Abstract

Learning robust 3D shape segmentation functions with deep neural networks has emerged as a powerful paradigm, offering promising performance in producing a consistent part segmentation of each 3D shape. Generalizing across 3D shape segmentation functions requires robust learning of priors over the respective function space and enables consistent part segmentation of shapes in presence of significant 3D structure variations. Existing generalization methods rely on extensive training of 3D shape segmentation functions on large-scale labeled datasets. In this paper, we proposed to formalize the learning of a 3D shape segmentation function space as a meta-learning problem, aiming to predict a 3D segmentation model that can be quickly adapted to new shapes with no or limited training data. More specifically, we define each task as unsupervised learning of shape-conditioned 3D segmentation function which takes as input points in 3D space and predicts the part-segment labels. The 3D segmentation function is trained by a self-supervised 3D shape reconstruction loss without the need for part labels. Also, we introduce an auxiliary deep neural network as a meta-learner which takes as input a 3D shape and predicts the prior over the respective 3D segmentation function space. We show in experiments that our meta-learning approach, denoted as Meta-3DSeg, leads to improvements on unsupervised 3D shape segmentation over the conventional designs of deep neural networks for 3D shape segmentation functions.

1. Introduction

3D part segmentation is a meaningful but challenging task, which has wide applications in the 3D computer vision field [25, 38, 33]. This task requires us to classify each sampled point from the target 3D shape into meaningful part clusters. As large scale 3D shapes dataset become available to public [2], learning-based data-driven methods become popular and demonstrate great success in part segmentation of 3D shapes [18, 19, 12, 24]. Earlier supervised learning-based models leverage deep neural networks as 3D shape segmentation functions which firstly encode every 3D point to a high-dimensional point signature, and then map the signature to the corresponding semantic part label. The deep learning models are usually trained with a large-scale labeled dataset to optimize the parameters of a model towards robust 3D segmentation. Recent advances show that neural implicit shape representation parameterized as multilayer perceptrons (MLP) show impressive performance in 3D shape segmentation [34, 4]. These methods firstly leverage convolutional encoders to regress a latent shape embedding, which is then decoded into a shape-conditioned 3D segmentation function via concatenation-based conditioning.

To generate consistent part segmentation of shapes in presence of significant 3D structure variations, it is important to generalize across 3D shape segmentation functions which often requires robust learning of priors over the respective function space. To this end, existing generalization methods rely on extensive training of 3D shape segmentation functions on large-scale labeled datasets. For example, in [18, 19], those methods generalize its 3D segmentation ability from training a large volume of data across different categories with the hope to directly predict the desired part labels at testing. In [4], the authors developed the per-category 3D segmentation model in a few-shot setting, which trains a 3D segmentation model for every category of 3D objects.

As shown in Figure [1], previous learning-based methods tend to learn a single 3D segmentation function (learner) for all 3D objects. Under this circumstance, the 3D segmentation learner generalizes its ability to segment a shape from an extensive training on a large number of labeled data. In contrast, we proposed to formalize the learning of a 3D shape segmentation function space as a meta-learning problem, aiming to predict a 3D segmentation model that can be quickly adapted to new shapes with no or limited training data. More specifically, as shown in Figure [1] we
define each task as learning a unique 3D segmentation function (learner) for each given 3D object. Besides, we design an auxiliary deep neural network as a meta-learner that can predict the prior over the respective 3D segmentation function space. As shown in Figure 1, the meta-learner is responsible for providing the optimal initialization of a 3D segmentation learner that is specialized to a new task (i.e. segmenting a new 3D object) via few steps of gradient descent. In general, our meta-learning-based approach gains competitive advantages over existing generalization methods that our Meta-3DSeg can uniquely parameterize the 3D segmentation function for each shape to provide an instance-wise part segmentation.

