Masked auto-encoding is a popular and effective self-supervised learning approach to point cloud learning. However, most of the existing methods reconstruct only the masked points and overlook the local geometry information, which is also important to understand the point cloud data. In this work, we make the first attempt, to the best of our knowledge, to consider the local geometry information explicitly into the masked auto-encoding, and propose a novel Masked Surfel Prediction (MaskSurf) method. Specifically, given the input point cloud masked at a high ratio, we learn a transformer-based encoder-decoder network to estimate the underlying masked surfels by simultaneously predicting the surfel positions (i.e., points) and per-surfel orientations (i.e., normals). The predictions of points and normals are supervised by the Chamfer Distance and a newly introduced Position-Indexed Normal Distance in a set-to-set manner. Our MaskSurf is validated on six downstream tasks under three fine-tuning strategies. In particular, MaskSurf outperforms its closest competitor, Point-MAE, by 1.2% on the real-world dataset of ScanObjectNN under the OBJ-BG setting, justifying the advantages of masked surfel prediction over masked point cloud reconstruction. Codes will be available at https://github.com/YBZh/MaskSurf.

1. Introduction

While deep learning has achieved great successes on various computer vision tasks, e.g., image classification [32, 30], object detection [19, 56], segmentation [50, 29], image restoration [12, 72], as well as point cloud understanding [44, 45], training deep models usually requires a large amount of labeled data with human annotations, which are expensive in practice. To solve this issue, self-supervised learning (SSL) [7, 11, 70] has been proposed to learn effective feature representations from unlabeled data. Generally speaking, SSL generates supervision signals from the data themselves by adopting various pretext tasks, such as contrastive learning [28, 6], masked auto-encoding [11, 27, 70], rotation estimation [18, 43], jigsaw puzzles [39] and so on [1, 21].

Among those pretext tasks, masked auto-encoding has demonstrated its effectiveness in many applications [11, 27, 62, 57, 70, 40], including point cloud learning [70, 40]. Specifically, by masking a portion of input data (e.g., points in point cloud processing), an auto-encoder is learned to reconstruct the masked data from the unmasked data. In this manner, the encoder is expected to learn semantic feature representations, which could be readily applied to various downstream tasks. The popular masked auto-encoding based point cloud learning methods usually adopt different masking strategies and backbones, but they all reconstruct the masked points as the pretext task [60, 70, 40].

Though masked auto-encoding has achieved impressive progresses in self-supervised point cloud learning [60, 70, 40], reconstructing the masked points only may sacrifice the local geometry information of point cloud. Though local geometry could be estimated from the point cloud data [54, 4, 48], existing point cloud models [44, 45, 61] are not effective to learn such local geometry. This can be validated by the fact that enhancing the point cloud inputs with local geometry (e.g., normal) could significantly boost the...
performance of point cloud models [45, 48], demonstrating the complementarity between the point location and local geometry in point cloud representation.

With the above consideration, we propose to incorporate local geometry into the masked auto-encoding explicitly for more effective point cloud understanding. Specifically, we make the first attempt to employ the surface element, i.e., surfel [42], for point cloud learning. The vanilla surfel is originally introduced for 3D rendering, and it comprises both shape (i.e., surfel position and orientation) and shade (i.e., multiple levels of texture colors) data [42]. The surface geometry is mainly described by its shape, while the shade information is more relevant to view synthesis and rendering. Considering that the goals of point cloud understanding are different from 3D rendering, we adopt a simplified surfel representation with only shape data of 3D position and orientation. As shown in Fig. 1, even the simplified surfel representation can capture more local geometry information of the surface over raw points. With surfel as the modeling element, different from those works predicting the point cloud [60, 70, 40], we propose a Masked Surfel Prediction (MaskSurf) network to predict the underlying surfel cloud from the masked point cloud.

Following [70, 40], we first group the point cloud into several local patches and randomly mask a large portion of them. As illustrated in Fig. 2, instead of reconstructing the masked point patches from unmasked point patches [40], we predict the masked surfels [42] by simultaneously estimating the surfel positions (i.e., points) and per-surfel orientations (i.e., normals) in a set-to-set manner. The point estimation is supervised by the Chamfer Distance (CD) [14], while a novel Position-Indexed Normal Distance (PIND) is proposed for point-paired normal prediction. As analyzed in Sec. 4.3, with surfel prediction, the learned features could capture more geometry information compared to the point only reconstruction [40].

Given the pre-trained encoder with MaskSurf, we validate its effectiveness on six downstream tasks, including object classification on real-world and synthetic datasets, few-shot learning, domain generalization, part segmentation and semantic segmentation. For each downstream task, we adopt various fine-tuning strategies [28, 27], including transferring features protocol, linear classification protocol and non-linear classification protocol. Our MaskSurf outperforms its closest competitor [40] on all downstream tasks under all strategies, justifying the advantage of masked surfel prediction over masked point cloud reconstruction. Notably, MaskSurf achieves 91.22% accuracy on the real-world dataset of ScanObjectNN in the OBJ-BG setting, boosting Point-MAE [40] by 1.2%.

2. Related Work

2.1. Self-supervised Learning for Point Cloud

SSL aims to learn efficient feature representation from unlabeled training samples using self-generated supervision signals [27, 28, 7, 6, 21, 11, 70, 40]. It is particularly important for 3D point cloud analysis, since the collection and annotation of point cloud data are much more expensive than 2D images. Popular SSL methods for point cloud include reconstruction [68, 16, 75, 60, 8, 25, 76, 70, 34, 40, 73, 65, 15], instance contrastive feature learning [49, 51], consistency feature learning against augmentations [31], and other pretext tasks [52, 43, 1]. Among these methods, the masked auto-encoding [60, 76, 70, 40] has been receiving more and more attention recently.

