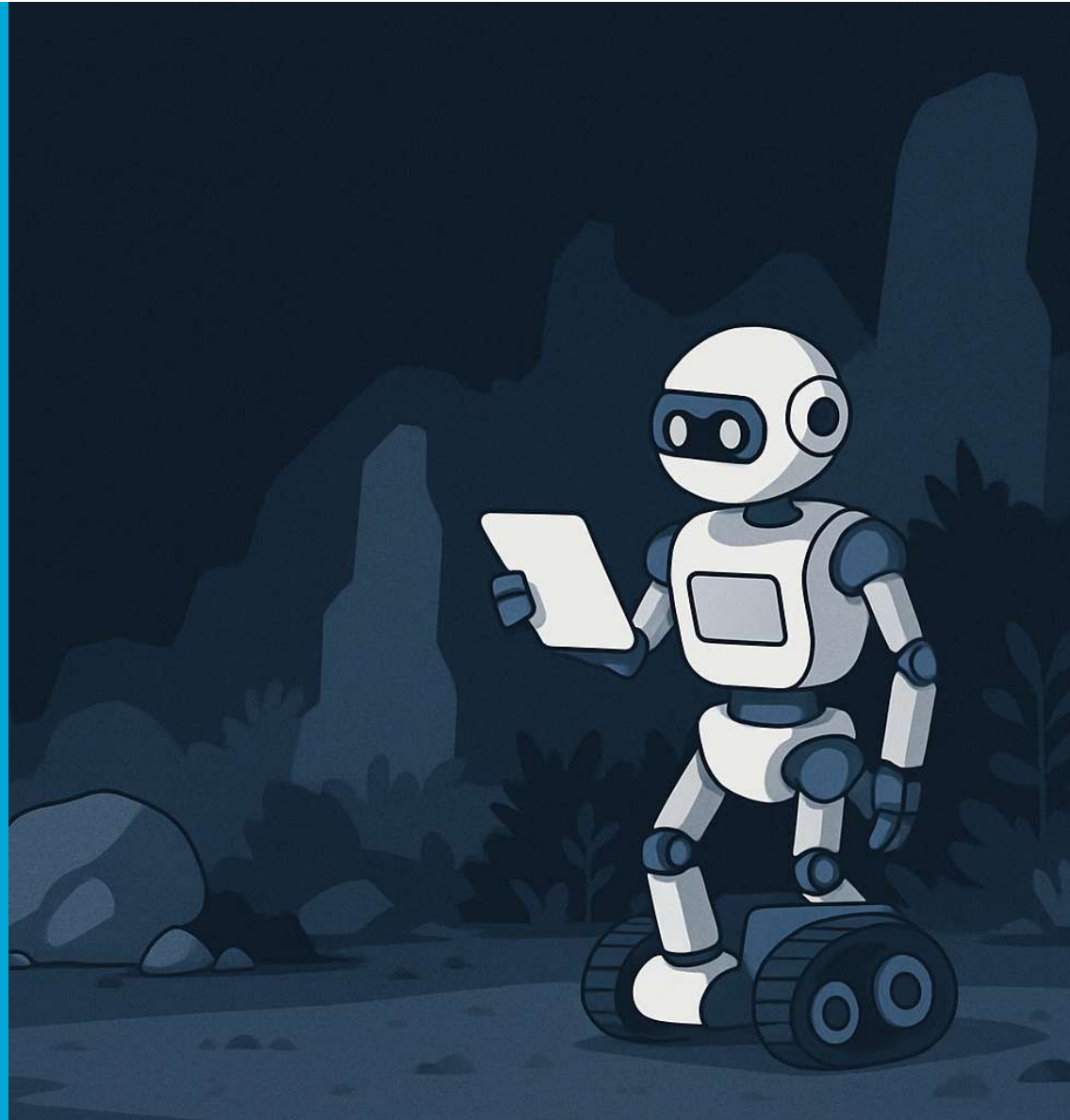


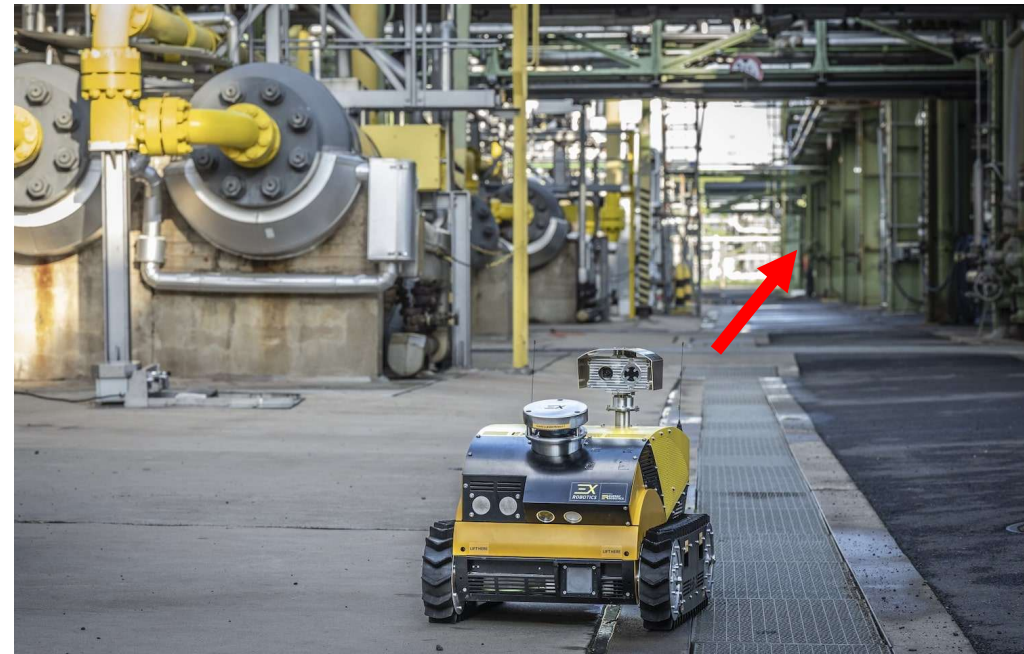
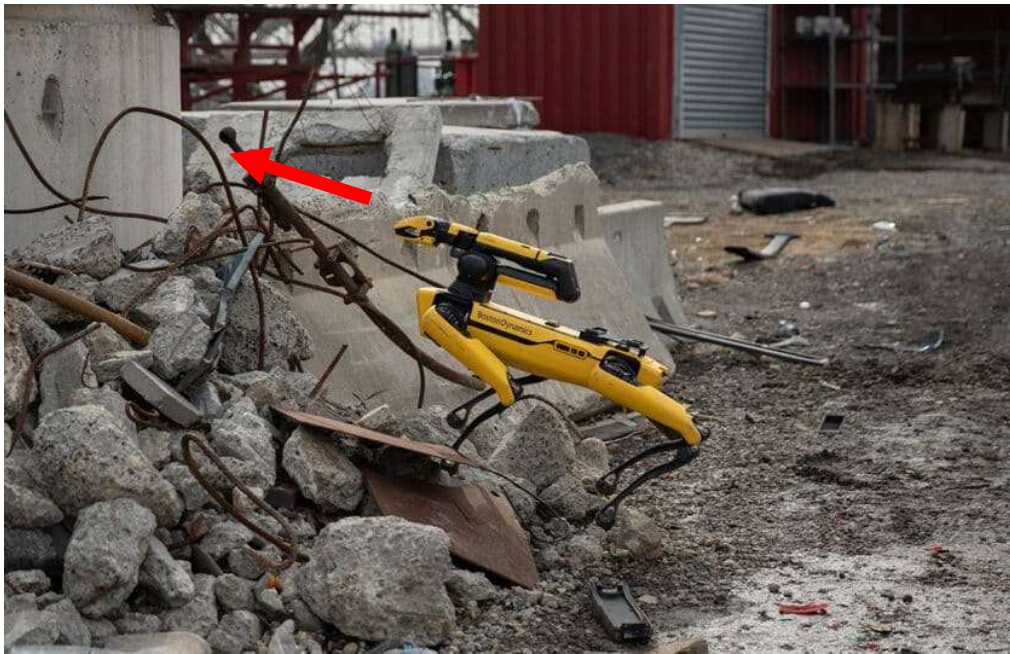
Liren Jin
University of Bonn

