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

Kazuto Nakashima*
Kyushu University

Yumi Iwashita
NASA/Caltech JPL

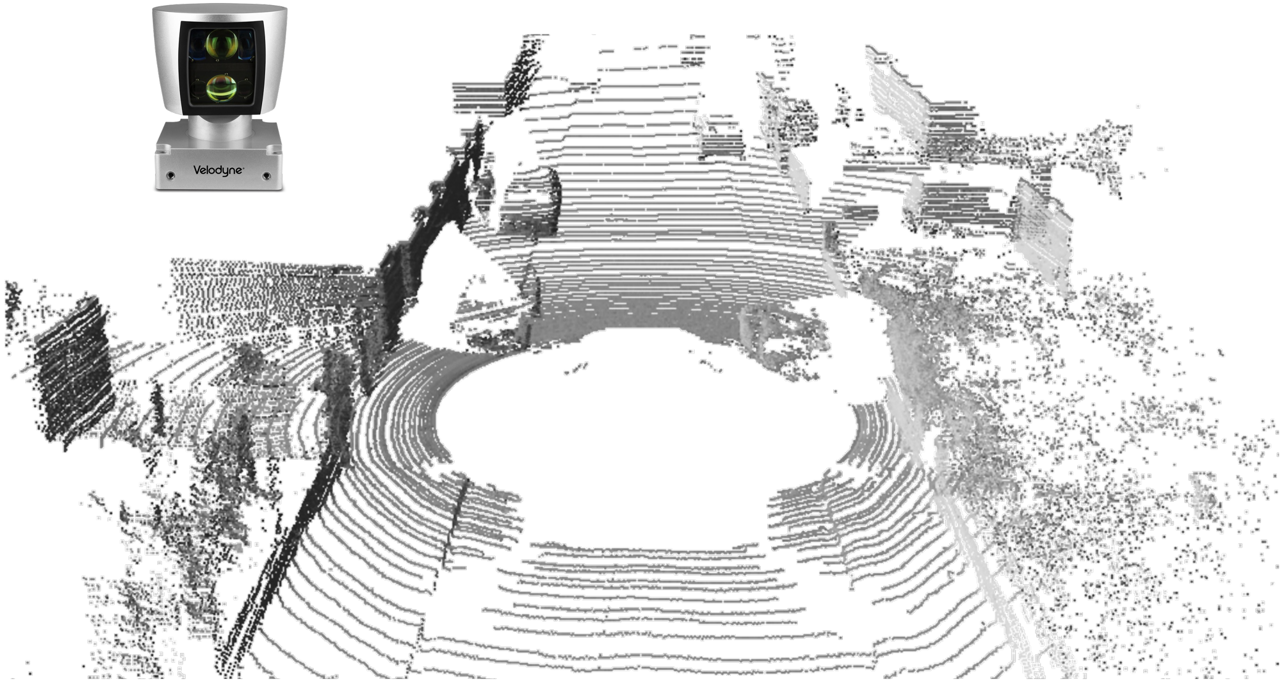
Ryo Kurazume
Kyushu University

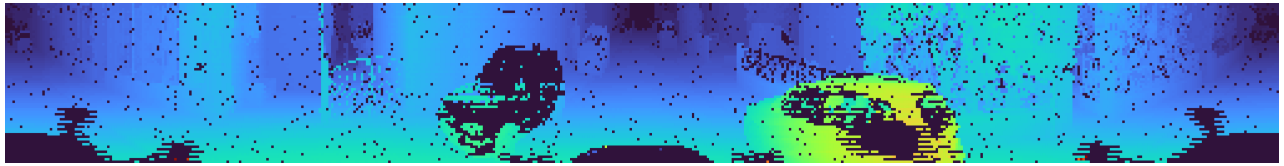
九州大学
KYUSHU UNIVERSITY

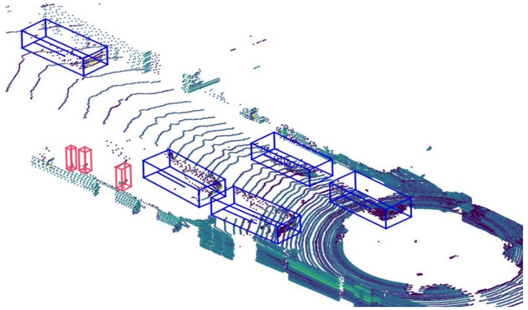
Jet Propulsion Laboratory
California Institute of Technology

Motivation

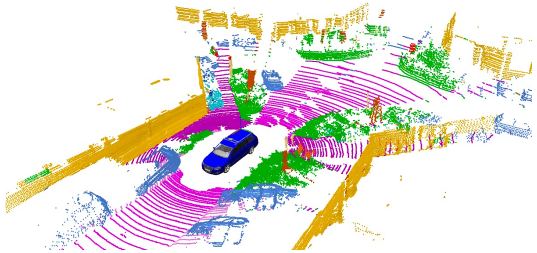
3D LiDAR sensors are important for robotics applications







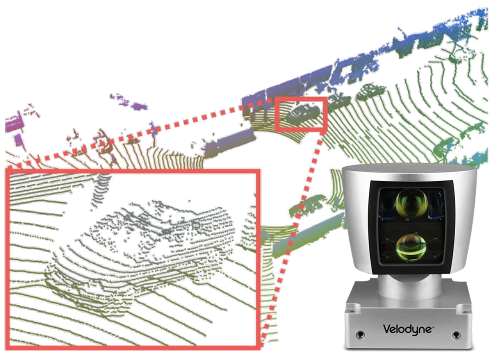
Obstacle detection
[Lang et al. CVPR'19]

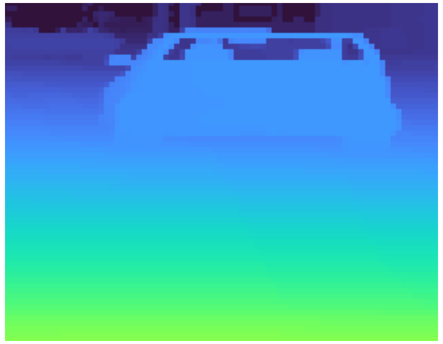


Semantic segmentation
[Behley et al. ICCV'19]

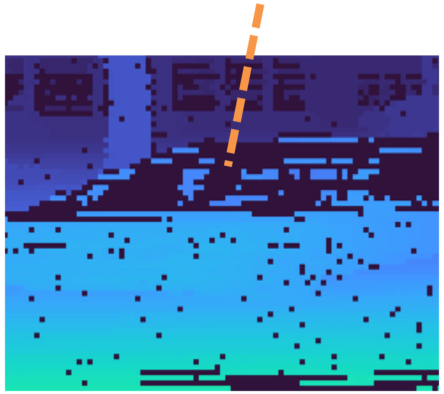
Motivation

Issue: domain gaps in LiDAR perception tasks





Ray-drop
(missing points)

