

# **Towards Safe Autonomous Driving: Capture Uncertainty in Deep Object Detectors**

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universität  
**uulm**



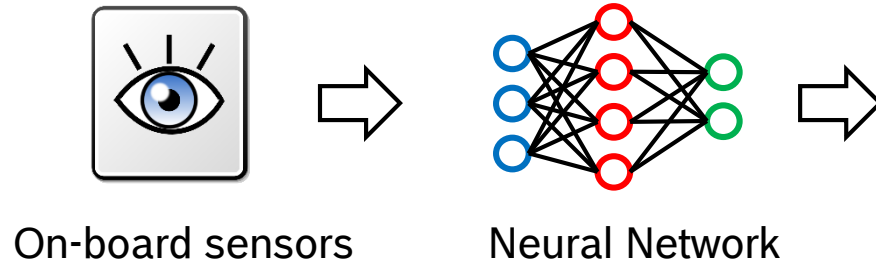
# Outline

- 1. Motivation**
- 2. Uncertainties in object detection networks**
- 3. Probabilistic LiDAR object detectors**
- 4. Challenges**

# 1. Motivation

## Object detection

- Bounding box (2D or 3D) + Classification score
- Deep learning has advanced object detection
- Most object detectors are deterministic – we need **probabilistic** detectors!



[Qi, et al., CVPR'18]

# 1. Motivation

## Autonomous car in the wild



Adverse weather



Night drive



Unseen objects

<https://www.flickr.com/photos/davidmoisan/3120533363/>  
<https://www.flickr.com/photos/wackelijmrooster/4095146153>  
<https://commons.wikimedia.org/wiki/Category:Embilipitiya>

# 1. Motivation

## Reliable uncertainty builds trust

*“From an ecological and evolutionary perspective, humans may turn out to be good intuitive statisticians ...”*

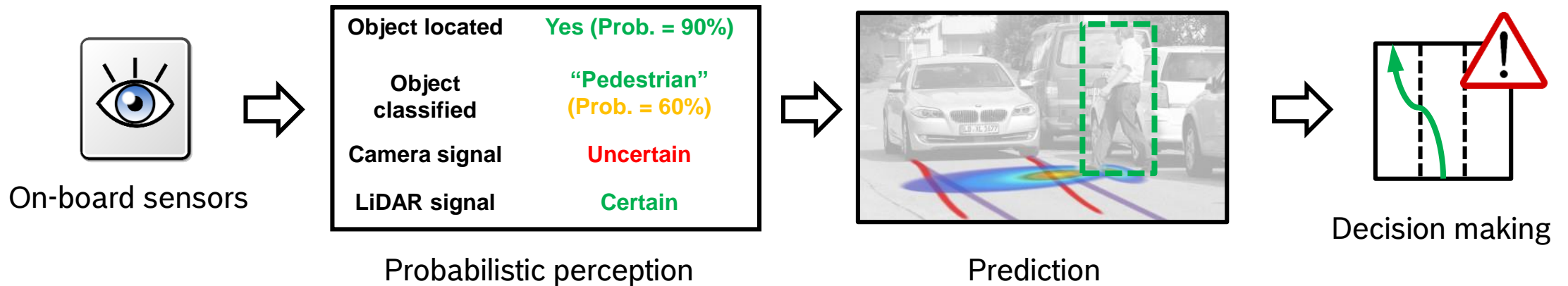
[Cosmides, et al., Cognition'96].



<https://spectrum.ieee.org/automaton/robotics/artificial-intelligence/robot-companions-to-befriend-sick-kids-at-european-hospital>

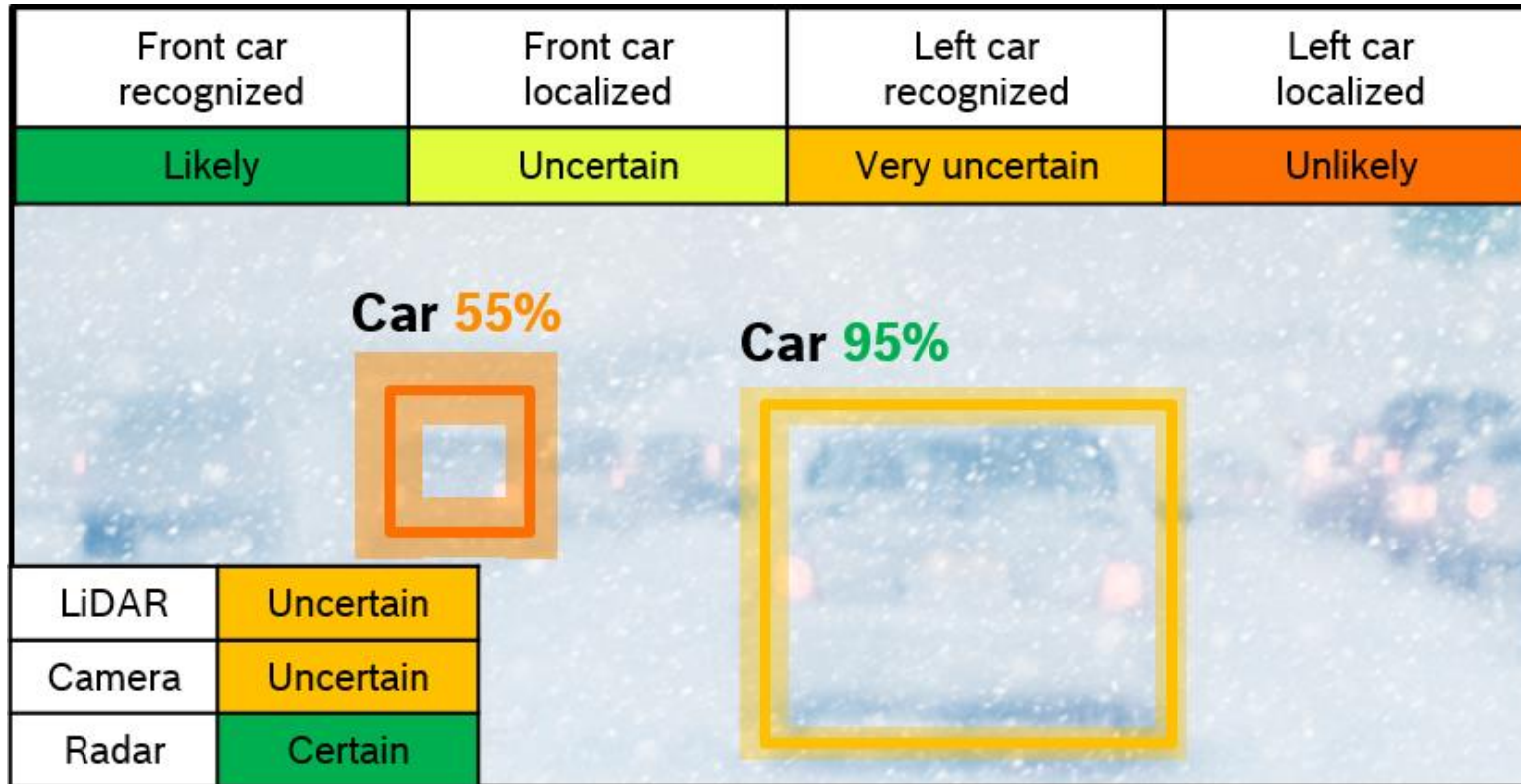
# 1. Motivation

## Increasing robustness of the general system



# 1. Motivation

What can an ideal probabilistic object detector look like?

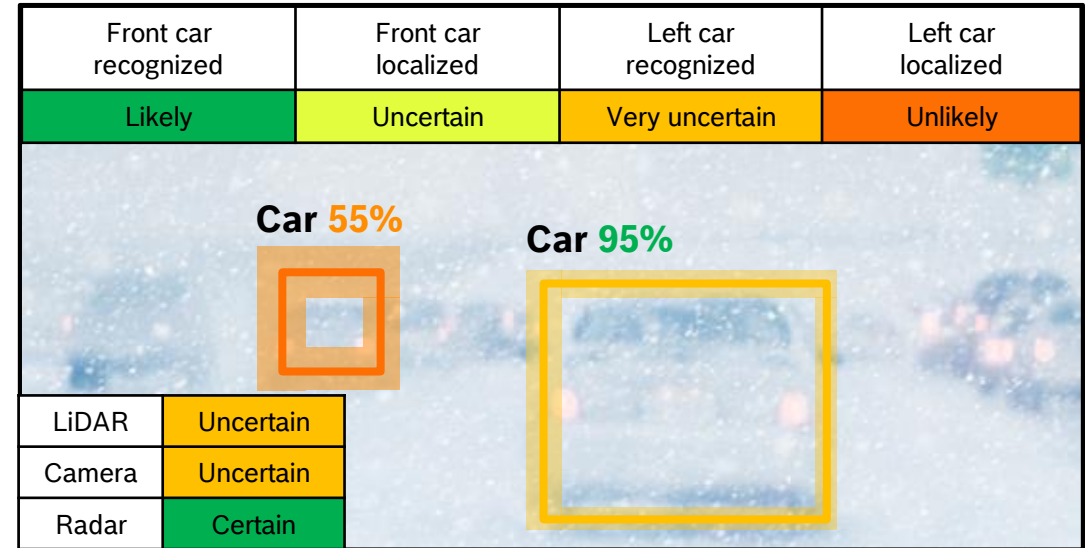




# 1. Motivation

An ideal object detector should model uncertainties ...

- **Holistic:** uncertainties in cls + reg
- **Well-calibrated:** represent empirical frequency
- **Explainable:**
  - reflect environmental noises
  - Comparable among sensors
  - reflect model deficiency
- **Useful**





# 1. Motivation

## Our attempts towards probabilistic object detectors

### Towards Safe Autonomous Driving: Capture Uncertainty in the Deep Neural Network For Lidar 3D Vehicle Detection

Di Feng<sup>1</sup>, Lars Rosenbaum<sup>1</sup>, Klaus Dittmayer<sup>2</sup>

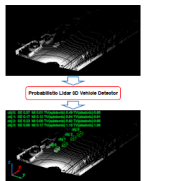


Fig. 1: Our proposed probabilistic Lidar 3D vehicle detection network takes the Lidar point clouds as input. It not only predicts object classes and 3D bounding boxes, but also predicts the model uncertainty and the sensor observation uncertainty. Shannon Entropy (SE) and Mutual Information (MI) quantify the classification uncertainty, and Total Variance (TV) the localization uncertainty. These scores will be described in Sec. IV.

