Capturing the Variety of Urban Logical Scenarios from Bird-view Trajectories

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Abstract: Driving scenarios are an essential part of validation of future highly automated driving (HAD) systems. In order to provide a valid proof of safety, it is crucial to test the system in as many realistic driving scenarios as possible. For this reason, it is necessary to extract driving scenarios from recorded data. A particular challenge in urban traffic is that there is a high degree of interaction between road users that needs to be considered. In this paper we present a concept for a maneuver-based extraction of driving scenarios. The extracted scenarios are provided in a format that supports a swift understanding of the content. In addition to the mere driving scenarios, parameter ranges for each scenario are grouped and aggregated from the data. Hence, the scenarios extracted with the presented concept can be used for re-simulation during the validation. We provide some results from the scenario extraction for an intersection from the INTERACTION data set.

1 INTRODUCTION

Early driver assistance systems, such as cruise control, Anti-lock Braking System (ABS) or Electronic Stability Program (ESP) were influenced solely by the driving condition of the driver's own vehicle (VDA, 2015). The ongoing automation of the driving task results in today's driver assistance systems being increasingly influenced by the vehicle's static and dynamic environment. Future Highly Automated Driving (HAD) systems, such as an urban intersection assistant, must additionally be able to operate freely within a traffic area. Thus, the interaction with the environment and surrounding traffic will become a crucial aspect for these systems. The possible driving situations in HAD systems can be assigned into four quadrants dependent on the risk and the knowledge about the driving situation, shown in Figure 1 (Stavesand, 2019). In order to be able to provide proof of safety during the validation process, a special emphasis must be placed on the unknown risks. Established test concepts utilize a requirement-based test approach that derives test cases from system requirements (Sax, 2008). Hence, the approach has the limitation that only known risks can be considered. Referring to the four quadrants in Fig 1, requirement-based testing can only address driving situations that are already known and additionally covered by requirements. Moreover, the consideration of all possible interactions in an open world context by system requirements in sufficient granularity is not feasible.

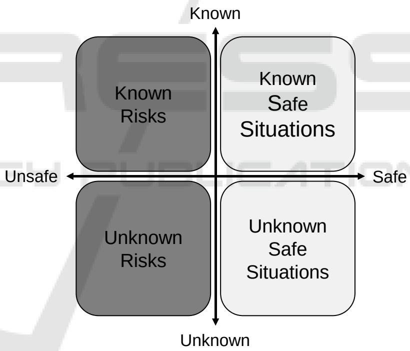

Figure 1: Classification of possible driving situations in highly automated driving according to (Stavesand, 2019).

A promising approach for the validation of HAD systems is scenario-based testing. In contrast to the requirement-based test approach, driving scenarios form the basis for test case creation (Pütz, 2017). The fundamental idea of scenario-based testing is that if all theoretically possible driving scenarios can be enumerated and the autonomous vehicle is tested in all scenarios, a statement about safety of the system can be derived (de Gelder and Paardekooper, 2017). The assumption is made that if a vehicle has successfully completed a particular scenario, that other, similar scenarios will also be successfully completed (Shwartz et al., 2017). In his work, Bagschik

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proposes three levels of abstraction for scenarios (Bagschik et al., 2017). Functional scenarios represent the highest and most abstract level of scenarios. At this level, operational scenarios of the development object are collected on a semantic level. The next level is formed by the so-called logical scenarios, which map the functional scenarios onto a physical state space. They represent driving scenarios by entities and relationships of these entities with the help of parameter ranges in the state space. Concrete scenarios are defined as the lowest level. They represent driving scenarios uniquely by entities and relationships of these entities using fixed values in the state space.

Within the project PEGASUS, funded by the German Federal Ministry for Economic Affairs and Energy (BMWi), a 6-level model was developed, which can be used for the description of scenarios, see Figure 2. This model uses different levels to represent the different aspects and properties of a scenario (PEGASUS-Projekt, 2018). The first two levels L1 and L2 of the model describe the basic road layout on which the scenario takes place. This includes both the road topology and its characteristics, as well as the guidance infrastructure such as construction barriers, lane markings and traffic signs. Temporary modifications, such as changed lane alignments or guidance facilities in construction sites, are described in the third level L3. Moving objects, as well as maneuver-based interaction between road users is part of the fourth level L4. The fifth level L5 is used for modeling environmental conditions and their influence on the levels L1 to L4. Digital information, such as Vehicle-to-Everything (V2X) communication or digital maps, is described in the last level L6.

