Safety Evaluation of Autonomous Vehicles in Long-tailed Environments

TONGJI UNIVERSITY

Zhaoyi Wang, M.S.Transportation Engineering, College of Automotive Studies, Tongji University, advised by Prof. Yanjun Huang

I Motivation

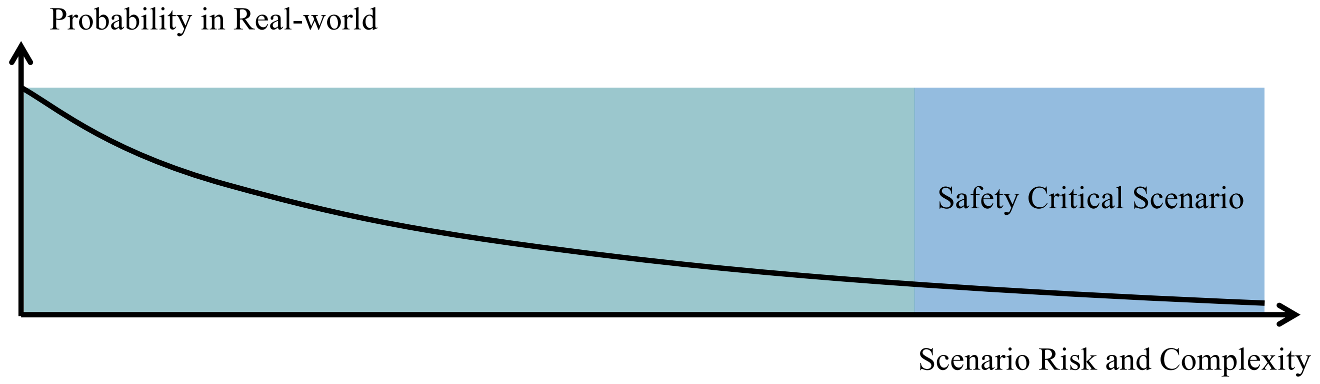


Fig.1 The long-tailed distribution in real-world driving environment.

The real world is in a **long-tailed** distribution, where scenarios that have a safety threat are often located on the edge of this distribution, this scenarios are called **safety-critical scenarios**. Due to the long-tailed nature of the open environment, the safety of autonomous vehicles (AV) cannot be fully guaranteed, which limits there further application.

My research focuses **on the safety of autonomous vehicles in long-tail environments**. Specifically, my work focuses on three main points:

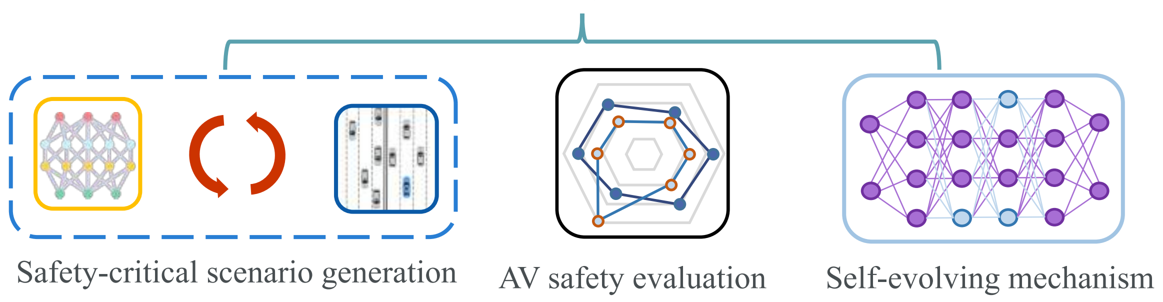


Fig.2 Research framework about safety of AV in long-tailed environments

II Safety-Critical Scenario Generation

Safety-critical scenario generation is the main approach to solving the problem of lack of data for edge scenarios. In our work, the generation of safety-critical scenarios is regarded as the problem of generating the **trajectories Y**, a **scenario** is defined as **the sequence of scenes**:

$$Y=\left[s^0,s^1,s^2,s^3,\ldots,s^t\right],\quad s^t=\left[s_1^t,s_2^t,\ldots,s_N^t\right],\quad s_i^t=\left[x_i^t,y_i^t,v_i^t,\theta_i^t\right],$$

Considering that the environment for testing autonomous driving is **Markovian**, where the next states are decided by the current states and the policies of all the vehicles.

$$s^t=f\left(s^{t-1},\pi_{av},\pi_1,\pi_2,\ldots,\pi_N\right),$$

Begin from the initial states, the scenarios evolve through the complex interactions of all traffic participants according to their driving policies respectively.

$$Y=g\left(s^0,\pi_{av},\pi_{bv}\right),\quad \pi_{bv}=\left[\pi_1,\pi_2,\ldots,\pi_N\right]$$

Thus, safety critical scenario generation is described as:

$$argmax_{(s^0,\pi_{abv})}R\left(s^0,\pi_{av},\pi_{bv}\right),s.t.Y\in h(M),$$

Therefore, we consider scenario generation in terms of **two factors:** the **policy of adversarial traffic participants** π_{abv}, and **the initial states** s^0

