UNIVERSITY OF TEXAS ARLINGTON

AI VIET NAM

Point Cloud Techniques and Applications

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Agenda

- Section 1 (24/4): Introduction to Point Cloud and basic techniques to process
- Section 2 (26/4): Machine Learning with Point Cloud

Requirement

- Linear Algebra
- Basic (numpy)
- Advanced (pytorch)

Hints to effectively learn this course

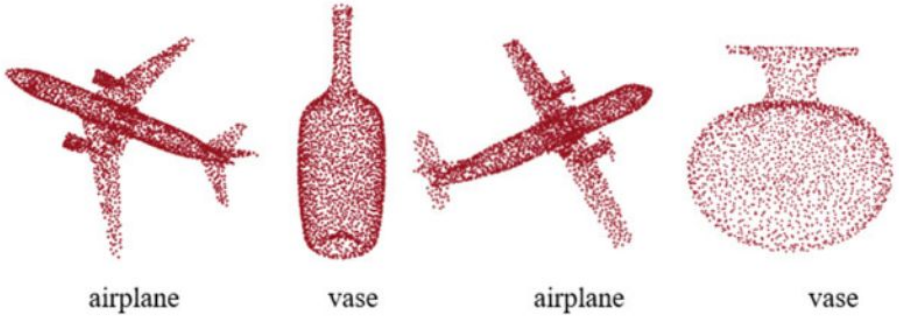
- Understanding is the key
- Concepts are connected in a chain: each concept is a link in a chain
- If you don’t understand some concepts at certain links, please stop or go back to review them
- Encourage ask questions even sometimes interrupt the instructor

Section 1
Introduction to Point Cloud and basic techniques to process

Content

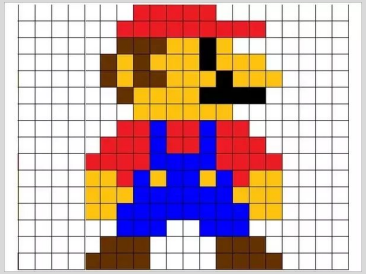
- Concepts of Point Cloud
- Data Acquisition, Sensors
- Camera Pinhole Model
- Noise Removal
- Sampling Techniques
- Surface Normal
- Surface Curvature
- Search on Point Cloud
- Data Structure for Efficient Search
- Registration
- Point Cloud Example Codes

What is a Point Cloud?



- A list of point 3D points:
  - [p1, p2, p3, ...]
- Each point can be represented
  - (X,Y,Z[,feature1,feature2...])
  - X,Y,Z
  - X,Y,Z,I (intensity)
  - X,Y,Z,R,G,B
  - ...
- The number of points may vary from one point cloud to another

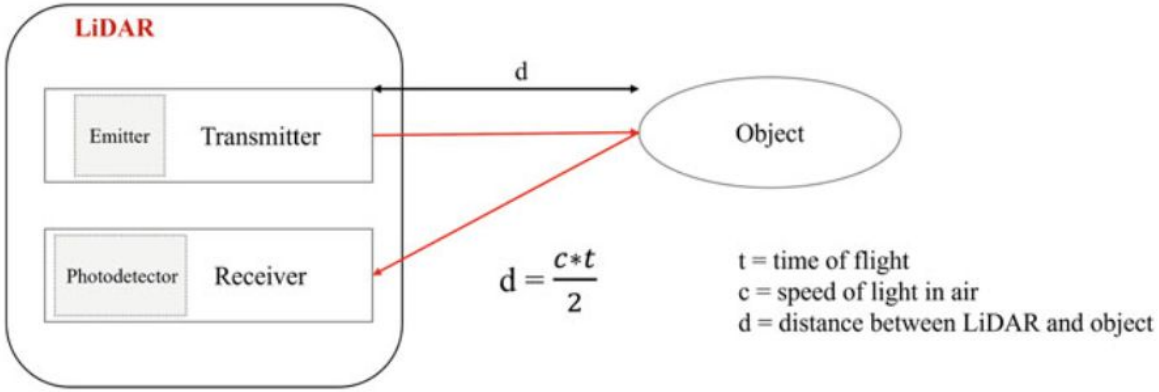
Point Cloud vs Image

	Unordered- irregular structure	Well-defined grid structure
Memory Space	 [p1, p2, …,] = [p2, p1, …,]	 WxHxC
Storage Space	txt, ply, bin	JPEG, PNG, BITMAP

