

Problem

Learning **3D shape completion** of sparse and noisy point clouds **without ground truth**.



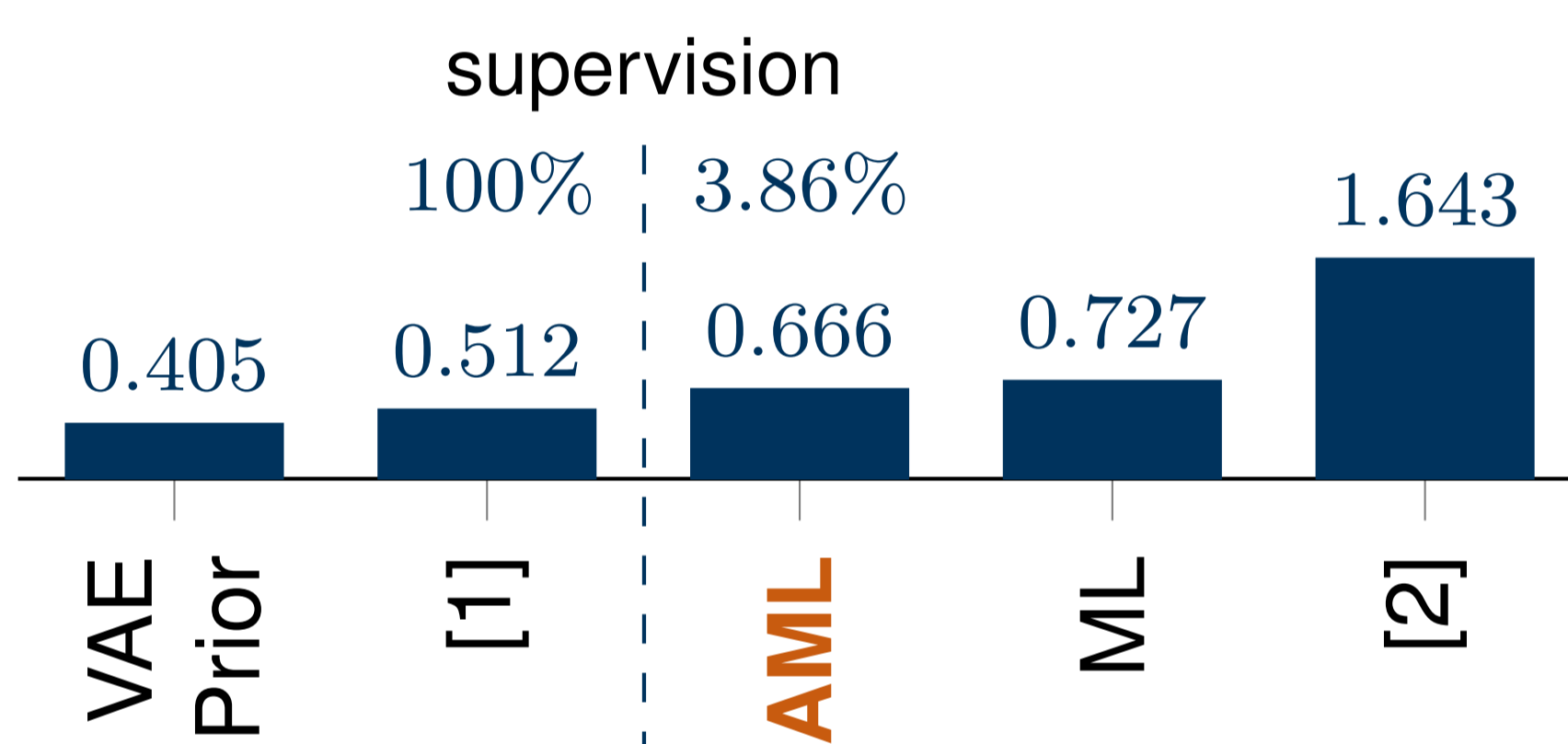
Contributions

- Learning-based, but weakly-supervised, amortized maximum likelihood (**AML**) approach.
- Synthetic and real benchmarks.

