Detecting Edge Cases from Trajectory Datasets Using Deep Learning Based Outlier Detection

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Abstract: The biggest challenge to overcome for automated vehicles is to prove their safety, as these vehicles are solely responsible for the passengers' safety. The scenario-based testing approach promises an efficient safety validation procedure by only testing the safety in relevant scenarios. An open question is how to select the relevant scenarios for testing. So-called edge cases are frequently named in the automated driving domain to be important scenarios for testing automated vehicles. However, it is not an easy task to define what an edge case is and to find and validate them. In this work, we present a novel data-driven approach to finding edge cases in trajectory datasets using deep learning-based outlier detection. We develop a method that calculates embeddings for driving scenarios in a two-stage process. In the dimensionally reduced embedding space, outliers represent potential edge cases. We apply the approach to the exiD dataset and find potential edge cases. For validation, we present the found potential edge cases to a group of experts. The experts validate that the approach is capable of detecting edge cases in trajectory datasets.

1 INTRODUCTION

Automated driving (AD) offers great benefits for the passengers and also for the whole traffic in general (Bjorvatn et al., 2021). To achieve these benefits, it is important to make sure that the automated driving systems (ADSs) act responsibly before they are released to the market. An approach for this safety validation is the scenario-based testing approach (Riedmaier et al., 2020). The idea is to not test a developed ADS in field tests only, but to expose it to systematically defined scenarios in simulations or on a test track to minimize the amount of testing in real world traffic. One promising type of scenarios are so-called edge cases (ECs). This is a term that is frequently used in the AD domain to refer to particularly relevant scenarios for testing. However, defining ECs generally yet precisely is a big challenge, because ultimately, the system under test should be involved (Vater et al., 2023). This lack of a precise definition makes finding potential ECs in traffic data and also validation of the found ones challenging.

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There exist different scopes when talking about ECs. One is to consider ECs with respect to the perception, i.e., the sensors of the vehicle (Breitenstein et al., 2020). Another scope is on trajectory level. Trajectory level means that only the interaction and behaviour of the road users are analysed to find ECs. On the one hand, many approaches are knowledge-driven starting from expert knowledge and trying to define top-down, which kind of situations might be challenging for the ADS (Ponn et al., 2020). On the other hand, there are statistical approaches, defining edge cases as "rare" situations. These data-driven approaches find ECs by detecting outliers in the parameter values of scenarios.

A category of ECs that is not found by both of these approaches is the *unknown unknown* EC, i.e., a category of ECs that is not yet known to experts and therefore cannot directly be searched for in data. Thus, it is impossible to find unknown unknown ECs using purely knowledge-based approaches. The unknown unknown ECs can be understood as semantic outliers. The search for these ECs in real-world trajectory data, including complex situations and interactions between many involved vehicles, can be expressed as the search for semantically different scenarios. Semantically different scenarios are not the same as an extreme parameter value. Therefore, using purely statistical approaches can also not find the unknown unknown edge cases. It is also challenging to validate found potential ECs. Previous EC detection methods have mainly qualitatively presented found ECs in their work (Souflas et al., 2022).

In this paper, we present a model-free EC detection approach that is not based on expert knowledge but works in a semi-supervised way, analysing whole trajectory datasets. In addition, we present a systematic validation method for EC detection algorithms based on an expert survey. Taking expert knowledge into the loop after the actual detection promises the benefit that the algorithm can first work unbiased, but then can still be validated using precious expert knowledge. In short, our main contributions in this paper are the following:

- A model-free semi-supervised approach to find ECs in large trajectory datasets,
- A validation method for EC detection algorithms based on an expert survey,
- Demonstrating how to use both methods on a publicly available large scale trajectory dataset.

The remainder of the paper is structured as follows: In Section 2, we present the related work that we built our method upon. In Section 3, we detail the methodology of our approach for EC detection and the knowledge-based validation approach. In Section 4, we show results of a case study we performed using our method on a large scale trajectory dataset and the result of the subsequently conducted expert survey. We then discuss the results in Section 5 and give a conclusion in Section 6.

