PointASNL: Robust Point Clouds Processing using Nonlocal Neural Networks with Adaptive Sampling

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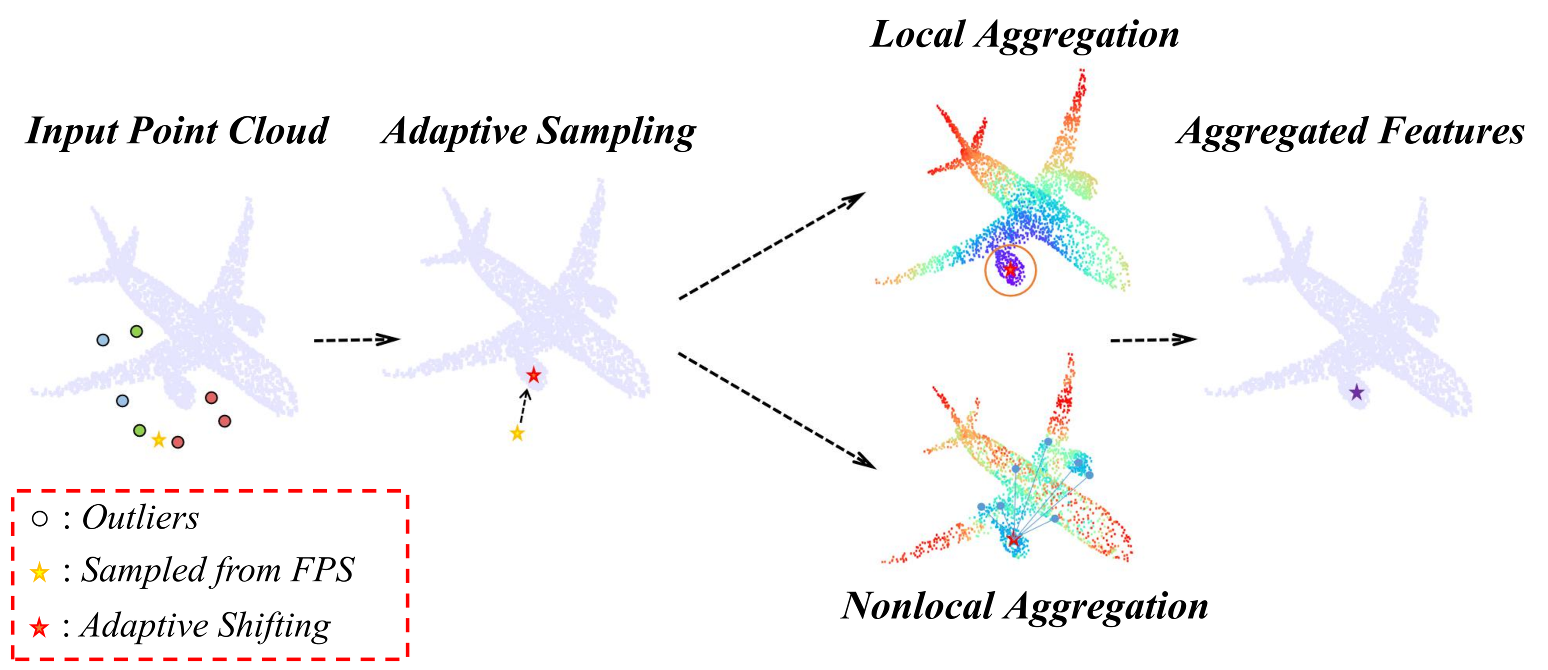
Problem and Contribution

Goal: Raw point clouds data inevitably contains outliers or noise through acquisition from 3D sensors or reconstruction algorithms. In this work, we present a novel end-to-end network for robust point clouds processing, which can deal with point clouds with noise effectively.



Key Contributions:

