KI DELTA LEARNING

Scalable AI for Automated Driving

Final Event | March 10, 2023

Unsupervised Learning for Detection of Abnormal Driving Behavior

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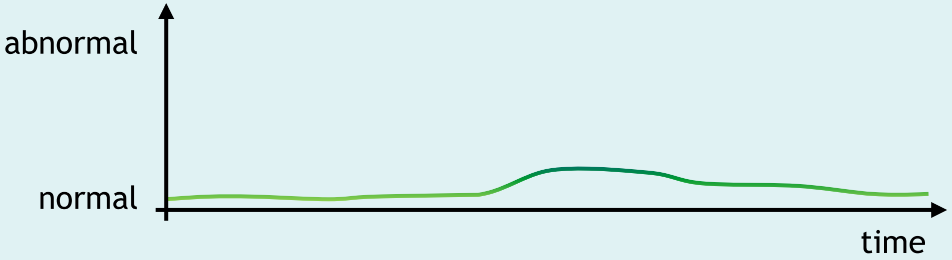
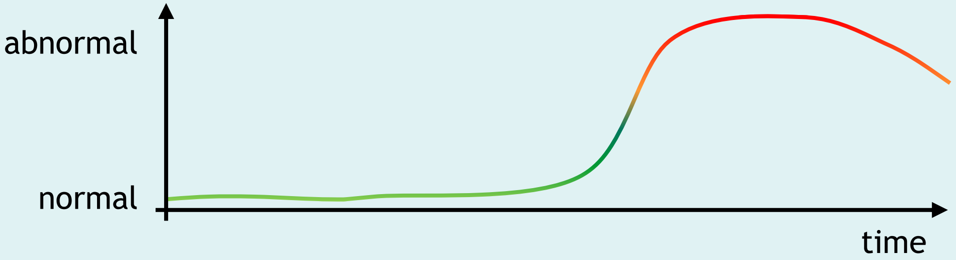
Public

Motivation

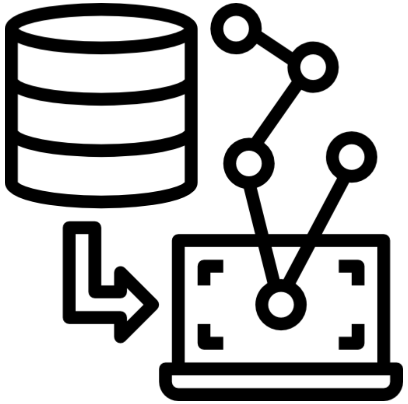
Human-rated anomaly score:





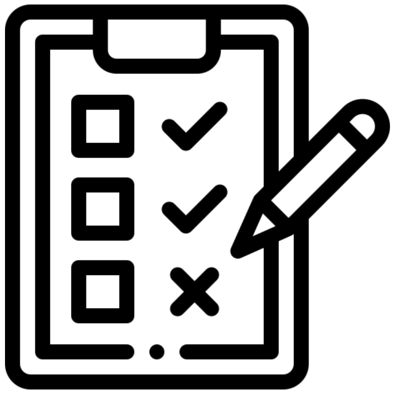
Automated cars need a similar sensibility on the criticality of a situation.
We propose anomaly detection to detect abnormal and critical driving in scenes with high complexity.

Contributions



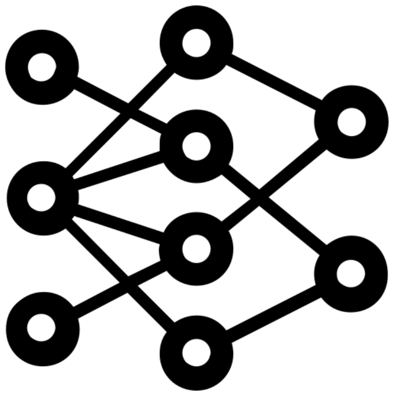
I. Dataset

Benchmark dataset for multi-agent anomaly detection created with hybrid simulation.



II. Protocol

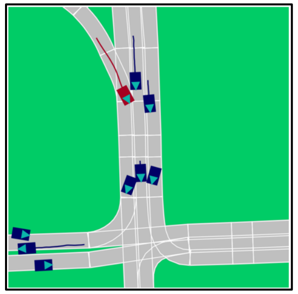
Detailed training and evaluation protocol including multiple metrices.



