



Multiscale Point Cloud Geometry Compression

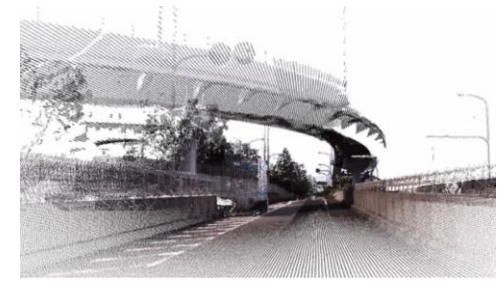
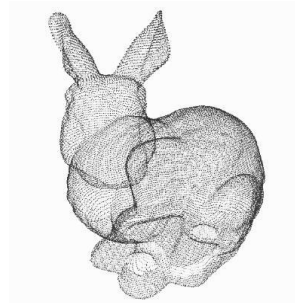
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Background: Demand for Point Cloud Compression

□ Point Cloud (PC)

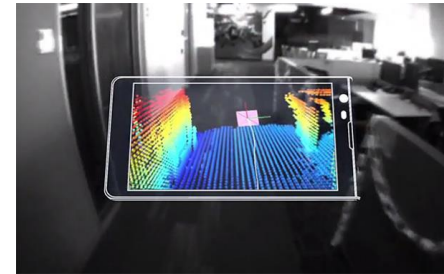
- Geometry (x, y, z)
- Attribute (color, etc)



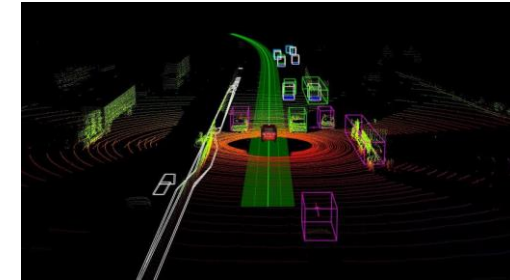
Various PCs

□ Emerging Applications

- Immersive Media (AR/VR)
- Autonomous Driving



AR\VR



Autonomous Driving

□ Demand for Compression

- Huge amount of data
- Unordered and unstructured data



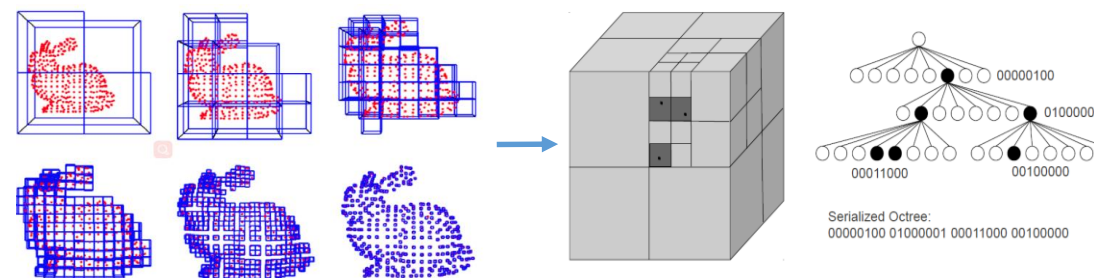
Unstructured Data

Background: PCC Methods

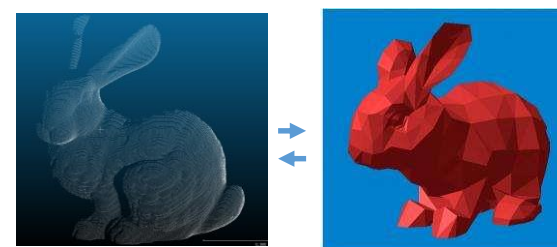
□ Geometry based PCC (G-PCC)

- Octree Geometry Codec
 - Occupancy Information Coding

- Trisoup Geometry Codec
 - Triangle Mesh Vertices Coding



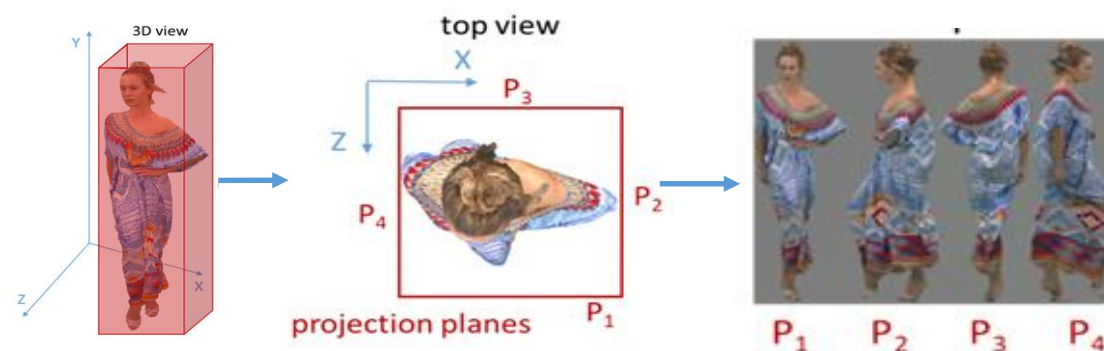
Octree Decomposition & Occupancy Information Coding



