ETH zürich EcoVision

Domain Alignment in Representation Space Using Cycle-Consistent Adversarial Learning

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Domain Adaptation in Remote Sensing

There are many possible sources for domain shift in remote sensing imaging data.

Different Sensors

Low resolution sensor

High resolution sensor

Domain Adaptation in Remote Sensing

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Different Seasons

Spring

Winter

Domain Adaptation in Remote Sensing

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Different Geographical Regions

Fribourg, Switzerland

Marrakech, Morocco

Flash Introduction to Change Detection

The (simplest) problem definition for change detection is fairly straightforward. How to accomplish it is often not.

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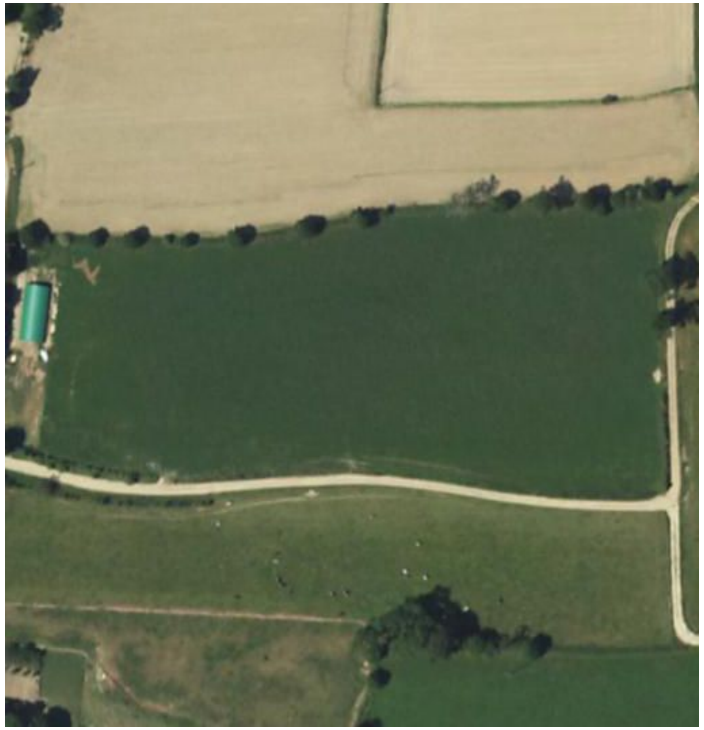

Image at T_1

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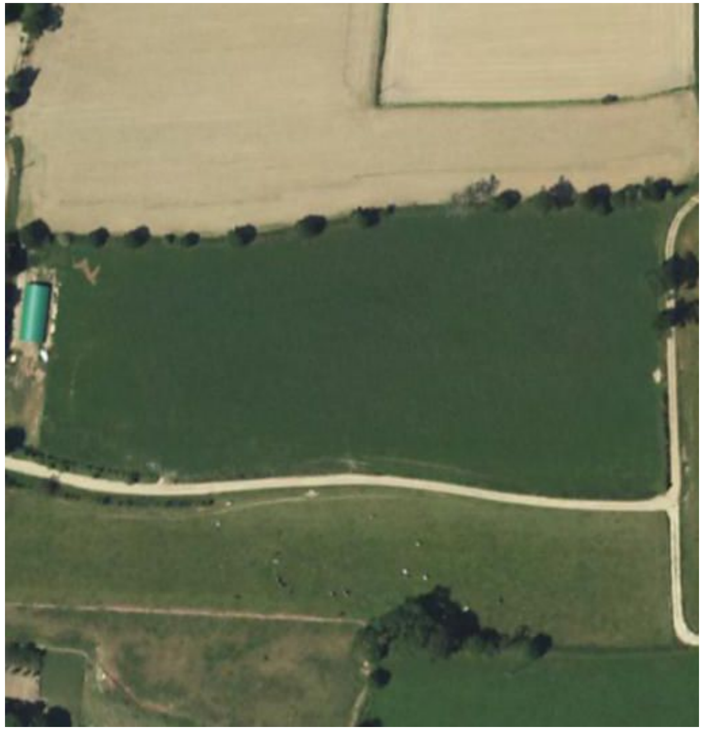

Image at T_1

Image at T_2

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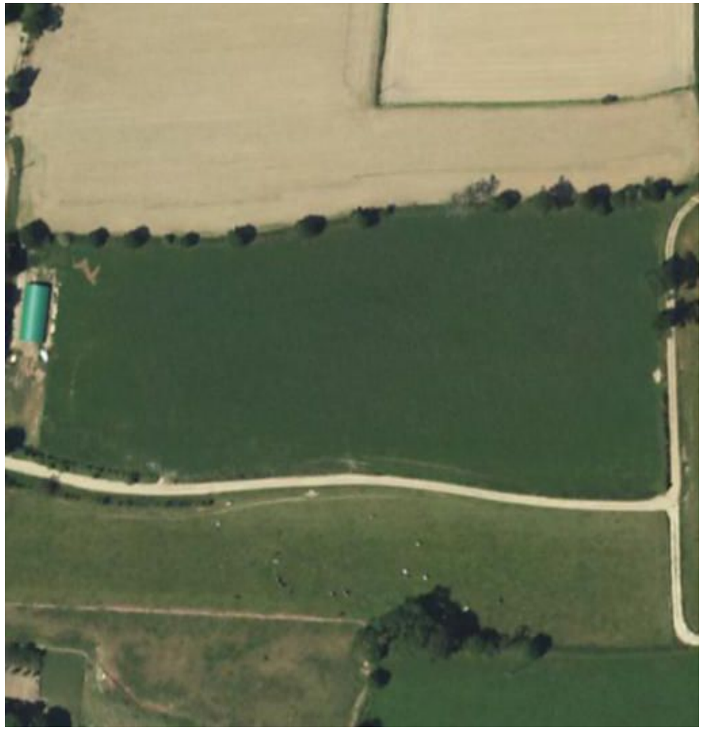

Image at T_1

Image at T_2

Change map

Domain Shifts in Change Detection

Domain shifts in change detection can be very subtle.

