RLLAB

Melissa Mozifian

McGill University

Real-time 3D Object Detection for Autonomous Driving

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Outline

Motivation

- The detection and localization of objects is a key problem in creating autonomous cars.
- 2D detectors with high accuracy are deployed in consumer products.

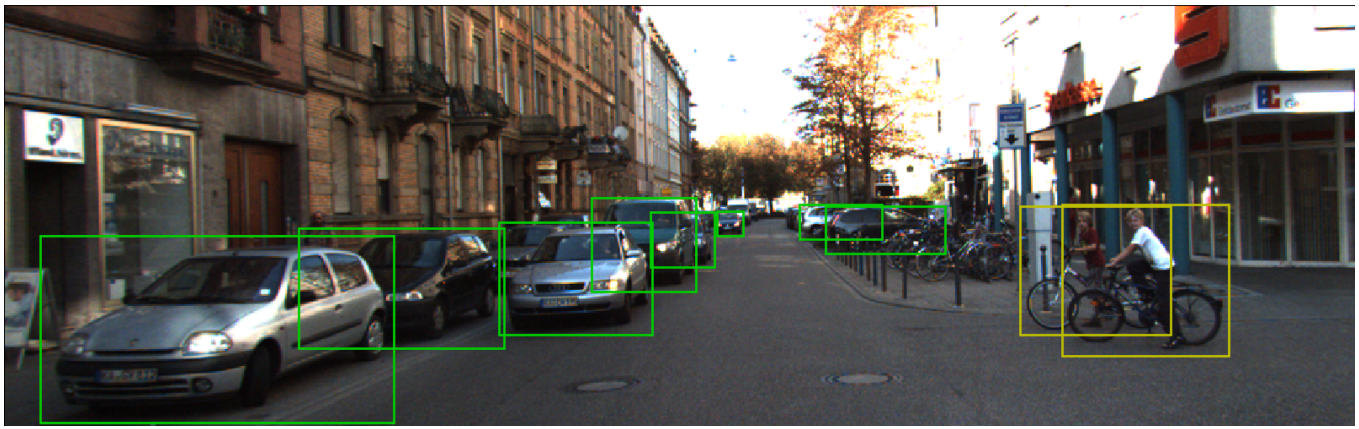


Figure: Example of 2D detection on KITTI dataset [1].

Motivation

- In the context of autonomous driving, 2D bounding boxes are not sufficient:
  - Lack of 3D pose and location.
  - Occlusion.
- The gap between 2D and 3D detections remains large due to:
  - Adding a third dimension.
  - Low resolution of 3D data.
  - Deterioration of quality of 3D data as a function of distance.

Motivation

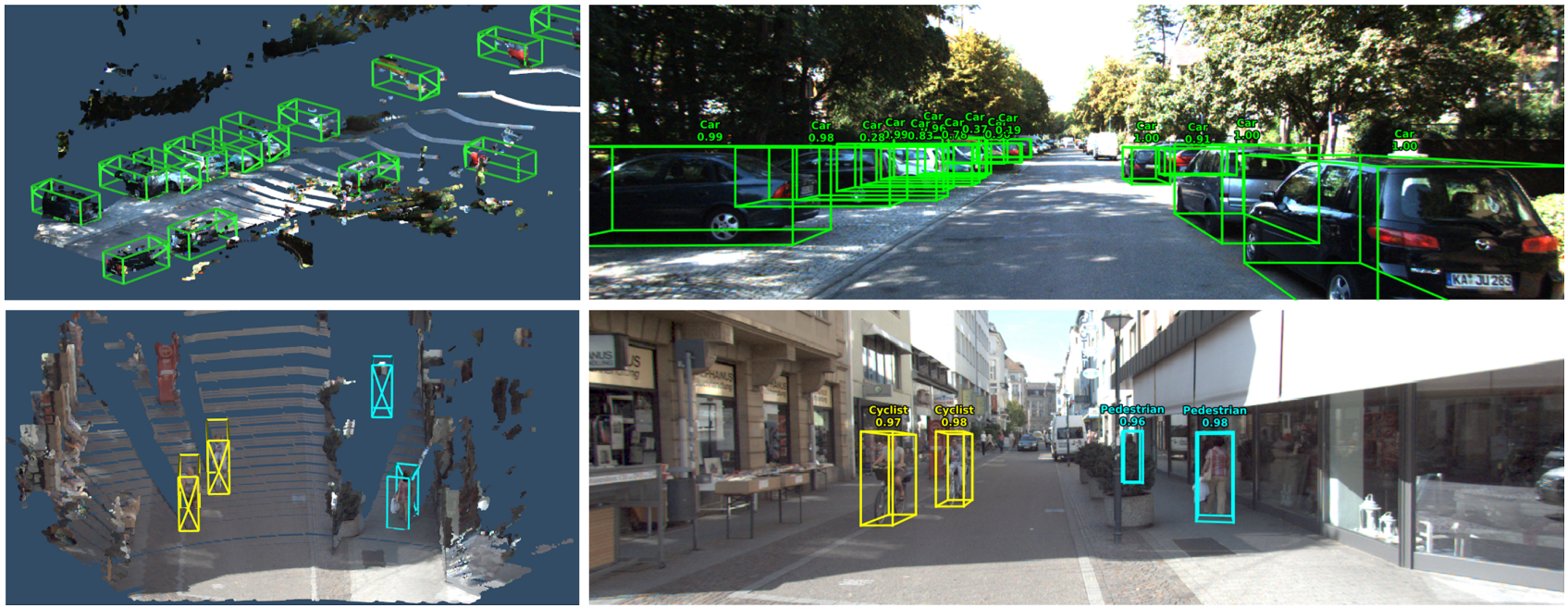


Figure: Example of 3D detection on KITTI dataset.

Background: Object Detection

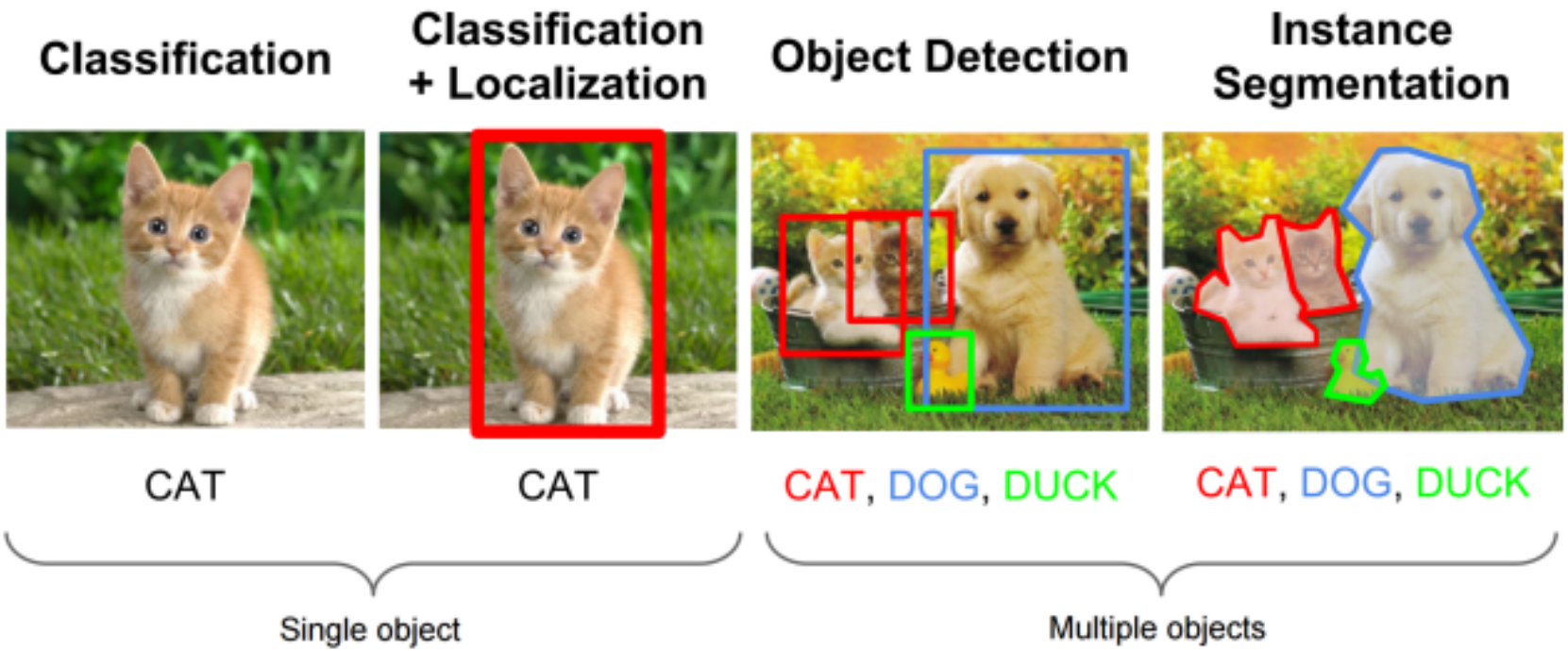


Figure: Example of object classification, localization and segmentation [2].

Background: Classic Object Detectors

- Most classical methods adopted the sliding-window technique which works by sliding a box around image and classifying each image crop inside a box.
- Pick a classifier (say SVM), run it at evenly spaced locations over the entire image, focusing on smaller areas of the feature map.

Background: Two-Stage Detection

- The dominant paradigm in modern object.
- **First stage**: Generates a set of candidate proposals that should contain all the objects.
- **Second stage**: Classifies the object proposals and refines the location estimation of objects.

Background: Faster R-CNN

- Region Proposal Network (RPN)
- Region of interest pooling (RoI pooling)

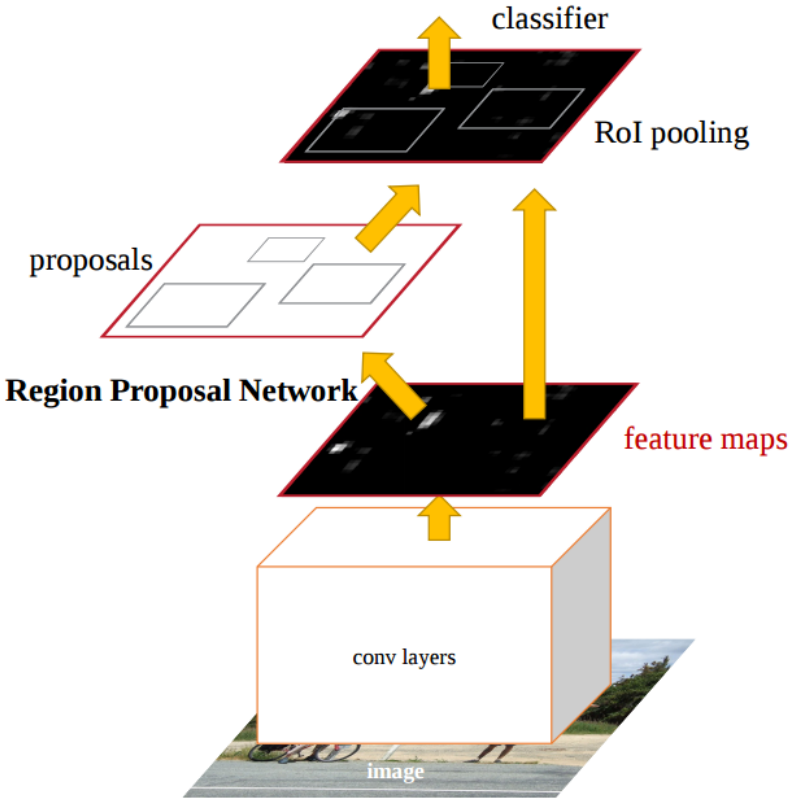


Figure: Faster R-CNN architecture overview [3].

