Integrity Monitoring of 3D Object Detection in Automated Driving Systems using Raw Activation Patterns and Spatial Filtering

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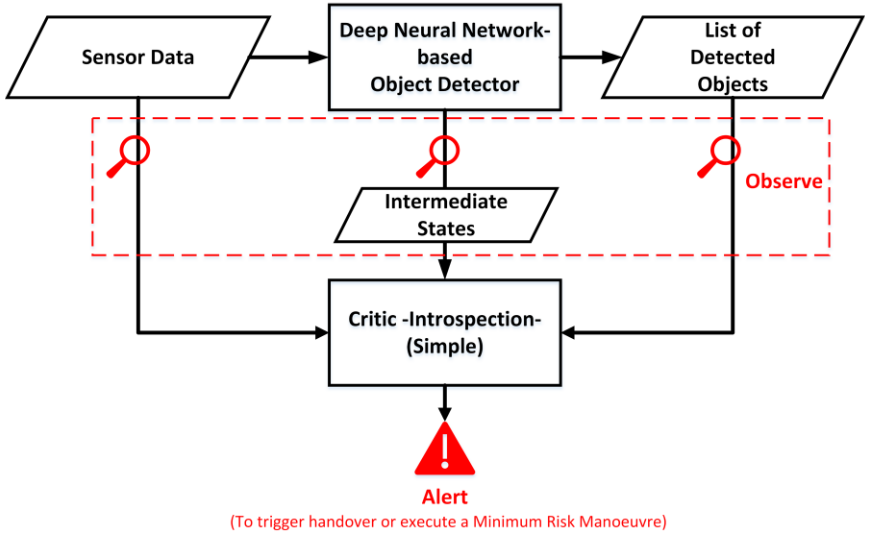
EVENTS

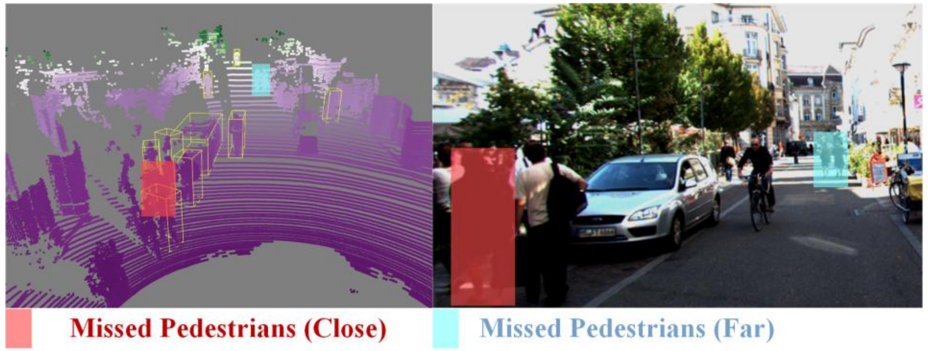
Outline

- Motivation for Using Perception Integrity Monitoring
- Proposed Integrity monitoring Mechanism for 3D LiDAR-based Object Detection
- Performance Evaluations
- Conclusions