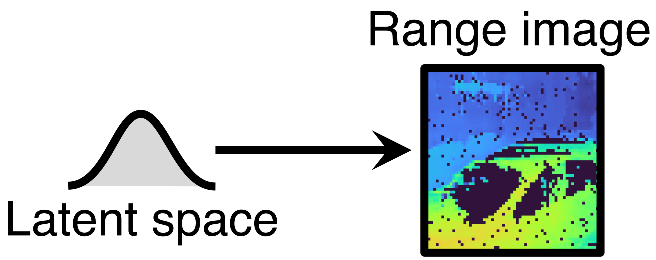


High resolution **Dense**	Low resolution **Sparse**	Simulation **Clean**	Real **Noisy**

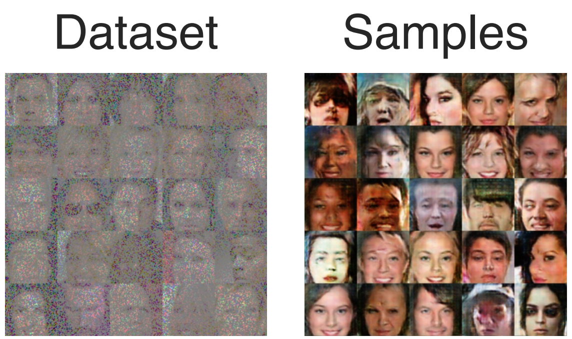
We propose LiDAR data priors for bridging the domain gaps
using **deep generative models**

images from [Yi et al. CVPR'21]

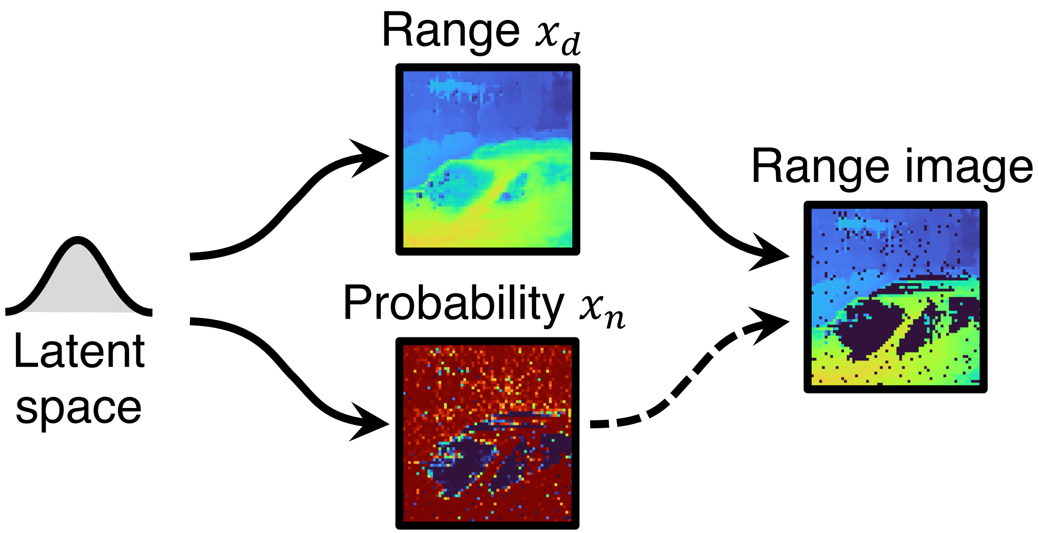
Towards LiDAR Generative Models



Training **GANs** on LiDAR images
[Caccia et al. IROS'19]



Training GANs w/ **invertible corruption**
[Bora et al. ICLR'18] [Kaneko et al. CVPR'20]

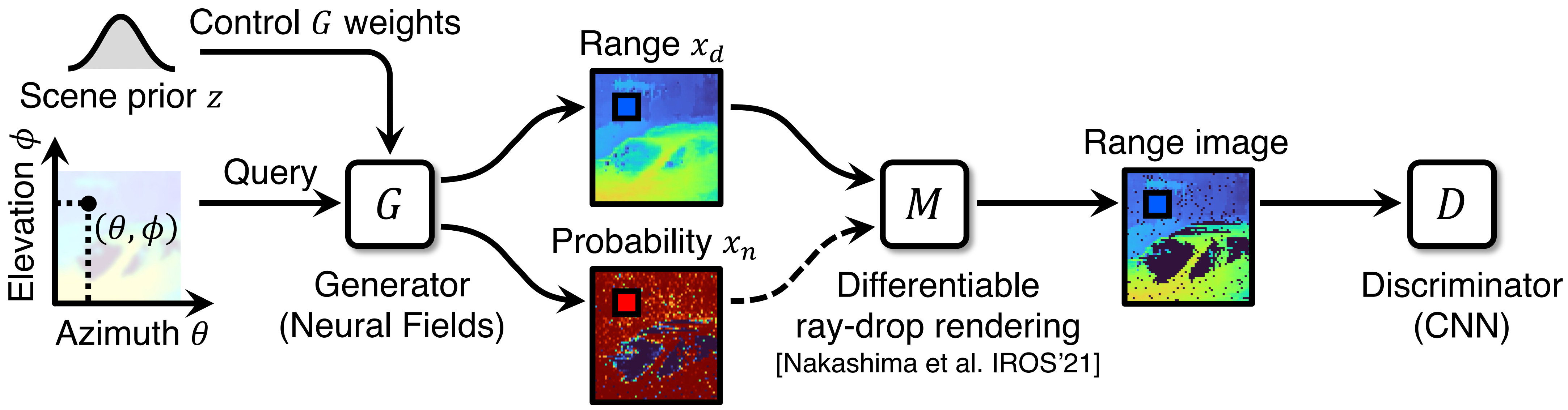


Noise-aware GAN on LiDAR images
[Nakashima et al. IROS'21]

