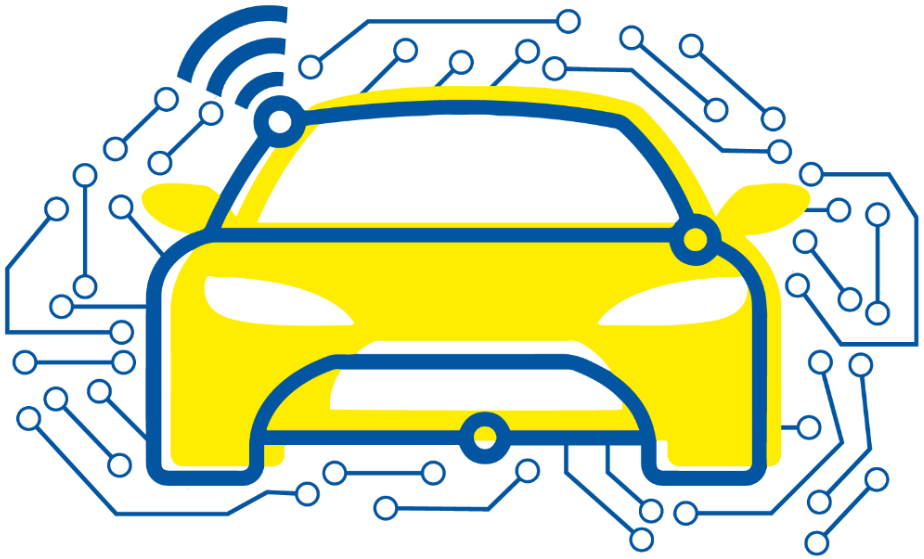
Automated and Connected Driving Challenges

Section 2 – Sensor Data Processing

Point Cloud Occupancy Grid Mapping

Deep Inverse Sensor Models



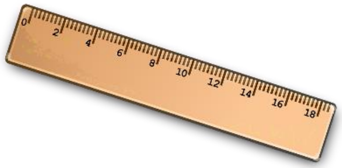
Bastian Lampe

Institute for Automotive Engineering

Point Cloud OGM – Deep ISM

Excursus: Hough Transformation

Images: pixabay, wixmp



Geometric approach

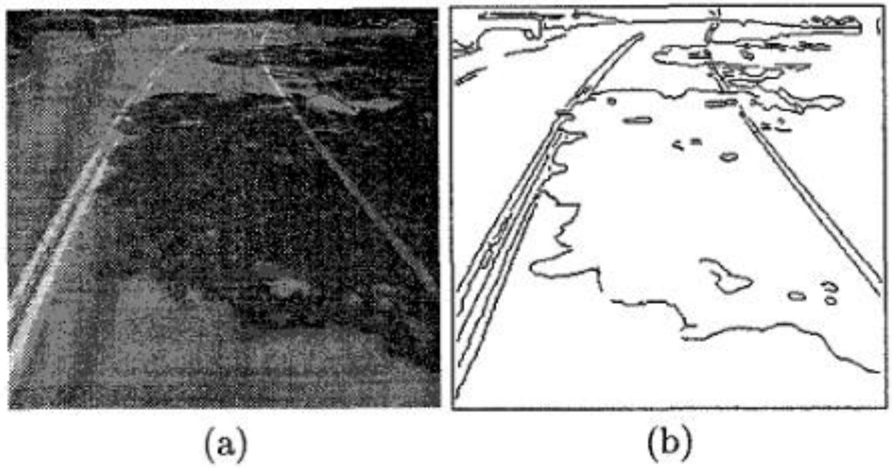
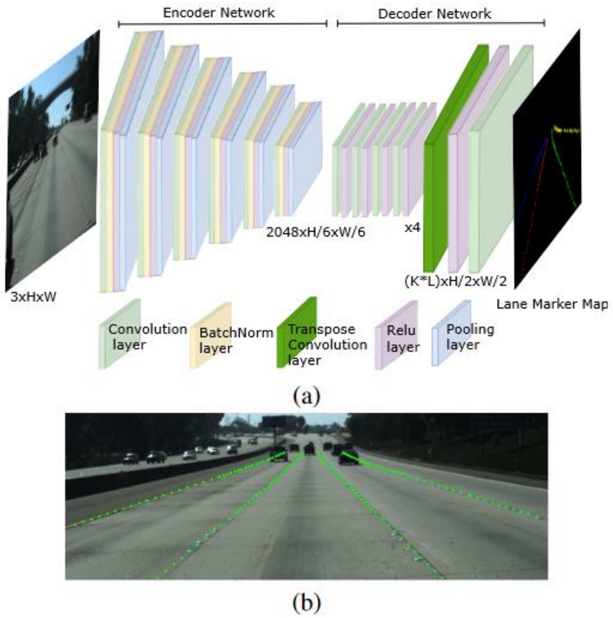