Background: Single-Staged Detectors

- Example architectures:
  - OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks (Zhang et al - 2013)
    - Multi-scale, sliding window approach
  - You Only Look Once: YOLO (Redmon et al - 2015)
    - Discretizes the image into grids and then each grid cell proposes potential bounding boxes and scores those boxes using convolutional features.
  - Single Shot Detector: SSD (Liu et al - 2016)
    - Discretizes the output space of bounding boxes into a set of default boxes over different aspect ratios and scales per feature map location

Background: Single-Stage Detection

- RPN free architectures.
- Example: You Only Look Once: YOLO (Redmon et al - 2015)

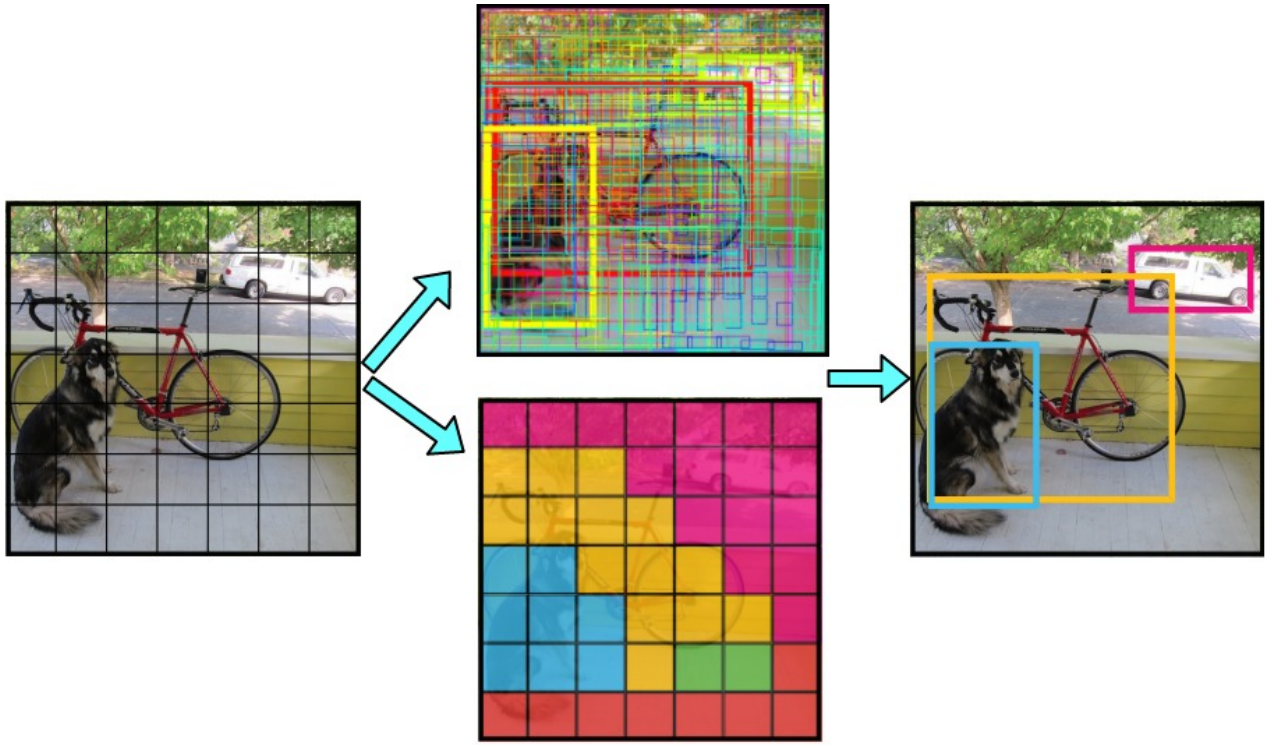
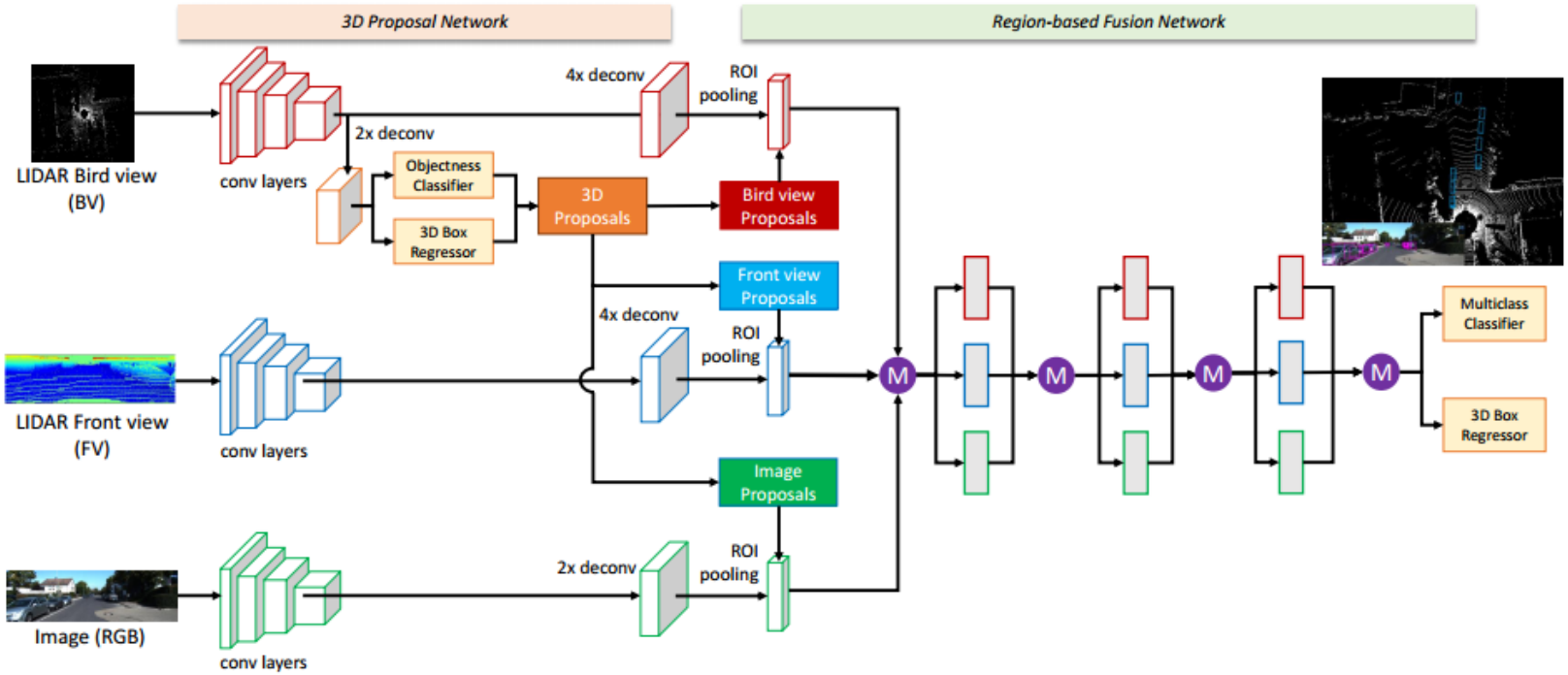


Figure: Yolo detection mechanism [8].

Background: 3D Object Detection

- **3D RPN**: Generates a set of candidate 3D boxes.
- **Second stage**: Classifies and regresses the 3D boxes.
- Example architectures:
  - **MV3D** - Multi-View 3D Object Detection Network for Autonomous Driving. (Chen et al 2017) [5]
  - **F-PointNet** - Frustum PointNets for 3D Object Detection from RGB-D Data. (Qi et al 2018) [6]

Background: 3D Object Detector - MV3D [1]



[1] Multi-View 3D Object Detection Network for Autonomous Driving(CVPR) 2017.

Background: MV3D

- A sensor fusion network.
- Encodes the sparse 3D point cloud into bird's eye view.
- **An RPN generates 3D candidate boxes from the bird's eye view representation.**
- **Uses 8 corner box representation to regress 3D bounding boxes.**

AVOD - Aggregate View Object Detection

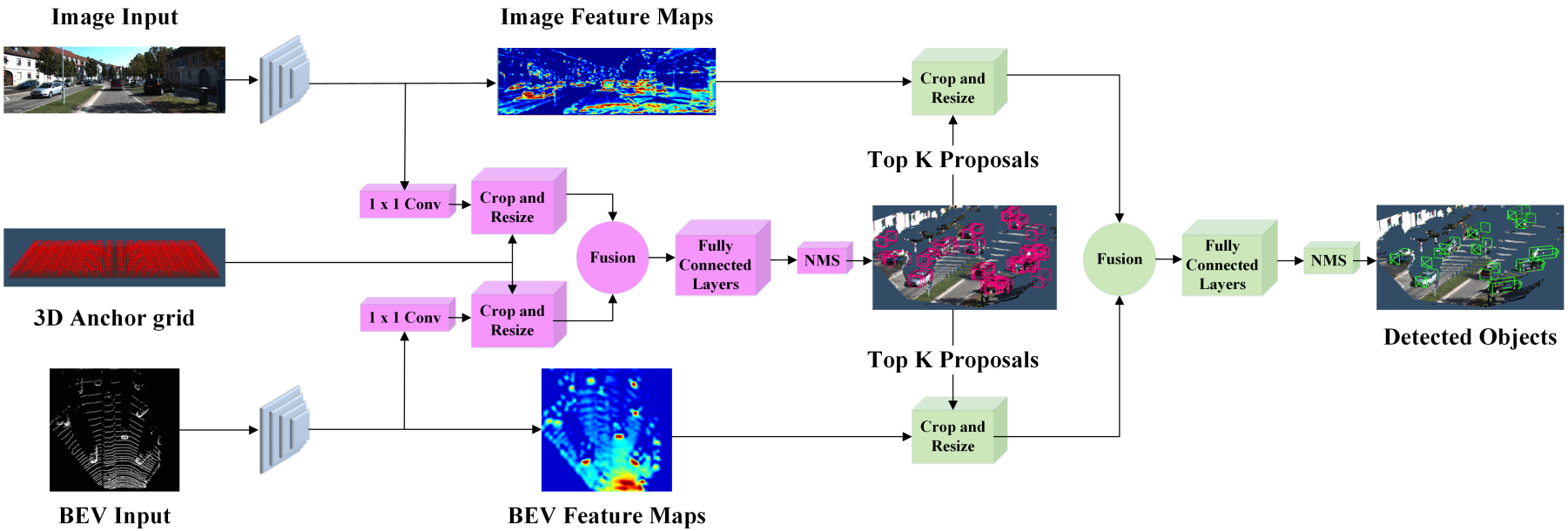
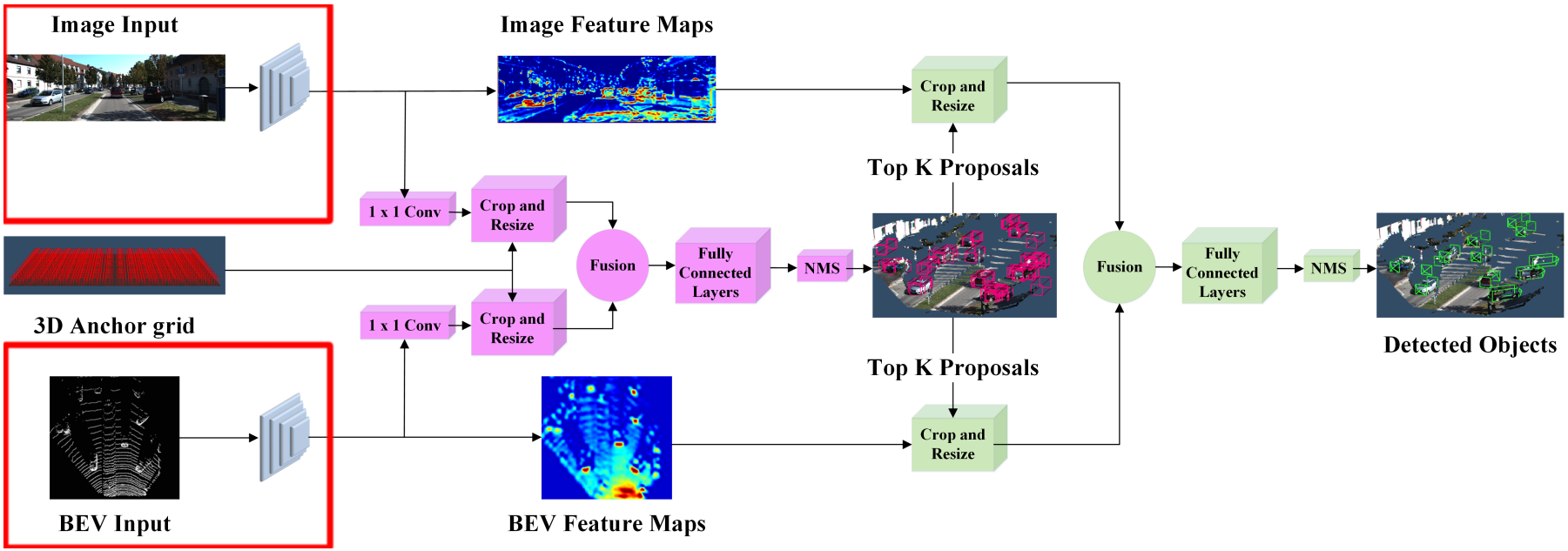