In order to obtain test scenarios for the validation either a knowledge or data-driven approach can be used (Stellet et al., 2015). The knowledge-driven approach derives test scenarios from system use cases and addresses known driving states. By filtering relevant cases from empirical data and extracting driving scenarios from it, the data-driven approach enables the identification from previously unknown driving states. The empirical data encompasses data from Naturalistic Driving Studies (NDS), Field Operational Tests (FOT), accidents as well as driving simulator and real world test trials (Ebner, 2014).

A major remaining challenge in scenario-based testing is to extract a comprehensive and representative set of driving scenarios from recorded real world data. To ensure that the extracted scenarios can also be used for validation, a semantic description must be available.

In this paper we present a concept for extracting

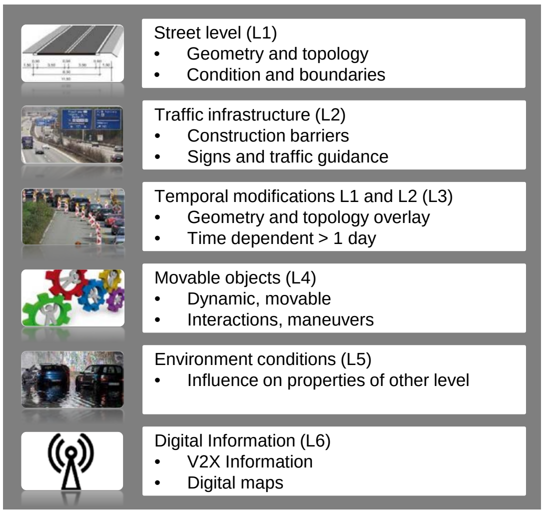

Figure 2: The 6-layer model to structure scenarios presented by PEGASUS(Project, 2019).

logical scenarios in an urban environment from birdview trajectories. This concept is applied on an intersection from the INTERACTION data set (Zhan et al., 2019). The presented approach considers each vehicle in the data set as a ego vehicle and is based on the assumption that each vehicle can experience multiple composite scenarios. Thus, a much greater variety of logical scenarios can be extracted from the data set. The description of the logical scenarios focuses on driving maneuvers and the interaction with other road users. Moreover, we present a visualization tool that makes the data set accessible and browsable on a logical scenario level. This tool can be used to search specifically for scenarios with a certain content.

This paper is structured as follows: Section II presents the related work regarding the extraction of logical scenarios. In the third section we introduce our concept. In Section IV we apply the concept on an intersection from the INTERACTION data set and show some results. After the evaluation in Section V, some conclusions and future work are presented in Section VI.

2 RELATED WORK

Zhao presents an open database that includes naturalistic driving scenarios extracted from public data collected by the Safety Pilot Model Deployment program in an urban environment (Zhao et al., 2017). The presented database covers six different types of scenarios:

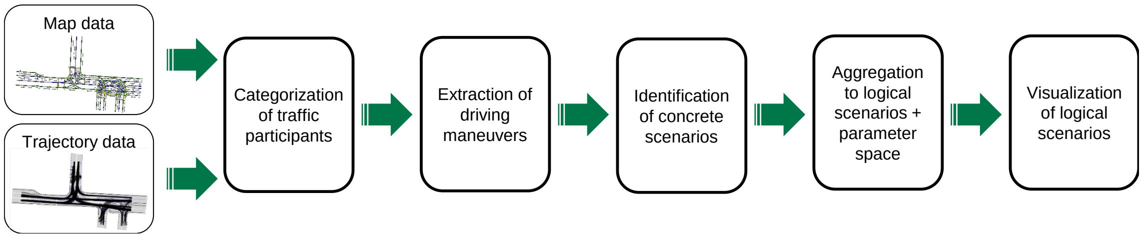

Figure 3: Required steps for the presented scenario extraction approach.

- Free flow scenario
- Car-following scenario
- Cut in scenario
- Lane change scenario
- Pedestrian crossing scenario
- Cyclist scenario

The data set used to perform the scenario extraction is comprised of of object-list data from radar sensors, information provided by a vision-based system from Mobileye as well as a trip summary. For each scenario Zhao provides an algorithm to query the respective scenarios from the open accessible data base.