Point Cloud & Mesh Model

□ Video based PCC (V-PCC)

- 3D-2D Projection
- Image/Video Coding
- State-of-the-art Efficiency



3D-to-2D Projections

Background: Emerging Learning based Methods

□ Voxel based Methods

- PC → Volumetric Model
- 3D CNN based Transform
- Classification Loss

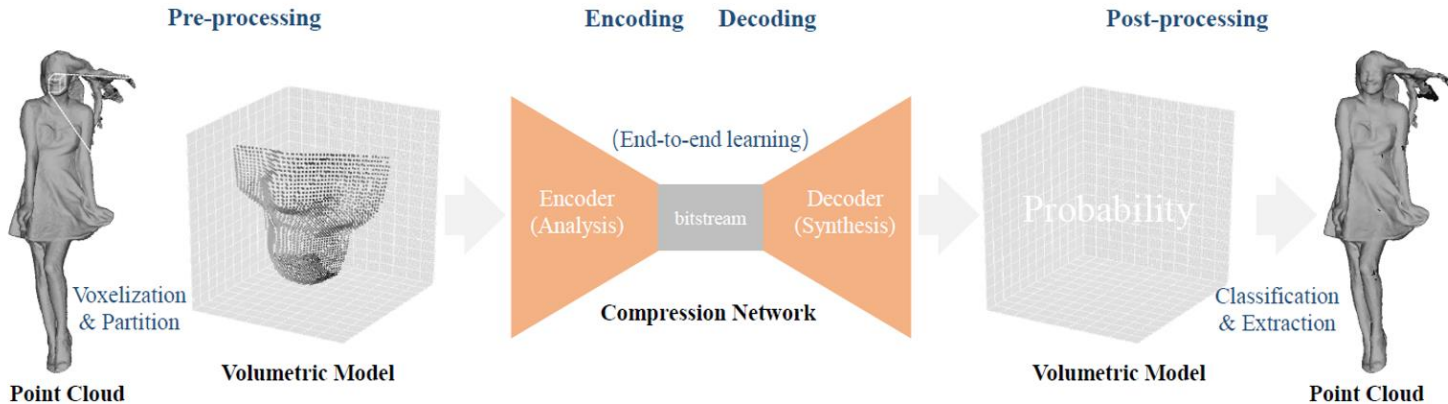
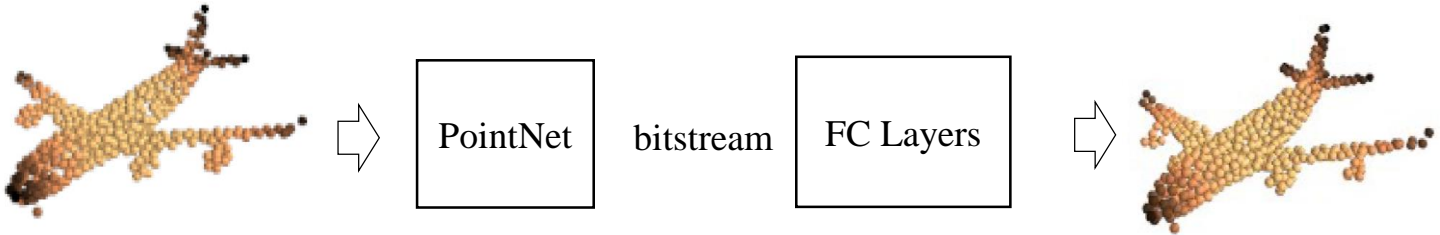


Figure from Wang et al, “Lossy Point Cloud Geometry Compression via End-to-End Learning.” accepted by IEEE TCSVT, Jan. 2021

□ Point based Methods

- Input Raw Points
- PointNet Structure
- Distance Loss



PCC based on PointNet AE

□ Drawbacks of Existing Learning based Methods

■ Voxel based Methods

- Huge Computation and Memory Cost

■ Point based Methods

- Poor Performance at High Bit Rates

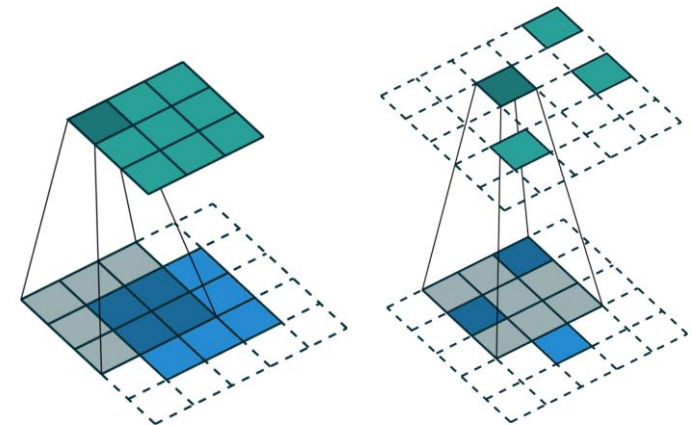
□ How to Improve?