Specifically, given an input point cloud masked at a high ratio, an encoder-decoder model is learned to reconstruct the masked points from the unmasked ones. In this way, the encoder could learn semantic feature representations, which can be readily applied to downstream tasks. However, the local geometry information may be overlooked by reconstructing the masked points only, since the local geometry is complementary to raw points for point cloud understanding [45, 48]. To address this issue, we propose to explicitly incorporate the local geometry into the masked auto-encoding and develop a novel MaskSurf framework. In MaskSurf, we predict the underlying masked surfels by simultaneously estimating the surfel positions and per-surfel normals, resulting in more effective feature representations.

2.2. Local Geometry and Surfel Representation

The importance of local geometry in point cloud understanding has been widely acknowledged in the community [2, 41], while normal is one of the most basic elements to represent local geometry information. Researchers typically enhance the point cloud data with point-wise normal for performance-boosting [45, 48]. What’s more, given points as input, point-wise normal estimation is widely adopted as a regularization method to train the model [53, 49, 65].

Surfel, i.e., surface element, is originally introduced as a rendering primitive, which provides a mere discretization of the geometry [42]. Then, surfel has been widely adopted in surface reconstruction [24, 63] due to its conceptual simplicity. The vanilla surfel comprises both shape and shade values, where the shape data describe the surface geometry, while the shade data are more relevant to rendering [42]. In this work, we adopt a simplified surfel representation with only shape data (i.e., 3D position and orientation) for model learning, considering the different objectives between point cloud understanding and 3D rendering. To our best knowledge, we are the first to apply surfel representation in self-supervised point cloud learning.
3. Masked Surfel Prediction

The overall framework of our MaskSurf is illustrated in Fig. 2. Given masked and embedded point patches, we learn the transformer-based encoder and decoder to predict the underlying masked surfels by simultaneously predicting the surfel points and per-surfel normals, which are supervised by the Chamfer Distance (CD) and a newly introduced Position-Indexed Normal Distance (PIND), respectively.

3.1. Training Data Preparation

Considering that collecting high quality 3D samples in real world is expensive, most of the existing SSL methods [60, 70, 40] sample training data from synthetic 3D dataset (e.g., ShapeNet [5]). Following this strategy, we sample a surfel cloud with $M$ surfels $S \in \mathbb{R}^{M \times 6}$ from a synthetic 3D surface. We then split the surfel cloud into surfel positions (i.e., points) $X \in \mathbb{R}^{M \times 3}$ and per-surfel orientations (i.e., normals) $N \in \mathbb{R}^{M \times 3}$. The masked point cloud will be used as the model input, while the normals will be only used to supervise the prediction of surfel orientations (see Sec. 3.3 for details).

We sample $N$ points from the point cloud $X$ as patch centers $C \in \mathbb{R}^{N \times 3}$ via the Farthest Point Sampling (FPS) method [45]. Then, for each center we introduce $N$ irregular point patches $P \in \mathbb{R}^{N \times K \times 3}$ by selecting the $K$ nearest points around the center via the K-Nearest Neighborhood (KNN) method:

$$P = KNN(X, C).$$  \hspace{1cm} (1)

Each point patch is then normalized by subtracting the center point from the point coordinates for better convergence. Note that the point patches $P$ may overlap if two patch centers in $C$ are close to each other.

Following [40], we mask each patch separately with a large ratio of point patches, keeping the information complete in each patch with rare patch overlap. More specifically, given a masking ratio $m \in (0, 1)$, the masked point patches and unmasked point patches are denoted as $P_{mask} \in \mathbb{R}^{mN \times K \times 3}$ and $P_{vis} \in \mathbb{R}^{(1-m)N \times K \times 3}$, respectively. We then apply the same grouping (cf. Equ. (1)) and masking strategies to the per-surfel normals $N$, resulting in the masked normal patches $N_{mask} \in \mathbb{R}^{mN \times K \times 3}$ and unmasked normal patches $N_{vis} \in \mathbb{R}^{(1-m)N \times K \times 3}$. The masked patch centers $C_{mask} \in \mathbb{R}^{mN \times 3}$ and unmasked patch centers $C_{vis} \in \mathbb{R}^{(1-m)N \times 3}$ are similarly introduced for the usage of positional embedding.

The unmasked point patches $P_{vis}$ are adopted as input to the following encoder model, while the masked point patches $P_{mask}$ and masked normal patches $N_{mask}$ are employed as the prediction supervision, which is detailed in the following subsections.

3.2. Model Architecture

**Token Embedding.** Before forwarding the visible point patches $P_{vis}$ to the encoder, we first embed them via token embedding. Following [40], we instantiate the token embedding with a lightweight PointNet [44], which is composed of multi-layer perceptrons (MLP) and a max pooling...
layer. The embedded visible tokens \( T_{vis} \in \mathbb{R}^{(1-m)N \times D} \) are then induced as:

\[
T_{vis} = \text{PointNet}(P_{vis}).
\]

**Encoder.** We construct the encoder with standard Transformer blocks [59]. Only the visible tokens \( T_{vis} \) are encoded, while the masked patches are not exposed to the encoder. This is not only computationally efficient but also avoids early leakage of the position information of masked patches [40]. Considering that the point patches are represented with normalized coordinates, we add in each transformer block the path-wise Positional Embedding (PE) to provide patch location information. Following the common practice [70, 40], we adopt a learnable MLP as the PE, i.e., \( PE_c: \mathbb{R}^{(1-m)N \times 3} \rightarrow \mathbb{R}^{(1-m)N \times D} \), which maps coordinates of the visible patch centers \( C_{vis} \) to the embedding dimension \( D \). Finally, the encoded visible tokens \( T_e \in \mathbb{R}^{(1-m)N \times D} \) are formulated as:

\[
T_e = \text{Encoder}(T_{vis}, PE_c(C_{vis})).
\]