Figure 1: An example: (a) input image; (b) edge detection.

Source: Bin Yu et. al., Lane boundary detection using a multiresolution Hough transform, Proceedings of International Conference on Image Processing, **1997**

Deep Learning-based approach



Source: Hussam Ullah Khan et. Al., Lane detection using lane boundary marker network with road geometry constraints, 2020 IEEE Winter Conference on Applications of Computer Vision (WACV), **2020**

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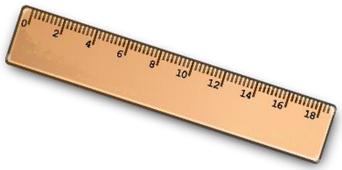
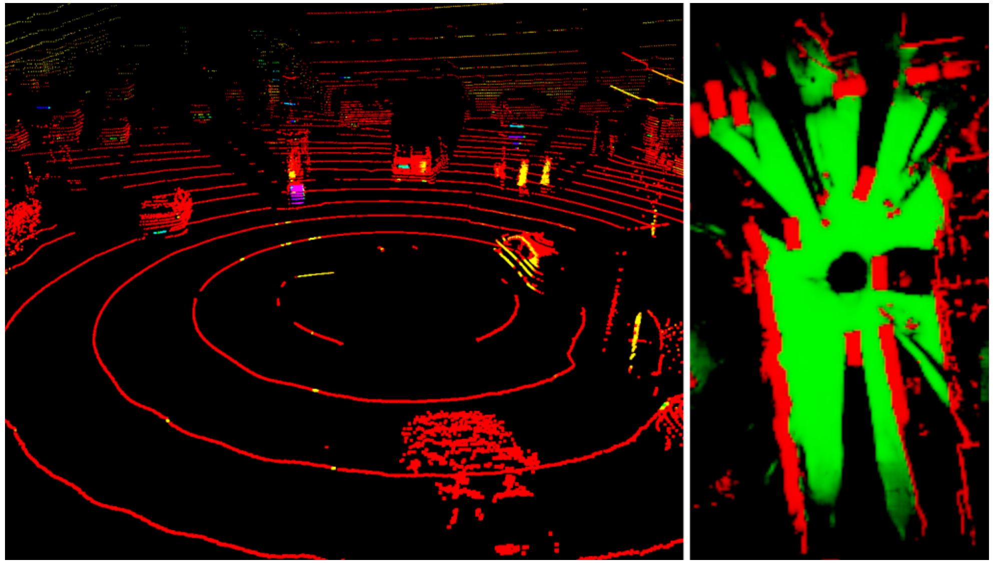
Approach



- **Geometric Inverse Sensor Models** use geometry to derive occupancy information from measurements

- **Deep Inverse Sensor Models** are trained to derive occupancy information from measurements
  - Supervised learning requires labeled training data, i.e. measurement and occupancy grid map



Images: pixabay, wixmp, ieee

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Approach

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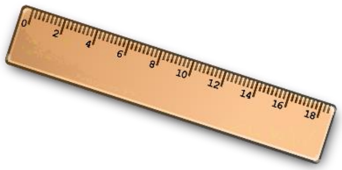

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    - **Cross-modal training**: E.g. use geometric ISM with lidar measurements to create label grid maps for radar measurements

