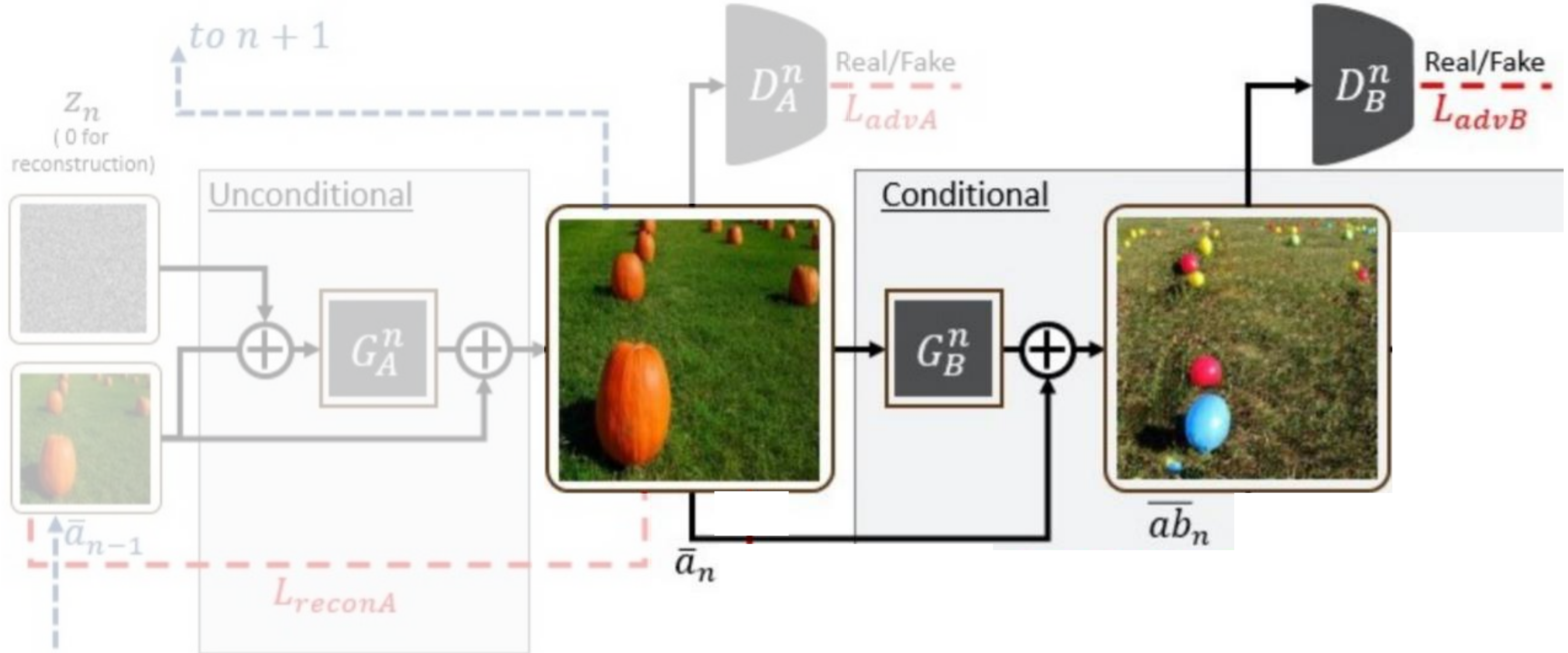
Unconditional Generation (Level 0)



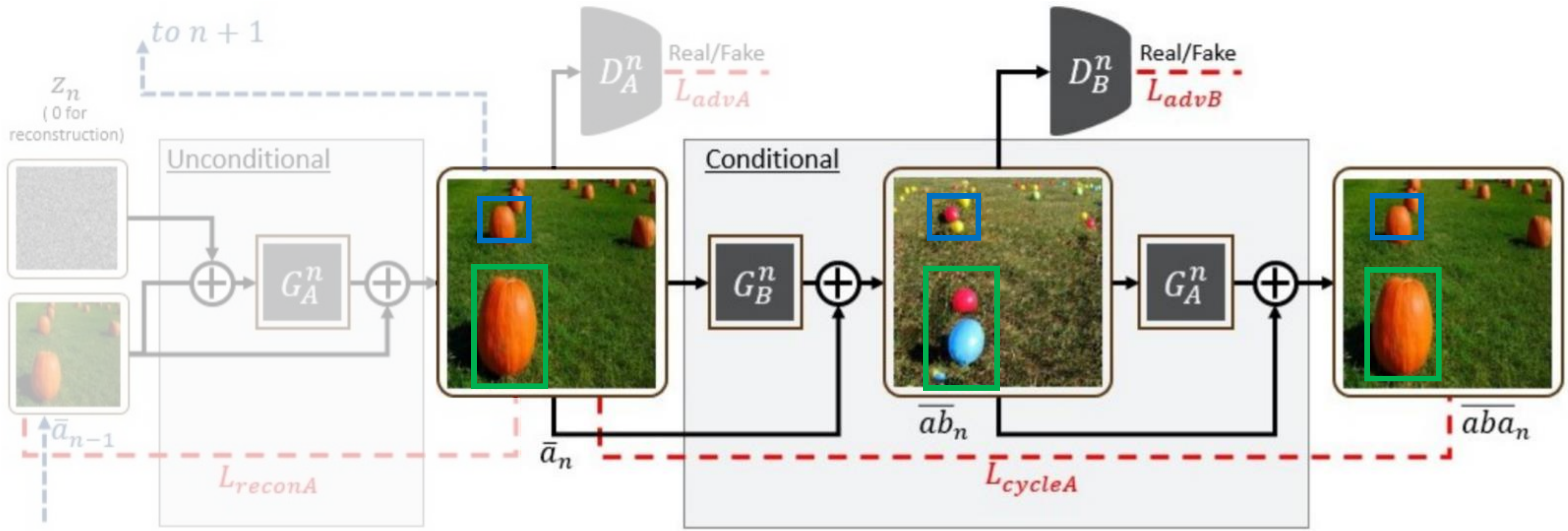
Unconditional Generation (Level n)



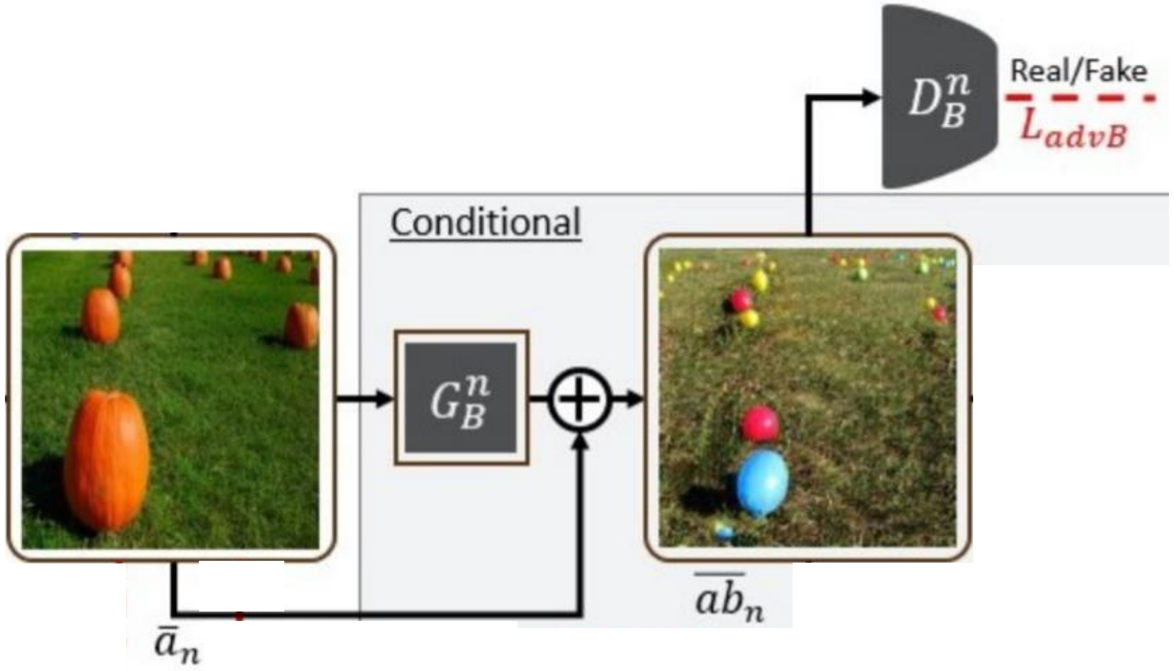
Conditional Generation (Level n)

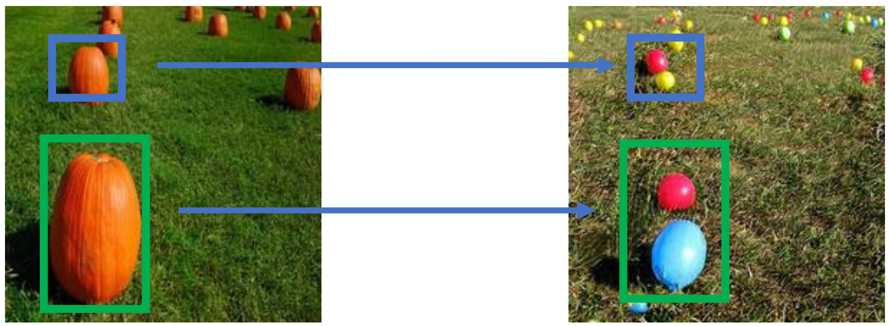


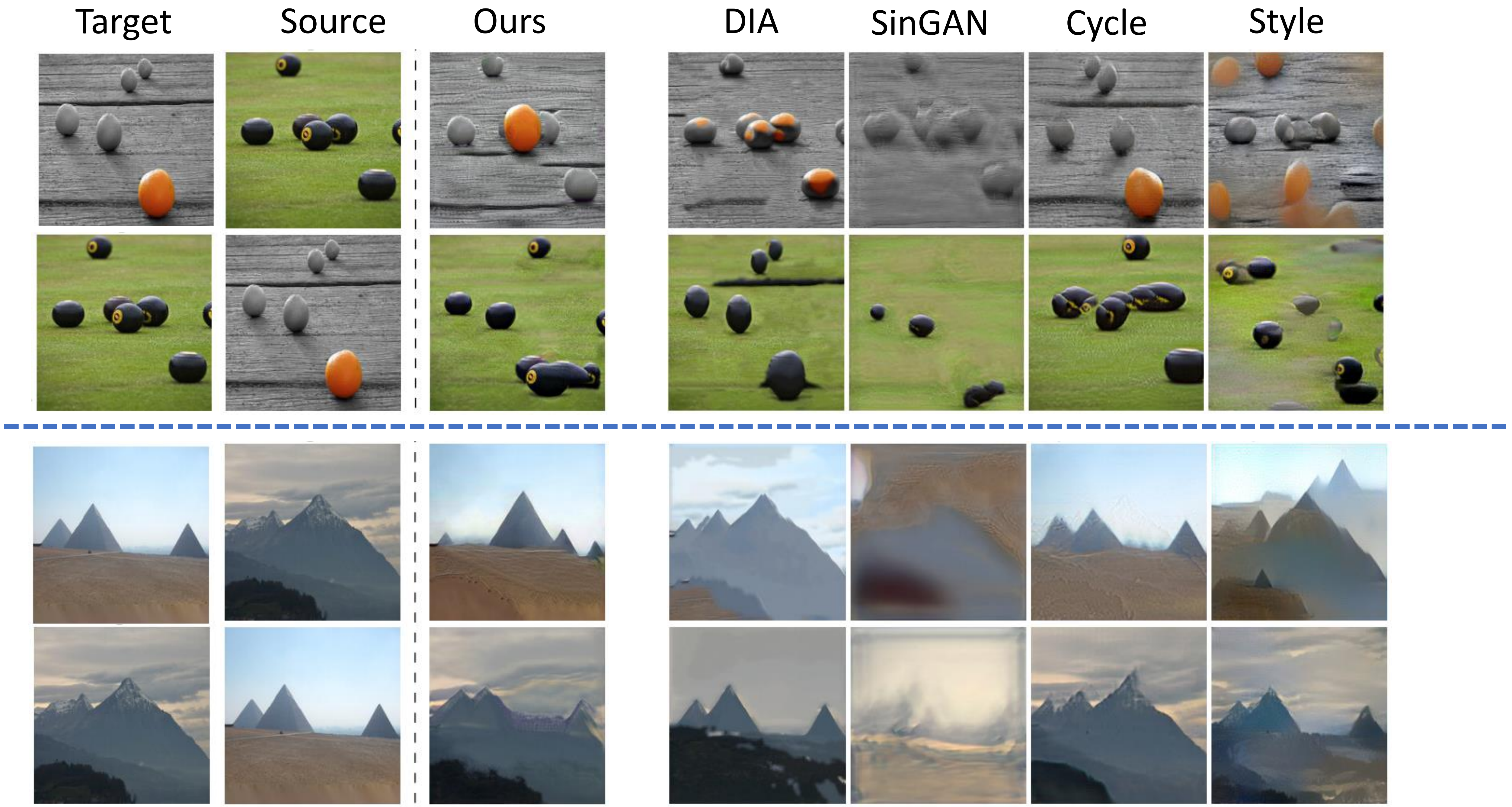
Conditional Generation (Level n)



Coarse and Mid Scales: Residual Training



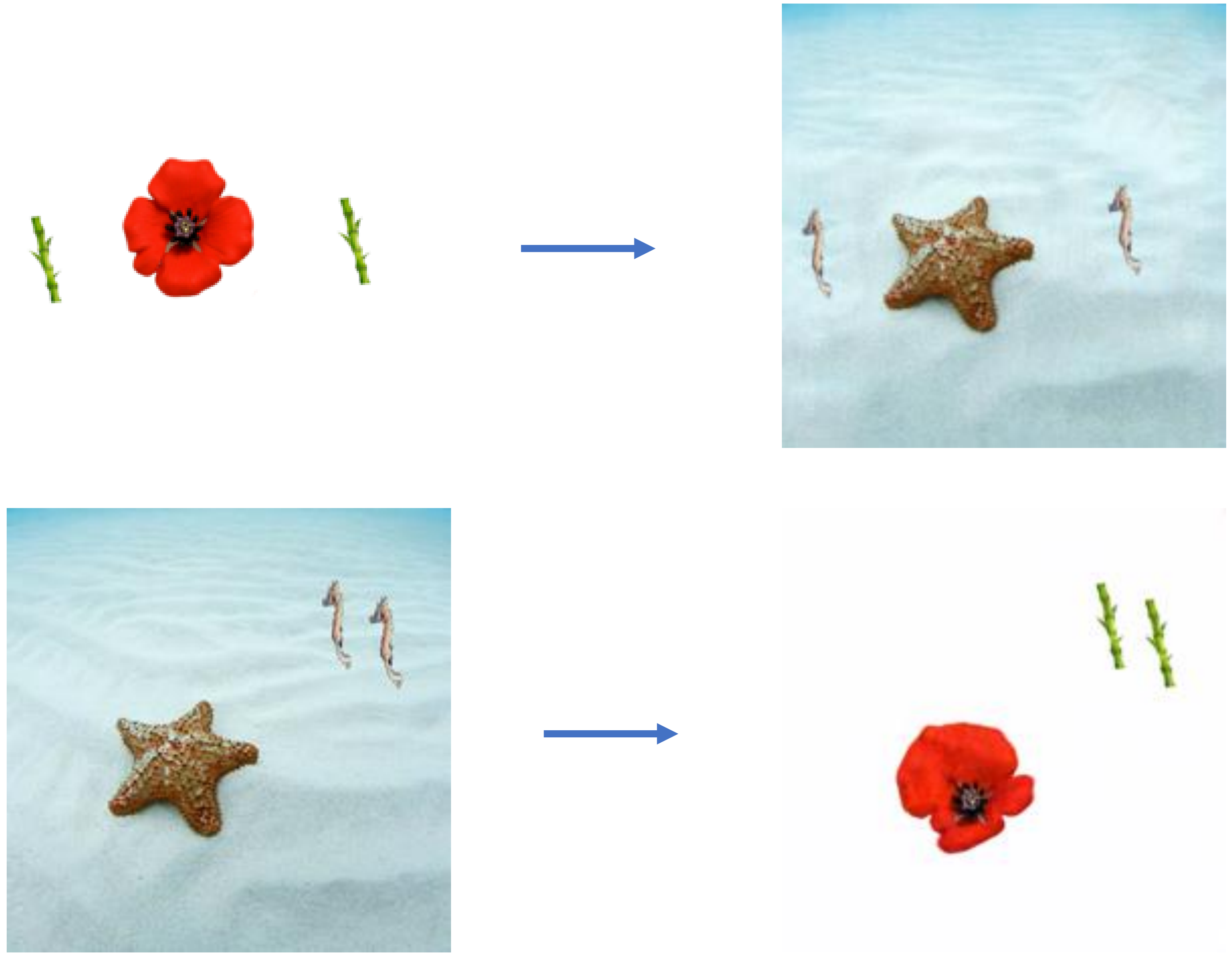



Target
Source
Ours
DIA
SinGAN
Cycle
Style

Multiple Class Types

Input

Output



Paint to Image

Input Sketch Ours Input Sketch Ours

Video Generation

Structure Manipulation for **Videos**

Hierarchical Patch VAE-GAN:
Generating Diverse Videos from a **Single Sample**

S. Gur*, **S. Benaim***, L. Wolf. NeurIPS 2020 (*Equal contribution)

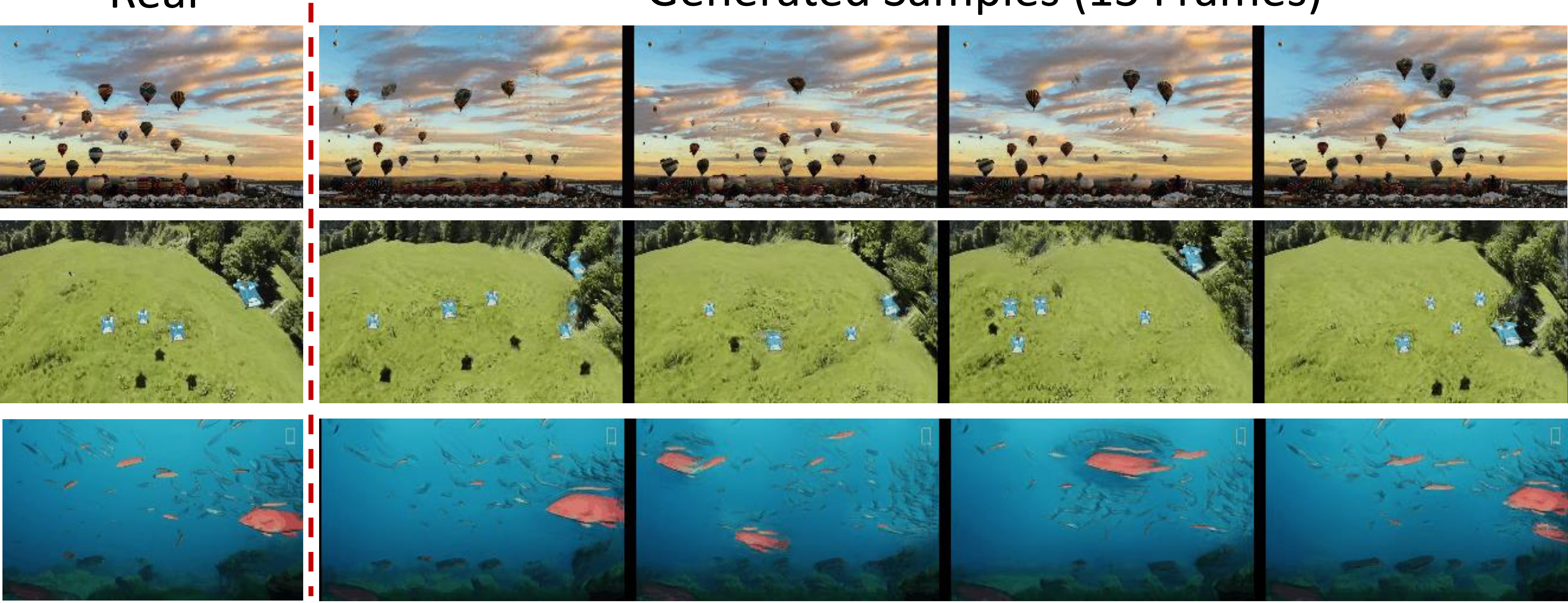
Real

Hierarchical Patch VAE-GAN:
Generating Diverse Videos from a Single Sample

S. Gur*, **S. Benaim***, L. Wolf. NeurIPS 2020 (*Equal contribution)

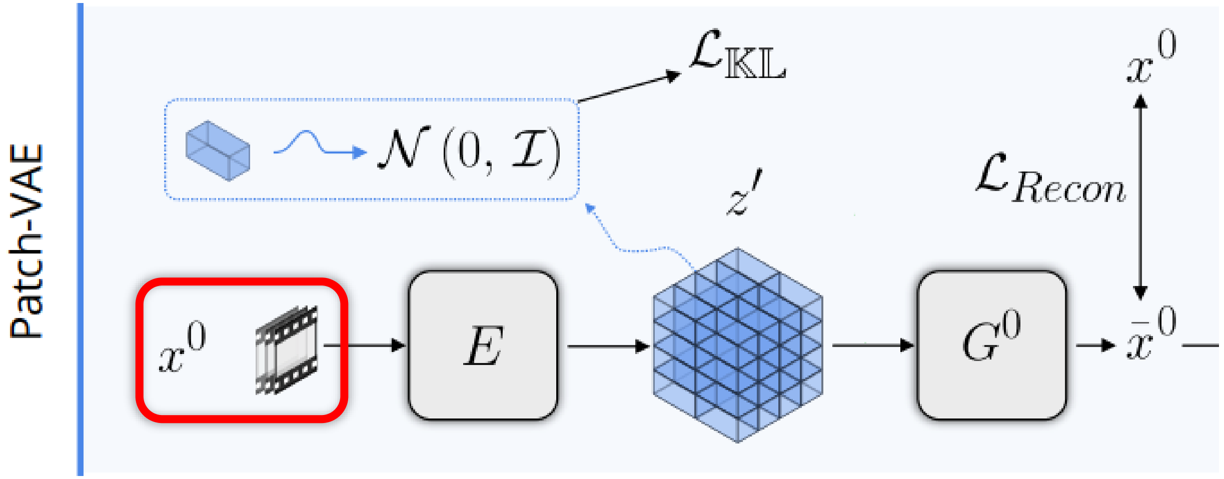
Real

Generated Samples (13 Frames)