2 RELATED WORK

In the context of scenario-based testing, scenarios can be described as a sequence of scenes (Ulbrich et al., 2015). We apply this definition, but use the term *frame* instead of scene. The 6-Layer Model (Scholtes et al., 2021) is a frequently used model for defining all relevant factors of a given scenario. In the remainder of the paper, we use the term driving scenario (DS) with the following definition:

*A **driving scenario** is a short period of driving defined by its main driving task (e.g. car following, lane change) or triggered by an event (e.g. an obstacle in the lane).* (Sonntag et al., 2023)

We explicitly include the term *driving* to emphasize the difference to (traffic) scenarios with a broader scope. Following this definition, a DS describes a range of driving scenario instances of one class, e.g., cut-ins. To differentiate a specific instance of a DS from the class, we use the term DS *instance*.

There exist multiple ideas of what ECs are. In a previous work (Vater et al., 2023), we have analyzed existing usages of the term edge case in the literature to derive a common definition that is as specific as possible while taking as much of the existing attributes of ECs into account. The definition for ECs we derived is the following:

*An **edge case** is a novel or rare situation that still needs specific design attention to be dealt with in a reasonable and safe way, as it is a boundary case of one parameter for the system. The quantification of "rare" is relative, and generally refers to situations or conditions that will occur often enough in a full-scale deployed fleet to be a problem.* (Vater et al., 2023)

It is slightly adapted from the already existing definition of (Koopman and Wagner, 2017) to make it more applicable in a wider range of contexts. Another finding of the literature review is that the term corner case, which is often used in similar contexts as the term edge case in the literature, has very similar attributes than an edge case (Vater et al., 2023). Therefore, in this paper, we will not differentiate between the two terms, but use just the term edge case for both.

The challenge is to identify those novel and rare cases to use them for scenario-based testing. Most data driven approaches utilize models based on expert knowledge to identify those cases. For example, (Ponn et al., 2020) use metrics to determine the complexity of DSs. They talk about challenging scenarios without using the term edge case. Other model-based approaches generate synthetic ECs based on accidents (Souflas et al., 2022). Those approaches have in common that the used model adds a bias to the identified ECs. This leads to the fact that elements not incorporated in those models might be overlooked, which is especially true for unknown unknown ECs, as they are rare things that have not been thought of before. Additionally, both approaches do not apply a validation step that is independent of an actual system implementation.

To find those unknown unknowns, general outlier detection methods utilizing deep-learning instead of knowledge based models can be applied. (Pang et al., 2021) present three different deep-learning based approaches. Most applicable for our work is the approach of learning feature representations of normality. The objective is to not just learn features, but to focus on learning specific features representing normality. (Pang et al., 2021) use the term anomaly detection. Although (Yang et al., 2021) define that there are slight differences between outlier detection and anomaly detection, the overall approaches are transferable.

Finding feature representations is a crucial step for detecting outliers, as it reduces the dimensionality of the data. In high dimensional spaces, there might be no clusters of data and, thus, no outliers, because of the high amount of possible combinations of parameters in all dimensions. Therefore, methods for reducing the dimensionality of DS representations are required. In the literature, different approaches were developed with the purpose of identifying clusters of DS instances to structure the space of possible DS. (Harmening et al., 2020) introduce two approaches considering only the dynamic objects, but neglecting the static environment. (Zhao et al., 2021) introduce a two stage process based on image representations of the scenes incorporating the dynamic objects as well as the street layout. In the first stage, embeddings for each scene are learned based on an autoencoder. In the second stage, a temporal representation of a sequence of scenes is learned using a recurrent neural network (RNN). Both publications do not optimize and use the representations for detecting outliers.

(Han et al., 2022) analyse different existing approaches for detecting global outliers. They identified that k-th nearest neighbour (Ramaswamy et al., 2000) is the most effective detector for identifying global outliers. It calculates the distance to the k-th nearest neighbour and takes this score as a measure for anomaly.

3 METHODOLOGY

The literature review reveals that there are no validated approaches for detecting ECs considered as unknown unknowns applied to large amounts of data. The presented method overcomes this lack. Figure 1 gives an overview of the developed method.

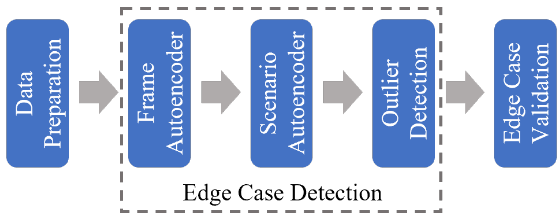

Figure 1: Edge Case Detection Method Overview.

