SAH-Drive: A Scenario-Aware Hybrid Planner for Closed-Loop Vehicle Trajectory Generation

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Motivation

Reliable planning is crucial for achieving autonomous driving. Trajectory planning primarily involves two types of algorithms: learning-based algorithms and rule-based algorithms.

Characteristic

Rule-based algorithm:
- High interpretability
- Robust within defined scenarios
- Computationally efficient
- Poor generalization
- Limited scenario coverage

Learning-based algorithm:
- Strong generalization ability
- Capable of modeling complex behaviors
- Low interpretability
- High computational cost
- Strong dependency on large-scale data

Applicable to

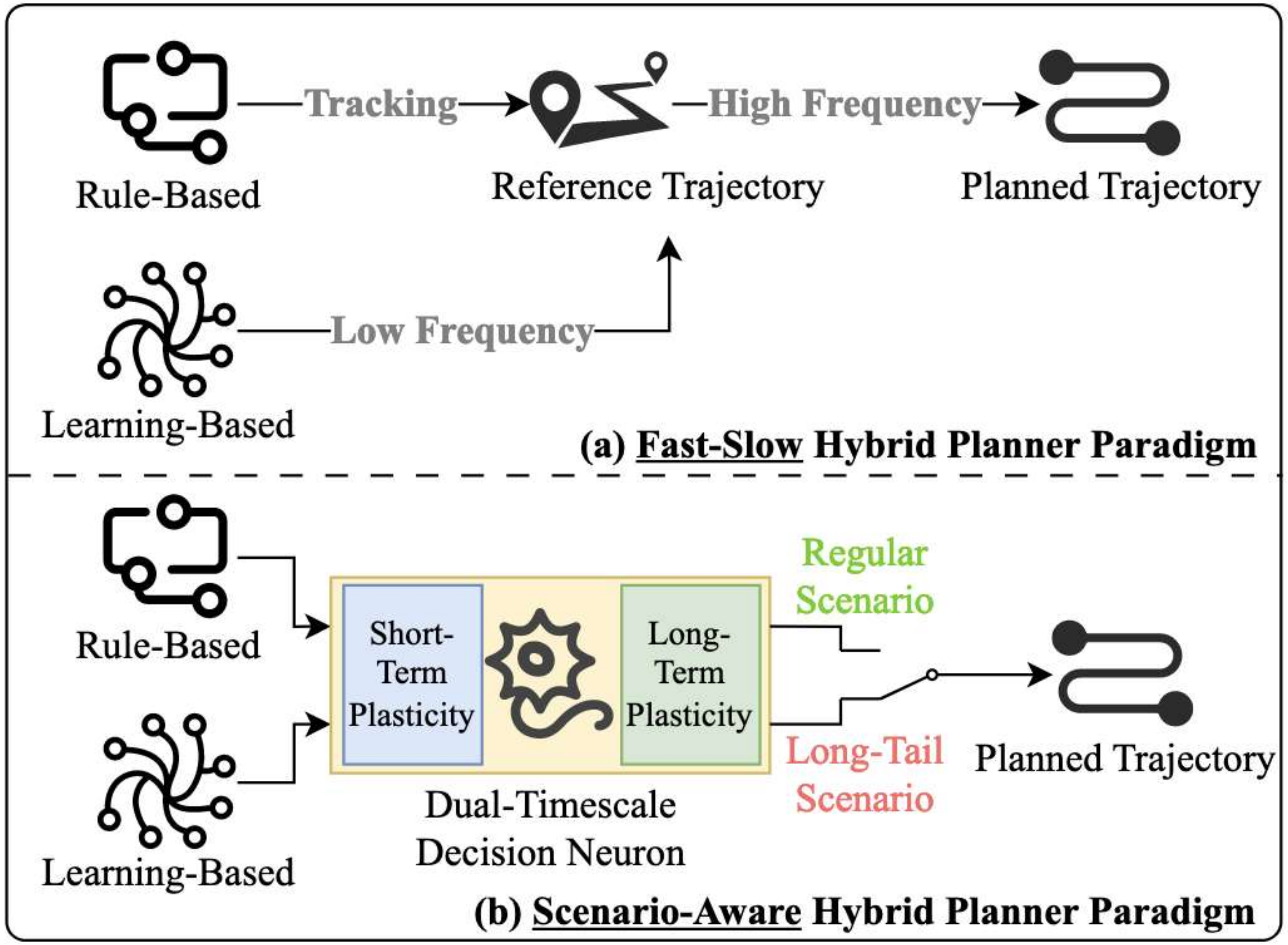
- simple, regular scenarios
- the majority of the driving process