II.A Dynamic Scenario Trajectories Generation

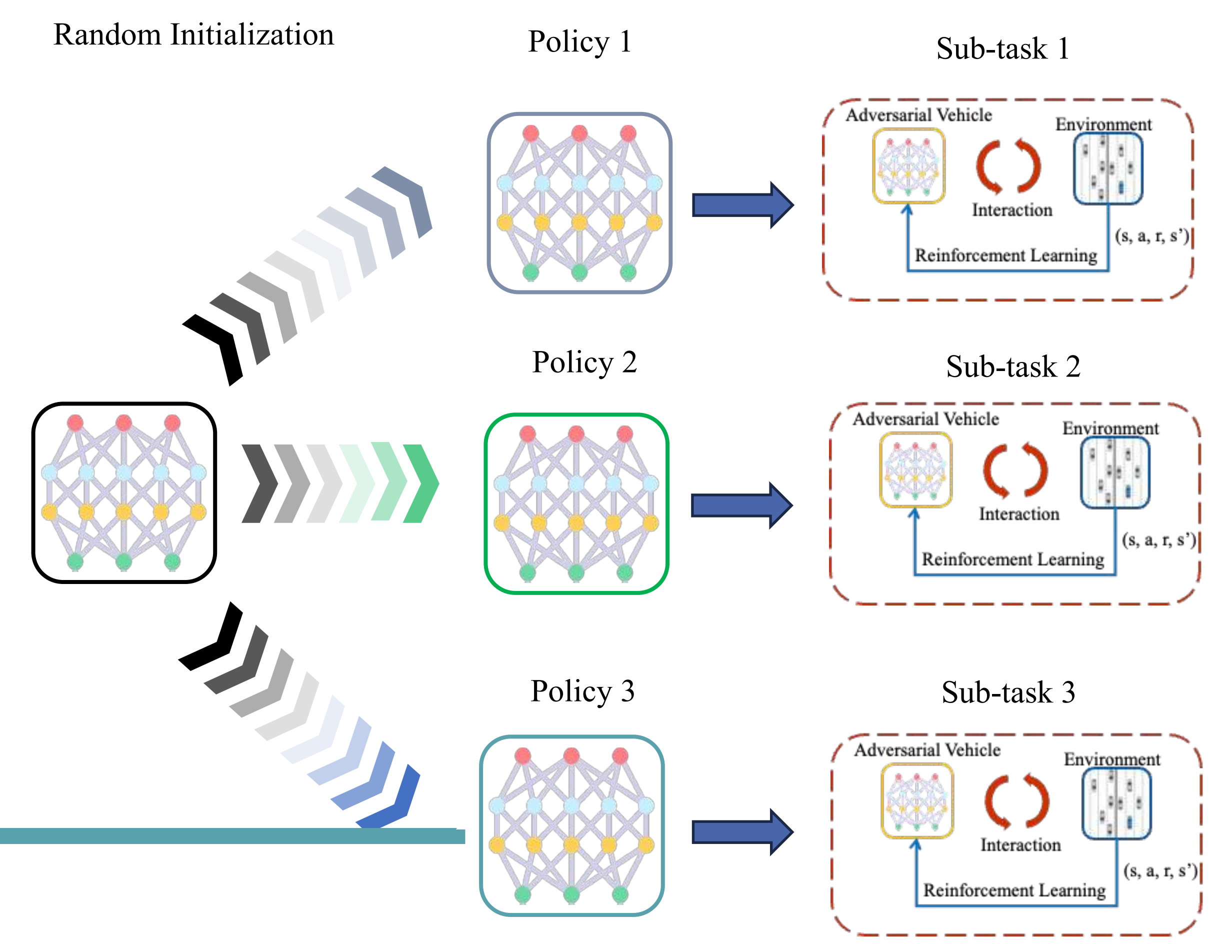


Fig.3 Ensembled RL Framework for safety-critical scenario generation

Ensembled Reinforcement Learning Framework

1. A lack of diversity in traditional approaches

RL's pursuit of optimal solutions leads to a tendency to adopt a single behavior resulting in a lack of diversity. To improve the generation efficiency, we designed an ensembled RL framework.

2. Ensembled RL framework for scenario generation

The generation of safety-critical scenarios is divided into a large number of sub-tasks according to different initial states. A large population of RL agents will be randomly initialized for these subtasks.

In each sub-task, the traffic participants will be controlled by the agents which aims to find the safety-critical scenarios. Once the required scenarios are found, the training process ends, and the scenarios are recorded. In this way, we generated scenarios with better diversity.

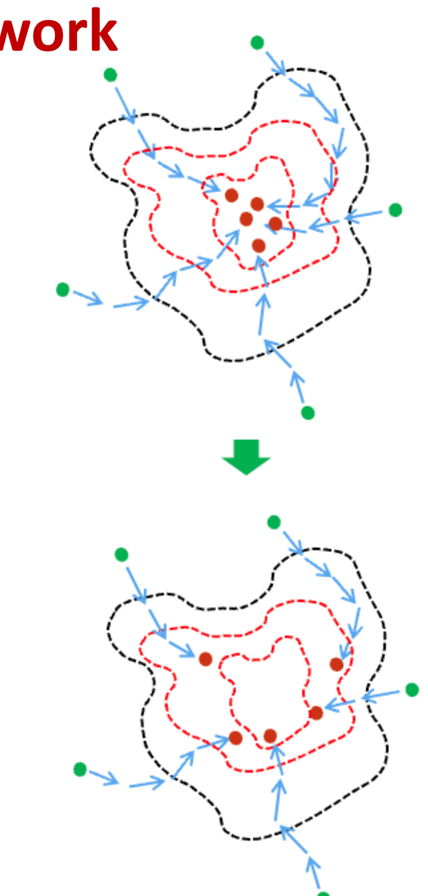
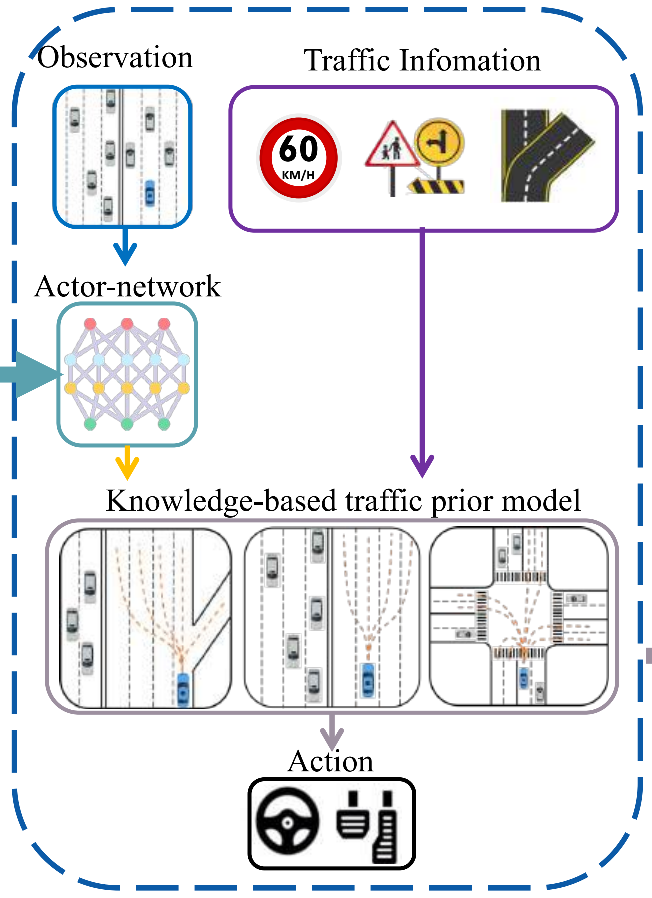
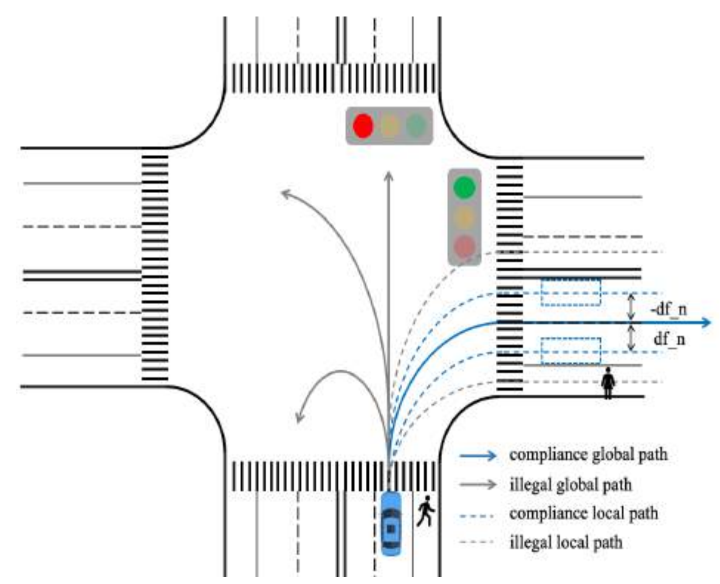


Fig.4 Difference between RL and ensembled RL

Traffic Participants Model combining RL and Traffic Prior





$$v_{tar}=\left(v_{max}+v_{min}\right)/2+y_1*\left(v_{max}-v_{min}\right)/2$$
$$d_{tar}=\left(d_{max}+d_{min}\right)/2+y_2*\left(d_{max}-d_{min}\right)/2$$
$$s_{lon}(t)=a_4*t^4+a_3*t^3+a_2*t^2+a_1*t+a_0$$
$$d_{lat}(t)=b_5*t^5+b_4*t^4+b_3*t^3+b_2*t^2+b_1*t+b_0$$

Fig.5 Traffic Participants Model

1. Low efficiency in task generalizability

Due to the lack of prior traffic knowledge in RL, agents are very prone to unreasonable behavior such as driving off the road and violating traffic rules during the optimization process. A lot of exploration and learning is needed for the agents to gradually master these basics, which leads to the inefficiency and a limitation of the expansion to different maps/tasks.