In the object detection network, it is indispensable for safe autonomous driving, as the epistemic uncertainty displays the limitation of detection models, while the aleatoric uncertainty can provide the sensor observation noises for object tracking. In this work, we develop practical methods to capture epistemic and aleatoric uncertainties in a 3D vehicle detector for Lidar point clouds. Our contributions are three-fold:

- We extract model uncertainty and observation uncertainty for the vehicle recognition and 3D bounding box regression tasks.
- We show an improvement of vehicle detection performance by modeling the aleatoric uncertainty.
- We study the difference between the epistemic and aleatoric uncertainty. The former is associated with the vehicle detection accuracy, while the latter is influenced by the vehicle distance and occlusion.

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<sup>2</sup> Klaus Dittmayer is with Institute of Measurement, Control and Microtechnology, University of Würzburg, 97082 Würzburg, Germany.  
The video in this paper can be found in the attachments.

### Leveraging Heteroscedastic Aleatoric Uncertainties for Robust Real-Time Lidar 3D Object Detection

Di Feng<sup>1,4</sup>, Lars Rosenbaum<sup>1,2</sup>, Fabian Timm<sup>1</sup>, Klaus Dittmayer<sup>2</sup>

**Abstract**—We present a robust real-time Lidar 3D object detector that leverages heteroscedastic aleatoric uncertainties to significantly improve its detection performance. A multi-loss function is designed to incorporate uncertainty estimation provided by auxiliary output layers. Using our proposed method, the network ignores to train from noisy samples, and focuses more on informative ones. We validate our method on the KITTI object detection benchmark. Our method suppresses the baseline method which does not explicitly estimate uncertainties by up to nearly 9% in terms of Average Precision (AP). It also produces state-of-the-art results compared to other methods while running with an inference time of only 72 ms. In addition, we conduct extensive experiments to understand how aleatoric uncertainties behave. Extracting aleatoric uncertainties brings about an additional computation cost during the deployment, making our method highly desirable for autonomous driving applications.

#### I. INTRODUCTION

A robust and accurate object detection system using on-board sensors (e.g., camera, LIDAR, Radar) is crucial for the road scene understanding of autonomous driving. Among different sensors, LIDAR can provide us with accurate depth information, and is robust under different illumination conditions, such as daytime and nighttime. These properties make LIDAR indispensable for safe autonomous driving. The recent Uber's autonomous driving fatal tragedy could have been avoided, if the LIDAR perception system had robustly detected the pedestrian, or had timely identified the human driver to trigger the emergency braking because it was uncertain with the driving situation [1].

Recently, deep learning approaches have brought significant improvement to the object detection problem [2]. Many methods have been proposed that use LIDAR point clouds [3]–[11] or fuse them with camera images [12]–[19]. However, they only give us deterministic bounding box regression and use softmax scores to represent recognition probability, which does not necessarily represent uncertainties in the network [20]. In other words, they do not provide detection confidence regarding classification and localization. For a robust perception system, we need to explicitly model the network's uncertainties.

Towards this goal, in this work we build a probabilistic 2-stage based object detector from LIDAR point clouds by point clouds [1, 13] employs a 3D fully convolutional neural network for discretized point clouds to predict an objectness map and a 3D bounding box map. Other works project 3D point clouds onto a 2D plane and use 2D convolutional network to process these LIDAR feature maps. They can be represented by front-view cylindrical images [4], [12],

introducing heteroscedastic aleatoric uncertainties – the uncertainties that represent sensor observation noises and vary with the data input. The method works by adding auxiliary outputs to model the aleatoric uncertainties, and training the network with a robust multi-loss function. In this way, the network learns to focus more on informative training samples and ignores the noisy ones. We call our method **PROB** (Probabilistic Real-time Object Detector). Our contributions can be summarized as follows:

- We model heteroscedastic aleatoric uncertainties in a 3D object detection network using LIDAR point clouds.
- We show that by leveraging the aleatoric uncertainties, the network produces state-of-the-art results and significantly increases the average precision up to 9% compared to the baseline method without any uncertainty estimations.
- We systematically study how the aleatoric uncertainties behave. We show that the uncertainties are related with each other and are influenced by multiple factors such as detection distance, occlusion, softmax score, and orientation.

In the sequel, we first summarize related works in Sec. II, and then describe our proposed method in Sec. III at detail. Sec. IV shows the experimental results regarding the improvement of object detection performance by leveraging aleatoric uncertainties and understanding how the uncertainties behave. Sec. V summarizes the work and discusses future research. The video of this work is provided as supplementary material.

#### II. RELATED WORKS

In the following, we summarize methods for LIDAR-based object detection in autonomous driving and uncertainty quantification in deep neural networks.

Many works process the LIDAR information directly from point clouds [13], [15], [17], [14], [15], [17]. For example, Zhou et al. [15] propose a voxel feature encoding layer to handle 3D point clouds [1, 13] employs a 3D fully convolutional neural network for discretized point clouds to predict an objectness map and a 3D bounding box map. Other works project 3D point clouds onto a 2D plane and use 2D convolutional network to process these LIDAR feature maps. They can be represented by front-view cylindrical images [4], [12],

### Deep Active Learning for Efficient Training of a Lidar 3D Object Detector

Di Feng<sup>1,4</sup>, Xiao Wei<sup>1,2</sup>, Lars Rosenbaum<sup>1</sup>, Atsuto Maki<sup>1</sup>, Klaus Dittmayer<sup>1</sup>

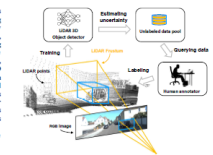


Fig. 1: Our proposed active learning method to efficiently train a LIDAR 3D object detector. The network iteratively estimates the uncertainty in the unlabeled data pool, queries the human annotator the most informative samples, and updates with the newly-labeled data.

Deep learning has been in recent years set the benchmark for object detection task on many open datasets (e.g. KITTI [11], Cityscapes [21]), and has become the de-facto for the perception module in autonomous driving. Despite its high performance, training a deep object detector usually requires a huge amount of labeled samples. Labeling them is a tedious and time-consuming work, especially for annotating 3D LIDAR points, as discussed in [1]. Therefore, developing methods to reduce labeling efforts is highly expected. Furthermore, a common way to optimize a deep object detector is feeding all training samples into the network with random shuffling. However, the informativeness of each training sample differs, i.e., some are more informative and contribute more to the performance gain, while some others are less informative. A more efficient training strategy is to optimize network with only the most informative samples. This is specifically helpful when adapting an object detector to new driving scenarios which are different from the previous training set, e.g. from highway to urban scenarios.

Active learning [4] is a training strategy to reduce human annotation efforts while maximizing the performance of a machine learning model (usually in supervised-learning fashion). In active learning, a model iteratively evaluates the

informativeness of unlabeled data, queries the most informative samples with human annotator, and updates with newly-labeled data. Active learning has long been applied to Support Vector Machine (SVM) or Gaussian Process (GP) [5]–[8], and has only recently been used in deep learning for classification of medical images [9] or hyperspectral images in remote sensing [10], road-scene image segmentation [11], and natural language processing [12].

In this work, we propose an active learning framework to efficiently train a LIDAR 3D object detector for autonomous driving, as in Fig. 1. We assume that there exists a large-scale unlabeled data pool for LIDAR point clouds, and the network can iteratively query the human annotator with the class label and 3D geometrical information of objects. We use the network's predictive uncertainty to quantify the informativeness of a sample in the unlabeled data pool. To further reduce the labeling efforts as well as to increase the learning process, we propose to leverage 2D object proposals in RGB images which can be provided by the searching algorithm (e.g., selective search) or pre-trained image detector (e.g., Detectron [13]). These proposals serve as seeds to locate objects, so that the human annotator only needs to label LIDAR points within footprints (see Fig. 1).

Our contributions can be summarized as follows: (1) We propose a deep active learning framework to significantly

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<sup>3</sup> Institute of Measurement, Control and Microtechnology, University of Würzburg, 97082 Würzburg, Germany.  
The video in this paper can be found at <https://youtu.be/825U71wq8>.

### Can We Trust You? On Calibration of a Probabilistic Object Detector for Autonomous Driving

Di Feng<sup>1,2</sup>, Lars Rosenbaum<sup>1</sup>, Claudius Glaser<sup>1</sup>, Fabian Timm<sup>1</sup>, Klaus Dittmayer<sup>2</sup>

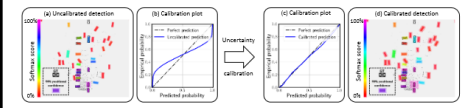


Fig. 1: A state-of-the-art probabilistic LIDAR 3D object detector produces uncalibrated uncertainties. (a). Each detection in the LIDAR line's eye view plane is colorized according to the softmax score. The 95% positional confidence intervals in the horizontal plane (marginals) are drawn as shaded areas around each detection. (b). We visualize the uncertainty miscalibration problem by the calibration plot. (c). Using our proposed uncertainty recalibration techniques, we significantly improve the uncertainty estimation quality. (d). The detection results after uncertainty recalibration.

**Abstract**—Reliable uncertainty estimation is crucial for perception systems in safe autonomous driving. Recently, many methods have been proposed to model uncertainties in deep learning-based object detectors. However, the estimated probabilities are often uncalibrated, which may lead to severe problems in safety-critical scenarios. In this work, we identify such uncertainty miscalibration problem in a probabilistic LIDAR 3D object detection network, and propose three practical methods to significantly improve the uncertainty estimation. Extensive experiments on several datasets show that our methods produce well-calibrated uncertainties, and generalize well between different datasets.

