

## Use-Case in Delta Learning

The need for cost-effective labeled data for environmental perception tasks (such as semantic segmentation) has resulted in the development of many synthetic datasets. However, training models on these synthetic datasets (source domain) often leads to lower performance when applied to real data (target domain) due to the domain gap. There are many tasks that deal with this domain gap. We investigated multiple methods in these different tasks. Additionally we developed a new method for contiguous adaptation during inference.

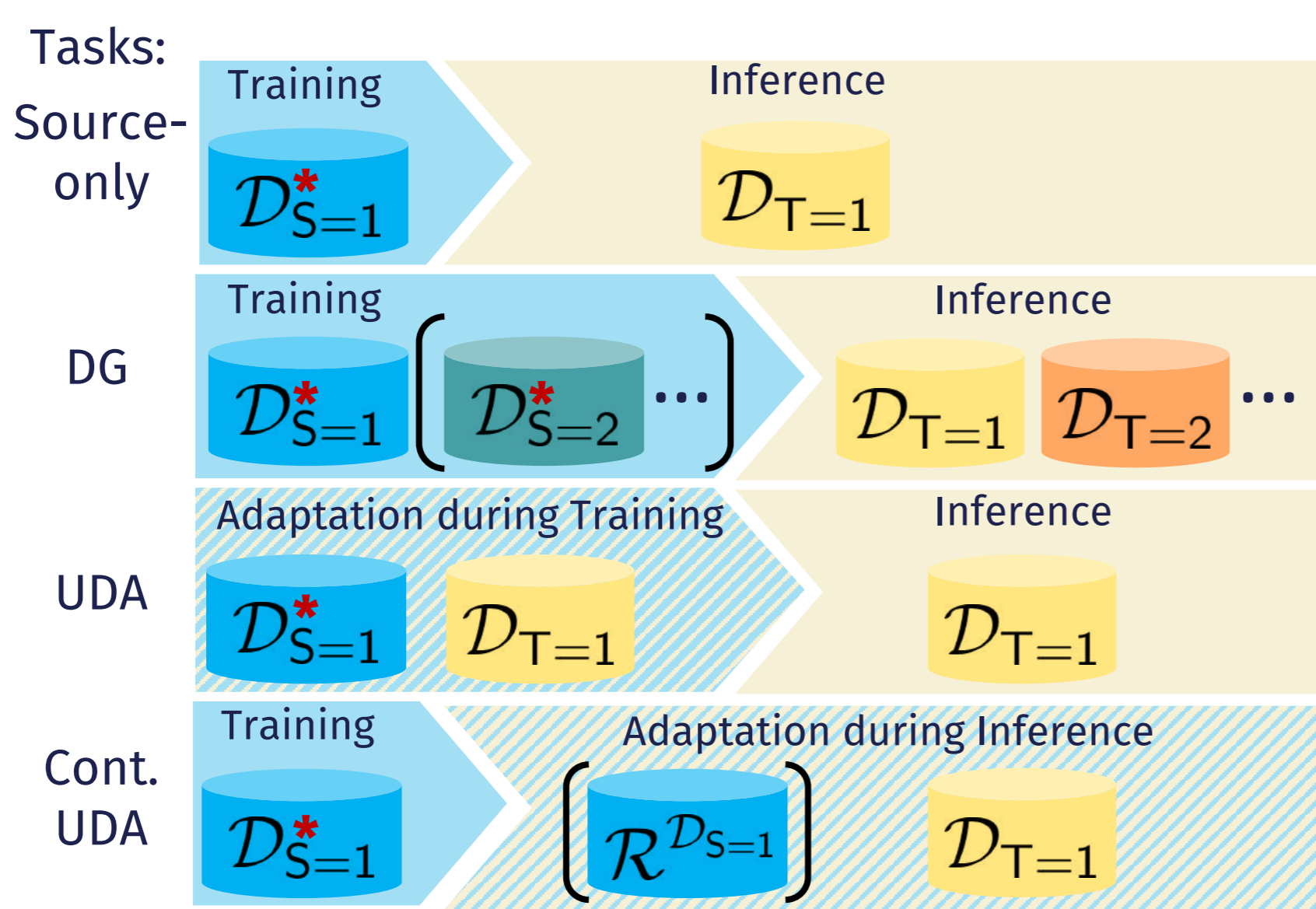


Figure 1: Simplified schematic visualization of different tasks. The red star indicates availability of labels. (© TU Braunschweig)

## Tasks and Approaches

The main tasks are depicted in Figure 1.

