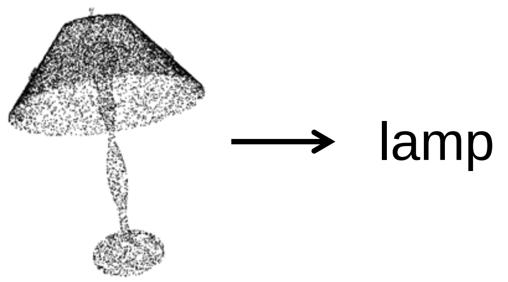
Deep Learning (CNN) in 3D Point Cloud Processing

Yongcheng Liu

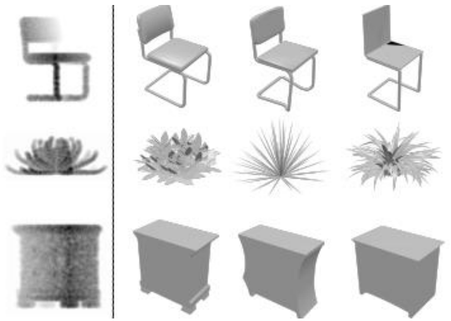
2019.04

Introduction

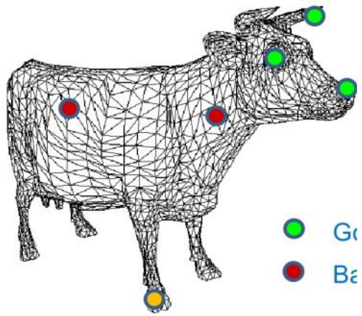
Introduction *tasks*



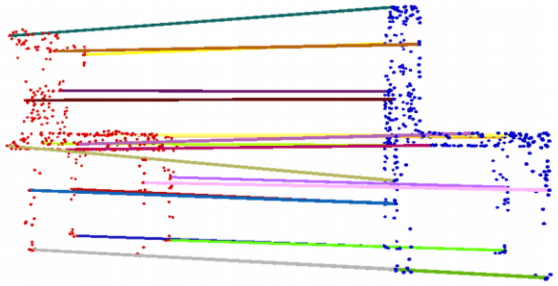
shape classification



shape retrieval

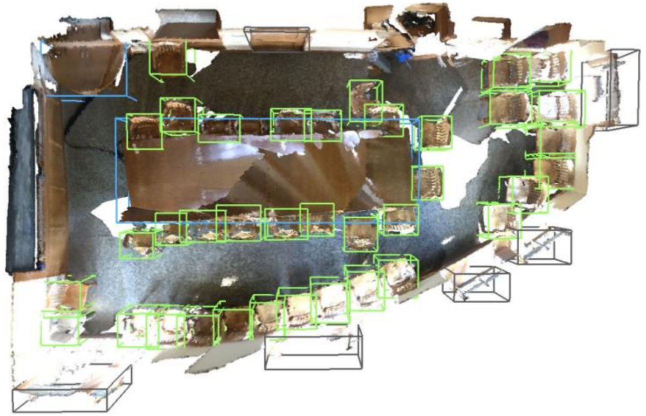


keypoint detection

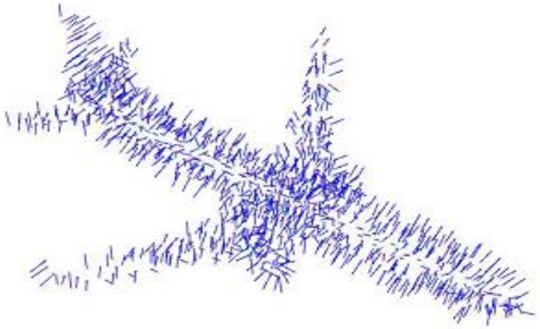


shape correspondence

semantic segmentation



object detection



normal estimation

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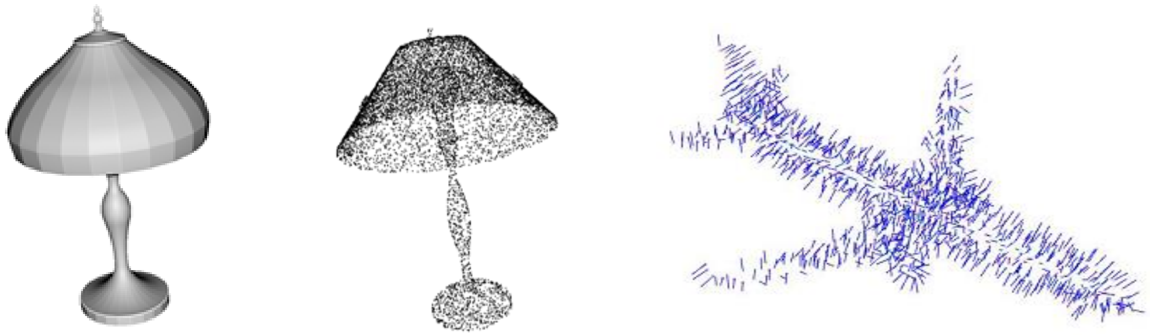
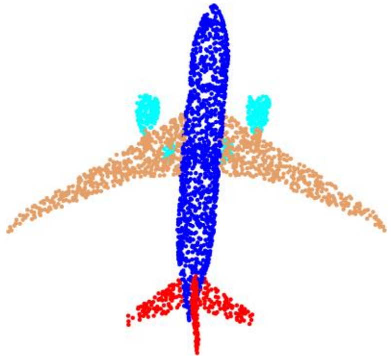
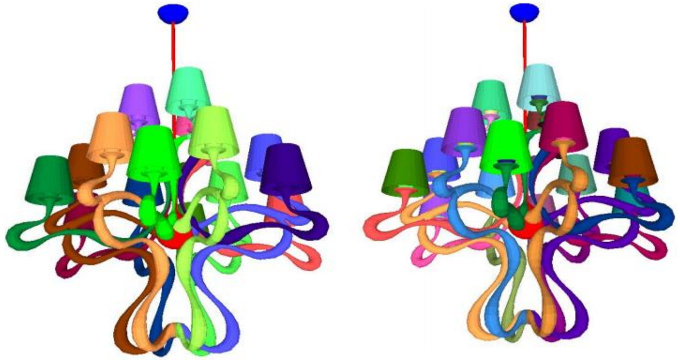
Introduction *datasets*



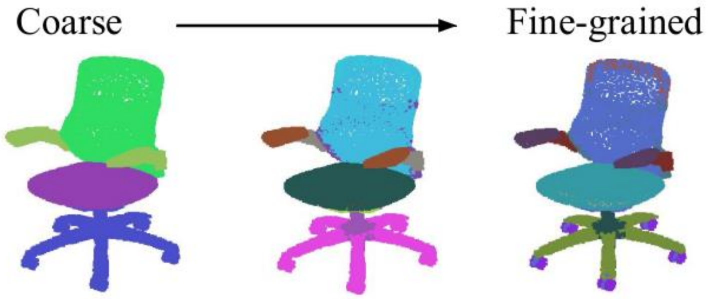
Princeton ModelNet: 1k



ShapeNet Part: 2k



PartNet models



Hierarchical Semantic Segmentation

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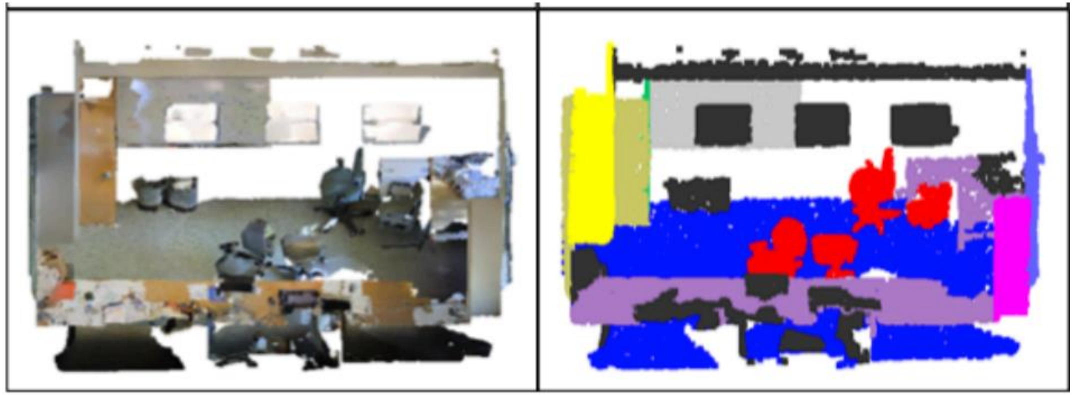
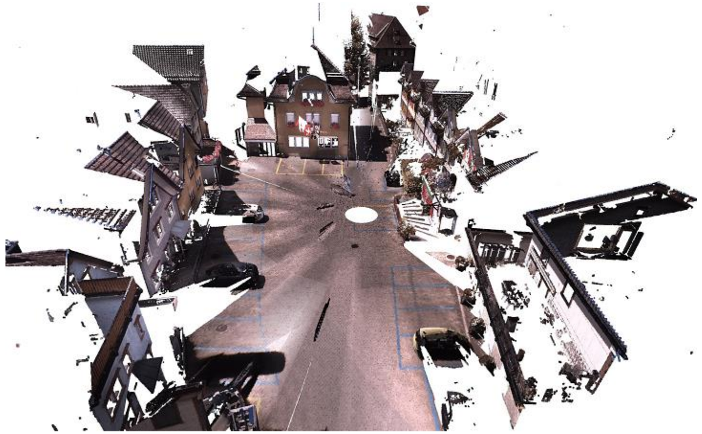
Mo et al. PartNet: A Large-scale Benchmark for Fine-grained and Hierarchical Part-level 3D Object Understanding. CVPR 2019.
Yi et al. A scalable active framework for region annotation in 3D shape collections. TOG 2016.
Wu et al. 3D ShapeNets: A Deep Representation for Volumetric Shapes. CVPR 2015.

Introduction *datasets*



Stanford 3D indoor scene: 8k



Semantic 3D: 4 billion in total

ScanNet: seg + det

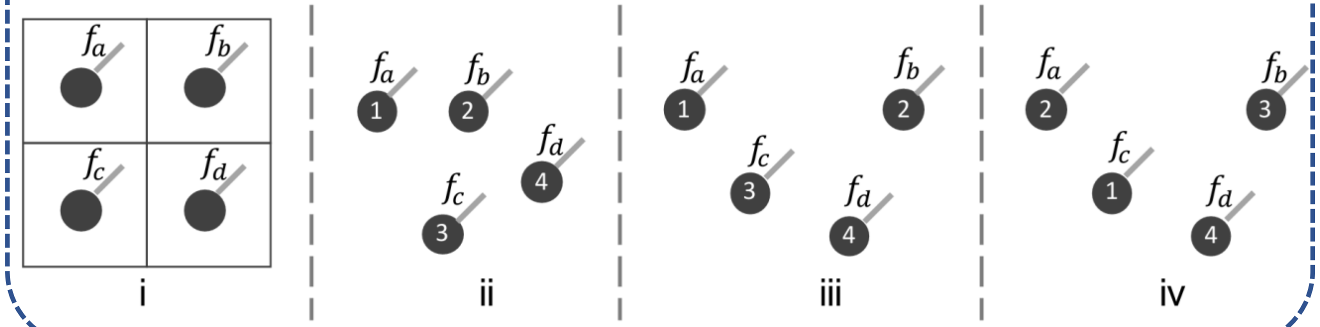
KITTI: det

……

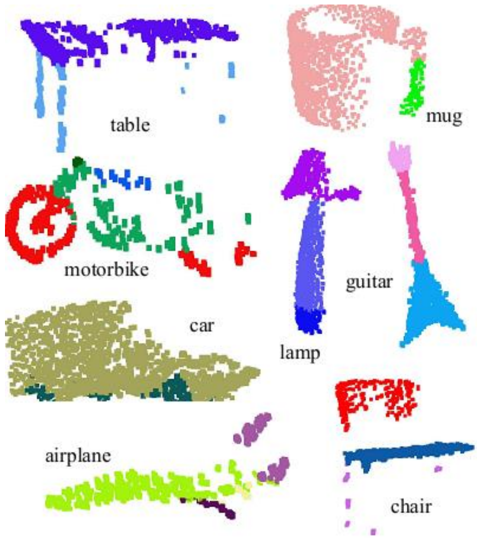
Dai et al. ScanNet: Richly-annotated 3D Reconstructions of Indoor Scenes. CVPR 2017.
Armeni et al. 3d semantic parsing of large-scale indoor spaces. CVPR 2016.
Hackel et al. Semantic3d. net: A new large-scale point cloud classification benchmark. ISPRS 2017.