Motivation

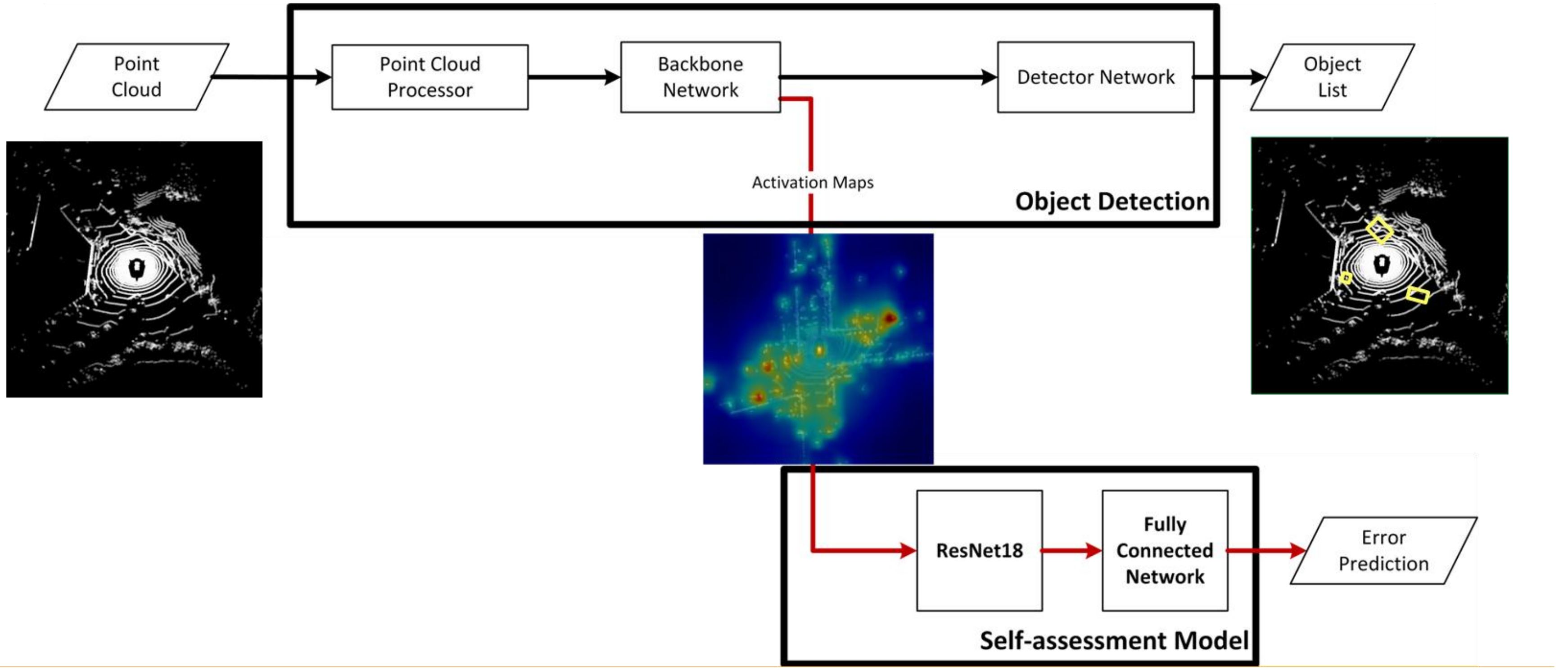
- DNN-based object detectors for perception are vulnerable to faults and failure for a variety of reasons.
- In automated driving systems (ADS), run-time perception monitoring mechanisms can mitigate the impact of these failures.
- We adopt an actor-critic architecture where the critic is a secondary system that continuously assesses the performance of the actor (perception system).
- Within a given scene, not all objects are equal for safety criticality– hence some filtering mechanism is recommended.





Activation Maps

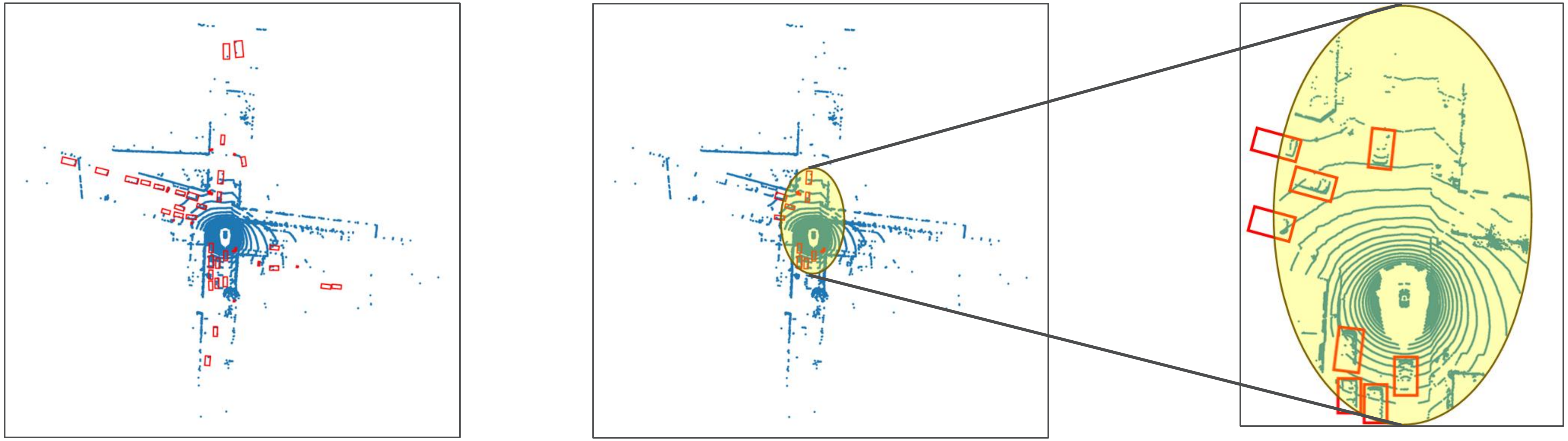
- For perception integrity monitoring (or self-assessment), we propose to use activations (features) extracted for 3D object detection.
- The aim is to associate the activations with the objects that might be missed.