Active Perception for Learning-based Robot Mapping

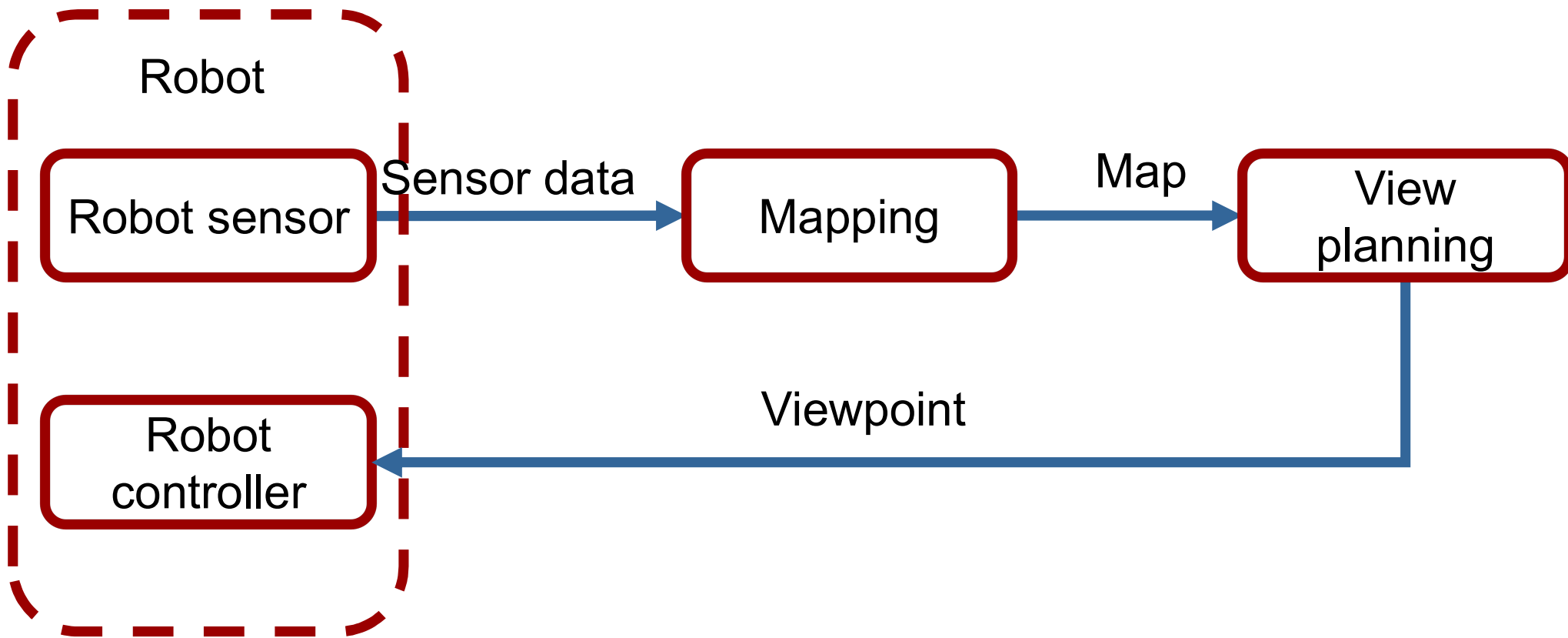
Marija Popović



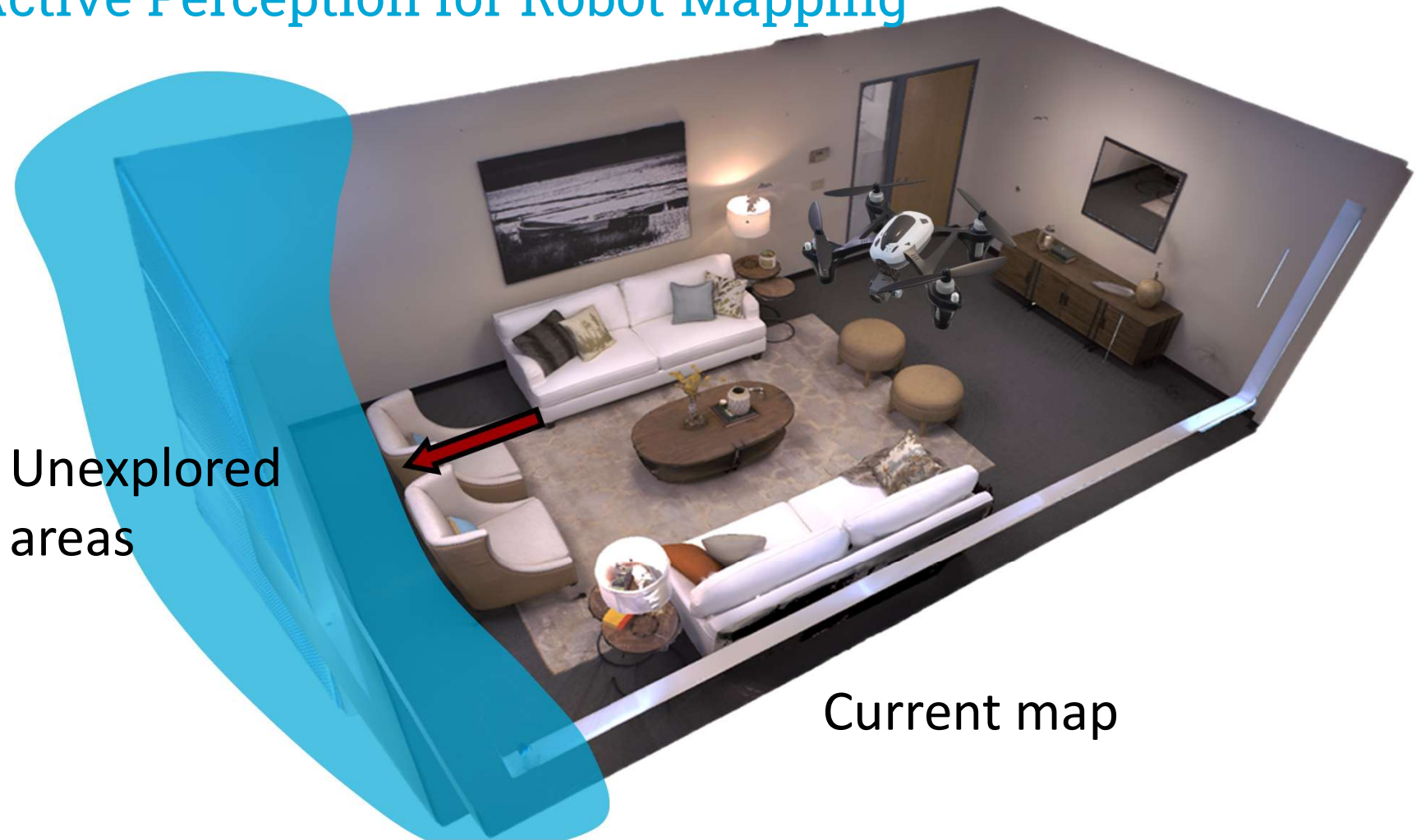
Motivation



Active Perception for Robot Mapping



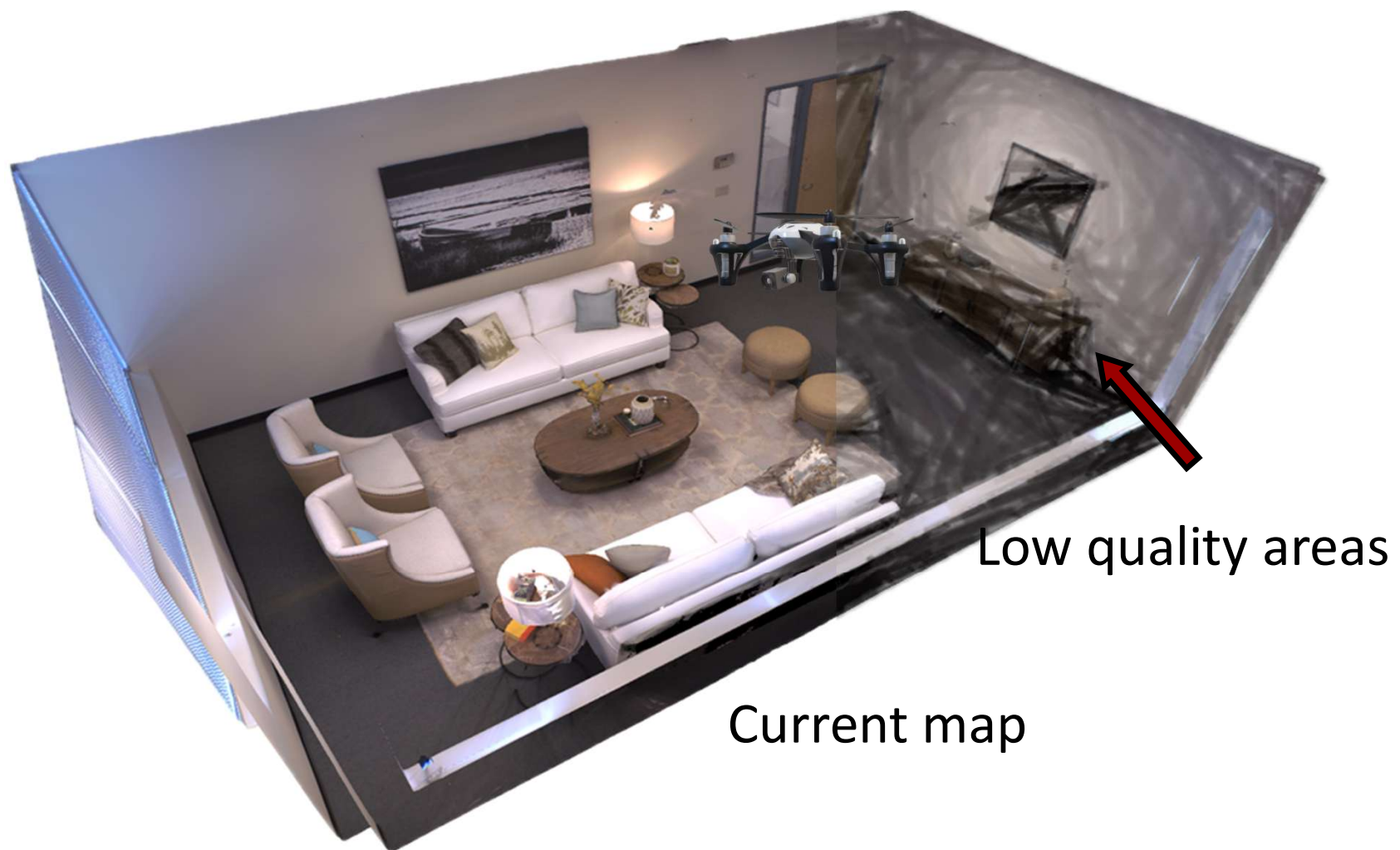
Active Perception for Robot Mapping



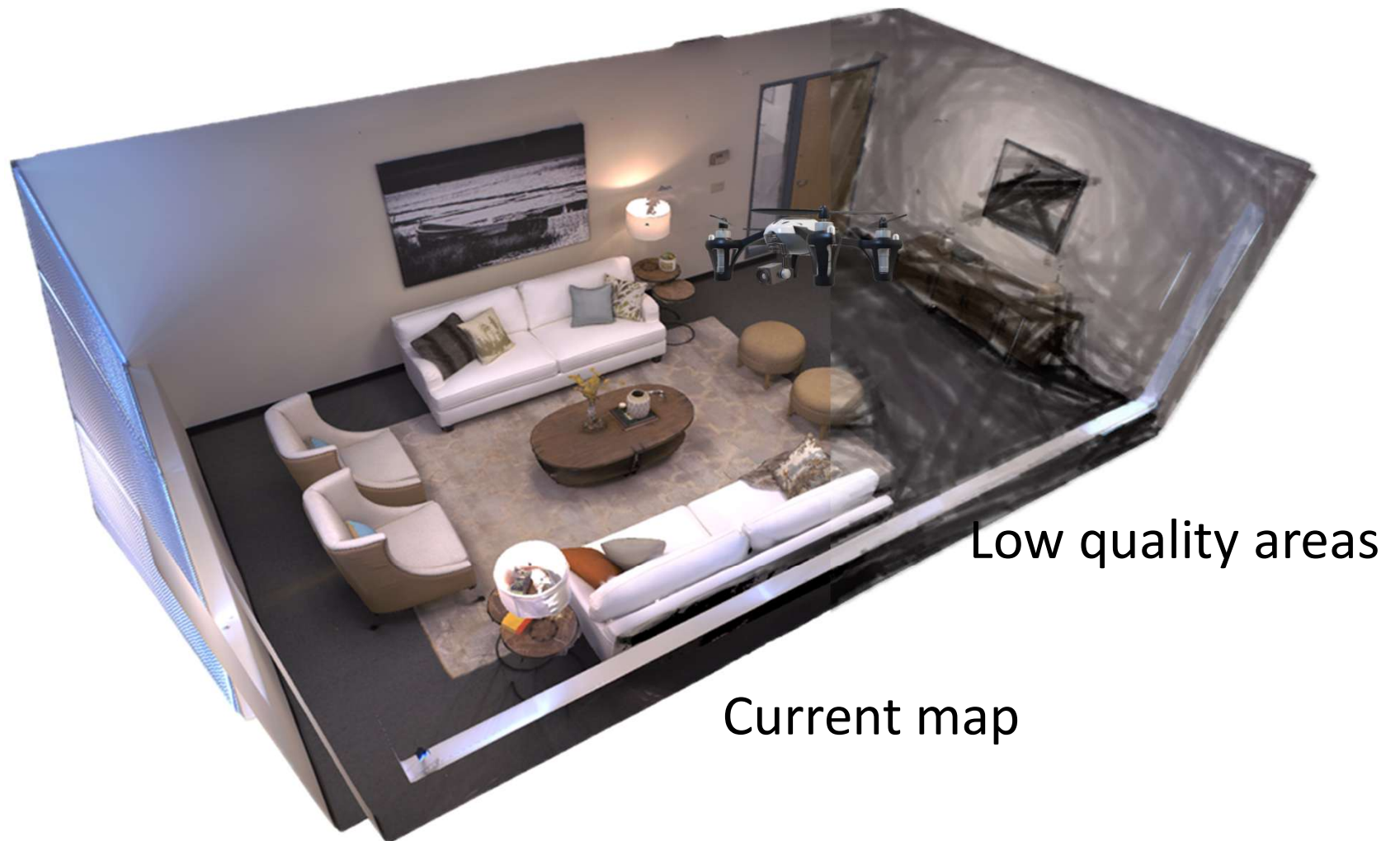
Active Perception for Robot Mapping



Active Perception for Robot Mapping



Active Perception for Robot Mapping