■ Low Complexity Representation and Computation

- Sparse Tensor and Sparse Convolution

■ Geometry Details Description and Reconstruction

- Hierarchical reconstruction
- Key points lossless compression



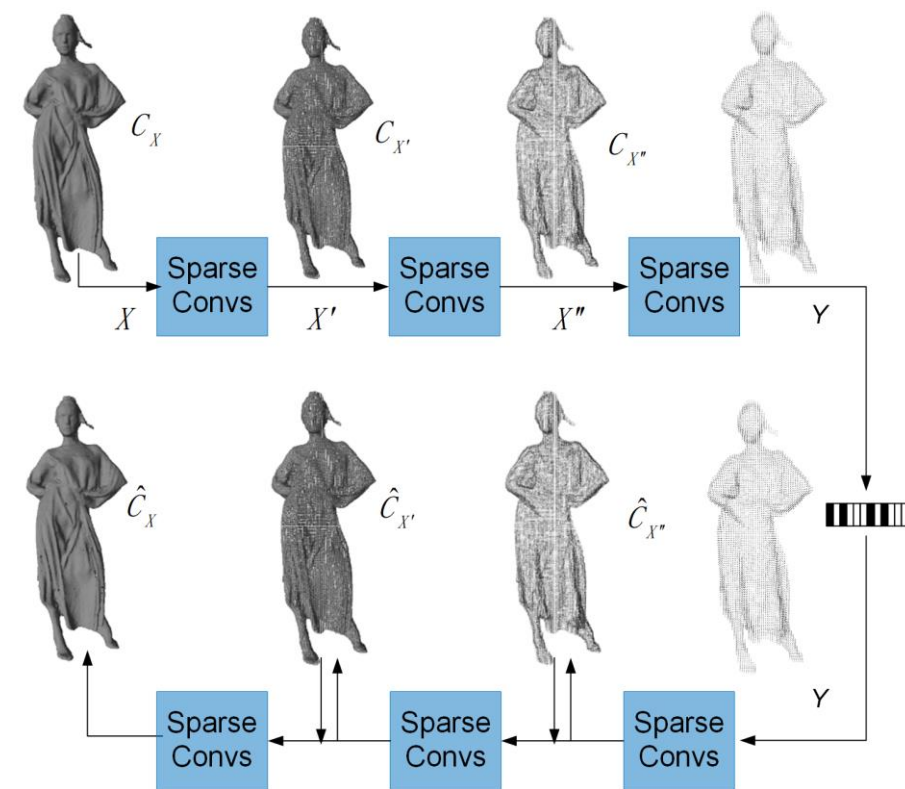
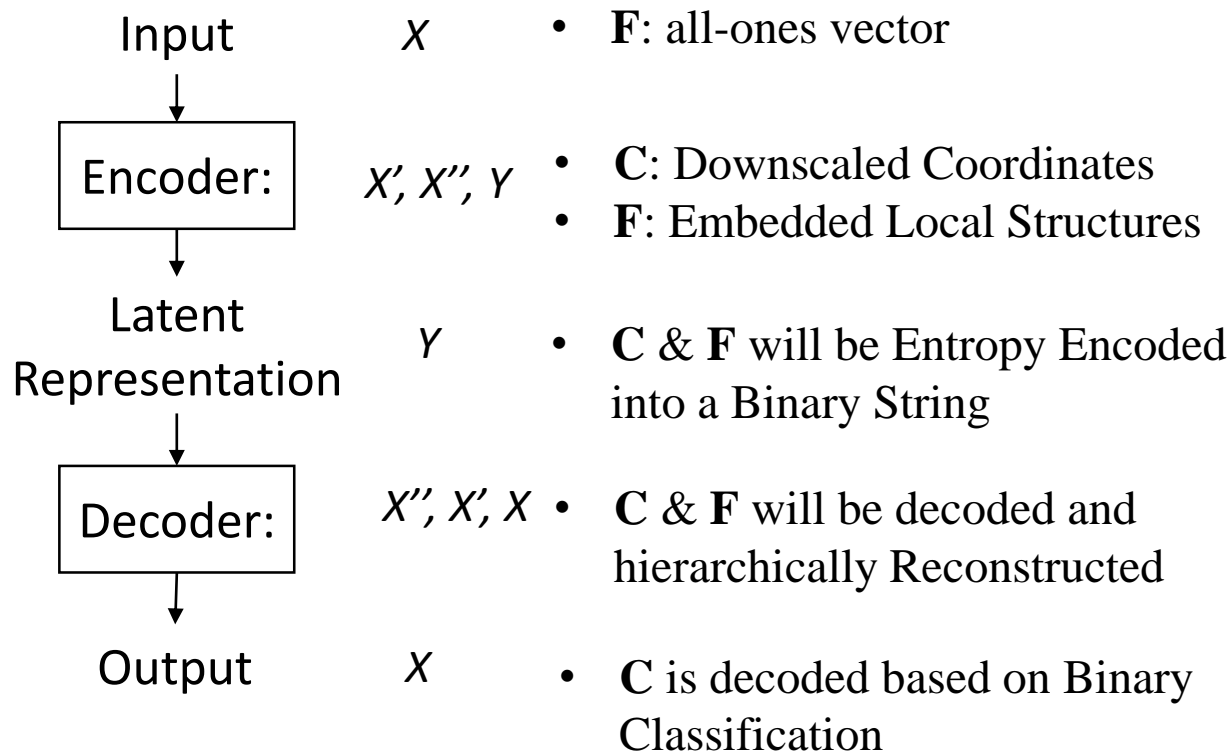
Dense Convolution vs Sparse Convolution

