

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

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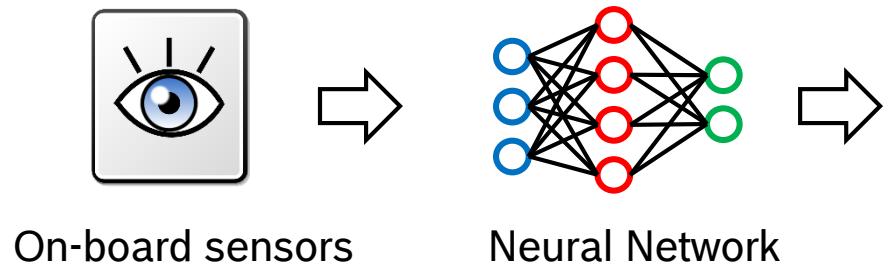
# Outline

- 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 ...”*

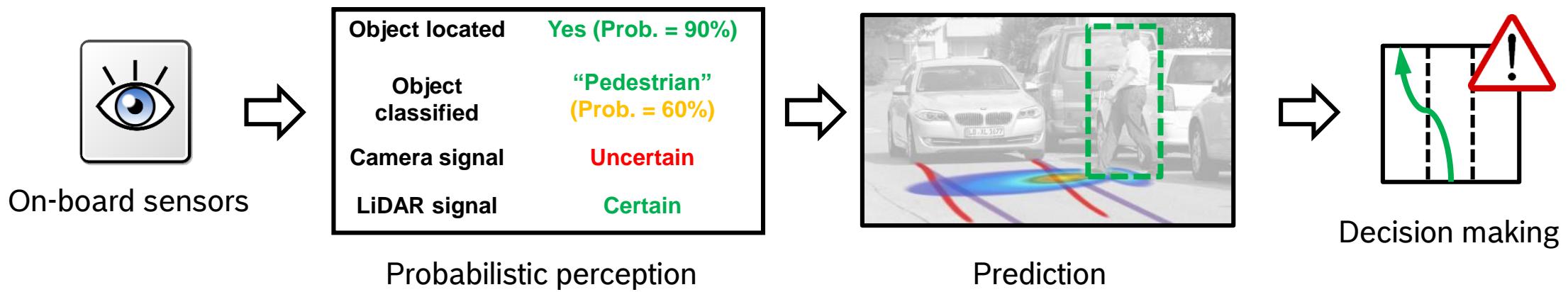
[Cosmides, et al., Cognition'96].



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

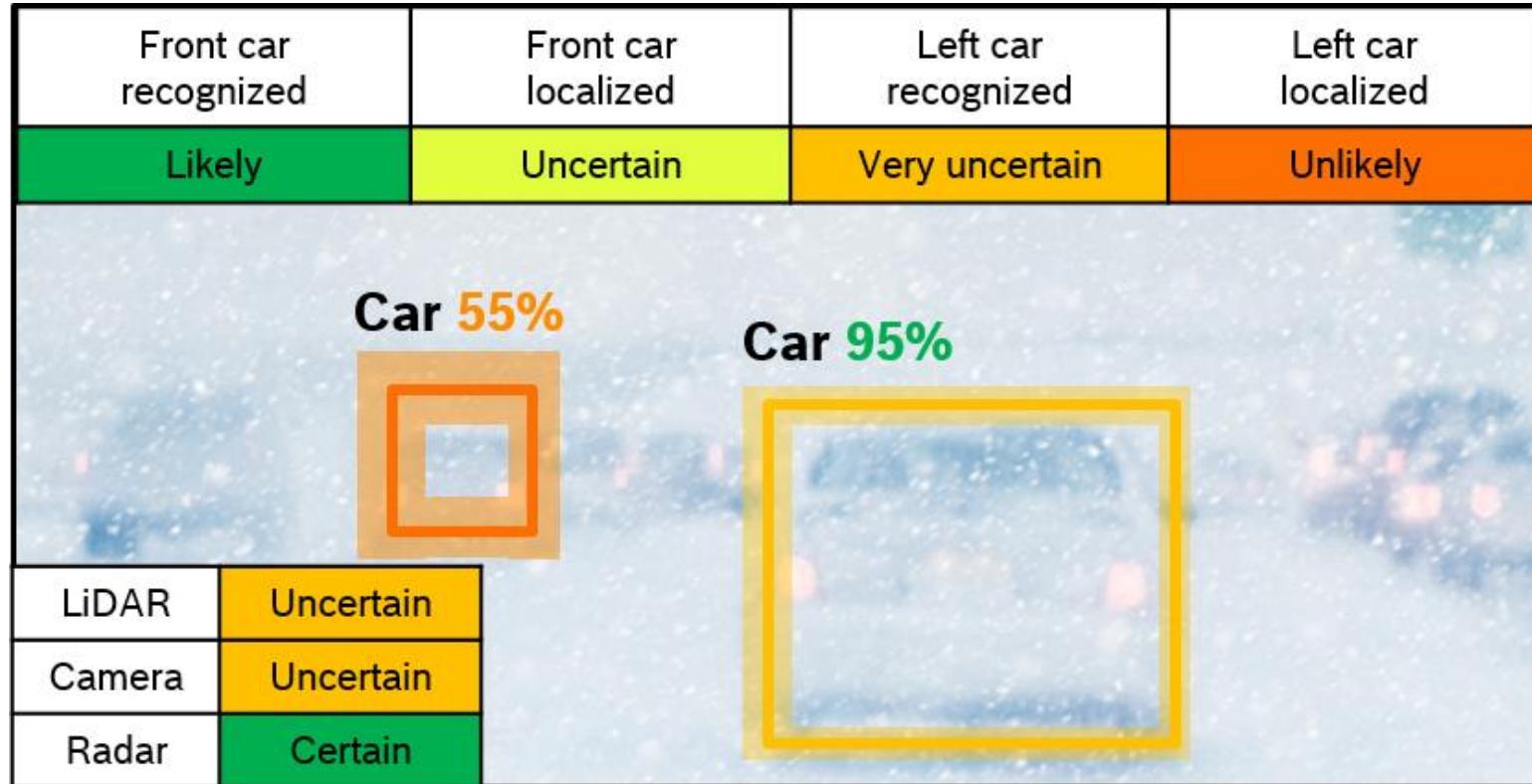
# 1. Motivation

## Increasing robustness of the general system



# 1. Motivation

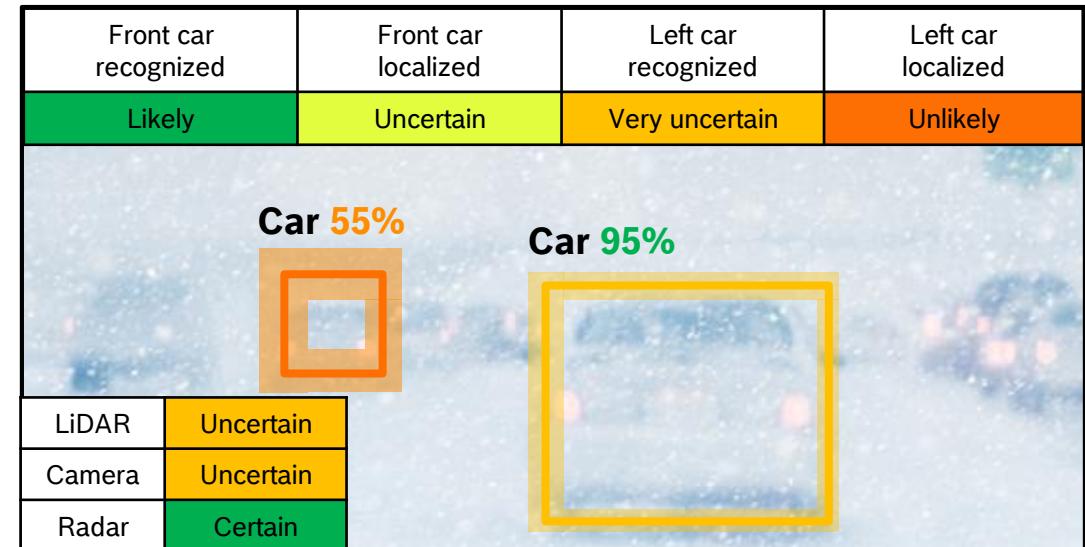
What can an ideal probabilistic object detector look like?



# 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 Dietmayer<sup>2</sup>



**Abstract**— To ensure that an autonomous car is driving safely on public roads, its object detection module should not only work correctly, but also show its prediction confidence as well. Current deep learning based detectors, however, do not explicitly model uncertainties in the neural network. We tackle with this problem by presenting practical methods to capture uncertainty in the deep neural network for 3D point clouds. The proposed probabilistic detector represents reliable epistemic uncertainty, which is useful for decision making and localization tasks. Experimental results show that the epistemic uncertainty is related to the detection accuracy, while the aleatoric uncertainty is related to sensor noise, weather and horizon. The results also show that we can improve the detection performance by 1% - 5% by modeling the aleatoric uncertainty.

### I. INTRODUCTION

Knowing what an object observes and what it unsure about is of paramount importance for safe autonomous driving. For example, if an autonomous car recognizes a front object as a pedestrian but is uncertain about its location, the system may move to avoid the pedestrian or the car at an early stage or slow down to avoid fatal accidents.

