深蓝学院
shenlanxueyuan.com

3D Point Clouds

Lecture 6 – 3D Object Detection

主讲人 黎嘉信

Aptiv 自动驾驶
新加坡国立大学 博士
清华大学 本科

- 1. Image Based Object Detector
- 2. Point Cloud – VoxelNet & PointPillars
- 3. Point Cloud – PointRCNN

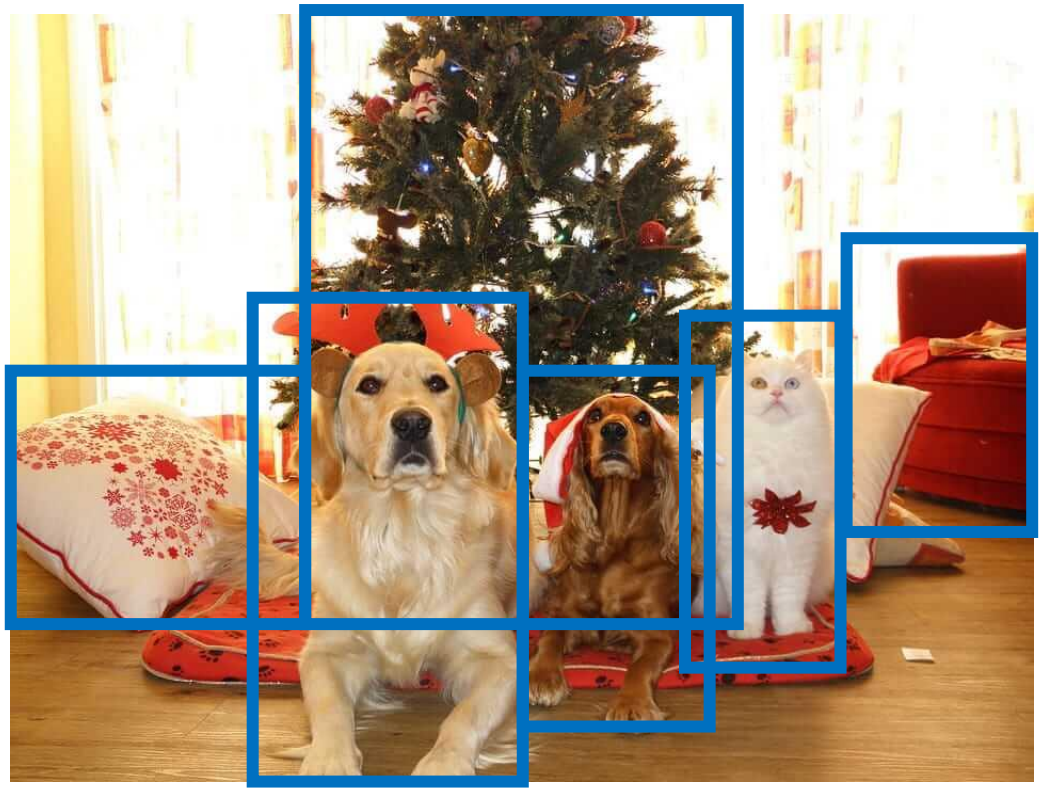
What is 3D Object Detection?

- Input: Point cloud and/or images
- Output: 3D bounding boxes – $[x, y, z, length, width, height, heading, category]$

Image source: PointPillars: Fast Encoders for Object Detection from Point Clouds, Alex Lang, et. al.

How to Perform Object Detection?

Object Localization



Object Classification

Dog? Yes
Cat? No
Tree? No
Pillow? No

Object Detection Difficulties

Image

- Occlusion
- Scale
- Class imbalance
- Rotation
- Generalization
- Illumination
- … …

- Point Cloud
  - Occlusion
  - ~~Scale~~
  - Class imbalance
  - Rotation
  - Generalization
  - ~~Illumination~~
  - Lack of texture
  - Sparsity

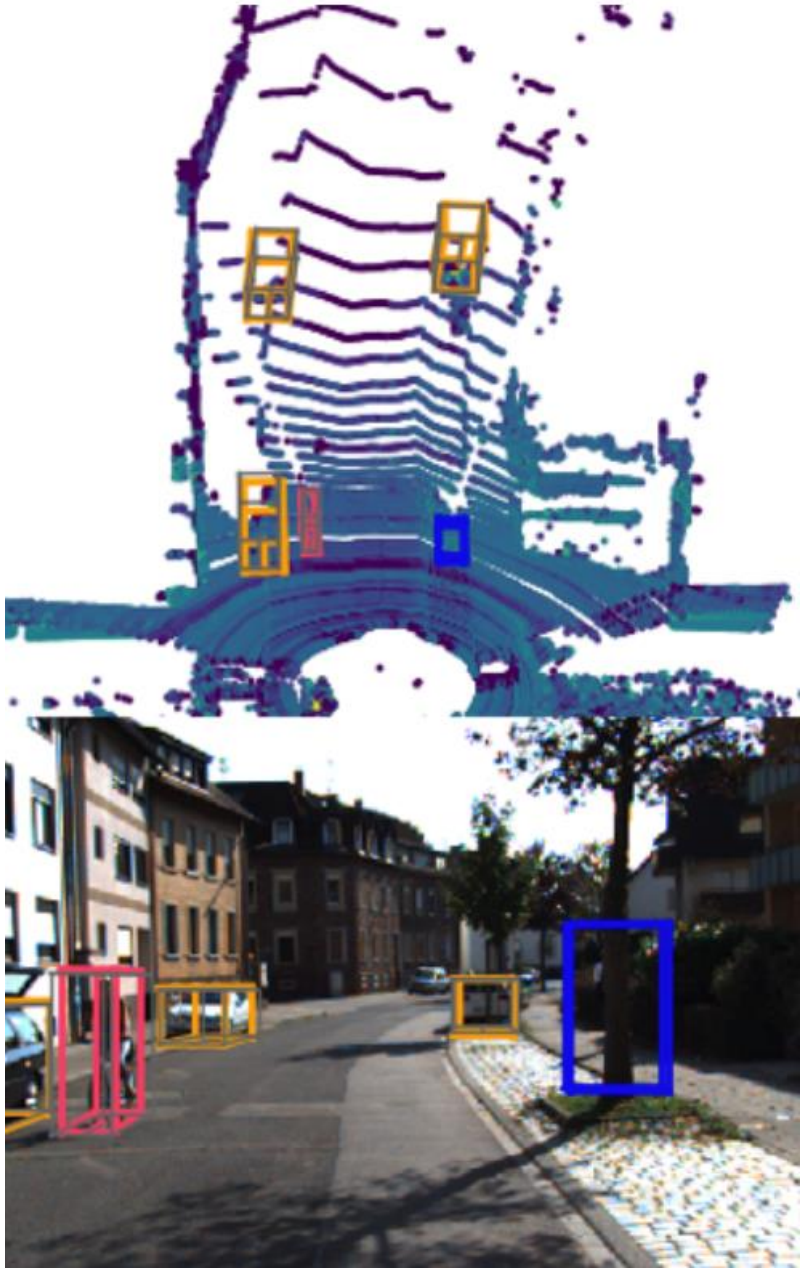


Image source: PointPillars: Fast Encoders for Object Detection from Point Clouds, Alex Lang et. al.

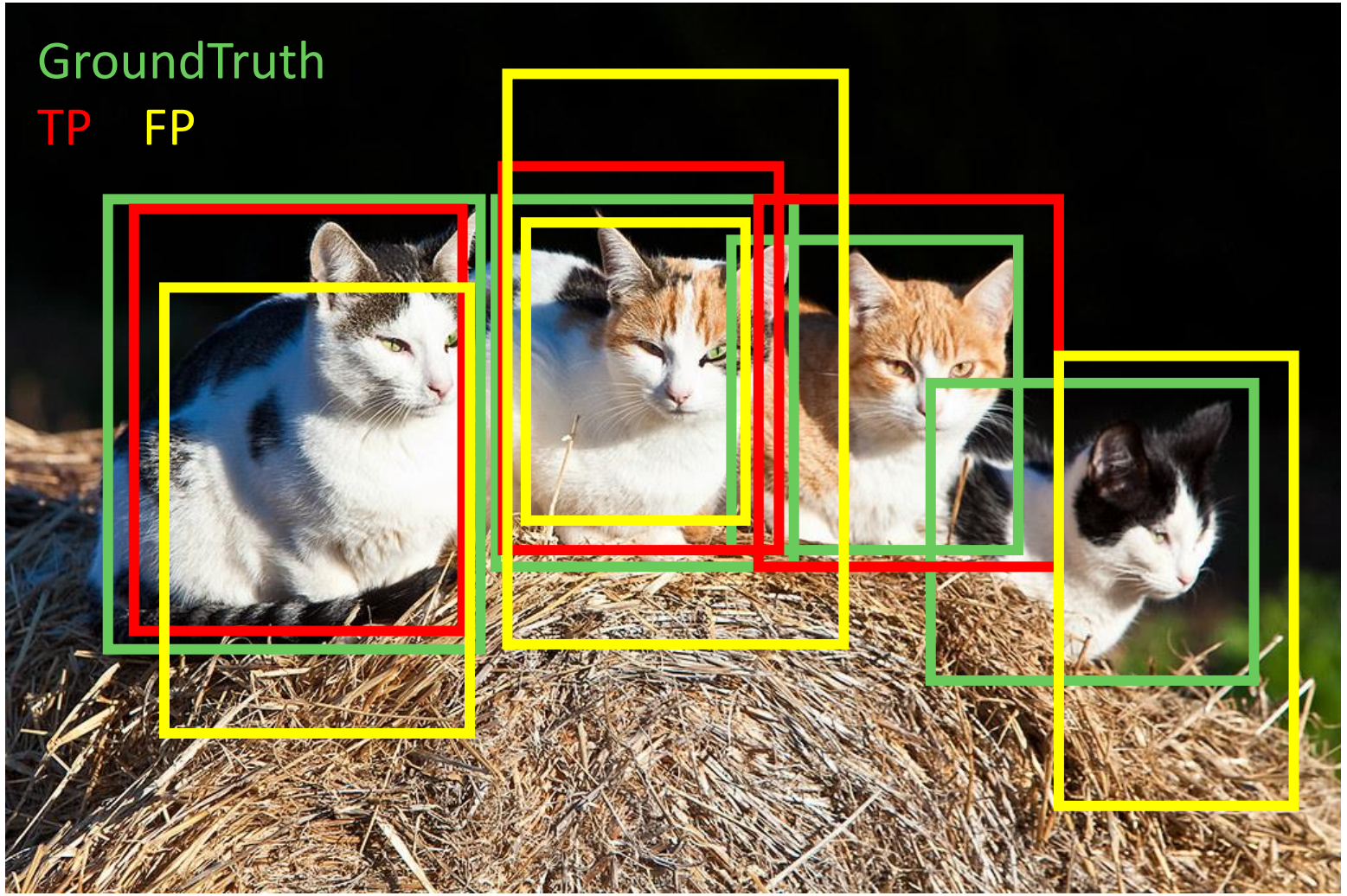
Face++ Human Body Detector

Results | Response JSON

Gender	Male
Upper Clothing	Gray Color Family
Lower Clothing	Gray Color Family

https://www.faceplusplus.com/body-detection/

How good is this detection result?



Intersection over Union (IoU)

- Determine whether a predicted box is matched with the ground truth box

$$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

Precision & Recall

How many selected items are relevant?

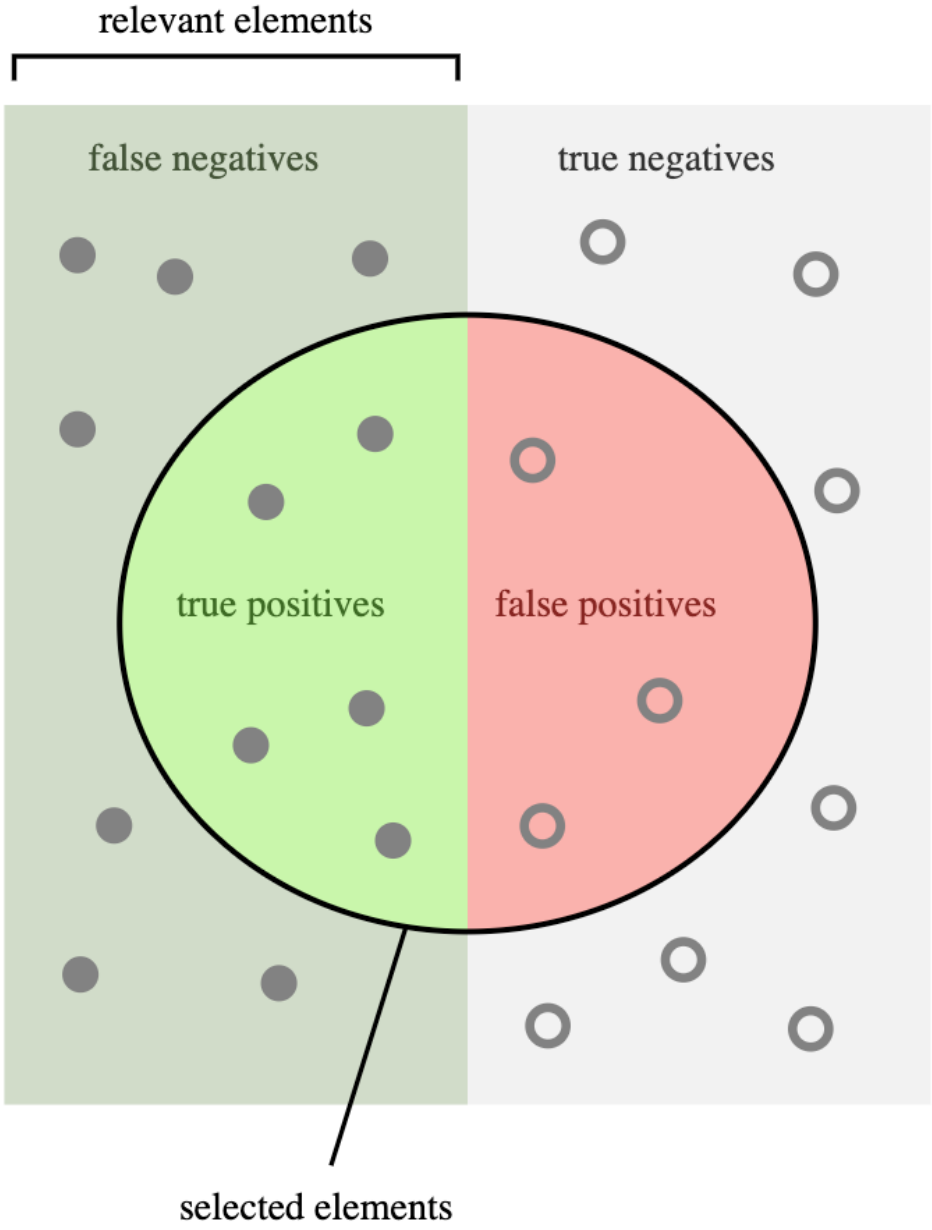
Precision = 

Precision $= \frac{TP}{TP+FP} = \frac{TP}{P}$

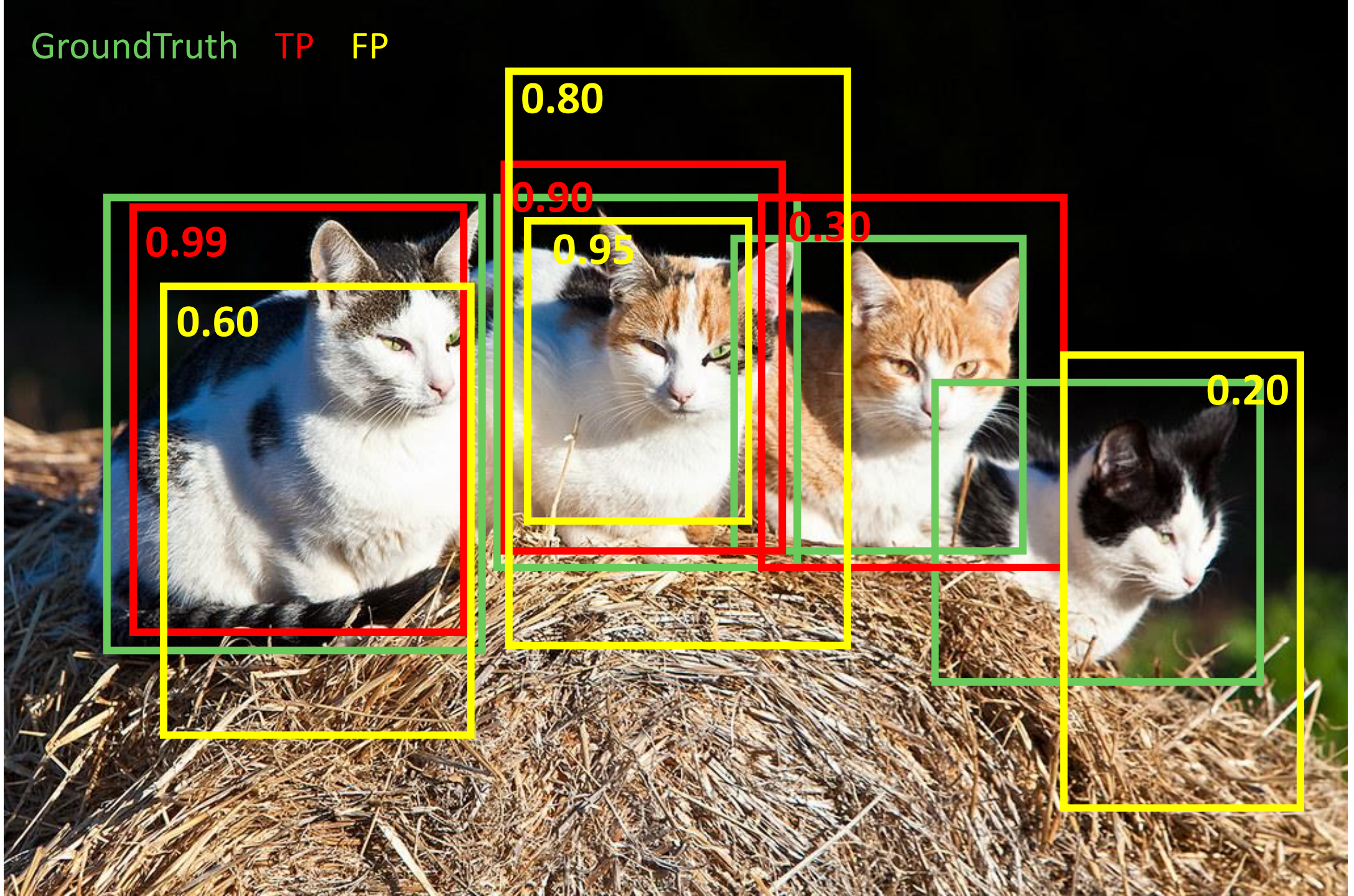
How many relevant items are selected?

Recall = 

Recall = $\frac{TP}{TP+FN}$



https://en.wikipedia.org/wiki/Precision_and_recall


GroundTruth
TP
FP
0.80
0.90
0.30
0.99
0.95
0.60
0.20

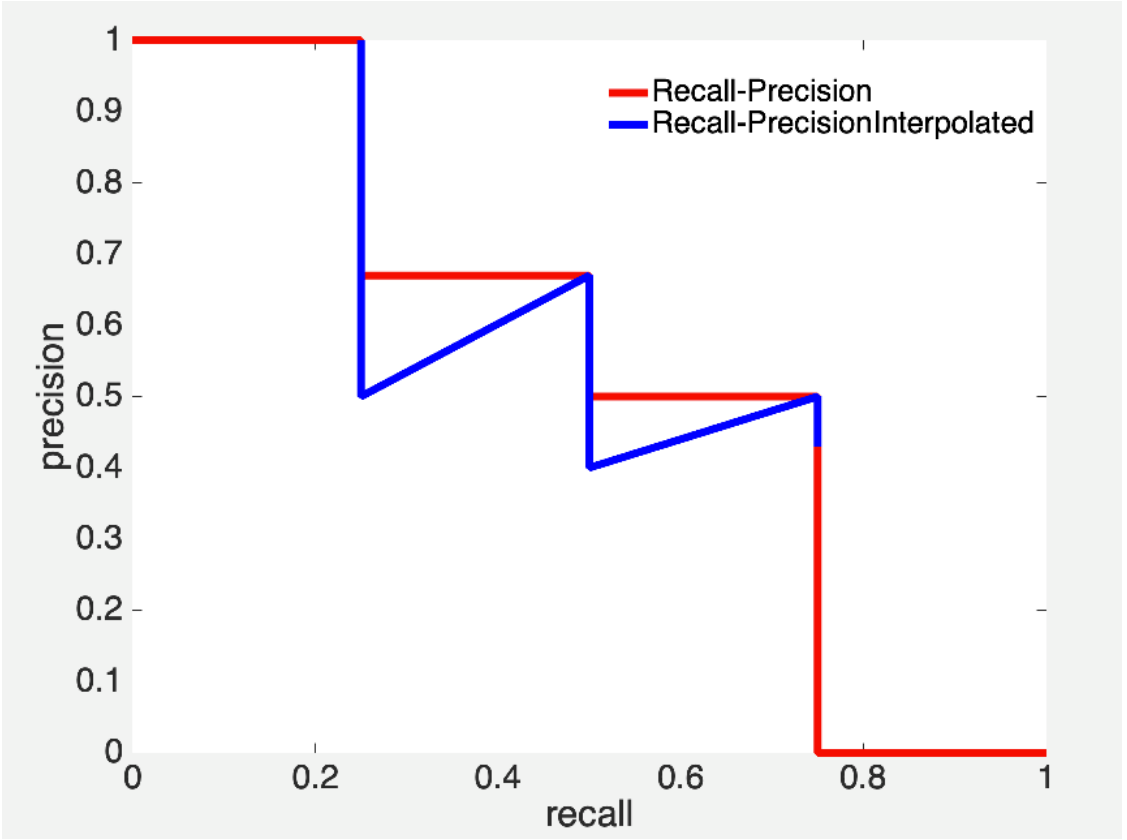
Average Precision (AP)

- For one category
  1. Choose IoU threshold
  2. Choose confidence threshold
     - Only choose boxes with confidence > threshold, of that category
  3. Determine each selected box is TP / FP
     - TP: IoU > threshold & Highest IoU – One TP per GT Box!
     - FP: IoU < threshold / Duplicated box
       - Duplicated box: each ground truth box can be associated with one TP only, others are FP.
  4. Compute Precision / Recall
  5. Get P-R curve by repeating 2-4 with decreasing confidence threshold
  6. Get AP by calculating the Area Under Curve (AUC)
- Repeat above for other categories
- Mean over all categories → mAP

Precision Interpolated:

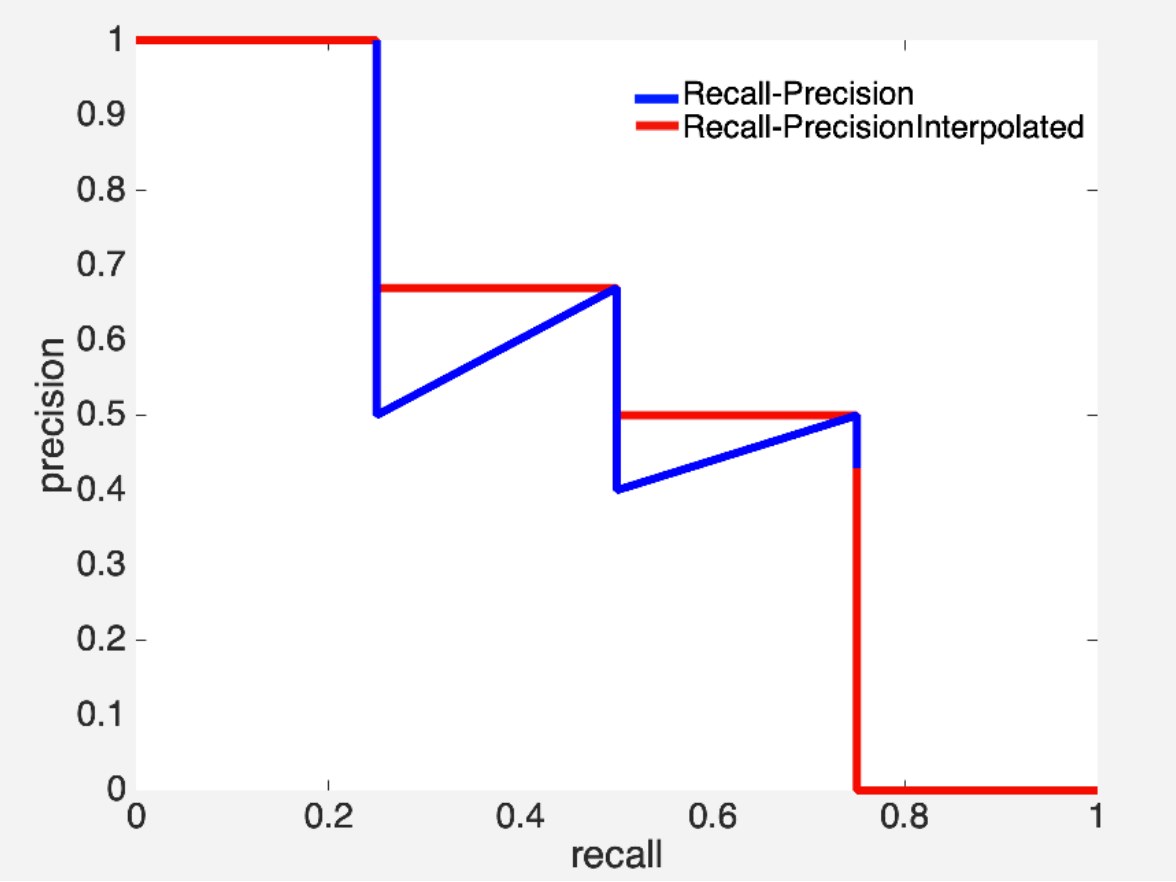
$$P_{interp}(r) = \max_{r' \geq r} p(r')$$

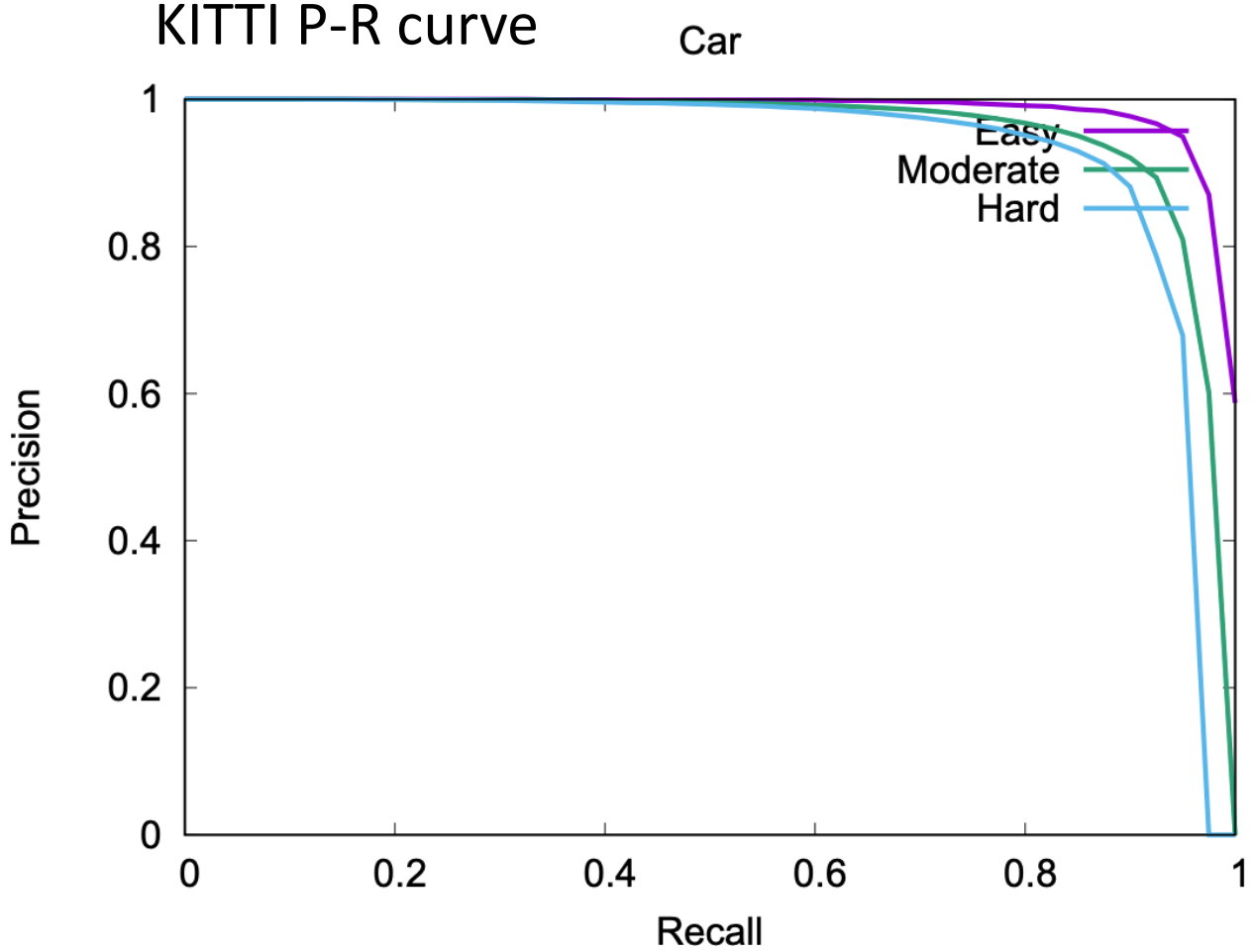
	Confidence	TP/FP	Precision	Recall	Precision Interpolated
1	0.99	TP	1/1=1	1/4=0.25	1
2	0.95	FP	1/2=0.5	1/4=0.25	1
3	0.9	TP	2/3=0.67	2/4=0.5	0.67
4	0.8	FP	2/4=0.5	2/4=0.5	0.67
5	0.6	FP	2/5=0.4	2/4=0.5	0.67
6	0.3	TP	3/6=0.5	3/4=0.75	0.5
7	0.2	FP	3/7=0.43	3/4=0.75	0.5



$$\text{Precision} = \frac{TP}{TP+FP} = \frac{TP}{P} \qquad \text{Recall} = \frac{TP}{TP+FN}$$

