
LCM: Locally Constrained Compact Point Cloud Model for Masked Point Modeling

Yaohua Zha^{1,2} Naiqi Li¹ Yanzi Wang¹ Tao Dai³ *
Hang Guo¹ Bin Chen⁴ Zhi Wang¹ Zhihao Ouyang⁵ Shu-Tao Xia^{1,2}

¹Tsinghua Shenzhen International Graduate School, Tsinghua University

²Institute of Visual Intelligence, Pengcheng Laboratory

³College of Computer Science and Software Engineering, Shenzhen University

⁴Harbin Institute of Technology, Shenzhen ⁵Bytedance Inc.

zyh1614399882@gmail.com

Abstract

The pre-trained point cloud model based on Masked Point Modeling (MPM) has exhibited substantial improvements across various tasks. However, these models heavily rely on the Transformer, leading to quadratic complexity and limited decoder, hindering their practice application. To address this limitation, we first conduct a comprehensive analysis of existing Transformer-based MPM, emphasizing the idea that redundancy reduction is crucial for point cloud analysis. To this end, we propose a **Locally constrained Compact point cloud Model (LCM)** consisting of a locally constrained compact encoder and a locally constrained Mamba-based decoder. Our encoder replaces self-attention with our local aggregation layers to achieve an elegant balance between performance and efficiency. Considering the varying information density between masked and unmasked patches in the decoder inputs of MPM, we introduce a locally constrained Mamba-based decoder. This decoder ensures linear complexity while maximizing the perception of point cloud geometry information from unmasked patches with higher information density. Extensive experimental results show that our compact model significantly surpasses existing Transformer-based models in both performance and efficiency, especially our LCM-based Point-MAE model, compared to the Transformer-based model, achieved an improvement of 1.84%, 0.67%, and 0.60% in average accuracy on the three variants of ScanObjectNN while reducing parameters by **88%** and computation by **73%**. Code is available at <https://github.com/zyh1614399882/LCM>.

1 Introduction

3D point cloud perception, as a crucial application of deep learning, has achieved significant success across various areas such as autonomous driving, robotics, and virtual reality. Recently, point cloud self-supervised learning [1, 58, 60], capable of learning universal representations from extensive unlabeled point cloud data, has gained much attention. Among which, masked point modeling (MPM) [8, 37, 60, 62, 65, 66], as an important self-supervised paradigm, has become mainstream in point cloud analysis and has gained immense success across diverse point cloud tasks.

The classical MPM [37, 60, 65], inspired by masked image modeling [2, 22, 59] (MIM), divides point clouds into patches and uses a standard Transformer [46] backbone. It randomly masks some patches in the encoder input and combines the unmasked patch tokens with randomly initialized

*Corresponding author. ✉ daitao.edu@gmail.com

masked patch tokens in the decoder input. It predicts the geometric coordinates or semantic features of the masked patches from the decoder output tokens, enabling the model to learn universal 3D representations. Despite the significant success, two inherent issues of Transformers still limit their practical deployment.

The first issue is that the Transformer architecture leads to quadratic complexity and huge model sizes. As shown in Figure 1 (a) and (b), MPM methods like Point-MAE [37] based on standard Transformer [46] require 22.1M parameters and complexity exponentially grows with an increase in the length of input patches. However, in practical point cloud applications, models are often deployed on embedded devices such as robots or VR headsets, where strict constraints exist regarding the model’s size and complexity. In this context, lightweight networks such as PointNet++ [40] are more popular in practical applications due to their lower parameter requirement (only 1.5M) even though they may have inferior performance.

Another issue is that when Transformers [46] are used as decoders in Masked Point Modeling (MPM), their potential to reconstruct masked patches with lower information density is limited. In the decoder input of MPM, randomly initialized masked tokens with lower information density are typically concatenated with unmasked tokens with higher information density and fed into the Transformer-based decoder. The self-attention layers then learn to process these tokens of varying information density based on loss constraints. However, relying solely on the loss to learn this objective is challenging due to the lack of explicit importance guidance for different densities. Additionally, in Section 5.1, we further explain from an information theory perspective that the self-attention mechanism, as a higher-order processing function, can limit the model’s reconstruction potential.

To address the above issues, as shown in Figure 2, we first conducted a comprehensive analysis of the effects of different top-K attention on the performance of the Transformer model, emphasizing the idea that redundancy reduction is crucial for point cloud analysis. To this end, we propose a **Locally constrained Compact point cloud Model (LCM)**, consisting of a locally constrained compact encoder and a locally constrained Mamba-based decoder, to replace the standard Transformer. Specifically, based on the idea of redundancy reduction, our compact encoder replaces self-attention with our local aggregation layers to achieve an elegant balance between performance and efficiency. The local aggregation layer leverages static local geometric constraints to aggregate the most relevant information for each patch token. Since static local geometric constraints only need to be computed once at the beginning and are shared across all layers, it avoids dynamic attention computations in each layer, significantly reducing complexity. Furthermore, it uses only two MLPs for information mapping, greatly reducing the network’s parameters.

In our decoder design, considering the varying information density between masked and unmasked patches in the inputs of MPM, our decoder introduces the State Space Model (SSM) from Mamba [13, 16, 19, 30, 71] to replace self-attention, ensuring linear complexity while maximizing the perception of point cloud geometry information from unmasked patches with higher information density. However, as discussed in Section 5.4, the directly replaced SSM layer exhibits a strong dependence on the order of input patches. Inspired by our compact encoder, we migrate the idea of local constraints to the feedforward neural network of our Mamba-based decoder, proposing the Local Constraints Feedforward Network (LCFFN). This eliminates the need to explicitly consider the sequence order of input in SSM layers because the subsequent LCFFN can adaptively exchange information among geometrically adjacent patches based on their implicit geometric order.

Our LCM is a universal point cloud architecture designed based on the characteristics of the point cloud to replace the standard Transformer. It can be trained from scratch or integrated into any existing pretraining strategy to achieve an elegant balance between performance and efficiency. For example, the LCM model pre-trained based on the Point-MAE strategy requires only 2.7M parameters, which is about $10 \times$ efficient compared to the original Transformer with 22.1M. Furthermore, in

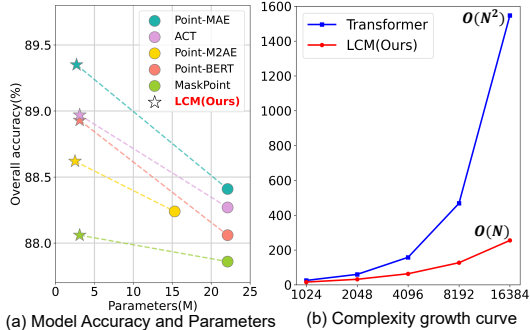


Figure 1: Comparison of our LCM and Transformer in terms of performance and efficiency.

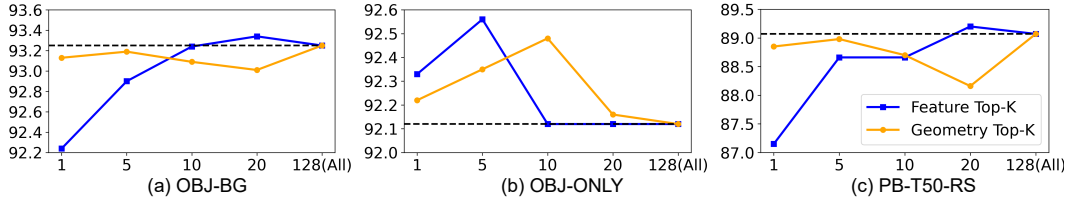


Figure 2: The effect of using top-K attention in feature space and geometric space by the Transformer on the classification performance in ScanObjectNN, all results are the averages of ten repeated experiments.

terms of performance, compared to the Transformer, the LCM shows significant improvements of 1.84%, 0.67%, and 0.60% in average classification accuracy of three variants of ScanObjectNN [44]. Additionally, in the detection task of ScanNetV2 [6], there are also significant improvements of **+5.2%** on AP_{25} and **+6.0%** on AP_{50} .

We summarize the contributions of our paper as follows: **1)** We propose a locally constrained compact encoder, which leverages static local geometric constraints to aggregate the most relevant information for each patch token, achieving an elegant balance between performance and efficiency. **2)** We propose a locally constrained Mamba-based decoder for masked point modeling, which replaces the self-attention layer with Mamba’s SSM layer and introduces a locally constrained feedforward neural network to eliminate the explicit dependency of Mamba on the input sequence order. **3)** Our locally constrained compact encoder and locally constrained Mamba-based decoder together constitute the efficient backbone LCM for masked point modeling. We combine LCM with various pretraining strategies to pre-train efficient models and validate our model’s superiority in efficiency and performance across various downstream tasks.

2 Related Work

Point Cloud Self-supervised Pre-training. Point cloud self-supervised pre-training [47, 54, 55, 58, 60] has achieved remarkable improvement in many point cloud tasks. This approach first applies a pretext task to learn the latent 3D representation and then transfers it to various downstream tasks. PointContrast [58] and CrossPoint [1] initially explored utilizing contrastive learning [36, 43] for learning 3D representations, which achieved some success; however, there were still some shortcomings in capturing fine-grained semantic representations. Recently, masked point modeling methods [37, 60–62] demonstrated significant improvements in learning fine-grained point cloud representations through masking and reconstruction. Many methods [4, 8, 21, 41, 66] have attempted to leverage multimodal knowledge to assist MPM in learning more generalized representations, yielding significant improvements. After obtaining a pre-trained point cloud model, many works [18, 64, 67, 70] remain to explore parameter-efficient fine-tuning methods to better adapt these pretrained models to a variety of downstream tasks. While the pre-trained models mentioned above have achieved tremendous success, they all rely on the Transformer architecture. In this paper, we focus on designing a more efficient architecture to replace the Transformer in these methods, significantly reducing computational and resource requirements.

3 Methodology

3.1 Observation of Top-K Attention

Standard Transformer [46] architecture requires computing the correlation between each patch with all input patches, resulting in quadratic complexity. While this architecture performs well in language data, its effectiveness in point cloud data has been under-explored. Not all points are equally important. As illustrated in Figure 3, the key points for aircraft recognition are mainly distributed on the wings, while for vase recognition, they are primarily located on the bottom of the vase. Therefore, directly skipping the attention computation for less important points provides a straightforward solution.



Figure 3: Point heatmap.

