3D Object Detection: The History, Present and Future

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2/2/2021

Agenda

- Backgrounds; The definition and applications of 3D object detection.
- The history and recent developments of 3D detection algorithms.
- Future directions of 3D detection research.
- Q&A, discussion.

Prior knowledge:
Although not required, it will be helpful to have some understanding of deep learning methods in 2D object detection. You can learn more about it here:
http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture11.pdf

The big picture: A.I. applications from the virtual world to the physical world

1998

Google was founded.
(Rise of the Internet)

2004

Facebook was founded.
(Rise of the Internet)

2007

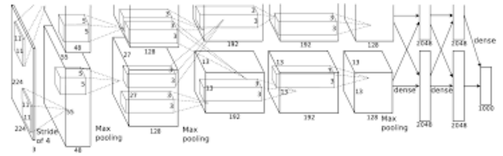
The release of the first iPhone
(Rise of the smart mobile devices)

2009

The ImageNet was released.

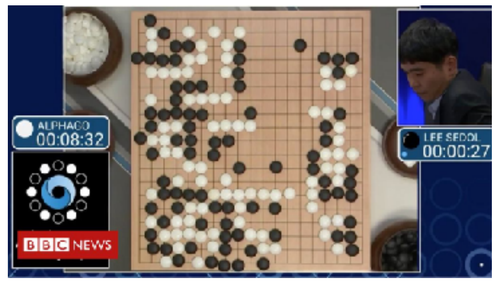
2012

The AlexNet breakthrough
(Rise of the deep learning for computer vision)

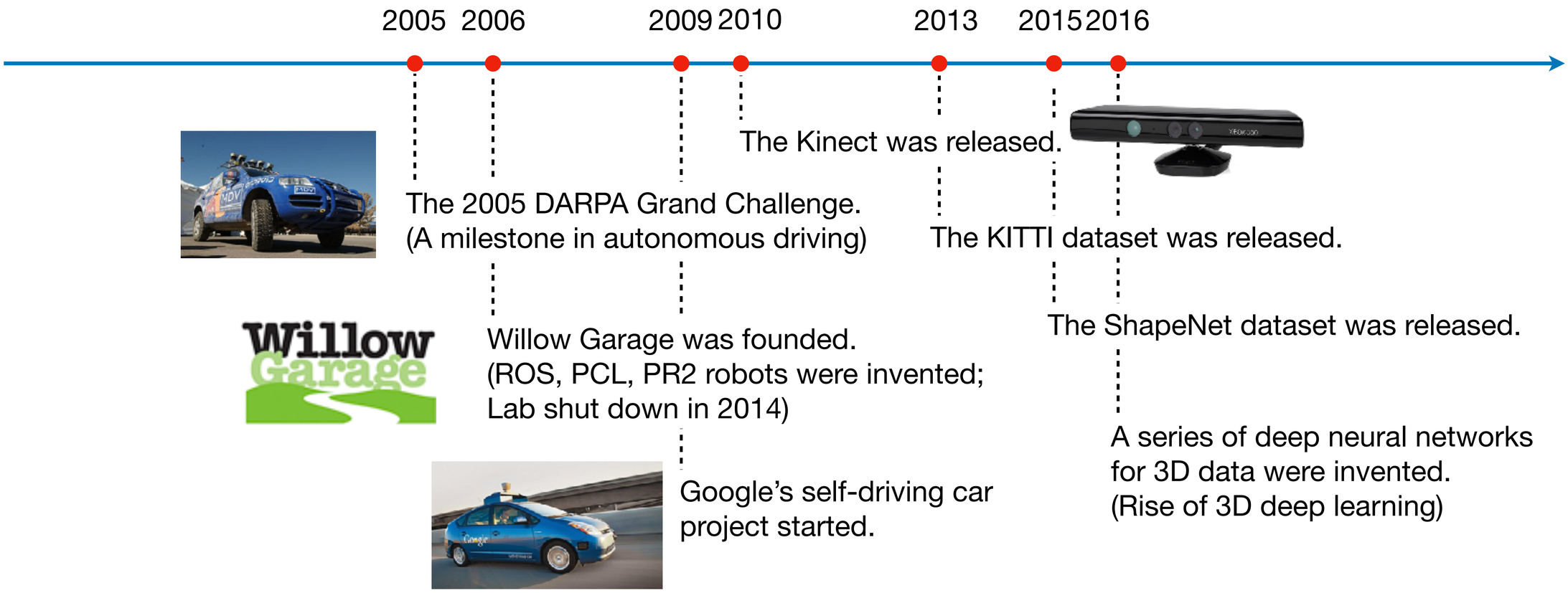


2016

AlphaGo defeated world champion Lee Sedol
(A major milestone of A.I.)



The big picture: A.I. applications from the virtual world to the physical world

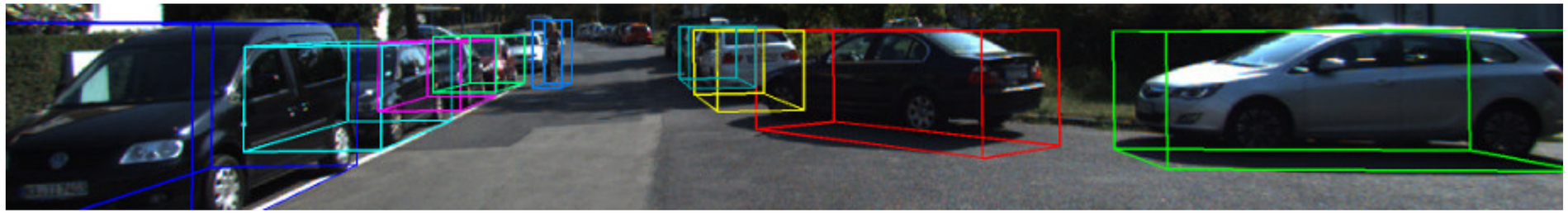


We are yet to reach the time where A.I. is widely applied to the "robots" in the physical world. 3D deep learning and 3D object detection are the core technologies towards that future!

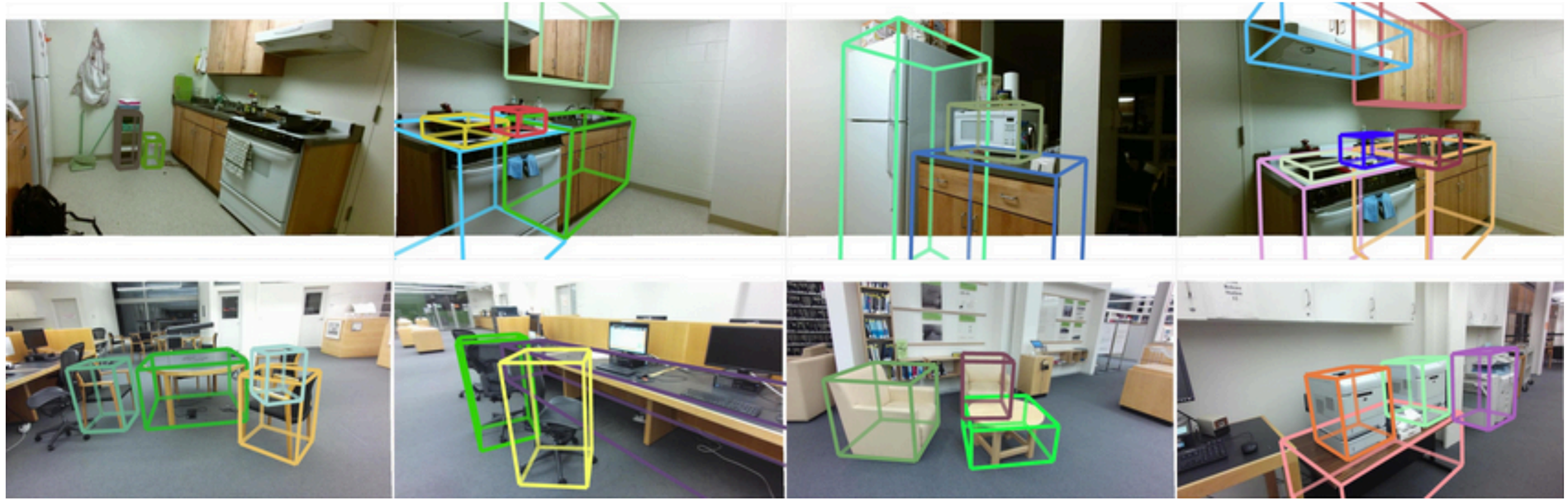
What is 3D object detection?

- **Input**: sensor data of a 3D scene. (RGB/depth/radar images)
- **Output**: localization, shape and semantics of the 3D objects in the scene. (3D amodal, oriented bounding boxes)

KITTI:



SUN RGB-D:



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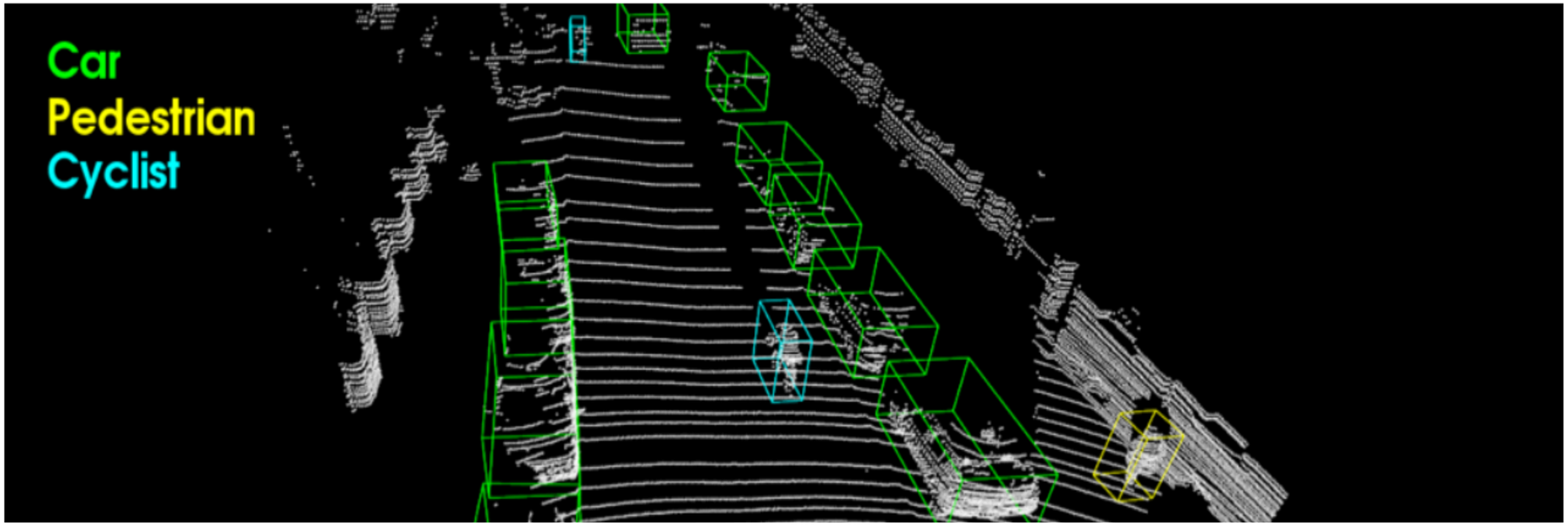


Figure from VoxelNet [Zhou et al. 2018]

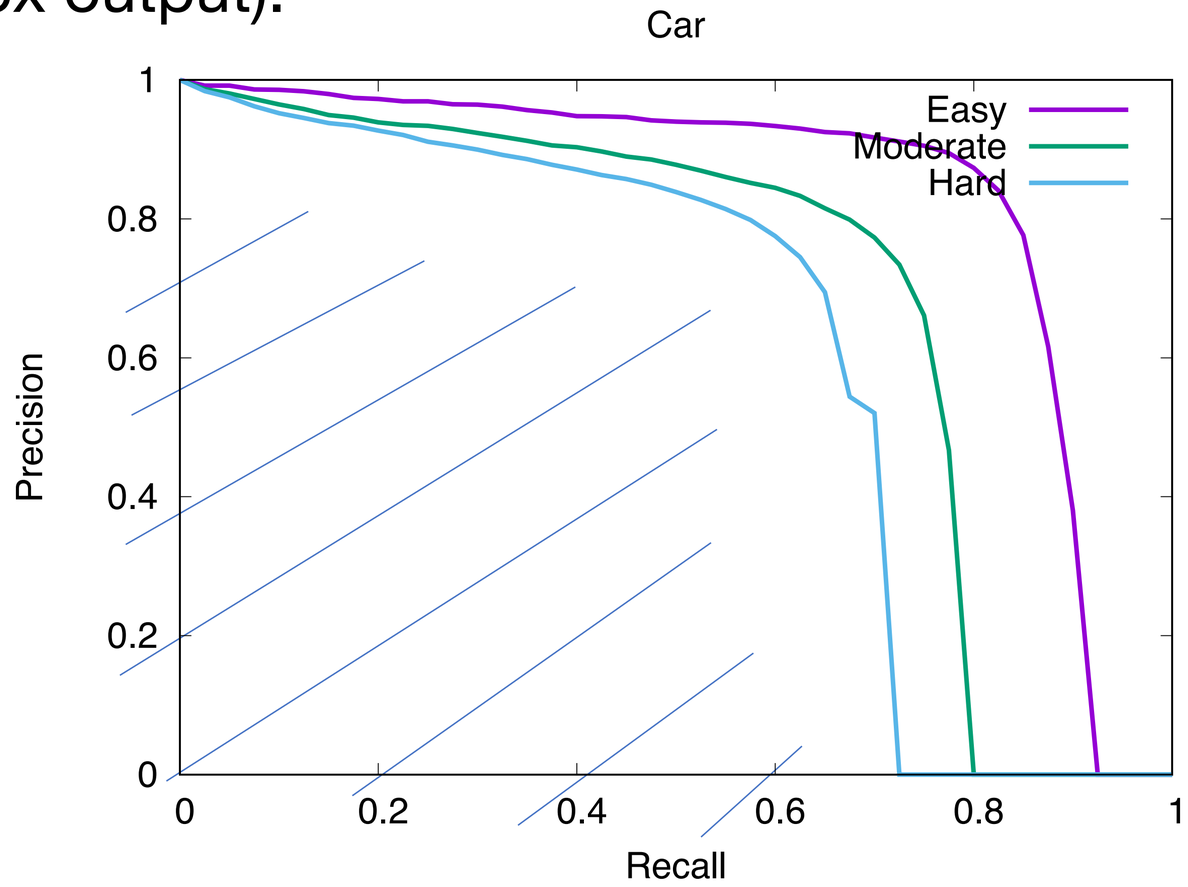
What is 3D object detection?

Evaluation Metric: Average Precision (AP) with a 3D Intersection over Union (IoU) threshold (assuming 3D bounding box output).

For each score threshold, we get an “operation point” on the PR curve — all predictions with scores higher than the threshold are considered “positive” detections while all others with scores lower than the threshold is considered “negative” detections.

By scanning through the score thresholds e.g. from 0 to 1, we get the PR curve.

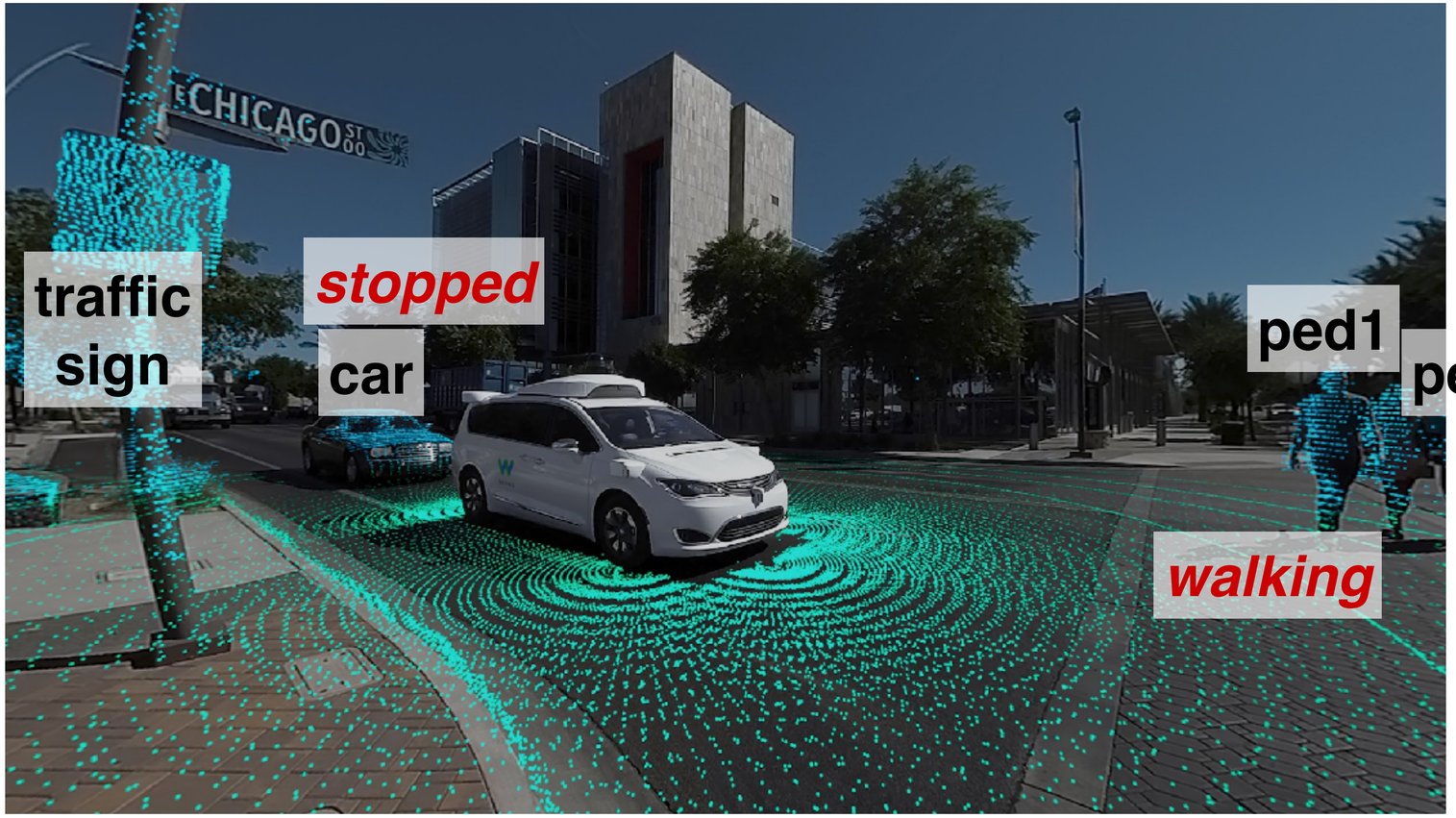
Average precision is the area under the curve.



A detailed explanation of the Average Precision metric:
https://jonathan-hui.medium.com/map-mean-average-precision-for-object-detection-45c121a31173

Applications of 3D object detection

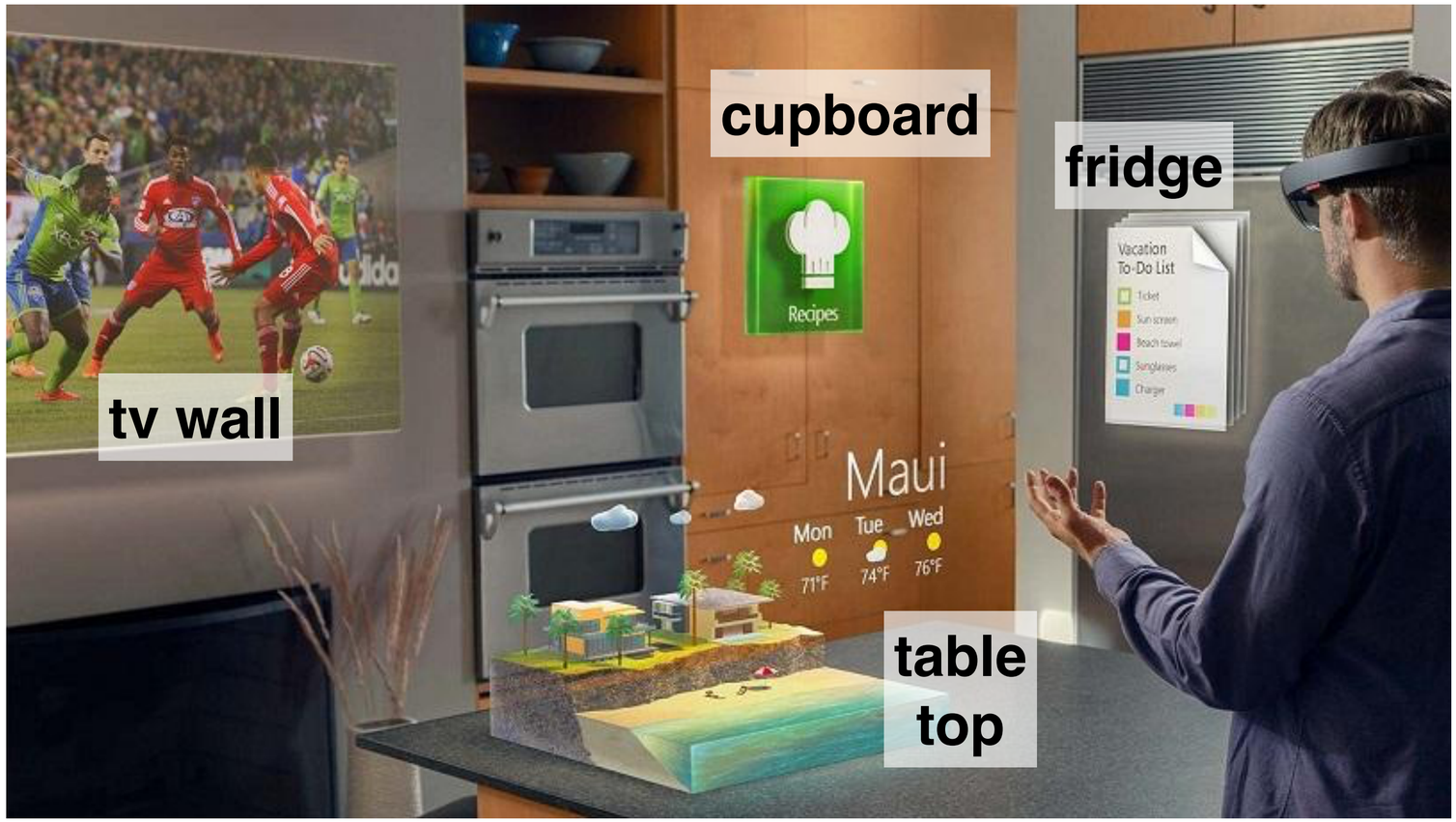
Autonomous Driving



source: Waymo

Applications of 3D object detection

Augmented Reality



source: Microsoft HoloLens

Applications of 3D object detection

Robot Grasping

source: NVIDIA

The history of 3D object detection

Pre deep learning:

Template-based:
Generalized Hough Voting (2010) [1]
Local/global descriptor+matching+ICP (2012) [2]

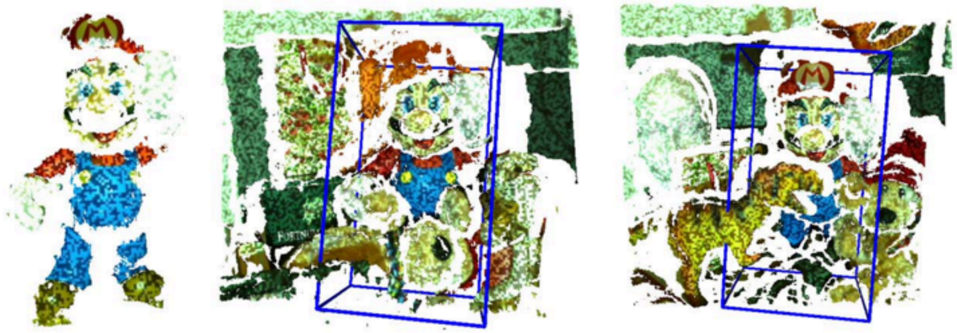


Figure from [1]

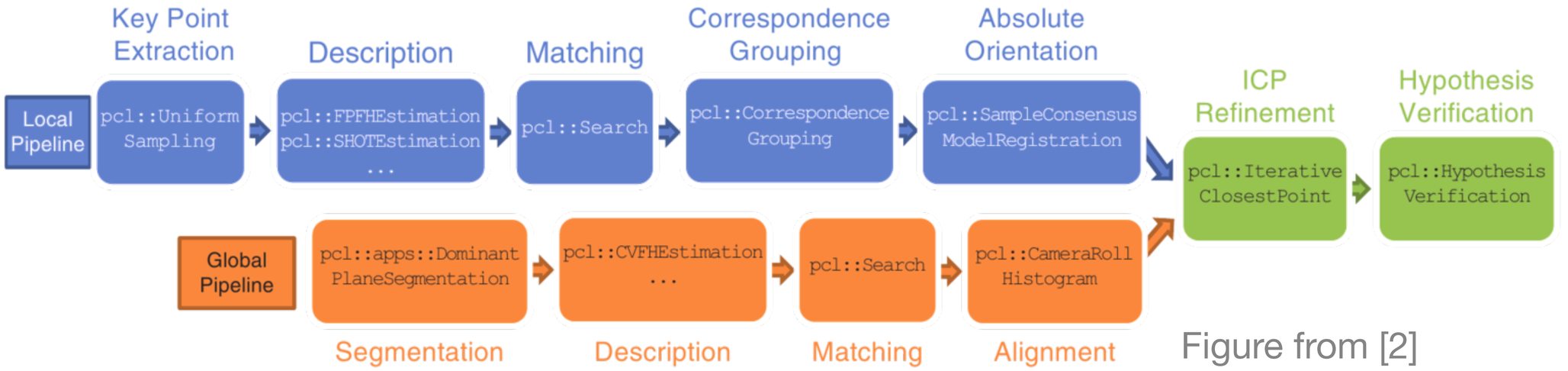


Figure from [2]

The history of 3D object detection

Pre deep learning:

Clustering-based:
Object Discovery in 3D scenes via Shape Analysis (2013) [3]
Data-driven “objectness” score prediction.