#### I. INTRODUCTION

Reliable uncertainty estimation in object detection systems is crucial for safe autonomous driving. Intuitively, a probabilistic object detector should predict uncertainties that match the natural frequency of correct predictions. For example, if the detector makes predictions with 0.9 probability, then 90% of these predictions should be correct. Reliable uncertainty estimation builds trust between a driverless car and its users, as humans have an intuitive notion of probabilities in a frequentist sense [1]. Moreover, the uncertainties captured in object detectors can be propagated to other modules, such as tracking and motion planning [2], so that the overall system robustness can be enhanced.

#### II. RELATED WORK

##### A. Uncertainty Estimation for Object Detection

The methods to model uncertainty in object detection can be categorized into two groups: the ensemble approach and the direct modeling approach. The former builds an ensemble of object detectors to approximate an output probability distribution with samples, e.g. using Monte Carlo Dropout [9]. This approach has shown to represent the model uncertainty.

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We thank our colleagues Fabian Fahn and Fabian Fahn for their suggestions and inspiring discussions. We also thank Rüdiger Brach for reading the script. The video in this paper can be found at <https://youtu.be/825U71wq8>.

# Outline

1. Motivation

**2. Uncertainties in object detection networks**

3. Probabilistic LiDAR object detectors

4. Challenges

## 2. Uncertainties in object detection networks

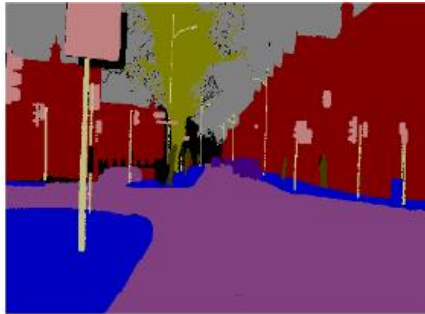
What kind of uncertainties can we model in object detection networks?

- Epistemic uncertainty: model's capability to describe data
- Aleatoric uncertainty: observation noises (e.g. environment, sensors)

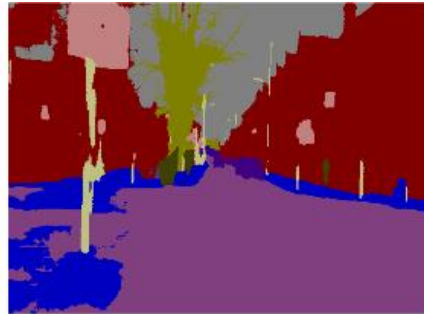
[Kendall et al., NeurIPS'17]



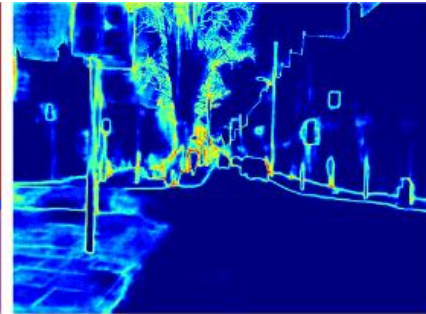
(a) Input Image



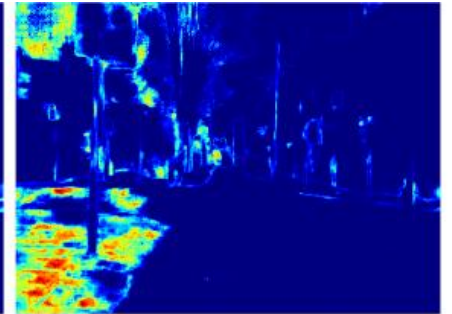
(b) Ground Truth



(c) Semantic Segmentation



(d) Aleatoric Uncertainty



(e) Epistemic Uncertainty

## 2. Uncertainties in object detection networks

Modeling uncertainties via Bayesian neural networks [MacKey, Neural'92]

$$\boxed{p(\mathbf{y}|\mathbf{x})} = \int \boxed{p(\mathbf{y}|\mathbf{x}, \mathbf{W})} \boxed{p(\mathbf{W}|\mathcal{D})} d\mathbf{W}$$

Predictive uncertainty

Aleatoric uncertainty

Epistemic uncertainty

$\mathbf{x}$  : Input vector

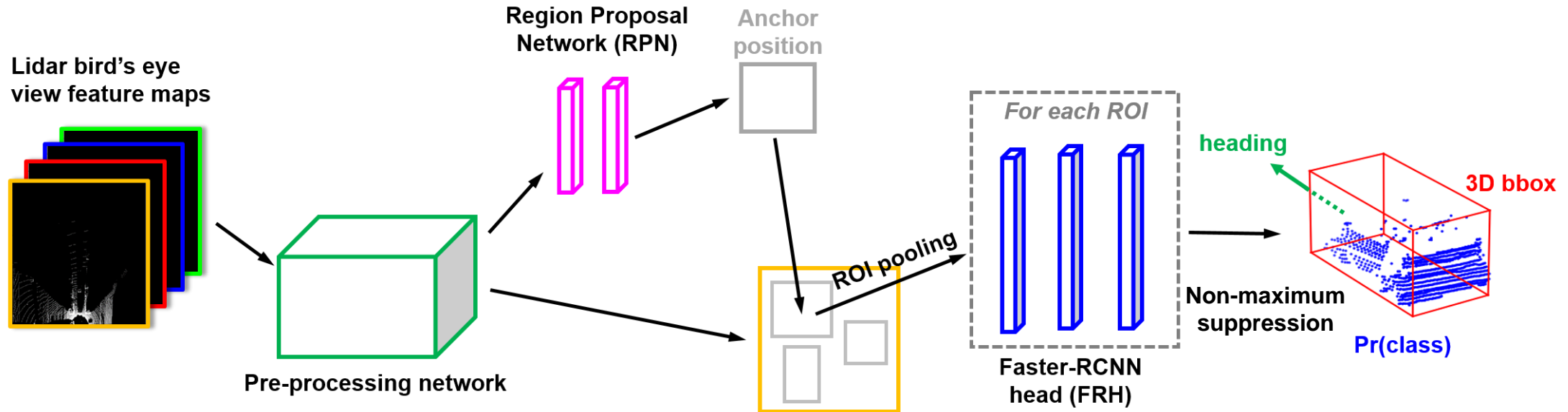
$\mathbf{y}$  : Prediction output vector

$\mathcal{D}$  : Training dataset

$\mathbf{W}$  : Network weight variables

## 2. Uncertainties in object detection networks

### Modeling uncertainties in object detection networks: a big work

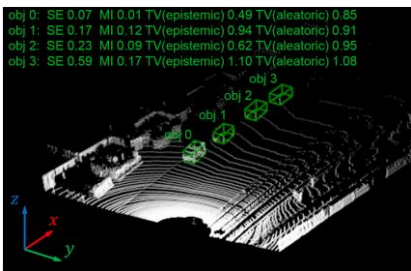


[Ren et al., NeurIPS'15]



# 2. Uncertainties in object detection networks

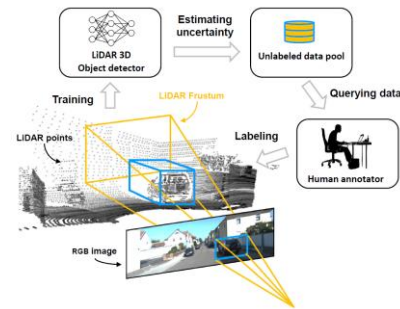
## State of the art



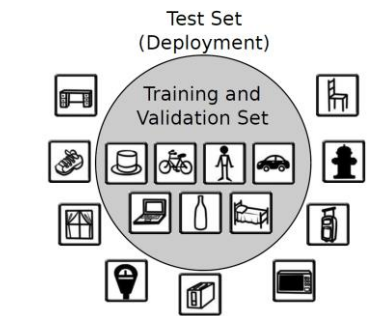
[Feng et al., ITSC'18]  
Uncertainties in a LiDAR detector



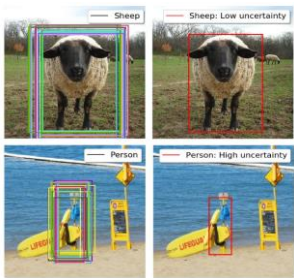
[Truong et al., ITSC'18]  
Uncertainties in an image detector



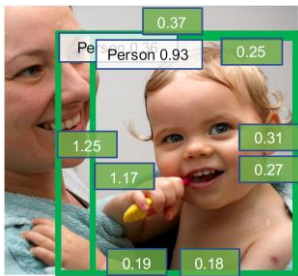
[Feng et al., IV'19b]  
Active learning for a probabilistic detector



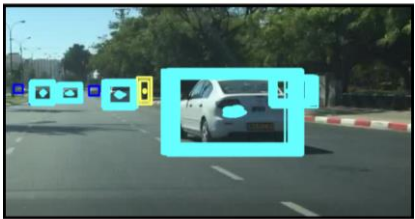
[Miller et al., ICRA'18]  
Detection in open-set conditions.



