ICLR | SR4AD Workshop

Benchmarking 3D Perception Robustness to Common Corruptions and Sensor Failure

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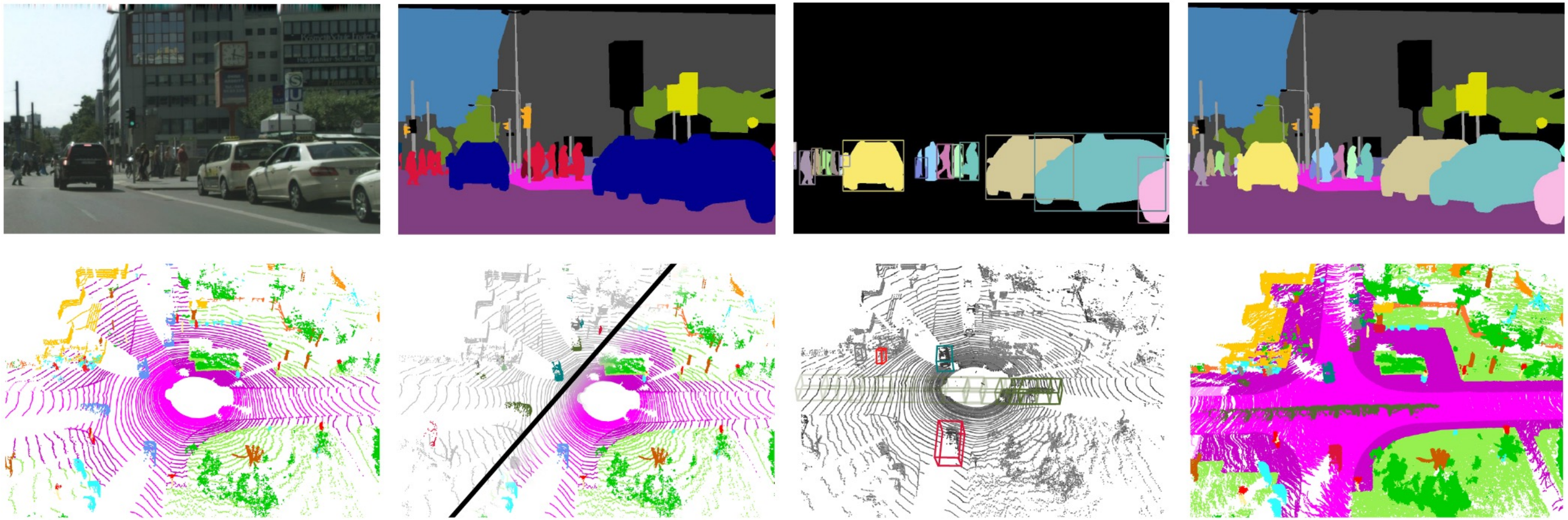
3D Perception in Autonomous Driving



From left to right:
- LiDAR semantic segmentation
- LiDAR panoptic segmentation
- 3D object detection
- 4D LiDAR panoptic segmentation

Why LiDAR sensors?
- Accurate depth sensing
- Robust at low-light conditions
- 3D positional information
- …

