

Context and Corner Cases

Context provided along with a dataset can be helpful by providing additional information without retrieval effort. Moreover, the context indicates how diverse a dataset is, i.e., how many samples per context category are available to train and test machine learning (ML) models. In this work, additional context annotations for the BDD100k[1] image dataset have been labeled. The annotations comprise, for instance, information about daytime, road condition (dry, wet, etc.), and dirt on the windshield. Sometimes, no or only little data are available for rare context combinations. However, data that matches these context conditions is crucial when discussing corner cases: Firstly, most ML models, e.g., object detectors, are not trained on such data, which leads to the assumption that they will perform poorly in these situations. Secondly, data containing corner cases are required for exhaustively validating ML models.

Added Context Attributes

- **Time of day:** daytime, dawn, dusk, night, undefined
- **Sky:** clear, partly cloudy, overcast, foggy, undefined
- **Illumination:** natural, sun glare, artificial, dark
- **Precipitation:** nothing, rain, snow
- **Infrastructure:** inner city, industrial, highway, suburb, nature, parking lot, gas station, undefined
- **Road:** dry, wet, slushy, snowy, undefined
- **Tunnel, Construction site, Clear windshield, Light exposure, Reflections:** true, false

	All	I1	I1*	I2	I3	I4	I4*	I5	I5*	I6	I6*
TOOD	50.0	48.0	73.8	60.4	67.4	50.1	56.7	55.8	67.1	52.1	63.1
Sparse R-CNN	50.0	45.6	77.6	62.9	67.3	56.7	63.9	56.2	65.2	52.3	65.8
FreeAnchor	46.6	43.5	73.8	55.3	61.7	50.7	57.8	52.4	66.3	48.2	56.8
DyHead	45.9	44.2	66.9	57.5	63.3	49.2	56.0	52.4	60.4	46.9	59.4
RetinaNet	45.9	44.1	70.5	65.1	61.1	49.1	54.9	51.9	60.3	47.2	62.4
FCOS	45.8	43.7	67.1	51.7	63.3	50.1	57.5	52.4	59.6	46.8	59.8
Libra R-CNN	45.5	44.1	71.6	50.1	62.8	48.7	55.9	51.9	60.2	46.8	58.0
DCNV2	45.4	43.2	71.3	62.0	63.0	48.3	54.0	52.3	60.3	46.3	61.8
HRNet	45.3	42.2	67.5	54.4	60.7	48.1	51.4	52.2	56.9	46.3	60.3
Cascade R-CNN	44.8	41.3	66.0	63.4	61.0	48.5	54.6	51.8	60.1	46.0	54.2
Faster R-CNN	44.5	41.3	66.2	57.0	61.4	48.8	54.4	50.9	51.1	45.9	54.1
CenterNet	44.4	42.6	65.7	53.0	61.3	49.6	55.7	51.0	58.9	45.5	58.9
ATSS	43.4	39.9	62.8	51.4	58.0	44.6	49.6	49.9	56.1	44.8	58.7
Model Mean	43.3	41.0	66.0	53.4	59.4	46.6	52.5	49.1	57.3	44.5	55.4
YOLOv3	40.2	40.4	65.4	46.9	56.9	44.2	48.6	45.5	53.3	40.6	49.0
EfficientNet	40.1	39.8	62.3	45.4	55.1	42.3	48.7	44.9	53.2	40.6	50.7
YOLOF	39.8	38.6	59.4	44.6	53.4	38.2	44.6	44.5	59.5	40.4	48.1
YOLOX-s	38.7	38.5	60.2	45.7	58.6	41.8	47.7	43.6	51.1	39.0	47.7
DETR	34.0	30.4	51.6	47.5	46.9	33.3	37.6	37.7	46.9	36.6	44.0
CornerNet	31.6	28.4	53.9	40.4	45.3	43.0	47.0	35.4	42.4	33.0	40.6

Table 1: Performance (mAP) of various 2D object detectors on one context combination. The symbol * indicates if this context combination contained many samples and was subsampled to be comparable in object size and number.

Context	Samples	Description
I1/I1*	4007/192	time of day: night, illumination: artificial
I2	145	time of day: dawn dusk, illumination: artificial
I3	146	time of day: dawn dusk, illumination: sun glare
I4/I4*	242/154	time of day: dawn dusk, illumination: natural
I5/I5*	1614/138	time of day: daytime, illumination: sun glare
I6/I6*	3815/147	time of day: daytime, illumination: natural

Table 2: Context combinations of Table



Figure 1: A small overview of example images from BDD100K [1] with different context attributes. The most outstanding context attribute is mentioned by name under each image.