Figure from Choy, C. et al. "4D Spatio-Temporal ConvNets: Minkowski Convolutional Neural Networks." 2019 IEEE/CVF CVPR.

Overview of Multiscale PCGC

□ Pipeline

- AutoEncoder (AE) based on Sparse Convolution
- All data is in representation of **Sparse Tensor** $\{C, F\}$

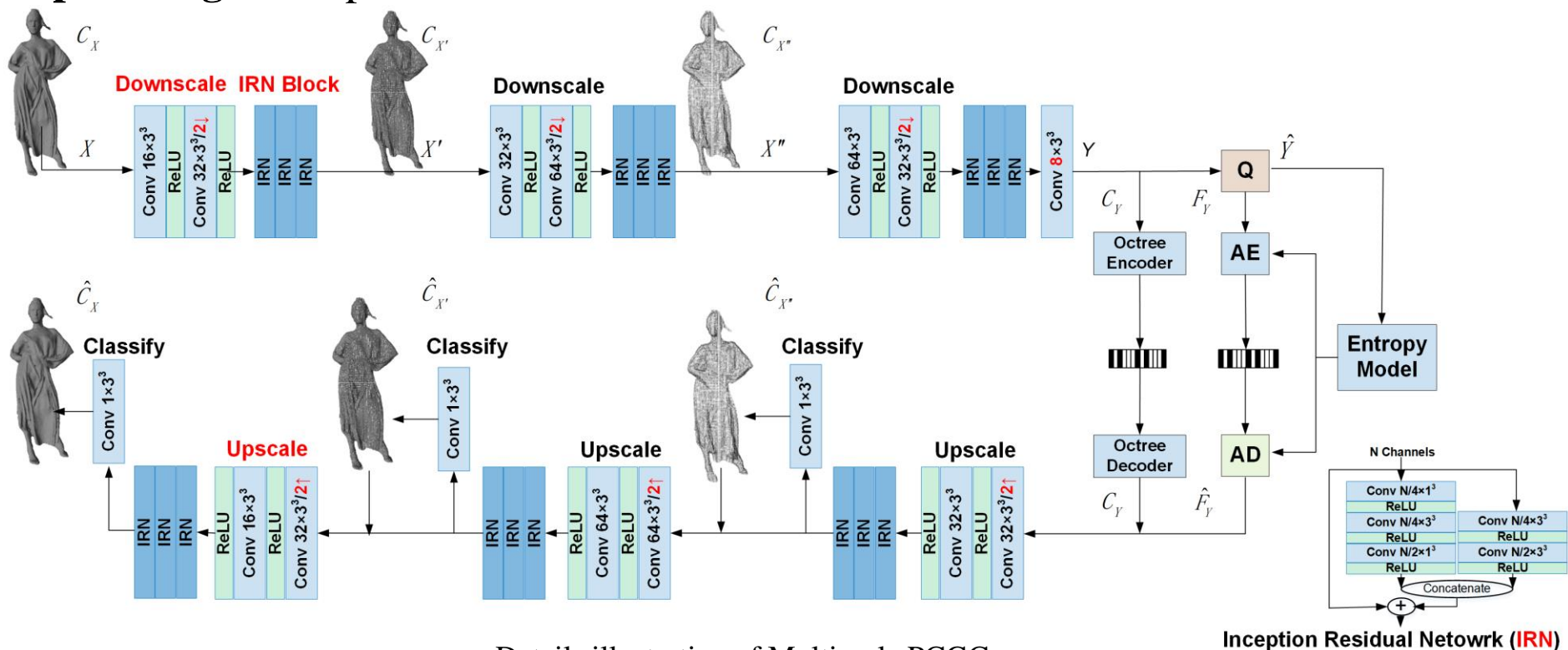


Overview of Multiscale PCGC

Sparse Convolution based Multiscale Resampling

□ Network Details

- **Basic Unit:** Inception Residual Network (IRN)
- **Down-scaling:** Convolution with a stride of two
- **Up-scaling:** Transpose convolution with a stride of two



