Radar-Camera Sensor Fusion for Joint Object Detection and Distance Estimation in Autonomous Vehicles

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Department of Electrical Engineering and Computer Science
The University of Tennessee Knoxville, USA

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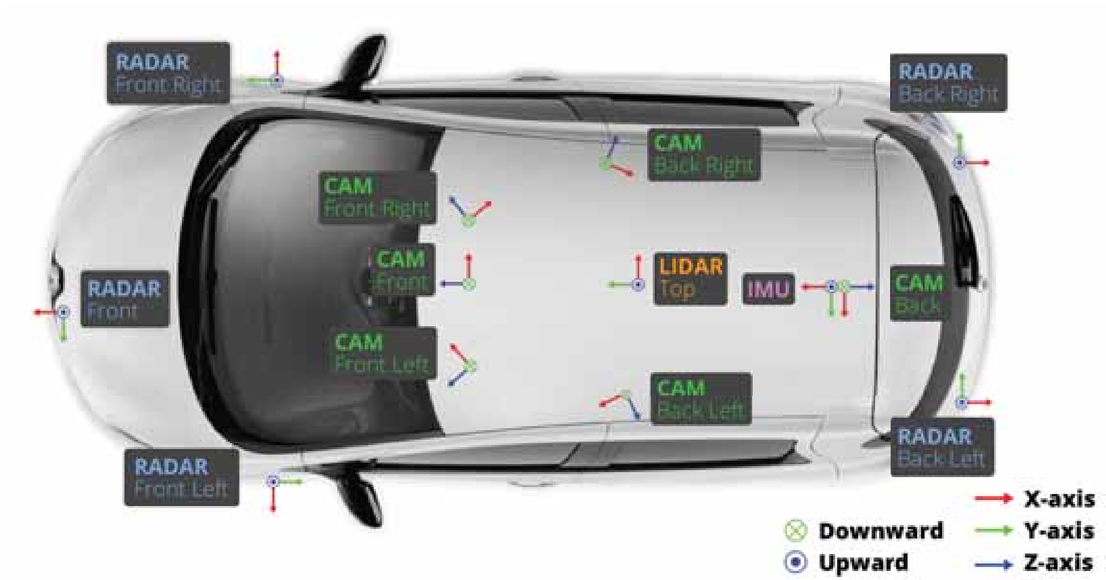
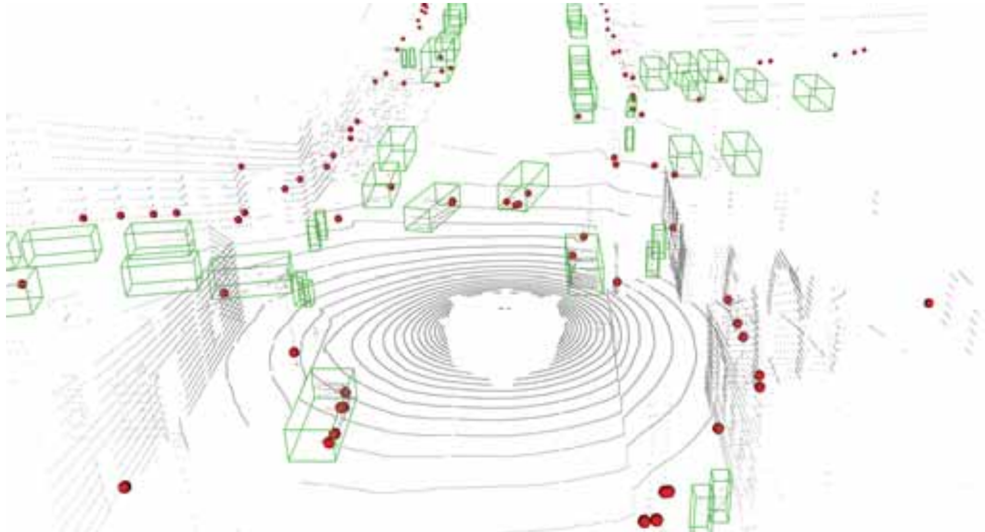
Object Detection for Autonomous Vehicles

- Modern autonomous vehicles are equipped with multiple sensors



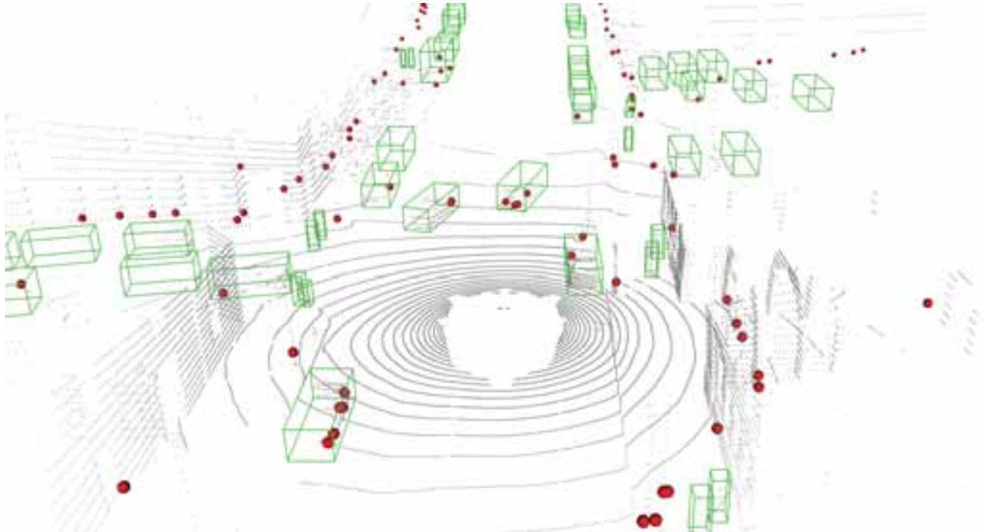
Object Detection for Autonomous Vehicles

- Modern autonomous vehicles are equipped with multiple sensors
- Sensor fusion is a crucial part of the perception system



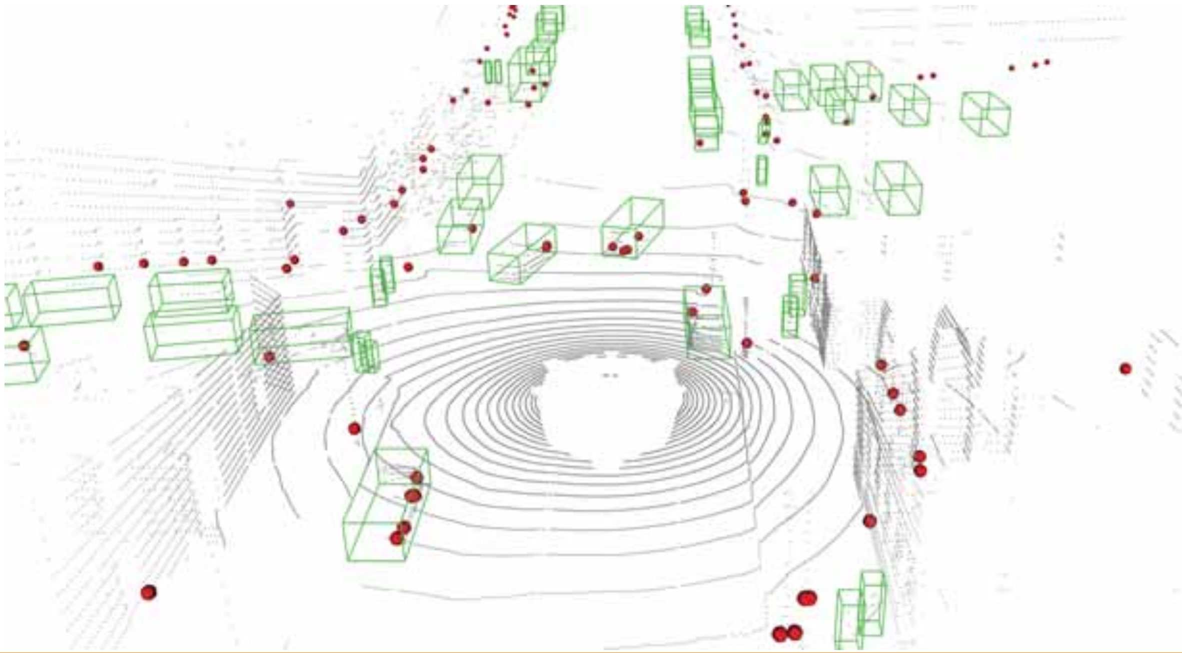
Object Detection for Autonomous Vehicles

- Modern autonomous vehicles are equipped with multiple sensors
- Sensor fusion is a crucial part of the perception system
- The focus of this work is on radar-camera sensor fusion