(Langner et al., 2019) extract scenarios of dynamic length for one traffic participant including traffic infrastructure from map data, such as curviness, slope and speed limits. The segmented scenarios are enriched with a feature vector, containing relevant information for the system under test. For combining the scenarios to logical scenarios, common cluster algorithms are applied on the feature vector.

(Hartjen et al., 2019a) provide a semantic description of extracted scenarios for urban traffic based on maneuvers. The maneuvers are grouped to infrastructure maneuvers, describing connections to the infrastructure, object-related maneuvers, describing interaction with other participants, and vehicle state maneuvers, describing behavior without a connection to external elements. The extracted maneuvers serve as basis for logical scenarios, whereby the individual maneuver parameters are combined to parameter-distributions. In further work, they show the application of the concept for scenarios with interactions with pedestrians (Hartjen et al., 2019b).

(Erdogan et al., 2019) extract scenarios based on recorded trajectories focusing cut-in/out and lane changes scenarios on highways. For detection of these, they implemented rule-based, supervised and unsupervised classification algorithms and compared their results.

(Elrofai et al., 2016) extract turns and lane change scenarios from only in-car sensor data. For the detection, a physical model is used. The extracted scenarios are enriched with characterizing parameters.

An important purpose of scenarios during the validation is that they serve as a basis for test definition. Therefore, they should be available as logical scenarios to enable the generalization approach. To test interactive systems, a simple replay of trajectories is no longer sufficient. The scenarios must therefore be extracted in a format that represents the relationships of the road users at an abstraction level that allows an interactive re-simulation. In addition, representative parameter spaces and parameter distributions are required for a reliable validation.

3 EXTRACTION CONCEPT

We present an approach that identifies scenarios with respect to the 6-layer model, shown in Figure 3. For this purpose, we place a special focus on the interactions with other road users at the layer L4, represented by driving maneuvers. The first step of the proposed concept comprises the identification and categorization of all relevant traffic participants from input data. Based on the classification, a driving maneuver extraction is performed. Subsequently, concrete scenarios are identified, which are then aggregated into logical scenarios. The final step is the visualization of the results to enable further use. The individual steps are described in more detail below.

Input Data. The input data for the extraction are vehicle trajectories, for example from the INTERACTION data set (Zhan et al., 2019), as well as map information. The map is represented in the Lanelet2 framework (Poggenhans et al., 2018) and includes lane information, a routing graph and regulatory elements. The entire processing chain from Figure 3 is performed for each vehicle in the data set. Thus, each vehicle can be both ego-vehicle and participant in the extracted logical scenarios.

Categorization of Traffic Participants. The initial step of the extraction concept is the *categorization of traffic participants*. All surrounding vehicles are examined to determine if they are a preceding vehicle

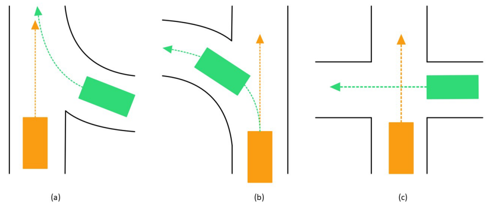

Figure 4: Possible interaction of ego vehicle (orange) with other road users (green): (a) merging, (b) diverging, (c) crossing.

or otherwise interacting with the ego vehicle. Hence, this work considers three different types of interaction between the ego vehicle and other road users, see Figure 4.

Merging. The trajectory of another road user merges on the ego trajectory and become a preceding vehicle.

Diverging. The trajectory of a preceding road user diverges from the ego trajectory.

Crossing. The trajectory crosses the ego trajectory in space and time.

In order to reduce complexity, non-interacting vehicles on adjacent lanes are not yet considered for scenario extraction in the work. The different interaction types are determined by crossing lanelet paths and trajectories. Moreover, a crossing requires a positive post encroachment time (PET). The PET describes the time interval between two objects when the first object leaves a conflict point and the second object enters into it (Paul, 2019).

Extraction of Driving Maneuvers. During the next step, a maneuver recognition is performed for all relevant surrounding vehicles. We use a maneuver model based on Hartjen (Hartjen et al., 2019a). A distinction between driving maneuvers and the driving context is introduced in addition to the work of Hartjen. The driving context includes interactions with other road users as well as further information on whether a lane change was performed, for example, on the crossing area or the access road. Since the data sets contains some lane changes that could not be trivially performed on the routing graph, the maneuver of *illegal lane change* is additionally introduced.

