POINT CLOUD GEOMETRY COMPRESSION VIA NEURAL GRAPH SAMPLING

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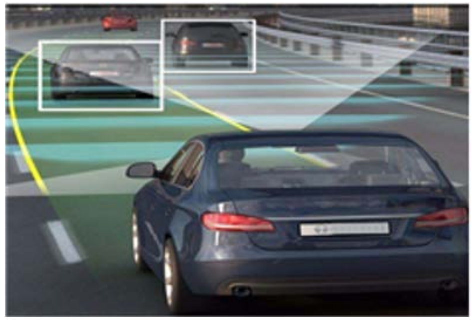
Background

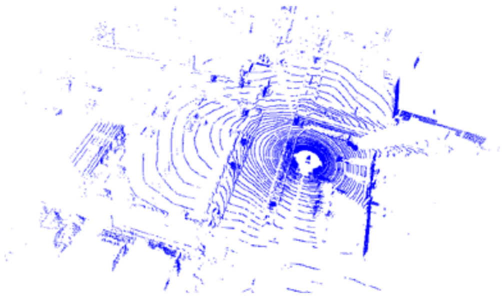
- **Emerging 3D Applications**
  - *Augmented reality*
  - *Autonomous driving*
- **Point Cloud**
  - *A set of points consists of geometry and attribute information*
  - *A 3D representation of real-life 3D objects and scenes*
- **Challenges for Geometry Compression**
  - *A huge amount of data*
  - *Irregular and unordered*

How to compress point clouds efficiently and effectively?

Augmented Reality



Autonomous Driving



3D Scene

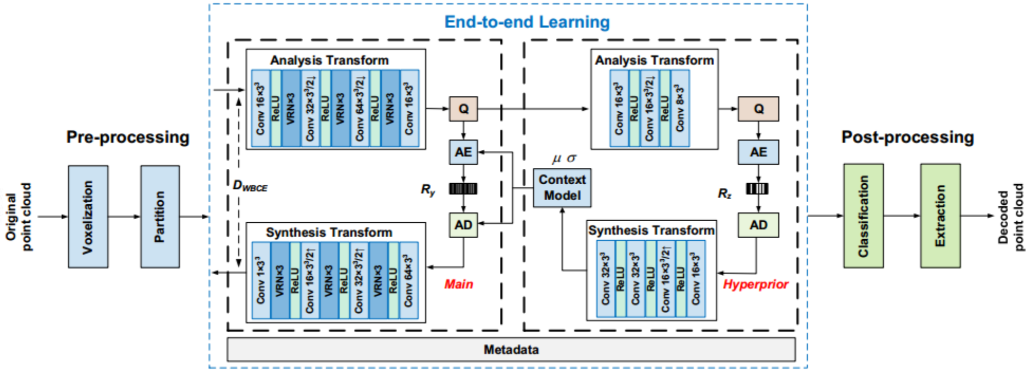
3D Object

Motivations

◻ *Volume-based Methods*

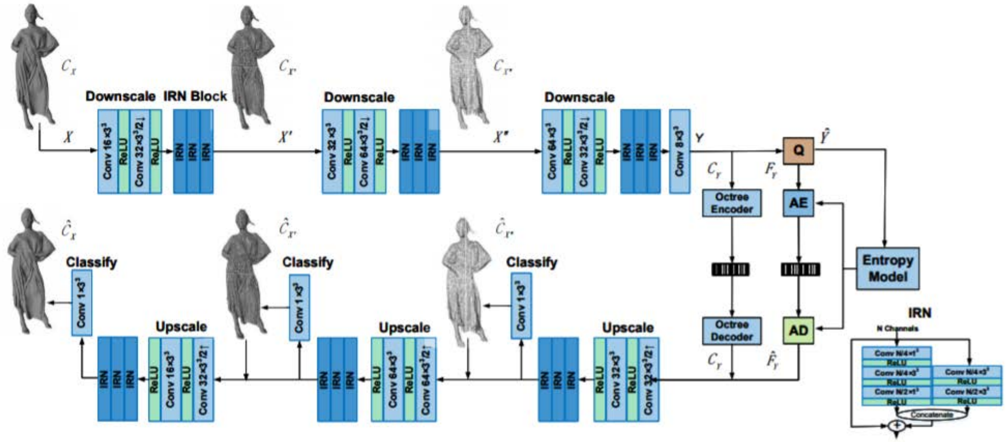
- ***3D CNN based Compression Network[1]***
  - *Preprocessing：Voxelization*
  - *3D CNN based Transformation*
  - *Distortion: Occupancy Classification loss*