- complex long-tail scenarios
- Rarely occur during driving

Problem

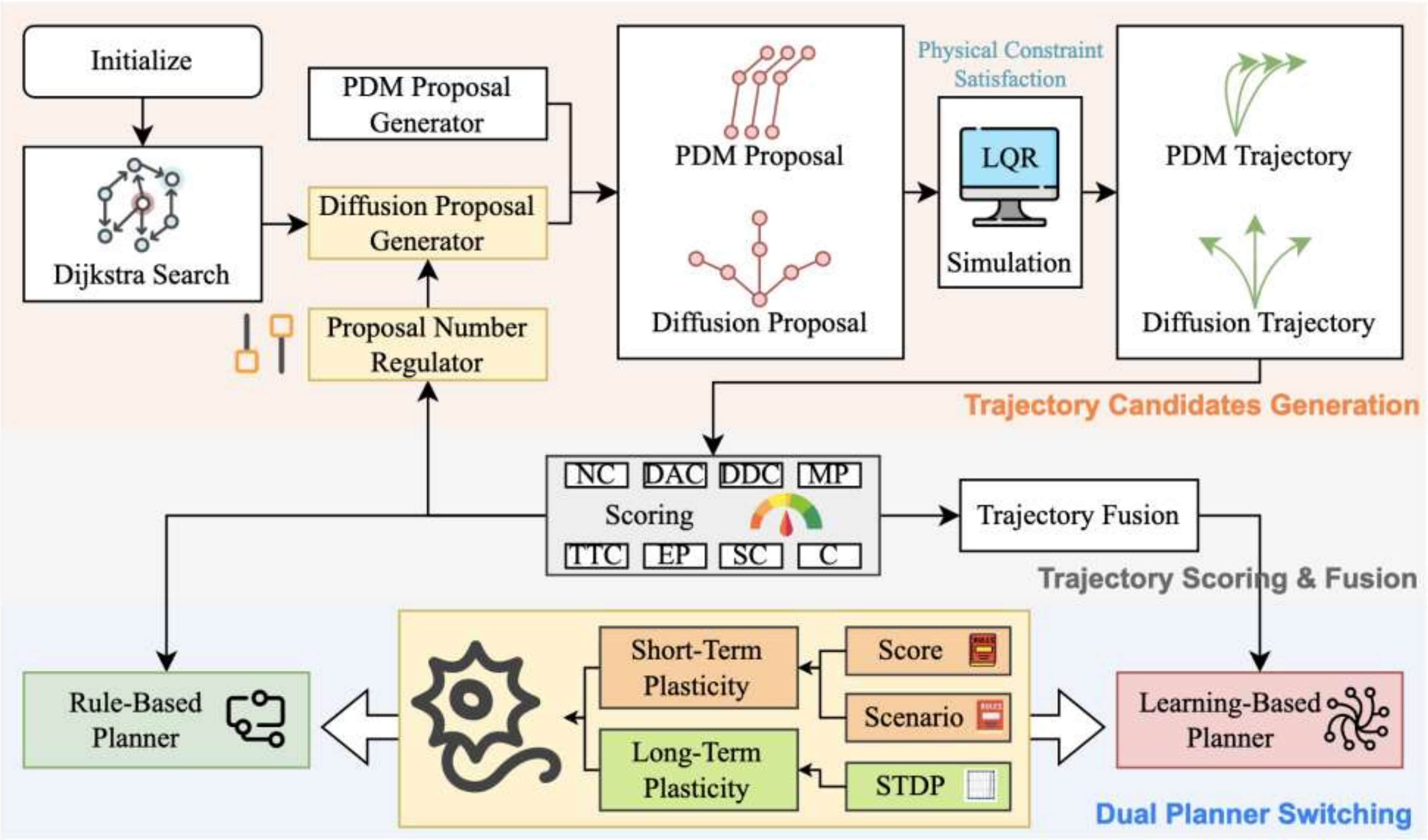
How to combine the advantages of rule-based and learning-based planners based on their characteristics and applicability?

