A Survey on 3D Point Cloud Compression Using Machine Learning Approaches

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- Introduction
- Autoencoders
- Fully Connected Neural Networks
- Recurrent Neural Networks
- Conclusion

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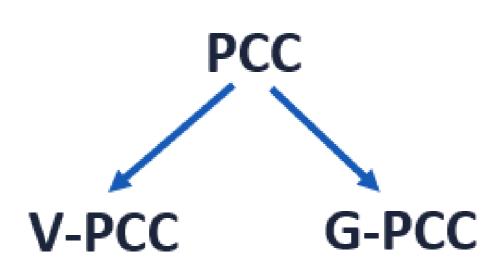


INTRODUCTION

- What is a Point cloud?
 - Geometry -> 3D coordinates
 - Attributes -> color information or normal vectors



- Applications: Cultural heritage, Autonomous driving, Robotics etc.
- Need of Point Cloud Compression.
- MPEG PCC standardization:



Conclusion



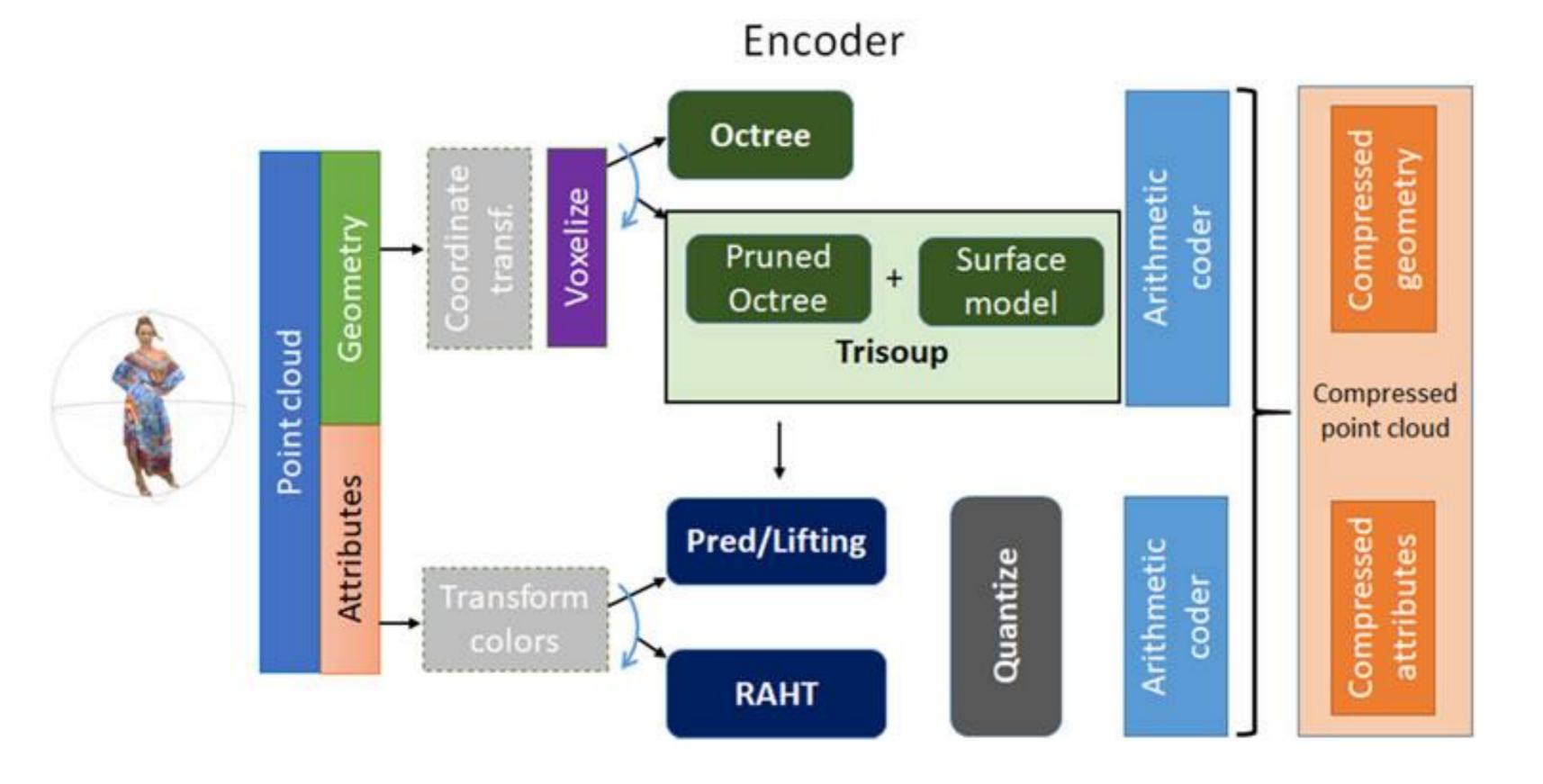






OVERVIEW

- Machine learning for media applications.
- Traditional Vs Machine learning based techniques.