At first, the trajectory data is preprocessed to provide the required information abstracted from the original object and map data. After that, within the EC detection, embeddings of these data are calculated. Those DS embeddings are used for detecting outliers. To validate the developed method, an expert survey is conducted.

3.1 Data Preparation

The preprocessing of the data as an input for the EC detection consists of a spatial and a temporal abstraction step. The spatial abstraction extracts and converts the relevant information per frame. The temporal abstraction step segments the recorded track into smaller chunks representing DSs. This chunking step is required, because having DSs all with similar length, makes them more comparable.

3.1.1 Spatial Abstraction

For the spatial abstraction of trajectory data, most relevant are the elements on layer 4 (dynamic objects) and layer 1 (street layer) of the 6-Layer Model (Scholtes et al., 2021). Therefore, the spatially abstracted trajectory data consists of two sets, which correspond to the two relevant layers of the 6-Layer Model: the traffic set and the street set.

The *traffic set* represents the dynamic objects. It includes the dynamics of all relevant dynamic objects that are in the surrounding of the ego vehicle. Objects are considered relevant when they are on the same road as the ego vehicle and within a radius of 50 meters. This value is selected, as in that range a precise perception with the ego vehicle's sensors is assumed and the behaviour of the close objects is assumed to influence the ego vehicle's behaviour. For each relevant object the relative position in x and y to the ego vehicle, the heading, the velocities in x and y, as well as the width and length are considered. The ego vehicle's position marks the origin of the coordinate system in each frame. In addition to the surrounding objects, the ego velocity is considered as well.

The *street set* represents the street layer. This novel approach of using a set to represent the street layer uses a 2D point cloud abstracting the lane markings. The point cloud is created using the points defining the lines in a Lanelet2 map (Poggenhans et al., 2018). Additional points along the lines are added, when there are long straight lines with more than 5 meters between the individual points, to achieve a minimum density of the points.

The result of the data preprocessing of an example frame is visualized in Figure 2. The street set and the traffic set are depicted as an overlay onto an image of the road segment and the Lanelet2 lines (green lines).

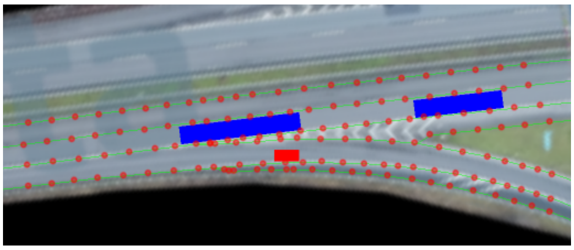

Figure 2: Visualization of the frame data as an overlay. Ego vehicle depicted as red rectangle.

3.1.2 Temporal Abstraction

The temporal abstraction cuts the recorded tracks into segments representing individual DS instances to reduce the number of manoeuvres and interactions per segment. This reduces the number of possible combinations of those within one segment, resulting in comparable tracks. The goal is to find meaningful segments in the data without being too specific and thereby influencing the outlier detection.

For this work, the DS concept developed within the Hi-Drive project is used as a basis (Sonntag et al., 2023). The concept allows using different levels of abstraction for DSs. For the presented approach, only segmenting the track is relevant, and no detailed classification is required, leading to a high level of abstraction. In fact, the tracks within the trajectory dataset are segmented first into *Driving in Lane*, *Changing Lane*, *Crossing*, and *Turning* according to the first level of the DS concept. As the driving-in-lane segments can still be rather long with multiple interactions, they are further segmented according to lower levels of the DS concept. This segmentation is done by detecting the DSs *Cut-in (passive)*, *Following a Lead Vehicle*, *Approaching a Lead Vehicle*, *Ego Vehicle Stationary*, and *Uninfluenced Driving*. When there are still segments exceeding a length of ten seconds, they are further segmented into uniform chunks of a duration of up to ten seconds.

3.2 Edge Case Detection

The EC detection approach itself consists of two main steps. First, the data is compressed to find compact representations for the individual DS instances in the data. The goal is to get an embedding for each DS instance within a lower-dimensional parameter space. Based on that, outliers are detected.

