

# Project Presentation

## 3D Object Detection(Waymo)

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Jay Patel  
Rutvik Patel

# Project Progress

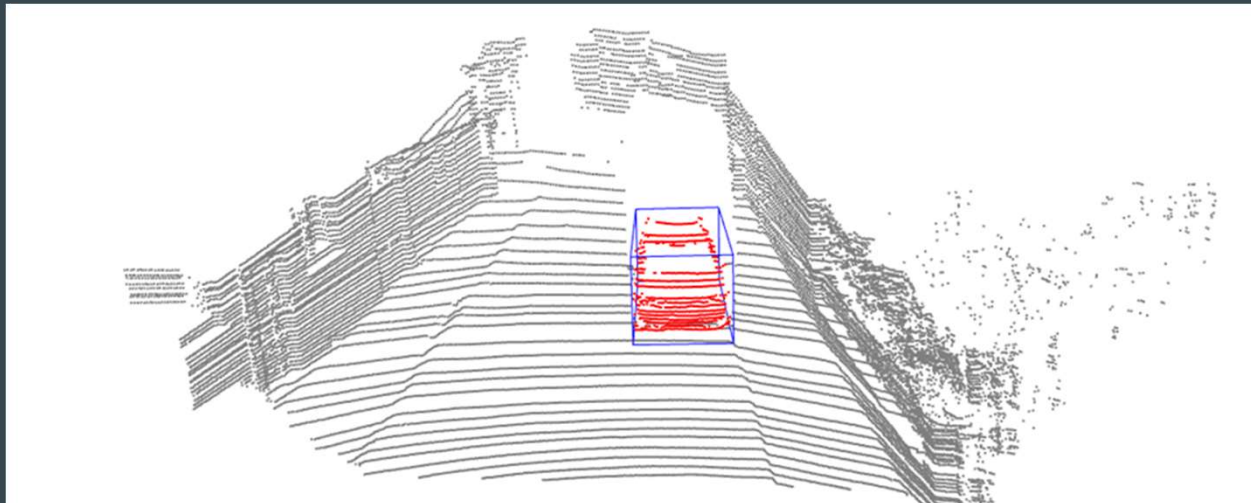
- Trained point pillars(MMDetection3D) on kitti dataset with secfpn backend and 25 epochs.
- Results:

```
Overall AP11@easy, moderate, hard:  
bbox AP11:75.7596, 70.9100, 65.3331  
bev AP11:72.2993, 65.6330, 61.2926  
3d AP11:67.1383, 58.3646, 53.9808  
aos AP11:54.19, 50.79, 46.40
```

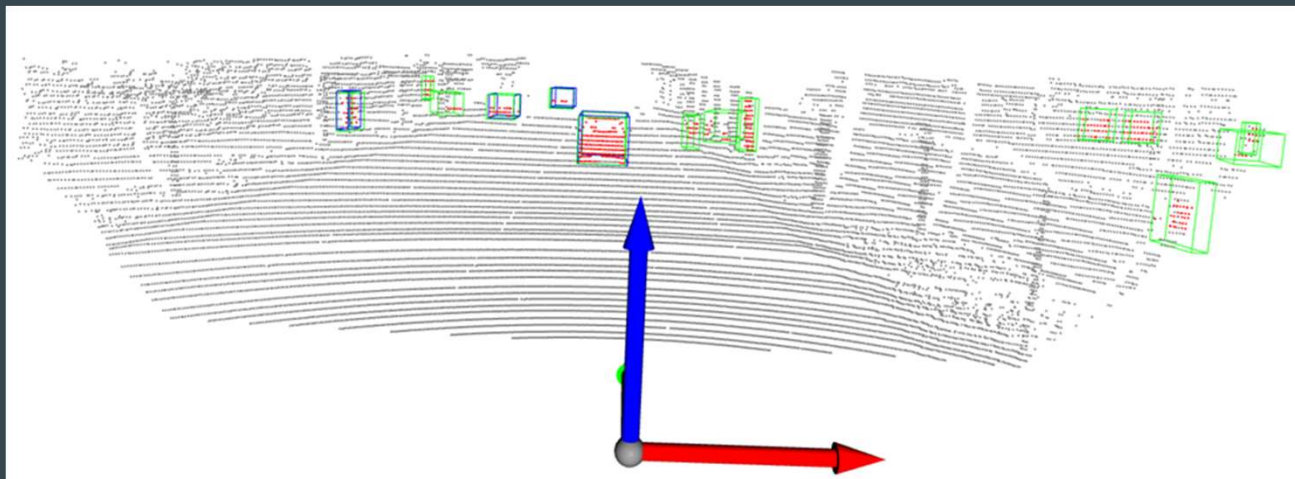
```
Overall AP40@easy, moderate, hard:  
bbox AP40:77.5056, 71.1530, 66.6518  
bev AP40:73.2140, 65.6435, 61.1554  
3d AP40:66.8896, 57.7339, 52.6973  
aos AP40:54.69, 49.76, 46.22
```

