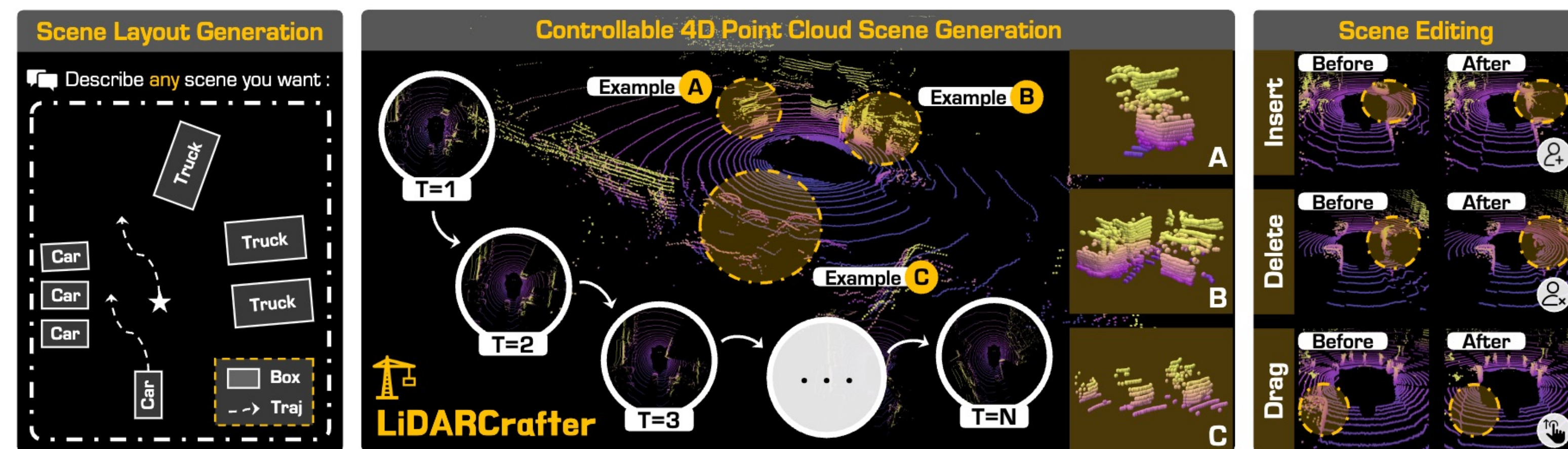


Learning to Generate 4D LiDAR Sequences

Abstract Paper @ ICCV 2025 Wild3D Workshop

Main Motivation & Key Contributions

- ❖ **LiDARCrafter** is a unified framework for 4D LiDAR generation and editing. Given free-form natural **language inputs**, we parse instructions into **ego-centric scene graphs**, which condition a tri-branch diffusion network to generate object structures, trajectories, and geometry cues.



