Time Series Segmentation for Driving Scenario Detection with Fully Convolutional Networks

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Abstract: Leveraging measurement data for Advanced Driver Assistant Systems and Automated Driving Systems requires reliable meta information about covered driving scenarios. With domain expertise, rule-based detectors can be a scalable way to detect scenarios in large amounts of recorded data. However, rules might struggle with noisy data, large number of variations or corner cases and might miss valuable scenarios of interest. Finding missing scenarios manually is challenging and hardly scalable. Therefore we suggest to complement rule-based scenario detection with a data-driven approach. In this work rule-based detections are used as labels to train Fully Convolutional Networks (FCN) in a weakly supervised setup. Experiments show, that FCNs generalize well and identify additional scenarios of interest. The main contribution of this paper is twofold: First, the scenario detection is formulated as a time series segmentation problem and the capability to learn a meaningful scenario detection is demonstrated. Secondly, we show how the disagreement between the rule-based method and the learned detection method can be analyzed to find wrong or missing detections. We conclude, that the FCNs provide a scalable way to assess the quality of a rule based scenario detection without the need of large amounts of ground truth infromation.

1 INTRODUCTION

With increasing capabilities of Advanced Driver Assistant Systems (ADAS) and Automated Driving Systems (ADS), recorded driving data becomes an essential aspect for data-driven development processes (Bach et al., 2017b). Before testing new features in costly measurement campaigns, recorded data can be used to gain a better understanding of relevant situations, detailing required test cases or testing functions by re-simulation (Bach et al., 2017a). With advances in machine learning, also function development itself can leverage large amounts of data. For example, imitation learning can be used to learn directly from recorded human driving (Bansal et al., 2019). However, safety is still an issue in the domain of automated driving (Wood et al., 2019).

For state of the art development processes, the Automotive Software Process Improvement and Capability dEtermination (ASPICE) reference model demands specification of system requirements that are validated with corresponding system qualification tests (VDA QMC Working Group 13 / Automotive SIG, 2015). Defining driving scenarios in a formal way is of great interest in current research as a traceable way to match requirements with concrete test cases (Menzel et al., 2018; Bach et al., 2017c; Sippl et al., 2019; Bock et al., 2019). One aspect of a scenario based development process is the identification of scenarios in recorded driving data (Elspas et al., 2020). Due to the large number of possible scenarios and huge amounts of recorded data, automated and scalable methods are needed to match scenarios of interest with slices of recorded data covering those.

Scenarios are often defined on an abstract level. Arbitrary interactions between different traffic participants and the traffic infrastructure can be used to describe scenarios. However, some interactions can be challenging to identify in recorded data. Information is restricted by the perception range and precision, and are prone to noise and uncertainty. While simple rules allow identifying basic scenarios, some variations might be missed or detected wrongly. Particularly, missing detections can lead to a oversimplification during the development process and cause malfunctions. However, finding missing detections (False

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Negatives) and wrong detections (False Positives) becomes a major effort with increasing amounts of data.

Another way for scenario detection are machine learning methods, which enjoy great popularity in a broad range of domains. Machine Learning shows strengths in leveraging large amounts of data, unless the availability of labeled training data is a bottleneck and limitation. In this work we suggest a combination of a rule-based approach, with a FCN for scenario detection in multivariate time series. The rule-based approach is used to create datasets of labeled data, which is used to train a FCN in a weakly supervised setting. With this approach we leverage the availability of recorded driving data along with the reasonable quality of rule-based detectors. As labeling is done programmatically, datasets can be created and adapted quickly. We observe that the FCNs do not perfectly replicate the rule-based detections, but generalize well and find missing labels. Exploring the deviations of the rule-based and the learned scenario detection provides a systematic approach to find additional scenarios of interest. In an iterative process these scenarios of interest can be used to improve the reliability of scenario detection.

We start this work with an overview of the state of the art in scenario detection, data programing and time series segmentation. In Section 3, we discuss the formulation of the scenario detection problem and adapt a FCN architecture, as commonly used for image segmentation, to be used for multivariate time series. Section 4 covers training and experiments to learn a model to detect lane changes and cut-ins. We evaluate additionally found and missing scenarios, which reveals good generalization capabilities. Manually labeled scenarios are used to verify the suggested method. Finally, in Section 5 we discuss our findings and give an outlook on future work.

