NEURAL INFORMATION PROCESSING SYSTEMS

Neural Lighting Simulation for Urban Scenes

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Siva Manivasagam[1,2], Wei-Chiu Ma[1,4], Raquel Urtasun[1,2]

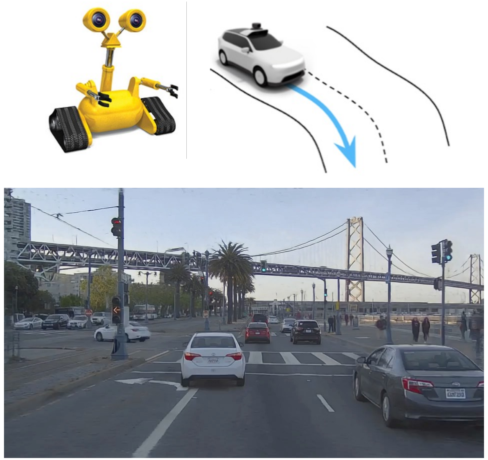
https://waabi.ai/lightsim

waabi UNIVERSITY OF TORONTO UNIVERSITY OF WATERLOO MIT

37th Conference on Neural Information Processing Systems (2023), New Orleans, USA

Simulation for Robust Image Perception in Robots

- Modern camera-based perception systems are not robust under different lighting
- Collecting data under various lighting are expensive and time-consuming
- We need scalable and affordable way to generate experiences - Simulation!



Real Data Collection

Simulation

Simulation Variations (Actor cut in + lighting changes)

Existing Simulators Lack Scale and Diversity

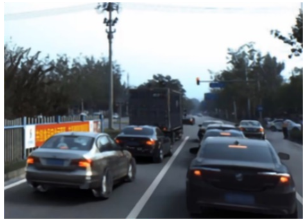
- Standard game engines for simulation such as CARLA [1]:
  - not scalable, lacking diversity, unrealistic
- Limited number of manually designed assets and lighting conditions
- Trained perception system generalizes poorly to the real world [2]

[1] CARLA: An open urban driving simulator. [Dosovitskiy, et al., CoRL 2017]
[2] Enhancing photorealism enhancement. [Richter et al., PAMI 2021]

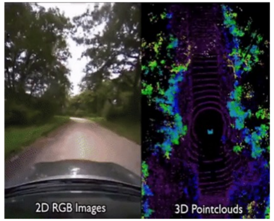
Existing Simulators Bake the Lighting

- Data-driven simulators build digital twins with baked lighting
  - Simulation limited to one single scene and cannot generalize
  - No lighting simulation (shadows, inter-object lighting effects)

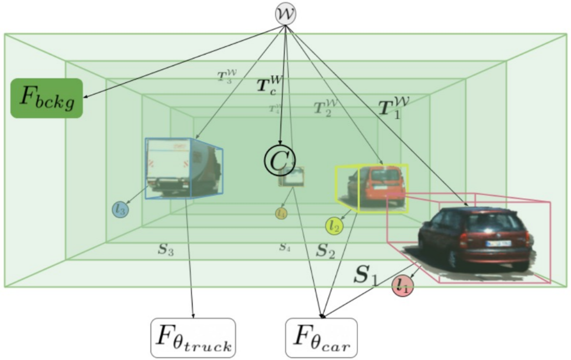
GeoSim [1]



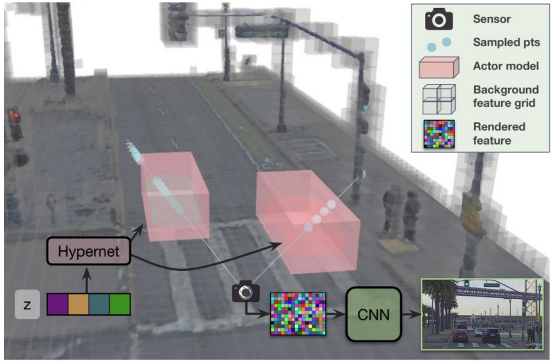
AADS [2]



VISTA 2.0 [3]



Neural Scene Graph [4]

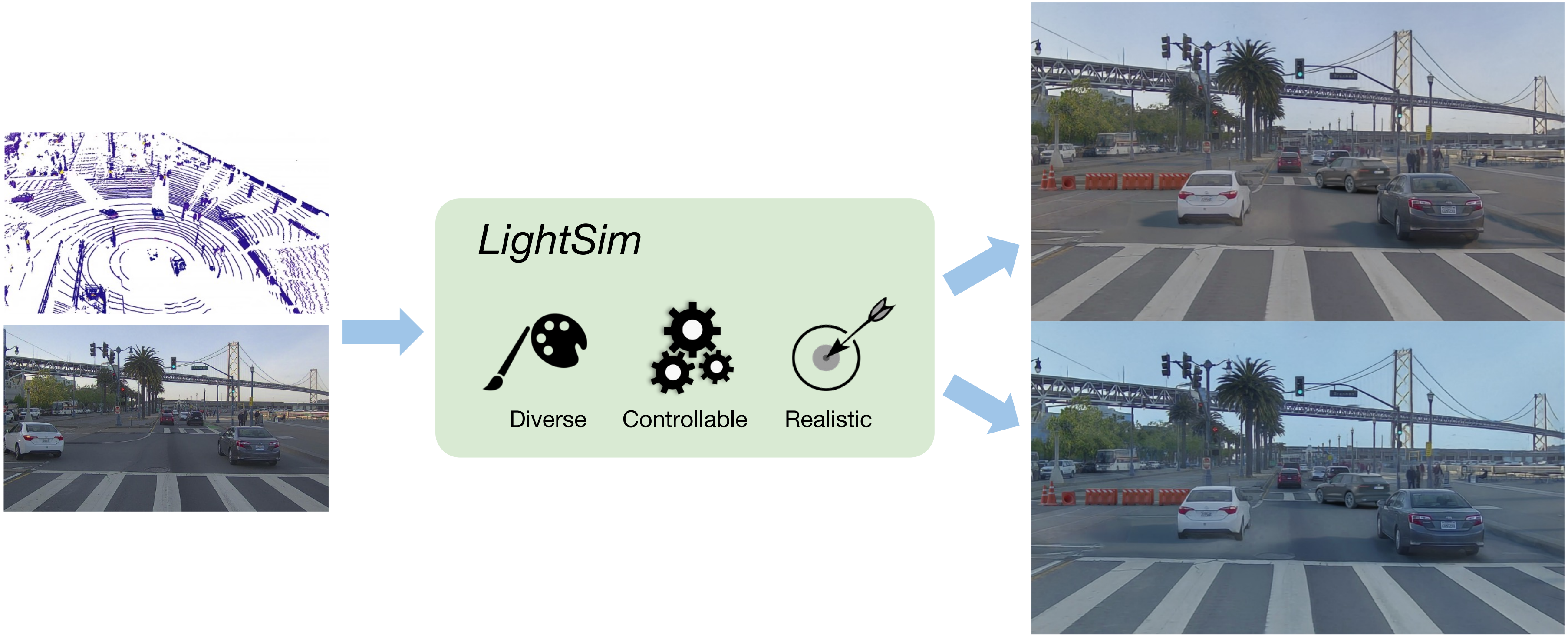


UniSim [5]