2. Traffic participants model combining RL and traffic prior

A layered model integrating traffic knowledge and the actor-network of reinforcement learning is proposed. Prior traffic knowledge mainly consists of road geometry, topology, traffic rules, and human driving habits. This enables the generation of scenarios for arbitrary working conditions.

Risk-Guided Adversarial Policy Optimization

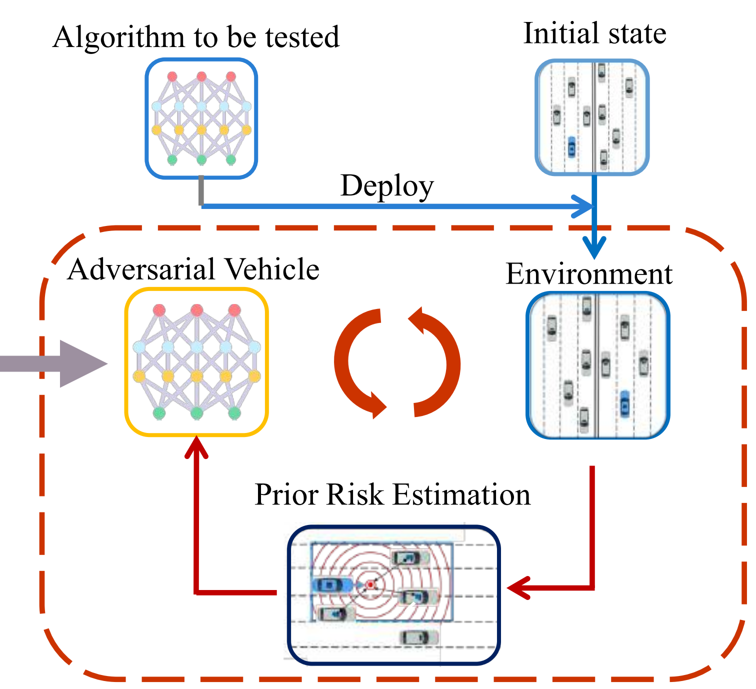


Fig.6 Adversarial policy optimization for safety-critical scenario generation.

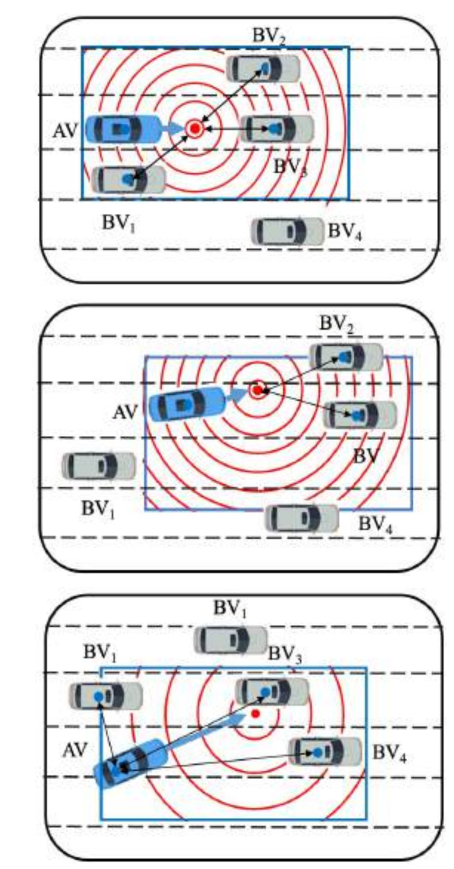


Fig.7 Prior risk estimation model

1. Unreasonable objectives affect the quality of scenario generation

Existing studies generally adopt the distance between the adversarial vehicle and the AV as the optimization objective, which affects the quality and efficiency of scenario generation. Essentially, the object of safety-critical scenario generation is to maximize the risk of the scenario. Thus it's more appropriate to use the quantified risk of a scenario as the object of optimization.

2. Risk-guided adversarial policy optimization

Based on the empirical knowledge of driving risk, we design a prior risk estimation model that integrates the state of the AV and the relative states of background vehicles. The model can provide dense rewards for all states to more efficiently guide scenario generation and improve the quality of the scenarios.

Zhaoyi Wang, Xincheng Li, Dengwei Wei, Liwen Wang, and Yanjun Huang, "Efficient Generation of Safety-Critical Scenarios Combining Dynamic and Static Scenario Parameters," in IEEE Transactions on Intelligent Vehicles, doi: 10.1109/TIV.2024.3402221.

II.B Combining Generation of Dynamic and Static Scenario Parameters

Alternatively Optimization of Static and Dynamic Parameters

$$argmax_{(s^0,\pi_{abv})}R\left(s^0,\pi_{av},\pi_{bv}\right),s.t.Y\in h(M),$$

1. A limitation of scene generation efficiency

Scenarios are constituted by two kind of parameters, dynamic parameters, which changes with time, and static parameters, which are constant during time. Due to the differences in the nature of the dynamic and static parameters, existing research in safety-critical scenario generation is unable to optimize both of them, which limits the efficiency of scenario generation.

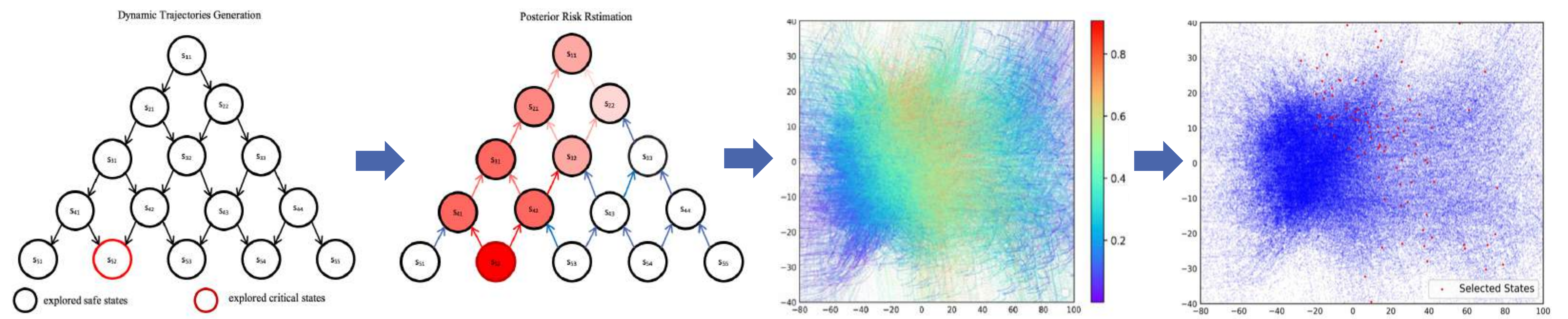
2. Alternatively optimization of static and dynamic parameters

We proposed a method to combine the generation of dynamic and static parameters by alternatively optimizing them. Dynamic scenario generation is considered as an optimization problem for trajectories as introduced before, while static scene parameter generation is modeled as a search problem in the high-dimensional natural staters space built from naturally collected data.