The approach for the DS encoding using a two stage process is adapted from (Zhao et al., 2021). But instead of using image representations of the scenes, a set-based representation is used as input. Using images leads to sparse inputs with strong focus on the street level, leading to issues during representation learning. First, each frame is encoded using the frame autoencoder. The purpose of the frame autoencoder is to generate a semantically meaningful and fixed-length representation for each time step. Those frame embeddings are then encoded again using an RNN autoencoder to find one embedding for each DS instance as a sequence of frame embeddings to allow outlier detection within fixed-length DS representations.

3.2.1 Frame Autoencoder

The design of the frame autoencoder is depicted in Figure 3. Each frame contains three distinct pieces of information that need to be treated differently. The core is an autoencoder. It encodes and decodes a concatenation of a street set vector, traffic set vector, and ego speed into a 64-element embedding vector using fully connected layers and ReLU non-linearities. The expectation is that the embedding produced by the core autoencoder is more semantically rich than a simple concatenation, as the input data are fused together within the bottleneck layer. The street set vector and traffic set vector are generated from the corresponding sets (cf. Section 3.1.1) by two adapted FSPool (Zhang et al., 2020) encoder-decoder pairs. The autoencoder itself uses the triplet loss similar to (Zhao et al., 2021) in addition to the reconstruction loss. This triplet loss ensures two things for frame representations in the embedding space:

- All frames from the same track are represented closer to each other than to frames from different tracks.
- Frames from the same track that are temporarily close are represented closer to each other than to temporally distant frames.

3.2.2 Driving Scenario Autoencoder

The DS autoencoder leverages the frame embeddings learned by the frame autoencoder. The structure brought to the frame embeddings' relations through the triplet loss is crucial for the DS autoencoder, as it makes them semantically more meaningful. This is required to further process them using RNNs. The design of the DS autoencoder is shown in Figure 4. All three RNNs depicted are implemented as two-layered LSTM networks

The input to the DS autoencoder are the different segments of the whole track as sequences of frames (cf. Section 3.1.2). The encoder only processes the frames with an even index, and an embedding is derived from the final state of the RNN. This embedding is used as initial states for the predictor and reconstructor. The predictor receives the even frames and

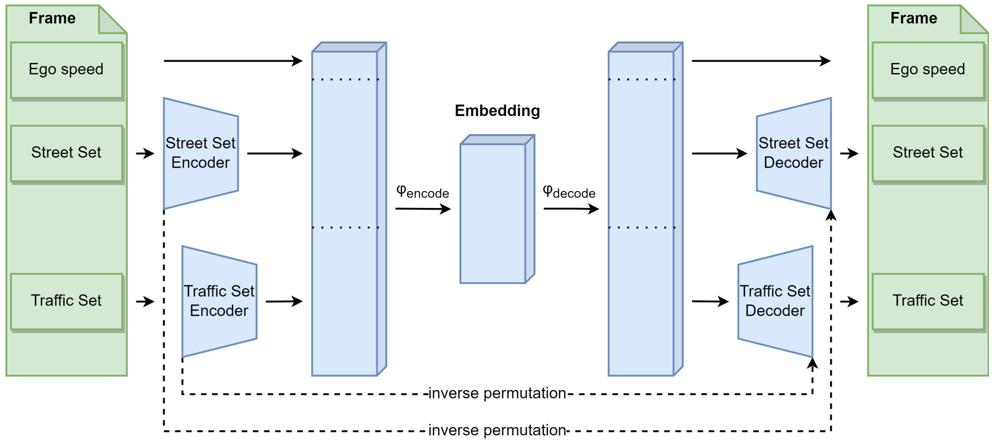

Figure 3: Frame autoencoder design. The functions φ_{encode} and φ_{decode} are both, two layer fully connected networks with a ReLU activation function in between the layers.

predicts the subsequent odd frames. The reconstructor's goal is to reconstruct the input sequence from the DS embedding in reverse order. This is supported by a linear layer $\varphi_{scenario}$ projecting the DS embedding into the right size to be used as an input for each time step to promote sequence learning.

