Transform Decomposition Switching for Efficient Attribute Compression of 3D Point Clouds Using Neural Networks

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Outline

- Introduction
- Problem Statement
- Neural Network Structure
- Simulation Results
- Conclusion

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INTRODUCTION

- What is a Point cloud?

  - Geometry -> 3D coordinates

  - Attributes -> color information or normal vectors

Point Cloud	
Geometry	Attribute

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

PCC

V-PCC G-PCC

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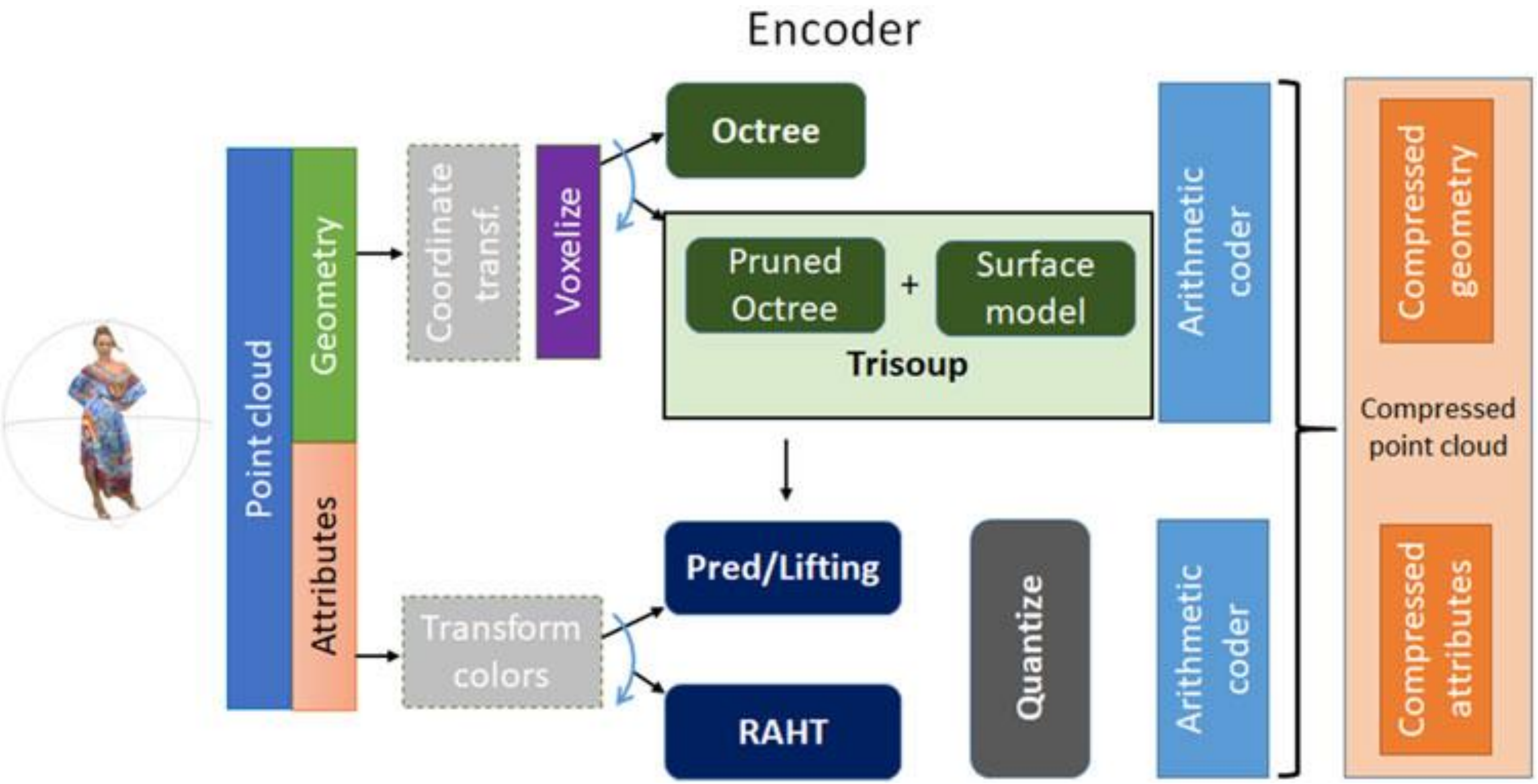
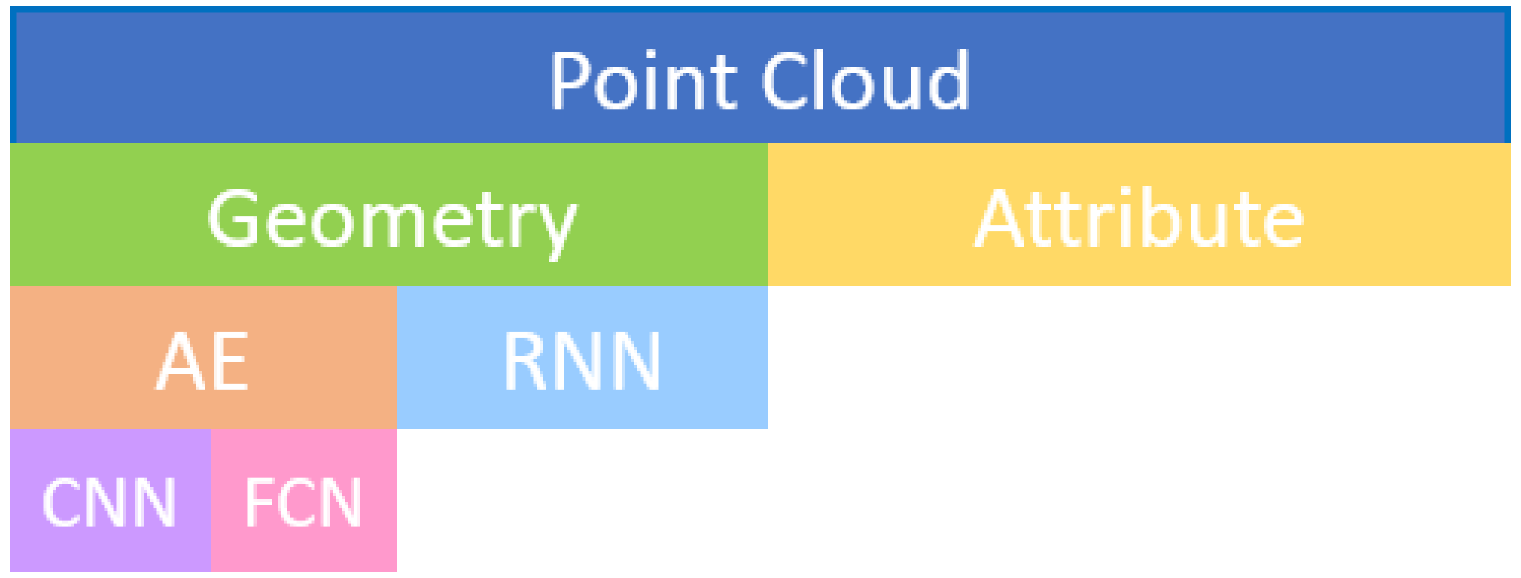
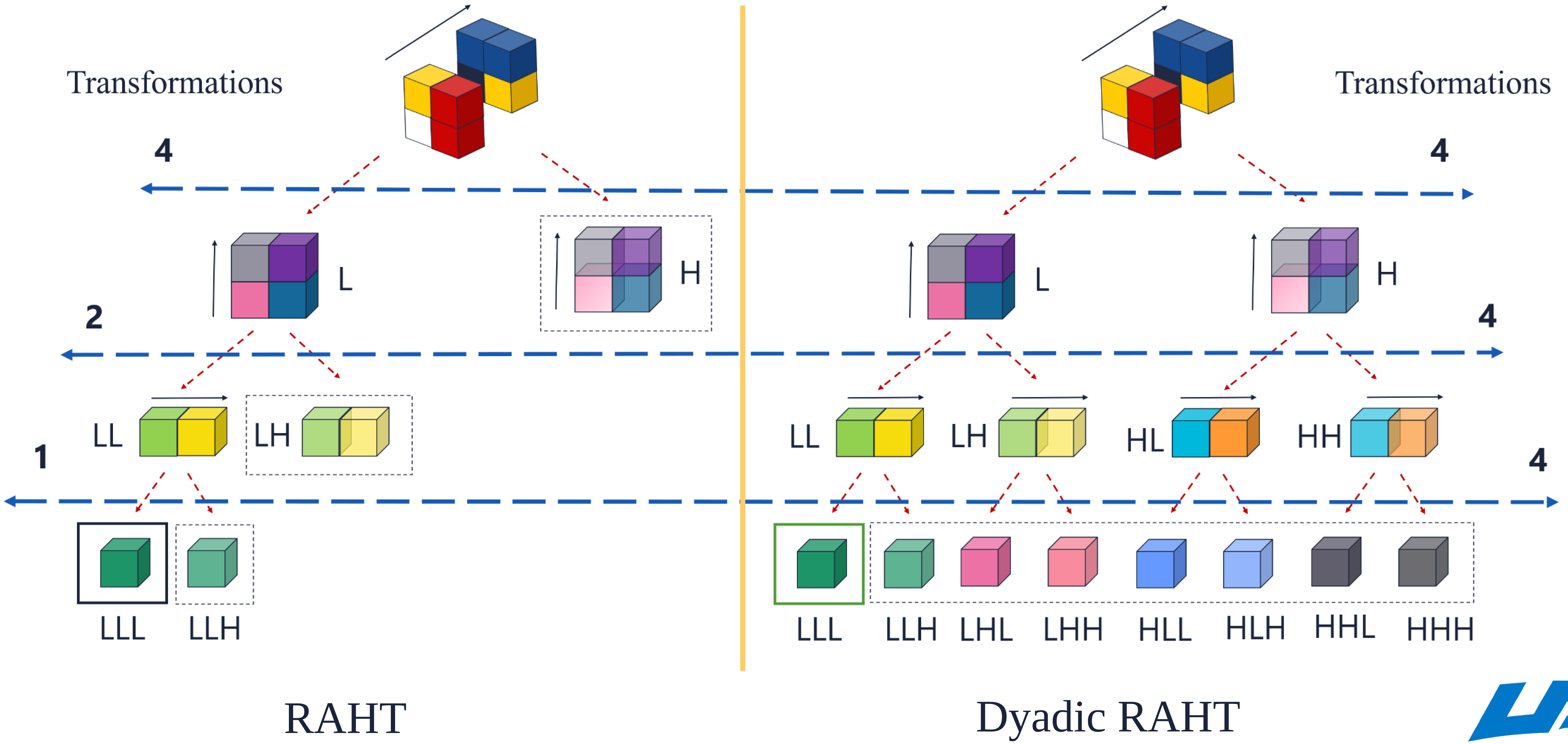
OVERVIEW