[1] GeoSim: Realistic Video Simulation via Geometry-Aware Composition for Self-Driving. [Chen at al., CVPR 2021]
[2] AADS: Augmented autonomous driving simulation using data-driven algorithms. [Li et al., Sci. Robotics. 2021]
[3] VISTA 2.0: An Open, Data-driven Simulator for Multimodal Sensing and Policy Learning for Autonomous Vehicles [Amini et al., ICRA 2022]
[4] Neural Scene Graphs for Dynamic Scenes. [Ost et al., CVPR 2021]
[5] UniSim: A Neural Closed-Loop Sensor Simulator. [Yang, et al. CVPR 2023]

Our Goal

- Create a diverse, controllable, and realistic simulator that can generate camera data of scenes at scale under diverse lighting conditions



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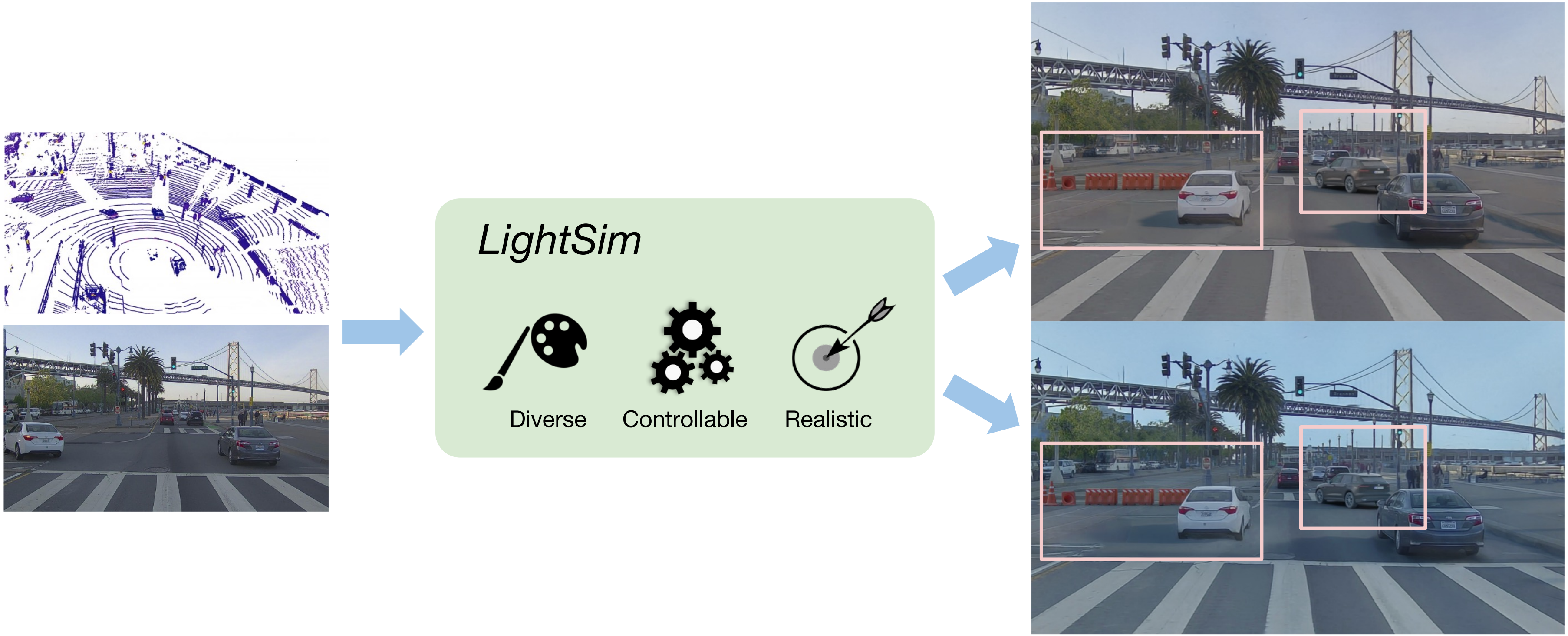

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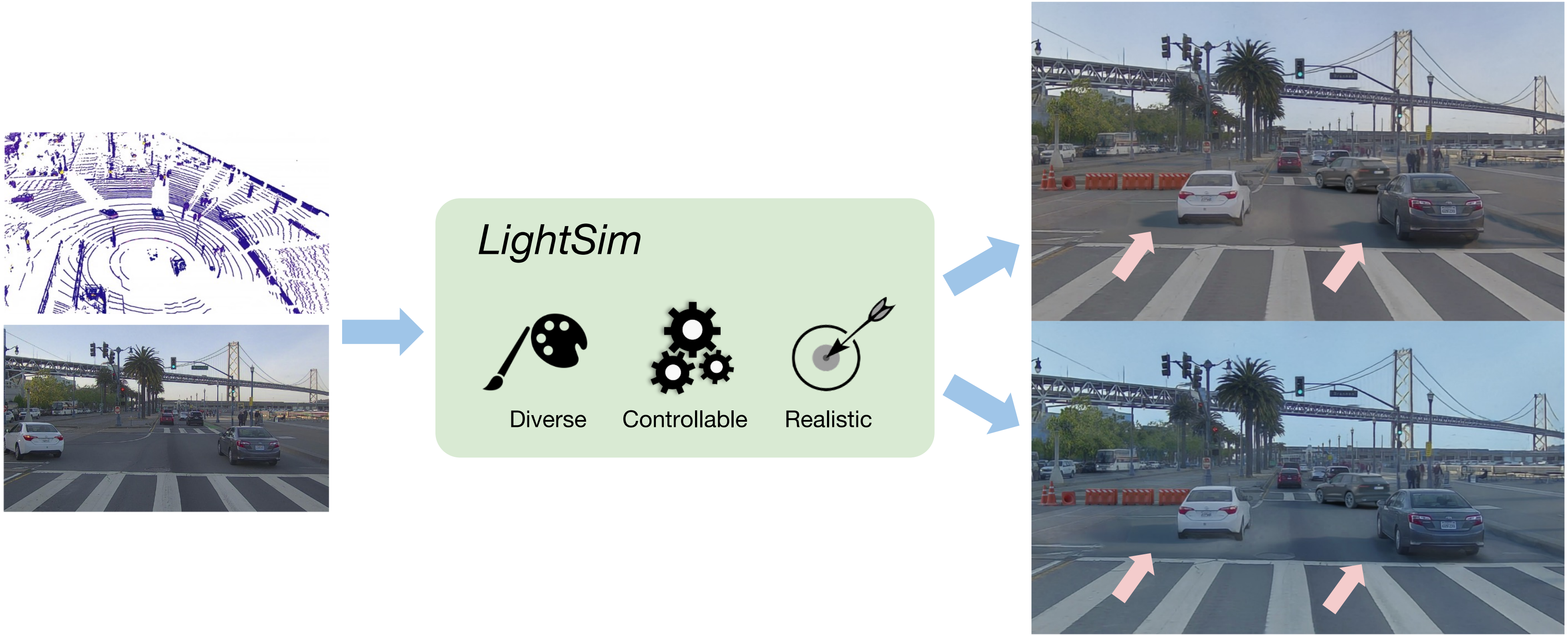
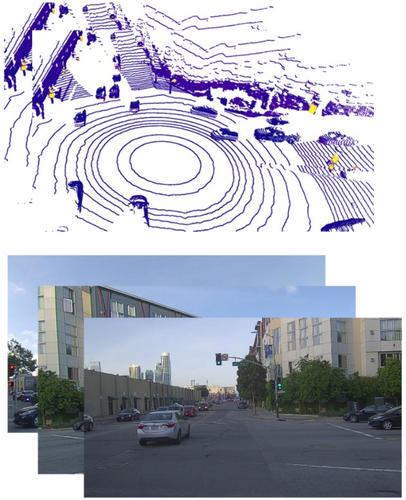


