RangeLDM: Fast Realistic LiDAR Point Cloud Generation

Qianjiang Hu, Zhimin Zhang, Wei Hu

hqjpku@pku.edu.cn zm_zhang@stu.pku.edu.cn forhuwei@pku.edu.cn

Wangxuan Institute of Computer Technology, Peking University

Motivation

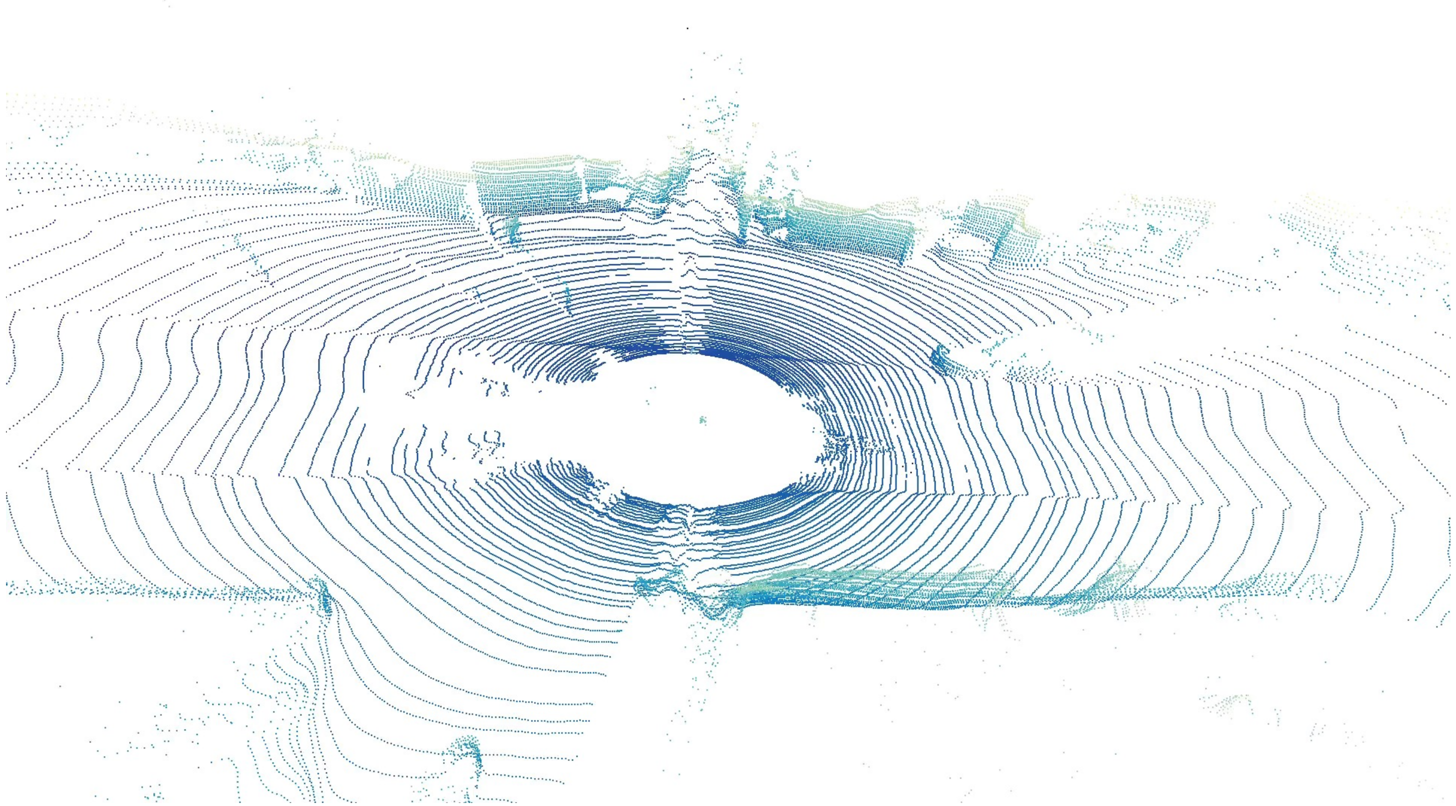
- Robust autonomous system relies on LiDAR to perceive 3D surroundings
  - The cost of physical LiDAR sensors presents a dataset scaling-up challenge

