Enhancing Local Feature Learning Using Diffusion for 3D Point Cloud Understanding

Haoyi Xiu$^{1,2}$, Xin Liu$^1$, Weimin Wang$^{2,3}$, Kyoung-Sook Kim$^2$, Takayuki Shinohara$^4$, Qiong Chang$^5$, and Masashi Matsuoka$^1$

$^1$ Department of Architecture and Building Engineering, Tokyo Institute of Technology, Tokyo, Japan
$^2$ Artificial Intelligence Research Center, AIST, Tokyo, Japan
$^3$ DUT-RU International School of Information Science and Engineering, Dalian University of Technology, Dalian, China
$^4$ Innovation Technology Office Research Center, PASCO Corporation, Tokyo, Japan
$^5$ Department of Computer Science, Tokyo Institute of Technology, Tokyo, Japan

Abstract. Learning point clouds is challenging due to the lack of connectivity information, i.e., edges. Although existing edge-aware methods can improve the performance by modeling edges, how edges contribute to the improvement is unclear. In this study, we propose a method that automatically learns to enhance/suppress edges while keeping the its working mechanism clear. First, we theoretically figure out how edge enhancement/suppression works. Second, we experimentally verify the edge enhancement/suppression behavior. Third, we empirically show that this behavior improves the performance. In general, we observe that the proposed method achieves competitive performance in point cloud classification and segmentation tasks.

Keywords: edge enhancement; edge suppression; edge awareness; diffusion; point clouds

1 Introduction

A 3D point cloud is the most basic shape representation in which the scanned surface is represented as a set of points in the 3D space. With the advent of cost-effective sensors, an increasing number of large-scale point cloud datasets have been released to researchers, facilitating deep learning–based point cloud understanding. Typical applications of such research include autonomous driving [9,31] and remote sensing [59,36].

A point cloud is naturally unordered and unstructured, hindering the application of convolutional neural networks (CNNs) that are suited for processing regular grid data. Therefore, many prior studies have focused on applying CNNs by projecting point clouds to regular grids [18,39,28,58]. However, there is information loss incurred by the projection and these approaches are suboptimal. To remedy this issue, PointNet applies shared multi-layer perceptrons (MLPs) and symmetric functions to raw 3D points, consuming point cloud in a
lossless manner [32]. PointNet++ subsequently applies PointNets to local subsets of points, obtaining CNN-like translation invariance [33]. Recently, various convolution methods that operate directly on raw point clouds have been developed [23, 47, 41, 24]. Despite these efforts, learning point cloud data remains challenging due to the difficulty in inferring the underlying continuous surface from discrete point samples.

In recent years, people find that exploring the connectivity information between points (i.e., edges) is beneficial for 3D point cloud understanding and developed edge-aware approaches. For instance, researchers treat edges as additional contextual features [44, 25, 48] or spatial weights [43, 55, 56] that describe local geometrical structures and incorporate them into their models. Although incorporating edge information successfully improves the model performance, the underlying mechanism of how edges contribute to the improvement is not clear. Moreover, some researchers explicitly supervise the model with edge information [17, 16, 53]. However, these methods require per-point and clean ground truth labels (possibly with additional annotations), which are costly and not always available in practice.

In this study, we go beyond edge awareness, and propose the diffusion unit (DU) that performs automatic edge enhancement/suppression learning without additional supervision. Built on the nonlinear diffusion theory [30, 45], DU adaptively enhances task-beneficial edges and suppress irrelevant ones so as to improve the performance. In contrast to existing works, the mechanism of edge enhancement/suppression is interpretable in terms of theoretical analysis and experimental verification. Specifically, 1) We theoretically figure out which component of our method is responsible for edge enhancement/suppression and how it works; 2) We experimentally observe and verify the edge enhancement/suppression behavior; 3) We empirically demonstrate that this behavior contributes to the performance improvement.

DU is generally applicable, as it can be seamlessly integrated with a convolution operator as a basic building block of deep neural networks. Particularly, we resort to KPConv [41] as the default convolution operator owing to its superiority in point cloud processing. Further, to better fitting to DU, we develop a lightweight variant of KPConv, namely KPConv-l, which provides decent performance while drastically reducing the number of parameters.

Stacking KPConv-l and DU as a basic building block, we construct DU-Nets to tackle point cloud understanding tasks. Extensive experiments across several standard benchmarks demonstrate its effectiveness. In particular, we achieve the state-of-the-art performance in point cloud classification and comparative performance in part segmentation and scene segmentation.