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





TYPES OF DECOMPOSITION



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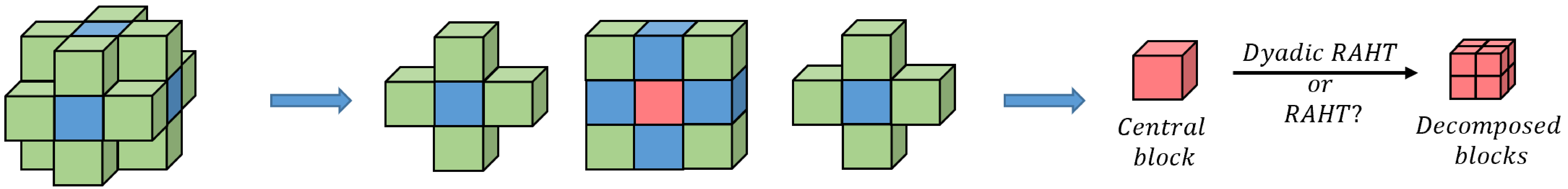
PROBLEM STATEMENT

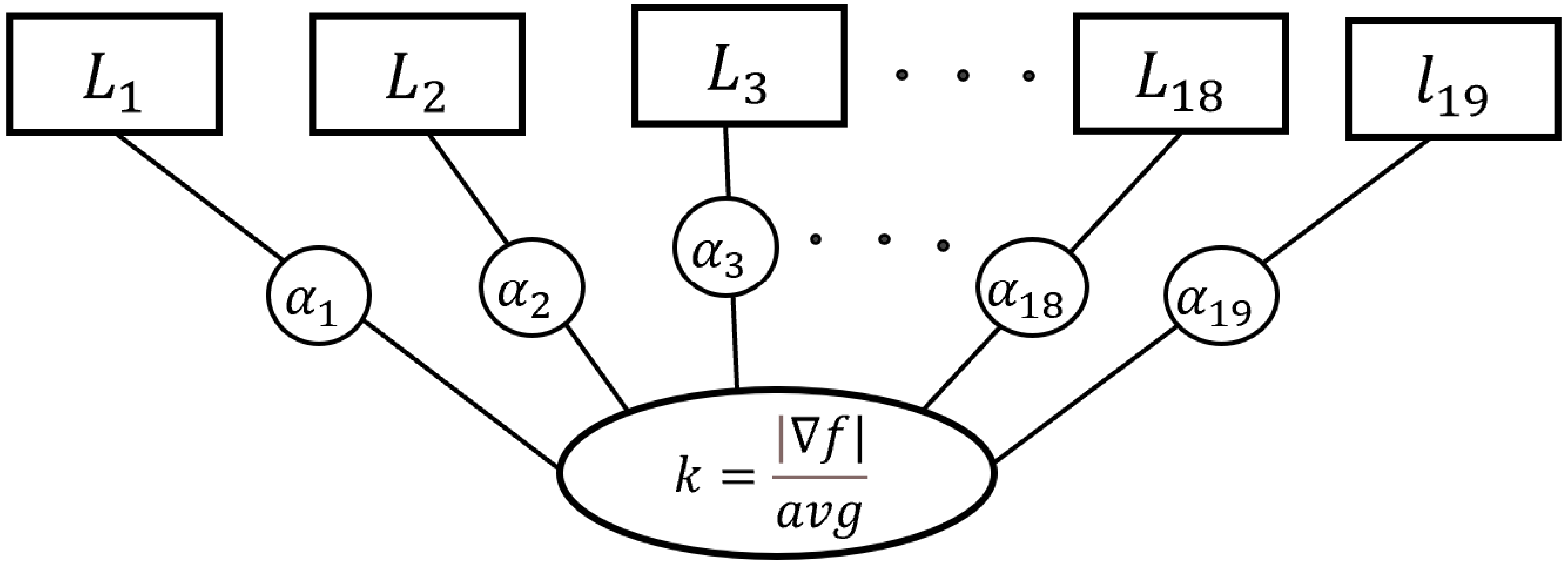
Edge detection based on the neighborhood



