CrashSimGen: Generating Critical Scenarios with Diffusion Models for self-Driving

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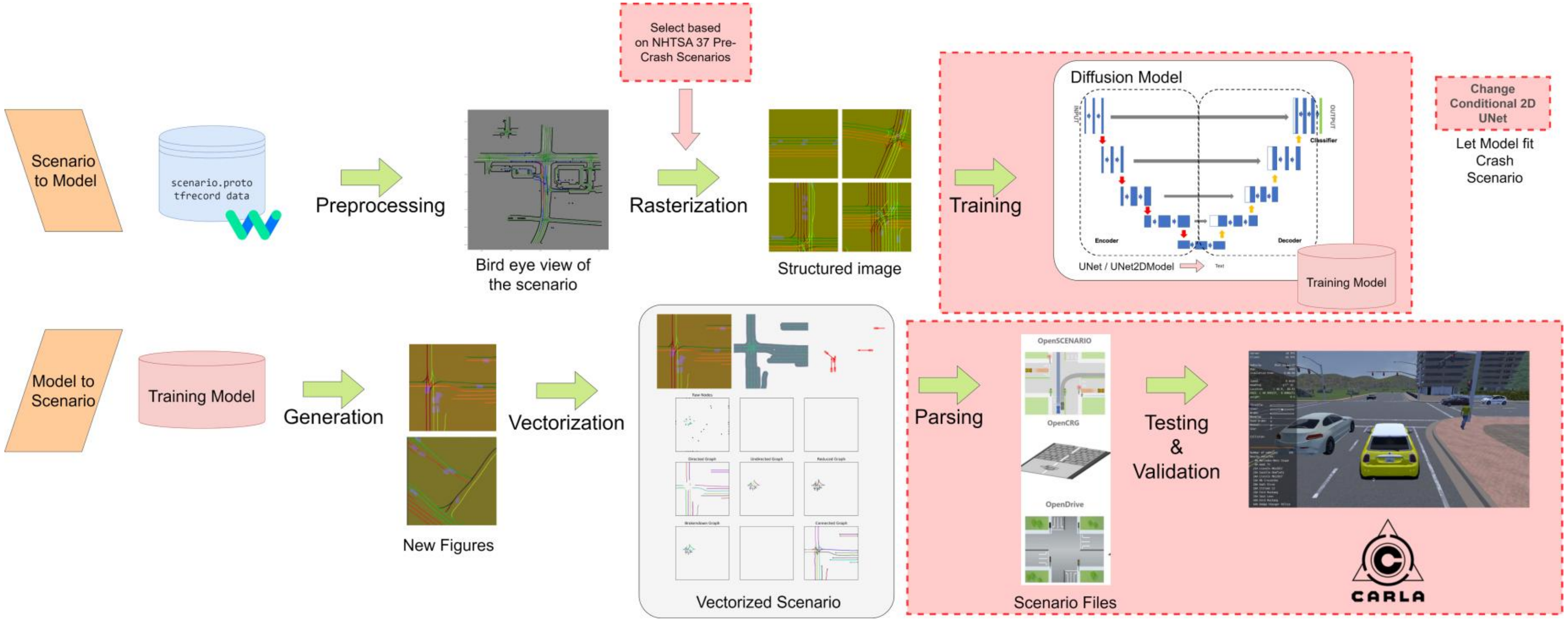
CS329 Machine Learning (H)
Project of Scenario Generation via Diffusion Model

Content



1 **Introduction**

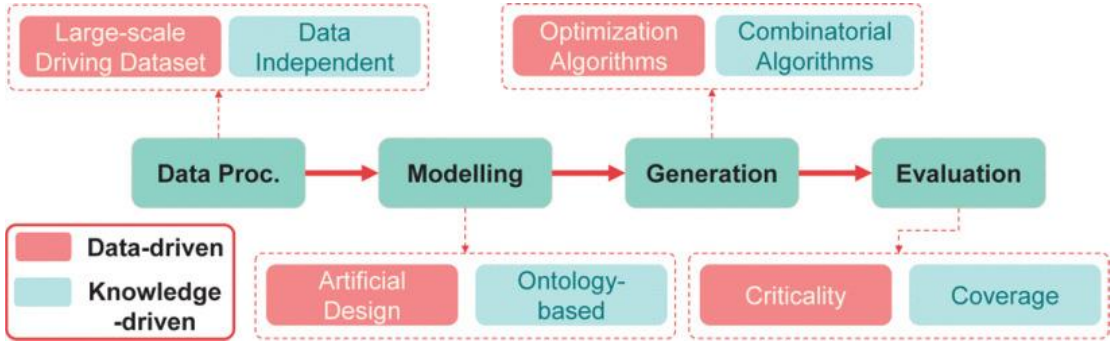
2 **Current Research Status & Motivation**

