Institute of Automotive Technology
TUM School of Engineering and Design
Technical University of Munich

Methods for Sensor Failure Mitigation in 3D Object Detection

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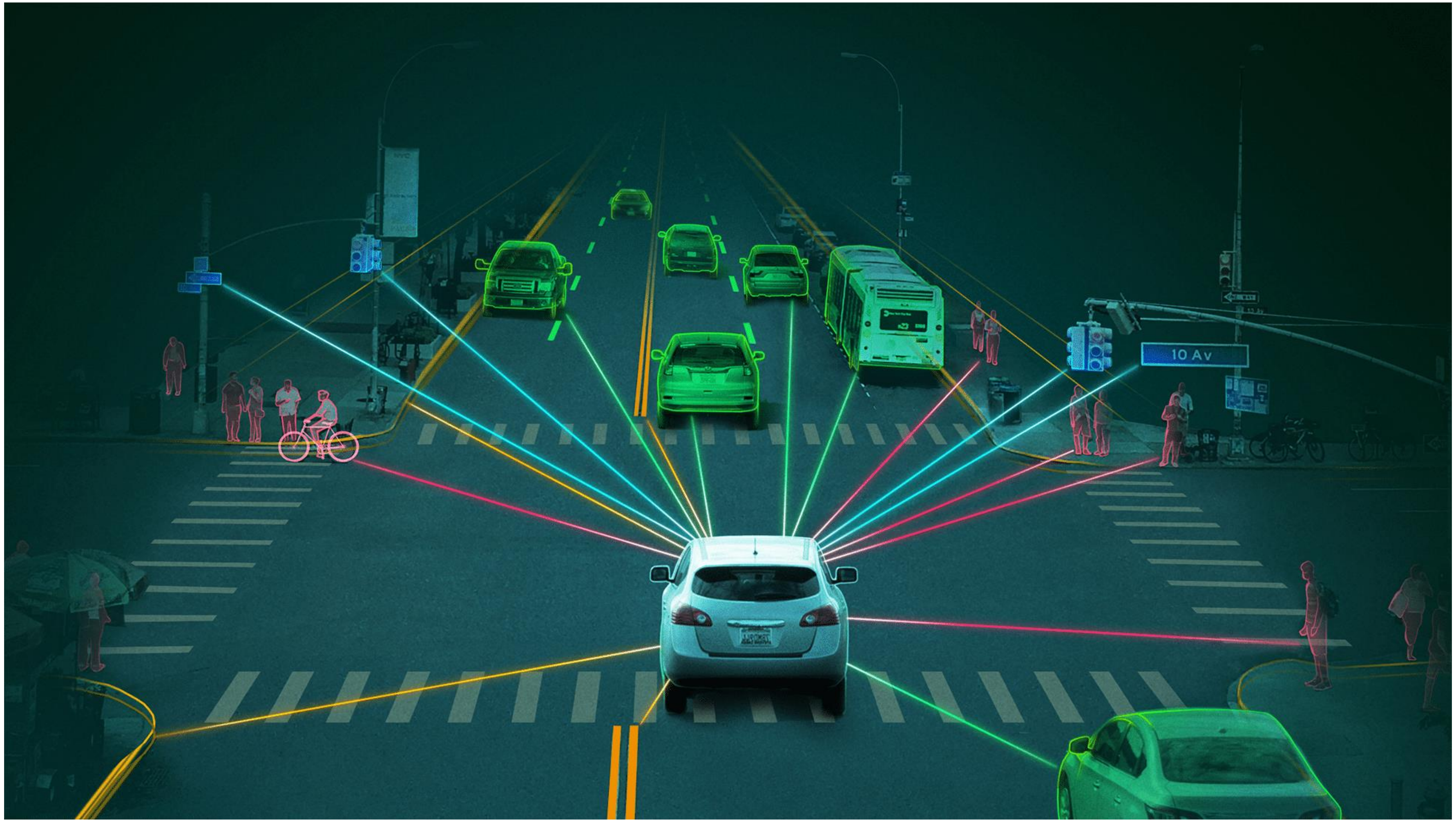
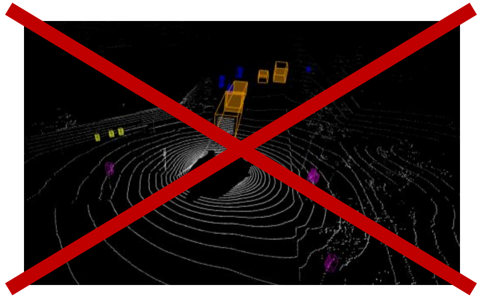
Sensing the Environment

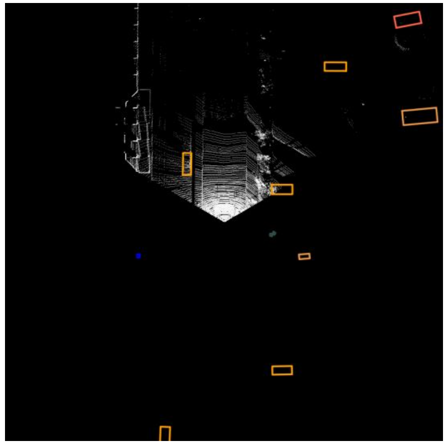


Real-World Conditions

Full Sensor Failure
(e.g. damaged sensor)



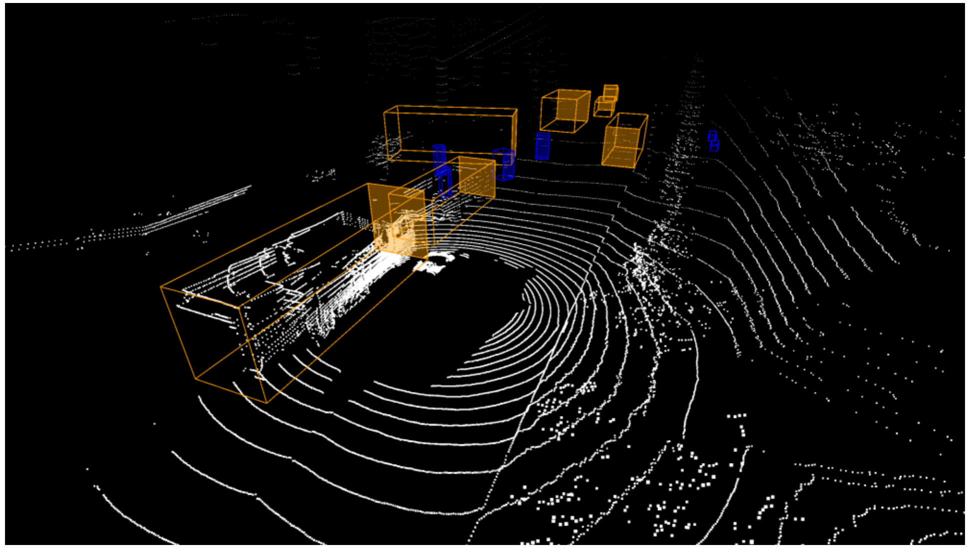
Partial Sensor Failure
(e.g. occlusion)