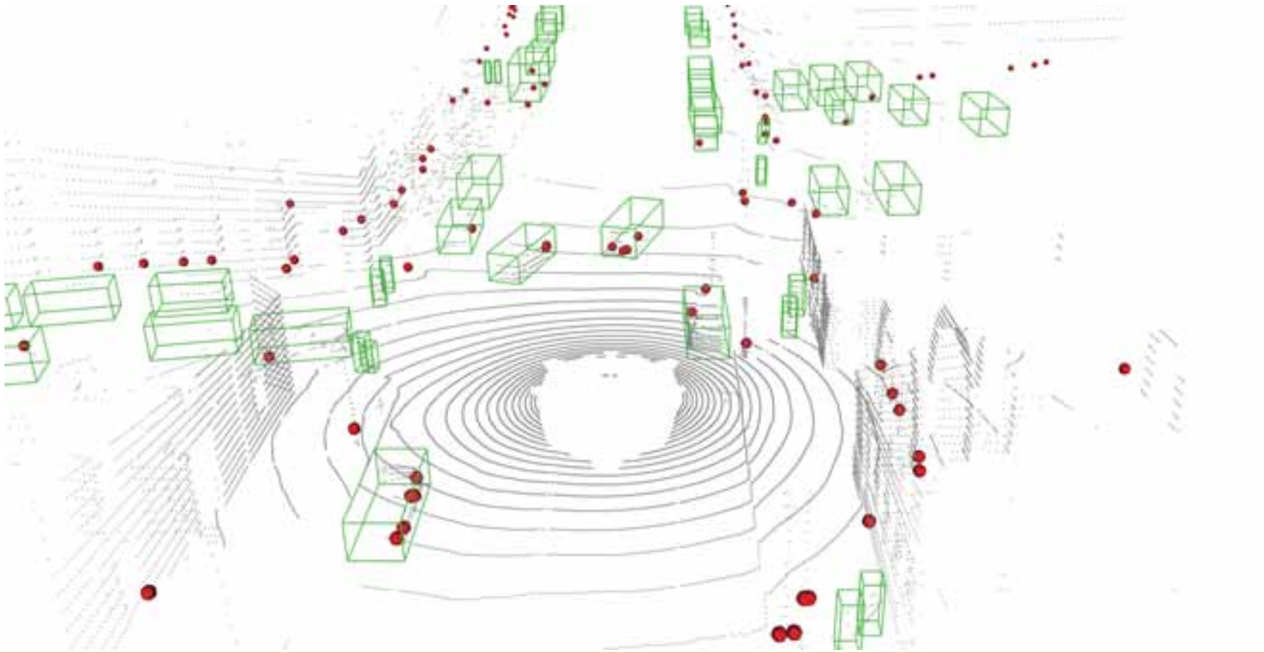
Challenges

- Radar point cloud is extremely sparse compared to LIDARs



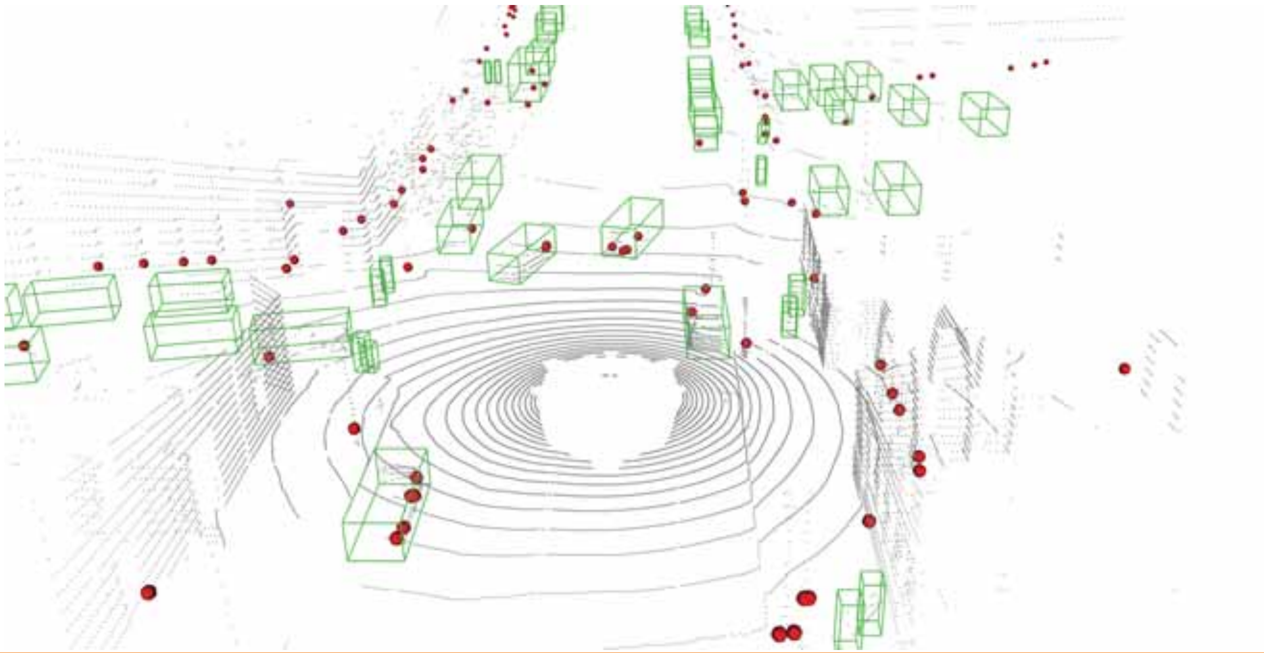
Challenges

- Radar point cloud is extremely sparse compared to LIDARs
- Radars are not good at classifying objects



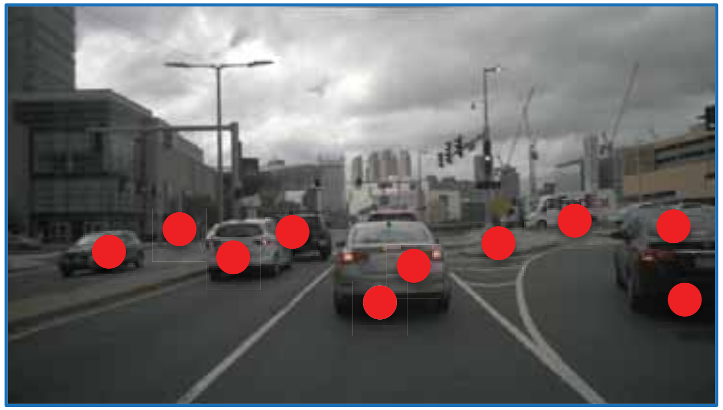
Challenges

- Radar point cloud is extremely sparse compared to LIDARs
- Radars are not good at classifying objects
- Most automotive radars do not provide height information for detections



Prior Work

- RRPN: Radar Region Proposal Network



R. Nabati and H. Qi, "RRPN: Radar Region Proposal Network for Object Detection in Autonomous Vehicles," 2019 IEEE International Conference on Image Processing (ICIP), Taipei, Taiwan, 2019, pp. 3093-3097, doi: 10.1109/ICIP.2019.8803392.

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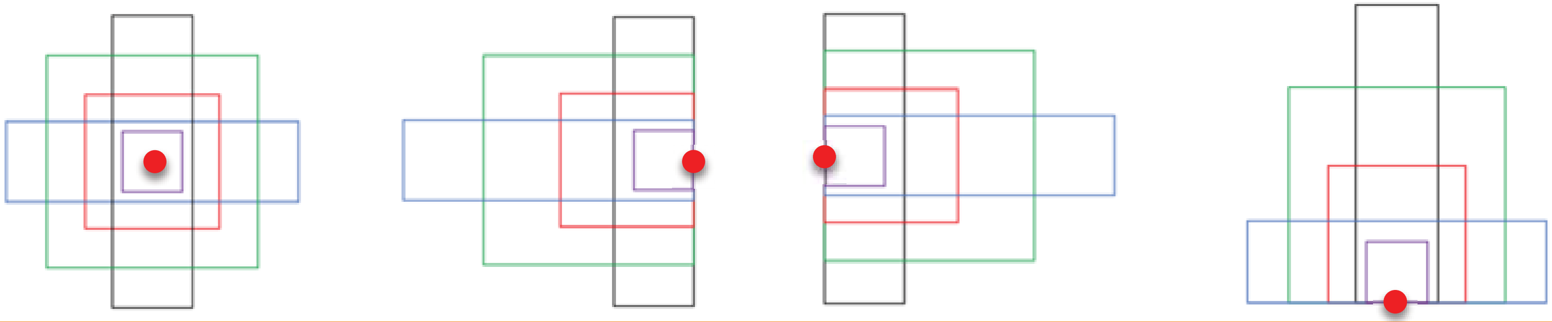

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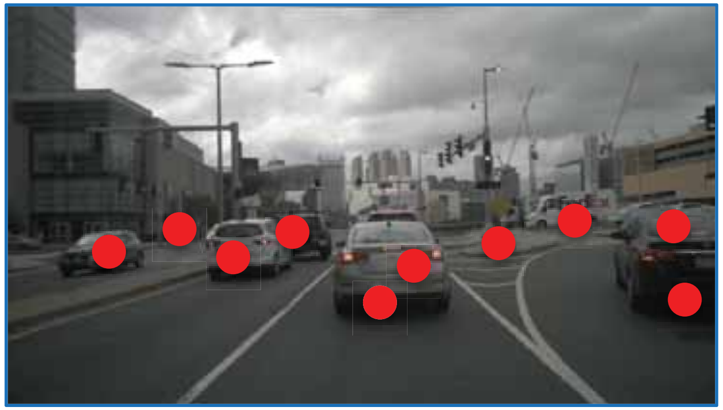

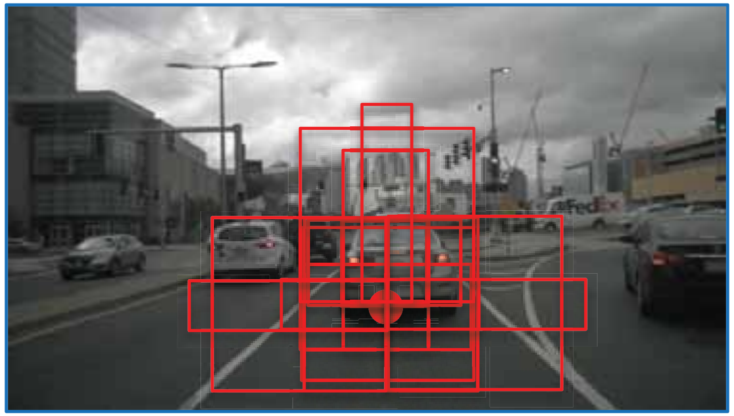

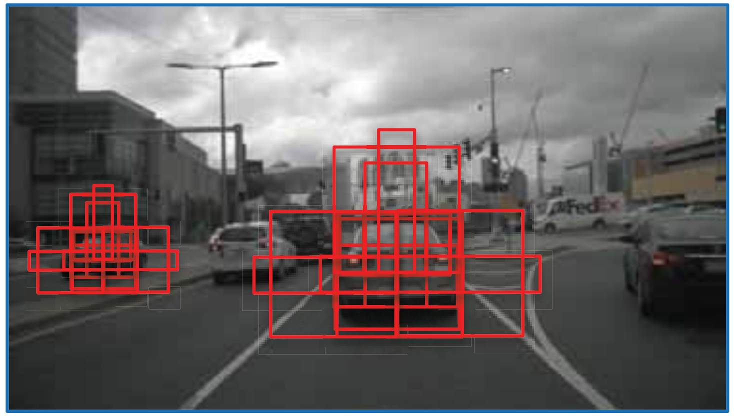

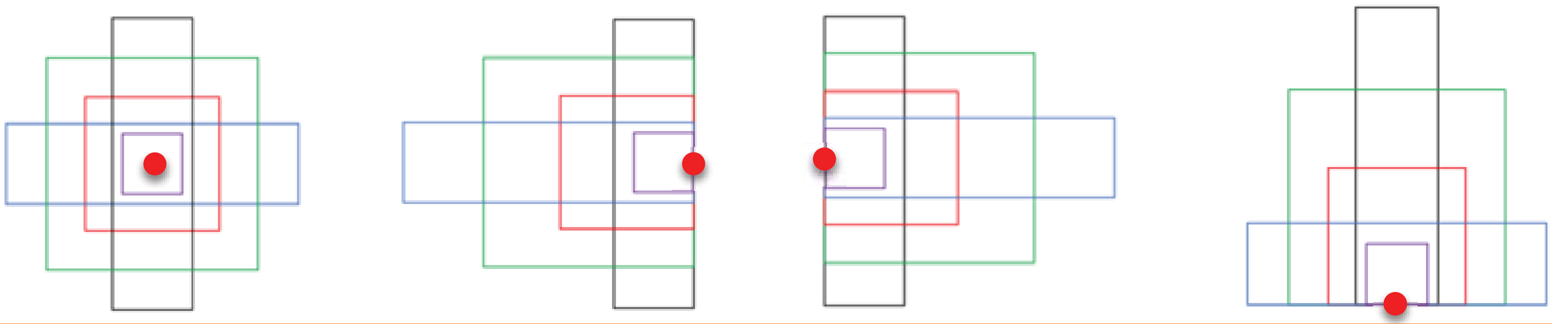

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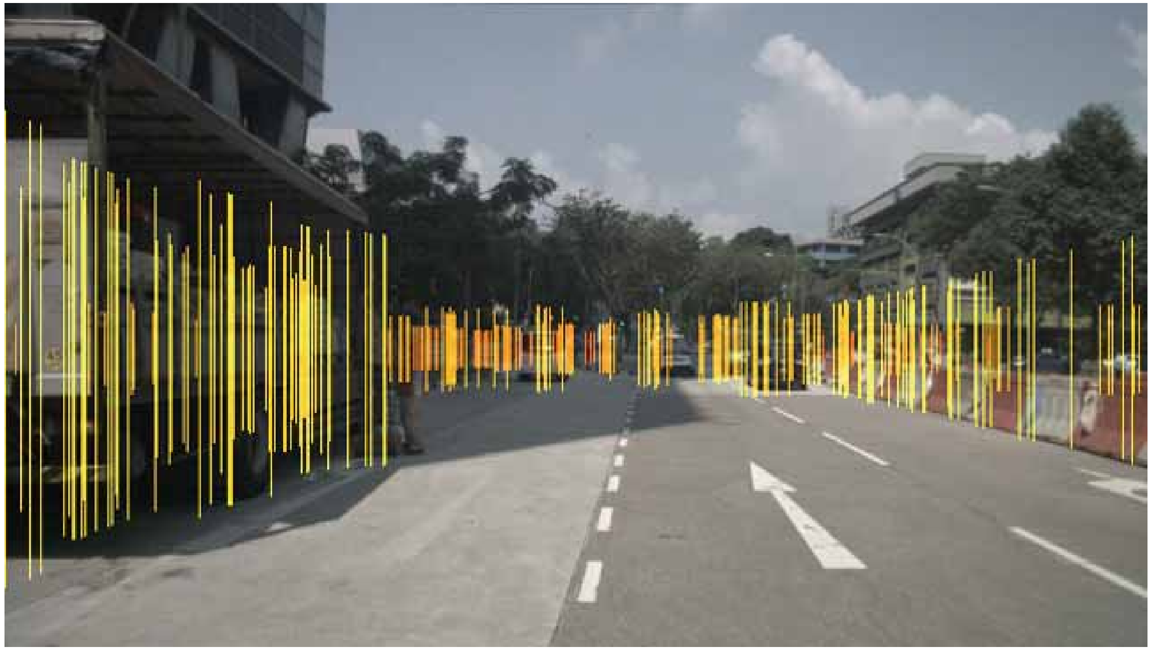
Prior Work

- CRF-Net



Nobis, Felix, et al. "A Deep Learning-based Radar and Camera Sensor Fusion Architecture for Object Detection." *2019 Sensor Data Fusion: Trends, Solutions, Applications (SDF)*. IEEE, 2019.