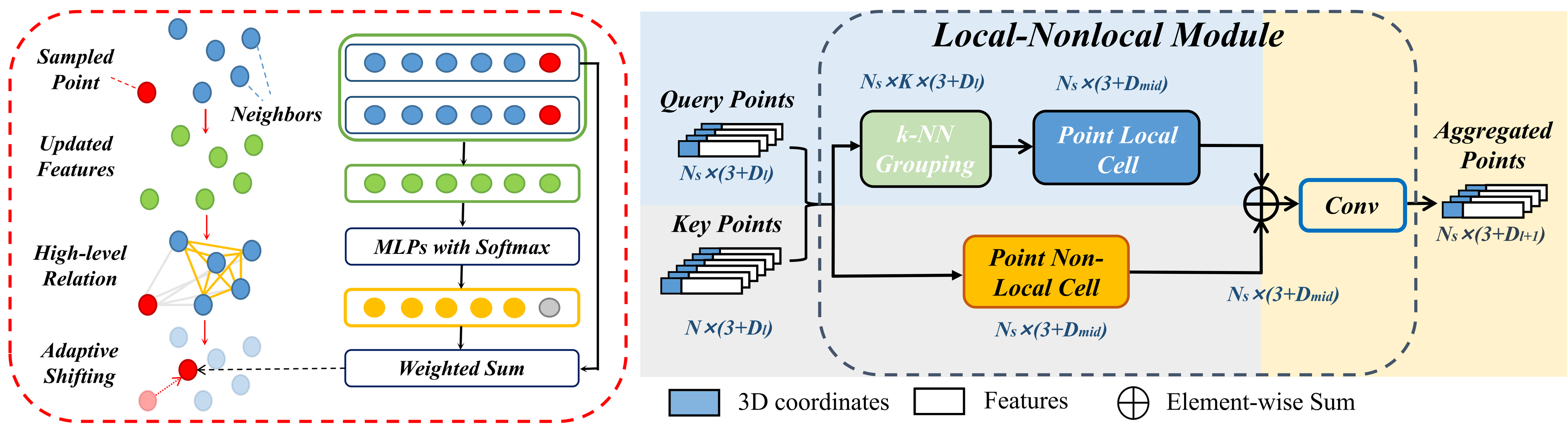
- We propose an end-to-end model for robust point clouds processing, PointASNL, which can effectively ease the influence of outliers or noise.
- With the proposed adaptive sampling (AS) module, PointASNL can adaptively adjust the coordinates of the initial sampled points, making them more suitable for feature learning with intrinsic geometry and more robust for noisy outliers.
- We further design a point nonlocal cell in the proposed local-nonlocal (L-NL) module, which enhances the feature learning in point local cells.

Method

Proposed Components:

In this paper, we propose two modules in PointASNL, namely adaptive sampling (AS) module in Part (a) and local-nonlocal (L-NL) module in Part (b).

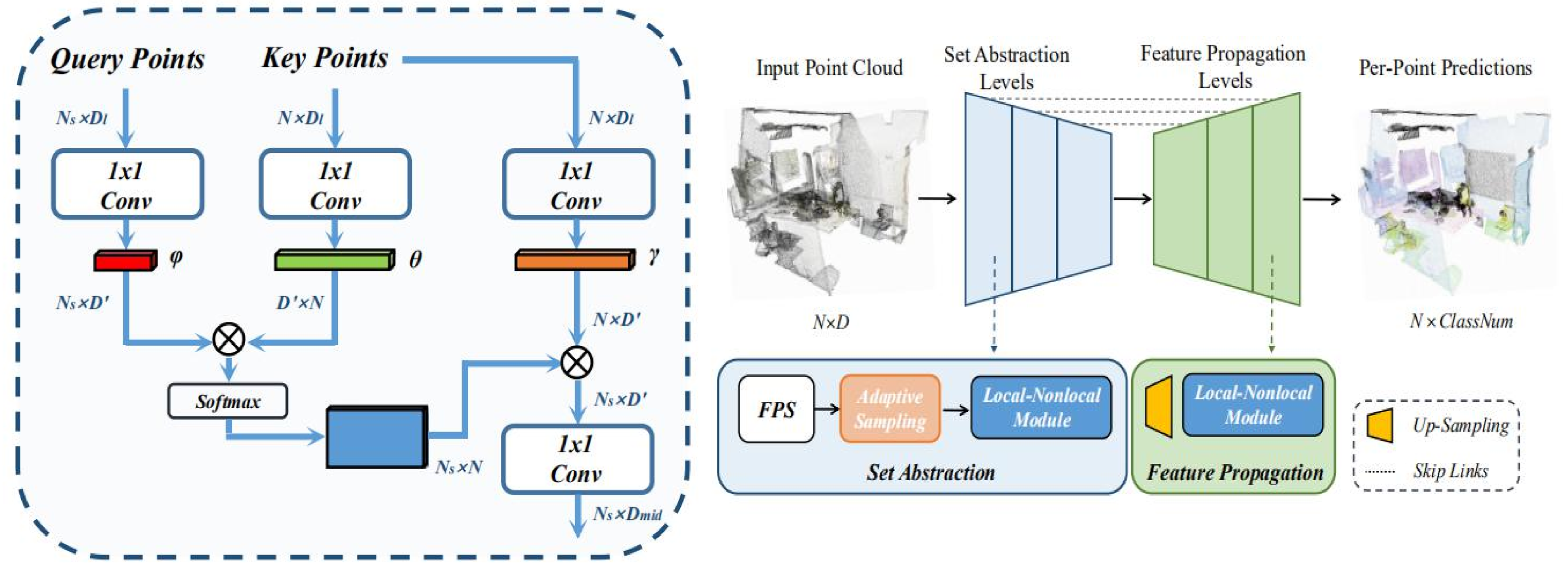
- AS module updates group features by using self-attention within all group members. Then, it outputs normalized weights for each coordinate axis and features and adaptively shifts both coordinate and features of the sampled point.
- Within L-NL module, there are two cells: point local (PL) cell and point nonlocal (PNL) cell. Specifically, the PL cell can be any appealing algorithms (e.g., PointNet++, PointConv), and the PNL cell innovatively considers the long distance dependency between sampled points and the entire point cloud.