**Decoder.** Similar to the encoder, we also build the decoder with standard Transformer but with fewer blocks. The decoder takes the encoded visible tokens \( T_e \), the learnable mask tokens \( T_m \in \mathbb{R}^{mN \times D} \), and their PEs as inputs, and outputs the decoded mask tokens \( T_d \in \mathbb{R}^{mN \times D} \):

\[
T_d = \text{Decoder}(T_e, T_m, PE_d(C)).
\]

where \( T_m \) is the duplication of a learnable and patch-shared mask token of \( D \) dimension, and \( PE_d(C) \) is the PE for all tokens (i.e., visible and mask tokens). As in [40], we adopt two separate PEs for encoder and decoder, respectively.

**Prediction Head.** Existing methods typically introduce self-supervision by reconstructing masked points [40, 70]. Considering that surfels capture more local geometry information than points, we propose to estimate the masked surfels by predicting the surfel point positions and per-surfel normals. Specifically, taking the decoded mask tokens \( T_d \) as inputs, the prediction head outputs patch-wise vectors, which are then reshaped and split into surfel position patches and per-surfel normal patches:

\[
\hat{P}N = \text{Reshape}(FC(T_d)),
\]

\[
\hat{P}, \hat{N} = \text{Split}(\hat{P}N),
\]

where \( \hat{P}N \in \mathbb{R}^{mN \times K \times 6} \) is the concatenation of predicted masked surfel position patches \( \hat{P} \in \mathbb{R}^{mN \times K \times 3} \) and the per-surfel normal patches \( \hat{N} \in \mathbb{R}^{mN \times K \times 3} \), and \( FC(\cdot) \) indicates one fully connected (FC) layer.

**3.3. Loss Functions**

To measure the performance of masked surfel prediction, we measure the estimation of masked surfel positions and per-surfel orientations in a set-to-set manner. For the convenience of expression, in the following development we define the loss functions on one surfel position patch \( p \in \mathbb{R}^{K \times 3} \) and its corresponding normal patch \( n \in \mathbb{R}^{K \times 3} \), which are sampled from \( P_{mask} \) and \( N_{mask} \), respectively; similarly, the predicted masked surfel position patch and normal patch are denoted as \( \hat{p} \in \mathbb{R}^{K \times 3} \) and \( \hat{n} \in \mathbb{R}^{K \times 3} \), respectively. The final loss is calculated by averaging over all masked patches.

Following 3D reconstruction methods [14, 40], we adopt the following Chamfer Distance (CD) loss to measure the divergence of point patches:

\[
\mathcal{L}_p = \frac{1}{K} \sum_{k=1}^{K} \min_{k' \in [1, K]} \|p_k - \hat{p}_{k'}\|_2^2 + \frac{1}{K} \sum_{k=1}^{K} \min_{k' \in [1, K]} \|\hat{p}_k - p_{k'}\|_2^2,
\]

where \( p_k \in \mathbb{R}^3 \) and \( \hat{p}_k \in \mathbb{R}^3 \) are the \( k \)-th row of \( p \) and \( \hat{p} \), respectively. The \( n_k \) and \( \hat{n}_k \) in the following Equ. (8) are similarly defined.

How to measure the prediction performance of position-paired normal patches in a set-to-set manner is less investigated. Here we propose the following Position-Indexed Normal Distance (PIND) loss to address this issue:

\[
\mathcal{L}_n = \frac{1}{K} \sum_{k=1}^{K} d\left(n_k, \hat{n}_{\text{arg min}_{k' \in [1, K]} \|p_k - \hat{p}_{k'}\|_2^2}\right) + \frac{1}{K} \sum_{k=1}^{K} d\left(\hat{n}_k, n_{\text{arg min}_{k' \in [1, K]} \|\hat{p}_k - p_{k'}\|_2^2}\right),
\]

where \( d(n, \hat{n}) \) is the absolute cosine angle distance between two normal vectors \( n, \hat{n} \in \mathbb{R}^3 \):

\[
d(n, \hat{n}) = 1 - \frac{n \cdot \hat{n}}{||n||_2 \cdot ||\hat{n}||_2}.
\]

Similar to the CD loss in Equ. (7), for each normal in one set, we find its ‘nearest neighbor’ in the other set and sum the distances up in the PIND loss. However, there are two differences between CD and PIND losses. Firstly, in PIND, we find the nearest neighbor of each normal according to the distance between corresponding positions, instead of the distance between normals, because the normal must be paired with one position to represent the surfel. Secondly, we adopt the absolute value of the cosine distance, instead of the Euclidean distance in CD loss, because the unoriented normal is sufficient for the surfel prediction.

The overall loss function is therefore defined as:

\[
\mathcal{L}_{all} = \mathcal{L}_p + \alpha \mathcal{L}_n,
\]

where \( \alpha \) is a hyper-parameter balancing the two terms.
4. Experiments

Our model is pre-trained on the ShapeNet [5] dataset, and then it is validated on various downstream tasks, including object classification on real-world and synthetic datasets, few-shot learning, domain generalization, part segmentation and semantic segmentation. Finally, we make in-depth analyses of the proposed components.