➔ Detection system should be **robust** against sensor failure

Input Modalities

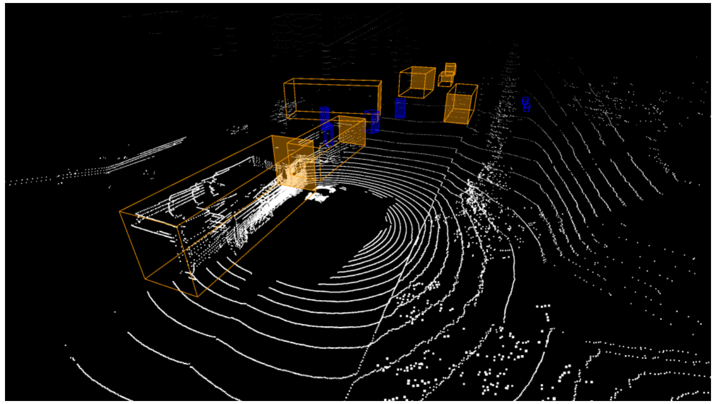
Camera

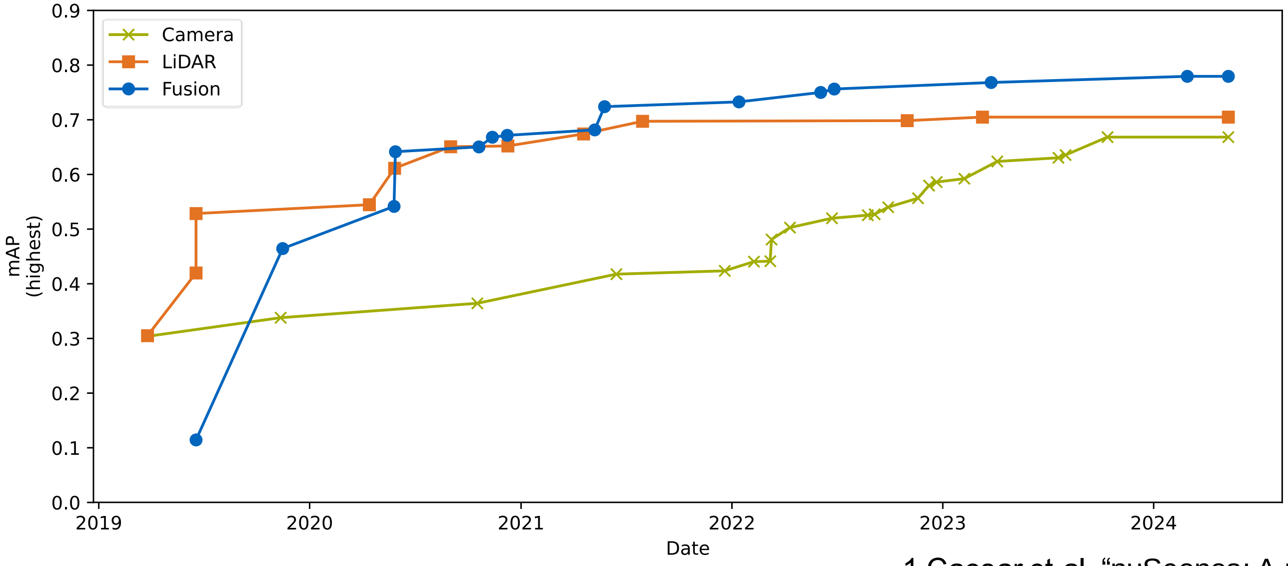


LiDAR

1 Caesar et al. “nuScenes: A multimodal dataset for autonomous driving“

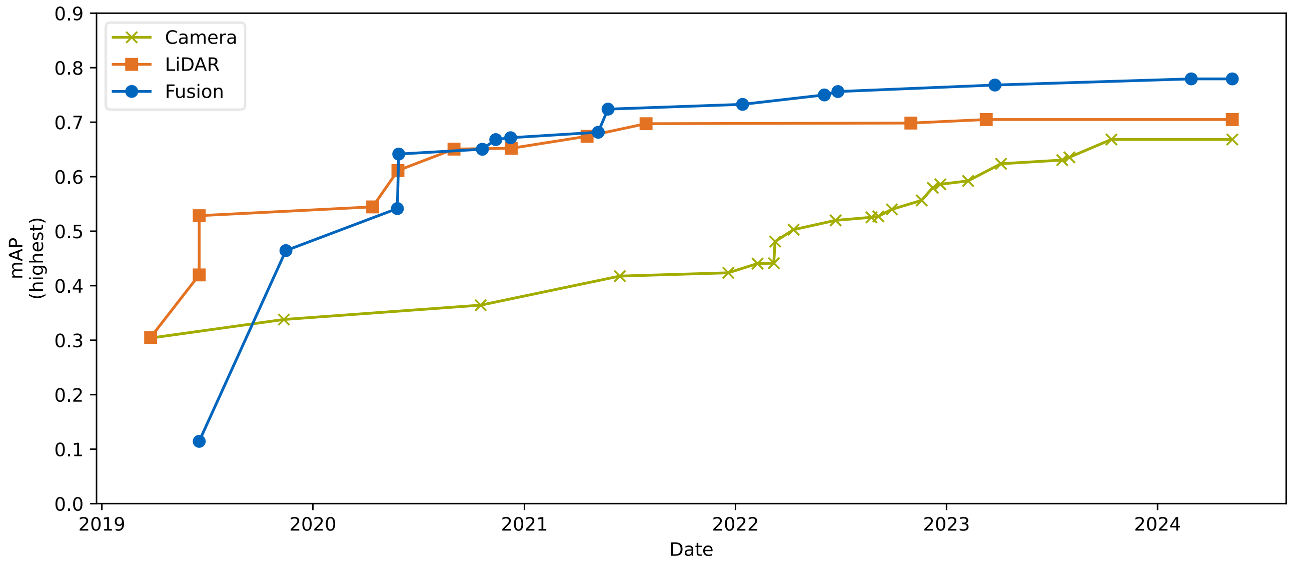
Input Modalities





1 Caesar et al. “nuScenes: A multimodal dataset for autonomous driving“

Input Modalities



LiDAR outperforms camera for 3D object detection

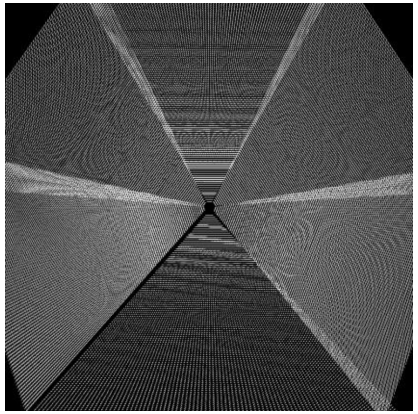
Fusion models have a higher reliance on LiDAR

1 Caesar et al. “nuScenes: A multimodal dataset for autonomous driving“

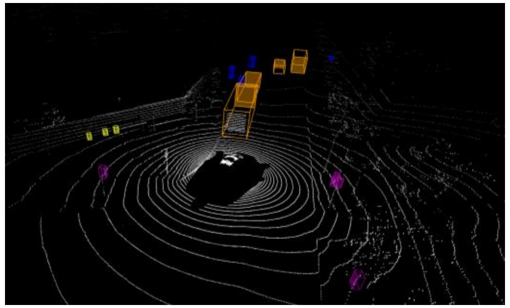
Sensor Fusion: Bird’s Eye View (BEV)

Camera

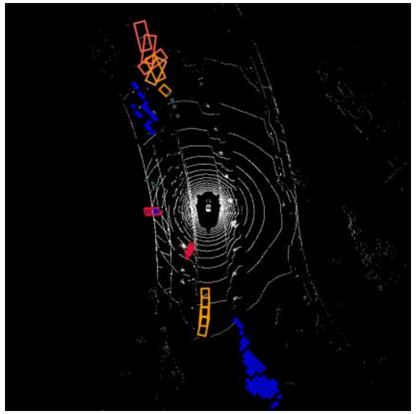
Explicit projection into 3D[2]



LiDAR



Flatten



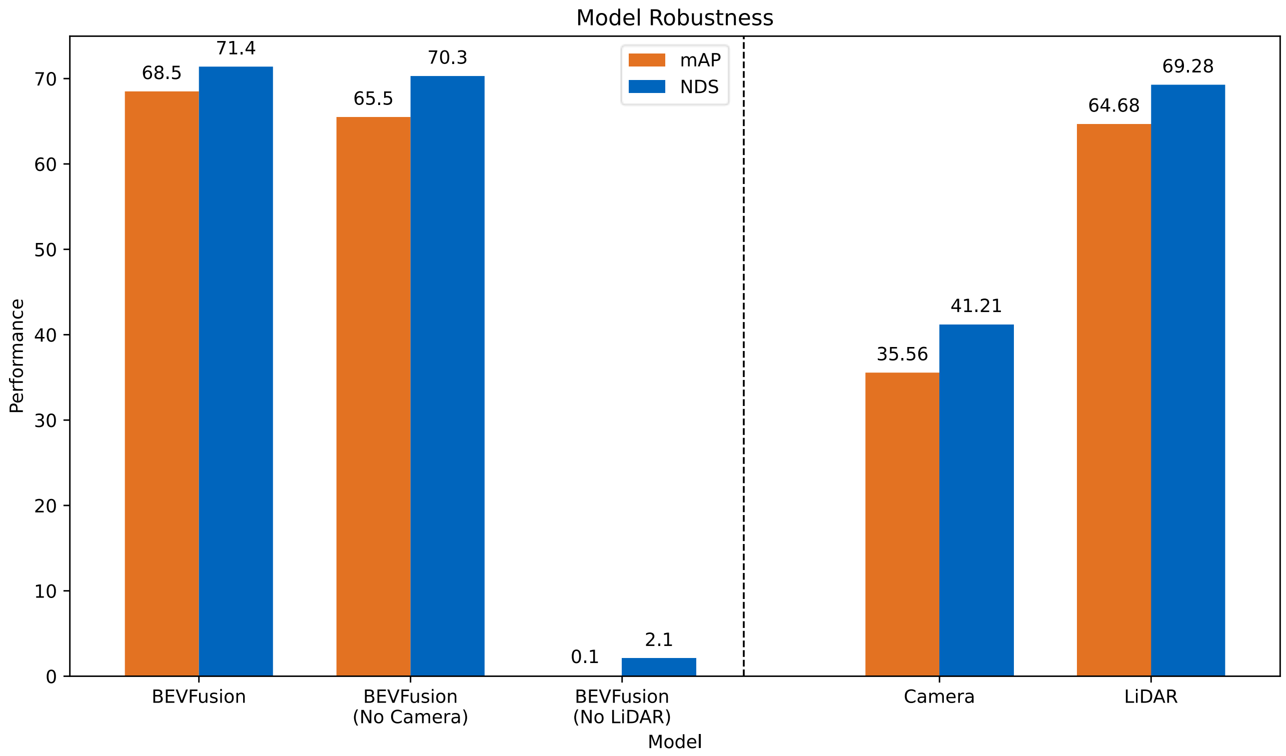
Fusion Model

2 J. Philion, S. Fidler “Lift, Splat, Shoot: Encoding Images from Arbitrary Camera Rigs by Implicitly Unprojecting to 3D”