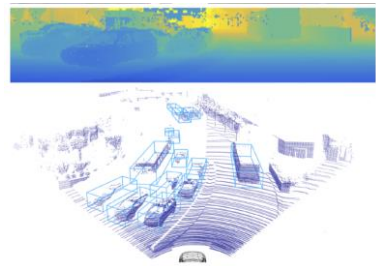
[Miller et al., ICRA'19]  
Uncertainty and merging strategy



[He et al., CVPR'19]  
Localization uncertainty and nms



[Harakeh et al., 19]  
Localization uncertainty and nms



[Meyer et al., CVPR'19]  
Localization uncertainty and nms

# Outline

1. Motivation

2. Uncertainties in object detection networks

**3. Probabilistic LiDAR object detectors**

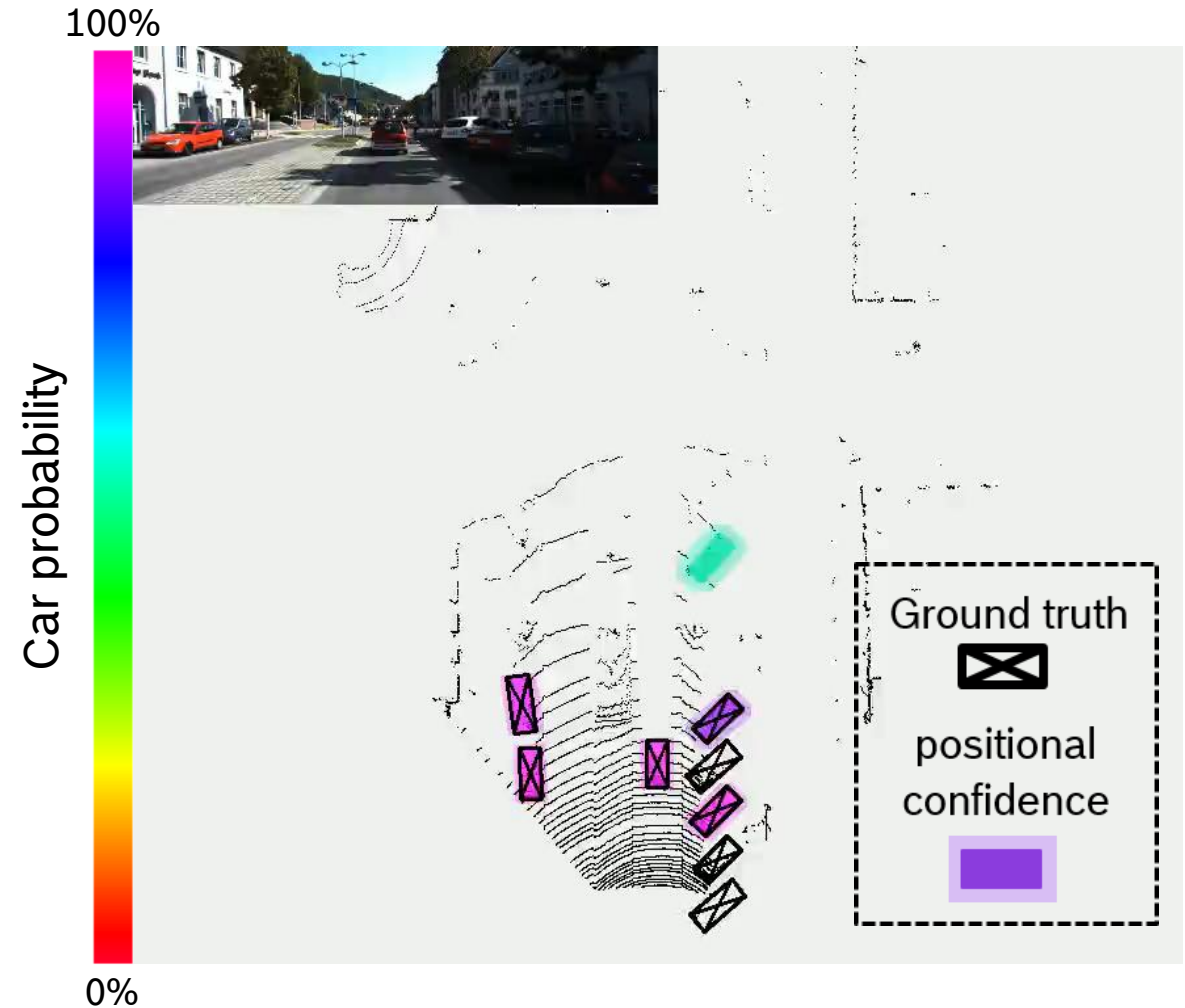
4. Challenges



# 3. Probabilistic LiDAR object detectors

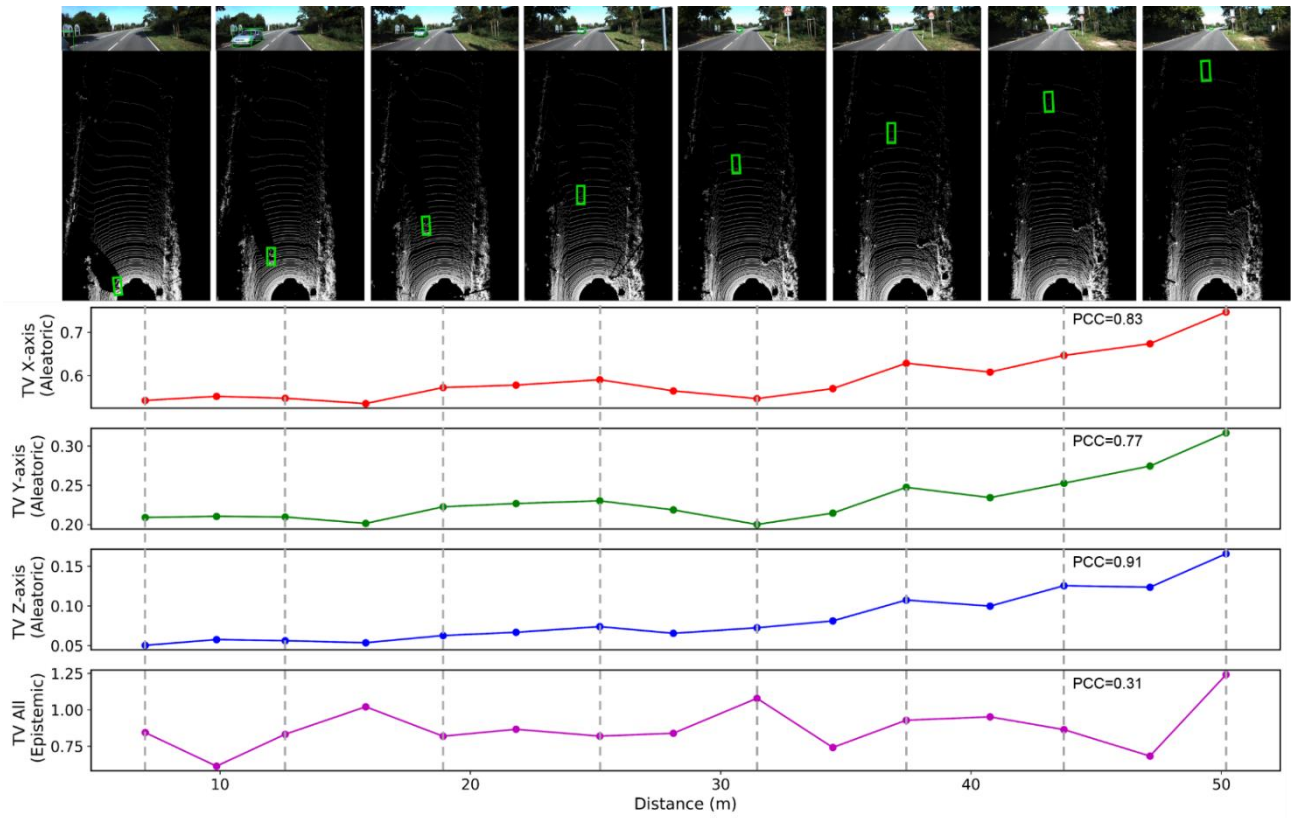
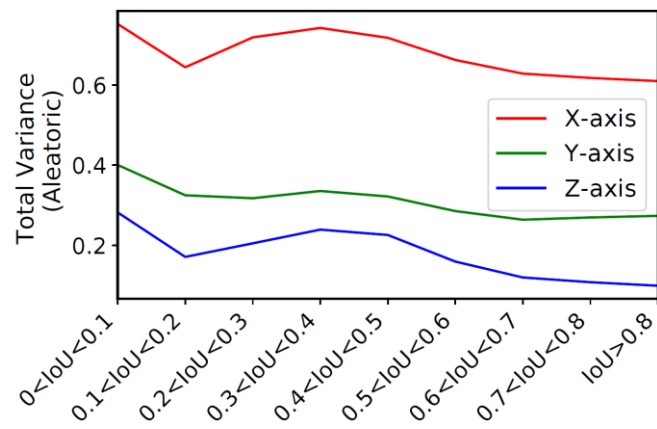
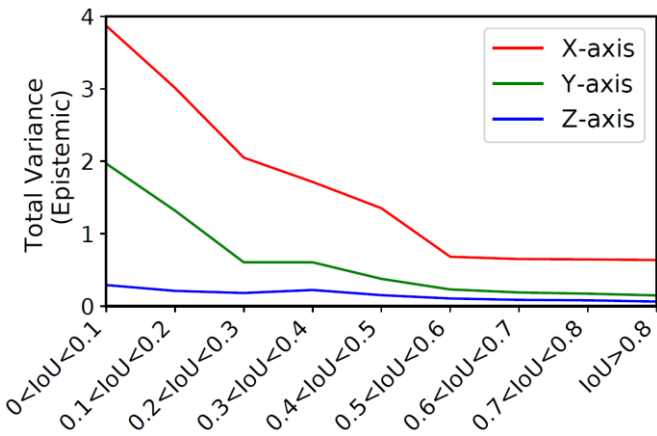
## Summary

- Bayesian neural network framework
  - Model-related uncertainties (epistemic)
  - Environmental noises (aleatoric)
- Two & One stage object detector
- Systematic analysis