For effective outlier detection based on the embeddings, a semantic meaningful embedding space is required. To achieve this semantic richness, a supervised contrastive loss adapted from (Vaze et al., 2022) is added. This loss adds a soft similarity constraint for the defined DSs to ensure that instances of the same DS are closer together in the embedding space.

3.2.3 Outlier Detection

By processing the trajectory data using the two consecutive autoencoders, we achieve a dimensionally reduced but still semantically rich representation of the DSs. Based on this embedding, it is feasible to detect outliers using the k-th nearest approach (Ramaswamy et al., 2000). The top n DS instances with the highest score, meaning that they have the highest distances to their k-th nearest neighbour, are classified as outliers and thus as potential ECs.

3.3 Validation Method

Validating the detection approaches is a crucial but challenging task. Evaluating, if an identified DS instance is an EC in an automated way requires having the actual ADS available to test the DS instance. Often, this is not available or the EC detection task is not limited to one specific ADS. With the presented approach, it is the goal to find DS instances, which are unlikely to be already considered by AD developers. Therefore, we propose an expert survey addressing AD developers for validating EC detection methods. The idea behind this validation approach is to use the intuition of the AD developers as potential users of ECs for improving their ADS.

The expert survey has two goals. The first goal (a) is to verify that the DS instances found by the EC detection algorithms are unusual. The second goal (b) is to validate that the DS instances found by the EC detection algorithm are actual ECs.

To address the first goal (a), a selection of DS instances are shown to the survey participants as short videos from the birds-eye perspective. The DS instances consist of the n DS instances with the highest score and m randomly selected DS instances from the base dataset. The hypothesis is that the n DS instances with the highest anomaly score are more unusual than the m randomly selected DS instances from the base dataset For each DS instance, they need to give a rating from ”normal” to ”very unusual”. In this first stage, the term edge case is not used to not bias the participants and only get a statement regarding the unusualness.

The second goal (b) of the survey is to validate if actual ECs are detected. This stage is required, as there can be DS instances with a high score, but the anomaly leading to this is not relevant for the usage of ECs. To address this second goal, the participants are asked, after inspecting all DS instances, if they consider at least one of the presented DS instances an EC.

4 RESULTS

The developed EC detection approach is evaluated on trajectory data recorded on motorways. First, the data

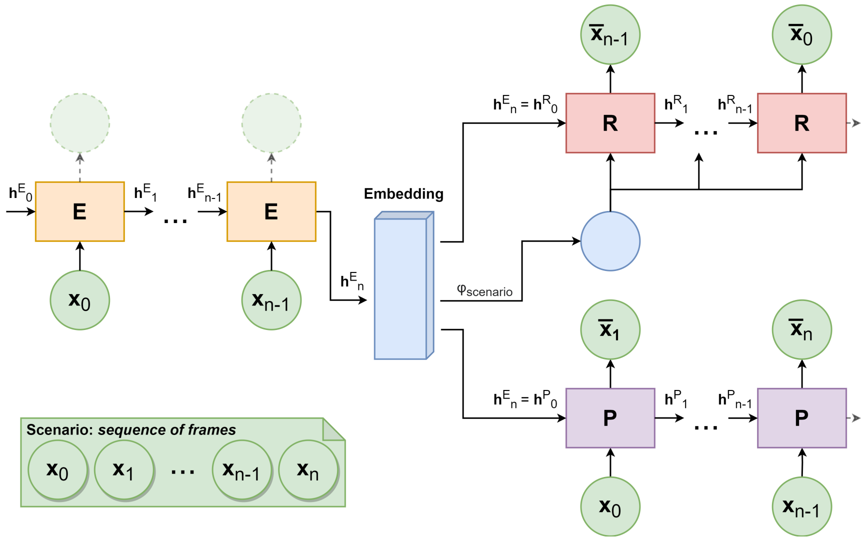

Figure 4: The RNNs are shown in unfolded view. The Encoder is labelled with E. The reconstructor as R, the predictor as P.

is presented in detail. After that, the results of the autoencoders calculating the embeddings are presented as a basis for the actual outlier detection. Finally, the results of the expert survey are shown for validating the approach.

