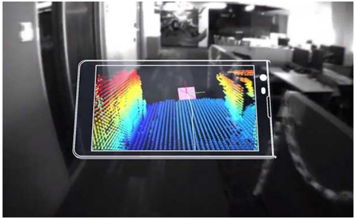
The Need for 3D Deep Learning

Robot Perception

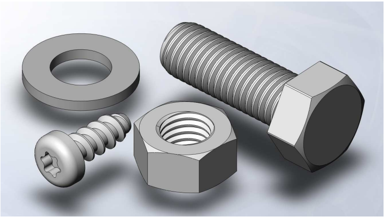
source: Scott J Grunewald

Augmented Reality



source: Google Tango

Shape Design



source: solidworks

A number of emerging 3D applications shape the need for 3D deep learning.

Figures and captions from CVPR presentation to [Qi+17a].

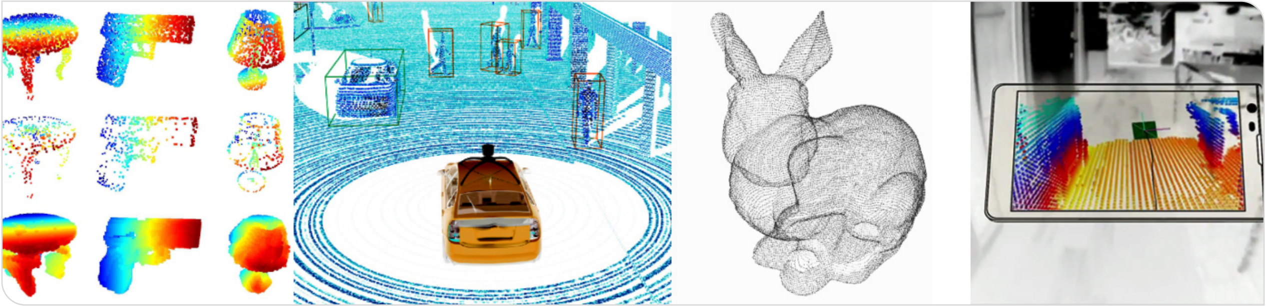
Karlsruhe Institute of Technology

Intelligent Sensor-Actuator-Systems

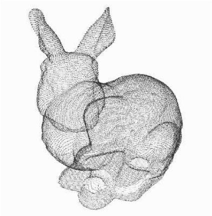
PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation

Felix Karg | 29. Juni 2022

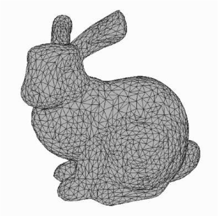
Betreuer: Antonio Zea



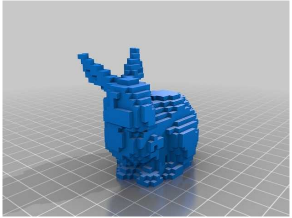
Common Representations of 3D Data



Point Cloud



Mesh



Volumetric

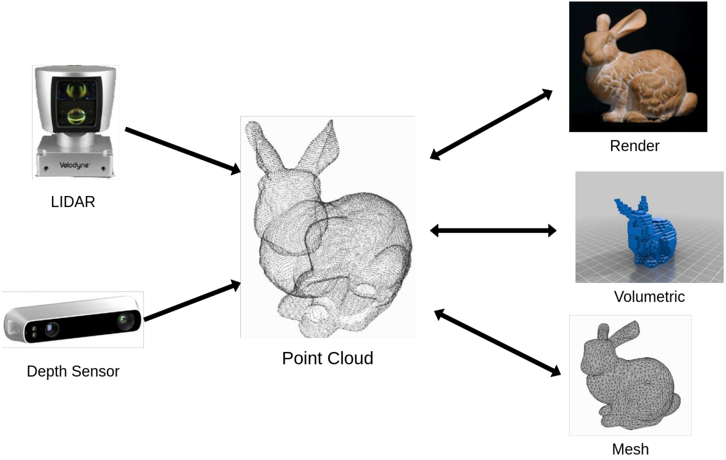
View Rendering

Contrary to 2D, 3D has many different popular representations.

Figures and captions (partially) from CVPR presentation to [Qi+17a].

