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Out-of-Distribution Detection in 3D Semantic Segmentation

Master Thesis

September 02, 2022

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1. Introduction

2. Experimental Setup & Methodology

3. Experiments & Results

4. Conclusion

Out-of-Distribution detection

- Tesla autonomous driving system detects the Moon as yellow traffic light
- These faulty predictions might result in unpredictable behaviour
- An ideal trustworthy visual recognition system
  - Produce accurate predictions on known samples
  - Detect and reject unknown samples

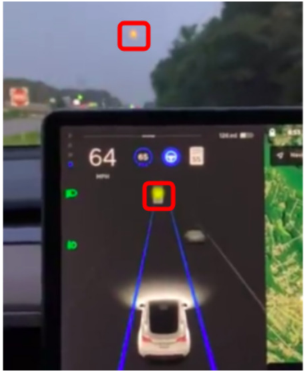

Figure 1: Misdetection of Moon as yellow signal light in Tesla driving platform. Image taken from [7].

Out-of-Distribution detection

- 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**) these OOD samples can be **Out-of-Distribution (OOD)**, the test samples can be
  - from different class
  - from different domain

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 propagate the error to motion planning
- This error affects the total vehicle control and might lead to unfortunate consequences

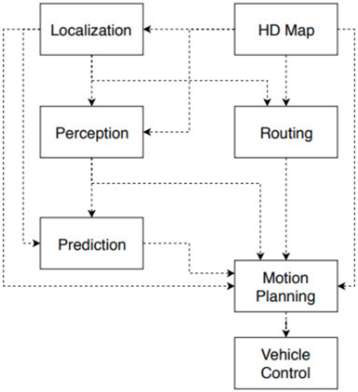

Figure 2: Module pipeline for Apollo autonomous driving platform. Image taken from [2].

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.
- Typically, features of each point in point cloud includes
  - Spatial features (XYZ)
  - Colour (RGB)
  - Intensity

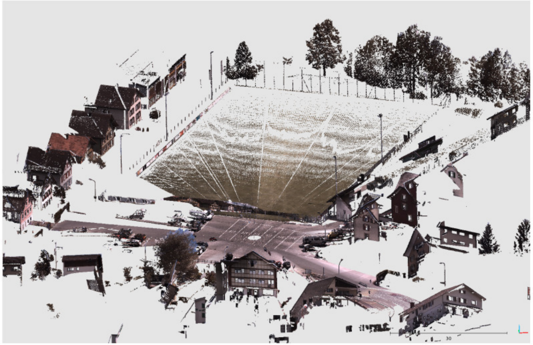

Figure 3: Sample LiDAR point cloud collected in a outdoor scene. Image taken from [4].

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**

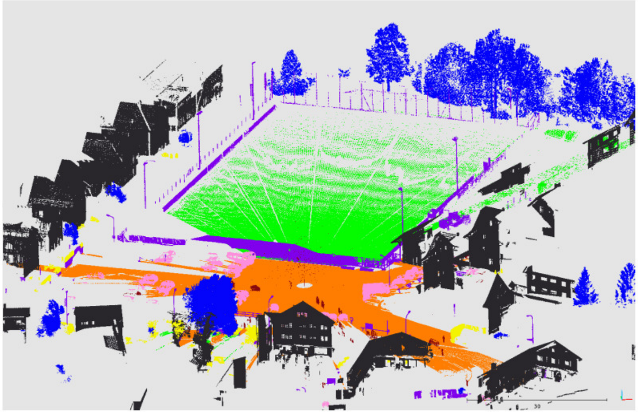

Figure 4: Segmented output of sample point cloud. Image taken from [4].

Thesis objective

- OOD detection in the 3D semantic segmentation setting
- Create **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

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Setup

- 3D Semantic Segmentation model
- Uncertainty methods
- OOD score methods
- Datasets

RandLA-Net

- Lightweight, efficient computation, memory usage and inputs 3D point cloud directly
- **Random point sampling** and **local feature aggregation module** are most important modules
- Local feature aggregation module is subdivided into local spatial encoding, attentive pooling and dilated residual block
- **Encoder-Decoder style** architecture as depicted in Figure 6

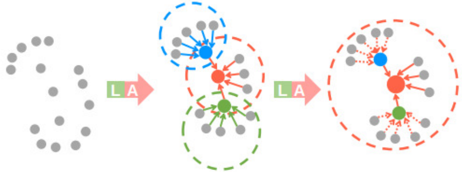

Figure 5: Image depicting the working of Dilated residual block with each circle representing the receptive field of the block for feature extraction. LA represents the combination of Local Spatial Encoding and Attentive Pooling modules combined. Image taken from [5].

