Generalizing discrete convolutions for unstructured point clouds

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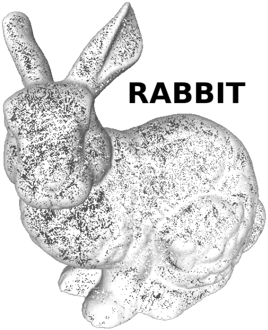
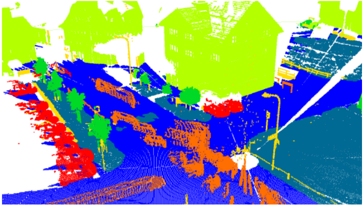
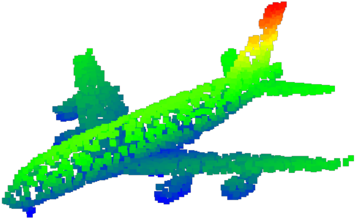


Classification



Semantic segmentation

Point clouds

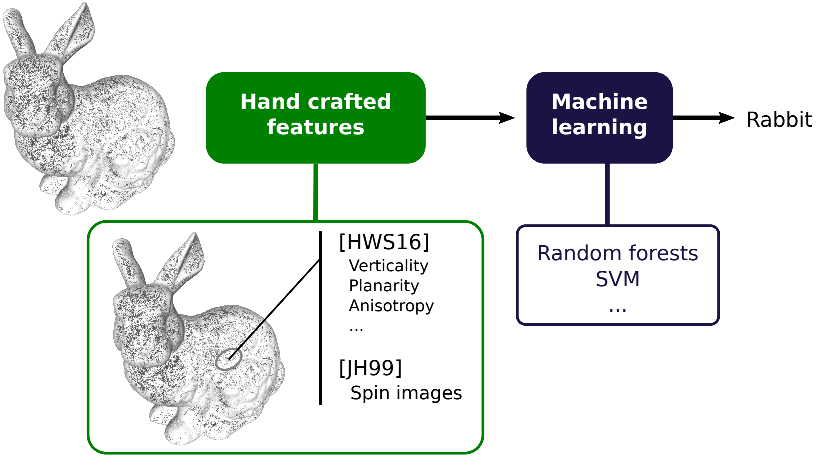


A point cloud is

- unstructured : not sampled on grid
- unordered : invariant by permutation of points
- scale less : e.g. CAD, photogrammetry
- defined by point coordinates only

Previous works

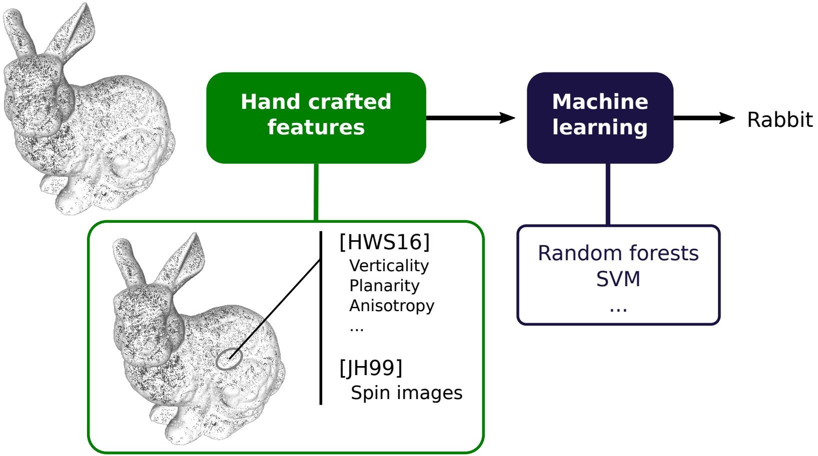
Hand crafted features



[HWS16] Hackel et al., Fast semantic segmentation of 3D point clouds with strongly varying density, ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences, 2016

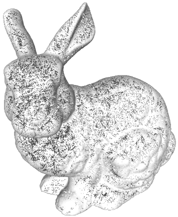
[JH99] Johnson et al., Using spin images for efficient object recognition in cluttered 3D scenes, IEEE PAMI 1999.