4.1. Pre-training on ShapeNet

We pre-train our model on the ShapeNet [5], which includes about $51K$ single clean 3D meshes shared by 55 categories. Following [70, 40], we split the vanilla dataset into a training subset and a test subset, and use only the training subset for pre-training. For each 3D mesh in the training subset, we sample $p = 1,024$ surfels from the surface and then split them as surfel positions and per-surfel normals. Data augmentations of standard random scaling and then split them as surfel positions and per-surfel normals. We then randomly mask the point patches with masking ratio of $m = 0.6$ by default. The other masking strategies are analyzed in Sec. 4.3.

We construct the encoder with 12 Transformer blocks, while the decoder is built with 4 Transformer blocks, where each Transformer block has 384 hidden dimensions and 6 heads. The AdamW optimizer [37] is adopted. The batch size is 128 and the weight decay is 0.05. The cosine learning rate schedule [36] is adopted with the total training epochs of 300 and an initial learning rate of 0.001. In order to reconstruct the indexing points first, we linearly increase the $\alpha$ from 0 to 0.01 in the training process. The predicted surfel cloud is visualized in Fig. 3.

4.2. Fine-tuning on Downstream Tasks

On downstream tasks, we initialize the encoder with the pre-trained weight parameters, while the decoder part of MaskSurf is discarded. The following three strategies are adopted to fine-tune pre-trained models on downstream tasks:

- Transferring features protocol, where we fine-tune all weight parameters, including the pre-trained encoder and a randomly initialized non-linear classifier.
- Linear classification protocol, where we freeze the pre-trained encoder and only fine-tune a randomly initialized linear classifier.
- Non-linear classification protocol, where we freeze the pre-trained encoder and only fine-tune a randomly initialized non-linear classifier.

In transferring features and non-linear classification protocols, we construct the non-linear classifier via three FC layers for all classification tasks following [40]. On segmentation tasks (i.e., part segmentation and semantic segmentation), we follow [40, 70] to sample 2,048 points and introduce 128 point patches. We strictly follow [40] to construct the classifier for segmentation, which is detailed in the supplementary material. In the ‘Transformer’ method, we train both the encoder and non-linear classifier from scratch, setting a fair baseline. We adopt the standard voting strategy [35] in the testing stage on ModelNet40 dataset following [40], while no voting is performed on the other datasets. Note that existing methods typically report the best result across multiple runs on the classification task; here, we advocate reporting more detailed results with standard deviation to reflect the performance fluctuation.

| Table 1. Classification results on the ScanObjectNN dataset. |
|------------------|------------------|------------------|
| Methods          | OBJ-BG | OBJ-ONLY | PB-T50-RS |
| PointNet [44]    | 73.3   | 79.2    | 68.0      |
| SpiderCNN [66]   | 77.1   | 79.5    | 73.7      |
| PointNet++ [45]  | 82.3   | 84.3    | 77.9      |
| DGCNN [61]       | 82.8   | 86.2    | 78.1      |
| PointCNN [33]    | 86.1   | 85.5    | 78.5      |
| BGA-DGCNN [58]   | –      | –      | 79.7      |
| GBNNet [47]      | –      | –      | 80.5 ± 0.3|
| Simple View [20] | –      | –      | 80.5 ± 0.3|
| PRA [9]          | –      | –      | 81.0      |
| PointMLP [38]    | –      | –      | 85.4 ± 0.3|
| Transformer [59] | 79.86  | 80.55   | 77.24     |

- Transferring features protocol

| Methods          | OBJ-BG | OBJ-ONLY | PB-T50-RS |
|------------------|------------------|------------------|
| Transformer-OC-Co [70] | 84.85 | 85.54 | 78.79 |
| Point-CAE [70]   | 87.43 | 88.12 | 83.07 |
| MaskSurf (Ours)  | 90.02 | 88.29 | 85.18 |
| Transformer [59] | 91.22 | 89.17 | 85.81 |

- Linear classification protocol

| Methods          | OBJ-BG | OBJ-ONLY | PB-T50-RS |
|------------------|------------------|------------------|
| Point-CAE [40]   | 86.17±0.00 | 82.10±0.00 | 71.48±0.00 |
| MaskSurf (Ours)  | 82.67±0.00 | 83.48±0.00 | 72.59±0.00 |

- Non-linear classification protocol

| Methods          | OBJ-BG | OBJ-ONLY | PB-T50-RS |
|------------------|------------------|------------------|
| Point-CAE [40]   | 82.56±0.22 | 86.29±0.08 | 75.64±0.12 |
| MaskSurf (Ours)  | 84.45±0.21 | 86.45±0.08 | 76.48±0.09 |

Object Classification on Real-World Dataset. Compared to 2D images, collecting and annotating 3D objects in the real world are much more expensive. Considering that many synthetic 3D objects are available on the web [5, 64], there is a massive demand to facilitate the real-world 3D tasks using synthetic 3D data. Therefore, we first validate our pre-trained models on the real-world dataset of ScanObjectNN [58], which includes about 15K point cloud samples shared by 15 categories. The objects are scanned indoor scene data, which are often cluttered with background and occluded by other objects.

We adopt three experiment variants: OBJ-BG, OBJ-ONLY and PB-T50-RS, which are detailed in the supplementary material. As illustrated in Tab. 1, our MaskSurf significantly boosts the vanilla Transformer base-
line with absolute improvements of 11.36%, 8.62%, and 8.57% on the settings of OBJ-BG, OBJ-ONLY, and PB-T50-RS, respectively. Meanwhile, MaskSurf consistently outperforms its closest SSL competitor Point-MAE [40], which is based on masked point cloud reconstruction, under all the three fine-tuning protocols, justifying the advantage of our masked surfel prediction.