Identification of Concrete Scenarios. Based on the driving maneuvers and the driving context we perform the identification of concrete scenarios. The presented work is based on the assumption that each vehicle can experience multiple composite scenarios. A brief example might clarify this concept, shown in

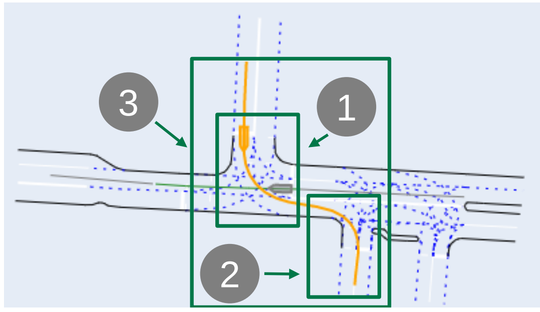

Figure 5: The ego vehicle (yellow) experiences three concrete scenarios: turn left with crossing participant (1), turn right (2) and turn left and turn right (3).

Figure 5. For the purpose of this contribution, the ego vehicle will always be represented by the orange object in the images. The example shows a vehicle turning to the left with crossing traffic and then directly turning right. In terms of the validation, both the turn left, the turn right and the combination of both are interesting. Therefore, the complete driving sequence can be considered as one scenario with two turns or two smaller scenarios with one turn each. Thus, three scenarios can be derived from this single driving sequence. This distinction can be particularly interesting for statements regarding a potential coverage. At the layer L4, the concrete scenario is represented as a sequence of maneuvers, while preserving the causality of the maneuver sequence. To reduce artifacts in scenario identification, we have introduced rules for when a scenario is considered valid:

- The track of the object does not start on a crossing area
- The object must cross an intersection

Finally, a parameter determination is carried out. The parameters depend on the maneuver performed. For instance, the minimum distance to the preceding vehicle can be determined during a follow maneuver, but not if the intersection is crossed alone.

Aggregation to Logical Scenarios. In the last extraction step, the concrete scenarios are aggregated into logical scenarios. We distinguish logical scenarios as different maneuver sequences. Thus, concrete scenarios with the identical maneuver sequence can be grouped into the same logical scenario and their explicit parameter values can be converted to parameter value ranges for the logical scenario. Lastly the logical scenarios are stored in a database with following information:

Meta-Information. Logical scenario ID, including concrete scenarios (Id, track id, start and stop time), Parameter space

L1/L2. Reference to the map

L4. Maneuver Sequence

Visualization of Logical Scenarios. To visualize the extracted logical scenarios we build a dashboard that represents scenarios in a searchable and structured way. For this purpose, a prefix graph is used in which nodes describe groups of logical scenarios. The maneuver sequences are represented as successions in the prefix graph and scenarios of the child nodes are more precise subdivisions of the respective parents. Additionally, we use a subset graph for a more in-depth visualization. The subset graph shows the logical scenarios included in the group of logical scenarios selected in the prefix graph. In contrast to the prefix tree, each node represents a logical scenario. The subset graph utilizes a tree ordering and each parent node includes the maneuver sequence of the child nodes. Additionally, the maneuver sequence and representative scene overviews from the scenarios are displayed to support the understanding of the logical scenario. This combination of a prefix graph and subset graph create a tool that allows a step-by-step filtering for scenarios with a certain content.

4 IMPLEMENTATION AND RESULTS

The proposed scenario extraction approach is implemented and applied on the *DR_USA_Intersection_EP* intersection from the INTERACTION data set. This demonstrates that the approach is suitable for extracting logical scenarios and representing them in a semantic browsable manner. Additionally, further information on occurrence probabilities and distributions of logical scenarios are determined. First, general information about the extracted logical scenarios is presented. Thereafter, the actual content of the extracted scenarios will be interpreted and discussed in more detail. The data set comprises an American intersection without traffic lights and with a total number of around 750 vehicles and a high density of aggressive behavior and near collision situations (Zhan et al., 2019). The topology of the considered road section is shown in Figure 6. The intersection is composed of two crossing areas and access roads from all directions. The indicated arrows visualize the direction of travel. For the sake of simplicity, the term *scenario* will refer to a logical scenario in this section. Concrete scenarios are explicitly mentioned.