(a) Adaptive Sampling (AS) Module (b) Local-NonLocal Module

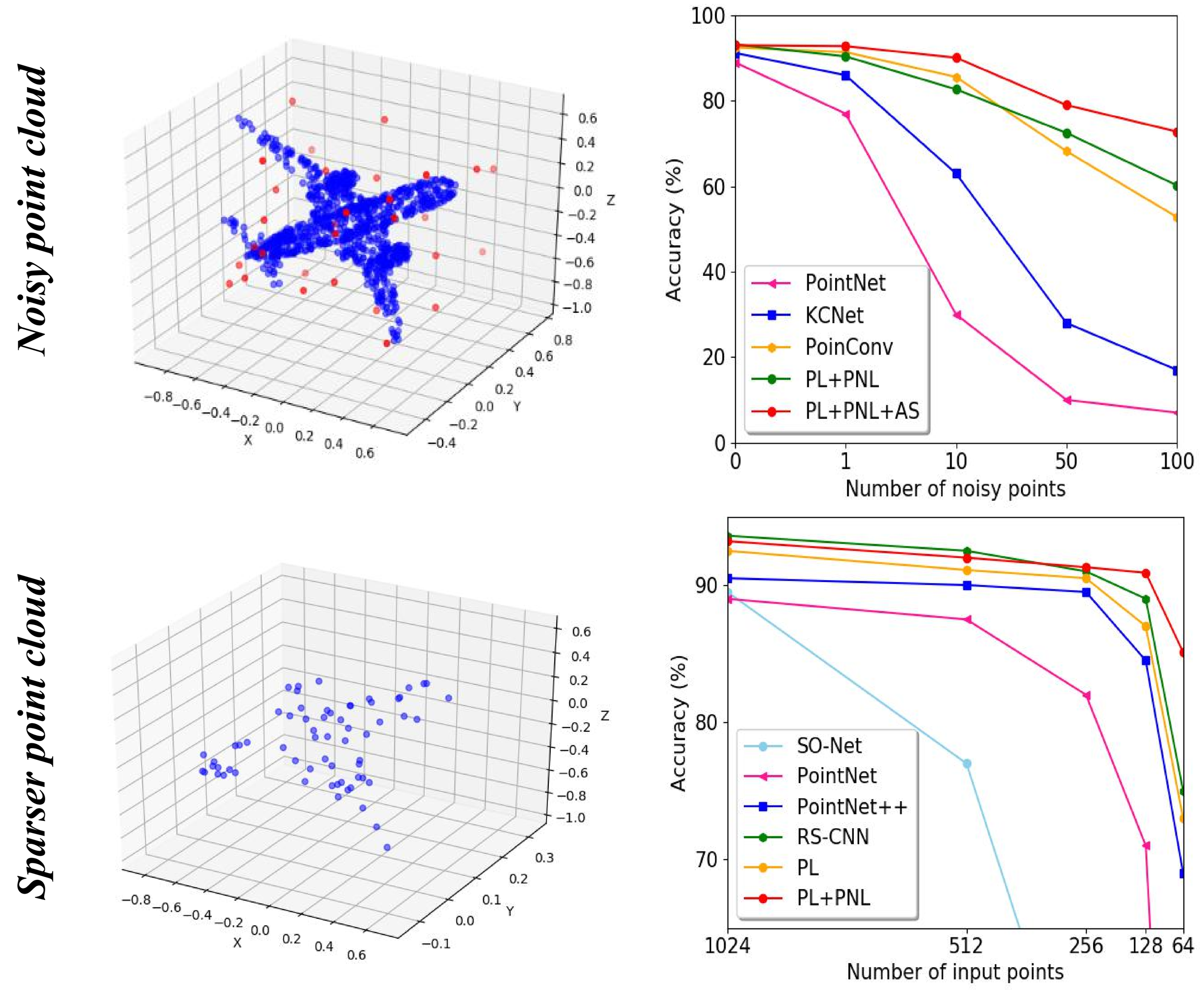
Experiments & Results

Inner structure of point nonlocal (PNL) cell and architecture.