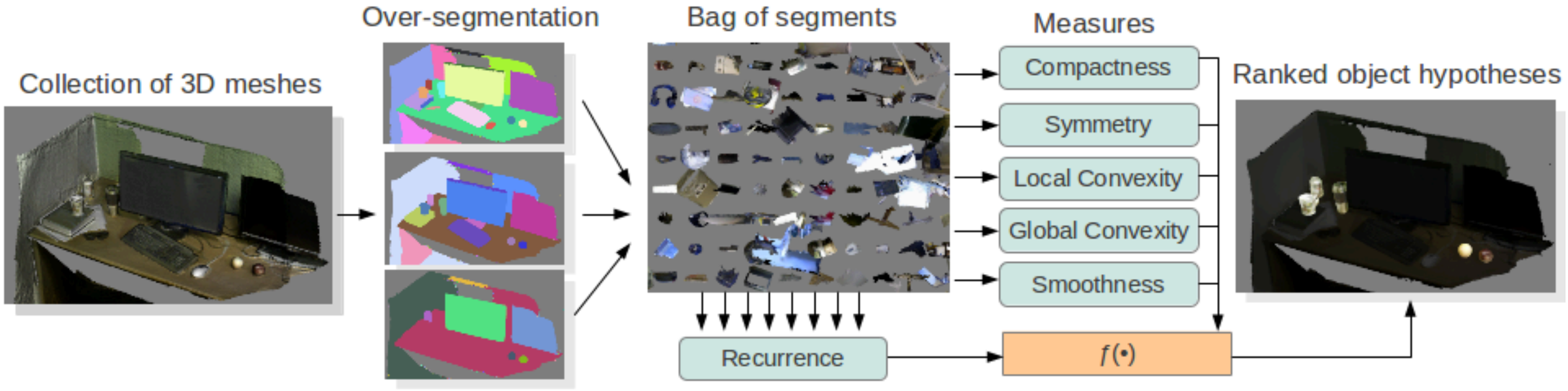
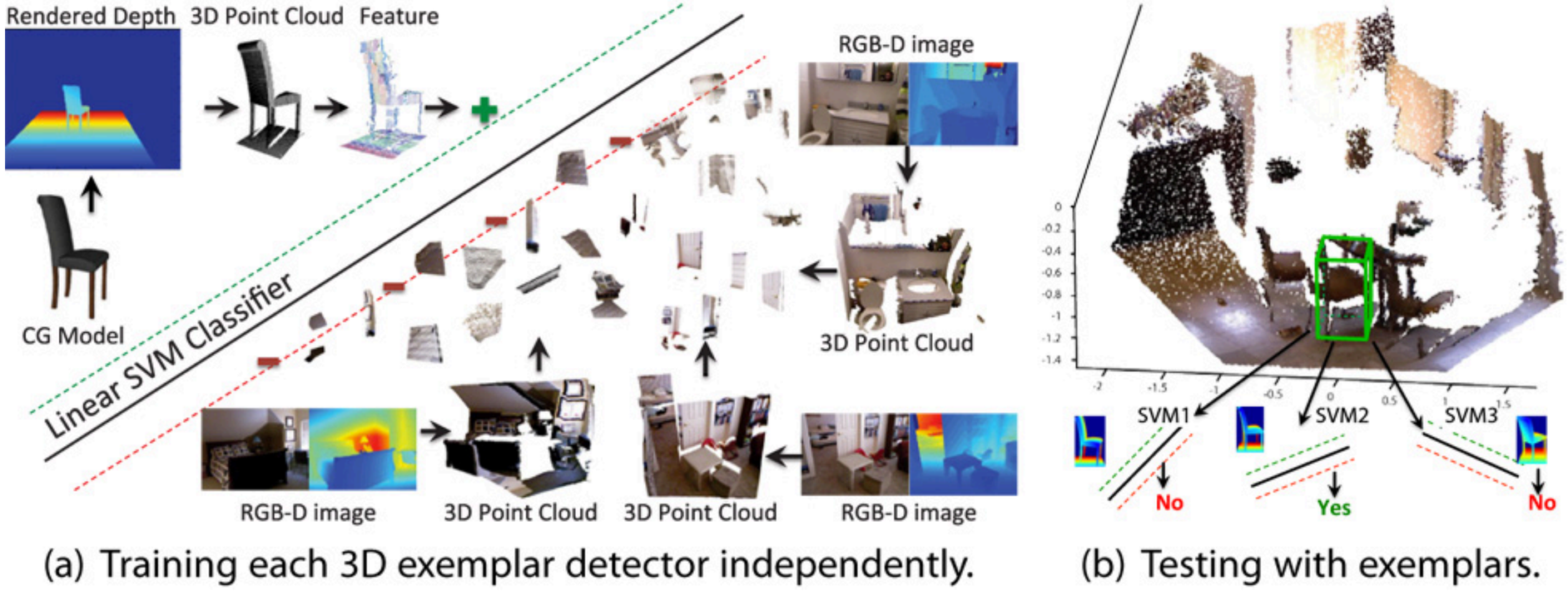


Figure from [3]

The history of 3D object detection

Pre deep learning:

Sliding shape based:
Sliding Shapes for 3D Object Detection in Depth Images (2014) [4]



(a) Training each 3D exemplar detector independently. (b) Testing with exemplars.

Figure from [4]

The deep learning era of 3d object detection

Three factors prepared us for this phase:

- **The rise of 3D sensors and access to large-scale 3D datasets**
  - Commercial depth cameras, Lidars.
  - KITTI, SUN RGB-D, ShapeNet, ScanNet…
- **The progresses of 2D object detectors**
  - R-CNN (deep nets for classification) -> Fast R-CNN (parallel processing) -> Faster R-CNN (region proposal network)…
- **The rise of 3D deep learning**
  - A series of novel deep neural network architectures for 3D data (MVCNN, 3DCNNs, PointNet, PointNet++ etc.) has been invented.

The deep learning era of 3d object detection

A first serious attempt of using deep nets for 3d detection:

Deep Sliding Shapes for Amodal 3D Object Detection in RGB-D Images (2016) [5]
- 3D CNNs for Faster-RCNN style region proposal.

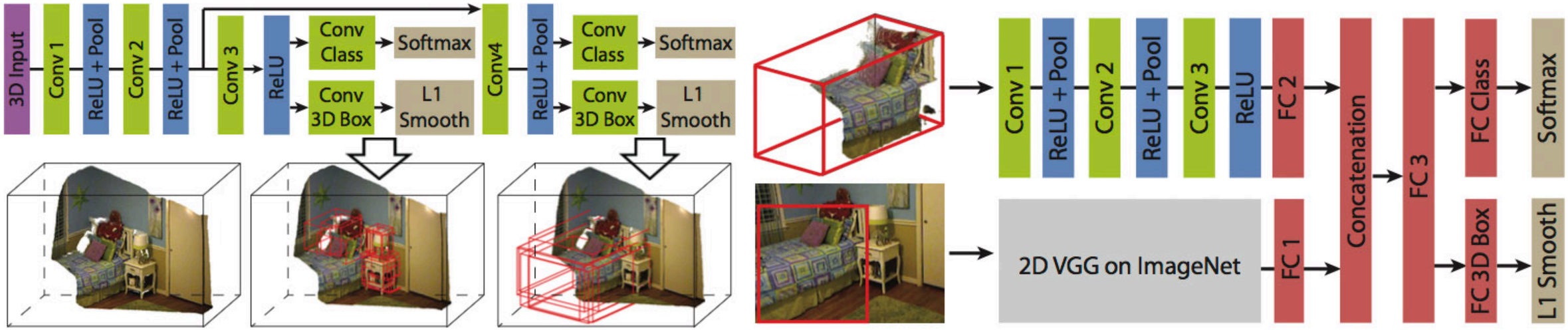


Figure from [5]

Con: 3D CNNs are very costly in both memory and time.

The deep learning era of 3d object detection

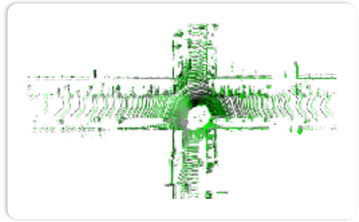
Solutions

Image-driven

Monocular view detectors
Frustum-based detectors

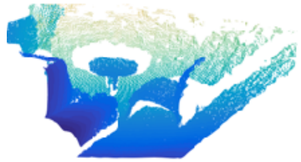
Dimension reduction

Bird's eye view detectors



Leveraging Sparsity in 3D

Point set deep nets
Sparse 3D conv, GNNs



E.g.: **Frustum PointNets [6]** **PointPillars [7]** **VoteNet [8]**

Image-driven 3D object detection

- Key idea: Leverage mature 2D object detectors to propose objects from RGB images.

Monocular or stereo view based

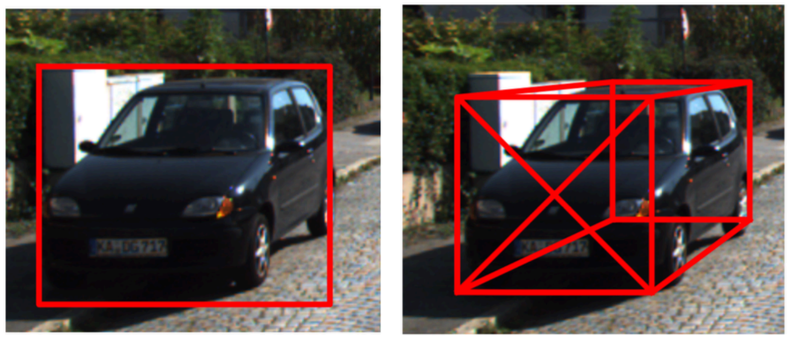
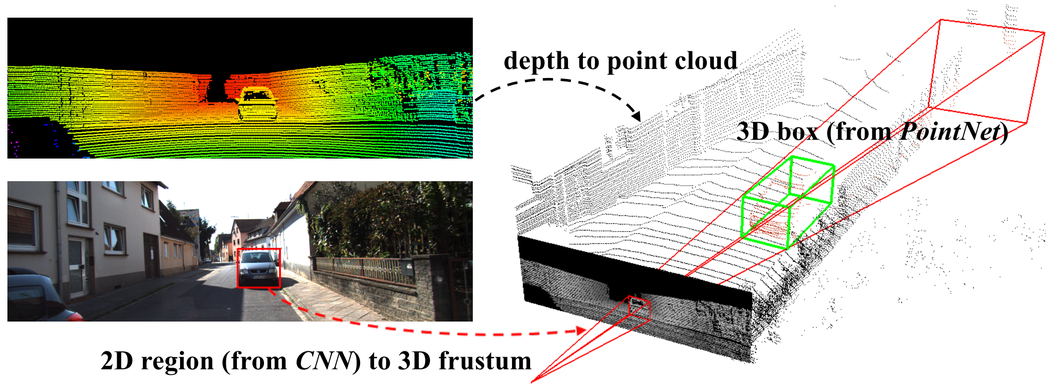


Figure from [9]

3d bounding box estimation using deep learning and geometry (2017) [9]
Pseudo-lidar (2019) [10]
Objects as Points (2019) [11]

RGB-D data based

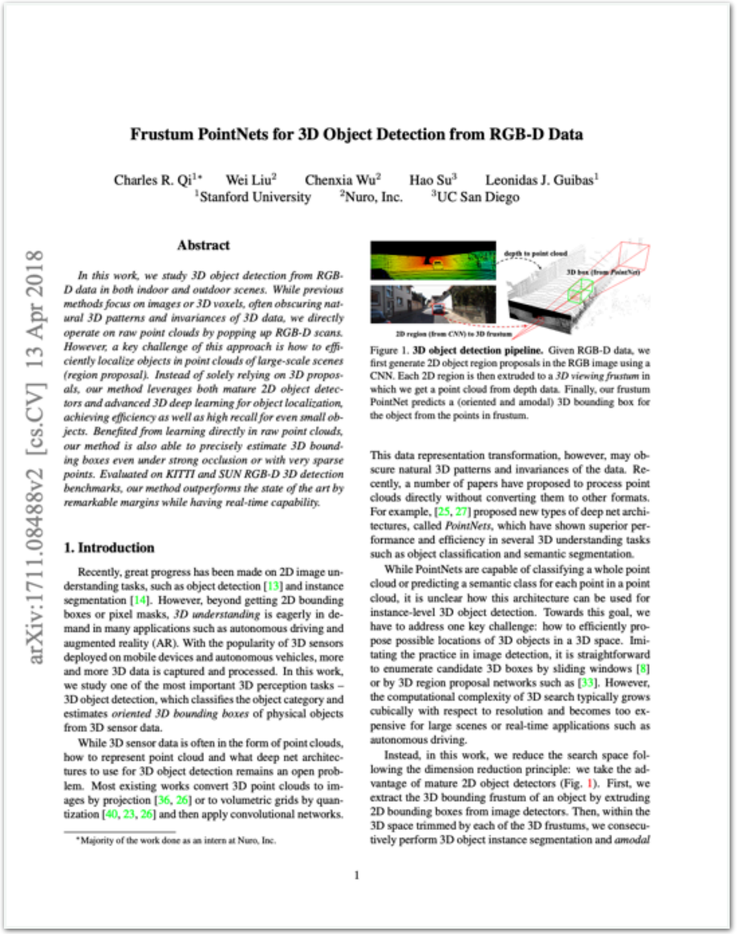


Frustum PointNets [6]

Frustum PointNets for 3D Object Detection from RGB-D Data

Charles R. Qi, Wei Liu, Chenxia Wu, Hao Su, Leonidas Guibas.

CVPR 2018



Frustum PointNets for 3D Object Detection from RGB-D Data

Charles R. Qi[1*] Wei Liu[2] Chenxia Wu[2] Hao Su[3] Leonidas J. Guibas[1]
[1]Stanford University [2]Nuro, Inc. [3]UC San Diego

Abstract

In this work, we study 3D object detection from RGB-D data in both indoor and outdoor scenes. While previous methods focus on images or 3D voxels, often obscuring natural 3D patterns and invariances of 3D data, we directly operate on raw point clouds by popping up RGB-D scans. However, a key challenge of this approach is how to efficiently localize objects in point clouds of large-scale scenes (region proposal). Instead of solely relying on 3D proposals, our method leverages both mature 2D object detectors and advanced 3D deep learning for object localization, achieving efficiency as well as high recall for even small objects. Benefited from learning directly in raw point clouds, our method is also able to precisely estimate 3D bounding boxes even under strong occlusion or with very sparse points. Evaluated on KITTI and SUN RGB-D 3D detection benchmarks, our method outperforms the state of the art by remarkable margins while having real-time capability.

1. Introduction

Recently, great progress has been made on 2D image understanding tasks, such as object detection [13] and instance segmentation [14]. However, beyond getting 2D bounding boxes or pixel masks, *3D understanding* is eagerly in demand in many applications such as autonomous driving and augmented reality (AR). With the popularity of 3D sensors deployed on mobile devices and autonomous vehicles, more and more 3D data is captured and processed. In this work, we study one of the most important 3D perception tasks – 3D object detection, which classifies the object category and estimates *oriented 3D bounding boxes* of physical objects from 3D sensor data.

While 3D sensor data is often in the form of point clouds, how to represent point cloud and what deep net architectures to use for 3D object detection remains an open problem. Most existing works convert 3D point clouds to images by projection [36, 26] or to volumetric grids by quantization [40, 23, 26] and then apply convolutional networks.

*Majority of the work done as an intern at Nuro, Inc.

Figure 1. **3D object detection pipeline.** Given RGB-D data, we first generate 2D object region proposals in the RGB image using a CNN. Each 2D region is then extruded to a *3D viewing frustum* in which we get a point cloud from depth data. Finally, our frustum PointNet predicts a (oriented and amodal) 3D bounding box for the object from the points in frustum.

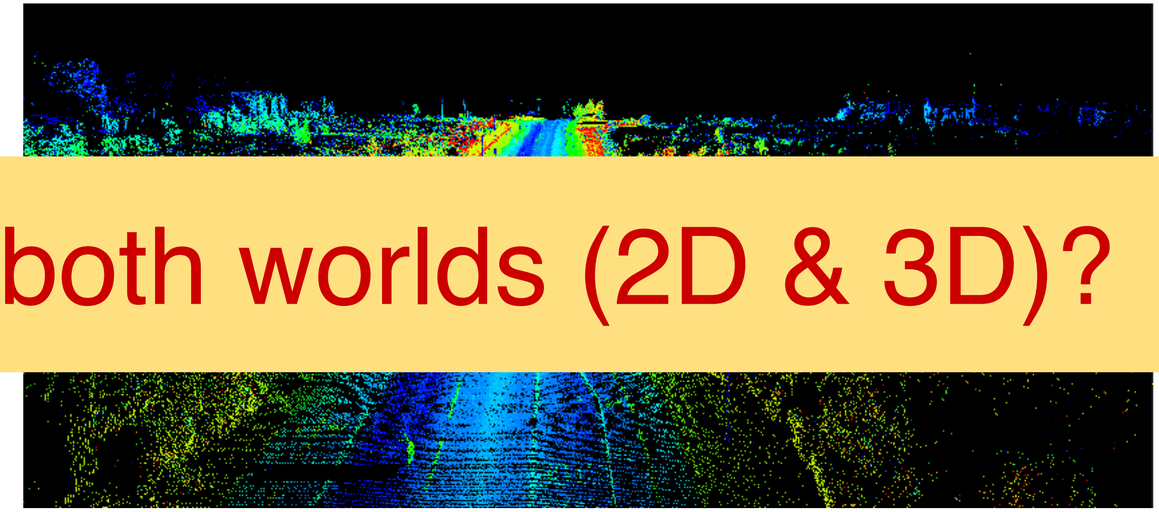
This data representation transformation, however, may obscure natural 3D patterns and invariances of the data. Recently, a number of papers have proposed to process point clouds directly without converting them to other formats. For example, [25, 27] proposed new types of deep net architectures, called *PointNets*, which have shown superior performance and efficiency in several 3D understanding tasks such as object classification and semantic segmentation.

While PointNets are capable of classifying a whole point cloud or predicting a semantic class for each point in a point cloud, it is unclear how this architecture can be used for instance-level 3D object detection. Towards this goal, we have to address one key challenge: how to efficiently propose possible locations of 3D objects in a 3D space. Imitating the practice in image detection, it is straightforward to enumerate candidate 3D boxes by sliding windows [8] or by 3D region proposal networks such as [33]. However, the computational complexity of 3D search typically grows cubically with respect to resolution and becomes too expensive for large scenes or real-time applications such as autonomous driving.

Instead, in this work, we reduce the search space following the dimension reduction principle: we take the advantage of mature 2D object detectors (Fig. 1). First, we extract the 3D bounding frustum of an object by extruding 2D bounding boxes from image detectors. Then, within the 3D space trimmed by each of the 3D frustums, we consecutively perform 3D object instance segmentation and *amodal*

1

Images and Point Clouds



Can we get the best of both worlds (2D & 3D)?

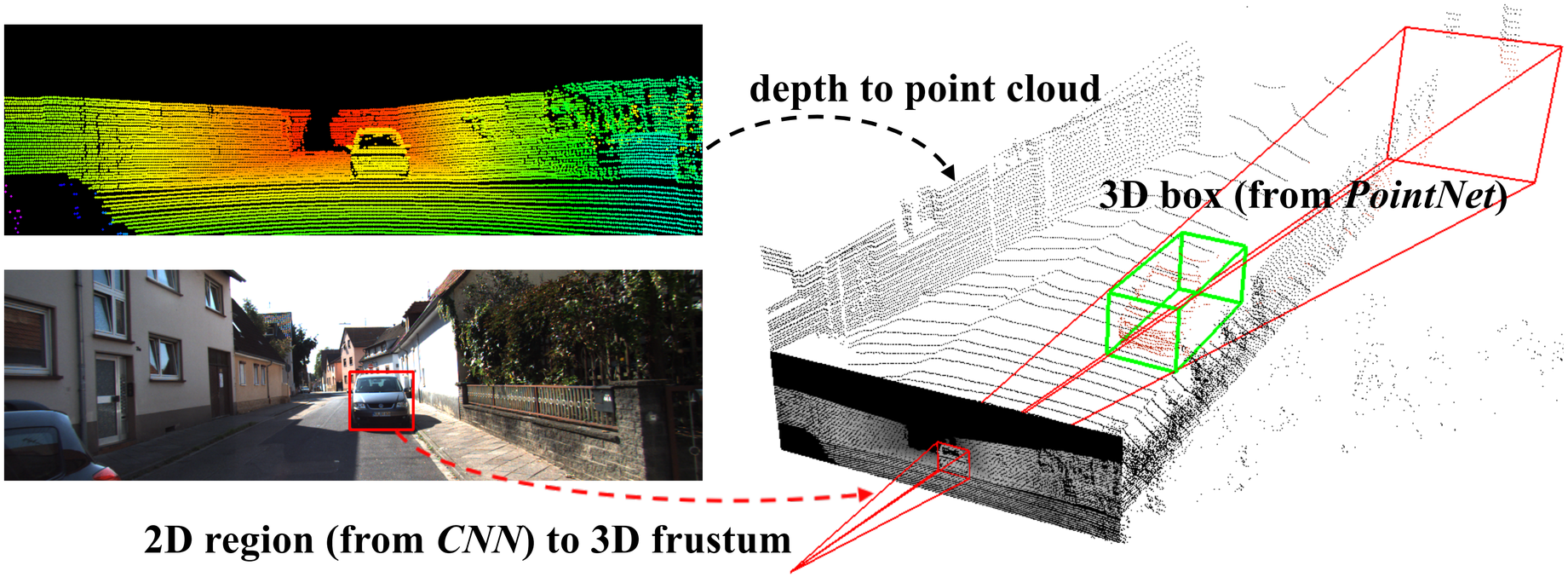
RGB images

High resolution
Rich textures

Lidar point clouds

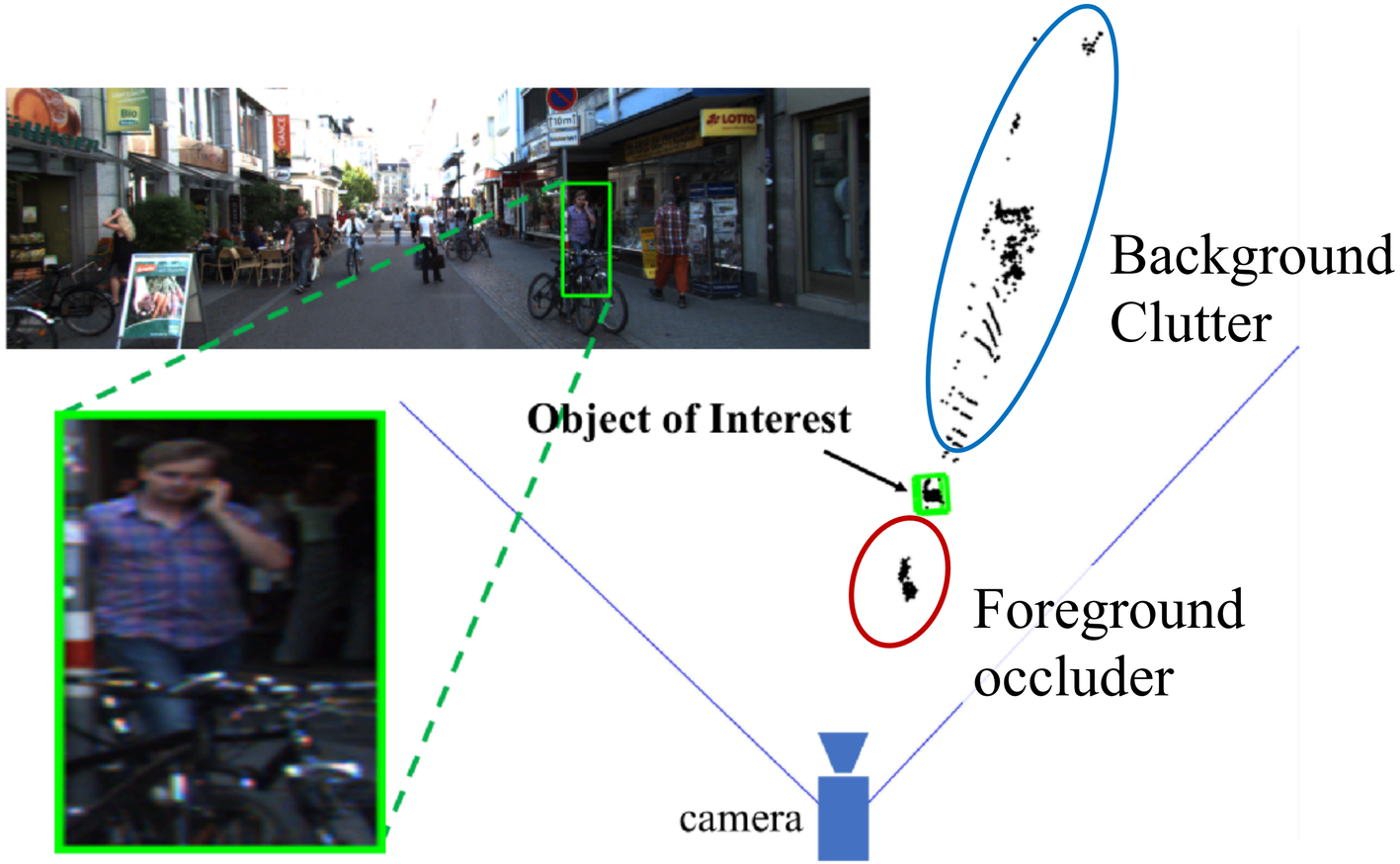
Accurate depth
Accurate 3D geometry

Frustum PointNets for 3D Object Detection



+ ***Leveraging mature 2D detectors** for region proposal. greatly reducing 3D search space.*
+ ***3D deep learning** for accurate object localization in frustum point clouds.*

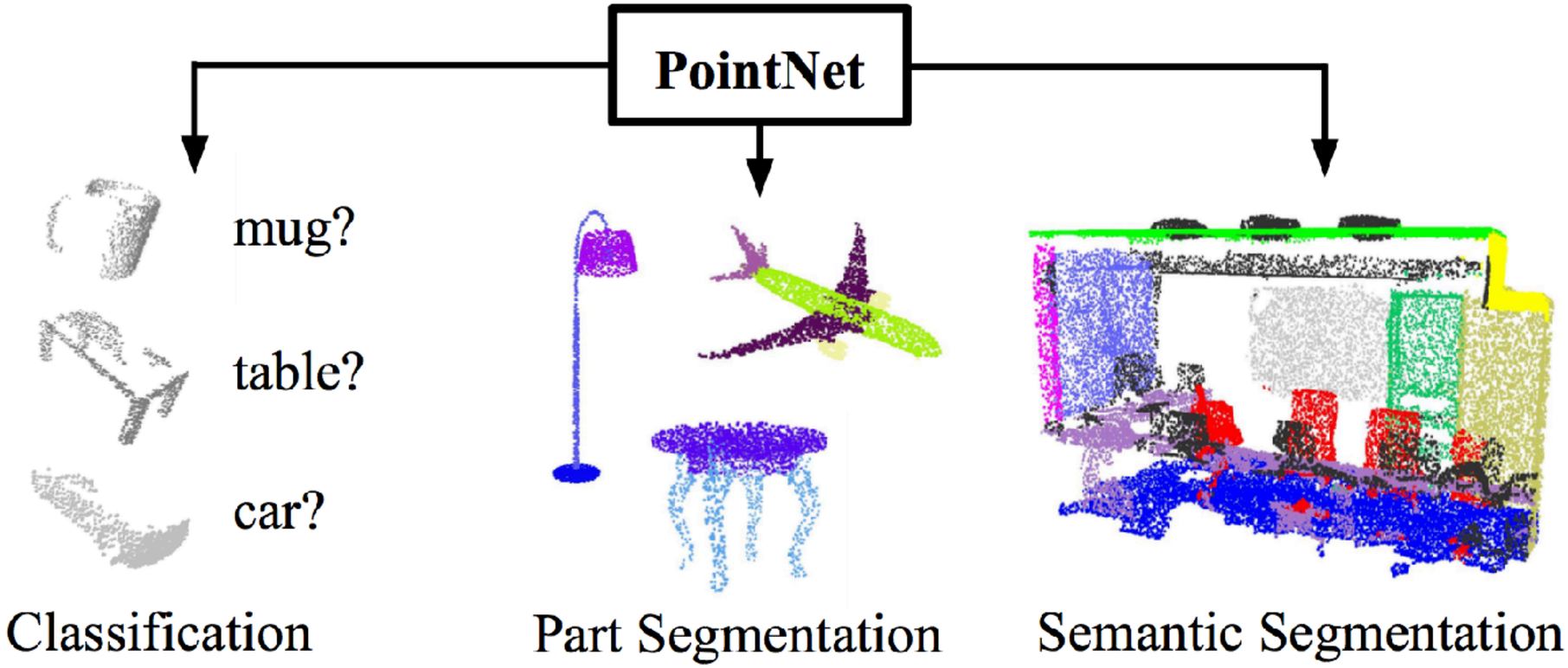
Frustum-based 3D Object Detection: Challenges



- Occlusions and clutters are common in frustum point clouds
- Large range of point depths

Frustum PointNets

Use **PointNets** for **data-driven** object detection in frustums.



