PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation

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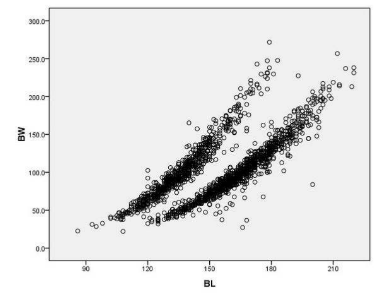
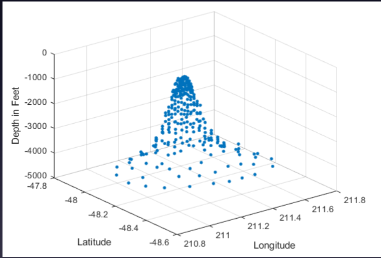
Introduction

- Point Set



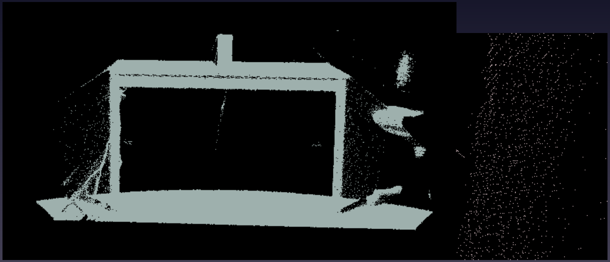
(a) 2D Point Set



(b) 3D Point Set (Point Cloud)

Traditional Point Cloud Processing

- Edge-based methods
- Model-based methods
- Region-based methods
- Attributes-based methods
- Graph-based methods

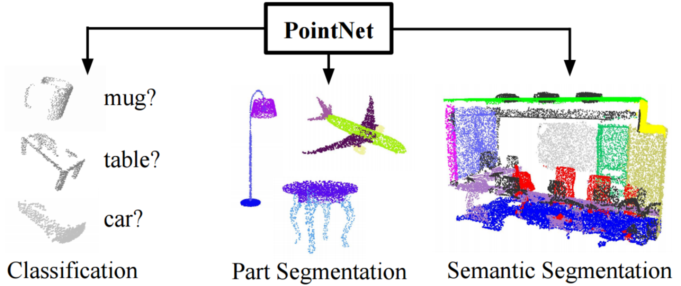


Neural Network Based Methods

- Volumetric CNNs: 3D voxel grids
  - Constrained by resolution
- Multi-view CNNs: collections of images
  - Nontrivial to extend them to scene understanding or other 3D tasks.

PointNet

- A novel deep net architecture
- Input: point set
- Tasks: 3D shape classification, shape part segmentation, and scene semantic parsing
- Simple, effective and robust



Problem Statement

- A point cloud is represented as a set of 3D points:
  - $\{P_i | i = 1, ..., n\}$
  - $P_i = (x, y, z)$
  - Extra feature channels: color, normal, etc.

object classification

- The input:
  Directly sampled from a shape Pre-segmented from a scene point cloud.
- The output:
  This deep network outputs k scores for all the k candidate classes.

semantic segmentation

- The input:
  A single object for part region segmentation A sub-volume from a 3D scene for object region segmentation.
- The output:
  This model will output $n \times m$ scores for each of the n points and each of the m semantic subcategories.

Deep Learning on Point Sets

- Properties of Point Sets
- PointNet Architecture

Properties of Point Sets

- Unordered
- Interaction among points
- Invariance under transformations

PointNet Architecture

- Symmetry Function for Unordered Input
- Local and Global Information Aggregation
- Joint Alignment Network

Experiments

- Applications
- Architecture Design Analysis
- Visualizing PointNet
- Time and Space Complexity Analysis

Applications-3D Object Classification

- 12,311 CAD models
- from 40 man-made object categories,
- split into 9,843 for training and 2,468 for testing

	input	#views	accuracy avg. class	accuracy overall
SPH [11]	mesh	-	68.2	-
3DShapeNets [25]	volume	1	77.3	84.7
VoxNet [15]	volume	12	83.0	85.9
Subvolume [16]	volume	20	86.0	**89.2**
LFD [25]	image	10	75.5	-
MVCNN [20]	image	80	**90.1**	-
Ours baseline	point	-	72.6	77.4
Ours PointNet	point	1	86.2	**89.2**

Table 1. **Classification results on ModelNet40.** Our net achieves state-of-the-art among deep nets on 3D input.

