KI DELTA LEARNING
Scalable AI for Automated Driving

Active Learning in Semantic Segmentation

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WP 3.3

Use-Case in Delta Learning

Building a new dataset for deep learning is expensive since large amounts of data are required, and the labelling process is slow. Hence in this research, we are working on methods to lower the amount of data needed for training by choosing only the relevant images for annotation. This process is called Active Learning.

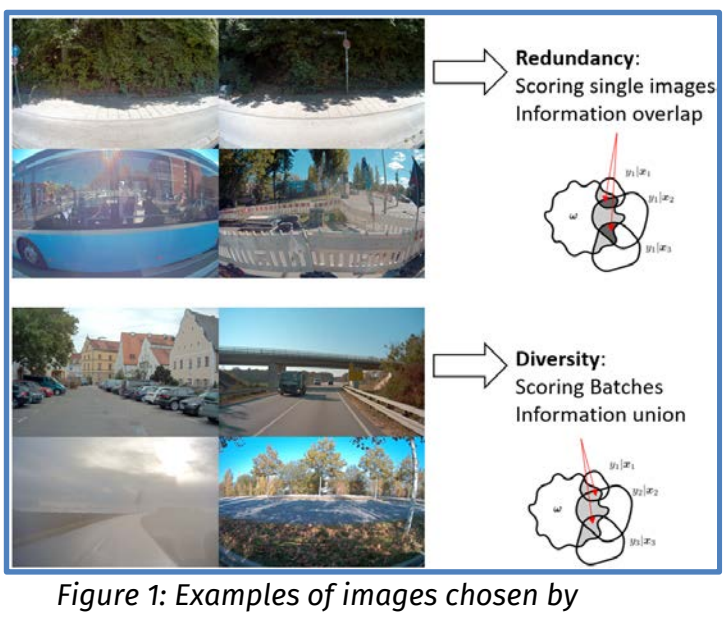

Figure 1: Examples of images chosen by acquisition functions based on single images (top) and whole batches (bottom).

Technical Problem

The process of Active Learning requires creating a so-called acquisition function that scores the value of a given sample for the formation of a new labeled training dataset. Such acquisition functions are, e.g., based on the epistemic uncertainty of the DNN model. However, choosing samples with the highest uncertainty requires retraining the model after the selection since the uncertainty changes depending on the dataset. Moreover, if we sample multiple samples without updating the model/uncertainty we risk sampling redundancies. In the case of Deep Learning retraining is, however, too resource-intensive. Hence we need scoring functions that score entire batches together, ensuring the diversity of the sampled data.

Table 1: Evaluation of acquisition functions and its cross-network validity

Approach	Random Sampling	Batch BALD
WideRes38	59.78%	60.86%
MobileNet	48.87%	49.54%

Technical Solution

We evaluate the existing approaches using measures like Mutual Information and Entropy as acquisition functions. The BatchBALD approach introduces an acquisition function that scores whole batches and hence introduces diversity sampling. Therefore, it avoids retraining after the acquisition of each new sample. In the case of semantic segmentation, BatchBALD is infeasible with respect to its resource demand. The challenge here is that a segmentation problem consists of height x width classification problems. Therefore, we reduced the complexity of BatchBALD by clever sampling.

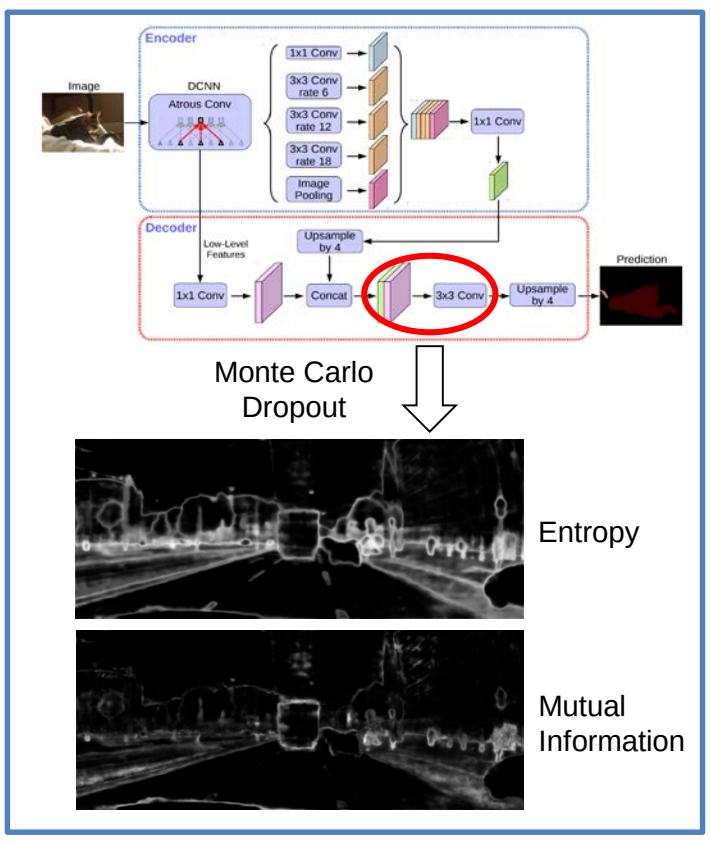

Figure 2: Our semantic segmentation architecture with Monte Carlo Dropout layers (red circle); two examples of epistemic uncertainty (bottom).

Evaluation

We evaluate our approach on the A2D2 dataset. Since this dataset contains more than 40,000 images, we were able to simulate the presence of a large pool of unlabeled data. We first evaluated our Active Learning approaches with a WideResNet38 as a backbone for the DeepLabv3+ framework. To verify that the chosen images are valid across architectures we trained the DeepLabV3+ with a Mobile net on the same sampled data. As shown in Table 1, BatchBALD outperforms random selection in both cases.

We are currently finetuning the system and verifying it under a bigger range of conditions.

Sensors / Environment

DLR

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Partners

External partners

KI Delta Learning is a project of the KI Familie. It was initiated and developed by the VDA Leitinitiative autonomous and connected driving and is funded by the Federal Ministry for Economic Affairs and Energy.

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Supported by: Federal Ministry for Economic Affairs and Energy on the basis of a decision by the German Bundestag

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