Spatial Filtering

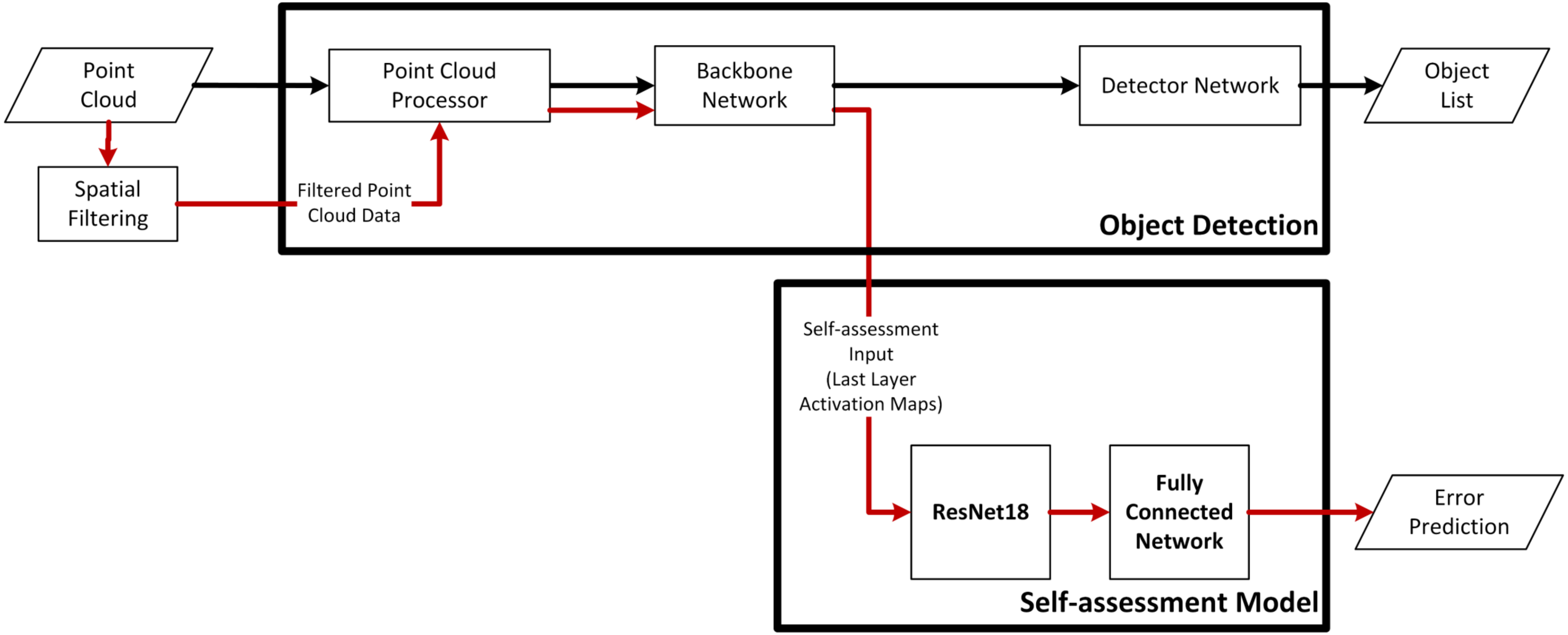
- To focus on the immediate danger zone within the local surroundings of the Ego vehicle, we propose spatial filtering of the 3D point cloud, removing any content outside an ellipse-shaped filter.
- **Filter Range:** [-20m,30m] longitudinal, [-15m,+15m] lateral.