Robustness of existing fusion methods

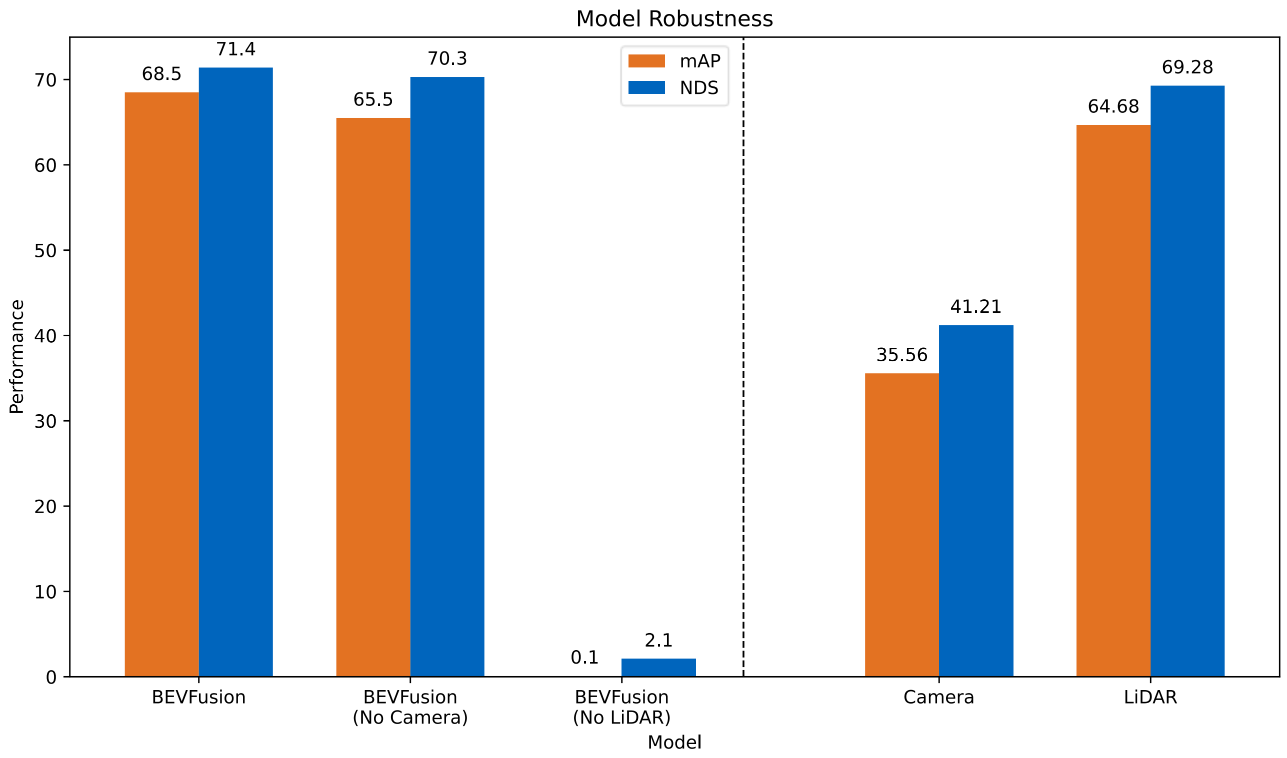
Performance in the event of **full sensor failure:**

Example: BEVFusion[3]



3 Liu et al. "BEVFusion: Multi-Task Multi-Sensor Fusion with Unified Bird's-Eye View Representation"

Robustness of existing fusion methods



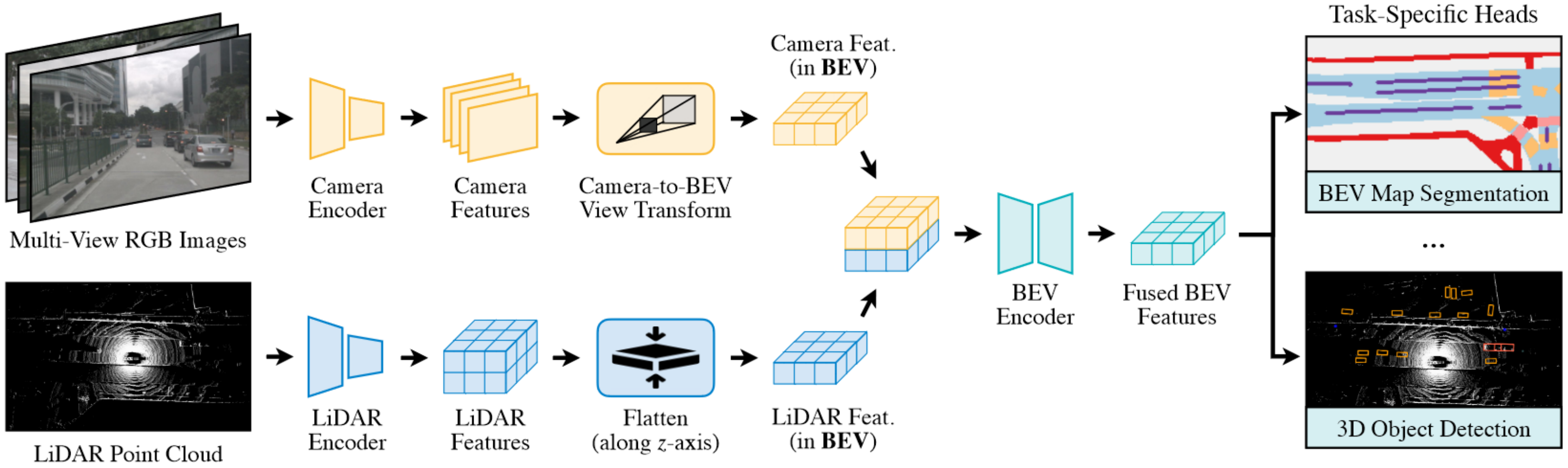
Existing sensor fusion methods **fail** when the LiDAR sensor fails