PointNet [Qi et al. CVPR 2017] *PointNet++ [Qi et al. NIPS 2017]*

Frustum PointNets

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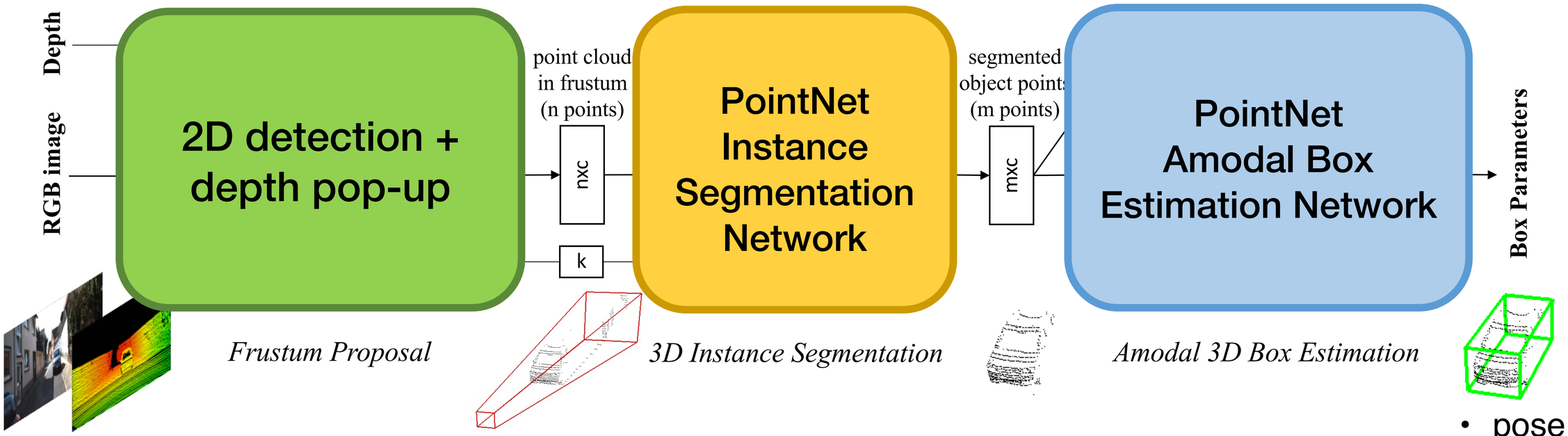
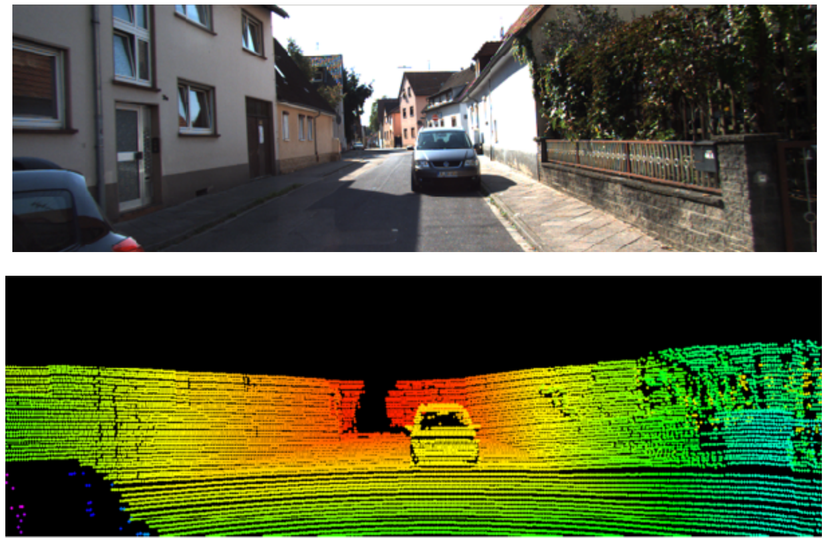
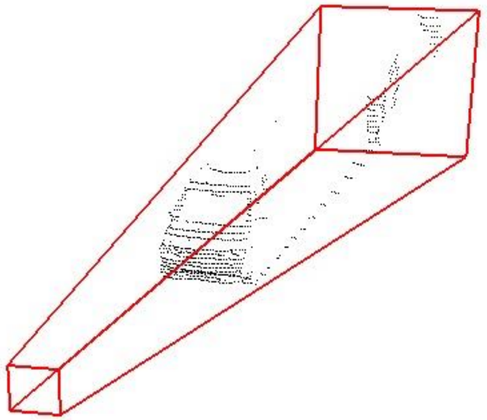


Frustum Proposal

Propose 3D frustums by 2D region proposals in images and depth pop-up



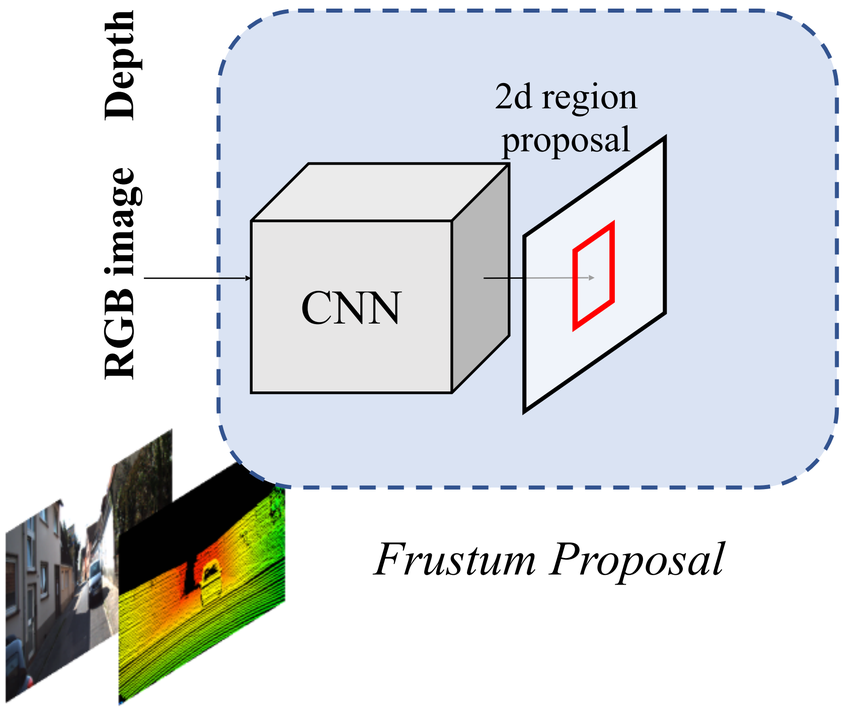


Frustum Proposal

Input: RGB-D data

RGB image Depth

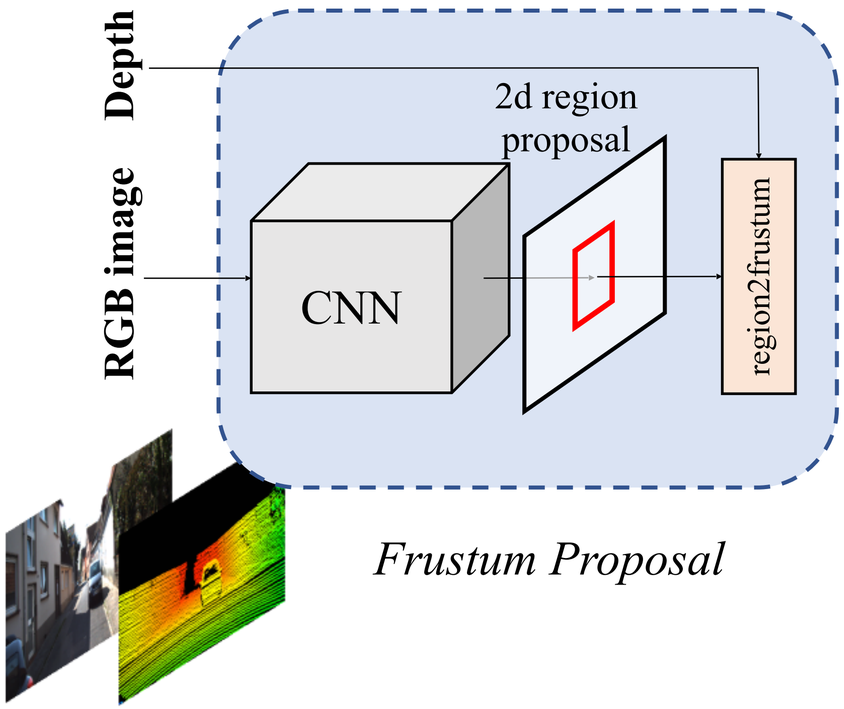
Frustum Proposal



Input: RGB-D data

Image region proposal using a 2D detector on RGB images (high resolution)

Frustum Proposal



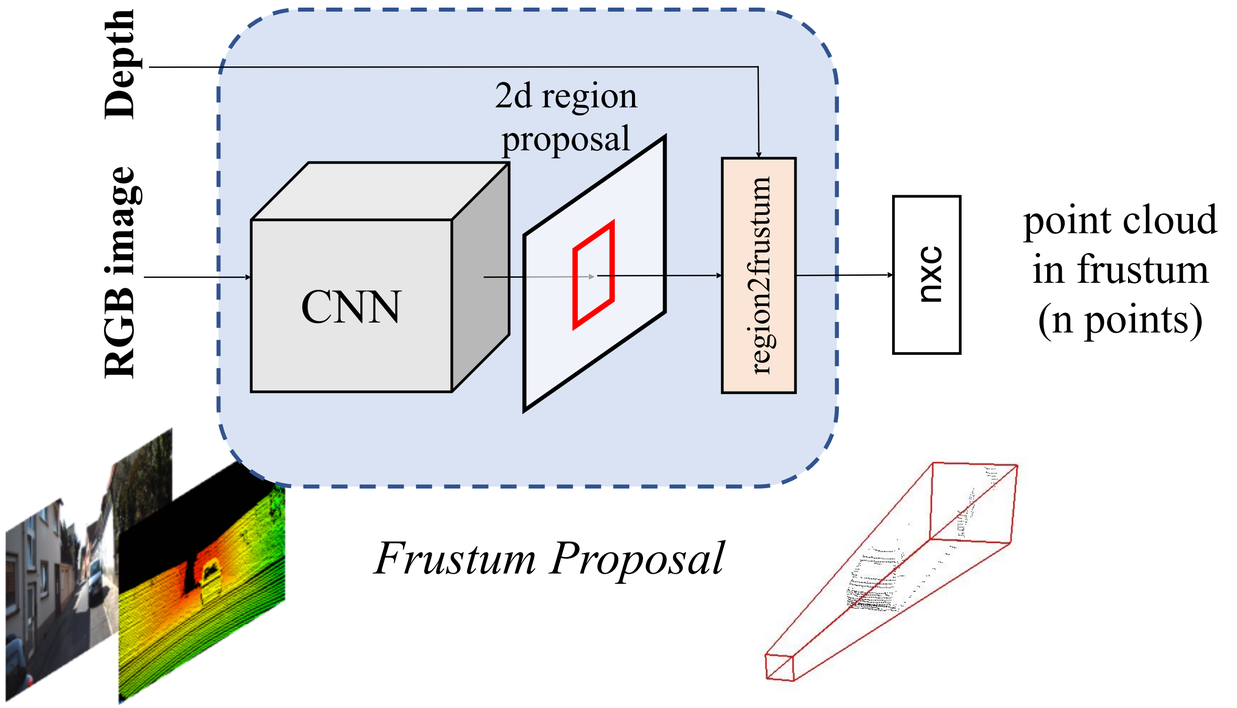
Frustum Proposal

Input: RGB-D data

Image region proposal using a 2D detector on RGB images (high resolution)

Frustum proposal by lifting a 2D region into a 3D frustum.

Frustum Proposal



Input: RGB-D data

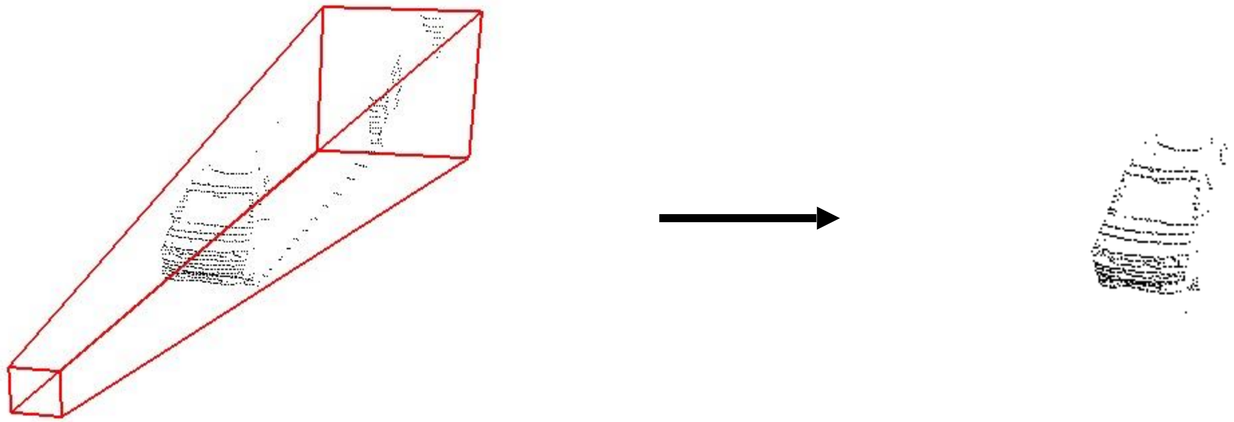
Image region proposal using a 2D detector on RGB images (high resolution)

Frustum proposal by lifting a 2D region into a 3D frustum.

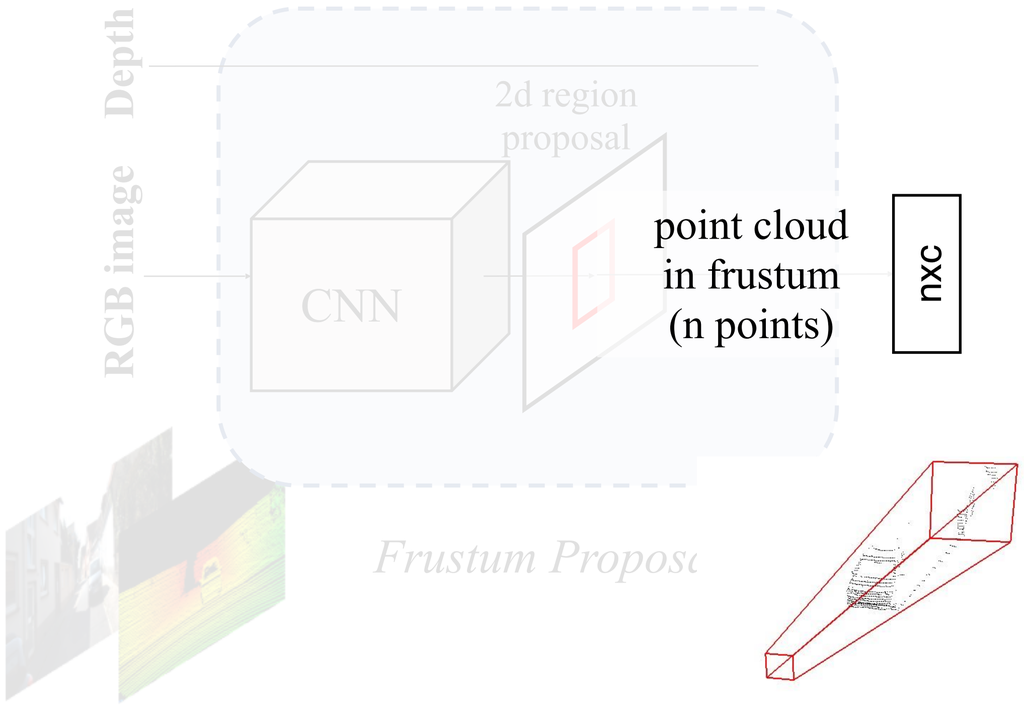
Points in the frustum are extracted and are called a *frustum point cloud*.

3D Instance Segmentation in Frustums

Localize objects in frustums by point cloud segmentation.

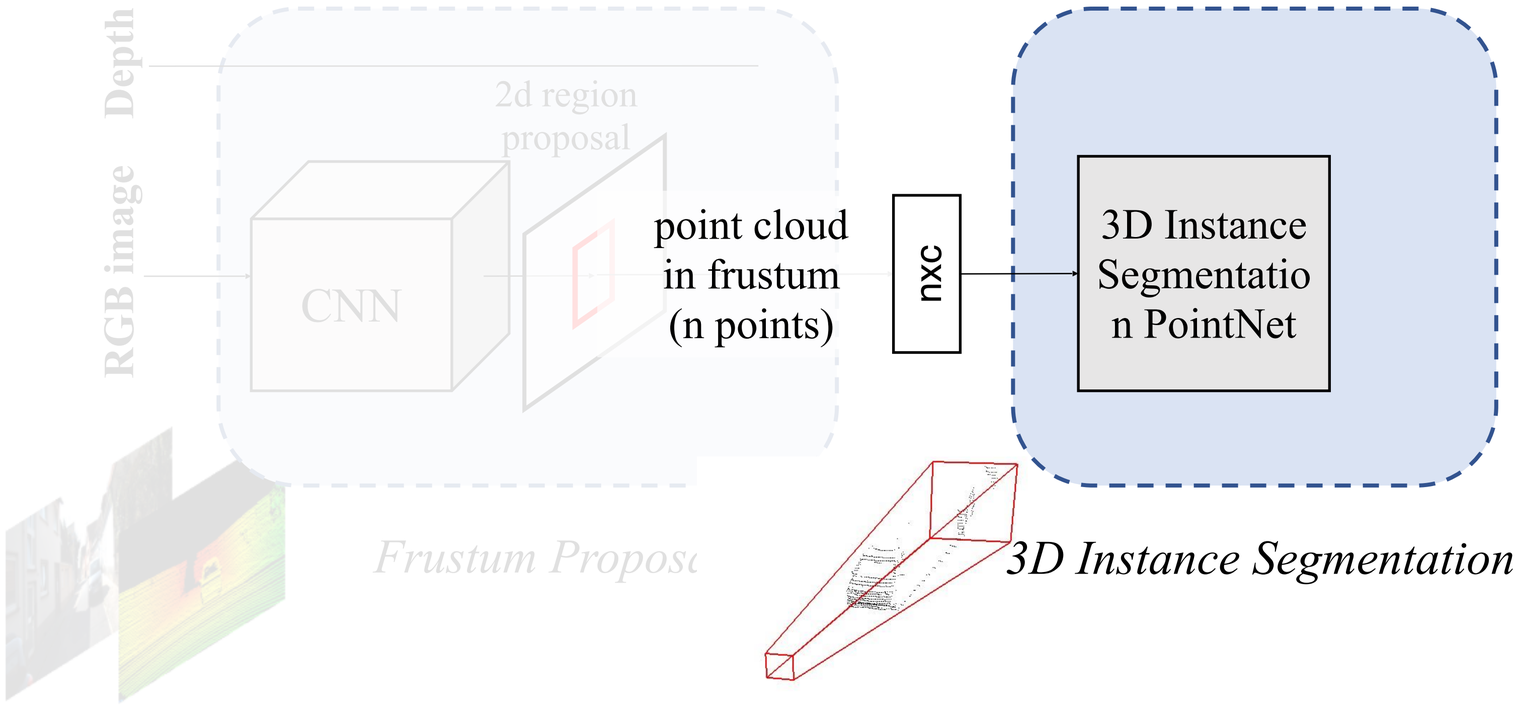


3D Instance Segmentation in Frustums



Input: frustum point cloud

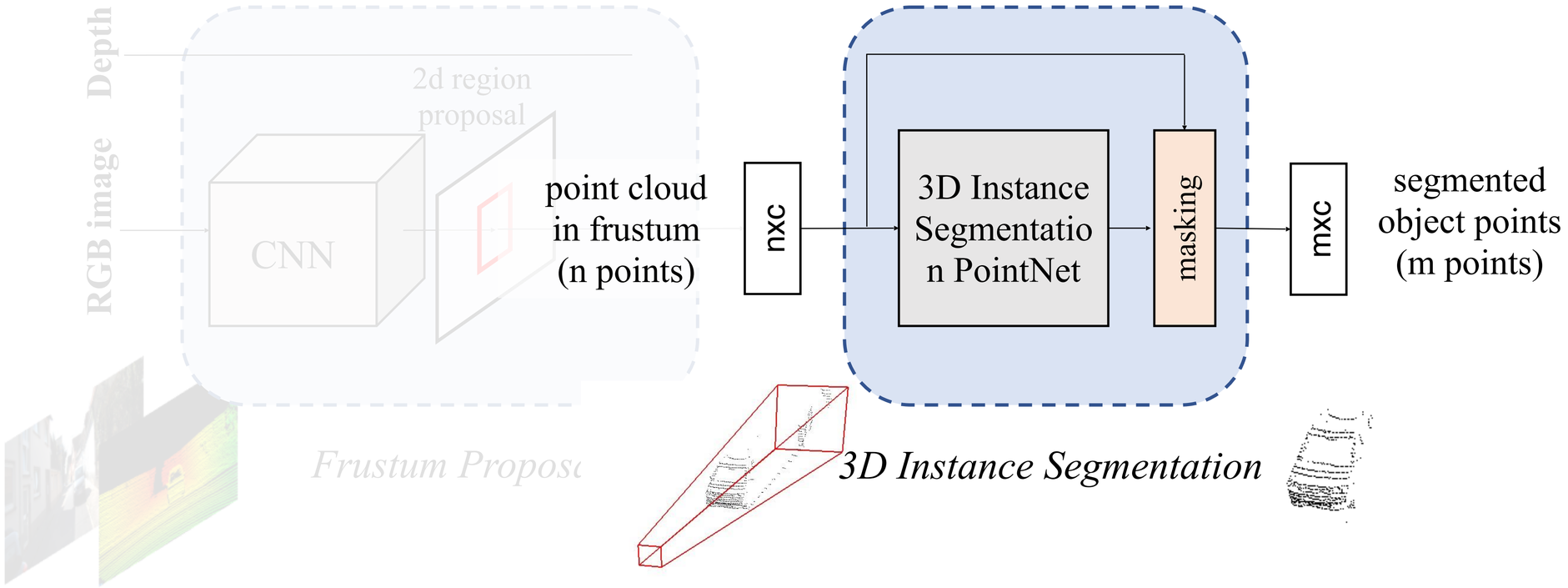
3D Instance Segmentation in Frustums



Input: frustum point cloud

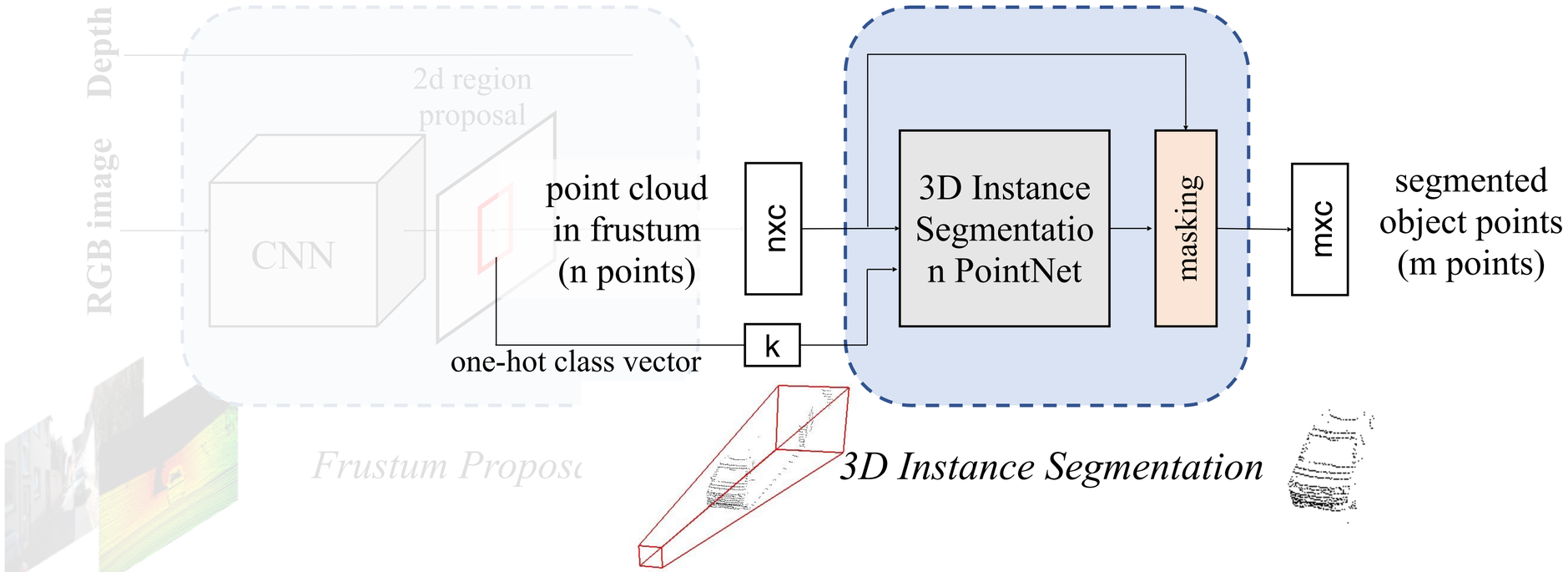
Point cloud binary segmentation with PointNet: object of interest v.s. others

3D Instance Segmentation in Frustums



Input: frustum point cloud
Point cloud binary segmentation with PointNet: object of interest v.s. others
Points that are classified as object points are extracted for the next step.

