PLT: Point Ladder Tuning with Multi-Scale Prompt for Point Cloud Parameter-Efficient Learning

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Abstract

Point cloud analysis has advanced significantly with the use of pre-trained models, which traditionally rely on fine-tuning approaches that involve fully updating model parameters. However, in this study, we demonstrate that superior performance in point cloud analysis can be achieved by selectively updating a minimal subset of parameters and focusing on local neighborhood information, eliminating the need for exhaustive parameter updates and global attention mechanisms. Our approach leverages parameter-efficient transfer learning to optimize task performance while minimizing parameter overhead. Specifically, we freeze the parameters of standard pre-trained models and introduce a Hierarchical Ladder Network (HLN) to extract essential local information directly from the input point cloud. This focus on local information facilitates more refined feature extraction without excessive dependence on global context. To bridge this local information with the backbone network's intermediate global representations, we propose a Local-Global Fusion (LGF) module, which effectively integrates multi-scale features. Furthermore, our approach employs dynamic prompts generated from these fused features, enhancing the backbone network's ability to produce global features optimized for various downstream tasks. Comprehensive experiments across tasks (point cloud object classification, dense prediction), demonstrate the effectiveness of our method. Our approach achieves superior performance while using substantially fewer parameters compared to full fine-tuning, requiring only 2.71% and 7.69% of the parameters for object classification and dense prediction, respectively.

1. Introduction

The growing accessibility of 3D scanning technology has elevated 3D point cloud learning to an emerging research area with diverse applications across computer vision and graphics fields, including autonomous driving (add citation), virtual and augmented reality (VR/AR) (add citation), and robotics (add citation). Unlike images, point clouds are inherently unstructured, sparse, and permutation-invariant, which poses unique challenges for effective analysis and processing. Consequently, deep learning-based methods [12, 26, 30, 33–35, 38, 48, 50, 51, 60, 64] specifically tailored for point cloud learning have been developed, incorporating specialized modules to directly handle point cloud data and achieving substantial improvements in performance.

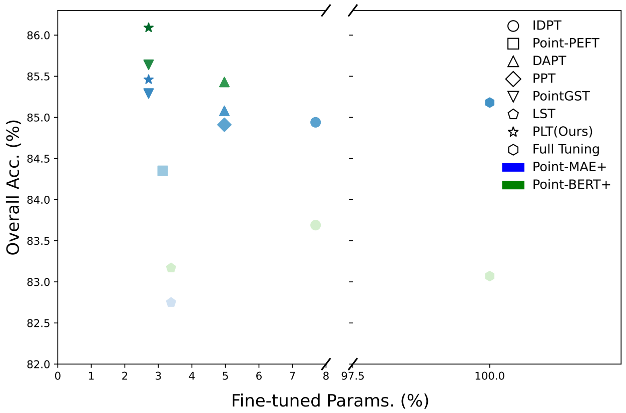


Figure 1. The comparison of several methods on the hardest variant of ScanObjectNN[46]. Different shapes stand for different methods. Blue and green respectively represent the results under the PointMAE[32] and PointBERT[57] baselines. The darker the color, the higher the accuracy (The accuracy is mapped to the range [0,1] by using max-min scaling[31]).

Inspired by the success of pre-trained models in natural language processing [3, 9, 23, 39, 44, 45] and computer vision [6, 7, 14, 15, 54, 55], recent research has extended this approach to point cloud analysis [1, 10, 29, 32, 36, 47, 53, 57, 61]. Following pre-training, these methods typically use a full fine-tuning strategy to adapt the models to downstream tasks, yielding significant performance gains and faster convergence compared to training from scratch. However, full fine-tuning may be suboptimal for point cloud analysis for several reasons: (1) Updating all parameters of the pre-trained model can lead to overfitting and catastrophic forgetting, undermining the rich embeddings learned during pre-training and resulting in degraded performance. (2) Each point cloud analysis task and dataset requires a separate model parameter set, creating storage challenges as demand scales. (3) To leverage the prior knowledge from pre-training fully, large models are often needed. Full fine-tuning incurs substantial computational costs, including increased GPU memory usage and extended training times, which can limit accessibility for researchers with limited hardware resources.

To address these challenges, our research will focus on Parameter-Efficient Fine-Tuning (PEFT) [5, 17–20, 22, 24, 25, 27, 42, 58], an approach popular in NLP and computer vision that freezes most parameters of pre-trained models, making only a few selected parameters—or newly introduced parameters—trainable during fine-tuning. This approach allows performance comparable to, or even exceeding, full fine-tuning while reducing parameter updates. Several pioneering PEFT methods have been developed for language and visual models: (1) Adapters [5, 17], which insert lightweight networks after Attention and Feed-Forward Network (FFN) layers in Transformers; (2) Prompt Tuning [19, 24, 25], which adds a small number of learnable parameters to the token sequence; and (3) Ladder Side Tuning [42], which employs a compact, independent network called Ladder, designed to take intermediate activations and refine them through rapid connections to the backbone network. These PEFT techniques have demonstrated notable performance improvements.

However, our empirical findings (in Sec. 4.2) indicate that directly applying fine-tuning methods developed for language and vision models to the point cloud domain often results in suboptimal performance. These findings highlight a key problem: **how can we develop a fine-tuning approach specifically designed for point clouds that not only matches but potentially exceeds the performance of full fine-tuning while being both efficient and effective?** Addressing this challenge is crucial for advancing parameter-efficient techniques in point cloud analysis, given the unique characteristics and demands of 3D data.