KITTI 3D Object Detection P-R Curve





http://www.cvlibs.net/datasets/kitti/eval_object_detail.php?&result=68edcafd4b26104dbb3f44608369d5ab712b90df

Non-Maximum Suppression (NMS)

- Usually there are multiple predicted boxes on one object
- Select the one with highest predicted score/confidence

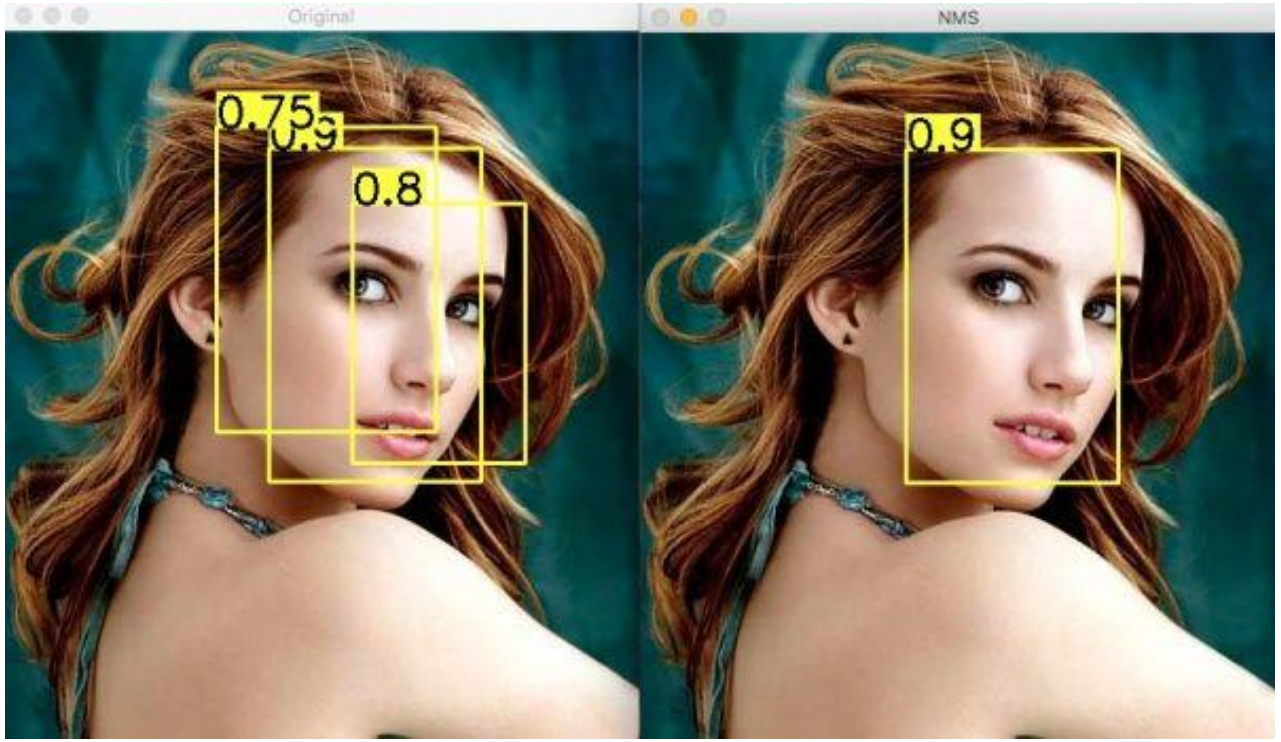


Image source: https://zhuanlan.zhihu.com/p/37489043

Steps for NMS

1. Keep all predicted boxes in the input list
2. Sort the predicted boxes by confidence
3. Pick the highest one, add it to the output list, remove it from the input list
4. Iterate all boxes in the input list
    1. Compute IoU between the picked box
    2. If IoU > threshold τ → remove the box from the input list
5. Repeat step 3, 4 until the input list is empty
6. Output list is the result.

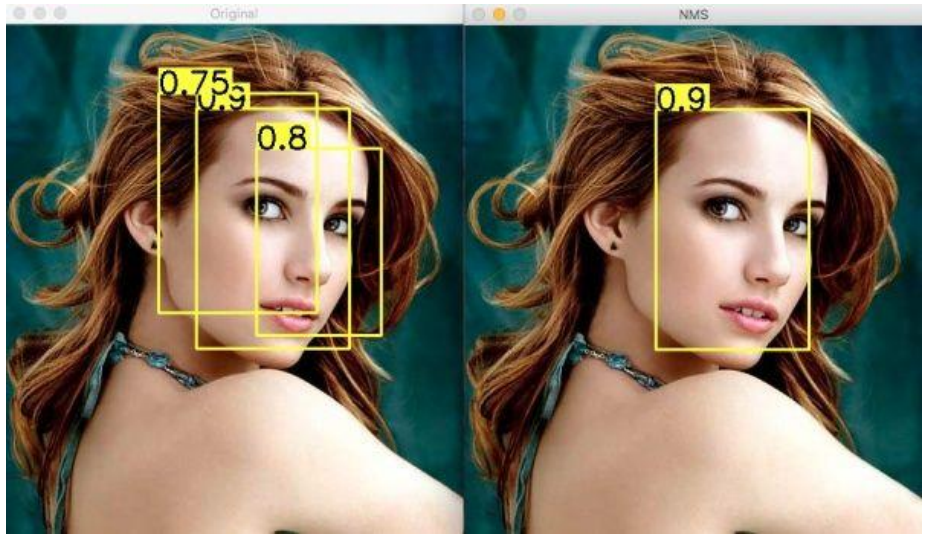
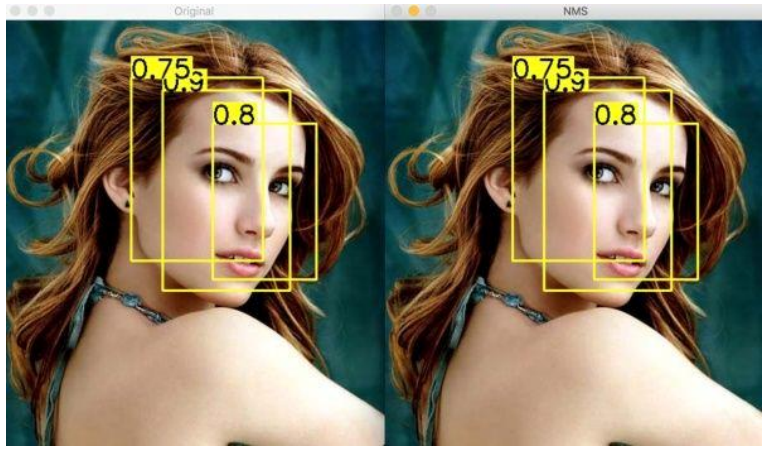


Image source: https://zhuanlan.zhihu.com/p/37489043

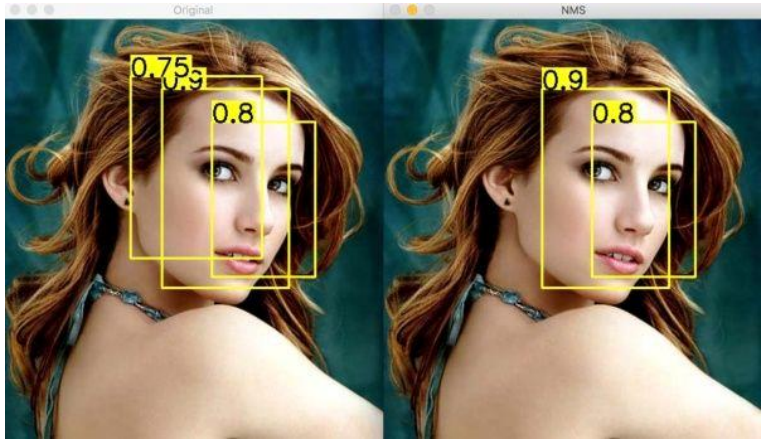
Non-Maximum Suppression (NMS)

- The larger is threshold τ, the more boxes NMS keeps

$\tau = 0.6$



$\tau = 0.5$



$\tau = 0.4$

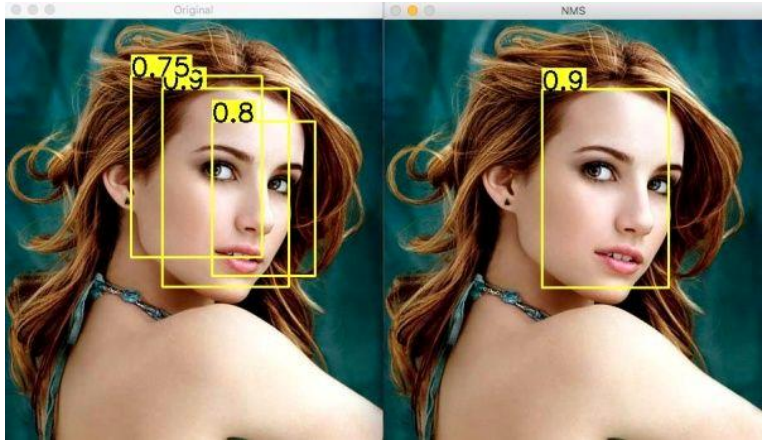
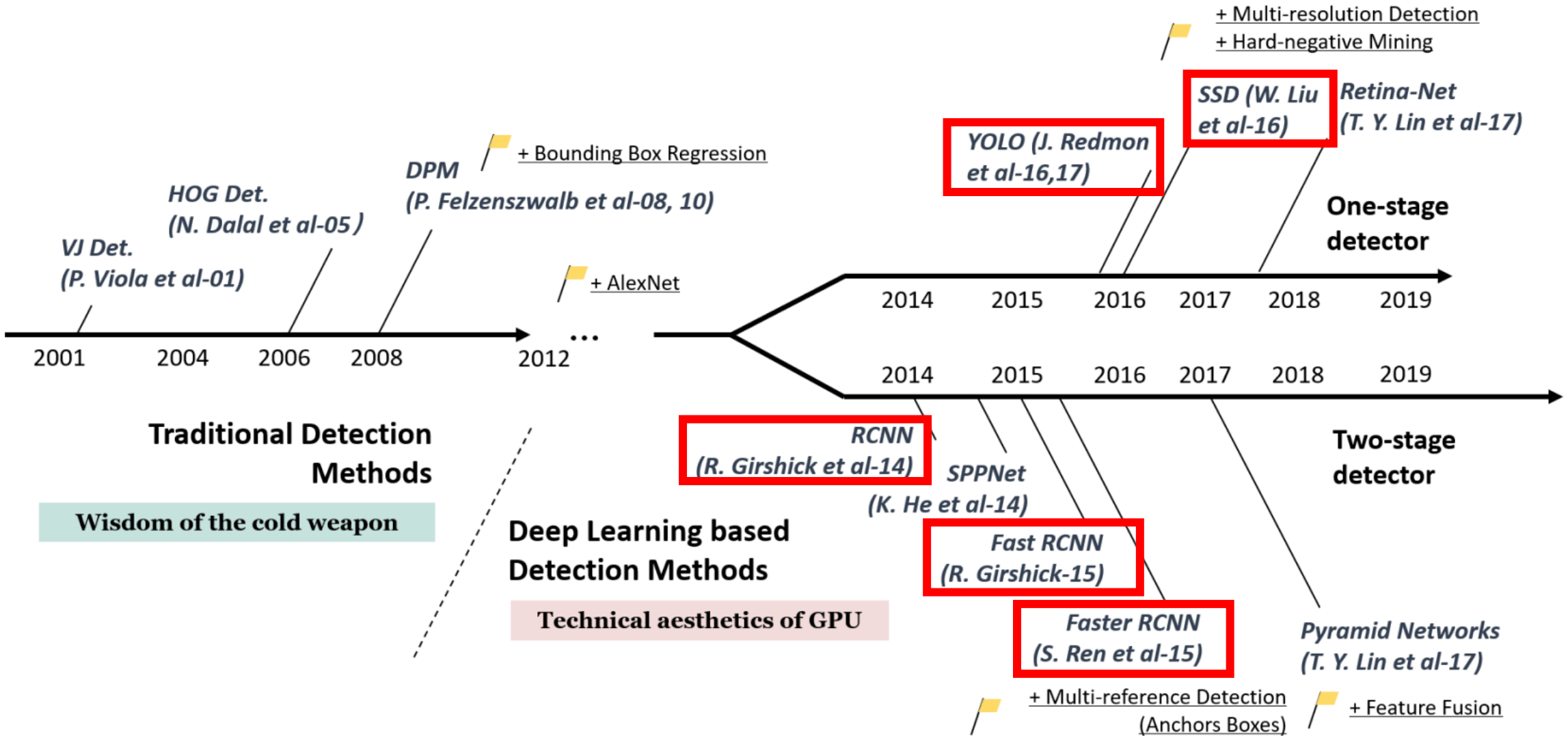


Image source: https://zhuanlan.zhihu.com/p/37489043

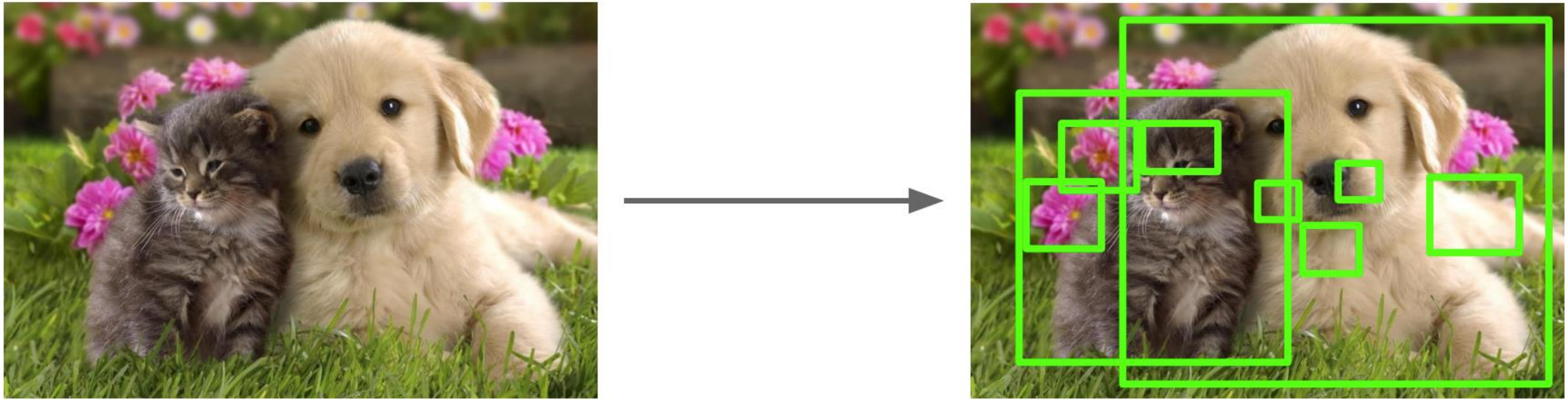
Object Detection Milestones



Object Detection in 20 Years: A Survey, Zhengxia Zou, et. al.

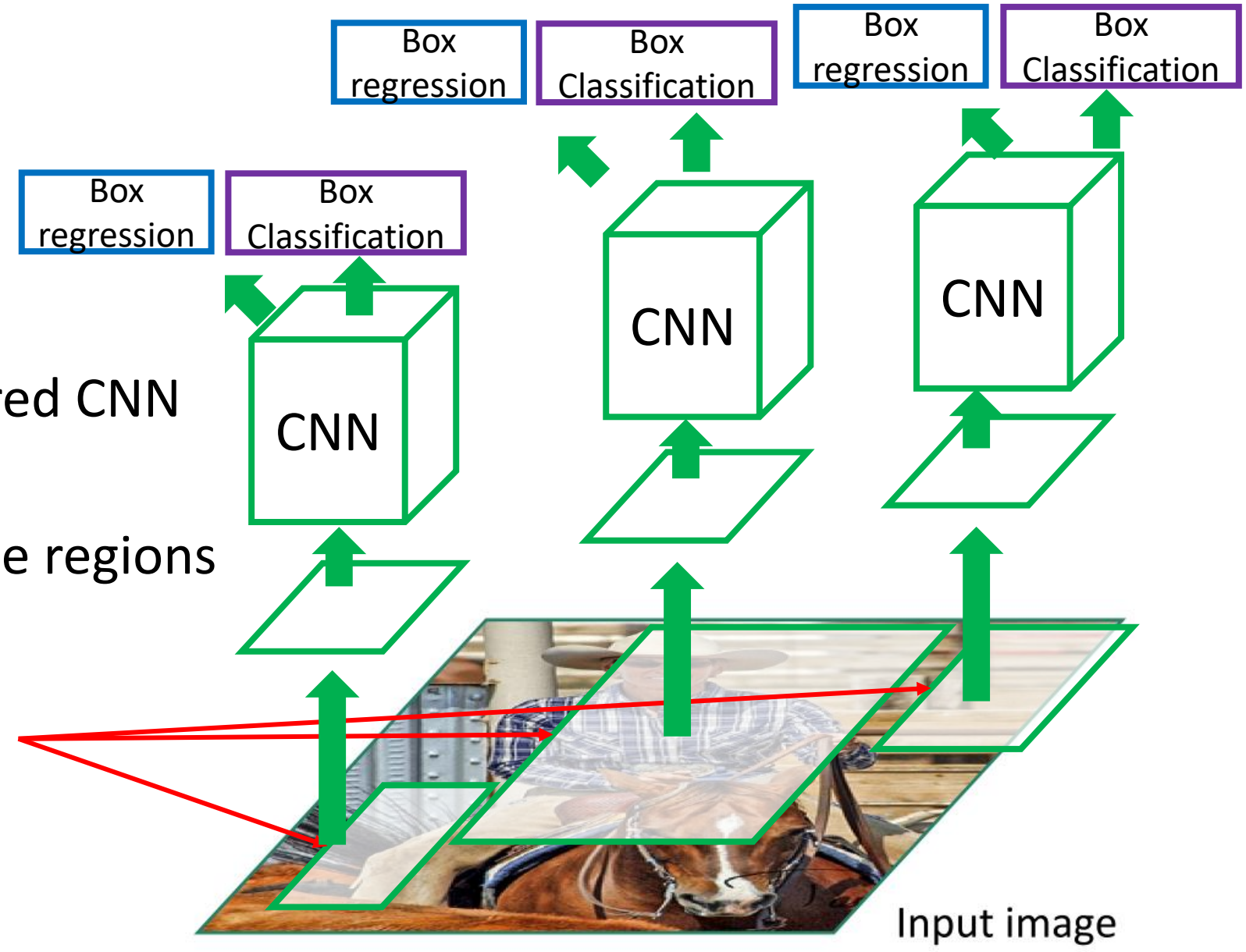
Detection = Localization + Classification

- Classification is well known
- What if we can get region proposals somewhere else?
  - E.g., color based clustering



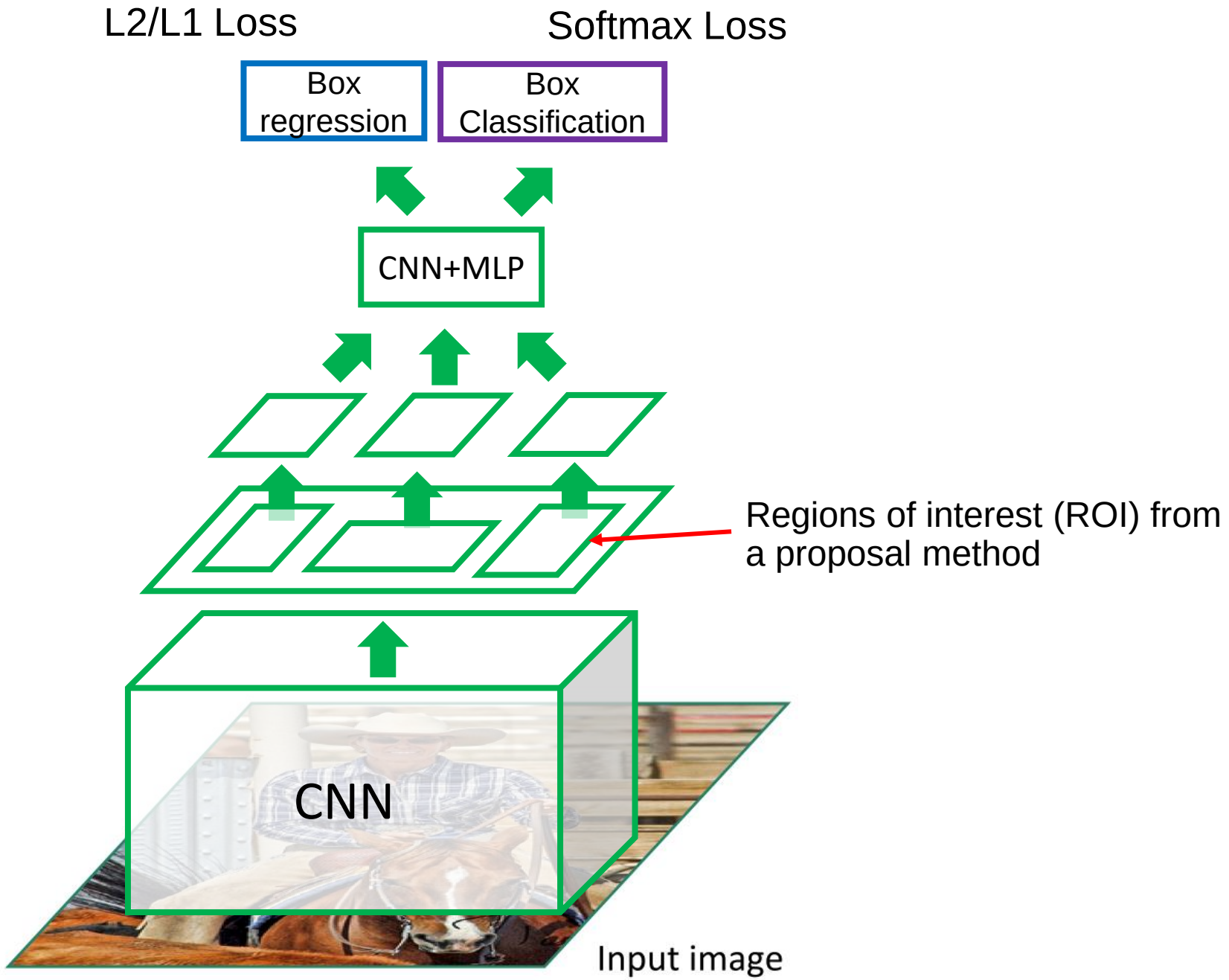
Source: CS231n, Stanford 2018, Fei-Fei Li, et. al.

RCNN



Source: CS231n, Stanford 2018, Fei-Fei Li, et. al.

Rich feature hierarchies for accurate object detection and semantic segmentation. R Girshick, et.al.



The feature map

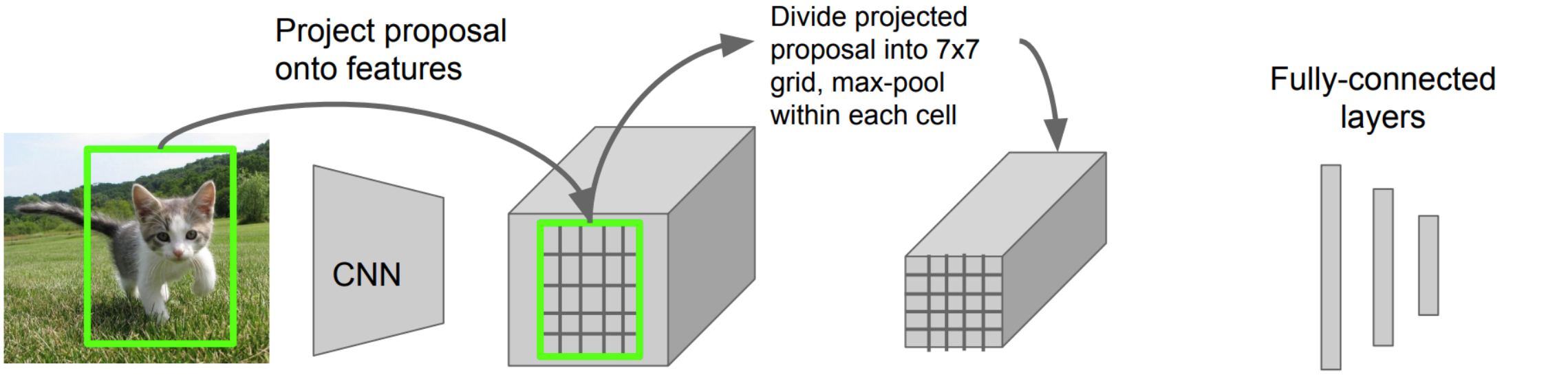
Single CNN:

Input: image

Output: Feature map

Source: CS231n, Stanford 2018, Fei-Fei Li, et. al.
Fast R-CNN, R Girshick, et.al.

Fast RCNN – ROI Pooling

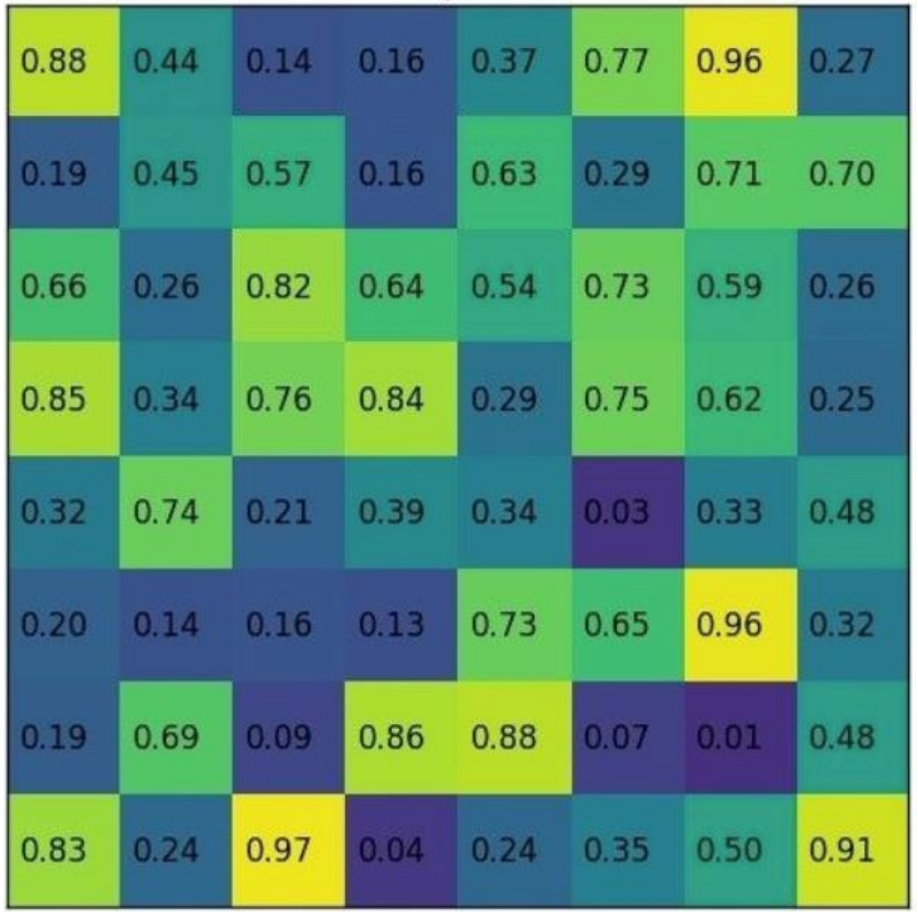


Girshick, "Fast R-CNN", ICCV 2015.

