

Introduction

Experiencing domain shifts during test-time is nearly inevitable in practice and likely results in a severe performance degradation. To overcome this issue, test-time adaptation continues to update the initial source model after deployment using the currently available test data. A promising direction are methods based on self-training which have been shown to be especially well suited for gradual domain adaptation, since reliable pseudo-labels can be provided.

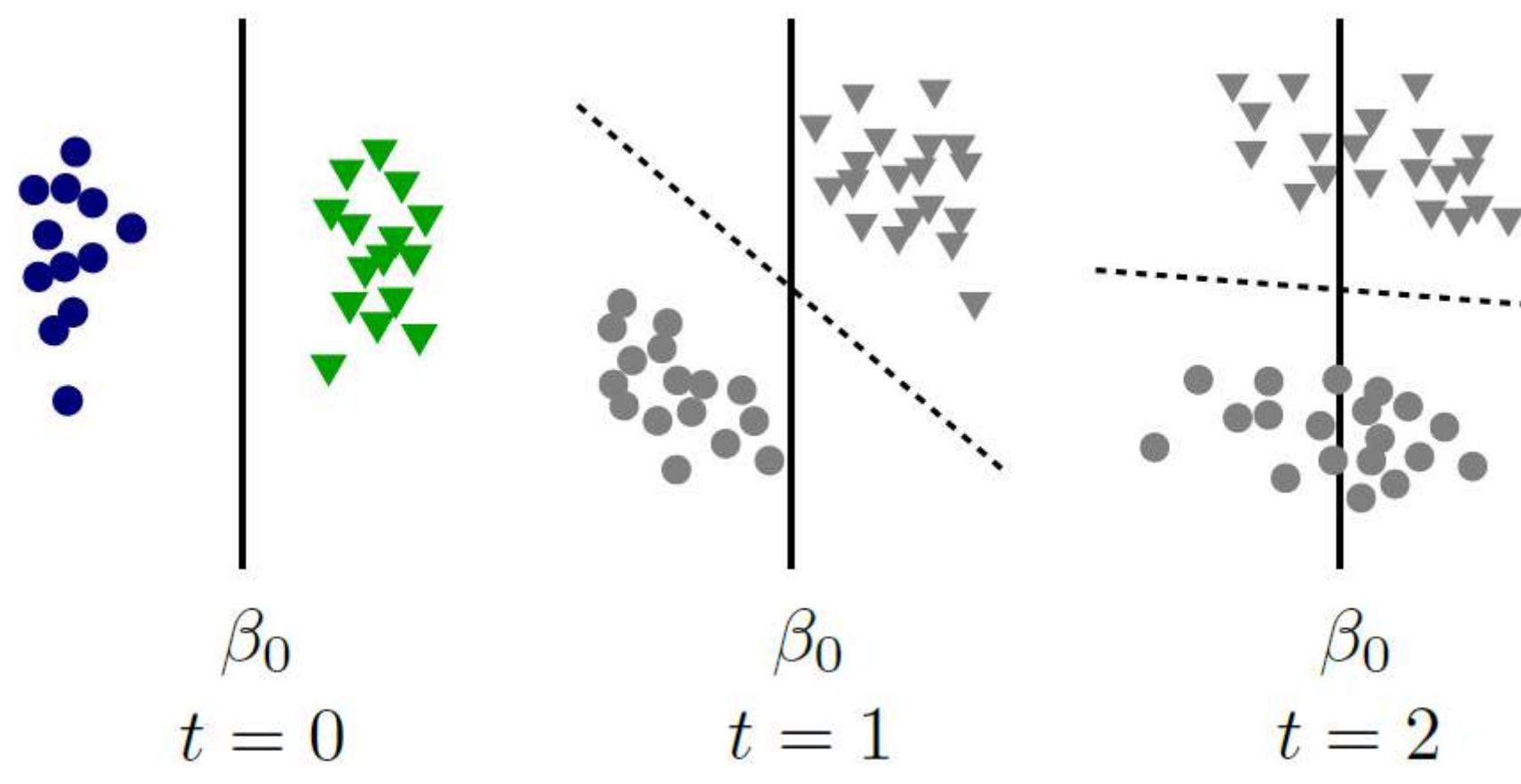


Figure 1: Illustration of a gradually evolving domain. In the beginning $t=0$ perfect classification is possible. When updating the model through self-training, the classification accuracy will remain high.

Looking at the nature of shifts in reality, for many applications they do not occur abruptly, but evolve gradually over time (e.g., changes in illumination and weather). However, in some cases this might be not true, e.g. when entering a tunnel. Therefore, we propose to convert each problem into a more gradual one. This is achieved by generating artificial intermediate domains using a batch of randomly sampled source data and the currently available test data.

Creating artificial intermediate domains

Depending on the type of domain shift, we propose two independent ideas to generate the intermediate domains: mixup and content-preserving light-weight style transfer.

Since performing style-transfer during test-time imposes some challenges, we leverage class-conditional adaptive instance normalization. In this case, style transfer is achieved by exchanging the first and second order moments of a content representation (source data) by the moments of a style representation (current test data). By saving the moments, style replay can also be used.

New Dataset: CarlaTTA

Currently, there are not many datasets that are suited for investigating gradual test-time adaptation. To close this gap we introduce CarlaTTA: a dataset that enables the exploration of gradual test-time adaptation for urban scene segmentation. We create five gradual test-sequences which all evolve from the stationary source domain representing clear weather at noon (see Fig. 2).