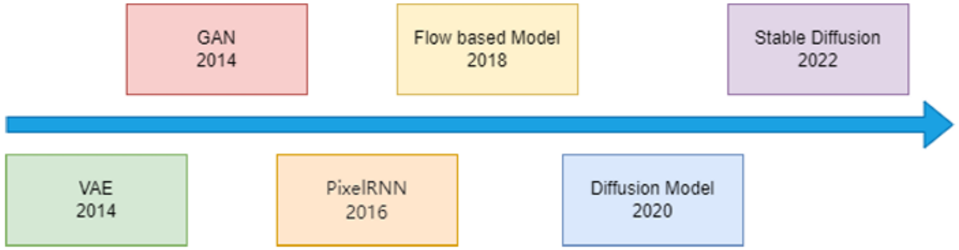
3 CrashSimGen Workflow

4 Methodology and Experiment

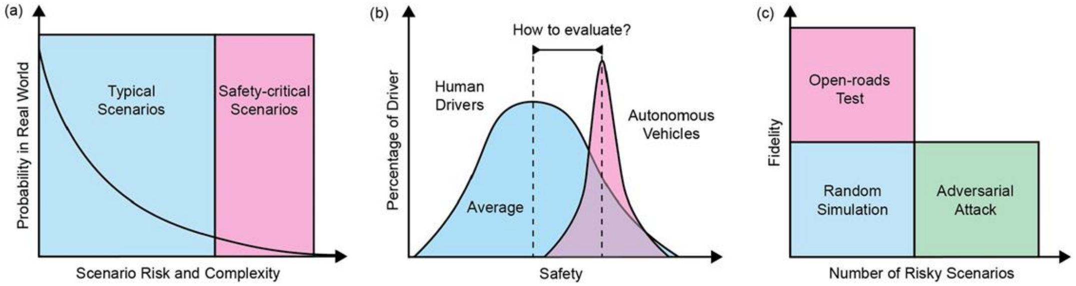
5 Research Plan and Expected Results

Introduction of Critical Scenario and Diffusion Model



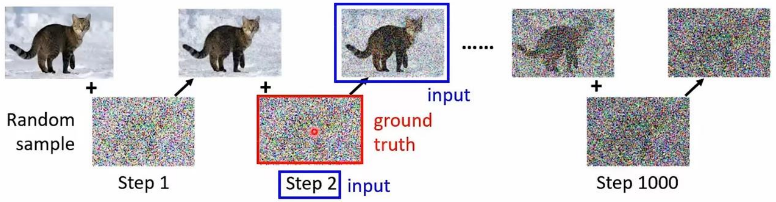


1. Critical Scenario data amount is small
2. Critical Scenario data is important for AV
3. Data-driven Model can generate more critical scenario



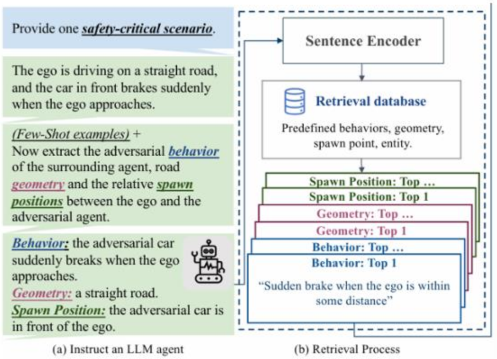
There have been several ways on data-driven critical scenarios generation with the rapid development of Generative Model.

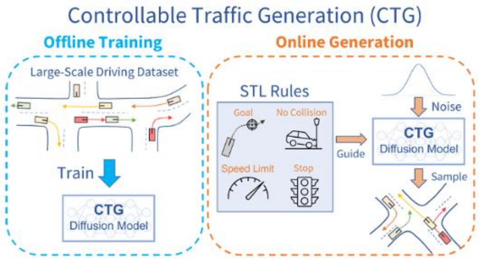
The Most Advance one is **Diffusion Model**

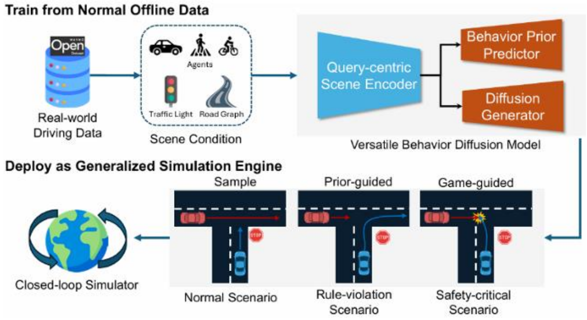


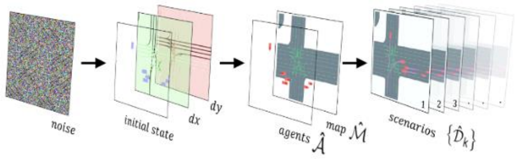
Current Research Status: Diffusion Model

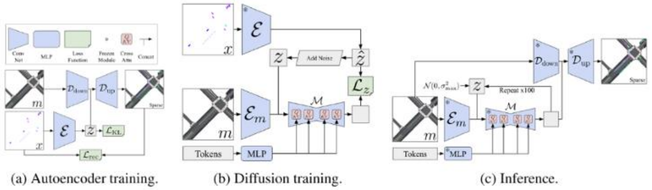
In recent years, generative models like Diffusion Models have gained prominence in critical scenario generation. DriveSceneGen uses a classical diffusion model to generate diverse driving scenarios aligned with real-world data distributions, but most generated scenarios are insufficiently denoised and tend to be too common or trivial. Yang et al. (2024) introduce WCDT, which uses Denoising Diffusion Probabilistic Models (DDPM) enhanced with Transformer (DiT) blocks to generate realistic and diverse trajectories, but their focus is mainly on trajectory generation rather than broader critical scenarios as defined by NHTSA 37. Zhong et al. (2022) offer a controllable and realistic traffic model using diffusion models, but their work is focused on safety scenarios rather than dangerous or high-risk situations.