Quantitative Results

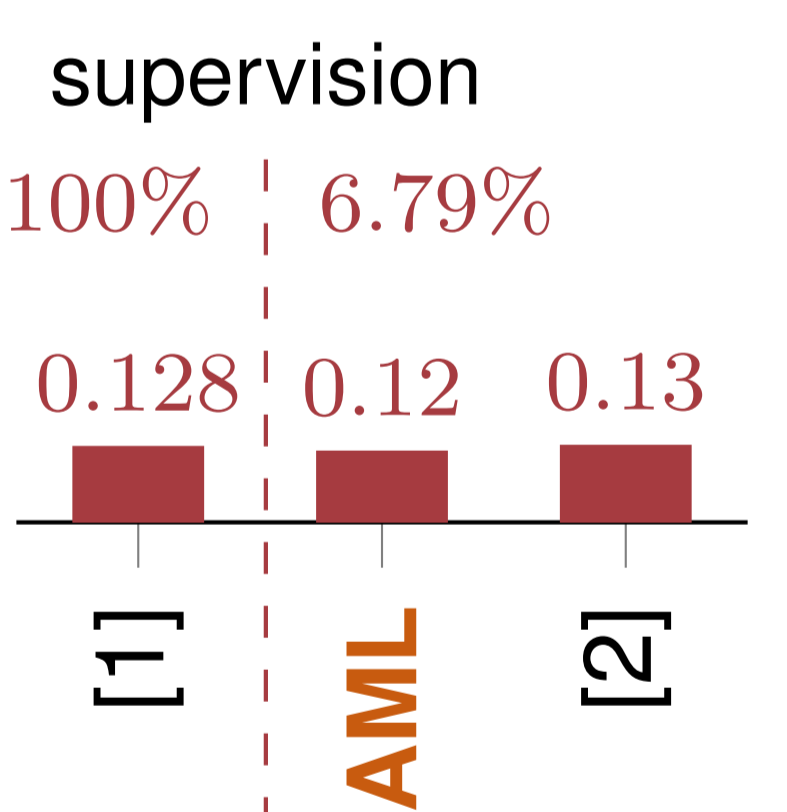
ShapeNet

Accuracy and Completeness [vx] ↓



