

# LiDAR-in-the-loop Hyperparameter Optimization

Felix Goudreault<sup>1</sup> Dominik Scheuble<sup>2</sup> Mario Bijelic<sup>3</sup> Nicolas Robidoux<sup>1</sup> Felix Heide<sup>1,3</sup>

<sup>1</sup>Algolux

<sup>2</sup>Mercedes-Benz AG

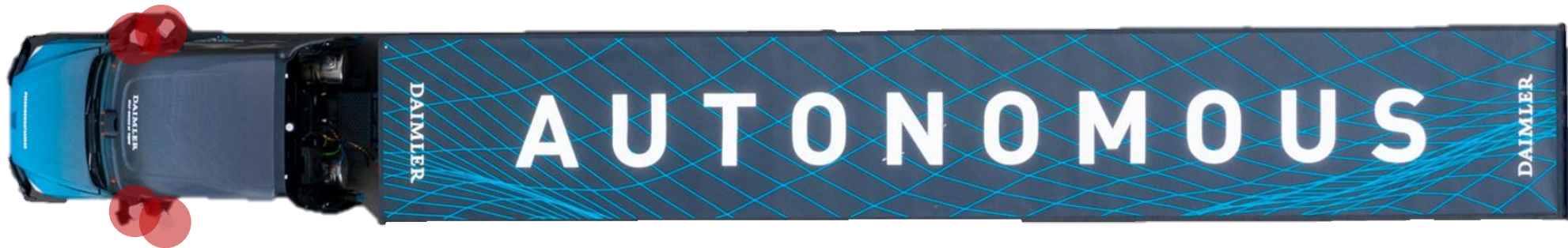
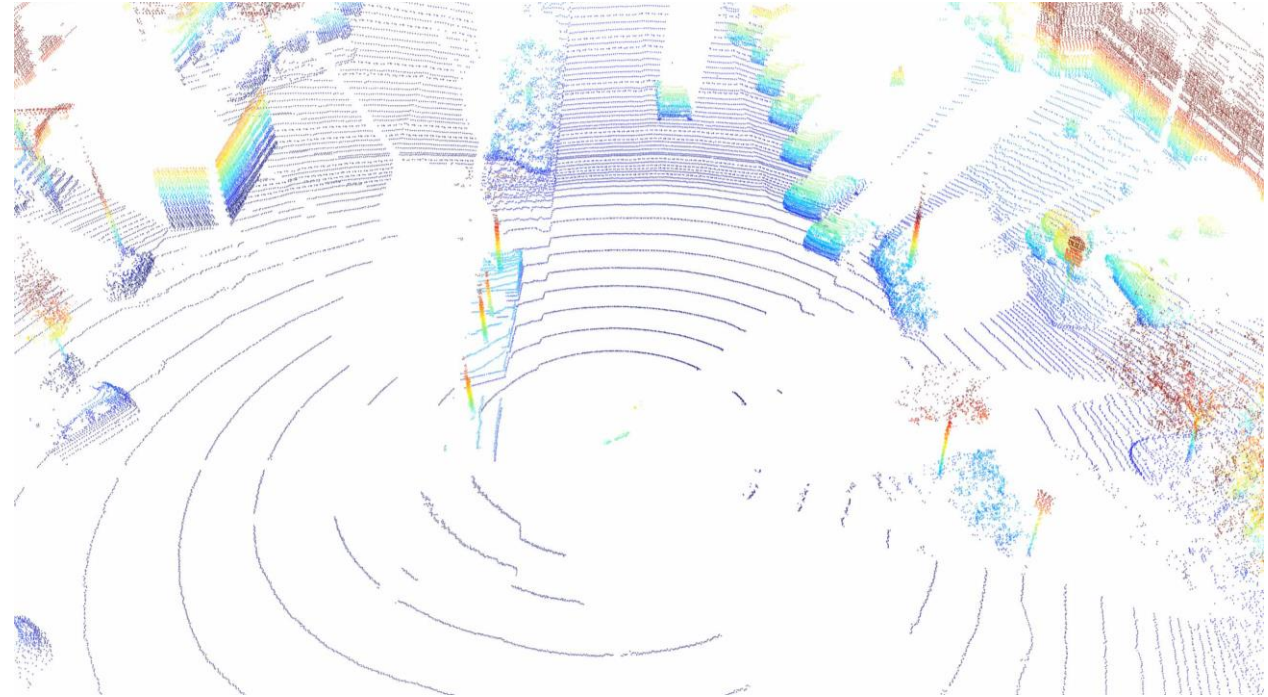
<sup>3</sup>Princeton University



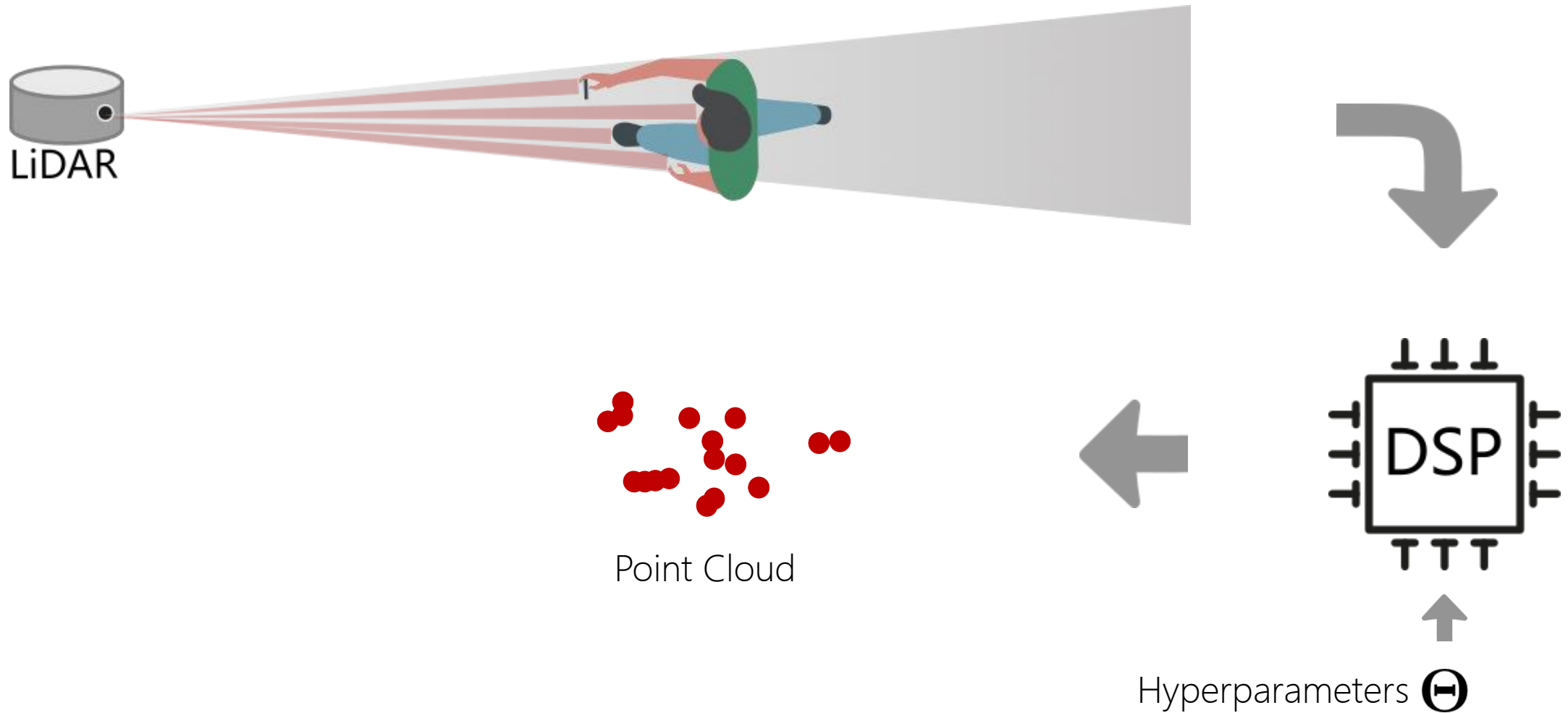
Website and Code:

<https://light.princeton.edu/lidar-in-the-loop-hyperparameter-optimization/>

# LiDAR as a Cornerstone Sensor Modality



# LiDAR Working Principles



# Learn LiDAR Hyperparameters

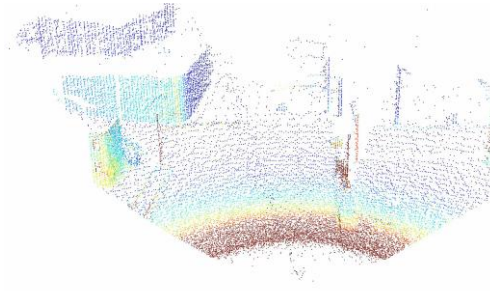
LiDAR-in-the-loop optimization for 3D object detection, depth and intensity estimation

0th-order solver for optimal LiDAR hyperparameters

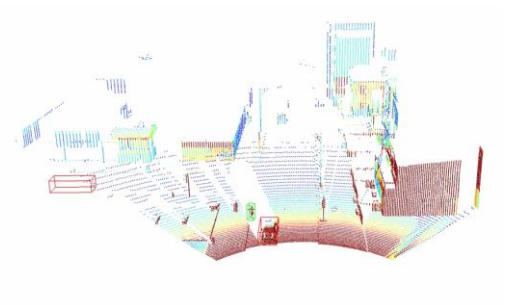
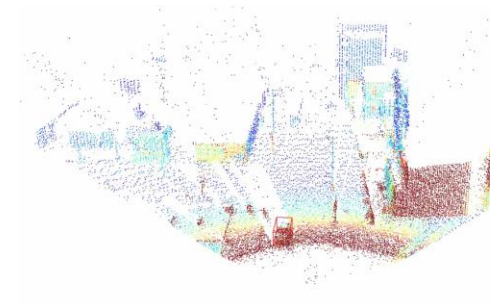
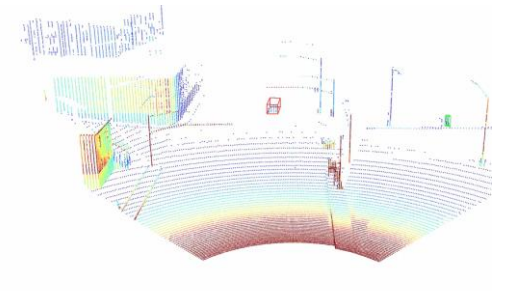
Realistic LiDAR waveform simulation for CARLA



Expert-Tuned: 7.33% mAP (↑)

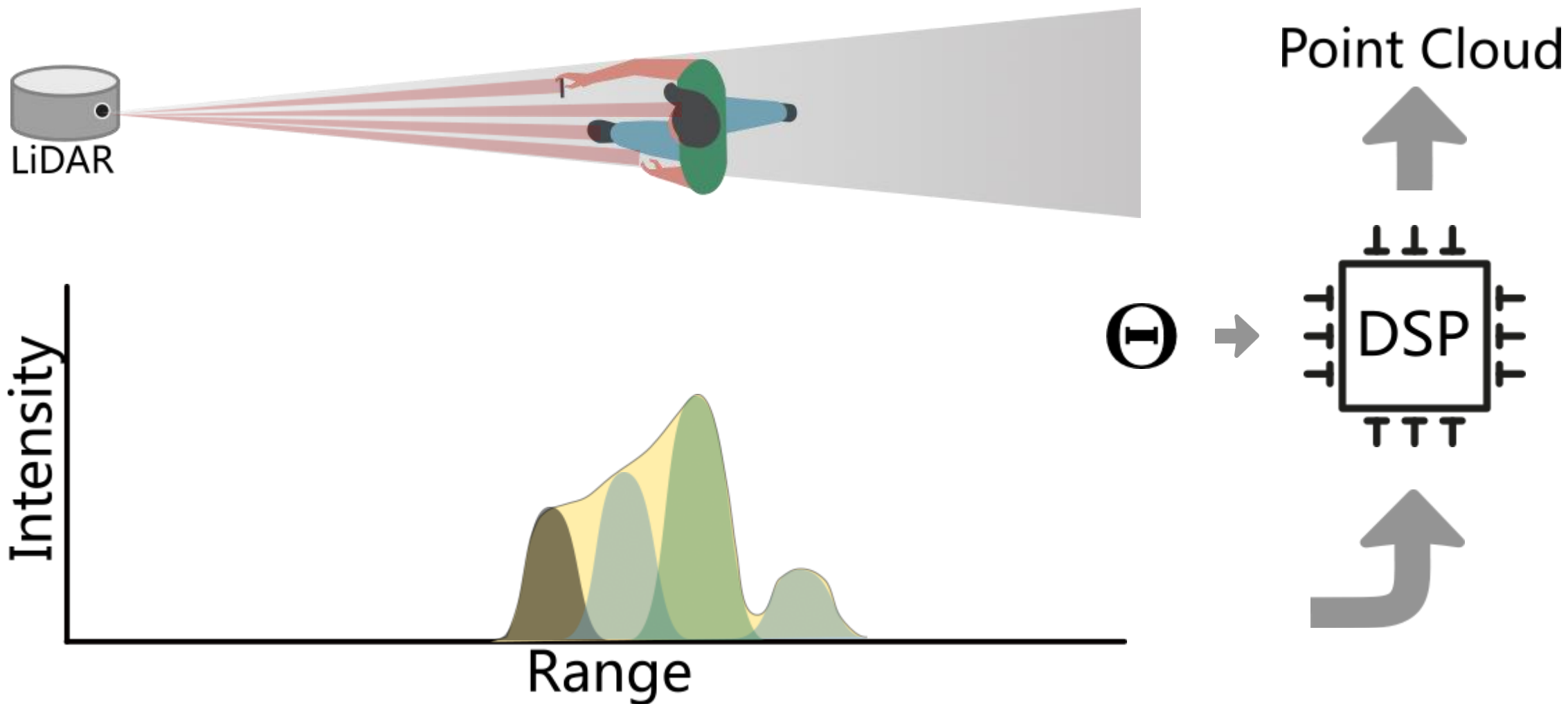


Optimized: 46.86% mAP(↑)



