**Reaction Report**

Semantic segmentation of 3D point clouds involve various challenges. These challenges have caused the hurdles in achieving better performance. Few of these challenges include the management of extensive amount of data on large scale also the lack of proper data structure that has served as crucial element in traditional CNN for better performance. There are different solutions which has been proposed over past few years to work around deep learning models performances on 3D point clouds. One of the major techniques proposed was to convert the 3D point cloud in 2D RGBD format and other one converts the point clouds in 3D voxel grid. Both of these methods have limitation such as loss of information due to conversion of 3d to (2d and voxel grid). In case of 2D format reconstruction of 3D later after segmentation require computation which will add to the cost and also a very expensive process.

An approach was proposed by Loic Landrieu and Martin Simonovsky in their paper Large-scale Point Cloud Semantic Segmentation with Superpoint Graphs which deals with major challenges of semantic segmentation of 3D point cloud by using a graph representation of point clouds. Methodology proposed has significantly changed the idea of representation of 3D point clouds. It transform the input point clouds into geometric shapes which are called superpoints and these super points are connected to each other with edges. These are not necessarily objects but could be part of objects and edges can help understand the contextual information for classification in later stage. This methodology is using PointNet for superpoint embedding and graphs convolutions for contextual segmentation. One of the advantage of using superpoints or geometric shapes is the reduction of size of large scale data points into limited points due to grouping which efficiently increased performance also utilization of contextual information. There is one interesting aspect which makes cluster semantically homogenous but doesn’t use class labels beyond validation. This stage of pipelining is highly unsupervised procedure. There are two energies local and global that has been identified using features calculated from point clouds such as colors, intensity, linearity, planarity, scattering and verticality also elevation of each point. Superpoint graphs are constructed using superedges which have been described by features which are described by features of adjacent superpoints such as length, volume and surface. PointNet transform the shapes into unit sphere before embedding which can be fed to model as input along position, observation and features also the actual shape details are concatenated which is used to transform the subsample of superpoints in actual shape after maxpooling. Last major step in the pipeline is classification which uses contextual information of super edges between super points to identify relationship and class labels for superpoints. It also utilizes the channels in graph convolution network which are essential for identifying the class label and ignore channels using lower weight for obvious class labels using Gating Recuurent Unit. Testing for such deep learning models can be made mmemory efficient by turning off layer activation as soon as the next layers have been computed. Performance was evaluated and proposed methodology has outperformed previous models in IoU and accuracy.

In my opinion proposed system has given an interesting approach to handle the major challenges in the 3D point cloud semantic segmentation using deep learning. It has catered the challenges by best available option and combination of existing methodologies. They have cleverly utilized the options of downsampling by using subsamples for embedding PointNet. Though using subsamples can be chaotic in different set of problems. It can cause and over fitting problem if the test error is high. Though it doesn’t lose much information due to utilization of graph representation and contextual information helps in class labelling but tuning weights for GRU where class labels are obvious can be very tricky and might require consideration of many aspects with respect to different set of data.