Therefore, directly skipping the attention computation for less important

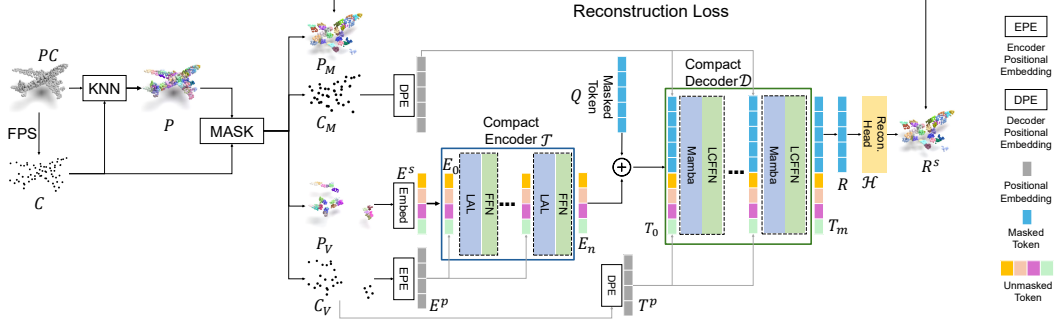


Figure 4: The pipeline of our Locally Constrained Compact Model (LCM) with Point-MAE pre-training. Our LCM consists of a locally constrained compact encoder and a locally constrained Mamba-based decoder.

We first replaced the computation of global attention for all patch tokens with calculations top-K attentions in both feature and geometric space. As shown in Figure 2, our empirical observations indicate that: **1)** In self-attention, it is often more effective to use attention weights based on the top-K most important patch tokens rather than using all patch; **2)** Compared to using top-K attention in a dynamic feature space, employing top-K attention in a static geometric space yields nearly identical representational capacity and offers the advantage of a smaller K value. Although this naive method of masking out unimportant attention still exhibits quadratic complexity, this redundancy reduction idea not only brings performance improvements but also provides a direction for further optimizing computational efficiency.

3.2 The Pipeline of Masking Point Modeling with LCM

The overall architecture of our Locally constrained Compact Model (LCM) is shown in Figure 4. The specific process is as follows.

Patching, Masking, and Embedding. Given an input point cloud $PC \in \mathbb{R}^{L \times 3}$ with L points, we initially downsample a central point cloud $C \in \mathbb{R}^{N \times 3}$ with N points by farthest point sampling (FPS). Then, we perform K-Nearest Neighborhood (KNN) around C to get point patches $P \in \mathbb{R}^{N \times K \times 3}$. Following this, we randomly mask a portion of C and P , resulting in masked elements $C_M \in \mathbb{R}^{(1-r)N \times 3}$ and $P_M \in \mathbb{R}^{(1-r)N \times K \times 3}$ and unmasked elements $C_V \in \mathbb{R}^{rN \times 3}$ and $P_V \in \mathbb{R}^{rN \times K \times 3}$, where r denotes the unmask ratio. Finally, we use MLP-based embedding layer (Embed) and position encoding layer (PE) respectively to extract semantic tokens $E_0 \in \mathbb{R}^{rN \times d}$ and central position embedding $E_P \in \mathbb{R}^{rN \times d}$ for the unmasked patches, where d is the feature dimension.

Encoder. We employ our locally constrained compact encoder \mathcal{T} to extract features from the unmasked features E_0 . It consists of n stacked encoder layers, each layer incorporating a local aggregation layer and a feedforward neural network, detailed in Figure 4. For the input feature E_{i-1} of the i -th layer, after adding its positional embedding E^P , it feeds to the i -th encoding layer \mathcal{T}_i to obtain the feature E_i . Therefore, the forward process of each encoder layer is defined as:

$$E_i = \mathcal{T}_i(E_{i-1} + E^P), \quad i = 1, \dots, n \quad (1)$$

Decoder. In the decoding phase, although various MPMs have different decoding strategies, they can generally be divided into feature-level or coordinate-level reconstruction, and their decoders mostly rely on the Transformer architecture. Here, we illustrate the decoding process of our locally constrained Mamba-based decoder using the coordinate-level reconstruction method Point-MAE [37] as an example.

We first concatenate unmasked tokens $E_n \in \mathbb{R}^{rN \times d}$ before the randomly initialized masked tokens $Q \in \mathbb{R}^{(1-r)N \times d}$ to obtain the input $T_0 \in \mathbb{R}^{N \times d}$ for the decoder. Then, we separately calculate the positional encoding for unmasked patches $T_V^P \in \mathbb{R}^{rN \times d}$ and masked patches $T_M^P \in \mathbb{R}^{(1-r)N \times d}$, and then concatenate them together to obtain the positional embeddings $T^P \in \mathbb{R}^{N \times d}$, shared by all layers of the decoder. Finally, for the input feature T_{i-1} of the i -th decoder layer, after adding their positional embeddings T^P , they are passed into the i -th decoder layer \mathcal{D}_i to compute the output

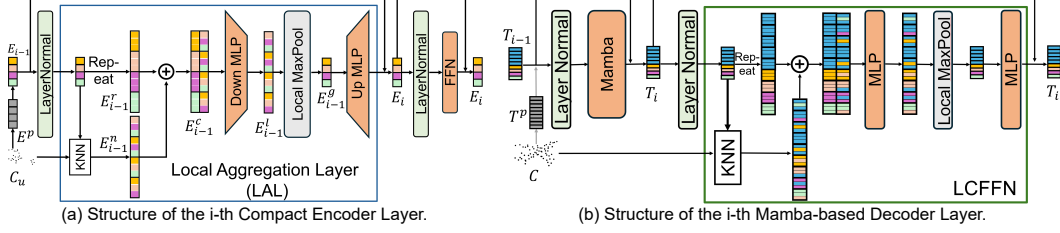


Figure 5: The structure of i -th locally constrained compact encoder layer (a) and i -th locally constrained Mamba-based decoder layer (b).

features T_i . Therefore, the forward process of each decoder layer is defined as:

$$T_i = \mathcal{D}_i(T_{i-1} + T^p), \quad i = 1, \dots, m, \quad (2)$$

Reconstruction. We utilize the features $R = T_m[rN :]$ decoded by the decoder to perform the 3D reconstruction. We employ multi-layer MLPs to construct coordinates reconstruction head \mathcal{H} and our reconstruction target is to recover the relative coordinates $R_M = \mathcal{H}(R)$ of the masked patches. We use the l_2 Chamfer Distance [9] (CD) as reconstruction loss. Therefore, our loss function \mathcal{L} is as follows

$$\mathcal{L} = CD(R_M, P_M) \quad (3)$$

3.3 Locally Constrained Compact Encoder

The classical Transformer [46] relies on the self-attention mechanism to perceive long-range correlations among all patches globally and has achieved great success in language and image domains. However, there remains uncertainty about whether directly transferring a Transformer-based encoder is suitable for point cloud data. Firstly, applications of point clouds are more inclined towards practical embedded devices such as robots or VR headsets. The hardware resources of these devices are limited, imposing higher limits on the model size and complexity, and the Transformer-based backbone demands significantly more resources than traditional networks, as illustrated in Table 1. Secondly, extensive research [34, 40, 50] and our empirical observation as illustrated in Figure 2 also indicate that the perception of local geometry in point cloud data far outweighs the need for global perception. Therefore, the computation of long-range correlations in self-attention leads to a considerable amount of redundant calculations. To address these practical issues, we propose a locally constrained compact encoder.

Our compact encoder consists of n stacked compact encoder layers, each layer comprising a local aggregation layer (LAL) and a feed-forward network (FFN), as shown in Figure 5 (a). For the i -th encoder layer, the output (E_{i-1}) of the preceding layer, added with the positional embedding and normalized by layer normal, is initially fed to the Local Aggregation Layer (LAL) for aggregating local geometric. Afterward, the result is added to the input residual, passed through layer normalization, and finally fed into a Feed-forward Network (FFN) to obtain the ultimate output feature (E_i). This process can be formalized as follows,

$$E_i = E_{i-1} + l_i(n_i^1(E_{i-1}), C_u) \quad (4)$$

$$E_i = E_i + f_i(n_i^2(E_i)) \quad (5)$$

where $l_i(\cdot)$ represents the LAM, $n_i^1(\cdot)$ and $n_i^2(\cdot)$ represents layer normalization, and $f_i(\cdot)$ represents the FFN.

In the local aggregation layer, we first use the k -nearest neighbors algorithm based on the central coordinates C_u of the features E_{i-1} to find the k nearest neighbors feature $E_{i-1}^n \in \mathbb{R}^{rkN \times d}$ for each token in E_{i-1} . We then replicate each token of E_{i-1} k times and concatenate them with their corresponding neighbors to obtain $E_{i-1}^c \in \mathbb{R}^{rkN \times 2d}$. Next, Down MLP performs a non-linear mapping on all local neighboring features to capture local geometric information. Subsequently, local max pooling is applied to aggregate all local features for each patch. Finally, Up MLP maps all patches to obtain locally enhanced features $E_i \in \mathbb{R}^{rN \times d}$. Our LAL consists of only two simple MLP layers,

significantly reducing the network’s parameters. Additionally, since static local geometric constraints only need to be computed once at the beginning and are shared across all layers thereafter, it avoids dynamic attention computations in each layer, significantly reducing computational requirements. It uses only two MLPs for information mapping, greatly reducing the network’s parameters.

3.4 Locally Constrained Mamba-based Decoder

The decoder for mask point modeling needs to recover information about masked patches based on the features E_n extracted from unmasked patches by the encoder. A common approach is to concatenate the features E_n of unmasked patches before randomly initialized features Q of masked patches as the input to the decoder, as shown in Figure 4. However, at this point, there is a significant difference in information density between features E_n and Q . The Transformer architecture and our local aggregation layer both treat each token in the input as equally important initially, it works well when the information density of all tokens is similar. It does not adapt well to cases where there is a large difference in information density in the input.

To efficiently extract more geometric priors from unmasked features E_n , we were inspired by the Mamba [13] model in time sequence and proposed using a Mamba-based decoder. This decoder can extract more prior information from the preceding tokens in the sequence based on the input order to aid the learning of subsequent tokens. Initially, we simply replaced the self-attention layer in the original Transformer-based [46] decoder with the state space model (SSM) layer from Mamba. We also sorted the input sequence based on the order of each patch’s center point coordinates, creating a naive Mamba-based decoder. Our experiments in Section 8 revealed that although this naive decoder is efficient enough, the simple sorting method cannot effectively model the complex spatial geometry of point clouds and leads to a strong dependence on the order of input patches.

To ensure that the SSM fully perceives the spatial geometry of point clouds, we further introduced the concept of local constraints from the local aggregation layer into the feedforward neural network layer of our decoder, getting the Local Constraints Feedforward Network (LCFFN). By feeding the tokens outputted by the SSM layer into the LCFFN, the LCFFN can implicitly exchange information between geometrically adjacent patches based on their central coordinates. This eliminates the limitation in the SSM layer where explicit sequential input fails to perceive complex geometry fully. Finally, in Section 5.1, we also qualitatively explain from an information theory perspective that this Mamba-based architecture has greater reconstruction potential compared to the Transformer.