Introduction



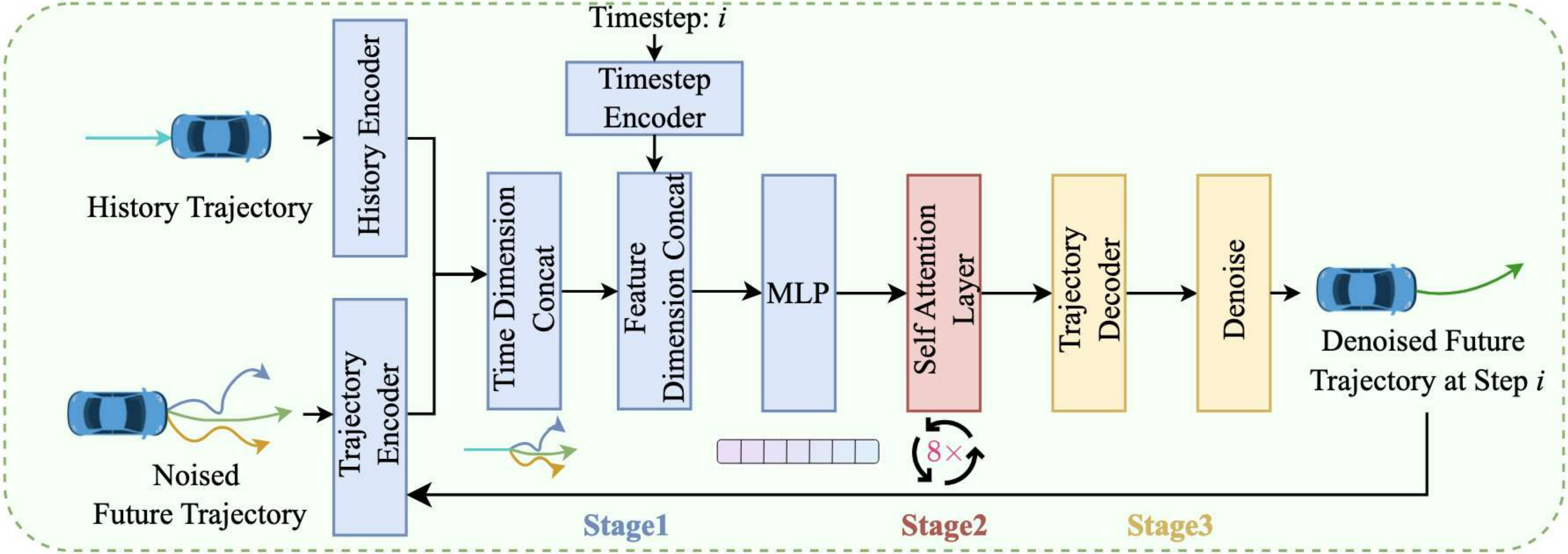
- **Traditional fast-slow hybrid planner paradigm** ignores the scenario differences, and the learning-based planner serves merely as guidance.
- **Human driving** is **effortless** in regular situations but becomes **cognitively demanding** and multimodal in complex long-tail scenarios.
- **Scenario-aware hybrid planner paradigm** mimics human neural mechanisms by comprehensively combining both types of planners, enhancing generalization for long-tail scenarios while maintaining high efficiency in regular scenarios.

Method



Initialize
Dijkstra Search
PDM Proposal Generator
Diffusion Proposal Generator
Proposal Number Regulator
PDM Proposal
Diffusion Proposal
Physical Constraint Satisfaction
LQR
Simulation
PDM Trajectory
Diffusion Trajectory
Trajectory Candidates Generation
NC
DAC
DDC
MP
Scoring
TTC
EP
SC
C
Trajectory Fusion
Trajectory Scoring & Fusion
Short-Term Plasticity
Long-Term Plasticity
Score
Scenario
STDP
Rule-Based Planner
Learning-Based Planner
Dual Planner Switching