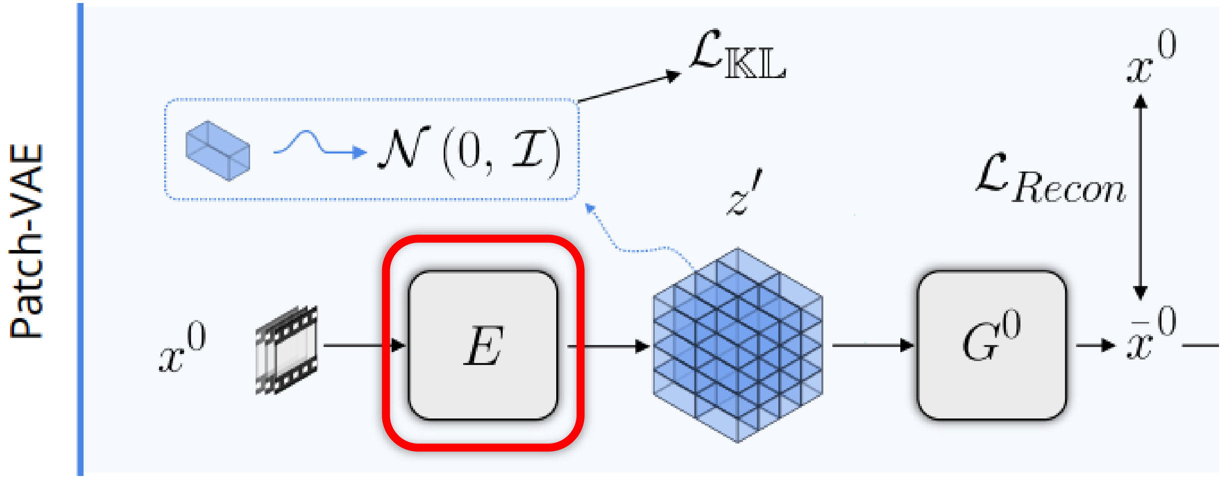
Proposed Approach: Patch VAE

Input video - x^0



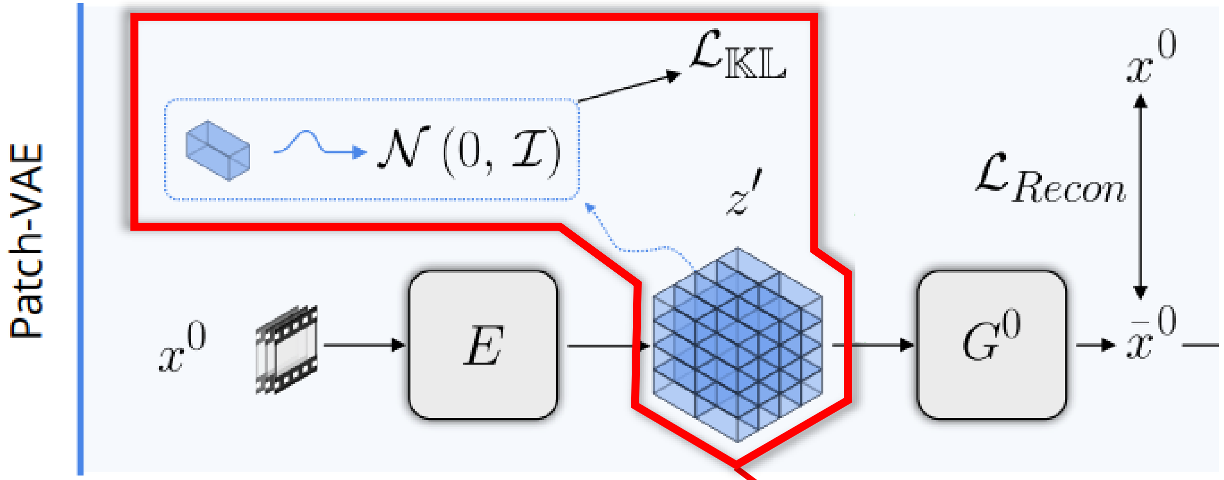
Proposed Approach: Patch VAE

Encoder – $\mathrm{E}(x^0)$

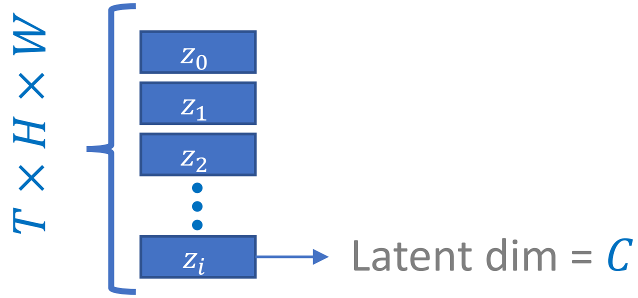


Proposed Approach: Patch VAE

KL Loss – z'

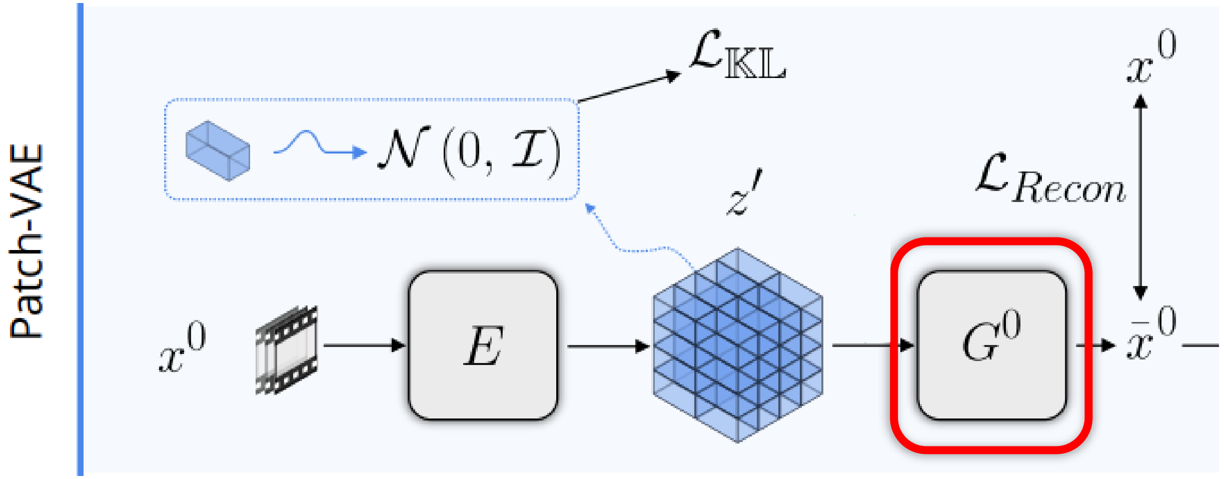


Each feature z_i , $i = [1 \ldots K], K = T \times H \times W$,
in the latent space is associated with a patch ω_i



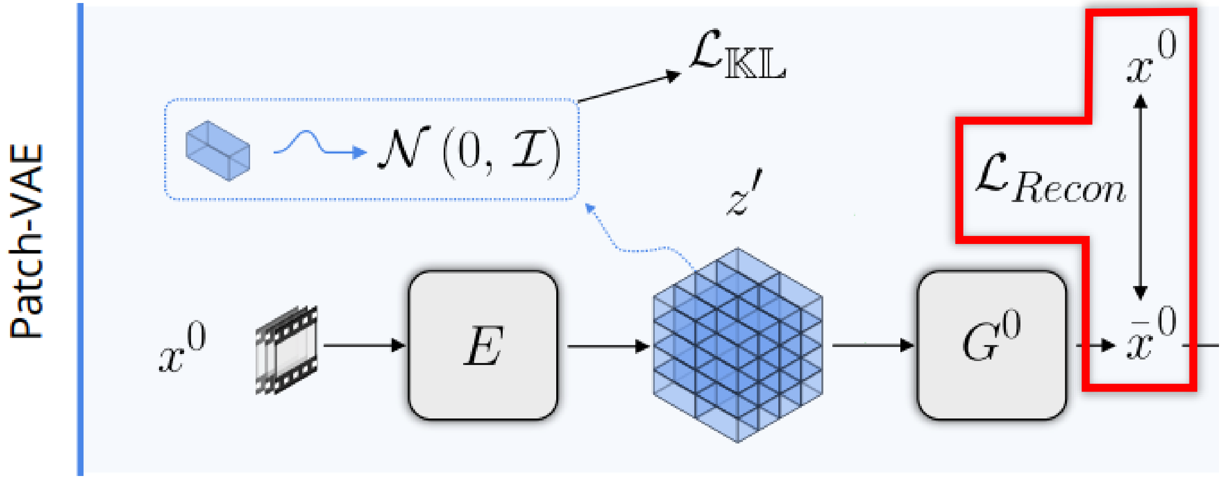
Proposed Approach: Patch VAE

Decoder - $\bar{x}^0$



Proposed Approach: Patch VAE

Reconstruction loss



Proposed Approach: Hierarchical Patch VAE

Coarsest scale:
Low resolution
and frame rate

x^0 (Real)
$\bar{x}^0$(Generated)

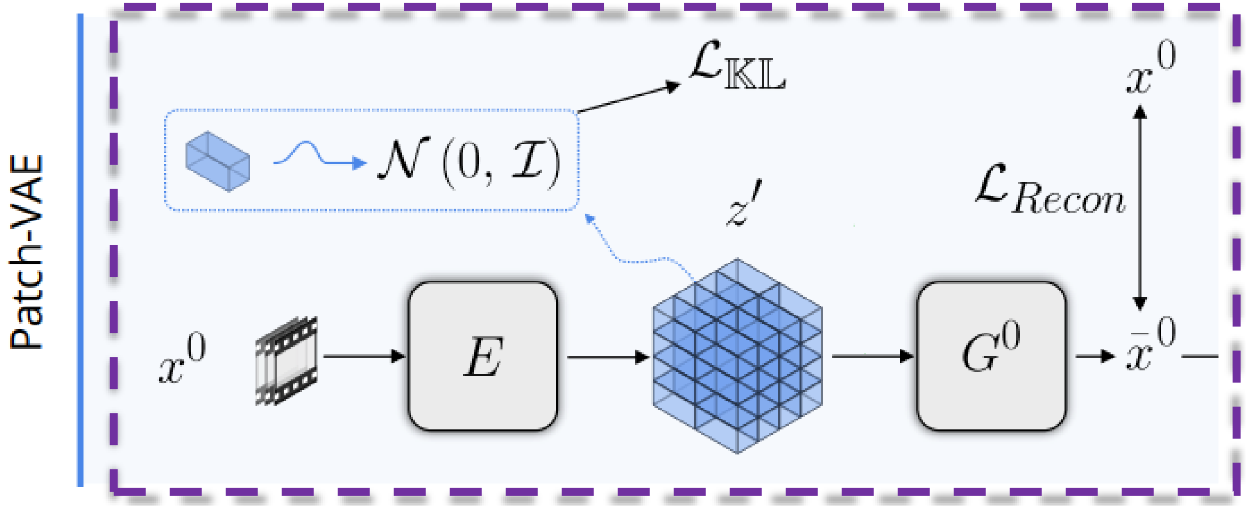
LEVEL $= 0$

Finest scale:
High resolution
and frame rate

x^N (Real)
$\bar{x}^N$(Generated)

LEVEL $= N$

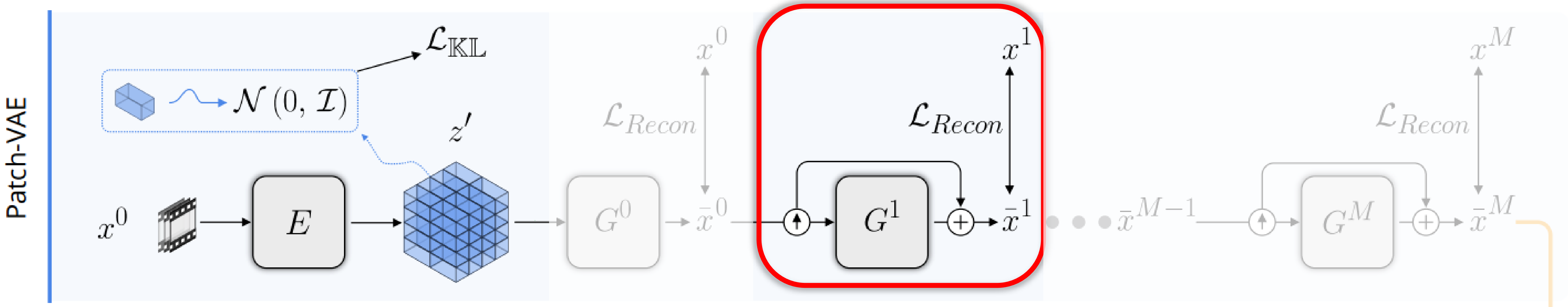
Proposed Approach: Hierarchical Patch VAE



LEVEL = 0

Proposed Approach: Hierarchical Patch VAE

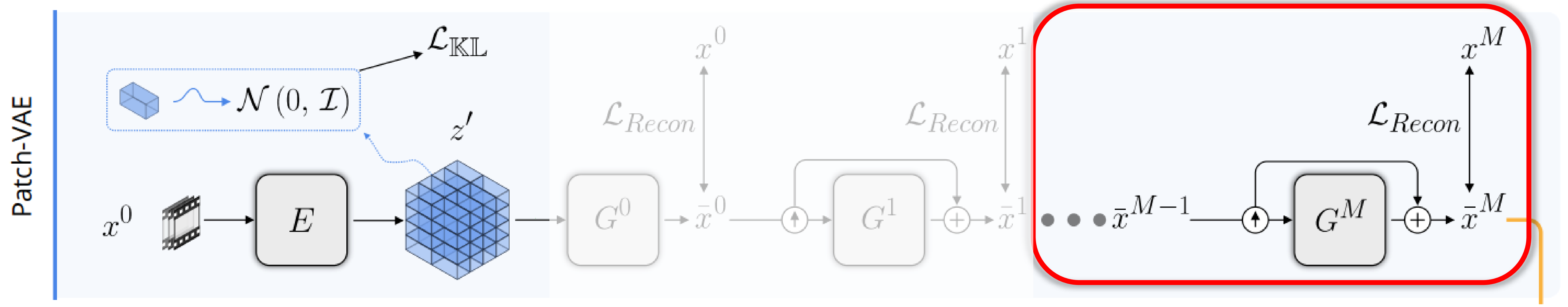
Up-sampling block - $\bar{x}^1$



LEVEL = 1

Proposed Approach: Hierarchical Patch VAE

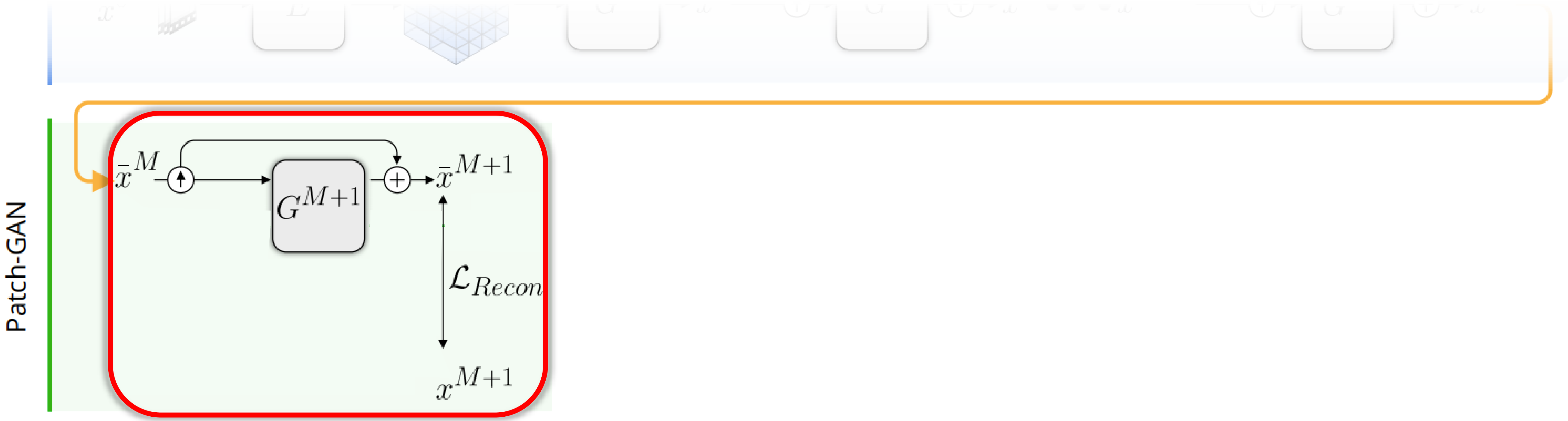
Hierarchical up-sampling up to $\bar{x}^M$