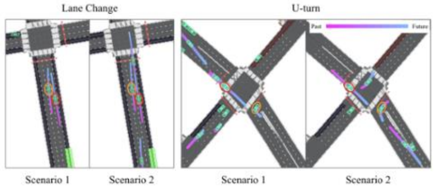








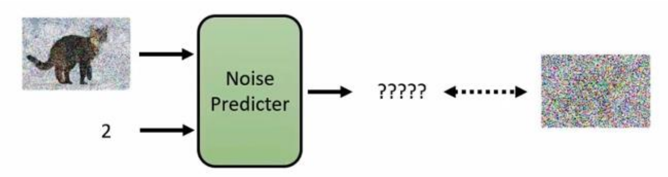


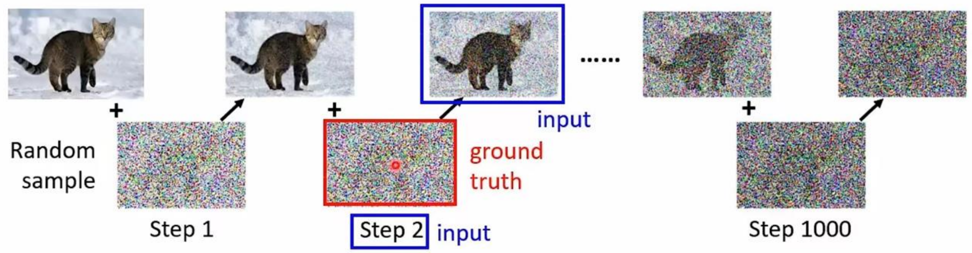


Zhang et al. (2024) leverage the power of Large Language Models (LLMs) to generate safety-critical scenarios for autonomous vehicles, but LLMs require specific instructions and are limited by token constraints, which restricts the variety of generated scenarios compared to real-world complexity. Huang (2024) proposes VBD, which utilizes diffusion generative models to predict scene-consistent, controllable multi-agent interactions in closed-loop settings. Pronovost (2023) combines latent diffusion, object detection, and trajectory regression to generate distributions of agent poses, orientations, and trajectories. While these methods address some aspects of diversity and controllability, challenges remain in denoising and generating truly critical scenarios. Overall, while progress has been made in generating realistic driving and behavioral scenarios, there is still room for improvement in generating complex, high-risk critical scenarios.

Maths Principle of Diffusion Model

Forward Process



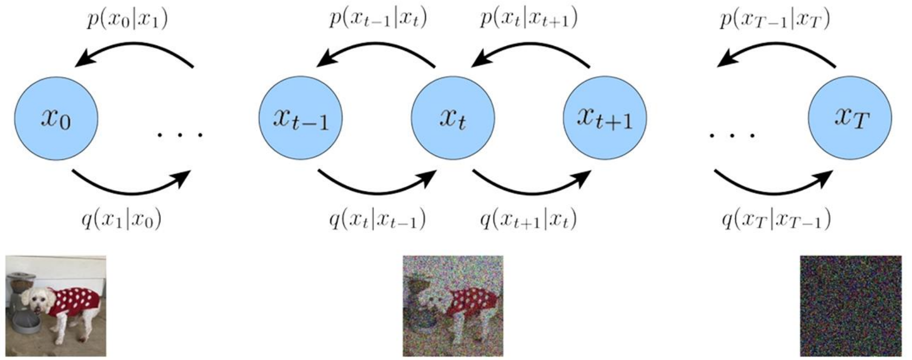


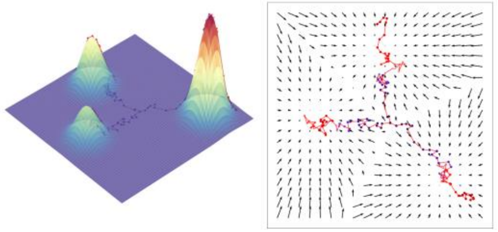
Forward Diffusion Process

$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{1-\beta_t}\mathbf{x}_{t-1}, \beta_t\mathbf{I})$$

Total Forward Process

$$q(\mathbf{x}_T|\mathbf{x}_0) = \prod_{t=1}^{T} q(\mathbf{x}_t|\mathbf{x}_{t-1})$$





Variational Diffusion Models

$$\mathbb{E}_{q_\phi(\boldsymbol{z}_{1:T}|\boldsymbol{x})}\left[\log \frac{p(\boldsymbol{x}, \boldsymbol{z}_{1:T})}{q_\phi(\boldsymbol{z}_{1:T}|\boldsymbol{x})}\right] = \mathbb{E}_{q_\phi(\boldsymbol{z}_{1:T}|\boldsymbol{x})}\left[\log \frac{p(\boldsymbol{z}_T)p_\theta(\boldsymbol{x}|\boldsymbol{z}_1)\prod_{t=2}^{T} p_\theta(\boldsymbol{z}_{t-1}|\boldsymbol{z}_t)}{q_\phi(\boldsymbol{z}_1|\boldsymbol{x})\prod_{t=2}^{T} q_\phi(\boldsymbol{z}_t|\boldsymbol{z}_{t-1})}\right]$$

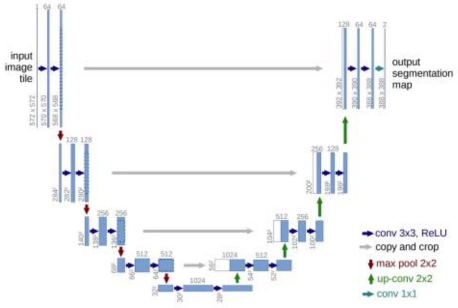
Reverse Process

Learning Process

$$p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \mu_\theta(\mathbf{x}_t, t), \sigma_\theta^2(t)\mathbf{I})$$

