

# Robust Volumetric Mapping in Changing Environments

AML / Microsoft SJRC

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# Robust Volumetric Mapping in Changing Environments

## Goal:

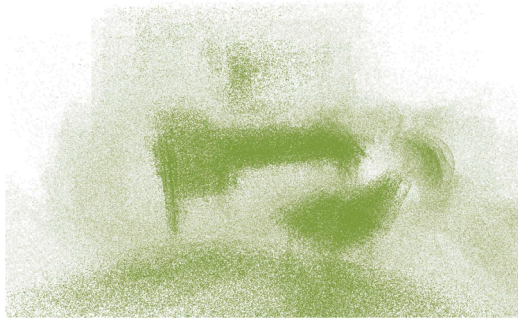
Enable robots to act intelligently in environments that are shared with other agents over longer periods of time.



# Robust Volumetric Mapping in Changing Environments

## Challenges

### Pose Errors



Accumulated noisy point clouds



TSDF reconstruction

### Long-term Scene Changes



Monolithic Map

# Robust Volumetric Mapping in Changing Environments

## How can the map representation help?

### Pose Errors



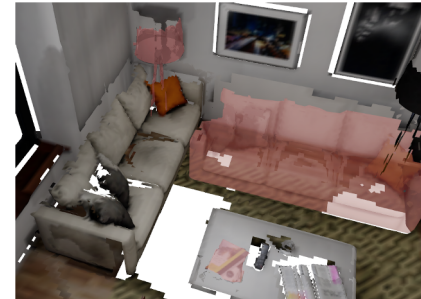
TSDF reconstruction



### Long-term Scene Changes



Monolithic Map

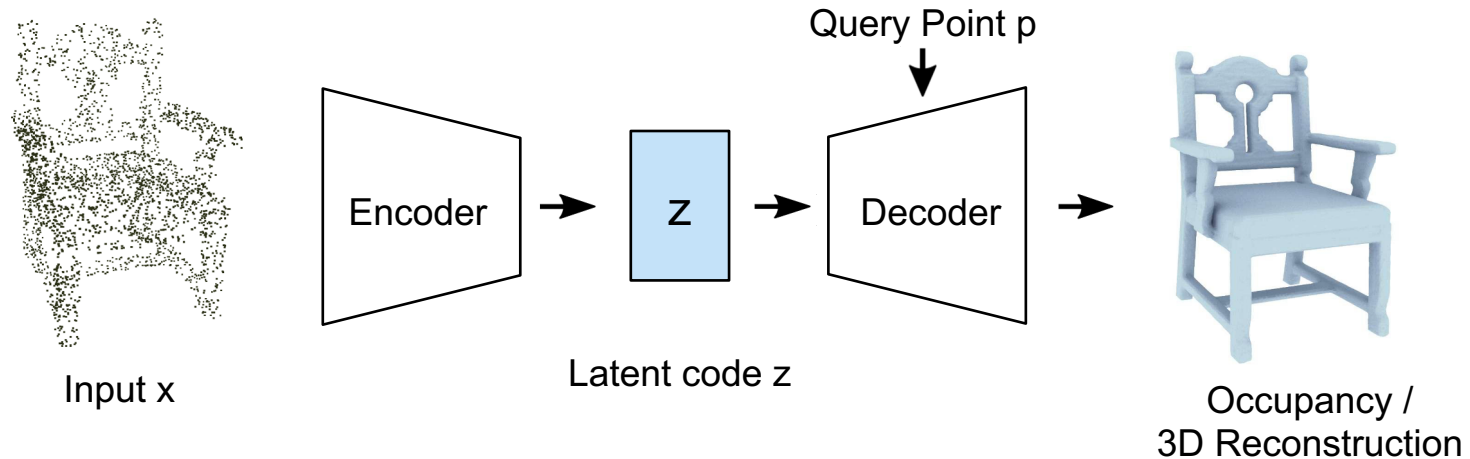


[S. Lionar\*, L. Schmid\*, C. Cadena, R. Siegwart, A. Cramariuc, "NeuralBlox: Real-Time Neural Representation Fusion for Robust Volumetric Mapping." 3DV 2021]

[L. Schmid, J. Delmerico, J. Schönberger, J. Nieto, M. Pollefeys, R. Siegwart, C. Cadena, "Panoptic Multi-TSDFs: a Flexible Representation for Online Multi-resolution Volumetric Mapping and Long-term Dynamic Scene Consistency." ICRA 2022]

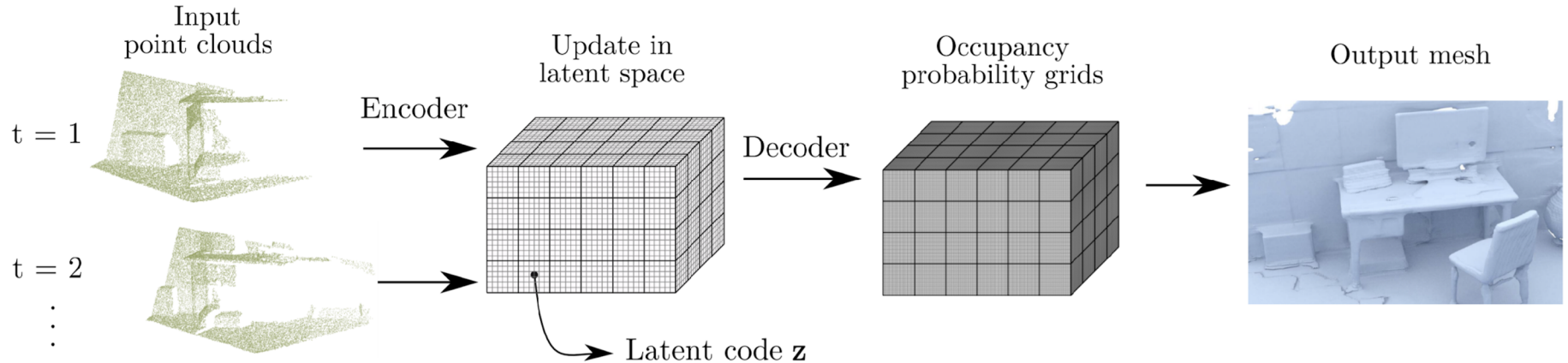
# NeuralBlox: Real-Time Neural Representation Fusion

- Recent progress in neural shape representation.
- Can we incrementally build a neural implicit map?
- Can we leverage geometric context for more robust fusion?



