KI DELTA LEARNING
Scalable AI for Automated Driving

Delta-Weather Gap in Lidar 3D Object Detection

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WP 2.4
WP 2.5

Use-Case in Delta Learning

Developing a Deep-learning based Lidar 3D object detector requires a lot of annotated data. The question arises, what performance gap can we expect, when running the detector in rare or unseen context, such as different surroundings, illumination, season, or weather. In particular, here we investigate the gap caused by bad weather, as opposed to nice weather. In doing so, we train/evaluate object detectors on data recorded in different situations and evaluate their performance.

weather	road condition
clear	dry
cloudy	wet
light rain	flooded
heavy rain	

Figure 1: Criteria for weather splits.

Technical Problem

The sensor data looks different, depending on the particular weather condition it was recorded in. In particular 1) there is a significant reduction of measured points in bad weather (as opposed to nice weather), and 2) we observe bad-weather induced artifacts such as spray behind the moving vehicles. E.g., Fig. 2 shows a significant amount of measured water drops, where a naive detector likely will produce False Positives.

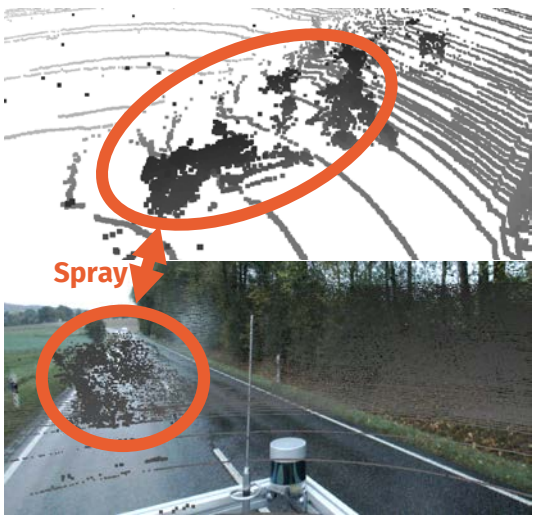


Figure 2: Spray behind measuring vehicle.

Technical Solution

We conduct a gap analysis on an internal dataset for Lidar object detection (2x Velodyne VLP-32C, 2x Hesai Pandar64P), where each frame includes annotations for the 3D boxes together with a frame-specific label for the weather and road condition (see Fig. 1). This way, we can generate splits for nice weather (clear/cloudy AND dry) and bad weather (light rain/heavy rain AND wet/ flooded). The gap analysis in Fig. 3 is based on these splits.

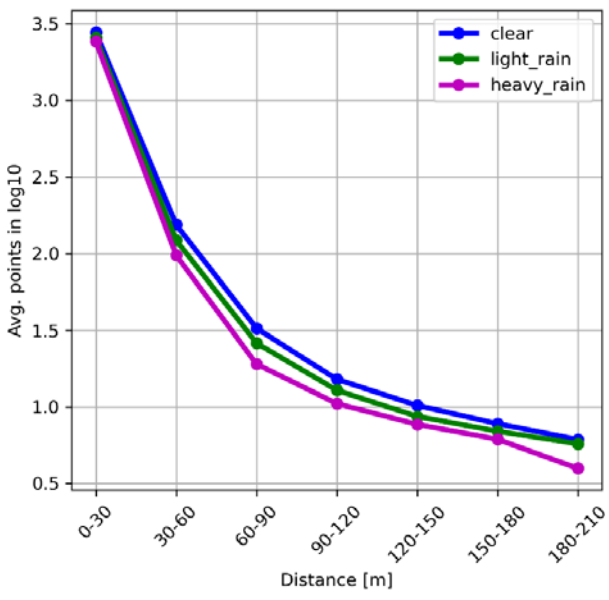


Figure 4: Number of points wrt. object distance.

Evaluation

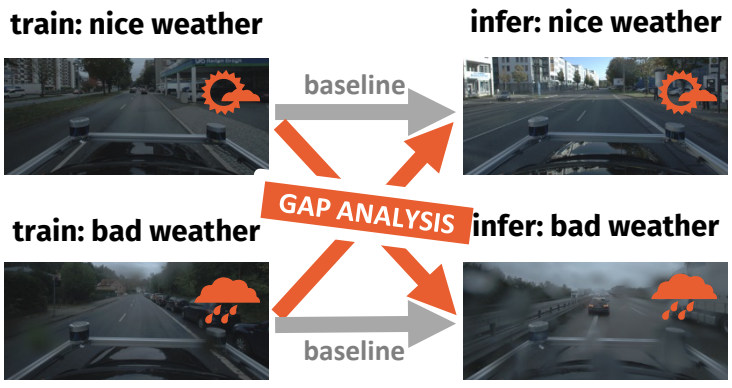
Main insights of (wrt. our setup):

1) Training a dedicated detector with annotated data from the target domain could slightly increase the performance.
2) Inference with nice-weather data instead of bad-weather data improves the performance for a given detector by >5%.
3) We can confirm results from related literature, which observe a reduction of measured points with increasingly bad weather (see Fig. 4).

Future work includes continuing the gap analysis, implementing approaches to close the gap, and study their effects.

train	infer	rel. mAP
nice	nice	0%
nice	bad	-7%

train	infer	rel. mAP
bad	bad	0%
bad	nice	5%



train	infer	rel. mAP
nice	nice	0%
bad	nice	-3%

train	infer	rel. mAP
bad	bad	0%
nice	bad	<1%

Figure 3: Highlevel gap analysis to quantify the gap in the overall performance.

Environment

BOSCH

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Partners

External partners

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KI FAMILIE

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