Segmenting 3D Hybrid Scenes via Zero-Shot Learning

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Abstract

This work is to tackle the problem of point cloud semantic segmentation for 3D hybrid scenes under the framework of zero-shot learning. Here by hybrid, we mean the scene consists of both seen-class and unseen-class 3D objects, a more general and realistic setting in application. To our knowledge, this problem has not been explored in the literature. To this end, we propose a network to synthesize point features for various classes of objects by leveraging the semantic features of both seen and unseen object classes, called PFNet. The proposed PFNet employs a GAN architecture to synthesize point features, where the semantic relationship between seen-class and unseen-class features is consolidated by adapting a new semantic regularizer, and the synthesized features are used to train a classifier for predicting the labels of the testing 3D scene points. Besides we also introduce two benchmarks for algorithmic evaluation by re-organizing the public S3DIS and ScanNet datasets under six different data splits. Experimental results on the two benchmarks validate our proposed method, and we hope our introduced two benchmarks and methodology could be of help for more research on this new direction.

1 Introduction

Recently, 3D point cloud semantic segmentation has achieved great success due to the application of deep learning techniques [Qi et al., 2017a; Hu et al., 2020]. However, such a success is generally based on two fundamental conditions: 1) point cloud segmentation is performed under the close-set condition, i.e. 3D points could only be classified in the seen-class space; 2) high-performance segmentation is dependent on expensive point-wise labeling resources. In realistic scenarios, not only seen-class objects but some unseen-class objects which are absent in the model training stage could also appear in testing 3D scenes, and annotating abundant training samples for all potential classes is not only expensive but also impossible, which significantly limits the application of existing 3D point cloud segmentation methods. This problem motivates us to investigate a more realistic problem of point cloud semantic segmentation in this paper: How to segment 3D hybrid scenes consisting of both seen-class and unseen-class 3D objects? as illustrated in Figure 1

In fact, the aforementioned problem could be considered as a special zero-shot learning problem [Xian et al., 2018a; Frome et al., 2013; Yu et al., 2020; Xian et al., 2018b], hence, it is named as zero-shot 3D scene semantic segmentation (denoted as Z3DS) for avoiding confusion hereinafter. The original idea of zero-shot learning is to classify objects from unseen classes by establishing a mapping between image features and auxiliary semantic features (such as semantic attributes [Lampert et al., 2013], text descriptions [Qiao et al., 2016], and word vectors [Frome et al., 2013]) and then classifying unseen-class images according to feature similarity. More recently, zero-shot learning has been applied to several new tasks other than image classification, such as image object detection [Rahman et al., 2018], image semantic segmentation [Bucher et al., 2019], and 3D shape classification [Cheraghian et al., 2019]. However, so far as we know, there is no related work to deal with our introduced zero-shot 3D scene semantic segmentation problem.

Note that the existing methods used for zero-shot learning on 2D images could not be straightforwardly used for our Z3DS task. In fact, compared with these zero-shot 2D image learning tasks, the Z3DS task is more complex and difficult because that 1) For 2D images, convolutional neural network (CNN) is powerful to extract discriminative features. However, there seems no such powerful architecture for irregular 3D point cloud; 2) semantic consistency between image features and semantic features is crucial for zero-shot learning on 2D images. For instance, images of elephant often contain ‘gray’ skin, which is consistent with the semantic attribute ‘gray’. However, point cloud feature extraction is mainly based on geometrical information, and there lacks such well-defined semantic features for 3D point cloud. In addition, zero-shot 3D scene segmentation is also considerably different from zero-shot 3D shape classification because 1) feature learning of different classes in 3D scene segmentation is interactive since local points used for feature learning often belong to multiple classes, meaning that unseen-class features are severely affected by seen-class feature learning in 3D scene segmentation. While feature learning of different classes in 3D shape classification is independent since points in single 3D shape belong to the same class; 2) 3D scenes are...
naturally class-level imbalanced.