Step 1: Building Relightable Digital Twins of the Real World

- Neural scene reconstruction to recover scene geometry and texture



Sensor data

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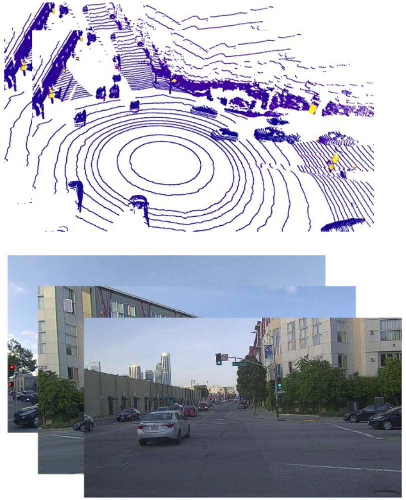
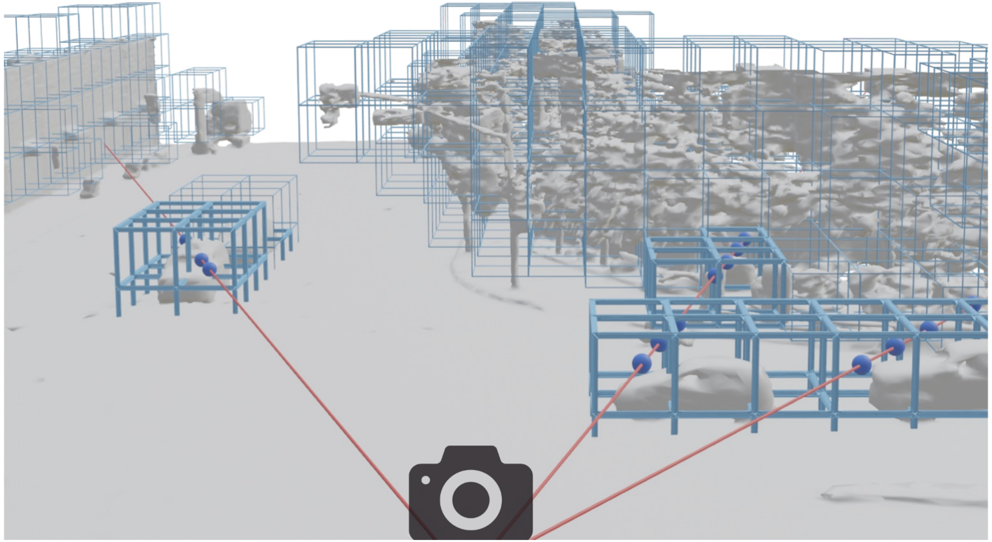


Sensor data

Neural Scene Reconstruction



Compositional neural radiance field (background + actors)

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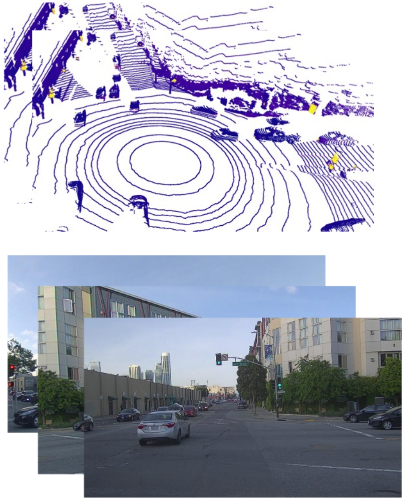

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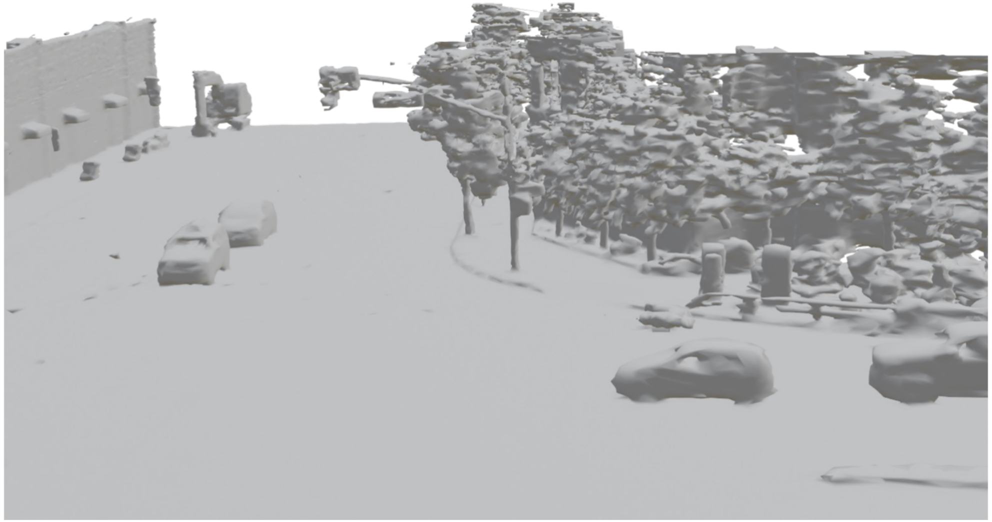
Neural Scene Reconstruction



Explicit digital twins (geometry, texture)