Figure: AVOD architectural diagram. The feature extractors are shown in **blue**, the region proposal network in **pink**, and the second stage detection network in **green**.

AVOD - Aggregate View Object Detection



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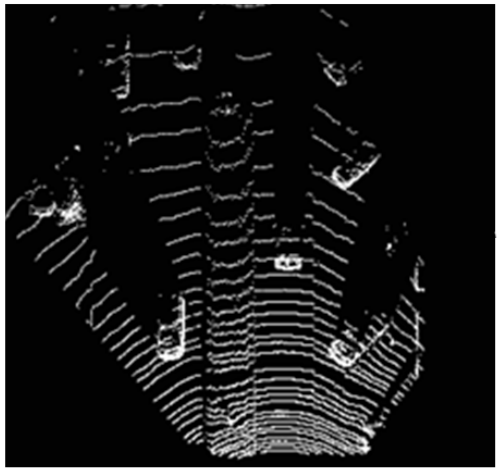
AVOD - Input Data

- RGB Image
- Bird's Eye View (**BEV**) Maps:
  - Small size variance.
  - Small variance in vertical location.
  - No issues with with occlusion.

Image Input

BEV Input



Generating Feature Maps

- VGG Feature Extractor:

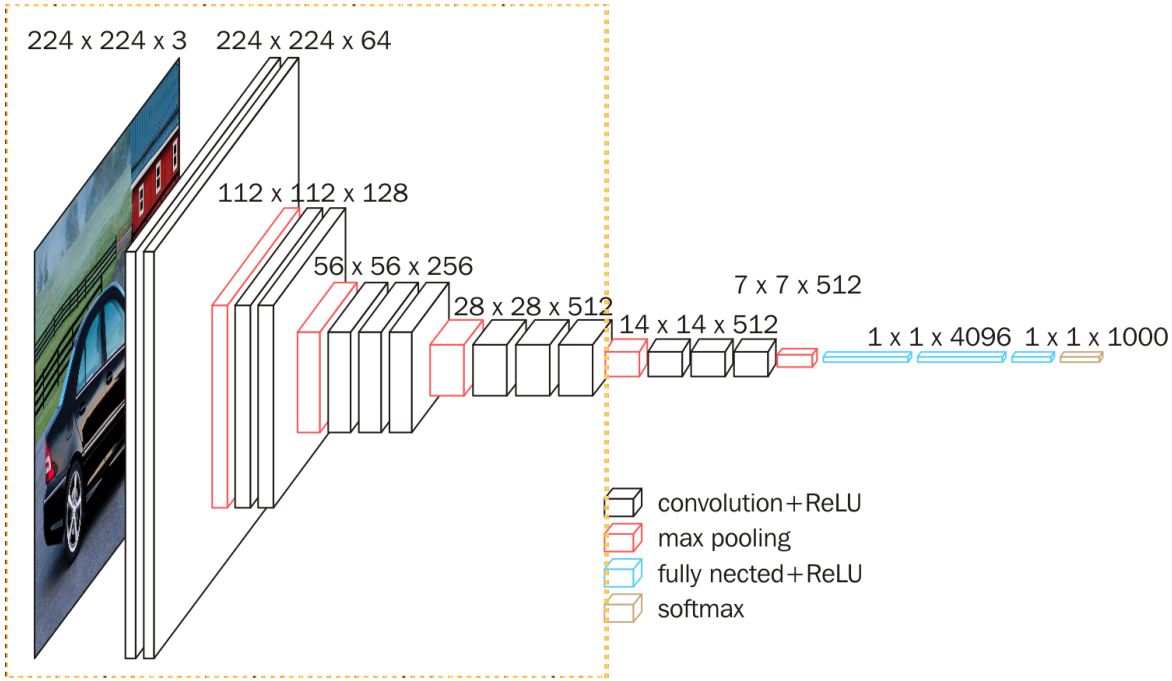


Figure: VGG16 architecture [4].

- Modified by resizing and reducing the layers.

Generating Feature Maps

- Feature Pyramid Feature Extractor

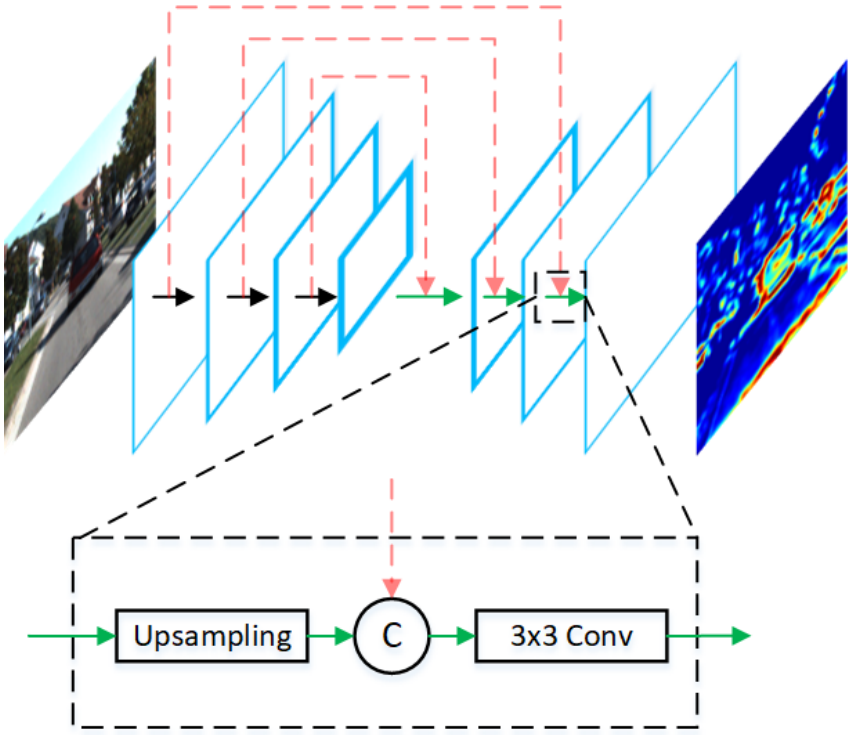


Figure: Feature maps are fused at every layer by an *upsampling* layer, followed by *concatenation*, and then mixing via a *convolutional* layer, resulting in a full resolution feature map.

RPN - Anchor Generation

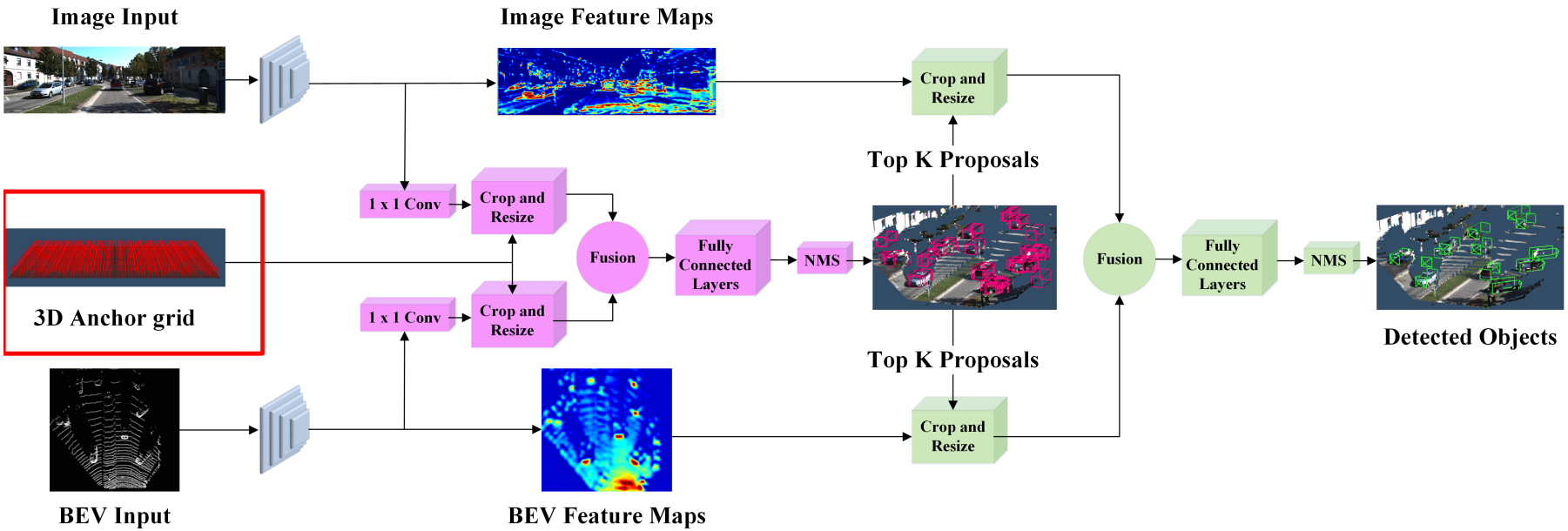


Figure: AVOD architectural diagram. The feature extractors are shown in **blue**, the region proposal network in **pink**, and the second stage detection network in **green**.

RPN - Anchor Generation

- **Anchors**: Initial guesses on where objects are located.
  - Encoded as $[x, y, z, l, w, h]$
- Take 3D box sizes from ground truth clusters.
- Generated on a grid on the ground plane, with 0° or 90° orientations.