Introduction *some challenges*

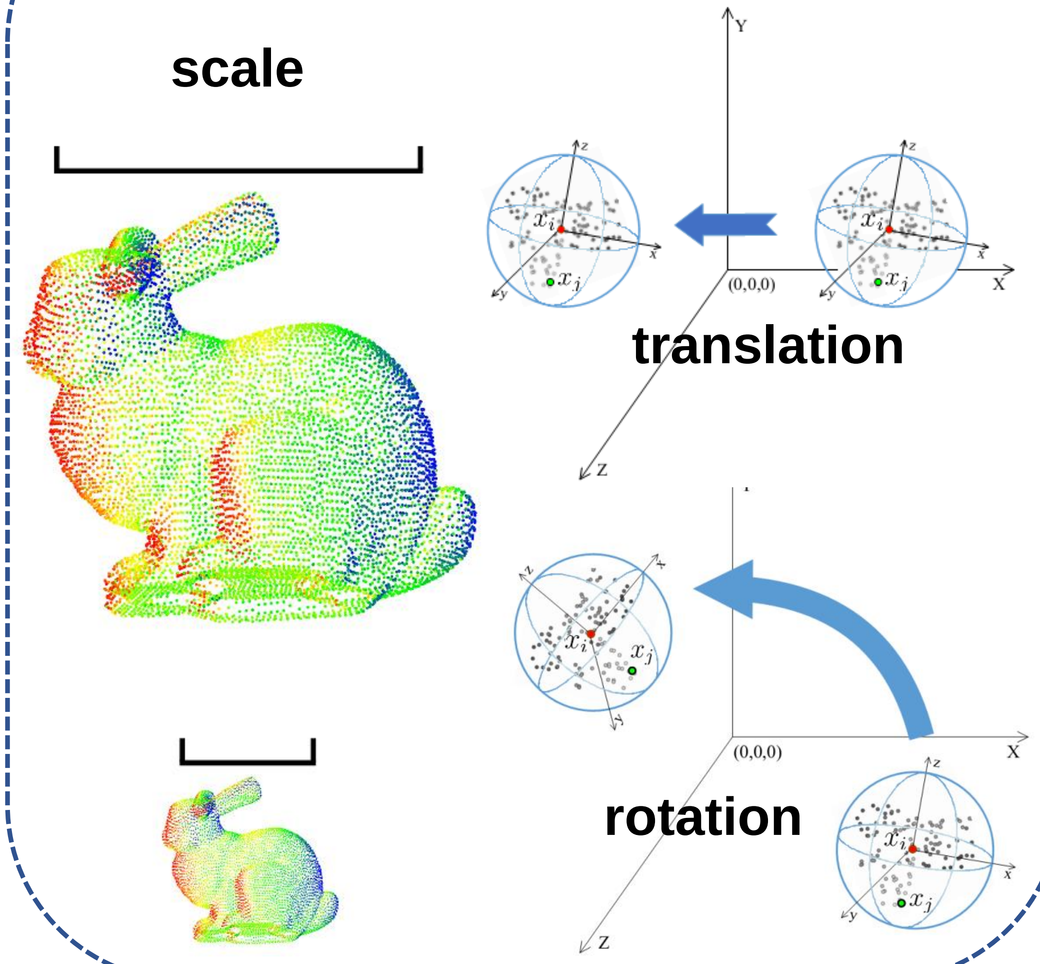
Irregular (unordered): permutation invariance



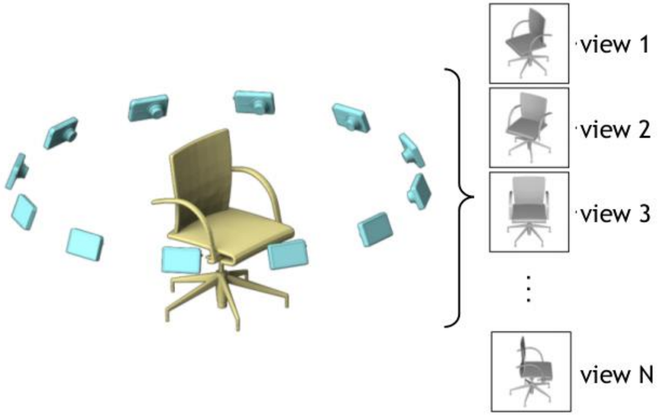
Robustness to corruption, outlier, noise; partial data



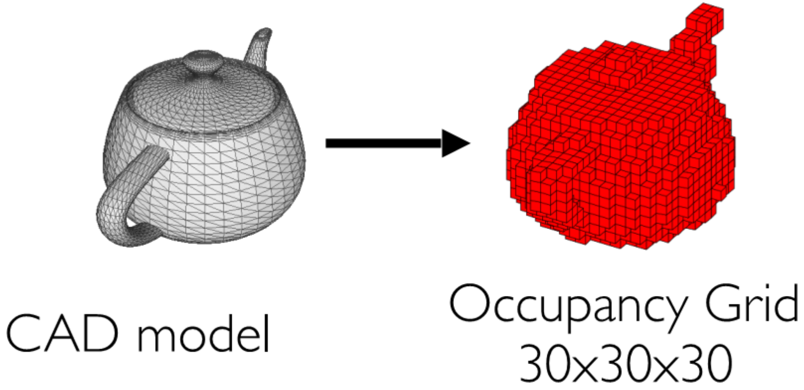
Robustness to rigid transformations



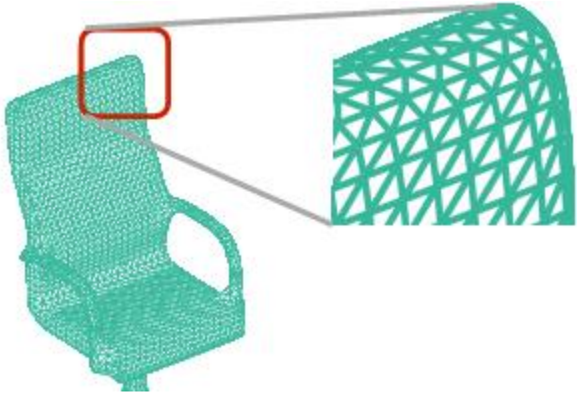
Introduction *3D representations*



multi-view images + 2D CNN



volumetric data + 3D CNN



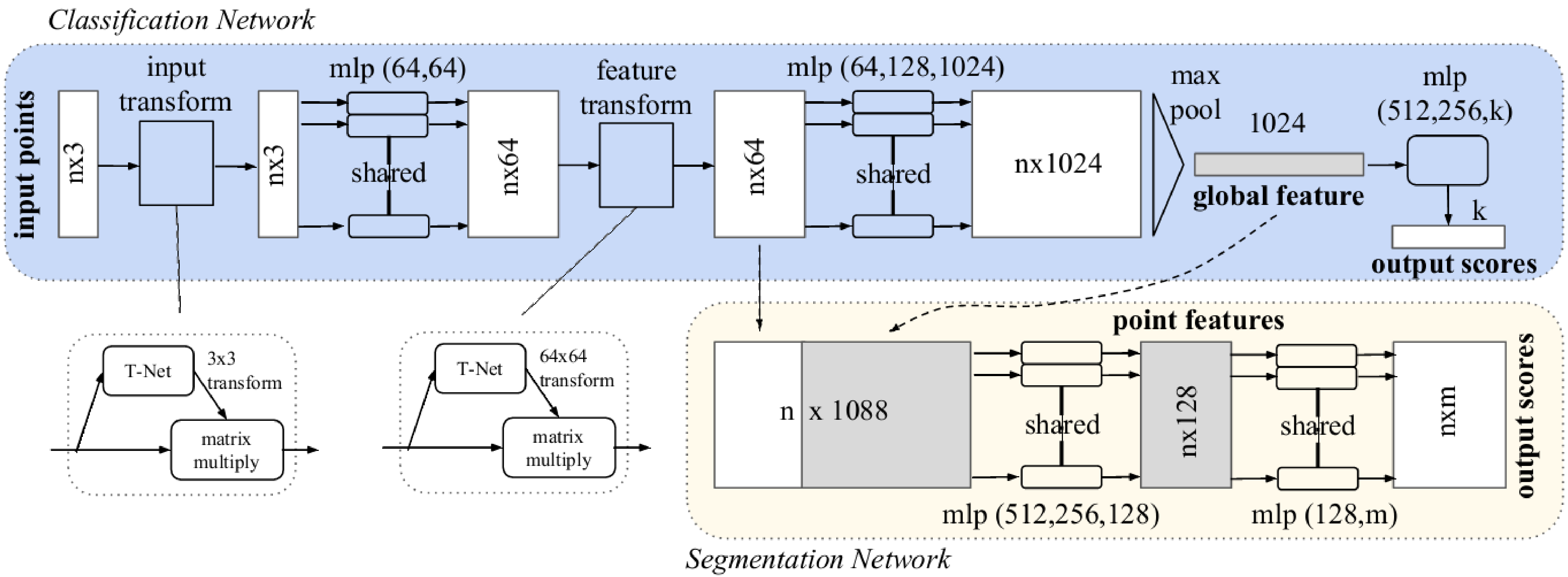
mesh data + DL (GNN) ?

image depth + CNN

point cloud + DL (CNN) ?

Related work – PointNet family

Related Work *PointNet: permutation invariance*

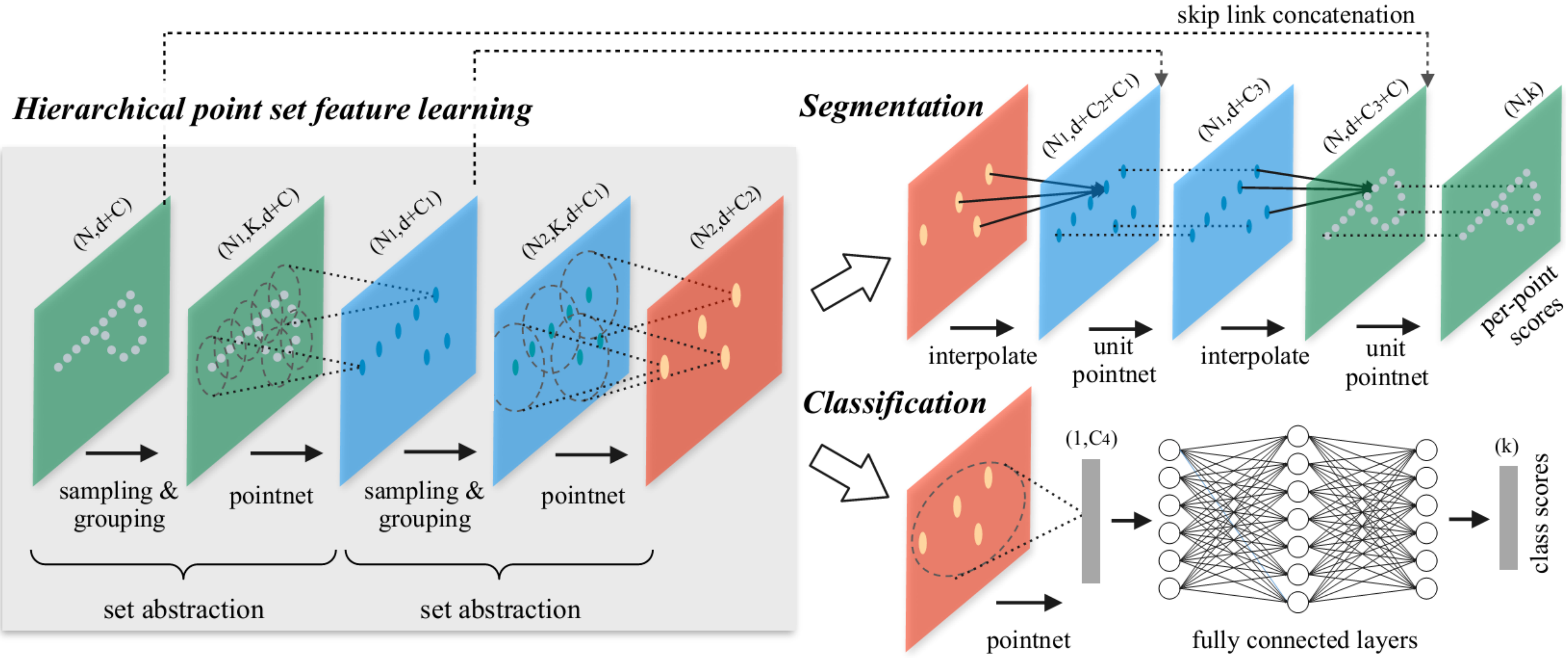


Shared MLP + max pool (symmetric function)

No local patterns capturing

Qi et al. PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation. CVPR 2017.

Related Work *PointNet++: local to global*

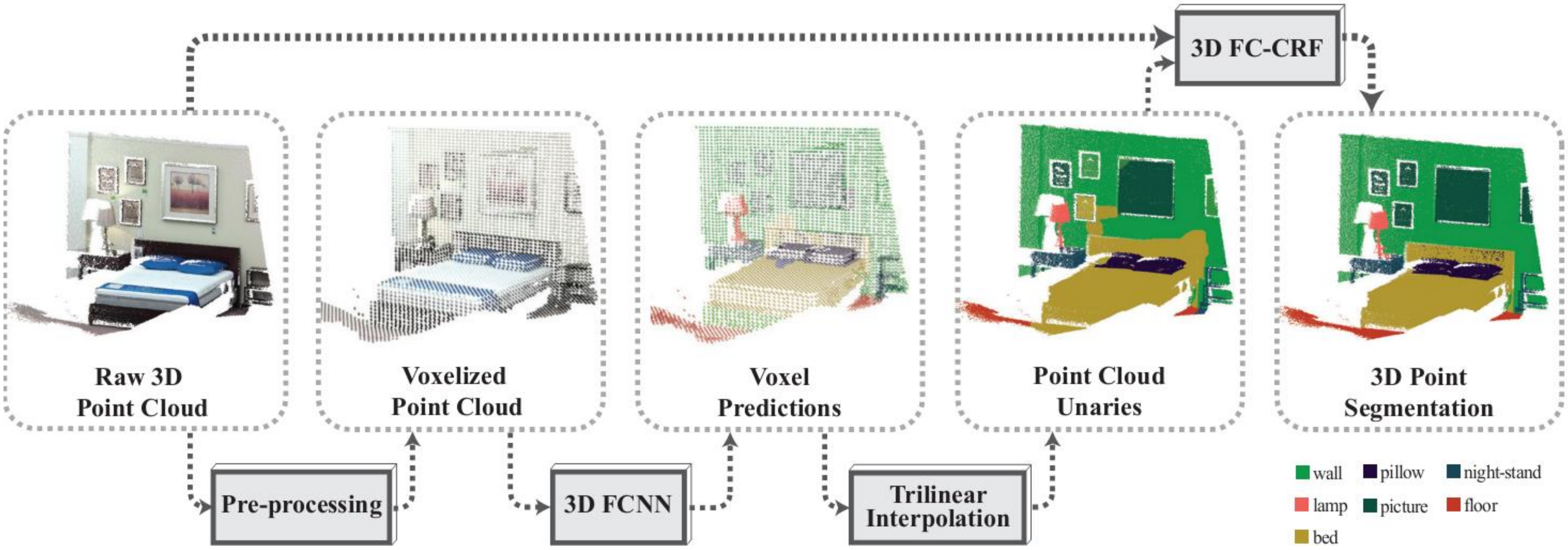


Sampling + Grouping + PointNet

Qi et al. PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space. NIPS 2017.

