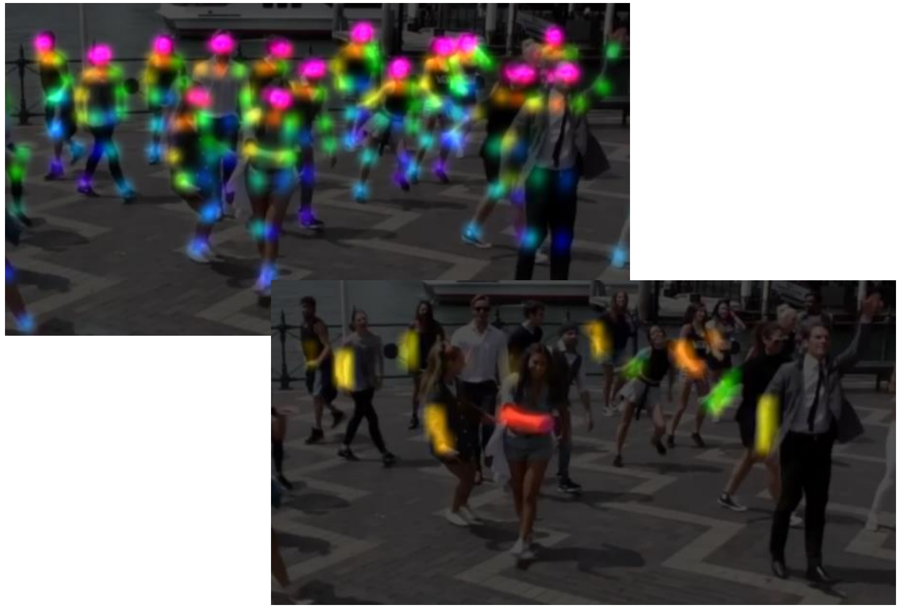
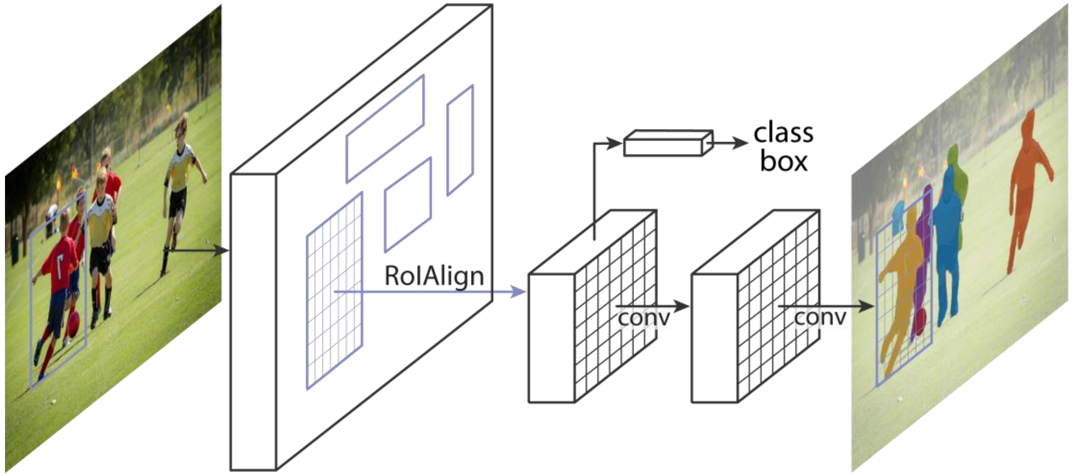
3D Point Processing and Lidar

James Hays

Recap – Structured Output from Deep Networks



Convolutional Pose Machines and follow up works



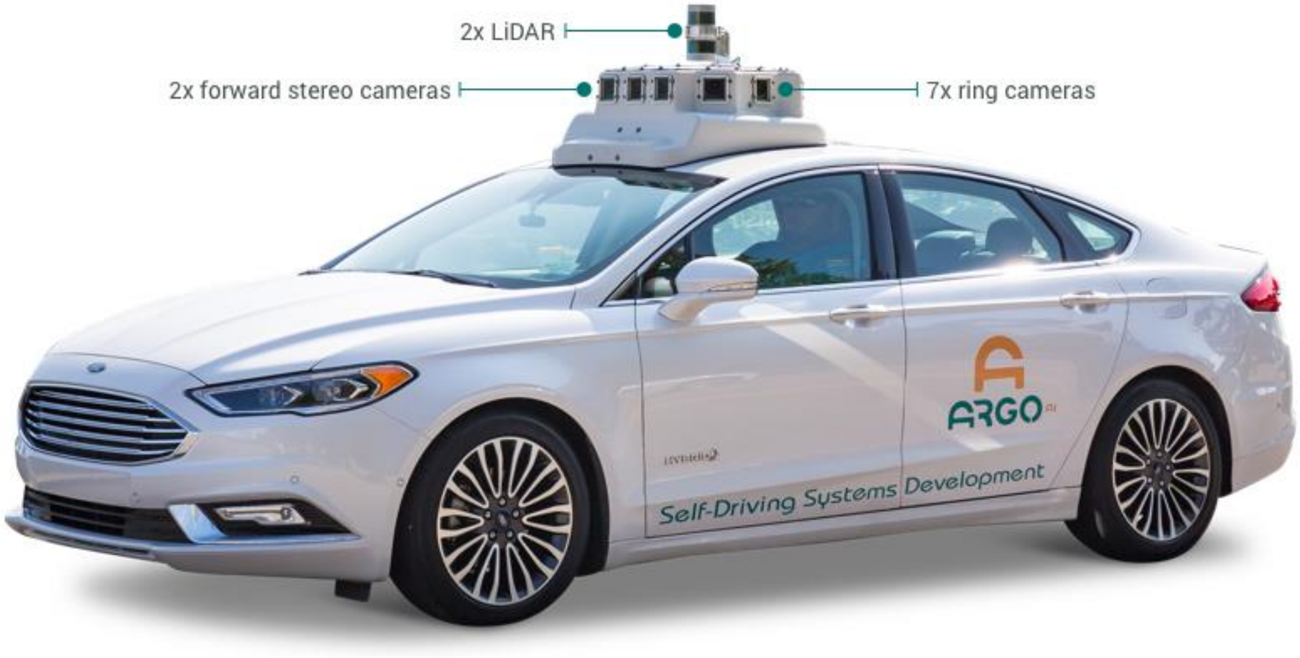
Mask R-CNN and “two stage” object detectors

A lot of machine learning tools, such as convolutional networks, don’t naturally handle tasks with arbitrary numbers of outputs. These are a couple of clever methods, typical of the literature as a whole, to work around this.

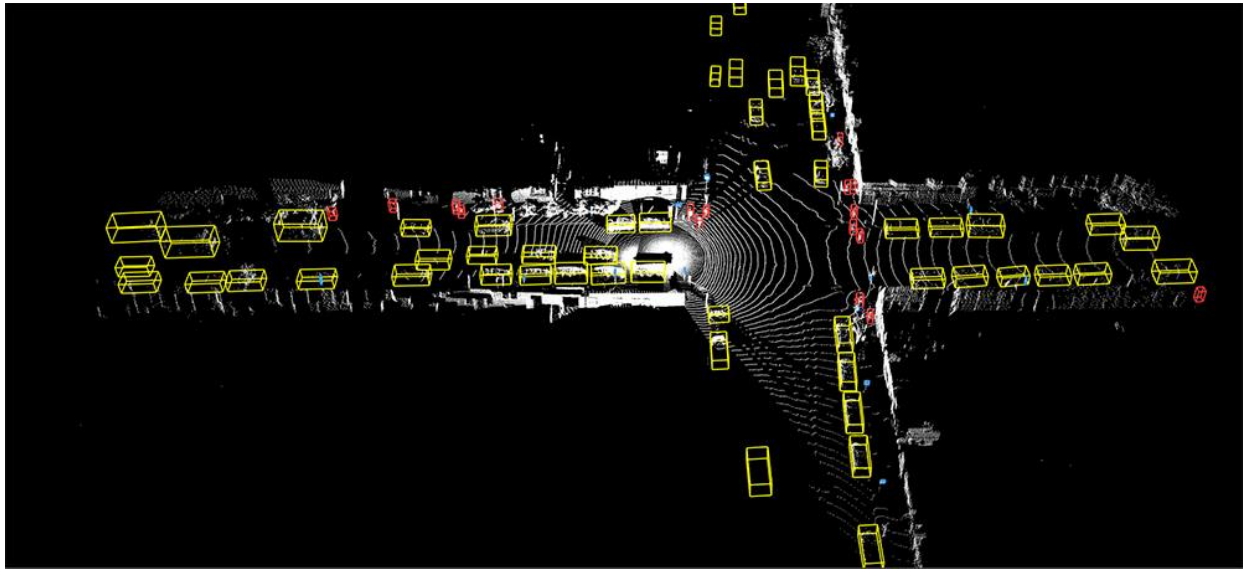
Outline

- What is lidar?
- How do we make decisions about point clouds?
  - PointNet – orderless point processing
  - VoxelNet – voxel-based point processing
  - PointPillars – bird’s eye view point processing
    - Exploiting Visibility for 3D Object Detection
  - LaserNet – range image point processing
- PseudoLidar – Bird’s eye view depth map processing

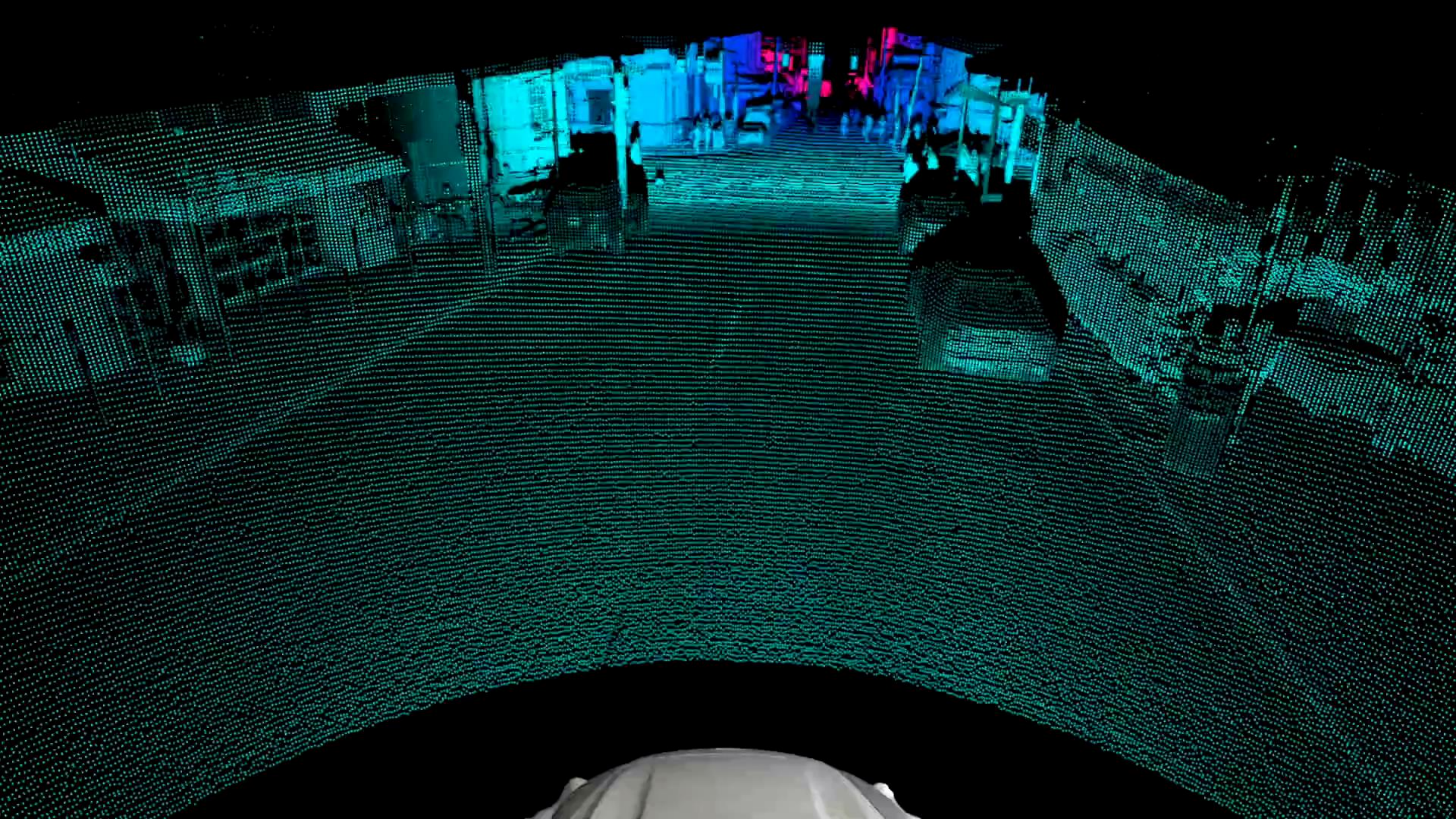
Lidar overview



Lidar overview



Source: Waymo Open Dataset



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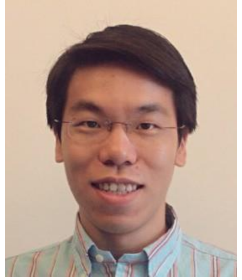
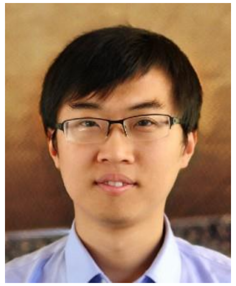
PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation

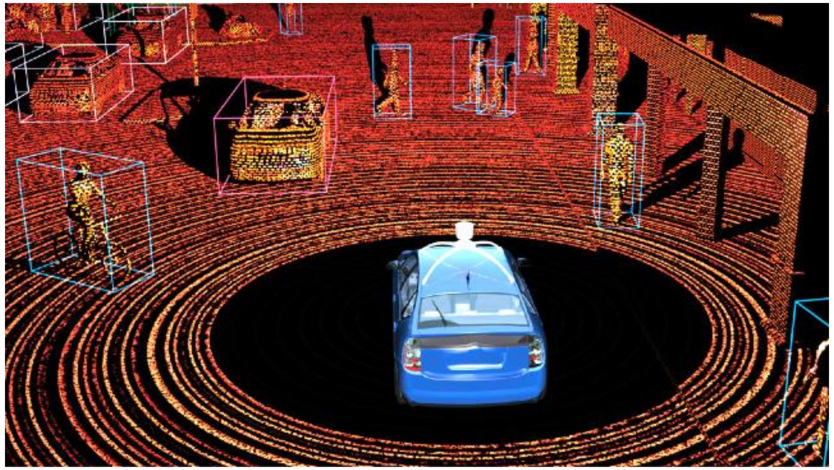
Charles R. Qi* Hao Su* Kaichun Mo Leonidas J. Guibas

Stanford University

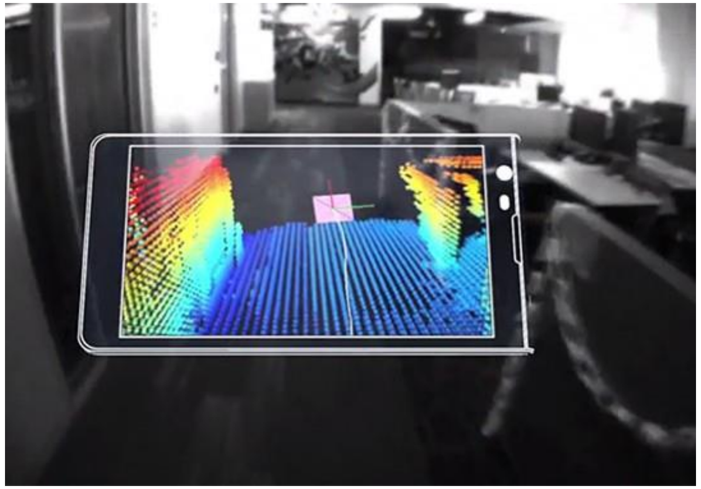
Big Data + Deep Representation Learning

Robot Perception



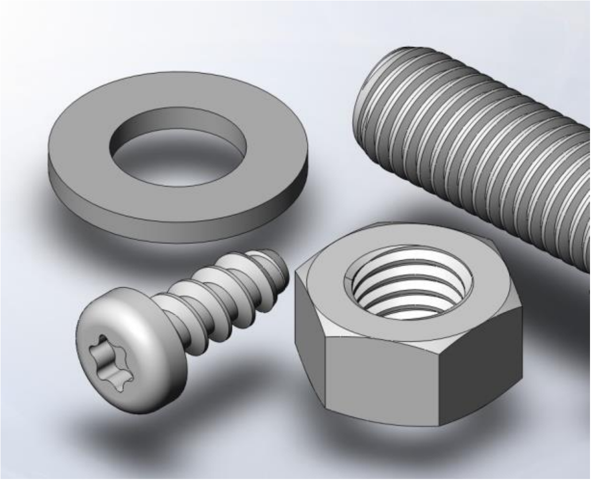
source: Scott J Grunewald

Augmented Reality



source: Google Tango

Shape Design



source: solidsolutions

Emerging 3D Applications

Big Data + Deep Representation Learning

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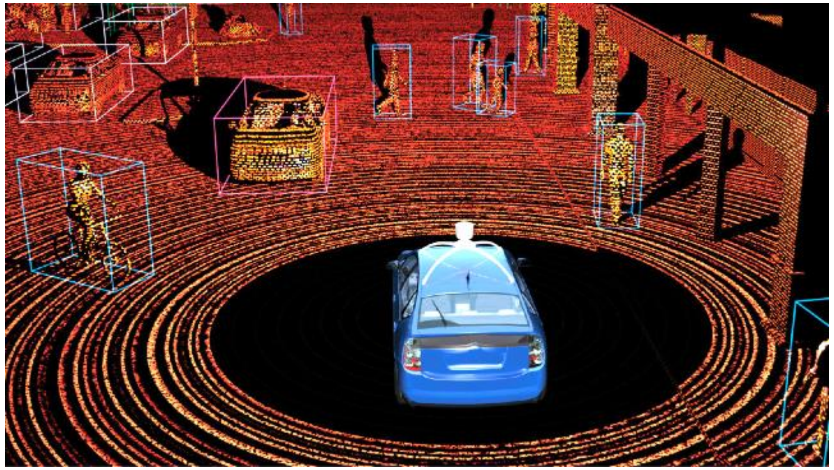

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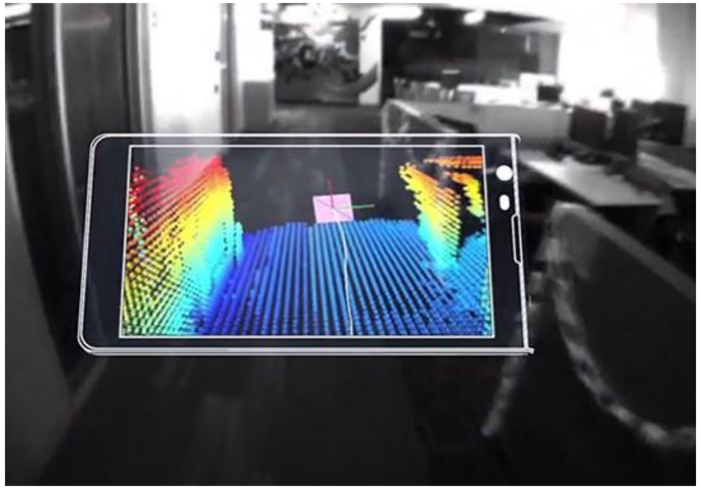

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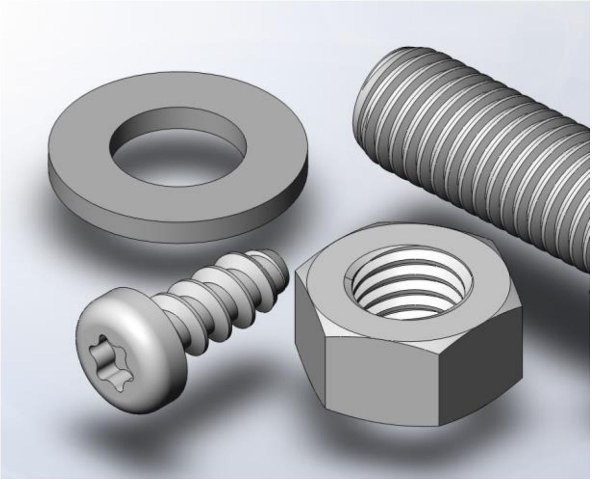
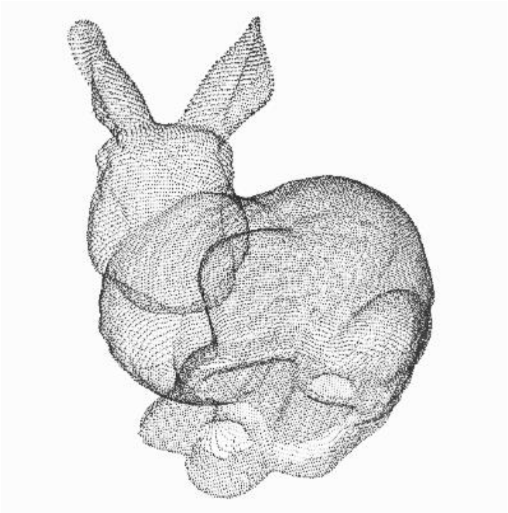


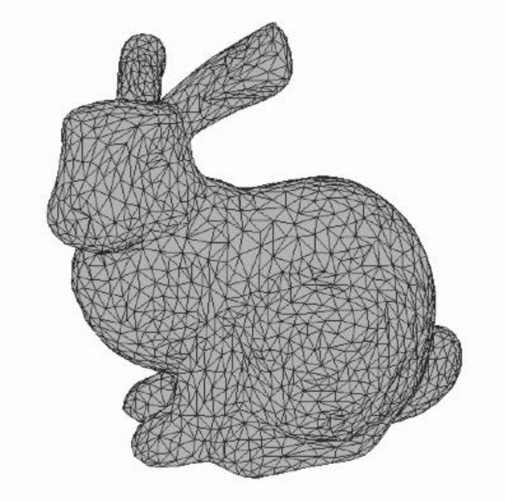
source: solidsolutions

Need for 3D Deep Learning!

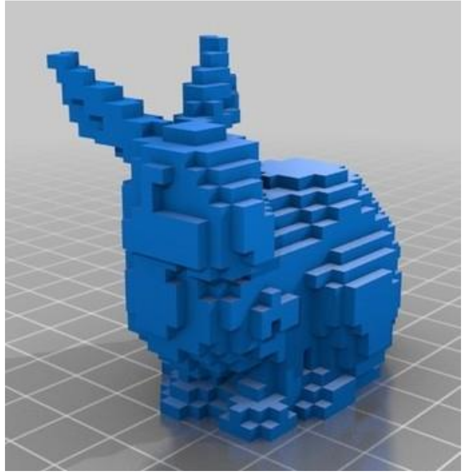
3D Representations



Point Cloud



Mesh



Volumetric

Projected View
RGB(D)

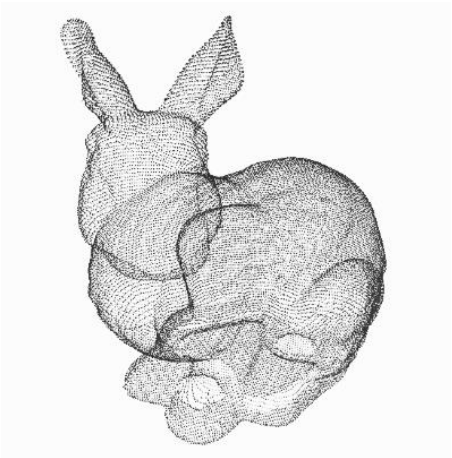
…

3D Representation: Point Cloud

Point cloud is close to raw sensor data

LiDAR

Depth Sensor



Point Cloud

3D Representation: Point Cloud

- Point cloud is close to raw sensor data
- Point cloud is canonical

LiDAR

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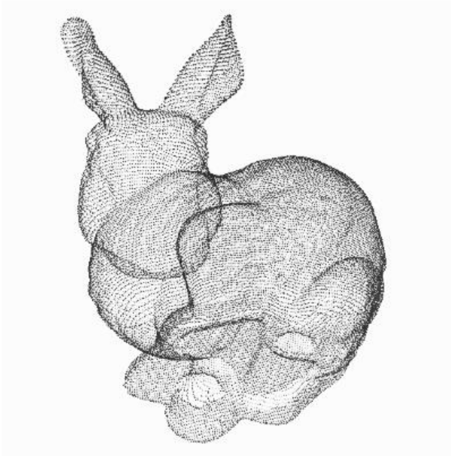

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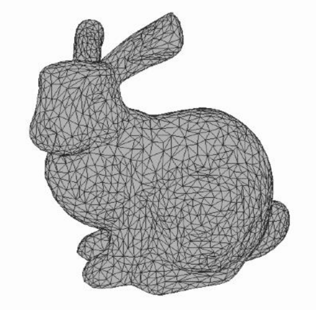

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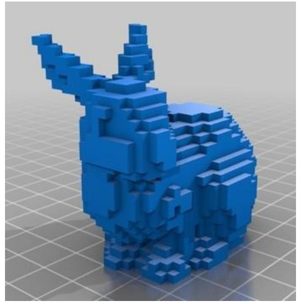

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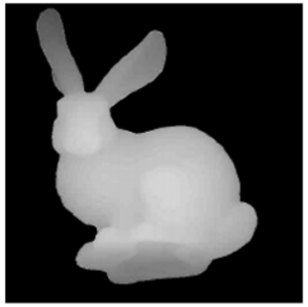


Depth Map

Previous Works

Most existing point cloud features are **handcrafted** towards specific tasks

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.

