

State of the Art This chapter will discuss the 3D LiDAR datasets available and classify them based on the type of acquisition. Among 3D LiDAR datasets, [?] classifies the available public datasets into three classes based on the data acquisition type.

Typically static datasets produce highly dense point clouds leading to rich geometric representations. The last type of 3D LiDAR dataset is the synthetic dataset. As the name suggests, these datasets are generated from simulation. The datasets belonging to each acquisition type are summed up in Table ?? . Most of the datasets from Table ?? are static.

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

We chose the Semantic3D dataset as the in-distribution (ID) training dataset from the available datasets. S3DIS is used for 3D Semantic Segmentation Models.

This section will discuss the methods available for 3D semantic segmentation. The discussion includes a brief peek into traditional and deep learning approaches.

**Traditional Approach** Traditional methods involve a complex feature extraction and passing these features to a classifier.

**Deep Learning Approach** Deep learning-based models are efficient at segmentation and can be divided into three types: point-based, projection-based, and graph-based.

**Point-based methods** Let us look briefly into the point-based methods. Point-based methods usually utilize fully connected layers or traditional CNNs.

**Projection-based methods** The other flavours of point-based methods include projection onto a d-dimensional lattice or making the point cloud into a 2D range image.

**Graph-based methods** In projection-based models, let us discuss the models that project the data onto a 2D range image. The first of this type is the range image.

**Bird eye view projection** We now discuss the projection-based models which involve bird eye view projection. These models are relatively new.

**Summary** Table ?? illustrates the detailed summary of each model and the number of parameters. Finally, graph neural networks are also discussed.

**Uncertainty Estimation Methods** This section will discuss existing methods to estimate uncertainty in deep neural networks.

**Epistemic and Aleatoric Uncertainty** [?] argues that there are two kinds of uncertainties, they are epistemic and aleatoric uncertainty. Epistemic uncertainty is due to lack of data.

**Ensembles** ensembles can be found in Section ??.

**Deep Learning Methods** Because of the higher computational complexity and resource intensiveness, there exist multiple flavours of the deep learning methods.

**Snapshot Ensembles** Other methods include snapshot ensembles [?] which iterate over multiple local optima in the optimization landscape.

**Bayesian Methods** Existing neural networks are trained in maximum likelihood, resulting in point estimates for the parameters.

Here  $\theta$  represents network parameters (weights),  $p(\theta)$  represents prior distribution over  $\theta$ , and  $x$  and  $y$  represent the input and output respectively.

Here  $\theta$  represents trained network parameters,  $x$  and  $y$  represent the training set, and  $x_t$  and  $y_t$  represent the test set. The goal is to learn a function  $f$  that maps  $x$  to  $y$ .

**VI** VI is an approximation method where the posterior probability  $p(\theta|x, y)$  is approximated by specific distributions  $q(\theta)$ .

**Monte Carlo Dropout** Another widely known example for VI is Monte Carlo Dropout (MC-Dropout), in which the dropout layers are re-sampled during inference.

**Out-of-Distribution detection** This section will discuss the difference between OOD, Anomaly using an example and how to detect them.

**OOD/Anomaly/Distributional shift** [h!] 0.333 [height=0.15width=0.95]images/intro\_ood\_anomaly/old\_ship.jpg 0.333

**Let us time travel back to 18<sup>th</sup> century** and assume that we had implemented a DNN model to detect ships. The data is from the 18<sup>th</sup> century.

**Anomaly** An anomaly can be defined as the patterns that do not conform to the expected training behaviour as proposed in [?].

**OOD** In the case of OOD, the input is drawn from an unknown distribution of unknown data, which is not near to the training data.

**OOD Detection Methods** This subsection will discuss the existing OOD detection methods for 2D classification and regression.

**Benchmarks** The most widely used benchmark datasets for 2D classification are CIFAR-10 vs SVHN [?], CIFAR-10 vs LSUN [?], and CIFAR-10 vs ImageNet [?].

[?] has proposed a threshold-based OOD detection method using the Mahalanobis distance as a confidence score. The Mahalanobis distance is defined as:

where  $h(x)$  is final layer activations,  $c$  is the constant and  $h^-(x)$  is ReAct output of  $h(x)$ . The score from this ReAct function is used to detect OOD samples.

The OOD data samples have higher uncertainty than ID samples, allowing us to use the uncertainty estimation method to detect OOD samples.

In recent years, OOD detection for the task of 2D semantic segmentation has been in limelight. [?] proposes the ad-