SK-Net: Deep Learning on Point Cloud via End-to-end Discovery of Spatial Keypoints

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Abstract
Since the PointNet was proposed, deep learning on point cloud has been the concentration of intense 3D research. However, existing point-based methods usually are not adequate to extract the local features and the spatial pattern of a point cloud for further shape understanding. This paper presents an end-to-end framework, SK-Net, to jointly optimize the inference of spatial keypoint with the learning of feature representation of a point cloud for a specific point cloud task. One key process of SK-Net is the generation of spatial keypoints (Skeypoints). It is jointly conducted by two proposed regulating losses and a task objective function without knowledge of Skeypoint location annotations and proposals. Specifically, our Skeypoints are not sensitive to the location consistency but are acutely aware of shape. Another key process of SK-Net is the extraction of the local structure of Skeypoints (detail feature) and the local spatial pattern of normalized Skeypoints (pattern feature). This process generates a comprehensive representation, pattern-detail (PD) feature, which comprises the local detail information of a point cloud and reveals its spatial pattern through the part district reconstruction on normalized Skeypoints. Consequently, our network is prompted to effectively understand the correlation between different regions of a point cloud and integrate contextual information of the point cloud. In point cloud tasks, such as classification and segmentation, our proposed method performs better than or comparable with the state-of-the-art approaches. We also present an ablation study to demonstrate the advantages of SK-Net.

1 Introduction
Rapid development in stereo sensing technology has made 3D data ubiquitous. The naive structure of most 3D data obtained by the stereo sensor is a point cloud. It makes those methods directly consuming points the most straightforward approach to handle the 3D tasks. Most of the existing point-based methods work on the following aspects: (1) Utilizing the multi-layer perceptron (MLP) to extract the point features and using the symmetry function to guarantee the permutation invariance. (2) Capturing the local structure through explicit or other local feature extraction approaches, and/or modeling the spatial pattern of a point cloud by discovering a set of keypoint-like points. (3) Aggregating features to deal with a specific point cloud task.

Despite being a pioneer in this area, PointNet (Qi et al. 2017a) only extracts the point features to acquire the global representation of a point cloud. For boosting point-based performance, the study advancing on above (2) has recently fostered the proposal of many techniques. One of these proposals is downsampling a point cloud to choose a set of spatial locations of a point cloud as local feature extraction regions. However, in this method, those locations are mostly obtained by artificial definition, e.g., FPS algorithm (Eldar et al. 1997), and do not reckon with the spatial pattern and the correlation between different regions of a point cloud. Similarly, (Xie et al. 2018; Hua, Tran, and Yeung 2018) achieve pointwise local feature extraction by corresponding each point to a region with respect to modeling the local structure of a point cloud. A special way is that (Le and Duan 2018; Li et al. 2018) combine the regular grids of 3D space with points, leveraging spatially-local correlation of regular grids to represent local information. However, performing pointwise local feature extraction and incorporating regular grids often require high computational costs, which is infeasible with large point injections and higher grid resolutions. Furthermore, SO-Net (Li, Chen, and Hee Lee 2018) introduces the Self-Organizing Map (SOM) (Kakuda et al. 1998) to produce a set of keypoint-like points for modeling the spatial pattern of a point cloud. Even though SO-Net takes the regional correlation of a point cloud into account, it trains SOM separately. This leaves the spatial modeling of SOM and a specific point cloud task disconnected.

To address these issues, this paper explores a method that can benefit from an end-to-end framework while the inference of Skeypoints is jointly optimized with the learning of the local details and the spatial pattern of a point cloud. By this means, those end-to-end learned Skeypoints are in strong connection with the local feature extraction and the spatial modeling of a point cloud. It is worth mentioning that related approaches of end-to-end learning of 3D keypoints usually require the keypoint location proposals (Georgakis et al. 2018; Georgakis et al. 2019) and expect the location con-
The contributions of this paper are as follows: Zhou et al. 2018; Georgakis et al. 2018; Suwajanakorn et al. 2018. Our work focuses on point cloud recognition tasks. Before producing the PD feature, all local features perform max-pooling to ensure that the local spatial pattern is of permutation invariance and fine shape-description. Thus the generated Skeypoints are not sensitive to location consistency. With further training under the adjustment of two regulating losses, these Skeypoints gradually spread to the entire space of a point cloud and distribute around the discriminative regions of the point cloud. The generation of Skeypoints and the preliminary spatial exploration of the point cloud is shown in Figure 1. The key contributions of this paper are as follows:

- We propose a novel network named SK-Net. It is an end-to-end framework that jointly optimizes the inference of spatial keypoints (Skeypoints) and the learning of feature representation in the process of solving a specific point cloud task, e.g., classification and segmentation. The generated Skeypoints do not require location consistency but are acutely aware of shape. It benefits the local detail extraction and the spatial modeling of a point cloud.
- We design a pattern and detail extraction module (PDE module) where the key detail features and pattern features are extracted and then aggregated to form the pattern-detail (PD) feature. It promotes correlation between different regions of a point cloud and integrates the contextual information of the point cloud.
- We propose two regulating losses to conduct the generation of Skeypoints without any location annotations and proposals. These two regulating losses are mutually reinforcing and neither of them can be omitted.
- We conduct extensive experiments to evaluate the performance of our method, which is better than or comparable with the state-of-the-art approaches. In addition, we present an ablation test to demonstrate the advantages of the SK-Net.

2 Related Work

2.1 Extraction of regional feature on point cloud

PointNet++ (Qi et al. 2017b) is the earliest proposed method that addresses the problem of local information extraction. In practice, this method partitions the set of points into overlapping local regions corresponding to the spatial locations chosen by the FPS algorithm through the distance metric of the underlying space. It enables the learning of local features of a local region with increasing contextual scales. Besides, Jiang et al. 2018; Liu et al. 2019 also perform the similar downsampling of a point cloud to obtain the spatial locations regarding local feature extraction. PointSIFT (Jiang et al. 2018) extends the traditional feature SIFT (Lowe 2004) to develop a local region sampling approach for capturing the local information of different orientations around a spatial location. It is similar to Xie et al. 2018 expanding from ShapeContext (Belongie, Malik, and Puzicha 2001). Point2Sequence (Liu et al. 2019a) explores the attention-based aggregation of multi-scale areas of each local region to achieve local feature extraction. And that, Hua, Tran, and Yeung 2018 defines a pointwise convolution operator to query each point’s neighbors and bin them into kernel cells for extracting pointwise local features. Shen et al. 2018 proposes a point-set kernel operator as a set of learnable 3D points that jointly respond to a set of neighboring data points according to their geometric affinities. Other techniques also exploit extension operators to extract local structure. For example, Klokov and Lempitsky 2017; Atzmon, Maron, and Lipman 2018 map the point cloud to different representation space, and Simonovsky and Komodakis 2017; Wu et al. 2018 dynamically construct a graph comprising edge features for each specific local sampling of a point cloud. In particular, Le and Duan 2018; Li et al. 2018 combine the regular grids of 3D space with points and leverage the spatially-local correlation of regular grids to achieve local information capture. Among the latest methods, the study of local geometric relations plays an important role. Lan et al. 2019 models geometric local structure through decomposing the edge features along three orthogonal directions. Liu et al. 2019b learns the geometric topology constraint among points to acquire an induc-tive local representation. By contrast, our method not only performs the relevant regional feature extraction in the PDE module, but also learns a set of Skeypoints corresponding to geometrically and semantically meaningful regions of the point cloud. In this way, our network can effectively model the spatial pattern of a point cloud and promotes the correlation between different regions of the point cloud.

Most related to our approach is the recent work, SO-Net (Li, Chen, and Hee Lee 2018). This work suggests utilizing the Self-Organizing Map (SOM) to build the spatial pattern of a point cloud. However, SO-Net is not proved to be generic to large-scale semantic segmentation. This is intuitively because its network is not end-to-end and the SOM.
is as an early stage with respect to the overall pipeline, so the SOM does not establish a connection with a specific point cloud task. In contrast, our method is capable of extending to large-scale point cloud analysis and achieving the end-to-end joint learning of Skeypoints and feature representation towards a specific point cloud task.

