Maneuver-based Visualization of Similarities between Recorded Traffic Scenarios

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Abstract: Since automated driving functions are safety-critical systems, extensive validation and verification is necessary. Scenario-based testing is a promising approach for this challenge. For selection of relevant scenarios, collected data and knowledge models are potential sources. In this paper we introduce a concept to use recorded trajectory and map data, abstracted to maneuvers, to describe the scenarios and visualize them intuitively. This enables a data-driven scenario-mining process to find relevant scenarios for the testing of automated driving functions. To compare the scenarios, a similarity measure based on the manuevers is designed and the scenarios and their similarities are represented as a graph. Graph-visualization methods, already successfully applied in other domains, structure the collected data for further analysis. The concept is exemplary applied to an urban traffic dataset.

1 INTRODUCTION

Automated driving functions on public roads have the potential to fundamentally change our transportation in the future. But validation and verification are major concerns to ensure a sufficiently high level of safety and acceptance (PEGASUS, 2019). As the functionality and operational design domain for automated driving functions increases, the combination of safety-critical systems in an unstructured open-world lead to new challenges in safety argumentation. Distance-based testing, as practiced to date, is no longer feasible to ensure safe systems because several billions of test kilometers would have to be driven for a valid test coverage (Wachenfeld and Winner, 2015) (Kalra and Paddock, 2016). Even with the usage of simulation tools, the required amount of test kilometers can not be achieved (Pfeffer, 2020). Therefore, a more efficient way to increase test coverage is needed. Current research projects and industry are focusing on scenario-based testing in this regard (PEGASUS, 2019)(Neurohr et al., 2020)(VVM, 2020)(Bagschik et al., 2017). This approach exploits the redundancy of traffic scenarios that occur during distance-based testing: Instead of testing the same scenarios several times, as they occur randomly in distance-based testing, they are selected from a scenario catalog. Since one test of the scenario is enough to ensure the safety of the driving function in this scenario, the test coverage increases more efficiently. The scenario catalog should contain all relevant scenarios for the operational design domain of the automated driving function to ensure a certain performance metric. However, one question is unanswered yet: How to build the scenario catalog and how to select the scenarios for execution and testing of automated driving functions?

Recorded real-world driving data from drones, traffic infrastructure, or vehicles include helpful information to support these challenges. They are the most realistic source for scenarios and contain information about their occurrence probabilities. Since the amount of data from recorded trips is too extensive for manual analysis and the unprocessed data does not provide information in directly useable form, methods are needed to extract the relevant information. The recorded data builds a scenario space with high redundancy. A structured and intuitive representation of the recorded scenarios, e.g. as maneuvers, enables efficient data mining in this scenario space. Different techniques can help to extract relevant information from the data: Grouping similar scenarios can reduce the high redundancy. E.g., all scenarios where a vehicle is driving alone on a straight road can be considered a scenario group. Also, the relationships between these groups contain relevant information. From a maneuver perspective, following another vehicle on a straight road is more similar to the previously described scenario, than driving

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over an intersection in an urban environment. In addition, there are rarely occurring exceptional corner cases that have to be identified, such as driving maneuvers executed by emergency vehicles against the rules for ordinary traffic participants, which must also be considered in the test process. All of these techniques need a similarity measure between the individual scenarios. Furthermore, this similarity can be used as an input for a graph representation for intuitive visualization. In other domains, this graph analysis approach is successfully used for challenges of visualizing data of similar data structures by many authors (Batagelj and Mrvar, 1998)(Pavlopoulos et al., 2017)(Bastian et al., 2009). In literature management (Perianes-Rodriguez et al., 2016) the relationships of various publications and journals are visualized. Biological (Shannon et al., 2003) and genomic data (Thimm et al., 2004) (Theocharidis et al., 2009) is represented as graphs for interpretation. Also social networks are analyzed with this method (Borgatti et al., 2002). This paper examines the extent to which the methods, already proven helpful in other domains, can achieve a structured and intuitive representation of the scenario space in the automotive context.