In this paper, we introduce a novel point cloud fine-tuning approach based on Ladder Side Tuning, termed Point Ladder Tuning (PLT). While the attention mechanism in the backbone network effectively captures global semantic information, it often lacks finer local detail. To address this, we design a hierarchical Ladder Network specifically to extract local information directly from the raw input. Additionally, we propose a Local-Global Fusion (LGF) module, which adaptively combines the local information from the Ladder Network with global features activated within the backbone network, producing multi-scale representations essential for improving network performance. To further optimize the pre-trained backbone network for downstream tasks, we introduce an adaptive prompt generation technique. This method learns to scale and translate the fused features, creating instance-specific multi-scale prompts that are easily optimized and enable the backbone to refine its instance-specific features more effectively.

Our main contributions can be summarized as follows:

- We propose Point Ladder Tuning (PLT), a fine-tuning method for point cloud data built upon Ladder Side Tuning (LST). PLT employs a hierarchical Ladder Network to extract local information, and a Local-Global Fusion (LGF) module to integrate this local information with global features, producing rich multi-scale representations.
- To further enhance network performance, we introduce a straightforward yet effective prompt generation module that linearly maps the output of the LGF module, injecting multi-scale information directly into the backbone network.
- Extensive experiments demonstrate that PLT achieves performance comparable to, and often surpassing, full fine-tuning across a range of tasks and datasets, while requiring significantly fewer parameters.

2. Related Work

The field of point cloud analysis has witnessed significant advancements in recent years, largely driven by the development of self-supervised pre-trained models and fine-tuning techniques. We give a review for pre-trained models and fine-tuning technologies for point cloud analysis.

2.1. 3D Pre-trained Models

Recent developments in self-supervised pre-trained point cloud models have attracted attention due to their exceptional performance across various computer vision tasks. These models are typically trained on large volumes of unlabeled data and later fine-tuned for specific downstream applications. Point cloud pre-training can be broadly categorized into three main approaches: contrastive learning-based, reconstruction-based, and hybrid methods that combine both. In contrastive learning, models such as PointContrast [53] and CrossPoint [1] exploit rich semantic priors by learning features through comparisons of different perspectives of a unified point cloud. PointBERT [57] adapts concepts from BERT [9] by predicting masked patches in the point cloud and comparing them with the output features of dVAE-based point cloud tokenizers. PointMAE [32], inspired by MAE [15], directly predicts the coordinates of masked points using an autoencoder framework. Meanwhile, ReCon [36] combines contrastive learning and mask reconstruction, incorporating additional modalities such as images and text to further enhance the quality of pre-training.

Traditionally, 3D pre-trained models are transferred to downstream tasks using full fine-tuning. However, this approach can be inefficient, often leading to the degradation of the valuable prior knowledge learned during pre-training and increasing the risk of catastrophic forgetting. Consequently, this paper focuses on exploring more efficient and effective strategies for transferring 3D pre-trained models to downstream tasks while preserving the performance benefits of pre-training.

2.2. Parameter Efficient Fine-tuning

Fine-tuning pre-trained models can be computationally and storage-intensive. To mitigate these challenges, many researchers in natural language processing (NLP) and computer vision have developed parameter-efficient fine-tuning (PEFT) techniques that enable the transfer of pre-trained knowledge to downstream tasks using a minimal number of parameters. Adapter-based methods [5, 17, 18] typically insert lightweight networks into frozen backbone models to adjust the pre-trained architecture. For example, AdaptFormer [5] adds adapters in parallel to the feed-forward network (FFN) for visual recognition tasks. Prompt-based methods [19, 25] incorporate a small number of learnable parameters into the input sequence, such as VPT-Deep [19], which inserts learnable parameters at the input of each layer. A different approach is Ladder Side Tuning (LST) [42], which introduces additional branches that use intermediate activations from the pre-trained model as inputs for prediction. However, simply applying these methods to 3D point clouds does not consistently yield satisfactory results.

Recently, several PEFT methods specifically designed for pre-training 3D point cloud models have shown promising performance improvements. IDPT [59] is the first PEFT approach tailored for point clouds, using DGCNN [48] to generate instance-level prompts, replacing traditional VPT methods. Point-PEFT [43] employs adapters to aggregate local features during fine-tuning, while DAPT [66] introduces dynamic adapters that assess the importance of each token, generating dynamic weights for downstream tasks. Although these methods reduce training costs, achieving consistent performance improvements across diverse tasks remains challenging. We argue that these approaches, which freeze the features of pre-trained models as input, hinder the learning of discriminative local features. Additionally, they fail to fully integrate global and local information, which is critical for dense prediction tasks [8]. To address these limitations, we propose Point Ladder Tuning (PLT), which utilizes a hierarchical Ladder Network to directly extract local information from point cloud inputs and fuses it with global features from the backbone network via attention mechanisms to generate multi-scale features. This approach significantly reduces the number of adjustable parameters and achieves notable performance improvements.

3. Methodology

Fine-tuning pre-trained models, though effective across domains, often incurs high computational and storage costs. To address this, we propose Point Ladder Tuning (PLT), an efficient fine-tuning approach for 3D point cloud learning that combines Ladder Side Tuning (LST) and prompt tuning to optimize parameter efficiency and task performance. While LST statically weights global activations but overlooks crucial local features, and prompt tuning lacks adaptability across instances, PLT integrates both local and global features to enhance optimization and adaptability.

PLT introduces a hierarchical Ladder network (HLN) that directly extracts local features from the input point cloud and fuses them with the global activations of the backbone network to create multi-scale representations. The HLN consists of two main components: (1) a set abstraction module, detailed in Sec. 3.1, and (2) a Local-Global Fusion module (LGF), discussed in Sec. 3.2. Further, dynamic prompt tokens generated from these fused features refine the backbone's global features, achieving high task-specific performance with minimal parameter updates, which is described in Sec. 3.3. This approach thus maintains the semantic richness of pre-trained models while substantially reducing computational demands, demonstrating effectiveness across point cloud applications like semantic segmentation. Our framework is shown in Fig. 2.