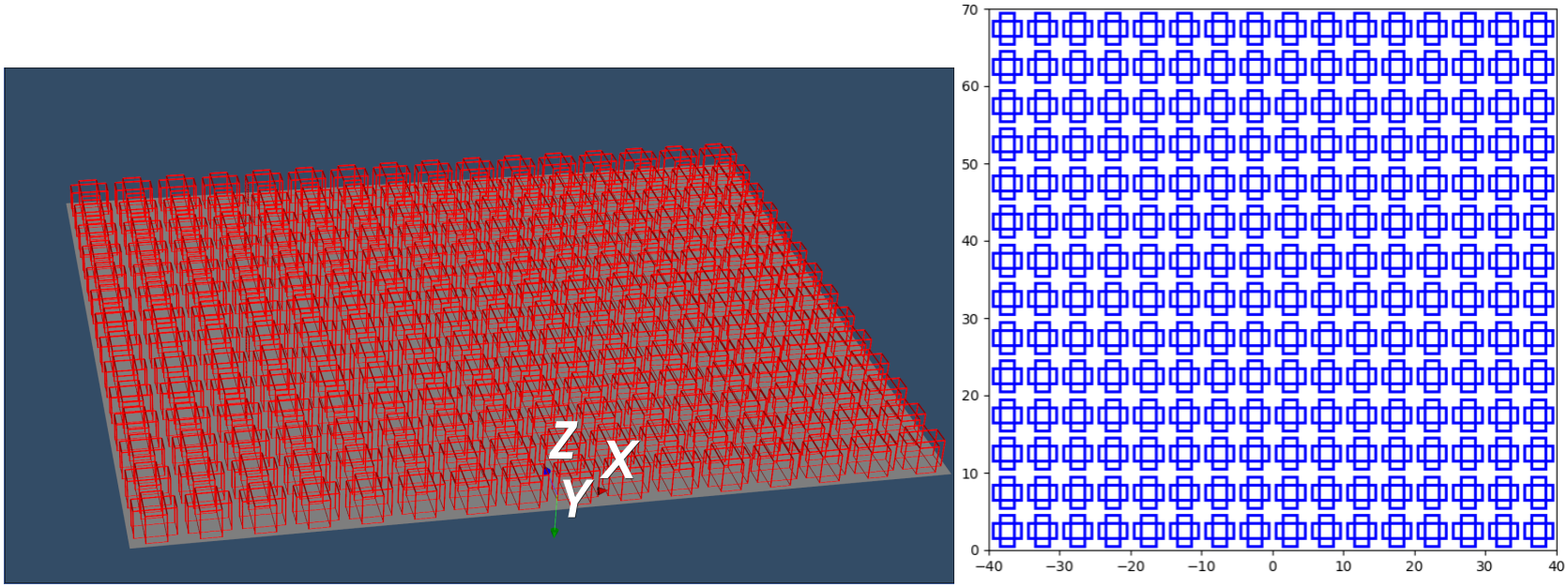
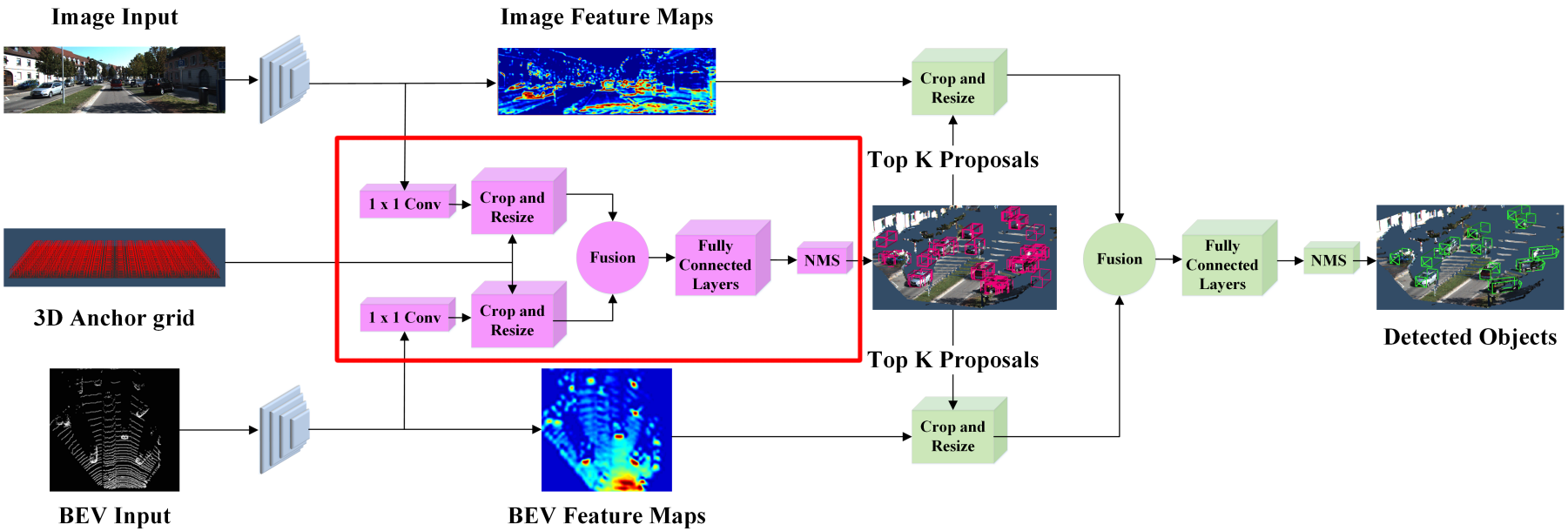


Figure: Left: Example of anchor grid with 1 cluster, and $5m$ stride. Right: Example of anchors projected into Bird's Eye View.

Region Proposal Network



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Region Proposal Network

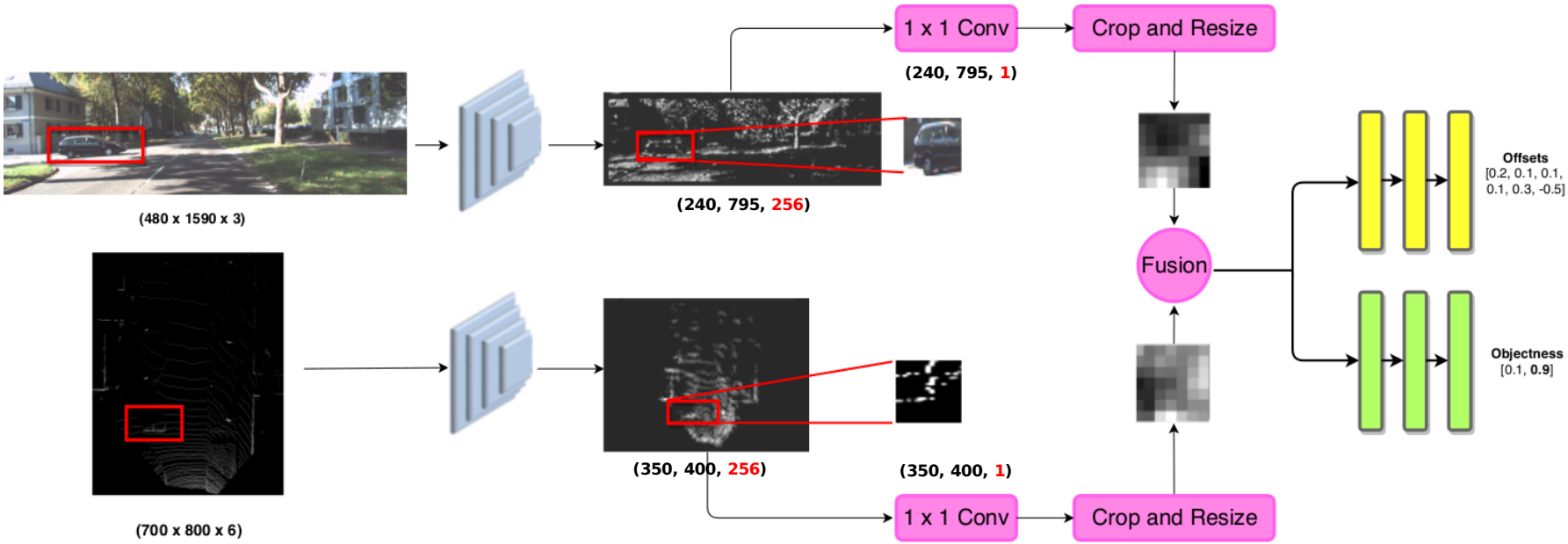


Figure: RPN fusion & proposal generation.

Second Stage Detection Network

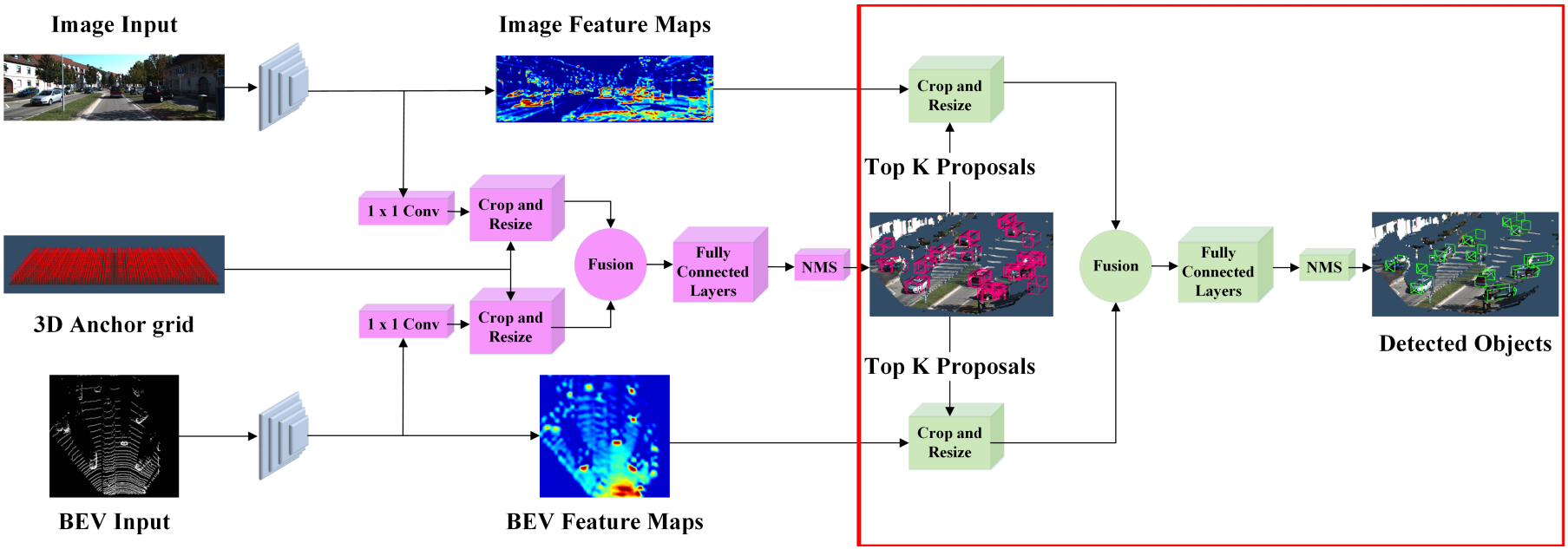


Figure: AVOD architectural diagram. The feature extractors are shown in **blue**, the region proposal network in **pink**, and the second stage detection network in **green**.

Second Stage Detection Network

- 3D Bounding Box Encoding
  - **Four corners and two heights**.