Canonical Representation: Point Cloud

- Point cloud is close to **raw depth sensor data**
- Point cloud is **canonical** (easy conversion from and to other representations)



Individual figures from CVPR presentation to [Qi+17a]

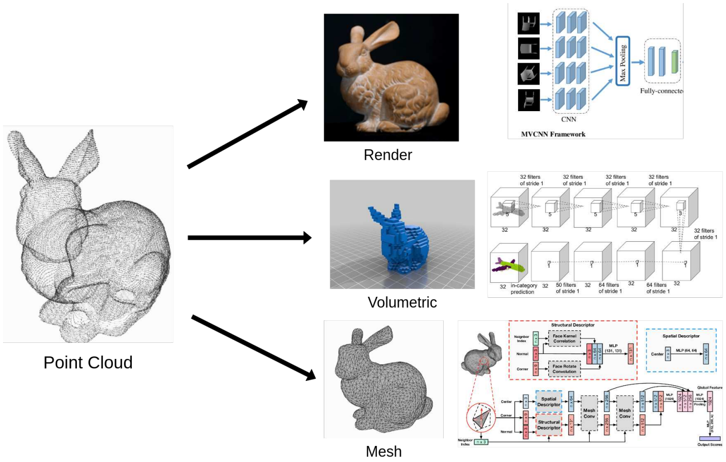
Point Cloud Features

Feature Name	Supports Texture / Color	Local / Global / Regional	Best Use Case
PFH	No	L	
FPFH	No	L	2.5D Scans (Pseudo single position range images)
VFH	No	G	Object detection with basic pose estimation
CVFH	No	R	Object detection with basic pose estimation, detection of partial objects
RIFT	Yes	L	Real world 3D-Scans with no mirror effects. RIFT is vulnerable against flipping.
RSD	No	L	
NARF	No	L	2.5D (Range Images)
ESF	No	G	

Overview from `https://github.com/PointCloudLibrary/pcl/wiki/Overview-and-Comparison-of-Features`

Most existing point cloud features are **handcrafted for specific tasks.**

Conversion to Other Representations



Figures from:

- Bunnies: CVPR presentation to [Qi+17a]
- MVCNN: [LXL19]
- 3D-CNN: Supplemental to [Qi+17a]
- Mesh-Net: [Fen+19]

Research Question:

Can we achieve effective **feature learning directly** on point clouds?

Introduction to PointNet

- End-to-end learning for unordered point cloud data
- Unified framework for previously seperate and specialized tasks
  - Object Classification
  - Object Part Segmentation
  - Semantic Scene parsing

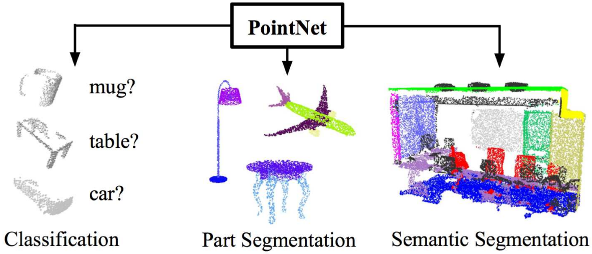
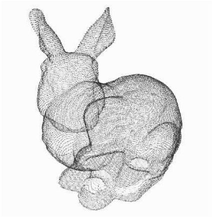


Figure from [Qi+17a].

Challenges

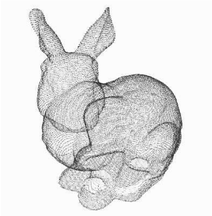
- Unordered point sets as input
  - Model needs to be invariant to $N!$ permutations

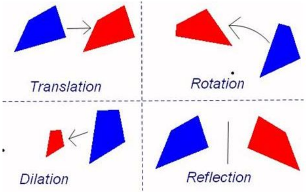


Point cloud figure from CVPR presentation to [Qi+17a].
Geometric transformation figure from [i2t19].

Challenges

- Unordered point sets as input
  - Model needs to be invariant to $N!$ permutations
- Invariance under geometric transformations
  - Geometric transformations applied to point cloud data should not alter classification results





Point cloud figure from CVPR presentation to [Qi+17a].
Geometric transformation figure from [i2t19].

Unordered Point Sets

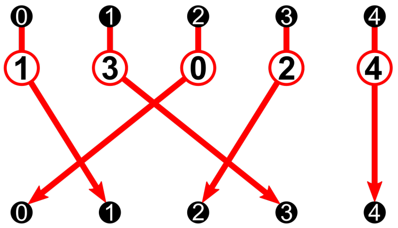
A set of points $p_i := (x_i, y_i, z_i)$

$$\{p_1, p_2, \ldots, p_n\}$$

might be represented by any of its vector

permutations $[p_{\pi_1}, p_{\pi_2}, \ldots, p_{\pi_n}]$ for any permutation π.