4.1 Data for Evaluation

The developed approach is evaluated on the exiD dataset (Moers et al., 2022). The dataset contains real world traffic recordings comprising approximately 16 hours of footage leading to nearly 70,000 trajectories captured by drone. The footage specifically focuses on seven distinct entrances and exits of German Autobahn sections. These recordings present a field of view of approximately 400 meters at each location. Within the exiD dataset, interesting interactions are expected due to the ramps.

The dataset is converted to the required format described in Section 3.1.1. From the dataset, 50,000 tracks are selected randomly. Each vehicle in the dataset is treated as an ego vehicle once, resulting in approximately 210 hours of combined ego driving footage at 5 Hz frame rate. The segmentation (cf. Section 3.1.2) results in approximately 100,000 DS instances.

4.2 Edge Case Detection Results

The basis for the detection of ECs using outlier detection is a semantically rich DS embedding. In the following section, the results of the autoencoders are presented.

4.2.1 Scenario Encoding Results

One indicator for checking the performance of the frame autoencoder is the reconstruction error. We achieve a meaningful frame embedding when we have low reconstruction errors for the street set and the traffic set. The resulting reconstruction error of the points in the 2D point cloud are 0.22 m for the x and 0.17 m for the y value.

The average error is in the order of magnitude of ten centimetres. Compared to the regular lane width of the lanes on German Autobahn of 3.5 to 3.75 metres, this error is in an acceptable range. The same is valid for the reconstruction error of the traffic set depicted in Table 1. Deviations in the given order of magnitude do not change the overall driving situation and the interactions.

Unlike the frame autoencoder, the DS autoencoder operates on frame vectors received from the frame autoencoder, instead of raw input variables. As a result, the reconstruction error cannot be meaningfully interpreted, both in terms of reconstruction and prediction errors. By analysing the resulting embedding space, we found out that the lane changes to the left and those to the right are largely separated without having this explicitly included during the training process. This gives at least indication on the semantic richness of the embedding space.

4.2.2 Outlier Detection Results

The resulting DS embeddings are used to detect outliers applying the k-th nearest neighbour metric (Ramaswamy et al., 2000), where $k = 10$. The anomaly scores of the DS instances, represented by the dis-

Table 1: Average error over all frames for the traffic set.

Parameter	Position x	Position y	Velocity x	Velocity y	Width	Length	Heading
Average error	0.39 m	0.39 m	0.42 m/s	0.21 m/s	0.04 m	0.13 m	1.17 deg

tance to the tenth nearest neighbour, are depicted as a histogram in Figure 5. It indicates that distance scores above 0.35 are exceptionally uncommon, encompassing approximately 15 out of the 100,000 DS instances. Therefore, n is set to 15. Beneath an anomaly score of 0.35, the histogram shows roughly a Gaussian distribution.

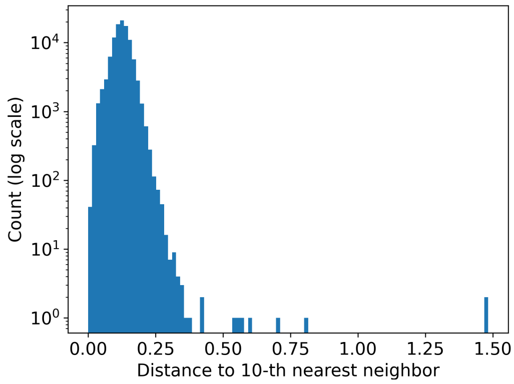

Figure 5: Histogram of the 10-th neighbour distances.

Within those DS instances with the highest anomaly scores, different interesting phenomena are present. Two instances revealed errors in the dataset. One object was detected as driving backwards with a high velocity due to a detection error. The second error found was the detection of one vehicle as two overlaying objects. Detecting those errors gives a first indication that unusual characteristics are found.

But also within the top DS instances with correct data, unusual situations happened, like a truck aborting exiting the motorway and driving with low speed from the exit lane back onto the Autobahn. Another example is depicted in Figure 6. It shows three frames of an unusual segment in the data. The ego vehicle is driving on the left lane, then doing multiple lane changes also crossing a solid line and finally stopping on the emergency lane.

4.3 Expert Survey Results

To quantify those qualitative findings, an expert survey is conducted. The survey is conducted with the top $n = 15$ DS instances, excluding the dataset errors. In addition, $m = 10$ DS instances are selected randomly from the dataset as a baseline.