RandLA-Net

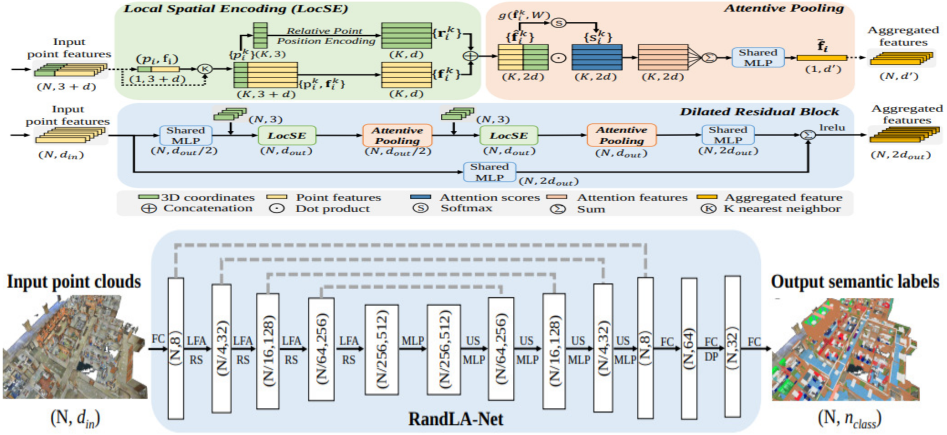

Figure 6: Illustration of local feature aggregation module in RandLa-Net in top image and architecture of RandLA-Net in bottom image. Both the images are taken from [5].

Setup

- 3D Semantic Segmentation model - RandLA-Net
- Uncertainty methods
- OOD score methods
- Datasets

Deep Ensembles

- Ensemble learning technique - train N randomly initialized models with same data
- Resulting N predictions are then averaged
- **Performance boosting** along with uncertainty value for a prediction
- Requires **more computation power**

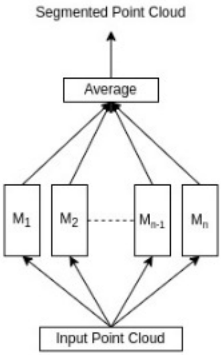

Figure 7: Illustration of test dataflow in Deep Ensembles, where input point cloud is fed into multiple randomly initialized models M_1 to M_n.

Flipout

- Introduced as a method to decorrelate gradients in a mini-batch of examples
- Add independent weight perturbations sampled from a distribution
- Train **single instance** of Flipout versioned network and then **perform multiple forward passes** for same input

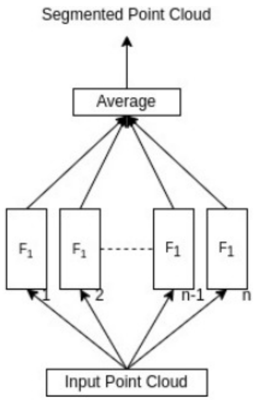

Figure 8: Illustration of test dataflow in Flipout. Here F_1 represents the Flipout trained model and we compute n forward passes of the same point cloud on F_1.

Setup

- 3D Semantic Segmentation model - RandLA-Net
- Uncertainty methods - Deep Ensembles & Flipout
- OOD score methods
- Datasets

OOD Score calculation

- We use the following two methods to generate the OOD scores.
- Maximum Softmax Probability
  - $max(y_n), y_n = [P(C_1), P(C_2), ..., P(C_n)]$
- Entropy
  - $-\sum_i P(x_i)log(P(x_i))$ with i iterates across all the classes for point x

Setup

- 3D Semantic Segmentation model - RandLA-Net
- Uncertainty methods - Deep Ensembles & Flipout
- OOD score methods - Maximum Softmax Probability & Entropy
- Datasets