Since point cloud data is orderless, it requires invariance over input permutations when consumed directly.



Example Permutation.
Figure under CC-BY-SA 4.0 from [Wat22]

Solution: Symmetric Functions

Symmetric functions are invariant over argument permutations π:

$$f(x_1, x_2, \ldots, x_n) \equiv f(x_{\pi_1}, x_{\pi_2}, \ldots, x_{\pi_n})$$

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$$f(x_1, x_2, \dots, x_n) \equiv f(x_{\pi_1}, x_{\pi_2}, \dots, x_{\pi_n})$$

Examples for symmetric functions:

- max
- sum / addition
- mean

Q: How to integrate a symmetric function into a neural network architecture?

One Symmetric Function is All You Need

A concatenation of functions ($\gamma \circ g(h, ..)$) is symmetric if the central function g is symmetric:

$$f(x_1, x_2, \ldots, x_n) = \gamma \circ g(h(x_1), \ldots, h(x_n))$$

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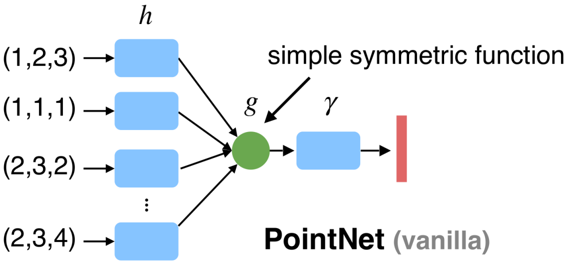

Figure from CVPR presentation to [Qi+17a].

Universal Set Function Approximation

PointNet (vanilla) is a universal set function approximator.

Theorem

A Hausdorff continuous symmetric function $f : 2^{\mathcal{X}} \mapsto \mathbb{R}$ can be arbitrarily approximated by PointNet.

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Theorem

A Hausdorff continuous symmetric function $f : 2^{\mathcal{X}} \mapsto \mathbb{R}$ can be arbitrarily approximated by PointNet.

$$\left| f(S) - \underbrace{\gamma\left(\underset{x_i \in S}{g}\{h(x_i)\}\right)}_{\text{PointNet (vanilla)}} \right| < \varepsilon$$

with $S \subseteq \mathbb{R}^d$

For details see [Qi+17a] and supplemental material.

Basic PointNet Architecture

In practice, both h and γ are **multi-layer perceptrons (MLP)** as generic function approximators. Empirically, **max pooling** provides the best results as symmetric function:

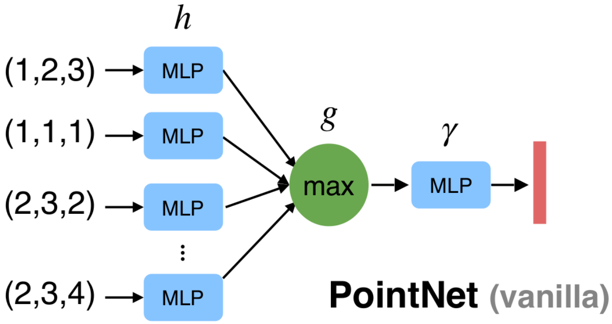


Figure from CVPR presentation to [Qi+17a].

Geometric Transformations

In particular, point cloud classification should be invariant to:

- Translation
- Rotation
- Scaling (Dilation)

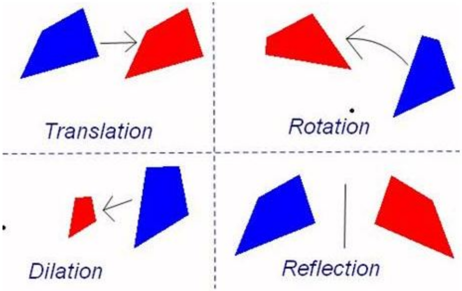


Figure from [i2t19].

Input Alignment by Transformer Network

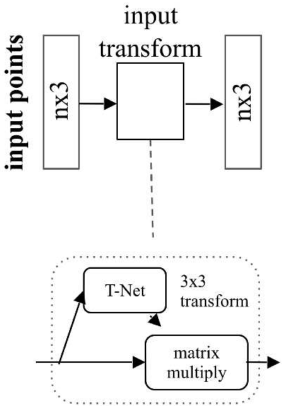


Figure from CVPR presentation to [Qi+17a].