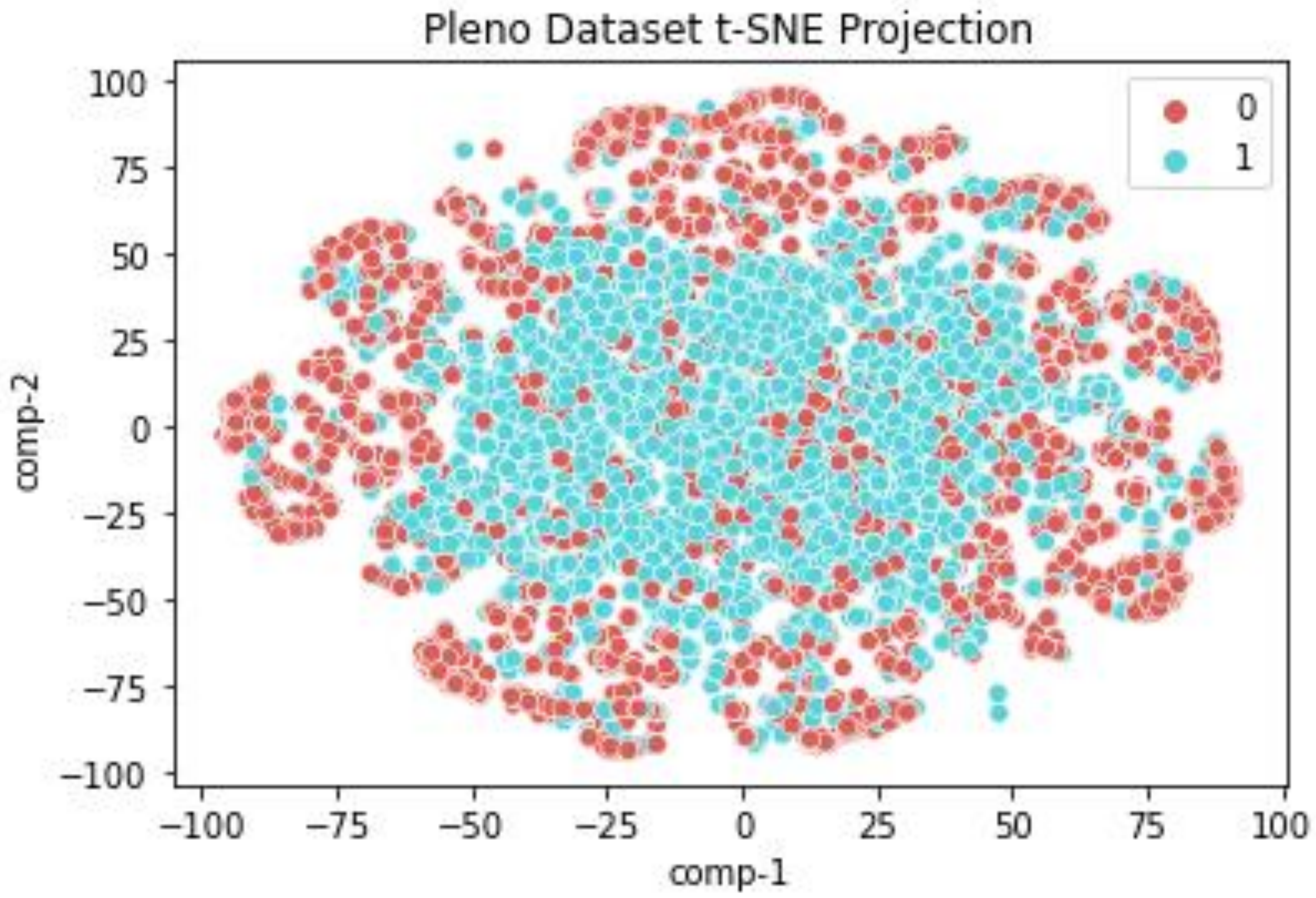
$(a)\ 18 - neigbourhood$ $(b)\ Seperated\ Neigbouring\ blocks$ $(c)\ Central\ block\ decomposition$

- Switching based on characteristics of the neighbors.
- RAHT for flat regions, Dyadic RAHT for discontinuous areas.
- Edge detection using Sobel filters.
- Limitation: threshold dependency.