Method

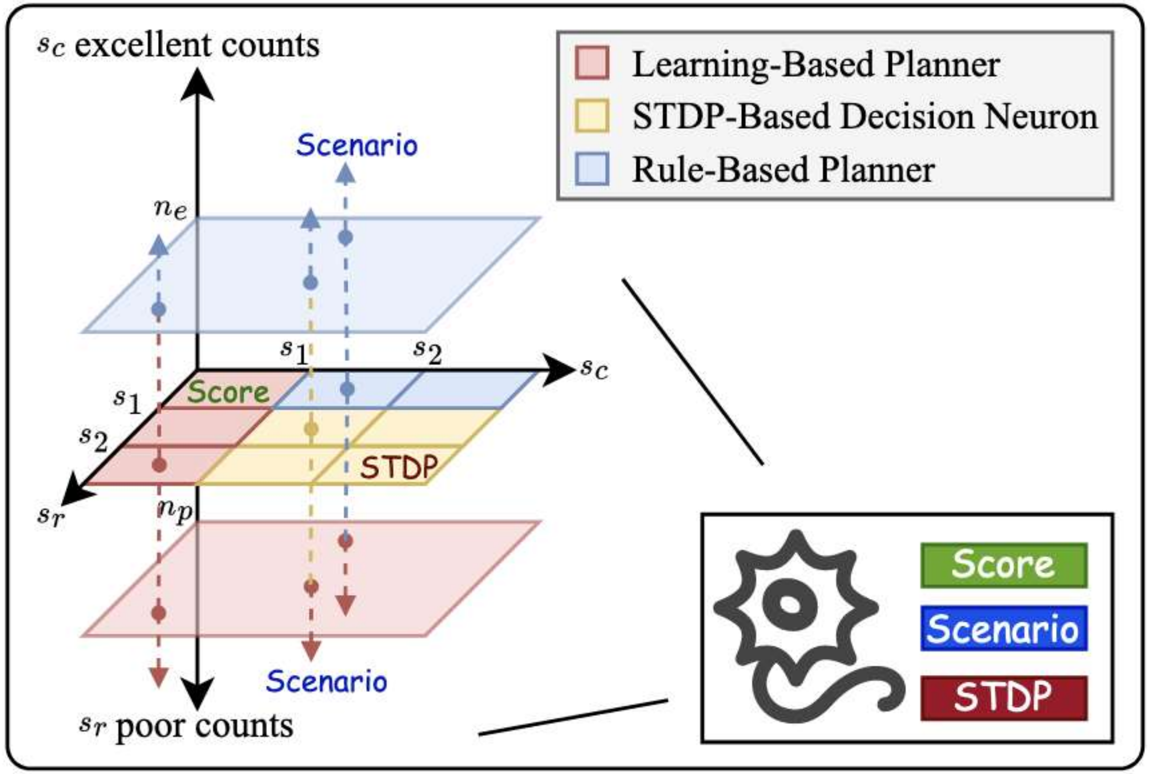


Feature Fusion

Self-Attention Fusion

Decoding and Denoising

Method



Algorithm 1 Planner Selection Using Dual-Timescale Decision Neuron

Require: Rule-based planner score s_c, Learning-based planner score s_r

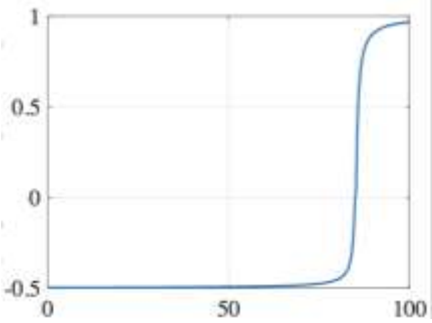
Ensure: Selected planner

1: Update weights w_r and w_c using Equation (5)
2: Update consecutive counts n_e and n_p
3: category $\leftarrow$ decision_space(s_r, s_c, n_e, n_p)
4: **if** category = score **then**
5: planner $\leftarrow$ score_rule(s_r, s_c)
6: **else if** category = scenario **then**
7: planner $\leftarrow$ scenario_rule(n_e, n_p)
8: **else**
9: planner $\leftarrow$ STDP_neuron(w_r, w_c)
10: **end if**
11: **return** planner

Score Rule: Set thresholds to classify trajectories into three categories and directly assign a planner based on the category.

Scenario Rule: Determine planner type based on its consecutive count.

STDP Neuron



$$\Delta w = \begin{cases} A^+ \cdot e^{-\frac{1}{(s_{\text{pre}}-s_{\text{post}})\tau^+}} & \text{if } s_{\text{post}} < s_{\text{pre}} \quad \text{(LTP)} \\ -A^- \cdot e^{\frac{1}{(s_{\text{pre}}-s_{\text{post}})\tau^-}} & \text{if } s_{\text{pre}} < s_{\text{post}} \quad \text{(LTD)} \end{cases}$$

Determine the planner based on connection strength.