Our main contributions are summarized as follows:

- We propose DU that performs automatic edge enhancement and suppression learning so as to improve the performance.
- We theoretically analyze and experimentally verify the edge enhancement and suppression behavior of DU.
We propose a lightweight version of KPConv, KPConv-l, which drastically reduces the number of parameters without compromising the performance. We design DU-Nets by stacking KPConv-l and DU as the basic building block and achieve the state-of-the-art performance in point cloud classification and comparative performance in part segmentation and scene segmentation tasks.

2 Related Work

2.1 Deep learning for 3D Point Clouds

Projection-based methods Projection-based methods project point clouds to regular grids (e.g., 2D planes [18, 39, 11] and 3D voxels [28, 58, 13, 7]) to make matured regular convolution applicable to point clouds. However, they lose fine-grained details through projections.

MLP-based methods Pioneered by PointNet [32], MLP-based methods prevent information loss by operating directly on the raw points. PointNet relies on shared MLPs and symmetric functions; both operations are permutation-invariant, and thus the irregularity of point clouds is well-resolved. Subsequently, PointNet++ [33] have made major steps toward the convolution-like operation by applying shared MLPs to local subsets of points [54, 21].

Convolution-based methods A variety of point convolutions have been realized by defining convolution operations on unstructured point clouds. Some studies construct regular kernels/grids on which the points are projected, thus enabling the faithful extension of the standard convolution [41, 27]; the others dynamically generate convolution filters based on positional features [23, 47]. Though being effective, convolution-based methods do not explicitly model local structures which potentially can provide more accurate representations of the underlying surface.

Edge-aware methods Edge-aware methods explicitly integrate edge information into the network design. Pioneered by EdgeConv [44], these methods perform convolution on the edge embedding to better model the local geometric structure. The idea of EdgeConv is adopted in numerous subsequent works (e.g.,

**Fig. 1.** Overview of the diffusion unit (DU). DU automatically learns to enhance task-beneficial edges or suppress irrelevant edges so as to improve the performance.
Although performance improves, it is difficult to analyze rigorously how it is improved. Furthermore, local edge features are simply fused with global ones by MLPs, which may be suboptimal since they are significantly distinct features. On the other hand, some methods regard edge information as a similarity measure, representing the semantic distance. In [43], such a similarity is used for describing connectivity among neighboring points; consequently, the information exchange is guided by edge information. Such an operation is often coupled with the attention mechanism [55,56,49], which converts edge into normalized spatial weights. However, the forced conversion may lose rich structural information (e.g., smoothness) contained in the edges. Another type of approach explicitly guides the network by edge-related supervision. Specifically, networks are taught to maintain spatial consistency [17], perform edge detection and other tasks jointly [16] or be aware of the location of edges [53]. Such methods involve dedicated loss functions or models, and often require clean and per-point ground truth, thereby making their practical applications challenging.

In contrast to the aforementioned edge-aware methods, the proposed DU goes beyond edge awareness by automatically learning to enhance task-beneficial edges and suppress irrelevant ones, thereby improving the performance. Furthermore, compared with existing edge-aware methods, DU offers significantly better interpretability through both theoretical and qualitative analysis.

2.2 Diffusion

In essence, diffusion methods, which are motivated by the diffusion equation, model the smoothing of data (e.g., images) as diffusion processes. The core of the diffusion methods is the diffusivity [30], which is often defined as a function of edge. As a result, diffusion methods remove small edges (small edges) while preserving significant edges [30], making them attractive to various applications. Therefore, such techniques are extensively studied in image processing [30,45,46,5] and later by other communities (e.g., computer graphics [10,18]). In the context of deep learning, although several works model the global information propagation [2,57,6] or the probabilistic point cloud generation [26] as diffusion processes, extending the diffusion equation for adaptive edge enhancement/suppression for 3D point cloud understanding, which we exclusively cope with in this study, remain unexplored.