Case study: detection of buildings damaged by different types of **natural disasters**.[1]

[1] https://xview2.org/

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Wildfire

Tsunami

Flood

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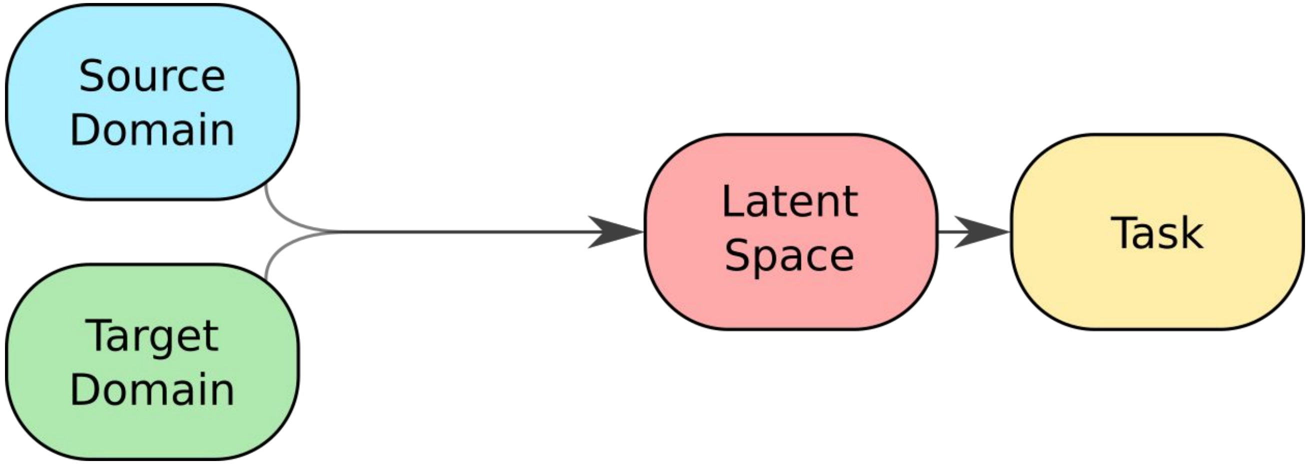
Main Objective: Domain Alignment

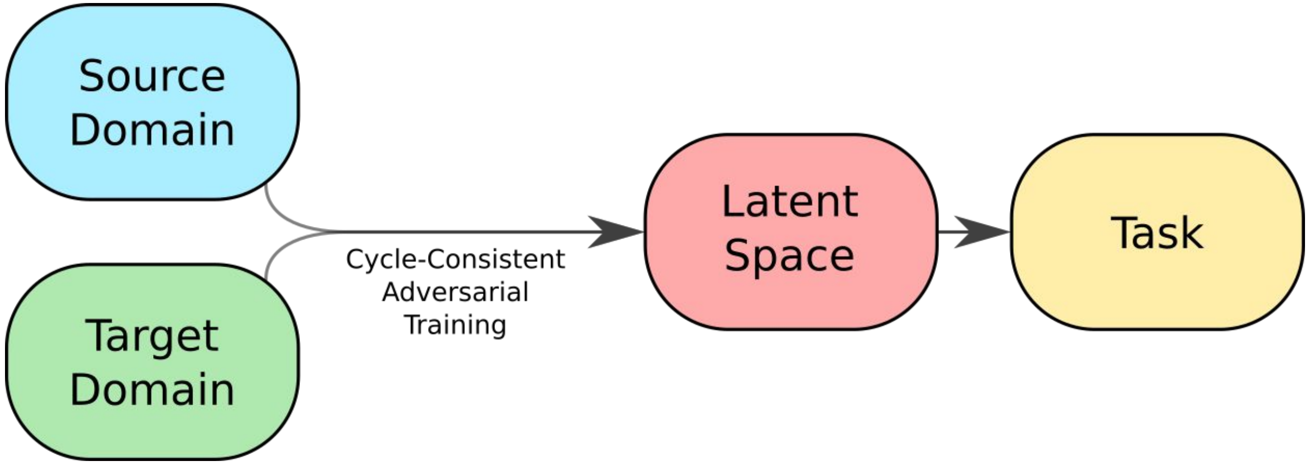
Our objective is to find a representation space (feature space) where the representation depends only on the contents of the input image and not on the domain of origin.



A hypothetical “same object” in two domains should have very similar representations in this latent space.

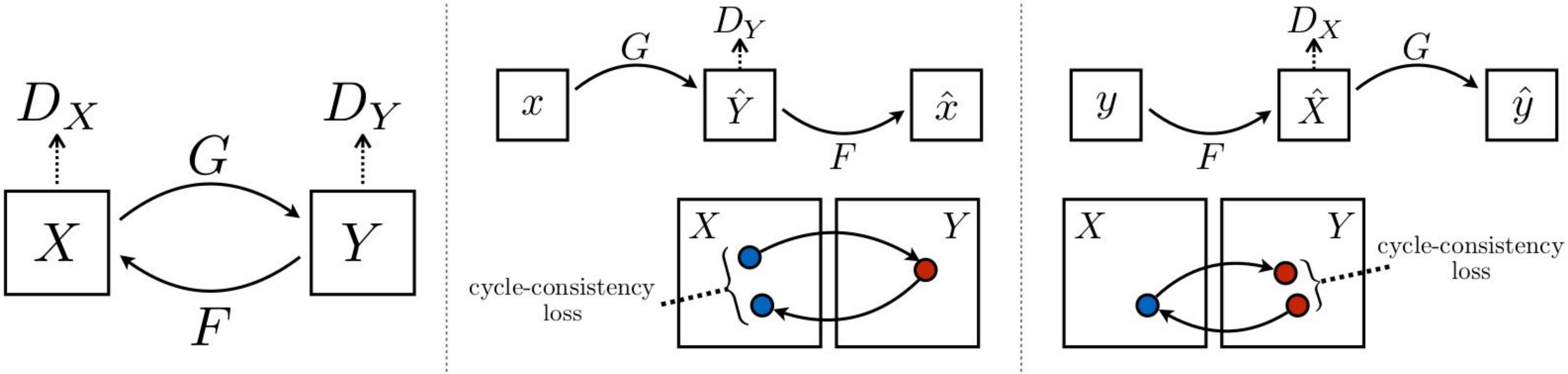
Main Objective: Domain Alignment

This is achieved using cycle-consistent adversarial training (originally proposed to develop the CycleGAN architecture).