PROBLEM STATEMENT



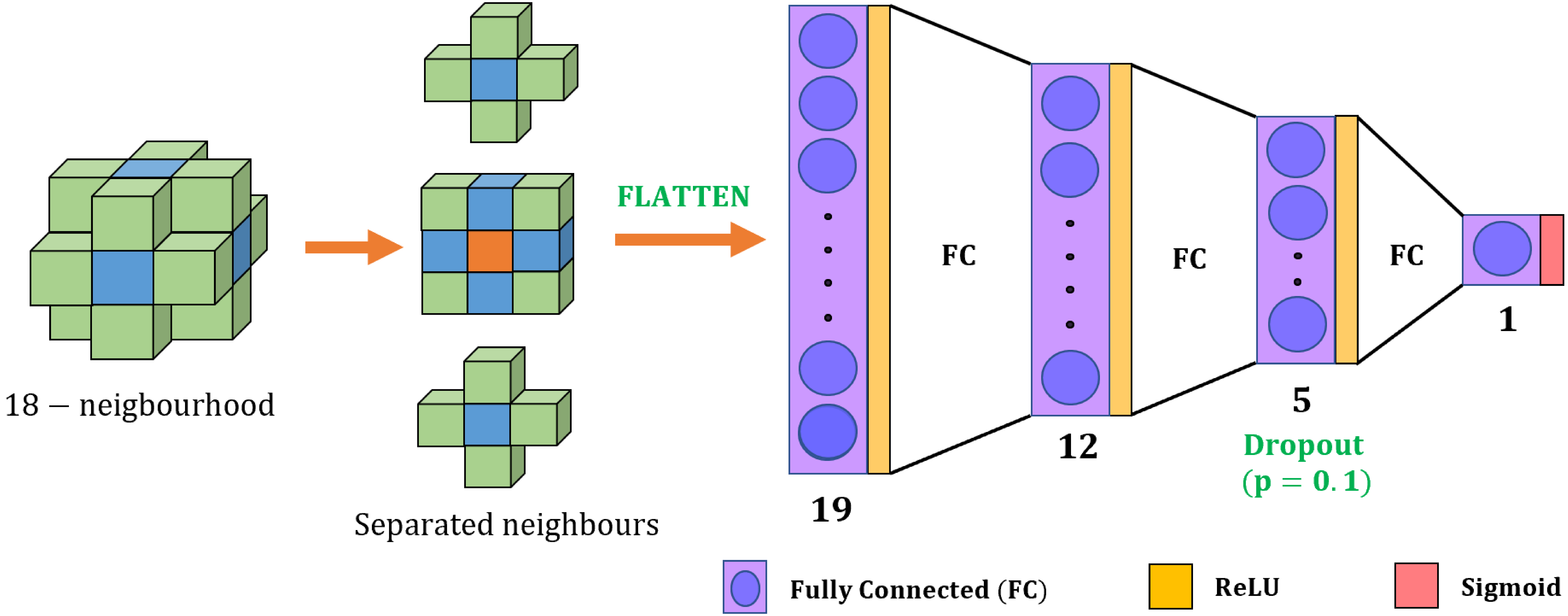
3D edge detection scheme



T-SNE visualization for Pleno data

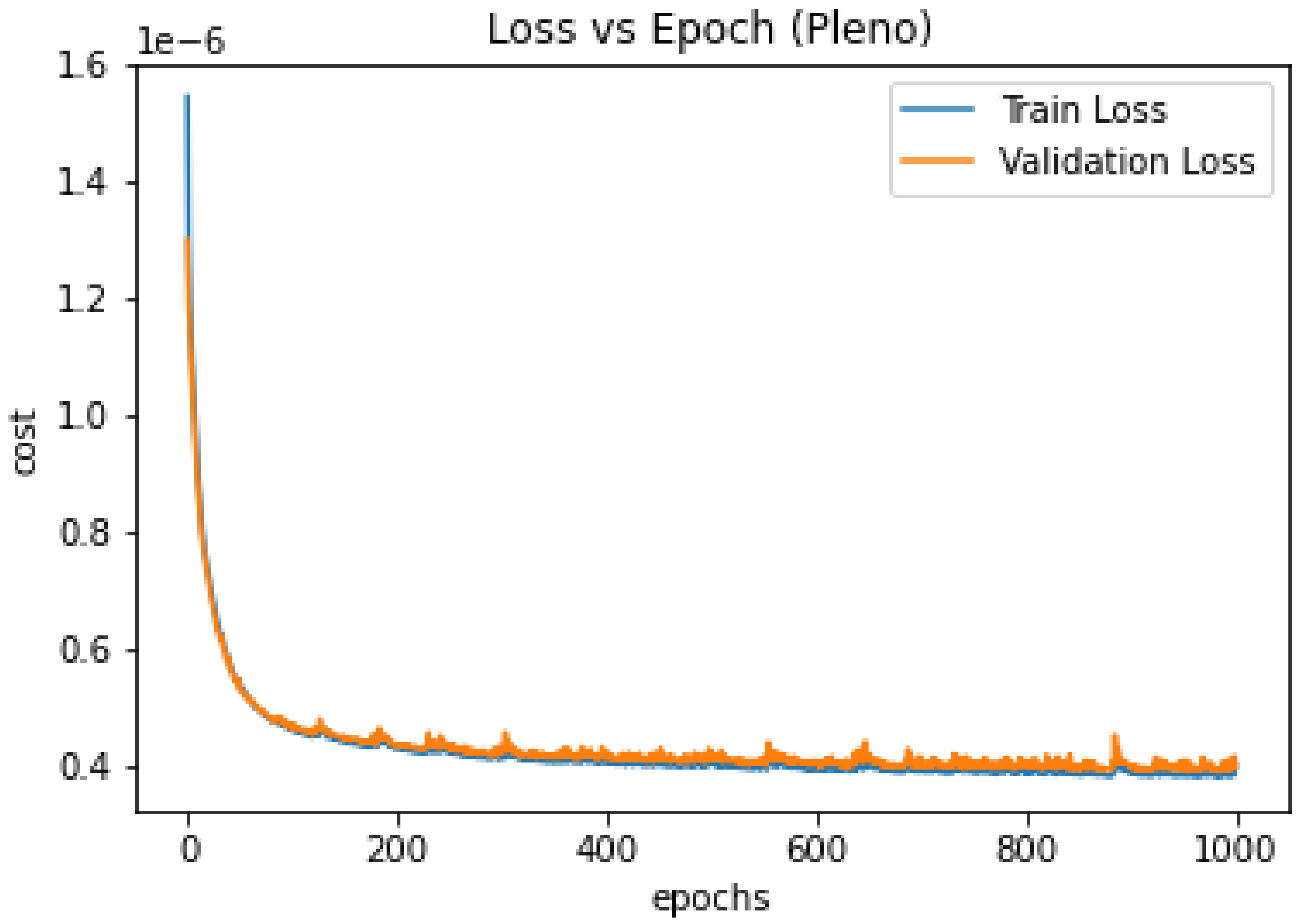
- The scheme can be perceived as Luma values multiplied by constant weights.
- k was chosen by trial and error, hindering generalized applicability.
- Data preprocessing: 18 Luma with targets and T-SNE plot for 15k points.