Deep learning has been introduced to object detection in the field of autonomous driving [1]–[10], where the most popular datasets that use cameras [1]–[3], LiDAR [4]–[10], and driving [11]–[17] are used. The most common metric for evaluating an object detector is the mean Average Precision (AP) over a set of categories. Softmax Entropy (SE) and Mutual Information (MI) quantify the epistemic uncertainty, and Total Variance (TV) the aleatoric uncertainty. These scores will be described in Sec. IV.

In the object detection network is indispensable for safe autonomous driving, as the epistemic uncertainty displays the degree of detection uncertainty, while the aleatoric uncertainty can provide sensor observation noises for tracking.

Recently, we developed practical methods to capture epistemic and aleatoric uncertainties in a 3D object detector for lidar-based vehicle detection [18]. Our findings are as follows:

- We extract model uncertainty and observation uncertainty for the vehicle recognition and 3D bounding box regression tasks.

We also improve of vehicle detection performance.

We study the difference between the epistemic and aleatoric uncertainty. The epistemic uncertainty is different from the training dataset may result in high epistemic uncertainty, while detecting a distant object may result in high aleatoric uncertainty.

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The code to this paper can be found in the statement.

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

Di Feng<sup>1</sup>, Lars Rosenbaum<sup>1</sup>, Fabian Timm<sup>1</sup>, Klaus Dietmayer<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 learn both aleatoric and epistemic uncertainty predicted by auxiliary output layers. Using our proposed method, the network learns to focus more on informative training samples and ignore the noisy ones. We call our method PROD (Probabilistic Robust Object Detection). 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, PROD can significantly reduce the detection error and significantly increases the average precision up to 9% compared to the baseline method without any uncertainty estimation.

**Keywords**— Object detection, deep neural network, active learning, autonomous driving

### I. INTRODUCTION

A robust and accurate object detection system using for onboard sensors (e.g., camera, LiDAR, Radar) is crucial for the road scene understanding of autonomous driving. Among different sensors, LiDAR is the most promising one for perception, information, and is robust under illumination conditions such as daytime and nighttime. These properties make LiDAR a key sensor for autonomous driving.

The recent Uber's autonomous driving fatal tragedy could have been avoided, if the LiDAR perception system had robustly detected the crosswalk and had informed the human driver to trigger the emergency braking because was uncertain with the driving situation [1].

Recently, deep learning approaches have brought significant improvements in the field of object detection [2]–[19]. However, they usually give no deterministic bounding box regression and no softmax scores for tracking. This motivates the improvement of object detection performance by leveraging aleatoric uncertainties and understanding how the uncertainties behave. Sec. V summarizes our 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 for autonomous driving and uncertainty quantification of deep neural networks.

#### A. LiDAR-Based Object Detection

Many works process the LiDAR information directly from point clouds [3], [15], [17], [14], [15], [17]. For example, Zhou et al. [3] propose a voxel feature encoding layer to handle 3D point clouds. Li [13] employs a 3D fully convolutional neural network to generate a 2D depth map and a 2D semantic map and a 3D bounding box. 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>, Atsuo Maki<sup>2</sup>, Klaus Dietmayer<sup>4</sup>

**Abstract**— Training a deep object detector for autonomous driving is a time-consuming task. Capturing training data via on-board sensors such as camera or LiDAR is relatively easy, annotating data is very tedious and time-consuming, especially for 3D object detection. Active learning has the potential to minimize human annotation efforts while maintaining detection performance. Therefore, we propose an active learning framework to train a LiDAR 3D object detector with the least number of labeled training data necessary to reach a target detection performance. The proposed framework uses LiDAR point clouds and the RGB images to reduce the search space of objects and scenes. The proposed framework can significantly outperform methods under different uncertainty estimations and uncertainty functions, and can save up to 90% labeling efforts while maintaining detection performance.

**Keywords**— Object detection, deep neural network, active learning, autonomous driving

### I. INTRODUCTION

Deep learning has in recent years set the benchmark for object detection tasks in many open datasets (e.g. KITTI [1], Cityscapes [2]), 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 annotated data, which is a time-consuming and costly work, especially for annotating 3D LiDAR points, as discussed in [3]. Therefore, developing methods to reduce the labeling effort is critical for the success of autonomous driving.

The recent Uber's autonomous driving fatal tragedy could have been avoided, if the LiDAR perception system had robustly detected the crosswalk and had informed the human driver to trigger the emergency braking because was uncertain with the driving situation [1].

In the sequel, we will summarize related works in Sec. III, and their descriptions are detailed in Sec. III in detail. In the following, we emphasize the experimental results and the improvement of object detection performance by leveraging aleatoric uncertainties and understanding how the uncertainties behave. Sec. V summarizes our work and discusses future research. The video of this work is provided as supplementary material.

### II. RELATED WORKS

In this section, we introduce the active learning framework to 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.

In the sequel, we introduce the active learning framework to train a LiDAR 3D object detector for autonomous driving. Despite its high performance, training a deep object detector usually requires a huge amount of annotated data, which is a time-consuming and costly work, especially for annotating 3D LiDAR points, as discussed in [3]. Therefore, developing methods to reduce the labeling effort is critical for the success of autonomous driving.

In the following, we emphasize the experimental results and the improvement of object detection performance by leveraging aleatoric uncertainties and understanding how the uncertainties behave. Sec. V summarizes our work and discusses future research. The video of this work is provided as supplementary material.

**Keywords**— Reliable uncertainty estimation is crucial for perception systems in safe autonomous driving. Recently, many methods have been proposed to model uncertainties in deep learning; these direct modeling approaches assumes a certain probability distribution over the network outputs (e.g. Gaussian distribution), and uses auxiliary output layers to predict probabilities often model uncertainties, which lead to severe problems in safety-critical scenarios. In this work, we identify such uncertainty modeling problems and propose three practical methods to address them. We evaluate the performance of our methods to reduce errors in uncertainty calibration. Extensive experiments on several datasets show that our methods produce well-calibrated uncertainties, and generalize well between different datasets.

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>, Claudio Gliser<sup>1</sup>, Fabian Timm<sup>1</sup>, Klaus Dietmayer<sup>2</sup>

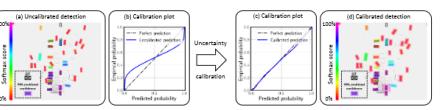


Fig. 1: A state-of-the-art probabilistic LiDAR 3D object detector produces uncalibrated uncertainties. (a) Each detection in the LiDAR bird's eye view plane is colored according to the softmax intervals. The 95% position confidence intervals in the unlabeled data pool, queried the human annotator the most informative samples, and updates with the newly-labeled data.

In recent years, many methods have been proposed to model uncertainties in deep neural networks. Among them, the direct modeling approach assumes a certain probability distribution over the network outputs (e.g. Gaussian distribution), and uses auxiliary output layers to predict probabilities often model uncertainties, which lead to severe problems in safety-critical scenarios. In this work, we identify such uncertainty modeling problems and propose three practical methods to address them. We evaluate the performance of our methods to reduce errors in uncertainty calibration. Extensive experiments on several datasets show that our methods produce well-calibrated uncertainties, and generalize well between different datasets.

### III. RELATED WORK

Reliable uncertainty estimation in object detection systems is crucial for safe autonomous driving. Intuitively, a probabilistic object detector should be able to distinguish between 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 better drivers, reduces car-to-car users, and humans, and can improve the quality of predictions in a frequentist sense [1]. Moreover, the uncertainties captured by object detectors can be propagated to other modules, such as tracking and motion planning [2], so that the overall system robustness can be enhanced.

**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 ensemble approach consists 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, but it is computationally expensive. The direct modeling approach assumes a certain probability distribution over the network outputs (e.g. Gaussian distribution), and uses auxiliary output layers to predict probabilities often model uncertainties, which lead to severe problems in safety-critical scenarios. In this work, we identify such uncertainty modeling problems and propose three practical methods to address them. We evaluate the performance of our methods to reduce errors in uncertainty calibration. Extensive experiments on several datasets show that our methods produce well-calibrated uncertainties, and generalize well between different datasets.

[Feng et al., ITSC'18]

[Feng et al., IV'19a]

[Feng et al., IV'19b]

[Feng et al., IROS'19]

# Outline

1. Motivation

**2. Uncertainties in object detection networks**

3. Probabilistic LiDAR object detectors

4. Challenges

## 2. Uncertainties in object detection networks

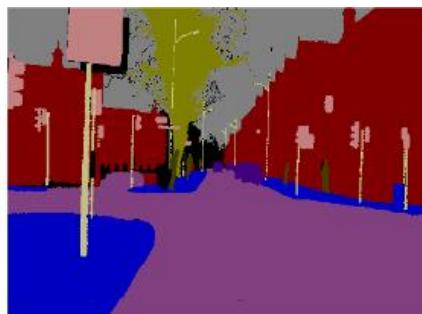
What kind of uncertainties can we model in object detection networks?

