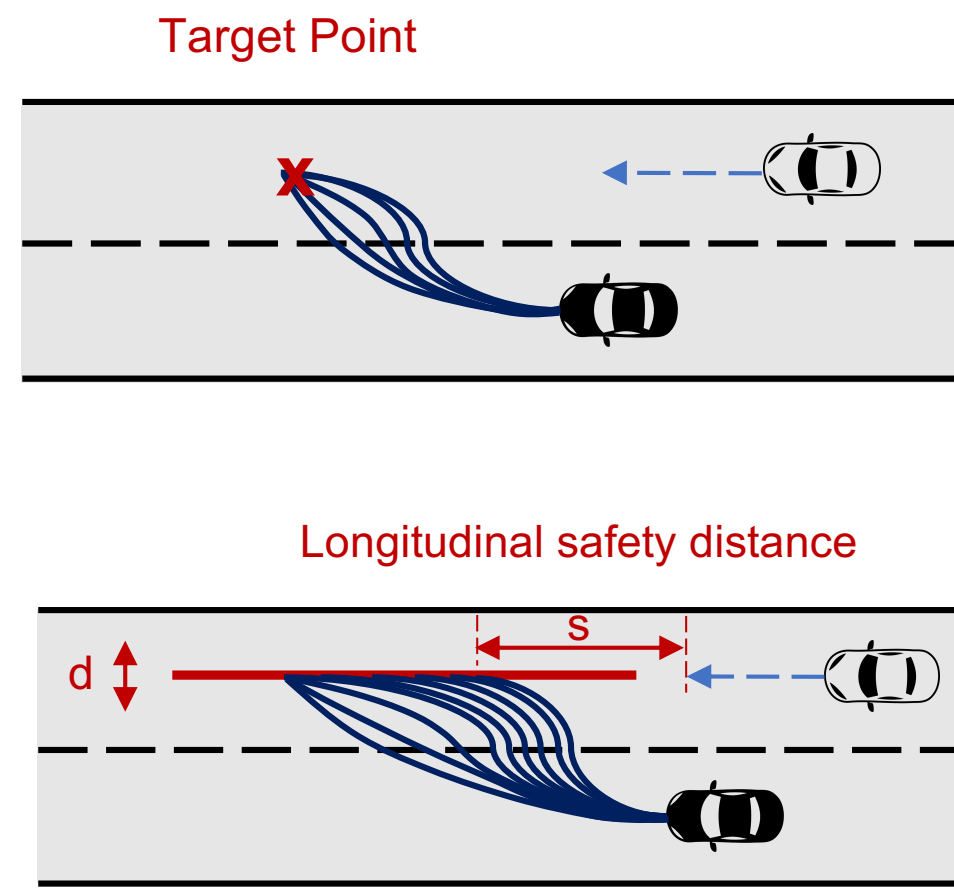


Motivation

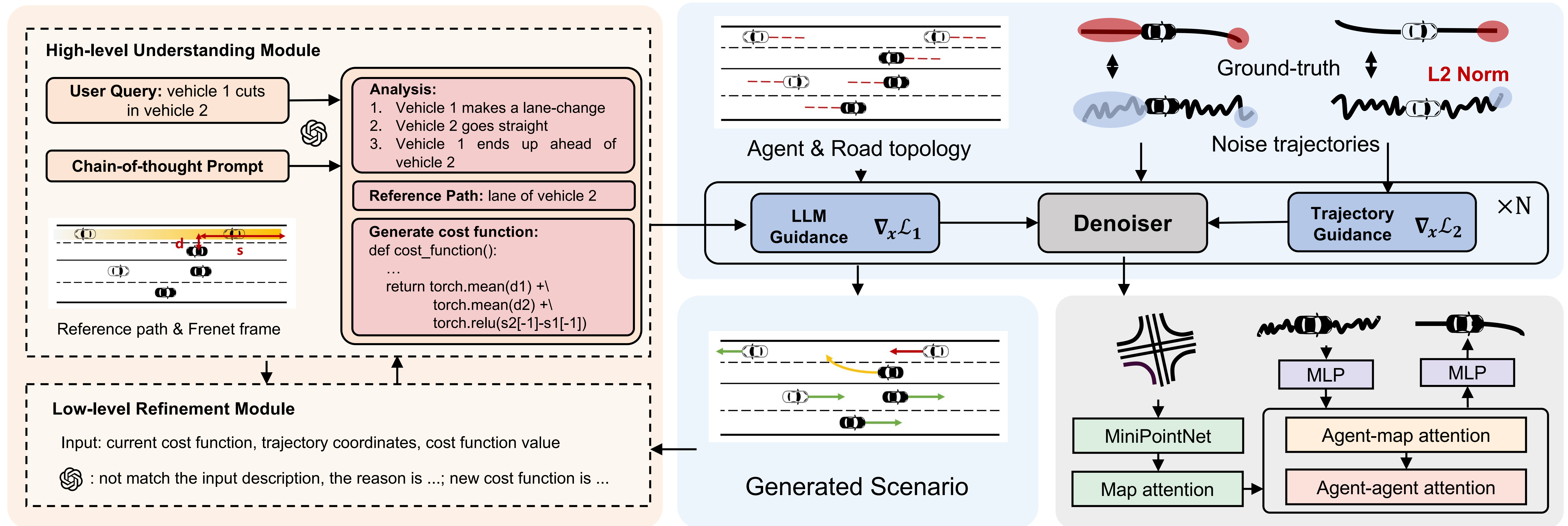
- Current simulation methods, constrained by fixed rules, exhibit **poor generality** when adapting to novel traffic conditions.
- Existing text-conditioned models **struggle with complex scene descriptions**.
- Utilize **diffusion test-time guidance** coupled with **LLM-driven reasoning** and a specialized **cost function formulation** to effectively interpret complex textual scene descriptions.
- Further inject diverse temporal contexts for various simulation tasks.



Contribution

- We propose a novel LLM-based framework designed to **interpret complex traffic scenarios** and **generate precise cost functions**, enabling more accurate and reliable traffic simulation.
- We innovatively address the effectiveness of **Frenet coordinate system** in traffic simulation domain, significantly enhancing the generative capabilities of LLMs and improving the success rate of diffusion-guided scenario generation.