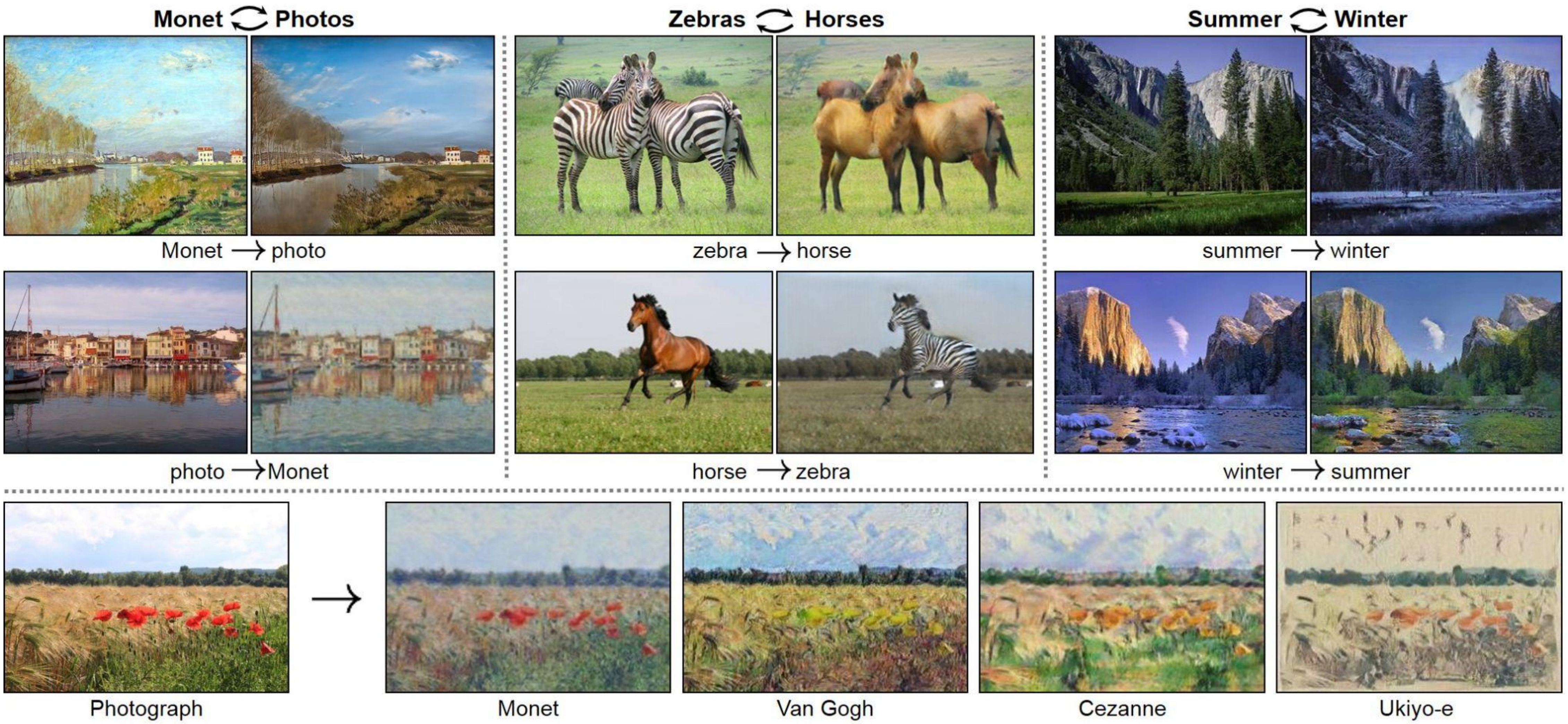
CycleGAN

Main concept: a **forward translation** and a **backward translation** should approach an **identity transformation** (i.e. should have a result close to the input).



One big advantage: CycleGAN learns from **unpaired data**!

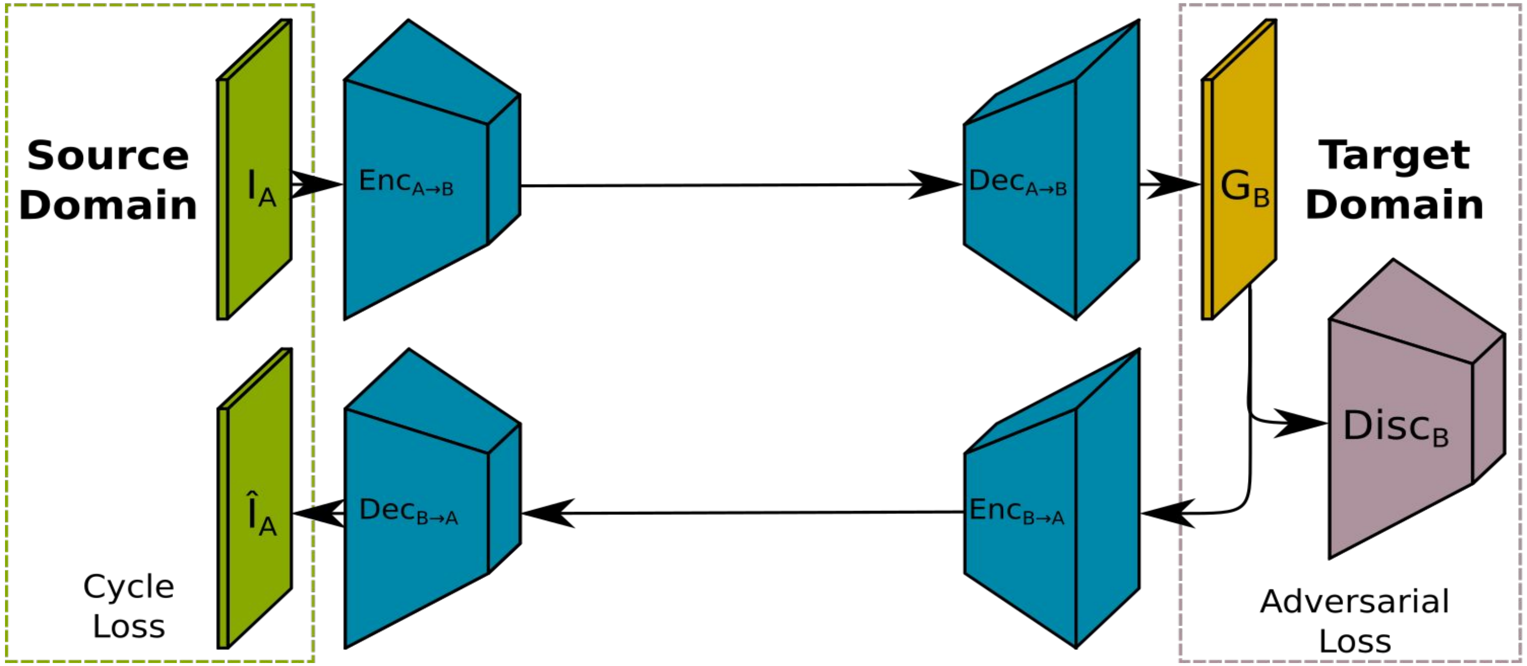
CycleGAN



Monet ⇄ Photos
Zebras ⇄ Horses
Summer ⇄ Winter
Monet → photo
zebra → horse
summer → winter
photo → Monet
horse → zebra
winter → summer
Photograph
→
Monet
Van Gogh
Cezanne
Ukiyo-e