Object Detection Performance

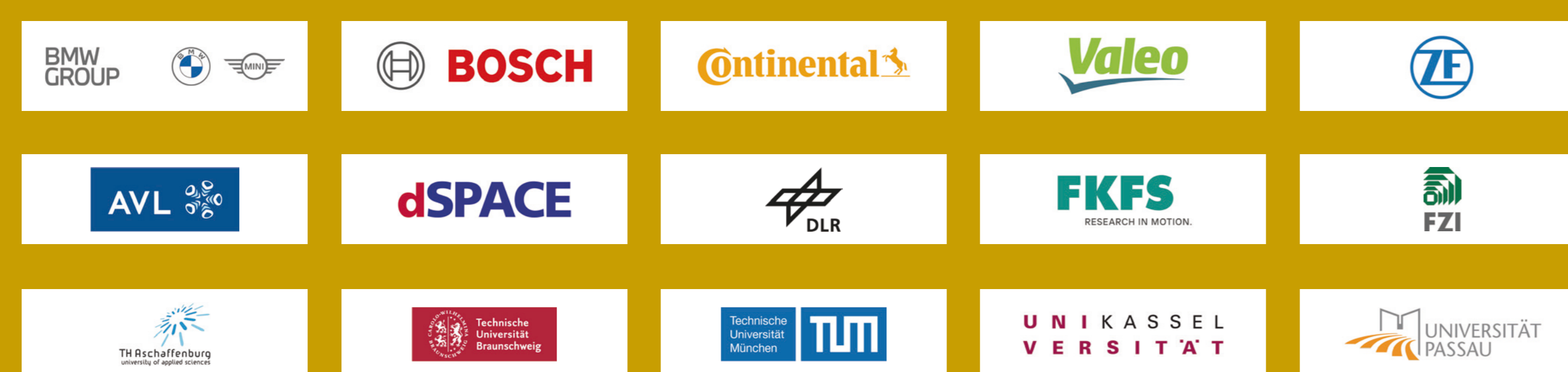
Table 1 presents a performance (mean Average Precision mAP_{IoU50}(%)) comparison of all tested models in the „All“ column, as well as some context-specific test subset (I1 to I6*). Intuitively, one would expect the performance on context combinations with fewer samples, i.e., more rare ones, to be worse than on more common combinations. A closer look at the Model Mean and the columns I1-6 reveals that I1 and I6 perform worst, which runs counter to this intuition, as they comprise the most samples. In contrast, the dawn or dusk contexts I2 & I3 result in the peak performance of the models, opposite to what intuition would suggest. This is due to the results in columns without a * marking being calculated over all test set samples matching the corresponding context attribute combination. Thus, there is a high imbalance among the different test subsets. To counteract the bias introduced by the cardinality of the test subsets, we applied histogram-matched undersampling, i.e., we sampled subsets from context attribute combinations with more images that roughly match the cardinality of the combinations with the smallest number of images. Additionally, we made sure that the numbers of small, medium, and large objects are comparable. After adjusting, we see the performance on the common context combinations I1* and I6* increase.

Additional context attributes for BDD100K dataset:
<https://doi.org/10.48662/daks-25>

References:

- [1] F. Yu, H. Chen, X. Wang, W. Xian, Y. Chen, F. Liu, V. Madhavan, and T. Darrell, "BDD100K: A Diverse Driving Dataset for Heterogeneous Multitask Learning," in Proc. of CVPR, Seattle, WA, USA, 2020, pp. 2636–2645.

Partners



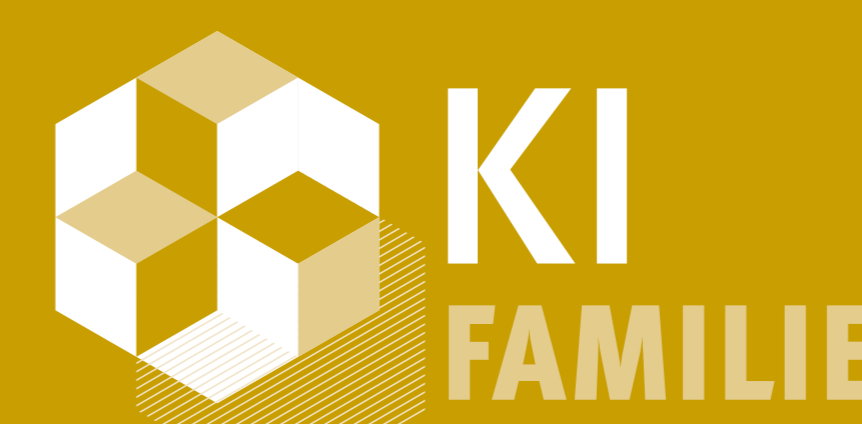
External partners



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