Our Mamba-based decoder consists of m stacked decoder layers, each layer comprising a Mamba SSM layer and a local constraints feedforward network (LCFFN), as shown in Figure 5 (b). For the i -th decoder layer, we first add the output (T_{i-1}) of the previous layer with the positional embeddings (T^p) and normalize it through layer normalization. Then, we use the Mamba SSM layer ($s_i(\cdot)$) to perceive geometry from unmasked features and predict masked features. Finally, in the LCFFN ($f_i^l(\cdot)$), we further perceive shape priors based on the central coordinates of each token from its geometrically adjacent tokens. This process can be formalized as follows:

$$T_i = T_{i-1} + s_i(n_i^1(T_{i-1})) \tag{6}$$

$$T_i = T_i + f_i^l(n_i^2(T_i), C) \tag{7}$$

4 Experiments

4.1 Pre-training

We pre-training our LCM using five different pretraining strategies: Point-BERT [60], MaskPoint [28], Point-MAE [37], Point-M2AE [65], and ACT [8]. For a fair comparison, we use ShapeNet [3] as our pre-training dataset, encompassing over 50,000 distinct 3D models spanning 55 prevalent object categories. For the hyperparameter settings during the pretraining phase, we used the same settings as previous methods.

4.2 Fine-tuning on Downstream Tasks

We assess the performance of our LCM by fine-tuning our models on various downstream tasks, including object classification, scene-level detection, and part segmentation.

Table 1: Classification accuracy on real-scanned point clouds (ScanObjectNN). We report the overall accuracy (%) on three variants. "#Params" represents the model's parameters and FLOPs refer to the model's floating point operations. GPT, CL, and MPM respectively refer to pre-training strategies based on autoregression, contrastive learning, and masked point modeling. \circ is the reported results from the original paper. \bullet is the result reproduced in our downstream settings.

Method	Pretrain	#Params(M)	FLOPs(G)	ScanObjectNN		
				OBJ-BG	OBJ-ONLY	PB-T50-RS
<i>Supervised Learning Only</i>						
\circ PointNe [39]	\times	3.5	0.5	73.3	79.2	68.0
\circ PointNet++ [40]	\times	1.5	1.7	82.3	84.3	77.9
\circ PointMLP [32]	\times	12.6	31.4	-	-	85.2
\circ Transformer [46]	\times	22.1	4.8	86.75	86.92	80.78
\circ PointMamba [27]	\times	12.3	-	88.30	87.78	82.48
\circ SFR [63]	\times	-	-	-	-	87.80
\bullet Transformer [46]	\times	22.1	4.8	91.95	91.39	86.65
\bullet LCM (Ours)	\times	2.7(\downarrow 88%)	1.3(\downarrow 73%)	92.77(\uparrow 0.82)	91.54(\uparrow 0.15)	87.75(\uparrow 1.10)
<i>Self-Supervised Learning</i>						
\circ Point-BERT [60]	MPM	22.1	4.5	87.43	88.12	83.07
\circ MaskPoint [28]	MPM	22.1	4.5	89.30	88.10	84.30
\circ Point-MAE [37]	MPM	22.1	4.8	90.02	88.29	85.18
\circ Point-MAE w/ IDPT [64]	MPM	23.3	7.1	91.22	90.02	84.94
\circ Point-MAE w/ DAPT [70]	MPM	22.7	5.0	90.88	90.19	85.08
\circ Inter-MAE [29]	MPM	22.1	4.8	88.70	89.60	85.40
\circ Point-M2AE [65]	MPM	12.9	7.9	91.22	88.81	86.43
\circ ACT [8]	MPM	22.1	4.8	93.29	91.91	88.21
\circ PointGPT-B [5]	GPT	120.5	36.2	93.60	92.50	89.60
\circ PointMamba [27]	MPM	12.3	-	93.29	91.91	88.17
\bullet Point-BERT [60]	MPM	22.1	4.5	92.48	91.60	87.91
\bullet MaskPoint [28]	MPM	22.1	4.5	92.17	91.69	87.65
\bullet Point-MAE [37]	MPM	22.1	4.8	92.67	92.08	88.27
\bullet Point-M2AE [65]	MPM	12.9	7.9	93.12	91.22	88.06
\bullet ACT [8]	MPM	22.1	4.8	92.08	91.70	87.52
\bullet Point-BERT w/ LCM	MPM	3.1 (\downarrow 86%)	2.5 (\downarrow 44%)	93.55 (\uparrow 1.07)	92.43 (\uparrow 0.83)	88.57 (\uparrow 0.66)
\bullet MaskPoint w/ LCM	MPM	3.1 (\downarrow 86%)	2.5 (\downarrow 44%)	93.31 (\uparrow 1.14)	91.98 (\uparrow 0.29)	87.75 (\uparrow 0.10)
\bullet Point-MAE w/ LCM	MPM	2.7 (\downarrow 88%)	1.3 (\downarrow 73%)	94.51 (\uparrow 1.84)	92.75 (\uparrow 0.67)	88.87 (\uparrow 0.60)
\bullet Point-M2AE w/ LCM	MPM	2.5 (\downarrow 81%)	6.7 (\downarrow 15%)	93.83 (\uparrow 0.71)	92.41 (\uparrow 1.19)	88.38 (\uparrow 0.32)
\bullet ACT w/ LCM	MPM	3.1 (\downarrow 86%)	2.8 (\downarrow 42%)	94.13 (\uparrow 2.05)	92.66 (\uparrow 0.96)	88.57 (\uparrow 1.05)

4.2.1 Object Classification

We initially assess the overall classification accuracy of our pre-trained models on both real-scanned (ScanObjectNN [44]) and synthetic (ModelNet40 [57]) datasets. ScanObjectNN is a prevalent dataset consisting of approximately 15,000 real-world scanned point cloud samples from 15 categories. These objects represent indoor scenes and are often characterized by cluttered backgrounds and occlusions caused by other objects. For the ScanObjectNN dataset, we sample 2048 points for each instance and report results without voting mechanisms. We applied simple scaling and rotation data augmentation of previous work [8, 37] in the downstream setting of ScanObjectNN. We reported the results of different models under our downstream setting, with \bullet marking the results. For the ModelNet40 dataset, due to space limitation, we will further analyze its results in Section 5.4.

To ensure a fair comparison, we conducted our experiments following the standard practices in the field (as used in previous work [8, 28, 37, 60, 65]). For each point cloud classification experiment, we used eight different random seeds (0-7) to ensure the robustness and reliability of our results. The performance reported in Table 1 represents the **average accuracy** achieved across these eight trials for each model configuration.

As presented in Table 1, our model has many exciting results. 1) **Lighter, faster, and more powerful**. When trained from scratch using supervised learning only, our LCM model demonstrates performance improvements of 0.82%, 0.15%, and 1.10% across three variant datasets compared to the Transformer architecture. Similarly, after pre-training (*e.g.*, Point-MAE), our model outperformed the standard Transformer by 1.84%, 0.67%, and 0.60% across the three variants of the ScanObjectNN dataset. Notably, these improvements are achieved despite an **88%** reduction in parameters and a **73%** reduction in FLOPs. This improvement is exciting as it indicates that our architecture is better suited for point cloud data compared to the standard Transformer. Additionally, due to its extremely high

Table 2: Object detection results on ScanNetV2. We adopt the average precision with 3D IoU thresholds of 0.25 (AP_{25}) and 0.5 (AP_{50}) for the evaluation metrics. † is our reproduction results, due to the lack of detection code in their paper.

Methods	Pretrain	AP_{25}	AP_{50}
<i>Supervised Learning Only</i>			
VoteNet [38]	✗	58.6	33.5
3DETR [34](baseline)	✗	62.1	37.9
Transformer [46]	✗	60.5	40.6
LCM (Ours)	✗	63.8 († 3.3)	46.4 († 5.8)
<i>Self-Supervised Learning</i>			
PointContrast [58]	CL	58.5	38.0
STRL [25]	CL	-	38.4
Point-BERT [60]	MPM	61.0	38.3
PiMAE [4]	MPM	62.6	39.4
Point-MAE† [37]	MPM	59.5	41.2
Point-M2AE† [65]	MPM	60.0	41.4
ACT [8]	MPM	63.8	42.1
DepthContrast [69]	CL	64.0	42.9
MaskPoint [28]	MPM	64.2	42.1
Point-BERT [60] w/ LCM	MPM	65.3 († 4.3)	47.3 († 9.0)
Point-MAE [37] w/ LCM	MPM	64.7 († 5.2)	47.2 († 6.0)
Point-M2AE [65] w/ LCM	MPM	63.5 († 3.5)	44.0 († 2.6)
ACT [8] w/ LCM	MPM	65.0 († 1.2)	45.8 († 3.7)
MaskPoint [28] w/ LCM	MPM	65.3 († 1.1)	46.3 († 4.2)

Table 3: Part segmentation results on the ShapeNetPart. The mean IoU across all categories, i.e., $mIoU_c$ (%), and the mean IoU across all instances, i.e., $mIoU_I$ (%) are reported.

Methods	Pretrain	$mIoU_c$	$mIoU_I$
<i>Supervised Learning Only</i>			
PointNet++ [40]	✗	81.9	85.1
DGCNN [50]	✗	82.3	85.2
Transformer [46]	✗	83.9	86.0
LCM (Ours)	✗	84.6 († 0.7)	86.3 († 0.3)
<i>Self-Supervised Learning</i>			
Transformer-OcCo [48]	CL	83.4	85.1
PointContrast [58]	CL	-	85.1
CrossPoint [1]	CL	-	85.5
Point-BERT [60]	MPM	84.1	85.6
IDPT [64]	MPM	83.8	85.9
MaskPoint [28]	MPM	84.4	86.0
Point-MAE [37]	MPM	84.2	86.1
ACT [8]	MPM	84.7	86.1
PointGPT-S [5]	MPM	84.1	86.2
PointGPT-B [5]	MPM	84.5	86.4
Point-M2AE [65]	MPM	84.9	86.5
Point-BERT [60] w/ LCM	MPM	85.0 († 0.9)	86.5 († 0.9)
MaskPoint [28] w/ LCM	MPM	85.1 († 0.7)	86.6 († 0.6)
Point-MAE [37] w/ LCM	MPM	85.1 († 0.9)	86.6 († 0.5)
Point-M2AE [65] w/ LCM	MPM	85.0 († 0.1)	86.5 (-)
ACT [8] w/ LCM	MPM	85.0 († 0.3)	86.7 († 0.6)

efficiency, it provides strong support for the practical deployment of these pre-trained models. 2) **Universal.** We have replaced the original Transformer architecture with our LCM model in five different MPM-based pre-training methods. All experimental results are exciting as our model achieved universal performance improvements with fewer parameters and computations, highlighting the versatility of our model. In the future, we will further adapt to additional pre-training methods.

4.2.2 Object Detection

We further assess the object detection performance of our pre-trained model on the more challenging scene-level point cloud dataset, ScanNetV2 [6], to evaluate our model’s scene understanding capabilities. Following the previous pre-training work [8, 28], we use 3DETR [34] as the baseline and only replace the Transformer-based encoder of 3DETR with our pre-trained compact encoder. Subsequently, the entire model is fine-tuned for object detection. In contrast to previous approaches [4, 8, 28], which necessitate pre-train on large-scale scene-level point clouds like ScanNet, our approach directly utilizes models pre-trained on ShapeNet. This further emphasizes the generalizability of our pre-trained models.