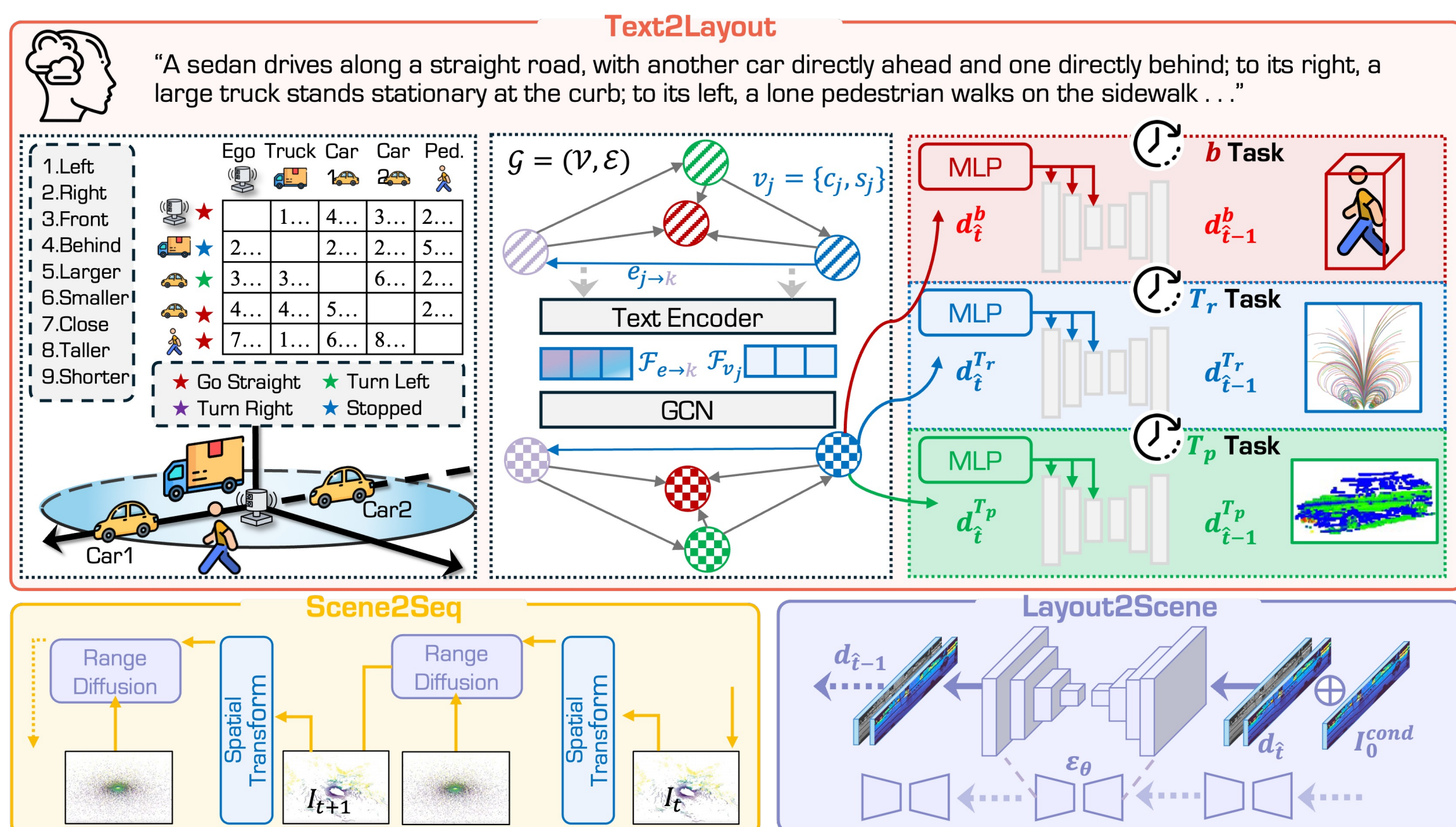
- ❖ Meanwhile, **LiDARCrafter** also leverages an **autoregressive module** to generate **temporally coherent** 4D LiDAR scenes with smooth transitions, conditioned on prior static 3D structures.

4D Scene Generation Pipeline & Framework

- ❖ **LiDARCrafter** is a **three-stage** framework. In the **Text2Layout** stage, the natural-language instructions are parsed into an **ego-centric scene graph**, and a **tri-branch diffusion network** generates 4D conditions for bounding boxes, future trajectories, and object point clouds.

