A Benchmark for Unsupervised Anomaly Detection in Multi-Agent Trajectories

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Abstract—Human intuition allows to detect abnormal driving scenarios in situations they never experienced before. Like humans detect those abnormal situations and take countermeasures to prevent collisions, self-driving cars need anomaly detection mechanisms. However, the literature lacks a standard benchmark for the comparison of anomaly detection algorithms. We fill the gap and propose the R-U-MAAD benchmark for unsupervised anomaly detection in multi-agent trajectories. The goal is to learn a representation of the normal driving from the training sequences without labels, and afterwards detect anomalies. We use the Argoverse Motion Forecasting dataset for the training and propose a test dataset of 160 sequences with human-annotated anomalies in urban environments. To this end we combine a replay of real-world trajectories and scene-dependent abnormal driving in the simulation. In our experiments we compare 11 baselines including linear models, deep auto-encoders and one-class classification models using standard anomaly detection metrics. The deep reconstruction and end-to-end one-class methods show promising results. The benchmark and the baseline models will be publicly available¹.

I. INTRODUCTION

Human drivers detect abnormal driving situations and immediately reduce velocity to prevent collisions. A self-driving car must contain a similar anomaly detection mechanism to supplement the perception and forecasting modules [14], [21], [24], [26], [31]. Recently, anomaly detection in traffic has gained interest [17], [18], [29], [32], however the literature lacks an annotated real-world benchmark with diverse anomalies for comparison of the algorithms.

In this work, we propose a benchmark for unsupervised anomaly detection in traffic scenes. It extends the Argoverse Motion Forecasting benchmark [5] to anomaly detection. The goal is to learn a representation of the normal behaviour only from real-world trajectory data without anomaly labels and to detect anomalies in our test set with manually annotated normal and abnormal driving behaviour. We compare linear models, deep auto-encoders and one-class classification models as baselines on our benchmark.

There is a rich literature on the prediction of future trajectories, mainly focused on real-world trajectories and HD-maps [4], [5], [35]. However, the majority of the driving scenarios show normal behaviour and they do not consider abnormal situations. Abnormal driving does not follow the normal driving rules and therefore the trajectory predictions may be inaccurate [16]. These situations can be identified using anomaly detection.

We present a benchmark with abnormal situations for anomaly detection. Similar to standard protocols in trajectory prediction [10], [14], we describe scenes with agent trajectories and HD-maps. Since anomalies are rare in the real-world and staging of abnormal scenarios is dangerous for the actors, simulation is employed to create driving anomalies [20], [25], [28], [32]. Instead of relying on simulation only, we propose to leverage as much real-world data as possible to do anomaly detection. In the training, we only use real-world data to learn from the normal behaviour, without any simulated data. In the testing, we detect anomalies in our test sequences. To create a test scenario, we take a real-world sequence and only animate a single car for the anomalies in the simulation. In addition to individual driving anomalies, we focus on anomalies in the interaction between agents, e.g. a ghost driver, in complex urban settings with many agents on the street. To create the benchmark, we use the well-known Argoverse dataset [5], as it provides multi-agent trajectories in diverse traffic scenes and detailed scene descriptions with HD-maps. Figure 1 illustrates the data generation process. Abnormal situations can happen at...
any driving time, e.g. a car can break rapidly without a warning or an inattentive truck driver can enter the wrong lane and drive against traffic. To evaluate anomaly detection continuously, we provide frame-wise human annotations for all anomalies in our benchmark.

To summarise our contributions, we present a benchmark for unsupervised multi-agent anomaly detection including detailed training and evaluation protocols. For training, we use real-world trajectories only. For testing, we create a hybrid test set. Each test sequence contains the animated trajectory of the target vehicle and the real-world trajectories of the remaining actors. In addition, we evaluate a set of algorithms including linear models, deep auto-encoders and one-class classification models for anomaly detection following the proposed protocol. The algorithms learn a representation of the normal trajectories from the training set and identify anomalies as outliers during testing.