Hand crafted features

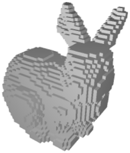


- Designing features is difficult $\rightarrow$ learn them with deep methods
- Exploit images processing approaches $\rightarrow$ adapt space

Deep approaches : voxelization



Space adaptation → **Machine learning** Representation and decision → Rabbit



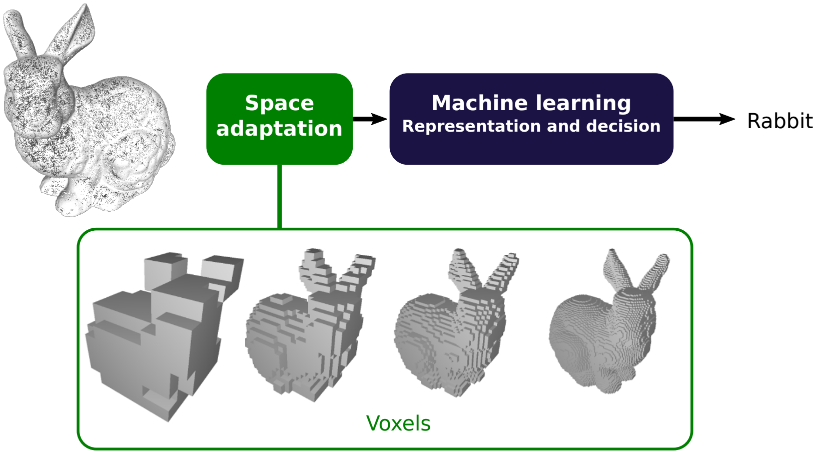
Voxels

3D CNNs
[MS15]

Sparse Conv.
[GEM18]

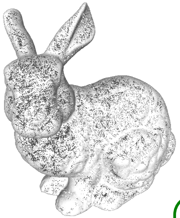
[MS15], Maturana and Scherer, Voxnet : A 3D convolutional neural network for real-time object recognition, IROS 2015
[GEM18] Graham et al. 3D semantic segmentation with submanifold sparse convolutional networks, CVPR 2018

Deep approaches : voxelization

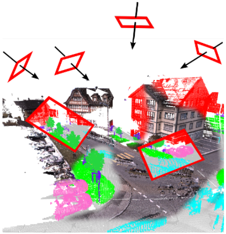


Difficulties : Voxel sizes ? Voxel orientation ?

Deep approaches : 2D approaches



Space adaptation → **Machine learning** Representation and decision → Rabbit

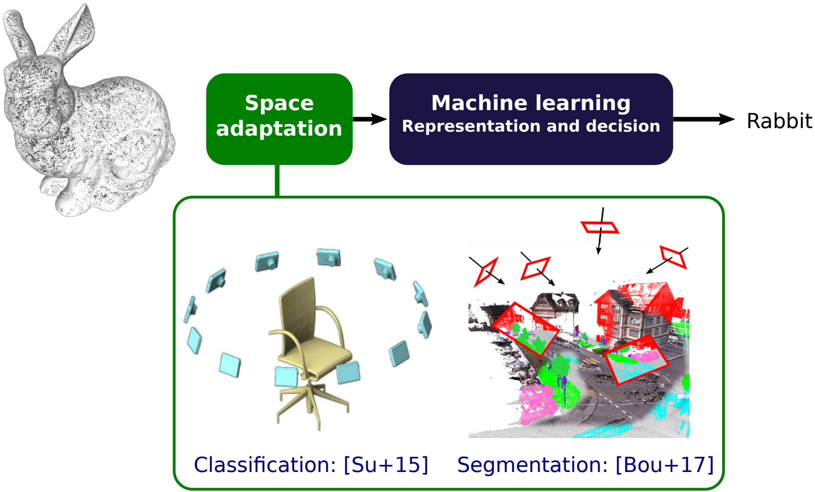


Classification: [Su+15]   Segmentation: [Bou+17]

[Su+15] Su et al, Multi-view convolutional neural networks for 3D shape recognition, ICCV, 2015

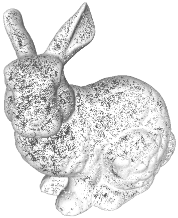
[Bou+17] Boulch et al, SnapNet : 3D point cloud semantic labeling with 2D deep segmentation networks, Computer & Graphics, 2017

Deep approaches : 2D approaches



Difficulties : Snapshot strategies ?