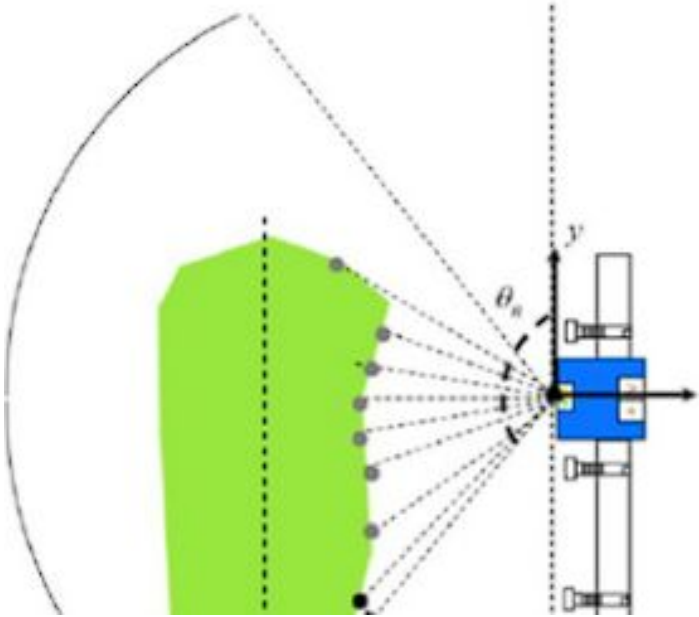
How to obtain pointcloud?

- LiDAR
- Depth images

LiDAR (outdoor)



Sing Beam

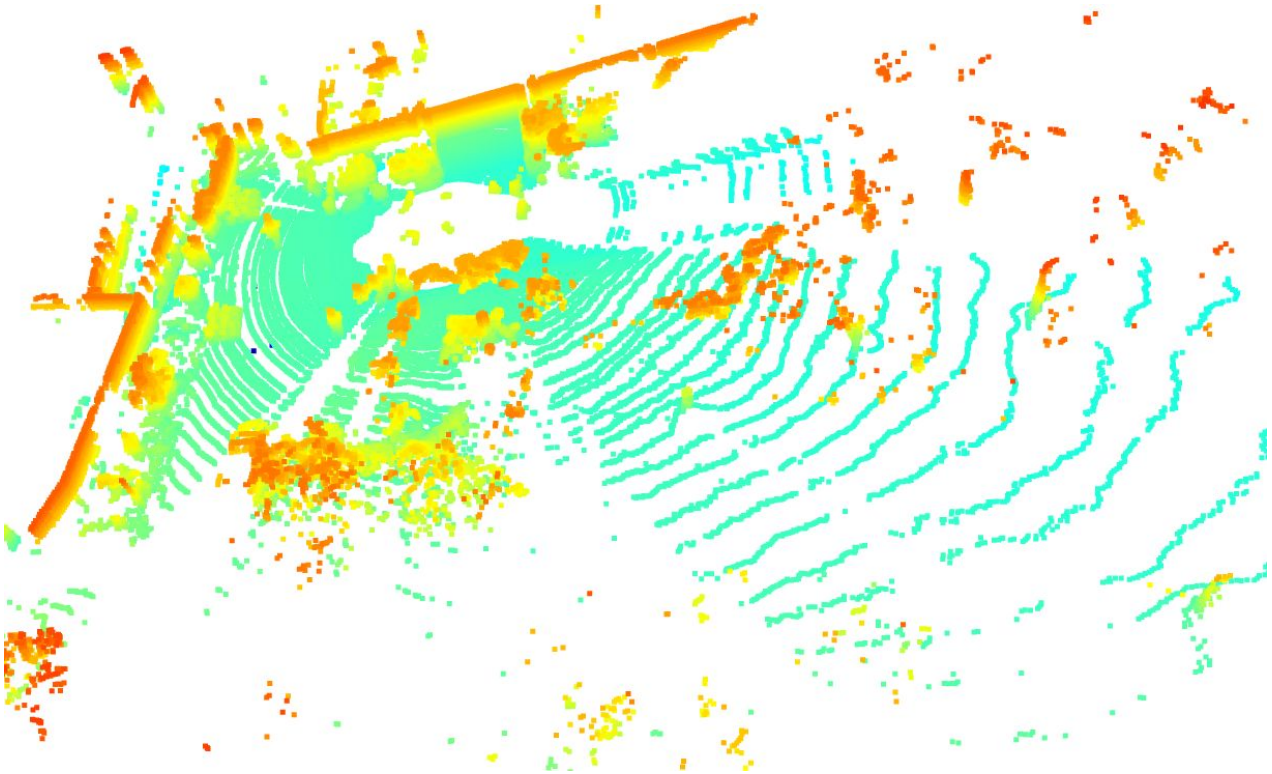


Multiple beams

For each point: (X,Y,Z, I)