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

[Kendall et al., NeurIPS'17]



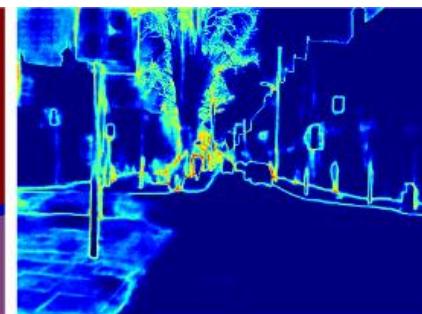
(a) Input Image



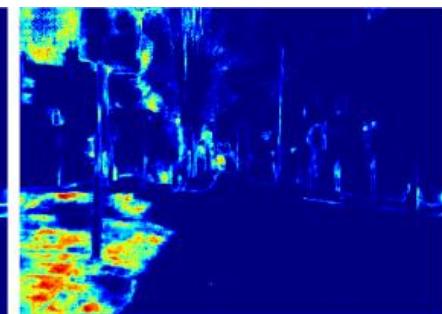
(b) Ground Truth



(c) Semantic Segmentation



(d) Aleatoric Uncertainty



(e) Epistemic Uncertainty

## 2. Uncertainties in object detection networks

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

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

Predictive uncertainty

Aleatoric uncertainty

Epistemic uncertainty

$\mathbf{x}$  : Input vector

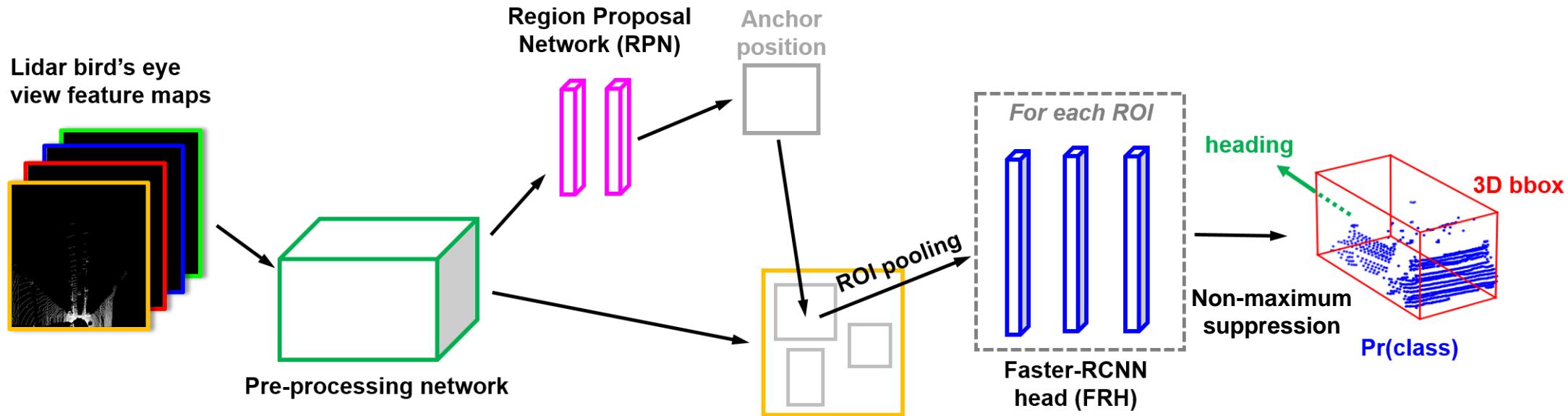
$\mathcal{D}$  : Training dataset

$\mathbf{y}$  : Prediction output vector

$\mathbf{W}$  : Network weight variables

## 2. Uncertainties in object detection networks

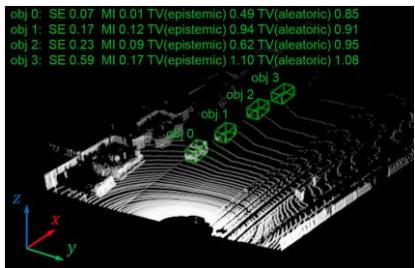
Modeling uncertainties in object detection networks: a big work



[Ren et al., NeurIPS'15]

## 2. Uncertainties in object detection networks

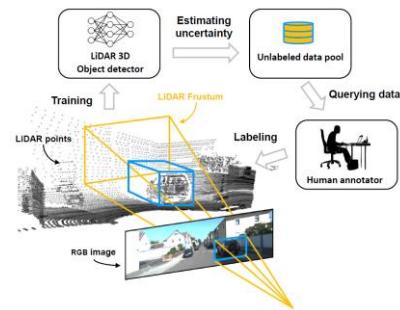
### State of the art



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



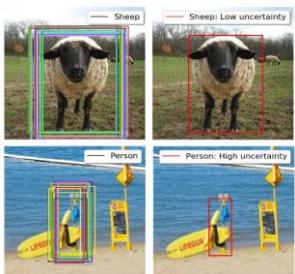
[Truong et al., ITSC'18]  
Uncertainties in an image detector



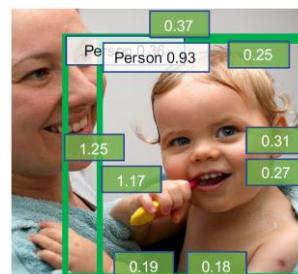
[Feng et al., IV'19b]  
Active learning for a probabilistic detector



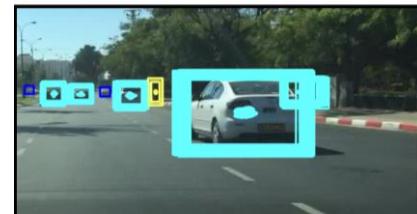
[Miller et al., ICRA'18]  
Detection in open-set conditions.



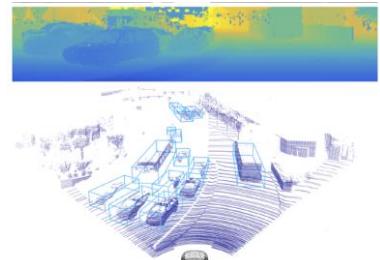
[Miller et al., ICRA'19]  
Uncertainty and merging strategy



[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

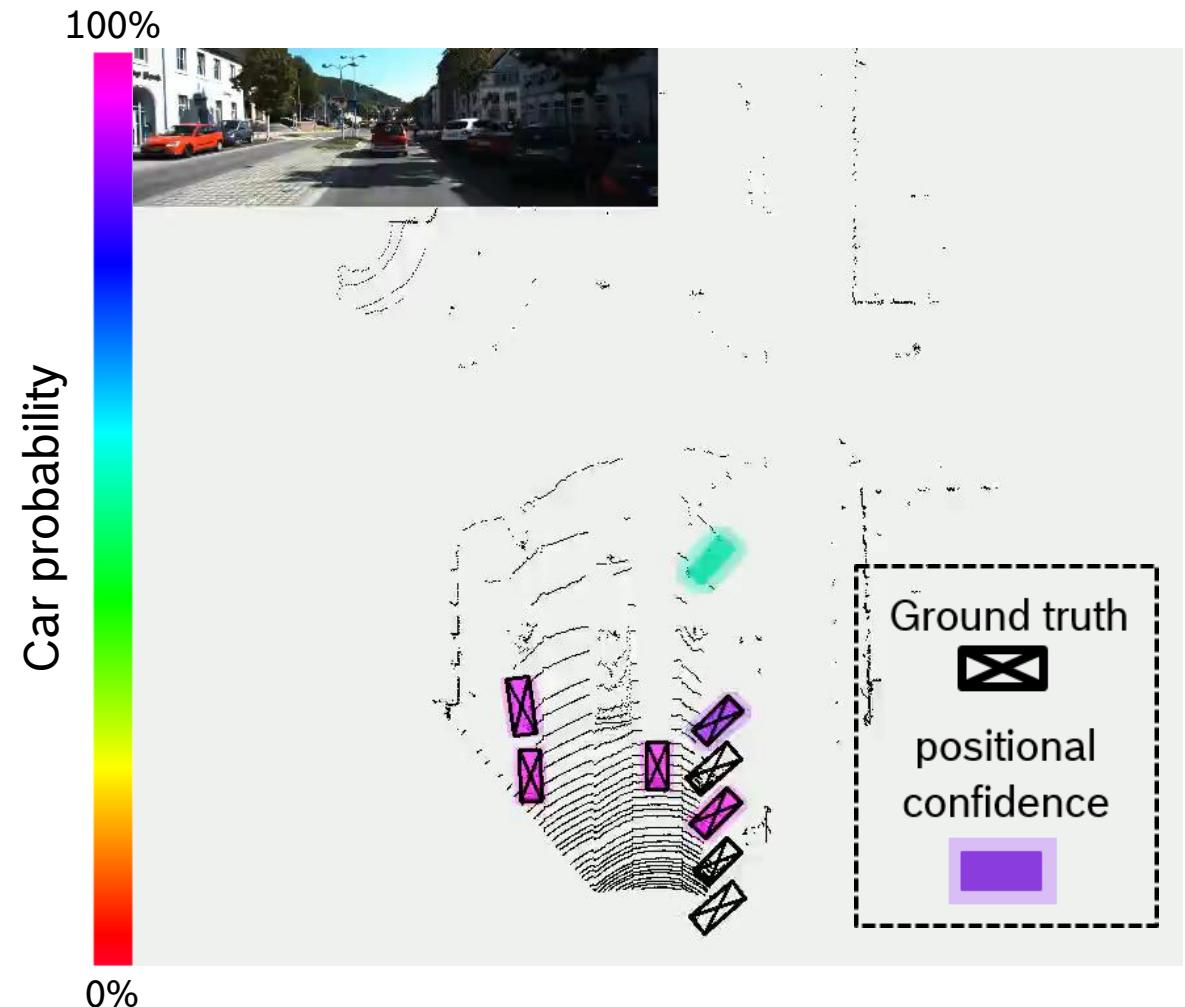
**3. Probabilistic LiDAR object detectors**