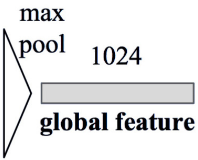
Deep approaches : raw data



Space adaptation → **Machine learning** Representation and decision → Rabbit

Machine learning
From raw data to decision → Rabbit

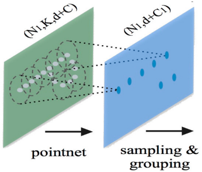
Deep approaches : raw data



PointNet : Qi et al [Qi+17a]

Permutation inv. : Max pooling.

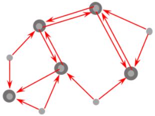
Use location as features.



PointNet++ : Qi et al [Qi+17b]

Hierarchical reprentation.

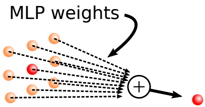
Use location as features.



PointCNN : Li et al [Li+18]

Input projection on kernel.

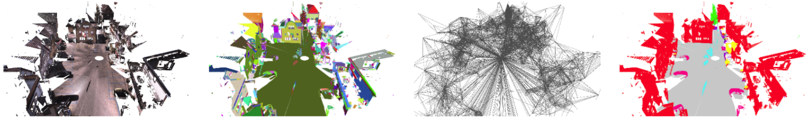
Use location as features.



PCCN : Wang et al [Wan+18a]

Feature weighting using MLP

Super-Point graph



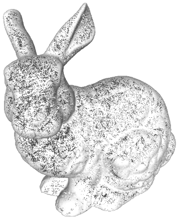
(a) RGB point cloud (b) Geometric partition (c) Superpoint graph (d) Semantic segmentation

- Offline segmentation
- Network : PointNet on each primitive + GRU for message passing

[LS18] Landrieu et al., Large-scale point cloud semantic segmentation with superpoint graphs, CVPR, 2018

Generalizing convolutions

Objective



Machine learning
From raw data to decision

→ Rabbit

CNNs have proved very efficient for image / voxel processing

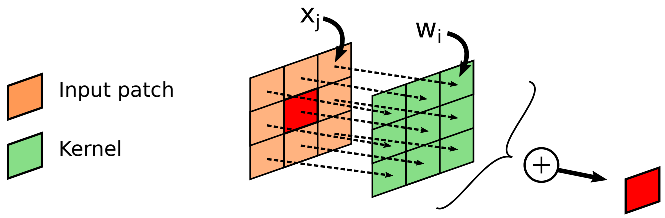
Objective

- Adapt convolutions do sparse, unstructured data
- Stick as mush as possible to the original formulation

Formulation for images

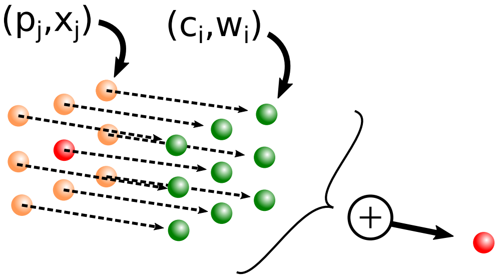
$$y = \beta + \sum_{i=1}^{N} \mathbf{w}_i \mathbf{x}_i = \beta + \sum_{i=1}^{N} \sum_{j=1}^{|X|} \mathbf{w}_i \mathbf{x}_j \mathbf{1}(i,j)$$

with X the input patch and $\mathbf{1}(i,j)$ the indicator function.