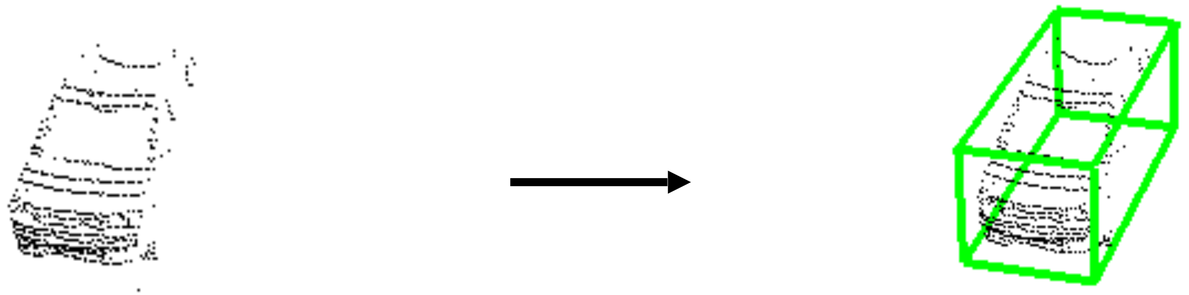
3D Instance Segmentation in Frustums



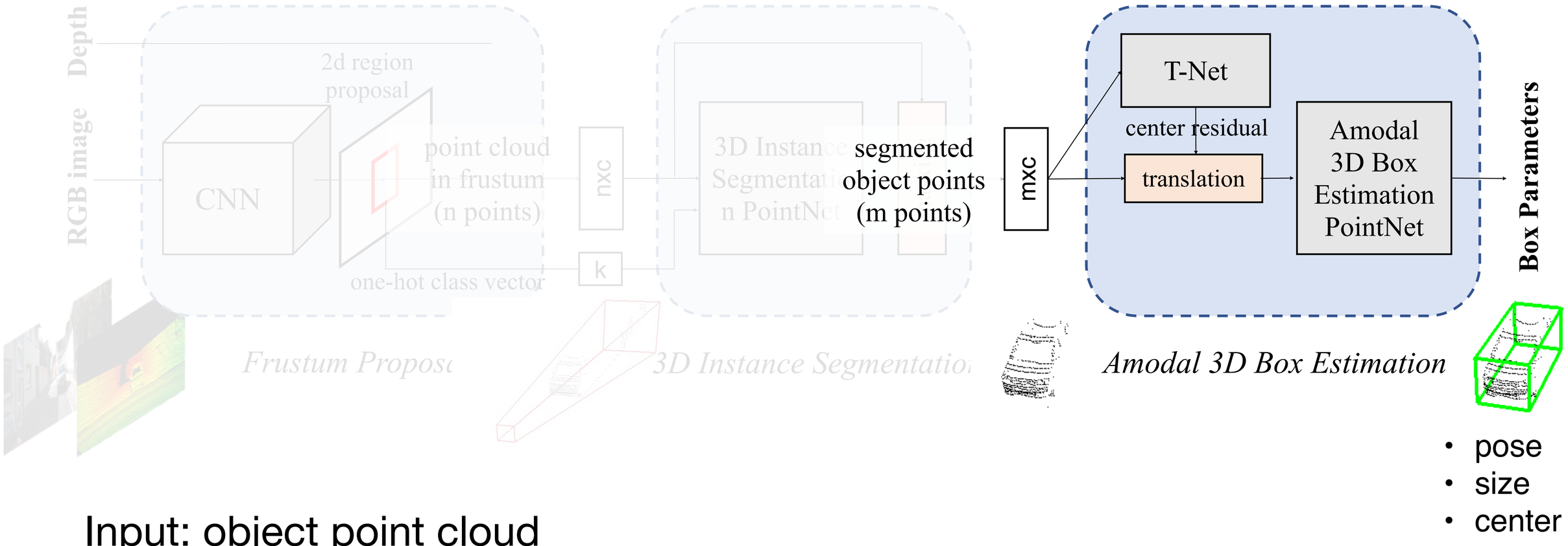
Input: frustum point cloud
Point cloud binary segmentation with PointNet: object of interest v.s. others
Points that are classified as object points are extracted for the next step.

Amodal 3D Bounding Box Estimation

Estimate 3D bounding boxes from segmented object point clouds.



Amodal 3D Bounding Box Estimation

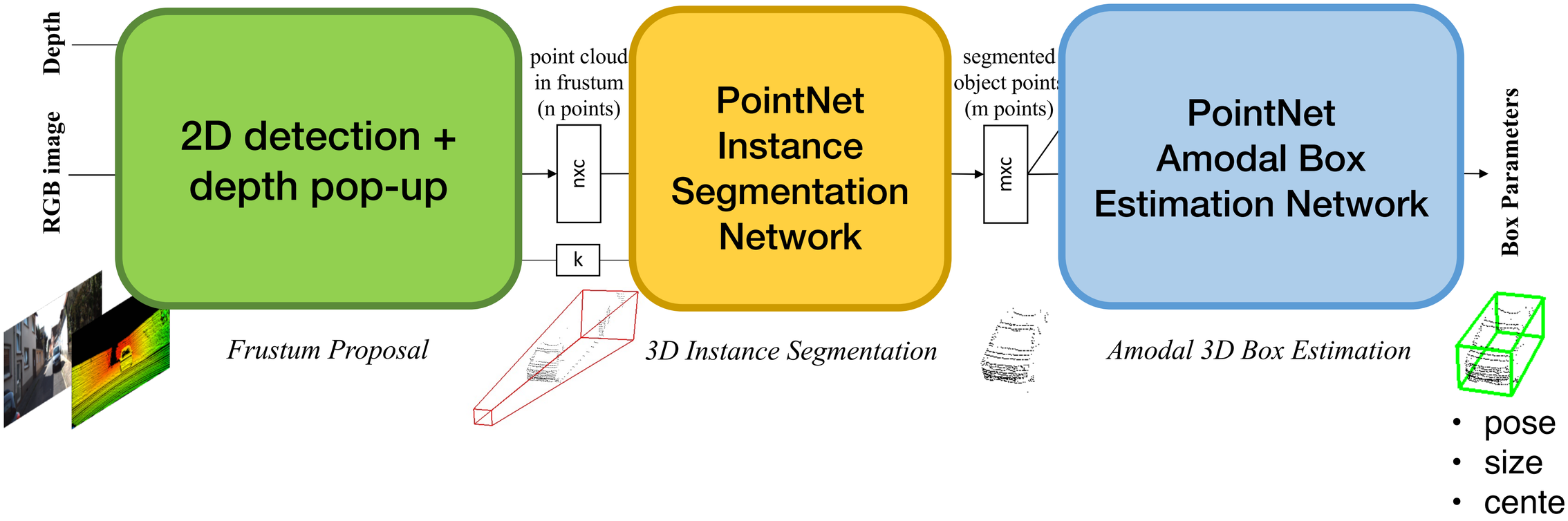


- pose
- size
- center

Input: object point cloud

A regression PointNet estimates amodal 3D bounding box for the object

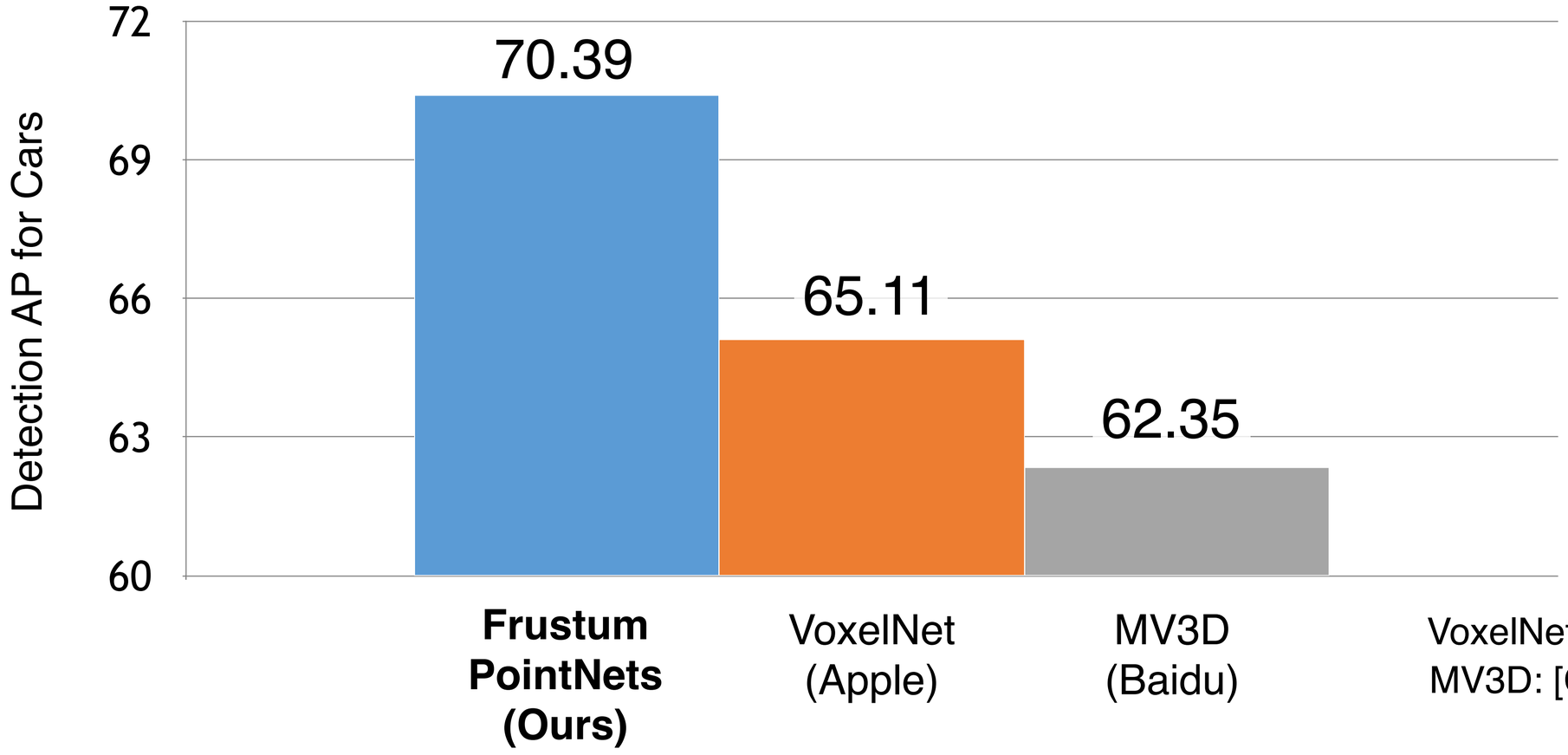
Frustum PointNets



KITTI Results: Quantitative

Leading performance on KITTI benchmark

(at the time of publication)



VoxelNet: [Zhou et al. 2018]

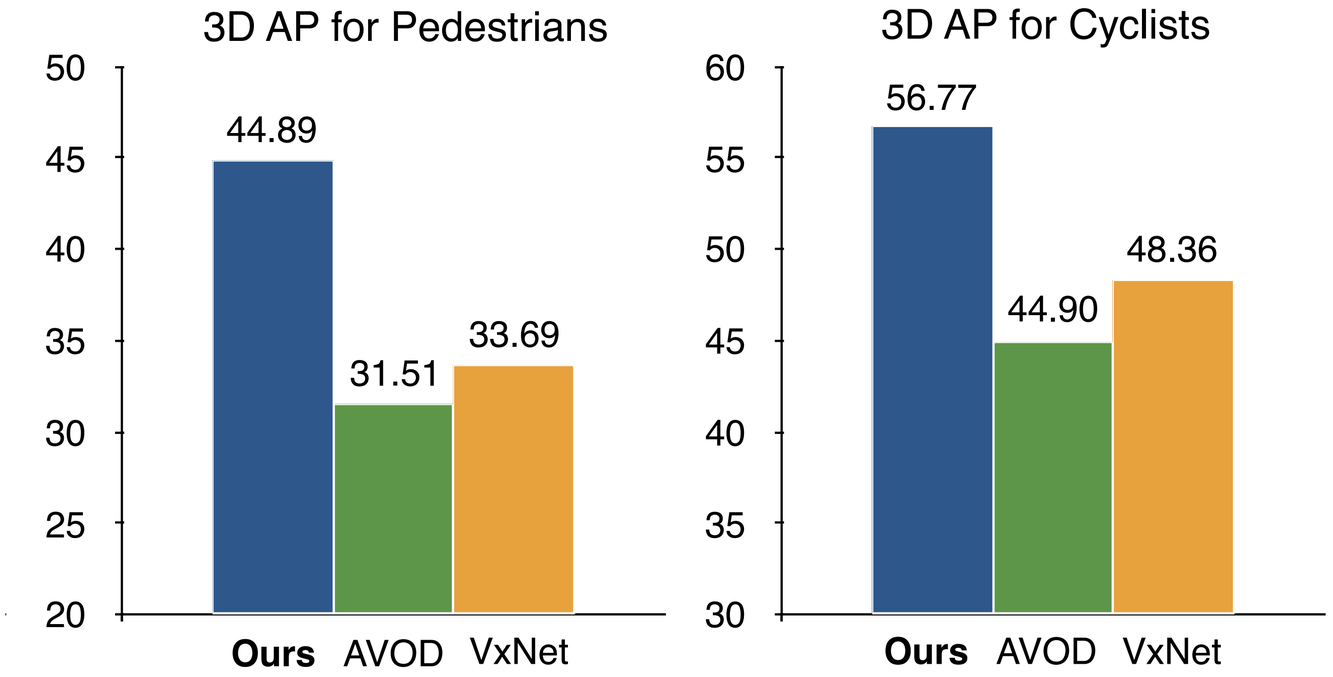
MV3D: [Chen et al. 2017]

KITTI Results: Quantitative

Leading performance on KITTI benchmark

(at the time of publication)

Especially leading at smaller objects (pedestrians and cyclists) – hard to localize with 3D proposals only.



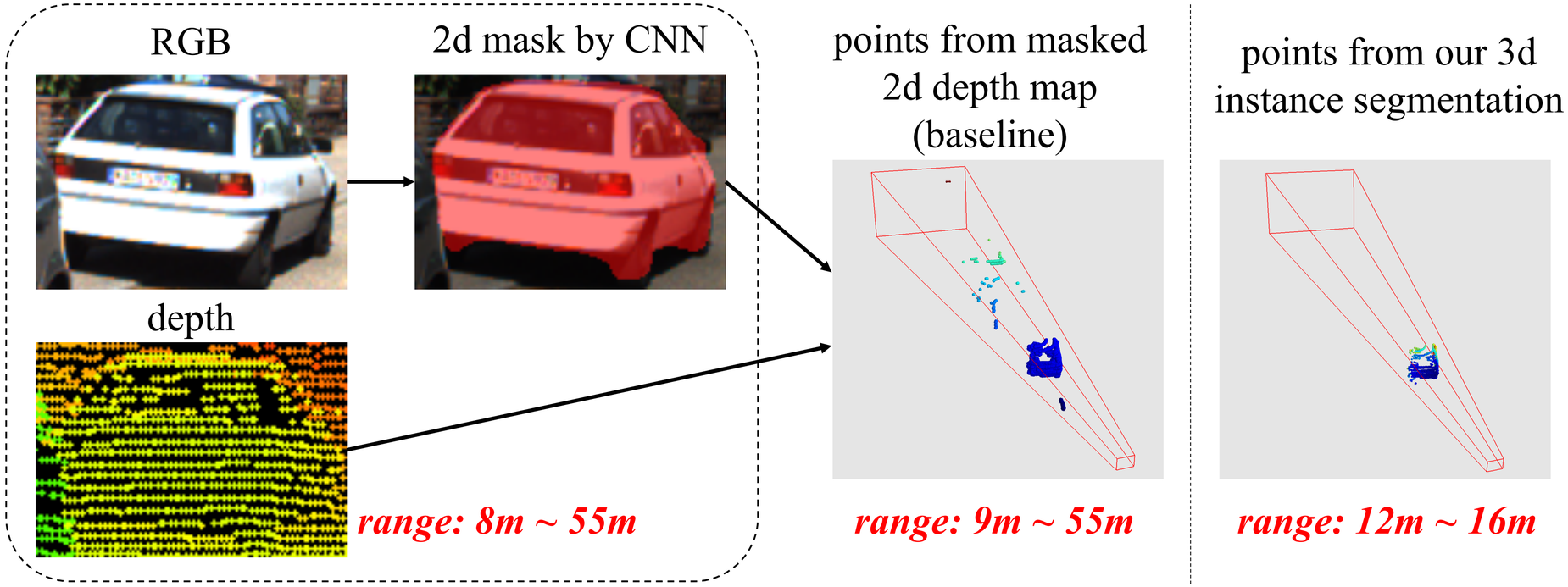
AVOD: [Ku et al. 2018]

VxNet: [Zhou et al. 2017]

Frustum PointNets: Key to our Success

- **Representation matters — 2D v.s. 3D**

  Instance segmentation: depth range maps v.s. point clouds.



Frustum PointNets: Key to our Success

- **Representation matters — 2D v.s. 3D**

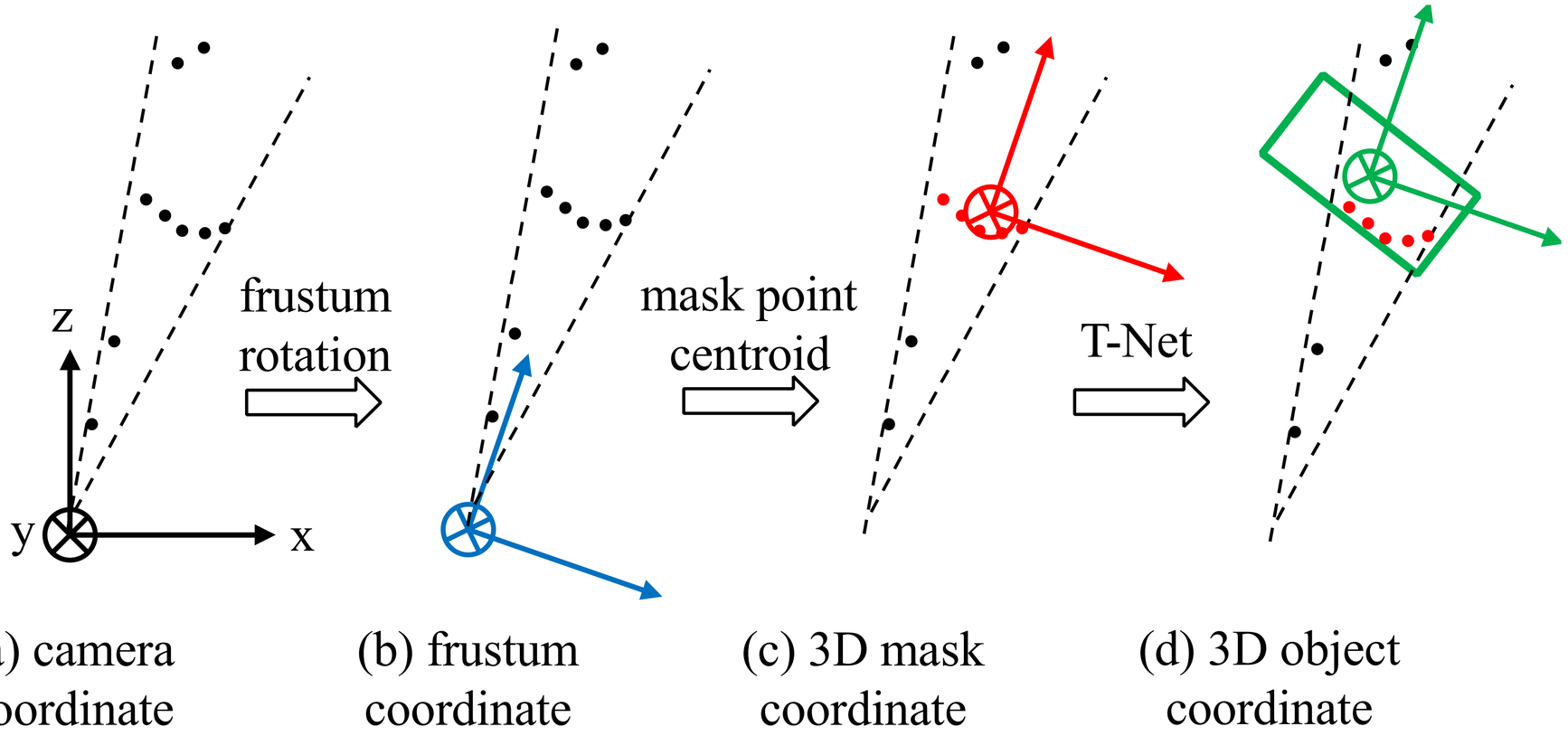
Effects of depth representation

network arch.	mask	depth representation	accuracy
ConvNet	-	image	18.3
ConvNet	2D	image	27.4
PointNet	-	point cloud	33.5
PointNet	2D	point cloud	61.6
PointNet	3D	point cloud	**74.3**
PointNet	2D+3D	point cloud	70.0

dataset: KITTI; metric: 3D bounding box estimation accuracy (%) under IoU 0.7

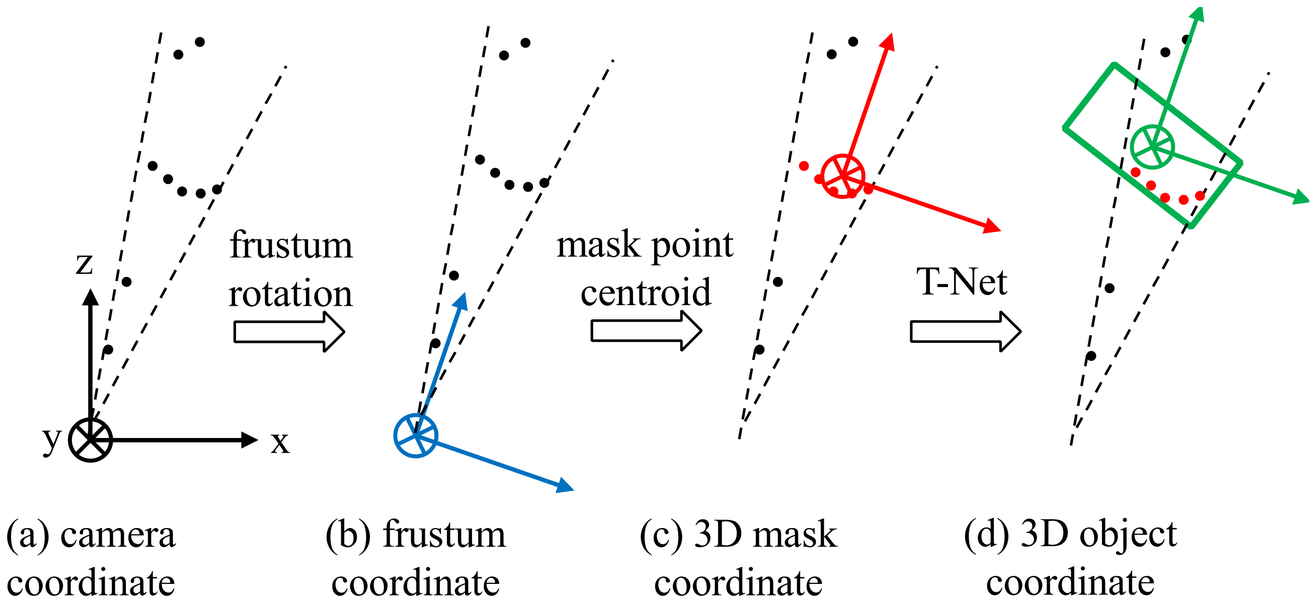
Frustum PointNets: Key to our Success

- **Canonicalize the problem with coordinate transformations**



Frustum PointNets: Key to our Success

- **Canonicalize the problem with coordinate transformations**



frustum rot.	mask centralize	t-net	accuracy
-	-	-	12.5
√	-	-	48.1
-	√	-	64.6
√	√	-	71.5
√	√	√	**74.3**

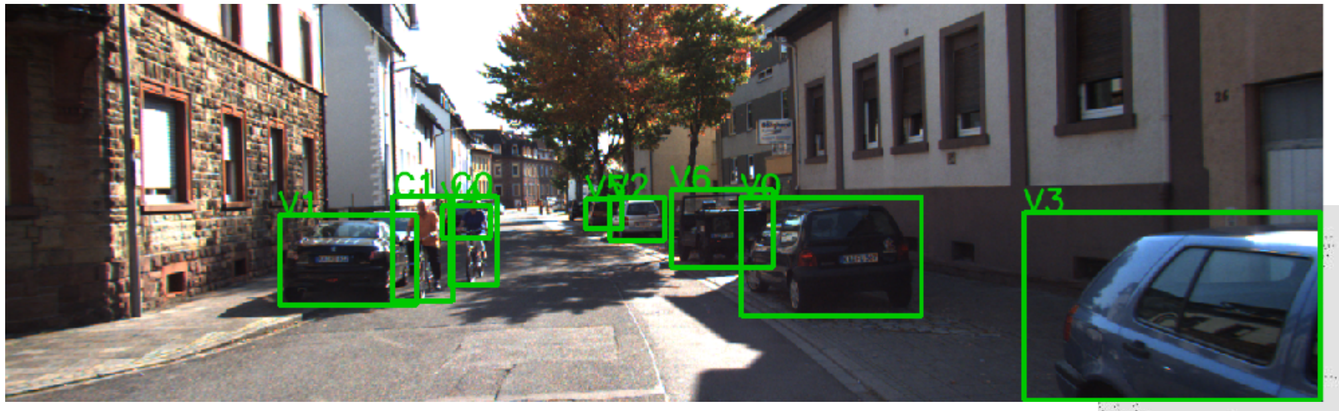
dataset: KITTI; metric: 3D bounding box estimation accuracy (%) under IoU 0.7

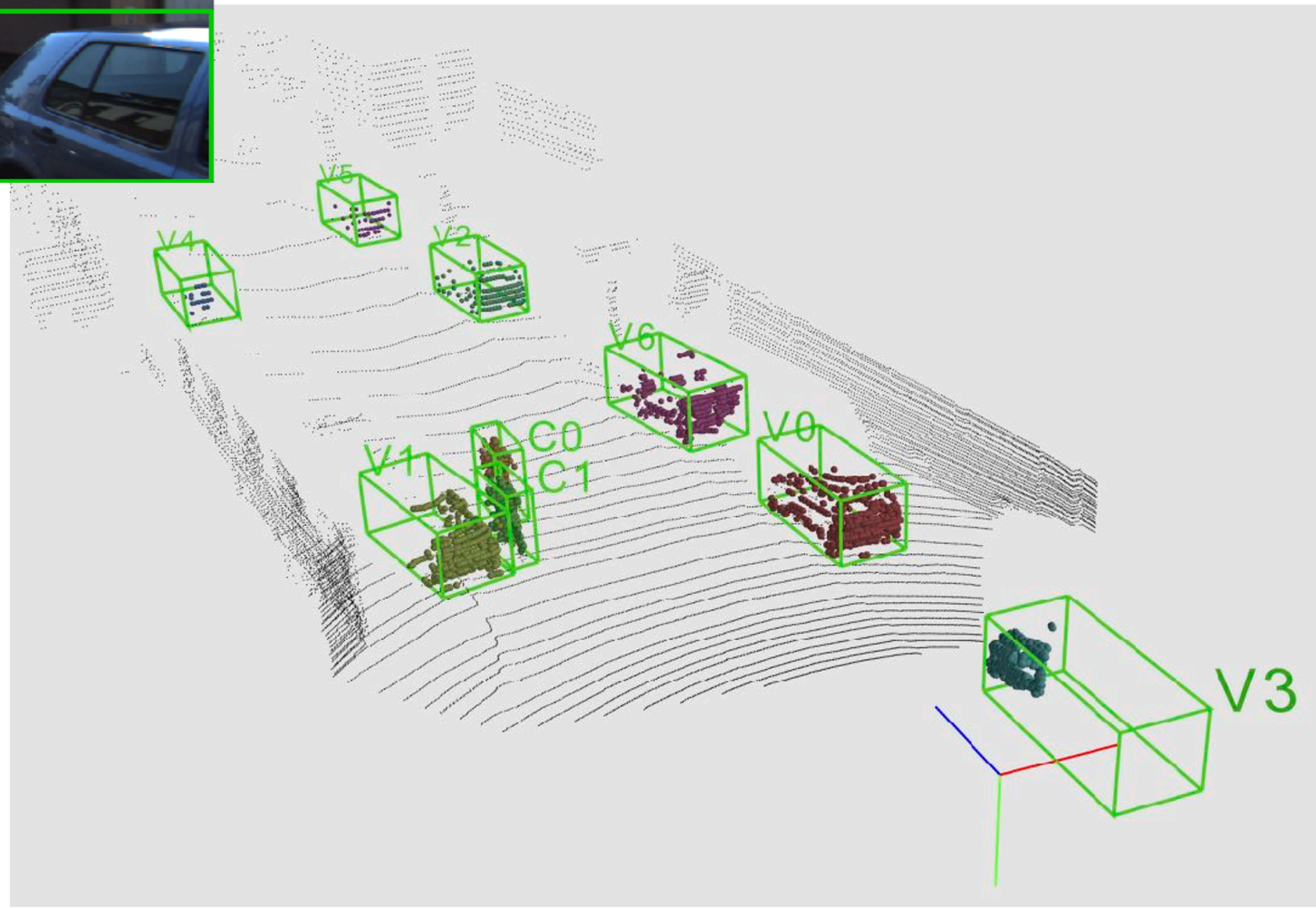
Frustum PointNets: Key to our Success

Respect and exploit 3D

- **Representation matters** — using 3D representation and 3D deep learning for the 3D problem.
- **Canonicalize the problem** — exploiting geometric transformations in point clouds.