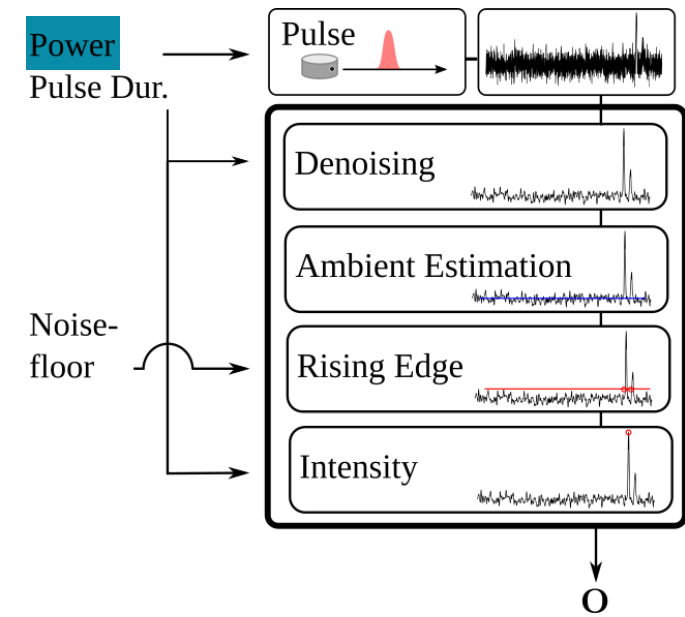
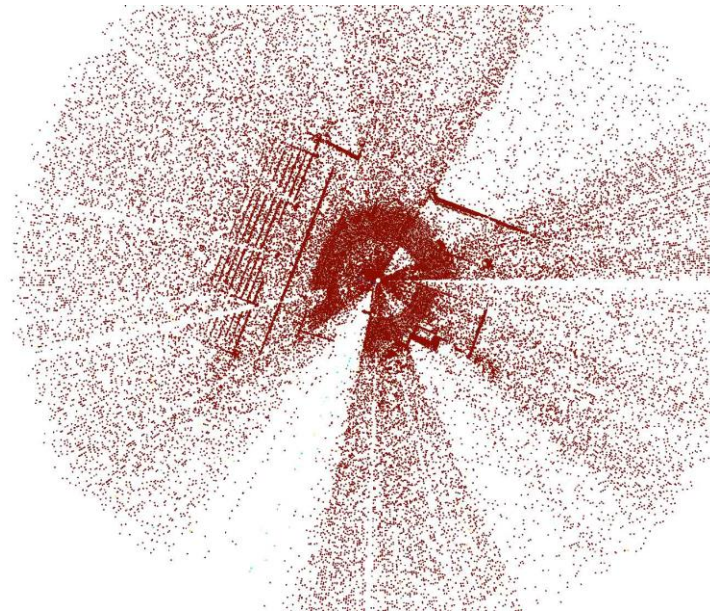
Webpage and Code at  
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# Scanning LiDAR Pipeline



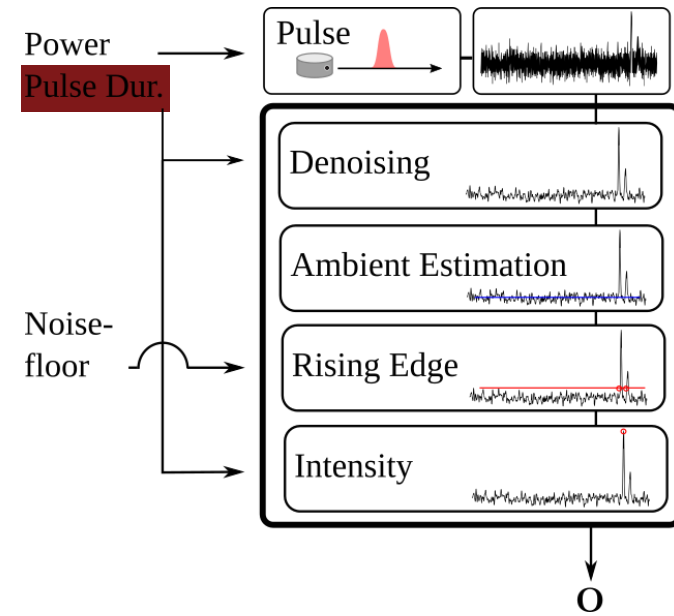
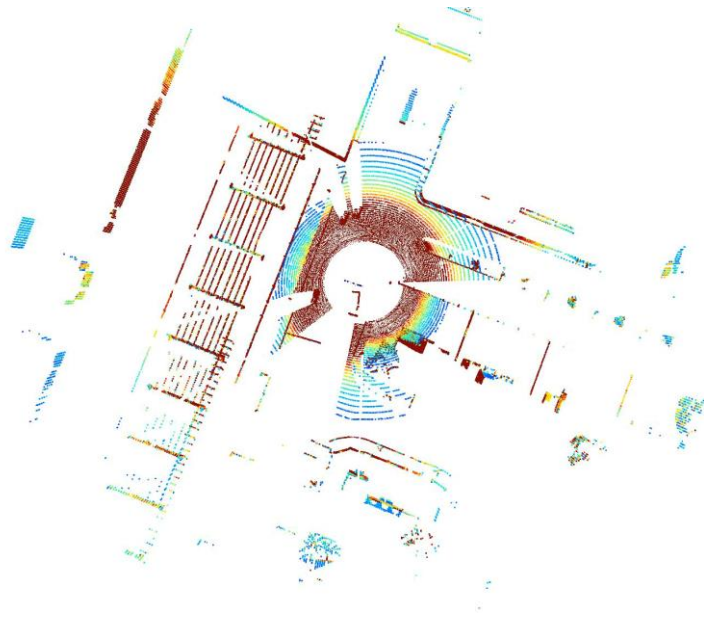
# LiDAR Sensing Hyperparameters

Power  
Pulse Dur.  
Noise floor



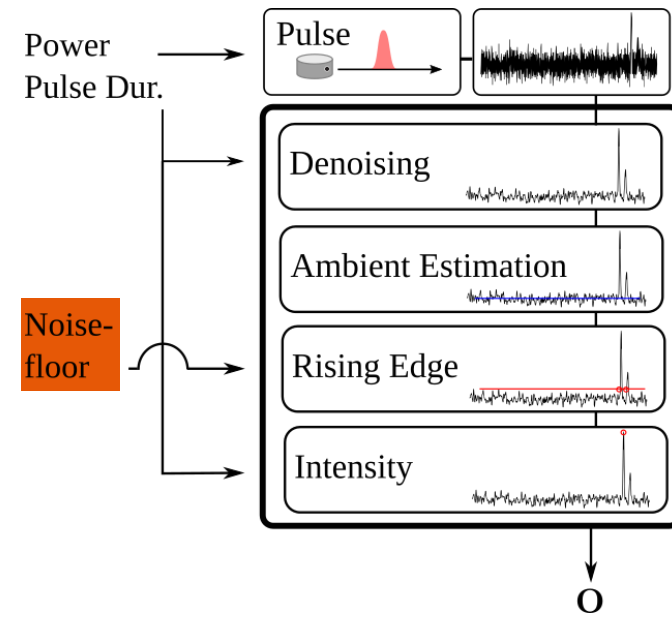
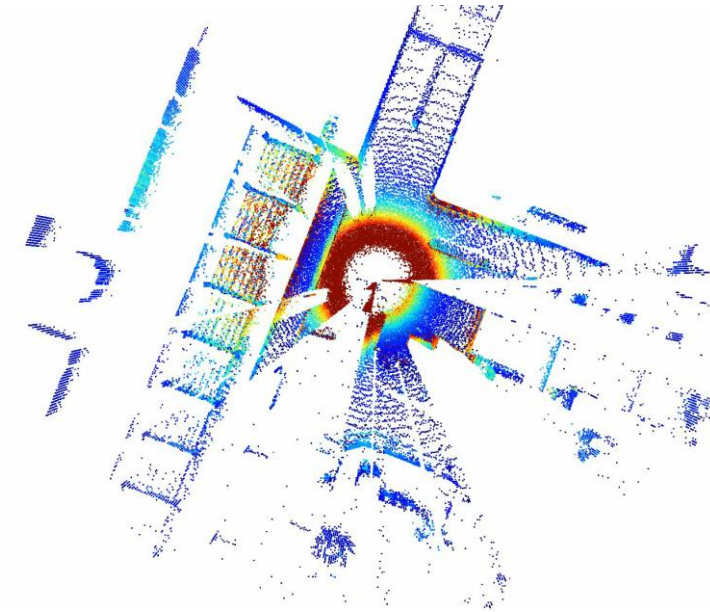
# LiDAR Sensing Hyperparameters