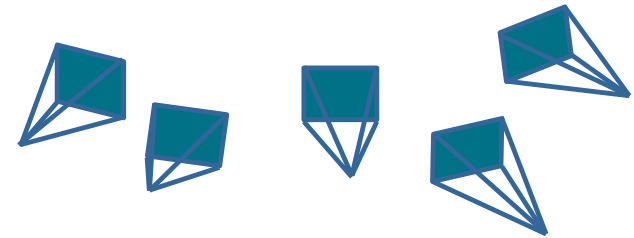


View Planning

1. Current map



2. Candidate viewpoints



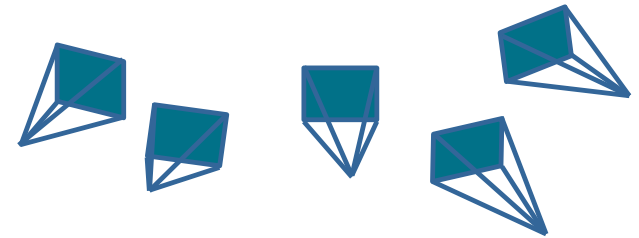
3. Utility function

View Planning

1. Current map



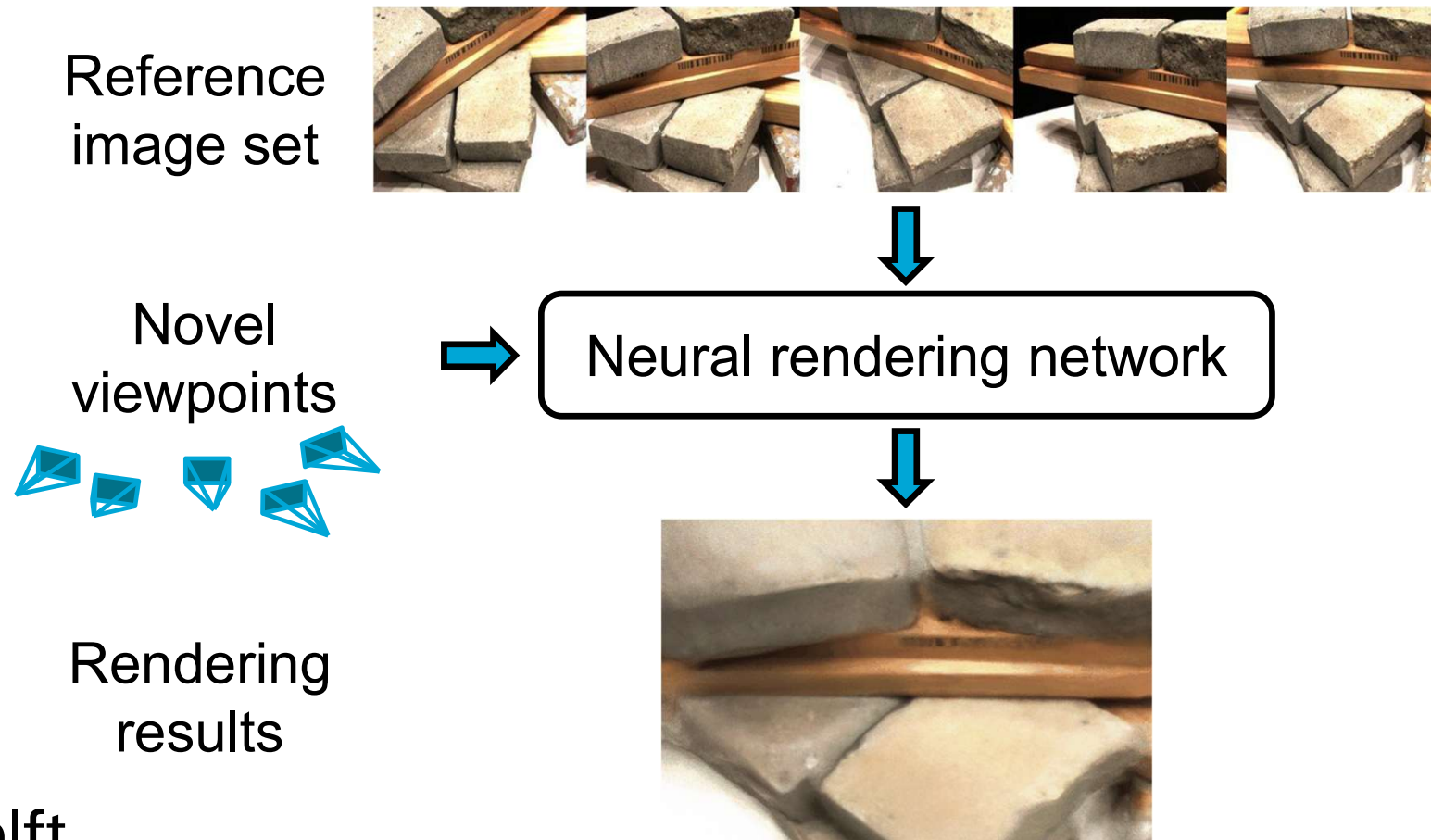
2. Candidate viewpoints



$$v^* = \arg \max_{v \in \mathcal{V}} I(\mathcal{M}, v)$$

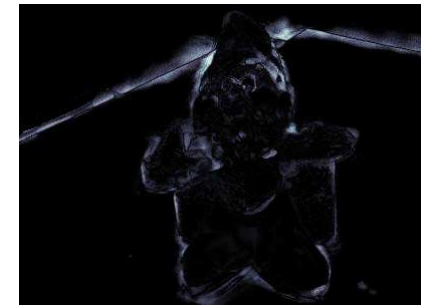
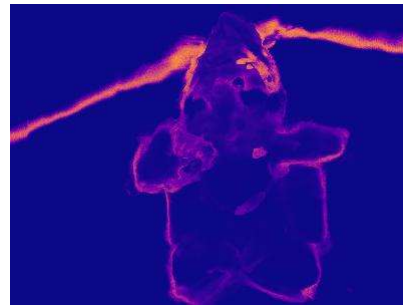
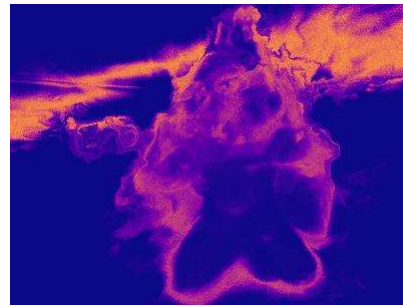
3. Utility function

