

## Domain Gaps in Lidar Perception

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. In KI-DL, we studied two instances of domain gaps:

1. delta-sensor (high  $\rightarrow$  low resolution) and
2. delta-weather (nice  $\rightarrow$  bad weather), where both can be (approximately) cast to a missing points gap (see Fig. 1), as both situations reduce the number of points measured from an object. Following up on this assumption, we observed that there is a positive correlation between number of points and detector performance.

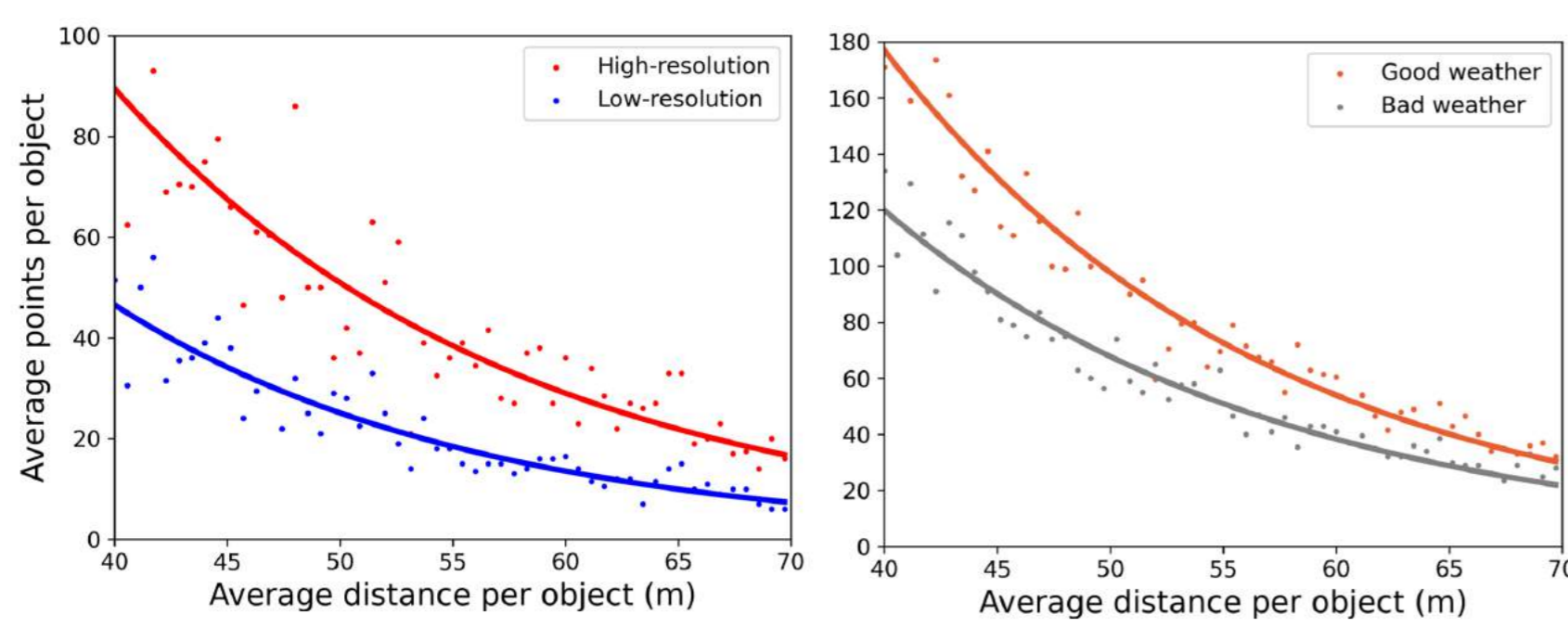


Figure 1: Missing point gap. (©Bosch)

## Bridging Approaches

We explored three different approaches to reduce the missing points gap where some modify the features and others the input data. We showed that all of them have the potential to reduce the gap to a certain degree, but none was able to completely close it. Next, we briefly introduce the approaches.

### Unsupervised Gradient Reversal Layer (GRL)

The key idea of GRL is to remove domain information from the features by intentionally getting worse on estimating the domain of the input data. To implement this idea, in addition to the primary object detection task, there is a domain classifier attached to the backbone that predicts the domain of the data (see Fig. 2). Then, during training, the gradient of this classification head is reversed (multiplied by -1) before propagating it back through the backbone, which theoretically removes all domain-specific information from the features.