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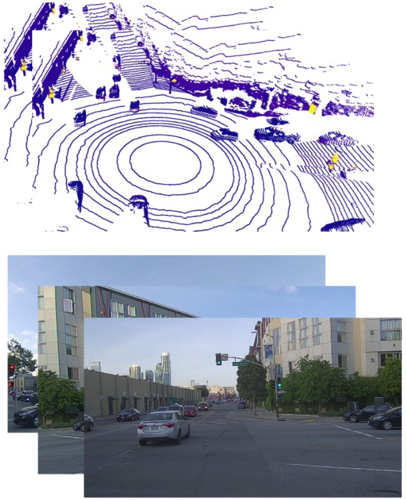
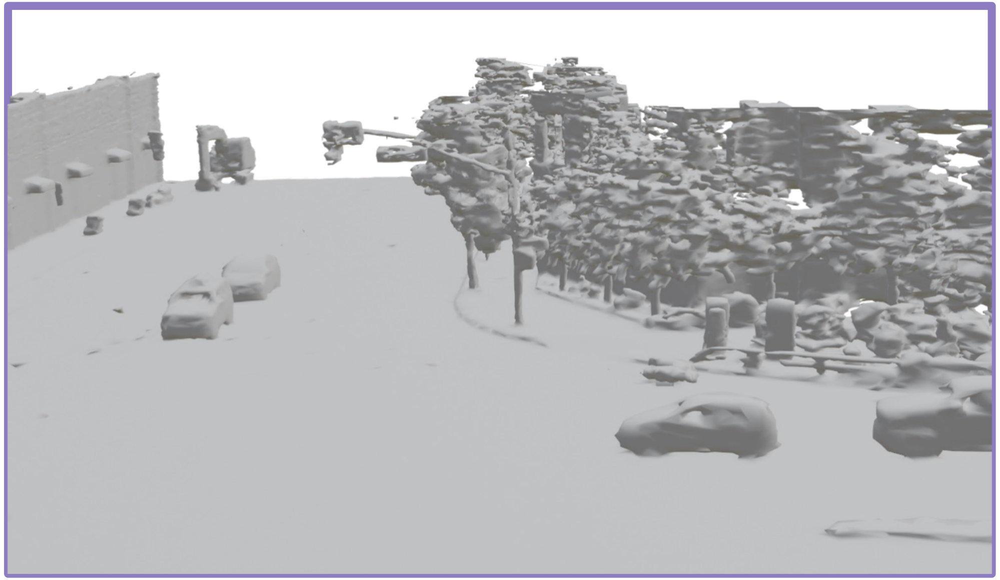


Sensor data

Neural Scene Reconstruction



Explicit digital twins (geometry, texture)

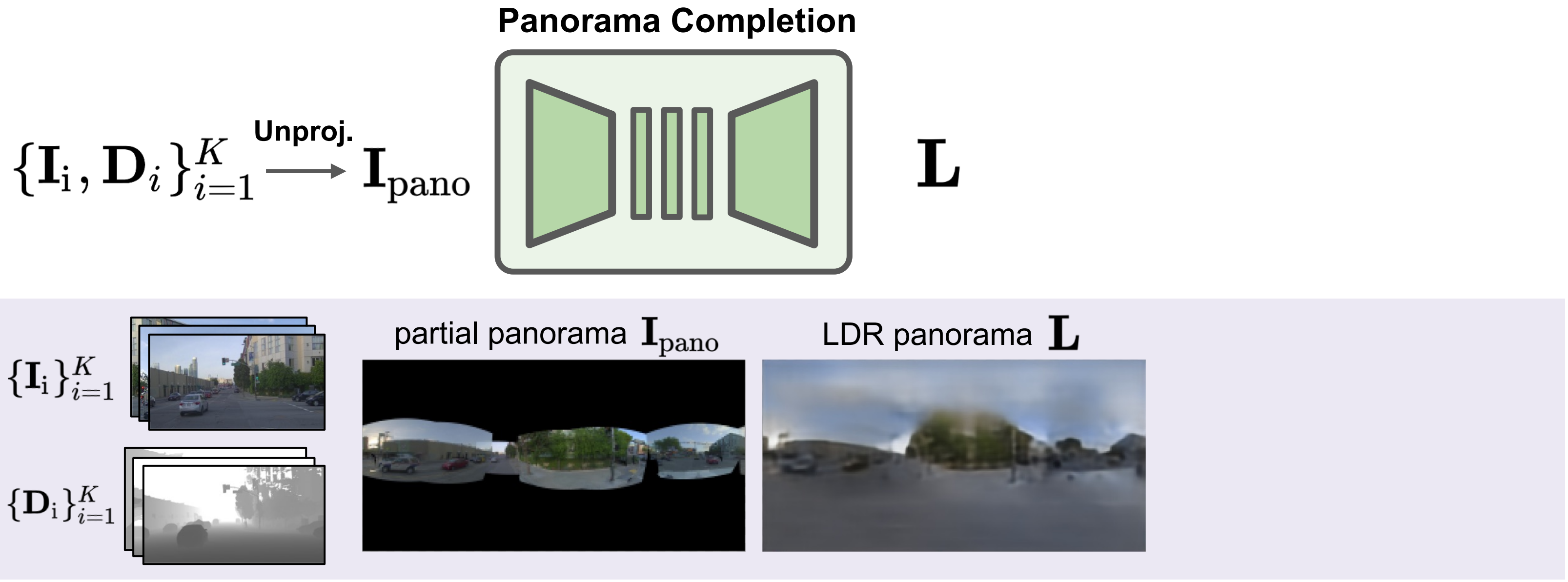
Step 1: Building Relightable Digital Twins of the Real World

- Neural lighting simulation to recover the HDR sky dome

$$\{\mathbf{I}_{\mathrm{i}}, \mathbf{D}_i\}_{i=1}^{K} \xrightarrow{\textbf{Unproj.}} \mathbf{I}_{\mathrm{pano}}$$