As discussed above, the existing zero-shot learning techniques could not be directly used for our introduced new Z3DS problem. Hence, we propose a semantically-regularized point feature generation network (called PFNet) to address the Z3DS problem, which employs a GAN architecture and an introduced semantic regularizer. The proposed PFNet is able to synthesize point features for various classes of objects by leveraging the semantic features of both seen and unseen object classes, and these synthesized features are then used to train a classifier for predicting the labels of the testing 3D scene points. The introduced semantic regularizer is used for consolidating the semantic relationship between seen-class and unseen-class features. Besides, in order to provide an algorithmic testbed for the introduced new problem, we also construct two benchmarks by re-organizing the public S3DIS and ScanNet datasets under six different data splits. For each data split, two different zero-shot setting are introduced, i.e. the conventional zero-shot segmentation and the generalized zero-shot segmentation. In sum, our contributions include:

- Under the framework of zero-shot learning, we introduce the new task of Z3DS (zero-shot 3D scene semantic segmentation) and construct two benchmarks for algorithmic evaluation. To our best knowledge, this is the first attempt to investigate the Z3DS problem.
- We propose an effective point feature generation network (called PFNet) for Z3DS. PFNet is able to generate an arbitrary number of semantically consistent point features for both seen and unseen classes, alleviating the problems of unseen-class sample lacking and seen-class sample imbalance simultaneously.
- Extensive experimental results on the two benchmarks with six different data splits demonstrate the effectiveness of the proposed method.

2 Related Work

2.1 3D Point Cloud Semantic Segmentation

Recently, many deep learning based methods [Xie et al., 2020; Han et al., 2020; You et al., 2020] have been proposed for 3D point cloud semantic segmentation. Among them, 3D convolution based methods [Graham et al., 2018] divided 3D point cloud into sets of occupancy voxels and used sparse convolution to perform voxel-wise segmentation. However, their performances are severely limited by the granularity of voxels. PointNet [Qi et al., 2017a] is the pioneering method to directly process 3D points using shared multi-layer perceptrons (MLPs) and max-pooling layers. Following PointNet, a large number of methods [Qi et al., 2017b; Hu et al., 2020; Li et al., 2018; Xu et al., 2018] used MLPs or more powerful convolution network as the basic unit in their network for capturing local geometry of 3D point cloud. More recently, graph convolution based methods [Wang et al., 2019b; Wang et al., 2019a] and recurrent neural network based methods [Ye et al., 2018] have also been proposed.

2.2 Zero-Shot 2D Image Semantic Segmentation

Zero-shot image semantic segmentation [Bucher et al., 2019; Gu et al., 2020; Xian et al., 2019] has received increasing attention very recently. Xian et al. [Xian et al., 2019] proposed a semantic projection network to perform semantic segmentation of novel classes, where they projected visual features into a semantic feature space and then classified novel classes according to similarities between the projected features and novel-class semantic features. Both Bucher et al. [Bucher et al., 2019] and Gu et al. [Gu et al., 2020] proposed methods which combined a deep visual segmentation model with a generative model to generate visual features from semantic features and trained a visual feature classifier to segment images.

3 Problem Specification and Methodology

3.1 Problem Specification

Here is a specification of our Z3DS: we are given a 3D scene training set, represented by 3D points \( \mathcal{D}_{te}^{N} = \{(x_{i}, y_{i})\}_{i=1}^{N} \), where \( x_{i} \) is a point in 3D scenes and \( y_{i} \) is the label of \( x_{i} \), belonging to the seen-class label set \( Y^{S} \). A semantic feature set \( \mathcal{W} = \{w_{y}|y \in Y\} \) is also given in the training stage, where \( Y \) is the all-class label set which includes not only the seen-class label set \( Y^{S} \) but also the unseen-class label set \( Y^{U} \).

In the testing stage, we segment the testing 3D scenes set by classifying 3D points \( \mathcal{D}_{te}^{M} = \{x_{m}\}_{m=1}^{M} \).

**Definition 1.** Z3DS: Suppose \( \mathcal{D}_{te} \) belongs to \( Y^{U} \), given \( \mathcal{D}_{tr}^{S} \) and \( \mathcal{W} \), the goal is to learn a mapping \( f : \mathcal{D}_{te} \rightarrow Y^{U} \).

**Definition 2.** Generalized Z3DS (GZ3DS): Suppose \( \mathcal{D}_{te} \) belongs to \( Y \), given \( \mathcal{D}_{tr}^{S} \) and \( \mathcal{W} \), the goal is to learn a mapping \( f : \mathcal{D}_{te} \rightarrow Y \).

