

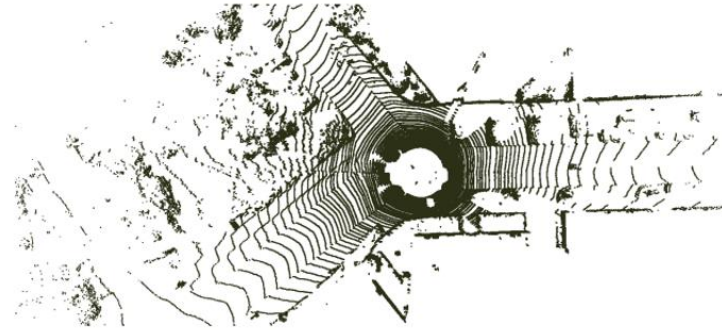


# AnyPcc: Compressing Any Point Cloud with a Single Universal Model

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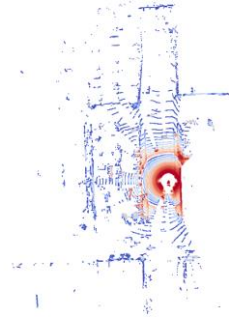
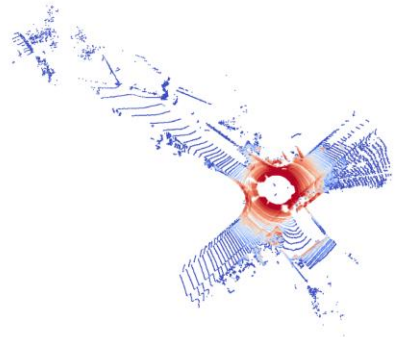
<https://anypcc.github.io/>



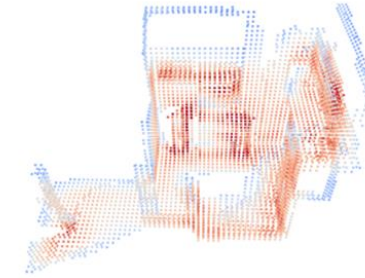
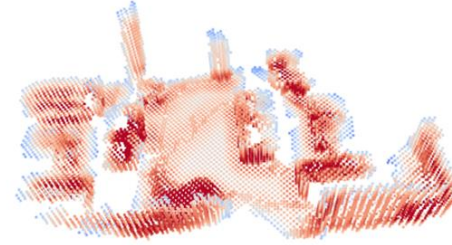
	xyz	feature	Pts/fps	Required bandwidth
RGB Point Cloud	10bit	8bit	80w/30fps	<b>1.2Gbps</b>
Lidar Scans	18bit	8bit	10w/10fps	<b>60Mbps</b>
3DGS Point Cloud	32bit	32bit	500w/1fps	<b>8.8Gbps</b>



**an urgent need for efficient 3D data compression algorithms!**



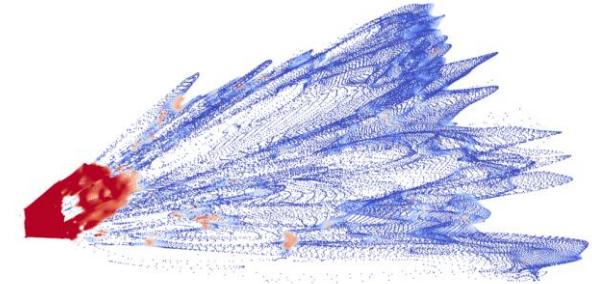
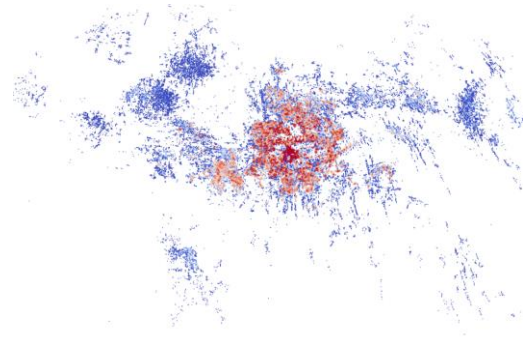
Lidar Scans: KITTI, Ford