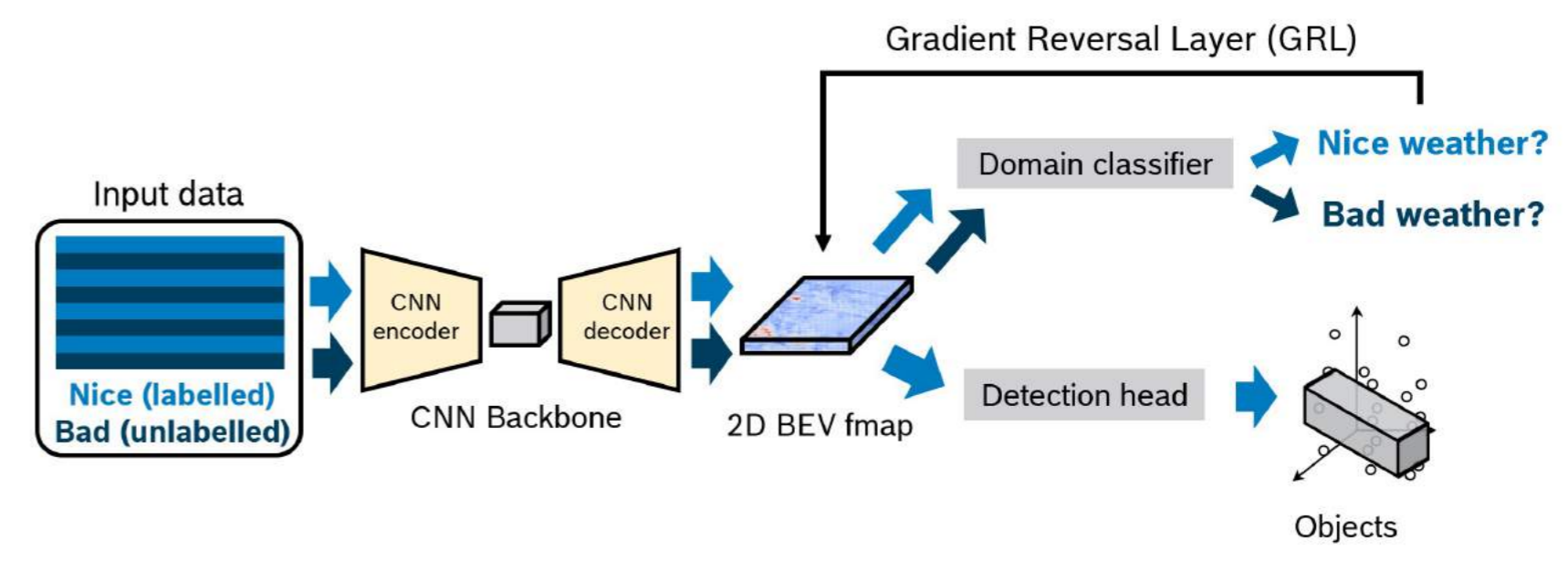


Figure 2: Overview of the **gradient reversal layer** approach. (©Bosch)

### Self-supervised Hide and Predict

Hide and predict essentially refers to inferring suppressed parts of the input data as an auxiliary task during training (See Fig. 3). That is, in addition to the primary object detection task, there is a point head attached to the backbone, which tries to predict missing data (on a 3D voxel grid). The motivation of this completion is to induce a general robustness against the missing points gap.

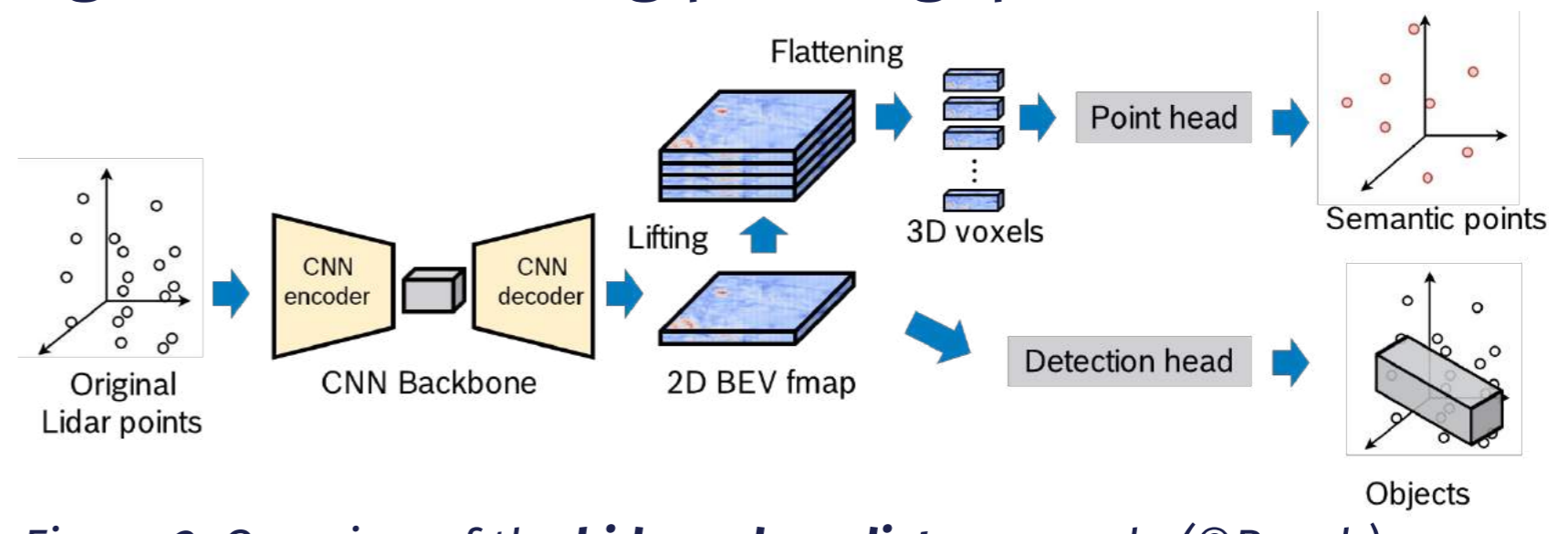


Figure 3: Overview of the **hide and predict** approach. (©Bosch)