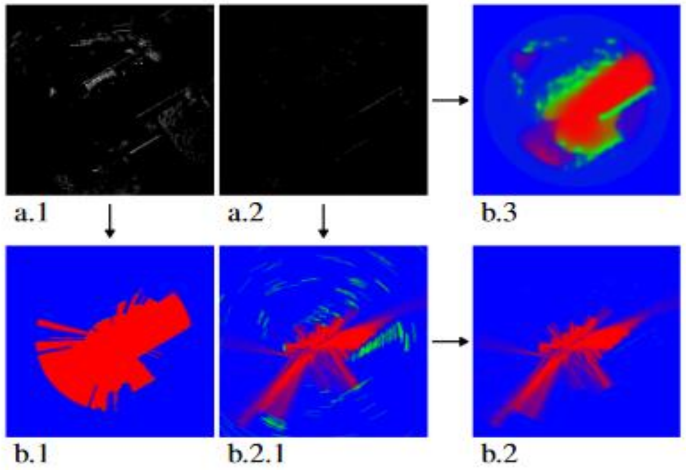

Fig. 2. Illustration of the lidar detections a.1 and the corresponding ray ILM b.1, the radar detections a.2, the intermediate and final ray IRM b.2.1, b.2 and the deep IRM b.3 (best viewed in color with zoom)

Images: pixabay, arxiv

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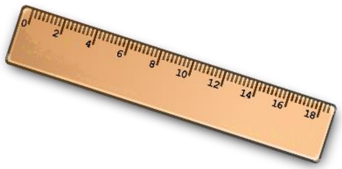
Approach



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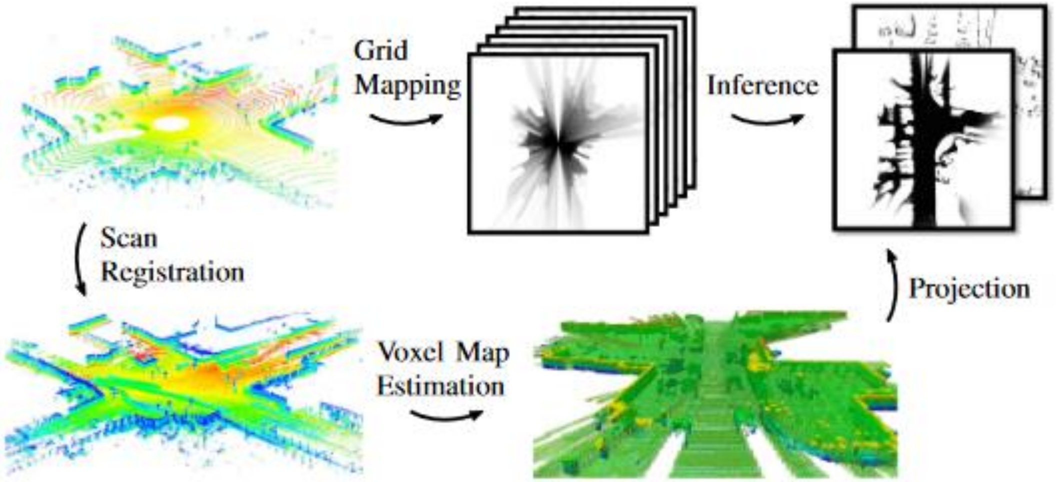

Images: pixabay, ieee

Point Cloud OGM – Deep ISM

Approach

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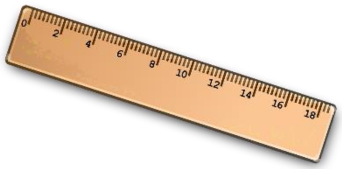