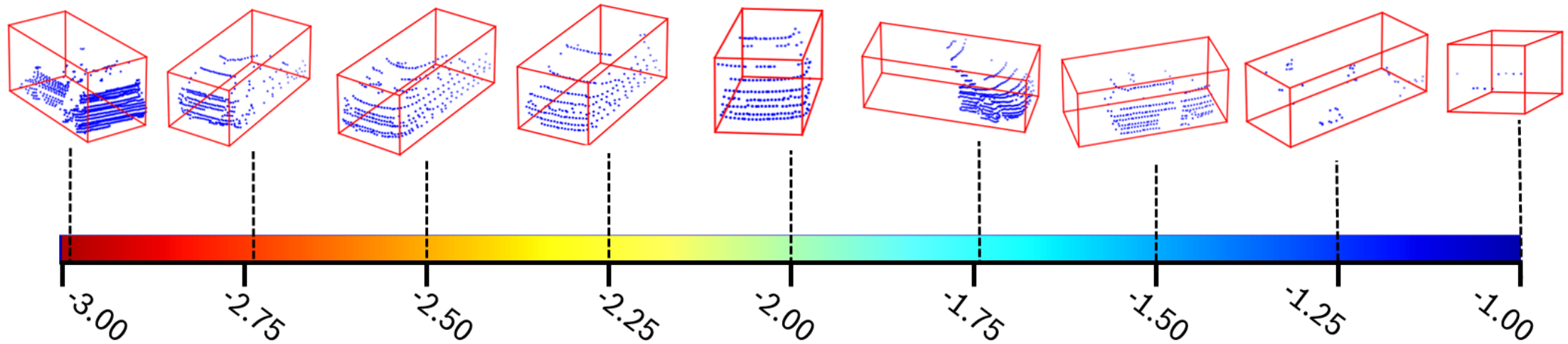
# 3. Probabilistic LiDAR object detectors

Epistemic and aleatoric uncertainties behave very differently [Feng et al., ITSC'18]

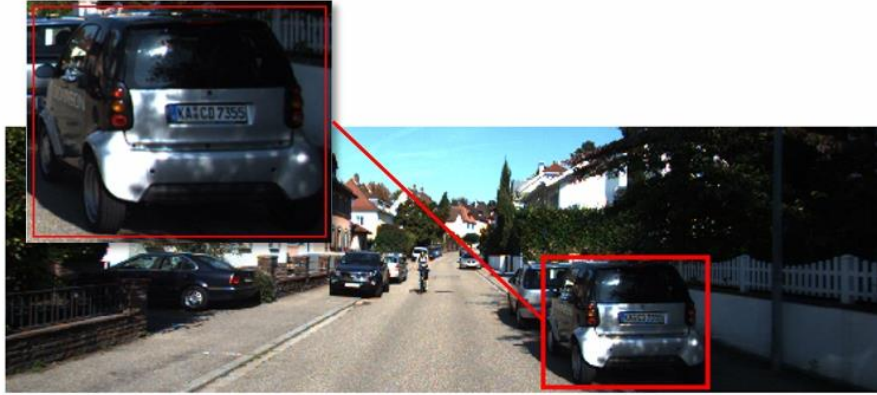


### 3. Probabilistic LiDAR object detectors

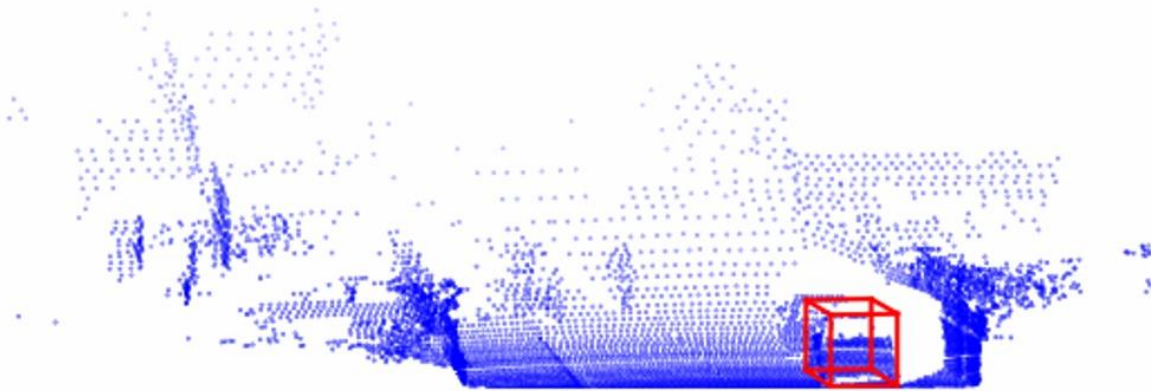
Aleatoric uncertainty represents environmental noises [Feng et al., IV'19a]



Uncertainty scores at log scale



Detection in RGB image



Detection in LiDAR point clouds

## Detection Information

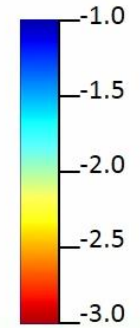
Uncertainty score: **-2.92**

Softmax score: 0.87

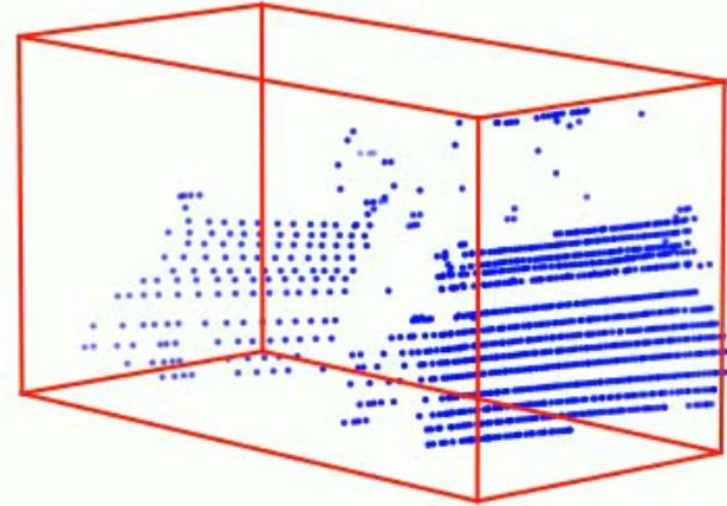
Distance: 7.5 m

Occlusion: fully visible

Orientation: 92.1°



Uncertainty scores at  
log scale



LiDAR points within the bounding box

### 3. Probabilistic LiDAR object detectors

Using aleatoric uncertainty to improve detection accuracy [Feng et al., IV'19a]

Comparison of 3D Car detection performance on KITTI val set [Geiger et al., CVPR'12]

Method	$AP_{3D}(\%)$			$AP_{BEV}(\%)$		
	Easy	Moderate	Hard	Easy	Moderate	Hard
F-PointNet (LiDAR)	69.50	62.30	59.73	-	-	-
PIXOR	-	-	-	86.79	80.75	76.60
VoxelNet	81.97	65.46	62.85	89.60	84.81	78.57
Baseline	71.50	63.71	57.31	86.33	76.44	69.72
<i>Ours</i>	<b>+7.31</b>	<b>+2.18</b>	<b>+7.88</b>	<b>+0.7</b>	<b>+0.71</b>	<b>+7.23</b>

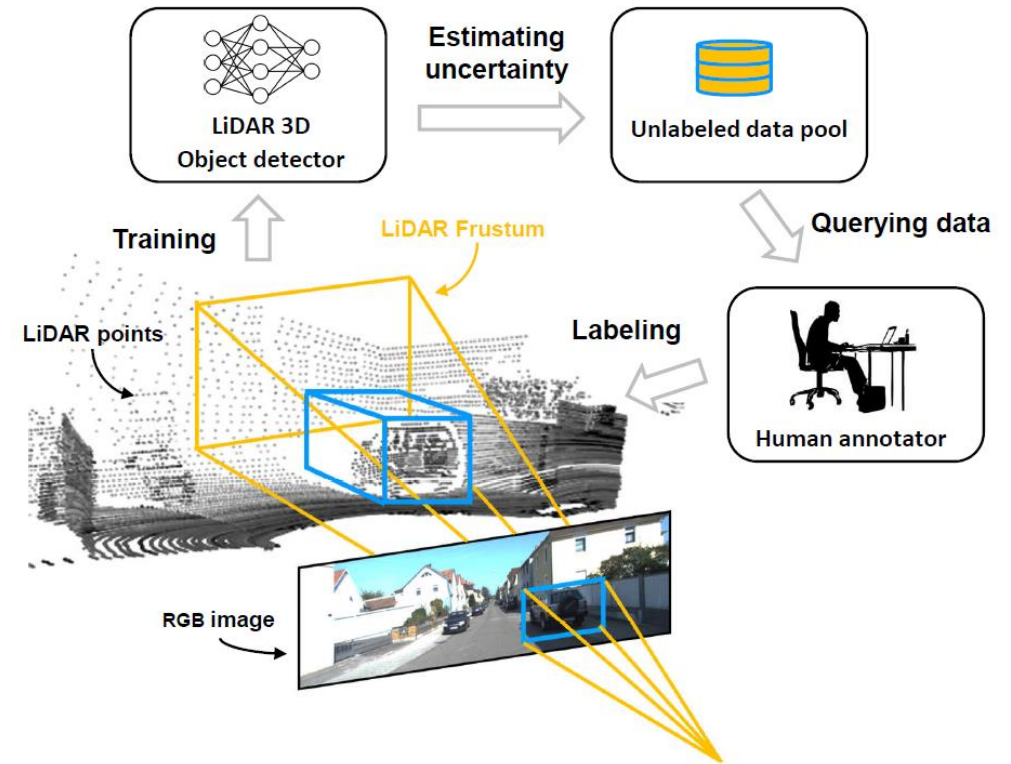
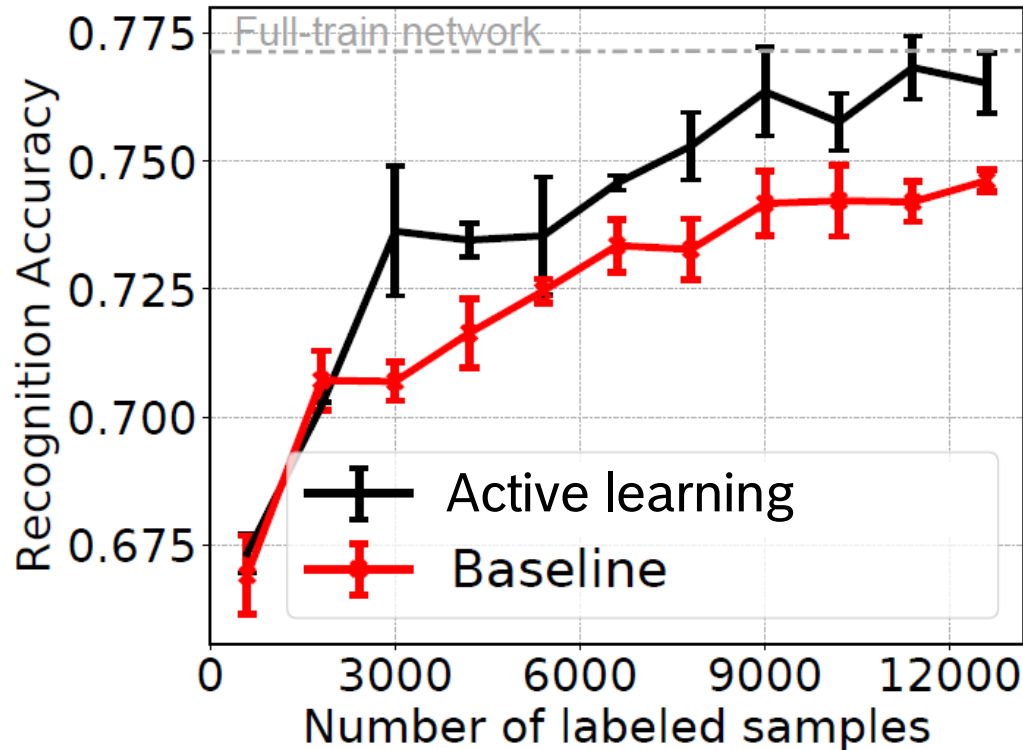
\* Baseline is the object detector without any uncertainty estimation.

