Potential Convolution: Embedding Point Clouds into Potential Fields

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Abstract

Recently, various convolutions based on continuous or discrete kernels for point cloud processing have been widely studied, and achieve impressive performance in many applications, such as shape classification, scene segmentation and so on. However, they still suffer from some drawbacks. For continuous kernels, the inaccurate estimation of the kernel weights constitutes a bottleneck for further improving the performance; while for discrete ones, the kernels represented as the points located in the 3D space are lack of rich geometry information. In this work, rather than defining a continuous or discrete kernel, we directly embed convolutional kernels into the learnable potential fields, giving rise to potential convolution. It is convenient for us to define various potential functions for potential convolution which can generalize well to a wide range of tasks. Specifically, we provide two simple yet effective potential functions via point-wise convolution operations. Comprehensive experiments demonstrate the effectiveness of our method, which achieves superior performance on the popular 3D shape classification and scene segmentation benchmarks compared with other state-of-the-art point convolution methods.

1. Introduction

Convolutional Neural Network (CNN) plays an important role in boosting a broad range of computer vision applications. Thanks to the regular structure of 2D images, the convolution operations can be done efficiently. However, the world around us is of a higher dimension. With the rapid development of capturing devices, obtaining 3D data is made much easier. As such, the need for processing and understanding 3D data is growing rapidly. As the raw format of 3D data captured by LIDAR sensors, the point cloud is an efficient representation, because it only stores occupied positions in the space. The unordered nature and irregular structure of point clouds make it difficult for researchers to simply apply the traditional convolutions to them.

Various approaches have been proposed to handle this issue. A straightforward way is to voxelize the space and to represent the 3D data using a grid, then 3D convolutions can be applied accordingly [23, 30, 33]. However, the resolution of the volumes is in general limited due to the extra memory and computational overhead and a large number of cells are empty [8]. It is thus more desirable to work with raw point clouds directly.

Initial trials were found to work with point-wise convolution, i.e., convolution with the kernel size of 1 [49, 26], which inspires a bunch of follow-ups [41, 17]. Though point-wise convolution can extract point feature with a slight computation burden, it fails to capture local neighborhood information like ordinary convolution operations.

Efforts on designing special convolution operations targeting point clouds draw much attention in recent years [2, 45, 20, 14, 13, 4, 22]. These methods define special convolutions on a set of points in a local neighborhood, sharing the idea that a convolution should contain customizable spatial kernels. We can classify current mainstream point convolutions into continuous ones and discrete ones, according to the type of their kernels. The continuous ones [43] aim to find a mapping function, typically an MLP, which directly convert the local point coordinates to the kernel weights. In other words, the continuous kernels are distributed around the local space and can naturally handle the arbitrary query positions. However, the design of mapping function is always a tricky issue. On the contrary, the discrete ones [37] assign an individual position to every kernel and the kernel weights are learned as parameters. By separating positions and weights, discrete point convolution can obtain a more clarified relationship between each input point and kernel. However, it also brings the problem of sparse space cover-
2. Related work

In this section, we review deep learning methods in analyzing 3D data, paying particular attention to the methods working on point clouds. Based on the format of the input data, they can be roughly categorized into three groups.

Image-based 3D data is projected onto planes to generate a set of 2D images, which can be further processed directly by 2D CNNs [5, 18, 34]. For point clouds, however, missing surfaces and density variations have negative impacts on the resulting projections.

Voxel-based 3D data is positioned in a volumetric grid and partitioned by the cells. Each cell records the status of occupancy, occlusion, distance to the surface, etc. [23, 31, 3]. This way, the data can be processed directly by CNNs using 3D kernels. However, the extra dimension means a cubic increase of computation and storage as the resolution of the grid increasing. So fine-grained details are often lost after vocalization using large cell size. Some efforts are made to take advantage of the sparsity of the volumes, such as octrees or hash maps [30, 8]. The idea of sparse convolution also improves the computation efficiency by a large extent [8, 9]. Similarly, [21] scans the 3D space to decide where computations are necessary. But their kernels are in general constrained to stay small subject to the large computation burden brought by 3D convolutions.