  Drawbacks: High Space&Time Complexity $O(N^3)$



- ***3D Sparse CNN based Compression Network[2]***
  - *Preprocessing：Voxelization*
  - *3D Sparse CNN based Transformation*
  - *Hierarchical Reconstruction*
  - *Distortion: Occupancy Classification Loss*

  Drawbacks: Inefficient for Sparse Point Cloud



Volume-based methods shows unprecedented coding gains than MPEG V-PCC and G-PCC which utilize the traditional coding tools for dense point cloud compression!

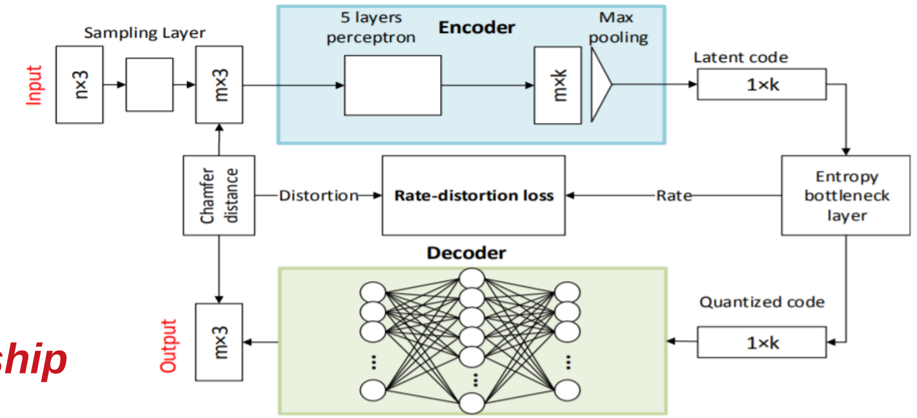
[1] Wang J, Zhu H, Liu H, et al. Lossy point cloud geometry compression via end-to-end learning[J]. IEEE Transactions on Circuits and Systems for Video Technology, 2021.
[2] Wang J, Ding D, Li Z, et al. Multiscale Point Cloud Geometry Compression[C]//2021 Data Compression Conference (DCC). IEEE, 2021: 73-82.

Motivations

☐ *Point-based Methods*

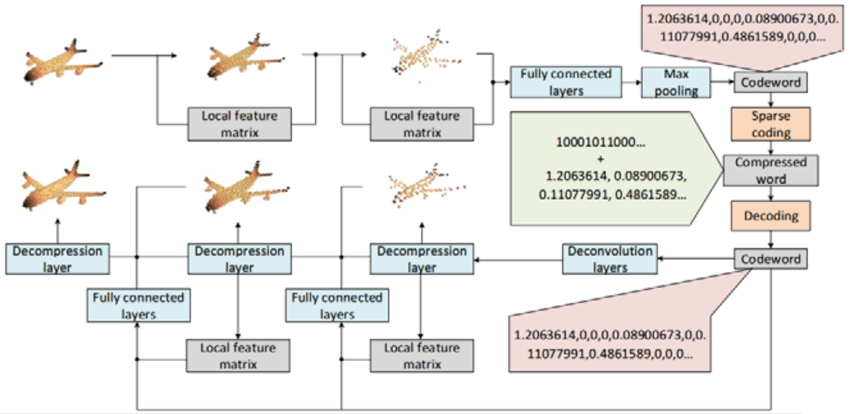
- ***PointNet based Compression Network[1]***
  - *Input Raw Points*
  - *PointNet based Autoencoder Structure*
  - *Distortion: Chamfer Distance Loss*