3.1. Hierarchical Ladder Network

Pre-trained models typically learn the global information of input point clouds through attention mechanisms but often overlook the importance of locality, which is crucial for downstream tasks, especially dense prediction tasks. Although Point PEF introduces a Geometry-Aware Adapter to capture local information, it still relies on the global intermediate activations of pre-trained models, which limits its ability to effectively learn local features within the original point cloud. Additionally, because pre-trained models often operate at a single scale throughout the learning process, lacking multi-scale information, this constraint further impedes performance on downstream tasks.

To address these problems, we introduce a hierarchical Ladder network to better capture the intrinsic local information of the input point cloud. The module includes multiple HLN layers that are capable of capturing point cloud features at different scales, which has been shown to be effective in subsequent experiments. The HLN Layer consists of two main components: (1) Set Abstraction (SA), and (2) Local-Global Fusion Module (LGF). Firstly, we will introduce the SA in this section and the LGF in Sec. 3.2.

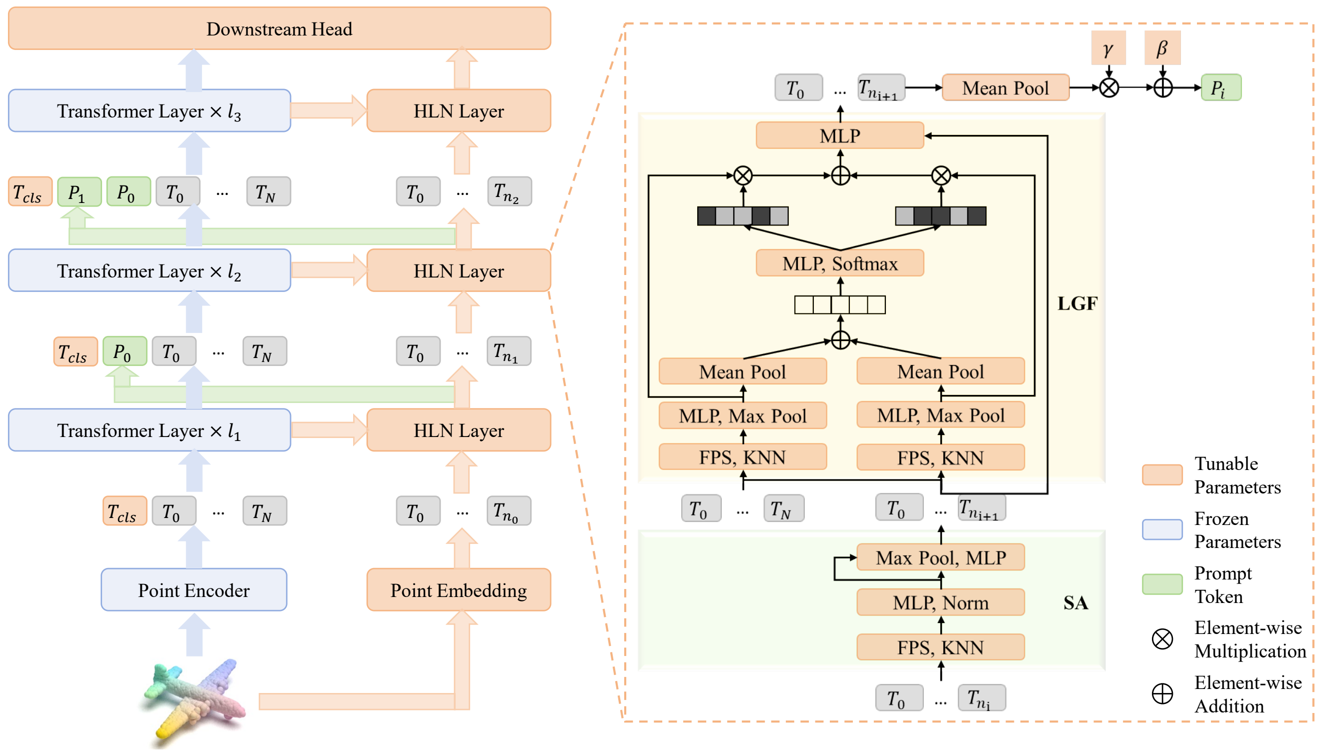


Figure 2. The overall of our PLT. During fine-tuning, we froze the pre-trained backbone network and only fine-tune the PLT branch and the class token. The PLT branch consists of two main components: 1) Set Abstraction (SA), and 2) Local-Global Fusion Module (LGF).

Given the input point cloud $P \in R^{N\times 3}$, where N is the num of the input point cloud, we first apply Point Embedding to map it into a high-dimensional space, obtaining the point cloud feature $F \in R^{N\times C}$, where is the dimension of the point cloud feature. Next, we use Set Abstraction (SA) to perform downsampling. This process begins with farthest point sampling (FPS) to select a set of center points $C = \{c_1, \ldots, c_n\}$. Then, we use k-nearest neighbors (KNN) to construct local neighborhoods $P(c) = \{p_c^1, \ldots, p_c^k\}$, $F(c) = \{f_c^1, \ldots, f_c^k\}$ for each center point c. Finally, we apply max pooling followed by a multi-layer perceptron (MLP) to obtain the output point cloud. The formula for this process is as follows:

$$\boldsymbol{f}_c = \varphi\left(\left[\boldsymbol{f}_c^j; (\boldsymbol{p}_c - \boldsymbol{p}_c^j)\right]\right) \tag{1}$$

$$\boldsymbol{f}_c^{'} = \boldsymbol{f}_c + \rho\left(h_{\boldsymbol{\Theta}}\left(\boldsymbol{f}_c\right)\right) \tag{2}$$

where ρ and φ represent a MLP respectively, $[\cdot, \cdot]$ represents concat operation. And $h_{\boldsymbol{\Theta}}$ represents the aggregation function. Unless otherwise specified, we use Max-Pooling.