Applications-3D Object Part Segmentation

- ShapeNet part data set
- 16,881 shapes from 16 categories, annotated with 50 parts in total
- mIoU?

	mean	aero	bag	cap	car	chair	ear phone	guitar	knife	lamp	laptop	motor	mug	pistol	rocket	skate board	table
# shapes		2690	76	55	898	3758	69	787	392	1547	451	202	184	283	66	152	5271
Wu [24]	-	63.2	-	-	-	73.5	-	-	-	74.4	-	-	-	-	-	-	74.8
Yi [26]	81.4	81.0	78.4	77.7	**75.7**	87.6	61.9	**92.0**	85.4	**82.5**	**95.7**	**70.6**	91.9	**85.9**	53.1	69.8	75.3
3DCNN	79.4	75.1	72.8	73.3	70.0	87.2	63.5	88.4	79.6	74.4	93.9	58.7	91.8	76.4	51.2	65.3	77.1
Ours	**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**

Table 2. **Segmentation results on ShapeNet part dataset.** Metric is mIoU(%) on points. We compare with two traditional methods [24] and [26] and a 3D fully convolutional network baseline proposed by us. Our PointNet method achieved the state-of-the-art in mIoU.

Applications-Semantic Segmentation in Scenes

- Stanford 3D semantic parsing data set
- The dataset contains 3D scans from Matterport scanners in 6 areas including 271 rooms. Each point in the scan is annotated with one of the semantic labels from 13 categories (chair, table, floor, wall etc)

Applications-Semantic Segmentation in Scenes

	mean IoU	overall accuracy
Ours baseline	20.12	53.19
Ours PointNet	**47.71**	**78.62**

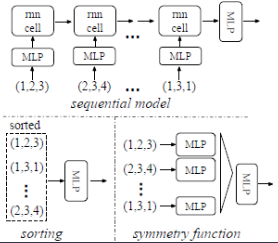
Table 3. **Results on semantic segmentation in scenes.** Metric is average IoU over 13 classes (structural and furniture elements plus clutter) and classification accuracy calculated on points.

	table	chair	sofa	board	mean
# instance	455	1363	55	137	
Armeni et al. [1]	46.02	16.15	**6.78**	3.91	18.22
Ours	**46.67**	**33.80**	4.76	**11.72**	**24.24**

Table 4. **Results on 3D object detection in scenes.** Metric is average precision with threshold IoU 0.5 computed in 3D volumes.

Architecture Design Analysis

- Three approaches to achieve order invariance.
- ModelNet40 shape classification problem



	accuracy
MLP (unsorted input)	24.2
MLP (sorted input)	45.0
LSTM	78.5
Attention sum	83.0
Average pooling	83.8
Max pooling	**87.1**

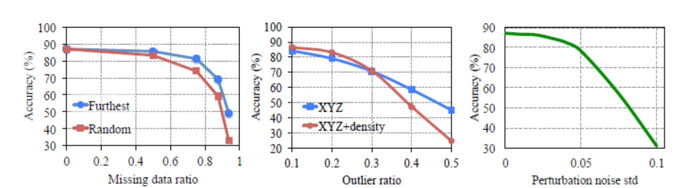
Architecture Design Analysis

- Effectiveness of Input and Feature Transformations
- ModelNet40 shape classification problem

Transform	accuracy
none	87.1
input (3x3)	87.9
feature (64x64)	86.9
feature (64x64) + reg.	87.4
both	**89.2**

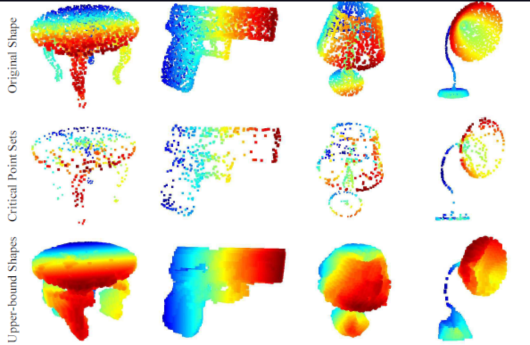
Architecture Design Analysis

- Robustness Test
- ModelNet40 shape classification problem



Visualizing PointNet

- critical point sets C_S & the upper-bound shapes N_S



Time and Space Complexity Analysis

- PointNet's space and time, complexity is O(N)
- point cloud classification: 1K objects/second
- semantic segmentation: 2 rooms/second
- 1080X GPU on TensorFlow

	#params	FLOPs/sample
PointNet (vanilla)	0.8M	148M
PointNet	3.5M	440M
Subvolume [16]	16.6M	3633M
MVCNN [20]	60.0M	62057M

Conclusion

- A brief introduction
- PointNet architecture
- Experiment result

Repeat the experiment

- Tensorflow
- CPU: i7 - 5700
- GPU: Geforce 1070
- Training time: 2h31min(classification) and 16h28min(part segmentation)