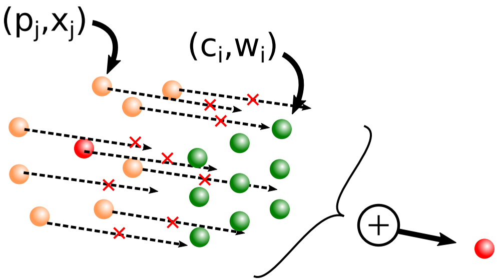
Formulation with points

$$y = \beta + \frac{1}{|X|}\sum_{j=1}^{|X|}\sum_{i=1}^{N} \mathbf{w}_i \mathbf{x}_j \mathbf{1}(\mathbf{c}_i, \mathbf{p}_j)$$



Valid for structured inputs.

Point cloud particularities



Unstructured inputs would lead to zero value almost all the time.

Indicator function is not the right function for unstructured inputs.

$$y = \beta + \frac{1}{|X|} \sum_{j=1}^{|X|} \sum_{i=1}^{N} \mathbf{w}_i \mathbf{x}_j \phi_i(p_j, C)$$

- Interpolation to neighbors

Somehow suppose a grid for the kernel.

Hang SU et al. "SPLATNet : Sparse Lattice Networks for Point Cloud Processing". In : *arXiv preprint arXiv :1802.08275* (2018)

Continuous convolution

$$y = \beta + \frac{1}{|X|} \sum_{j=1}^{|X|} \sum_{i=1}^{N} \mathbf{w}_i \mathbf{x}_j \phi_i(p_j, C)$$

ϕ construction :

- dicrease with the a distance
- deal with relative positions of kernel elements

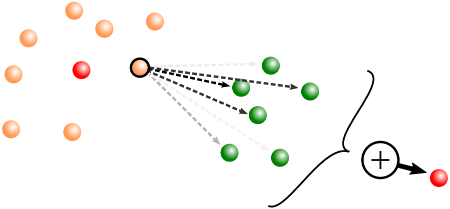
Inverse ℓ_2 distance ? Gaussian functions ? ...

How to tune parameters ?

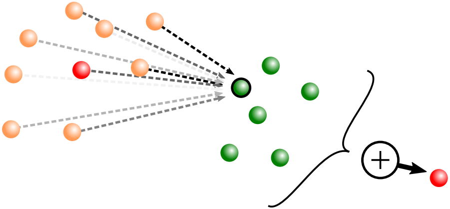
Our approach

Use a MLP for ϕ function [Li+18 ; Wan+18a] :

$$y = \beta + \frac{1}{|X|} \sum_{j=1}^{|X|} \sum_{i=1}^{N} \mathbf{w}_i \mathbf{x}_j MLP_i(p_j - C)$$



Each input influences each kernel elements



Each kernel element sees the whole input

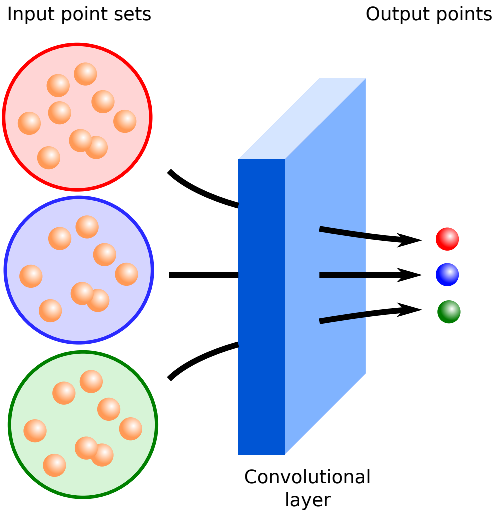
Our approach

Use a MLP for ϕ function [Li+18 ; Wan+18a] :

$$y = \beta + \frac{1}{|X|} \sum_{j=1}^{|X|} \sum_{i=1}^{N} \mathbf{w}_i \mathbf{x}_j MLP_i(p_j - C)$$

Properties

- **Permutation invariance** : ϕ function of p_j and C
- **Translation invariance** : C centered on the neighborhood
- **Low sensibility to input size** : normalized by $|X|$
- **Low sensibility to input scale** : X normalized to unit ball



