点云是一种重要的几何数据,但是由于其不规则性,许多研究者把点云转换为规则的数据格式,例如3D Voxel和不同视角下的投影的图片.然而这样做将会造成数据量的增加(点云只有点,但是voxel是实心的网格,不同视角的图像就很大),因此会造成一些问题.本文提出了一种直接以点为输入的网络,称为PointNet.PointNet很好的处理了输入点云的置换不变性.PointNet提供了一种可以完成通用的(点云)任务的网络的框架,包括:物体分类,部件分割,语义理解.实验结果表明,有的任务上PointNet的性能超过了SOTA,有的任务上则和SOTA的性能等同.此外,本文给出了理论上的分析,说明了网络到底学到了些什么,以及为什么在面对(点云的)置换和坍塌的时候PointNet具有鲁棒性.

PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation

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Abstract

Point cloud is an important type of geometric data structure. Due to its irregular format, most researchers transform such data to regular 3D voxel grids or collections of images. This, however, renders data unnecessarily voluminous and causes issues. In this paper, we design a novel type of neural network that directly consumes point clouds, which well respects the permutation invariance of points in the input. Our network, named PointNet, provides a unified architecture for applications ranging from object classification, part segmentation, to scene semantic parsing. Though simple, PointNet is highly efficient and effective. Empirically, it shows strong performance on par or even better than state of the art. Theoretically, we provide analysis towards understanding of what the network has learnt and why the network is robust with respect to input perturbation and corruption.

本文探讨了能够对诸如点云和网格数据进行推理的深度学习网络结构.传统的基于卷积的网络需要输入的数据具有规范的格式,从而进行权值共享和其他的核优化的方法.

1. Introduction

In this paper we explore deep learning architectures capable of reasoning about 3D geometric data such as point clouds or meshes. Typical convolutional architectures require highly regular input data formats, like those of image grids or 3D voxels, in order to perform weight sharing and other kernel optimizations. Since point clouds or meshes are not in a regular format, most researchers typically transform such data to regular 3D voxel grids or collections of images (e.g, views) before feeding them to a deep net architecture. This data representation transformation, however, renders the resulting data unnecessarily voluminous — while also introducing quantization artifacts that can obscure natural invariances of the data.

正是因为点云不规则性,许多研究者都是先把点云转换为规则的数据,例如三维网格或者多视角图片,然后在丢到网络中去.可是这样做的一个问题就是会把原始数据处理的过于庞大,而由于量化会人为的引入的问题

For this reason we focus on a different input representation for 3D geometry using simply point clouds – and name our resulting deep nets *PointNets*. Point clouds are simple and unified structures that avoid the combinatorial irregularities and complexities of meshes, and thus are easier to learn from. The PointNet, however, still has to respect the fact that a point cloud is just a set of points and therefore invariant to permutations of its members, necessitating certain symmetrizations in the net computation. Further invariances to rigid motions also need to be considered.

因此,本文关注于从另外一种不同的3D数据:点云中进行学习,因此我们把本文提出的深度网络称为PointNet.点云是一种简单的,统一的结构,因此可以避免掉结合不规则性和网格数据的复杂性,因此更加容易去学习

点云中的每一个点以一个三维坐标(x,y,z)的形式出现,随着计算的进行,每一个点可能会增加新的表示全局/局部特征的维度

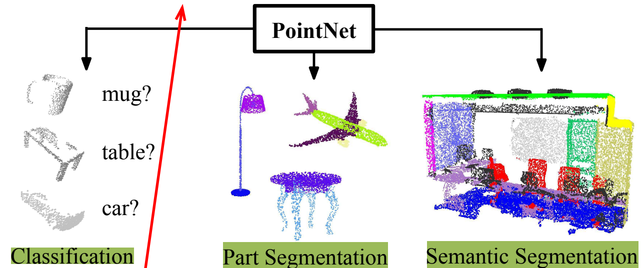


Figure 1. **Applications of PointNet.** We propose a novel deep net architecture that consumes raw point cloud (set of points) without voxelization or rendering. It is a unified architecture that learns both global and local point features, providing a simple, efficient and effective approach for a number of 3D recognition tasks.

但是不管怎么说,点云依旧是一组点的集合,因此就需要对点云的置换不变性进行特殊的处理.本文的处理就是在计算中引入对称性计算

Our PointNet is a unified architecture that directly takes point clouds as input and outputs either class labels for the entire input or per point segment/part labels for each point of the input. The basic architecture of our network is surprisingly simple as in the initial stages each point is processed identically and independently. In the basic setting each point is represented by just its three coordinates (x, y, z). Additional dimensions may be added by computing normals and other local or global features.

本文提出的PointNet是一个统一的结构,他可以直接输入整个点云,然后输出整个点云的类别,或着逐点的label.PointNet的网络结构是非常简单的,因为网络对所有的点进行了相同的,独立的操作

Key to our approach is the use of a single symmetric function, max pooling. Effectively the network learns a set of optimization functions/criteria that select interesting or informative points of the point cloud and encode the reason for their selection. The final fully connected layers of the network aggregate these learnt optimal values into the global descriptor for the entire shape as mentioned above (shape classification) or are used to predict per point labels (shape segmentation).

PointNet中最核心的就是使用了一个对称函数MaxPool,网络学习到了一些可以从点云选出最有信息的点.最终通过一个全连接来获得用于后续任务的全局描述符

Our input format is easy to apply rigid or affine transformations to, as each point transforms independently. Thus we can add a data-dependent spatial transformer network that attempts to canonicalize the data before the PointNet processes them, so as to further improve the results.

在点处理的过程中,因为输入是三维坐标的点云,因此非常简单就可以进行仿射变换这类操作,因此在点云被输入到点云中前,可以进行一些不需要从数据中学习的,独立的变换,这样来进一步提升结果.

