DHGCN: Dynamic Hop Graph Convolution Network for Self-Supervised Point Cloud Learning

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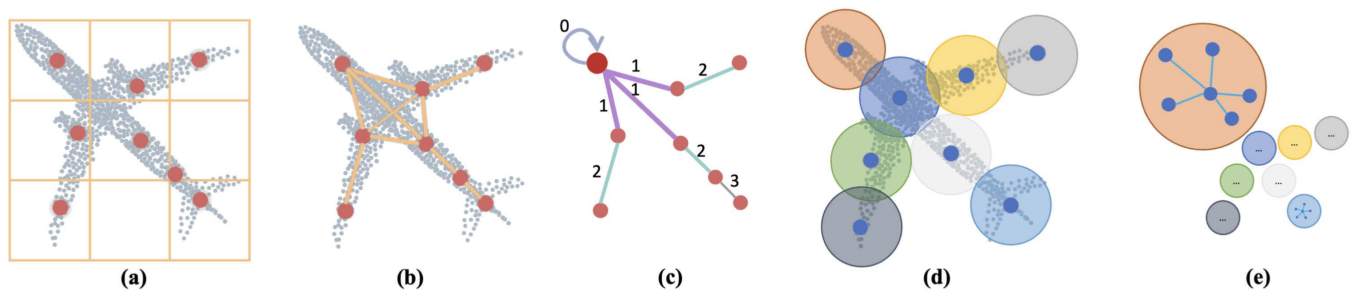
Contributions

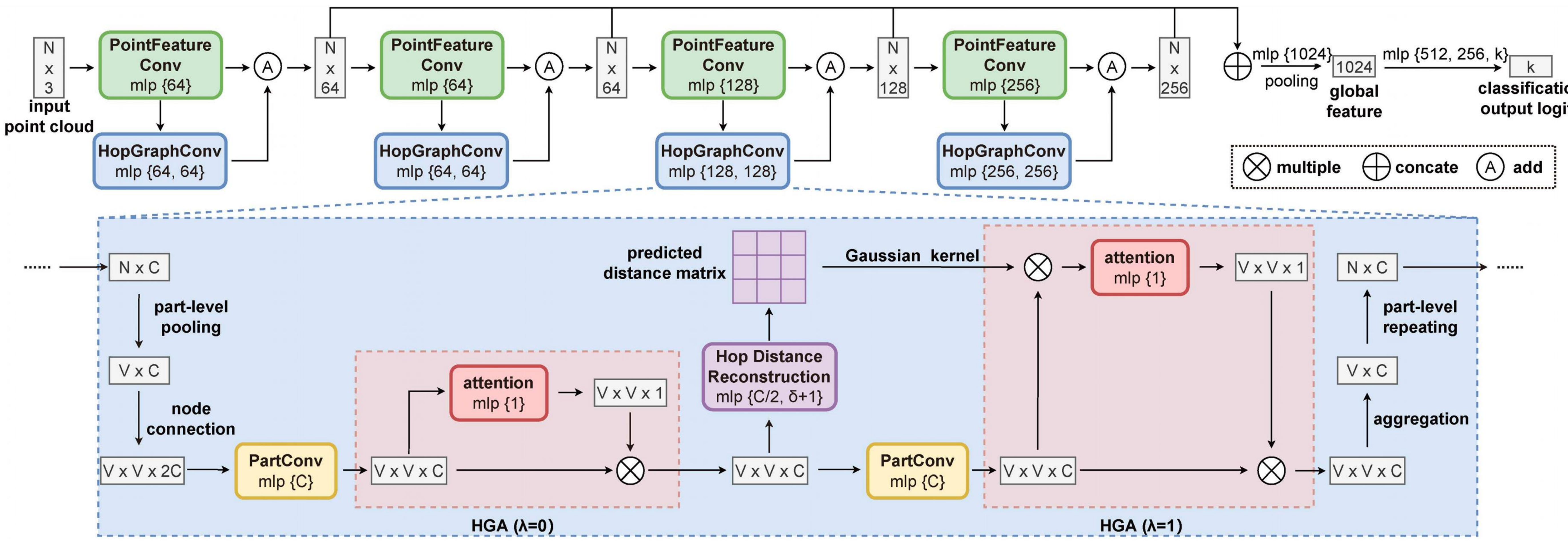
- A novel self-supervised hop distance reconstruction task and a hop distance loss for learning the contextual relationships between point parts explicitly.
- Hop Graph Attention allows dynamically updated hop distance to contribute distinctively in aggregation.
- DHGCN can be easily embedded in point-based backbone networks.
- DHGCN achieves state-of-the-art performance on different downstream tasks.