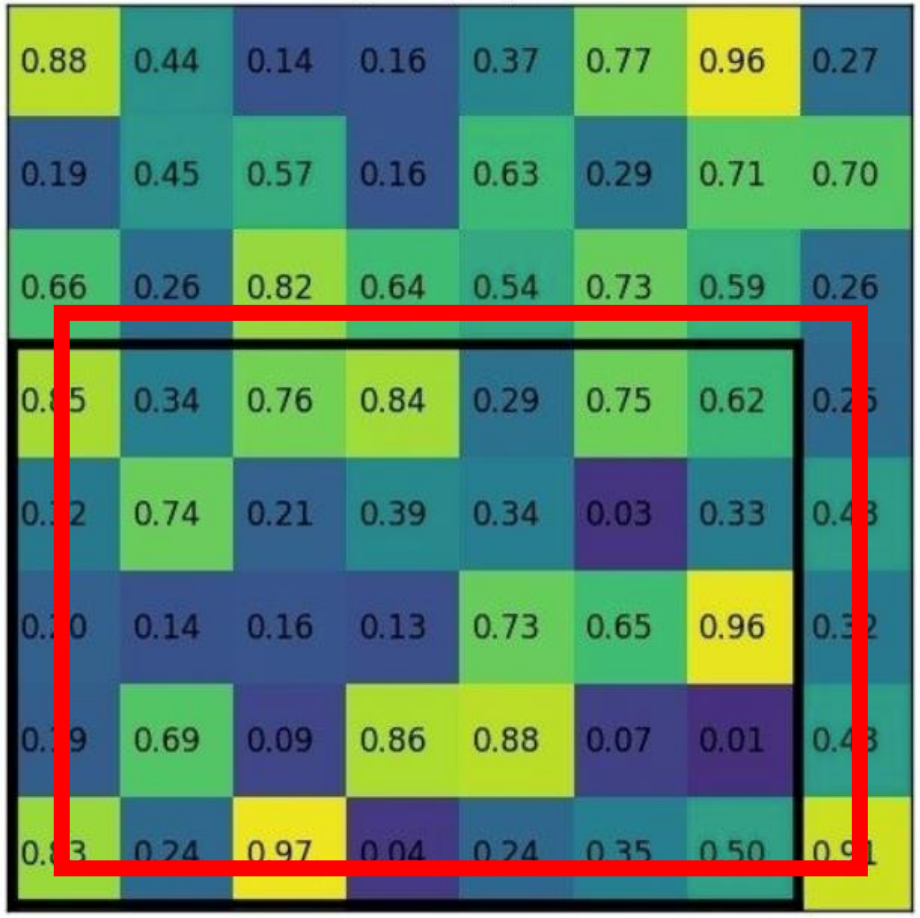
Source: CS231n, Stanford 2018, Fei-Fei Li, et. al.
Fast R-CNN, R Girshick, et.al.

ROI Pooling

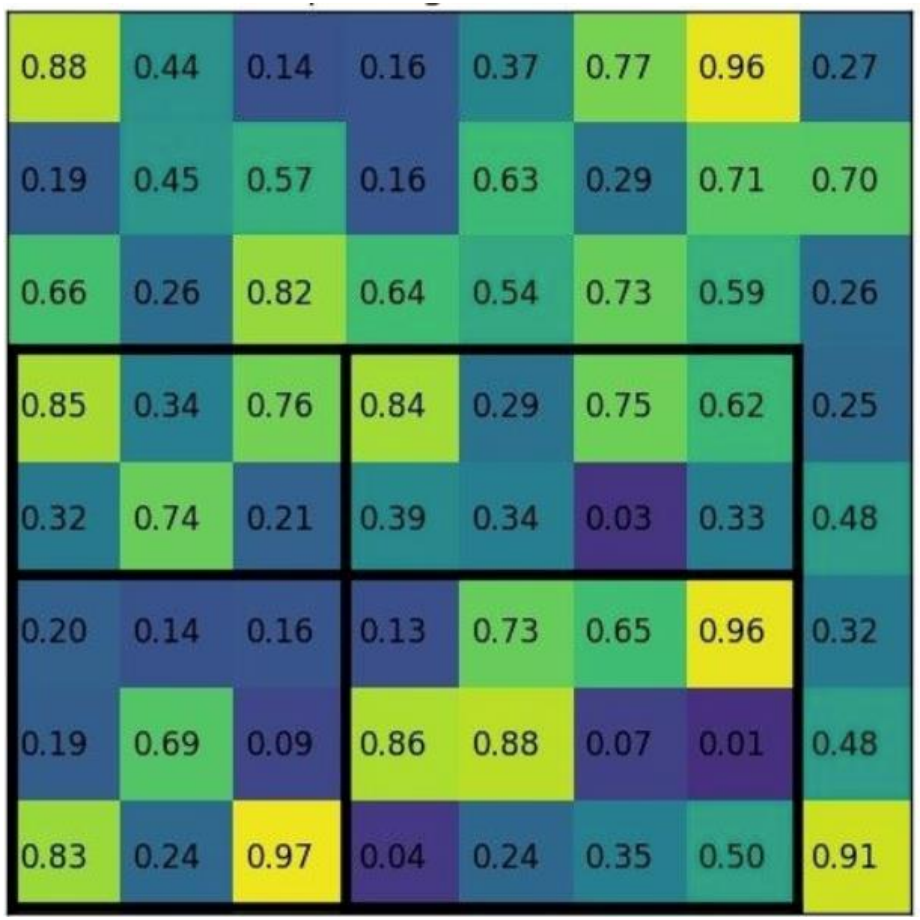
Feature Map

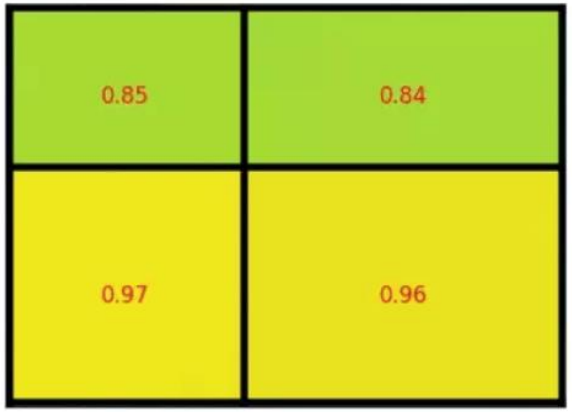


ROI at Feature Map (**Before** and **after** floor operation)



The ROI pooling outputs size 2x2

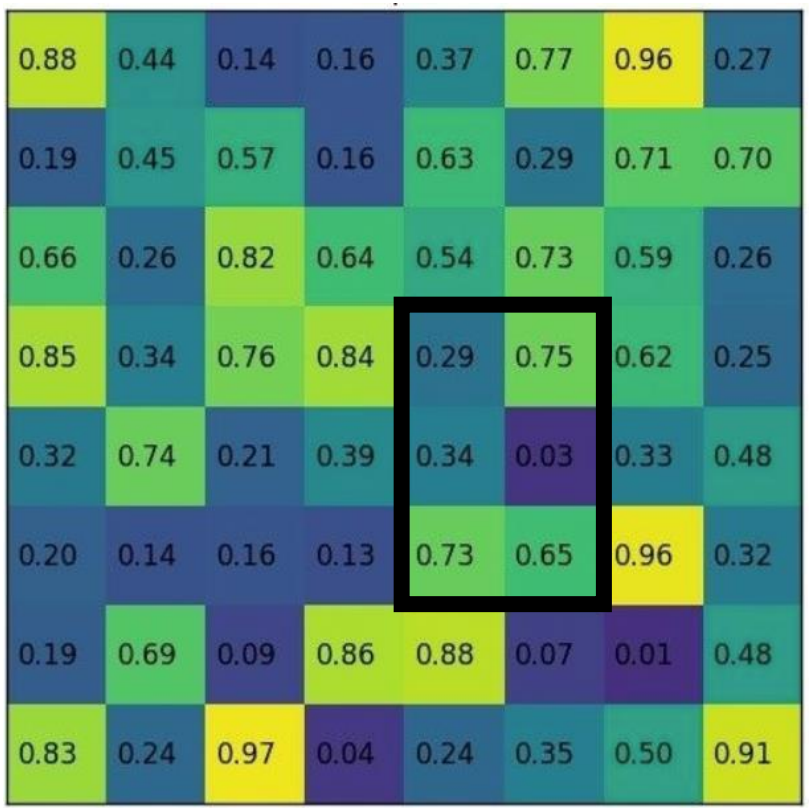




What if ROI is smaller than output?

Similar to image resize

- Interpolation by nearest neighbor



$3 \times 2 \rightarrow 4 \times 4$

Ratio: $\left(\frac{3}{4}, \frac{2}{4}\right) = (0.75, 0.5)$

Coordinate (a, b) in output → coordinate range on feature map ROI:

i: $[\ 0.75a\ ,\ 0.75(a+1)\ )$

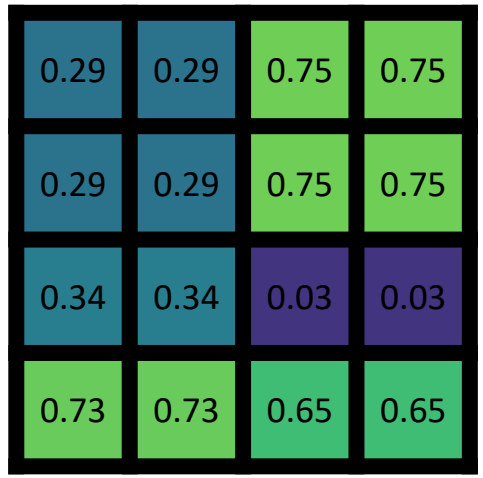
j: $[\ 0.50b\ ,\ 0.50(b+1)\ )$

Floor operation

i: $[\ \lfloor 0.75a \rfloor,\ \lfloor 0.75(a+1) \rfloor\ )$

j: $[\ \lfloor 0.50b \rfloor,\ \lfloor 0.50(b+1) \rfloor\ )$

Maxpool for the range



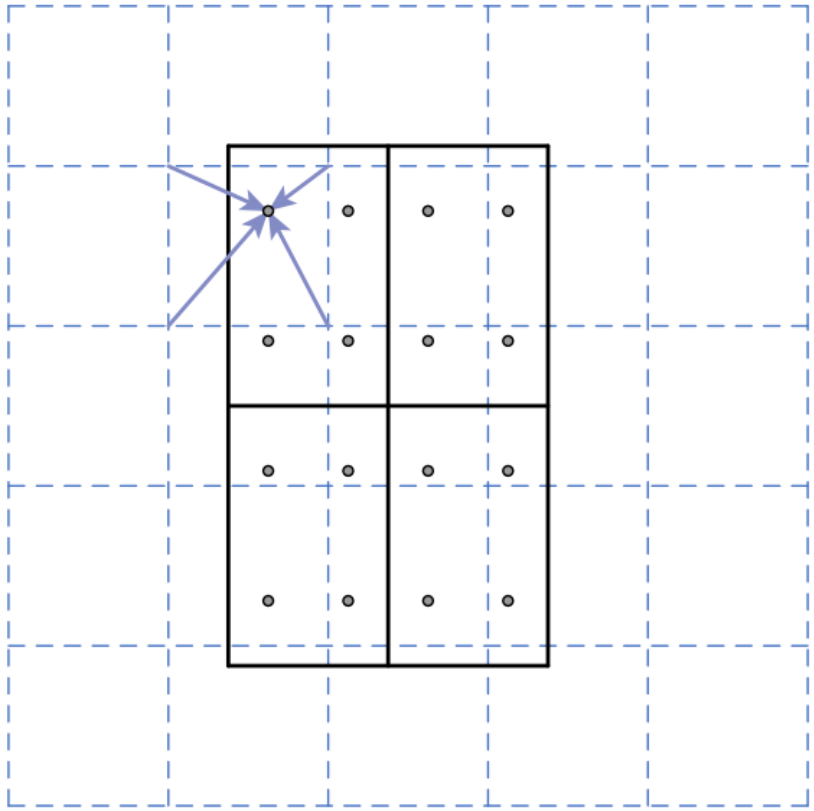
- Image resize: interpolation is better than nearest neighbor
- Same for feature map resize: ROI Pooling → ROI Align

Dash grid: 5×5 feature map

Solid Rectangle: $H \times W$ ROI at feature map

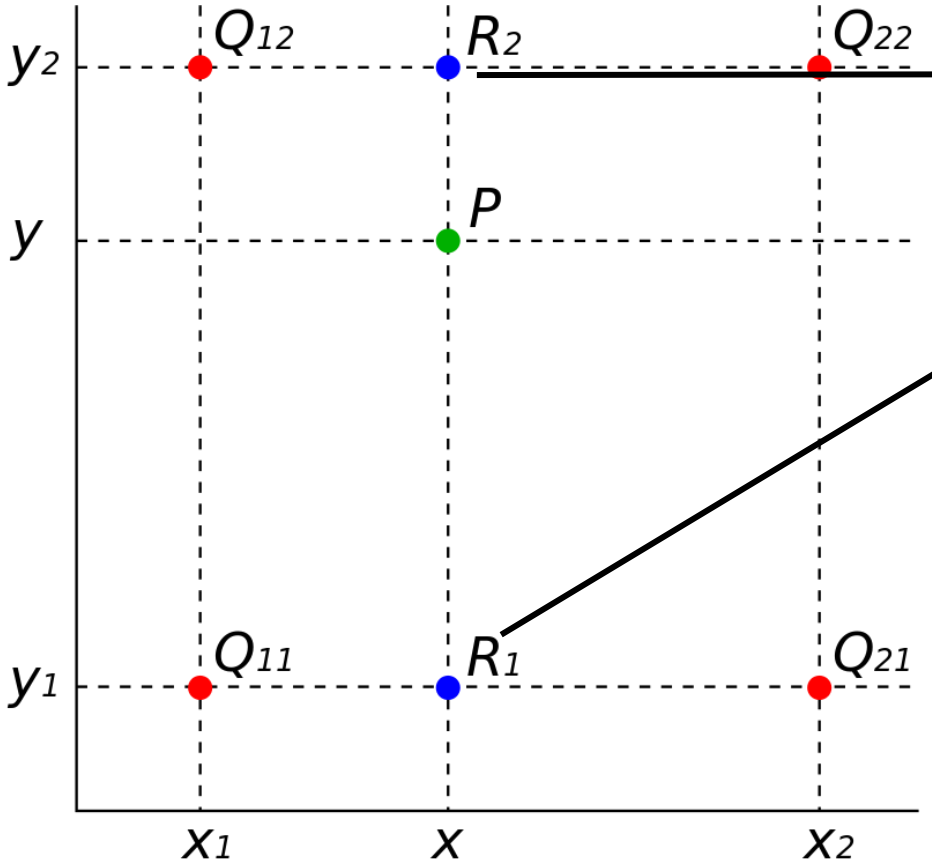
Output: 2×2 solid grid

1. Each cell in 2×2 output is sampled with 4 points
2. Each point is bilinear interpolation into dash grid
3. Each cell is max/avg pool of the 4 points



Source: Mask R-CNN, Kaiming He, et. al.

ROI Align – Bilinear Interpolation



$$f(x, y_2) \approx \frac{x_2 - x}{x_2 - x_1} f(Q_{12}) + \frac{x - x_1}{x_2 - x_1} f(Q_{22})$$

$$f(x, y_1) \approx \frac{x_2 - x}{x_2 - x_1} f(Q_{11}) + \frac{x - x_1}{x_2 - x_1} f(Q_{21})$$

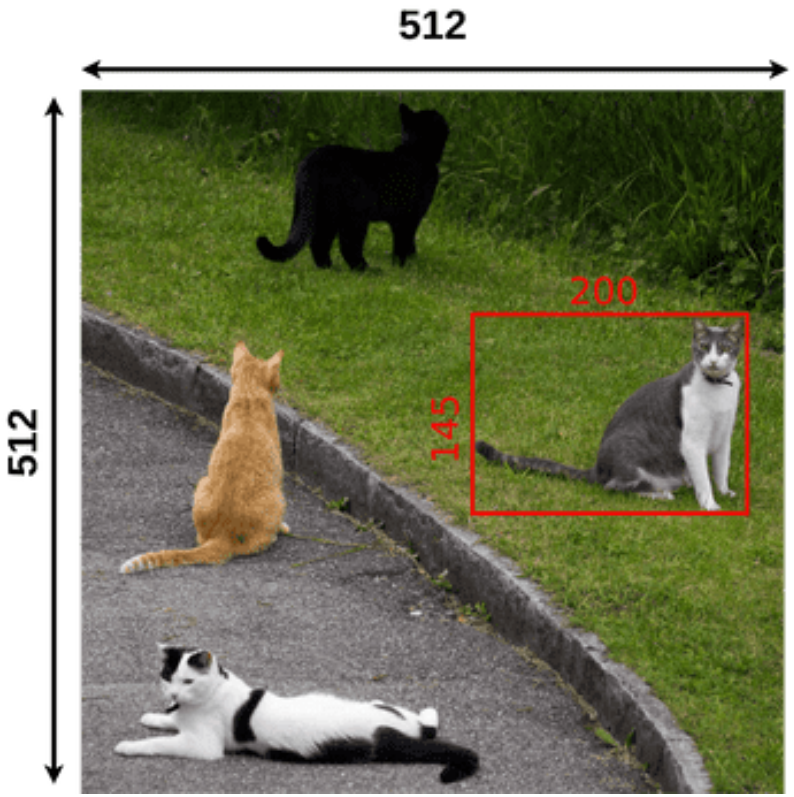
$$f(x, y) \approx \frac{y_2 - y}{y_2 - y_1} f(x, y_1) + \frac{y - y_1}{y_2 - y_1} f(x, y_2)$$

$$= \frac{1}{(x_2 - x_1)(y_2 - y_1)} \begin{bmatrix} x_2 - x & x - x_1 \end{bmatrix} \begin{bmatrix} f(Q_{11}) & f(Q_{12}) \\ f(Q_{21}) & f(Q_{22}) \end{bmatrix} \begin{bmatrix} y_2 - y \\ y - y_1 \end{bmatrix}$$

Source: https://en.wikipedia.org/wiki/Bilinear_interpolation

ROI Align Example

Input Image and Proposed Region



Feature map

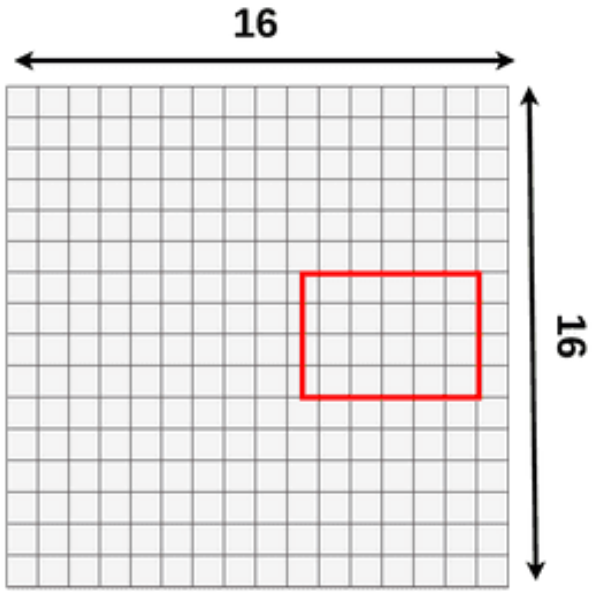
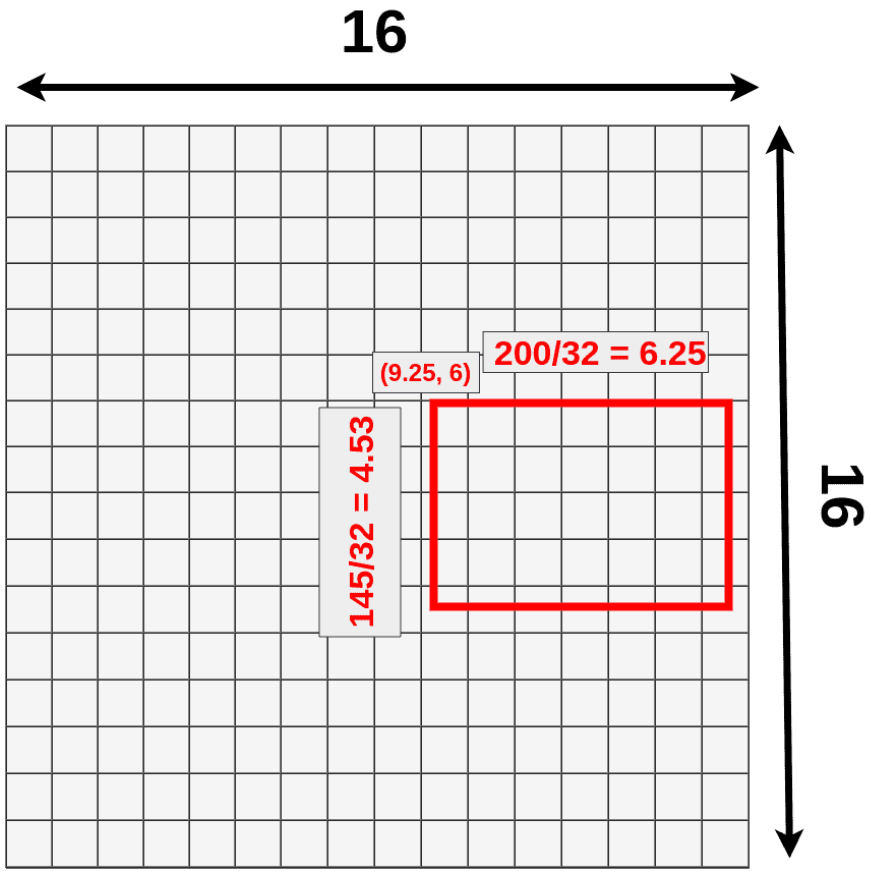


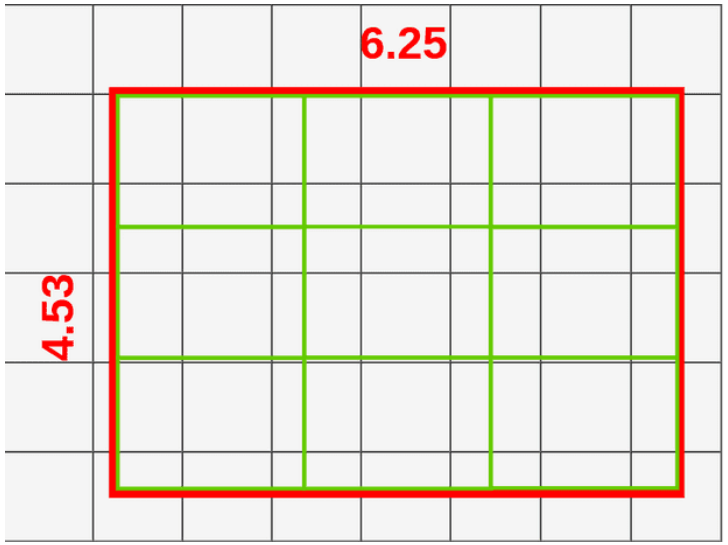
Image source: https://towardsdatascience.com/understanding-region-of-interest-part-2-roi-align-and-roi-warp-f795196fc193

ROI Align Example



ROI Align into 3x3

- Object size in image = 145x200
- Scale factor = 32 (ratio between feature map and image)



3x3 RoI Pooling

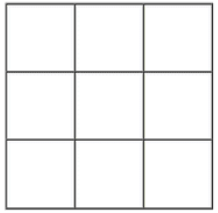


Image source: https://towardsdatascience.com/understanding-region-of-interest-part-2-roi-align-and-roi-warp-f795196fc193

ROI Align Example

- Each cell
  - Width = 6.25 / 3 = 2.0833
  - Height = 4.53 / 3 = 1.51
- Sample 4 points in each cell.
  - 9.25 + (2.0833 / 3) * 1 = 9.94
  - 6 + (1.51 / 3) * 1 = 6.50
  - … …
  - 9.25+ (2.0833 / 3) * 2 = 10.64
  - 6 + (1.51 / 3) * 3 = 7.01
  - … …

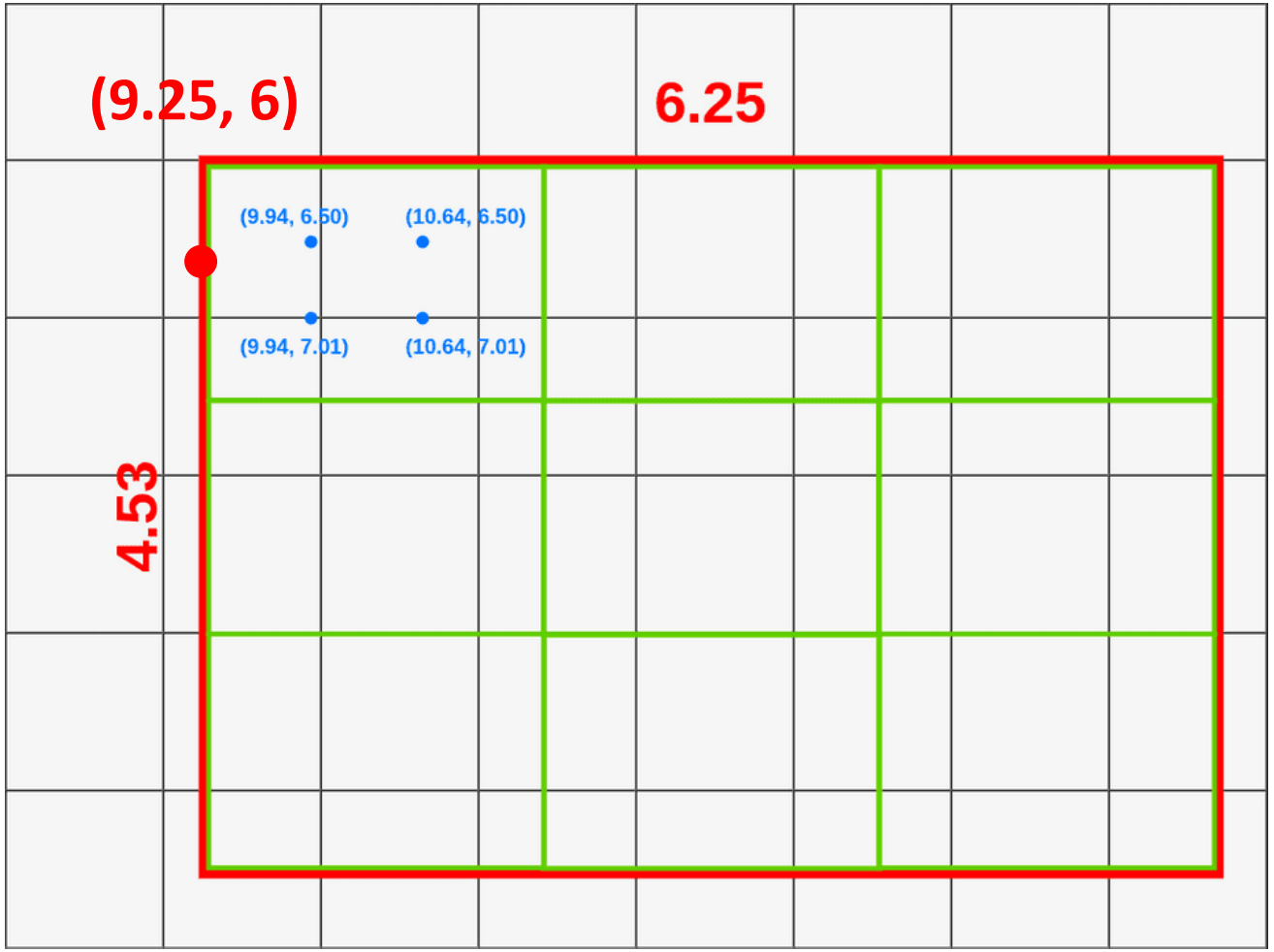
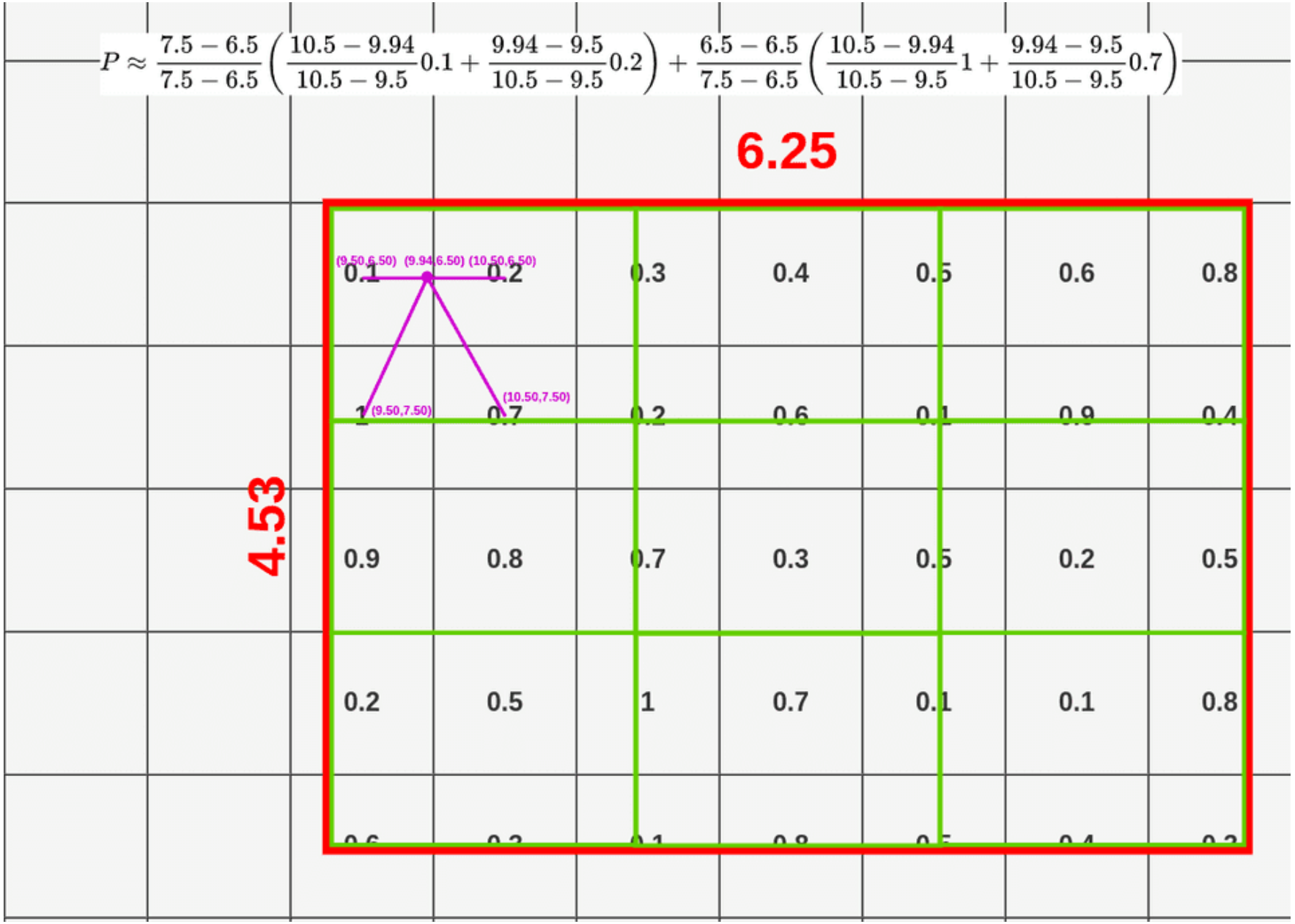