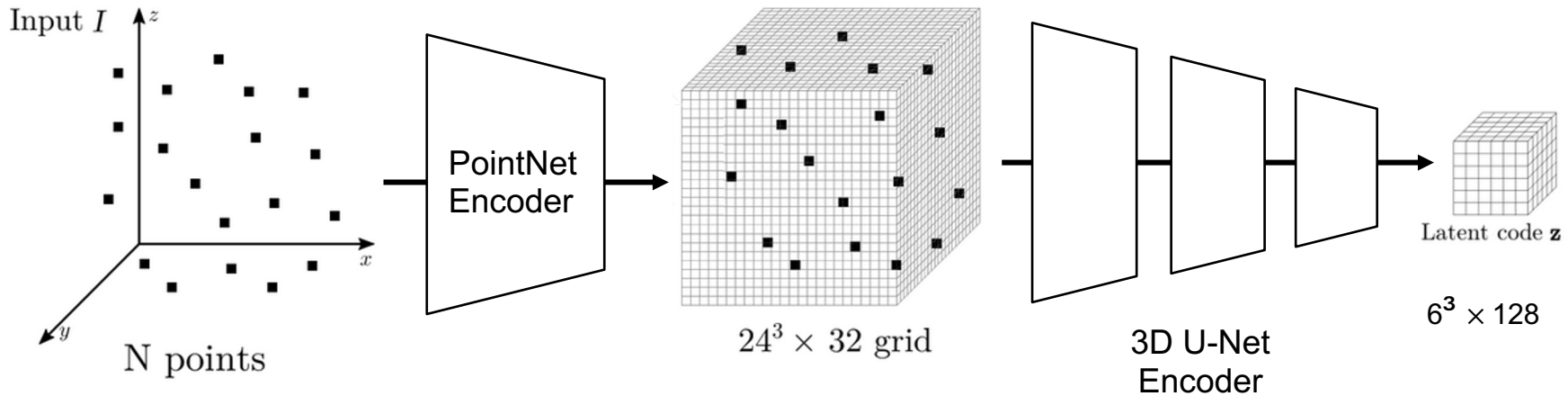
# NeuralBlox: Real-Time Neural Representation Fusion

## Pipeline Overview



# NeuralBlox: Real-Time Neural Representation Fusion

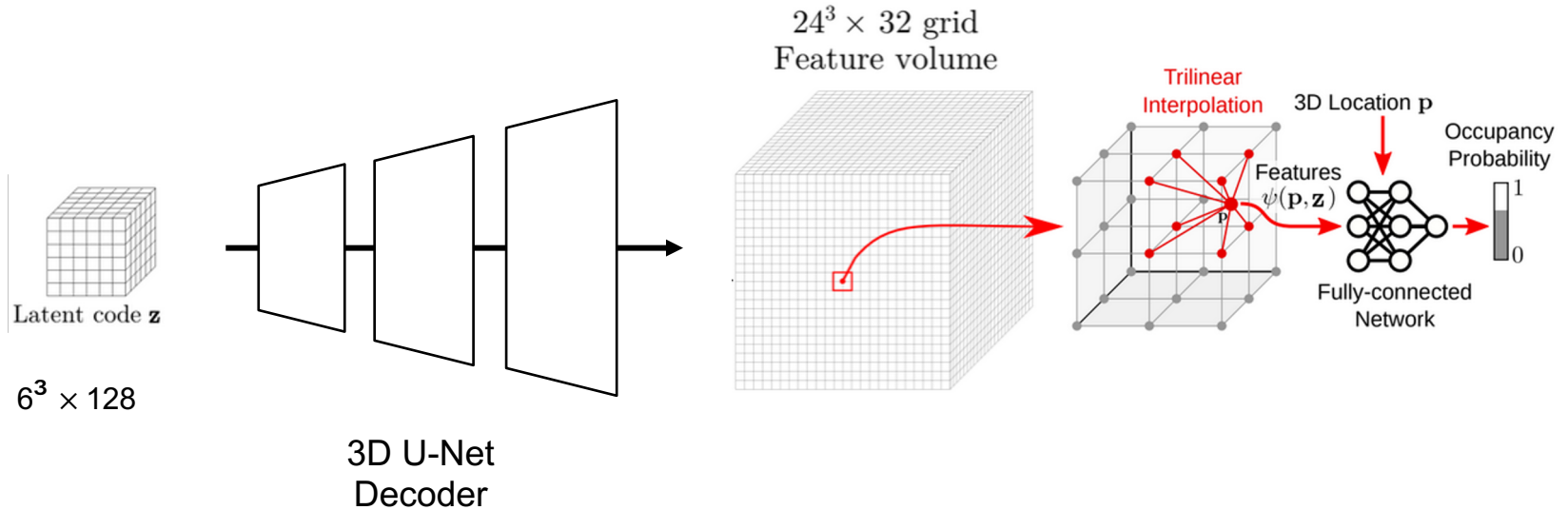
- Decouple problem, train shape representation independently on ShapeNet.



[S. Peng et al. "Convolutional Occupancy Networks." ECCV 2020]

# NeuralBlox: Real-Time Neural Representation Fusion

- Decouple problem, train shape representation independently on ShapeNet.