Our proposed Meta-3DSeg includes two modules as shown in Figure 2: 3D segmentation learner and 3D segmentation meta-learner. The 3D segmentation meta-learner includes two parts. The first part is a variational encoder that maps shape representations to a distribution over 3D segmentation tasks, which gives the priors over the 3D segmentation function space and the second part is to sample from the task distribution to predict optimal initialization for the parameters of the 3D shape segmentation function. The 3D segmentation learner is a multi-layer perceptron (MLP) conditioned on a 3D shape embedding to represent shape segmentation. Our contributions are listed as below:

- In this paper, to the best of our knowledge, it is the first time to formalize learning of a 3D shape segmentation function space as a meta-learning problem. With this, a 3D segmentation model can be quickly adapted to new shapes with no or limited labeled training data.
- In this paper, we propose a novel variational encoder that maps shape representations to a distribution over 3D segmentation tasks, contributing to robust learning of priors over the 3D segmentation function space.
- In this paper, our Meta-3DSeg can uniquely parameterize the 3D segmentation function for each shape to provide an instance-wise part segmentation.
Figure 2. Our pipeline. The proposed paradigm includes two main parts: 3D segmentation learner and 3D segmentation meta-learner. The 3D segmentation learner includes shape embedding and part label predictors. The 3D segmentation meta-learner includes the task distribution estimator and the learner’s initialization predictor. \( P_n \) denotes the n-th part probability score.

- In this paper, we demonstrated superior 3D segmentation performance over other state-of-the-art supervised/unsupervised methods on various datasets even without training on any labeled data.

2. Related Works

2.1. 3D shape segmentation

3D point cloud part segmentation is an important 3D computer vision task that aims to predict the part-specific label for each point of a point cloud. As we all know, traditional architectures such as voxels and image grids have regular data formats. However, the representation of point clouds is unstructured and unordered which makes the learning of point-wise labels very challenging. Early methods [9, 17, 25, 38] were built on the effective extraction of low-level features from 3D shapes for segmentation. Descriptors such as scale-invariant heat kernel signatures (SIHKS) [38], shape diameter function (SDF) [23], Gaussian curvature (GC) [7] and so on, are widely used for this task. In recent years, deep learning-based methods demonstrated great success in many fields of computer vision [14, 3, 32, 41, 13]. For 3D shape segmentation, PointNet [18] firstly proposed an efficient way to directly learn the features from unordered 3D point sets. Following works including PointNet++ [19], SO-Net [12], SplatNet [28], PointCNN [15], D-FCN [35], KPConv [30] and so on, further improved the PointNet for 3D point cloud segmentation from various aspects such as points density, points sampling, local feature extraction and so on. Other researchers introduced 3D CNN extended from 2D CNN on voxelized 3D shapes for learning the gridded voxel features [29, 31, 10]. Wang et al. proposed DGCNN [34] which uses a module called the EdgeConv that can capture local structures. The BAE-Net [4] successfully introduced a branched autoencoder network for the co-segmentation of 3D shapes. Although these previous researches provided successful attempts to design a good 3D segmentation learner for this task, large amounts of training data are required since they mostly directly predict 3D shape segmentation in the training process. In real-world scenarios, training data is expensive and hard to acquire which limits the use of those strong supervised methods. In comparison, our paper focuses on how to build a 3D segmentation meta-learner that can provide optimal initialization for the segmentation learner’s parameters based on the priors over the 3D segmentation function space.

2.2. Meta Learning Network

Traditional learning-based methods with a small number of training datasets can severely lead to overfitting problems and unsatisfied performance. Meta-learning [11, 22, 8] demonstrated its effectiveness in 2D computer vision field. As a subfield of machine learning, it introduced a novel approach to focus on the task distribution other than the data distribution to faster and more efficiently adapt the learned pattern to a novel dataset with zero/few shots. Parameters prediction [5, 6, 11] is one of the strategies in meta-
learning, which refers to a network that is trained to provide optimal initialization of another network via gradient descent. MAML [5] proposed by Finn et al. is a pioneer work in meta-learning that starts multiple tasks at the same time and learns a common best base model by different tasks. Santoro et al. [21] introduced the model MANN to use an explicit storage buffer to rapidly learn the new task information. Ravi et al. [20] proposed an LSTM structure for training a meta-learning network in a few-shot setting. Prototype-based networks were proposed by Snell et al. [27] for solving the few-shot classification task. In the 3D computer vision field, the meta-learning-based works are less explored. Littwin et al. [16] proposed the first structure to leverage a network of the network for learning the 3D shape representation. Yang et al. [39] proposed Meta3D to use external memory for storing image features with corresponding volumes. Meta-SDF [26] was further proposed by Sitzmann et al. which leverages gradient-based meta-learning for the learning of neural implicit function spaces.