Table 2 showcases our experimental results, our compact model has shown significant improvements in scene-level point cloud data, such as Point-MAE [37] achieving a 5.2% improvement in AP_{25} and a 6.0% improvement in AP_{50} compared to the Transformer. This improvement is remarkable, and we believe this is primarily due to the presence of a large number of background and noise points in the scene-level point cloud. Using a local constraint modeling approach effectively filters out unimportant background and noise, allowing the model to focus more on meaningful points.

4.2.3 Part Segmentation

We also assess the performance of LCM in part segmentation using the ShapeNetPart dataset [3], comprising 16,881 samples across 16 categories. We utilize the same segmentation setting after the pre-trained encoder as in previous works [37, 65] for fair comparison. As shown in Table 3, our LCM-based model also exhibits a clear boost compared to Transformer-based models. These results demonstrate that our model exhibits superior performance in tasks such as part segmentation, which demands a more fine-grained understanding of point clouds.

Table 4: Effects of the Network Structure of the Locally Constrained Compact Encoder.

Local	Local	MLPs	FFN	Param(M)	ScanObjectNN
A	✗	✗	✓	1.4	85.45
B	✗	✓	✓	2.3	85.74
C	✓	✓	✗	1.8	87.77
D	✓	✓	✓	2.7	88.06

Table 5: Effects of Locally Constrained Mamba-based Decoder.

Decoder	ScanObjectNN
Transformer	88.76
LAL	88.38
Mamba	88.62
Transformer w/ LCFFN	88.79
LAL w/ LCFFN	88.51
Mamba w/ LCFFN	89.35

4.3 Ablation Study

Effects of Locally Constrained Compact Encoder. We explore the performance of our locally constrained compact encoder by comparing it with a Transformer-based encoder in classification, detection, and part segmentation. The results from Tables 1, Table 2, and Table 3, obtained solely through supervised learning from scratch, clearly demonstrate the advantages of our LCM encoder over the Transformer-based encoder in terms of performance and efficiency, particularly in detection tasks, with an improvement of up to 6.0% in the AP_{50} metric.

This substantial improvement is attributed to the compact encoder’s focused attention on the most crucial information for each point patch, such as local neighborhoods while disregarding unimportant details. This is similar to a redundancy-reducing compression concept, which is crucial for point cloud analysis, especially in large-scale scene-level point clouds where significant redundancy and noise points often exist. Our local constraint approach enables the model to focus on critical areas, leading to a combined improvement in efficiency and performance. Moreover, this redundancy-reducing concept helps our model avoid overfitting the training dataset. We provide detailed explanations of this phenomenon in the Section 5.5.

Effects of the Network Structure of the Locally Constrained Encoder. As shown in Figure 5(a), each layer of our locally constrained compact encoder consists primarily of three parts: a locally constrained unit based on k-NN, MLPs mapping unit composed of Down MLP and Up MLP, and the final FFN layer. We explore the effects of each unit separately. Specifically, we train Encoders with different structures from scratch on the ScanObjectNN [44] dataset and test their classification performance. As shown in Table 4, comparing A and B reveals that a simple two-layer MLP without local aggregation does not substantially improve the network’s performance. In contrast, the results of C and D compared to A and B demonstrate a significant performance improvement. This improvement is mainly attributed to the introduction of local geometric perception and aggregation. Comparing the results of C and D, the introduction of FFN brings a slight improvement. Therefore, FFN is not indispensable in our compact encoder, but we choose to incorporate FFN to further perform mapping. These experiments further indicate the necessity of local geometric perception and aggregation for point cloud feature extraction.

Effects of Locally Constrained Mamba-based Decoder. We further compared the impact of different decoder designs during the pre-training phase. Specifically, we compared the vanilla Transformer-based decoder, our LAL-based decoder, and the vanilla Mamba-based architecture, as well as their performance after incorporating LCFFN. As shown in Table 5, the results indicate that the Vanilla Transformer slightly outperforms the Vanilla Mamba in terms of performance, likely due to the limitation imposed by the simple geometric sequential input sequences on the Vanilla Mamba’s capabilities. After incorporating LCFFN, the Mamba decoder exhibits a significant improvement due to the introduction of implicit geometric order. In contrast, the Transformer’s improvement is slight because the geometric order is already implicitly captured by self-attention.

4.4 Limitation

Our current model does have limitations in handling dynamic importance perception and long-range dependency modeling. Our design prioritizes efficiency, which can be at odds with the increased complexity required for capturing dynamic importance and long-range dependencies. This focus on efficiency led us to simplify the model in certain aspects, and as a result, we did not fully integrate mechanisms for dynamic importance perception and long-range dependency modeling in this version

of our model. Despite these constraints, the current model has demonstrated significant improvements in performance across various tasks. Nevertheless, we also acknowledge that incorporating dynamic importance perception and long-range dependency modeling could further enhance the model’s capabilities, particularly in more complex scenarios. We are actively exploring methods to address these limitations in future work.

4.5 Conclusion

In this paper, we propose a compact point cloud model, LCM, specifically designed for masked point modeling pre-training, aiming to achieve an elegant balance between performance and efficiency. Based on the idea of redundancy reduction, we propose focusing on the most relevant point patches ignoring unimportant parts in the encoder, and introducing a local aggregation layer to replace the vanilla self-attention. Considering the varying information density between masked and unmasked patches in the decoder inputs of MPM, we introduce a locally constrained Mamba-base decoder to ensure linear complexity while maximizing the perception of point cloud geometry information from unmasked patches. By conducting extensive experiments across various tasks such as classification and detection, we demonstrate that our LCM is a universal model with significant improvements in efficiency and performance compared to traditional Transformer models.

4.6 Acknowledgements

This work is supported in part by the National Key Research and Development Project of China (Grant No. 2023YFF0905502), the National Natural Science Foundation of China, under Grant (62302309, 62171248), Shenzhen Science and Technology Program (JCYJ20220818101014030, JCYJ20220818101012025), and the PCNL KEY project (PCL2023AS6-1).

References

- [1] Mohamed Afham, Isuru Dissanayake, Dinithi Dissanayake, Amaya Dharmasiri, Kanchana Thilakarathna, and Ranga Rodrigo. Crosspoint: Self-supervised cross-modal contrastive learning for 3d point cloud understanding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9902–9912, 2022. 1, 3, 8
- [2] Hangbo Bao, Li Dong, Songhao Piao, and Furu Wei. Beit: Bert pre-training of image transformers. *arXiv preprint arXiv:2106.08254*, 2021. 1
- [3] Angel X Chang, Thomas Funkhouser, Leonidas Guibas, Pat Hanrahan, Qixing Huang, Zimo Li, Silvio Savarese, Manolis Savva, Shuran Song, Hao Su, et al. Shapenet: An information-rich 3d model repository. *arXiv preprint arXiv:1512.03012*, 2015. 6, 8, 17
- [4] Anthony Chen, Kevin Zhang, Renrui Zhang, Zihan Wang, Yuheng Lu, Yandong Guo, and Shanghang Zhang. Pimae: Point cloud and image interactive masked autoencoders for 3d object detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 5291–5301, Vancouver, Canada, Jun 18-22 2023. 3, 8
- [5] Guangyan Chen, Meiling Wang, Yi Yang, Kai Yu, Li Yuan, and Yufeng Yue. Pointgpt: Auto-regressively generative pre-training from point clouds. volume 36, 2024. 7, 8, 18
- [6] Angela Dai, Angel X Chang, Manolis Savva, Maciej Halber, Thomas Funkhouser, and Matthias Nießner. Scannet: Richly-annotated 3d reconstructions of indoor scenes. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 5828–5839, 2017. 3, 8, 17, 20
- [7] Tao Dai, Beiliang Wu, Peiyuan Liu, Naiqi Li, Jigang Bao, Yong Jiang, and Shu-Tao Xia. Periodicity decoupling framework for long-term series forecasting. In *The Twelfth International Conference on Learning Representations*, 2024. 16
- [8] Runpei Dong, Zekun Qi, Linfeng Zhang, Junbo Zhang, Jianjian Sun, Zheng Ge, Li Yi, and Kaisheng Ma. Autoencoders as cross-modal teachers: Can pretrained 2d image transformers help 3d representation learning? Kigali, Rwanda, May 1-5 2023. 1, 3, 6, 7, 8, 17, 18
- [9] Haoqiang Fan, Hao Su, and Leonidas J Guibas. A point set generation network for 3d object reconstruction from a single image. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 605–613, Honolulu, Hawaii, USA, July 21-26 2017. 5
- [10] Hao Fang, Bin Chen, Xuan Wang, Zhi Wang, and Shu-Tao Xia. Gifd: A generative gradient inversion method with feature domain optimization. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 4967–4976, 2023. 16