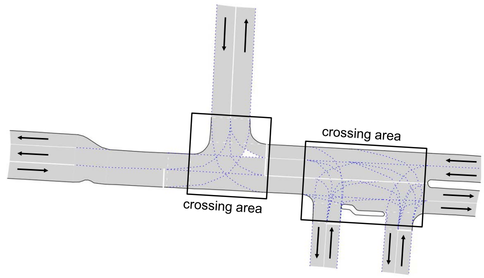

Figure 6: Intersection *DR_USA_Intersection_EP* from the INTERACTION data set with marked driving directions(Zhan et al., 2019).

4.1 General Analysis of the Results

Throughout the data set, the presented approach identified 1172 concrete scenarios, which are then clustered into 504 logical scenarios. From the figures it is apparent that a significant number of vehicles experience several concrete scenarios. Figure 7 shows the distribution of the number of concrete scenarios per vehicle. The abscissa shows the number of concrete scenarios per vehicle. The ordinate shows how many vehicles have the respective number of concrete scenarios. Approximately 100 vehicles in the data set do not meet the requirements listed in Sec. 3 and therefore no concrete scenario can be identified for them. The majority of vehicles have one or two concrete scenarios. The proportion of vehicles with 3 concrete scenarios is about the same as that with 0 concrete scenarios. There are vehicles for which 4 or in one exception even 6 concrete scenarios are identified. The next analysis examines how the concrete scenarios are distributed among the logical scenarios, shown in Figure 8. The abscissa represents the num-

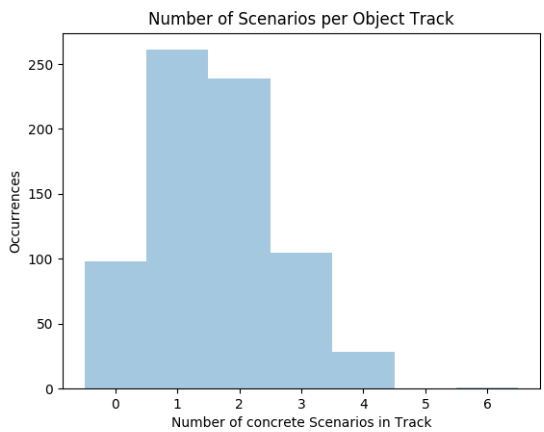

Figure 7: Distribution of the number of concrete scenarios per vehicle.

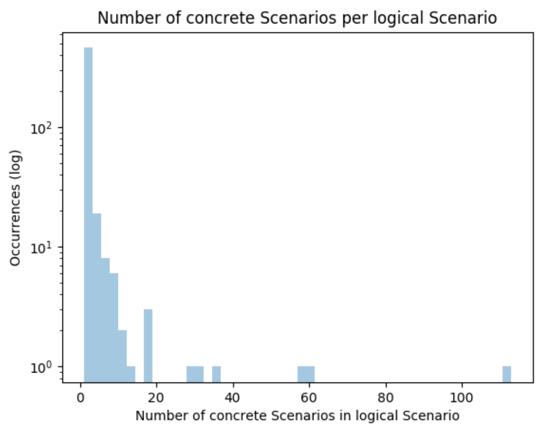

Figure 8: Distribution of the number of concrete scenarios per logical scenario.

ber of concrete scenarios in a logical scenario and on the ordinate the occurrences is shown on a logarithmic scale. As it can be seen from Figure 8, there are only a few logical scenarios that encompasses a large number of concrete scenarios. The largest logical scenario comprises 113 concrete scenarios, which corresponds to around 9.6% of the total number of concrete scenarios. This *scenario* solely involves a straight passing of an crossing area without any interaction with other road users and thus serves as the basis for a variety of larger *scenarios*.

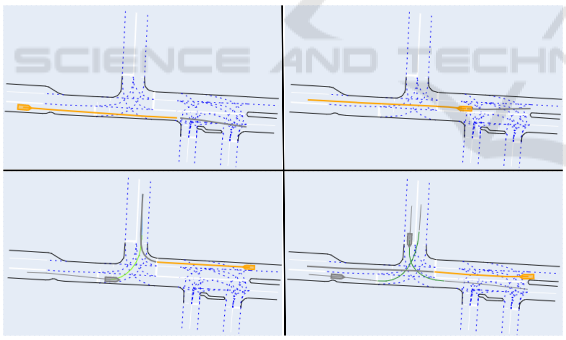

Figure 9: Four concrete scenarios from the largest logical scenario.