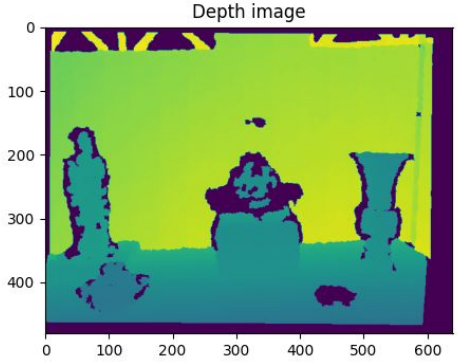
Industry LiDAR

LiDAR Data



Generated from: https://github.com/tuantdang/pointcloud_lessons/blob/main/session1/load_point_clouds.py

RGB-D camera (most popular, indoor)



Generated from: https://github.com/tuantdang/pointcloud_lessons/blob/main/session1/registration.py

Commercial RGB-D cameras

Microsoft
Kinect

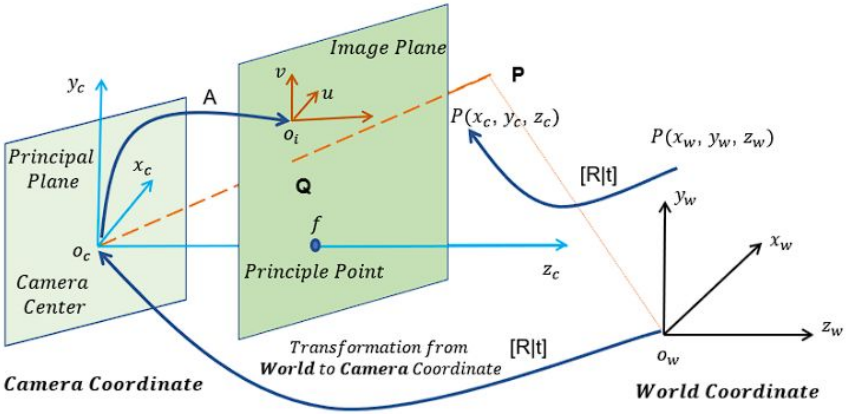
Intel
Realsense D435

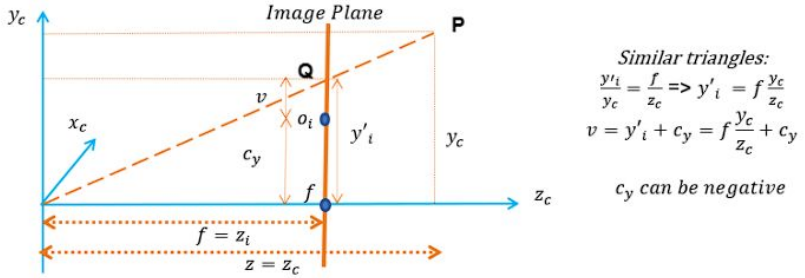
Intel
Realsense L515

Depth Measurement

- Stereo Vision
- Structure Light
- LiDAR with MEMS

Camera model (Pinhole)





Similar triangles:

$$\frac{y'_i}{y_c} = \frac{f}{z_c} \Rightarrow y'_i = f\frac{y_c}{z_c}$$

$$v = y'_i + c_y = f\frac{y_c}{z_c} + c_y$$

c_y can be negative

From world to camera

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \frac{1}{z}\begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix}\begin{bmatrix} x_c \\ y_c \\ 1 \end{bmatrix}$$

From Camera to World

$$\begin{bmatrix} x_c \\ y_c \\ z_c \end{bmatrix} = R\begin{bmatrix} x_w \\ y_w \\ z_w \end{bmatrix} + t = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix}\begin{bmatrix} x_w \\ y_w \\ z_w \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix}$$

or can be written as:

$$\begin{bmatrix} x_c \\ y_c \\ z_c \\ 1 \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix}\begin{bmatrix} x_w \\ y_w \\ z_w \\ 1 \end{bmatrix}$$

Point cloud processing

- Filter noises
  - Downsampling
  - Noise Removal
- Search
- Registration

Voxel Grid Sampling

- Build voxel grid
- Select point strategies
  - Random
  - Center point
  - Centroid point

Build Voxel Grid Coordinate

$$
\begin{aligned}
x_{\min} &= \min(x_1, x_2, \cdots, x_n), \\
x_{\max} &= \max(x_1, x_2, \cdots, x_n), \\
y_{\min} &= \min(y_1, y_2, \cdots, y_n), \\
&\vdots \\
z_{\max} &= \max(z_1, z_2, \cdots, z_n).
\end{aligned}
$$