➔ **Goal:** Make sensor fusion robust against LiDAR failure

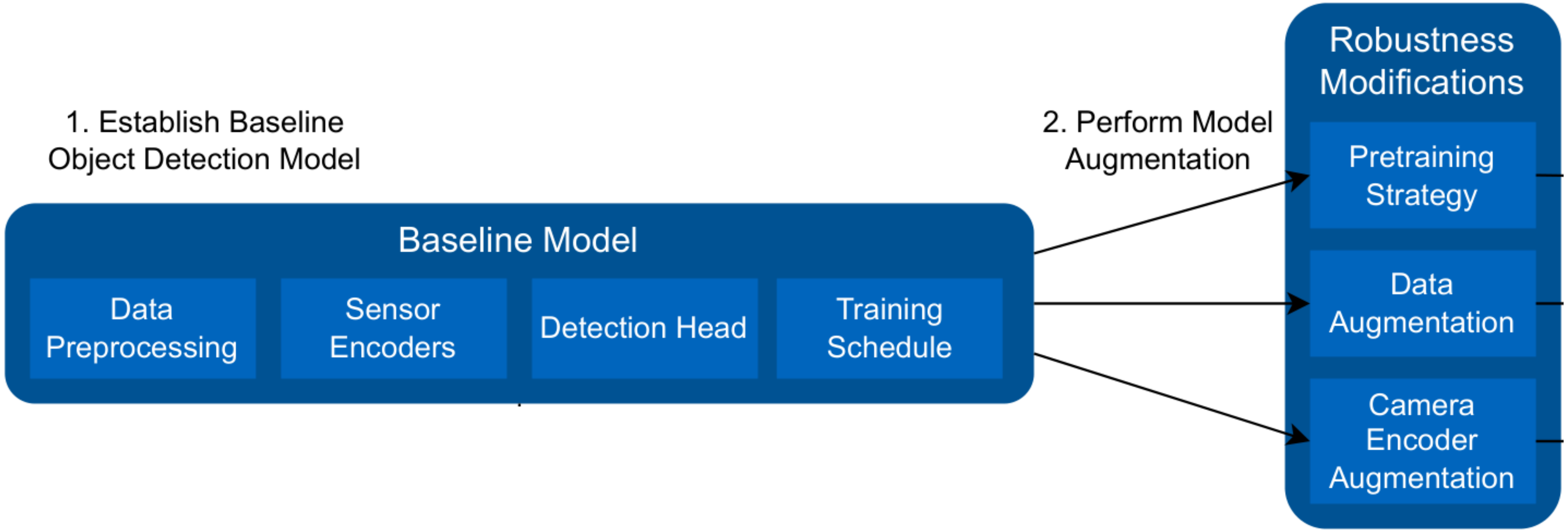
Approach: Baseline

Baseline Model

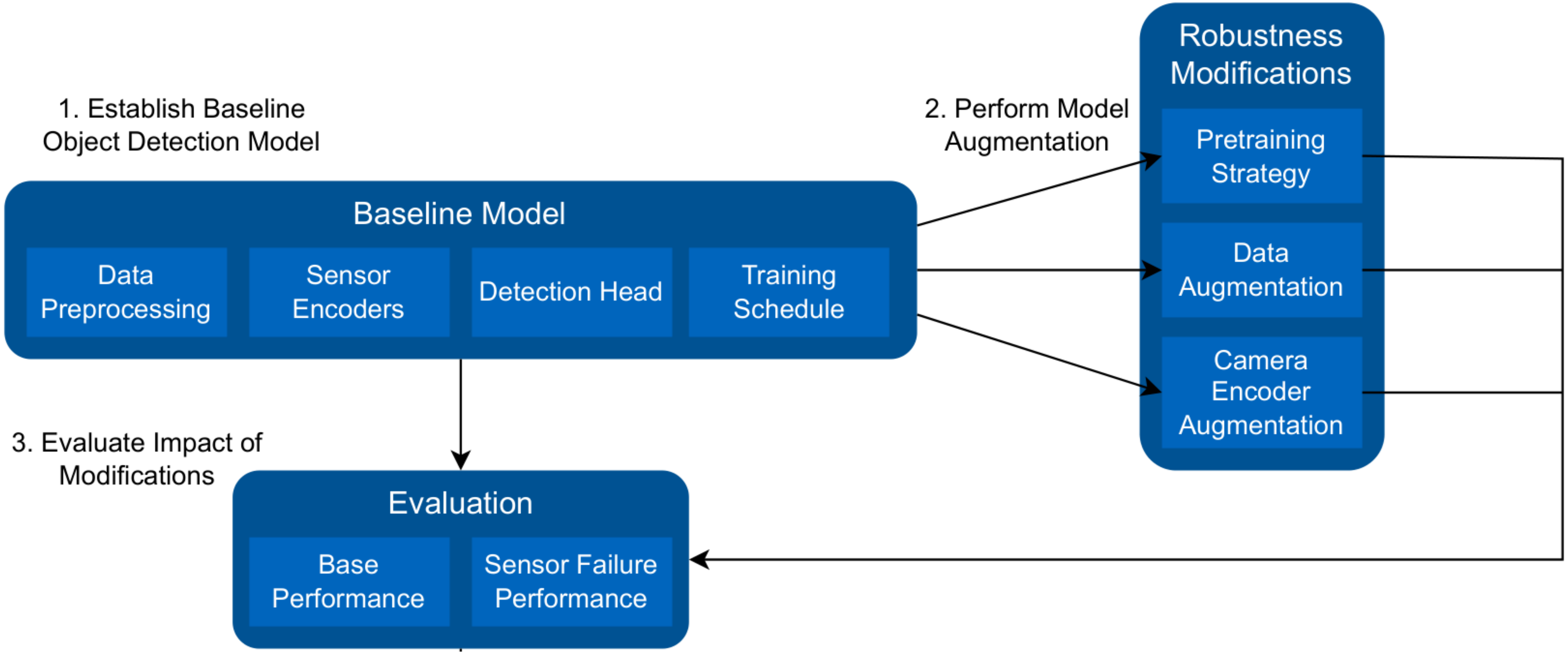
Data Preprocessing | Sensor Encoders | Detection Head | Training Schedule



Approach: Modifications

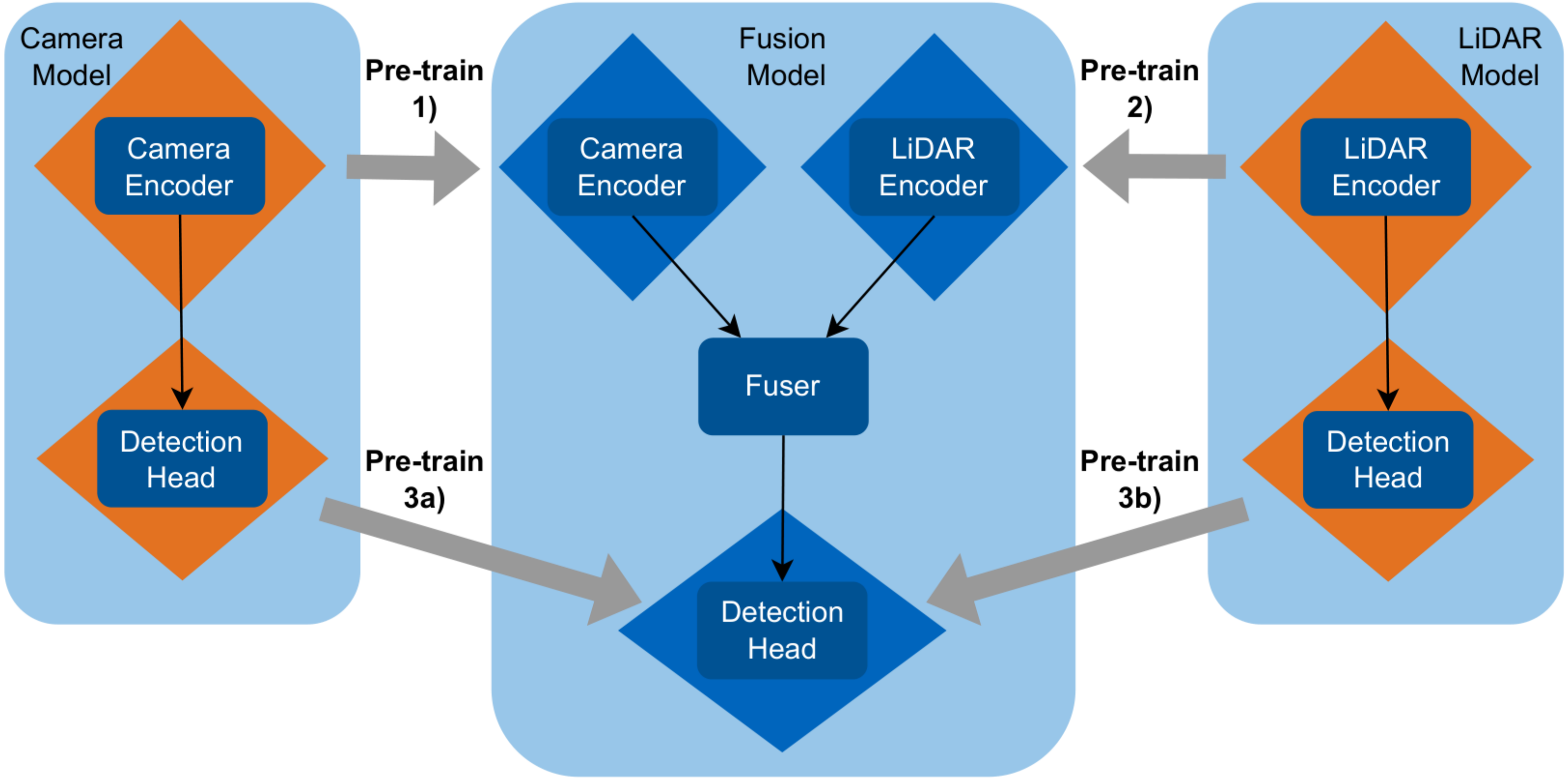


Approach: Evaluation



Method #1: Pretraining Strategy

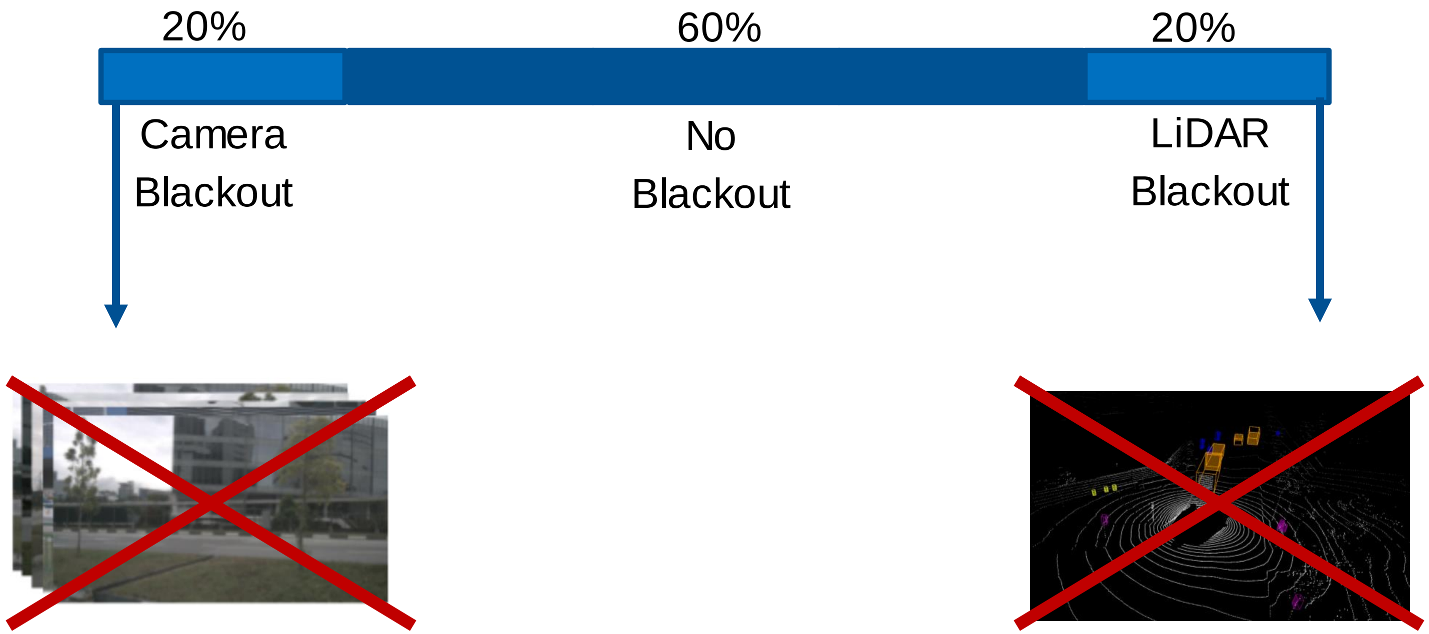
Original BEVFusion: **only pretrain LiDAR** model