3.2. Local-Global Fusion Module

To make better use of the local information captured in the PLT Branch and the global information captured in the pre-trained backbone network, we propose a local-global fusion module that adaptively aggregates both types of information through selective attention. Given the input point cloud P_s and their corresponding features F_s from the HLN layer, as well as the output point cloud P_m and its corresponding features F_m from the backbone network, we firstly use W to map the output features of the backbone network to match the same feature dimension as the input point cloud feature vectors of the HLN layer:

$$\boldsymbol{F}_m^{'} = \boldsymbol{F}_m W \tag{3}$$

Next, we use the same operations as Set Abstraction (SA) to extract both the global features F_g, which are derived from the interaction between the input point cloud P_s of the HLN layer and the output point cloud P_m of the backbone network, and the local features F_l, which are obtained from the interaction between the input point clouds P_s of the HLN layer.

Finally, we apply a selective attention mechanism to adaptively fuse the global and local features. This mechanism allows the model to focus on the most relevant information from each source, ensuring that both global context and fine-grained local details are effectively integrated. Firstly, we apply the aggregation function $\mathcal{A}$, with average pooling as the default, to the global and local features to obtain the corresponding global and local feature vectors:

$$\boldsymbol{f}_g, \boldsymbol{f}_l = \mathcal{A}(\boldsymbol{F}_g), \mathcal{A}(\boldsymbol{F}_l) \tag{4}$$

Then, we add the global and local features and pass them through a MLP to obtain z_g and z_l:

$$\boldsymbol{z}_g, \boldsymbol{z}_l = \alpha\left(\boldsymbol{f}_g + \boldsymbol{f}_l\right) \tag{5}$$

where α represents a MLP.

Next, we apply Softmax to compute the attention weights s_g and s_l for the global and local features:

$$\boldsymbol{s}_g^i = \frac{e^{\boldsymbol{z}_g^i}}{e^{\boldsymbol{z}_g^i} + e^{\boldsymbol{z}_l^i}}, \boldsymbol{s}_l^i = \frac{e^{\boldsymbol{z}_l^i}}{e^{\boldsymbol{z}_g^i} + e^{\boldsymbol{z}_l^i}} \tag{6}$$

Subsequently, the global and local features are weighted according to their attention scores to produce the fused multi-scale features:

$$\boldsymbol{F}_{ms} = \boldsymbol{s}_g \boldsymbol{F}_g + \boldsymbol{s}_l \boldsymbol{F}_l \tag{7}$$

Finally, we use an MLP τ to perform feature mapping and add the result to the input features:

$$\boldsymbol{F}_o = \boldsymbol{F}_s + \tau\left(\boldsymbol{F}_{ms}\right) \tag{8}$$

By selectively emphasizing the most relevant local and global features through attention, our LGF ensures the effective integration of both types of information, enhancing the model's ability to capture multi-scale features. This is crucial for tasks that require a balance between fine-grained local details and the broader global structure of point clouds, especially in dense prediction tasks.

3.3. Fine-tuning on the Backbone Network

To enable the pre-trained backbone network to generate more effective global features for downstream tasks, we propose a dynamic prompt generation method based on the multi-scale point cloud features output F_o by the Local-Global Fusion (LGF) module. Firstly, F_o is mean-pooled to obtain a compact representation. These pooled features are then scaled and translated using learnable parameters γ and β to generate multi-scale prompt p. To efficiently utilize parameters, we reuse W to align the dimensions of the multi-scale prompts with the dimensions of the backbone network features. The formula can be expressed as follows:

$$p = \left(\boldsymbol{\gamma} \times \frac{1}{n} \sum_{i}^{n} \boldsymbol{F}_o^i + \boldsymbol{\beta}\right) W^T \tag{9}$$

where n is the num of tokens in F_o.

Finally, we incorporate multi-scale prompts into the backbone network for learning. The output of the l-th transformer layer x_l can be expressed as

$$\boldsymbol{x}_l = L_l\left(\left[\boldsymbol{T}_{cls}; \boldsymbol{p}_0, \ldots, \boldsymbol{p}_{i-1}; \boldsymbol{T}\right]\right) \tag{10}$$

To enhance performance further, we follows ssf [27] and applies scaling and shifting to the output of each module within the backbone network, enabling the extraction of task-specific global information. Given an input x, the output y can be expressed as:

$$\boldsymbol{y} = \boldsymbol{s} \times \boldsymbol{x} + \boldsymbol{t} \tag{11}$$

where s and t represents scaling and shifting parameter respectively, which are learnable.

4. Experiments

In this section, we present a comprehensive evaluation of the proposed Point Ladder Tuning (PLT) method through a series of experiments across multiple point cloud datasets and tasks. Our goal is to demonstrate the effectiveness of PLT in terms of both performance and parameter efficiency compared to existing state-of-the-art methods.

4.1. Experimental Settings

To ensure a fair comparison, we used the same experimental setup as the default fine-tuning method [59, 66] for each baseline. During training, we freeze the weights of the pre-trained model and only fine-tune a small number of parameters for adding modules. All experiments were conducted on a single GeForce RTX 3090 GPU.