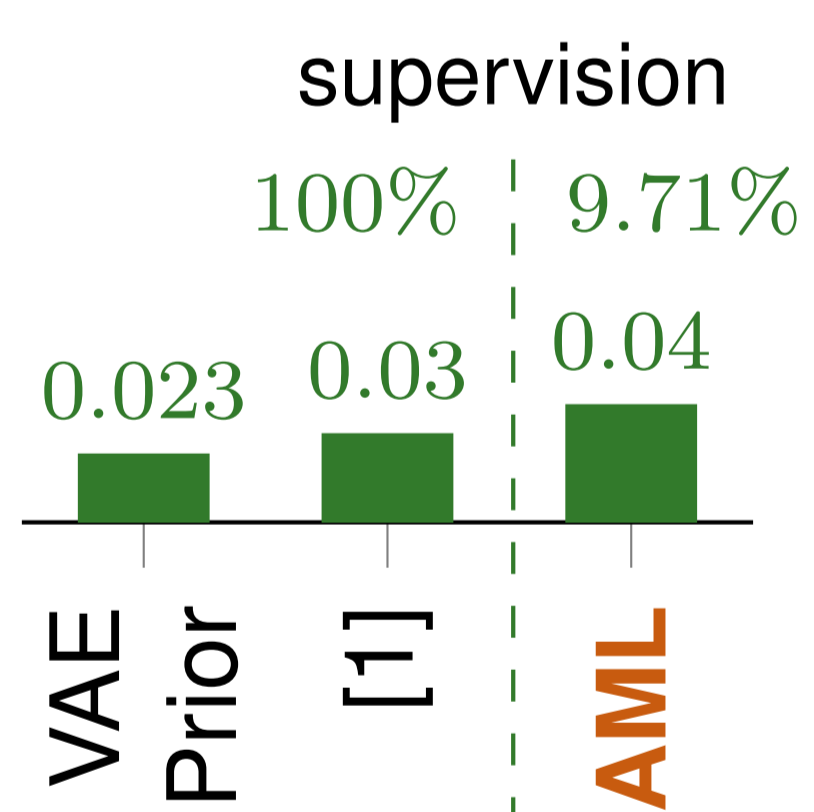
KITTI

Completeness [m] ↓

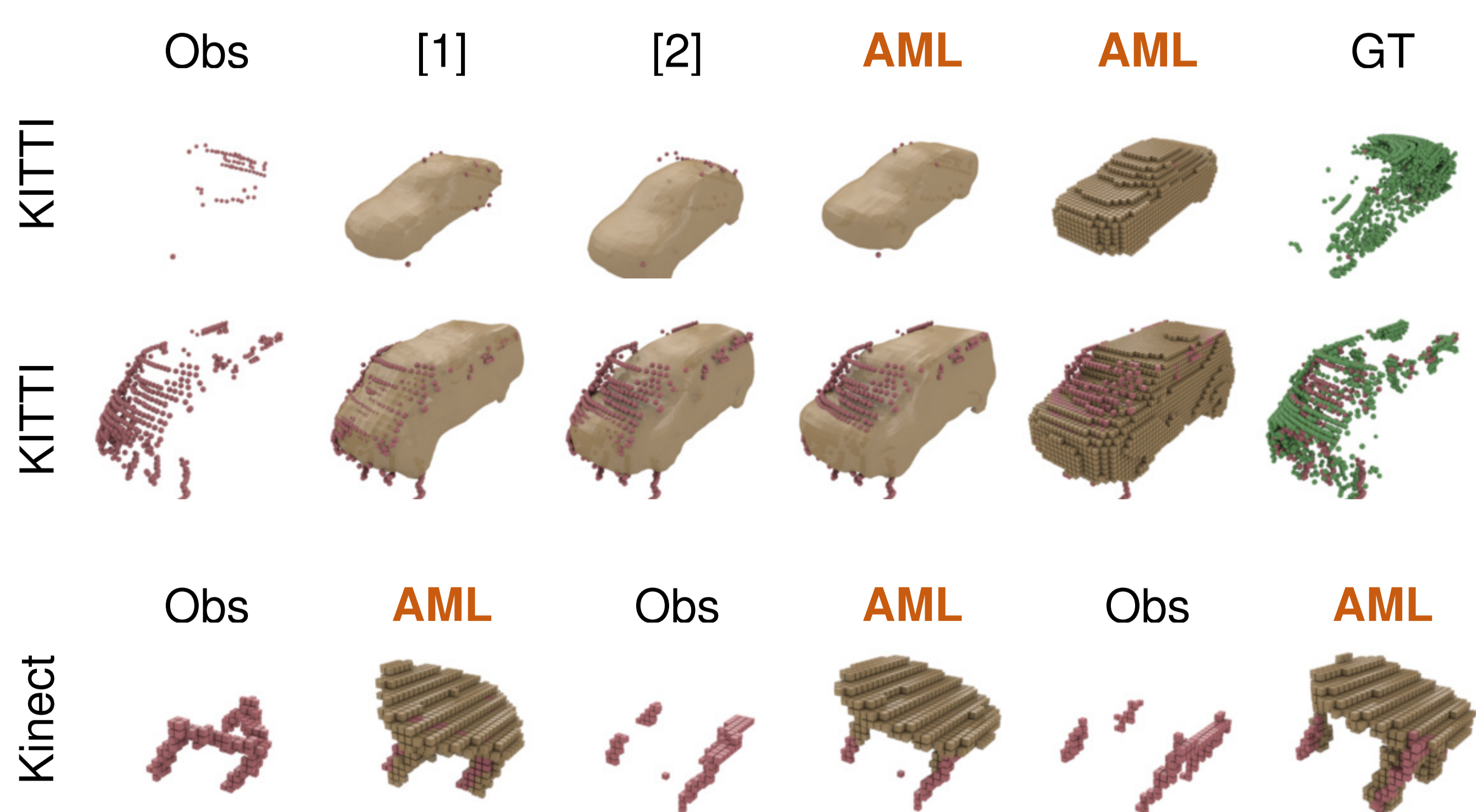


ModelNet10