Indoor Scans: ScanNet, S3DIS



Human Point Clouds: 8IVFB, OwlII



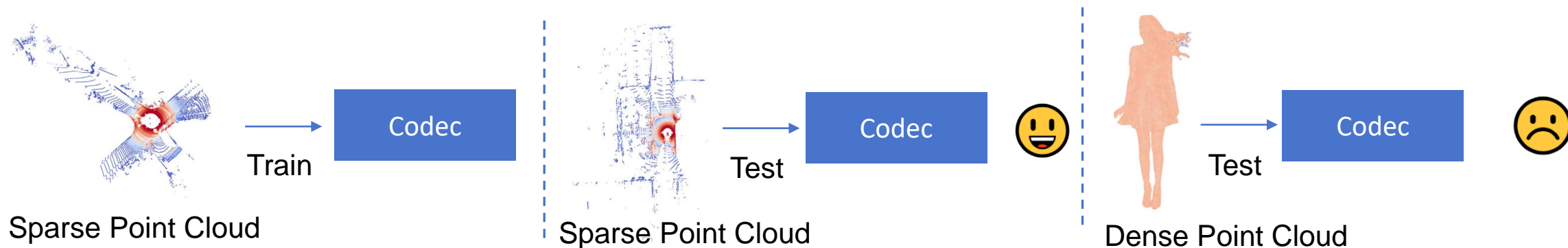
Reconstruct Point Maps: 3DGS, VGGT



Real-world point clouds are **diverse**. Can we use a single model to efficiently compress these heterogeneous point clouds?

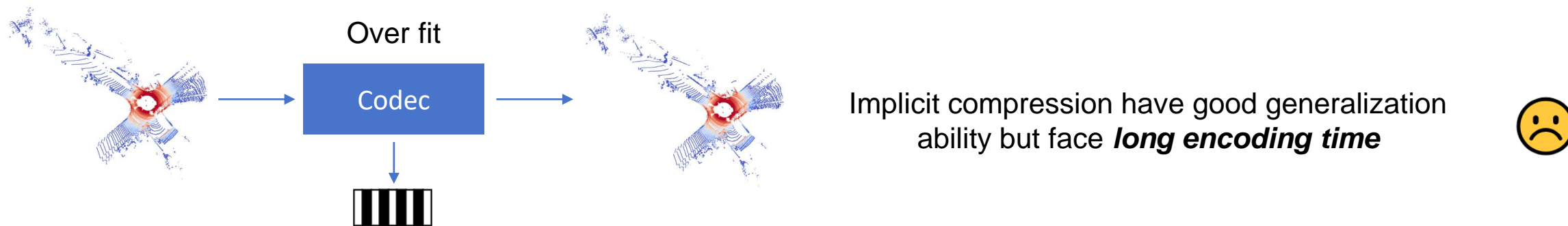
# Revisit the existing approach

1. Deep learning-based method: training on ID data, testing on ID data.



Deep learning-based methods suffer from performance degradation when faced with OOD data.

