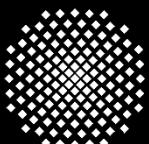


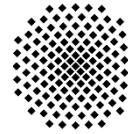
Synthesizing realistic high-resolution LiDAR Point Clouds by Up-Sampling with Neural Networks

Masterthesis
Larissa Triess

Supervisor: Prof. Dr.-Ing. Rainer Ott, INUE
Dr. rer. nat. David Peter, Daimler AG

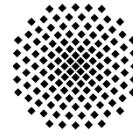


University of Stuttgart
Institute of Telecommunications
Prof. Dr.-Ing. Stephan ten Brink



Agenda

- I. Introduction and Motivation
- II. Fundamentals
- III. Implemented Network Systems
- IV. Results
- V. Summary and Outlook



Agenda

I. Introduction and Motivation

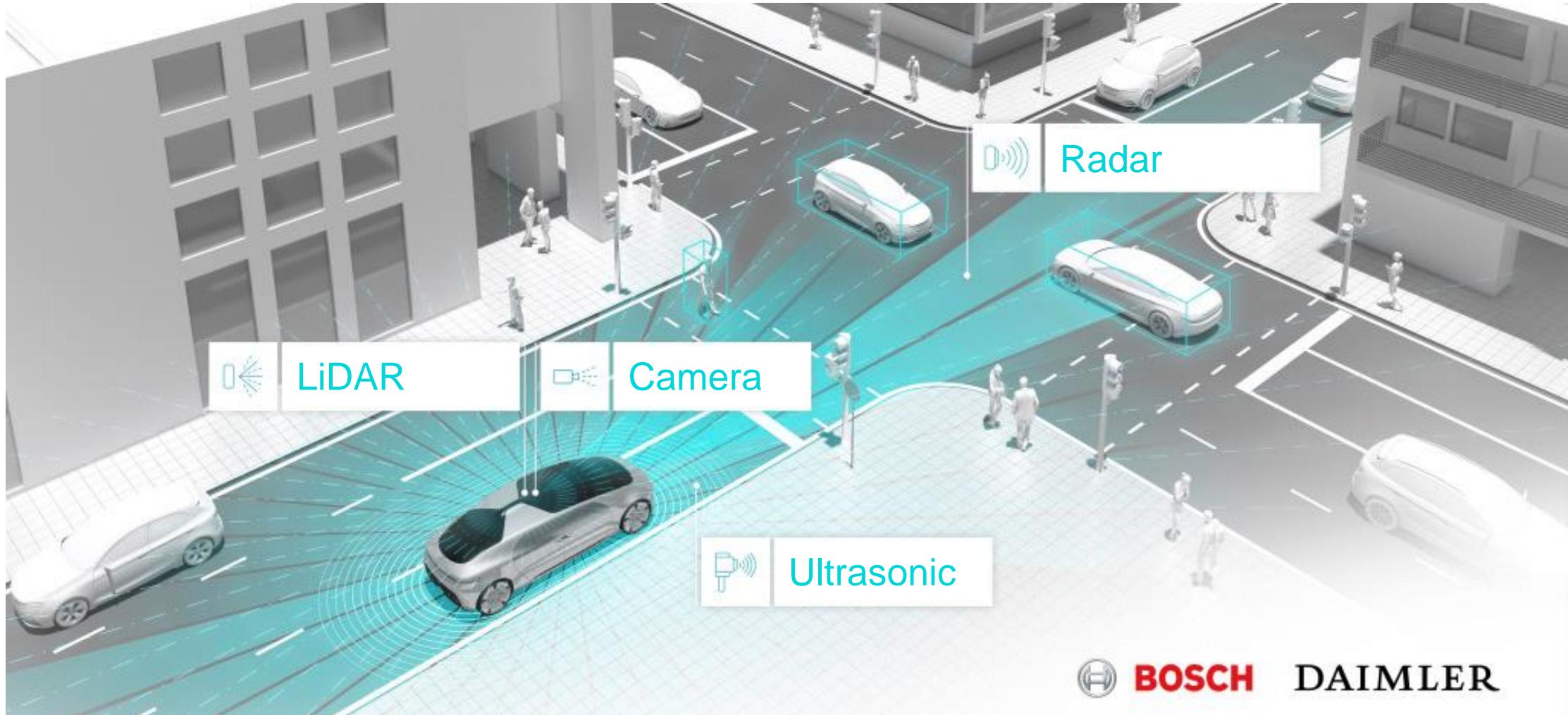
II. Fundamentals

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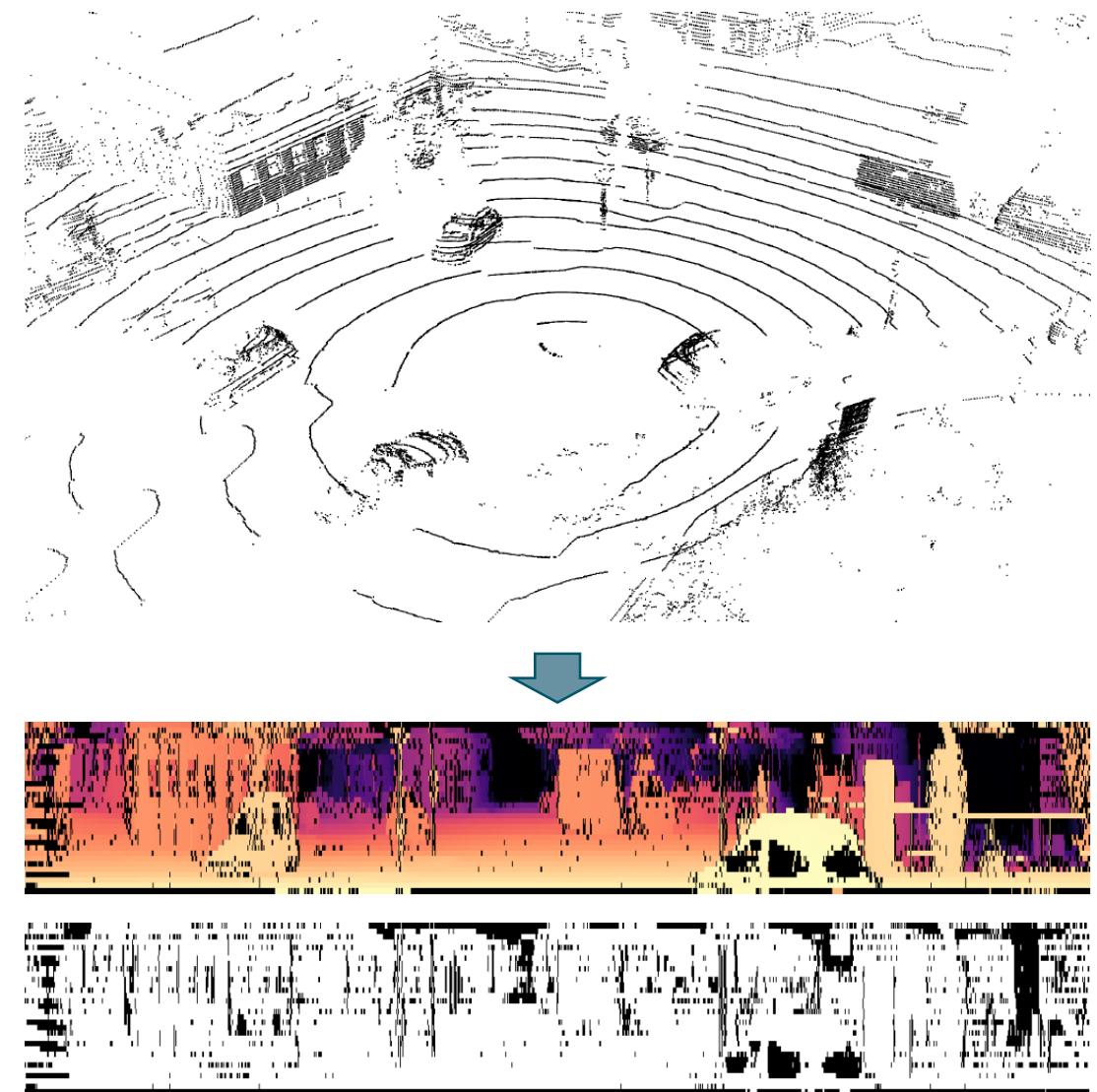
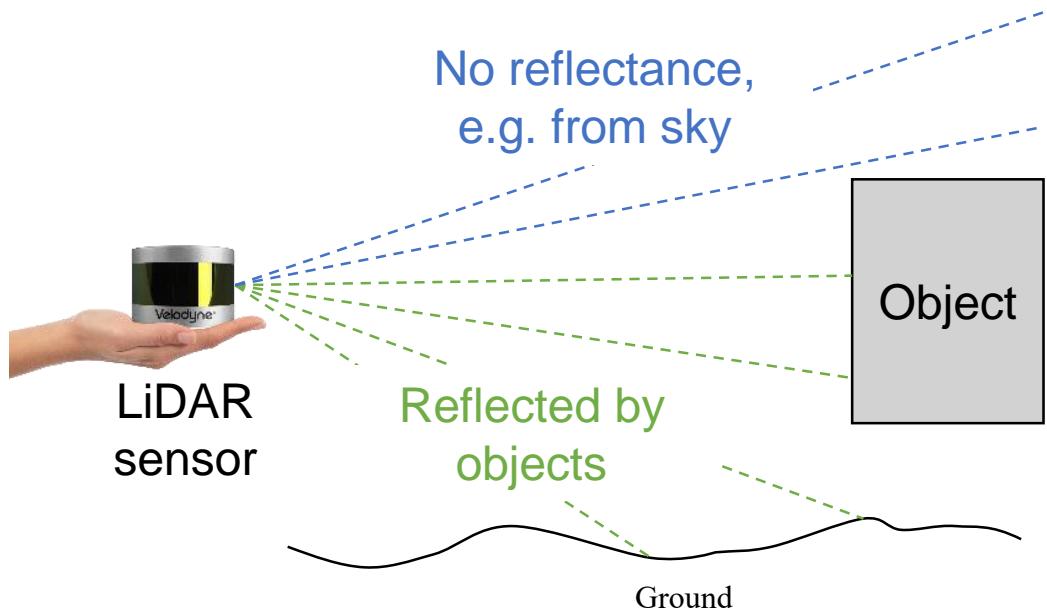
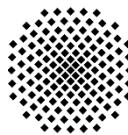
Motivation

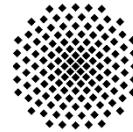


BOSCH

DAIMLER

LiDAR Sensor

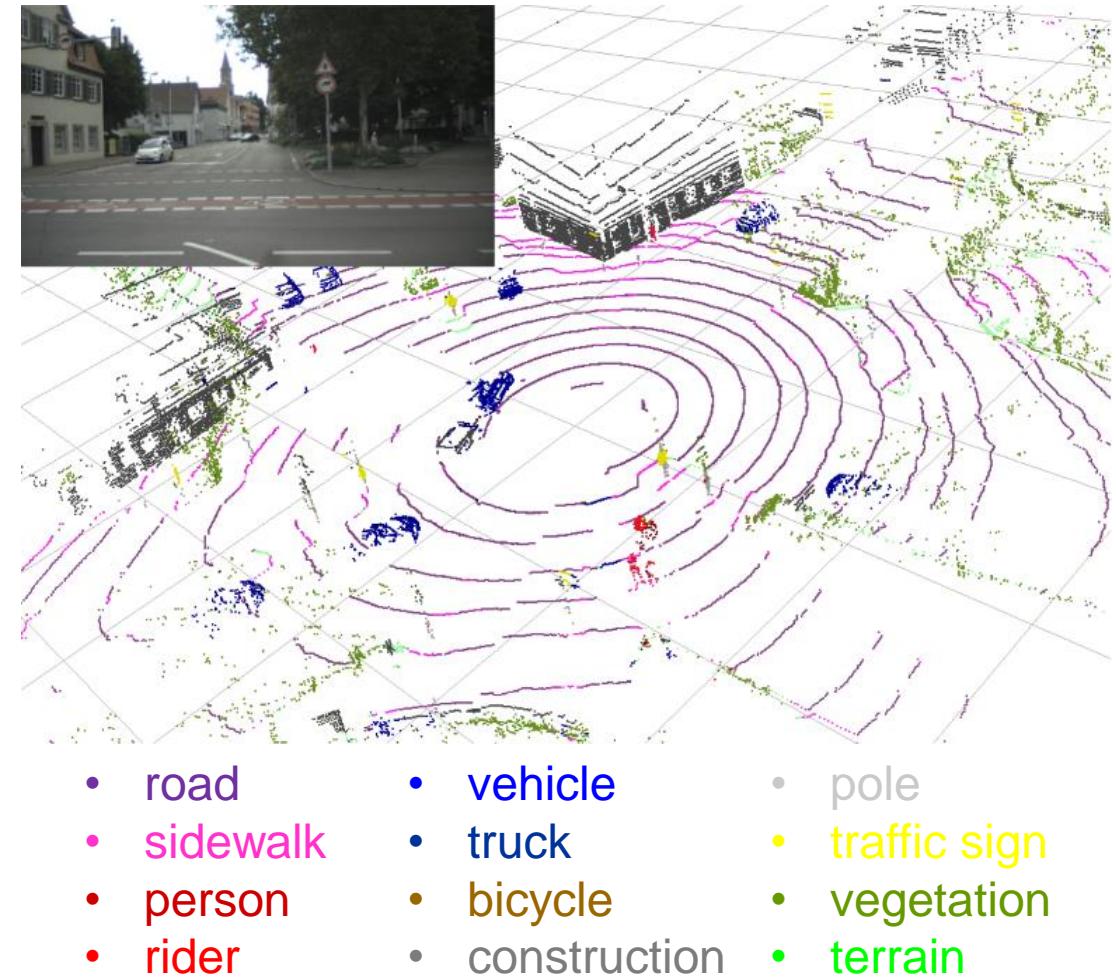


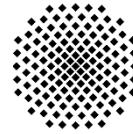


Dataset

	Training	Validation	Testing
	62 %	13 %	25 %
Original frames	343,926	73,473	137,636
Optimized frames	57,324	12,261	22,983

- Urban and rural scenes
- Single sensor mounted on roof of vehicle
- Sequence based dataset split
- Total dataset equals 15.5 hours of recording





