Point Discriminative Learning for Unsupervised Representation Learning on 3D Point Clouds

Fayao Liu¹, Guosheng Lin², and Chuan-Sheng Foo¹

¹Institute for Infocomm Research, A*STAR
²Nanyang Technological University

Abstract

Recently deep learning has achieved significant progress on point cloud analysis tasks. Learning good representations is of vital importance to these tasks. Most current methods rely on massive labelled data for training. We here propose a point discriminative learning method for unsupervised representation learning on 3D point clouds, which can learn local and global geometry features. We achieve this by imposing a novel point discrimination loss on the middle level and global level point features produced in the backbone network. This point discrimination loss enforces the features to be consistent with points belonging to the shape surface and inconsistent with randomly sampled noisy points. Our method is simple in design, which works by adding an extra adaptation module and a point consistency module for unsupervised training of the encoder in the backbone network. Once trained, these two modules can be discarded during supervised training of the classifier or decoder for down-stream tasks. We conduct extensive experiments on 3D object classification, 3D part segmentation and shape reconstruction in various unsupervised and transfer settings. Both quantitative and qualitative results show that our method learns powerful representations and achieves new state-of-the-art performance.

1. Introduction

Nowadays, there is a growing surge in 3D related researches due to the increasing demand on 3D applications such as augmented reality (AR), robotic vision, autonomous driving etc. Among the various 3D representation methods such as voxels, meshes, implicit functions etc., point clouds have become an increasingly popular option. Point cloud analysis has therefore become an important research area. Learning discriminative and transferrable shape representations is a core problem in many point cloud analysis tasks.

Supervised methods rely on massive labelled data, which require large amounts of annotation efforts. In contrast, unsupervised representation learning work by self-supervision without human labelling. The tremendous success achieved by unsupervised representation learning in the 2D domain [17, 15, 4] has stimulated research on its 3D counterparts.

Various methods for unsupervised representation learning on point clouds have been proposed [32, 1, 36, 39, 13, 14, 27, 38, 28, 26, 35]. They can be roughly classified into three categories, i.e., self-reconstruction or auto-encoding based, generative adversarial networks (GAN) [10] based
and self-supervised methods relying on pretext tasks beyond self-reconstruction. Most current methods fall into the first category. They mainly work by mapping an input point cloud into a global latent representation [36, 19, 26, 28] or a latent distribution in the variational case [13, 14] through an encoder and then attempt to reconstruct the input by a decoder. Auto-encoding models need to calculate the distance between the input and the reconstructed point clouds. However, as discussed in [27], it is non-trivial to directly measure the similarity of two shapes represented by different 3D point sets. Currently the most commonly used metrics are Chamfer distance (CD) and Earth-mover distance (EMD), which are both approximated measurements. GAN based methods [32, 1] attempt to exploit the strong generative capability of GAN [10] and can obtain an unsupervised global feature vector through the discriminator. Self-supervised methods without self-reconstruction attempt to learn representations through self-supervision by performing a pretext task. Designing such pretext tasks is not as straightforward as in the 2D domain. In [27], the authors propose a part rearrangement task for self-supervised feature learning on point clouds by extending the patch rearrangement method [24] in 2D domains to 3D domains.

In this work, we propose a point discriminative learning method for unsupervised representation learning on 3D point clouds, which falls into the third category, i.e., self-supervised methods without self-reconstruction. Our motivation is that the learned shape features should be consistent with points from the shape surface and inconsistent with points outside the shape surface. Fig. 1 gives an illustration of our proposed method. We design a point discrimination loss to maximize the consistency scores of learned features with their corresponding positive points, and at meantime minimize the consistency scores of features with negative noisy points. Our method does not rely on point set similarity functions as in auto-encoding methods. We summarize our contributions in the following:

- We propose a point discriminative learning method for unsupervised representation learning on 3D point clouds, which learns local and global shape features through self-supervision. This self-supervision is achieved by enforcing learned features to be consistent with points belonging to the input point cloud using a point consistency module and a cross-entropy loss.

- Our method is simple in design and easy to implement. It works by adding an extra adaptation module and a point consistency module to the PointNet++ [25] backbone network for unsupervised training of the encoder. Once trained, these two modules can be discarded during supervised training of the classifier or decoder for downstream learning tasks.

- We conduct extensive experiments on 3D object classification, 3D part segmentation and shape reconstruction tasks to validate our method. Quantitative and qualitative results show that our method learns discriminative and generalizable unsupervised representations, achieving new state-of-the-art results.