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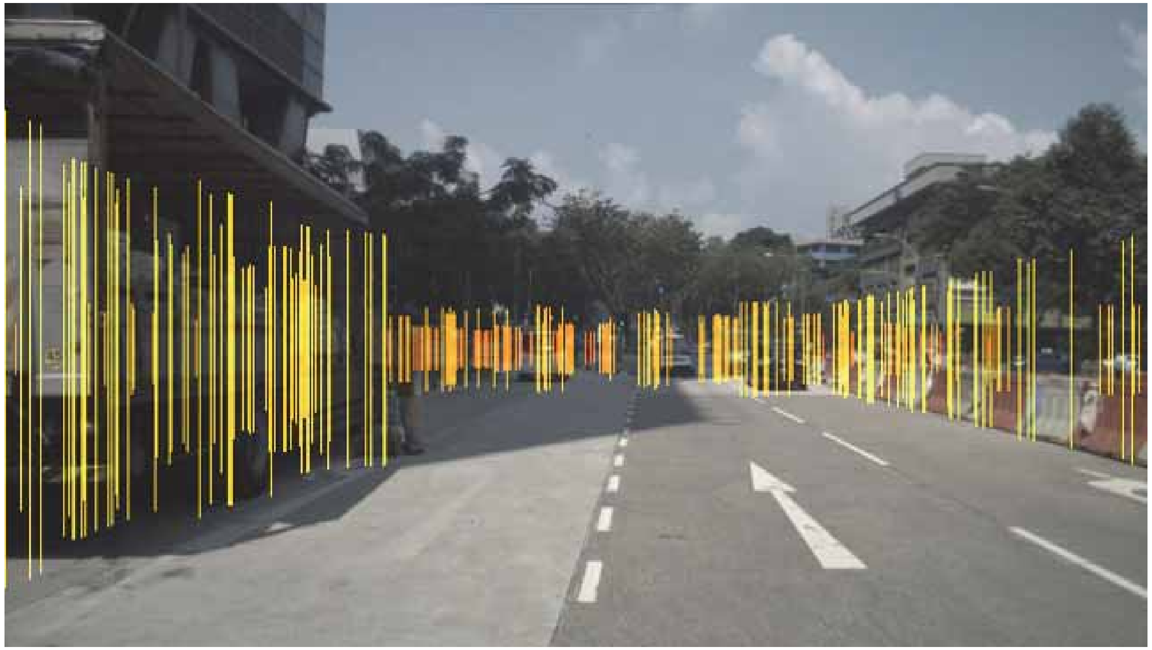

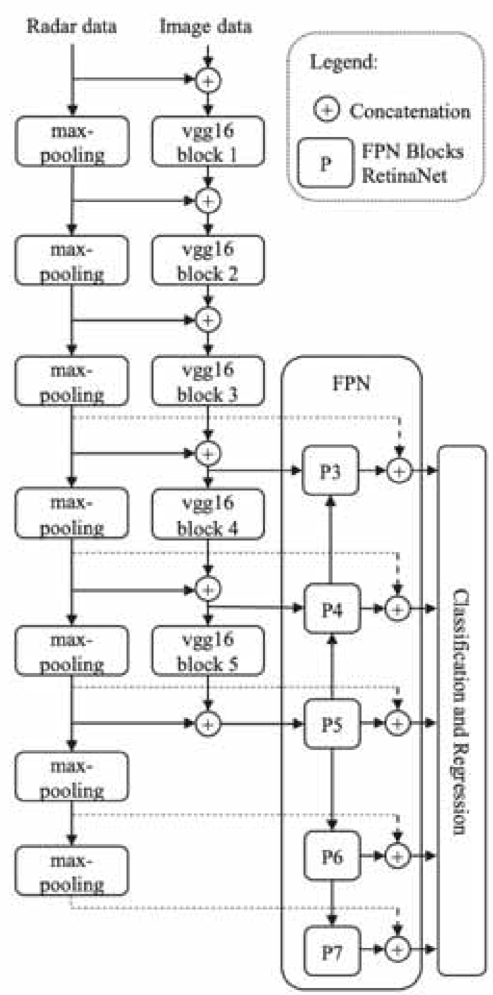

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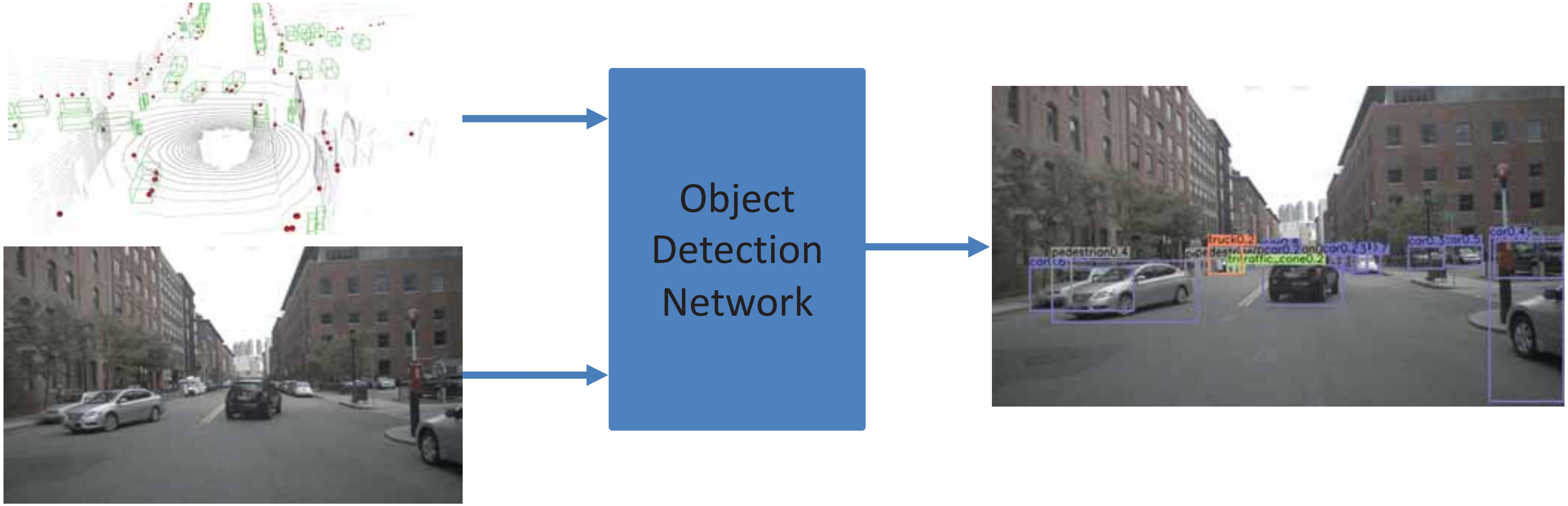
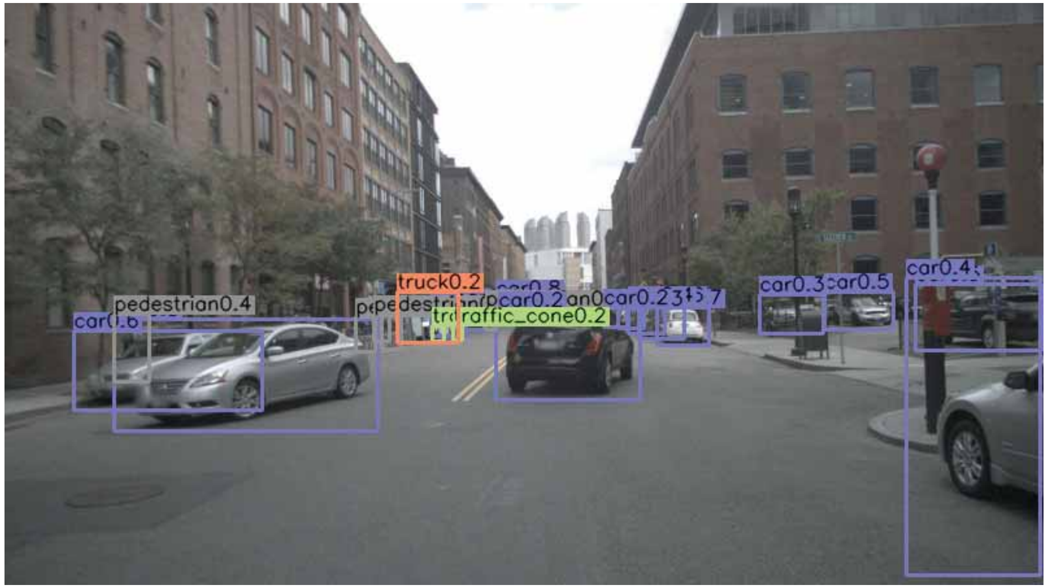
Motivation