Agenda

I. Introduction and Motivation

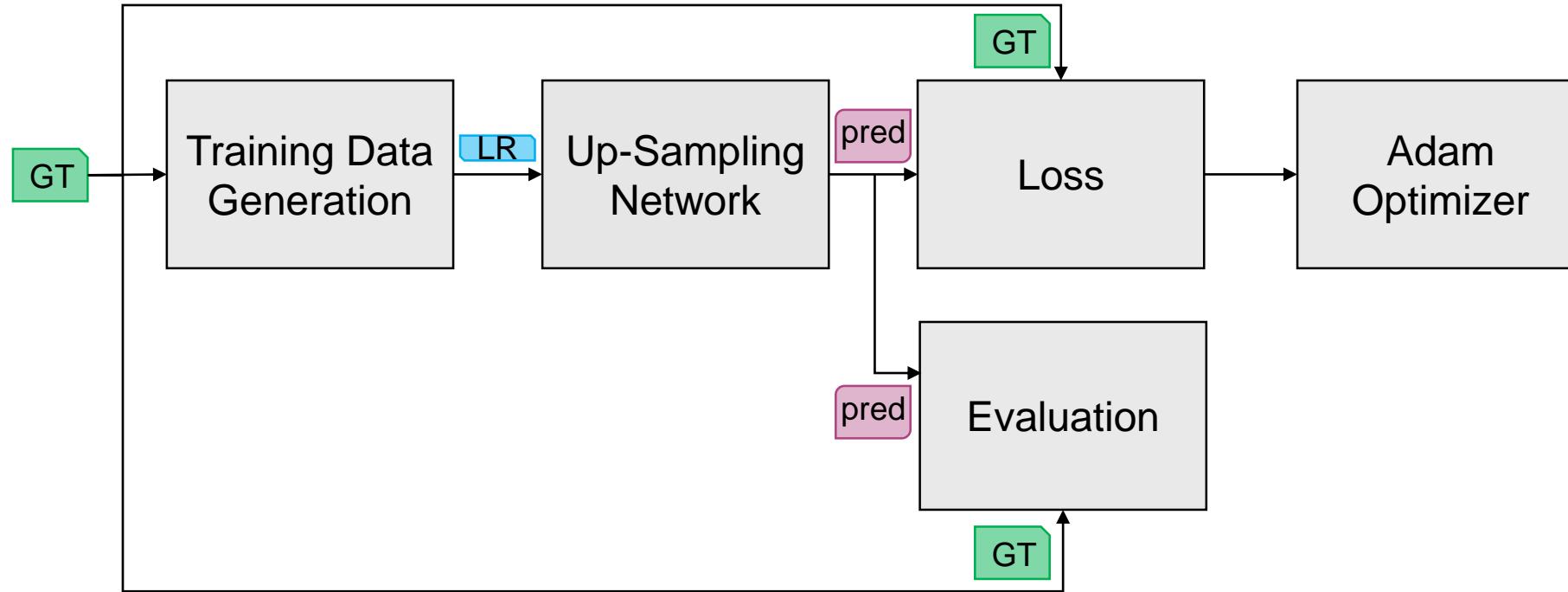
II. Fundamentals

III. Implemented Network Systems

IV. Results

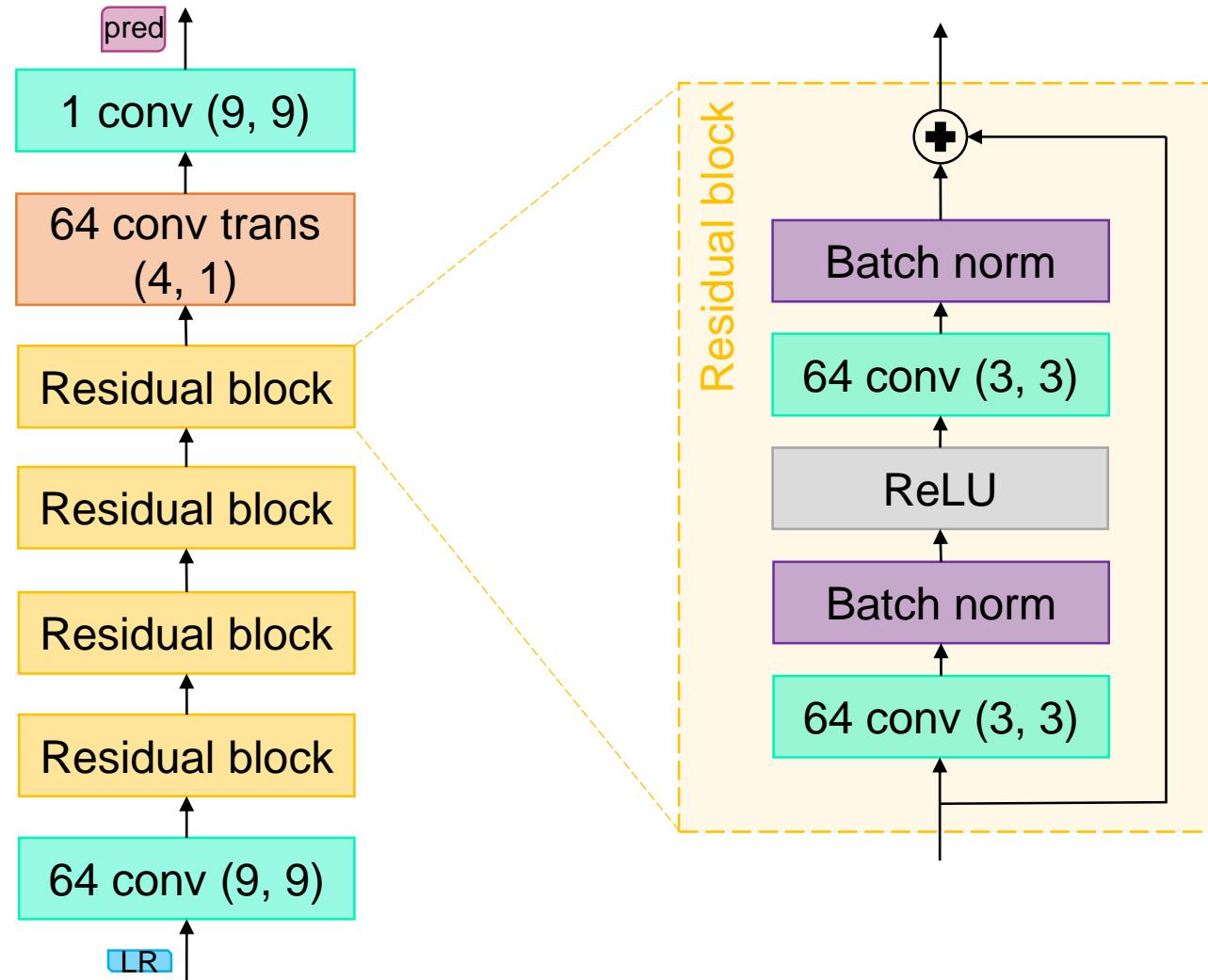
V. Summary and Outlook

System Overview

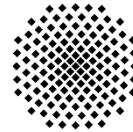


GT High-resolution ground truth data (H, W)
LR Low-resolution network input ($H/2, W$)
pred Predicted high-resolution output (H, W)

Up-Sampling Network



LR Low-resolution network input ($H/2, W$)
pred Predicted high-resolution output (H, W)



Loss Functions / Evaluation Metrics

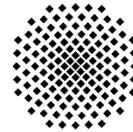
L2-Loss or Mean Squared Error (MSE)

$$\text{MSE} = \frac{1}{HW} \sum_{h,w} |d_{h,w}^{pred} - d_{h,w}^{gt}|^2$$

L1-Loss or Mean Absolute Error (MAE)

$$\text{MAE} = \frac{1}{HW} \sum_{h,w} |d_{h,w}^{pred} - d_{h,w}^{gt}|$$

H, W – height and width LiDAR image; $d_{h,w}$ distance at position h, w



Loss Functions / Evaluation Metrics

L2-Loss or Mean Squared Error (MSE)

$$\text{MSE} = \frac{1}{HW} \sum_{h,w} \left| d_{h,w}^{pred} - d_{h,w}^{gt} \right|^2 \cdot \text{valid}_{h,w}$$

L1-Loss or Mean Absolute Error (MAE)

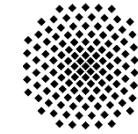
$$\text{MAE} = \frac{1}{HW} \sum_{h,w} \left| d_{h,w}^{pred} - d_{h,w}^{gt} \right| \cdot \text{valid}_{h,w}$$

Extension for point cloud up-sampling:

$$\text{valid}_{h,w} \in \{0, 1\}$$

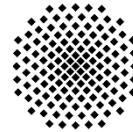
0 – missing measurement
1 – valid point

H, W – height and width LiDAR image; $d_{h,w}$ distance at position h, w



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Implemented Network Systems

Traditional Methods (Baseline)

Regular Architecture

Multi-Task Learning

Feature Reconstruction

Semantically Guided

} Learning-based approaches

Implemented Network Systems

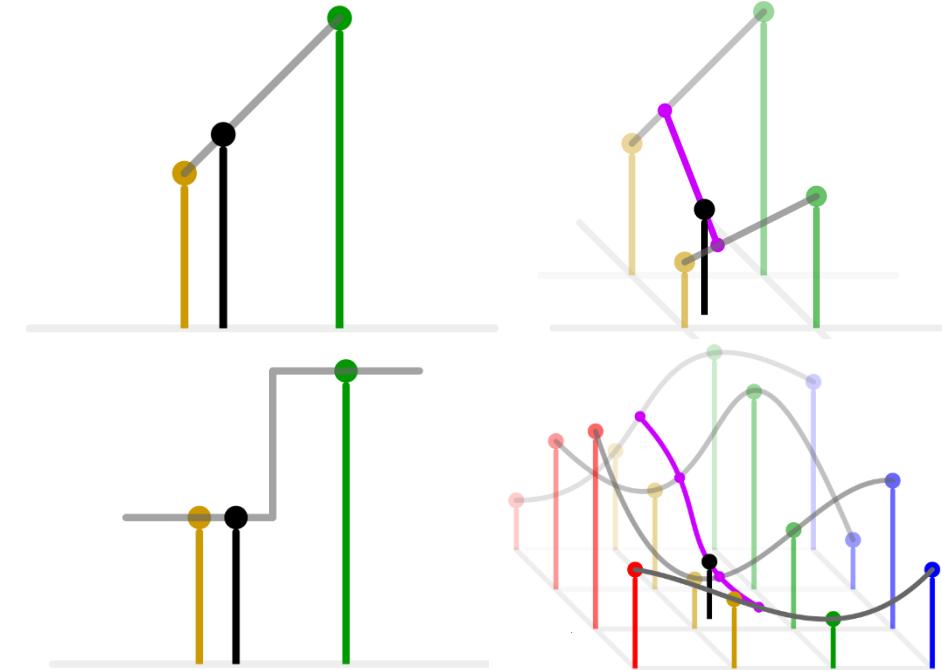
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Implemented Network Systems

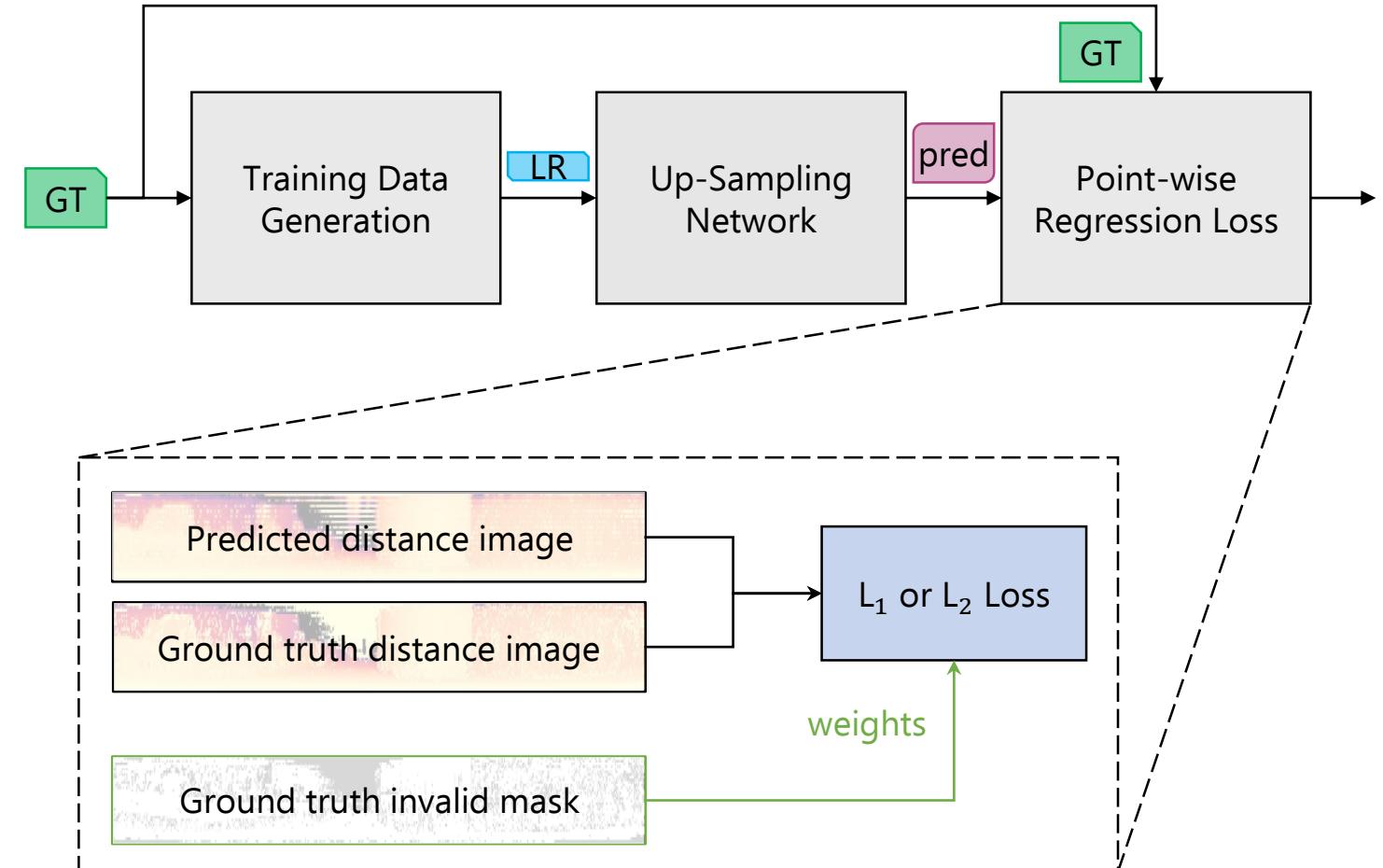
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Implemented Network Systems