4.2. 3D Object Classification

Object Classification on Real-World Dataset. Pre-trained Point cloud models are typically trained on the ShapeNet dataset [4], which consists of clean, uniformly distributed point clouds. However, real-world point clouds often suffer from issues such as noise and missing point, leading to diverse and challenging distributions. To evaluate the performance in these more realistic conditions, we use the ScanObjectNN dataset [46], which contains approximately 15k point cloud samples across 15 categories. These point clouds are captured in indoor scenes and often include background interference and occlusions from other objects. As shown in Tab.1 We conduct experiments on on three variants of the ScanObjectNN dataset [46] (OBJ_BG, OBJ_ONLY, and PB_T50_RS), using two baseline models, PointBERT [57] and PointMAE [32], to assess the effectiveness of our PLT. Notably, PLT achieved better accuracy than full fine-tuning across all settings while utilizing only 2.71% of the parameters. Especially, PLT achieved increases of 4.14%, 1.73%, and 3.02% in the three ScanObjectNN [46] variants on Point-BERT. Compared to the state-of-the-art model PointGST, our LST improved accuracy by 0.45% on PointBERT [57] and 0.17% on PointMAE [32] under the most challenging setting, PB_T50_RS, in ScanObjectNN [46].

Object Classification on Synthetic Dataset. We also conduct experiments on the ModelNet dataset [52], which includes 12,311 clean 3D CAD models across 40 categories. Following DAPT [66], we split the ModelNet40

Table 1. Classification on three variants of the ScanObjectNN [46] and the ModelNet40[52], including the number of trainable parameters and overall accuracy (OA). All methods utilize the default data argumentation as the baseline[66]. * denotes reproduced results. We report ScanObjectNN[46] results without voting. ModelNet40[52] results are without and with voting, referred to (-/-).

Method	Reference	Tunable params. (M)	FLOPs (G)	ScanObjectNN			ModelNet40	
				OBJ_BG	OBJ_ONLY	PB_T50_RS	Points Num.	OA (%)
Supervised Learning Only								
PointNet [34]	CVPR 17	3.5	0.5	73.3	79.2	68.0	1k	- / 89.2
PointNet++ [35]	NeurIPS 17	1.5	1.7	82.3	84.3	77.9	1k	- / 90.7
DGCNN [48]	TOG 19	1.8	2.4	82.8	86.2	78.1	1k	- / 92.9
MVTN [13]	ICCV 21	11.2	43.7	-	-	82.8	1k	- / 93.8
PointNeXt [38]	NeurIPS 22	1.4	1.6	-	-	87.7	1k	- / 94.0
PointMLP [30]	ICLR 22	13.2	31.4	-	-	85.4	1k	- / 94.5
RepSurf-U [40]	CVPR 22	1.5	0.8	-	-	84.3	1k	- / 94.4
ADS [16]	ICCV 23	-	-	-	-	87.5	1k	- / 95.1
Self-Supervised Representation Learning (Full fine-tuning)								
OcCo [47]	ICCV 21	22.1	4.8	84.85	85.54	78.79	1k	- / 92.1
Point-BERT [57]	CVPR 22	22.1	4.8	87.43	88.12	83.07	1k	- / 93.2
MaskPoint [29]	ECCV 22	22.1	-	89.70	89.30	84.60	1k	- / 93.8
Point-MAE [32]	ECCV 22	22.1	4.8	90.02	88.29	85.18	1k	- / 93.8
Point-M2AE [61]	NeurIPS 22	15.3	3.6	91.22	88.81	86.43	1k	- / 94.0
ACT [10]	ICLR 23	22.1	4.8	93.29	91.91	88.21	1k	- / 93.7
ReCon [36]	ICML 23	43.6	5.3	94.15	93.12	89.73	1k	- / 93.9
Self-Supervised Representation Learning (Efficient fine-tuning)								
Point-BERT [57] (baseline)	CVPR 22	22.1 (100%)	4.8	87.43	88.12	83.07	1k	92.7 / 93.2
+ IDPT [59]	ICCV 23	1.7 (7.69%)	7.2	88.12(+0.69)	88.30(+0.18)	83.69(+0.62)	1k	92.6(-0.1) / 93.4(+0.2)
+ DAPT [66]	CVPR 24	1.1 (4.97%)	5.0	91.05(+3.62)	89.67(+1.55)	85.43(+2.36)	1k	93.1(+0.4) / 93.6(+0.4)
+ PointGST [28]	Arxiv 24	**0.6** (**2.71**%)	5.0	91.39(+3.96)	89.67(+1.55)	85.64(+2.57)	1k	93.4(+0.7) / 93.8(+0.6)
+ LST [42]	NeurIPS 22	0.8 (3.38%)	-	89.15(+2.72)	89.50(+1.38)	83.17(+0.10)	1k	92.9(+0.2) / 93.3(+0.1)
+ PLT (ours)	-	**0.6** (**2.71**%)	5.0	91.57(+4.14)	89.85(+1.73)	86.09(+3.02)	1k	93.5(+0.8) / 94.2(+1.0)
Point-MAE [32] (baseline)	ECCV 22	22.1 (100%)	4.8	90.02	88.29	85.18	1k	93.2 / 93.8
+ IDPT [59]	ICCV 23	1.7 (7.69%)	7.2	91.22(+1.20)	90.02(+1.73)	84.94(-0.24)	1k	93.3(+0.1) / 94.4(+0.6)
+ Point-PEFT* [43]	AAAI 24	0.7 (3.13%)	-	90.19(+0.17)	89.50(+1.21)	84.35(-0.83)	1k	94.2(+0.4) / -
+ DAPT [66]	CVPR 24	1.1 (4.97%)	5.0	90.88(+0.86)	90.19(+1.90)	85.08(-0.10)	1k	93.5(+0.3) / 94.0(+0.2)
+ PPT* [63]	Arxiv 24	1.1 (4.97%)	5.0	89.50(-0.52)	89.50(+1.21)	84.91(-0.27)	1k	93.7(+0.5) / -
+ PointGST[28]	Arxiv 24	**0.6** (**2.71**%)	5.0	91.74(+1.72)	90.19(+1.90)	85.29(+0.11)	1k	93.5(+0.3) / 94.0(+0.2)
+ LST [42]	NeurIPS 22	0.8 (3.38%)	5.0	89.67(-0.25)	89.67(+1.38)	82.75(-2.43)	1k	93.2(+0.0) / 93.8(+0.0)
+ PLT (ours)	-	**0.6** (**2.71**%)	5.0	90.88(+0.86)	90.02(+1.73)	85.46(+0.28)	1k	93.8(+0.6) / 94.0(+0.2)

dataset into 9,843 training samples and 2,468 testing samples. During training, we applied standard data augmentation techniques, including random scaling and random translation. As shown in Tab.1, without voting, our PLT achieved accuracy rates of 93.8% and 93.5% on PointMAE and PointBERT, respectively, which were 0.6% and 0.8% higher than full fine-tuning.. With voting, PLT continues to outperform full fine-tuning, especially on PointBERT, with an accuracy increase of 1.0%.