Input

Point sets (neighborhoods) : locations + features

Output

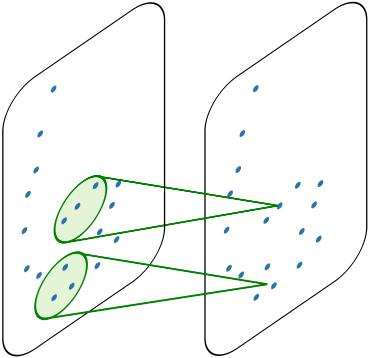
Features at given output locations (center of neighborhoods)

No dimension reduction

One neighborhood for each point of the input cloud.

Images :

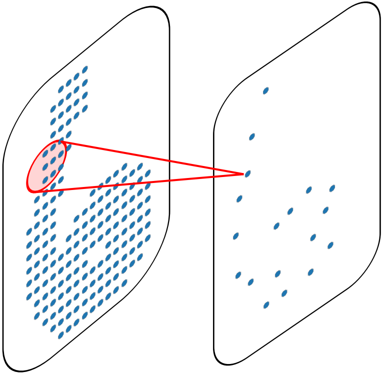
Convolution with stride 1.



Number of neighborhoods lower than input cloud size.

Images :

Convolution with stride ≥ 2.

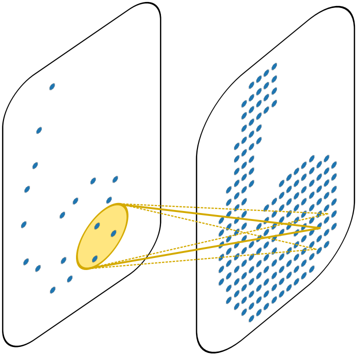


Dimension increase

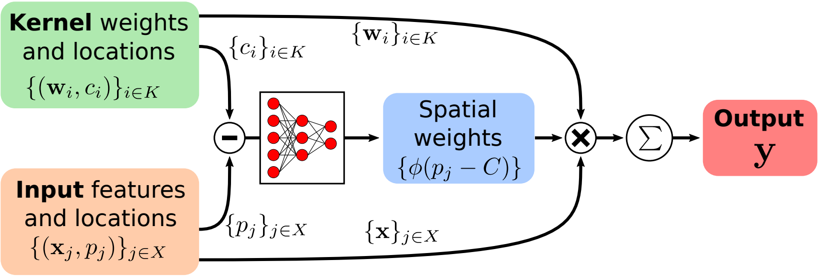
Output point cloud size greater than input cloud size.

Images :

Convolution transpose.



Implementation


Kernel weights
and locations
$\{(\mathbf{w}_i, c_i)\}_{i \in K}$
Input features
and locations
$\{(\mathbf{x}_j, p_j)\}_{j \in X}$
$\{c_i\}_{i \in K}$
$\{\mathbf{w}_i\}_{i \in K}$
$\{p_j\}_{j \in X}$
$\{\mathbf{x}\}_{j \in X}$
Spatial
weights
$\{\phi(p_j - C)\}$
$\sum$
Output
$\mathbf{y}$

Practical implementation

Python implementation

Only differentiable operations Autograd usage (PyTorch or Tensorflow)

```
# Neighborhoods
features = input.view(-1, input.size(2))[indices]
pts = points.view(-1, points.size(2))[indices]

# Relative positions
pts = pts - next_points.unsqueeze(2)

# Normalization
if normalize:
    maxi = torch.sqrt((pts**2).sum(3).max(2)[0])
    maxi[maxi==0] = 1
    pts = pts / maxi.view(maxi.size()+(1,1,))

# wieghting MLP
dists = pts.view(pts.size()+(1,)) - centers
dists = dists.view(dists.size(0), dists.size(1),
                   dists.size(2), -1)
dists = F.relu(l1(dists))
dists = F.relu(l2(dists))
dists = F.relu(l3(dists))
dists = dists.unsqueeze(3)

# Features
features = features.view(features.size()+(1,)) * dists
features = features.mean(2)
features = features.view(features.size()+(1,)) * weight
features = features.sum([2,3])

# Bias
features = features + bias
```