Input Alignment by Transformer Network

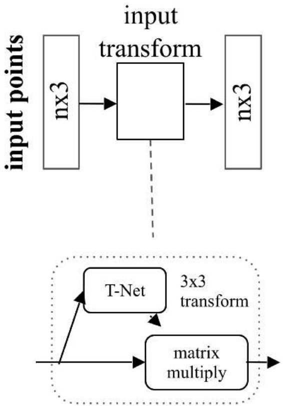


Figure from CVPR presentation to [Qi+17a].

Solution

Have a transformer network (T-Net) figure out data-dependent transformations.

A T-Net is a PointNet (vanilla) with a matrix as output.

Input Alignment by Transformer Network

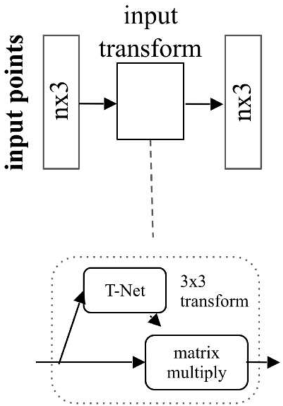


Figure from CVPR presentation to [Qi+17a].

Solution

Have a transformer network (T-Net) figure out data-dependent transformations.

A T-Net is a PointNet (vanilla) with a matrix as output.

Additionally, regularize matrix close to orthogonal:

$$L_{reg} = ||I - AA^T||_F^2$$

Effects of T-Net and Regularization

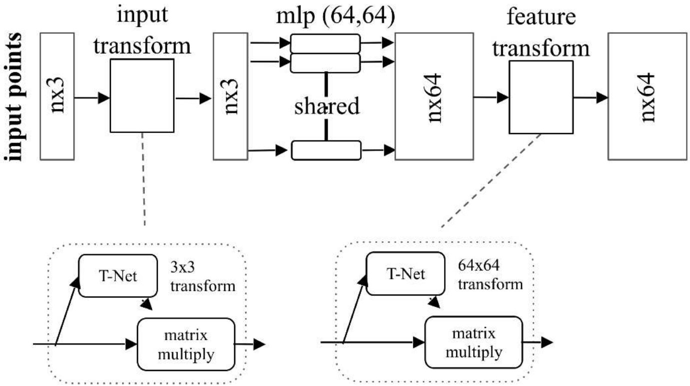


Figure from CVPR presentation to [Qi+17a].

Effects of T-Net and Regularization

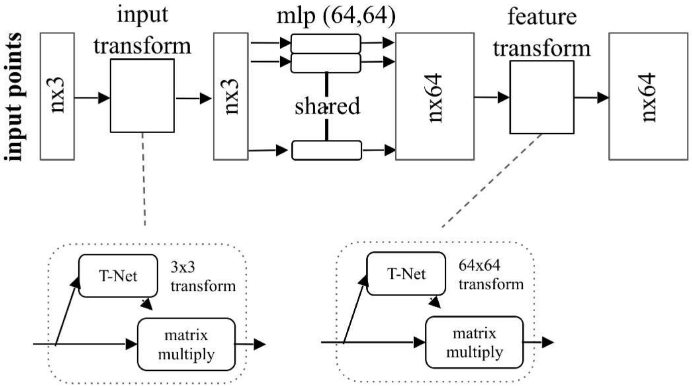


Figure from CVPR presentation to [Qi+17a].

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

Effects of input feature transforms. Based on overall classification accuracy on the ModelNet40 [Wu+15] test set. Table from [Qi+17a].

PointNet Classification Network

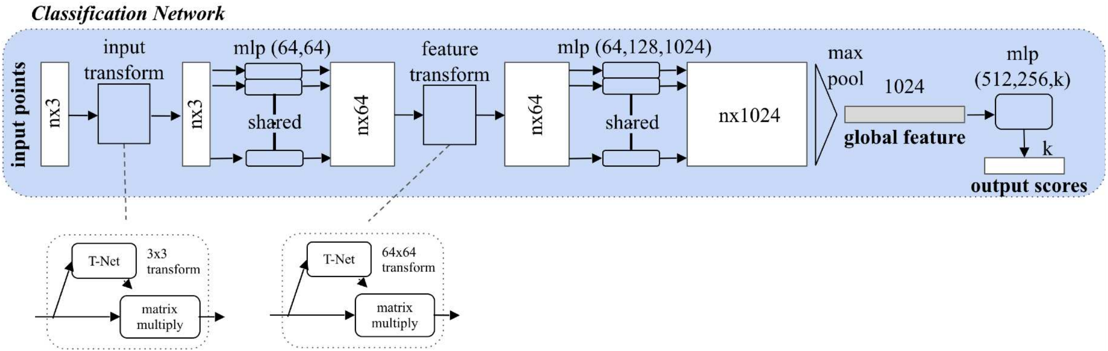


Figure from CVPR presentation to [Qi+17a].

