PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space

NIPS 2017

Summary

PointNet++ presents an extension of the PointNet architecture, addressing the limitations of PointNet in dealing with fine-grained structures and non-uniform input point clouds. PointNet++ introduces hierarchical feature extraction at different scales using fine-to-coarse grouping and PointNet layers as local feature extractors. Furthermore, density-adaptive layers are presented which increase performance on input point clouds of non-uniform density by intelligently aggregating features based on local point density.

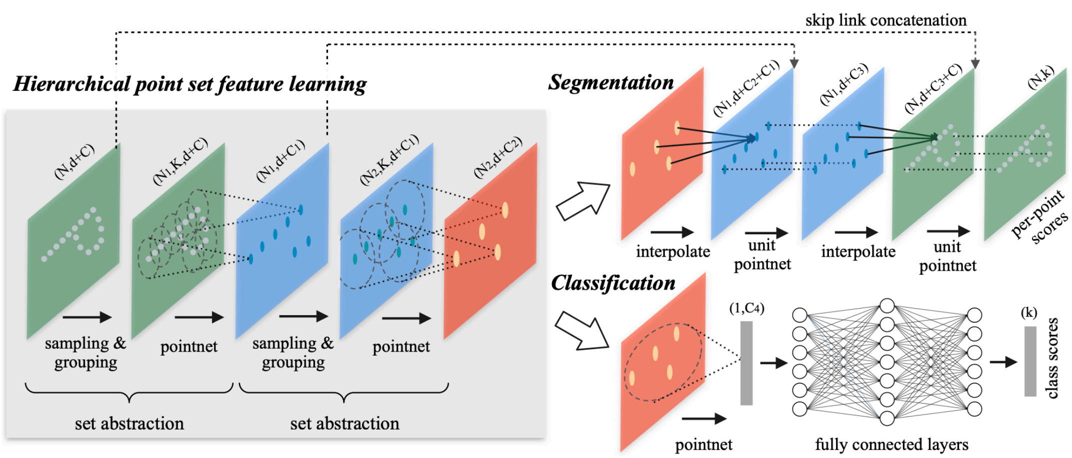

Figure 1: Illustration of the PointNet++ architecture. Stacked Set Abstraction Levels extract density-dependent multi-scale features. For segmentation tasks, a feature propagation module is used to up-sample to the original number of points.

Main Contributions

- **Hierarchical Feature Extraction** The feature extraction pipeline consists of several so-called *Set Abstraction Levels*, each consisting of three main components: 1) a sampling layer which computes a set of centroid points using farthest point sampling; 2) a grouping layer that forms clusters by assigning points to the previously computed centroids and 3) a PointNet layer which computes a feature vector for each region. By stacking several Set Abstraction Levels, the final feature vectors consist of information extracted at different scales.

- **Density-adaptive Grouping Layers** Robustness to non-uniform point cloud densities is an important property as models trained on dense point clouds don't necessarily generalize well to sparse input data. The authors propose two different density-adaptive grouping layers, Multi-Scale Grouping (MSG) and Multi-Resolution Grouping (MRG). Consequently, each set abstraction level extracts features at different scales and combines them intelligently by taking into account local point density.

Implementation Details

- **Multi-Scale Grouping** Instead of generating one neighborhood of fixed size in the grouping layer, several neighborhoods are created for each of which a PointNet layer extracts a feature vector which are then concatenated to form a multi-scale feature. To enforce an optimal combination of multi-scale features, the network is trained using *random input dropout*. By randomly dropping input points, the network is presented with point clouds of varying sparsity and uniformity.

- **Multi-Resolution Grouping** Multi-Scale Grouping is computationally expensive as a PointNet layer is used for each centroid point. Multi-Resolution Grouping is obtained by concatenating two feature vectors. One is computed by summarizing the abstracted features from a lower, higher-resolution level and the second by applying a PointNet layer to all local points at the current level. In case of low density, the second component proves to be more reliable, whereas high-resolution information can be obtained from the first feature in case of high density.

- **Feature Propagation** For segmentation tasks, the number of input points has to be preserved. However, the Set Abstraction Levels sub-sample the input point cloud to obtain a hierarchical representation. In order to restore the original number of points, inverse distance weighted average based on k-NN is applied in combination with skip-connections to invert the sub-sampling.

Evaluation

- **Density Robustness Analysis** In order to test robustness to non-uniform densities, virtual scans are created from ScanNet data by simulating a camera projection that results in higher densities close to the camera. The results of the experiments on ScanNet for uniform and non-uniform densities are displayed in Figure 2. It can be observed that hierarchical feature learning drastically improves performance compared to a voxelized 3D-CNN baseline as well as PointNet. This observation holds even for non-uniform input point clouds, showing the positive impact of the density-adaptive modules.

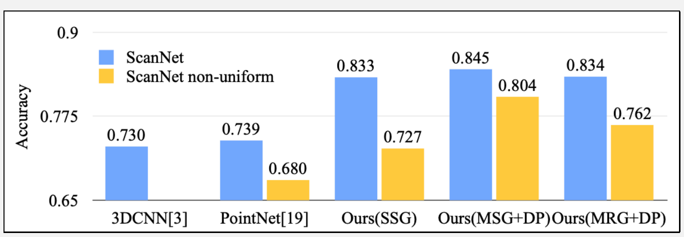

Figure 2: Results of Density Robustness Analysis.

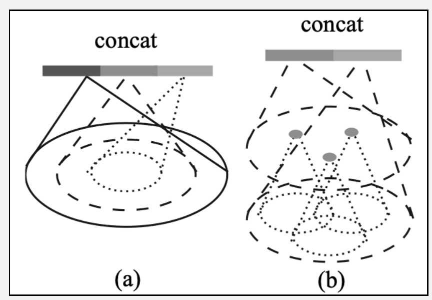

Figure 3: Illustration of the density-adaptive Grouping Layers. a) MSG; b) MRG.

References

This summary is solely based on my understanding of the original paper. All images used here are taken from the original paper as well. The paper can be found under the following link:
`https://arxiv.org/pdf/1706.02413.pdf`