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

Previous Works

Point cloud is **converted to other representations** before it's fed to a deep neural network

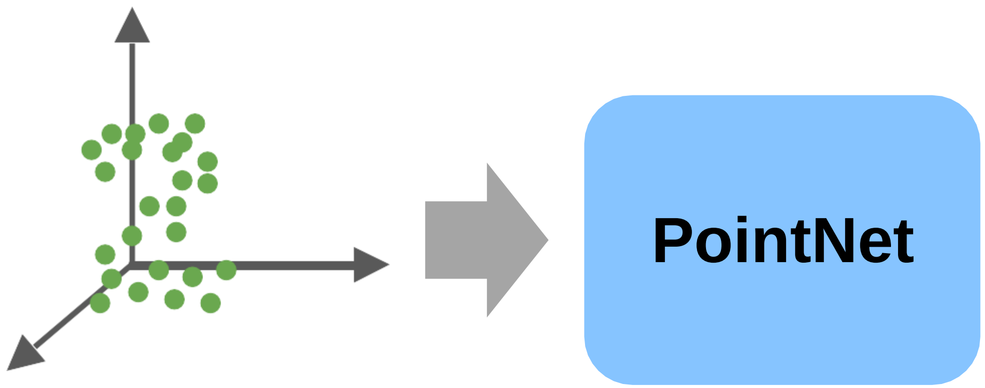
Conversion	Deep Net
Voxelization	3D CNN
Projection/Rendering	2D CNN
Feature extraction	Fully Connected

Research Question:

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

Our Work: PointNet

End-to-end learning for **scattered, unordered** point data



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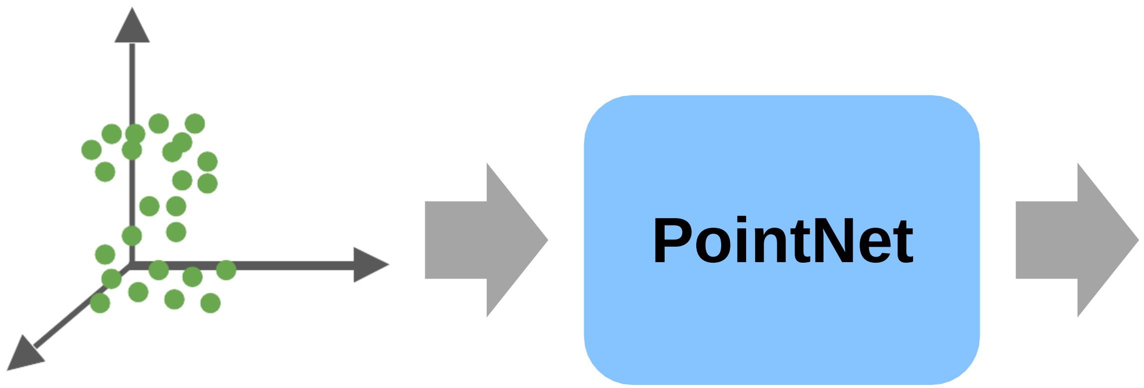
End-to-end learning for **scattered, unordered** point data

Unified framework for various tasks



Object Classification

Object Part Segmentation

Semantic Scene Parsing

...

Our Work: PointNet

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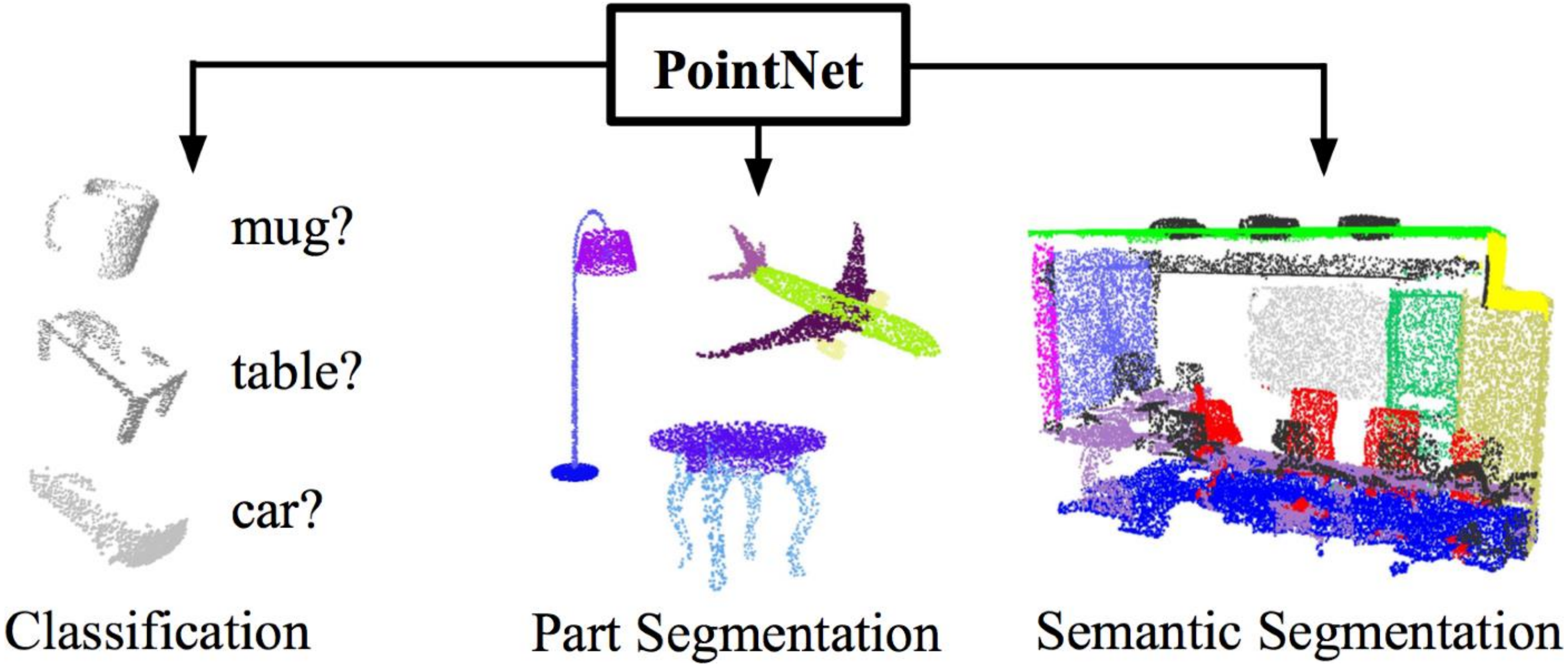

Challenges

<u>Unordered</u> point set as input

Model needs to be invariant to N! permutations.

Invariance under <u>geometric transformations</u>

Point cloud rotations should not alter classification results.

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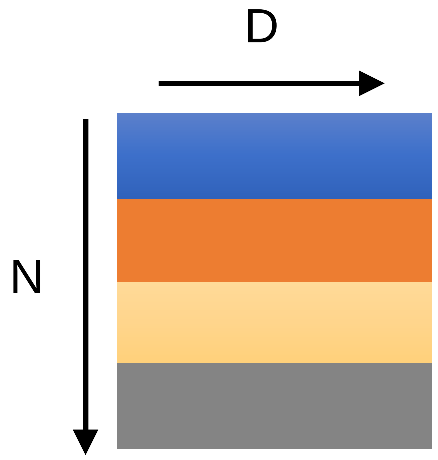
Unordered Input

Point cloud: N **orderless** points, each represented by a D dim vector



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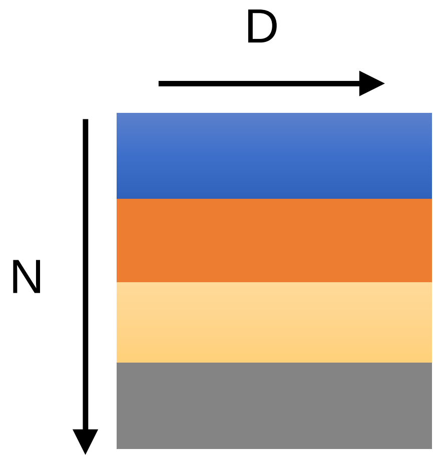
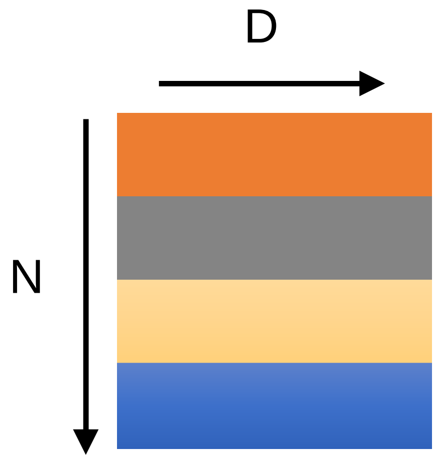


represents the same **set** as



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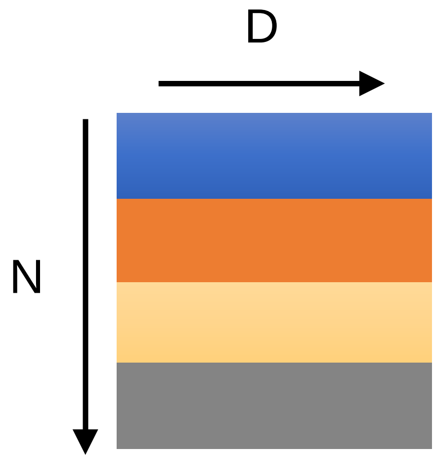

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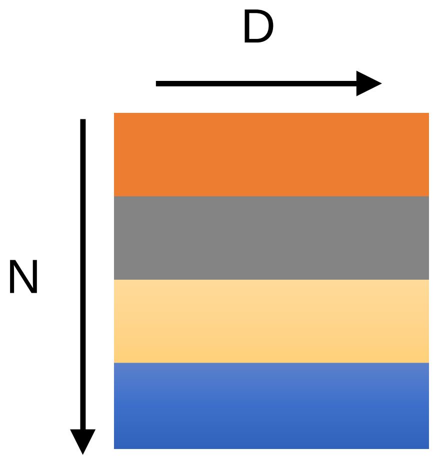

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Permutation Invariance: Symmetric Function

$$f(x_1, x_2, \ldots, x_n) \equiv f(x_{\pi_1}, x_{\pi_2}, \ldots, x_{\pi_n}), \quad x_i \in \mathbb{R}^D$$

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Examples:

$$f(x_1, x_2, \ldots, x_n) = \max\{x_1, x_2, \ldots, x_n\}$$

$$f(x_1, x_2, \ldots, x_n) = x_1 + x_2 + \ldots + x_n$$

$\ldots$

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$\ldots$

How can we construct a family of symmetric functions by neural networks?

Permutation Invariance: Symmetric Function

Observe:

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

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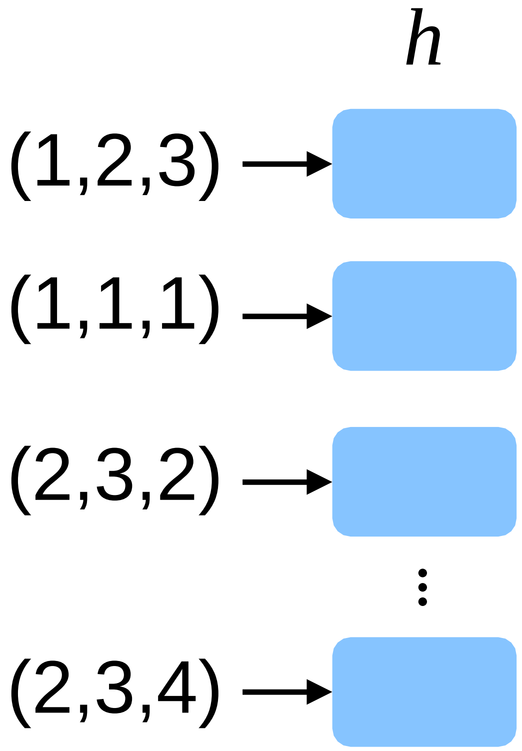

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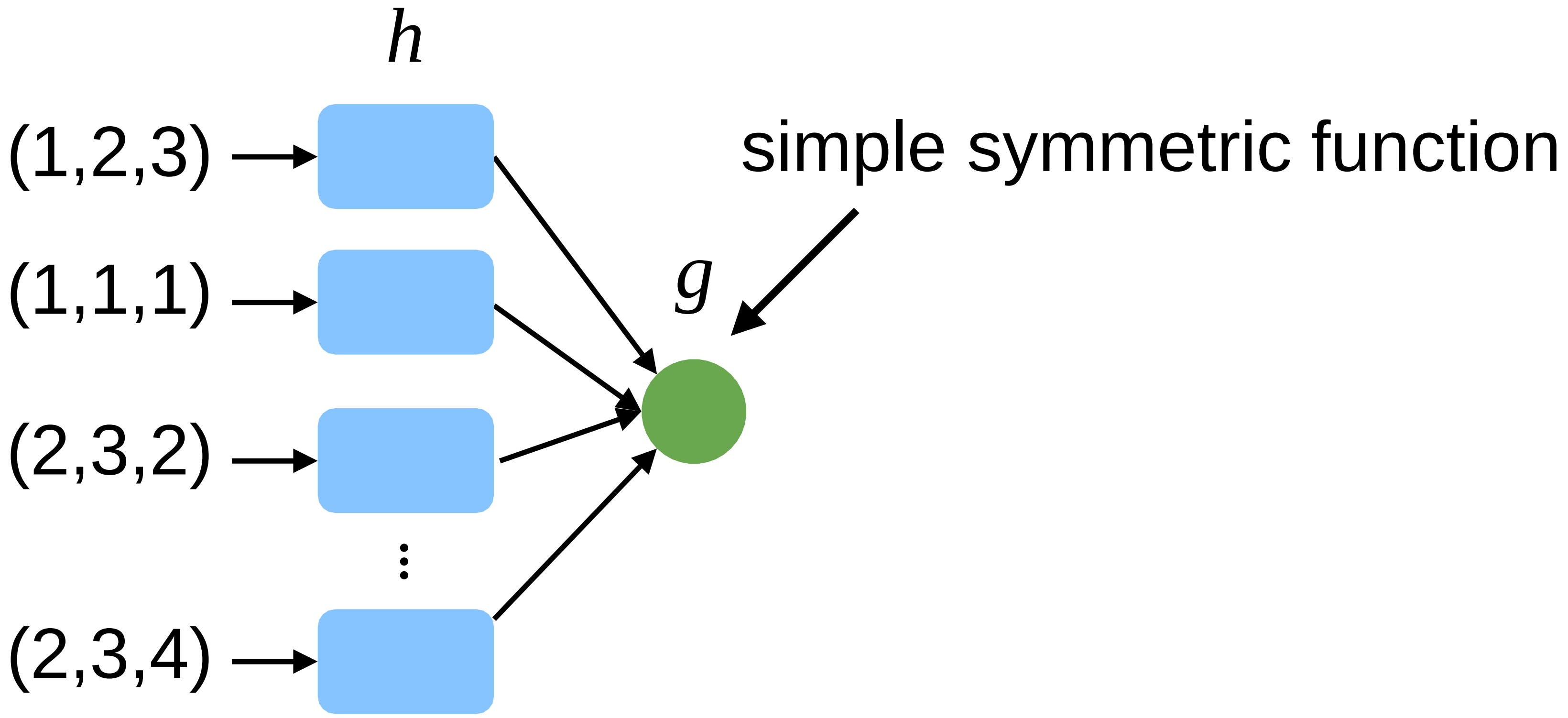

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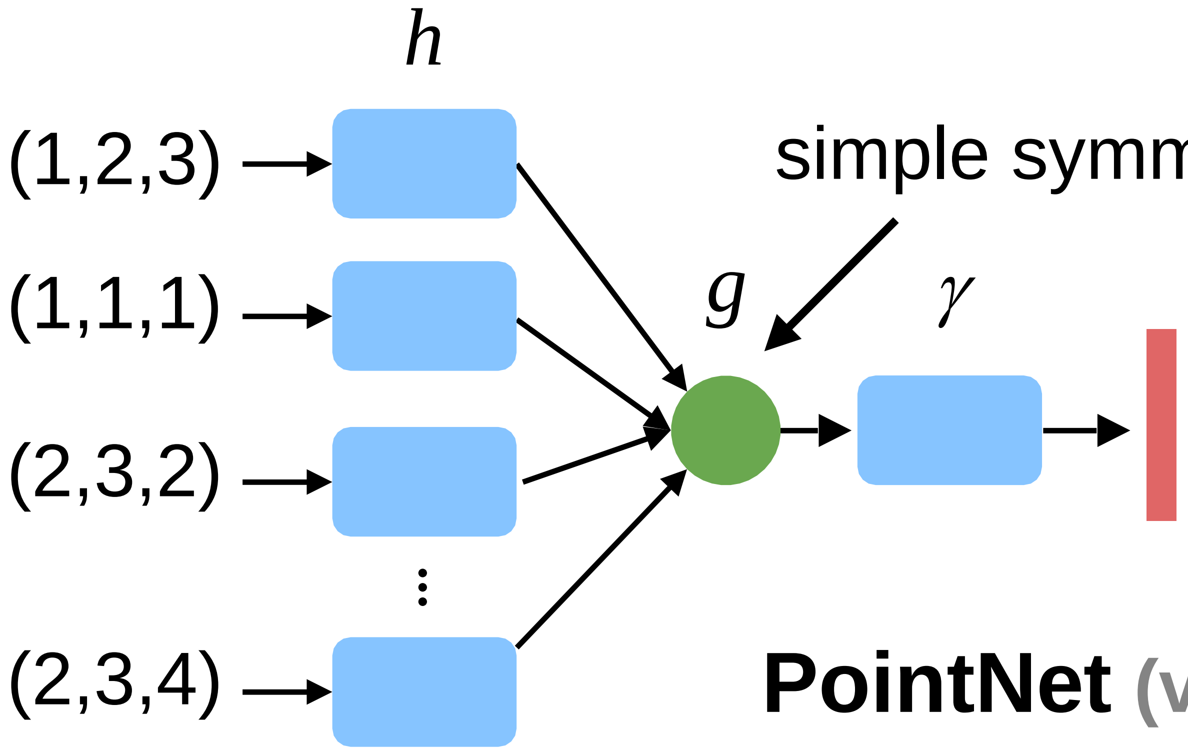
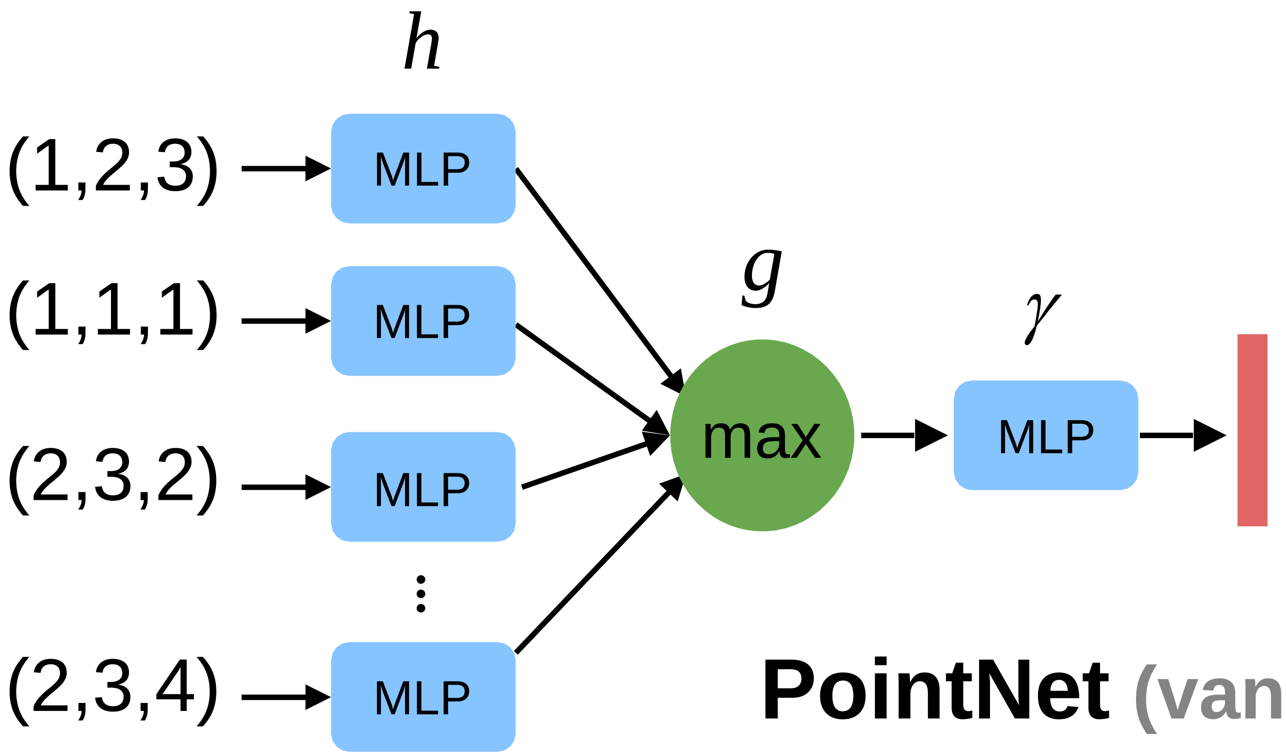


PointNet (vanilla)

Basic PointNet Architecture

Empirically, we use **multi-layer perceptron (MLP)** and **max pooling**:



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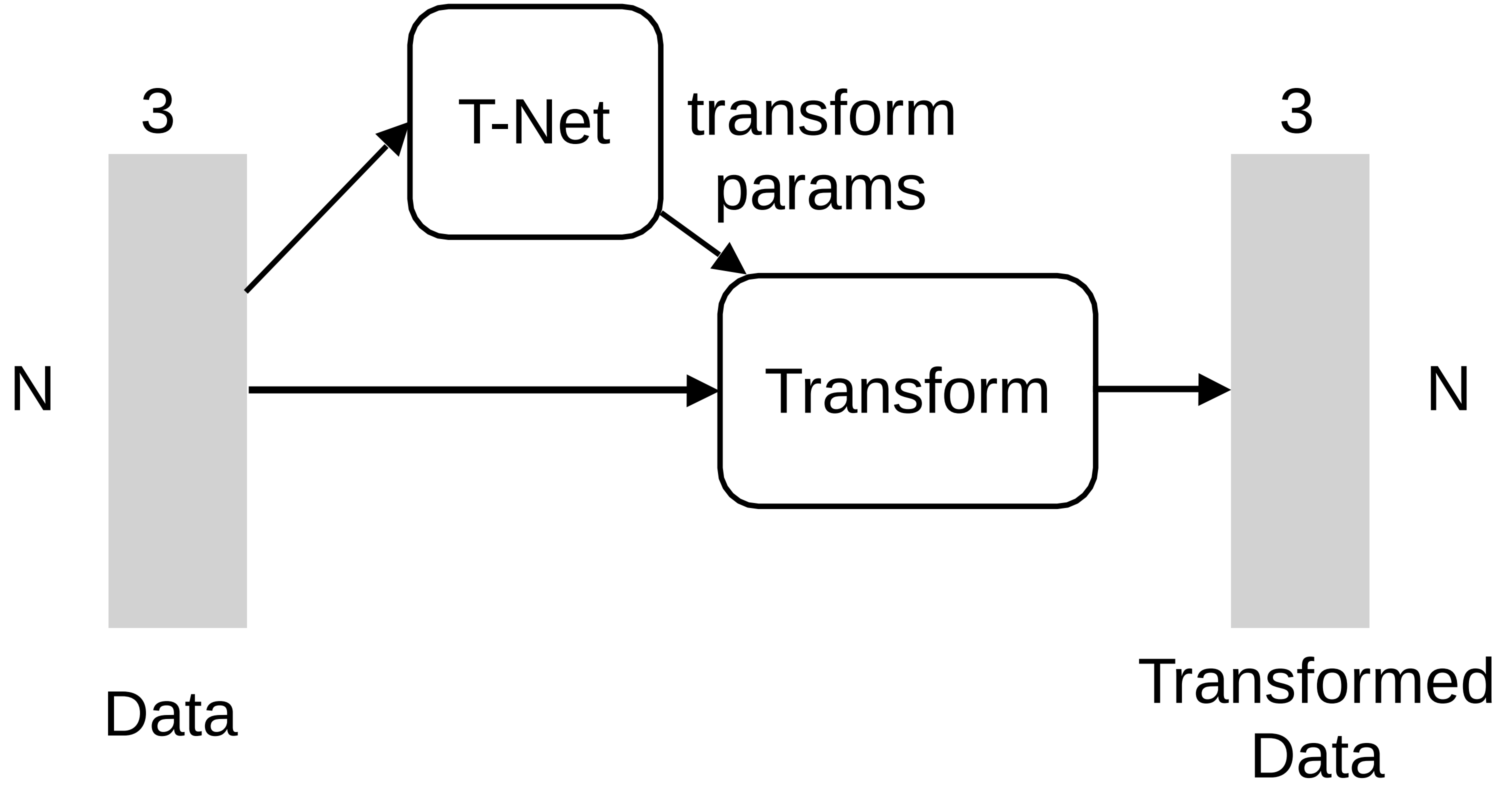
Input Alignment by Transformer Network