NeU-NBV: Image-based Neural Rendering



Predicting Rendering Uncertainty

$\text{logit}(c) \sim N(\mu, \sigma^2)$ uncertainty before image capture

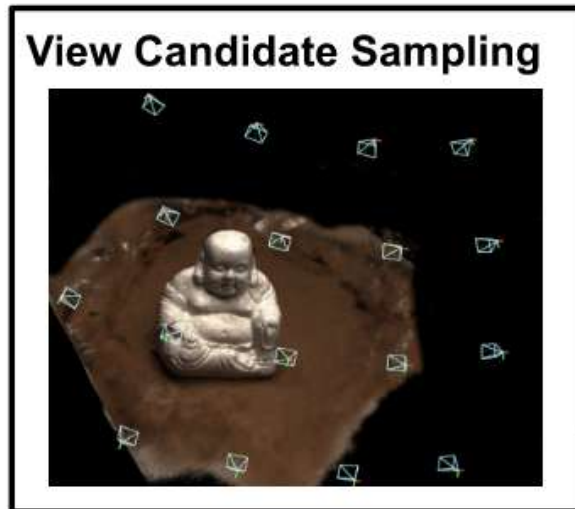


 Rendered RGB
TU Delft

Predicted uncertainty

Actual error

Image-based Rendering for Next Best View Planning