➔ Try different variations

Method #2: Data Augmentation

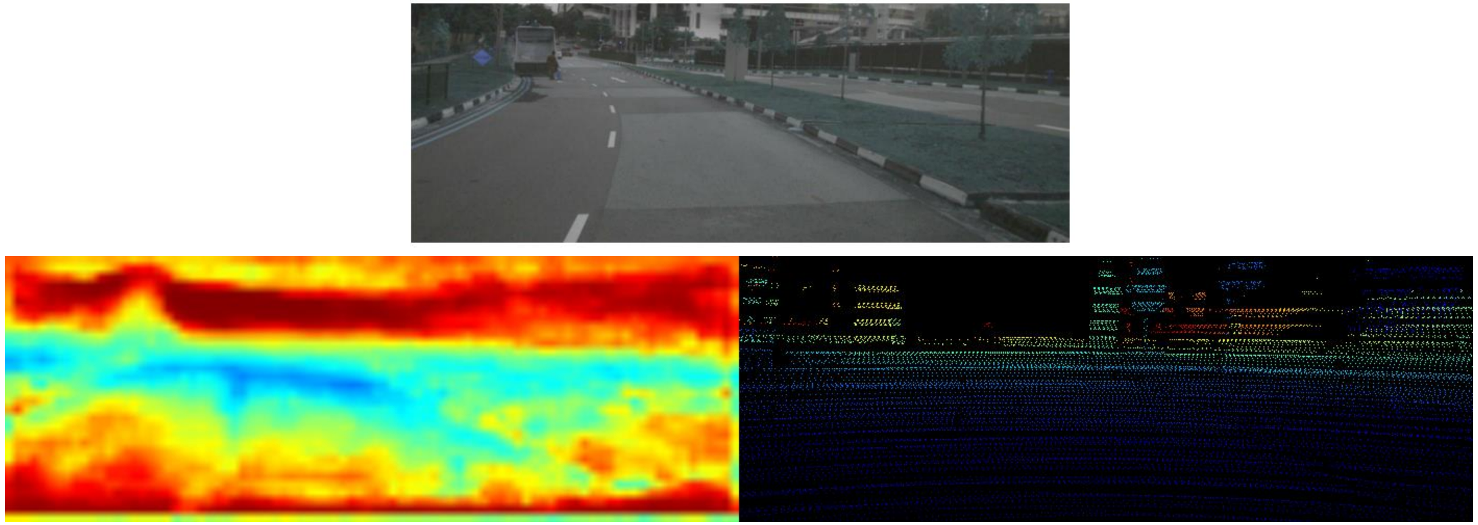
Simulate **total** sensor failure during training.



Blackout is applied randomly for each batch at 20% chance.

Method #3: Strengthen Camera Encoder

Strengthening the camera model could improve performance when the LiDAR sensor fails.



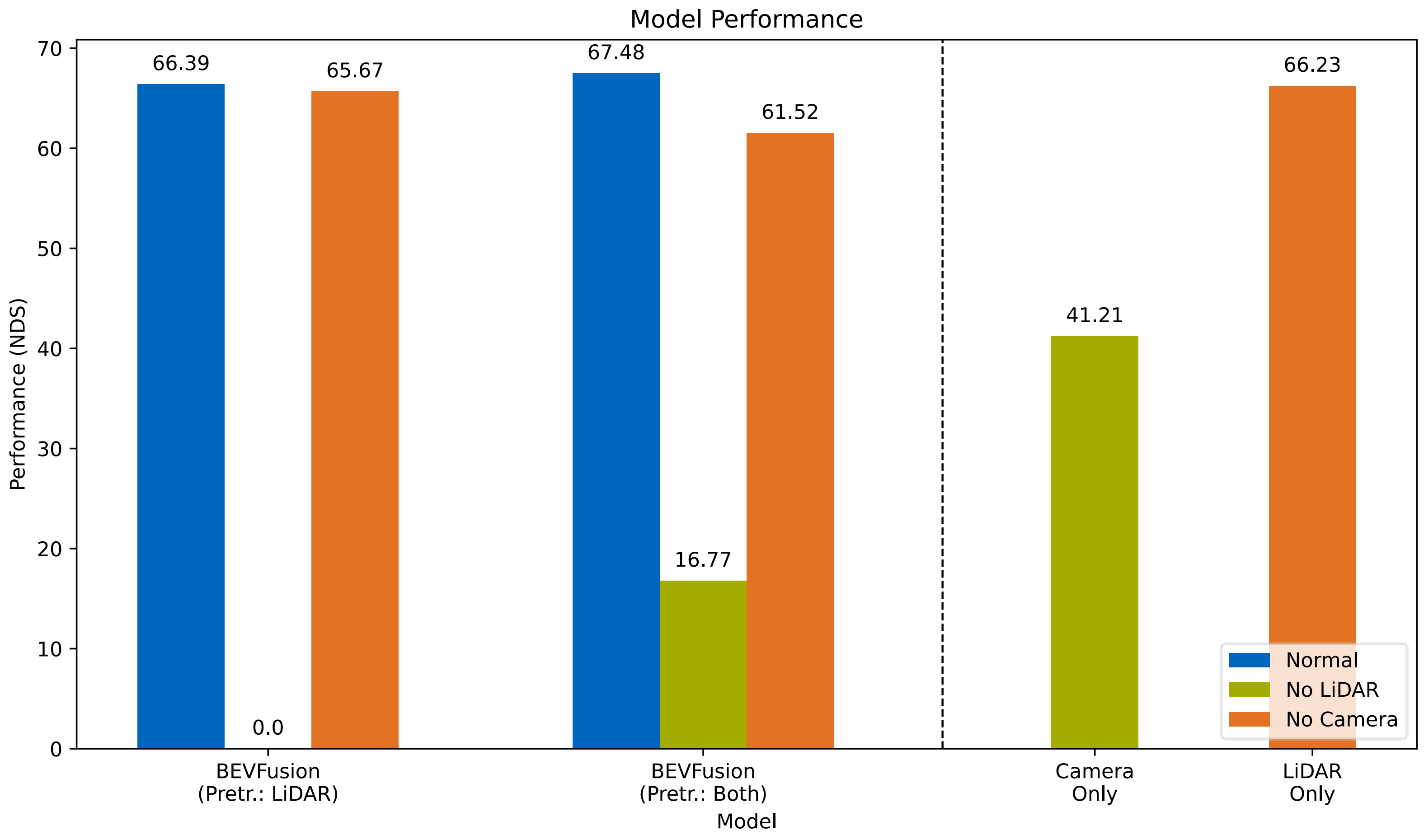
Camera depth prediction	True LiDAR-based depth

The camera model **explicitly predicts** the **depth** of each pixel.
This prediction is very inaccurate.