  Drawbacks: Cannot Capture Local Geometry Relationship



- ***PointNet++ based Compression Network[2]***
  - *Input Raw Points*
  - *PointNet++ based Autoencoder Structure*
  - *Hierarchical Reconstruction*
  - *Distortion: Chamfer Distance Loss*

  Drawbacks: High Computational Complexity with FPS



Point-based methods shows ability to process sparse point cloud and outperform the SOTA MPEG G-PCC at low bit rates!

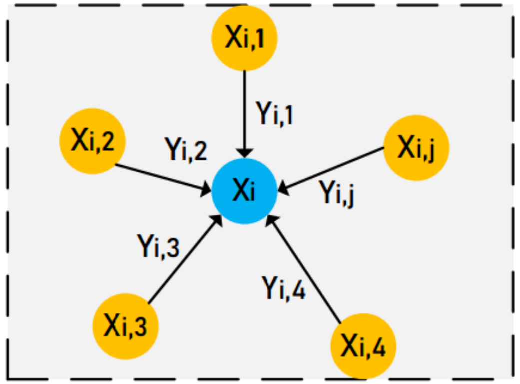
[1] Wei Yan, Shan Liu, Thomas H Li, Zhu Li, Ge Li, et al., “Deep autoencoder-based lossy geometry compression for point clouds,” arXiv preprint arXiv:1905.03691, 2019.
[2] Tianxin Huang and Yong Liu, “3d point cloud geometry compression on deep learning,” in ACM International Conference on Multimedia, 2019.

Proposed Method

☐ *How to improve?*

- ***To well exploit the local geometric correlation***
  - *Construct the local graph of each point*
  - *Aggregating neighbor information of each point*

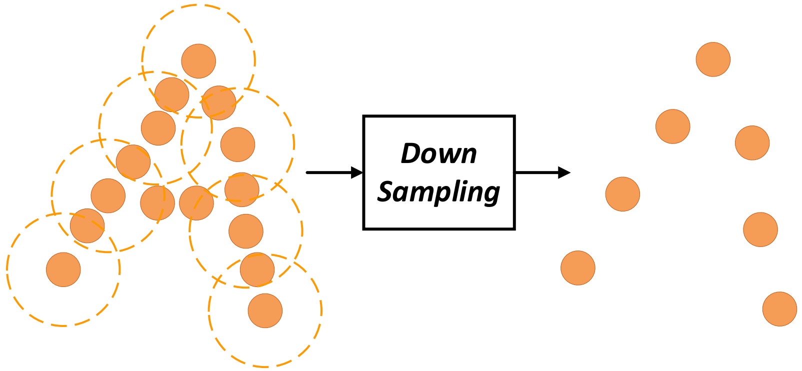
  Enrich the representation of original point clouds



KNN Graph

- ***To reduce computation complexity of sampling***
  - *Low complexity down-sampling operation*
  - *Matrix parallel process*