Table 2. Classification results on ModelNet40 dataset. ‘ST’ indicates whether the backbone is a standard Transformer without any special design or inductive bias. ‘Our rep.’ means that the result is reproduced or produced by us using the official codes. Note that Point-MAE [40] only reports the result under the transferring features protocol in the original paper.

| Methods                  | ST? | Accuracy (%) |
|--------------------------|-----|--------------|
| PointNet [44]            | –   | 89.2         |
| PointNet++ [45]          | –   | 90.7         |
| PointCNN [33]            | –   | 92.5         |
| KPConv [55]              | –   | 92.9         |
| DGCNN [61]               | –   | 92.9         |
| RS-CNN [35]              | –   | 92.9         |
| PCT [23]                 | N   | 93.2         |
| PVT [71]                 | N   | 93.6         |
| PointTransformer [74]    | N   | 93.7         |
| Transformer [59]         | Y   | 91.4         |

| Transferring features protocol |
|------------------------------|
| DGCNN + OcCo [60]           | –   | 93.0         |
| DGCNN + STRL [31]           | –   | 93.1         |
| DGCNN + FoldingNet [68]     | –   | 93.1         |
| Transformer-Occo [70]       | Y   | 92.1         |
| Point-BERT [70]             | Y   | 93.2         |
| Point-MAE [40]              | Y   | **93.8**     |
| Point-MAE (Our rep.)        | Y   | 93.27        |
| MaskSurf (Ours)             | Y   | 93.40        |

Detailed results with standard deviation.
Point-MAE (Our rep.)          Y 93.06±0.18
MaskSurf (Ours)              Y 93.18±0.15

| Linear classification protocol |
|-------------------------------|
| DGCNN + Multi-Task [26]       | –   | 89.1         |
| DGCNN + Self-Contrast [13]    | –   | 89.6         |
| DGCNN + Jigsaw [52]           | –   | 90.6         |
| DGCNN + FoldingNet [68]       | –   | 90.1         |
| DGCNN + Rotation [43]         | –   | 90.8         |
| DGCNN + STRL [31]             | –   | 90.9         |
| DGCNN + Occo [60]             | –   | 89.2         |
| DGCNN + CrossPoint [1]        | –   | 91.2         |
| DGCNN + IAE [67]              | –   | 92.1         |
| Point-MAE (Our rep.)          | Y   | 91.41±0.00   |
| MaskSurf (Ours)               | Y   | **92.26±0.00** |

| Non-linear classification protocol |
|-----------------------------------|
| Point-MAE (Our rep.)              | Y   | 92.59±0.13   |
| MaskSurf (Ours)                   | Y   | **93.44±0.03** |

Object Classification on Synthetic Datasets. Besides the real-world dataset discussed above, we also test MaskSurf on synthetic datasets of ModelNet40 [64] and ShapeNet [5]. Compared to the real-world ScanObjectNN dataset, these two tasks are much easier since the input point clouds are clean and complete, resulting in a smaller gap to the dataset used for pre-training. Note that the ShapeNet dataset is also used in the pre-training stage, as detailed in Sec. 4.1. The ModelNet40 includes 12,311 clean 3D CAD models for 40 categories. Following the standard split, 9,843 and 2,468 samples are used for training and testing, respectively.

Table 3. Classification results on the ShapeNet dataset.

| Methods                  | Accuracy (%) |
|--------------------------|--------------|
| Transformer [59]         | 90.86±0.05   |

| Transferring features protocol |
|-------------------------------|
| Point-MAE [40]                | **90.84±0.02** |
| MaskSurf (Ours)               | **90.84±0.04** |

| Linear classification protocol |
|--------------------------------|
| Point-MAE [40]                | 89.08±0.12    |
| MaskSurf (Ours)               | **89.62±0.12** |

| Non-linear classification protocol |
|-----------------------------------|
| Point-MAE [40]                   | 90.40±0.06    |
| MaskSurf (Ours)                  | **91.09±0.05** |

Results on ModelNet40 and ShapeNet datasets are illustrated in Tab. 2 and Tab. 3, respectively. Our MaskSurf consistently improves over PointMAE [40], which is based on masked point cloud reconstruction, under all the three fine-tuning protocols. Specifically, under the transferring features protocol, different reconstruction-based SSL methods achieve comparable performance, since the two datasets are relatively easy. Under more challenging settings (i.e., linear classification and non-linear classification protocols), where the pre-trained encoder is frozen, our MaskSurf shows more significant advantages over its closest competitor Point-MAE (e.g., 0.85% on ModelNet40 and 0.69% on ShapeNet under the non-linear classification protocol). Note that such improvements are significant since the results are getting saturated on these two tasks.

In addition, we have three interesting observations. Firstly, on the challenging real-world dataset of ScanObjectNN, the transferring features protocol is preferred, since there is a large domain gap between the synthetic pre-training data and the real-world testing data. The results of different methods vary on easier downstream tasks with synthetic samples. Specifically, under the transferring features protocol, Point-MAE achieves better results, while under the non-linear classification protocol, models pre-trained with MaskSurf are preferred. This may be because fine-tuning the pre-trained encoder may degrade the local geometry perception ability of our MaskSurf. Secondly, on the ShapeNet dataset, under the non-linear classifica-
Applying models trained on synthetic domains to real-world applications has great practical value. We evaluate the cross-domain generalization performance of MaskSurf on the PointDA-10 dataset [46], whose detailed information can be found in the supplementary material. Specifically, we adopt the synthetic 3D datasets of ModelNet-10 and ShapeNet-10 as the training set, and test the domain generalization performance on the real-world ScanNet-10 dataset with the model selection of training-domain validation [22]. As shown in Tab. 4, our MaskSurf consistently outperforms its competitors, including the Transformer baseline and Point-MAE [40].