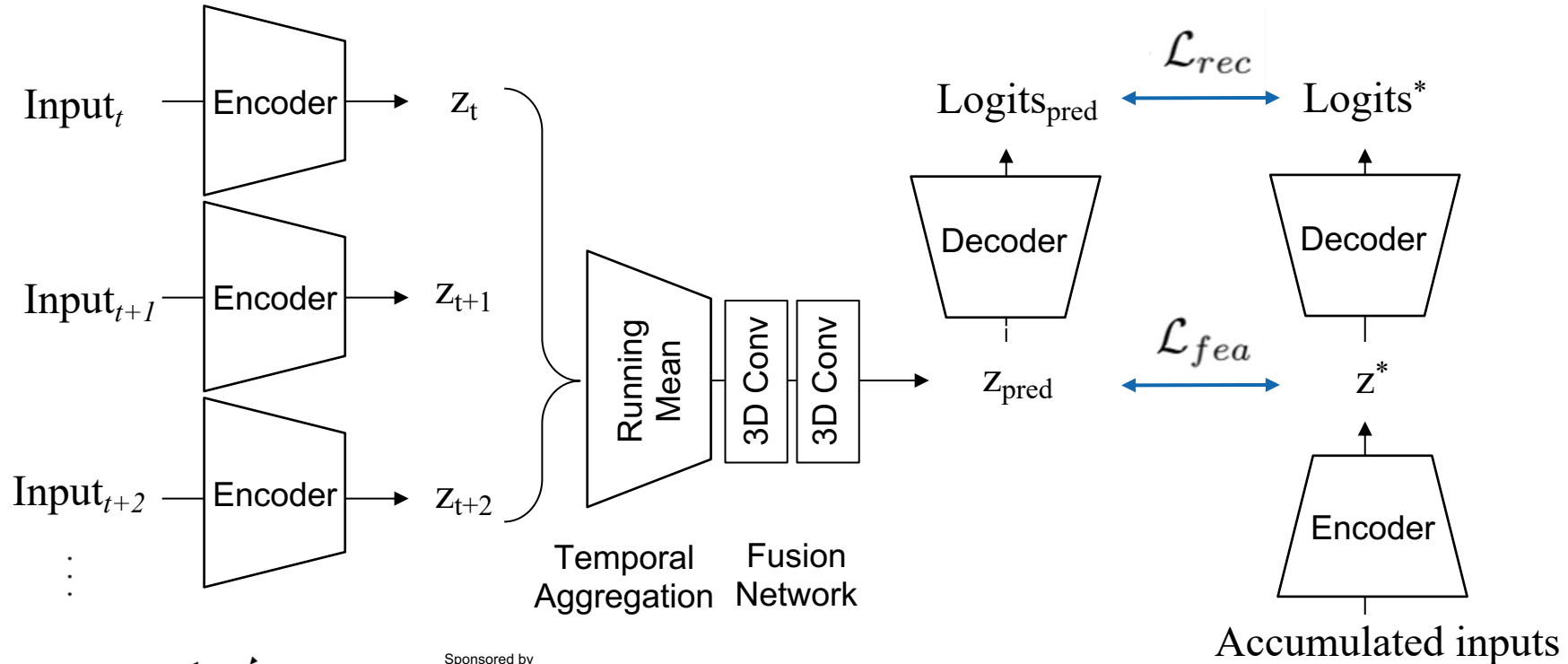


[S. Peng et al. "Convolutional Occupancy Networks." ECCV 2020]



# NeuralBlox: Real-Time Neural Representation Fusion

- Train incremental fusion of pre-trained neural implicit representations.

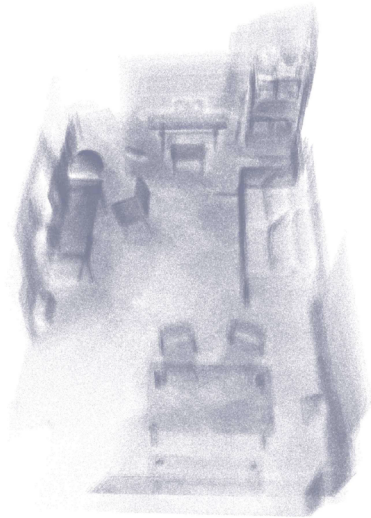


# NeuralBlox: Real-Time Neural Representation Fusion

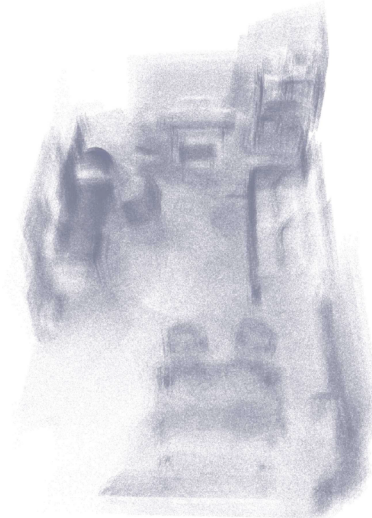
- Test on real scenes of Redwood dataset.
- Sensor pose uncertainty.