II. RELATED WORK

Anomaly Detection (AD) is a long-standing problem with many applications in diverse fields. It is used to localise tumours in medical imaging [27], to identify fake news in social networks [13] and to uncover payment card frauds [1]. Below, we discuss the related methods and datasets and focus on anomaly detection in the field of automated driving.

Anomaly Detection in Automated Driving. Recently, anomaly detection has been applied to automotive related tasks, for example to detect brake light transitions of leading vehicles [30], failures in the brake system of a bus [6] or traffic incidents [36]. For self-driving cars the detection of anomalies in traffic is of particular interest. Every missed abnormal situation, like a driver who is distracted by writing a text message on the phone, can have fatal consequences to all participants in the scene. Often machine learning methods are explored to classify abnormal driving behaviour using explicit behaviour annotations during training on simulated datasets [18], [29]. However, by definition, anomalies are rare in the real-world and the annotation of anomalies in the entire training set is an exhaustive task. Therefore, we focus on the task of unsupervised anomaly detection. Currently, unsupervised representation learning techniques like deep auto-encoder networks determine the anomaly detection domain [8], [19], [37]. For the detection of driving anomalies auto-encoders with a single trajectory as input and hand-crafted features are employed [17]. Driving anomalies often occur in interaction between vehicles, for example a ghost driver on a collision course with the oncoming traffic. To this end, spatio-temporal graph auto-encoders, considering the trajectories of all agents in the scene, have been developed by Wiederer et al. [32]. Based on simulation, they create a highway dataset with two agents in the scene for evaluation. Similar, our baselines model the interaction between agents, but in complex urban environments with many agents on the street.

Anomaly DetectionDatasets in Automated Driving. In trajectory forecasting, state-of-the-art datasets contain large sets of real-world traffic scenes with high-quality tracks of all agents and HD-maps describing the static context [4], [5], [9], [11], [15], [33], [35]. However, they do not consider the critical cases of anomalies. Although some of them include critical situations and near-collision scenarios, the number is small and they do not contain behaviour annotations what limits the anomaly detection. Since anomalies are rare and staging is prohibitive due to danger for the actors, in many cases simulation is leveraged to create abnormal driving data on the cost of realism, for example by tuning the parameters of traffic and vehicle models [17], [20], [28]. A more realistic approach was proposed by Shah et al. [25], they record anomalous scenarios with the scene description language Scenic and the CARLA simulator. Wiederer et al. [32] employ an OpenAI Gym simulation to generate driving anomalies in an interactive highway scenario, where all vehicles are controlled by human players. Instead of relying on simulation only, in this work, we propose to use mostly real-world trajectory data and reduce simulation to a minimum. More specific, we use the real trajectories of a trajectory prediction dataset as unsupervised training data. Next, for the creation of the test set we replay real trajectories in our simulation and animate only one agent to drive anomalies by the control of a human (see Fig. 1). Using this hybrid process, the source of all training and test data is the real-world, except for the abnormal trajectories, which are animated by a human player. In addition we provide dense human annotations of all anomalies and a detailed evaluation protocol.

III. MULTI-AGENT ANOMALY DETECTION BENCHMARK

We introduce a benchmark in Real-world Urban settings for Multi-Agent Anomaly Detection, namely the R-U-MAAD benchmark. The remaining sections present the formation, the annotation and the properties of the R-U-MAAD benchmark.

A. Benchmark Formation

We consider multi-agent anomaly detection as an unsupervised learning problem with anomaly labels only during testing. As a result, our benchmark is composed of a training and validation set without labels and a test set with anomaly labels for evaluation. We extend the Argoverse Motion Forecasting dataset [5] to the task of unsupervised anomaly detection. The Argoverse Motion Forecasting dataset provides a large number of vehicle trajectories in diverse urban settings. In the original setting, the task is to forecast the trajectory of the target vehicle; in the next 3 seconds given 2 seconds of history. For our benchmark, we use the training and validation sequences as provided in the Argoverse dataset during training. For testing, we create scenes with diverse labelled anomalies.