Motivations



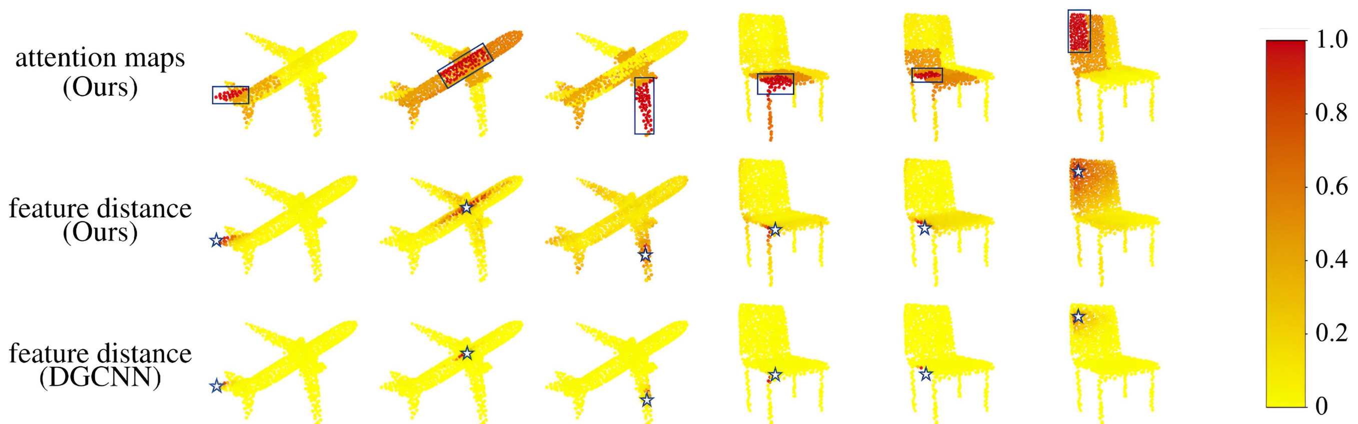
- Previous strategies (d)-(e) focus on extracting local features of point sets.
- The distance in geometric space between point sets explicitly represents their contextual relationships.
- The point sets act as graph nodes to compute the distance matrix, depicting the degree of adjacency quantitatively.

DHGCN: Dynamic Hop Graph Convolution Network



- PointFeatureConv extracts point-wise representations.
- HopGraphConv layer extracts parts features while also predicting the hop distance matrix.
- Hop Graph Attention (HGA) embeds the learned geometric information into point features.