3D LiDAR datasets

acquisition mode	dataset	frames	total points (in million)	classes	scene type
static	Oakland [60]	17	1.6	44	outdoor
	Paris-lille-3D [71]	3	143	50	outdoor
	Paris-rue-Madame [74]	2	20	17	outdoor
	S3DIS [5]	5	215	12	indoor
	ScanObjectNN [85]	-	-	15	indoor
	Semantic3D [31]	30	4009	8	outdoor
	TerraMobilita/IQmulus [88]	10	12	15	outdoor
	TUM City Campus [26]	631	41	8	outdoor
	DALES [90]	40 (tiles)	492	8	outdoor
sequential	A2D2 [27]	41277	1238	38	outdoor
	AIO Drive [96]	100	-	23	outdoor
	KITTI-360 [100]	100K	18000	19	outdoor
	nuScenes-lidarseg [12]	40000	1400	32	outdoor
	PandaSet [99]	16000	1844	37	outdoor
	SemanticKITTI [7]	43552	4549	28	outdoor
	SemanticPOSS [62]	2988	216	14	outdoor
	Sydney Urban [19]	631	-	26	outdoor
	Toronto-3D [79]	4	78.3	8	outdoor
synthetic	SynthCity [30]	75000	367.9	9	outdoor

Table 1: 3D LiDAR datasets classified based on the acquisition type. Table updated from [3].

Semantic3D

- Huge 3D point cloud benchmark classification static dataset with 4 million points
- Scenes are taken in european streets around church, stations and fields
- Point features include XYZ, RGB and Intensity values.
- It has 8 classes with distribution of points represented in Figure 9
- [4] states that the scanning artefacts, hardscapes and cars are the most challenging classes

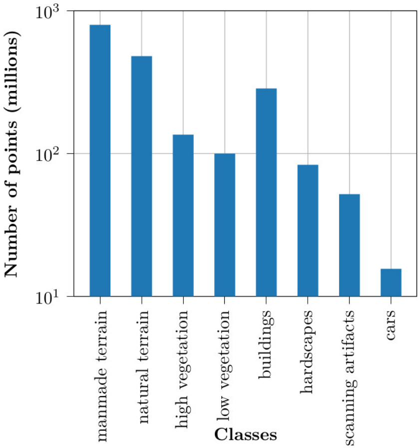

Figure 9: Graph depicting the number of points per class (in millions) in the Semantic3D dataset.

Semantic3D

Figure 10: Illustration of the Semantic3D point clouds of various outdoor scenes. Dataset from [4].

S3DIS

- Indoor dataset with scans from various buildings
- Dataset include scans of personal offices, restrooms, open spaces, lobbies and hallways
- It has 12 classes, further subdivided into two types
  - structural elements
  - everyday items
- One of the most evaluated datasets for indoor semantic segmentation

Figure 11: Illustration of the S3DIS point clouds of various indoor scenes. Dataset from [1].

OOD Benchmark datasets

ID dataset	OOD dataset	OOD detection difficulty	Summary
Semantic 3D	S3DIS	Easy	• No class overlap • Less structural similarity • Different domain(outdoor-vs-indoor)
	Semantic3D without colour	Hard	• Same structural properties • Difference in RGB values • Same domain as ID dataset • Same classes

Table 2: Table representing the ID dataset and corresponding OOD datasets, difficulty in OOD detection and the summary of reasons to chose this OOD dataset.

Setup

- 3D Semantic Segmentation model - RandLA-Net
- Uncertainty methods - Deep Ensembles & Flipout
- OOD score methods - Maximum Softmax Probability & Entropy
- Datasets - Semantic3D-vs-S3DIS & Semantic3D-vs-Semantic3D without colour

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Experiments

- Semantic3D-vs-S3DIS
  - Deep Ensembles
  - Flipout
  - Area Under Receiver Operating Characteristic (AUROC) score comparison
- Semantic3D-vs-Semantic3D without colour

Semantic3D-vs-S3DIS - Deep Ensembles

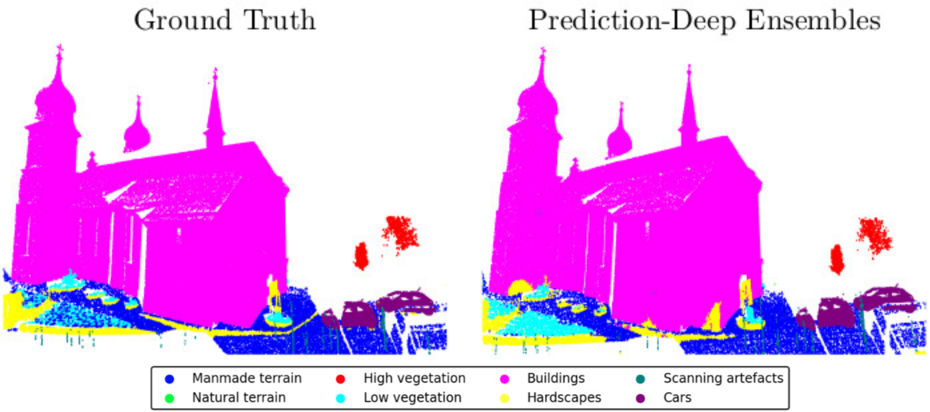


Figure 12: Image representing the predictions (last column) from Deep Ensemble with an ensemble size of 15 on Semantic3D dataset. The first column depict the ground truth.