LEVEL $\leq M$

Proposed Approach: Hierarchical Patch VAE GAN

Up-sampling block $\bar{x}^{M+1}$

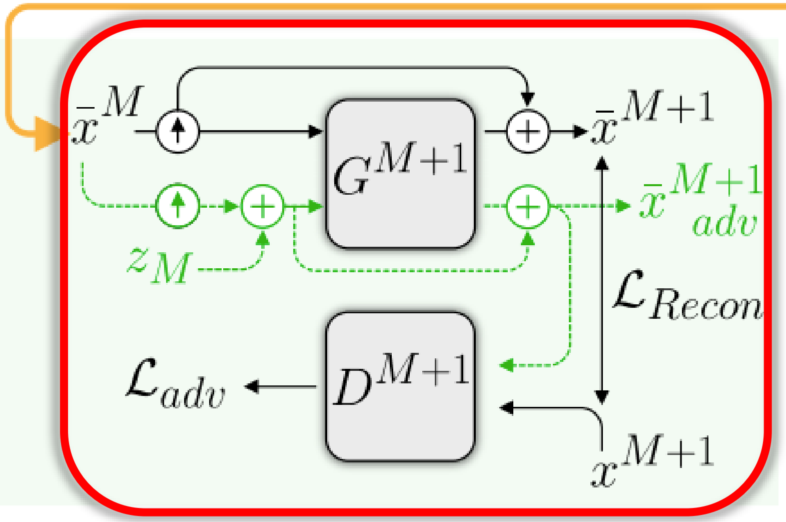


LEVEL = $M + 1$

Proposed Approach: Hierarchical Patch VAE GAN

Adversarial training

Patch-GAN

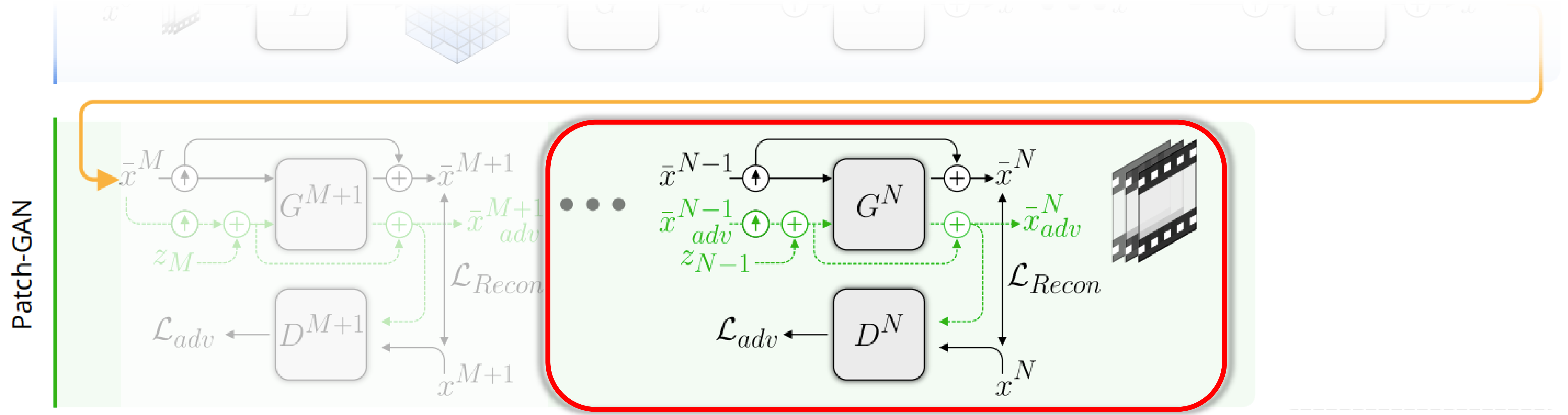


Added noise z_M

LEVEL $= M + 1$

Proposed Approach: Hierarchical Patch VAE GAN

Hierarchical up-sampling up to final resolution $\bar{x}^N$



$M + 1 <$ LEVEL $\leq N$

Effect of Number of patch-VAE levels

Training Video

9 Levels Total

1 p-VAE – 8 p-GAN

8 p-VAE – 1 p-GAN

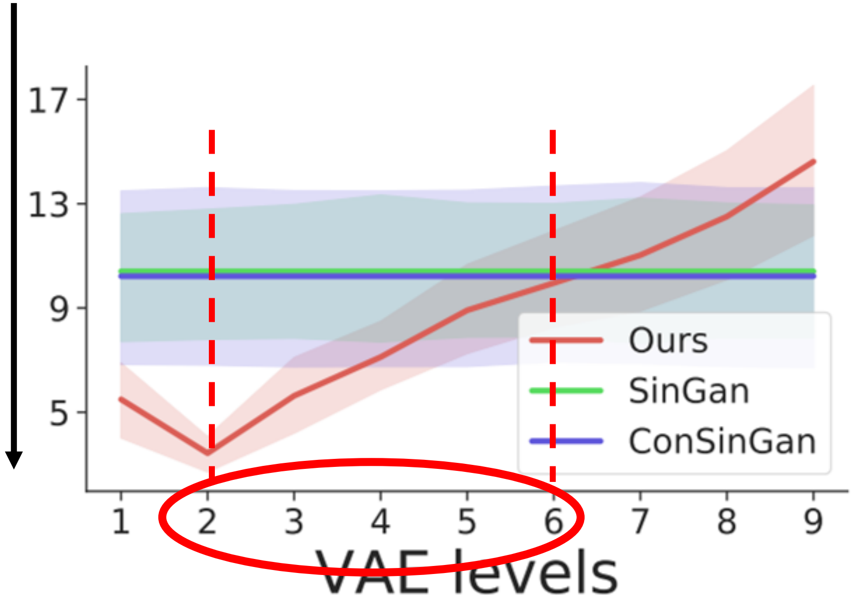
3 p-VAE – 6 p-GAN

Effect of Number of patch-VAE levels

Total of 9 layers

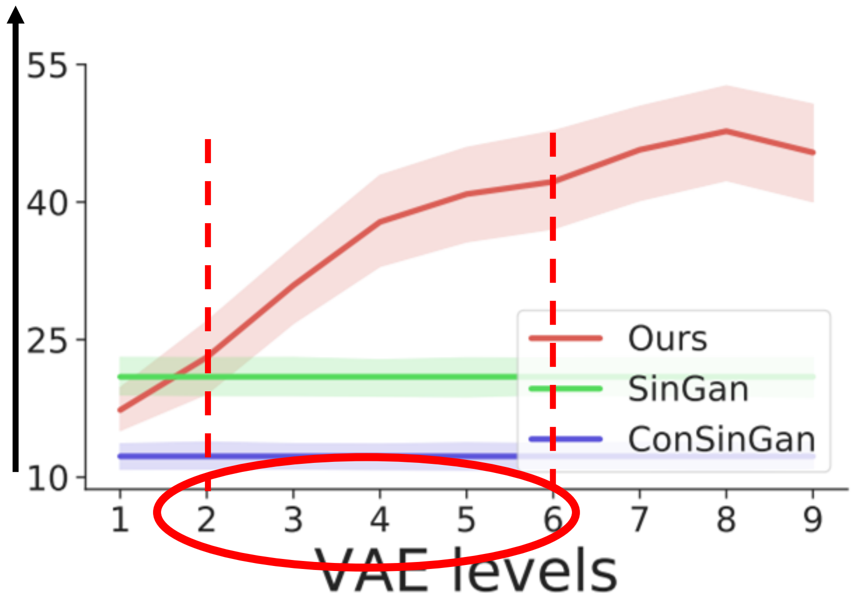
Quality

(**Lower** is Better)



Diversity

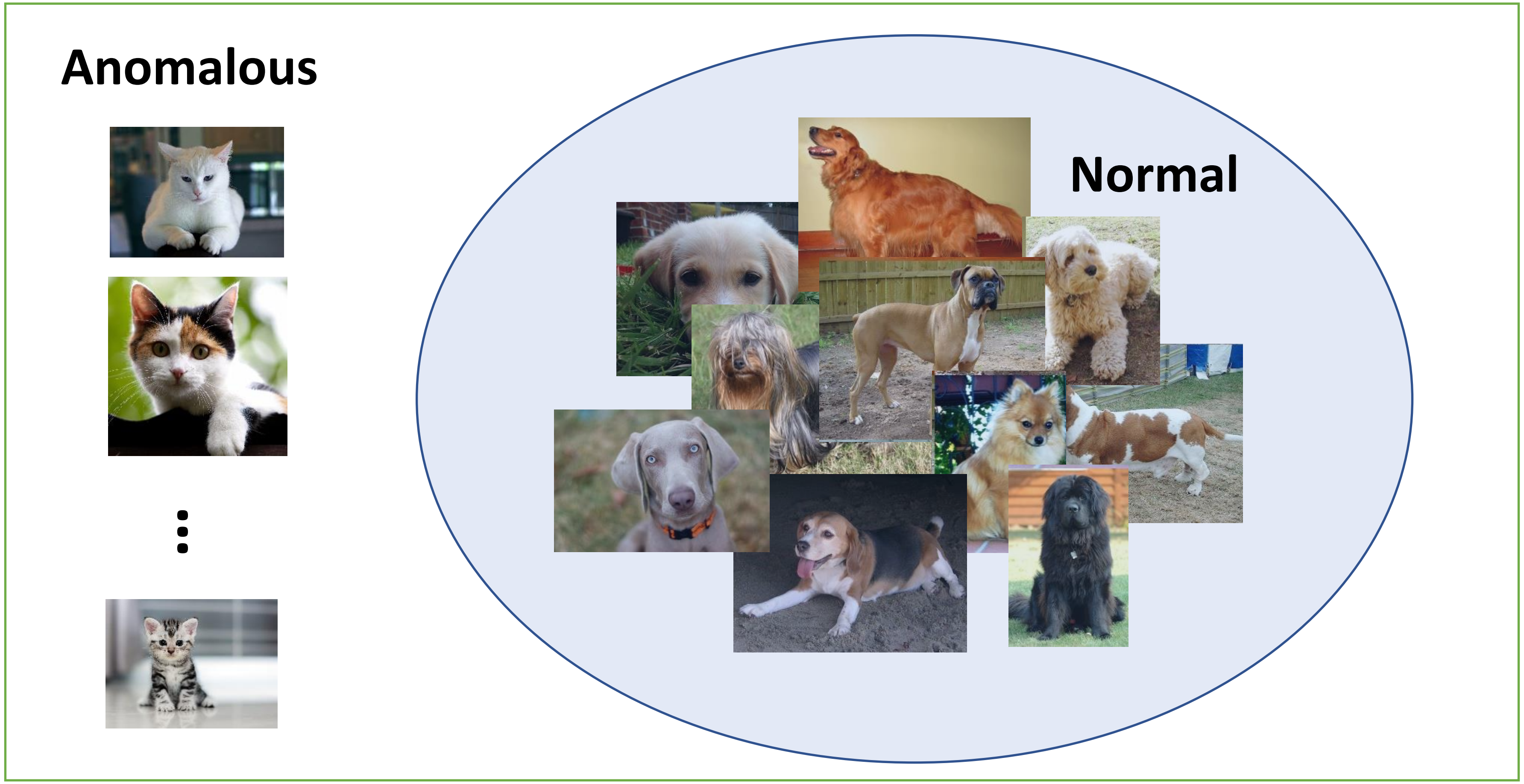
(**Higher** is Better)



Structure Manipulation for **Downstream Tasks**

A Hierarchical Transformation-Discriminating Generative Model for **Few Shot Anomaly Detection**

S. Sheynin*, **S. Benaim***, L. Wolf. In Submission to ICCV 2021. (*Equal contribution)



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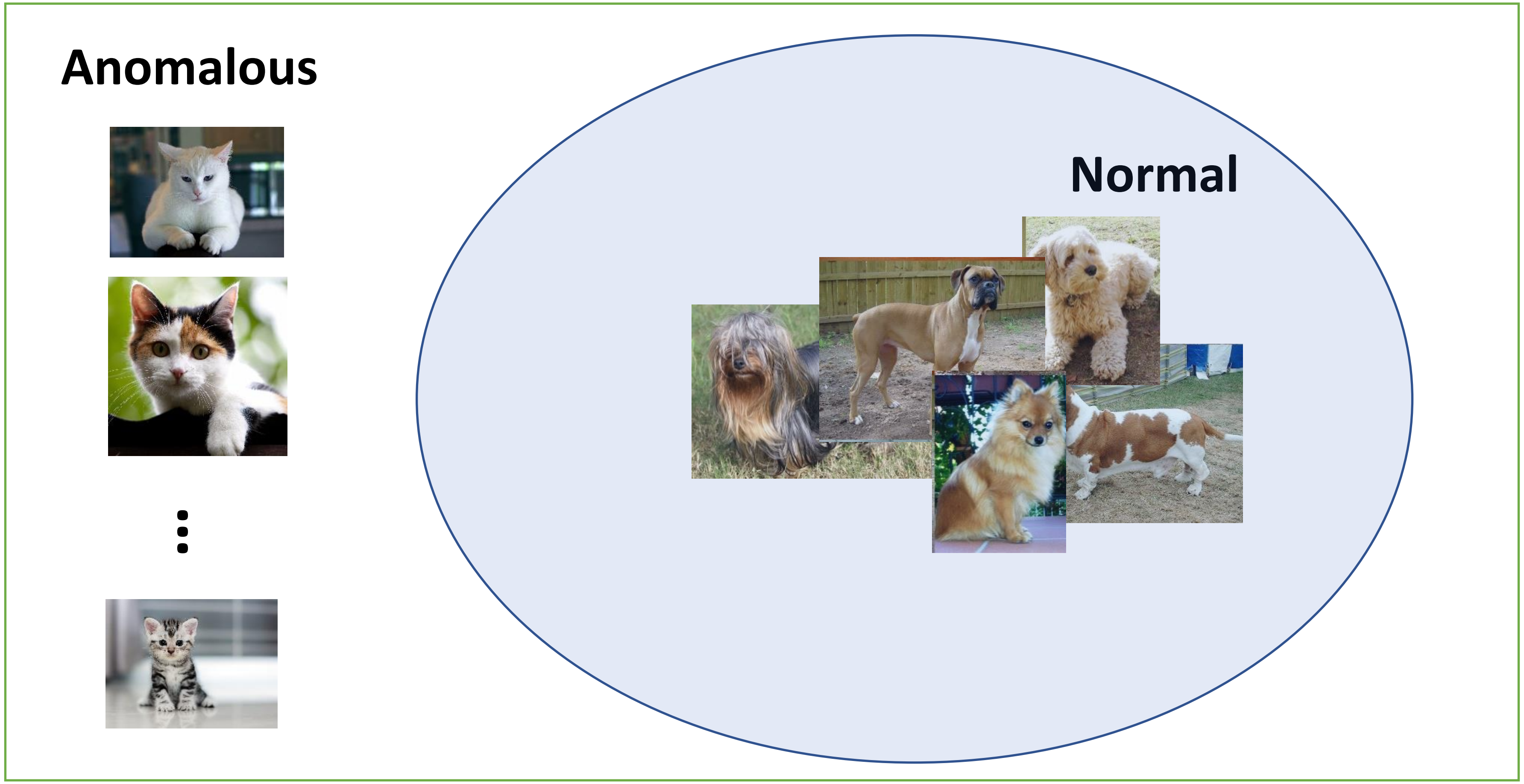

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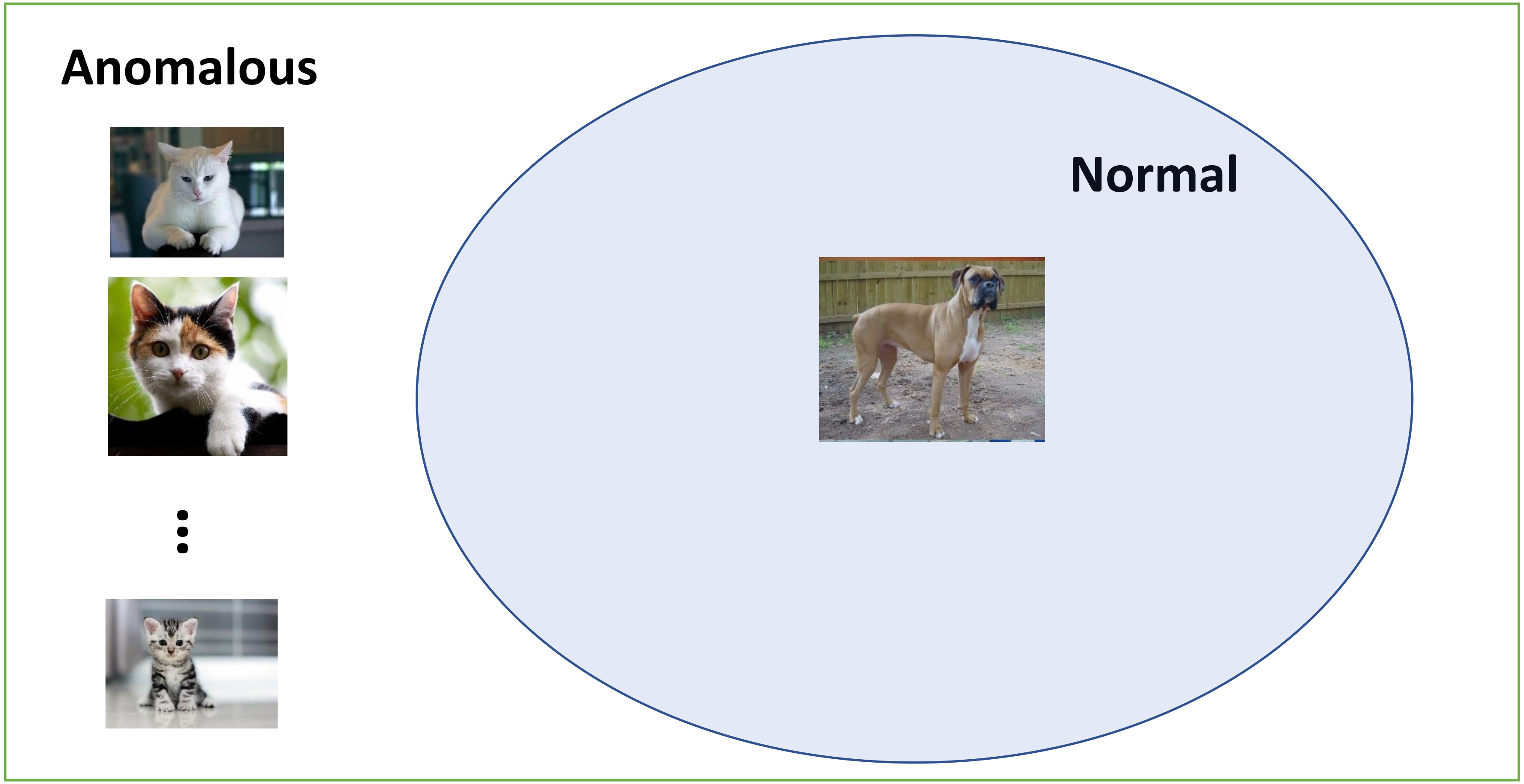
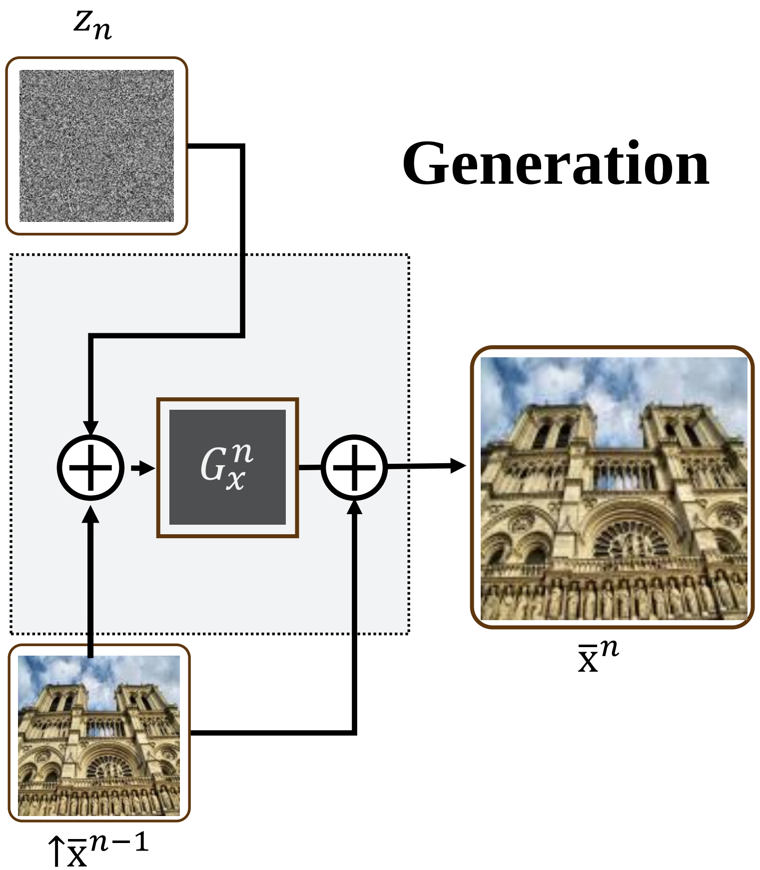
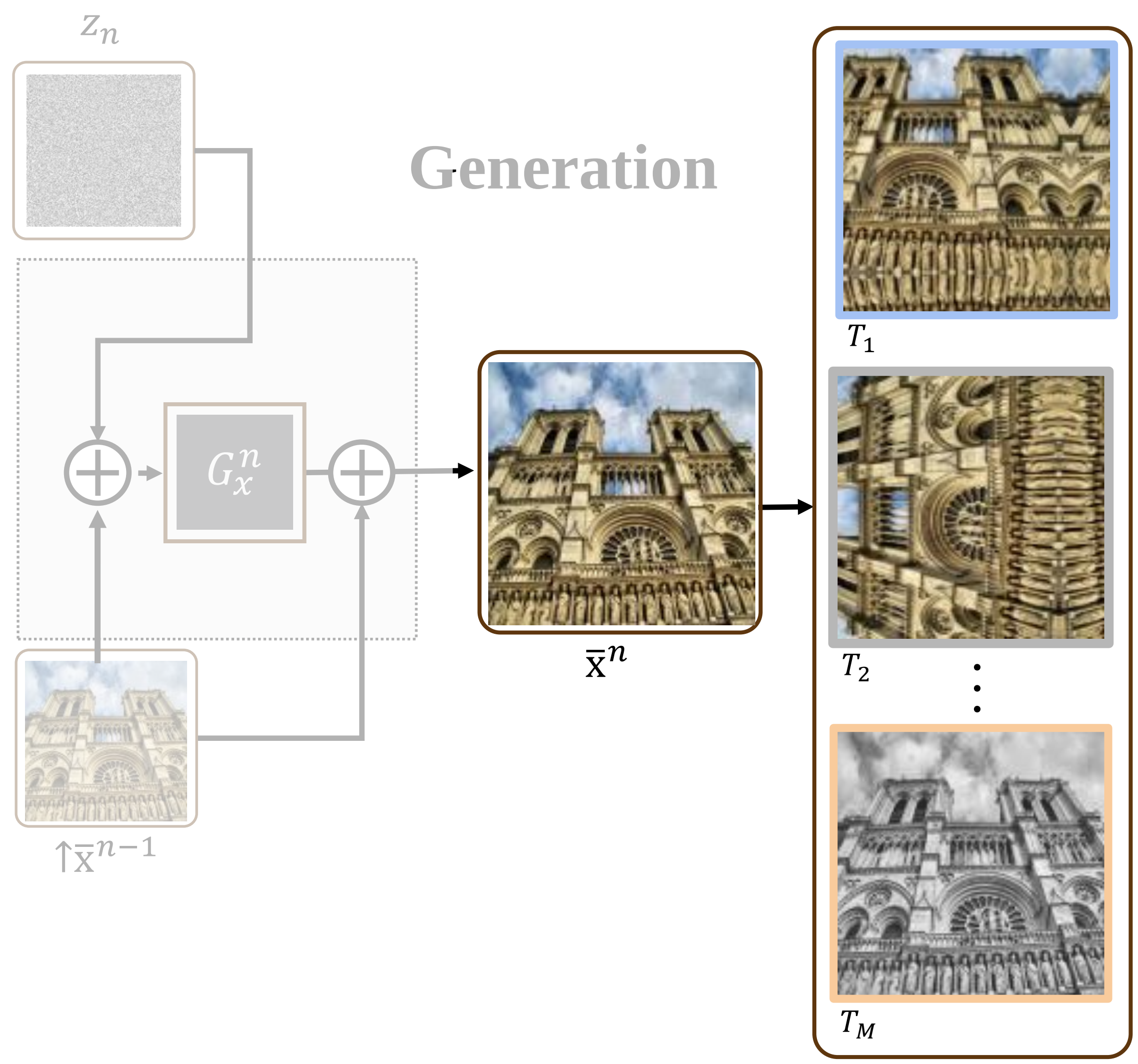


