Identification of Challenging Highway-Scenarios for the Safety Validation of Automated Vehicles Based on Real Driving Data

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Abstract—For a successful market launch of automated vehicles (AVs), proof of their safety is essential. Due to the open parameter space, an infinite number of traffic situations can occur, which makes the proof of safety an unsolved problem. With the so-called scenario-based approach, all relevant test scenarios must be identified. This paper introduces an approach that finds particularly challenging scenarios from real driving data (RDD) and assesses their difficulty using a novel metric. Starting from the highD data, scenarios are extracted using a hierarchical clustering approach and then assigned to one of nine pre-defined functional scenarios using rule-based classification. The special feature of the subsequent evaluation of the concrete scenarios is that it is independent of the performance of the test vehicle and therefore valid for all AVs. Previous evaluation metrics are often based on the criticality of the scenario, which is, however, dependent on the behavior of the test vehicle and is therefore only conditionally suitable for finding "good" test cases in advance. The results show that with this new approach a reduced number of particularly challenging test scenarios can be derived.

Keywords—Automated vehicles; safety; critical scenarios; complex scenarios; challenging scenarios; real driving data; highway; scenario classification.

I. INTRODUCTION

For the validation and certification of automated vehicles (AVs; Level 3 and higher according to SAE [1]), the so-called scenario-based approach is a promising method for efficiently achieving a reliable safety statement about the AV. The scenario-based approach is intended to reduce the test effort by limiting the tests to meaningful scenarios. However, the question remains open as to how all necessary scenarios can be identified. The aim is to have a scenario catalog or database with scenarios that contains all "good" test cases for the safety assessment.

Scenarios can be generated either knowledge-based or data-based [2]. The advantage of knowledge-based generation (e.g. using ontologies [3]) is that a comprehensive set of scenarios can be defined quickly and cost-effectively. However, the more time-consuming data-based approach is more promising for the creation of a complete set.

The data-based approach uses real driving data (RDD; e.g. highD-dataset [4]) and extracts scenarios from it. First, individual scenarios are extracted from the large amount of data using clustering and classification methods, which is the first focus of this paper. In this initial step, as is the basic principle of the scenario-based approach, all free driving and similar uninteresting situations are omitted, thus reducing the amount of data (Fig. 1).

Subsequently, the extracted scenarios can be examined in more detail. One category of scenarios can be, for example, cut-in scenarios. Because this scenario category occurs frequently in RDD, the measured data will contain a large number of cut-in situations. Not all of them should be stored in the database and then used as test cases, because many of them are redundant or contribute only minor to the safety assessment. Therefore, there are different metrics with which scenarios can be evaluated and thus a selection of particularly difficult (complex) test cases can be performed. The development of such

Fig. 1: Data reduction during scenario extraction out of RDD.
a novel complexity-based metric is the second focus of this paper. As a result, a reduced number of particularly interesting (in relation to the metric used) scenarios is obtained for an efficient assessment of AVs. Therefore, the contributions of this paper are as follows:

- Providing definitions for the differentiation of critical, challenging and complex scenarios (Section II-B3)
- Overall approach for the definition of a reduced set of ‘good’ scenarios based on complexity (Section III-A)
- Scenario clustering and classification based on RDD (Section III-B)
- Novel and comprehensive metric for the assessment of scenarios regarding Layer 4 for the highway use-case which is the main contribution (Section III-C)

II. RELATED WORK

This section first defines important terms and then explains various methods for evaluating scenarios for AV testing.

A. Terms and Definitions

Scenario: In the context of this work, the definition of Ulbrich et al. [5] is used, according to which a scenario is a temporal sequence of scenes, whereby actions and events of the elements involved occur within this sequence. By actions and events are meant, for example, maneuvers such as a cut-out situation or approaching the end of a traffic jam. On this basis, Menzel et al. [6] define three different categories of scenarios. These are the so-called functional, logical and concrete scenarios. Starting with a verbal description of the functional scenarios, through the logical scenarios defined by parameter ranges and distributions, to the concrete scenarios defined by exact parameter values, the level of detail and machine readability increases. For logical and concrete scenarios, all parameters that describe the scenario are required. For this purpose, a five-layer model for structuring the parameters is presented in [3]. The five layers are defined as below:

Layer 1: Road-level
Layer 2: Traffic infrastructure
Layer 3: Temporary manipulation of L1 and L2
Layer 4: Objects
Layer 5: Environment

Traffic Participants (TP): In general, all movable objects, such as pedestrians and cyclists are TPs. Due to highways as the considered use case represented by the used RDD, the term traffic participant is used in this paper as a synonym for passenger cars and trucks.

