KI DELTA LEARNING
Scalable AI for Automated Driving

Uncertainty Estimation for LiDAR-based Semantic Segmentation

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WP 2.5
WP 4.1

Environment

Use-Case in Delta Learning

Environment perception is a crucial element in autonomous driving: it provides the basis for path- & behavior planning of self-driving cars. Thus, deep learning models have to be particularly robust to operate properly in the highly ambiguous open world environment. Therefore, they need a way to deal with uncertain situations or domain shifts (e.g. rain or fog). Especially the LiDAR sensor has limitations when encountering adverse weather conditions - detecting and dealing with those limitations is essential for robust perception algorithms.
A large body of research demonstrates impressing results on semantic segmentation of LiDAR point clouds [1, 2, 3]. Nevertheless, the general robustness against adverse conditions can be enhanced by implementing an uncertainty estimation into the model's predictions.

Technical Problem

[4] demonstrated that interpreting the softmax output of a classification model as the model confidence leads to overly confident estimations. To overcome this, bayesian deep learning is an suitable method to quantify uncertainty [5]. Instead of point estimates, distributions are assigned to the neural network's weights, so that the variance of the distribution over the output classes can be interpreted as the model's uncertainty. The main problem here is to find a tractable solution to approximate the true posterior.

Technical Solution

In practice, simulating a non-deterministic behavior in otherwise deterministic models is usually done with sampling-based techniques.

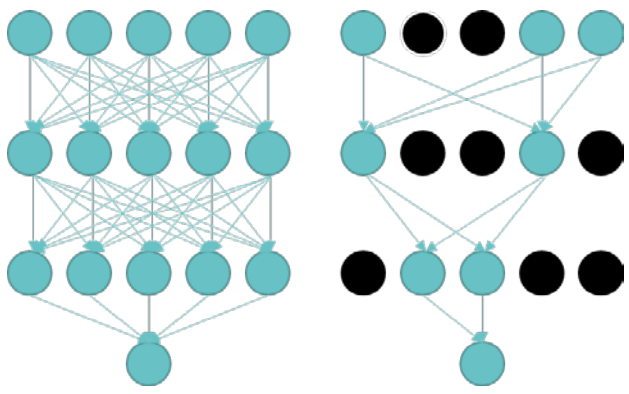

Figure 1: Schematic illustration of a model inference with and without Monte Carlo Dropout.

One popular example is Monte Carlo Dropout [6]. The main idea here is to conduct multiple (stochastic) forward passes through the same network with dropout at inference time (Fig.1). The variance of the softmax probabilities of all outputs can be interpreted as the model uncertainty. These uncertainty estimation methods produce reliable results in terms of the model's confidence calibration and are considered State-of-the-Art in safety critical applications (Fig. 2).

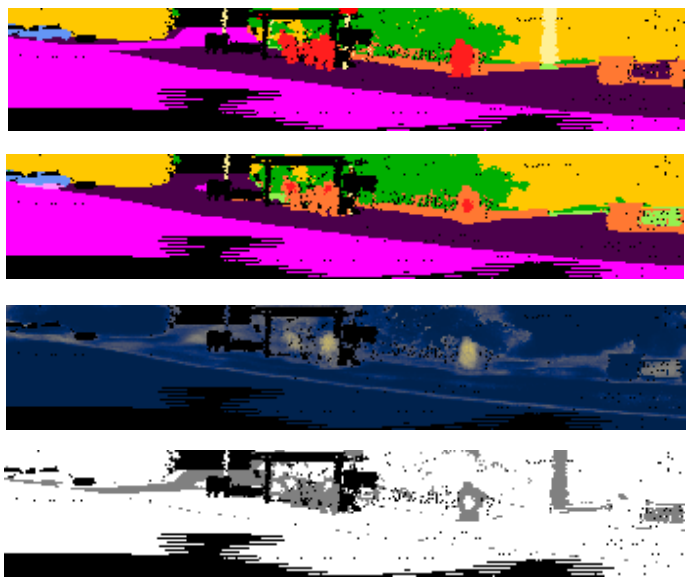

Figure 2: Example of uncertainty quantification using Monte Carlo Dropout (bus stop scene, black = invalid points).
a) Semantic label ground truth
b) Prediction of the semantic label (SalsaNext-based architecture, trained on SemanticKITTI)
c) Uncertainty quantification using MCD (the brighter the color the higher the uncertainty)
d) Difference between ground truth label and prediction (white = correct, gray = incorrect)
It can be seen that in regions, where the model predicted wrong classes, the uncertainty is higher than in regions where it did correct predictions (e.g. the pedestrians waiting at the bus stop).

Nevertheless, sampling at inference time is computationally expensive and not always applicable in autonomous driving tasks.
One possible approach to overcome this is an implicit uncertainty estimation using hierarchical classification models. The idea here is to have a fallback option for each class in highly uncertain situations. The most crucial question here is to quantitatively compare this approach with existing and established uncertainty estimation methods. Factors like suitable network architectures, training strategies, and evaluation metrics have to be taken into consideration.

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Partners

External partners

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