Unconditional **Generation** (Level n)



Transform Generated Sample



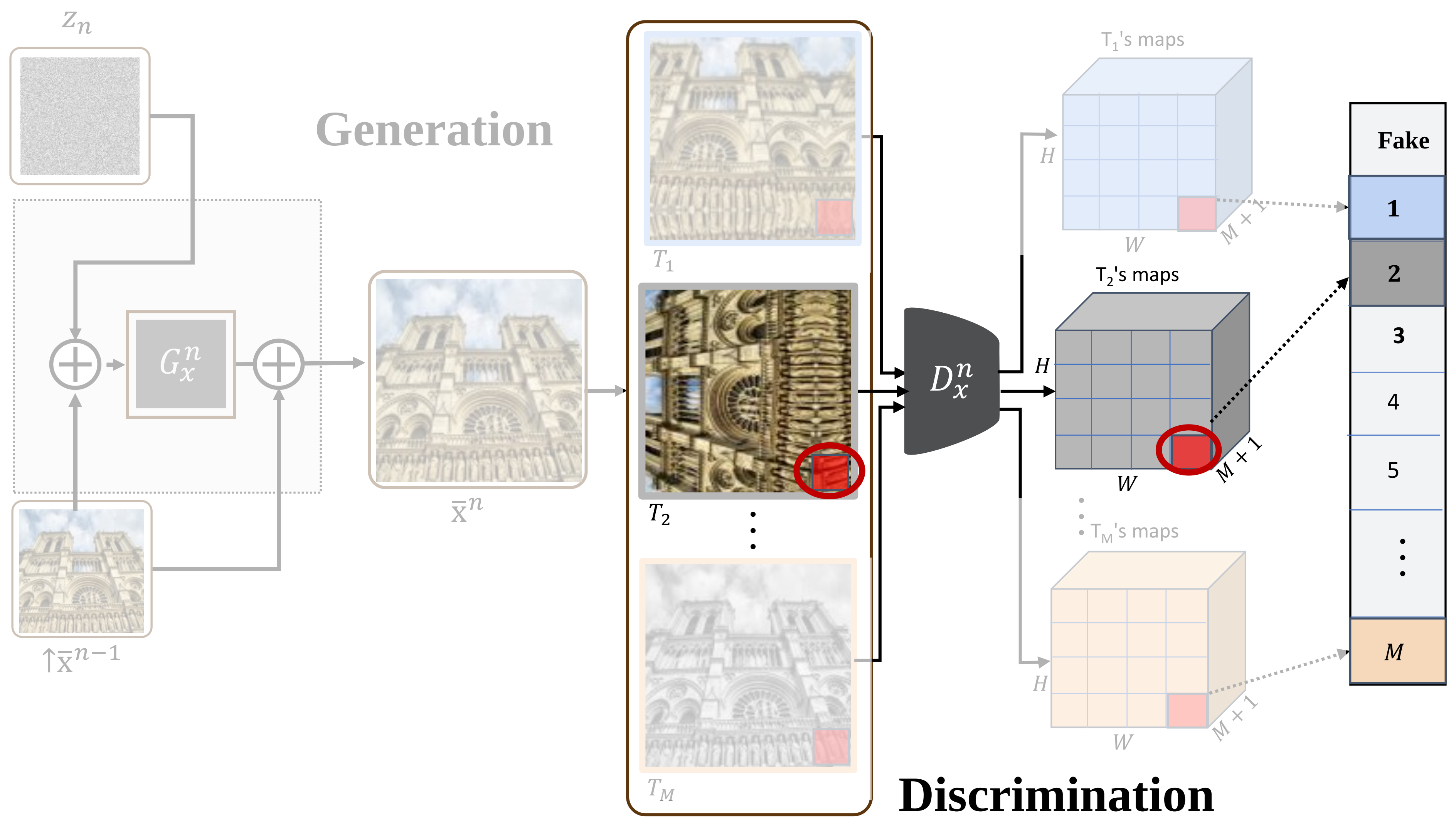
T_1: Horizontal Flip, Translation (y-axis)

T_2: 90° Rotation, Translation (x-axis), Translation (y-axis)

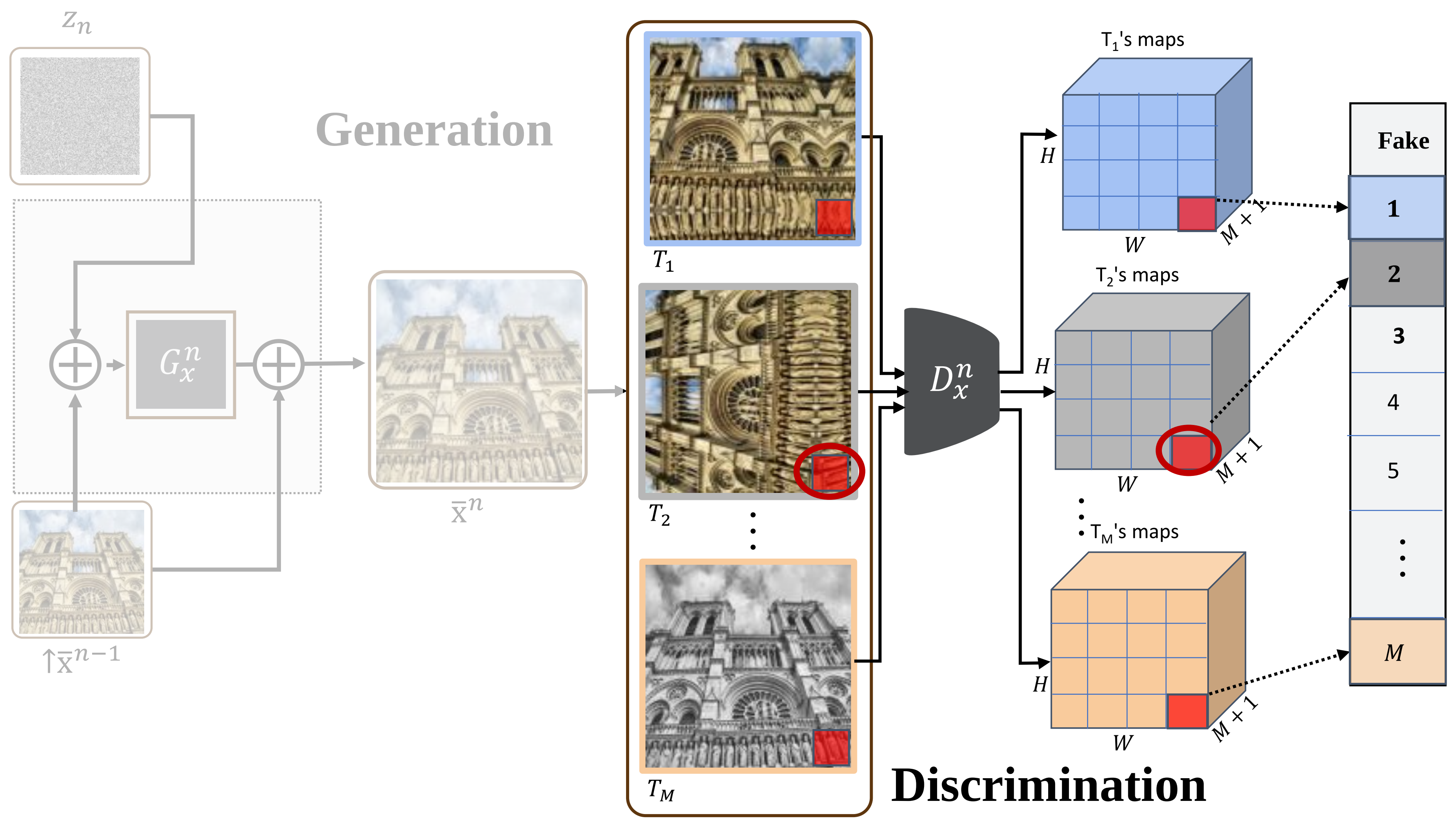
…

T_M: Grayscale (y-axis)

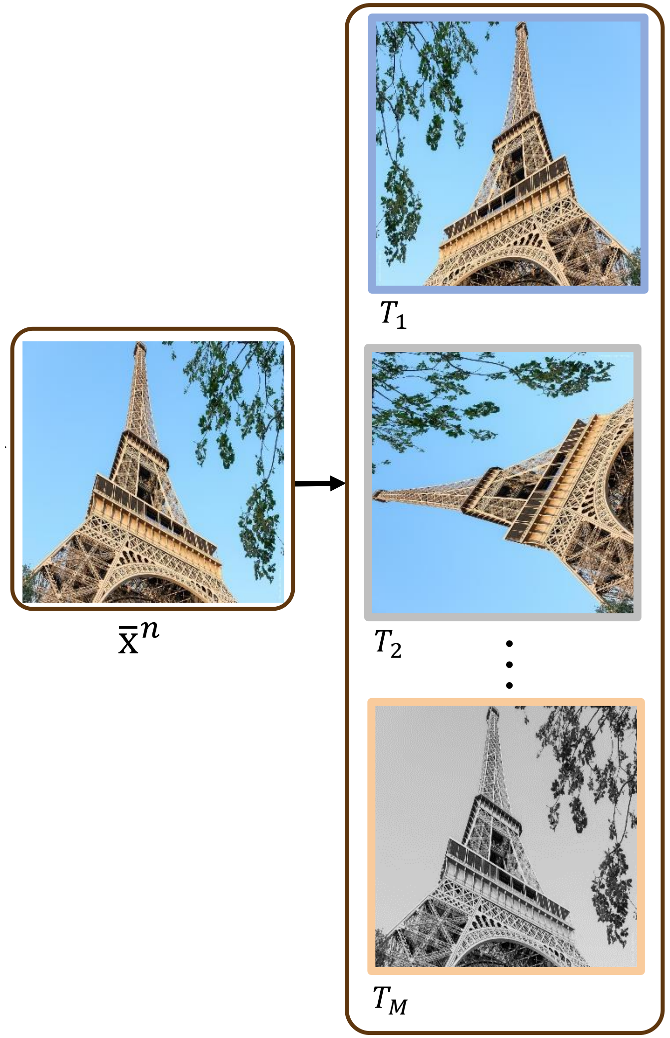
Patch-Based **Self Supervised Task**



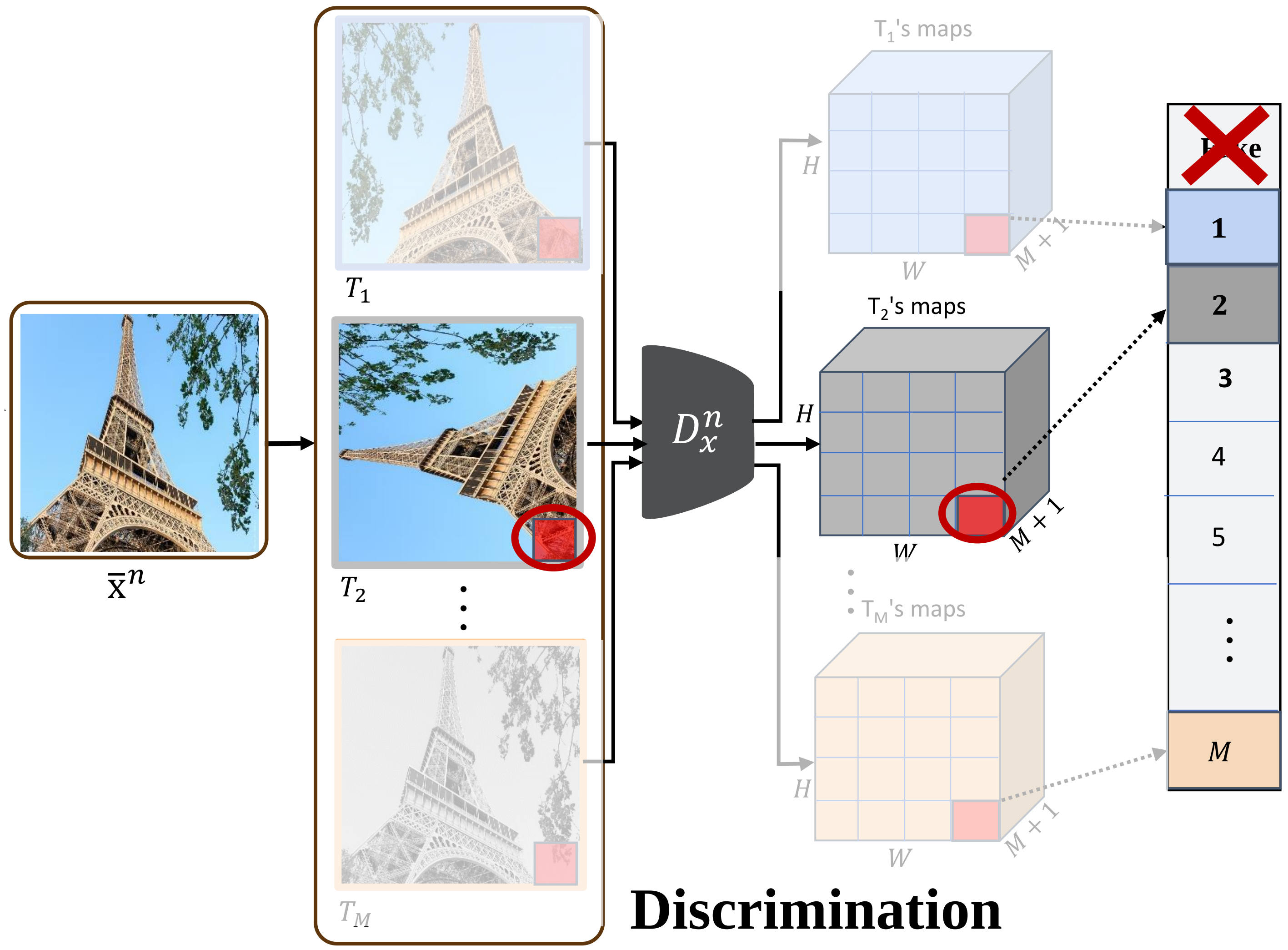
Patch-Based **Self Supervised Task**



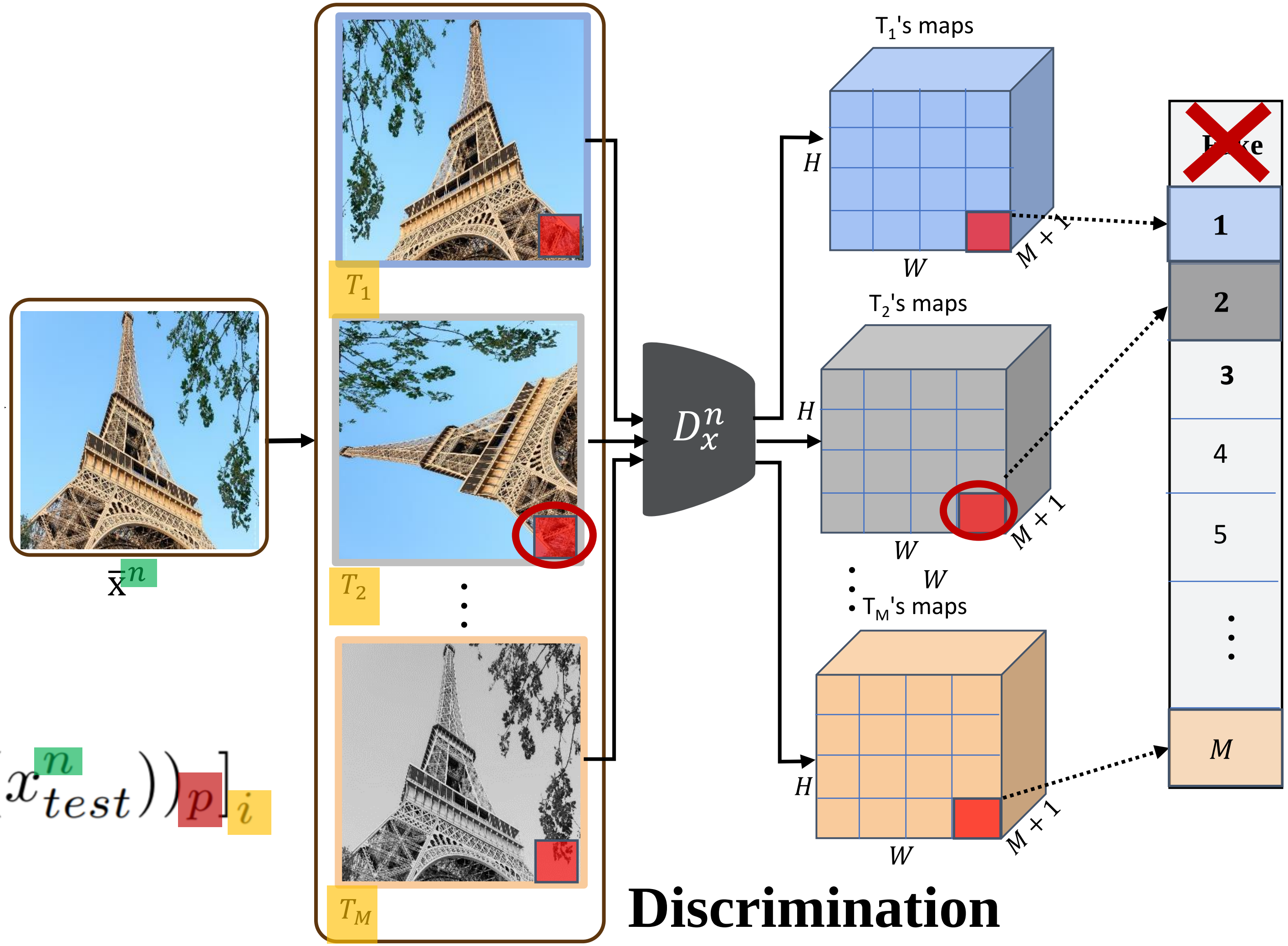
Test Time: Anomaly Score (Scale n)