- Made an attempt to train the model on Waymokitti dataset.
- Getting data folder velodyne\_reduced not found error.

# Point pillar training on kitti dataset



# PointPillar testing on kitti dataset



# 3D Object Detection

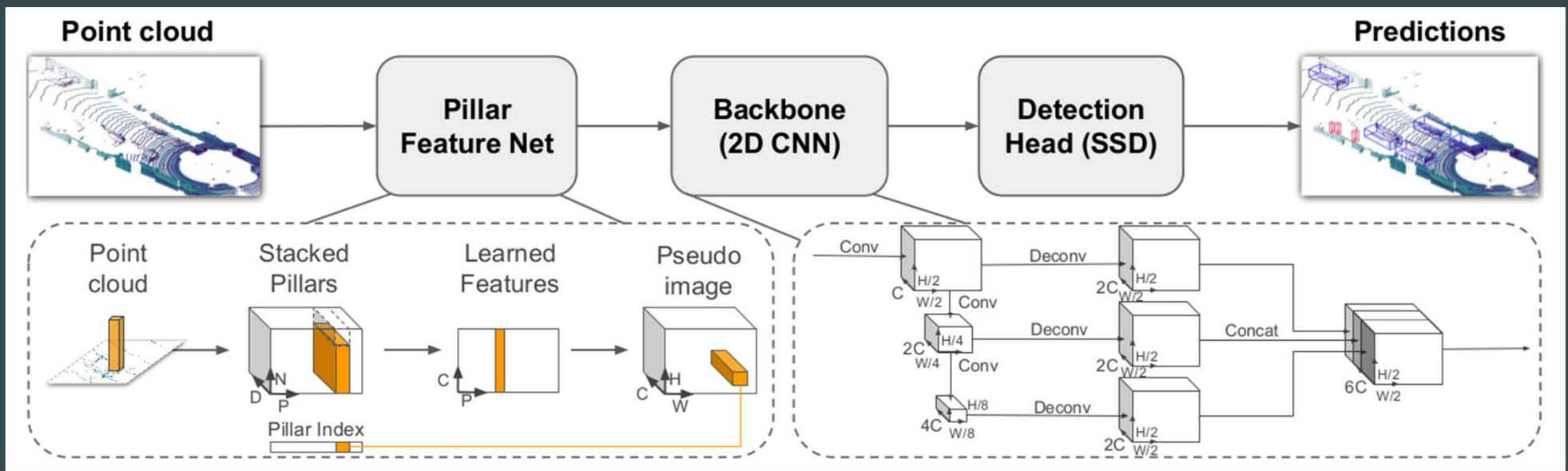
There are two main detection directions for object detection in Lidar information.

1. Project a 3D point cloud to a 2D image (fast speed, high reference resources, low precision)
2. Feature extraction directly using 3D point clouds (high accuracy, low inference speed)