Few-shot Learning. We further conduct experiments on ModelNet40 to evaluate its transfer learning ability in few-shot setting. Following prior work [32, 59, 66], we adopt the n-way, n-shot setting. As shown in Tab. 2, PLT outperforms fully fine-tuned models and state-of-the-art models like IDPT [59] and DAPT [66] in most cases, demonstrating its effectiveness in few-shot learning.

Compared with Other PETL Methods. As illustrated in Tab. 4, using VPT [19] for fine-tuning in PointMAE [32] leads to a notable performance drop compared to full fine-tuning, particularly with a 4.09% decrease in the PB_T5_RS setting. Similarly, while adapters [17] shows slight improvements on the OBJ_ONLY task, but significant performance drops in other settings. LST [42] demonstrate substantial gains on OBJ_ONLY, but underperformed elsewhere. We also compare PEFT methods PEFT methods from various fields on the challenging PB_T50_RS variant of ScanObjectNN [46]. As shown in the Tab. 3, our methods are more effective than those proposed in NLP, 2D, and 3D areas.

4.3. 3D Dense Prediction Task

For dense prediction tasks, such as part segmentation and semantic segmentation, we employ a prediction head similar to that of PointNext. This design allows us to leverage multi-scale information, enhancing performance while minimizing the number of trainable parameters.

Table 2. Few-shot learning on ModelNet40[52]. Overall accuracy (%)±the standard deviation (%) without voting is reported.

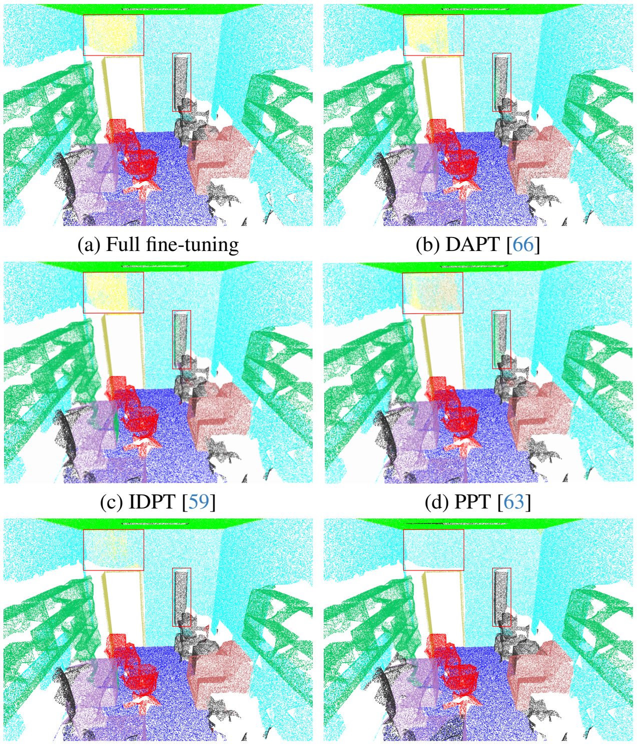
Methods	Reference	5-way		10-way	
		10-shot	20-shot	10-shot	20-shot
with Self-Supervised Representation Learning (Full fine-tuning)					
OcCo [47]	ICCV 21	94.0±3.6	95.9±2.3	89.4±5.1	92.4±4.6
Point-BERT [57]	CVPR 22	94.6±3.1	96.3±2.7	91.0±5.4	92.7±5.1
MaskPoint [29]	ECCV 22	95.0±3.7	97.2±1.7	91.4±4.0	93.4±3.5
Point-MAE [32]	ECCV 22	96.3±2.5	97.8±1.8	92.6±4.1	95.0±3.0
Point-M2AE [61]	NeurIPS 22	96.8±1.8	98.3±1.4	92.3±4.5	95.0±3.0
ACT [10]	ICLR 23	96.8±2.3	98.0±1.4	93.3±4.0	95.6±2.8
VPP [37]	NeurIPS 23	96.9±1.9	98.3±1.5	93.0±4.0	95.4±3.1
I2P-MAE [62]	CVPR 23	97.0±1.8	98.3±1.3	92.6±5.0	95.5±3.0
RECON [36]	ICML 23	97.3±1.9	98.9±1.2	93.3±3.9	95.8±3.0
with Self-Supervised Representation Learning (Efficient fine-tuning)					
Point-BERT [57] (baseline)	CVPR 22	94.6±3.1	96.3±2.7	91.0±5.4	92.7±5.1
+ IDPT [59]	ICCV 23	96.0±**1.7**	97.2±2.6	91.9±4.4	93.6±3.5
+ DAPT [66]	CVPR 24	95.8±2.1	97.3±1.3	92.2±4.3	94.2±3.4
+ PointGST [28]	Arxiv 24	96.5±2.4	97.9±2.0	92.7±4.2	95.0±**2.8**
+ PLT (**ours**)	-	**96.9**±2.0	**98.8**±**1.1**	**93.3**±**4.0**	**95.5**±3.1
Point-MAE [32] (baseline)	ECCV 22	96.3±2.5	97.8±1.8	92.6±4.1	95.0±3.0
+ IDPT [59]	ICCV 23	97.3±2.1	97.9±1.1	92.8±4.1	95.4±**2.9**
+ DAPT [66]	CVPR 24	96.8±**1.8**	98.0±1.0	93.0±**3.5**	**95.5**±3.2
+ PLT (**ours**)	-	**97.2**±2.2	**98.9**±**0.9**	**93.2**±4.2	**95.5**±**2.9**

Table 3. Comparisons of parameter efficient transfer learning methods from NLP and 2D Vision on the hardest variant of ScanObjectNN [46]. Overall accuracy (%) without voting is reported. #TP represents the tunable parameters. * denotes reproduced results.