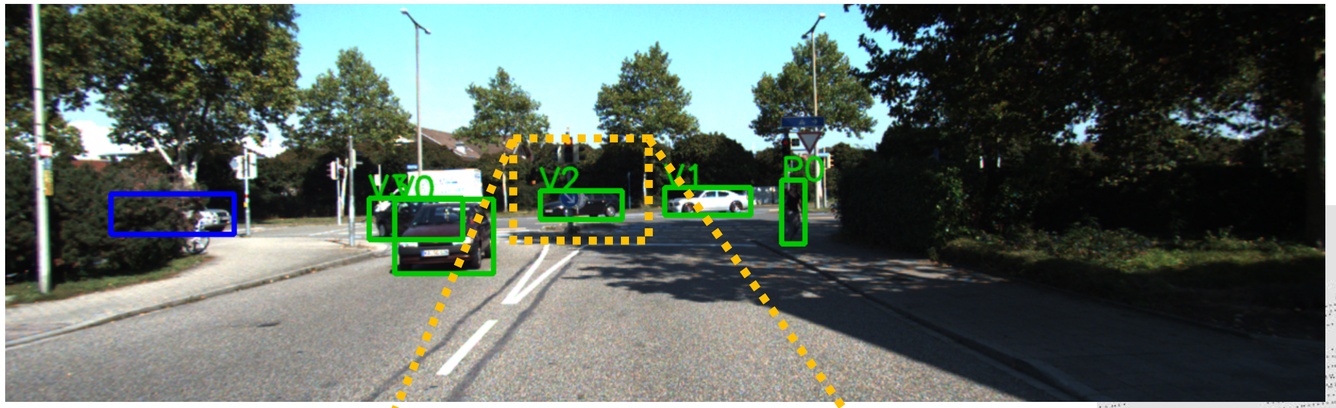
KITTI Results: Qualitative



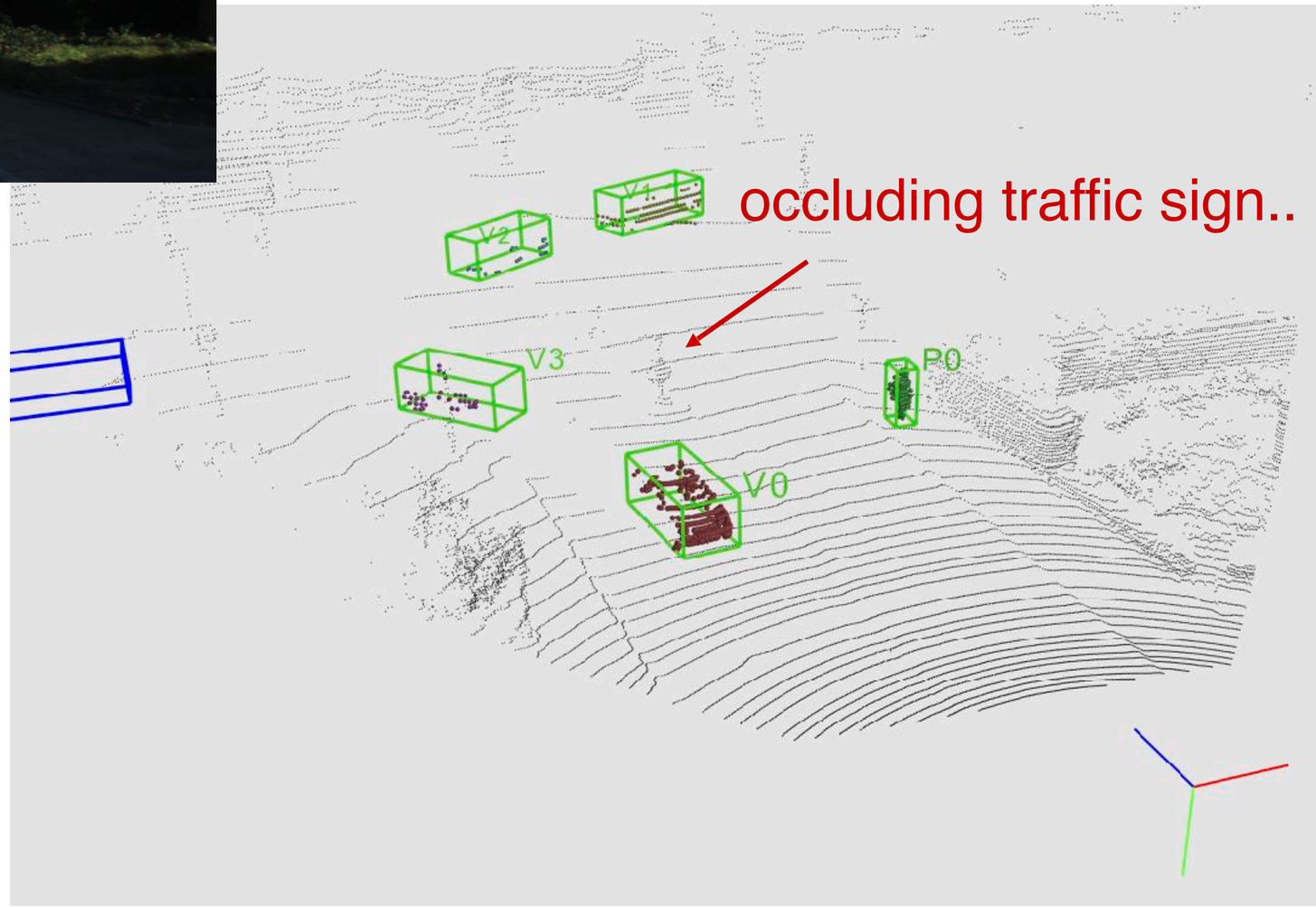


Remarkable box estimation accuracy even with a dozen of points or with very partial point clouds.

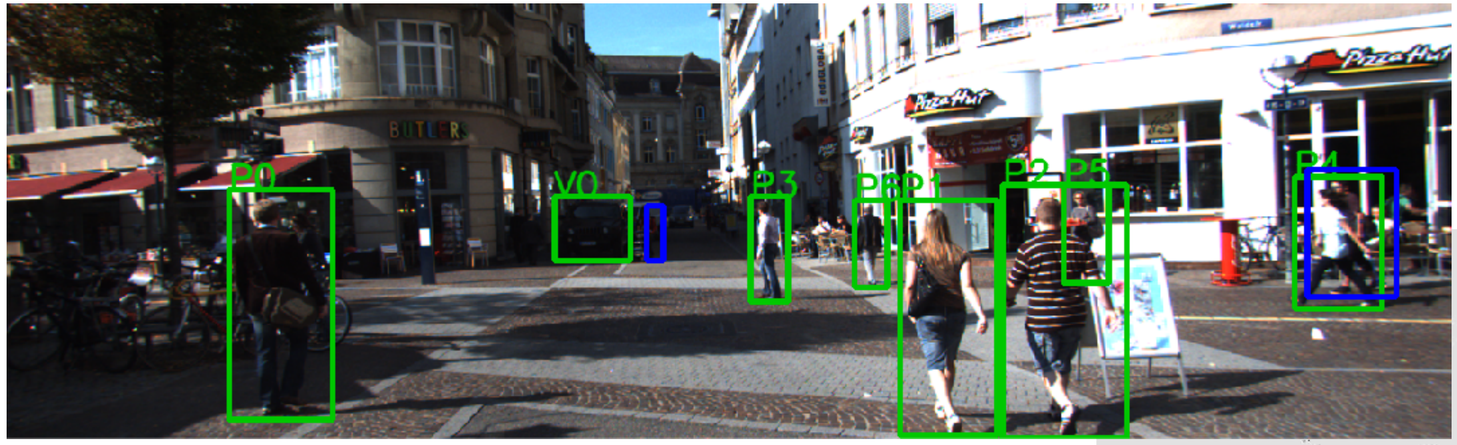
KITTI Results: Qualitative



Correct segmentation in point clouds with heavy occlusion.

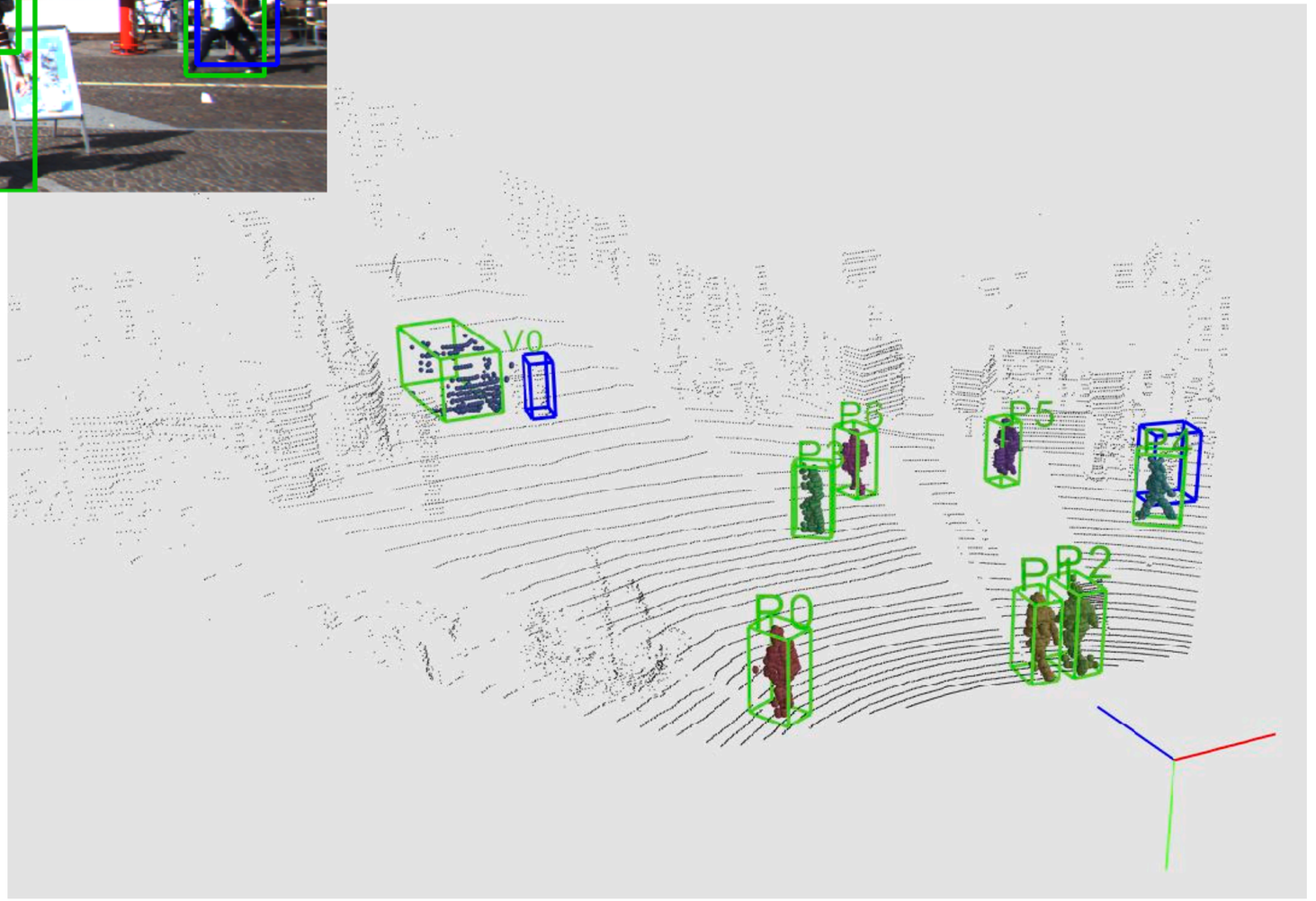


KITTI Results: Qualitative

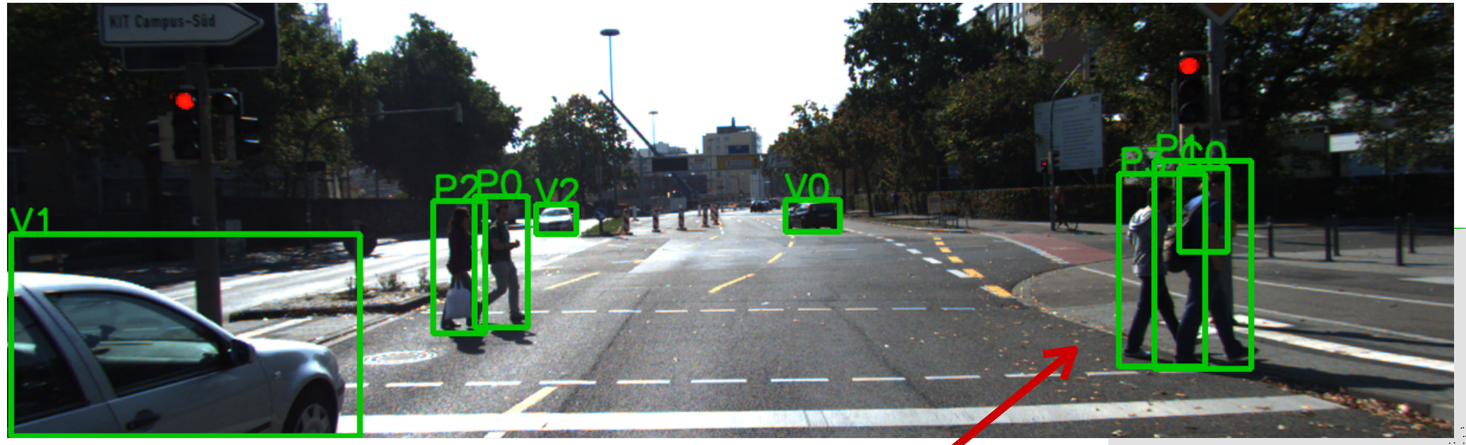


Missing 2D detection results in no 3D detection

Multiple ways of proposal could help (e.g. bird's eye view, multiple 2D proposal networks)

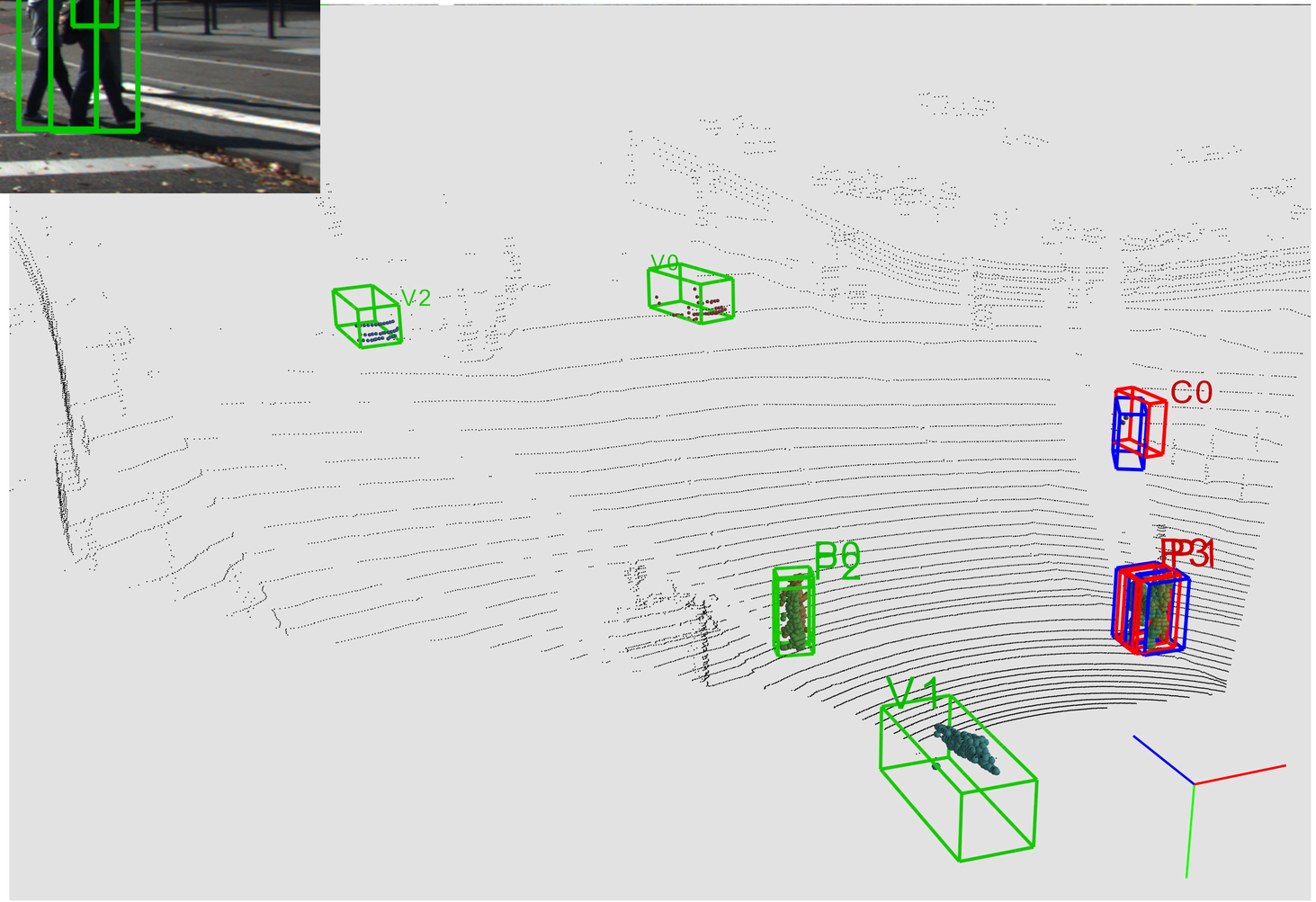


KITTI Results: Qualitative



Very strong occlusion.

Challenging case for instance segmentation (multiple close-by objects in a single frustum)



Limitation of the Frustum PointNets

- Hard dependence on 2D detections: will miss objects due to strong occlusions in 2D views or unfavorable illumination conditions.
- No support of multiple 3D proposals in a frustum.

Solution: *object proposal from 3D point clouds.*

(VoteNet & ImVoteNet)

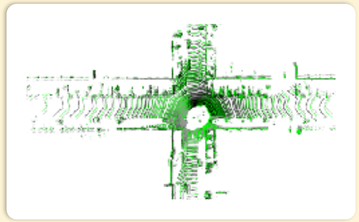
The deep learning era of 3d object detection

Image-driven

Monocular view detectors
Frustum-based detectors

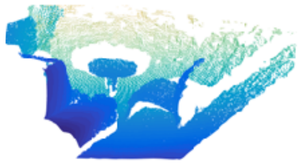
Dimension reduction

Bird's eye view detectors



Leveraging Sparsity in 3D

Point set deep nets
Sparse 3D conv, GNNs



E.g.: **Frustum PointNets [6]** **PointPillars [7]** **VoteNet [8]**

Bird’s eye view 3D object detector

- Key idea: Converting the 3D learning problem to a 2D learning problem.

Volumetric and Multi-View CNNs for Object Classification on 3D Data (CVPR’16) by Qi et al. [12]

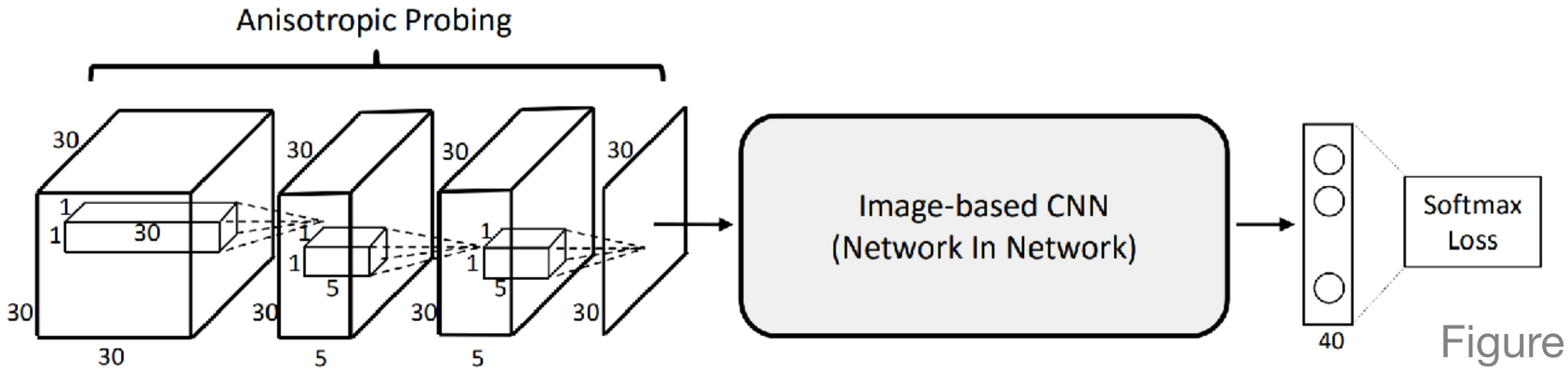


Figure from [12]

3D CNN with Anisotropic Probing kernels.
We **use an elongated kernel to convolve the 3D cube and aggregate information to a 2D plane.**
Then we use a 2D NIN (NIN-CIFAR10 [23]) to classify the 2D projection of the original 3D shape.

Bird’s eye view 3D object detector

- Key idea: Converting the 3D learning problem to a 2D learning problem.

The work that started the KITTI 3D object detection challenge:

Multi-View 3D Object Detection Network for Autonomous Driving (2017) [13]
- Hand designed features are used to convert a 3D scene point cloud to a bird’s eye image.

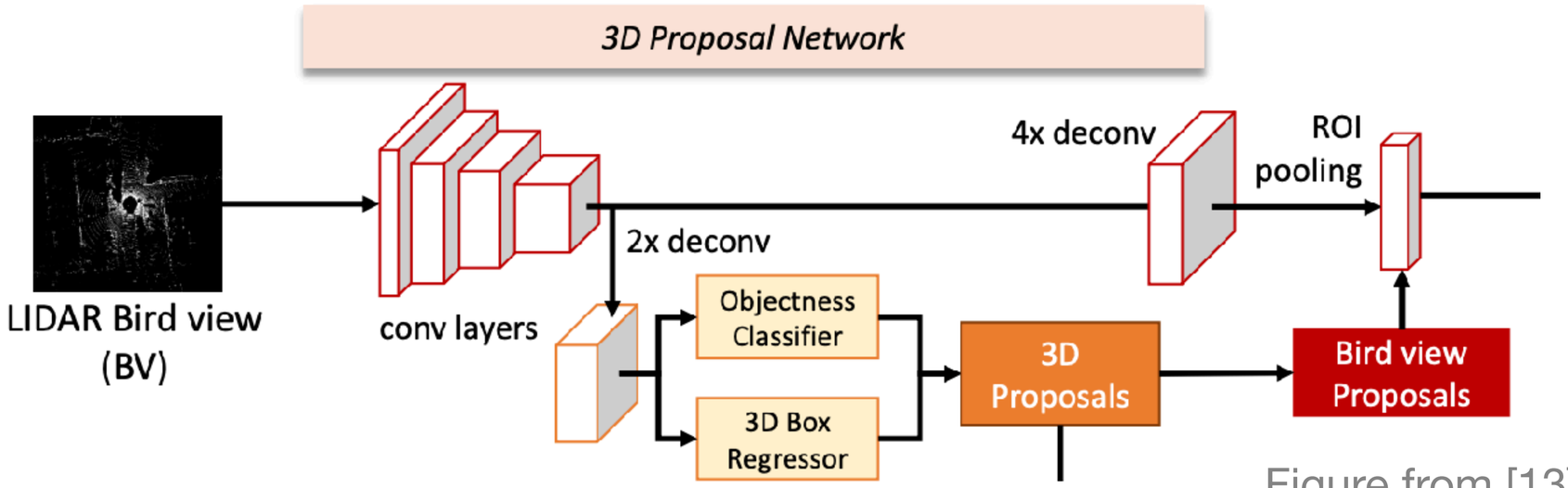


Figure from [13]

Bird’s eye view 3D object detector

- From hand designed projection to data-driven projection (with PointNet like architectures).