$\sigma_s = 0.025$



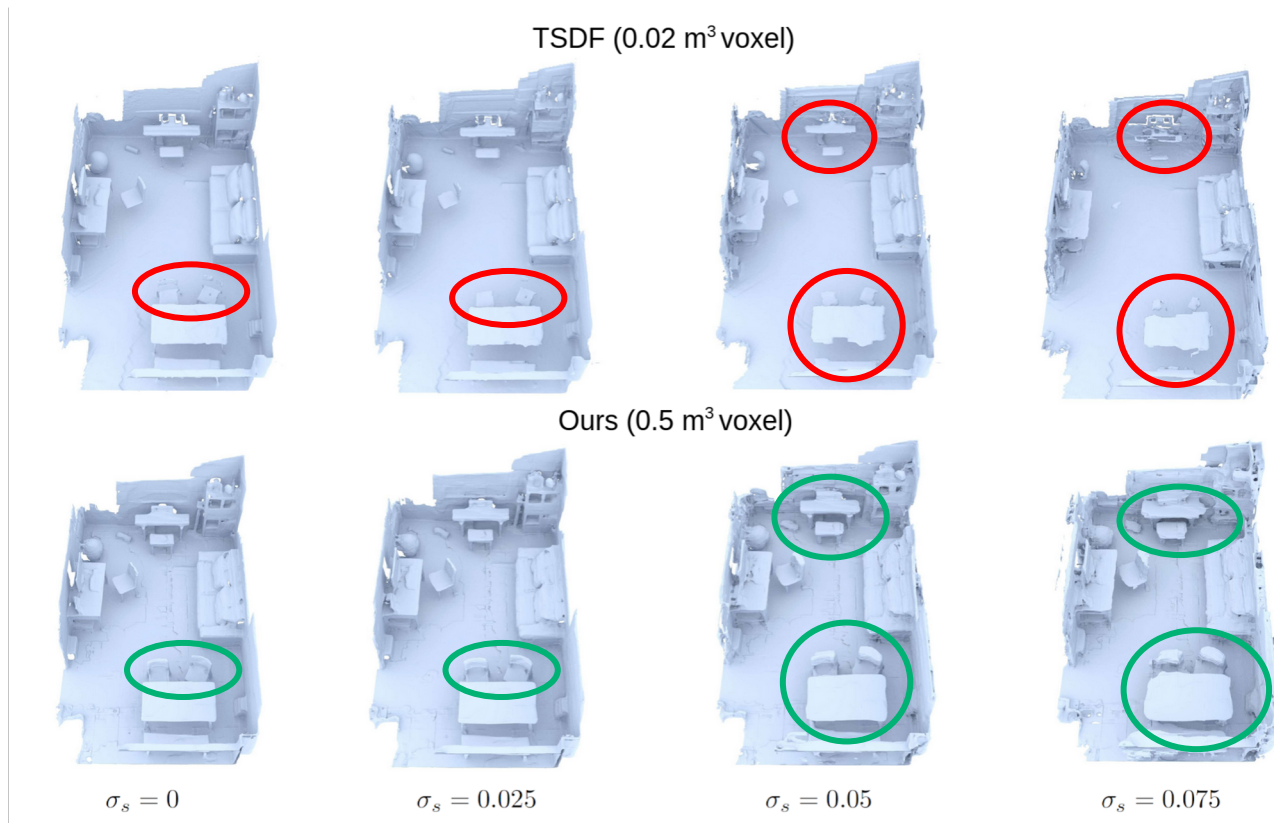
$\sigma_s = 0.05$



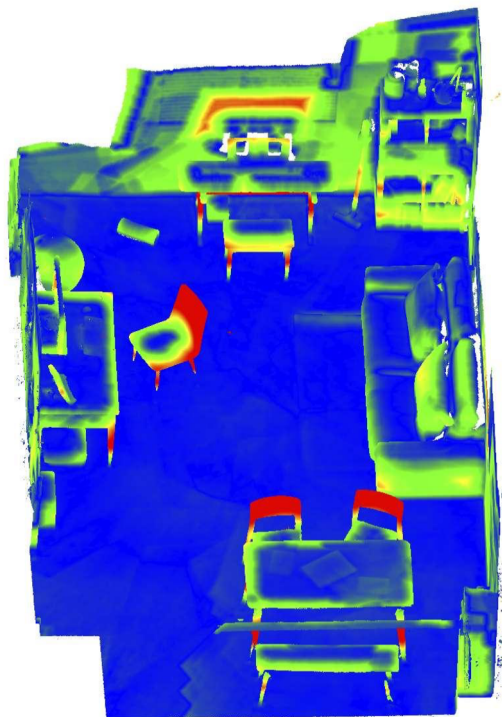
$\sigma_s = 0.075$



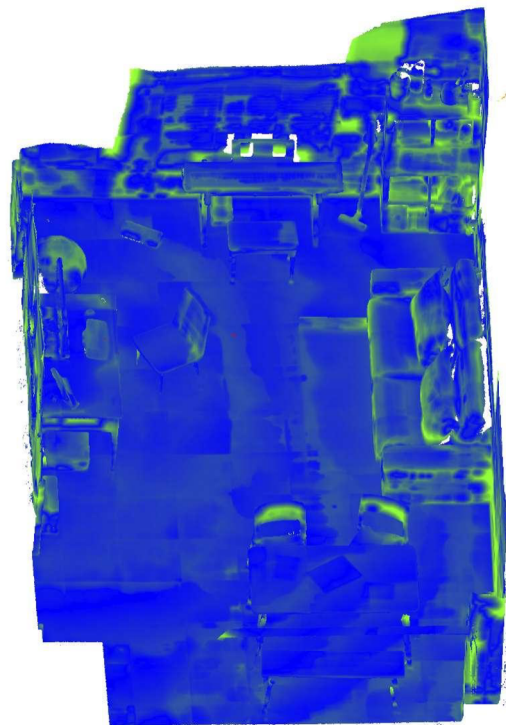
# NeuralBlox: Real-Time Neural Representation Fusion



# NeuralBlox: Real-Time Neural Representation Fusion



TSDF (0.02 m voxel)



Ours (0.5 m voxel)

25+

Reconstruction Error [cm]

0

# NeuralBlox: Real-Time Neural Representation Fusion

$\sigma_s$ (m)	<i>Left: TSDF</i> (0.02 m <sup>3</sup> ) [3]. <i>Right: Ours</i> (0.5 m <sup>3</sup> ).							
	<i>Accuracy</i>		<i>Completeness</i>		<i>Recall</i>		<i>Recall*</i>	
0	<b>0.0175</b>	0.0225	0.0137	<b>0.0135</b>	0.988	<b>0.990</b>	0.984	<b>0.986</b>
0.025	<b>0.0213</b>	0.0253	0.0202	<b>0.0155</b>	0.926	<b>0.990</b>	0.888	<b>0.986</b>
0.050	0.0377	<b>0.0350</b>	0.0352	<b>0.0202</b>	0.756	<b>0.952</b>	0.625	<b>0.928</b>
0.075	0.0535	<b>0.0526</b>	0.0486	<b>0.0241</b>	0.635	<b>0.886</b>	0.438	<b>0.827</b>

\*the ground is excluded

# NeuralBlox: Real-Time Neural Representation Fusion

- Robotic volumetric mapping based on implicit neural representations.
- Incremental fusion of sensor data directly in latent space.
- Can robustly capture surfaces in the presence of pose errors, sensing uncertainty, and sparse sensor inputs.
- Runs at interactive rates on a CPU only!