- Power
- Pulse Dur.
- Noise floor



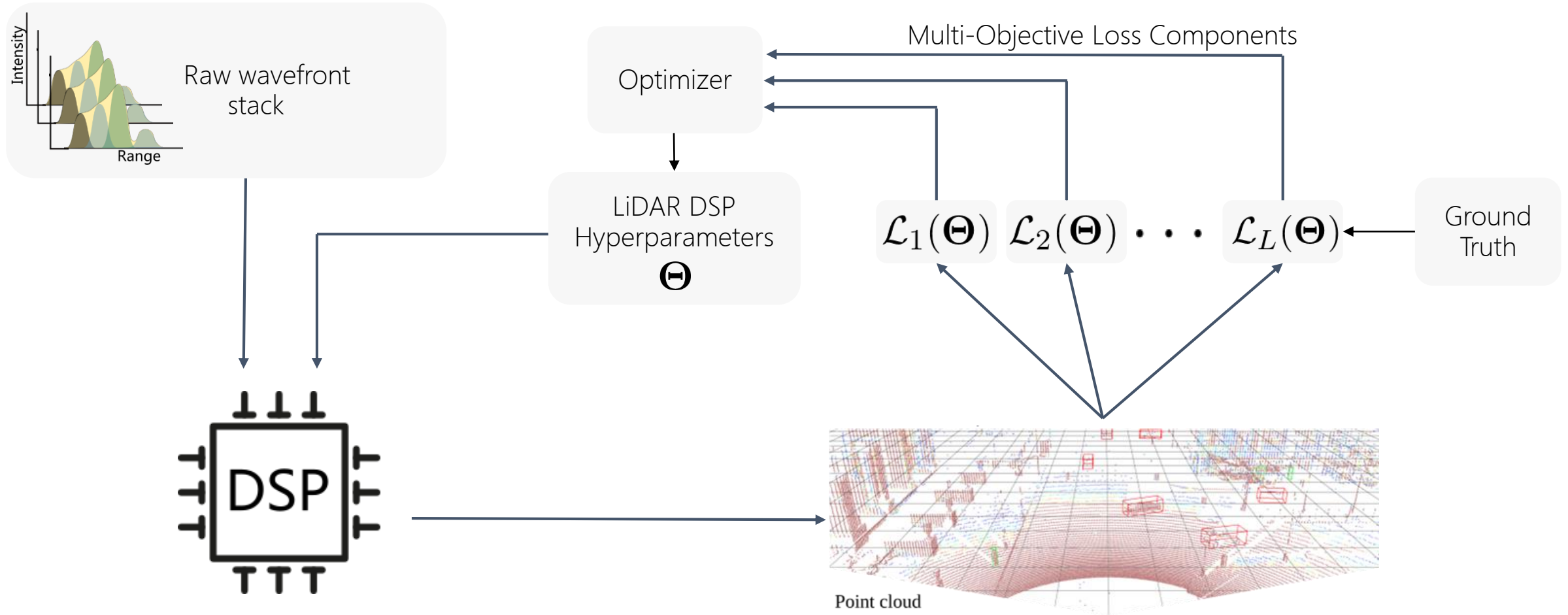
# LiDAR Sensing Hyperparameters

Power  
Pulse Dur.  
Noise floor

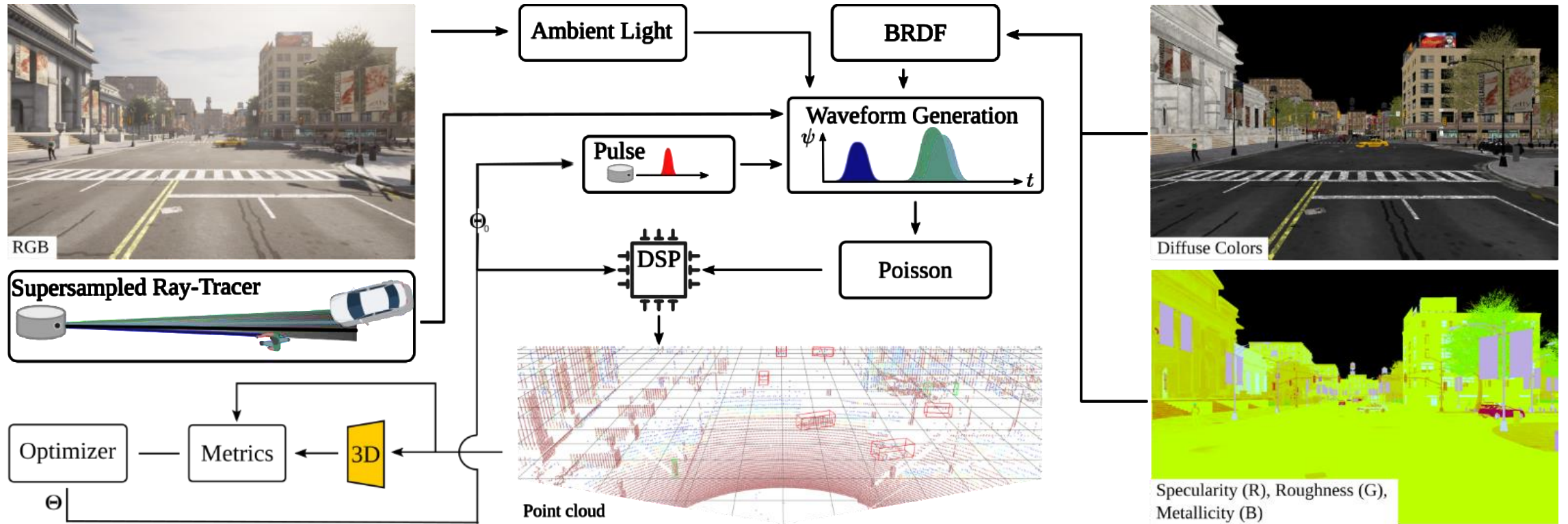




# LiDAR-in-the-Loop Optimization



# Raw LiDAR Simulation



# Black Box Multi-Objective Solver

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**Algorithm 1** LiDAR Hyperparameter Optimization.

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**Require:** LiDAR  $\Phi$ ,  $\Theta \in [0, 1]^P$  (initial hyperparameter vector),  
 $N \in \mathbb{N}^*$  (number of generations),  $\varepsilon \in (0, \frac{1}{3})$  (small bound),  
 $\mathbf{C} \in \mathbb{R}^{P \times P}$  (CMA-ES “directional” covariance matrix factor),  
 $\sigma \in [\varepsilon, \frac{1}{3}]$  (square root of covariance matrix “scale” factor)

