Assessing the Completeness of Traffic Scenario Categories for Automated Highway Driving Functions via Cluster-Based Analysis

Overview

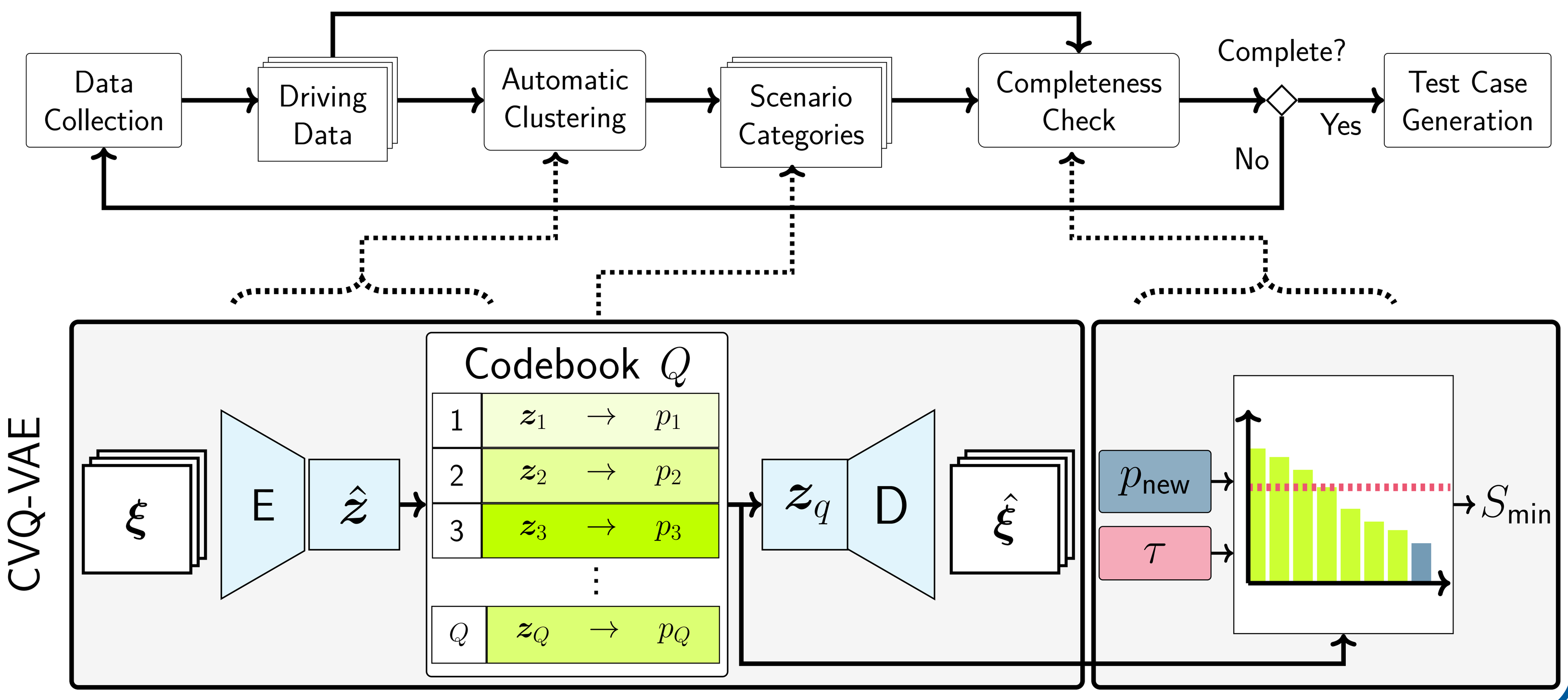
- Introudction of a novel pipeline for traffic scenario clustering and the analysis of scenario category completeness.
- The Clustering Vector Quantized - Variational Autoencoder (CVQ-VAE) is employed for the clustering of highway traffic scenarios [1].
- Various catalogs with differing numbers of traffic scenario categories can be created.
- The impact of the number of categories on the completeness considerations of the traffic scenario catalogs is analyzed.
- The trade-off between cluster quality and the amount of required data to maintain completeness is discussed based on the publicly available highD dataset.

Method

- Based on a dataset $\mathcal{D} = \{(\boldsymbol{\xi}^{(m)}, s^{(m)})\}_{m=1}^{M}$ consisting of M samples, the aim is to identify a total of Q representative traffic scenario categories.
- Each data sample consists of the traffic scenario $\boldsymbol{\xi}^{(m)} \in \mathbb{R}^{N\times F\times T_{\text{obs}}}$ and a rule-based pre-grouping $s^{(m)} \in \{1, 2, \dots, K\}$. F denotes the vehicle features for up to a total number of N vehicles over the observation time T_{obs}.
- The objective is to utilize the data to train a model g, performing