2.2 End-to-end learning of 3D keypoints

Approaches for end-to-end learning 3D keypoints have been investigated. Most of them focus on handling 3D matching or 3D pose estimation tasks. They do not extend to point cloud recognition tasks, especially classification and segmentation [Georgakis et al. 2018; Suwajanakorn et al. 2018; Zhou et al. 2018; Georgakis et al. 2019; Feng et al. 2019; Lu et al. 2019]. Some of these methods usually require keypoint proposals. For example, [Georgakis et al. 2018] proposes that using a Region Proposal Network (RPN) to obtain several Region of Interests (ROIs) then determines the keypoint locations by the centroids of those ROIs. Similarly, [Georgakis et al. 2019] casts a keypoint proposal network (KPN) comprising two convolutional layers to acquire the keypoint confidence score in evaluating whether the candidate location is a keypoint or not. In addition, Keypoint-Net [Suwajanakorn et al. 2018] presents an end-to-end geometric reasoning framework to learn an ordered set of 3D keypoints, whose discovery is guided by the carefully constructed consistency and relative pose objective functions. These approaches tend to depend on the location consistency of keypoints of different views [Georgakis et al. 2018; Suwajanakorn et al. 2018; Zhou et al. 2018; Georgakis et al. 2019]. Moreover, [Feng et al. 2019] presents an end-to-end deep network architecture to jointly learn the descriptors for 2D and 3D keypoints from an image and point cloud, establishing 2D-3D correspondence. [Lu et al. 2019] end-to-end trains its keypoint detector to enable the system to avoid the inference of dynamic objects and leverage the help of sufficiently salient features on stationary objects. By contrast, our SK-Net focuses on point cloud classification and segmentation. In addition, our Skeypoints not only are inferred without any location annotations or proposals but also are insensitive to location consistency. This greatly benefits the spatial region relation exploration of a point cloud.

3 End-to-end optimization of Skeypoints and feature representation

In this section, we present the end-to-end framework of our SK-Net. First, the architecture of SK-Net is introduced. Then its important process, PDE module, is discussed in detail. Finally, the significant properties of Skeypoints are analyzed.

3.1 SK-Net architecture

The overall architecture of SK-Net is shown in Figure 2. The backbone of our network consists of the following three components: (a) point feature extraction, (b) skeypoint inference and (c) pattern and detail extraction.

(a) Point feature extraction. Given an input point cloud \( P \) with size of \( N \), i.e., \( P = \{ p_i \subseteq \mathbb{R}^3, i = 0, 1, \ldots, N - 1 \} \), where each point \( p_i \) is a vector of its \((x, y, z)\) coordinates, \( P \) goes through a series of multi-layer perceptrons (MLPs) to extract its point features. Next, we use the symmetry function of max-pooling to acquire the global feature.

(b) Skeypoint inference. \( \mathcal{S} \) Skeypoints, \( \mathcal{S} = \{ s_j \subseteq \mathbb{R}^3, j = 0, 1, \ldots, M - 1 \} \), are regressed by stacking three fully connected layers on the top of the global feature. \( s_j \) represents the \( j \)-th Skeypoint. Note that the MLP-64 point features are used to handle point cloud segmentation tasks. Meanwhile, the interpolating operation proposed by [Qi et al. 2017b] is utilized.

(c) Pattern and detail extraction. The generated Skeypoints are forwarded into the PDE module to get PD features. More details are presented in the next subsection.

Finally, our network combines the PD feature aggregated in the PDE module with the global feature obtained in (a), for a specific point cloud task e.g., classification and segmentation.

3.2 Pattern and detail extraction module

The PDE module is shown in Figure 3. The PDE module consumes \( M \) generated Skeypoints and \( N \) input points. It contains three parts: (1) extraction of local details, (2) capture of local spatial patterns, (3) integration of features.

**Extraction of local details** In this part, we apply a simple kNN search to sample the local region. The number of local regions to extract local information from is identical with the number of generated Skeypoints. Consequently, \( M \) local neighborhoods captured by the Skeypoints are grouped to form a \( M \times H \times 3 \) tensor named local detail tensor. We use the \((x, y, z)\) coordinate as our tensors channels. The captured points are the points live in the local neighborhood captured by a generated Skeypoint and are denoted by \( C_{ps_j}, j = 0, 1, \ldots, M - 1 \). \( H \) is the number of captured points of each generated Skeypoint. Each captured point of a local neighborhood is denoted by \( cp_h, h = 0, 1, \ldots, H - 1 \). The \( M \) set of captured points can be formulated by:

\[
C_{ps_j} = kN N(cp_h|sk_j, h = 0, 1, \ldots, H - 1)
\]  

(1)

Subsequently, PDE module applies a series of MLPs on the local detail tensor to extract the \( M \times 256 \) detail feature. It is worth mentioning that there are other ways to sample local regions. We will present relevant experiments in the next
section to illustrate the superiority of using the kNN search in our scheme.