Semantic3D-vs-S3DIS - Deep Ensembles

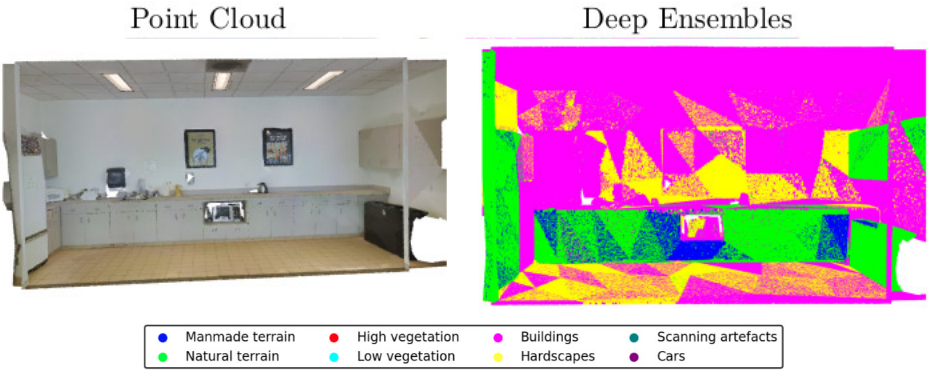


Figure 13: Predictions of RandLA-Net on S3DIS (OOD) dataset. First column representing the point cloud, second column presenting the predictions of Deep Ensembles (15 Ensemble size).

Semantic3D-vs-S3DIS - Deep Ensembles

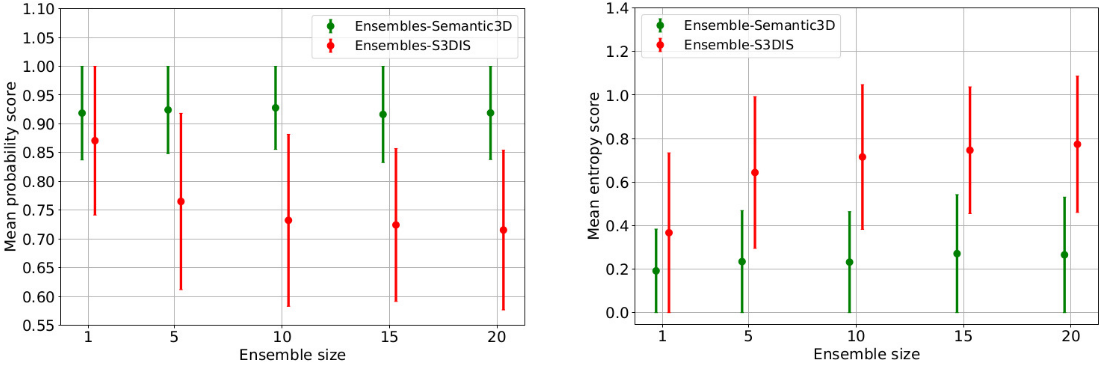


Figure 14: Graphs representing the mean probability value and mean entropy as a dot for Semantic3D (ID) in green and S3DIS (OOD) in red when using Deep Ensembles. The variance is represented via the error bars.