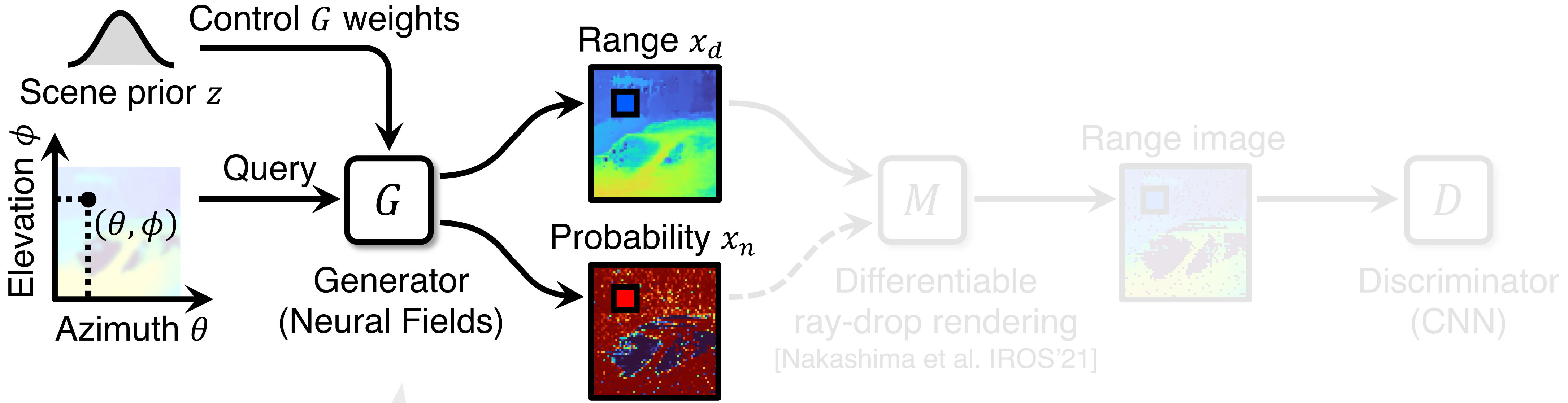
+ Robustness on ray-drop noises

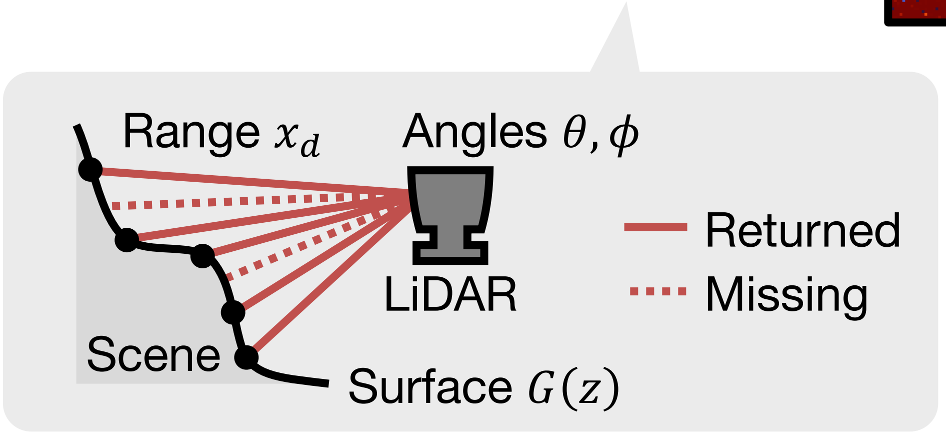
– Fixed resolution = LiDAR dependence
– No demonstration on perception tasks