Step 1: Building Relightable Digital Twins of the Real World

- Neural lighting simulation to recover the HDR sky dome



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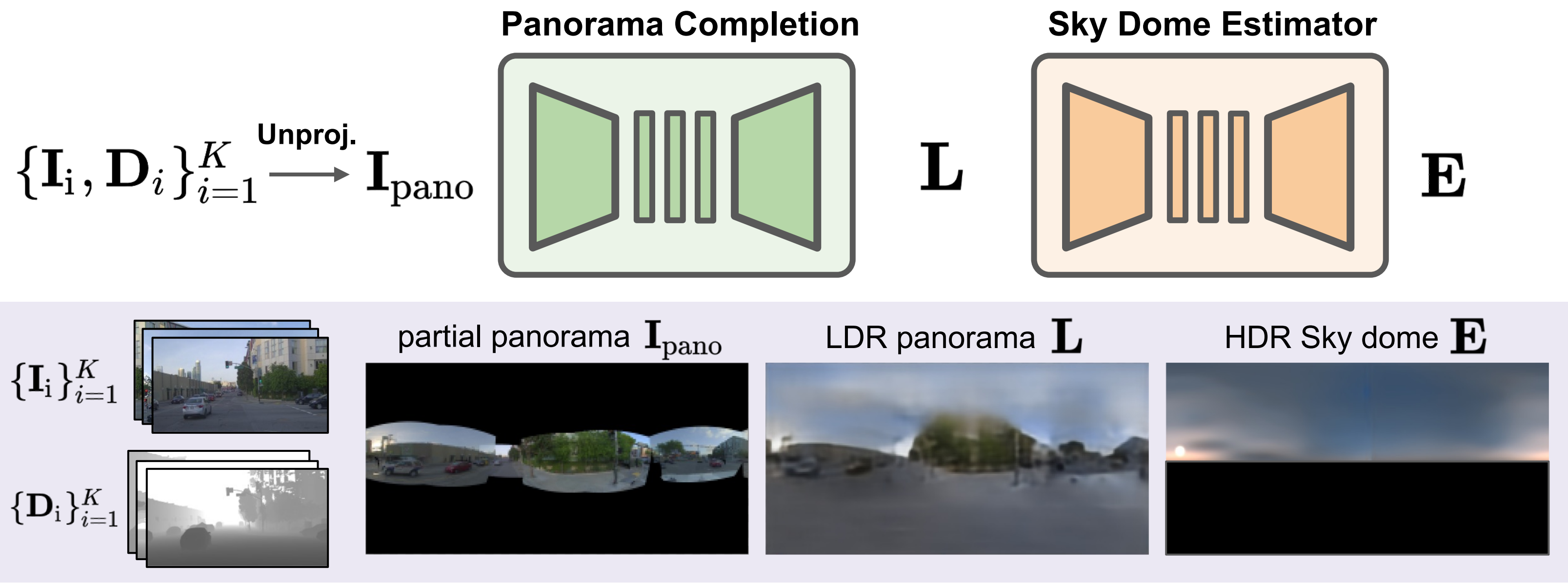

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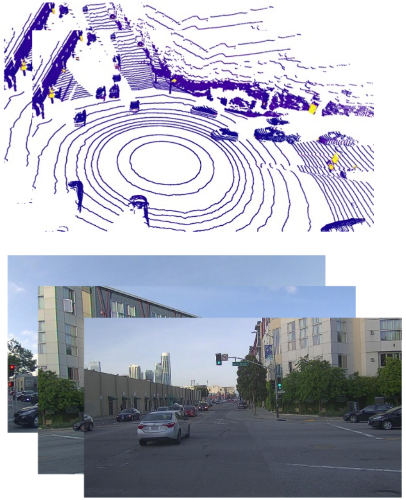
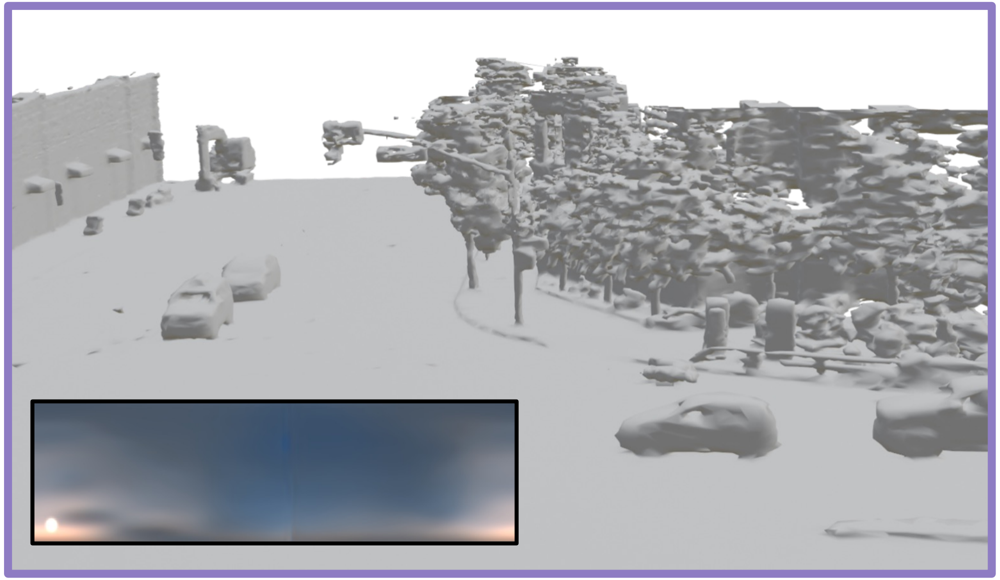
- Neural scene reconstruction to recover scene geometry and texture
- Neural lighting simulation to recover the HDR sky dome



Sensor data

Neural Scene Reconstruction

Neural Lighting Estimation



Relightable digital twins (geometry, texture, lighting)

Step 2: Neural Lighting Simulation of Dynamic Urban Scenes

- Derive augmented reality representation from digital twins
- Generate lighting-relevant data with physically-based rendering
- Neural deferred rendering for lighting simulation

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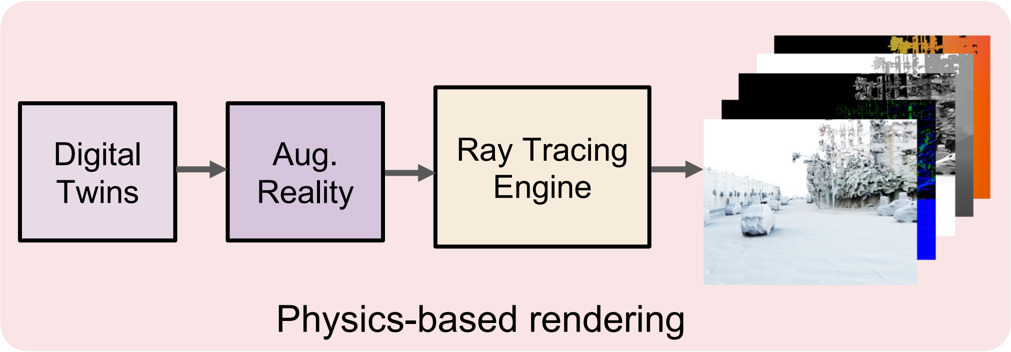