Point-based Raw point clouds can be taken as input directly without converting them to another regular structured format. It is drawing more and more attention as it enjoys full sparsity [29, 26, 28, 33, 34, 14, 10, 39]. PointNet [26, 29] proposes to use shared multi-layer perceptrons and max pooling layers to extract features of point clouds. PointNet++ [28] is an enhanced version of PointNet [26] by adding a hierarchical structure. It is similar to the one used in image-based CNNs by extracting features, starting from small local regions and gradually extending to larger regions. The key components used in both PointNet [26] and PointNet++ [28] to aggregate features from different points are max-pooling layers. However, they keep only the strongest activation of features across a set of points, which may not be the optimal and some useful information might be lost. Regarding this, researchers strive to find a better way of transforming and aggregating features for point clouds. Different point convolutions are proposed for this purpose.

Based on the type of kernels used, we further classify them into two categories.

- **Continuous kernel** Unlike discrete kernel, continuous kernel parameterizes a continuous weight space in the
local coordinate system. When applied to point clouds, each point will get a specific weight based on its position in the local neighborhood. Yet, to accurately estimate the weight for each point is more challenging and requires more computation [43, 4].

- Discrete kernel: The kernel can be viewed as a set of discrete points distributed in the space and each carries a weight. In most cases, the shape of the kernel, i.e., positions of the kernel points, is manually designed and rigid. When applied to point clouds, each point is associated with the closest kernel weight [14, 45, 2].

A deformable version which learns to add a shift to each kernel point is found to be more flexible and improve the representation capability [7, 37]. However, the performance of such methods will drop drastically if the input points are extremely sparse or abnormal.

As mentioned above, both of them have some limitations for point cloud processing. The discrete kernels suffer from the discrete and sparse kernel coverage in the entire space, and the continuous kernels suffer from the inaccurate estimation of the weight for each position.

In this work, we drop the conventional notation of discrete and continuous kernel type, and embed kernel into learnable potential fields instead. As shown in Fig. 1, it is not necessary for potential convolution to learn position of each kernel, while only the potential function is needed to be learned. Compared with the kernel points distributed discretely in the local space, our potential field can cover the whole local space and make it more suitable to fit different input points. In the meantime, the computation of potential function is efficient, and we can provide an accurate potential value for each input point. The potential value will act as a factor to adjust the weight vector. The adjusted weight vector contains both geometry and feature information about local points, and is finally applied to the input features.

Once the appropriate potential functions defined, potential convolution can be well adapted into various network structures without any data-dependent hyper-parameters. We provide two simple but effective potential functions to demonstrate the superiority of our potential convolution, compared with the state of the art continuous/discrete point convolution methods. We also give a novel illustration from the geometric aspect to show that why potential convolution works better than discrete one and find that potential kernel contains more complex geometric information.

3. Potential Convolution

In this section, we present our potential convolution, whose kernel functions are built on top of the potential fields. The potential fields have been frequently adopted in robot path planning [6, 24, 38]. Each position in the field is granted a potential value via some parameterized function, indicating properties of interest. As such, we import potential fields into our design of kernel functions to quantitatively measure the relationships between points and the learned kernel weights, which are further utilized to aggregate the local information embedded.

3.1. A Kernel Function Defined by Potential Fields

A general definition of a point convolution can be written as

\[
\mathcal{F} \ast g(x) = \sum_{x_i \in \mathcal{N}_i} g(x_i) f_i,
\]

where \( \mathcal{N}_i \in \mathbb{R}^{K \times 3} \) is the set of points in the neighborhood of \( x \) and \( \mathcal{F} \in \mathbb{R}^{K \times D} \) stands for the collection of their corresponding features. \( K \) is the number of neighboring points and \( g \) refers to a specialized kernel function. \( x_i \) and \( f_i \) are members from \( \mathcal{N}_i \) and \( \mathcal{F} \) respectively.

There are different ways of defining a local neighborhood. We opt for the radius-based one to ensure the robustness to varying densities as in [13]. It is also shown by [36] that a better handcrafted 3D features can be obtained this way as opposed to the KNN-based version. Nevertheless, the choice of constructing a neighborhood has only a minor influence on our method as potential convolution pays more attention to the underlying shape information represented by the set of points instead of individual points themselves.

The most important part in Eq. 1 is the implementation of the kernel function \( g \), that is how point convolutions differ from each other. Usually, \( g \) takes the coordinates of the points in \( \mathcal{N}_i \) re-centralized by \( x \) as input, i.e. \( y_i = x_i - x \). As our neighborhood is defined by the radius \( r \), the input domain of \( g \) is the ball \( \mathcal{B}^3_r = \{ y \in \mathbb{R}^3 \mid \| y \| \leq r \} \). In the discrete and continuous kernels, \( g \) will apply different weights to different areas inside this domain based on their position relationship, as shown in Fig. 2. In potential kernels, \( g \) will apply different weights to different areas inside this domain based on their potential values, as shown in Fig. 4. There are many ways to define areas in 3D space used for discrete and continuous convolution, and points are the most intuitive as features are localized by them. But in potential convolution, we can directly define the potential fields as the whole local 3D space \( \mathcal{B}^3_r \), and any point \( y_i \) possess its own potential value as the adaptive factor for kernel weights.