### Domain Generalization

Table 4. Cross-domain generalization performance. ‘S’ denotes the real-world ScanNet-10 dataset.

| Methods          | ModelNet-10→S | ShapeNet-10→S |
|------------------|---------------|---------------|
| DGCNN [61]       | 43.8±2.3      | 42.5±1.4      |
| DANN [17]        | 42.1±0.6      | 50.9±1.0      |
| PointDAN [46]    | 44.8±1.4      | 45.7±0.7      |
| Transformer [59] | 44.43±2.38    | 42.62±1.45    |

| **Transferring features protocol** |
|-----------------------------------|
| Point-MAE [40] | 47.16±1.51 | 46.67±0.03 |
| MaskSurf (Ours) | **47.20±0.95** | **48.26±1.80** |

| **Linear classification protocol** |
|-----------------------------------|
| Point-MAE [40] | 46.73±3.01 | 47.88±0.58 |
| MaskSurf (Ours) | **46.90±3.12** | **48.69±1.19** |

| **Non-linear classification protocol** |
|---------------------------------------|
| Point-MAE [40] | 40.31±0.02 | 40.93±0.03 |
| MaskSurf (Ours) | **46.13±0.01** | **47.37±0.02** |

Few-shot Learning. We conduct the experiments of few-shot learning on the ScanObjectNN dataset under the “n-way, m-shot” setting, where n is the number of randomly sampled classes and m is the number of samples in each class. The n × m samples are adopted for training, while we randomly sample 20 unseen objects from each class for testing. We report the results of each setting with 10 independent experiments. Results with n = {5, 10} and m = {10, 20} are presented in Tab. 5. MaskSurf consistently outperforms its competitors under all fine-tuning protocols. Similar results can be observed on the ModelNet40 dataset. Please see the supplementary material for details.

Table 5. Few-shot classification performance on ScanObjectNN.

| Methods          | 5-way 10-shot | 20-shot 10-shot | 10-way 20-shot |
|------------------|---------------|----------------|---------------|
| Transformer [59] | 51.9±8.3     | 61.6±8.5       | 38.5±5.9     |
| **Transferring features protocol** |
| Point-MAE [40]   | 63.9±7.0     | 77.0±5.2       | 53.6±5.4     |
| MaskSurf (Ours)  | **65.3±4.9** | **77.4±5.2**   | **53.8±5.3** |
| **Linear classification protocol** |
| Point-MAE [40]   | 51.0±8.2     | 59.8±7.9       | 41.7±9.2     |
| MaskSurf (Ours)  | **60.8±6.6** | **68.3±6.7**   | **46.6±6.4** |
| **Non-linear classification protocol** |
| Point-MAE [40]   | 56.4±6.8     | 67.2±6.5       | 44.3±6.2     |
| MaskSurf (Ours)  | **60.8±6.5** | **68.3±6.7**   | **46.6±6.4** |

Semantic Segmentation. We conduct the semantic segmentation on the Stanford 3D Indoor Scene Dataset (S3DIS) [3], which contains 6 large-scale indoor areas with points shared by 13 classes. Different from most segmentation methods [44, 33, 55] that adopt both xyz and rgb colors as input, we adopt the xyz as input since the pretrained model only accepts point cloud data. However, as shown in Tab. 7, MaskSurf still shows clear improvement over the competing methods, validating its advantages in feature representation.

Summary on Downstream Tasks. Our MaskSurf demon-
Table 7. Semantic segmentation results on the S3DIS Area 5.

| Methods         | Input | OA   | mAcc  | mIoU  |
|-----------------|-------|------|-------|-------|
| PointNet [44]   | xyz+rgb | –   | 49.0  | 41.1  |
| PointCNN [33]   | xyz+rgb | 85.9 | 63.9  | 57.3  |
| KPConv [55]     | xyz+rgb | –   | 72.8  | 67.1  |
| Transformer [59] | xyz   | 86.8 | 68.6  | 60.0  |

| Methods | Input | OA   | mAcc  | mIoU  |
|---------|-------|------|-------|-------|
| Point-MAE [40] | xyz   | 87.4 | 69.4  | 61.0  |
| MaskSurf (Ours) | xyz   | 88.3 | 69.9  | 61.6  |

Figure 3. Visualization of the predicted point cloud and surfel cloud with frozen encoders. In surfel cloud, the blue color means that the unoriented angular difference between estimated surfel normal and ground truth normal is less than 30 degrees, while the red color means that the unoriented angular difference is larger than 30 degrees.

strates considerable advantages on more challenging tasks (e.g., the ScanObjectNN dataset and the linear classification protocol), while results of different SSL methods are comparable on easier tasks (e.g., classification on ModelNet40 and ShapeNet under the transferring features protocol). Moreover, the generation-based SSL methods (e.g., PointBERT, Point-MAE, and our MaskSurf) bring marginal improvement in segmentation tasks, implying the need for segmentation-specific SSL strategies.

4.3. Analyses and Discussions

Pre-trained Encoders. We freeze the pre-trained encoders and learn decoders from scratch with our proposed surfel prediction objective (cf. Equ. (10)). As shown in Tab. 8, MaskSurf achieves better surfel prediction performance (e.g., lower $L_p$ and $L_n$) than Point-MAE, which is also visualized in Fig. 3.

Variants of Normal Distance. Results with unoriented normal distance (i.e., Equ. (9) without absolute function) are compared in Fig. 4. Unoriented normal distance presents clear advantage, which is adopted as the default setting.