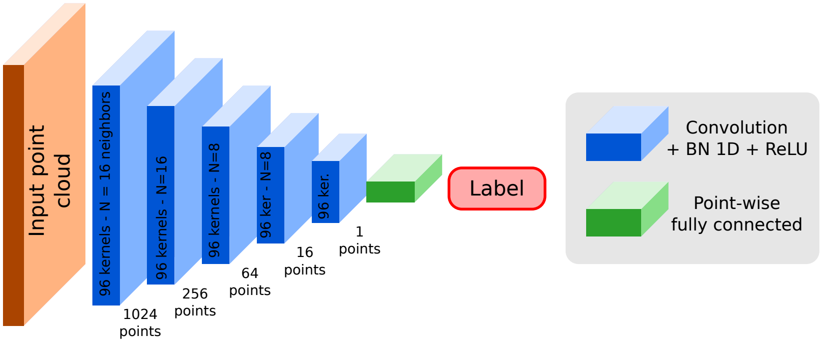
Neighborhoods computation

Computed using search trees from Scikit-learn.

Precomputation for efficiency, all neighborhoods are computed in the data loader.

Experiments

Network for classification



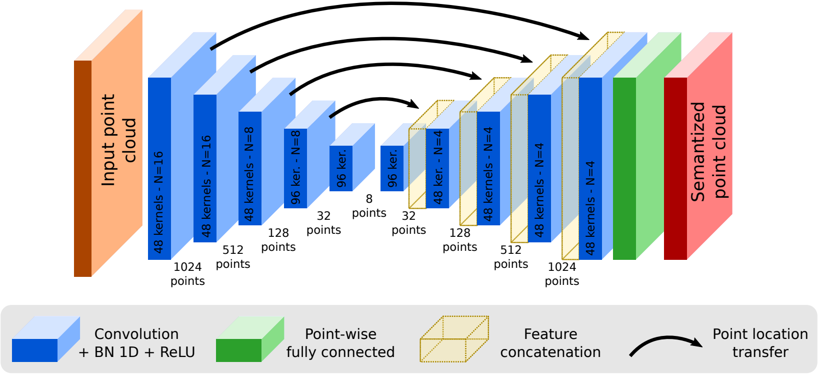
MNIST dataset

Methods	OA
NiN [LCY13]	99.53
PointNet++ [Qi+17b]	99.49
PointCNN [Li+18]	99.54
Ours	
16 samplings	**99.61**

ModelNet40 dataset

Methods	OA	AA
DGCNN [Wan+18c]	92.2	**90.2**
PointNet++ [Qi+17b]	90.7	
PointCNN	**92.2**	88.1
Ours		
16 samplings	91.6	88.1

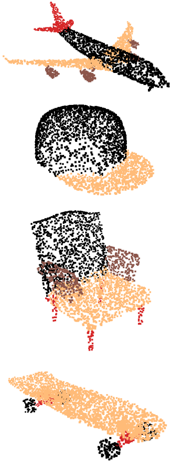
Network for segmentation



Part segmentation

Shapenet dataset

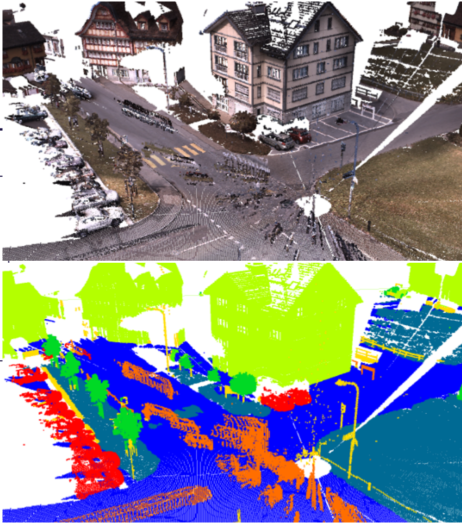
Method	pIoU	mpIoU
SPLATNet [Su+18]	85.4	83.7
DGCNN [Wan+18c]	85.1	82.3
PointNet [Qi+17a]	83.7	80.4
PointNet++ [Qi+17b]	85.1	81.9
SGPN [Wan+18b]	85.8	82.8
PointCNN [Li+18]	86.14	**84.6**
Ours 1024 pts 16 trees	**93.1**	82.6