Test Time: Anomaly Score (Scale n)

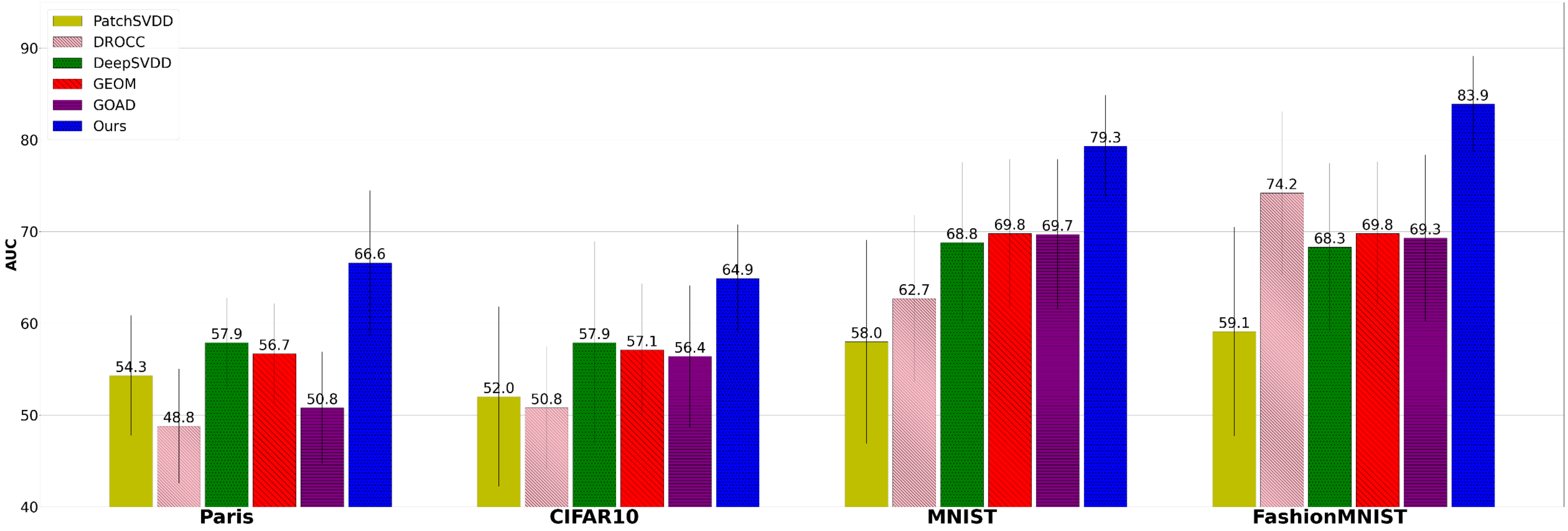


Test Time: Anomaly Score (Scale n)



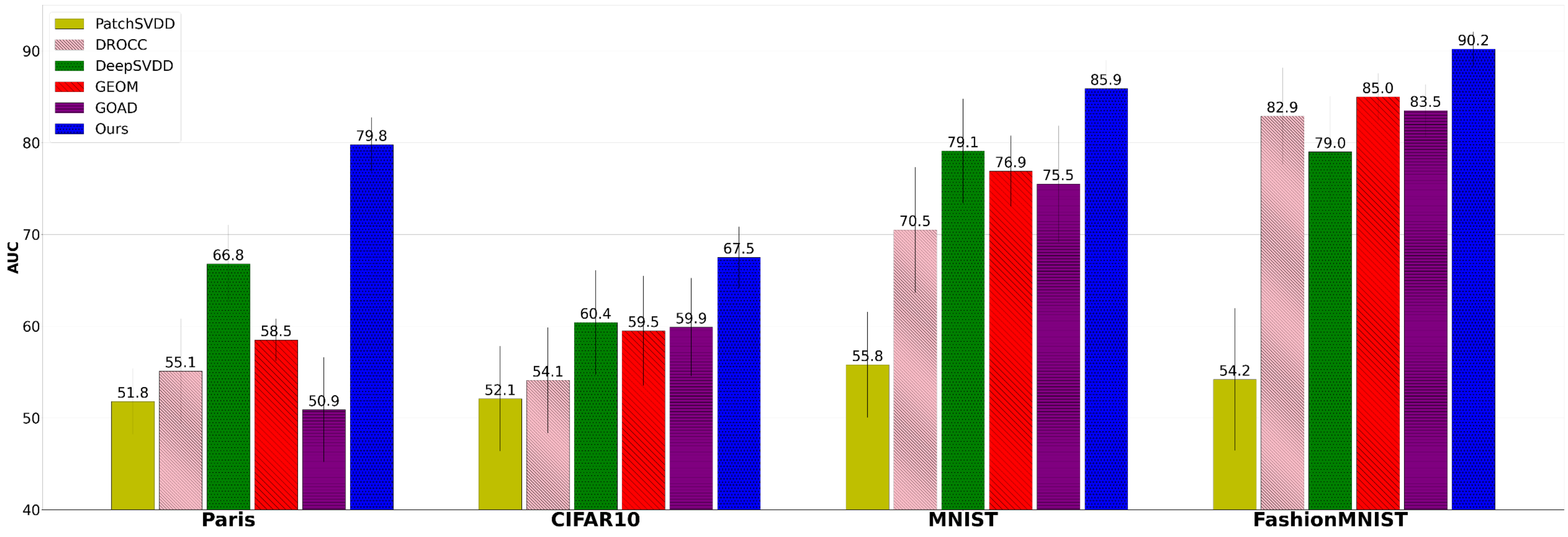
$$\sum_{n=0}^{N}\sum_{i=1}^{M}\sum_{p\in H\,x\,W}[D_x^{n*}(T_i(x_{test}^{n}))_p]_i$$

One-Shot



PatchSVDD
DROCC
DeepSVDD
GEOM
GOAD
Ours
AUC
90
80
70
60
50
40
54.3
48.8
57.9
56.7
50.8
66.6
52.0
50.8
57.9
57.1
56.4
64.9
58.0
62.7
68.8
69.8
69.7
79.3
59.1
74.2
68.3
69.8
69.3
83.9
Paris
CIFAR10
MNIST
FashionMNIST

Five-Shot


PatchSVDD
DROCC
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90
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51.8
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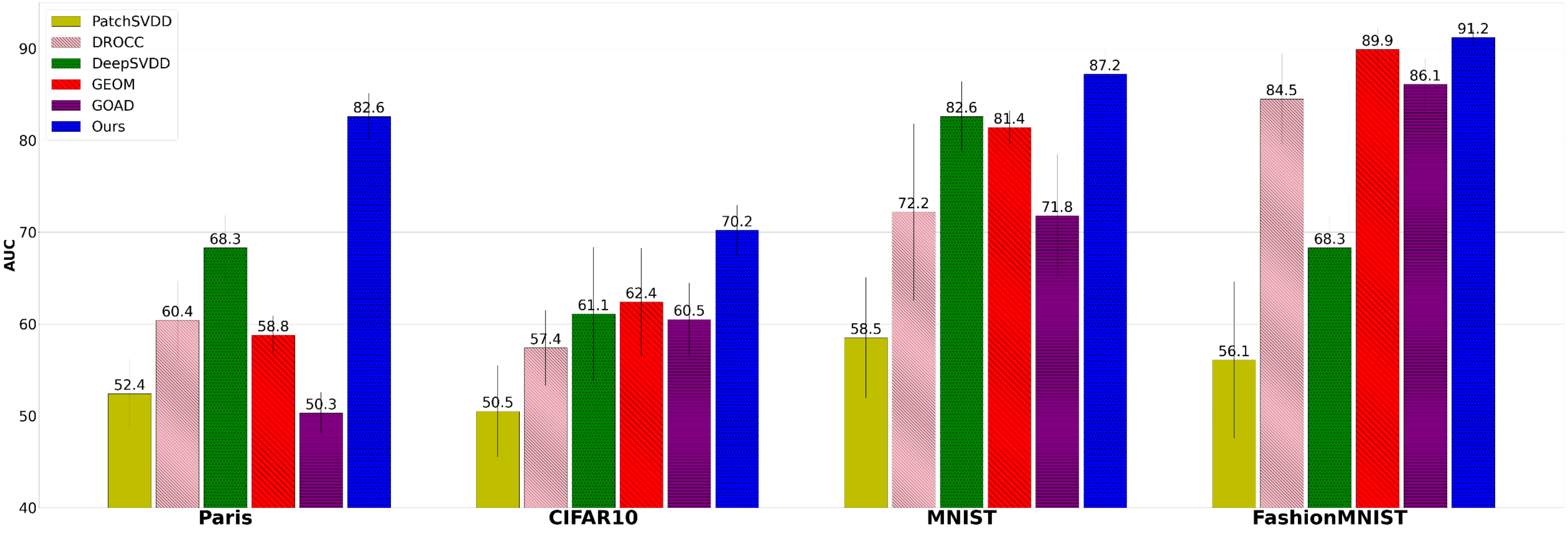
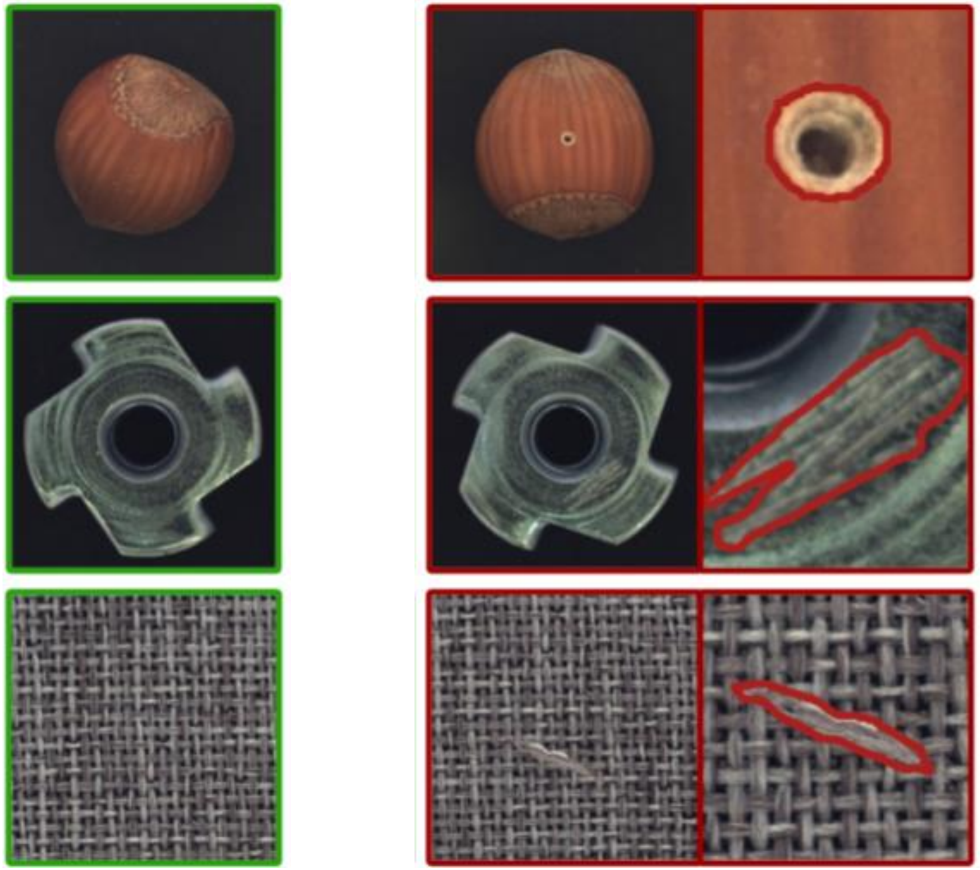
50.9
79.8
52.1
54.1
60.4
59.5
59.9
67.5
55.8
70.5
79.1
76.9
75.5
85.9
54.2
82.9
79.0
85.0
83.5
90.2
Paris
CIFAR10
MNIST
FashionMNIST

Ten-Shot

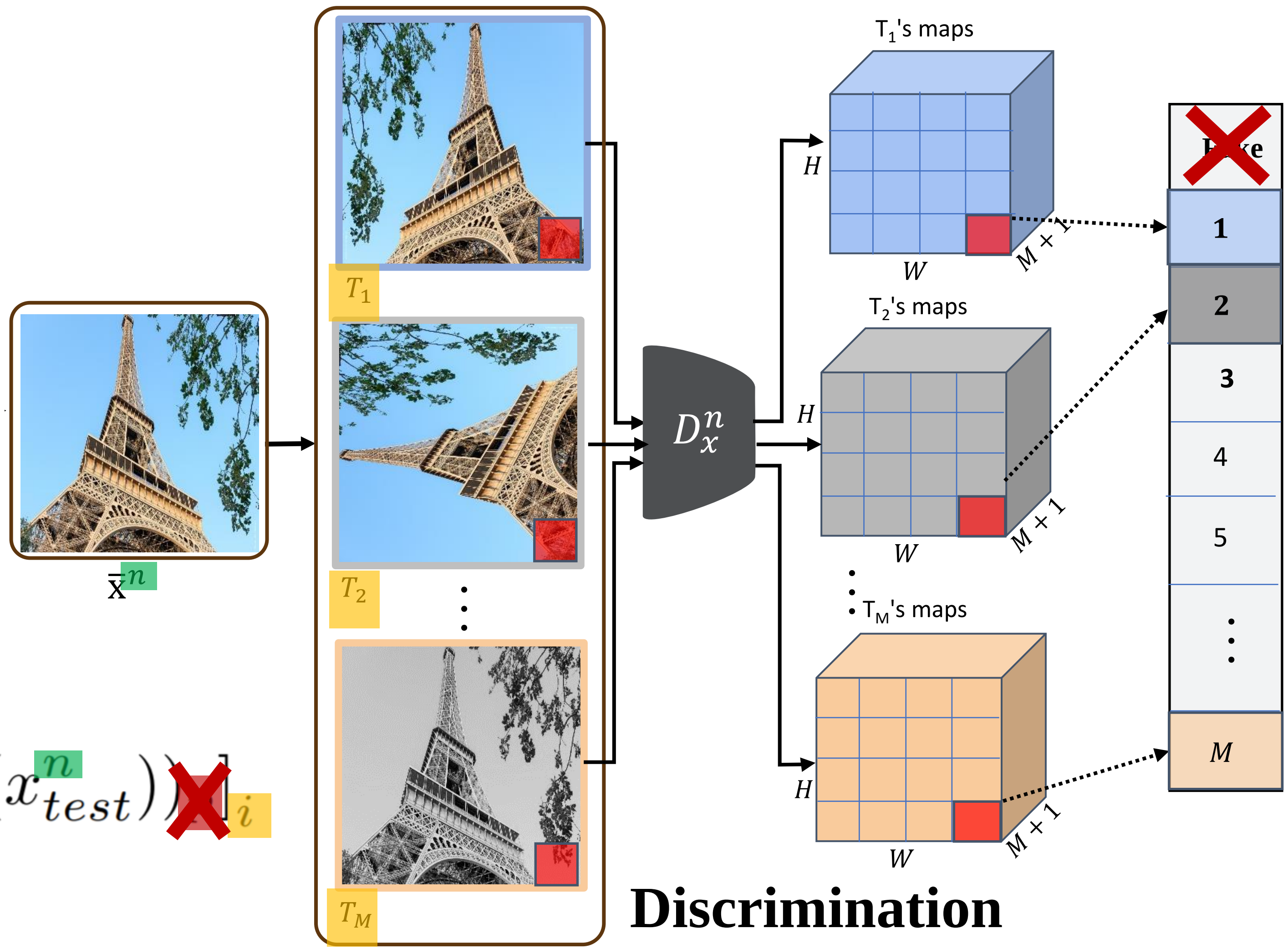


PatchSVDD
DROCC
DeepSVDD
GEOM
GOAD
Ours
AUC
40
50
60
70
80
90
52.4
60.4
68.3
58.8
50.3
82.6
50.5
57.4
61.1
62.4
60.5
70.2
58.5
72.2
82.6
81.4
71.8
87.2
56.1
84.5
68.3
89.9
86.1
91.2
Paris
CIFAR10
MNIST
FashionMNIST

