Structured feature detection from point cloud data

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What is Point Cloud ?

Collection of points that represent a 3D shape or feature

Each point has its own set of X, Y and Z coordinates

In some cases additional attributes like reflectance etc.

Most often created by methods used in photogrammetry or remote sensing

- LiDAR sensors are very common tool to collect information about the shape and feature of objects

Attributes

Unlike 2D pixel arrays (images) or 3D voxel arrays, point clouds have an unstructured representation in that the data is simply a collection (more specifically, a set) of the points captured during a lidar or radar sensor scan.

LiDAR

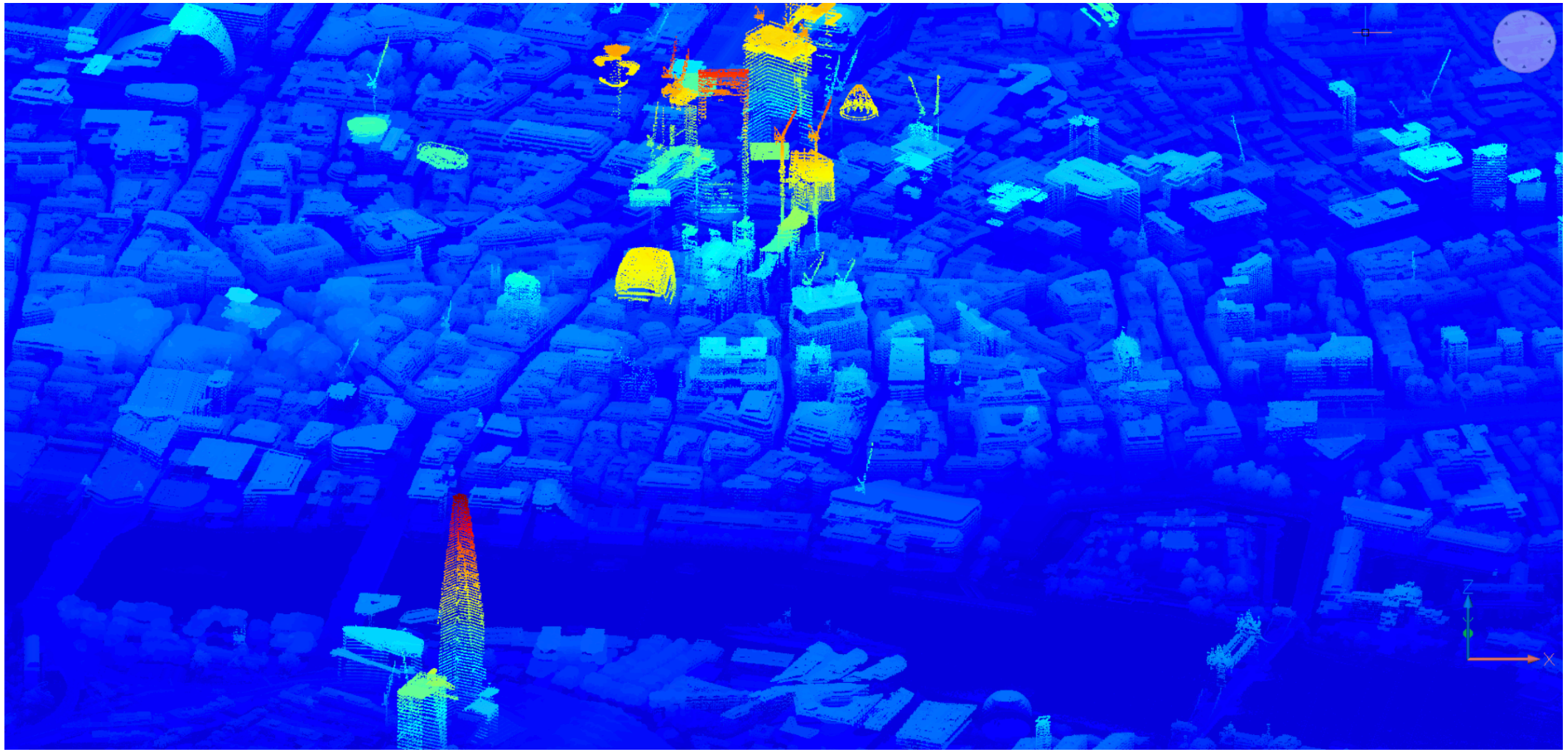
"Light Detection and Ranging"

Mounted to aerial vehicles to send laser pulses to the Earth's surface and once the laser returns back to the sensor, the it will record data based on information received

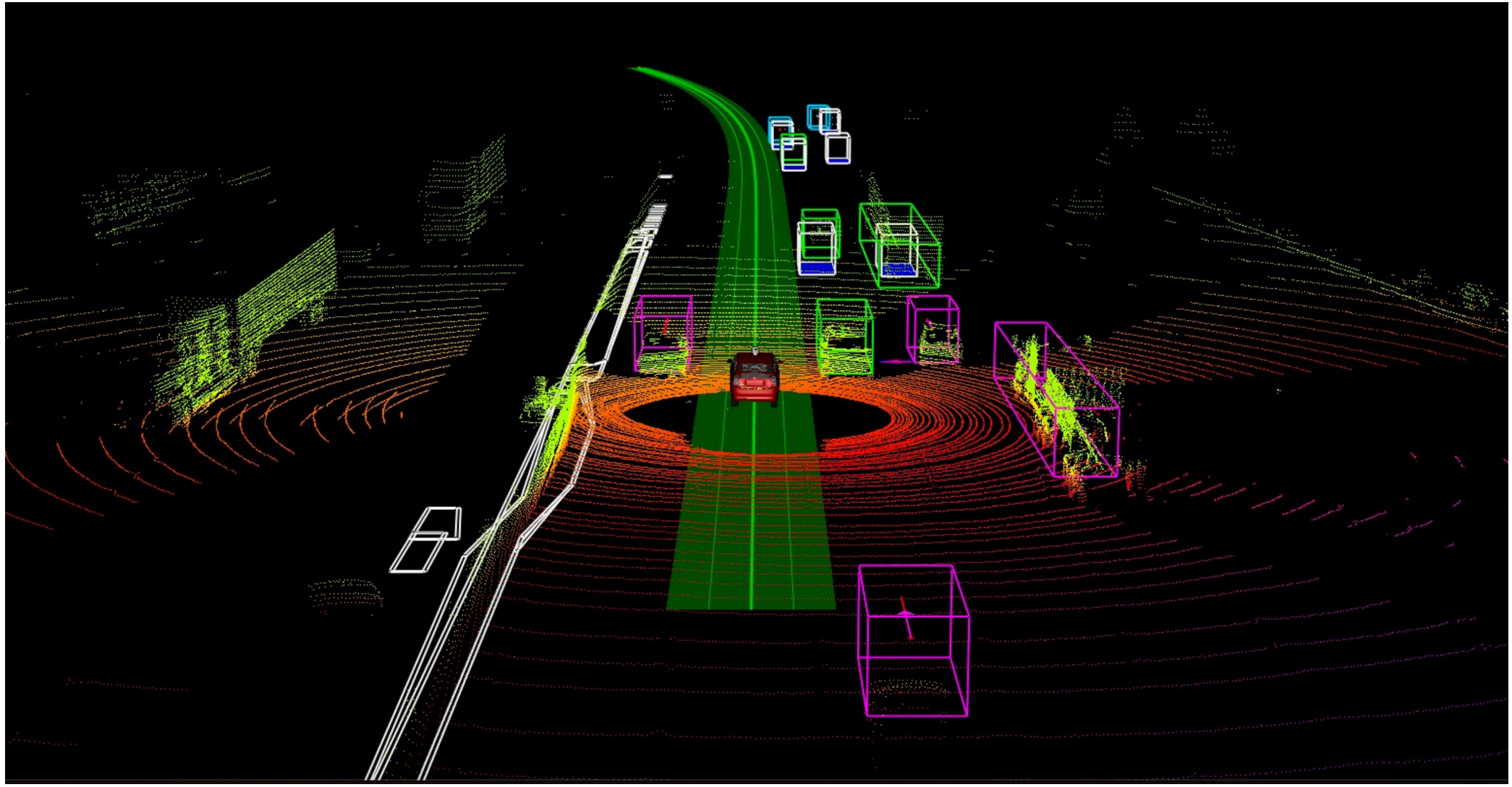
Requires many components to record data, like a GPS, so that each point will have accurate data attached

