Input Coverage Analysis using Domain Models and Combinatorial Testing

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KI ABSICHERUNG
Safe AI for Automated Driving

DNN specific Safety Concern: Data distribution is not a good approximation of real world (SC-2.1)

Semantic Domain Models

Semantic domain models capture important features of the input space of a DNN that need to be contained in the data used for training and testing. Examples of semantic features for a camera-based pedestrian detection include lighting conditions, visual appearance of a pedestrian, or the pedestrian's pose. Semantic domain models, e.g., based on a SCODE model or an ontology have been developed in AP 4.1.

Input Coverage Analysis using Combinatorial Testing

Input Coverage denotes to what degree a dataset covers the elements of the semantic domain model. Since semantic domain models for computer vision quickly become huge, a full exploration using test data is prohibitive. Therefore, we leverage combinatorial testing techniques that provide a weaker notion of coverage and, thus, a better scalability to larger domain models.

Combinatorial testing uses a combinatorial factor n that denotes that all combinations of semantic features of length n need to be covered. For n=2 (pairwise), this means that each value of a semantic feature is combined at least once with every other semantic feature in the semantic domain model.

Experimental Results

We analyzed the input coverage for the training and test data provided by MackeVision in the data tranches #4, #5, and #6. Figure 1 shows the results for the training data for a combinatorial factor n=1. In addition to the plain coverage, we also computed how the possible values for the semantic features are distributed. The results show significant imbalance for some values.

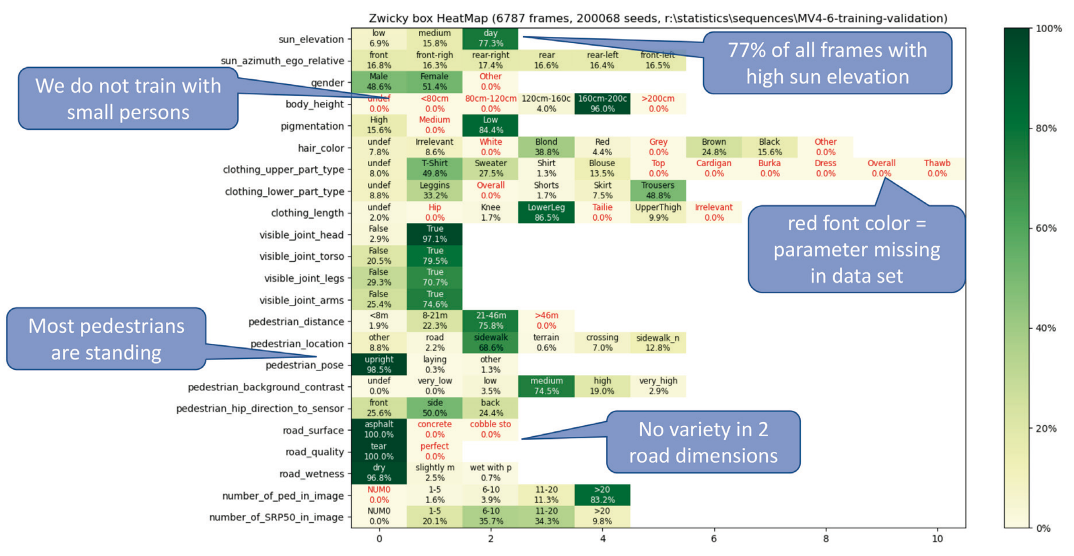

Figure 1: Results of Input Coverage Analysis for Macke Vision Training Data with n=1

Safety Hypothesis:
The method addresses the safety concern Data distribution is not a good approximation of real world. It allows to identify sematic features that are underrepresented in the provided training or test data based on a domain model or ontology.

In addition, we analyzed the impact on DNN performance resulting from the imbalances. Therefore, we used the test data in combination with the SSDr3v2. Figure 2 shows the results indicating, in particular, a significant drop in performance for the underrepresented „laying" pose of pedestrians.

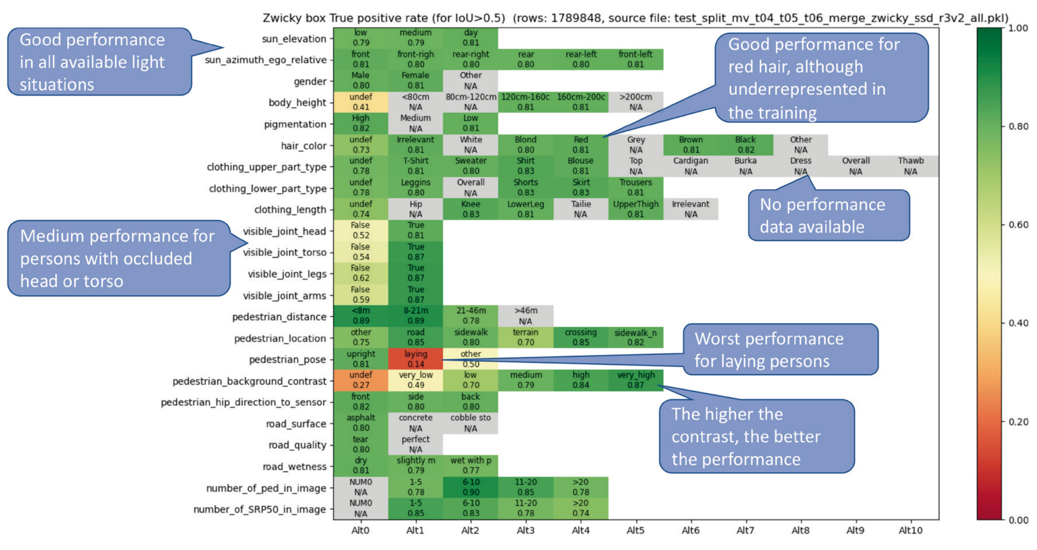

Figure 2: DNN Performance for Test Data with n=1

We also conducted the experiments for a combinatorial factor n=2, which provided additional insights.

Use in Safety Argumentation

Finally, we included the input coverage based on combinatorial testing into the safety argumentation. In particular, we created two GSN solutions to assert evidences using the experimental results. There are:

- Check coverage of each equivalence partition
- Comparison of distributions

Here, the coverage for each equivalence partition can be assessed with different combinatorial factors n.

References:

C. Gladisch, C. Heinzemann, M. Herrmann, M. Woehrle: Leveraging combinatorial testing for safety-critical computer vision datasets. In: 2nd Workshop on Safe Artificial Intelligence for Automated Driving (SAIAD), June, 2020.

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