- Depth information lost in the network



Motivation

- Depth information lost in the network
- 3D object detection is costly



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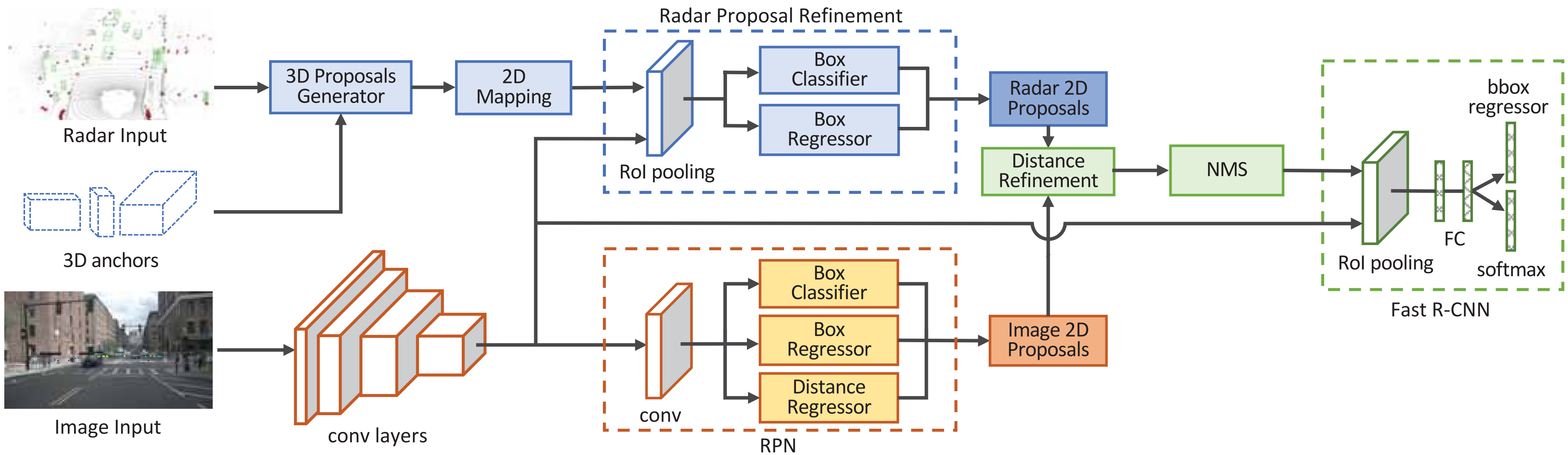
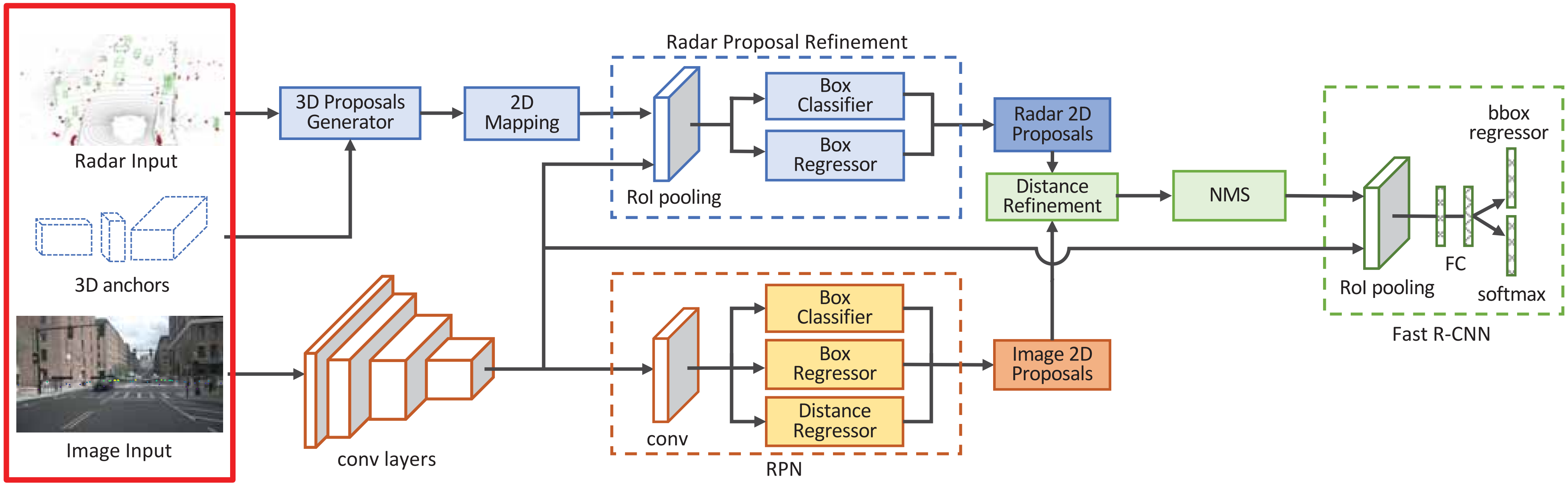
Network Architecture




Radar Input
3D anchors
Image Input
3D Proposals Generator
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conv layers
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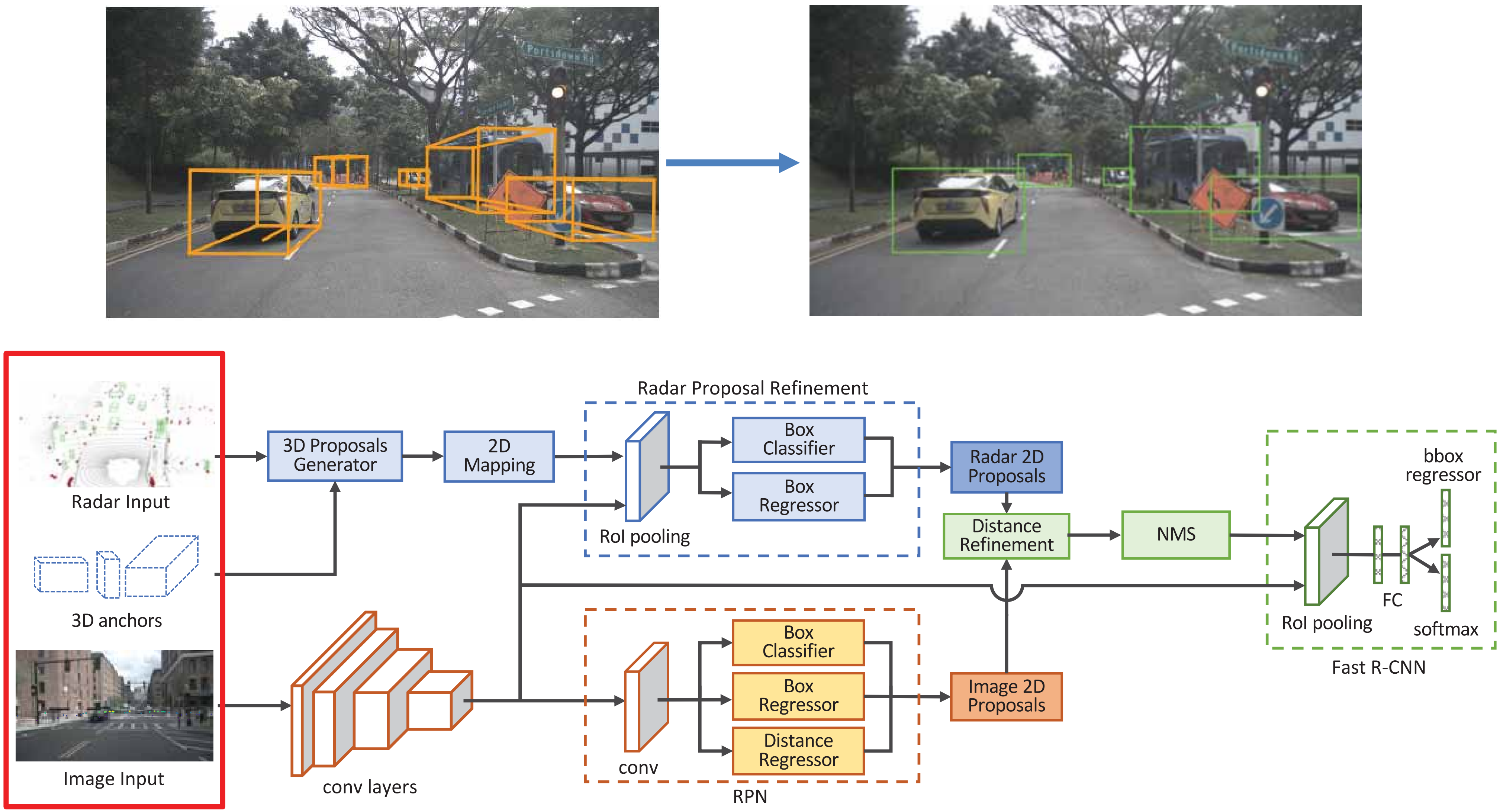
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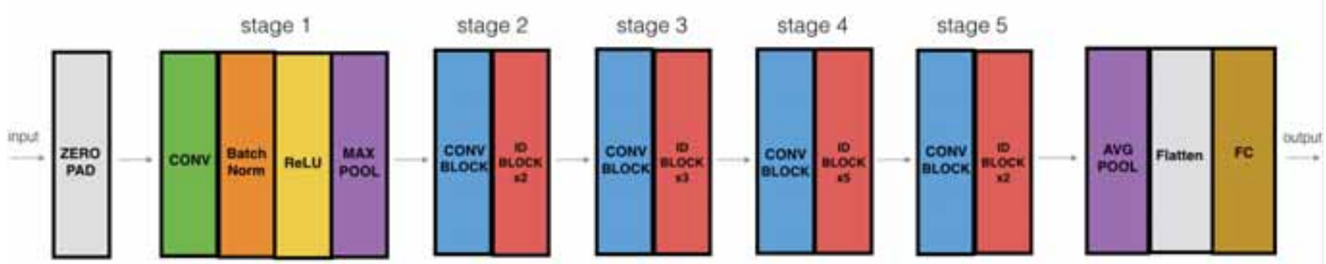
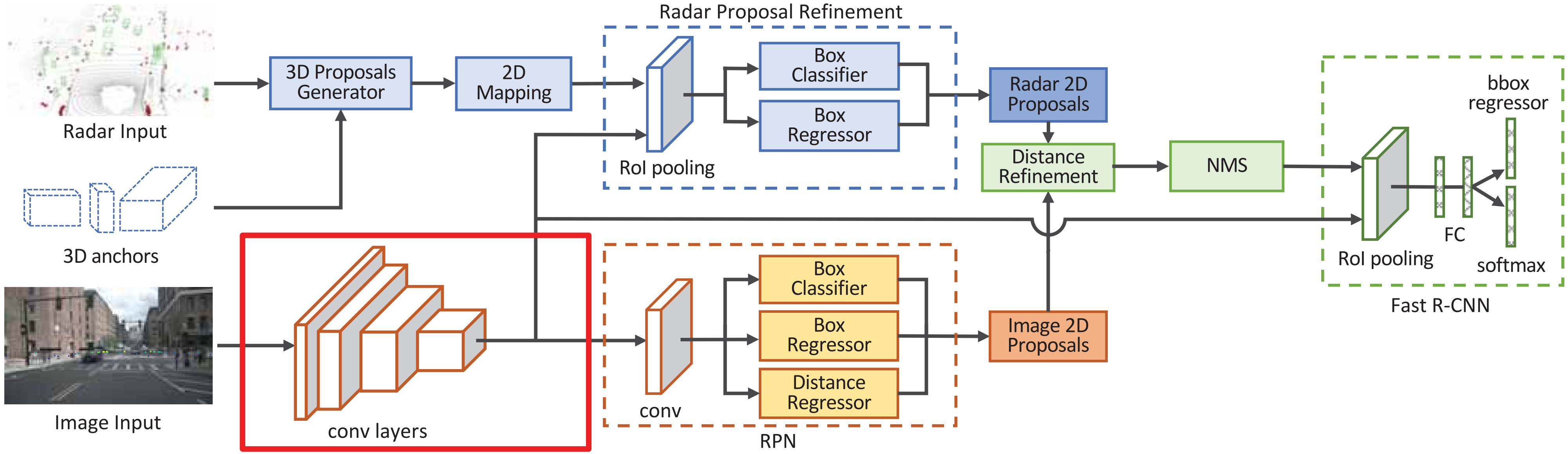
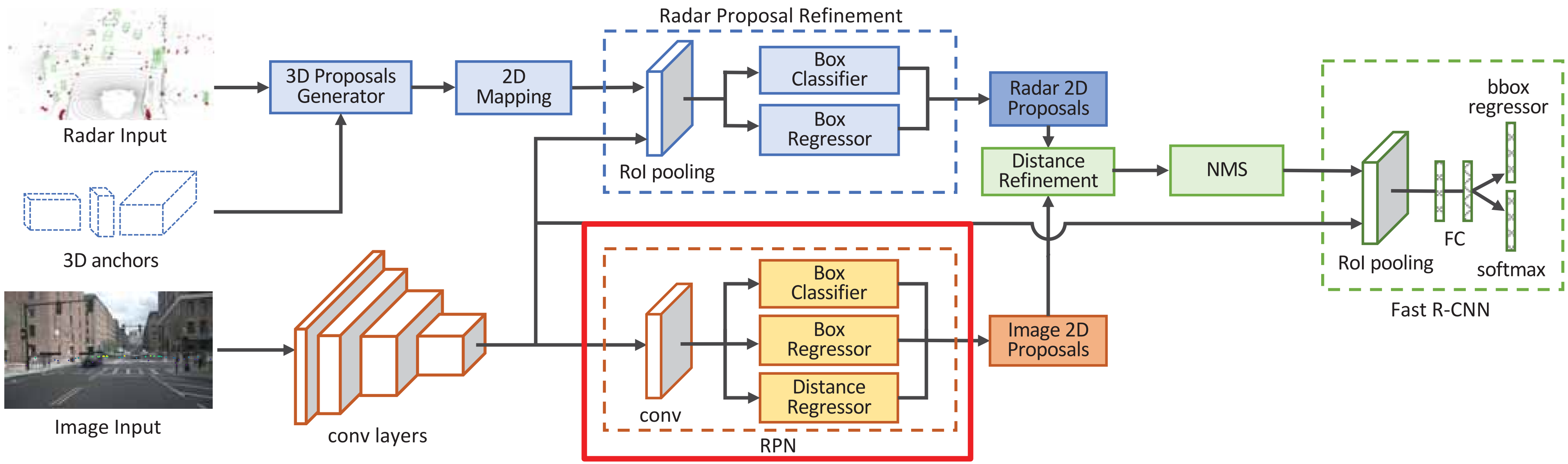