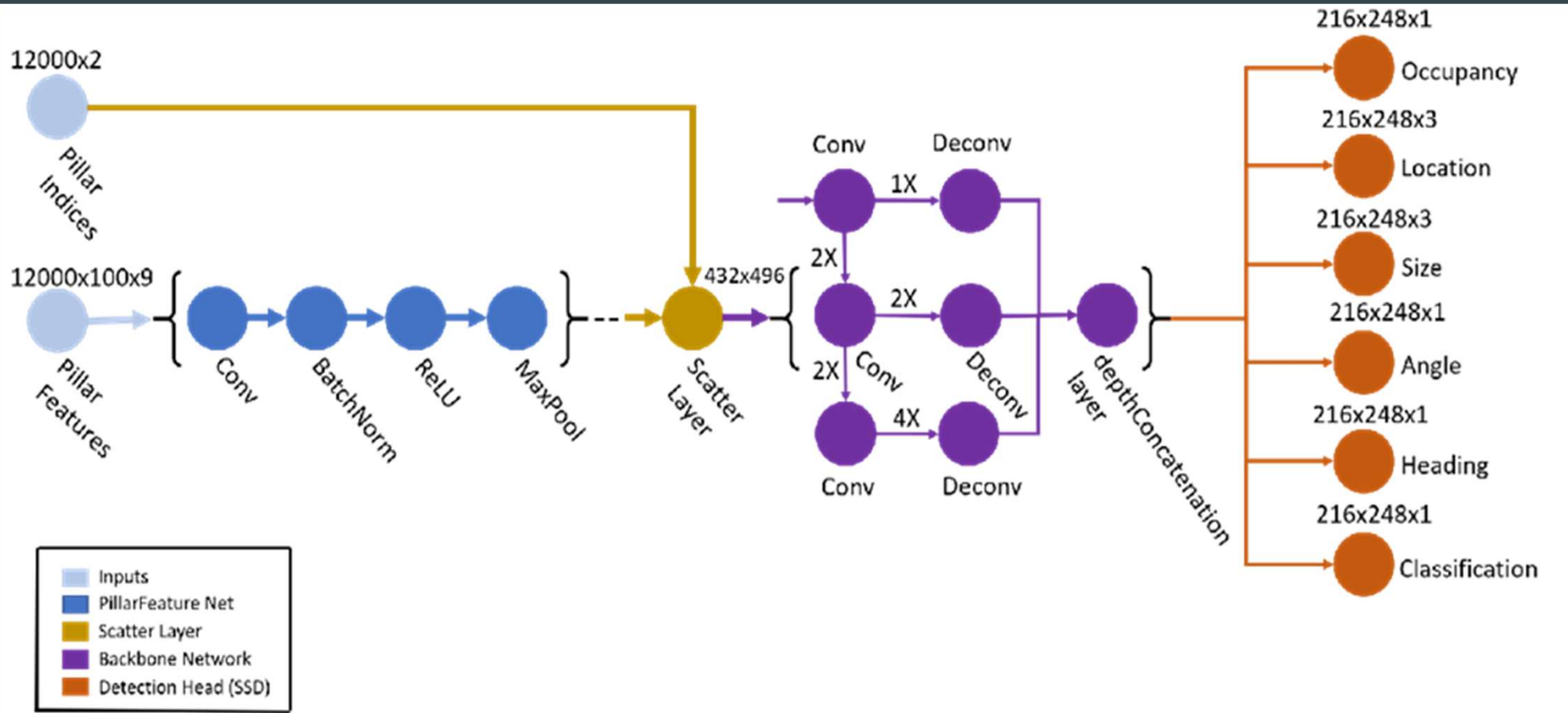
# 3D Object Detection

- The PointPillars method (abbreviated as PP) is quite excellent.
- The accuracy of the classification of the vehicle category is roughly equivalent to CONTFUSE, but the inference speed can reach 60hz far higher than other networks.
- PointPillars run at 62 fps which is orders of magnitude faster than the previous works in this area.
- Near-real-time object detection of point cloud data is almost possible.