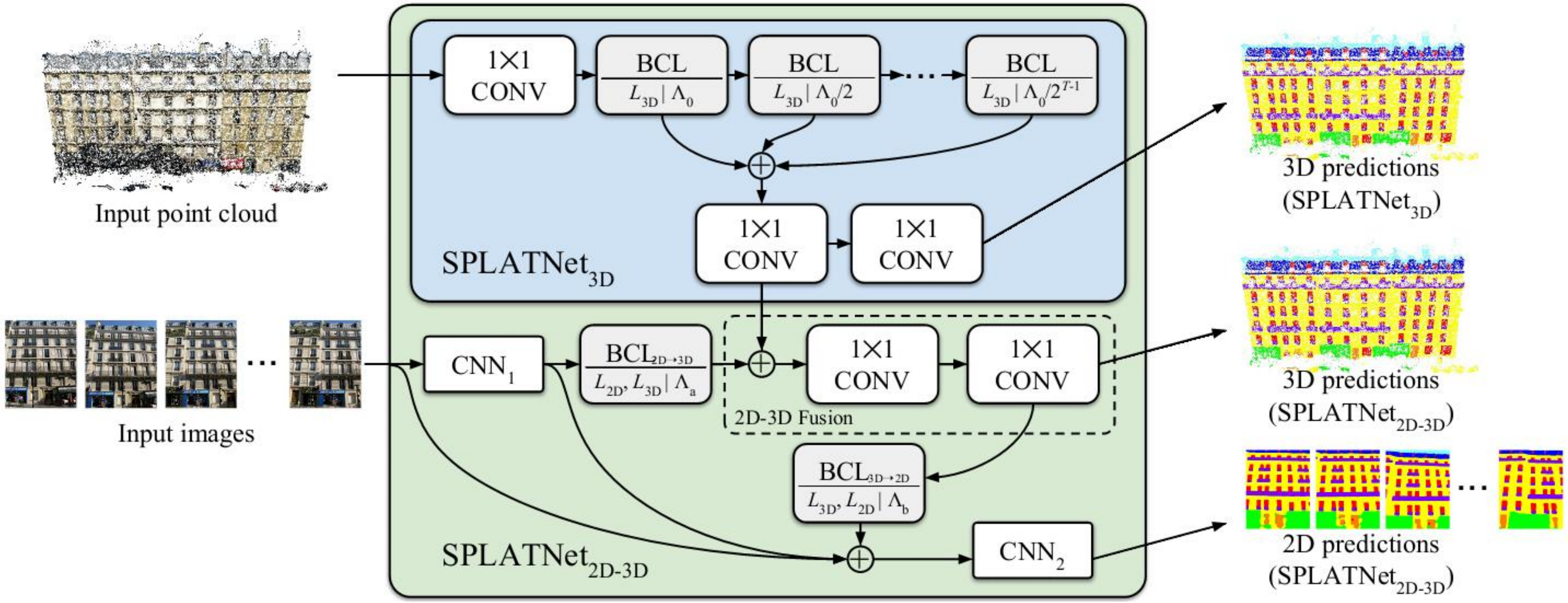
Related work – regularization

Related Work SEGCloud: voxelization

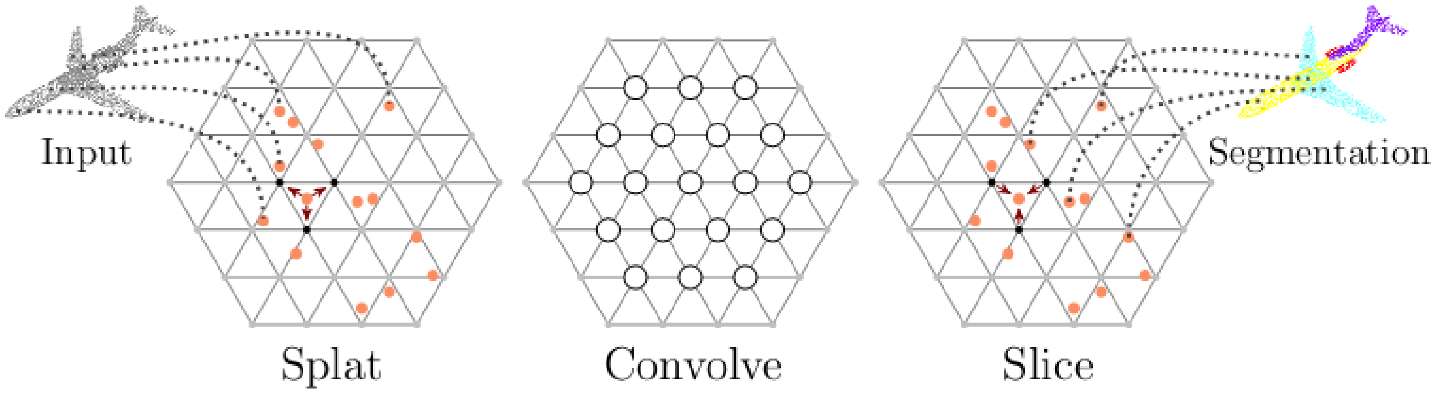


Tchapmi et al. SEGCloud: Semantic Segmentation of 3D Point Clouds. I3DV 2017.

Related Work *SPLATNet: high-dimensional lattice*

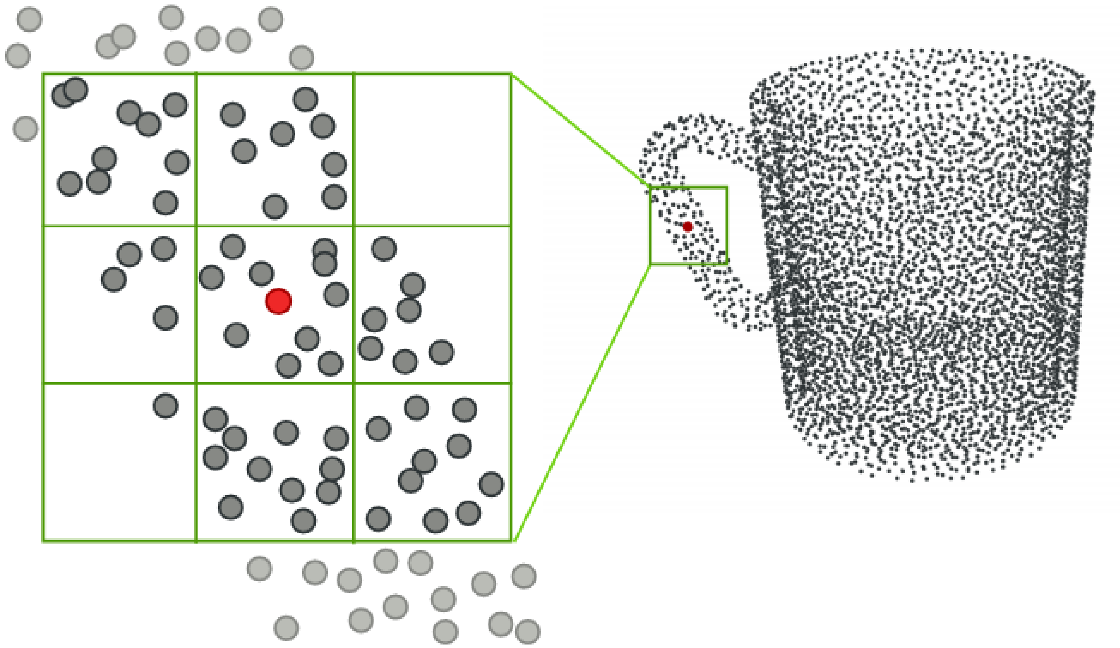


BCL: Bilateral convolution layer



Su et al. SPLATNet: Sparse Lattice Networks for Point Cloud Processing. CVPR 2018.

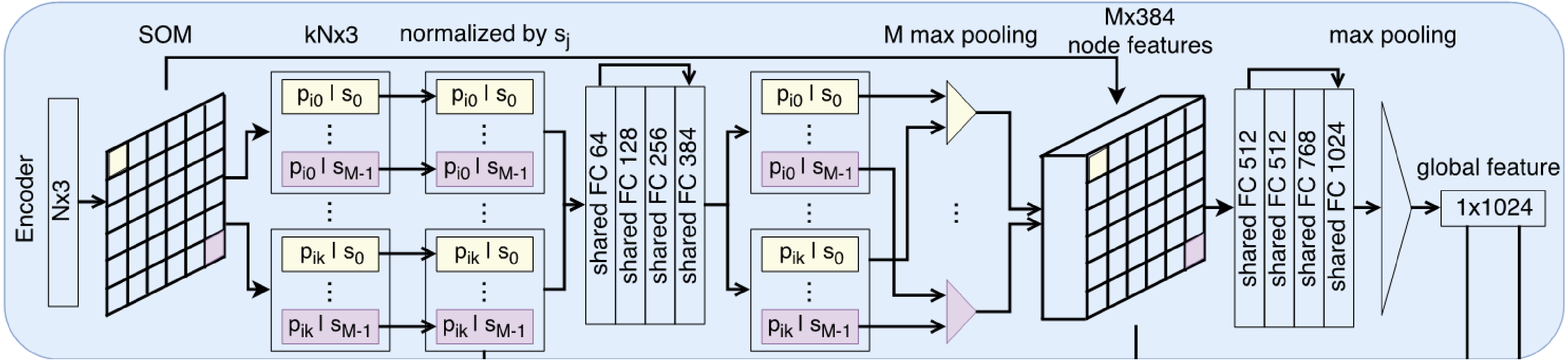
Related Work *Pointwise CNN: k-NN binned kernel*



$$x_i^\ell = \sum_k w_k \frac{1}{|\ \Omega_i(k)\ |} \sum_{p_j \in \Omega_i(k)} x_j^{\ell-1}$$

Hua et al. Pointwise Convolutional Neural Networks. CVPR 2018.

Related Work <u>*SO-Net: Self-Organizing Map (SOM)*</u>

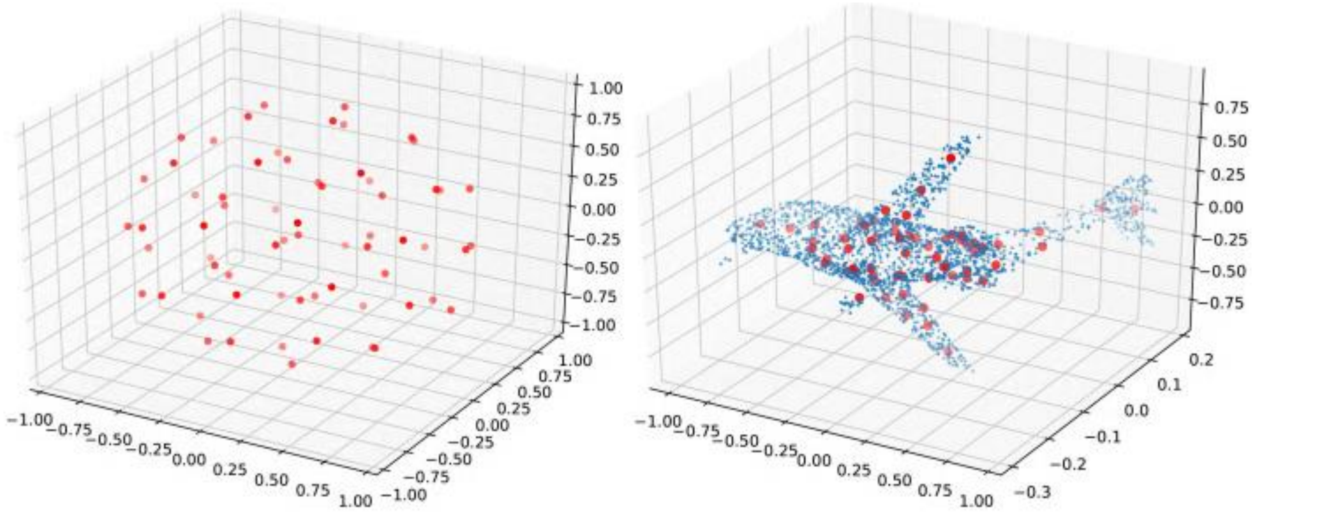


$$s_{ik} = \mathrm{kNN}(p_i \mid s_j,\ j = 0, \cdots, M-1).$$

$$p_{ik} = p_i - s_{ik}.$$

$$p_{ik}^{l+1} = \phi(W^l p_{ik}^l + b^l).$$

$$s_j^0 = \max(\{p_{ik}^l, \forall s_{ik} = s_j\}).$$



Li et al. SO-Net: Self-Organizing Network for Point Cloud Analysis. CVPR 2018.

Related Work *PointCNN: X-transformation*

In this paper, we propose to learn a $K \times K$ $\mathcal{X}$-transformation for the coordinates of K input points $(p_1, p_2, ..., p_K)$, with a multilayer perceptron [39], i.e., $\mathcal{X} = MLP(p_1, p_2, ..., p_K)$. Our aim is to use it to simultaneously weight and permute the input features, and subsequently apply a typical convolution on the transformed features. We refer to this process as $\mathcal{X}$-Conv, and it is the basic

ALGORITHM 1: $\mathcal{X}$-Conv Operator

Input : $\mathbf{K}$, p, $\mathbf{P}$, $\mathbf{F}$

Output : $\mathbf{F}_p$ ▷ Features "projected", or "aggregated", into representative point p

1: $\mathbf{P}' \leftarrow \mathbf{P} - p$ ▷ Move $\mathbf{P}$ to local coordinate system of p

2: $\mathbf{F}_\delta \leftarrow MLP_\delta(\mathbf{P}')$ ▷ **Individually** lift each point into C_δ dimensional space

3: $\mathbf{F}_* \leftarrow [\mathbf{F}_\delta, \mathbf{F}]$ ▷ Concatenate $\mathbf{F}_\delta$ and $\mathbf{F}$, $\mathbf{F}_*$ is a $K \times (C_\delta + C_1)$ matrix

4: $\mathcal{X} \leftarrow MLP(\mathbf{P}')$ ▷ Learn the $K \times K$ $\mathcal{X}$-transformation matrix

5: $\mathbf{F}_\mathcal{X} \leftarrow \mathcal{X} \times \mathbf{F}_*$ ▷ Weight and permute $\mathbf{F}_*$ with the learnt $\mathcal{X}$

6: $\mathbf{F}_p \leftarrow \mathrm{Conv}(\mathbf{K}, \mathbf{F}_\mathcal{X})$ ▷ Finally, typical convolution between $\mathbf{K}$ and $\mathbf{F}_\mathcal{X}$

Li et al. PointCNN: Convolution On X-Transformed Points. NIPS 2018.