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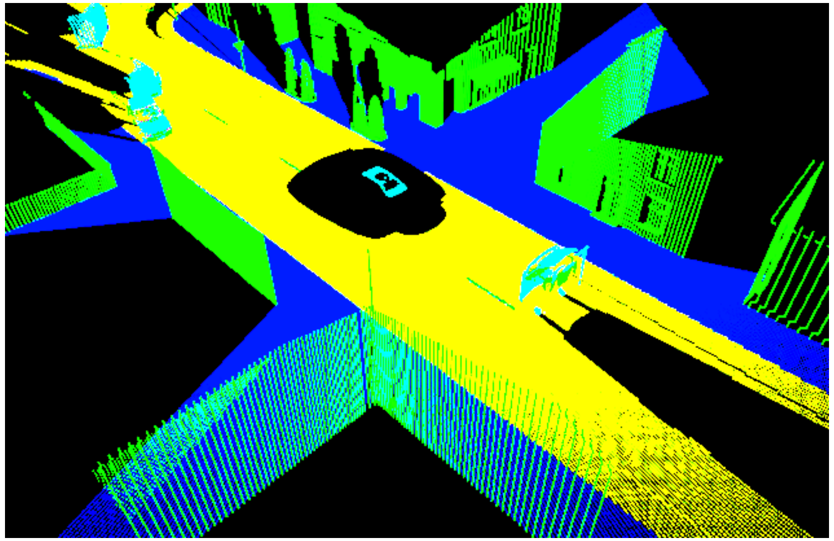
    - **Cross-modal training**: E.g. use geometric ISM with lidar measurements to create label grid maps for radar measurements
    - **Training Data Augmentation**: Fuse sequential grid maps to generate dense label grid maps
    - **Synthetic training data**: Use simulation with sensor models to generate measurement data and corresponding label occupancy grid maps



Images: pixabay, ieee

Sources: Bauer et al. 2020, Wirges et al. 2018, van Kempen et al. 2021

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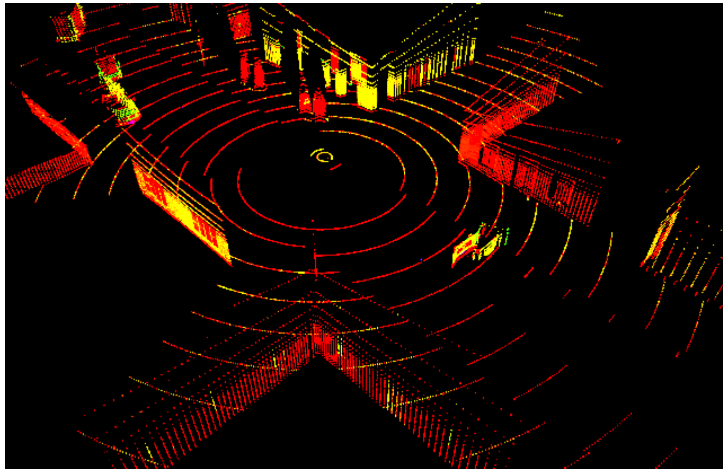
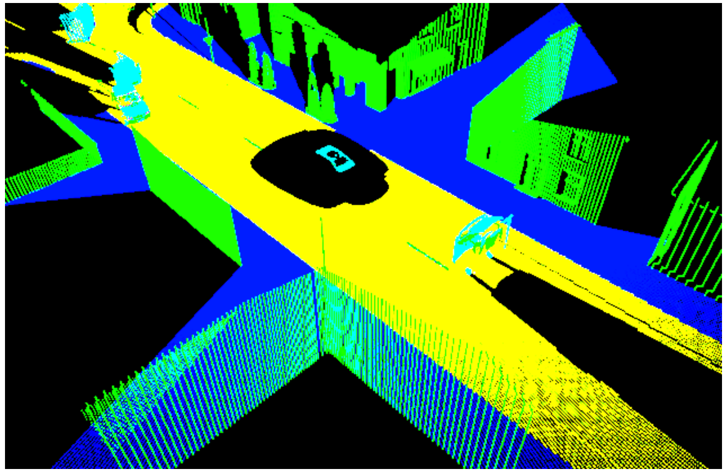
Synthetic Training Data

- Simulation with complex urban scenarios, including **a lot of vehicle types and pedestrians**.
- Textures include **material properties**, e.g. reflectivity.
- **Physically-based sensor model** uses ray tracing and material properties to simulate sensor data