In this paper, we first propose a meta-learning strategy that uses a 3D segmentation meta-learner to learn the general information over a variety of part segmentation tasks so that it can provide optimal initialization of the 3D segmentation learner and enable the 3D segmentation learner’s network to rapidly adapt to the new part segmentation tasks.

3. Methods

We introduce our approach in the following sections. In section 3.1 we introduce the problem statement of our method. Section 3.2 illustrates the network structure of our 3D segmentation learner. We explain the 3D segmentation meta-learner in section 3.3. The loss function is defined in section 3.4.

3.1. Problem Statement

We define our meta-learning formulation at first. Given a dataset \( D = \{ P_1 \} \), where \( P_1 \subset \mathbb{R}^3 \), \( P_1 \) denotes the input point clouds. We assume the existence of a parametric function \( g_\phi(P_1) = \phi \) using a neural network structure, where \( \phi \) is the part label estimation function which is able to predict the part labels of each points in a point cloud. The 3D segmentation learner \( g \) includes two sets of parameters: \( \theta_m \) and \( \theta_l \). \( \theta_m \) is predicted by another parametric function \( f_\sigma \) which is called 3D segmentation meta-learner and \( \theta_l \) is learned during the fine-tune process. We aim to optimize the weights of 3D segmentation meta-learner using a stochastic gradient descent-based algorithm. For a given training dataset \( D_{\text{train}} \), we optimize the \( \sigma \) as follows:

\[
\sigma^* = \arg\min_{\sigma} \mathbb{E}_{(P_1) \sim D_{\text{train}}} [L(g(\theta_m, \theta_l)(P_1))] 
\]  

(1)

where \( L \) represents the pre-defined loss function.

For the given testing dataset \( D_{\text{test}} \), we fix the weights of 3D segmentation meta-learner \( \sigma^* \) which predict the optimal parameters \( \theta_m^* \) for the 3D segmentation learner. We optimize the parameters of 3D segmentation learner \( \theta_l^* \):

\[
\theta_l^* = \arg\min_{\theta_l} \mathbb{E}_{(P_1) \sim D_{\text{test}}} [L(g(\theta_m^*, \theta_l)(P_1))] 
\]  

(2)

3.2. 3D segmentation learner

We aim to represent the shape with a deep neural network multi-class classification function which takes points in 3D space as input and predicts the part labels guided by a self-supervised 3D shape reconstruction loss. The 3D segmentation learner includes two modules: shape embedding (3.2.1) and part label predictor (3.2.2). We discuss them in the following subsections.

3.2.1 Shape Embedding

For the input point clouds and corresponding voxels which are sampled in the 3D space surrounding the input shape and the inside-outside status of the sampled points. The shape embedding is a CNN-based neural network that can extract shape features and capture geometric information. Formally, let \( P_i \) denotes the input point clouds, \( V_i \) denotes the corresponding input voxels and \( f_v \subset \mathbb{R}^m \) denotes the feature of \( v \), \( \forall v \in V_i \). We define the encoding network \( f_1: \mathbb{R}^3 \to \mathbb{R}^m \) which uses convolution neural network (CNN) with ReLu activation function for feature extraction between the input voxels and local feature. We aggregate the information as follows:

\[
f_v = g_1(v)_{v \in V_i} 
\]  

(3)

The feature information is combined by the extracted feature and point coordinates \( x \), \( \forall x \in P_i \). Specifically, \( \forall x \in P_i \), we concatenate the learned feature \( f_v \) with the coordinates \( x \) as the combined feature \( [f_v, x] \in \mathbb{R}^p \). Note that the weights in \( g \) includes two-component: the meta-learned weights and the learned weights. The weights for \( g \) is the element-wise summation of the meta-learned weights and the learned weights. Thus the shape embedding of input point cloud \( P_i \) is: \( \{[f_v, x]\}_{x \in P_i} \).

3.2.2 Part Label Predictor

In this section, we introduce the network structures for 3D segmentation learner. In order to learn the point information between extracted feature and point coordinates, we define the decoding network \( g_2: \mathbb{R}^p \to \mathbb{R}^q \), where \( p = m + 3 \). \( g_2 \) is a non-linear MLP-based function. \( \forall x \in P_i \), we denote the point information feature \( p_x \) as:
\[ p_x = g_2([f_v, x])_{x \in P_i} \]  

(4)

where \([\cdot]\) denotes the operation of concatenation.