Let \( \{ \tilde{p}_k[k < D'] \} \subset \mathcal{B}^3_r \) be the potential fields lies in local 3D space, \( D' \) is the number of potential fields, i.e. the output dimension of potential convolution. Let \( \{ w_k[k < D'] \} \subset \mathbb{R}^D \) be the associated weight matrix that map features form dimension \( D \) to \( D' \). We define the kernel function \( g \) for any point \( y_i \in \mathcal{B}^3_r \) in each potential field \( \tilde{p}_k \) as:

\[
g_k(y_i) = (h \circ \tilde{p}_k)(y_i)w_k,
\]

where \( h(\cdot) \) is the correlation function that should be higher when \( y_i \) obtain a lower potential value under \( \tilde{p}_k \). In other
words, if \( y_i \) gets closer to the zero-potential surface, we think it can better fit into current potential fields, and a higher correlation value should be returned by \( h(\cdot) \).

Inspired by [2], we also use the Gaussian function to calculate the correlation value:

\[
h(p) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(p-\mu)^2}{2\sigma^2}\right),
\]

where \( \sigma, \mu \) is the variance and mean factor of Gaussian function, and \( p = \tilde{p}_k(y_i) \). Rather than [37], which used a simpler linear correlation function, we find that Gaussian function benefit learning a more stable potential field \( \tilde{p} \). On the other way, we also make a simplification of the standard Gaussian function. We choose \( \sigma = \frac{1}{\sqrt{2}} \), \( \mu = 0 \) and ignore the coefficient terms \( \frac{1}{\sqrt{2\pi}\sigma} \), which yields:

\[
h(p) = \exp(-p^2).
\]

The simplification eases the computation as well as stabilizes the training process.

### 3.2. Linear or Quadratic Potential Field

Potential functions \( \tilde{p}_k \) are critical to the convolution operator. The computation of potential functions should be efficient. There are many ways to define different potential functions, even using a small neural network. However, it is more convincing for us to adapt a simple potential function than a complex one to demonstrate the powerful feature extraction capabilities of our method. Hence, we provide two kinds of the simplest potential functions, i.e. linear one \( \tilde{p}^1_k \) and quadratic one \( \tilde{p}^2_k \).

**Linear Potential Function**  The linear potential function is defined as:

\[
\tilde{p}^1_k(y_i) = a_k y_i^T + d_k,
\]

where \( a_k \in \mathbb{R}^3 \) is learnable parameters of potential function and \( d_k \in \mathbb{R} \) is bias. Furthermore, we can easily extend this function to a more general version. For example, if normal vector \( n_{yi} \) is given, we can extend \( \tilde{p}^1_k \) to:

\[
\tilde{p}^1_k(y_i, n_{yi}) = a_k (y_i + n_{yi})^T + d_k.
\]

**Quadratic Potential Function**  The quadratic potential function is defined as:

\[
\tilde{p}^2_k(y_i) = a_k y_i^T + b_k (y_i^2)^T + d_k,
\]

where \( a_k, b_k \in \mathbb{R}^3 \) is linear and quadratic learnable parameters respectively, \( d_k \in \mathbb{R} \) is bias.

### 3.3. An Analysis from Geometric Aspect

Here, we provide an analysis from the geometric aspect to explain why our proposed linear and quadratic potential function works better than existing point convolution methods.

As for \( \tilde{p}^1_k \), we can recognize the linear terms as a point-normal equation of plane. Therefore, the linear potential fields shape planes lied in different directions on local
space, i.e. \( B^3 \). The potential value of input point indicates different distance to planes. If we take normal vector \( n_i \) into account, \( \tilde{p}_k \) also encodes the direction between the plane and input points. In order to better demonstrate the learned linear potential fields with different directions, we colorize each point with the color of most related potential fields. As shown in Fig. 3, we find that points lie in different positions activate with respect to different potential fields.

As for \( \tilde{p}_k^2 \), it is a special kind of quadratic surface equation with removing the cross items. However, this simplified formulation can still maintain a lot of different geometric shape. Every neighborhood \( N_i \) can build a local shape, and only the local shape matches well with the quadratic surface, they can have a stronger correlation value. That is very different from discrete convolution, which only takes the point-to-point relationship into consideration. In contrast, our potential convolution will take the point-to-shape relationship into account. We visualize the learned quadratic potential fields in Fig. 4.

