# Spatially Invariant Unsupervised 3D Object-Centric Learning and Scene Decomposition

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#### Overview

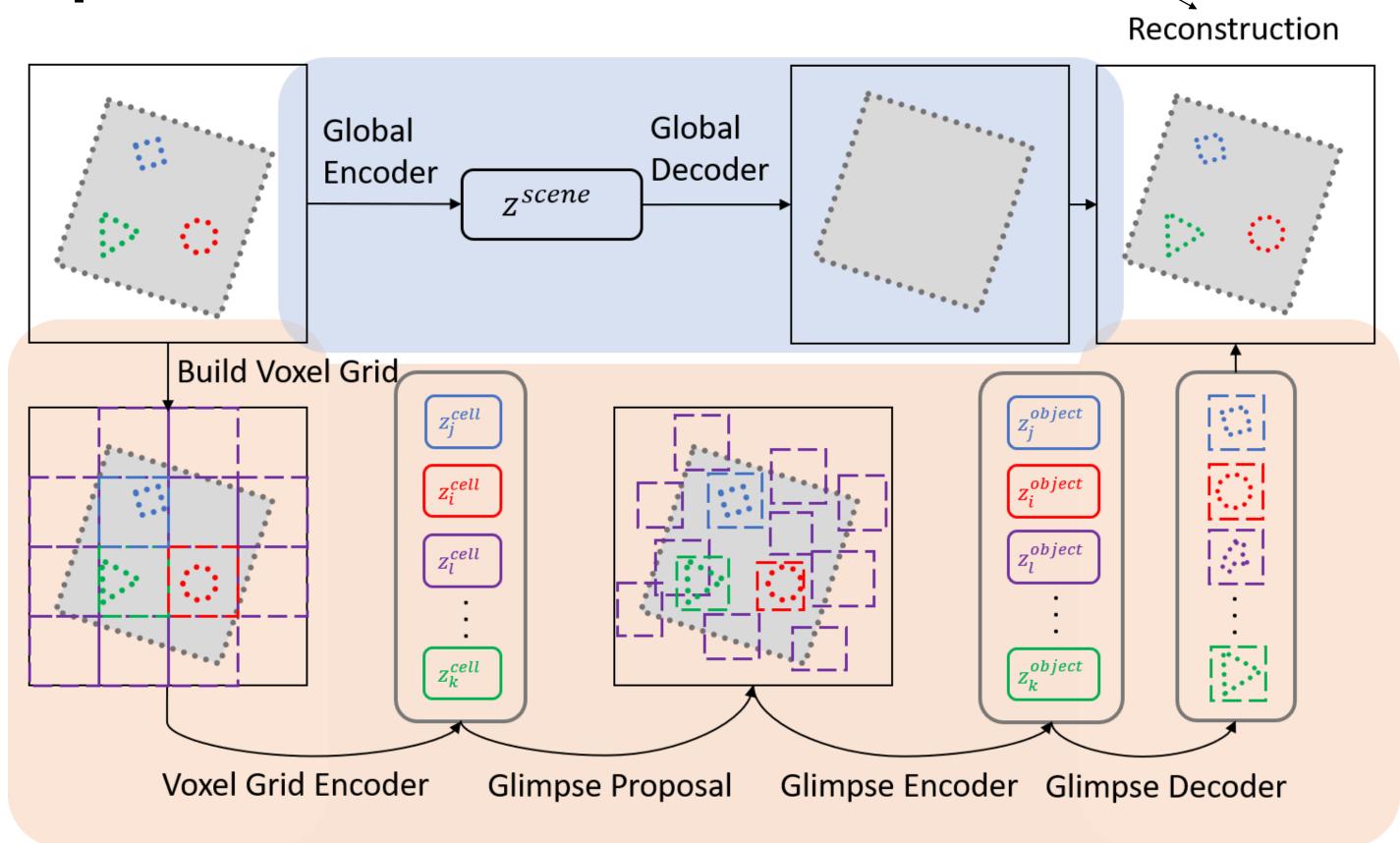
We tackle the unsupervised 3D point cloud object-centric problem combining variational inference and spatial invariant attention mechanism. We demonstrate that our model learns to detect object on both simulated and real-world dataset. t-SNE visualization shows our model learns meaningful object representations.

### Motivation

Unsupervised object-centric learning is an act of defining objectness. We define an object to be a collection of highly correlated matters that can be exploited during a compression-decompression process. For a scene point cloud (colorless), we exploit variational autoencoder to trade-off between compression rate and reconstruction quality.