Test Set for Anomaly Detection. Based on a recording script for the driving scenarios, we record both normal and abnormal sequences in diverse urban settings. We create abnormal behaviour under the assumption that the abnormal driving happens before the neighbouring vehicles can react to
it. This is often the case in real driving where anomalies occur suddenly with limited reaction time. Therefore, we make use of driving scenes recorded in real traffic and add driving anomalies in the simulation. To this end, we replay all agents of a scene in the OpenAI Gym simulation [2] and remotely control one actor by a human player. We use a subset of the Argoverse validation set as pre-recorded scenes to create our anomaly detection test set. The data generation process is visualised in Figure 1. A powertrain model translates the discrete keyboard commands \{gas, break, steer left, steer right\} into forces and a kinematic car model transforms the forces into smooth trajectories. The parameters of the car model are tuned to create motion dynamics, e.g. velocity and acceleration, similar to the original Argoverse trajectories. The initial conditions of the animated actor are set to the position and velocity of the original Argoverse \textsc{agent} estimated from the first two time steps. We record the 2D birds-eye view centre coordinates of our animated vehicle at 10 Hz temporally synchronised with the other agents. We follow the Argoverse protocol and select the \textsc{target vehicle} for animation. Figure 2 illustrates samples of our dataset.

B. Normal and Abnormal Driving Annotation

We define abnormal driving as the set of all uncommon and rare scenarios and provide a test set with frame-wise annotations of diverse driving anomalies. It includes driving against social rules (e.g. thwarting a following vehicle), violating regulatory driving rules (e.g. entering the wrong lane after a turn), aggressive behaviour (e.g. driving close to the vehicle ahead in order to signal the intention of an overtake) or inattentive behaviour (e.g. leaving the road because of drowsiness). In total, this results in 13 anomaly classes\(^2\). Besides individual driving anomalies, like staggering, the test set contains many anomalies which are abnormal in the context of the neighbouring agents (actor-interactive), like tailgating, abnormal in the context of the map information (map-interactive), like leaving the road, or abnormal with respect to both the static and the dynamic context, like a ghost driver. Table I shows the abnormal classes and the categorisation into actor-interactive and map-interactive. Two manoeuvres, \textit{swerving left and right}, can be either interactive or non-interactive, depending on the reason for the swerving manoeuvre, e.g. another vehicle or inattentiveness. Actor- and map-interactive anomalies favour the development of interaction-aware anomaly detection.

Similar to [32] we annotate the normal driving as well. The normal manoeuvres are described by 9 classes\(^3\). The annotation of both the positive and negative classes supports detailed failure analysis in cases where an abnormal class is confused with a normal class. For example, an algorithm ignoring the neighbouring agents is likely to confuse an aggressive shearing manoeuvre with a normal lane change. Aggressive shearing happens in close distance to the oncoming traffic (see Figure 2c), whereas a normal lane change keeps sufficient safety distance. Our label definition allows to uncover this confusion. Besides normal or abnormal annotations, we label ignore regions in cases where a categorisation of pure normal or pure abnormal is not possible, e.g. in transition phases. Ignore regions are not considered during evaluation, such that errors in ignored time steps do not contribute to the result.

Our annotation process is completely manual. Human annotators watch the video of a scene from the birds-eye perspective as shown in Figure 2 and annotate intervals with the defined classes. All annotators are provided with detailed label instructions to ensure high label quality. We use ELAN [3] as the software for annotating time series.

C. Dataset Properties

The R-U-MAAD dataset is a composed of the 205,942 train and 39,472 validation sequences from the Argoverse

\(^2\)The abnormal classes are: \textit{ghost driver}, \textit{leave road}, \textit{thwarting}, \textit{cancel turn}, \textit{last minute turn}, \textit{enter wrong lane}, \textit{staggering}, \textit{pushing away}, \textit{swerving left and right}, \textit{aggressive shearing left and right and tailgating}.