Full Scene with All Objects | Full Scene with Only Objects Filtered | Spatially Filtered Scene



Activation maps and Spatial Filtering

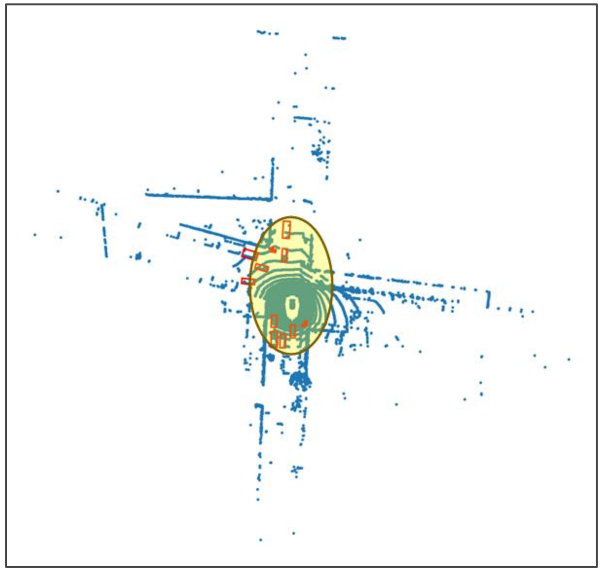
- To identify erroneous scenes while operating with spatial filtering the following architecture is used.



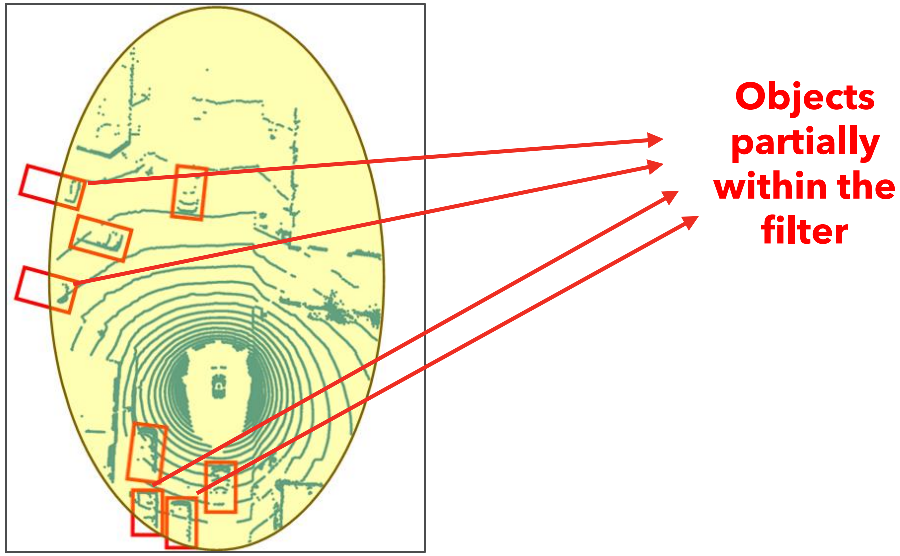
Proposed Mechanism

- We may be losing information if an object lies partially within the spatial filter.
- We also investigate error detection with full scene point cloud data where only the labels filtered.

Full Scene with Only Labels Filtered



Spatially Filtered Scene



Performance Evaluations

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Datasets

KITTI Dataset:
- ~7000 Samples.
- Only the front of the ego vehicle is annotated.
- Car, pedestrian and cyclist classes are used.

NuScenes Dataset:
- ~34k samples (~850 scenes).
- 360° Annotation.
- Vehicles and pedestrian classes are used.

Object Detectors

Point Pillars:
- Common baseline model.
- Processes point cloud into 2D xy plane as pillars.
- Provided in common frameworks, and Autoware Auto's software stack.

Centerpoint:
- Better performing baseline model for ADS.
- Provided in the latest Autoware Auto software stack and currently used in WMG's prototype vehicle.

Metrics

AUROC:
- An indicator of how well a classifier distinguishes between the positive ('error') and negative ('no-error') classes.

Recall:
- Measures the classifier's ability to correctly identify the class.
- Both positive and negative class recall is calculated.

Implementation Details

Libraries and Frameworks

- PyTorch
- Torchvision
- Torchmetrics
- OpenMMDetection3D
- Grad-CAM

Training Parameters & Hyperparameter Tuning

Loss Function: Focal Loss

$$L(q) = -\sum \alpha_i \ (1 - q_i)^{\gamma} \log(q_i) \qquad i \in \{0, 1\}$$

where:

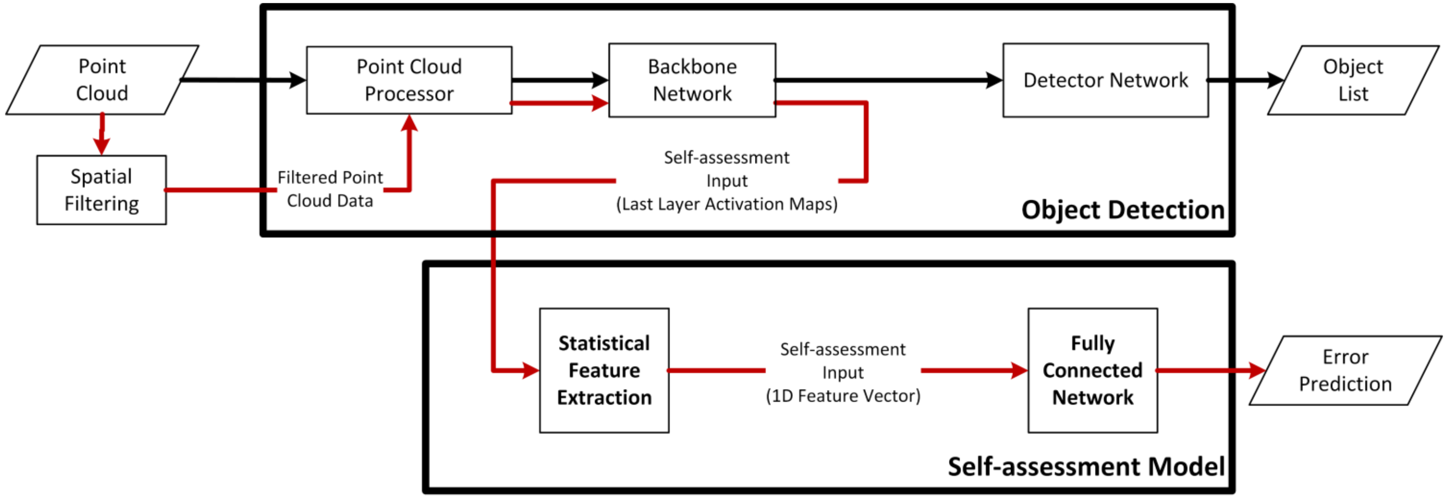
- log is the natural logarithm
- q is the predicted probability vector for the,
- α_i is a scaling factor (class weights)
- $\gamma \in \{0,2,4,5\}$ is a parameter that down-weights easy examples and emphasises hard examples.

Optimizers: **Stochastic Gradient Descent (SGD)**, Adam
Batch Sizes: 32,**64**,128
Learning Rates: 0.1, **0.01**, 0.001, 0.0005

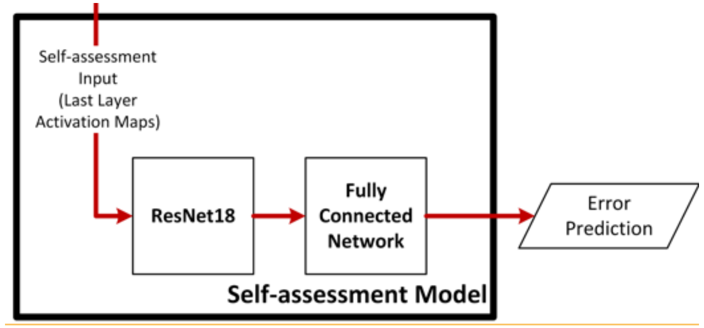
Best performing model is obtained with the hyperparameters shown in **red**.

SOTA Mechanism

- The state-of-the-art (SOTA) mechanism adapted from literature for comparison is called Statistical Features [1].
- It performs global pooling of the last layer activation maps with max, mean and standard deviation functions to create a 1D feature vector.



Statistical Features



Proposed

[1] Q. M. Rahman, N. Sunderhauf, and F. Dayoub, "Per-frame map prediction for continuous performance monitoring of object detection during deployment," in 2021 IEEE Winter Conference on Applications of Computer Vision Workshops (WACVW), 2021, pp. 152–160

Performance Evaluations

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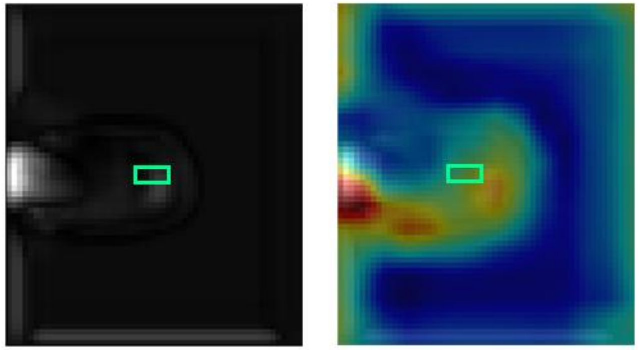
Dataset / Method	Input	Rec(-)	Rec(+)	AUROC
KITTI / PointPillars	Statistical Features	0.9649	0.0625	0.6193
	Filtered Activations	**0.6368**	**0.7091**	**0.7384**
NuScenes / Centerpoint	Statistical Features	0.4819	0.8067	0.7317
	Filtered Activations	**0.5330**	**0.8646**	**0.8092**