Posterior Risk Estimation Model

A **data-driven posterior risk estimation model** is proposed, which learns from the generated scenario trajectories to estimate the risk of unknown states for AV. Subsequently, the posterior risk model will make inferences about the risk distribution in natural state space to guide the sampling of the next batch of initial states.

$$V^t(s)=E\left[G_t|s_t=s\right],$$
$$G_t=r_{(t+1)}+\gamma*r_{(t+2)}+\gamma^2*r_{(t+3)}+\cdots+\gamma^{(T-t-1)}*r_T,$$
$$r'(s)=\begin{cases}1, & \text{if collision happens,}\\ 0, & \text{otherwise.}\end{cases}$$
$$G'_t=\begin{cases}\gamma^{(T-t-1)}, & \text{if collision happens,}\\ 0, & \text{otherwise.}\end{cases}$$



Posterior risk estimation learns from selected scenario data. The risk distribution of the natural state space Sampling initial states from high-risk region

Fig.8 Static parameter optimization process

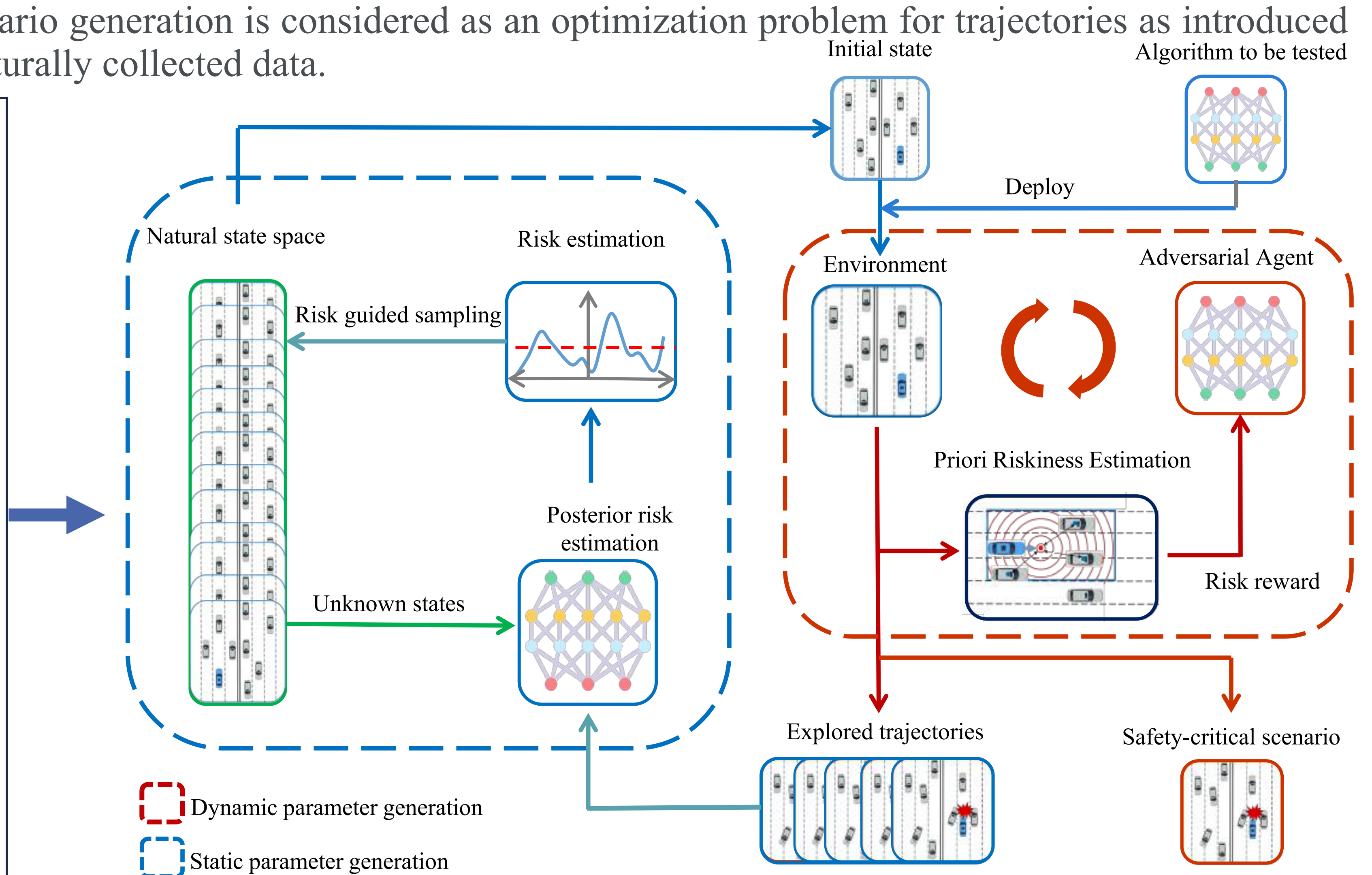


Fig.9 Combining generation of dynamic and static scenario parameters

Zhaoyi Wang, Xincheng Li, Dengwei Wei, Liwen Wang, and Yanjun Huang, "Efficient Generation of Safety-Critical Scenarios Combining Dynamic and Static Scenario Parameters," in IEEE Transactions on Intelligent Vehicles, doi: 10.1109/TIV.2024.3402221.

II.C Diversity Enhancement based on Novelty Qualification

1. Reasons for the lack of diversity:

1) Parameter overlap between the generated scenarios for probabilistic reasons when a large number of scenarios are generated

2) Limitations of the original dataset

2. Diversity enhancement based on novelty qualification

1) Dynamic trajectory generation: Introducing **dynamic trajectory novelty loss** into the objective function.

2) Static scene generation: Learning from explored scene data via VAE to quantize scene novelty via **reconstructed probabilities**. Modeling the **novelty distribution** of the initial state space to drive diverse scene generation.

3) Learning the distributions from natural scene databases via VAE and sampling to obtain more scenes in similarly distribution.