Semantic3D-vs-S3DIS - Flipout

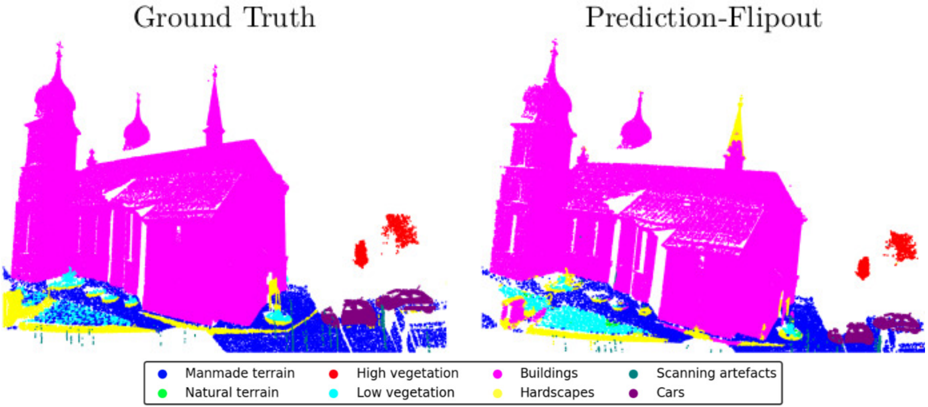


Figure 15: Image representing the predictions (last column) from Flipout with 15 number of passes on Semantic3D dataset. The first column depict the ground truth.

Semantic3D-vs-S3DIS - Flipout

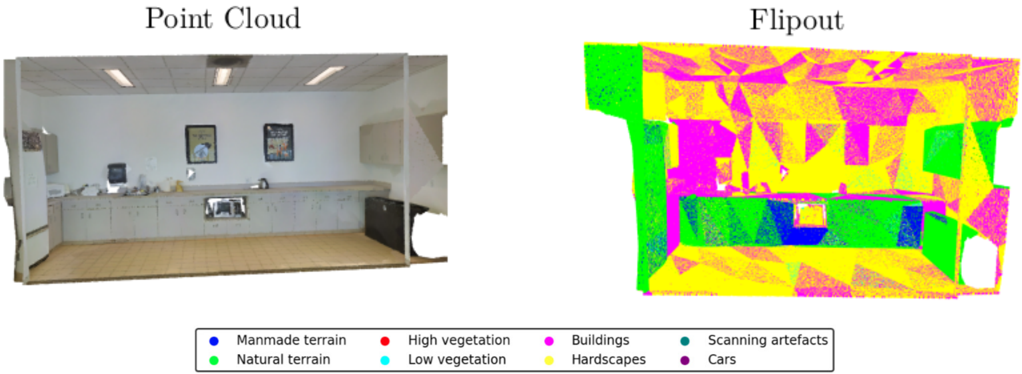


Figure 16: Predictions of RandLA-Net on S3DIS (OOD) dataset. First column representing the point cloud, second column presenting the predictions from Flipout (15 number of passes).

Semantic3D-vs-S3DIS - Flipout

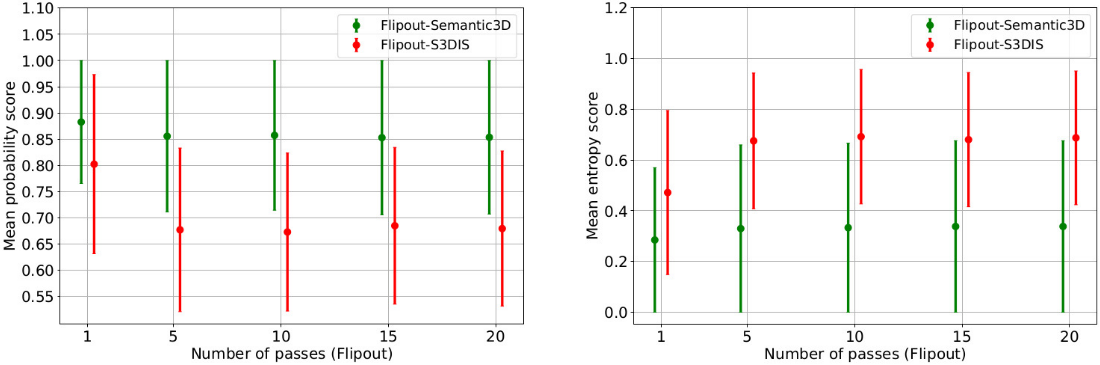


Figure 17: Graphs representing the mean probability value and mean entropy as a dot for Semantic3D (ID) in green and S3DIS (OOD) in red when using Flipout. The variance is represented via the error bars.

