Generative Range Imaging for Learning Scene Priors of 3D LiDAR Data

Kazuto Nakashima[1] Yumi Iwashita[2] Ryo Kurazume[1]
[1]Kyushu University [2]Jet Propulsion Laboratory, Caltech
九州大学 KYUSHU UNIVERSITY
Jet Propulsion Laboratory California Institute of Technology

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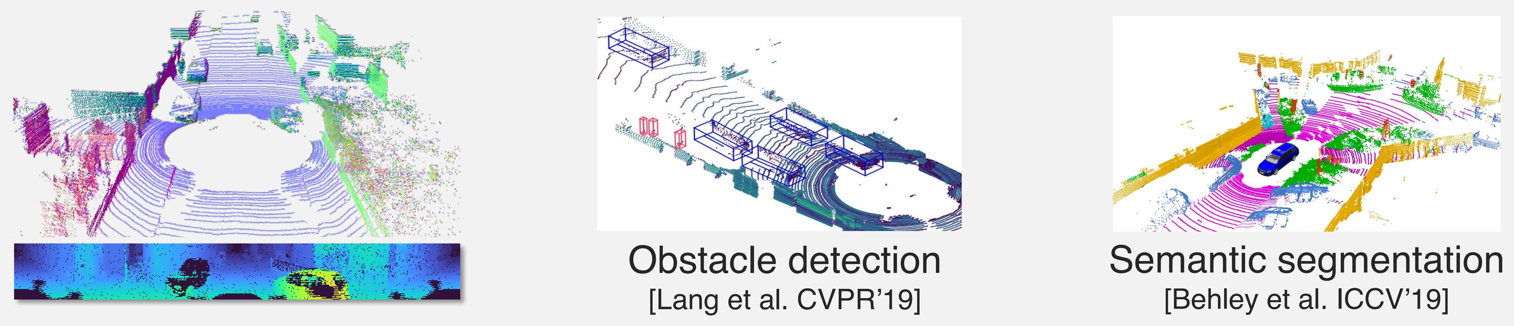
Motivation

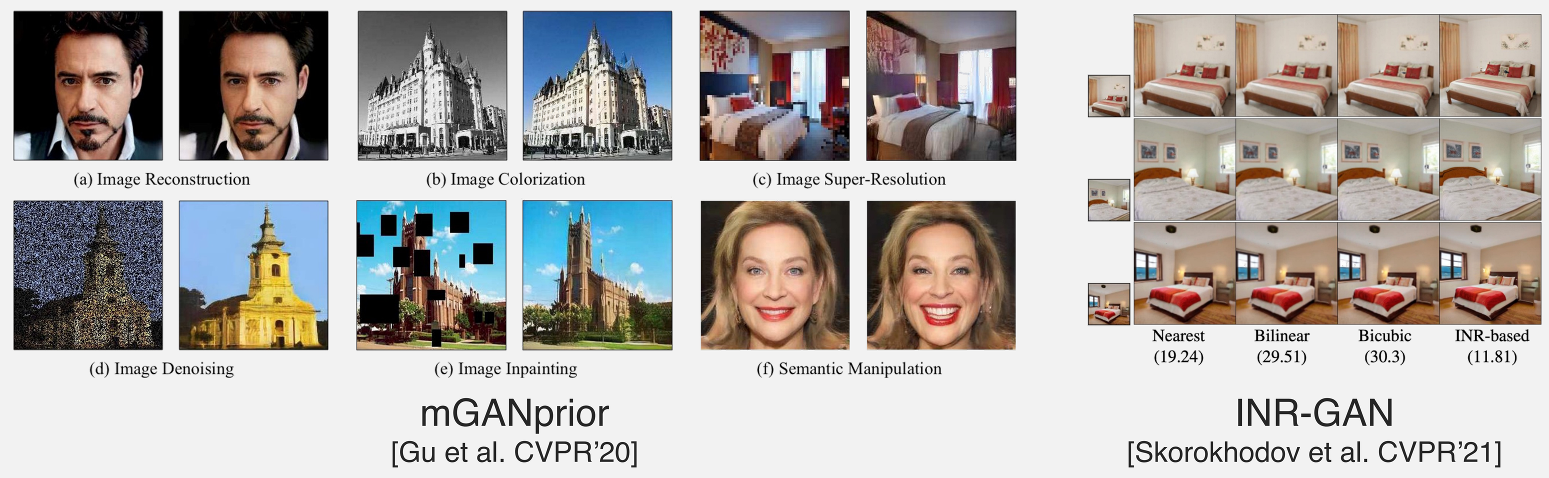
- **3D LiDAR sensors** are indispensable for robotics applications