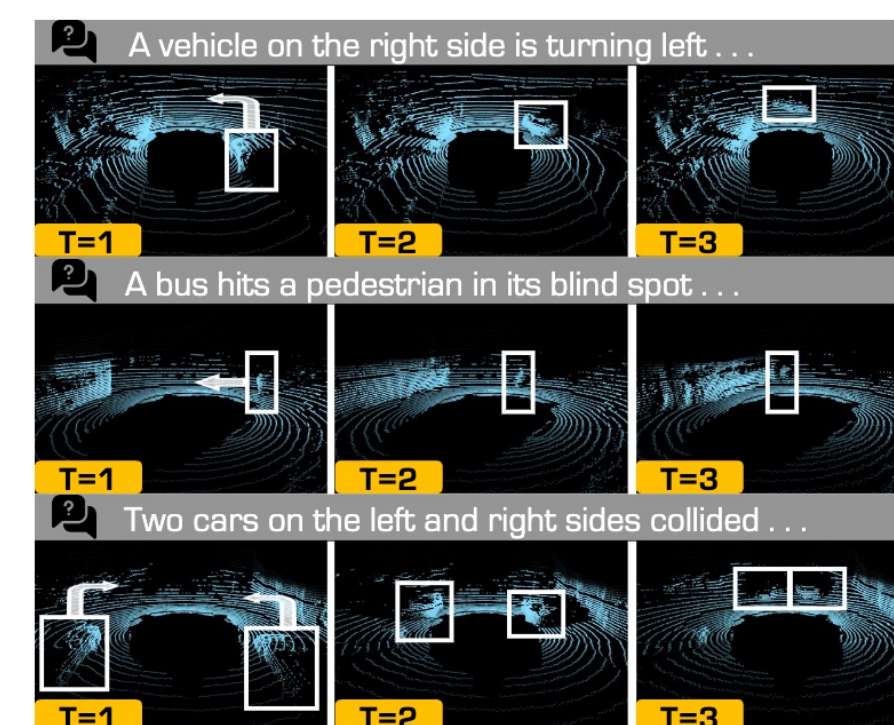
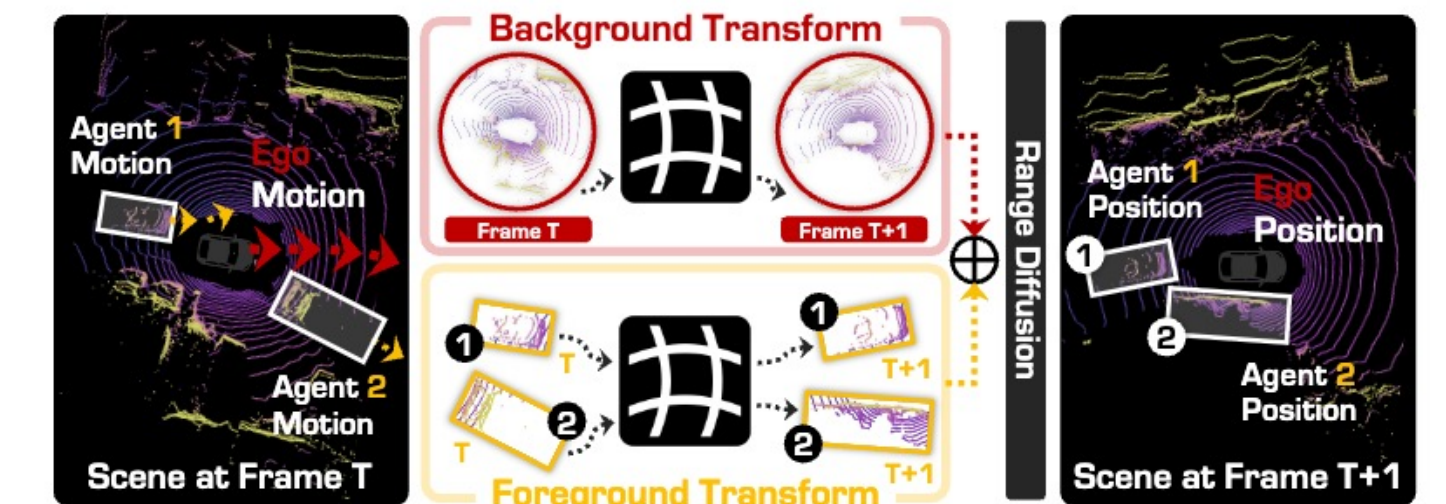
- ❖ The **Layout2Scene** stage uses a **range-view diffusion** and the three generated conditions as inputs to generate a **static** LiDAR frame.

- ❖ For **Scene2Seq**, we use **autoregressive modules** to warp the historical points with ego & motion priors, generating a consistent 4D scene.



Modeling 4D Worlds from LiDAR Sequences

- ❖ The cornerstone of **LiDARCrafter** is an explicit **4D foreground layout** that tailored to bridge the **descriptive power** of language and the **geometric rigor** acquired by LiDAR point clouds.
- ❖ We feeds the layout to a range-image diffusion network and produces a **high-fidelity** first scan. The explicit layout modeling also enables **fine-grained controls** of the static 3D scene, such as inserting, deleting, and dragging operations.



- ❖ We then generate remaining LiDAR frames **autoregressively**, warping past 3D points with **motion priors** to maintain strong **temporal coherence**, enabling a diverse set of applications.
- ❖ To support **standardized evaluation** on LiDAR-based 4D scene generation, we establish a comprehensive suite and toolkit with diverse evaluation metrics, spanning **scene-**, **object-**, as well as **sequence-level** aspects for comparing existing approaches.