Motivation

PEKING UNIVERSITY

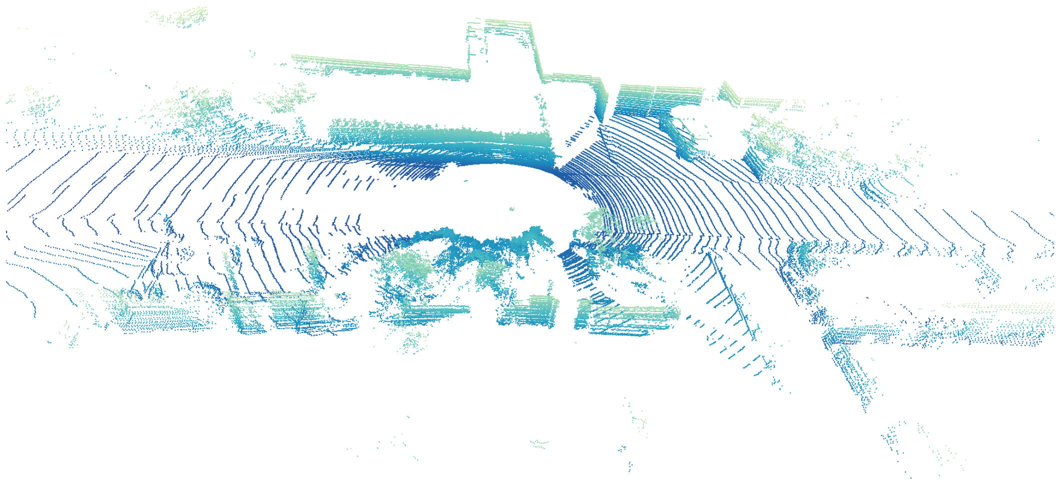
➢Robust autonomous system relies on LiDAR to perceive 3D surroundings

- The cost of physical LiDAR sensors presents a dataset scaling-up challenge
- Our solution: LiDAR generation

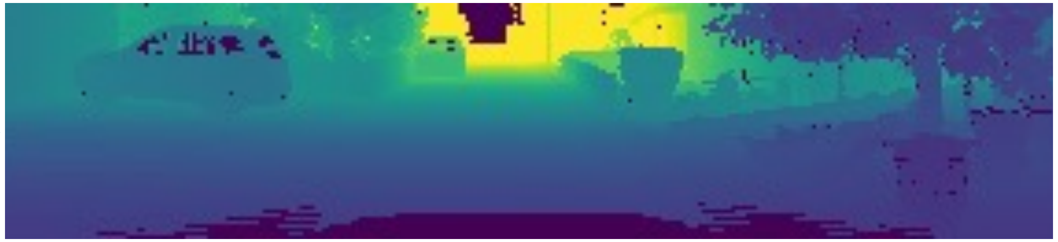


Our Solution

- We introduce **RangeLDM** for rapidly generating high-quality LiDARs
- Why Range image?
  - Range images are compact and closely mimic the sampling conditions of LiDAR
  - 2D image generation techniques such are relatively mature

