Example-Based Query to Identify Causes of Driving Anomaly With Few Labeled Samples

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Motivation

Background:

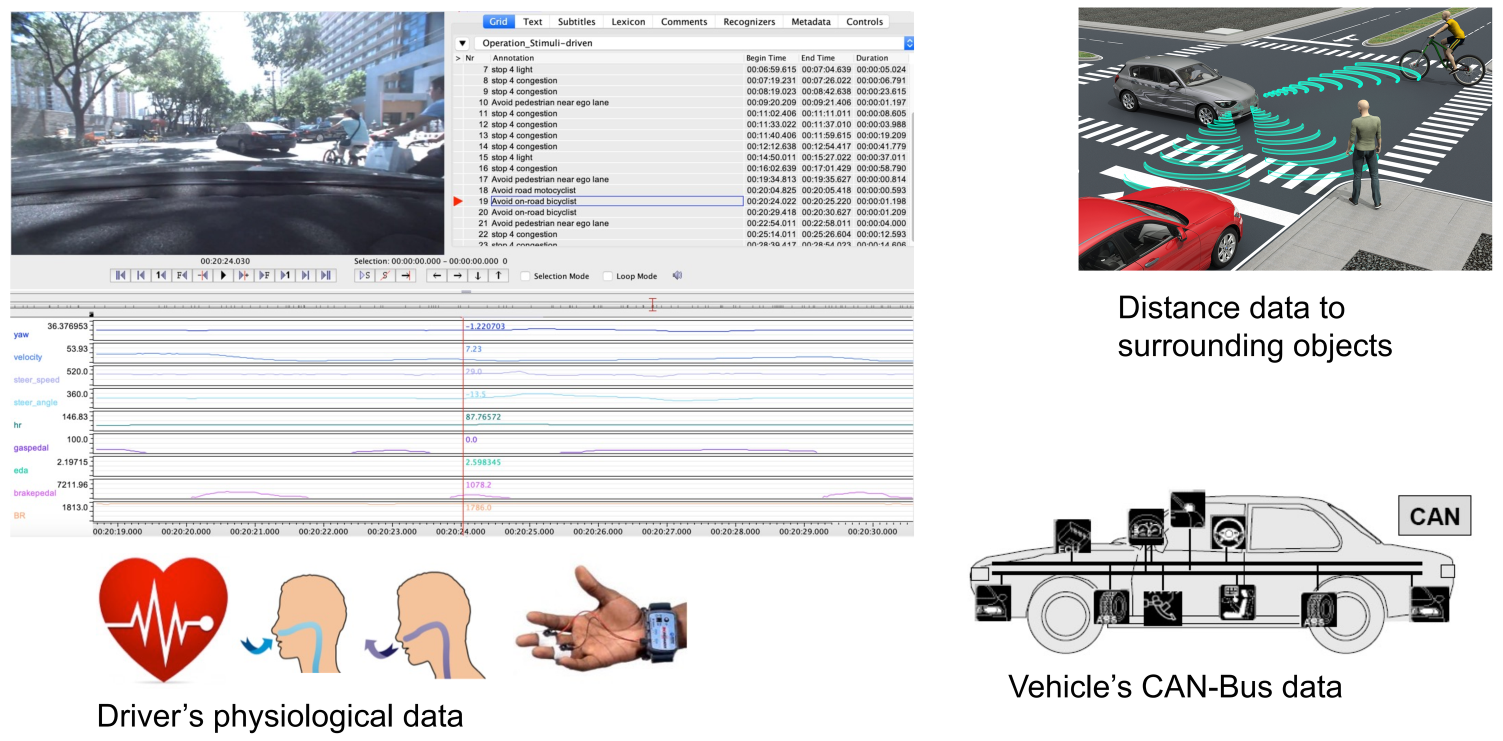
- Unsupervised driving anomaly detection can identify deviation from normal driving conditions
- A challenge with unsupervised models is the lack of interpretability

Our Work:

- Introduce an example-based query method to interpret the causes of driving anomalies
- The approach only needs a few examples per cause, creating a powerful tool for unsupervised models
- No need to define particular abnormal driving styles