Binary Classification based Hierarchical Reconstruction



□ Steps

For each scale:

■ Upsampling

- Generate 8 sub-voxels from 1 voxel

■ Feature Augmentation

- Generate the probabilities of voxel-being-occupied

■ Classifying & Pruning

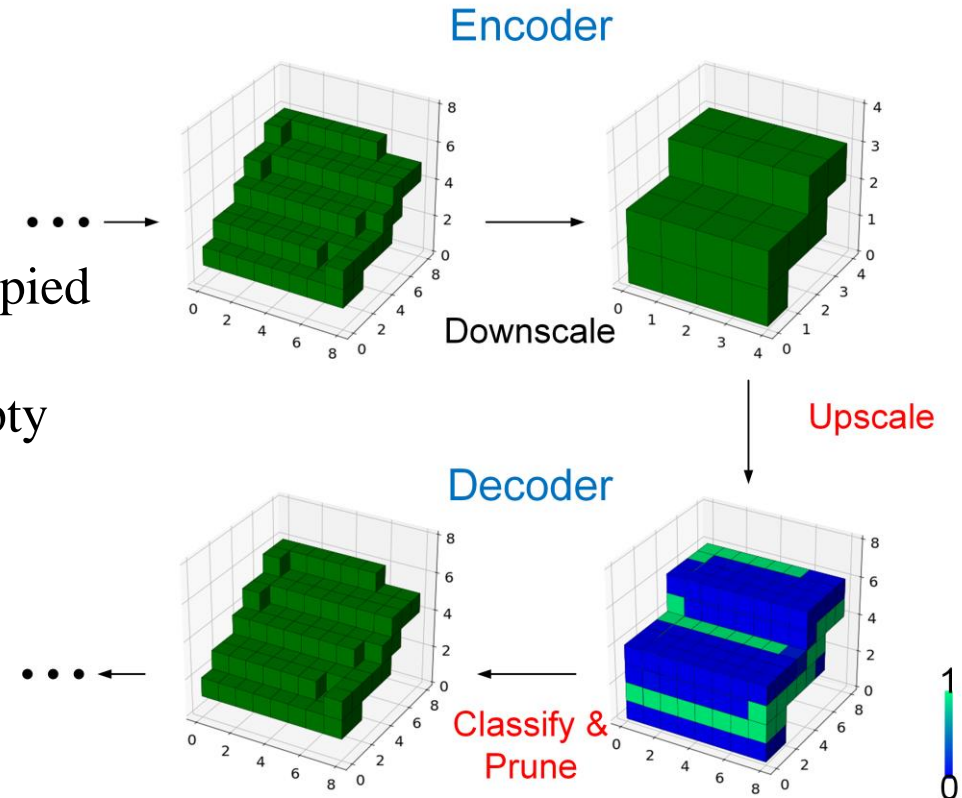
- Whether generated voxels are occupied or empty