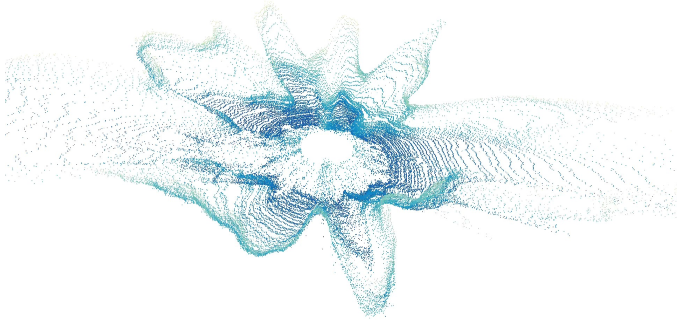


Point cloud

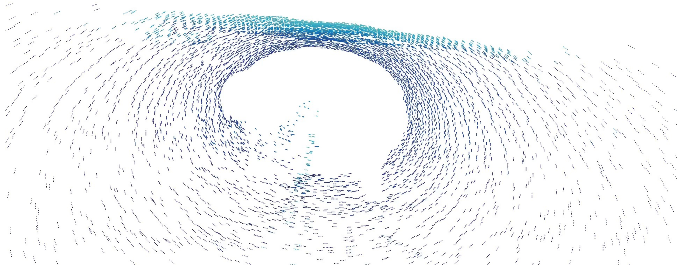


Range image

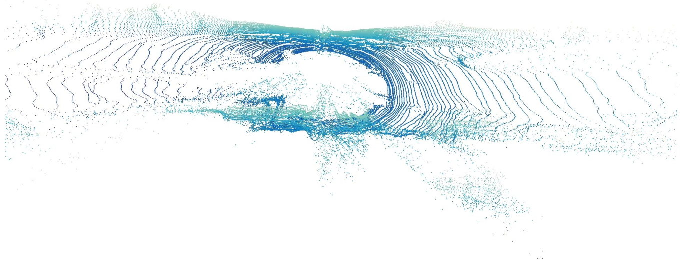
Unconditional generation on KITTI-360



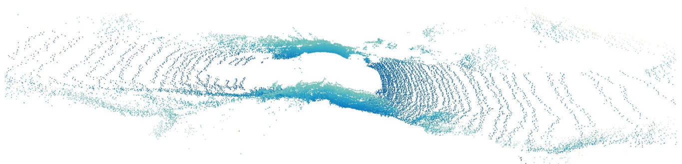
LiDAR VAE



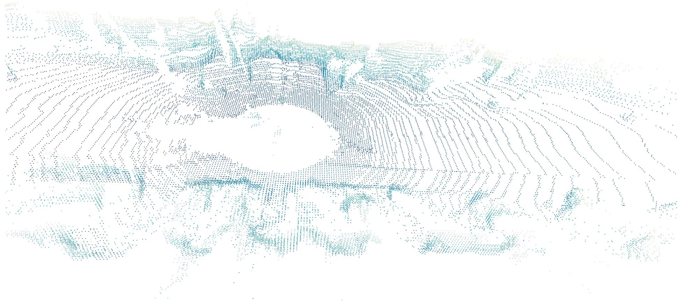
LiDAR GAN



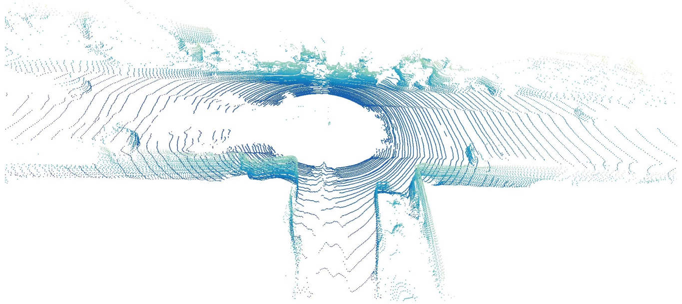
ProjGAN



LiDARGen



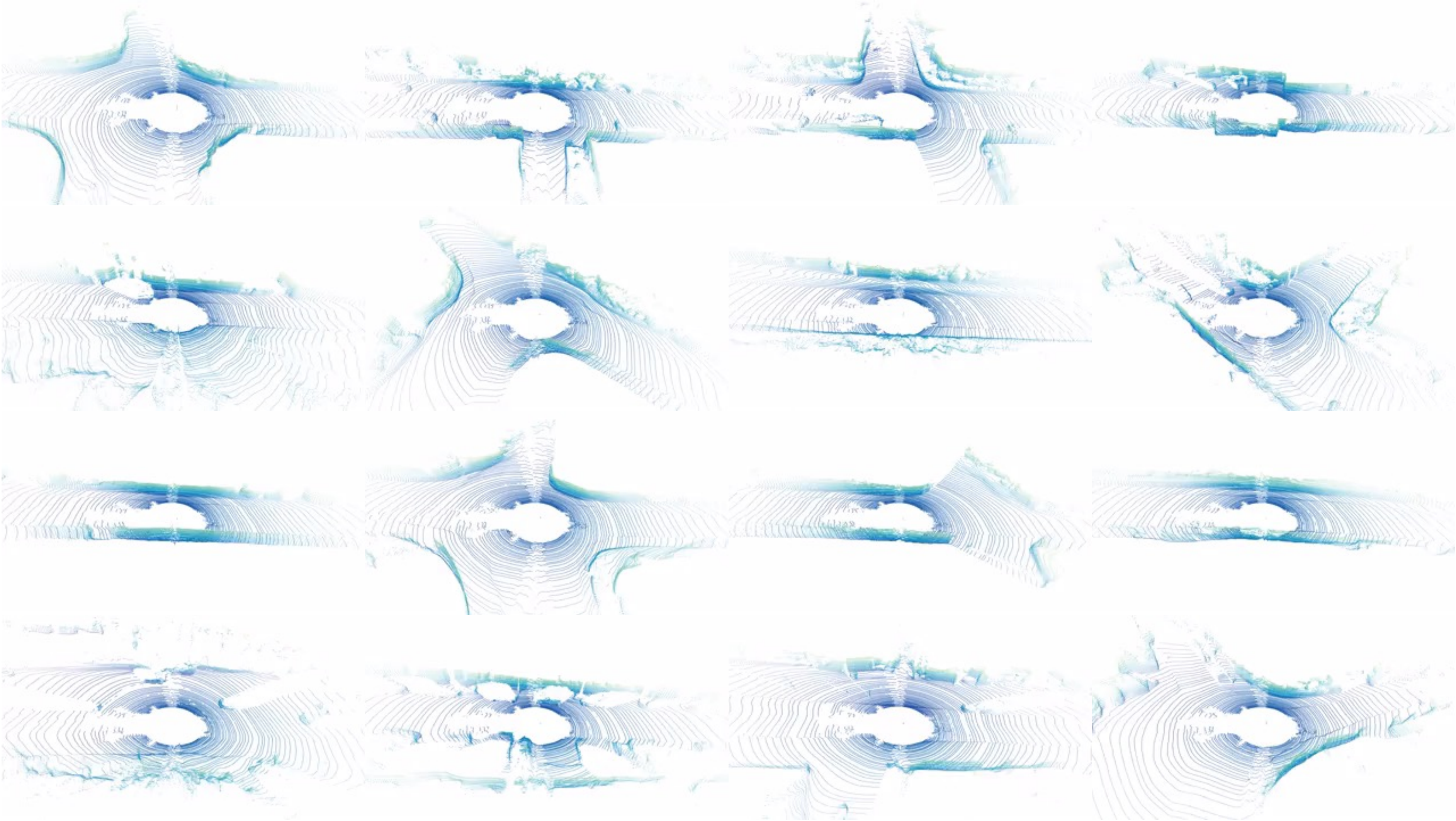
UltraLiDAR



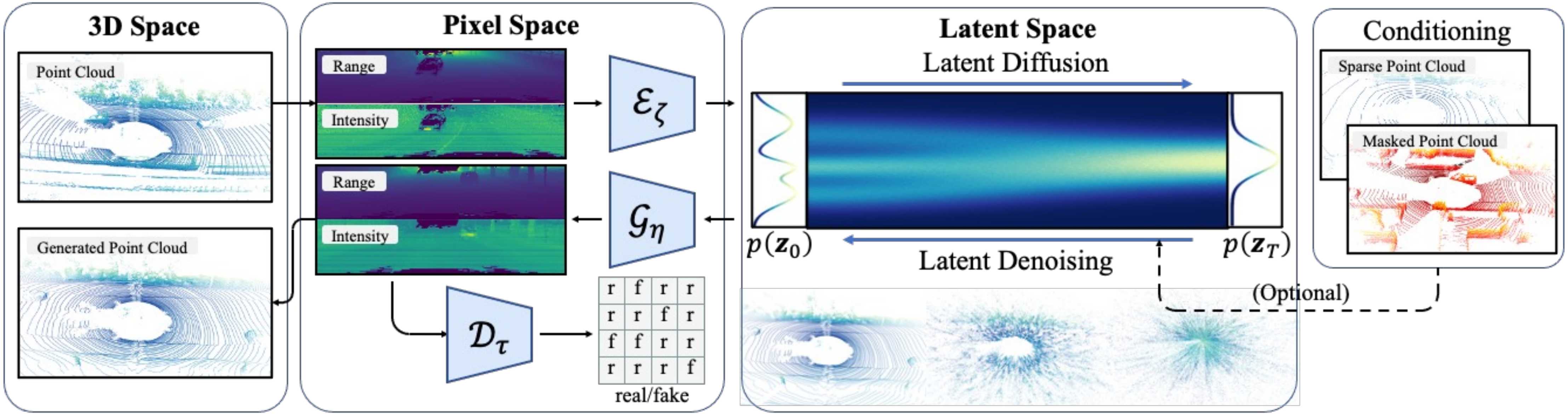
Ours

Unconditional generation on KITTI-360

PEKING UNIVERSITY

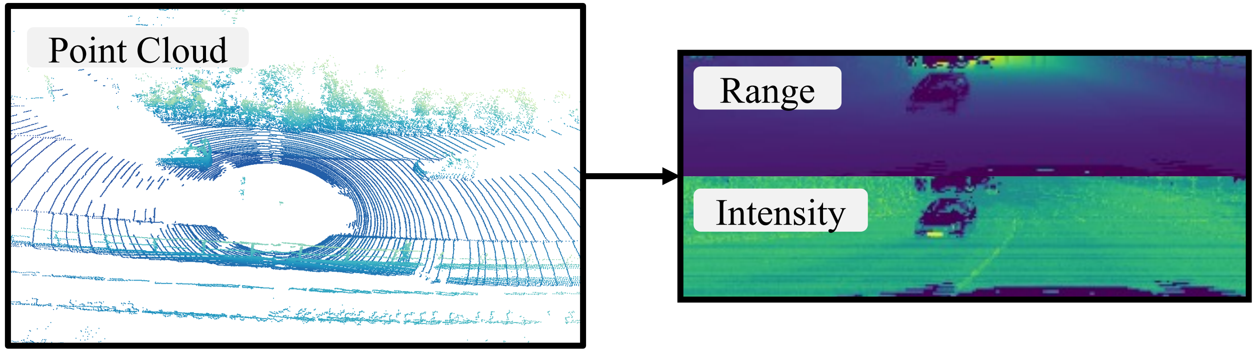


Framework



3D Space
Point Cloud
Generated Point Cloud
Pixel Space
Range
Intensity
Range
Intensity
$\mathcal{E}_\zeta$
$\mathcal{G}_\eta$
$\mathcal{D}_\tau$
r f r r
r r f r
f f r r
r r r f
real/fake
Latent Space
Latent Diffusion
$p(\mathbf{z}_0)$
$p(\mathbf{z}_T)$
Latent Denoising
(Optional)
Conditioning
Sparse Point Cloud
Masked Point Cloud

High-Quality Range Projection



- ➢ Multiple lasers from the LiDAR system do not share a common origin

- Converting directly from Cartesian to spherical coordinates introduces errors
- We Adopt Hough Voting to estimate heights and pitch angles for sensors