Point Cloud Range

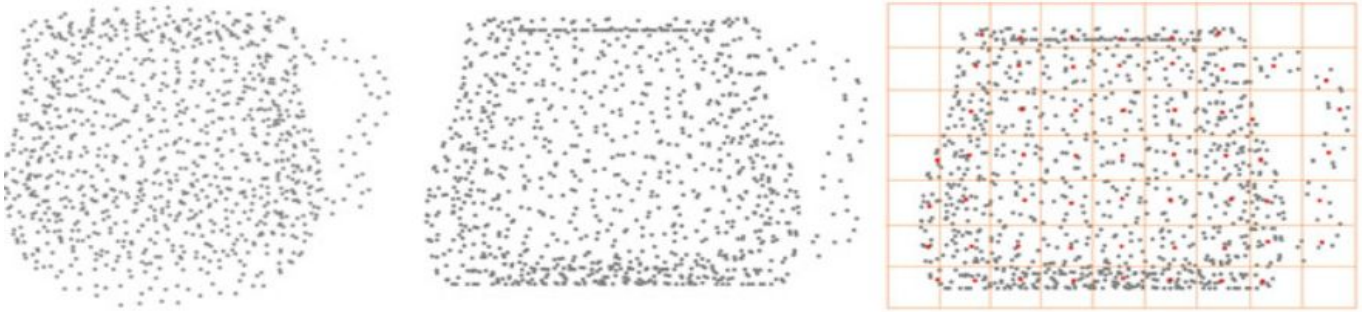
$$
\begin{aligned}
N_x &= (x_{\max} - x_{\min})/r, \\
N_y &= (y_{\max} - y_{\min})/r, \\
N_z &= (z_{\max} - z_{\min})/r,
\end{aligned}
$$

Grid Dimensions

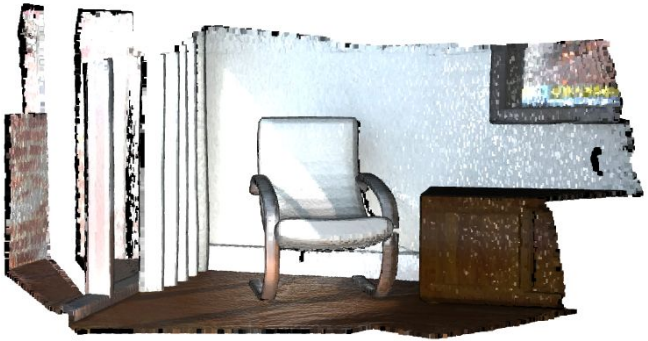
r : voxel size

$$
\begin{aligned}
i_x &= \lfloor (x - x_{\min})/r \rfloor, \\
i_y &= \lfloor (y - y_{\min})/r \rfloor, \\
i_z &= \lfloor (z - z_{\min})/r \rfloor, \\
i &= i_x + i_y * N_x + i_z * N_x * N_z.
\end{aligned}
$$

Voxel indexing
0,1,..., NxNyNz-1

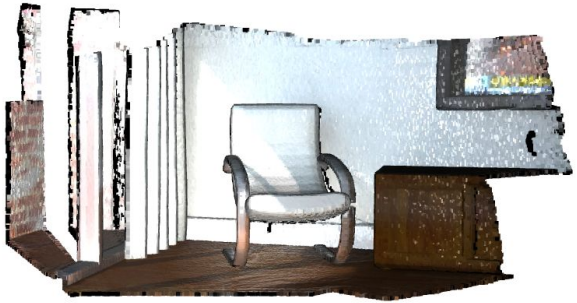


Center Point Selection

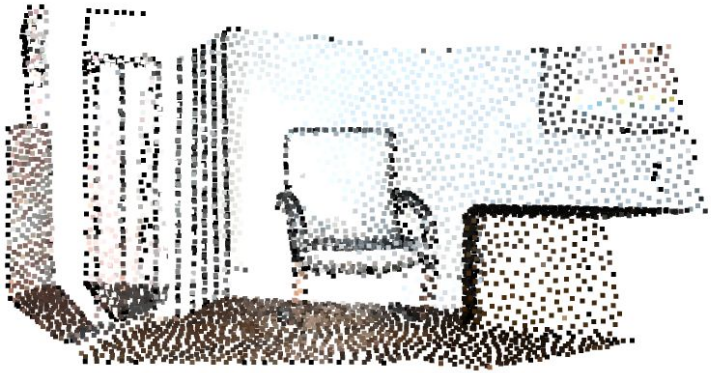


Furthest Point Sampling (FPS)

- This heuristic algorithm
- Algorithm
  - Step 1: Random select a point
  - Step 2: Calculate distances between current selected point to all remaining points
  - Step 3: Select a point which is the furthest to the previous point
  - Step 4: Loop step 2 & 3 until m points are chosen
- Advantages
  - Evenly across original point cloud
  - Capture Esen



Voxel Sampling



FPS

Generated from: https://github.com/tuantdang/pointcloud_lessons/blob/main/session1/down_sampling.py