2. Related work

Unsupervised representation learning on point clouds

One straightforward approach to perform unsupervised representation learning on point clouds is to conduct self-reconstruction by exploiting auto-encoding models. Most current methods [1, 19, 36, 13, 14, 39, 26] belong to this category. These approaches mostly lack effective exploitation of local geometry supervisions, as discussed in [13]. A more recent auto-encoding based method for unsupervised point cloud feature learning was proposed in [13], which can capture the local geometry by multi-angle half-to-half prediction. Different from [13], we enforce a point discrimination loss on different levels of feature maps produced by the encoder, which can well capture the global and local geometries of the input point cloud. There are unsupervised representation learning methods recently proposed [27, 28] that do not rely on point cloud self-reconstruction. In [27], the authors propose a pretext task for self-supervision by part shuffling, which is an extension of the patch re-ordering method in 2D domains [24]. Shi et al. [28] propose a maximum likelihood estimation method to restore the input point cloud from the one perturbed by Gaussian random noises. Other generative models like generative adversarial networks [10] are also exploited for unsupervised feature learning in [32, 1].

Contrastive learning

Recently contrastive learning [11] has become a representative and powerful approach for unsupervised feature learning in the 2D domain [7, 24, 17, 4, 15]. They mainly work by designing a pretext task and then perform dictionary look-up, where a query is enforced to be similar to its positive match and dissimilar to others by optimizing a contrastive loss [15]. Such pretext tasks include exploiting agreement between examples generated by data augmentation strategies [7, 4], maximizing the mutual information between local patches and global images [17] etc. A popular contrastive loss is the InfoNCE [29], which is formulated as a classification problem and implemented with a cross-entropy loss. Our point discrimination loss is also designed as a cross-entropy loss similar to InfoNCE, which is used for maximizing the consistency scores of learned features with positive points in a comparative manner.

In the 3D domain, the authors in [38] propose an object part contrasting method named ClusterNet based on graph convolutional neural networks [18] for unsupervised feature learning on point clouds. Their method is trained to determine whether two randomly sampled parts are from the same object. Most recently, another contrastive learning
method for unsupervised point cloud feature learning using the InfoNCE loss [29] was proposed in [35] and named as PointContrast. They exploit point cloud correspondences between different views in a data augmentation fashion, which is a common practice used in the 2D domain. Different from ClusterNet [38] and PointContrast [35], we propose a point discriminative learning method to directly enforce the learned features to be consistent with local and global geometries. Unlike [35], our method does not rely on data augmentation techniques, which is still an underexplored field for 3D point clouds. Instead, it learns to discriminate points belonging to the shape surface from randomly sampled noisy points conditioning on the learned features, thus providing supervisions for feature learning.

3. Proposed method

Consider $M$ point clouds $\{P_i\}_{i=1,\ldots,M}$, where each $P_i \in \mathbb{R}^{N_i \times 3}$ with each row being a single point $p_k \in \mathbb{R}^3$. Here $N_i$ is the total number of points in a single point cloud. We here aim to train a model that can unsupervisedly learn the point cloud representations. Towards this goal, we propose a point discriminative learning method by maximizing the consistency scores of learned features with positive points belonging to the 3D shape. Meanwhile we minimize the consistency scores of features with randomly sampled negative points. We expect this discrimination task can provide supervisions for learning representations that well capture the global and local shape features.

3.1. Method overview

Our method is based on the PointNet++ backbone [25]. We show an overview of our method in Fig. 2. The encoder of the backbone is denoted by the green box while our unsupervised training part is outlined by the red box. The input point cloud is first encoded into a sequential of down-sampled feature maps and then decoded into a category label in the classification task or point-wise predictions in the segmentation task.

We propose a point discriminative learning method to provide self-supervisions for the encoder learning. Specifically, for the feature maps produced by the $l$-th layer of the backbone encoder $F^l_1 \in \mathbb{R}^{N_i \times C_l}$, we first use an adaptation module to map $F^l_1$ to a unified dimension $D$ to obtain new feature maps $F^l_2 \in \mathbb{R}^{N_i \times D}$. We then define a point discrimination loss over the features $z_j \in \mathbb{R}^D$ in $F^l_2$ by discriminating positive points $p^+$ from negative points $p^-$ ($p^+, p^- \in \mathbb{R}^3$ are 3 dimensional point coordinates) conditioning on $z_j$. It is implemented with a point consistency module and a cross-entropy loss. The positive points $p^+$ are defined as points that are within the corresponding local region of $z_j$ in the input point cloud. Negative points $p^-$ are randomly sampled noisy points. The proposed unsupervised point discriminative learning enforces learned feature descriptors to be consistent with the local and global geometries of the point cloud. In the unsupervised training stage, the backbone encoder (outlined by the green box) and our unsupervised training part (outlined by the red box) are optimized through back-propagation. After the unsupervised training stage, the unsupervised training part can be discarded. We can use the learned encoder as an initialization for supervised training of the whole backbone to perform downstream tasks including point cloud classification and segmentation.