III. Methods

Diverse models for anomaly detection including linear models, deep auto-encoders and one-class classification models.

Problem Definition



Input scenario:
- Observed agent states.
- HD-map.
- Target agent (red).

Anomaly Detection Model

Behavior labels

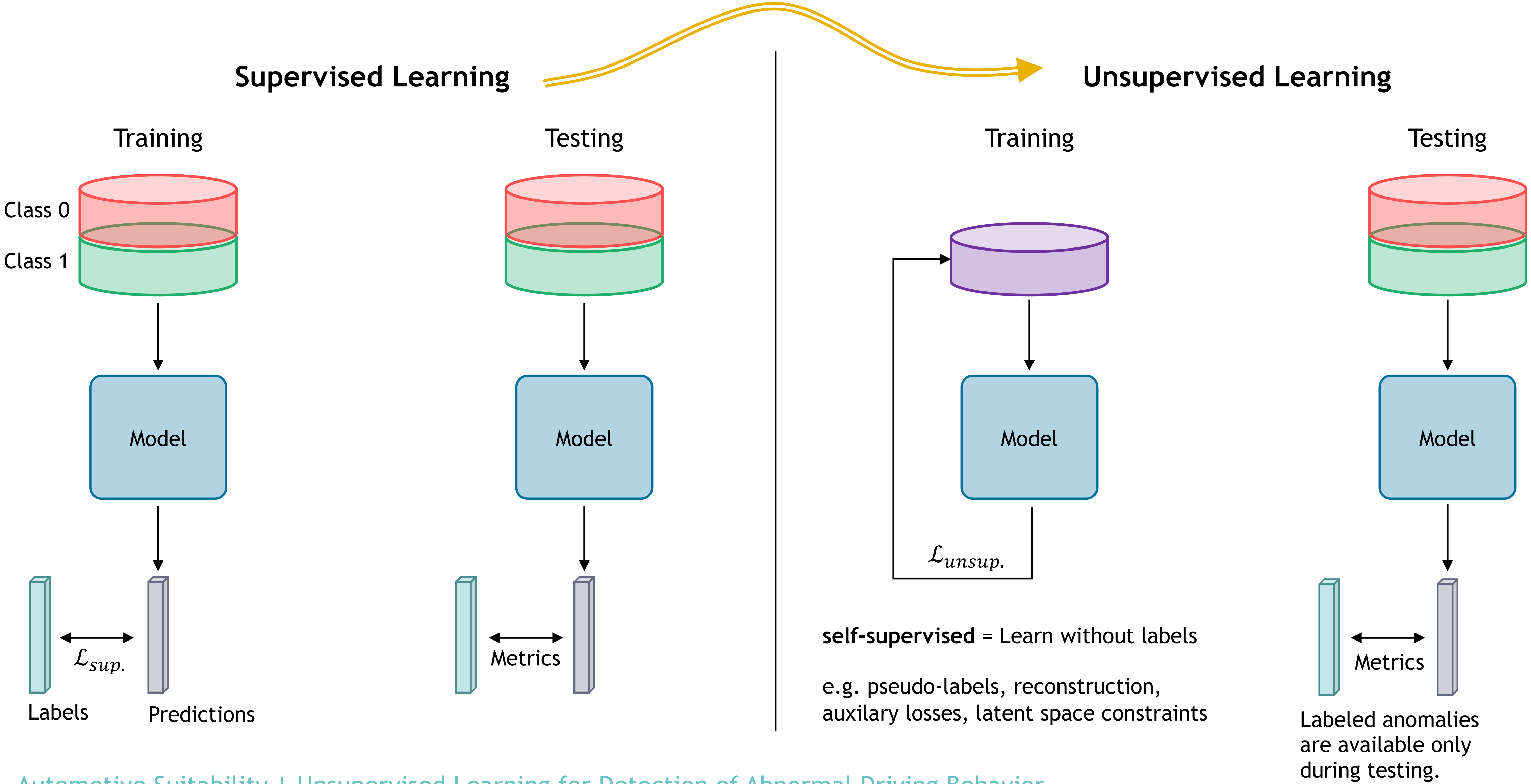
{normal = 0,
abnormal = 1}

Anomaly score α

→ The higher, the more abnormal.