Using CycleGAN for Unsupervised Domain Adaptation

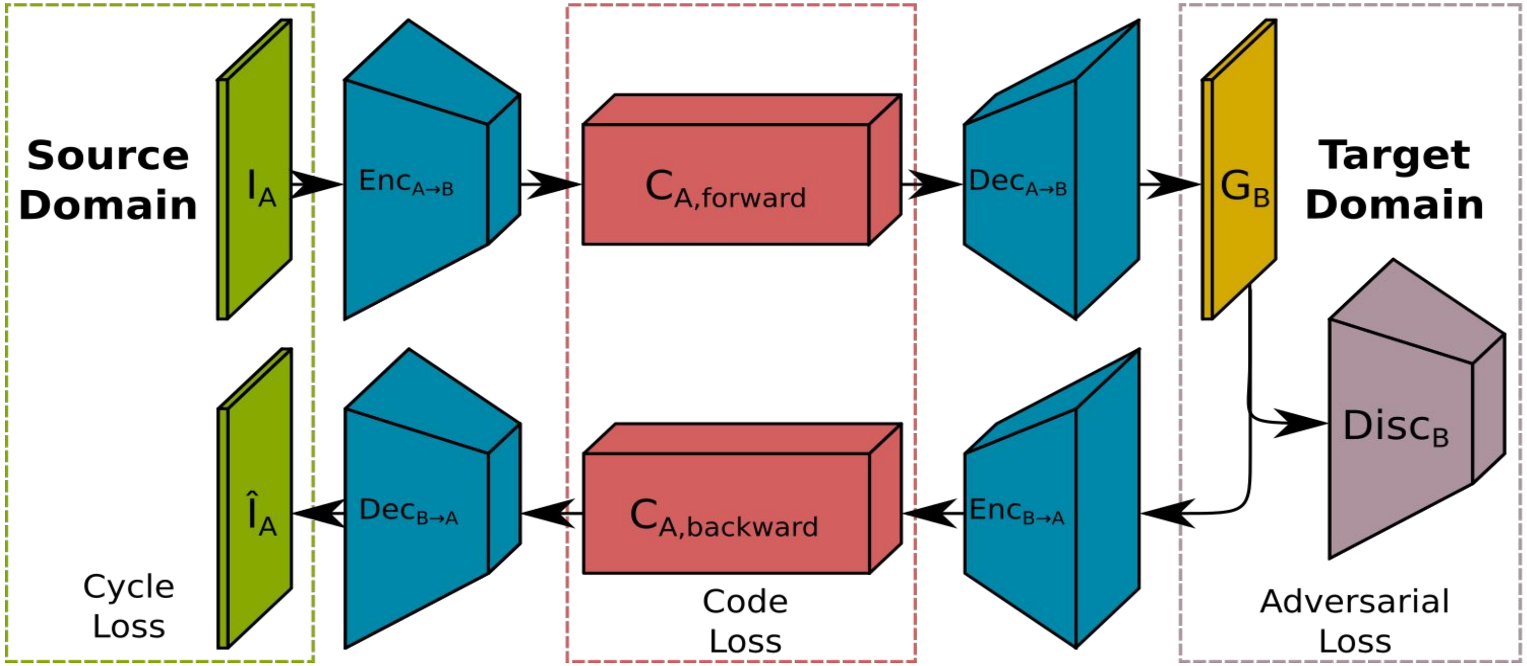
CycleGAN uses once encoder-decoder network for each translation direction.



Only one path is shown here for simplicity, but two are possible: A-B-A and B-A-B.

Using CycleGAN for Unsupervised Domain Adaptation

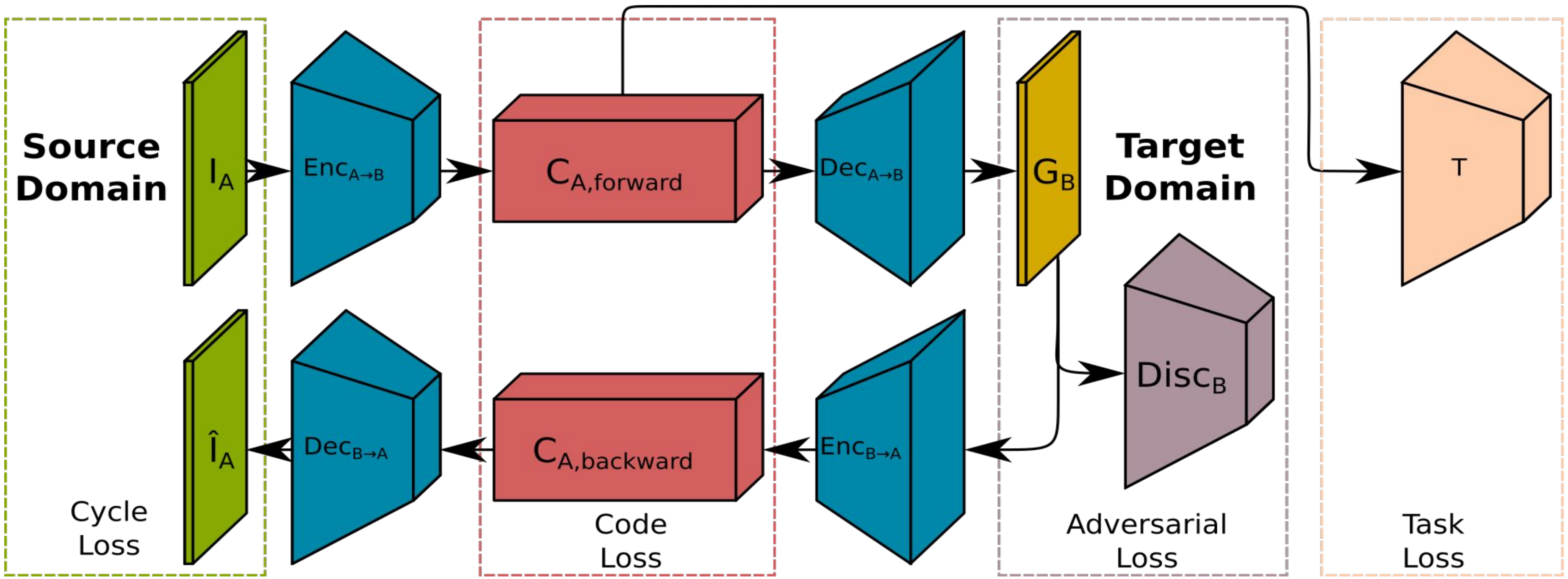
The encoded representation in the forward and backward translations are what we are trying to align (not done in the original CycleGAN).