After we obtained the point feature \([p_x]_{x \in P_i}\) from decoding network \(g_3\), we define the segmentation network \(g_3 : \mathbb{R}^q \rightarrow \mathbb{R}^c\) to learn the part label for each point in the point cloud, where \(c\) refers to the pre-defined number of part categories. \(g_3\) is a non-linear MLP-based function. We have the predicted part label \(o_x\) as:

\[ o_x = \text{Maxpool}\{\text{Sigmoid}(g_3(p_x))\} \]  

(5)

We note the trained weights in \(g\) as \(\theta_t\) and the meta-learned weights in \(g\) as \(\theta_m\). The weights for \(g\) is the element-wise summation of \(\theta_t\) and \(\theta_m\).

3.3. 3D Segmentation meta-learner

We aim to learn priors over the respective 3D segmentation function space based on mapping the reference learning shape embedding onto the parameters of our 3D segmentation learner. The 3D segmentation meta-learner includes two modules: task distribution estimator (3.3.1) and learner’s initialization predictor (3.3.2). We discuss them in the following subsections.

3.3.1 Task Distribution Estimator

To enable the 3D segmentation meta-learner to learn the function priors over task distribution, we introduce a variational auto-encoder (VAE) network. More specifically, we use a multi-layer MLP-based function \(f_1 : \mathbb{R}^{m+3} \rightarrow \mathbb{R}^v\) to learn the mean and variance of the data distribution. We denote \((\mu_m, \sigma_m)\) as the mean and the standard deviation of data distribution space:

\[ \mu_m, \sigma_m = f_1([f_v, x])_{x \in P_i} \]  

(6)

Therefore, we are able to sample \(I_m \sim N(\mu_m, \sigma_m)\).

3.3.2 Learner’s Initialization Predictor

After we sample \(I_m \sim N(\mu_m, \sigma_m)\), we use the multi-layer MLP based architecture \(f_2 : \mathbb{R}^v \rightarrow \mathbb{R}^w\), where \(w\) indicates the dimension of all the weights included in \(\{\theta_k\}_{k=1,...,H}\). We denote the weights in \(f_2\) as \(\varphi_3\). The meta-learned weights in the 3D segmentation learner are predicted from the following. \(\forall X \in \mathcal{D}\), we have:

\[ \theta_1, ..., \theta_H = f_2(I_m) \]  

(7)

During the fine-tuning process, our 3D part segmentation learner can be rapidly adapted by adding the meta-learned weights of \(\theta_m = \{\theta_1, ..., \theta_H\}\) from the 3D segmentation meta-learner together with the fine-tuned weights of \(\theta_t\) which are learned from the testing dataset.

3.4. Loss Function

We define the loss function in this section. As for our unsupervised learning-based method, we do not have the ground truth part labels for supervision. Therefore, we leverage a mean square loss to compute the inside-outside status of the sampled points, which allows us to reconstruct the shape in the output layer. Specifically, For the input 3D shape \(X \in \mathcal{D}\), \(\forall x \in X\), we have label \(y_x = 1\). For any sampled point \(x \in X'\) and \(X' = \mathbb{R}^3 / X\), we have label \(y_x = 0\). \(\forall x \in \mathbb{R}^3\), we define \(L_1(x, y_x)\) as:

\[ \mathcal{L}(x) = (f(x) - f^*(x))^2 \]  

(8)

where \(f(x)\) is the output value of our network for each point in the point cloud and \(f^*(x)\) is the ground truth inside-outside status for a point \(p\). Thus, we have total reconstruction loss as follows:

\[ \mathcal{L}_{\mathcal{R}} = \frac{1}{|X| + |X'|} \sum_{x \in X \cup X'} \mathcal{L}(x) \]  

(9)

4. Experiments

In this section, we conduct experiments to demonstrate the effectiveness of the modules in our proposed unsupervised method and evaluate its 3D point cloud segmentation performance. Section 4.1 describes the preparation of the dataset in our experiments. Section 4.2 outlines our experimental settings. In section 4.3, we compare different settings and initialization of our designed meta-learning-based network on ShapeNet dataset, from which deduce and demonstrate the superiority of our proposed method. We illustrate the influences of using various numbers of 3D shapes sampled points in 4.4. Further comparison with other supervised methods is demonstrated in section 4.5.