* indicates equal contributions.

最后本文给出了对本文方法的理论和实验上的分析.通过理论分析发现了本文提出的网络可以逼近任意的连续的以集合作为输入的函数.有趣的是,结果表明,本文的模型会把输入的点云总结为一个稀疏的关键点的集合,可视化的结果表明,这些关键点总体上是原来点云的框架

We provide both a theoretical analysis and an experimental evaluation of our approach. We show that our network can approximate any set function that is continuous. More interestingly, it turns out that our network learns to summarize an input point cloud by a sparse set of key points, which roughly corresponds to the skeleton of objects according to visualization. The theoretical analysis provides an understanding why our PointNet is highly robust to small perturbation of input points as well as to corruption through point insertion (outliers) or deletion (missing data).

理论的分析解释了为什么PointNet对小的置换和输入的坍塌具有强大的鲁棒性

On a number of benchmark datasets ranging from shape classification, part segmentation to scene segmentation, we experimentally compare our PointNet with state-of-the-art approaches based upon multi-view and volumetric representations. Under a unified architecture, not only is our PointNet much faster in speed, but it also exhibits strong performance on par or even better than state of the art.

最后在三个任务的不同的数据集上比较的结果就是PointNet不仅更快,而且性能更好

The key contributions of our work are as follows:

- We design a novel deep net architecture suitable for consuming unordered point sets in 3D;
- We show how such a net can be trained to perform 3D shape classification, shape part segmentation and scene semantic parsing tasks;
- We provide thorough empirical and theoretical analysis on the stability and efficiency of our method;
- We illustrate the 3D features computed by the selected neurons in the net and develop intuitive explanations for its performance.

The problem of processing unordered sets by neural nets is a very general and fundamental problem – we expect that our ideas can be transferred to other domains as well.

2. Related Work

现存的大多数点云的特征都是手工设计的,这些特征包含了点云的特定的统计性质,并且对一些变换具有不变性.这些手工的特征可以分为:内部和外部,或者局部/全局特征

Point Cloud Features Most existing features for point cloud are handcrafted towards specific tasks. Point features often encode certain statistical properties of points and are designed to be invariant to certain transformations, which are typically classified as intrinsic [2, 21, 3] or extrinsic [18, 17, 13, 10, 5]. They can also be categorized as local features and global features. For a specific task, it is not trivial to find the optimal feature combination.

可是最关键的问题就是对于一个特定的任务,很难去设计,找到这样的特征

Deep Learning on 3D Data 3D data has multiple popular representations, leading to various approaches for learning. *Volumetric CNNs*: [25, 15, 16] are the pioneers applying 3D convolutional neural networks on voxelized shapes. However, volumetric representation is constrained by its resolution due to data sparsity and computation cost of 3D convolution. FPNN [12] and Vote3D [23] proposed special methods to deal with the sparsity problem; however, their operations are still on sparse volumes, it's challenging for them to process very large point clouds. *Multiview CNNs*: [20, 16] have tried to render 3D point cloud or shapes into 2D images and then apply 2D conv nets to classify them. With well engineered image CNNs, this line of methods have achieved dominating performance on shape classification and retrieval tasks [19]. However, it's nontrivial to extend them to scene understanding or other 3D tasks such as point classification and shape completion. *Spectral CNNs*: Some latest works [4, 14] use spectral CNNs on meshes. However, these methods are currently constrained on manifold meshes such as organic objects and it's not obvious how to extend them to non-isometric shapes such as furniture. *Feature-based DNNs*: [6, 8] firstly convert the 3D data into a vector, by extracting traditional shape features and then use a fully connected net to classify the shape. We think they are constrained by the representation power of the features extracted.

因为3D数据具有很多的表示方法,因此就有很多的方法被开发出来来从这些表示中进行学习.1.体素的卷积网络对体素化的点云进行学习.可是点云的稀疏性和三维卷积带来的巨大开销限制了体素化的方法.FPNN和Vote3D提出了一些方法来解决稀疏的问题,但是他们的方法还是用于稀疏的点云,无法扩展到大型的点云上去

Multiview的方法则是通过把点云投影到多个视角下形成多个2D的图像,然后再使用2D卷积的方法来进行识别.而在2D图像上CNN得到了fully engineered,因此这类方法在点云分类和检索上取得了巨大的成果,可是多视角的问题就在于难于运用到分割,分类,检索以及补全这类任务上去

一些最新的方法把谱卷积网络运用到mesh这类3D数据上去但是他们通常只能处理一些规则的物体,对于一些非等距的形状,例如家具就很难处理

基于特征的深度网络则是先把3D的数据转换成了向量,然后再从中抽取到传统的特征,最后使用一个全连接网络来进行分类,

这种方法的缺点就是模型的性能会受到抽取的feature的限制

Deep Learning on Unordered Sets From a data structure point of view, a point cloud is an unordered set of vectors. While most works in deep learning focus on regular input representations like sequences (in speech and language processing), images and volumes (video or 3D data), not much work has been done in deep learning on point sets.

从数据结构的角度来说,点云就是一个无序的向量的集合.可是现在目前绝大部分方法都关注于从规则的表示中进行学习,只有很少的一部分工作才是从点集中进行学习

One recent work from Oriol Vinyals et al [22] looks into this problem. They use a read-process-write network with attention mechanism to consume unordered input sets and show that their network has the ability to sort numbers. However, since their work focuses on generic sets and NLP applications, there lacks the role of geometry in the sets.

Oriol等人的工作开始尝试处理这种数据.他们通过一个具备了注意力机制的读处理写的网络来证明他们的网络有排序的能力,但是他们更加关注一般的集合并且是以NLP任务为载体

3. Problem Statement

We design a deep learning framework that directly consumes unordered point sets as inputs. A point cloud is represented as a set of 3D points $\{P_i|\ i = 1, ..., n\}$, where each point P_i is a vector of its (x, y, z) coordinate plus extra feature channels such as color, normal etc. For simplicity and clarity, unless otherwise noted, we only use the (x, y, z) coordinate as our point's channels.