Region of Interest (ROI): For the extraction of scenarios from RDD all relevant data about the environment of the ego-vehicle have to be considered. In this paper we focus on the objects from Layer 4 according to the five-layer model of [3] and consider the surrounding traffic participants analogous to [7] as relevant when within the ROI of the ego-vehicle. The definition of the ROI is visualized in Fig. 2.

B. Scenario Selection Methods

This section first presents selection approaches that describe if a scenario is critical and/or challenging. It becomes apparent that there is no common understanding in the literature about the definition of these terms. Therefore, a clear distinction of the terms is proposed at the end of this section.

1) Selection of Critical Scenarios: The use of a criticality metric for scenario selection is a commonly applied approach. The best known metric is the time-to-collision (TTC) [8]. An overview of criticality metrics can also be found in [9]. If the used RDD were recorded by human drivers, the problem with criticality-based selection of scenarios is that the same traffic situations do not necessarily have to be as critical for AVs as for human drivers.

Hallerbach et al. [10] define four types of criticality: individual, nanoscopic, microscopic and macroscopic. This is used to evaluate criticality in different spatial areas around the AV. They use a learning-based procedure to make an overall binary decision based on the four criticality areas as to whether the scenario is critical or not. The generation of critical scenarios based
on RDD is the focus of [11], [12]. The criticality of a scenario is calculated based on the size of the area that can be safely used by the AV. Optimization by means of evolutionary algorithms maximizes the criticality of the scenarios by adapting the behavior of surrounding TPs and minimizes the area that can be safely used. In [13], a method is introduced that allows the risk of RDD to be efficiently determined in order to select critical scenarios for testing AVs. The risk in a spatial location relates to the position and speed of surrounding traffic participants.

2) Selection of Challenging Scenarios: The use of the Analytic Hierarchy Process to identify challenging scenarios is investigated by [14]–[16]. WANG ET AL. [17] use a two-stage assessment to determine if the static environment and the dynamic surrounding is challenging. QI ET AL. [18] use the so called Scenario Character Parameter (SCP) based on the trajectories, which lead to an insufficient ego-vehicle performance. By analyzing the SCP, scenario groups can be created and reduced to one challenging scenario. An optimization-based approach (without concrete implementation) for defining challenging scenarios is presented in [19]. Aspects of this method are examined in more detail in [20], [21]. BOLTE ET AL. [22] extract challenging scenarios from data based on the difficulty of predicting the future behavior of surrounding TPs.

Compared to criticality-based selection, there is little literature available for identifying challenging scenarios. It is noticeable, however, that the terms challenging and complex are often mixed up and used as synonyms. In rare cases it is also called a corner case. What all three terms have in common is that they describe a scenario that is particularly difficult for the AV.

3) Differentiation Between Critical and Challenging Scenarios: The terms critical, challenging and complex are not used consistently in literature. In our understanding, challenging and complex cannot be separated from each other clearly. However, it is possible to clearly separate these terms from criticality. The separation is done according to the purpose of the evaluation and whether it can be performed before or after the test case execution. If criticality is evaluated, the behavior of the ego-vehicle is assessed in a concrete scenario. This evaluation can only be made after execution of the test case. If, on the other hand, the concrete scenario itself is to be evaluated, it can be classified as challenging/complex. According to this, the scenarios of [11], [12] should be assigned to challenging even when the authors use the term critical. In the context of our work, we also consider challenging as an umbrella term for complex scenarios. While the difficulty of challenging scenarios can exist in any parameter layer, complex scenarios describe particularly difficult ones in relation to Layer 4 (Fig. 3). The contribution of the present paper can thus be assigned to complexity. Therefore, we use the following definitions:

**Critical**: Assessment of the performance of the ego-vehicle behavior in a concrete scenario. It is only determinable after test case execution and the behavior of different AV-functions lead to different criticality-results for the same concrete scenario.