LiDAR Range Images as 2D Neural Fields



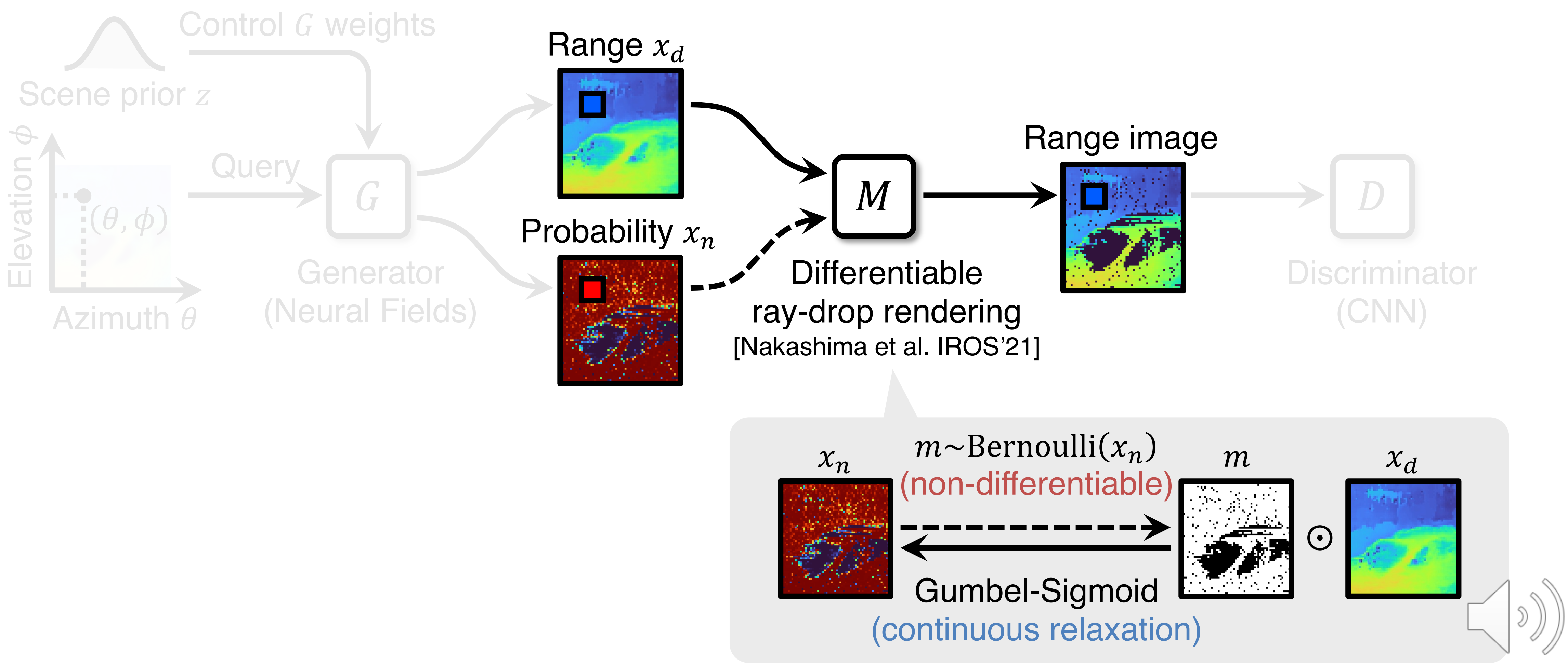
LiDAR Range Images as 2D Neural Fields



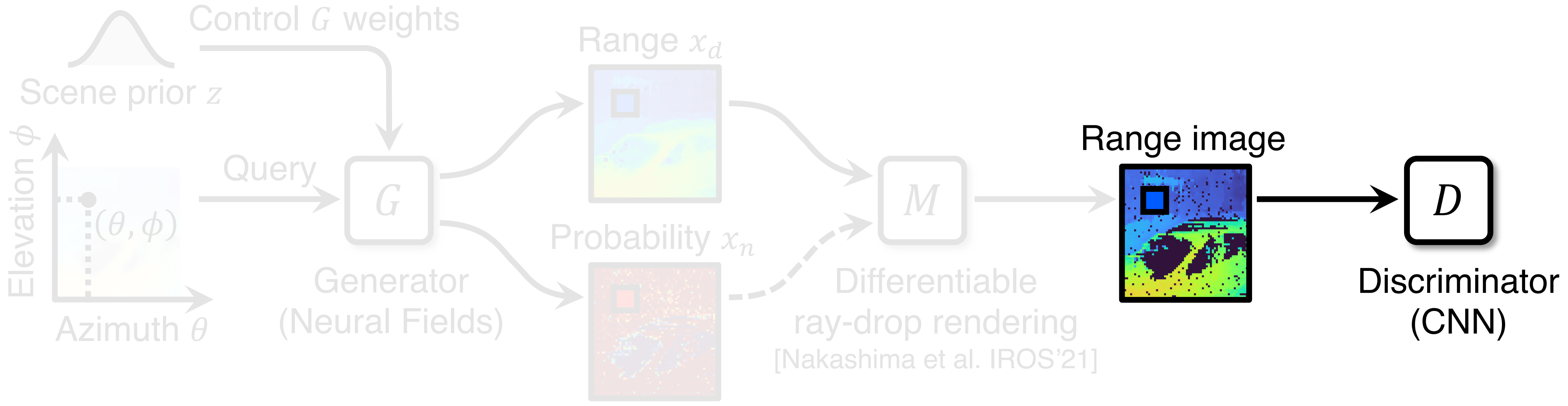


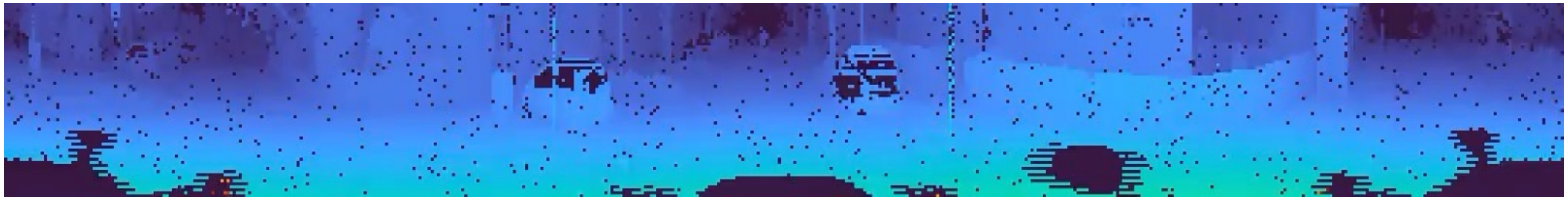
Analogy of LiDAR measurement

LiDAR Range Images as 2D Neural Fields

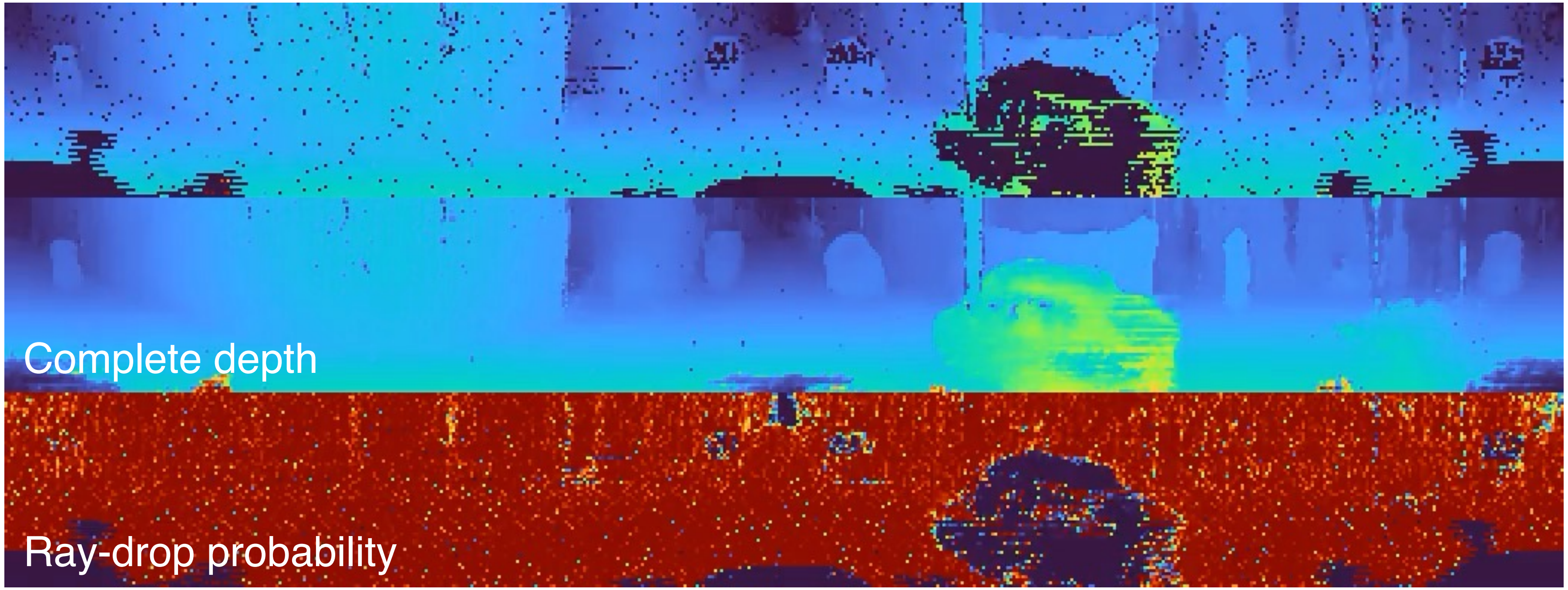


LiDAR Range Images as 2D Neural Fields





Training data (KITTI)