Original Range Image

Range Image with Hough Voting

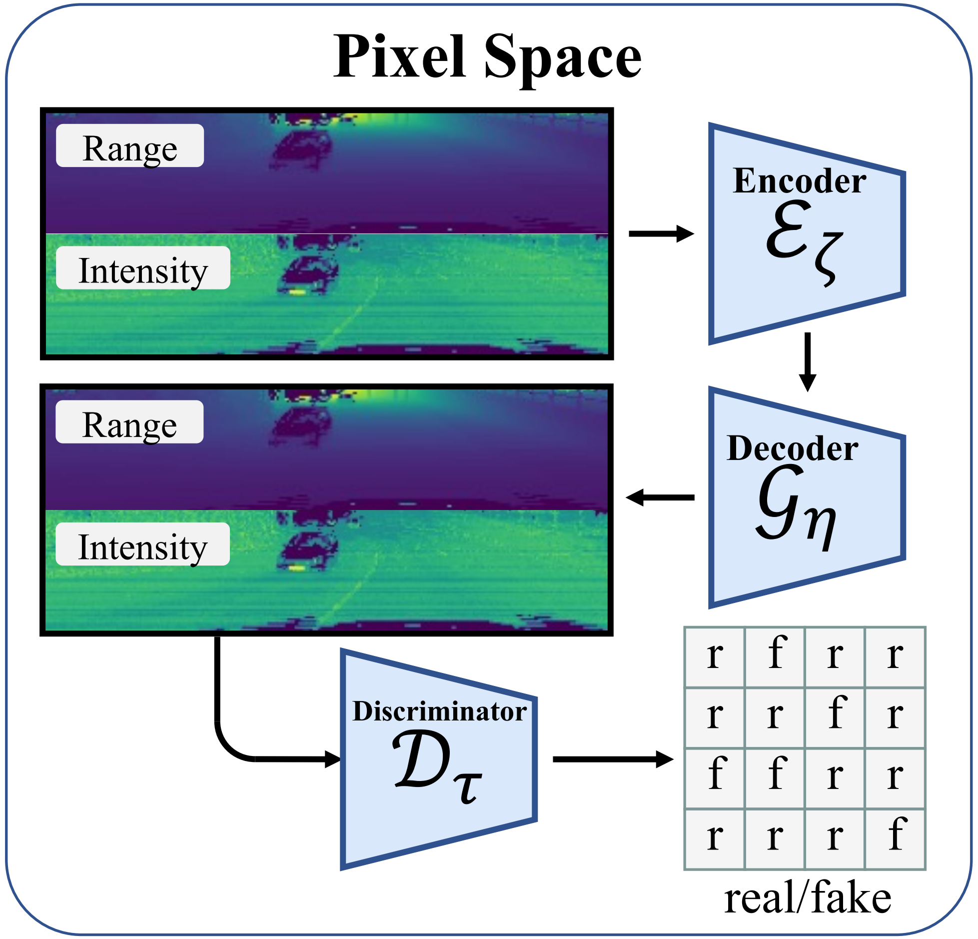
Method	$\text{MMD}_{\text{BEV}} \downarrow$	FRD $\downarrow$	$\text{JSD}_{\text{BEV}} \downarrow$
LiDARGen	3.87×10^{-4}	2040.1	0.067
+Hough Voting	$\mathbf{1.41 \times 10^{-4}}$	**1453.1**	**0.064**