### Sensor Emulation

Sensor emulation refers to transforming data from the source domain in a way that it looks like being measured in the target domain (See Fig. 4). We explored a geometric approach where we first emulated a target depth image (given target resolution and fov) from a source point cloud, and then projected it back to 3D. Using this re-sampled point cloud in training, the detection model could adapt to the specific data structure of the target sensor.

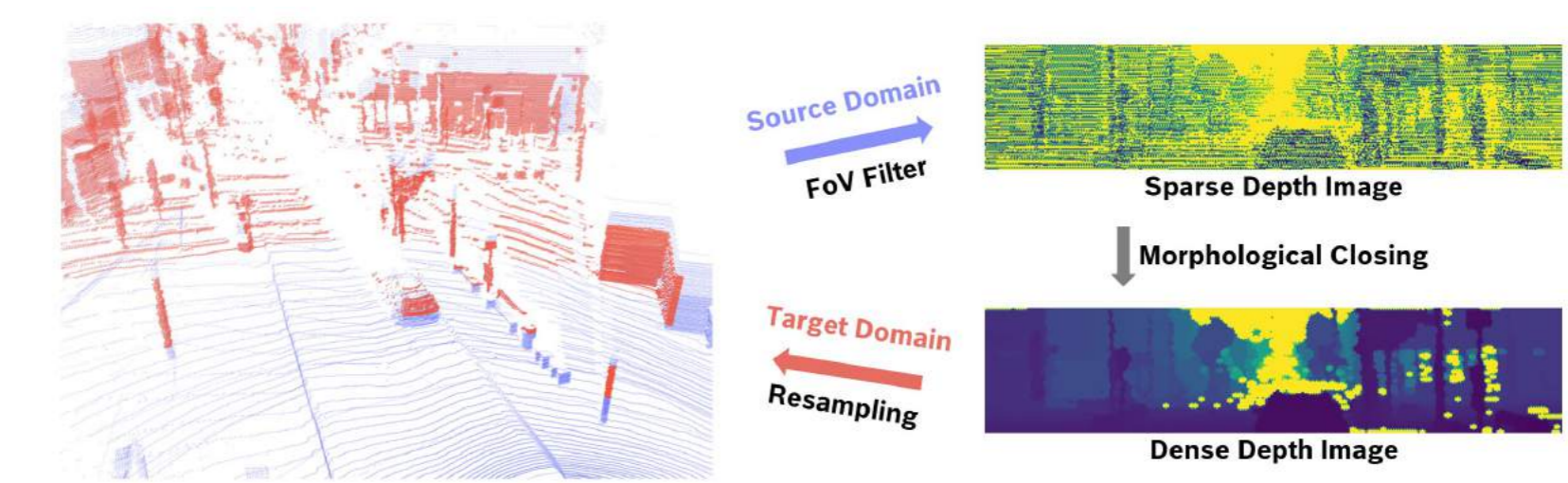


Figure 4: Overview of the **sensor emulation** approach. (©Bosch)

## Conclusions

All approaches work to some degree (5-15% relative performance gain in target domain), yet none could fully close the gap. In addition to bridging gaps, all approaches (and combinations of them) can be used as general-purpose augmentation methods to increase robustness of detectors.

	Gradient Reversal Layer	Hide and Predict	Sensor Emulation
<b>Working principle</b>	Learn domain agnostic features	Learn to complete missing information in data	Train detector with emulated data of target domain
<b>Additional requirements</b>	Unlabelled data from the target domain	-	Specs of target sensor (resolution, fov)
<b>Shortcomings by design</b>	Hard to train (known issue from GANs)	Not directly addresses origin of any gap	Ignores intensity, only works for delta-sensor gap

## Partners



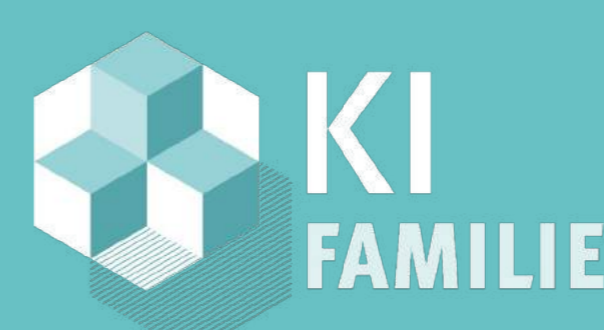
## External partners



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