Driving Anomaly Dataset

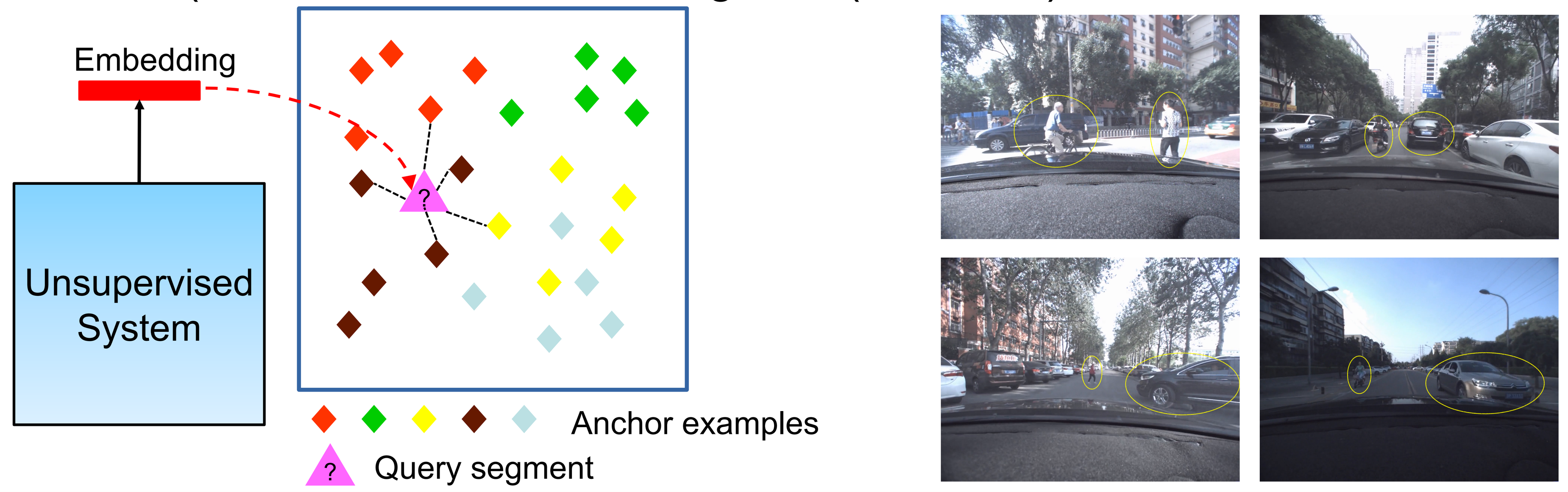
- Naturalistic urban driving recordings (84 hours)
- Collected by Honda Research Institute Inc. (HRI), with a car driving in an urban city
- Road conditions recorded by with a forward-facing camera
- The data has manual annotations of driving events



Example-Based Query Model

Formulation:

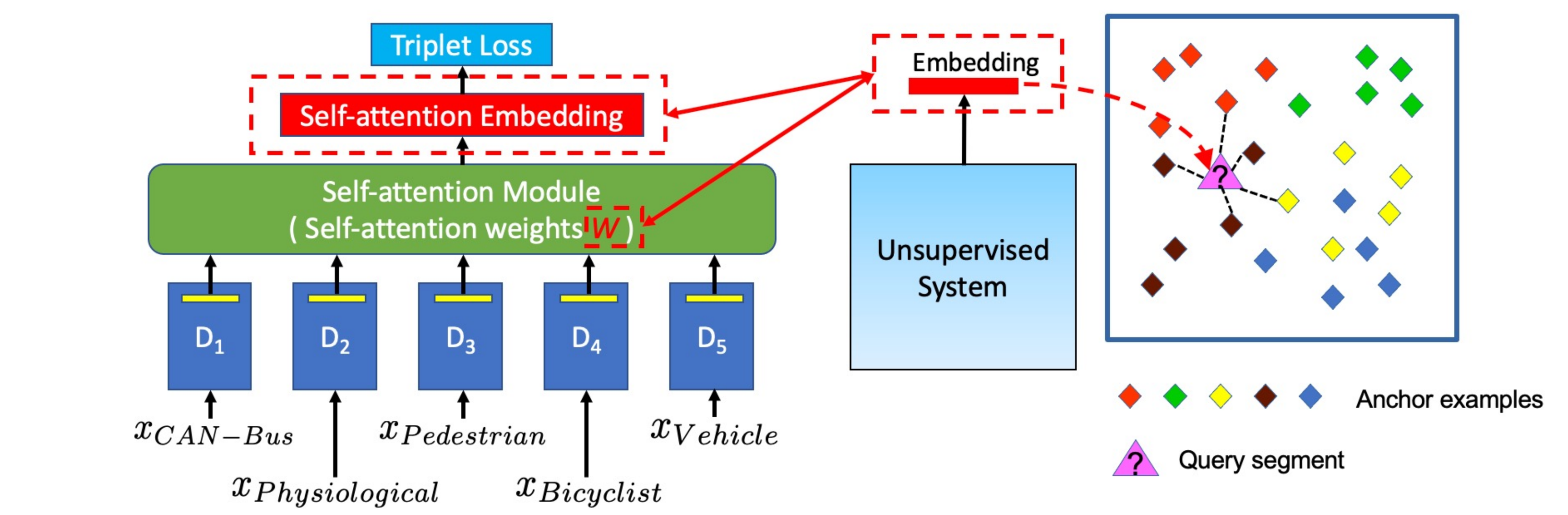
- Feature embedding extracted from an unsupervised model
- Abnormal driving segments with the highest scores are manually labeled
  - Pedestrian, bicyclist, motorcyclist, other cars, and bad driver maneuvers
- Select few examples per class to be used as prototypical anchors
- Interpret the causes of query driving segment according to the k nearest anchors (Multi-label k nearest neighbor (ML-KNN)[1]