Idea: Data dependent transformation for automatic alignment



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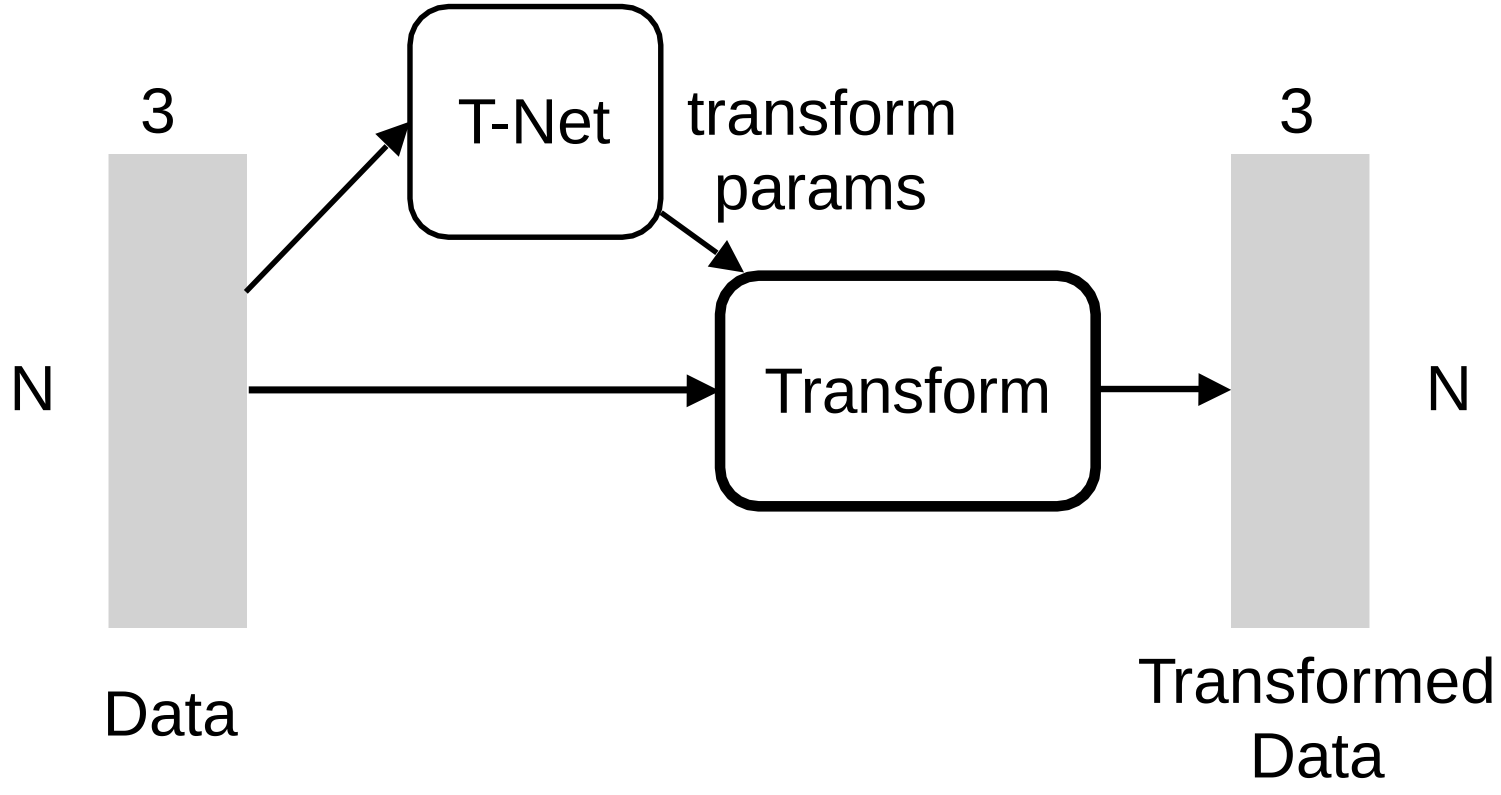

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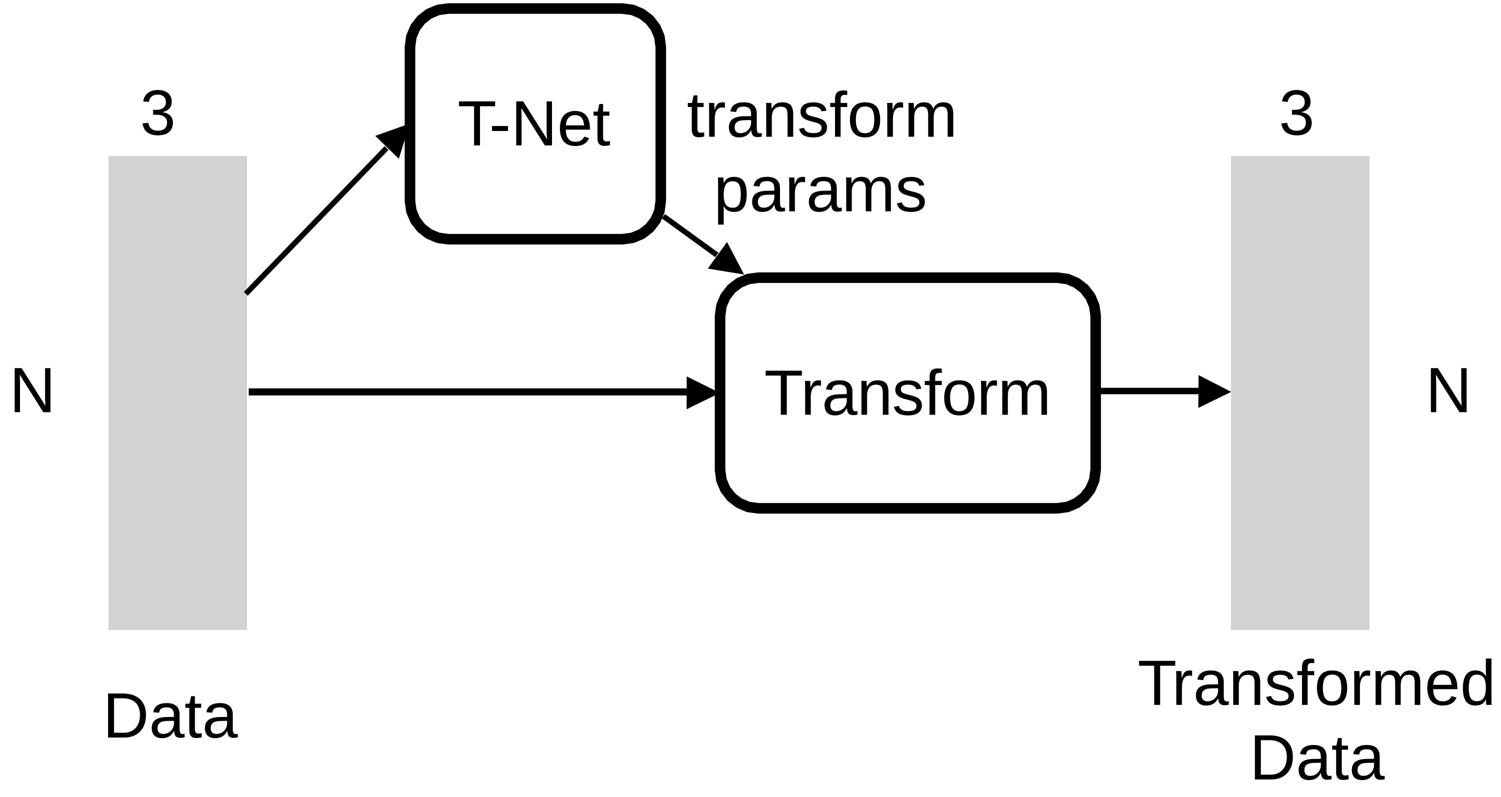
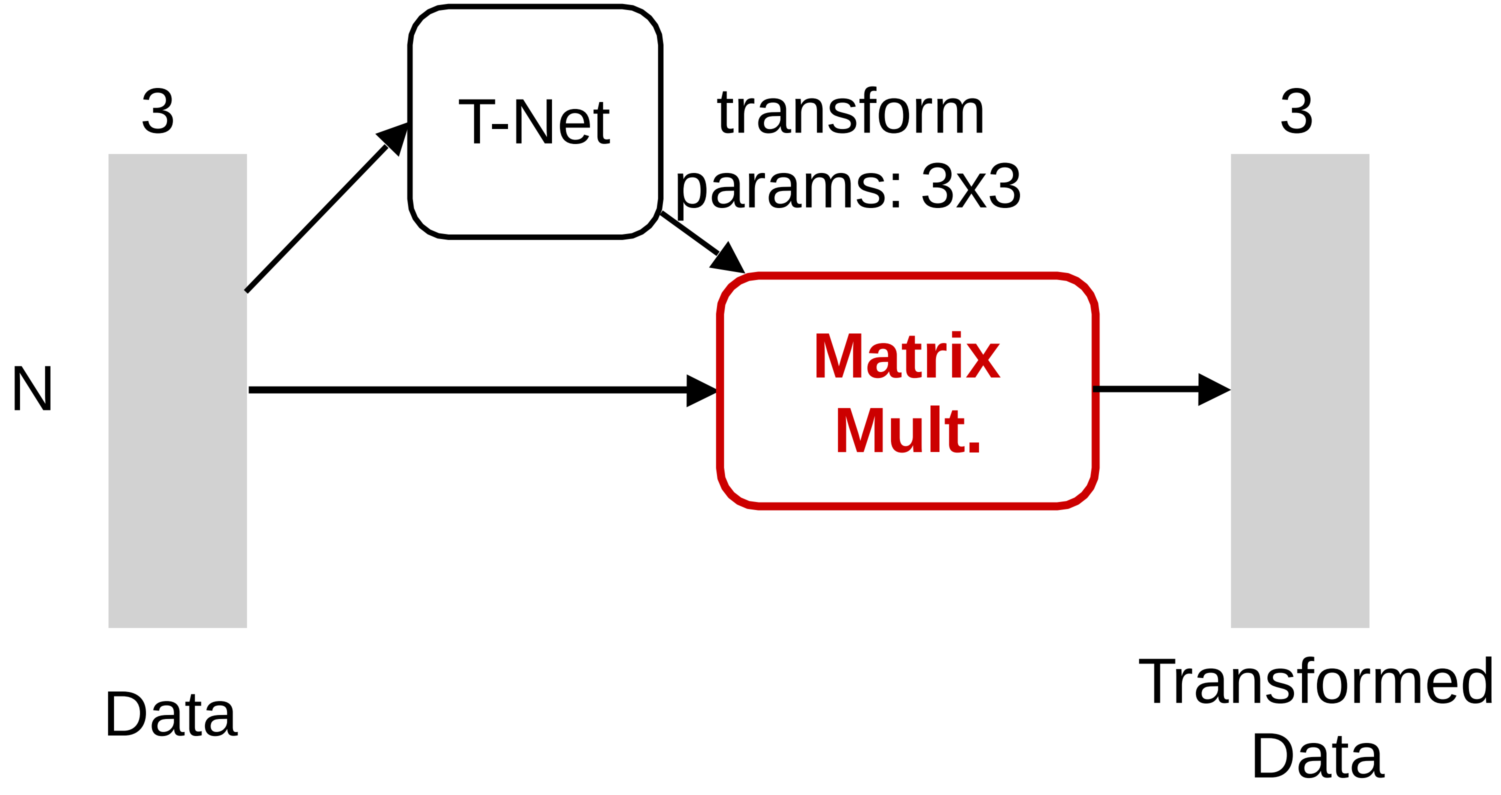
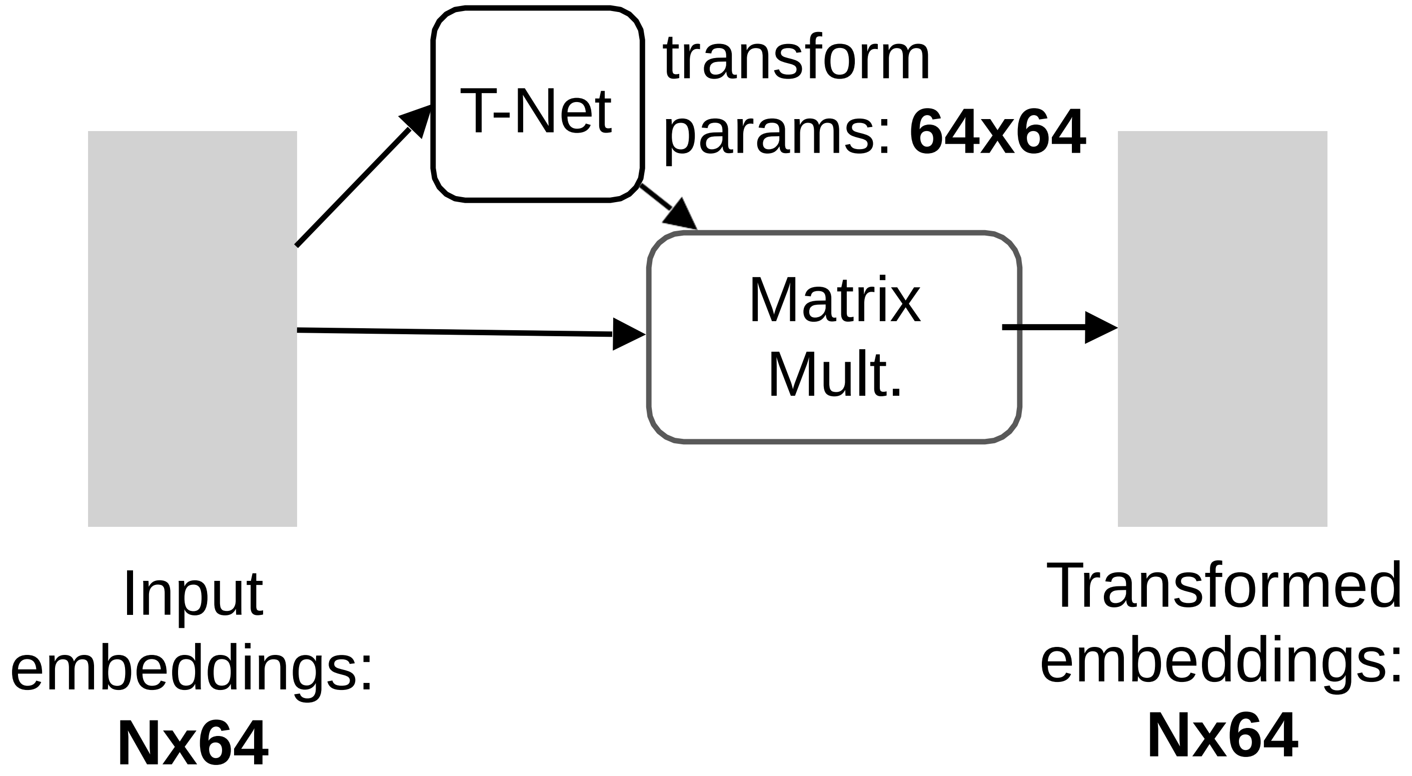


Input Alignment by Transformer Network

The transformation is just matrix multiplication!



Embedding Space Alignment



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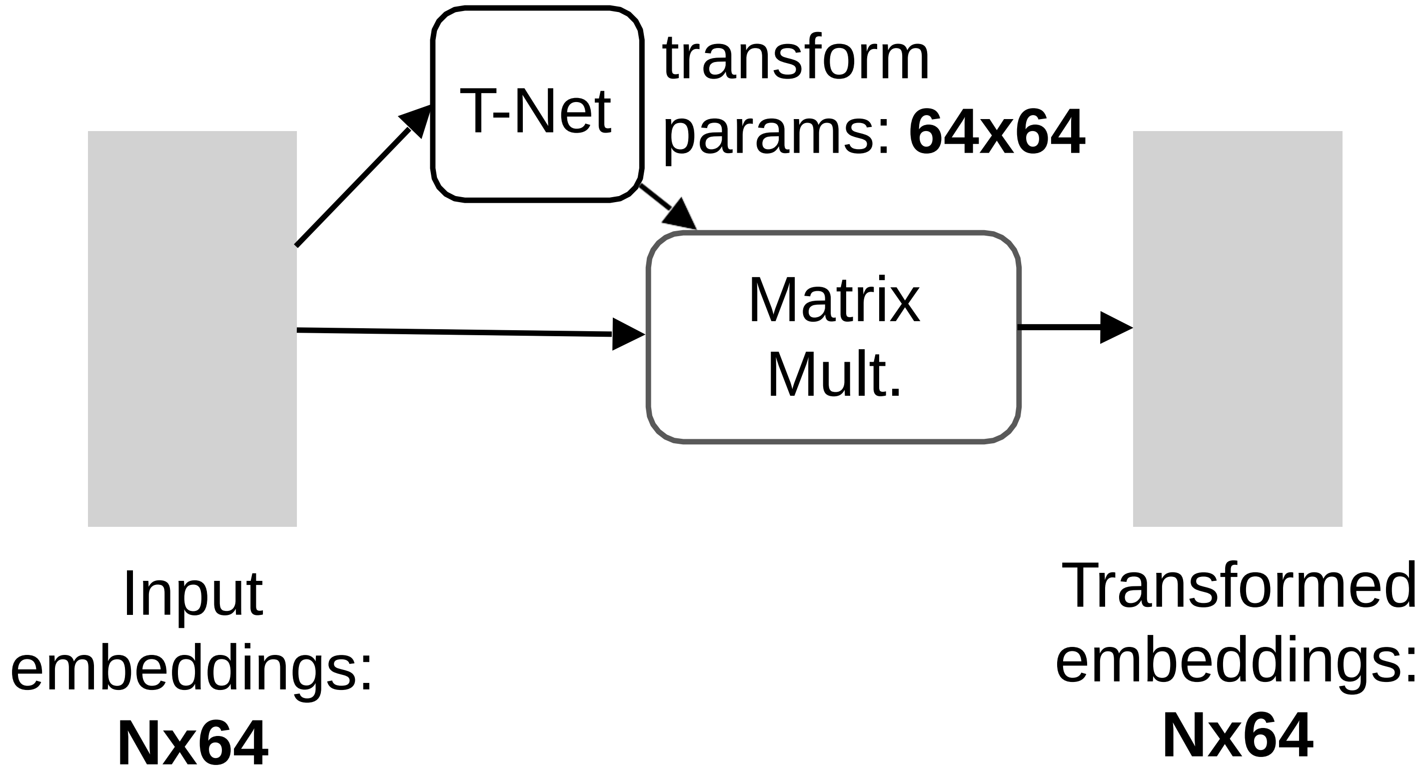

Regularization:

Transform matrix A 64x64 close to orthogonal:

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

PointNet Classification Network

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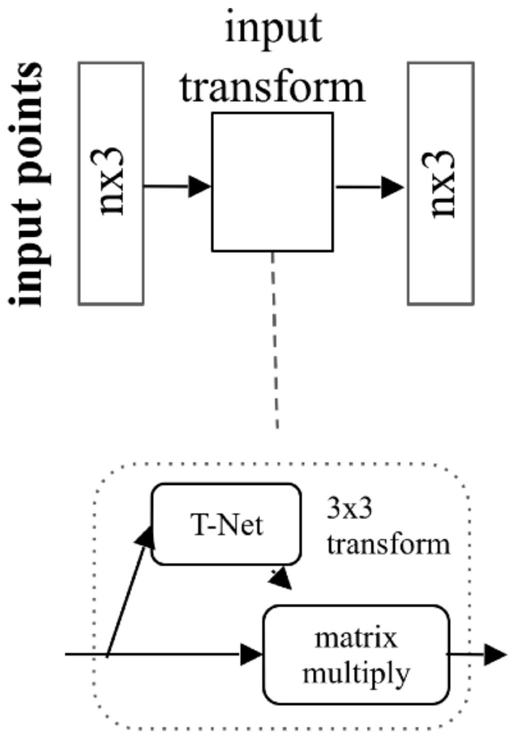

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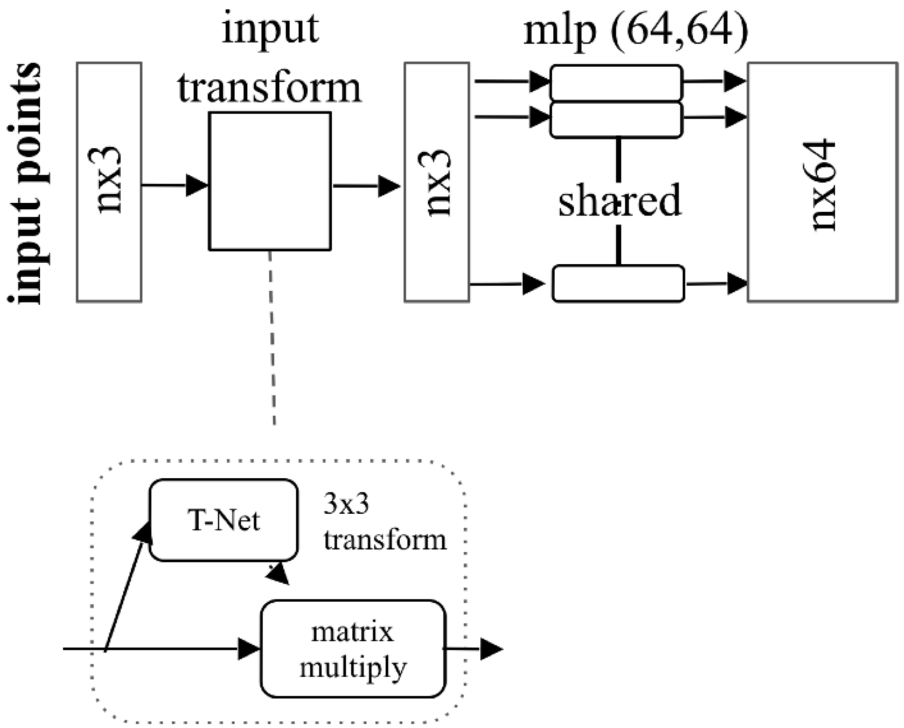

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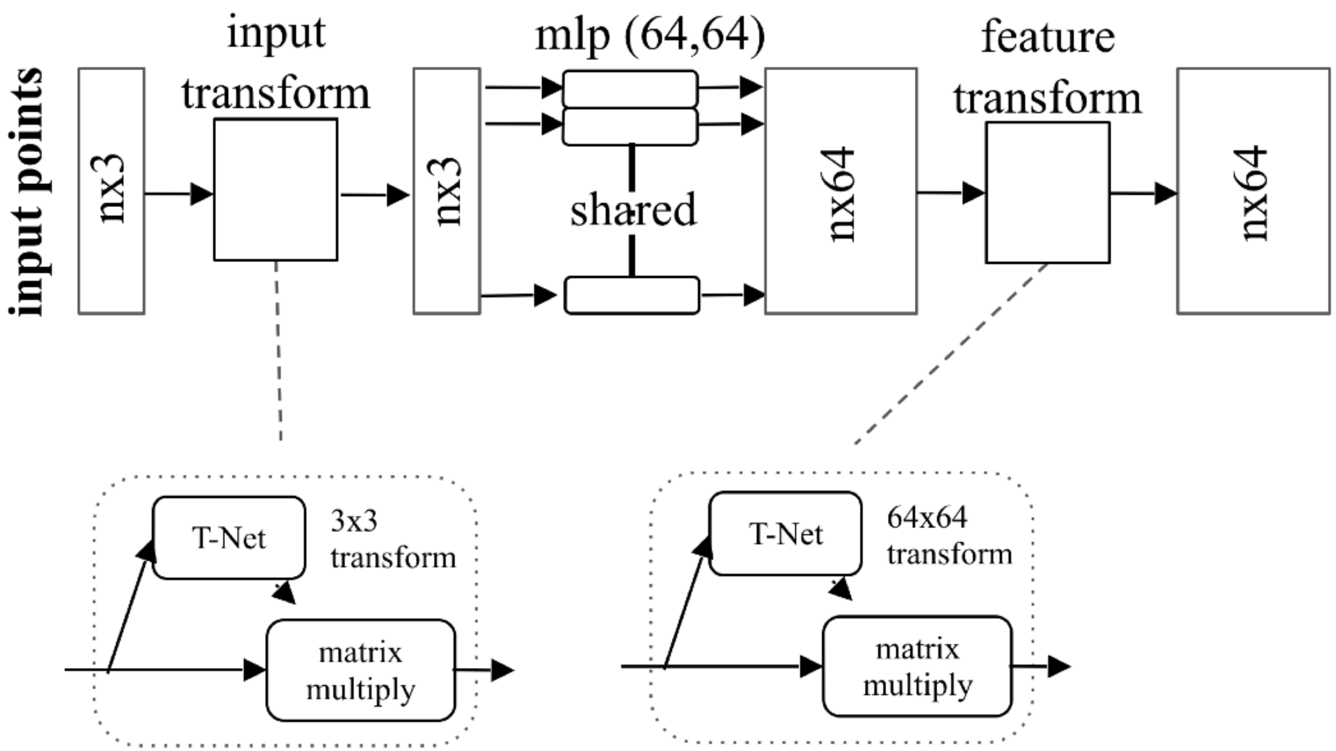

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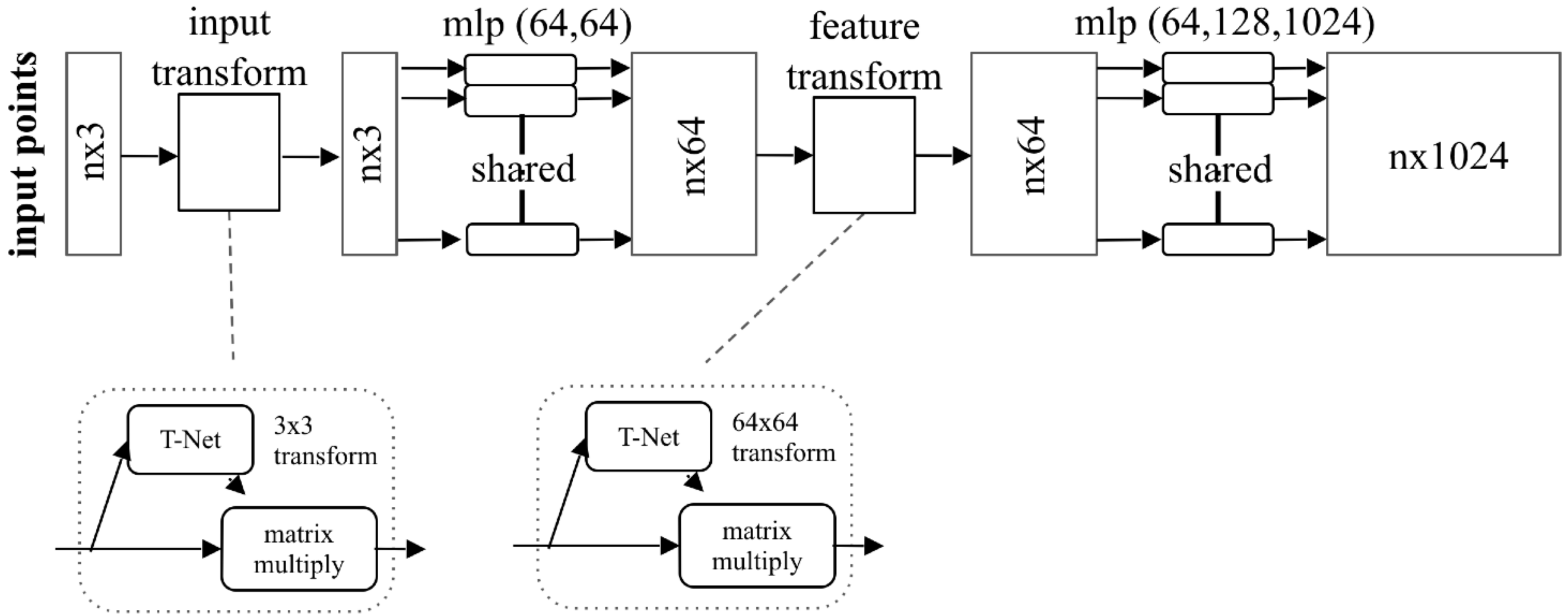