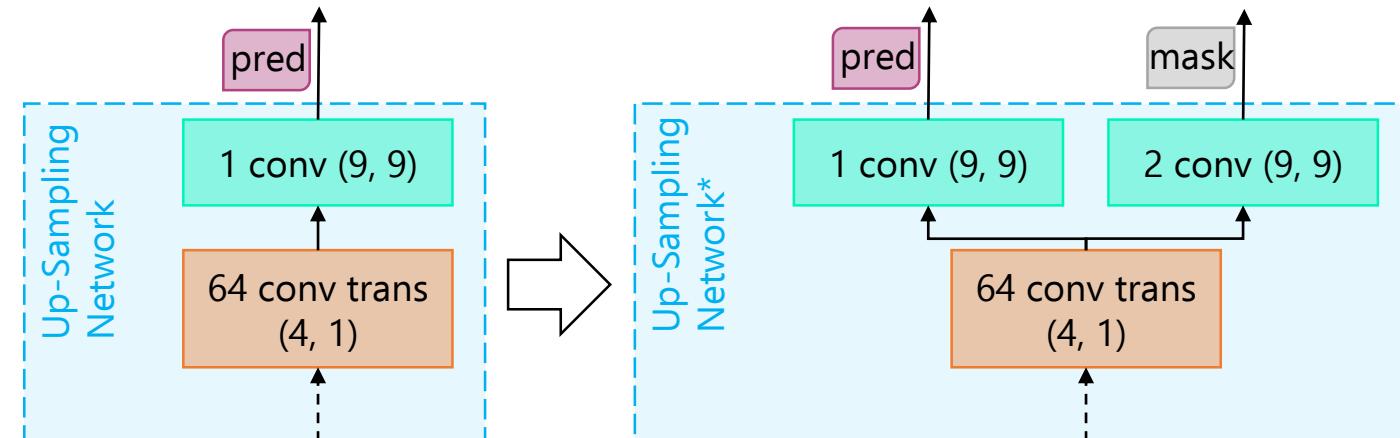
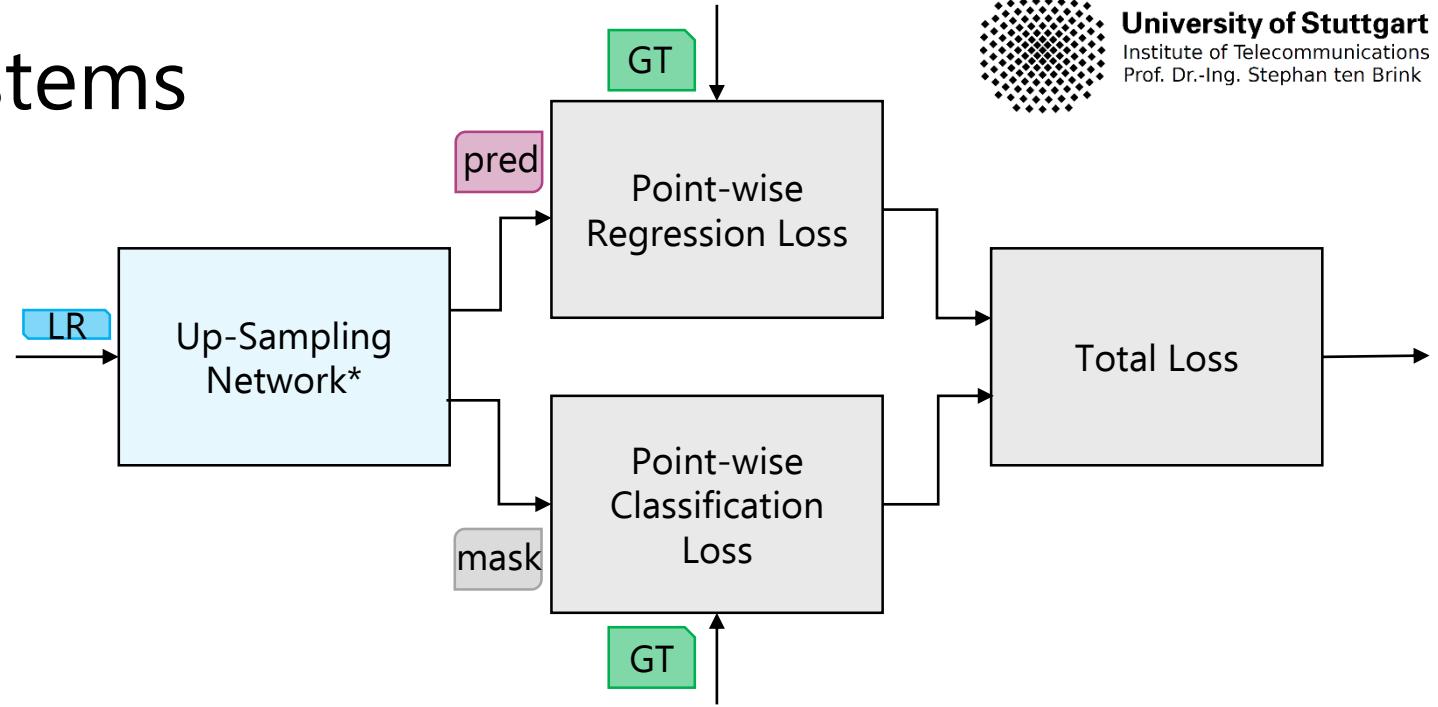
Traditional Methods (Baseline)

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Implemented Network Systems

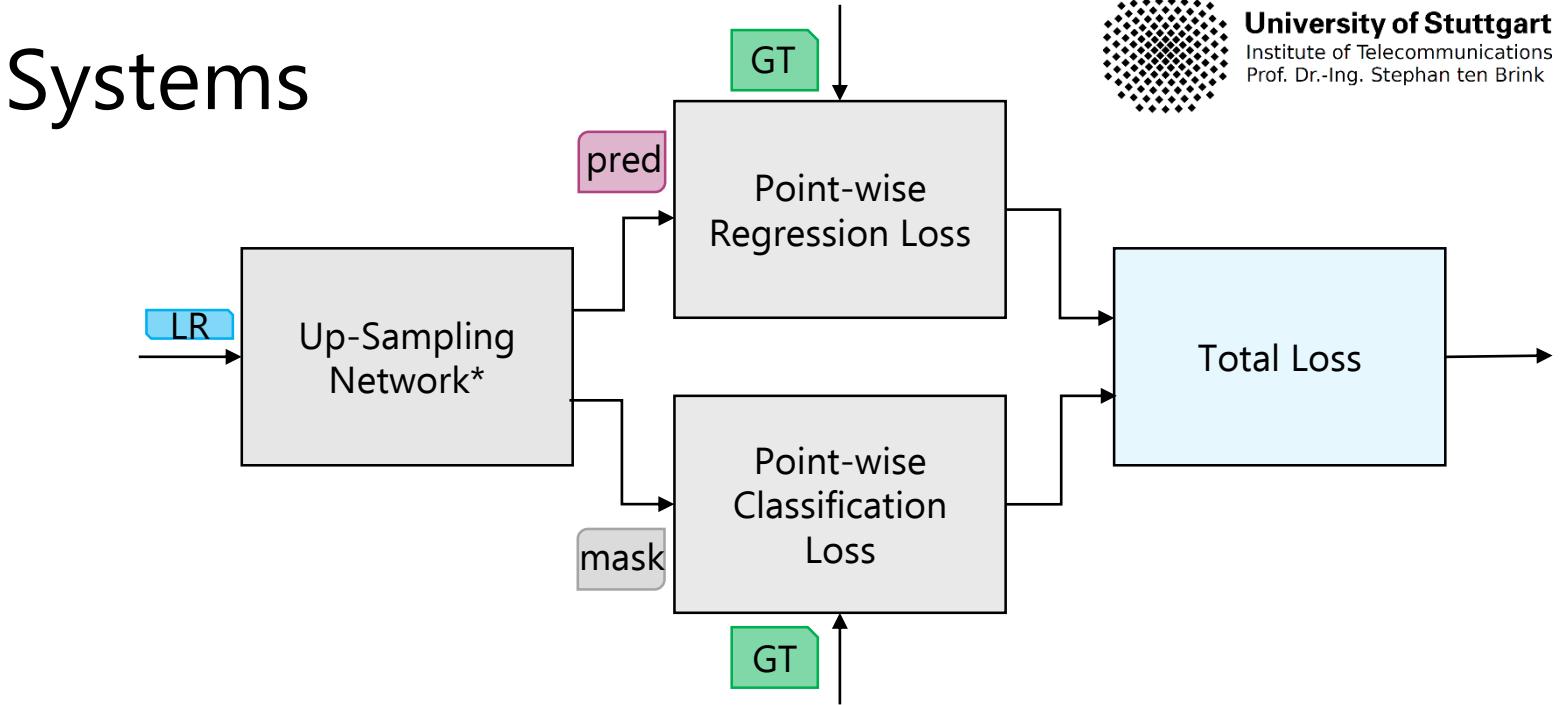
Traditional Methods (Baseline)

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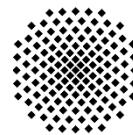
Semantically Guided



$$\mathcal{L}_{\text{total}} = (1 - p) \mathcal{L}_r + p \mathcal{L}_c \quad p = \text{const}$$

$$\mathcal{L}_{\text{total}} = \frac{1}{2\sigma_r^2} \mathcal{L}_r + \log \sigma_r + \frac{1}{\sigma_c^2} \mathcal{L}_c + \log \sigma_c$$

Trainable Variables



Implemented Network Systems

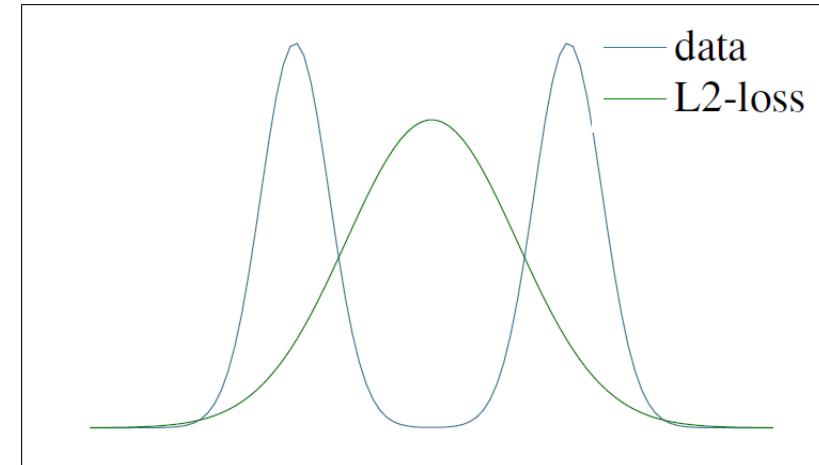
Traditional Methods (Baseline)

Regular Architecture

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Semantically Guided



input



output



ground truth

Implemented Network Systems

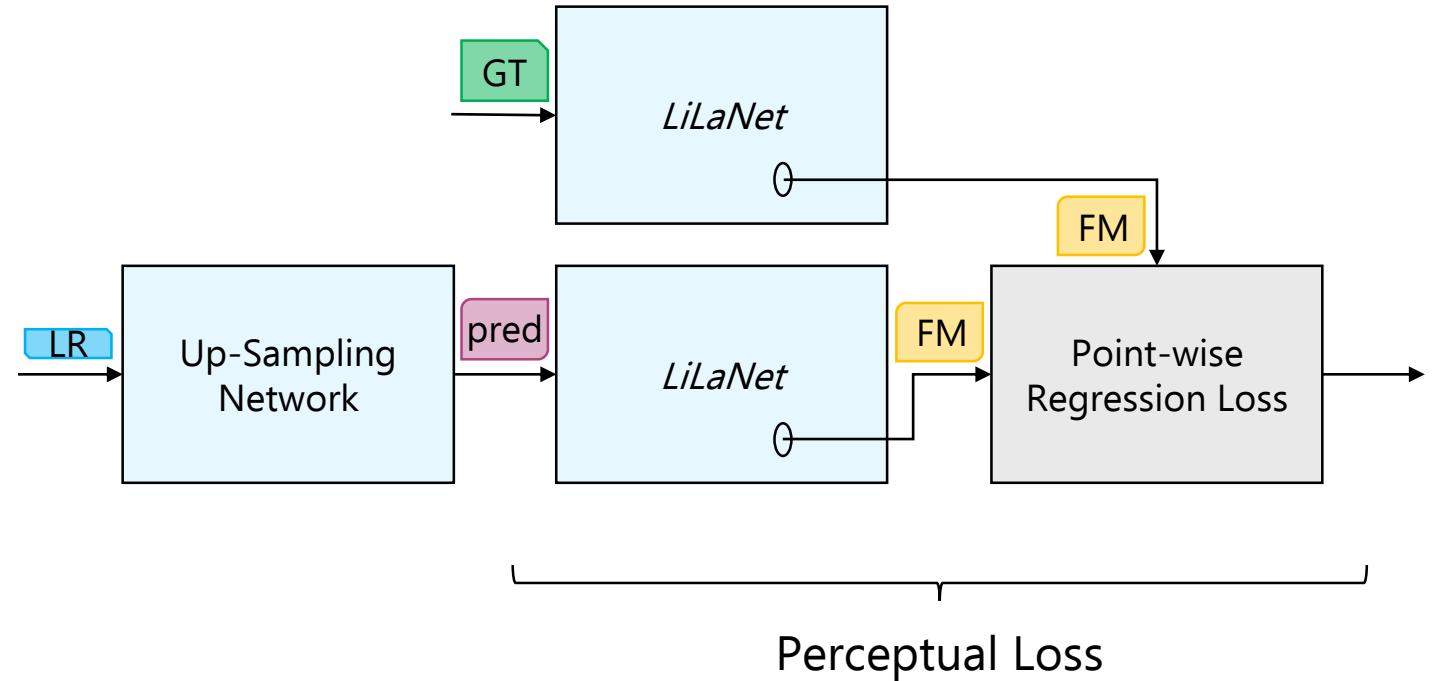
Traditional Methods (Baseline)