Compute Reconstruction Loss

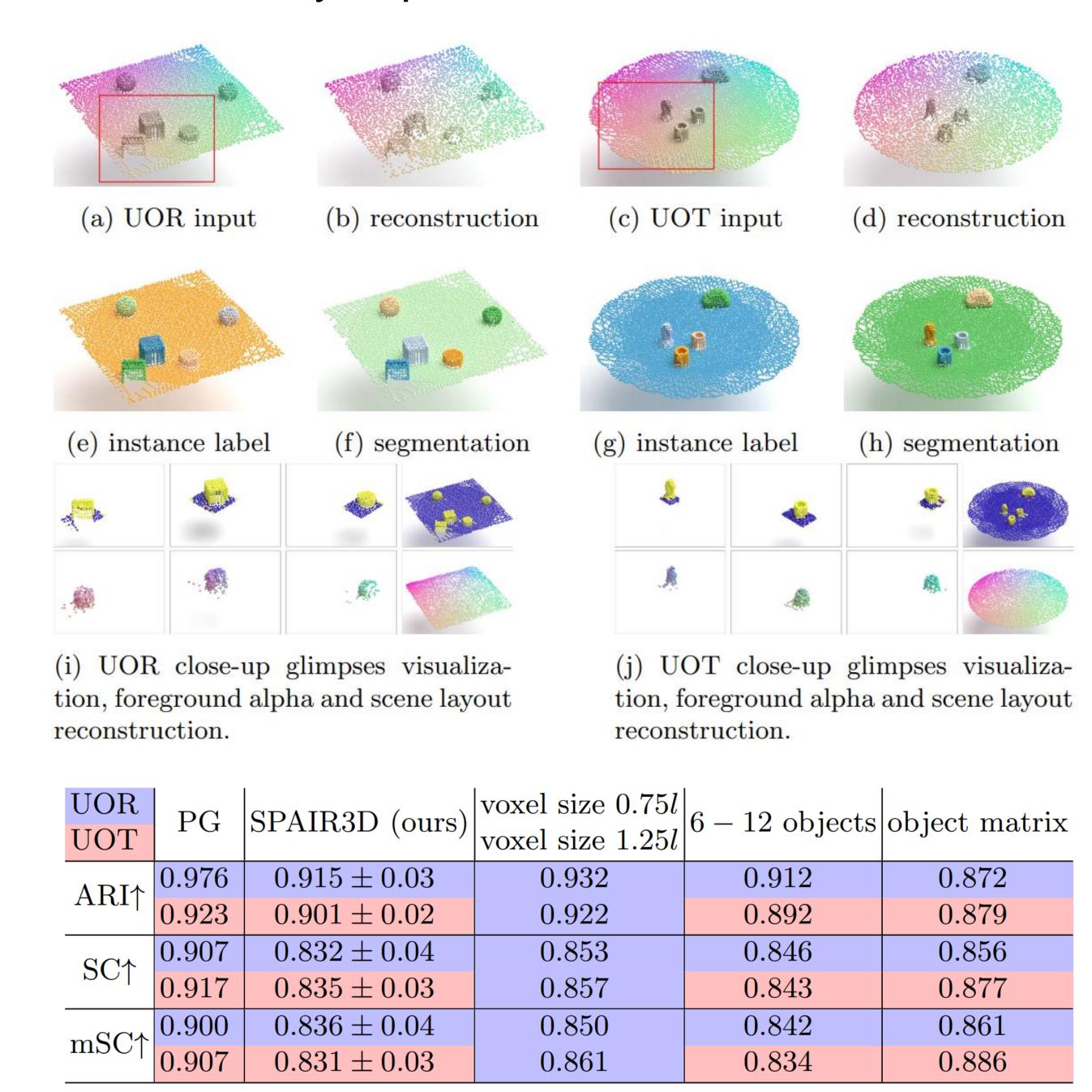




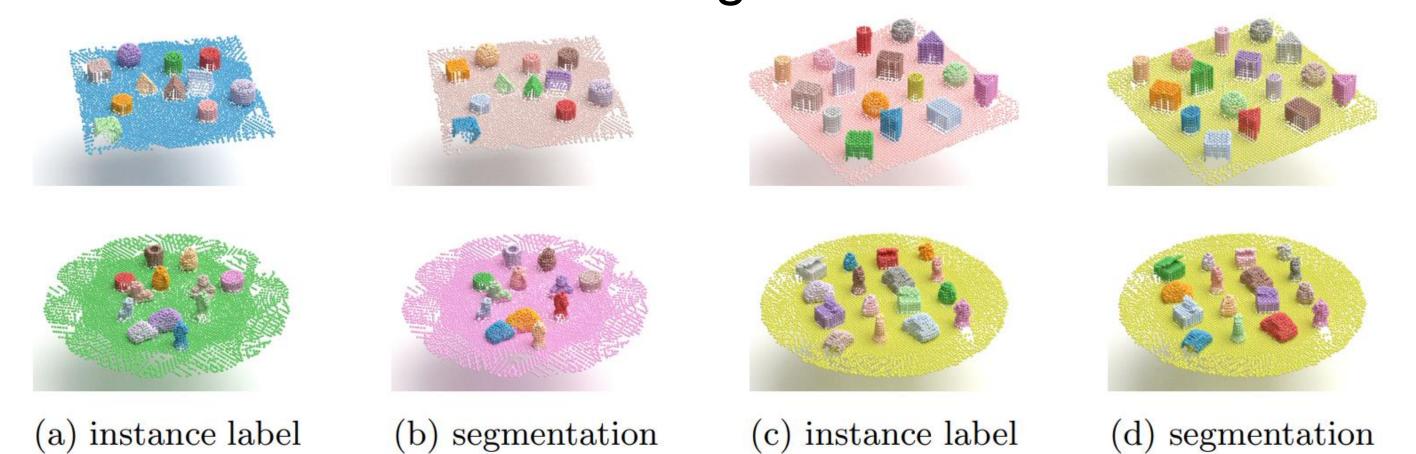
We evenly divide a 3D point cloud scene with a voxel grid and infer an object candidate from each grid cell. Each object candidate is

defined by location, span  $\mathbf{z}_i^{cell} = \{\mathbf{z}_i^{where}, \mathbf{z}_i^{apothem}\}$  and its