3.2. Point discriminative learning

We propose a point discriminative learning method for unsupervised point cloud representation learning. As shown in Fig. 2, this unsupervised loss can be imposed on the middle level and global level point feature maps output by the encoder network. When imposed on the global feature vector, it enforces the learned global feature to capture the overall shape of the input point cloud. We present details of each component of our method in the following.

Point discrimination loss We define the point discrimination loss for a training mini-batch as:

$$L_{\text{pointdisc}} = \sum_{j=1}^{[8]} L(z_j).$$  (1)
Here $z_j \in \mathbb{R}^D$ are feature vectors in feature maps $F^l_2$ with $l$ indicating the layer on which we intend to impose our point discrimination loss. $|B|$ is the total number of $z_j$ we use to calculate the loss in one mini-batch.

We define $\mathcal{L}(z_j)$ by enforcing $z_j$ to be consistent with positive points $p_j^+ \in R(c_j)$. Here $c_j \in \mathbb{R}^3$ denotes the centroid of the input local region that corresponds to $z_j$. $R(c_j)$ is the set of input points that are within the neighborhood of $c_j$. To measure the agreement between features and points, we propose a point consistency module $\text{cons}()$ to output the consistency score. We then enforce $\text{cons}(z_j, p_j^+)$ to be larger than any $\text{cons}(z_j, p^-)$ with $p^-$ being randomly sampled negative points. To achieve this goal, we define $\mathcal{L}(z_j)$ in a discrimination fashion with the cross-entropy loss:

$$
\mathcal{L}(z_j) = - \frac{1}{K} \sum_{i=1}^{K} \log \frac{\exp \left( \text{cons}(z_j, p_j^+)/\tau \right)}{\exp \left( \text{cons}(z_j, p_i^+)/\tau \right) + S^-},
$$

where

$$
S^- = \sum_{t=1}^{T} \exp \left( \text{cons}(z_j, p_t^-)/\tau \right).
$$

Here $K$, $T$ are the numbers of positive and negative points sampled respectively. $\tau$ is the temperature hyperparameter. During implementation, for each point cloud in a single mini-batch, we randomly sample 4000 groups of $(z_j, p_j^+, \ldots, p_K^+)$ for calculating the point discrimination loss. Therefore, we have $|B| = 4000 \times B$ in Eq. (1) where $B$ is the training batch size of the input point clouds.

**Point consistency module** The point consistency module $\text{cons}: \mathbb{R}^D \times \mathbb{R}^3 \rightarrow \mathbb{R}$ outputs the consistency score of a learned representation $z$ with a point $p$. We use a neural network to achieve this purpose, shown in Fig. 3. The concatenation $\hat{z} = [p, z]$ is used as the network input. Following the architecture used in [23, 2], we first map the input $\hat{z}$ to a hidden dimension of 256 using a fully connected layer. It is then followed with a pre-activation ResNet block [16] with conditional batch normalization (CBN) [6]. Specifically, the ResNet block consists of two sets of CBN, a ReLU activation layer and a fully-connected (FC) layer with dimension of 256 for the hidden layer. The output of the ResNet block is fed to another set of CBN, ReLU and FC layer to produce the 1-dimensional consistency score, which is used for calculating the point discrimination loss in Eq. 2.

For the CBN module, it takes $\hat{z}$ as the condition code, which is passed through two FC layers to output the batch normalization parameters, i.e., 256-dimensional vectors $\gamma(\hat{z})$ and $\beta(\hat{z})$. Then for an input $x$, the output of CBN is calculated as:

$$
\text{CBN}(x) = \gamma(\hat{z}) \frac{x - \mu}{\sigma} + \beta(\hat{z}),
$$

where $\mu$ and $\sigma$ are the mean and standard deviation of the batch data. Compared with standard BN where $\gamma$ and $\beta$ are fixed after learning, here CBN produces dynamic $\gamma$ and $\beta$ for different inputs using a neural network. Our experiments show that adding the CBN module leads to more stable training and better generalization. We show this point consistency module design outperforms the one without CBN in the ablation studies in Sec. 5.