- Through extensive experiments, we demonstrate that our method can handle **more intricate scenario descriptions** and generate **a wider variety of traffic scenarios** in a controllable manner, including complex interactions and accident simulations.

Methodology



Experiment Result

Evaluation of Methods for Translating Scene Constraints into Cost Functions

Category	Description	CTG++	Scene Diffuser	Ours w/o understanding	Ours zero-shot CoT	Ours w/o Frenet	Ours
Basic rules	vehicle drives at a speed limit 10m/s	✓	✓	✓	✓	✓	✓
	vehicle reaches target point (25, 25)	✓	✓	✓	✓	✓	✓
	no collisions between all vehicles	✓	✓	✓	✓	✓	✓
Behavior and interactions	vehicle makes a left-lane-change	✓		✓	✓	✓	✓
	vehicle moves to the rightmost lane		✓		✓	✓	✓
	vehicle 1 cuts in vehicle 2				✓	✓	✓
Abnormal behaviors	vehicle drives in reverse			✓			✓
	vehicle drives out of the road						✓
	vehicle drives left and right within the lane		✓				✓

Traffic Simulation Results

Method	ADE (m) ↓	FDE (m) ↓	JSD ($\times 10^{-2}$) ↓	Collision (%) ↓	Off Road (%) ↓
Actions-Only [38]	4.81	11.89	10.4	19.9	27.6
DT [39]	1.56	3.07	8.4	5.3	11.0
CtRL-Sim [9]	1.25	2.04	7.9	5.3	11.0
CTG++ [15]	1.73	4.02	7.4	5.9	15.0
Ours	1.17	1.93	8.2	5.1	12.8