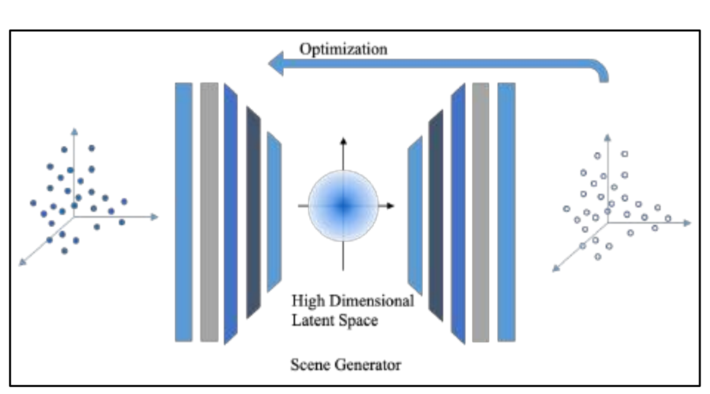


Fig.10 Training of scene generator

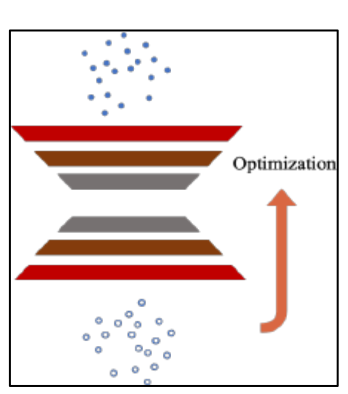


Fig.11 Training of novelty estimator

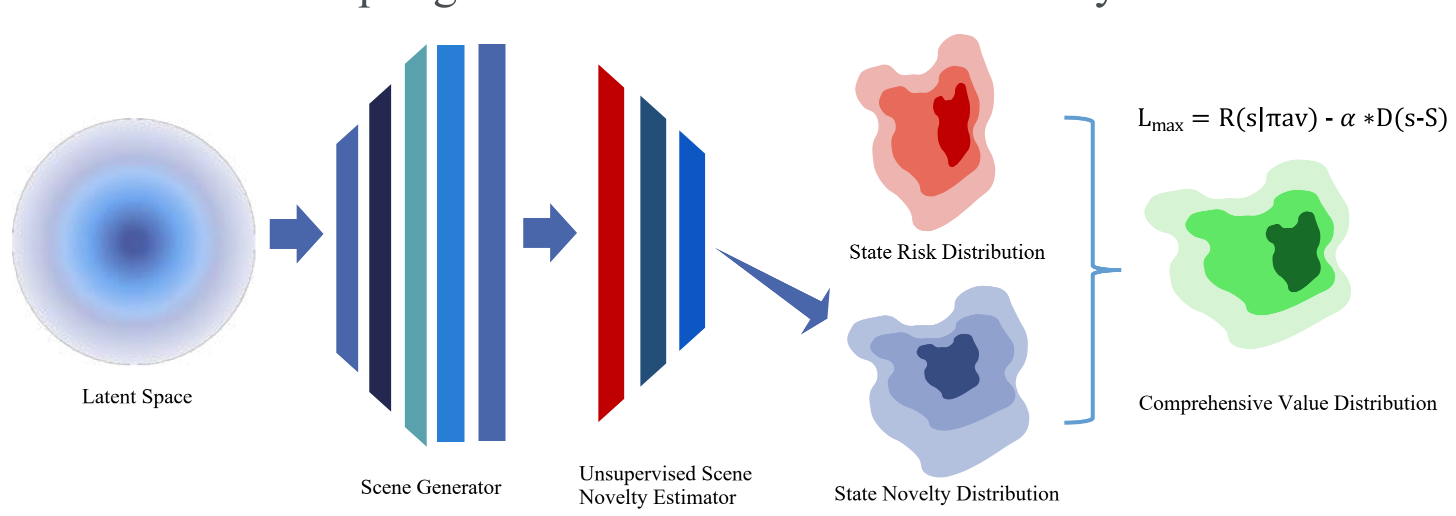


Fig.12 Scene novelty qualification and and the calculation comprehensive value distribution

III.A Feature Extraction and Distribution Analysis

A safety analysis framework for AV in long-tailed environments is proposed.

1. Key feature extraction

A nonlinear feature extractor is designed to extract key features from a scenario. High-dimensional scenario data are mapped into a low-dimensional feature space.

2. Latent Space Clustering for Type Analysis

Features are clustered to reveal the main type of safety-critical scenarios.

3. Distribution Analysis

Modeling the distribution of safety scenarios and accident scenarios in latent space through kernel density estimation, visualizing the parameter distribution of the scenarios.

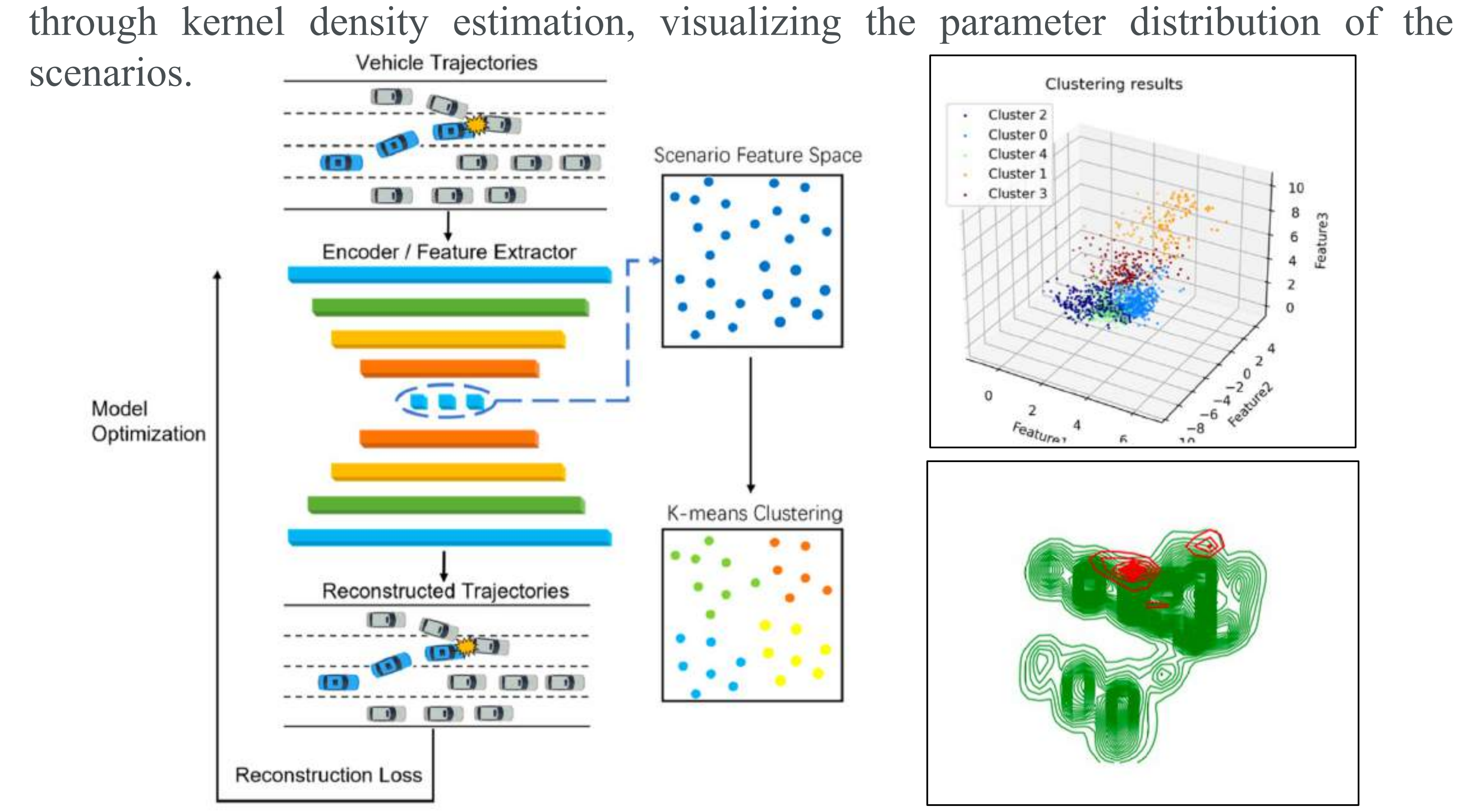
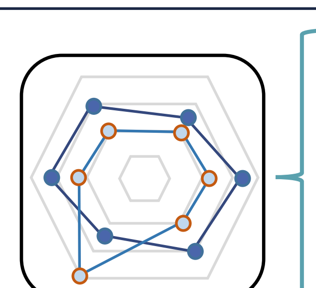


Fig.14 Scenariof feature extraction, clustering and distribution modeling

Zhaoyi Wang, Xincheng Li, Shuo Yang, Shizhen Li, Jiatong Du, Xinyu Zhang, Yanjun Huang, "Safety Evaluation of Autonomous Driving Based on Safety-Critical Scenario Generation", in IEEE Intelligent Transportation System Conference, 2024. (accepted)

III Safety evaluation of AV in long-tailed environments

The generation of safety-critical scenarios makes up for the lack of long-tail data, however, due to the unknown, complexity, and uncertainty of the open environment. There are fewer approaches for the safety analysis of AV from large, high-dimensional, and complex scenarios data.