Capture of local spatial patterns To effectively capture the local spatial patterns of a point cloud, we define a concept named normalized Skeypoint. We average the location coordinates of points which live in the local neighborhood captured by each generated Skeypoint for acquiring the \( M \) normalized Skeypoints, \( S_{\text{knorm}} \), where \( sk_{\text{norm}} \) is defined by:

\[
sk_{\text{norm}} = \text{average}(C_{psj}) \quad (2)
\]

The normalized Skeypoints are distributed into the discriminative regions of a point cloud surface, as illustrated in Figure 4. It is beneficial to perform the entire spatial modeling of the point cloud. After that, we use kNN search on normalized Skeypoints themselves to capture the local spatial patterns of the point cloud. Next, we group the search results to get the \( M \times K \times 3 \) local spatial pattern tensor, where \( K \) is the number of normalized Skeypoints in each local spatial region. The \( M \times 256 \) pattern feature is extracted by the same approach as obtaining the detail feature.

![Figure 4: Each pair contains a point cloud (the left) generated by Skeypoints and corresponding one generated by normalized Skeypoints.](image)

Integration of features In this part, the PDE module concatenates the pattern feature with the detail feature to form \( M \times 512 \) intermediate result. This result is further aggregated through a stack of shared FC layers to acquire the pattern-detail (PD) feature. The PD feature builds the connections between different regions of a point cloud and integrates the contextual information of the point cloud.

3.3 Properties of Skeypoints

The fact that a point set is permutation invariant requires certain symmetrizations in the net computation. It is the same in our Skeypoint inference and relevant feature formation in order to perform the permutation invariance. Moreover, for our scheme and point cloud tasks, it requires that our Skeypoints are distinct from each other (distinctiveness), adapted to the spatial modeling of a point cloud (adaptation) and close to geometrically and semantically meaningful regions (closeness). However, due to the lack of keypoint annotations, the Skeypoints might either tend to be extremely close and even collapse to the same 3D location, or may stray away from the point cloud object. Because of these issues, we propose two regulating losses to conduct the generation of Skeypoints. They guarantee the distinctiveness, adaptation, and closeness of Skeypoints.

Permutation invariance We employ a modified PointNet framework to acquire the global feature of a point cloud. It is basis of the inferring of Skeypoints. After that, the activated outputs of the Skeypoint inference component are directly reshaped to obtain Skeypoints. Each coordinate of a Skeypoint is regressed independently. These procedures make Skeypoint generation satisfy permutation invariance. Note that the nonlinear activation function PReLU [He et al. 2015] is adopted to guarantee that each layer activation matches the location distribution of the point cloud and the regressive consequence is well-adapted and robust. Moreover, all local features use max-pooling to ensure their permutation invariance before producing the PD feature.

Distinctiveness and adaptation In order to achieve these characteristics, we take the separation distance between Skeypoints as a hyperparameter \( \delta \) and propose the separation loss \( L_{\text{sep}} \). Hyperparameter \( \delta \) provides a prior knowledge of the location distribution of the point cloud. It makes the generated Skeypoints adapted to the spatial modeling of a point cloud and boosts the convergence of our network. The separation loss \( L_{\text{sep}} \) prompts the \( M \) Skeypoints to be distinct from each other and penalizes two Skeypoints if their distance is less than \( \delta \). The \( L_{\text{sep}} \) is formulated by:

\[
L_{\text{sep}} = \frac{1}{M^2} \sum_{i=1}^{M} \sum_{i \neq j}^{M} \max(0, \delta - ||sk_i - sk_j||^2) \quad (3)
\]

Closeness In order to make Skeypoints correspond to geometrically and semantically meaningful regions of a point cloud, the network should encourage Skeypoints to close to the discriminative regions of the point cloud surface. A regulating loss named close loss \( L_{\text{close}} \) is proposed to penalize a Skeypoint and its captured points live in the local structure of this Skeypoint if they are farther than the value of hyperparameter \( \theta \) in 3D Euclidean space. The \( L_{\text{close}} \) is represented by:

\[
L_{\text{close}} = \frac{1}{MH} \sum_{i=1}^{M} \sum_{h=1}^{H} \max(0, ||sk_i - cp_h||^2 - \theta) \quad (4)
\]
These two loss terms allow our network to discover satisfactory Skeypoints as far as possible. Besides, they prompt our network to extract more compact local features with respect to the regions corresponding to the learned Skeypoints and to capture the effective spatial pattern of a point cloud by utilizing the normalized Skeypoints.