- For both datasets, the proposed mechanism performs better than statistical features regarding AUROC and error class recall.
- Spatial Filtering has reduced the number of error frames on both datasets when compared with previous work [2], highlighting that significantly less critical frames are labelled as errors without filtering.

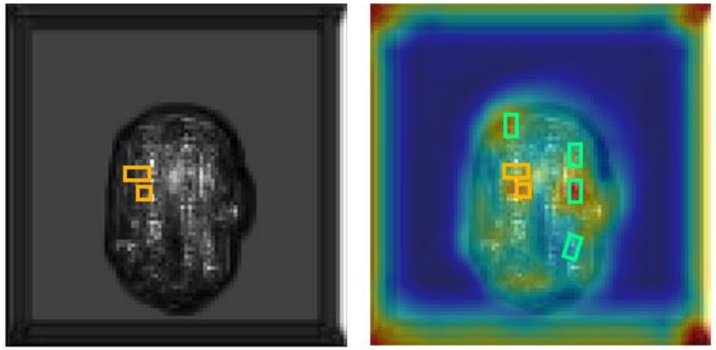
[2] H. Y. Yatbaz, M. Dianati, K. Koufos, R. Woodman, "Run-time Monitoring of 3D Object Detection in Automated Driving Systems Using Early Layer Neural Activation Patterns," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, 2024, pp. 3522-3531

Performance Evaluations

- Channel-wise maximum of activation maps (left images).
- Activation visualization with EigenCAM Heatmap of model attention (right images). (**red**: high, **blue**: low)
- Diving direction is from left to right for KITTI, and from bottom to top for NuScenes.



KITTI



NuScenes

Correctly Detected Object

Missed Object

- The self-assessment mechanism directly focuses on the area of interest with spatial filtering, and the missed objects have got higher attention.

Conclusion

- Our mechanism outperforms the state-of-the-art mechanism (statistical features) by around 7% in overall with AUROC and 6% in identifying error class.

- The reduction in the number of error frames with filtering highlights that a significant number of errors in the datasets are caused by point cloud sparsity for far away objects, which are less safety-critical.

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Thank you.

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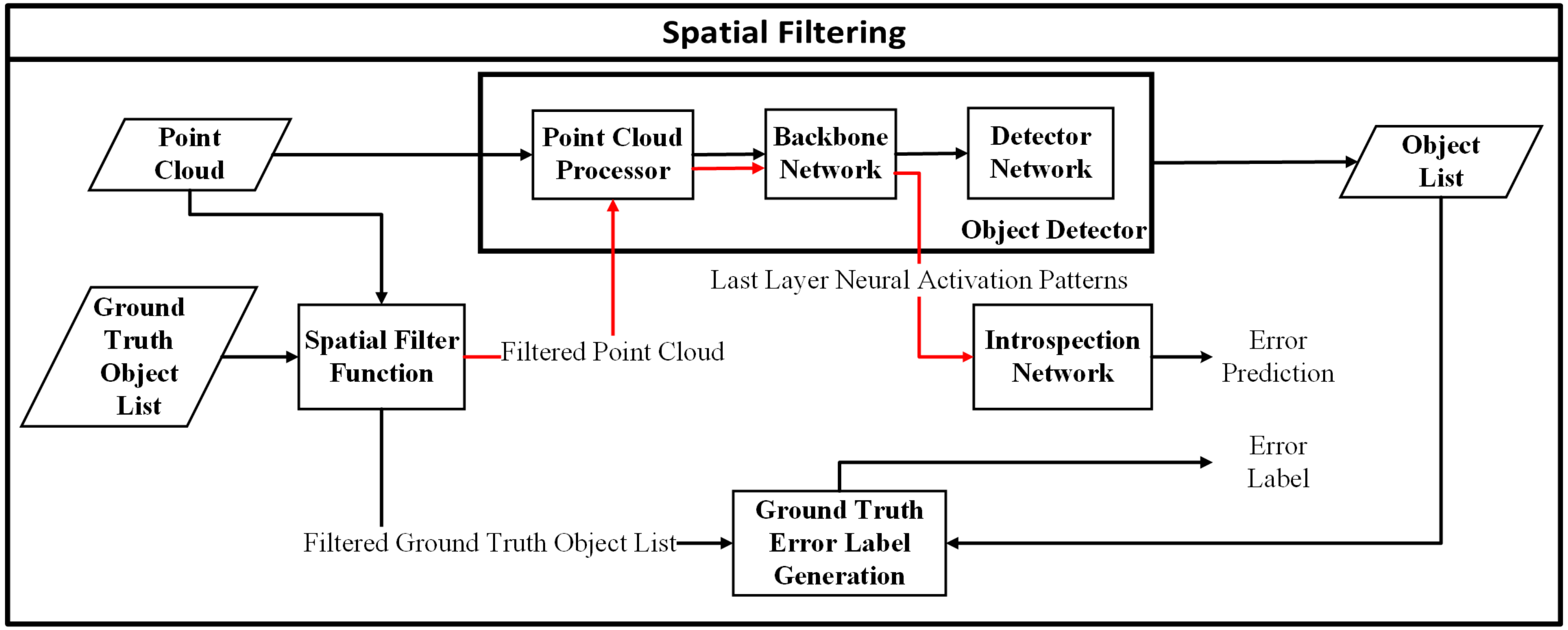
Q&A