Intuitively, a discriminator would align the codes. In practice we show that this is not a good idea, and a simple L1 loss is more efficient.

Using CycleGAN for Unsupervised Domain Adaptation

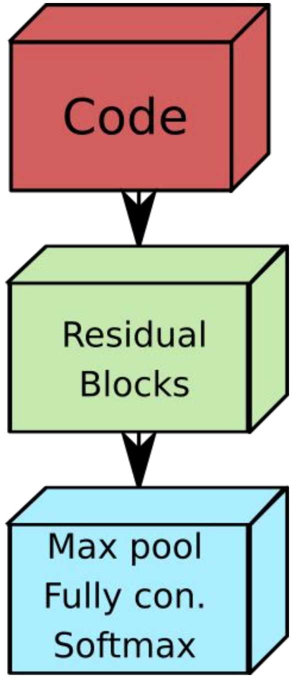
A task can then be performed using this representation as input.



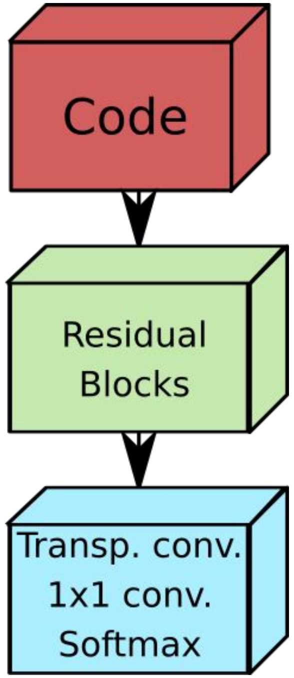
Simultaneous training of all the elements also encourages the encoders to learn a representation that is useful for the desired task.

Using CycleGAN for Unsupervised Domain Adaptation

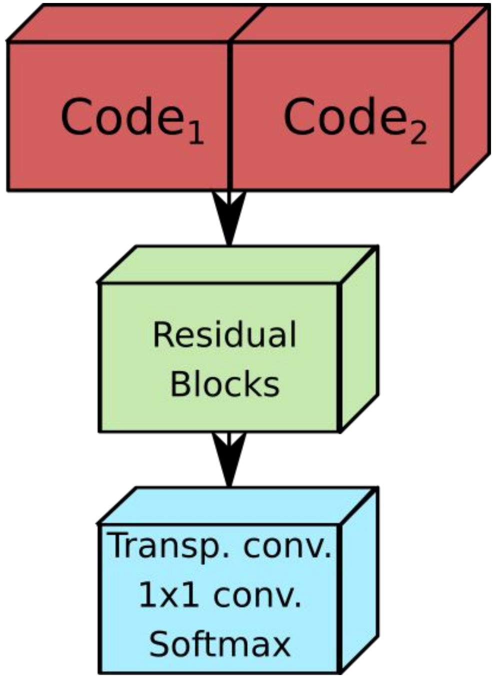
We can input the code into different task networks to accomplish different tasks.



Classification

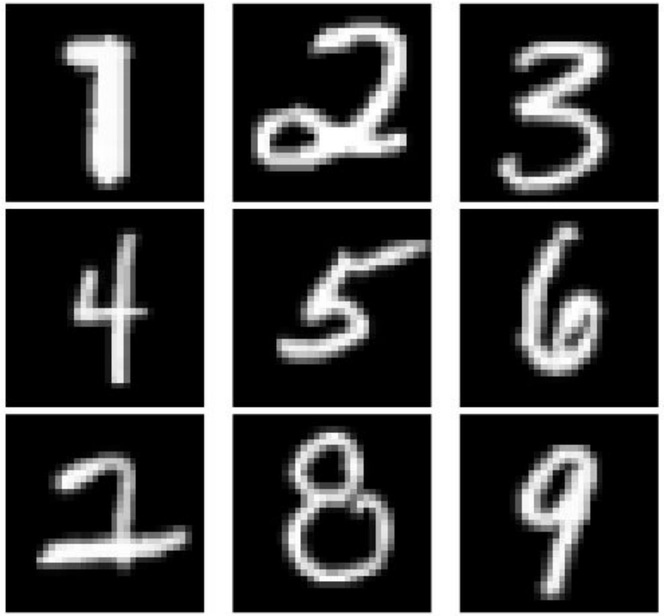


Semantic segmentation

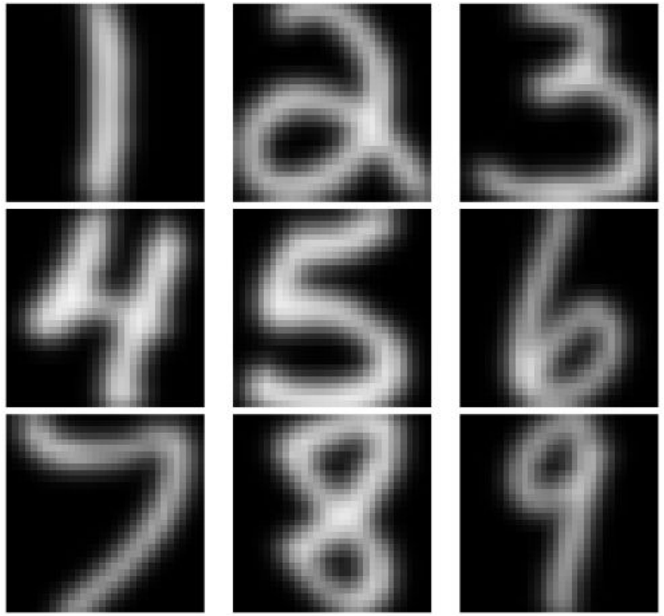


Cosegmentation
(change detection)