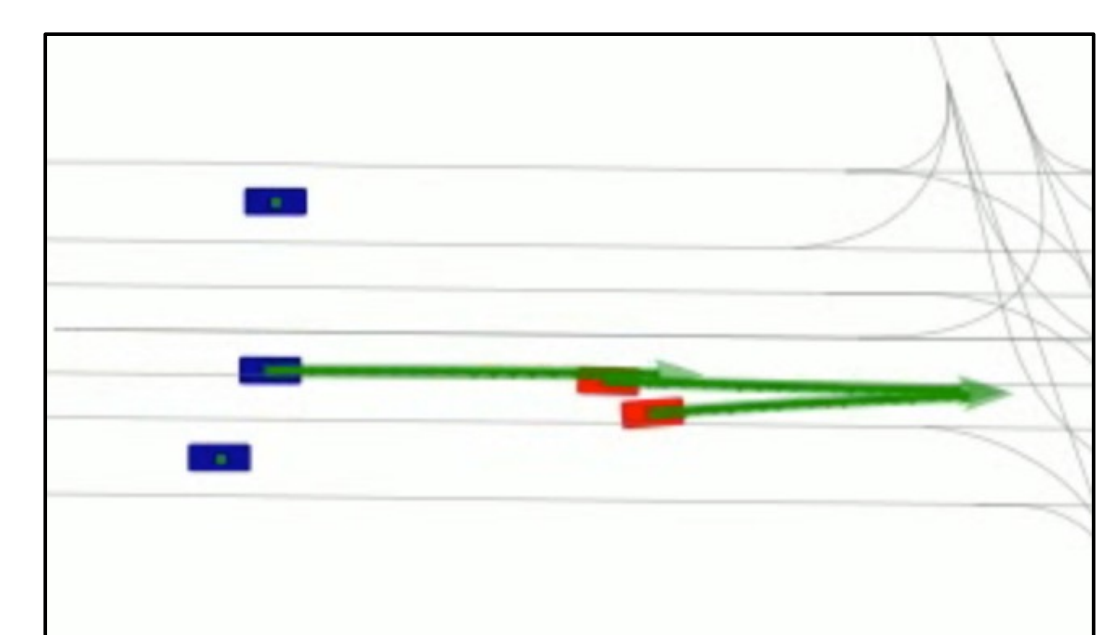
Success Rate of Diffusion Guidance under Typical Traffic Conditions

Scenario Type	Scene Diffuser	Ours w/o Refine	Ours w/ Refine
Cut in	0.45	0.65	0.85
Out of road	-	0.70	0.90
Yield	0.40	0.70	0.85
Rightmost	-	0.75	0.95