2. Implicit Based : Transforming the task of point cloud compression into model compression.

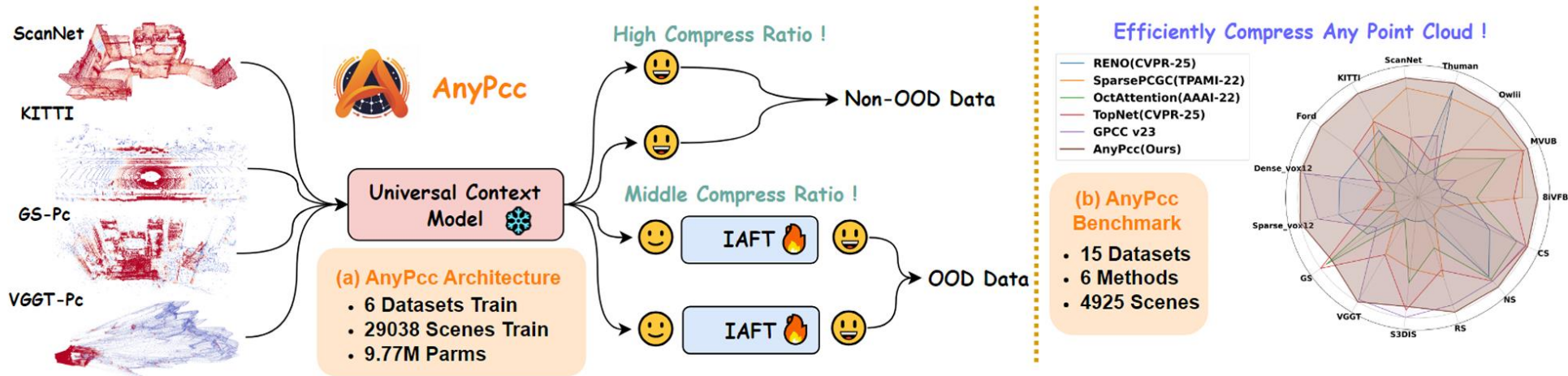


## Key Challenges

1. **One model** for heterogeneous point clouds
2. **Robustness** to OOD data
3. **Fast encoding** for implicit compression



AnyPcc unified point cloud geometry compression solution



AnyPcc = Powerful Universal Context Model (UCM) + Instance Adaptive Fine-Tuning (IAFT)

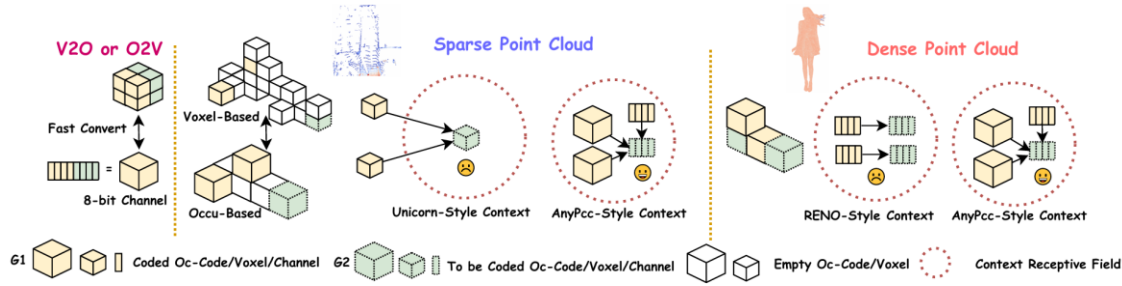
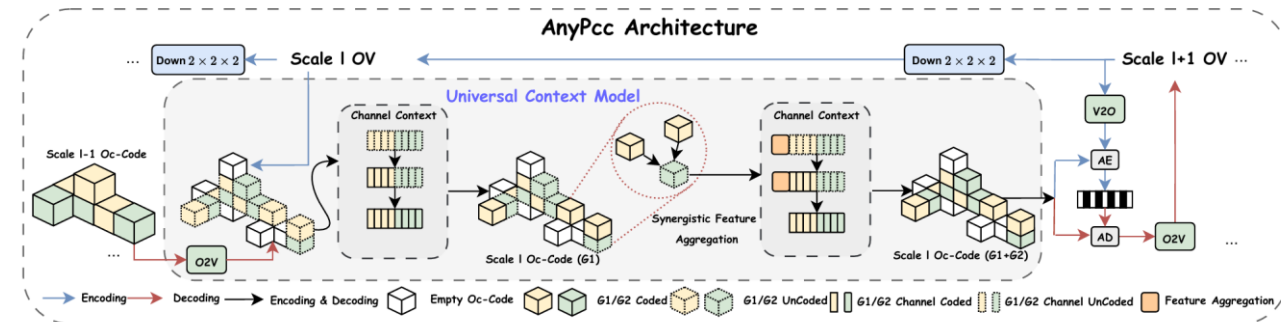
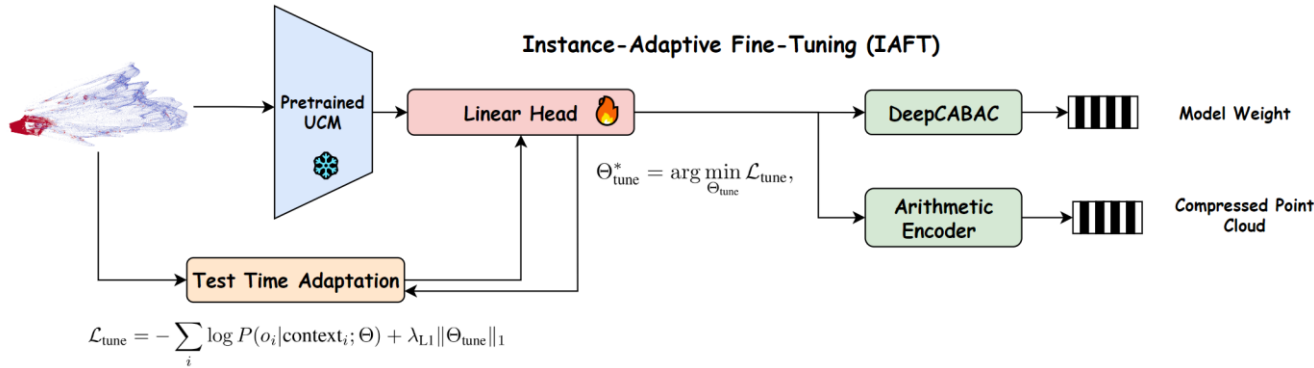


