PC-Net: A Deep Network for 3D Point Clouds Analysis

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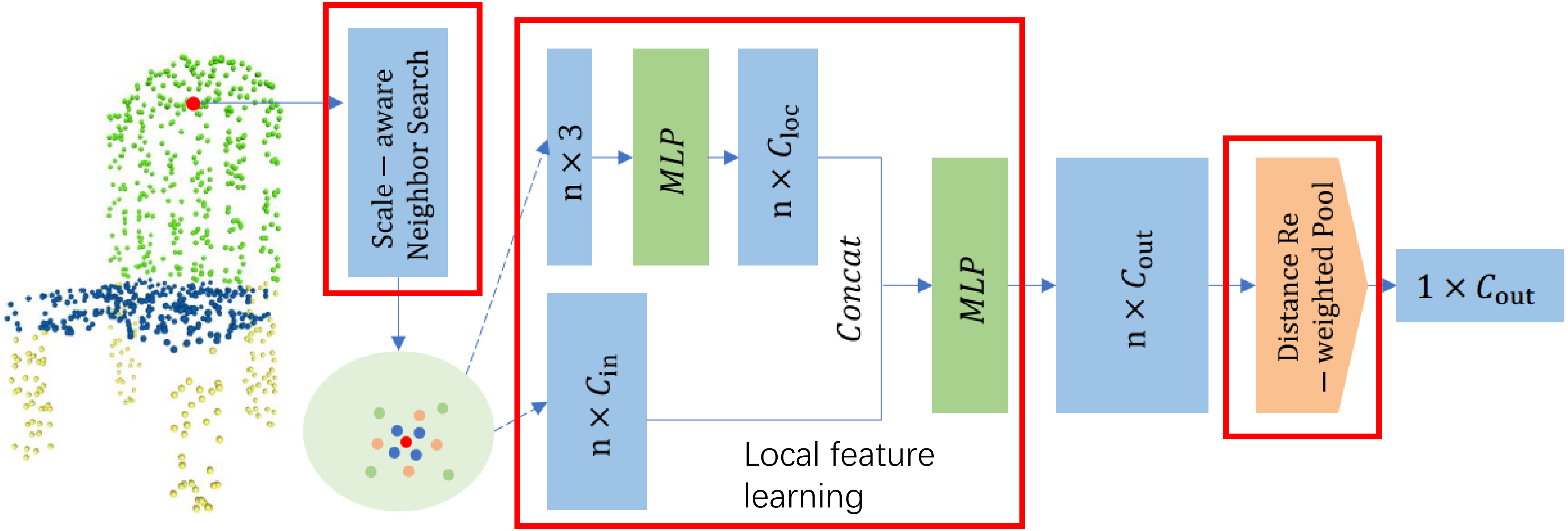
Contributions

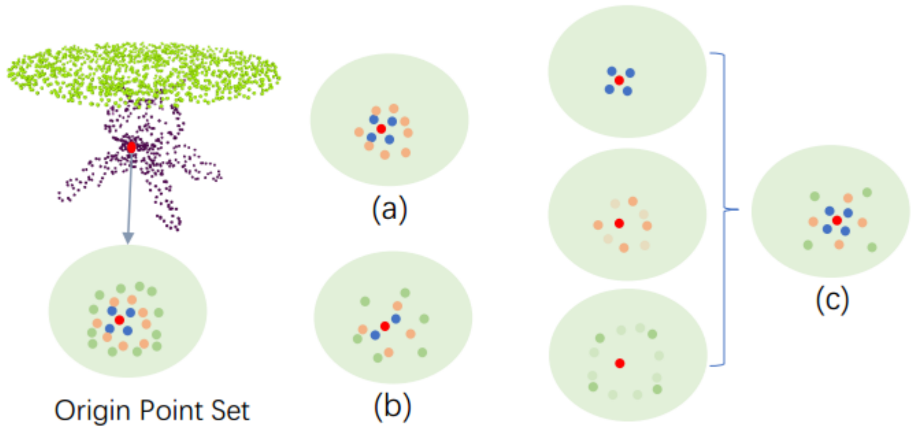
- We proposed a simple but effective method for point cloud analysis, called PC-Net, which includes three novel operations:
  - Scale-aware neighbor search
  - Local feature learning
  - Distance re-weighted pooling
- We designed effective network architecture with PC-Net
  - For classification
  - For segmentation