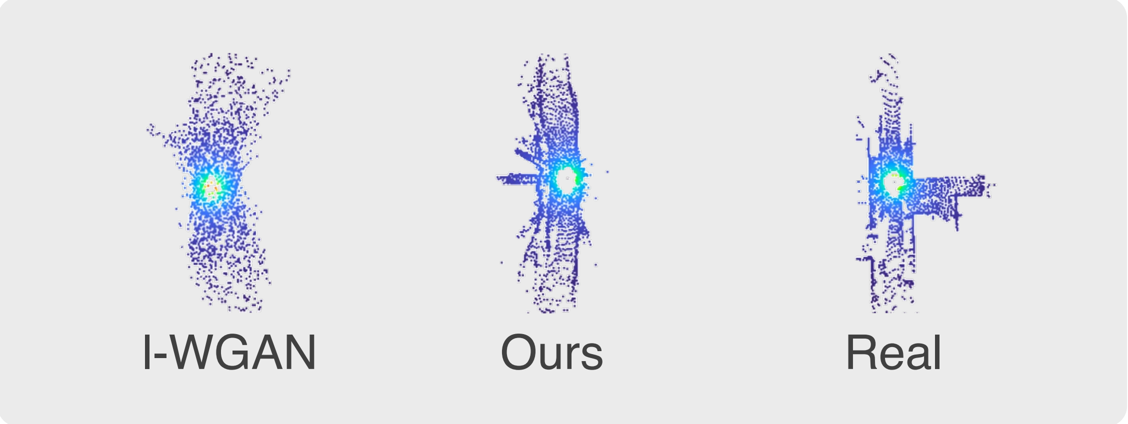
Latent interpolation w/ our GAN

Fidelity and Diversity

Image-level:

SWD on inverse depth maps

Method	16 × 128	32 × 256	64 × 512	Mean
Vanilla GAN [7]	0.397	0.371	0.746	0.505
DUSty [30]	**0.353**	0.353	0.768	0.491
Ours	0.378	**0.278**	**0.611**	**0.422**
Training set	0.257	0.207	0.765	0.410



Point-level:

JSD, COV, MMD, and 1-NNA

Method	JSD ↓	COV ↑	MMD ↓	1-NNA ↓
r-GAN [1]	21.73	0.013	17.51	1.000
l-WGAN [1]	4.91	0.324	**8.62**	0.896
Vanilla GAN [7]	10.31	0.290	12.34	0.986
DUSty [30]	**3.00**	0.375	9.41	0.898
Ours	3.04	**0.388**	9.12	**0.892**
Training set	2.80	0.362	0.765	0.890

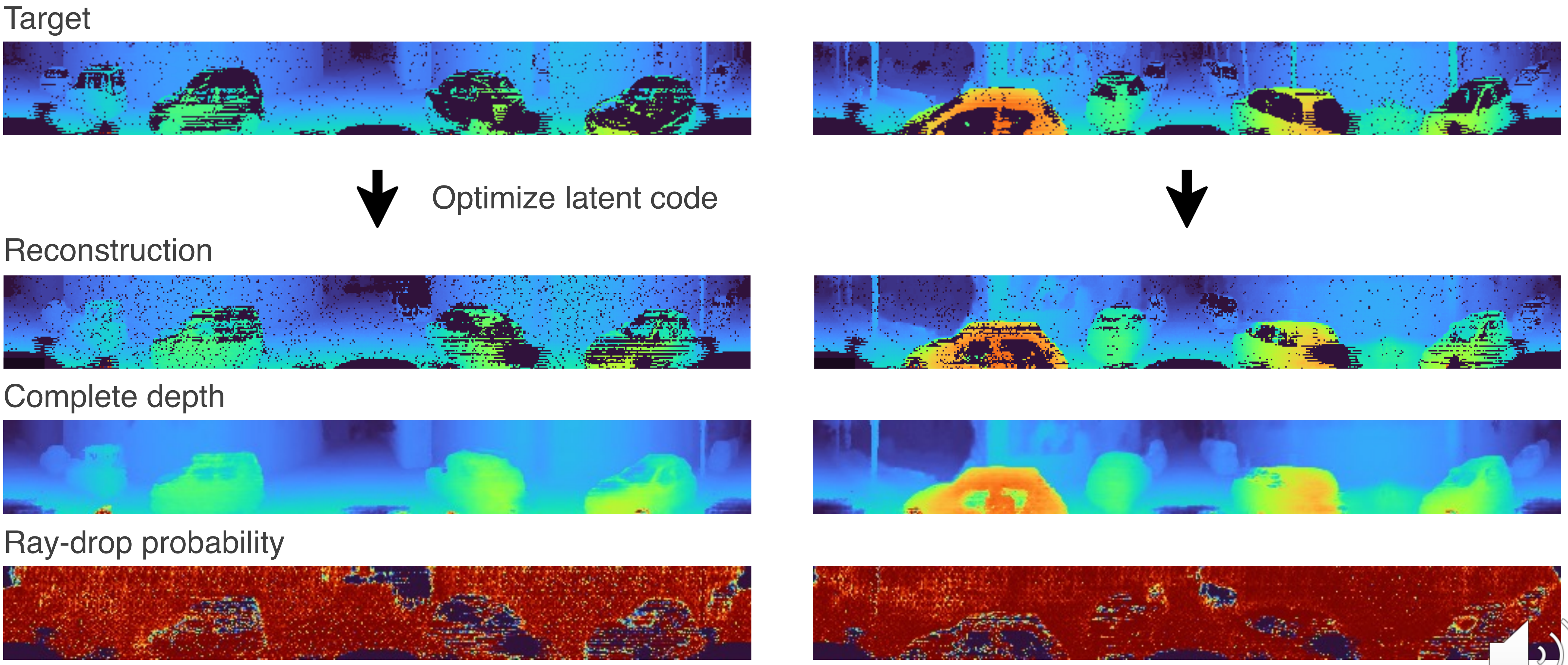
Feature-level:

FPD and MMD^2 on PointNet features

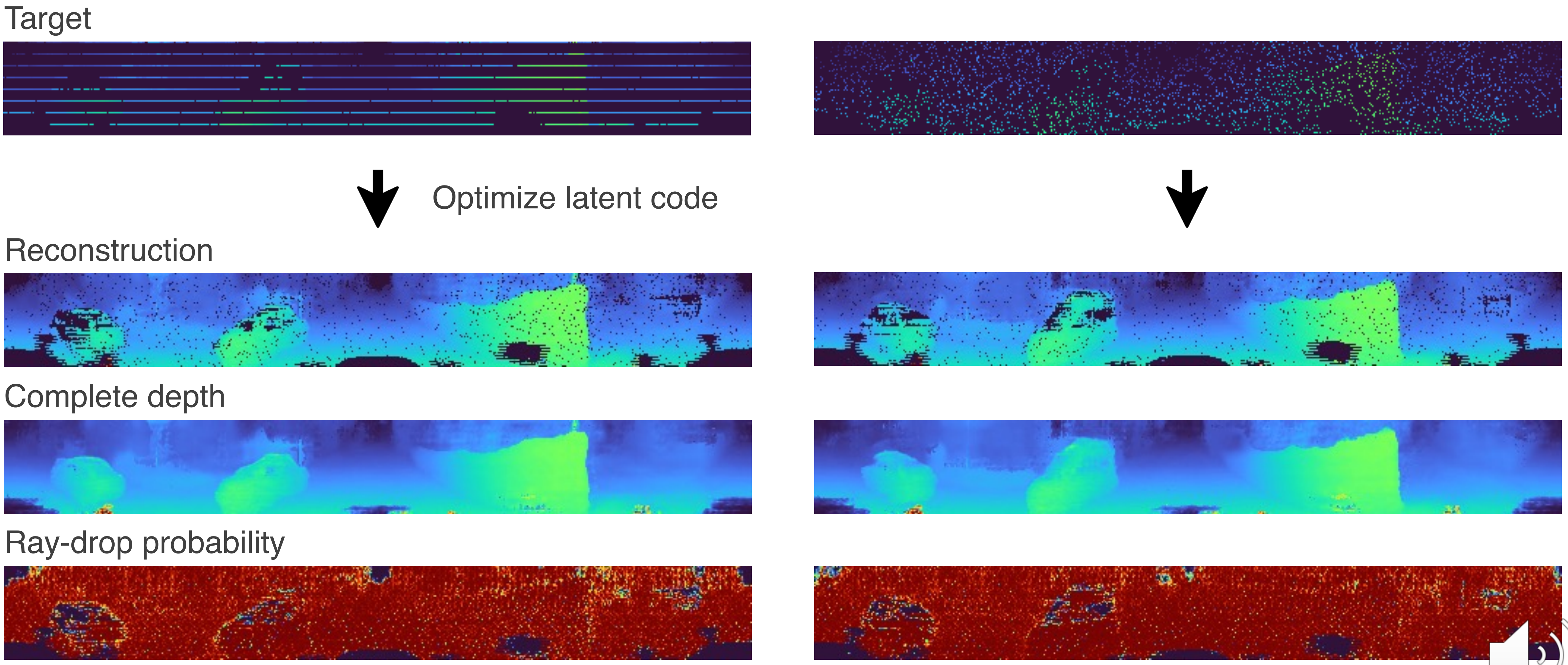
	2048 points		64 × 512 (full)	
Method	FPD ↓	MMD^2 ↓	FPD ↓	MMD^2 ↓
r-GAN [1]	787.45	45.02	–	–
l-WGAN [1]	129.35	10.65	–	–
Vanilla GAN [7]	3629.36	671.14	3648.68	675.24
DUSty [30]	232.90	39.62	241.32	42.66
Ours	**96.11**	**3.66**	**93.85**	**3**[illegible]