Related Work <u>*PointSift: SIFT-like network*</u>

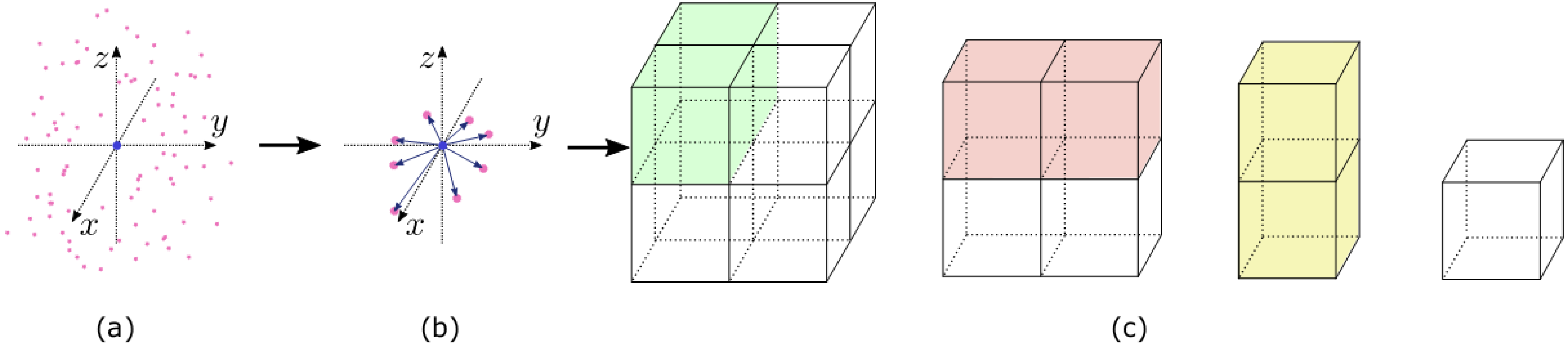
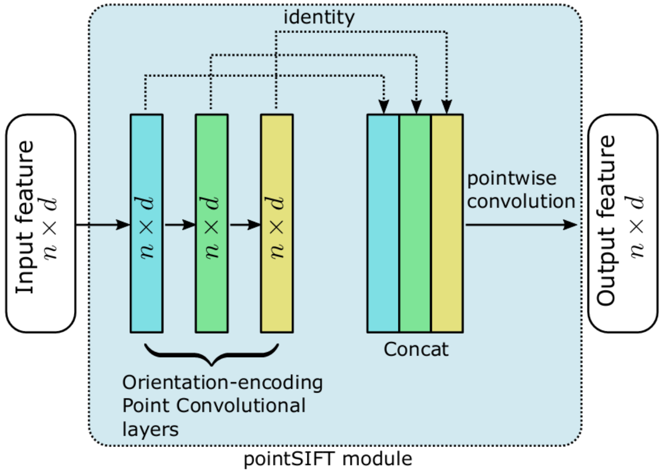


Figure 4: Illustration of the details in Orientation-encoding Point Convolutional layer. (a): point clouds in 3D space. (b) neighbors in eight directions. (c) three stages convolution combines all the features.

SIFT :

- orientation-encoding
- scale-awareness (shortcut connections)



Jiang et al. PointSIFT: A SIFT-like Network Module for 3D Point Cloud Semantic Segmentation. arXiv 2018.

Related work – robustness to rigid transformation

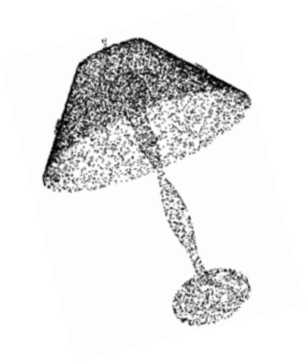
Related Work

Normalization:

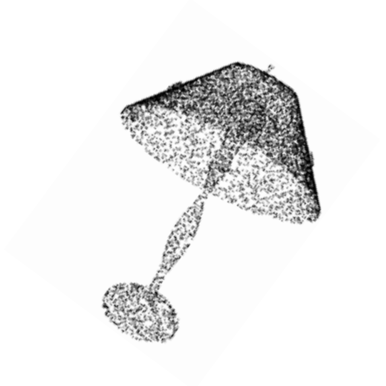
✓ Translation

✓ Scale

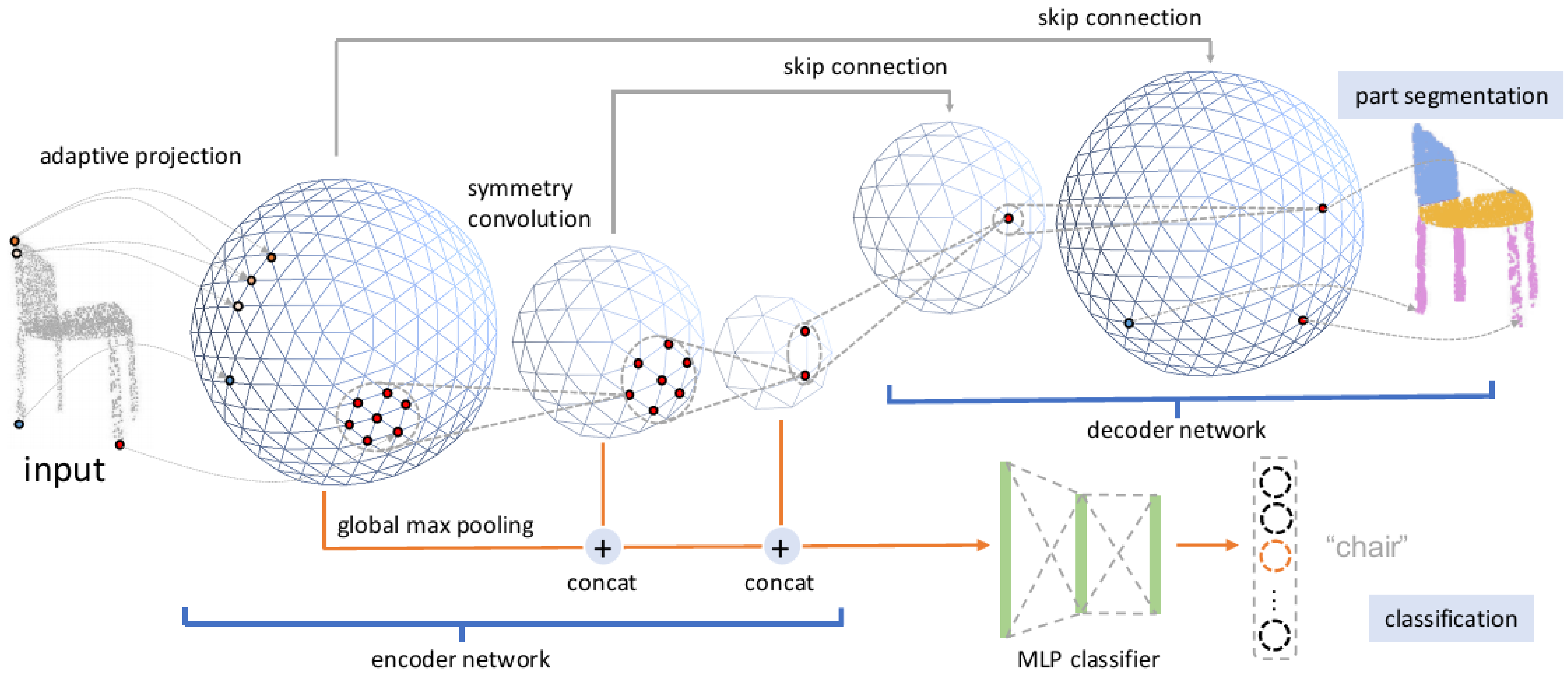
x Rotation



X · **R,** (Nx3) · (3x3)



Related Work <u>*SFCNN: Spherical Fractal CNN*</u>



Cohen et al. Spherical CNNs. ICLR 2018.

Rao et al. Spherical Fractal Convolution Neural Networks for Point Cloud Recognition. CVPR 2019.

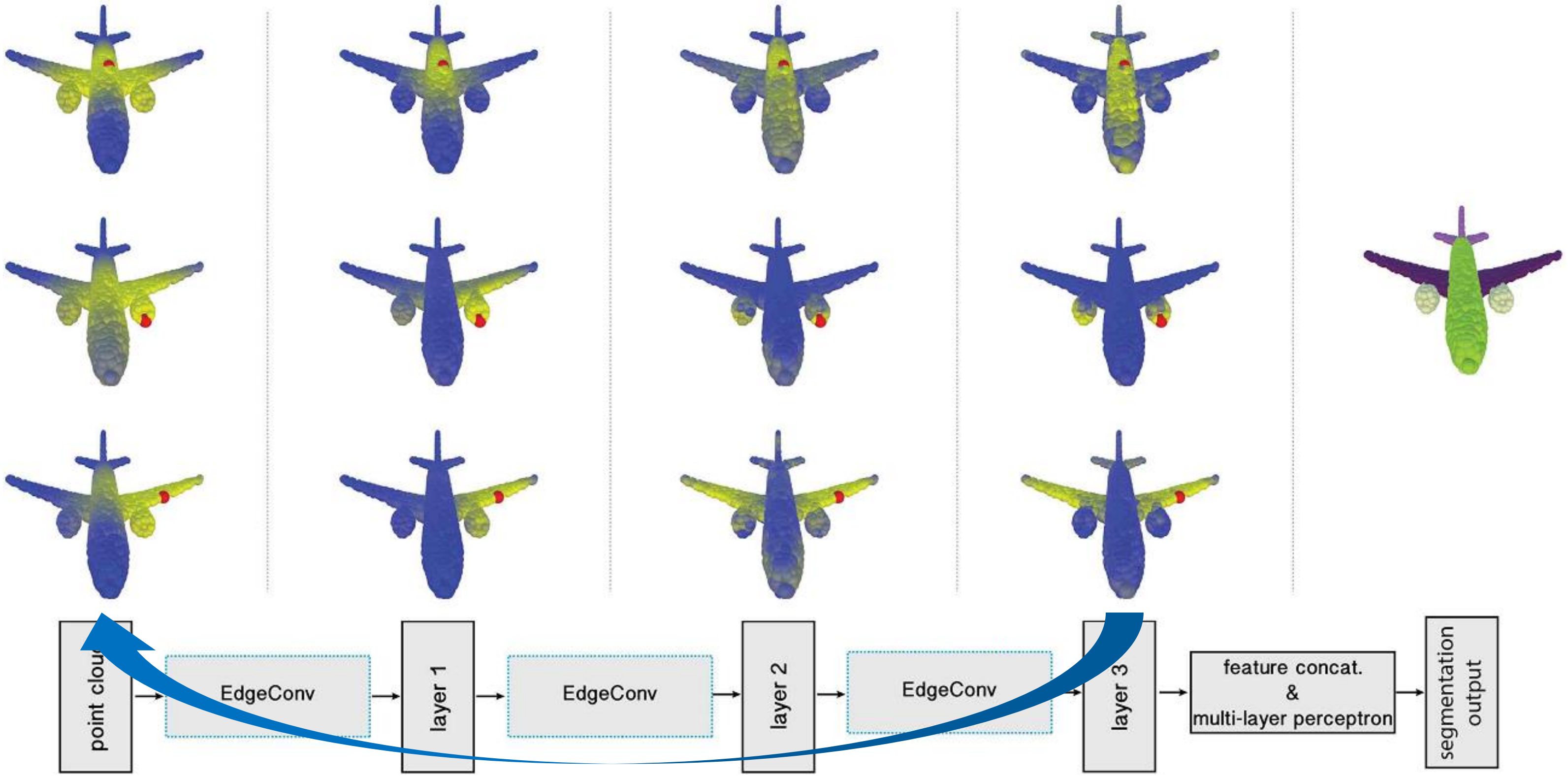
Related work – relation modeling

Related Work <u>*DGCNN*</u>

Dynamic Graph CNN (DGCNN)

Points in high-level feature space captures semantically similar structures.

Despite a large distance between them in the original 3D space.



Wang et al. Dynamic Graph CNN for Learning on Point Clouds. 2018.

Related Work DGCNN

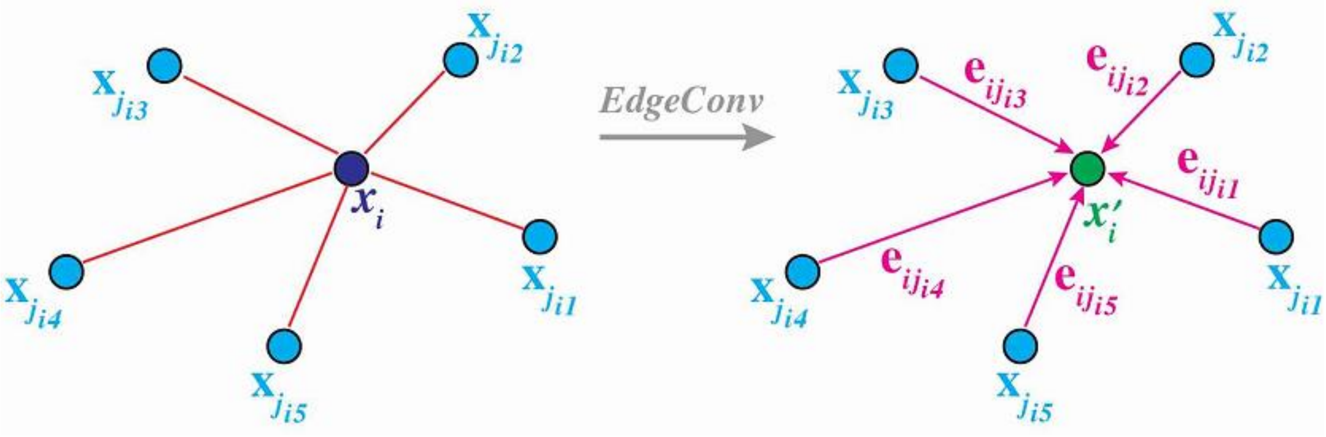
global info. local info.