In conclusion, we claim that the linear potential function can well encode the direction and distance information of input points, and the quadratic potential function can better encode more complex shape information between local neighborhoods and potential fields.

### 3.4. Simplification

In previous sections, we describe the computation process on only one single potential field. The naive implementation of \( \tilde{p}_k^1, \tilde{p}_k^1, \tilde{p}_k^2 \) is inefficient, and we find that the computation process of linear and quadratic functions can be highly paralleled by formulating them as point-wise convolution operations.

We can rewrite the above Eq. 5, Eq. 6, Eq. 7 to paralleled matrix multiplication:

\[
\tilde{p}^1(y_i) = Ay_i^T + D
\]

\[
\tilde{p}^1(y_i, n_i) = A(y_i + n_i)^T + D
\]

\[
\tilde{p}^2(y_i) = Ay_i^T + B(y_i)^T + D,
\]

where \( A \in \mathbb{R}^{D' \times 3}, B \in \mathbb{R}^{D' \times 3}, D \in \mathbb{R}^{D'} \) are the stacked parameters of potential function, i.e. \( A_k = a_k, B_k = b_k, D_k = d_k \).

And then, we can obtain the convolution kernels by:

\[
g(y_i) = (h \circ \tilde{P})(y_i)W,
\]

where \( W \in \mathbb{R}^{D' \times D} \) and \( W_k = w_k \). Then, we put Eq. 9 into Eq. 1, yields:

\[
(F \ast g)(x) = \sum_{x_i \in N_k} (h \circ \tilde{P})(x_i - x)Wf_i.
\]

### Implementation Details

The above formulation shows that potential convolution can be formulated as two terms, the potential fields related term \((h \circ \tilde{P})(x_i - x)\), and the feature related term \(Wf_i\). As for \((h \circ P)(x_i - x)\), the main computation is brought by the calculation of potential value. As shown in Eq. 8, we can implement each matrix multiplication as a point-wise convolution operator. As for \(\tilde{P}^1, \tilde{P}^2\), we can implement it via a point-wise convolution, whose kernel weight is \(A\) and bias is \(D\). As for \(\tilde{P}\), we can implement it via two point-wise convolution operators, one of them contains the kernel weight \(A\) without bias, and the other contains the kernel weight \(B\) with bias \(D\). Sequentially, \(Wf_i\) can be implemented via a point-wise convolution, whose kernel weight is \(W\).

### 4. Experiments

In order to evaluate the performance of potential convolution, we conduct experiments on several widely used datasets, ModelNet40 [44], ShapeNet [47], Semantic3D [11] and S3DIS [1]. To more fairly compare the effectiveness of our methods, we do not attempt to design a special network structure for potential convolution, but reuse the popular networks proposed by other related methods and plug in our potential convolution to the basic framework or replace the original point convolution with ours. We also
follow the default experiment settings as original papers and do not select specified hyper-parameters for potential convolution. All experiments show that potential convolution can well adapt to different structures and is not sensitive to experiment settings.

4.1. 3D Shape Classification

We use ModelNet40 [44] to evaluate the classification performance of our methods. There are 12,311 CAD models from 40 man-made object categories, split into 9,843 for training and 2,468 for testing. Rather than designing new network models, we directly reuse the most simple and popular model from PointNet [26] and PointNet++ [28] but replace the original point-wise convolution with our potential convolution.

**Classification Performance on ModelNet40** As shown in Tab. 2, our potential convolution outperforms other methods. By simply replacing the original point-wise convolution of PointNet [26], the performance has been largely improved. What’s more, normal vector gives benefit to the final accuracy, too. However, the quadratic potential convolution seems more proven to be overfitting in such an easy task, and achieves a lower performance in the validation set.
Table 1. Semantic segmentation results on S3DIS.