3 Diffusion Unit

In this part, we first provide a brief background about the diffusion equation to build intuition. Next, we present the (continuous) definition of DU. Then, we perform a theoretical analysis to reveal the underlying mechanism of edge enhancement/suppression learning. Subsequently, we provide the discretization scheme that enables an efficient implementation of DU on modern machines. To enable a seamless integration of DUs to modern CNN-based frameworks, we explain how DUs can be integrated with KPConv-l. Lastly, we describe the network architectures used for various analyses and experiments in this study.
3.1 Preliminary

The diffusion equation describes the movement of diffusive substances from regions of higher concentration to lower concentration without creating or destroying mass \[45\]. For instance, when hot water is poured into cold water, heat diffuses until the temperature of the water becomes the same everywhere. Let \( u(p, t) \) denote the concentration at the position \( p \) and time \( t \). The amount of substances that flow through per unit area per unit time (the flux) is described by Fick’s law:

\[
s = -g \cdot \nabla u ,
\]

where \( \nabla \) denotes the gradient operator and \( g \) denotes the diffusivity. The fact that diffusion processes do not create or destroy mass is expressed by the continuity equation:

\[
\partial_t u = -\text{div}(s) .
\]

The continuity equation indicates that the change of concentration is caused only by the flux, which is measured by the divergence operator (div). Finally, the diffusion process is described by combining the above two equations:

\[
\partial_t u = \text{div}(g \cdot \nabla u) \quad t \geq 0 ,
\]

with the initial condition \( u(p, 0) = u_0(p) \) and the boundary condition as appropriate.

3.2 Definition of Diffusion Unit

Inspired by the diffusion equation, we propose diffusion unit (DU) that facilitates the edge enhancement learning for 3D point clouds. Suppose a continuous spatial-temporal multi-channel point cloud \( u = u(p, t) = (u_1(p, t), u_2(p, t), ..., u_d(p, t)) \), where \( d \) is the number of channels, \( t \) is time, \( p \) denotes the position vector, and the initial condition is \( u(p, 0) = h \). DU is defined as:

\[
\partial_t u = \text{div}(\phi(\nabla u)), \quad t \geq 0 ,
\]

where \( \partial_t u \in \mathbb{R}^d \) is the output of DU at time \( t \), \( \nabla u \) encodes channel-wise spatial gradient. Note that the choice of diffusivity \( g \) in Eq. \[3\] has a significant impact on performance. Finding the appropriate \( g \) often requires domain knowledge and involves numerous trials and errors \[4\]. In our definition, we replace the handcrafted \( g \) with a trainable filter \( \phi : \mathbb{R}^d \to \mathbb{R}^d \) so that the diffusivity function can be learned w.r.t data and task. In practice, we use \textit{1D-Conv} to implement \( \phi \) to maintain the local behavior. Note that \( \phi \) is a multi-channel filter that mixes information in all channels, since each channel may contain a fragment of information with certain degrees of noise.
### 3.3 Edge Enhancement/Suppression Learning

Now we explain how DU performs edge enhancement/suppression learning.

For simplicity, we consider a step edge convolved by a Gaussian. Ideally, such a structure can be detected by the spatial gradient $\nabla u$. Without loss of generality, we assume that the edge is aligned with $x$ axis ($u_y = u_z = 0$). The profile of the step edge and its derivatives are illustrated in Fig. 2. Now we focus on a single output channel $i$ for brevity.

In this context, Eq. (4) can be simplified as

$$\left( \frac{\partial_t u}{\partial x} \right)_i = \frac{\partial}{\partial x} \left( \phi_i(u_x) \right) = \nabla \phi_i \cdot u_{xx}$$

(5)

$$= \sum_{j=1}^{d} (\phi'_i)_j \cdot (u_{xx})_j, \quad i = 1, 2, ..., d.$$  \hspace{1cm} (6)

We are interested in the evolution of the edge over time, i.e., how $u_x$ changes during applications of DU.

We can derive that:

$$\left( \frac{\partial_t u_x}{\partial x} \right)_i = \left( \frac{\partial}{\partial t} \frac{\partial u}{\partial x} \right)_i = \frac{\partial}{\partial x} \left( \frac{\partial u}{\partial t} \right)_i$$

(7)

$$= \frac{\partial}{\partial x} \left( \sum_{j=1}^{d} (\phi'_i)_j \cdot (u_{xx})_j \right)$$

(8)

$$= \sum_{j=1}^{d} (\phi''_i)_j \cdot (u_{xx})^2_j + (\phi'_i)_j \cdot (u_{xxx})_j.$$  \hspace{1cm} (9)

As shown in Fig. 2 at the inflection point $u_{xx} = 0$ and $u_{xxx} < 0$. Therefore, the contribution of a particular input channel $j$ to the output channel $i$ (the sign of Eq. (9)) is determined by the sign of $(\phi'_i)_j$. Specifically, channel $j$ has a positive impact if $(\phi'_i)_j < 0$, whereas it has a negative impact if $(\phi'_i)_j > 0$.