Perception Environment



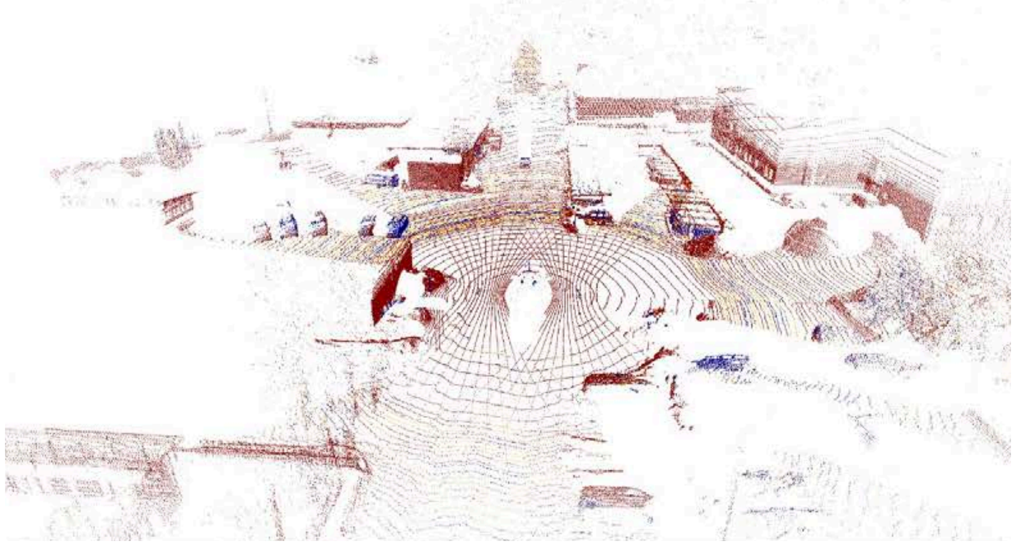



*Image credit: https://zod.zenseact.com

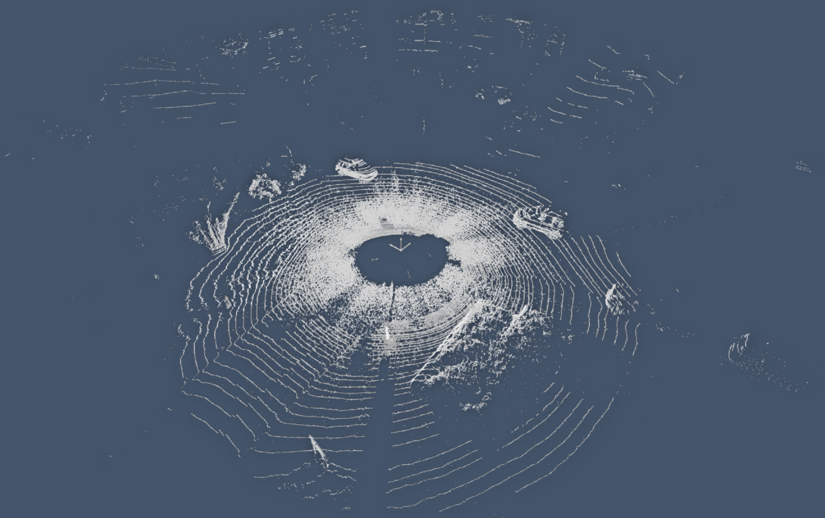
Robo3D

TL;DR

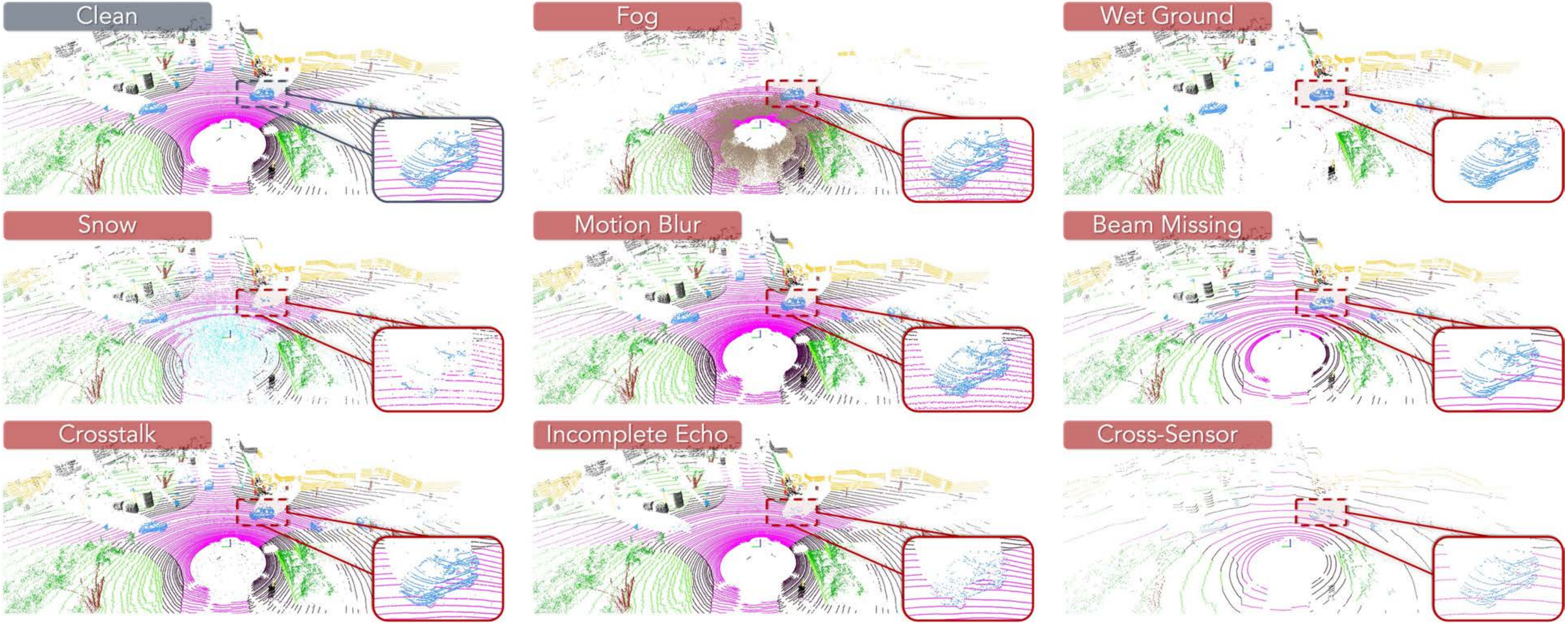
- We introduce Robo3D, the first systematically-designed robustness evaluation suite for LiDAR-based 3D perception under corruptions and sensor failure

- We benchmark 34 perception models for LiDAR-based semantic segmentation and object detection tasks, on their robustness against corruptions.