L. Jin, X. Chen, J. Rückin and M. Popović. NeU-NBV. In: *IEEE/RSJ IROS*, 2023.

Image-based Rendering for Next Best View Planning

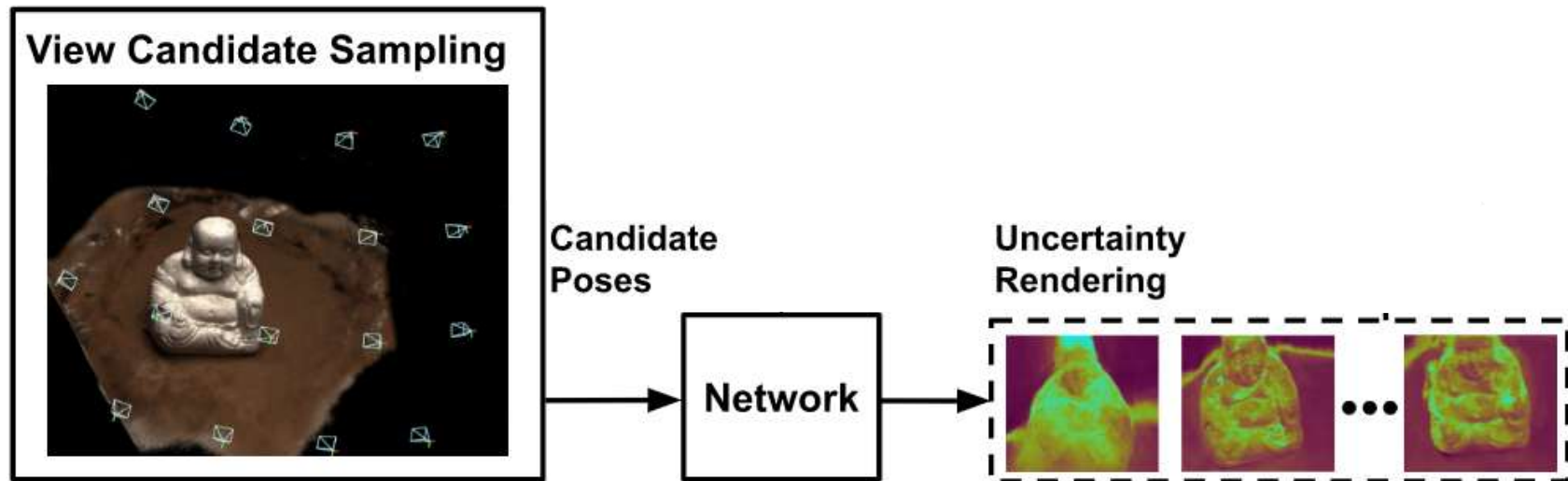


Image-based Rendering for Next Best View Planning

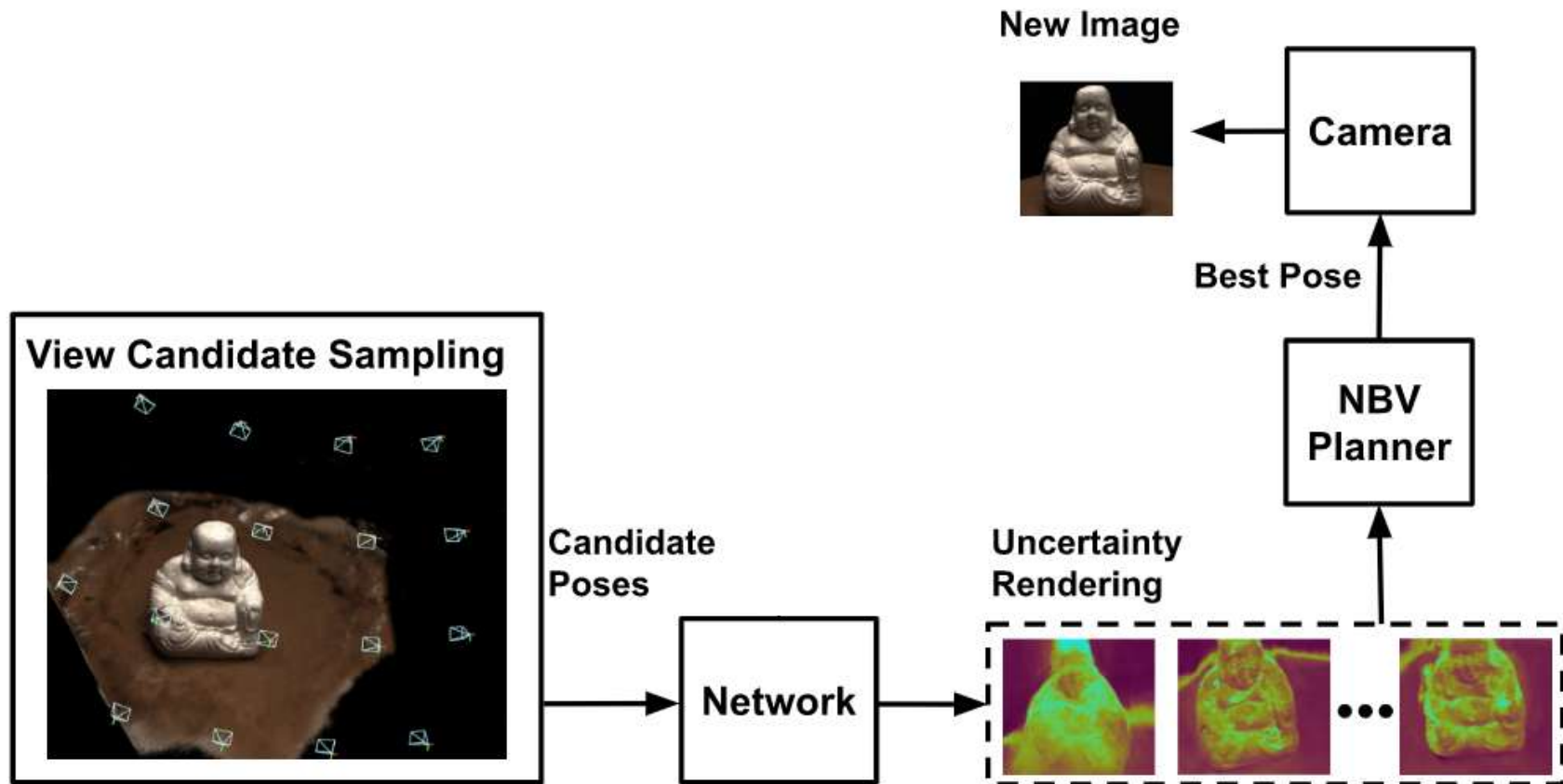
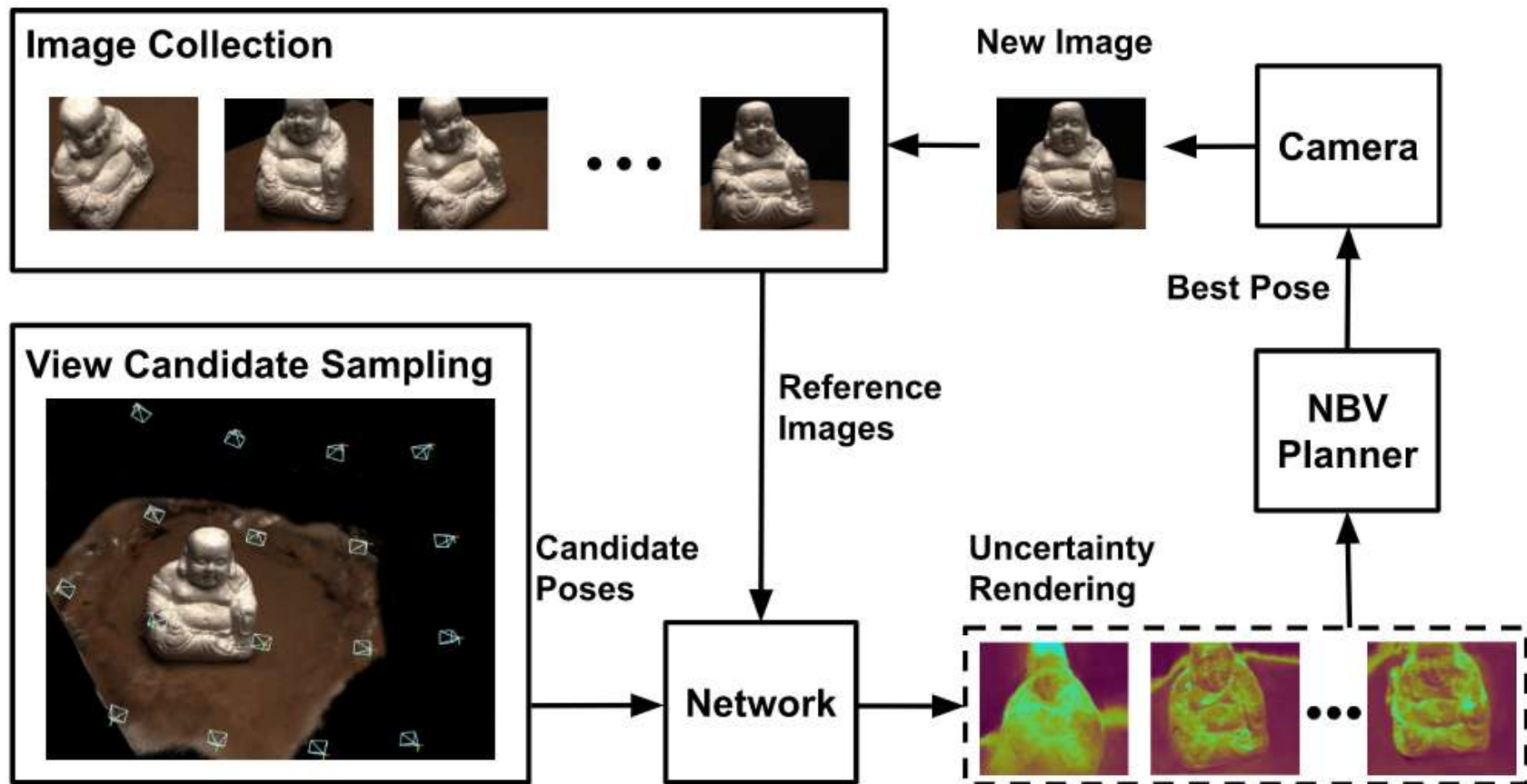
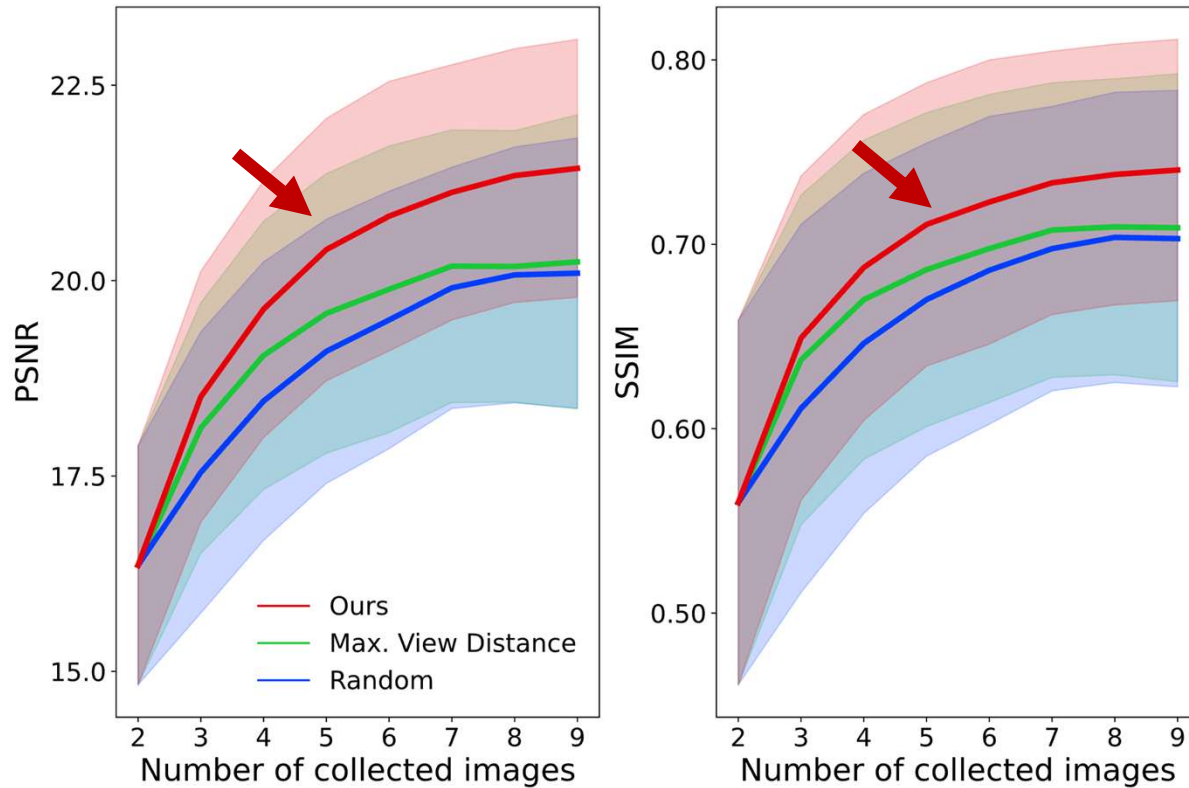