For the object classification task, the input point cloud is either directly sampled from a shape or pre-segmented from a scene point cloud. Our proposed deep network outputs k scores for all the k candidate classes. For semantic segmentation, the input can be a single object for part region segmentation, or a sub-volume from a 3D scene for object region segmentation. Our model will output $n \times m$ scores for each of the n points and each of the m semantic subcategories.

对于物体分类任务而言,输入的点云要么是直接从物体的形状上获得的,要么是从一个场景中分割得到的.而分类的输出就是k个类的得分

对于部分/语义分类,输入是一个单独的物体,或者是一个3D场景中的一部分.模型输出是n*m的每个点对于的label

点云的特征:1.无序性,图像和voxel grid不同,他们都是像素或者voxel的矩阵,点云只是一些点的集合.因此,一个吃入了N个点的点云的模型应该对N!中顺序具有不变性.
2.局部语义性,点云中的点都是来自于具有欧几里得测度的空间中的.因此每个点都不是孤立的.一个点和周围的点在一起构成了丰富的语义信息.因此,一个点云模型需要能够从局部或者周围的点抽取得到特征,以及结合局部特征
3.变换不变性,因为点云是从一个形状上采集得到的,因此形状发生旋转,放缩这类变换的时候,点云也会发生对应的变化,可是因为还是同一个物体,因此分类,分割等等模型得到的结果都应该不变

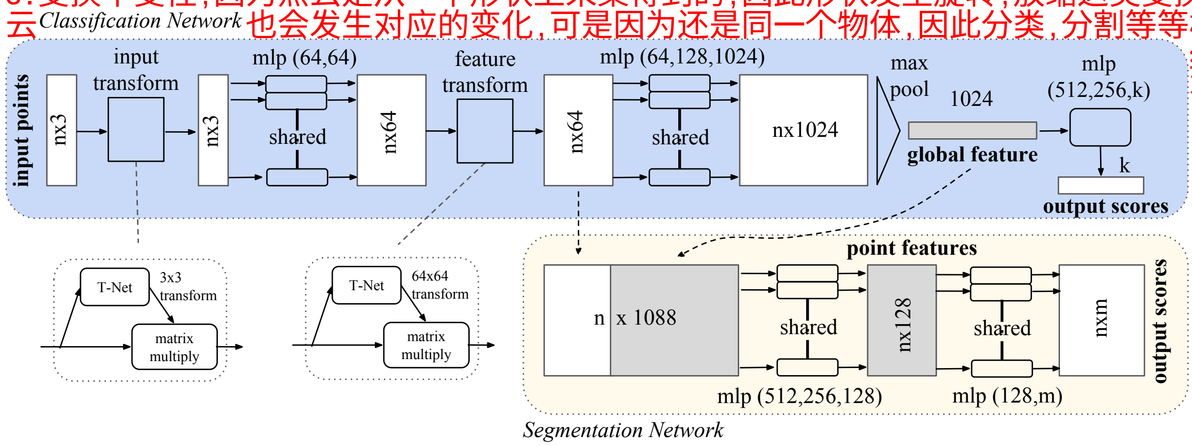


Figure 2. **PointNet Architecture.** The classification network takes n points as input, applies input and feature transformations, and then aggregates point features by max pooling. The output is classification scores for k classes. The segmentation network is an extension to the classification net. It concatenates global and local features and outputs per point scores. "mlp" stands for multi-layer perceptron, numbers in bracket are layer sizes. Batchnorm is used for all layers with ReLU. Dropout layers are used for the last mlp in classification net.

4. Deep Learning on Point Sets

The architecture of our network (Sec 4.2) is inspired by the properties of point sets in $\mathbb{R}^n$ (Sec 4.1).

4.1. Properties of Point Sets in $\mathbb{R}^n$

Our input is a subset of points from an Euclidean space. It has three main properties:

- Unordered. Unlike pixel arrays in images or voxel arrays in volumetric grids, point cloud is a set of points without specific order. In other words, a network that consumes N 3D point sets needs to be invariant to $N!$ permutations of the input set in data feeding order.
- Interaction among points. The points are from a space with a distance metric. It means that points are not isolated, and neighboring points form a meaningful subset. Therefore, the model needs to be able to capture local structures from nearby points, and the combinatorial interactions among local structures.
- Invariance under transformations. As a geometric object, the learned representation of the point set should be invariant to certain transformations. For example, rotating and translating points all together should not modify the global point cloud category nor the segmentation of the points.

4.2. PointNet Architecture

网络的主体部分是用于抽取通用特征的backbone,针对不同的后续任务后面接的模块不一样

Our full network architecture is visualized in Fig 2, where the classification network and the segmentation network share a great portion of structures. Please read the caption of Fig 2 for the pipeline.

Our network has three key modules: the max pooling layer as a symmetric function to aggregate information from all the points, a local and global information combination structure, and two joint alignment networks that align both input points and point features.

为了能够让模型具有置换不变性,有三种可能的思路:1.把无序的输入排序为有序的输入;2.把输入的点云当做一个序列,然后用一个RNN来训练,训练的时候使用各种顺序的点云来进行据增强;3.使用一个对称函数来从每个点中抽取到信息然后聚合

We will discuss our reason behind these design choices in separate paragraphs below.

Symmetry Function for Unordered Input In order to make a model invariant to input permutation, three strategies exist: 1) sort input into a canonical order; 2) treat the input as a sequence to train an RNN, but augment the training data by all kinds of permutations; 3) use a simple symmetric function to aggregate the information from each point. Here, a symmetric function takes n vectors as input and outputs a new vector that is invariant to the input order. For example, $+$ and $*$ operators are symmetric binary functions.