**Positive and negative point sets construction** For a particular feature $z_j$ in the feature maps $F^l_2$, we define its positive points $p_j^+$ as the input points that are within a neighborhood region of $c_j$. Here $c_j$ is the centroid of the input local region that corresponds to $z_j$. For a single feature in the feature maps $F^l_1$, the centroid of its corresponding input local region is obtained by farthest point sampling in the sampling layer in PointNet++ [25]. In our unsupervised training part, since the adaptation module only performs pointwise convolution, thus the corresponding input regions of features in $F^l_1$ remain the same as features in $F^l_2$. Therefore we can easily get the centroid $c_j$ for $z_j$ from the sampling layer in the PointNet++ backbone. We then use ball query within a predefined radius to find $R(c_j)$.

For a particular $z_j$, the negative point set is denoted as $\mathcal{T}(R(z_j))$ with $\mathcal{T}(\cdot)$ being a random perturbation operation. We define $\mathcal{T}(\cdot)$ as adding some random noise $\epsilon \sim \mathcal{U}[-a, a]$ to the coordinates of the input point. $\mathcal{U}$ denotes a uniform distribution with $a$ being a scalar parameter. Gaussian noise can be an alternative option here. We perform several ablation studies on the negative point set construction strategies in Sec. 5.

**Feature aggregation for classification** According to prior researches [13, 26], aggregating features from different levels can always help improve the classification performance. The aggregated features for performing classification are obtained by:

$$
F = [\text{maxpool}(F^1_1), \ldots, \text{maxpool}(F^L_1)].
$$

Here $\text{maxpool}(\cdot)$ denotes the max pooling operation and $[\cdot]$ denotes concatenation. $L$ is the total number of layers of the
encoder that produce feature maps. Note that both $F_1^l$ and $F_2$ can be aggregated to perform classification. According to our experiments, they lead to similar performance. Considering that $F_2$ is more compact (with a dimension of $D \times L$ for aggregated features), we use $F_2$ for classification in our experiments.

4. Experiments

4.1. Experimental setup

We evaluate our method on 3D object classification, part segmentation and shape reconstruction tasks.

Datasets We perform 3D object classification and shape reconstruction evaluations on the ModelNet benchmark [33], which is composed of CAD models from different objects. ModelNet40 and ModelNet10 each consists of 9832/2468 and 3991/908 training/test objects coming from 40 and 10 classes respectively. We uniformly sample 1024 points for each example. The metric used for performance evaluation is the overall classification accuracy. We perform part segmentation experiments on the ShapeNetPart dataset [37], which consists of 16881 objects from 16 categories, with each object segmented into 2 to 6 parts. There are 50 parts in total. We follow the standard train/test/val splits for all tasks unless otherwise stated. For evaluation metrics, we use the instance mean Intersection-over-Union (mIoU) following prior works [27, 35].

Implementation details The adaptation module is designed as a 2-layer multi-layer perceptron (MLP) network with batch normalization and ReLU activation layers. Each layer has a dimension of 256 and the output dimension $D$ is set to 256. The outputs of the adaptation module are $L_2$ normalized. For finding $R(c_j)$, we use ball query within a predefined radius according to the radius parameters of the grouping layers in PointNet++ [25]. We normalize all point clouds by centering their bounding boxes to the origin and scaling them by a constant such that all points range within the cube $[−1, 1]^3$ following [2]. The parameter $a$ is set to 1 for the uniform noisy points sampling. For classification, we use aggregated $F_2$ as in Eq. 4. For segmentation, we use $F_1^l$ to perform feature propagation to get pointwise predictions. We train the network with Adam optimizer for 200 epochs. For both tasks, the learning rate of unsupervised training is initialized as 0.005, and with an exponential decay rate of 0.97 per epoch. For part segmentation, we set the initial fine-tuning learning rate of the encoder as 0.0005 and the decoder as 0.005, both with an exponential decay rate of 0.97. We use a batch size of 24 for input point clouds during training. The temperature $\tau$ in Eq. (2) is set to 0.1.

4.2. 3D object classification

Classification results Following the common protocol used in unsupervised representation learning [27, 28], we train our unsupervised learning model on the training set to learn features and then train a linear SVM as the classifier. We report the classification results on the ModelNet40 and ModelNet10 datasets comparing against state-of-the-art unsupervised learning methods using different input modalities in Table 1. As we can see, our method achieves the best results on ModelNet10 and comparable results on ModelNet40 with the most recent state-of-the-art method [26]. † indicates that the model is trained on the ShapeNet dataset.