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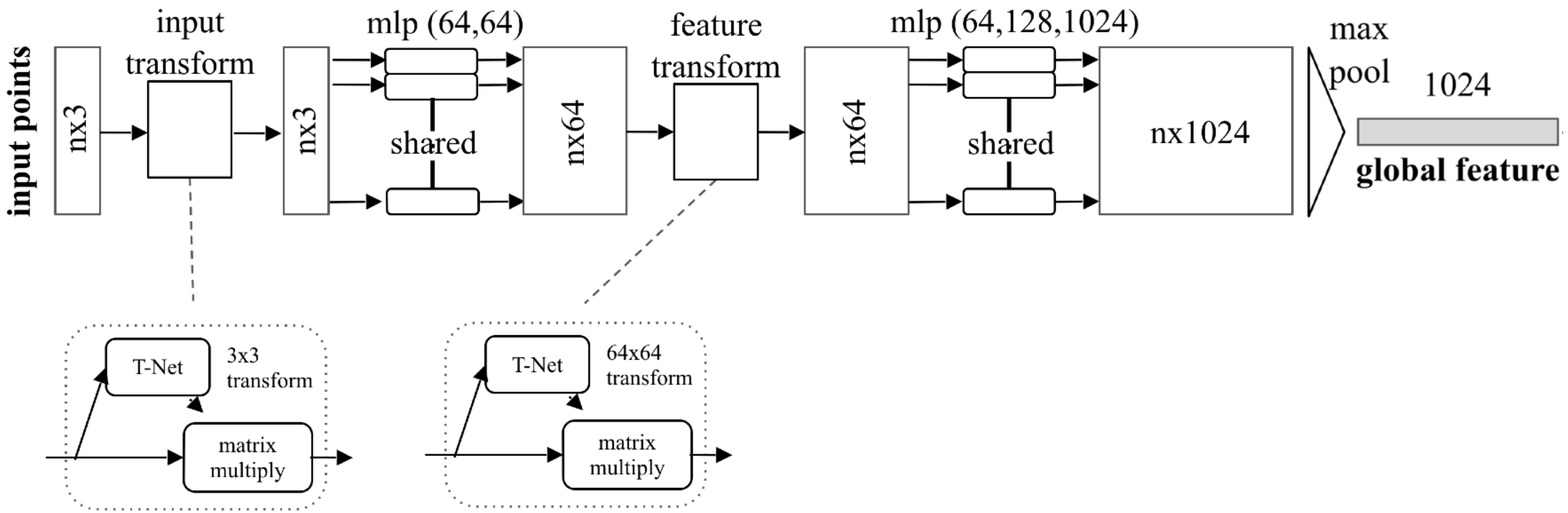

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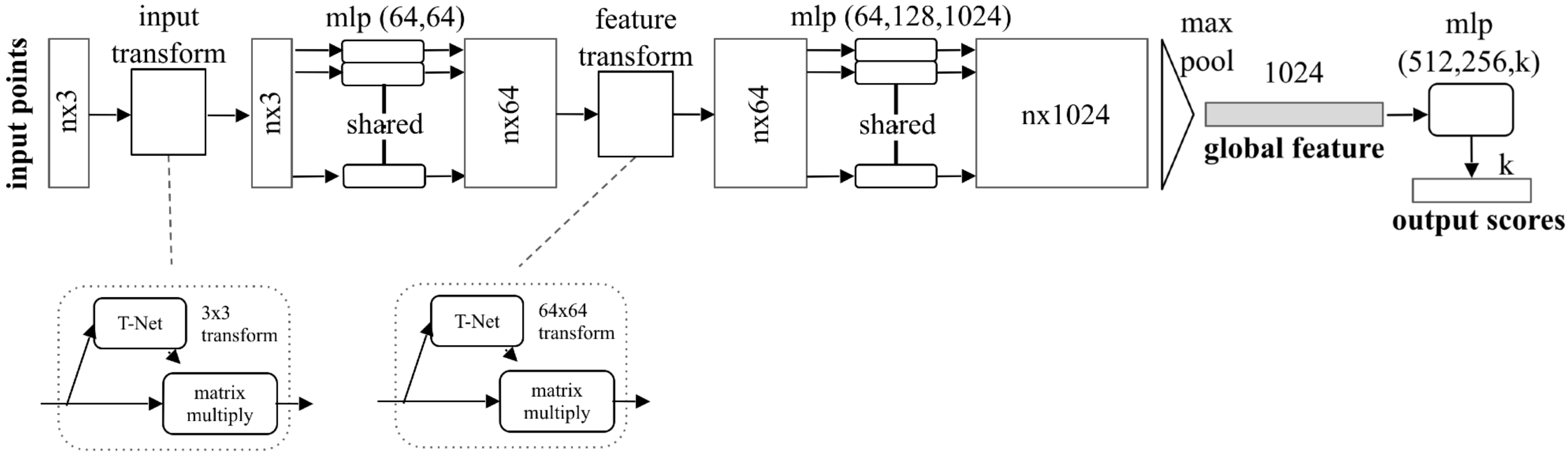
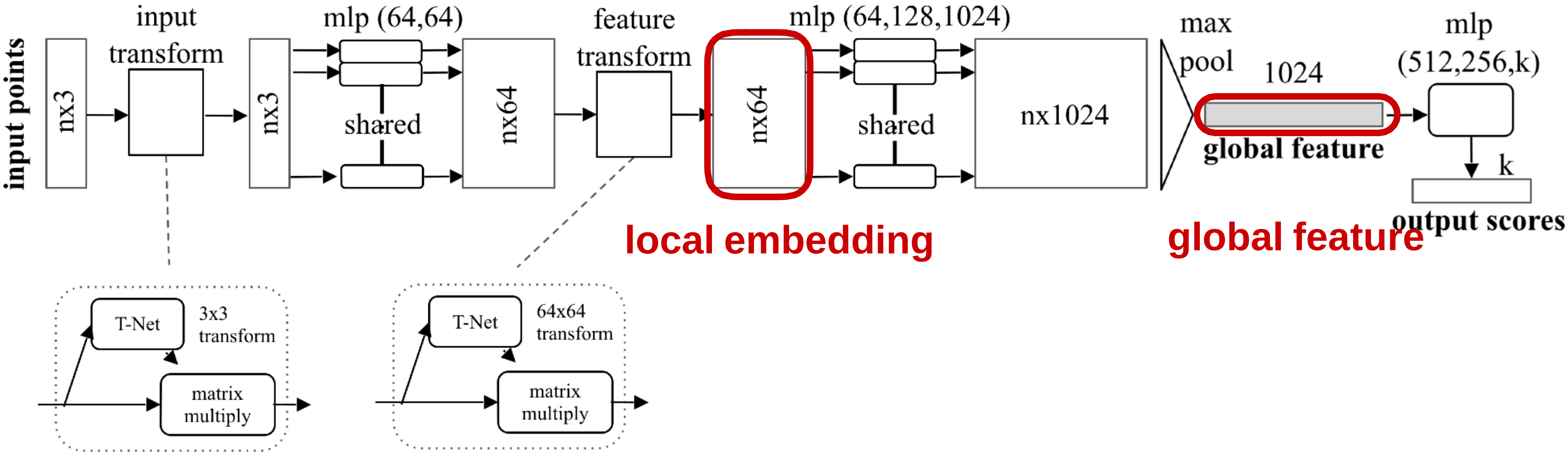


Extension to PointNet Segmentation Network



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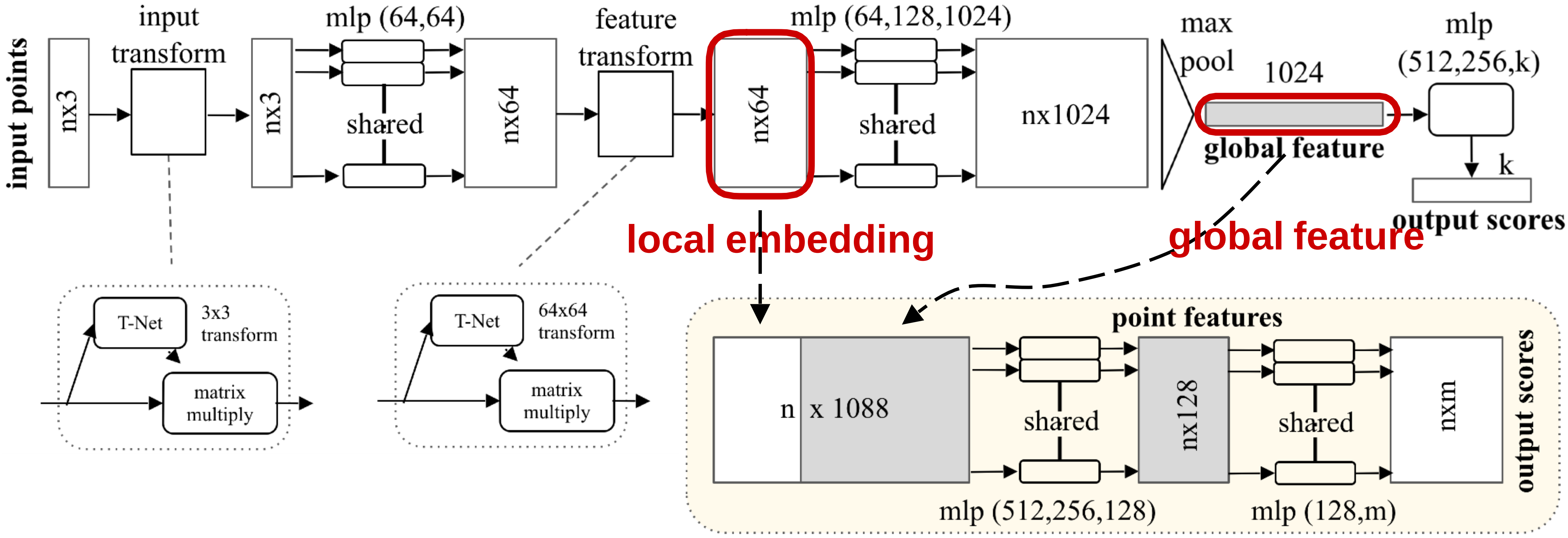


Results

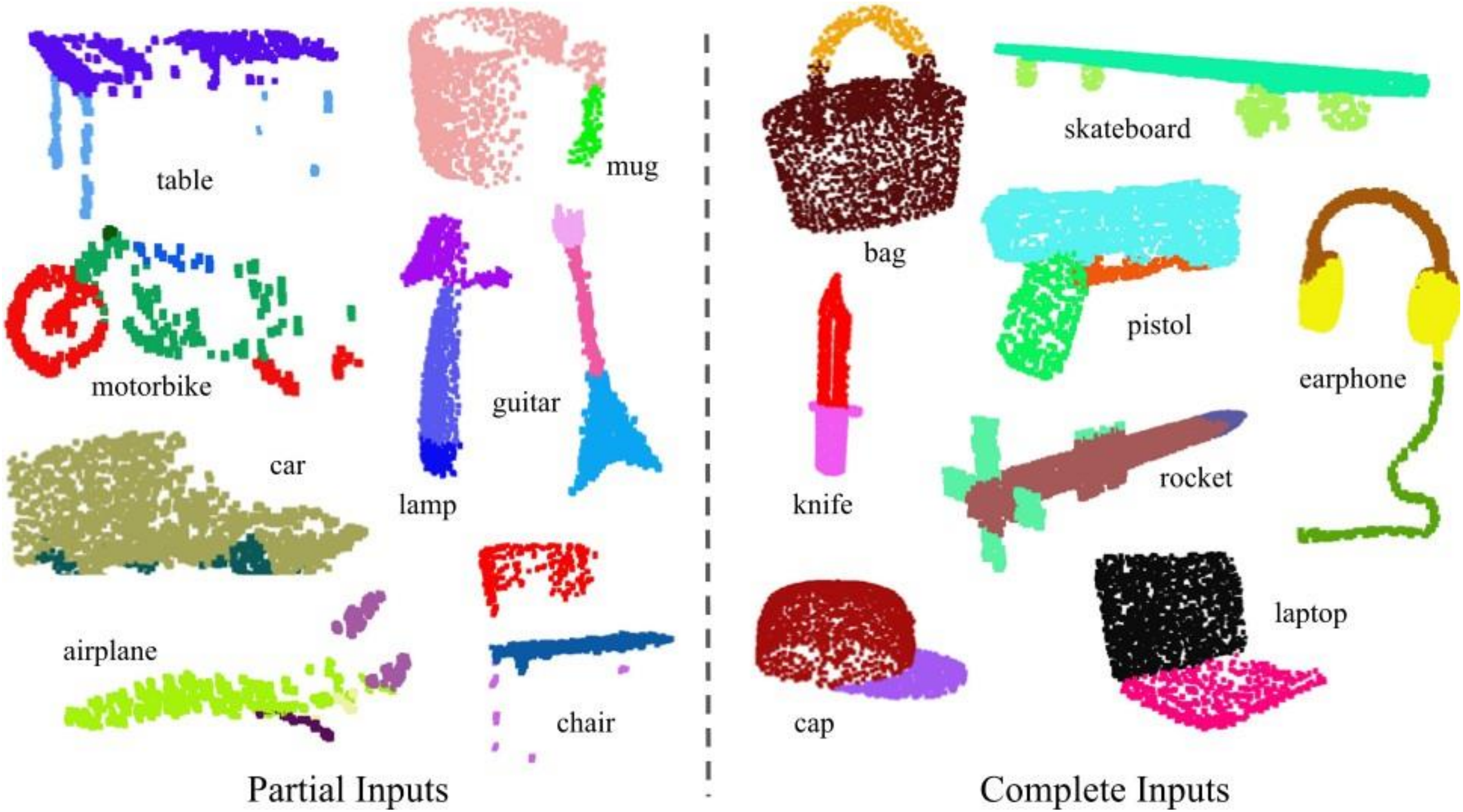
Results on Object Classification

3D CNNs

	input	#views	accuracy avg. class	accuracy overall
SPH [12]	mesh	-	68.2	
3DShapeNets [29]	volume	1	77.3	84.7
VoxNet [18]	volume	12	83.0	85.9
Subvolume [19]	volume	20	86.0	**89.2**
LFD [29]	image	10	75.5	-
MVCNN [24]	image	80	**90.1**	-
Ours baseline	point	-	72.6	77.4
Ours PointNet	point	1	86.2	**89.2**

dataset: ModelNet40; metric: 40-class classification accuracy (%)

Results on Object Part Segmentation



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 [28]	-	63.2	-	-	-	73.5	-	-	-	74.4	-	-	-	-	-	-	74.8
Yi [30]	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**

dataset: ShapeNetPart; metric: mean IoU (%)

Results on Semantic Scene Parsing

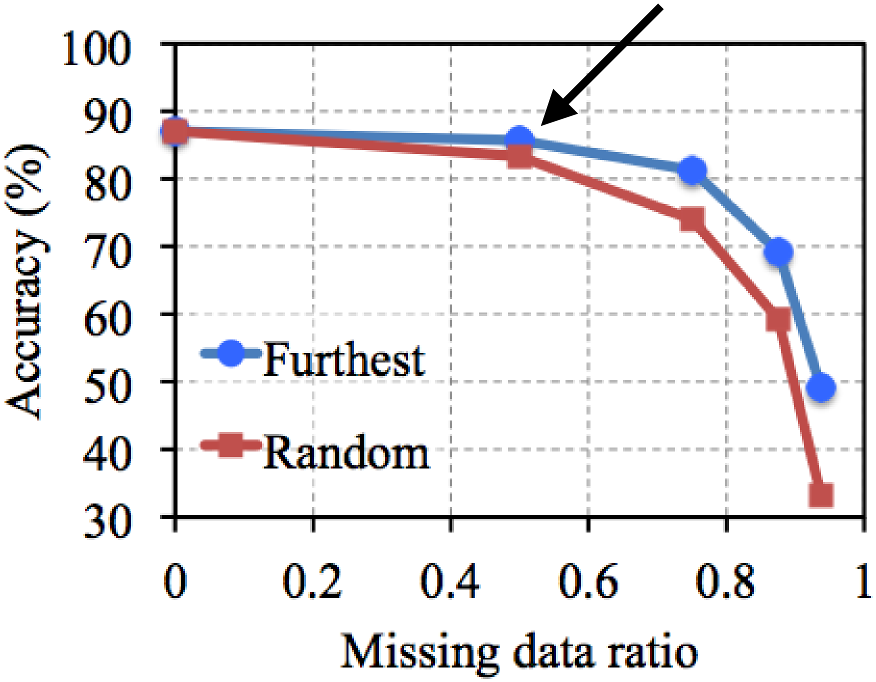
dataset: Stanford 2D-3D-S (Matterport scans)

Robustness to Data Corruption

dataset: ModelNet40; metric: 40-class classification accuracy (%)

Robustness to Data Corruption

Less than 2% accuracy drop with 50% missing data



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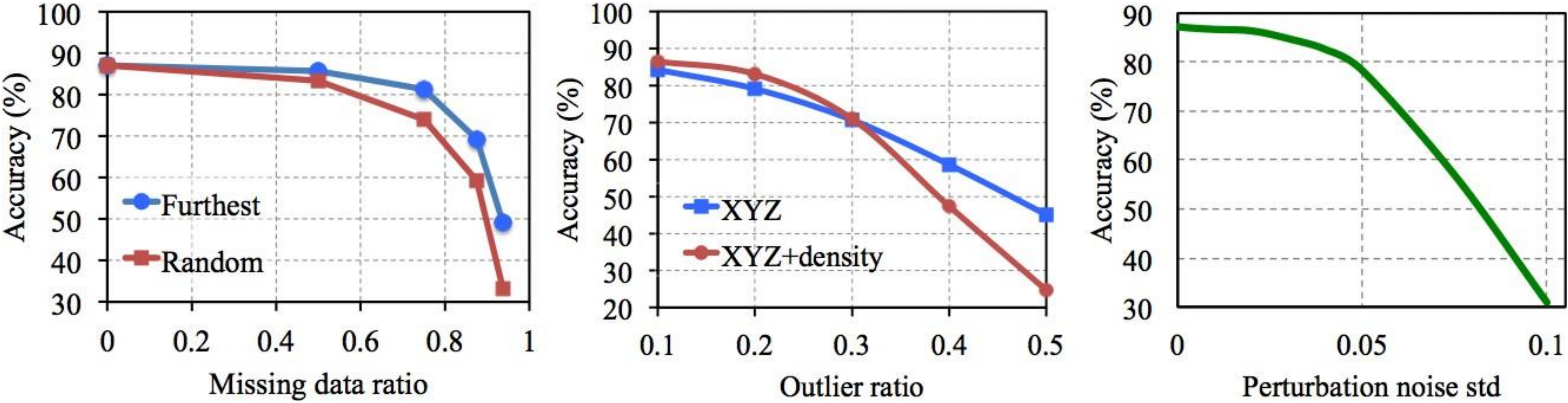

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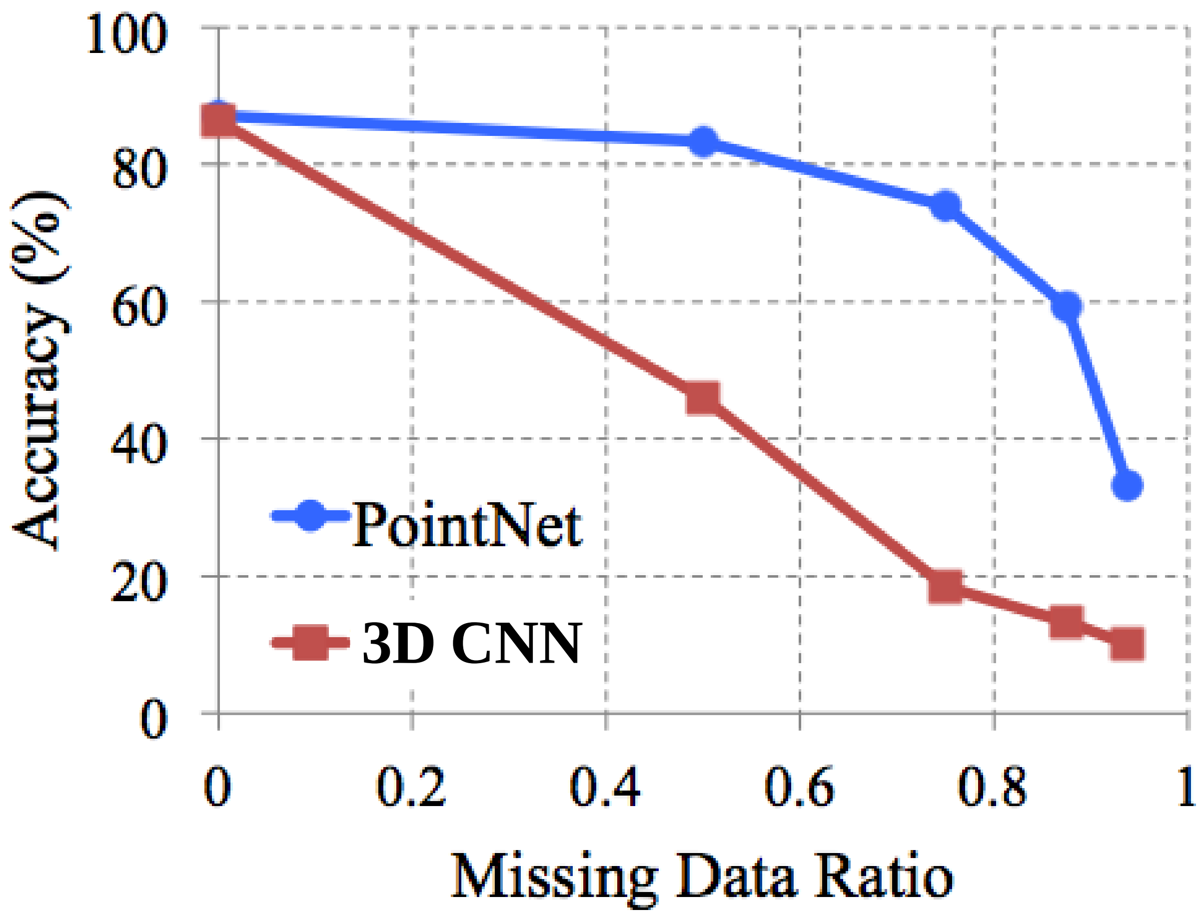
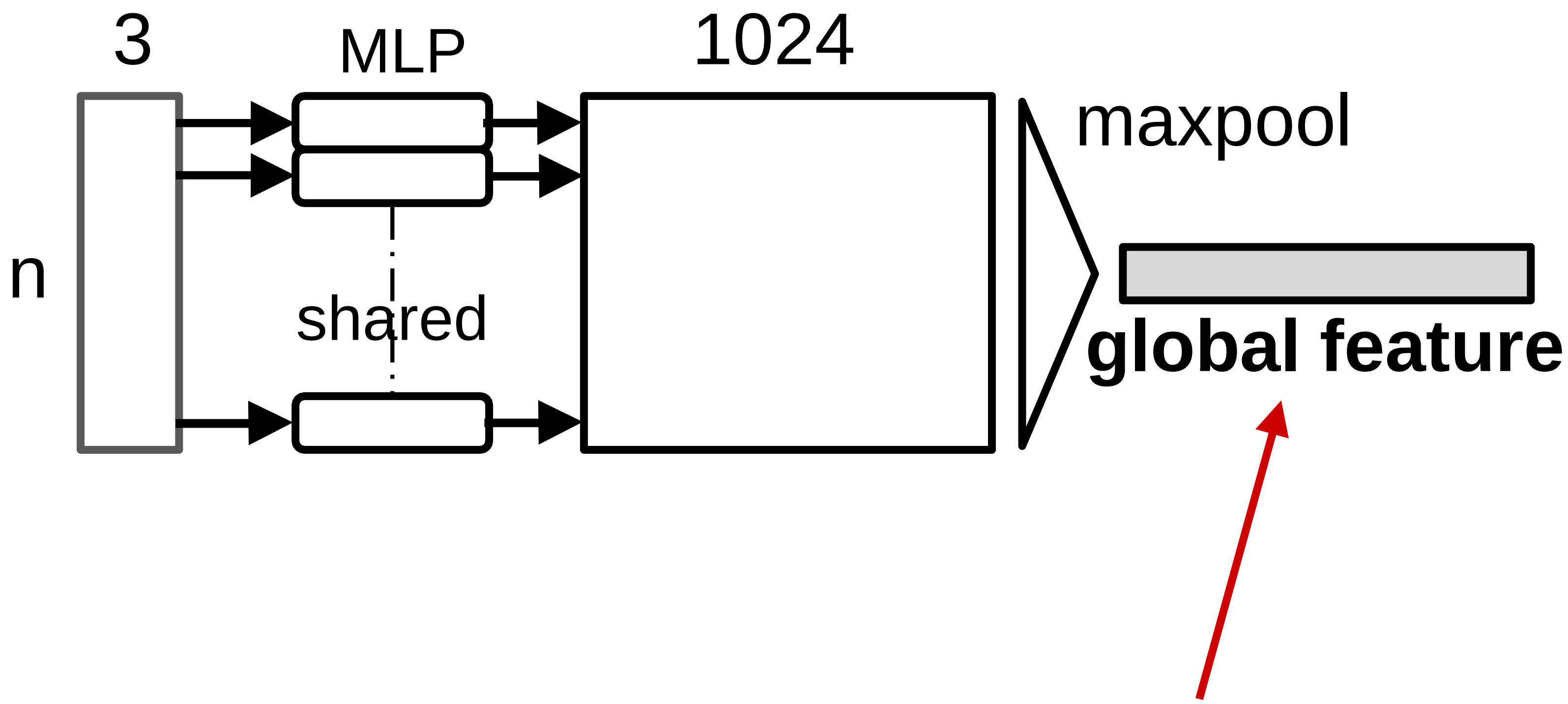


Why is PointNet so robust to missing data?