=> Improve prediction by using LiDAR-based depth as supervision during training

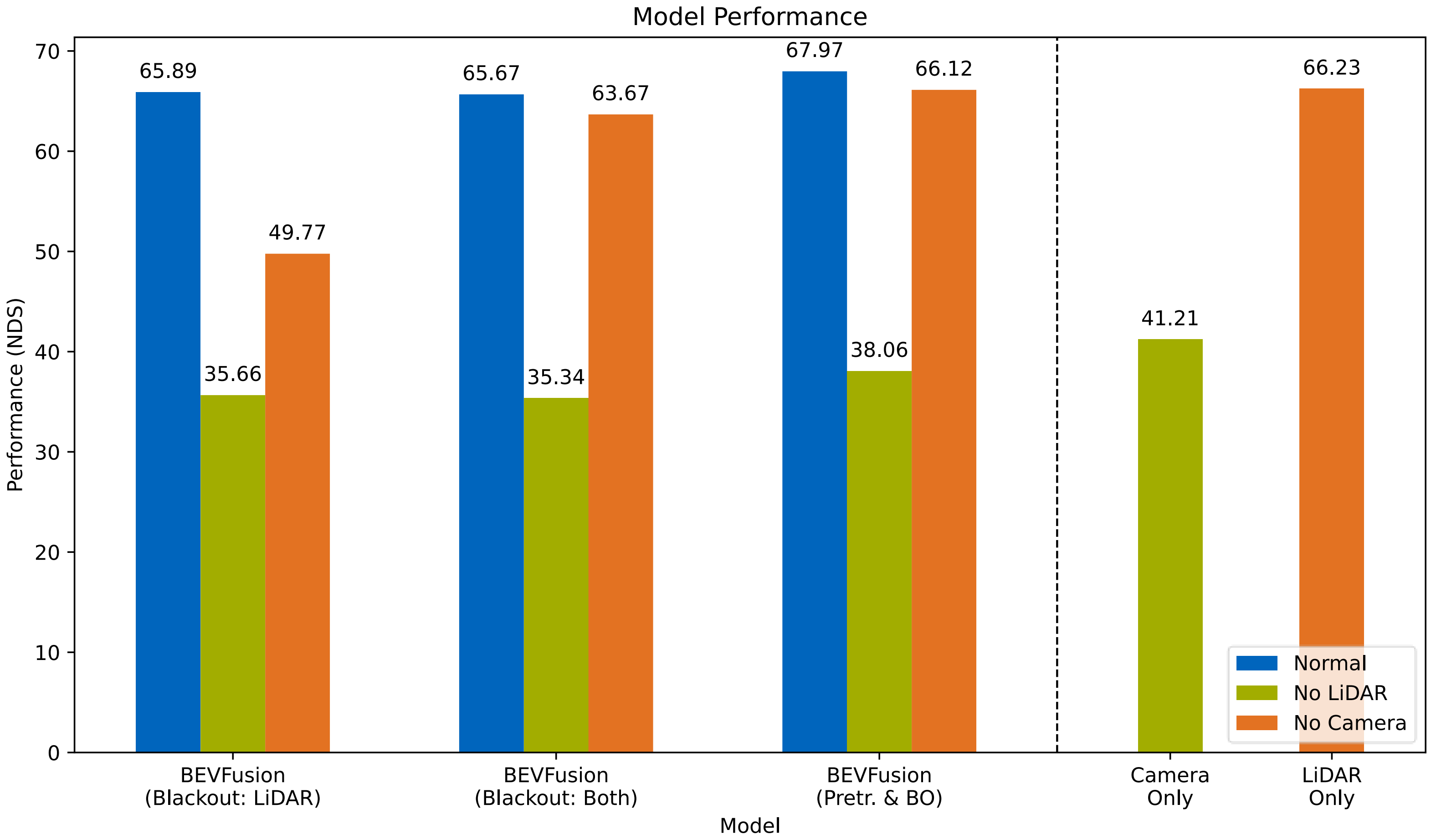
4 Li et al. “BEVDepth: Acquisition of Reliable Depth for Multi-view 3D Object Detection”

Results: Pretraining



=> Pretraining has a noticeable effect on robustness against sensor failure

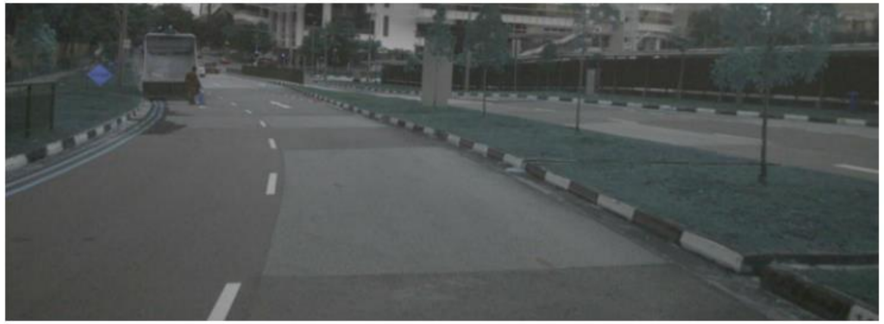
Results: Data Augmentation



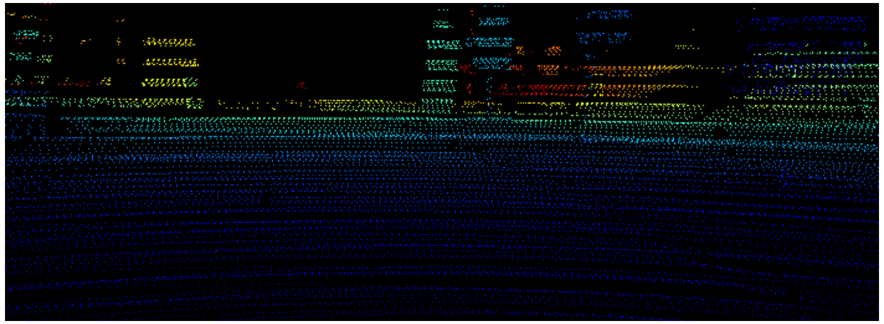
=> <u>Data augmentation has a substantial effect on robustness against sensor failure</u>