Regular Architecture

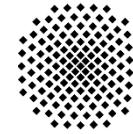
Multi-Task Learning

Feature Reconstruction

Semantically Guided



Implemented Network Systems



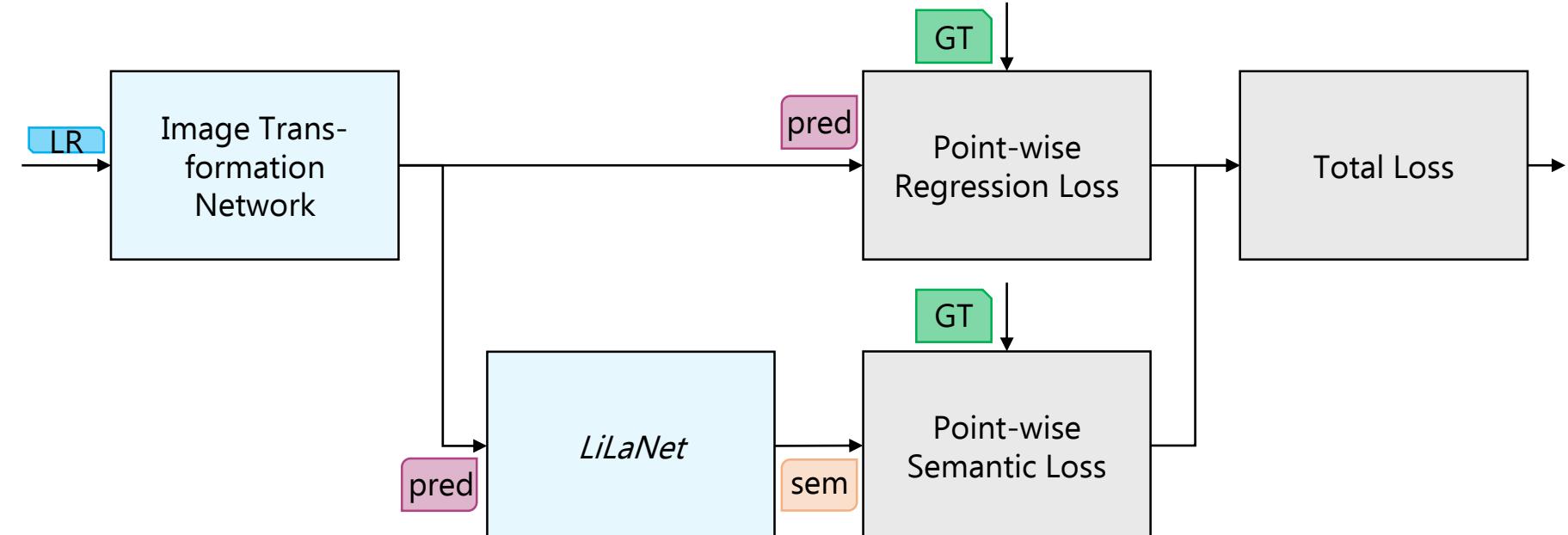
Traditional Methods (Baseline)

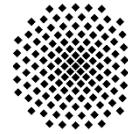
Regular Architecture

Multi-Task Learning

Feature Reconstruction

Semantically Guided

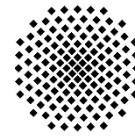




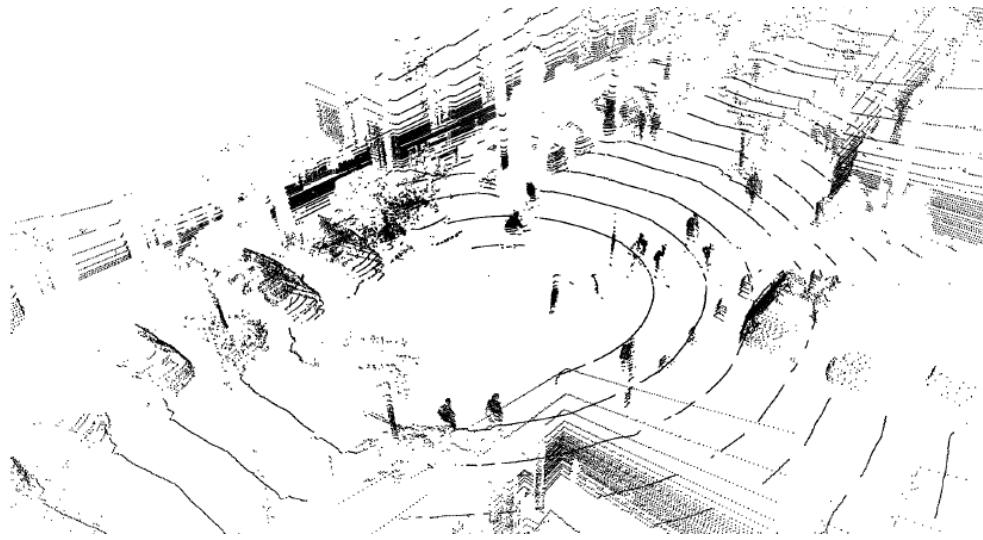
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Results – L1 vs. L2 Loss