□ Training Loss

- Multiscale Binary Cross Entropy (BCE) Loss

□ Inferring Method

- Binary Classification based on **Adaptive Thresholding**



Binary Classification based Reconstruction

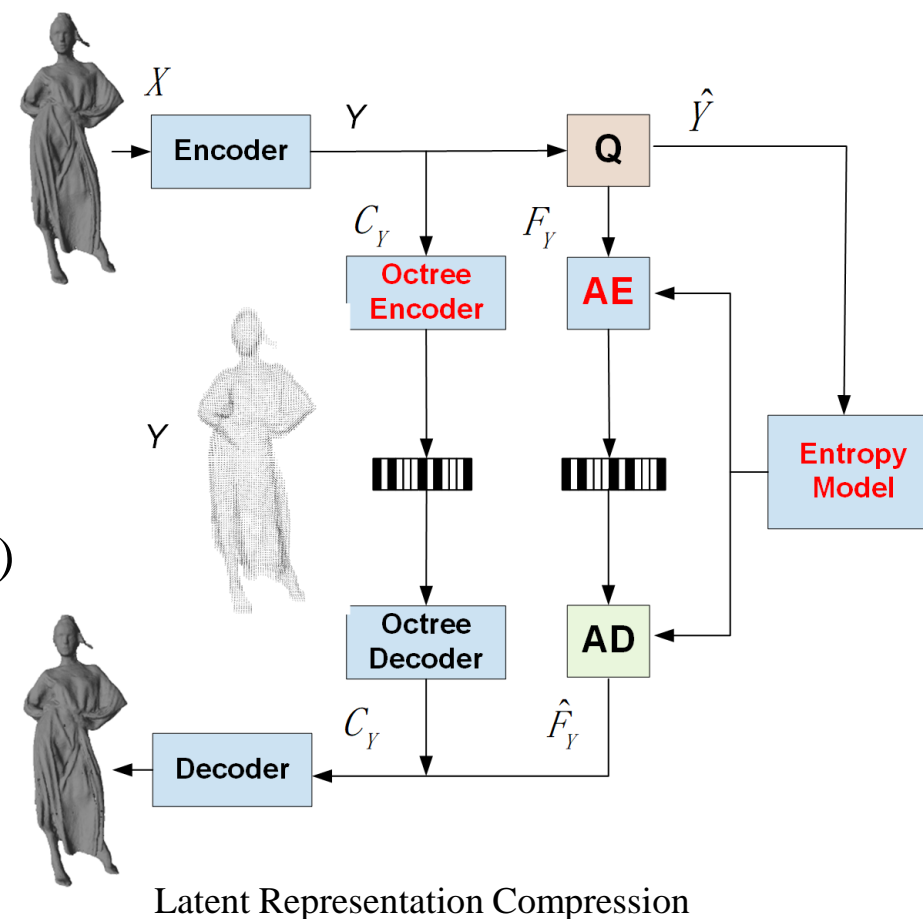
Latent Representation Compression

□ Coordinates C_Y

- Skeleton Key points
- Lossless Compression using **Octree Codec**
- $\approx 0.025\text{bpp}$

□ Features F_Y

- Implicitly Embedded Geometry Features
- Lossy Compression using Arithmetic Encoding (**AE**)
- Entropy Model based on Factorized Prior
 - Autoregressive Prior and Hyper prior can achieve additional BD-Rate gains



Experimental results

□ Experiment Settings

■ Dataset

- Training: ShapeNet
- Testing: 8iVFB, OwlII dataset, MVUB

■ Anchors

- G-PCC: octree, trisoup
- V-PCC
- Learned-PCGC

■ Objective Metrics

- Point-to-point Distance (D1)
- Point-to-plane Distance (D2)

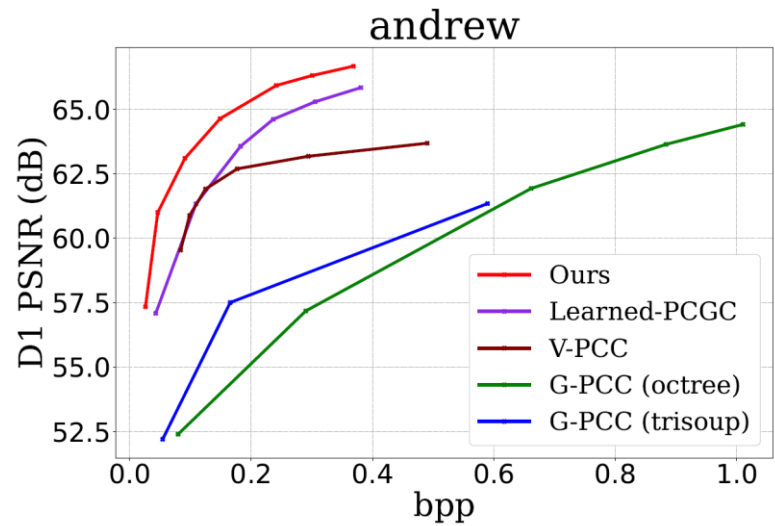
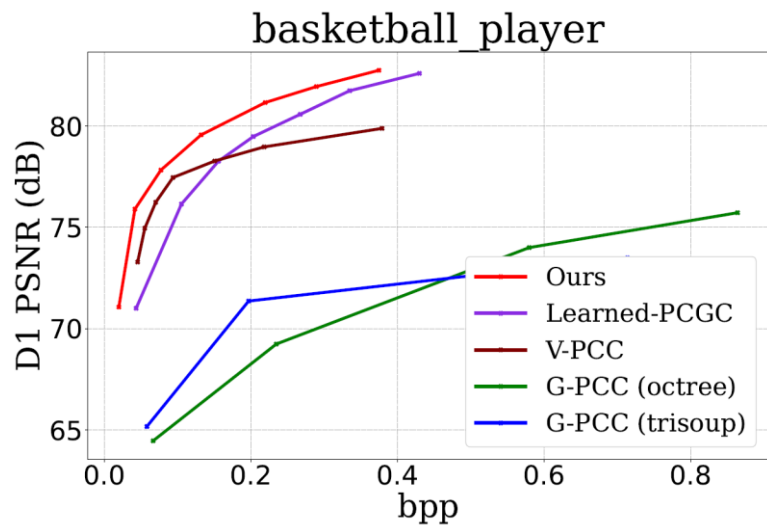
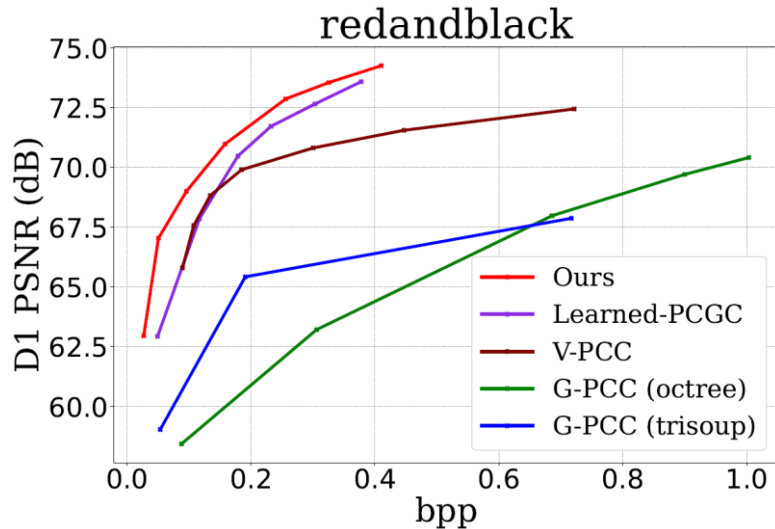
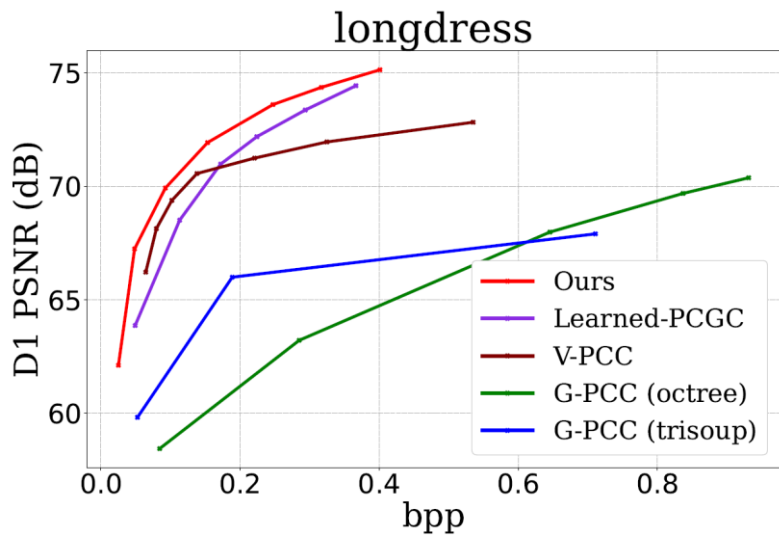
□ Performance Evaluation