\(^3\)The normal classes are: \textit{straight}, \textit{turn left and right}, \textit{following}, \textit{side-by-side}, \textit{lane change left and right}, \textit{brake and accelerate}.
TABLE I
THE DISTRIBUTION OF THE ABNORMAL SUB-CLASSES. WE DISTINGUISH BETWEEN ACTOR-INTERACTIVE AND MAP-INTERACTIVE ANOMALIES.

| Class               | Actor-Interactive | Map-Interactive | # of Timesteps |
|---------------------|-------------------|-----------------|----------------|
| ghost driver        | ✓                 | ✓               | 202            |
| leave road          | ✓                 | ✓               | 186            |
| thwarting           | ✓                 | ✗               | 179            |
| cancel turn         | ✓                 | ✗               | 156            |
| last minute turn    | ✗                 | ✓               | 114            |
| enter wrong lane    | ✓                 | ✓               | 101            |
| staggering          | ✓                 | ✗               | 92             |
| pushing away        | ✓                 | ✗               | 84             |
| swerving (l)        | ✓                 | ✓               | 77             |
| swerving (r)        | ✓                 | ✗               | 26             |
| tailgating          | ✓                 | ✗               | 69             |
| agr. shearing (l)   | ✓                 | ✗               | 62             |
| agr. shearing (r)   | ✓                 | ✗               | 64             |

dataset and our test sequences. We record 160 test sequences with 80 normal and 80 abnormal scenes. The sequences range from 1.7 to 10.1 seconds in length\(^4\). In total 7,545 time steps are annotated with 1,412 abnormal, 5,695 normal and 438 ignore labels. Table I shows the distribution of the abnormal categories. In particular the manoeuvres ghost driver, leave road, thwarting and cancel turn occur more often as they are usually longer compared to the under-represented categories like swerving or aggressive shearing manoeuvre. In total each class consists of a sufficient amount of annotations to evaluate anomaly detection algorithms.

IV. PROBLEM FORMULATION

The task of unsupervised anomaly detection in agent trajectories is defined as follows: Agent \(i\) has the state \(s_i^t = (x_i^t, y_i^t)\), consisting of its \(x\) and \(y\) coordinates at timestep \(t\) in a birds-eye perspective. The trajectory of an actor \(i\) is defined as \(S_i = \{s_i^t|t = -T + 1, \ldots, 0\}\), with \(T\) being the number of observed timesteps. Available input data for the task of anomaly detection in multi-agent trajectories are the past trajectories \(S = \{S_i|i = 1, \ldots, N\}\) of \(N\) agents and additional context information \(\mathcal{C}\). Context information \(\mathcal{C}\) is most commonly provided by an HD-map. The goal of anomaly detection is to use this given input data in order to predict an anomaly score \(\alpha_i\) of agent \(i\) behaving abnormally. We present different models for anomaly detection in the following.

V. UNSUPERVISED ANOMALY DETECTION BASELINES

As baselines for our anomaly detection benchmark, we evaluate 11 different anomaly detection models including reconstruction and one-class classification methods. For both types, temporal trajectory modelling captures the temporal dependencies in the anomalies. Figure 3 illustrates the proposed baselines.

\(^4\)Note, some sequences in the Argoverse dataset are longer than 5 seconds.