Surface Normal

- A vector that is **perpendicular** to the plane
- A plane can be determined by
  - Perpendicular vector (a,b,c)
  - A point in the plane (x,y,z)
- Plane equation from perpendicular vector and inner-point: **a**x+**b**y+**c**z+d = 0

$$\mathbf{n} = [n_x, n_y, n_z]^T = \frac{[a, b, c]^T}{\|[a, b, c]^T\|}.$$

Normal vector in Practise

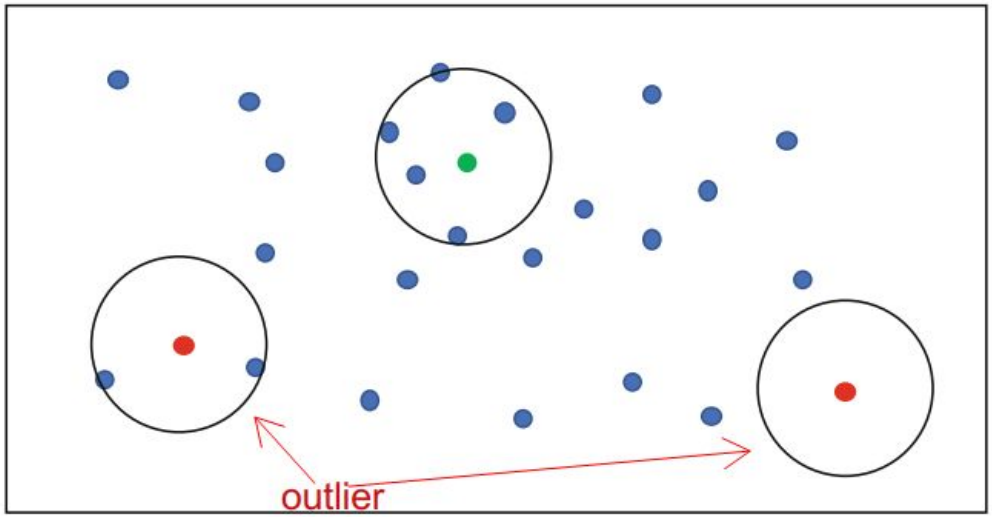
- Not points are perfect in a plane => eigenvector
- Collect a set of point
- Calculate eigenvectors and eigenvalues (λ1, λ2, λ3)
- The least driven-value is normal vector: **n = λ3**

Surface variance = Curvature

$$c = \frac{\lambda_3}{\lambda_1 + \lambda_2 + \lambda_3}$$

Noise Removal: Radius Outlier Removal

- Search around query point **p** with radius r, call **ball(p, r)**
- If number of points in the ball < k_{min}, **p** is outlier.



Radius outlier removal: $k_{min} = 4, r = 1$

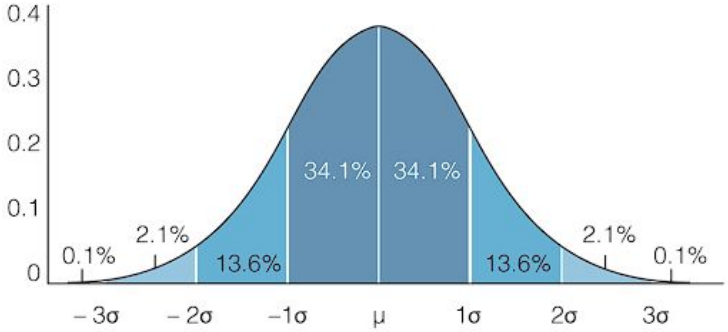
Statistical Outlier Removal

Model inlier as Gaussian **N(μ, σ) distribution**

- n : number of points, k neighbors, **c : variance steps**
- dij : distance from point i to point j

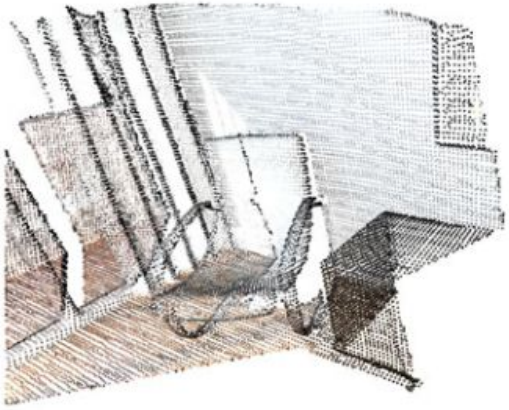
$$\mu = \frac{1}{nk}\sum_{i=1}^{n}\sum_{j=1}^{k} d_{ij}, \quad \sigma = \sqrt{\frac{1}{nk}\sum_{i=1}^{n}\sum_{j=1}^{k}(d_{ij}-\mu)^2}.$$

$$\frac{1}{k}\sum_{j=1}^{k} d_{ij} > \mu + c\sigma \quad \text{or} \quad \frac{1}{k}\sum_{j=1}^{k} d_{ij} < \mu - c\sigma, \; c \in \mathbb{R}^{+}.$$

