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Out-of-Distribution Detection in 3D Semantic Segmentation

Master Thesis

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Out-of-Distribution detection

- An ideal trustworthy visual recognition system
  - Produce accurate predictions on known examples
  - Detect and reject unknown examples
- Deep Neural Networks (DNNs) are trained based on closed world assumption
- closed world assumption - test data is assumed to be drawn from same distribution as training data which is called In-Distribution (ID)
- When deployed in real world (open world scenario) the test samples can be Out-of-Distribution (OOD) i.e. the test samples can be,
  - from different class
  - from different domain

Out-of-Distribution detection

- A real world example for OOD object is described in Figure 1
- Tesla autonomous driving system detects the moon as the yellow traffic light
- These faulty predictions might result in output of the autonomous driving system being catastrophic

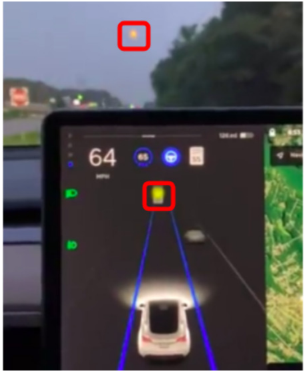

Figure 1: Caption

Importance of OOD detection

- Figure 2 depicts the pipeline of modules in Apollo driving platform.
- Prediction and motion planning module are dependent on perception module.
- A misdetection of an OOD sample will propogate the error to motion planning and affects the total vehicle control and this might lead to unfortunate consequence

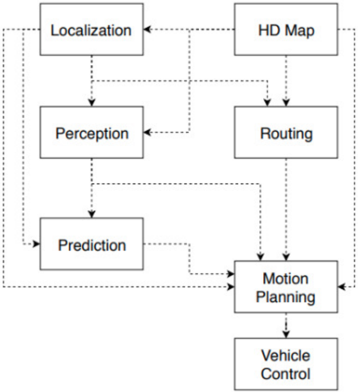

Figure 2: Caption

3D Light Detection And Ranging (LiDAR)

- Uses pulsed lasers to find the range to the objects
- Unlike images, LiDAR is insusceptible to illumination and provide rich 3D information.
- Figure 3 depicts the sample point cloud with LiDAR is placed in round white circle found at the center of point cloud
- Typically, features of each point in point cloud include
  - spatial features (XYZ)
  - Color (RGB)
  - Intensity

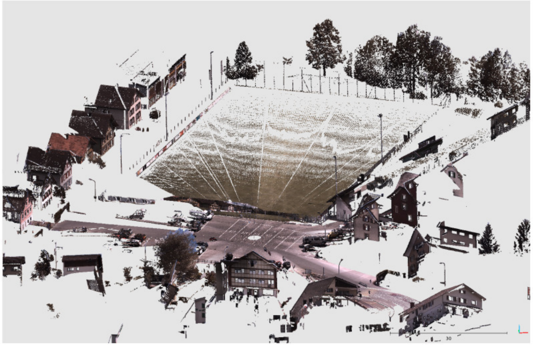

Figure 3: Caption

3D Semantic Segmentation

- An important task in computer vision because of its use in scene understanding
- Further helps in navigation and planning of robots
- Objective - Assign each point in the point cloud a specific class

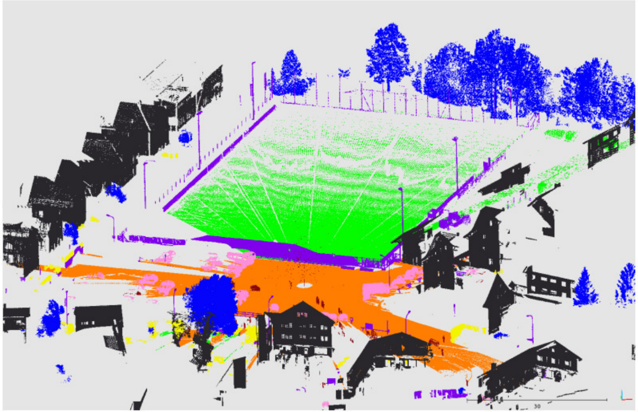

Figure 4: Caption

Thesis objective

- OOD detection in the 3D semantic segmentation setting
- Create a benchmark datasets for OOD detection among existing 3D LiDAR datasets. We define OOD data based on two categories
  - if the point is from different class than training data
  - if the point has inferior quality
- We also study whether uncertainty estimation is a practical approach for OOD detection in 3D domain