Note that 3D scene semantic segmentation problem is actually a point-level classification problem so that we could segment 3D scenes by classifying 3D points. Z3DS assumes that we have the prior that testing points come from only the
unseen-class label set, which is not always the case in practice. While GZ3DS makes no assumption about the testing class space, which is more practical but harder.

3.2 Methodology Overview

To address the (G)Z3DS problem, our main idea is to learn a network with the labeled seen-class points in 3D scene training set, which is able to generate point features conditioned on semantic features, and then generate unseen-class point features via the learned network according to unseen-class semantic features. With these synthetic unseen-class point features, we train a classifier to classify the points in testing 3D scenes, finally achieving (G)Z3DS. Based on the above points, we propose a pipeline as shown in Figure 2, where a semantically-regularized point feature generation network (called PFNet) is proposed to synthesize semantically consistent point features conditioned on semantic features, and a point feature classifier is used to classify 3D points. In the following, we firstly explain the proposed PFNet in detail, and then introduce the point feature classifier.

3.3 Semantically-Regularized Point Feature Generation Network

The goal of the proposed semantically-regularized point feature generation network (PFNet) is to learn a conditional point feature generator which can generate semantically consistent point features conditioned on semantic features. As shown in Figure 2, PFNet consists of a backbone network \(F\), a point feature generator \(G\), a discriminator \(D\), and a semantic regularizer \(R\). Given an input 3D point cloud, a semantic feature set \(W\), we first extract point features with the backbone network \(F\) from the input 3D point cloud, and the extracted point feature of each 3D point is denoted as \(x\). For a seen-class point, its label is available, denoted as \(y\), while the label of an unseen-class point is unavailable. Then, we employ the point feature generator \(G\) to generate fake point feature \(\hat{x}\) conditioned on the corresponding semantic feature \(w_y\), and the generated point feature is expected to be indistinguishable from the real one. Hence we adversarially train the generator with the discriminator \(D\) using the labeled seen-class point features as follows:

\[
L_{\text{egan}} = \min_G \max_D E_{(x,y) \in D^{S}_{tr}} [D(x, w_y)] - E_{y \in D^{S}_{tr}} [D(\hat{x}, w_y)] - \lambda E_{(x,y) \in D^{S}_{tr}} [||\nabla \hat{x} D(\hat{x}, w_y) ||^2 - 1]^2
\]  

(1)

where \(D^{S}_{tr}\) is the seen-class point feature dataset, \(\hat{x}\) is generated by the generator \(G\) according to the semantic feature \(w_y\) and a standard Gaussian noise \(z \sim \mathcal{N}(0, 1)\), i.e. \(\hat{x} = G(w_y, z)\), \(\hat{x} = \alpha x + (1 - \alpha) \hat{x}\) with \(\alpha \sim \mathcal{U}(0, 1)\), and \(\lambda\) is a hyper-parameter which is usually set as 10.

After adversarial training, the trained generator would be able to generate unseen-class point features conditioned on unseen-class semantic features. However, the above point feature generation process could not explicitly reflect the semantic relationship between seen and unseen classes, which will damage the quality of synthetic unseen-class point features. Hence, we propose a semantic regularizer to embed semantic relationship into the point feature generation. Specifically, we project the generated point feature \(\hat{x}\) into the semantic feature space via a semantic regularizer \(R\). Then, the projected features of seen classes are trained to have the highest similarity with the semantic feature of their corresponding labels while have the lowest similarity with unseen-class semantic features. This regularizer is implemented as follows:

\[
L_{\text{reg}} = E_{(x,y) \in D^{S}_{tr}} [- \sum_{i \in Y} y_i \log(p(\hat{x}))_i + \sum_{j \in Y^U} p(\hat{x})_j]
\]  

(2)

where \(D^{S}\) is a synthetic seen-class feature dataset, \(y\) is one-hot label, and \(p(\hat{x}) = S((R(\hat{x}), W))\) where \(S(\cdot)\) and \((\cdot)\) are softmax function and dot product respectively. In sum, the overall cost function is:

\[
L = L_{\text{egan}} + \beta L_{\text{reg}}
\]  