2 RELATED WORK

2.1 Scenario Sources and Description

A formal definition for scenarios is presented in the (ISO21448, 2019): A scenario describes the temporal development between several scenes in a sequence of scenes. Compared to a scene, which is a snapshot without temporal expansion, a scenario spans a certain amount of time. According to the PEGASUS Project (PEGASUS, 2020) and (Neurohr et al., 2020), there are two sources for scenarios: Knowledge-based and data-based. In the knowledge-based approach, scenarios are created using expert knowledge and a knowledge model (Bagschik et al., 2018)(Ponn et al., 2019) (Neurohr et al., 2021). For the data-based approach, recorded real-world traffic, simulated traffic, test drives and accident databases build a possible set of source for the scenarios (Koopman and Wagner, 2018)(PEGASUS, 2020)(Hartjen et al., 2019a)(Weber et al., 2021)(Lizenberg et al., 2021).

(Scholtes et al., 2021) propose a 6 layer model to describe different aspects of the scenarios: Street level (L1), traffic infrastructure (L2), temporal modifications of L1 and L2 (L3), movable objects (L4), environment conditions (L5) and digital information (L6).

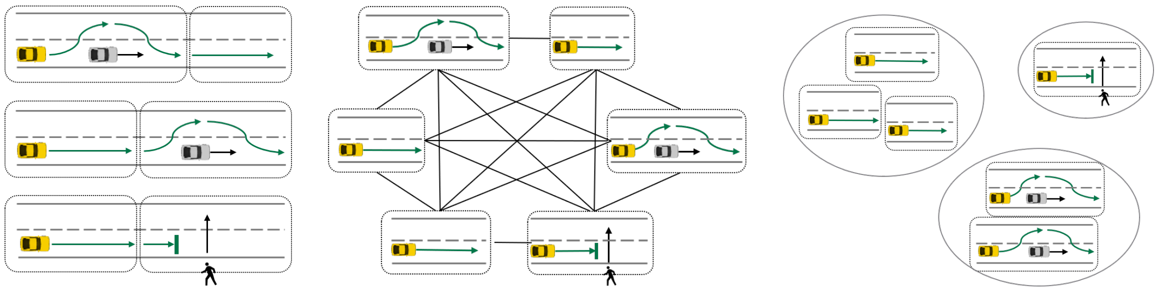
For the dynamic description of the movable objects in L4, which is the focus of this paper, a sequence of driving maneuvers is an established way (ASAM, 2020)(Pfeffer, 2020) (Hartjen et al., 2019b)(Braun et al., 2021)(King et al., 2021). A maneuver is an abstract description of the behavior of a participant during a specified timespan (Bach, 2018). Compared to a description with trajectories, the maneuvers are more concise and semantically interpretable and therefore offer easier further processing.

2.2 Scenario Similarity and Clustering

While not much literature exist on similarities between scenarios, there is ongoing research on the related method of scenario clustering. (Ries et al., 2021) uses a DTW-comparison of recorded trajectories to cluster scenarios. (King et al., 2021) cluster scenarios based on a maneuver extraction. Scenarios with the same maneuvers are considered as equal and build a cluster. A more sophisticated measure for similarities between non-equal scenarios is not created. (Hartjen et al., 2020) also define the equality based on extracted maneuvers and investigate how often new scenarios occurs during recordings. (Balasubramanian et al., 2021) introduce a random forest activation pattern to build clusters of traffic scenarios based on iterative optimization of self-supervised networks. (Langner et al., 2019) derives the cluster based on the static elements of the scenarios. (Ries et al., 2020) convert trajectories to driving states to represent scenarios and use them for a semantic comparison of the recorded scenarios.

2.3 Graph-visualization

As stated in chapter 1, visualization methods for graphs give an intuitive representation of the underlying data. The position of the nodes in this visualization is called layout and can be calculated by different algorithms: Force-directed algorithms offer a flexible and domain-independent way to create layouts. The underlying concept of these categories of layout algorithm is to model the graph as a system of particles which all exert forces on each other depending on their position in the layout and their actual relationship in the graph structure. From a general view, force directed layouts try to find an appropriate positioning of the nodes by minimizing the corresponding energy in the modelled system. A comprehensive comparison of existing force-directed methods is given in (Kobourov, 2012). Besides the force-embedders, multidimensional scaling is a collective



(a) Recorded trajectories and segmenation to scenarios.

(b) Segmented scenarios as a graph with similarities as edges.

(c) Scenario graph visualization (similar scenarios are close to each other).

Figure 1: Concept for extraction of scenarios, building a graph and a visualization based on similarities.

term for methods whose goal is to visualize the similarity relations of objects by the suitable arrangement of points in low-dimensional space (Cox and Cox, 2008). While multidimensional scaling is often used as a method for dimension reduction, (Gansner et al., 2004) and (Klimenta, 2012) consider the application of this method as a layout for (fully connected) graphs.