Feature embedding visualization To further gain a better understanding of the unsupervised representation learning capability of our proposed method, we visualize the feature embeddings of the ModelNet10 test dataset produced by our method using tSNE [30] in Fig. 4. The model is trained on the ModelNet10 training set. The left figure in Fig. 4 shows the visualization results of [27] reproduced from their paper. As we can see, for both methods, the embeddings of “nightsand” and “dresser” are mixed together due to their strong visual similarities. In general, our method produces more separable clusters than [27], which demon-

| Method          | Input  | Accuracy (%) |
|-----------------|--------|--------------|
| GLR (PointNet++) [26]† | Points | 92.22        |
| VSL [21]       | Voxels | 90.69        |
| VIPGAN [12]    | View   | 85.70        |
| LGAN [1]       | Points | 89.10        |
| FoldingNet [37] | Points | 89.15        |
| ClusterNet [38] | Points | 88.60        |
| MRTNet [8]     | Points | 88.40        |
| LGAN† [13]     | Points | 88.40        |
| VIPGAN [12]    | View   | 91.00        |
| FoldingNet [37] | Points | 91.00        |
| LGAN [1]       | Points | 91.85        |
| FoldingNet [37] | Points | 90.15        |
| LGAN [1]       | Points | 89.15        |
| LGAN [1]       | Points | 85.70        |
| FoldingNet [37] | Points | 91.85        |
| LGAN [1]       | Points | 85.70        |
| FoldingNet [37] | Points | 90.15        |
| LGAN [1]       | Points | 90.69        |
| FoldingNet [37] | Points | 91.85        |
| LGAN [1]       | Points | 89.10        |
| FoldingNet [37] | Points | 89.15        |
| LGAN [1]       | Points | 85.70        |
| FoldingNet [37] | Points | 91.00        |
| LGAN [1]       | Points | 91.85        |
| FoldingNet [37] | Points | 90.15        |
| LGAN [1]       | Points | 89.15        |
| FoldingNet [37] | Points | 91.85        |
| LGAN [1]       | Points | 85.70        |
| FoldingNet [37] | Points | 90.15        |
| LGAN [1]       | Points | 90.69        |

Table 1. Classification results on the ModelNet40 and ModelNet10 datasets produced by different unsupervised feature learning methods. A linear classifier is trained over the unsupervisedly learned features. Our method achieves the best results on ModelNet10 and comparable results on ModelNet40 with the most recent state-of-the-art method [26]. † indicates that the model is trained on the ShapeNet dataset.

We report the results of [26] using the same backbone as us.


| Method              | Accuracy (%) |
|---------------------|--------------|
| Supervised          |              |
| PointNet++ [25]     | 90.7         |
| PointCNN [20]       | 92.2         |
| DGCNN [31]          | 92.2         |
| Point2Seq [32]      | 92.6         |
| Unsupervised        |              |
| 3D-DescripNet [34]  | 83.8         |
| 3D-GAN [32]         | 83.3         |
| FoldingNet [36]     | 81.9         |
| PointDist [28]      | 84.7         |
| Ours                | **90.6**     |

Table 2. Classification results on ModelNet40 by training on the ShapeNet 7 classes. A linear SVM is trained over the unsupervisedly learned features. Our method outperforms the most recent state-of-the-art method [28] by a large margin.

Transferring and out-of-category generalization evaluation

To demonstrate the transferring and generalization capabilities of our unsupervisedly learned features, following [28, 32], we train our unsupervised feature learning model on the 7 major categories (chairs, sofas, tables, boats, airplanes, rifles, and cars) of the Shapenet dataset [3] and then perform test evaluation on the whole test set of the ModelNet40. Similarly a linear SVM is trained over the learned features to perform classification. Since most of the objects are not seen during training, this task can well demonstrate the transferability and out-of-category generalization capability of our method. We report the results compared against state-of-the-art supervised and unsupervised methods in Table 2. From the table, we can observe that our method outperforms all the unsupervised methods by large margins. The result almost can compete with supervised methods, especially PointNet++ [25] which uses the same backbone as us. It is also worth noting that we have gained significant improvement (+5.9 in accuracy) over the most recent state-of-the-art method PointDist [28]. This demonstrates that our method learns unsupervised representations with strong transferring and generalization capabilities.

4.3. 3D part segmentation

In contrast to classifying a point cloud into a single category in the classification case, part segmentation is a fine-grained point-wise classification task which requires detailed local geometry features. We conduct experiments on the ShapeNetPart dataset. Following prior works [25, 27], we use the one-hot encoded category label of the object as an extra input for supervised training. During our unsupervised learning, a random class label is given to each object.

To compare with the unsupervised feature learning methods in [27, 35], we run experiments under the same settings, i.e., first unsupervisedly pre-train the encoder on the whole ShapeNetPart training dataset and then fine-tune the encoder and the decoder with different percentages of labeled data. The compared mIoU results under different training data budget, i.e., 1%, 5%, 100% are reported in Table 3. The results of models learned from scratch using random initializations are reported as baselines. As we can see, the performance gains brought about by our pre-training method are more significant under all different training budget settings than [35] and [27]. This demonstrates the effectiveness of our unsupervised representation learning for model pre-training. Fig. 5 shows some qualitative examples. We can see that our method can well segment fine-grained parts.