Source-only training serves as a baseline.

**Domain generalization (DG)** is a task where a model is trained to perform well on multiple domains, without access to (labeled) data from each domain during training.

**Unsupervised domain adaptation (UDA)** is a task where a model is trained on a labeled source domain and is adapted to perform well on an unlabeled target domain at the same time. No target domain labels are available during training.

**Continuous UDA** is a task where a model is continuously adapted to new target domains as it encounters them. Again, without access to (labeled) target domain data during training.

We evaluated multiple methods for each task. In the following we will show results for strong color augmentations, WildNet [1], self-supervised augmentation consistency (SSAC) [2] and online frequency domain style transfer (OFDST) [3]. The training was always performed on the synthetic GTA5 dataset.

Source Domain / Method	mIoU [%] on				Mean mIoU [%]
	$D_{CS}^{test*}$	$D_{MV}^{test*}$	$D_{BDD}^{test*}$	$D_{ACDC}^{test*}$	
$D_{CS}^{train}$	<b>69.3</b>	50.3	41.3	37.8	49.7
$D_{MV}^{train}$	61.9	<b>67.2</b>	53.7	50.2	<b>58.2</b>
$D_{BDD}^{train}$	53.2	53.0	<b>55.3</b>	41.7	50.8
$D_{ACDC}^{train}$	48.1	47.9	39.5	<b>59.7</b>	48.8
UDA [2] (target: CS)	<b>53.8</b>	48.9	40.2	35.6	44.6
UDA [2] (target: MV)	49.6	<b>51.3</b>	<b>45.3</b>	<b>39.7</b>	<b>46.5</b>
Color Aug. DG	44.0	47.2	38.6	31.7	43.3
WildNet [1] DG	45.8	47.1	41.7	-	-
Cont. UDA [3]	43.1	45.9	40.3	32.9	40.5
$D_{GTA5}^{full}$	41.0	46.0	39.2	32.1	39.6

Table 1: All methods employ a ResNet101-based model, with source domain GTA5.

## Evaluation

We evaluate all methods on multiple real-world datasets that serve as target domains. We showed that the best performance can be achieved with UDA methods. Additionally, some UDA methods are even suitable for domain generalization when adapted to the right “representative” target domains/data and perform better than state-of-the-art DG methods. Color augmentation is a simple and effective DG method. With continuous UDA it is possible to adapt continuously to the target domain during inference. Here, we showed first performance improvements over the baseline.

## References:

- [1] S. Lee, et al.. WildNet: Learning Domain Generalized Semantic Segmentation from the Wild. In Proc. of CVPR, pages 9936–9946, New Orleans, LA, USA, June 2022
- [2] N. Arslanov, et al. Self-Supervised Augmentation Consistency for Adapting Semantic Segmentation. In Proc of CVPR, pages 15384–15394, virtual, Jun. 2021
- [3] J.-A.Termöhlen, et al. Continual Unsupervised Domain Adaptation for Semantic Segmentation by Online Frequency Domain Style Transfer. In Proc. of ITSC, pages 2881–2888, Nashville,TN, USA, Sep. 2021

## Partners



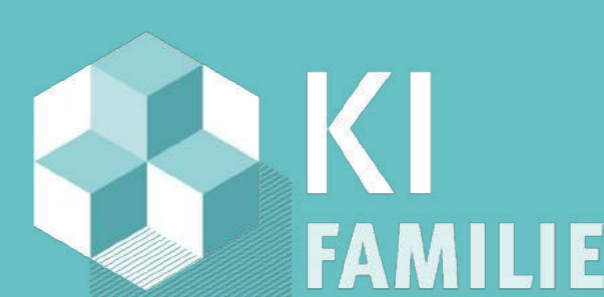
## External partners



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