3 CONCEPT FOR SCENARIO SPACE VISUALIZATION

The concept contains the following steps (Fig. 1): Abstraction of the trajectories to maneuvers sequences, segmentation and extraction of scenarios, calculation of similarities between the scenarios and graph visualization based on the similarities.

3.1 Abstraction through Representation as Maneuver Matrix

A modified version of the maneuver list of (Hartjen et al., 2019a) is used to describe the behavior of the traffic participants. Each participant gets assigned a maneuver state for each maneuver type for each timestep. For demonstration purposes, this paper will mainly focus on the maneuver type "vehicle state", which describes the longitudinal motion, and the maneuver type "turn", which describes the behavior on intersections. Nevertheless, the concept is applicable to any other maneuver types. The state of maneuver type "vehicle state" can be "cruise", "decelerate", or "standstill". The state of maneuver type "turn" can be "turn left" or "turn right" for the direction when crossing an intersection or "no turn", if the participant does not perform a turn maneuver. A maneuver matrix M, containing the timesteps as columns and the extracted maneuvers of each type as rows as shown in Fig. 2, serves as a formalized abstract representation for further processing.

Building on the trajectories and map data, the maneuvers are identified with a rule-based algorithm also used in previous work (King et al., 2021). Deceleration, standstill and cruise maneuvers are calculated by analyzing the vehicle speed, turn maneuvers by comparing the map with the position and yaw-angle of the traffic participant.

3.2 Scenario Segmentation and -Extraction

Since the recorded driving data can contain many hours of driving and includes multiple scenarios, the data is segmented to extract the scenarios. Depending on the focus of the analysis, meaningful definitions of start and end points can vary. We use a flexible maneuver-based segmentation algorithm: The start and end of the scenario is is determined by the change of the state of a single maneuver type, as exemplarily shown in Fig. 2. To get the maneuver matrix of the scenario, the corresponding columns are cut out.

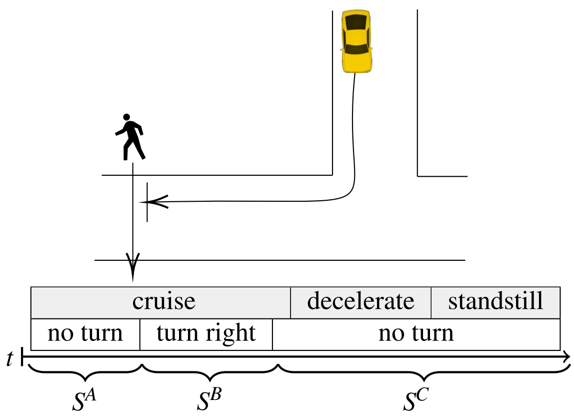


Figure 2: Example abstraction of trajectories to "vehicle state" and "turn" maneuvers. Segmentation of the scenarios S^A, S^B and S^C using "turn" maneuvers.

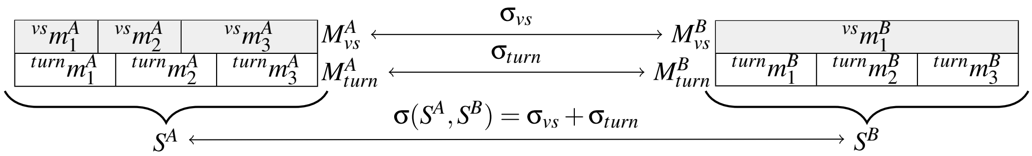


Figure 3: Relationships between the maneuvers of the maneuver types "vehicle state" (vs) and "turn" ($turn$), their maneuver sequences M, maneuver-similarities σ_t and scenario-similarity σ for two scenarios.

