1. Point-MAE: Masked Autoencoders for Point Cloud Self-supervised Learning, ECCV 2022, ArXiv
2. OpenShape: Scaling Up 3D Shape Representation Towards Open-World Understanding, 2023, arxiv
3. Ulip-2: Towards scalable multimodal pre-training for 3d understanding, 2024, link
4. Pointllm: Empowering large language models to understand point clouds, 2024, link
5. ShapeLLM: Universal 3D Object Understanding for Embodied Interaction, 2024, link
6. Uni3d: Exploring unified 3d representation at scale, 2023, link
7. Sonata: Self-Supervised Learning of Reliable Point Representations, 2025, link
8. Tensor field networks: Rotation- and translation-equivariant neural networks for 3D point clouds: https://arxiv.org/abs/1802.08219
9. DeltaConv: Anisotropic Operators for Geometric Deep Learning on Point Clouds: https://arxiv.org/pdf/2111.08799.pdf
10. Möbius Convolutions for Spherical CNNs: https://arxiv.org/abs/2201.12212
    - Janis AIAD
    - Christopher Calvet
11. AtlasNet: A Papier-Mâché Approach to Learning 3D Surface Generation: https://arxiv.org/abs/1802.05384
12. Vector Neurons: A General Framework for SO(3)-Equivariant Networks https://github.com/FlyingGiraffe/vnn
13. NeuroMorph: Unsupervised Shape Interpolation and Correspondence in One Go https://arxiv.org/pdf/2106.09431.pdf
14. 3D-CODED : 3D Correspondences by Deep Deformation https://arxiv.org/pdf/1806.05228.pdf
15. What Do Single-view 3D Reconstruction Networks Learn? https://arxiv.org/pdf/1905.03678.pdf (not sure about this one)
16. Learning Joint Surface Atlases https://arxiv.org/pdf/2206.06273.pdf
17. Neural Dual Contouring https://arxiv.org/pdf/2202.01999.pdf
18. Neural Jacobian Fields: Learning Intrinsic Mappings of Arbitrary Meshes https://arxiv.org/pdf/2205.02904.pdf
19. Neural Subdivision https://arxiv.org/pdf/2005.01819.pdf
20. NeRF++: Analyzing and Improving Neural Radiance Fields https://arxiv.org/abs/2010.07492
21. CAT3D: Create Anything in 3D with Multi-View Diffusion Models https://cat3d.github.io/
22. Single Mesh Diffusion Models with Field Latents for Texture Generation https://single-mesh-diffusion.github.io/
23. Spatially and Spectrally Consistent Deep Functional Maps https://arxiv.org/abs/2308.08871
24. 3dshape2vecset: A 3d shape representation for neural fields and generative diffusion models https://arxiv.org/abs/2301.11445
25. Zero-1-to-3: Zero-shot One Image to 3D Object https://arxiv.org/pdf/2303.11328
26. Zero123++: A Single Image to Consistent Multi-view Diffusion Base Model

27. TutteNet: Injective 3D Deformations by Composition of 2D Mesh Deformations, https://arxiv.org/pdf/2406.12121
28. Generative Escher Meshes https://arxiv.org/pdf/2309.14564
29. Gaussian Cube: A Structured and Explicit Radiance Representation for 3D Generative Modelling" https://arxiv.org/pdf/2403.19655
30. Neural Splines: Fitting 3D Surfaces with Infinitely-Wide Neural Networks, https://openaccess.thecvf.com/content/CVPR2021/papers/Williams_Neural_Splines_Fitting_3D_Surfaces_With_Infinitely-Wide_Neural_Networks_CVPR_2021_paper.pdf
31. Reach For the Arcs: Reconstructing Surfaces from SDFs via Tangent Points, https://odedstein.com/projects/reach-for-the-arcs/reach-for-the-arcs.pdf
32. Constructive Solid Geometry on Neural Signed Distance Fields, https://zoemarschner.com/papers/csg_on_neural_sdfs.pdf
33. Neural Implicit Shape Editing Using Boundary Sensitivity, https://arxiv.org/abs/2304.12951
34. efunc: An Efficient Function Representation without Neural Networks, Biao Zhang, Peter Wonka https://arxiv.org/html/2505.21319v1
35. Radiance Surfaces: Optimizing Surface Representations with a 5D Radiance Field Loss, Ziyi Zhang, Nicolas Roussel, Thomas Muller, Tizian Zeltner, Merlin Nimier-David, Fabrice Rousselle, Wenzel Jakob
36. Splat and Replace: 3D Reconstruction with Repetitive Elements , Nicolas Violante, Andreas Meuleman, Alban Gauthier, Fredo Durand, Thibault Groueix, George Drettakis
37. Lifting the Winding Number: Precise Discontinuities in Neural Fields for Physics Simulation, Yue Chang, Mengfei Liu, Zhecheng Wang, Peter Yichen Chen, Eitan Grinspun
38. SDFs from Unoriented Point Clouds using Neural Variational Heat Distances, Samuel Weidemaier, Florine Hartwig, Josua Sassen, Sergio Conti, Mirela Ben-Chen, and Martin Rumpf