A. Reconstruction Methods

Reconstruction methods rely on the error between the input trajectory \(S_i\) and an approximation of the input trajectory \(\hat{S}_i\) as a score for anomalies \(\alpha = \|S_i - \hat{S}_i\|\). We compare two concepts to approximate the input trajectory, linear approximation and deep neural network auto-encoders. The linear models include:

- **CVM**: The constant velocity model from [23]. Estimate the velocity \(v_i\) from the first two time steps \(t = \{-T + 1, -T + 2\}\) and extrapolate for \(T - 1\) time steps starting at the first state \(s_i^{-T+1}\) using \(v_i\) as constant velocity.
- **LTI**: The linear temporal interpolation model (LTI) as defined in [32]. Approximate the trajectory as equidistant samples on a straight line between the location at the first time step \(s_i^{-T+1}\) and the current time step \(s_i^0\).

For the deep neural networks, we develop three auto-encoder networks, one interaction-free and two interaction-aware models. Given the input \(X\) the auto-encoder computes a latent representation \(Z = e(X)\) with the encoder. Based on the latent representation \(Z \in \mathbb{R}^F\) with feature dimension \(F\) the decoder reconstructs the input \(\hat{X} = d(Z)\). Both encoder and decoder are designed as neural networks and trained end-to-end with a similarity-based loss, e.g. the MSE loss. The deep auto-encoders are defined as follows:

- **Seq2Seq**: The interaction-free model takes a single agent trajectory, the trajectory of the target agent as input, \(X = S_{i=1}\). We use the motion forecasting baseline from Argoverse, which is composed of the LSTM encoder and the LSTM decoder, and adapt it for trajectory reconstruction [5].

- **STGAE**: Our first interaction-aware model is a variant of the spatio-temporal graph auto-encoder, which is used to detect anomalies in highway scenarios [32]. Given the trajectories of all agents as input, \(X = S\), it aggregates neighbouring agent features with the graph convolutional operator and a linear residual connection [32]. We use the Seq2Seq model as described above for the temporal encoding and decoding.

- **LaneGCN-AE**: Our second interaction-aware model takes all trajectories \(S\) and the context \(\mathcal{C}\), given by the HD-map, as input, \(X = (S, \mathcal{C})\). We adapt the motion forecasting model LaneGCN for trajectory reconstruction [14]. Therefore we denote the original FusionNet, a graph neural network for actor and map encoding, as encoder and reduce the multiple prediction headers to a single reconstruction header.

Given the additional information on neighbouring actors or the scene, both interaction-aware models are capable to learn from interaction. The auto-encoders are trained with the MSE loss \(\mathcal{L}_r = \frac{1}{T} \sum_{t=0}^{T-1} \|s_i^t - \hat{s}_i^t\|\) on the reconstruction of the target agent states \(\hat{s}_i^t\) with \(i = 1\).

B. One-Class Classification Methods

One-class classification methods follow a different principle to detect anomalies. The goal is to learn a model which describes the normal data accurately. Samples which do not
follow this description are scored as anomalies given by a distance measure. For the one-class classification methods we develop two-stage models and models with end-to-end training. For the two-stage models we train the one-class SVM (OC-SVM) on the latent representation $Z$ of the entire training set \[22\]. Note, we first train the auto-encoder and second train the one-class method. The OC-SVM finds a hyperplane, which represents most of the input data samples and keeps a maximum distance to the origin. Anomalies are scored by the distance to this hyperplane. We propose two-stage models for the interaction-free and interaction-aware encoders:

- **Seq2Seq+OC-SVM:** The OC-SVM is trained on the interaction-free features of the target agent computed by the Seq2Seq encoder.
- **STGAE+OC-SVM:** Similar to the OC-SVM variant in \[32\], we train the OC-SVM on the neighbour-aware features of the target agent as provided by the STGAE encoder.
- **LaneGCN-AE+OC-SVM:** With the OC-SVM using the neighbour- and map-aware target agent encodings of the LaneGCN-AE encoder.