(3)

where \(\beta\) is a hyper-parameter. In the proposed method, the backbone is fixed, while the generator \(G\), the discriminator \(D\), and the semantic regularizer \(R\) are jointly trained.
follows: we train an unseen-class classifier $F_{\text{z\_3ds}}$ with the synthetic unseen-class point features and their corresponding labels as follows:

$$L = E_{(x,y)\in\bar{D}_{U}}[C(S(F_{\text{z\_3ds}}(x)), y)]$$

(4)

where $\bar{D}_{U}$ is the synthetic point feature dataset, $S(\cdot)$ and $C(\cdot)$ are softmax function and cross-entropy loss function respectively. After training, given a testing point feature $x$, its label $y$ is predicted by:

$$y = \arg\max_{y\in Y} S(F_{\text{z\_3ds}}(x))$$

(5)

For GZ3DS, we generate a large number of seen-class and unseen-class point features conditioned on their corresponding semantic features, denoted as $\mathcal{D}_{S}$ and $\mathcal{D}_{U}$ respectively. Then, an all-class classifier $F_{\text{gz\_3ds}}$ is trained with these synthetic point features and their corresponding labels as follows:

$$L = E_{(x,y)\in\bar{D}_{U}\cup\bar{D}_{S}}[C(S(F_{\text{gz\_3ds}}(x)), y)]$$

(6)

After training, for a given testing point feature $x$, we predict its label $y$ by:

$$y = \arg\max_{y\in Y} S(F_{\text{gz\_3ds}}(x))$$

(7)

By classifying the points in testing 3D scenes, we could finally achieve (G)Z3DS.

4 Experiments

4.1 Experimental Setup

Benchmark Construction

We construct two benchmarks by re-organizing two widely used 3D scene datasets: S3DIS [Armeni et al., 2016] and ScanNet [Dai et al., 2017]. S3DIS is an indoor scene dataset which includes 3D scans of 272 rooms distributed in 6 areas from 12 semantic categories and a ‘clutter’ category. ScanNet is a dataset which contains 1,513 3D indoor scenes belonging to 20 semantic categories and a ‘clutter’ category. Due to the limited space, we introduce the two datasets briefly in Supplementary Material. Here we mainly describe how we re-organize them. In S3DIS, we consider the 12 semantic categories as valid categories, and we split them into seen classes and unseen classes in 3 different manners: 10/2, 8/4, 6/6 as seen classes/unseen classes respectively. Note that the 4 unseen classes in 8/4 split contain the 2 unseen classes in 10/2 split, and similarly for 6/6 split and 8/4 split. In ScanNet, although there are 20 semantic categories in total, we choose 19 semantic categories as valid categories and ignore the ‘clutter’ category and the ‘other furniture’ category. The ‘other furniture’ category is discarded since it is semantically confused with ‘furniture’ category. The 19 semantic categories are split into seen classes and unseen classes in 3 different ways, i.e. 16/3, 13/6, 10/9 splits as seen classes/unseen classes respectively. Like in S3DIS, the 6 unseen classes in 13/6 split contain the 3 unseen classes in 16/3 split, etc. The specific unseen classes in S3DIS and ScanNet are reported in Table A1 in Supplementary Material, and the corresponding seen classes are the remaining classes. We use the same training/testing dataset in both S3DIS and ScanNet as done in conventional 3D scene segmentation task. For clarity, we denote the re-organized S3DIS and ScanNet as S3DIS-0 and ScanNet-0 respectively.

We employ two kinds of semantic features to perform (G)Z3DS tasks: 1) word2vec embedding learned on Google News and 2) glove embedding learned on Wikipedia2014 and Gigaword5. Both word2vec embedding and glove embedding are 300-dimensional vectors.

Comparative Methods

We compare the proposed method with two methods, a fully-supervised network and a baseline method adapted from [Frome et al., 2013] by us. The fully-supervised network is used to set an upper limit to show the gap between the performance achieved by a Z3DS method and the ideal performance, which was trained by typical cross-entropy loss function with labeled 3D point cloud from all valid semantic categories. The baseline method learned a mapping between 3D points and semantic features using 3D point cloud labeled with the corresponding seen classes, where point features were firstly extracted by a backbone network from the input 3D point cloud and then they were projected into a semantic feature space by a feature transformer. The backbone network and the feature transformer are jointly trained by a compatibility based loss function.