- \approx **40%** BD-Rate gains against **V-PCC**
- $>$ **70%** BD-Rate gains against **G-PCC**
- $>$ **30%** BD-Rate gains against **Learned PCGC**

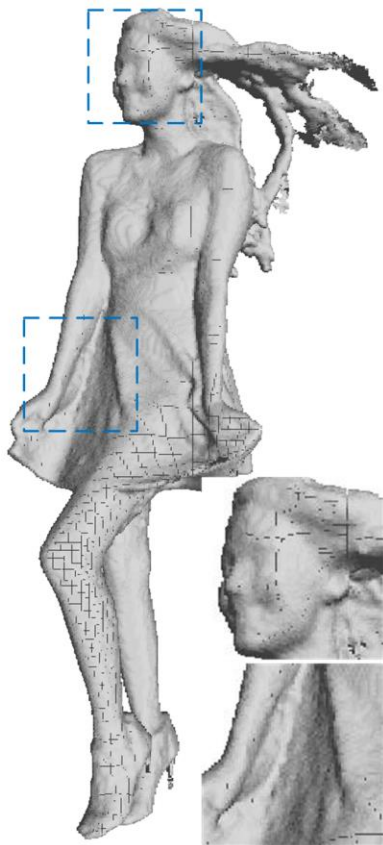
BD-Rate Gains against other compression methods using D1 and D2 distortion measurements.

	V-PCC		G-PCC (octree)		G-PCC (trisoup)		Learned-PCGC [4]	
	D1	D2	D1	D2	D1	D2	D1	D2
8iVFB	-39.4	-41.8	-90.8	-84.7	-78.5	-72.8	-36.4	-32.6
OwlII	-38.4	-35.2	-94.8	-90.5	-90.9	-79.1	-50.8	-43.8
MVUB	-60.6	-53.5	-90.4	-83.4	-87.8	-79.7	-46.7	-39.0
Average	-47.7	-45.1	-91.5	-85.4	-84.7	-76.9	-43.4	-37.4