One Shot Defect Localization

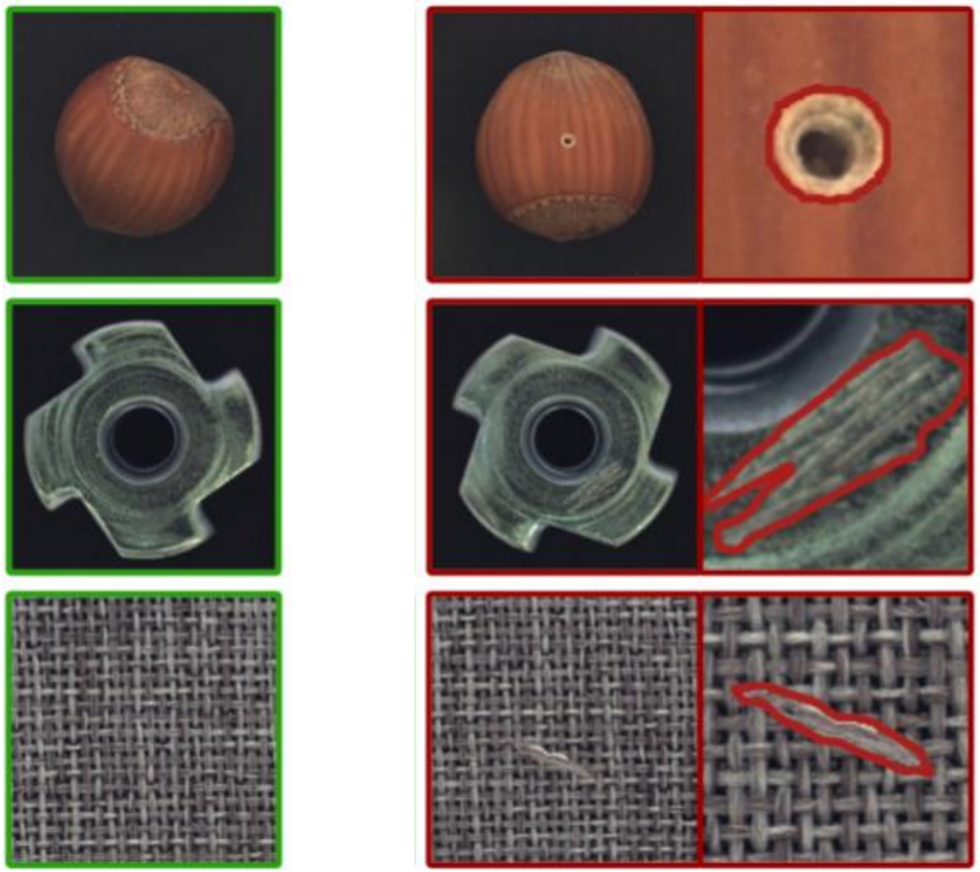


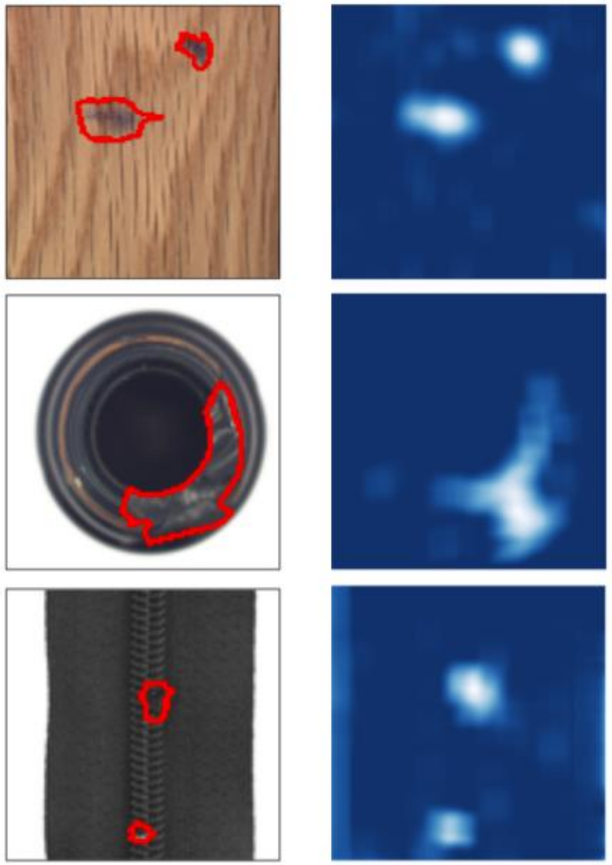
One Shot Defect Localization

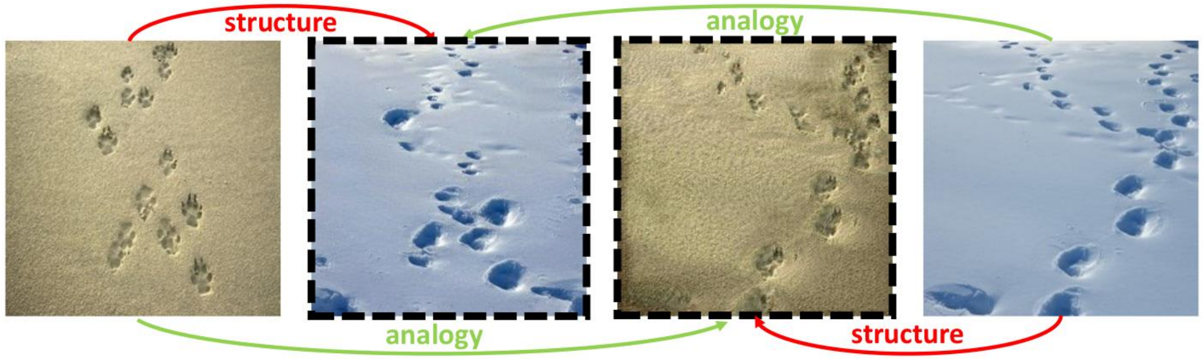


$$\sum_{n=0}^{N}\sum_{i=1}^{M}\cancel{\sum_{p\in H\,x\,W}}[D_x^{n*}(T_i(x_{test}^{n}))\cancel{_p}]_i$$

One Shot Defect Localization

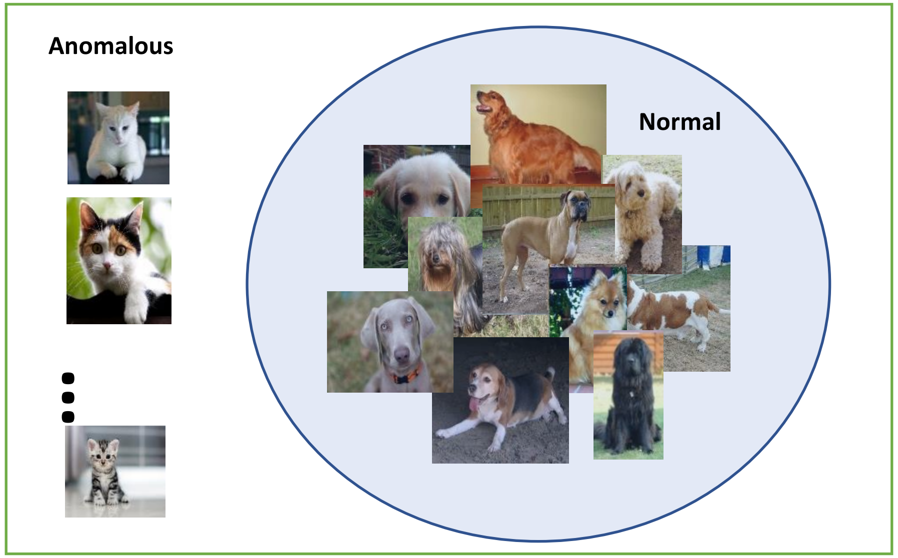


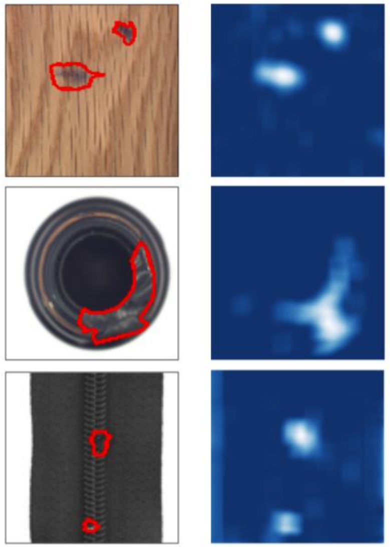




Part II: Manipulating Structure

by Understanding Structure





SpeedNet: **Learning the Speediness in Videos**

S. Benaim, A. Ephrat, O. Lang, I. Mosseri, W. T. Freeman, M. Rubinstein, M. Irani, T. Dekel.
CVPR 2020.

Slower

Normal speed

Faster

https://speednet-cvpr20.github.io/

Automatically predict “speediness”

Uniform Speed Up (2x)

Adaptive speed up (2x)

Other Applications:

- Self-supervised action recognition
- Video retrieval

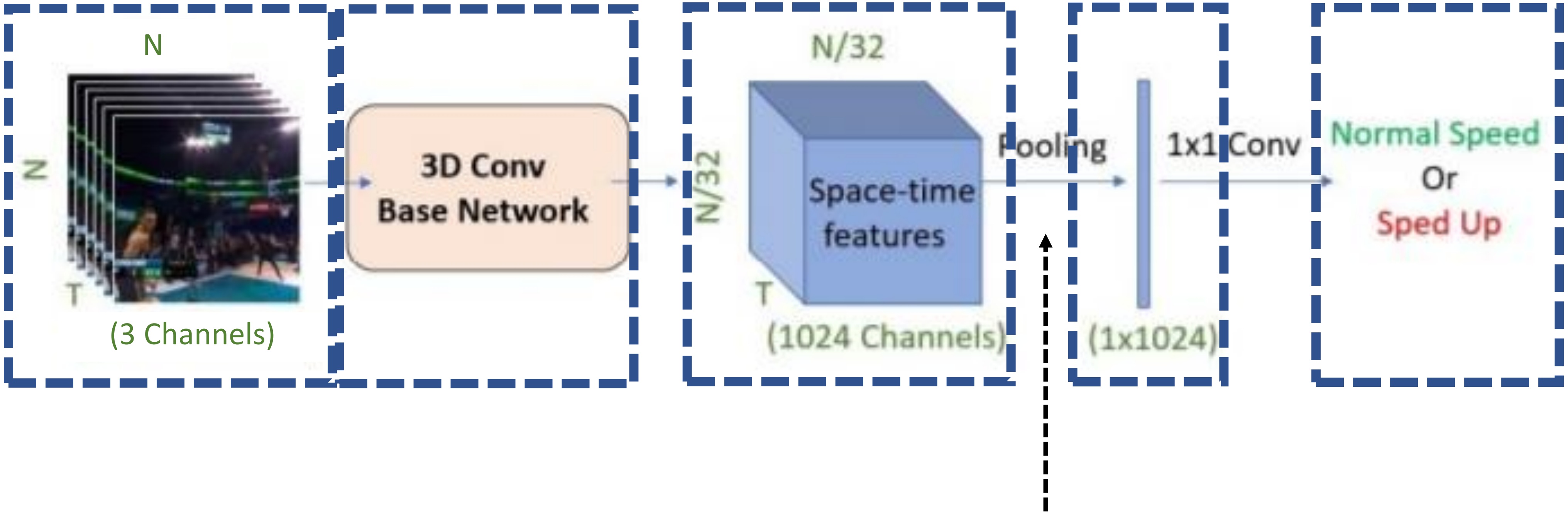
Training SpeedNet

Self-supervised training

Input video

Sped Up

Training SpeedNet



Spatial Max Pooling
Temporal Average Pooling

`

Training SpeedNet: Artificial Cues

- Spatial augmentations.
- Temporal augmentations
- Same-batch training.

Spatial Augmentations

- Random resize of input (both downsample and upsample)
- Network cannot rely on size dependent factors

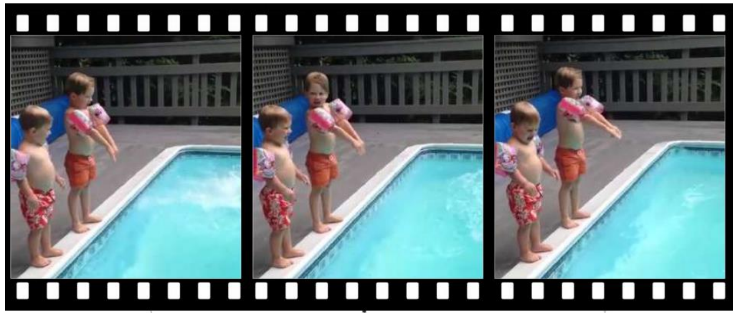
Temporal Augmentations

- Normal speed sample rate: 1-1.2x
- Sped up sample rate: 1.7-2.2x
- Randomly skip frames with probability 1 – 1/f where f is randomly chosen randomly in the desired range.

Same Batch Training

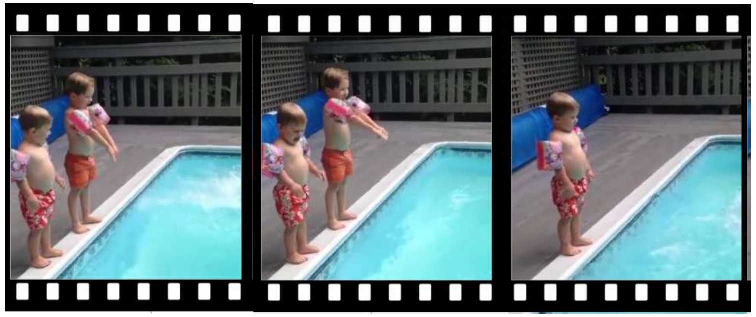
Same Batch

Normal speed



...

Speed up



...

Training SpeedNet: Artificial Cues

- NFS: Need For Speed dataset taken at 240 FPS

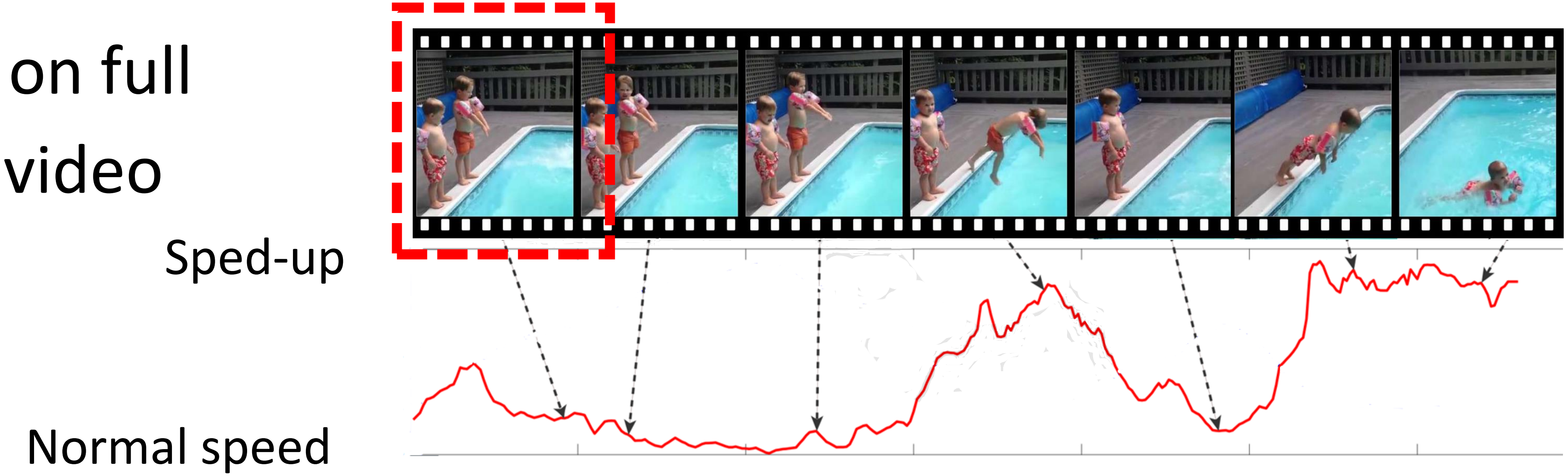
	Model Type		Accuracy	
Batch	**Temporal**	**Spatial**	**Kinetics**	**NFS**
Yes	Yes	Yes	75.6%	73.6%
No	Yes	Yes	88.2%	59.3%
No	No	Yes	90.0%	57.7%
No	No	No	96.9%	57.4%

No “Shortcuts” – A gap of 2%

“Shortcuts” – A gap of > 28%

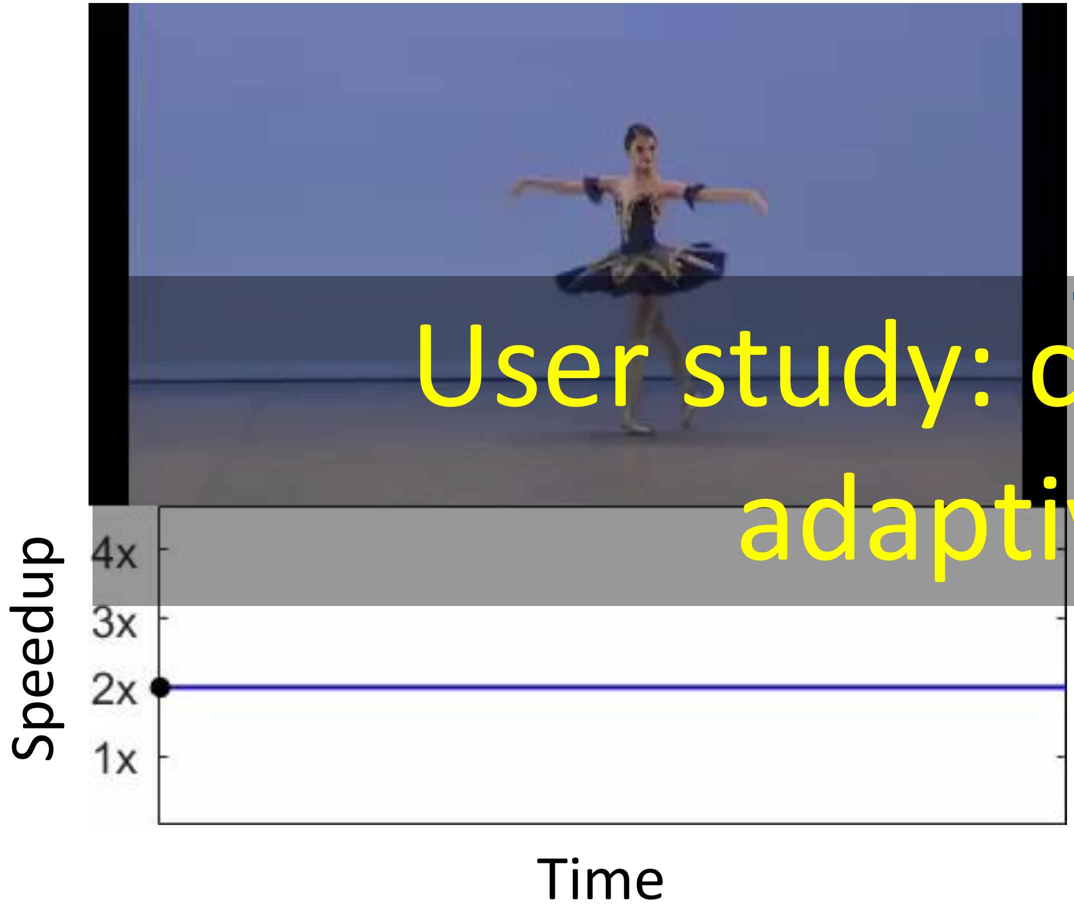
Adaptive video speedup

Inference on full **sped-up** video



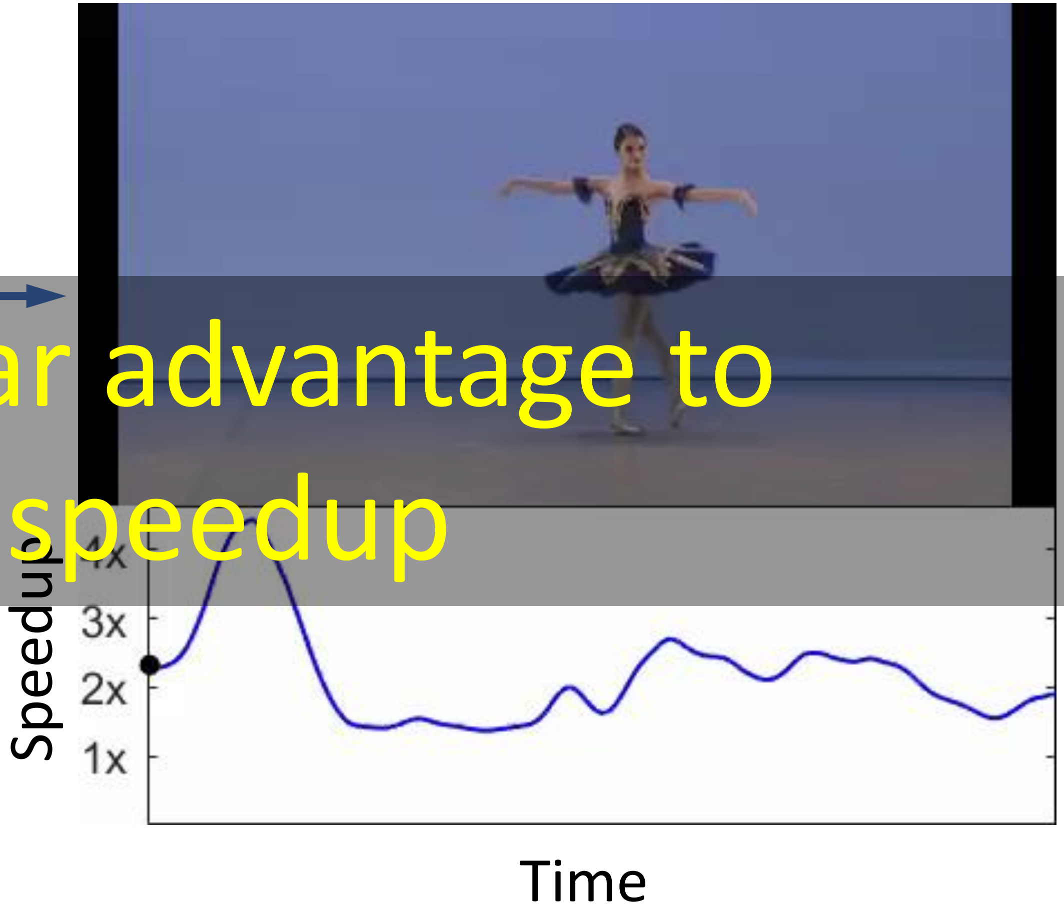
Adaptive video speedup

Total time = $\frac{1}{2}$ input time



Uniform Speedup

Total time = $\frac{1}{2}$ input time

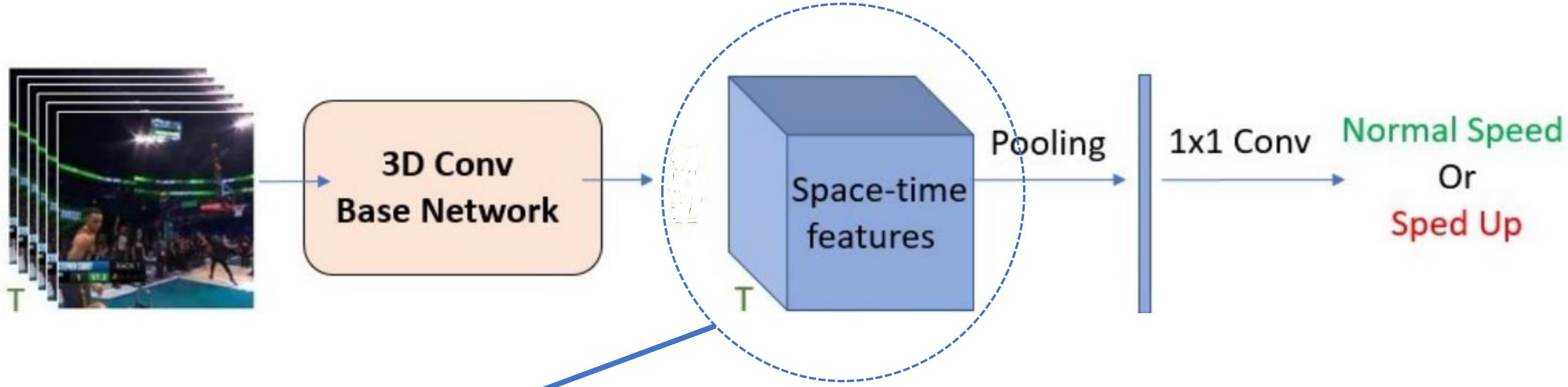


Adaptive Speedup (ours)