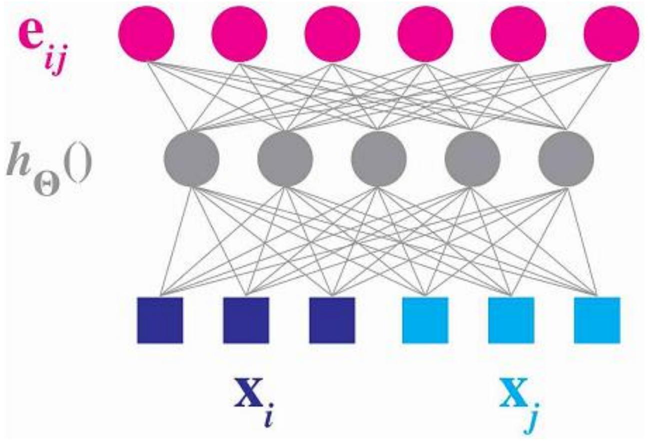
$$h_\Theta(\boxed{x_i}, \boxed{x_j - x_i})$$

$$x'_i = \mathop{\square}\limits^{\text{max}}_{j:(i,j)\in\mathcal{E}} h_\Theta(x_i, x_j).$$

- Neighbors are found in feature space
- Learn from semantically similar structures

DGCNN —— EdgeConv





Wang et al. Dynamic Graph CNN for Learning on Point Clouds. 2018.

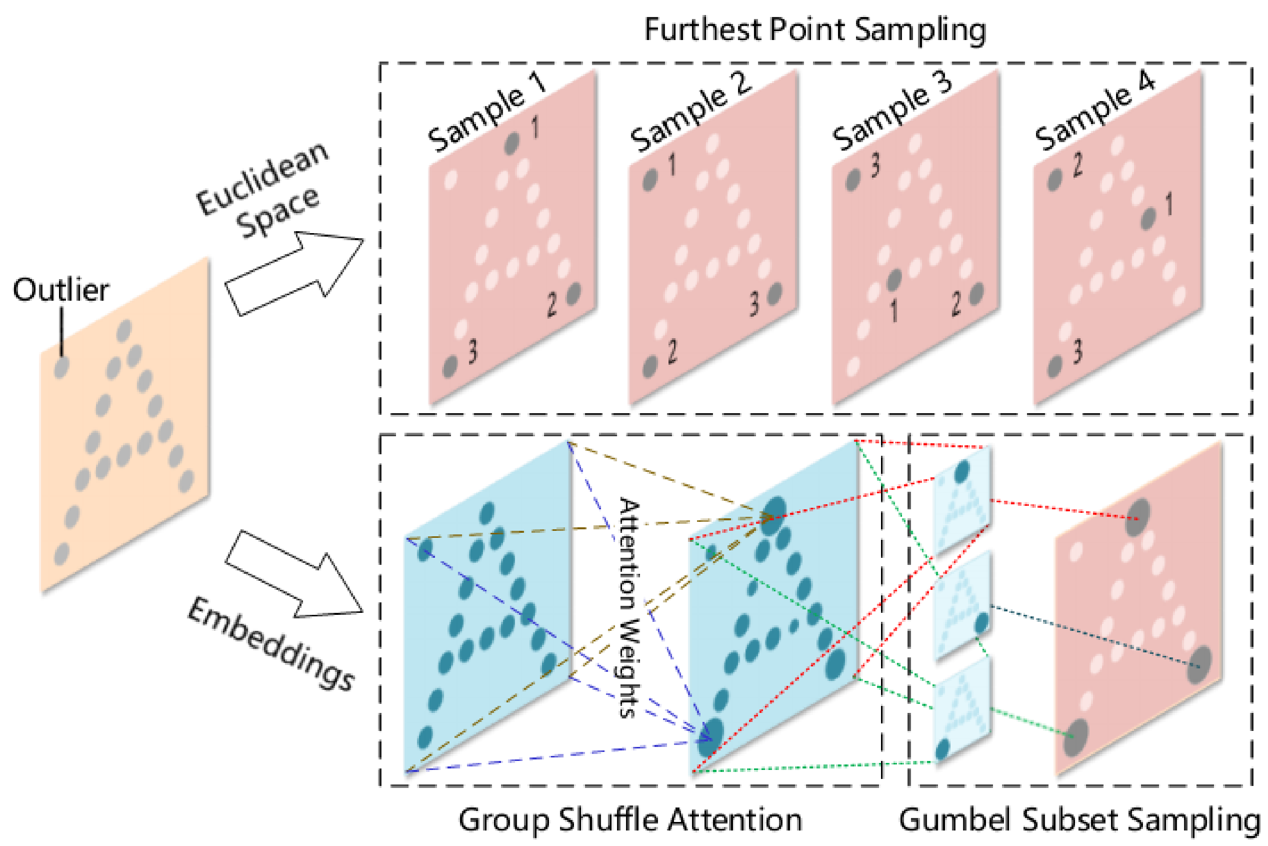
Related Work <u>*self-attention*</u>

- Relation modeling: self-attention
- Gumbel Subset Sampling VS. Farthest Point Sampling

  — permutation-invariant

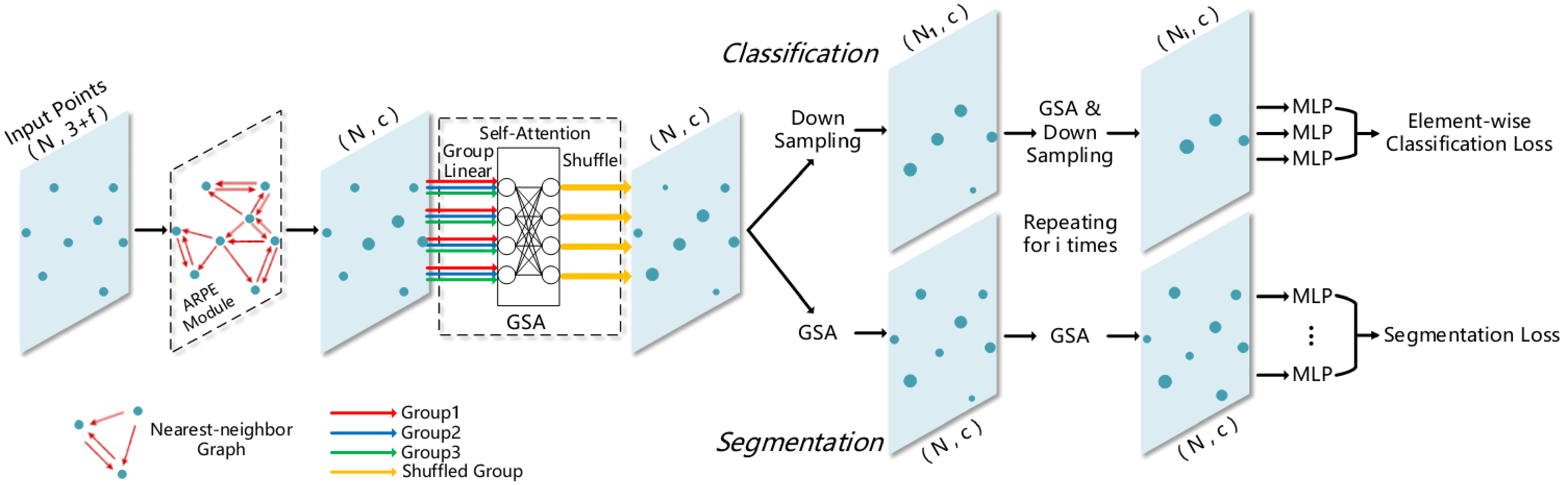
  — high-dimension embedding space

  — differentiable



Yang et al. Modeling Point Clouds with Self-Attention and Gumbel Subset Sampling. CVPR 2019.

Related Work <u>*self-attention*</u>



Embedding：PointNet

$$X'_p = \{(x_p, x_i - x_p) \,|\, i \neq p\}.$$

Self-attention：

group convolution + channel shuffle + pre-activation

Yang et al. Modeling Point Clouds with Self-Attention and Gumbel Subset Sampling. CVPR 2019.

Related Work *self-attention*

$$X_i \in \mathbb{R}^{N_i \times c}$$

$$X_{i+1} \in \mathbb{R}^{N_{i+1} \times c} \subseteq X_i$$

Gumbel Subset Sampling:

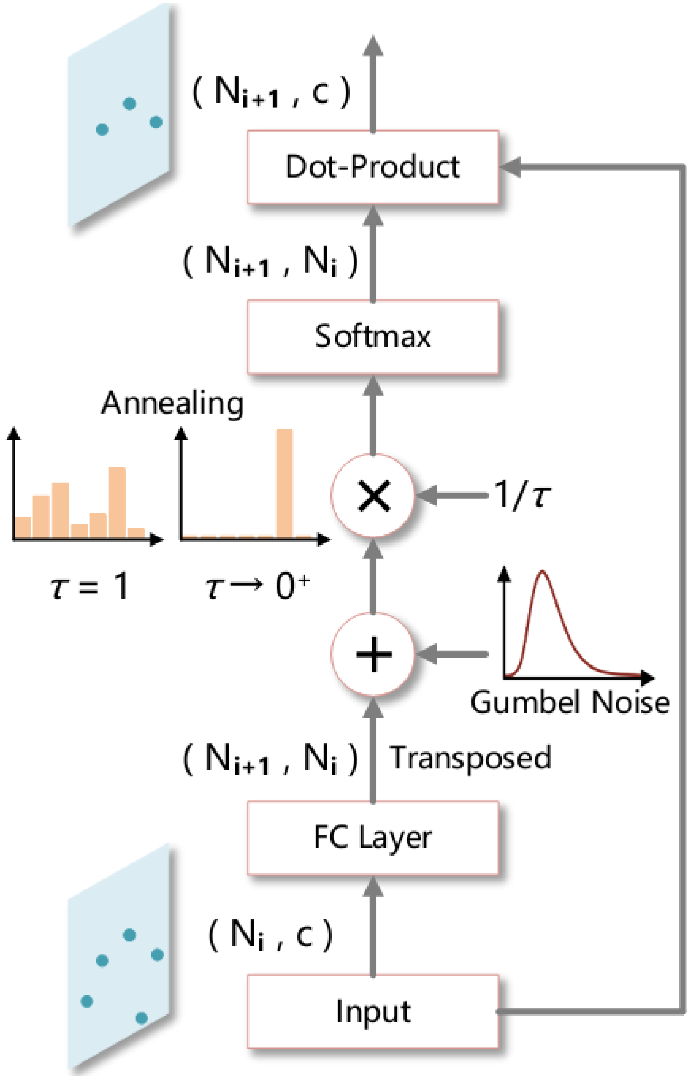
$$y = softmax(wX_i^T) \cdot X_i, \quad w \in \mathbb{R}^c.$$

discrete reparameterization trick

$$y_{gumbel} = gumbel\_softmax(wX_i^T) \cdot X_i, \quad w \in \mathbb{R}^c.$$

multiple point version

$$GSS(X_i) = gumbel\_softmax(WX_i^T) \cdot X_i, \quad W \in \mathbb{R}^{N_{i+1} \times c}.$$



Maximilian et al. Attention-based deep multiple instance learning. ICML 2018.
Yang et al. Modeling Point Clouds with Self-Attention and Gumbel Subset Sampling. CVPR 2019.

Related work – convolution on point cloud

Related Work   *Kernel Point Convolution*

$$(\mathcal{F} * g)(x) = \sum_{x_i \in \mathcal{N}_x} g(x_i - x) f_i$$

$$y_i = x_i - x$$

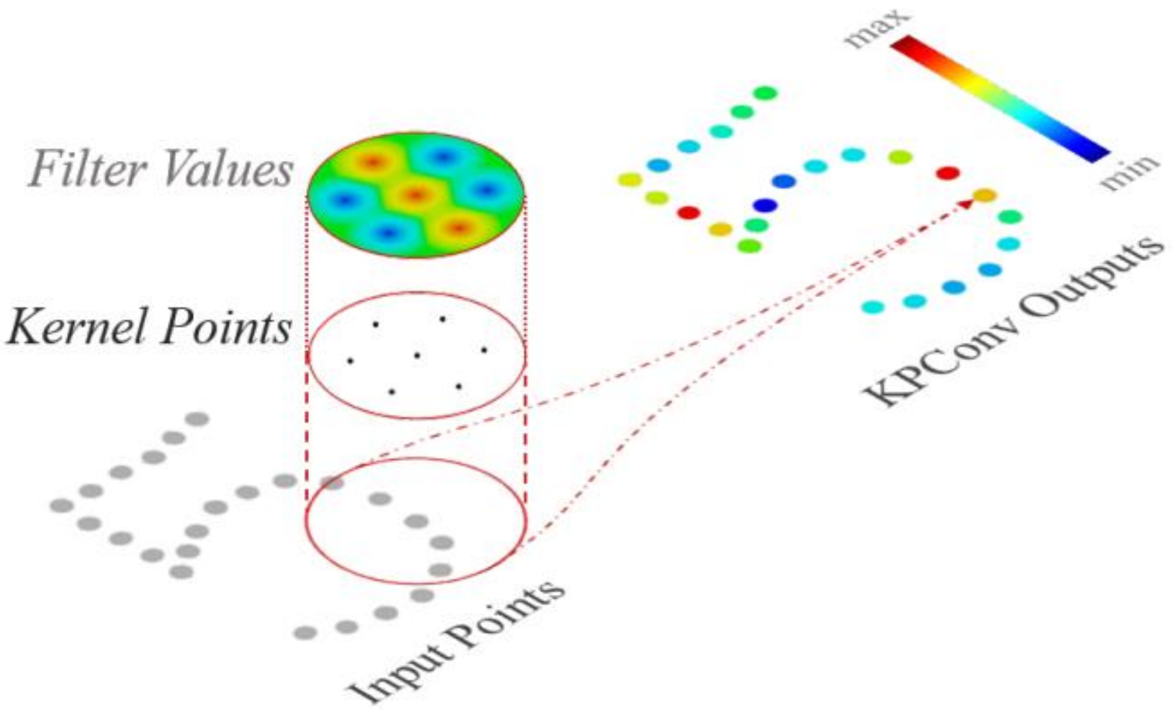
$$\mathcal{B}_r^3 = \{y \in \mathbb{R}^3 \mid \|y\| \leqslant r\}$$

$$g(y_i) = \sum_{k<K} h(y_i, \widetilde{x}_k) W_k$$

kernel points: $\{\widetilde{x}_k \mid k < K\} \subset \mathcal{B}_r^3$

$\{W_k \mid k < K\} \subset \mathbb{R}^{D_{in} \times D_{out}}$

$$h(y_i, \widetilde{x}_k) = \max\left(0, 1 - \frac{\|y_i - \widetilde{x}_k\|}{\sigma}\right)$$



Hugues et al. KPConv: Flexible and Deformable Convolution for Point Clouds. arXiv 2019.