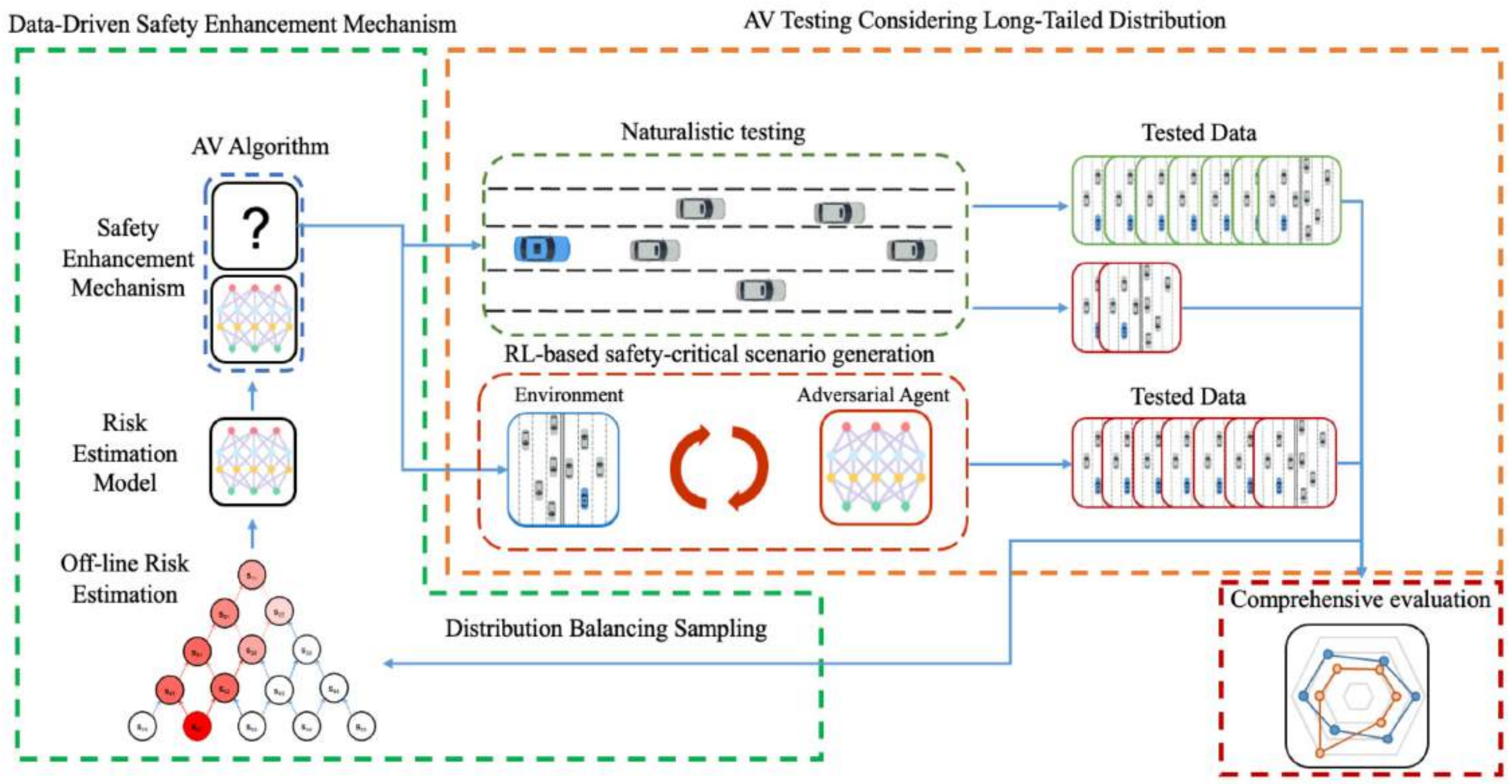
Type and distribution of safety-critical scenarios

AV robustness evaluation under unknown disturbances

Safety boundary of AV

Fig.13 Research framework for AV safety evaluation

III.B Robustness Evaluation and Safety Boundary Inference



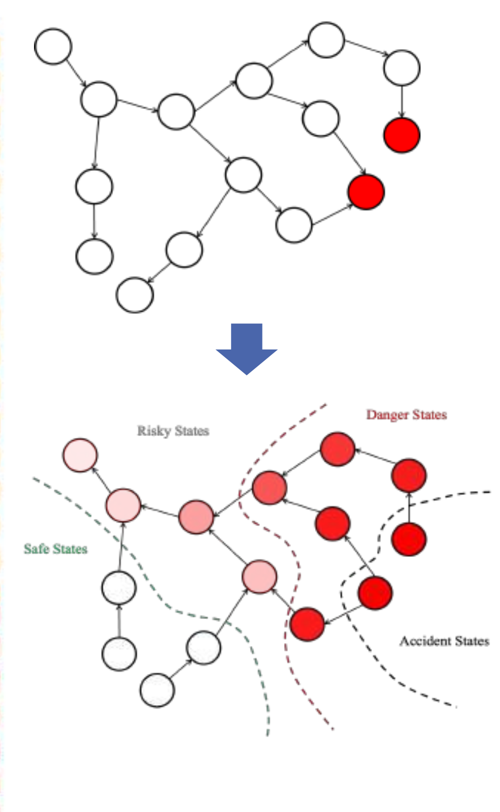


Fig.15 The framework of AV testing under long-tailed distribution and data-driven safety boundary identification

Fig.16 Safety boundary analysis

Knowing its **safety boundary** is important for the operation of AV in open environments. However, scenarios faced by AV in open environments tend to have more **complexity and higher uncertainty**. Even with a large amount of test data, it's still challenging to analyze AV's safety.

Considering the complexity of the scenarios as spatio-temporal sequences, as well as their high dimensionality and complexity, we consider them as **Markov reward processes**, which enable online inference of accidents and safety boundaries identification being achieved through **data-driven risk estimation** model which learns from test data of the given algorithm. In addition, considering that existing methods can only test the safety of algorithms in known scenarios, we propose to test **the robustness of algorithms** to unknown disturbances by the **cost of generating accident scenarios**.

Zhaoyi Wang, Jialei Nie, Xincheng Li, Yanjun Huang, "Safety Boundary Online Identification for Autonomous Vehicle Considering Long-tailed Distribution", in IEEE Transactions on Intelligent Transportation System, 2024. (under review)

IV Cloud Enabled Self-Evolve Mechanism

Safety-critical scenarios are endless due to the long-tailed distribution in the real world. Therefore, a good algorithm should be able to continuously explore and overcome safety-critical scenarios to realize self-evolution.

IV.A Cloud Collaborative Mixed-Reality Testing Platform

Real-vehicle testing is limited by efficiency and cost to adequately assess algorithm performance, while simulation environments suffer from simulation-reality gap problems and lack accuracy. Therefore, a mixed-reality testing environment is implemented by cloud injection of virtual traffic scenarios, which ensures the accuracy of the vehicle dynamics and road surface disturbance while maximizing the diversity and efficiency of testing.