The second type of one-class methods are auto-encoder networks jointly trained with the reconstruction loss $L_r$ and an anomaly detection based objective $L_a$. We use the one-class deep support vector data description objective (DSVDD) proposed by \[19\] as the anomaly detection based objective. The DSVDD objective is applied on the latent representation $Z \in \mathbb{R}^F$ of the auto-encoder penalising the distance of the representation from a centre $c \in \mathbb{R}^F$. It tries to optimise for a hypersphere with minimum volume encapsulating all latent representations of the training data. During testing, we compute the anomaly score $\alpha = \|Z_t - c\|$ as the Euclidean distance of an agent feature vector $Z_t$ from the centre. We define the following models:

- **Seq2Seq+DSVDD:** Applying the DSVDD loss on the latent features of the Seq2Seq.
- **STGAE+DSVDD:** Applying the DSVDD objective on the latent interaction-aware features of the STGAE.
- **LaneGCN+DSVDD:** Applying the DSVDD loss on the map- and actor-dependent features of the LaneGCN-AE.

All networks are trained end-to-end minimising the unweighted sum of both losses $\mathcal{L} = L_r + L_a$.

### VI. EXPERIMENTAL SETUP

This section describes the training and evaluation protocol for unsupervised anomaly detection and the implementation details of our baseline models.

#### A. Training and Evaluation Protocol

We train and validate the algorithms on the original training and validation sets of the Argoverse dataset in an unsupervised manner. For the testing, our simulated test set is used. We use a history of 1.6 $s$, which is in similar range to those of publicly available trajectory prediction datasets, such as Argoverse (2 $s$) \[5\] and WAYMO (1 $s$) \[9\]. We randomly clip a segment of 1.6 seconds, $T = 16$ frames, from each sequence in the training and validation set. For the testing, we predict an anomaly score in each time step using a sliding window approach of length $T = 16$ and stride $s = 1$. We do not predict an anomaly score for the first 15 time steps of a sequence to avoid padding. For the reconstruction methods, the anomaly score is equal to the reconstruction loss, for the one-class methods, the anomaly score is equal to the distance of the feature vector from the hyperplane or from the hypersphere centre for the OC-SVM and the DSVDD variants, respectively.
To evaluate the algorithms, we use the standard anomaly detection metrics [7], [34], [32]: AUPR-Abnormal, AUPR-Normal, AUROC and FPR-95%-TPR. In classification problems with imbalanced datasets AUPR and AUROC tell different stories. While the AUROC metric tries to cover both classes in one score, AUPR focuses on the positive minority class. Therefore, we define the Area Under the Precision-Recall (AUPR) curve as our main metric, since it is able to adjust for class imbalances, which is the case in anomaly detection. Our test set contains around 80% normal and 20% abnormal time steps. In the case of anomaly detection in automated driving, leaving the abnormal situation undetected can lead to critical situations and is more severe compared to false alarms. However, for a complete evaluation we show both AUPR scores, the AUPR-Abnormal, where we treat the abnormal class as positive, and the AUPR-Normal, where we treat the normal class as positive. The best anomaly detector has the highest AUPR-Abnormal score. As a second performance measure, we compute metrics from the Receiver Operating Characteristic curve (ROC). To this end, we integrate over the area under the ROC curve to get the AUROC metric and identify the False Postive Rate (FPR) at 95% True Positive Rate (TPR), namely FPR-95%-TPR.

B. Implementation Details

We follow [14] and transform all agents in a local coordinate system, where the target agent is centred at $t = 0$. The positive $x$-axis is defined as the orientation of the target agent, estimated from the location at $t = -1$ to the location at $t = 0$. The Seq2Seq and STGAE models use absolute coordinates in this local coordinate system, while for the LaneGCN-AE we compute positional displacements, which are proportional to the velocity, by subtracting locations of consecutive time steps. We only consider actors which are present in the last frame of the sequence. For the agents which appear in the middle of a sequence, we use zero padding to fill the missing states in the beginning of the sequence. Disappearing agents are ignored, since they have less influence and often disappear in far distance from the target agent. To include map information in LaneGCN-AE, we compute the lane graph as proposed in [14].