Overview of PC-Net



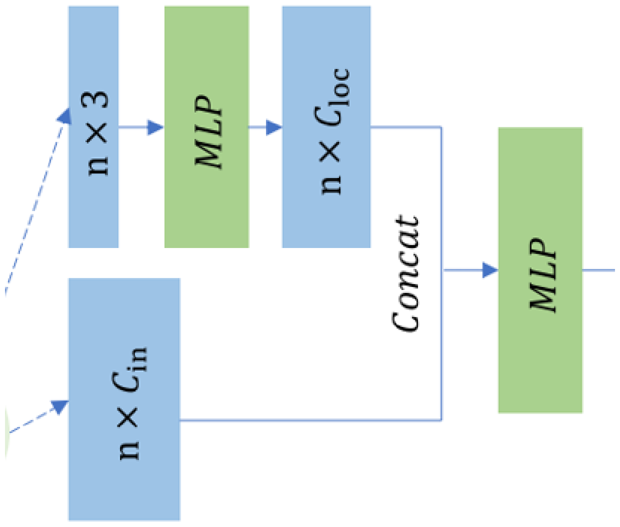
Overview of PC-Net. For a representative point, we first apply a scale-aware neighbor search on the point cloud for adaptive neighborhood extracting. Then for each neighboring point, we lift its coordinate into *Cloc* dimensional space and concatenate its associated feature and this local spatial feature. At the end, PC-Net uses a distance re-weighted pooling operation to aggregate information from all the neighboring points.

Scale-aware neighbor search



An illustration of different neighbor search strategies to get K neighbors (K = 12 in this example). (a) Directly taking in K nearest neighbors. (b) Uniformly sampling K input points from $K \times D$ neighboring points (D denotes the dilation rate and equals to 3 in this example). (c) Scale-aware neighbor search, which uses different sampling rates to extract points at different scales of the neighboring points.

Local feature learning



The spatially-local correlation in the neighborhood of representative points is important information to help generate output features.
First, learning local geometric features by applying MLP(·) function on the local coordin-ates of Pn as:

$$\mathbf{F_l} = MLP(\mathbf{P_n} - p),$$

which lifts local coordinates into high dime-nsional feature space.
Then we concatenate Fl and Fn together as the new input features of Prep and forward them to another MLP(·) function:

$$\mathbf{F_p} = MLP([\mathbf{F_l}\ \mathbf{F_n}]).$$

Distance re-weighted pooling

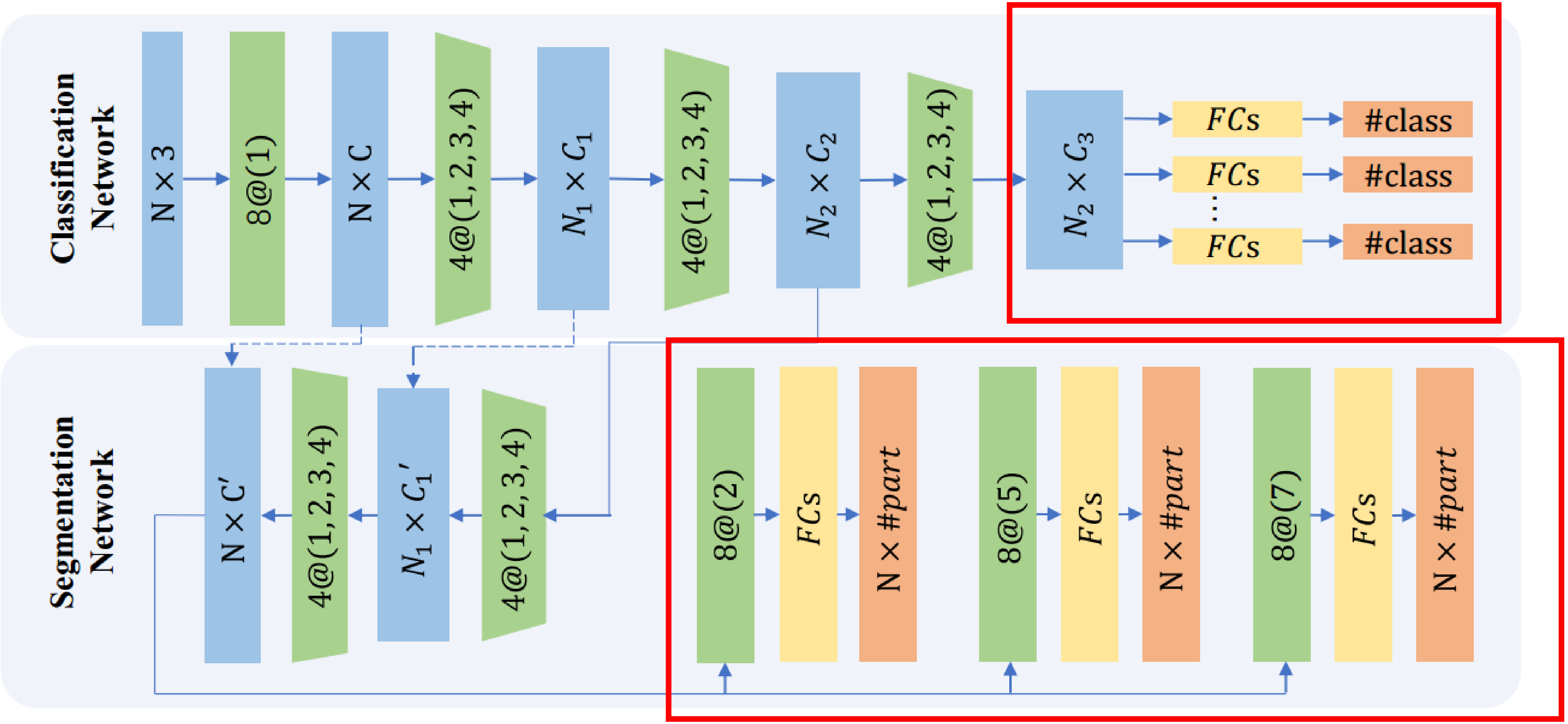
To exploit the distance correlation between neighboring points and *p*, we add a weight term Wp, which is defined as:

$$\mathbf{W_p}(i) = exp(- \parallel p_i - p \parallel),$$

where each feature associated with pi in Fp is re-weighted by the function of distance. The selection of Wp is based on the intuition that neighboring points close to the representative point should have more impact on each other. Consequently, the learned feature of p is:

$$\mathbf{f_p} = MaxPool_c(\mathbf{W_p} \times \mathbf{F_p}).$$

The network architecture for point cloud understanding



Experimental Result

Classification

TABLE I
COMPARISONS OF MEAN PER-CLASS ACCURACY (MA) AND OVERALL ACCURACY (OA) (%) ON MODELNET10.

Method	mA	OA
MPNN	-	92.07
PointNet++	-	92.51
SplineCNN	-	92.65
PointCNN	-	93.28
Kd-Net	93.5	94.0
KCNet	-	94.4
Ours	**95.09**	**95.37**