- However, **domain gaps** are problematic on perception tasks

Related Work

- Recent **GANs** solved many image processing tasks

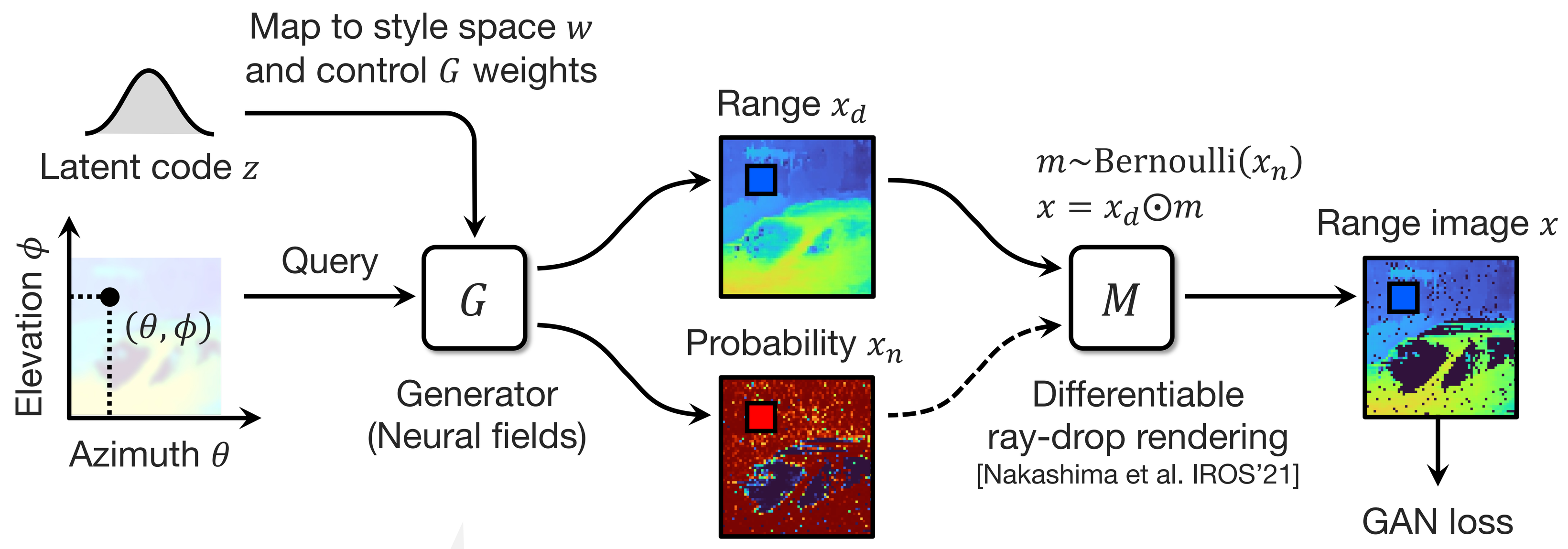


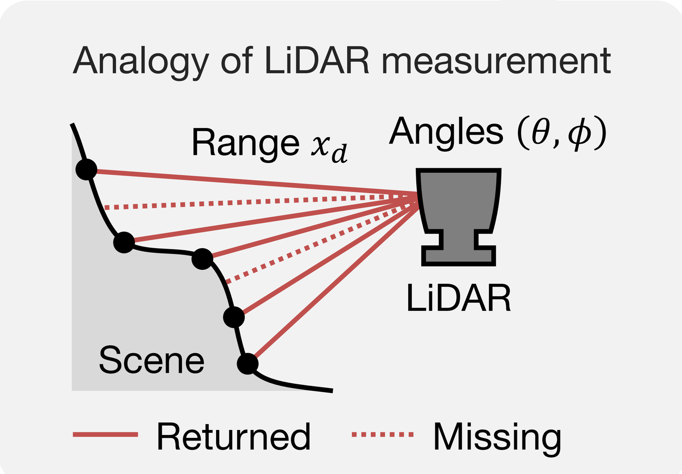
Challenges:

- Generative modeling of 3D LiDAR data using GANs
- Data-level domain adaptation using the trained GAN