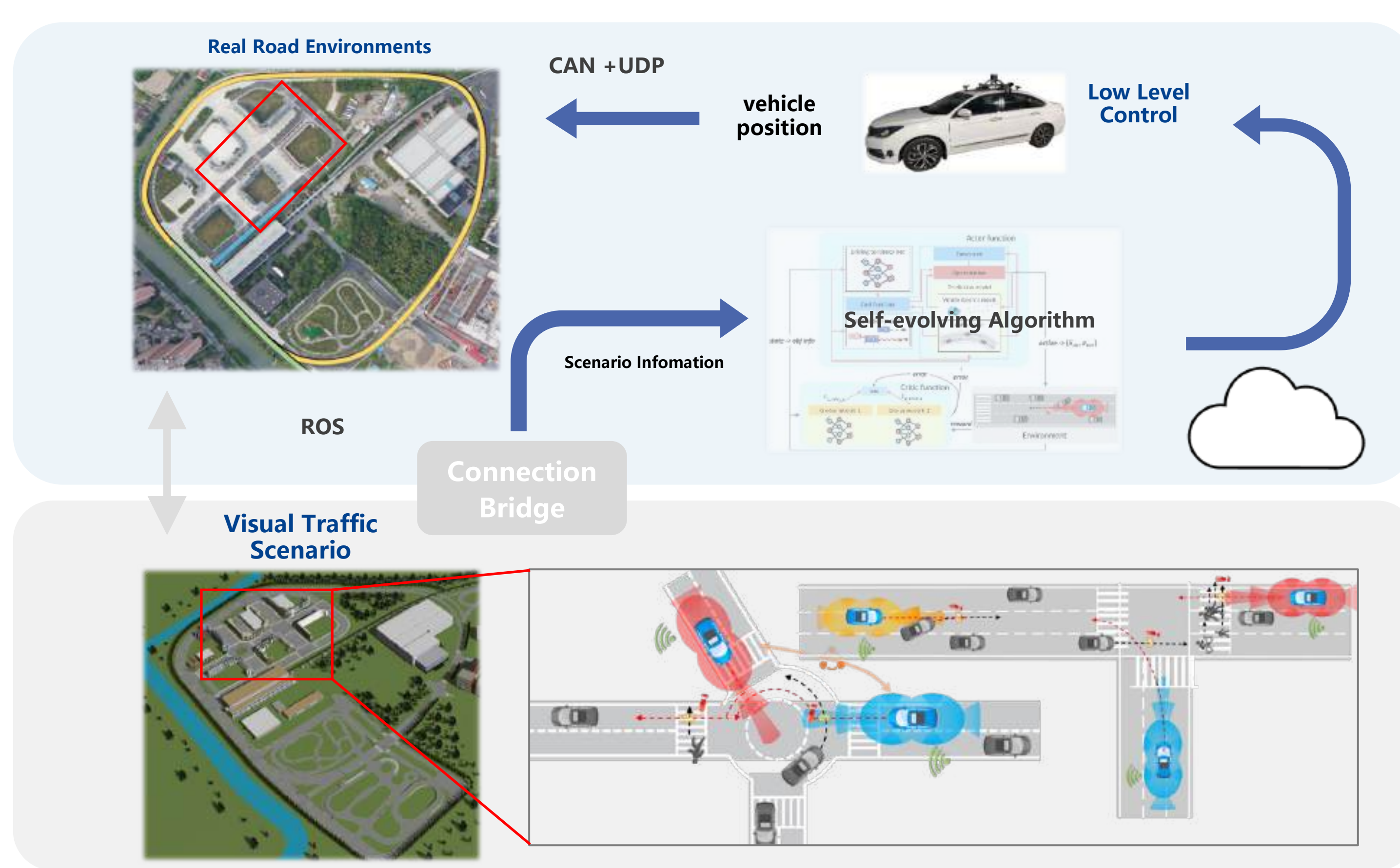


Fig.17 Case of mixed-reality testing

Fig.18 Framework of cloud collaborative mixed-reality testing

IV.B Data-Closed Loop Self-Evolving Mechanism

Data-Closed Loop

Current autonomous driving algorithms still lack self-evolving mechanisms and the capability of maintaining performance-enhancing. Therefore, we provide an overview of the modules of the DCL architecture of AV and proposes a mechanism of the DCL architecture.