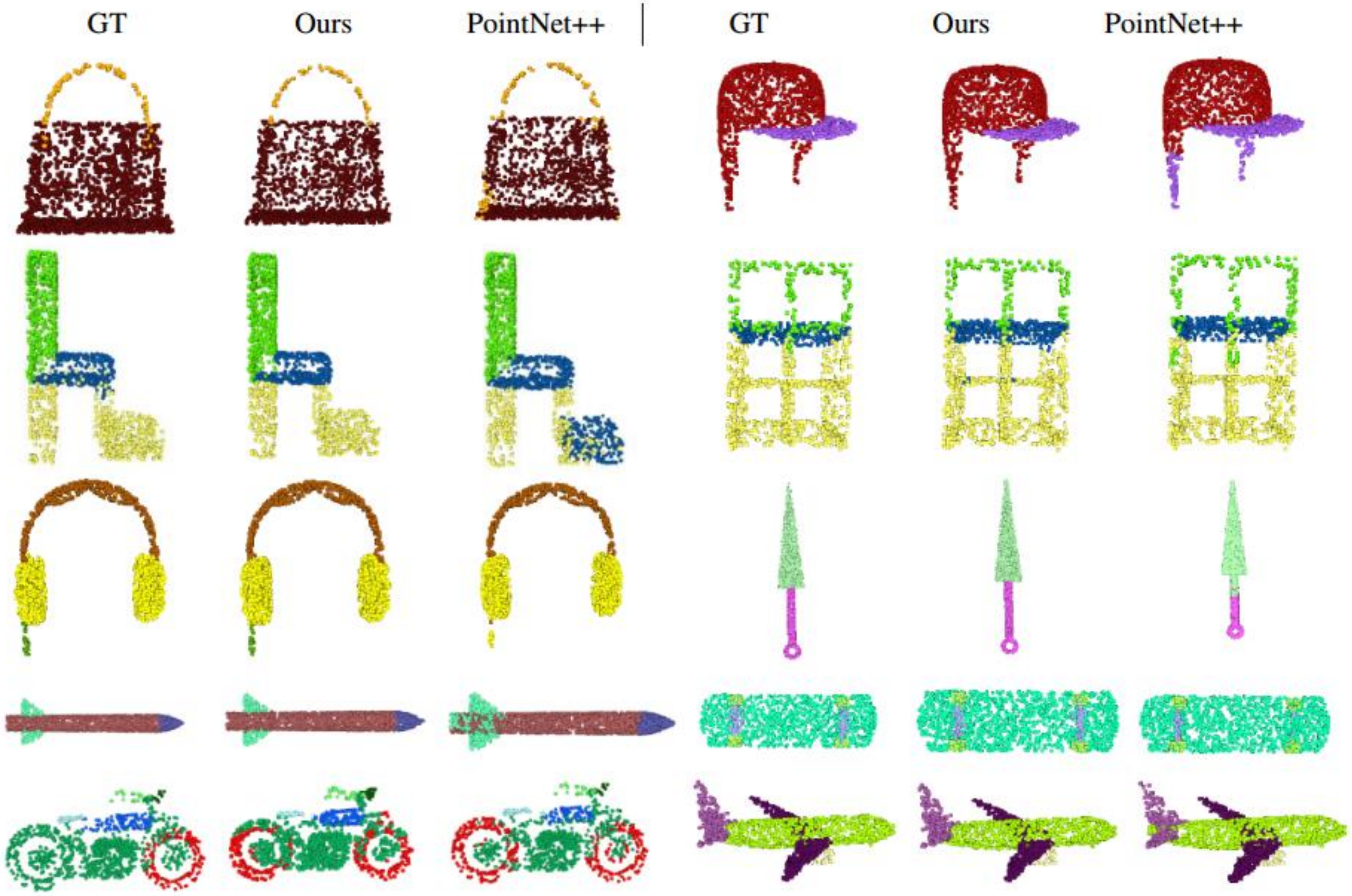
TABLE II
COMPARISONS ON MODELNET40.

Method	mA	OA
VoxNet	83.0	85.9
Kd-Net	88.5	90.6
PointNet	86.2	89.2
PointNet++	-	90.7 (91.9, PN5000)
SO-Net	-	90.7 (93.4, PN5000)
3DmFV-Net	-	91.4 (91.6, P2048)
PCNN	-	92.3
KCNet	-	91.0
SpecGCN	-	91.5 (92.1, PN2048)
PointCNN	88.8	92.5
PointConv	-	92.5
Ours	**89.97**	**93.33**

Segmentation

COMPARISONS OF AVERAGE MIO

Method	Shape-Net
Ins. mIoU	81.4
Cat. mIoU	79
airplane	81.0
bag	78.4
cap	77.7
car	75.7
chair	87.6
earphone	61.9
guitar	92
knife	85.4
lamp	82.5
laptop	95.7
motor	70.6
mug	91.9
pistol	85.9
rocket	53.1
skateboard	69.8
table	75.3



Ablation Study

TABLE V
ABLATION STUDY ON MODELNET40 TEST DATA.

Module used in PointNet++	**OA**
PointNet	89.4
PC-Net	91.5
w/o Scale-aware neighbor search	90.4
w/o Local spatial feature	90.1
w/o Distance re-weighted pooling	91.2
Multiple Classifiers	**OA**
without MC	91.5
with MC in PointCNN	92.8
with our MC	93.3

TABLE VI
ABLATION STUDY ON SHAPENET TEST DATA.

Multi-scale Features Recognition	**mIoU**
without multi-scale predictions	84.6
with multi-scale predictions	85.12

Thank you !