Hop Graph Attention



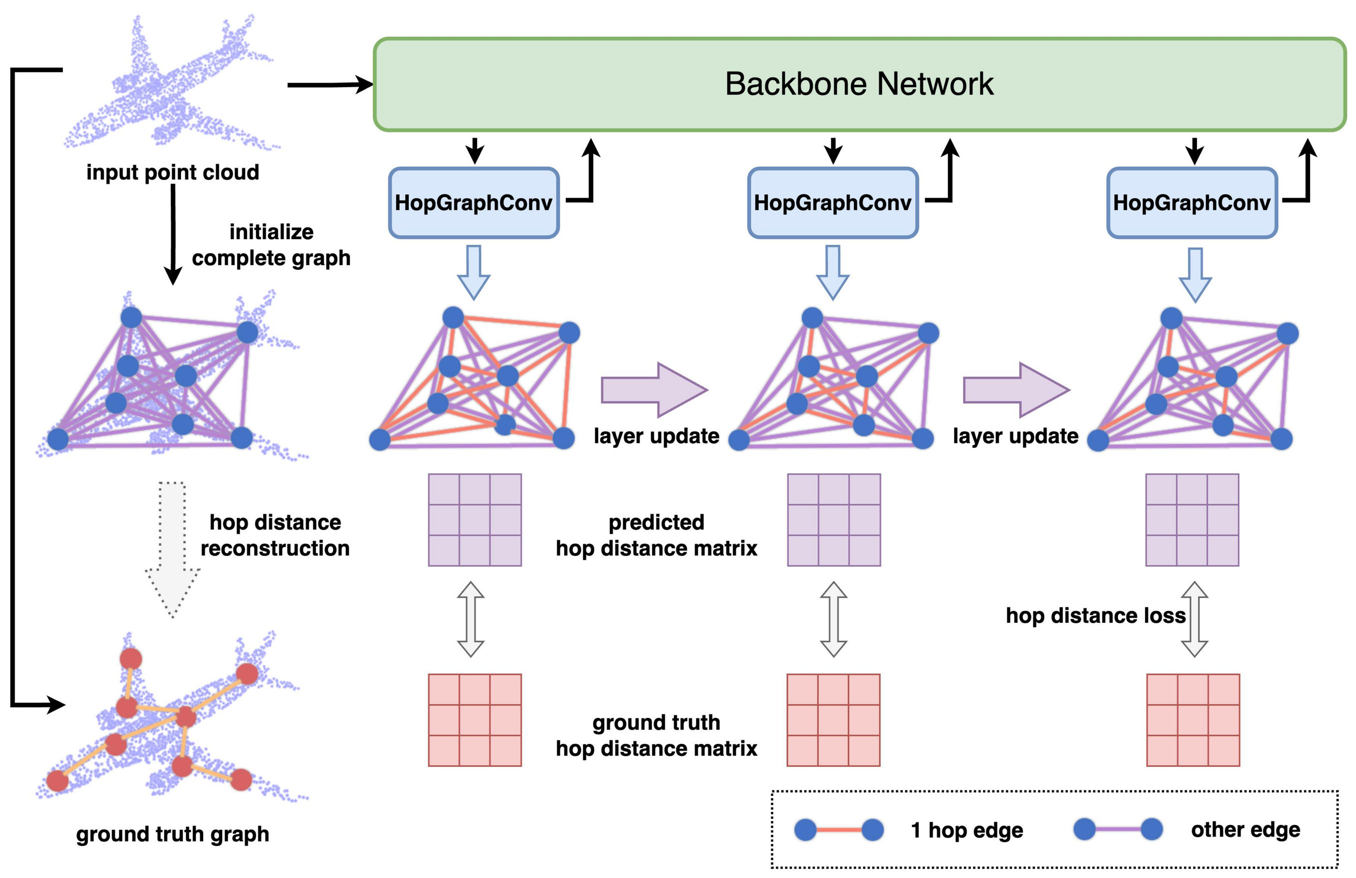
HGA embeds the learned geometric structure information into high-level point cloud contextual features by assigning more attention weights to edge features between neighboring parts in the geometric space (i.e., parts with low hops).

$$t_{ij} = g_a\left(\lambda \cdot \mathbb{G}(\tilde{D}_{ij})e'_{ij} + (1-\lambda)e'_{ij}\right)$$

$g_a : \mathbb{R}^C \to \mathbb{R}$ is a shared attention MLP.

$\mathbb{G}(x) = \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{1}{2\sigma^2}x^2\right)$ represents Gaussian kernel, allowing edge features to contribute distinctively in aggregation.

Dynamic Hop Distance



DHGCN reconstructs the topology from the initialized complete graph. The hop distance loss supervises the predicted distance matrix, which undergoes dynamic updates in each layer.

Experimental Results

Methods	Pretrained dataset	# Points	Acc.	Methods	Pretrained dataset	# Points	Acc.
LatentGAN	SN	2k	85.7	FoldingNet	MN	2k	84.4
FoldingNet	SN	2k	88.4	LatentGAN	MN	2k	87.3
PointCapsNet	SN	2k	88.9	PointCapsNet	MN	1k	87.5
VIPGAN	SN	2k	90.2	Multi-task	MN	2k	89.1
STRL	SN	2k	90.9	MAP-VAE	MN	2k	90.2
SSC (RSCNN)	SN	2k	92.4	GraphTER	MN	1k	92.0
CrossPoint	SN	2k	91.2	GLR (RSCNN)	MN	1k	92.2
DHGCN (DGCNN)	SN	2k	**93.2**	DHGCN (DGCNN)	MN	1k	93.0
DHGCN (AdaptConv)	SN	2k	**93.2**	**DHGCN (AdaptConv)**	MN	1k	**93.3**