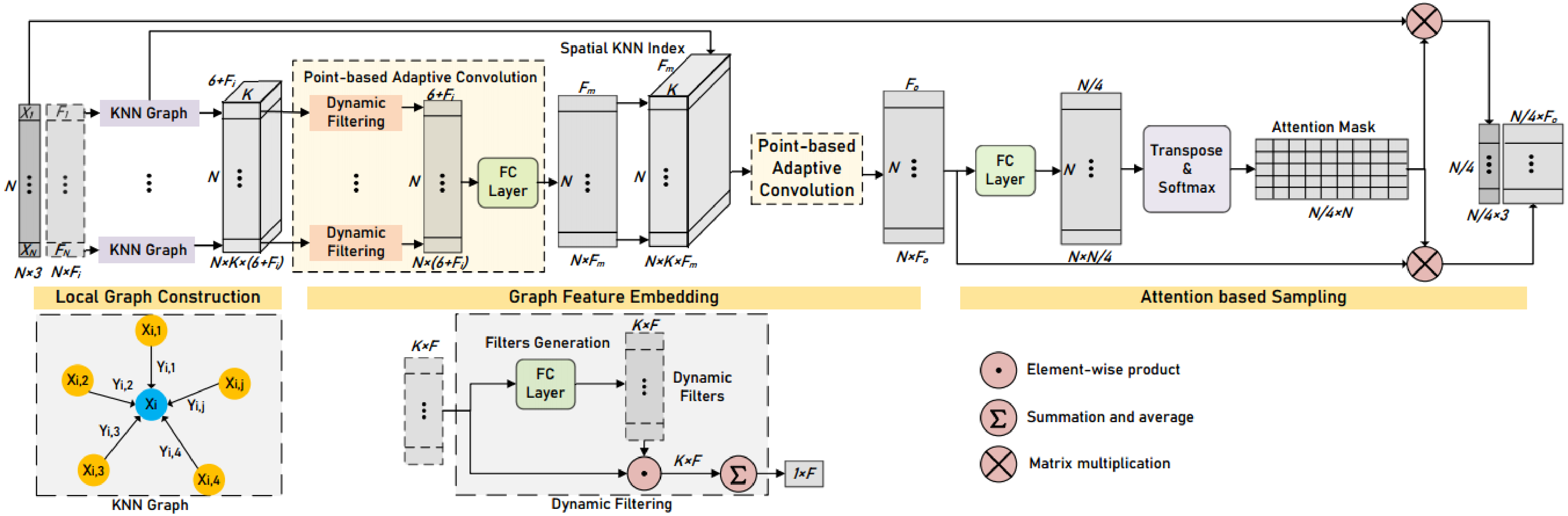
  Lower computational complexity during sampling



Proposed Method

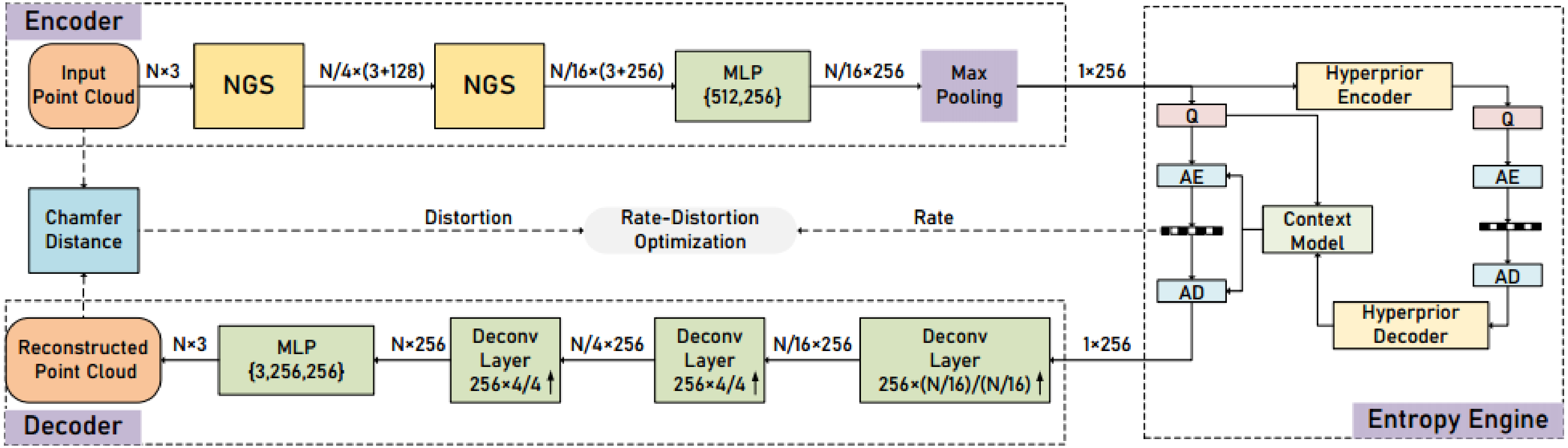
Proposed Neural Graph Sampling(NGS) Module