Semantic3D-vs-S3DIS - AUROC Scores

Ensemble size/ #passes	Method	AUROC	
		MSP	Entropy
1	Dropout	0.53311	0.53041
	Flipout	**0.69988**	**0.69368**
	Deep Ensembles	0.62020	0.62529
5	Dropout	0.58439	0.57821
	Flipout	0.77885	0.76934
	Deep Ensembles	**0.84013**	**0.83665**
10	Dropout	0.60168	0.59925
	Flipout	0.78728	0.78327
	Deep Ensembles	**0.87929**	**0.87541**
15	Dropout	0.59773	0.59557
	Flipout	0.7667	0.76741
	Deep Ensembles	**0.88486**	**0.88246**
20	Dropout	0.59766	0.59661
	Flipout	0.77331	0.77237
	Deep Ensembles	**0.89338**	**0.89052**

Table 3: AUROC scores calculated for all the points in the test sets of Semantic3D and S3DIS for Dropout, Flipout, and Deep Ensembles generated using MSP and entropy values for various ensemble sizes and forward passes.

Semantic3D-vs-S3DIS - AUROC Scores

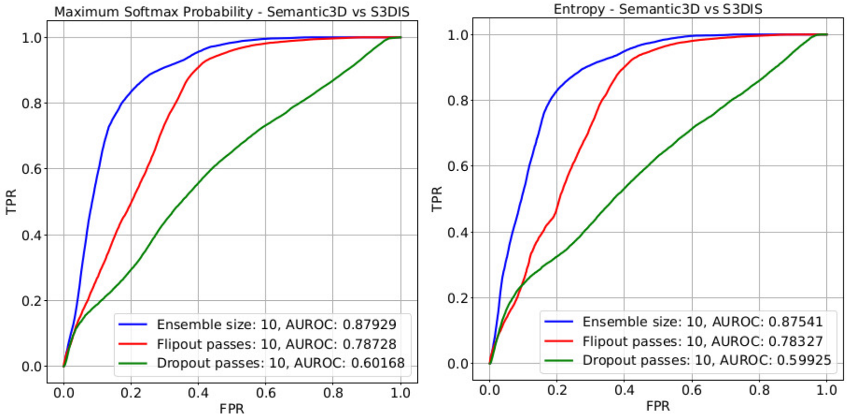


Figure 18: ROC curves of Semantic3D-vs-S3DIS for 10 Ensembles, 10 forward passes for Flipout and Dropout using Maximum Softmax Probability and Entropy respectively.

Experiments

- Semantic3D-vs-S3DIS
- Semantic3D-vs-Semantic3D without colour
  - Deep Ensembles
  - Flipout
  - Area Under Receiver Operating Characteristic (AUROC) score comparison

Semantic3D colour-vs-without colour - Deep Ensembles

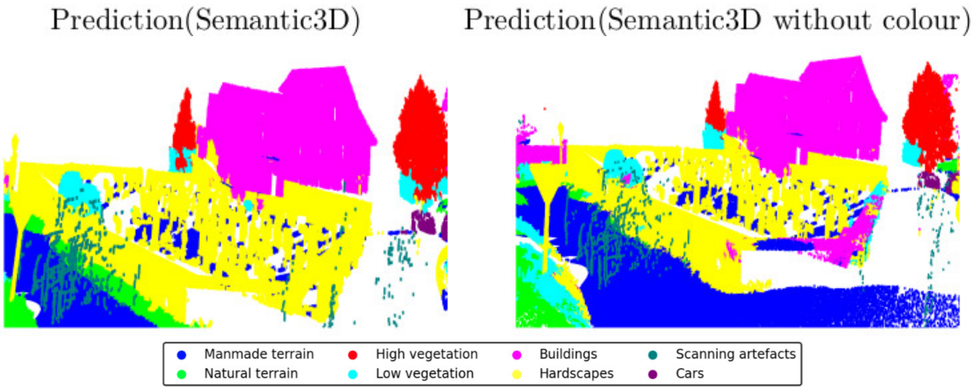
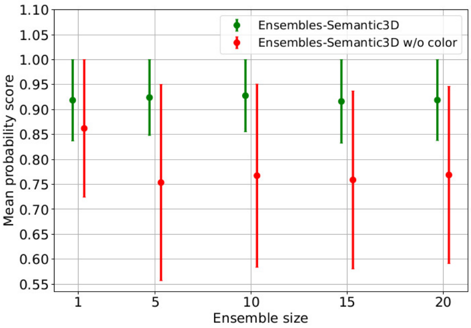


Figure 19: Output predictions of the RandLA-Net over the Semantic3D dataset and Semantic3D without colour dataset using Deep Ensembles (Ensemble size of 10).

