

Methodology and Setup This chapter will discuss the RandLA-Net used for 3D semantic segmentation, especially in random point sampling. We select K points uniformly from the original point cloud in random point sampling and Figure ?? represents the local features aggregation module for the RandLA-Net. This module is applied parallelly on Local Spatial Encoding The local spatial encoding (LocSE) module takes each point ( $p_i$ ) in the point cloud (P) and 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)

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. (

Where  $g$  is the softmax function and  $W$  is the attention weights,  $\hat{f}_i^k$  is the input feature vector to the attentive pooling Dilated Residual Block Dilated Residual Block is a ResNet inspired module claimed by authors and represented as To summarize, up to this point, we have studied the unique feature of RandLA-Net. That is how random point sampling RandLA-Net Architecture RandLA-Net is an encoder-decoder architecture with skip connections used in various segmentation We chose RandLA-Net because of the following reasons:

Efficient extraction of complex structures progressively using Local Feature Aggregation (LFA) module.  
Fewer parameters (1.24M) compared to other SOTA 3D semantic segmentation models, making training efficient, as 3D Proven performance over various datasets such as Semantic3D and SemanticKITTI, along with ablation study of each step No preprocessing such as range image representation as in [?] or farthest point sampling with a computational complexity State of the art performance in point-based methods, consisting of Multi-Layer Perceptrons (MLP) and without expensive 3D Semantic Segmentation Evaluation Metrics To evaluate the performance of RandLA-Net over the training datasets Mean Intersection-over-Union (mIoU) Mean Intersection-over-Union is a widely used metric for performance evaluation

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

Where TP, TN, FP and FN are True Positives, True Negatives, False Positives and False Negatives, respectively, from the 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 Flipout In this thesis, we also employed the Flipout version of the RandLA-Net model for uncertainty estimates, and

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. Also the vectors  $r_n$  and  $s_n$  are input

At a glance, these random weight perturbations give us slightly different output estimates for every forward pass. In [scale=0.5]images/flipout.jpg Illustration of test dataflow in Flipout. Here  $F_1$  represents the Flipout trained model and OOD Estimates In this section, we discuss the two methods used to generate the OOD score for classifying the OOD Maximum Softmax Probability First proposed in [?], Maximum Softmax Probability (MSP) uses the probability of

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 OOD Detection Evaluation Metrics This section will discuss the metrics used for evaluating OOD detection. Firstly 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 depictions and we need a single scalar value Experimental Setup This section will discuss the libraries used and training parameters of the RandLA-Net for Deep

Python - 3.6

Tensorflow - 1.15.0

Tensorflow probability - 0.7.0

Open3d-python - 0.3.0 (training), 0.13.0 (visualizations)

Deep Ensembles For Deep Ensembles, we trained 20 randomly initialized instances of RandLA-Net on the SemanticKITTI dataset every  $5^{th}$  forward pass. [scale=0.42]images/fout,randlanet.png Flipout – versioned RandLA – Net where the last three forward