- **Virtual "high-definition" lidar** detects material that caused reflection



Input Point Cloud



HD Material Point Cloud

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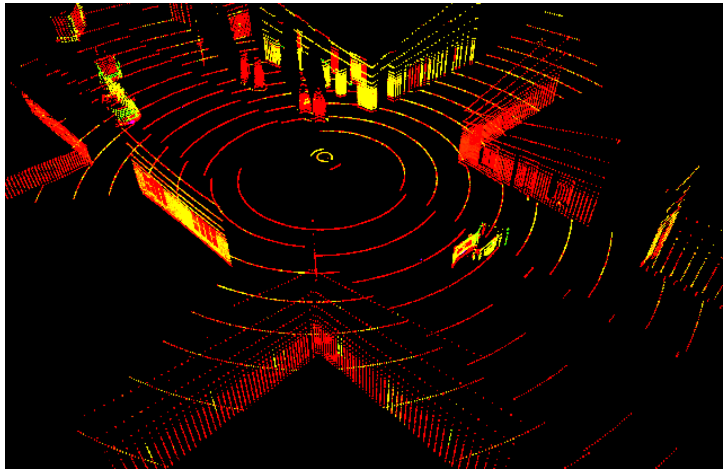
Synthetic Training Data

- Simulation with complex urban scenarios, including **a lot of vehicle types and pedestrians**.
- Textures include **material properties**, e.g. reflectivity.
- **Physically-based sensor model** uses ray tracing and material properties to simulate sensor data

- **Virtual "high-definition" lidar** detects material that caused reflection
- Occupancy grid map is derived from **material classes**
- **Object positions** are inserted into grid map



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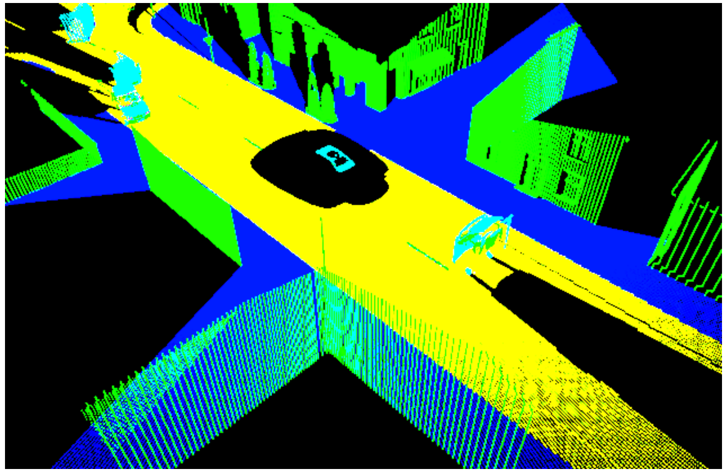
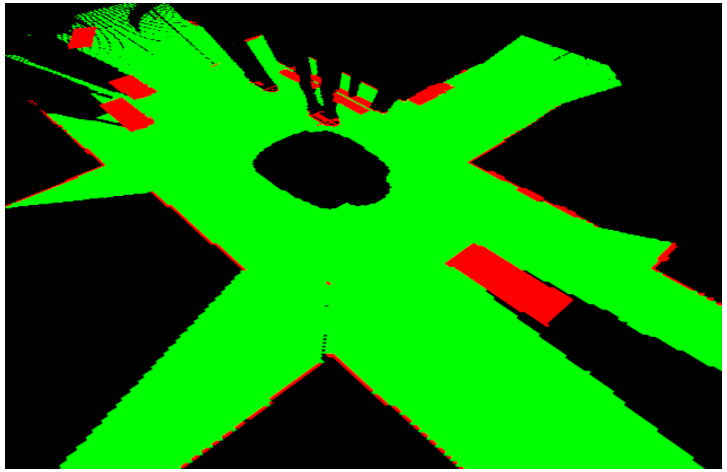


