OmniObject3D: Large-Vocabulary 3D Object Dataset for Realistic Perception, Reconstruction and Generation

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Introduction

TL;DR
We propose OmniObject3D, a large vocabulary 3D object dataset with massive high-quality real-scanned 3D objects to facilitate the development of 3D perception, reconstruction, and generation in the real world.
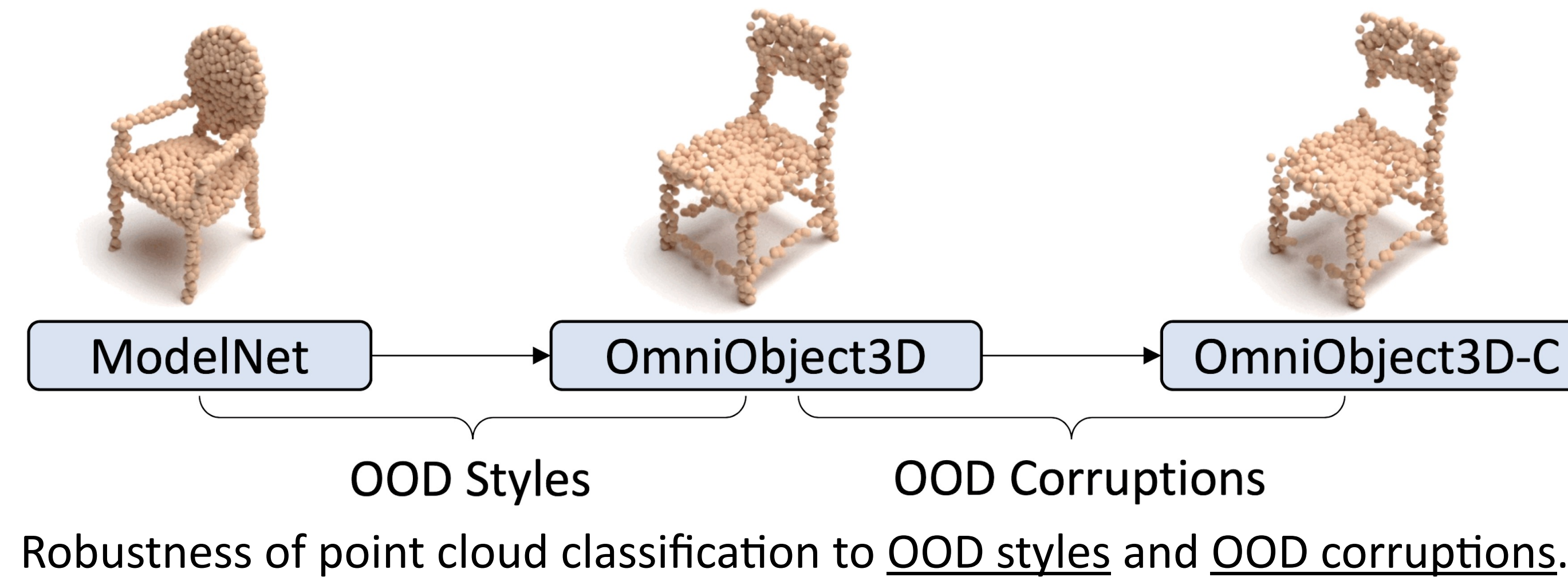
Properties:
- **Large Vocabulary**: 6k models and 190 categories
- **Rich Annotations**: scans, videos, multi-view renders, point clouds
- **Realistic Scans**: professional scanner with 0.1mm precision
- **Abundant down-stream tasks**
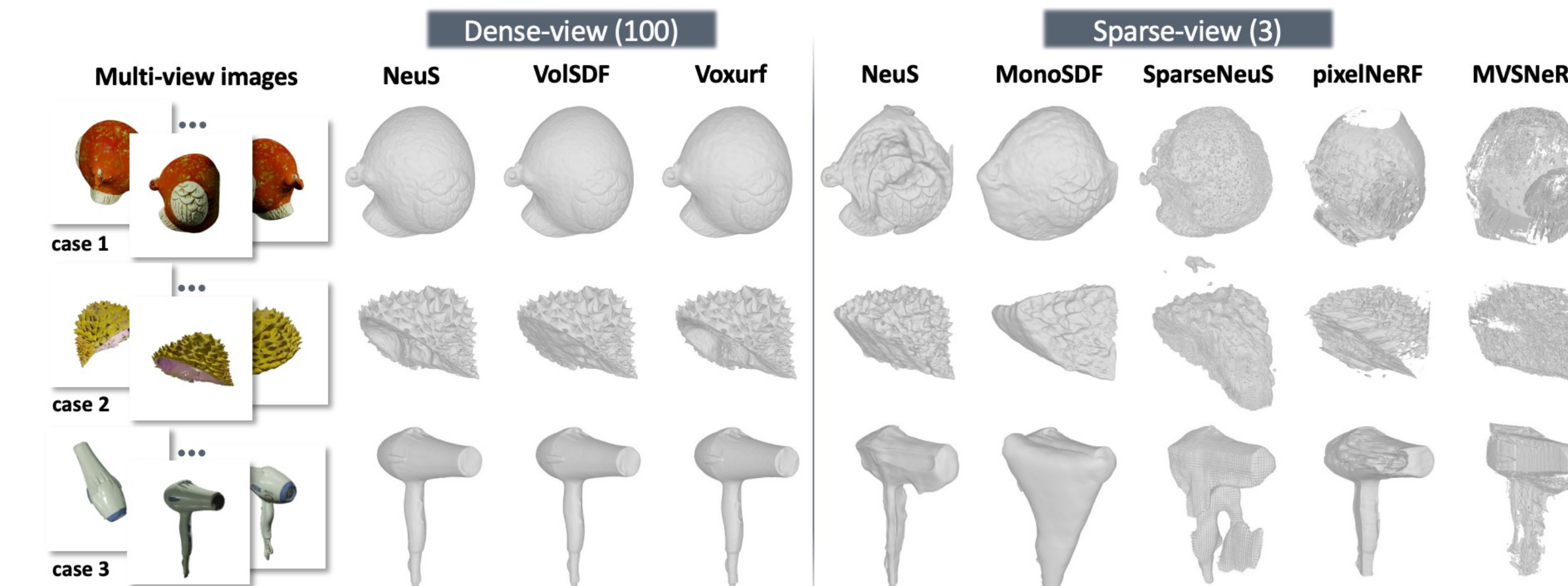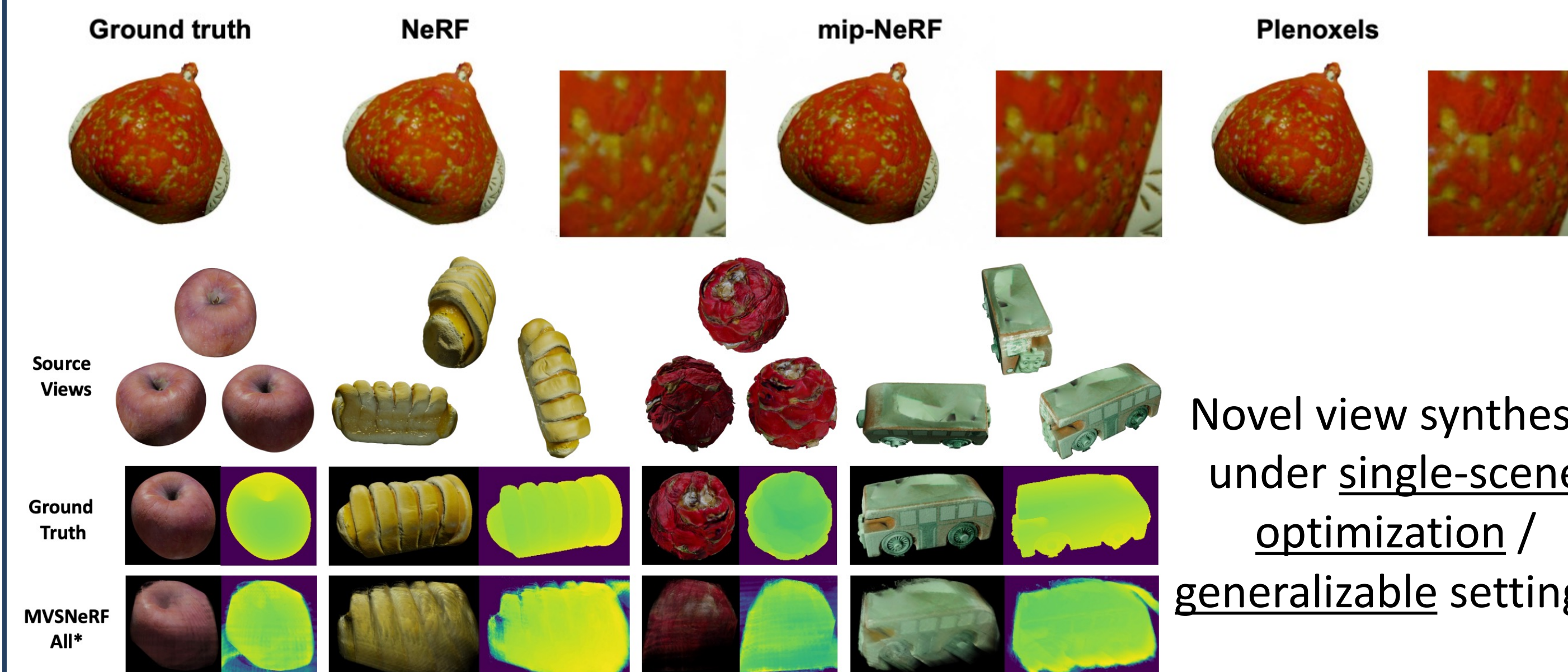
Data Distribution