Evaluation Protocol

On S3DIS, average per-class Top-1 accuracy ($mACC$) and average per-class IoU ($mIoU$) are two widely used metrics to evaluate 3D segmentation performance. We also employ the two metrics to evaluate (G)Z3DS performance on S3DIS-0. Specifically, in Z3DS, we evaluate performance by $mACC$ and $mIoU$ on unseen classes. In GZ3DS, as done in the generalized zero-shot learning [Xian et al., 2018a], we first compute $mACC$ on both seen classes and unseen classes, and then their harmonic mean $HACC$ is computed to evaluate the overall performance by:

$$HACC = \frac{2 \times mACC_s \times mACC_u}{mACC_s + mACC_u}$$

(8)

where $mACC_s$ and $mACC_u$ are seen-class $mACC$ and unseen-class $mACC$ respectively. We also compute seen-class $mIoU$, unseen-class $mIoU$, and their harmonic mean by the same way to evaluate GZ3DS performance, denoted as $mIoUs$, $mIoUu$, and $HIoU$ respectively. On ScanNet, average per-class Top-1 accuracy ($mACC$) and average per-class voxel accuracy ($mVACC$) are often used to evaluate performance. We compute the corresponding metrics on unseen classes and seen classes and their harmonic mean on ScanNet-0 as done on S3DIS-0.

Implementation Details

The backbones in the proposed method and the compared methods are all implemented by DGCNN [Wang et al.,]
Table 1: Comparative results on the S3DIS-0 dataset.

| Method       | Z-3DS | GZ-3DS |
|--------------|-------|--------|
|              | mACC  | mIoU   | mACC  | mIoU   | HACC  | mACC  | mACC  | mACC  | mIoU   | mACC  | mACC  | HACC  | mACC  | mACC  | mACC  |
| Fully-Supervised |       |        |       |        |       |       |       |       |       |       |       |       |       |       |       |       |
| 10/2 Baseline | 92.1  | 86.1   | 0.0   | 52.2   | 0.0   | 0.0   | 39.1  | 0.0   | 0.0   | 48.3  | 22.8  |       |       |       |       |       |
| PFNet(ours)  | 94.7  | 90.8   | 53.9  | 46.5   | 61.4  | 31.0  | 48.3  | 22.8  |       |       |       |       |       |       |       |       |
| 8/4 Baseline | 48.5  | 19.4   | 0.0   | 67.8   | 0.0   | 0.0   | 52.1  | 0.0   |       |       |       |       |       |       |       |       |
| PFNet(ours)  | 52.4  | 33.3   | 41.1  | 57.0   | 32.1  | 14.1  | 47.7  | 8.0   |       |       |       |       |       |       |       |       |
| 6/6 Baseline | 30.3  | 11.3   | 36.2  | 76.8   | 44.3  | 51.1  | 69.2  | 40.5  |       |       |       |       |       |       |       |       |
| PFNet(ours)  | 33.7  | 15.4   | 33.4  | 45.5   | 26.4  | 10.2  | 62.3  | 5.6   |       |       |       |       |       |       |       |       |

Table 2: Comparative results with/without semantic regularizer.

| Method | 10/2 | 8/4 | 6/6 |
|--------|------|-----|-----|
| w/o SR | 94.7 | 53.9| 52.4| 41.1| 33.7| 33.4|
| w  SR  | 94.7 | 53.9| 52.4| 41.1| 33.7| 33.4|

The generator, discriminator, regularizer, and classifier are all implemented by multi-layer fully-connected neural networks, whose architectures are reported in Supplementary Material. The generator, discriminator, and regularizer are jointly trained by 10 epochs with batch size 4 and learning rate 0.0005. The classifier is trained by 10 epochs with batch size 4096 and learning rate 0.0001. All the models are trained with Adam optimizer. Note that in the training stage, the whole point cloud are inputted into the models, however, only the labeled seen-class points are used to compute gradients and the unlabeled unseen-class points are not computed in the back-propagation process. We consider this training setting satisfies the Z3DS setting and it is not a transductive Z3DS setting because 1) the unlabeled unseen-class points provide no supervision signal for model learning and 2) the testing point cloud are not used in the training stage.