Preliminaries

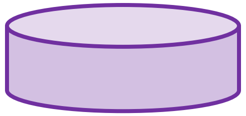
Anomalies are rare and not annotated on large-scale.



Data for Training and Testing

Unsupervised Learning

Training

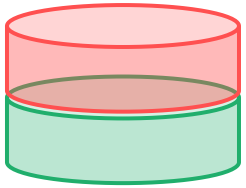


- Absense of real-world data
- Staging is dangerous and prohibited

Hybrid Simulation & Human Annotation

HybridSim(,)

Testing



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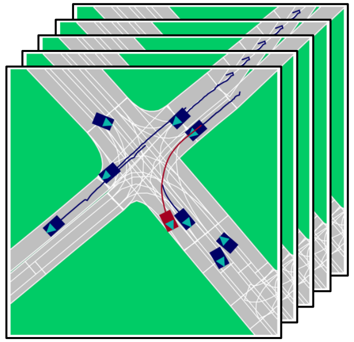
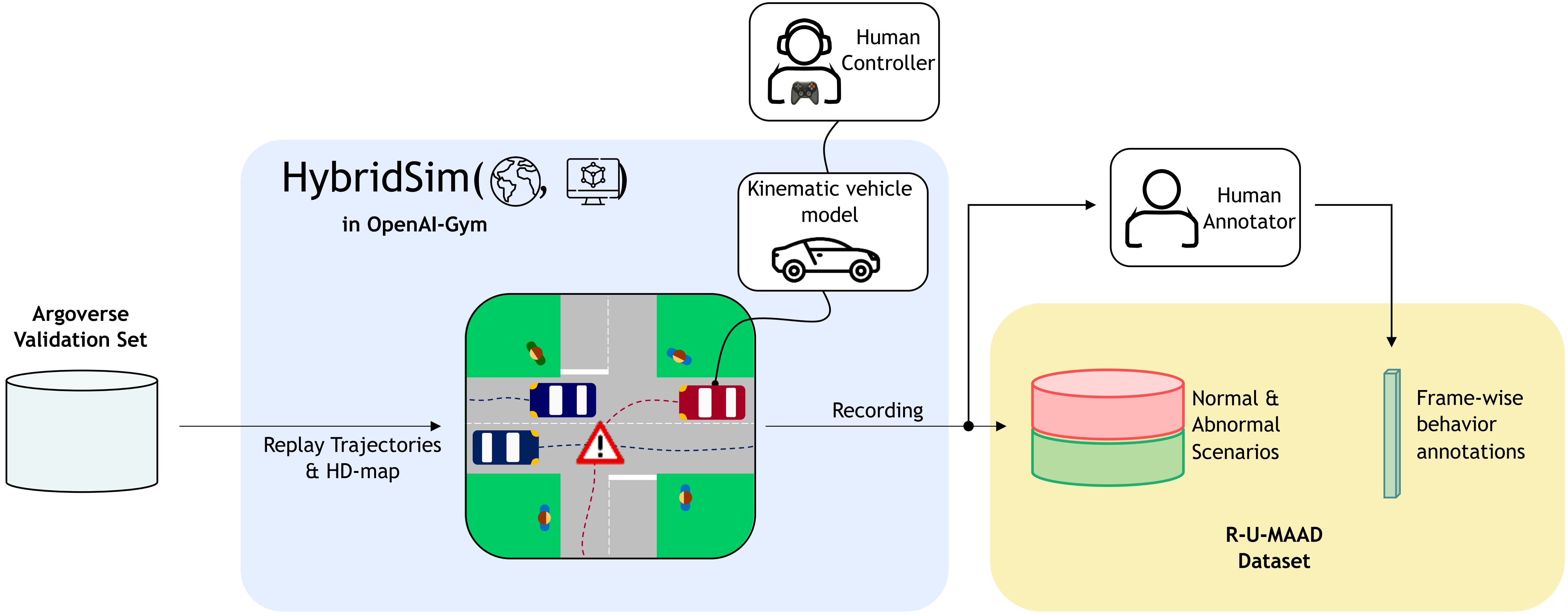


Real-world traffic scenarios from the training set of the Argoverse Motion Forecasting dataset [1].