Semantic3D colour-vs-without colour - Deep Ensembles



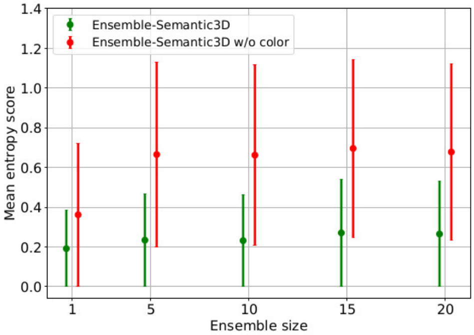
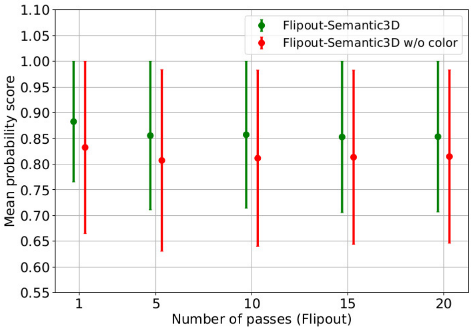


Figure 20: Graphs representing the mean probability value and mean entropy as a dot for Semantic3D (ID) in green and Semantic3D without colour (OOD) in red when using Deep Ensembles. The variance is represented via the error bars.

Semantic3D colour-vs-without colour - Flipout



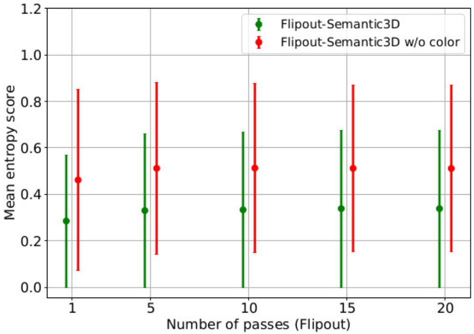


Figure 21: Graphs representing the mean probability value and mean entropy as a dot for Semantic3D (ID) in green and Semantic3D without colour (OOD) in red when using Flipout. The variance is represented via the error bars.

Semantic3D colour-vs-without colour - AUROC Scores

Ensemble size/ #passes	Method	AUROC	
		MSP	Entropy
1	Dropout	0.66349	0.65908
	Flipout	0.64221	0.66157
	Deep Ensembles	**0.67855**	**0.67866**
5	Dropout	0.69448	0.68507
	Flipout	0.63743	0.66536
	Deep Ensembles	**0.76769**	**0.77120**
10	Dropout	0.68568	0.68004
	Flipout	0.63712	0.66535
	Deep Ensembles	**0.77837**	**0.78142**
15	Dropout	0.68975	0.68347
	Flipout	0.63022	0.65976
	Deep Ensembles	**0.77302**	**0.77881**
20	Dropout	0.68447	0.68199
	Flipout	0.63017	0.65934
	Deep Ensembles	**0.77031**	**0.77584**

Table 4: AUROC scores in case of Semantic3D-vs-Semantic3D without colour for Dropout, Flipout, and Deep Ensembles generated using MSP and entropy values for various ensemble sizes and forward passes.

Semantic3D colour-vs-without colour - AUROC Scores

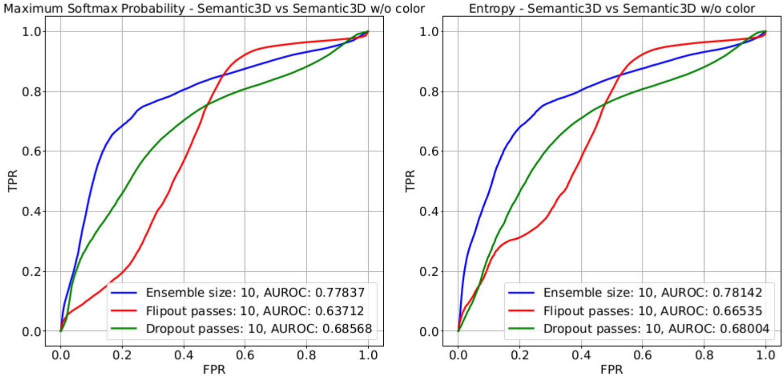


Figure 22: ROC curves of Semantic3D-vs-Semantic3D without colour for 10 ensembles, 10 forward passes for Flipout and Dropout using Maximum Softmax Probability and Entropy scores respectively.