(a) Inner structure of PNL cell (b) Architecture of PointASNL

Results of robustness experiment. We use point clouds with noise and sparser point clouds as inputs to evaluate the robustness of our model.



Visualized results of AS module. (a) Sampled points via farthest point sampling (FPS). (b) Sampled points ajusted by AS module.

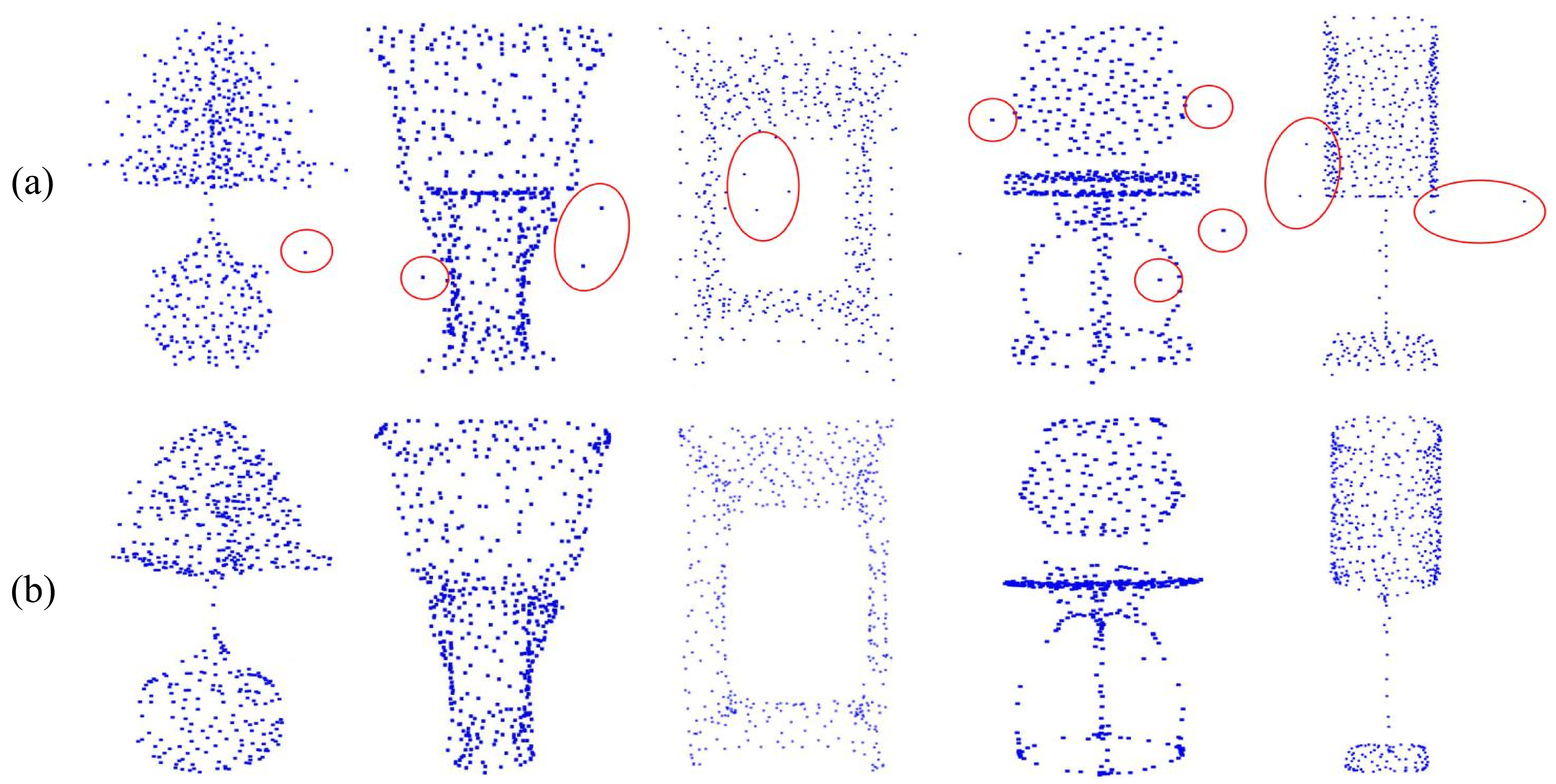


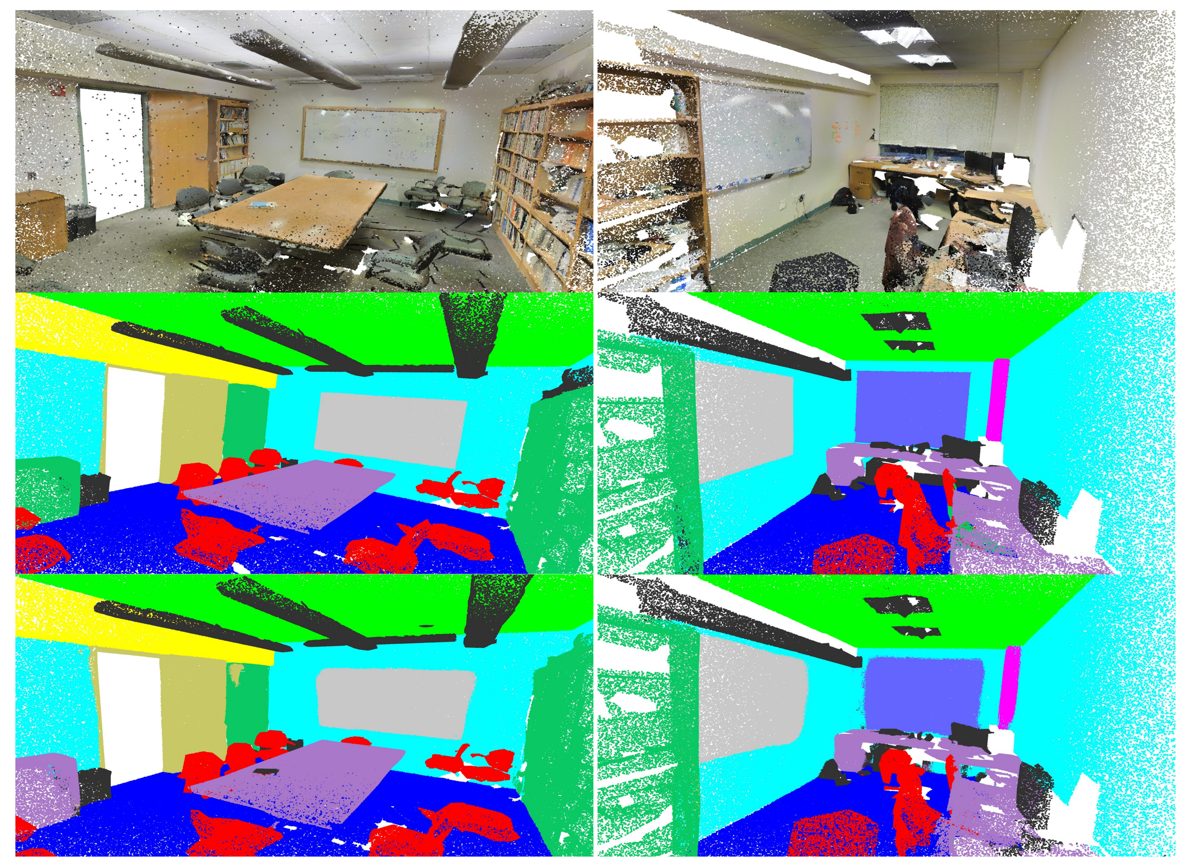
Table 1: Overall accuracy on ModelNet40 (M40) datasets. "pnt" stands for coordinates of point and "nor" stands for normal vector.

Method	input	#points	*M40*
PointNet	pnt	1k	89.2
PointNet++	pnt, nor	5k	91.9
PointCNN	pnt	1k	92.2
DGCNN	pnt	1k	92.2
PointConv	pnt, nor	1k	92.5
KPConv	pnt	7k	92.9
PointASNL	pnt	1k	92.9
PointASNL	pnt, nor	1k	**93.2**

Table 2: Segmentation results on indoor S3DIS, ScanNet and SemanticKITTI datasets in mean per-class IoU (mIoU,%).

Method	S3DIS	ScanNet	SemKitti
methods use unspecific number of points as input			
TangentConv	52.8	40.9	40.9
SPGraph	62.1	-	17.4
KPConv	**70.6**	**68.4**	-
methods use fixed number of points as input			
PointNet++	53.4	33.9	20.1
DGCNN	56.1	-	-
PointCNN	65.4	45.8	-
PointConv	-	55.6	-
HPEIN	67.8	61.8	-
PointASNL	**68.7**	**63.0**	**46.8**

Visualization results on S3DIS datset.



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