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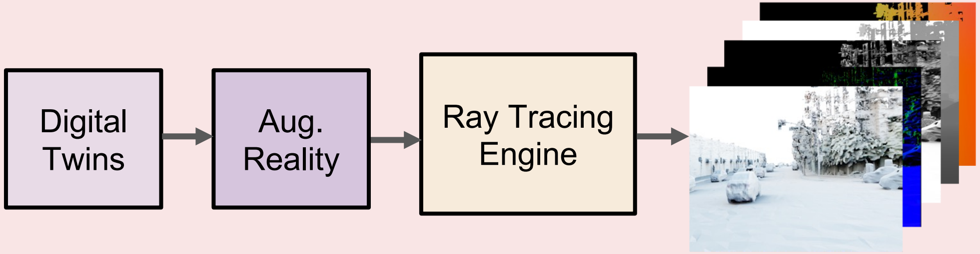
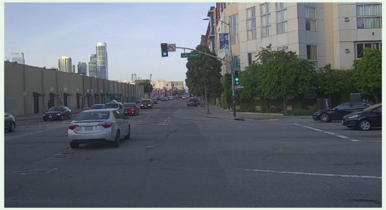
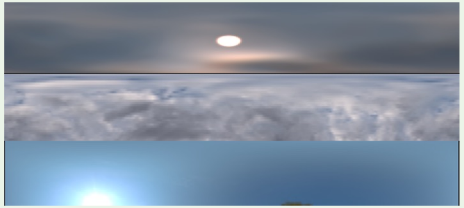


Physics-based rendering



Source



Target Lighting

Step 2: Neural Lighting Simulation of Dynamic Urban Scenes

- Derive augmented reality representation from digital twins
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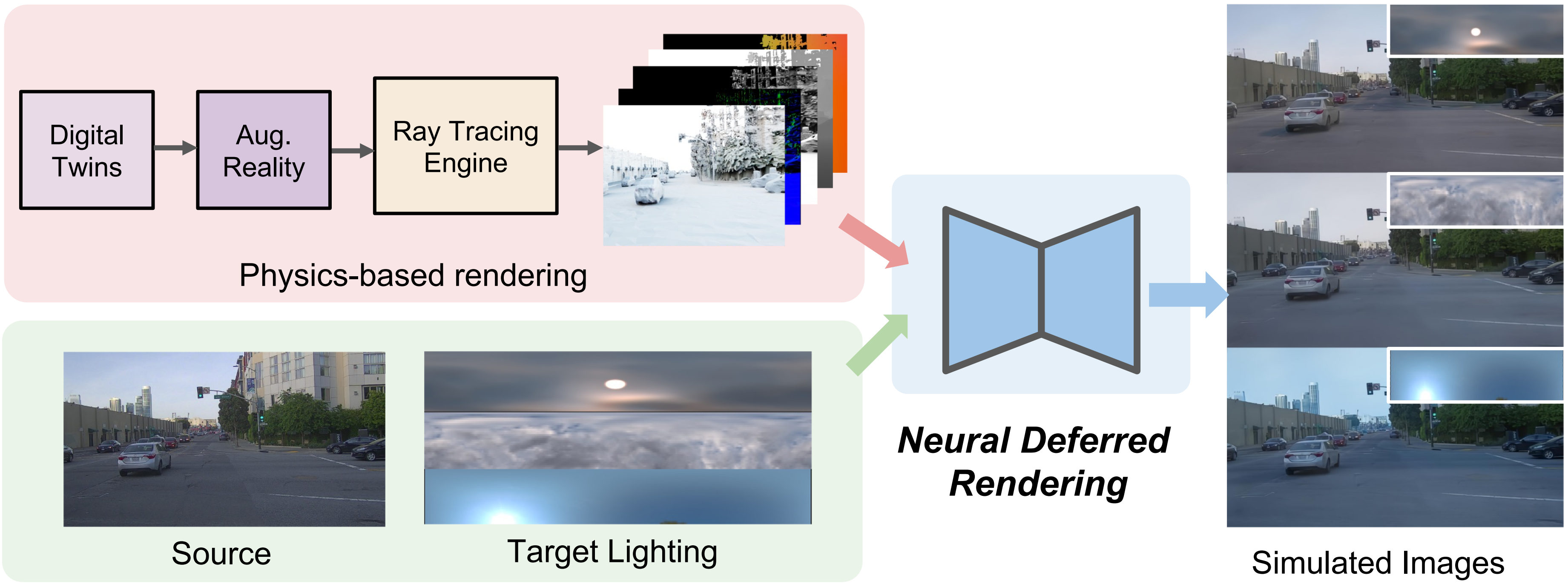
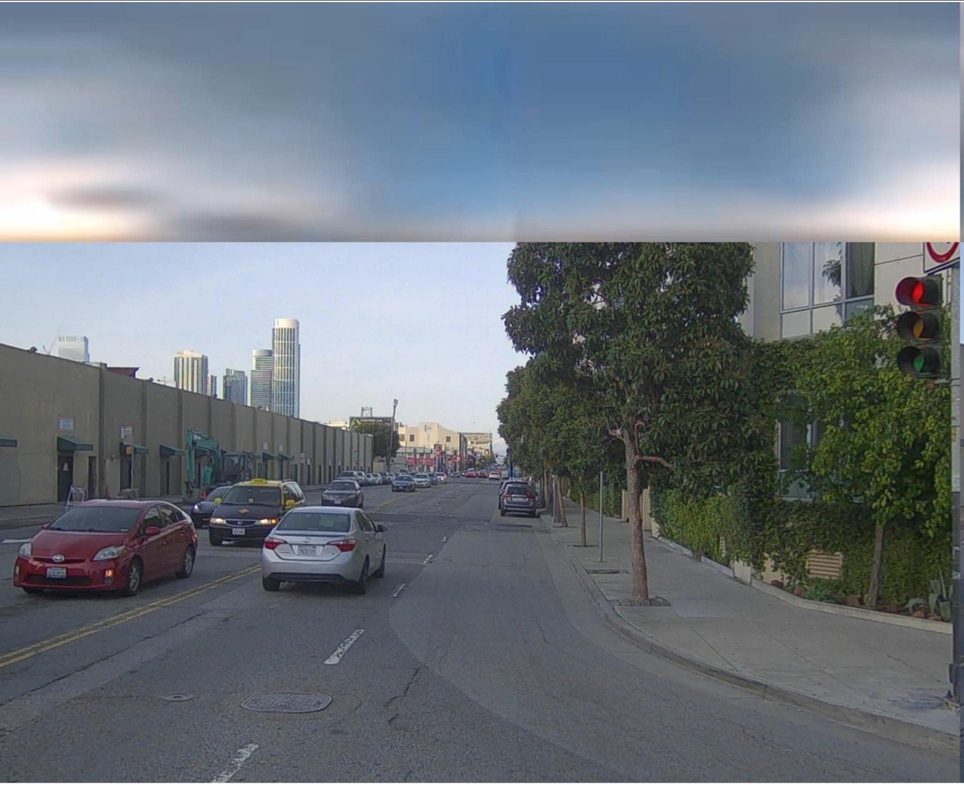