对称函数的意思,就是不同的顺序计算得到的结果是一样的函数

While sorting sounds like a simple solution, in high dimensional space there in fact does not exist an ordering that is stable w.r.t. point perturbations in the general sense. This can be easily shown by contradiction. If such an ordering strategy exists, it defines a bijection map between a high-dimensional space and a $1d$ real line. It is not hard to see, to require an ordering to be stable w.r.t point perturbations is equivalent to requiring that this map preserves spatial proximity as the dimension reduces, a task that cannot be achieved in the general case. Therefore, sorting does not fully resolve the ordering issue, and it's hard for a network to learn a consistent mapping from input to output as the ordering issue persists. As shown in experiments (Fig 5), we find that applying a MLP directly on the sorted point set performs poorly, though slightly better than directly processing an unsorted input.

虽然把无序的点云排序听起来是一个简单有效地方法,但是考虑到点云的无序性的时候,这样的排序方法其实是不存在的

The idea to use RNN considers the point set as a sequential signal and hopes that by training the RNN

使用RNN来学习点云的想法来源于把点云视为是一个序列的数据,然后希望在随机置换的点云序列上学习的RNN可以学习到对置换的不变性

可是，OrderMatter的作者认为即便是在随机置换的点云上学习的RNN依然无法完全解决置换不变性，置换还是会有影响．更重要的是，当输入的序列比较短的时候，RNN确实可以比较好的解决置换不变形，可是点云中一个输入往往就会长达几千，这个时候就很难让RNN去学习了．实验的结果表明这样得到的模型效果并不如我们的方法好

with randomly permuted sequences, the RNN will become invariant to input order. However in “OrderMatters” [22] the authors have shown that order does matter and cannot be totally omitted. While RNN has relatively good robustness to input ordering for sequences with small length (dozens), it's hard to scale to thousands of input elements, which is the common size for point sets. Empirically, we have also shown that model based on RNN does not perform as well as our proposed method (Fig 5).

我们的想法就是先对变换之后的点云使用一个对不同顺序通用的对称函数

Our idea is to approximate a general function defined on a point set by applying a symmetric function on transformed elements in the set:

$$f(\{x_1,\dots,x_n\}) \approx g(h(x_1),\dots,h(x_n)), \tag{1}$$

x_i表示不同的点，h是特征提取函数，g是实现置换不变性的函数，f是任务网络

h把输入的feature维度从n转换到k

where $f: 2^{\mathbb{R}^N} \rightarrow \mathbb{R}$, $h: \mathbb{R}^N \rightarrow \mathbb{R}^K$ and $g: \underbrace{\mathbb{R}^K \times \dots \times \mathbb{R}^K}_{n} \rightarrow \mathbb{R}$ is a symmetric function.

Empirically, our basic module is very simple: we approximate h by a multi-layer perceptron network and g by a composition of a single variable function and a max pooling function. This is found to work well by experiments. Through a collection of h, we can learn a number of f's to capture different properties of the set.

在实践中h就是一个全连接网络．g是变量函数和一个maxpool层．因为一个全连接网络学习一种特征．因此通过不同的全连接层就能学到不同的特征

While our key module seems simple, it has interesting properties (see Sec 5.3) and can achieve strong performace (see Sec 5.1) in a few different applications. Due to the simplicity of our module, we are also able to provide theoretical analysis as in Sec 4.3.

Local and Global Information Aggregation The output from the above section forms a vector $[f_1,\dots,f_K]$, which is a global signature of the input set. We can easily train a SVM or multi-layer perceptron classifier on the shape global features for classification. However, point segmentation requires a combination of local and global knowledge. We can achieve this by a simple yet highly effective manner.

上面网络f最终的输出就是一个描述原始点云特征的向量因此接下来就可以通过SVM或者MLP来完成分类．可是分割这样的任务需要局部和全局信息，因此其实还需要进一步的处理

Our solution can be seen in Fig 2 (*Segmentation Network*). After computing the global point cloud feature vector, we feed it back to per point features by concatenating the global feature with each of the point features. Then we extract new per point features based on the combined point features - this time the per point feature is aware of both the local and global information.

With this modification our network is able to predict per point quantities that rely on both local geometry and global semantics. For example we can accurately predict per-point normals (fig in supplementary), validating that the network is able to summarize information from the point's local neighborhood. In experiment session, we also show that our model can achieve state-of-the-art performance on shape part segmentation and scene segmentation.

对点云的语义表示需要对一些明确的几何变换具有不变形．例如只改变视角而不改变形状或者大小的rigid transformation．因此我们就希望网络具备这样的能力，换而言之，同一个点云经过这样变换之后得到的多个不同的点云经过你模型之后得到的特征应该是一样的

Joint Alignment Network The semantic labeling of a point cloud has to be invariant if the point cloud undergoes certain geometric transformations, such as rigid transformation. We therefore expect that the learnt representation by our point set is invariant to these transformations.

要实现这样的能力一个自然的想法就是把输入的集合对齐到一个正则空间中．Jaderberg等人通过设计一个在GPU上定制的层来实现2D图像的对齐

A natural solution is to align all input set to a canonical space before feature extraction. Jaderberg et al. [9] introduces the idea of spatial transformer to align 2D images through sampling and interpolation, achieved by a specifically tailored layer implemented on GPU.

Our input form of point clouds allows us to achieve this goal in a much simpler way compared with [9]. We do not need to invent any new layers and no alias is introduced as in the image case. We predict an affine transformation matrix by a mini-network (T-net in Fig 2) and directly apply this transformation to the coordinates of input points. The mini-network itself resembles the big network and is composed by basic modules of point independent feature extraction, max pooling and fully connected layers. More details about the T-net are in the supplementary.