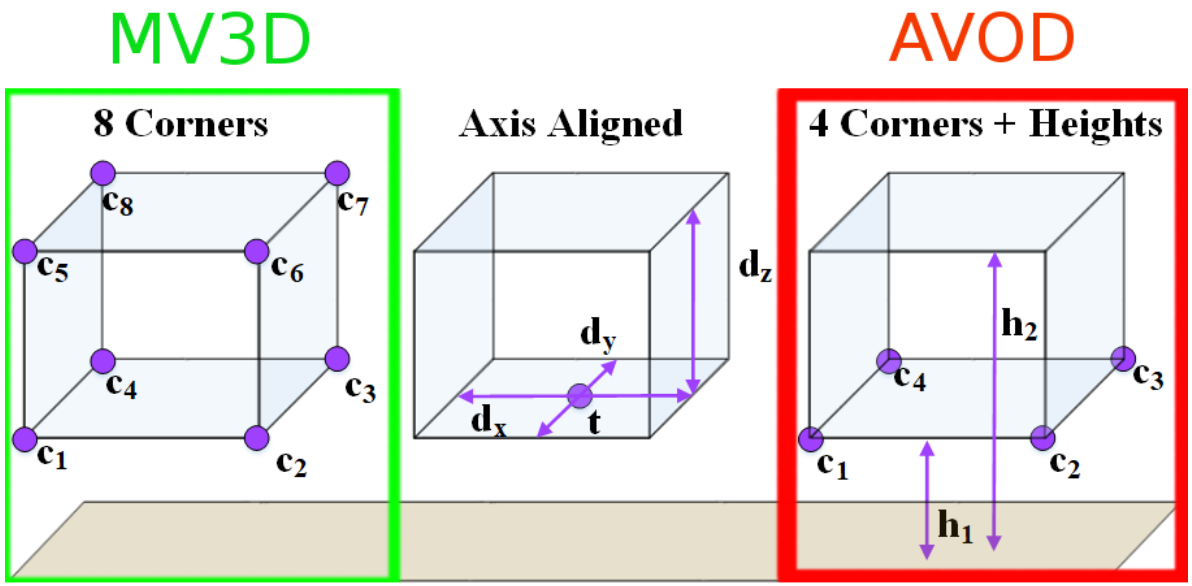


Figure: A visual comparison between the 8 corner box encoding, the axis aligned box encoding and AVOD's 4 corner encoding.

Explicit Orientation Vector Regression

- AVOD remedies this by computing: $(x_{or}, y_{or}) = (\cos(\theta), \sin(\theta))$
- Handles angle wrapping as every $\theta \in [-\pi, \pi]$ can be represented by a unique unit vector in the BEV space.

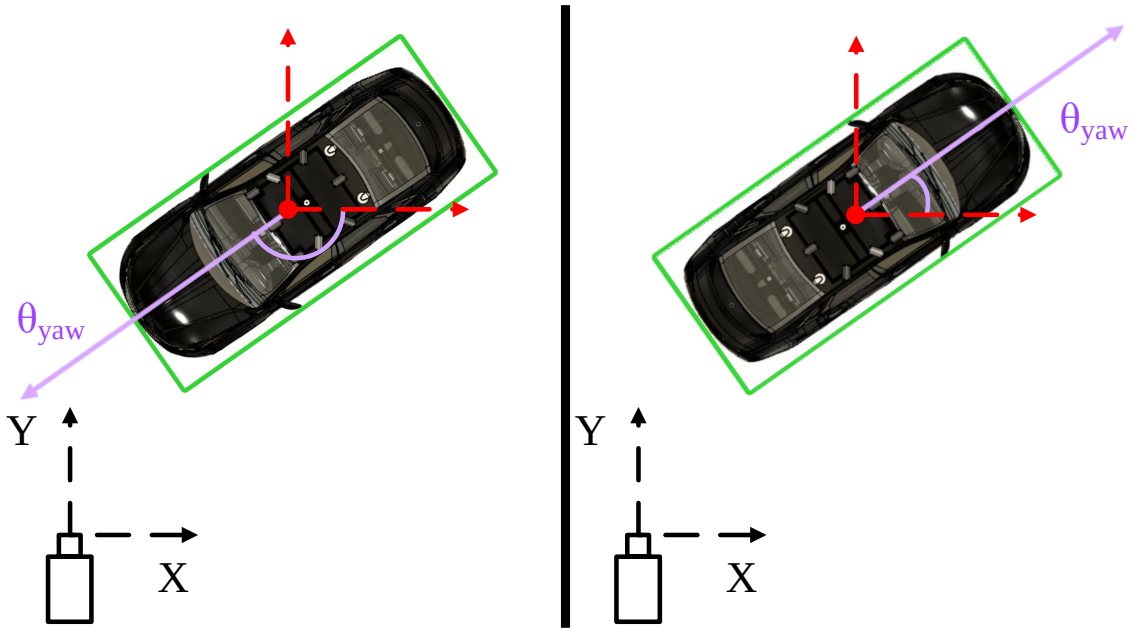


Figure: Object's bounding box does not change when the orientation (**purple**) is shifted by $\pm\pi$ radians.

Second Stage Detection Network

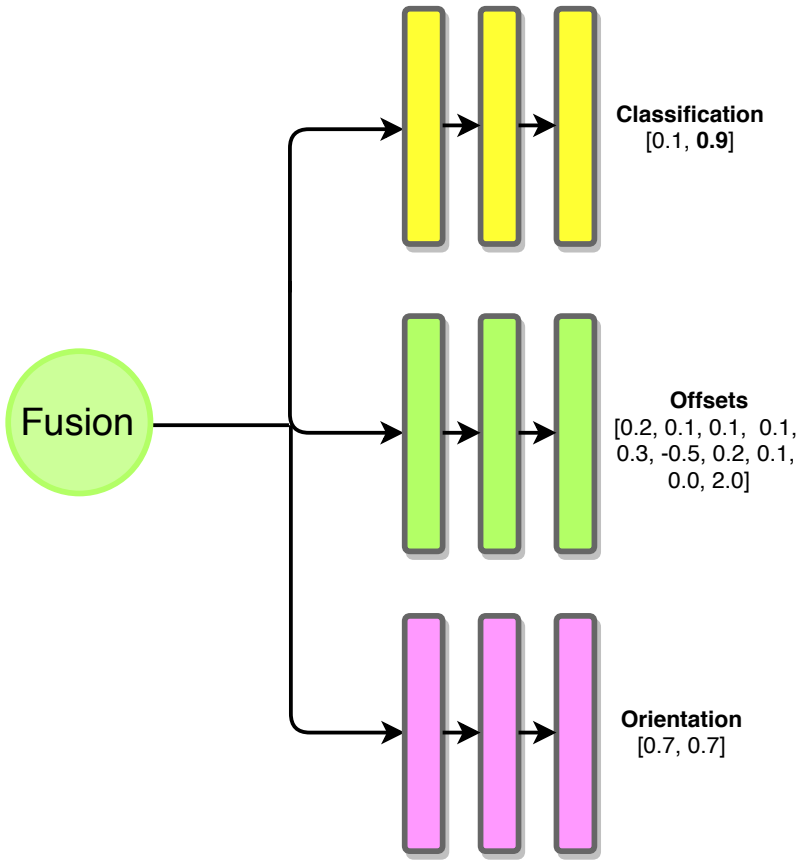


Figure: AVOD second stage task specific layers.

Orientation Ambiguity

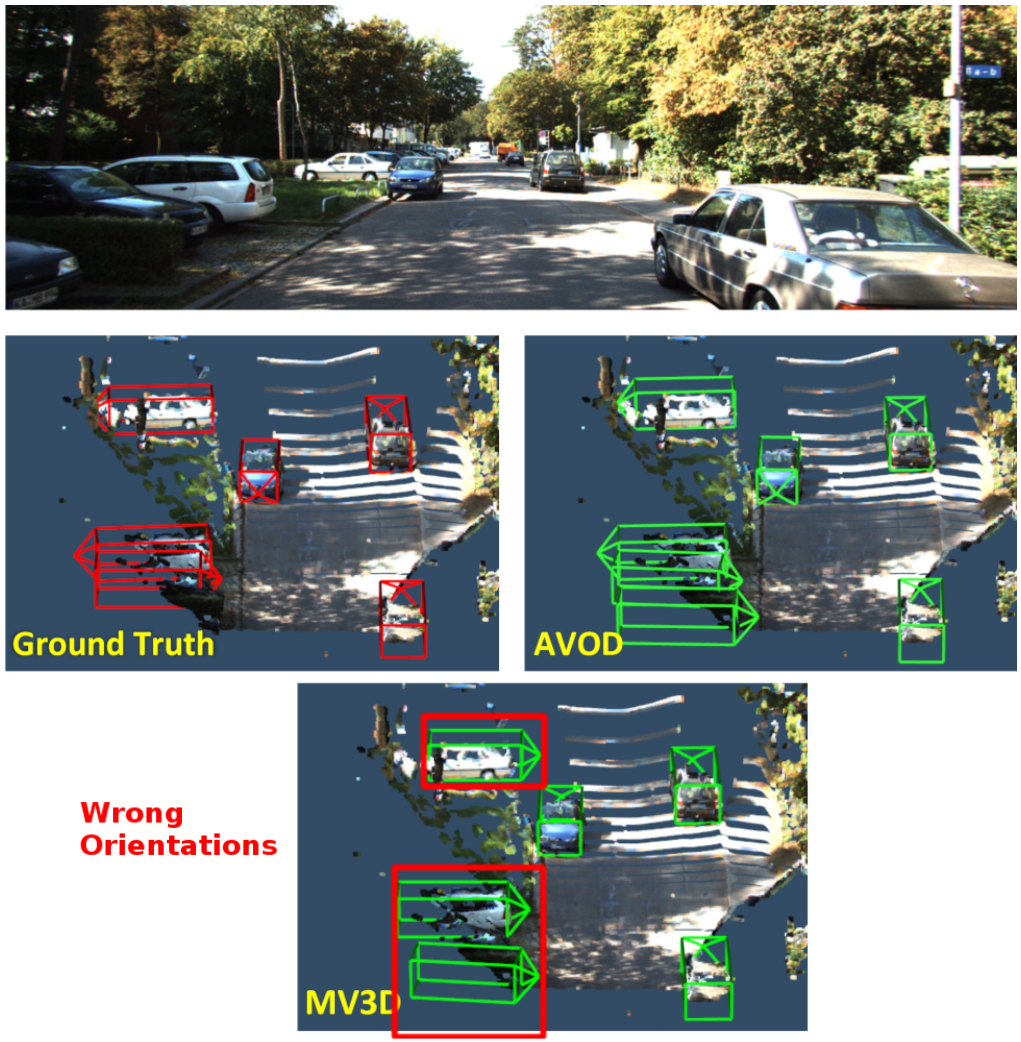


Figure: Qualitative comparison between MV3D and AVOD.