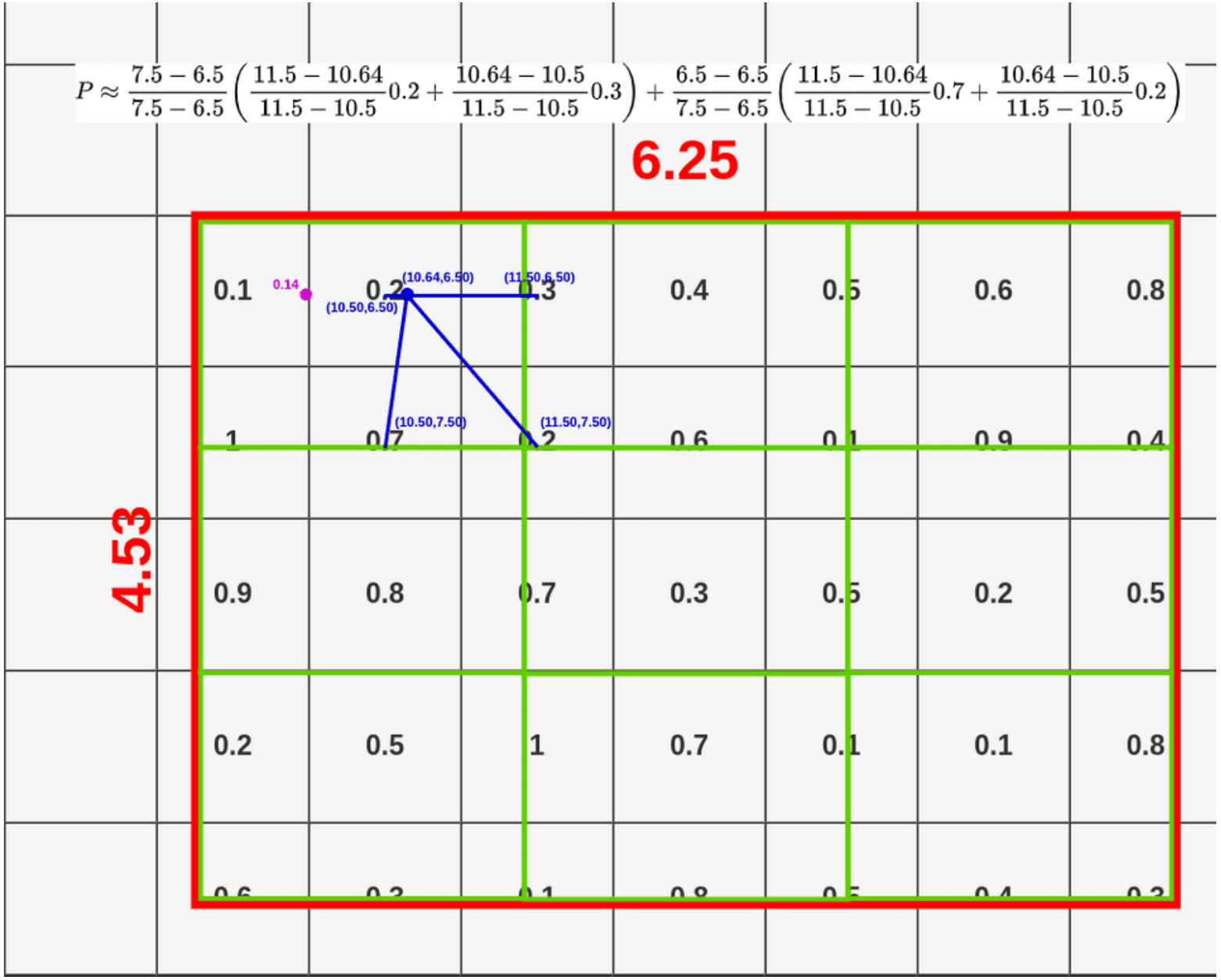
Image source: https://towardsdatascience.com/understanding-region-of-interest-part-2-roi-align-and-roi-warp-f795196fc193

ROI Align

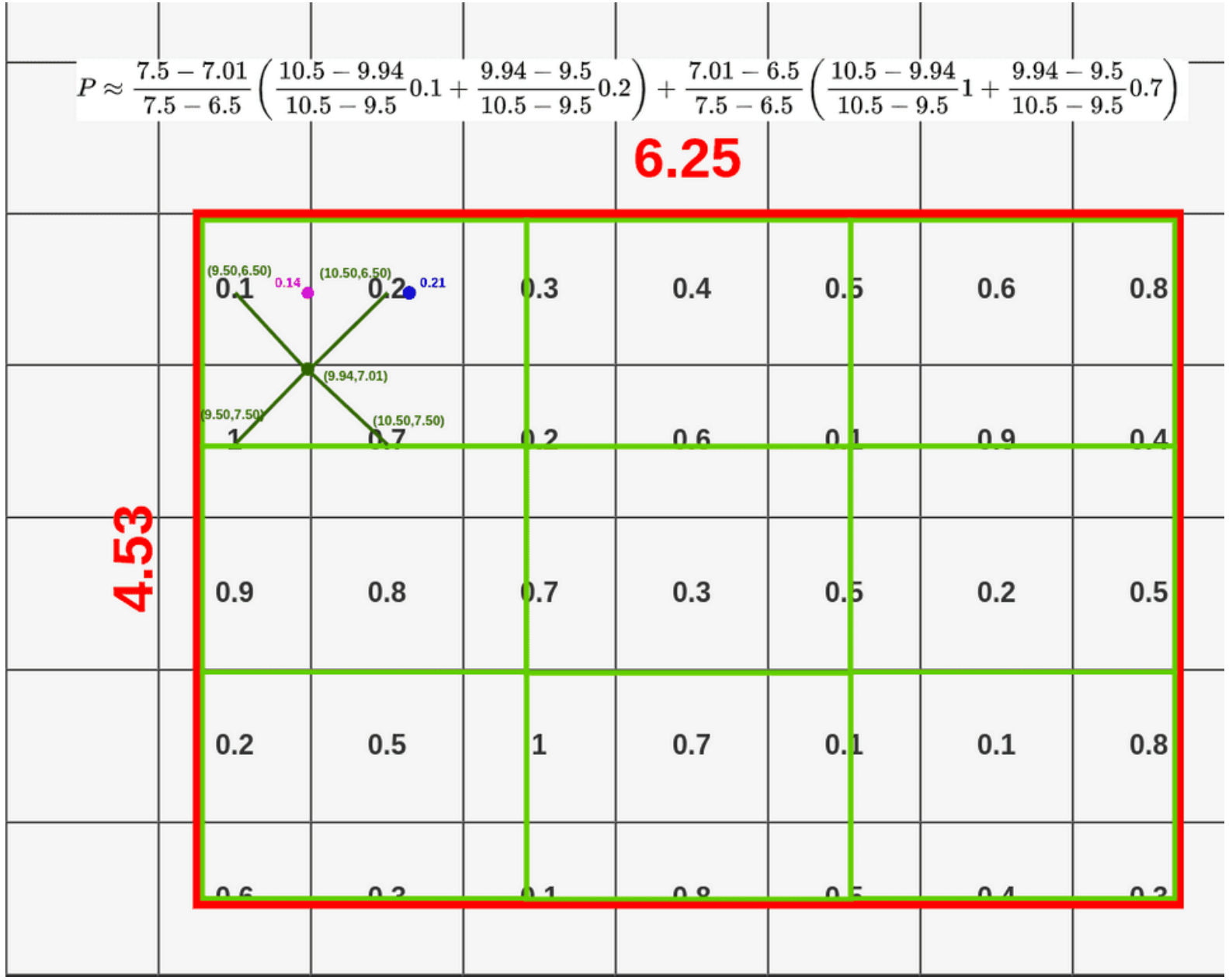
- Interpolation for each sampled point.



- Interpolation for each sampled point.

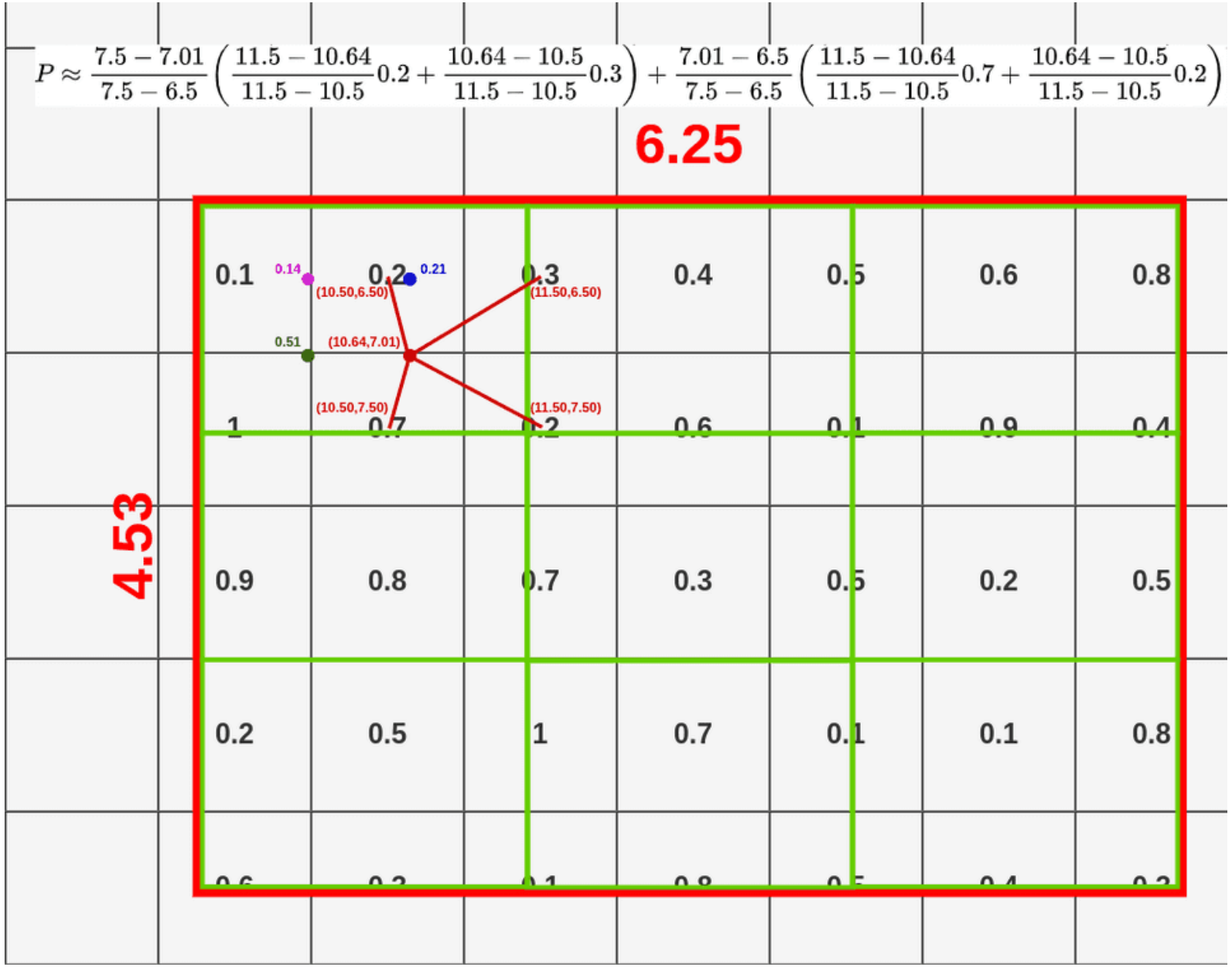


- Interpolation for each sampled point.

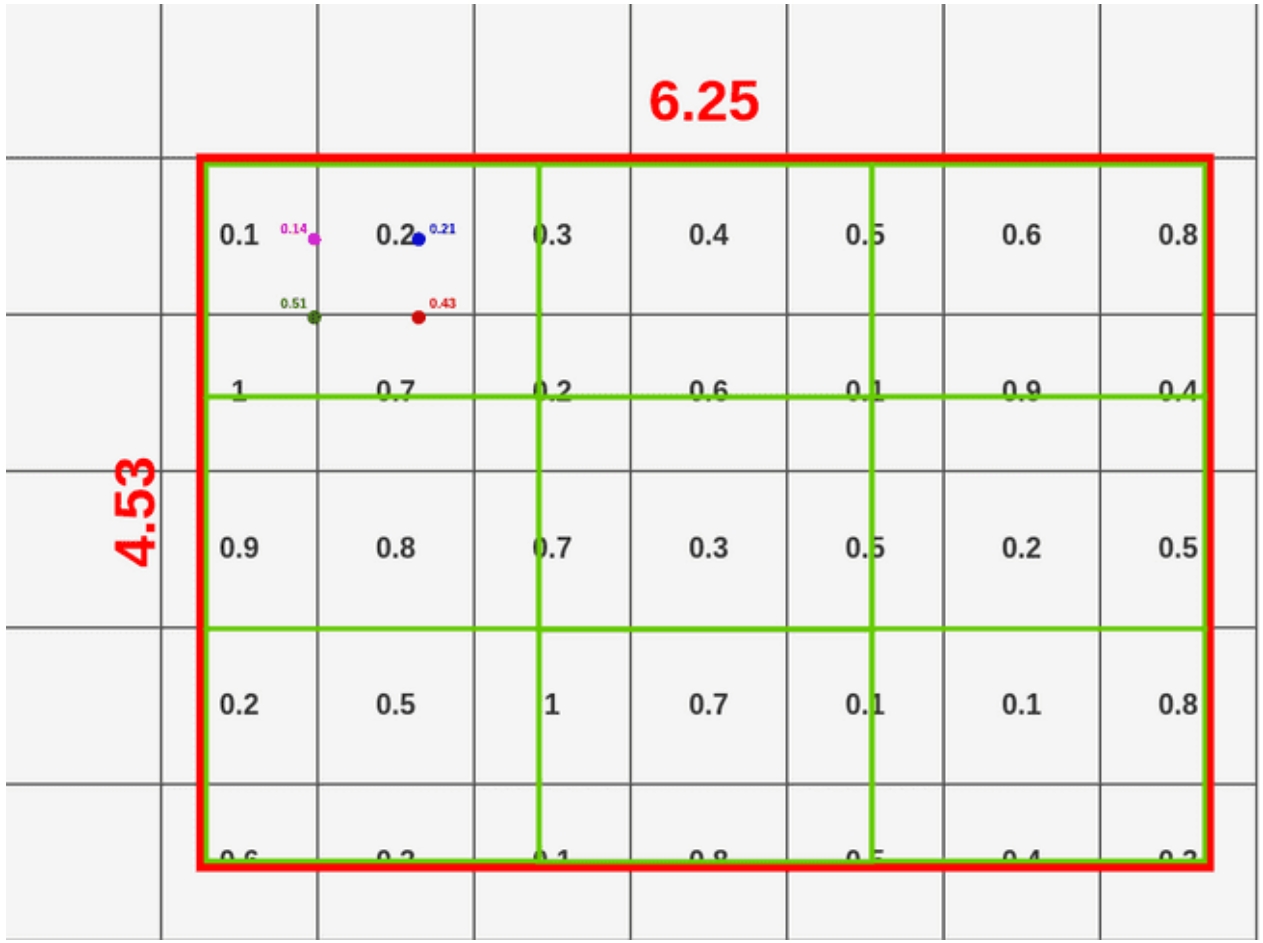


ROI Align

- Interpolation for each sampled point.



- Max/Average pooling of the 4 sampled points to get a cell



1x1 = MAX(0.14, 0.21, 0.51, 0.43) = 0.51

3x3 RoIAlign

0.51		

ROI Align Example

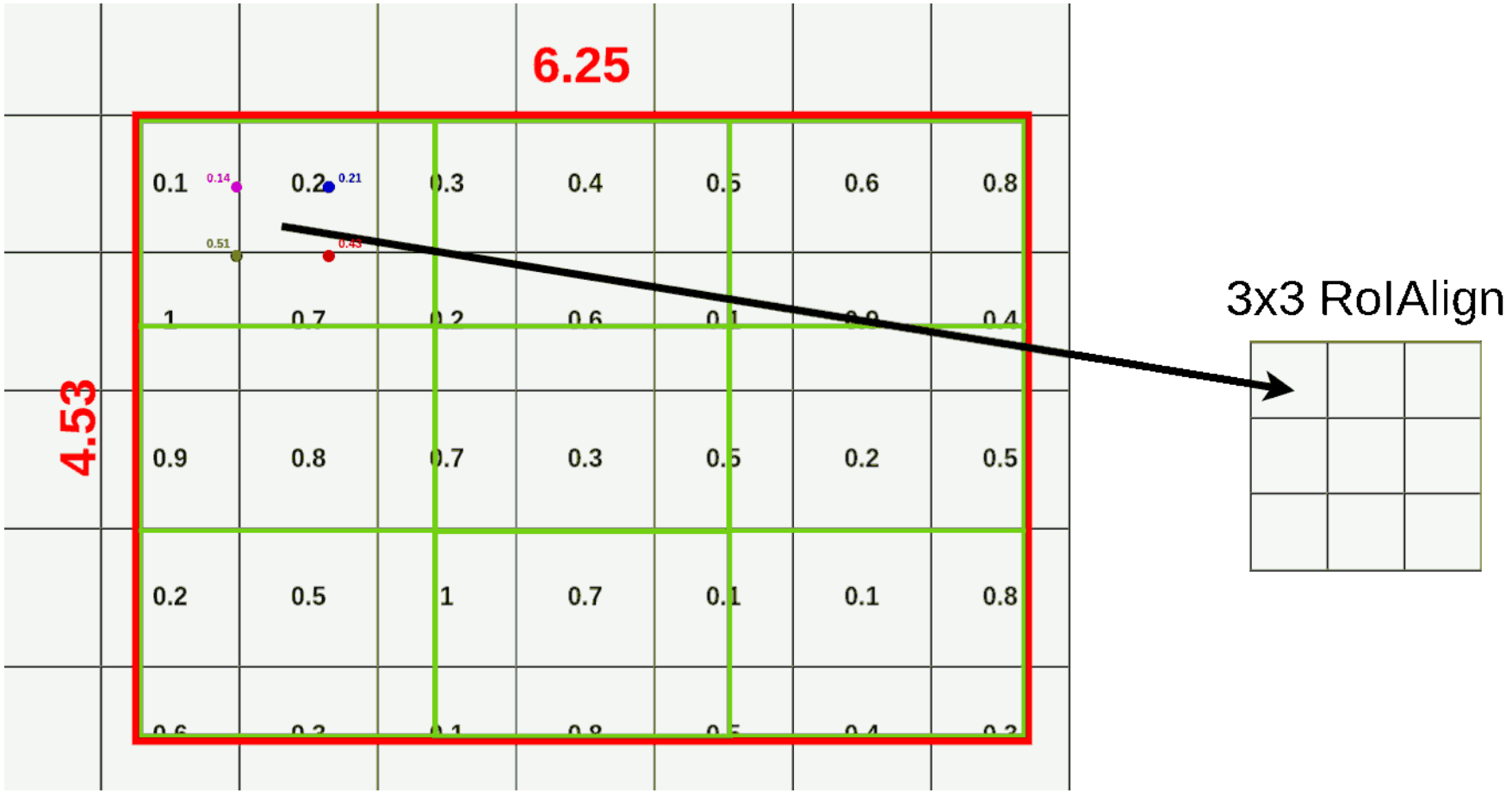
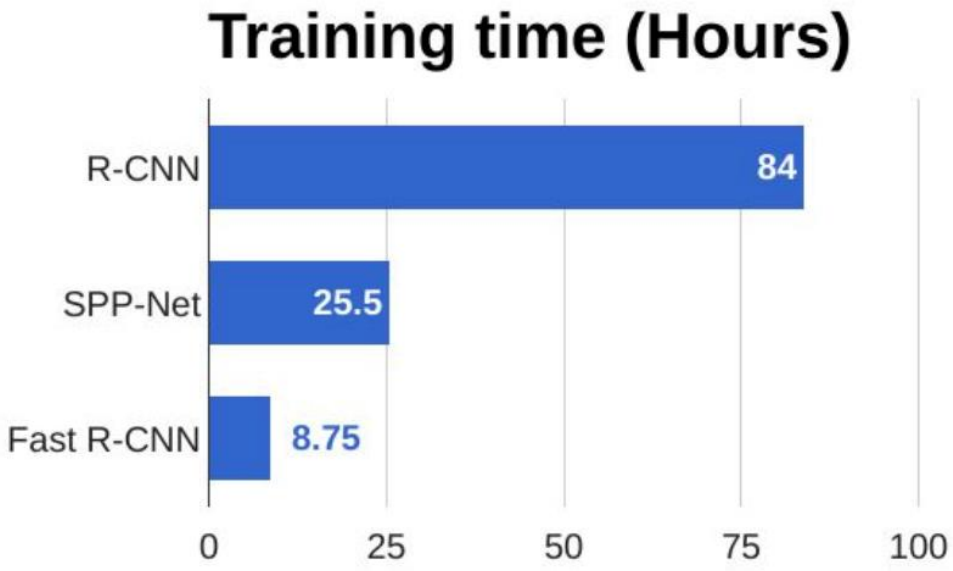
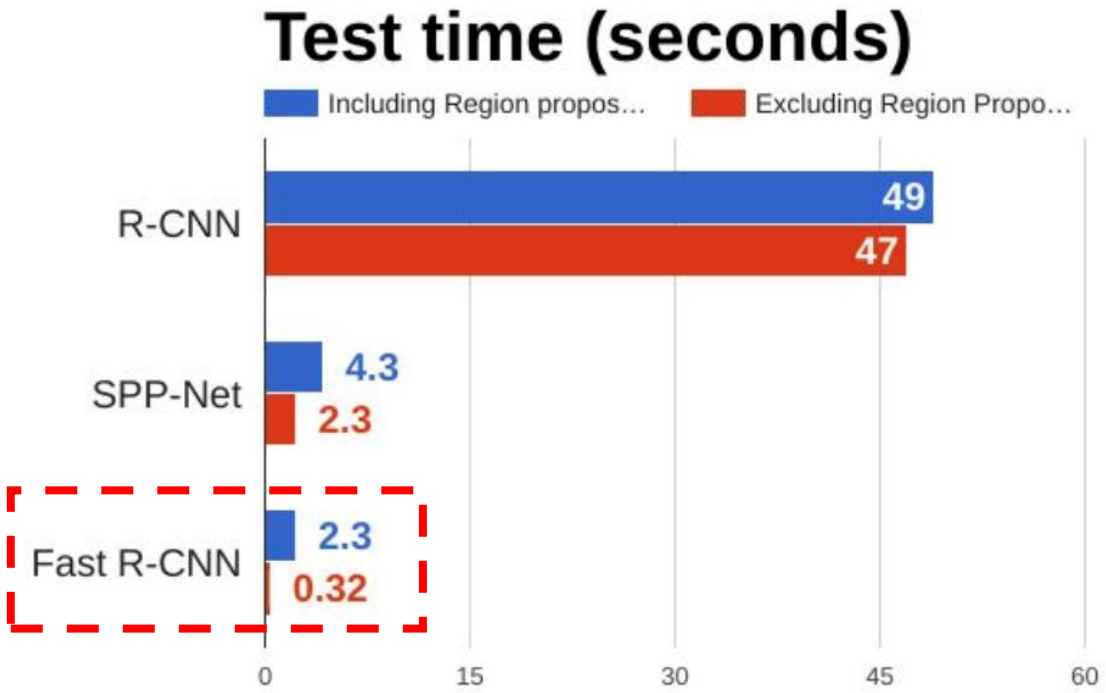


Image source: https://towardsdatascience.com/understanding-region-of-interest-part-2-roi-align-and-roi-warp-f795196fc193

RCNN v.s. Fast RCNN

Fast RCNN is fast compared to RCNN, because of the shared feature extraction.



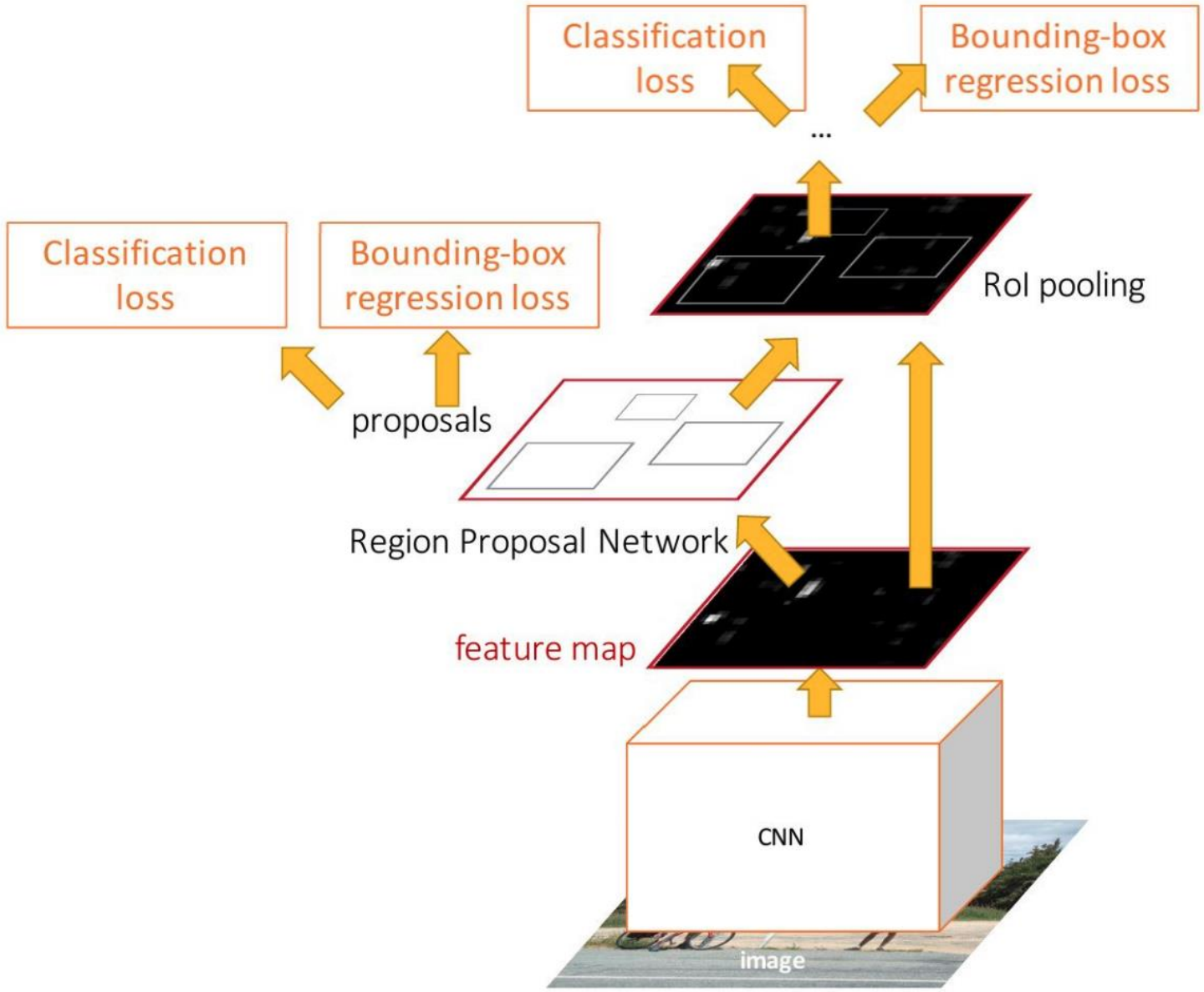


Runtime dominated by non-deep learning region proposal

Source: CS231n, Stanford 2018, Fei-Fei Li, et. al.

