

Methodology This chapter will discuss the RandLA-Net used for 3D semantic segmentation, especially network architecture. RandLA-Net utilizes random point sampling among the other sampling methods such as Farthest Point Sampling, etc. Figure ?? represents the local features aggregation module for the RandLA-Net. This module is applied parallelly on the point cloud. Local Spatial Encoding (LocSE) The local spatial encoding module takes each point ( $p_i$ ) in the point cloud (P) and performs the following operations:

- Finding nearest neighbours
- Relative position encoding
- Feature augmentation

In step 1, neighbour points for point ( $p_i$ ) are collected using the euclidean distance-based K-nearest neighbour (KNN) method.

where  $r_i^k$  is the relative position of point  $p_i$  with respect to  $p_i^k$ , here in  $p_i$  and  $p_i^k$  only the x,y and z positions are used.  $r_i^k = p_i - p_i^k$ .

Dilated Residual Block Dilated Residual Block is a ResNet inspired module claimed by authors and represented as in Figure 3.10. To summarize, up to this point, we have studied the unique feature of RandLA-Net. That is how random point sampling is used in the RandLA-Net architecture. RandLA-Net is an encoder-decoder architecture with skip connections used in various segmentation tasks. We chose RandLA-Net because of the following reasons:

- Efficient extraction of complex structures progressively using Local Feature Aggregation (LFA) module.
- Has fewer parameters (1.24M), making training efficient, as 3D semantic segmentation models are computationally expensive.
- Proven performance over various datasets such as Semantic3D and SemanticKITTI, along with ablation study of each module.
- No preprocessing such as range image representation as in [?] or farthest point sampling with a computational complexity of  $O(N^2)$ .
- State of the art performance in point-based methods, consisting of Multi-Layer Perceptrons (MLP) and without expensive attention mechanisms.
- Evaluation metrics-Semantic Segmentation To evaluate the performance of RandLA-Net over the training dataset (KITTI), we used the following metrics:
- Mean Intersection-over-Union (mIoU) Mean Intersection-over-Union is a widely used metric for performance evaluation in semantic segmentation.

Where  $N$  is the number of classes,  $p_k$  and  $g_k$  are predicted mask and ground truth mask of  $k^{th}$  class.

Accuracy Accuracy is another widely used metric, which can be quantified as a number of points in the point cloud correctly classified.

Where TP, TN, FP and FN are True Positives, True Negatives, False Positives and False Negatives, respectively, from the confusion matrix. Here, we conclude the study of RandLA-Net, the reason for its effective performance, argue the reasons to choose RandLA-Net. Despite their performance boosting ability, they are also used to estimate uncertainty as in [?]. [?] proposes that with the help of Flipout. Flipout In this thesis, we also employed the Flipout version of the RandLA-Net model for uncertainty estimates, and the results are discussed in Chapter 5.

So the node output of the neural network is modified as

Here  $\phi$  is the activation function, and  $x_n$  is the  $n^{th}$  input example in the mini batch. This whole operation is vectorized as

Authors also argue that the Flipout reduces the variance in gradients when compared to shared perturbation but has a slight overhead.

At a glance, these random weight perturbations give us slightly different output estimates for every forward pass. In Figure 3.11, we illustrate the test dataflow in Flipout. Here  $F_1$  represents the flipout trained model and  $y$  represents the ground truth. OOD estimates In this section, we discuss the two methods used to generate the OOD score for classifying the OOD samples. Maximum Softmax Probability First proposed in [?], uses the probability of the classification from the Softmax for OOD estimation.

Entropy Entropy is defined by [?] as an "ill-defined notion of chaos or uncertainty". Entropy has its roots in thermodynamics.

In theory, following this formula, if the point in the point cloud is from In Distribution (ID), the softmax output is high. Evaluation metric-OOD detection This section will discuss the metrics used for evaluating OOD detection. Firstly, we generate a ROC curve. A ROC curve is generated, given a set of probabilities/scores and their true labels which are either positive or negative. Area Under an ROC curve Since the ROC curves are a two dimensional depiction and we need a single scalar value to represent the OOD detection performance, we use the Area Under the Curve (AUC) metric.