<b>Encoding</b>	<b>Decoding</b>	
4.7 FPS	15.6 voxel/s	2.1 FPS <sup>3</sup>

# Panoptic Multi-TSDFs: Online multi-resolution volumetric mapping with long-term dynamic scene consistency

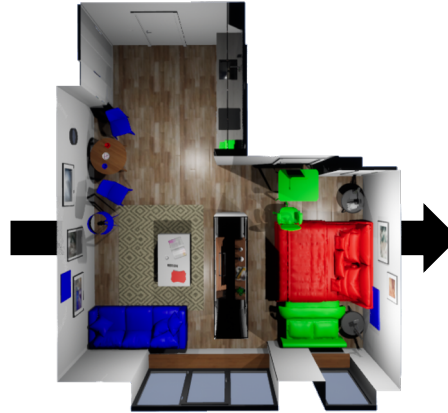
- World typically does not change at random, but in a semantically consistent way.
- Can we leverage high-level semantic information to build temporally consistent maps online?



Day 1



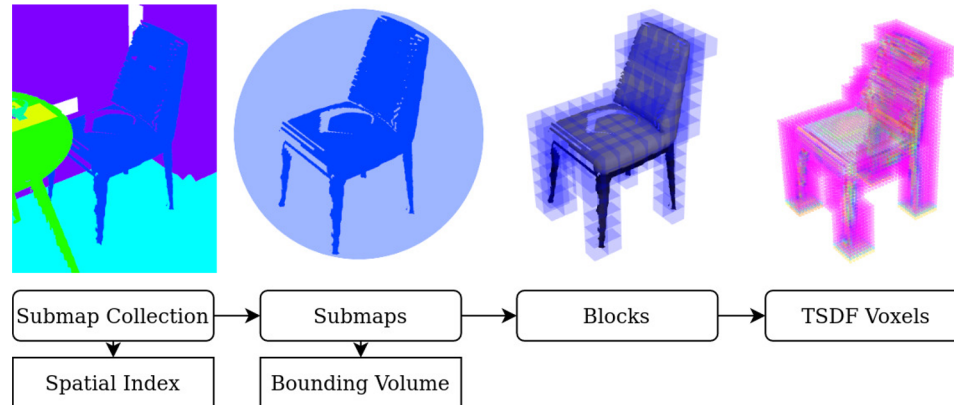
Day 2



Single TSDF map

# Panoptic Multi-TSDFs: Online multi-resolution volumetric mapping with long-term dynamic scene consistency

- Hierarchical map representation based on semantically and temporally consistent submaps.
- Only integrate submaps that are successfully tracked over time.
- Reason about change or persistence on the set of submaps.