4. Challenges

### 3. Probabilistic LiDAR object detectors

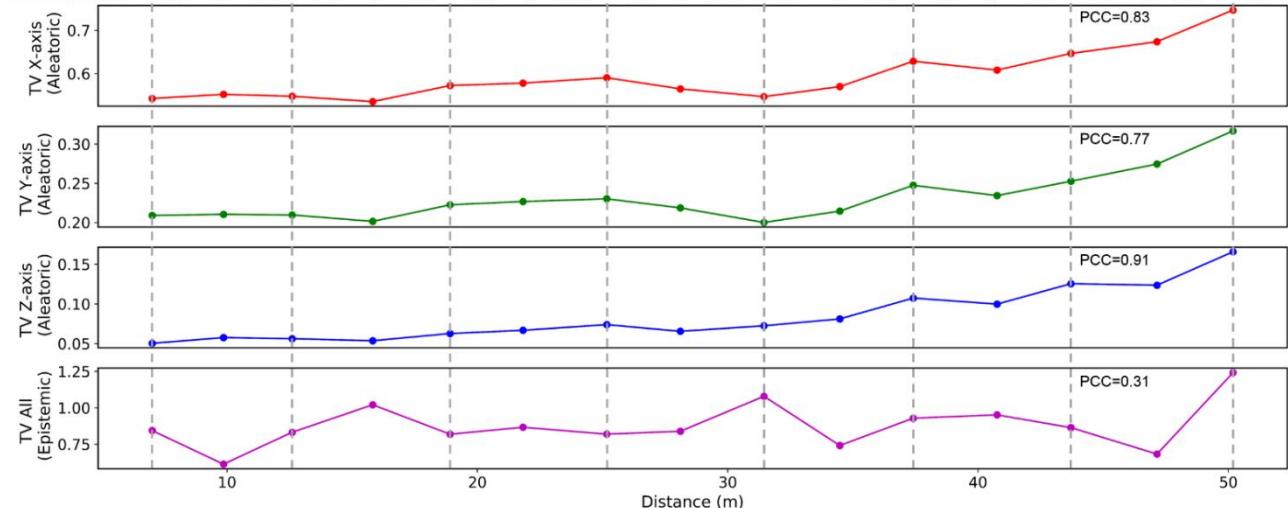
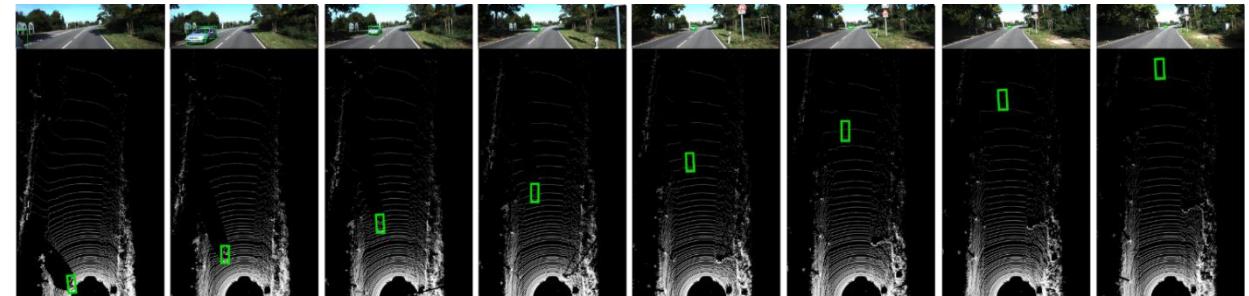
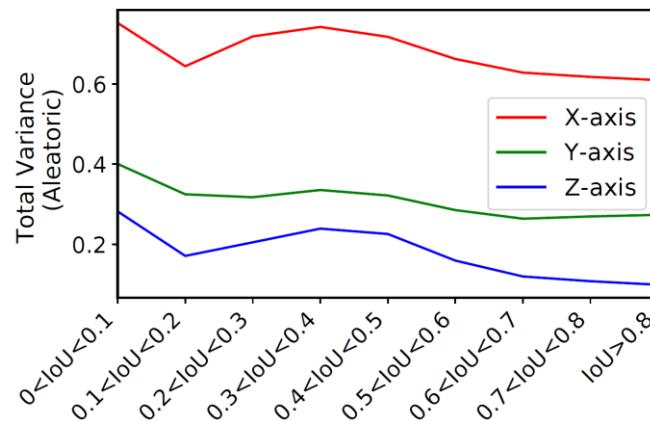
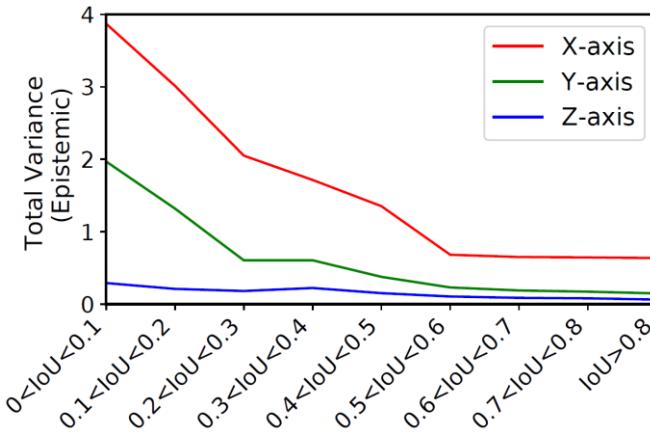
#### Summary

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



### 3. Probabilistic LiDAR object detectors

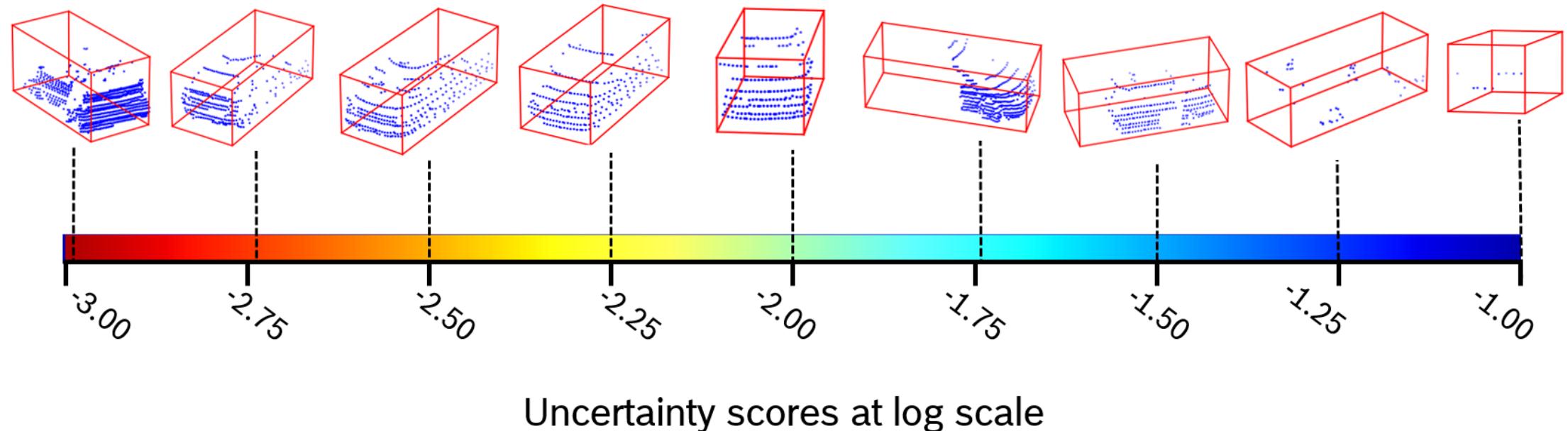
Epistemic and aleatoric uncertainties behave very differently [Feng et al., ITSC'18]