Outdoor, large scale segmentation : Semantic8

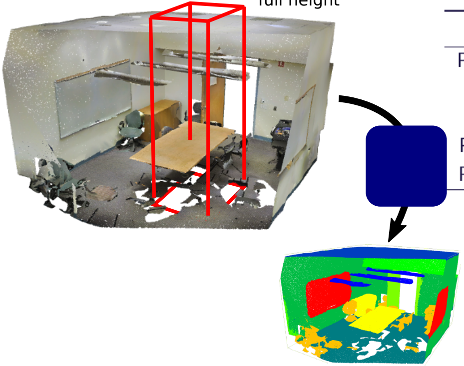
Semantic8 dataset

Method	AvIoU	OA
TML-PC [MZ+14]	0.391	0.745
TMLC-MS [HWS16]	0.494	0.850
PointNet++ [Qi+17b]	0.631	0.857
SnapNet [Bou+17]	0.674	0.910
SPGraph [LS18]	**0.762**	**0.929**
Ours	0.666	0.898
ranking	*3*	*3*



Indoor segmentation : S3DIS

Box:
2 meter based
full height

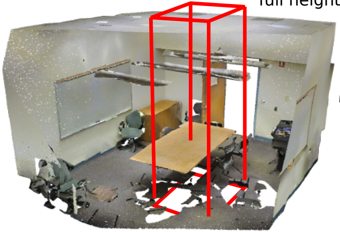


S3DIS dataset

Method	OA	mAcc	mIoU
PointNet [Qi+17a]	78.5	66.2	47.6
SPGraph [LS18]	85.5	73.0	62.1
RSNet [HWN18]	-	66.45	56.47
PCCN [Wan+18a]	-	67.01	58.27
PointCNN [Li+18]	**88.14**	**75.61**	**65.39**
Ours			
1 scale 2m	84.05	-	55.36

Indoor segmentation : S3DIS

Box:
2 meter based
full height



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PointNet [Qi+17a]	78.5	66.2	47.6
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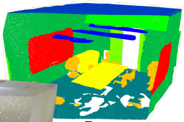
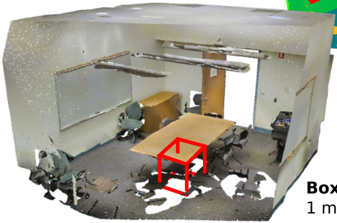
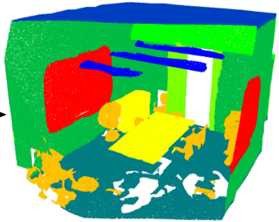
PointCNN [Li+18]	**88.14**	**75.61**	**65.39**
Ours			
1 scale 2m	84.05	-	55.36
2 scales 2m,1m	84.93	-	58.54





Box:
1 meter side



Perspectives and conclusions

Perspectives

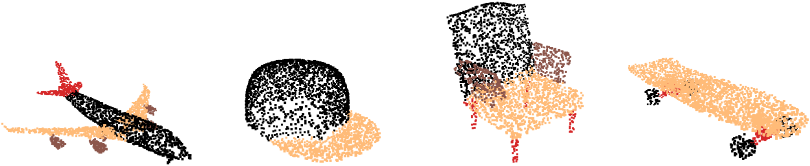
- Work on architecture design
- Training strategy : multiscale, layer initialization . . .
- Extend layers

Conclusion

- Competitive results
- A single architecture on all datasets
- Trained on a 12G NVidia Titan GPU

Code available

`https://github.com/aboulch/ConvPoint`



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