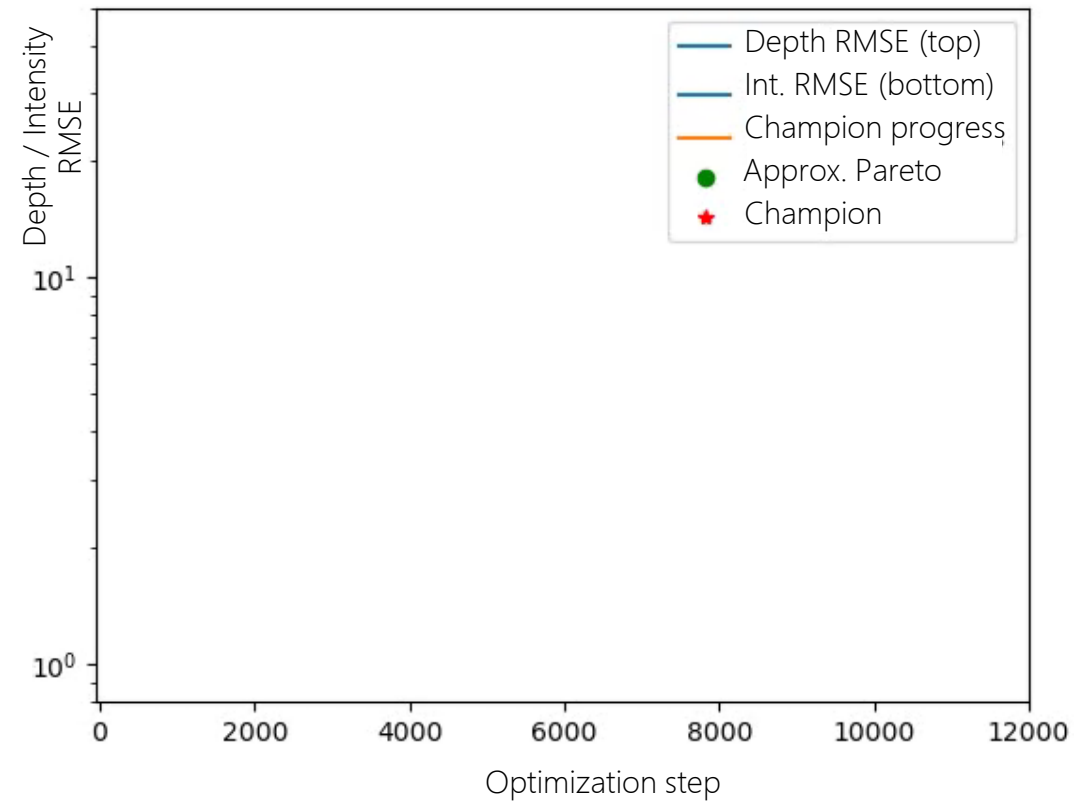
- 1:  $\mathbf{p} \leftarrow \mathbf{0}$ ,  $\mathbf{c} \leftarrow \mathbf{0}$  (CMA-ES path vectors),  $\Theta_{\text{center}} \leftarrow \Theta$
- 2: **for**  $n = 1$  **to**  $N$  **do**
- 3:  $\Theta^{0,n} \leftarrow \Theta$
- 4:  $\mathcal{L}^{0,n} \leftarrow$  losses for LiDAR  $\Phi$  modulated by  $\Theta^{0,n}$
- 5: **for**  $p = 1$  **to**  $4P$  **do**
- 6:  $\Theta^{p,n} \leftarrow$  random draw from Gaussian distribution with covariance matrix  $\sigma^2 \mathbf{C}$  centered at  $\Theta_{\text{center}}$
- 7:  $\Theta^{p,n} \leftarrow \Theta^{p,n} +$  Gaussian distribution with diagonal covariance matrix proportional to square of quantization grain [48]
- 8:  $\Theta^{p,n} \leftarrow \Theta^{p,n}$  reflected back into  $[0, 1]^P$
- 9:  $\mathcal{L}^{p,n} \leftarrow$  losses for LiDAR  $\Phi$  modulated by  $\Theta^{p,n}$
- 10: **end for**
- 11: Compute  $\{\mathcal{M}^{q,m,n}\}_{q \in \{0, \dots, 4P\}, m \in \{1, \dots, n\}}$  by including  $\{\mathcal{L}^{p,n}\}_{p \in \{0, \dots, 4P\}}$  in rank computations
- 12: Use “eager” [36] centroid weights with  $\lambda = 4P$ ,  $\mu = 3P$
- 13: **if**  $n$  is odd **then**
- 14: Use “stable” [48] centroid weights with  $\lambda = \mu = 4P$
- 15: **end if**
- 16: Standard CMA-ES update [21] of  $\Theta$ ,  $\sigma$ ,  $\mathbf{C}$ ,  $\mathbf{p}$ ,  $\mathbf{c}$  based on  $\{\Theta^{p,n}\}_{p \in \{1, \dots, 4P\}}$  and  $\{\mathcal{M}^{p,n,n}\}_{p \in \{1, \dots, 4P\}}$
- 17:  $\Theta_{\text{center}} \leftarrow \Theta$
- 18: **if**  $\min_{p \in \{0, \dots, 4P\}} \mathcal{M}^{p,n,n} < \min_{q \in \{0, \dots, 4P\}, m \in \{1, \dots, n\}} \mathcal{M}^{q,m,n}$  **then**
- 19:  $\Theta_{\text{center}} \leftarrow$  minimizer closest to centroid of minimizers
- 20: **end if**
- 21: **end for**
- 22: **return**  $\Theta^{p,n}$  in the (guaranteed nonempty) intersection of the Pareto front and the set of minimizers of  $\mathcal{M}^{q,m,N}$ , with ties resolved by choosing the one closest to their centroid and remaining ties resolved by maximizing  $n$ , then  $p$

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# Optimization Process



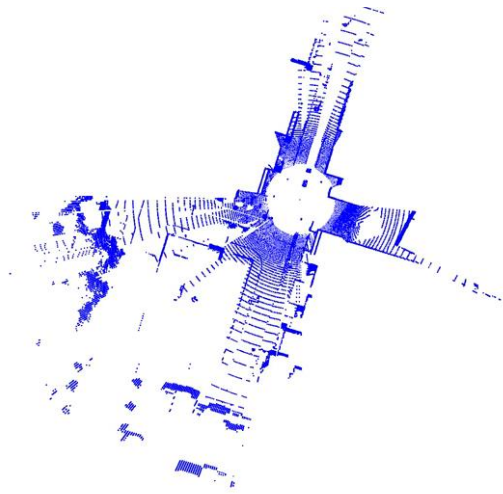
Point cloud depth error for every optimization step



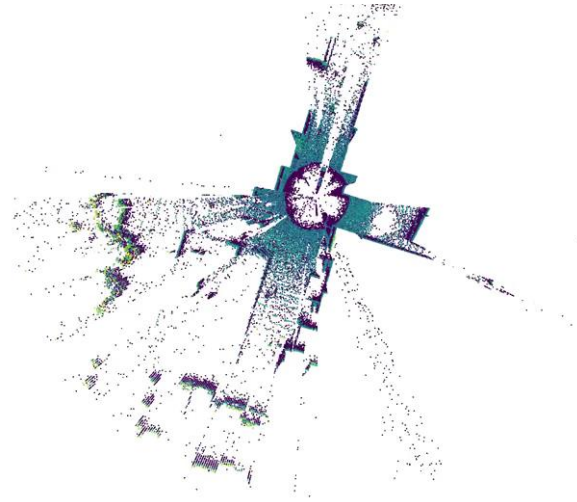
Convergence of depth and intensity RMSE showing current champion and approximate Pareto points