Long-tailed distribution, sharing common classes with popular 2D datasets
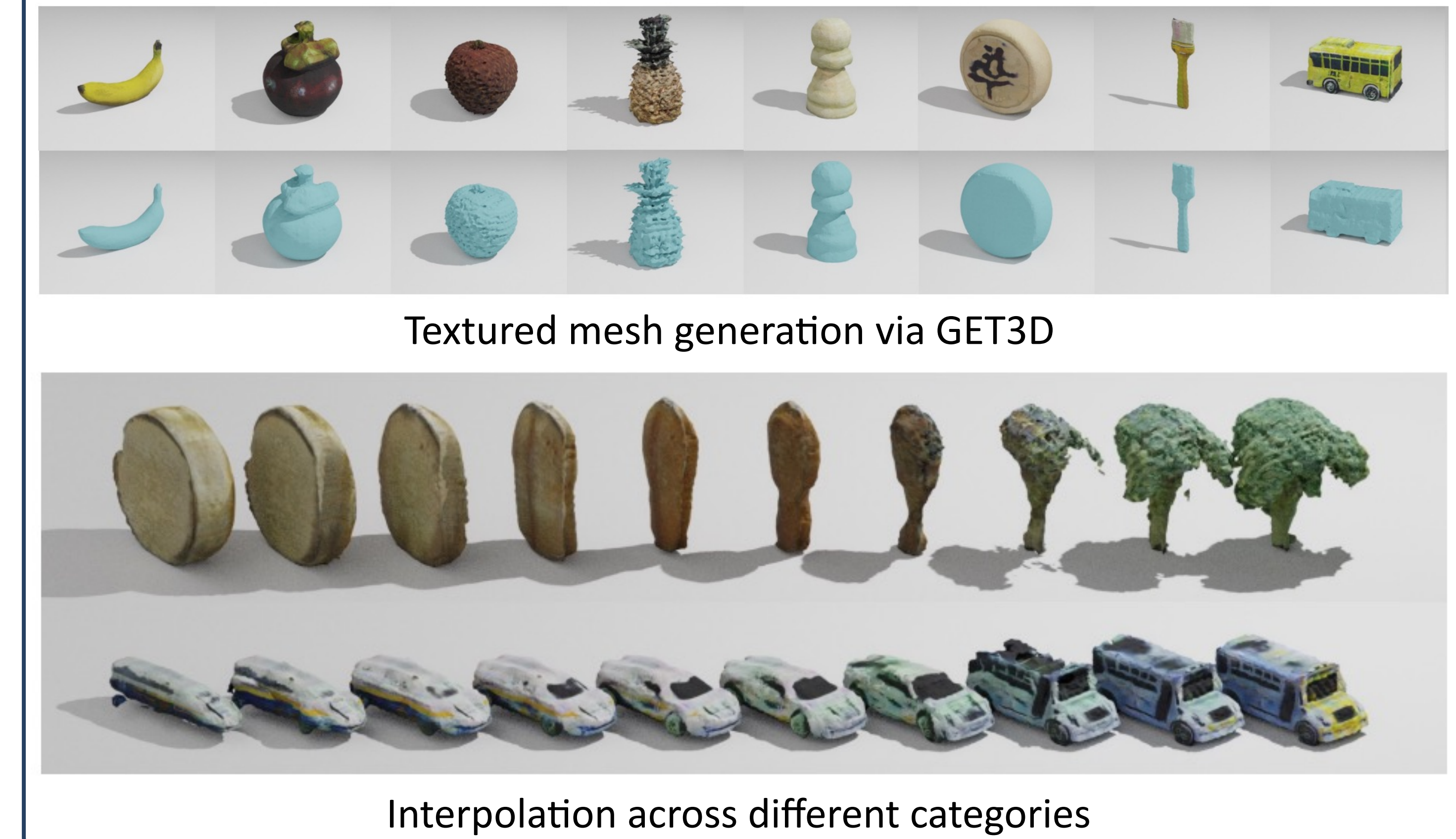
Track 1: Point cloud classification