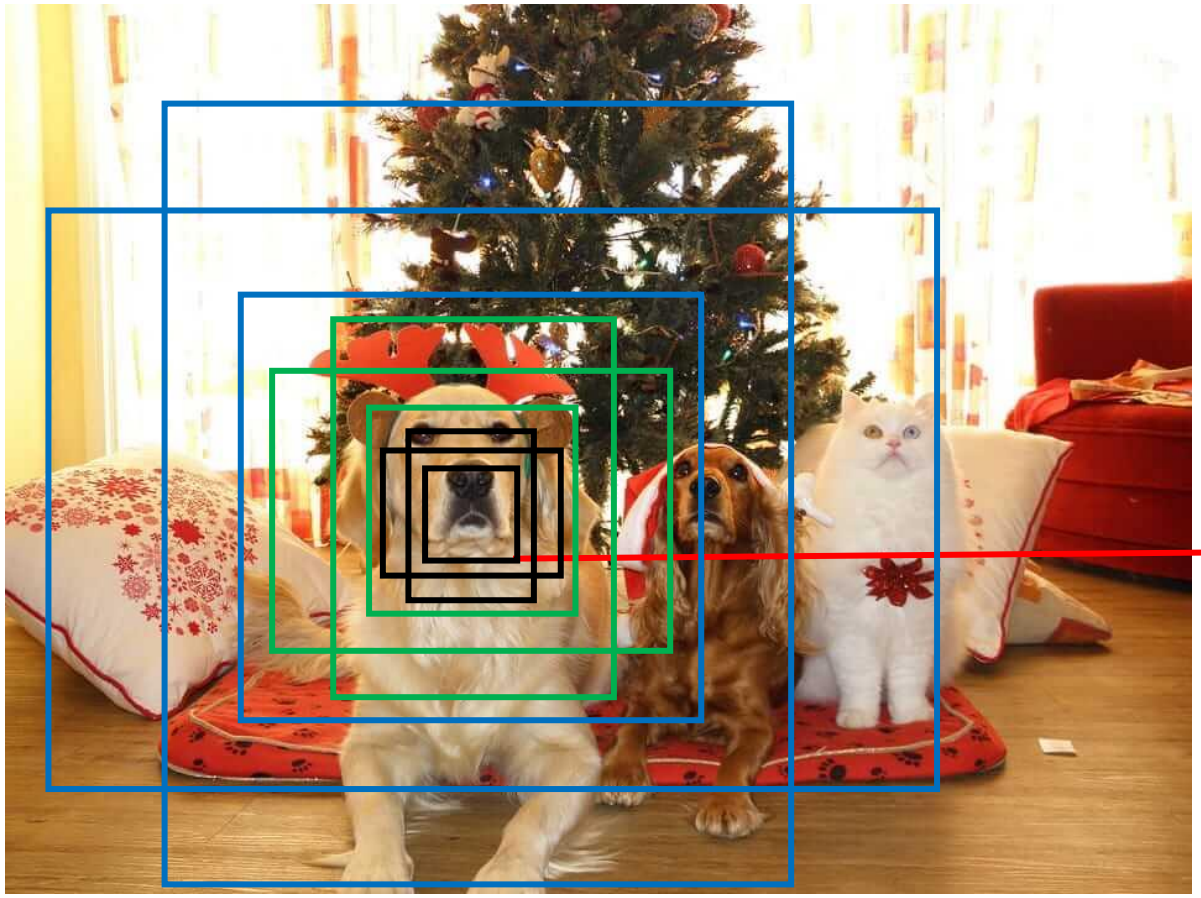
Region Proposal Network (RPN)

- Input:
  - Feature map
  - Anchors
- Output:
  - Object proposals (x, y, h, w)

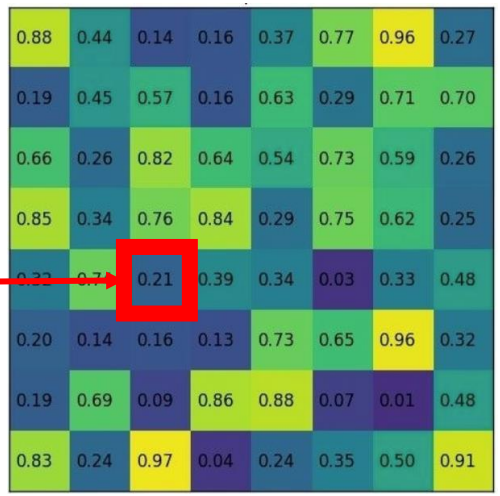


Source: CS231n, Stanford 2018, Fei-Fei Li, et. al.
Faster R-CNN: Towards real-time object detection with region proposal networks. Ren Shaoqing, et.al.

Anchors → Proposals

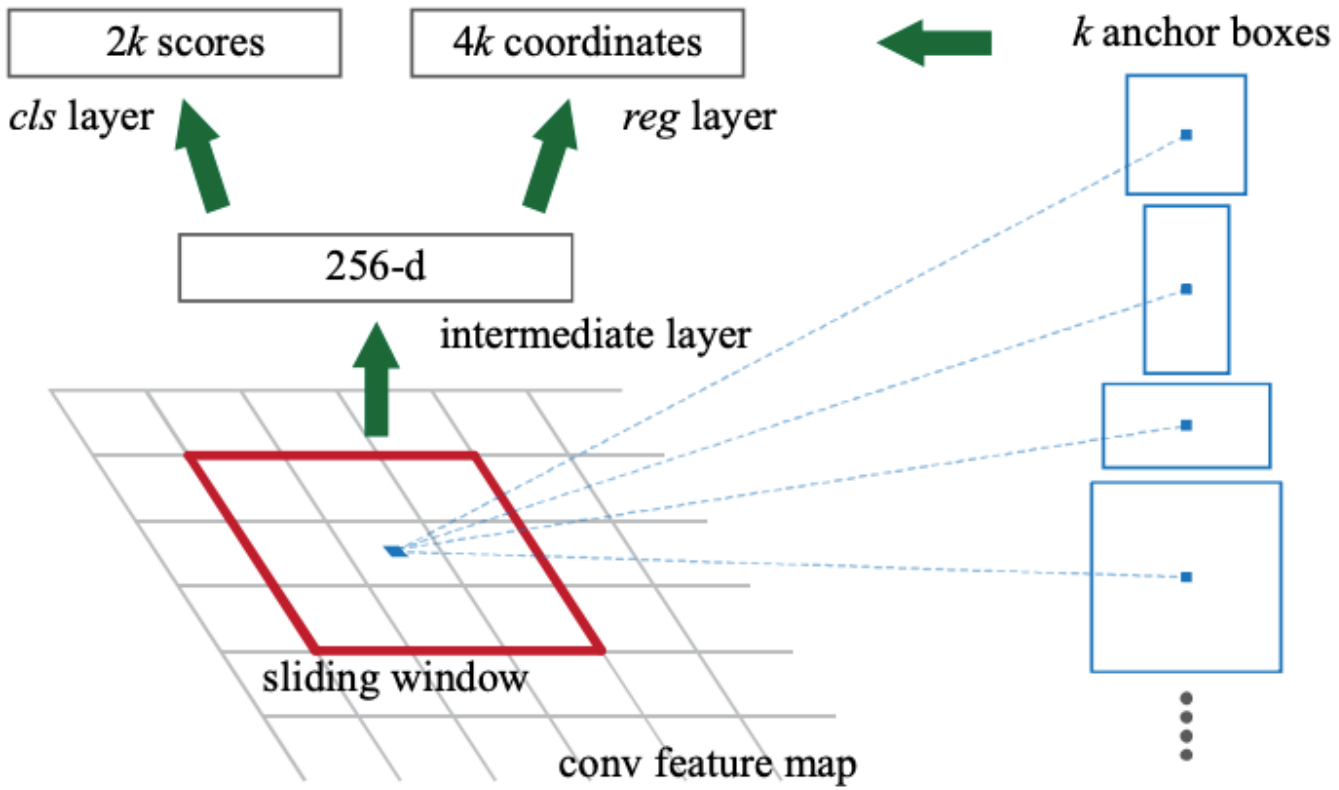


- 1 position in feature map
- k anchors in image



Region Proposal Network (RPN)

- RPN determines
  - Object or NOT-Object
    - 2k scores
  - If yes, [x,y,h,w] of the object box
    - 4k coordinates
- Doesn't care about categories of the objects



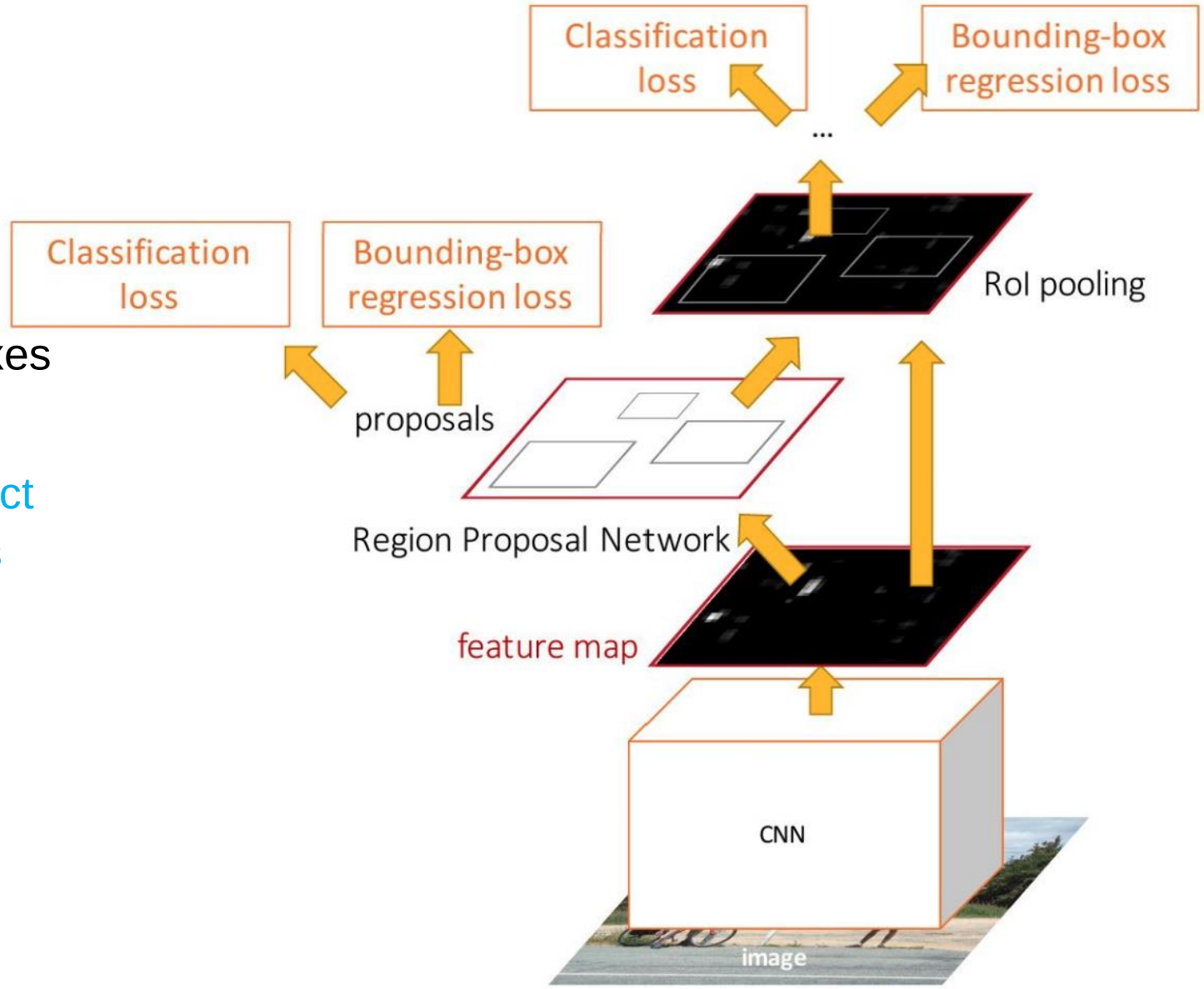
Source: Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, Shaoqing Ren, et. al.

Steps

1. CNN → Feature Map
2. RPN → Proposals
3. ROI Pooling
4. CNN + MLP → bounding boxes

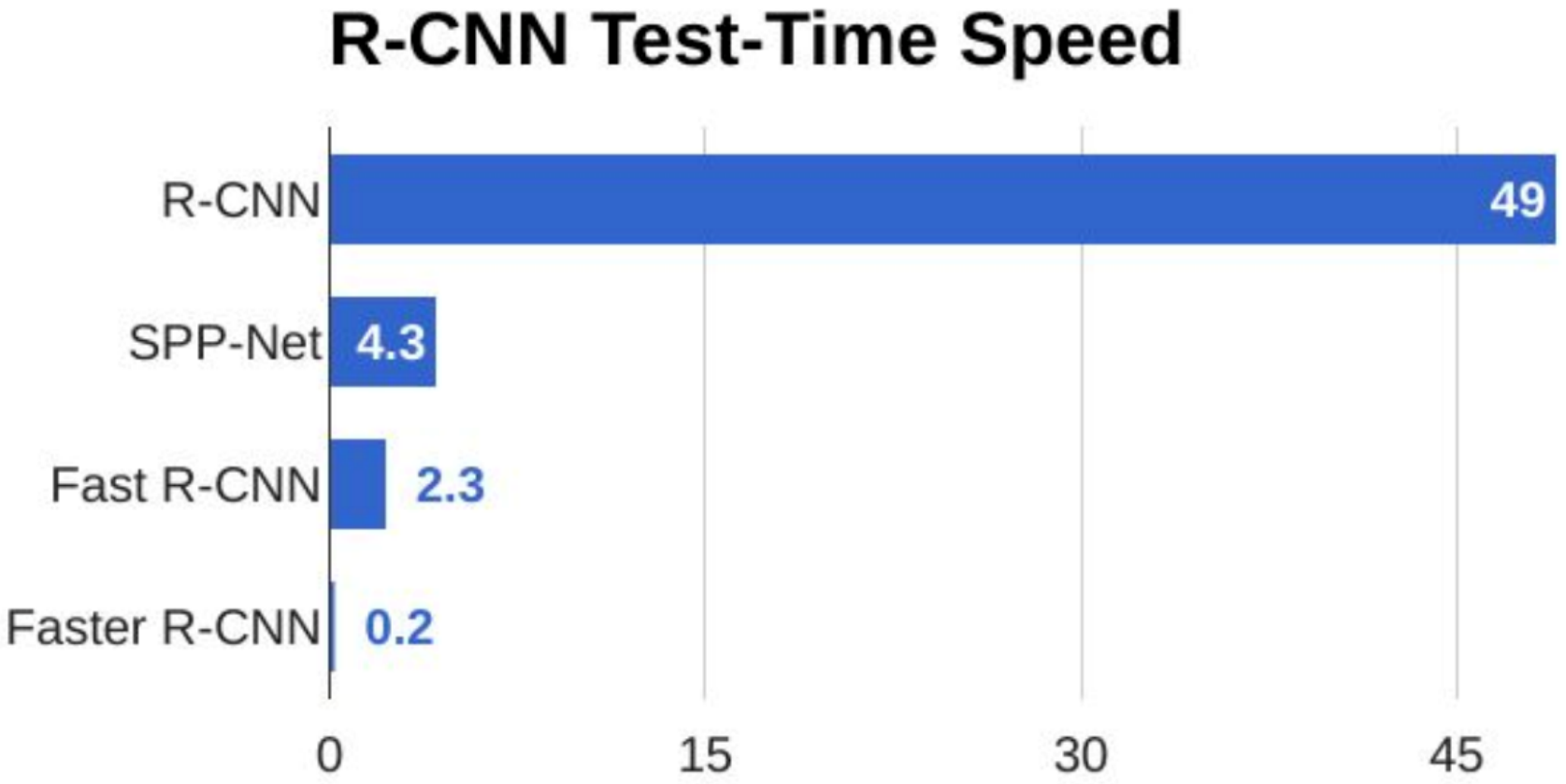
Losses:

1. RPN classify object / not object
2. RPN regress box coordinates
3. Final box classification
4. Final box coordinates



Source: CS231n, Stanford 2018, Fei-Fei Li, et. al.

Faster RCNN vs Fast RCNN vs. RCNN

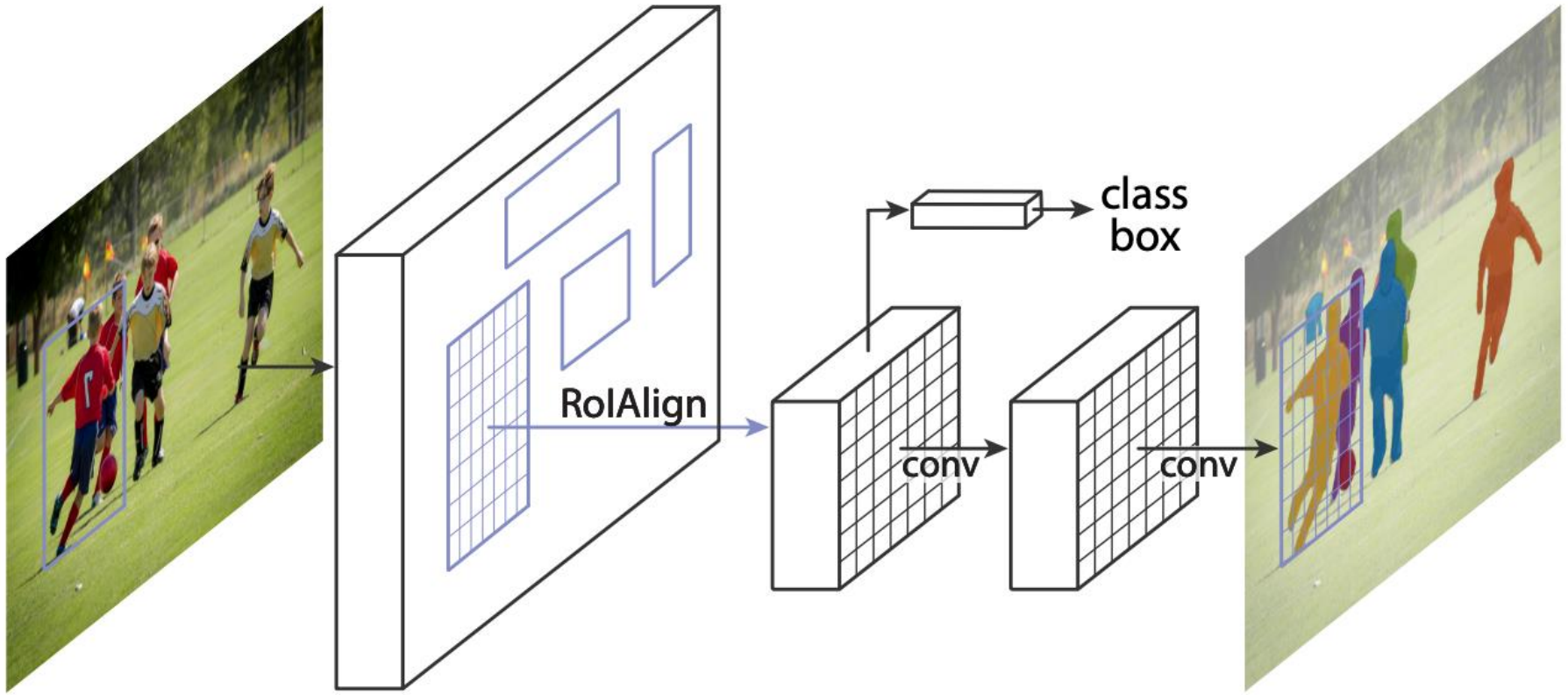


Source: CS231n, Stanford 2018, Fei-Fei Li, et. al.

Mask RCNN

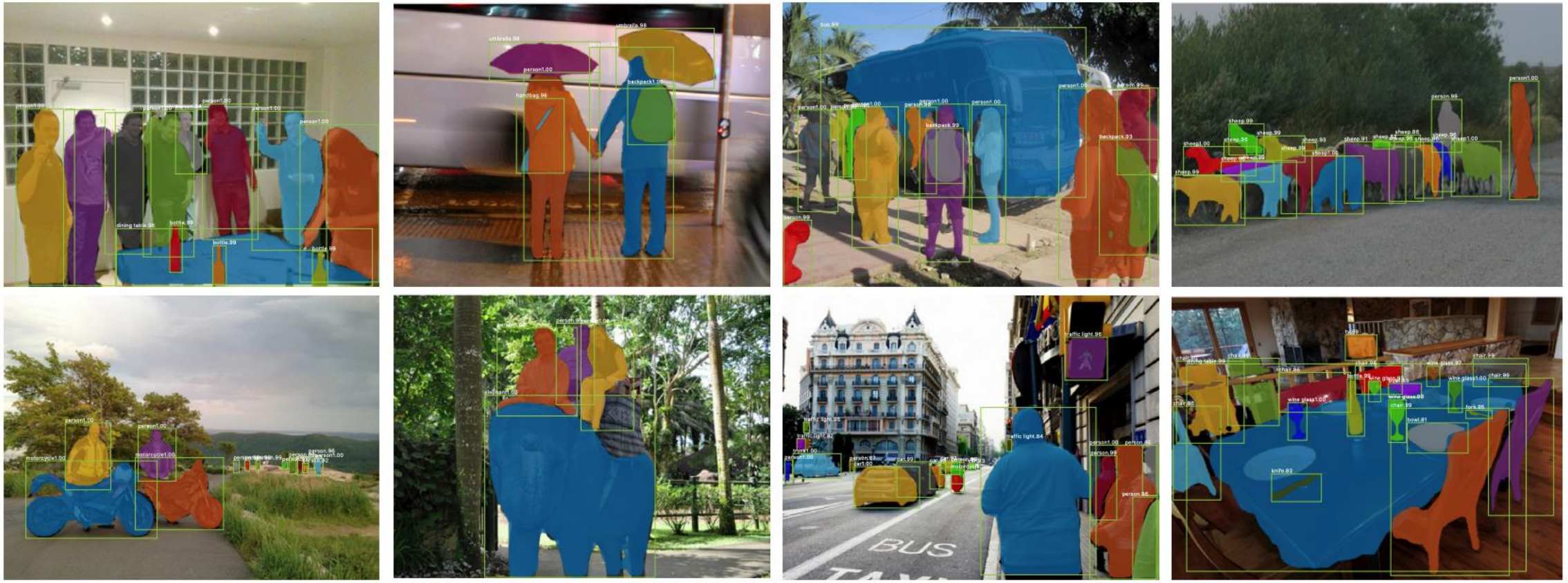
- Input: Image
  Output:
  - Object boxes
  - Per-pixel mask

- Two of the improvements over Faster RCNN
  - ROI Align
  - Object detection + Instance Segmentation



Source: Mask R-CNN, Kaiming He, et. al.

Mask RCNN



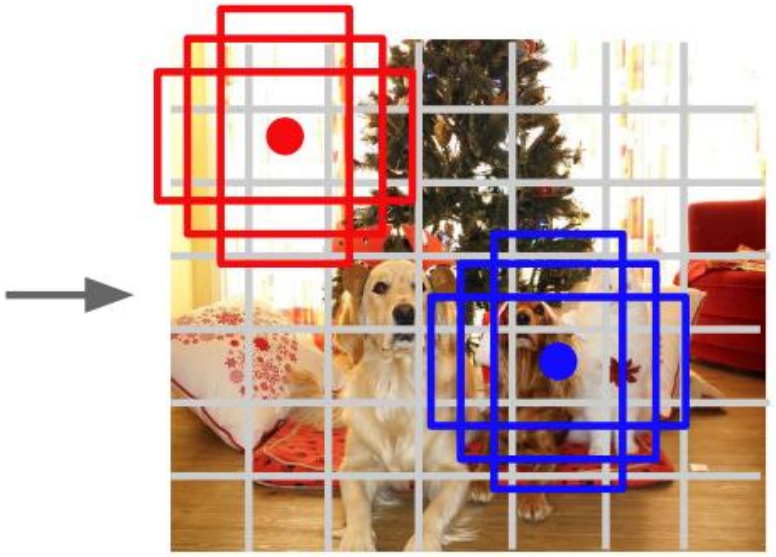
Source: Mask R-CNN, Kaiming He, et. al.

RCNN Family Summary

	RCNN	Fast RCNN	Faster RCNN	Mask RCNN
Region Proposal	External	External	RPN	RPN
Region processing	ROI crop on Image	ROI pooling on feature map	ROI pooling on feature map	ROI align on feature map
Multi-task	No	No	No	Instance Seg.

One Stage Detector – No ROI Pooling

Input image
3 x H x W



Divide image into grid
7 x 7

i.e. 7×7 feature map after CNN

Each cell corresponds to B prior bounding boxes, here $B = 3$

With each cell:

- Regression of B boxes
  - dx, dy, dh, dw, confidence
  - "d" means relative to prior box
- Classification of this cell: C classes
- Output:

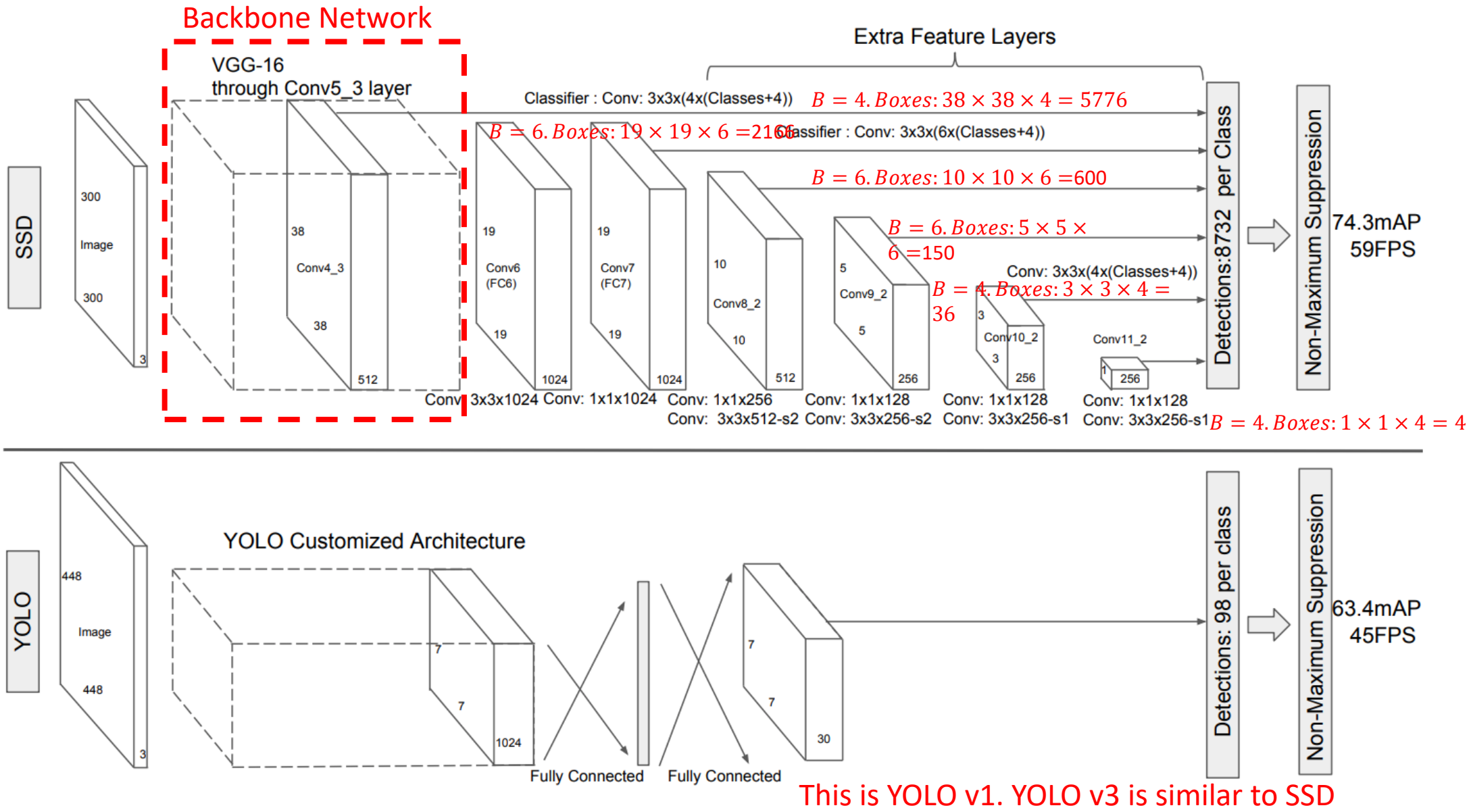
$$7 \times 7 \times (B \times 5 + C)$$

or

$$7 \times 7 \times (B \times (4 + C))$$

Source: CS231n, Stanford 2018, Fei-Fei Li, et. al.