4.1. Dataset preparation

We evaluate our proposed method for 3D point cloud part segmentation on ShapeNet part dataset [40]. The ShapeNet dataset is an open-source collection, which consists of 16,881 shapes from 16 object categories. Each object category has 2 to 5 part labels (50 in total). To ensure a fair comparison, we follow the official split to preprocess our dataset [37].

For evaluation of point cloud part segmentation performance, we use mean IoU (Intersection-over-Union) on
In this experiment, we conduct a series of experiments to verify the effects under different model initialization and settings.

**Experiment setting:** In this experiment, we conduct a series of experiments to examine and verify the effects under different model initialization and settings. In the weight-setting-A, without our meta-learning strategy, the network parameters of the 3D segmentation learner are pre-trained using all shapes in the original dataset and fine-tuned using the chair dataset as the new task. In the weight-setting-B, the network parameters of the 3D segmentation learner are meta-learned by the 3D segmentation meta-learner and then fine-tuned using the testing dataset. Specifically, we first sample multiple tasks using all shapes in the original dataset as our training dataset. We trained our 3D segmentation meta-learner on the sample dataset to learn the priors over the 3D segmentation function space. Then we fix our 3D segmentation meta-learner and fine-tune our 3D segmentation learner using all shapes in the chair category. Note that in the weight-setting-B, we directly use MLPs to learn the function prior which is further send to the prediction of the learner as input to predict the parameters of the 3D segmentation Learner. In the weight-setting-C, with our meta-learning strategy, instead of directly using the MLPs to map the input shape to the function prior, we add a variational auto-encoder (VAE) to learn the task distribution of the input 3D shape, which can be further sampled as the function prior over task distribution for the learner predictor to estimate the optimal weights of the 3D segmentation learner.

We further verify the efficiency of our model under different model initialization and settings in Figure 3. As for the learner for a particular category, without a meta-learning strategy, the network parameters of the 3D segmentation learner are pre-trained using all shapes in the original dataset and fine-tuned using the target category dataset as the new task. As for our model, we leverage the proposed 3D segmentation meta-learner which can learn the prior over the 3D segmentation function space and provide the optimal parameters of the 3D segmentation learner. Specifically, we first sample multiple tasks using all shapes in the original dataset as our training dataset. We trained our 3D segmentation meta-learner on the sample dataset to learn the priors over the 3D segmentation function space. Then we fix our 3D segmentation meta-learner and fine-tune our 3D segmentation learner using all shapes in the target category. Note that, our proposed method is trained in a purely unsupervised manner without any ground-truth labels.

### Results:

From the first two rows in Table 1, we notice that the experimental results of the weight-setting-A which simple pre-trained using all shapes in the original dataset and then directly optimized in the chair category dataset achieves 83.7% mIoU and 88.2% segmentation accuracy. Compared with the first setting, the results of the weight-setting-B which use meta-learned weights improved 4.7% mIoU and 4.2% segmentation accuracy in the chair category. This indicates that our meta-learning method can learn the general information over several part segmentations.
tion tasks and benefit the part segmentation learner from good meta-learned initialized weights. Moreover, as indicated in row 2 and 3, the experimental results of the weight-setting-C are better than the weight-setting-B, which indicates that the task distribution generated by the VAE in the 3D segmentation meta-learner can gather the prior over the 3D segmentation function space and further sampled for the learner predictor to predict the optimal parameters of the 3D segmentation learner. This indicates that our meta-learning strategy can learn the general information over some part segmentation tasks and benefit the part segmentation learner from good meta-learned network parameters.

Besides, as illustrated from the qualitative results shown in Figure 3, our method is more accurate in estimating part-specific labels of point clouds. As for the bag category, the part segmentation results in rows 2 and 3 indicate that there are some points (black circled region) in the handle area that are mistakenly labeled as the body by the Learner - Bag. In contrast, with the 3D segmentation meta-learner, our Meta-3DSeg can better align these challenging points to the right part labels.

4.4. Study on number of sampled points

We conduct the experiments to verify the effects using shapes with different numbers of sampled points.

**Experiment setting:** In this experiment, we aim to verify our model’s performance using the various number of sampled points of 3D shapes. As for the number of sampled points in 3D shape, we choose three different levels: 512, 1024, and 2048.