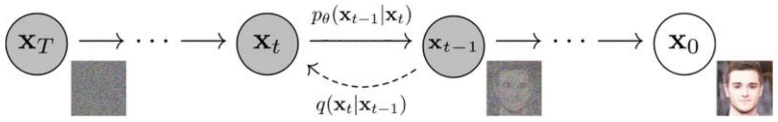
Objective Function

$$L(\theta) = E_{q(\mathbf{x}_0,\mathbf{x}_1,\ldots,\mathbf{x}_T)}\left[\sum_{t=1}^{T} \|\mathbf{x}_t - \hat{\mathbf{x}}_t\|^2\right]$$



Inference Process

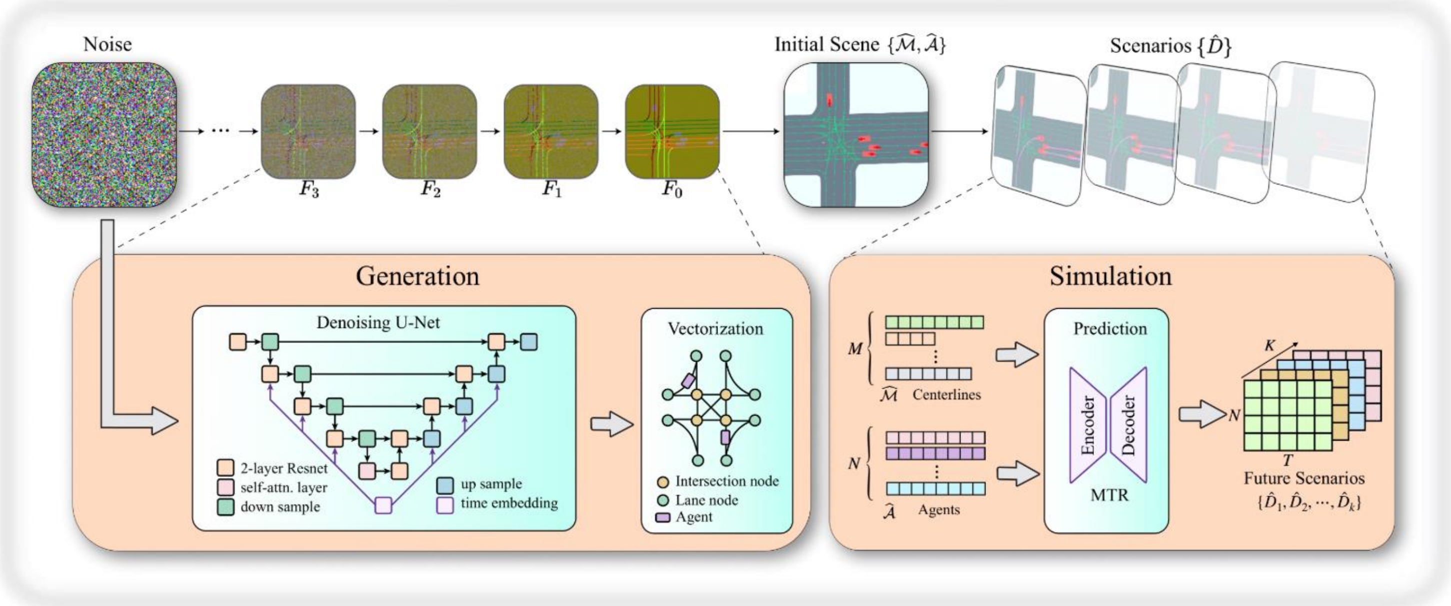
$$\mathbf{x}_{T-1} \sim p_\theta(\mathbf{x}_{T-1}|\mathbf{x}_T)$$

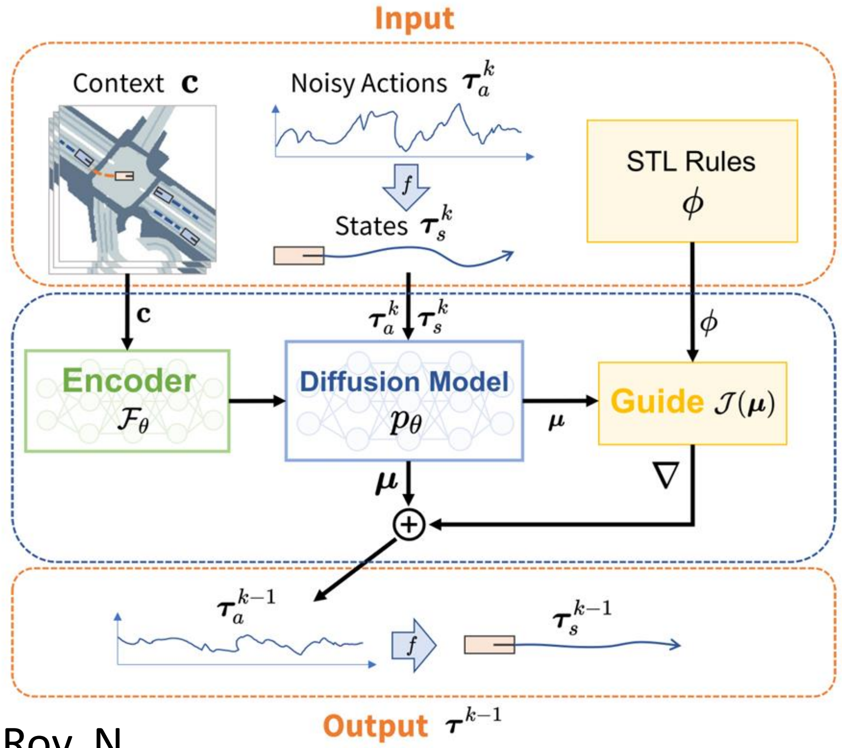


$$\sim \mathcal{N}(\boldsymbol{x}_t; \sqrt{\bar{\alpha}_t}\boldsymbol{x}_0, (1-\bar{\alpha}_t)\mathbf{I})$$

Motivation

- Can we utilize Diffusion Model to generate high quality critical scenario?