Extension to PointNet Segmentation Network

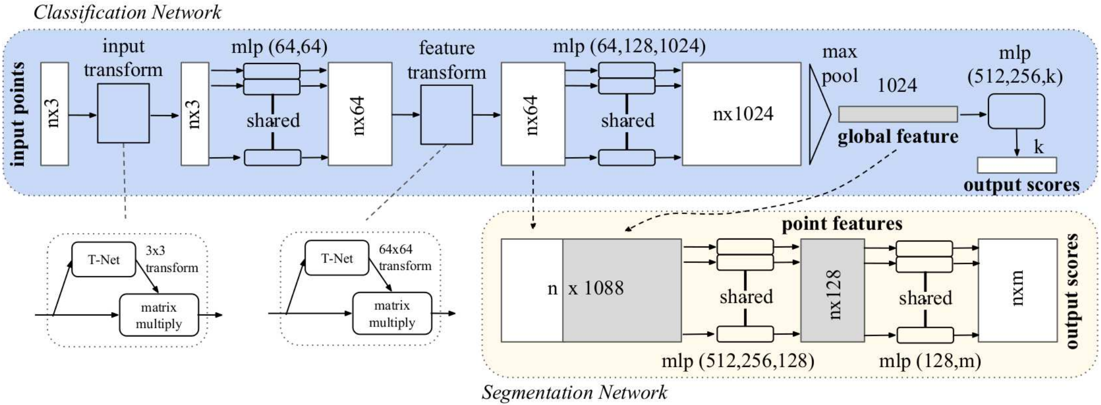


Figure from [Qi+17a].

Results on Object Classification

	input	#views	accuracy avg. class	accuracy overall
SPH [KFR03]	mesh	-	68.2	-
3DShapeNets [Wu+15]	volume	1	77.3	84.7
VoxNet [MS15]	volume	12	83.0	85.9
Subvolume [Qi+16]	volume	20	86.0	**89.2**
LFD [Wu+15]	image	10	75.5	-
MVCNN [Su+15]	image	80	**90.1**	-
Ours baseline	point	-	72.6	77.4
Ours PointNet	point	1	86.2	**89.2**

Classification results on ModelNet40. PointNet achieves state-of-the-art among deep nets on 3D input. Table from [Qi+17a].

Visualization of Object Part Segmentation

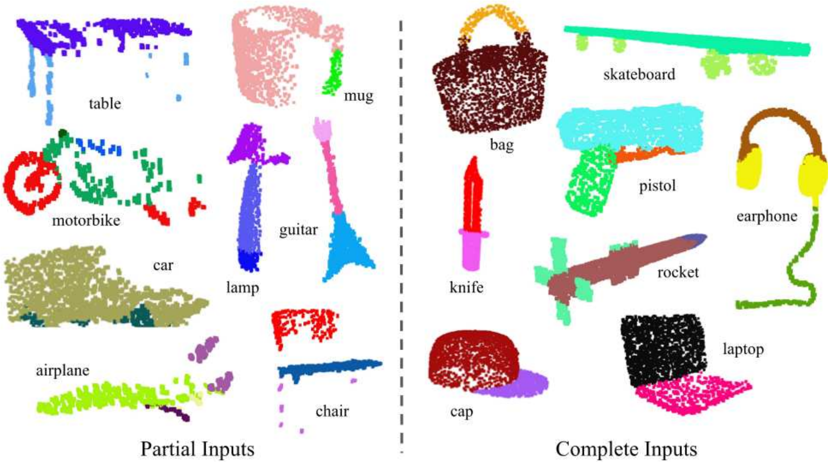


Figure from [Qi+17a].