NEURAL NETWORK ARCHITECTURE

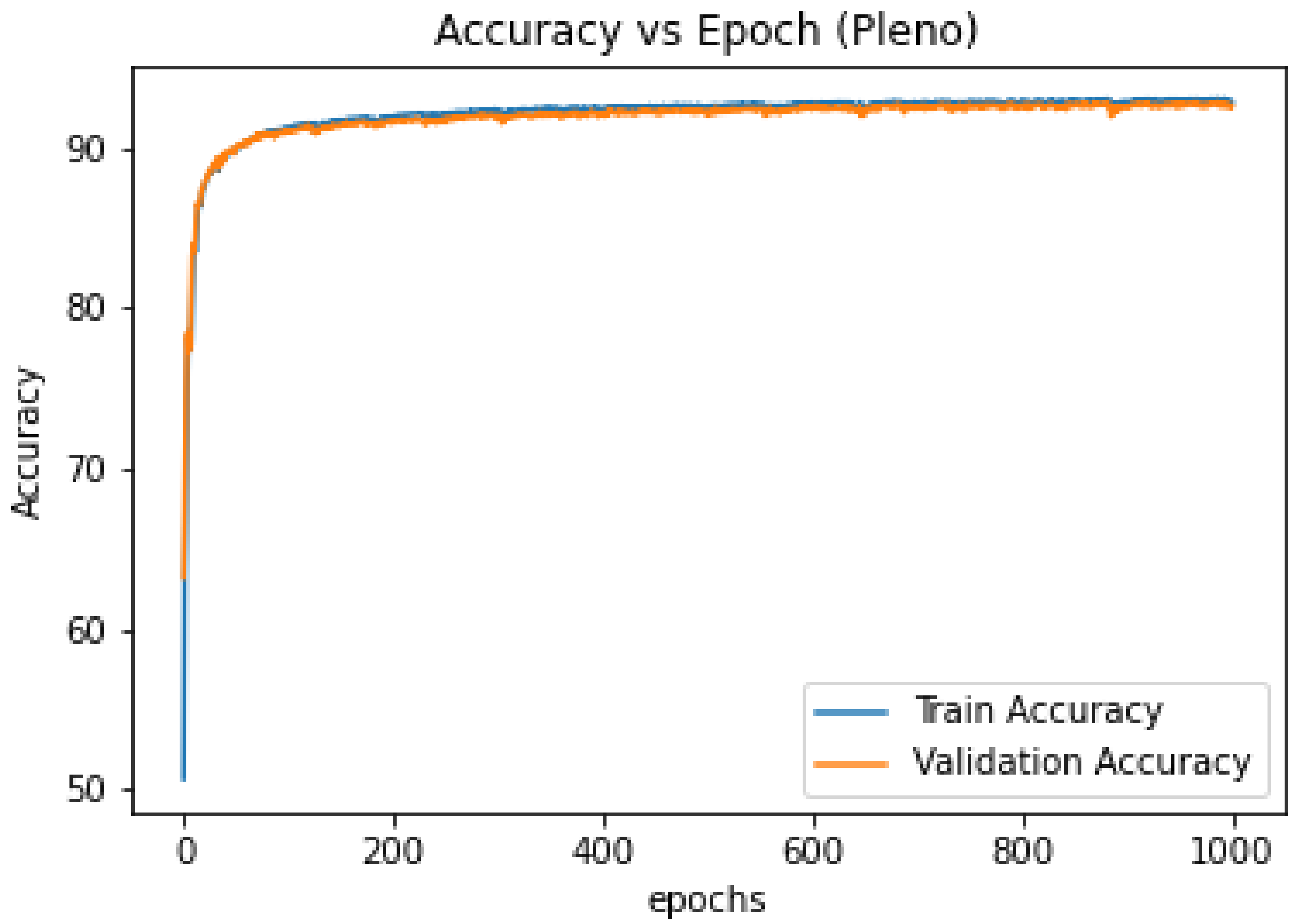


Fully connected neural network (FCNN) architecture

SIMULATION RESULTS



Training Vs validation loss