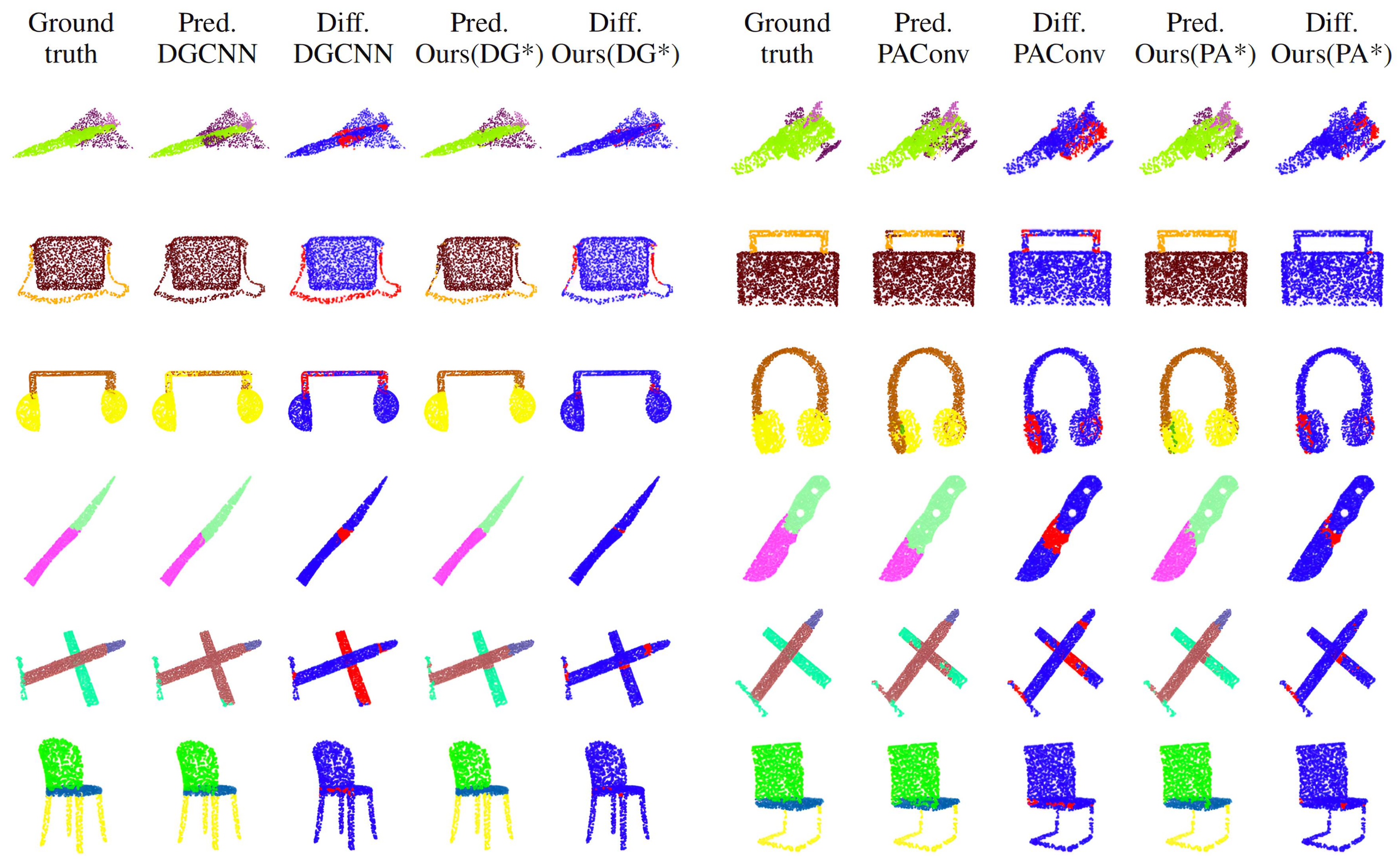
Classification results of unsupervised methods on ModelNet40

Methods	Sup.	OBJ_ONLY	OBJ_BG	PB_T50_RS
PointNet	✓	79.2	73.3	68.2
PointNet++	✓	84.3	82.3	77.9
PointCNN	✓	85.5	86.1	78.5
DGCNN	✓	86.2	82.8	78.1
Point-BERT	✓	88.1	87.4	83.1
Point-MAE	✓	88.3	90.0	85.2
Jigsaw	✗	-	59.5	-
OcCo	✗	-	78.3	-
STRL	✗	-	77.9	-
CrossPoint	✗	-	81.7	-
DHGCN	✗	**85.0**	**85.9**	**81.9**

