

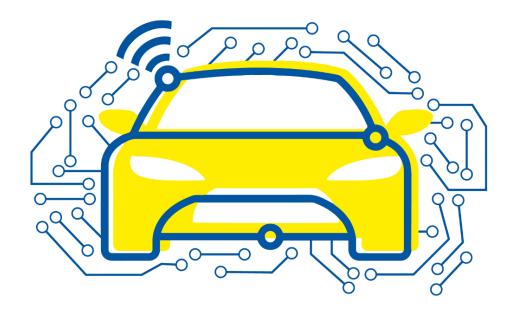
Automated and Connected Driving Challenges

Section 2 – Sensor Data Processing

Object Detection
Training

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Data Acquisition

- Large ground truth data have to be available
- Using existing reference data
 - Reference data is from another domain (sensor setup, geolocation) → domain shift
 - Reference model is only trained on reference data → no info on *generalization capabilities*
 - Lack of full, variable annotated public datasets



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Data Acquisition

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 - Lack of full, variable annotated public datasets
- Creating own datasets
 - High manual effort for creating own datasets
 - Simulation data
 - Real-world data: measurement vehicle, infrastructure sensors, drones
 - Labeling approaches
 - Manual labeling
 - **Semi-artificial** data: real-world data + synthetic labels





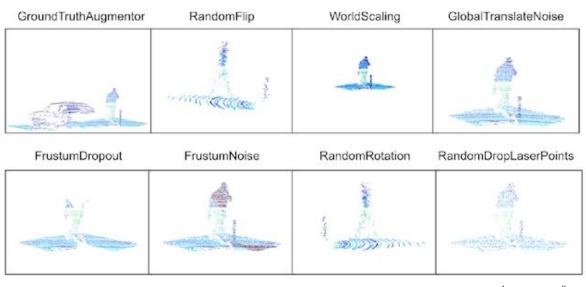


Data Preprocessing



Preprocessing

- Dataset split in training / validation / testing
- Intensity normalization
- Augmentation
 - Flipping
 - Scaling
 - Cropping
 - Translating
 - Adding noise
 - Rotating



Images: medium

→ All steps can be applied to the global scene or individual objects

Original



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Network Architecture

- Input is unstructured representation
 - List of 3D coordinates
 - Unknown or variable point amount
 - Not always one sensor source

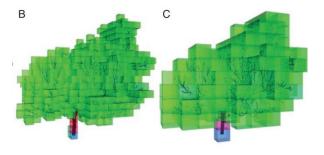
Range view

- Cylindrical projection
- 2D image-like
- Easy and efficient with CNN
- Not feasible in fused data

Source: Triess et al. 2020

Voxel based view

- Discretization along XYZ
- Processing with CNN possible
- Low runtime performace



Source: Lecigne et al. 2018



Network Architecture



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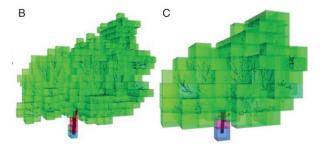
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Voxel based view

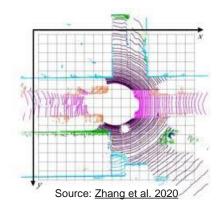
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Source: Lecigne et al. 2018

Bird eye view

- Structured grid in xy-plane
- Max point amount in vertical pillars
- z-axis encoded as features



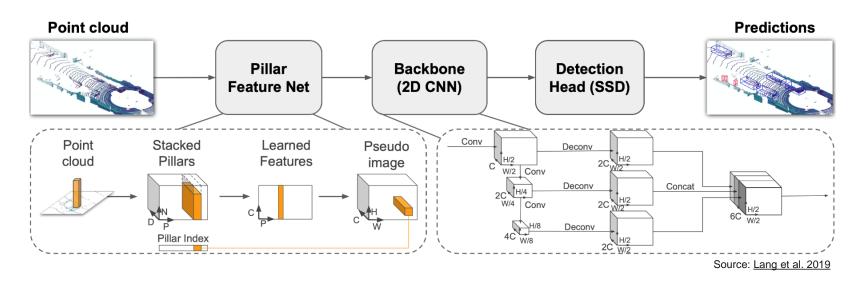


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PointPillars

Idea: efficient feature encoding in vertical pillars directly from raw pointclouds

(62 Hz on KITTI - GPU)



Preprocessing: create pillars grid and anchors

 $P \times N \times D = 12000 \times 100 \times 9$

Pillar Feature Net: extract 64 learnable features for each grid cell

Backbone: 2D CNN with stacked grid cell features as input

Detection Head: SSD for prediction of target vector* for each anchor and grid cell

Postprocessing: bounding box generation based on target vectors and anchor boxes

^{*}target vector contains: location, dimension, orientation, classification

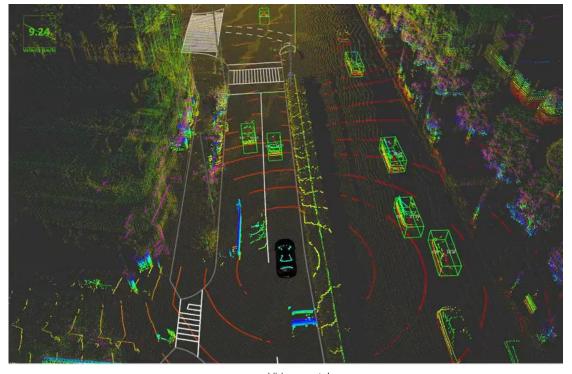


Training



Hyper parameters

- batch size
- epochs
- learning rate
- ...
- anchor box setup
- Training (PointPillars)
 - 7481 KITTI training / validation samples
 - 160 epochs
- Inference
 - **88.7% AP** on *KITTI Car medium b*enchmark
 - 62 FPS on KITTI Benchmarks



Video: youtube



Summary



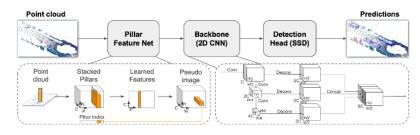


Data preprocessing (e.g. data split, normalization, augmentation)

Different approaches for 3D point clouds

Training process with variety of hyperparameters

PointPillars architecture



Source: Lang et al. 2019