Training Vs validation accuracy

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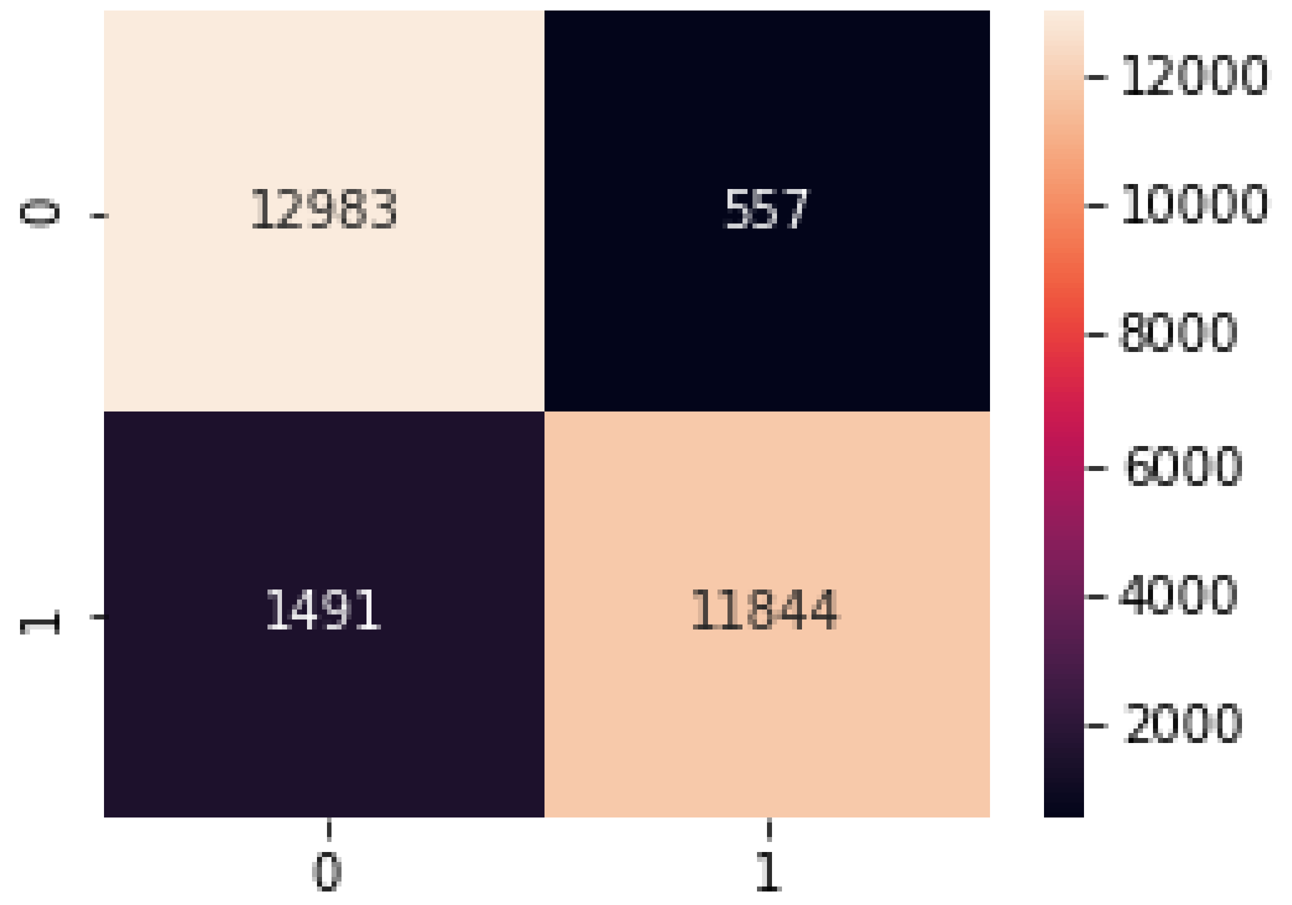
SIMULATION RESULTS