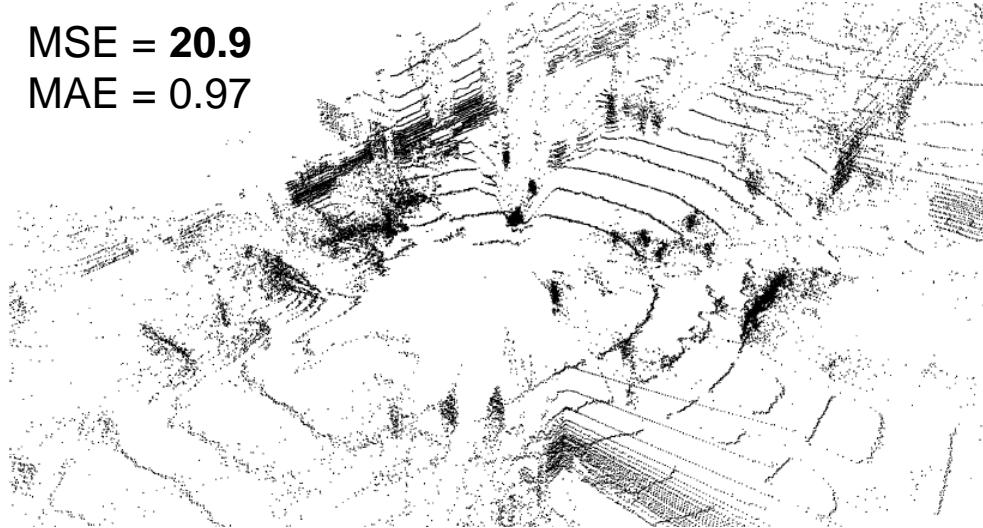


Ground Truth



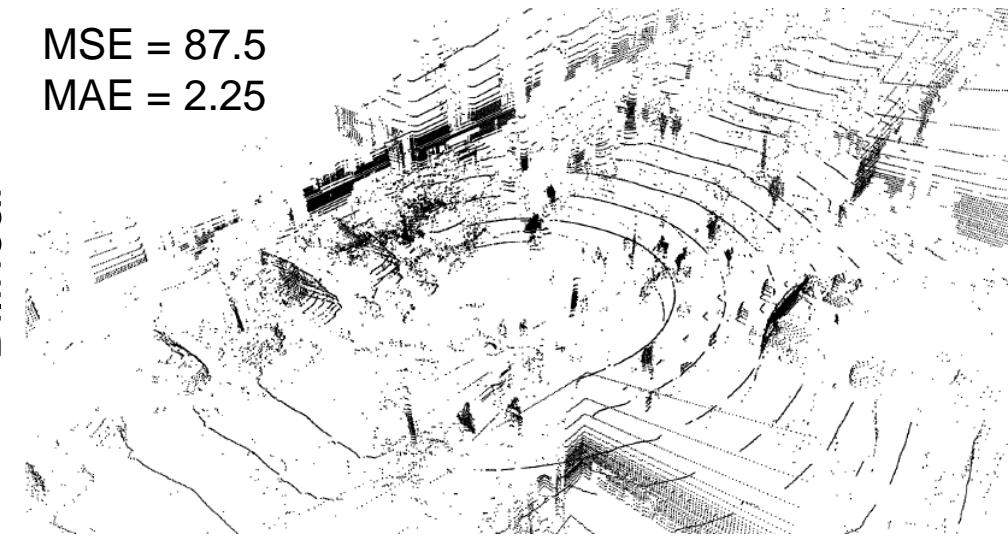
MSE = 20.9
MAE = 0.97

L2-LOSS



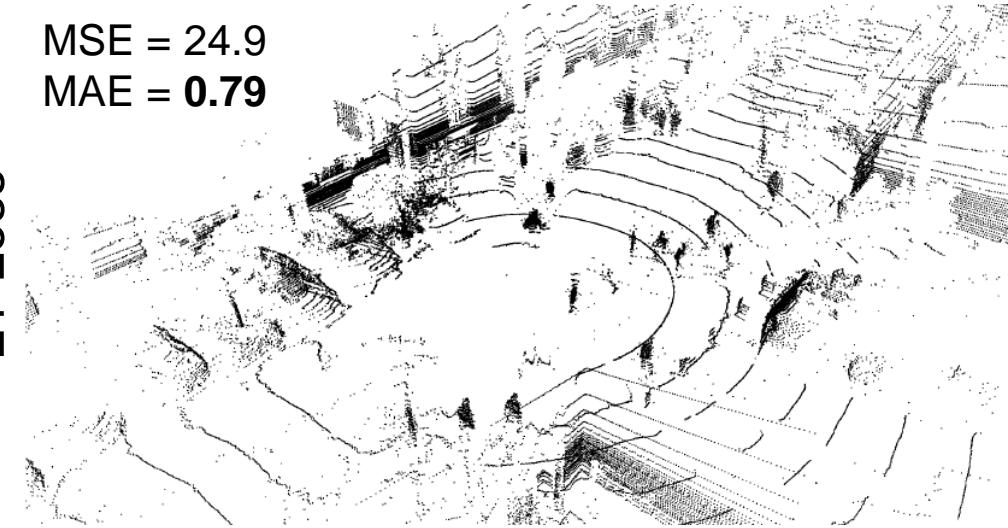
24.10.2018

Bilinear



MSE = 87.5
MAE = 2.25

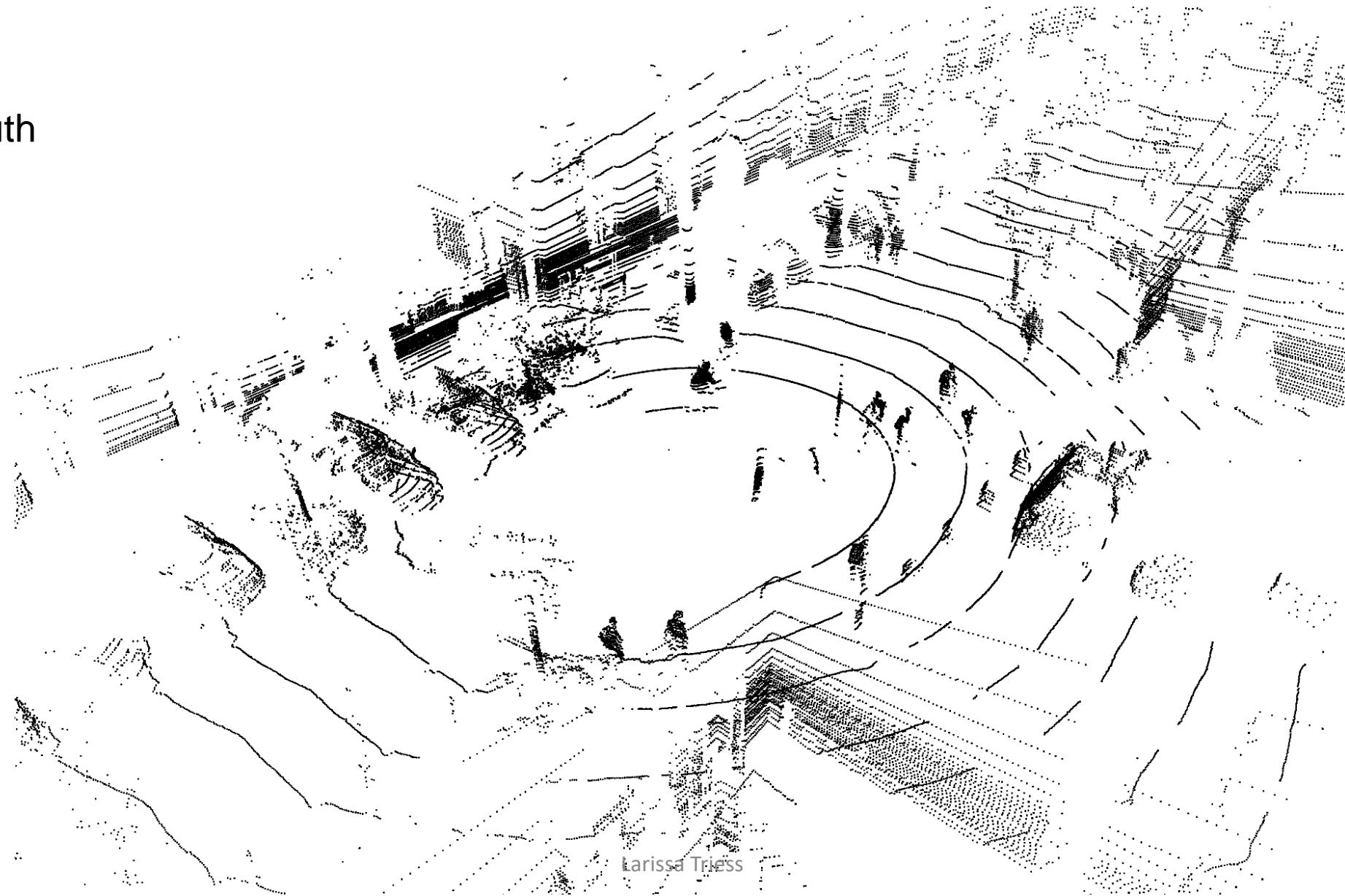
L1-LOSS

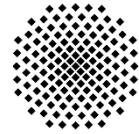


MSE = 24.9
MAE = 0.79

Results – L1 vs. L2 Loss

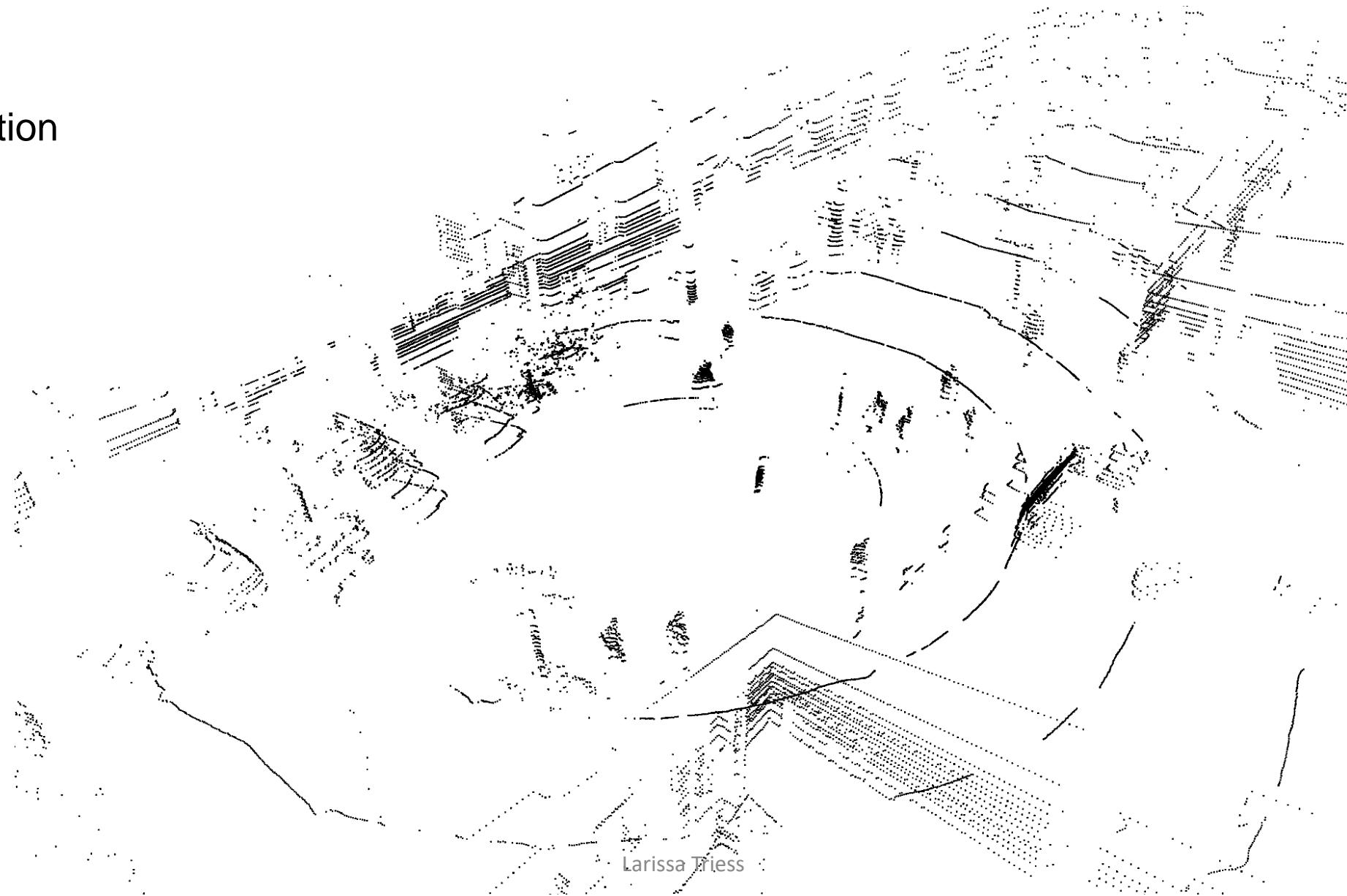
Ground Truth





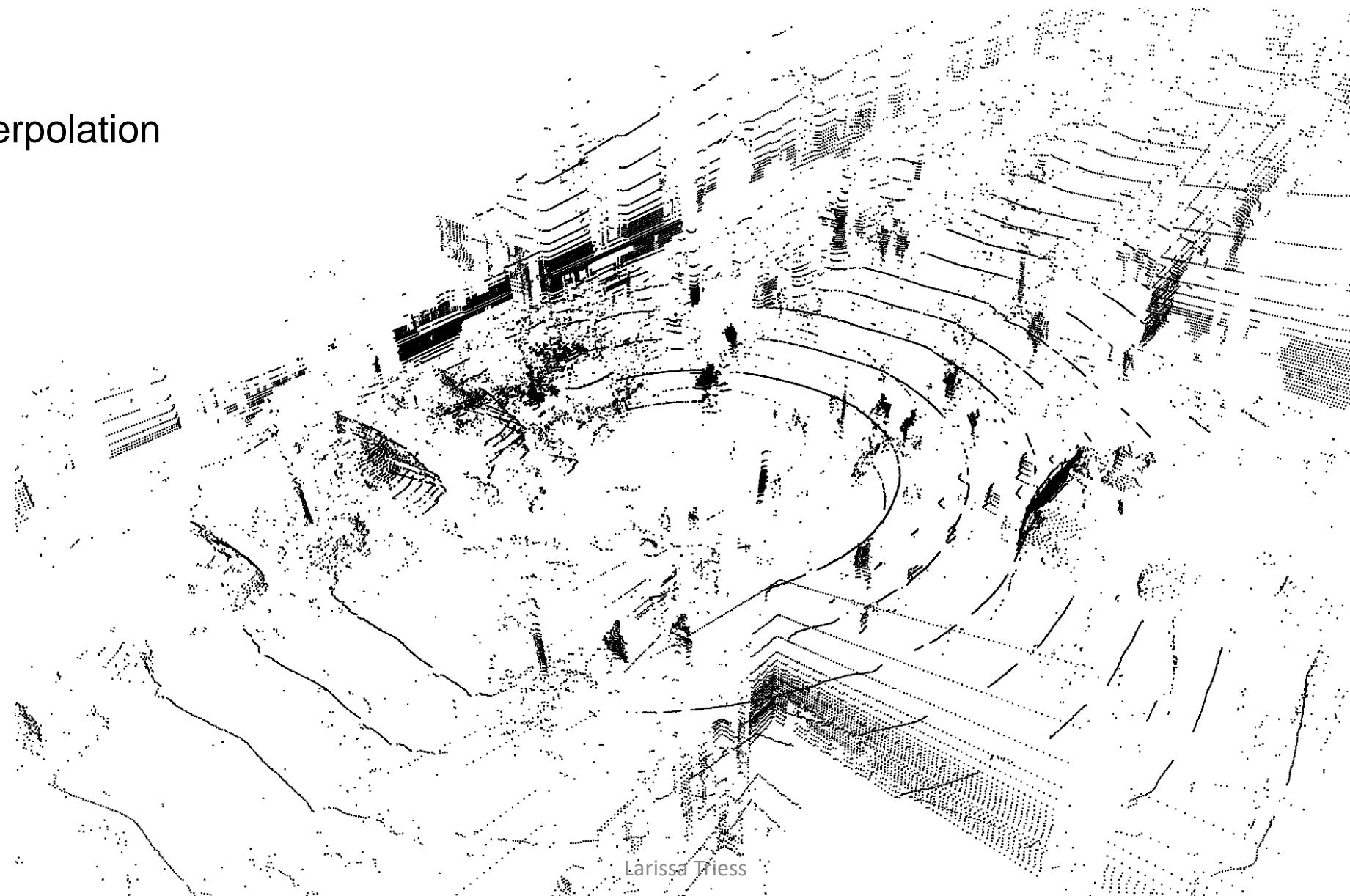
Results – L1 vs. L2 Loss

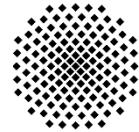
Low resolution



Results – L1 vs. L2 Loss