# PointPillar Architecture

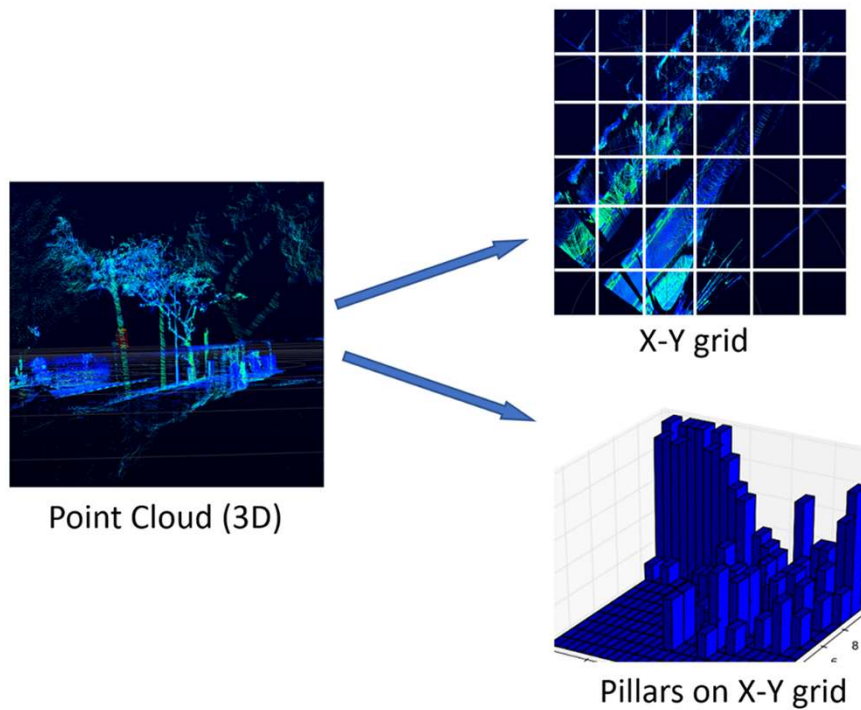


# Point Pillar : layers



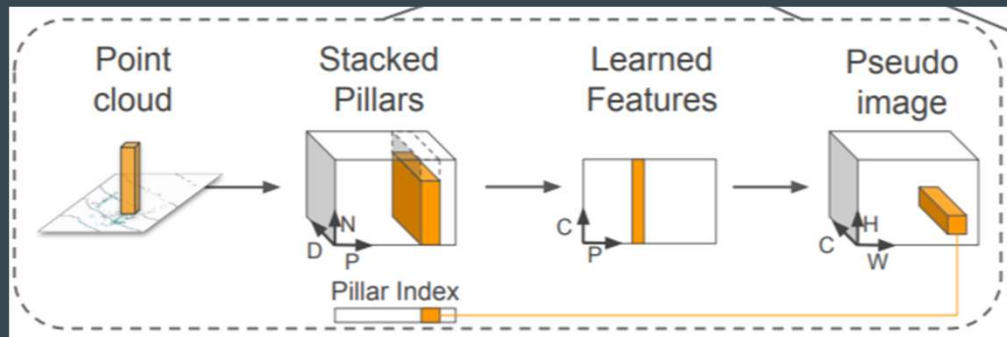


# Feature Encoder (Pillar feature net)



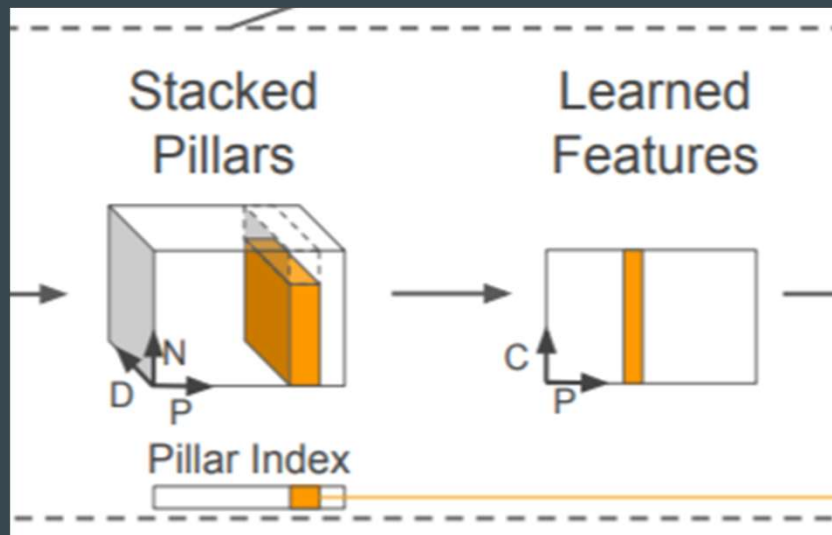
- Converts the point cloud into a sparse pseudo image. First, the point cloud is divided into grids in the x-y coordinates, creating a set of pillars. Each point in the cloud, which is a 4-dimensional vector ( $x, y, z$ , reflectance), is converted to a 9-dimensional vector containing the additional information explained as follows:
- $X_c, Y_c, Z_c$  = Distance from the arithmetic mean of the pillar  $c$  the point belongs to in each dimension.
- $X_p, Y_p$  = Distance of the point from the center of the pillar in the x-y coordinate system.
- Hence, a point now contains the information  $D = [x, y, z, r, X_c, Y_c, Z_c, X_p, Y_p]$ .