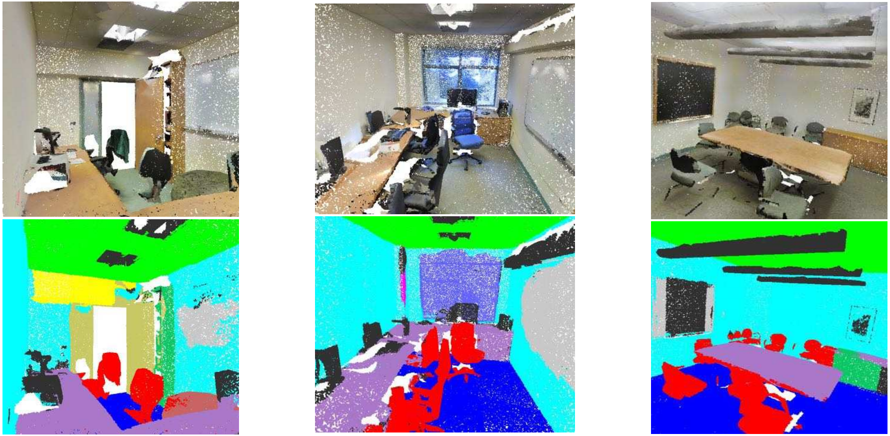
Results on Object Part Segmentation

	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**

Segmentation results on ShapeNet part dataset. The metric used is mIoU(%) on points. Figure/Table from [Qi+17a].

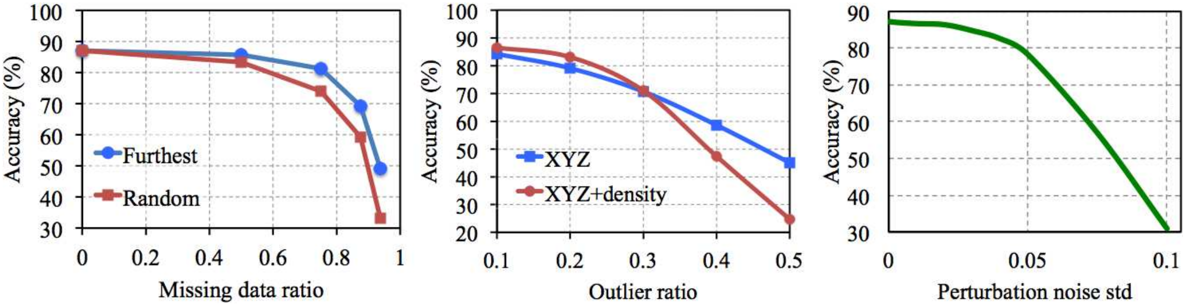
Semantic Scene Parsing

- Input
- Output



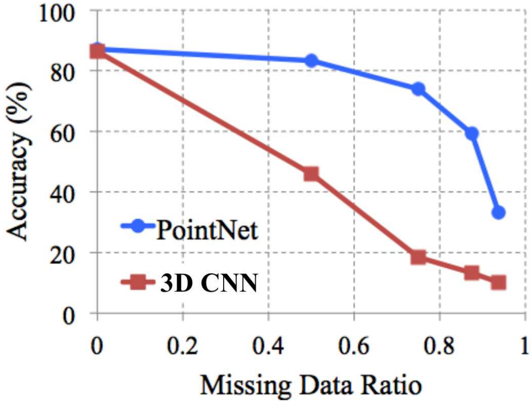
Figures from [Qi+17a].

Robustness to Data Corruption



Robustness tests. Accuracy measured on ModelNet40. Figure from [Qi+17a].

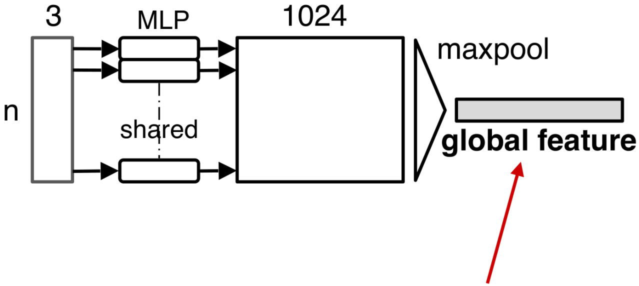
Robustness in comparison



Q: Why is PointNet so robust to missing data?

Robustness in comparison with 3D CNN. Figure from CVPR presentation to [Qi+17a].

Visualizing Global Point Cloud Features



Which points contribute to the global feature vector? (**critical points**)

Which additional points won't affect the global feature vector? (**upper bound**)

Figure from CVPR presentation to [Qi+17a].