As a result, enhancing ($\left( \frac{\partial_t u_x}{\partial x} \right)_i > 0$) or suppressing ($\left( \frac{\partial_t u_x}{\partial x} \right)_i < 0$) the edge can be adaptively learned by the filter $\phi$, by collectively using fragmentary information in all channels.

### 3.4 Discretization

To deal with discrete point clouds, discretization of Eq. (4) is necessary. Let $u_s, u_n \in \mathbb{R}^d$ denote the feature of the center point and its spatial neighbors, respectively. Let $n \in N_s$ represents $n$-th neighbor of the center point. First, we adopt the explicit scheme for time discretization and have:

$$\partial_t u_s \approx u^{t+1}_s - u^t_s.$$  \hspace{1cm} (10)

![Fig. 2. Profiles of the smoothed step edge and its derivatives.](image-url)
Second, we discretize the space using the finite difference and have:

$$\text{div}(\phi(\nabla u)) \approx \frac{1}{|N_s|} \sum_{n \in N_s} \phi(u^t_n - u^t_s),$$

where $|N_s|$ represents the number of neighbors. Combining Eqs. (4), (10), (11), we have

$$u^{t+1}_s = u^t_s + \left( \frac{1}{|N_s|} \sum_{n \in N_s} \phi(u^t_n - u^t_s) \right).$$

Moreover, we incorporate Batch Normalization and ReLU activation function $\varphi = \text{BatchNorm} \cdot \text{ReLU} : \mathbb{R}^d \rightarrow \mathbb{R}^d$ into the second term on the right-hand side of Eq. (12) to facilitate training and encourage sparsity. Finally, the discretized DU is defined as:

$$u^{t+1}_s = u^t_s + \varphi \left( \frac{1}{|N_s|} \sum_{n \in N_s} \phi(u^t_n - u^t_s) \right).$$

Note that the neural network functions $\phi$ and $\varphi$ work together and are responsible for the learning of enhancing or suppressing edges (we provide qualitative analysis on the behavior of $\phi$ and $\varphi$ in Sec. 4.1). The above definition can be efficiently computed and easily parallelized, fitting to modern GPU-empowered deep learning frameworks. The computation flow of DU is shown in Fig. 3.

### 3.5 Integrating with a Lightweight Point Convolution

DU can be integrated with a convolution operator to build a basic building block of a deep neural network. In particular, we choose KPConv as the default convolution operator, owing to its superiority in point cloud processing. However, it suffers from high memory consumption, hindering its application to voluminous data. Therefore, we further develop a lightweight version of KPConv (KPConv-l) to achieve decent performance while drastically reducing the model parameters.

**Lightweight KPConv** KPConv adapts the standard convolution for regular data to the point cloud setting by constructing artificial convolution kernels, to which the input points are projected. However, the resulting convolution is parameter-consuming, which limits its applications to voluminous point clouds.
Specifically, let $l$ denote the number of neighbors involved in the convolution. Further, let $d_{in}, d_{out}$ denote the dimensions of input channel and output channel, respectively. The standard convolution requires $l \times d_{in} \times d_{out}$ parameters, which leads to excessive memory consumption. To remedy this issue, we borrow the idea from prevalent depthwise separable convolution (DSC) \cite{37} to simplify the KPConv into depthwise KPConv (with a depth multiplier \cite{15}). As a result, the number of parameters is reduced to $l \times d_{out}$, thereby significantly reducing the memory consumption.

A potential concern is that, unlike data that have regular spacing between elements (e.g., image), point clouds typically have irregular spacing, which poses a great challenge to capacity-limited depthwise KPConv. Therefore, we apply relative positional encoding on the raw input points to assist depthwise KPConv to learn the irregular spacing. Specifically, relative positional encoding transforms the position-concatenated point features by an MLP such that subsequent operations become position-aware. Though simple, this trick effectively reduces memory consumption without compromising the performance. The differences of KPConv and KPConv-l are shown in Fig. 4.

**Integration Strategy** In this study, we stack a KPConv-l and a DU to obtain the feature representation. Concretely, the input is transformed by a KPConv-l, which is followed by a DU. Popular architectures in point cloud processing typically down-sample the input in a convolution layer; therefore, attaching DU to each convolution layer facilitates the network to learn the multi-resolution edge hierarchy.