CVM and LTI approximate the trajectory with linear equations. The CVM extrapolates the velocity estimated from the locations at the first two time steps $t = -T + 1$ and $t = -T + 2$ over sequence length $T$. The LTI model computes equidistantly sampled locations on a straight line between the start location at $t = -T + 1$ and the end location at $t = 0$. For the Seq2Seq auto-encoder we employ the symmetric encoder-decoder architecture as proposed in [5] with 8 linear embedding and 16 hidden LSTM units. We use the same Seq2Seq auto-encoder for the STGAE, but with the interaction-aware features from the spatial graph embedding as input. The spatial graph embedding layer transforms the trajectories of all agents into an embedding space and aggregates neighboring features using the distance-based adjacency matrix. The LaneGCN-AE follows the structure of the original LaneGCN [14]. We remove the multi-modal prediction and employ a single head for trajectory reconstruction given the actor feature vector from the FusionNet. We decrease the actor feature space from 128 to 16 to limit the representation space of the auto-encoder. We train all deep auto-encoders with the Adam optimiser [12] over 36 epochs and a batch size of 32. After 32 epochs the learning rate gets updated from $10^{-3}$ to $10^{-4}$. For subsequent evaluation, we always pick the model of the epoch with the lowest loss on the validation set. After training the auto-encoders we train the OC-SVM variants. The OC-SVM is implemented with a Gaussian kernel and hyperparameters are selected using grid search with $\gamma \in \{2^{-10}, 2^{-9}, ..., 2^{-1}\}$ and $\nu \in \{0.01, 0.1\}$. For validation of the hyperparameters, we randomly select 20% of the annotated test data. Therefore OC-SVM has a minor supervised advantage. The latent space centre $c$ for the DSVDD loss is initialised as the mean of the latent representations of all training samples computed by an initial forward pass [19].

VII. RESULTS

We compare the results of all baselines on our presented benchmark. In addition, we illustrate qualitative results for different abnormal and normal situations.

Comparison of Baselines. Table II shows the results of all baselines, cross and check marks indicate the use of dynamic or static context information in addition to the target agent trajectory. In total we compare the results of 11 methods including the reconstruction and the one-class classification methods. Of all model types the deep auto-encoder networks show the best results. In particular the STGAE wins in two out of four metrics including our main metric AUPR-abnormal where it reaches 59.65%. Seq2Seq and LaneGCN-AE are on par with their performances. Interestingly, both interaction-aware models, STGAE and LaneGCN-AE, cannot improve the results further using additional dynamic and static context information in comparison to the single-agent Seq2Seq model. Algorithms, which learn useful features from the additional context, e.g. by employing new loss functions, are required to improve the anomaly detection quality. We leave this as a future research direction. In general, the linear models fall behind the deep reconstruction methods. The assumption that anomalies in multi-agent trajectories are linearly separable from the normal driving is too simple, resulting in low performance for the linear models. It is only correct for a few anomalies with high dynamics, i.e. anomalies characterised by high acceleration or sharp turns, but does not generalise to complex driving anomalies.

Compared to each other, the one-class methods do not show consistent results. In particular the OC-SVM variants show lower values in the metrics compared to the deep reconstruction methods. The OC-SVM is not able to learn a useful representation of the normal data neither using the latent features from the Seq2Seq nor from STGAE model. The separation of anomalies seems easier in the output space, as for the deep reconstruction methods, than in the latent space, as for the OC-SVM-based methods. Other for the DSVDD variants, after training jointly on the reconstruction


TABLE II
COMPARISON OF THE BASELINES USING THE DEFINED ANOMALY DETECTION METRICS. BEST VALUES HIGHLIGHTED IN BOLD.