Image-based Rendering for Next Best View Planning



NeU-NBV: Reconstruction Results



Max. distance

PSNR 18.91



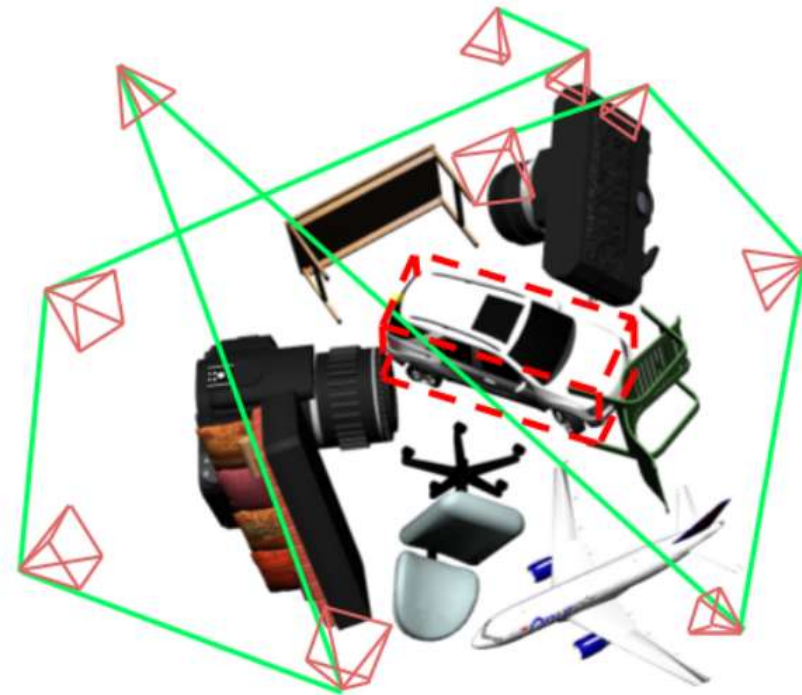
NeU-NBV

PSNR 20.59

STAIR: Reconstructing Objects of Interest

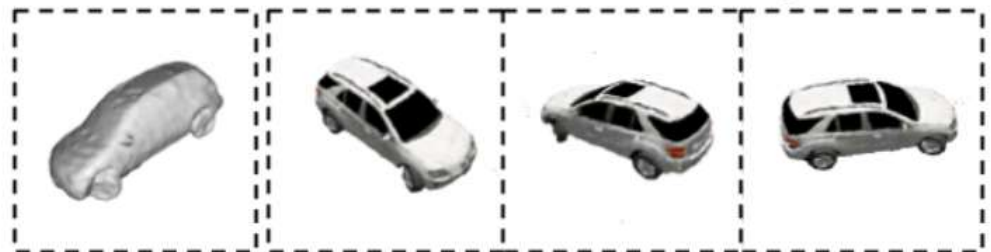
**Which objects matter
for the task?**

Learn occupancy, colour
and semantic fields

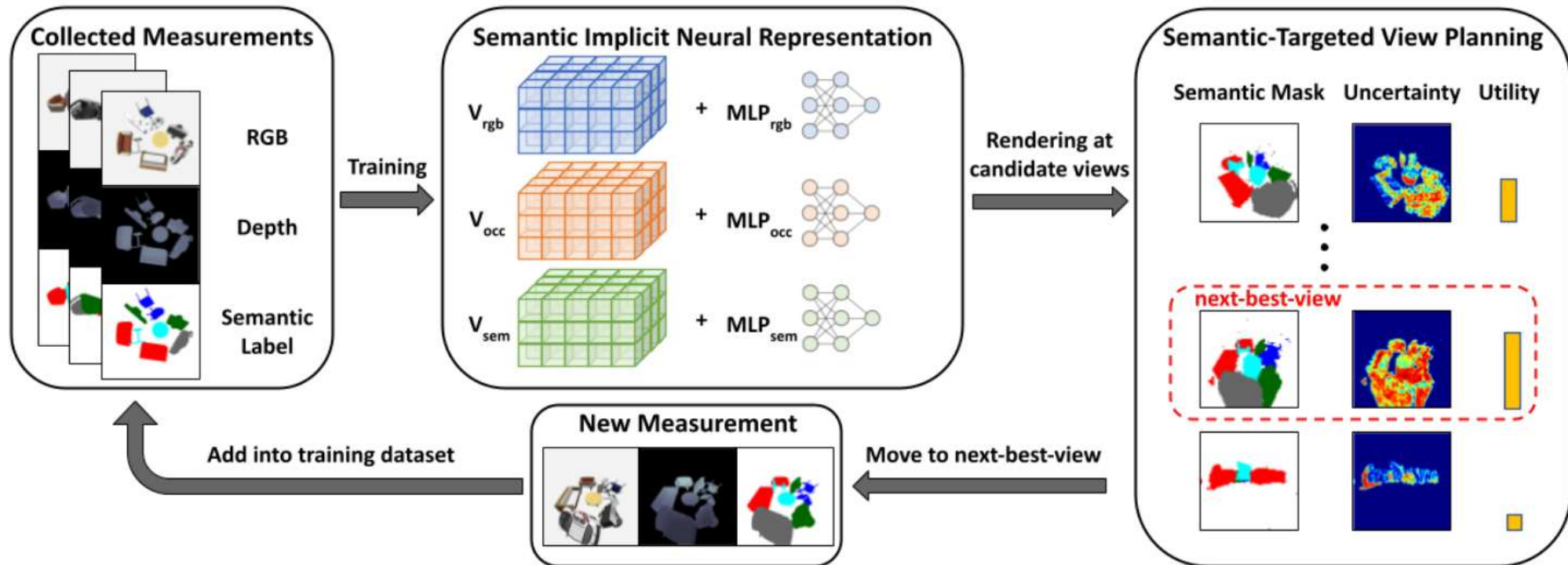


Mesh

Novel View Rendering



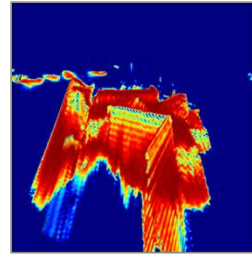
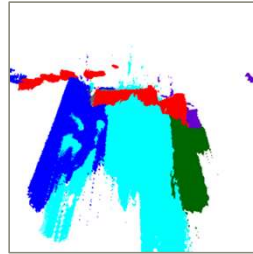
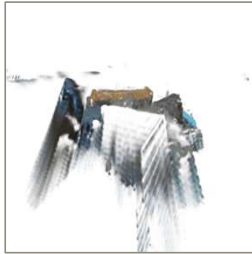
STAIR: Semantic-Targeted View Planning



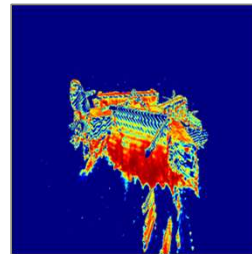
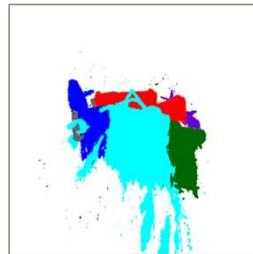
$$I(\text{view}) = \text{target uncertainty} + \epsilon \times \text{total uncertainty}$$

Semantic-Targeted Active Implicit Reconstruction

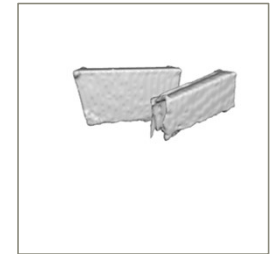
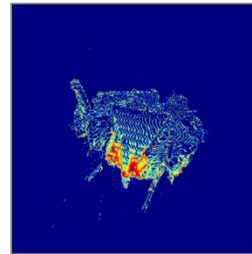
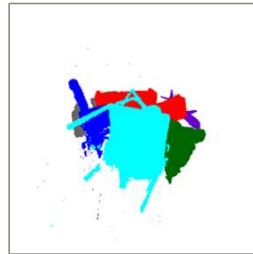
Step 2



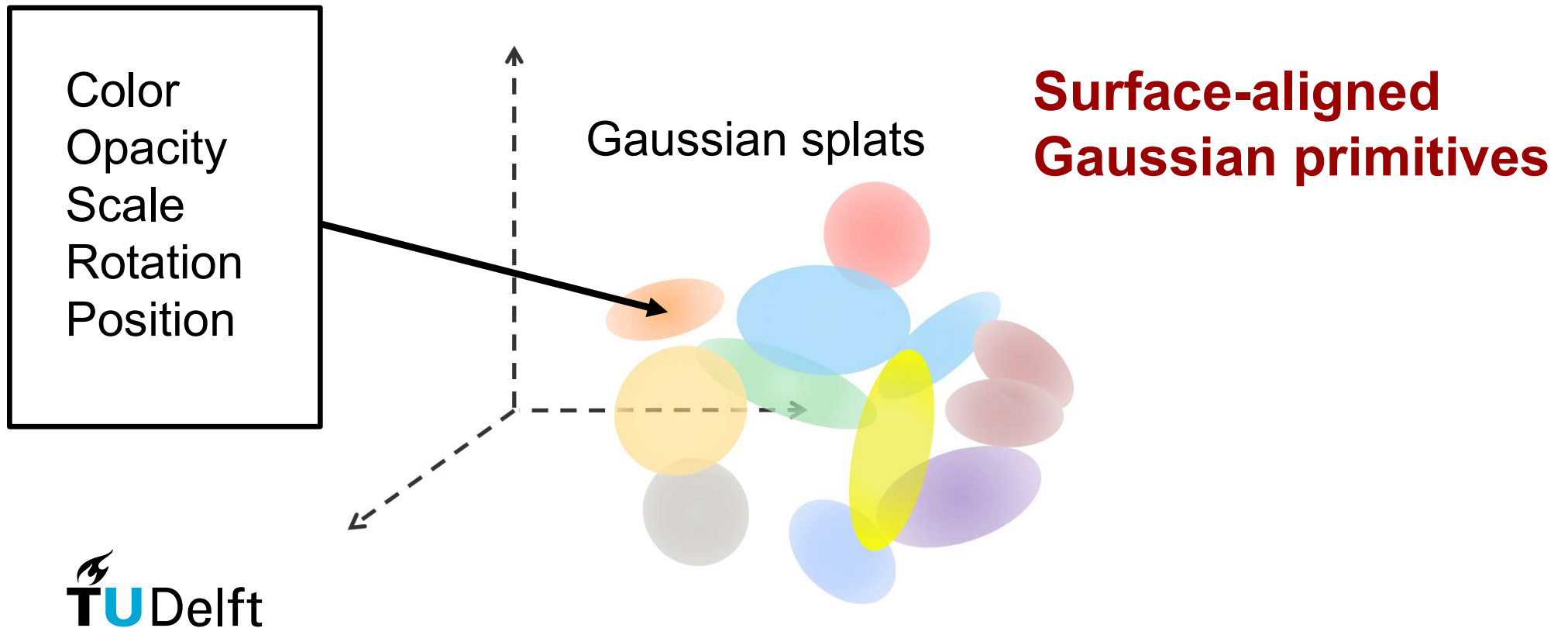
Step 4



Step 10



ActiveGS: Gaussian Splatting Maps



Observation-based Confidence

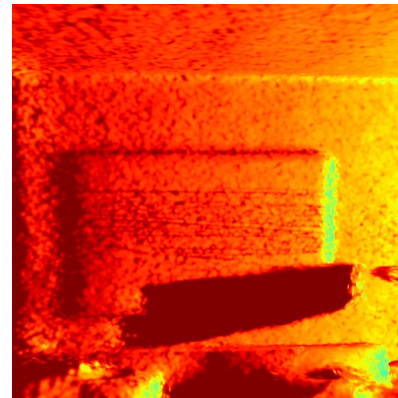
$$k_i = \gamma_i \exp(\beta_i)$$

γ_i **observation support**

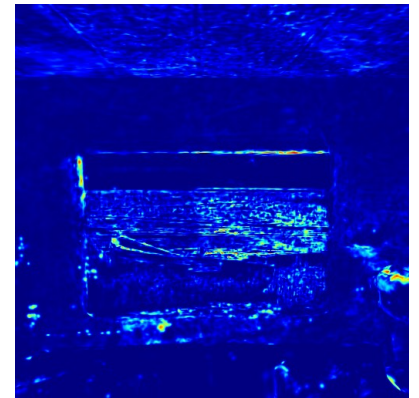
Number, distance and incidence angle

β_i **viewpoint diversity**

Dispersion of observing directions

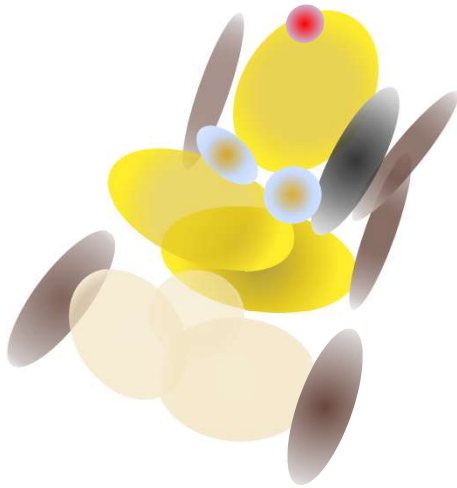


Low confidence



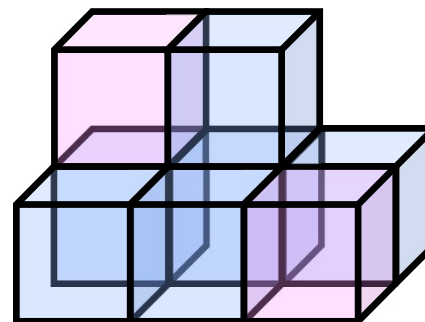
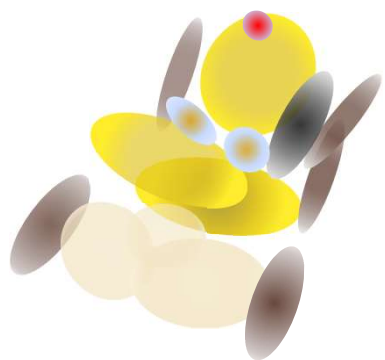
High confidence

Hybrid Map Representation



Gaussian splatting map

Hybrid Map Representation for View Planning



Gaussian splatting map

Coarse voxel map



Utility:

Confidence
rendering

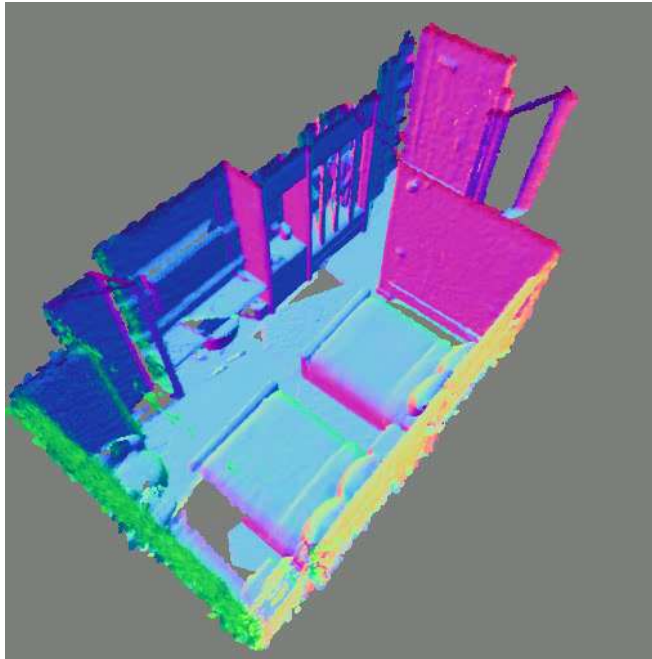


Unexplored
voxels

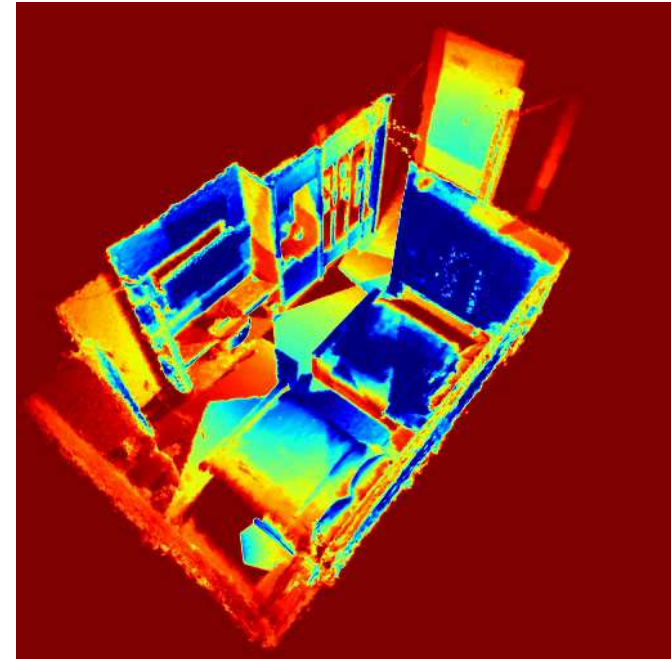
ActiveGS: Online Reconstruction



RGB and camera path

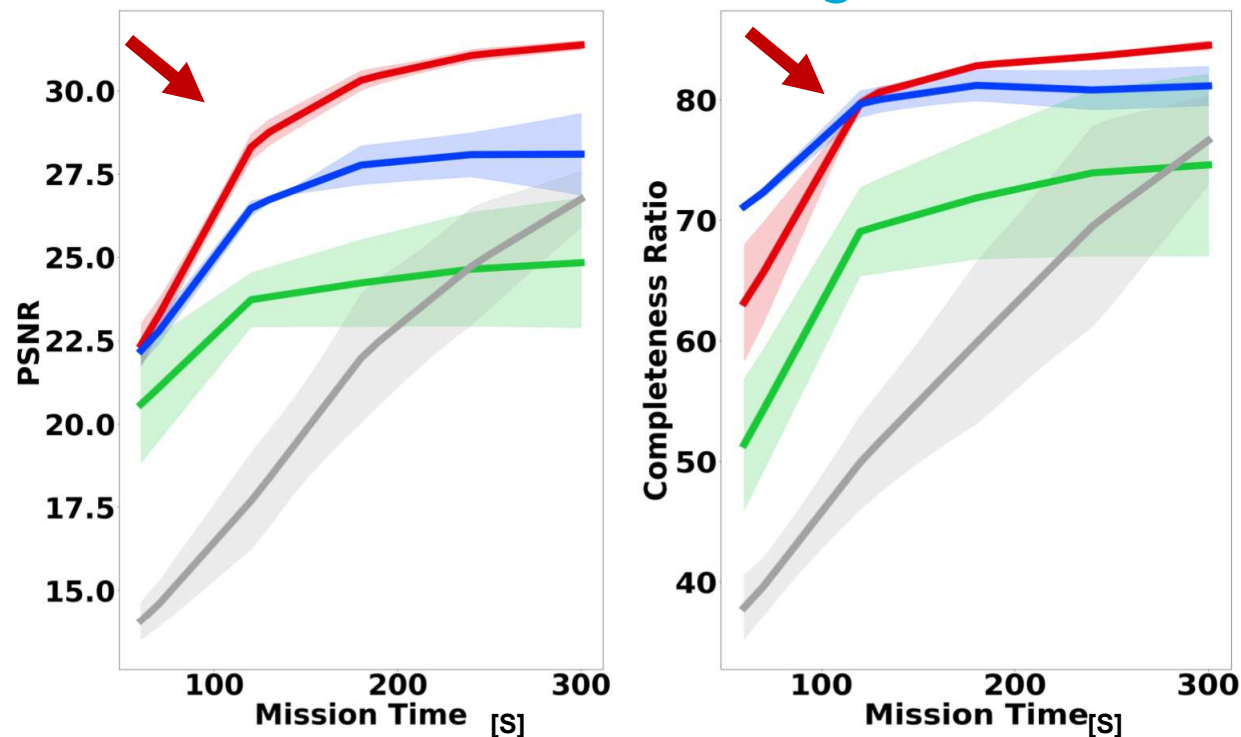


Surface normals



Confidence

ActiveGS: Reconstruction within a Time Budget



L. Jin, X. Zhong, Y. Pan, J. Behley, C. Stachniss and M. Popović. ActiveGS. In: *IEEE RA-L*, vol.10, no.5, pp.4866-4873, 2025.

[FBE] Yamauchi, Brian. "A frontier-based approach for autonomous exploration." 1997 CIRA.

[FisherRF] Jiang, Wen, et al. "Fisherrf: Active view selection and mapping with radiance fields using fisher information." 2024 ECCV.

[NARUTO] Feng, Ziyue, et al. "Naruto: Neural active reconstruction from uncertain target observations." 2024 CVPR.

ActiveGS: Reconstruction Results



ActiveGS: Ground Robot Experiment

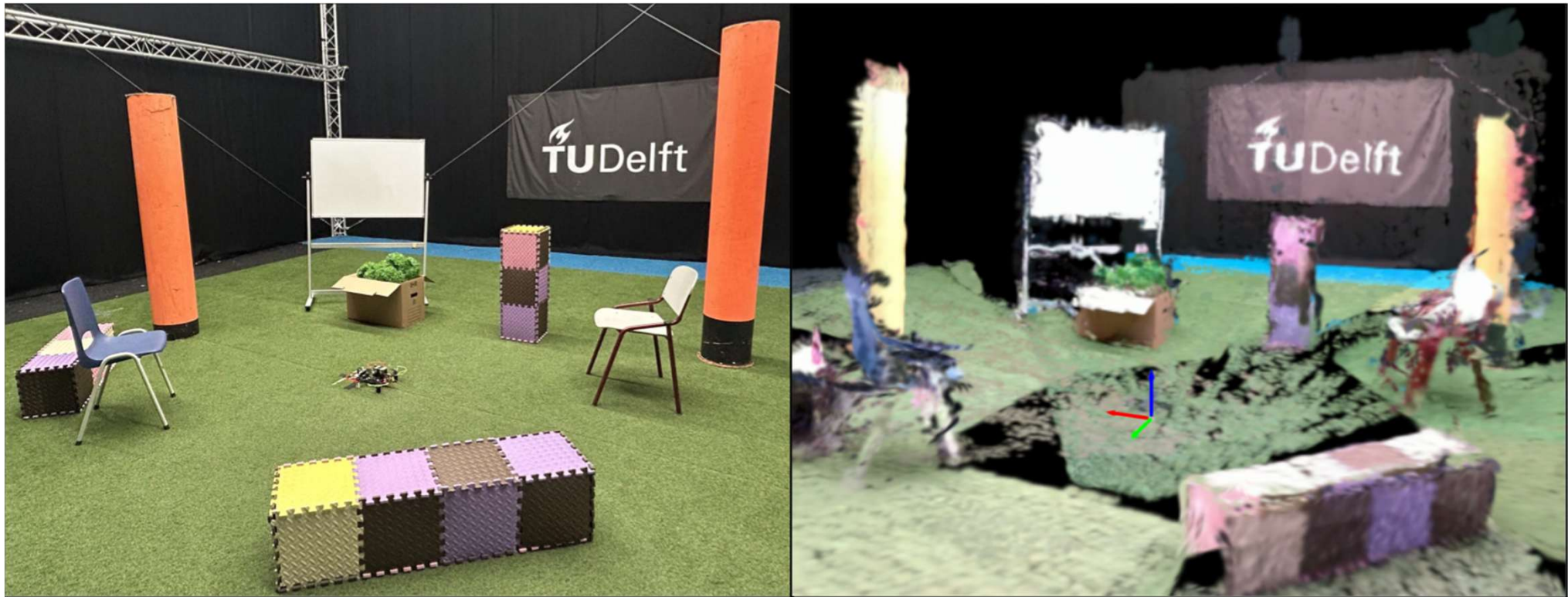


ActiveGS: Ground Robot Experiment



**Novel-view rendering from the
reconstructed kitchen map**

ActiveGS: UAV Experiment



Assumptions and Open Research Questions

NeU-NBV	Pre-trained renderer and uncertainty transfer
STAIR	Known poses, GT semantics, constrained candidate views
ActiveGS	Accurate poses, scene bounds, desktop computation

How should view planning account for pose and semantic uncertainty?