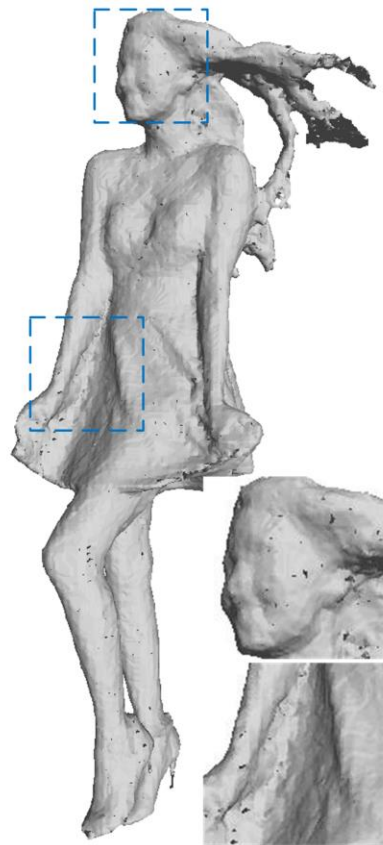
Objective Comparison



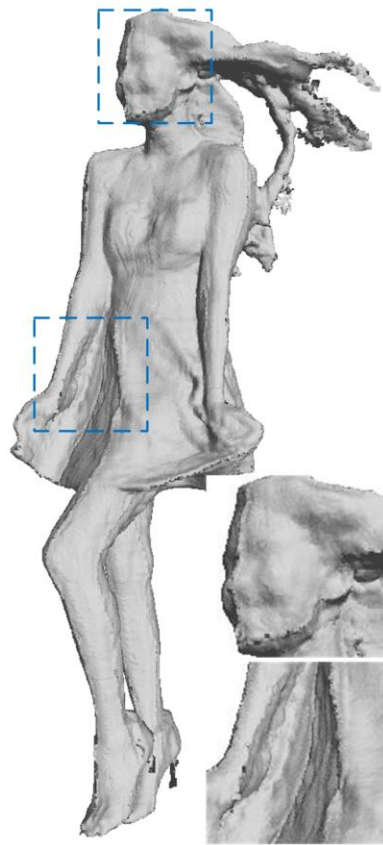
Subjective Comparison



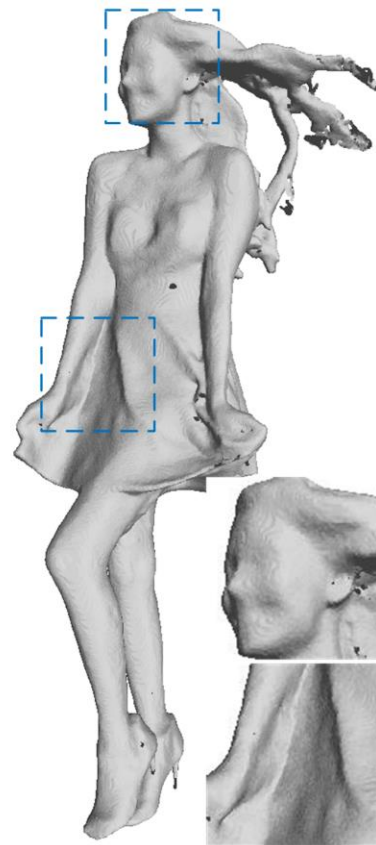
G-PCC (octree)
211242
0.305bpp 63.20dB



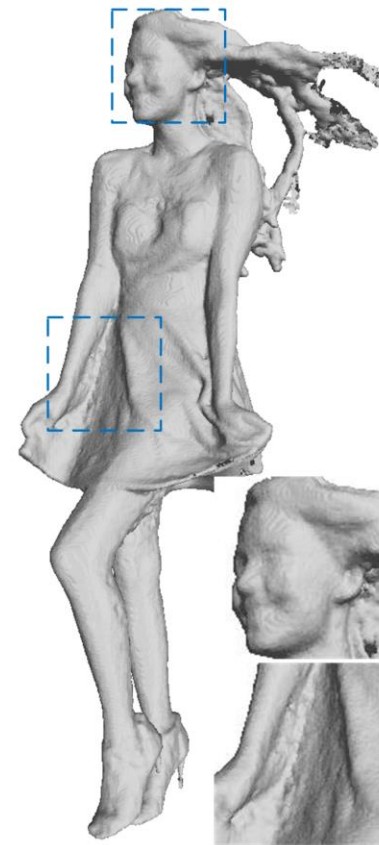
G-PCC (trisoup)
559054
0.190bpp 65.42dB



V-PCC
791645
0.184bpp 69.89dB



Ours
757691
0.157bpp 70.97dB



Ground Truth
757691 points

Complexity Comparison

□ Runtime comparison of different methods

	V-PCC	G-PCC (octree)	G-PCC (trisoup)	Learned-PCGC	Ours (Update)
Enc (s)	103.4	1.6	8.1	9.3	1.6 (0.80)
Dec (s)	0.7	0.6	6.6	9.5	5.4 (0.82)

Benchmarked on a workstation with an Intel Core i7-8700 CPU and Geforce GTX 1070 GPU

□ Complexity comparison of multi-scale and single-scale reconstruction

	Multi-scale reconstruction / Single-scale reconstruction
running memory	1/4
runtime	1/3

□ Contribution

- Introduce a novel **multiscale PCGC** method based on **sparse convolution**.
- The proposed method is more **computationally and memory efficient** than the previous Learned PCGC.
- The proposed method achieves **> 40%** BD-Rate gains over the SOTA **V-PCC**.

□ Future Woks

- Extend this work to include the color attributes and sparse PCs.
- Use quality measures that better match subjective perception.

Thank you for your attention!

More details can be found on <https://njuvision.github.io/PCGCv2/>