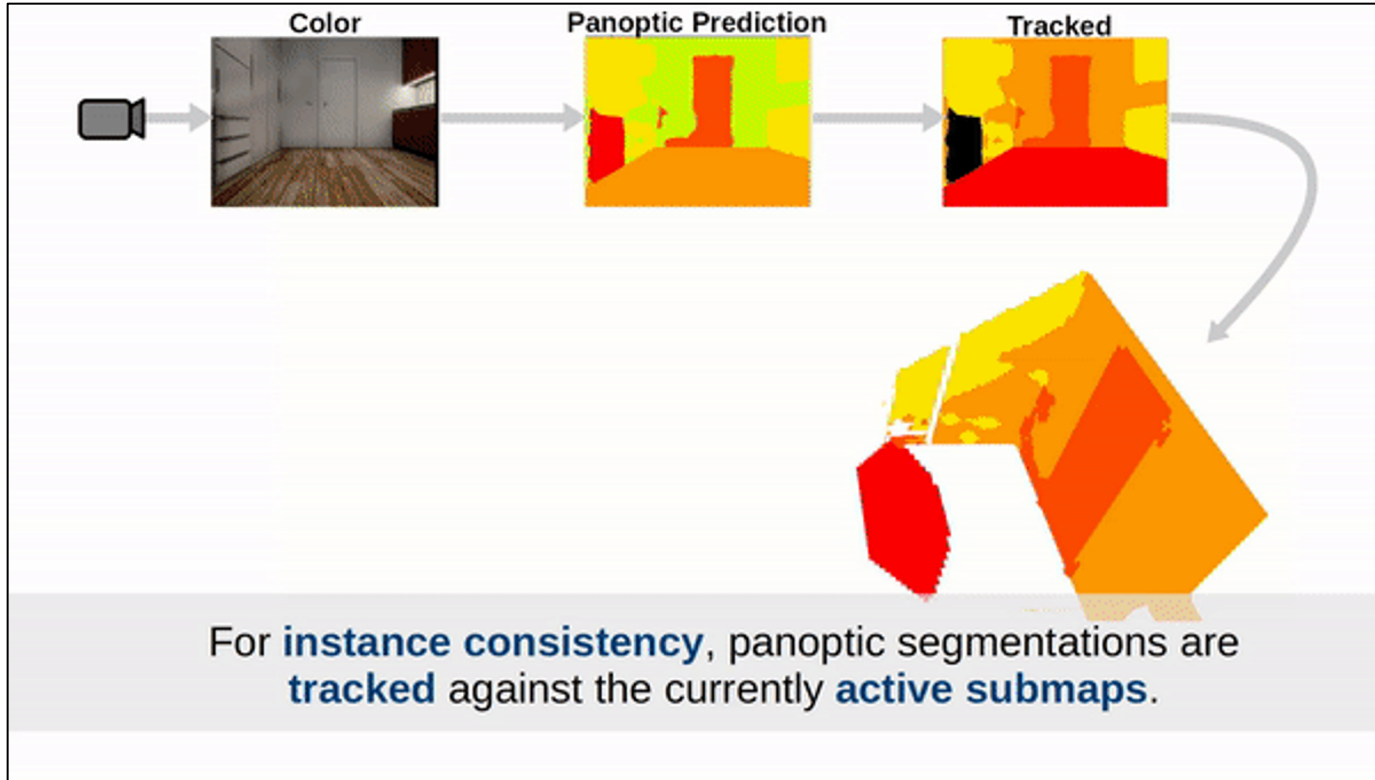


# Panoptic Multi-TSDFs: Online multi-resolution volumetric mapping with long-term dynamic scene consistency

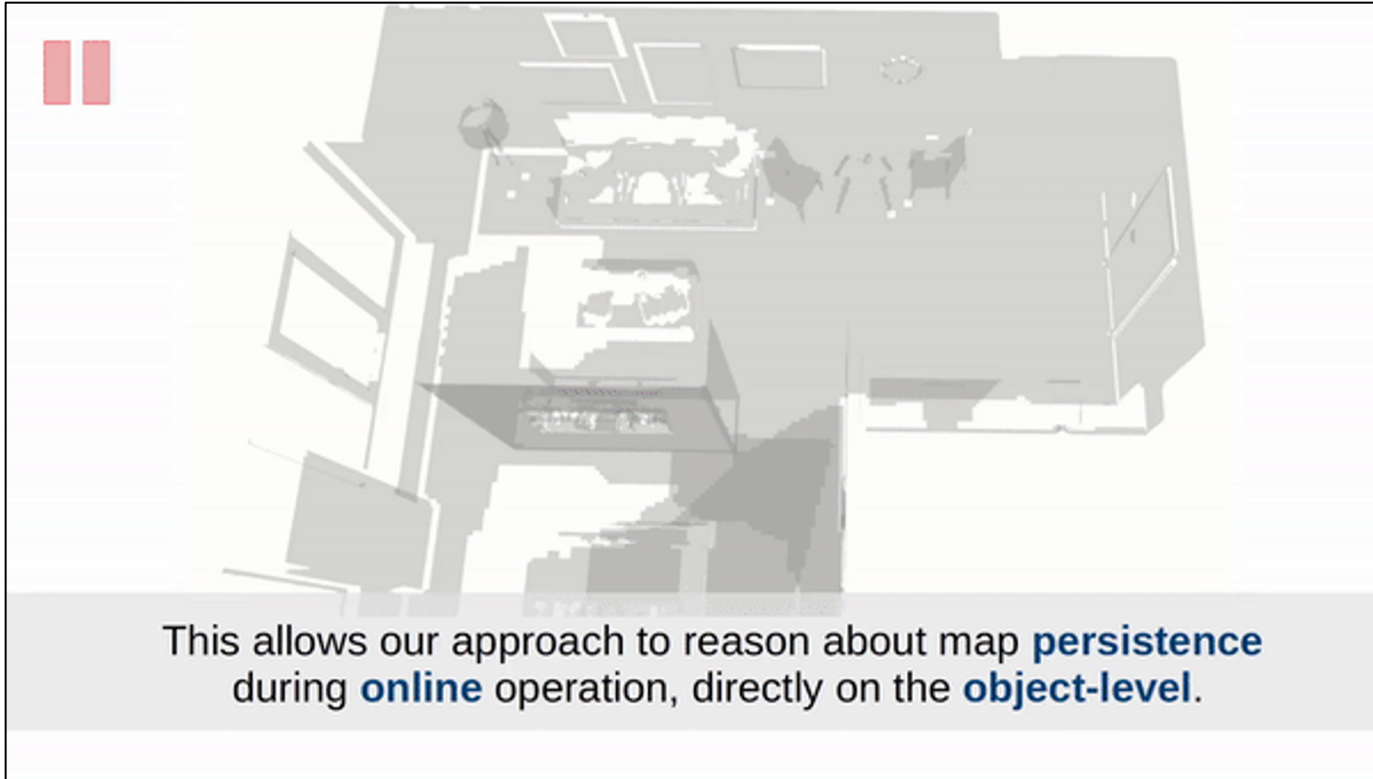


To this end, we propose **Panoptic Multi-TSDFs** as a flexible map representation for **online volumetric** mapping in **changing** scenes.