Intensity, flight angle, or even class may be recorded

A sample point Cloud



A sample point Cloud



Why is it useful ?

SAVE SURVEYING TIME

ACCURATE RESULTS

DETAILED OBJECT (EX. BUILDING) ANALYSIS

DESIGN ASSESSMENT FOR RENOVATION

SEAMLESS COLLABORATION BETWEEN MULTIPLE TEAMS

REDUCING OVERALL COST

Traditional ways to extract features from Point Cloud

Polygonal mesh

Point-sampled geometry

Clustering

pcl library

Issues with traditional approach

Geometric features, extracted from point clouds can be used with traditional ML for semantic segmentation, but it would lag from the aspect of:

- ✓Robustness – might need heuristics-based approach for finding the bounding box
- ✓Scalability – the proposed heuristics might not scale up
- ✓Not Generic – require separate geometric model for different types of objects

From 3D point cloud to polygonal mesh surface, followed by some post processing

Deep Learning based approaches

Generalized

Does not need separate algorithms for individual features

Might not always require 2D transformation or voxelization

Scalable if applied on properly transformed 3D point cloud (2D BEV or RV)

More on DL based approaches

Project the 3D cloud into 2D top-down Bird Eye View

Project the 3D cloud into 2D top-down Range View

- Apply 2D convolution with other DL methods or heuristics-based approaches

Discretizing the LiDAR point cloud into 3D voxel

Directly use 3D point cloud data

- Apply 3D convolution

Bird Eye View vs Rear View

- ✓ **Preserves object size with range**
- ✓ **Provides a strong prior for learning**
- ✓ **The Z-axis is treated as a feature channel for 2D convolutions**

- ✓ **Suffers from occlusion and object size variation w.r.t. distance**
- ✓ **Low latency due to the dense representation compared to the sparser bird eye view**

Some relevant NN Architectures

2D

- R-CNN
- Fast R-CNN
- Faster R-CNN
- Mask R-CNN
- Cascade R-CNN

3D

- PointNet
- PointNet++
- Point R-CNN

Some Practical Issues of object detection

Draw a bounding box around the object of interest to locate it within the image

There could be many bounding boxes representing different objects of interest within the image (not know how many beforehand)

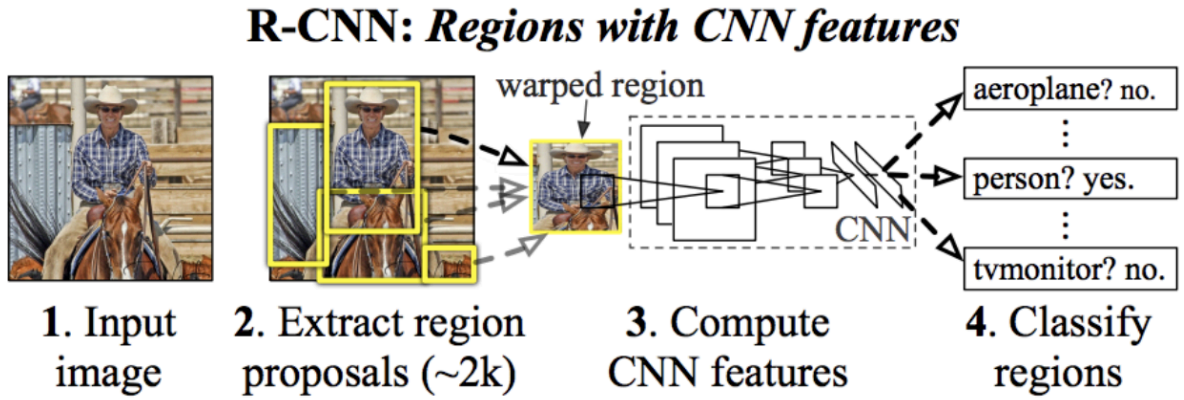
Take different regions of interest from the image and use a CNN to classify the presence of the object within that region

But objects of interest might have different spatial locations within the image and different aspect ratios

Need to select a huge number of regions and this could computationally blow up

R-CNN

- Use selective search to extract just 2000 regions from the image -region proposals
- Selective Search:
  - Generate initial sub-segmentation, we generate many candidate regions
  - Use greedy algorithm to recursively combine similar regions into larger ones
  - Use the generated regions to produce the final candidate region proposals



R-CNN - issues

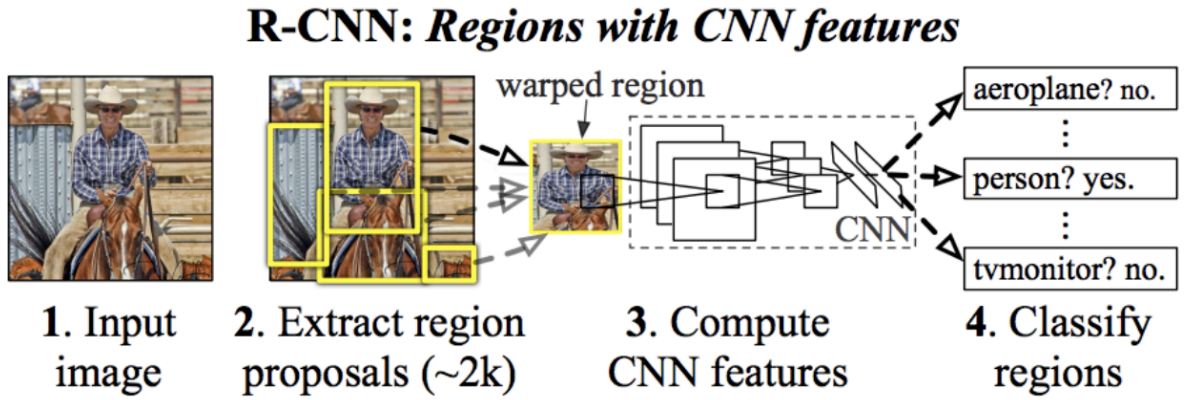
Still takes a huge amount of time to train the network as you would have to classify 2000 region proposals per image

Can not be implemented real time as it takes around 47 seconds for each test image.

The selective search algorithm is a fixed algorithm. Therefore, no learning is happening at that stage. This could lead to the generation of bad candidate region proposals.

