KI DELTA LEARNING
Scalable AI for Automated Driving

Anomaly Detection in Multi-Agent Trajectories

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WP 2.2
WP 3.1
WP 4.1

Traffic

Use-Case in Delta Learning

Traffic participants, like cars or pedestrians, usually follow the social rules and street regularities, but can break these rules in rare cases. For example a wrong-way driver breaks to driving rules. Breaking the rules often leads to situations with high criticality and can cause accidents. Human drivers evolve a sensible sense through many hours of driving for these abnormal traffic situations. After they recognize imminent danger they adopt their driving behaviour to avoid accidents. An autonomous car needs a similar detection mechanism to react for example to a wrong-way driver. We call this mechanism anomaly detection.

Technical Problem

Anomaly Detection is a widely studied field in image and video processing to detect abnormal scenes or activities [1]. In most of the cases deep learning based approaches are used. Nevertheless, the prior work only addresses single agent anomalies [2, 3]. We detect anomalies in multi-agent trajectories. The input to our approach is set of N agent trajectories as time series of length T. The goal is to predict the class $c_t = \{0, 1\}$, i.e. normal or abnormal, of an unseen frame during testing, while only showing normal scenes during training.

References
[1] Hu, Derek Hao, et al. "Abnormal activity recognition based on hdp-hmm models." ICAI 2009.
[2] Morais, Romero, et al. "Learning regularity in skeleton trajectories for anomaly detection in videos." CVPR 2019.
[3] McAllister, Rowan, et al. "Robustness to out-of-distribution inputs via task-aware generative uncertainty." ICRA 2019.

Technical Solution

We propose a two stage approach. At first we train a spatio-temporal graph auto-encoder (STGAE) to learn a joint latent space of the multi-agent trajectories. After training, we approximate the distribution of the latent feature vectors using a kernel density estimation (KDE) and detect anoma-lies in regions with lower density. Figure 1 visualizes our approach during training.

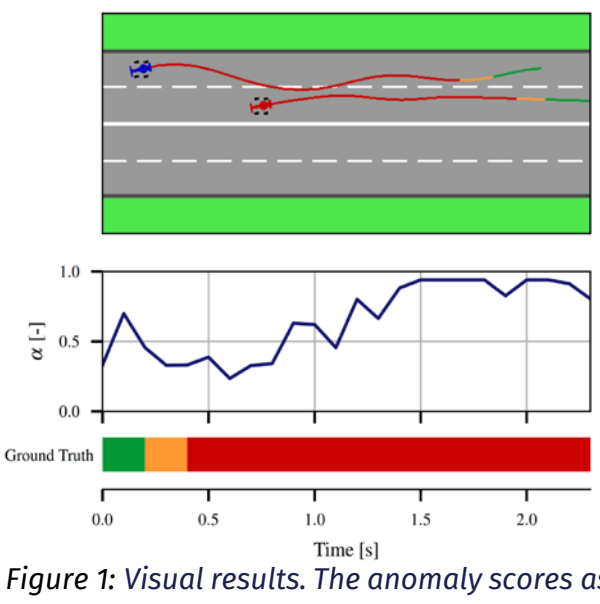

Figure 1: Visual results. The anomaly scores as the abnormal behavior of the blue car happens.

Evaluation

For evaluation we propose a simulated highway dataset with two interacting agents for multi-agent anomaly detection (MAAD). Given the input trajectories of the two agents, the model predicts a frame-wise anomaly score. We show qualitative results in Figure 2 and a comparison with both single- and multi-agent baselines in Table 1. Our approach shows higher anomaly detection performance in all metrics compared to the baselines.

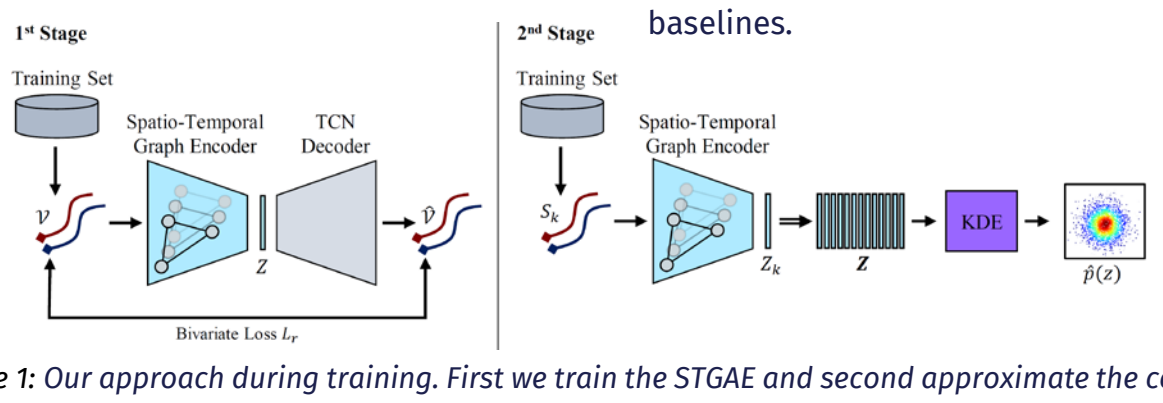

Figure 1: Our approach during training. First we train the STGAE and second approximate the common distribution of the normal samples.

	Method	One-class vs. Reconstruction	AUROC (↑)	AUPR-Abnormal	AUPR-Normal	FPR-95%-TPR
Single-Agent	CVM	Reconstruction	83.11	54.47	95.99	74.62
	Seq2Seq	Reconstruction	56.81	17.85	89.67	84.56
Multi-Agent	STGAE-mse	Reconstruction	85.60	50.23	96.20	64.35
	STGAE-biv+KDE (Ours)	One-class	**87.71**	**58.41**	**97.42**	**49.20**

Table 1: Qualitative results. Our proposed approach outpferoms both single- and multi-agent baselines.

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Partners

External partners

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KI FAMILIE

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