# Panoptic Multi-TSDFs: Online multi-resolution volumetric mapping with long-term dynamic scene consistency

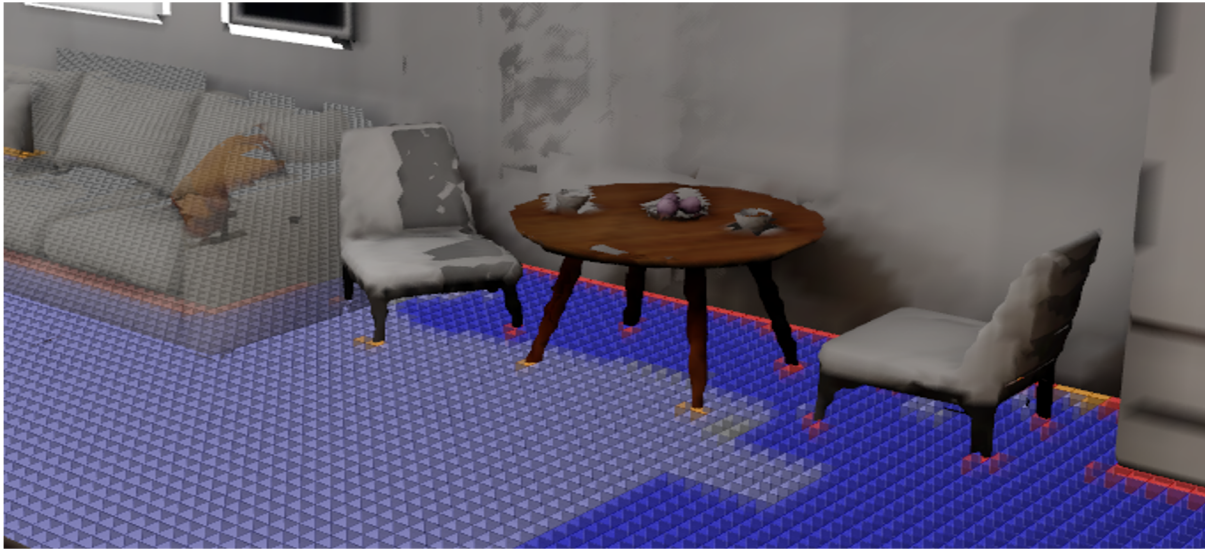








# Panoptic Multi-TSDFs: Online multi-resolution volumetric mapping with long-term dynamic scene consistency



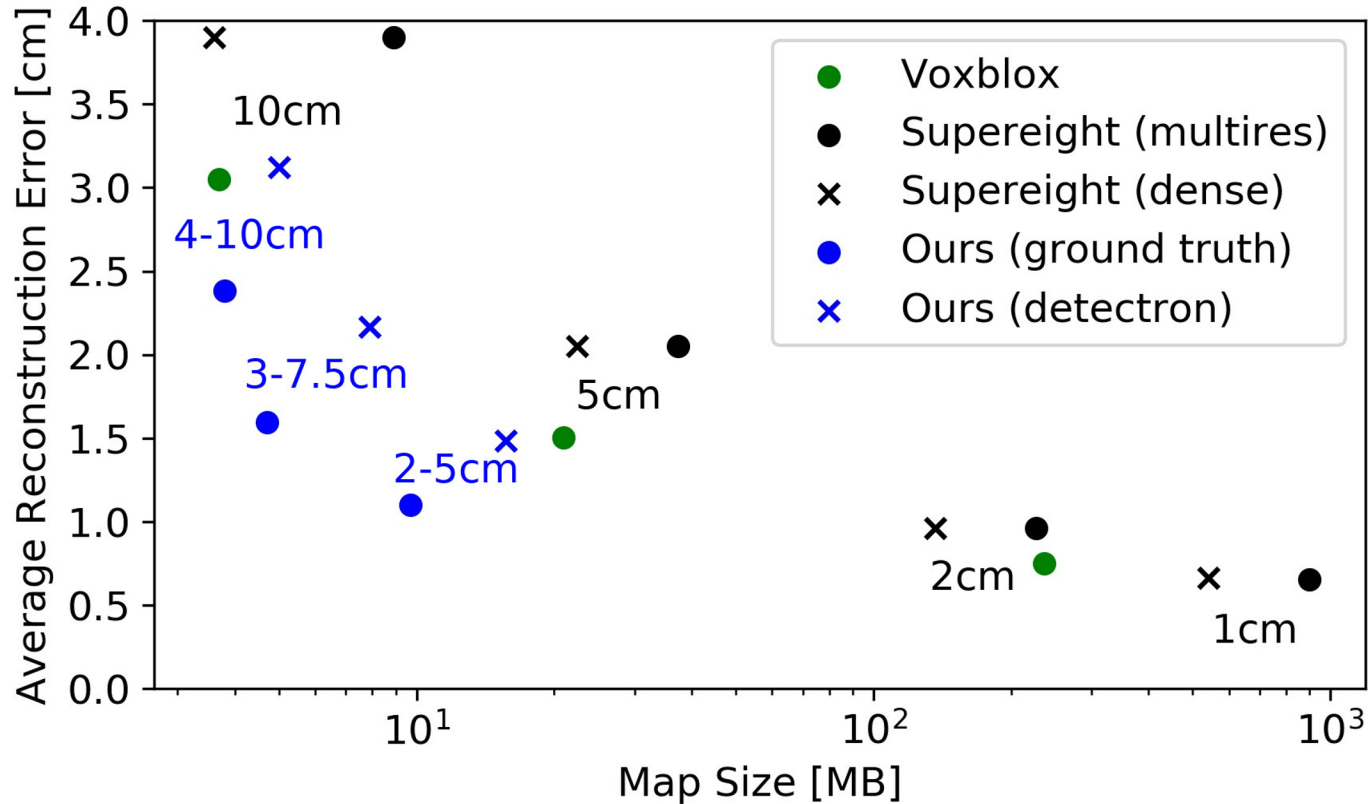
# Panoptic Multi-TSDFs: Online multi-resolution volumetric mapping with long-term dynamic scene consistency

- Spatio-temporal map queries.