Point Cloud							
Geometry			Attribute				
AE		RNN					
CNN	FCN		1				

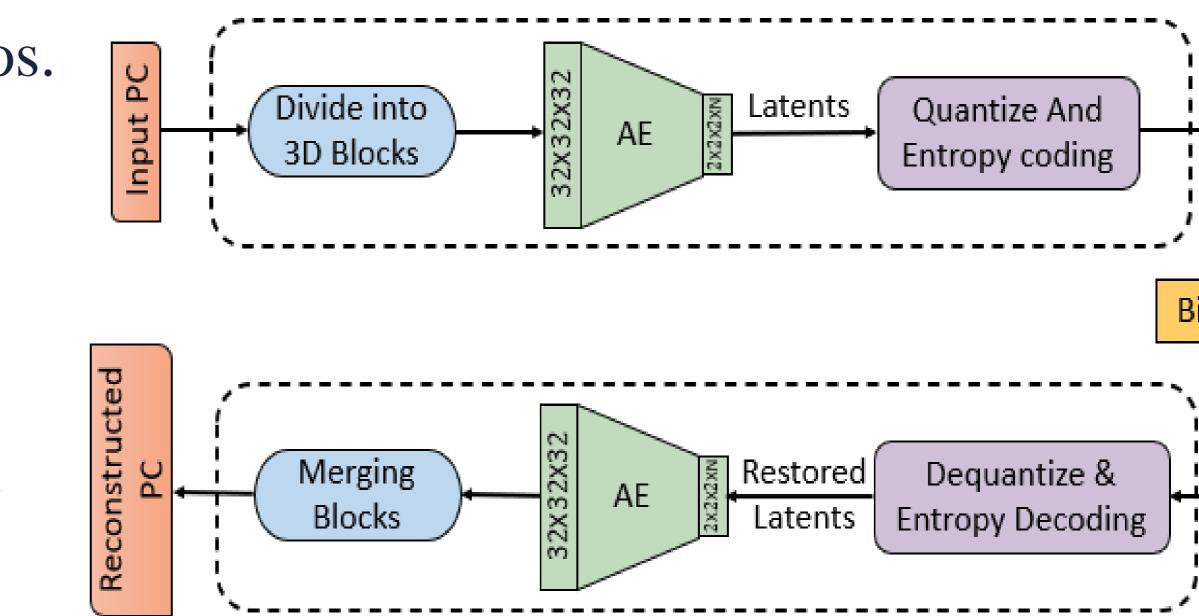


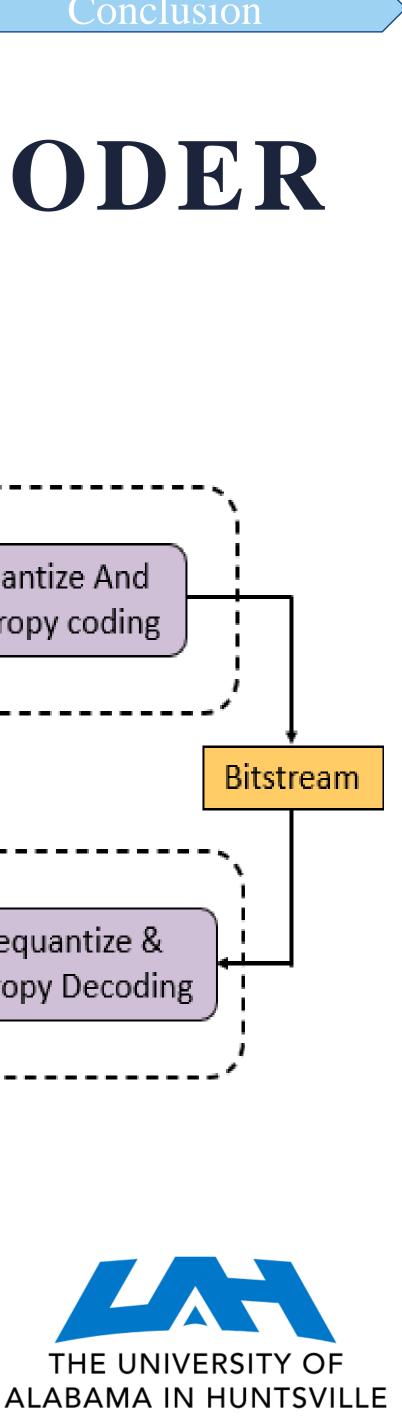




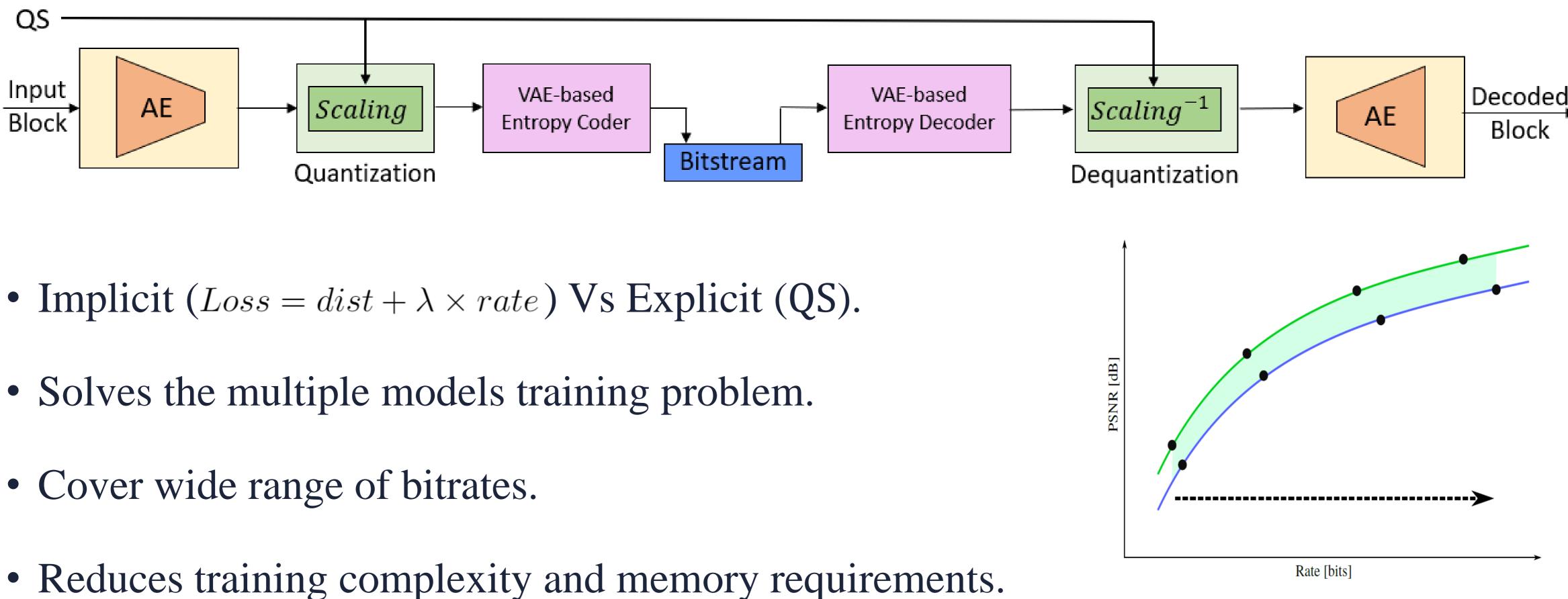
POINT CLOUD GEOMETRY AUTOENCODER

- CNNs: Most effective in extracting features.
- Characteristics found in images and videos.
- PCG-AE: Basic implementation.
- Occupancy signaled by '1' and '0'.
- Adaptive forward and Inverse Transform.
- Four models, for N = 32, 64, 96 and 128.
- MPEG dataset, PCL as benchmark, RD performance.