Method

□ Proposal Number Regulator

To improve planning efficiency, we implemented a dynamic proposal number regulator that adaptively adjusts the number of diffusion proposals in real-time based on the highest diffusion trajectory score.

$$N' = \begin{cases} \frac{N}{2}, & s_{\text{diff}} > \tau, \\ 2N, & s_{\text{diff}} < \tau. \end{cases} \qquad N' = \max(N_{\min}, \min(N', N_{\max}))$$

□ Trajectory Fusion for the Learning-Based Planner

To mitigate the risk of excessively aggressive diffusion trajectories, which could pose high driving risks to the ego vehicle, we propose to fuse the highest-scoring diffusion trajectory with the highest-scoring PDM trajectory.

$$p_{\text{fused}} = \frac{e^{\alpha(s_{\text{PDM}} - s_{\max})} p_{\text{PDM}} + e^{\alpha(s_{\text{diff}} - s_{\max})} p_{\text{diff}}}{e^{\alpha(s_{\text{PDM}} - s_{\max})} + e^{\alpha(s_{\text{diff}} - s_{\max})}}$$

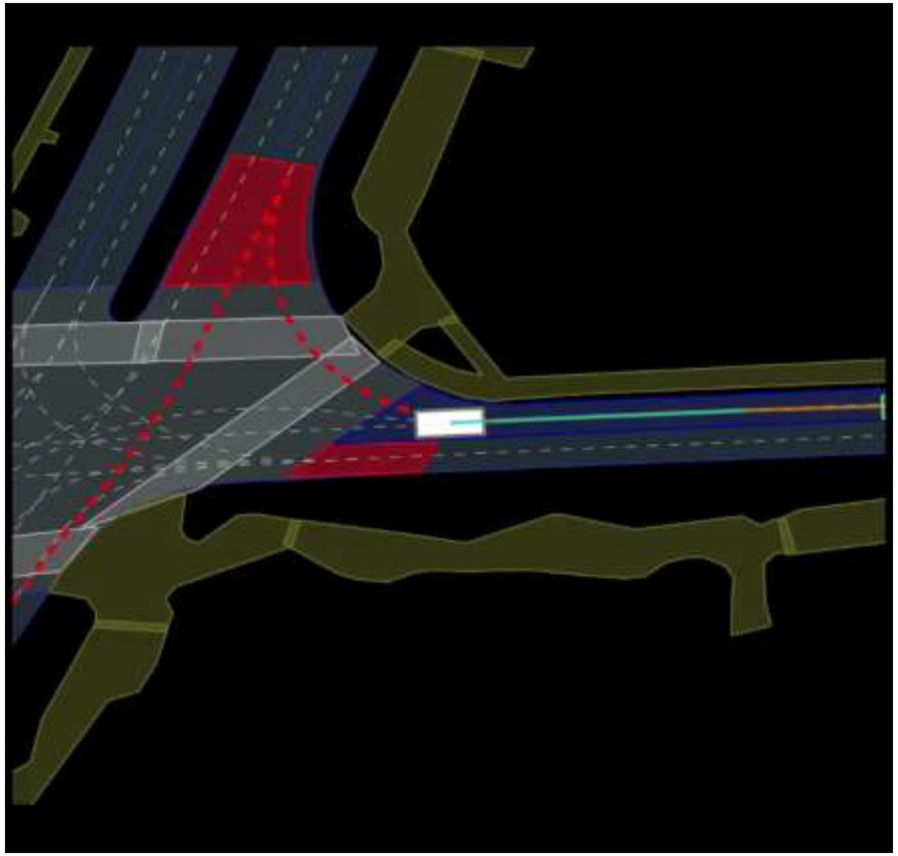
Experiment

	Planner	Type	interPlan	Constr.	Acc.	Jayw.	Nudge	Overt.	LTD	MTD	HTD
SOTA	PDM-Closed (CoRL 2023)	Rule	42	18	0	48	74	9	62	62	62
	STR2 (arxiv 2024)	Learning	46	/	/	/	/	/	/	/	/
	HybridLLMPlanner (IROS 2024)	Hybrid	53	27	20	48	**93**	28	**81**	48	**80**
	Diffusion-ES (CVPR 2024)	Learning	57	71	**51**	13	88	52	61	58	61