Conclusions

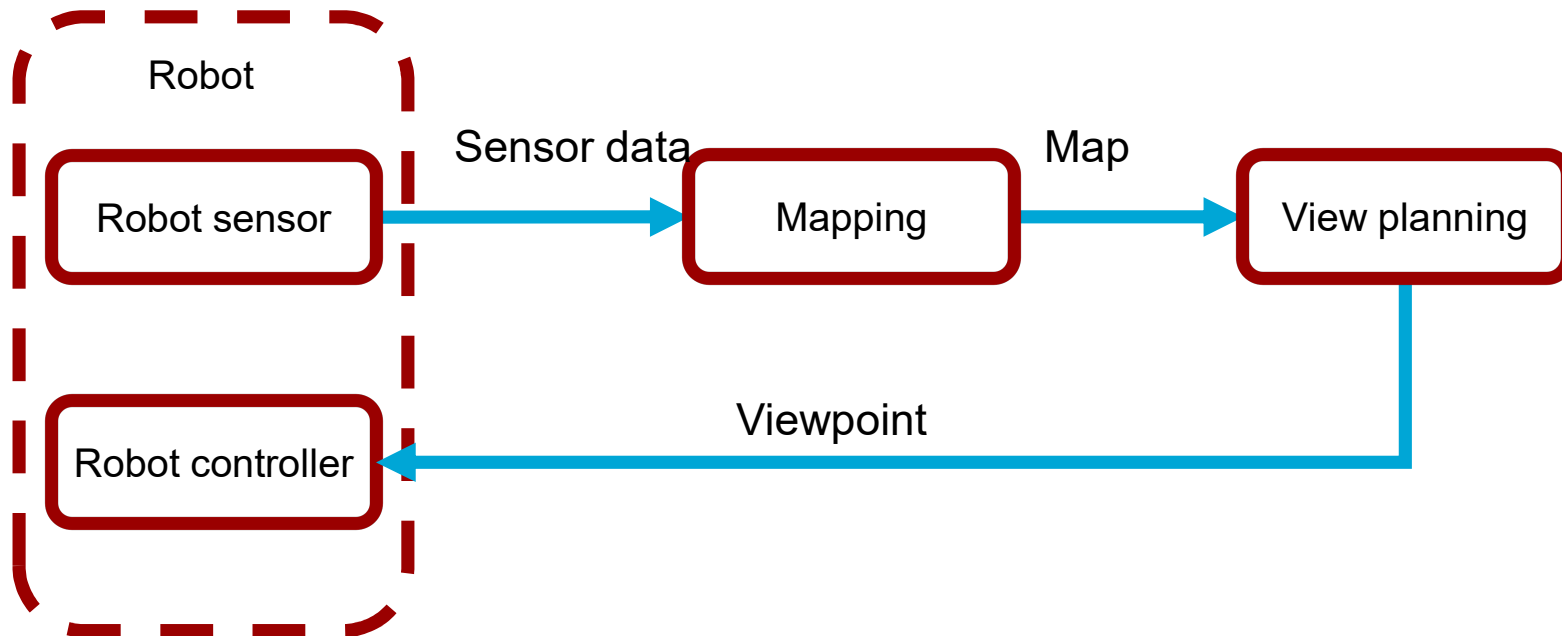
- **Rendering uncertainty** helps identify informative viewpoints before collecting new images
- **Semantic targeting** directs observations towards objects relevant to the task
- **Exploration and surface refinement** together improve map completeness and detail

Thank you!

NeU-NBV - github.com/dmar-bonn/neu-nbv
STAIR - github.com/dmar-bonn/stair
ActiveGS - github.com/dmar-bonn/active-gs

Backup: Mapping and View Planning

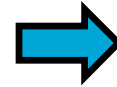
The current map guides the next observation



Backup: Reference Image Selection



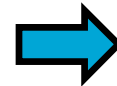
Reference image set 1



Rendered RGB & error



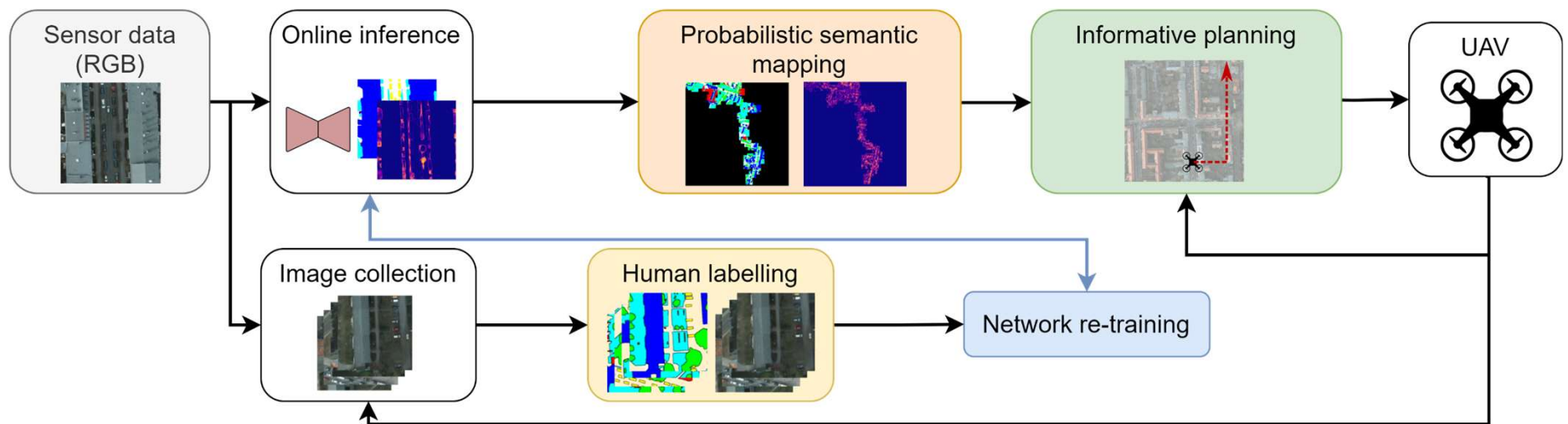
Reference image set 2



Rendered RGB & error

Backup: Connection to Active Learning

Robot trajectories can also improve the perception model



Backup: NeU-NBV Uncertainty Model

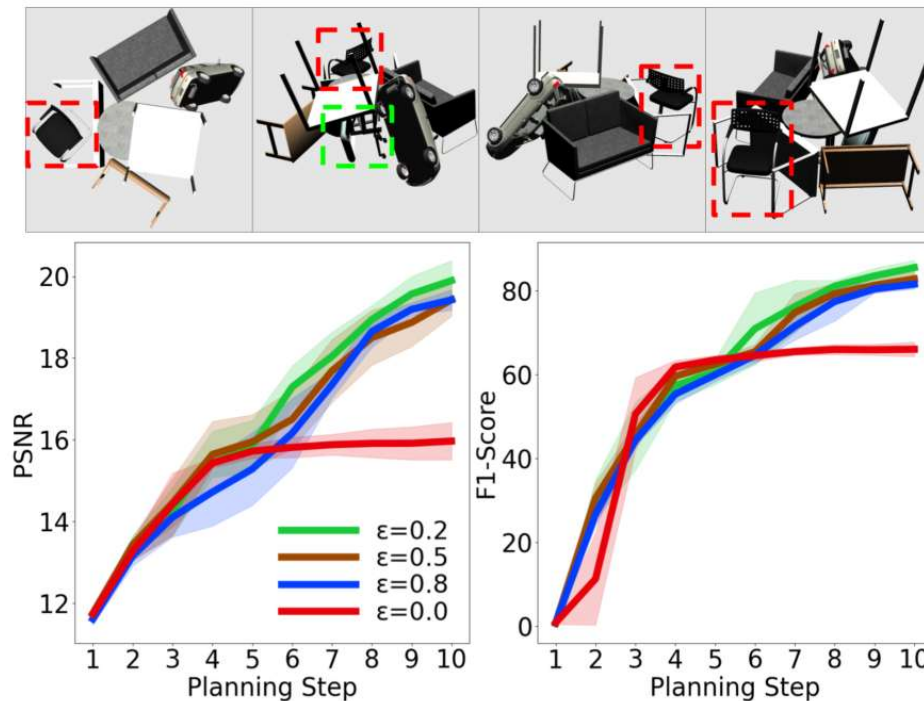
$$\mathcal{L} = \sum_{i=1}^3 \overbrace{\frac{(\text{logit}(y_i) - \mu_i)^2}{2\sigma_i^2}}^{\text{Reconstruction}} + \overbrace{\frac{1}{2} \log(\sigma_i^2)}^{\text{Regularization}}$$

y_i - Ground truth

μ_i - Predicted mean

σ_i - Predicted std. dev.

Backup: STAIR Needs Exploration



**Target-only
planning can
miss occluded
targets**

A small exploration
term
allows further discovery

Backup: ActiveGS Experimental Scope

Known camera poses and a scene bounding box

Published UAV experiment

RealSense D455, OptiTrack, desktop computation

Desktop timing in the paper

Mapping ≈ 1 s, planning ≈ 0.5 s per step
Intel Core i9-10940X + NVIDIA RTX A5000

References

NeU-NBV

Jin, Chen, Rückin and Popović. IROS 2023.

arxiv.org/abs/2303.01284

STAIR

Jin, Kuang, Pan, Stachniss and Popović. IROS 2024.

arxiv.org/abs/2403.11233

ActiveGS

Jin, Zhong, Pan, Behley, Stachniss and Popović. RA-L 2025.

arxiv.org/abs/2412.17769

Informative planning for active learning

Rückin, Magistri, Stachniss and Popović. T-RO 2023.

39(6), 4279–4296

Backup: ActiveGS Results Across Eight Scenes