- ***Local Graph Construction:*** *Search for KNN to construct local graph of each point*
- ***Graph Feature Embedding:*** *Propose **Dynamic Filtering** to aggregating neighbor information*
- ***Attention based Sampling:*** *Select a representative subset of points to reduce spatial redundancy*



Proposed Method

- **_Autoencoder based E2E compression pipeline_**
  - ***Encoder:*** *Exploit stacked NGS Module to extract and aggregate local features*
  - ***Entropy Engine:*** *Utilize hyperpriors for accurate entropy modeling of latent features*
  - ***Decoder:*** *Layered deconvolutions for refining progressively the reconstructed point cloud*
  - ***Loss Function:*** *Chamfer Distance loss for distortion and RDO*



Results

Experiment settings

- ***Dataset***
  - *Training: ShapeNetCoreV2 train dataset*
  - *Test: ShapeNetCoreV2 test dataset*
- ***Anchor***
  - *PointNet based Autoencoder Structure[1]*
  - *PointNet++ based Autoencoder Structure[2]*
  - *MPEG G-PCC*
- ***Objective Metrics***
  - *Point-to-point Distance (D1)*
  - *Point-to-plane Distance (D2)*

Performance Evaluation

- *Our method's total test time of encoding and decoding process is much faster than [2] with FPS.*

Table: Average test time comparison

Method	Yan	Huang(VAE)	Ours
Test time	0.004s	0.291s	**0.016s**

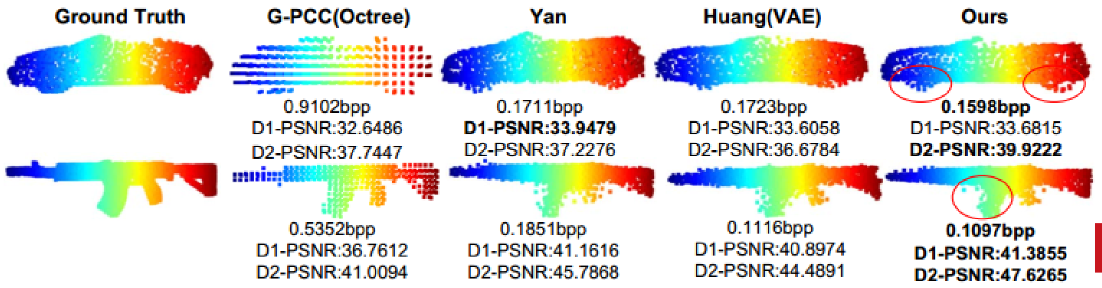
Performance Evaluation

- *Compared with other point-based learning PCC methods, our proposed method achieves the best performance.*

Table: BD-Rate Gains against other point-based methods using D1 and D2 distortion measurements.

Class	Ours vs Yan		Ours vs Huang(VAE)	
	D1	D2	D1	D2
Airplane	-68.15	-70.74	-38.80	-52.29
Pistol	-75.17	-86.30	-30.27	-59.00
Table	-70.11	-68.75	-39.35	-51.98
Chair	-65.12	-62.14	-39.14	-52.23
Average	**-69.63**	**-71.98**	**-36.89**	**-53.87**
Overall	**-74.38**	**-68.33**	**-49.01**	**-56.44**

- *Compared with all the anchors, our method achieves lower bit rate at almost the same PSNR.*



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Conclusion

Contributions

- *Introduce a three-step **Neural Graph Sampling (NGS)** to well exploit the unconstrained geometric correlation of input point cloud.*
- *The proposed method is **more computational and memory efficient** than the previous point-based E2E point cloud geometry compression methods.*
- *The proposed method achieves **> 49%** BD-Rate gains over the SOTA point cloud compression method.*

Future works

- *Extend this work to sparse large-scale point cloud geometry compression.*
- *Extend this work to compress point cloud attributes .*

Thanks!

Q&A

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