LiDARGen with Houth Voting

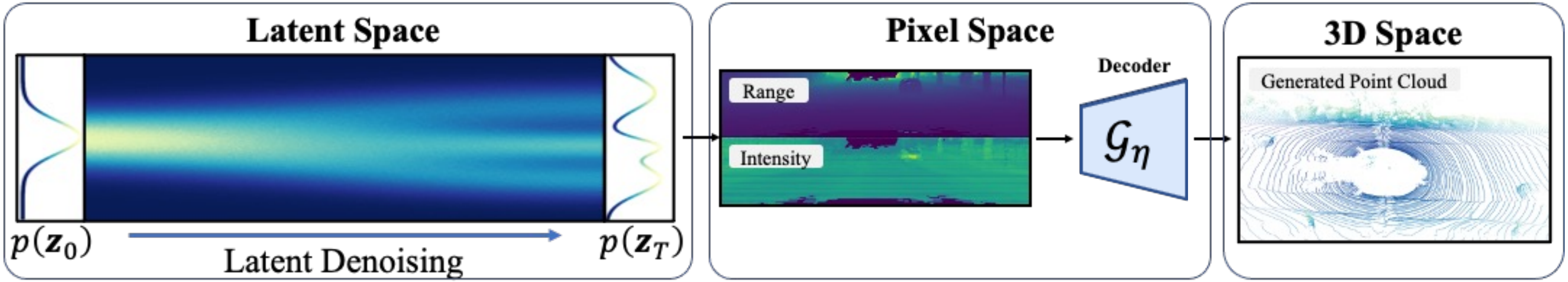
PEKING UNIVERSITY

Range-Guided Discriminator

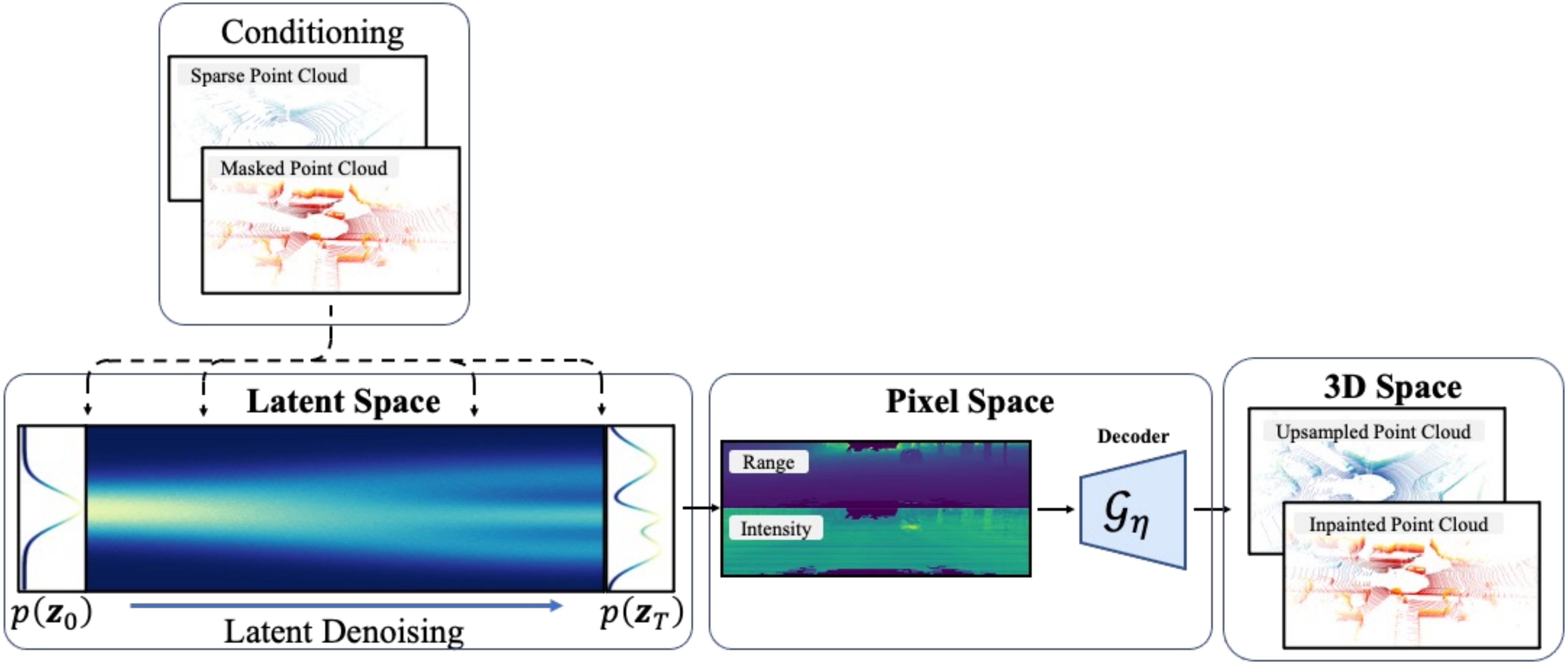
- ➢ Adapt the Meta-Kernel to replace the convolution in the discriminator
- Be aware of local 3D structures
- Make it challenging for the decoder to deceive the discriminator
- Encourage the decoder to generate more realistic range images