Occupancy Error ↓



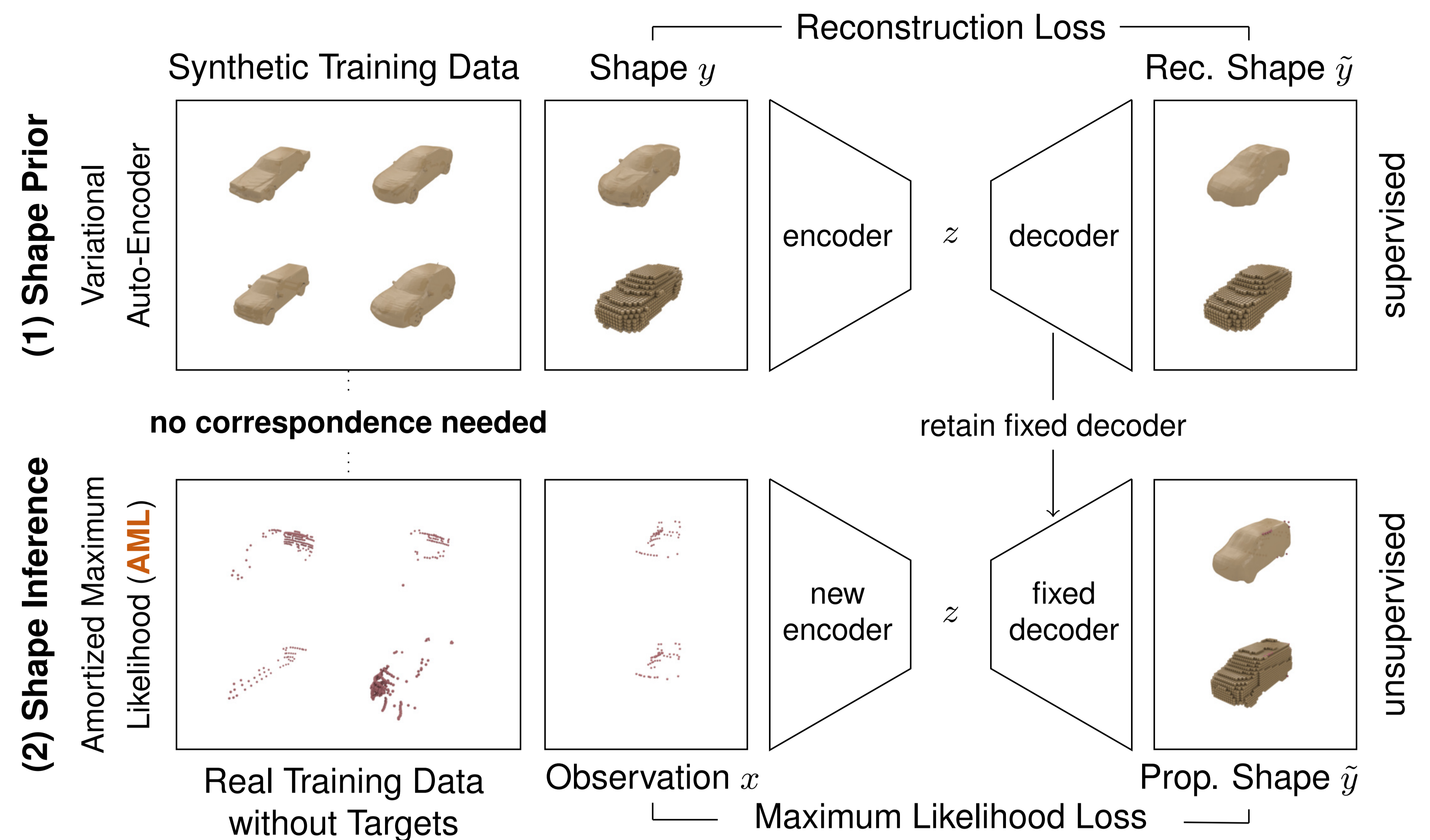
Qualitative Results on KITTI and Kinect (Real)