HD Material Point Cloud



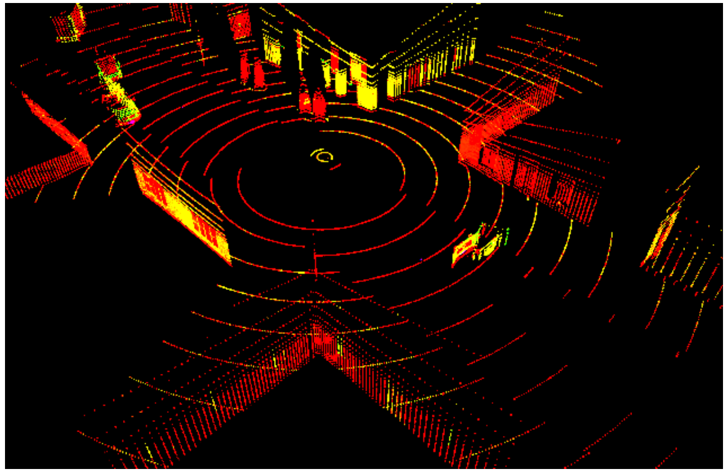
Label Occupancy Grid Map

Images: ieee

Point Cloud OGM – Deep ISM

Synthetic Training Data

- **Challenges**
  - Support **domain shift**
    - Close **reality gap** (difference between real and synthetic data)
    - Create **diverse training data** (world model, vehicles, pedestrians, obstacles, …)
  - Find suitable **data representation** and **neural network architecture**



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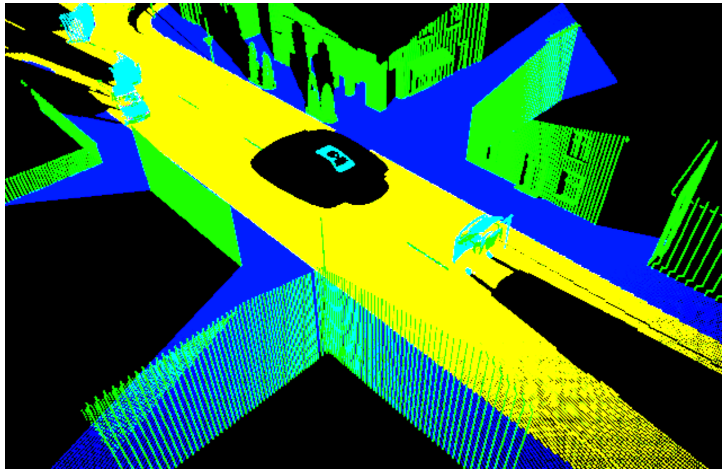

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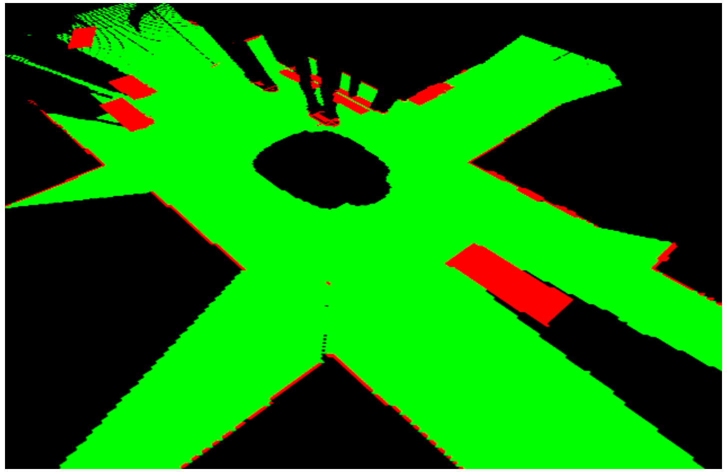

Label Occupancy Grid Map

Images: ieee

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Network Architecture

- Do not re-invent the wheel → **Literature Review!**
- **Adapt architectures** that have shown to perform well on similar tasks