- Based on our observations, we draw in-depth discussions on the receipt of designing robust and reliable 3D perception models.

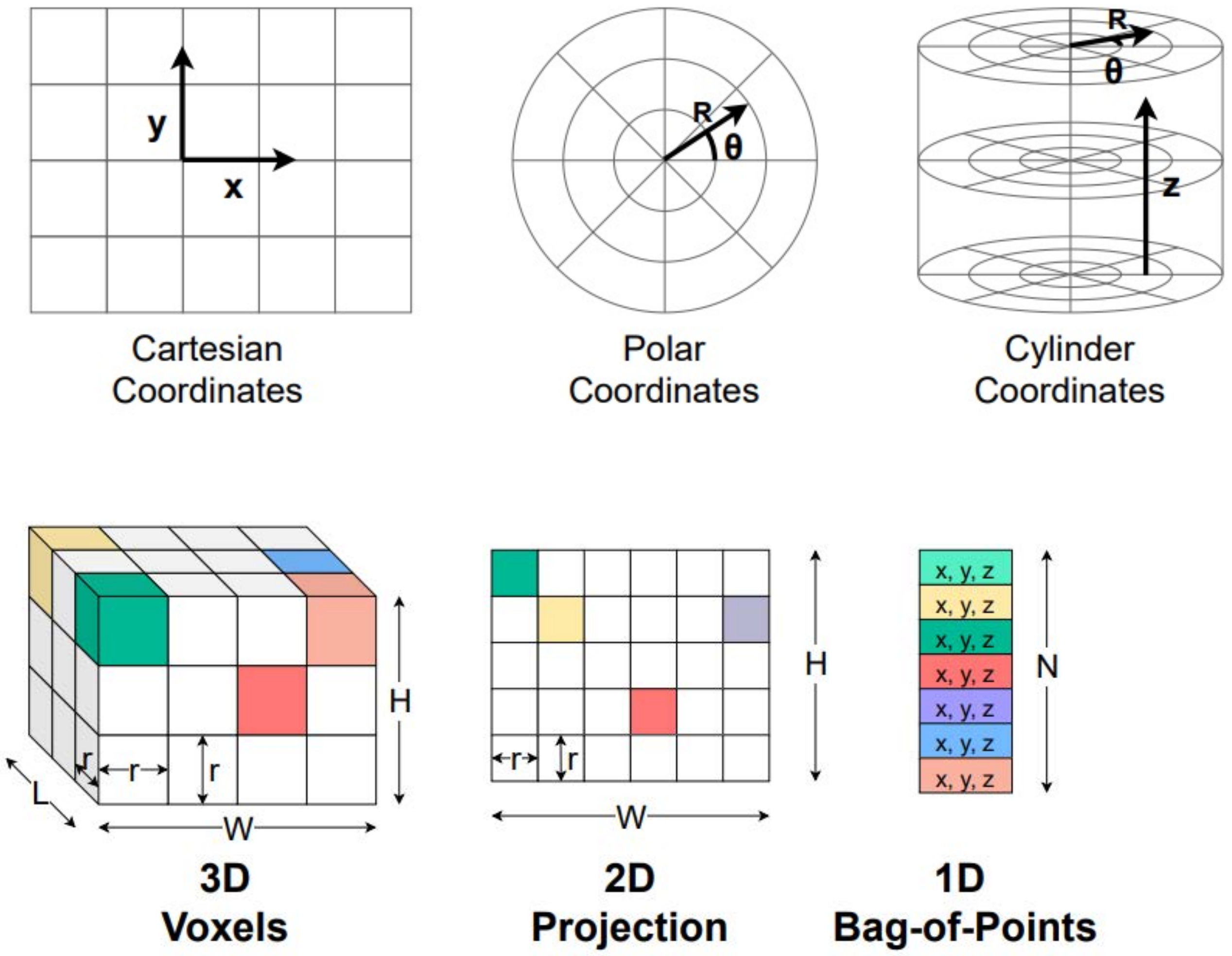


Robo3D: Taxonomy



*More examples at: https://ldkong.com/Robo3D

Robo3D: Representation



Representation:

- **2D:** range view, bird's eye view
- **3D:** cubic voxel, cylinder voxel

Operator:

- **3D:** Conv3d, SparseConv, etc.
- **2D:** Conv2d, Linear, etc.
- **1D:** Conv1d, Linear, etc.

M. Uecker, et al. "Analyzing deep learning representations of point clouds for real-time in-vehicle LiDAR perception," *arXiv*, 2022.