我们是通过一个小型的tnet来预测旋转矩阵．然后把旋转矩阵直接乘到输入的点的坐标上去

This idea can be further extended to the alignment of feature space, as well. We can insert another alignment network on point features and predict a feature transformation matrix to align features from different input point clouds. However, transformation matrix in the feature space has much higher dimension than the spatial transform matrix, which greatly increases the difficulty of optimization. We therefore add a regularization term to our softmax training loss. We constrain the feature transformation matrix to be close to orthogonal matrix:

不仅仅是坐标对变换的关系，对齐这个概念也可以类比到特征上去．但是由于特征的维度太高了，因此学习这样的变换矩阵就很困难，因此我们就给最后的分类损失中加入了一想来强迫模型学到的变换矩阵接近正交矩阵

$$L_{reg} = \|I - AA^T\|_F^2, \tag{2}$$

where A is the feature alignment matrix predicted by a mini-network. An orthogonal transformation will not lose information in the input, thus is desired. We find that by adding the regularization term, the optimization becomes more stable and our model achieves better performance.

4.3. Theoretical Analysis

Universal approximation We first show the universal approximation ability of our neural network to continuous set functions. By the continuity of set functions, intuitively, a small perturbation to the input point set should not greatly change the function values, such as classification or segmentation scores.

下面首先证明了我们的网络可以逼近任意一个连续的以集合作为输入的函数

Formally, let $\mathcal{X} = \{S : S \subseteq [0,1]^m \text{ and } |S| = n\}$, $f : \mathcal{X} \rightarrow \mathbb{R}$ is a continuous set function on $\mathcal{X}$ w.r.t to Hausdorff distance $d_H(\cdot,\cdot)$, i.e., $\forall \epsilon > 0, \exists \delta > 0$, for any $S, S' \in \mathcal{X}$, if $d_H(S,S') < \delta$, then $|f(S) - f(S')| < \epsilon$. Our theorem says that f can be arbitrarily approximated by our network given enough neurons at the max pooling layer, i.e., K in (1) is sufficiently large.

对于分割任务，我们在通过分类网络获得了全局点云的描述符之后，我们通过把全局的特征拼接到单点的特征上，这样最终得到的feature其实就包含了局部和全局的特征

豪斯多夫距离量度度量空间中真子集之间的距离。Hausdorff距离是另一种可以应用在边缘匹配算法的距离，它能够解决SED方法不能解决遮挡的问题。

X表示输入的点云，f是定义在X上的连续函数，我们的定理证明了在神经元数足够的时候，我们的网络可以毕竟一个任意的连续函数

定理1证明了PointNet的网络结构能够拟合任意的连续集合函数。其作用类似证明神经网络能够拟合任意连续函数一样。同时，作者发现PointNet模型的表征能力和maxpooling操作输出的数据维度(K)相关，K值越大，模型的表征能力越强。

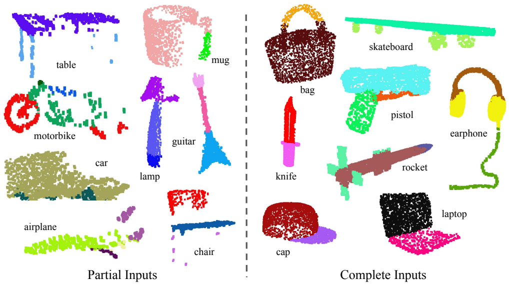


Figure 3. **Qualitative results for part segmentation.** We visualize the CAD part segmentation results across all 16 object categories. We show both results for partial simulated Kinect scans (left block) and complete ShapeNet CAD models (right block).

Theorem 1 *Suppose $f : \mathcal{X} \rightarrow \mathbb{R}$ is a continuous set function w.r.t Hausdorff distance $d_H(\cdot,\cdot)$. $\forall \epsilon > 0$, $\exists$ a continuous function h and a symmetric function $g(x_1, \ldots, x_n) = \gamma \circ MAX$, such that for any $S \in \mathcal{X}$,*

$$\left| f(S) - \gamma\left(\underset{x_i \in S}{MAX}\{h(x_i)\}\right)\right| < \epsilon$$

where $x_1, \ldots, x_n$ is the full list of elements in S ordered arbitrarily, γ is a continuous function, and MAX is a vector max operator that takes n vectors as input and returns a new vector of the element-wise maximum.

这里表示g这个对称函数由一个作用于单点的函数h,max函数和一个连续函数gamma组成

The proof to this theorem can be found in our supplementary material. The key idea is that in the worst case the network can learn to convert a point cloud into a volumetric representation, by partitioning the space into equal-sized voxels. In practice, however, the network learns a much smarter strategy to probe the space, as we shall see in point function visualizations.

从实践和理论上，我们发现模型的能力是受限于maxpool层的大小的因为h把点从n个feature转换到k个feature上去，然后对称函数g再进行转换

Bottleneck dimension and stability Theoretically and experimentally we find that the expressiveness of our network is strongly affected by the dimension of the max pooling layer, i.e., K in (1). Here we provide an analysis, which also reveals properties related to the stability of our model.