Table 8. Quantitative analyses of the surfel prediction on the ShapeNet test subset with frozen encoders. The quality of point reconstruction and normal prediction are measured by values of $L_p$ and $L_n$, respectively.

| Methods            | $L_p$ ↓ | $L_n$ ↓ |
|--------------------|---------|---------|
| Point-MAE [40]     | $2.26 \times 1e-3$ | 0.57    |
| MaskSurf (Ours)    | $2.19 \times 1e-3$ | 0.51    |

4.3. Analyses and Discussions

Pre-trained Encoders. We freeze the pre-trained encoders and learn decoders from scratch with our proposed surfel prediction objective (cf. Equ. (10)). As shown in Tab. 8, MaskSurf achieves better surfel prediction performance (e.g., lower $L_p$ and $L_n$) than Point-MAE, which is also visualized in Fig. 3.

Variants of Normal Distance. Results with unoriented normal distance (i.e., Equ. (9)) and oriented normal distance (i.e., Equ. (9) without absolute function) are compared in Fig. 4. Unoriented normal distance presents clear advantage, which is adopted as the default setting.

Masking Strategies. As illustrated in Fig. 5, random masking leads to higher accuracy over the block masking strategy [70], and the best results are achieved when the mask ratio $m = 0.6$, which is adopted as the default setting.

Reconstructing Masked Surfels or All Surfels? Similar to observations in [27], better results are achieved by reconstructing masked parts only, as shown in Fig. 6.

Results with Estimated Surfels. To pre-train MaskSurf on a pure point cloud dataset (e.g., when the underlying 3D
surfaces are not accessible), we could estimate the surfel cloud from the point cloud [54] and adopt the estimated surfels as the supervision. As illustrated in Fig. 7, although estimated surfels result in lower performance than ground truth surfels, they still lead to better performance than reconstructing point cloud only (i.e., Point-MAE), revealing the broader applications of MaskSurf.

Figure 7. Classification results with various reconstruction targets. ‘PC’ is short for point cloud.

Hyper-parameter \( \alpha \). As illustrated in Fig. 8, \( \alpha = 0.01 \) leads to the best performance, which is adopted as the default setting in all experiments.

Figure 8. Classification results on the PB-T50-RS setting of ScanObjectNN dataset with different \( \alpha \) values.

Complexity Analysis. As illustrated in Tab. 9, MaskSurf introduces about 0.1% additional parameters and multiply-accumulates (MACs) compared to Point-MAE in the pre-training stage, while it has the same complexity as the baseline Transformer on downstream tasks.

Table 9. Illustrations of the model parameters and computational complexity. The ‘Fine-tuning’ is reported on the downstream classification tasks.

| Methods               | Pre-training | Fine-tuning |
|-----------------------|--------------|-------------|
|                       | Params | MACs | Params | MACs |
| Transformer [59]      | –      | –   | 22.1M  | 2.4G  |
| Point-MAE [40]        | 29.0M  | 2.5G | +0%    | +0%   |
| MaskSurf (Ours)       | +0.127% | +0.069% | +0%    | +0%   |

5. Conclusion

We proposed a novel self-supervised point cloud learning method by explicitly incorporating the local geometry information into the masked auto-encoding. Unlike popular methods that reconstructed masked cloud points from the unmasked cloud points, we validated that predicting the masked surfels is more effective, which was justified on six downstream tasks under various fine-tuning strategies. Our method revealed the importance of local geometry in self-supervised point cloud learning, which could facilitate more subsequent studies in point cloud understanding.

A. Supplementary Material

A.1. Task Settings on ScanObjectNN Dataset

We validate our MaskSurf with three task settings (i.e., OBJ-ONLY, OBJ-BG, and PB-T50-RS) on the ScanObjectNN dataset [58]. Specifically, the samples are segmented objects in the OBJ-ONLY setting, which is used to investigate the model robustness to deformed geometric shape and non-uniform surface density. In the OBJ-BG setting, background points near the objects are also included, which is used to investigate the influence of background elements. Additionally, to simulate more challenging cases in practice, bounding box perturbation is introduced. In the PB-T50-RS setting, the bounding boxes are randomly shifted up to 50% of its size from the box centroid, and then rotated and scaled. The PB-T50-RS setting is the most challenging one among all three settings.

A.2. Domain Generalization on PointDA-10 Dataset

We investigate the synthetic-to-real domain generalization performance on the PointDA-10 dataset [46], which includes two synthetic datasets of ModelNet-10 and ShapeNet-10 and one real-world dataset of ScanNet-10. Specifically, samples of ModelNet-10, ShapeNet-10 and ScanNet-10 are from shared categories of ModelNet40 [64], ShapeNet [5], and ScanNet [10], respectively.

A.3. Few-Shot Performance on ModelNet40

As illustrated in Tab. 10, our MaskSurf consistently outperforms Point-MAE, justifying the advantage of masked surfel prediction over masked point prediction.

A.4. Classifier Architecture for Segmentation

We strictly follow [40] to construct the classifier for segmentation. Specifically, given learned features form the 4th, 8th and 12th layers of Transformer block, we concatenate the multi-scale patch features and apply the max pooling and average pooling to them, resulting in two global feature representations. We follow [45] to up-sample the concatenated path features to obtain interpolated features of each point. In semantic segmentation, we concatenate the interpolated point features and two global features as complete point features. While in part segmentation, where the part label is associated to the object label, the complete point

9
Table 10. Few-shot classification performance on ModelNet40.

| Method                | 5-way 10-way | 5-way 10-way |
|-----------------------|--------------|--------------|
|                       | 10-shot      | 20-shot      | 10-shot      | 20-shot      |
| DGCNN [60]            | 31.6±2.8     | 40.8±4.6     | 19.9±2.1     | 16.9±1.5     |
| Transformer [59]      | 87.8±5.2     | 93.3±4.3     | 84.6±5.5     | 89.4±6.3     |