Experiments & Observations

- ❖ Experiments on the nuScenes dataset demonstrate that **LiDARCrafter** achieves state-of-the-art performance in **fidelity**, **controllability**, and **temporal consistency** across all aspects.

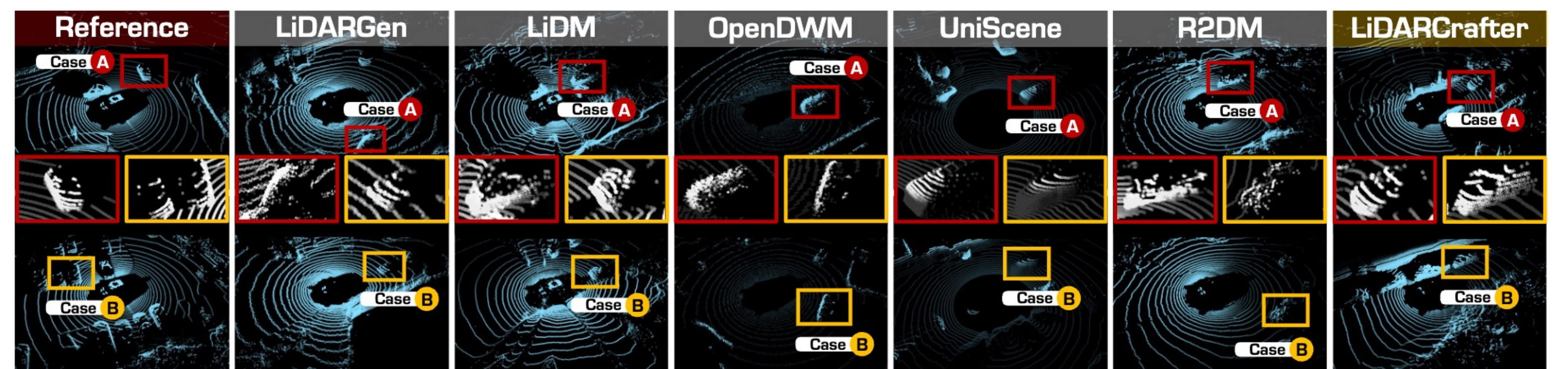


Table 1: Evaluations of **scene-level fidelity** for LiDAR generation on the *nuScenes* dataset. MMD values are reported in 10^{-4} and JSD in 10^{-2} . Lower is better for all metrics ($\downarrow$).

#	Method	Venue	Range		Points		BEV
			FRD↓	MMD↓	FPD↓	MMD↓	
Voxel	UniScene	CVPR'25	–	–	976.47	29.06	31.55
	OpenDWM	CVPR'25	–	–	714.19	21.95	20.17
	OpenDWM-DiT	CVPR'25	–	–	381.91	12.46	19.90
							13.61
Range	LiDARGen	ECCV'22	759.65	1.71	159.35	35.52	5.74
	LiDM	CVPR'24	495.54	0.18	210.20	8.45	5.86
	RangelDM	ECCV'24	–	–	–	–	5.47
	R2DM	ICRA'24	243.35	1.40	33.97	1.62	3.51
							0.71
	LiDARcrafter	Ours	194.37	0.08	8.64	0.90	3.11

Table 2: Comparison of **foreground object quality** using FDC ($\uparrow$), which reflects detector confidence on generated scenes. #Box is the average number of boxes per frame.

#	Method	Venue	Car $\uparrow$	Ped $\uparrow$	Truck $\uparrow$	Bus $\uparrow$	#Box
Uncond.	LiDARGen	ECCV'22	0.57	0.29	0.42	0.38	0.364
	LiDM	CVPR'24	0.65	0.22	0.45	0.31	0.28
	R2DM	ICRA'24	0.54	0.29	0.39	0.35	0.53
Cond.	UniScene	CVPR'25	0.53	0.28	0.35	0.25	0.98
	OpenDWM	CVPR'25	0.74	0.30	0.51	0.44	0.54
	OpenDWM-DiT	CVPR'25	0.78	0.32	0.56	0.51	0.64
	LiDARCrafter	Ours	0.83	0.34	0.55	0.54	1.84

- ❖ Code and dataset are **public** and free to use for future research.



中国科学院大学
University of Chinese Academy of Sciences



復旦大學
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