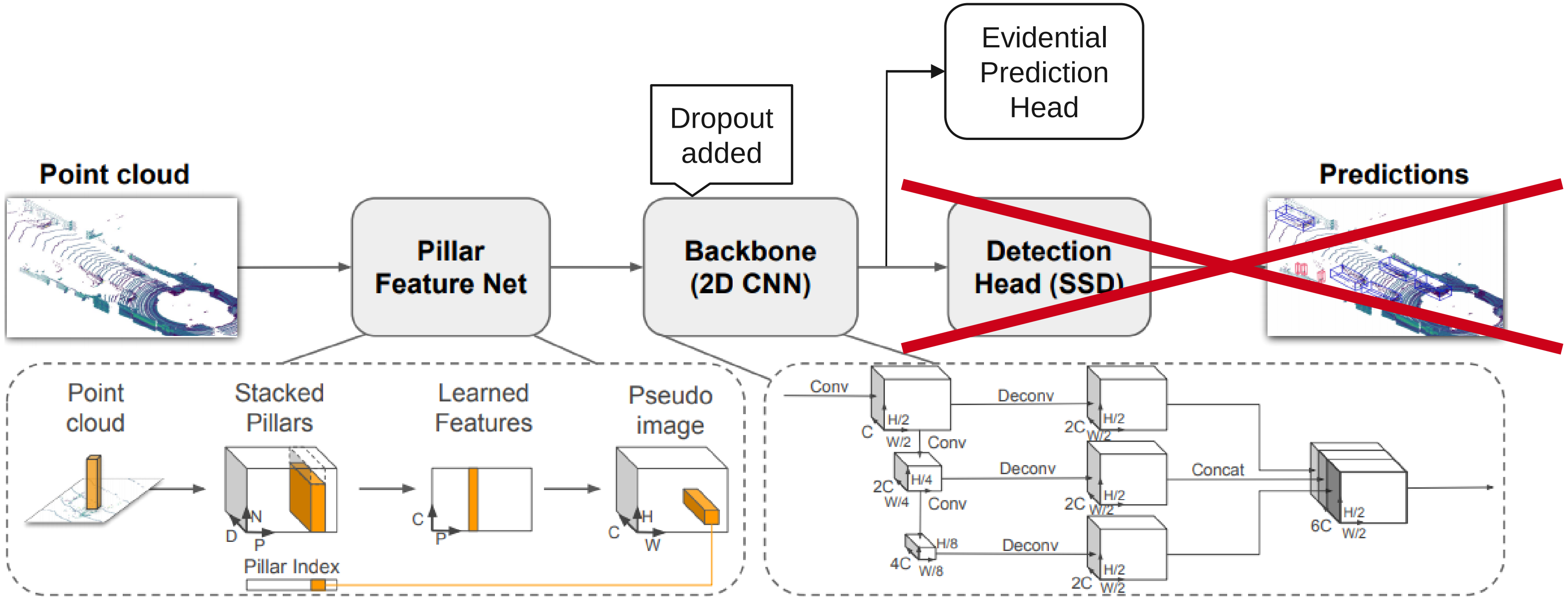

Image: ieee

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Network Architecture

- Do not re-invent the wheel → **Literature Review!**
- **Adapt architectures** that have shown to perform well on similar tasks
- How to measure performance? Find a suitable **loss function**.

```python
# Evidential Prediction Head
prediction = tf.keras.layers.Conv2D(filters=2, kernel_size=(3, 3),
                                    padding="same",
                                    name="ogm/conv2d",
                                    activation="relu")(output)
```

Evidence for the singletons in the FOD $e_A \geq 1, A \in \Theta$ can be converted to parameters of a Dirichlet PDF and to a subjective opinion $(\boldsymbol{b}, u)$ with the number of classes $K = |\Theta|$ and the Dirichlet strength $S = \sum_{A \in \Theta} \alpha_A$:

$$\begin{aligned} \alpha_A &= e_A + 1\,, \qquad && A \in \Theta \\ b_A &= \frac{e_A}{S} && \Theta = \{F, O\} \\ u &= \frac{K}{S} \end{aligned}$$