**Challenging and Complex**: It means an assessment of a concrete scenario itself. It is determinable before test case execution and independent of the AV-performance. Whether a concrete scenario is challenging / complex or not, depends on the chosen parameter values. Therefore, challenging or complex can be seen as the difficulty for the AV to master the concrete scenario without the occurrence of a critical situation. The main assumption herein is that more complex scenarios lead more often to critical situations when they are executed.

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**III. METHODOLOGY**

This section first gives a brief overview of the overall method and then explains in detail the approach of the scenario clustering and classification as well as the metric for complexity assessment.

**A. Overall Approach**

The overall method is a procedure to identify a reduced set of particularly important scenarios based on RDD, with which various automated driving functions can be tested. A visualization as well as the highlighting of the sub-methods discussed in this paper can be seen in Fig. 4.
The scenario clustering and classification method as well as the complexity assessment are explained in detail in Sections II-B and II-C. Scenario optimization, simulation, and the assessment of the AV are not covered in this paper and are only briefly explained here for the sake of completeness. In scenario optimization, the complexity of the scenarios extracted from the RDD is further increased in order to improve the quality of the scenarios. This is achieved by adapting the behavior of the surrounding TPs. The optimized scenarios can then be stored in a database. In scenario simulation, an actual driving function is used for the first time in the methodology. Its performance in the optimized scenarios is then examined and evaluated using, for example, criticality-based key performance indicators.

B. Scenario Clustering and Classification

The basis for clustering and classifying scenarios are RDD. In this paper, we use the highD data set [4]. The developed process consists of four steps, that are shown in Fig. 5.

1) Hierarchical Clustering: The highD data consists of a 420 m long highway section recorded by a drone. The vehicles need in median 13.6 s to pass through this section. Hierarchical clustering is used in combination with the ROI defined in Section II-A to extract individual scenarios from the several minutes of recorded data. Each cluster consists of an ego-vehicle and all relevant surrounding TPs. Thereby, uninteresting free driving situations (no surrounding TPs exist) are sorted out to reduce the amount of data.

2) Semantic Maneuver Classification: We use a rule-based approach for maneuver classification as all driving situations in highway traffic can be distinguished with a manageable amount of rules. Furthermore as [23] claims, the rule-based performance is almost as good as with learning-based approaches. For each TP in the scenario, a rule-based decision tree is used to define the maneuver with respect to the ego-vehicle. The correct maneuver is selected from 13 different maneuvers, such as ‘overtaking’, ‘following drive of the ego-vehicle’ or ‘driving parallel to the ego-vehicle’.

3) Challenger Identification: Challengers are defined as TPs that force reactions by the ego-vehicle, in order to avoid potential collisions. The determination of those vehicles is accomplished by predicting the trajectories of the ego-vehicle and analyzing potential intersections with other TPs. A scenario can have none, one or several challengers. Scenarios without a challenger can be sorted out because no reaction of the ego-vehicle is necessary and therefore no contribution to the safety assessment is made. For scenarios with a Challenger all other TPs are also relevant, as they can represent action restrictions for the ego-vehicle. For scenarios with more than one challenger, the first challenger is considered decisive for the following scenario classification.

4) Scenario Classification: Based on the trajectory of the challenger, the scenario is assigned to one of nine functional scenarios used in the PEGASUS project [24] (Fig. 5). The maneuver classification in step 2) uses more than nine categories, because the behavior of all TPs (including non challenger) is classified.

In summary, concrete scenarios assigned to one of nine functional scenarios based on the trajectory of the challenger represent the result of the clustering and classification method. In addition, the amount of data is reduced by neglecting scenarios without challengers.

C. Definition of the Complexity Metric

To further reduce the number of scenarios and thus the amount of data, the classified scenarios are evaluated using a novel complexity metric. This allows us to sort out uninteresting scenarios and to focus on highly complex scenarios that are more difficult for the AV. Under the assumption made in Section II-B3, this leads to a higher probability of the occurrence of erroneous behavior of the AV.
The developed complexity metric aims at evaluating the difficulty of the scenario itself without considering ego-vehicle’s behavior. Thereby the following assumptions are made:

- There are different attributes of a traffic situation that contribute to complexity,
- All attributes are calculated for all TPs within the ROI,
- Different attributes have different importance,
- Coupling effects between attributes are neglected,
- Every attribute has linear contribution to the overall complexity,
- The maximum complexity during the scenario is used as the descriptive value.