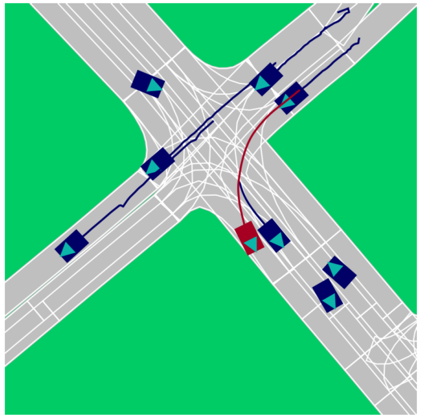
[1] Chang, Ming-Fang, et al. "Argoverse: 3d tracking and forecasting with rich maps." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2019.

Hybrid Simulation & Human Annotation

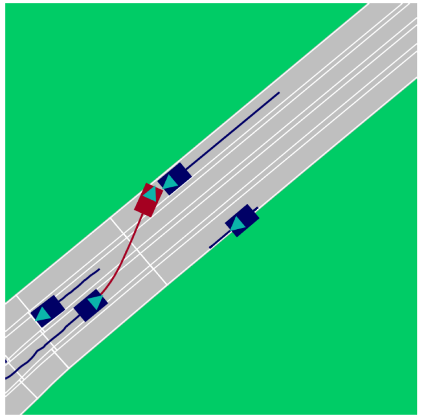


The R-U-MAAD Dataset (Wiederer et al. 2022)

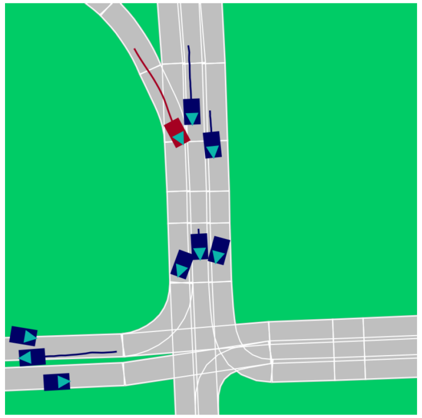
A dataset in Realistic Urban settings for Multi-Agent Anomly Detection



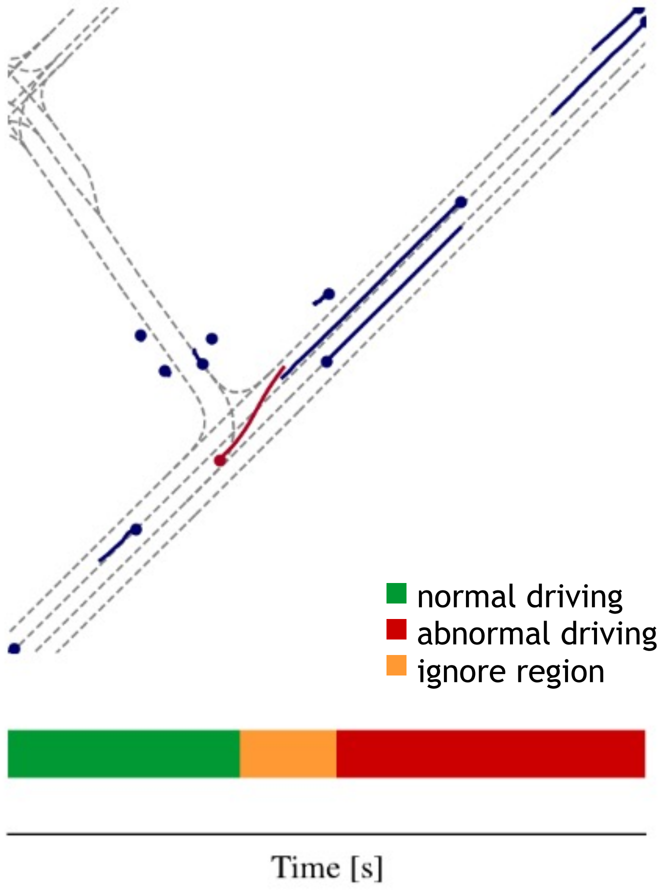
Normal Scenario:
Left Turn.



Abnormal Scenario:
Ghost driving.