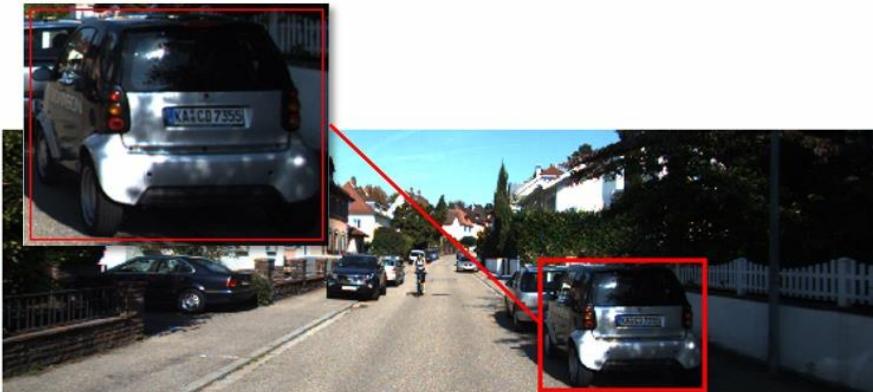


PCC: Pearson Correlation Coefficient

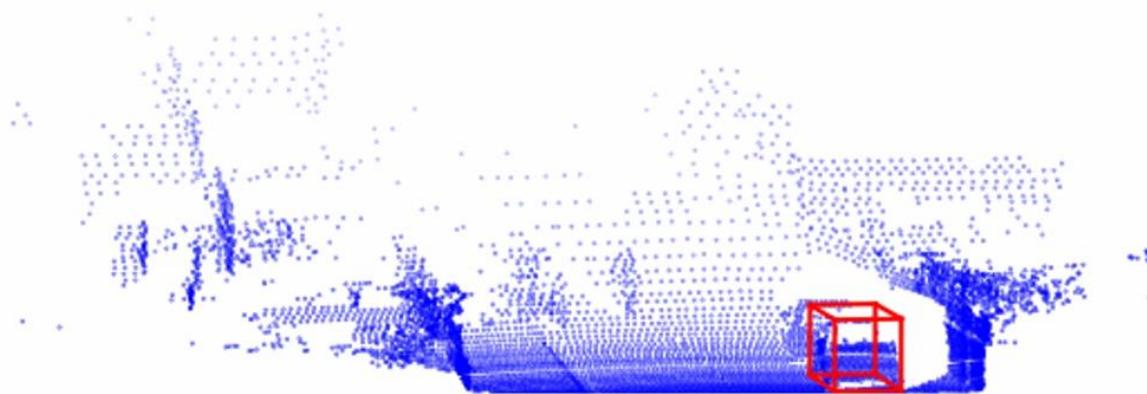
### 3. Probabilistic LiDAR object detectors

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





Detection in RGB image



Detection in LiDAR point clouds

## Detection Information

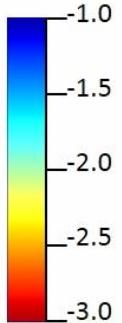
Uncertainty score: **-2.92**

Softmax score: 0.87

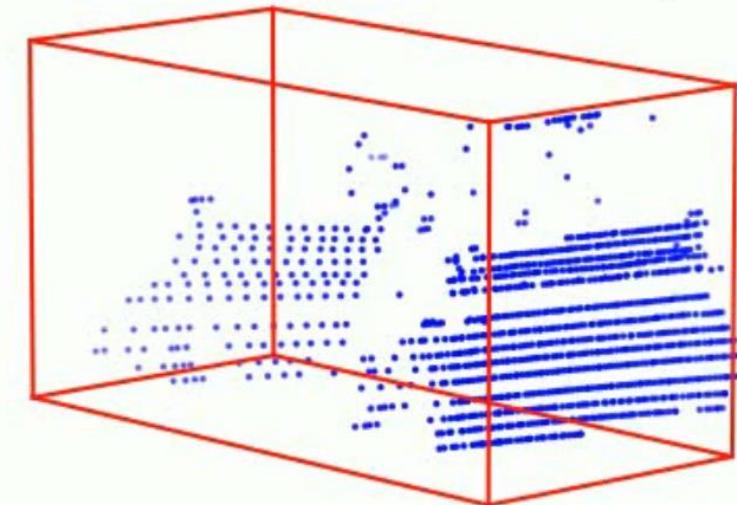
Distance: 7.5 m

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.

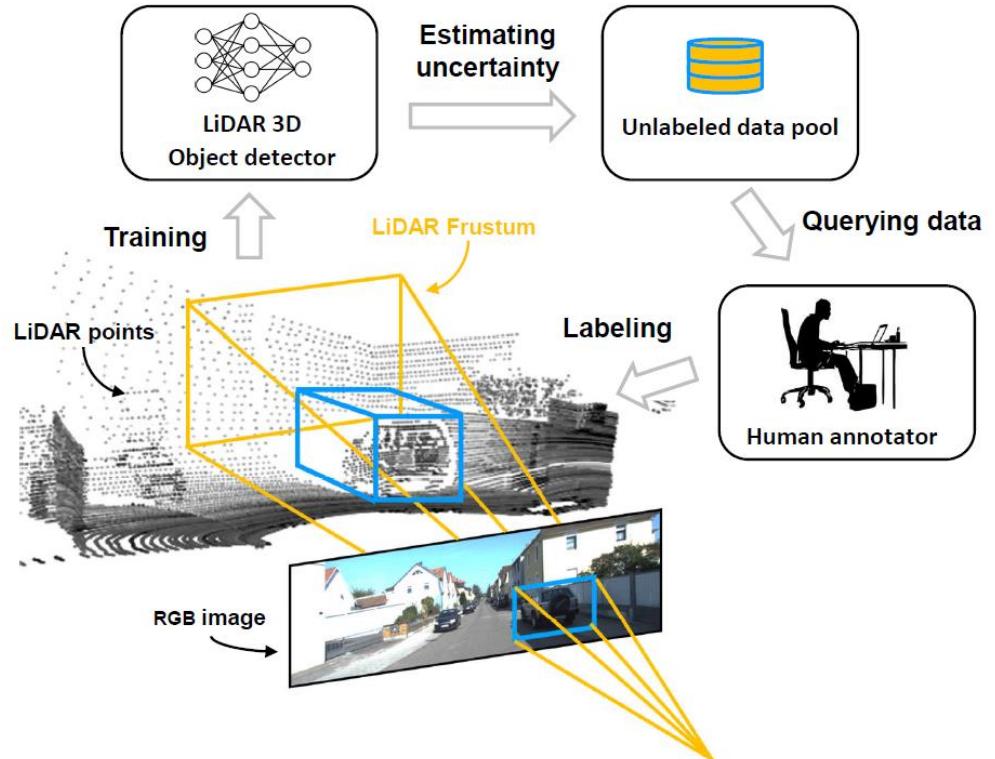
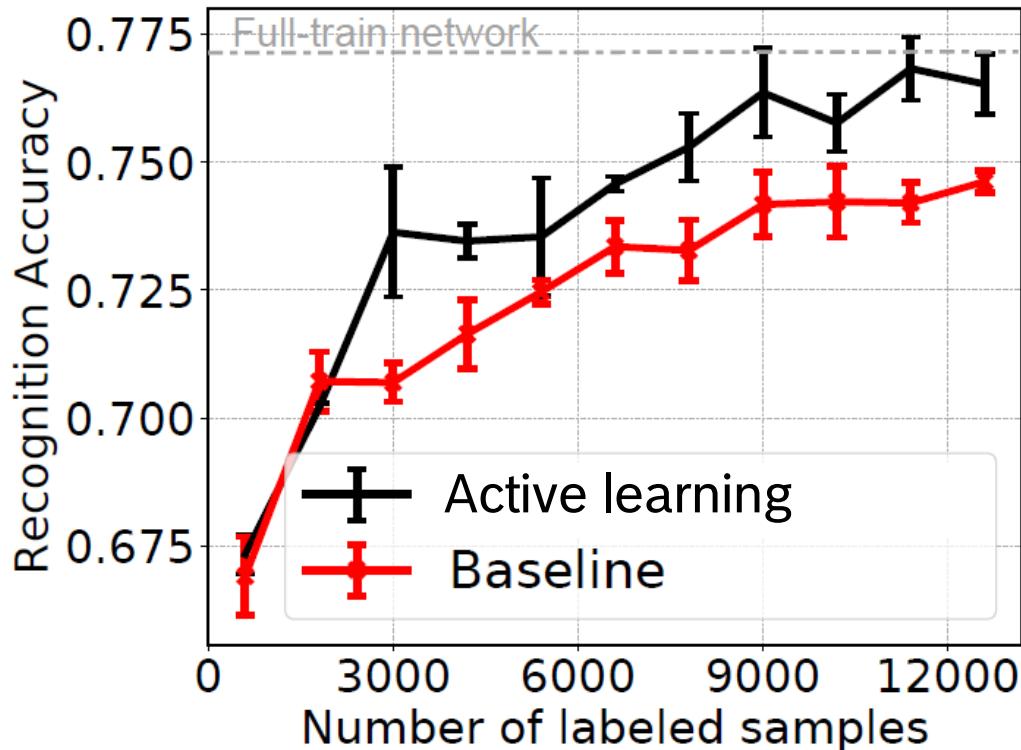
[Qi et al., CVPR'18]

[Zhou et al., CVPR'18]

[Yang et al., CVPR'18]