Pronovost, E., Reddy Ganesina, M., Hendy, N., Wang, Z., Morales, A., Wang, K., & Roy, N. (2023). Scenario diffusion: Controllable driving scenario generation with diffusion.

Work Flow

CrashSimGen: Generating Dangerous Scenarios with Diffusion Models for self-Driving

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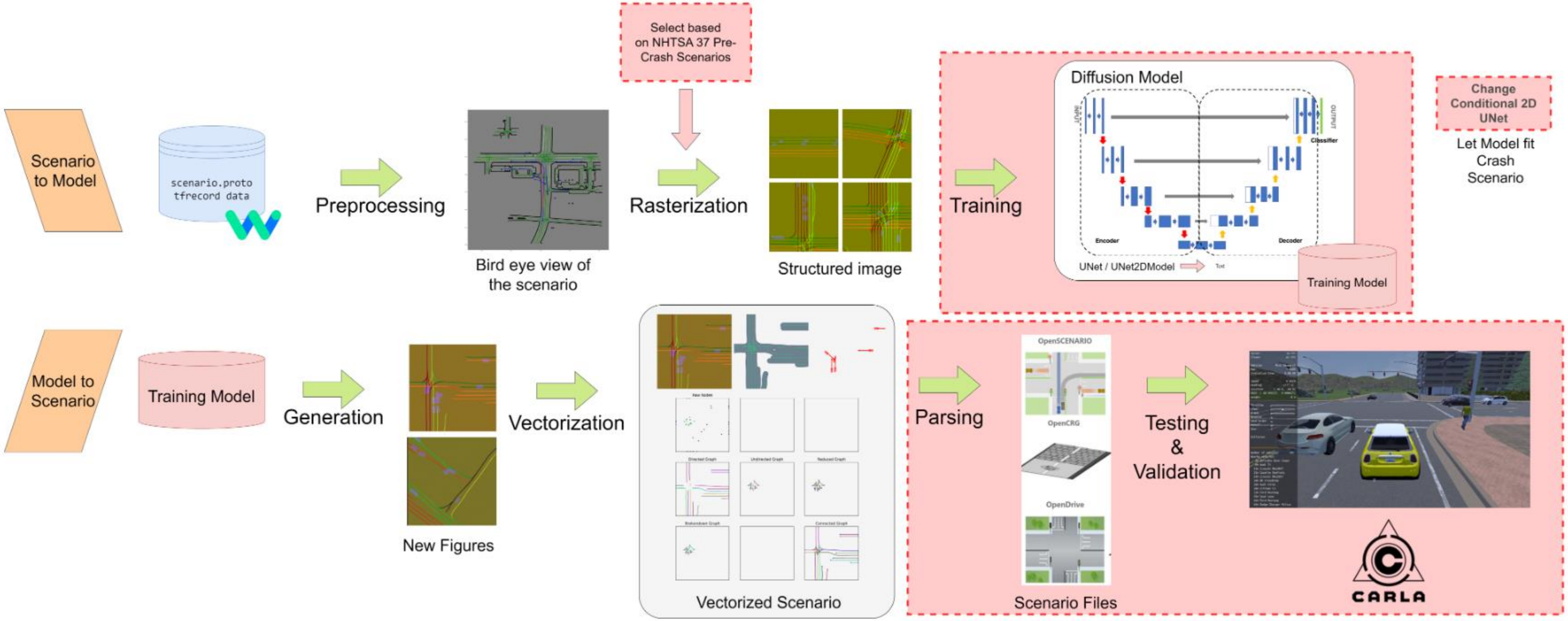


Current Status: What we have done

Done list

Learning:	Diffusion Model Understanding, Principle. ✓	Critical Scenario Generation Understanding. ✓
Summary on privious work	Diffusion Model's Development ✓	Different ~~sta~~ stragies on scenario generation, scoring critical ✓
Running out base line.	work out ~~Run out~~ a model and generate vector file ✓	① parse vector file to opendrive ② load opendrive to Carla. X Not yet.
Tuning.	① Select a better dataset with a recognition model X ② improve UNet Model with LDM X Working	③ ① Select good algorithm run on Carla Working