Ingredients

- Datasets
- 3D Semantic Segmentation model
- Uncertainty methods
- Evaluation methods

3D LiDAR datasets

Semantic3D

S3DIS

OOD Benchmark datasets

Ingredients

- ~~Datasets~~ - Semantic3D, S3DIS & Semantic3D w/o colour
- 3D Semantic Segmentation model
- Uncertainty methods
- Evaluation methods

RandLA-Net

Ingredients

- ~~Datasets~~ - Semantic3D, S3DIS & Semantic3D w/o colour
- ~~3D Semantic Segmentation model~~ - RandLA-Net
- Uncertainty methods
- Evaluation methods

Deep Ensembles

Flipout

Ingredients

- ~~Datasets~~ - Semantic3D, S3DIS & Semantic3D w/o colour
- ~~3D Semantic Segmentation model~~ - RandLA-Net
- ~~Uncertainty methods~~ - Deep Ensembles & Flipout
- Evaluation methods

OOD Score calculation

Area Under ROC curve

Ingredients

- ~~Datasets~~ - Semantic3D, S3DIS & Semantic3D w/o colour
- ~~3D Semantic Segmentation model~~ - RandLA-Net
- ~~Uncertainty methods~~ - Deep Ensembles & Flipout
- ~~Evaluation methods~~ - AUROC

1. Introduction

2. Methodology

3. Experiments & Results

4. Conclusion

Conclusion

Lessons Learned

Learning's during the duration of the thesis are

1. Training and evaluation of 3D DNNs are time consuming and resource intensive.
2. Finding the proper prior for Flipout layers is hard and currently we use brute force to find the best fitting prior.
3. OOD benchmarking require in depth analysis of datasets like studying the structural similarties in the datasets and also color spectrum.
4. LiDAR datasets have large memory requirements especially for the preprocessing and metric computation.
5. Getting 100% OOD detection performance is not possible with the post-hoc methods used as some points in the ID dataset also have low probability scores.

Future Work

This thesis can be extended in the following ways.

1. This thesis is limited to only point based models, this can be extended to graph and projection based models.
2. The datasets involved are only static datasets and this thesis study can be further extended to other type of datasets such as synthetic and sequential datasets.
3. Since this thesis utilzes post-hoc threshold methods for OOD detection. Other methods such as Mahalanobis distance based OOD detection [1] or MetaSeg [2] can be added as an extension to this thesis.

References

Kimin Lee, Kibok Lee, Honglak Lee, and Jinwoo Shin.
A simple unified framework for detecting out-of-distribution samples and adversarial attacks.
Advances in neural information processing systems, 31, 2018.

Philipp Oberdiek, Matthias Rottmann, and Gernot A. Fink.
Detection and retrieval of out-of-distribution objects in semantic segmentation.
In *IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR Workshops*, pages 1331–1340. Computer Vision Foundation / IEEE, 2020.

What is OOD Detection?

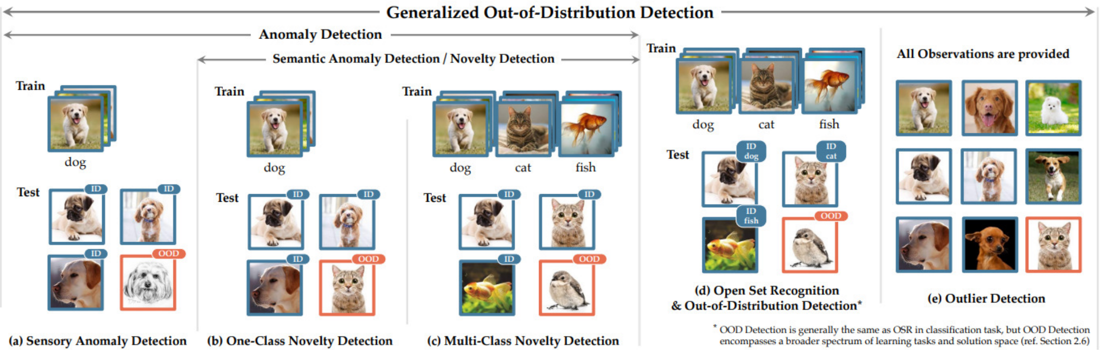

Figure 5: Generalized Out-of-Distribution Detection: A Survey