### 3.6 Network Architecture

In this study, we tackle point cloud classification and segmentation. We construct Diffusion Unit–Enhanced Networks (DU-Nets) by stacking KPConv-l and DU as the basic building block. For classification, we follow multi-scale PointNet++ \cite{33} to construct an encoder composed of four pairs of KPConv-l and DU. Each layer downsamples the input point cloud using the furthest point sampling \cite{33}. The global representation is obtained by applying a pooling layer to the last layer of the encoder, and is subsequently fed to the MLPs to generate the class scores. For segmentation, we adopt the same encoder as the classification model. Then, the output of the encoder is successively upsampled to the original resolution.
using 3-nearest neighbor upsampling layers. Notably, each interpolation layer is followed by a DU such that salient edges are kept sharpened. The final per-point scores are obtained by feeding the output of the decoder to a series of MLPs. In addition, U-Net \cite{ronneberger2015u}-like skip connections are used to assist the feature upsampling. The architecture is illustrated in Fig. 5.

4 Experiment

In this section, we conduct experiments to answer the following questions:

Q1. Does DU really perform edge enhancement/suppression?
Q2. How much does DU contribute to improve the performance?
Q3. Is DU-Net better than existing deep leaning models?
Q4. Is the design of the different components of DU-Net reasonable?

To answer these questions, we use standard benchmark tests on point cloud classification, part segmentation, and scene segmentation tasks.

For classification, we use ScanObjectNN \cite{yi2016scalable}, which is a challenging dataset consisting of real-world 3D scans. In total, it contains 15k objects, each being labeled into one of the 15 categories.

For part segmentation, we use ShapeNet Part dataset \cite{yi2016scalable}, which includes 16,880 models 3D models. It includes 16 object classes and 50 object parts, each of which is annotated into two to six parts. For a fair comparison, we use the data provided by \cite{wu20153d}.

For scene segmentation, Stanford large-scale 3D indoor spaces (S3DIS) \cite{armeni2016s3dis} is used to measure the performance. In total, it has 272 indoor environments where each point is assigned a class out of 13 classes.

4.1 Verifying the Behaviors of DU

We have theoretically analyzed that the neural network functions $\phi$ and $\varphi$ work together and are responsible for the learning of enhancing or suppressing edges.
Fig. 6. Visualization of the smoothness using ShapeNet dataset (part segmentation). Red rectangles show the examples of enhanced part, while yellow ones show the suppressed part. DU successfully enhances the part boundaries while smoothing out other edges.

Here we experimentally verify the edge enhancement/suppression behaviors. Specifically, we perform qualitative analysis on smoothness, which reflects the effects of DU. Let $f \in \mathbb{R}^d$ denote the processed features. Formally, the smoothness is defined as: $|\sum_{n \in N_s} f_n - f_s|$, which essentially summarizes how the center point is different from its neighbors. As such, we compute the smoothness before and after applying DU to analyze the behavior of DU.

Fig. 6 and 7 show several examples from ShapeNet and S3DIS datasets on which our part and scene segmentation models are trained. For each example, smoothness distributions before and after DU are extracted and compared. We find that 1) DU successfully enhances the part boundaries and smooths out other intra-region edges in the part segmentation task; 2) DU manages to enhance inter-category edges while suppressing intra-category ones, making object boundaries more salient. Therefore, the task-beneficial edge enhancement/suppression behavior of DU can be verified.

4.2 Point Cloud Classification

We use the most difficult set of the dataset and adopt the official train-test split [42]. The performance is measured by the overall accuracy (OA). We use Adam [20] optimizer with an initial learning rate of 0.001. The input is augmented by random rotation, scaling, and translation. Only the 3D coordinates are used as input features. Furthermore, we vary the input number of points (1,024 and 2,048) to investigate the impact of the increased training data.

The result is listed in Table 1. The DU-Nets outperform the previous leading methods by significant margins under both experimental settings, which verifies their effectiveness on the classification task. We observe that increasing the number of input points significantly improves the performance. We conjecture
Fig. 7. Visualization of the smoothness using S3DIS dataset (scene segmentation). Red rectangles show the examples of enhanced part, while yellow ones show the suppressed part. DU manages to enhance the task-related edges while suppressing irrelevant ones (e.g., the table in the last row).