2 STATE OF THE ART

While simulation becomes more and more important in the development of ADAS and ADS, real world testing, offering the highest possible validity, still remains necessary. Virtualization is not yet capable to fully compensate real world variations. To identify the covered scenarios within a given large data collection, automated scenario detection is a major concern. Domain knowledge can be expressed with context-free grammars (Lucchetti et al., 2016) or with regular expressions (Elspas et al., 2020) as rule-based approaches of scenario detection. Unsupervised learning can be used to identify scenarios as repeating patterns in recorded data. Recent work in (Langner et al., 2019) and (Montanari et al., 2020), suggests that found clusters can match well with different driving situations. In (Ries et al., 2020) word embeddings were used to compare driving states in a lower-dimensional space. However, it remains challenging to match requirements and formally defined scenarios to real world driving data.

A paradigm to tackle the bottleneck of labeled data for supervised learning was introduced as data programming (Ratner et al., 2016). Experts are encouraged to define heuristic labeling functions while noisy labels are derived by the agreement or disagreement of multiple labeling functions. Discriminative models can be trained on such programmatically generated labels to leverage generalization capabilities of neural networks in a weakly supervised setup. In this work, we incorporate the basic paradigm of programmatic labeling functions to train discriminative models for scenario detection. However, assumptions on conditionally independent labeling functions to learn generative models (Ratner et al., 2016) seem hardly applicable to the given domain. Time series are temporal dependent and the underlying information for scenario detection, like object lists, are strongly correlated.

With the availability of labeled data, supervised learning can be used to detect scenarios. In the context of time series, e.g. the loggings from the bus interfaces of a vehicle, various problem formulations can be used: Fu (Fu, 2011) distinguishes between representation and indexing, similarity measure, segmentation, visualization, and mining. The general capabilities of deep neural networks for time series classification tasks were shown in (Wang et al., 2017) and (Fawaz et al., 2019). Classically, segmentation of time series deals with finding the best representation of the time series with respect to a given number of segments or a given error function (Keogh et al., 2004). While semantic segmentation with deep convolutional networks is widely used for computer vision, e.g. (Ronneberger et al., 2015), semantic segmentation of time series is less popular. However, the successful application of semantic time series segmentation was demonstrated for sleep staging (Perslev et al., 2019).

3 TIME SERIES SEGMENTATION FOR DRIVING SCENARIOS

In this work, we use loggings from the bus interface of the vehicle's communication network. Due to the highly distributed electronics architecture in current vehicles, the bus loggings provide comprehensive in-

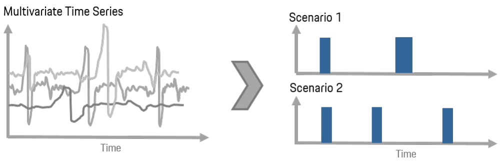


Figure 1: Scenario detection as a semantic segmentation problem of multivariate time series.

formation for scenario detection. From the data perspective the bus loggings are multivariate time series. The data preprocessing includes a use-case specific selection of relevant signals and upsampling to a fixed sampling rate. Detected scenarios are represented as a list of scenario tuples $s = (l, t_s, t_e, m)$ with a semantic label l, start time t_s, end time t_e, and a reference to the corresponding measurement m. As a varying number of scenarios can occur within a measurement, a direct prediction with neural networks is not well conditioned. Instead we suggest a two step procedure: We estimate a scenario probability for each time step and extract the scenario by identifying consecutive time steps with a high scenario probability.

Figure 1 shows a multivariate time series as input data with binary scenario labels. As each point in time can indicate the presence or absence of one or multiple scenarios of interest, the problem becomes a semantic segmentation problem similar to semantic image segmentation, where each pixel is assigned to one out of n semantic classes. However, we do not demand disjunct classes to support potentially simultaneous and overlapping scenarios.

3.1 Dataset Creation

For supervised learning, labeled data is a common bottleneck. Manual labeling becomes infeasible with growing amounts of data and potentially changing requirements. Therefore, we use a programmatic labeling approach. With numerical and Boolean expressions, multivariate signals are combined to a single, univariate time series of relevant states. Thereafter, regular expressions are used to find a pattern of state changes. These two steps provide a flexible and expressive way to describe patterns that are associated with a scenarios of interest.