- [11] Hao Fang, Jiawei Kong, Wenbo Yu, Bin Chen, Jiawei Li, Shutao Xia, and Ke Xu. One perturbation is enough: On generating universal adversarial perturbations against vision-language pre-training models. *arXiv preprint arXiv:2406.05491*, 2024. 16
- [12] Hao Fang, Yixiang Qiu, Hongyao Yu, Wenbo Yu, Jiawei Kong, Baoli Chong, Bin Chen, Xuan Wang, and Shu-Tao Xia. Privacy leakage on dnns: A survey of model inversion attacks and defenses. *arXiv preprint arXiv:2402.04013*, 2024. 16
- [13] Albert Gu and Tri Dao. Mamba: Linear-time sequence modeling with selective state spaces. *arXiv preprint arXiv:2312.00752*, 2023. 2, 6, 15, 16
- [14] Albert Gu, Tri Dao, Stefano Ermon, Atri Rudra, and Christopher Ré. Hippo: Recurrent memory with optimal polynomial projections. *Advances in neural information processing systems*, 33:1474–1487, 2020. 16
- [15] Albert Gu, Karan Goel, Ankit Gupta, and Christopher Ré. On the parameterization and initialization of diagonal state space models. *Advances in Neural Information Processing Systems*, 35:35971–35983, 2022.
- [16] Albert Gu, Karan Goel, and Christopher Ré. Efficiently modeling long sequences with structured state spaces. *arXiv preprint arXiv:2111.00396*, 2021. 2, 15, 16
- [17] Albert Gu, Isys Johnson, Karan Goel, Khaled Saab, Tri Dao, Atri Rudra, and Christopher Ré. Combining recurrent, convolutional, and continuous-time models with linear state space layers. *Advances in neural information processing systems*, 34:572–585, 2021. 16
- [18] Hang Guo, Tao Dai, Yuanchao Bai, Bin Chen, Shu-Tao Xia, and Zexuan Zhu. Adaptir: Parameter efficient multi-task adaptation for pre-trained image restoration models. *arXiv preprint arXiv:2312.08881*, 2023. 3
- [19] Hang Guo, Jinmin Li, Tao Dai, Zhihao Ouyang, Xudong Ren, and Shu-Tao Xia. Mambair: A simple baseline for image restoration with state-space model. *arXiv preprint arXiv:2402.15648*, 2024. 2
- [20] Meng-Hao Guo, Jun-Xiong Cai, Zheng-Ning Liu, Tai-Jiang Mu, Ralph R Martin, and Shi-Min Hu. Pct: Point cloud transformer. *Computational Visual Media*, 7(2):187–199, 2021. 16
- [21] Ziyu Guo, Renrui Zhang, Longtian Qiu, Xianzhi Li, and Pheng Ann Heng. Joint-mae: 2d-3d joint masked autoencoders for 3d point cloud pre-training. In *Proceedings of International Joint Conference on Artificial Intelligence (IJCAI)*, Macao, China, August 19-25 2023. 3
- [22] Kaiming He, Xinlei Chen, Saining Xie, Yanghao Li, Piotr Dollár, and Ross Girshick. Masked autoencoders are scalable vision learners. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 16000–16009, 2022. 1
- [23] Xinwei He, Silin Cheng, Dingkan Liang, Song Bai, Xi Wang, and Yingying Zhu. Latformer: Locality-aware point-view fusion transformer for 3d shape recognition. *Pattern Recognition*, 151:110413, 2024. 16
- [24] David Hilbert and David Hilbert. Über die stetige abbildung einer linie auf ein flächenstück. *Dritter Band: Analysis: Grundlagen der Mathematik: Physik Verschiedenes: Nebst Einer Lebensgeschichte*, pages 1–2, 1935. 19
- [25] Siyuan Huang, Yichen Xie, Song-Chun Zhu, and Yixin Zhu. Spatio-temporal self-supervised representation learning for 3d point clouds. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 6535–6545, 2021. 8
- [26] Md Mohaiminul Islam, Mahmudul Hasan, Kishan Shamsundar Athrey, Tony Braskich, and Gedas Bertasius. Efficient movie scene detection using state-space transformers. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 18749–18758, 2023. 16
- [27] Dingkan Liang, Xin Zhou, Xinyu Wang, Xingkui Zhu, Wei Xu, Zhikang Zou, Xiaoqing Ye, and Xiang Bai. Pointmamba: A simple state space model for point cloud analysis. *arXiv preprint arXiv:2402.10739*, 2024. 7, 16, 18
- [28] Haotian Liu, Mu Cai, and Yong Jae Lee. Masked discrimination for self-supervised learning on point clouds. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 657–675, Tel Aviv, Israel, October 23-27 2022. 6, 7, 8, 17, 18
- [29] Jiaming Liu, Yue Wu, Maoguo Gong, Zhixiao Liu, Qiguang Miao, and Wenping Ma. Inter-modal masked autoencoder for self-supervised learning on point clouds. *IEEE Transactions on Multimedia*, 2023. 7, 18
- [30] Yue Liu, Yunjie Tian, Yuzhong Zhao, Hongtian Yu, Lingxi Xie, Yaowei Wang, Qixiang Ye, and Yunfan Liu. Vmamba: Visual state space model. *arXiv preprint arXiv:2401.10166*, 2024. 2, 16
- [31] Jun Ma, Feifei Li, and Bo Wang. U-mamba: Enhancing long-range dependency for biomedical image segmentation. *arXiv preprint arXiv:2401.04722*, 2024. 16
- [32] Xu Ma, Can Qin, Haoxuan You, Haoxi Ran, and Yun Fu. Rethinking network design and local geometry in point cloud: A simple residual mlp framework. In *Proceedings of International*

- Conference on Learning Representations (ICLR)*, page 31, Online, Apr. 25-29 2022. 7, 16, 18
- [33] Harsh Mehta, Ankit Gupta, Ashok Cutkosky, and Behnam Neyshabur. Long range language modeling via gated state spaces. *arXiv preprint arXiv:2206.13947*, 2022. 16
- [34] Ishan Misra, Rohit Girdhar, and Armand Joulin. An end-to-end transformer model for 3d object detection. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2906–2917, 2021. 5, 8, 16, 17
- [35] Eric Nguyen, Karan Goel, Albert Gu, Gordon Downs, Preey Shah, Tri Dao, Stephen Baccus, and Christopher Ré. S4nd: Modeling images and videos as multidimensional signals with state spaces. *Advances in neural information processing systems*, 35:2846–2861, 2022. 16
- [36] Aaron van den Oord, Yazhe Li, and Oriol Vinyals. Representation learning with contrastive predictive coding. *arXiv preprint arXiv:1807.03748*, 2018. 3
- [37] Yatian Pang, Wenxiao Wang, Francis EH Tay, Wei Liu, Yonghong Tian, and Li Yuan. Masked autoencoders for point cloud self-supervised learning. In *Proceedings of the European Conference on Computer Vision (ECCV)*, Tel Aviv, Israel, October 23-27 2022. 1, 2, 3, 4, 6, 7, 8, 16, 17, 18
- [38] Charles R Qi, Or Litany, Kaiming He, and Leonidas J Guibas. Deep hough voting for 3d object detection in point clouds. In *proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 9277–9286, 2019. 8
- [39] Charles R Qi, Hao Su, Kaichun Mo, and Leonidas J Guibas. Pointnet: Deep learning on point sets for 3d classification and segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 652–660, Honolulu, HI, USA, July 21-26 2017. 7, 16, 17, 18
- [40] Charles Ruizhongtai Qi, Li Yi, Hao Su, and Leonidas J Guibas. Pointnet++: Deep hierarchical feature learning on point sets in a metric space. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, page 30, Long Beach, CA, USA, Dec. 4-9 2017. 2, 5, 7, 8, 16, 18
- [41] Zekun Qi, Runpei Dong, Guofan Fan, Zheng Ge, Xiangyu Zhang, Kaisheng Ma, and Li Yi. Contrast with reconstruct: Contrastive 3d representation learning guided by generative pretraining. In *International Conference on Machine Learning*, 2023. 3
- [42] Jimmy TH Smith, Andrew Warrington, and Scott W Linderman. Simplified state space layers for sequence modeling. *arXiv preprint arXiv:2208.04933*, 2022. 16
- [43] Yonglong Tian, Dilip Krishnan, and Phillip Isola. Contrastive multiview coding. In *ECCV*, pages 776–794. Springer, 2020. 3
- [44] Mikaela Angelina Uy, Quang-Hieu Pham, Binh-Son Hua, Thanh Nguyen, and Sai-Kit Yeung. Revisiting point cloud classification: A new benchmark dataset and classification model on real-world data. In *Proceedings of IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 1588–1597, Seoul, Korea, Oct 27- Nov 2 2019. 3, 7, 9, 17, 20
- [45] Laurens Van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *Journal of machine learning research*, 9(11), 2008. 20
- [46] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, page 30, Long Beach, CA, USA, Dec. 4-9 2017. 1, 2, 3, 5, 6, 7, 8, 16, 20
- [47] Chengyao Wang, Li Jiang, Xiaoyang Wu, Zhuotao Tian, Bohao Peng, Hengshuang Zhao, and Jiaya Jia. Groupcontrast: Semantic-aware self-supervised representation learning for 3d understanding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 4917–4928, 2024. 3
- [48] Hanchen Wang, Qi Liu, Xiangyu Yue, Joan Lasenby, and Matt J Kusner. Unsupervised point cloud pre-training via occlusion completion. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 9782–9792, 2021. 8
- [49] Jue Wang, Wentao Zhu, Pichao Wang, Xiang Yu, Linda Liu, Mohamed Omar, and Raffay Hamid. Selective structured state-spaces for long-form video understanding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6387–6397, 2023. 16
- [50] Yue Wang, Yongbin Sun, Ziwei Liu, Sanjay E Sarma, Michael M Bronstein, and Justin M Solomon. Dynamic graph cnn for learning on point clouds. *Acm Transactions On Graphics (TOG)*, 38(5):1–12, 2019. 5, 8, 16, 18
- [51] Ziyi Wang, Xumin Yu, Yongming Rao, Jie Zhou, and Jiwen Lu. P2p: Tuning pre-trained image models for point cloud analysis with point-to-pixel prompting. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, New Orleans, Louisiana, USA, December 1-9 2022. 18

- [52] Xiaoyang Wu, Li Jiang, Peng-Shuai Wang, Zhijian Liu, Xihui Liu, Yu Qiao, Wanli Ouyang, Tong He, and Hengshuang Zhao. Point transformer v3: Simpler, faster, stronger. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, volume 35, Seattle, USA, Jun 17-21 2024. 16
- [53] Xiaoyang Wu, Yixing Lao, Li Jiang, Xihui Liu, and Hengshuang Zhao. Point transformer v2: Grouped vector attention and partition-based pooling. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, volume 35, pages 33330–33342, New Orleans, Louisiana, USA, November 28 - December 9 2022. 16
- [54] Xiaoyang Wu, Zhuotao Tian, Xin Wen, Bohao Peng, Xihui Liu, Kaicheng Yu, and Hengshuang Zhao. Towards large-scale 3d representation learning with multi-dataset point prompt training. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 19551–19562, 2024. 3
- [55] Xiaoyang Wu, Xin Wen, Xihui Liu, and Hengshuang Zhao. Masked scene contrast: A scalable framework for unsupervised 3d representation learning. In *Proceedings of the IEEE/CVF Conference on computer vision and pattern recognition*, pages 9415–9424, 2023. 3
- [56] Yue Wu, Jiaming Liu, Maoguo Gong, Peiran Gong, Xiaolong Fan, A Kai Qin, Qiguang Miao, and Wenping Ma. Self-supervised intra-modal and cross-modal contrastive learning for point cloud understanding. *IEEE Transactions on Multimedia*, 26:1626–1638, 2023. 18
- [57] Zhirong Wu, Shuran Song, Aditya Khosla, Fisher Yu, Linguang Zhang, Xiaoou Tang, and Jianxiong Xiao. 3d shapenets: A deep representation for volumetric shapes. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 1912–1920, 2015. 7, 17, 20
- [58] Saining Xie, Jiatao Gu, Demi Guo, Charles R Qi, Leonidas Guibas, and Or Litany. Pointcontrast: Unsupervised pre-training for 3d point cloud understanding. In *European conference on computer vision*, pages 574–591. Springer, 2020. 1, 3, 8
- [59] Zhenda Xie, Zheng Zhang, Yue Cao, Yutong Lin, Jianmin Bao, Zhuliang Yao, Qi Dai, and Han Hu. Simmim: A simple framework for masked image modeling. In *CVPR*, pages 9653–9663, 2022. 1
- [60] Xumin Yu, Lulu Tang, Yongming Rao, Tiejun Huang, Jie Zhou, and Jiwen Lu. Point-bert: Pre-training 3d point cloud transformers with masked point modeling. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 19313–19322, New Orleans, Louisiana, USA, June 21-24 2022. 1, 3, 6, 7, 8, 16, 17, 18
- [61] Yaohua Zha, Tao Dai, Yanzi Wang, Hang Guo, Taolin Zhang, Zhihao Ouyang, Chunlin Fan, Bin Chen, Ke Chen, and Shu-Tao Xia. Block-to-scene pre-training for point cloud hybrid-domain masked autoencoders. *arXiv preprint arXiv:2410.09886*, 2024.
- [62] Yaohua Zha, Huizhen Ji, Jinmin Li, Rongsheng Li, Tao Dai, Bin Chen, Zhi Wang, and Shu-Tao Xia. Towards compact 3d representations via point feature enhancement masked autoencoders. In *Proceedings of the AAAI Conference on Artificial Intelligence (AAAI)*, VANCOUVER, CANADA, February 20-27 2024. 1, 3, 16
- [63] Yaohua Zha, Rongsheng Li, Tao Dai, Jianyu Xiong, Xin Wang, and Shu-Tao Xia. Sfr: Semantic-aware feature rendering of point cloud. In *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 1–5. IEEE, 2023. 7
- [64] Yaohua Zha, Jinpeng Wang, Tao Dai, Bin Chen, Zhi Wang, and Shu-Tao Xia. Instance-aware dynamic prompt tuning for pre-trained point cloud models. In *Proceedings of IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 14161–14170, Paris, France, October 4-6 2023. 3, 7, 8
- [65] Renrui Zhang, Ziyu Guo, Peng Gao, Rongyao Fang, Bin Zhao, Dong Wang, Yu Qiao, and Hongsheng Li. Point-m2ae: Multi-scale masked autoencoders for hierarchical point cloud pre-training. In *Proceedings of Advances in Neural Information Processing Systems (NeurIPS)*, New Orleans, Louisiana, USA, November 28 - December 9 2022. 1, 6, 7, 8, 17, 18
- [66] Renrui Zhang, Lihui Wang, Yu Qiao, Peng Gao, and Hongsheng Li. Learning 3d representations from 2d pre-trained models via image-to-point masked autoencoders. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 21769–21780, Vancouver, Canada, Jun 18-22 2023. 1, 3
- [67] Taolin Zhang, Jiawang Bai, Zhihe Lu, Dongze Lian, Genping Wang, Xinchao Wang, and Shu-Tao Xia. Parameter-efficient and memory-efficient tuning for vision transformer: A disentangled approach. *arXiv preprint arXiv:2407.06964*, 2024. 3
- [68] Taolin Zhang, Sunan He, Tao Dai, Zhi Wang, Bin Chen, and Shu-Tao Xia. Vision-language pre-training with object contrastive learning for 3d scene understanding. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pages 7296–7304, 2024. 16