Current Status: What we have done

- Dataset Acquisition
- Data preprocessing

TensorFlow

- Model Training

PyTorch

- Model Inference

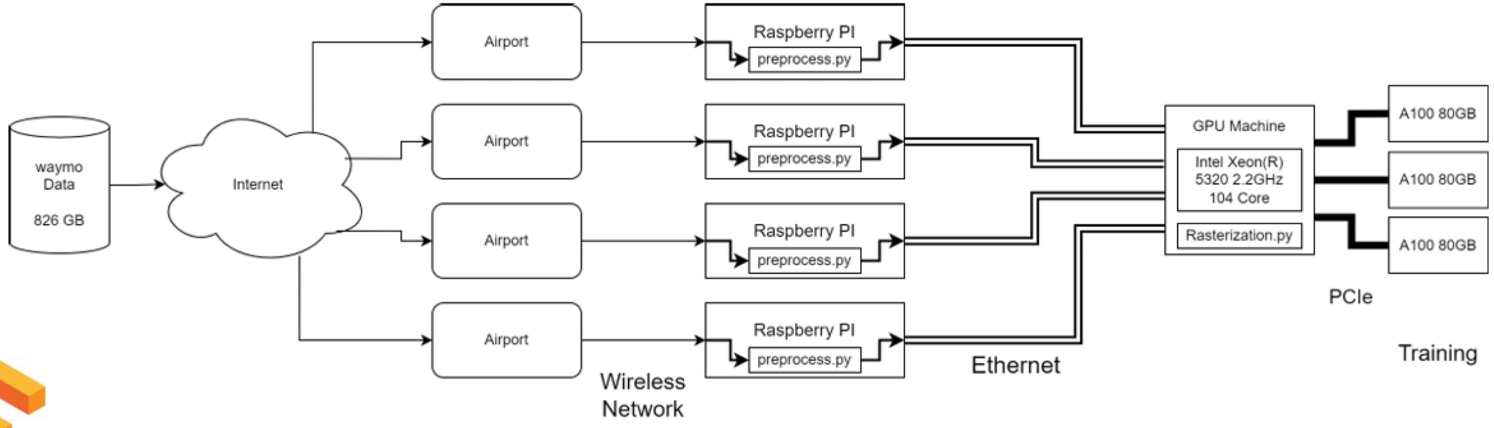
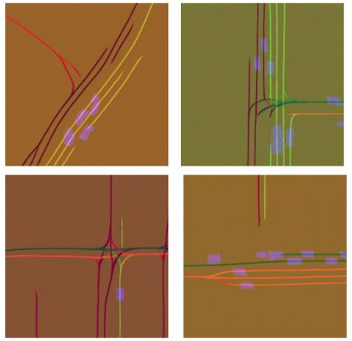
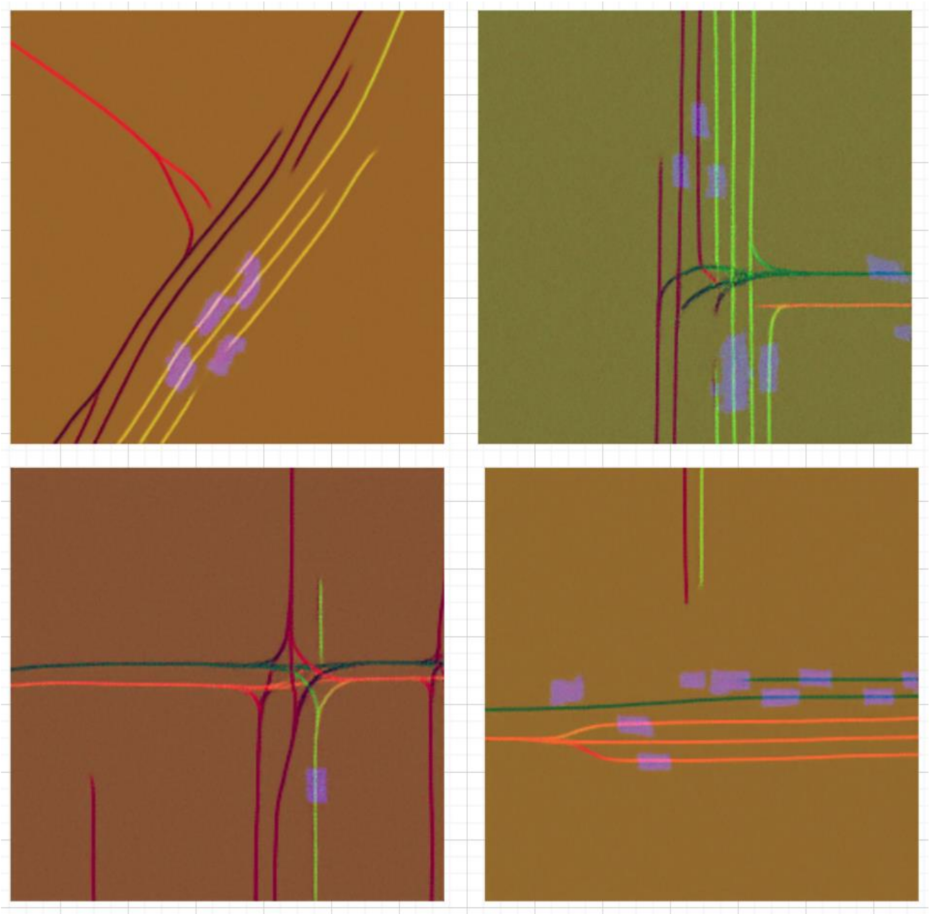
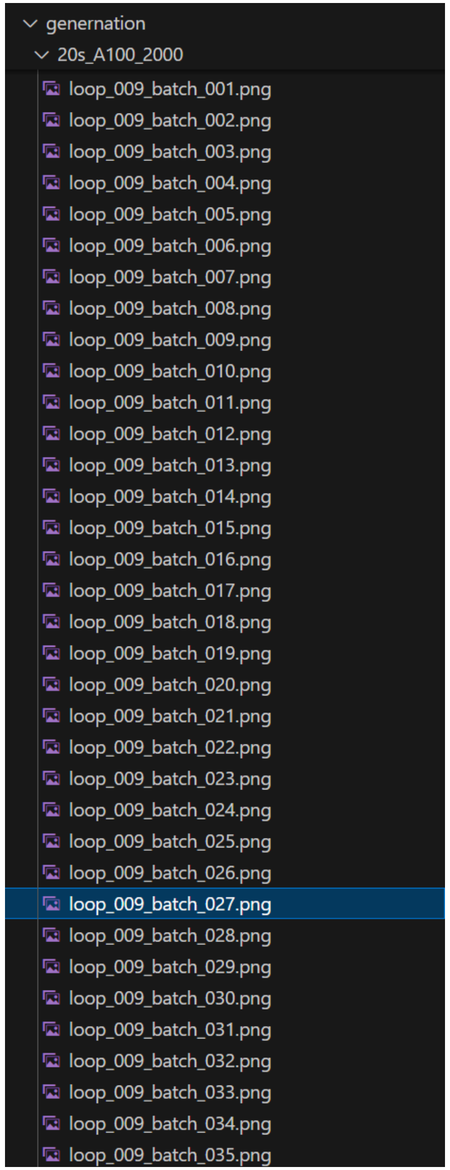