We also conduct experiments to compare with [19, 39, 14] by using the same semi-supervised settings, i.e., first pre-training the encoder with unsupervised feature learning and then training the decoder without fine-tuning the encoder. We report the global accuracu and instance mIoU
| Method                        | 1% training | 5% training | 100% training |
|------------------------------|-------------|-------------|---------------|
| Self-Sup (randinit) [27]     | -           | -           | 85.1          |
| Self-Sup (pre-trained) [27]  | -           | -           | 85.3 (+0.2)   |
| PointContrast (randinit) [35]| 71.8        | 79.3        | 84.7          |
| PointContrast (pre-trained) [35]| 74.0 (+2.2) | 79.9 (+0.6) | 85.1 (+0.4)   |
| Ours (randinit)              | 72.4        | 79.8        | 84.9          |
| Ours (pre-trained)           | 77.1 (+4.7) | 81.4 (+1.6) | 85.3 (+0.4)   |

Table 3. Performance comparisons (mIoU) of part segmentation on the ShapeNetPart dataset using different labelled training data budget (1%, 5%, 100%). “Pre-trained” indicates the model uses unsupervisedly trained encoder as initialization while “randinit” denotes the model is trained from scratch using random initializations. Our method achieves the largest performance gains in almost all settings.

Table 4. Performance comparisons of part segmentation on the ShapeNetPart dataset using different percentages of labelled training data. Our method achieves the best mIoU performance.

| Method      | 1% training | 5% training |
|-------------|-------------|-------------|
|             | Acc | mIoU | Acc | mIoU |
| SO-Net [19] | 78.0 | 64.0 | 84.0 | 69.0 |
| PointCapsNet [39] | 85.0 | 67.0 | 86.0 | 70.0 |
| Muti-task [14] | 88.6 | 68.2 | **93.7** | 77.7 |
| Ours        | **89.2** | **76.3** | 92.2 | **80.3** |

4.4. Shape reconstruction and interpolation

To show that our method learns meaningful shape representations, we conduct experiments to perform shape reconstruction on ModelNet40. We train a folding based decoder [36] to reconstruct the input point cloud from shape features learned by our unsupervisedly trained encoder. The decoder is trained by optimizing the Chamfer distance (CD) loss while the encoder is trained beforehand with our point discrimination loss and kept fixed. We also report the results of fine-tuning the trained encoder together with the decoder training. As a baseline, we train the encoder and decoder from scratch by optimizing the CD loss for point cloud reconstruction. For all methods, we train a single autoencoding model for all shape categories. We report the training and test loss comparisons in terms of CD in Table 5. We can see that our method with fine-tuning achieves the lowest training and test loss values, improving the results of training from scratch model. It should be noted that although our encoder is not trained with the reconstruction loss, the encoded features can still achieve fair point cloud reconstruction performance, as shown by the results of “Ours (w/o finetune)” in Table 5. Fig. 6 shows some reconstruction examples on the test set using our encoded features without finetune. We can see that our method well reconstructs local and global geometries even though the encoded features are not learned for point cloud reconstruction.

We further conduct experiments to perform shape interpolation to show that our method learns continuous representations. Specifically, we take the encoder trained with our point discrimination loss without fine-tuning to extract latent features from input point clouds. We then interpolate the latent shape features of two point clouds and then decode it with the decoder trained for reconstruction. Fig. 7 shows some visual examples from the test dataset of ModelNet40. As we can see, our method learns latent features that lead to plausible and continuous shape interpolations.

5. Ablation study and analysis

In this section, we perform ablation studies of our method for detailed analysis. All experiments are conducted by training our unsupervised representation learning
Table 5. Shape reconstruction results on the ModelNet40 dataset in terms of Chamfer distance (multiplied by $10^3$). Note that a single autoencoding model is trained for all shape categories.

![Visualizations of shape interpolation in the latent space.](image1)

![Figure 8. Left: Linear SVM classification accuracy on the ModelNet40 test dataset with respect to different values of T. Right: Time in seconds per iteration with respect to different values of T.](image2)

Table 6. Performance comparison of our method using different components. We evaluate the linear SVM classification accuracy on the ModelNet40 dataset.

The conclusion is that the uniform noise leads to slightly better classification accuracy than the Guassian noise (92.30 vs. 91.82). For all later experiments, we use the uniform noise sampling.