AVL F-FEM-DDC SNAP-IN
AVL F-FEM-AIT SNAP-IN
25 TO 36
AVL PRESSURE MEASUREMENT SNAP-IN
AVL SNAP-IN
AVL

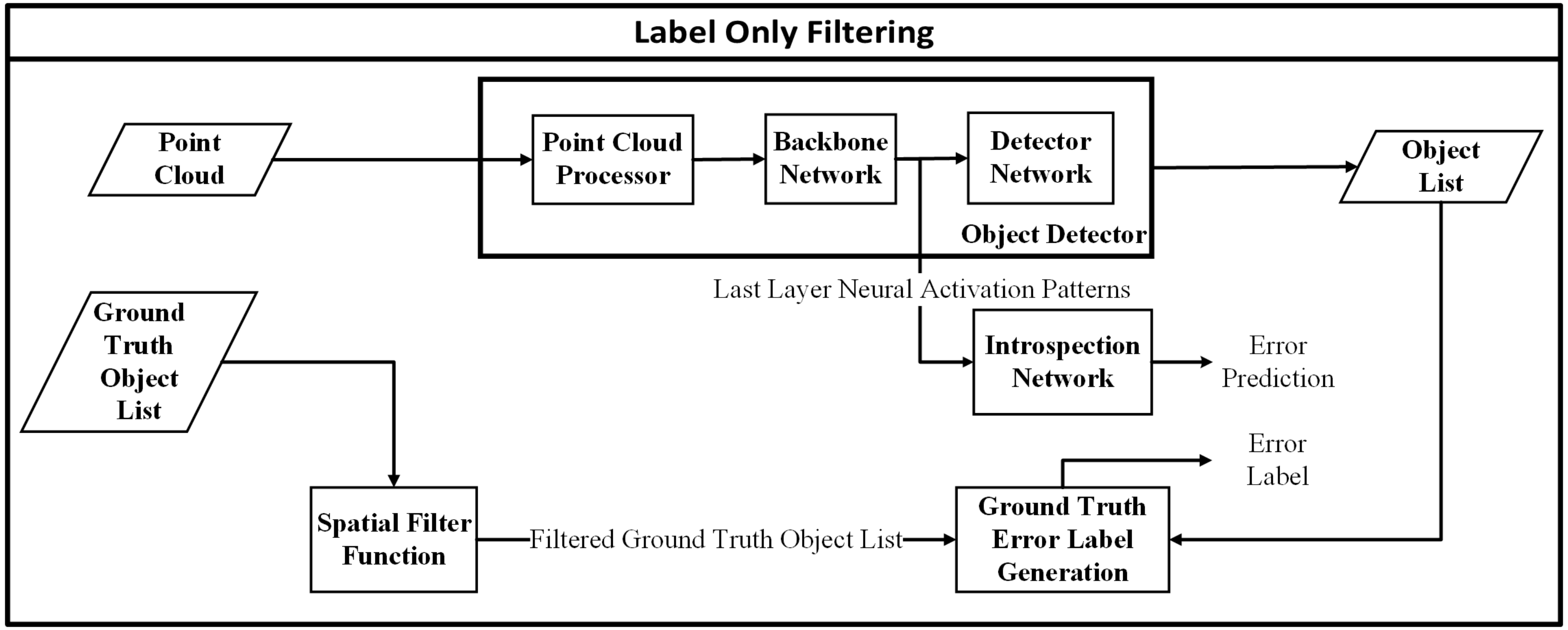
Proposed Mechanism

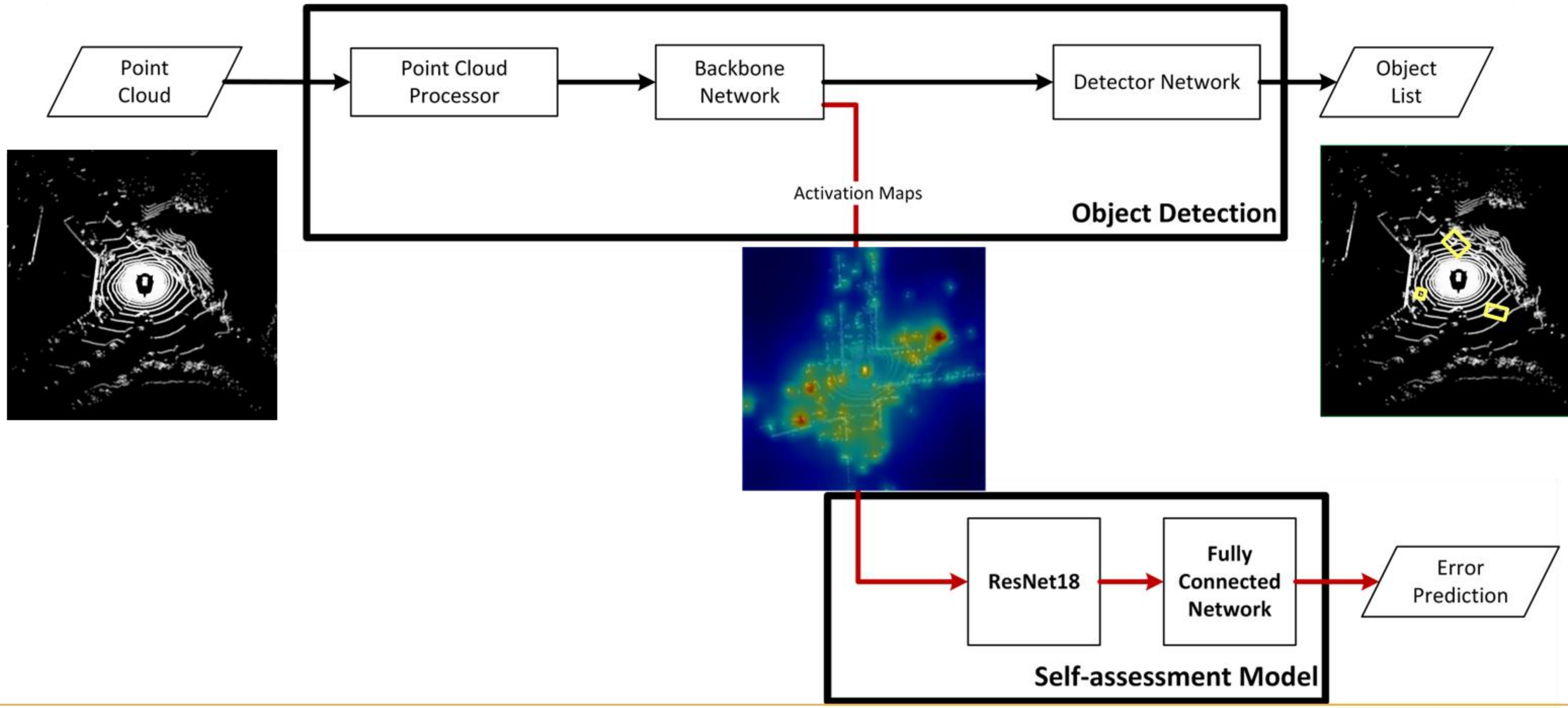
- To identify erroneous scenes while operating with spatial filtering the following architecture is used.



Proposed Mechanism

- To identify erroneous scenes, with label only filtering:





Point Cloud
Point Cloud Processor
Backbone Network
Detector Network
Object List
Activation Maps
Object Detection
ResNet18
Fully Connected Network
Error Prediction
Self-assessment Model