Fast R-CNN

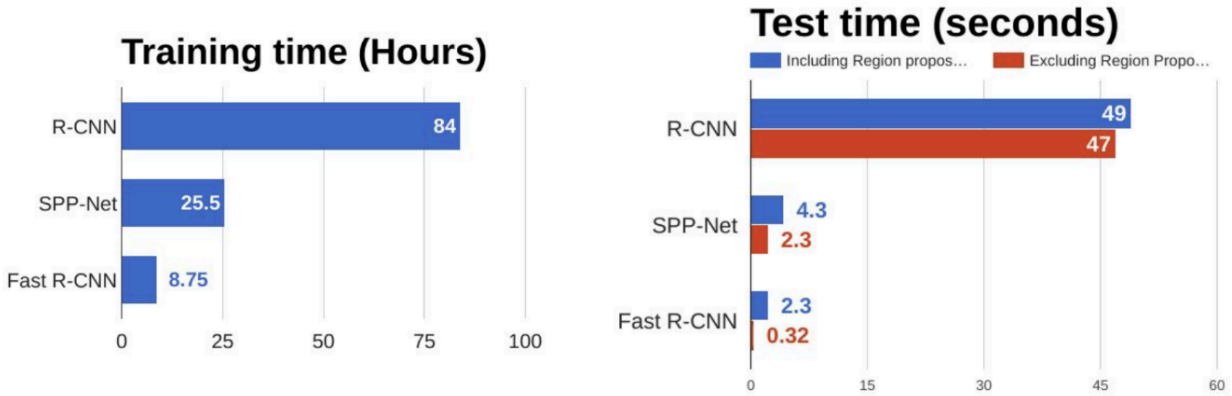
- Feed the input image to the CNN to generate a convolutional feature map
- Identify the region of proposals
- Warp them into squares and by using a RoI pooling layer reshape them into a fixed size so that it can be fed into a fully connected layer
- From the RoI feature vector, use a softmax layer to predict the class of the proposed region (also the offset values for the bounding box)



R-CNN

Fast R-CNN

- The reason “Fast R-CNN” is faster than R-CNN - you don’t have to feed 2000 region proposals to the convolutional neural network every time
- The convolution operation is done only once per image and a feature map is generated from it.
- However, including region proposals slows down the algorithm significantly when compared to not using region proposals

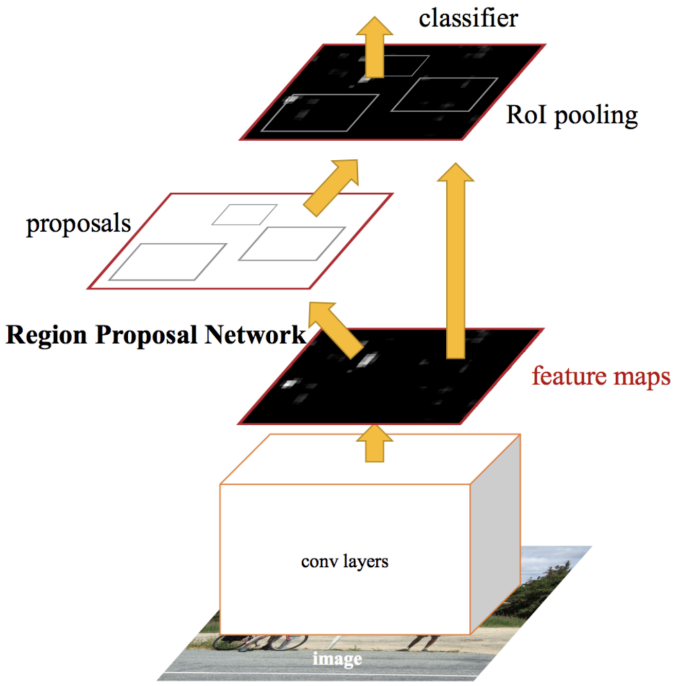


Comparison of object detection algorithms

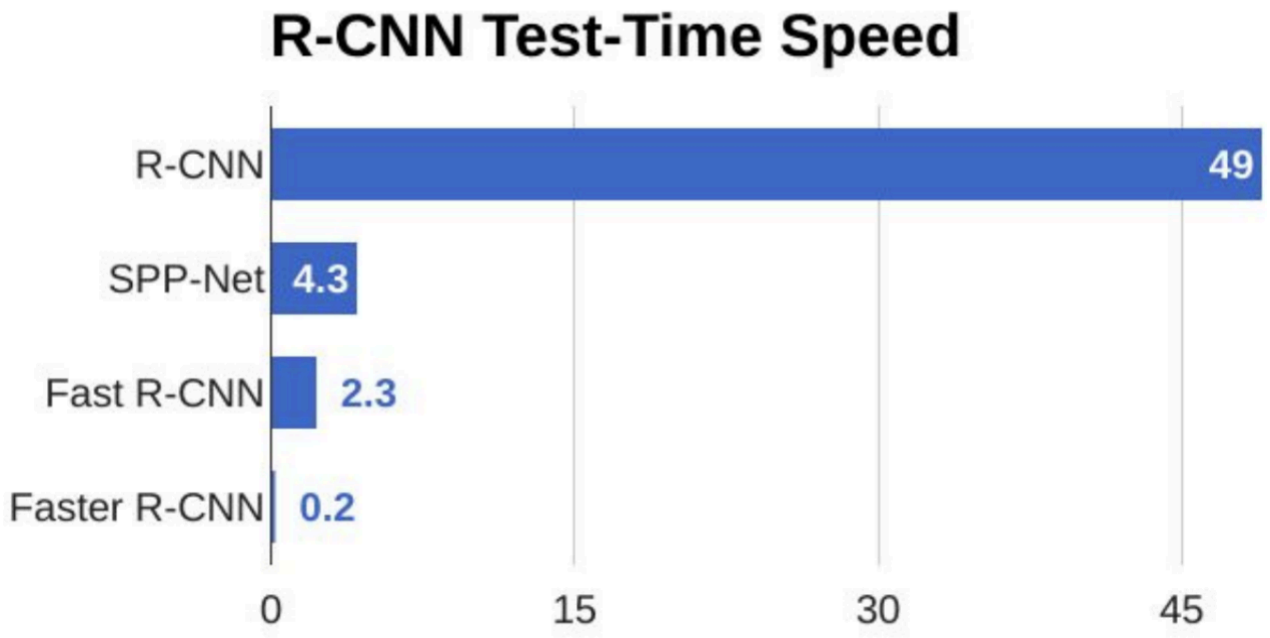
Faster R-CNN

- Selective search is a slow and time-consuming process affecting the performance of the network
- Faster R-CNN eliminates the selective search algorithm and lets the network learn the region proposals
- Image is provided as an input to a convolutional network which provides a convolutional feature map
- Instead of using selective search algorithm on the feature map to identify the region proposals, a separate network is used to predict the region proposals
- The predicted region proposals are reshaped using a RoI pooling layer
- Classify the image within the proposed region and predict the offset values for the bounding boxes.