Do noisy points near the shape surface harm point discriminative learning? During sampling of negative points, some sampled points may be very close to the local shape surface, which may cause confusion to the point discriminative learning. To figure out this issue, we conduct an ablation study to exclude those points that are within a small distance (0.1) of $R(e_j)$. Experimental results show that there is no statistical differences between models that

with and without this point exclusion strategy. We conjecture that those near-the-boundary points only consists a small portion of the sampled points, which does not bring negative effect to the point discriminative learning.

Table: **Number of positive and negative points sampled per** $z_j$ We study the effects of sampling different numbers of positive and negative points $K$, $T$ per $z_j$ in Eq. (2). For $K$, we experimentally find that setting $K$ to larger than 1 converges to similar solutions as setting $K =$ 1. For $T$, we choose it from $\{1, 5, 10, 20, 50\}$ to train our unsupervised representation learning model. We plot the classification accuracies and computation time consumed for different values of $T$ in Fig. 8. As we can see, with $T$ increases from 1 to 10, the classification accuracy keeps improving, though the differences are not significant. When $T$ is larger than 10, the classification accuracy shows no further gains. This indicates that the performance of our method is not so sensitive to the value of $T$. On the other hand, the computation time is in linear with respect to $T$, which is resulted from the $(T + 1)$-way Softmax calculation in Eq. (2). We set $K =$ 1 and $T =$ 10 in our later experiments.

Component analysis We analyze in detail the contributions of each component in our model with results shown in Table 6. As shown in Fig. 2, our self-supervised point discrimination loss can be imposed on features learned from any intermediate layers or the global level feature (last layer). Our first ablation factor is the contributions of imposing our point discrimination loss on different layers with “l3” indicating the last layer (model A, B, D in Table 6). Our second ablation factor is the CBN in the point consistency module, which is replaced by conventional batch normalization (BN) for the setting without the CBN (model C in Table 6). As we can see from Table 6 that imposing the point discrimination loss on more intermediate layers consistently improves the classification performance. Compared to the model without CBN, our full model yields better results which validates the effectiveness of our point consistency module design.

5.1. Discussions on model size and training time

The total number of parameters of our model for classification is 1.8M (622K for PointNet++ backbone encoder+576K for adaptation modules+598K for point consistency module). We also calculate the number of parameters
for [26] using the same backbone as us, which is 4.79M. The large network used in [26] contains 23.22M parameters. Our model contains much less parameters and yet achieves better or comparable performance. The reason is that in self-reconstruction based unsupervised feature learning methods like [26], a decoder is required to perform input reconstruction, which is typically large. While our method does not rely on self-reconstruction but a lightweight point consistency module. For training time, our method runs at ~230s per epoch on ModelNet40 with a single GPU. [26] runs at ~290s for using the same backbone as us and ~665s using the large network. Our method is much more efficient. We show in Fig. 9 the convergence comparisons of training from scratch and fine-tuning with our pre-trained model for part segmentation under 1% and 5% training budgets. Our method generally converges after 70 epochs training while training from scratch takes twice epochs to converge.

5.2. Visualizations of local shapes learned by our point consistency module

After the unsupervised training of our method, we obtain an encoder network and a point consistency module network. The encoder network is used to produce down-sampled feature maps and global features for input point clouds. The point consistency module $\text{cons}(\cdot)$ can discriminate positive points belonging to the shape surface from noisy points outside the shape surface given a learned feature. For a particular learned feature $z$, we can evaluate the consistency scores of $z$ with randomly sampled points around its corresponding centroid. By only keeping those points that have high consistency scores with $z$, we can visualize what is learned by our point consistency module.

Specifically, for an input point cloud, we use our trained model on the ModelNet40 dataset to generate down-sampled feature maps $F_2$ (we here demonstrate with the second layer feature maps). We then take a single feature $z \in F_2$, which corresponds to a centroid $c$ in the point input cloud. We randomly sample 5000 points $q_i$ from a uniform distribution within the neighborhood of $c$, and evaluate their consistency scores with $z$, i.e., $\text{cons}(z, q_i)$. We then visualize the top 100 points with the highest consistency scores. Fig. 10 shows the results. The first row shows the input point clouds, with each example showing a centroid (indicated by "+") and the neighboring region (indicated by the black circle) corresponding to a particular $z$. The second row shows ground-truth local shapes (corresponding local part in the input point cloud obtained by ball query within a neighborhood of the centroid). They are positive points corresponding to $z$ that are used to train our point discriminative learning method. The third row shows local shapes learned by our point consistency module (points with the top 100 highest consistency scores). We can see that our method produces local shapes that are highly consistent with the ground-truth parts. This demonstrate that our method learns unsupervised representations that can well capture local shape features.