Voxelnet: End-to-end learning for point cloud based 3d object detection (2018) [14]
Pointpillars: Fast encoders for object detection from point clouds (2019) [7]

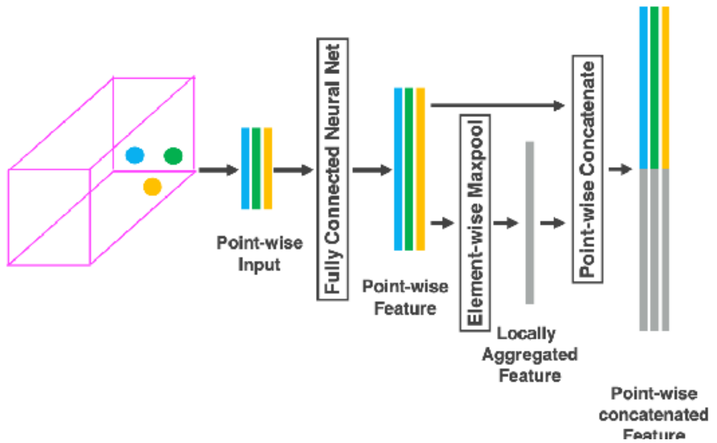


Figure from [14]

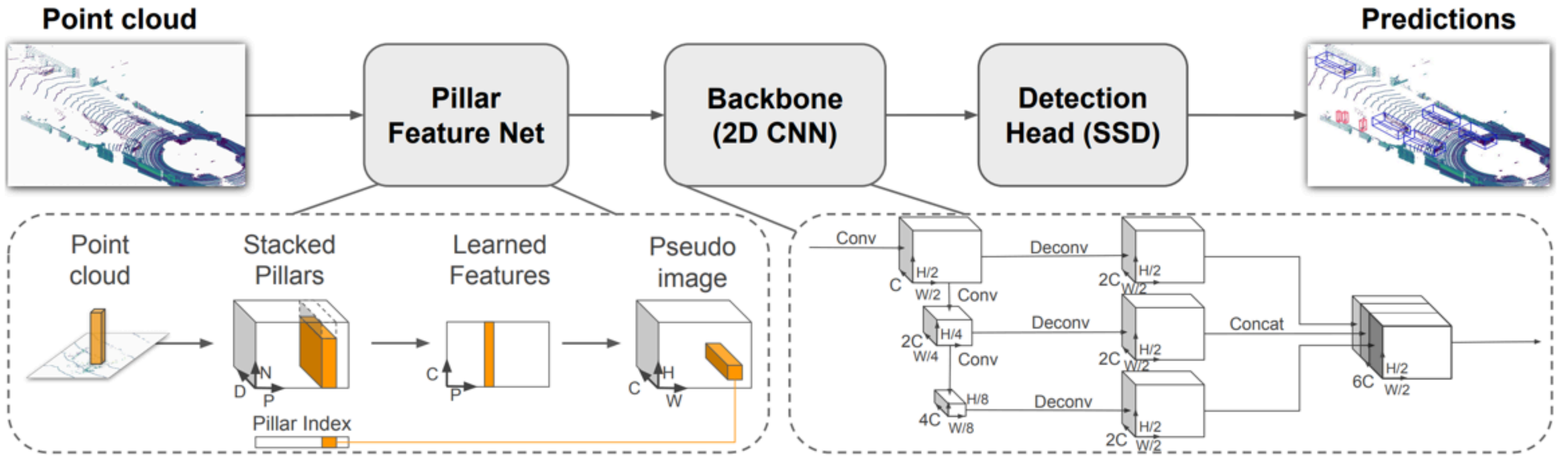
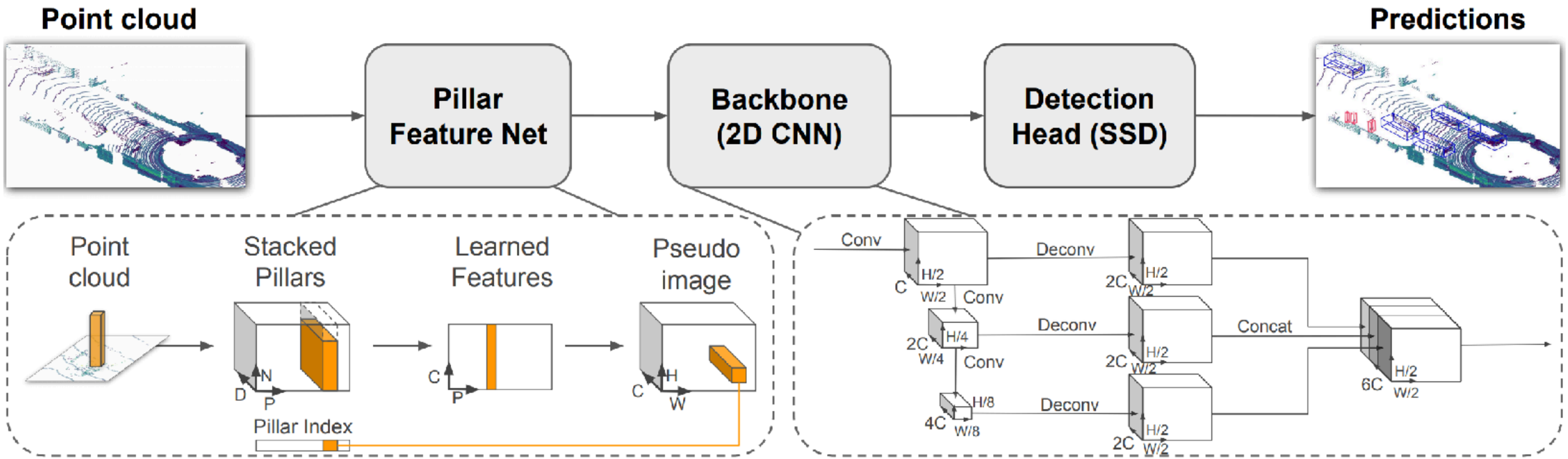


Figure from [7]

PointPillars



Handling sparsity in the top-down image (typically, >90% of the pixels are empty):
D: point dimension/number of channels.
P: the maximum number of non-empty pillars per sample (the buffer size).
N: the maximum number of points to keep per pillar (the buffer size).

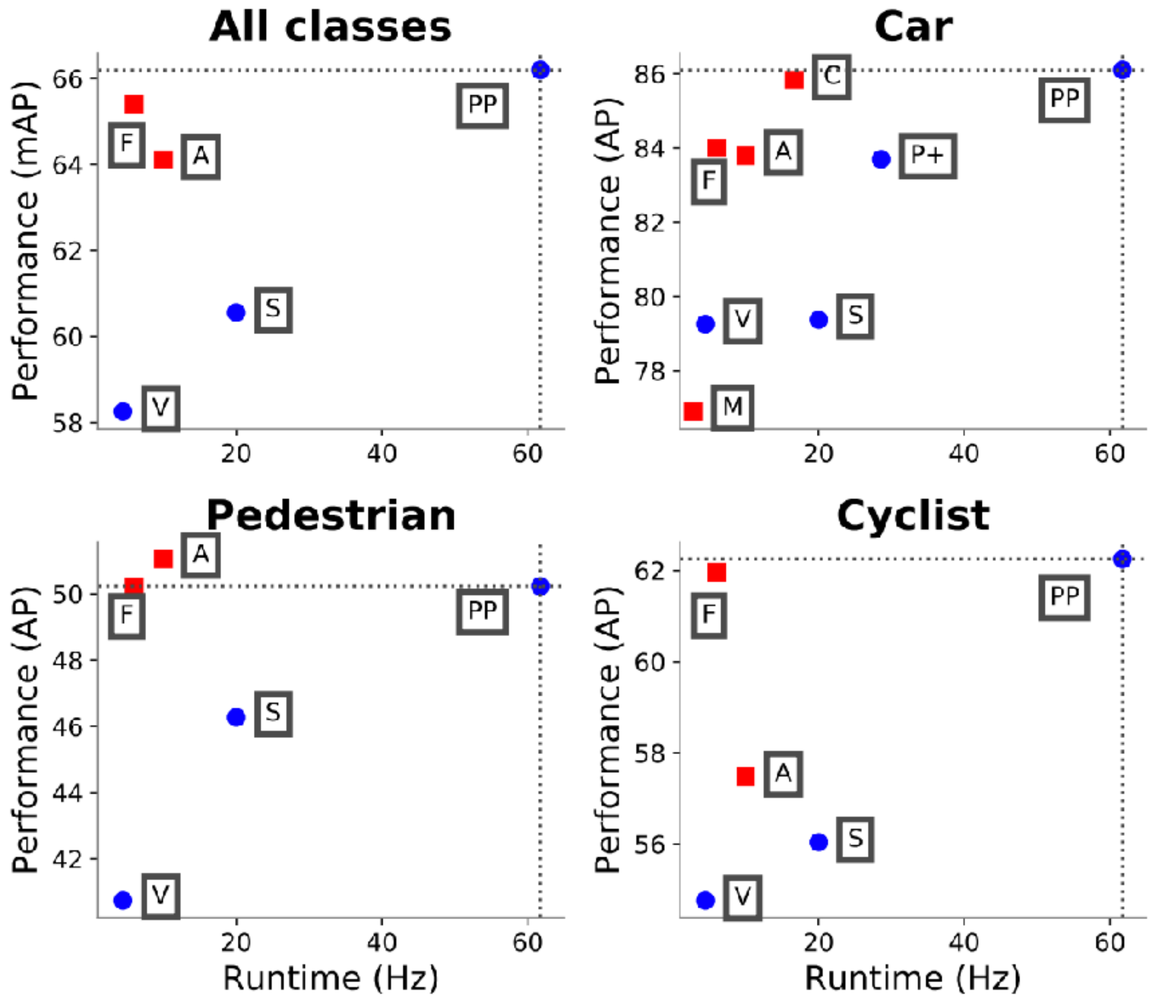
PointPillars

The biggest advantages:

- Inference speed.
- Simplicity.

Weaknesses:

- Assumption of a projection plane (not generalizable to more complex 3d scenes).
- Aggressive compression of the dimension.



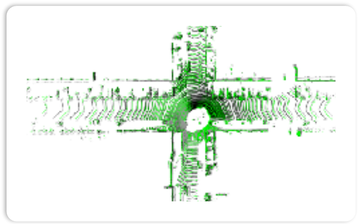
The deep learning era of 3d object detection

Image-driven

Monocular view detectors
Frustum-based detectors

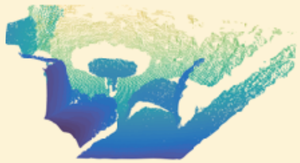
Dimension reduction

Bird's eye view detectors



Leveraging Sparsity in 3D

Point set deep nets
Sparse 3D conv, GNNs



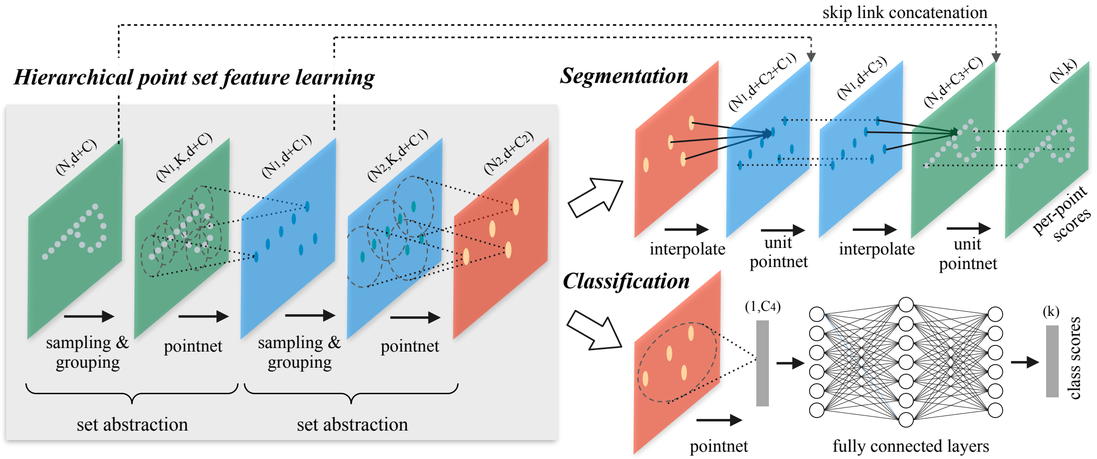
E.g.: **Frustum PointNets [6]** **PointPillars [7]** **VoteNet [8]**

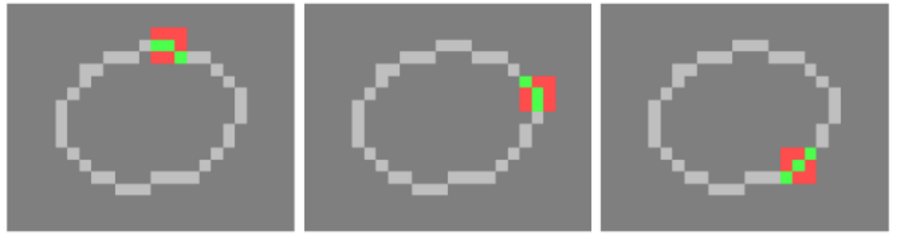
Point cloud based 3D object detectors

- Key idea: Use sparsity aware backbone architectures (e.g. PointNet++, Sparse 3D convnet) and design 3D detection frameworks that leverage sparsity.

Deep Hough Voting for 3D Object Detection in Point Clouds (2019) [8]
PointRCNN: 3D Object Proposal Generation and Detection from Point Cloud (2019) [15]
STD: Sparse-to-Dense 3D Object Detector for Point Cloud (2019) [16]
3DSSD: Point-based 3D Single Stage Object Detector (2020) [17]
Pv-rcnn: Point-voxel feature set abstraction for 3d object detection (2020) [18]

PointNet++





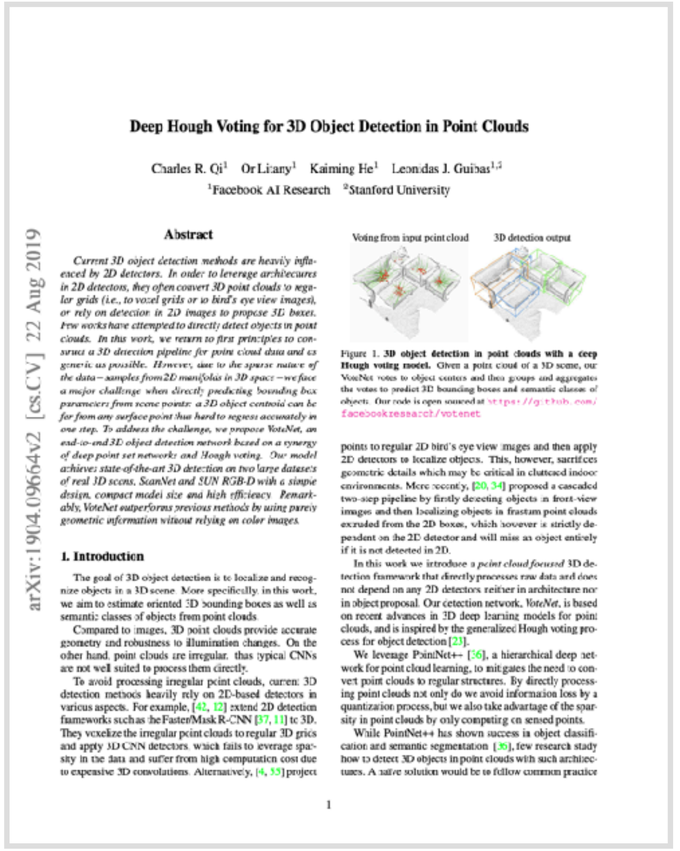
Sub manifold sparse 3d conv

Deep Hough Voting for 3D Object Detection in Point Clouds

Charles R. Qi, Or Litany, Kaiming He, Leonidas Guibas.

ICCV 2019

Best Paper Nominee



Deep Hough Voting for 3D Object Detection in Point Clouds

Charles R. Qi[1] Or Litany[1] Kaiming He[1] Leonidas J. Guibas[1,2]
[1]Facebook AI Research [2]Stanford University

arXiv:1904.09664v2 [cs.CV] 22 Aug 2019

Abstract

Current 3D object detection methods are heavily influenced by 2D detectors. In order to leverage architectures in 2D detectors, they often convert 3D point clouds to regular grids (i.e., to voxel grids or to bird's eye view images), or rely on detection in 2D images to propose 3D boxes. Few works have attempted to directly detect objects in point clouds. In this work, we return to first principles to construct a 3D detection pipeline for point cloud data and as generic as possible. However, due to the sparse nature of the data – samples from 2D manifolds in 3D space – we face a major challenge when directly predicting bounding box parameters from scene points: a 3D object centroid can be far from any surface point thus hard to regress accurately in one step. To address the challenge, we propose VoteNet, an end-to-end 3D object detection network based on a synergy of deep point set networks and Hough voting. Our model achieves state-of-the-art 3D detection on two large datasets of real 3D scans, ScanNet and SUN RGB-D with a simple design, compact model size and high efficiency. Remarkably, VoteNet outperforms previous methods by using purely geometric information without relying on color images.

1. Introduction

The goal of 3D object detection is to localize and recognize objects in a 3D scene. More specifically, in this work, we aim to estimate oriented 3D bounding boxes as well as semantic classes of objects from point clouds.

Compared to images, 3D point clouds provide accurate geometry and robustness to illumination changes. On the other hand, point clouds are irregular, thus typical CNNs are not well suited to process them directly.

To avoid processing irregular point clouds, current 3D detection methods heavily rely on 2D-based detectors in various aspects. For example, [42, 12] extend 2D detection frameworks such as the Faster/Mask R-CNN [37, 11] to 3D. They voxelize the irregular point clouds to regular 3D grids and apply 3D CNN detectors which fails to leverage sparsity in the data and suffer from high computation cost due to expensive 3D convolutions. Alternatively, [4, 33] project

Voting from input point cloud 3D detection output

Figure 1. **3D object detection in point clouds with a deep Hough voting model.** Given a point cloud of a 3D scene, our VoteNet votes to object centers and then groups and aggregates the votes to predict 3D bounding boxes and semantic classes of objects. Our code is open sourced at https://github.com/facebookresearch/votenet

points to regular 2D bird's eye view images and then apply 2D detectors to localize objects. This, however, sacrifices geometric details which may be critical in cluttered indoor environments. More recently, [20, 34] proposed a cascaded two-step pipeline by firstly detecting objects in front-view images and then localizing objects in frustum point clouds extruded from the 2D boxes, which however is strictly dependent on the 2D detector and will miss an object entirely if it is not detected in 2D.

In this work we introduce a *point cloud focused* 3D detection framework that directly processes raw data and does not depend on any 2D detectors neither in architecture nor in object proposal. Our detection network, *VoteNet*, is based on recent advances in 3D deep learning models for point clouds, and is inspired by the generalized Hough voting process for object detection [23].

We leverage PointNet++ [36], a hierarchical deep network for point cloud learning, to mitigates the need to convert point clouds to regular structures. By directly processing point clouds not only do we avoid information loss by a quantization process, but we also take advantage of the sparsity in point clouds by only computing on sensed points.

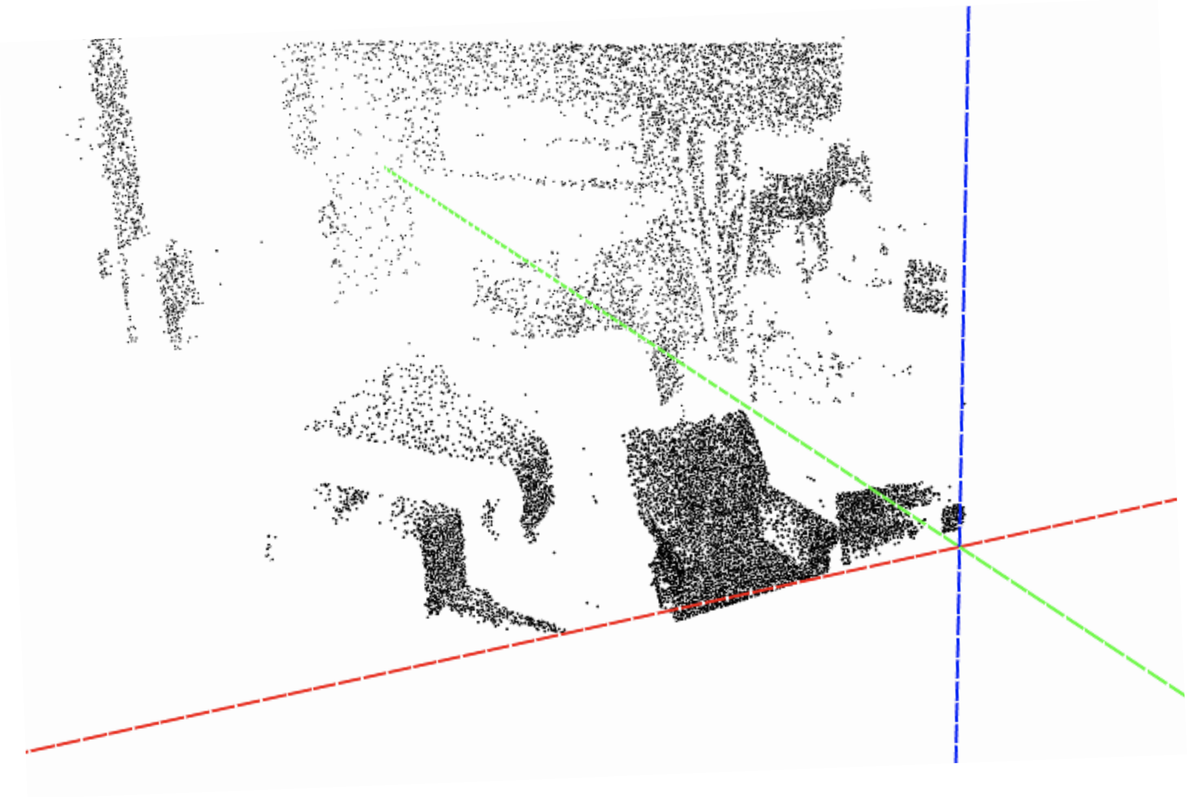
While PointNet++ has shown success in object classification and semantic segmentation [36], few research study how to detect 3D objects in point clouds with such architectures. A naive solution would be to follow common practice

1

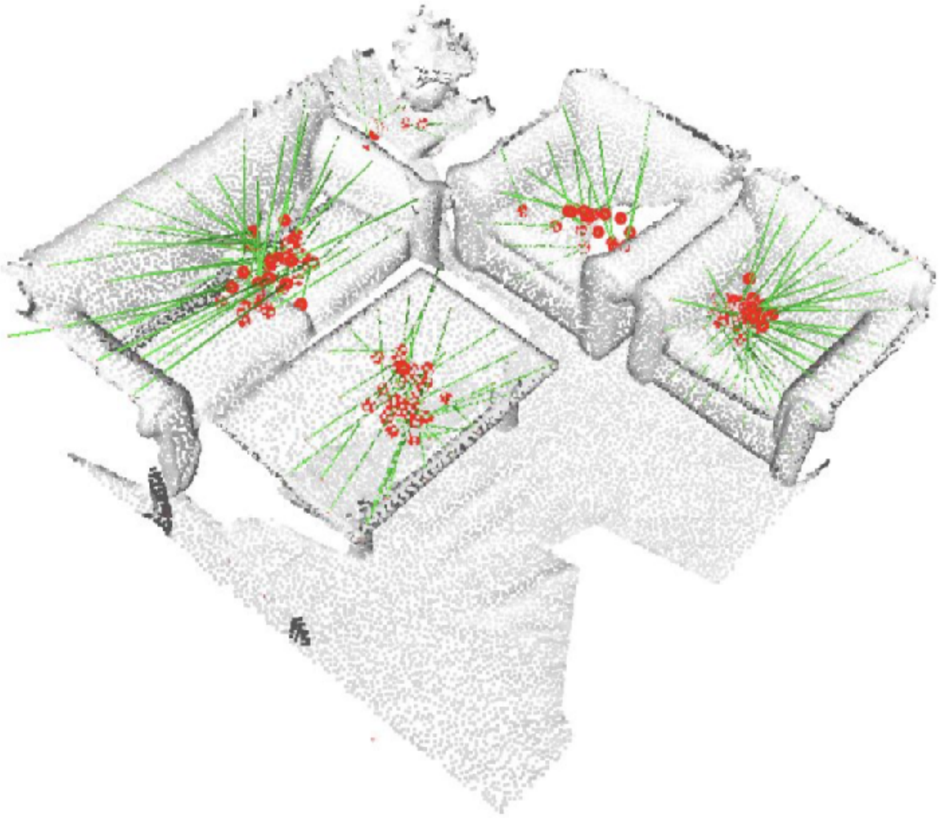
Observation: 2D v.s. 3D

Dense 2D pixel array

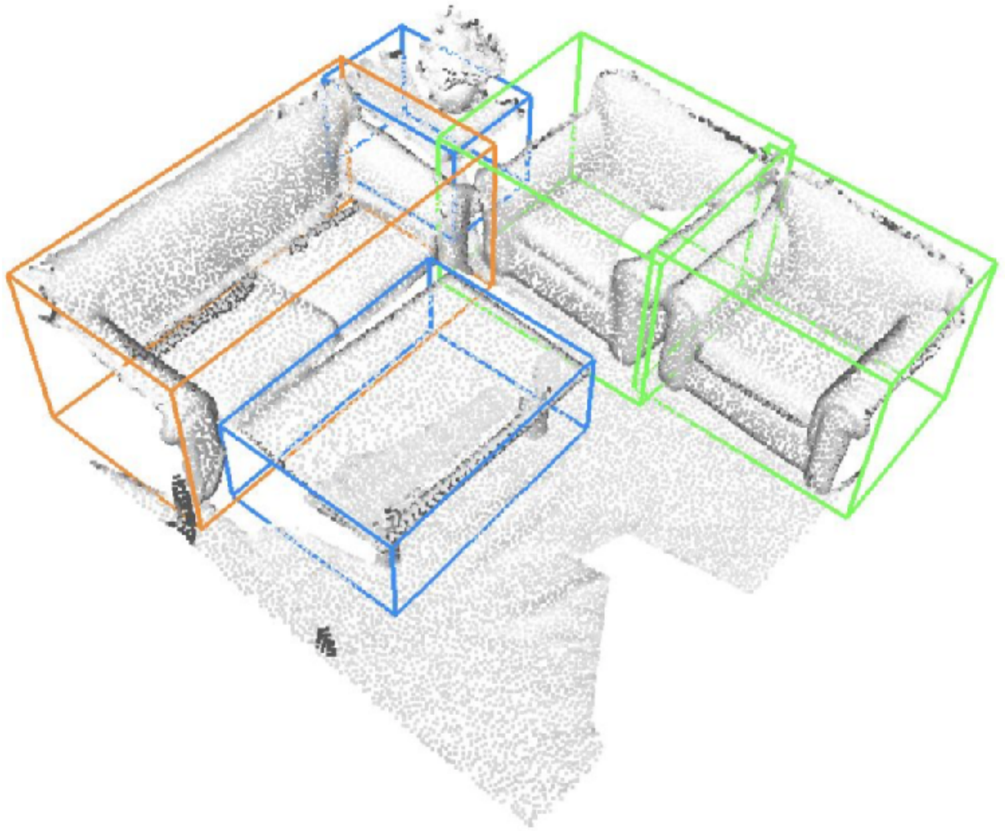
Sparse 3D points
(only on object surfaces)



Our solution: Voting



Voting from surface points



Detected 3D bounding boxes

GENERALIZING THE HOUGH TRANSFORM TO DETECT ARBITRARY SHAPES*

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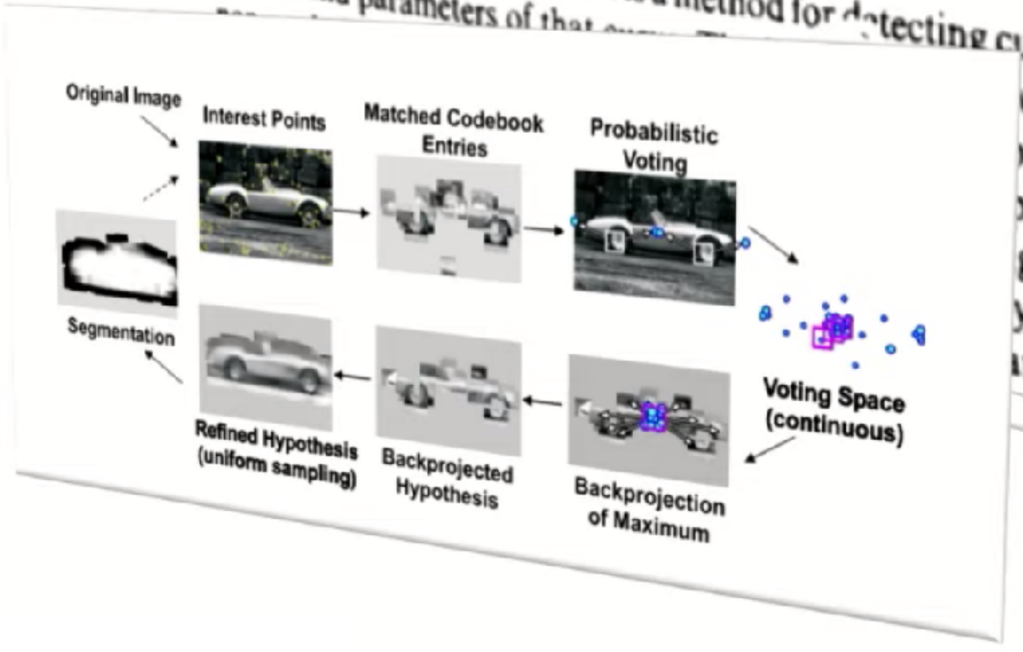
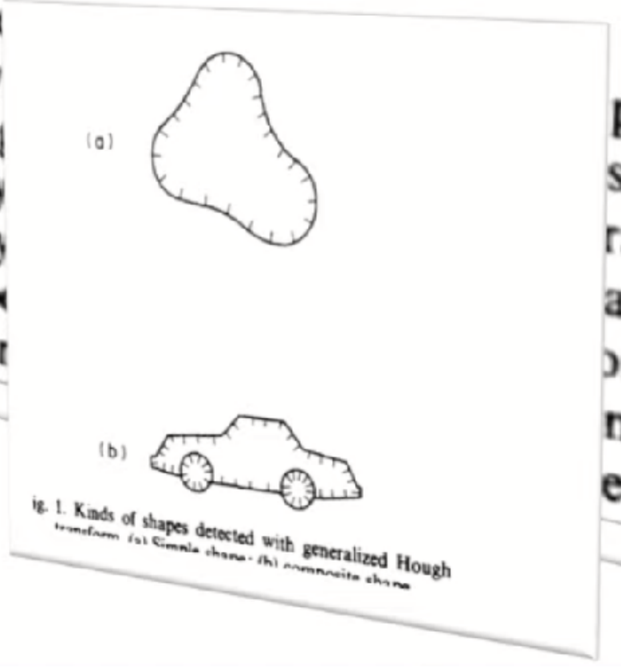
Computer Science Department, University of Rochester, Rochester, NY 14627, U.S.A.