3.3 Maneuver-based Scenario Similarity

A generally valid definition of scenario similarities is not possible, since different elements of the scenario are in focus depending on the context. Therefore, the methods to calculate such a similarity also vary. This paper introduces a definition based on the maneuver matrices of the scenarios. To determine the similarity of the matrices, the maneuver types are compared independently in a first step. The scenario similarity is then a weighted sum of individual simmiliarities w.r.t. to the different maneuver types used for representation of the scenarios (Equ. 1, Fig. 3). Using the definitions

- S^A: Scenario with id A
- $\sigma(S^A, S^B)$: similarity between the scenarios S^A, and S^B,
- t: maneuver type (e.g. turn or vehicle state),
- $^t m_i^A$: maneuver at index i of scenario A
- $M_t^A = \{^t m_1^A, ^t m_2^A, \ldots, ^t m_n^A\}$: maneuver sequence of maneuver type t of scenario S_A,
- $\sigma_t(M_t^A, M_t^B)$: similarity for the maneuver type t between scenarios S_A and S_B,
- c_t: weighting factor for different maneuver types,

the scenario similarity is calculated by:

$$\sigma(S_A, S_B) = \sum^{t} c_t \cdot \sigma_t(M_t^A, M_t^B) \tag{1}$$

We use the pattern matching technique of sequence alignment on the maneuver sequences. For the calculation of the sequence aligment the Needleman-Wunsch algorithm (Needleman and Wunsch, 1970a) is used. Sequence alignment was originally developed for amino acid comparison (Needleman and Wunsch, 1970b), but is also used in other domains (Abbott and Forrest, 1986) (Čavojskỳ and Drozda, 2019). The similarity of the two sequences is determined by the number of matches, mismatches and gaps between two sequences of categorical data, like the maneuver sequences (Fig. 4). The scores for matches, mismatches and gaps can be parameterized for various analyses.

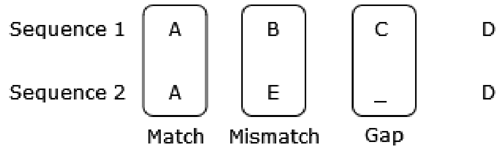


Figure 4: Match, Mismatch and Gap for sequence alignment of two categorical sequences.

A normalization step is performed for the results of the sequence alignment, to keep the maximum similarity independent of the length of the maneuver sequences:

$$\sigma_{norm} = \frac{\sigma}{0,5 \cdot (n^A + n^B)}, \tag{2}$$

where n^S is the number of maneuvers in scenario S.

3.4 Graph-representation and Visualization

The similarities between the scenarios form the basis for a graph-representation of the extracted scenarios. Each node in the graph represents an extracted scenario, each edge the calculated similarity between these two scenarios. For visualization of the scenarios, state-of-the-art layout algorithms are used as described in section 2.3. In our experience, multidimensional scaling (Cox and Cox, 2008) gives the best results for the scenario graphs. Nevertheless, other layout methods, such as Fruchterman-Reingold (Fruchterman and Reingold, 1991) and Kamada-Kawai (Kamada et al., 1989), can be used.

4 EVALUATION

4.1 Dataset

For an exemplary evaluation, an intersection of the INTERACTION dataset (Zhan et al., 2019) is used. It contains recordings of urban traffic with various interactions and was created using a drone. In addition to the recorded trajectories, map data of the intersection is included and used for the maneuver identification.

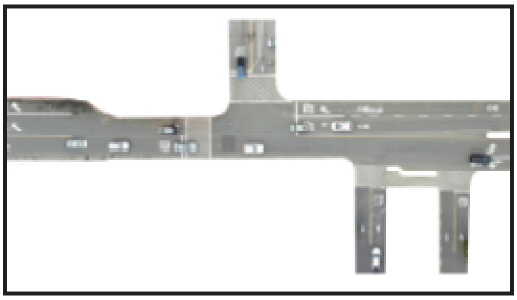


Figure 5: Considered intersection of the INTERACTION dataset (Zhan et al., 2019).

Fig. 5 shows a snapshot of the intersection from the drones perspective. The recording area of the selected intersection includes four intersecting road segments and thus a comparatively large variety of possible traffic scenarios. The intersection records include a total of 732 individual road users over approximately 45 minutes. All graphs are visualized using multidimensional scaling as layout.

4.2 Grouping by Turn Maneuvers

Figure 6: Scenario graph visualization for turn maneuver sequences for all scenarios while crossing the intersection.

In the visualization in Fig. 6 each point represents a scenario. A scenario here contains the trajectories of a participant over the whole intersection, so no segmentation based on maneuvers is performed. For the similarity, only the turn maneuvers are considered, so in terms of the terminology introduced in section 3.3 this corresponds to $c_{vs} = 0$ and $c_{turn} = 1$. For validation purpose of the layout algorithm, the color represent the turn maneuver sequence of the corresponding scenario. Table 1 shows the turn maneuver sequence of selected groups, Fig. 7 the recorded trajectories with the same color coding.