With such a rule-based labeling approach we do not expect perfect ground truth labels. But, as our experiments suggest, the label quality is sufficient to learn a meaningful scenario detection. Since no manual labeling is needed, the detection rules can be adapted and we were able to create datasets quickly and on demand.

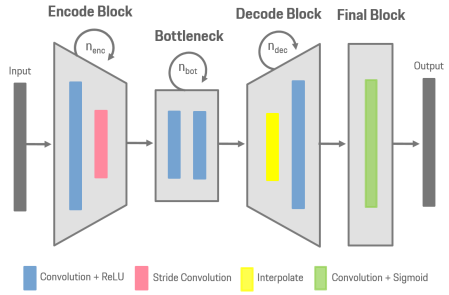


Figure 2: Structural overview of the neural network architecture.

3.2 Neural Network Architecture

While recurrent neural networks are commonly used for time series, we follow the argumentation in (Perslev et al., 2019), that recurrent networks are often difficult to optimize and can be replaced by feed-forward networks for many tasks, as shown in (Bai et al., 2018) and (Chen and Wu, 2017). As the scenario detection in recorded data is an offline problem, the scenario classification for time step can be based on past and future data points. A complete time sequence can be directly fed into the model and no recurrent units are needed to cover the dimension of time.

Based on the success of Fully Convolutional Networks (FCN) for semantic image segmentation, we adapt the popular U-Net architecture (Ronneberger et al., 2015) for multivariate time series, as shown in Figure 2. We replace 2D-Convolution layers by 1D-Convolutions along the time domain. Due to the fully convolutional architecture, the network can be applied to input sequences of different lengths. Furthermore, we keep the basic principles of an encoder block to reduce the resolution of the time series, bottleneck layers to add further depth, and a decode layer to restore the original temporal resolution of the input.

The encoder consists of n_{enc} downsampling blocks with strided convolutions (Springenberg et al., 2015) in each second convolutional layer. The bottleneck layer consists of n_{bot} residual blocks to avoid vanishing gradients (He et al., 2016). The decoder restores the original temporal resolution with $n_{dec} = n_{enc}$ upsampling blocks with an interpolation layer followed by a convolution layer. All layers in the network use ReLU as activation, only the final layer uses the sigmoid function. Finally, the network is trained with the binary cross entropy as loss function using stochastic gradient descent with momentum.

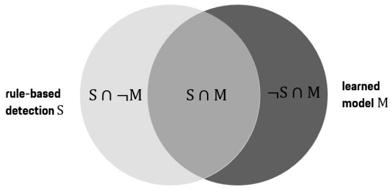


Figure 3: Schematic representation of the overlapping sequences of the rule-based detector and the neural network.

3.3 Event based Evaluation

In the context of driving scenarios, exact start and end points are often unprecise. For example the start of a lane change could be chosen as the first movement towards the lane markings or, more conservatively, the first time the lane marking is crossed. Noisy data makes sharp start and end times further unpractical. Therefore, we suggest an event based evaluation of the detected scenarios: Instead of evaluating the correct detection for each time step, we summarize consecutive time steps with the same scenario label and evaluate the number of correctly detected events. So the evaluation consists of two steps: First we transform the time series into events. By filtering events with implausible short duration we avoid model uncertainty to cause large numbers of false positive detections. Secondly, we find matching events between the set of all detections S from the rule-based approach and the detections M from the learned model. As shown in Figure 3, we get a set of matching events $S \cap M$ that were identified by both approaches, a set $S \cap \neg M$ not found by the learned model, and a set $\neg S \cap M$ not found by the rule-based approach. Commonly, the terms True Positives (TP), False Positives (FP) and False Negatives (FN) are used for these sets respectively. However, due to the weak supervision setup, we avoid these terms to stress that the training labels do not represent ground truth information. High Precision and Recall indicate that the learned model can reproduce the rule-based detections, but do not assess the quality of the scenario detection. Instead, we explicitly investigate the additional detections $\neg S \cap M$ and the missing ones $S \cap \neg M$ from the rule-based detection as a systematic approach to identify FP and FN respectively.

4 DRIVING SCENARIO DETECTION

We use the proposed concept for the detection of two basic driving scenarios: lane changes and cut-ins. This section describes how we generate the training set and chose hyperparameters for the FCN model, before we evaluate the learning results and verify those.