The scalar complexity of a scenario $C_{\text{scenario}}$ can then be calculated according to Equation 1.

$$C_{\text{scenario}} = \max(w^T \cdot a_i) \quad \text{with} \quad i \in \{1, \ldots, m\} \quad (1)$$

Hereby $w \in (n \times 1)$ is the weighting vector, $a_i \in (n \times 1)$ the attribute vector, $m$ is the number of scenes in the scenario and $n$ is the number of attributes. The sum of all $n$ weights $w_j$ and the normalization of all attributes $a_{i,j}$ is shown in Equation 2 where $a_{i,j}$ denotes the $j$-th entry of the attribute vector in the $i$-th scene of the scenario under consideration.

$$\sum_{j=1}^{n} w_j = 1 \quad \text{and} \quad a_{i,j} \in [0, 1] \quad (2)$$

The number of scenes in a scenario $m$ can be calculated using Equation 3, where $t_{\text{scenario}}$ is the time duration of the scenario. The time step size $\Delta t$ in the highD data is specified as 0.04 s since the camera of the drone has a frequency of 25 Hz. With 13.6 s as median appearance of the vehicles, the median number of scenes $m$ is 340.

$$m = \frac{t_{\text{scenario}}}{\Delta t} \quad (3)$$

The choice of attributes $a_j$ has a crucial influence on the calculation of the complexity. A complete list of influencing factors cannot be determined objectively, therefore $n = 13$ different attributes are defined based on literature as well as expert knowledge from industry and research. A brief summary is given below and a more comprehensive description can be found in our preliminary investigation in [25].

1) Number of surrounding TPs
2) Types (car, truck, ...) of surrounding TPs
3) Dynamic (velocity, acceleration) of surrounding TPs
4) Variation of dynamic parameters of surrounding TPs
5) Number of action dependencies of surrounding TPs
6) Predictability (with simple constant acceleration model) of future behavior of surrounding TPs
7) Time-gap between ego-vehicle and surrounding TPs
8) Possible actions of ego-vehicle (due to action restriction by other TPs)
9) Possible actions of surrounding TPs (due to action restriction by other TPs)
10) Occluded area for ego-vehicle due to line-of-sight obstruction by other TPs
11) Number of actions performed by surrounding TPs during the scenario
12) Time to brake for ego-vehicle to avoid accidents
13) Number of actions of ego-vehicle during the scenario

All attributes that cannot be calculated in every scene, such as the number of actions of individual TPs, are calculated at the end of the scenario and their values are used for all scenes. This ensures a consistent comparison between different scenarios. To also make the influence of the attributes on the overall complexity comparable, all attributes are normalized to a value range from 0 to 1 according to Equation 2.

IV. RESULTS

This section shows the results of the scenario classification and complexity assessment. Finally, the complexity metric is validated.

A. Scenario Clustering and Classification

The highD data set contains 110,507 vehicles, which means that theoretically 110,507 concrete scenarios can be extracted. As described in Section III-B1, clustering already eliminates all scenarios without surrounding TPs.
Fig. 7: Number of concrete scenarios in the highD dataset which include a challenger. They are assigned to the nine defined functional scenarios from Fig. 6.

Fig. 8: Distribution of the number of involved vehicles per scenario, whereby the ego vehicle is also counted. The median is seven and the maximum is 19 vehicles.

After this step, 110,007 scenarios remain from the highD data for further processing. The number of relevant scenarios can be further reduced to 67,455 by the challenger consideration (Section III-B3). These 67,455 concrete scenarios are assigned to the nine defined functional scenarios using the classification method from Section III-B4. The distribution of the functional scenarios can be seen in Fig. 7.

Figure 8 shows the number of vehicles involved in the scenarios. The ego-vehicle is also included, so the minimum number of vehicles is two. In these scenarios only the challenger is present in addition to the ego-vehicle. These types of scenarios only account for 0.59% of the total scenarios. In all other scenarios there are additional TPs that have to be considered when planning a safe trajectory and which can also represent action restrictions for the ego-vehicle.