Visualizing Global Point Cloud Features



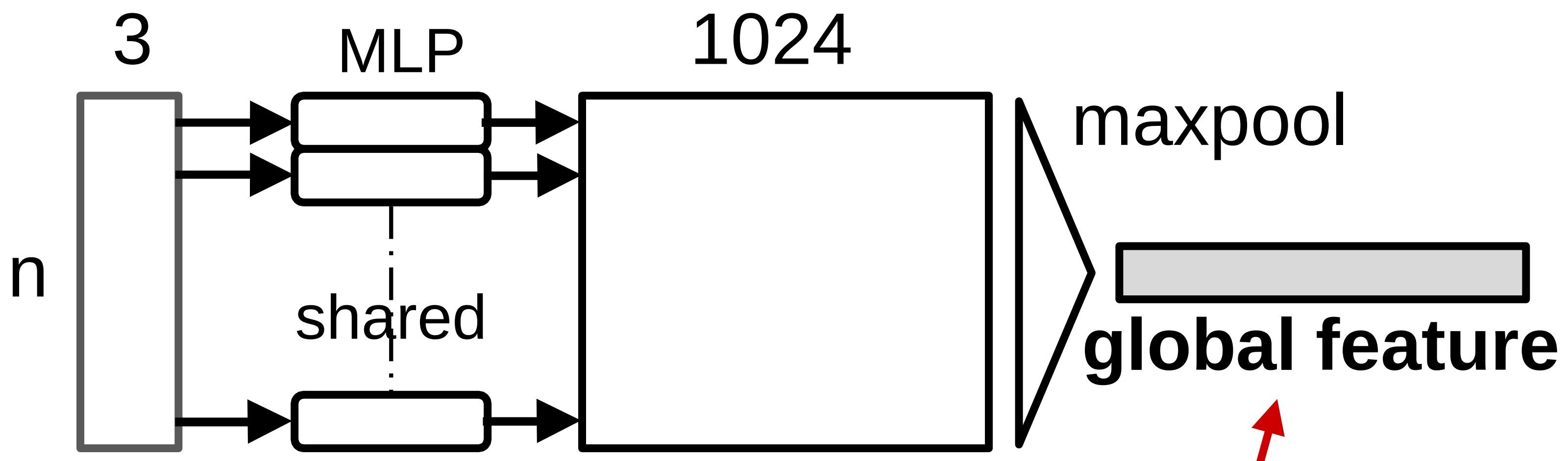
Which input points are contributing to the global feature?
(critical points)

Visualizing Global Point Cloud Features

Original Shape:

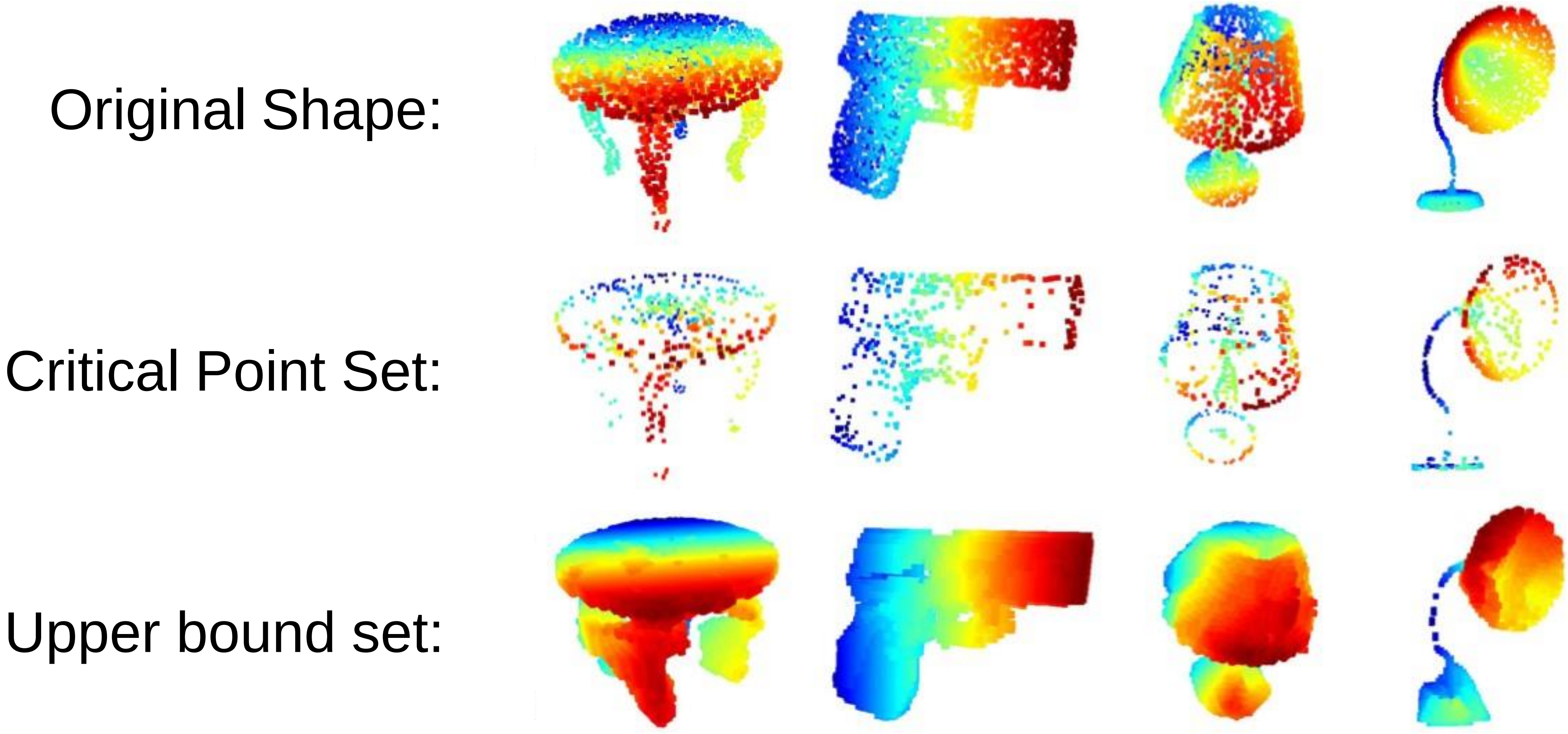
Critical Point Sets:

Visualizing Global Point Cloud Features



Which points won't affect the global feature?

Visualizing Global Point Cloud Features

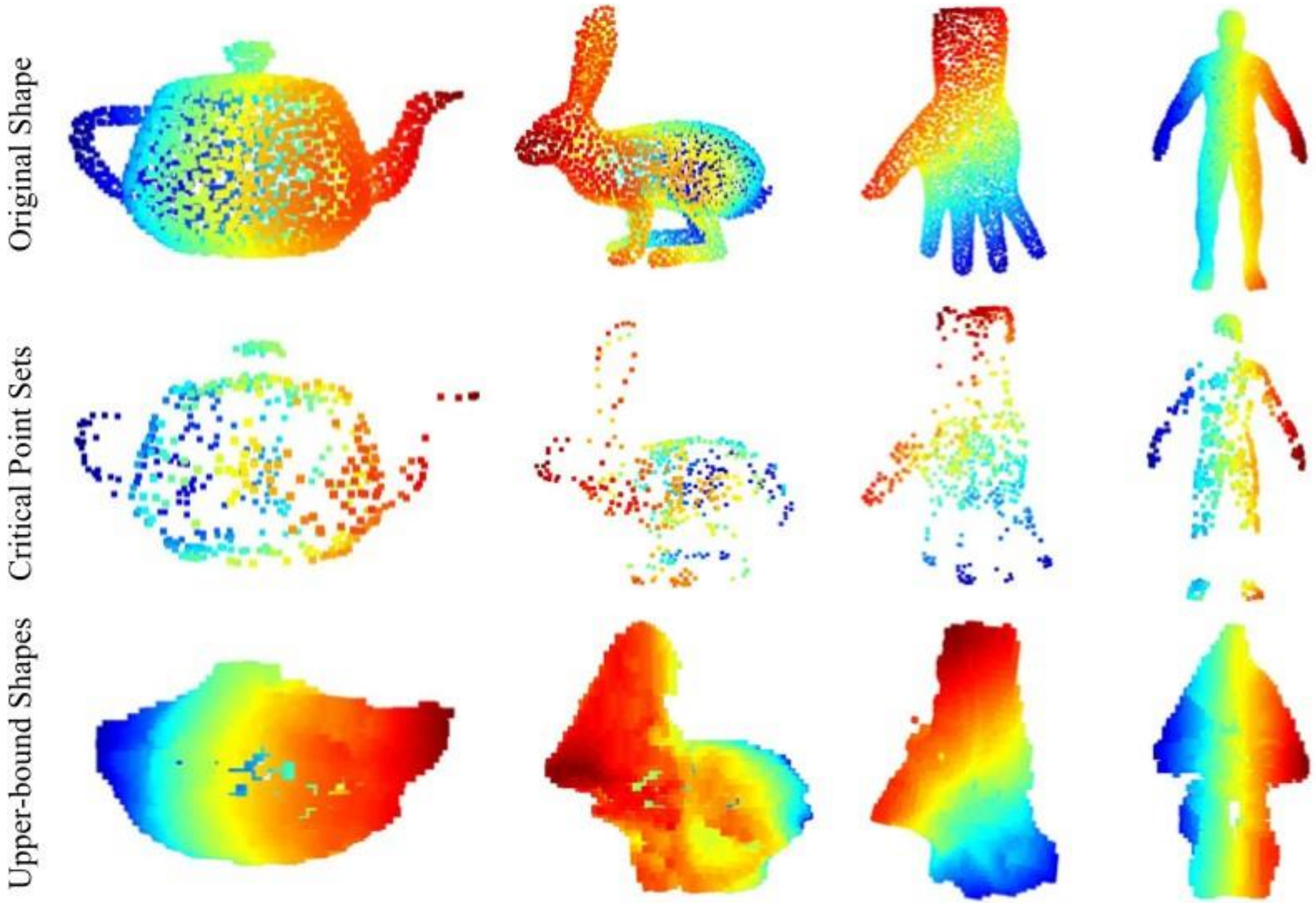


Visualizing Global Point Cloud Features (OOS)

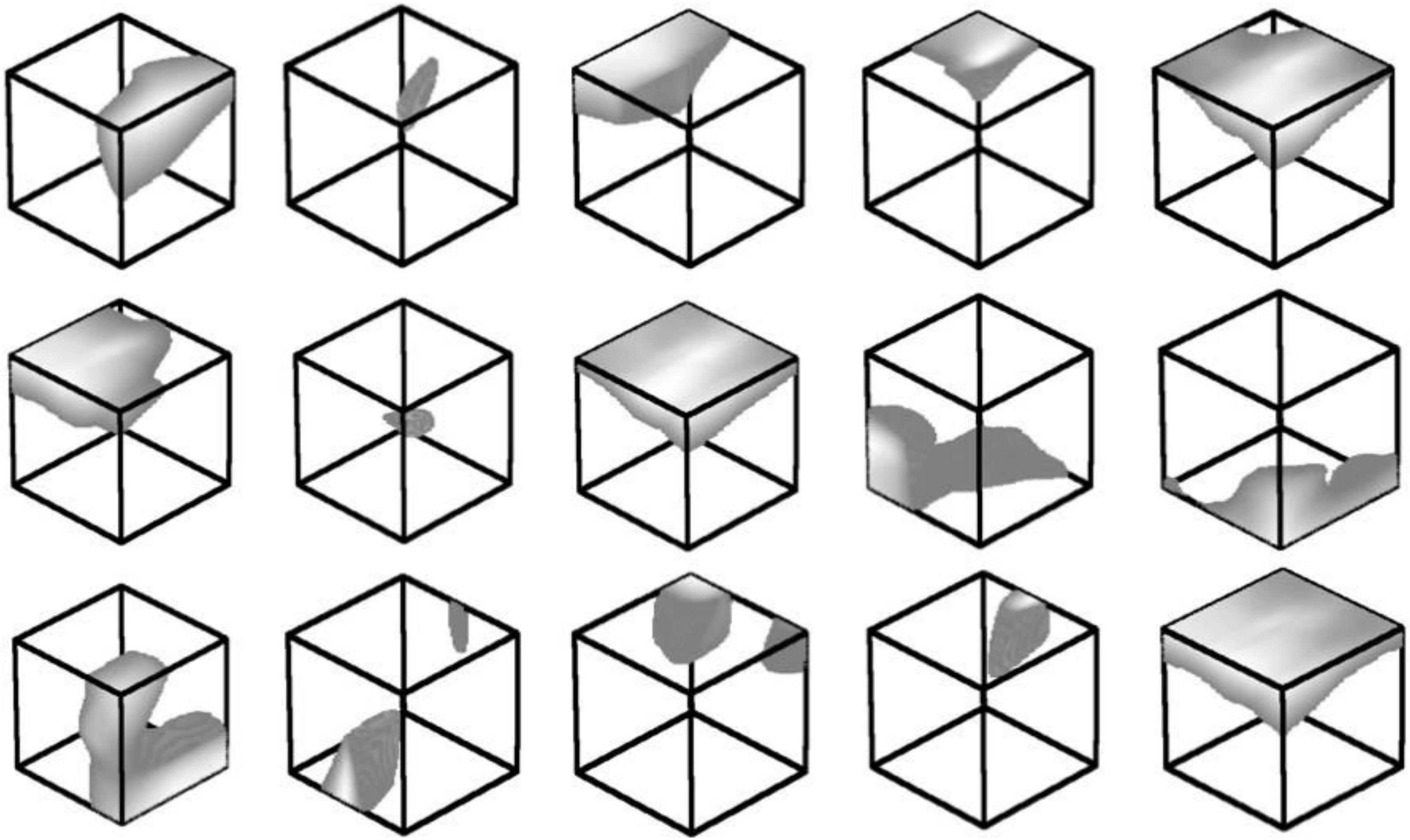
Original Shape:

Critical Point Set:

Upper bound Set:

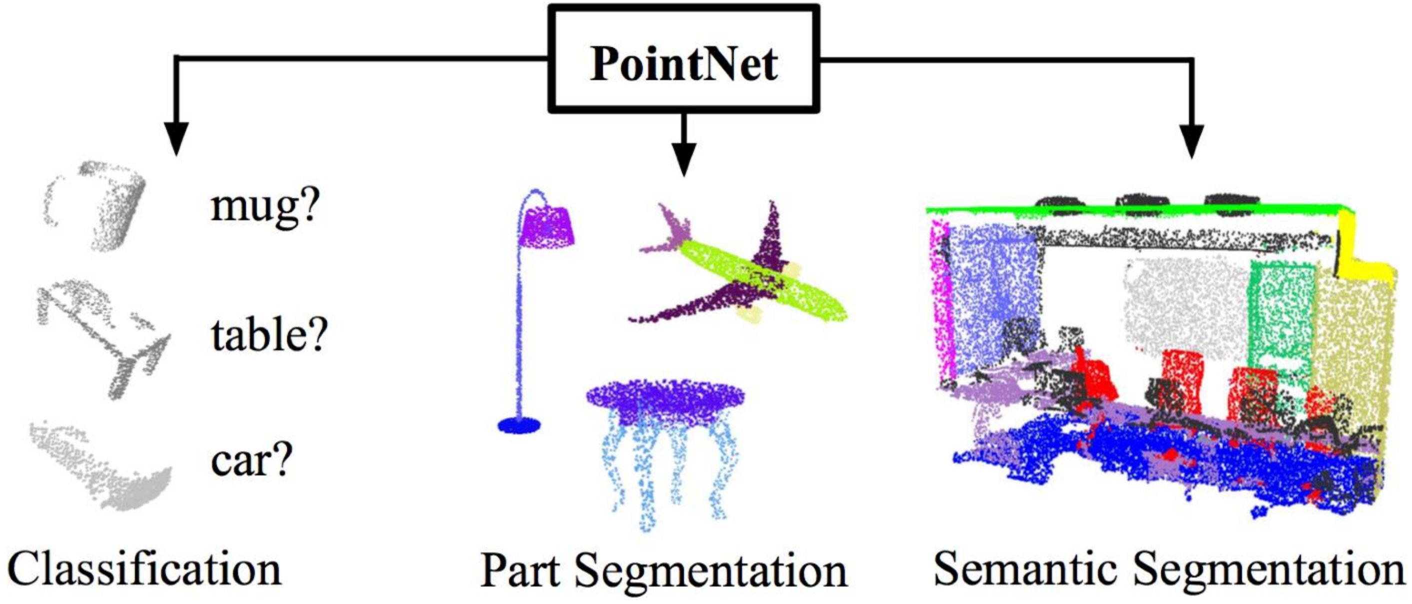


Visualizing Point Functions



Conclusion

- PointNet is a novel deep neural network that directly consumes point cloud.
- A unified approach to various 3D recognition tasks.
- Rich theoretical analysis and experimental results.



Code & Data Available!
http://stanford.edu/~rqi/pointnet

Speed and Model Size

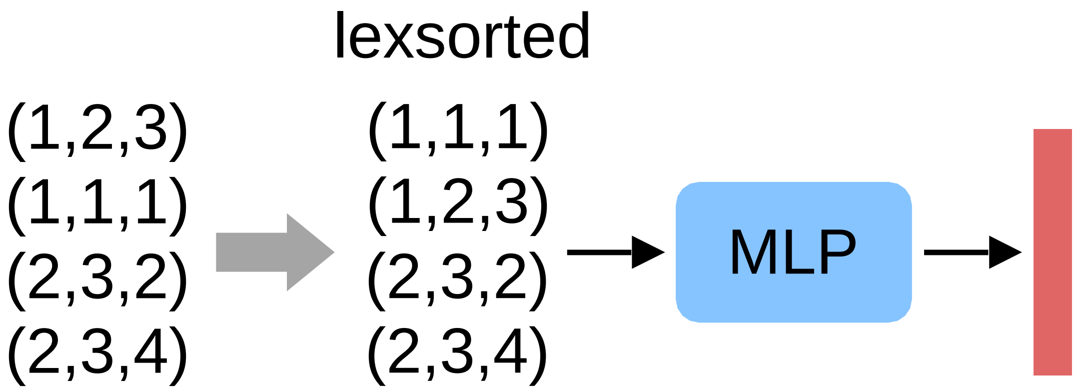
	#params	FLOPs/sample
PointNet (vanilla)	0.8M	148M
PointNet	3.5M	440M
Subvolume [16]	16.6M	3633M
MVCNN [20]	60.0M	62057M

Inference time 11.6ms, 25.3ms GTX1080, batch size 8

Permutation Invariance: How about Sorting?

"Sort" the points before feeding them into a network.

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



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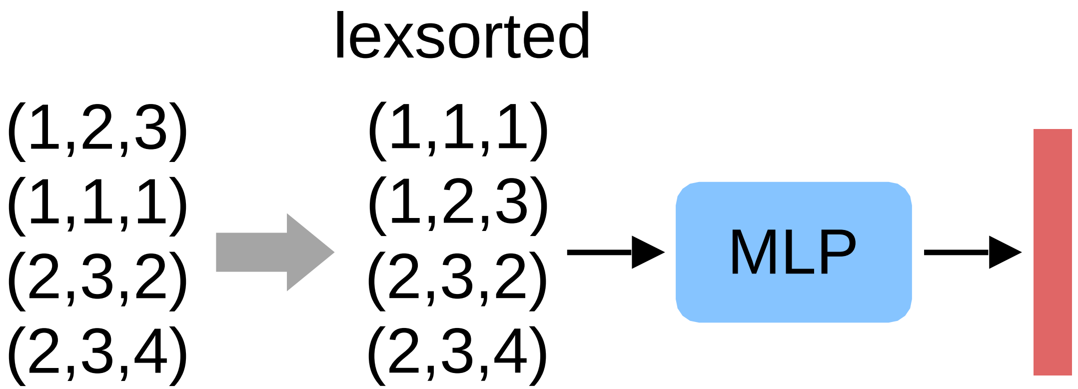


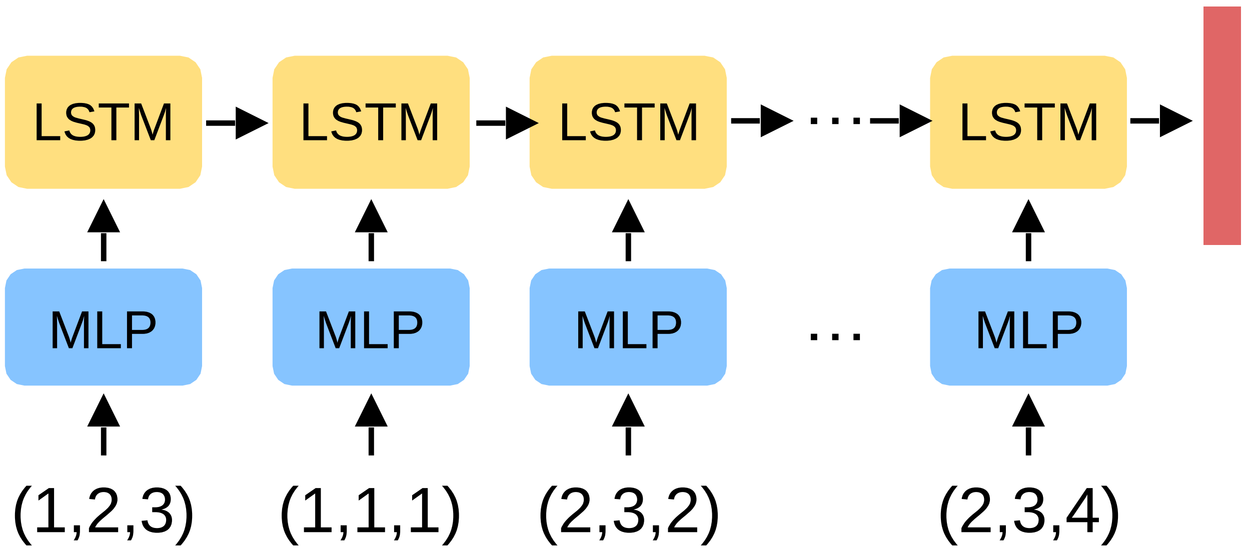
Multi-Layer Perceptron
(ModelNet shape classification)

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

Permutation Invariance: How about RNNs?

Train RNN with permutation augmentation.

However, RNN forgets and order matters.



Permutation Invariance: How about RNNs?