For our experiments we use 105 hours of bus loggings from 9 cars of 3 different models. The recording was done during 16 days in 4 different countries. For scenario detection we rely on information from the inertial measurement unit, the ego velocity and yaw rate, and the perception from a front camera, i.e. detections of lane markings and other traffic participants. The camera detections are available as object lists in the recordings from the vehicle bus. Videos from a front camera were used to review few scenarios manually. This proved especially useful for corner cases which were noticed, irregular visualizations of detected scenarios.

4.1 Lane Changes

Lane changes are a common maneuver with a clear pattern in the lateral distance to the left and right lane markings from the onboard perception. However, missing detections and noise make it challenging to find all lane change scenarios and potential corner cases with a rule-based approach.

4.1.1 Data Labeling

First, we generate a training set by extracting a set of relevant signals: We chose the lateral distance to the detected left and right lane markings, as well as the velocity and yaw rate from the ego vehicle. We define a rule-based detector to create a set of labels S_l, as suggested in (Elspas et al., 2020): We identify driving close to the left and close to the right lane markings as relevant driving states A and D respectively. Driving on the left and right lane markings, is defined as states B and C. Now, a lane change to the left is detected as a state transitions $A \to B \to C \to D$. Similarly, lane changes to the right can be found by the pattern $D \to C \to B \to A$. Due to sensor noise and perception uncertainty, these patterns miss some lane change situations as revealed by reviewing few video recordings. By also matching patterns where the lane markings are lost for up to one second during the maneuver, we make the labeling more robust. With these robust patterns, we create a second set of label denoted by S_l^r. This increases the number of detected lane changes from $|S_l| = 1380$ to $|S_l^r| = 1677$.

We use both sets of labels to train a FCN to show that, even with different quality of the labels, the FCN learns a meaningful scenario detection and reveals missing labels.

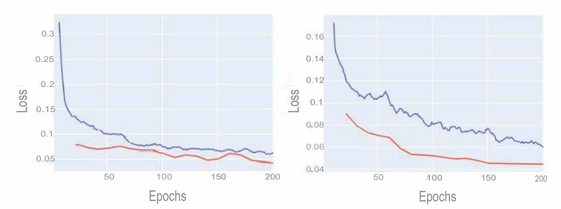


Figure 4: Training loss (blue) and validation loss (red) for two models trained with labels from the simple rule-based detector (left) and the improved rule-based detector (right).

4.1.2 Training

Before training the FCN model, described in section 3.2, some crucial hyperparameters need to be chosen. First, we note that the training data is highly imbalanced. Lane changes have a mean duration of 6 seconds and account for 2.8% of the time. Therefore we use undersampling and drop sequences without a lane change with a drop probability of $p_{drop} = 70\%$. We chose $n_{enc} = n_{dec} = 3$, so that the temporal resolution is reduced from originally 0.1 seconds to 0.8 seconds in the bottleneck layer. We argue, that this granularity is sufficient.

Figure 4 shows the decreasing training and validation loss for training the FCN for 200 epochs with the rule-based detections in S_l (left) and the more robust detections S_l^r as labels. Note, that the lower validation loss in Figure 4 is caused by missing data balancing in the validation set.

4.1.3 Results

As discussed in Section 3.3, the loss can be a misleading metric, because it depends highly on the scenario duration and is prone to the label distribution. We use the loss as indication for a converging model, but further evaluation is based on events, extracted from scenario predictions of the FCN: The threshold 0.5 is used as decision boundary for the presence of scenarios, rising and falling edges indicate start and end times of the events. Implausible events with a duration below 1 second are removed from the resulting sets. This prevents potentially large numbers of toggling detections for situations, where the model is unsure and predicts scenario probabilities around the threshold. The set of events learned from the simple labels S_l is called M_l, the set of detections from the improved labels M_l^r.

Table 1: Event based evaluation of lane changes.

S	M	$\lvert S \cap M \rvert$	$\lvert S \cap \neg M \rvert$	$\lvert \neg S \cap M \rvert$
S_l	M_l	1370	10	412
S_l^r	M_l^r	1670	7	413

Comparing the sets of rule-based detections S with the detections from the learned models M in Table 1 shows only few missing detections from the learned model ($S \cap \neg M$), but few hundred additional detections ($\neg S \cap M$).