[Qi et al., CVPR'18]    [Zhou et al., CVPR'18]    [Yang et al., CVPR'18]



### 3. Probabilistic LiDAR object detectors

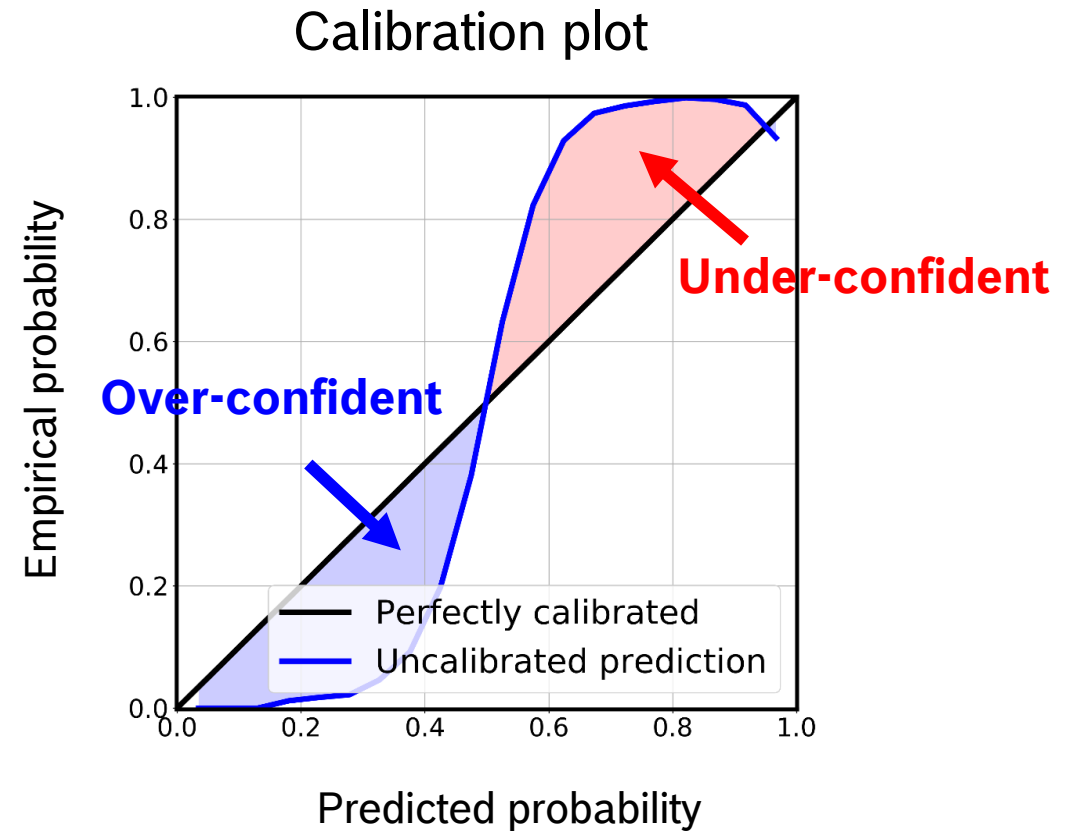
Using epistemic uncertainty to improve training efficiency [Feng et al., IV'19b]



### 3. Probabilistic LiDAR object detectors

Can we trust uncertainty estimation? [Feng et al., IROS'19]

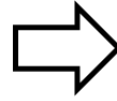
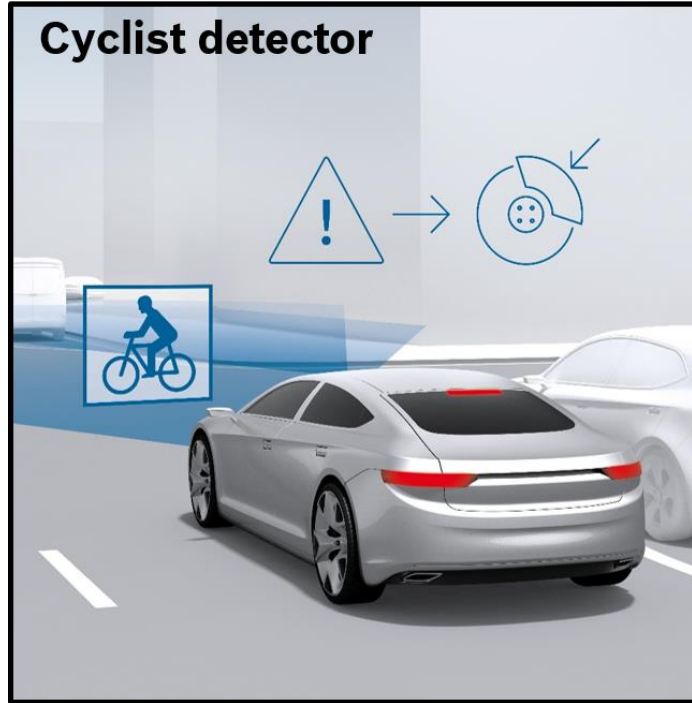
*If a model makes predictions with 0.8 probability score, 80% of those predictions should be correct.*





# 3. Probabilistic LiDAR object detectors

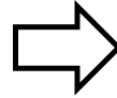
## Importance of well-calibrated uncertainty



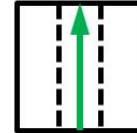
**Over-confident detection**



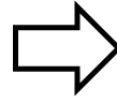
Uncomfortable  
braking



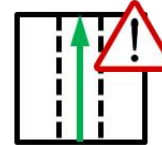
**Under-confident detection**



Fatal accident !



**Reliable detection**

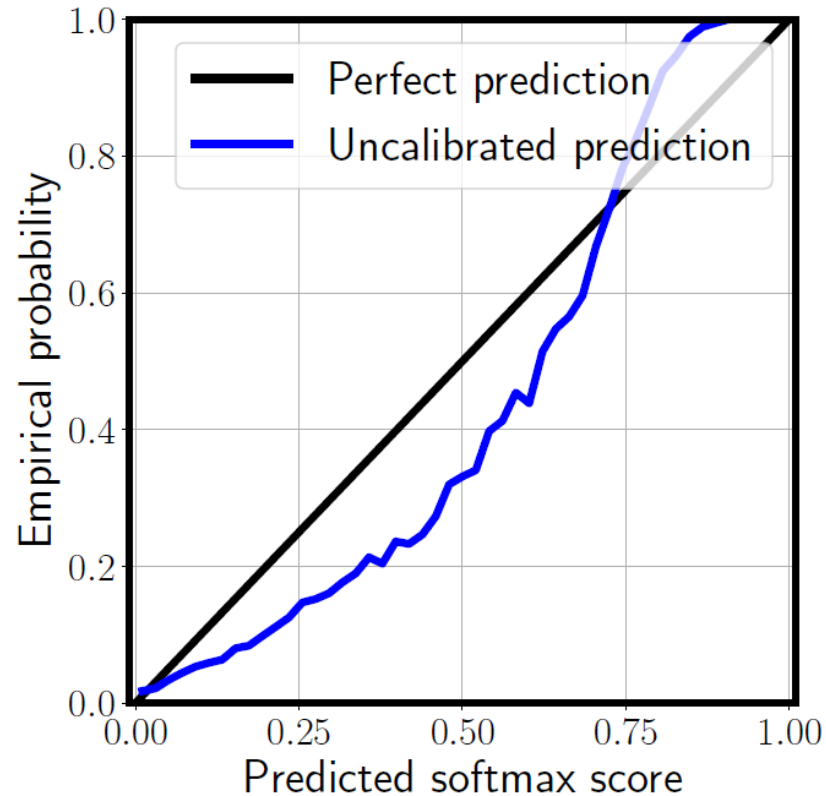


Safe and sound

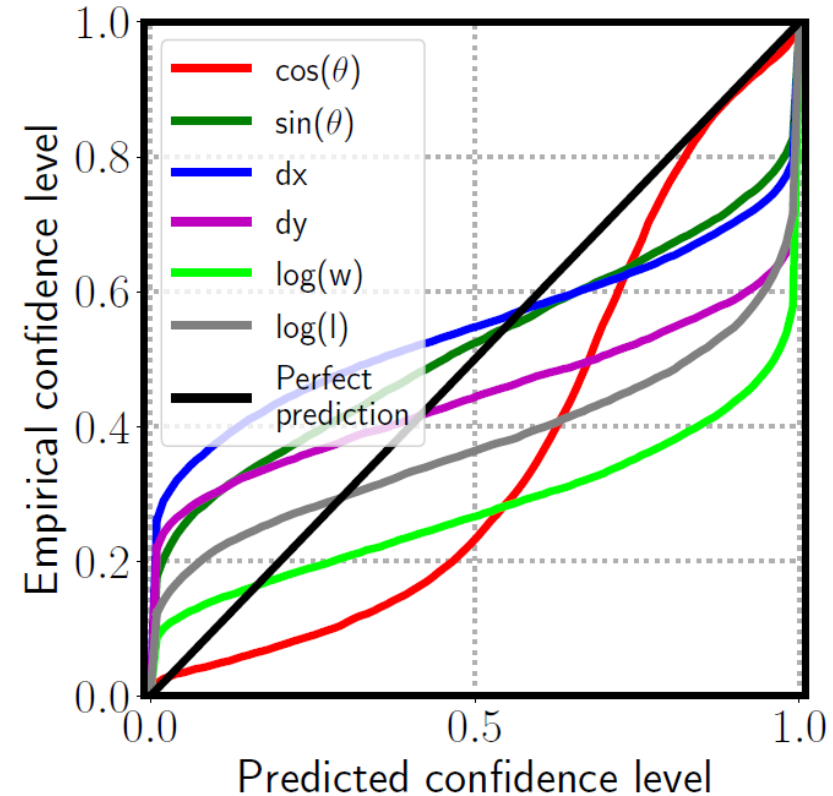
### 3. Probabilistic LiDAR object detectors