ResNet-50 Model*





Radar Proposal Refinement
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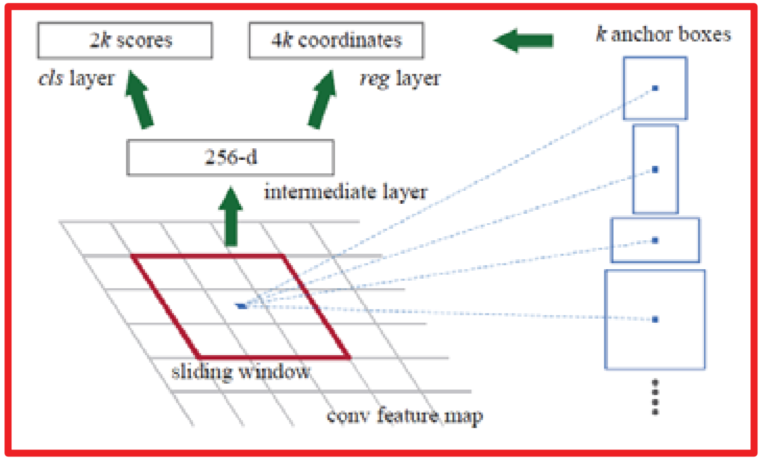
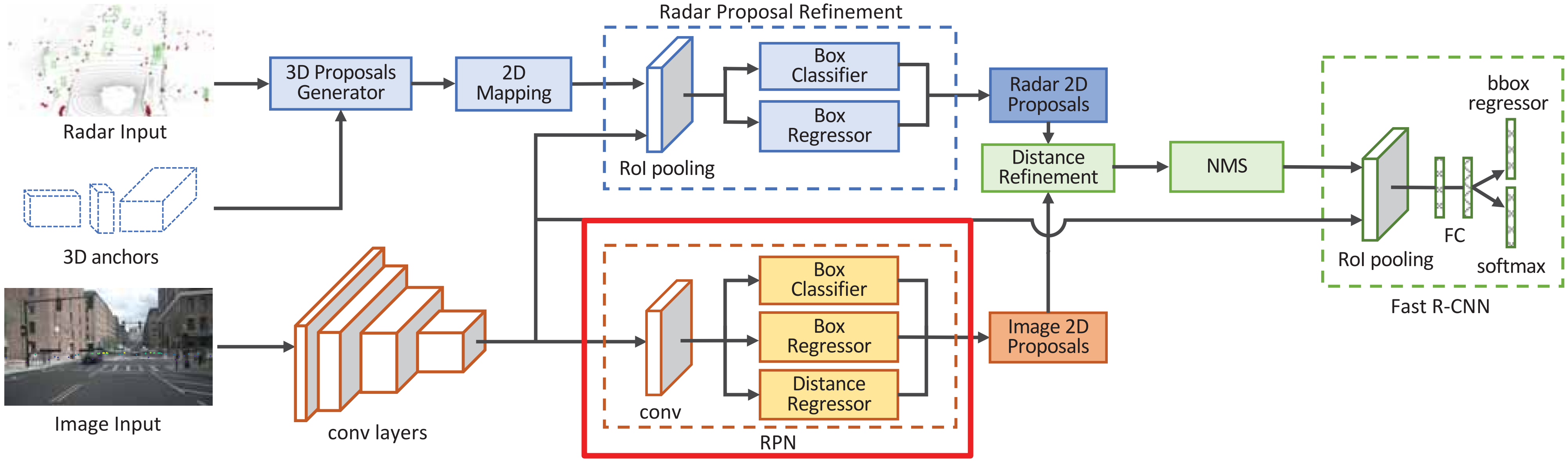
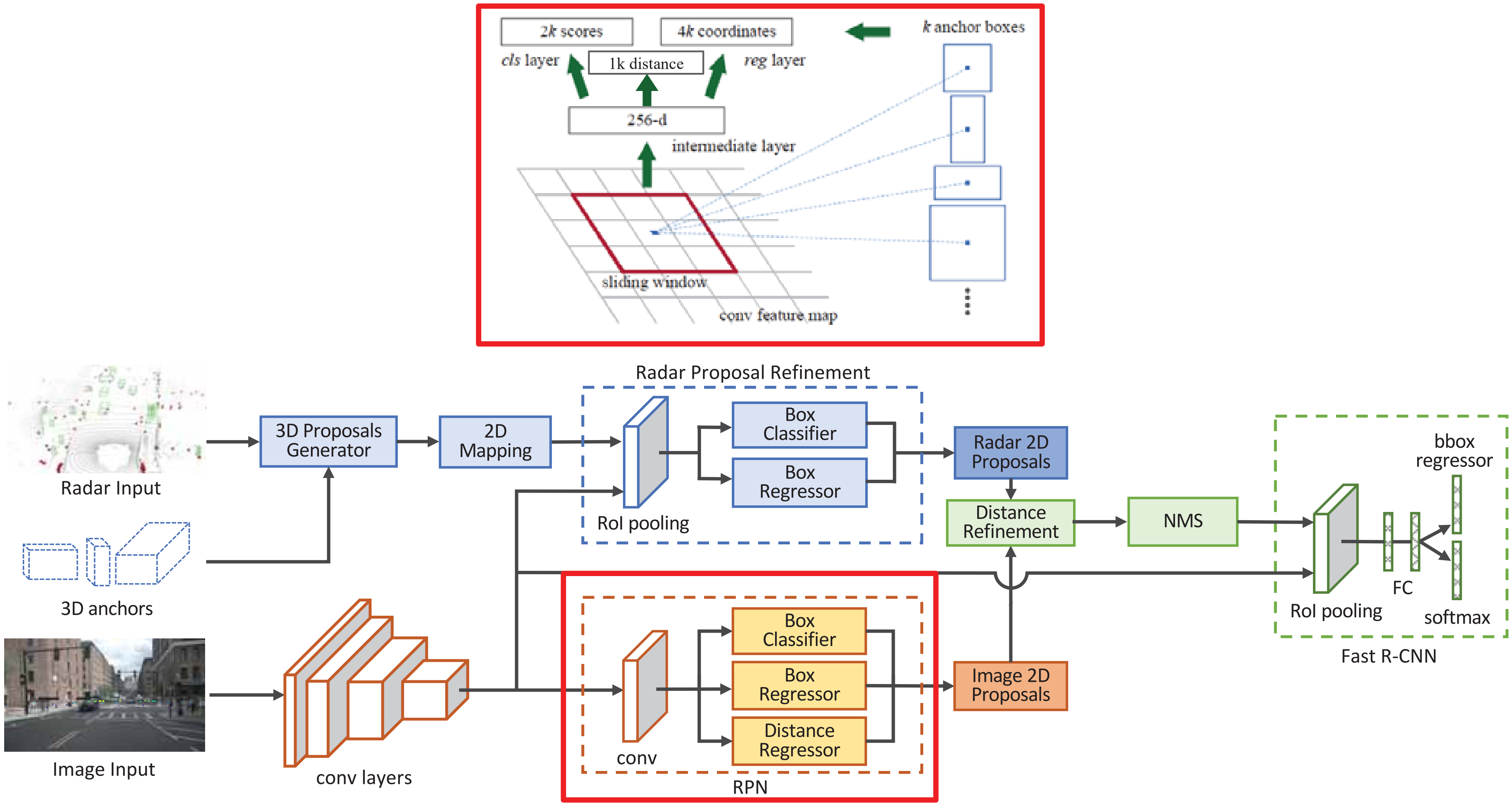