Related Work <u>*Kernel Point Convolution*</u>

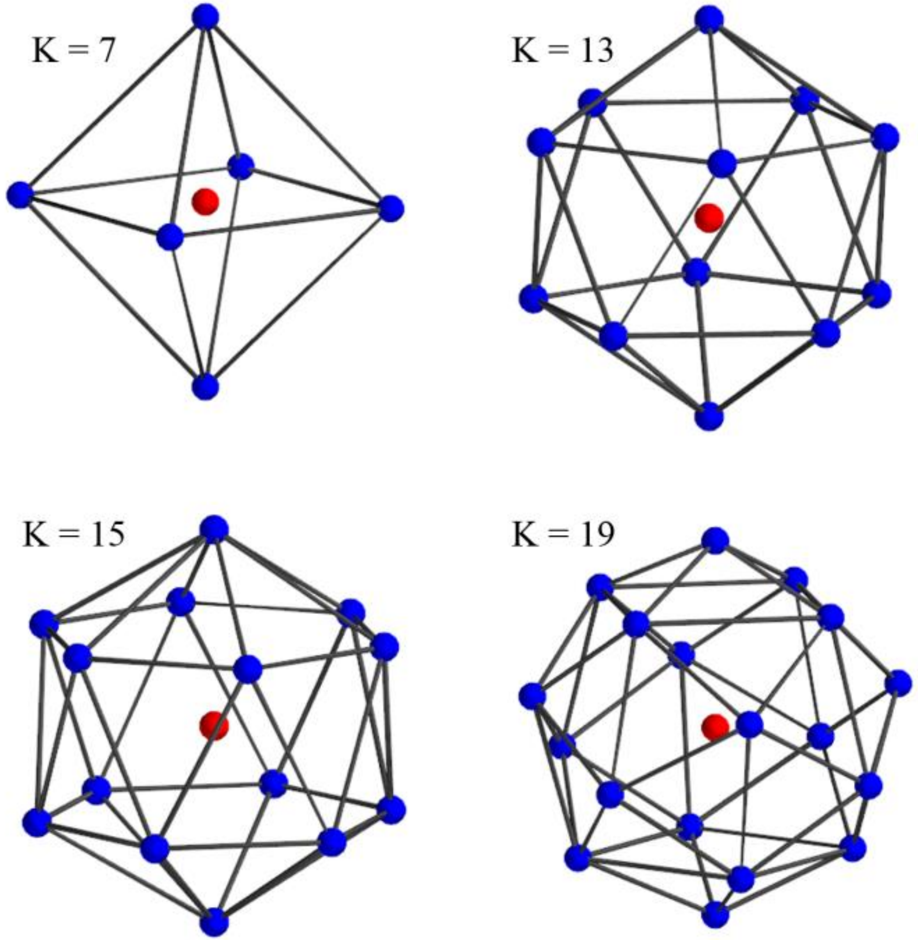
repulsive potential:

$$\forall x \in \mathbb{R}^3, \quad E_k^{rep}(x) = \frac{1}{\|x - \widetilde{x}_k\|}$$

attractive potential:

$$\forall x \in \mathbb{R}^3, \quad E^{att}(x) = \|x\|^2$$

$$E^{tot} = \sum_{k<K} \left(E^{att}(\widetilde{x}_k) + \sum_{l \neq k} E_k^{rep}(\widetilde{x}_l) \right)$$



Hugues et al. KPConv: Flexible and Deformable Convolution for Point Clouds. arXiv 2019.

Related Work Kernel Point Convolution

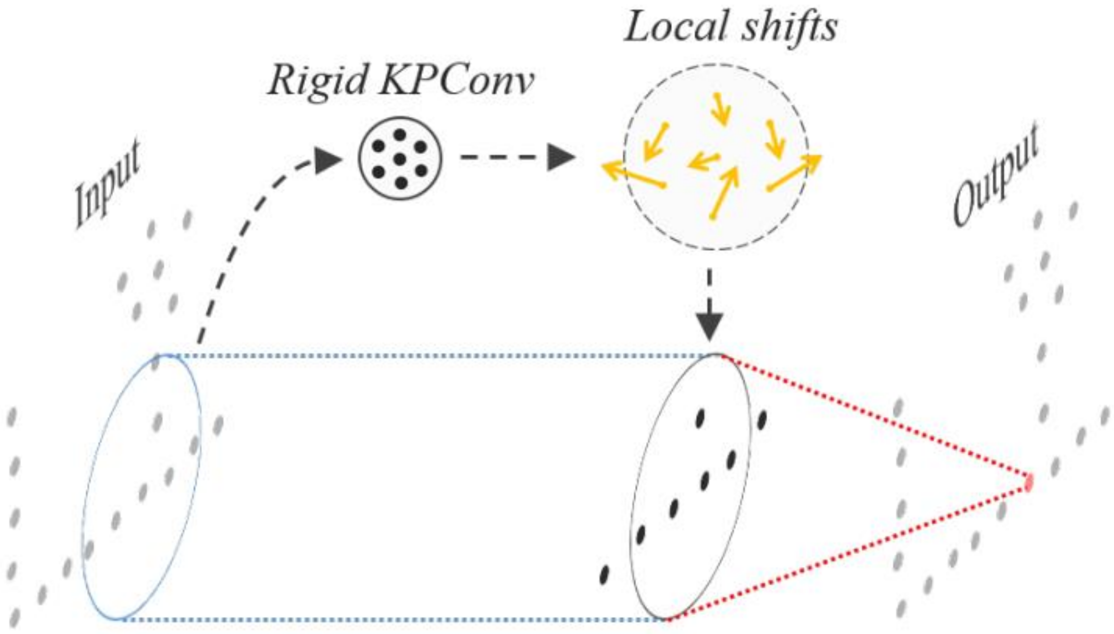
Rigid: $$(\mathcal{F} * g)(x) = \sum_{x_i \in \mathcal{N}_x} g(x_i - x) f_i$$

$$g(y_i) = \sum_{k<K} h\left(y_i, \widetilde{x}_k\right) W_k$$

Deformable: fit the local geometry

$$(\mathcal{F} * g)(x) = \sum_{x_i \in \mathcal{N}_x} g_{deform}(x - x_i, \Delta(x)) f_i$$

$$g_{deform}(y_i, \Delta(x)) = \sum_{k<K} h\left(y_i, \widetilde{x}_k + \Delta_k(x)\right) W_k$$



Hugues et al. KPConv: Flexible and Deformable Convolution for Point Clouds. arXiv 2019.