Figure 2. The superiority of our UCM in capturing contextual information across diverse point cloud types (e.g., dense and sparse).



UCM: Channel-Spatial grouping solves the generalization problem under different data densities.



**IAFT:** Online fine-tuning during encoding enables fast adaptation to OOD samples. The bitstream transmits the adapted weights and compressed point cloud.

AnyPcc = Powerful Universal Context Model (UCM) + Instance Adaptive Fine-Tuning (IAFT)

# AnyPcc Results

Table 1. Performance comparison on the AnyPcc Benchmark. The table presents the compression performance of AnyPcc against six methods across 15 diverse datasets, with the best and second-best results highlighted in red and yellow cells.

Dataset	Cond <sup>†</sup>	OOD	RENO	SparsePCGC	Unicorn*	OctAttention	TopNet	GPCC	Ours	Ours-U
8iVFB	E	✗	0.70	0.57	0.57	0.68	0.59	0.76	0.54	0.57
MVUB		✗	1.00	0.69	0.69	0.76	0.69	0.94	0.67	0.75
OwlII		✗	0.59	0.48	0.48	0.62	0.56	0.59	0.47	0.47
Thuman		✗	1.64	1.70	1.70	2.31	2.20	2.00	1.58	1.64
ScanNet		✗	2.15	1.86	1.86	2.13	2.03	2.03	1.83	1.88
KITTI		✗	7.06	6.80	6.50	7.21	6.85	8.19	6.18	6.45
Ford		✗	9.38	9.77	8.44	9.10	8.54	10.32	8.40	8.57
Dense		✗	5.81	6.37	5.48	6.55	6.38	5.32	5.27	5.55
Sparse	M	✗	9.64	9.98	9.42	10.40	10.02	9.35	9.11	9.26
GS		✗	13.89	15.82	/	11.31	10.95	14.46	11.65	11.74
VGGT		✓	8.24	7.84	/	8.22	7.83	7.33	7.30	7.06
S3DIS		✓	13.06	11.88	/	11.52	10.84	10.66	10.93	10.79
RS		H	✓	4.02	3.88	/	4.05	3.92	3.72	3.68
NS	✓		4.96	6.54	/	4.89	4.84	4.85	4.69	4.67
CS	✓		3.94	4.94	/	3.40	3.21	3.23	3.18	3.08
CR Gain over GPCC ↓			2.96%	2.07%	/	1.32%	-4.04%	0.00%	-11.93%	-10.75%
Enc/Dec Time (s) ↓			0.22/0.23	2.6/2.2	/	7.7/1324	8.7/1740	3.8/2.7	2.84/0.46	
Total Parameters (M) ↓			9.03	26.43	/	29.61	23.59	/	68.39	9.77