B. Complexity Assessment

In order to calculate the complexity, the weights $w_j$ of all attributes were determined by an online expert survey. Using a two-part online survey, 25 experts from the field of safety assessment of AVs were first asked how important they consider each of the $n$ attributes in terms of complexity for AVs. Then, in a second part, a subgroup of 20 experts were shown 20 scenarios of the highD dataset on video\footnote{The videos are available via https://www.youtube.com/channel/UC3IV32GfmVKXouqVf74jMFG/videos?view=0&sort=dd&shelf_id=0} which they evaluated from low to high complexity. The weights were then determined by means of a compromise in such a way that both the expert opinion on the importance of each attribute as well as the evaluation of the scenarios were represented by the developed metric. This compromise is necessary because the results of the two parts of the online survey do not match exactly, i.e. if high rated attributes of the experts are weighted too high, the metric reflects the expert opinion worse in the evaluation of the 20 scenarios. The resulting weighting vector $w_j$ is

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w = [0.01, 0.087, 0.087, 0.087, 0.077, 0.087, 0.087, 0.087, 0.02, 0.084].
\]

Using the determined weighting factors, all challenger scenarios are evaluated with the complexity metric.

Figure 9a shows the complexity distribution for all scenarios. Additionally, Fig. 9b depicts the distribution for the functional scenario I. The distribution for scenario class I (as well as all other functional scenarios) is similar to the distribution for all scenarios. This means that no conclusions can be drawn about complexity based on the scenario class.

Due to space limitations, the complexity distribution of only one functional scenario (Scenario I) is shown in Fig. 9b. It is noticeable that a large number of scenarios from RDD have only a low and medium complexity, respectively. Given the complexity levels used, if only scenarios with high complexity are considered for the further process, this corresponds to an additional reduction of 99.99%. A comparison between a low complexity scenario and a high complexity scenario is shown in Fig. 10. It can be seen that in the scenario with high complexity, it is more difficult for the AV to plan a safe trajectory.

It is interesting to compare our approach with a criticality-based selection of scenarios. In [13], vehicle 1034 from highD track 25 is used as an example for a critical scenario. Exactly this scenario is assigned to the functional scenario I in our framework and evaluated with only a moderate complexity of 0.37. The reason for this is the low speed of approximately 20 km/h and the sufficient space for an evasive maneuver. So the...
scenario itself is not very difficult, but the performance of the human driver was not optimal, so that a critical situation occurred. Including this test case in the database therefore offers no benefit if a reliable database for the evaluation of different AVs is to be established.

C. Validation

One aspect of validation is the completeness of the attributes. This was evaluated in the online expert survey. When assessing the importance of the individual attributes, the experts were asked to recommend changes in the implementation of the attribute. At the end of the 13 attributes, the experts were asked for additional attributes that they deemed should be taken into account. For the former, only minor changes were suggested by the experts and for the latter, no new attribute was named by the experts. Thus the complexity metric can be considered complete.

The second aspect is the validation of the statement from Section II-B3 that more complex scenarios lead more often to critical situations. For this purpose, a simple automated driving function is developed in Matlab/Simulink using the Automated Driving Toolbox. Subsequently, scenarios from the highD data set are simulated, which can be seen as a simplified implementation of the block 'Scenario Simulation' from Figure 4. The simple driving function thereby substitutes the ego-vehicle from the original highD scenario and consists of a combination of existing examples from the Automated Driving Toolbox, which include ACC, LKA and an emergency brake assistant. In addition, a lane change function is implemented so that the vehicle can change lanes when the adjacent lane is free. Since all highD data were recorded on highways, these four sub-functions are sufficient to enable a vehicle to drive automatically in the considered highway use case.

The scenarios from the highD data set are created using the Scenario Designer of the Automated Driving Toolbox. Because the complexity metric is not completely independent of the behavior of the ego-vehicle, the scenarios are started at the time with the highest complexity of the scenario. The behavior of the surrounding road users is predefined and not adapted to the actions of the ego-vehicle (the AV to be tested). Therefore accidents can occur where the ego-vehicle is not to blame. Examples are situations in which a TP drives into the rear of the ego-vehicle because the AV drives slower than the original ego-vehicle from the highD data set. These scenarios are not considered in the evaluation.