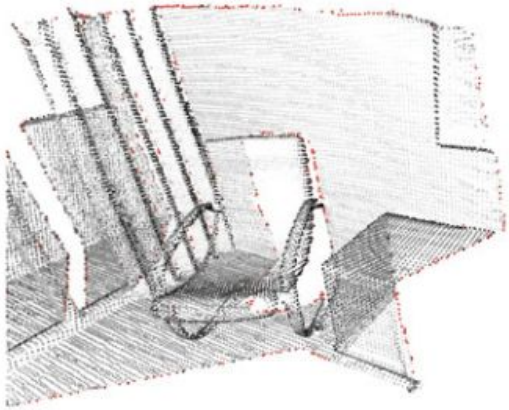


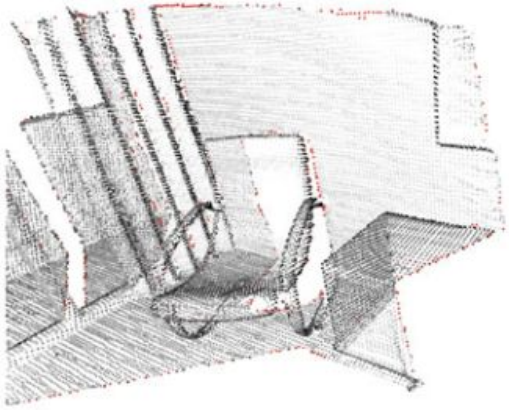
Examples

Original



(a) (b) Voxel size = 0.02





(c) (d)

kmin=16,r=0.05

Statistical Outlier removal k=20,c=2

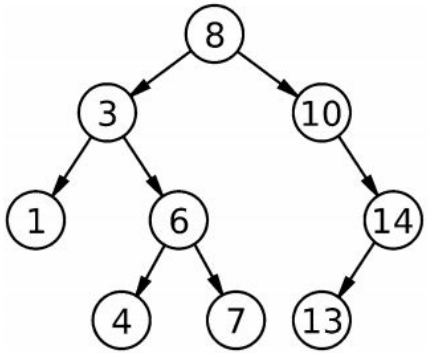
Search Nearest Neighbors (-NN)

- Why searching neighbors?
- K-NN : O(NlogN) or O(NlogK) since using sort algorithm
- Radius-NN : O(N) compute and compare

Comparison of K-NN and Radius-NN. (**a**) K-NN. (**b**) Radius-NN

1D-BST = 1D Binary Search Tree

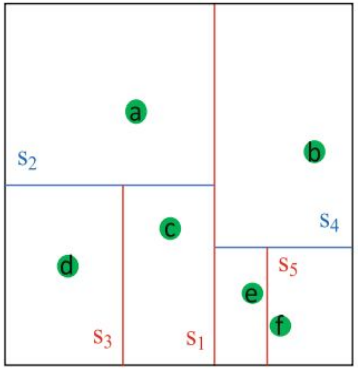
8,3,10,1,6,14,4,7,14

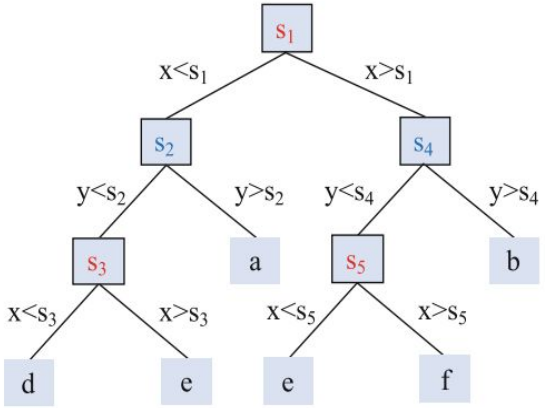


5

k-dimensional tree = k-d tree

- K-d tree is a BST where each node is k-dimensional point
- Example:
  - Input 2D points: a,b,c,d,e,f
  - Draw a line: perpendicular x-axis to separate two subsets
  - For each subset, draw lines:
    - perpendicular y-axis
    - Separate two subsets
  - Repeat until no more data
- Note: Using round-robin
  - 2D: perpendicular lines: x>y>x>y>...
  - 3D: perpendicular planes: x>y>z>x>y>z>...