(Received 10 October 1979; in revised form 9 September 1980; received for publication 23 September 1980)

Abstract—The Hough transform is a method for detecting curves by
a curve and parameters of that



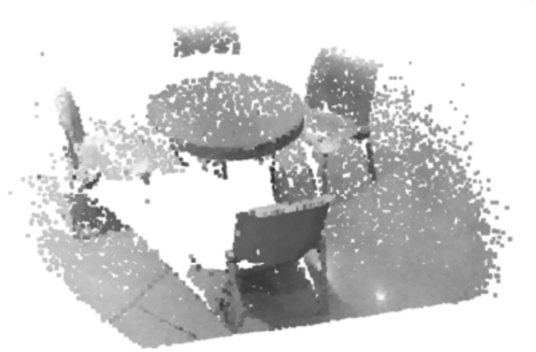


ig. 1. Kinds of shapes detected with generalized Hough

points on
s[1,2] and
ralized to
as.[6] The
ons.[7,8,9]
mapping
es of that

Deep Hough voting: Detection pipeline

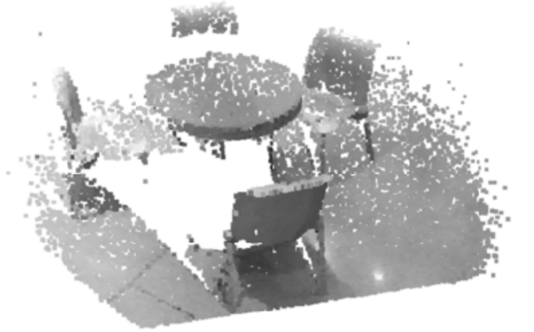
Input:
point cloud



PointNet++

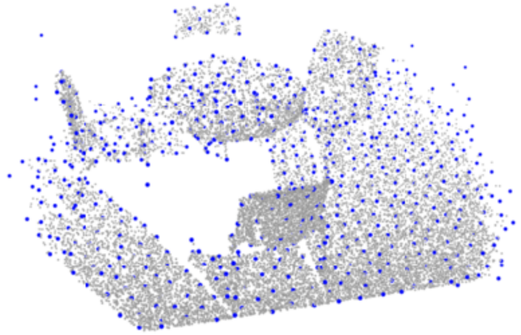
Deep Hough voting: Detection pipeline

Input:
point cloud



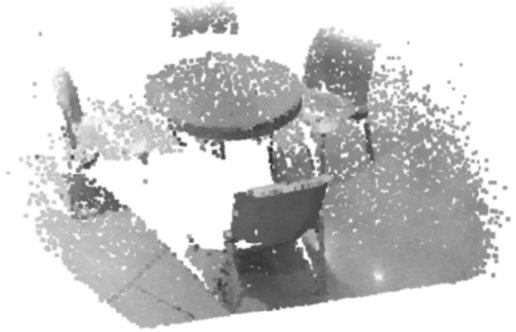
PointNet++

Seeds
(XYZ + feature)



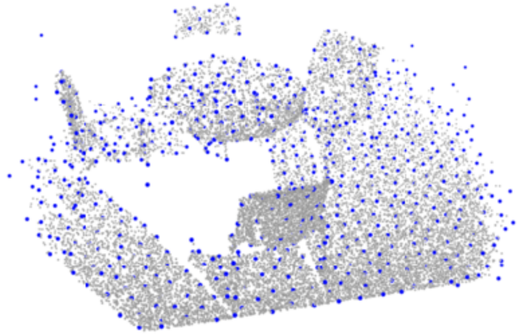
Deep Hough voting: Detection pipeline

Input:
point cloud

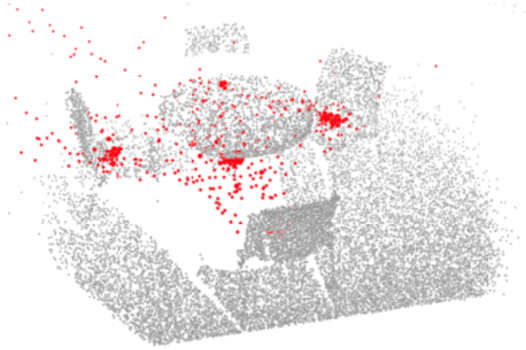


PointNet++

Seeds
(XYZ + feature)

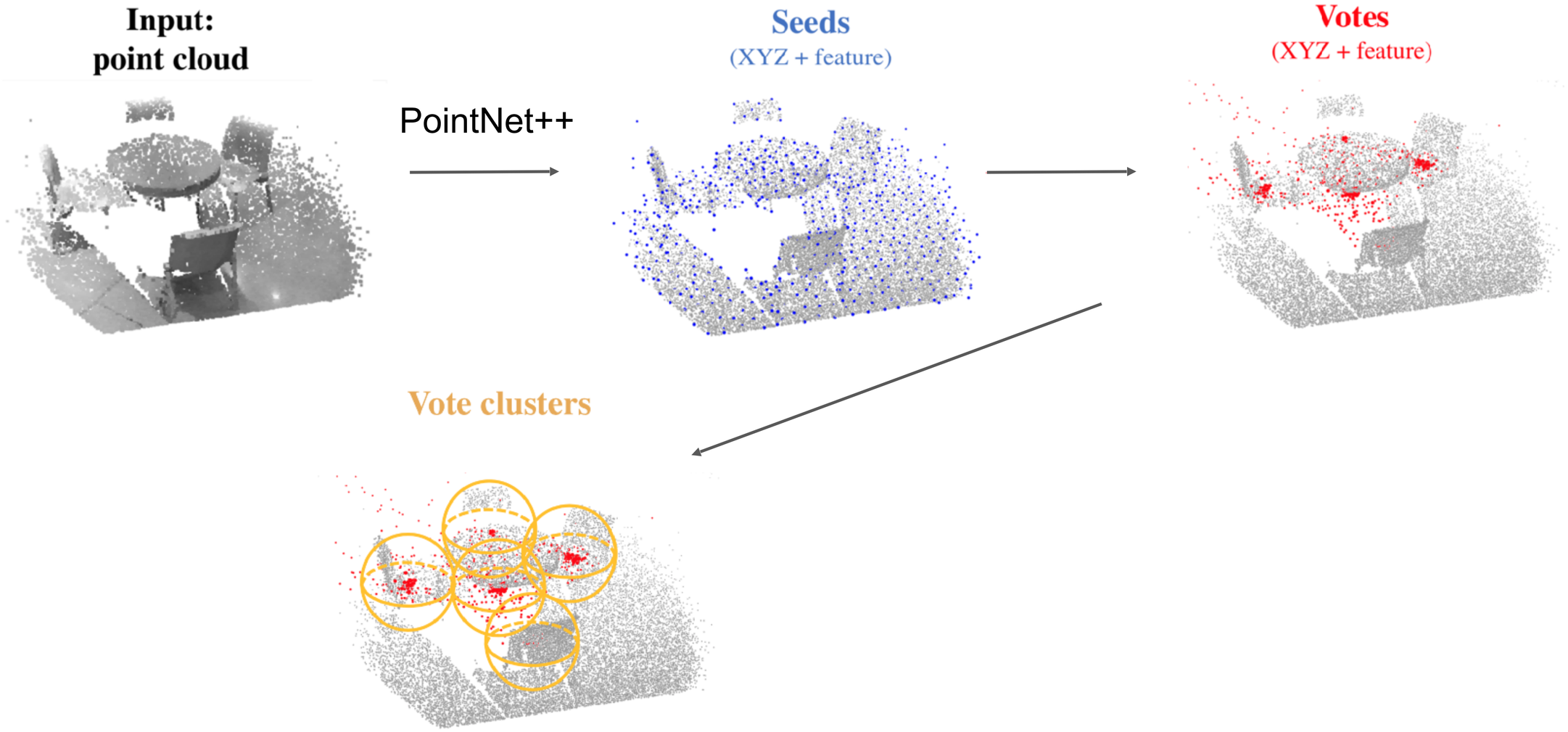


Votes
(XYZ + feature)

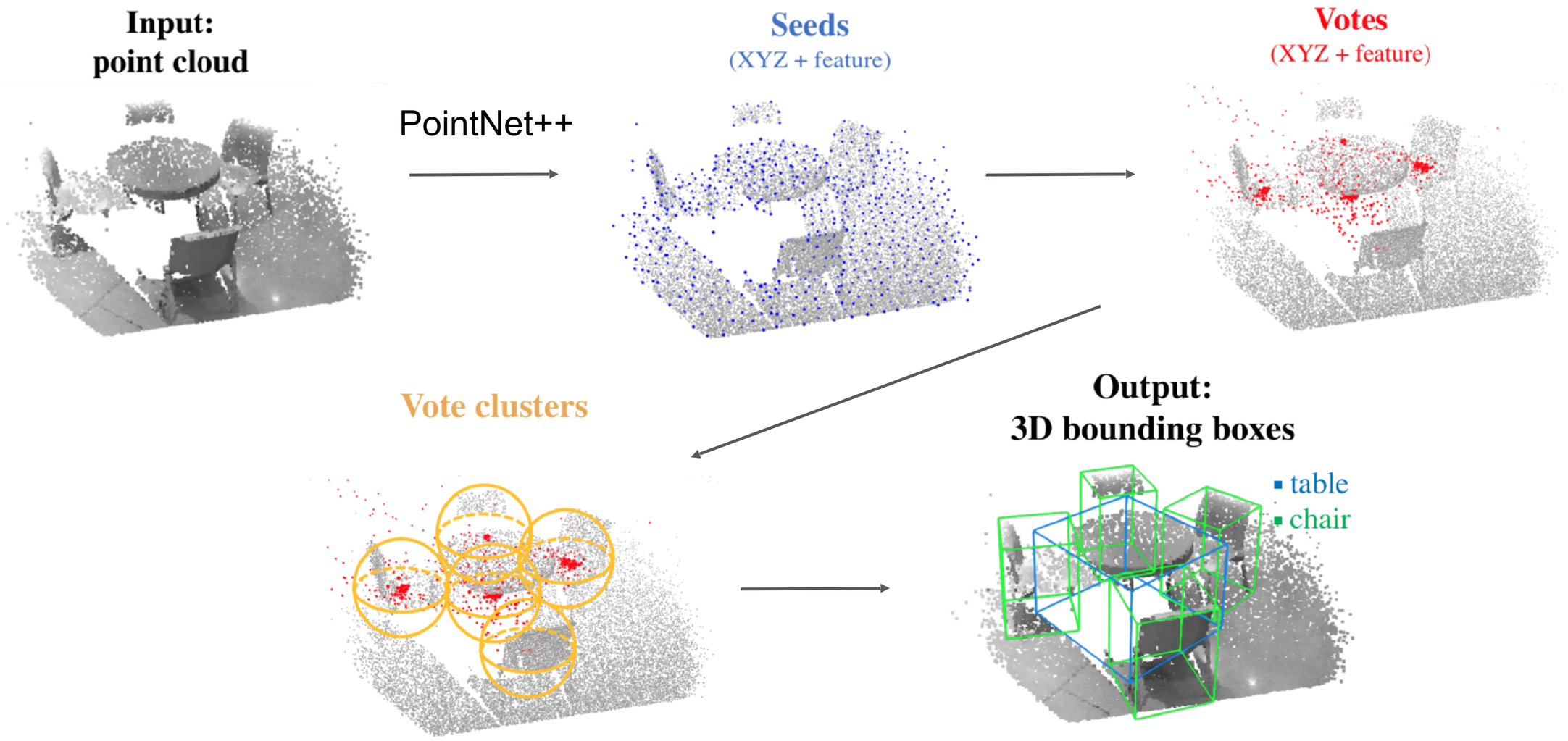


Explicit supervision for the votes (the XYZ translations)

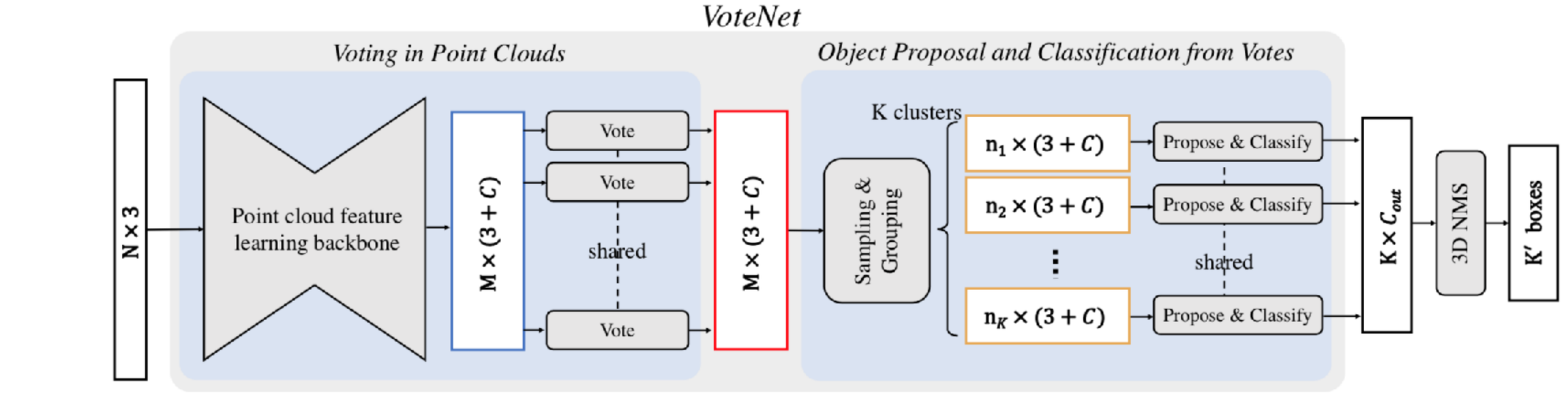
Deep Hough voting: Detection pipeline



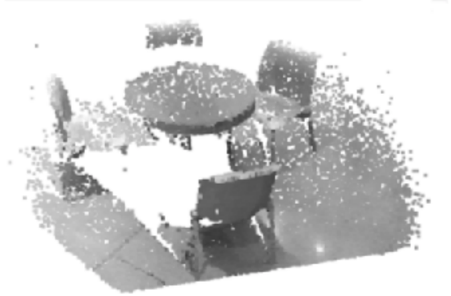
Deep Hough voting: Detection pipeline



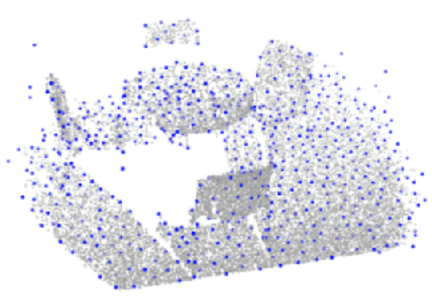
Deep Hough voting: Detection pipeline



Input:
point cloud

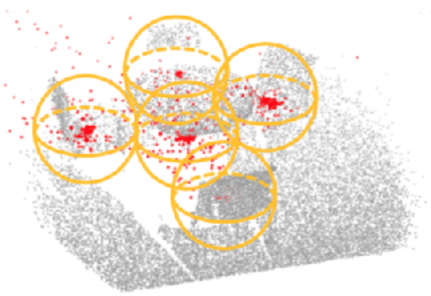


Seeds
(XYZ + feature)

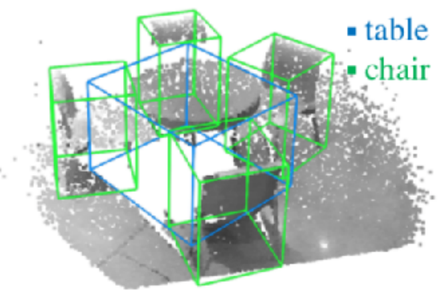


Votes
(XYZ + feature)

Vote clusters



Output:
3D bounding boxes

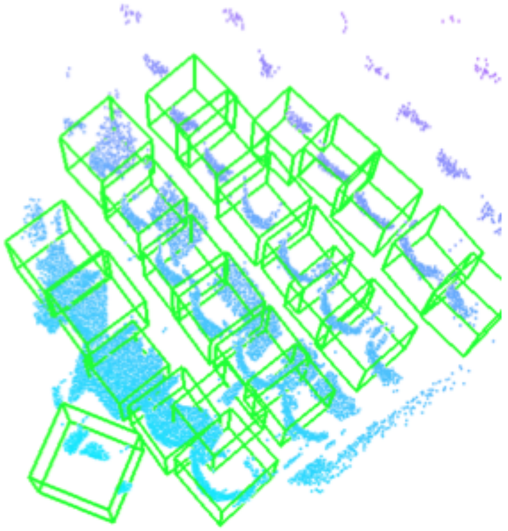


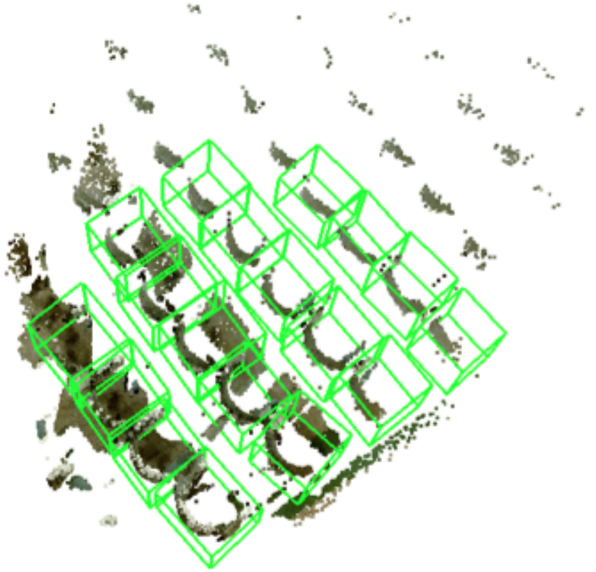
Results: SUN RGB-D (single depth images)

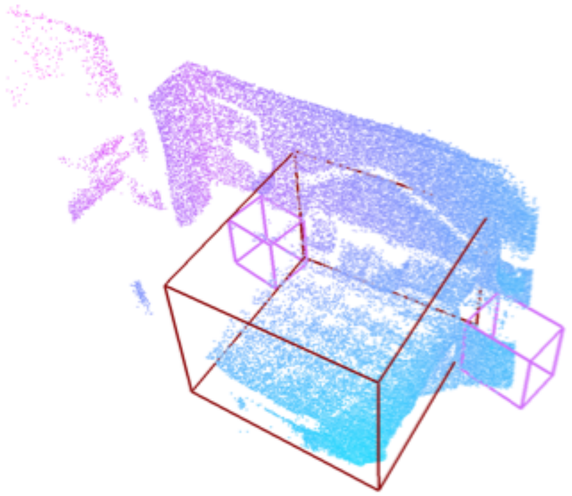
Image of the scene

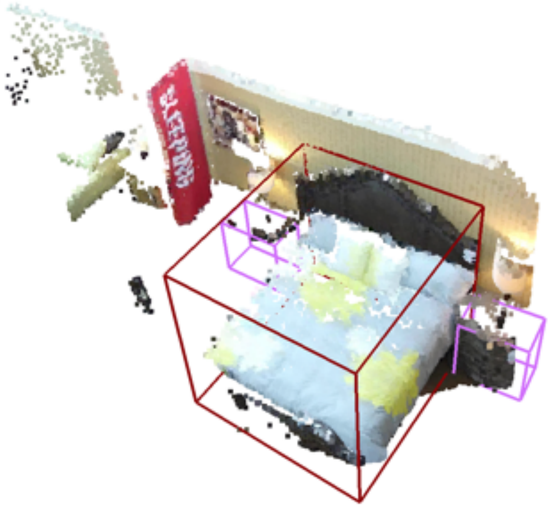
VoteNet prediction

Ground truth



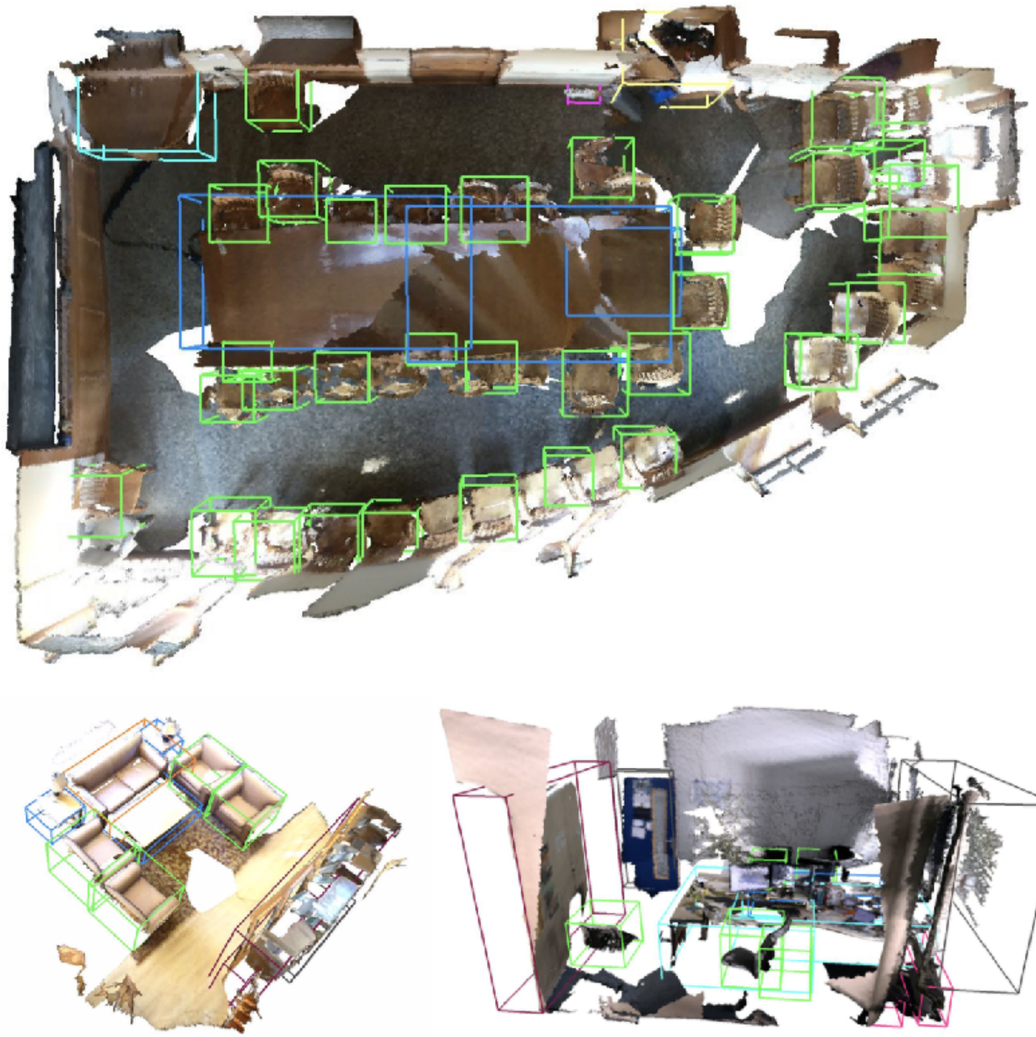




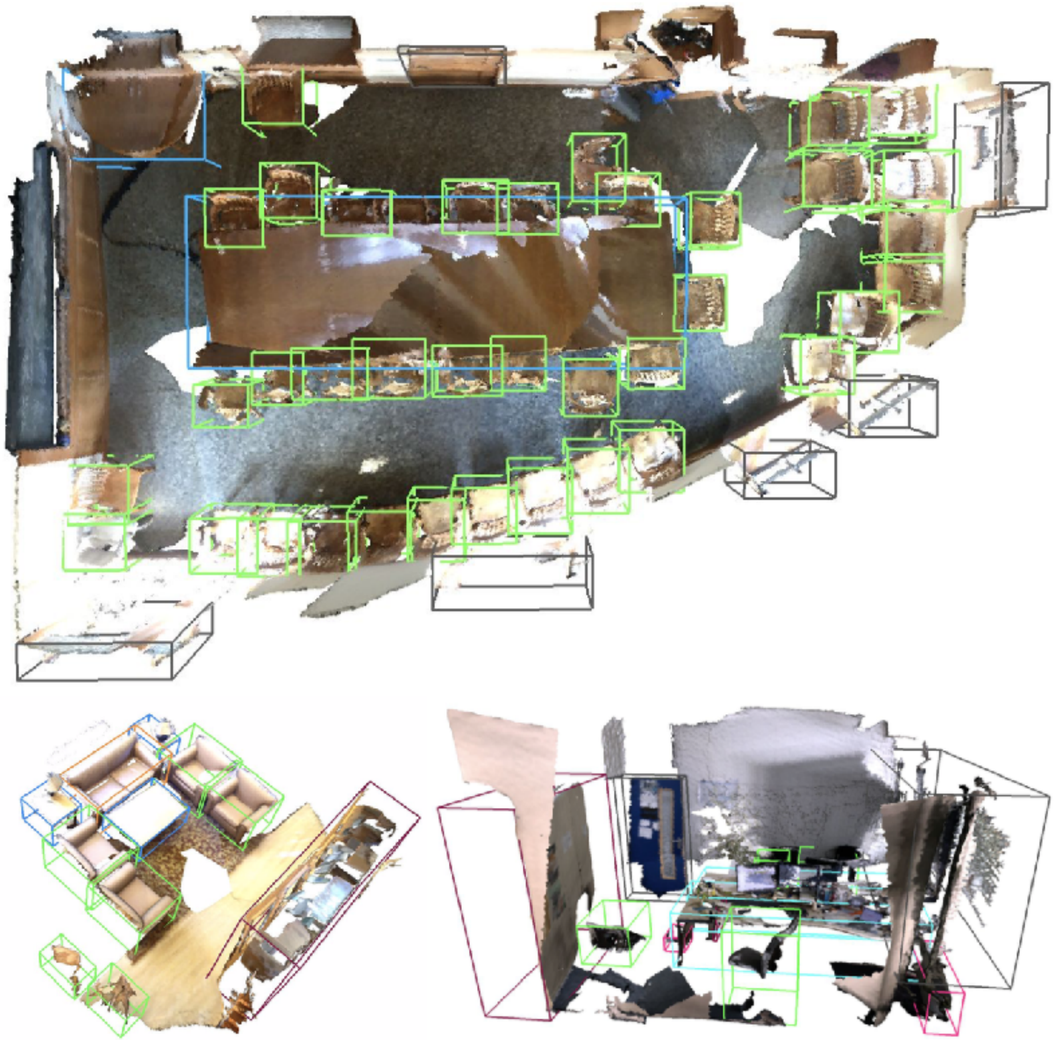


Results: ScanNet (3D reconstructions)