# Experimental Results – Depth and Intensity

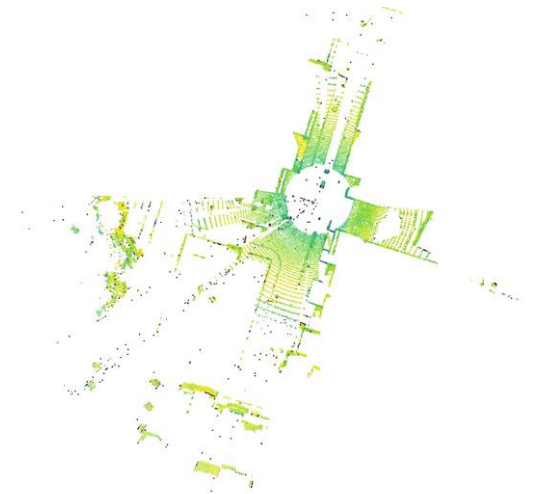
Ground Truth



Expert-Tuned



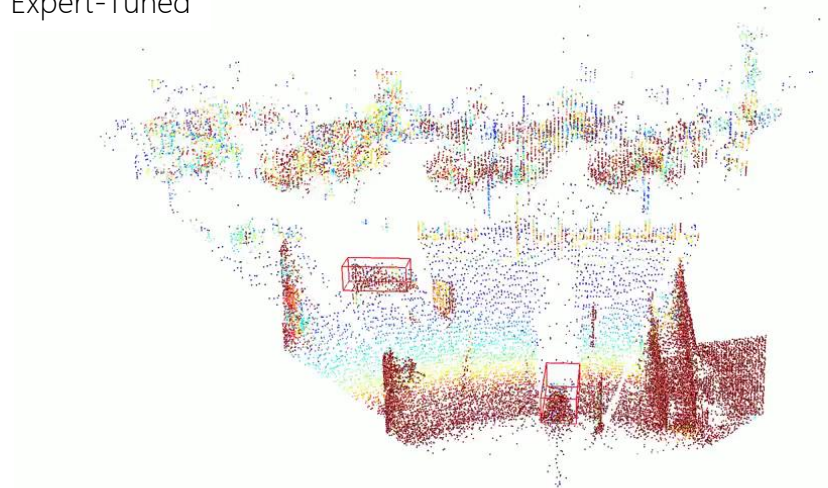
Optimized



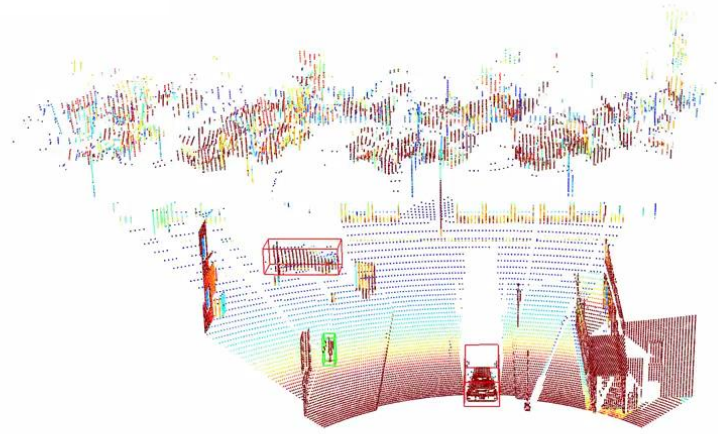
# Experimental Results – Object Detection



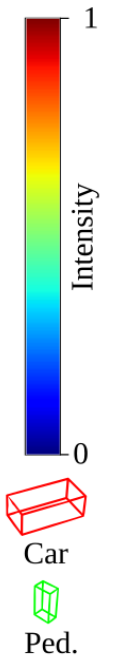
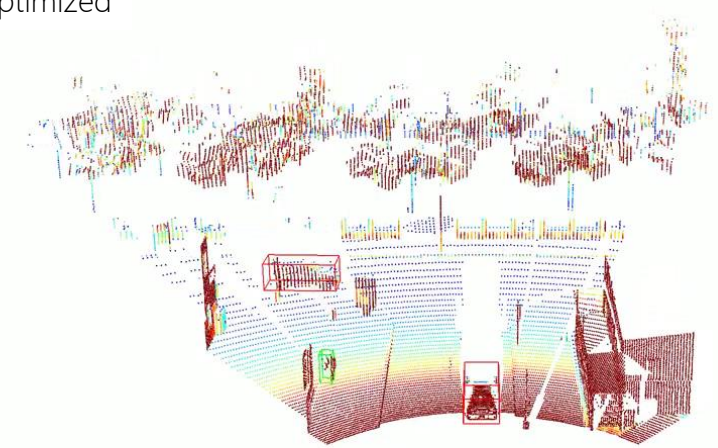
Expert-Tuned



Ground Truth



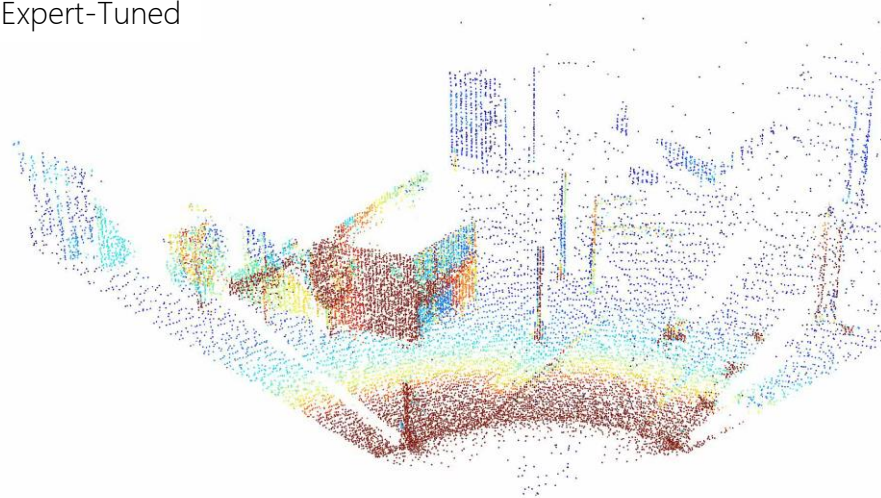
Optimized



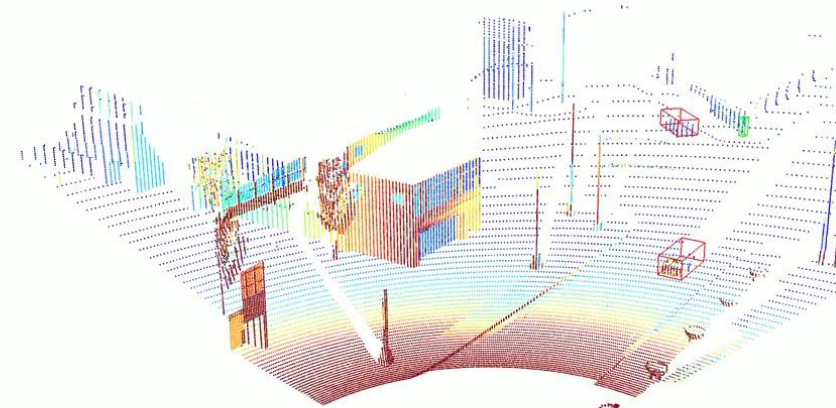
# Experimental Results - Object Detection