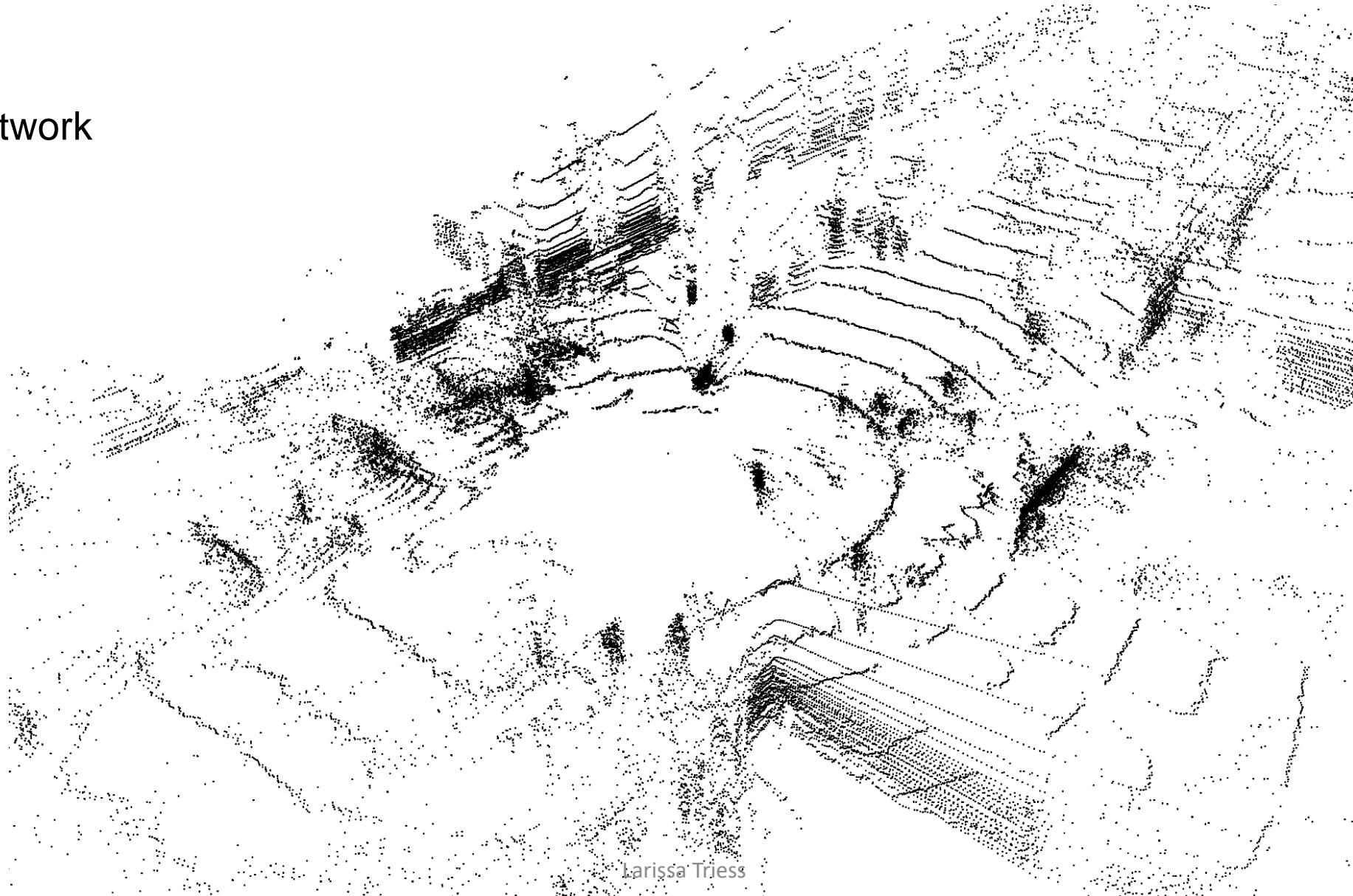
Bilinear interpolation





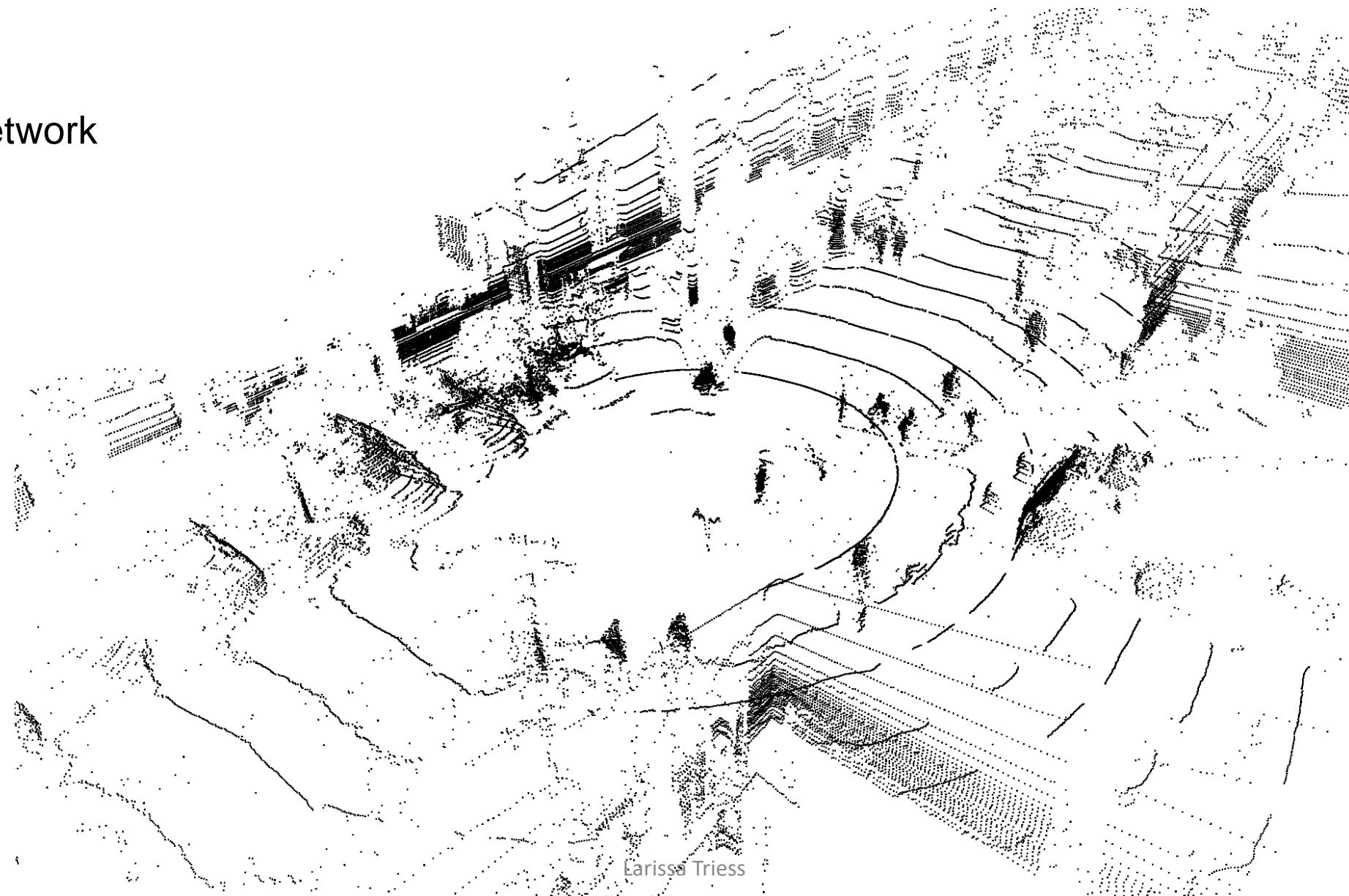
Results – L1 vs. L2 Loss

Regular Network
L2-Loss



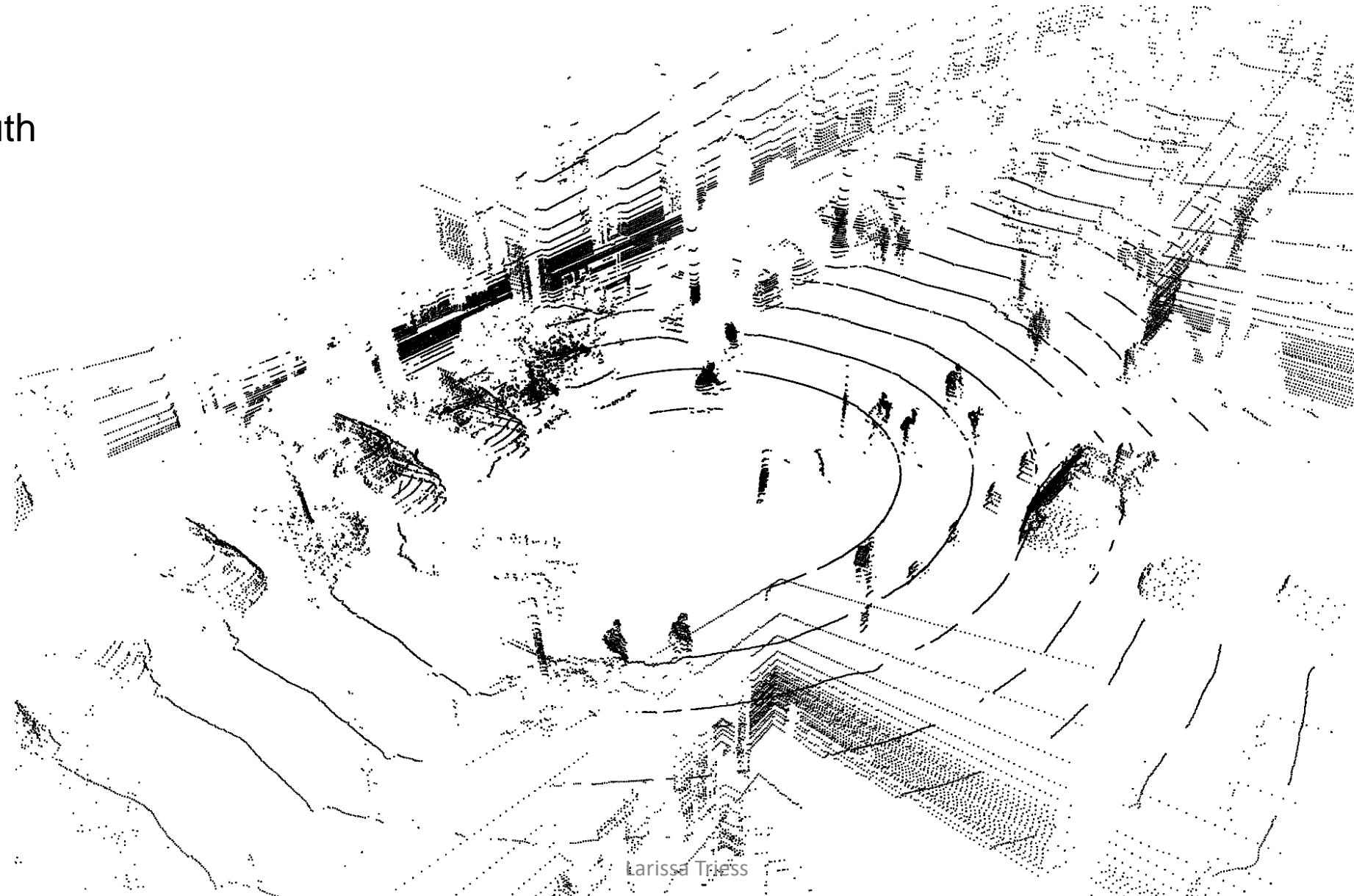
Results – L1 vs. L2 Loss

Regular Network
L1-Loss

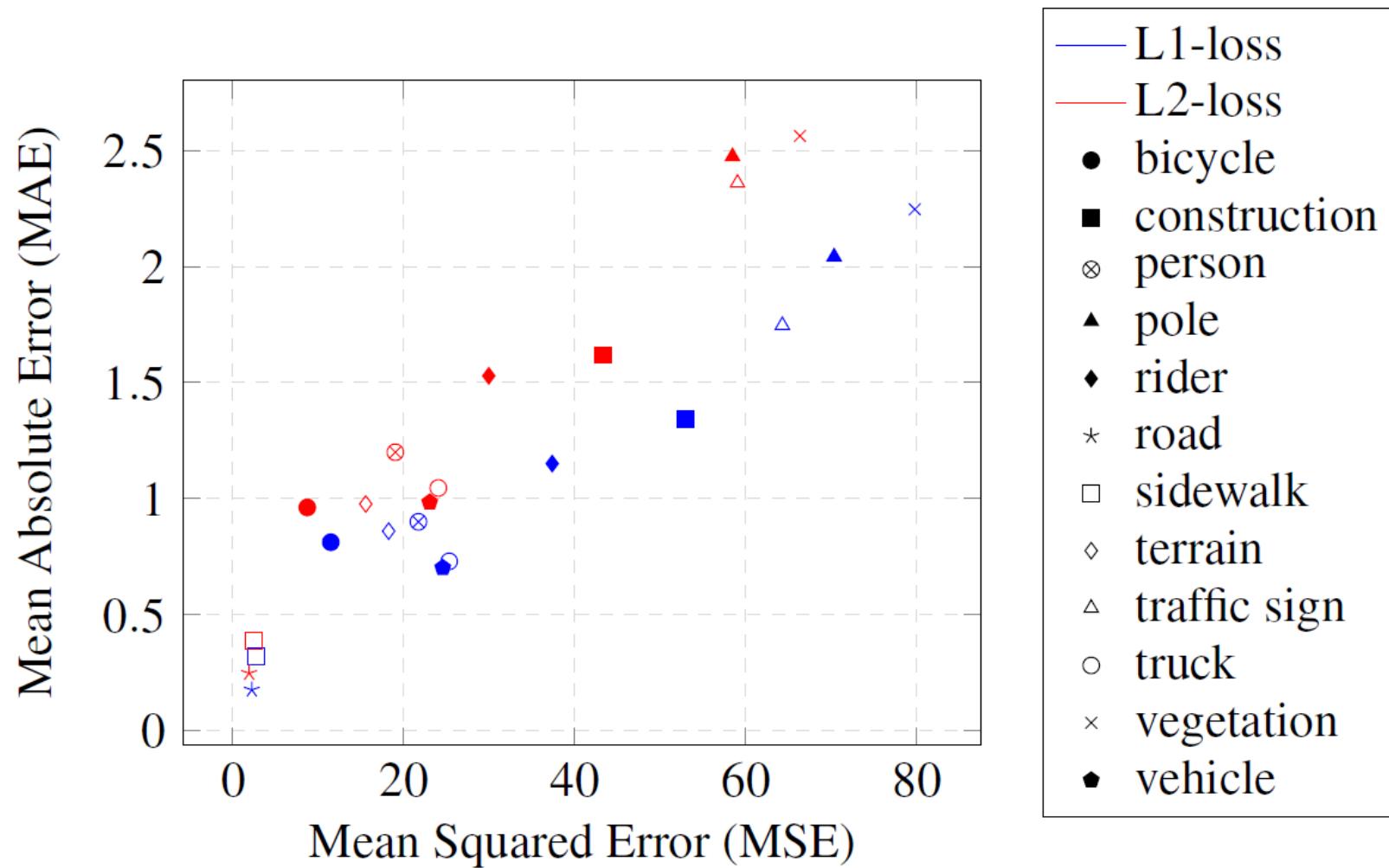


Results – L1 vs. L2 Loss

Ground Truth

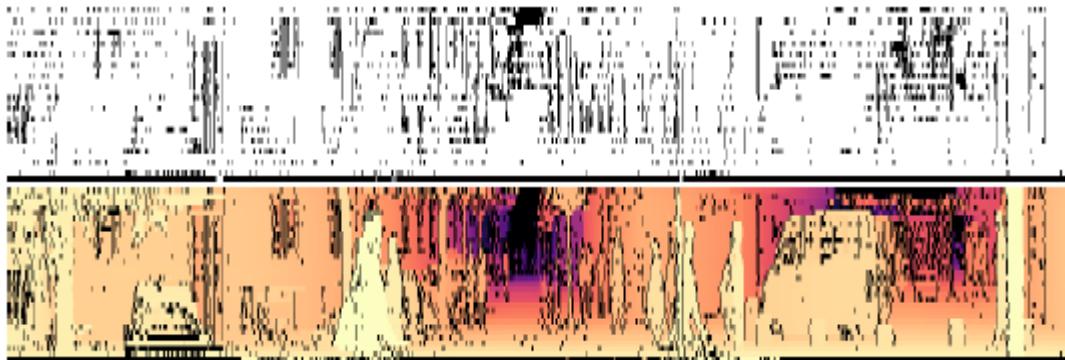
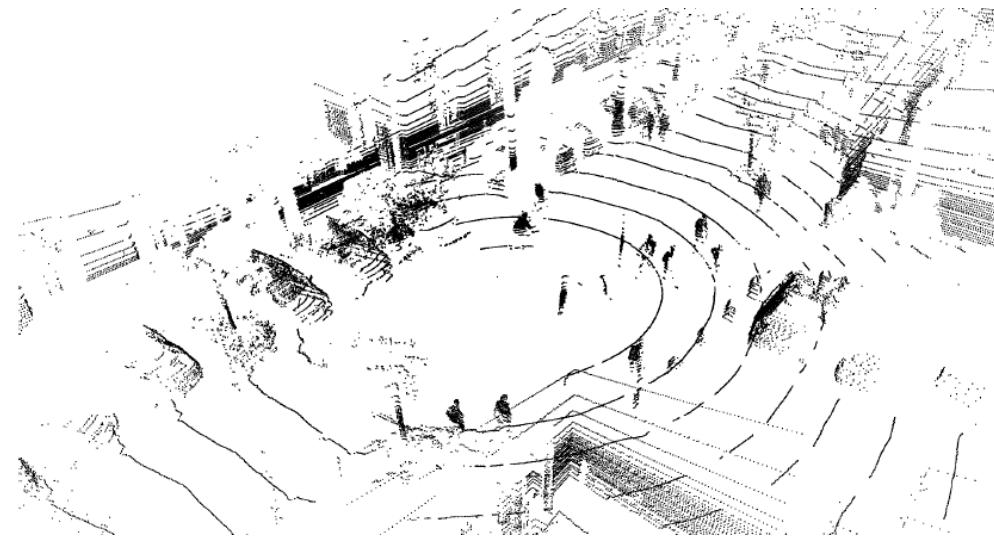


Evaluation per Object Class



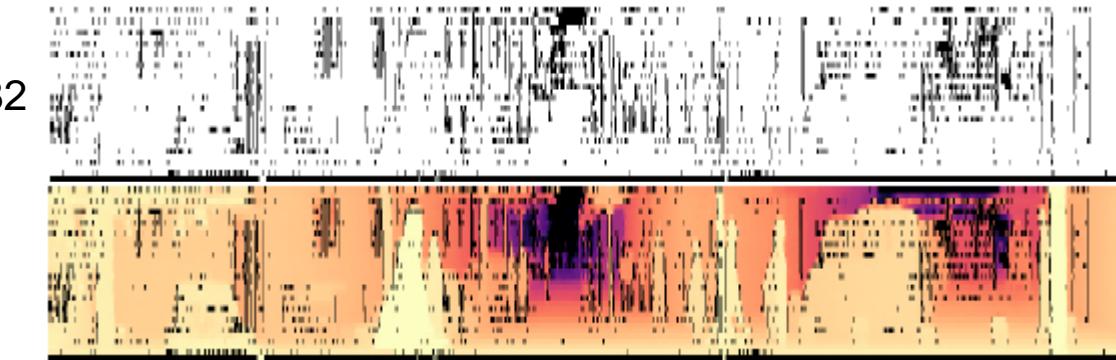
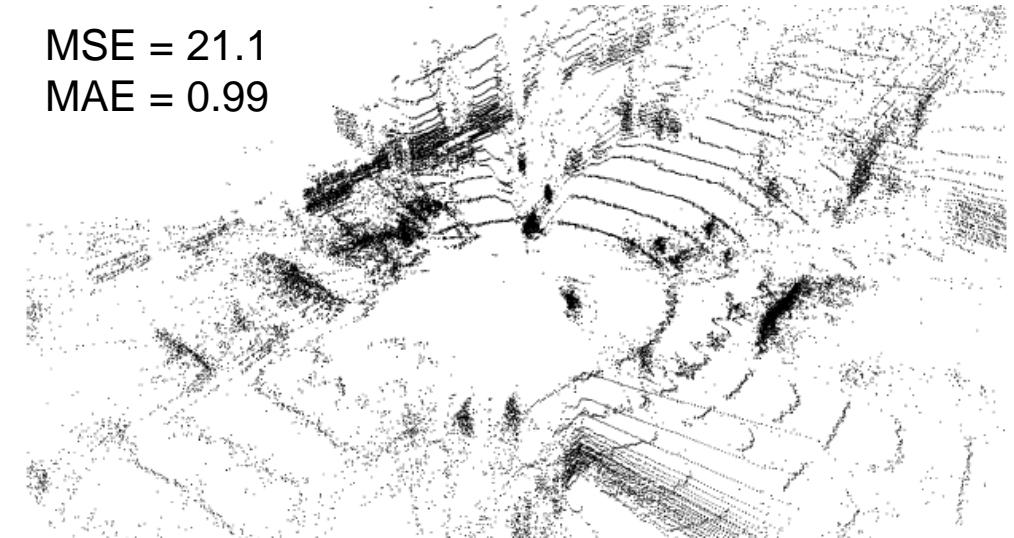
Results – Multi-Task Learning