To determine whether the additional detections are real lane changes or not, top-down views with the odometry of the ego vehicle (blue) and the detected lane markings (grey), as in Figure 5, can be reviewed. Such visualizations allow simple visual inspection of detected scenarios. Reviewing the 10, respectively 7, missing detections from the learned model confirms all those situations as lane changes (e.g. Figure **??**). We interpret this as a strong indication for a high Precision of the rule-based approach: Even the lane changes that were hard to learn for the FCN model were correctly identified by the rule-based detection.

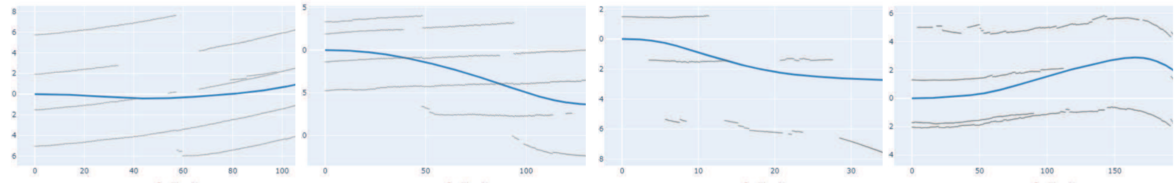
Similarly, we check the additional detections from the learned model: In the 412 additional detections in $\neg S_l \cap M_l$ roughly 58% of the detections are real lane changes. This proves the learned models' ability to detect a significant number of lane changes, which were not labeled.

Even training with the improved labels, which identified 297 additional lane changes in S_l^r compared to S_l, the learned model predicts 413 additional scenarios. Reviewing those scenarios reveals 86 further lane changes. Some of those have clearly missing detections from the lane perception as shown in Figure 5b. Also corner cases like changed lanes for roadworks or holding on the sidewalk were found and are shown in Figure 5c. Furthermore, the learned model identifies 46 situations in which the lane marking is temporarily crossed, see Figure 5d. While such lane crossings might be no lane changes as such, those are clearly related scenarios and identifying such can be beneficial to further detail the discrimination of the scenario of interest.

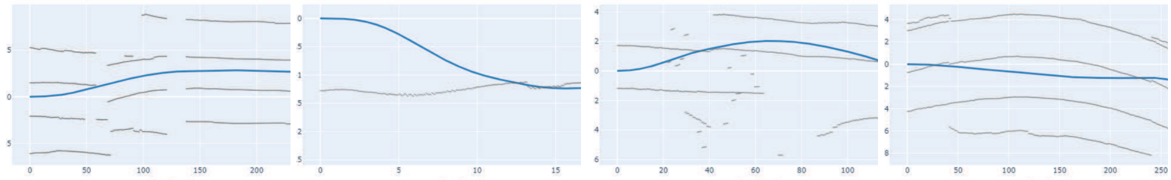
4.1.4 Verification

Evaluating the sets in which the rule-based and learned method disagree, does not directly provide metrics about the detection quality: The detections from both methods $S \cap M$ were only evaluated on a sample base and could include FP. Furthermore, the data could contain lane changes detected by neither method.

To verify that the proposed methods provides a reasonable scenario detection, we label all lane changes within a subset of the recorded data manually. With this ground truth information we can calculate Precision, Recall and F1-Score of the different approaches. Hence we can also account for scenarios missed by both methods.



(a) Lane changes not detected by the learned model in $S \cap \neg M$. (b) Lane changes with missing lane information in $\neg S \cap M$.



(c) Corner cases in $\neg S \cap M$. (d) Temporary lane crossing in $\neg S \cap M$.

Figure 5: Lane changes where the improved labels M_l^r and detections S_l^r from the corresponding learned model do not match. Also corner cases with modified lanes due to roadwork or holding on the sidewalk where found (c).

Table 2: Performance metrics for for lane change detection.

	Precision	Recall	F1-Score
S_l	0.992	0.717	0.832
M_l	0.921	0.873	0.896
S_l^r	**0.994**	0.890	0.939
M_l^r	0.953	**0.936**	**0.945**

The results, shown in Table 2, verify the expectations in Section 4.1.3: As indicated by no FP in $S \cap \neg M$, the rule-based detections S have a high Precision. The Recall for the simple rules is rather low with 72%, which was indicated by the large number of additional detections from the learned model.