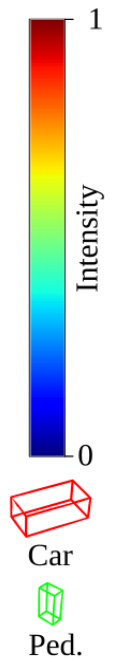
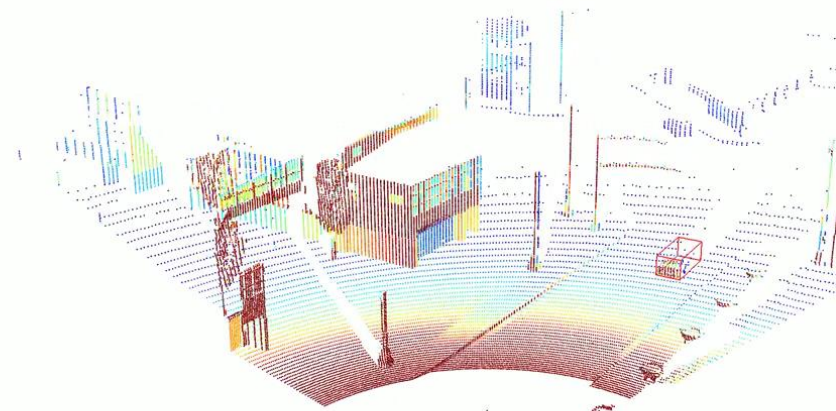
Expert-Tuned