Four exemplary concrete scenarios from this logical scenario are illustrated in Figure 9. Furthermore, Fig 8 reveals that most of the extracted logical scenarios are formed by only one concrete scenario. In this context, the term *singular logical scenarios* is introduced. Possible reasons for this can be the special characteristics of the *scenarios* on the one hand or the limited size of the data set on the other hand. Since only concrete scenarios with an identical maneuver sequence are combined into a logical scenario, even small variations ensure that concrete scenarios are no longer combined. Therefore, we have analyzed the influence of the different maneuver types on the number of *scenarios*. For this purpose, we examine in a first step how many *scenarios* would have been identified without a certain maneuver type. In the second step, the scenario extraction is performed with this investigated maneuver type. By comparing the *scenarios* found, a conclusion is drawn about the influence of the maneuver type. A key finding from this analysis is, that temporal variations in the maneuvers concerning only the ego vehicle's state, e.g. acceleration or standing still, lead to the biggest increase in *scenarios*. Additionally, the preceding object maneuver also highly influence the number of *scenarios*. Overall, 91% of the logical scenarios contain only three or less concrete scenarios, 95% six or less.

4.2 Interpretation of Extracted Scenarios

In order to be able to use *scenarios* for validation, the content of the individual scenarios must be known. Hence, we analyze on the one hand how the vehicle navigates through the road network and on the other hand how it interacts with other road users. This information can then be used, for instance, for scenario design during re-simulation.

Navigation through Road Network. The *scenarios* are examined with regard to the turn and lane change maneuvers, see Table 1. 39.29% of the vehicles in the data set did not perform any turn maneuvers and crossed the intersection straight ahead. The remaining vehicles performed at least one left or right turn. Thus, 31.94% of the *scenarios* include at least one turn left and 28.77% involve at least one turn right.

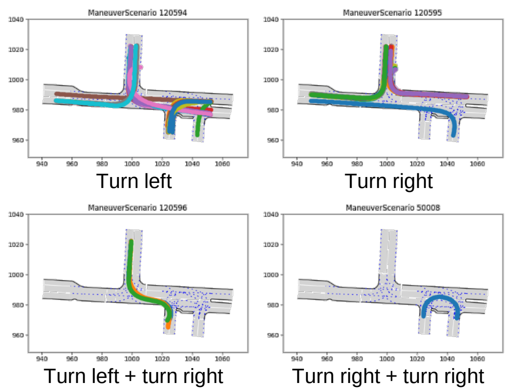

Figure 10: Logical scenarios with different turn maneuvers extracted from the dataset.

The data suggest that the maneuvers are reason-

Table 1: Number of extracted logical scenarios regarding turn and lane change maneuvers.

	Scenario defining maneuver	**Number of extracted logical scenarios** total	relative
Turn maneuver	Turn left	161	31.94%
	Turn right	145	28.77%
	Cross straight	192	39.29%
	Turn left + turn right	8	1.59%
	Turn right + turn right	2	0.39%
Lane change maneuver	Follow lane	363	72.02%
	Lane change	141	27.98%
	Illegal lane change	34	6.7%

ably evenly distributed. Moreover, eight vehicles first performed a turn left and then a turn right. Two vehicles performed two turn rights in succession. An illustration of the various turn maneuvers is shown in Figure 10. It can be seen from the figures that 27.98% of the vehicles perform a lane change maneuver. Among these 141 logical scenarios, 34 *scenarios* include a vehicle that performs an illegal lane change. A logical scenario that includes a composition of all three lane change maneuvers is shown in Fig 11. Since (Zhan et al., 2019) do not provide any information about the exact location of the intersection we do not know the surrounding infrastructure. Based on the trajectory in

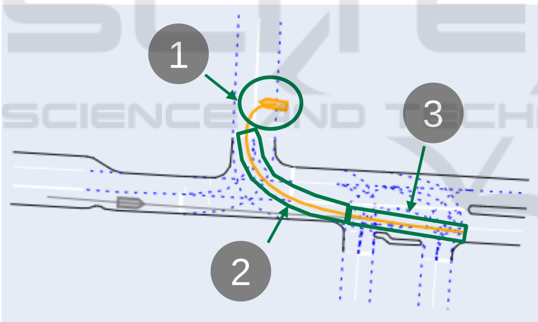

Figure 11: Logical scenario composed of an illegal lane change (1), follow lane (2) and a lane change (3).