RD CONTROL THROUGH IMPLICIT AND EXPLICIT QUANTIZATION



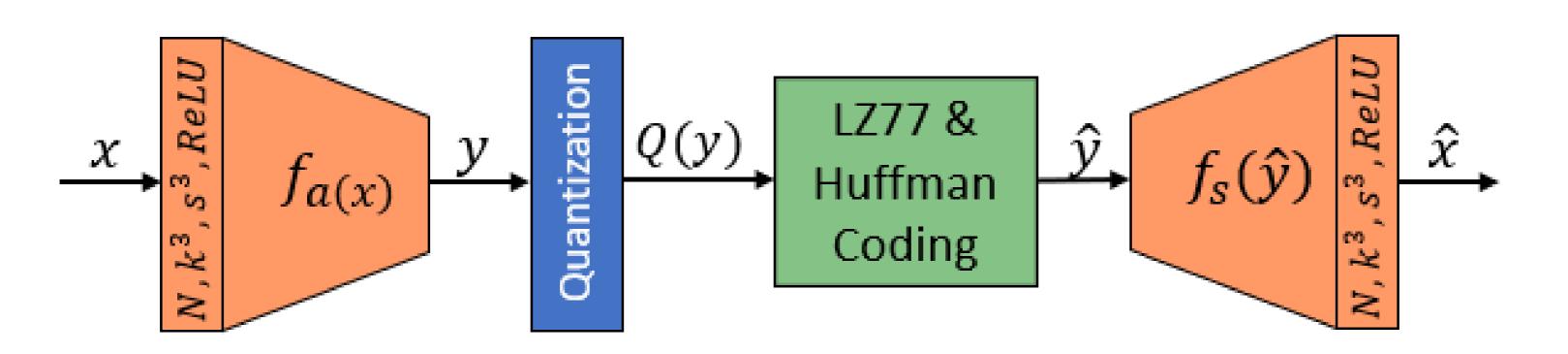






Introduction

LEARNED CONVOLUTIONAL TRANSFORMS



- Directly operates on voxels and decoding-> Classification problem
- Analysis and synthesis transform.
- Number of filters, filter size and strides.
- Convolution and transpose convolution.
- Trained on ModelNet40, Tested on MVUB, MPEG anchor (51.5%).