| Methods                     | OA(%) | mAcc(%) | mIoU(%) | ceil. | floor | wall | beam | col. | wind. | door | chair | table | book. | sofa | board | clut. |
|-----------------------------|-------|---------|---------|-------|-------|------|------|------|-------|------|-------|-------|-------|------|-------|------|
| PointNet [26]               | 85.9  | 63.9    | 57.3    | 92.3  | 98.2  | 79.4 | 0.1  | 17.6 | 22.8  | 62.1 | 80.6  | 74.4  | 66.7  | 31.7 | 62.2  | 56.7 |
| PointCNN [20]               | 90.0  | 73.7    | 67.7    | 90.5  | 97.4  | 77.0 | 0.0  | 20.7 | 39.0  | 31.3 | 69.4  | 71.5  | 38.5  | 57.3 | 48.8  | 39.8 |
| TangentConv [34]            | -     | 62.2    | 52.6    | 90.0  | 97.3  | 74.0 | 0.0  | 20.7 | 39.0  | 31.3 | 69.4  | 71.5  | 38.5  | 57.3 | 48.8  | 39.8 |
| ParamConv [40]              | -     | 67.1    | 58.3    | 92.3  | 96.2  | 75.9 | 0.3  | 6.0  | 69.5  | 63.5 | 66.9  | 66.5  | 57.3  | 68.9 | 59.1  | 46.2 |
| SegCloud [35]               | -     | 57.4    | 48.9    | 90.1  | 96.1  | 69.9 | 0.0  | 18.4 | 38.4  | 23.1 | 75.9  | 70.4  | 58.4  | 40.9 | 13.0  | 41.6 |
| SPGraph [17]                | 86.4  | 66.5    | 58.0    | 89.4  | 96.9  | 78.1 | 0.0  | 42.8 | 48.9  | 61.6 | 84.7  | 75.4  | 69.5  | 64.1 | 21.2  | 52.2 |
| Eff 3D Conv [50]            | -     | 68.3    | 51.8    | 79.8  | 93.9  | 69.0 | 0.2  | 28.3 | 38.5  | 48.3 | 71.1  | 73.6  | 48.7  | 59.2 | 29.3  | 33.1 |
| RNN Fusion [46]             | -     | 63.9    | 57.3    | 92.3  | 98.2  | 79.4 | 0.0  | 17.6 | 22.8  | 62.1 | 74.4  | 80.6  | 31.7  | 66.7 | 62.1  | 56.7 |
| SSP+SPG [16]                | 87.9  | 68.2    | 61.7    | 91.9  | 96.7  | 80.8 | 0.0  | 28.8 | 60.3  | 57.2 | 85.5  | 76.4  | 70.5  | 49.1 | 51.6  | 53.3 |

Point Convolution

| Methods        | OA(%) | Settings   |
|----------------|-------|------------|
| Subvolume [27] | 89.2  | voxel      |
| MVCNN [13]     | 92.0  | mesh       |
| PointNet [26]  | 89.2  | 1024 pts   |
| PointNet++ [28]| 91.9  | 5000 pts   |
| ECC [32]       | 87.4  | graph      |

Point Convolution

| Methods        | OA(%) | Settings   |
|----------------|-------|------------|
| KPConv [37]    | 92.9  | 6800 avg. pts |
| FPConv [22]    | 92.5  | 1024 pts + nor |
| PointConv [43] | 92.5  | 1024 pts + nor |
| ConvPoint [4]  | 92.5  | 2048 pts + nor |
| PointNet++ [3] | 91.5  | 1024 pts   |
| PointNet++ [2] | 92.6  | 1024 pts + nor |
| PointNet++ [3] | 93.0  | 1024 pts + nor |

Table 2. Classification accuracy on ModelNet40. ● indicates that we reuse the previous network frameworks but replace the original point-wise convolution operation with our potential convolution.

| # Points | 64 | 128 | 256 | 512 | 1024 |
|----------|----|-----|-----|-----|------|
| PointConv [43] | 86.8 | 87.8 | 89.9 | 90.8 | 92.5 |
| KPConv [37] | 75.3 | 81.8 | 86.3 | 88.5 | 90.0 |
| Ours       | 90.2 | 91.1 | 91.5 | 91.6 | 92.6 |

Table 3. The performance under sparse input. (OA (%) is reported.)

Tolerance of sparse point clouds In this experiment, we compare the performance of different kernels under sparse input. We select KPConv [37] and PointConv [43], the most competitive discrete and continuous convolution methods, as our baseline. We use the same network as PointNet [26] but replace the point-wise convolution with our potential convolution.

All the experiments are implemented using the PyTorch [25] deep learning framework. The implementation of KPConv 1 and PointConv 2 are both directly taken from the official released source code. All experiment settings keep the same with the default implementation, except that the input point number is changed. We also use the corresponding protocols to train and evaluate with default parameters, which means that the training and evaluation phase may vary among different methods. We think it would be fair to compare performance for different methods with their original settings.