BD-RATE GAINS FOR PROPOSED SCHEME OVER DYADIC RAHT ON MICROSOFT VOXELIZED UPPER BODY (MVUB) DATASET.

Test Sequences	No. of Points	BD-rate Luma	BD-rate Cb	BD-rate Cr	Cumulative Gain
Andrew	277038	-0.9%	-8.4%	-3.6%	-12.9%
Phil	336323	0.2%	-5.4%	-2.1%	-7.3%
Ricardo	952178	-1.2%	-3.8%	-3.8%	-8.8%
Sarah	304528	-0.9%	-4.9%	-4.4%	-10.2%
David	302584	-2.9%	-3.7%	-2.9%	-9.5%

Confusion matrix



Sensitivity: 95.88%

Specificity: 88.88%

Precision: 89.69%

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SIMULATION RESULTS

Pleno dataset

CUMULATIVE BD-RATE GAINS FOR PROPOSED SCHEME OVER DYADIC RAHT ON 10 RANDOM FRAMES ON MVUB DATASET.

Test	Cumulative Gain										Average
Sequences	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Gain**
Andrew	-12.9%	-12.7%	-10.0%	-9.5%	-8.3%	-8.0%	-6.6%	-6.3%	-5.7%	-5.3%	-8.53%
Phil	-7.3%	-5.9%	-5.6%	-3.6%	-3.4%	-3.0%	-2.7%	-2.3%	-2.0%	-1.7%	-3.75%
Ricardo	-8.8%	-8.4%	-6.8%	-5.2%	-4.2%	-4.1%	-3.9%	-3.5%	-3.0%	-2.7%	-5.06%
Sarah	-10.2%	-8.5%	-8.2%	-6.6%	-5.6%	-4.9%	-4.4%	-4.2%	-2.4%	-2.2%	-5.72%
David	-9.5%	-8.2%	-7.6%	-7.3%	-5.7%	-5.4%	-5.2%	-4.6%	-2.7%	-2.5%	-5.87%

SIMULATION RESULTS

8i Voxelized full body dataset

BD-RATE GAINS FOR PROPOSED SCHEME OVER DYADIC RAHT ON 8I VOXELIZED FULL BODIES (8IVFB) DATASET .

Test Sequences	Cumulative Gain 1	2	3	4	Average Gain
Soldier	-4.8%	-4.0%	-3.8%	-3.4%	-4.0%
Loot	-8.5%	-6.9%	-5.5%	-3.9%	-6.2%
Long dress	-1.3%	-1.0%	-0.6%	-0.4%	-0.825%
Red and Black	-3.0%	-1.9%	-1.6%	-1.5%	-2.0%

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CONCLUSION

- Neural network-based approach for compression of static PC.
- Addressed the threshold dependency problem.
- Main steps: data collection, training SNN, deploying trained network.
- Compared to MPEG-GPCC with only Dyadic.
- Considerable cumulative gain on MVUB and minor gains on 8iVFB datasets.
- Future work: Could use other channels to improve accuracy and performance.

Thank You!

Questions?