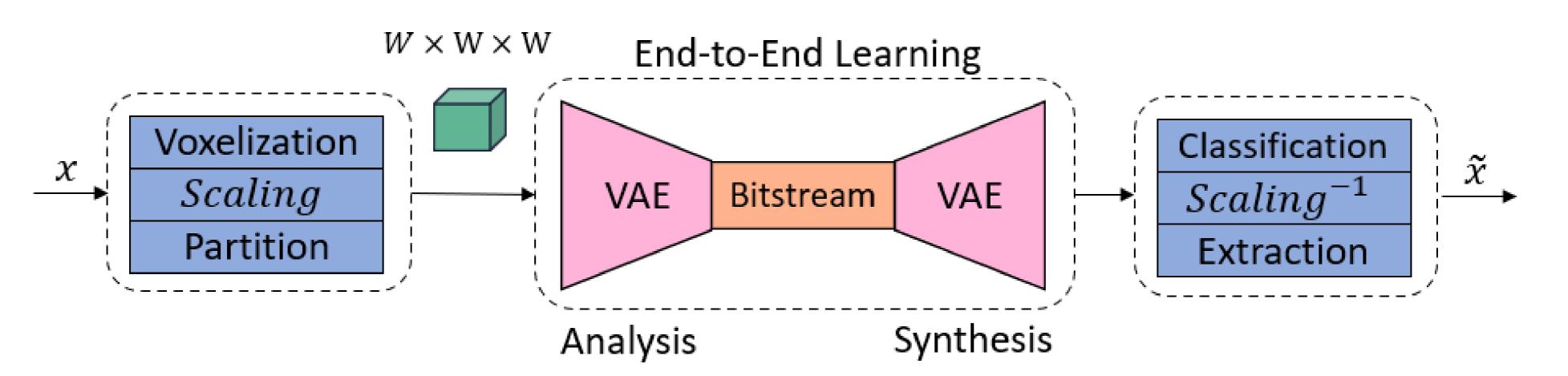








LEARNED PC GEOMETRY COMPRESSION



- Preprocessing: Voxelization is an optional step, Scaling $(\times s)$ to reduce sparsity, Partition into non-overlapping blocks and metadata.
- VAE based encoder with Voxeption Resnet (VRN).
- Extraction: Volumetric to raw format.
- End-to-End training by changing λ .
- Training: ShapeNet, Testing: MPEG and JPEG Pleno.
- Outperforms GPCC and PCL (>50%).