Point Cloud Generation



Conditional Point Cloud Generation



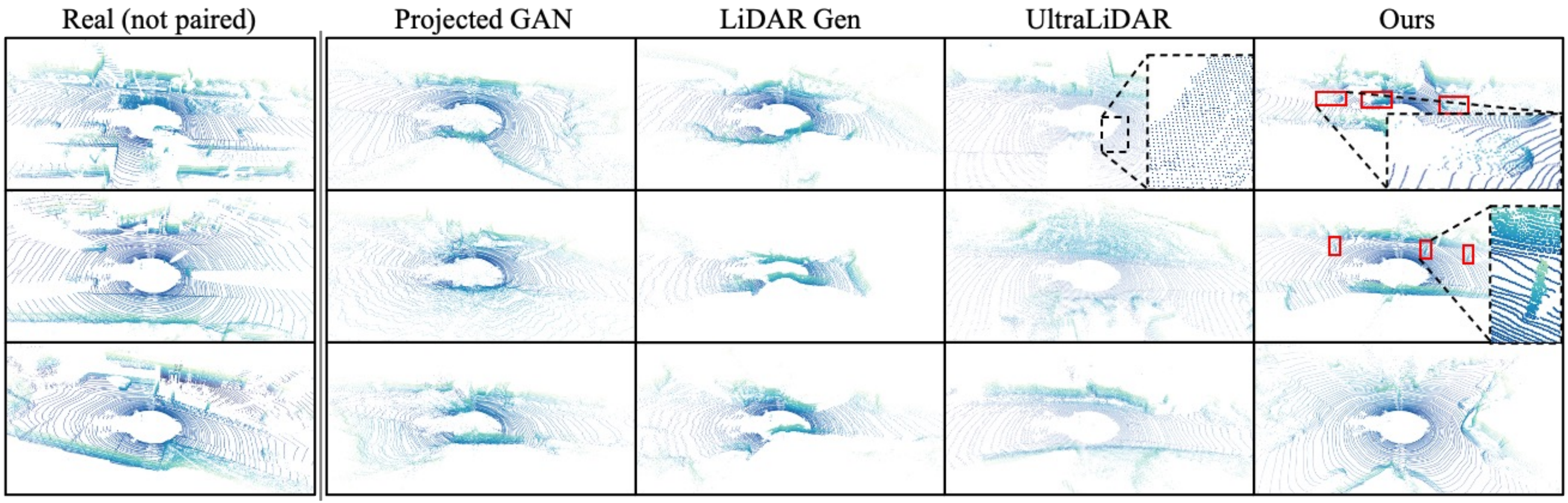
Unconditional generation on KITTI-360

北京大學 PEKING UNIVERSITY

Method	Years	$\text{MMD}_{\text{BEV}} \downarrow$	FRD $\downarrow$	$\text{JSD}_{\text{BEV}} \downarrow$
LiDAR GAN [5]	IROS 2019	3.06×10^{-3}	3003.8	-
LiDAR VAE [5]	IROS 2019	1.00×10^{-3}	2261.5	0.161
Projected GAN [58]	NeurIPS 2021	3.47×10^{-4}	2117.2	0.085
LiDARGen [95]	ECCV 2022	3.87×10^{-4}	2040.1	0.067
UltraLiDAR [79]	CVPR 2023	1.96×10^{-4}	-	0.071
Ours		$\mathbf{3.07 \times 10^{-5}}$	**1074.9**	**0.045**