SSD



Source: SSD: Single Shot MultiBox Detector, Wei Liu, et. al.

- Ground truth boxes: $\{x^g, y^g, w^g, h^g, p\}, p$ is the label
- Network output: a set of boxes $\{x, y, w, h, \{c_0, c_1, \cdots c_k\}\}$
  - Category 0 is background / not-object
- Loss function contains two parts
  - Classification for both positive and negative matches, CrossEntropyLoss

$$L_{cls} = \alpha L_{cls}^{pos} + \beta L_{cls}^{neg} = \alpha \sum -\log \frac{\exp c_p}{\sum \exp c_i} + \beta \sum -\log \frac{\exp c_0}{\sum \exp c_i}$$

  - Regression for positive matches:

$$L_{reg}^{pos} = \sum \rho\left(\frac{x^g - x}{w}\right) + \rho\left(\frac{y^g - y}{h}\right) + \rho\left(\log \frac{w^g}{w}\right) + \rho\left(\log \frac{h^g}{h}\right)$$

Training/Inference Steps for 2D Detectors

Training steps:

- Establish positive matching – which output boxes are associated with ground truth boxes
  - IoU > threshold or the largest IoU with one of the ground truth boxes
- Establish negative matching – which output boxes are not matched to any ground truth box
  - IoU < threshold
- Compute $L = \alpha L_{cls}^{pos} + \beta L_{cls}^{neg} + L_{reg}^{pos}$

Inference steps:

- Pick boxes with high classification scores
- Non-Maximum Suppression (NMS)

2D Detector Performance

- Two stage methods are usually more accurate, but slower
- The same method's speed & accuracy can be very different, depending on
  - Network design
  - Training configuration
  - Parameter setting,
    - image/feature map resolution,
    - number of anchor/prior boxes,
    - how to select anchors/prior boxes
    - … …

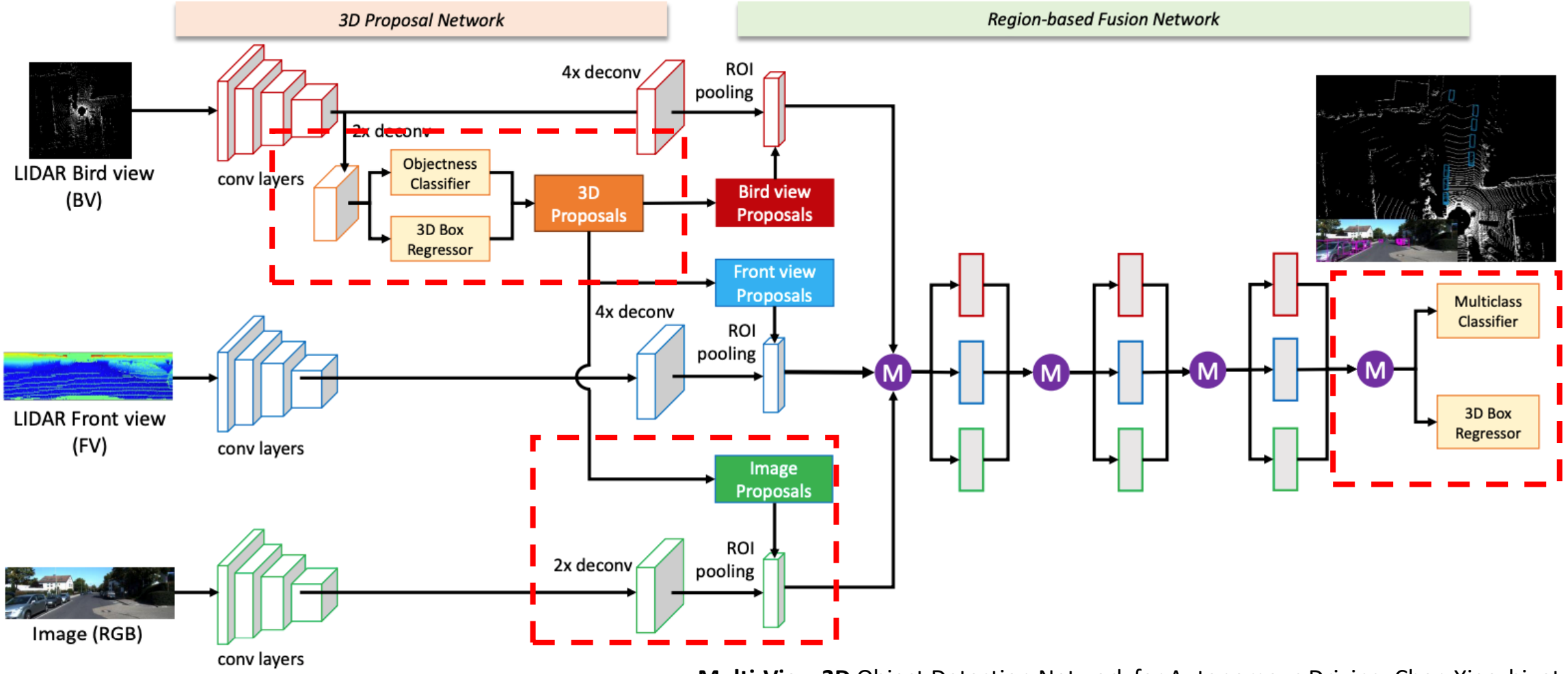
	Train Time (s/iter)	Inference Time (fps)	Box AP
Fast RCNN	0.462	10.9	38.9
Faster RCNN	1.04	7.3	41.3
Mask RCNN	1.102	6.5	42.1
SSD	0.412	25.4	29.3

Source: MMDetection, https://github.com/open-mmlab/mmdetection

- Multi-view Projection
- Build image-like feature map with PointNet
  - PointNet to convert point cloud detection into image detection + normal 2D CNN
  - Two-stage / One-stage
- Point-wise operation
  - Replace 2D CNN with point-wise operations like PointNet
  - Two-stage / One-stage
- Point cloud & image fusion

MV3D

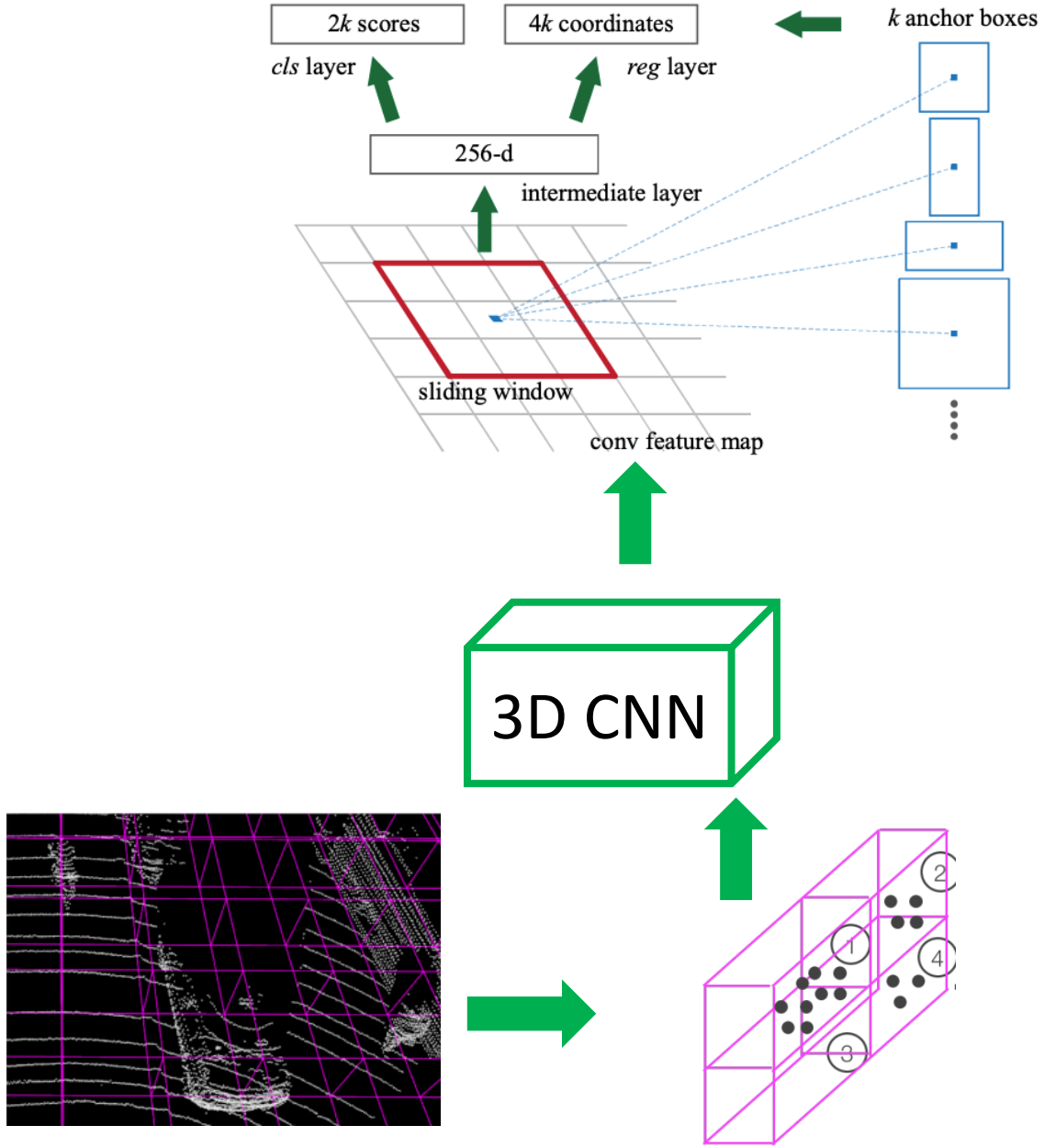
- Multi-view projection + Faster RCNN
  - 3D proposal from BV, project into other views
  - ROI pooling in each view, combined for Cls./Reg.
- Pioneer work but not frequently used nowadays



Multi-View 3D Object Detection Network for Autonomous Driving, Chen Xiaozhi, et. al.

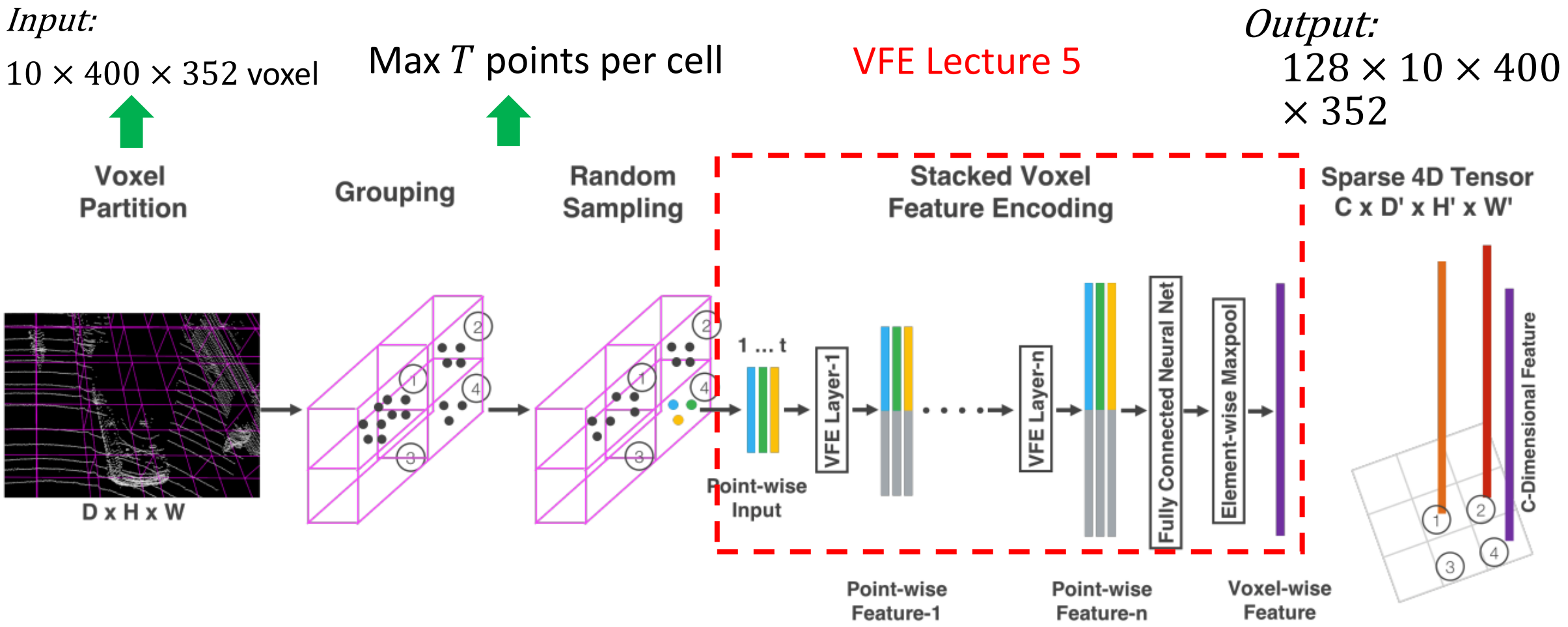
VoxelNet

1. Build voxel grid
2. Get feature per-cell
   - PointNet
3. 3D voxel → 2D feature map
   - 3D convolution
4. Region Proposal Network (RPN)
   - One network for one category.
   - RPN is only predicting if the anchor box is an object



VoxelNet: End-to-End Learning for Point Cloud Based 3D Object Detection, Yin Zhou, et.al.

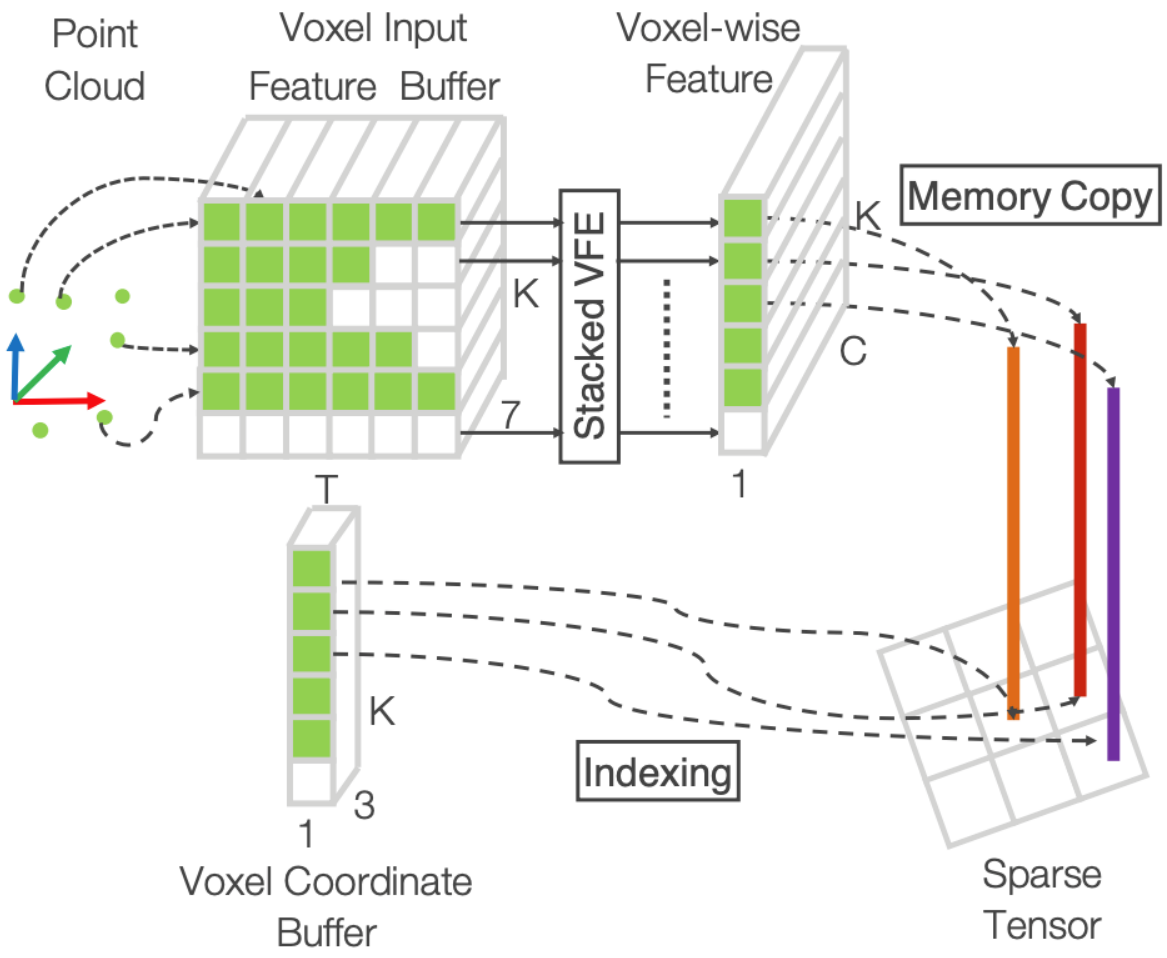
VoxelNet – Voxel Feature Encoding (VFE)



VoxelNet: End-to-End Learning for Point Cloud Based 3D Object Detection, Yin Zhou, et.al.

VoxelNet – Voxel Feature Encoding

- $10 \times 400 \times 352$ cells, Run VFE for all of them?
  - No, 90% cells are empty
- 1. Build two containers
  - a) K – maximum number of non-empty voxels
  - b) T – maximum number of points per voxel
  - *c)* $K \times T \times 7$ for points $(x_i, y_i, z_i, r_i, x_i - v_{ix}, y_i - v_{iy}, z - v_{iz})$
  - *d)* $K \times 3$ for voxel coordinates
- 2. Iterate each point
  1. Determine voxel coordinate (h_x, h_y, h_z)
     - Hash(h_x, h_y, h_z) → index k in container (c)(d)
  2. If k-th element exist in (c)/(d), append to (c)
  3. If not, create k-th element in (c) (d)
- 3. VFE / PointNet on (c) → $K \times 128$
- 4. Put (c) back to the voxel grid → $128 \times 10 \times 400 \times 352$

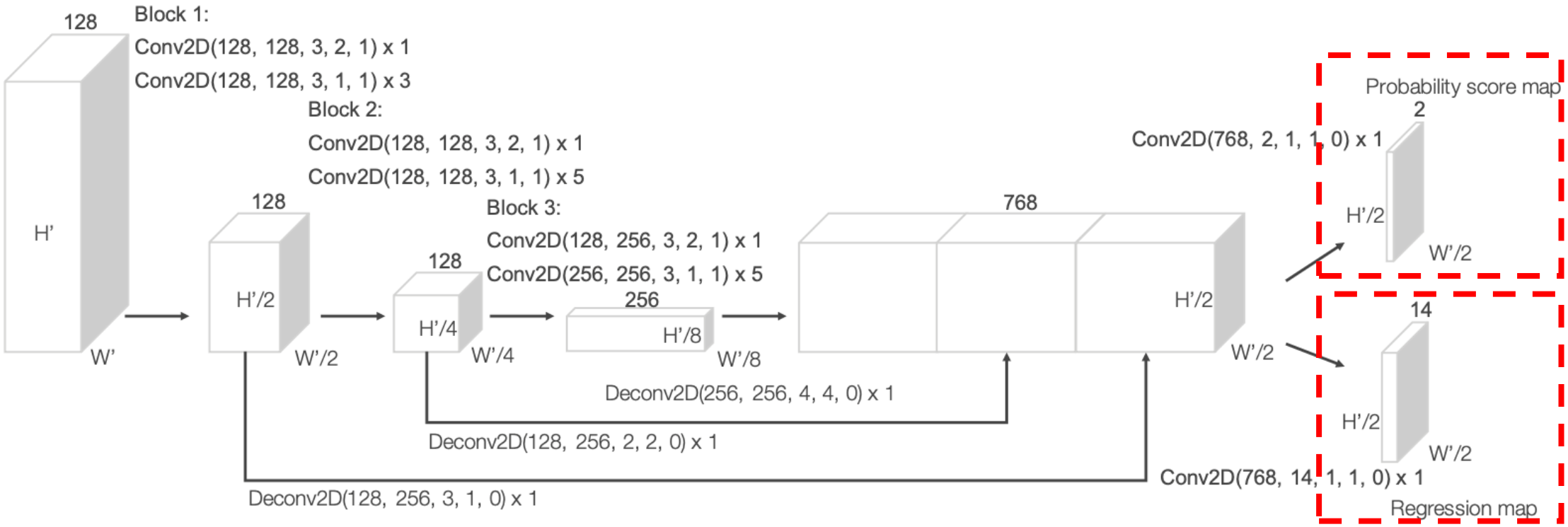


VoxelNet: End-to-End Learning for Point Cloud Based 3D Object Detection, Yin Zhou, et.al.

VoxelNet – Convolutional Middle Layers / 3DCNN

- Input: $128 \times 10 \times 400 \times 352$
- Conv3D
  - Output channel # 64, kernel (3, 3, 3), stride (2, 1, 1), padding (1, 1, 1)
  - Output channel # 64, kernel (3, 3, 3), stride (1, 1, 1), padding (0, 1, 1)
  - Output channel # 64, kernel (3, 3, 3), stride (2, 1, 1), padding (1, 1, 1)
- Output: $C' \times D' \times H' \times W'$ – Homework
  - Answer is $64 \times 2 \times 400 \times 352$
- Reshape into 2D feature map $2C' \times H' \times W'$
  - This is image-like feature map!

VoxelNet – Region Proposal Network (RPN)



Two anchor boxes

- $x, y, z, l, w, h, \theta = 0°$
- $x, y, z, l, w, h, \theta = 90°$

VoxelNet – Loss Function

Loss function for VoxelNet

$$L = \alpha \frac{1}{N_{\text{pos}}} \sum_i L_{\text{cls}}(p_i^{\text{pos}}, 1) + \beta \frac{1}{N_{\text{neg}}} \sum_j L_{\text{cls}}(p_j^{\text{neg}}, 0) + \frac{1}{N_{\text{pos}}} \sum_i L_{\text{reg}}(\mathbf{u}_i, \mathbf{u}_i^*)$$

L_{cls} is “Binary Cross Entropy Loss” – in fact not a standard one

- VoxelNet represents the ”objectness confidence” with only 1 number, instead of 2.
- $L_{cls}(p_i^{pos}) = \log\left(\sigma\left(e^{p_i^{pos}}\right)\right)$
- $L_{cls}(p_i^{neg}) = \log\left(1 - \sigma\left(e^{p_i^{neg}}\right)\right)$
- Sigmoid $\sigma(x) = \frac{e^x}{e^x+1} \in (0, 1)$

- What is positive / negative anchor box?
- Thousand readers have one thousand Hamlet.

- E.g.
  - Positive anchor box
    - $IoU > 0.5$ with any ground truth box
    - Has highest IoU with a ground truth box (each ground truth box will be associated with at least one anchor box).
  - Negative anchor box
    - $IoU < 0.35$ with every ground truth box
  - Don’t care
    - $0.35 \leq IoU \leq 0.5$ with every ground truth box

VoxelNet – Loss Function

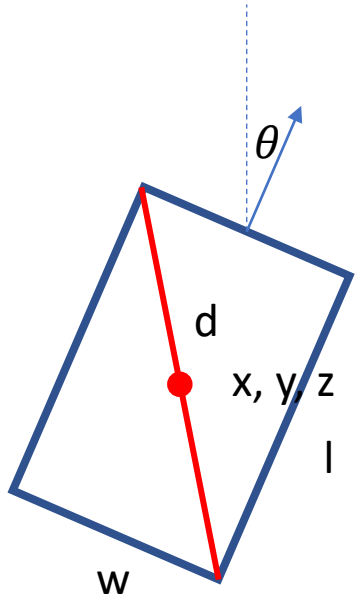
- Ground truth box: $\mathbf{u}^* = \left(x_c^g, y_c^g, z_c^g, l^g, w^g, h^g, \theta^g\right)$
- A matching anchor box (positive box): $\mathbf{u} = (x_c^a, y_c^a, z_c^a, l^a, w^a, h^a, \theta^a)$
- Loss between Ground truth and positive anchor box:

$$L_{reg}(\mathbf{u}, \mathbf{u}^*) = \rho(\Delta x, \Delta y, \Delta z, \Delta l, \Delta w, \Delta h, \Delta\theta)$$

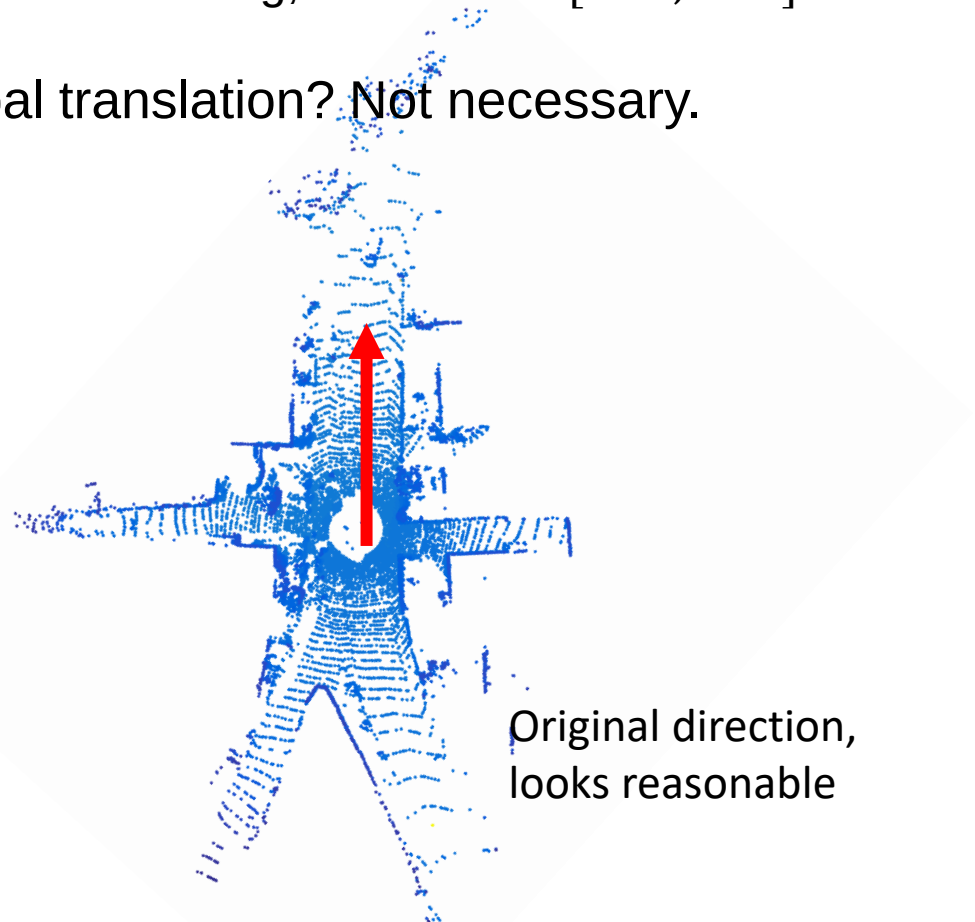
$$\Delta x = \frac{x_c^g - x_c^a}{d^a}, \Delta y = \frac{y_c^g - y_c^a}{d^a}, \Delta z = \frac{z_c^g - z_c^a}{h^a},$$

$$\Delta l = \log\left(\frac{l^g}{l^a}\right), \Delta w = \log\left(\frac{w^g}{w^a}\right), \Delta h = \log\left(\frac{h^g}{h^a}\right),$$

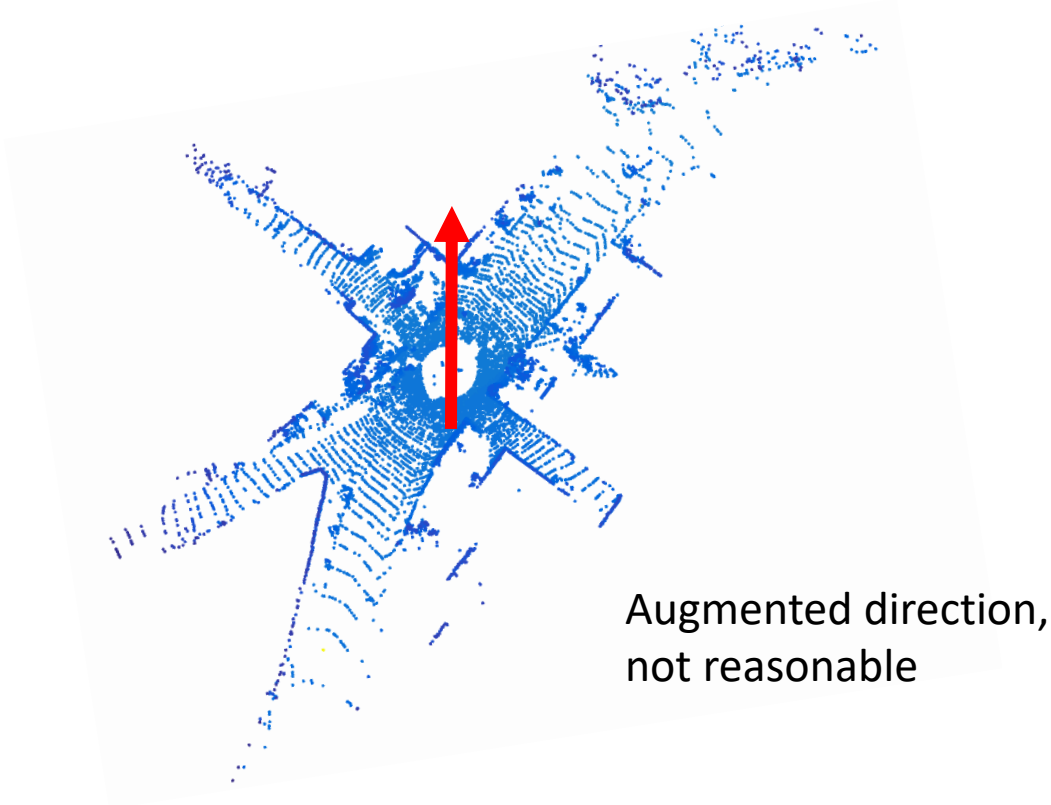
$$\Delta\theta = \theta^g - \theta^a \qquad d^a = \sqrt{(l^a)^2 + (w^a)^2}$$



- Global rotation around the up-axis
  - Uniform $\theta \in [-\frac{\pi}{4}, \frac{\pi}{4}]$, why not $[-\pi, \pi]$?
  - Global scaling, uniform $s \in [0.95, 1.05]$
- Global translation? Not necessary.