Source: https://arxiv.org/abs/1311.2524



2k scores
4k coordinates
k anchor boxes
cls layer
1k distance
reg layer
256-d
intermediate layer
sliding window
conv feature map
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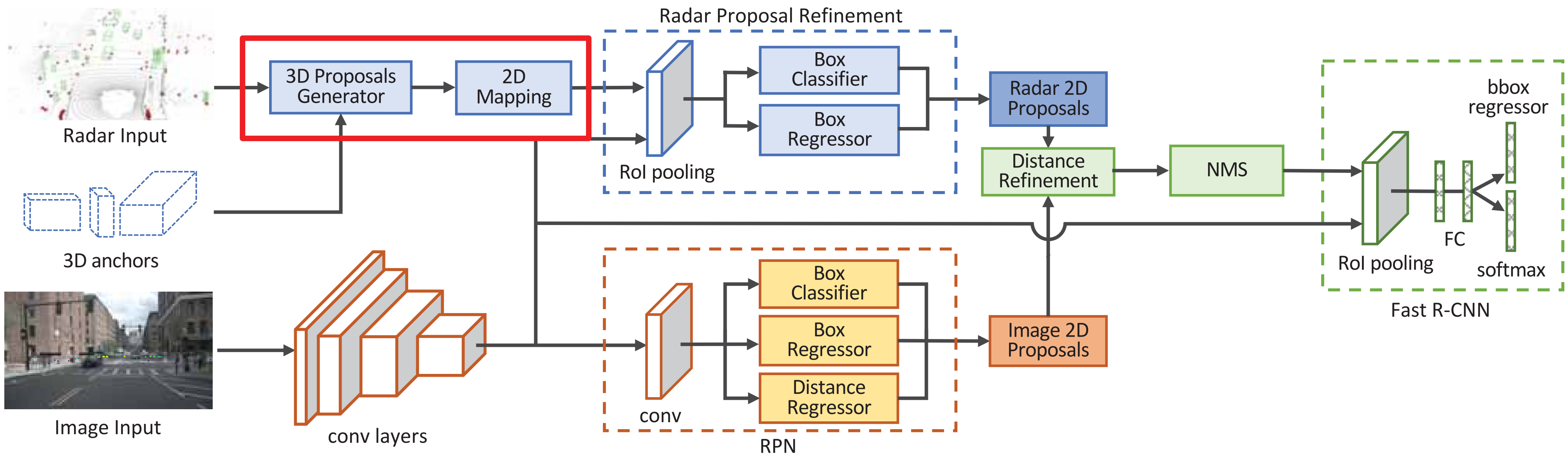
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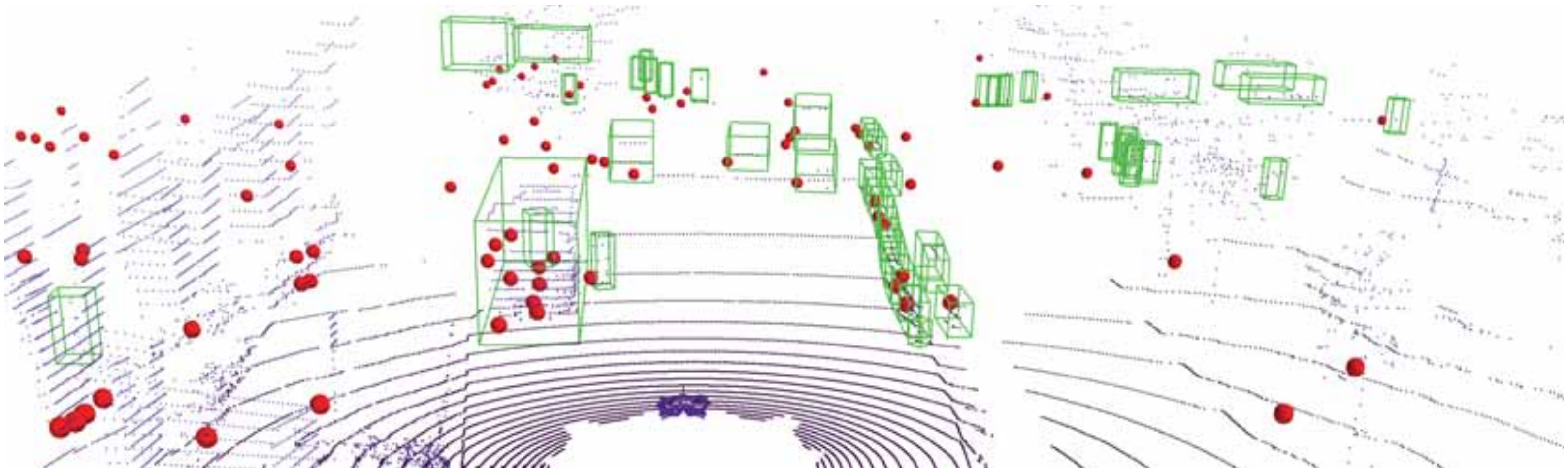

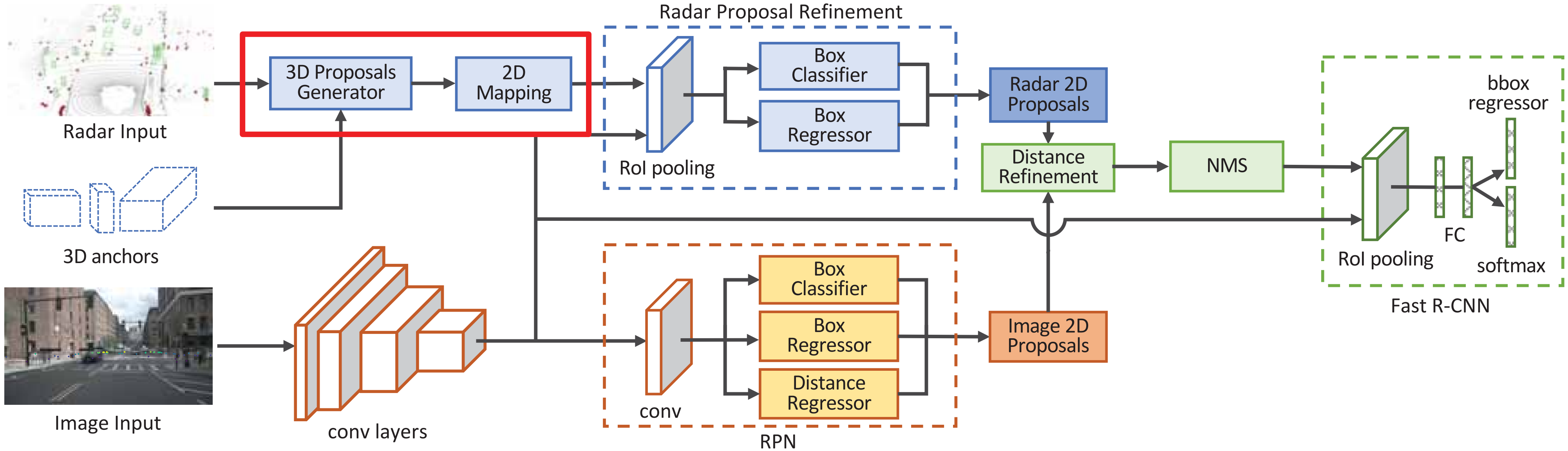
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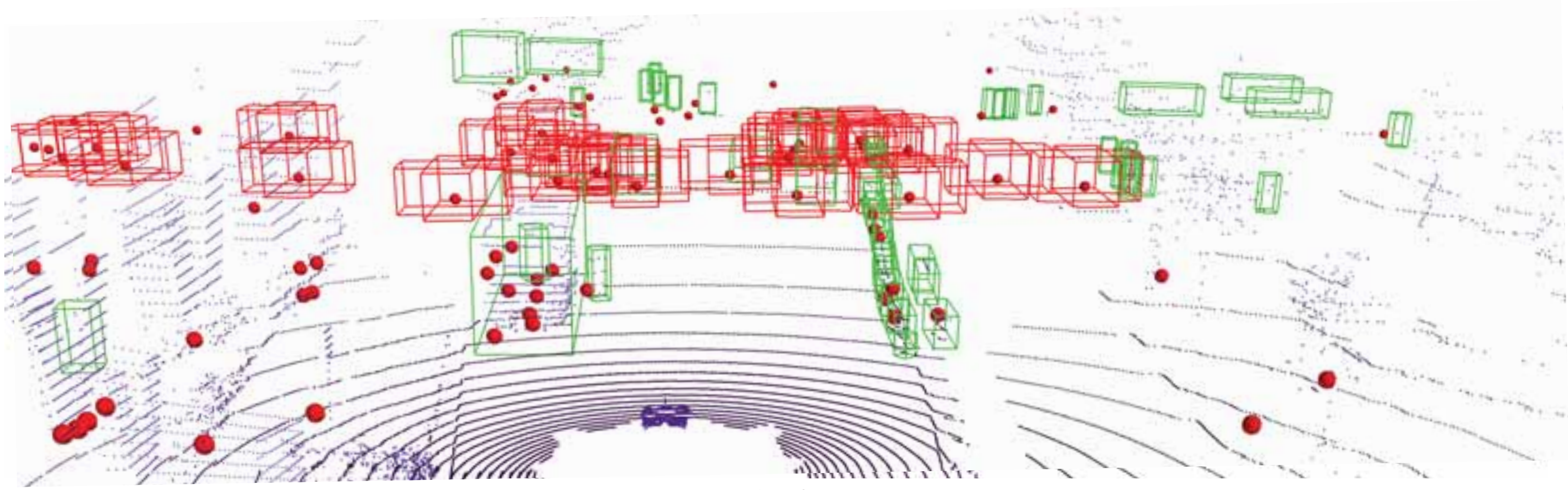