6. Conclusion

We propose a point discriminative learning method for unsupervised representation learning on 3D point clouds. Our method works by adding additional modules to the PointNet++ backbone network. By imposing a point discrimination loss on middle level and global level point features, our method enforces the learned features to capture local and global shape geometry. Extensive experiments demonstrate that the propose method has strong feature learning capability, and can be used as an initialization strategy for the backbone encoder training.

References

[1] Panos Achlioptas, Olga Diamanti, Ioannis Mitliagkas, and Leonidas J. Guibas. Learning representations and generative models for 3d point clouds. In ICML, volume 80, pages 40–49. PMLR, 2018. 1, 2, 5

[2] Ruojin Cai, Guandao Yang, Hadar Averbuch-Elor, Zekun Hao, Serge Belongie, Noah Snavely, and Bharath Hariha-
[3] Angel X. Chang, Thomas A. Funkhouser, Leonidas J. Guibas, Pat Hanrahan, Qi-Xing Huang, Zimo Savaresi, Manolis Savva, Shuran Song, Hao Su, Jianxiong Xiao, Li Yi, and Fisher Yu. Shapenet: An information-rich 3d model repository. *CoRR*, abs/1512.03012, 2015.

[4] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey E. Hinton. A simple framework for contrastive learning of visual representations. *CoRR*, abs/2002.05709, 2020.

[5] C. Cortes and V. Vapnik. Support vector machines. *Machine Learning*, 20, 1995.

[6] Harm de Vries, Florian Strub, Jérémie Mary, Hugo Larochelle, Olivier Pietquin, and Aaron C. Courville. Modulating early visual processing by language. In *NIPS*, pages 6594–6604, 2017.

[7] Alexey Dosovitskiy, Jost Tobias Springenberg, Martin A. Riedmiller, and Thomas Brox. Discriminative unsupervised feature learning with convolutional neural networks. In *NIPS*, pages 766–774, 2014.

[8] Mathew Gadelha, Rui Wang, and Subhransu Maji. Multiresolution tree networks for 3d point cloud processing. In *ECCV*, volume 1211 of *Lecture Notes in Computer Science*, pages 105–122, 2018.

[9] Rohit Girdhar, David F. Fouhey, Mikel Rodriguez, and Abhinav Gupta. Learning a predictable and generative vector representation for objects. In *ECCV*, volume 9910, pages 484–499, 2016.

[10] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron C. Courville, and Yoshua Bengio. Generative adversarial nets. In *NIPS*, pages 2672–2680, 2014.

[11] Raia Hadsell, Sumit Chopra, and Yann LeCun. Dimensionality reduction by learning an invariant mapping. In *CVPR*, pages 1735–1742, 2006.

[12] Zhirong Wu, Shuran Song, Aditya Khosla, Fisher Yu, Linguang Zhang, Xiaou Tang, and Jianxiong Xiao. 3d
shapenets: A deep representation for volumetric shapes. In *CVPR*, pages 1912–1920. IEEE Computer Society, 2015. 5

[34] Jianwen Xie, Zilong Zheng, Ruiqi Gao, Wenguan Wang, Song-Chun Zhu, and Ying Nian Wu. Learning descriptor networks for 3d shape synthesis and analysis. In *CVPR*, pages 8629–8638. IEEE Computer Society, 2018. 6

[35] Saining Xie, Jiatao Gu, Demi Guo, Charles R Qi, Leonidas J Guibas, and Or Litany. Pointcontrast: Unsupervised pre-training for 3d point cloud understanding. 2020. 1, 3, 5, 6, 7

[36] Yaoqing Yang, Chen Feng, Yiru Shen, and Dong Tian. Foldingnet: Point cloud auto-encoder via deep grid deformation. In *CVPR*, pages 206–215. IEEE Computer Society, 2018. 1, 2, 5, 6, 7

[37] Li Yi, Vladimir G. Kim, Duygu Ceylan, I-Chao Shen, Mengyan Yan, Hao Su, Cewu Lu, Qixing Huang, Alla Sheffer, and Leonidas J. Guibas. A scalable active framework for region annotation in 3d shape collections. *ACM Trans. Graph.*, 35(6):210:1–210:12, 2016. 5

[38] Ling Zhang and Zhigang Zhu. Unsupervised feature learning for point cloud understanding by contrasting and clustering using graph convolutional neural networks. In *ICDV*, pages 395–404, 2019. 1, 2, 3, 5

[39] Yongheng Zhao, Tolga Birdal, Haowen Deng, and Federico Tombari. 3d point capsule networks. In *CVPR*, pages 1009–1018, 2019. 1, 2, 5, 6, 7