ModelNet → OmniObject3D → OmniObject3D-C

OOD Styles   OOD Corruptions

Robustness of point cloud classification to <u>OOD styles</u> and <u>OOD corruptions</u>.

Track 2 & 3: NVS & Surface Reconstruction

Ground truth | NeRF | mip-NeRF | Plenoxels

Source Views
Ground Truth
MVSNeRF All*

Novel view synthesis under <u>single-scene optimization</u> / <u>generalizable</u> settings.

Multi-view images | Dense-view (100): NeuS | VolSDF | Voxurf | Sparse-view (3): NeuS | MonoSDF | SparseNeuS | pixelNeRF | MVSNeRF

case 1
case 2
case 3

Surface reconstruction with <u>dense-view</u> or <u>sparse-view</u> observations

Track 4: 3D Generation

Textured mesh generation via GET3D

Interpolation across different categories

Future Works

Continuous data growing
- More data
- Broader distribution
- More modalities
- Higher complexity

More downstream tasks

Project page

References

[1] Ren et al., Benchmarking and analyzing point cloud classification under corruptions, in ICML, 2022.
[2] Mildenhall et al., Nerf: Representing scenes as neural radiance fields for view synthesis, in ECCV 2020.
[3] Barron et al., Mip-nerf: A multiscale representation for anti-aliasing neural radiance fields, in ICCV 2021.
[4] Yu et al., Plenoxels: Radiance fields without neural networks, in CVPR 2022.
[5] Yu et al., pixelnerf: Neural radiance fields from one or few images, in CVPR 2021.
[6] Chen et al., MNSNeRF: Fast generalizable radiance field reconstruction from multi-view stereo, in ICCV 2021.
[7] Wang et al., Ibrnet: Learning multi-view image-based rendering, in CVPR 2021.
[8] Wang et at., NeuS: Learning neural implicit surfaces by volume rendering for multi-view reconstruction, in NeurIPS 2021.
[9] Yariv et al., Volume rendering of neural implicit surfaces, in NeurIPS 2021.
[10] Wu et al., Voxurf: Voxel-based efficient and accurate neural surface reconstruction, in ICLR 2023.
[11] Yu et al., Monosdf: Exploring monoculargeometric cues for neural implicit surface reconstruction, in NeurIPS 2022.
[12] Long et al., Sparseneus: Fast generalizable neural surface reconstruction from sparse views, in ECCV 2022.
[13] Gao et al., GET3D: A generative model of high quality 3d textured shapes learned from images, in NeurIPS 2022.