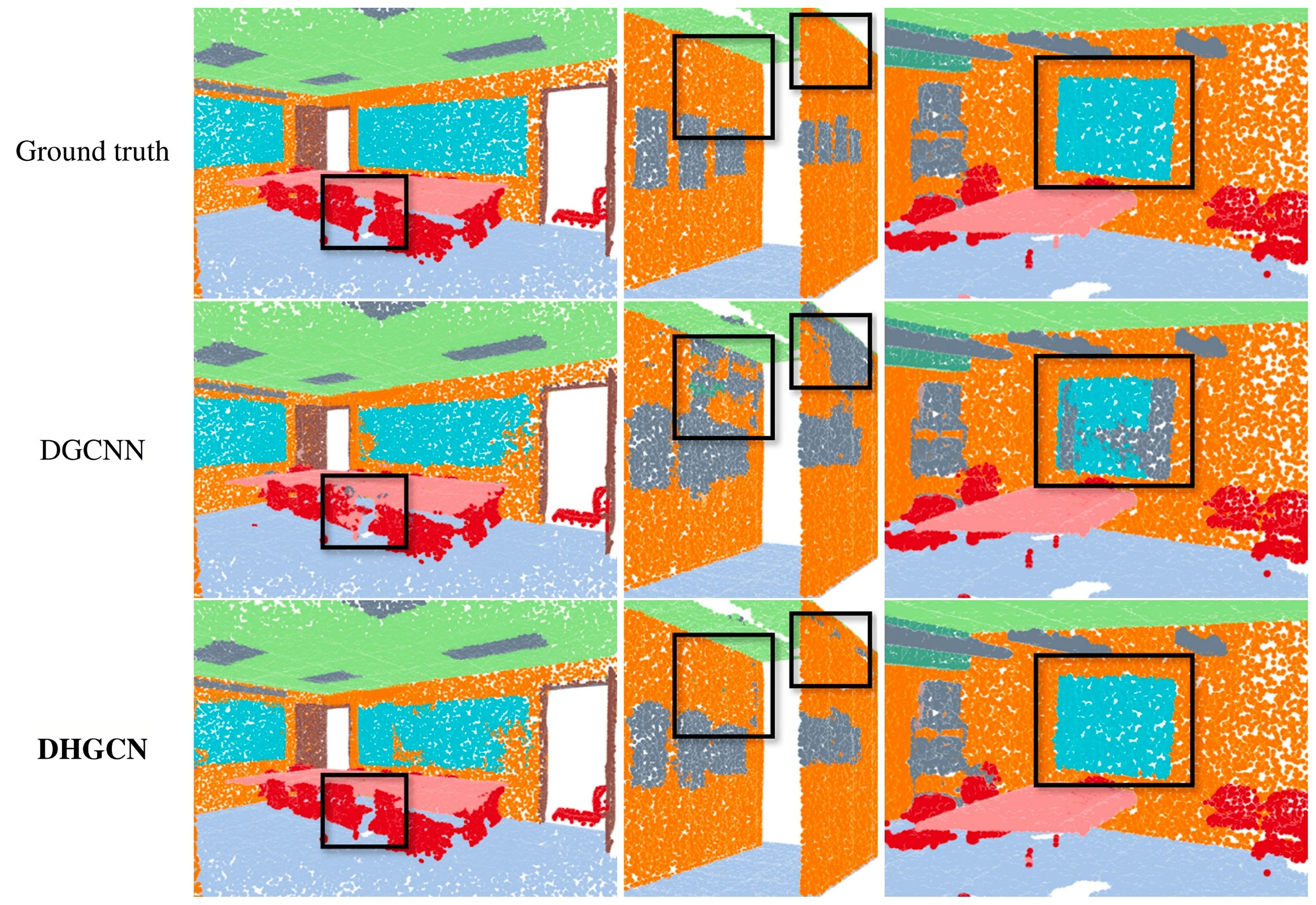
Classification results on ScanObjectNN

Methods	Sup.	Class mIOU	Instance mIOU
PointNet	✓	80.4	83.7
PointNet++	✓	81.9	85.1
DGCNN	✓	82.3	85.2
KPConv	✓	85.1	86.4
PAConv	✓	84.2	86.0
Point-BERT	✓	84.1	85.6
LatentGAN	✗	57.0	-
MAP-VAE	✗	68.0	-
GrpahTER	✗	78.1	81.9
CTNet	✗	75.5	79.2
DHGCN	✗	**82.9**	**84.9**

Shape part segmentation results on ShapeNet Part



Visual results of shape part segmentation on ShapeNet Part



Visual results of sematic segmentation on S3DIS

Contact Us

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