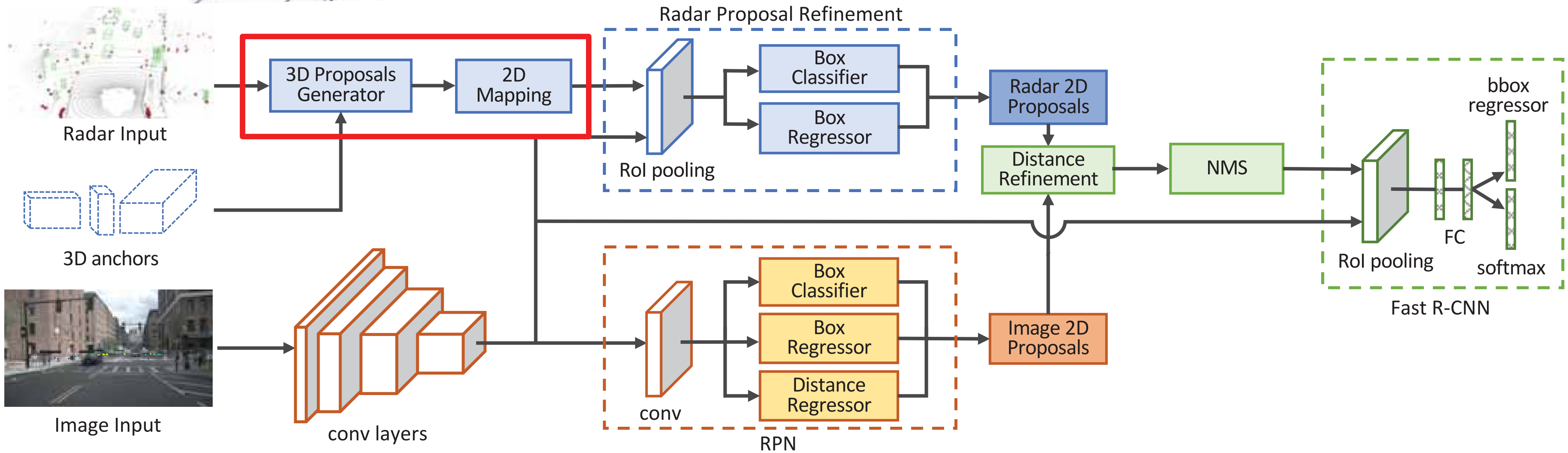

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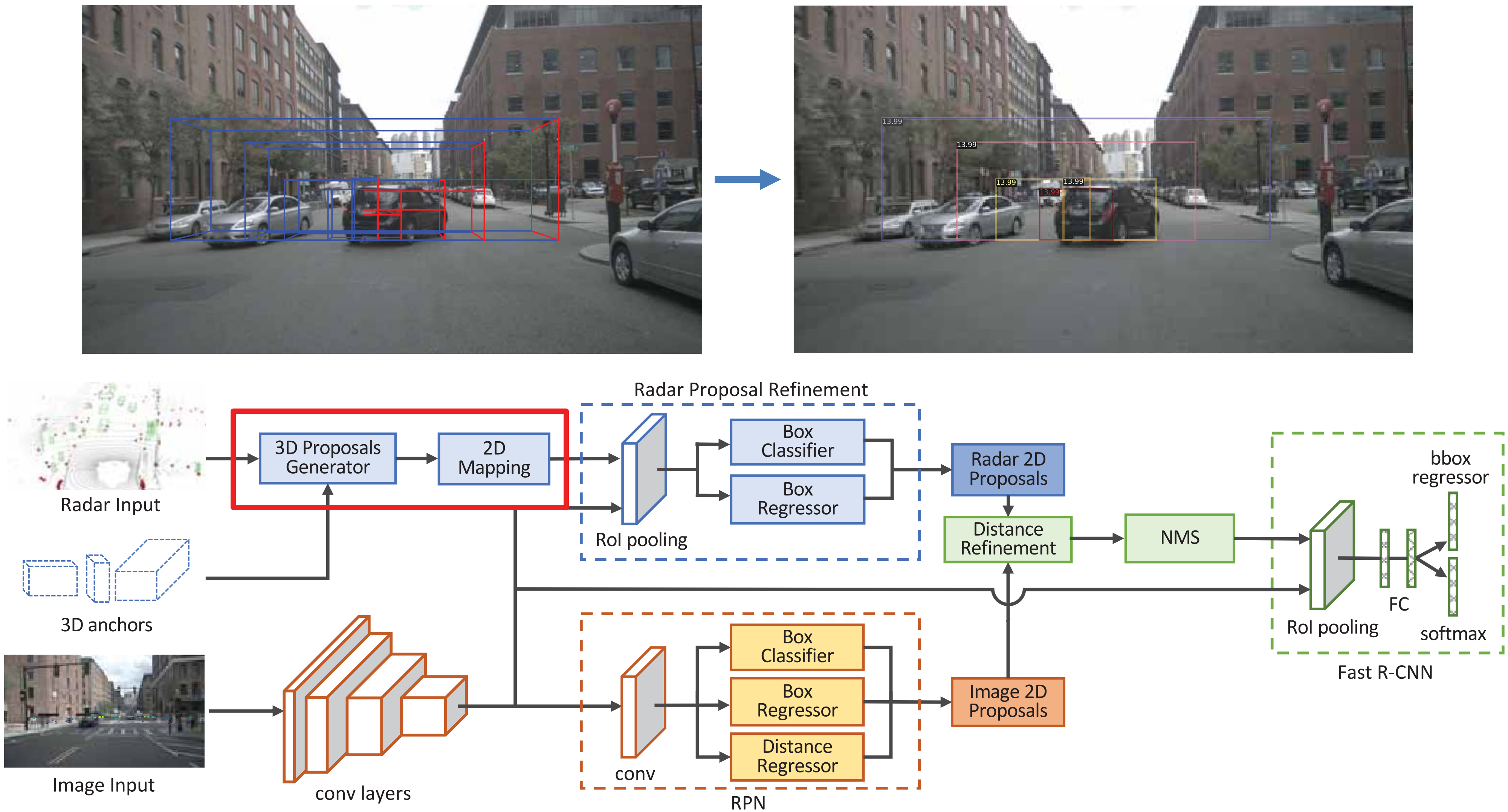
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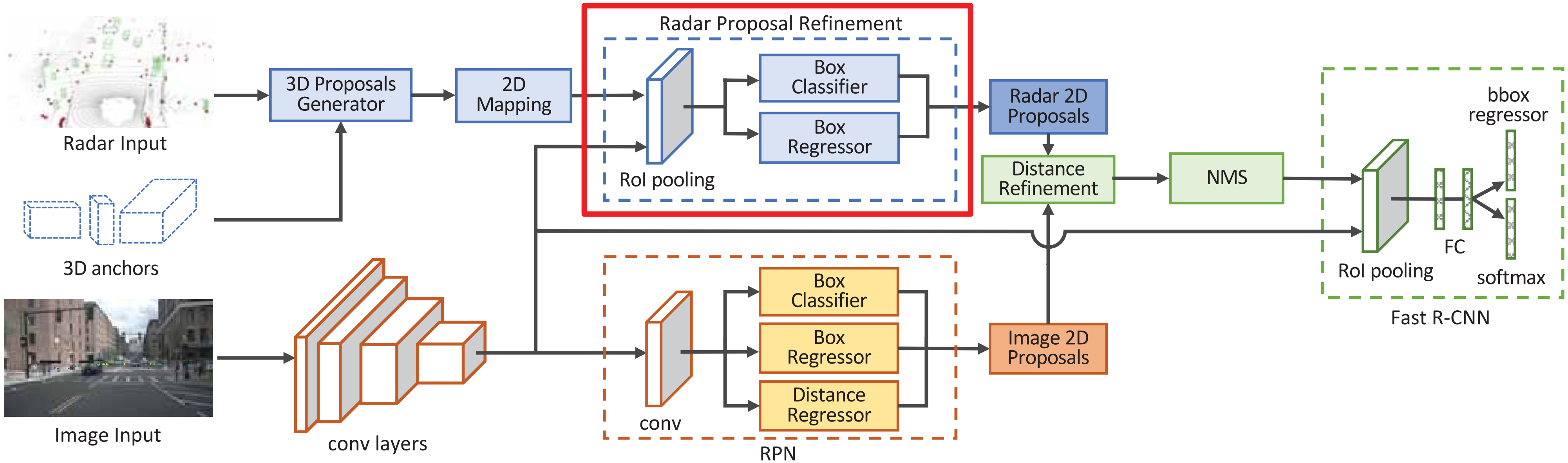
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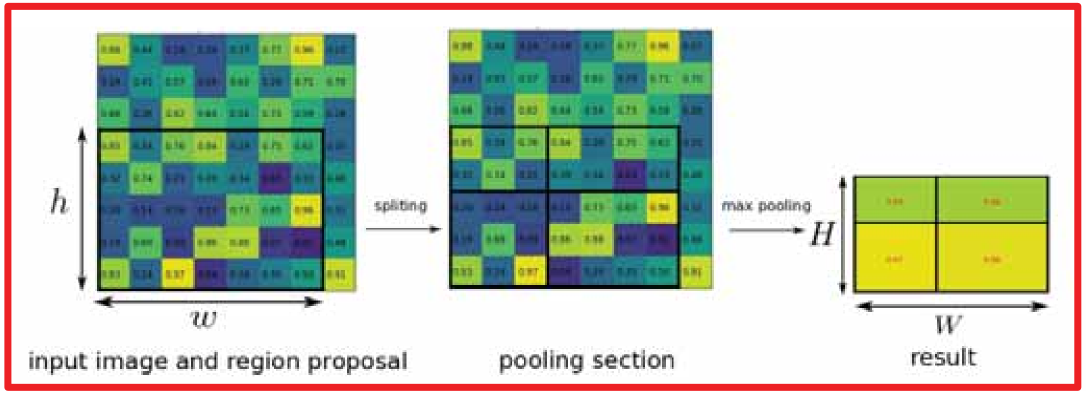

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max pooling
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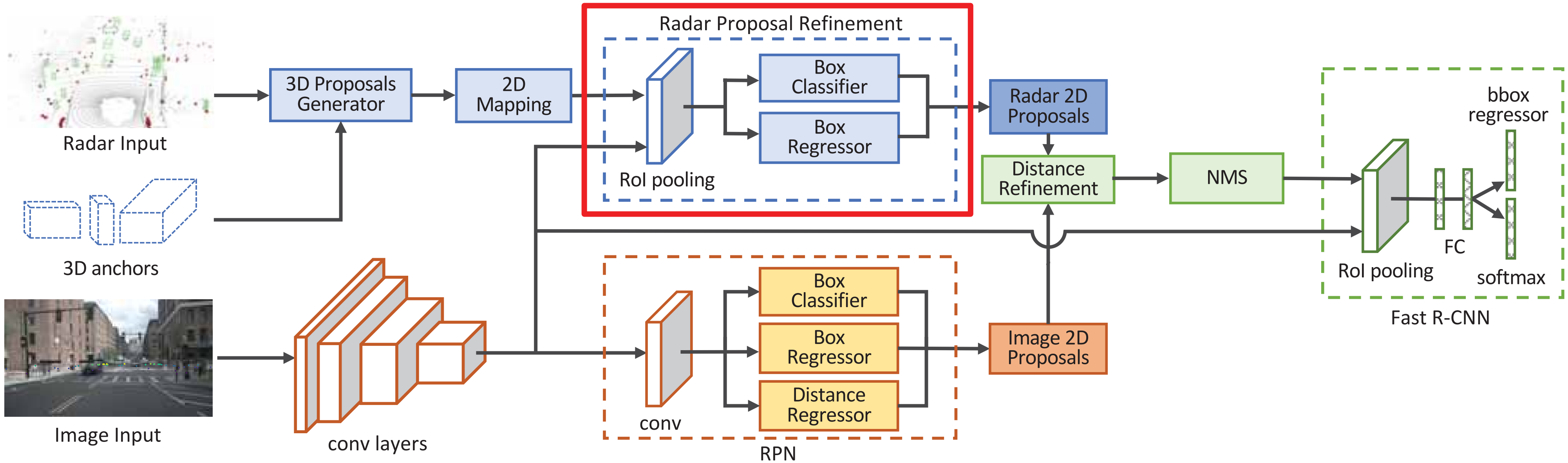
input image and region proposal
pooling section
result



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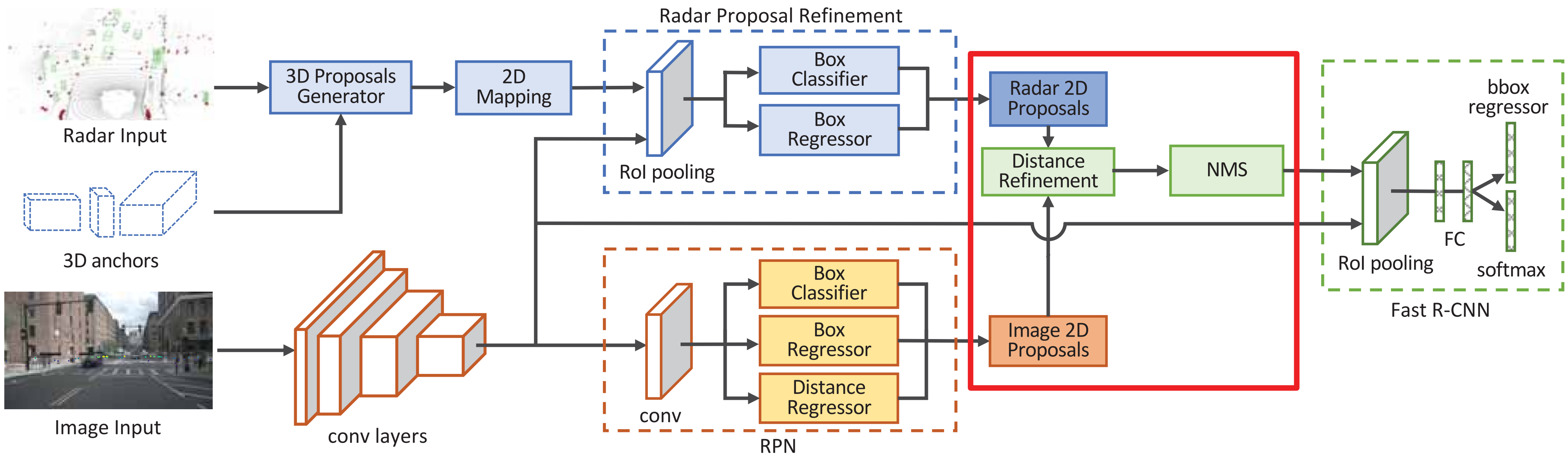
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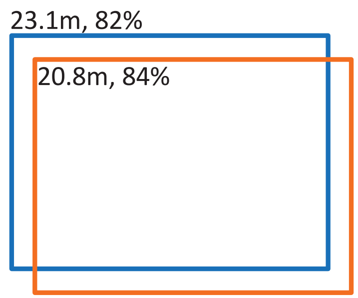
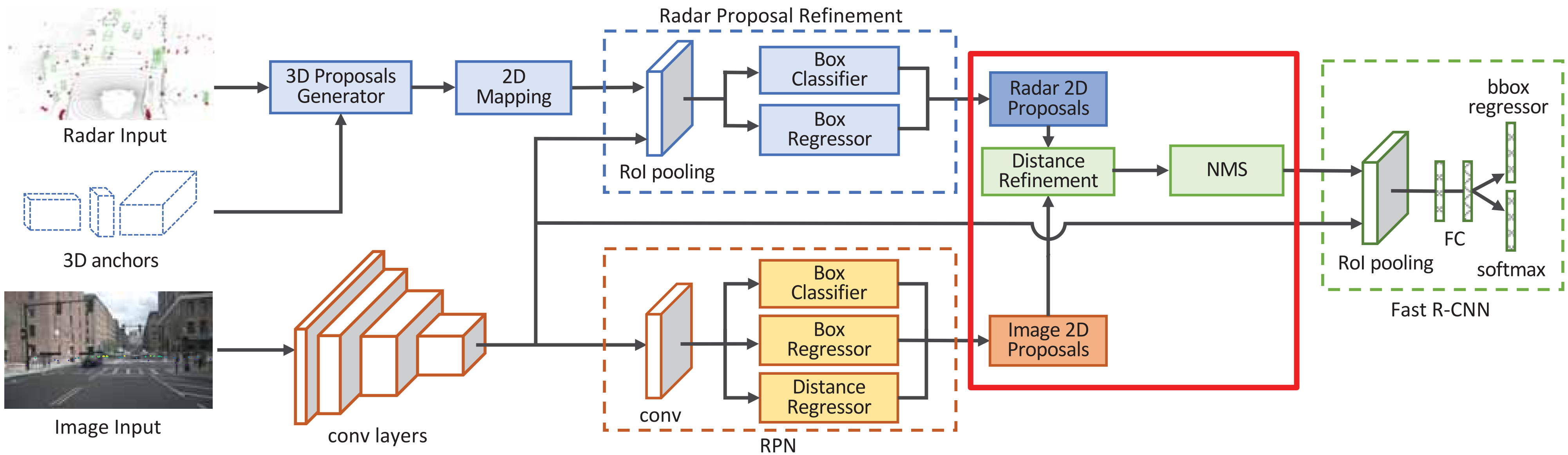