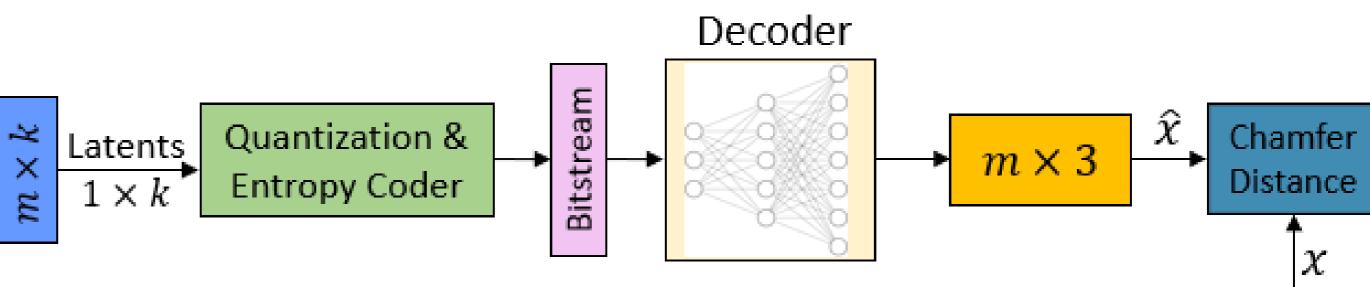




Input

DEEP AE-BASED POINT CLOUD GEOMETRY COMPRESSION

Encoder

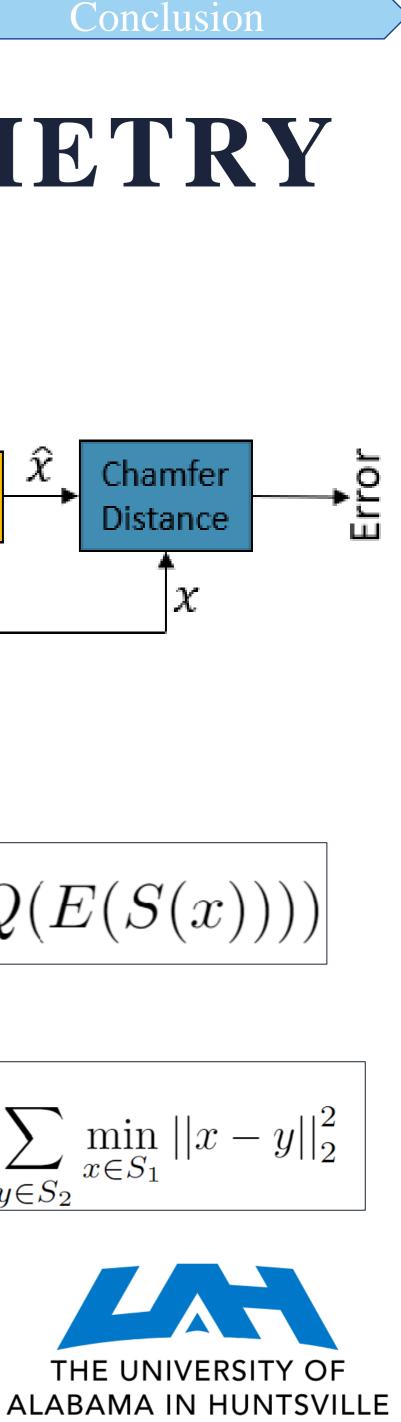


Sampling Merging 1D CNN layers $n \times 3$ $m \times 3$ Block

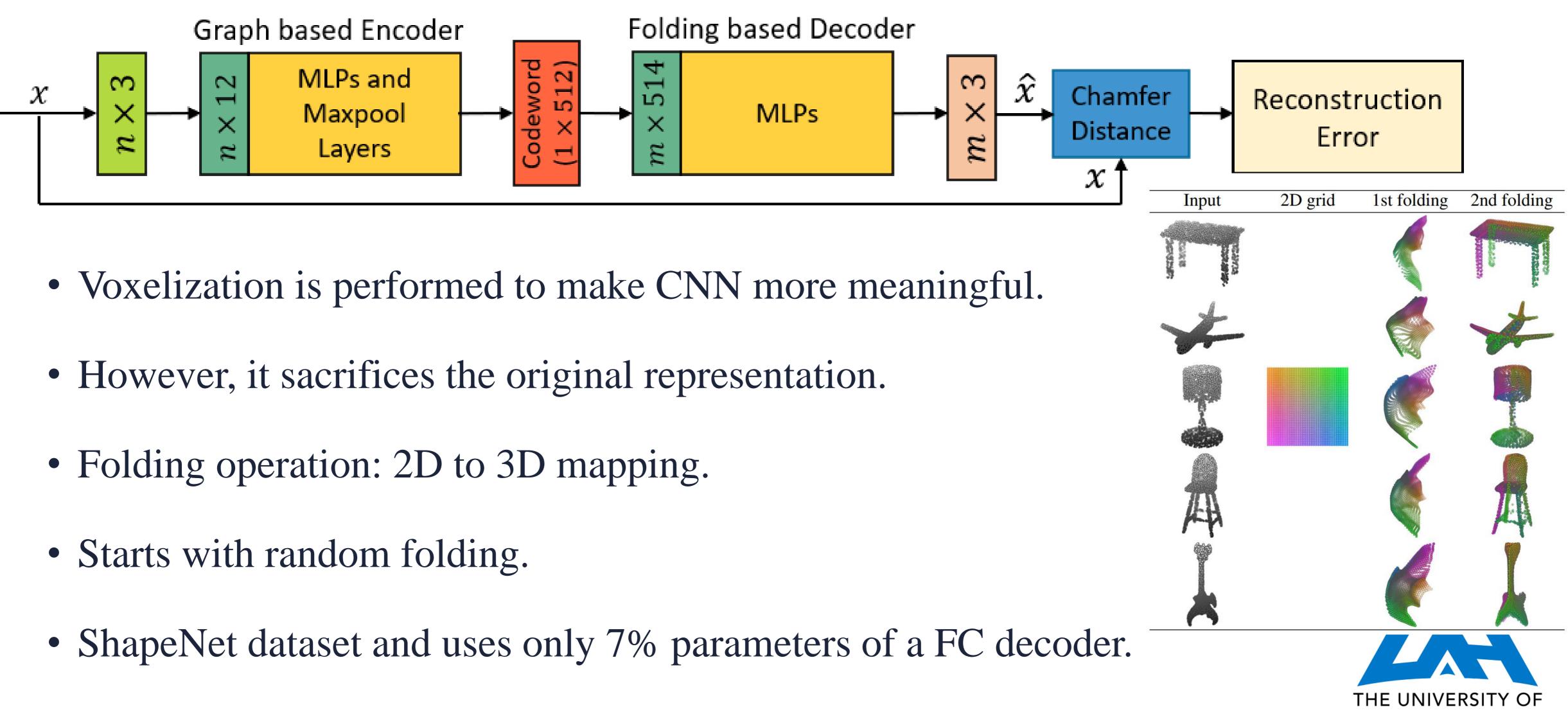
- Advantages of CNNs: Retain spatial relations and weight sharing.
- FCNN: It works directly on the geometry coordinate.
- Filters in each layer: 64, 128, 128, 256 and k (no. of input points).
- MPEG-GPCC: 73.17% average gain.