### 3. Probabilistic LiDAR object detectors

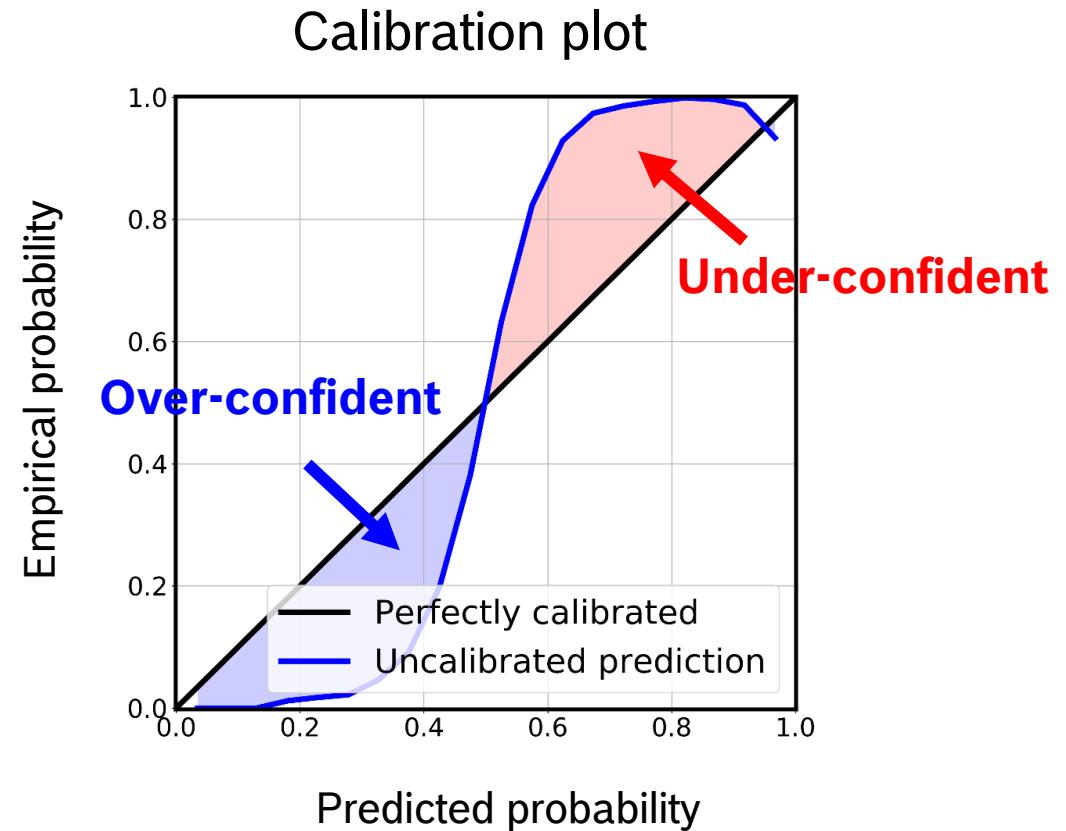
Using epistemic uncertainty to improve training efficiency [Feng et al., IV'19b]



### 3. Probabilistic LiDAR object detectors

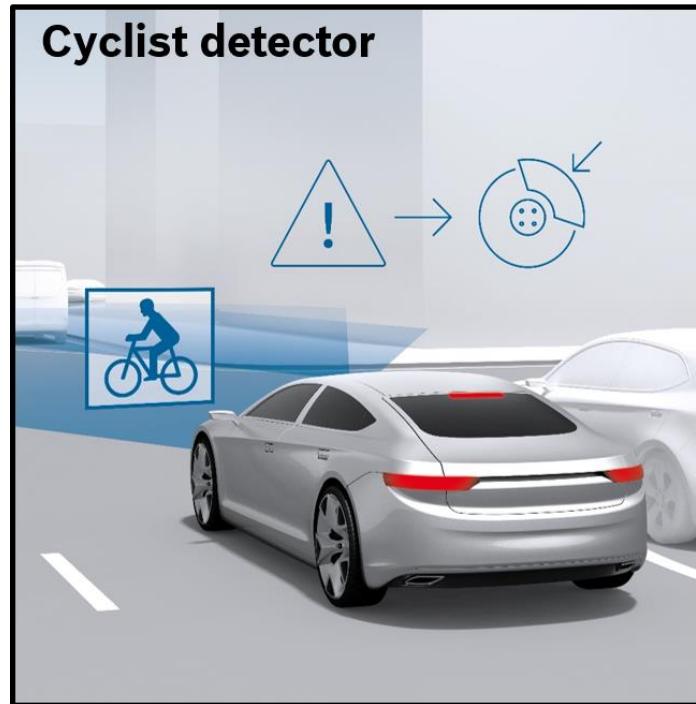
Can we trust uncertainty estimation? [Feng et al., IROS'19]

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



### 3. Probabilistic LiDAR object detectors

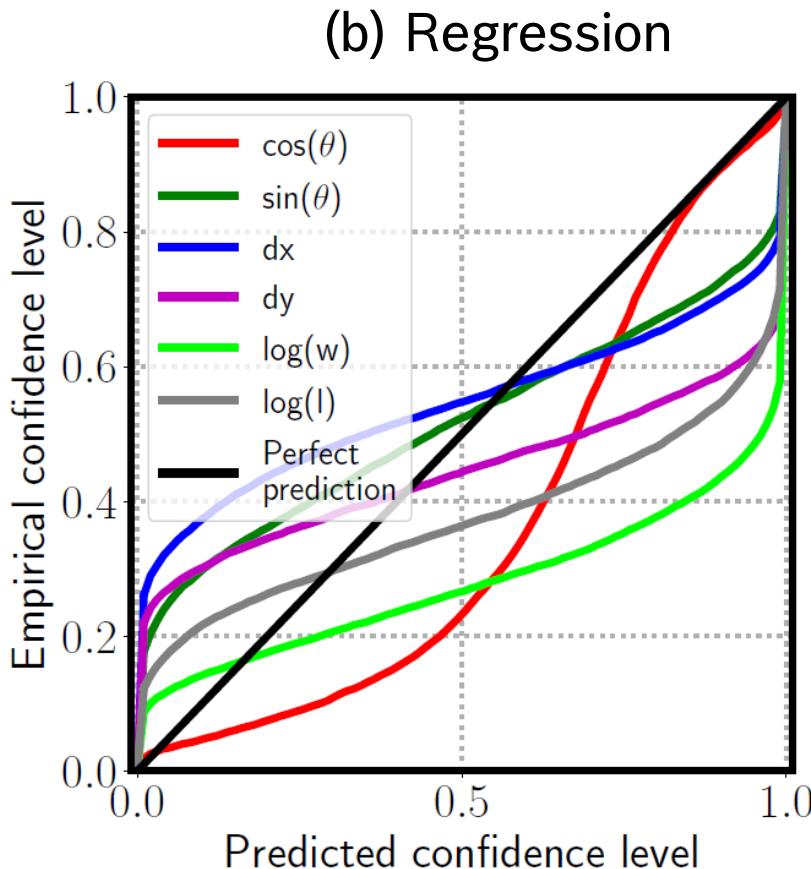
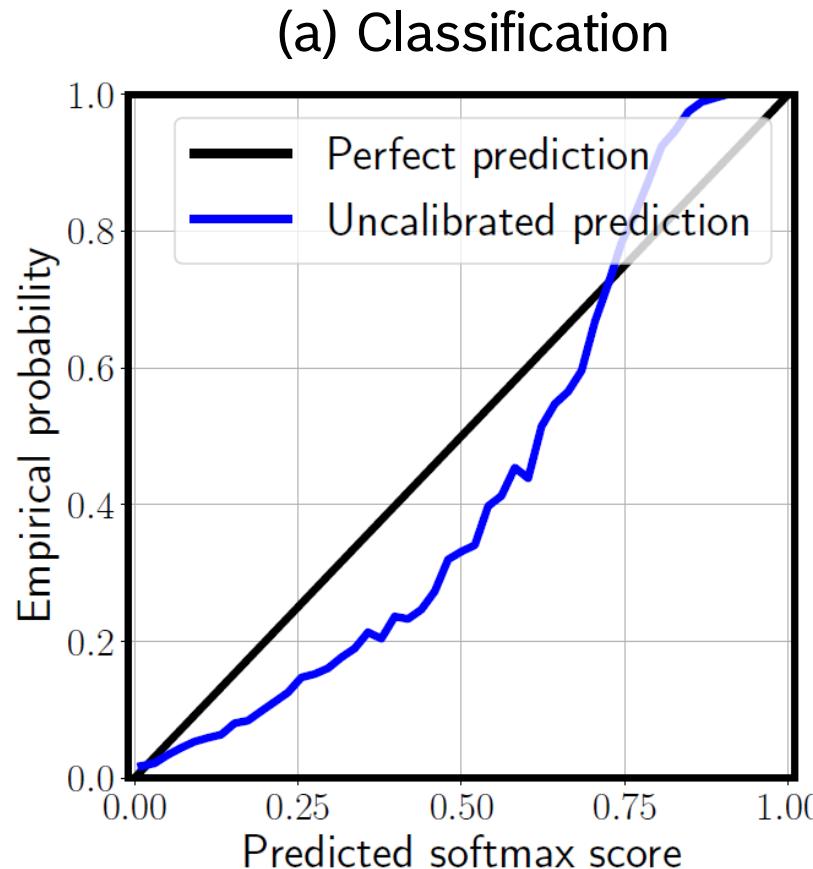
#### Importance of well-calibrated uncertainty