User study: clear advantage to adaptive speedup

Other self supervised tasks

Train SpeedNet

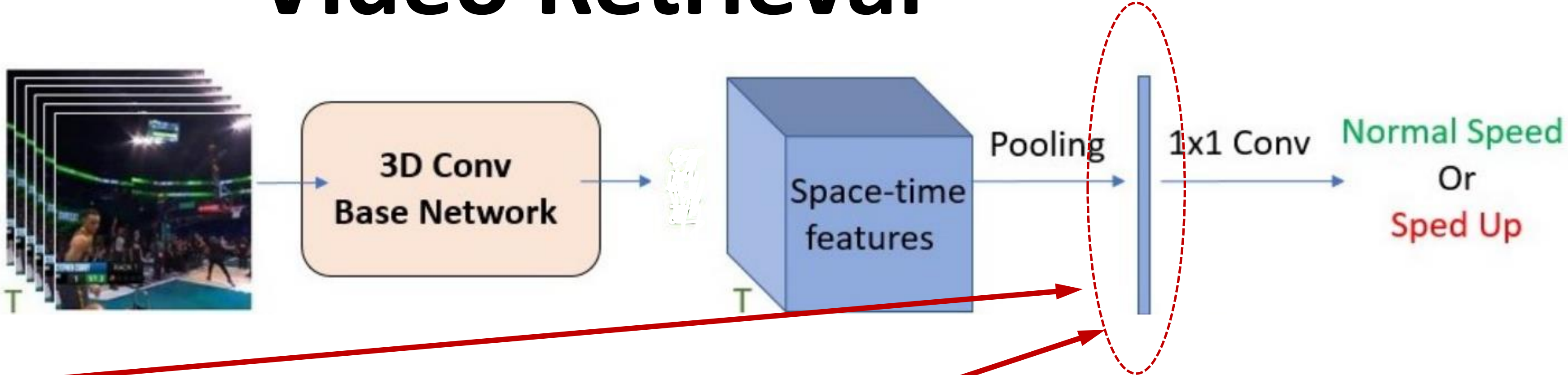


Self Supervised Action Recognition

Method	Initialization Architecture	Supervised accuracy UCF101	HMDB51
Random init	S3D-G	73.8	46.4
ImageNet inflated	S3D-G	86.6	57.7
Kinetics supervised	S3D-G	96.8	74.5
CubicPuzzle [19]	3D-ResNet18	65.8	33.7
Order [40]	R(2+1)D	72.4	30.9
DPC [13]	3D-ResNet34	75.7	35.7
AoT [38]	T-CAM	79.4	-
SpeedNet (Ours)	S3D-G	**81.1**	**48.8**
Random init	I3D	47.9	29.6
SpeedNet (Ours)	I3D	66.7	43.7

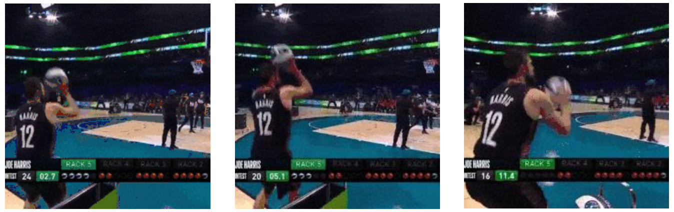
Other self supervised tasks: Video Retrieval

Train SpeedNet

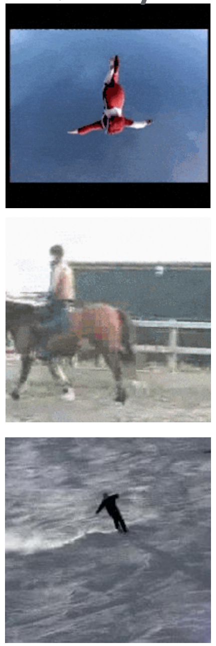


Query

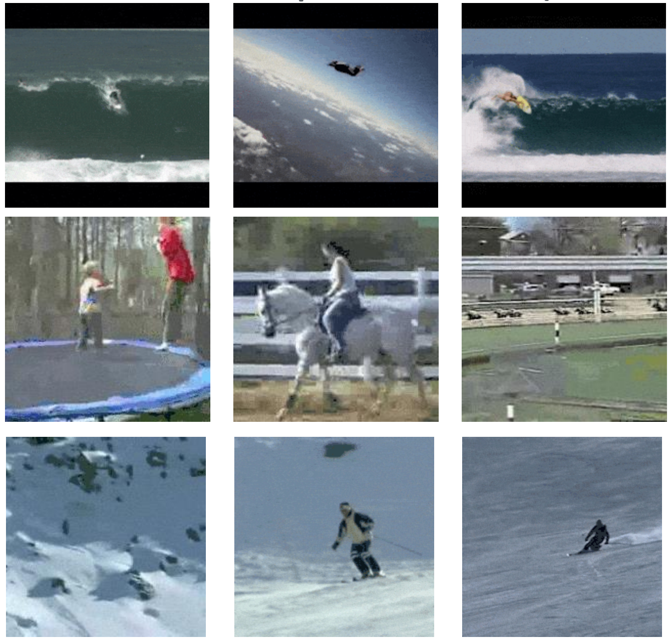
Retrieved top-3 results (Within)



Query



Retrieved top-3 results (Across)



“Memory Eleven”: An artistic video by Bill Newsinger:
https://www.youtube.com/watch?v=djylS0Wi_Io

Spatio-Temporal Visualizations

blue/green = normal speed

yellow/orange = slowed down

Permuted AdaIN: Reducing the Bias Towards Global Statistics in Image Classification

O. Nuriel, **S. Benaim**, L. Wolf. CVPR 2021.

Swap the **global statistics** of an image while preserving its **structure**

Structure Preserving Transformation

Style

Content

Result

Huang et al., Arbitrary Style Transfer in Real-time with Adaptive Instance Normalization. ICCV2017

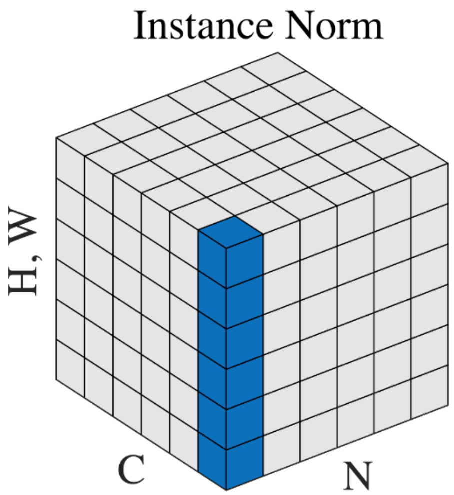
Structure Preserving Transformation

- $a \in \mathbb{R}^{C \times H \times W}$ and $b \in \mathbb{R}^{C \times H \times W}$ be the activations of some encoder E applied on images I_a and I_b respectively.

$a = E($  $)$

$b = E($  $)$

Instance Normalization



$b = E($  $)$

$$IN(b)_{chw} = \left(\frac{a_{chw} - \mu_c(b)}{\sigma_c(b)}\right)$$

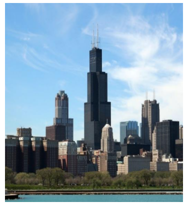
Adaptive Instance Normalization

$a = E($  $)$

$b = E($  $)$

$$AdaIN(a,b)_{chw} = \sigma_c(a)\left(\frac{a_{chw} - \mu_c(b)}{\sigma_c(b)}\right) + \mu_c(a)$$

Adaptive Instance Normalization



$$AdaIN(a,b)_{chw} = \overbrace{\sigma_c(a)}^{\text{Global Statistics}} \underbrace{\left(\frac{a_{chw} - \mu_c(b)}{\sigma_c(b)}\right)}_{\text{Structure}} + \overbrace{\mu_c(a)}^{\text{Global Statistics}}$$

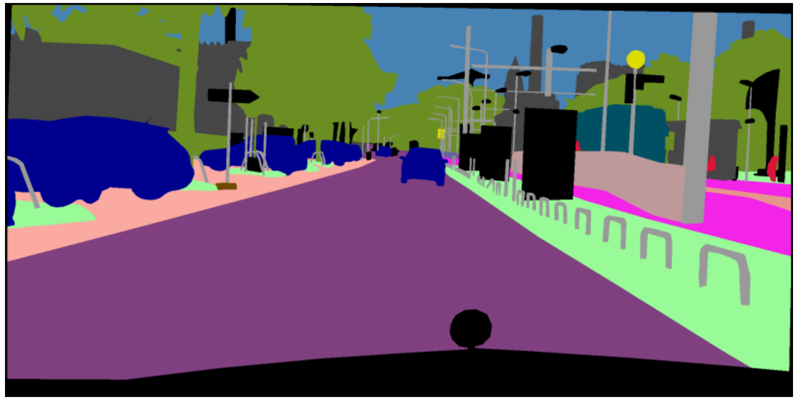
- AdaIN **swaps the global statistics** of a to those of b
- μ and σ represent the **global statistics** of an image (such as brightness, contrast, lighting, global color changes and global texture)
- **Structure** represents information relating to shape of objects

Domain Adaptation

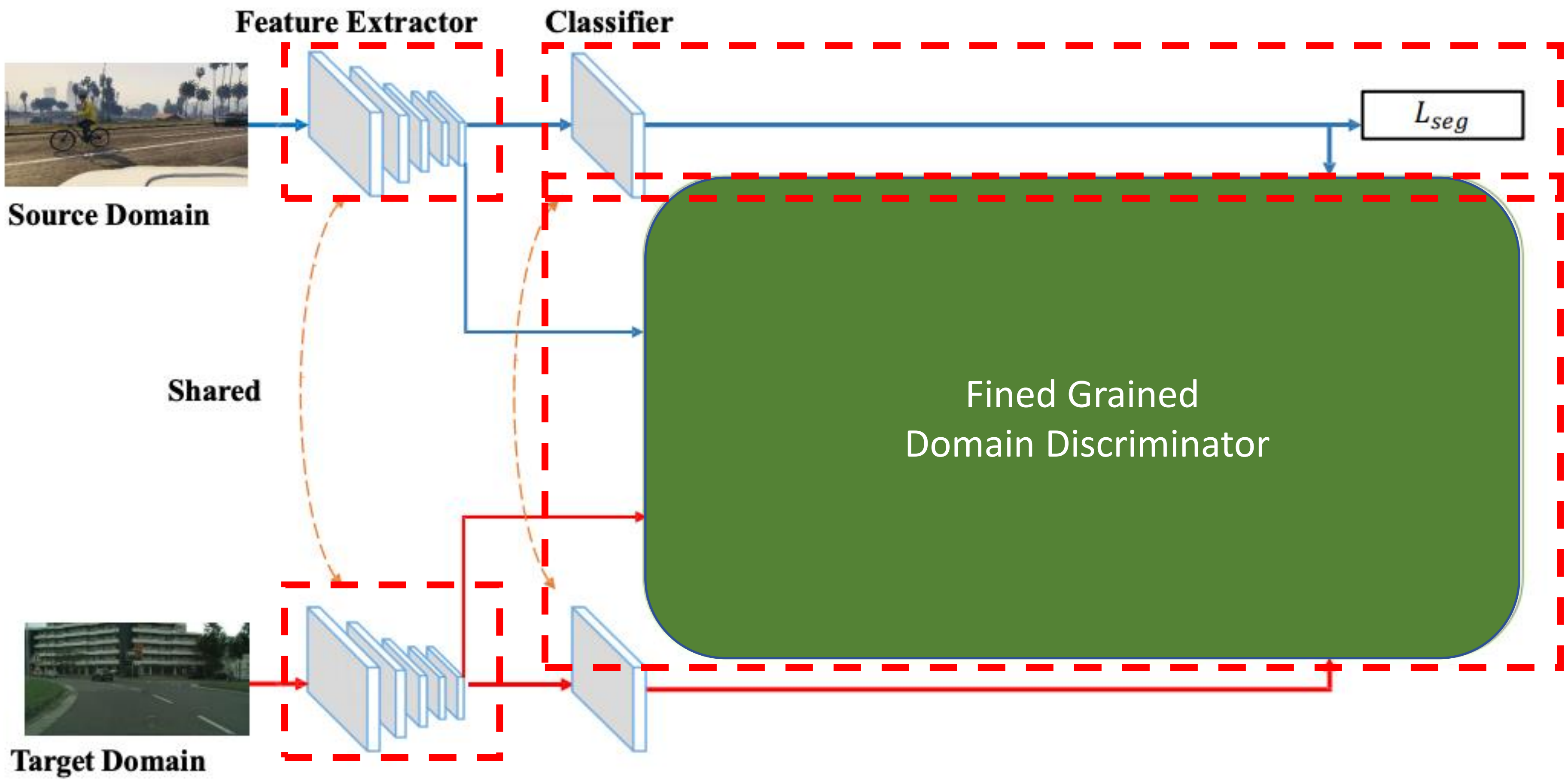
Supervised training on source domain and unsupervised on target domain

Source: GTAV

Target: Cityscapes



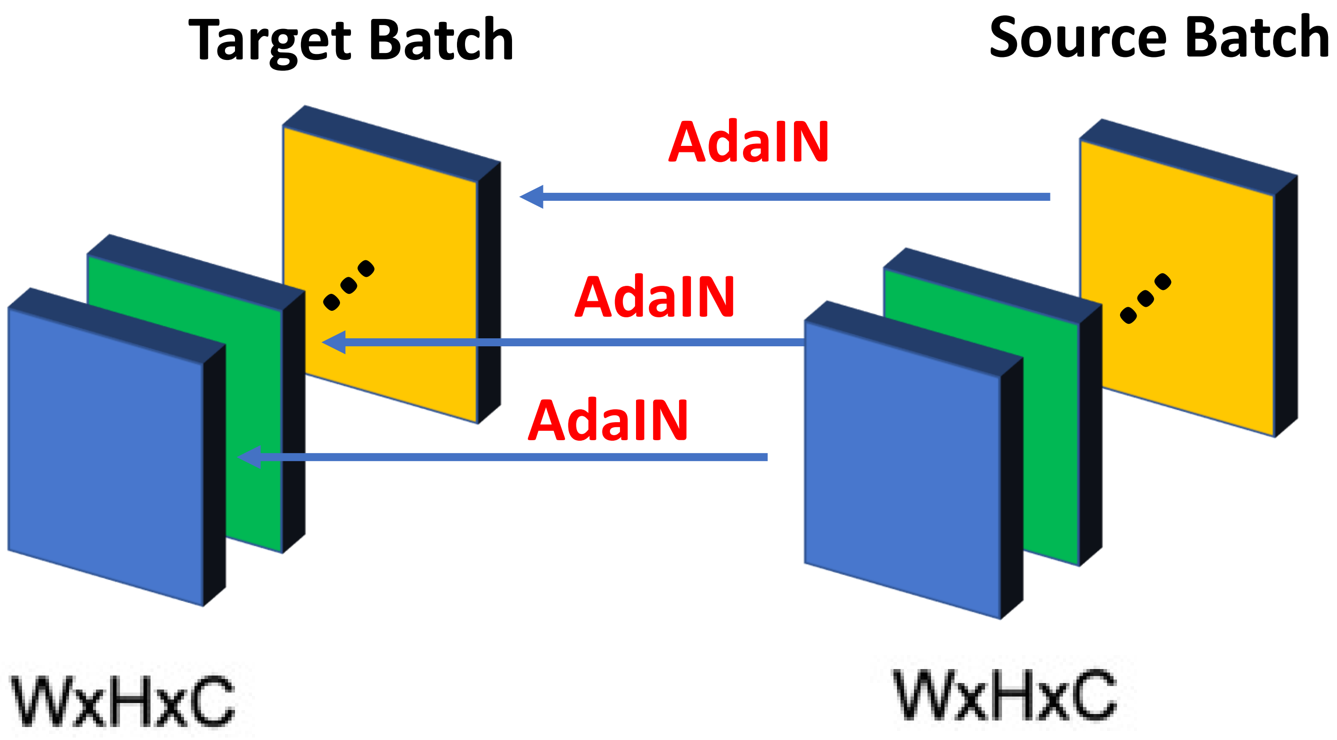
Domain Adaptation



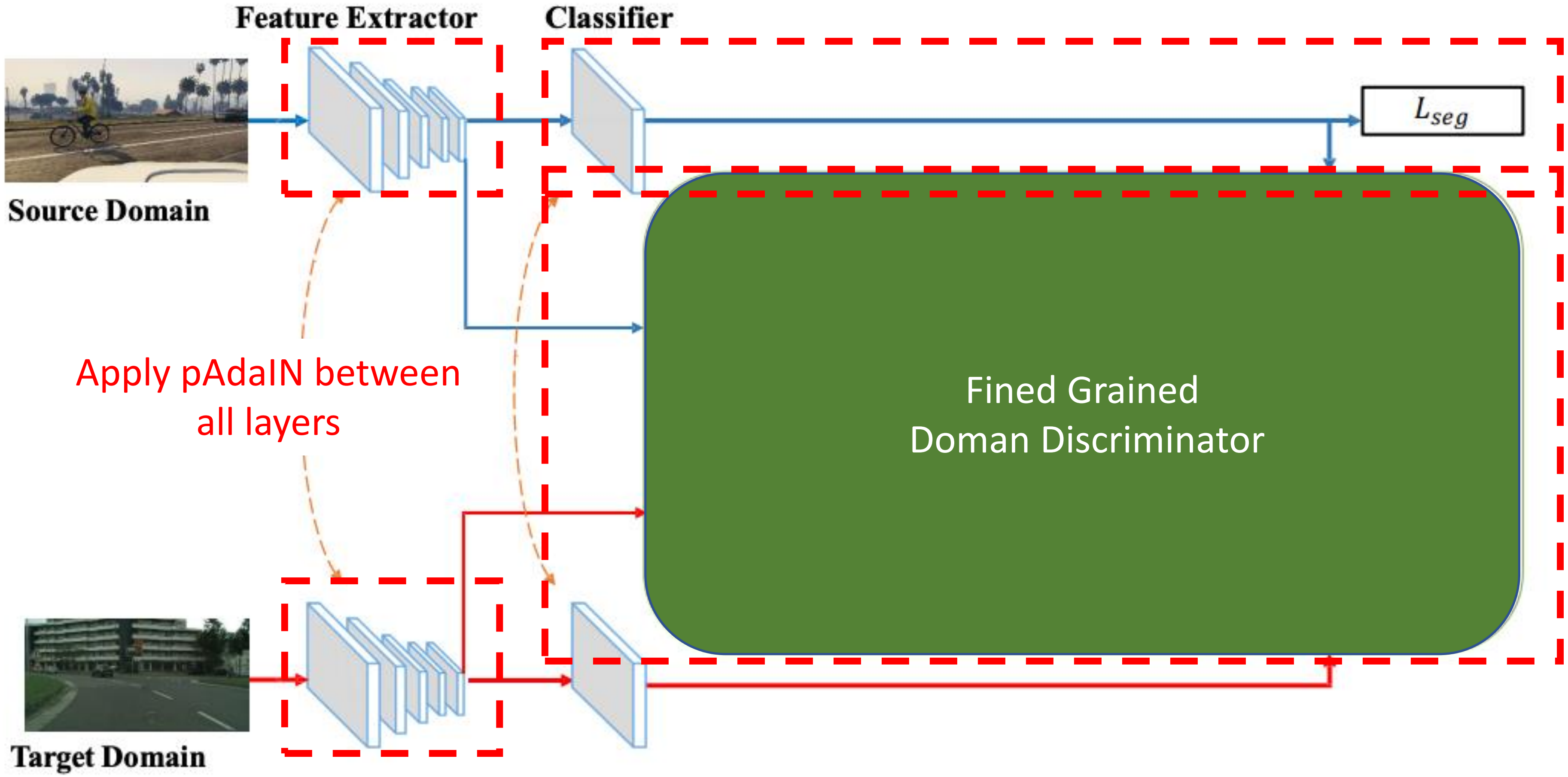
Classes Matter: A Fine-grained Adversarial Approach to Cross-domain Semantic Segmentation. Wang et al., ECCV 2020.