structure, reconstruction weights and its existence flag  $\mathbf{z}_i^{object} = \{\mathbf{z}_i^{what}, \mathbf{z}_i^{mask}, \bar{z}_i^{pres}\}$ .

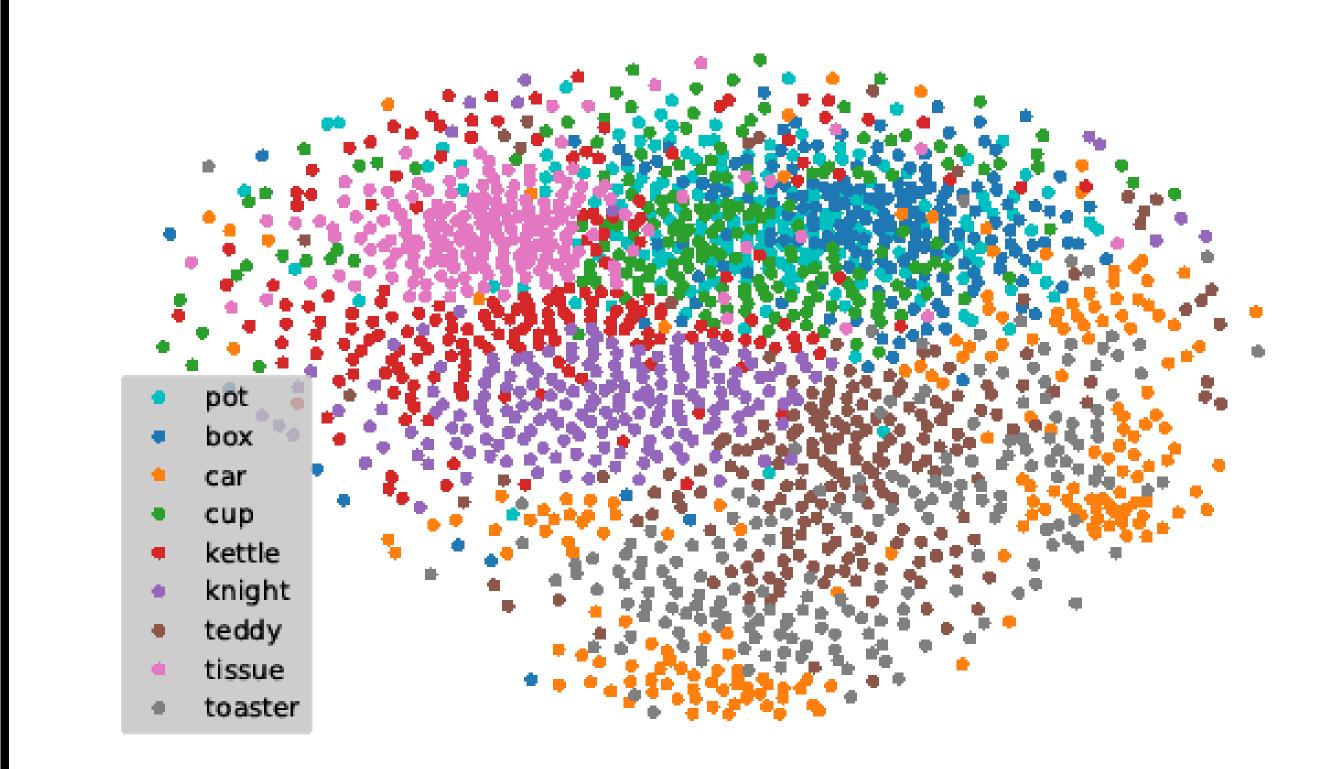
Object-centric learning on simulated dataset
Segmentation and reconstruction results on
simulated UOR and UOT dataset.PointGroup (PG)
baseline is fully supervised.