We define $\mathbf{u} = \underset{x_i \in S}{\mathrm{MAX}}\{h(x_i)\}$ to be the sub-network of f which maps a point set in $[0,1]^m$ to a K-dimensional vector. The following theorem tells us that small corruptions or extra noise points in the input set are not likely to change the output of our network:

Theorem 2 *Suppose $\mathbf{u} : \mathcal{X} \rightarrow \mathbb{R}^K$ such that $\mathbf{u} = \underset{x_i \in S}{MAX}\{h(x_i)\}$ and $f = \gamma \circ \mathbf{u}$. Then,*

(a) $\forall S, \exists\, \mathcal{C}_S, \mathcal{N}_S \subseteq \mathcal{X}$, $f(T) = f(S)$ if $\mathcal{C}_S \subseteq T \subseteq \mathcal{N}_S$;

(b) $|\mathcal{C}_S| \leq K$

	input	#views	accuracy avg. class	accuracy overall
SPH [11]	mesh	-	68.2	-
3DShapeNets [25]	volume	1	77.3	84.7
VoxNet [15]	volume	12	83.0	85.9
Subvolume [16]	volume	20	86.0	**89.2**
LFD [25]	image	10	75.5	-
MVCNN [20]	image	80	**90.1**	-
Ours baseline	point	-	72.6	77.4
Ours PointNet	point	1	86.2	**89.2**

Table 1. **Classification results on ModelNet40.** Our net achieves state-of-the-art among deep nets on 3D input.

We explain the implications of the theorem. (a) says that $f(S)$ is unchanged up to the input corruption if all points in $\mathcal{C}_S$ are preserved; it is also unchanged with extra noise points up to $\mathcal{N}_S$. (b) says that $\mathcal{C}_S$ only contains a bounded number of points, determined by K in (1). In other words, $f(S)$ is in fact totally determined by a finite subset $\mathcal{C}_S \subseteq S$ of less or equal to K elements. We therefore call $\mathcal{C}_S$ the *critical point set* of S and K the *bottleneck dimension* of f.

对于模型来说，把S简化为小于等于K个点的真子点云是等价的

Combined with the continuity of h, this explains the robustness of our model w.r.t point perturbation, corruption and extra noise points. The robustness is gained in analogy to the sparsity principle in machine learning models. **Intuitively, our network learns to summarize a shape by a sparse set of key points.** In experiment section we see that the key points form the skeleton of an object.

所以说模型其实学会了把一个点云总结为一些关键点的集合

5. Experiment

Experiments are divided into four parts. First, we show PointNets can be applied to multiple 3D recognition tasks (Sec 5.1). Second, we provide detailed experiments to validate our network design (Sec 5.2). At last we visualize what the network learns (Sec 5.3) and analyze time and space complexity (Sec 5.4).

实验部分被分成了三大组实验，第一组实验证明了我们的方法可以用到多个3D任务上，第二组实验对网络的设计进行了验证，最后验证了网络学习到的内容，并且对时间和空间复杂度进行了验证

5.1. Applications

In this section we show how our network can be trained to perform 3D object classification, object part segmentation and semantic scene segmentation [1]. Even though we are working on a brand new data representation (point sets), we are able to achieve comparable or even better performance on benchmarks for several tasks.

3D Object Classification Our network learns global point cloud feature that can be used for object classification. We evaluate our model on the ModelNet40 [25] shape classification benchmark. There are 12,311 CAD models from 40 man-made object categories, split into 9,843 for

[1]More application examples such as correspondence and point cloud based CAD model retrieval are included in supplementary material.

定理2(a)说明对于任何输入数据集S，都存在一个最小集Cs和一个最大集Ns，使得对Cs和Ns之间的任何集合T，其网络输出都和S一样。这也就是说，模型对输入数据在有噪声(引入额外的数据点，趋于Ns)和有数据损坏(缺少数据点，趋于Cs)的情况都是鲁棒的。定理2(b)说明了最小集Cs的数据多少由maxpooling操作输出数据的维度K给出上界。换个角度来讲，PointNet能够总结出表示某类物体形状的关键点，基于这些关键点PointNet能够判别物体的类别。这样的能力决定了PointNet对噪声和数据缺失的鲁棒性。

	mean	aero	bag	cap	car	chair	ear phone	guitar	knife	lamp	laptop	motor	mug	pistol	rocket	skate board	table
# shapes		2690	76	55	898	3758	69	787	392	1547	451	202	184	283	66	152	5271
Wu [24]	-	63.2	-	-	-	73.5	-	-	-	74.4	-	-	-	-	-	-	74.8
Yi [26]	81.4	81.0	78.4	77.7	**75.7**	87.6	61.9	**92.0**	85.4	**82.5**	**95.7**	**70.6**	91.9	**85.9**	53.1	69.8	75.3
3DCNN	79.4	75.1	72.8	73.3	70.0	87.2	63.5	88.4	79.6	74.4	93.9	58.7	91.8	76.4	51.2	65.3	77.1
Ours	**83.7**	**83.4**	**78.7**	**82.5**	74.9	**89.6**	**73.0**	91.5	**85.9**	80.8	95.3	65.2	**93.0**	81.2	**57.9**	**72.8**	**80.6**

Table 2. **Segmentation results on ShapeNet part dataset.** Metric is mIoU(%) on points. We compare with two traditional methods [24] and [26] and a 3D fully convolutional network baseline proposed by us. Our PointNet method achieved the state-of-the-art in mIoU.

training and 2,468 for testing. While previous methods focus on volumetric and mult-view image representations, we are the first to directly work on raw point cloud. We uniformly sample 1024 points on mesh faces according to face area and normalize them into a unit sphere. During training we augment the point cloud on-the-fly by randomly rotating the object along the up-axis and jitter the position of each points by a Gaussian noise with zero mean and 0.02 standard deviation.

从每个网格中采样得到1024个点，训练过程中进行了数据增强，包括沿z轴旋转和随机添加高斯噪声

In Table 1, we compare our model with previous works as well as our baseline using MLP on traditional features extracted from point cloud (point density, D2, shape contour etc.). Our model achieved state-of-the-art performance among methods based on 3D input (volumetric and point cloud). With only fully connected layers and max pooling, our net gains a strong lead in inference speed and can be easily parallelized in CPU as well. There is still a small gap between our method and multi-view based method (MVCNN [20]), which we think is due to the loss of fine geometry details that can be captured by rendered images.