In the first stage of the survey, 21 AD develop-

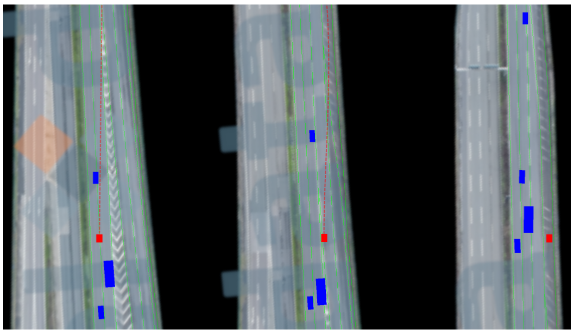

Figure 6: Three frames of a DS instance extracted from exiD (Moers et al., 2022) where the ego vehicle (red) crosses multiple lanes to get onto the right shoulder.

ers were asked to rate how unusual (cf. Section 4.3) the individual DS instances are based on a top view video similar to the frame representation in Figure 6. The aggregated results of this survey are aggregated in Figure 7. While the baseline is considered rather normal, the rating of the top 15 DS instances detected with the presented approach is rather equally distributed.

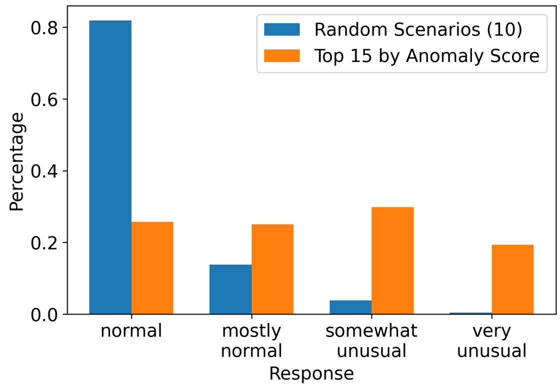

Figure 7: Histogram of how often a response label is assigned to the control group of ten randomly selected DS instances versus the test group of top 15 anomaly score instances.

In the second stage of the survey, approximately 80 percent of the respondents indicated that there was an EC within the presented 25 DS instances. Approximately half of the experts explicitly mentioned the DS instance depicted in Figure 6 as an EC.

5 DISCUSSION

The low reconstruction loss for the frame embeddings and the implications of visualizing the DS embeddings indicate that using the developed approach, it is possible to calculate semantically rich embeddings for the analysed data. This is the basis for detecting outliers based on those DS embeddings.

The clear tendency in the survey towards rating the detected outliers as unusual verifies that the method identifies rather unusual DS instances compared to a random selection. This is supported by the ability of finding dataset errors as unusual DS instances. But still, some DS instances with a high anomaly score are considered as normal by the experts. This indicates that there might be some features in the DS embedding space making DS instances unusual that are not seen relevant by the asked experts. On the other hand, the used dataset is still rather small for the purpose of detecting real ECs. It is highly unlikely that the analysed 100,000 motorway DS instances contain a high amount of clear ECs. E.g. no accidents are in the data. In general, the majority of the experts indicates that the developed approach is capable of detecting unusual DS instances that can be considered as ECs.

6 CONCLUSIONS

In this work, we presented an approach for detecting edge cases in trajectory data using deep-learning based outlier detection. This two-staged approach encodes the data of the dynamic objects and the street layout first for each time step based on an autoencoder. Second, the resulting per-time-step embeddings are aggregated over the duration of basic driving scenarios DS based on an RNN autoencoder. Those driving scenarios are used to segment the continuous driving data into less complex segments. Based on the calculated driving scenario embeddings, outliers are detected using the k-th nearest neighbour metric. The approach was evaluated on motorway data from the exiD drone dataset. The results were validated with an expert survey containing identified potential edge cases as well as randomly selected driving scenario instances. The survey showed that using the developed approach, we were able to identify unusual driving scenario instances that can be considered as edge cases.

For future work, the approach will be extended for urban data as the situations happening on urban domain are more diverse, leading to more challenging outlier detection and requiring larger amounts of data. The identified edge cases will be collected in a database developed within the Hi-Drive project to allow test case derivation for AD development.

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