Evaluation Metrics for Object Detection

- Precision & Recall

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

RPN Input Variations

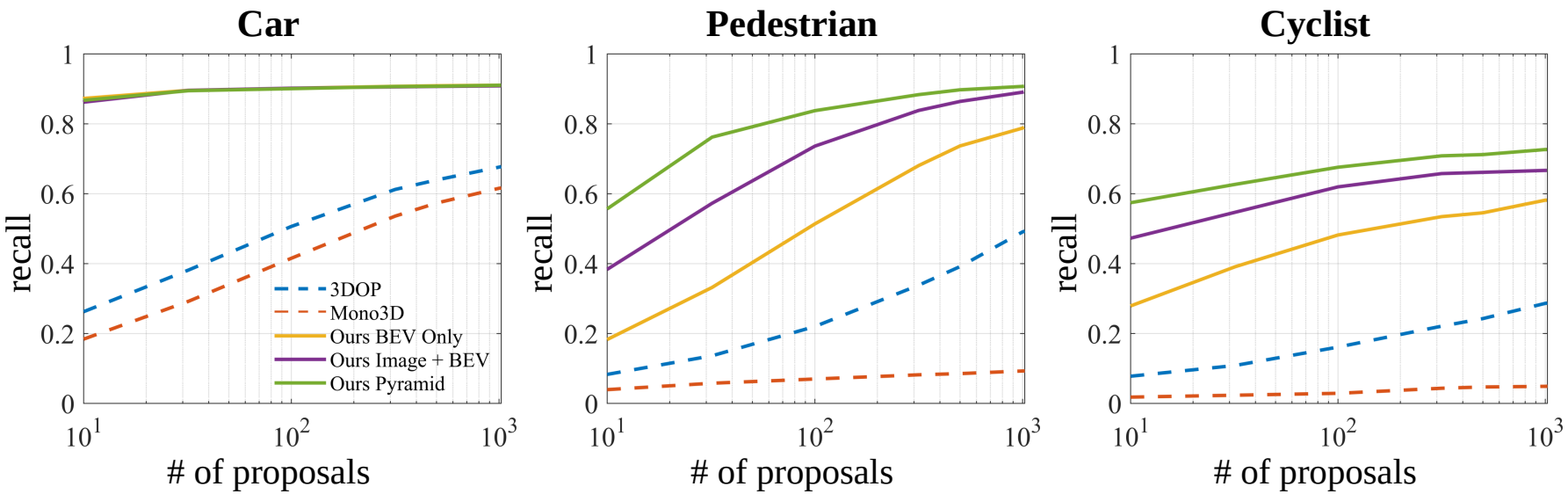
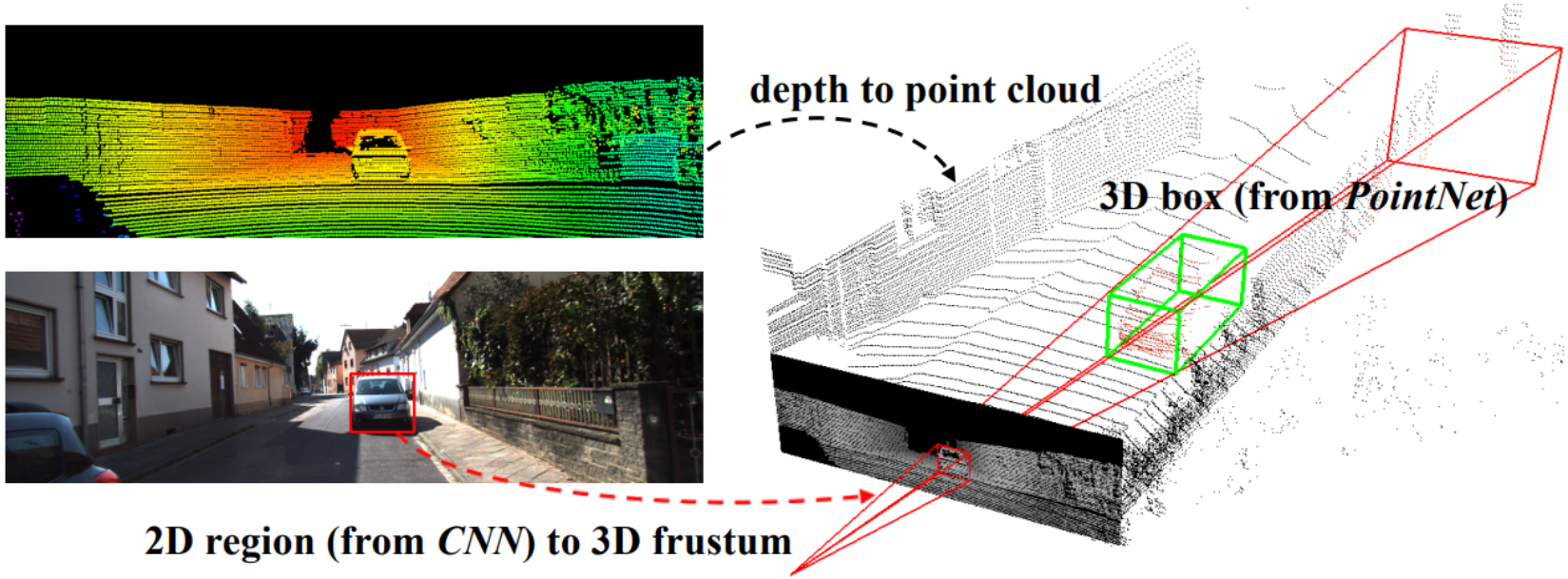


Figure: The recall vs number of proposals at a 3D IoU threshold of 0.5.

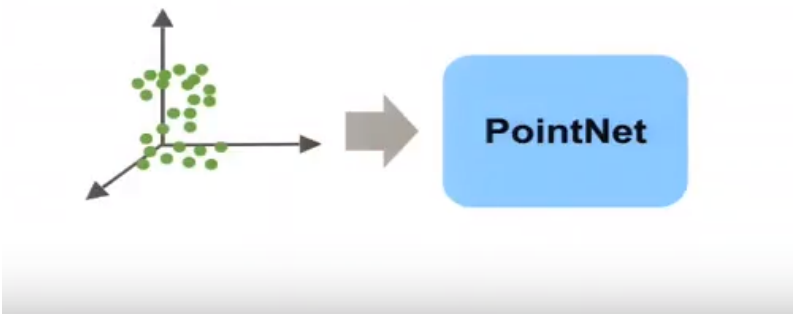
Background: F-PointNet [2]



[2] Frustum PointNets for 3D Object Detection from RGB-D Data (CVPR) 2018

Background: PointNet

- Avoid converting pointcloud to other representations
  - Voxelization
  - Projection/Rendering
  - Feature extraction
- Pointcloud feature learning
  - Unordered point set as input
  - Invariance under geometric transformations



Permutation Invariance: Symmetric Function

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

- **Examples**:

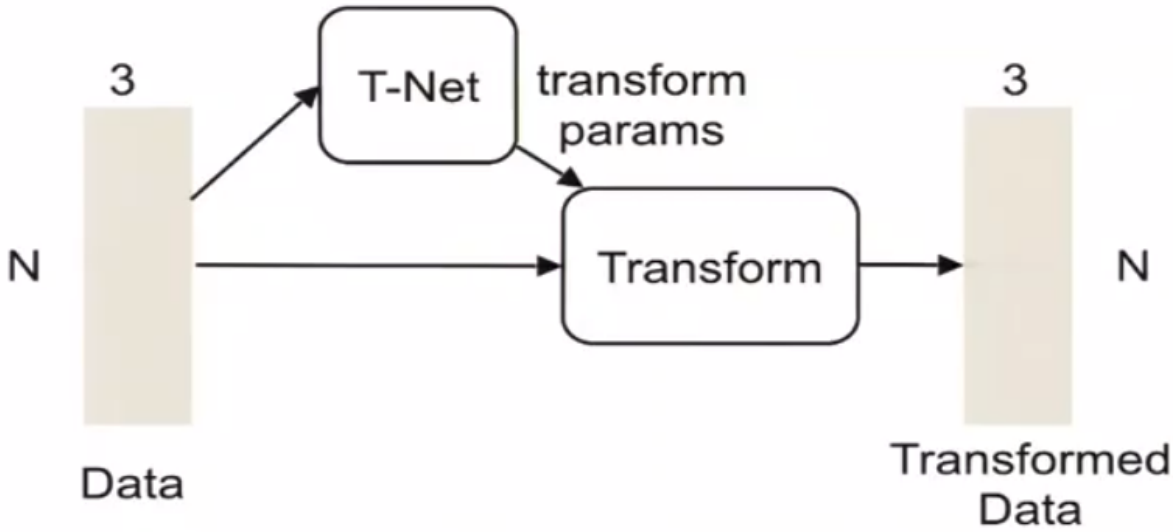
$$f(x_1, x_2, ..., x_n) = \max\{x_1, x_2, ..., x_n\}$$

$$f(x_1, x_2, ..., x_n) = x_1 + x_2 + ... + x_n$$

- Idea: Construct a family of symmetric functions by neural networks.

Input Alignment by Transformer Network

- Data dependent transformation for automatic alignment



PointNet Architecture

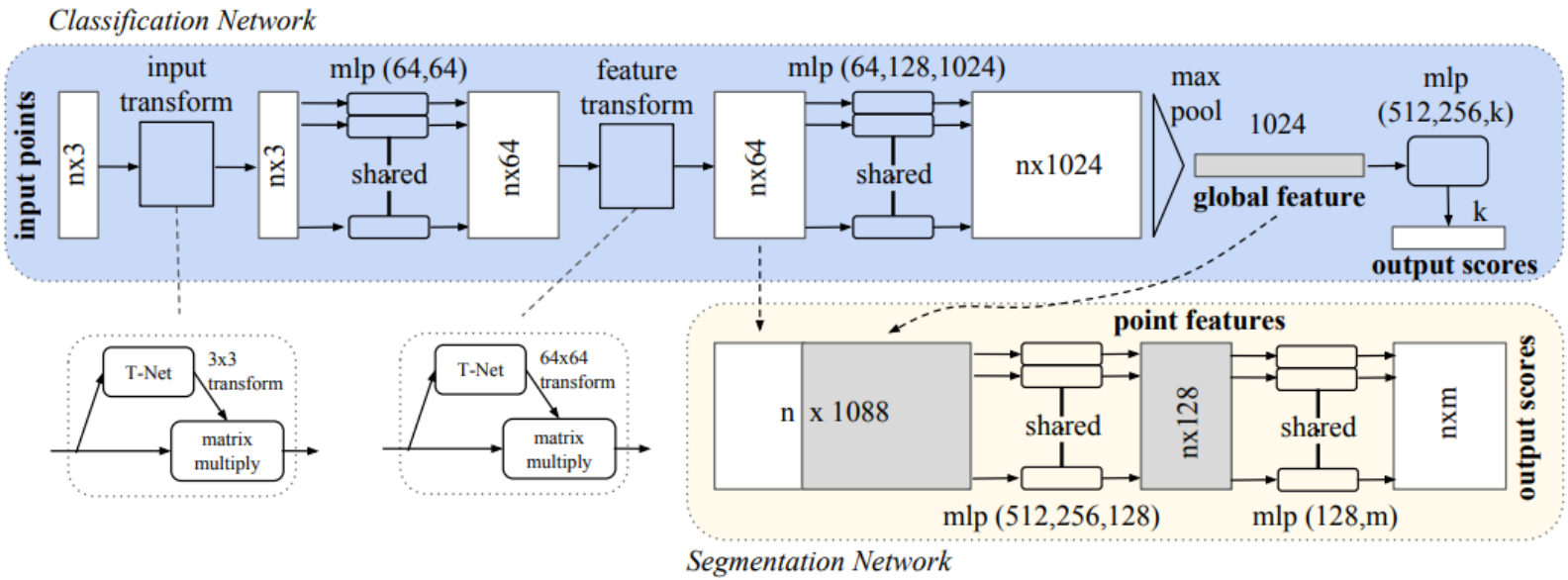
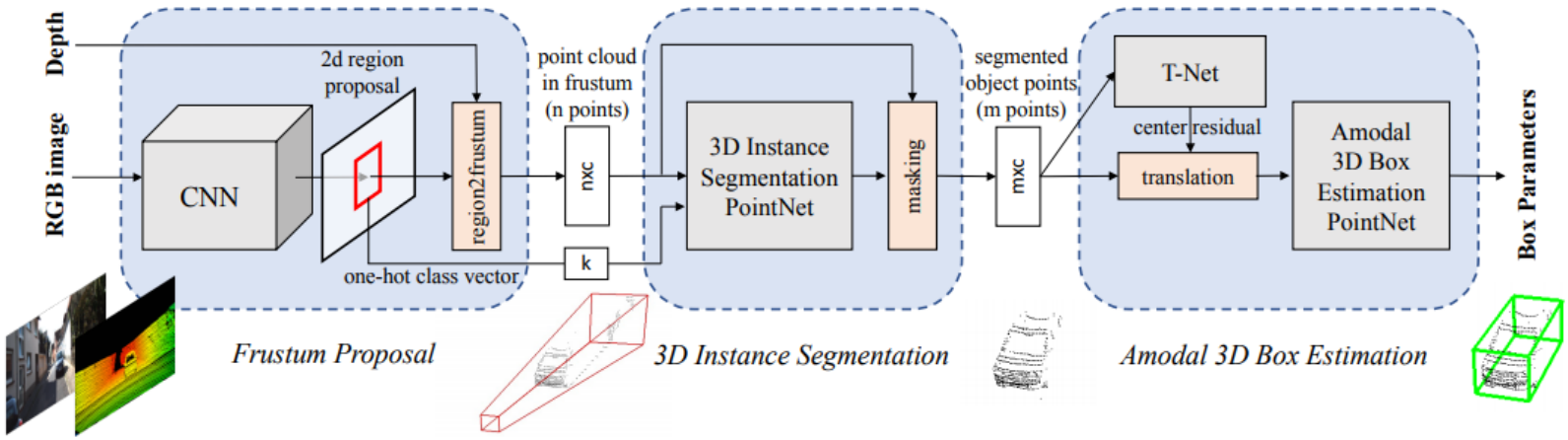