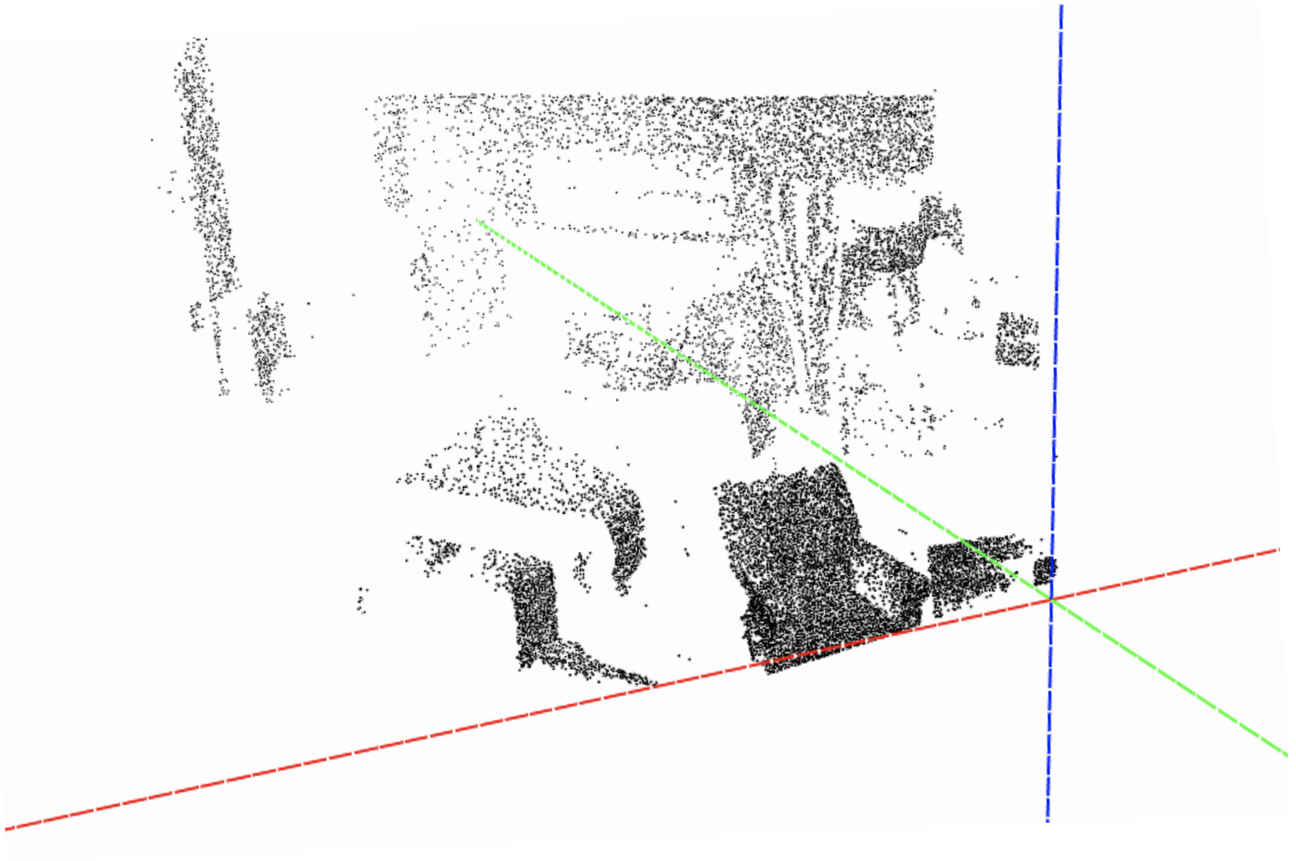
VoteNet prediction



Ground truth



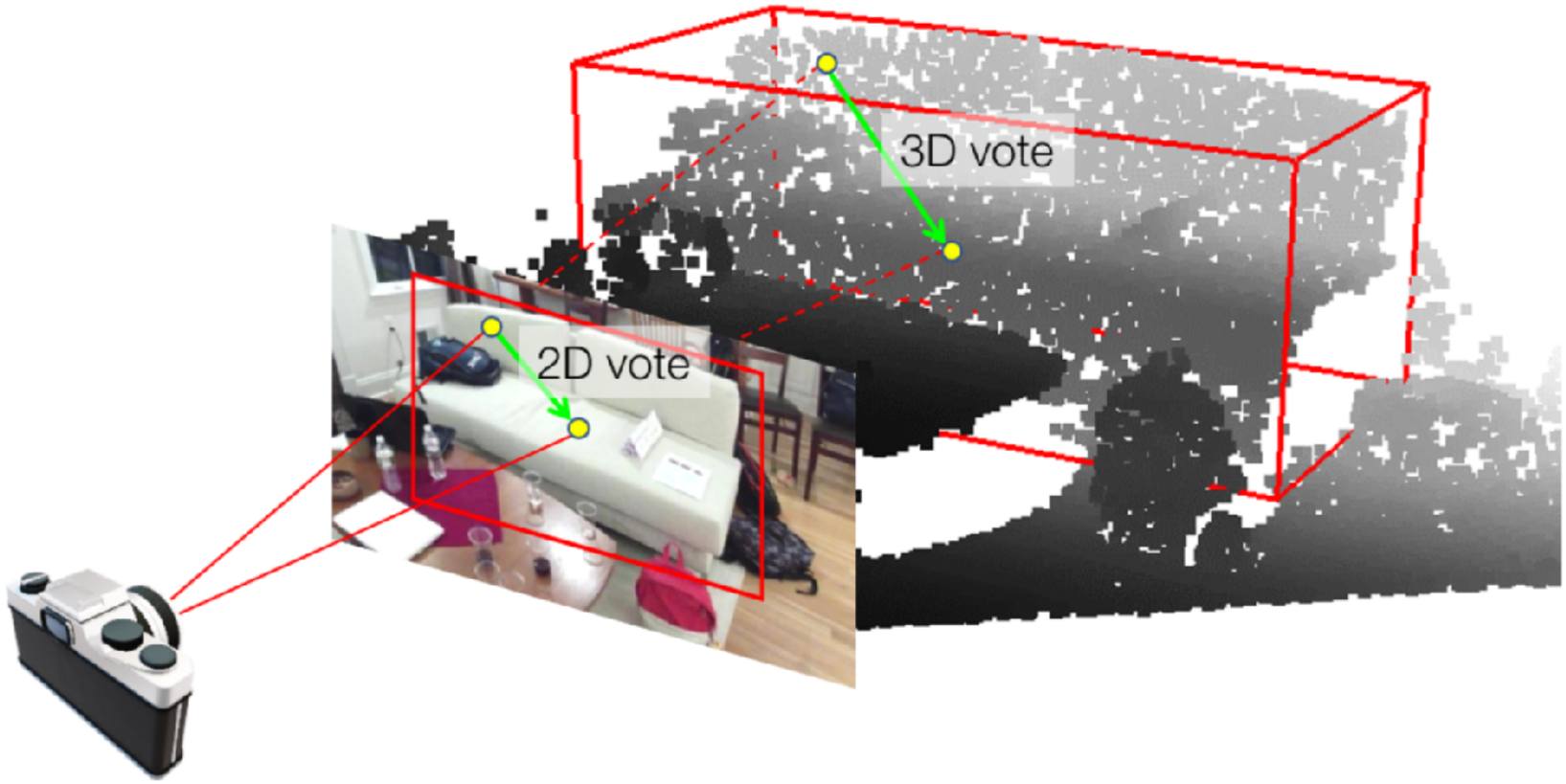
Can images help the VoteNet detection?



*Images are in **high resolution**, have **rich texture**, and can even provide useful geometric cues for object localization & shape/pose estimation.*

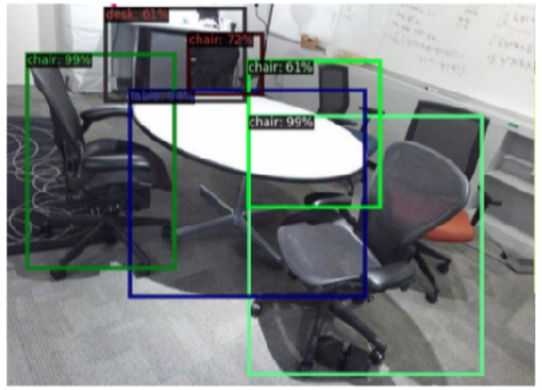
ImVoteNet: Boosting 3D Object Detection in Point Clouds with Image Votes [19]

Charles R. Qi*, Xinlei Chen*, Or Litany, Leonidas Guibas. CVPR 2020.

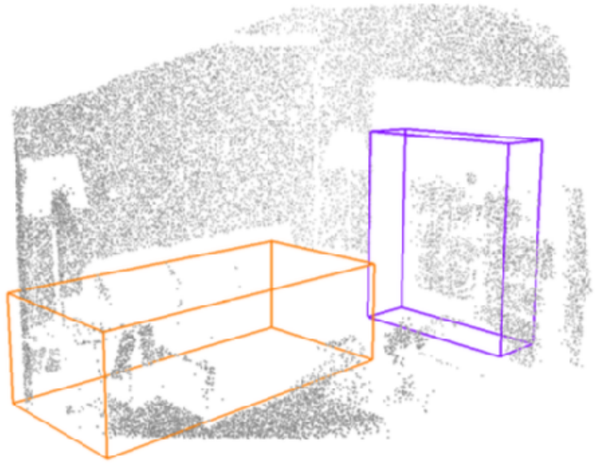


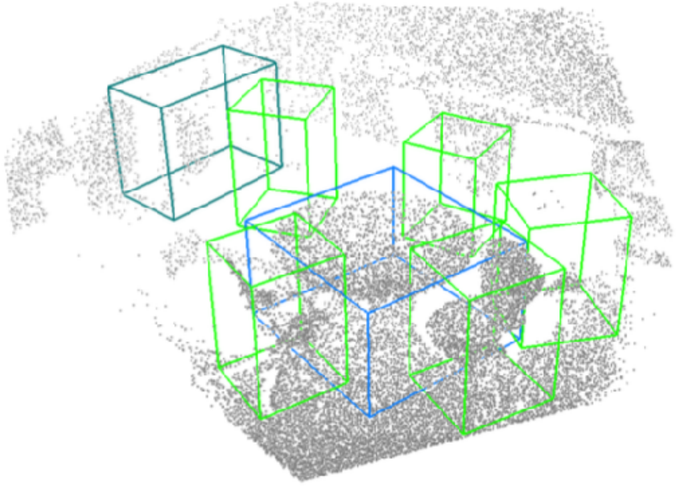
Results on SUN RGB-D

Ours 2D detection

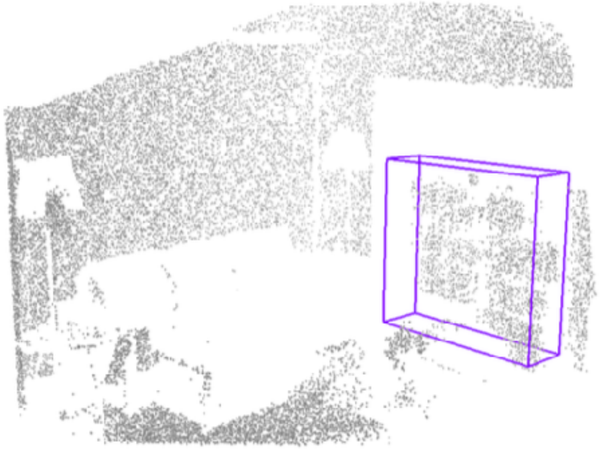


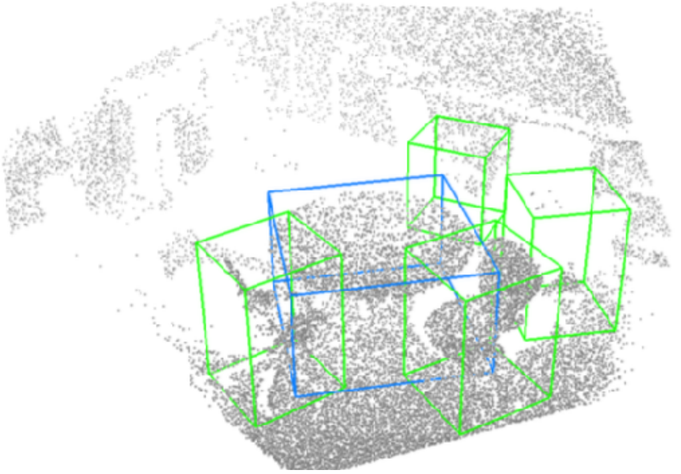
ImVoteNet





VoteNet

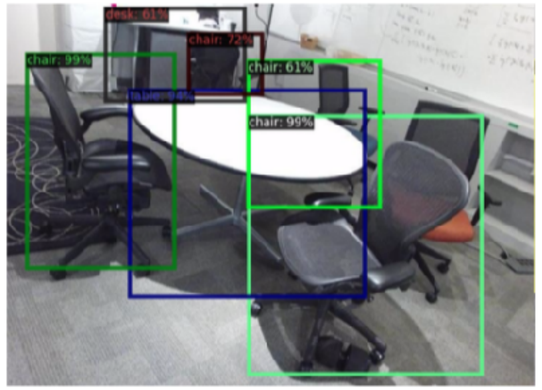




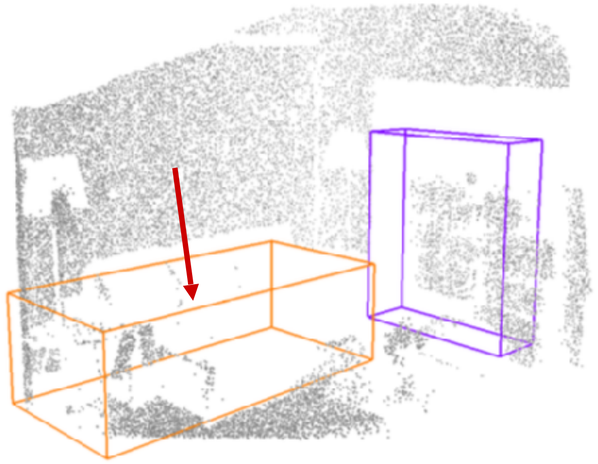
sofa bookshelf chair table desk

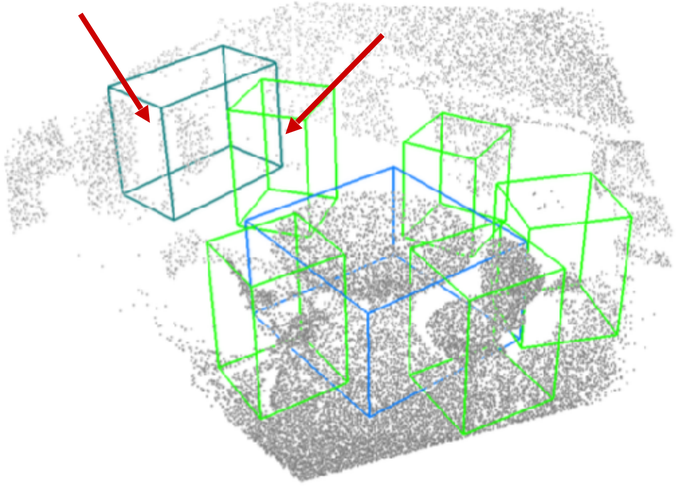
Results on SUN RGB-D

Ours 2D detection

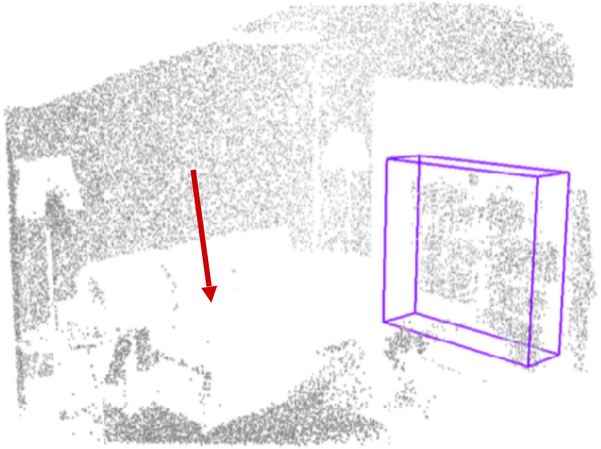


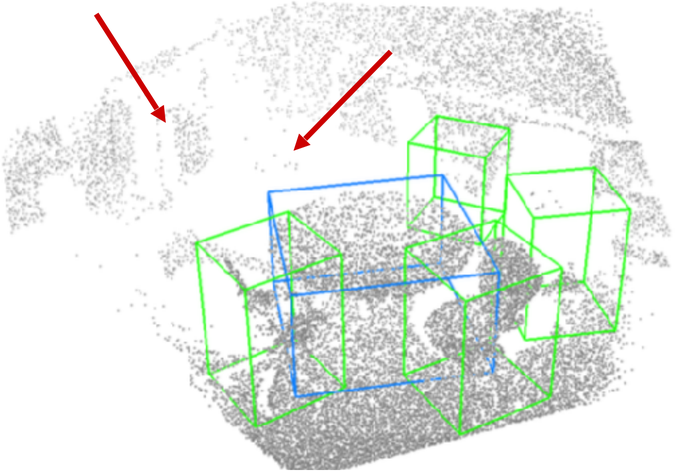
ImVoteNet





VoteNet





sofa bookshelf chair table desk

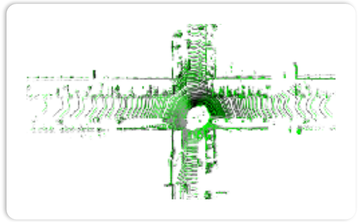
The deep learning era of 3d object detection

Image-driven

Monocular view detectors
Frustum-based detectors

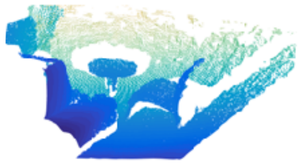
Dimension reduction

Bird's eye view detectors



Leveraging Sparsity in 3D

Point set deep nets
Sparse 3D conv, GNNs



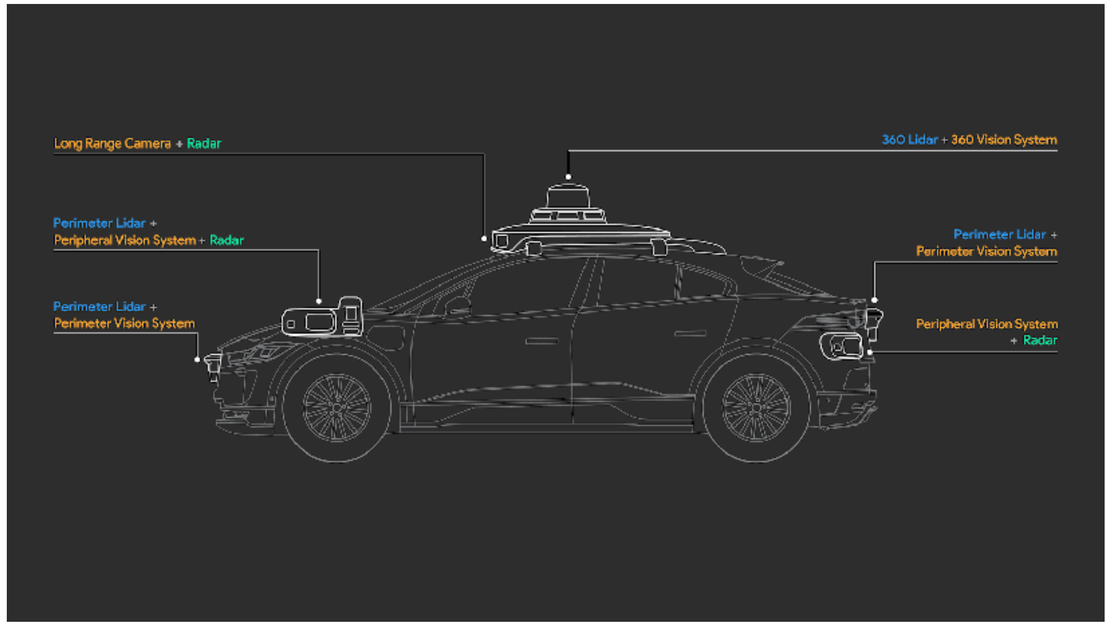
E.g.: **Frustum PointNets [6]** **PointPillars [7]** **VoteNet [8]**

The future of 3D object detection

Input:

Multi-modal input (multi-camera RGB images, Lidar point clouds/depth images, SLAM/SfM point clouds, radar, audio etc.)

Temporal input i.e. sequences.



Source: Waymo (5th generation Waymo driver)

The future of 3D object detection

Machine learning:

Semi-supervised learning
Self-supervised learning
Weakly-supervised learning
Multi-task learning
Adversarial learning
Domain adaptation
Life-long learning
…

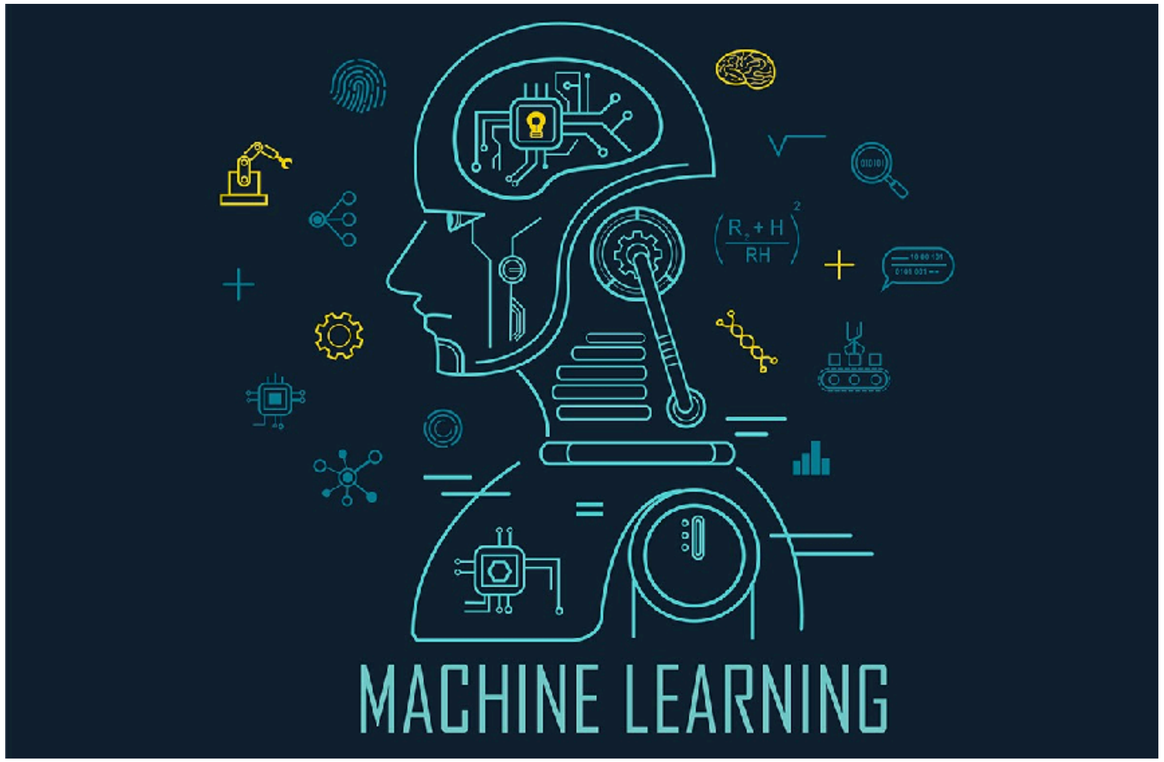


Fig from Anmol Behl

The future of 3D object detection

Robotics:

3D instance detection
6D pose estimation
Template based detection
Few-shot detection
…

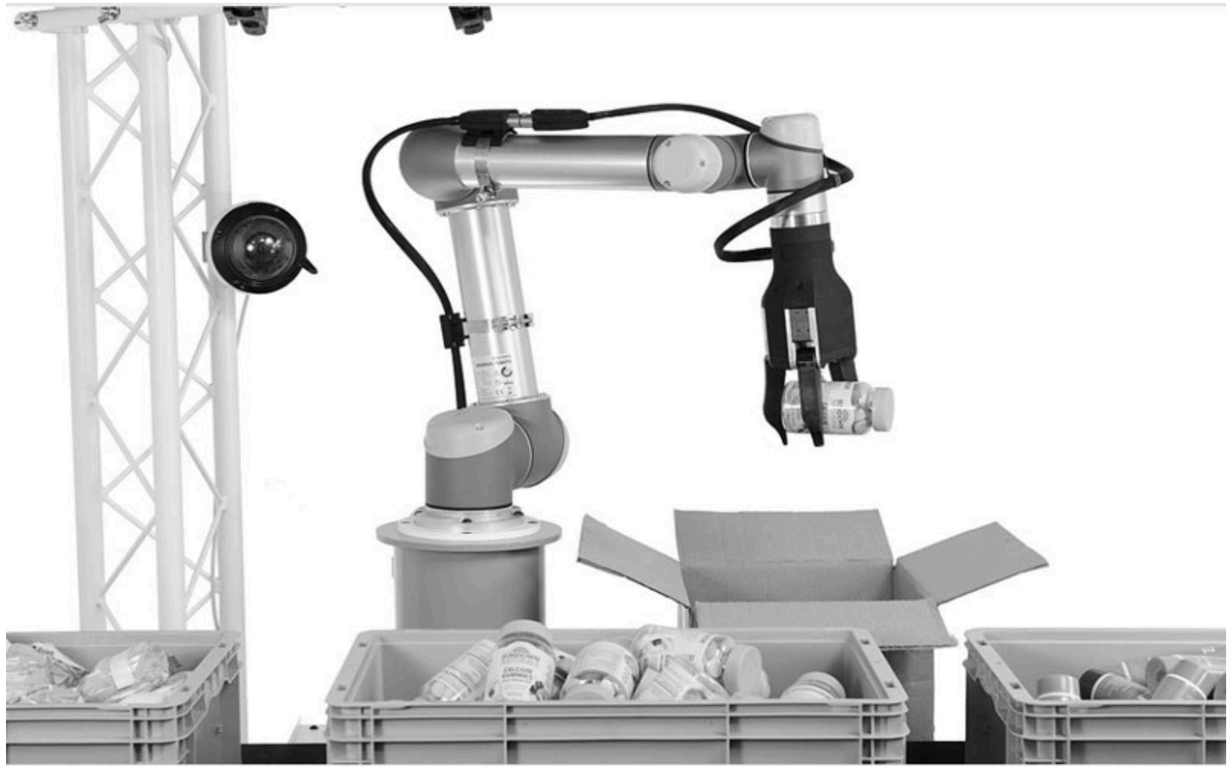


Fig from Frank Tobe

The future of 3D object detection

Continue to push the boundaries

Occluded cases
Long-tail categories
Extreme conditions (no 3d data, bad weather etc.)
…

Source: https://depositphotos.com/vector-images/mountain-climber.html

Summary

- Motivation: A.I. applications in the physical world —> 3D object recognition.
- The history and recent progresses of 3D object detection algorithms.
- Deep dive into three specific 3D object detectors:
  - Frustum PointNets, PointPillar and VoteNet.
- Future research directions of 3D object detection.

Thank you for listening! Q&A time

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