	PlanTF (ICRA 2024)	Learning	33	9	0	33	49	9	50	40	73
	Pluto (arxiv 2024)	Learning	48	54	9	56	82	17	47	47	68
	Diffusion Planner (ICLR 2025)	Learning	24	17	0	7	70	15	41	22	17
	SAH-Drive (Ours)	Hybrid	**64**	**72**	44	47	80	**78**	64	**63**	63
Suboptimal	Urban Driver (CoRL 2022)	Learning	4	0	0	0	0	0	0	29	0
	GameFormer (ICCV 2023)	Learning	11	0	0	48	0	0	0	20	21
	DTPP (ICRA 2024)	Learning	25	18	18	44	10	0	40	36	34
	IDM (Phys. Rev. E)	Rule	31	0	0	**66**	0	0	61	61	61

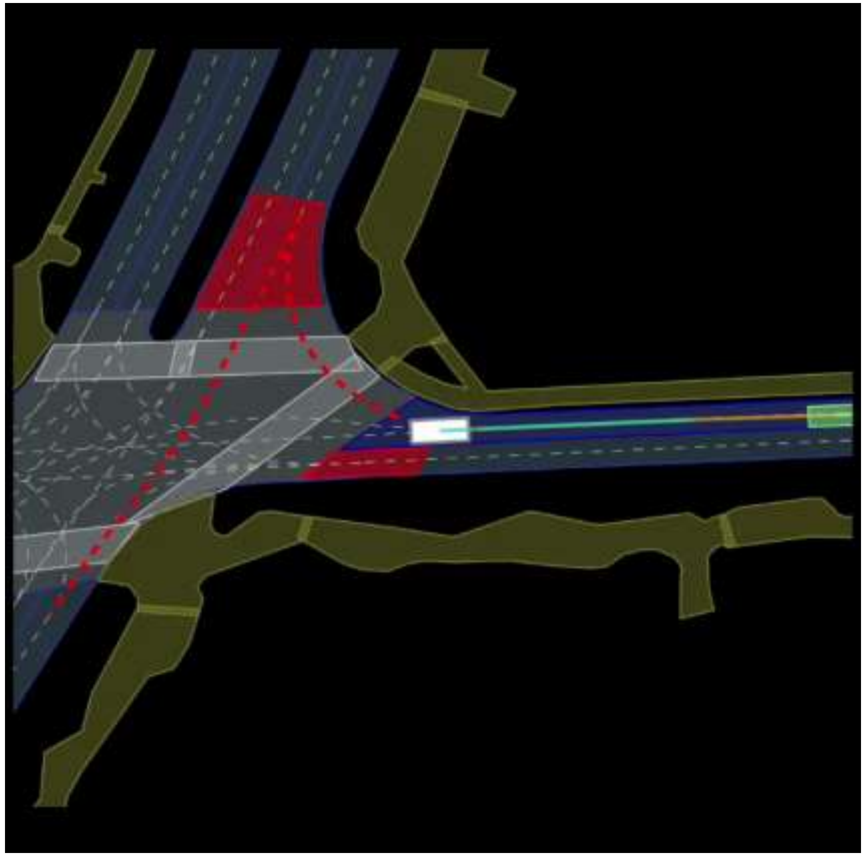
	Planner	Type	interPlan	Val14 (R)	Val14 (NR)	Test14-Random (R)	Test14-Random (NR)	Test14-Hard (R)	Test14-Hard (NR)
SOTA	PDM-Closed	Rule	42	92	**93**	**91**	**90**	75	65
	STR2	Learning	46	**93**	/	/	/	/	/
	HybridLLMPlanner	Hybrid	53	/	/	/	/	/	/
	Diffusion-ES	Learning	57	92	/	/	/	77	77
	PlanTF	Learning	33	77	84	80	85	61	69
	Pluto	Learning	48	78	89	78	89	60	70
	DiffusionPlanner	Learning	24	83	90	83	89	69	75
	SAH-Drive	Hybrid	**64**	90	89	87	86	**83**	**78**
Suboptimal	UrbanDriver	Learning	4	50	69	67	52	49	50
	GameFormer	Learning	11	75	80	82	84	67	68
	DTPP	Learning	25	73	/	/	/	/	/
	IDM	Rule	31	77	75	74	70	62	56

Only trained on nuPlan mini

Experiment



SAH-Drive



PDM-Closed

Thakns for your listening!

project link: https://sah-drive-web.github.io/