4.2 The Conventional Z3DS Performance

Here we evaluate the proposed method and the compared methods in the conventional Z3DS setting on S3DIS-0 and ScanNet-0 with 6 different seen/unseen splits. The results of S3DIS-0 and those of ScanNet-0 are reported in Table 1 and Table 3 respectively. From Table 1 and Table 3, we can see that the proposed method achieves significantly superior performances over the baseline method in all data splitting cases on both S3DIS-0 and ScanNet-0. For instance, improvements of mACC_u on ScanNet-0 are 8.4%, 22.1% and 9.2% in the 16/3, 13/6, and 10/9 splitting cases respectively, and improvements of mACC_u on S3DIS-0 are 2.6%, 3.9% and 3.4% in the 10/2, 8/4, and 6/6 splitting cases respectively. The mIoU_u on S3DIS-0 and mVACC_u on ScanNet-0 are also improved similarly. These significant improvements demonstrate the effectiveness of the proposed method, and they largely own to the following two reasons: 1) classification in one-hot label space as done by the proposed method is better than classification in semantic feature space as done by the baseline method; 2) the proposed method is able to generate arbitrary number of unseen-class point features, which is beneficial to train a powerful classifier with augmented data, and is also helpful to alleviate data imbalance problem, a notorious issue in 3D scene segmentation. However, we also find that Z3DS performances decrease significantly as the number of seen classes decreases, especially on the S3DIS-0 benchmark. This indicates that a considerable number of seen classes are necessary to achieve high-performance Z3DS.

4.3 The Generalized Z3DS Performance

Here we evaluate the proposed method and the compared methods in the generalized Z3DS setting on S3DIS-0 and ScanNet-0 with 6 different seen/unseen splits. Table 1 and Table 3 report the results on S3DIS-0 and ScanNet-0 respectively. As seen from Table 1 and Table 3, the baseline method achieves very bad GZ3DS performances. Specifically, HACC, HIoU, and HVACC are all 0. These bad performances are caused by the fact that outputs of the model in the baseline method are biased to seen classes since the model is trained on seen classes, resulting in 0 unseen-class accuracy. Compared with the baseline method, the proposed method achieves dramatically better performances, e.g., improvements of HACC on S3DIS-0 are 53.9%, 41.1% and 33.4% in the 10/2, 8/4, and 6/6 splitting cases respectively, and improvements of HACC on ScanNet-0 are 33.1%, 26.2% and 23.0% in the 16/3, 13/6, and 10/9 splitting cases respectively, all demonstrating the effectiveness of the proposed method for GZ3DS. The direct reason for the excellent GZ3DS performances achieved by the proposed method is the unseen-class accuracy is hugely improved. An underlying cause could be that the proposed point feature generator is able to generate a large number of unseen-class point features similar to the real ones according to the semantic relations and thus the learned classifier has good ability to classify real point features.

In addition, since the proposed method segments point cloud in the all-class space as done by the fully-supervised method, we also compare it with the fully-supervised one. As seen from Table 1 and Table 3, the proposed method has achieved relatively satisfactory performances even compared with the fully-supervised method in some cases where the number of unseen classes is relatively small, e.g., the performance gap between the proposed method and the fully-supervised one is only 8.8% in the 16/3 splitting case on ScanNet-0. This achievement is notable considering that the proposed method uses largely less label resources than the fully-supervised one. However, as the number of unseen classes increases, the performance gap becomes more significant, demonstrating GZ3DS is a hard task. Besides, we find that the gap between unseen-class mIoU and seen-class mIoU is significantly larger than that between unseen-class mACC and seen-class mACC on S3DIS-0. This is because the proposed method is implicitly trained to increase the pre-
In this paper, we study a new problem of point cloud semantic segmentation for 3D hybrid scenes consisting of both seen-class and unseen-class 3D objects under the framework of zero-shot learning, denoted as (G)Z3DS. To this end, we propose a novel point feature generation network, called PFNet, where a point feature generator is used to generate point features conditioned on semantic features and a semantic regularizer is proposed to help embed semantic relations into features. The performance on (G)Z3DS tasks on S3DIS-0 with the 10/2 split, where different number of synthetic unseen-class features are used to train models in Z3DS and GZ3DS, and the used number of synthetic seen-class features is fixed as 20000 in GZ3DS. The Z3DS results ($mACC$ and $H1IoU$ on unseen classes) and GZ3DS results ($HACC$ and $H1IoU$ on all classes) are shown in Figure 3. From Figure 3 we can see that Z3DS performance is generally not sensitive to the number of synthetic unseen-class features when the number reaches a certain scale, e.g., 10000. While GZ3DS performance firstly increases as the number of synthetic unseen-class samples increases, and gradually becomes stable. The reason for the increase of GZ3DS performance is due to the increase of the corresponding unseen-class $mACC$, and $HACC$ becomes the best when seen-class $mACC$ and unseen-class $mACC$ reach a balance.