Scene Relighting

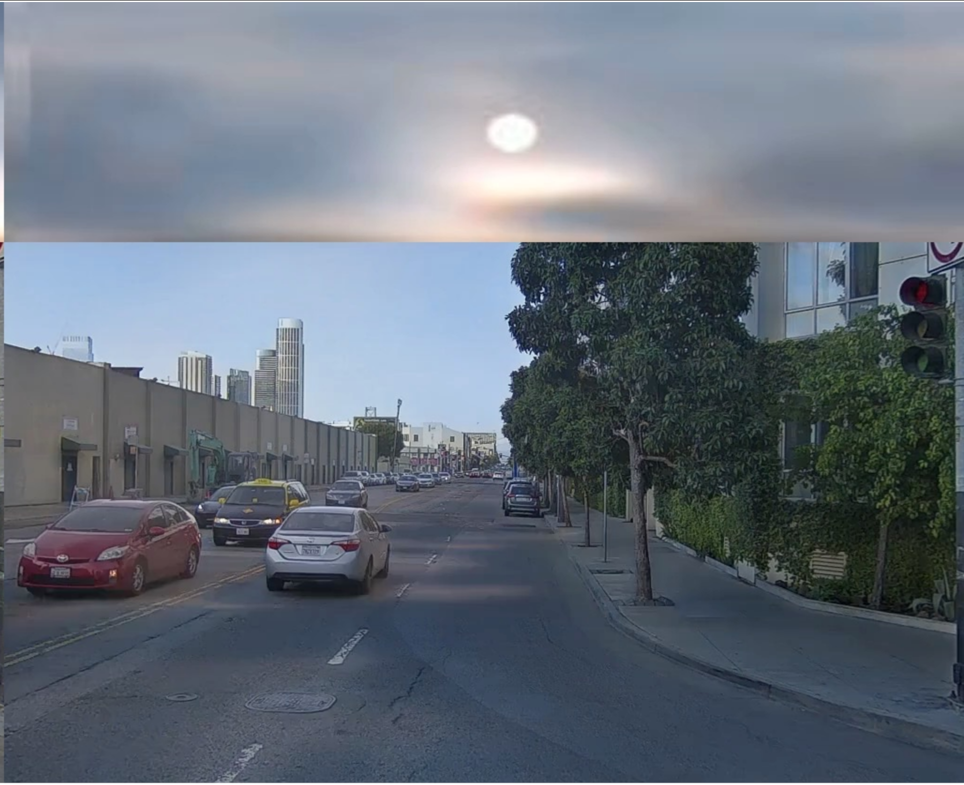
Real Video and Estimated Source Lighting

Simulated Video with Target Lighting

Shadow Editing



Real Image and Estimated Source Lighting



Simulated Video with Rotated Lighting

Lighting-aware Actor Insertion

Controllable Camera Simulation

Controllable Camera Simulation – variation 1

Original

Simulated Variations

Controllable Camera Simulation – variation 2

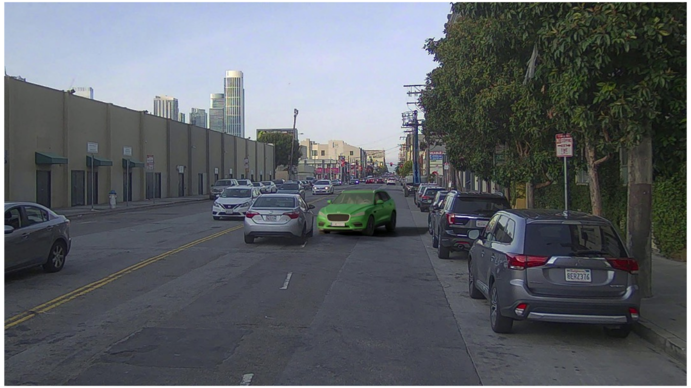
Original

Simulated Variations

Lighting Estimation Evaluation via Actor Insertion

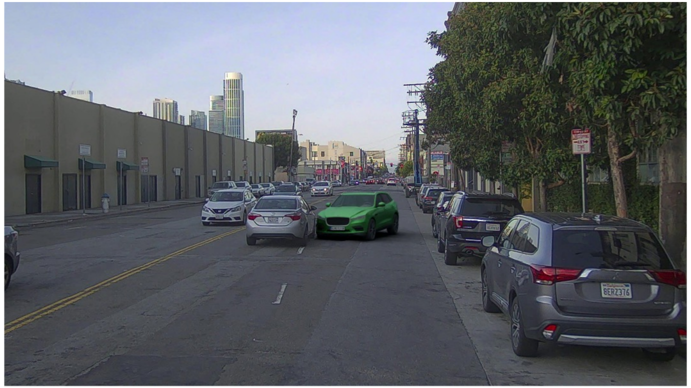
Original

SOLD-Net



NLFE* (Panorama)

Ours



*HDR skydome only

Lighting Estimation Evaluation via Actor Insertion

Original

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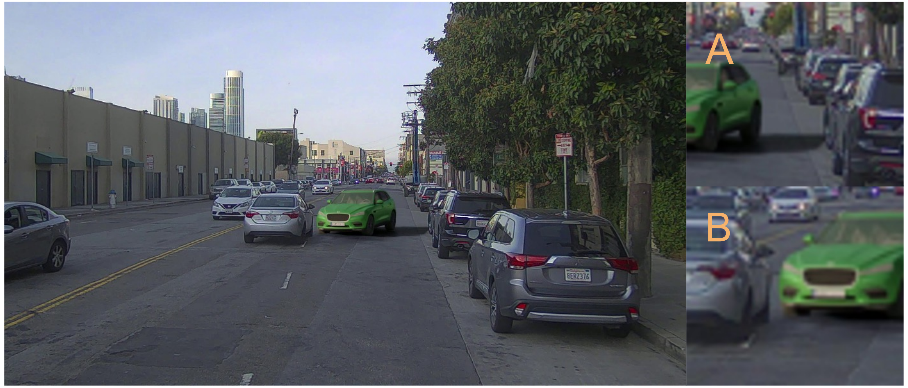


NLFE* (Panorama)

Ours

*HDR skydome only

Generalization on nuScenes

Real

LightSim Simulated

Downstream Perception Training

- Realistic lighting simulation can help improve the performance of downstream object detection task under unseen lighting conditions