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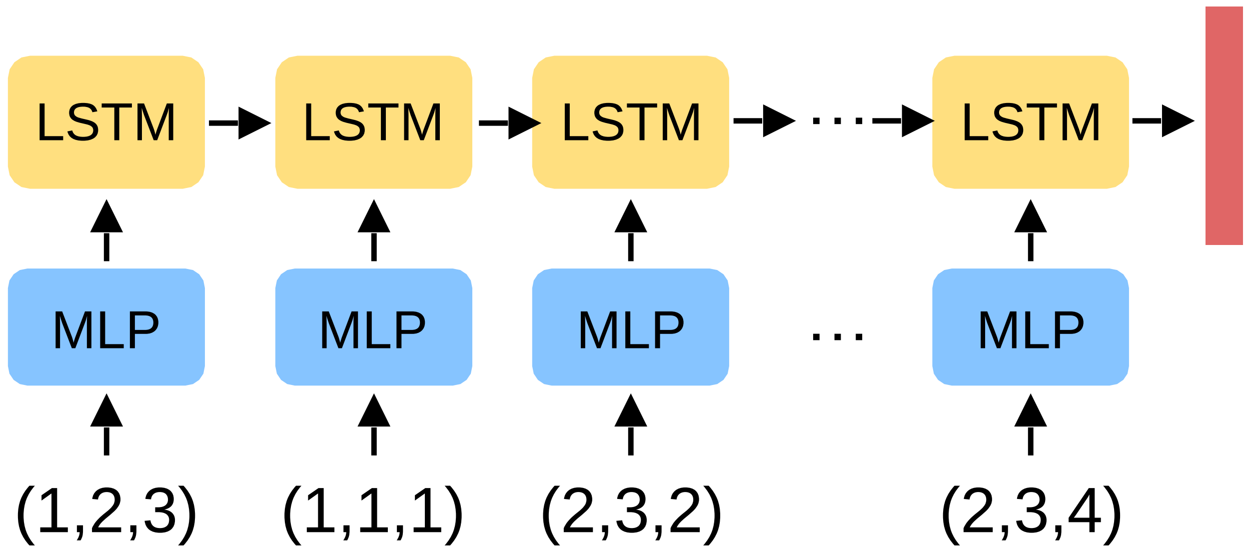

LSTM Network
(ModelNet shape classification)

	Accuracy
LSTM	75%
PointNet (vanilla)	**87%**

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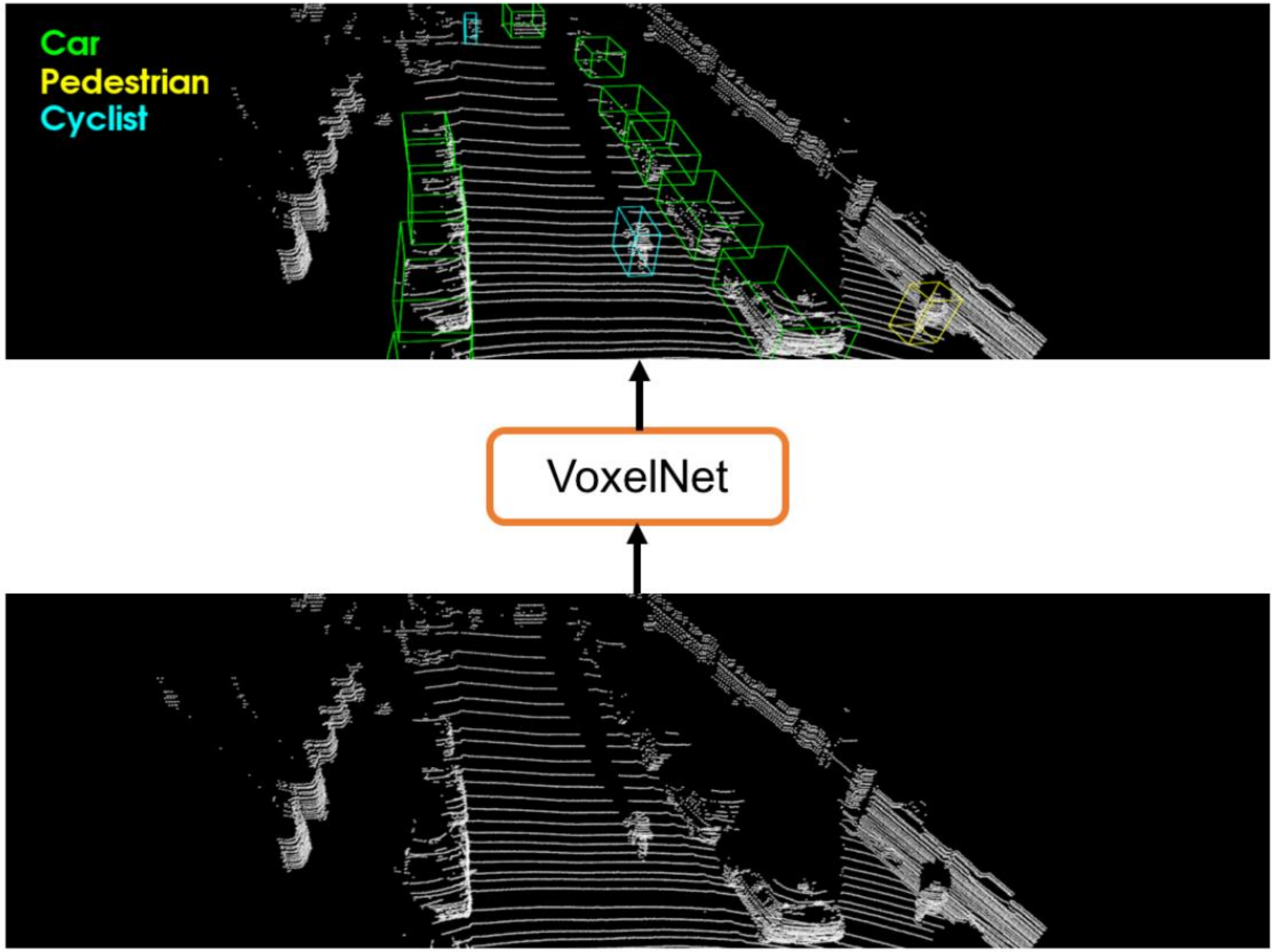
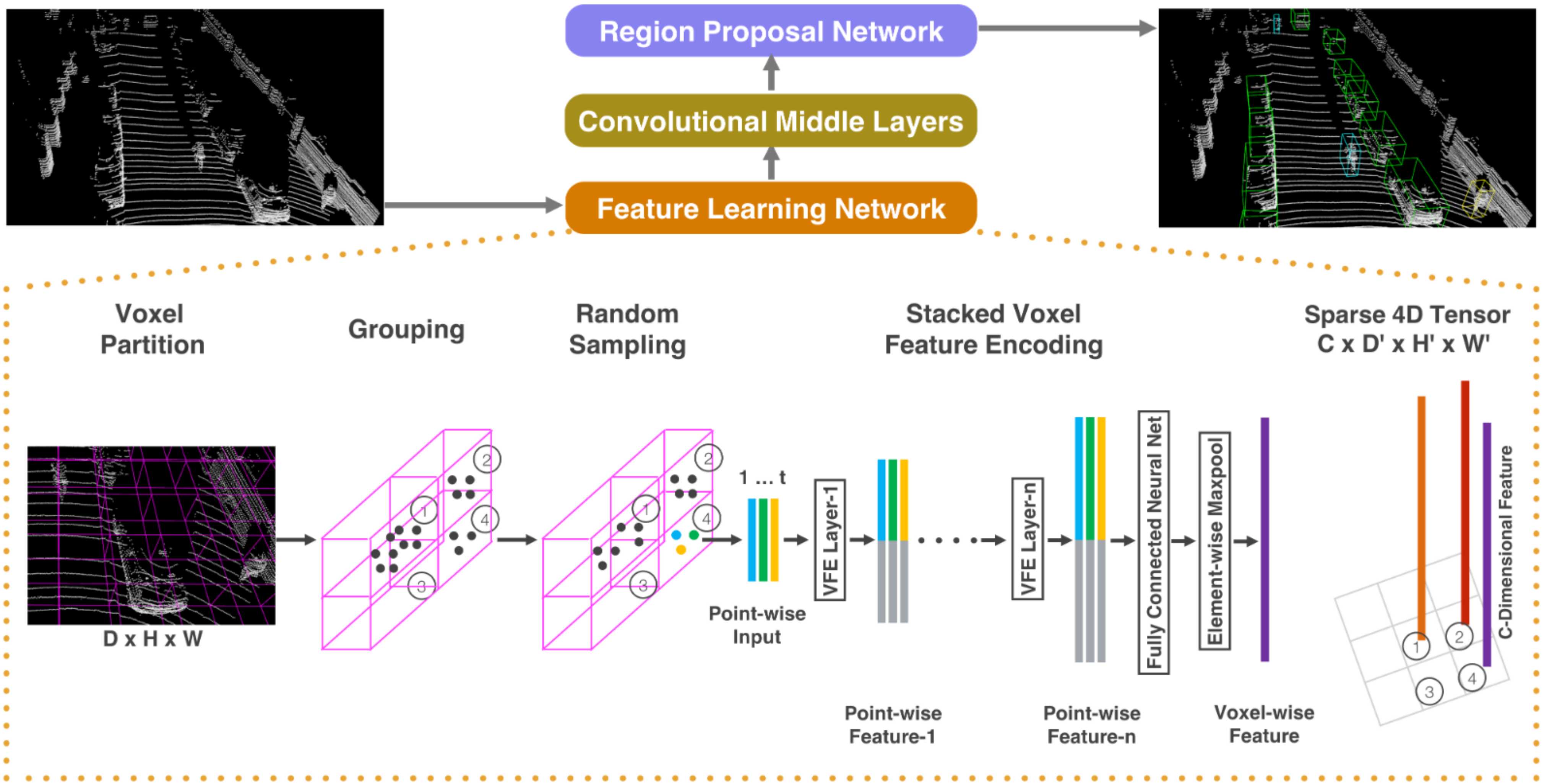
VoxelNet

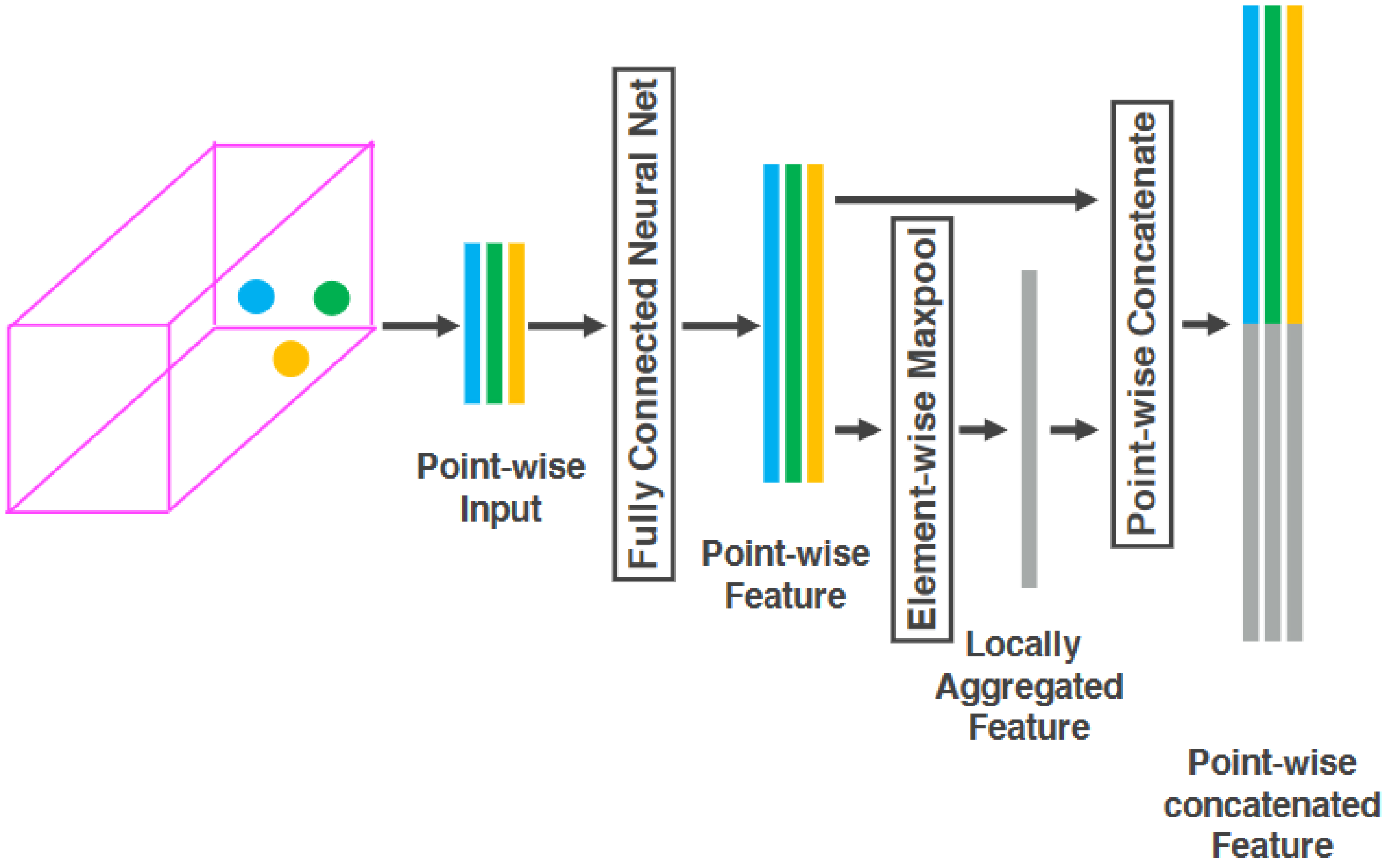


VoxelNet: End-to-End Learning for Point Cloud Based 3D Object Detection
Yin Zhou and Oncel Tuzel. CVPR 2018

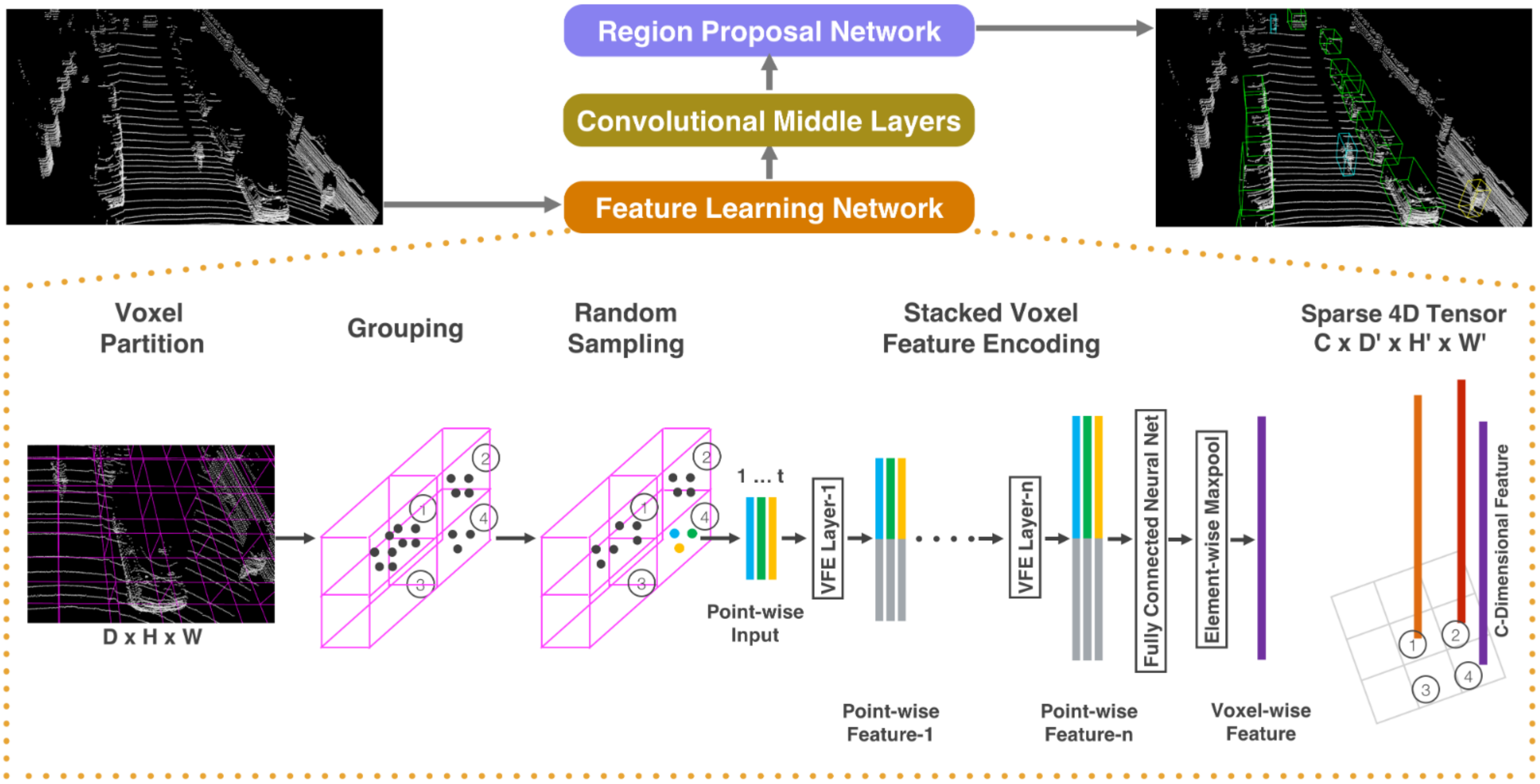
VoxelNet Overview



VoxelNet Voxel encoding looks a lot like PointNet



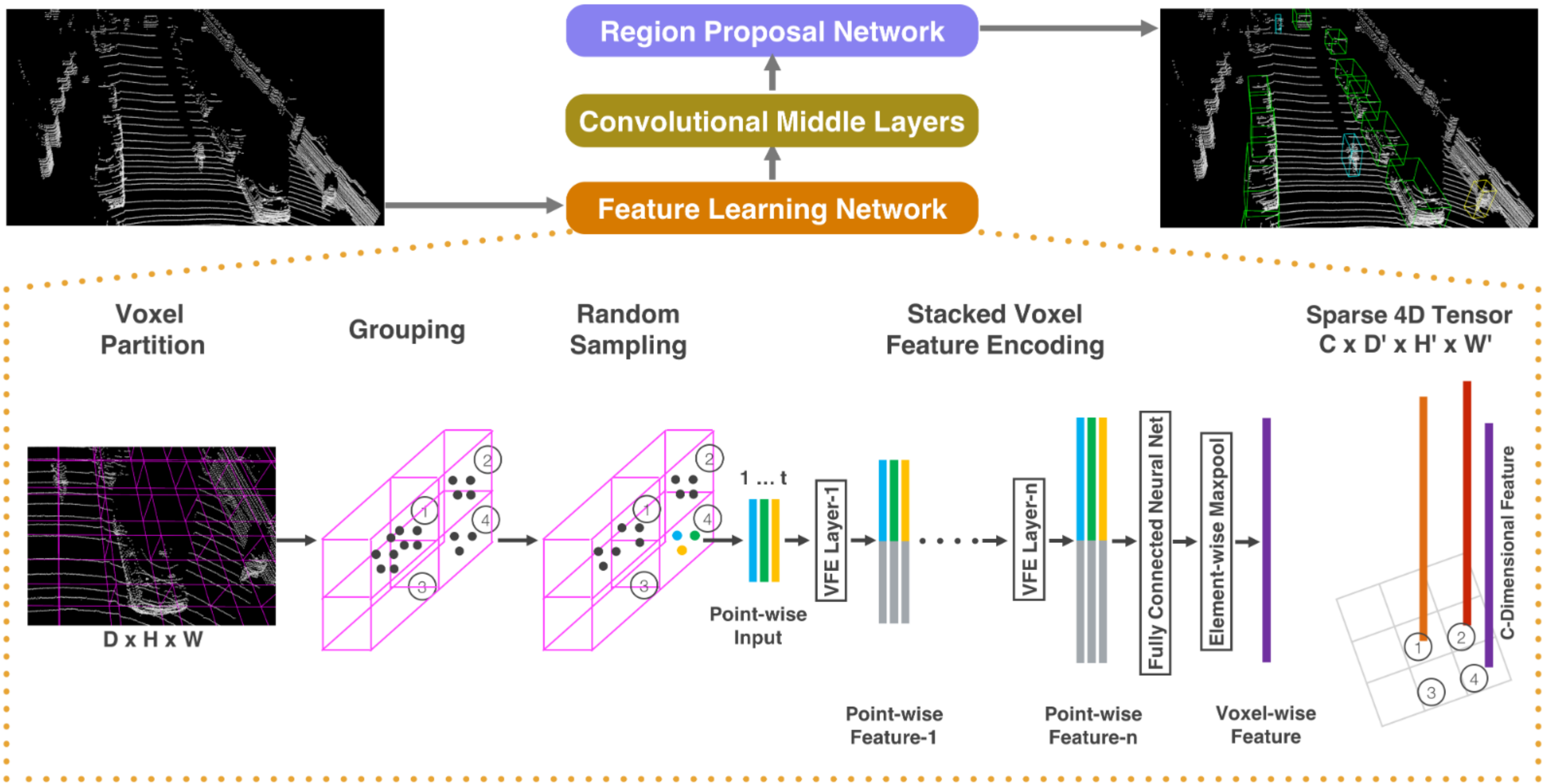
VoxelNet Overview



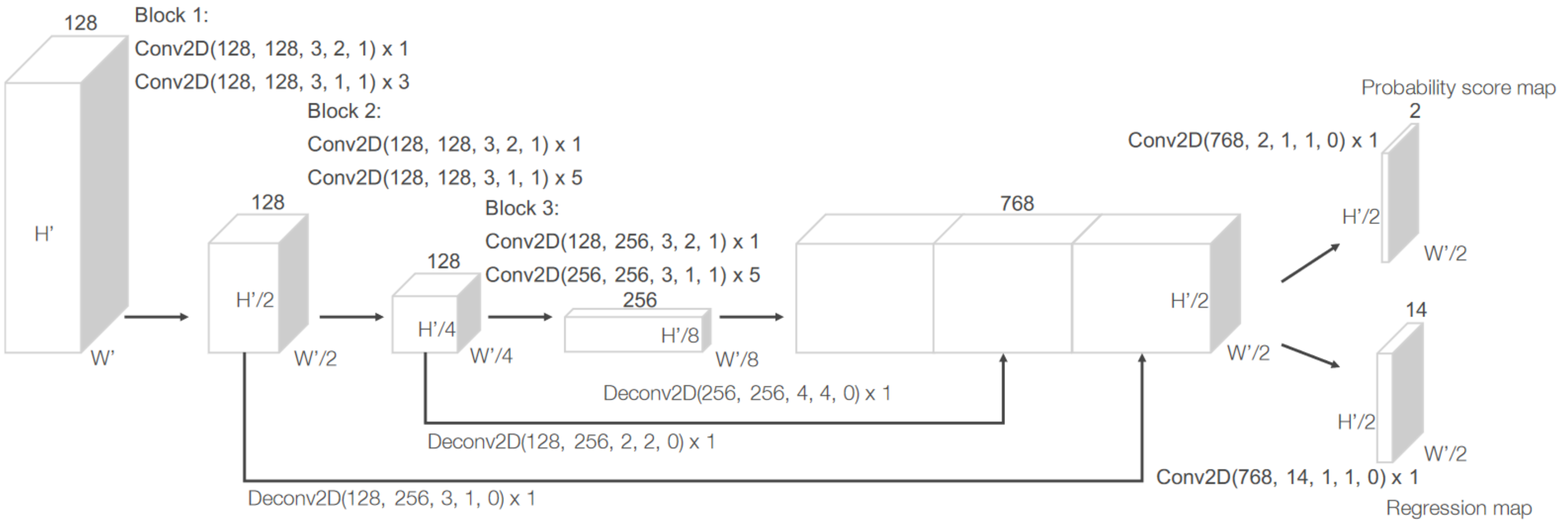
VoxelNet “Convolutional Middle Layers”

- For car detection, divide the world into 10 x 400 x 352 voxels, corresponding to voxels that are 40 cm tall and 20 cm in width/length.
- Uses **3D** convolutions instead of 2D as we’ve seen before.
- The Z / height dimension gets downsampled away after many layers

VoxelNet Overview

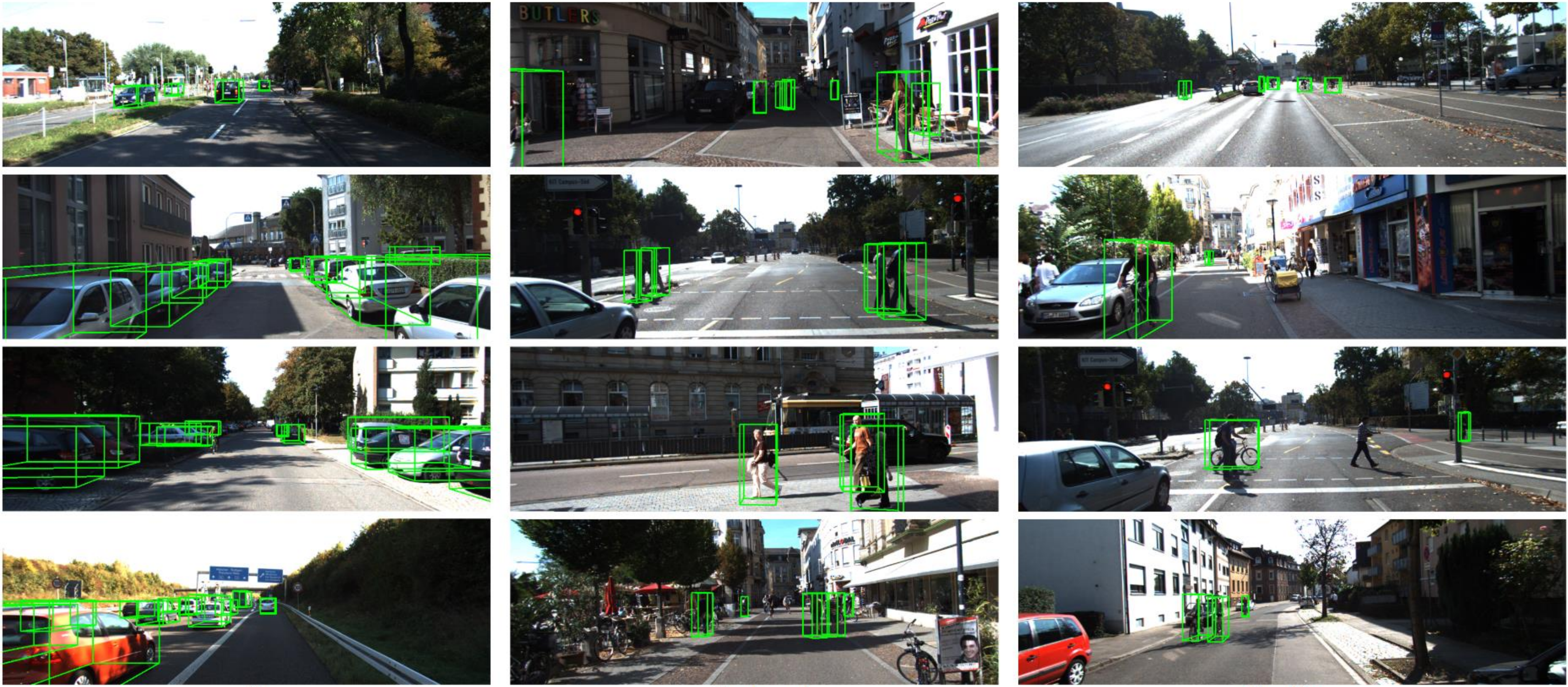


VoxelNet Region Proposal Network



$$(x_c^g, y_c^g, z_c^g, l^g, w^g, h^g, \theta^g)$$

VoxelNet qualitative results



Car Pedestrian Cyclist

VoxelNet quantitative results

Method	Modality	Car			Pedestrian			Cyclist		
		Easy	Moderate	Hard	Easy	Moderate	Hard	Easy	Moderate	Hard
Mono3D [3]	Mono	2.53	2.31	2.31	N/A	N/A	N/A	N/A	N/A	N/A
3DOP [4]	Stereo	6.55	5.07	4.10	N/A	N/A	N/A	N/A	N/A	N/A
VeloFCN [22]	LiDAR	15.20	13.66	15.98	N/A	N/A	N/A	N/A	N/A	N/A
MV (BV+FV) [5]	LiDAR	71.19	56.60	55.30	N/A	N/A	N/A	N/A	N/A	N/A
MV (BV+FV+RGB) [5]	LiDAR+Mono	71.29	62.68	56.56	N/A	N/A	N/A	N/A	N/A	N/A
HC-baseline	LiDAR	71.73	59.75	55.69	43.95	40.18	37.48	55.35	36.07	34.15
VoxelNet	LiDAR	**81.97**	**65.46**	**62.85**	**57.86**	**53.42**	**48.87**	**67.17**	**47.65**	**45.11**