Generated Accidents



Collision during turning



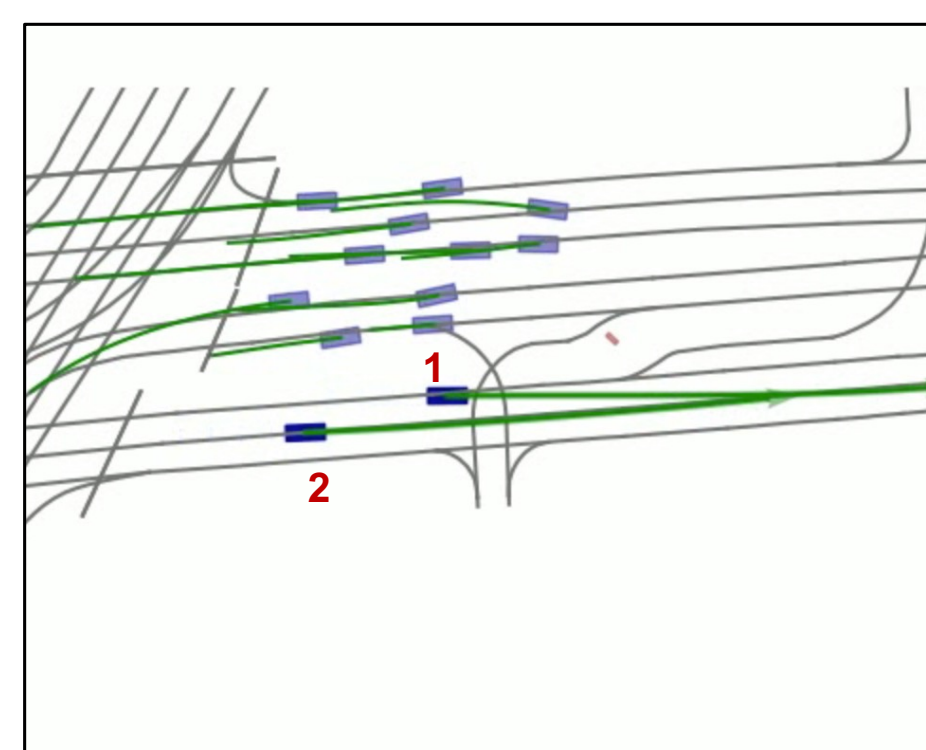
Collision during lane change

GPT solution

Analysis: Single event
1. vehicle 1 makes a right-lane-change
2. vehicle 2 moves straight and keep distance to vehicle 1

Search Reference Path:
Vehicle 1 & 2 : lane of vehicle 2

Cost functions:
Vehicle 1: $\mathcal{L}_1 = \sum |d_{1,x}|$
Vehicle 2: $\mathcal{L}_2 = \sum |d_{2,x}| + ReLU(s_{1,x} - s_{2,x})$

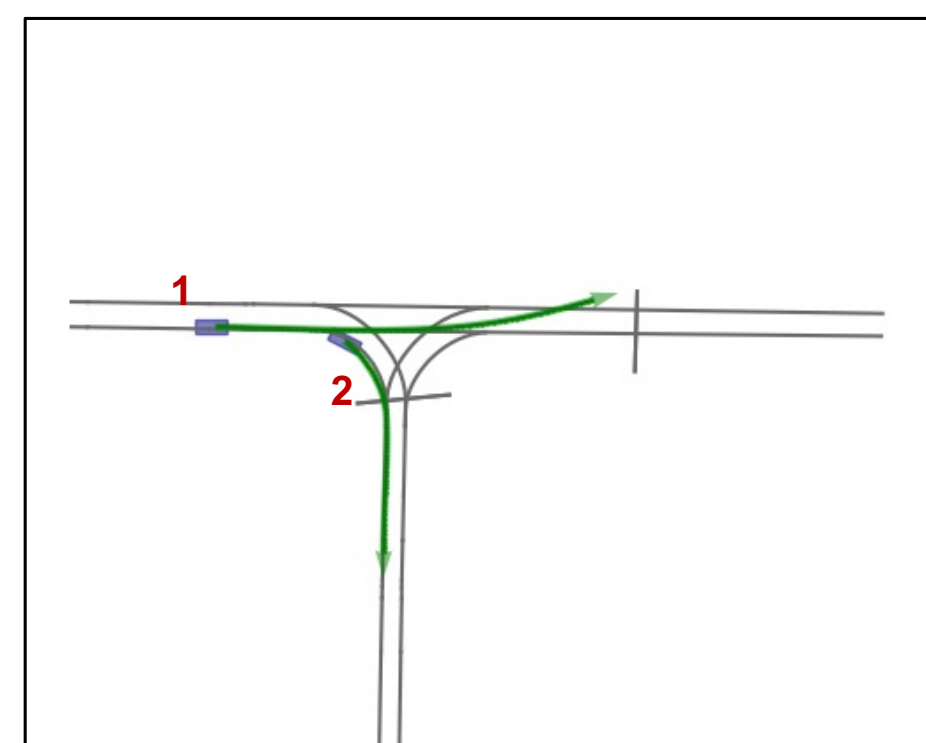


GPT solution

Analysis: Multiple events
1. vehicle 1 drives in reverse
2. vehicle 1 drives out of road
3. vehicle 2 turns right