**Results:** As shown in Table 2 while the numbers of sampled points are changed, the IoU metric results do not change significantly for different shapes in all categories. Specifically, the IoU value only decreases approximately 1.0 if we quarter the point count. Thus, this experiment verifies the robustness and effectiveness of our unsupervised model trained across all categories.

4.5. Comparative Study

In this section, we conduct the experiments with other learning-based supervised and unsupervised methods.

**Experiment setting:** In this experiment, we evaluate the general segmentation performance extended to more shape categories and compare the performance with other state-of-the-art approaches. We trained each supervised model independently for each shape category using the same 10 randomly chosen samples to generate a fair comparison. Note that we report the performance of these learning-based models which are pre-trained with all samples in the base categories for reference since our method is trained using shapes in base categories during the training process. We use all available datasets including annotated samples with target shapes during training for WPS-NET[33], PointNet[18], PointNet++[19], and PointConv[36]. Note that to enhance its performance, BAE-NET is trained category-by-category that means there will be a category-specific BAE-NET model for each category after training. In comparison, our model is trained across different categories which enable the robust learning of priors over the respective function space. Specifically, for our model, we sample multiple tasks using all shapes in all categories as our training dataset. We trained our 3D segmentation meta-learner on the sample dataset in multiple tasks to learn the function prior to multiple tasks. Then we fix our 3D segmentation meta-learner and fine-tune our 3D segmentation...
Table 3. Quantitative result. Comparison with other supervised methods

| Categories | Supervision | Ours | BAE-NET | WPS-NET | PointNet | PointNet++ | PointConv | PointNet (all) |
|------------|-------------|------|---------|---------|----------|------------|-----------|----------------|
| Airplane   | N           | 62.3 | 61.1    | 67.3    | 63.3     | 62.3       | 65.1      | 83.4           |
| Airplane   | Y           | 82.4 | 80.4    | -       | -        | -          | -         | -              |
| Bag        | Y           | 81.3 | 82.5    | 74.4    | 64.9     | 67.4       | 68.2      | 78.7           |
| Cap        | Y           | 86.4 | 87.3    | 86.3    | 75.2     | 80.0       | 80.7      | 82.5           |
| Chair      | Y           | 68.8 | 65.5    | 83.4    | 73.8     | 61.6       | 66.1      | 89.6           |
| Chair      | Y           | 90.2 | 86.6    | -       | -        | -          | -         | -              |
| Mug        | Y           | 94.1 | 93.4    | 90.9    | 80.9     | 83.1       | 86.0      | 93.0           |
| Table      | Y           | 79.7 | 78.7    | 74.2    | 72.2     | 72.2       | 72.5      | 80.6           |
| Table      | Y           | 89.9 | 87.0    | -       | -        | -          | -         | -              |

Figure 4. Qualitative results. Randomly selected qualitative results of point clouds part segmentation on multiple categories of the ShapeNet dataset.

Results: Table 3 presents the per-category IoU for each model we trained on. The data indicates that our model achieves much better performance on most shape categories contrasted to all supervised methods under the sample training process. For instance, our result has approximately 10 IoU improvement in mug and 7 improvement in table comparing to PointNet and PointNet++. Our model has better capacity than BAE-NET in most categories, like the chair, mug, table, and airplane. The inherent training difficulty of our Meta-3DSeg model is the hardest since it is purely unsupervised and trained across all categories. Nevertheless, the training result is still promising and improved from previous, which justifies the effectiveness of our meta-learning design. Compared with the PointNet result using all training samples, our approach only lags behind with a reasonable margin. Figure 4 shows some randomly selected qualitative results of our Meta-3DSeg on novel categories of the ShapeNet dataset.

5. Conclusion

In this paper, we introduce a novel meta-learning strategy to our research community for 3D point cloud part segmentation. Compared with previous learning-based methods, our Meta-3DSeg can learn the distribution of tasks instead of the distribution of data. With the prior over the respective 3D segmentation function space over multiple similar tasks, our Meta-3DSeg is capable to rapidly adapt and have good generalization performance on new tasks. Note that, our proposed meta-learning strategy can hopefully benefit our 3D community by providing an efficient and effective learning algorithm to train the mainstream 3D

learner using all shapes in the target category. Note that our model is trained without using any ground-truth information in comparison to the supervised methods. Also, we include the performance of PointNet trained by all samples in the original dataset for reference and making the cross-comparison clearer and background more similar. Furthermore, we use the subscript to specify the number of classes since various algorithms probably would generate different segmentation results. For instance, our model and BAE-NET would occasionally segment the airplane object into three parts rather than four due to the incapability of splitting wings and engines.
part segmentation learners. To the best of our knowledge, our method firstly leveraged a novel meta-learning strategy for this task and we experimentally verified the effectiveness of our model and achieved superior unsupervised part segmentation results on the ShapeNet 3D point cloud part segmentation dataset.