Approach: LiDAR Range Images as 2D Neural Fields

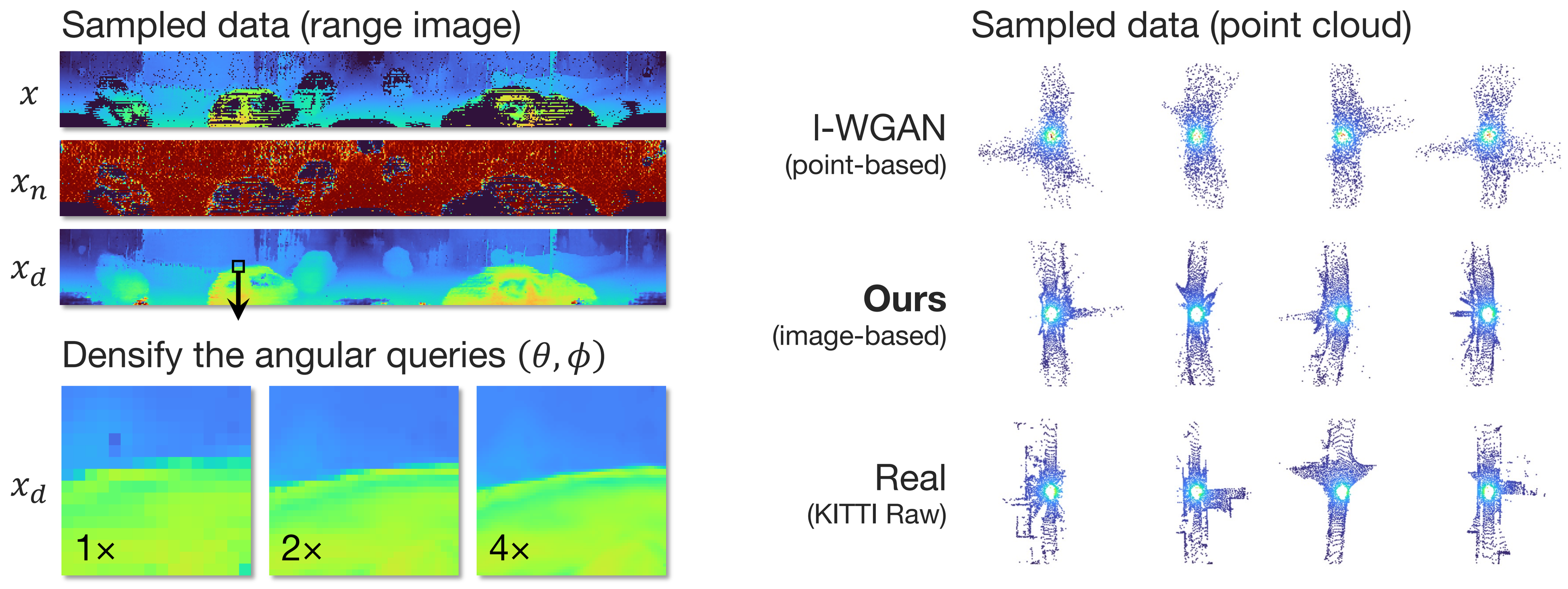
- We assume a function G that transforms angles (θ, ϕ) to {range x_d, ray-drop probability x_n} conditioned by latent z





- **Training:** the function G is trained as a GAN generator
- The ray-drop sampling is approximated by Gumbel-Sigmoid
- **Inversion:** optimize the style code w (+ tune G weights) by minimizing masked pixel-wise error