**Transferring features protocol**

| Method                | 5-way 10-way | 5-way 10-way |
|-----------------------|--------------|--------------|
|                       | 10-shot      | 20-shot      | 10-shot      | 20-shot      |
| DGCNN-OcCo [60]       | 90.6±2.8     | 92.5±1.9     | 82.9±1.3     | 86.5±2.2     |
| Transformer-OcCo [70] | 94.0±3.6     | 95.9±2.3     | 89.4±5.1     | 92.4±4.6     |
| Point-BERT [70]       | 94.6±3.1     | 96.3±2.7     | 91.0±5.4     | 92.7±5.1     |
| Point-MAE [40]        | 96.3±2.5     | 97.8±1.8     | 92.6±4.1     | 95.0±3.0     |
| MaskSurf (Ours)       | 96.5±2.5     | 98.0±1.4     | 93.0±4.1     | 95.3±3.0     |

**Linear classification protocol**

| Method                | 5-way 10-way | 5-way 10-way |
|-----------------------|--------------|--------------|
|                       | 10-shot      | 20-shot      | 10-shot      | 20-shot      |
| Point-MAE [40]        | 82.3±6.3     | 90.6±5.6     | 88.3±6.5     | 94.9±3.5     |
| MaskSurf (Ours)       | 87.1±4.6     | 92.3±4.9     | 89.3±4.2     | 94.9±3.2     |

**Non-linear classification protocol**

| Method                | 5-way 10-way | 5-way 10-way |
|-----------------------|--------------|--------------|
|                       | 10-shot      | 20-shot      | 10-shot      | 20-shot      |
| Point-MAE [40]        | 93.7±3.5     | 97.4±1.7     | 90.9±5.0     | 94.2±4.2     |
| MaskSurf (Ours)       | 95.4±2.9     | 97.6±1.4     | 90.9±4.6     | 94.7±3.3     |

Table 11. Part segmentation results on the ShapeNetPart dataset. The mean IoU across all categories, i.e., \( \text{mIoU}_c \) (%), the mean IoU across all instances, i.e., \( \text{mIoU}_I \) (%), and IoU (%) for each category are reported.

| Methods               | \( \text{mIoU}_c \) | \( \text{mIoU}_I \) | \( \text{aero} \) | \( \text{bag} \) | \( \text{cap} \) | \( \text{car} \) | \( \text{chair} \) | \( \text{earph.} \) | \( \text{guitar} \) | \( \text{knife} \) | \( \text{lamp} \) | \( \text{laptop} \) | \( \text{motor} \) | \( \text{mug} \) | \( \text{pistol} \) | \( \text{rocket} \) | \( \text{skateb.} \) | \( \text{table} \) |
|-----------------------|---------------------|---------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| PointNet [44]          | 80.39               | 83.7                | 83.4             | 81.7             | 82.5             | 84.9             | 88.6             | 80.2             | 89.1             | 93.0             | 84.8             | 83.8             | 84.5             | 89.1             | 83.8             | 89.1             | 84.5             | 89.1             |
| PointNet++ [45]        | 81.85               | 85.1                | 82.4             | 79.0             | 87.7             | 77.3             | 90.8             | 91.0             | 85.9             | 83.7             | 95.3             | 71.9             | 94.1             | 81.3             | 58.7             | 76.1             | 82.6             |
| DGCNN [61]             | 82.32               | 85.2                | 84.0             | 83.4             | 86.7             | 77.8             | 90.6             | 74.7             | 91.2             | 87.5             | 82.8             | 95.7             | 66.3             | 94.9             | 81.1             | 63.5             | 74.5             | 82.6             |
| Transformer [59]       | 83.42               | 85.1                | 82.9             | 85.4             | 87.7             | 78.8             | 90.5             | 80.8             | 91.1             | 87.7             | 85.3             | 96.6             | 73.9             | 94.9             | 83.5             | 61.2             | 74.9             | 80.6             |
| Transformer-OcCo [70]  | 84.11               | 86.1                | 84.3             | 85.0             | 88.3             | 80.5             | 91.3             | 78.5             | 92.1             | 87.4             | 86.1             | 96.1             | 75.2             | 94.6             | 84.7             | 63.5             | 77.1             | 82.4             |
| Point-BERT [70]        | 84.19               | 86.1                | 84.3             | 85.0             | 88.3             | 80.5             | 91.3             | 78.5             | 92.1             | 87.4             | 86.1             | 96.1             | 75.2             | 94.6             | 84.7             | 63.5             | 77.1             | 82.4             |
| Point-MAE [40]         | 84.36               | 86.1                | 84.7             | 84.8             | 89.1             | 81.1             | 91.4             | 77.8             | 91.8             | 87.7             | 86.1             | 96.5             | 75.9             | 95.2             | 84.9             | 65.6             | 75.4             | 82.1             |
| MaskSurf (Ours)        | 84.36               | 86.1                | 84.7             | 84.6             | 89.1             | 81.1             | 91.4             | 77.8             | 91.8             | 87.7             | 86.1             | 96.5             | 75.9             | 95.2             | 84.9             | 65.6             | 75.4             | 82.1             |

features are achieved by concatenating interpolated point features, two global features and one additional object feature, which are encoded with one FC layer from the object label. Finally, the point-wise prediction is obtained by forwarding the complete point features to three FC layers.

### A.5. Segmentation Results and Visualizations

The detailed part segmentation results with category-wise mIoU are illustrated in Tab. 11. In addition, the results of part segmentation and semantic segmentation are visualized in Fig. 9 and Fig. 10, respectively.
Figure 9. Visualization of the part segmentation results on the ShapeNetPart test set.
Figure 10. Visualization of the semantic segmentation results on the S3DIS Area5.
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