With more robust rules the recall is largely increased to 89%. The learned model, trained on this data, is still able to find further missing detections, resulting in an even higher Recall of 93%. However, the learned model tends to predict some false positives as well, which leads to a lower Precision.

In both cases, the high Precision from the rule-based approach was not reached, however, the learned model was able to outperform the rule-based approach in Recall and in F1-Score.

4.2 Cut-ins

While lane changes can be rather easily identified by the lane markings, cut-ins are a more complex scenario where other traffic participants interact with the lane infrastructure in relation to the ego vehicle. Due to a limited detection range of the lane perception, not all detected objects can be reliably mapped to lanes. In combination with potentially strong road curvatures, various variations of cut-in scenarios can occur.

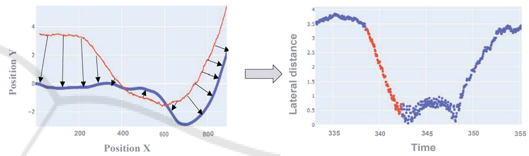


Figure 6: Trajectories from the ego vehicle in blue and a detected object in red (left). The decreasing minimal distance between the trajectories is used for cut-in detection (right).

4.2.1 Data Labeling

First, we write a rule-based cut-in detector to create a dataset with noisy labels programmatically. The front camera provides detected vehicles in form of object lists. Those object lists include the relative positions to the ego vehicle as features. Leveraging a kinematic single-track model, based on odometry signals as ego velocity and yaw rate, we transform the relative positions to trajectories in global coordinates. This representation, visualized in Figure 6, is used to calculate the minimum distance from each position of the detected objects to the future trajectory of the ego vehicle. With this information cut-ins can be detected by a decreasing lateral distance between the trajectories. For our experiments we assign state A for a decreasing lateral distance above 1.5 meters, state B for a lateral distance between 1 and 1.5 meters and finally state C for a lateral distance below 1 meter. Then cut-ins are identified as the state transition $A \rightarrow B \rightarrow C$. As lane changes of the ego vehicle behind a leading vehicle on the neighbor lane result in similar patterns of approaching trajectories, we filter out scenarios where the detected lane markings are crossed. With this approach we find $|S_c| = 472$ cut-ins in the used dataset.

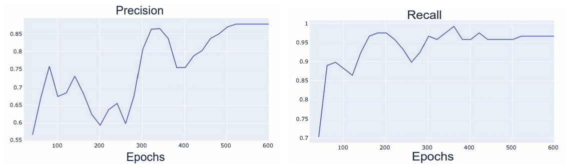


Figure 7: Event based precision (left) and recall (right) for cut-in detection based on the training labels.

4.2.2 Training

Similar to lane changes, cut-ins are rather rare events with an average duration of 5.7 seconds that account for 0.7% of the recorded time. For data balancing we chose the drop probability $p_{drop} = 80\%$ for samples without cut-ins. The sample rate of the input data is 40 ms and $n_{enc} = n_{dec} = 4$ is chosen to get a temporal resolution of 0.64 s in the bottleneck layer.

Figure 7 shows the increasing event-based Precision and Recall with respect to the labels from the rule-based cut-in detection. The high Recall indicates, that the learned model is able to find almost all labeled cut-ins, while the lower Precision indicates various additional detections. Assuming rather conservative labeling rules, a lower Precision during training can be in favor of a well generalizing model, that is able to detect scenarios with missing labels.

4.2.3 Results

We extract the sets of detected cut-in events from the learned model trained for 400 epochs as M_c^{400} and from the model trained for 600 epochs as M_c^{600}. Those detections are compared with the rule-based labels S_c, as shown in Table 3.

Table 3: Event based evaluation of cut-ins.

S	M	$\|S \cap M\|$	$\|S \cap \neg M\|$	$\|\neg S \cap M\|$
S_c	M_c^{400}	462	10	171
S_c	M_c^{600}	463	9	86

To evaluate the detected scenarios we create a visualization of those scenarios as exemplarily shown in Figure 8. The visualization includes the trajectory from the ego vehicle, the distance to the detected lane markings, as well as the color encoded trajectories of all detected objects during the relevant sequence.