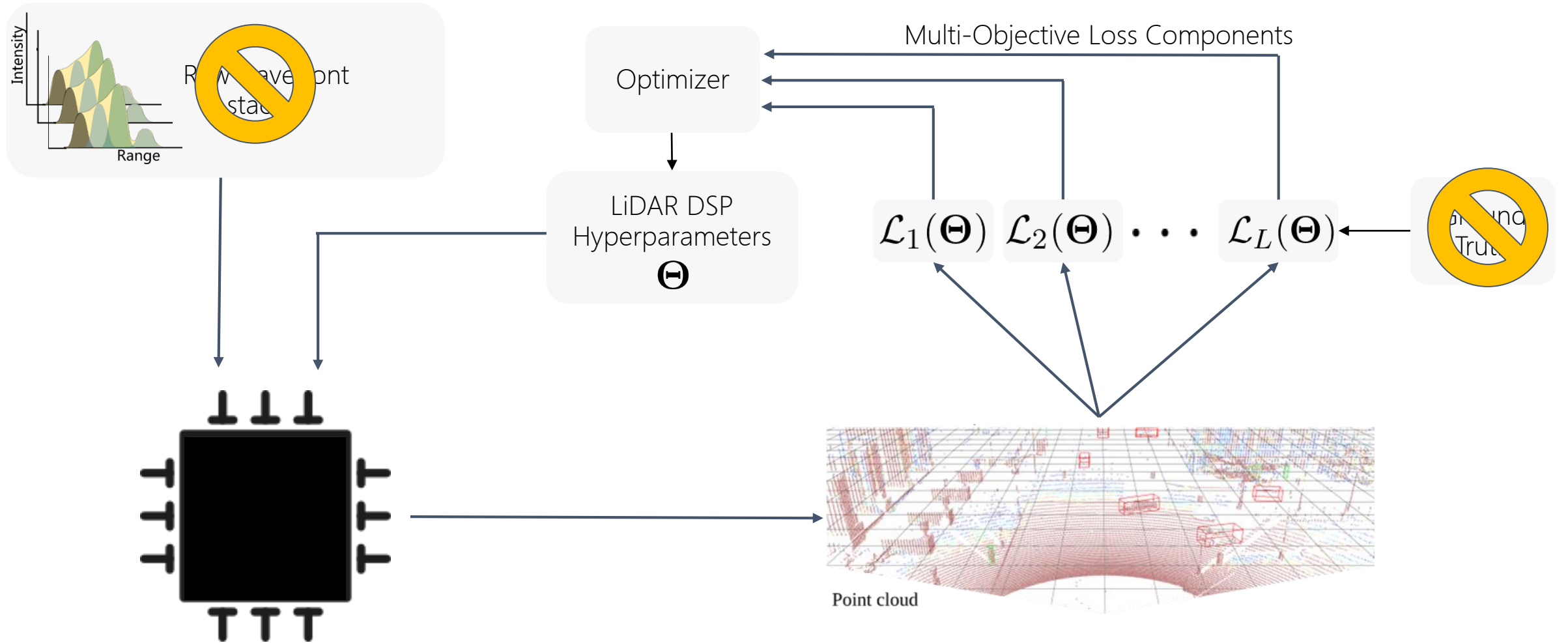
Ground Truth



Optimized

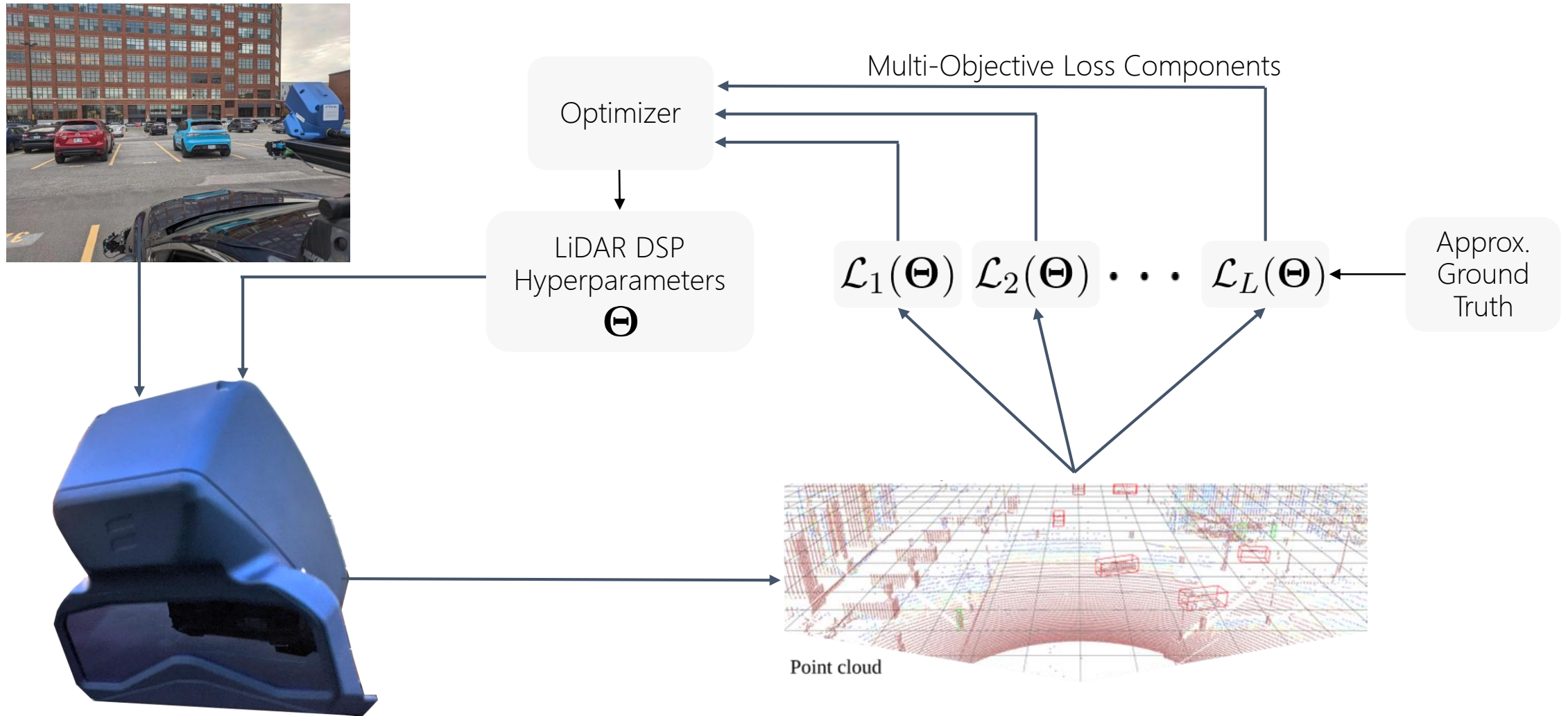


# Blackbox LiDAR-in-the-Loop Optimization



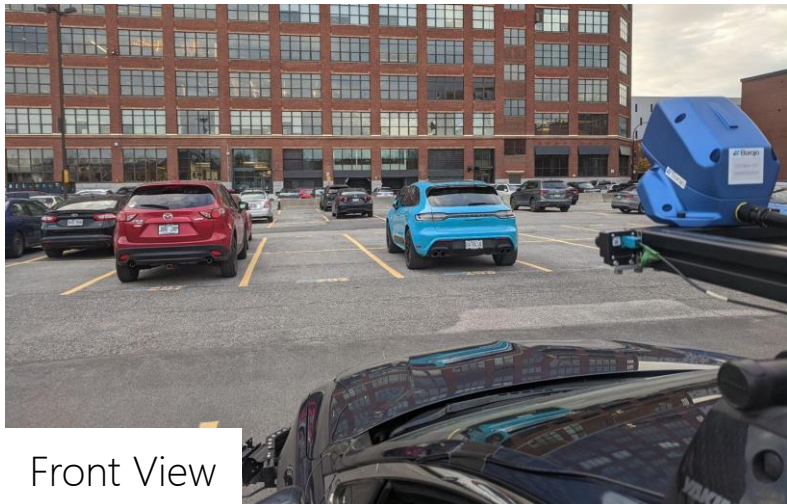


# Hardware-in-the-Loop Optimization



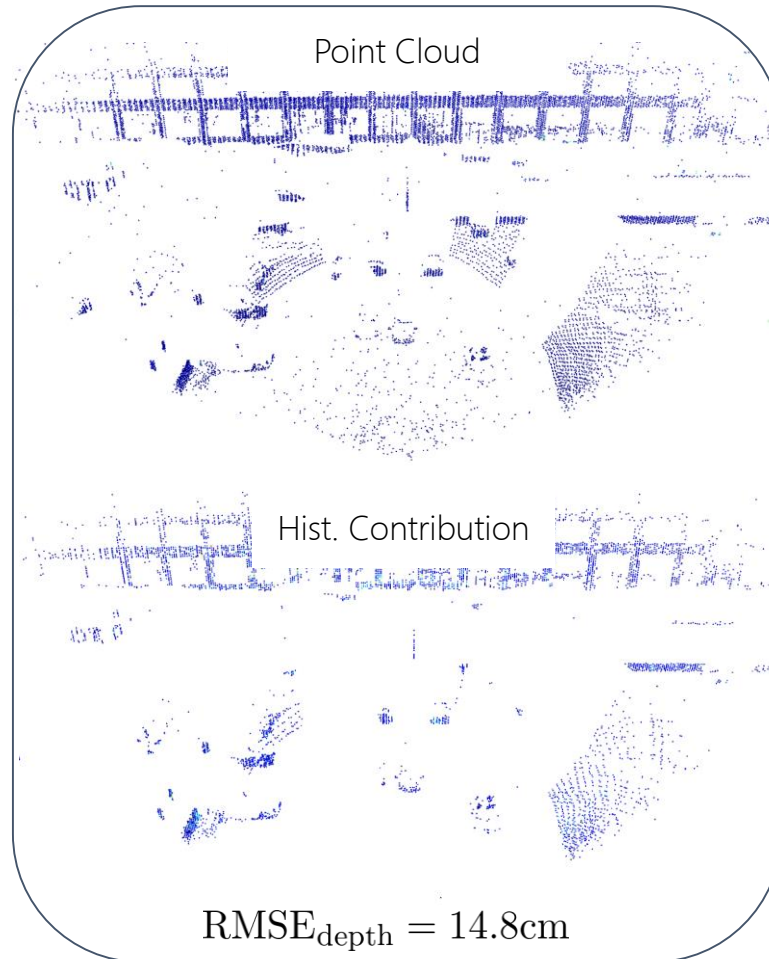
# Experimental Results – Hardware-in-the-Loop

Ground Truth



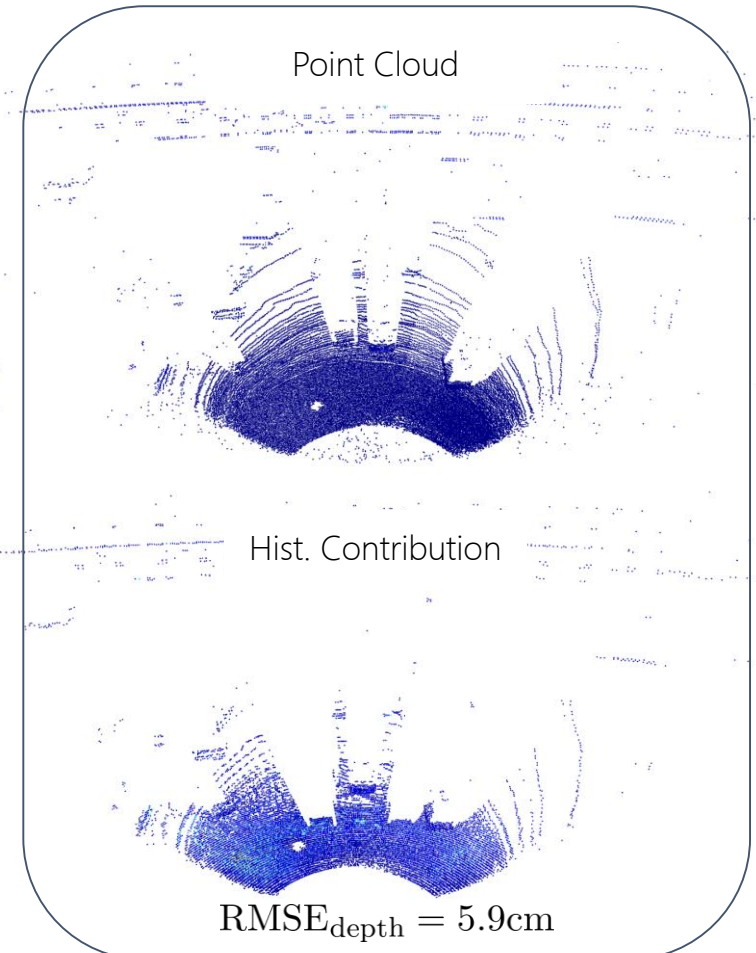
Front View

Expert-Tuned



$RMSE_{depth} = 14.8cm$

Optimized



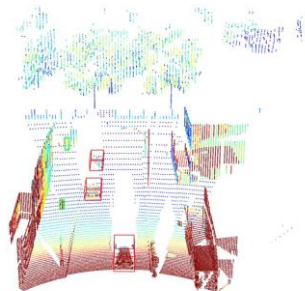
$RMSE_{depth} = 5.9cm$

# LiDAR-in-the-loop Hyperparameter Optimization

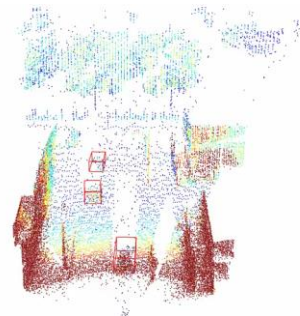
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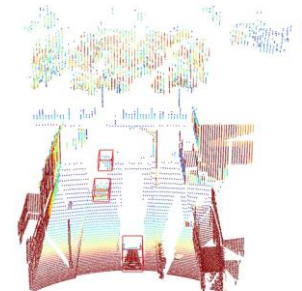
Ground Truth



Expert-Tuned



Optimized



Website and Code:



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