Figure: PointNet Classification and Segmentation Network.

F-PointNet



- Get a 3D frustum from a 2D image region.
- Given a point cloud in a frustum, the object instance is segmented.
- T-Net aligns points such that their centroid is close to amodal box center.

Evaluation Metrics for Object Detection

- Average Precision (AP)

$$AP = \frac{1}{11} \sum_{r \in 0, 0.1, \ldots, 1} p_{interp}(r)$$

$$p_{interp}(r) = \max_{\hat{r}:\hat{r} \geq r} p(\hat{r})$$

  - where $p(\hat{r})$ is the measured precision at recall $\hat{r}$.

AVOD - Results on Car Detection

Method	Moderate	Easy	Hard	Runtime
AVOD-FPN	**71.88**	**81.94**	**66.38**	0.1
F-PointNet	70.39	81.20	62.19	0.17
AVOD	65.78	73.59	58.38	**0.08**
VoxelNet	65.11	77.47	57.73	0.25
MV3D	62.35	71.09	55.12	0.36

Table: A comparison of the performance of AVOD with the state of the art 3D object detectors evaluated on KITTI's dataset. Results are generated by KITTI's evaluation server.

AVOD - Results on Pedestrian Detection

Method	Moderate	Easy	Hard	Runtime
F-PointNet	**44.89**	**51.21**	40.23	0.17
AVOD-FPN	42.81	50.80	**40.88**	0.1
VoxelNet	33.69	39.48	31.51	0.25
AVOD	31.51	38.28	26.98	**0.08**

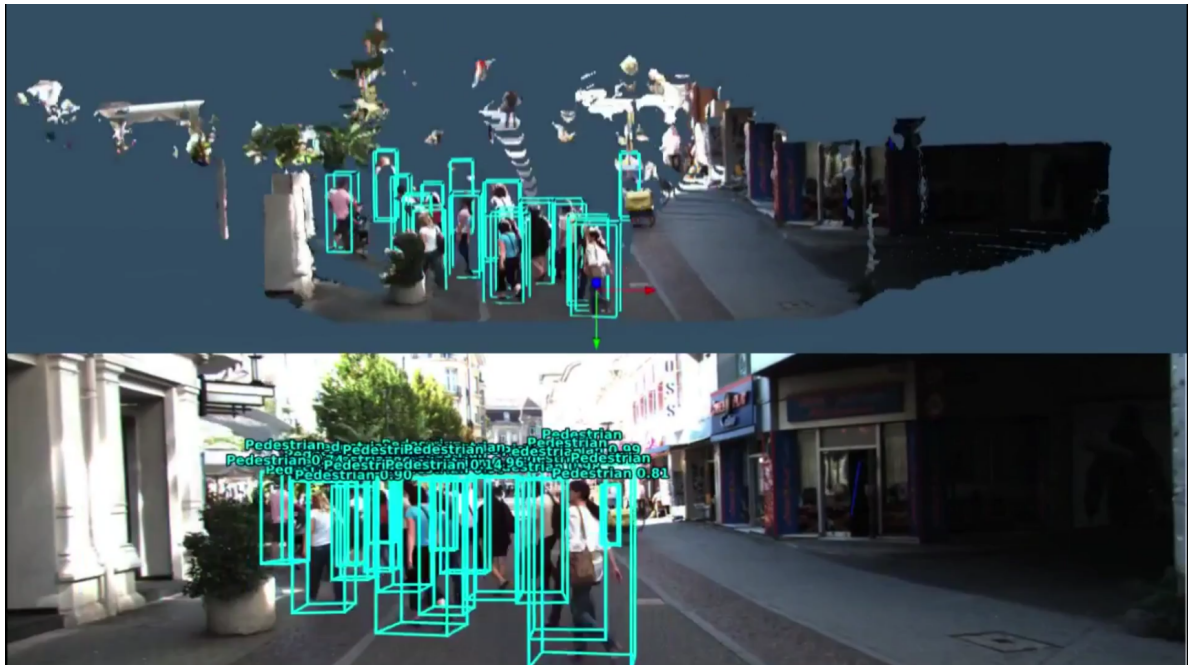
Table: A comparison of the performance of AVOD with the state of the art 3D object detectors evaluated on KITTI's dataset. Results are generated by KITTI's evaluation server.

AVOD - Results on Cyclist Detection

Method	Moderate	Easy	Hard	Runtime
F-PointNet	**56.77**	**71.96**	**50.39**	0.17
AVOD-FPN	52.18	64.00	46.61	0.1
VoxelNet	48.36	61.22	44.37	0.25
AVOD	44.90	60.11	38.80	**0.08**

Table: A comparison of the performance of AVOD with the state of the art 3D object detectors evaluated on KITTI's dataset. Results are generated by KITTI's evaluation server.

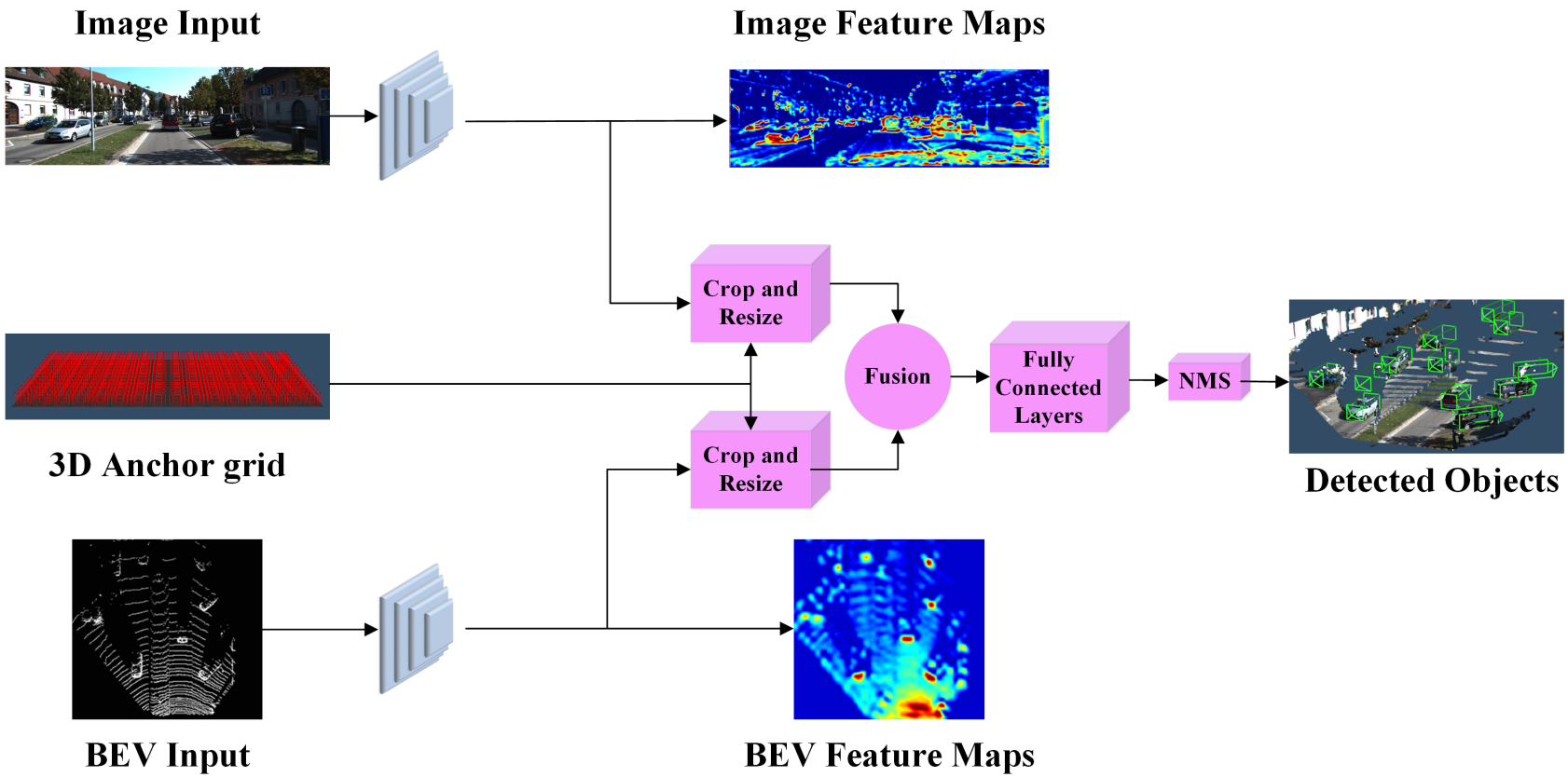
AVOD Results on KITTI and Autonomoose



Motivation: Single Stage Detector

- The highest accuracy object detectors to date are based on two-stage detectors.
- Single stage object detection algorithms are *simple*:
  - Eliminate proposal generation and feature resampling stage.
  - Encapsulate all computation into a **single** stage.

AVOD-Single Stage Detector Architecture



Class Imbalance

- Evaluate $10 - 100K$ candidate locations but only a few locations contain objects.
- This imbalance causes two problems:
  - Training is *inefficient*.
  - Easy negatives are overwhelming.
- Common solutions:
  - Hard negative mining.
  - More complex sampling technique.

Focal Loss

- Designed to address class imbalance by down-weighting *easy* examples:
  - So that their contribution to the total loss is small even if their number is large.
- Focuses training on *hard* examples.