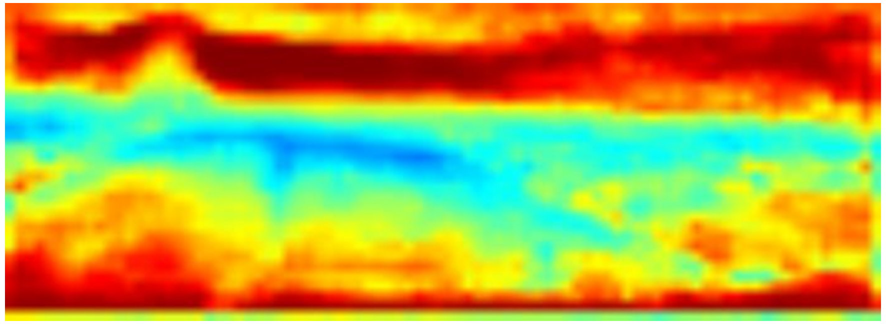
Results: Camera Encoder

Camera view

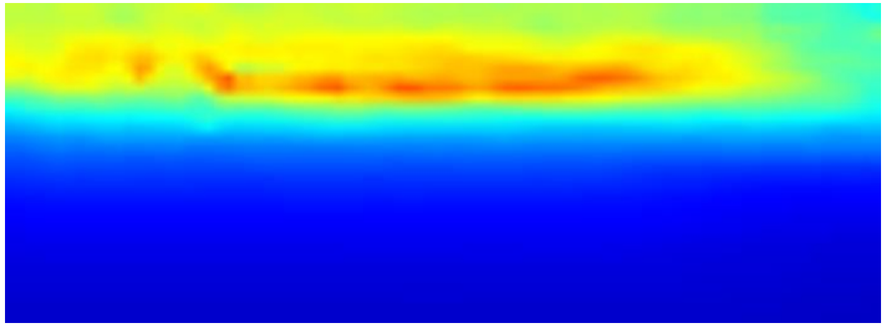


LiDAR-based depth





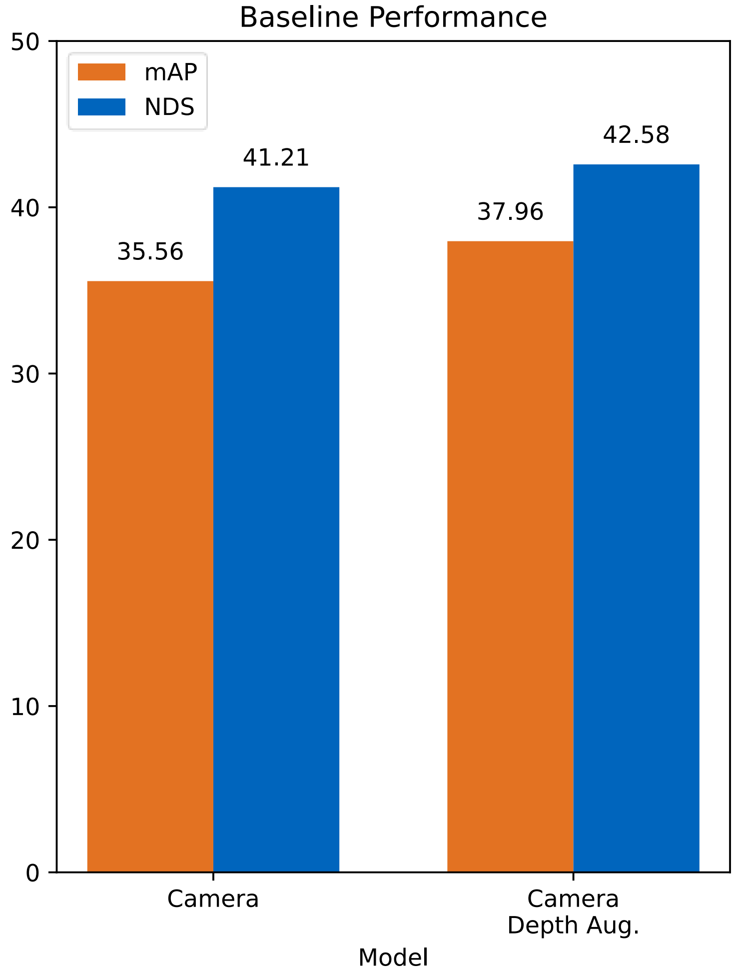
Original depth prediction



Improved depth prediction

Results: Camera Encoder

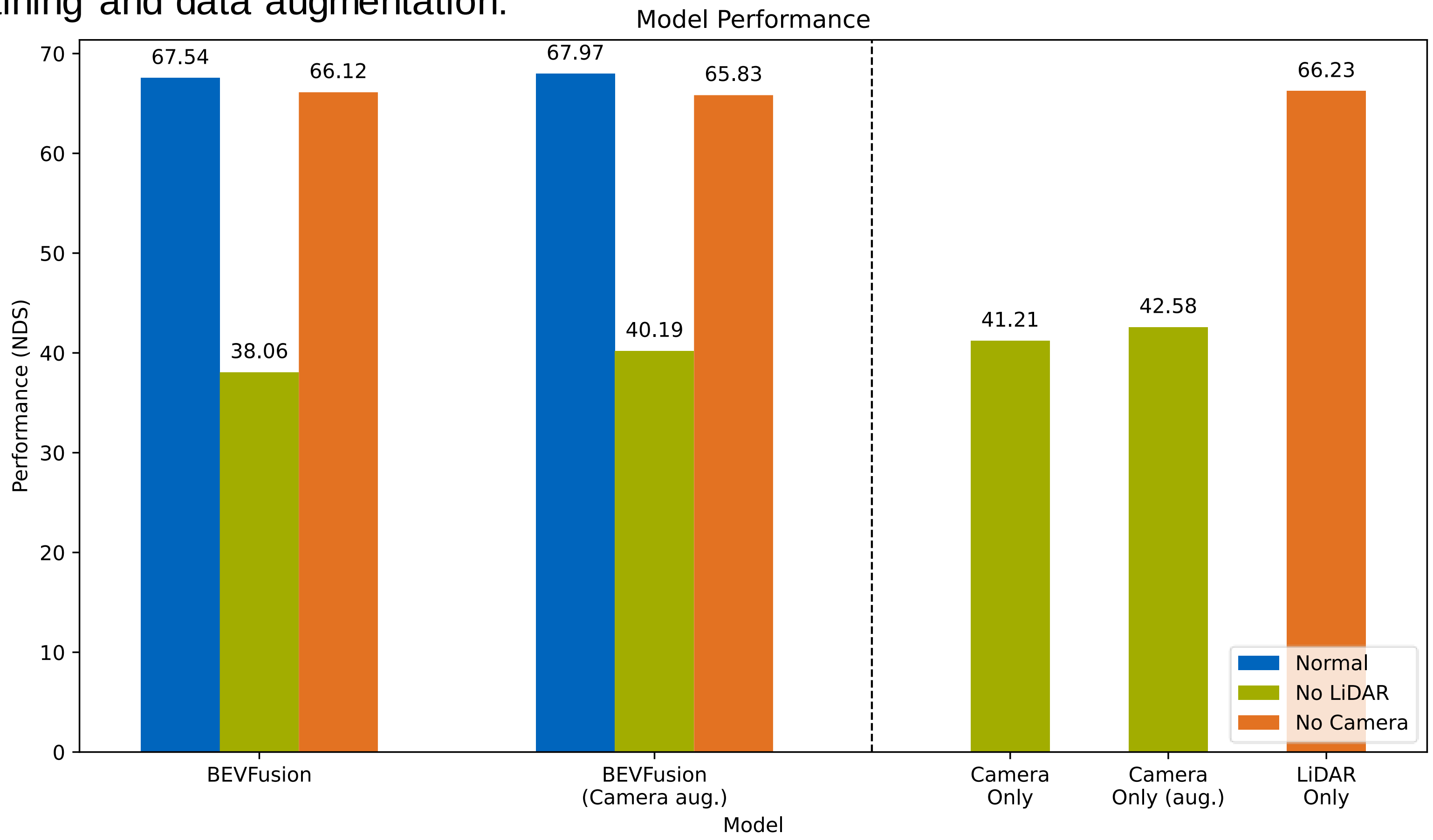
Noticeable increase in performance for the base camera model.



➔ Does this translate to the fusion model?

Results: Camera Encoder

Effect, including pretraining and data augmentation:

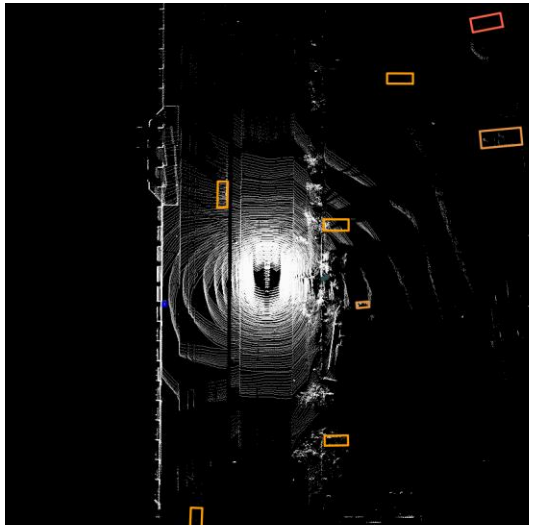


=> <u>Increased camera model performance directly translates to improved robustness during fusion</u>

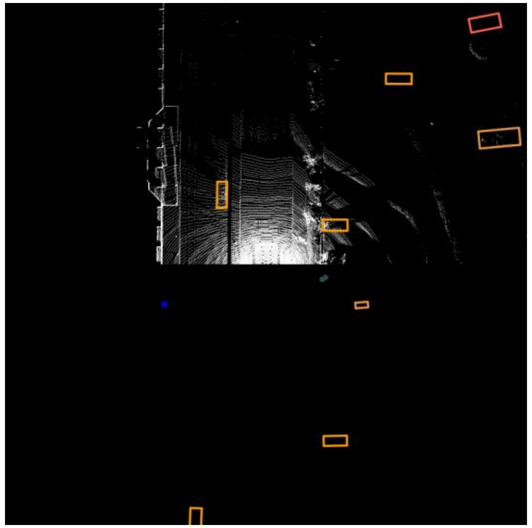
Generalization to partial sensor failure

So far, the focus has been only on **full** sensor failure (blackout)

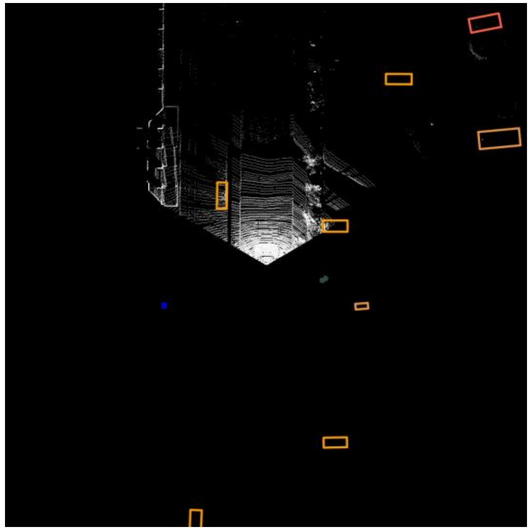
Do the presented methods improve performance in the event of **partial** sensor failure?