Table 1: Turn maneuver sequences of scenario groups in Fig. 6.

<table>
<tr><th>group</th><th colspan="5">turn maneuver sequence</th></tr>
<tr><td>blue</td><td colspan="5">no turn</td></tr>
<tr><td>red</td><td colspan="2">no turn</td><td>turn right</td><td colspan="2">no turn</td></tr>
<tr><td>pink</td><td colspan="2">no turn</td><td>turn left</td><td colspan="2">no turn</td></tr>
<tr><td>brown</td><td colspan="3">no turn</td><td colspan="2">turn right</td></tr>
<tr><td>green</td><td colspan="2">turn right</td><td colspan="3">no turn</td></tr>
<tr><td>turquoise</td><td colspan="3">no turn</td><td colspan="2">turn left</td></tr>
<tr><td>purple</td><td colspan="2">turn left</td><td colspan="3">no turn</td></tr>
<tr><td>black</td><td>no turn</td><td>turn left</td><td>no turn</td><td>turn right</td><td>no turn</td></tr>
</table>

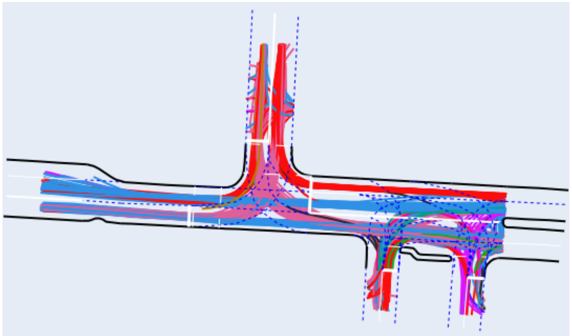


Figure 7: Trajectories of scenarios in Fig. 6 on the intersection.

To validate the layout algorithm, the positions of scenarios with equal turn maneuver sequences, represented by the color, are examined. As expected, similar scenarios have smaller distance to each other and form separated groups.

Additionally, similarities between the different groups can be analyzed by looking at the relative positions of the groups: Scenarios of the purple and turquoise groups, which have maneuver sequences mixed of the blue and pink groups, are positioned in between of these two groups. Also, the scenario in the black group, that contains “turn left” and “turn right” maneuvers interspersed by “no turn” maneuvers, is positioned in the middle of the red and blue groups, that contain either a “turn left” or a “turn right” maneuver separated by “no turn” maneuvers. Furthermore, a symmetry of right and left turn scenarios can be observed: The red and pink group, the purple and the turquoise group and the brown and the green group, which all contain equivalent maneuver sequences regarding the turn direction, are mirrored on an axis. The scenario of group f, containing a “turn left” and a “turn right” maneuver, and the middle of the blue group, containing no turn maneuvers, is part of this axis.

The visualization also gives a fast impression of the frequency of the scenarios: there are almost equal numbers of left and right turn scenarios, but most of the participants do not perform a turn maneuver.

4.3 Grouping by Turn and Vehicles State Maneuvers

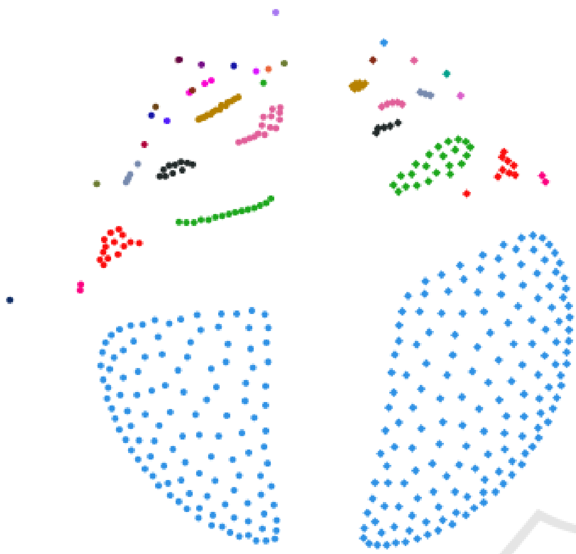


Figure 8: Scenario graph visualization for a combination "turn" and "vehicle state" maneuver sequences during turn scenarios.