Application: Digit Recognition



MNIST



USPS

SVHN

Application: Digit Recognition

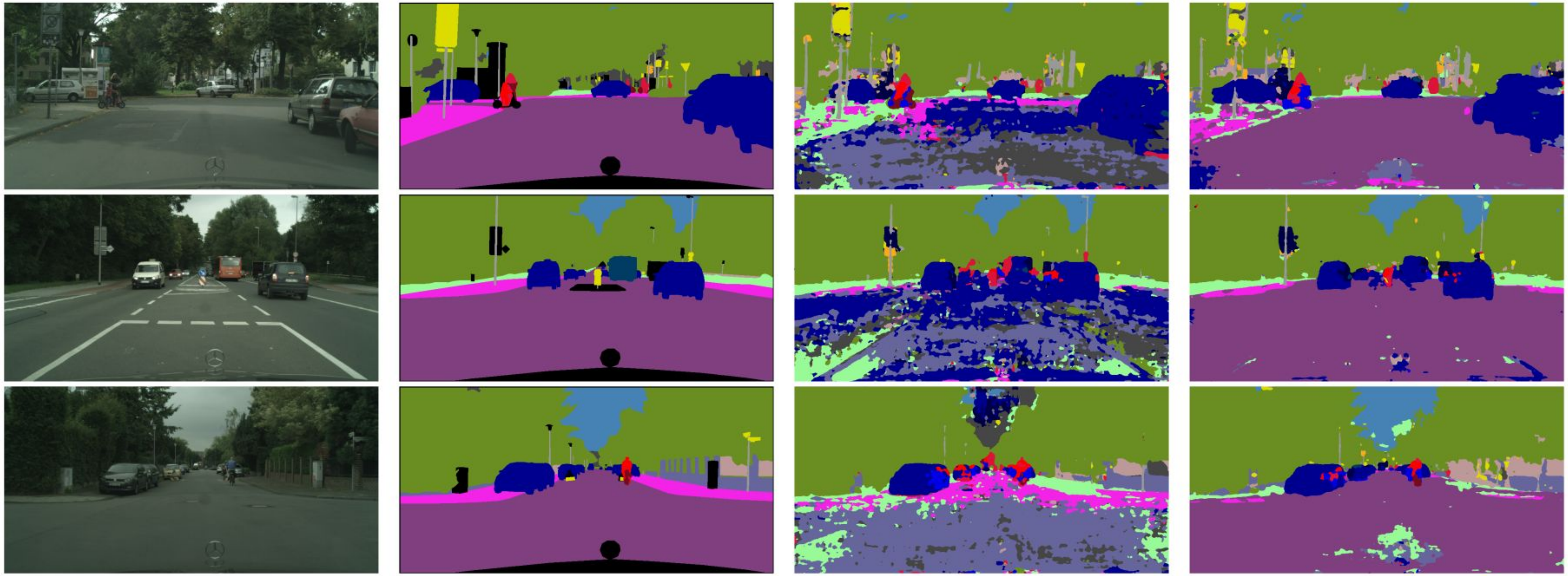
Model	MNIST $\rightarrow$ USPS	USPS $\rightarrow$ MNIST	SVHN $\rightarrow$ MNIST
Source only	0.957	0.779	0.723
DANN	-	-	0.736
DTN	-	-	0.844
CoGAN	0.912	0.891	-
ADDA	0.894	0.901	0.760
CyCADA	0.956	0.965	**0.904**
DINE (shared enc.)	**0.982**	0.973	0.713*
DINE (normal)	**0.982**	**0.981**	0.803
Target only	0.973	0.995	0.995

Application: Semantic Segmentation

GTA 5

Cityscapes

Application: Semantic Segmentation



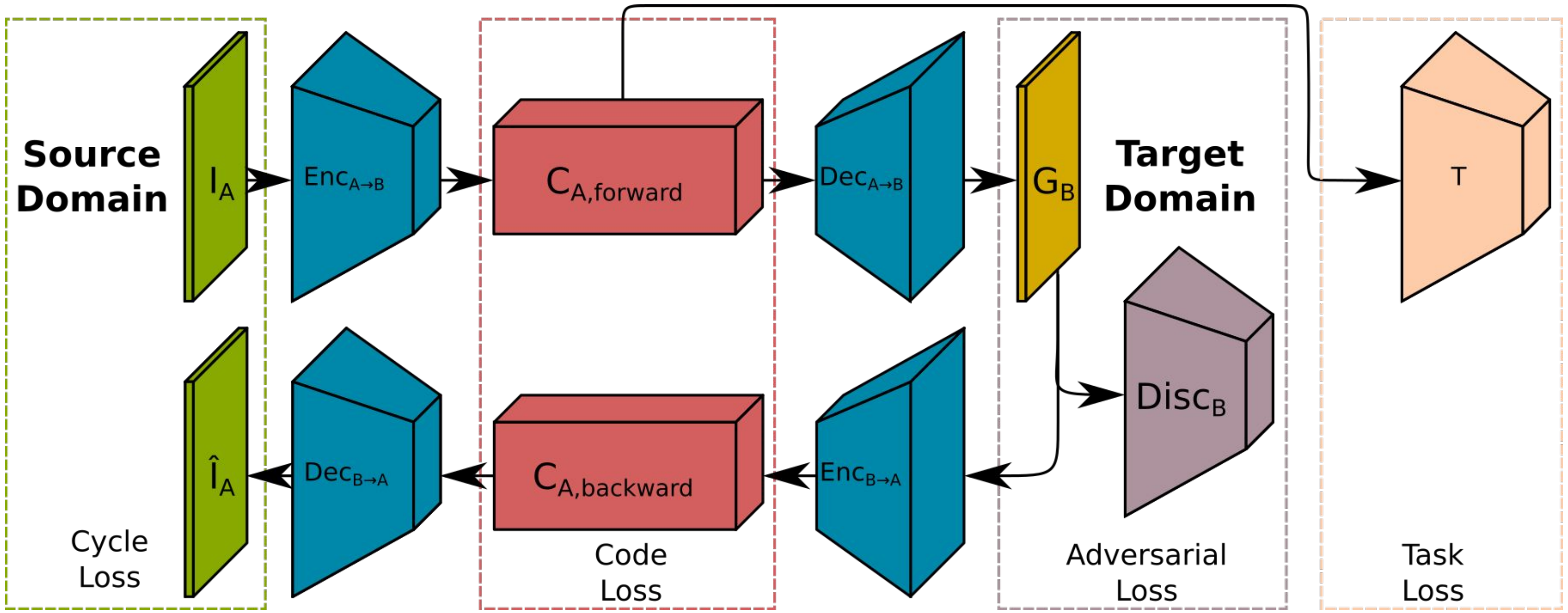
Input Ground truth Source supervision DINE