Identifying miscalibrated uncertainties in an one-stage detector [Feng et al., IROS'19]

(a) Classification

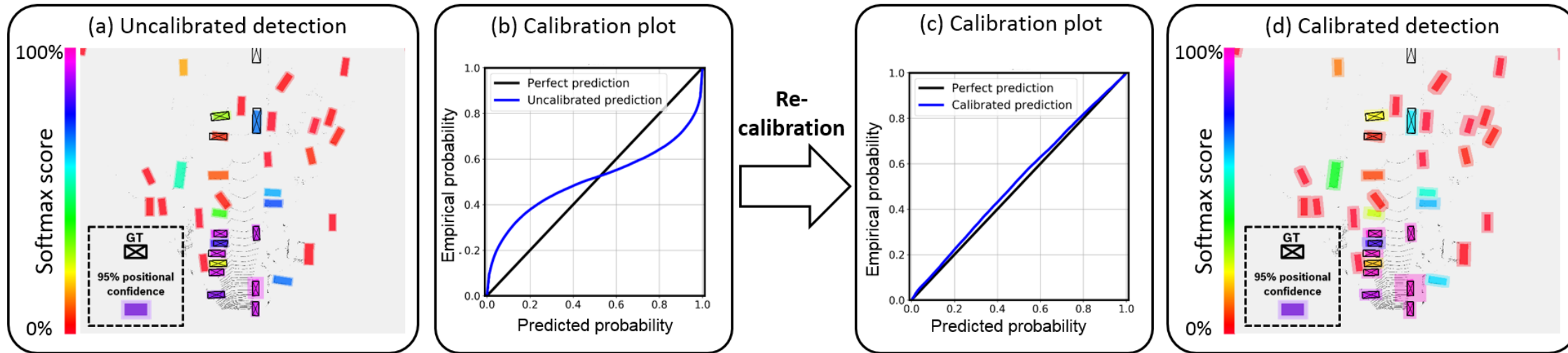


(b) Regression



### 3. Probabilistic LiDAR object detectors

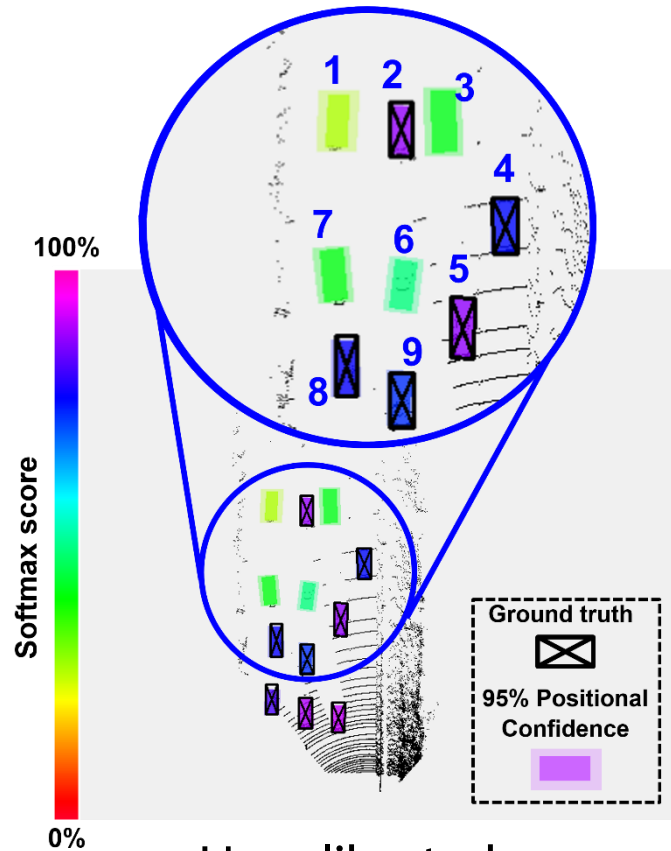
Proposing three uncertainty recalibration methods to largely reduce uncertainty calibration error



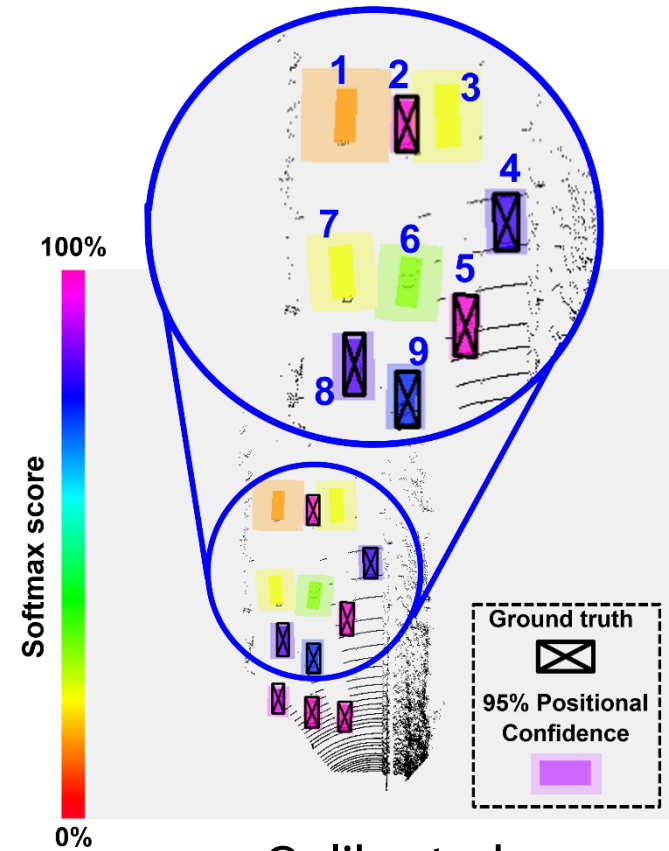
[Feng et al., IROS'19]

### 3. Probabilistic LiDAR object detectors

Recalibrating uncertainties – classification [Feng et al., IROS'19]



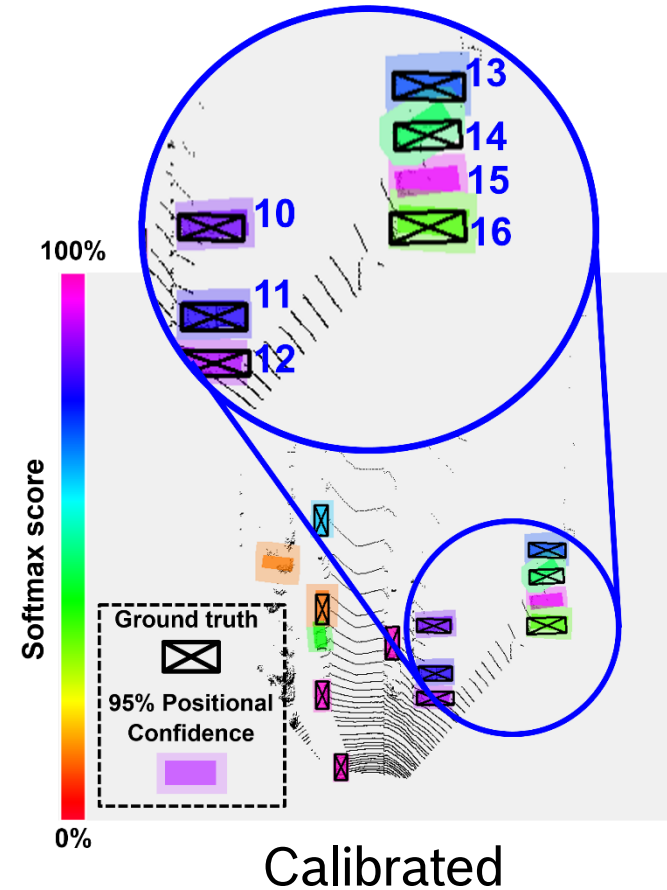
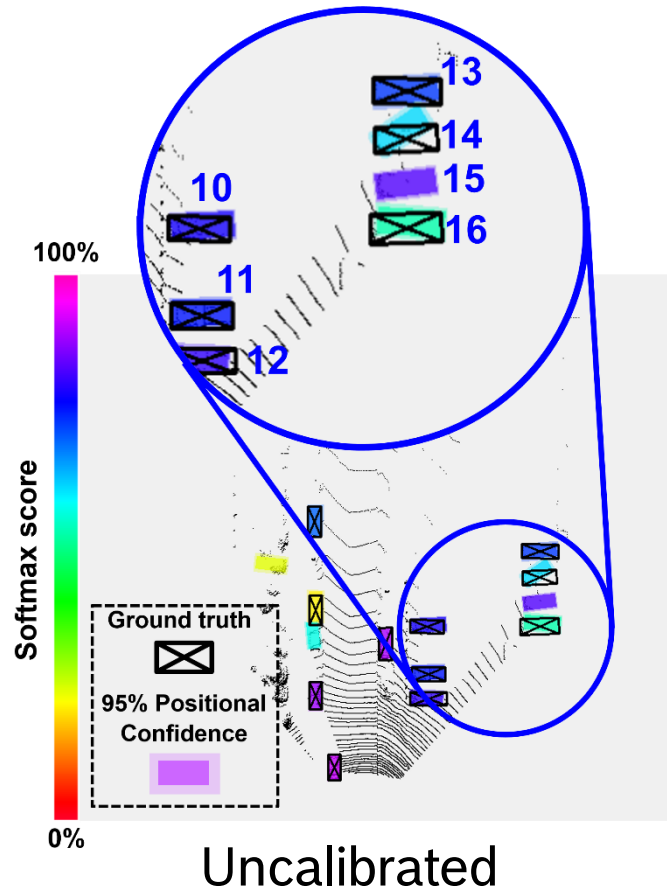
Uncalibrated