Robo3D: Statistics

Corruption Type:

- Include 8 types, each with 3 severity levels

Dataset (6 different sets):

- **LiDAR Semantic Segmentation:** [1]SemanticKITTI-C, [2]nuScenes-C (Seg3D), [3]WOD-C (Seg3D)
- **3D Object Detection:** [4]KITTI-C, [5]nuScenes-C (Det3D), [6]WOD-C (Det3D)

Model & Algorithm (34 perception models):

- **LiDAR Semantic Segmentation:** 22 segmentors
- **3D Object Detection:** 12 detectors
- **Data Augmentation:** 3 augmentation techniques

Robo3D

Robo3D: Metrics

Task-Specific Accuracy (Acc):

- **LiDAR Semantic Segmentation:** mean IoU (**mIoU**)
- **3D Object Detection:** mean AP (**mAP**), nuScenes Detection Score (**NDS**)

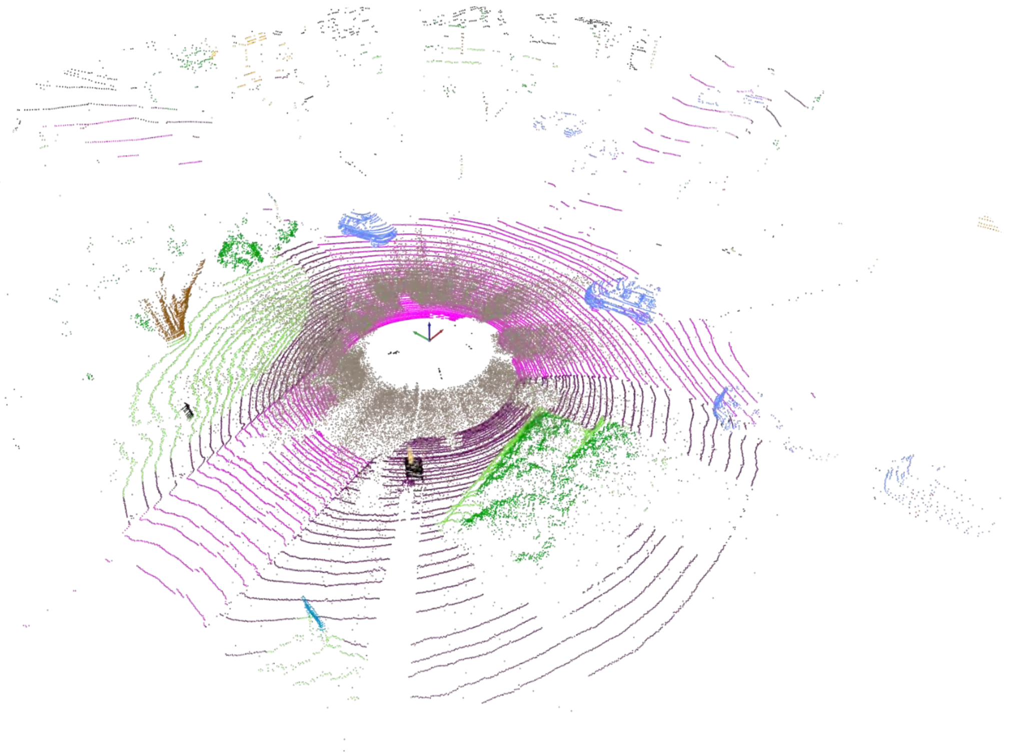
Robustness Metrics:

- **Mean Corruption Error (mCE):**

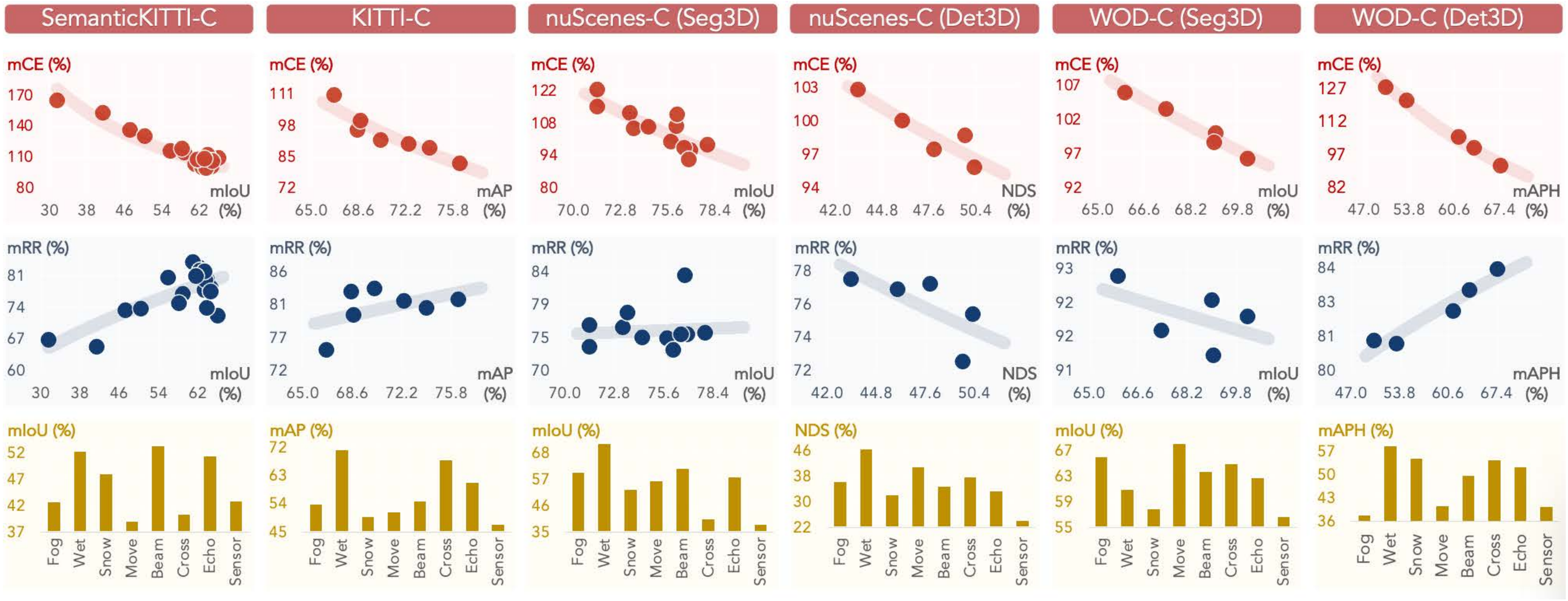
$$\mathrm{CE}_i = \frac{\sum_{l=1}^{3}(1-\mathrm{Acc}_{i,l})}{\sum_{l=1}^{3}(1-\mathrm{Acc}_{i,l}^{\mathrm{baseline}})}, \quad \mathrm{mCE} = \frac{1}{N}\sum_{i=1}^{N}\mathrm{CE}_i$$

- **Mean Resilience Rate (mRR):**

$$\mathrm{RR}_i = \frac{\sum_{l=1}^{3}\mathrm{Acc}_{i,l}}{3\times \mathrm{Acc}_{\mathrm{clean}}}, \quad \mathrm{mRR} = \frac{1}{N}\sum_{i=1}^{N}\mathrm{RR}_i$$