Evaluation on KITTI according to 3D IoU

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- What is lidar?
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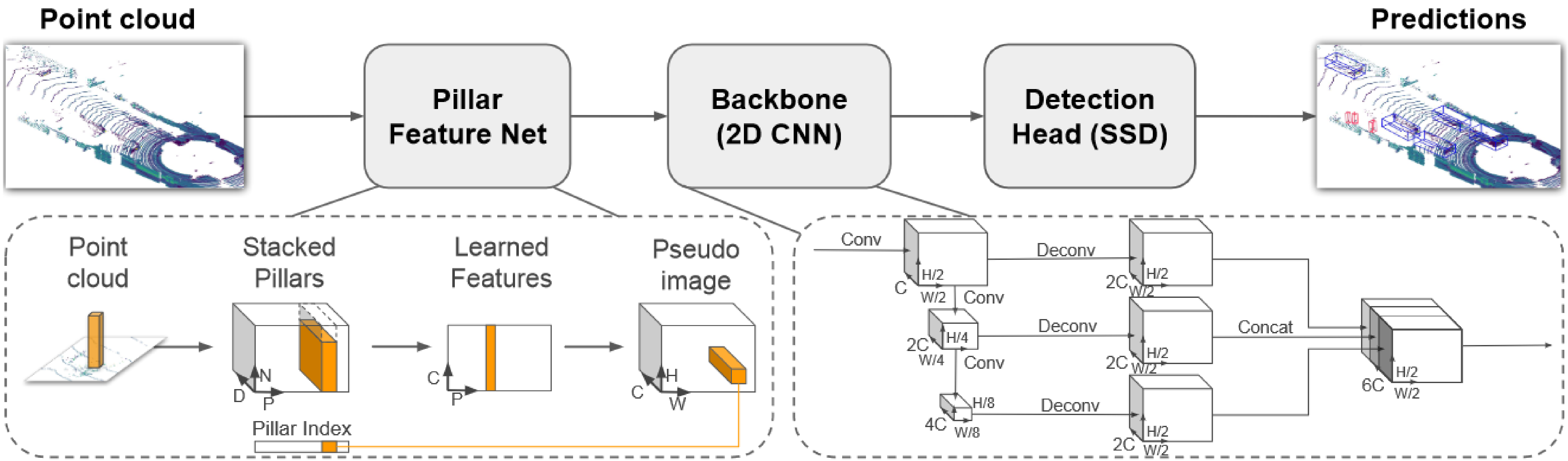
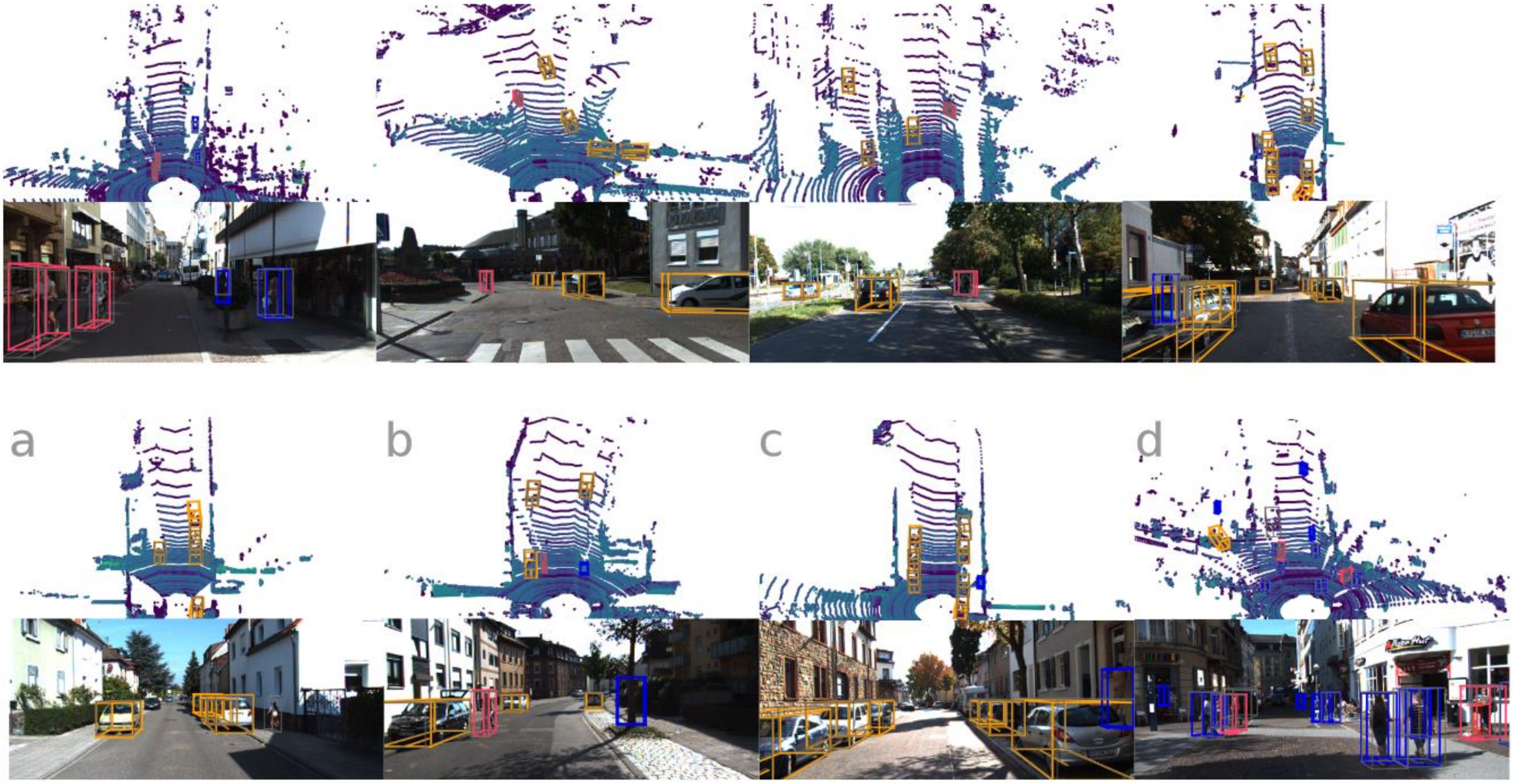
- PseudoLidar – Bird's eye view depth map processing

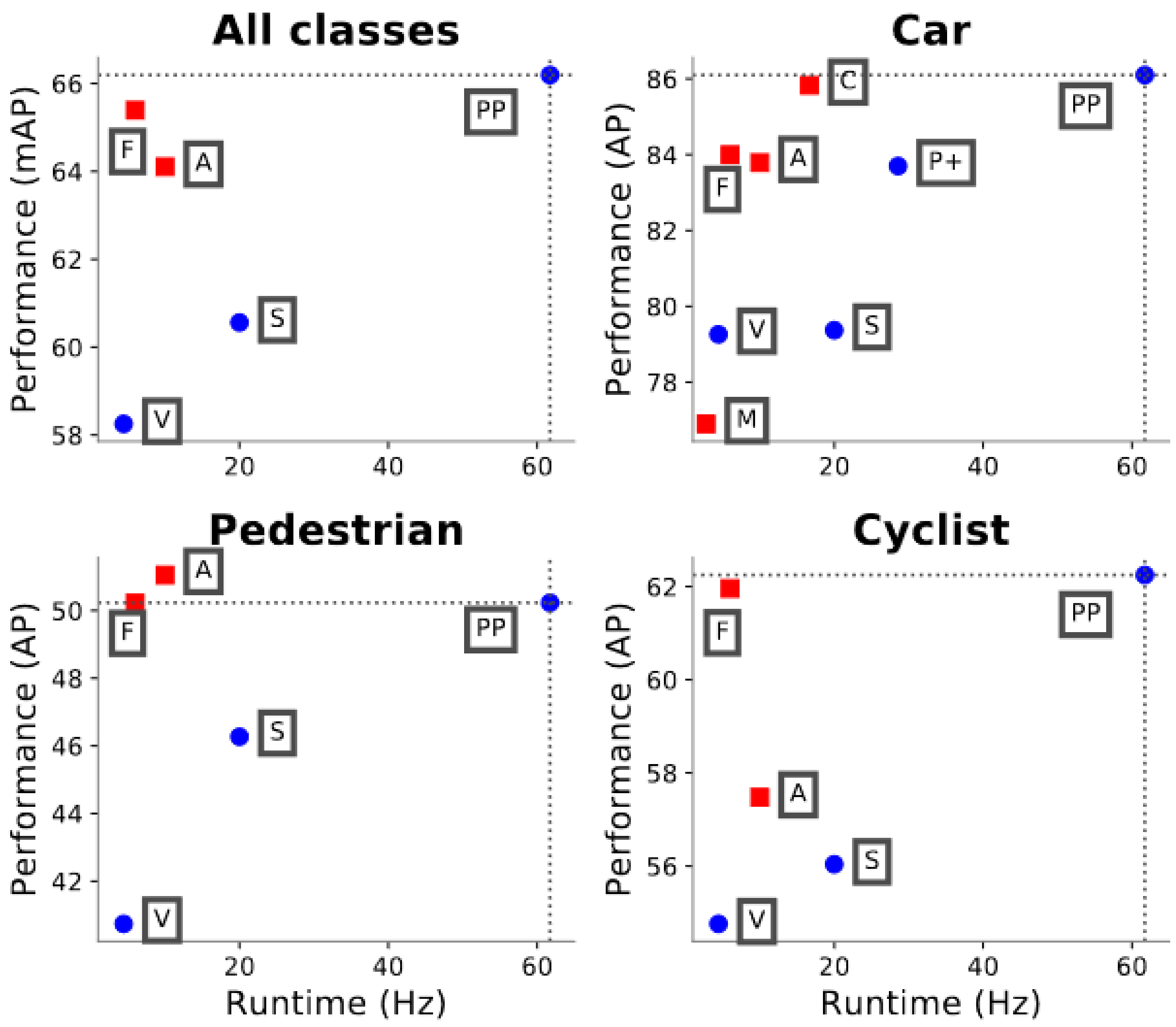
PointPillars



PointPillars: Fast Encoders for Object Detection from Point Clouds
Alex H. Lang, Sourabh Vora, Holger Caesar, Lubing Zhou, Jiong Yang, Oscar Beijbom. CVPR 2019


a
b
c
d

Runtime / accuracy tradeoff



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What You See Is What You Get
Exploiting Visibility for 3D Object Detection

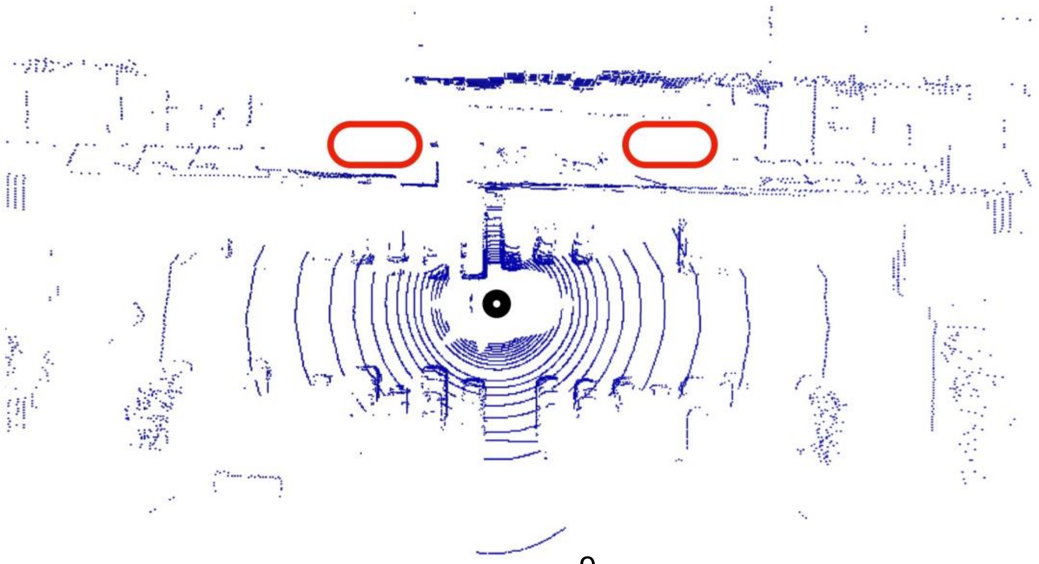
Peiyun Hu, Jason Ziglar, David Held, Deva Ramanan

Carnegie Mellon University

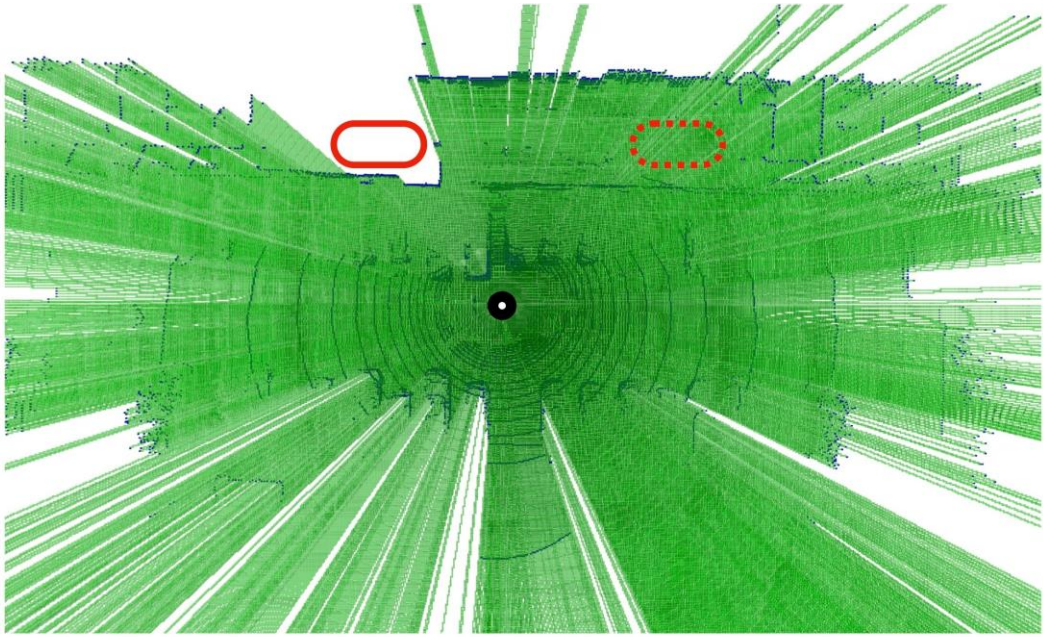
Argo AI

CVPR 2020

What is a good representation for LiDAR data?

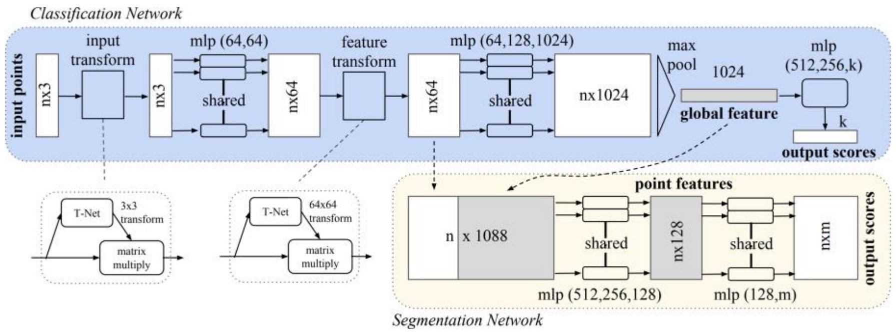


9
0



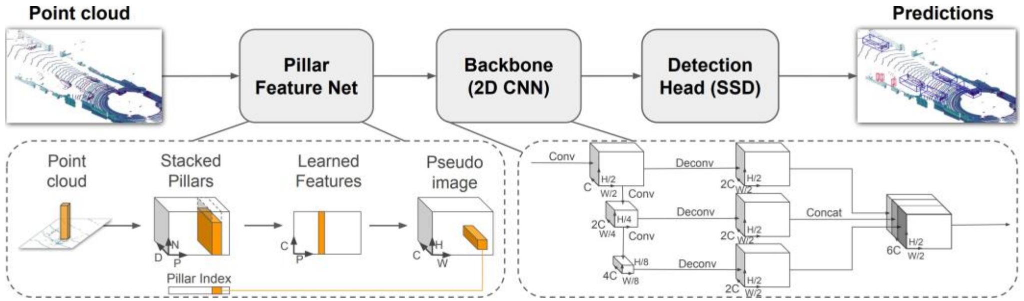
- LiDAR data provides more than just point measurements
- Rays emanating from the sensor to each 3D point must pass through free space
- Representing LiDAR data as (x, y, z)s fundamentally destroys such freespace information

What representations do we have?



Deep Point Representation

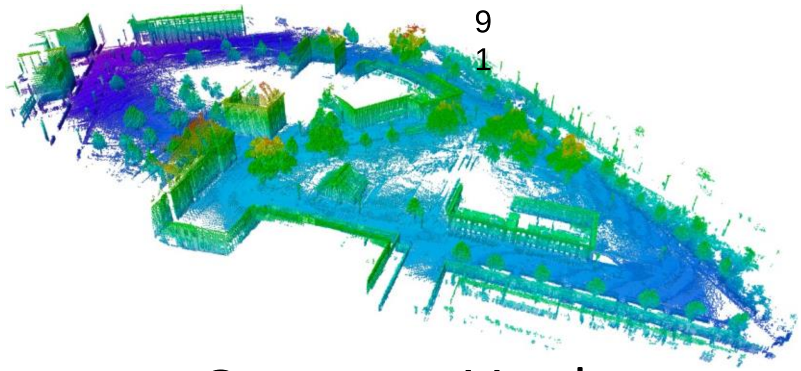
PointNet, Qi et al., CVPR'17



Deep Voxel Representation

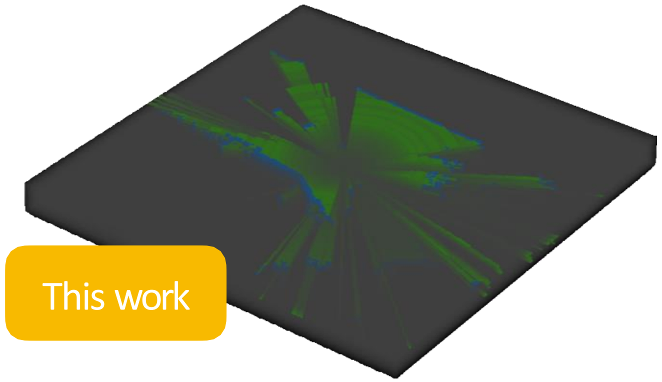
PointPillars, Lang et al., CVPR'19

9
1



Occupancy Voxels

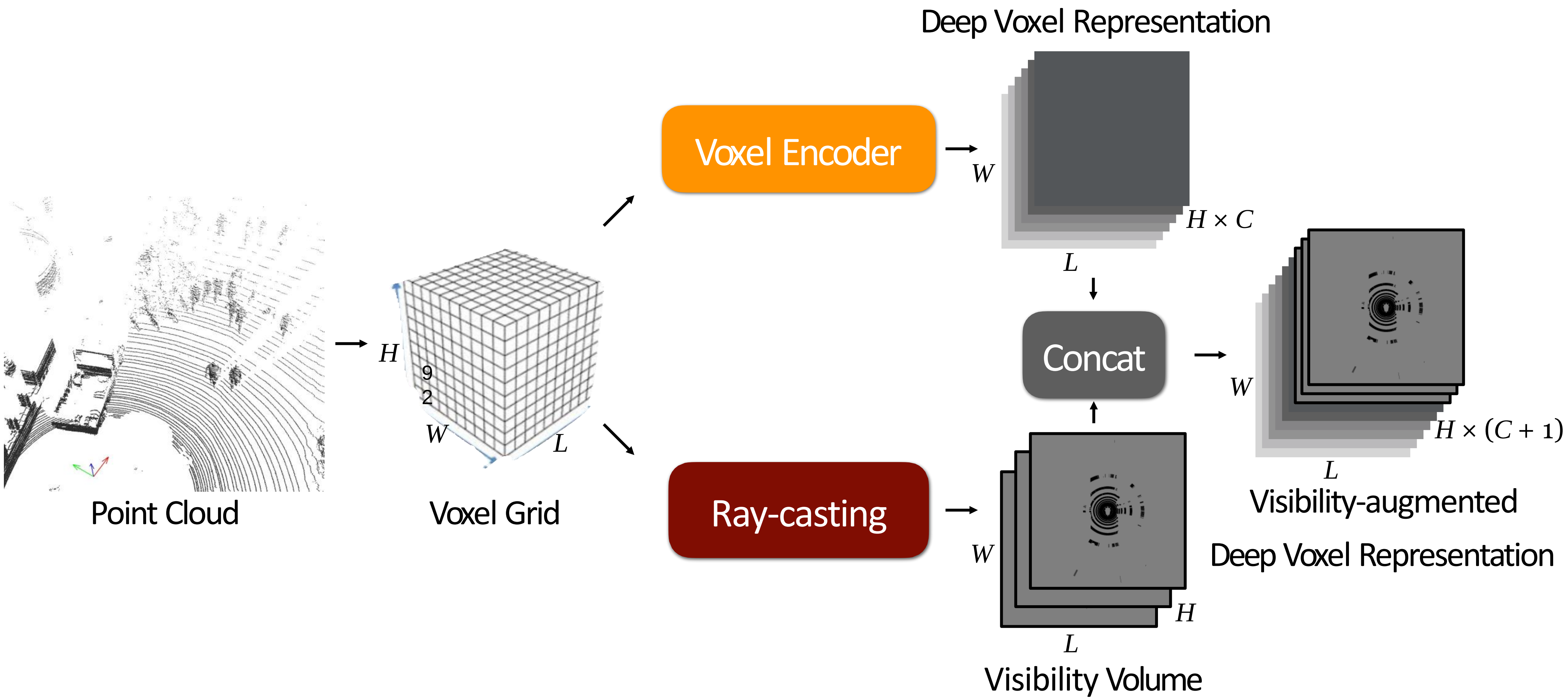
OctoMap, Hornung et al., Autonomous Robots'13



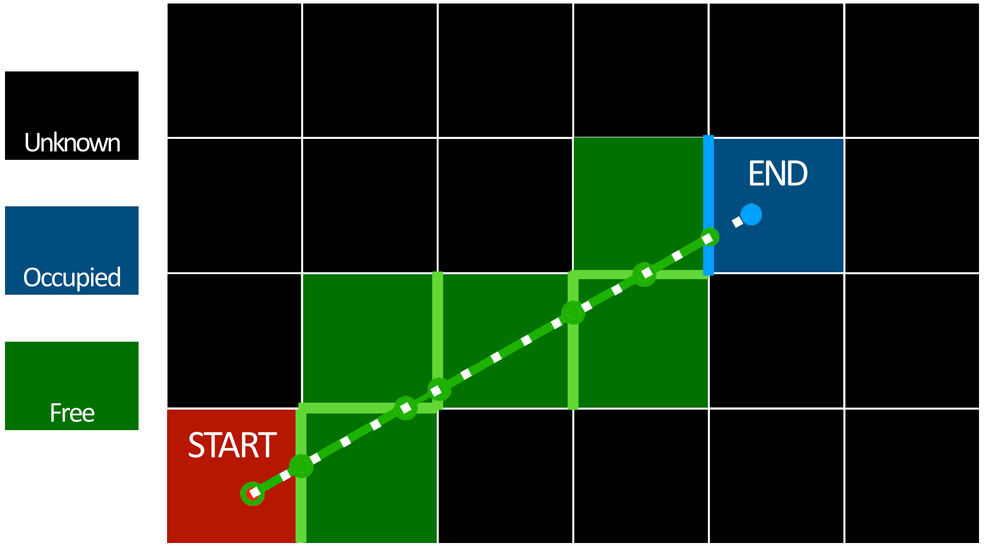
Visibility Augmented Deep Voxels

WYSIWYG, Hu et al., CVPR'20

A Simple Approach to Augment Visibility



Efficient Ray-casting via Voxel Traversal

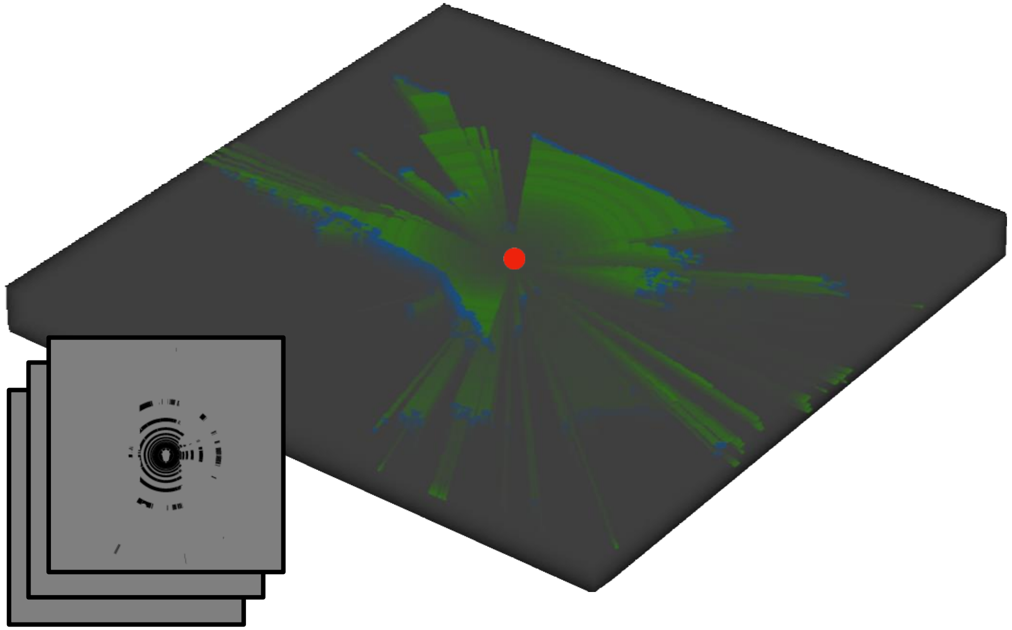


Though animated in 2D, the idea generalizes in 3D.