Faster R-CNN



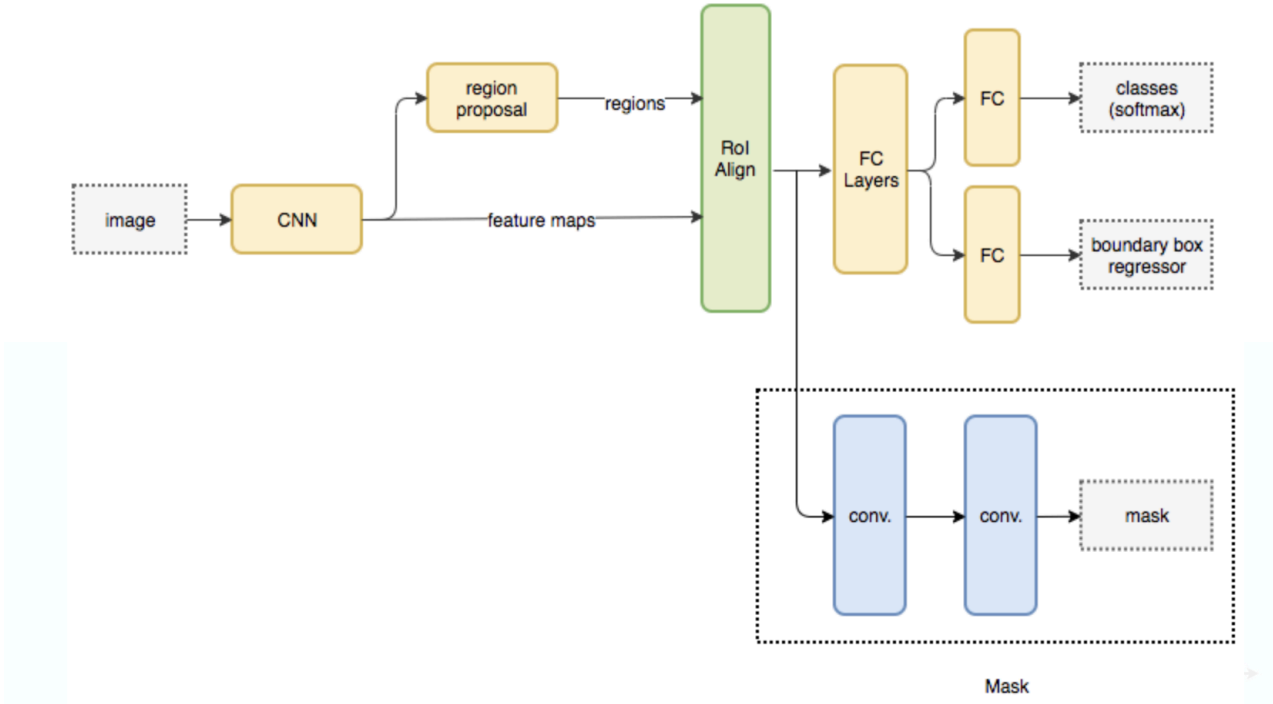
Faster R-CNN



Comparison of test-time speed of object detection algorithms

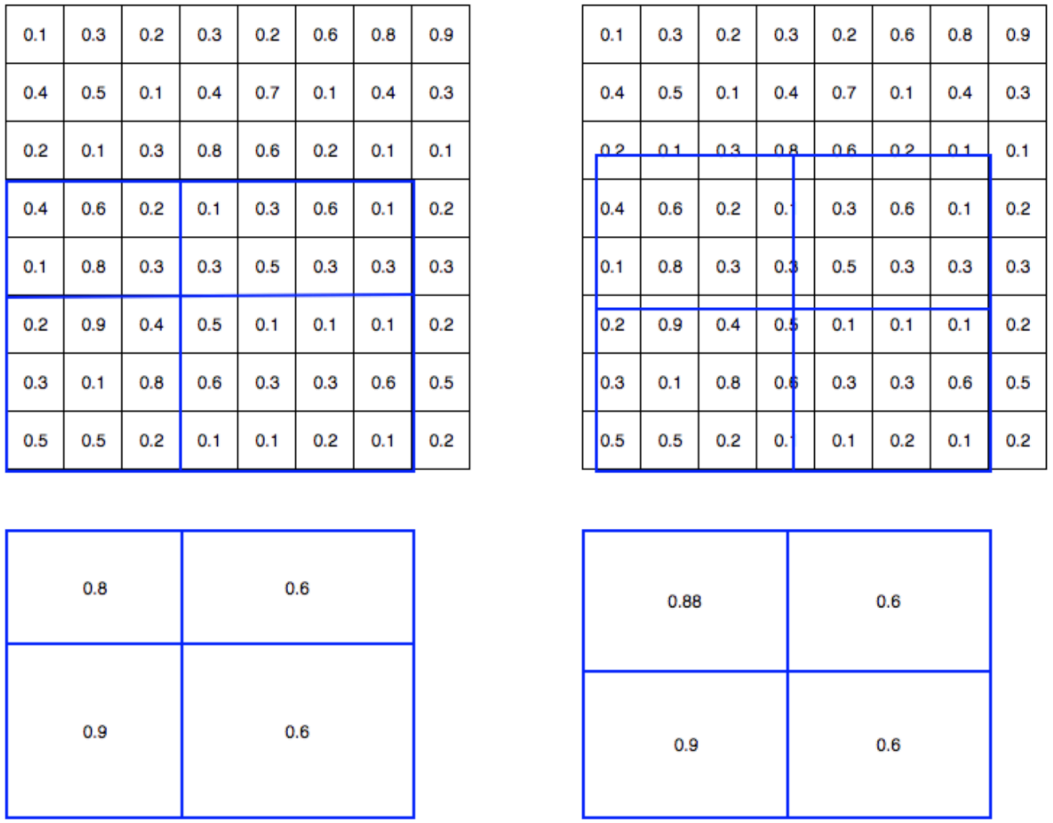
Mask R-CNN

- The Faster R-CNN builds all the ground works for feature extractions and ROI proposals for Mask R-CNN
- After the ROI pooling, 2 more convolution layers are added to build the mask