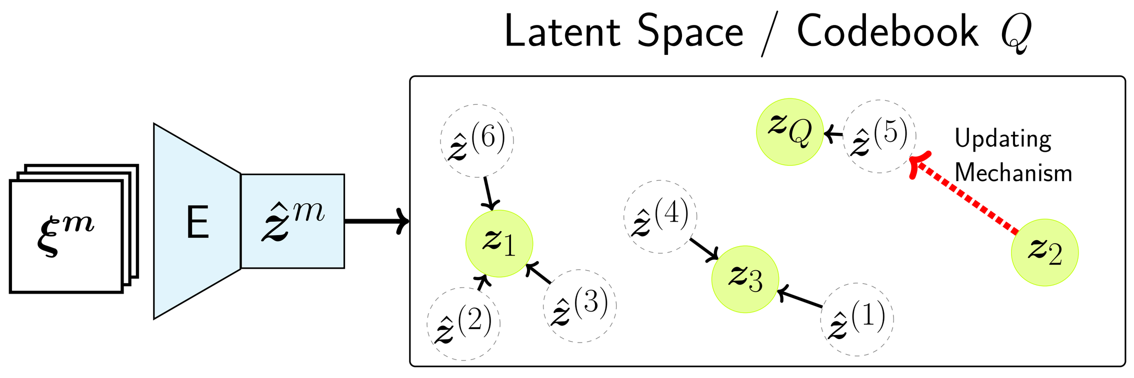
$$g : \left(\boldsymbol{\xi}^{(m)}, s^{(m)}\right) \mapsto q, \qquad (1)$$

assigning each traffic scenario to a traffic scenario category $q = 1, \dots, Q$, where $Q > K$.
- Completeness Check: The resulting traffic scenario catalogs are evaluated for their scenario category completeness utilizing the Coupon Collector's Problem.



Model Architecture for Traffic Scenario Clustering

- An encoder E maps the input traffic scenario $\boldsymbol{\xi}^{(m)}$ to a latent representation $\hat{\boldsymbol{z}}^{(m)} \in \mathbb{R}^{R_q}$, E : $(\boldsymbol{\xi}^{(m)}) \mapsto \hat{\boldsymbol{z}}^{(m)}$.
- The continuous latent representations $\hat{\boldsymbol{z}}^{(m)}$ are discretized and assigned to the closest codebook entry $\boldsymbol{z}_q^{(m)}$.
- The selected discrete codebook entry $\boldsymbol{z}_q^{(m)}$ is used by a decoder to reconstruct a representative traffic scenario for the corresponding traffic scenario category. D : $(\boldsymbol{z}_q) \mapsto \hat{\boldsymbol{\xi}}^{(m)}$ with $\hat{\boldsymbol{\xi}}^{(m)} \in \mathbb{R}^{N\times F\times T_{\text{obs}}}$.
- The model iteratively updates less utilized codebook entries stronger, compared to frequently utilized entries [1].



z_2 is pulled towards $\hat{z}^5$ since no scenario is assigned to z_2 (symbolic visualization).

Completeness of Traffic Scenario Categories

- **Coupon Collectors Problem:** Each traffic scenario category as a "coupon" that must be observed with a specified confidence level τ [2].
- A new category with probability p_{new} is introduced to account for unknown scenario categories.
- In experiments sampling until each category is drawn takes place.
- Calculating the number of scen. S_{min} ensures that, with the confidence level τ, the dataset contains every category with a prob. larger p_{new}.