Evaluation:

We evaluate our approach on all sequences of CarlaTTA and compare it with methods from one-shot domain adaptation and test-time adaptation, achieving new state-of-the-arts.

Table 1: Mean intersection-over-union for CarlaTTA.

Method	source-free	day2night	clear2fog	clear2rain	dynamic	highway
BN-0 (source)	✓	58.4	52.8	71.8	46.6	28.7
BN-0.1	✓	62.7	56.5	72.8	52.1	37.2
BN-1	✓	62.0	56.8	71.4	52.6	32.8
BN-EMA	✓	63.4	58.3	73.4	53.9	31.9
MEMO	✓	61.0	55.1	71.6	50.3	35.2
TENT-continual	✓	61.5	56.0	70.9	50.3	32.0
TENT-episodic	✓	61.9	56.8	71.4	52.6	32.8
CoTTA	✓	61.4	56.8	70.7	46.4	33.8
ASM	✗	58.5	53.0	69.2	50.2	39.4
SM-PPM	✗	63.1	56.7	72.7	53.2	33.4
self-training	✗	63.2	54.1	74.4	50.3	33.2
style-transfer	✗	66.0	62.2	74.6	59.1	41.9
GTTA-ST	✗	66.7	61.6	74.7	60.3	44.8

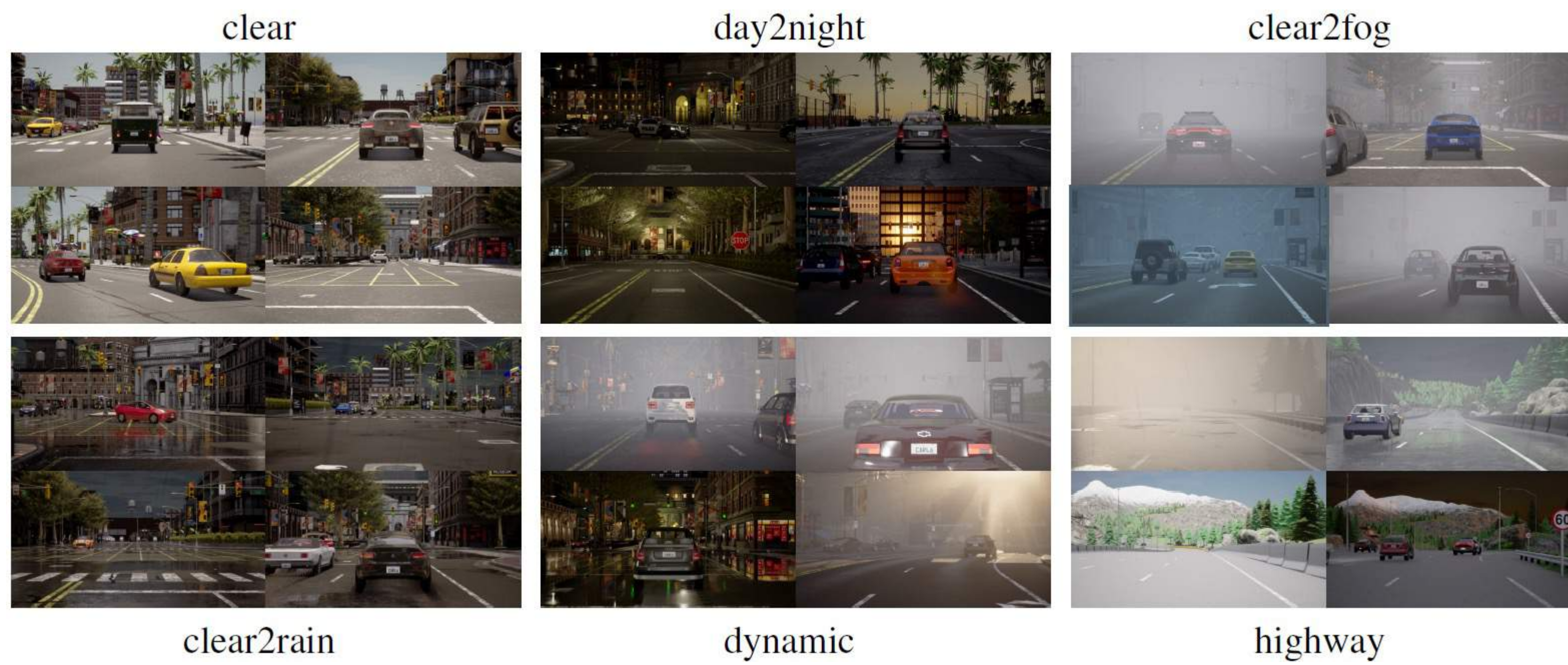


Figure 2: A few example images for each split contained in our new synthetic dataset called CarlaTTA. Starting from the source domain „clear“, every domain evolves gradually over time. The split „dynamic“ combines multiple domain shifts at a time and thereby even creates new shifts. „Highway“ further introduces a shift in the class priors. (© University of Stuttgart)

Partners



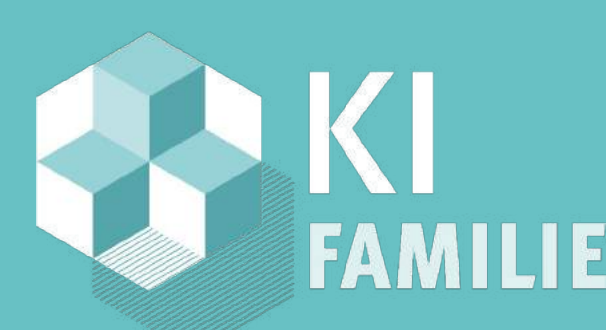
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