性能和MVCNN比起来还是有一点差距

3D Object Part Segmentation Part segmentation is a challenging fine-grained 3D recognition task. Given a 3D scan or a mesh model, the task is to assign part category label (e.g. chair leg, cup handle) to each point or face.

We evaluate on ShapeNet part data set from [26], which contains 16,881 shapes from 16 categories, annotated with 50 parts in total. Most object categories are labeled with two to five parts. Ground truth annotations are labeled on sampled points on the shapes.

我们把部分分割任务视为逐点分类问题

We formulate part segmentation as a per-point classification problem. Evaluation metric is mIoU on points. For each shape S of category C, to calculate the shape's mIoU: For each part type in category C, compute IoU between groundtruth and prediction. If the union of groundtruth and prediction points is empty, then count part IoU as 1. Then we average IoUs for all part types in category C to get mIoU for that shape. To calculate mIoU for the category, we take average of mIoUs for all shapes in that category.

In this section, we compare our segmentation version PointNet (a modified version of Fig 2, *Segmentation Network*) with two traditional methods [24] and [26] that both take advantage of point-wise geometry features and correspondences between shapes, as well as our own 3D CNN baseline. See supplementary for the detailed modifications and network architecture for the 3D CNN.

In Table 2, we report per-category and mean IoU(%) scores. We observe a 2.3% mean IoU improvement and our net beats the baseline methods in most categories.

We also perform experiments on simulated Kinect scans to test the robustness of these methods. For every CAD model in the ShapeNet part data set, we use Blensor Kinect Simulator [7] to generate incomplete point clouds from six random viewpoints. We train our PointNet on the complete shapes and partial scans with the same network architecture and training setting. Results show that we lose only 5.3% mean IoU. In Fig 3, we present qualitative results on both complete and partial data. One can see that though partial data is fairly challenging, our predictions are reasonable.

Semantic Segmentation in Scenes Our network on part segmentation can be easily extended to semantic scene segmentation, where point labels become semantic object classes instead of object part labels.

We experiment on the Stanford 3D semantic parsing data set [1]. The dataset contains 3D scans from Matterport scanners in 6 areas including 271 rooms. Each point in the scan is annotated with one of the semantic labels from 13 categories (chair, table, floor, wall etc. plus clutter).

为了把part分类运用到场景分类中，把每个房间分割成了1m*1m的小块

To prepare training data, we firstly split points by room, and then sample rooms into blocks with area 1m by 1m. We train our segmentation version of PointNet to predict

	mean IoU	overall accuracy
Ours baseline	20.12	53.19
Ours PointNet	**47.71**	**78.62**

Table 3. **Results on semantic segmentation in scenes.** Metric is average IoU over 13 classes (structural and furniture elements plus clutter) and classification accuracy calculated on points.

	table	chair	sofa	board	mean
# instance	455	1363	55	137	
Armeni et al. [1]	46.02	16.15	**6.78**	3.91	18.22
Ours	**46.67**	**33.80**	4.76	**11.72**	**24.24**

Table 4. **Results on 3D object detection in scenes.** Metric is average precision with threshold IoU 0.5 computed in 3D volumes.

Figure 4. **Qualitative results for semantic segmentation.** Top row is input point cloud with color. Bottom row is output semantic segmentation result (on points) displayed in the same camera viewpoint as input.

per point class in each block. Each point is represented by a 9-dim vector of XYZ, RGB and normalized location as to the room (from 0 to 1). At training time, we randomly sample 4096 points in each block on-the-fly. At test time, we test on all the points. We follow the same protocol as [1] to use k-fold strategy for train and test.

We compare our method with a baseline using hand-crafted point features. The baseline extracts the same 9-dim local features and three additional ones: local point density, local curvature and normal. We use standard MLP as the classifier. Results are shown in Table 3, where our PointNet method significantly outperforms the baseline method. In Fig 4, we show qualitative segmentation results. Our network is able to output smooth predictions and is robust to missing points and occlusions.

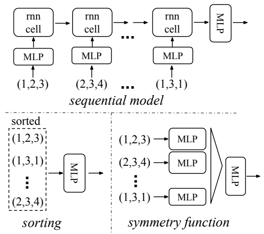
Based on the semantic segmentation output from our network, we further build a 3D object detection system using connected component for object proposal (see supplementary for details). We compare with previous state-of-the-art method in Table 4. The previous method is based on a sliding shape method (with CRF post processing) with SVMs trained on local geometric features and global room context feature in voxel grids. Our method outperforms it by a large margin on the furniture categories reported.

5.2. Architecture Design Analysis

In this section we validate our design choices by control experiments. We also show the effects of our network's hyperparameters.

Comparison with Alternative Order-invariant Methods As mentioned in Sec 4.2, there are at least three options for consuming unordered set inputs. We use the ModelNet40 shape classification problem as a test bed for comparisons of those options, the following two control experiment will also use this task.

The baselines (illustrated in Fig 5) we compared with include multi-layer perceptron on unsorted and sorted points as $n \times 3$ arrays, RNN model that considers input point as a sequence, and a model based on symmetry functions. The symmetry operation we experimented include max pooling, average pooling and an attention based weighted sum. The attention method is similar to that in [22], where a scalar score is predicted from each point feature, then the score is normalized across points by computing a softmax. The weighted sum is then computed on the normalized scores and the point features. As shown in Fig 5, max-pooling operation achieves the best performance by a large winning margin, which validates our choice.



	accuracy
MLP (unsorted input)	24.2
MLP (sorted input)	45.0
LSTM	78.5
Attention sum	83.0
Average pooling	83.8
Max pooling	**87.1**

Figure 5. **Three approaches to achieve order invariance.** Multi-layer perceptron (MLP) applied on points consists of 5 hidden layers with neuron sizes 64,64,64,128,1024, all points share a single copy of MLP. The MLP close to the output consists of two layers with sizes 512,256.