Table 1. Results of point cloud classification on ScanObjectNN dataset. The best, average, and standard deviations of our results in three runs are reported.

| Method         | #point | OA    |
|----------------|--------|-------|
| PointNet       | 1,024  | 68.2  |
| PointNet++     | 1,024  | 77.9  |
| DGCNN          | 1,024  | 78.1  |
| PointCNN       | 1,024  | 78.5  |
| BGA-PN++       | 1,024  | 80.2  |
| BGA-DGCNN      | 1,024  | 79.7  |
| SimpleView     | 1,024  | 80.5  |
| DynamicScale   | 1,024  | 82.0  |
| **Ours**       | 1,024  | **85.8 (85.77±0.06)** |
| MVTN           | 2,048  | 82.8  |
| **Ours**       | 2,048  | **87.0 (86.83±0.16)** |

that increased density provides a better approximation of the underlying surface, thus leading to a significant improvement.

4.3 Part Segmentation

We use 2,048 points with normal information as the input. Random anisotropic scaling and random translation are used for data augmentation. SGD is used for optimization. The initial learning rate is set to 0.1. We use voting for post-processing, as it is a common practice. The instance-wise average intersection over union (mIoU) \(^{33}\) is used for the performance assessment.

The results are listed in Table 2. The DU-Net achieves competitive performance among cutting-edge models. We believe that DU-Net is especially effective in recognizing object part boundaries, as DUs try to preserve structures while simplifying/smoothing within boundary regions. Although AGCN \(^{19}\) achieves
Table 2. Results of part segmentation on ShapeNet and scene segmentation on S3DIS (Area 5). The three-run best, average, and standard deviations are reported. Note that we report preprocessing methods for the S3DIS dataset because of their significant impact on the final performance [51,50].

| Method           | ShapeNet (I. mIoU) | preproc. | S3DIS (mIoU) | preproc. |
|------------------|-------------------|----------|--------------|----------|
| PointConv [47]   | 85.7              | -        | -            | -        |
| RS-CNN [24]      | 86.2              | -        | -            | -        |
| CurveNet [48]    | 86.8              | -        | -            | -        |
| AGCN [19]        | 87.9              | -        | -            | -        |
| KPConv-rigid [41]| 86.2              | Grid     | 65.4         |          |
| KPConv-d [41]    | 86.4              | Grid     | 67.1         |          |
| Point Transformer [56] | 86.6          | Grid     | 70.4         |          |
| PointNet [32]    | 83.7              | BLK      | 41.1         |          |
| PointNet++ [33]  | 85.1              | BLK      | 57.3         |          |
| PointCNN [23]    | 86.1              | BLK      | 57.3         |          |
| PAConv [50]      | 86.1              | BLK      | 66.6         |          |
| Ours             | 87.0 (86.94±0.08) | BLK      | 66.8(66.72±0.07) |          |

Fig. 8. Qualitative results of part and scene segmentation.

strong performance, it relies on a different training setting and a discriminator network with adversarial training in addition to the segmentation network, which considerably increases the complexity. The qualitative results are shown in Fig. 8.

4.4 Scene Segmentation

Similar to [40], we advocate using Area five for testing and others for training. Following [55], we randomly extract a 1m×1m pillar and take 4,096 points as the input. During the test, we test on all points. We use 3D coordinates, RGB, and normalized 3D coordinates with respect to the maximum coordinates in a room as the inputs. We use SGD with an initial learning rate of 0.1 and train the models for 100 epochs, with each epoch set to 1.5k iterations. Random vertical rotation, random anisotropic scaling, Gaussian jittering, and random color dropout are used for data augmentation. The performance is assessed using the point-average IoU.
The results are reported in Table 2. As mentioned by [51] and [50], the choice of preprocessing methods has a significant impact on the results, which makes comparisons of methods that use different preprocessing procedure difficult. Primarily, we compare our model with other models using the same preprocessing (BLK). We achieve the best performance under the same preprocessing method. The qualitative results are shown in Fig. 8.