Method	Reference	Design for	#TP (M)	PB_T50_RS
Point-MAE [32]	ECCV 22	-	22.1	85.18
Linear probing	-	-	0.3	75.99
+ Adapter [17]	ICML 19	NLP	0.9	83.93
+ Perfix tuning [25]	ACL 21	NLP	0.7	77.72
+ BitFit [58]	ACL 21	NLP	0.3	82.62
+ LST [42]	NeurIPS 22	NLP	1.1	82.75
+ LoRA [18]	ICLR 22	NLP	0.9	81.74
+ DEPT [41]	ICLR 24	NLP	0.3	79.70
+ FourierFT [11]	ICML 24	NLP	0.3	78.57
+ VPT-Deep [19]	ECCV 22	2D	0.4	81.09
+ AdaptFormer [5]	NeurIPS 22	2D	0.9	83.45
+ SSF [27]	NeurIPS 22	2D	0.4	82.58
+ FacT [20]	AAAI 23	2D	0.5	78.76
+ BI-AdaptFormer [21]	ICCV 23	2D	0.4	83.66
+ SCT [65]	IJCV 24	2D	0.3	80.40
+ IDPT [59]	ICCV 23	3D	1.7	84.94
+ Point-PEFT* [43]	AAAI	3D	0.7	84.35
+ DAPT [66]	CVPR 24	3D	1.1	85.08
+ PPT* [63]	Arxiv 24	3D	1.1	84.91
+ PointGST [28]	Arxiv 24	3D	0.6	85.29
+ PLT (**ours**)	-	3D	0.6	**85.46**

We validate the effectiveness of PLT on ShapeNetPart dataset [56]. As shown in the Tab. 6, PLT achieves comparable results on Inst. mIoU, while significantly improving Cls. mIoU, particularly on PointBERT, where it outperforms DAPT by 0.5%.

We evaluate the proposed PLT on the semantic segmentation task using the S3DIS dataset [2], with results shown in Tab. 7. It is clear that our PLT significantly outperforms other methods. When using ACT as the baseline, PLT achieves improvements of 7.2%, 4.7%, 4.8%, and 1.9% over IDPT, PointPEF, DAPT, and PointGST, respectively. Similarly, when using PointMAE as the baseline, PLT consistently outperforms other methods, further validating its effectiveness in dense prediction tasks. Meanwhile, as shown in the Fig. 3, the semantic segmentation results on the S3DIS dataset clearly demonstrate that our proposed PLT achieves clearer segmentation boundaries and fewer misclassifications compared to other methods.



(a) Full fine-tuning
(b) DAPT [66]
(c) IDPT [59]
(d) PPT [63]
(e) PLT (Ours)
(f) GT

Figure 3. The visualizations from the Area5 of S3DIS using a pretrained PointMAE with different fine-tuning strategies.

Table 4. The overall accuracy (%) for classical fine-tuning strategies on three variants of ScanObjectNN [46] is reported. '#TP' means the number of tunable parameters. Linear probing indicates head-tuned only.

Tuning Strategy	#TP(M)	OBJ_BG	OBJ_ONLY	PB_T50_RS
Point-MAE [32]	22.1	90.02	88.29	85.18
Linear probing	0.3	87.26(**-2.76**)	84.85(**-3.44**)	75.99(**-9.19**)
+ Adapter [17]	0.9	89.50(**-0.52**)	88.64(**+0.35**)	83.93(**-1.25**)
+ VPT [19]	0.4	87.26(**-2.76**)	87.09(**-1.20**)	81.09(**-4.09**)
+ LST [42]	0.8	89.67(**-0.25**)	89.67(**+1.38**)	82.75(**-2.43**)

4.4. Ablation Study

Analysis on each component. We conduct experiments to prove the effectiveness of the proposed components of Our PLT. As shown in the Tab. 8, when all modules are used, the performance on PB T50 RS reaches 85.46%. However, re-

Table 5. Ablation on hyper-parameters and settings of LST, including the num of neighbors K, feature dim d and the num of layers in Hierarchical Ladder Network (HLN). The tunable parameters (#TP) and the overall accuracy (%) on the hardest variant of ScanObjectNN[46] are reported.

(a) Ablation on K in HLN.

K	#TP (M)	PB_T50_RS
[16, 16, 16]	0.60	84.46
[4, 4, 4]	0.60	84.66
[4, 8, 16]	0.60	84.91
[16, 8, 4]	0.60	**85.46**

(b) Ablation on d in HLN.

Feature Dim	#TP (M)	PB_T50_RS
[8, 16, 32, 64]	0.46	83.17
[32, 64, 128, 256]	1.00	84.25
[16, 32, 64, 128]	0.60	**85.46**

(c) Ablation on the num of layers.

Layer num	#TP (M)	PB_T50_RS
1	0.40	83.55
2	0.45	84.84
3	0.60	**85.46**
4	1.09	85.05

Table 6. Part segmentation on the ShapeNetPart [56]. The mIoU for all classes (Cls.) and for all instances (Inst.) are reported. #TP represents the tunable parameters. * denotes reproduced results.