23.1m, 82%
20.8m, 84%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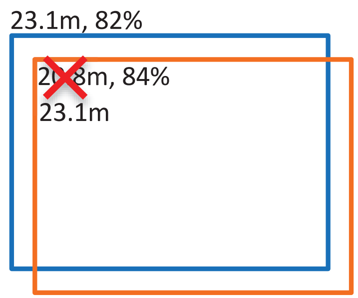
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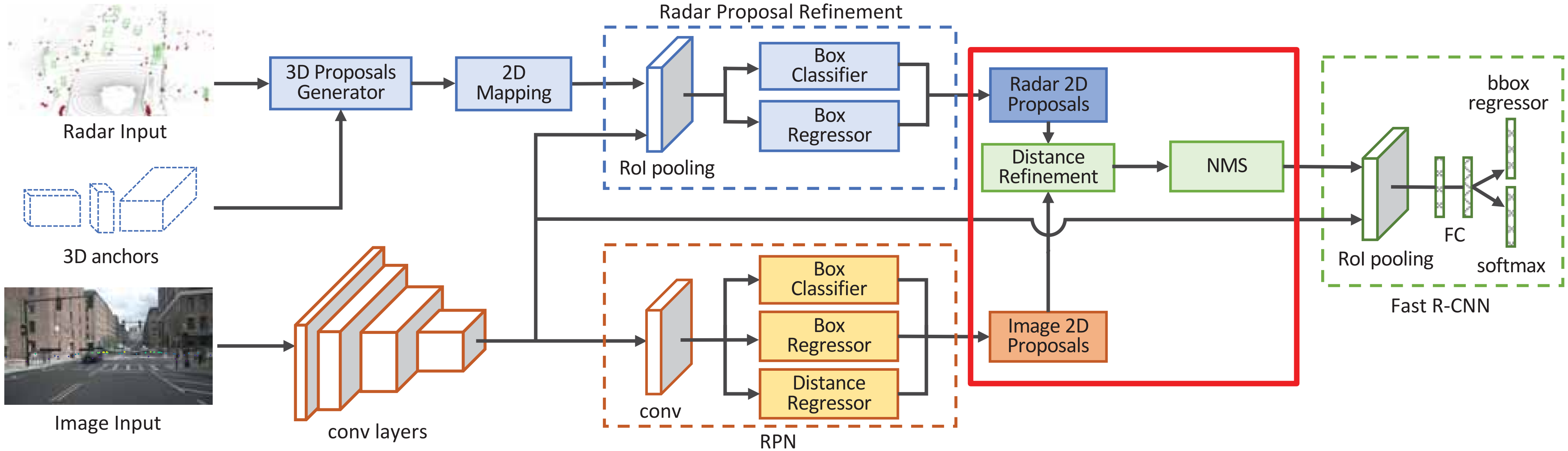
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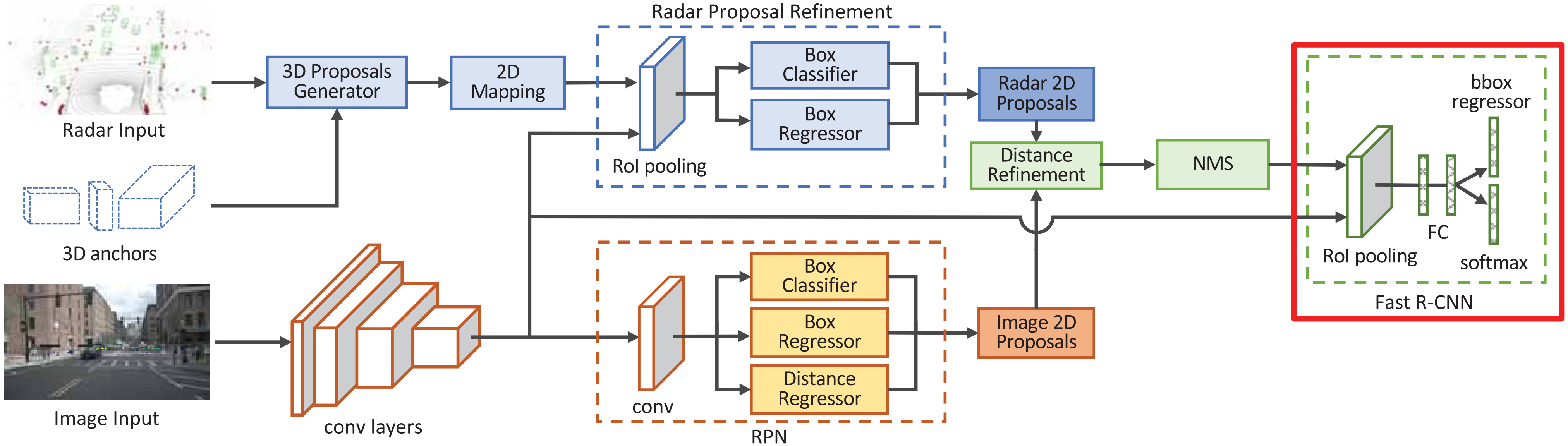
pedestrian 75% - 19.5m
car 90% - 18.5m
car 87% - 54.9m
car 100% - 16.5m
car 83% - 47.4m
car 70% - 40.8m
car 95% - 42.0m
car 94% - 26.6m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Results

TABLE I: Performance on the nuScenes validation set.

	Weighted AP	AP	AP50	AP75	AR	MAE
Faster R-CNN	No	34.95	58.23	36.89	40.21	-
RRPN	No	35.45	59.00	37.00	**42.10**	-
Ours	No	**35.60**	**60.53**	**37.38**	**42.10**	2.65
Faster R-CNN	Yes	43.78	-	-	-	-
CRF-Net	Yes	43.95	-	-	-	-
Ours	Yes	**44.49**	-	-	-	-

TABLE II: Per-class performance

	Car	Truck	Person	Bus	Bicycle	Motorcycle
Faster R-CNN	51.46	33.26	27.06	47.73	24.27	25.93
RRPN	41.80	**44.70**	17.10	**57.20**	21.40	**30.50**
Ours	**52.31**	34.45	**27.59**	48.30	**25.00**	25.97

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} = \frac{\sum_{i=1}^{n} |e_i|}{n}.$$

TABLE III: Per-class Mean Absolute Error (MAE) for distance estimation

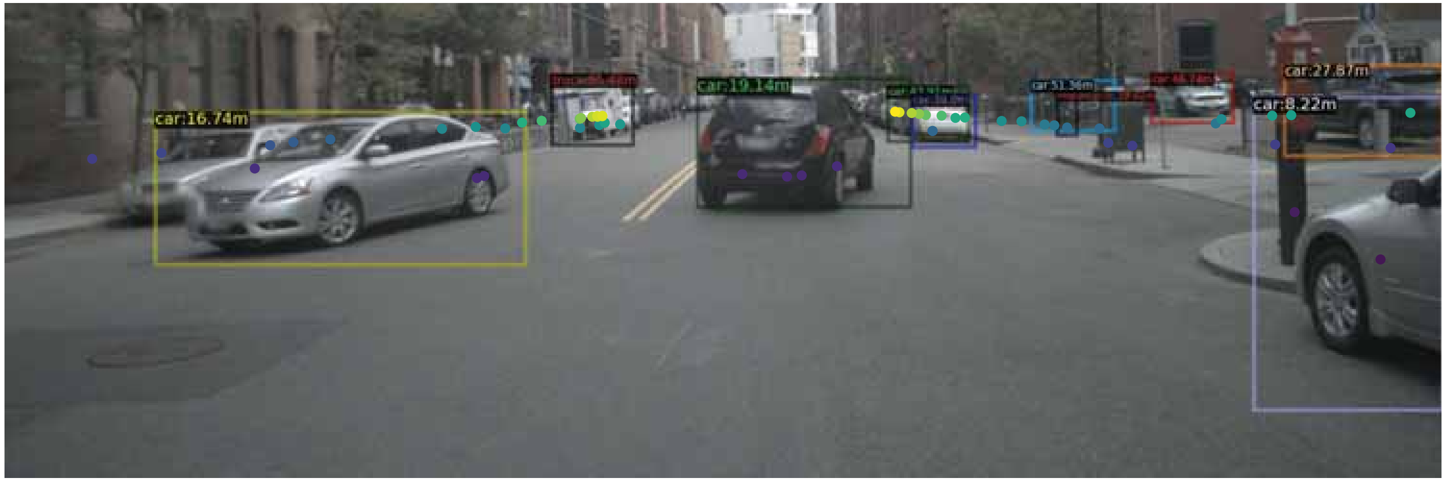
Category	Car	Truck	Person	Bus	Bicycle	Motorcycle
MAE	2.66	3.26	2.99	3.187	1.97	2.81

Results


pedestrian:8.26m
pedestrian:13.16m
pedestrian:17.56m
pedestrian:20.16
pedestrian:21.43m
pedestrian:20.77m
estrian:15.7m


pedestrian 99% - 8.5m
pedestrian 94% - 12.0m
pedestrian 89% - 12.2m
- 10.7m
pedestrian 74% -
pedestrian 87% - 14.6m
pedestrian 87%
pedestrian 81% - 20.5m
pedestrian 78% - 21.6m
pedestrian 63% - 23.2m

Results


car:16.74m
car:19.14m
car:51.36m
car:27.87m
car:8.22m


pedestrian 75% - 19.5m
car 90% - 18.5m
car 87% - 54.9m
car 100% - 16.5m
car 83% - 47.4m
car 70% - 40.8m
car 95% - 42.0m
car 94% - 26.6m

Conclusion

- Contributions
  - A framework for radar-camera sensor fusion
  - Joint object detection and distance estimation

- Future work
  - Improve distance estimation by aggregating radar detections for large objects
  - Perform a thorough ablation study to evaluate the influence of each part of the proposed network

Thanks!

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