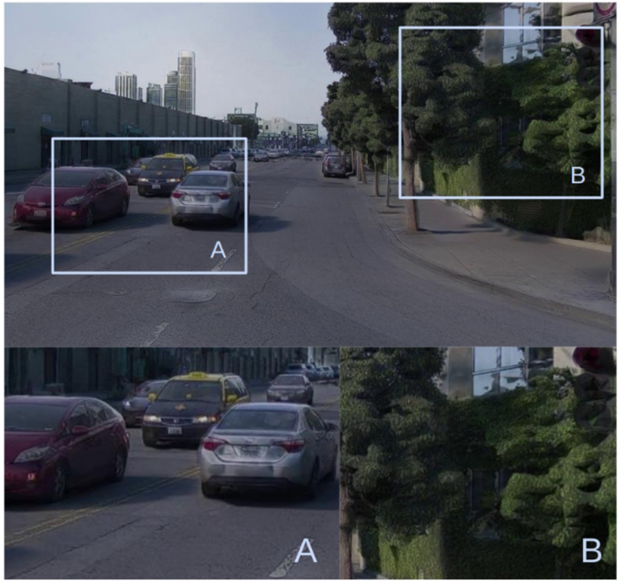
Model	mAP (%)
Real	32.1
Real + Color aug. [41]	33.8 (+1.7)
Real + Sim (Self-OSR)	30.3 (−1.8)
Real + Sim (EPE)	32.5 (+0.4)
Real + Sim (Color Transfer)	35.1 (+3.0)
Real + Sim (Ours)	**36.6** (**+4.5**)

Comparison in Scene Relighting

Ablation Study

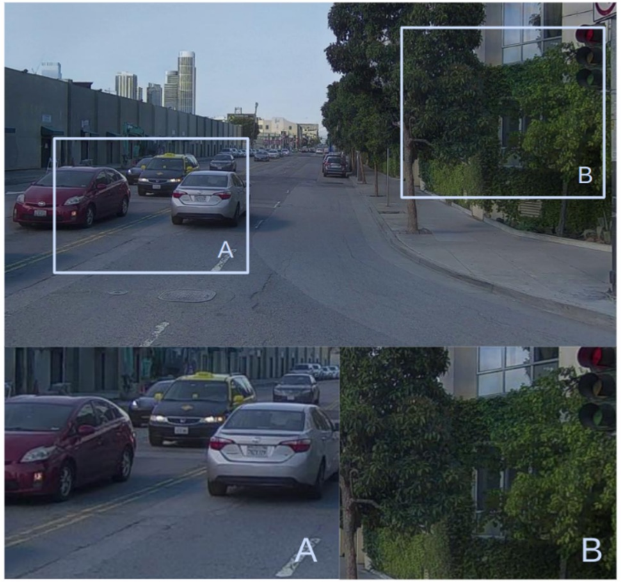
- Content-preserving loss

$\lambda_{\text{edge}} = 0$



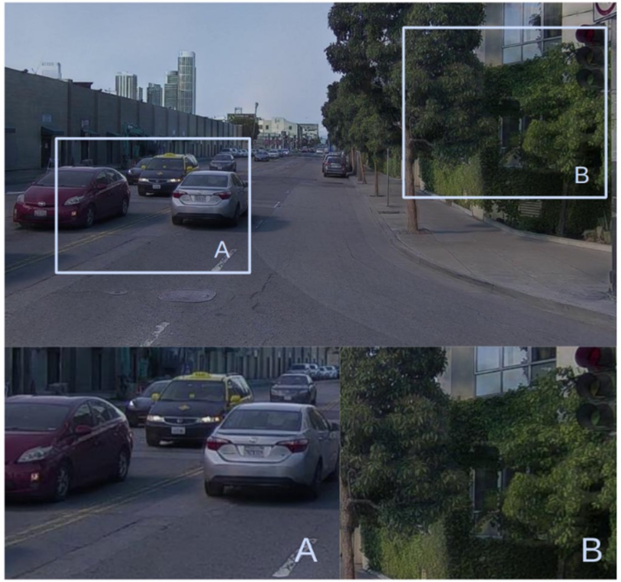
FID = 109.8

$\lambda_{\text{edge}} = 800$



FID = 57.3

Ours ($\lambda_{\text{edge}} = 400$ **)**



FID = 55.4

Ablation Study

- *sim-to-real* and *identity* pairs

w/o sim-real pairs

FID = 60.9

w/o identity pairs

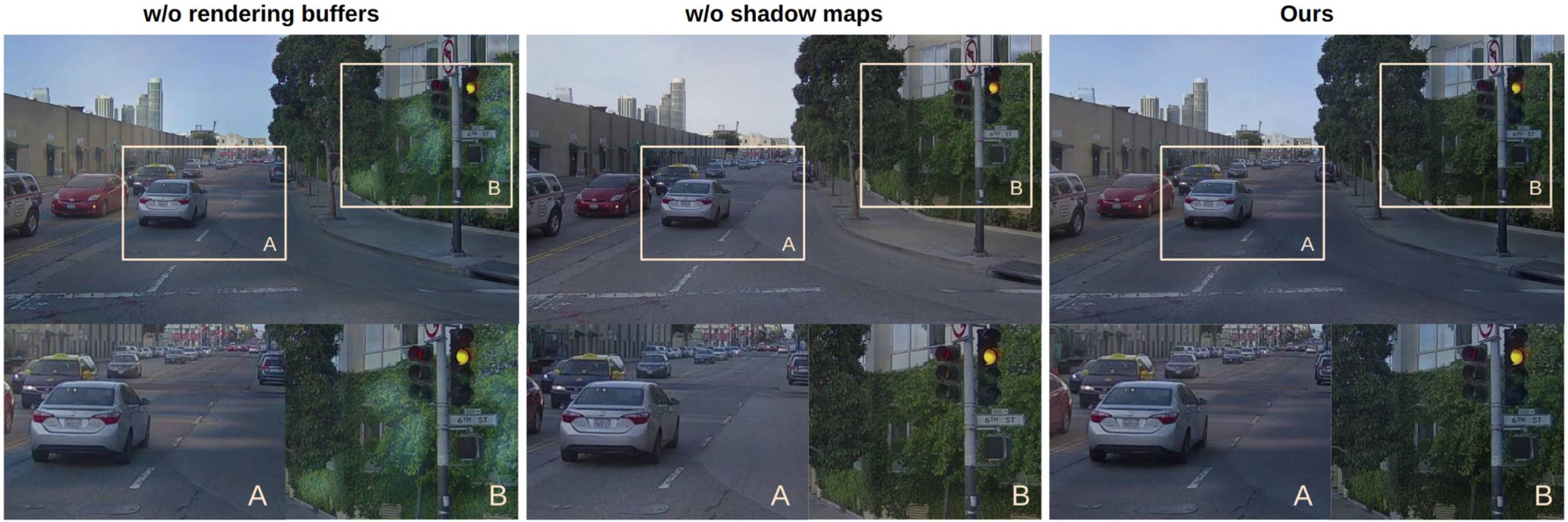
FID = 62.5

Ours

FID = 55.4

Ablation Study

- Rendering buffers and shadow maps



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Thank you!

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