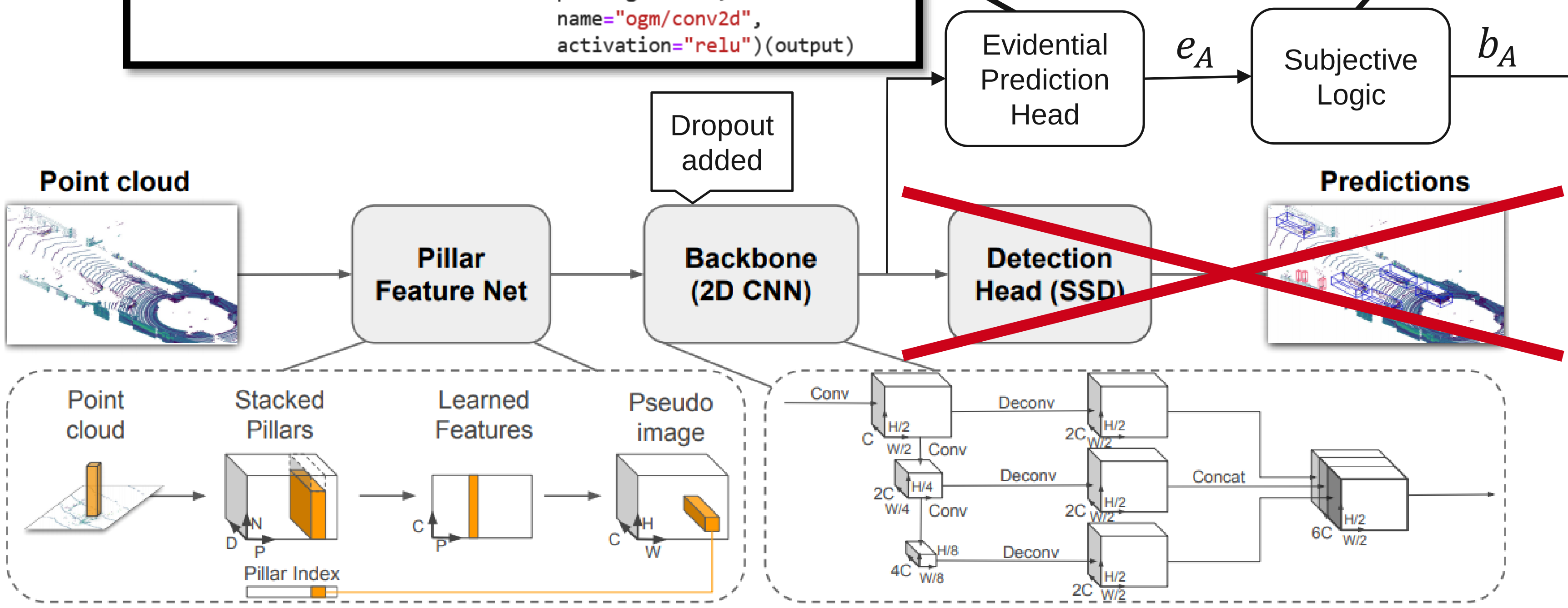
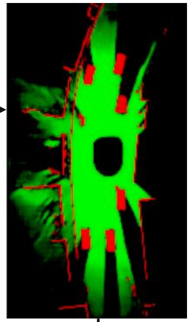
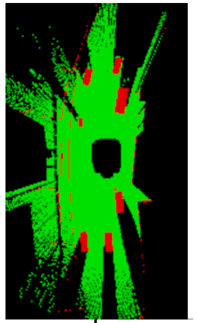


Image: ieee

Predicted Occupancy Grid Map



Label Occupancy Grid Map



Images: ieee

$$\mathcal{L}(w) = \sum_{i=1}^{N} \mathcal{L}_i(w) + \lambda_t \mathrm{KL}\left[\mathrm{Dir}(\boldsymbol{p_i}|\tilde{\boldsymbol{\alpha}}_i) || \mathrm{Dir}(\boldsymbol{p_i}|\boldsymbol{1})\right]$$

Loss Function