- **Over-confident detection**  
! Uncomfortable braking
- **Under-confident detection**  
↑ Fatal accident !
- **Reliable detection**  
! ↑ Safe and sound

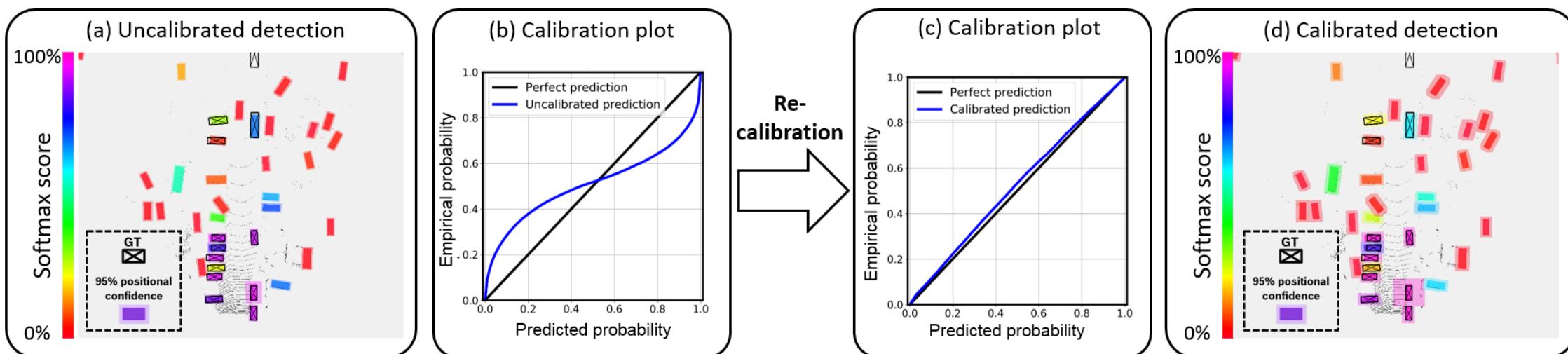
### 3. Probabilistic LiDAR object detectors

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



### 3. Probabilistic LiDAR object detectors

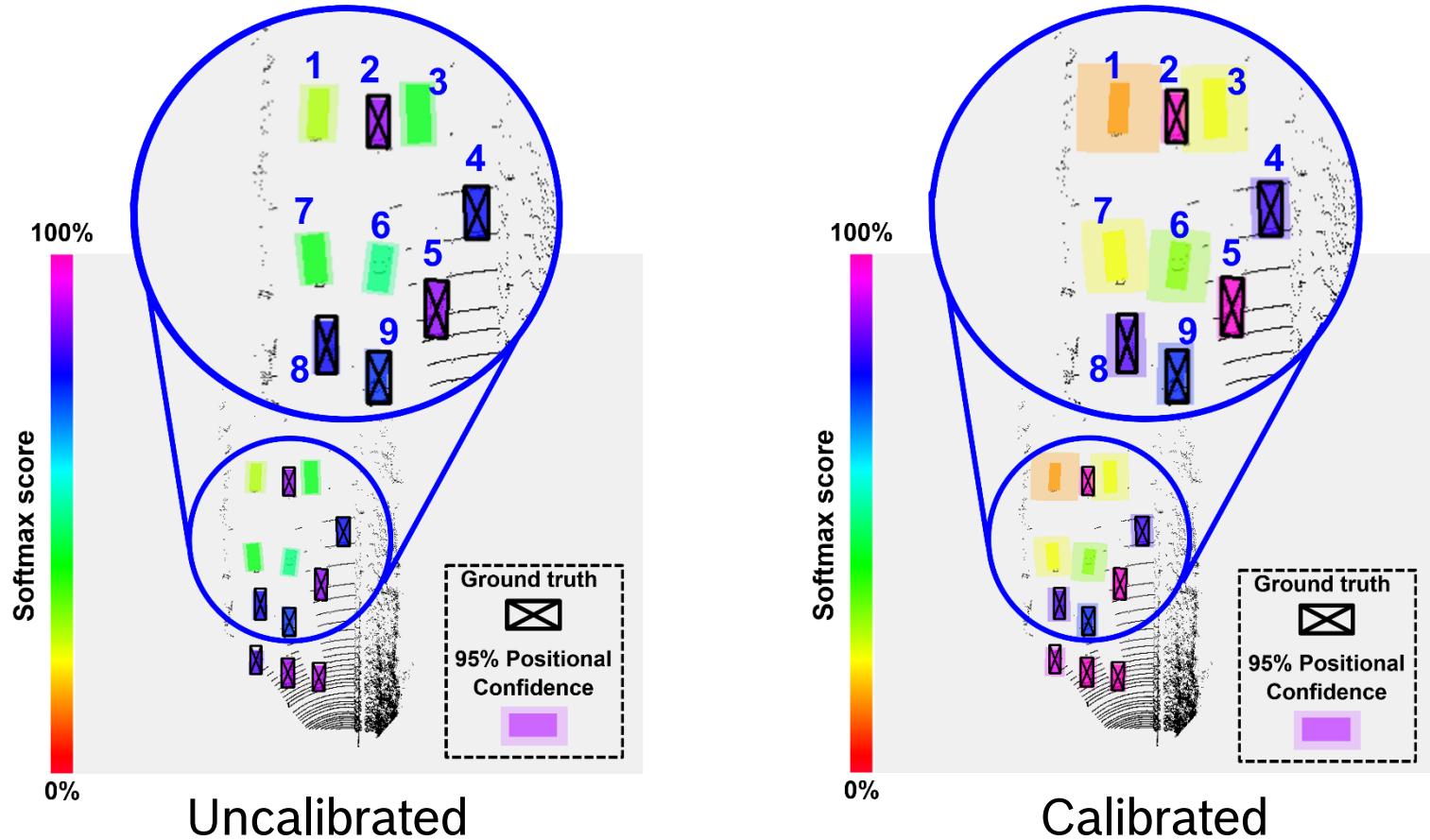
Proposing three uncertainty recalibration methods to largely reduce uncertainty calibration error



[Feng et al., IROS'19]

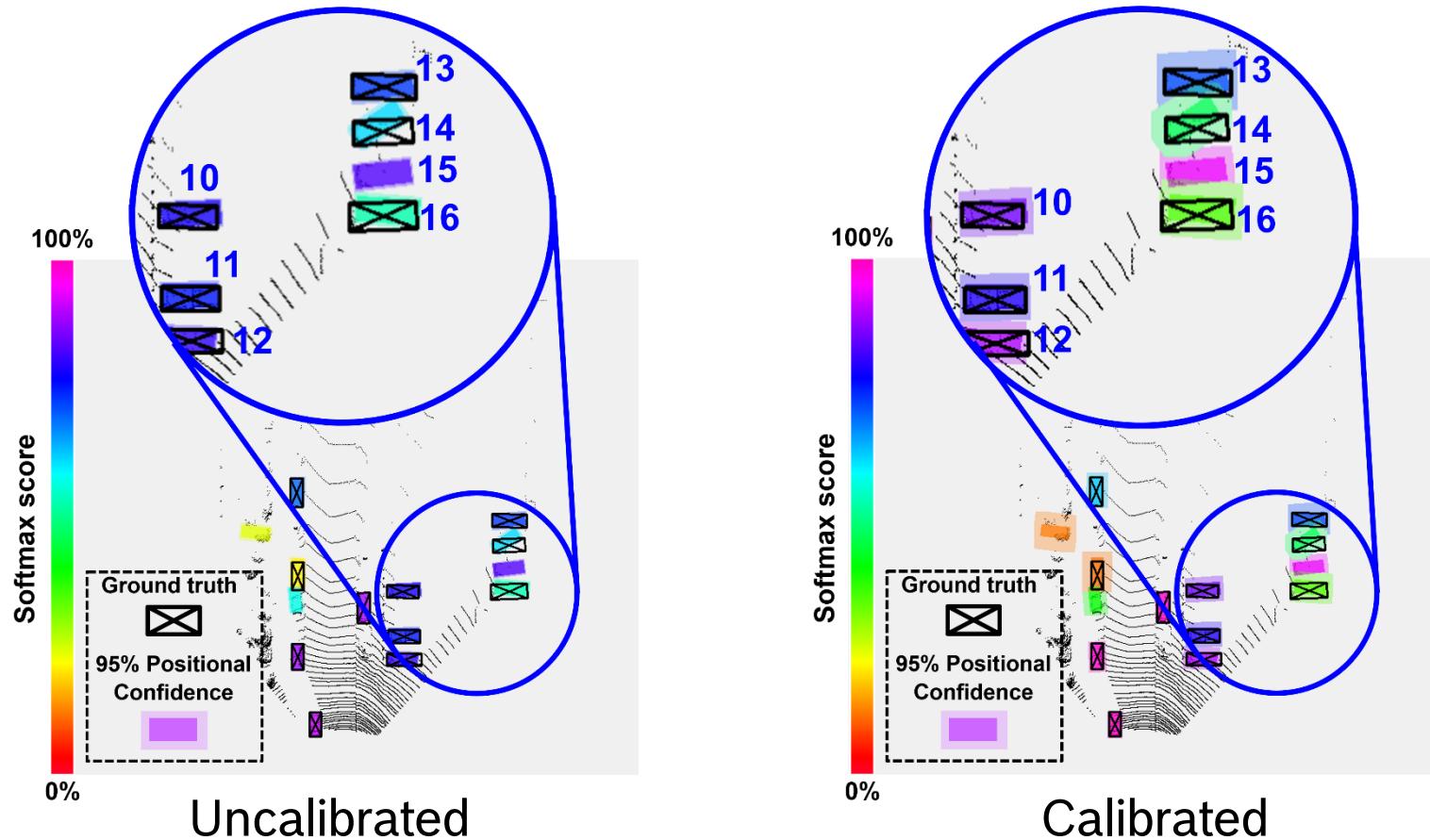
### 3. Probabilistic LiDAR object detectors