Application: Semantic Segmentation

Model	Backbone	Parameters	mIoU
Source supervision	ResNet-9	11.4 M	0.117
FCNs in the Wild	VGG-16	50.5 M	0.271
Adapt-SegNet	Deeplab-v2 VGG16	29.6 M	0.350
Adapt-SegNet	Deeplab-v2 ResNet-101	44.5 M	0.424
CyCADA	VGG16-FCN8s	134.4 M	0.354
CyCADA	DRN-26	20.6 M	0.395
AdvEnt	ResNet-101	44.5M	**0.438**
AdvEnt	ResNet-9	11.4 M	0.108
CyCADA	ResNet-9	11.4 M	0.117
Adapt-SegNet	ResNet-9	11.4 M	0.125
DINE (shared enc.)	ResNet-9	11.4 M	0.137
DINE (normal)	ResNet-9	11.4 M	**0.201**

Application: Semantic Segmentation

This structure allows us to visually verify domain alignment.



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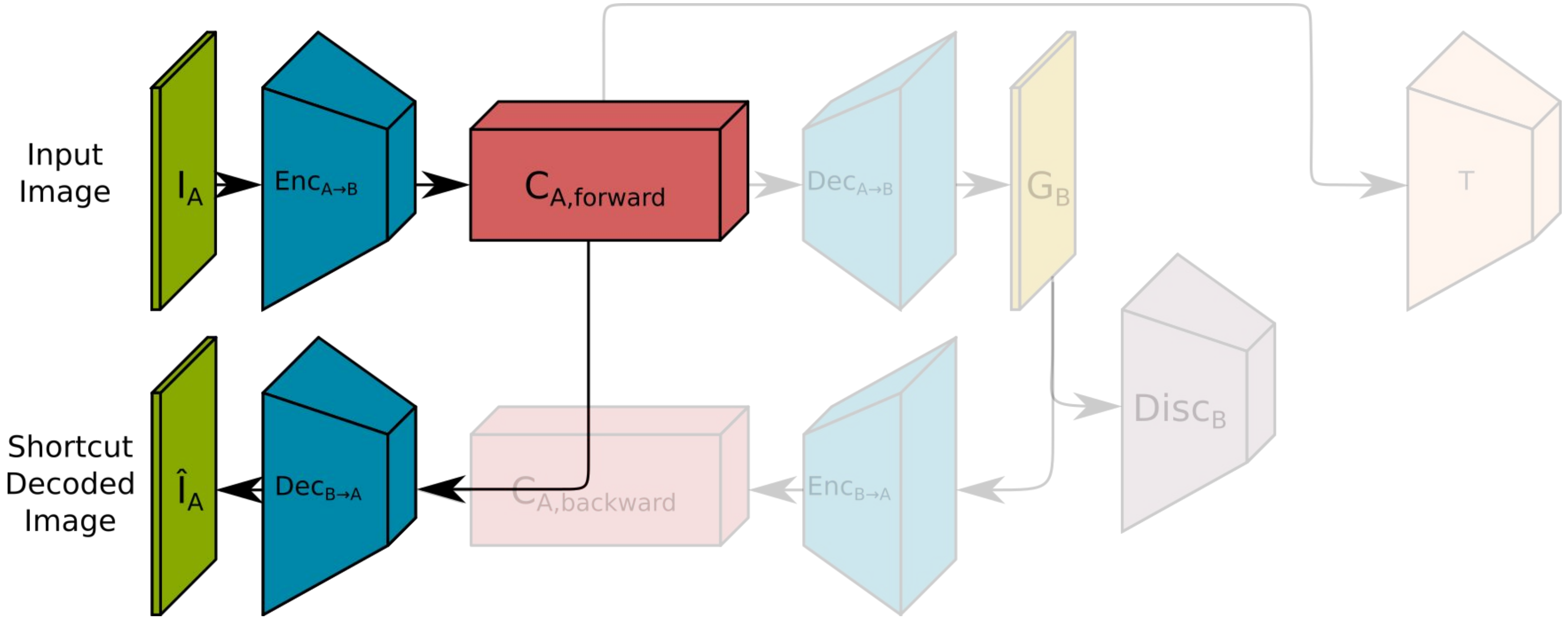
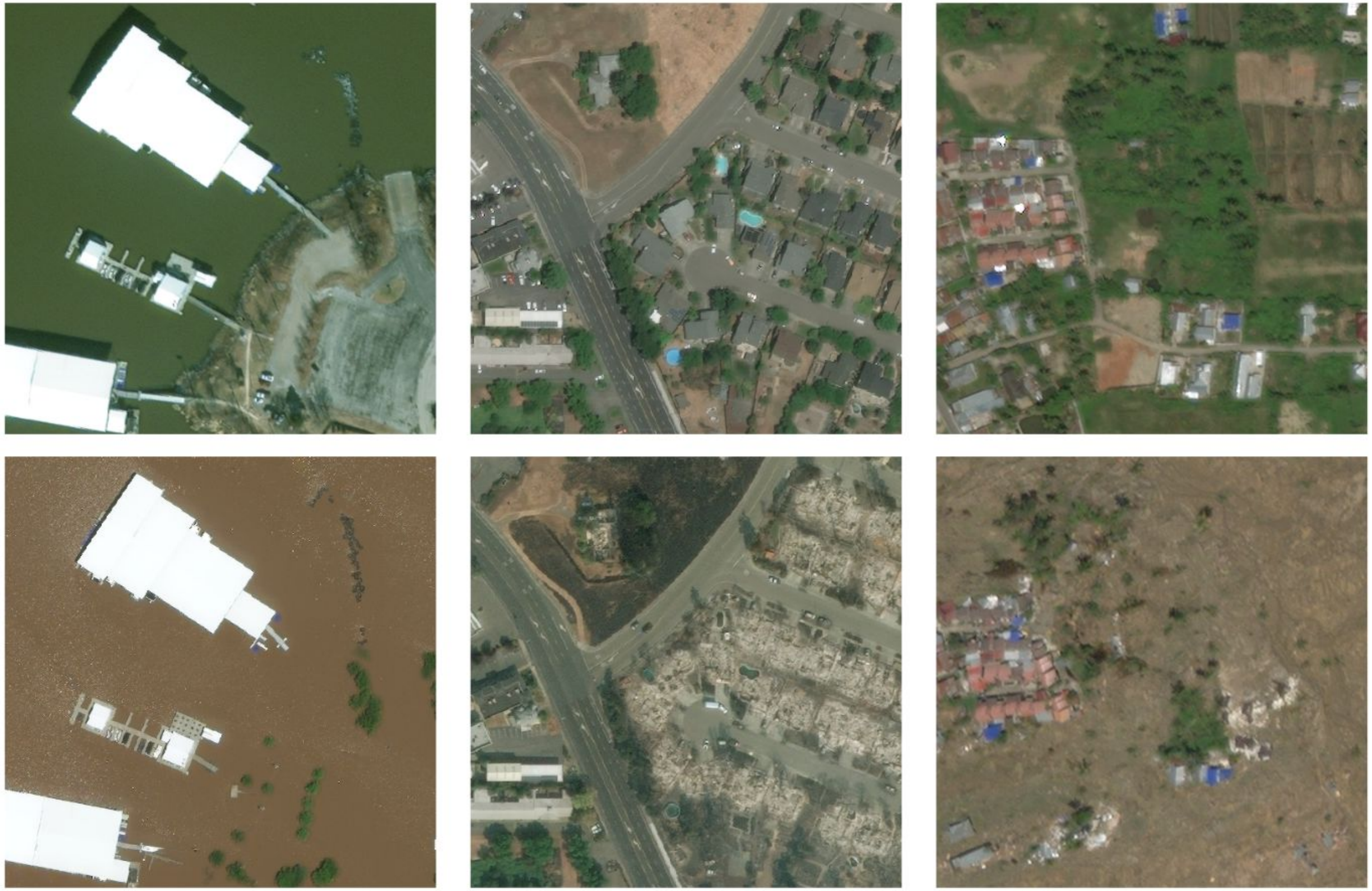