Original direction,
looks reasonable

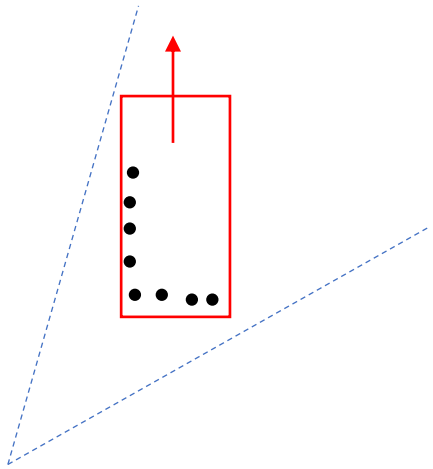


Augmented direction,
not reasonable

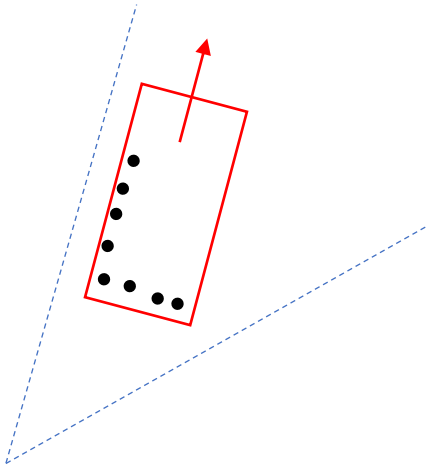
VoxelNet – Data Augmentation

For each ground truth box:

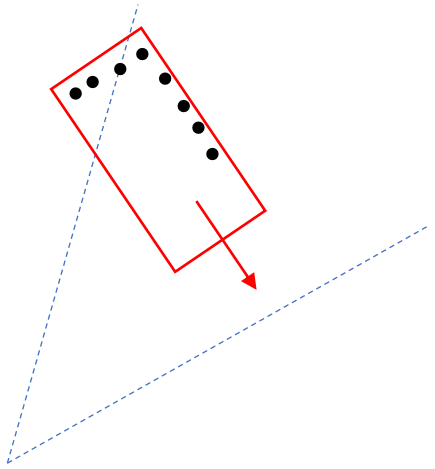
- Random rotate it and points inside it by uniform $\theta \in \left[-\frac{\pi}{10}, \frac{\pi}{10}\right]$
- Random translate $[\Delta x, \Delta y, \Delta z], \Delta * \sim \mathcal{N}(0, 1)$
- If there collision for two boxes after augmentation, give up augmentation.



Original data



Proper augmentation

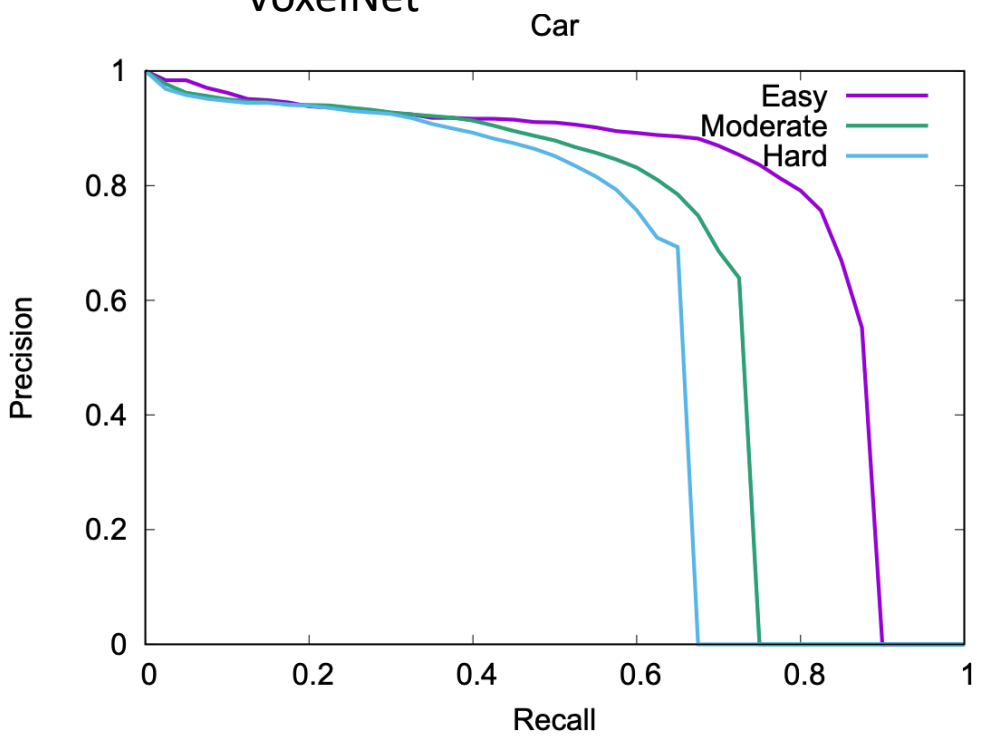


Too much augmentation

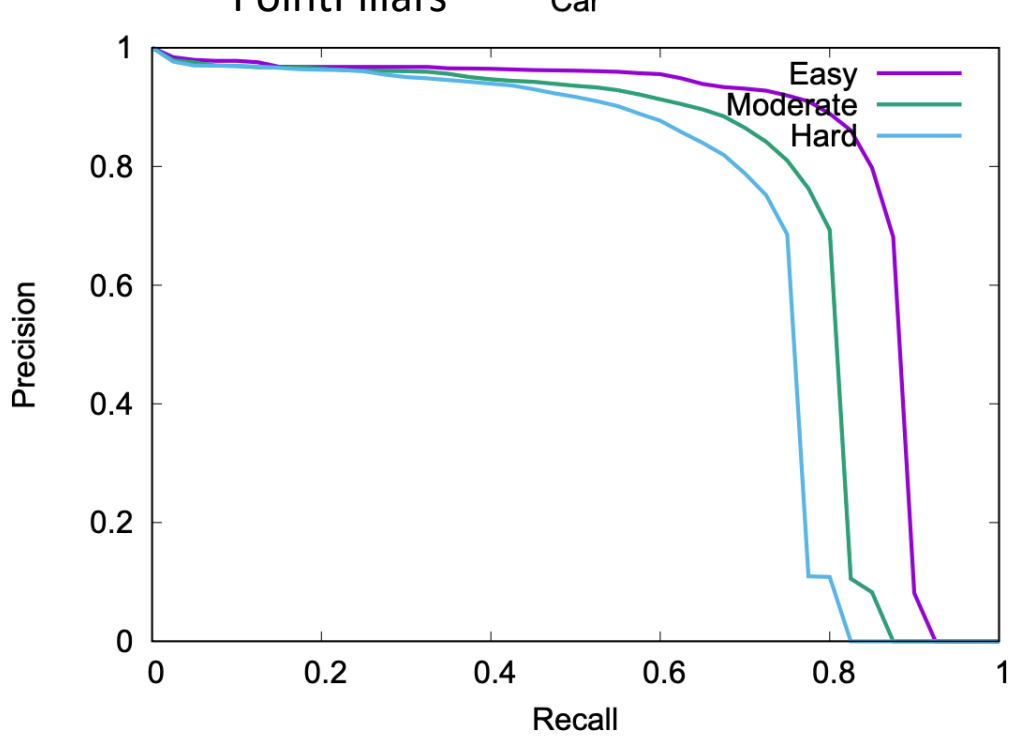
VoxelNet – Performance on KITTI

	Method	Setting	Code	Moderate	Easy	Hard	Runtime
125	VoxelNet(Unofficial)			64.17 %	77.82 %	57.51 %	0.5 s
77	PointPillars		code	74.31 %	82.58 %	68.99 %	16 ms

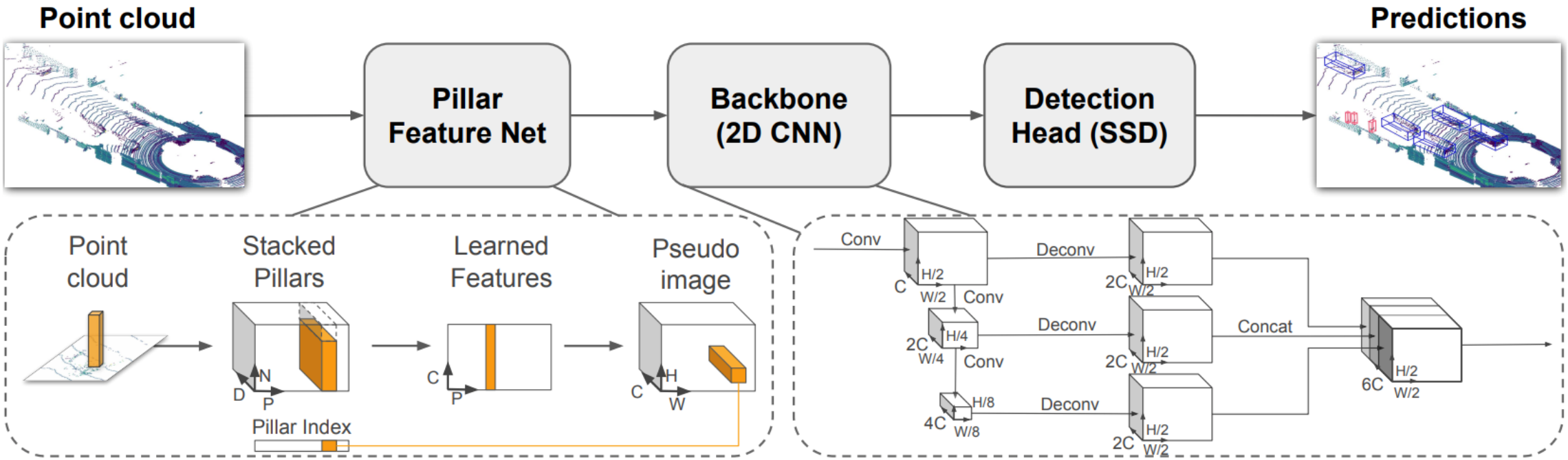
VoxelNet



PointPillars



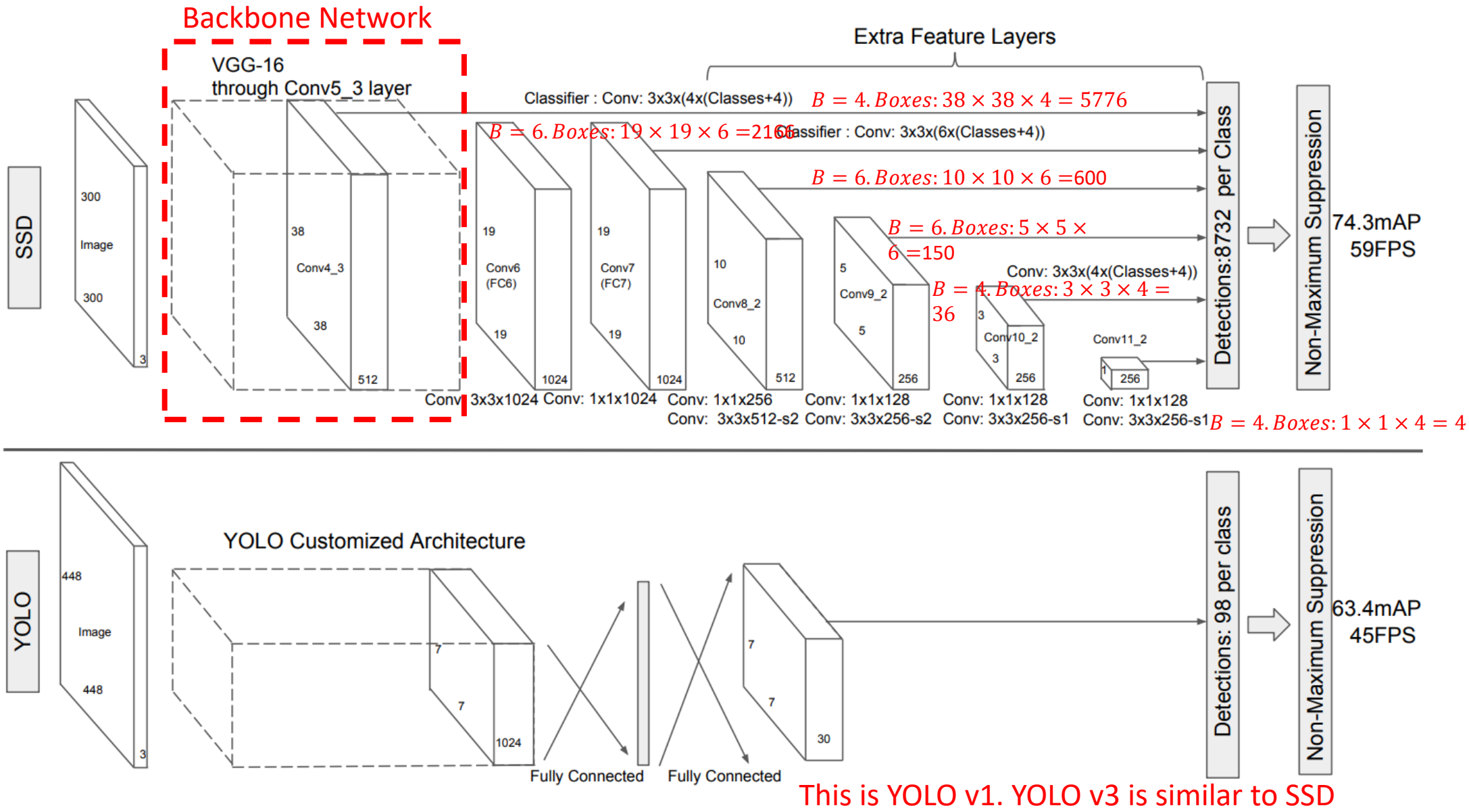
PointPillars



- Why 3D voxel grid?
- Directly compress point cloud into $C \times H \times W$ feature map!

PointPillars: Fast Encoders for Object Detection from Point Clouds. AH Lang, et.al.

SSD



Source: SSD: Single Shot MultiBox Detector, Wei Liu, et. al.

- Overall loss function

$$\mathcal{L} = \frac{1}{N_{pos}}(\beta_{loc}\mathcal{L}_{loc} + \beta_{cls}\mathcal{L}_{cls} + \beta_{dir}\mathcal{L}_{dir})$$

- L_{loc}: regression loss, almost same as VoxelNet, except

$$\Delta\theta = \sin(\theta^g - \theta^a)$$

- L_{dir}: the sin in L_{loc} can't distinguish $180°$ flip
  - Add a softmax classification loss on the discretized directions
  - E.g., divide the rotation into 4 bins, [0, 90], [90, 180], [180, 270], [270, 360]
- L_{cls}: similar to VoxelNet, but use FocalLoss instead of CrossEntropyLoss

- Consider an example,
  - 1 ground truth “human” box
  - Network predicts 100 boxes
    - $p_{background} = 0.6$ for the first 99 boxes
    - $p_{human} = 0.2$ for the 100th box
- Cross Entropy Loss

$$L_{CE} = \sum_{t} -\log p_t = -99 \log 0.6 - \log 0.2 = 50.57 + 1.61$$

- The loss caused by wrong box classification (the 100th box) is 1.61
- The loss caused by correct box classification (the 99 boxes) is 50.57
- Easy, network just predict everything as background!

Focal Loss

- Cross Entropy Loss $L_{CE}(p_t) = -\log p_t$
- Focal Loss $L_{FL} = -(1-p_t)^{\gamma} \log p_t$
- Come back to our example, with $\gamma = 2$.

$$L_{FL} = -99(1-0.6)^2 \log 0.6 - (1-0.2)^2 \log 0.2 = 8.09 + 1.03$$

- The loss caused by wrong classification is taking a larger percentage now.

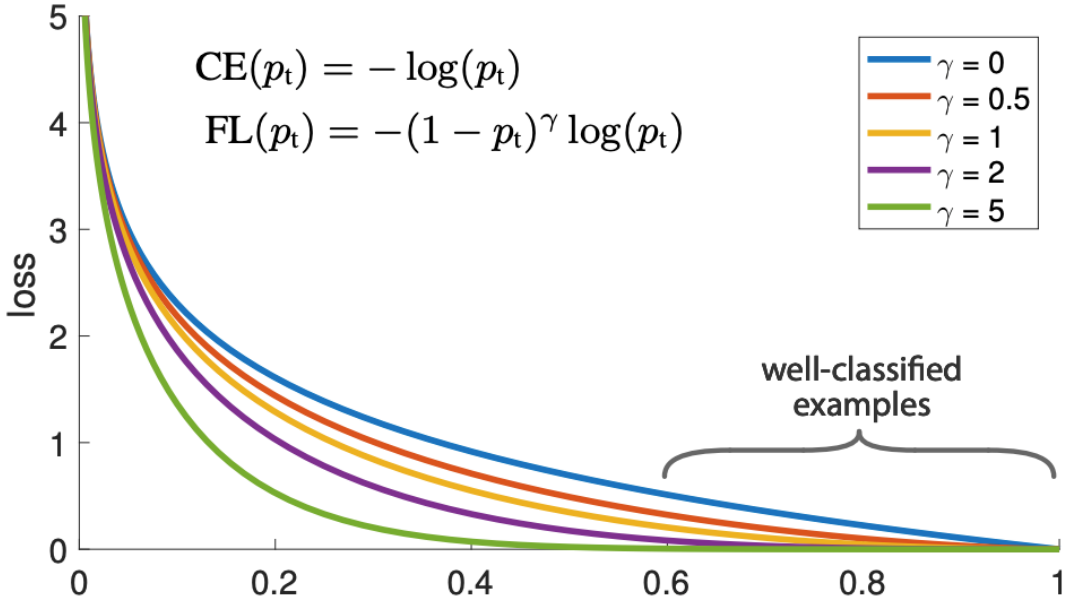


Figure: Focal Loss with various γ
Original Paper: Focal Loss for Dense Object Detection

- Focal Loss is designed for unbalanced classification
- Reduce the relative loss for well-classified examples ($p_t > 0.5$)
- Focus on hard, mis-classified examples ($p_t \leq 0.5$)

3D Object Detector

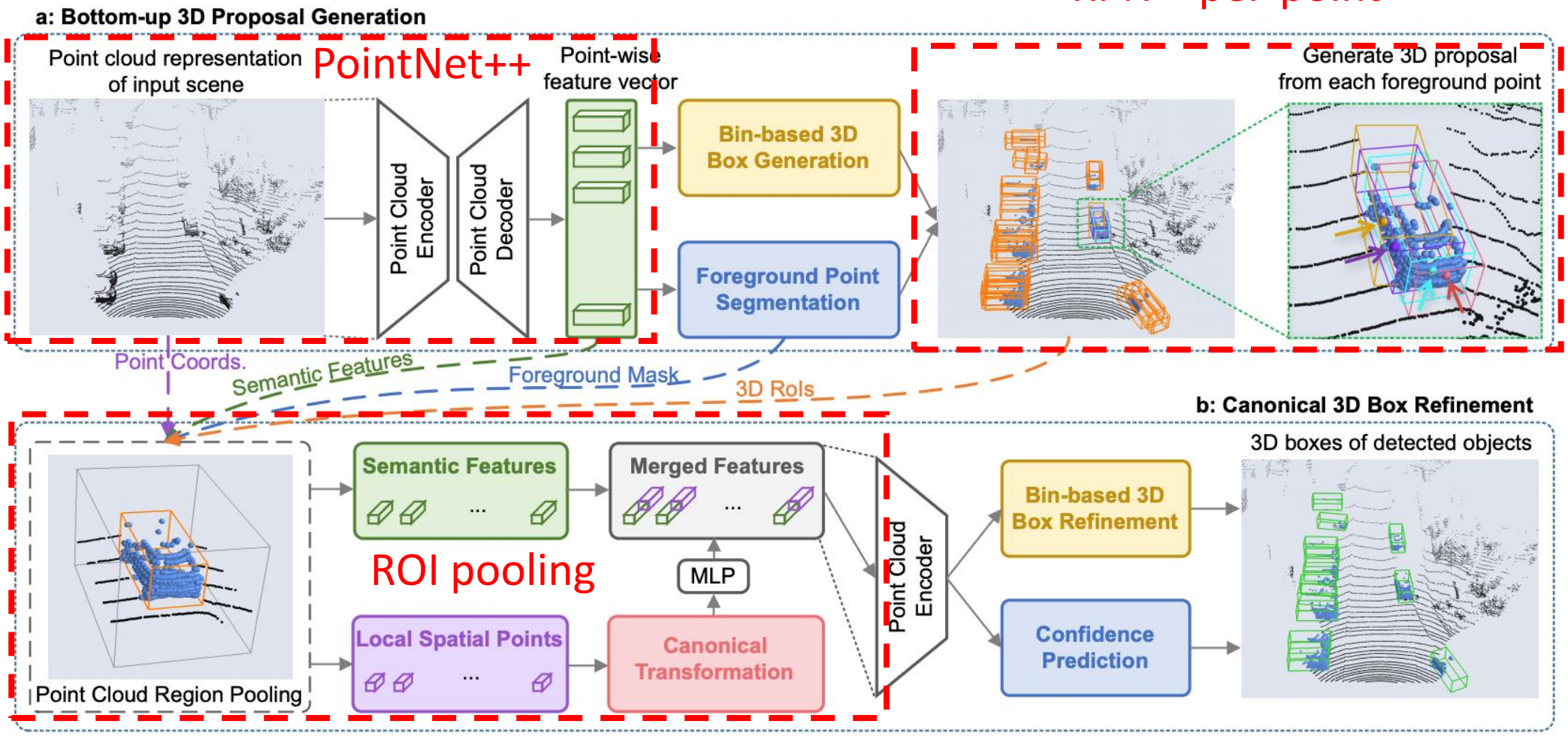
- Multi-view Projection
- Build image-like feature map with PointNet
  - PointNet to convert point cloud detection into image detection + normal 2D CNN
  - Two-stage / One-stage
- Point-wise operation
  - Replace 2D CNN with point-wise operations like PointNet
  - Two-stage / One-stage
- Point cloud & image fusion
  - Core idea only, not in detail.

- VoxelNet / PointPillar
  - Convert point cloud into image-like feature map
  - Single stage detector – RPN / SSD, no ROI pooling

- How about native method on point cloud?
- How about two stage method?
- PointRCNN

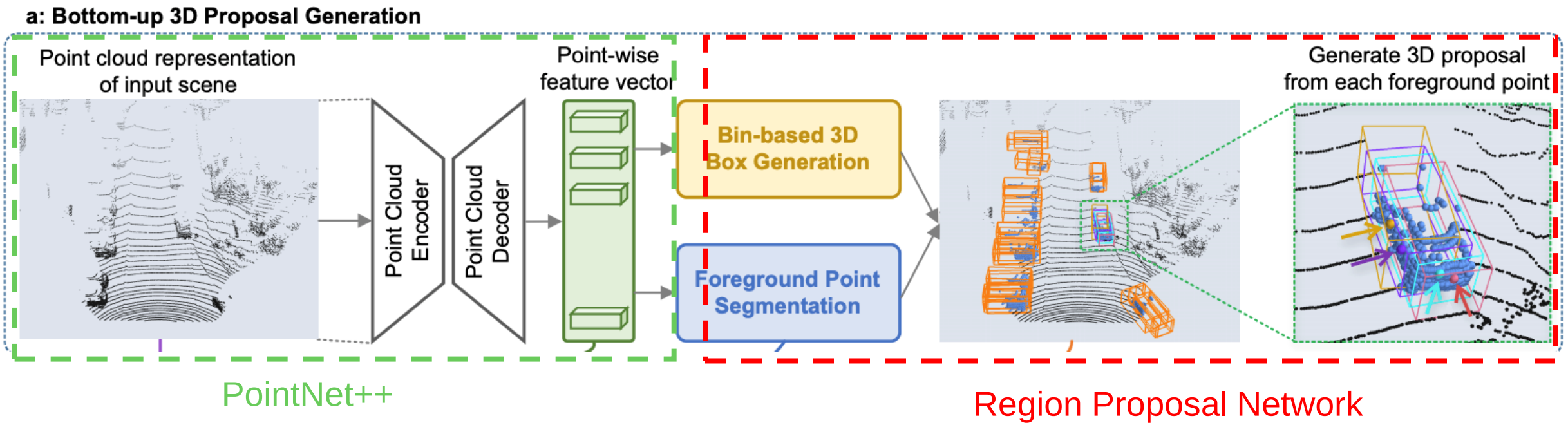
	Method	Setting	Code	Moderate	Easy	Hard	Runtime
125	VoxelNet(Unofficial)			64.17 %	77.82 %	57.51 %	0.5 s
77	PointPillars		code	74.31 %	82.58 %	68.99 %	16 ms
61	MMLab-PointRCNN		code	75.64 %	86.96 %	70.70 %	0.1 s

PointRCNN - Architecture



PointRCNN： 3D Object Proposal Generation and Detection from Point Cloud, S Shi, et.al.