Domain Adaptation

- **Swap global statistics of target features with those of source features** by applying AdaIN with probability p.
- Apply at every layer of the feature extractor.



Domain Adaptation



Classes Matter: A Fine-grained Adversarial Approach to Cross-domain Semantic Segmentation. Wang et al., ECCV 2020.

Domain Adaptation

GTAV to Cityscapes

AdaptSegNet [35]	86.5	36.0	79.9	23.4	23.3	23.9	35.2	14.8	83.4	33.3	75.6	58.5	27.6	73.7	32.5	35.4	3.9	30.1	28.1	42.4
SIBAN [28]	88.5	35.4	79.5	26.3	24.3	28.5	32.5	18.3	81.2	40.0	76.5	58.1	25.8	82.6	30.3	34.4	3.4	21.6	21.5	42.6
CLAN [29]	87.0	27.1	79.6	27.3	23.3	28.3	**35.5**	24.2	83.6	27.4	74.2	58.6	28.0	76.2	33.1	36.7	6.7	31.9	31.4	43.2
AdaptPatch [36]	92.3	51.9	82.1	29.2	25.1	24.5	33.8	**33.0**	82.4	32.8	82.2	58.6	27.2	84.3	33.4	46.3	2.2	29.5	32.3	46.5
ADVENT [38]	89.4	33.1	81.0	26.6	26.8	27.2	33.5	24.7	83.9	36.7	78.8	58.7	30.5	84.8	38.5	44.5	1.7	31.6	32.4	45.5
FADA [40]	92.5	47.5	85.1	37.6	**32.8**	**33.4**	33.8	18.4	85.3	37.7	83.5	63.2	**39.7**	87.5	32.9	47.8	1.6	34.9	**39.5**	49.2
FADA [40] + pAdaIN	**93.3**	**55.7**	**85.6**	**38.3**	29.6	31.2	34.2	17.8	**86.2**	**41.0**	**88.8**	**65.1**	37.1	**87.6**	**45.9**	**55.1**	15.1	**39.4**	31.1	**51.5**

Domain Adaptation

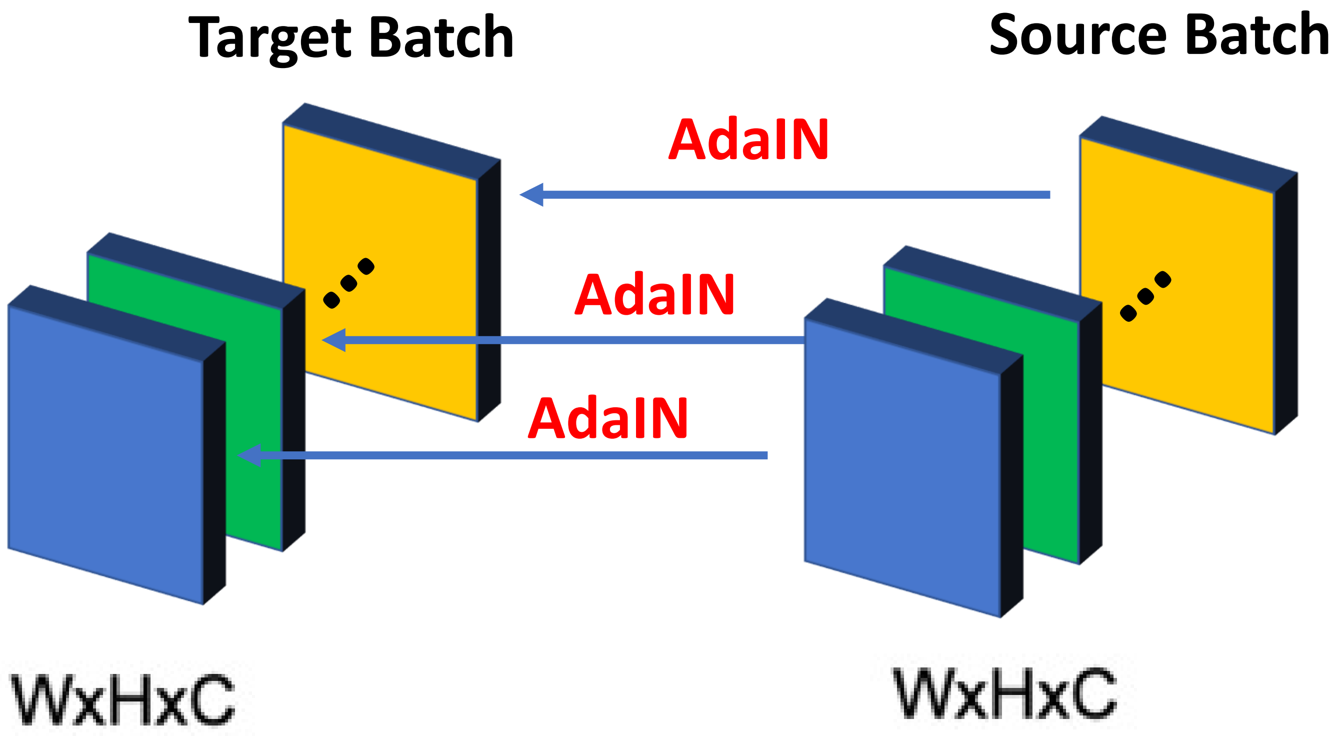


Image Classification

Swap global statistics between every two elements in the batch

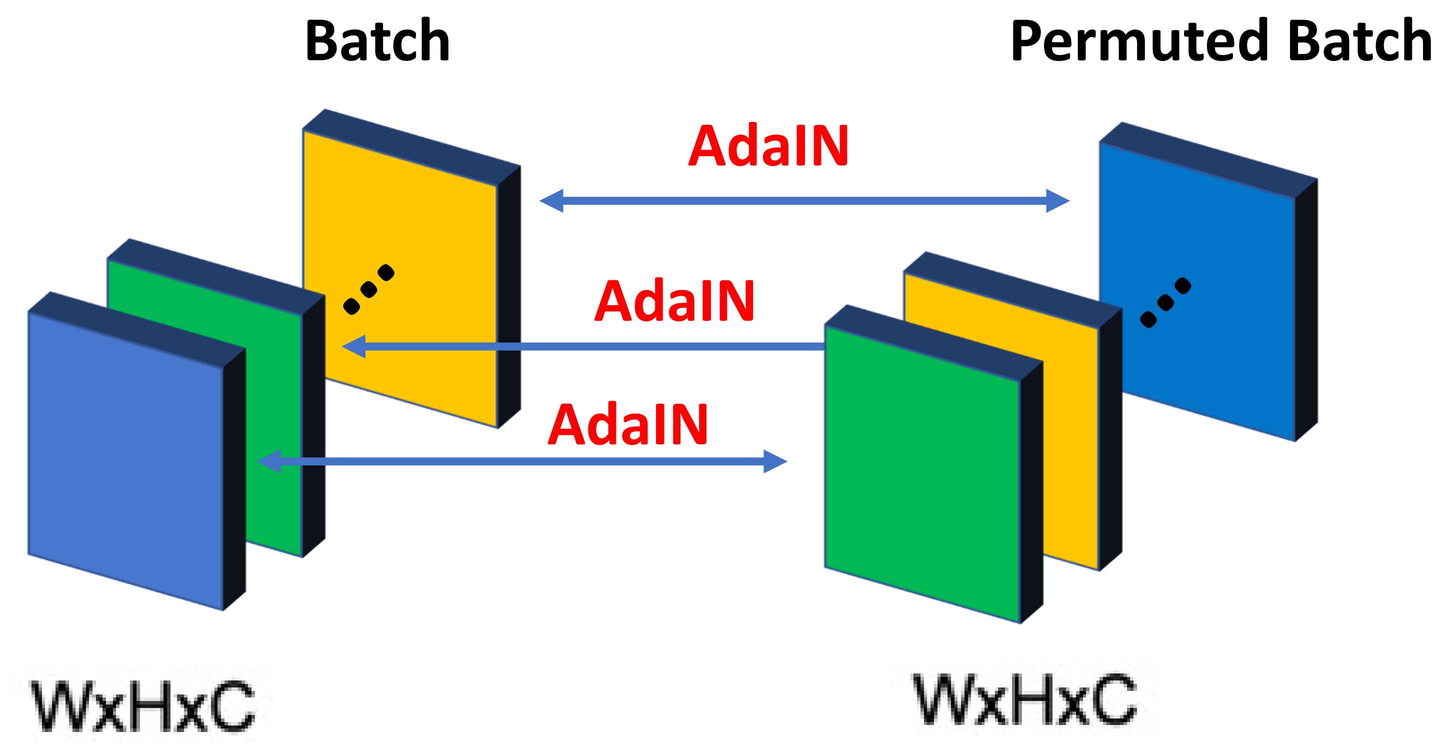


Image Classification

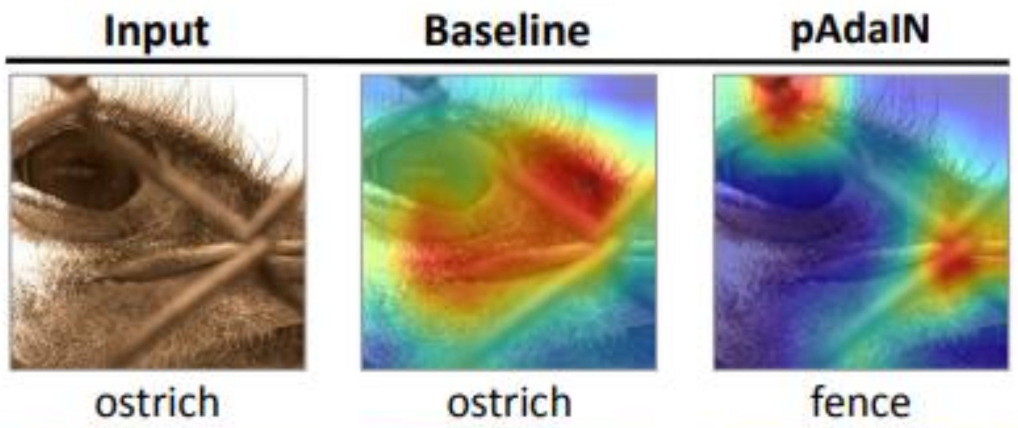
ImageNet

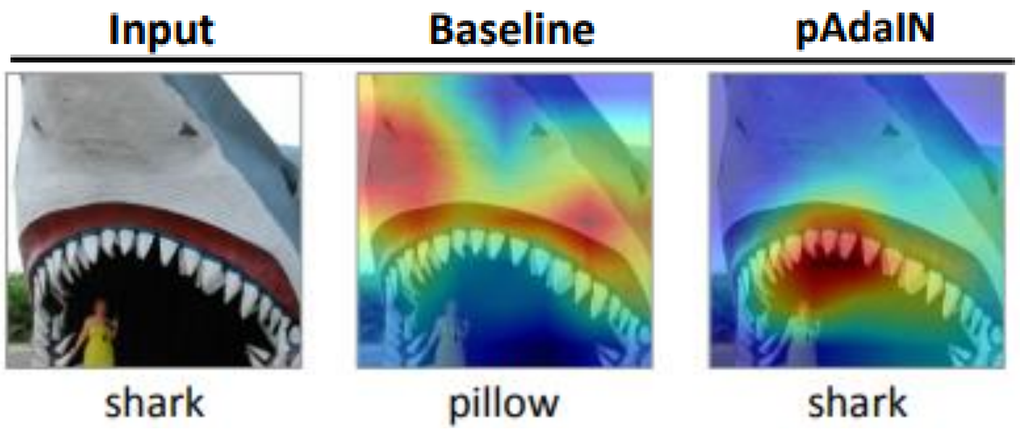
Method	Architecture	Top-1 Accuracy	Top-5 Accuracy
Baseline	ResNet50	77.1	93.63
pAdaIN	ResNet50	**77.7**	**93.93**
Baseline	ResNet101	78.13	93.71
pAdaIN	ResNet101	**78.8**	**94.35**
Baseline	ResNet152	78.31	94.06
pAdaIN	ResNet152	**79.13**	**94.64**

Cifar100

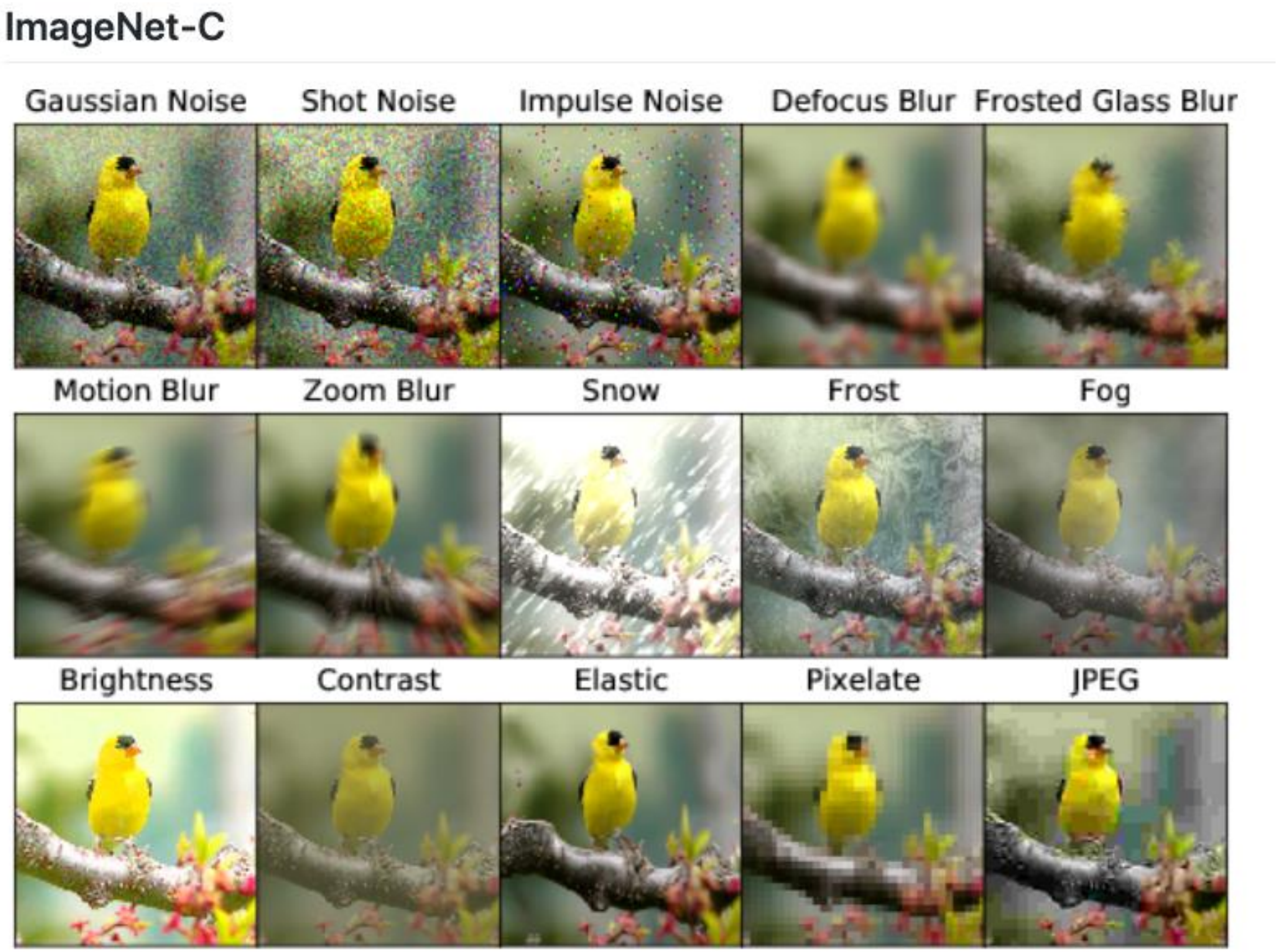
Method	Architecture	CIFAR 100
Baseline	PyramidNet	83.49
pAdaIN	PyramidNet	**84.17**
Baseline	ResNet18	76.13
pAdaIN	ResNet18	**77.82**
Baseline	ResNet50	78.22
pAdaIN	ResNet50	**79.03**

Image Classification





Robustness Towards Corruption



Robustness Towards Corruption

CIFAR100-C

	Baseline	Cutout [8]	Mixup [43]	CutMix [43]	Auto-Augment [7]	Adversarial Training [30]	Augmix [18]	pAdaIN+ Augmix
DenseNet-BC	59.3	59.6	55.4	59.2	53.9	55.2	38.9	**37.5**
ResNext-29	53.4	54.6	51.4	54.1	51.3	54.4	34.4	**31.6**

Category Wise Breakdown

Dataset	Network	Architecture	E	mCE	Noise			Blur				Weather				Digital			
					Gauss.	Shot	Impulse	Defocus	Glass	Motion	Zoom	Snow	Frost	Fog	Bright	Contrast	Elastic	Pixel	JPEG
INet-C	Baseline	ResNet50	22.9	76.7	80	82	83	75	89	78	80	78	75	66	57	71	85	77	77
INet-C	pAdaIN	ResNet50	**22.3**	**72.8**	**78**	**79**	**81**	**70**	**87**	**74**	**76**	**74**	**71**	**64**	**55**	**65**	**82**	**66**	**71**
C100-C	Augmix [18]	DenseNet-BC	24.2	38.9	60	51	41	27	55	31	29	36	39	35	28	37	33	39	41
C100-C	Augmix+pAdaIN	DenseNet-BC	**22.2**	**37.5**	**58**	**49**	**40**	**26**	**54**	**30**	**28**	**35**	**38**	**33**	**25**	**36**	**32**	**37**	**40**
C100-C	Augmix [18]	ResNext-29	21.0	34.4	**56**	**48**	32	23	**49**	27	25	32	35	32	24	32	30	34	37
C100-C	Augmix+pAdaIN	ResNext-29	**17.3**	**31.6**	58	**48**	**24**	**20**	54	**23**	**21**	**28**	**30**	**25**	**19**	**27**	**27**	**33**	**36**

Manipulating Structure

- Multi-sample approaches
- Structural analogies
- Novel videos of similar structure
- Few shot anomaly detection

Manipulating by Understanding Structure

- Speed up videos “gracefully” using “speed” as supervision
- Image classification and domain adaptation using structure preserving manipulation

Structure is Key to Image Understanding

Demonstrate using Structure Aware Manipulation

Next?

- 3D-aware structure manipulation
- Manipulating multiple objects in videos
- Functional relationships: A person riding a bike vs a person beside a bike

Thank You! Questions?