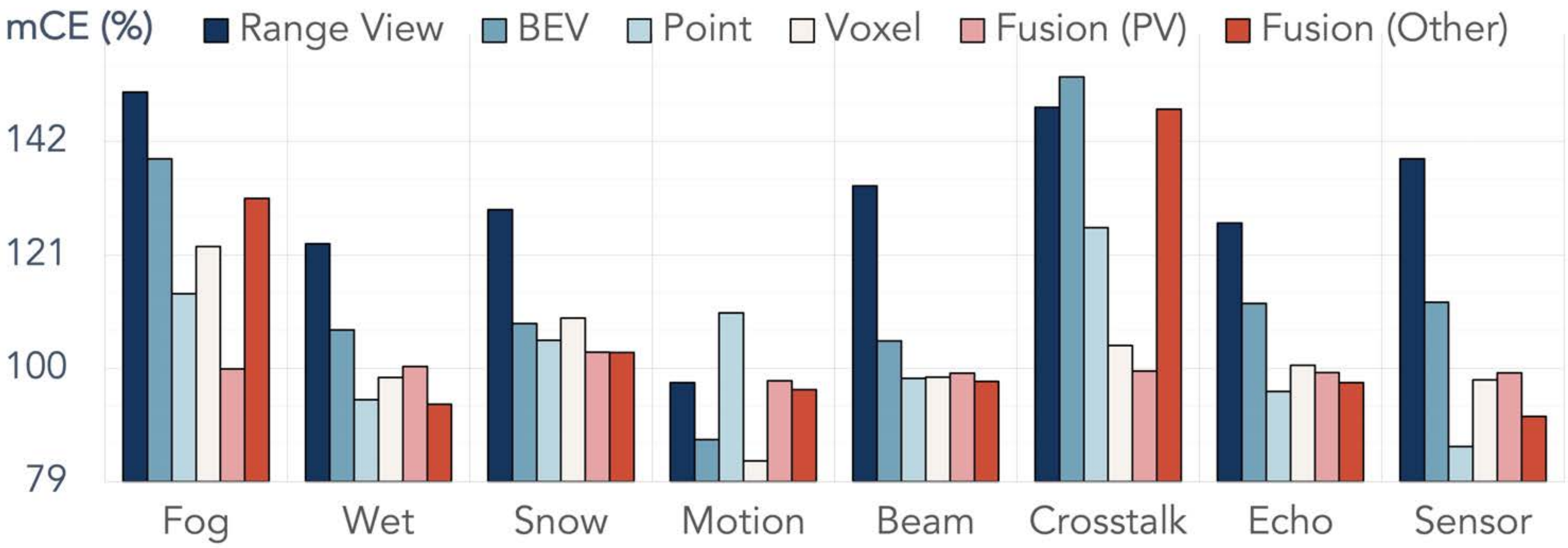
Robo3D: Benchmarking Result



*More results and analysis at: https://github.com/ldkong1205/Robo3D

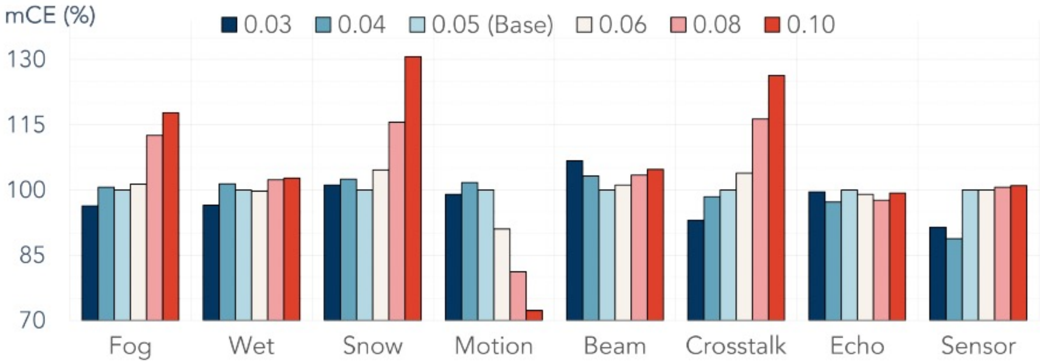
Robo3D: Key Observation

1. Existing 3D detectors and segmentors are **vulnerable** to real-world corruptions.
2. Models trained with LiDAR data from different sources (sensor setups) exhibit **inconsistent sensitivities** to each corruption type.
3. Representing the LiDAR data as raw **points**, sparse **voxel**, or the **fusion** of them tend to yield better robustness.

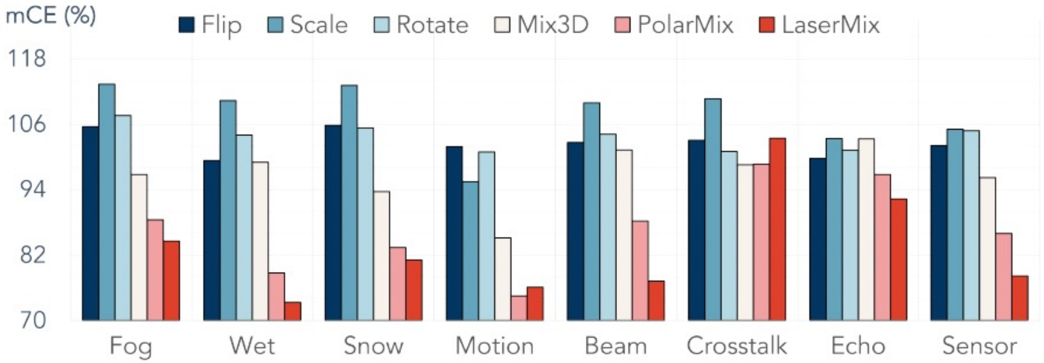


Robo3D: Key Observation

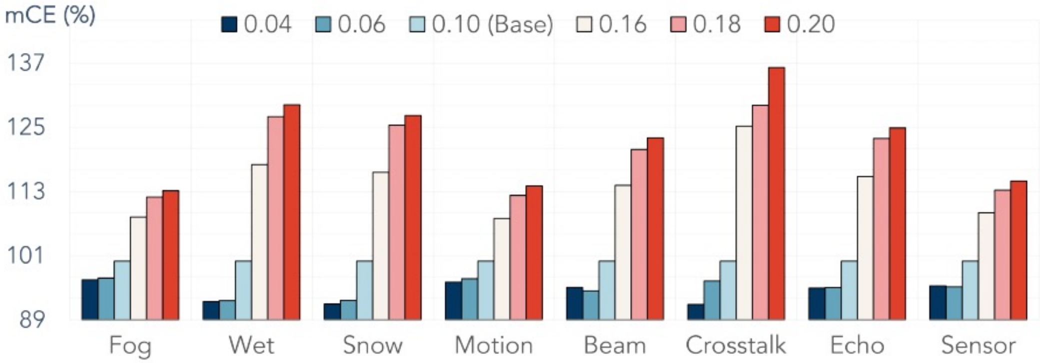
4. The 3D detectors and segmentors show different **sensitivities** to corruption scenarios.
5. The recent **out-of-context augmentation techniques** improve 3D robustness by large margins; the flexible rasterization strategies help learn more robust features.