Search Reference Path:
Vehicle 1: the leftmost lane
Vehicle 2: the right turn lane

Cost functions:
Vehicle 1: $\mathcal{L}_1 = \sum ReLU(-d_{1,x})$ (positive d is left side)
Vehicle 2: $\mathcal{L}_2 = \sum |d_{2,x}| + ReLU(s_{1,x} - s_{2,x})$ (reverse)

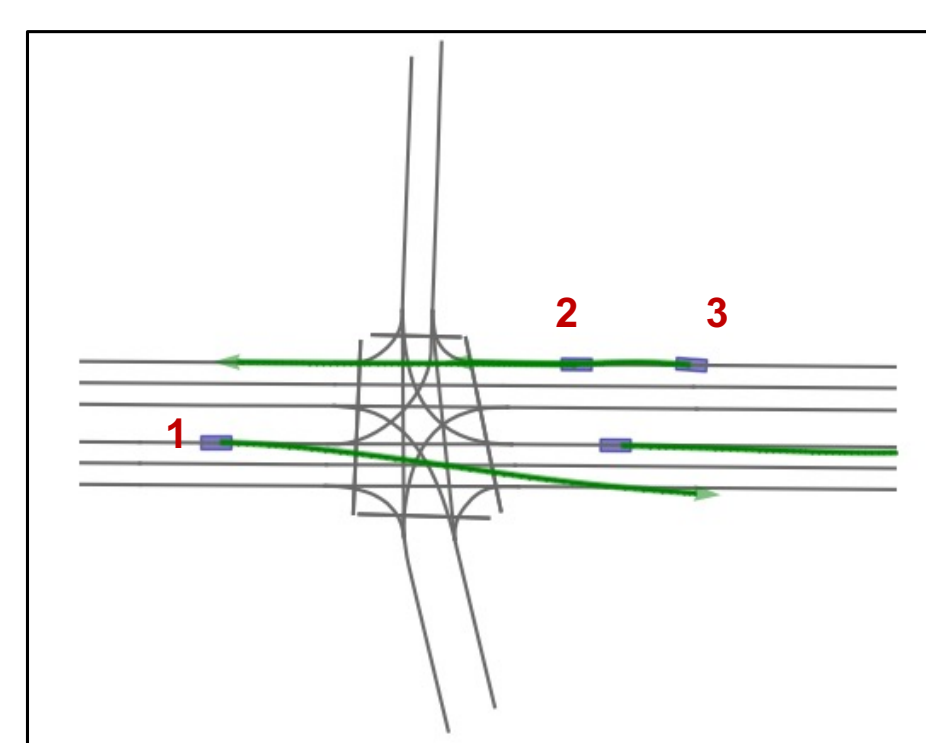


GPT solution

Analysis: Multiple events
1. vehicle 1 moves to the rightmost
2. vehicle 2 moves straight
3. vehicle 3 moves straight and keeps a distance to vehicle 2

Search Reference Path:
Vehicle 1: the rightmost lane
Vehicle 2 & 3: their current lane

Cost functions:
Vehicle 1: $\mathcal{L}_1 = \sum |d_{1,x}|$
Vehicle 2: $\mathcal{L}_2 = \sum |d_{2,x}|$
Vehicle 3: $\mathcal{L}_3 = \sum |d_{3,x}| + ReLU(s_{2,x} - s_{3,x})$



GPT solution

Analysis: Multiple events
1. vehicle 1 drives left and right within its lane
2. vehicle 2 keeps straight and keeps distance to vehicle 1

Search Reference Path:
Vehicle 1 & 2 : their current lanes

Cost functions:
Vehicle 1: $\mathcal{L}_1 = \sum |d_{1,x}| + \sin(kt) - d_{1,x}$
Vehicle 2: $\mathcal{L}_2 = \sum |d_{2,x}| + ReLU(s_{1,x} - s_{2,x})$