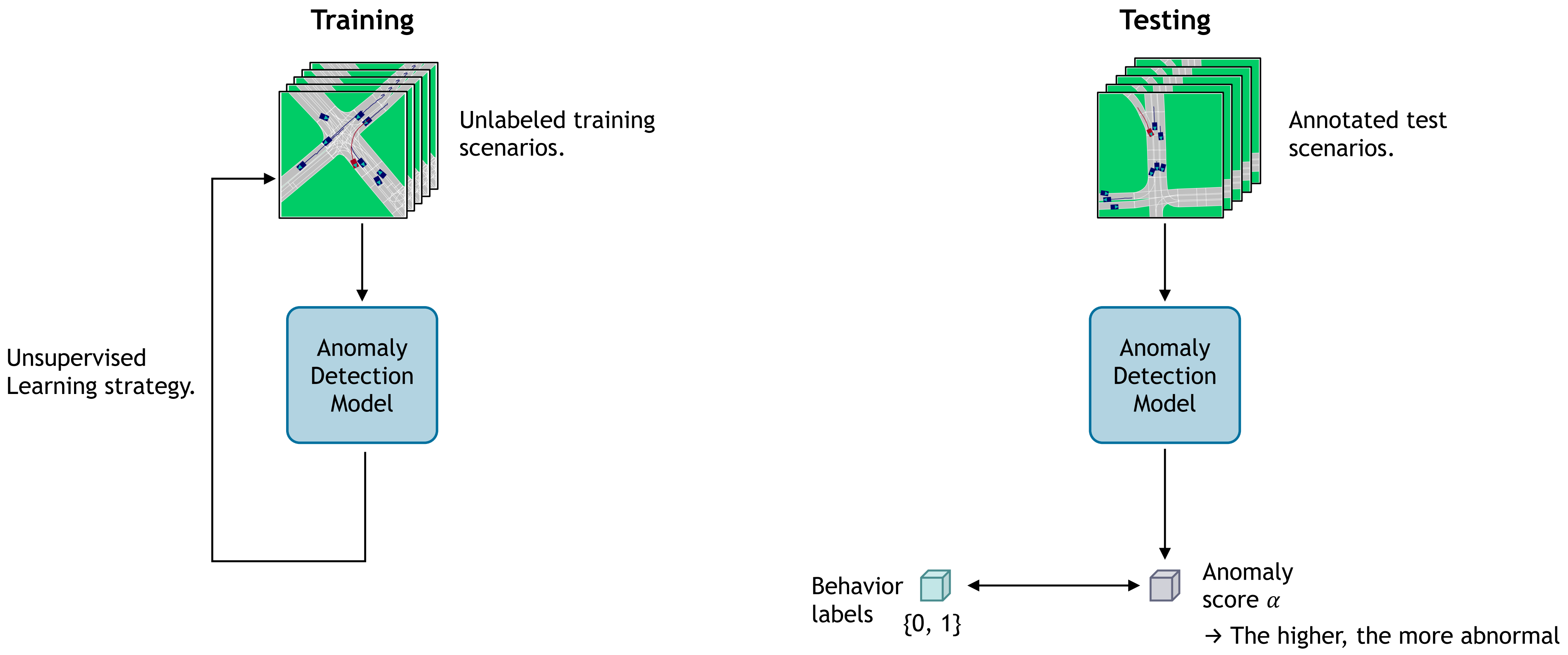


Abnormal Scenario:
Aggressive Shearing.

