Highly Automated Labeling for Perception in Automated Driving

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Highly Automated Labeling

Training and validation of machine learning, especially deep learning methods, requires vast amounts of data. However, labeling, in particular for object detection, is a time-consuming and therefore costly task. In our research we investigate different methods to significantly reduce the labeling effort [1].

Pre-Labeling via Cross-Domain Label Transfer

In this approach, we consider that many modern vehicles are equipped with various sensors, including cameras, LiDAR, and RADAR. We exploit this sensor diversity (i.e., the strengths and weaknesses of the respective sensors) by transferring labels between different sensor modalities [2]. Our approach is illustrated in Figure 1. First, we train probabilistic object detectors for each of the sensors. We further use their predictions as so-called pre-labels. These can, in turn, be used to improve the object detectors of the other sensor modality, e.g., by means of fusion. We apply human-in-the-loop learning, such as active learning, to realize a quality checking process in a cost-efficient manner.

Probabilistic Object Detection

An integral component of our approach to highly automated labeling is the probabilistic modeling of the utilized AI methods. To intelligently select data to be labeled, we must model the certainty of predictions and we need to determine those things which the AI does not know, i.e., unknown and new object instances. To do so, we leverage Bayesian neural networks or their approximations via Monte-Carl Dropout. This allows to model the epistemic as well as aleatory uncertainty of object detection networks. Furthermore, we use methods of probability calibration to improve the quality of the model's uncertainty estimates. These probabilistic predictions can then be utilized either in fusion approaches or active learning.

Active Learning

To reduce the costs in data annotation and model training, active learning provides methods to iteratively select only those data samples that are deemed to be most useful for model training. Most often, the corresponding acquisition functions are based on a model's uncertainty about its own predictions, e.g., estimated by the aforementioned Monte-Carlo Dropout technique. We apply a variety of such acquisition functions to the object detection task in the BDD100K dataset and show that a subset of the available data suffices to achieve good performances while drastically reducing the labeling costs (as measured by the number of objects to be labeled).

Cost vs. Performance rel. to Random Sampling

	bim	cex	cem	cbx	bix	rdm	oex	obx	abx	cbm	ob9	oem	obm	ob5	oe5	oe9
Cost [$\%_{rdm}$]	89	67	54	95	96	100	100	108	107	131	140	143	135	140	144	144
mAP [$\%_{rdm}$]	95	95	95	99	100	100	100	100	101	101	101	102	102	102	102	102

References:

[1] Schneegans, J., Bieshaar, M., Heidecker, F., Sick, B.: Intelligent and Interactive Video Annotation for Instance Segmentation using Siamese Neural Networks. Workshop ICPR. Milan, Italy (2021).

[2] Bieshaar, M., Herde, M., Huselijc, D., Sick, B.: A Concept for Highly Automated Pre-Labeling via Cross-Domain Label Transfer for Perception in Autonomous Driving. Workshop ECML PKDD (2021).

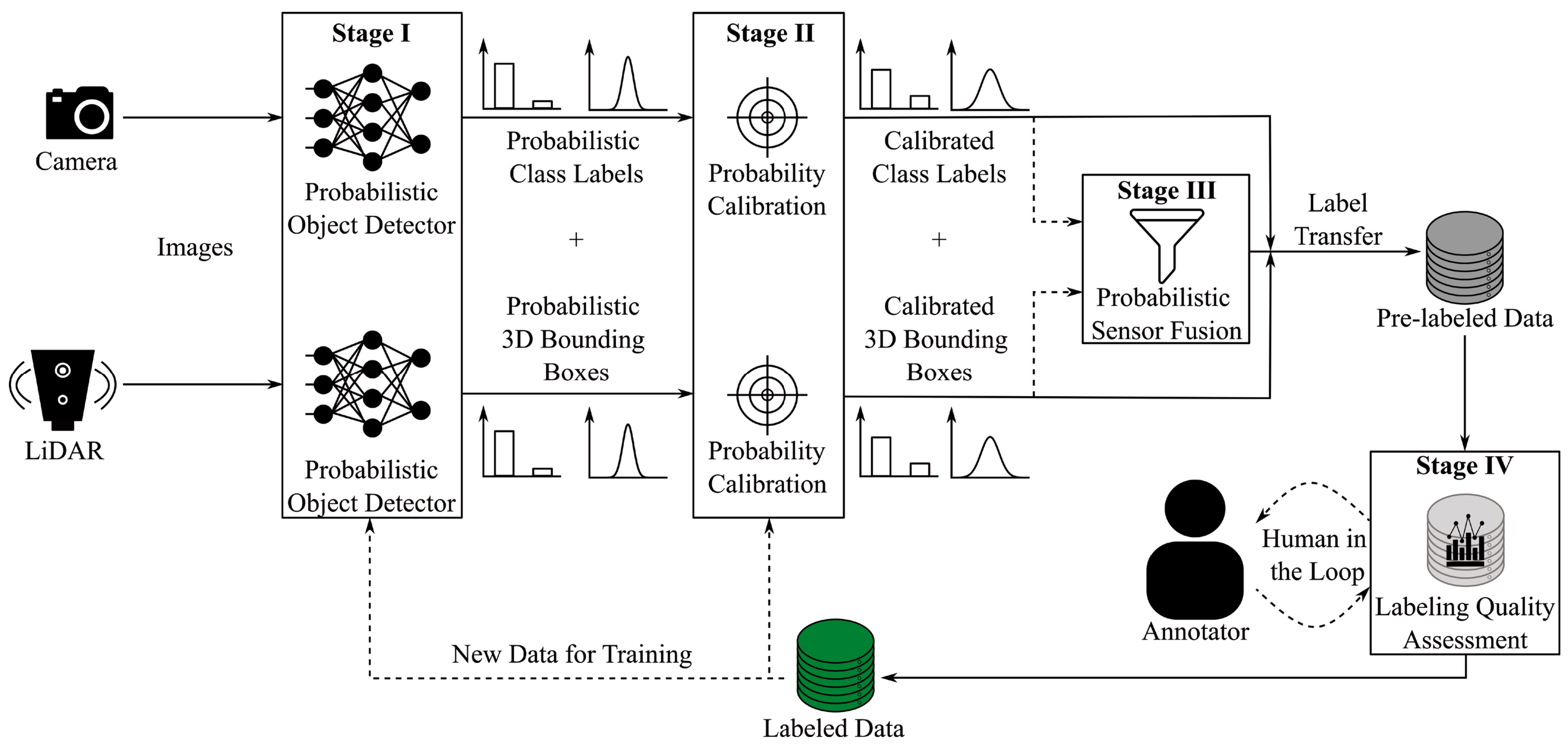

Figure 1: Illustration of proposed highly automated labeling process exemplarily shown for two sensors

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