Figure 11 we assume that there might be a parking space in the top right corner. However, driving onto or off the road has not been explicitly classified as a maneuver and is therefore identified as an illegal lane change.
The distribution of lane change and turn maneuvers depends on the intersection and the traffic flow. Nevertheless, the given results are a representative distribution for the presented intersection.

Interaction with Other Road Users. Considering the extracted logical scenarios with respect to interactions with the surrounding traffic, we find that 22.82% of the *scenarios* take place without any preceding vehicle. 68.85% of the *scenarios* include at least one follow maneuver and 50.79% approach maneuvers, see Table 2. As mentioned before, the preceding maneuver is the second largest influencing factor on the number of *scenarios*. This is also reflected in the variety of possible maneuver sequences. Figure 12 visualizes all existing maneuver sequences as a prefix tree. Starting at a root node each path to a final node represents an existing maneuver sequence of a *scenario*. We used following color code within the graph:

Table 2: Number of extracted logical scenarios regarding the preceding maneuver.

Scenario defining maneuver	**Number of extracted logical scenarios** total	relative
No preceding	115	22.82%
Approach	256	50.79%
Follow	347	68.85%

no preceding yellow circle

approach red circle

follow green circle

final node blue circle

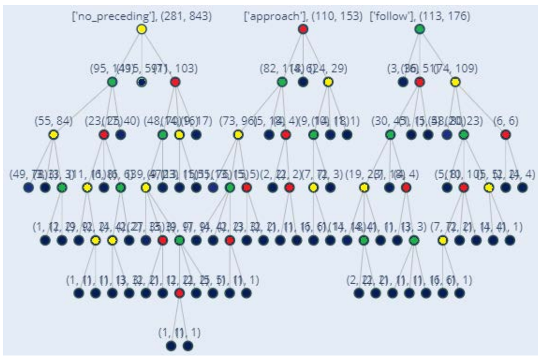

Figure 12: Visualization of existing maneuver sequences as a prefix tree (yellow circle = no preceding, red circle = approach, green circle = follow, blue circle = final node).

Table 3: Number of extracted logical scenarios regarding the interaction types.

Interaction type	Number of logical Scenarios total	relative	Max Number of Vehicles
Crossing	163	32.34%	9
Merging	194	38.49%	6
Diverging	111	22.02%	3
Crossing + Merging	53	10.51%	Crossing:3 Merging: 2
Crossing + Diverging	23	4.56%	Crossing: 2 Diverging: 2
Merging + Diverging	26	5.16%	Merging: 3 Diverging: 1
Crossing+ Merging+ Diverging	16	3.17%	Crossing: 2 Merging: 1 Diverging: 1

The shortest *scenario* consists of one maneuver and is created through the slicing of larger *scenarios*. The longest maneuver sequence consists of two consecutive sequences: ”no preceding” - ”approach” - ”follow”. During the design of test scenarios, the prefix tree from Figure 12 can be used to search for real logical scenarios with a certain maneuver sequence.
In addition to the preceding object, different types of interaction with other road users are also considered. For this purpose, the logical scenarios are examined in more detail with regard to the different types of interactions presented in Figure 4. Moreover, we also consider the number of participants within the interaction as a parameter of the logical scenario. By looking at the figures in Table 3, one can see that merging is the most common type of interaction with a cumulative frequency of occurrence of 38.49%. In contrast, crossing has the highest number of involved objects, with a total number of nine crossing vehicles within a logical scenario. Figure 13 shows a more detailed histogram about the number of vehicles for each interaction type. The number of interacting vehicles is plotted on the abscissa and the frequency of occurrence is plotted on the ordinate on a logarithmic scale. According to the diagram, most interactions involve one or two vehicles.

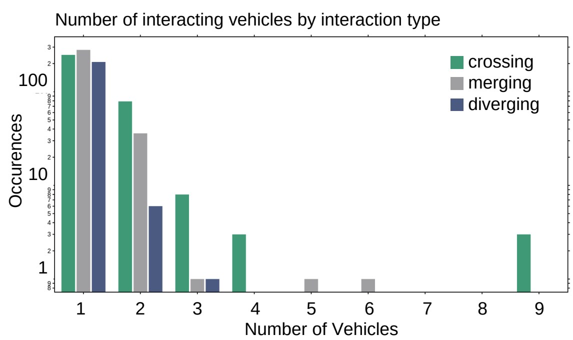

Figure 13: Distribution of the number of interaction vehicles by interaction type.