As shown in Tab. 3, either discrete or continuous convolution suffers from the sparse input points, but our potential convolution has a better tolerance to this issue, and can even achieve an accuracy over 90% with only 64 points as input.

4.2 3D Shape Segmentation

Given a point cloud, the part segmentation task is to recognize the different constitutive parts of the shape. We evaluate our model on the ShapeNet [47] part segmentation benchmark. It is composed of 16680 models belonging to 16 shape categories and split train/test sets. Each category is annotated with 2-to-6-part labels, from 50-part classes in total.

We use point class and instance average intersection-over-union (IoU) to evaluate our potential convolution, same as other part segmentation algorithms [26, 28, 37, 43, 4]. As shown in Tab. 5, we have achieved better performance than baseline and achieve comparable results among all methods. We also visualize the segmentation results in Fig. 6.

4.3 3D Scene Segmentation

This experiment shows how potential convolution generalizes to indoor and outdoor scenes. To this end, we choose to evaluate our method on the indoor S3DIS [1] dataset and outdoor Semantic3D [11] datasets. S3DIS covers six large-scale indoor areas from three different buildings with a to-

pytorch
### Table 4. Semantic segmentation results on Semantic3D.

| Methods            | OA(%) | mIoU(%) | man-made. | natural. | high veg. | low veg. | buildings | hard scape | scanning art. | cars |
|--------------------|-------|---------|-----------|----------|-----------|----------|-----------|------------|----------------|------|
| TMLC-MSR [12]      | 86.2  | 54.2    | 89.8      | 74.5     | 53.7      | 26.8     | 88.8      | 18.9       | 36.4           | 44.7 |
| DeePr3SS [18]      | 88.9  | 58.5    | 85.6      | 83.2     | 74.2      | 32.4     | 89.7      | 18.5       | 25.1           | 59.2 |
| SnapNet [5]        | 88.6  | 59.1    | 82.0      | 77.3     | 79.7      | 22.9     | 91.1      | 18.4       | 37.3           | 64.4 |
| RF_MSSF [36]       | 90.3  | 62.7    | 87.6      | 80.3     | 81.8      | 36.4     | 92.2      | 24.1       | 42.6           | 56.6 |
| MSDeepVoxNet [31]  | 88.4  | 65.3    | 83.0      | 67.2     | 83.8      | 36.7     | 92.4      | 31.3       | 50.0           | 78.2 |
| ShellNet [51]      | 93.2  | 69.3    | 96.3      | 90.4     | 83.9      | 41.0     | 94.2      | 34.7       | 43.9           | 70.2 |
| SegCloud [35]      | 88.1  | 61.3    | 83.9      | 66.0     | 86.0      | 40.5     | 91.1      | 30.9       | 27.5           | 64.3 |
| SPGraph [17]       | 94.0  | 73.2    | 97.4      |          |           |          |           |            |                |      |

Table 4. Semantic segmentation results on Semantic3D. ● indicates that we reuse the previous network frameworks but replace the original point-wise convolution operation with our potential convolution. We list the most competitive point convolution methods, some others also reported as a reference.

### Table 5. Results on ShapeNet part dataset. Class avg. is the mean IoU averaged across all object categories, and instance avg. is the mean IoU across all objects. ● indicates that we plugin our potential convolution operation to the previous network frameworks.

| Methods            | OA(%) | mAcc(%) |
|--------------------|-------|---------|
| Kd-Net [15]        | 77.4  | 82.3    |
| SO-Net [19]        | 81.0  | 84.9    |
| PCNN by Ext [2]    | 81.8  | 85.1    |
| PointNet++ [28]    | 81.9  | 85.1    |
| DGCNN [42]         | 82.3  | 85.1    |
| SPLATNet [33]      | 83.7  | 85.4    |

Table 5. Results on ShapeNet part dataset. Class avg. is the mean IoU averaged across all object categories, and instance avg. is the mean IoU across all objects. ● indicates that we plugin our potential convolution operation to the previous network frameworks.

Performance on Semantic3D As shown in Tab. 4, our methods can achieve state of the art performance in outdoor Semantic3D scenes. We visualize the segmentation results on Semantic3D in Fig. 5.

### 5. Conclusion

In this work, we propose a new type of point convolution, named as potential convolution. A learnable potential field is associated with each kernel to uncover the relationship between the points and the kernel weight. We provide two simple yet effective potential functions, explain why they would work and how they could be implemented efficiently using pointwise convolutions. Thorough experiments on the 3D vision tasks including shape classification, shape segmentation and scene segmentation demonstrate the superior performance of our methods.
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