A Fast Voxel Traversal Algorithm for Ray Tracing

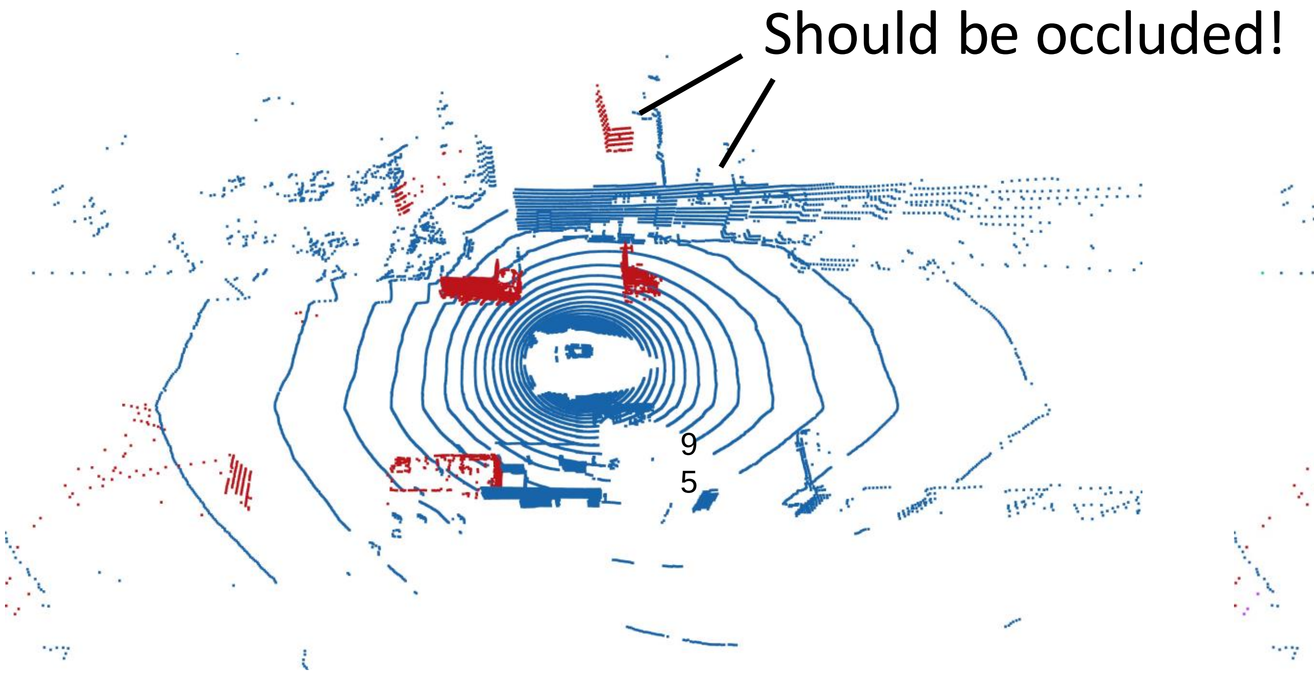
John Amanatides, Andrew Woo

Eurographics 1987



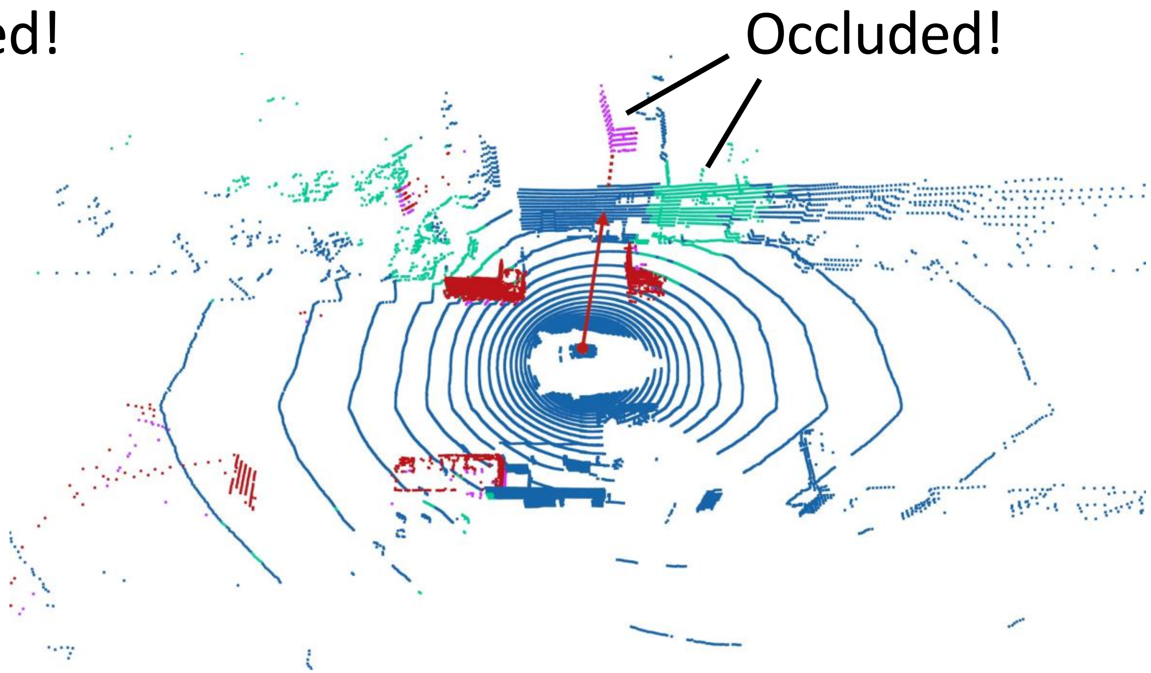
3D Visibility Volume

Visibility-aware LiDAR Synthesis



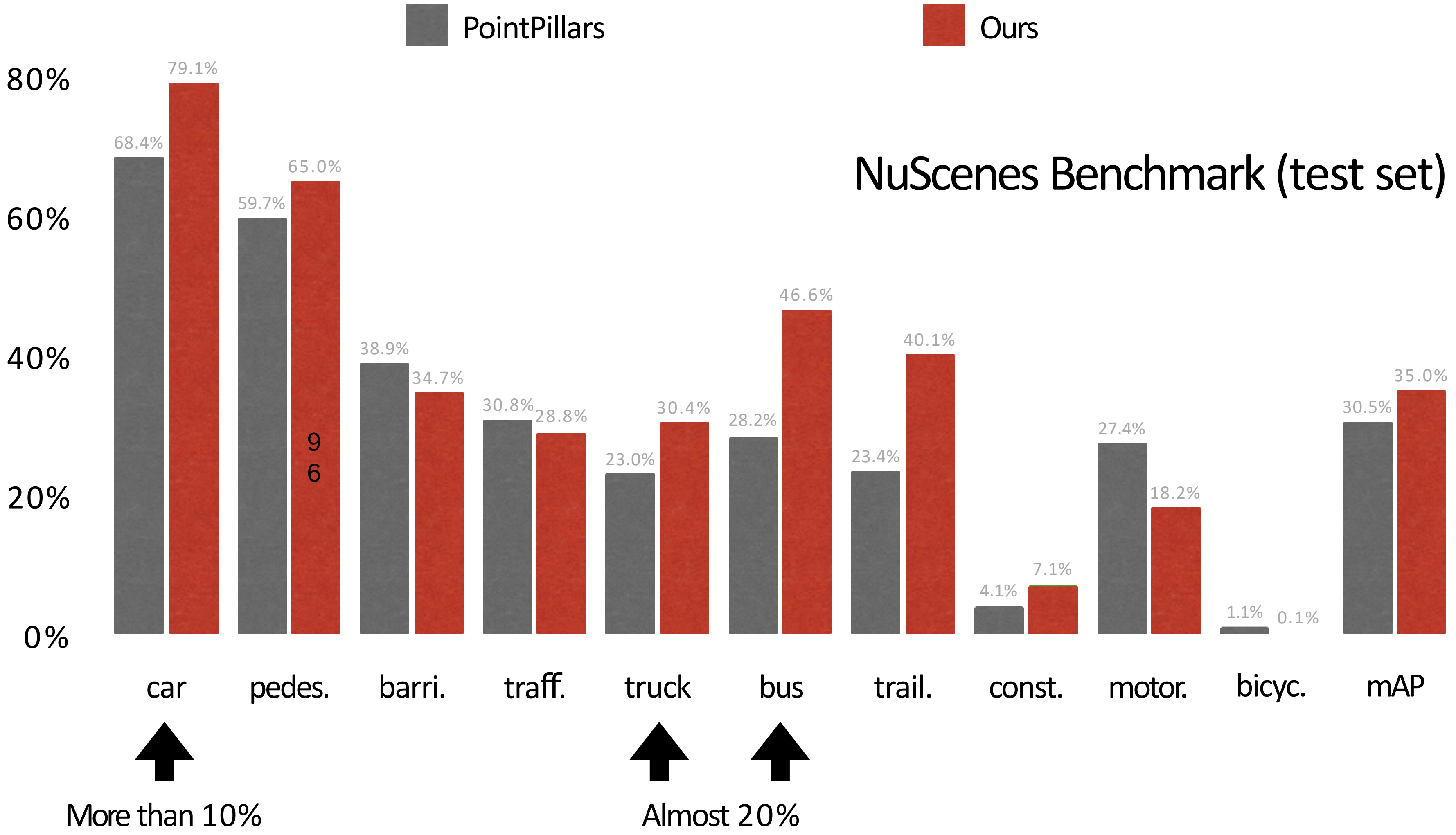
Naive Object Augmentation

PointPillars, Lang et al., CVPR'19
SECOND, Yan et al., Sensors'18



Visibility-aware Object Augmentation

Improve PointPillars by 4.5% in overall mAP



car | pedestrian | barrier | traffic cone | truck | bus | trailer | construction vehicle | motorcycle | bicycle

https://cs.cmu.edu/~peiyunh/wysiwyg

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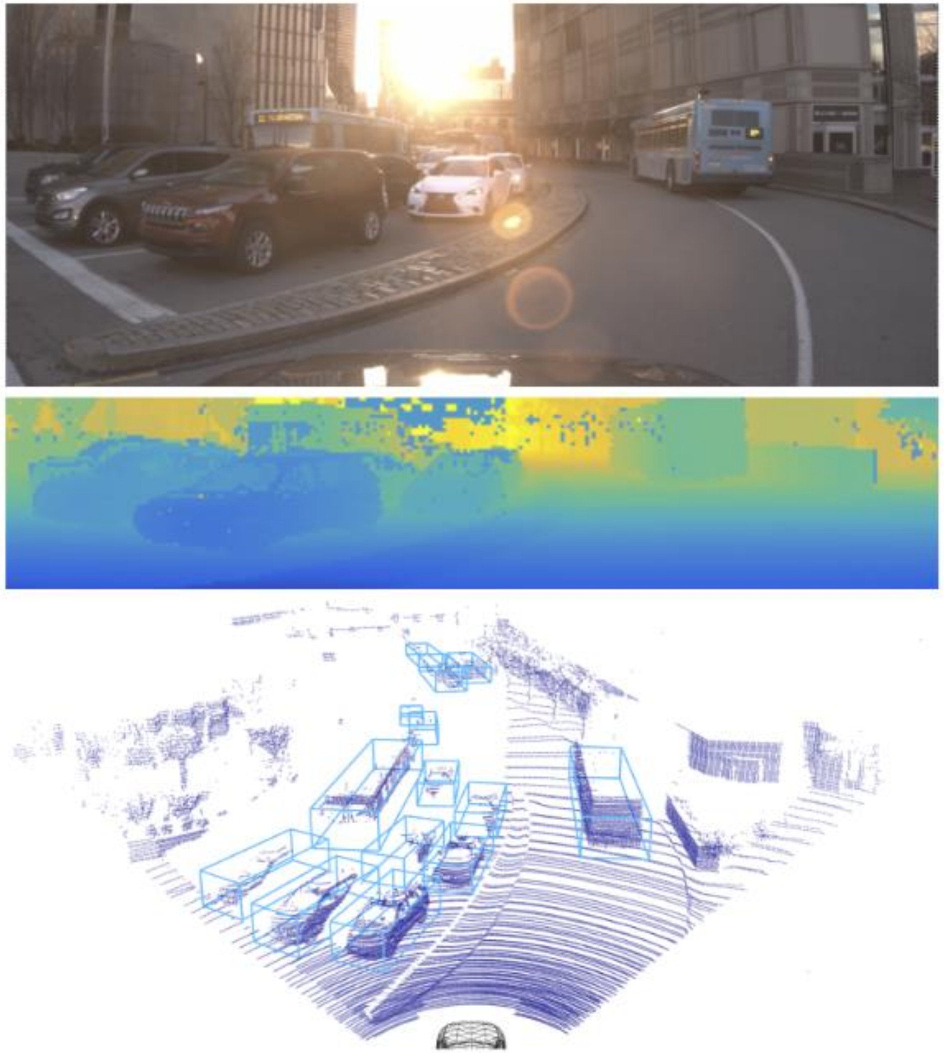

Table 4: BEV Object Detection Performance on KITTI

Method	Input	Vehicle $AP_{0.7}$ Easy	Moderate	Hard
LaserNet (Ours)	LiDAR	78.25	73.77	66.47
PIXOR [28]	LiDAR	81.70	77.05	72.95
PIXOR++ [27]	LiDAR	**89.38**	83.70	**77.97**
VoxelNet [30]	LiDAR	89.35	79.26	77.39
MV3D [5]	LiDAR+RGB	86.02	76.90	68.49
AVOD [15]	LiDAR+RGB	88.53	83.79	77.90
F-PointNet [22]	LiDAR+RGB	88.70	84.00	75.33
ContFuse [17]	LiDAR+RGB	88.81	**85.83**	77.33

Table 3: Runtime Performance on KITTI

Method	Forward Pass (ms)	Total (ms)
LaserNet (Ours)	**12**	**30**
PIXOR [28]	35	62
PIXOR++ [27]	35	62
VoxelNet [30]	190	225
MV3D [30]	-	360
AVOD [15]	80	100
F-PointNet [22]	-	170
ContFuse [17]	60	-

LaserNet: An Efficient Probabilistic 3D Object Detector for Autonomous Driving
Gregory P. Meyer*, Ankit Laddha*, Eric Kee, Carlos Vallespi-Gonzalez, Carl K. Wellington
Uber Advanced Technologies Group. CVPR 2019

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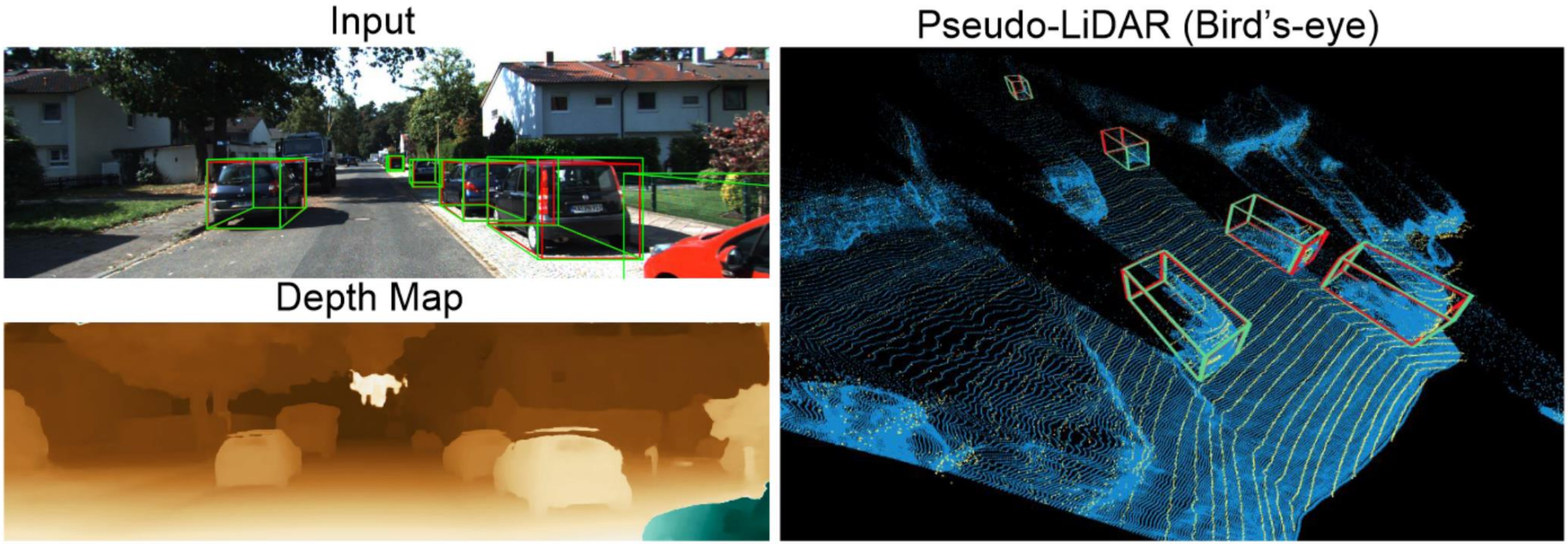


Pseudo-LiDAR from Visual Depth Estimation: Bridging the Gap in 3D Object Detection for Autonomous Driving
Yan Wang, Wei-Lun Chao, Divyansh Garg, Bharath Hariharan, Mark Campbell, and Kilian Q. Weinberger.
CVPR 2019

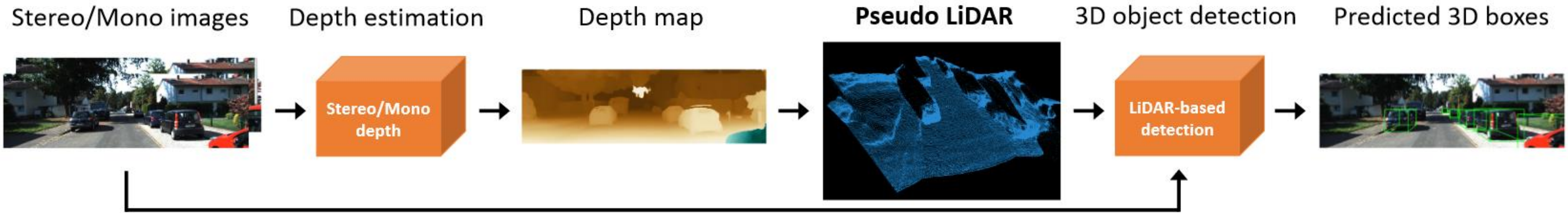
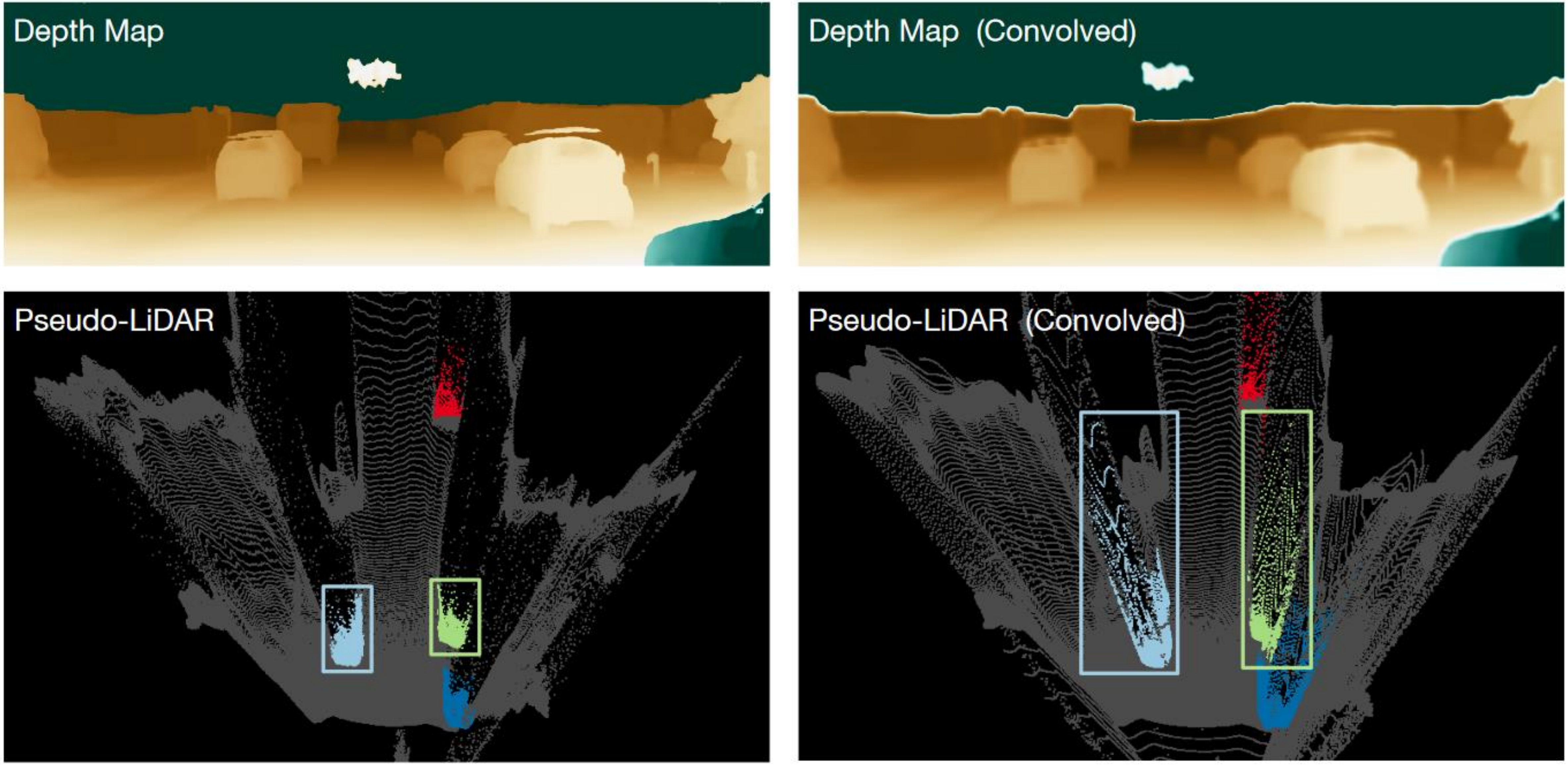


Table 1: 3D object detection results on the KITTI validation set. We report AP_{BEV} / AP_{3D} (in %) of the **car** category, corresponding to average precision of the bird's-eye view and 3D object box detection. Mono stands for monocular. Our methods with *pseudo-LiDAR* estimated by PSMNET⋆ [3] (stereo) or DORN [10] (monocular) are in blue. Methods with LiDAR are in gray. Best viewed in color.

Detection algorithm	Input signal	IoU = 0.5			IoU = 0.7		
		Easy	Moderate	Hard	Easy	Moderate	Hard
MONO3D [4]	Mono	30.5 / 25.2	22.4 / 18.2	19.2 / 15.5	5.2 / 2.5	5.2 / 2.3	4.1 / 2.3
MLF-MONO [33]	Mono	55.0 / 47.9	36.7 / 29.5	31.3 / 26.4	22.0 / 10.5	13.6 / 5.7	11.6 / 5.4
AVOD	Mono	61.2 / 57.0	45.4 / 42.8	38.3 / 36.3	33.7 / 19.5	24.6 / 17.2	20.1 / 16.2
F-POINTNET	Mono	70.8 / 66.3	49.4 / 42.3	42.7 / 38.5	40.6 / 28.2	26.3 / 18.5	22.9 / 16.4
3DOP [5]	Stereo	55.0 / 46.0	41.3 / 34.6	34.6 / 30.1	12.6 / 6.6	9.5 / 5.1	7.6 / 4.1
MLF-STEREO [33]	Stereo	-	53.7 / 47.4	-	-	19.5 / 9.8	-
AVOD	Stereo	89.0 / 88.5	77.5 / 76.4	68.7 / 61.2	74.9 / 61.9	56.8 / 45.3	49.0 / 39.0
F-POINTNET	Stereo	89.8 / 89.5	77.6 / 75.5	68.2 / 66.3	72.8 / 59.4	51.8 / 39.8	44.0 / 33.5
AVOD [17]	LiDAR + Mono	90.5 / 90.5	89.4 / 89.2	88.5 / 88.2	89.4 / 82.8	86.5 / 73.5	79.3 / 67.1
F-POINTNET [25]	LiDAR + Mono	96.2 / 96.1	89.7 / 89.3	86.8 / 86.2	88.1 / 82.6	82.2 / 68.8	74.0 / 62.0


Depth Map
Depth Map (Convolved)
Pseudo-LiDAR
Pseudo-LiDAR (Convolved)

Summary

- Popular CNN backbones aren’t a direct fit for 3D point processing tasks.
- It’s not clear how to use deep learning on 3D data
  - Use a truly permutation invariant representation (PointNet)
  - Use a voxel representation (VoxelNet)
  - Use a bird’s a view representation (PointPillars)
  - Create a range image (LaserNet)
- These alternate representations might be applicable more broadly, e.g. reasoning about depth estimates might be easier in bird’s eye view (PseudoLidar)