To prove the assumption that more complex scenarios lead more often to critical situations, scenarios with low, medium and high complexity are simulated, evaluated and the criticality is compared on the basis of the minimum TTC that occurred. Since there are only a few scenarios with high complexity in the entire data set, about one percent (650 scenarios) of the 67,455 scenarios with the lowest and highest complexity rating are selected respectively. In addition, 650 scenarios are selected that are closest to the average complexity of 0.38. This allows the three categories of lowest, average and highest complexity to be compared.

The evaluation (Table I) shows that of the 650 scenarios per class, different numbers of scenarios remain after sorting out the irrelevant accidents. It can be seen that accidents in which the AV is not to blame occur more frequently with higher complexity. Despite the slightly lower number of test scenarios, accidents caused by the AV occur most frequently in highly complex scenarios and most frequently fall below the critical TTC value of 1.5 seconds. The critical TTC value is based on [26].
TABLE I: Results of the Matlab/Simulink simulation. The number of scenarios is not identical because all accidents that are not caused by the AV are sorted out. The critical TTC value is 1.5 seconds and is based on [26].

| Complexity class | Lowest | Average | Highest |
|------------------|--------|---------|---------|
| Number of Scenarios | 645    | 595     | 416     |
| Scenarios below critical TTC | 2      | 7       | 9       |
| Number of accidents | 2      | 13      | 22      |

Fig. 11: Cumulative distribution functions of the TTC of the lowest, average and highest rated scenarios. The three categories each contain approximately one percent of the scenarios shown in Figure 9a. It can be seen that scenarios with higher complexity more often show small TTC values. This means that more complex scenarios are on average more critical.

The most significant influence on the quality of the results is the complexity metric being used. The basic idea is to evaluate only the scenario itself without considering the behavior of the ego-vehicle (which is often a human driver in case of currently available RDD). This is not 100% possible because a scenario is a dynamic sequence of scenes where the ego-vehicle behavior influences the behavior of the surrounding TP and vice versa. Nevertheless, the evaluation is much less dependent on the behavior of the ego-vehicle than with the criticality-based selection of scenarios.

V. DISCUSSION

With the developed methodology it has been shown, that a reduced set of particularly challenging scenarios can be derived, at least with respect to Layer 4 of the five-level model of [3]. This can be very helpful especially for spot checking during certification of AV conducted by independent third parties. However, a further research
question arises, which share of scenarios should be further processed to scenario optimization. Thereby, a distance measure can be used to measure the uniqueness of the scenario in order not to store too many similar scenarios in the database and at the same time not lose too much in completeness. In addition, individual functional scenarios can be examined more intensively in future work and an individual selection of scenarios can be made.

During the simulation of the scenarios, accidents occur for which the AV is not to blame. This can be analyzed and eliminated in further work by specifically adapting the behavior of the surrounding TP in such cases. A more sophisticated driving function can also be used to achieve a performance in the scenario evaluations that is more comparable with that of the human driver.

Although this approach is a promising method for identifying relevant scenarios, further sources for filling the scenario database will be necessary for a comprehensive safety assessment. Especially after small changes to the driving function, it can be advantageous to focus on critical scenarios of the previous version.

VI. CONCLUSION

This contribution addresses a novel method for complexity-based identification of a reduced set of especially challenging scenarios from real driving data. In contrast to commonly used criticality metrics, which evaluate the performance of the ego-vehicle behavior within a scenario, the developed complexity metric evaluates the scenario itself and can derive a generally valid catalog of 'good' test scenarios. Already during the clustering and classification of the scenarios about 39% of the data can be classified as uninteresting based on a challenger consideration and thus be sorted out. Using an equidistant classification into low, medium and high complexity, the most challenging scenarios can be identified and used for the further processing steps, allowing a further reduction of the data amount. The results prove the validity of the metric and therefore, the methodology presented here can contribute significantly to an efficient safety assessment of automated vehicles.

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Thomas Ponn (corresponding author) initiated and wrote this paper. He was involved in all stages of development and primarily developed the research question as well as the concept. Matthias Breitfuß wrote his thesis on scenario clustering and classification and implemented the clustering and classification algorithms during his thesis. Xiao Yu wrote her thesis on the development of a complexity metric and implemented the complexity assessment algorithms during her thesis. Frank Diermeyer contributed to the conception of the research project and revised the paper critically for important intellectual content. He gave final approval of the version to be published and agrees to all aspects of the work. As a guarantor, he accepts responsibility for the overall integrity of the paper.

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