5 Design Analysis

### Table 3. Results of the ablation study on DU

| Model | #DU | ϕ | φ | #neigh. I | mIoU |
|-------|-----|----|----|----------|------|
| A     | 1   | ✓  | ✓  | 16       | 85.4 |
| B     | 1   | ✓  | ✓  | 16       | 86.3 |
| C     | 1   | ✓  | ✓  | 16       | 86.3 |
| D     | 1   | ✓  | ✓  | 16       | **86.8** |
| E     | 2   | ✓  | ✓  | 16       | 86.7 |
| F     | 3   | ✓  | ✓  | 16       | **86.8** |
| G     | 1   | ✓  | ✓  | 4        | 86.5 |
| H     | 1   | ✓  | ✓  | 8        | 86.6 |
| I     | 1   | ✓  | ✓  | 24       | 86.7 |

### Table 4. Incorporating DUs with various convolutions. We take the architecture in Fig. 5 as the base model and investigate the performance change by replacing KPConv-l with other convolution methods or unstacking DUs. The reported performance indicate I. mIoU

| Convolutions       | w/o DU | w/ DU | Δ   |
|--------------------|--------|-------|-----|
| PointConv [47]     | 86.0   | 86.7  | +0.7 |
| RSConv [24]        | 86.1   | 86.4  | +0.3 |
| KPConv [41]        | 86.0   | 86.3  | +0.3 |
| KPConv-l (ours)    | **86.4** | **86.8** | +0.4 |

### Table 5. Comparison of DU with other edge-aware methods. We take the architecture in Fig. 5 as the base model and replace DUs other methods

| Method              | I. mIoU | # params (M) | Running time (ms) |
|---------------------|---------|--------------|-------------------|
| EdgeConv [44]       | 85.5    | 4.0          | 28.4              |
| Point Trans. [56]   | 86.5    | 5.6          | 27.9              |
| DU                  | **86.8** | 4.0          | **26.6**          |

### Table 6. Comparison of KPConv and KPConv-l in terms of memory consumption and inference time with different numbers of input points

| Method   | 10k | 20k | 40k | 80k |
|----------|-----|-----|-----|-----|
| Memory (M) |     |     |     |     |
| KPConv [41] | 1894 | 2246 | 3068 | 4616 |
| KPConv-l   | 1608 | 1844 | 2288 | 3096 |
| Inference (ms) |   |     |     |     |
| KPConv [41] | 94.5 | 300.5 | 952.7 | 3491.9 |
| KPConv-l   | 88.4 | 275.6 | 922.0 | 3440.9 |
In this section, we validate the design choices regarding DU. All experiments are conducted on the ShapeNet (without voting post-processing) because the part segmentation task is sufficiently complex.

**DU components.** We investigate the influence of DU components. The results are listed in Table 3 (A, B, C, and D). Removing both $\phi$ and $\varphi$ leads to significantly degraded performance. Equipping DU with only $\phi$ or $\varphi$ achieves acceptable performance (models B and C). The performance reaches a peak when both components are incorporated into DU (model F), which successfully verifies our design choice.

**Number of DUs.** We investigate the impact of the number of DUs applied to each KPConv-l. As shown in Table 3 (D, E, and F), the performance is not sensitive to the number. Consequently, we set #DUs=1 for all tasks.

**Neighborhood size.** As listed in Table 3 (D, G, H, and I), the best performance is achieved when #neigh is selected as 16; therefore, we use 16 as our default choice.

**Integrating DU with various convolutions.** To show the general applicability of DU, we replace KPConv-l with various popular point convolutions and perform a comparative study. As shown in Table 4, DU successfully boosts other convolution methods, demonstrating its general applicability.

**DU vs. other edge-aware methods.** We compare DU with EdgeConv [44,22,29] and Point Transformer [56]. For a fair comparison, we replace DUs with other methods in our model. The result is listed in Table 5. Evidently, DU is superior to or on par with other methods in terms of performance, number of parameters, and running time.

**KPConv-l vs. KPConv.** As shown in Table 6, KPConv-l has a faster inference speed and requires less memory consumption than KPConv. This indicates the usefulness of our trick in the design of KPConv-l.

6 Conclusion

Learning point clouds are difficult due to the lack of connectivity information (i.e., edges). Various edge-aware methods in which constructed edges are used as additional information are proposed, which successfully improve the performance. However, how the edges improve the performance is hardly interpretable. In this study, we go beyond edge awareness, and propose the diffusion unit (DU) that performs edge enhancement and suppression adaptively in an interpretable manner. A theoretical analysis is conducted to reveal the underlying mechanism of DU, which is confirmed by the following qualitative analysis using the smoothness information. Concretely, the above analysis reveals that DU learns to enhance task-related edges while suppressing others. Extensive experiments show that the network powered by DUs (DU-Nets) can achieve competitive performance across various challenging benchmarks. In particular, DU-Net achieves the state-of-the-art performance in point cloud classification.
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