# From pillars to a dense tensor(stackd pillars)



- The set of pillars will be mostly empty due to sparsity of the point cloud, and the non-empty pillars will in general have few points in them. This sparsity is exploited by imposing a limit both on the number of non-empty pillars per sample ( $P$ ) and on the number of points per pillar ( $N$ ) to create a dense tensor of size  $(D, P, N)$ . If a sample or pillar holds too much data to fit in this tensor the data is randomly sampled. Conversely, if a sample or pillar has too little data to populate the tensor, zero padding is applied.
- Note that  $D = [x, y, z, r, X_c, Y_c, Z_c, X_p, Y_p]$  as explained in the previous section.

# From Stacked Pillars to Learned Features

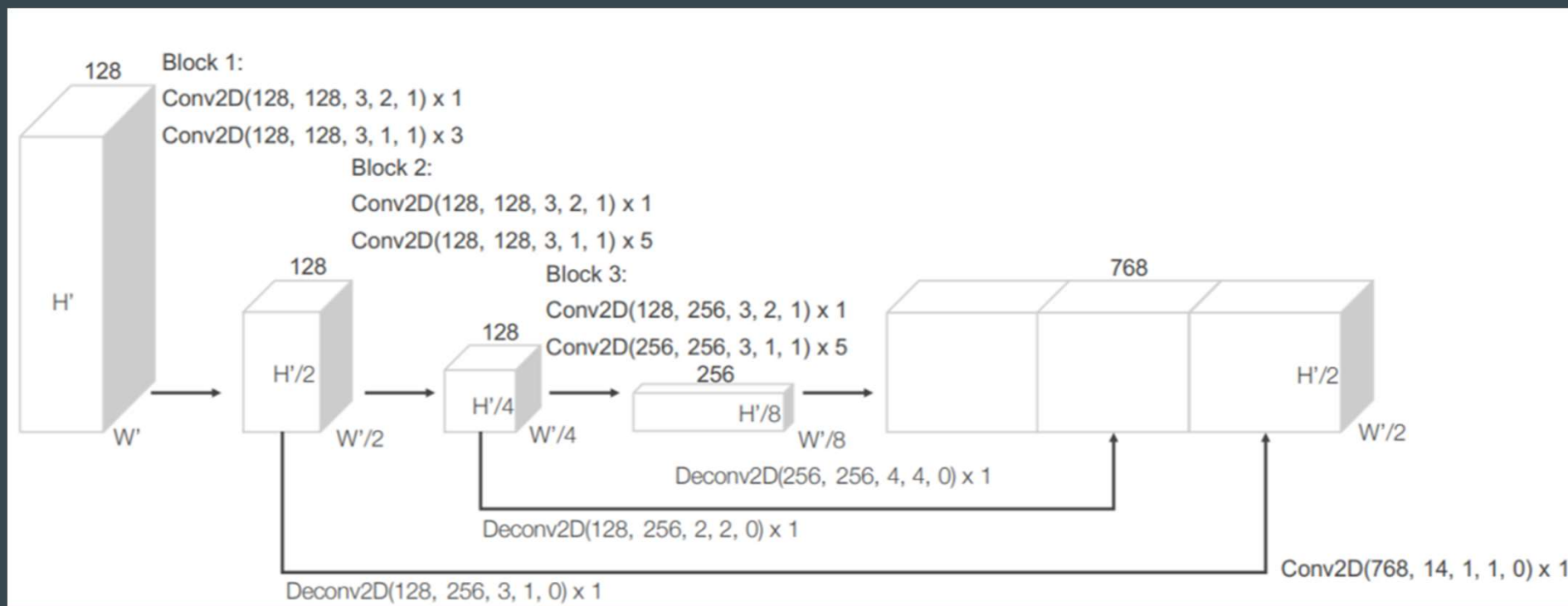


- We use PointNet to extract features from a point cloud type of data.
- PointNet basically applies to each point, a linear layer followed by BatchNorm and ReLU to generate high-level features, which in this case is of dimension  $(C,P,N)$ . This is followed by a max pool operation which converts this  $(C,P,N)$  dimensional tensor to a  $(C,P)$  dimensional tensor.

