KI DELTA LEARNING
Scalable AI for Automated Driving

Active Learning based on a Taxonomy for Scene Description

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Active Learning

Introduction

The active selection of subsets of an unlabeled data pool for annotation and training is subject to Active Learning. This work focuses on Active Learning based on a derived taxonomy for the scene description. The goal is to use scene descriptive information for the selection of the new subset(s). Thus, the network selects new queries based on the taxonomy, e.g., pedestrians at night.

Taxonomy for Scene Description

An automotive scene can be defined in manifold ways. Using BDD100K[1], we restrict ourselves to the provided annotations and derive the following taxonomy:

[*Object*] at **[*Time of Day*]** on/at **[*Scene*]**

[Object]:	Pedestrian, Rider, Car, Truck, etc.
[Time of Day]:	Daytime, Night, Dawn/Dusk
[Scene]:	City Street, Highway, Residential, etc.

Method

We investigate Object Detection as downstream task and employ in addition to the Faster-RCNN network a domain classification network. This classification network is trained concurrently. Based on the validation losses, loss weights are inferred and used to weight the sampling distribution. Additionally, we further use a modified weighting loss for the i^{th} and j^{th} domain:

$$al\_loss_{i,j} = val\_loss_{i,j}^2 * \sqrt{\frac{n_{i,j}}{n_{all}}}$$

Experiments

For simplicity, we neglect object instances and utilize ground truth information for the query selection. In the first experiments, we evaluated the domains ***Time of Day*** and ***Scene*** individually, as depicted in Figure 1. The second experiment employs the modified sampling weights for the both domains. The weighting loss and normalized sampling weights are depicted in Figure 2 and 3.

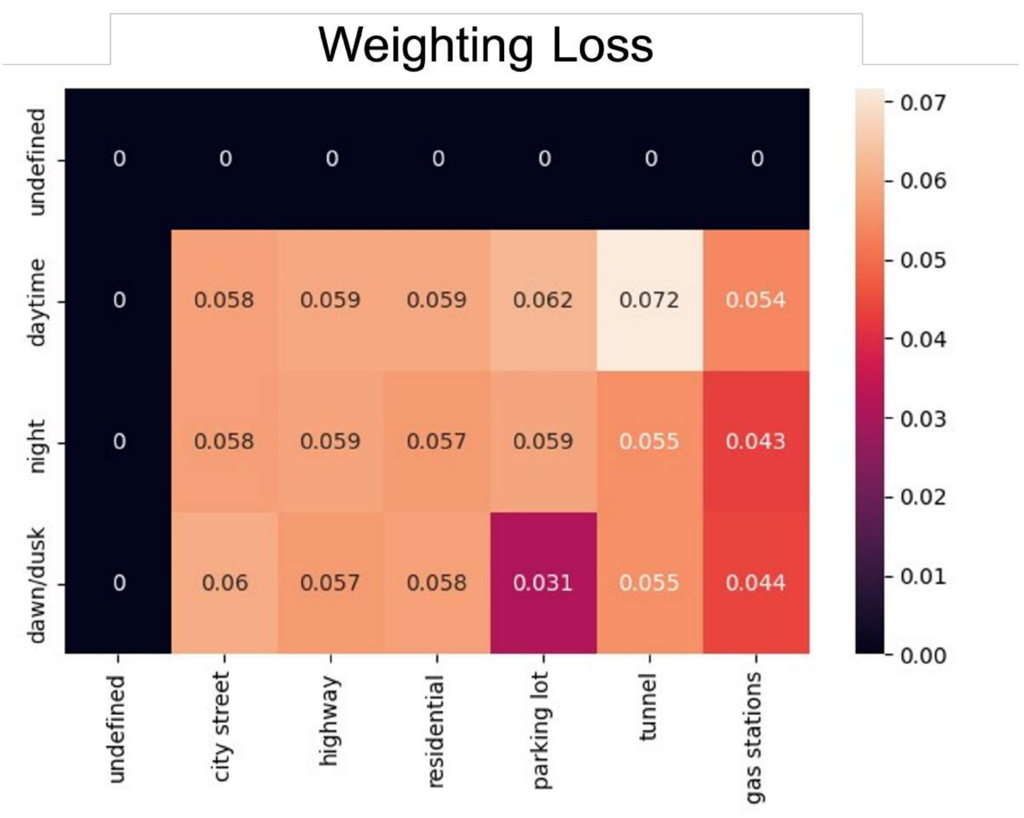

Figure 2: Squared validation loss as weighting term for each tuple for the domains Time of Day and Scene. (©ZF Group)