Applications

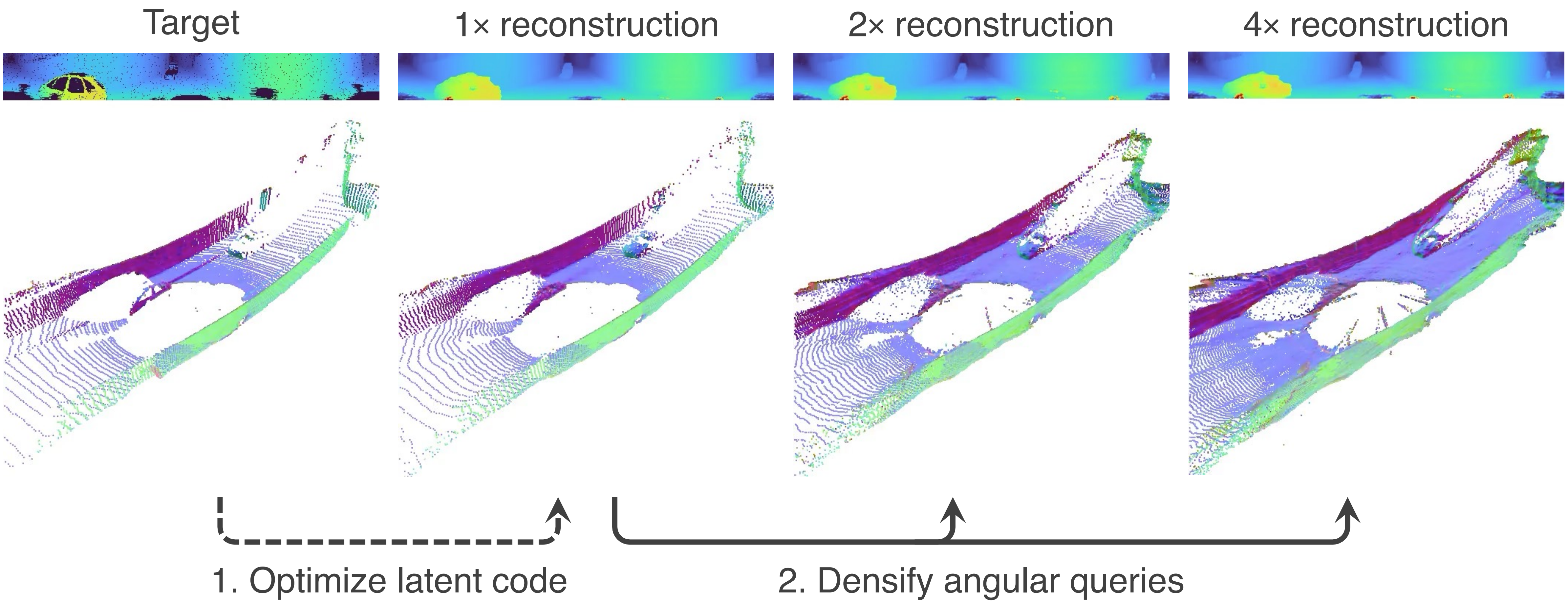
Decomposition



Restoration

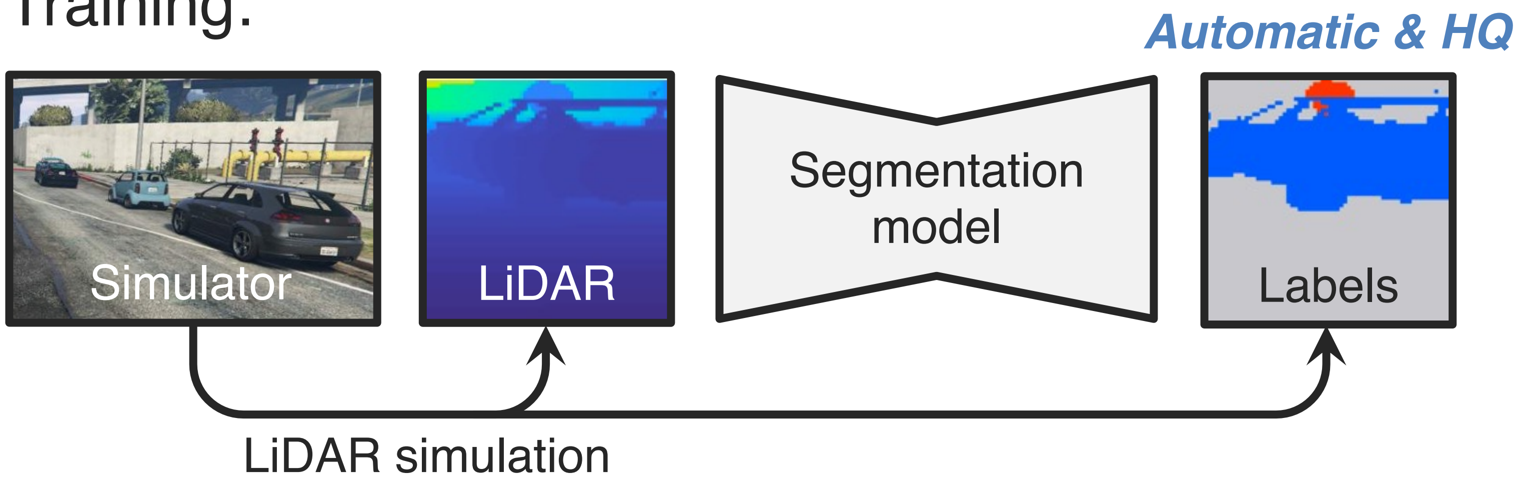


Upsampling


Target
1× reconstruction
2× reconstruction
4× reconstruction
1. Optimize latent code
2. Densify angular queries

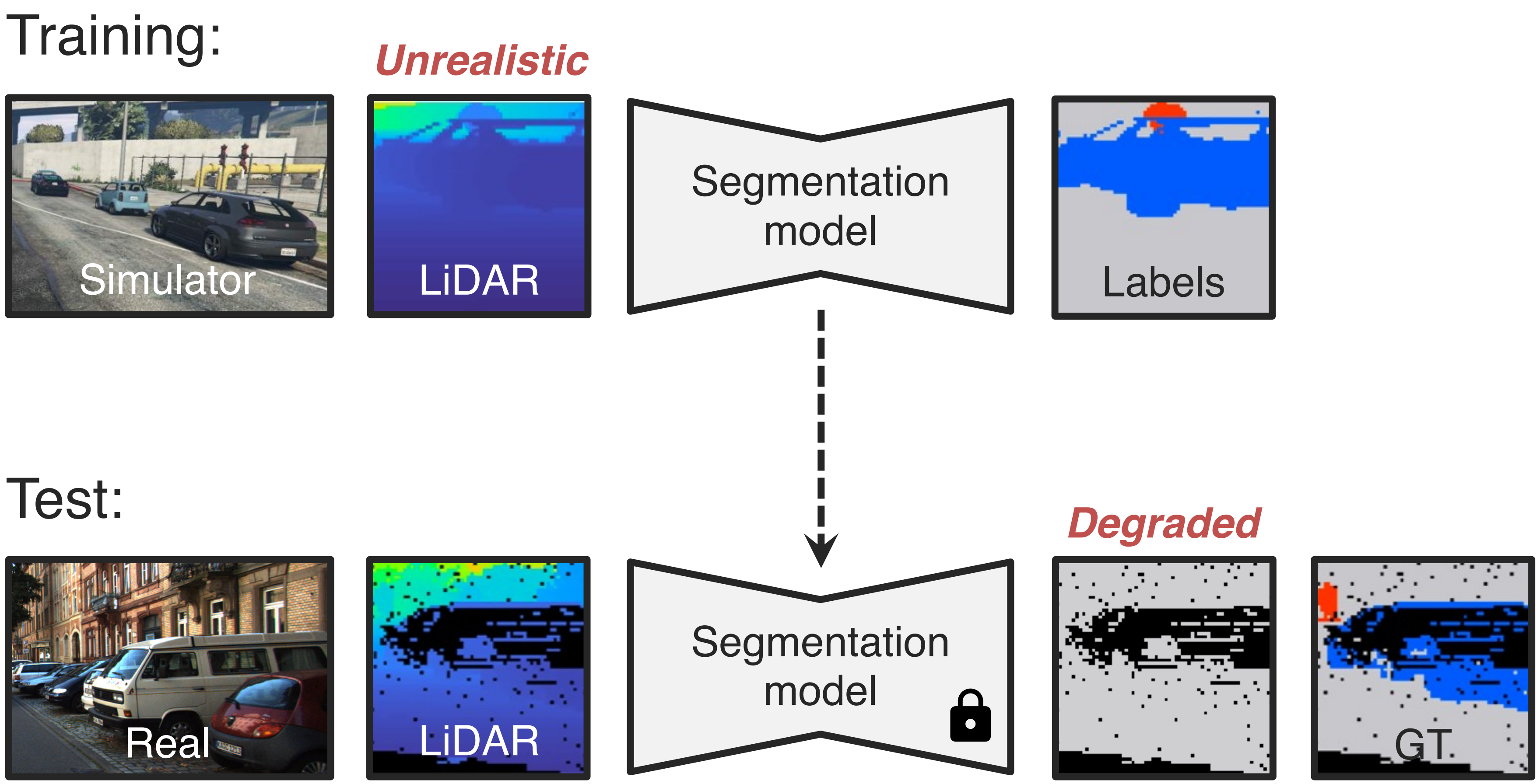
Sim2Real Sementic Segmentation

Training:

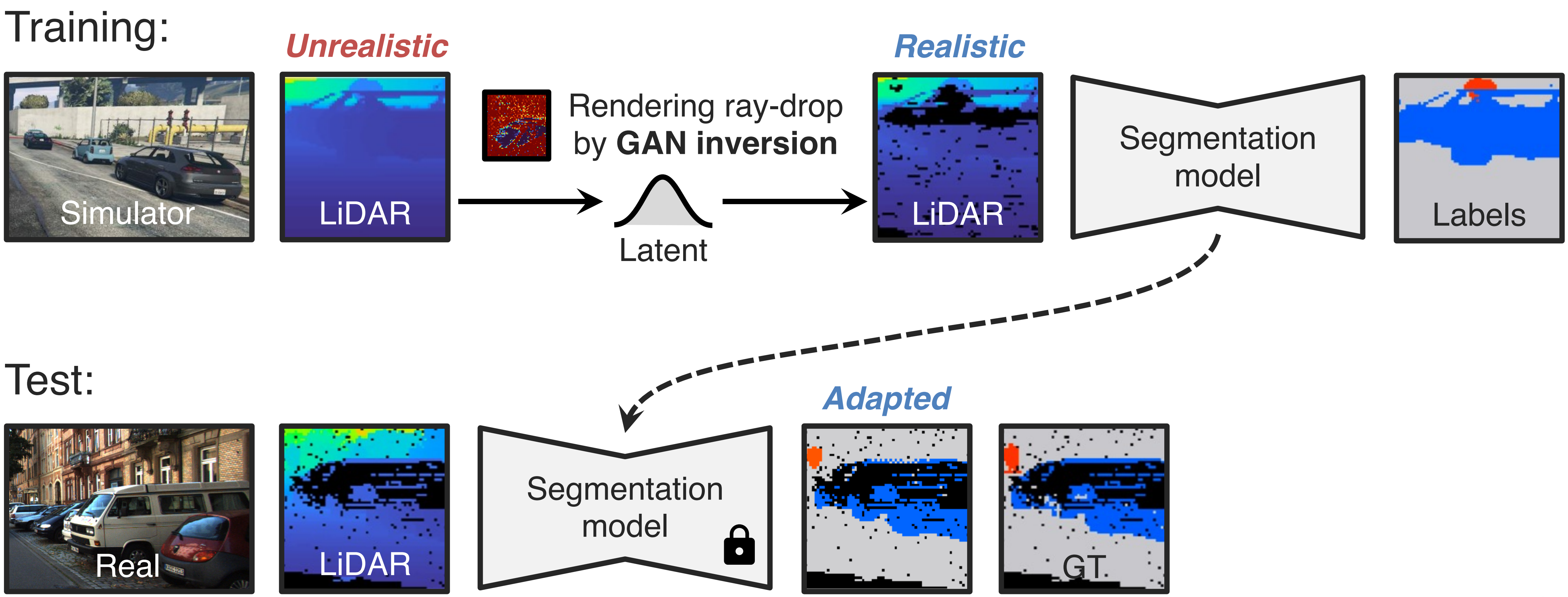


Test:

Sim2Real Sementic Segmentation



Sim2Real Sementic Segmentation



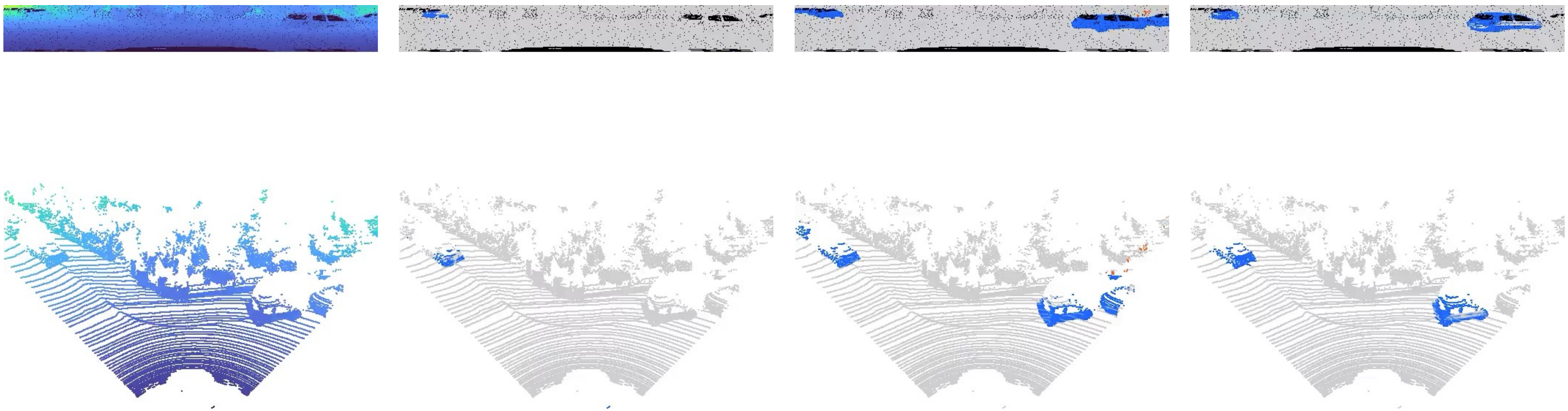
Sim2Real Sementic Segmentation

Input

Baseline

Ours

GT



1.7% mIoU

46.3% mIoU

w/ our ray-drop rendering

Sim2Real Sementic Segmentation

GTA-LiDAR (simulation) → **KITTI** (real) [Wu+, ICRA'19]

	DA[†]		Input modality[‡]				Car			Pedestrian			
Method	D	F	C	R	I	M	Precision	Recall	IoU	Precision	Recall	IoU	mIoU
SqueezeSegV2 [47][§]	✓	✓	✓	✓	✓	✓	–	–	57.4	–	–	23.5	40.5
DAN [25]		✓	✓				56.3	76.4	47.8	20.8	**68.9**	19.0	33.4
CORAL [41]		✓	✓				56.5	82.1	50.2	26.0	50.3	20.7	35.5
HoMM [9]		✓	✓				59.4	85.2	53.9	26.2	66.8	23.2	38.6
ADDA [45]		✓	✓				56.7	83.5	50.7	24.7	58.5	21.0	35.9
CyCADA [15]	✓	✓	✓				40.9	72.1	35.3	17.8	52.4	15.3	25.3
ePointDA [52][§]	✓	✓	✓				73.4	81.9	63.4	**29.4**	56.0	23.9	43.7
ePointDA [52]	✓	✓	✓				**75.2**	84.7	66.2	28.7	65.2	24.8	45.5
Ours (config-E)[§]	✓		✓	✓			74.8	**87.0**	**67.3**	28.8	67.1	**25.2**	**46.3**

Thank you!

Code and models are available at

https://kazuto1011.github.io/dusty-gan-v2