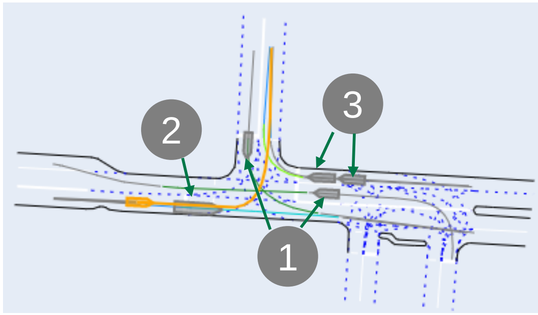

Figure 14: Logical scenario that include crossing (1), diverging (2) and merging (3) objects.

Moreover, scenarios that have a combination of two or three interactions are also present in the data set and have been identified. Figure 14 shows a logical scenario that include all three types of interaction. The scenarios includes a preceding object that diverges from the ego trajectory and passes the intersection straight ahead. Additionally, the ego vehicle have to wait for two crossing objects from left and the oncoming traffic as well as two vehicles merge into the ego trajectory.
The representation of the logical scenarios in a prefix and subset graph allows an easy and direct selection of more remarkable scenarios like the one presented in Figure 14. The selection setup for this scenario is ”turn left” in the prefix graph and ”merging + crossing + diverging” in the subset graph.

5 EVALUATION

Currently, there is no set of reference for scenarios extracted from the data set or any other type of ground truth that could be used to validate the results of the presented extraction. Thus, the evaluation has to be done empirically. For the validation of the scenarios with respect to turn and lane change maneuvers, a ground truth is constructed from the existing data. For this purpose, all tracks entering or leaving the map on certain lanelets are identified. These track clusters are then be compared to the extracted scenarios. No mismatches are found from the extracted scenarios to the created ground truth. A random manual review of logical scenarios is used to validate the scenarios regarding the interactions with other road users. In the process, it is checked for selected logical scenarios whether the assigned concrete scenarios matched in terms of content. Although all logical scenarios considered are judged to be plausible and correct, no general claim to correctness can be derived from this small reviewing sample. In a third step, we re-simulate individual scenarios in a simulation environment and apply the scenario detection to the simulated data. The results show that our approach is able to correctly identify the initial scenario again.

The presented approach provides the capability to search specifically for logical scenarios with a certain content in the data set. In addition, it provides important information relevant to scenario design and possible coverage statements, such as distribution of certain maneuvers or scenario parameter.

6 CONCLUSIONS AND FUTURE WORK

In this contribution, we presented a concept for the extraction of logical scenarios in an urban environment. Thereby, a special focus is on the interaction with other road users. The presented approach therefore operates centrally on the performed driving maneuvers and the existing driving context. In particular, interactions such as crossing, merging and diverging are considered.

We presented some results from the application of our approach to an intersection from the INTERACTION data set. A total number of 1172 concrete scenarios were extracted from this data set, which can be aggregated into 504 logical scenarios. Based on the extracted logical scenarios a dashboard is created that allows an easy analysis of the scenarios as well as enables a semantic browsability of the data. For each logical scenario the maneuver sequence is shown, as well as all assigned concrete scenarios and the parameter ranges with their distribution.

As discussed earlier and shown in Figure 8, our set of logical scenarios consists mainly of *singular logical scenarios* and only a few larger logical scenarios are found. At this point, it must be examined to what extent an increase in the volume of the data set results in the filling of known logical scenarios or the creation of new logical scenarios. Considering a sufficiently large and representative data set, such *singular logical scenarios* would represent corner cases. An extension of the maneuver catalog to include pedestrian-related maneuvers as well as following objects or objects on adjacent lanes is also necessary in order to adequately consider these interactions as well. Although a complete validity proof is not possible due to the lack of reference scenarios or ground truth, we are convinced that the work will make a valuable contribution to the validation of HAD. The extracted scenarios can be used for a scenario-based testing approach and with the availability of a representative data set, statements about the coverage and relevance of individual logical scenarios can also be made. Future work will also focus on the application of the approach on the entire INTERACTION data set as well as other available data sets. As part of this, the aggregation of results will also become a future research question.

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