Figure 12: Our High Performance Cluster

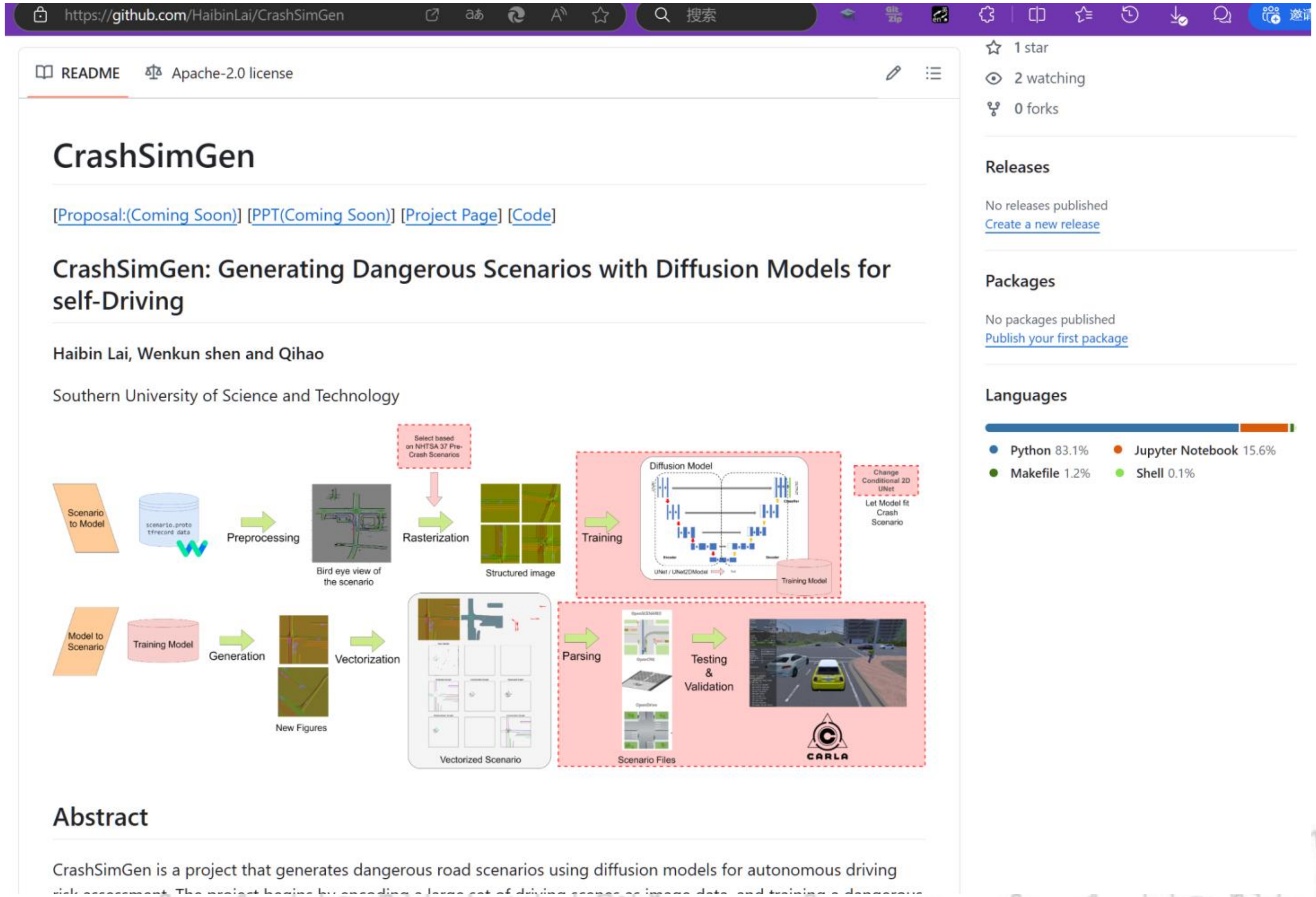


Model Generation Result





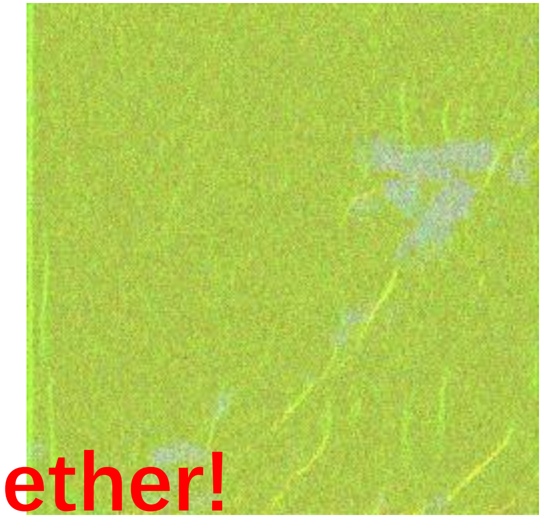
Project Github &Website



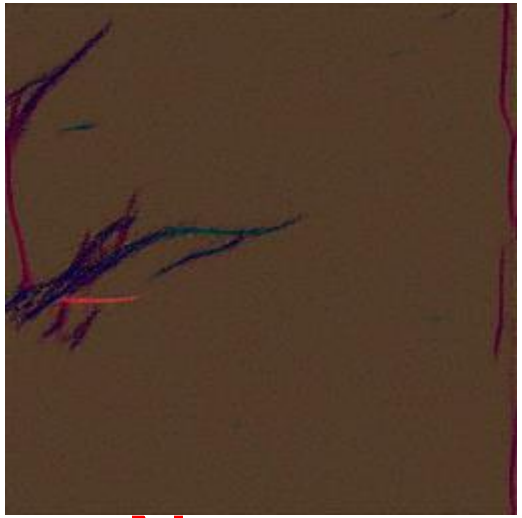
https://github.com/HaibinLai/CrashSimGen.git

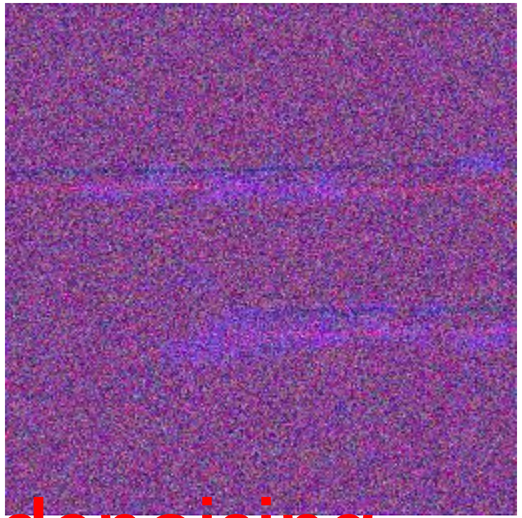
[CrashSimGen | Source code of our project: Generating Dangerous Road Scenarios with Diffusion Models for Autonomous Driving Risk Assessment]()

Bad generation …

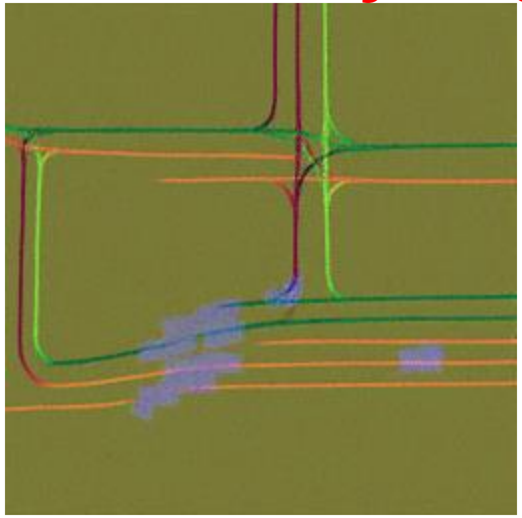


Cars all stay together!

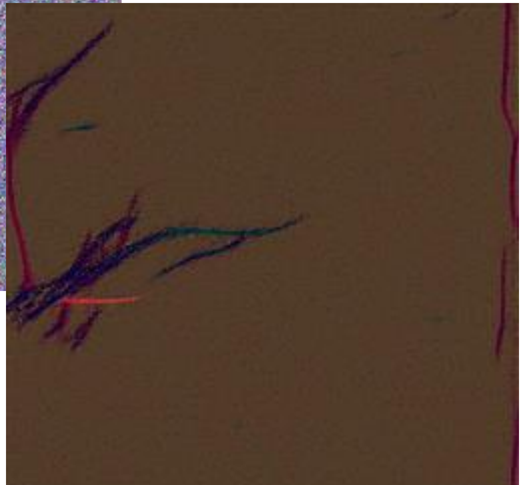




Not enough denoising and training iteration!



Bad Road Generation



Improvement: 2 stage

6 Research Plan and Expected Results

Primary Step

In this step, We expected to transform the driving figures into driving scenarios. We will test the scenarios in the Carla simulator platform and we expect these scenarios generated by our model can successfully pass the test.

Level Up

In this step, We will select the dangerous scenarios from the dataset and use these data to train the LDM(Latent Diffusion Model).

Potential Challenges

Security assessment	Limitations of computing resources and Storage cost	Image recognition accuracy
There are no reference standards available	Requires a large amount of computing resources	May not have completed denoising

Project Scheduling

Week14	Transform the figures into scenarios
Week15	Test in the Carla simulation platform
Week16	Select dataset and retrain model

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