$$z = D(Q(E(S(x)$$

• ShapeNet with 90%, 10% split from a single class. $|d_{CH}(S_1, S_2) = \sum_{x \in S_1} \min_{y \in S_2} ||x - y||_2^2 + \sum_{y \in S_2} \min_{x \in S_1} ||x - y||_2^2$



FOLDING NET: DEEP GRID FORMATION

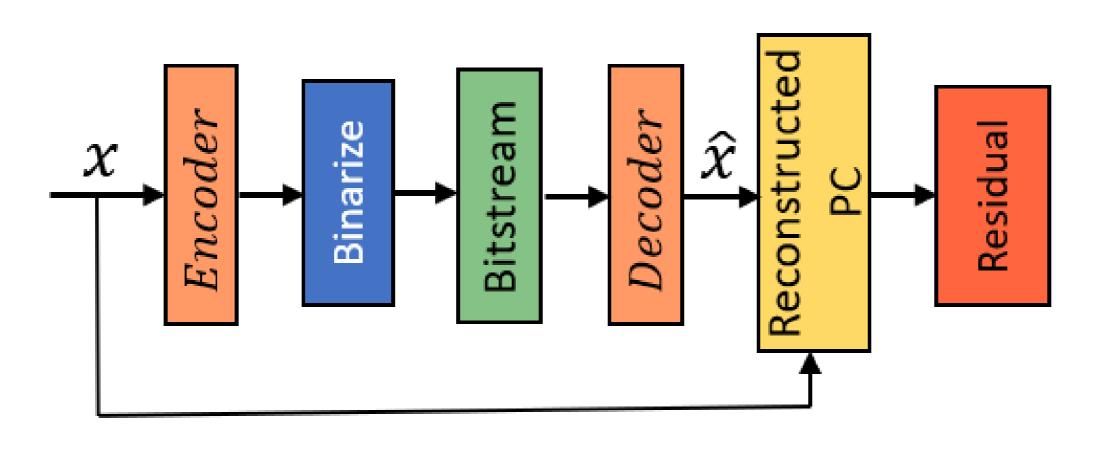


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RECURRENT NEURAL NETWORK (RNN)

- Limited research on usage of RNN for PCC.
- Focused on data from 3D LiDAR sensors (Driving data from 11 areas of Japan)
- Challenging data to compress and hence works on raw packets.
- Raw packets to 2D matrices losslessly.
- Uses residual blocks for accurate decompression.









CONCLUSION

COMPARISON OF MACHINE LEARNING BASED METHODS FOR PCC.

	Feature	Technique	Dataset	Benchmark	Metrics	Loss Function	Optim
CNN -	Geometry	CNN-based AE	MPEG	PCL	RD curve, D1	SGD (BCE)	Ada
	Geometry	CNN-based AE	MPEG	MPEG GPCC	RD curve, D1	RD Loss	-
	Geometry	3D CNN AE	Train: ModelNet40 Test: MVUB	MPEG GPCC	D1, D2	RD Loss	Ada
	Geometry	3D Stacked CNN	Train: ShapeNet Test :MPEG, JPEG	MPEG GPCC, PCL MPEG VPCC	D1, D2	RD Loss WBCE	-
FCNN -	Geometry	FCNN, MLPs	ShapeNet	MPEG GPCC	D1	RD Loss Chamfer Dist	Ada
	Geometry	Folding-based NN	ShapeNet ModelNet10	Fully connected decoder	_	Chamfer Dist	Ada
RNN -	Geometry	RNN	TierIV	Octree, JPEG	SNNRMSE	_	_

- An emerging research area of PCC using ML/DL.
- Most existing work focuses on geometry compression.
- Most common choice is CNN-based AE with few FCNN and even fewer RNN.









Thank You! Questions?





