Learning with Noisy Labels for Robust Point Cloud Segmentation

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PNAL Framework

Warm-up Stage
- According to the study of memorization effects, in the presence of noisy labels, DNNs are prone to learn clean, easy samples first. Therefore, in the warm-up stage, we train the network with a common cross-entropy loss.

Noise Cleaning Stage
- Point-Level Confidence Selection aims to select reliable samples from each mini-batch and obtain the confidential labels for these samples that can be corrected with high probability. In detail, a sample with consistent label prediction history is regarded as the reliable sample, and its most frequently predicted label is the reliable label.

- Cluster-Level Label Correction aims to correct the noise at the cluster level, considering local relationship between point labels. Cluster-wisely, we count the occurrences of reliable labels for each class. Then we get a winner label by voting from the top reliable labels, and overwrite the labels within this cluster with it and iteratively correct the training set.

Results
- Qualitative results on artificial noisy data: results of our framework is more in line with clean GT.
- Quantitative results on artificial noisy data: our framework produces much better results than all baselines. Even on 60% noise, our results is comparable to trained completely clean dataset.
- Qualitative results on real-world noisy data: results of our framework is more reasonable than GT labels given by ScanNetV2 validation set.
- Quantitative results on real-world noisy data: our framework achieves significant performance gain.
- Visualization of the label correction process during training. The correction process spreads from large areas to small objects and to whole training set as the training proceeds.

Motivation
- To correct the instance-level label noise, we create a cluster-based noise correction method, since instance label may not be available.
- While noise rate is unknown, variant and possibly heavy for real-world noisy dataset, we design a novel noise-rate blind framework.
- To take neighbor point correlations into consideration and generate the best possible label, we propose a voting strategy.

Background and Introduction
- Clean 3D data labels are difficult to obtain because of massive point number and complex annotation process. Even the commonly used 3D scene dataset ScanNetV2 suffers from noisy label problem.
- Most noisy-robust works focus on image classification. And they are not applicable or suboptimal to apply on point segmentation.
- In this work, we take the lead in solving this issue by proposing a novel Point Noise-Adaptive Learning (PNAL) framework.

Problem Description
- Formally, we denote point cloud data as \( X \in \mathbb{R}^{N \times C} \) of \( N \) points with \( C \) features of coordinates and \( RGB \) values possibly, and its noisy semantic label as \( Y \), and \( M \) as the class number. Our target is to train a model \( f_{\theta}(X) \) robust to the label noise in the training set. Based on our observation and its official annotation pipeline of popular real-world dataset, label noise is mainly at instance level.

Highlight
- We are the first to investigate noisy label problem on point cloud data which has a wide and urgent need for 3D applications where the volume of data is growing drastically.
- A novel and effective noise-rate blind framework PNAL is proposed with point-level confidence selection and cluster-level label correction with voting mechanism.
- We refine the validation set of ScanNetV2 with more accurate labels to facilitate point segmentation and noisy label learning.

Code: https://github.com/pleaseconnectwifi/PNAL
- Computationally efficient implementation
- Dataset: https://shuquanye.com/PNAL_website/
- A re-labeled clean ScanNetV2 validation

Dataset:

- Code: ☑
- Training: Related: OA
- GT
- Qualitative: (PNAL)