Visualizing Global Point Cloud Features

- Original Shape
- Critical Point Set
- Upper Bound Set

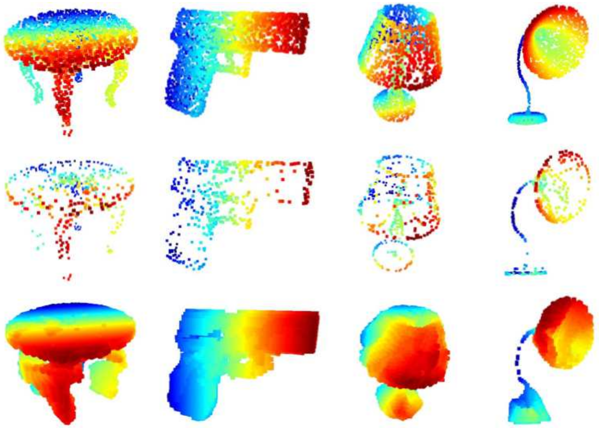


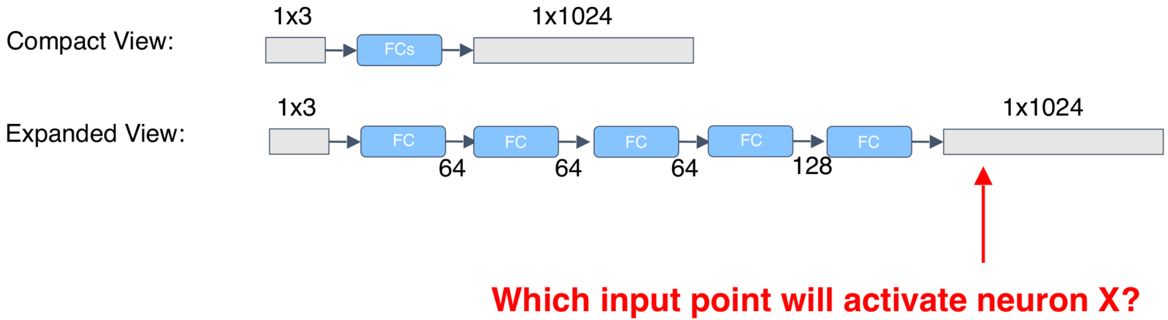
Figure from [Qi+17a].

Visualizing Global Point Cloud Features (OOS)

- Original Shape
- Critical Point Set
- Upper Bound Set

Figure from [Qi+17a].

Approach to Features Visualization



Find the top-K points in a dense volumetric grid that activates neuron X.

Figure from CVPR presentation to [Qi+17a].

Selective Visualization of Activation Features

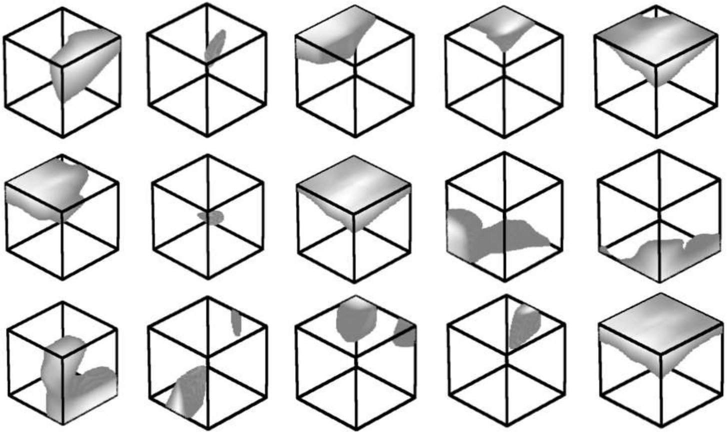


Figure from [Qi+17a].

Derivative Works of PointNet

Pointnet: Deep learning on point sets for 3d classification and segmentation [PDF] thecvf.com

CR Qi, H Su, K Mo, LJ Guibas - Proceedings of the IEEE …, 2017 - openaccess.thecvf.com

… Our network, named **PointNet**, provides a unified architecture for applications ranging from object classification, part segmentation, to scene semantic parsing. Though simple, **PointNet** …

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Derivative Works of PointNet

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... Our network, named **PointNet**, provides a unified architecture for applications ranging from object classification, part segmentation, to scene semantic parsing. Though simple, **PointNet** ...
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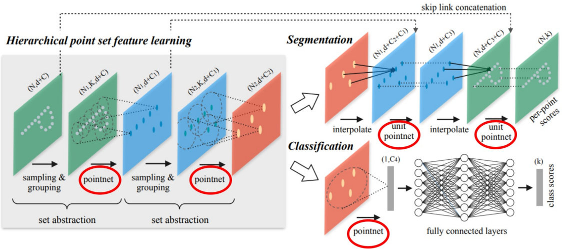
Core architecture ideas were adapted in:

- A sift-like network module [JWL18]
- Similarity group proposal network [Wan+18]
- Point cloud upsampling [Yu+18]
- Application to Neuroanatomy [GW18]
- Frustum pointnets [Qi+18]
- Pointcnn [Li+18]
- many more ...