FoV 360°

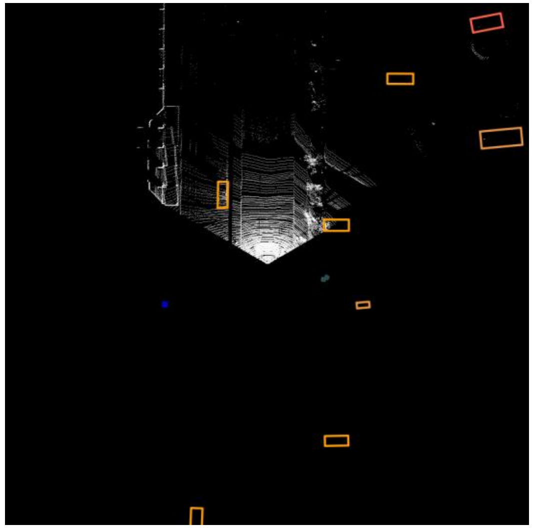


FoV 180°

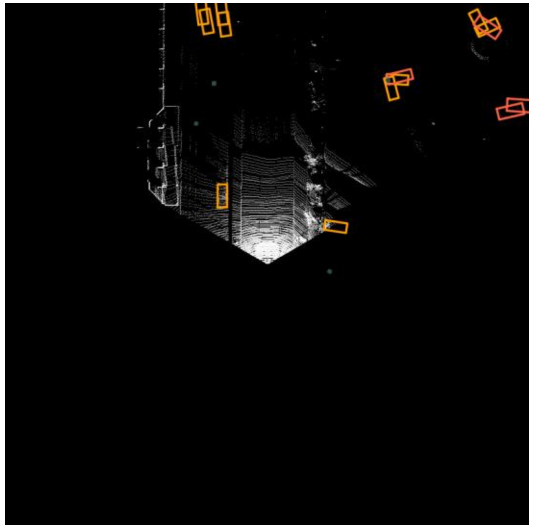


FoV 120°

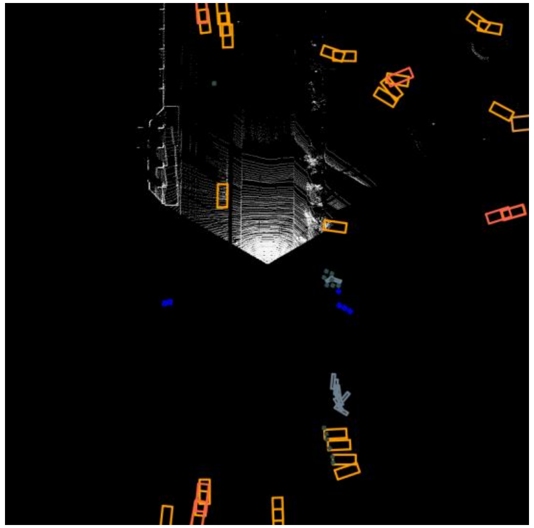
Generalization to partial sensor failure



Ground Truth



Baseline Model

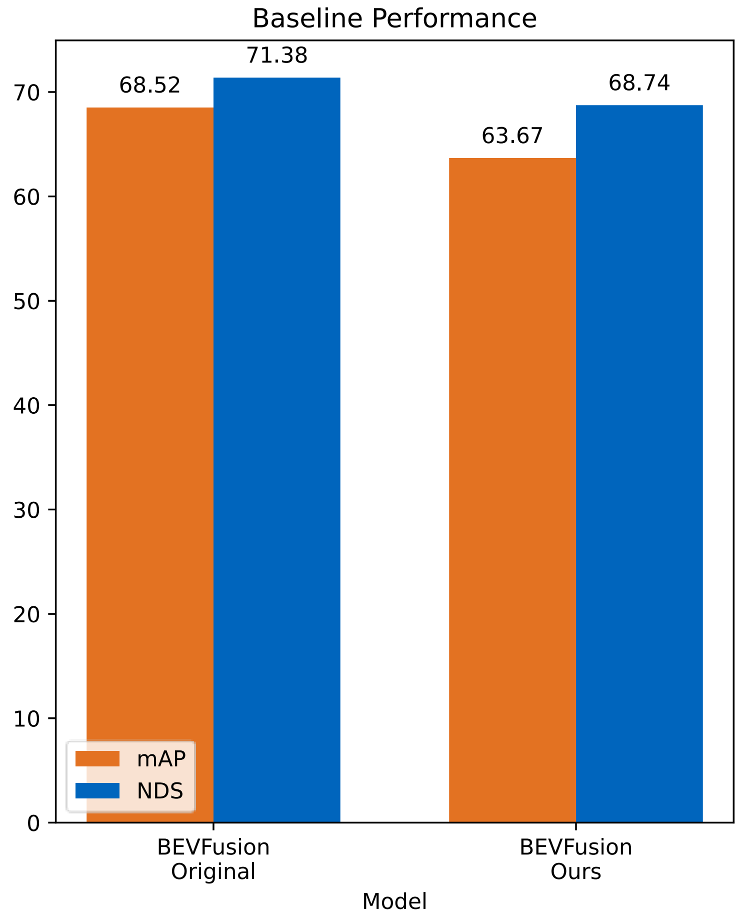


Augmented Model

=> Performance for **partial** sensor failure **increases significantly**

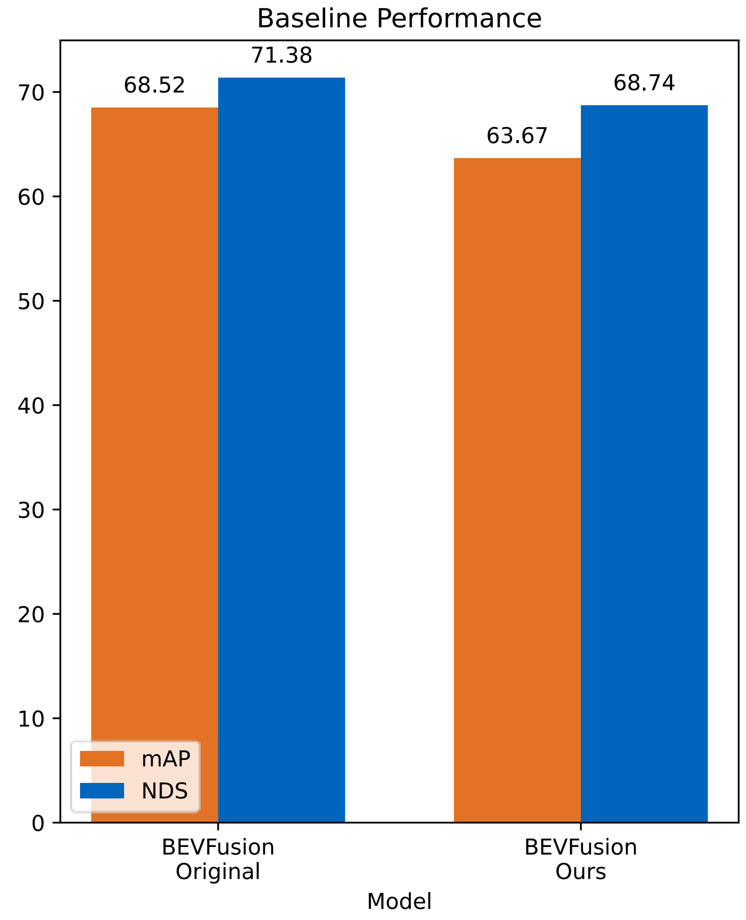
Limitations

- Reduced baseline performance vs. BEVFusion (resource and time constraints)
  - Higher performance might lead to trade-off with robustness



Limitations

- Reduced baseline performance vs. BEVFusion (resource and time constraints)
  - Higher performance might lead to trade-off with robustness
- Limited camera model performance
  - Possible trade-off between LiDAR and camera contribution
- Generalization to other sensor failure types unclear

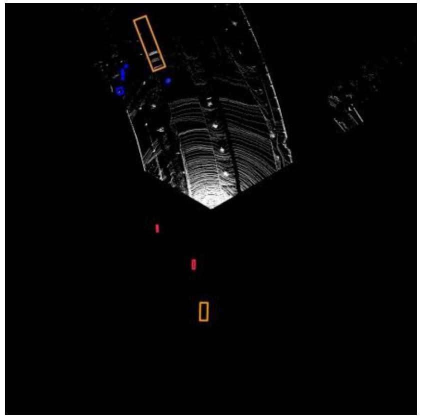


Summary

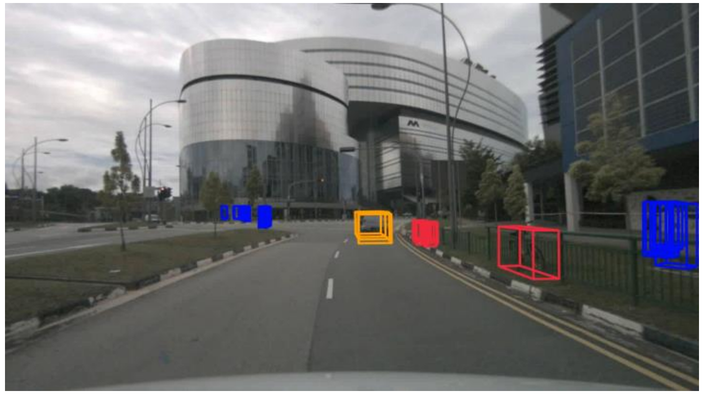
Visualization of LiDAR sensor failure

Before and after:

LiDAR view: Ground truth



Back view: Original model



Back view: Augmented model

Summary

Existing sensor fusion methods struggle in the event of sensor failure

- The presented methods **significantly** **increase robustness** against sensor failure
  - **Both** the camera failure and the LiDAR failure **cases** are **improved**
  - Strong results are achieved when using only **train-time** augmentations
- The **negative impact** on base performance is **negligible**
- Methods generalize well to partial sensor failure

Open Questions

- Do the presented methods also have a positive effect on **other** failure cases? (e.g. sensor miscalibration/misalignment)

- Are the presented methods also effective for **other** detection **tasks**? (e.g. map segmentation)

- When increasing base performance, is there a trade-off between a **robust** and a **high-performance** model?

Image Sources

https://www.eetindia.co.in/wp-content/uploads/sites/4/images/9d124bd9-84d5-4089-8e87-64831cb754d9.jpg