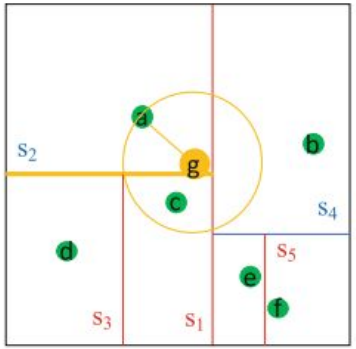


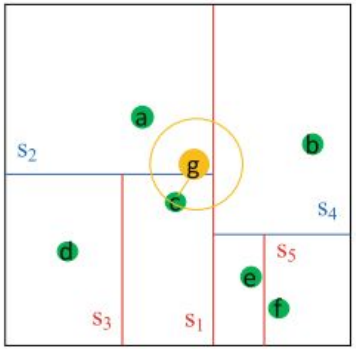
Construct 2-d tree from 2D data

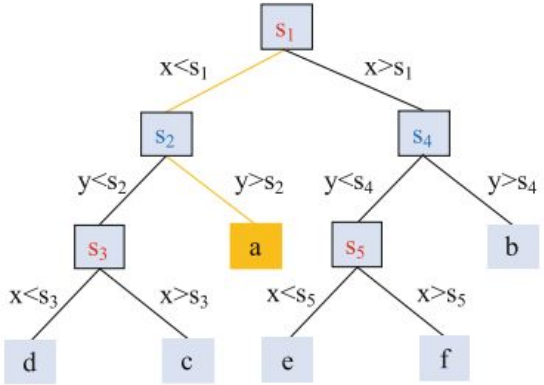
K-NN search on k-d tree

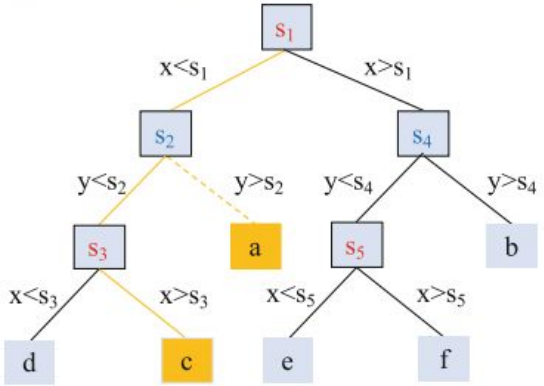
Example with K=2 and query **g, with worst distance d = infinity**

- Search from root s1
  - gx < s1 and gy >s2 where ||g-a|| < d store **a**.
  - Update d = ||g - a||
  - Since |gx-s1|<d and |gy-s2| < d, **c** is stored
  - Update d = ||g - c||
  - ....
- Complexity O(logN): best case and O(N) worst case