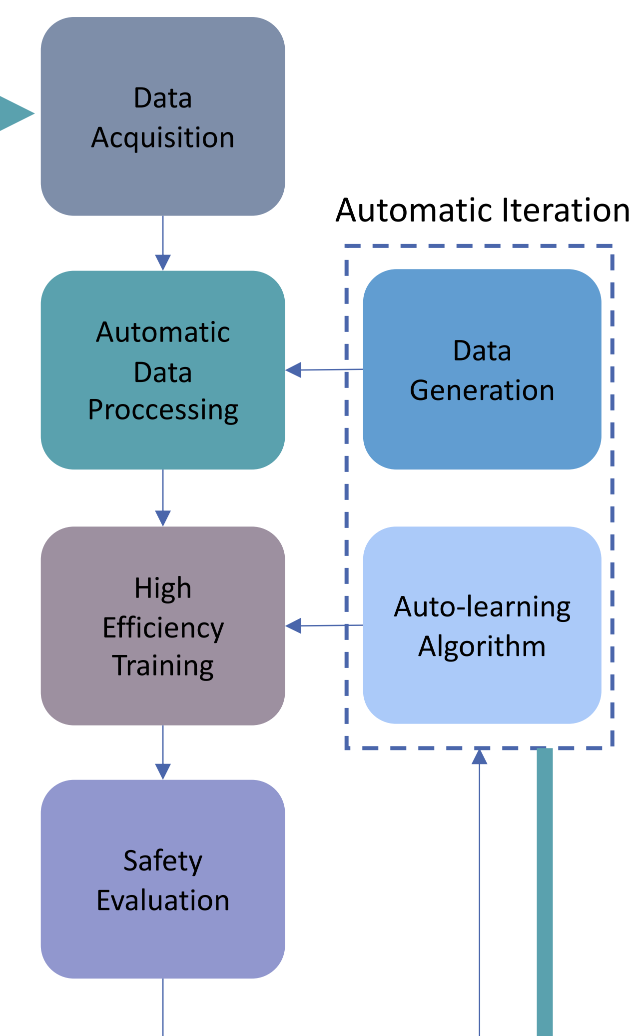


Fig.19 Data-closed loop framework

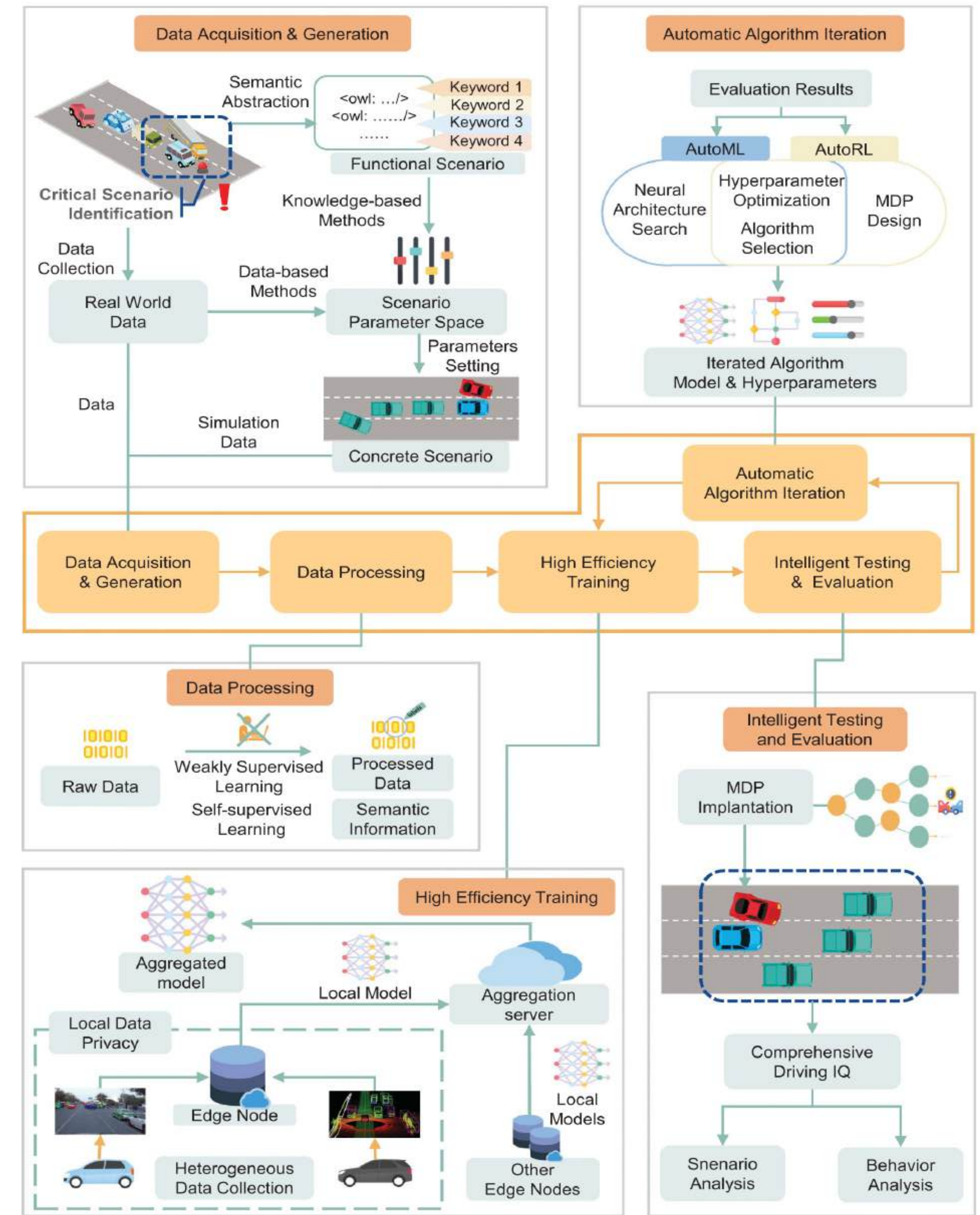


Fig.20 Overview of the modules of the DCL architecture

Automatic Iteration

A **continuous learning** approach based on **weights freeze** and **progressive neural networks** is used to avoid the **catastrophic forgetting problem** in the process of continuous policy optimization, which in turn ensures the performance of AV in self-evolution.

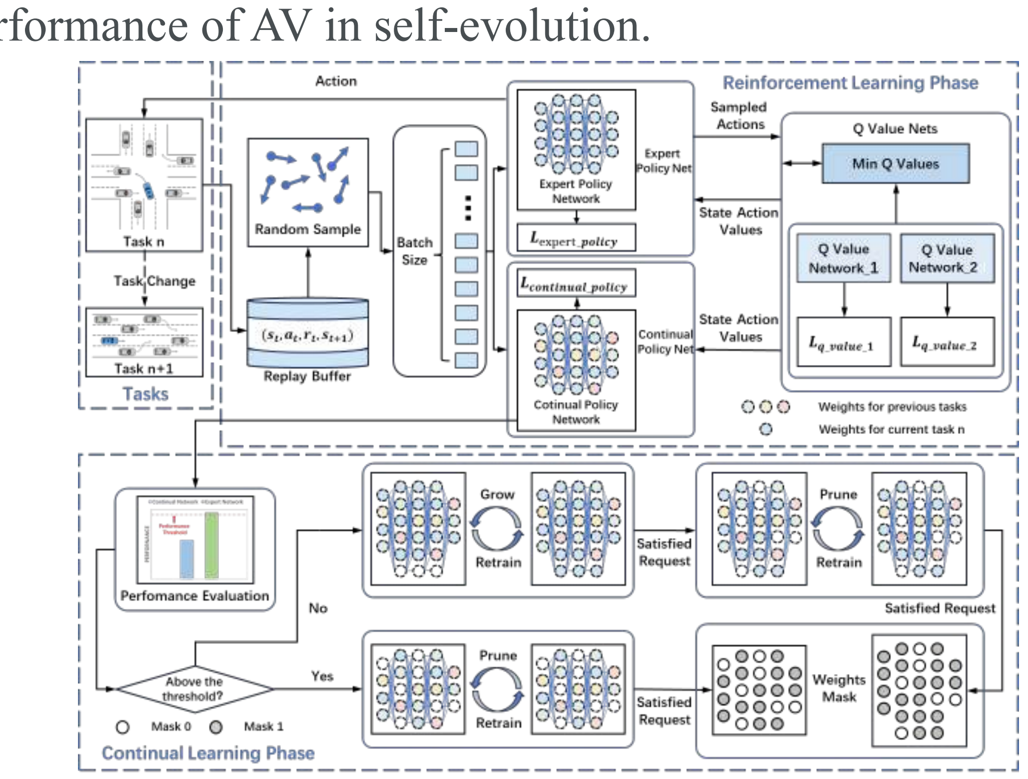


Fig.21 Proposed continual learning approach

Data Generation

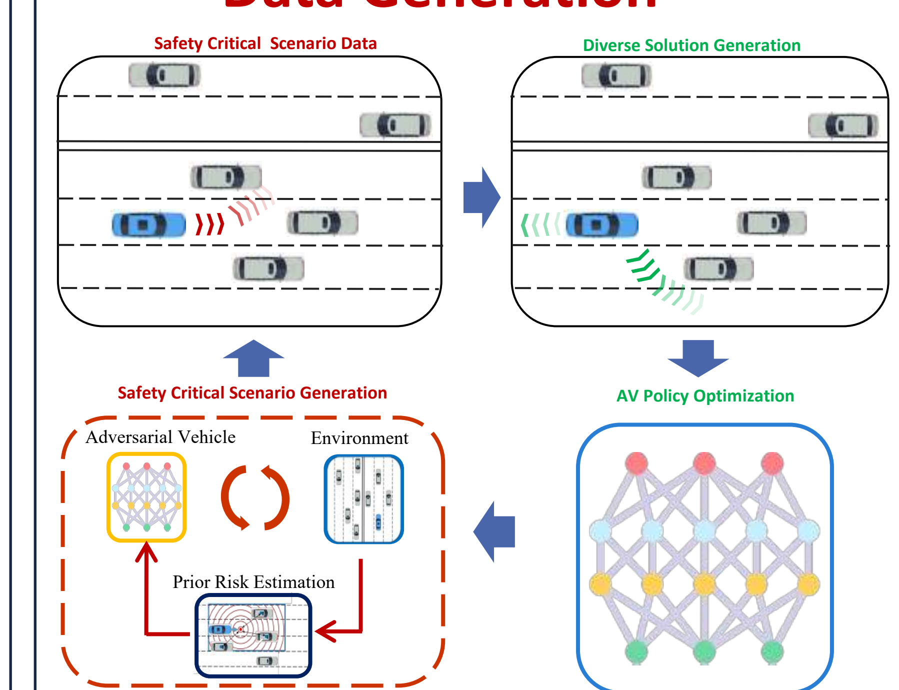


Fig.22 RL-based solution data generation framework

Efficiently explore optimal solutions for safety-critical scenarios based on an ensembled RL framework, and continuously generate high-quality demonstration solution data under edge scenarios based on the data closed-loop framework.

Xincheng Li, Zhaoyi Wang, Yanjun Huang, and Hong Chen, "A Survey on Self-Evolving Autonomous Driving: A Perspective on Data Closed-Loop Technology," in IEEE Transactions on Intelligent Vehicles, vol. 8, no. 11, pp. 4613-4631, Nov. 2023, doi: 10.1109/TIV.2023.3319689.