Focal Loss Continued

- To introduce the formulation of focal loss, we start with cross entropy (CE) loss for binary classification:

$$CE(p, y) = \begin{cases} -log(p), & \text{if } y = 1 \\ -log(1-p), & \text{otherwise} \end{cases}$$

- In the above equation $y \in \{\pm 1\}$ specifies the ground-truth class and $p \in [0, 1]$ is the model's estimated probability for the class with label $y = 1$.

Focal Loss Continued

- For notational convenience, we define p_t:

$$p_t = \begin{cases} p, & \text{if } y = 1 \\ 1 - p, & \text{otherwise} \end{cases}$$

- Then we can rewrite $\text{CE}(p, y) = \text{CE}(p_t) = -log(p_t)$.

Balanced Cross Entropy

- Weighting factor $\alpha \in [0, 1]$.
- α for class 1, and $1 - \alpha$ for class -1.

$$BCE(p_t) = -\alpha_t log(p_t)$$

Focal Loss Definition

- α balances the importance of **positive** and **negative** examples, it does not differentiate between **easy** and **hard** examples.
- Focal loss uses a modulating factor $(1 - p_t)^\gamma$ with the cross entropy loss, with a tunable *focusing* parameter $\gamma \geq 0$.

$$FL(p_t) = -\alpha_t(1 - p_t)^\gamma log(p_t)$$

Focal Loss Plot

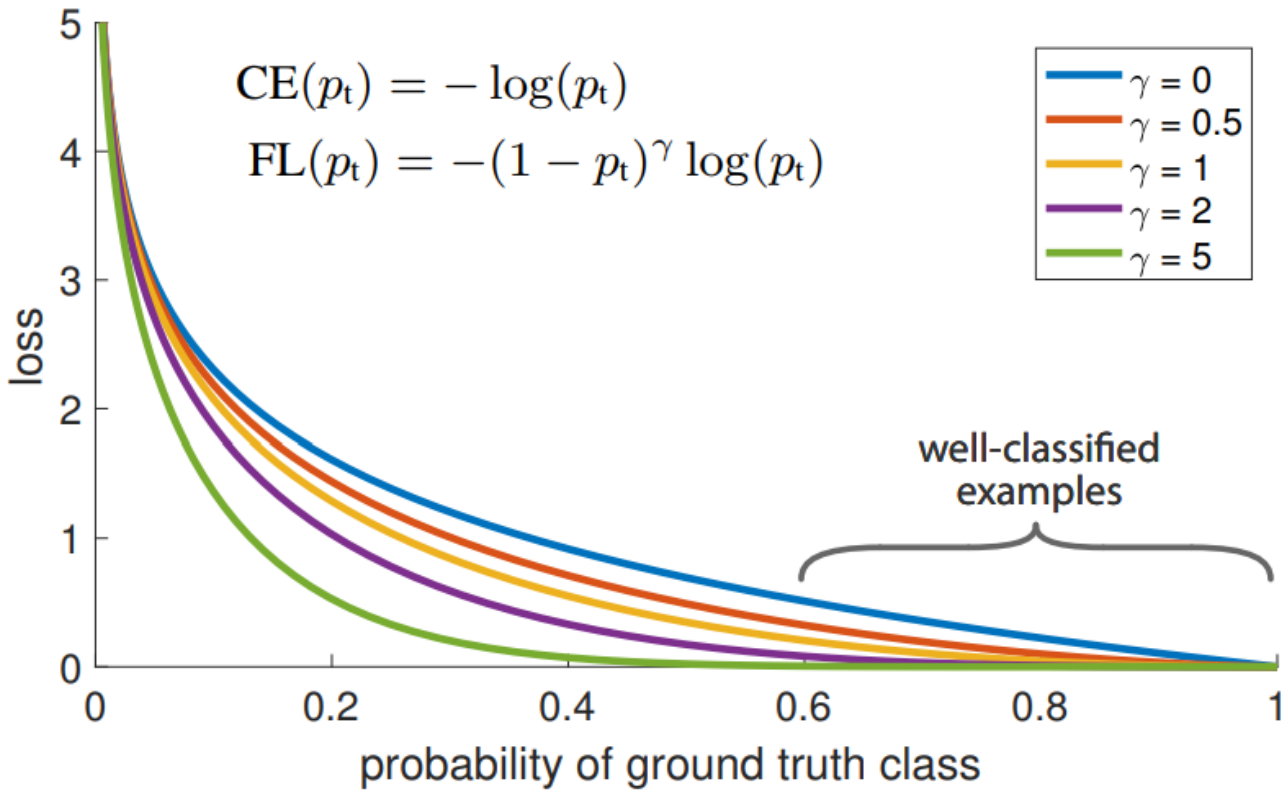


Figure: The focal loss visualized for several values of $\gamma \in [0, 5]$ [7].

AVOD-SSD Experiment Results

Architecture	Car $AP_{3D}(0.7)$	Car $AHS_{3D}(0.7)$	Runtime speed (s)
AVOD	74.23	73.97	**0.08**
AVOD-FPN	**74.81**	**74.53**	0.1
AVOD-FPN(High Res BEV)	73.74	73.11	0.14
AVOD-SSD(FPN) **without** Focal Loss	61.52	60.32	0.09
AVOD-SSD(VGG)	56.11	55.89	0.2
AVOD-SSD(FPN)	73.93	73.32	0.09
AVOD-SSD(FPN + High Res BEV)	74.53	74.08	0.16

Table: Performance analysis of **AVOD**, **AVOD-FPN** and **AVOD-SSD** on the *validation* set and *moderate* difficulty.

AVOD-SSD Experiment Results

			AP_{3D} (%)			AP_{BEV}(%)			AP_{2D}(%)		
Method	Runtime (s)	Class	Easy	Moderate	Hard	Easy	Moderate	Hard	Easy	Moderate	Hard
AVOD-FPN	0.1	**Car**	**81.94**	**71.88**	**66.38**	**88.53**	83.79	**77.90**	**89.99**	87.44	80.05
AVOD	**0.08**		73.59	65.78	58.38	86.80	**85.44**	77.73	89.73	**88.08**	**80.14**
AVOD-SSD	0.09		73.64	63.87	56.90	86.14	77.66	75.68	88.94	85.71	78.05

Table: Performance analysis of **AVOD**, **AVOD-FPN** and **AVOD-SSD** on the KITTI's evaluation server.

Recall and Precision of AVOD vs AVOD-SSD

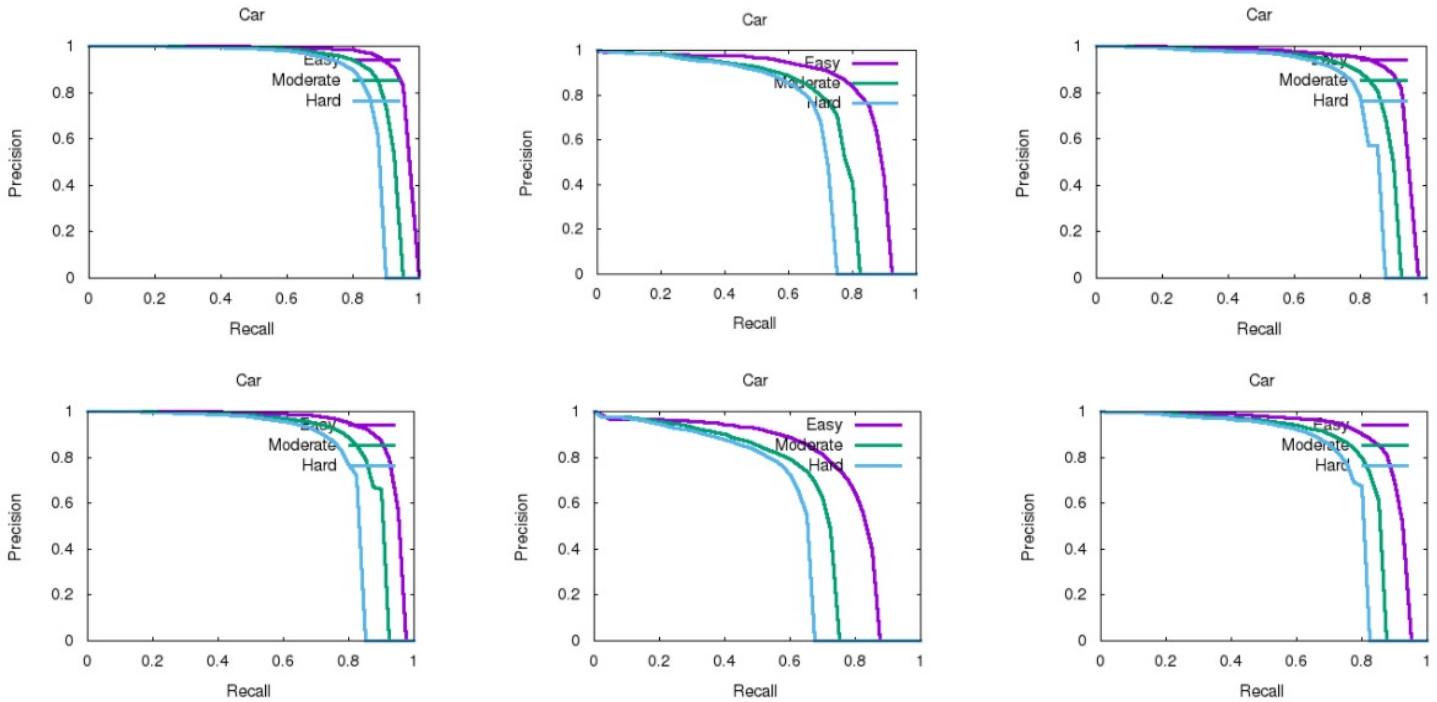


Figure: Comparison of Precision-Recall curve of AVOD-FPN(top) vs AVOD-SSD(bottom) for 2D, 3D and BEV detection respectively, on the *test* set.

AVOD Limitations

- 2D representation of 3D data
  - Raw 3D data has much richer information where such information is being discarded.
- Accurate estimated ground-plane assumption.
- Objects appear within certain distance above the ground-plane.

Future Work

- Speed Optimization
- Faster 3D Single Stage Detector
- Processing Temporal Information
  - Combined pipeline for object detection and tracking where tracking information can also guide object detection and vice versa.

References

Kitti 3D Object Detection Benchmark. Access: http://www.cvlibs.net/datasets/kitti/eval_object.php?obj_benchmark=3d.

Artificial Intelligence GitBook. Leonardo Araujo dos Santos. Access: https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/object_localization_and_detection.html.

Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. Ren, Shaoqing and He, Kaiming and Girshick, Ross and Sun, Jian. Access: https://arxiv.org/abs/1506.01497.

VGG16 Architecture. Heuritech. Access: https://blog.heuritech.com/2016/02/29/a-brief-report-of-the-heuritech-deep-learning-meetup-5/.

Multi-view 3d object detection network for autonomous driving. Chen, Xiaozhi and Ma, Huimin and Wan, Ji and Li, Bo and Xia, Tian. Access: https://arxiv.org/abs/1611.07759.

Frustum PointNets for 3D Object Detection from RGB-D Data. Qi, Charles R and Liu, Wei and Wu, Chenxia and Su, Hao and Guibas, Leonidas J. Access: https://arxiv.org/abs/1711.08488.

Focal loss for dense object detection. Lin, Tsung-Yi and Goyal, Priya and Girshick, Ross and He, Kaiming and Dollár, Piotr. Access: arXivpreprintarXiv:1708.02002.

You only look once: Unified, real-time object detection. Redmon, Joseph and Divvala, Santosh and Girshick, Ross and Farhadi, Ali. Proceedings of the IEEE conference on computer vision and pattern recognition

Thank you!
Questions?