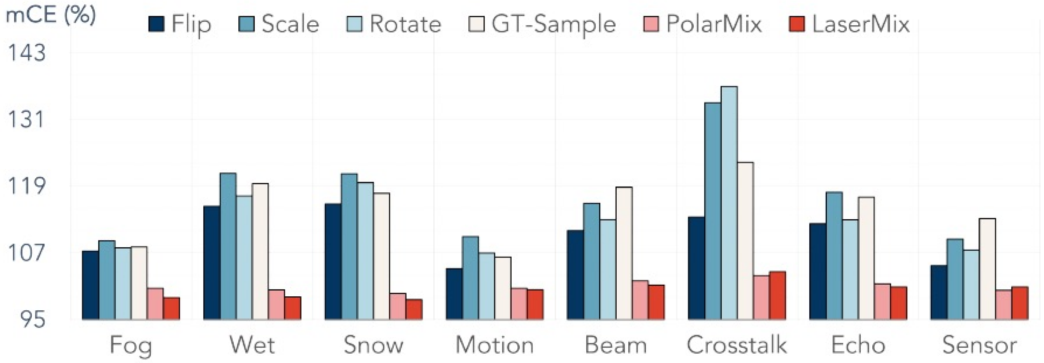
(a) Voxel Size on *SemanticKITTI-C* (Seg3D)



(b) Augmentation on *SemanticKITTI-C* (Seg3D)

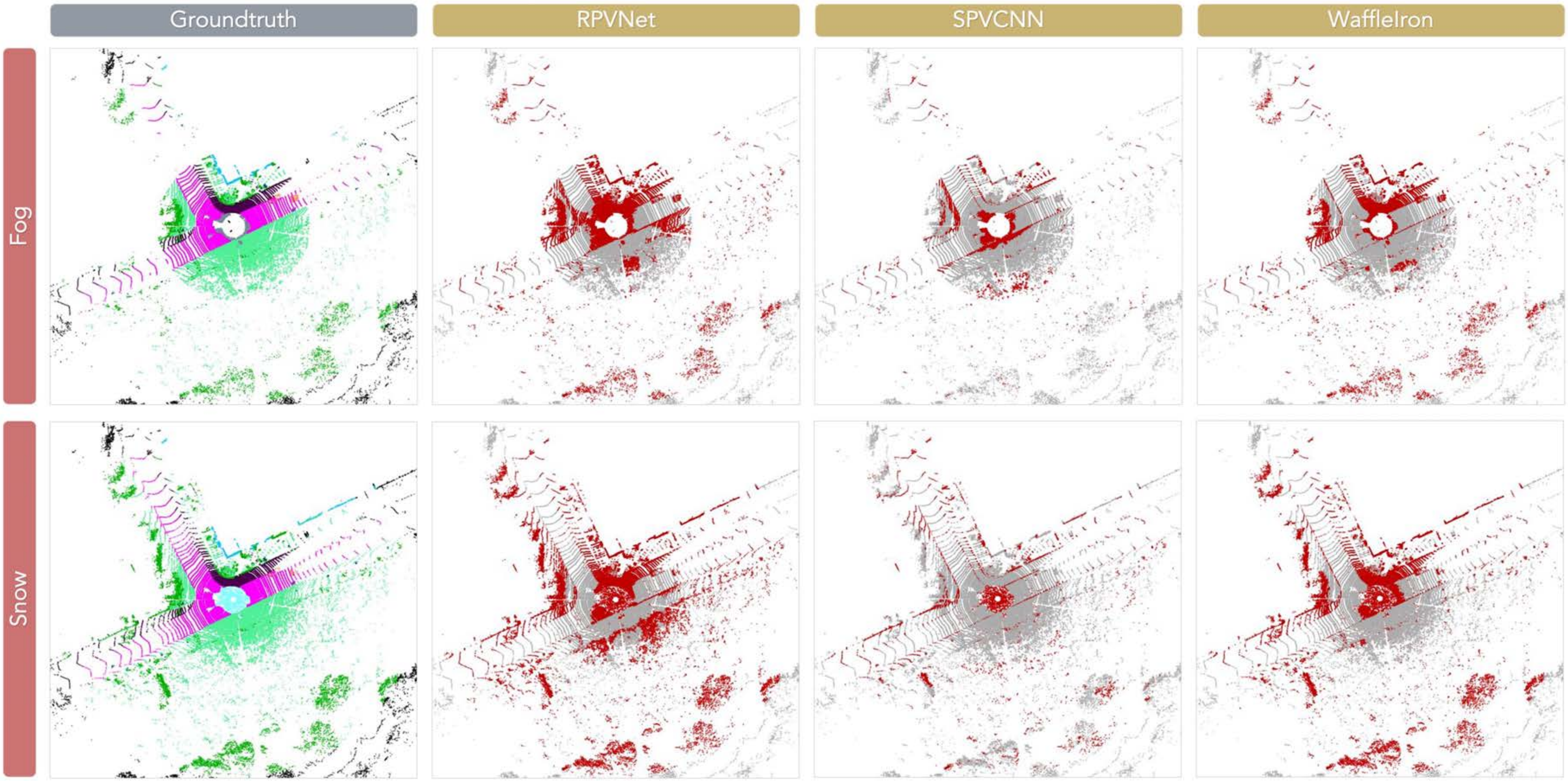


(c) Voxel Size on *WOD-C* (Det3D)