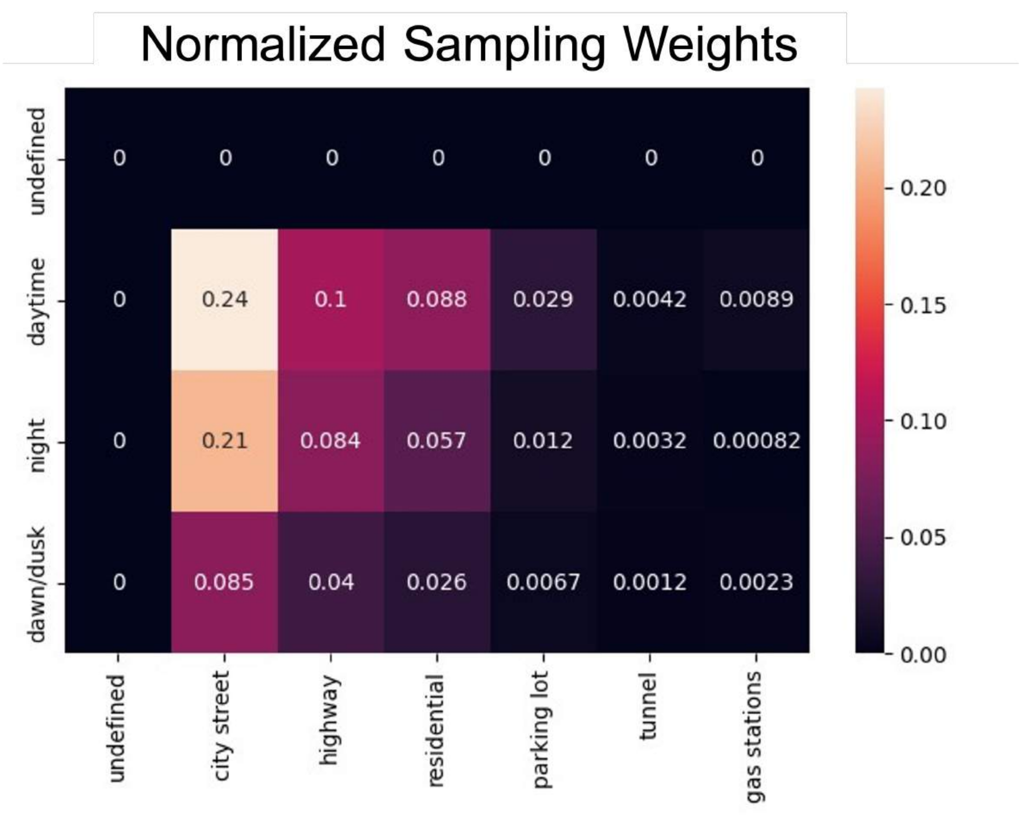

Figure 3: Normalized sampling weights. (©ZF Group)

Results & Conclusion

For single domain evaluation, the weighted domain distribution quickly converges to the non-weighted distribution as the losses per domain and thus the weighting are very similar. Using the modified weighting loss, we observe a slower convergence behavior towards the actual data distribution. Yet, the proposed active selection based on the scene descriptors show a very similar performance to the random sampling baseline.

References

[1] F. Yu et al., "BDD100k: A diverse driving dataset for heterogeneous multitask learning," in Conference on Computer Vision and Pattern Recognition (CVPR), 2020

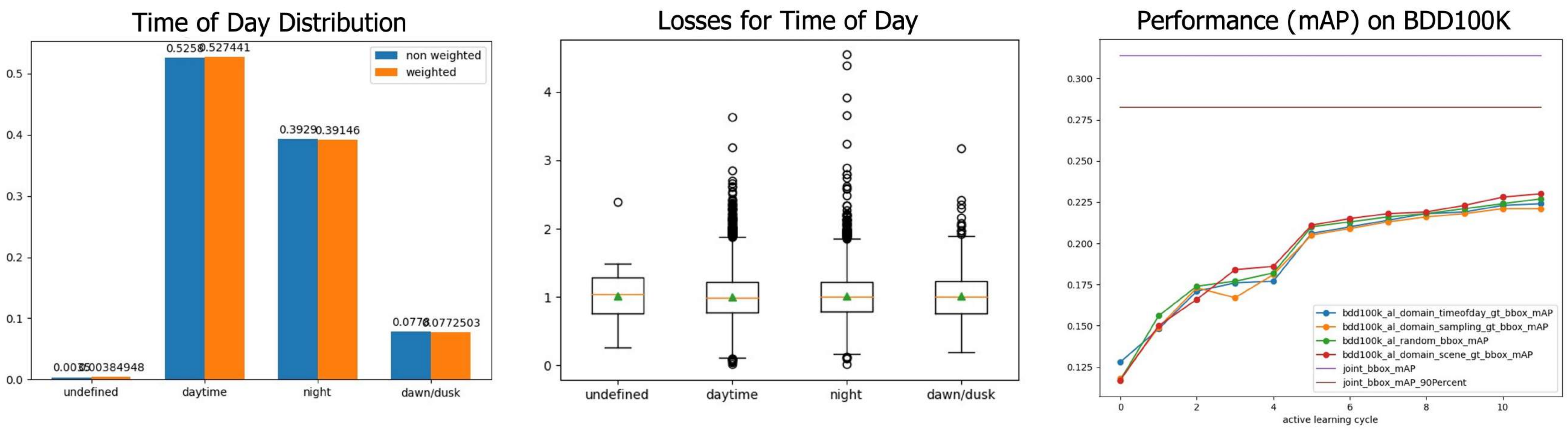

Figure 1: a) Weighted and non-weighted sampling distribution for the Time of Day domain after 6 Active Learning cycles b) Losses for the respective Time of Day elements after 6 Active Learning cycles c) Overall Object Detection performance for single and joint domain evaluation, as well as random sampling (lower baseline) and entire training (upper baseline). (©ZF Group)

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