- Generated samples

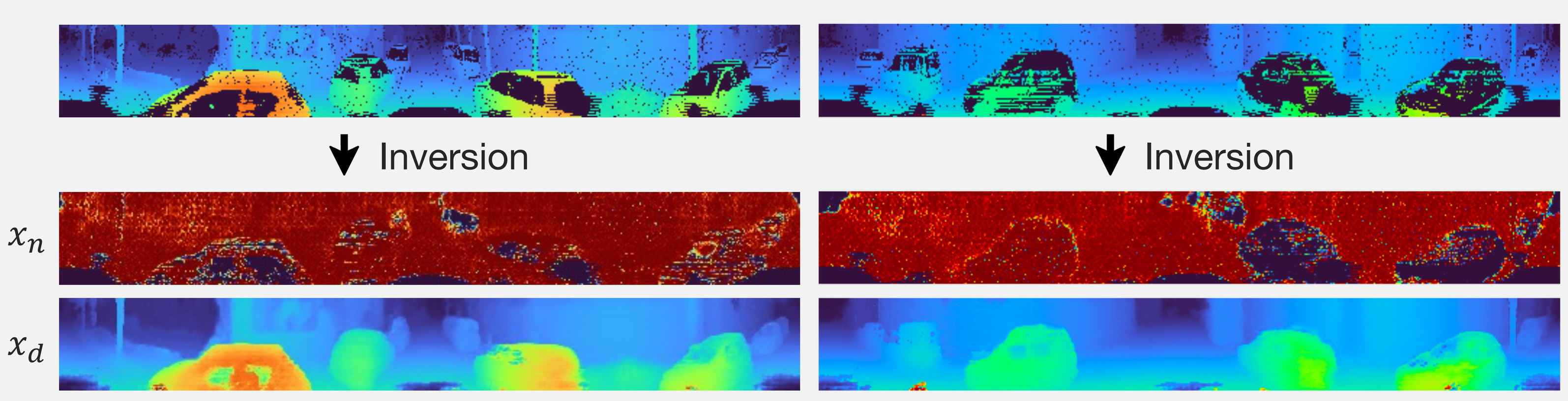


- Quantitative comparison in fidelity and diversity

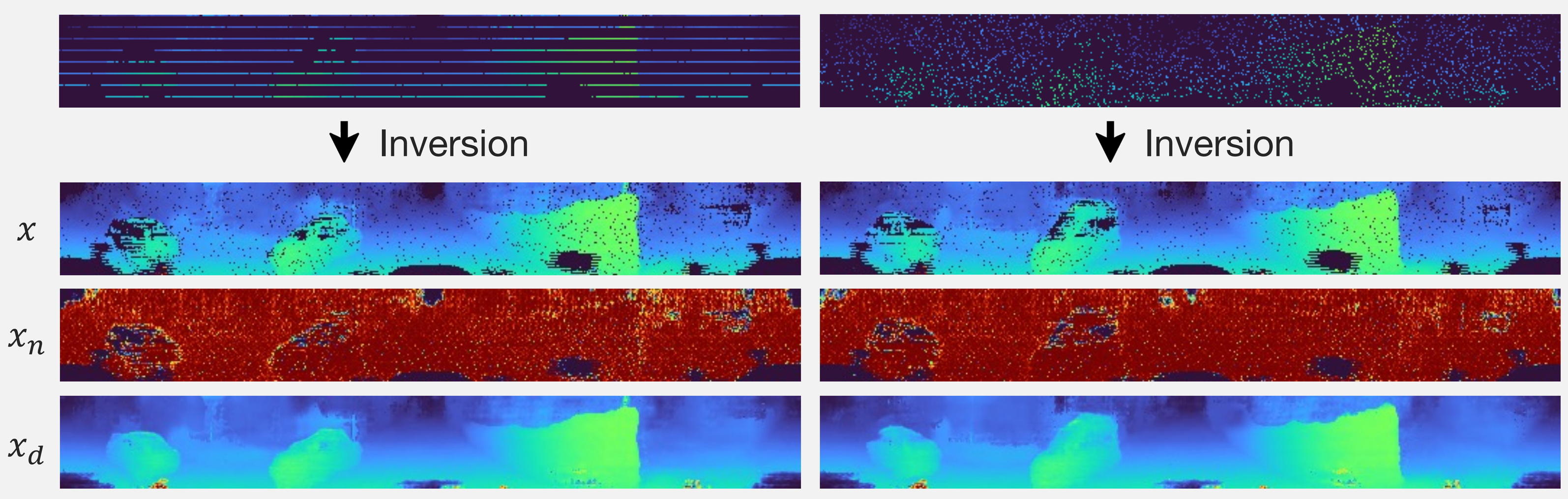
	Method	Image-level SWD↓	Point-level 1-NNA↓	Feature-level (PointNet) FPD↓	Feature-level (PointNet) MMD²↓
Point-based GAN	r-GAN [Achilioptas et al. ICML'18]	N/A	1.000	787.45	45.92
	l-WGAN (EMD) [Achilioptas et al. ICML'18]	N/A	0.896	129.35	10.65
Image-based GAN	Vanilla GAN [Caccia et al. IROS'19]	0.505	0.986	3629.36	671.14
	DUSty [Nakashima et al. IROS'21]	0.491	0.898	232.90	39.62
	Ours	**0.422**	**0.892**	**96.11**	**3.66**