References

[1] Marcin Andrychowicz, Misha Denil, Sergio Gomez, Matthew W Hoffman, David Pfau, Tom Schaul, Brendan Shillingford, and Nando De Freitas. Learning to learn by gradient descent by gradient descent. In *Advances in Neural Information Processing Systems*, pages 3981–3989, 2016.

[2] 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.

[3] Jianchun Chen, Lingjing Wang, Xiang Li, and Yi Fang. Arbicon-net: Arbitrary continuous geometric transformation networks for image registration. In *Advances in Neural Information Processing Systems*, pages 3410–3420, 2019.

[4] Zhiqin Chen, Kangxue Yin, Matthew Fisher, Siddhartha Chaudhuri, and Hao Zhang. Bae-net: Branched autoencoder for shape co-segmentation. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 8490–8499, 2019.

[5] Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In *Proceedings of the 34th International Conference on Machine Learning-Volume 70*, pages 1126–1135. JMLR. org, 2017.

[6] Chelsea Finn, Kelvin Xu, and Sergey Levine. Probabilistic model-agnostic meta-learning. In *Advances in Neural Information Processing Systems*, pages 9516–9527, 2018.

[7] Ran Gal and Daniel Cohen-Or. Salient geometric features for partial shape matching and similarity. *ACM Transactions on Graphics (TOG)*, 25(1):130–150, 2006.

[8] Timothy Hospedales, Antreas Antoniou, Paul Micaelli, and Amos Storkey. Meta-learning in neural networks: A survey. *arXiv preprint arXiv:2004.05439*, 2020.

[9] Qixing Huang, Vladlen Koltun, and Leonidas Guibas. Joint shape segmentation with linear programming. In *ACM transactions on graphics (TOG)*, volume 30, page 125. ACM, 2011.

[10] Evangelos Kalogerakis, Melinos Averkiou, Subhransu Maji, and Siddhartha Chaudhuri. 3d shape segmentation with projective convolutional networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3779–3788, 2017.

[11] Yoonho Lee and Seungjin Choi. Gradient-based meta-learning with learned layerwise metric and subspace. *arXiv preprint arXiv:1801.05558*, 2018.

[12] Jiaxin Li, Ben M Chen, and Gim Hee Lee. So-net: Self-organizing network for point cloud analysis. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 9397–9406, 2018.

[13] Xiang Li, Hanzhang Cui, John-Ross Rizzo, Edward Wong, and Yi Fang. Cross-safe: A computer vision-based approach to make all intersection-related pedestrian signals accessible for the visually impaired. In *Science and Information Conference*, pages 132–146. Springer, 2019.

[14] Xiang Li, Lingjing Wang, and Yi Fang. Pc-net: Unsupervised point correspondence learning with neural networks. In *2019 International Conference on 3D Vision (3DV)*, pages 145–154. IEEE, 2019.

[15] Yangyan Li, Rui Bu, Mingchao Sun, Wei Wu, Xinhan Di, and Baopuqian Chen. Pointcnn: Convolution on x-transformed points. In *Advances in Neural Information Processing Systems*, pages 820–830, 2018.

[16] Gidi Littwin and Lior Wolf. Deep meta functionals for shape representation. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 1824–1833, 2019.

[17] Min Meng, Jiazhi Xia, Jun Luo, and Ying He. Unsupervised co-segmentation for 3d shapes using iterative multi-label optimization. *Computer-Aided Design*, 45(2):312–320, 2013.

[18] Charles Qi, Hao Su, Kaichun Mo, and Leonidas J Guibas. Pointnet: Deep learning on point sets for 3d classification and segmentation. *Proc. Computer Vision and Pattern Recognition (CVPR)*, IEEE, 1(2):4, 2017.

