Conclusions Advancements in deep learning made the Deep Neural Networks (DNN) ready to deploy in real world.

We propose two benchmark datasets for OOD detection, one being Semantic3D-vs-S3DIS (Outdoor vs Indoor) and

The difference in MSP and entropy between ID and OOD is high in the case of S3DIS, as the environment is very c

Overall, the performance of OOD detection is better with Deep Ensembles than with Flipout or Dropout in both th

Lessons Learned The following are the lessons learned during the duration of the thesis

Training and evaluation of 3D DNNs are time-consuming and resource-intensive. Even a single forward pass on the test

LiDAR datasets have huge memory requirements even for preprocessing or computing metrics.

With this level of requirements, finding a proper prior for Flipout layers is hard. In turn, this makes the tuning of the F

Picking the suitable candidates for the OOD benchmark requires in depth analysis of datasets like structural similarities

We observe few points in the training (ID) dataset are classified as OOD points. These points have a lower probability s

Future Work

We found three major ways to extend this thesis. First one is regarding the 3D semantic segmentation models. We

Second way to extend this thesis is with the OOD datasets. We grouped datasets into three kinds static, sequential