Effectiveness of Input and Feature Transformations In Table 5 we demonstrate the positive effects of our input and feature transformations (for alignment). It's interesting to see that the most basic architecture already achieves quite reasonable results. Using input transformation gives a 0.8% performance boost. The regularization loss is necessary for the higher dimension transform to work. By combining both transformations and the regularization term, we achieve the best performance.

Robustness Test We show our PointNet, while simple and effective, is robust to various kinds of input corruptions. We use the same architecture as in Fig 5's max pooling network. Input points are normalized into a unit sphere. Results are in Fig 6.

As to missing points, when there are 50% points missing, the accuracy only drops by 2.4% and 3.8% w.r.t. furthest and random input sampling. Our net is also robust to outlier

Transform	accuracy
none	87.1
input (3x3)	87.9
feature (64x64)	86.9
feature (64x64) + reg.	87.4
both	**89.2**

Table 5. **Effects of input feature transforms.** Metric is overall classification accuracy on ModelNet40 test set.

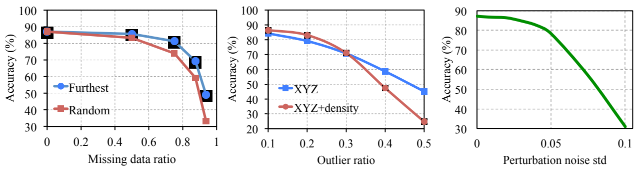


Figure 6. **PointNet robustness test.** The metric is overall classification accuracy on ModelNet40 test set. Left: Delete points. Furthest means the original 1024 points are sampled with furthest sampling. Middle: Insertion. Outliers uniformly scattered in the unit sphere. Right: Perturbation. Add Gaussian noise to each point independently.

points, if it has seen those during training. We evaluate two models: one trained on points with (x, y, z) coordinates; the other on (x, y, z) plus point density. The net has more than 80% accuracy even when 20% of the points are outliers. Fig 6 right shows the net is robust to point perturbations.

5.3. Visualizing PointNet

In Fig 7, we visualize some results of the *critical point sets* $\mathcal{C}_S$ and the *upper-bound shapes* $\mathcal{N}_S$ (as discussed in Thm 2) for some sample shapes S. The point sets between the two shapes will give exactly the same global shape feature $f(S)$.

We can see clearly from Fig 7 that the *critical point sets* $\mathcal{C}_S$, those contributed to the max pooled feature, summarizes the skeleton of the shape. The *upper-bound shapes* $\mathcal{N}_S$ illustrates the largest possible point cloud that give the same global shape feature $f(S)$ as the input point cloud S. $\mathcal{C}_S$ and $\mathcal{N}_S$ reflect the robustness of PointNet, meaning that losing some non-critical points does not change the global shape signature $f(S)$ at all.

The $\mathcal{N}_S$ is constructed by forwarding all the points in a edge-length-2 cube through the network and select points p whose point function values $(h_1(p), h_2(p), \cdots, h_K(p))$ are

颜色表示深度

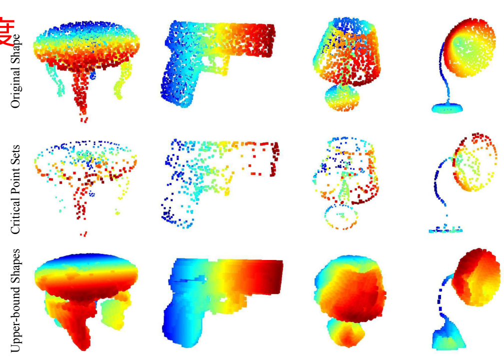


Figure 7. **Critical points and upper bound shape.** While critical points jointly determine the global shape feature for a given shape, any point cloud that falls between the critical points set and the upper bound shape gives exactly the same feature. We color-code all figures to show the depth information.

N是上界,S是下届

no larger than the global shape descriptor.

5.4. Time and Space Complexity Analysis

Table 6 summarizes space (number of parameters in the network) and time (floating-point operations/sample) complexity of our classification PointNet. We also compare PointNet to a representative set of volumetric and multi-view based architectures in previous works.

While MVCNN [20] and Subvolume (3D CNN) [16] achieve high performance, PointNet is orders more efficient in computational cost (measured in FLOPs/sample: *141x* and *8x* more efficient, respectively). Besides, PointNet is much more space efficient than MVCNN in terms of #param in the network (*17x* less parameters). Moreover, PointNet is much more scalable – it's space and time complexity is $O(N)$ – *linear* in the number of input points. However, since convolution dominates computing time, multi-view method's time complexity grows *squarely* on image resolution and volumetric convolution based method grows *cubically* with the volume size.

Empirically, PointNet is able to process more than one million points per second for point cloud classification (around 1K objects/second) or semantic segmentation (around 2 rooms/second) with a 1080X GPU on TensorFlow, showing great potential for real-time applications.

	#params	FLOPs/sample
PointNet (vanilla)	0.8M	148M
PointNet	3.5M	440M
Subvolume [16]	16.6M	3633M
MVCNN [20]	60.0M	62057M

Table 6. Time and space complexity of deep architectures for 3D data classification. PointNet (vanilla) is the classification PointNet without input and feature transformations. FLOP stands for floating-point operation. The "M" stands for million. Subvolume and MVCNN used pooling on input data from multiple rotations or views, without which they have much inferior performance.

6. Conclusion

In this work, we propose a novel deep neural network *PointNet* that directly consumes point cloud. Our network provides a unified approach to a number of 3D recognition tasks including object classification, part segmentation and semantic segmentation, while obtaining on par or better results than state of the arts on standard benchmarks. We also provide theoretical analysis and visualizations towards understanding of our network.

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