POINTNET++: DEEP HIERARCHICAL FEATURE LEARNING ON POINT SETS IN A METRIC SPACE

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INTRODUCTION

- **Context:** Analyzing geometric point sets, such as those from 3D scans, is crucial for applications like autonomous vehicles.
- **Challenges:** Point clouds must be invariant to permutations, and their local structures vary due to factors like scanning density.
- **Prior Work:** PointNet directly processes 3D data but lacks the ability to capture local geometric structures effectively.
- **New Approach:** Introducing PointNet++, a hierarchical network that processes points in a metric space to capture fine to coarse geometric structures.

INTRODUCTION (CONT'D)

- **Design Goals:** PointNet++ uses overlapping local regions and a recursive application of PointNet to abstract point features hierarchically.
- **Unique Aspects:**
  - Overlapping partitions defined by a farthest point sampling (FPS) algorithm to ensure coverage.
  - Multi-scale neighborhood processing to handle non-uniform densities effectively.
- **Advantages:** Adapts to data and metric, ensuring efficient and effective feature extraction compared to traditional CNN approaches.

PROBLEM STATEMENT

- **Metric Space Definition:** $\mathcal{X} = (M, d)$ where $M \subseteq \mathbb{R}^n$ and d is the distance metric derived from Euclidean space.
- **Goal:** Develop function f that can process $\mathcal{X}$ to produce semantic outputs, such as classification or segmentation.
- **Challenge:** Non-uniform density of M, impacting the effectiveness of local pattern learning.
- **Relevance:** Processing the varying densities and scales of point sets to extract meaningful semantic information.

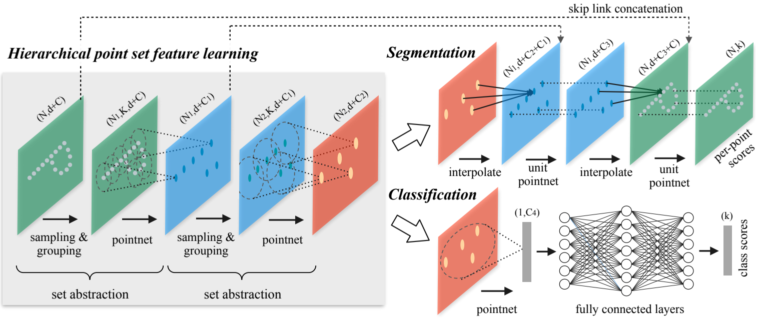
REVIEW OF POINTNET

- PointNet processes unordered point sets directly, using a multi-layer perceptron (MLP) to encode spatial information of each point.
- Aggregates features using a max pooling operation, ensuring permutation invariance.

$$f(x_1, x_2, ..., x_n) = \gamma\left(\underset{i=1,...,n}{\mathrm{MAX}}\left\{h(x_i)\right\}\right) \tag{1}$$

HIERARCHICAL POINT SET FEATURE LEARNING

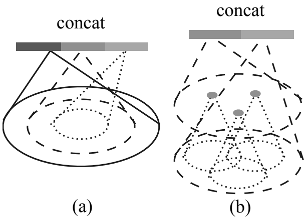
- Hierarchically grouping points to abstract local regions progressively.



Hierarchical feature learning architecture in PointNet++.

ROBUST FEATURE LEARNING UNDER NON-UNIFORM SAMPLING

- PointNet++ uses multi-scale grouping (MSG) and multi-resolution grouping (MRG) to handle varying densities.
- Adapts to local density changes, improving robustness and detail capture:
  - MSG learn to combine the multi-scale features with random input dropout.
  - MRG combines features by concatenate lower-level layer with raw data processing in the local region.



Multi-scale and multi-resolution grouping in PointNet++.

FEATURE PROPAGATION FOR SET SEGMENTATION

- Hierarchical feature propagation strategy interpolates features from sampled to original points for original point set for segmentation.
- Inverse distance weighting for KNN, MLP with ReLu for feature update. Repeated until get back the original point set with sematic features:

$$f^{(j)}(x) = \frac{\sum_{i=1}^{k} w_i(x) f_i^{(j)}}{\sum_{i=1}^{k} w_i(x)} \quad \text{where} \quad w_i(x) = \frac{1}{d(x, x_i)^p}, \; j = 1, \ldots, C \qquad (2)$$

EXPERIMENTS: OVERVIEW OF DATASETS

- **MNIST:** 60k training and 10k testing samples of handwritten digits.
- **ModelNet40:** 9,843 training and 2,468 testing samples of 3D CAD models.
- **SHREC15:** 1,200 shapes from 50 categories, using five-fold cross-validation.
- **ScanNet:** 1,513 scanned and reconstructed indoor scenes with 1,201 for training and 312 for testing.

CLASSIFICATION EXPERIMENTS ON MNIST AND MODELNET40

- Evaluated on MNIST (2D) and ModelNet40 (3D).
- **MNIST:** Images converted to 2D point clouds.
- **ModelNet40:** 3D point clouds sampled from mesh surfaces.
- Networks trained with 512 points for MNIST and 1024 points for ModelNet40.
- Additional features and more points used for higher performance.
- Evaluating Robustness to Point Density Variation
  - Test robustness by randomly dropping points during test, reducing point density.
  - Effectiveness of multi-scale and resolution strategies.

SEMANTIC SCENE LABELING EXPERIMENT ON SCANNET DATASET

- Goal: Predict semantic labels for points in indoor scans.
- Compared with baselines on the ScanNet dataset.
- Hierarchical feature learning captures multi-scale geometric features.

POINT SET CLASSIFICATION IN NON-EUCLIDEAN METRIC SPACE

- Metric Space and Intrinsic Features: Using geodesic distances to create a metric space and intrinsic features like WKS, HKS, enabling classification despite pose variations.
- Methodology and Implementation: Constructs a geodesic metric space, samples and groups points based on this space, and uses PointNet++ to learn multi-scale intrinsic structures
- Performance and Results: Outperforms state-of-the-art approaches