[19] Charles Ruizhongtai Qi, Li Yi, Hao Su, and Leonidas J Guibas. Pointnet++: Deep hierarchical feature learning on point sets in a metric space. In *Advances in Neural Information Processing Systems*, pages 5099–5108, 2017.

[20] Sachin Ravi and Hugo Larochelle. Optimization as a model for few-shot learning. 2016.

[21] Adam Santoro, Sergey Bartunov, Matthew Botvinick, Daan Wierstra, and Timothy Lillicrap. Meta-learning with memory-augmented neural networks. In *International conference on machine learning*, pages 1842–1850, 2016.

[22] Jürgen Schmidhuber. Learning to control fast-weight memories: An alternative to dynamic recurrent networks. *Neural Computation*, 4(1):131–139, 1992.

[23] Lior Shapira, Ariel Shamir, and Daniel Cohen-Or. Consistent mesh partitioning and skeletonisation using the shape diameter function. *The Visual Computer*, 24(4):249, 2008.

[24] Zhenyu Shu, Chengwu Qi, Shiqing Xin, Chao Hu, Li Wang, Yu Zhang, and Ligang Liu. Unsupervised 3d shape segmentation and co-segmentation via deep learning. *Computer Aided Geometric Design*, 43:39–52, 2016.

[25] Oana Sidi, Oliver van Kaick, Yanir Kleiman, Hao Zhang, and Daniel Cohen-Or. Unsupervised co-segmentation of a set of shapes via descriptor-space spectral clustering, volume 30. ACM, 2011.

[26] Vincent Sitzmann, Eric R Chan, Richard Tucker, Noah Snavely, and Gordon Wetzstein. Metasdf: Meta-learning signed distance functions. *arXiv preprint arXiv:2006.09662*, 2020.

[27] Jake Snell, Kevin Swersky, and Richard Zemel. Prototypical networks for few-shot learning. In *Advances in neural information processing systems*, pages 4077–4087, 2017.

[28] Hang Su, Varun Jampani, Deqing Sun, Subhransu Maji, Evangelos Kalogerakis, Ming-Hsuan Yang, and Jan Kautz. Splatnet: Sparse lattice networks for point cloud processing.
[29] Hang Su, Subhransu Maji, Evangelos Kalogerakis, and Erik Learned-Miller. Multi-view convolutional neural networks for 3d shape recognition. In Proceedings of the IEEE international conference on computer vision, pages 945–953, 2015.

[30] Hugues Thomas, Charles R Qi, Jean-Emmanuel Deschaud, Beatriz Marcotegui, François Goulette, and Leonidas J Guibas. Kpconv: Flexible and deformable convolution for point clouds. In Proceedings of the IEEE International Conference on Computer Vision, pages 6411–6420, 2019.

[31] Chu Wang, Marcello Pelillo, and Kaleem Siddiqi. Dominant set clustering and pooling for multi-view 3d object recognition. In Proceedings of British Machine Vision Conference (BMVC), volume 12, 2017.

[32] Lingjing Wang and Yi Fang. Unsupervised 3d reconstruction from a single image via adversarial learning. arXiv preprint arXiv:1711.09312, 2017.

[33] Lingjing Wang, Xiang Li, and Yi Fang. Few-shot learning of part-specific probability space for 3d shape segmentation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 4504–4513, 2020.

[34] 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.

[35] Congcong Wen, Lina Yang, Xiang Li, Ling Peng, and Tianhe Chi. Directionally constrained fully convolutional neural network for airborne lidar point cloud classification. ISPRS Journal of Photogrammetry and Remote Sensing, 162:50–62, 2020.

[36] Wenxuan Wu, Zhongang Qi, and Li Fuxin. Pointconv: Deep convolutional networks on 3d point clouds. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2019.

[37] 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.

[38] Zizhao Wu, Yunhai Wang, Ruyang Shou, Baoquan Chen, and Xinguo Liu. Unsupervised co-segmentation of 3d shapes via affinity aggregation spectral clustering. Computers & Graphics, 37(6):628–637, 2013.

[39] Shuo Yang, Min Xu, and Hongxun Yao. Meta3d: Single-view 3d object reconstruction from shape priors in memory. arXiv preprint arXiv:2003.05711, 2020.

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

[41] Jing Zhu and Yi Fang. Learning object-specific distance from a monocular image. In Proceedings of the IEEE International Conference on Computer Vision, pages 3839–3848, 2019.