4 Experiments

Datasets We validate on four datasets to demonstrate the effectiveness of our SK-Net. Object classification on ModelNet40(Wu et al. 2015) is evaluated by accuracy, part segmentation on ShapeNetPart(Yi et al. 2016) is evaluated by mean Intersection over Union (mIoU) on points and semantic scene labeling on ScanNet(Dai et al. 2017) is evaluated by per-point accuracy.

- ModelNet. This includes two datasets which respectively contain CAD models of 10 and 40 categories. ModelNet10 consists of 4,899 object instances which are split into 2,468 training samples and 909 testing samples. ModelNet40 consists of 12,311 object instances among which 9,843 objects belong to the training set and the other 3,991 samples for testing.
- ShapeNetPart. 16,881 shapes from 16 categories, labeled with 50 parts in total. A large proportion of shape categories are annotated with two to five parts.
- ScanNet. 1,513 scanned and reconstructed indoor scenes. We follow the experiment setting in (Qi et al. 2017b) and use 1201 scenes for training, 312 scenes for test.

Implementation details Sk-Net is implemented by Tensorflow in CUDA. We run our model on GeForce GTX Titan X for training. In general, we set the number of the Skeypoints to 192, and $K$ to 16, $H$ to 32 in the PDE module. In most experiments, the hyperparameters $\delta$, $\theta$ of our two regulating losses are both 0.05, and the weights of all loss terms are identical. In addition, we use Adam(Kingma and Ba 2014) optimizer with an initial learning rate of 0.001 and the learning rate is decreased by staircase exponential decay. Batch size is 16. All layers are implemented with batch normalization. PReLU activation is applied to the layers of the point feature extraction and Skeypoint inference components, while ReLU activation is applied to every layer of the subsequent network.

4.1 Classification on ModelNet

For a fair comparison, the ModelNet10/40 datasets for our experiments are preprocessed by (Qi et al. 2017b). By default, 1024 input points are used. Moreover, we attempt to use more points and surface normals as additional features for improving performance. Table 1 shows the classification accuracy of state-of-the-art methods on point cloud representation. In ModelNet10, our network outperforms state-of-the-art methods by 95.8% with 1024 points and achieves a better accuracy of 96.2% with 5000 points and normal information. In ModelNet40, the network performs a comparable result of 92.7% through training with 5000 points and surface normal vectors as additional features. Although SO-Net presents the best result in ModelNet40, its network is trained separately and not generic to large-scale semantic segmentation, while our proposed model is trained end-to-end and does extend to large-scale point cloud analysis.

4.2 Part segmentation on ShapeNetPart

Part segmentation is more challenging than object classification and can be formulated as a per-point classification problem. We use the segmentation network to do this. Fairly, ShapeNetPart dataset is prepared by (Qi et al. 2017b) and we also follow the metric protocol from (Qi et al. 2017b). The results of the related approaches are illustrated in Table 2. Although the best mIoU of all shapes is performed by (Liu et al. 2019a), ours outperforms state-of-the-art methods in six categories and achieves comparable results in the remaining categories. We provide ShapeNetPart segmentation visualization in the supplementary material.

4.3 Semantic scene labeling on ScanNet

We conduct experiments on ScanNets Semantic Scene Labeling task to validate that our method is suitable for large-scale point cloud analysis. We use our segmentation network to do this. To perform this task, we set the point cloud to be normalized into $[-1, 1]$ because the $L_{sep}$ is sensitive to the distribution of point clouds. All experiments use 8192 points. We compare the per-point accuracy and the number of the local region features in each method, as shown in Table 3. Our approach is better than PointNet and slightly behind PointNet++. However, the number of our local region features is only 192 which is much smaller than that in PointNet++. These results show that our method is extendable to large-scale semantic segmentation and the local region features obtained by our method are compact and efficient.