Ground Truth

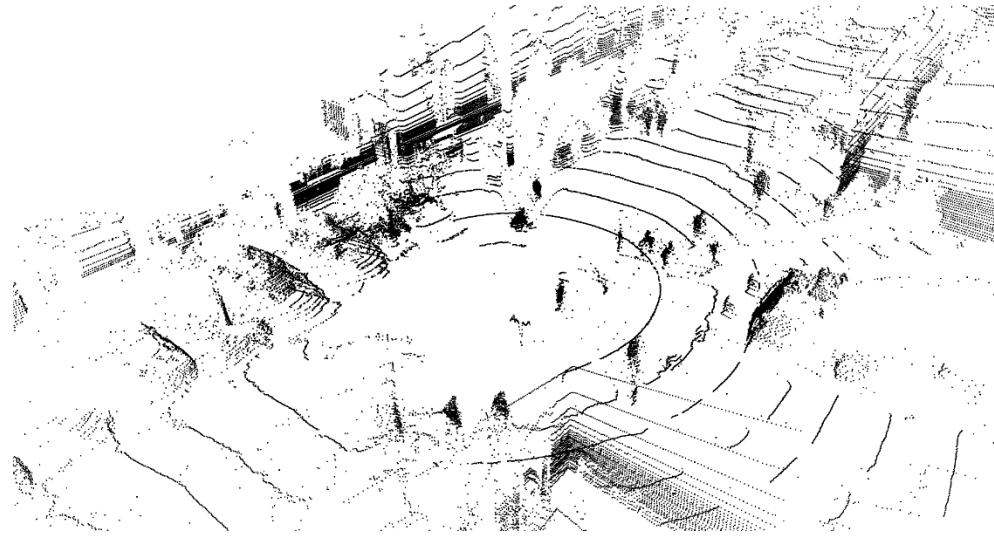
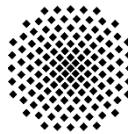