Github: awesome-point-cloud-analysis

```
- Recent papers (from 2017)
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Keywords

`dat.` : dataset | `cls.` : classification | `rel.` : retrieval | `seg.` : segmentation
`det.` : detection | `tra.` : tracking | `pos.` : pose | `dep.` : depth
`reg.` : registration | `rec.` : reconstruction | `aut.` : autonomous driving
`oth.` : other, including normal-related, correspondence, mapping, matching, alignment, compression...

2017

- [CVPR] PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation. [tensorflow][pytorch] [`cls.` `seg.` `det.`]
- [CVPR] Dynamic Edge-Conditioned Filters in Convolutional Neural Networks on Graphs. [`cls.`]
- [CVPR] SyncSpecCNN: Synchronized Spectral CNN for 3D Shape Segmentation. [torch] [`seg.` `oth.`]
- [CVPR] ScanNet: Richly-annotated 3D Reconstructions of Indoor Scenes. [project][git] [`dat.` `cls.` `rel.` `seg.` `oth.`]
- [CVPR] Scalable Surface Reconstruction from Point Clouds with Extreme Scale and Density Diversity. [`oth.`]
- [CVPR] Efficient Global Point Cloud Alignment using Bayesian Nonparametric Mixtures. [code] [`oth.`]
- [CVPR] Discriminative Optimization: Theory and Applications to Point Cloud Registration. [`reg.`]
- [CVPR] 3D Point Cloud Registration for Localization using a Deep Neural Network Auto-Encoder. [git] [`reg.`]

Relation-Shape Convolutional Neural Network for Point Cloud Analysis (RS-CNN)

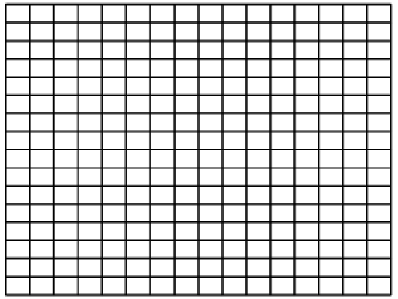
Yongcheng Liu, Bin Fan, Shiming Xiang, Chunhong Pan

CVPR 2019 **Oral Presentation**

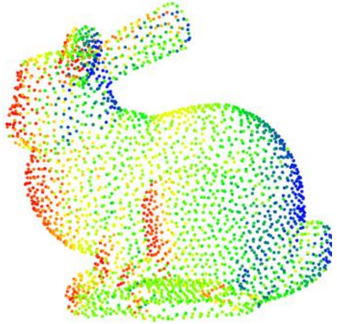
Project Page: https://yochengliu.github.io/Relation-Shape-CNN/

RS-CNN *Motivation*

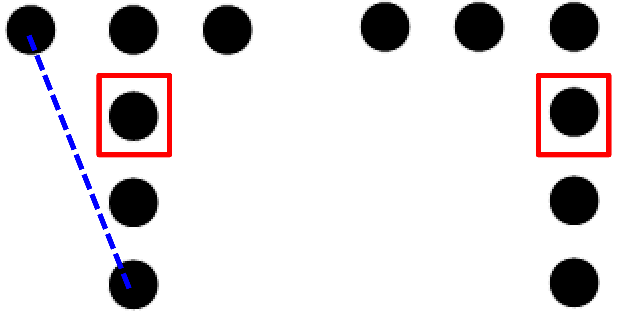
2D image



3D point cloud



3D **Shape** Learning



Relation Learning

Deep Learning (CNN)

RS-CNN *Method*

Relation-Shape Convolution (RS-Conv)

local point subset $P_{\text{sub}} \subset \mathbb{R}^3$ → spherical neighborhood: x_i + $x_j \in \mathcal{N}(x_i)$

$$\mathbf{f}_{P_{\text{sub}}} = \sigma\big(\mathcal{A}(\{\mathcal{T}(\mathbf{f}_{x_j}),\ \forall x_j\})\big)^1,\ d_{ij} < r\ \forall x_j \in \mathcal{N}(x_i) \qquad y = \sigma(\sum \mathbf{W} * \mathbf{X})$$

$\mathcal{T}$: feature transformation $\mathcal{A}$: feature aggregation

- Permutation invariance: only when A is symmetric and T is shared over each point
- Limitations of CNN: weight is not shared

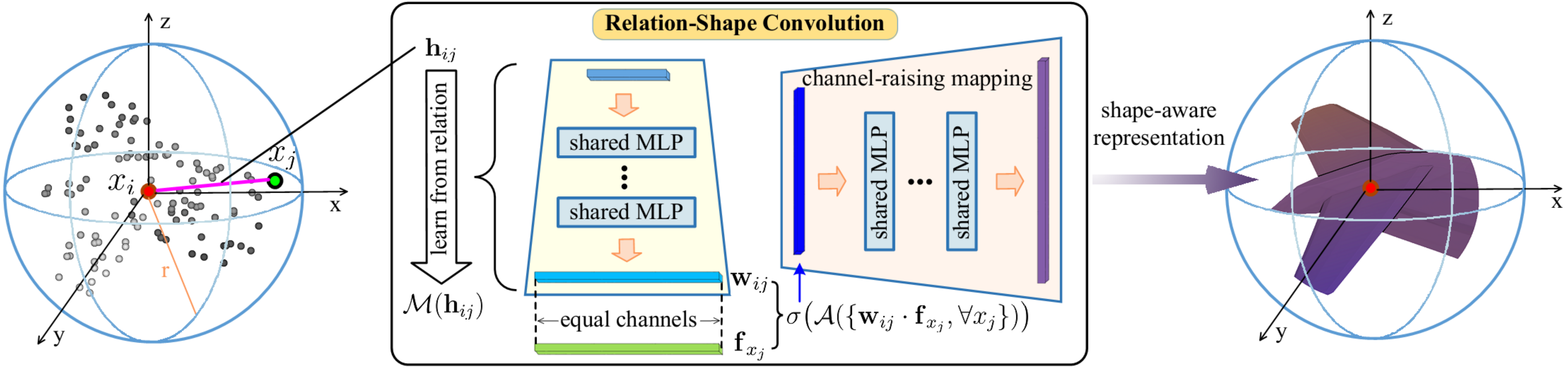
  gradient only w.r.t single point - implicit $\mathcal{T}(\mathbf{f}_{x_j}) = \mathbf{w}_j \cdot \mathbf{f}_{x_j}$
- Conversion: learn from relation $\mathcal{T}(\mathbf{f}_{x_j}) = \mathbf{w}_{ij} \cdot \mathbf{f}_{x_j} = \mathcal{M}(\mathbf{h}_{ij}) \cdot \mathbf{f}_{x_j}$

$\mathbf{h}_{ij}$: predefined geometric priors → low-level relation

$$\mathbf{f}_{P_{\text{sub}}} = \sigma\big(\mathcal{A}(\{\mathcal{M}(\mathbf{h}_{ij}) \cdot \mathbf{f}_{x_j},\ \forall x_j\})\big)$$

$\mathcal{M}$: mapping function(shared MLP) → high-level relation

RS-CNN *Method*



high-level relation encoding + channel raising mapping

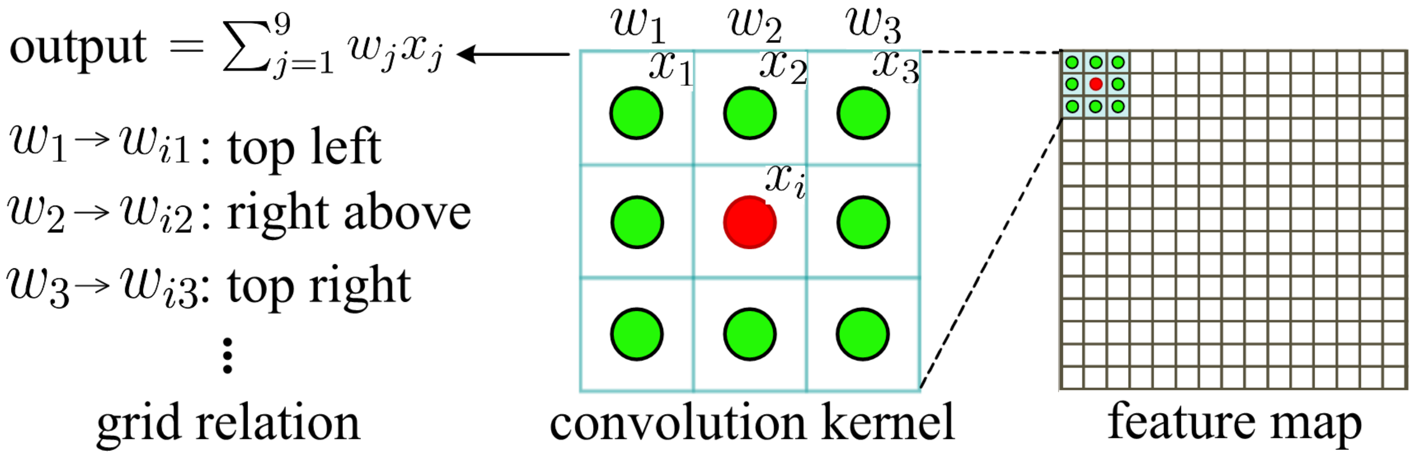
low-level relation $\mathbf{h}_{ij}$: (3D Euclidean distance, $x_i - x_j$, x_i, x_j) 10 channels

RS-CNN *RS-Conv: Properties*

$$\mathbf{f}_{P_{\text{sub}}} = \sigma\Big(\mathcal{A}(\{\mathcal{M}(\mathbf{h}_{ij}) \cdot \mathbf{f}_{x_j}, \ \forall x_j\})\Big)$$

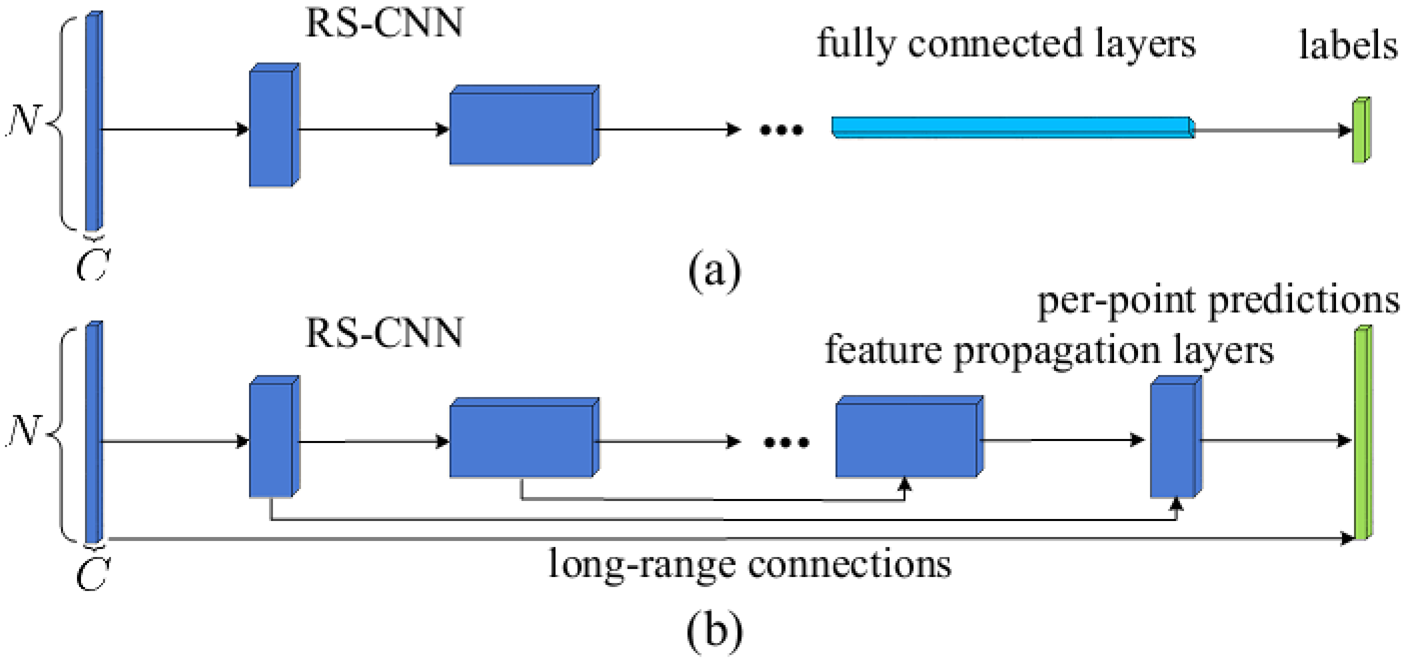
- ✓ Permutation invariance
- ✓ Robustness to rigid transformation in Relation Learning, e.g., 3D Euclidean distance
- ✓ Points' interaction
- ✓ Weight sharing

Revisiting 2D Conv:



RS-Conv with relation learning is more general and can be applied to model 2D grid spatial relationship.

RS-CNN *RS-CNN*

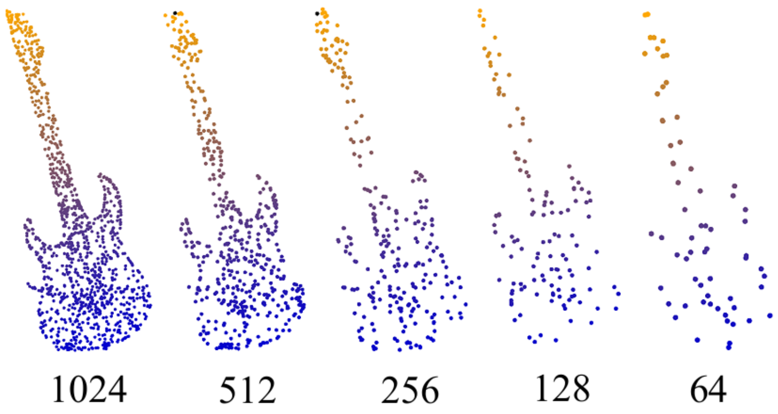


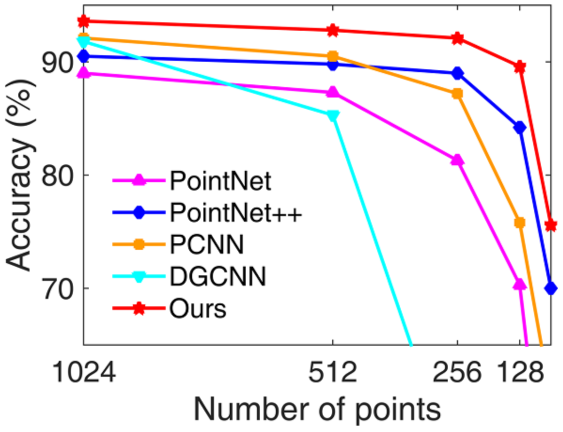
Farthest Point Sampling + Sphere Neighborhood + RS-Conv

RS-CNN *Shape classification*

ModelNet40 benchmark

Robustness to sampling density





method	input	#points	acc.
Pointwise-CNN [10]	xyz	1k	86.1
Deep Sets [48]	xyz	1k	87.1
ECC [31]	xyz	1k	87.4
PointNet [24]	xyz	1k	89.2
SCN [44]	xyz	1k	90.0
Kd-Net(depth=10) [16]	xyz	1k	90.6
PointNet++ [26]	xyz	1k	90.7