| Category   | Using dyn. Context | Using stat. Context | Method         | AUPR-Abnormal ↑ | AUPR-Normal ↑ | AUROC ↑ | FPR-95%-TPR ↓ |
|------------|---------------------|----------------------|----------------|----------------|---------------|---------|---------------|
| Recon       | ×                    | ×                    | CVM [23]       | 47.19          | 86.00         | 72.30   | 81.20         |
|            | ×                    | ✓                    | LIT            | 50.45          | 85.71         | 73.14   | 82.22         |
|            | ×                    | ✓                    | Seq2Seq [5]    | 59.21          | 88.07         | 76.56   | 77.62         |
|            | ✓                    | ×                    | STGAE [32]     | 59.65          | 87.85         | 76.75   | 76.48         |
|            | ✓                    | ✓                    | LaneGCN-AE [14]| 57.19          | 87.22         | 75.25   | 75.94         |
| Two-stage  | ×                    | ×                    | Seq2Seq+OC-SVM | 34.47          | 70.25         | 50.47   | 98.33         |
|            | ✓                    | ✓                    | STGAE+OC-SVM [32]| 33.32         | 77.71         | 59.16   | 91.27         |
|            | ✓                    | ✓                    | LaneGCN-AE+OC-SVM | 51.88         | 86.93         | 72.94   | 82.02         |
| End-to-End | ✓                    | ✓                    | Seq2Seq+DSVDD  | 51.37          | 82.47         | 69.34   | 88.79         |
|            | ✓                    | ✓                    | STGAE+DSVDD    | 48.09          | 83.59         | 69.65   | 85.44         |
|            | ✓                    | ✓                    | LaneGCN-AE+DSVDD | 53.14         | 85.21         | 72.33   | 85.55         |

Fig. 4. Qualitative anomaly detection results of the STGAE model. At the top we show the scene visualised by the street centre lines as well as the actor trajectories, with the target agent in red and all other actors in blue. Trajectories of the first 1.6 seconds of the sequence are dashed. The model predicts an anomaly score $\alpha$ for the remaining time, which is illustrated as error band around the trajectory of the target agent. In the middle and the bottom, the anomaly score $\alpha$, normalised by the highest score in the test set, and the ground truth annotation are visualised over time, respectively. For the ground truth we encode normal behaviour labels in green, abnormal behaviour labels in red and ignore regions in orange. The anomaly score increases for the abnormal behaviour in Figure 4a and 4b and remains low for the normal lane change manoeuvre in Figure 4c.

and the DSVDD loss, the similarity between a latent feature vector and the hypersphere centre is a reasonable measure to detect anomalies. Still, they cannot reach the performance of the deep reconstruction methods. Especially the deep reconstruction methods and the end-to-end one-class methods are valuable baselines for multi-agent anomaly detection.

**Qualitative Results.** Figure 4 shows qualitative results of the STGAE model for two abnormal and one normal scene. We observe the increasing anomaly score in the abnormal scenarios. In Figure 4a the target vehicle cancels a turn in the middle of the intersection. The dynamics in the trajectory highly deviates from the normal driving in the training data. Therefore, the STGAE is not able to fully reconstruct the input, which leads to an increase of the reconstruction error and consequently of the anomaly score. Similar, the anomaly score in Figure 4b increases. It shows a last minute turn at the end of the sequence. This is not the case for the normal scenario. The manoeuvre of a lane change is reconstructed with low reconstruction error by the STGAE model resulting in a low anomaly score during the entire scene.

**VIII. Conclusion**

We present a benchmark for anomaly detection in multi-agent driving trajectories. Our main contribution is the R-U-MAAD benchmark that builds on top of the Argoverse dataset with multiple interactive and non-interactive anomalies in diverse road scenarios. We provide 11 anomaly detection baseline models including linear methods, deep auto-encoders as well as deep one-class classification models. The deep baselines learn a representation of normal driving behaviour from the Argoverse training data in an unsupervised manner. Using this representation, they recognise anomalies in novel scenes during testing. With the presented work we hope to advance research in the area of multi-agent anomaly detection and want to establish a benchmark for the comparison of future algorithms.
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