Methods	Reference	#TP (M)	Cls. mIoU (%)	Inst. mIoU (%)
Supervised Learning Only				
PointNet [34]	CVPR 17	-	80.39	83.7
PointNet++ [35]	NeurIPS 17	-	81.85	85.1
DGCNN [48]	TOG 19	-	82.33	85.2
APES [49]	CVPR 23	-	83.67	85.8
Self-Supervised Representation Learning (Full fine-tuning)				
OcCo [47]	ICCV 21	27.09	83.42	85.1
MaskPoint [29]	ECCV 22	-	84.60	86.0
Point-BERT [57]	CVPR 22	27.09	84.11	85.6
Point-MAE [32]	ECCV 22	27.06	84.19	86.1
ACT [10]	ICLR 23	27.06	84.66	86.1
Self-Supervised Representation Learning (Efficient fine-tuning)				
Point-BERT [57] (baseline)	CVPR 22	27.09	84.11	85.6
+ IDPT* [59]	ICCV 23	5.69	83.50	85.3
+ DAPT [66]	CVPR 24	5.65	83.83	85.5
+ PLT (**ours**)	-	**2.08**	**83.85**	**86.0**
Point-MAE [32] (baseline)	ECCV 22	27.06	84.19	86.1
+ IDPT [59]	ICCV 23	5.69	83.79	85.7
+ DAPT [66]	CVPR 24	5.65	84.01	85.7
+ PLT (**ours**)	-	**2.08**	83.90	**85.9**

Table 7. Semantic segmentation on the S3DIS [2]. The mean accuracy (mAcc) and mean IoU (mIoU) are reported. Params. represents the trainable parameters. #TP represents the tunable parameters.

Methods	Reference	#TP (M)	mAcc (%)	mIoU (%)
Point-MAE [32] (baseline)	ECCV 22	27.02	69.9	60.8
+ Linear probing	ICCV 23	5.20	63.4	52.5
+ IDPT [59]	ICCV 23	5.64	65.0	53.1
+ Point-PEFT [43]	ICCV 23	5.58	66.5	56.0
+ DAPT [66]	CVPR 24	5.61	67.2	56.2
+ PointGST [28]	Arxiv 24	5.55	68.4	58.6
+ PLT (**ours**)	-	**2.04**	**70.7**	**59.3**
ACT [10] (baseline)	ICLR 23	27.02	71.1	61.2
+ Linear probing	ICCV 23	5.20	64.1	52.0
+ IDPT [59]	ICCV 23	5.64	64.1	52.1
+ Point-PEFT [43]	ICCV 23	5.58	66.0	54.6
+ DAPT [66]	CVPR 24	5.61	64.7	54.5
+ PointGST [28]	Arxiv 24	5.55	67.6	57.4
+ PLT (**ours**)	-	**2.04**	**70.8**	**59.3**

Table 8. The effect of each component of our LST. The tunable parameters (#TP) and the overall accuracy (%) on the hardest variant of ScanObjectNN[46] are reported.

SSF	DP	HLN	#TP (M)	PB_T50_RS
Full fine-tuning			22.1	85.18
Linear Probing			0.27	75.99
	✔	✔	0.49	84.52
✔		✔	0.60	84.66
✔			0.37	83.34
✔	✔	✔	0.60	**85.46**

Table 9. Fusion way for local and global information in point clouds. The tunable parameters (#TP) and the overall accuracy (%) on the hardest variant of ScanObjectNN[46] are reported.

Fusion Way	#TP (M)	PB_T50_RS
Add	0.58	85.01
Concat	0.62	84.63
Only Global	0.56	84.52
Only Local	0.56	82.86
LGA with Sigmoid	0.59	84.59
LGA with Softmax	0.60	**85.46**

Table 10. Comparison between HLN and PLT. The tunable parameters (#TP) and the overall accuracy (%) on the hardest variant of ScanObjectNN are reported.

Method	#TP (M)	PB_T50_RS
Point-MAE	22.1	85.18
HLN	0.2	80.74
PLT(Ours)	0.6	**85.46**

moving any of the proposed modules leads to performance degradation, further highlighting the necessity of each module.

Ablation on hyper-parameters. We conduct an in-depth exploration of the hyperparameters of Hierarchical Ladder Network (HLN), as shown in the Tab. 5, and found that the performance is optimal when the number of layers is 3, with feature dimensions of [16, 32, 64, 128], and the number of neighbors set to [16, 8, 4].

Fusion way for or local and global information in point clouds. As shown in the Tab. 9, we explored various fusion methods and found that the proposed LGF with Softmax achieved the best performance. Additionally, when using only local information, the performance was worse than using only global information. This may be due to the fact that local information is learned from scratch, while global information benefits from pre-trained prior knowledge.

Comparison between HLN and PLT. As shown in the Tab. 10, when training with only HLN, we observed a significant performance drop of 4.72% compared to full fine-tuning, likely due to the absence of pre-trained global prior information. However, by using our proposed PLT to integrate the features of both HLN and the backbone network, we achieved superior performance than full fine-tuning.

5. Conclusion and Limitation

In this study, we propose a parameter-efficient fine-tuning strategy, named PLT, for point cloud analysis. PLT effectively freezes the parameters of the backbone network and utilizes a hierarchical Ladder Network (HLN) to directly extract local information from the input point cloud. To aggregate this local information with the backbone network's intermediate global activation, we introduce a Local-Global Fusion (LGF) module. Additionally, to further enhance performance, fused multi-scale features are used to generate dynamic prompts, enabling the backbone network to produce global features optimized for downstream tasks. Our method demonstrates impressive performance in tasks such as object classification and dense prediction, while maintaining a minimal parameter footprint. However, a limitation of this approach is that it has not yet been validated on additional tasks, such as point cloud object detection and point cloud generation, which we leave as future work.

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