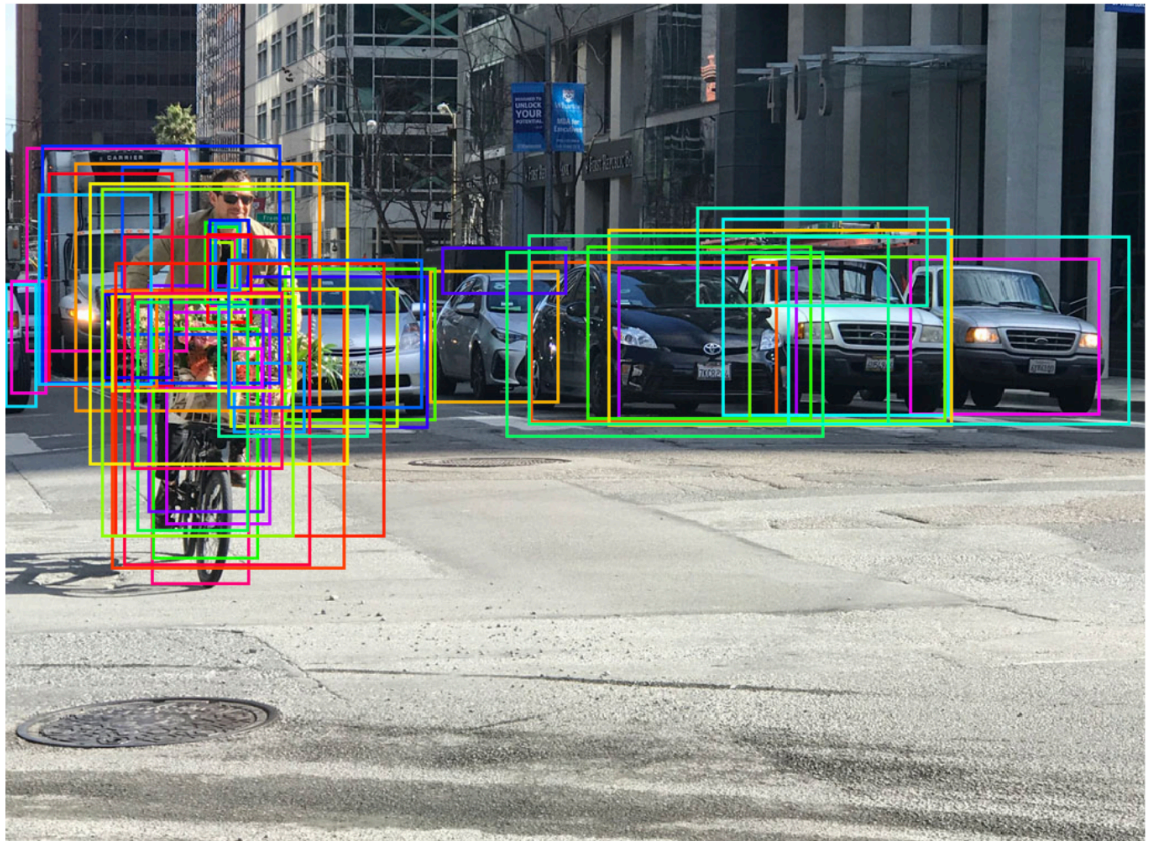


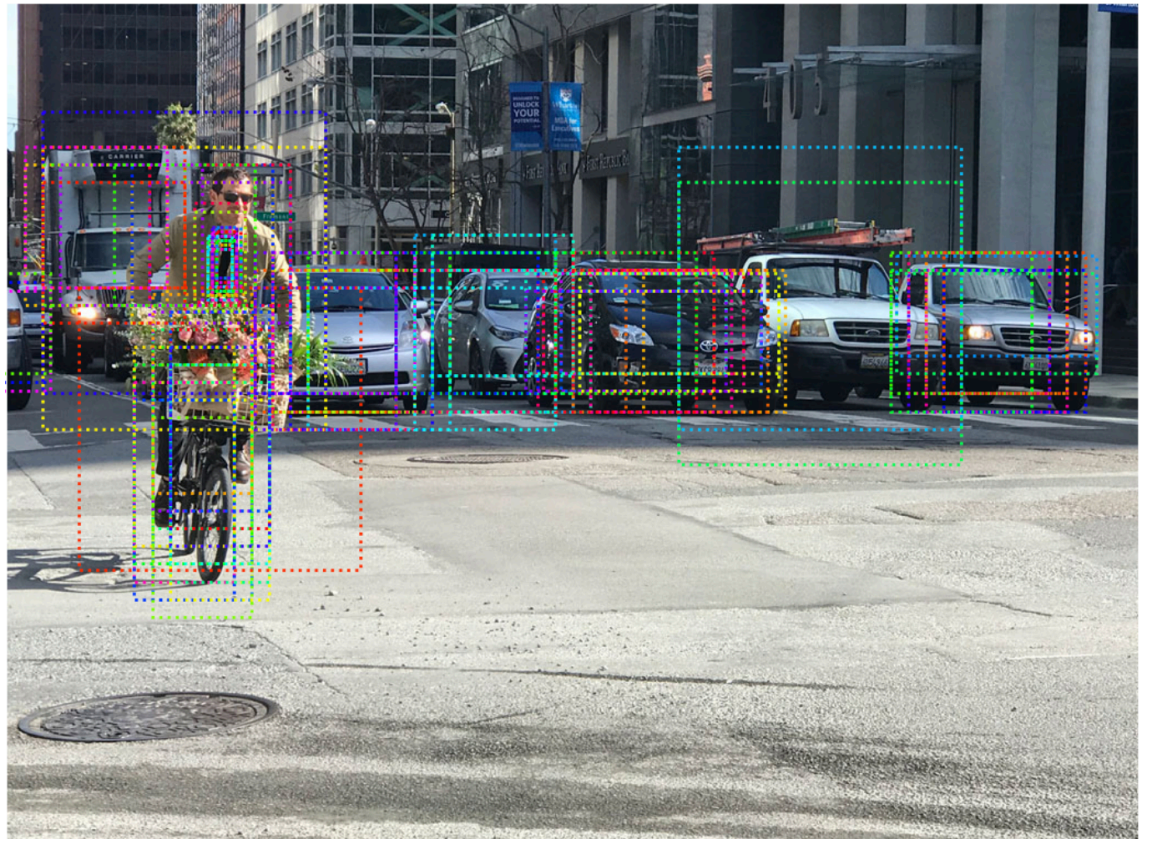
Mask R-CNN

- Another major contribution of Mask R-CNN is the refinement of the ROI pooling

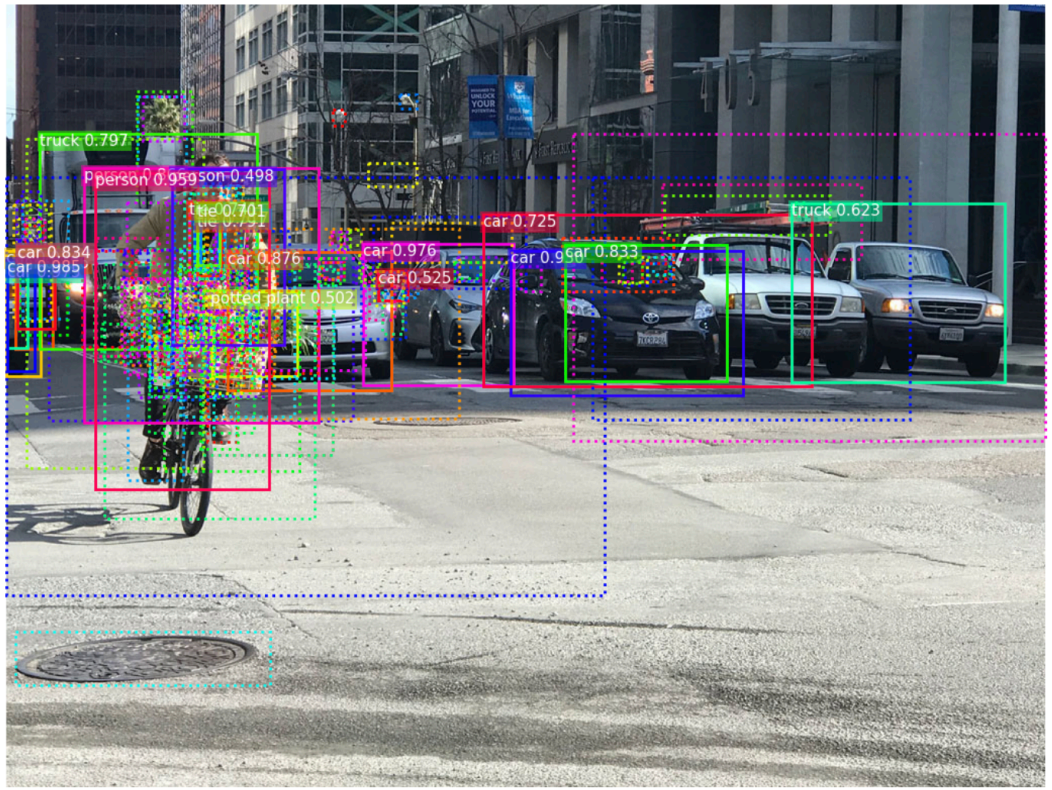


Mask R-CNN

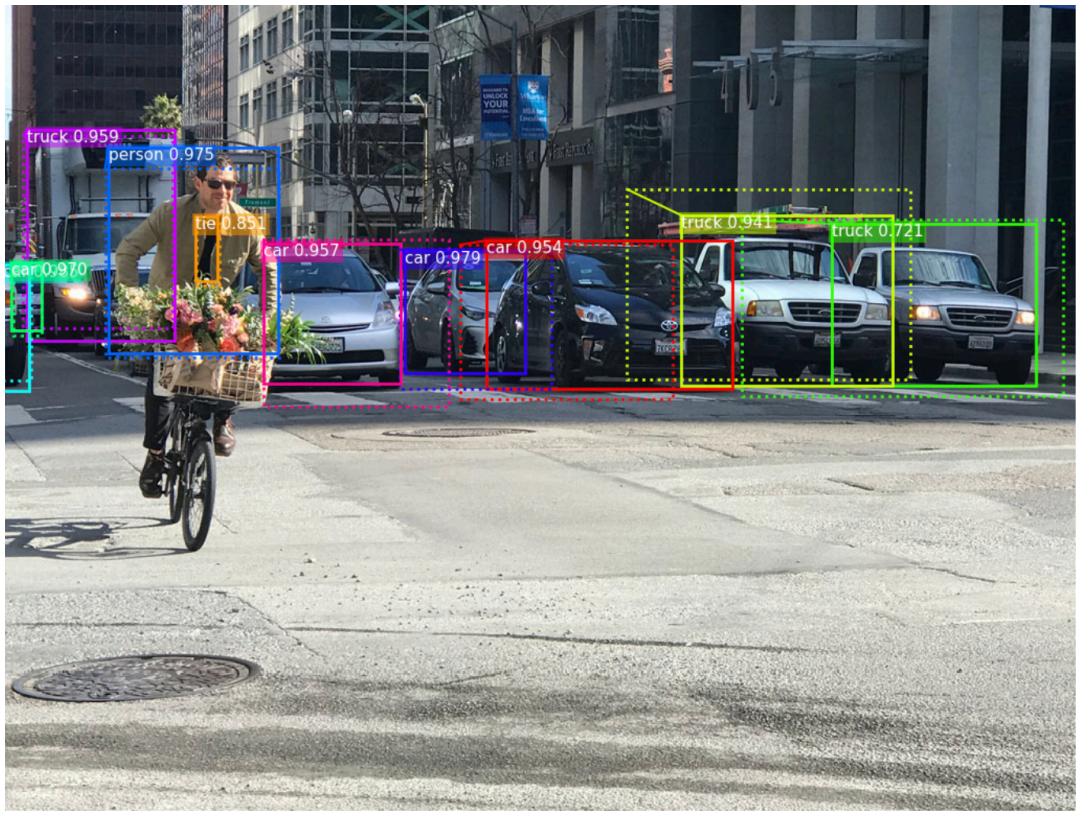




Mask R-CNN



Classification with ROIs (dotted lines). Final refinements (solid lines).



After nms. Solid line is the refined boundary box.

Cascade R-CNN

In R-CNN based approaches detection is framed as a multi-task learning problem combining classification and bounding box regression

An intersection over union (IoU) threshold is required to define positives/negatives in object detection

Object detector is trained with low IoU threshold- produces noisy detections

Detection performance tends to degrade with increasing the IoU thresholds

Overfitting during training, due to exponentially vanishing positive samples, and