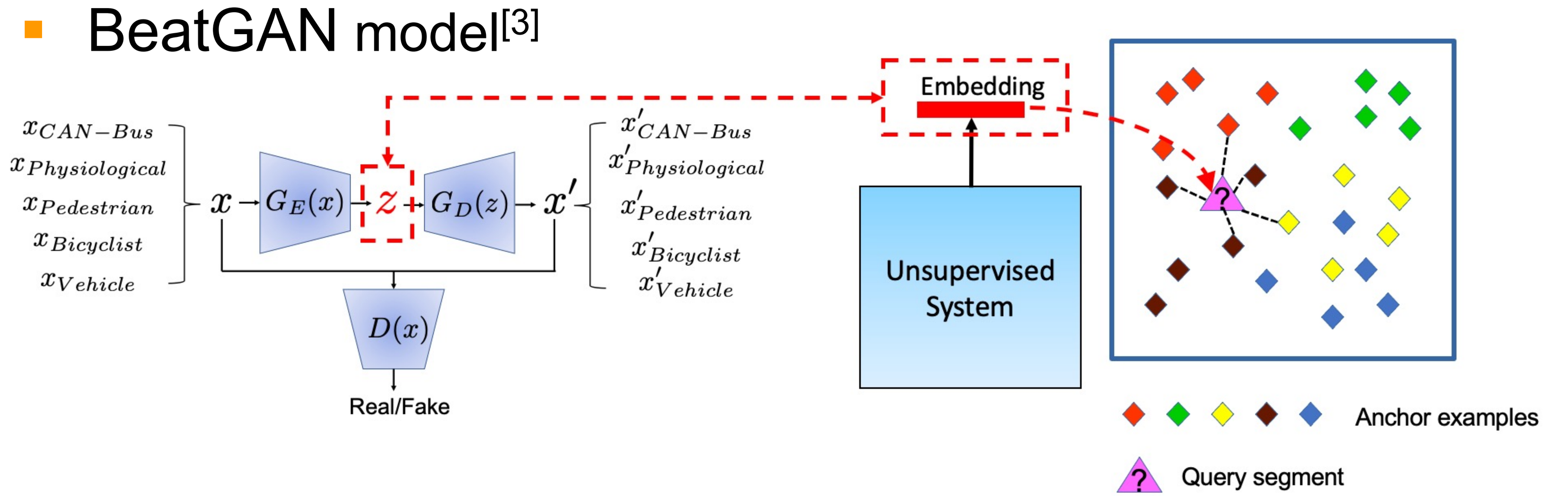
Model Performance

Unsupervised driving anomaly detection system:

- Self-attention based model[2]



- BeatGAN model[3]



Experimental results:

- Single-label evaluation
  - Retrieval Accuracy: the proportion of correct predictions

	SVM	LR	RF	ML-KNN
Attention Model (Embedding)	33.3%	29.6%	26.9% (0.032)	**54.8%**
Attention Model (Attention Weights)	23.0%	27.4%	27.9% (0.029)	**71.1%**
BeatGAN (z Embedding)	31.1%	31.61%	30.71% (0.031)	**62.2%**

- Multi-label evaluation
  - HL: Hamming loss
  - RL: Ranking loss
  - AR: Average precision
  - RA: Retrieval accuracy

Feature	Metric	Value of k						
		11	12	13	14	15	16	17
Attention Model (Embedding)	HL (↓)	0.439	0.413	0.384	**0.412**	0.416	0.388	0.415
	RL (↓)	0.501	0.462	0.448	**0.443**	0.485	0.480	0.492
	AP (↑)	0.502	0.509	0.543	**0.538**	0.517	0.503	0.5
	RA (↑)	0.319	0.319	0.430	**0.548**	0.467	0.415	0.356
Attention Model (Attention Weights)	HL (↓)	0.350	0.339	0.302	0.382	**0.283**	0.287	0.370
	RL (↓)	0.339	0.313	0.299	0.362	**0.330**	0.314	0.329
	AP (↑)	0.582	0.608	0.683	0.604	**0.684**	0.690	0.542
	RA (↑)	0.533	0.563	0.593	0.378	**0.644**	0.615	0.711
BeatGAN (z Embedding)	HL (↓)	0.425	0.390	0.341	**0.397**	0.450	0.542	0.391
	RL (↓)	0.403	0.394	0.362	**0.347**	0.442	0.477	0.438
	AP (↑)	0.450	0.498	0.564	**0.506**	0.450	0.406	0.522
	RA (↑)	0.356	0.429	0.540	**0.622**	0.452	0.363	0.511

Conclusions

- Similar anomalies cluster together in the unsupervised embeddings
- The proposed approach:
  - uses few anchors to improve interpretability.
  - is flexible to different unsupervised systems
  - provides a possible solution for automatic annotation of databases

References:

[1] M. Zhang and Z. Zhou. 2007. "ML-KNN: A lazy learning approach to multi-label learning". Pattern Recognition 40, 7 (2007), 2038–2048.

[2] Y. Qiu, T. Misu and C. Busso, "Unsupervised Scalable Multimodal Driving Anomaly Detection." in IEEE Transactions on Intelligent Vehicles (2022)

[3] B. Zhou, S. Liu, B. Hooi, et al. "BeatGAN: Anomalous Rhythm Detection using Adversarially Generated Time Series", IJCAI. 2019: 4433-4439.