# Generating the Pseudo Image from Learned features

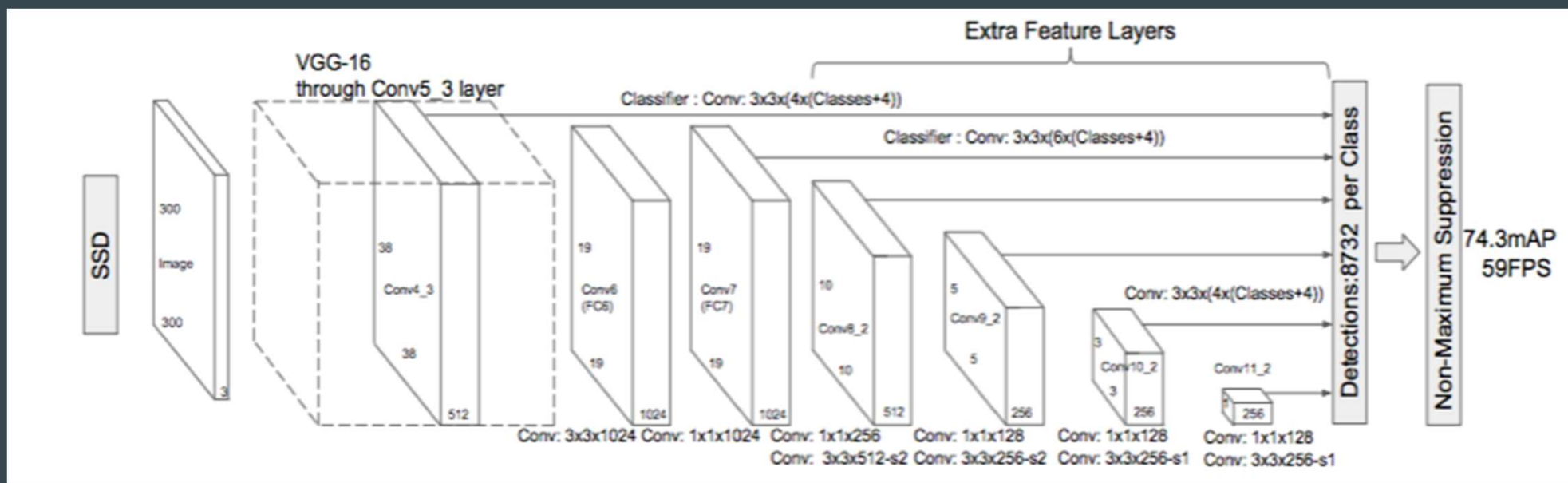
- The generated (C, P) tensor is transformed back to its original pillar using the Pillar index for each point.
- So originally, where the point was converted to a D dimensional vector, now it contains a C dimensional vector, which are the features obtained from a PointNet.

# Backbone



An example of a backbone (RPN) Region Proposal Network used in Point Pillars.

# Detection Head (SSD)



The objective of the SSD network is to generate 2D bounding boxes on the features generated from the backbone layer of the Point Pillars network.

## Detection Head(SSD) contd.

Several important reasons for choosing SSD as a one-shot bounding box detection algorithm are:

- Fast inference.
- Uses features from well-studied networks like VGG.
- Great Accuracy.

# References

1. Lang, Alex H., et al. “Pointpillars: Fast Encoders for Object Detection from Point Clouds.” 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, <https://doi.org/10.1109/cvpr.2019.01298>.