Similar to the lane changes, the neural network detects almost all labels found by the rule-based approach ($S \cap \neg M$ is small) and finds several additional detections ($\neg S \cap M$). Those reveal cut-in situations that were missed by the rule-based approach, as in Figure 8a. Besides correctly detected cut-ins, several corner cases were identified that show rather challenging situations with multiple detected objects and strong curvatures. A repeating corner case was cut-ins going hand in hand with a lane change of the ego vehicle. Such scenarios, as exemplarily visualized in Figure 8b, are clearly hard to categorize. However, data samples of such corner cases can support finding different variations of these scenarios and defining necessary distinctions.

4.2.4 Verification

For verification of the cut-in detections we calculate Precision, Recall and F1-Score for the rule-based and the learned detections (Table 4).

Table 4: Performance metrics for cut-in detection.

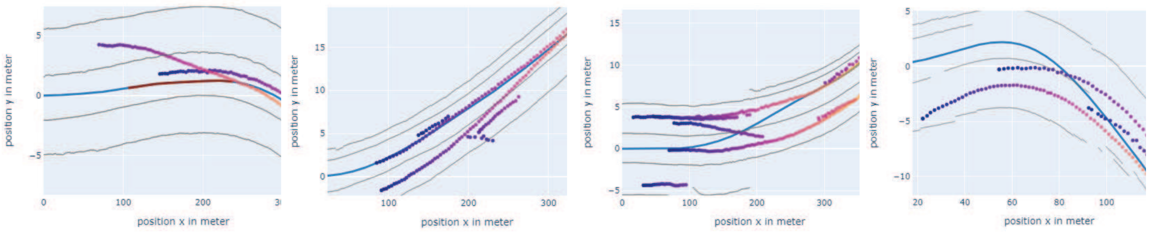
	Precision	Recall	F1-Score
S_c	**0.95**	0.74	0.83
M_c^{400}	0.87	**0.82**	0.84
M_c^{600}	0.91	0.80	**0.85**

Again the learned model can not reach the high Precision of the rule-based approach. However, the recall and the F1-Score were improved by the learned model. Comparing the metrics for M_c^{400} and M_c^{600} shows that the model is approaching towards the performance of the rule-based approach: The Precision is increasing, but the Recall is decreasing. Consequently, training less epochs can reveal even more missing labels. On the other hand evaluating the converged model after 600 epochs reveals less additional detections and causes less evaluation effort.

5 DISCUSSION AND CONCLUSION

Due to the large amounts of data, manual scenario detection becomes less and less feasible. Automated methods are needed for scalability and adaptability to new or changing requirements. Domain knowledge and expertise can be leveraged by rule-based labeling functions. In our examples the rule-based approaches are rather conservative. They provide a high Precision, but lower Recall. It seems reasonable, that developers start with rules that are based on a typical understanding of a scenario. Variations with noisy or missing data, as well as corner cases are hard to consider in the first place. While detected events can be reviewed rather quickly for false positives, finding missing detections (false negatives) requires huge efforts.

In this work we showed, that learning a model from programmatically labeled data provides a systematic approach to identify wrong or missing detections. Instead of reviewing hundreds of hours of



(a) Cut-ins detected by the learned model.

(b) Corner cases with cut-in and lane changes.

Figure 8: Top-Down visualization of not labeled cut-ins detected by the learned model ($\neg S \cap M$). The ego trajectory is shown in blue, detected lane markings in grey and the trajectories of detected objects are color encoded with brighter colors with ongoing time.

recorded data, we could identify few hundreds of samples as candidates for manual review. With an effective visual representation, such candidates can be quickly reviewed to estimate the quality of the rule-based detection approach.

The FCN architecture for time series segmentation proved to be well suited for learning from weak scenario labels. The suggested model was inspired by popular network architectures for semantic image segmentation and was able to learn a meaningful generalization of the provided labels. Not only missing labeled were identified, but also similar scenarios and related corner cases.

We expect the presented method to be a valuable complement for improving the quality and robustness of rule-based scenario detections. In future work, the processing pipeline can be further automated and integrated into iterative development processes, where domain experts develop new rules which are automatically challenged by learning methods. Furthermore, the concept could be extended to compare the detections from multiple approaches for scenario detection. This could include several rule-based methods, as well as multiple learned models.

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