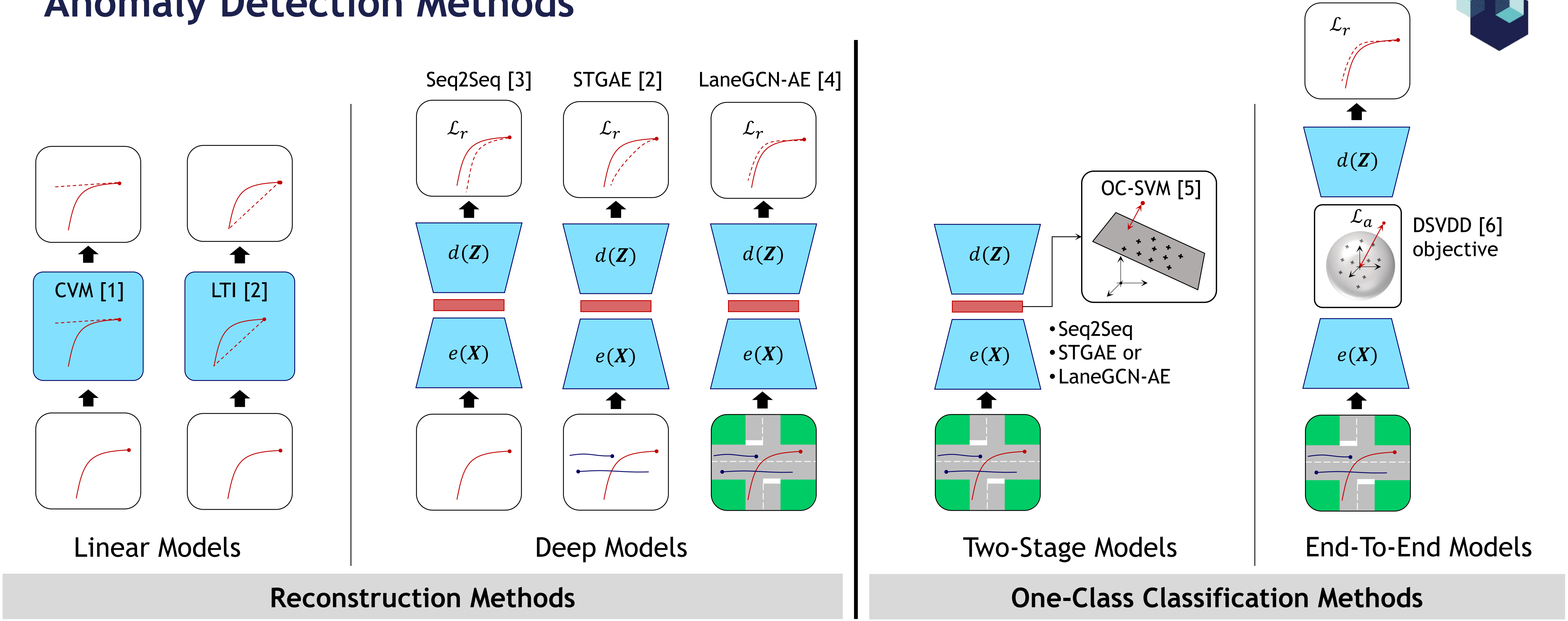


- Frame-wise annotation of each sequence in the test set.
- Annotation with behavior labels for anomaly detection.
  - Three behavior labels {normal driving, abnormal driving, ignore region}
- Annotation with sub-behavior labels for detailed evaluation, e.g. ghost driver, thwarting, leave road, staggering.