### 5 Conclusion and Future Works

In this paper, we study a new problem of point cloud semantic segmentation for 3D hybrid scenes consisting of both seen-class and unseen-class 3D objects under the framework of zero-shot learning, denoted as (G)Z3DS. To this end, we propose a novel point feature generation network, called PFNet, where a point feature generator is used to generate point features conditioned on semantic features and a semantic regularizer is proposed to help embed semantic relations into feature generation process. In addition, we introduce two benchmarks for algorithmic evaluation by re-organizing the S3DIS and ScanNet datasets. Experimental results indicate that the proposed method is an effective method for (G)Z3DS. We hope the introduced benchmarks and methodology would en...

| Method       | Semantic Feature | mACC | mVACC | mIoU | HIoU | Z3DS | GZ3DS |
|--------------|------------------|------|-------|------|------|------|-------|
| Fully-Supervised |                | 0.0  | 0.0   | 0.0  | 0.0  | 0.0  | 0.0   |
| Baseline     | Word2Vec        | 91.0 | 0.0   | 68.5 | 0.0  | 0.0  | 0.0   |
| Baseline     | Glove           | 94.7 | 35.9  | 52.4 | 41.1 | 35.7 | 33.4  |
| PFNet        | Word2Vec        | 94.4 | 52.5  | 58.9 | 41.2 | 36.2 | 30.8  |

Table 3: Comparative results on the ScanNet-0 dataset.

| Method       | Semantic Feature | mACC | mVACC | mIoU | HIoU | Z3DS | GZ3DS |
|--------------|------------------|------|-------|------|------|------|-------|
| Fully-Supervised |                | 0.0  | 0.0   | 0.0  | 0.0  | 0.0  | 0.0   |
| Baseline     | Word2Vec        | 91.0 | 0.0   | 68.5 | 0.0  | 0.0  | 0.0   |
| Baseline     | Glove           | 94.7 | 35.9  | 52.4 | 41.1 | 35.7 | 33.4  |
| PFNet        | Word2Vec        | 94.4 | 52.5  | 58.9 | 41.2 | 36.2 | 30.8  |

Table 4: Comparative results with different semantic features.

**4.4 Results Analysis**

**Effect of Semantic Regularizer**

Here we investigate the effect of semantic regularizer (SR) on (G)Z3DS performance. To this end, we conduct (G)Z3DS tasks on S3DIS-0 with 3 different seen/unseen splits using 1) the proposed method (w SR) and 2) the proposed method without semantic regularizer (w/o SR). The Z3DS results ($mACC$ on unseen classes) and GZ3DS results ($HACC$ on all classes) are reported in Table 2. From Table 2 we can see that the proposed method achieves better performances than that without semantic regularizer, which indicates that semantic regularizer is helpful to generate semantically consistent point features.

**Effect of Semantic Features**

Semantic features play a key role in (G)Z3DS. Here we analyze the effect of two different semantic features (word2vec and glove) on (G)Z3DS performance by performing (G)Z3DS tasks on S3DIS-0 with 3 different seen/unseen splits using both the proposed method and the baseline method. Table 4 reports the Z3DS results ($mACC$ on unseen classes) and GZ3DS results ($HACC$ on all classes). We can see from Table 4 that word2vec and glove have generally comparable effect on (G)Z3DS performance. This is reasonable considering that word2vec features and glove features are both learned from large-scale language dataset in an unsupervised manner and the class names on S3DIS-0 are both common words in the Google News dataset and the Wikipedia2014 dataset.

**Effect of Number of Synthetic Features**

In the proposed method, we achieve (G)Z3DS by generating a number of unseen-class (and seen-class) point features. Intuitively, a larger number of synthetic features could be beneficial to the performance, which however results in more training cost. Here we investigate the effect of number of synthetic features on the performance, which however results in more training cost. We hope the introduced benchmarks and methodology would en...
courage more research on this new problem. In future, we will explore a network which can embed both semantic information and spatial information into feature learning process.

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