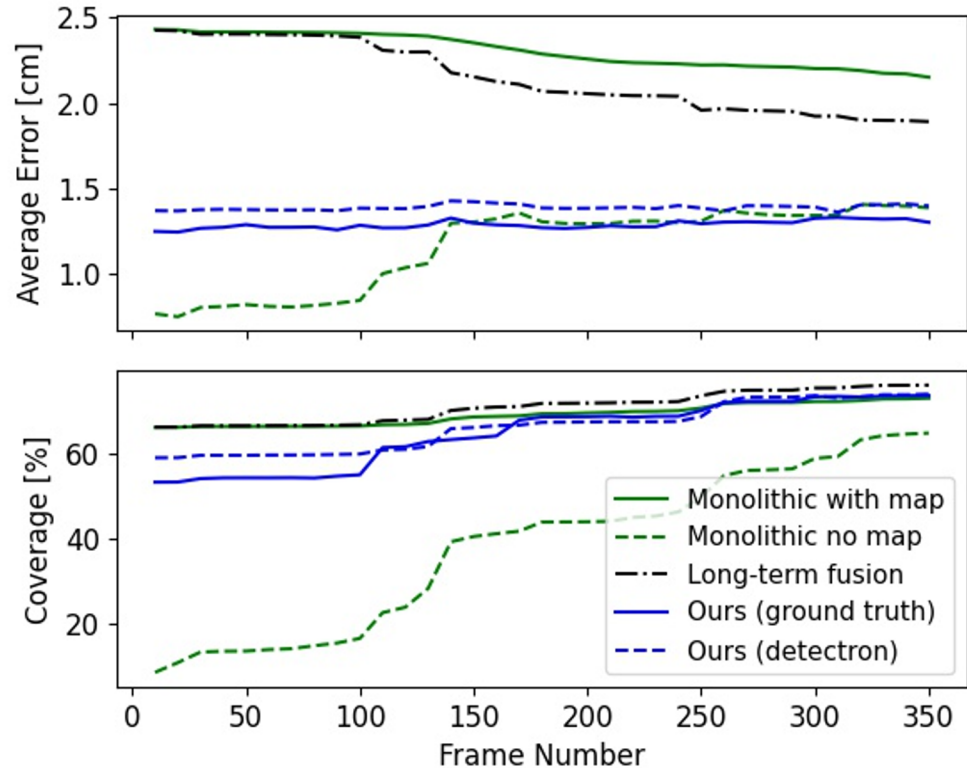


-  *Observed Free*
-  *Observed Occupied*
-  *Expected Free*
-  *Expected Occupied*
-  *Occupied due to semantic consistency*
-  *Unknown*

# Panoptic Multi-TSDFs: Online multi-resolution volumetric mapping with long-term dynamic scene consistency



# Panoptic Multi-TSDFs: Online multi-resolution volumetric mapping with long-term dynamic scene consistency



# Panoptic Multi-TSDFs: Online multi-resolution volumetric mapping with long-term dynamic scene consistency

Setting	Resolution	Tracking	Integration	Management	FPS*
Flat, ground truth	2-5 cm	70.2 ± 8.4	104.3 ± 14.4	199.1 ± 54.1	5.1
	4-10 cm	63.9 ± 4.4	89.2 ± 7.8	182.1 ± 44.3	5.8
Flat, detectron	2-5 cm	57.8 ± 5.5	91.1 ± 11.1	192.1 ± 54.3	5.9
	4-10 cm	54.7 ± 5.1	80.3 ± 7.4	183.5 ± 49.2	6.5
RIO, detectron	2-5 cm	21.8 ± 4.6	21.8 ± 5.9	33.2 ± 23.8	21.3
	4-10 cm	16.8 ± 3.4	13.3 ± 3.5	9.5 ± 4.5	32.2

\* Final frame rate is computed performing change detection every 10 frames.

# Panoptic Multi-TSDFs: Online multi-resolution volumetric mapping with long-term dynamic scene consistency

- Hierarchical map representation based on semantically and temporally consistent submaps.
- Reason about change or persistence on the set of submaps that together constitute a full volumetric map.
- Can be incrementally built, maintained, and queried on compute constrained robots.

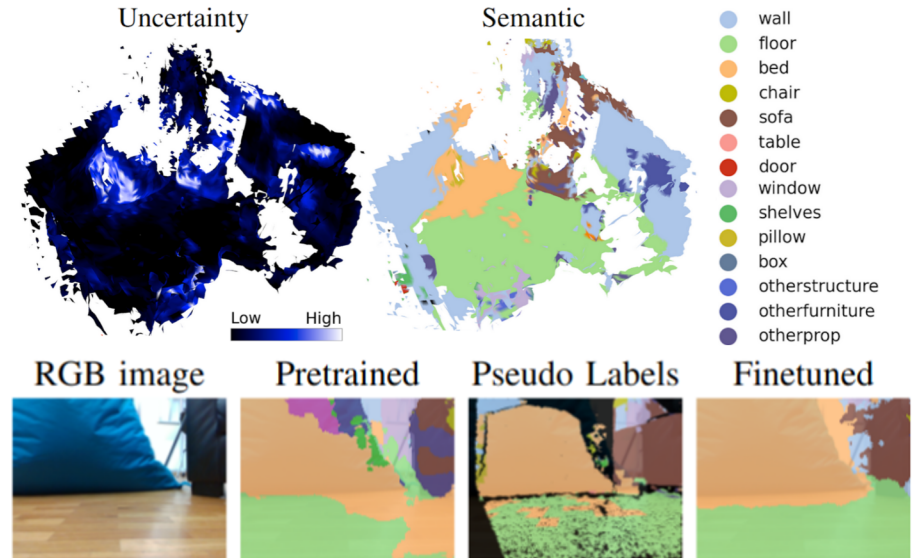


# Conclusions

- Learning-based methods show high potential for surface representation and scene understanding.
- Common map representations not yet there to effectively capture and reason about complex, changing, shared environments.
- Combine low-level geometry and high-level abstractions to reason at the adequate scale.

# Outlook

- Spatio-temporal volumetric mapping.
- Active Perception to improve scene understanding and map building.



[L. Schmid, C. Ni, Y. Zhong, R. Siegwart, and O. Andersson, "Fast and Compute-efficient Sampling-based Local Exploration Planning via Distribution Learning." ArXiv 2022]

[R. Zurbrugg, H. Blum, C. Cadena, R. Siegwart, and L. Schmid, "Embodied Active Domain Adaptation for Semantic Segmentation via Informative Path Planning." ArXiv 2022]

## NeuralBlox



# Questions?



<https://github.com/ethz-asl/neuralblox>

## Panoptic Mapping



[https://github.com/ethz-asl/panoptic\\_mapping](https://github.com/ethz-asl/panoptic_mapping)