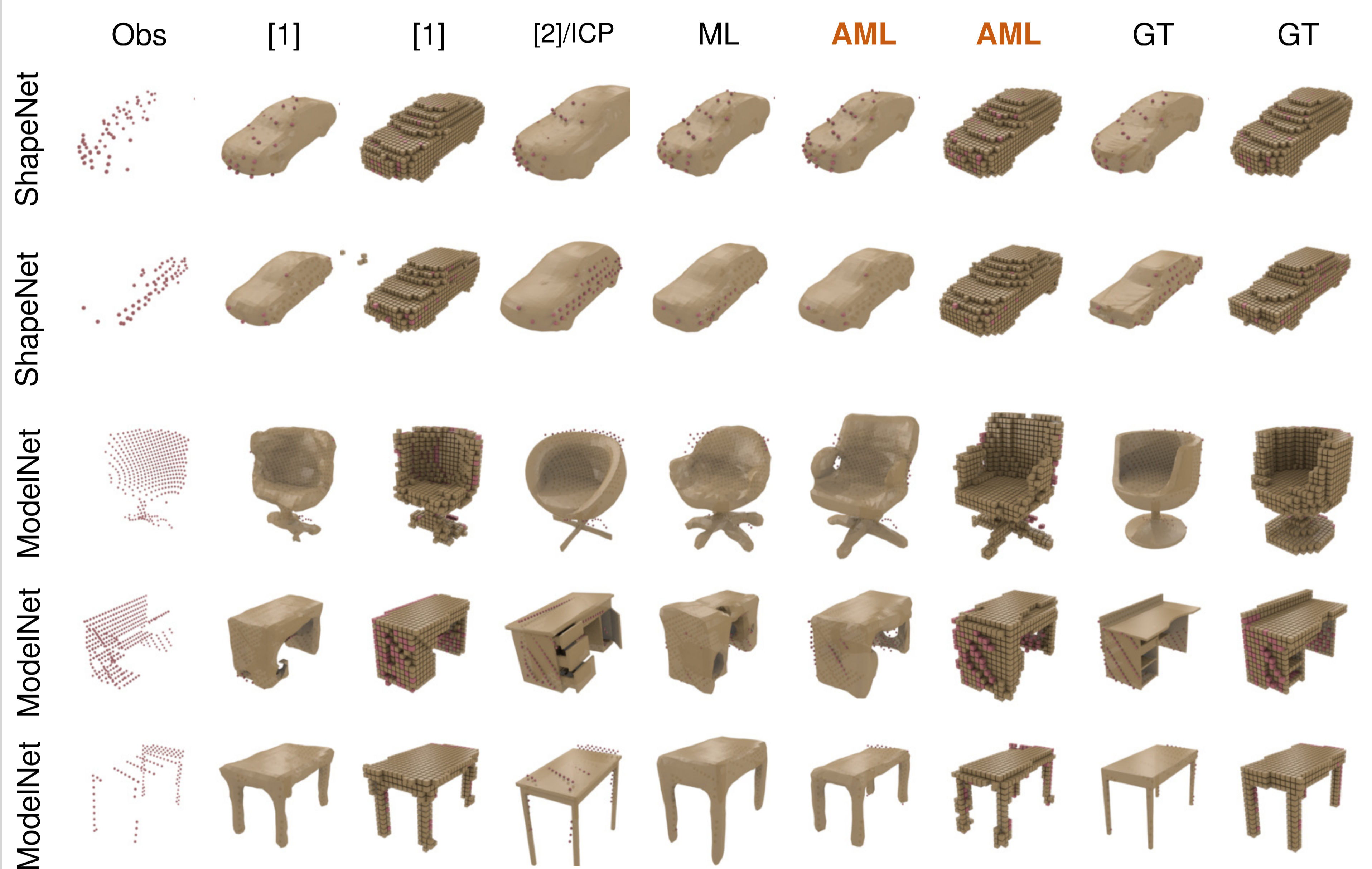
References

- [1] A. Dai et al. "Shape Completion using 3D-Encoder-Predictor CNNs and Shape Synthesis". In: *CVPR*. 2017
 [2] F. Engelmann et al. "Joint Object Pose Estimation and Shape Reconstruction in Urban Street Scenes Using 3D Shape Priors". In: *GCP*. 2016
 [3] A. Geiger et al. "Are we ready for Autonomous Driving? The KITTI Vision Benchmark Suite". In: *CVPR*. 2012

Method



Qualitative Results on ShapeNet and ModelNet (Synthetic)

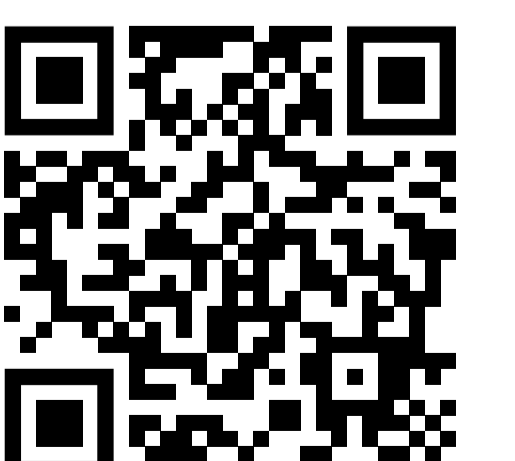


Conclusion

We proposed a learning-based, but weakly-supervised, amortized maximum likelihood (**AML**) approach to 3D shape completion.

- Outperforms data-driven approach [2]; but 84 times faster.
- Competitive to learning-based approach [1]; but up to 96% less supervision.

Paper, Code and Data:
davidstutz.de/mlss2018



- [4] A. X. Chang et al. "ShapeNet: An Information-Rich 3D Model Repository". In: *arXiv.org* 1512.03012 (2015)
 [5] Z. Wu et al. "3D ShapeNets: A deep representation for volumetric shapes". In: *CVPR*. 2015
 [6] B. Yang et al. "3D Object Dense Reconstruction from a Single Depth View". In: *arXiv.org* abs/1802.00411 (2018)