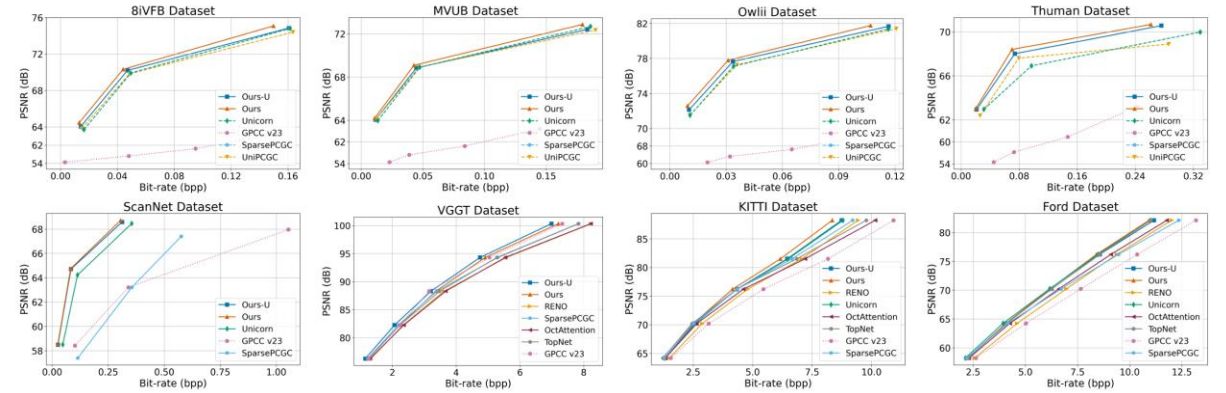
<sup>†</sup> Cond represents the test difficulty of the testsets, and we divide the test set into easy (E), medium (M), and hard (H).

\* The results for Unicorn are cited directly from the original publication as its implementation is not open-source.

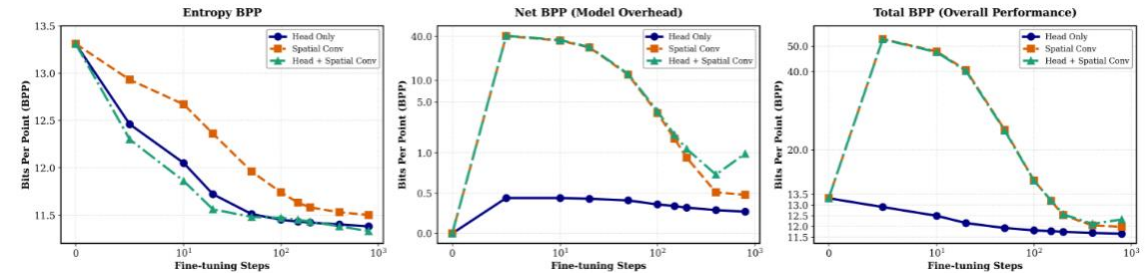
## AnyPcc Future Work

1. Scaling Laws of Compression Models

2. Self-Supervised Learning and Data Curation



**SOTA Performance on lossy and lossless compression, with strong generalization on diverse dataset!**



Online fine-tuning curves



# **AnyPcc: Compressing Any Point Cloud with a Single Universal Model**

**Thanks !**