- [69] Zaiwei Zhang, Rohit Girdhar, Armand Joulin, and Ishan Misra. Self-supervised pretraining of 3d features on any point-cloud. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 10252–10263, October 2021. 8
- [70] Xin Zhou, Dingkang Liang, Wei Xu, Xingkui Zhu, Yihan Xu, Zhikang Zou, and Xiang Bai. Dynamic adapter meets prompt tuning: Parameter-efficient transfer learning for point cloud analysis. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14707–14717, 2024. 3, 7
- [71] Lianghai Zhu, Bencheng Liao, Qian Zhang, Xinlong Wang, Wenyu Liu, and Xinggang Wang. Vision mamba: Efficient visual representation learning with bidirectional state space model. *arXiv preprint arXiv:2401.09417*, 2024. 2, 16

5 Appendix

5.1 An Information Theoretic Perspective of Our Mamba-based Decoder for MPM.

Here, we provide an information-theoretic perspective for our decoder design, using mutual information to qualitatively demonstrate that the Mamba-based SSM can perceive more information from unmasked patches to predict masked patches compared to a Transformer-based self-attention. The mutual information between random variables X and Y , $I(X; Y)$, measures the amount of information that can be gained about a random variable X from the knowledge about the other random variable Y . Therefore, based on the decoder input's different information densities, we can simply divide the input into X_1 , representing unmasked patches with higher information density, and X_2 , representing randomly initialized masked patches with lower information density. As illustrated in Figure 6, after being processed by the decoder, X_1 and X_2 respectively yield outputs Y_1 for unmasked patches and Y_2 for masked patches. We reconstruct the masked points based on Y_2 .

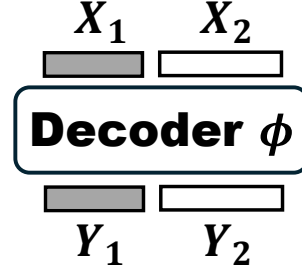


Figure 6: A simple illustration of information processing of MPM decoder.

Ideally, Y_2 needs to perceive sufficient geometric priors from both X_1 and X_2 to recover the masked points, more mutual information represents more recovery potential. Therefore, we would like to maximize the mutual information $I(Y_2; X_1, X_2)$. In what follows, we demonstrate that the mutual information preserved by our proposed Mamba-based decoder is larger than that of the standard transformer decoder.

Theorem 1. Let Y_1^M, Y_2^M and Y_1^T, Y_2^T denote the outputs of the Mamba-based and Transformer-based decoders respectively, $I(Y_2^M; X_1, X_2)$ denote the mutual information preserved by the Mamba-based decoder, and $I(Y_2^T; X_1, X_2)$ denote that of the Transformer-based decoder. We have $I(Y_2^M; X_1, X_2) \geq I(Y_2^T; X_1, X_2)$.

Proof. The first step is to formalize the input-output relation of the two decoding structures. For the Mamba decoder, as defined in [13, 16], the output can be expressed as:

$$\begin{aligned} Y_2^M &= C\bar{A}\bar{B}X_1 + C\bar{B}X_2 \\ &= AX_1 + BX_2. \end{aligned}$$

For the Transformer decoder, the attention mechanism can be expressed in the following matrix form:

$$\begin{bmatrix} X_1^\top W_q^\top W_k X_1 & X_1^\top W_q^\top W_k X_2 \\ X_2^\top W_q^\top W_k X_1 & X_2^\top W_q^\top W_k X_2 \end{bmatrix} \begin{bmatrix} W_v X_1 \\ W_v X_2 \end{bmatrix} = \begin{bmatrix} Y_1^T \\ Y_2^T \end{bmatrix}.$$

Thus,

$$Y_2^T = X_2^\top W_q^\top W_k X_1 \cdot W_v X_1 + X_2^\top W_q^\top W_k X_2 \cdot W_v X_2.$$

Compared with the linear relation captured by Y_2^M , Y_2^T models higher-order interactions of the input variables. So for any given Mamba parameters A and B , there exists Transformer parameters W_k, W_q, W_v and a function g , such that $Y_2^T = g(Y_2^M)$.

As Y_2^T is a function of Y_2^M , $(X_1, X_2) \rightarrow Y_2^M \rightarrow Y_2^T$ forms a Markov chain. So (X_1, X_2) and Y_2^T are independent when conditioned on Y_2^M , i.e., $p(Y_2^T, X_1, X_2 | Y_2^M) = p(Y_2^T | Y_2^M)p(X_1, X_2 | Y_2^M)$. According to the definition of conditional mutual information, this implies

$$I(X_1, X_2; Y_2^T | Y_2^M) = 0.$$

On the other hand, by the chain rule of mutual information we have

$$\begin{aligned} I(X_1, X_2; Y_2^M, Y_2^T) &= I(X_1, X_2; Y_2^M) + I(X_1, X_2; Y_2^T | Y_2^M) \\ &= I(X_1, X_2; Y_2^T) + I(X_1, X_2; Y_2^M | Y_2^T). \end{aligned}$$

Since we already show that $I(X_1, X_2; Y_2^T | Y_2^M) = 0$, and mutual information is non-negative, we have

$$I(X_1, X_2; Y_2^M) = I(X_1, X_2; Y_2^T) + I(X_1, X_2; Y_2^M | Y_2^T) \geq I(X_1, X_2; Y_2^T).$$

□

5.2 Additional Related Work

Deep Network Architecture for Point Cloud. With the development of deep learning, various deep neural network-based models [7, 10, 12, 13, 23, 46, 52, 53, 68] have become the mainstream approach for 3D point cloud analysis. PointNet [39], a pioneer in point cloud analysis, introduced an MLP-based network to address the disorder of point clouds. Subsequently, PointNet++ [40] further proposed adaptive aggregation of multiscale features on MLPs and incorporated local point sets for effective feature learning. DGCNN [50] introduced the graph convolutional networks dynamically computing local graph neighboring nodes to extract geometric information. PointMLP [32] suggested efficient point cloud representation solely relying on pure residual MLPs. Recently, many Transformer-based models [20, 34, 37, 62], benefiting from attention mechanisms, have achieved notable improvements in point cloud analysis. However, this led to a significant increase in model size, posing considerable challenges for practical applications. PointMamba [27] first attempted to introduce the Mamba architecture based on the state space model to point clouds, but it still has high complexity and parameters. In this paper, we focus on designing more efficient point cloud architectures specific to pre-training models.

State Space Models. State Space Models [14–17, 42] (SSMs) originate from classical control theory and have been introduced into deep learning as the backbone of state space transformations. They combine the parallel training capabilities of CNNs with the fast inference characteristics of RNNs, capturing long-range dependencies in sequences while maintaining linear complexity. The Structured State-Space Sequence model [16] (S4) is a pioneer work for the deep state-space model in modeling the long-range dependency. S5 [42] proposed based on S4 and introduces MIMO SSM and efficient parallel scan. GSS [33] leverages the gating structure in the gated attention unit to reduce the dimension of the state space module. Recently, Mamba [13] with efficient hardware design and selective state space, outperforms Transformers [46] in terms of performance and efficiency. Subsequent works [11, 26, 30, 31, 35, 49, 71] have attempted to introduce Mamba into the visual domain, achieving significant improvements. For example, Vision Mamba [71] and VMamba [30] directly apply Mamba to image processing and design corresponding scanning methods tailored for image data. As for point cloud, PointMamba [27] is the first to introduce Mamba into point cloud analysis, traversing the input sequences from the x, y, and z geometric directions. In this paper, we introduce Mamba into the decoder for masked point modeling and discuss its advantages from an information-theoretic perspective. Additionally, we propose a locally constrained feedforward neural network for Mamba block to adaptively exchange information among geometrically adjacent patches based on their implicit geometry.

5.3 Implementation Details

Top-K Attention Settings in Observation. In Figure 2, we replace the global attention computation of all patch tokens in Self-Attention with top-K attention computation in both feature space and geometric space to demonstrate the significant amount of redundant computation in the vanilla Transformer. Specifically, after computing all global attention, we further compute a mask matrix. We then add negative infinity to the attention values that need to be masked. After that, we calculate the softmax, where the attention values that were set to negative infinity will become 0, ensuring that the sum of the attention values of the unmasked top-K patches equals 1. We compute different top-K values in both feature space and geometric space, and pretrain the corresponding models. Subsequently, we fine-tune these pretrained models on the three variants of ScanObjectNN using the same top-K attention algorithm, evaluating their accuracy on classification tasks. To minimize error, we report the average accuracy over 10 repeated experiments.