Conclusion

- We propose two benchmark datasets
  - Semantic3D-vs-S3DIS (Outdoor-vs-Indoor) - Easy OOD identification
  - Semantic3D-vs-Semantic3D without colour - Hard OOD identification
- The second case is hard because of same point geometry between ID and OOD datasets
- Both Maximum Softmax Probability and Entropy are able to identify OOD points
- Deep Ensembles outperform Flipout and Dropout in both the benchmark datasets

Lessons Learned

- Training and evaluation of 3D DNNs are time-consuming and resource-intensive.
- Finding the proper prior for Flipout layers is hard and currently we use brute force to find the best fitting prior.
- LiDAR datasets have large memory requirements especially for preprocessing and metric computation.
- 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 is limited to only point-based models, this can be extended to graph and projection-based models.
- 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.
- Since this thesis utilizes post-hoc threshold methods for OOD detection. Other methods such as Mahalanobis distance-based OOD detection [6] or MetaSeg [8] can be added as an extension to this thesis.

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What is OOD Detection?

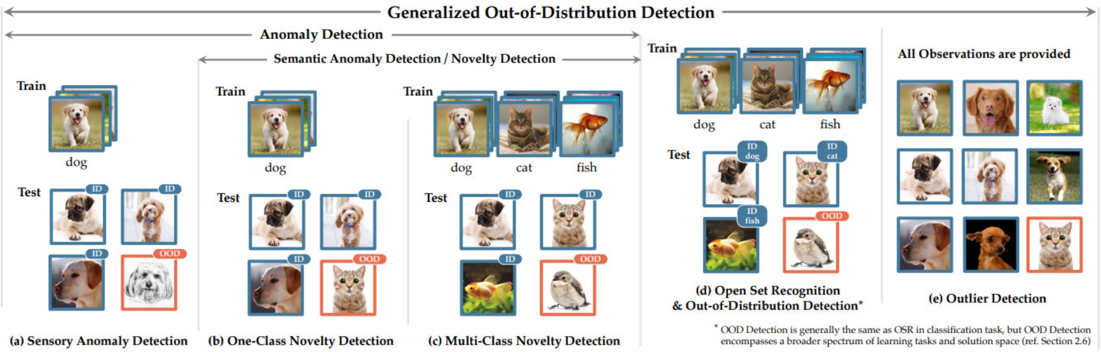

Figure 23: Generalized Out-of-Distribution Detection: A Survey

Semantic3D-Deep Ensembles

		IoU per-class								
Ensemble size	**meanIoU**	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**Accuracy**
1	68.19	94.55	81.19	84.67	29.43	81.37	18.85	64.74	90.74	88.78
5	69.51	94.73	81.92	84.42	28.05	**86.41**	28.50	61.03	91.03	90.04
10	69.97	95.25	83.73	86.63	30.36	84.13	18.60	**66.01**	92.61	89.94
15	70.32	95.27	83.54	**88.22**	**32.19**	84.82	26.17	61.67	90.75	**90.57**
20	**70.80**	**95.55**	**84.11**	86.65	29.60	85.41	**29.58**	62.47	**93.06**	90.56

Table 5.1: Illustration of performance of RandLA-Net on Semantic3D over ensemble size. meanIOU, IOU per-class and overall accuracy are represented here. C1 to C8 are the classes of Semantic3D which are Manmade terrain, Natural terrain, High vegetation, Low vegetation, Buildings, Hardscapes, Scanning artefacts, and Cars.

Semantic3D-Flipout

		IoU per-class								
#Passes	MeanIoU	C1	C2	C3	C4	C5	C6	C7	C8	Accuracy
1	69.95	94.24	80.09	86.16	22.48	88.70	39.41	57.42	91.12	90.71
5	69.83	94.38	80.21	84.10	23.32	87.80	39.68	57.75	91.43	90.43
10	69.84	94.38	80.16	83.90	23.46	87.73	39.75	57.83	91.47	90.40
15	69.86	94.38	80.17	83.80	23.48	87.73	39.82	57.96	91.57	90.40
20	69.87	94.38	80.18	83.80	23.57	87.72	39.84	57.92	91.57	90.40

Table 5.2: Illustration of performance of Flipout-versioned RandLA-Net on Semantic3D dataset. meanIOU, IOU per-class and overall accuracy are represented here. C1 to C8 are the classes of Semantic3D which are Manmade terrain, Natural terrain, High vegetation, Low vegetation, Buildings, Hardscapes, Scanning artefacts, and Cars.