Inference-time mismatch between the IoUs for which the detector is optimal

Cascade R-CNN

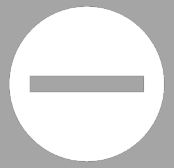
Cascade R-CNN, is proposed to address these problems

It consists of a sequence of detectors trained with increasing IoU thresholds, to be sequentially more selective against close false positives

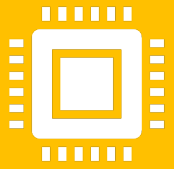
Detectors are trained stage by stage, leveraging the observation that the output of a detector is a good distribution for training the next higher quality detector

PointNet

So far, we discretized a point cloud by taking multi-view projections onto 2D to leverage existing techniques built around 2D convolutions,

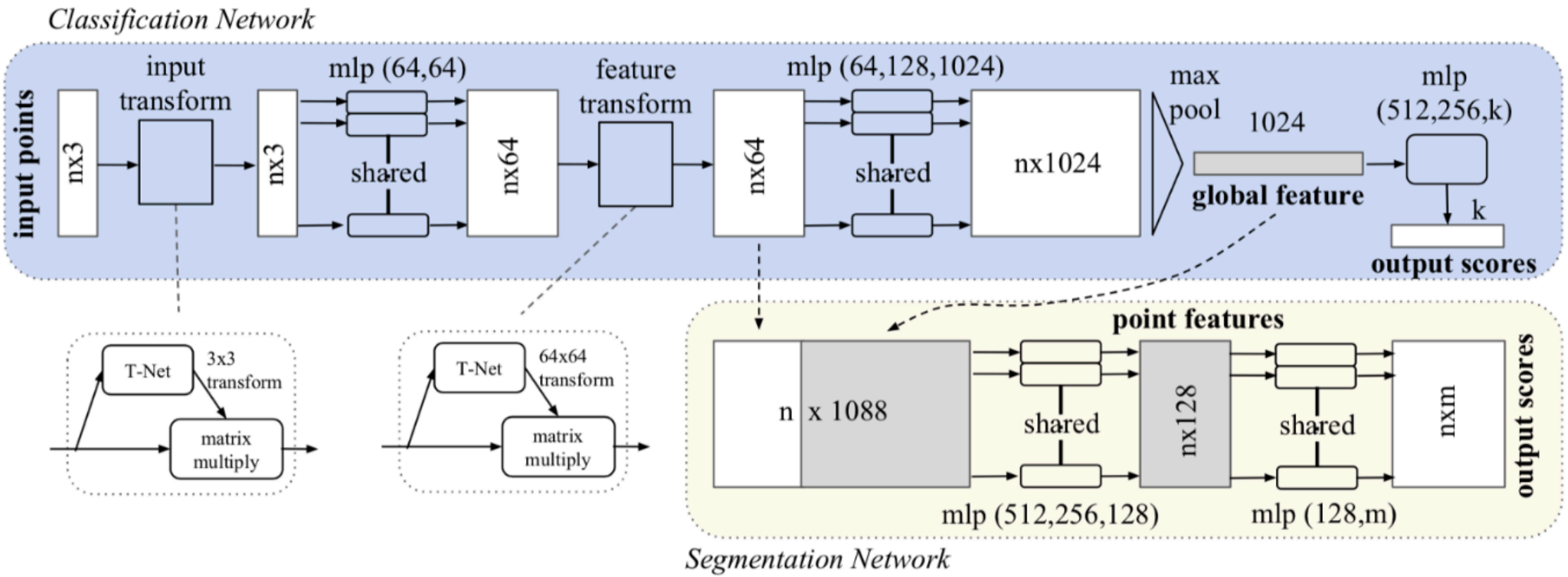


Given that the original data is manipulated, it can have negative impact



PointNet Takes raw point cloud data as input, which is typically collected from either a lidar or radar sensor