Positional Encodings. To complement the 3D spatial information, we apply positional encodings to all encoder and decoder layers. As shown in Figure 4, we first use the Encoder Positional Encoding (EPE) to compute the positional encoding E^p for C_V , which is then shared across all layers of the encoder. In the decoding stage, we use the Decoder Positional Encoding (DPE) to calculate the positional encoding for the unmasked C_V and the masked patches C_M . These positional encodings are concatenated to form decoder positional encodings T^p , which is shared across all layers of the decoder. Following previous work [37, 60], we utilize a two-layer MLP to encode its corresponding 3D coordinates $C_V \in \mathbb{R}^{rN \times 3}$ or $C_M \in \mathbb{R}^{(1-r)N \times 3}$ into d -channel vectors $E^p \in \mathbb{R}^{rN \times d}$ or $T^p \in \mathbb{R}^{N \times d}$, and element-wisely add them with the token features before feeding into the attention layer.

Token Embedding. We follow the approach of previous works [37, 60] and use a simple PointNet [39] to map the point patches $P_V \in \mathbb{R}^{r \times N \times K \times 3}$ from coordinate space to feature space $E^s \in \mathbb{R}^{r \times N \times d}$. For Point-BERT [60], MaskPoint [28], Point-M2AE [65], and ACT [8], we use the exact same embedding structures as described in their original papers. For Point-MAE [37], we further simplify the embedding, using only a two-layer MLP with dimensions 3-128-384 as the embedding, which further reduces the parameters and computational complexity, as shown in Table 1.

Object Classification. Due to significant differences in the settings used for downstream fine-tuning tasks of point cloud classification on the ScanObjectNN [44] dataset in previous self-supervised learning methods [8, 28, 37, 60, 65], such as input point quantity, data augmentation, and the input of the classification task head, we conducted extensive experiments to obtain a performance-friendly downstream fine-tuning setting. Furthermore, we re-evaluated most of the previous methods under our setting, while also conducting a fair comparison between our LCM model and the previous Transformer model under our setting. We mark the results of our downstream fine-tuning setting with an "●" in Table 1.

It can be observed that, compared to the results reported in the original paper, the fine-tuning results using our downstream settings have achieved significant performance improvements. For instance, Point-BERT has shown improvements of **5.34%**, **3.62%**, and **4.99%** on the three variants of the ScanObjectNN dataset, respectively. This improvement is surprising, indicating that there is further potential to be explored in earlier self-supervised learning methods such as Point-BERT, Point-MAE, etc.

Experiments Compute Resources. Due to the surprisingly lightweight and efficient of our LCM model, we were able to complete the pre-training tasks using just a single 24GB NVIDIA GeForce RTX 3090 GPU. For downstream classification and segmentation tasks, we used a single RTX 3090 GPU for each. For detection tasks, to accelerate training, we utilized four parallel RTX 3090 GPUs.

3D Object Detection. We pre-train and fine-tune Point-MAE for 3D object detection both on ScanNetV2 [6]. In our detection experiments on ScanNetV2, we evaluate our model’s understanding of scene-level tasks. Specifically, in the downstream detection fine-tuning experiments, we use 3DETR [34] as the baseline model and replace 3DETR’s pre-encoder and encoder with our embed layer and compact encoder, respectively, while keeping all other training settings identical to 3DETR. Unlike many previous methods [8, 28, 65] that require retraining models on ScanNet, we initialize the embed layer and compact encoder with models pre-trained directly on ShapeNet [3]. While this may result in some loss of performance due to the gap between ShapeNet and ScanNet data, it demonstrates the universality of our pre-trained models.

5.4 Additional Experiments

Object Classification on ModelNet40. ModelNet40 [57] is a well-known synthetic point cloud dataset, comprising 12,311 meticulously crafted 3D CAD models distributed across 40 categories. Following previous work [37, 60, 65], for the ModelNet40 dataset, we sample 1024 points for each instance and report overall accuracy with voting mechanisms. In ModelNet40, we no longer differentiate between the results reported in the paper and our results, as we use the exact same downstream fine-tuning settings as previous methods [8, 28, 37, 65]. Table 6 presents our experimental results, and the overall conclusions are consistent with Section 4.2.1. Our LCM model outperforms the Transformer architecture in terms of both efficiency and performance, indicating the superiority of our model.

Effects of Locally Constrained K Value. We further explore the impact of using different numbers of neighbors K in local constraints on performance and efficiency. K=1 indicates no consideration of neighboring information. As K increases, the consideration of local geometry for each point patch also increases, but so does the computational complexity. We train object classification from scratch on the PB-RS-T50 variant of ScanObjectNN, and Figure 7 presents our ablation results. The area of the circle represents the computational floating-point operations (FLOPs). We found that a smaller K, such as 5, is sufficient to achieve satisfactory results in terms of performance and efficiency. Performance initially increases slowly, but when K exceeds a certain threshold, it tends to decline. This is mainly due to larger K values introducing excessive redundancy, thereby limiting the learning capacity.

Table 6: Classification accuracy on synthetic (ModelNet40) point clouds. In ModelNet40, following previous work, we report the overall accuracy (%) with voting mechanisms. For a fair comparison, we used the same downstream task settings as in previous studies.

Method	#Params(M)	FLOPs(G)	ModelNet40
<i>Supervised Learning Only</i>			
PointNet [39]	3.5	0.5	89.2
PointNet++ [40]	1.5	1.7	90.7
DGCNN [50]	1.8	2.4	92.9
PointMLP [32]	12.6	31.4	94.5
P2P-HorNet [51]	195.8	34.6	94.0
Transformer [27]	22.1	4.8	92.3
PointMamba [27]	12.3	-	92.4
Transformer [27]	22.1	2.4	92.3
LCM (Ours)	2.7	0.6	93.6
<i>Self-Supervised Learning</i>			
Point-BERT [60]	22.1	2.3	93.2
CrossNet [56]	1.8	2.4	93.4
Inter-MAE [29]	22.1	2.3	93.6
MaskPoint [28]	22.1	2.3	93.8
Point-MAE [37]	22.1	2.4	93.8
Point-M2AE [65]	12.8	4.7	94.0
ACT [8]	22.1	2.4	93.7
PointGPT-S [5]	29.2	2.3	94.0
PointGPT-B [5]	120.5	18.1	94.2
PointMamba [27]	12.3	-	93.6
Point-BERT w/ LCM	3.1	1.3	93.8
MaskPoint w/ LCM	3.1	1.3	94.1
PointM2AE w/ LCM	2.5	1.7	94.1
ACT w/ LCM	3.1	1.4	93.9
Point-MAE w/ LCM	2.7	0.6	94.2

Figure 7: Effects of locally constrained K value.

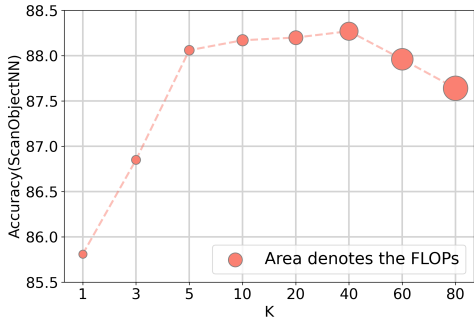


Table 7: Effects of K-NN Space.

K	Feature K-NN	Geometry K-NN
1	85.70	85.81
5	87.65	88.06
10	87.51	88.17
20	87.20	88.20

Effects of K-NN Space. We further explored the impact of performing K-NN based on Euclidean distance in both the feature space and the geometric space of our compact encoder. Geometric K-NN in the geometric space imposes explicit geometric constraints, serving as a static importance measure that greatly benefits point cloud analysis. Searching for K-NN based on feature Euclidean distance in the feature space can be considered a simple form of dynamic importance. We analyzed the effect of this approach on point cloud classification from scratch on ScanObjectNN, evaluating geometric K-NN and feature K-NN at different K values.

As shown in Table 7, we found that feature K-NN performed consistently lower than geometric K-NN in almost all cases. This result suggests that the naive idea of assigning dynamic importance to point patches based on Euclidean distance in the feature space does not lead to substantial improvements. Efficient computation of dynamic importance for each point patch remains an area for further exploration.

Effects of Patch Order and LCFFN for Mamba-based Decoder. The ordering of input patches significantly impacts our Mamba-based Decoder. To more effectively illustrate this effect on Mamba’s SSM model, we analyze the issue from a different perspective. Specifically, we use our Mamba-

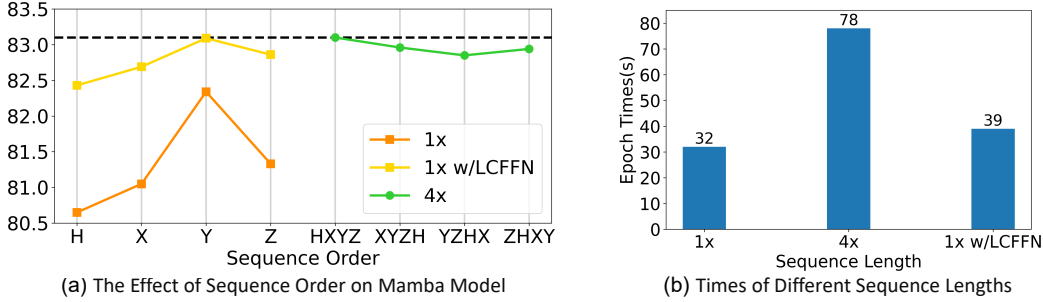


Figure 8: Training and testing curves for different encoders trained from scratch. We present the training and testing curves for both the classification task on ScanObjectNN and the detection task on ScanNetV2. All encoders were not pretrained.

based Decoder as an Encoder to directly extract features from the input point cloud and perform classification on ScanObjectNN. This substitution is straightforward, as our Mamba-based Decoder can also be viewed as an Encoder.

We trained our Mamba-based encoder from scratch for the classification task on the PB-RS-T50 variant of ScanObjectNN without using any data augmentation strategies, and we took the average of ten repeated experiments as the final result. We first experimented with a naive Mamba-based decoder using a traditional FFN to illustrate the impact of different sequence orders on the original Mamba. We selected four different patch ordering methods: sorting by the center point of the patch along the x-axis (X), y-axis (Y), and z-axis (Z), and Hilbert curve [24] ordering (H), as shown by the orange curve in Figure 8 (a). Furthermore, we also conducted experiments with combinations sequences, combining these four orderings "H+X+Y+Z (HXYZ)", "X+Y+Z+H (XYZH)", "Y+Z+H+X (YZHX)", and "Z+H+X+Y (ZHXY)", as shown by the green curve in Figure 8 (a). Finally, based on the single-order sequence, we used our proposed LCFFN to demonstrate the performance of Mamba with added implicit geometric constraints, as shown by the yellow curve in Figure 8 (a). The experimental results, as illustrated in Figure 8, lead us to the following conclusions:

1) *The performance of the Mamba model is greatly influenced by the different orders of input patches.* The orange line represents the results for individual sequences, highlighting that different sequences have a significant impact on the final model performance. For example, the Y-order achieves the highest classification accuracy at 82.34%, while the Hilbert order performs the worst at 80.65%, resulting in a difference of 1.69%.