Table 2: "Vehicle state" maneuver sequences scenario groups in Fig. 8.

group	vehicle state maneuver sequence			
blue	cruise			
red	standstill	decelerate		
green	decelerate	cruise		
purple	cruise			decelerate
black	decelerate	standstill		cruise
pink	cruise	decelerate		cruise
brown	cruise	decelerate	standstill	cruise
others	various longer combinations of vehicle state maneuvers			

The scenarios in Fig. 8 are segmented by turn maneuver type and filtered for "turn left" or "turn right" maneuver during the scenario. Hence, only trajectories during a left or right turn are considered. The turn maneuver with a weight of $c_{turn} = 0.1$ and the vehicle state with a weight of $c_{vs} = 0.9$ form the calculation of the similarities. The color represents the vehicle state maneuver series, the shape the turn direction (turn right: diamond, turn left: circle).

Similar to the previous graph, scenarios with the same maneuver sequence are mapped close to each other and form groups. The combination of both, vehicle state and turn maneuvers, lead to symmetrical positions of the scenarios. "Turn right" maneuvers (diamond) are mapped on the right, "turn left" maneuvers (circle) on the left, groups with the same vehicle state maneuver sequences (same color) are opposite each other. Most of the scenarios have maneuver sequences with a maximum of two maneuvers (blue, red and green groups). The length of the maneuver sequence grows from bottom to top of the graph. The size of the groups decreases with the length of the maneuver sequence. The share of scenarios without deceleration or standstill maneuvers (blue groups) in the total number of scenarios is lower for left turn scenarios, which is plausible considering the traffic rules for the intersection.

Figure 9: Scenario graph visualization for a combination "turn" and "vehicle state" maneuver sequences for all scenarios.

Fig. 9 shows an extension of the previous Fig. 8, where additional to the "turn right" an "turn left" scenarios also all scenarios with the "no turn" maneuver are included. So the entire recorded data is visualized in the graph. The calculations for the similarity remains the same as in the previous graph, the color represents the combination of turn and vehicle state maneuver series.
Some large, well-separated groups of similar scenarios can be identified, formed by scenarios with short maneuver sequences. Like in the previous graphs, groups with similar maneuver sequences are arranged close to each other.

In regions with scenarios of larger maneuver sequences, fewer groups are formed. In addition, there are a number of outliers that cannot be assigned to any group.

4.4 Benefits for Scenario-based Testing

This visible redundancy and outlier detection brings several benefits for the use of the scenarios in the scenario-based testing workflow: Instead of working on the complete set of scenarios, each group can be represented by one member. Rare, and therefore possibly unknown scenarios, can be easily identified in a visual manner or following automated processing. E.g. the participant in Fig. 6 which drives a trajectory that is not allowed by the traffic rules of the considered intersection, is shown isolated in the graph. Further, correlations between the maneuvers in the scenarios can be identified. E.g. "turn left" maneuvers occur more often in a combination with standstill than "turn right" maneuvers (Fig. 8). The frequency of the detected scenarios can be a basis for prioritization of test scenarios. Analysis and visualization of the scenario space make the frequency of scenarios intuitively visible and is thus a support for specification and test engineers.

5 CONCLUSION AND FUTURE WORK

Scenario-based testing is supposed to play a significant role in the testing of highly automated vehicles, but the building of a scenario catalog and the selection of the relevant scenarios for efficient testing is up to now an unanswered question. In this paper, we support to master these challenges with the use of recorded traffic data. For this purpose, the data is represented in a scenario-graph structure. The extraction of maneuvers builds the basis for a semantic interpretation of the data. To describe similarities between the scenarios, a metric based on the maneuvers is introduced. Interpreting the similarities as the weights of a graph, state-of-the-art methods for graph visualizations create an intuitive representation for the scenario catalog. The concept was exemplary applied to a dataset of urban traffic on an intersection. The created graphs show how this representation can present a rich variety of information in a compact way, including information on which scenarios have occurred, how the scenarios can be grouped, with what frequency these groups occur and whether there are any outliers that need special attention or represent previously unknown scenarios. This analysis supports the building of a scenario catalog from data and increases the test coverage for highly automated vehicles efficiently by selecting suitable test scenarios. In addition, the method can be used flexibly, since different maneuvers and weights can be selected for composing a suitable similarity measure depending on the use case.

Future work will focus on various maneuvers and datasets, also including data from simulation tools. Additional similarity metrics, using maneuver or trajectories without abstraction, will be evaluated. Based on the positions of the scenarios in the visualization of a graph, a clustering algorithm could automatically find clusters of the scenarios and outliers.

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