4.4 Ablation study

In this subsection, we further conduct several ablation experiments to investigate various setup variations and to demonstrate the advantages of SK-Net.

Effects of features extracted in PDE module We present an ablation test on ModelNet10 classification to show the effect of the features extracted by PDE module i.e. detail features and pattern features, as shown in Figure 3. The accuracy of the experiments as follows: 93.9% (using only detail features), 93.3% (using only pattern features), and 95.8% (using their concatenated result). It demonstrates that our proposed PD feature promotes correlation between different regions of a point cloud and is more effective in modeling the whole spatial distribution of the point cloud.

Complementarity of regulating losses Ablation experiments of the losses are presented to validate the effect of our loss functions (classification loss: $L_{cls}$, separation loss: $L_{sep}$, close loss: $L_{close}$). As shown in Table 4, EXP.1 is the baseline and only the classification loss is used. The results show that our method is effective. EXP.2,3,4 show that the two regulating losses proposed by our scheme are mutually
reinforcing and neither of them can be omitted. The effect of combining these two losses can refine the spatial model and improve the performance by 1.5%.

Table 4: Ablation test of the losses on ModelNet10 classification.

| EXP | $L_{cls}$ | $L_{spt}$ | $L_{size}$ | accuracy |
|-----|-----------|-----------|-----------|----------|
| 1   | ✓         | −         | −         | 94.3%    |
| 2   | ✓         | ✓         | −         | 93.8%    |
| 3   | ✓         | −         | ✓         | 93.2%    |
| 4   | ✓         | ✓         | ✓         | 95.8%    |

Effects of local region samplings In this part, we experiment using other techniques (ball query and sift query proposed by Jiang et al. 2018) to sample local regions and also play with the general search radii: 0.1, 0.2. For all experiments, the number of sample points is 32 and the number of input points is 1024. As shown in Table 4, the sift query is the least effective method and the ball query is slightly worse than kNN. This shows kNN is the most beneficial to our scheme.

Effectiveness of Sk keypoints In order to exhibit the effectiveness of our Sk keypoints, we eliminate the Sk keypoints. And then the network is trained respectively with random dropout, farthest point sampling (FPS) algorithm and the SOM. We use these methods to discover a set of keypoints- like points for building the spatial pattern of a point cloud. Note that the keypoints are jittered slightly to avoid turning into naive downsampling in the random dropout and FPS methods. In addition, we use $11 \times 11$ SOM nodes processed by SO-Net (Li, Chen, and Hee Lee 2018) and likewise the number of keypoints is 121 for all comparative experiments. Subsequently, we evaluate the accuracy of different spatial modeling methods on ModelNet10. Visualization examples and the accuracy results are illustrated in Figure 5 and Figure 6. It is interesting that the keypoints respectively selected by the FPS algorithm and learned by SOM, are more well-distributed than our method but have approximately 2-3 percent lower accuracy than ours. Moreover, it is more sensitive to the density perturbation of points with the unlearned random dropout and FPS algorithm. By contrast, our Sk keypoints are jointly optimized with the feature learning for a specific point cloud task, promoting the robustness of the variability of points density and performing better performance.

Table 1: Object classification accuracy (%) on ModelNet.

| Method          | Representation | Input | ModelNet10 class | ModelNet40 class |
|-----------------|----------------|-------|------------------|------------------|
| PointNet (Qi et al. 2017) | points 32 | 1024 | 92.1 | 89.2 |
| PointNet (Qi et al. 2017) | points-normal | 5000 | 6 | 91.9 |
| KD-Net (Klokov and Lempitsky 2017) | points 32 | 1024 | 91.5 | 89.6 |
| Ours (Qi et al. 2017) | points 32 | 1024 | 92.1 | 91.8 |
| SCN (Xie et al. 2018) | points 32 | 1024 | 92.1 | 91.8 |
| ERF (Vsevolovsky and Komodakis 2017) | points 1000 | 32 | 90.0 | 89.8 |
| KC-Net (Klokov and Lempitsky 2017) | points 32 | 1024 | 94.4 | 93.1 |
| DGCNN (Wang et al. 2019) | points 32 | 1024 | 92.1 | 92.1 |

Table 2: Object part segmentation results on ShapeNetPart dataset.