Calibrated

### 3. Probabilistic LiDAR object detectors

Recalibrating uncertainties – regression (marginal probability) [Feng et al., IROS'19]

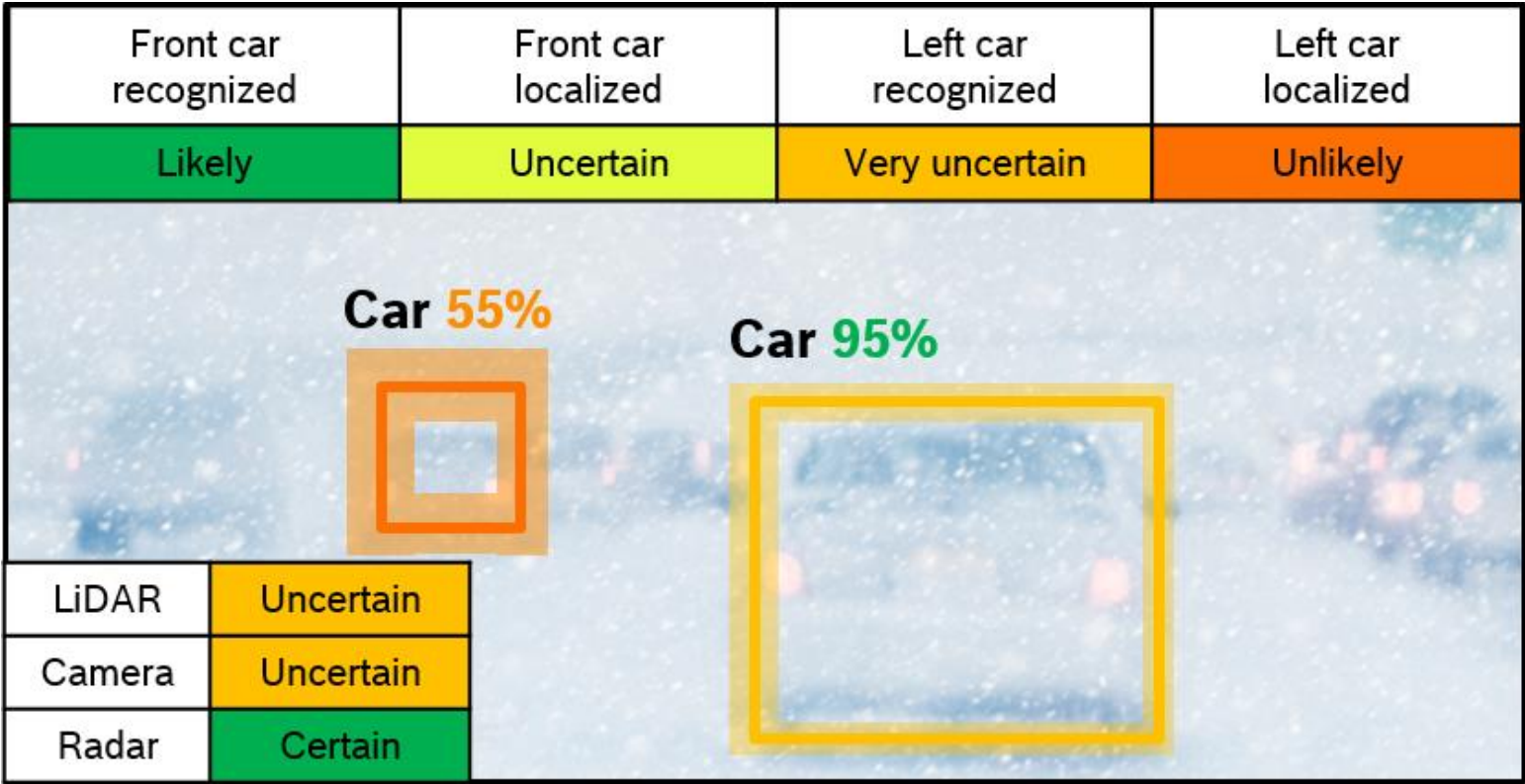


# 3. Probabilistic LiDAR object detectors

Our LiDAR object detectors model uncertainties:

- **Holistic:** cls+reg; in two/one-stage detectors; epistemic/aleatoric uncertainties
- **Well-calibrated:** after uncertainty recalibration [Feng et al., IROS'19]
- **Explainable:**
  - Reflect environmental noises such as distance & occlusion [Feng et al., ITSC'18 & IV'19a]
  - Reflect model's accuracy [Feng et al., ITSC'18]
- **Useful**
  - Improve detection performance [Feng et al., IV'19a]
  - Improve training efficiency via active learning [Feng et al., IV'19b]

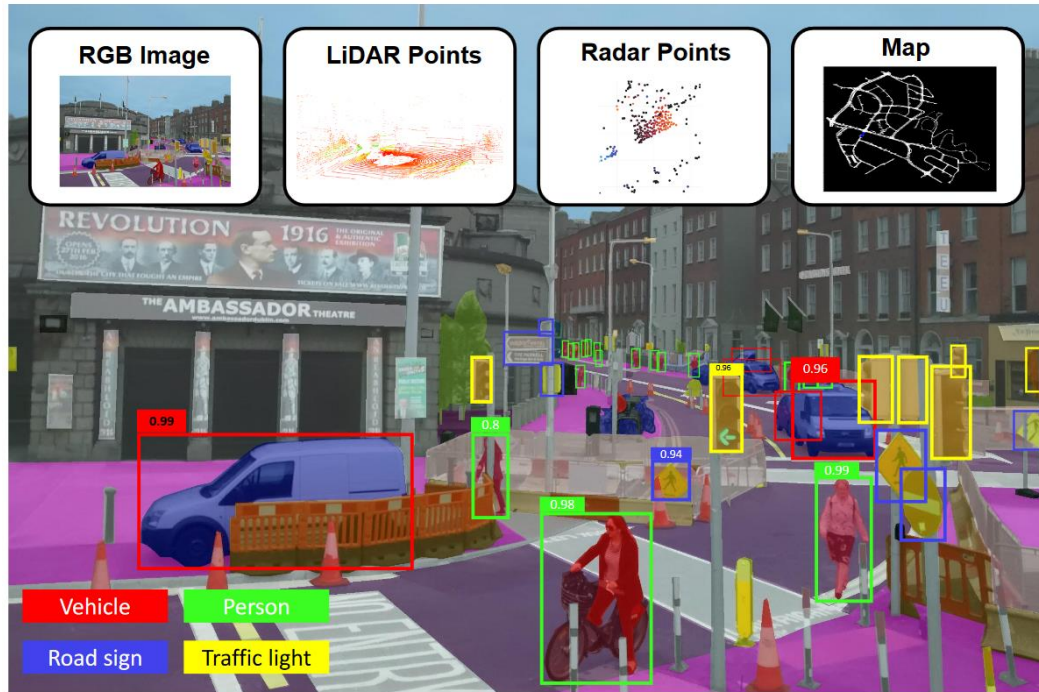
# Problem solved? No!





## 4. Challenges

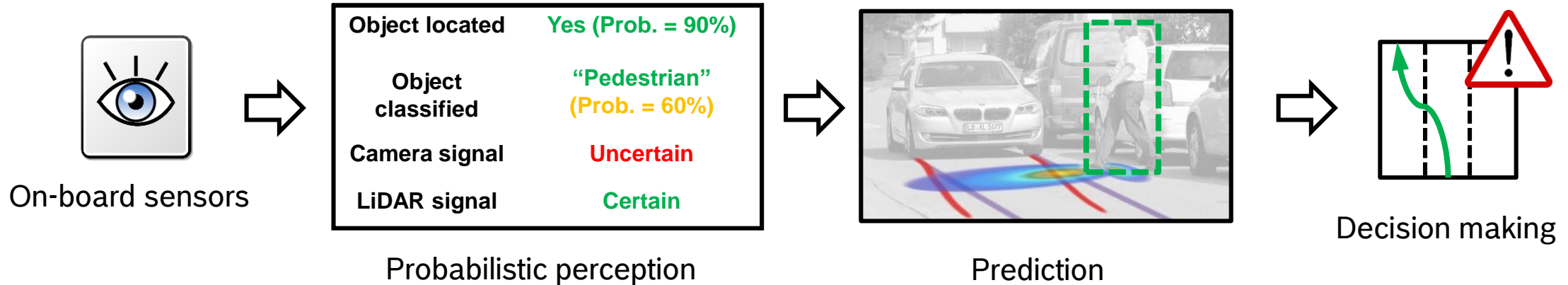
# Can we compare uncertainties in multi-modal perception systems?



Feng et al., "Deep Multi-modal Object Detection and Semantic Segmentation for Autonomous Driving: Datasets, Methods, and Challenges." *IEEE Transactions on Intelligent Transportation Systems* (2019). Minor revision.

# 4. Challenges

Are those captured uncertainties useful?



- Can uncertainty improve the tracking performance?
- Where can we really see the benefit of uncertainty? (e.g. safety-critical scenarios)





# THANK YOU

**Perception and Sensors for Autonomous Driving**  
**Bosch research**

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