2) *The more combinations of sequences, the better the representation of point cloud geometry, resulting in improved performance, but also increased computational complexity.* The green line represents the combinations sequences. While different combinations sequences do affect the final model performance, the impact is relatively minor. This indicates that the Mamba model can compensate for information across different sequences, allowing it to capture nearly complete geometric information for each patch. Consequently, this significantly enhances the model’s performance. However, this approach leads to a significant increase in computational complexity due to the increase in the length of the input sequence, as shown in Figure 8 (b). The processing time for the sequences of the four orders is approximately $3\times$ longer than that of a single order.

3) *Introducing LCFFN allows for better perception of point cloud geometry through implicit local geometric constraints, thereby mitigating the dependence on sequence order.* The yellow line represents the experimental results of using LCFFN to replace FFN for single-order input. It can be observed that the overall classification accuracy is significantly improved, surpassing the combinations sequence in the y-order and showing only slight differences from the combinations sequence in other orders. Moreover, in terms of runtime efficiency, as shown in Figure 8 (b), our single-order + LCFFN method exhibits a considerable improvement compared to the combinations sequence, indicating the superiority of our design.

5.5 Additional Visualization

Effects of the Compact Encoder from the Perspective of Overfitting. While our compact encoder has fewer parameters compared to Transformer-based encoders, its performance surpasses that of Transformer-based encoders [46], as analyzed in Section 4.2.1. One significant reason for this lies in the reduced risk of overfitting in downstream tasks due to the redundancy reduction. Given the challenging nature of acquiring point cloud data, existing point cloud datasets for downstream tasks are often small, such as ScanObjectNN [44] and ModelNet40 [57], each comprising just over 10,000 point clouds, and ScanNetV2 [6] with only 1,000 scenes. These dataset sizes are much smaller than those commonly found in image and language tasks. Therefore, fine-tuning in these size-limited datasets can be more prone to overfitting when considerable redundancy exists in the computation.

We visualize the training and testing curves for different encoders on the classification task in ScanObjectNN and the detection task in ScanNetV2 in Figures 9 and 10. Figure 9 illustrates the classification and detection curves for our compact encoder and a Transformer-based encoder after pretraining. It can be observed that during training, the classification accuracy and AP25 metric of the Transformer-based encoder are significantly higher than those of our compact encoder. However, during testing, our compact encoder exhibits superior performance compared to the Transformer encoder. This starkly indicates that the Transformer-based encoder tends to overfit the training set, demonstrating poorer generalization. Conversely, our compact encoder displays stronger generalization capabilities, indicating the superiority of the design of our compact encoder.

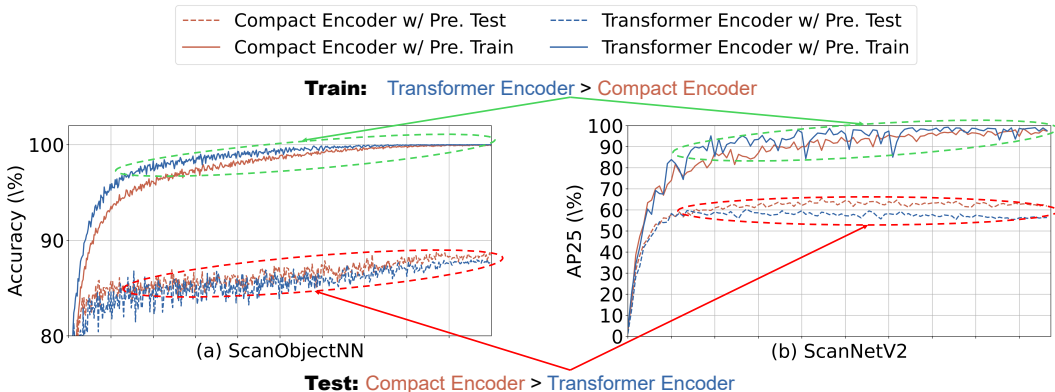


Figure 9: Training and testing curves of different pre-trained encoders. We present the training and testing curves for both the classification task on ScanObjectNN and the detection task on ScanNetV2. All encoders are pre-trained.

Figure 10 displays the classification and detection curves of our compact encoder and the Transformer-based encoder trained from scratch. In comparison to its counterpart in Figure 9, although it shows a slower convergence, the overfitting issue of the Transformer-based encoder still emerges in the late stages of training, reaffirming our conclusion. Meanwhile, the phenomenon of slow convergence in Figure 10 is reasonable as it is an encoder trained from scratch without a better initialization.

t-SNE Visualization. We further used t-SNE [45] to visualize the feature distributions extracted by our LCM model and the Transformer. In Figure 11, we visualized the two-dimensional (2D) feature distributions of the two models, pretrained using Point-MAE, when directly transferred to the test set of the ModelNet40 [57] dataset without downstream fine-tuning. In Figure 12, we visualized the 2D feature distributions of the two pre-trained models after fine-tuning on the most challenging variant of the ScanObjectNN [44] dataset, PB-RS-T50, using its test set.

In the 2D t-SNE visualizations, instances from the same category tend to be distributed in relatively clear and tight clusters. The compactness of the feature distributions of different instances from the same category can be viewed as the model’s ability to represent features of the same category. A more compact distribution indicates a stronger modeling capability. As shown in Figure 11 and Figure 12, our LCM model achieves more compact feature distributions for instances of the same

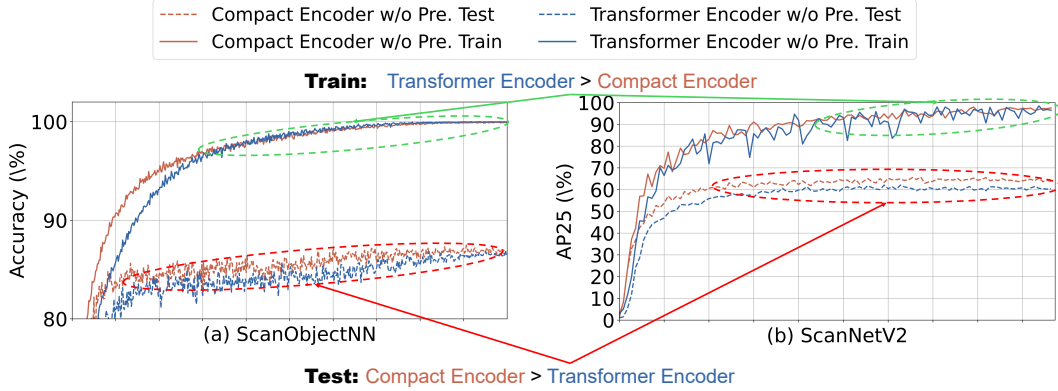


Figure 10: Training and testing curves for different encoders trained from scratch. We present the training and testing curves for both the classification task on ScanObjectNN and the detection task on ScanNetV2. All encoders were not pretrained.

category compared to the Transformer model in most cases, indicating that our LCM model has a stronger ability to model the general representations of the same category.

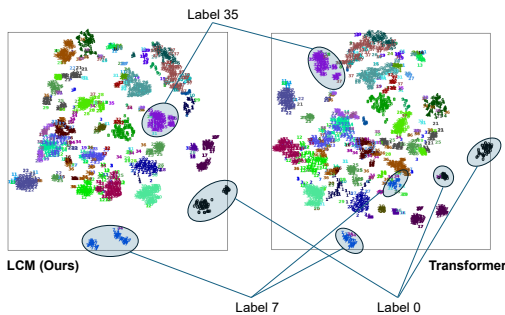


Figure 11: The feature distribution visualization of the pre-trained models on the test set of ModelNet40.

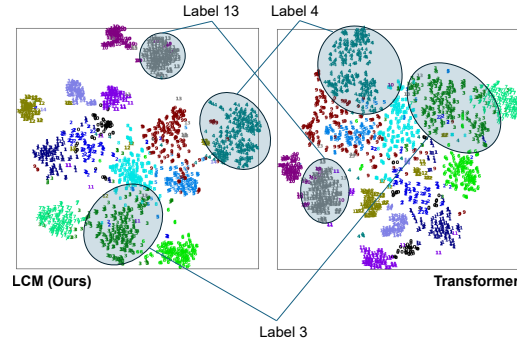


Figure 12: The feature distribution visualization of the fine-tuned models on the test set of ScanObjectNN.

5.6 Broader Impacts and Safeguards

Our designed compact point cloud network will greatly facilitates the deployment of existing point cloud pre-training models on resource-constrained devices, which would significantly advance existing point cloud applications. However, the proliferation of more point cloud applications may lead to privacy data leaks, such as personal housing layout point cloud leaks, and human feature point cloud leaks. Therefore, we advocate for the implementation of strict security measures during the actual deployment of applications to prevent malicious access or tampering of data. Below are some corresponding measures:

- 1) Access Control: Implement stringent access control policies to restrict data access to authorized users or systems only.
- 2) Data Encryption: Utilize robust encryption algorithms to encrypt sensitive point cloud data during transmission and storage, ensuring its security against unauthorized access.
- 3) Anonymization: Anonymize sensitive information whenever possible to reduce the risk of data leaks. For instance, remove or blur identifiable information, retaining only essential data for analysis.

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [Yes]

Justification: Our abstract and introduction illustrate our contribution and scope.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [Yes]

Justification: We discuss the limitations in Section 4.4.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory Assumptions and Proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [Yes]

Justification: Our assumptions and proofs are in Section 5.1.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental Result Reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: We discuss the experimental information in section 4 and 5.3.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: We have provided the complete code, checkpoints, and running instructions.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental Setting/Details

Question: Does the paper specify all the training and test details (e.g., data splits, hyper-parameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: We specify all the experimental training and test details in Section 4 and 5.3.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment Statistical Significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [No]

Justification: We report the average of the experiment results and therefore do not report error bars.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).

- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments Compute Resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: We detail the compute resources in Section 5.3.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code Of Ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: The research of our study complies with the NeurIPS ethical guidelines in all aspects.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader Impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [Yes]

Justification: We illustrate this impacts in 5.6

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.

- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [\[Yes\]](#)

Justification: We illustrate some solution in [5.6](#)

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [\[Yes\]](#)

Justification: We have correctly cited the assets used in the paper and adhered to their licenses.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.

- If this information is not available online, the authors are encouraged to reach out to the asset’s creators.

13. **New Assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [No]

Justification: We will release all newly generated assets from the paper, including code and models, after the paper is accepted.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and Research with Human Subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [NA]

Justification: The paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional Review Board (IRB) Approvals or Equivalent for Research with Human Subjects**

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA]

Justification: The paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.