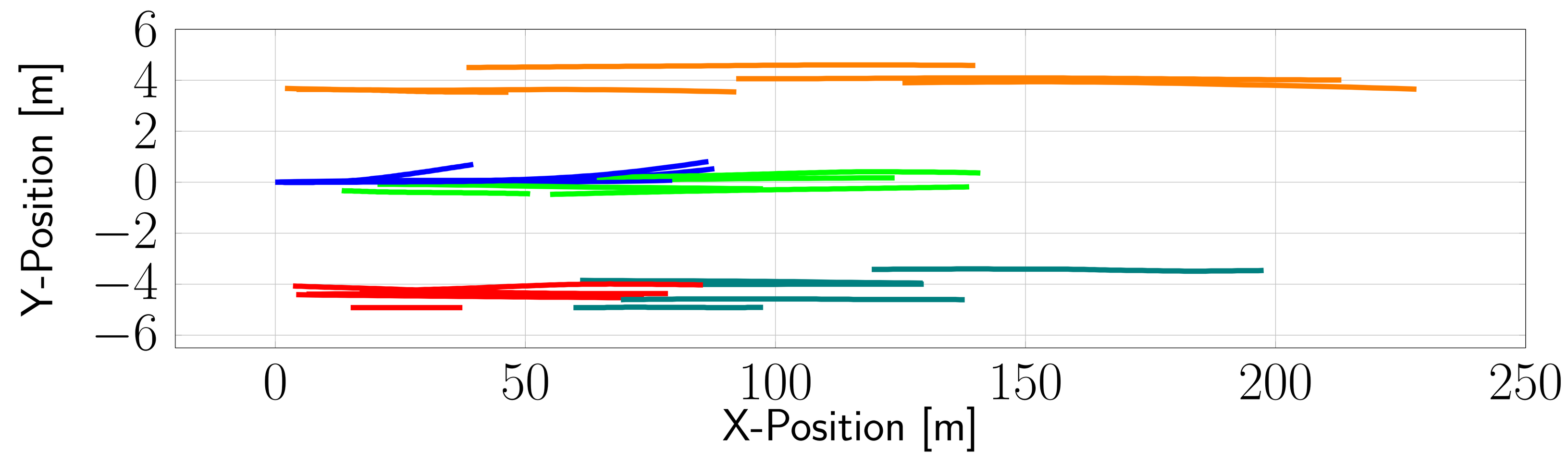
Results

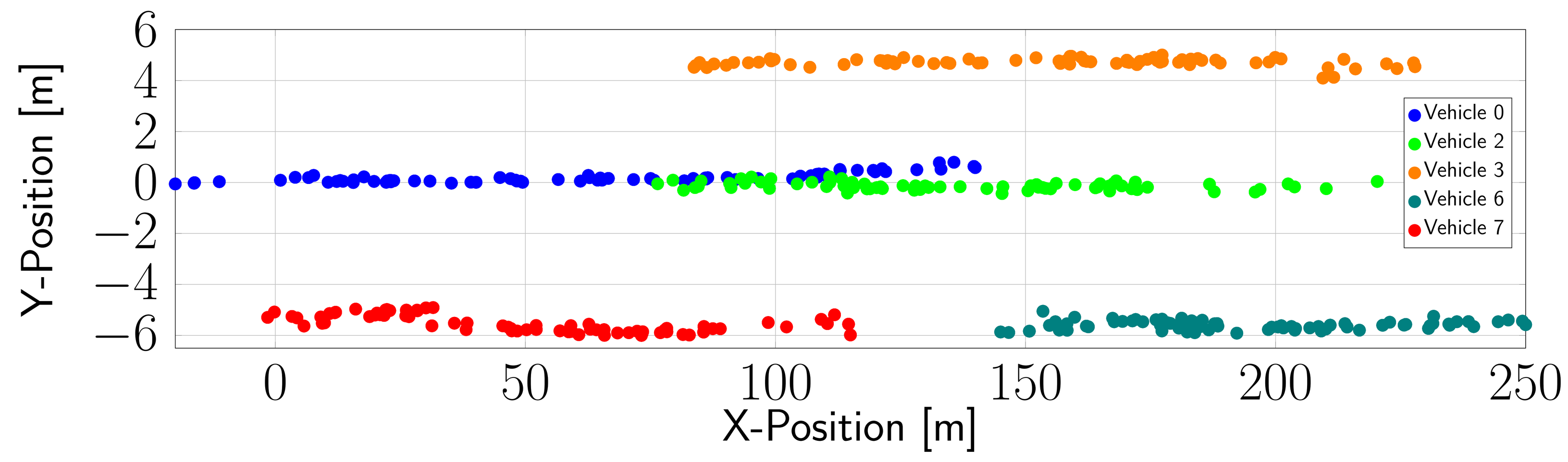
- **Effective Codebook Usage:** All entries are fully used for $Q_1 = 64$, $Q_2 = 128$, and for $Q_3 = 256$ a number of 253 entries are utilized.
- **Improved Reconstruction $\mathcal{L}_{\text{R}}$:** Increasing the number of codebook entries results in lower reconstruction errors and more coherent clusters.
- **Codebook Entry Purity:** The average Shannon entropy H_{avg} improves with more entries, indicating more consistent scenario categories.
- **Comparison to Previous Work:** The CVQ-VAE outperforms earlier approaches (VQ-VAE) in terms of codebook utilization and quality.

Table 1: Performance Comparison of Different Models

Model	Codebook Usage ↑	$\mathcal{L}_{\text{R,train}}$ ↓	$\mathcal{L}_{\text{R,test}}$ ↓	$H_{\text{avg,train}}$ ↓	$H_{\text{avg,test}}$ ↓
VQ-VAE [3]	49/60	-	-	0.01	0.39
CVQ-VAE: Q_1	64/64	0.41	4.40	0.042	0.56
CVQ-VAE: Q_2	**128/128**	0.32	3.50	0.021	0.53
CVQ-VAE: Q_3	253/256	**0.23**	**2.70**	**0.004**	**0.35**

- Selected scenarios assigned to one codebook entry and the reconstructed representative scenario is shown below.





- **Codebook Completeness:** Increasing the number of scenario categories (Q) leads to more categories with lower occurrence probabilities, thereby requiring more data to achieve dataset completeness.
- There is a trade-off between codebook entry purity and completeness. This research work presents a framework to quantitatively analyze this trade-off.

References

[1] C. Zheng and A. Vedaldi, "Online clustered codebook," in *2023 IEEE/CVF International Conference on Computer Vision (ICCV)*, 2023.

[2] F. Hauer, T. Schmidt, B. Holzmüller, and A. Pretschner, "Did we test all scenarios for automated and autonomous driving systems?," in *IEEE Intelligent Transportation Systems Conference (ITSC)*, 2019.

[3] M. Neumeier, S. Dorn, M. Botsch, and W. Utschick, "Reliable trajectory prediction and uncertainty quantification with conditioned diffusion models," in *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, 2024.

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