Generation of Multiple Types of Driving Scenarios with a Unified Generative Model for Autonomous Driving

Ensuring the safety and reliability of automated driving systems requires comprehensive and systematic testing. Among the various testing strategies, scenario-based testing has become a widely used and effective method. However, the reliability and effectiveness of this approach depends heavily on the quality of the test scenarios used. Traditional methods for generating test scenarios are often based on parametric, rule-based models. In these approaches, specific maneuver types are defined using expert knowledge and a set of fixed parameters. While such models are easy to interpret, they have several limitations: they are time-consuming and costly to design, require expert input for each maneuver type, and are difficult to extend to new or rare scenarios.

To overcome these limitations, recent research turned to deep generative models for data-driven scenario generation, which learn directly from real-world or simulated data. This enables them to capture even complex behavior patterns that are hard to be modeled analytically. Among them, Variational Autoencoders (VAEs) and diffusion models have shown strong potential in modeling high-dimensional behavior distributions and generating realistic or critical trajectories that capture the diversity and complexity of driving behavior across real and simulated domains.

This work, therefore, proposes a unified generative framework that can simultaneously generate multiple types of driving scenarios, including cut-in left (CIL), cut-in right (CIR), cut-out left (COL), cut-out right (COR), cut-through left (CTL), and cut-through right (CTR), thus covering six distinct driving behaviors. The model not only learns to generate realistic trajectories but also reflects the same statistical properties as observed in real-world data, which is essential for risk assessment. Comprehensive evaluations, including quantitative metrics and visualizations from detailed latent and physical space analyses, demonstrate that the unified model achieves comparable performance to individually trained models.

Figure 1 illustrates one such evaluation, where a t-SNE projection of the latent space reveals six well-separated clusters corresponding to the six maneuver types. Cut-in and cut-out maneuvers occupy distinct, direction-specific regions, while cut-through maneuvers lie in between, reflecting their intermediate nature. This well-structured clustering enables representative trajectory generation and targeted synthesis by sampling near cluster centers.

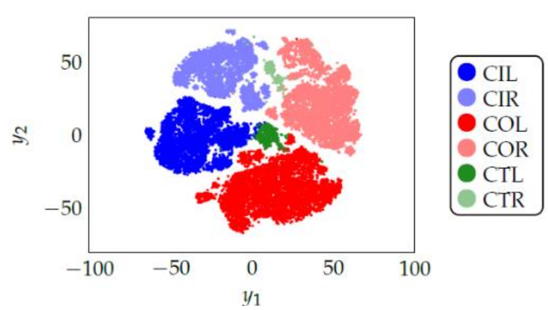

Figure 1: Latent sample-based cluster analysis of scenario types by t-SNE

The main advantage of the proposed unified VAE framework is its ability to capture diverse driving behaviors within a single generative architecture, maintaining high fidelity while reducing modeling complexity. Experimental results, including comparisons against baseline models, further confirm performance same as individually trained approaches while preserving correct maneuver-type probabilities.