High quality segmentation that can generalize to scenes denser than training set.

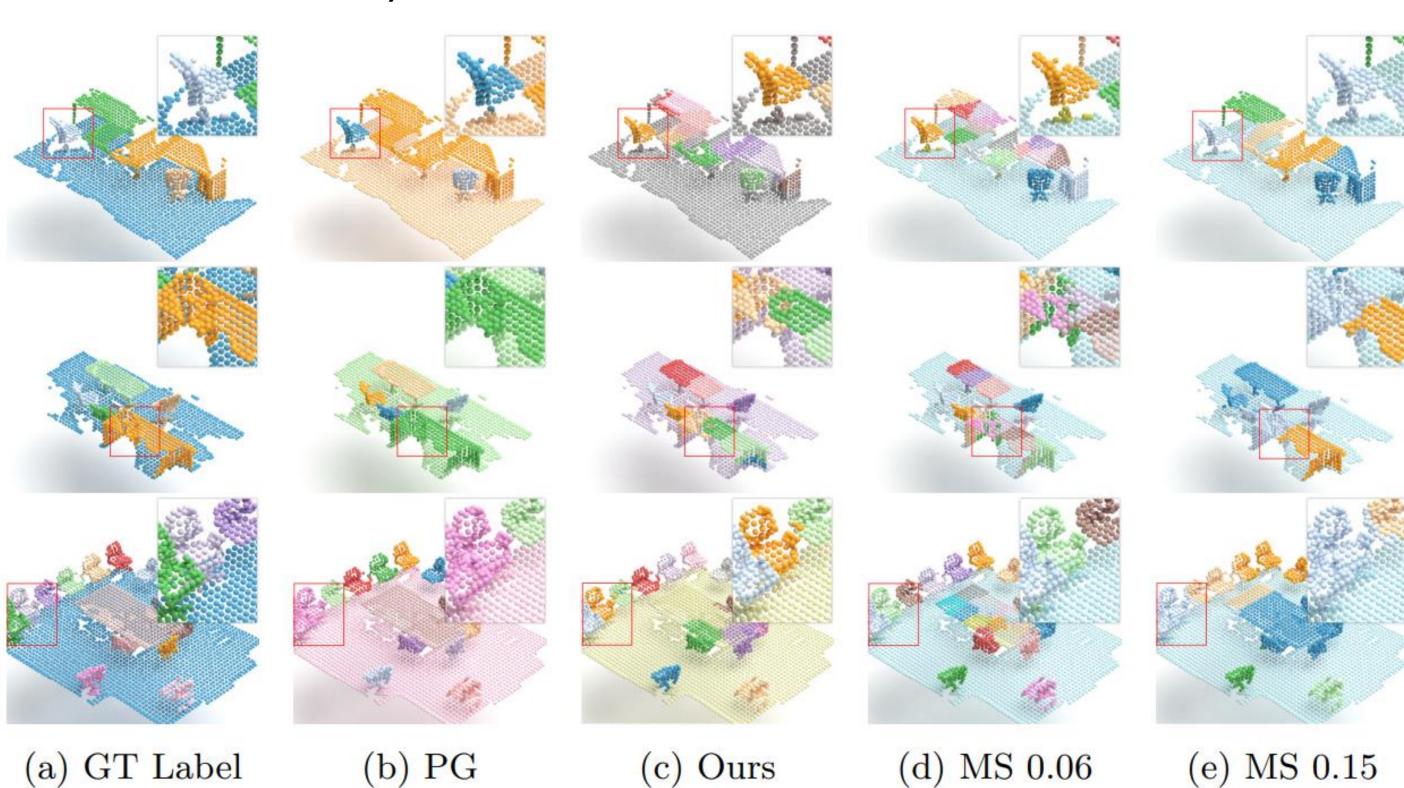


## Latent space visualization



## Real-world scene segmentation

Segmentation and reconstruction results on simulated UOR and UOT dataset compared with PointGroup (PG) (supervised baseline) and mean-shift (rule-based baseline).



		Chair ↑	Table ↑	Sofa ↑	macro-avg ↑
PG	S	0.61	0.69	0.52	0.60
$\overline{\mathrm{MS}\ 0.06}$	U	0.75	0.34	0.36	0.48
MS 0.15	U	0.33	0.46	0.38	0.39
SPAIR3D (ours)	U	0.59	0.43	0.49	0.50

Per-class mIoU score