KCNet [30]	xyz	1k	91.0
MRTNet [3]	xyz	1k	91.2
Spec-GCN [38]	xyz	1k	91.5
PointCNN [21]	xyz	1k	91.7
DGCNN [41]	xyz	1k	92.2
PCNN [1]	xyz	1k	92.3
Ours	**xyz**	**1k**	**93.6**
SO-Net [19]	xyz	2k	90.9
Kd-Net(depth=15) [16]	xyz	32k	91.8
O-CNN [39]	xyz, nor	-	90.6
Spec-GCN [38]	xyz, nor	1k	91.8
PointNet++ [26]	xyz, nor	5k	91.9
SpiderCNN [45]	xyz, nor	5k	92.4
SO-Net [19]	xyz, nor	5k	93.4

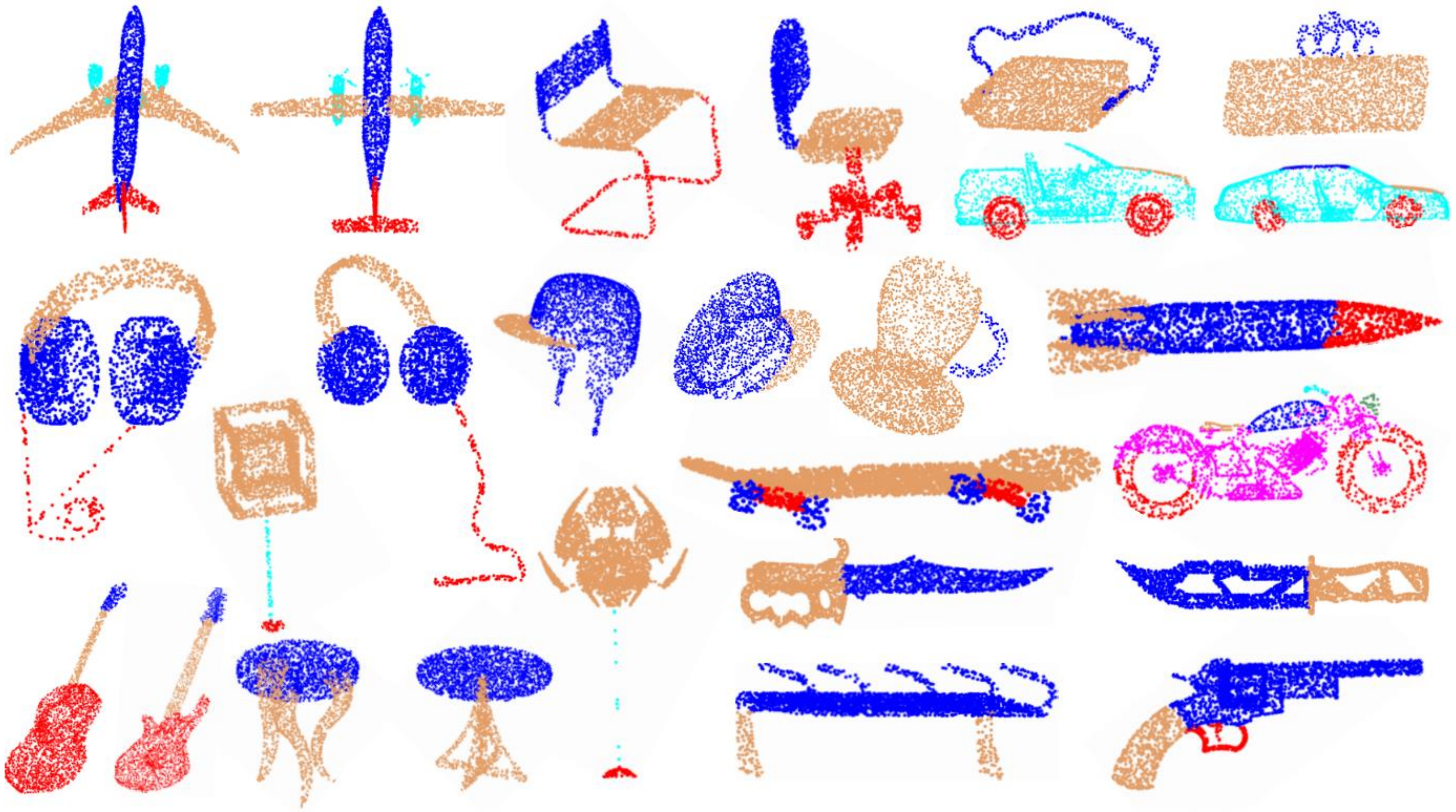
RS-CNN *ShapePart Segmentation*

method	input	class mIoU	instance mIoU	air plane	bag	cap	car	chair	ear phone	guitar	knife	lamp	laptop	motor bike	mug	pistol	rocket	skate board	table
Kd-Net [16]	4k	77.4	82.3	80.1	74.6	74.3	70.3	88.6	73.5	90.2	87.2	81.0	94.9	57.4	86.7	78.1	51.8	69.9	80.3
PointNet [24]	2k	80.4	83.7	83.4	78.7	82.5	74.9	89.6	73.0	91.5	85.9	80.8	95.3	65.2	93.0	81.2	57.9	72.8	80.6
RS-Net [11]	-	81.4	84.9	82.7	**86.4**	84.1	78.2	90.4	69.3	91.4	87.0	83.5	95.4	66.0	92.6	81.8	56.1	75.8	82.2
SCN [44]	1k	81.8	84.6	83.8	80.8	83.5	79.3	90.5	69.8	**91.7**	86.5	82.9	96.0	69.2	93.8	82.5	**62.9**	74.4	80.8
PCNN [1]	2k	81.8	85.1	82.4	80.1	85.5	79.5	90.8	73.2	91.3	86.0	85.0	95.7	73.2	94.8	83.3	51.0	75.0	81.8
SPLATNet [34]	-	82.0	84.6	81.9	83.9	88.6	79.5	90.1	73.5	91.3	84.7	84.5	**96.3**	69.7	**95.0**	81.7	59.2	70.4	81.3
KCNet [30]	2k	82.2	84.7	82.8	81.5	86.4	77.6	90.3	76.8	91.0	87.2	84.5	95.5	69.2	94.4	81.6	60.1	75.2	81.3
DGCNN [41]	2k	82.3	85.1	**84.2**	83.7	84.4	77.1	90.9	78.5	91.5	87.3	82.9	96.0	67.8	93.3	82.6	59.7	75.5	82.0
Ours	**2k**	**84.0**	**86.2**	83.5	84.8	**88.8**	**79.6**	**91.2**	**81.1**	91.6	**88.4**	**86.0**	96.0	**73.7**	94.1	**83.4**	60.5	**77.7**	**83.6**
PointNet++ [26]	2k,nor	81.9	85.1	82.4	79.0	87.7	77.3	90.8	71.8	91.0	85.9	83.7	95.3	71.6	94.1	81.3	58.7	76.4	82.6
SyncCNN [47]	mesh	82.0	84.7	81.6	81.7	81.9	75.2	90.2	74.9	93.0	86.1	84.7	95.6	66.7	92.7	81.6	60.6	82.9	82.1
SO-Net [19]	1k,nor	80.8	84.6	81.9	83.5	84.8	78.1	90.8	72.2	90.1	83.6	82.3	95.2	69.3	94.2	80.0	51.6	72.1	82.6
SpiderCNN [45]	2k,nor	82.4	85.3	83.5	81.0	87.2	77.5	90.7	76.8	91.1	87.3	83.3	95.8	70.2	93.5	82.7	59.7	75.8	82.8

class mIoU 1.7↑ instance mIoU 1.1↑

Best results over 10 categories

RS-CNN ***ShapePart Segmentation***



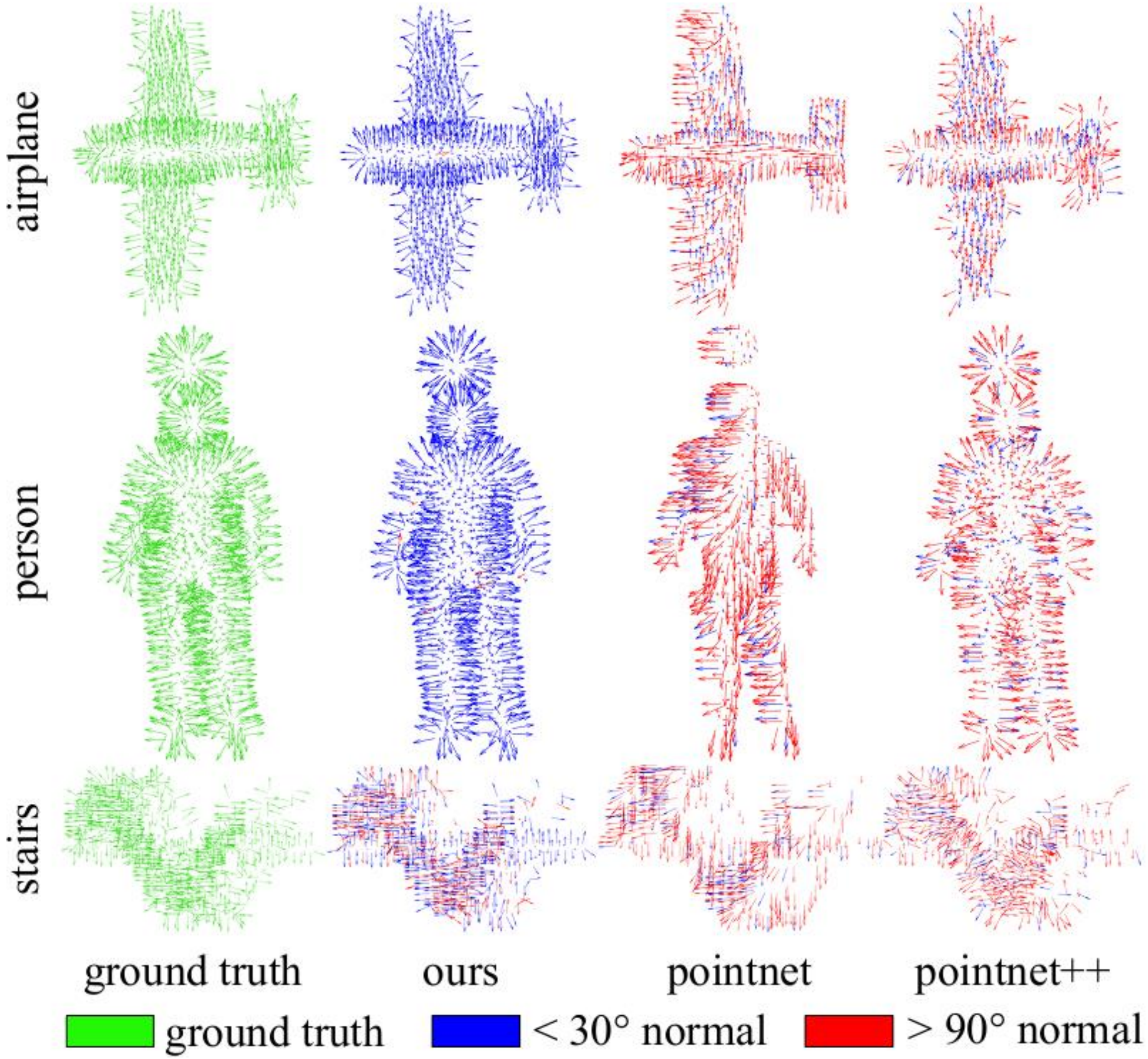
Diverse, confusing shapes

RS-CNN *Normal estimation*

Table 3. Normal estimation error on ModelNet40 dataset.

dataset	method	#points	error
ModelNet40	PointNet [1]	1k	0.47
	PointNet++ [1]	1k	0.29
	PCNN [1]	1k	0.19
	Ours	**1k**	**0.15**

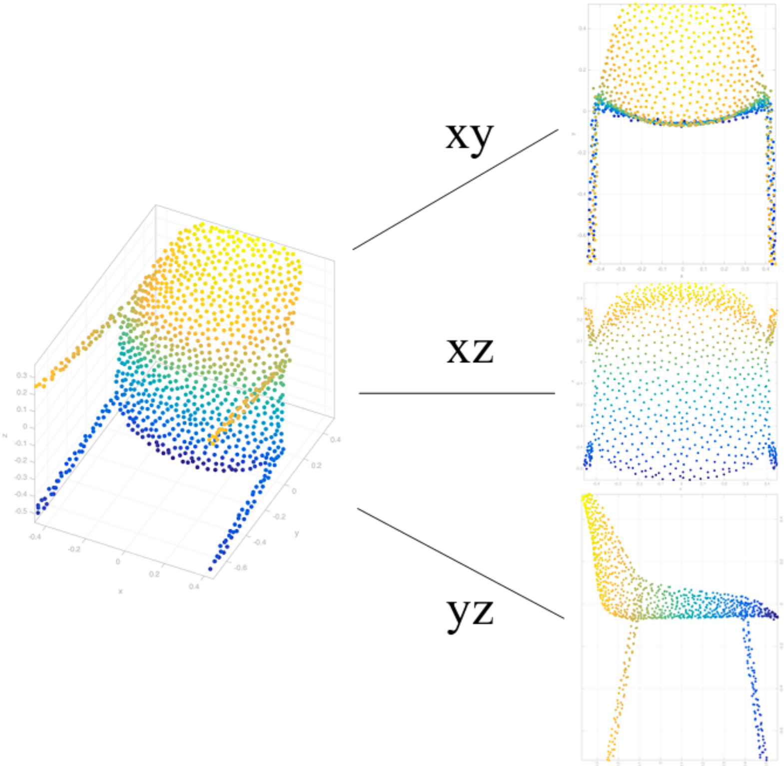
less effective for some intractable shapes, such as spiral stairs and intricate plants



RS-CNN *Geometric priors*

$$\mathbf{f}_{P_{\text{sub}}} = \sigma\big(\mathcal{A}(\{\mathcal{M}(\mathbf{h}_{ij}) \cdot \mathbf{f}_{x_j},\ \forall x_j\})\big)$$

model	low-level relation $\mathbf{h}$	channels	acc.
A	(3D-Ed)	1	92.5
B	(3D-Ed, $x_i - x_j$)	4	93.0
C	(3D-Ed, $x_i - x_j$, x_i, x_j)	10	**93.6**
D	(3D-cosd, x_i^{nor}, x_j^{nor})	7	92.8
E	(2D-Ed, $x'_i - x'_j$, x'_i, x'_j)	10	≈ 92.2



low-level relation $\mathbf{h}$	channels	acc.
(XY-Ed, $x_i^{\text{xy}} - x_j^{\text{xy}}$, x_i^{xy}, x_j^{xy})	10	92.1
(XY-Ed, $x_i^{\text{xz}} - x_j^{\text{xz}}$, x_i^{xz}, x_j^{xz})	10	92.1
(XY-Ed, $x_i^{\text{yz}} - x_j^{\text{yz}}$, x_i^{yz}, x_j^{yz})	10	92.2
fusion of above three views		92.5

RS-CNN *Model analysis*

Robustness to point permutation and rigid transformation

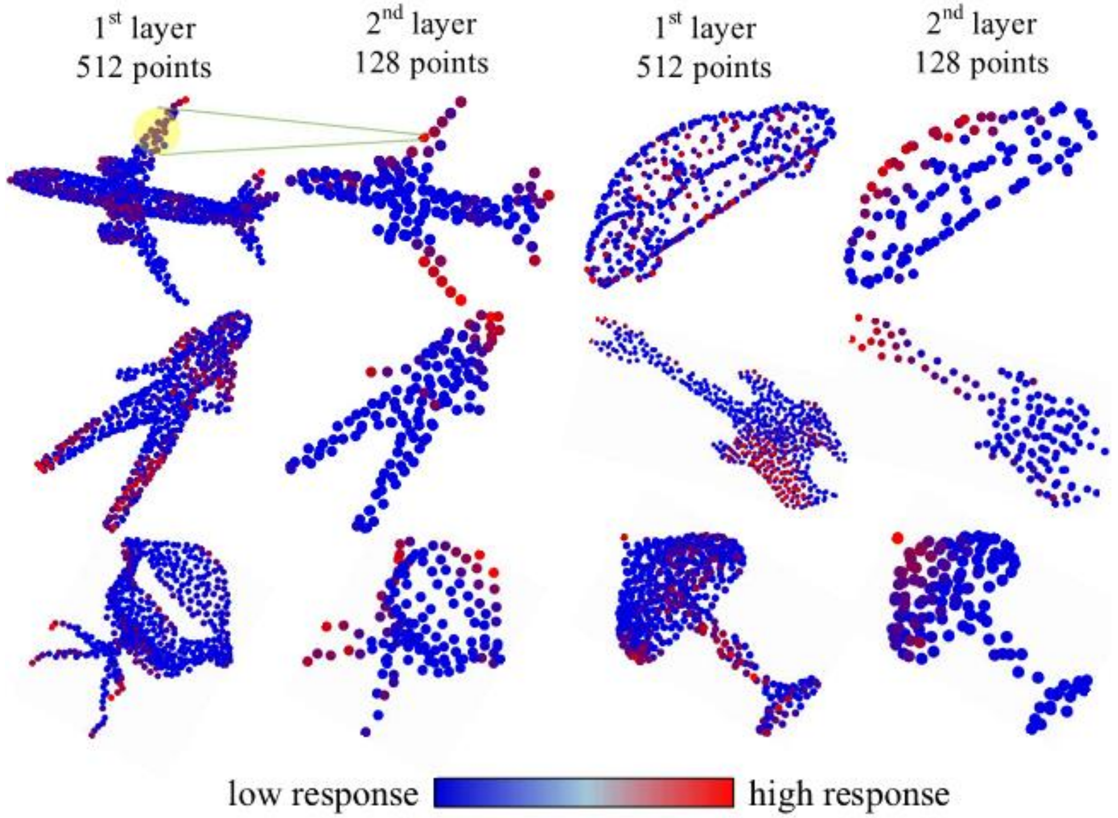
relation: 3D Euclidean distance

method	acc.	perm.	+0.2	-0.2	90°	180°
PointNet [24]	88.7	88.7	70.8	70.6	42.5	38.6
PointNet++ [26]	88.2†	88.2	88.2	88.2	47.9	39.7
Ours	**90.3**†	**90.3**	**90.3**	**90.3**	**90.3**	**90.3**

$$\mathbf{f}_{P_{\text{sub}}} = \sigma\big(\mathcal{A}(\{\mathcal{M}(\mathbf{h}_{ij}) \cdot \mathbf{f}_{x_j},\ \forall x_j\})\big)$$

Model complexity

method	#params	#FLOPs/sample
PointNet [24]	3.50M	440M
PointNet++ [21]	1.48M	1684M
PCNN [21]	8.20M	**294M**
Ours	**1.41M**	295M



Relation-Shape Convolutional Neural Network for Point Cloud Analysis

We propose a learn-from-relation convolution operator, which extends 2D CNN to irregular configuration for point cloud analysis.

Thanks for your attention !