| Method          | Interaction over Union (IoU) | mean | car | bag | cap | chair | cat | gat | knife | lamp | lap | mower | mug | posted | rocket | skate | table |
|-----------------|-----------------------------|-------|-----|-----|-----|-------|-----|-----|-------|------|-----|-------|-----|--------|--------|-------|-------|
| PointNet (Qi et al. 2017) | 83.7 | 81.4 | 78.3 | 82.5 | 74.9 | 80.6 | 73.0 | 91.8 | 85.9 | 80.8 | 95.1 | 62.5 | 91.0 | 81.2 | 57.9 | 72.8 | 80.6 |
| PointNet++ (msg) | 85.1 | 82.4 | 79.0 | 83.7 | 77.3 | 90.5 | 71.9 | 91.0 | 85.9 | 82.7 | 95.3 | 71.6 | 94.3 | 83.3 | 58.7 | 76.4 | 82.6 |
| PointNet++ (msg) | 82.1 | 80.1 | 74.6 | 74.3 | 70.1 | 80.5 | 73.0 | 90.2 | 81.0 | 94.5 | 69.2 | 94.4 | 83.6 | 60.1 | 75.2 | 81.1 |
| KC-Net (Shen et al. 2018) | 85.1 | 84.2 | 83.7 | 84.4 | 77.1 | 90.9 | 74.5 | 91.5 | 87.2 | 84.5 | 95.1 | 89.6 | 91.3 | 82.6 | 59.7 | 75.5 | 82.0 |
| SO-Net (Li, Chen, and Hee Lee 2018) | 85.2 | 82.6 | 81.4 | 85.7 | 72.1 | 90.8 | 71.1 | 91.1 | 86.9 | 83.9 | 95.7 | 70.8 | 94.6 | 75.3 | 58.4 | 75.2 | 82.8 |

Table 3: Comparisons of per-point classification on ScanNet.

| Method          | Local regions | Local selection operator | accuracy |
|-----------------|---------------|--------------------------|----------|
| PointNet++ (sng) | [1024, 256, 64, 16] | FPS | 77.7% |
| PointNet++ (msg) | [512, 128] | FPS | 82.6% |
| Ours | 192 | End-to-end learning | 81.4% |

Table 5: Effects of local sample choices on ModelNet10 classification.

| kNN | ball query ($r=0.1$) | sift query ($r=0.2$) |
|-----|----------------------|----------------------|
| 95.8% | 94.3% | 94.7% | 92.5% | 92.7% |
Effects of preferences  Our proposed method is more than simply using the end-to-end learned Skeypoints to choose the local regions for extracting the local features, as an existing method (Qi et al. 2017b) does. The Skeypoints also play an important role in the spatial modeling of a point cloud, enhancing the regional associations and prompting our model to get more compact regional features, as illustrated in Table 3. Therefore, the number of generated Skeypoints should be adapted to urge the Skeypoints to embrace the point cloud adequately, and the size $K$ of the normalized Skeypoints of a local spatial region should properly reinforce the region correlation of the point cloud. As shown in Figure 8(a), our network gradually performs better accuracy with the Skeypoints increasing from 32 to 192, while the accuracy decreases slightly with 256 Skeypoints. And then the effect of the size $K$ is also shown in Figure 8(b) on condition that the number of generated Skeypoints remains at 128. The best accuracies are achieved when $K$ is 16.

5 Conclusions

In this work, we propose an end-to-end framework named SK-Net to jointly optimize the inference of Skeypoints with the feature learning of a point cloud. These Skeypoints are generated by two complementary regulating losses. Specifically, their generation requires neither location labels and proposals nor location consistency. Furthermore, we design the PDE module to extract and integrate the detail feature and pattern feature, so that local region feature extraction and the spatial modeling of a point cloud can be achieved efficiently. As a result, the correlation between different regions of a point cloud is enhanced, and the learning of the contextual information of the point cloud is promoted. In addition, we conduct experiments to show that for both point cloud classification and segmentation, our method achieves better or similar performance when compared with other existing methods. The advantages of our SK-Net is also demonstrated by several ablation experiments.

Acknowledgement

Yunqi Lei is the corresponding author. This work was supported by the National Natural Science Foundation of China (61671397). We thank all anonymous reviewers for their constructive comments.
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