Application: Semantic Segmentation

Input | Translated | Full cycle | Shortcut (DINE) | Shortcut (code discr.)

Application: Change Detection

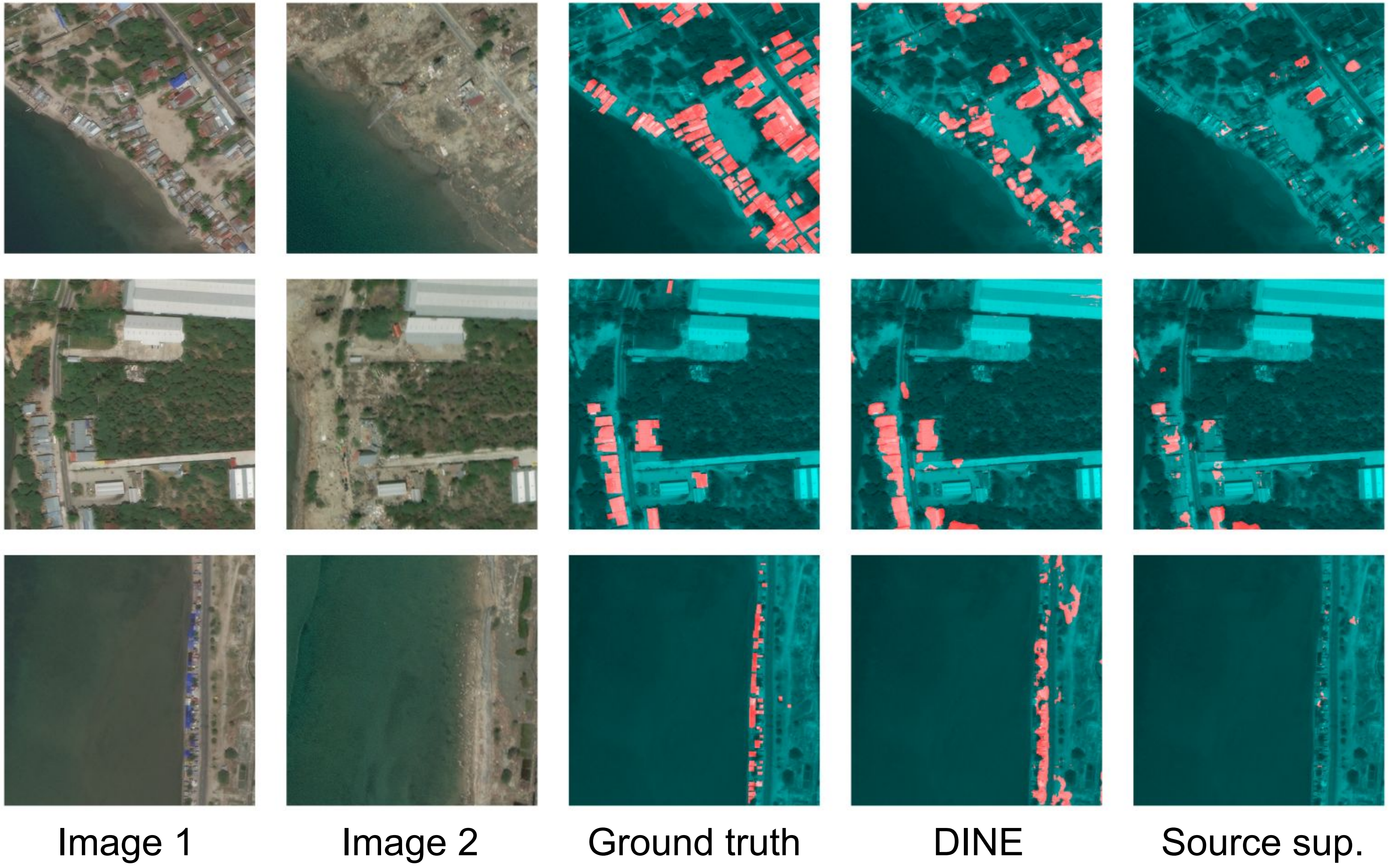


Flood Wildfire Tsunami

Application: Change Detection

Image 1 Image 2 Ground truth DINE Source sup.

Application: Change Detection



Application: Change Detection

Image 1	A -> B	A -> B	Image 2	B -> A	B -> A
(domain A)	(clean data)	(all data)	(domain B)	(clean data)	(all data)

Conclusion

- Cycle-consistent adversarial learning was used to find a common representation space using unpaired data from different domains

- Method was tested for classification, semantic segmentation, and semantic cosegmentation (change detection)

- Notably, this method surpassed target domain supervision in one of our tests

- Method allows for visual verification of domain alignment in representation space

- Using data containing changes for training GANs may lead to bad results due to hallucinations

Acknowledgements

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TELECOM Paris

IP PARIS

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Thank you for your attention!

Questions?