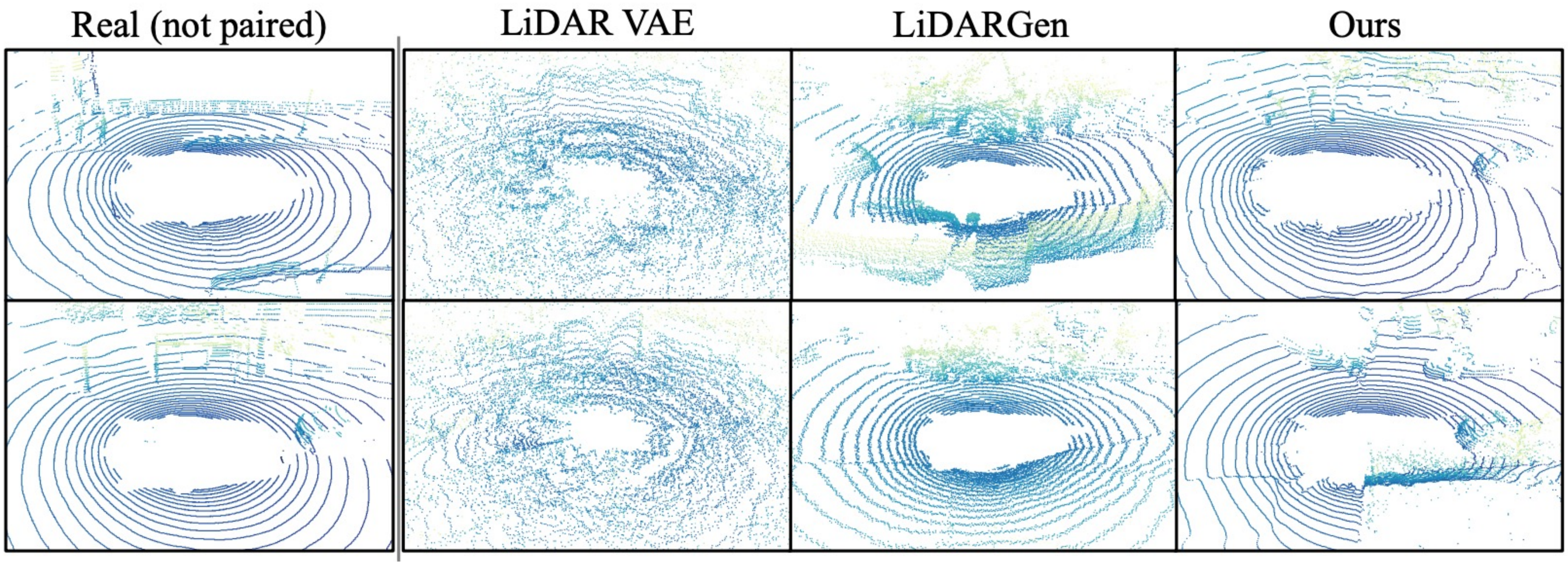
Quantitative results on KITTI-360

Unconditional generation on KITTI-360



Unconditional generation on nuScenes

北京大學 PEKING UNIVERSITY

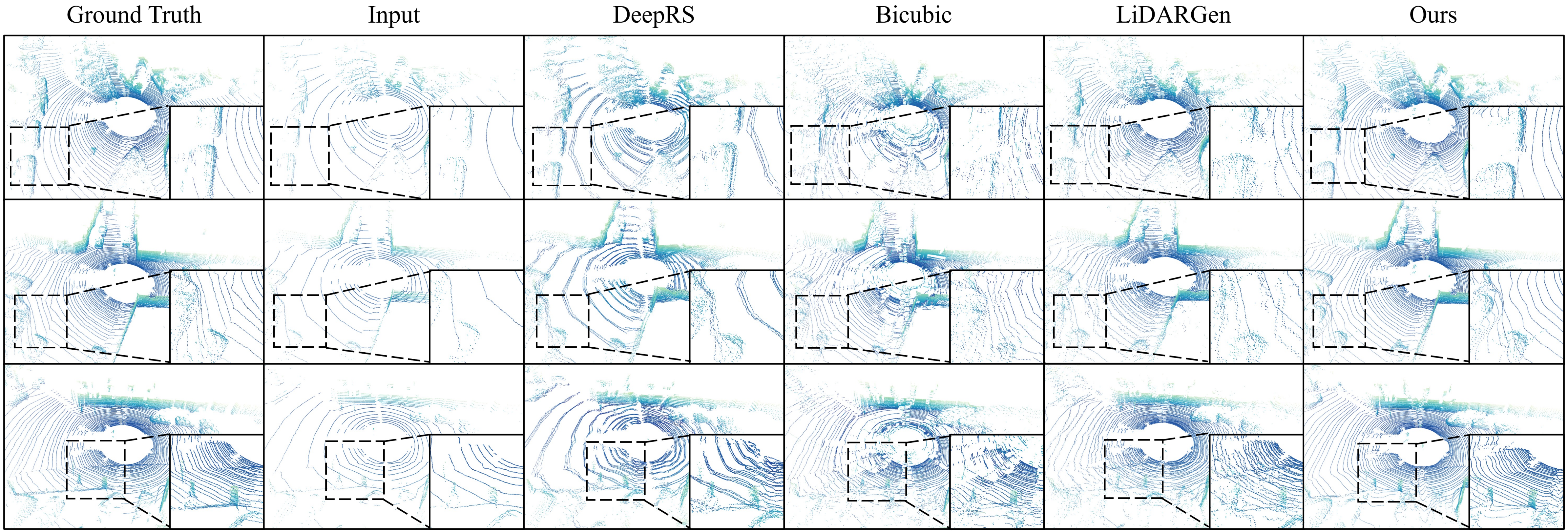


Generation Efficiency

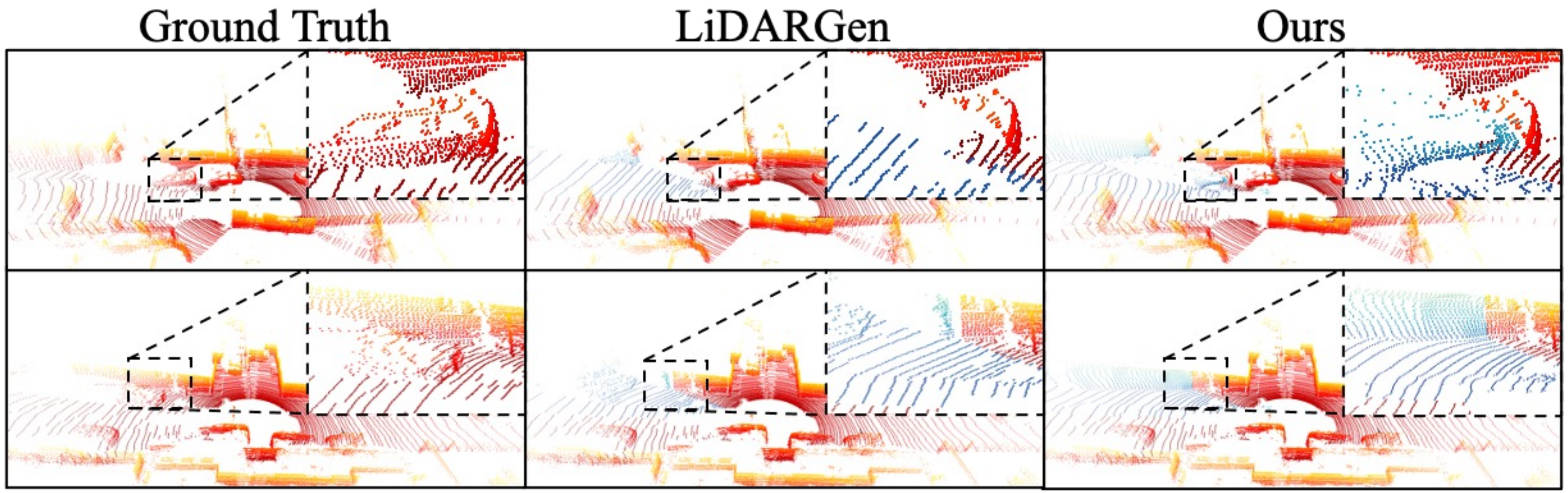
Method	Throughput ↑ (samples/s)
LiDARGen [95]	0.02
UltraLiDAR [79]	0.16
Ours	**4.86**

Inference Speed

LiDAR Point Cloud Upsampling Results



LiDAR Point Cloud Inpainting Results



Conclusion

北京大学 PEKING UNIVERSITY

- We present RangeLDM to generate realistic range-view LiDAR point clouds at a fast speed
- We ensure the quality of projection from point clouds to range images with correct distribution via Hough Voting
- We enhance the range-image reconstruction quality of the VAE with a range-guided discriminator
- Experiments conducted on KITTI-360 and nuScenes datasets demonstrate the superior generation quality and sampling efficiency of our method

Code

Paper