IoU = 0.82

Multi-Task Learning

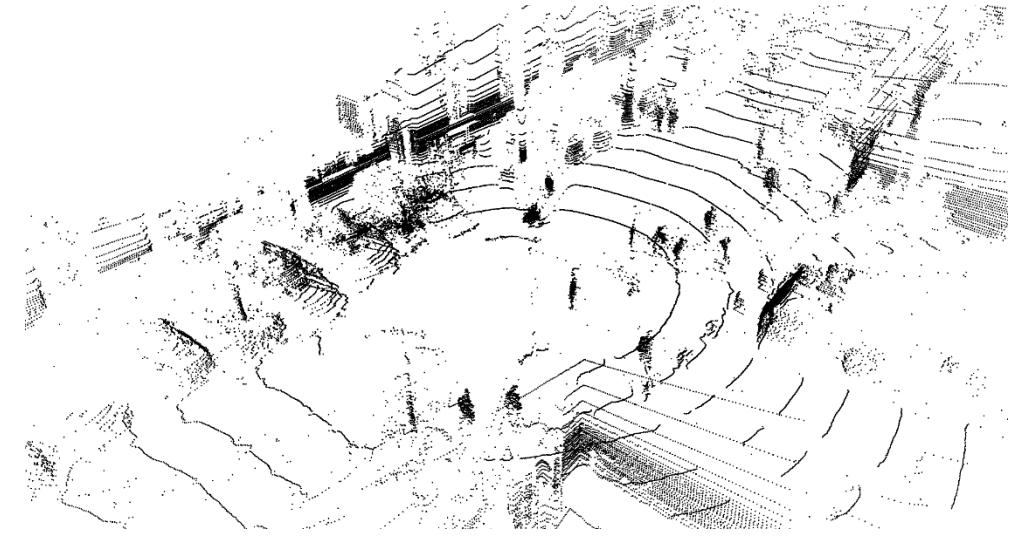


Results – Feature Reconstruction



Regular Network trained with L1-Loss

MSE = 24.9, MAE = 0.79

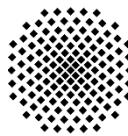


Fine-tuned Feature Reconstruction Network

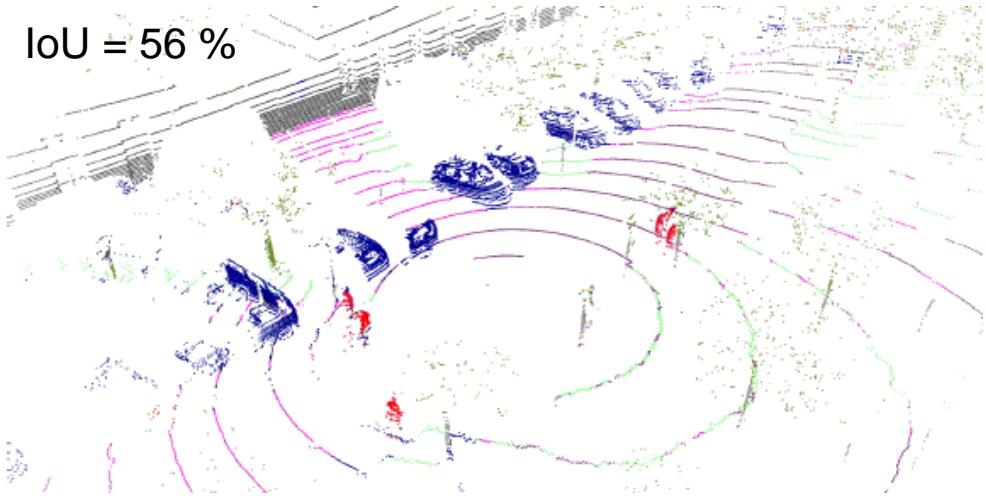
MSE = 30.6, MAE = 1.15

Similar or better perceptual quality though
higher point-wise errors

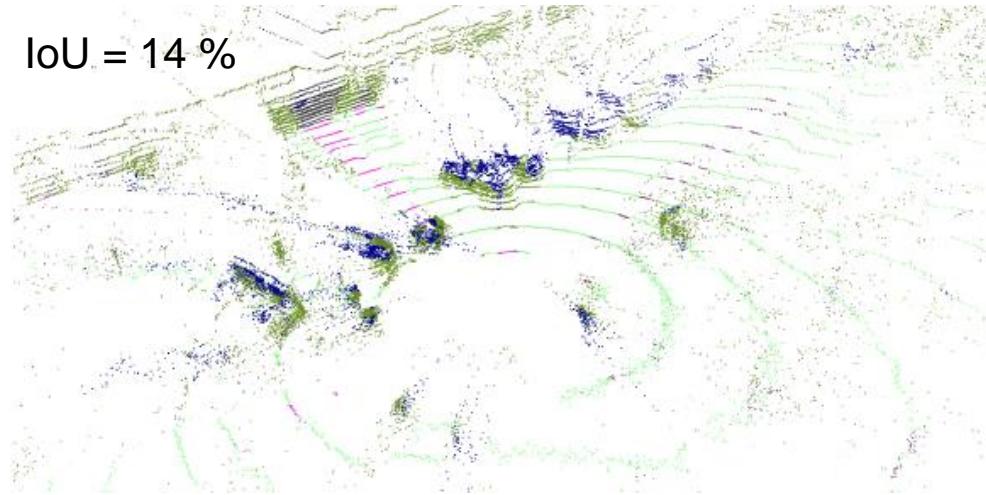
Semantic Segmentation Assessment



Ground Truth

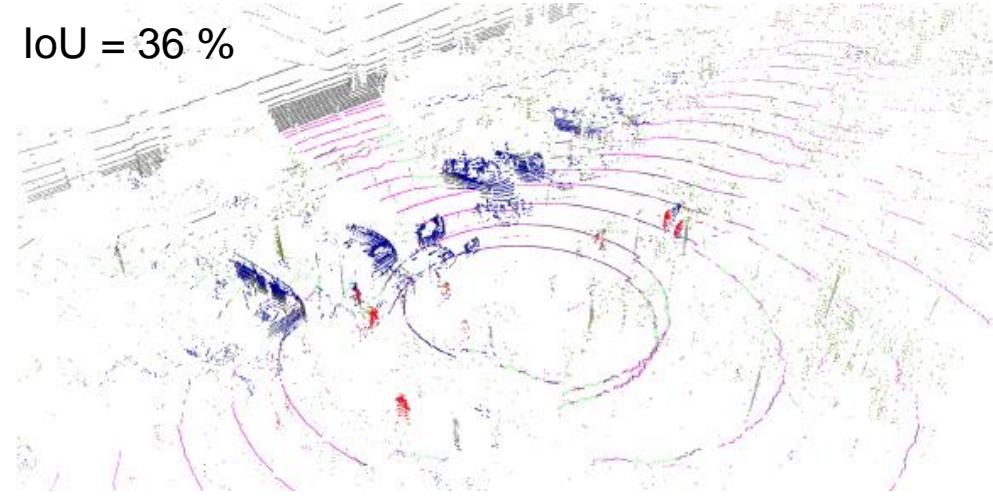


L2-Loss

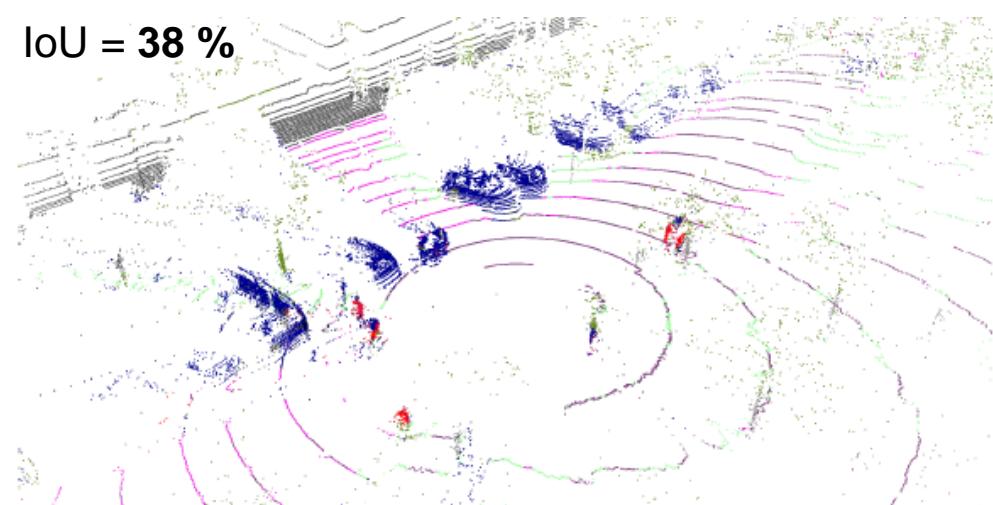


IoU = 56 %

Bilinear



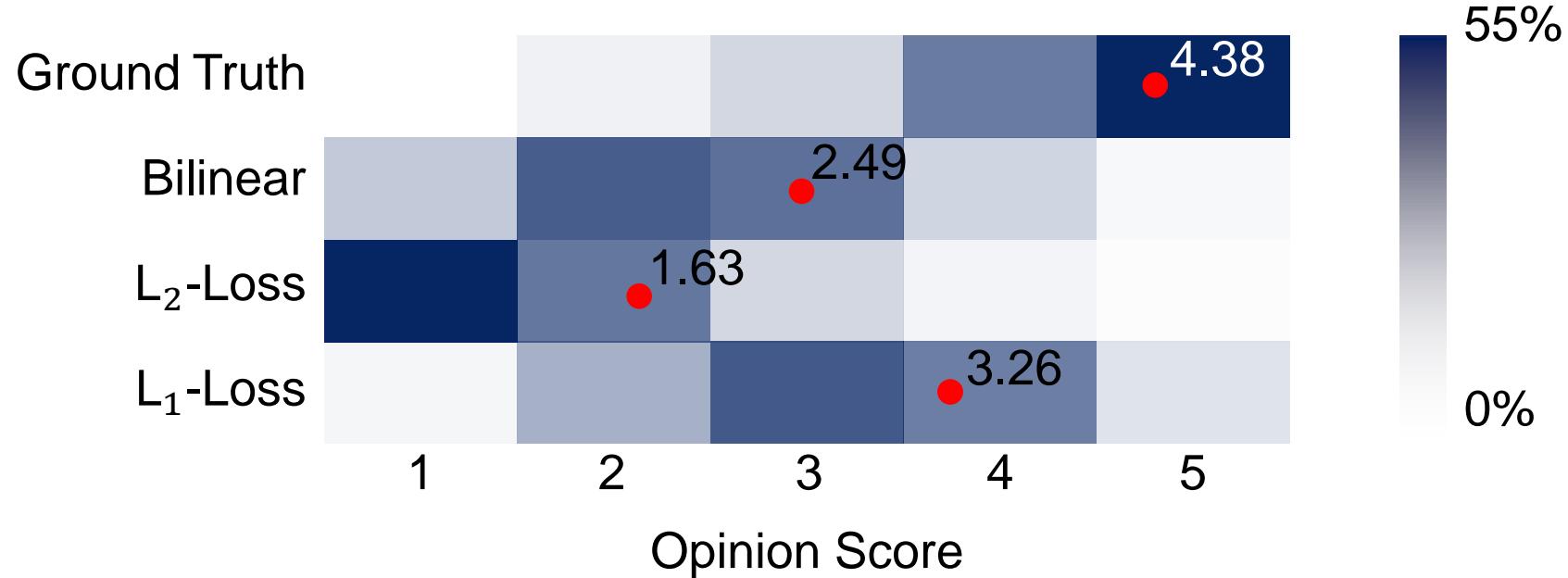
L1-Loss



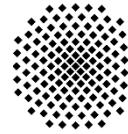
IoU = 36 %

IoU = 38 %

Mean Opinion Score Testing*



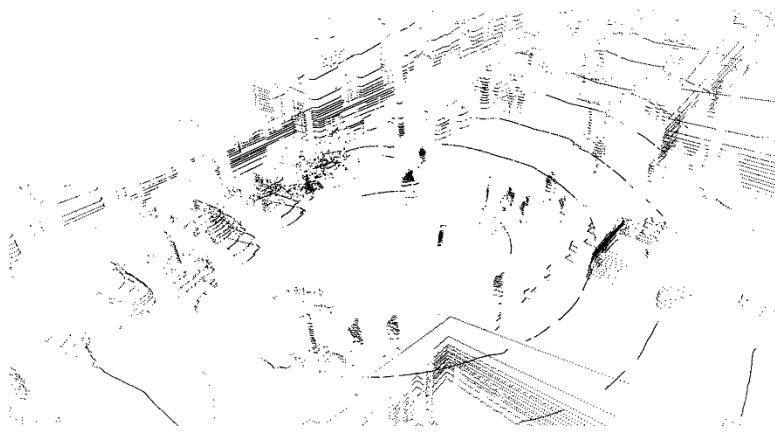
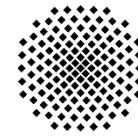
* Survey among 18 human raters with 9 scenes for each of the 4 shown categories
(9 images times 18 raters = 162 samples per method have been assessed)



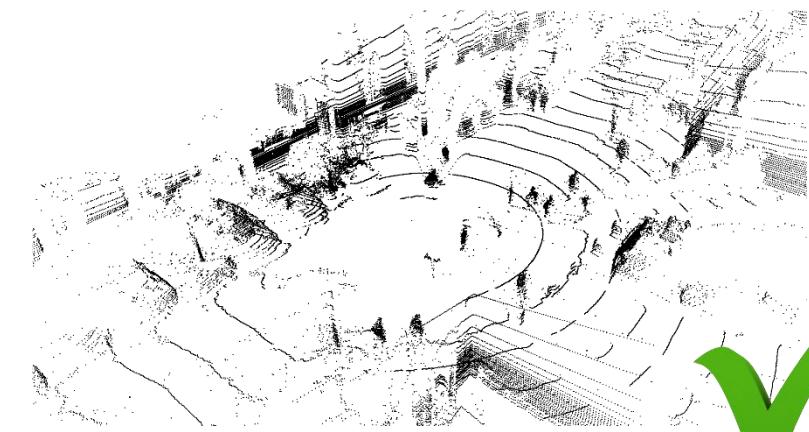
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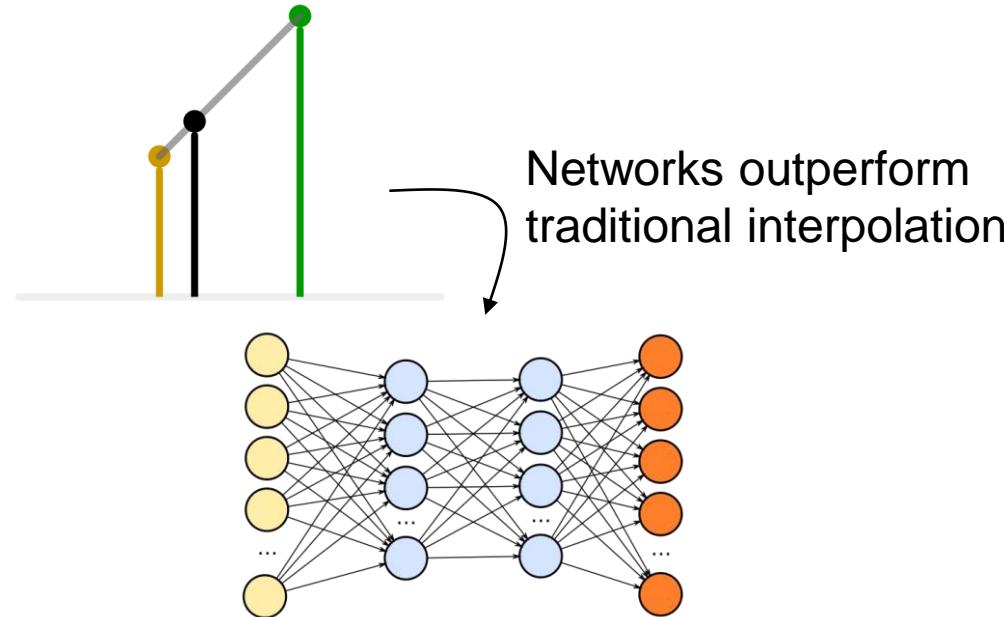
Summary



Up-Sampling



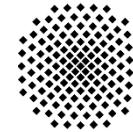
Successful up-sampling



\mathcal{L}_1 vs. \mathcal{L}_2

\mathcal{L}_1 yields more realistic output than \mathcal{L}_2

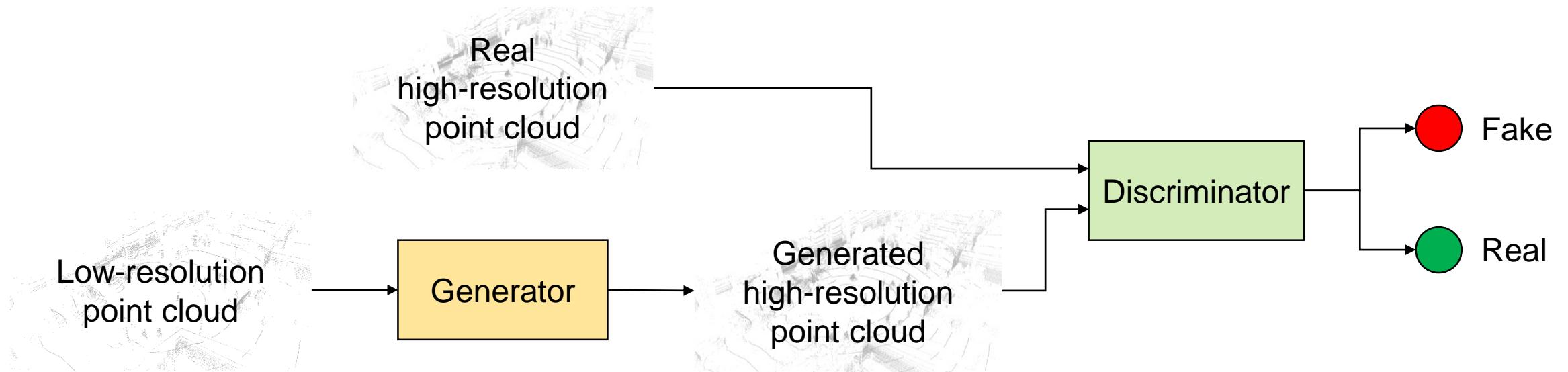
Outlook



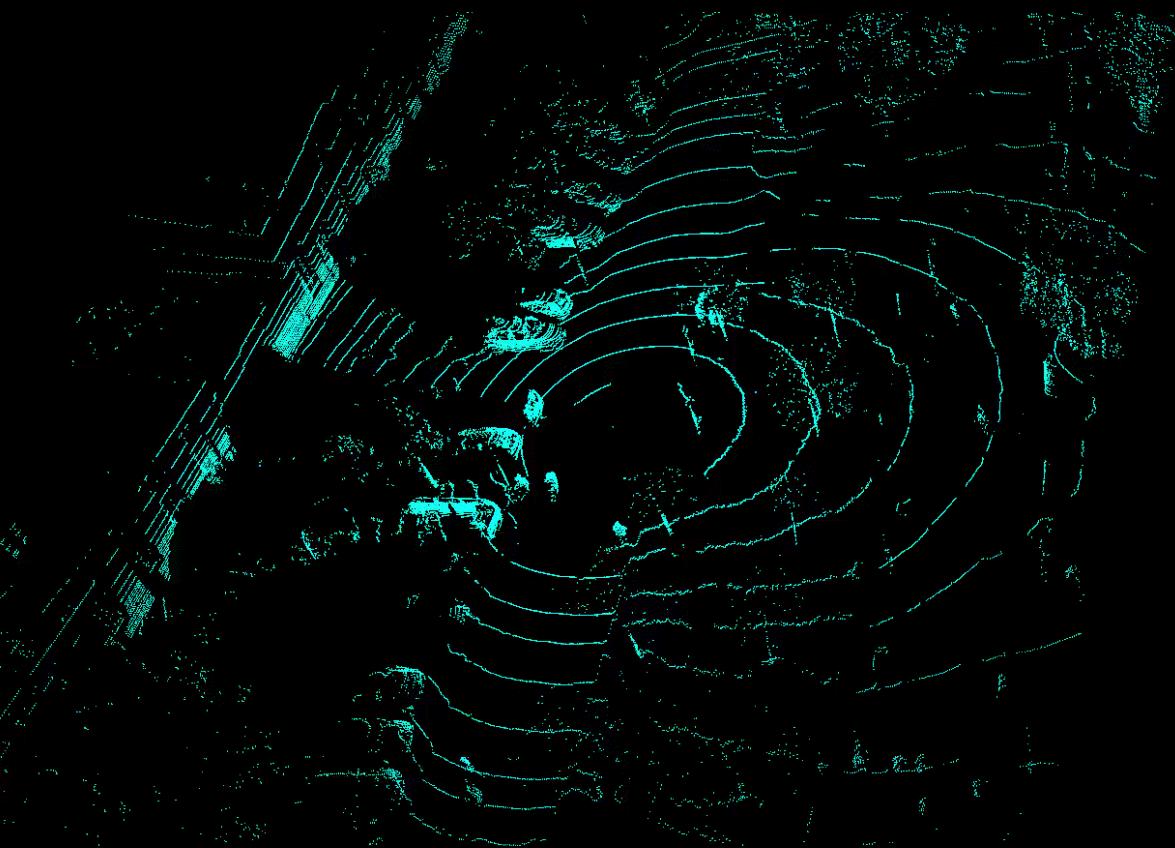
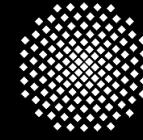
- Test using additional camera input information or data accumulation over time



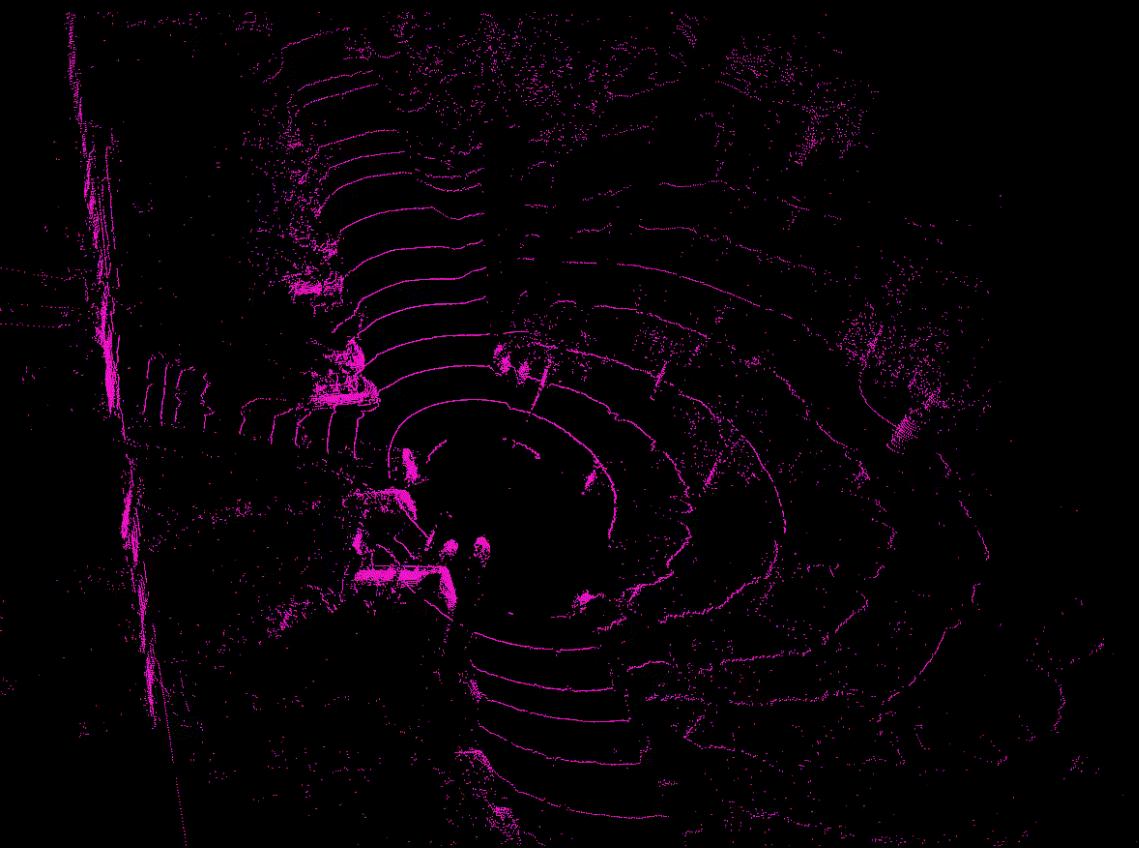
- Use a generative model for more realistic LiDAR up-sampling, for example a Cycle GAN



Video



Ground Truth



Regular Network trained with L1-Loss

Questions?