PointRCNN – Stage 1



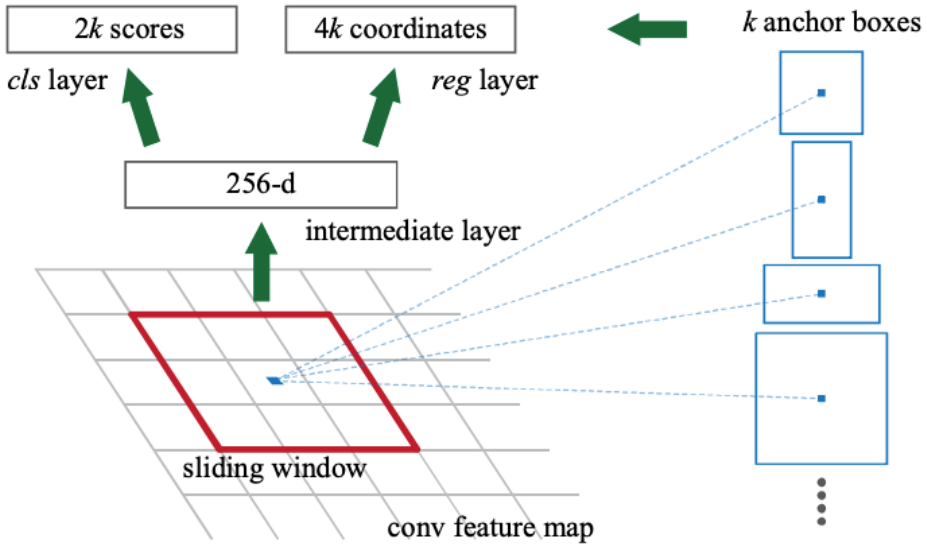
- Backbone – PointNet++
  - Input: point cloud $4 \times N$ (x, y, z, intensity)
  - Output: per-point feature $C \times N$
- RPN
  - Each foreground point generate a proposal

PointRCNN：3D Object Proposal Generation and Detection from Point Cloud, S Shi, et.al.

PointRCNN – Stage 1

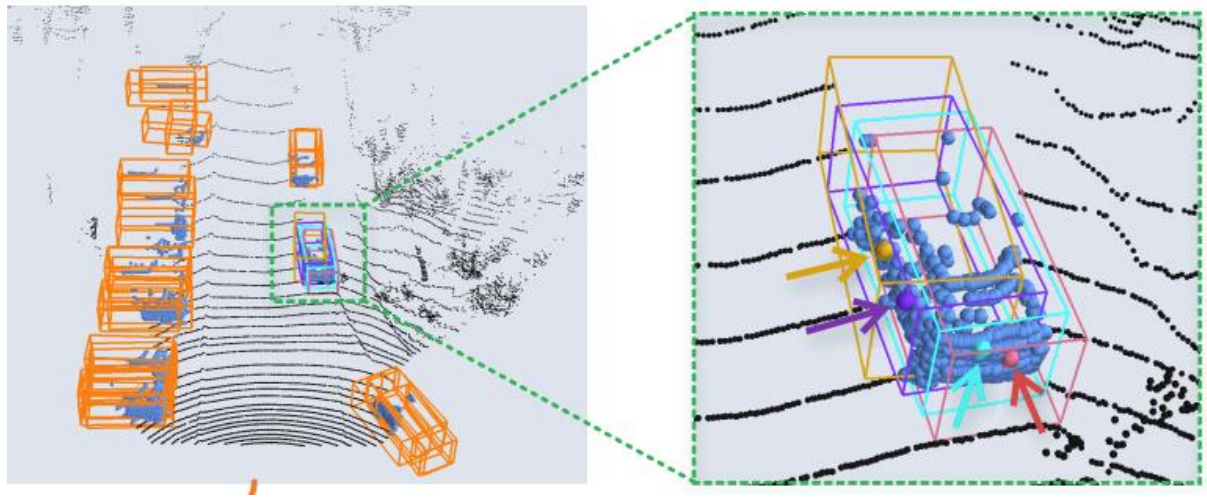
What is image based RPN?

- Box classification (is it an object or not)
- Box regression



What is PointRCNN Stage 1?

- Foreground / Background classification
- Bin-based 3D box generation



PointRCNN： 3D Object Proposal Generation and Detection from Point Cloud, S Shi, et.al.

- Foreground – points inside ground truth boxes
- Background – other points
- Loss function: Focal Loss

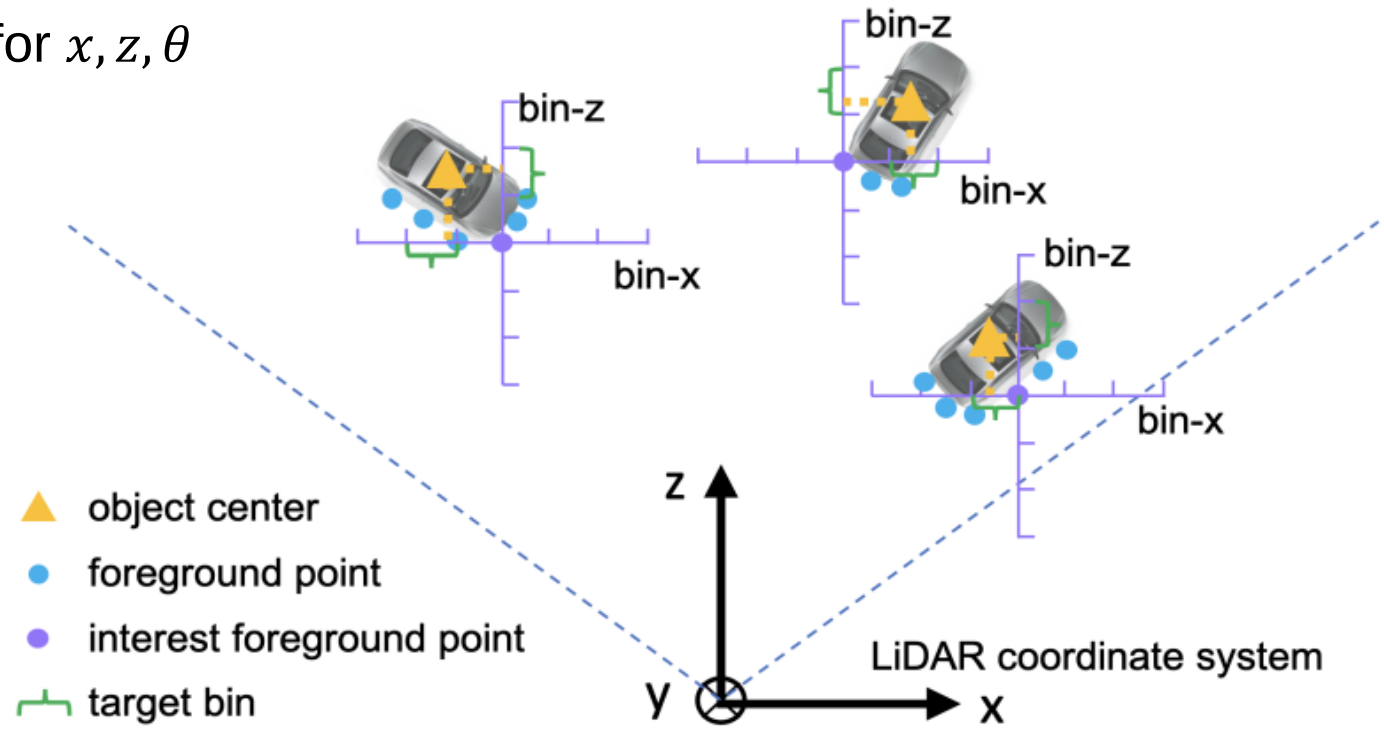
$$\mathcal{L}_{\text{focal}}(p_t) = -\alpha_t (1 - p_t)^{\gamma} \log(p_t),$$

$$\text{where } p_t = \begin{cases} p & \text{for forground point} \\ 1 - p & \text{otherwise} \end{cases}$$

- E.g., network predicts the background/foreground score $[c_0, c_1]$ for each point
  - $p = p_{foreground} = \frac{e^{c_1}}{e^{c_0}+e^{c_1}}, \quad p_{background} = 1 - p = \frac{e^{c_0}}{e^{c_0}+e^{c_1}}$

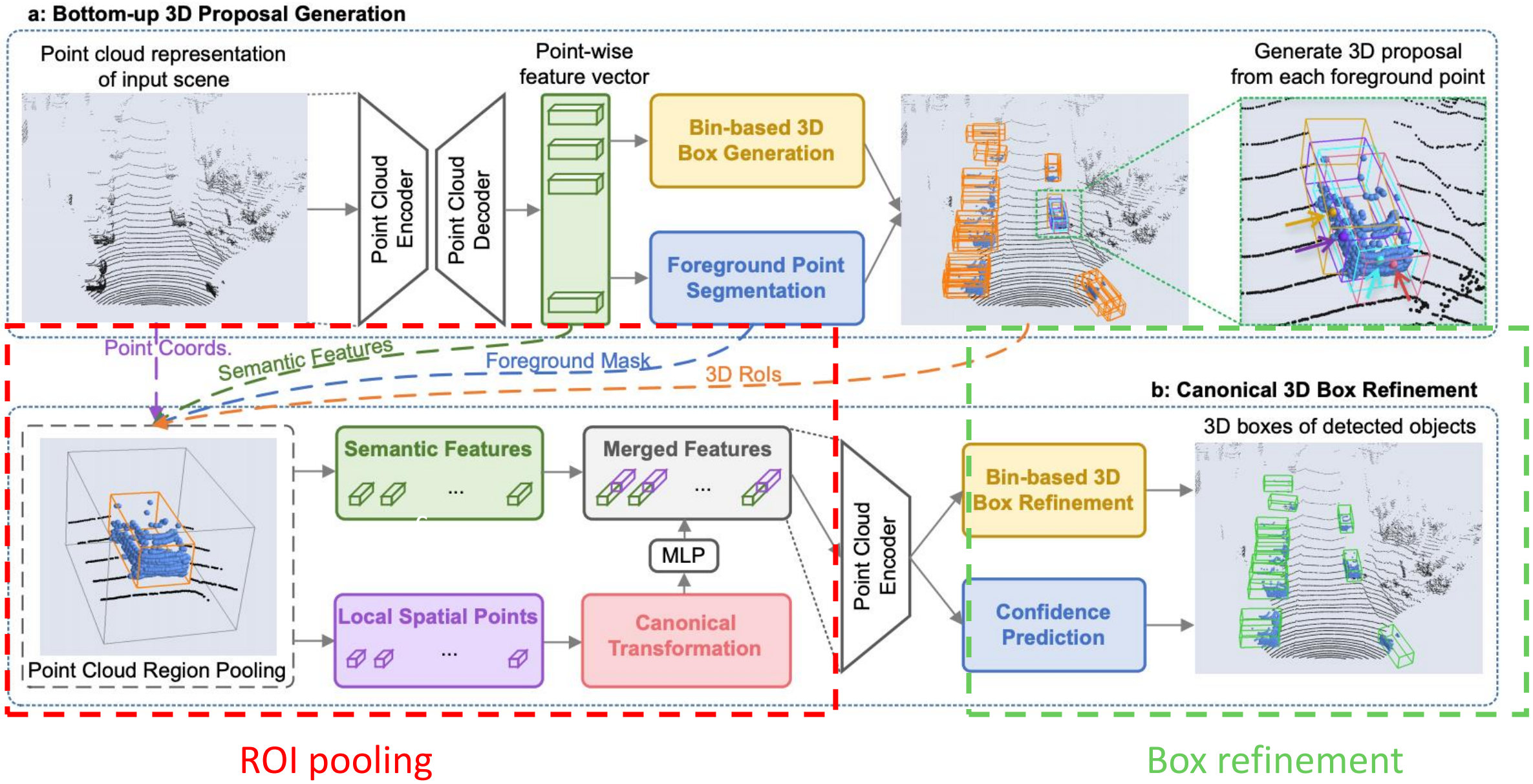
- Objective: generate one box / foreground point
- Regression for x, y, z, l, w, h, θ?
  - Classification + Finetuning residual for x, z, θ
  - Direct regression for y, l, w, h

- For a foreground point, how to determine box center x?
  1. Classify which bin
  2. Predict the residual to bin center
  3. $x = bin_{center} + res_x$



PointRCNN：3D Object Proposal Generation and Detection from Point Cloud, S Shi, et.al.

PointRCNN – Stage 2



PointRCNN： 3D Object Proposal Generation and Detection from Point Cloud, S Shi, et.al.

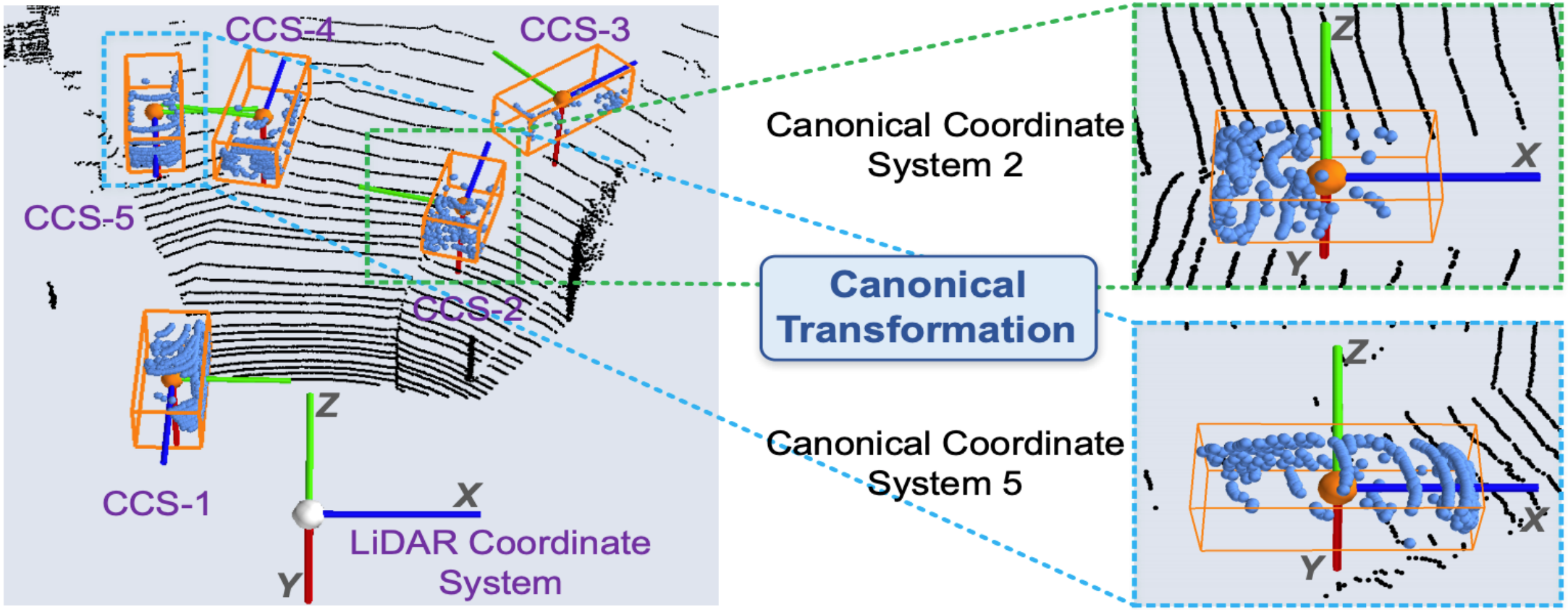
- NMS on the Stage 1 proposals. (300 for training, 100 for inference)
- Enlarge the Stage 1 proposals
- Get information in the enlarged box
  - Point coordinate, x_i, y_i, z_i
    - Canonical Transformation
  - Point intensity, r_i
  - Point's distance to origin, $d_i = \sqrt{x_i^2 + y_i^2 + z_i^2}$
  - Foreground / background prediction, m_i

Fed into MLP

Concatenate

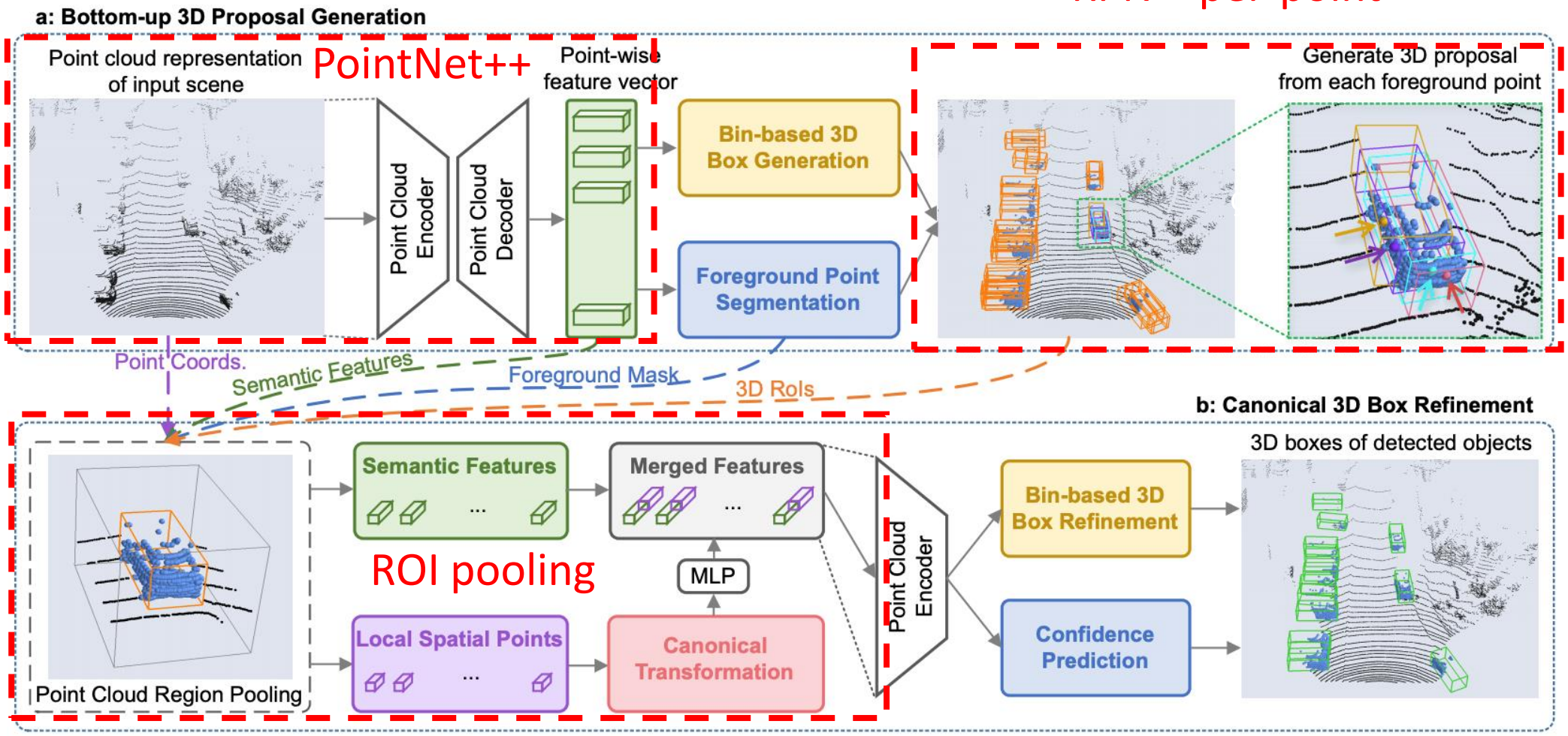
  - Per-point features from PointNet++

PointRCNN – Stage 2 – ROI Pooling



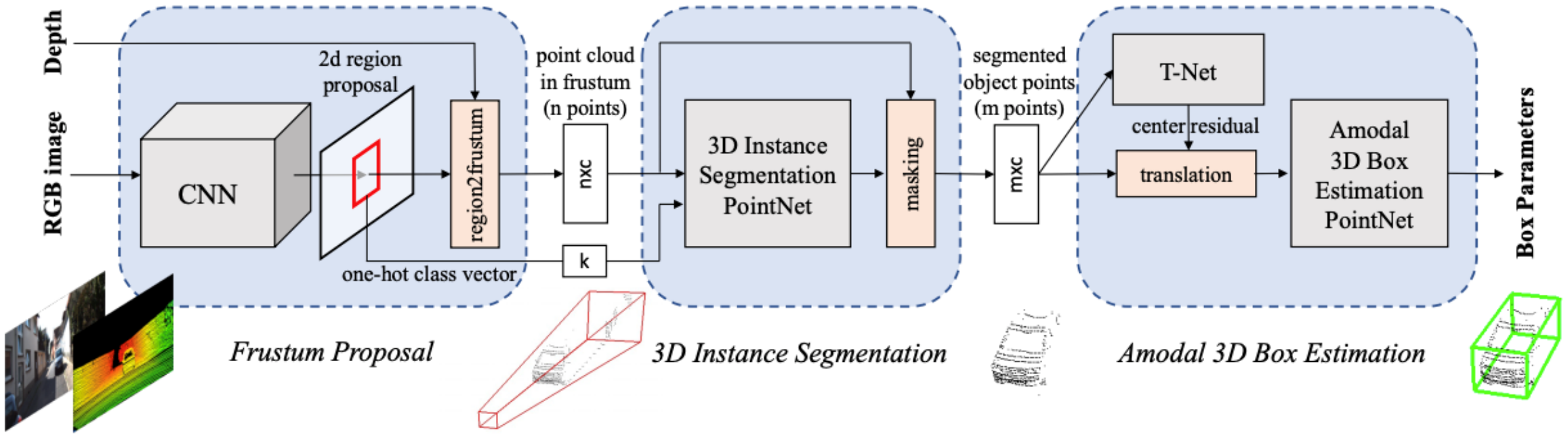
- Canonical Transformation
  - Normalized points so that their center is box proposal center
  - Rotate the points box proposal heading is x-axis

PointRCNN - Summary



- Multi-view Projection
- Build image-like feature map with PointNet
  - PointNet to convert point cloud detection into image detection + normal 2D CNN
  - Two-stage / One-stage
- Point-wise operation
  - Replace 2D CNN with point-wise operations like PointNet
  - Two-stage / One-stage
- Point cloud & image fusion
  - Core idea only, not in detail.

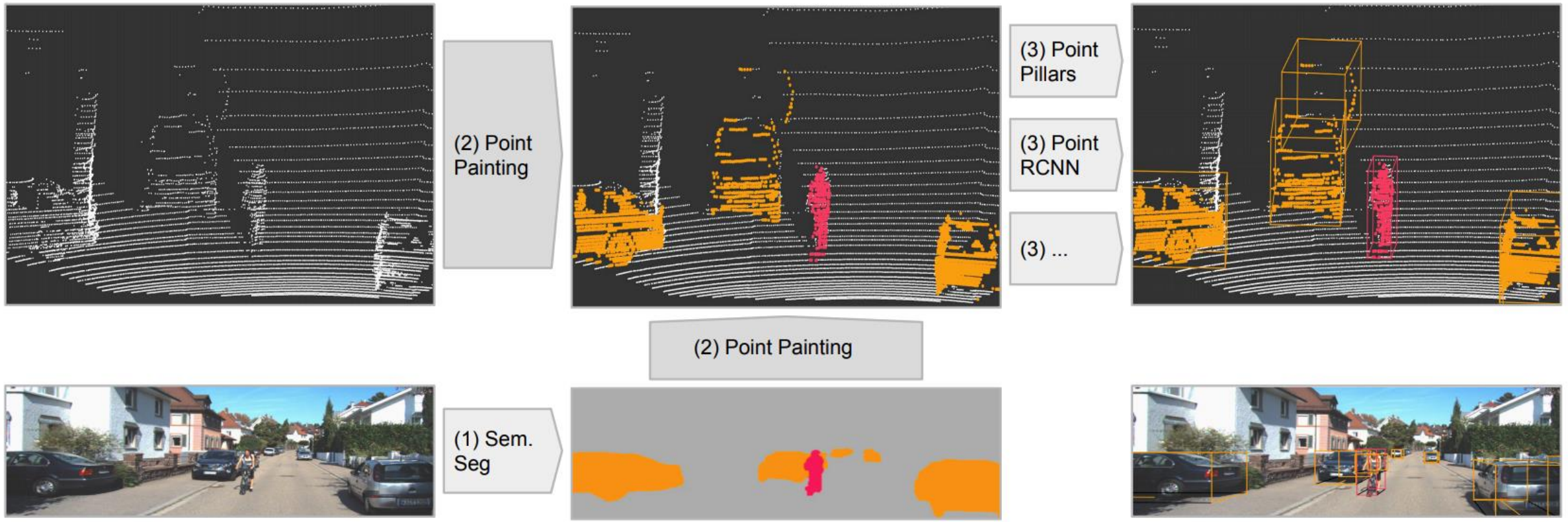
Frustum PointNet



- Object proposal from 2D image based detector.
- ROI pooling is actually the frustum extraction.

Frustum PointNets for 3D Object Detection from RGB-D Data, Charles R. Qi, et.al.

PointPainting



- Augment each point with the semantic segmentation label from an image based semantic segmentation network.

PointPainting: Sequential Fusion for 3D Object Detection, Sourabh Vora, et.al.

- Multi-view Projection
- Build image-like feature map with PointNet
  - PointNet to convert point cloud detection into image detection + normal 2D CNN
  - Two-stage / One-stage
- Point-wise operation
  - Replace 2D CNN with point-wise operations like PointNet
  - Two-stage / One-stage
- Point cloud & image fusion
  - Core idea only, not in detail.

Homework

1. Setup the KITTI object detection evaluation environment
    1. git clone https://github.com/prclibo/kitti_eval.git
    2. g++ -O3 -DNDEBUG -o evaluate_object_3d_offline evaluate_object_3d_offline.cpp
    3. sudo apt-get install gnuplot
    4. sudo apt-get install texlive-extra-utils
2. Download and read the KITTI Object Detection dataset ”devkit” readme.
3. Divide the KITTI Object Detection into training set and validation set.
    - KITTI train/val split used in 3DOP/Mono3D/MV3D
    - “train.txt” for training, “val.txt” for testing, ignore the ”test.txt/trainval.txt”
4. Generate object detection results on KITTI validation set
    1. Option 1: find any open-source 3d object detector, run it.
    2. Option 2: copy the ground truth as the result, but you need to process it into the correct format.
5. Write a report.

What does KITTI Label / Result look like?

#Values	Name	Description
1	type	Describes the type of object: 'Car', 'Van', 'Truck', 'Pedestrian', 'Person_sitting', 'Cyclist', 'Tram', 'Misc' or 'DontCare'
1	truncated	Float from 0 (non-truncated) to 1 (truncated), where truncated refers to the object leaving image boundaries
1	occluded	Integer (0,1,2,3) indicating occlusion state: 0 = fully visible, 1 = partly occluded 2 = largely occluded, 3 = unknown
1	alpha	Observation angle of object, ranging [-pi..pi]
4	bbox	2D bounding box of object in the image (0-based index): contains left, top, right, bottom pixel coordinates
3	dimensions	3D object dimensions: height, width, length (in meters)
3	location	3D object location x,y,z in camera coordinates (in meters)
1	rotation_y	Rotation ry around Y-axis in camera coordinates [-pi..pi]
1	score	Only for results: Float, indicating confidence in detection, needed for p/r curves, higher is better.

What does KITTI Label / Result look like?

- Label example:
  - 000000.txt
    - Pedestrian 0.00 0 -0.20 712.40 143.00 810.73 307.92 1.89 0.48 1.20 1.84 1.47 8.41 0.01

- Result example:
  - data/000000.txt
    - Pedestrian 0.00 0 -0.20 712.40 143.00 810.73 307.92 1.89 0.48 1.20 1.84 1.47 8.41 0.01 10.0
    - Pedestrian 0.00 0 -0.20 712.40 143.00 810.73 307.92 1.89 0.48 1.20 1.84 1.47 8.41 0.01 8.0
    - Pedestrian 0.00 0 -0.20 712.40 143.00 810.73 307.92 1.89 0.48 1.20 1.84 1.47 8.41 0.01 6.0

Homework

- 5. ./evaluate_object_3d_offline gt_dir result_dir
- 6. Submit your result folder as a zip file.

- 7. Build your own object classification dataset from KITTI
    1. Extract points in car/pedestrian/cyclist as point cloud
    2. The category label, of course, is the label of the box

- 8. Design and train your own classification network on this dataset

    This is part of the final project.

Object detection pipeline for lidar

- Use KITTI 3D object detection dataset
- Step 1. Remove the ground from the lidar points
  - Any method you want – LSQ, Hough, RANSAC
- Step 2. Clustering over the remaining points
  - Any method you want
- Step 3. Classification over the clusters
- Step 4. Report the detection precision-recall for three categories: vehicle, pedestrian, cyclist

- Step 3. Classification over the clusters

  – vehicle / pedestrian / cyclist / other

  - Step 3.1. Build dataset from KITTI 3D object detection dataset
    - Extract objects in the box for vehicle / pedestrian / cyclist
    - Other objects? Clustering!
  - Step 3.2. Build deep network to classify them.
  - Step 3.3. Report classification accuracy

- Step 4. Report the detection Precision-Recall for three categories: vehicle, pedestrian, cyclist
  - Fit a cuboid over object detected as vehicle / pedestrian / cyclist
  - Generate object detection results for KITTI
    - IoU threshold set to 0.2 (This is very low because fitting cuboid is not easy)
    - Modify evaluate_object_3d_offline.cpp, line 55 to everything 0.2. Then re-compile.