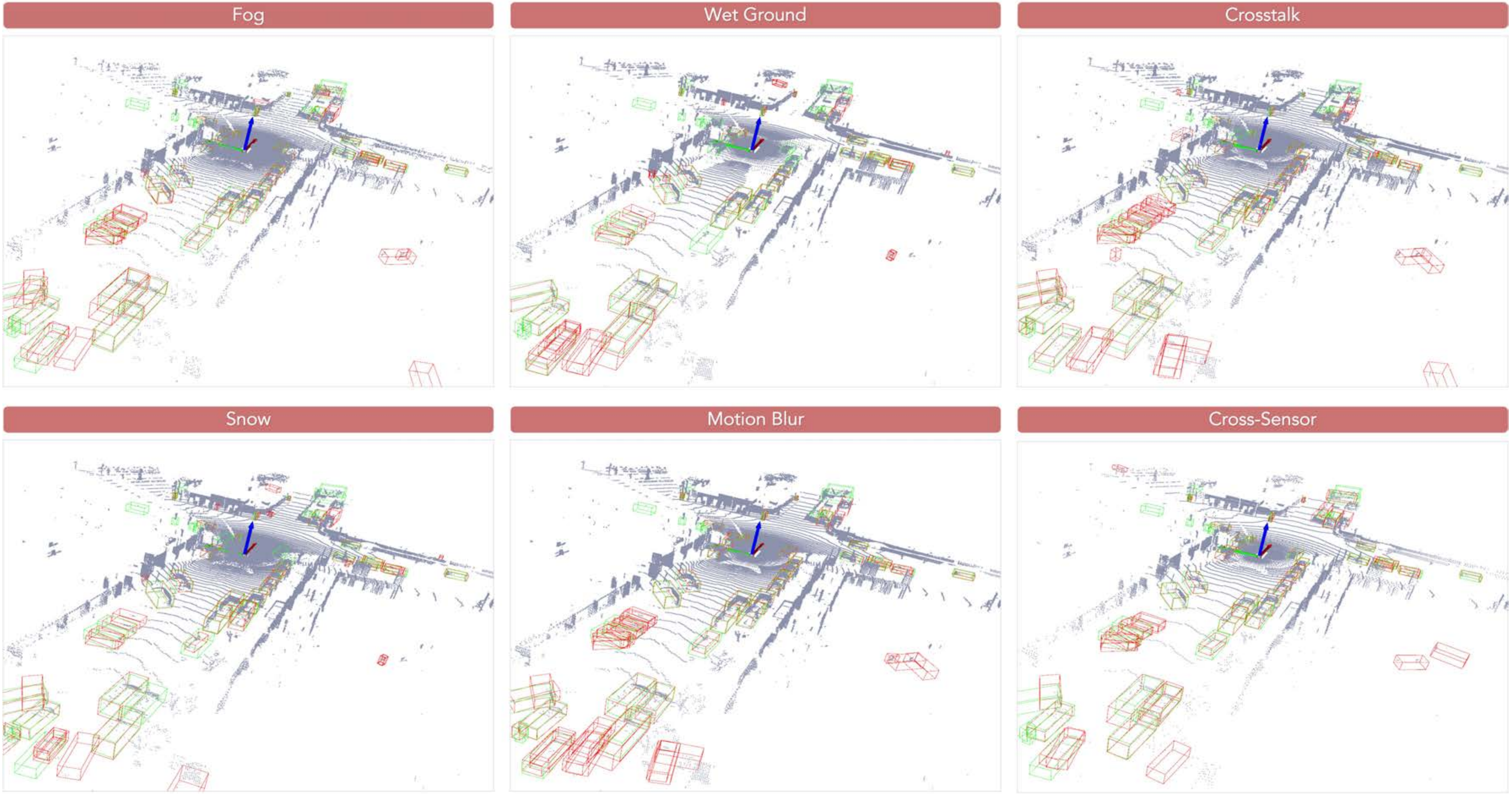


(d) Augmentation on *WOD-C* (Det3D)

Robo3D: Qualitative Assessment



Robo3D: Qualitative Assessment



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Thank you for your attention!

Robo3D

Paper

Code

MMDet3D