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



### 3. Probabilistic LiDAR object detectors

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

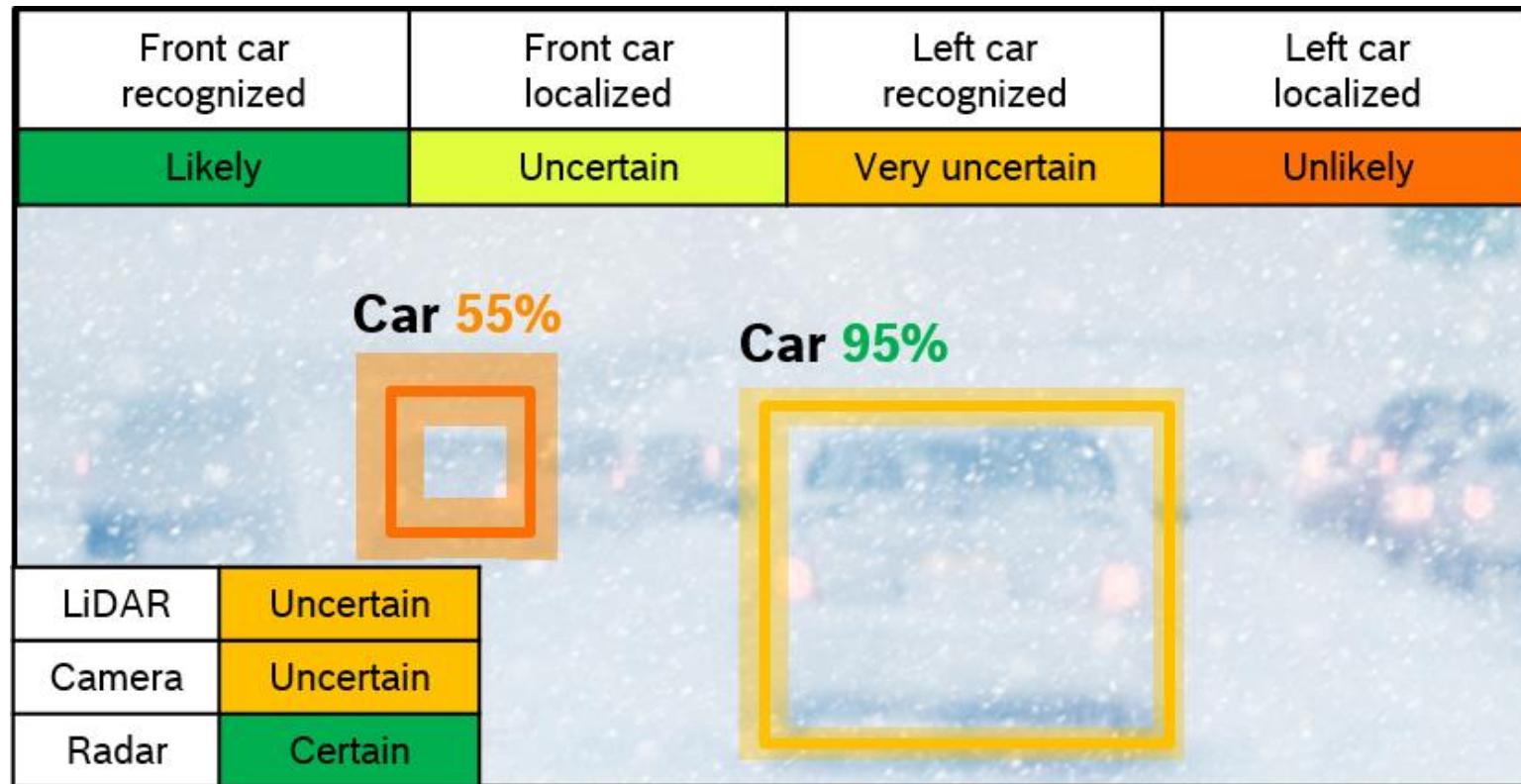


### 3. Probabilistic LiDAR object detectors

Our LiDAR object detectors model uncertainties:

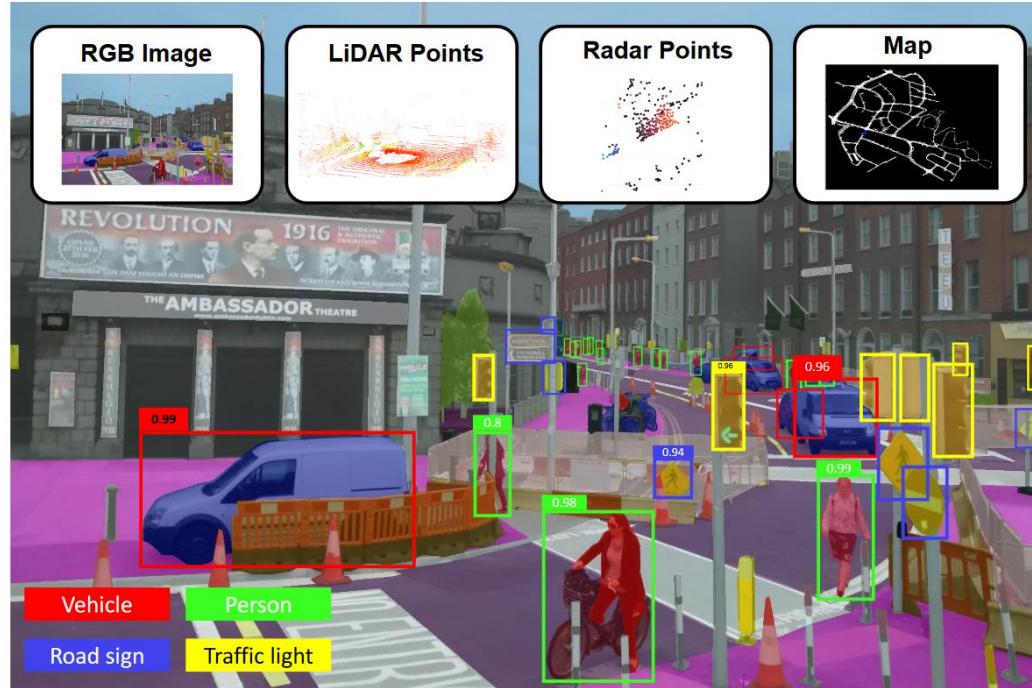
- **Holistic:** cls+reg; in two/one-stage detectors; epistemic/aleatoric uncertainties
- **Well-calibrated:** after uncertainty recalibration [Feng et al., IROS'19]
- **Explainable:**
  - Reflect environmental noises such as distance & occlusion [Feng et al., ITSC'18 & IV'19a]
  - Reflect model's accuracy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

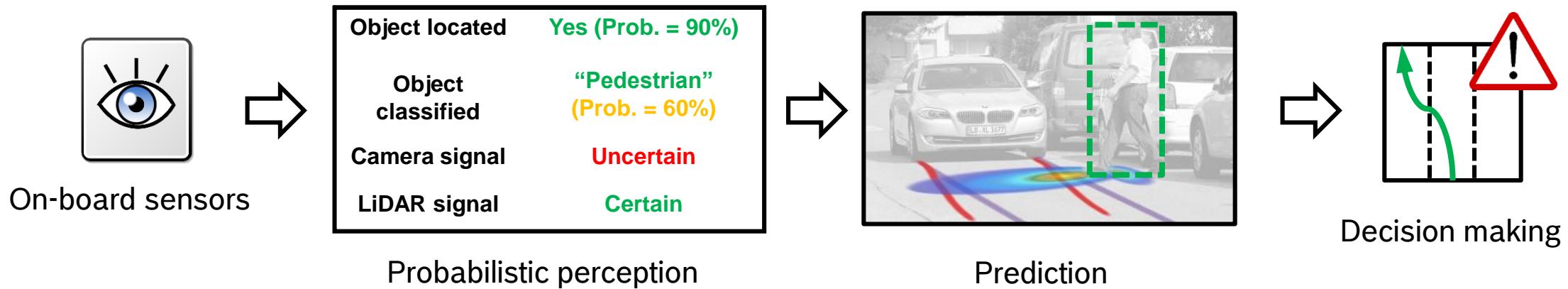
Can we compare uncertainties in multi-modal perception systems?



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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