Derivative Works of PointNet II

PointNet has been used as a module in:

- PointNet++ [Qi+17b]
- SyncSpecCNN [Yi+17]
- VoxelNet [ZT18]
- ...



Architecture of PointNet++ with highlighted PointNet layers. Figure adapted from PointNet++ [Qi+17b]

Conclusion

- PointNet is a novel deep neural network directly consuming point cloud data
- Enabling a unified approach to various 3D recognition tasks
- Task performance is on par or better than state of the art
- PointNet saw usage as a module in other architectures
- Core ideas (symmetry, T-Nets, ...) have been adapted too

Paper, code, presentation and slides are available at
`https://stanford.edu/~rqi/pointnet`

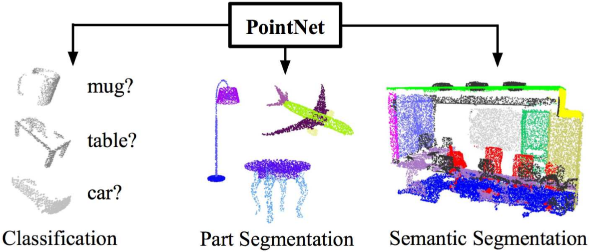
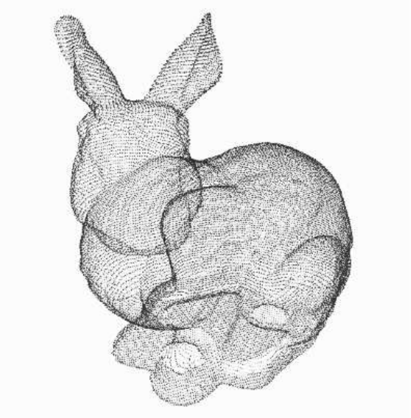


Figure from [Qi+17a].

What are your Questions?



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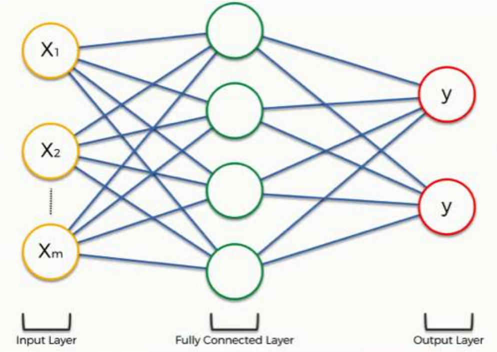
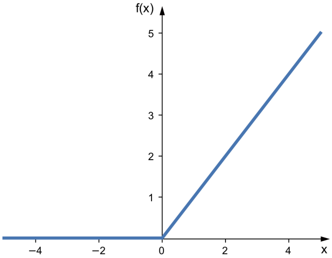
Multi-Layer Perceptron



Multi-Layer Perceptron with one fully connected layer. Alternative names include 'dense', 'fully connected' and 'mlp' layer. Figure from [Sup18].



Common activation function: ReLU, short for Rectified Linear Unit.

Based on PointNet

A number of works build on PointNet [Qi+17a]:

- Implementations and tools for visualization: [cha19; ald21; yun21; Yan19]
- Further attempts at explaining what PointNet learned: [Zha+19; Hua+19]
- Application of PointNet to different domains and problems: [Thi+22; GW18; Tri+21; Lia+19; Zha+18; Mro+18]

Speed and Model Size

	#params	FLOPs/sample
PointNet (vanilla)	0.8M	148M
PointNet	3.5M	440M
Subvolume [Qi+16]	16.6M	3633M
MVCNN [Su+15]	60.0M	62057M

Time and space complexity of different deep learning architectures for 3D data classification. PointNet (vanilla) is the classification PointNet without input and feature T-Net transformation networks. FLOP is floating-point operations. The “M” stands for a million units. Both Subvolume and MVCNN used input data pooling from multiple rotations or views, without which they have much inferior performance. Table from [Qi+17a].

Permutation Invariance: Sorting

Unfortunately, there is no canonical order in high dim space.

	Accuracy
Unordered Input	12%
Lexsorted Input	40%
LSTM	75%
PointNet (vanilla)	**87%**

Validation on the ModelNet40 dataset. Table from CVPR presentation to [Qi+17a].