Applications

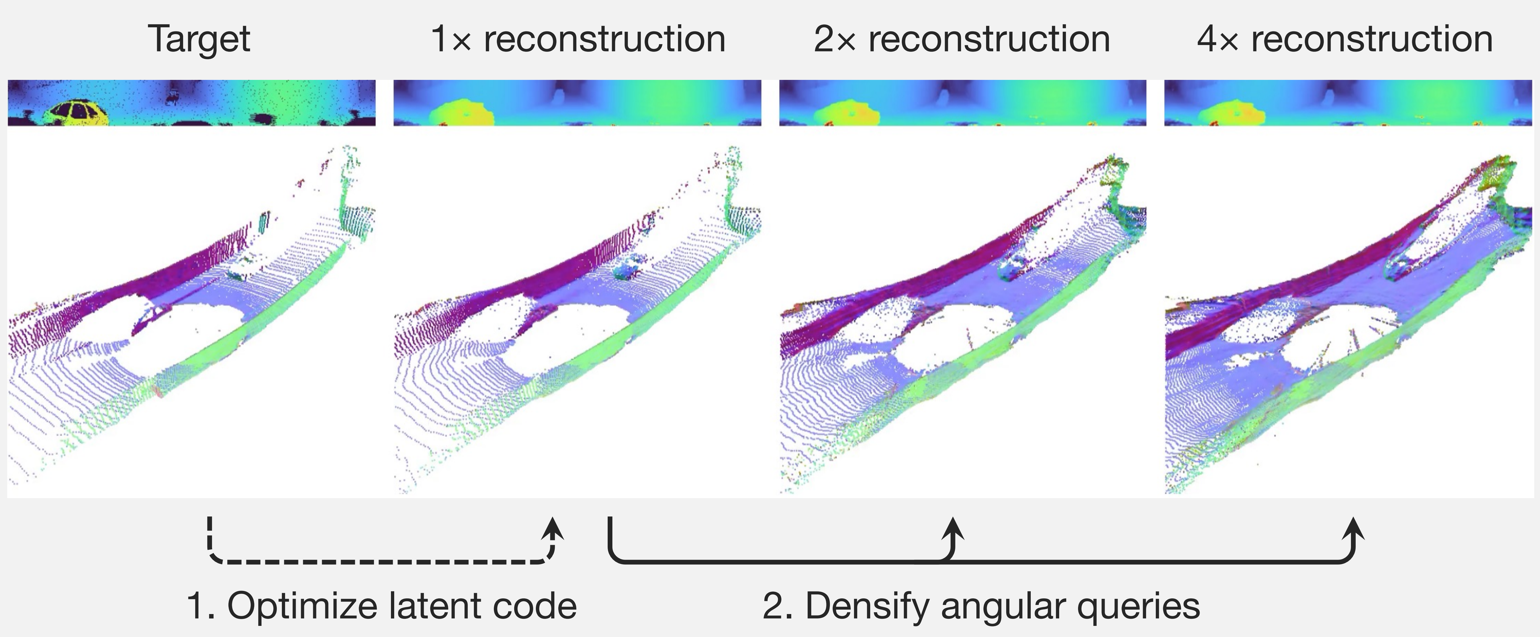
- Decomposition



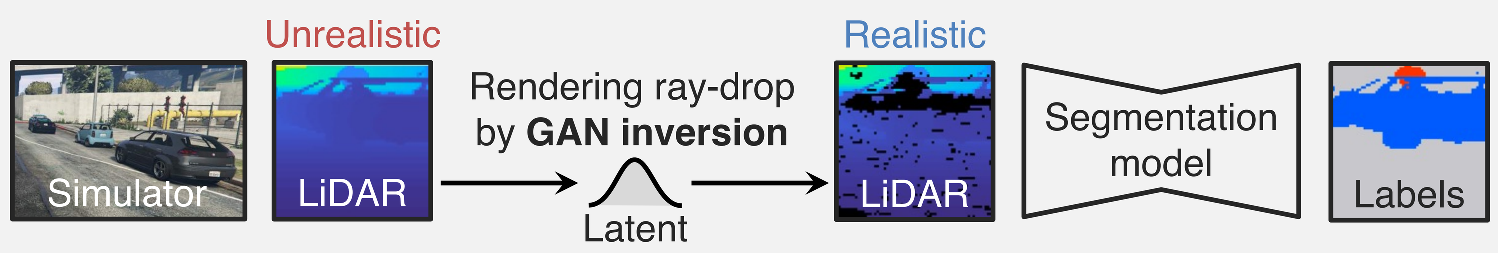
- Restoration

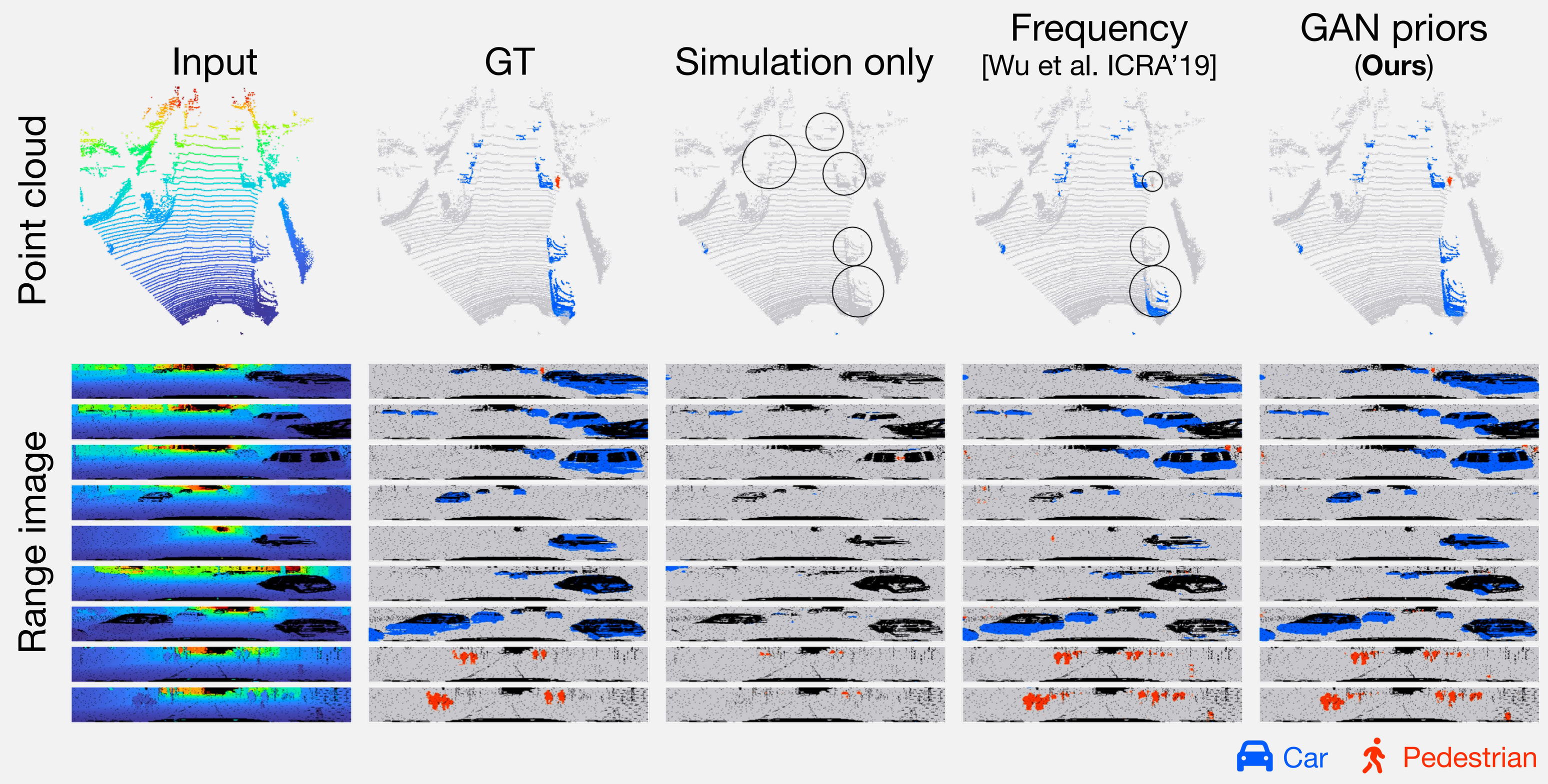


- Upsampling



- **Sim2Real semantic segmentation:** the ray-drop probability can be used for rendering ray-drop noises on simulation data





Comparison with SOTA results (GTA-LiDAR to KITTI task)

Method	Ray-drop rendering	IoU (intersection over union) Car	IoU Pedestrian	IoU Mean
SqueezeSegV2 [Wu et al. ICRA'19]	Frequency from KITTI	57.4	23.5	40.5
ePointDA [Zhao et al. AAAI'21]	CycleGAN-based	66.2	24.8	45.5
Ours	**GAN inversion**	**67.3**	**25.2**	**46.3**

- For more details and results: kazuto1011.github.io/dusty-gan-v2