Unsupervised Anomaly Detection



Anomaly Detection Methods



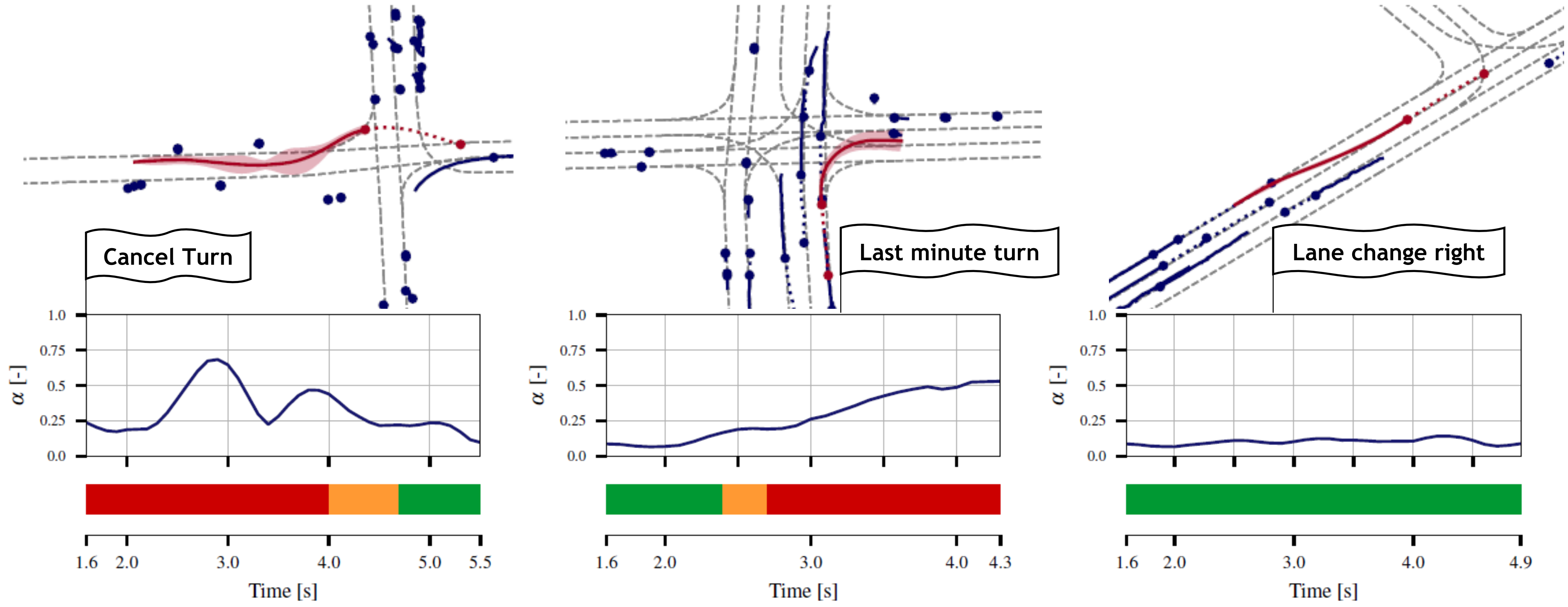
[1] Schöller, Christoph, et al. "What the constant velocity model can teach us about pedestrian motion prediction." IEEE Robotics and Automation Letters. 2020.
[2] **Wiederer, Julian**, et al. "Anomaly Detection in Multi-Agent Trajectories for Automated Driving." Conference on Robot Learning. PMLR. 2022.
[3] Chang, Ming-Fang, et al. "Argoverse: 3d tracking and forecasting with rich maps." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2019.
[4] Liang, Ming, et al. "Learning lane graph representations for motion forecasting." European Conference on Computer Vision. 2020.
[5] Schölkopf, Bernhard, et al. "Support vector method for novelty detection." Advances in neural information processing systems. 1999.
[6] Ruff, Lukas, et al. "Deep one-class classification." International conference on machine learning. PMLR. 2018.

Quantitative Results

	Category	Using dyn. Context	Using stat. Context	Method	AUPR-Abnormal ↑	AUPR-Normal ↑	AUROC ↑	FPR-95%-TPR ↓
Recon-struction	Linear	✗	✗	CVM [21]	47.19	86.00	72.30	81.20
		✗	✗	LTI	50.45	85.71	73.14	82.22
	Deep	✗	✗	Seq2Seq [4]	59.21	**88.07**	76.56	77.62
		✓	✗	STGAE [28]	**59.65**	87.85	**76.75**	76.48
		✓	✓	LaneGCN-AE [13]	57.19	87.22	75.25	**75.94**
One-Class	Two-stage	✗	✗	Seq2Seq+OC-SVM	34.47	70.25	50.47	98.33
		✓	✗	STGAE+OC-SVM [28]	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

- The group of **deep auto-encoder networks show best** results in all metrics.
- The **STGAE method wins** in two out of four metrics and is on paar with Seq2Seq and LaneGCN on the other metrics.
- The **second best group are the end-to-end one-class methods**, i.e. trained with the deep support vector data description loss (DSVDD).
- The linear models fall behind the learnt methods.

Qualitative Results of the STGAE Method



- From top to bottom: scene, anomaly score α and ground truth. The past trajectory is shown in dashed lines.
- The anomaly score is low for normal driving and increases with the anomaly.
- In the cancel turn scenario, the STGAE model is uncertain as the anomaly score is fluctuating.

Conclusion

- R-U-MAAD benchmark: A benchmark in **R**ealistic **U**rban settings for **M**ulti-**A**gent **A**nomaly **D**etection.
- Unsupervised representation learning of normal driving behavior.
- Detection of individual and interactive driving anomalies as outliers.
- Comparison of 11 baselines including linear methods, deep auto-encoders and deep one-class classification methods.
- Deep auto-encoder networks outperform other baselines on the task of anomaly detection.

GET CODE
MAAD

Code and Dataset

https://github.com/againerju/maad_highway
https://github.com/againerju/r_u_maad

GET CODE
R-U-MAAD

KIDELTA LEARNING

Scalable AI for Automated Driving

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KI FAMILIE

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