PointNet


Classification Network
input points
nx3
input transform
nx3
mlp (64,64)
shared
nx64
feature transform
nx64
mlp (64,128,1024)
shared
nx1024
max pool
1024
global feature
mlp (512,256,k)
k
output scores
T-Net
3x3 transform
matrix multiply
T-Net
64x64 transform
matrix multiply
point features
n x 1088
shared
nx128
shared
nxm
output scores
mlp (512,256,128)
mlp (128,m)
Segmentation Network

PointNet

Can not capture local structure induced by the metric space points

The max pooling operation takes the full cloud as input to produce a global feature

PointNet does not really tackle the problem related to the desertion of shape

Makes it unlikely to learn fine grained patterns or to understand complex scenes

PointNet++

Pointnet++ is built upon Pointnet

A hierarchical network that applies Pointnet recursively on a nested portioning of the input point cloud

Proposes novel set learning layers to adaptively combine features from multiple scales from varying densities

Like CNNs, it extracts local features from a small neighborhood and further groups into larger units to produce higher level features

This process is recursive until we obtain the feature of the whole point set

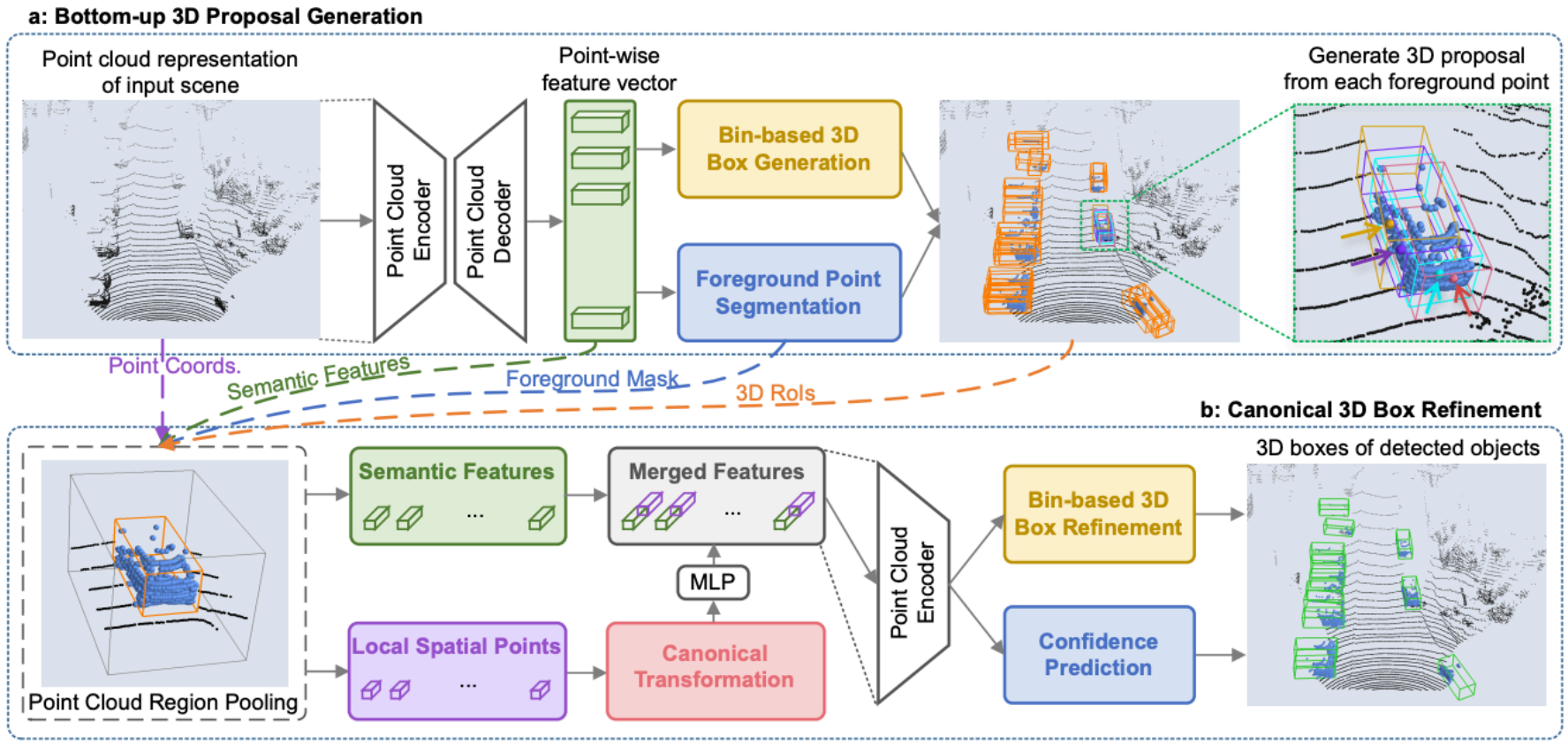
Point R-CNN

- The whole framework is composed of two stages:
  - Stage-1: Bottom-up 3D proposal generation:

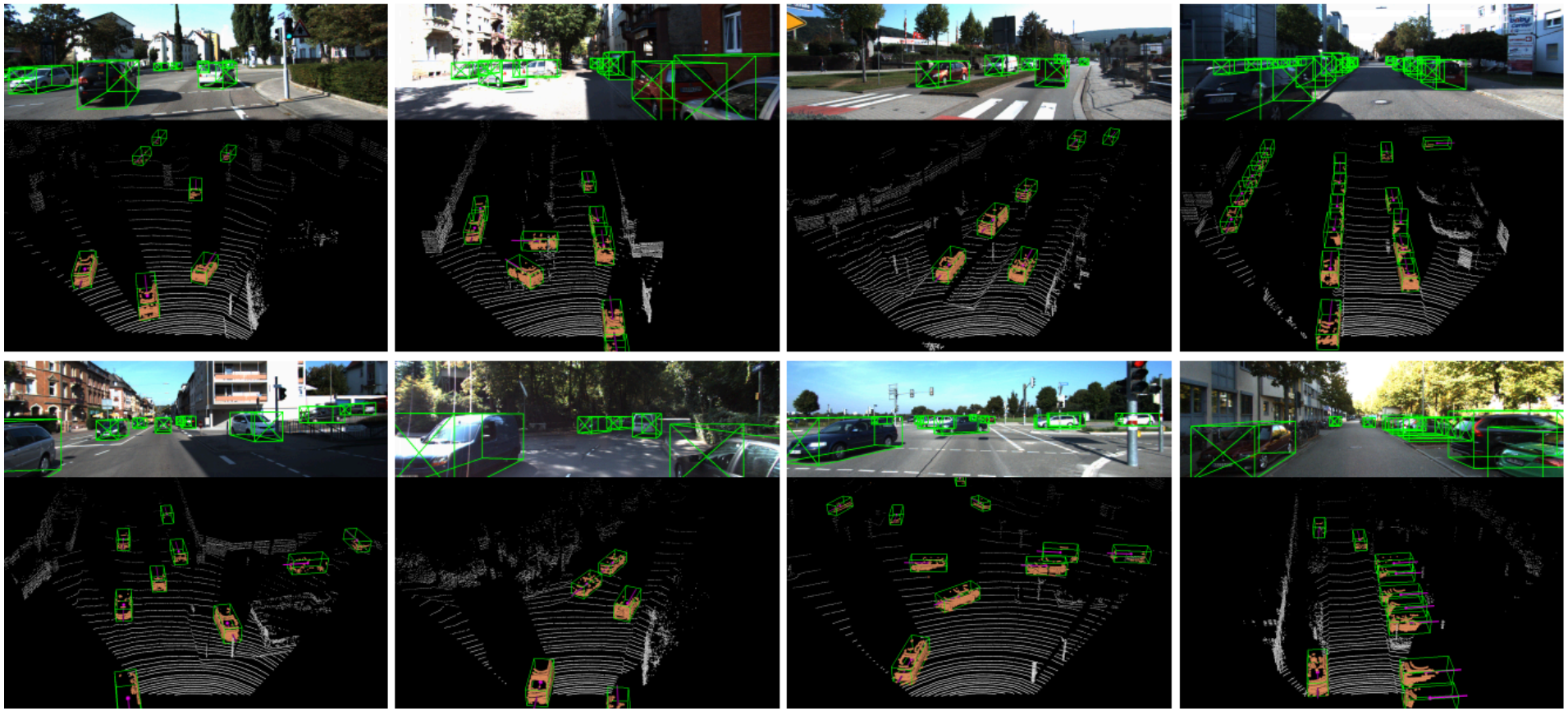
    Instead of generating proposals from RGB image or projecting point cloud to bird's view or voxels, stage-1 sub-network directly generates a small number of high-quality 3D proposals from point cloud in a bottom-up manner via segmenting the point cloud of the whole scene into foreground points and background
  - Stage-2 Refining proposals to obtain the final detection results:

    Transforms the pooled points of each proposal to canonical coordinates to learn better local spatial features, which is combined with global semantic features of each point learned in stage-1 for accurate box refinement and confidence prediction

Point R-CNN


a: Bottom-up 3D Proposal Generation
Point cloud representation of input scene
Point Cloud Encoder
Point Cloud Decoder
Point-wise feature vector
Bin-based 3D Box Generation
Foreground Point Segmentation
Generate 3D proposal from each foreground point
Point Coords.
Semantic Features
Foreground Mask
3D RoIs
b: Canonical 3D Box Refinement
Point Cloud Region Pooling
Semantic Features
Merged Features
MLP
Local Spatial Points
Canonical Transformation
Point Cloud Encoder
Bin-based 3D Box Refinement
Confidence Prediction
3D boxes of detected objects

Point R-CNN



Summary

- We introduced point cloud and some tools to analyze it
- Deep learning is used widely on this type of data
- 2D (BEV or RV) and 3D based approach
- Presented several DL based object detection approaches that work on 2D or 3D data
- Discussed pros and cons of these approaches and their sequential evolution

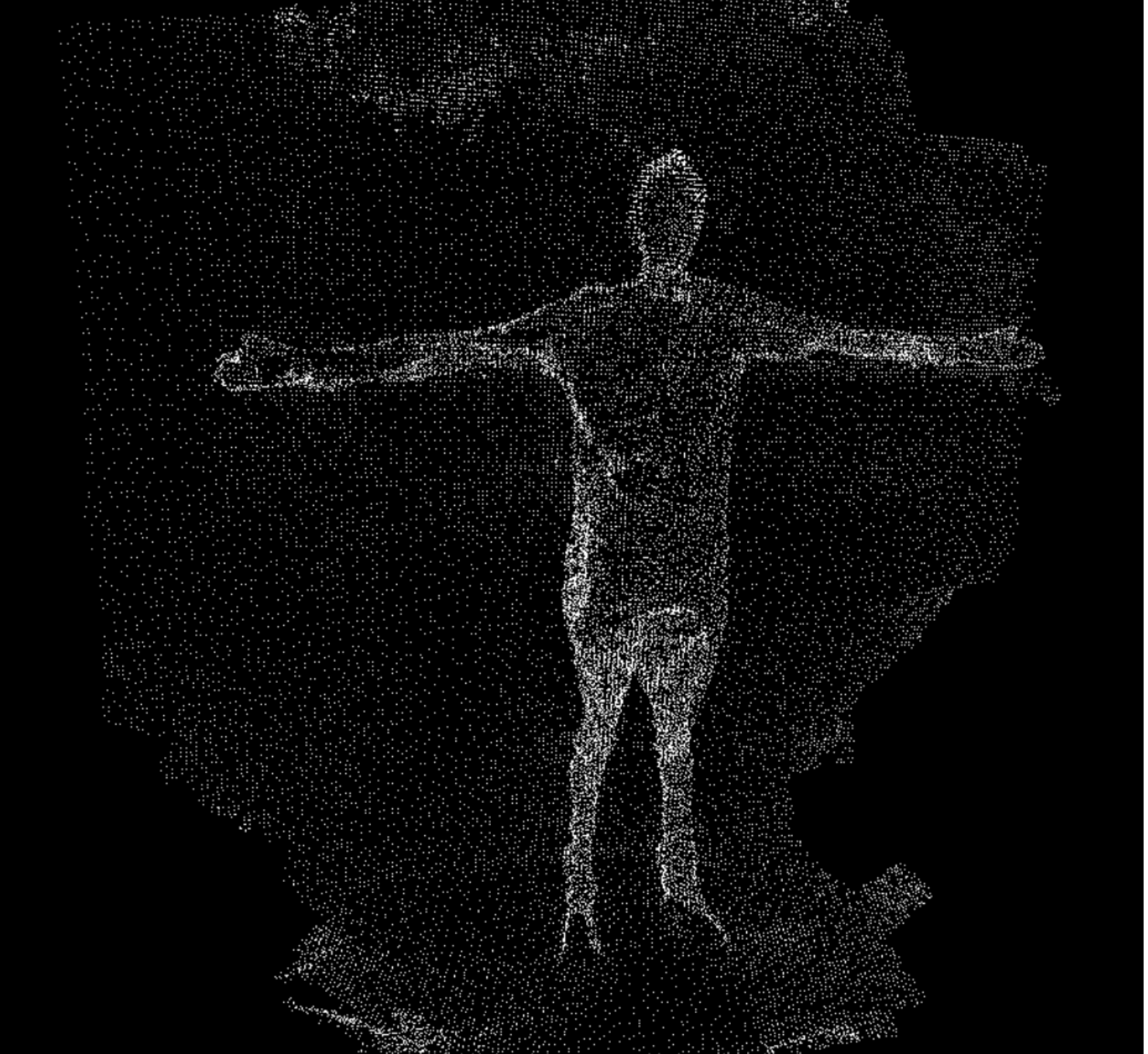
Conclusion

Object detection on 2D projection is simpler, however we might loose some information.

Reconstructing 3D objects after detecting 2D objects from the projections can be a bottleneck in terms of generalization and performance

Several works on 3D object detection without data transformation –can be compute intensive

Approaches like Point R-CNN can be a potential future direction



Thank You