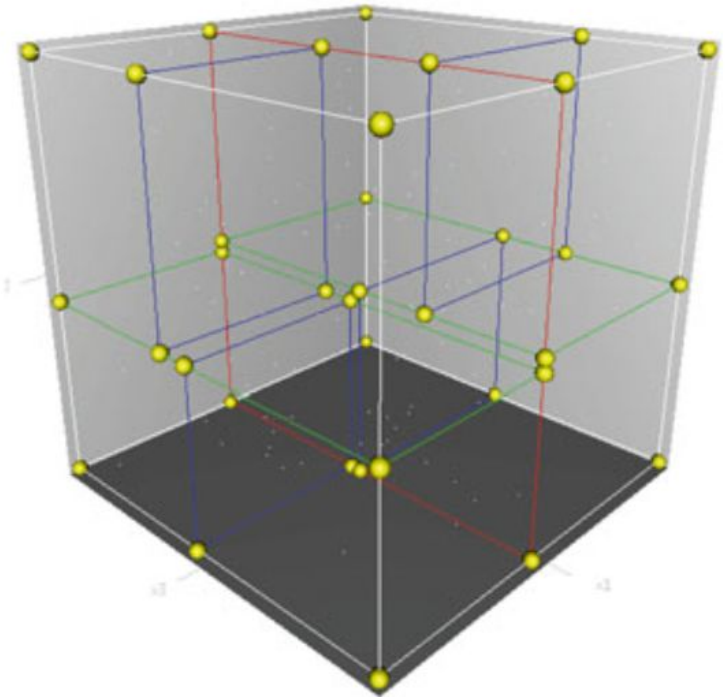






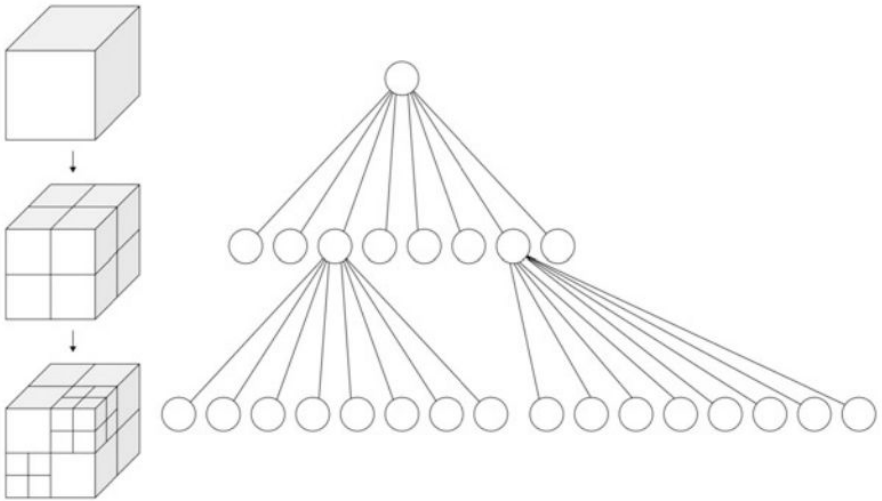


k-d tree with k=3



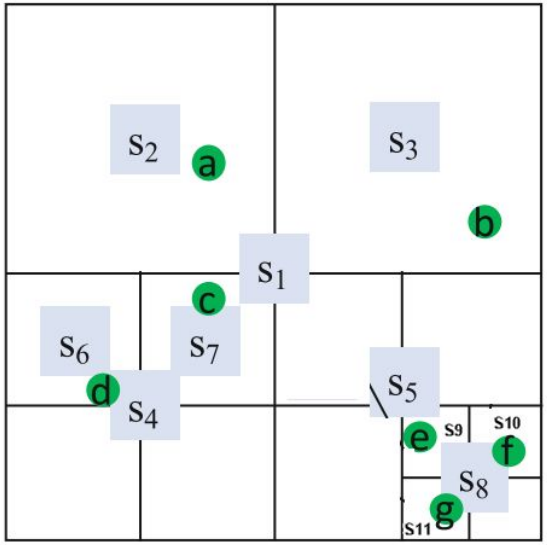
Octree

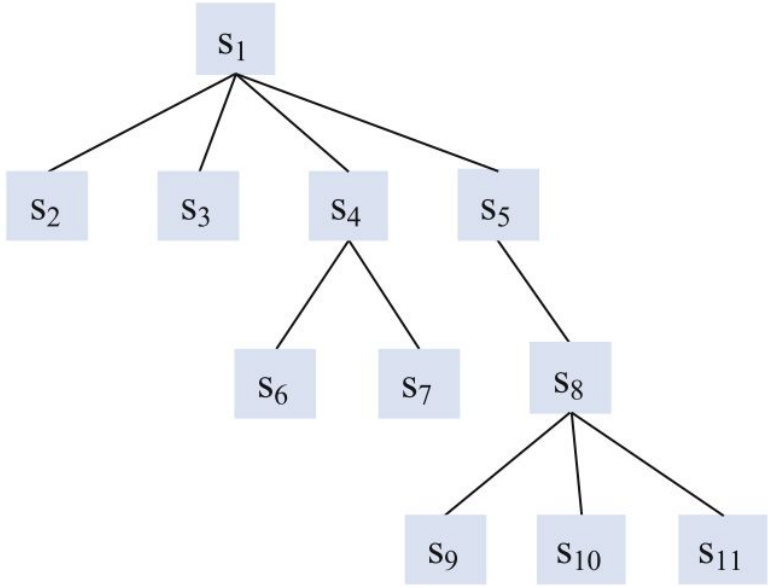
- k-d tree split along **a dimension** while octree split along **a point**.
- The center represents for the regions and has 8 children (3D) or 4 children (2D)



Octree construction

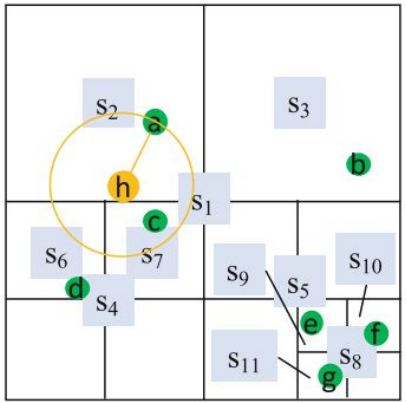
2D example a(4, 6), b(7,5), c(4,4), d(2,2), e(6, 3), f(8,2), g(7,1)

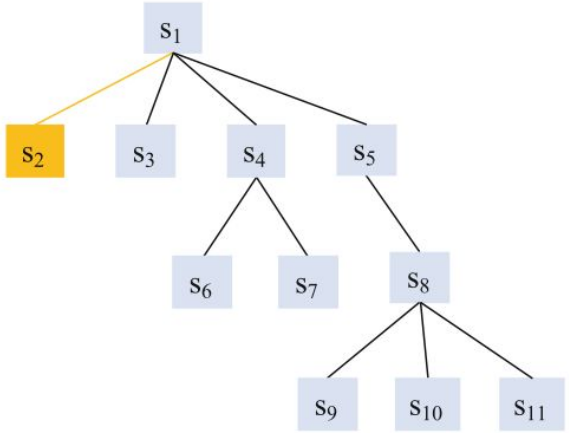


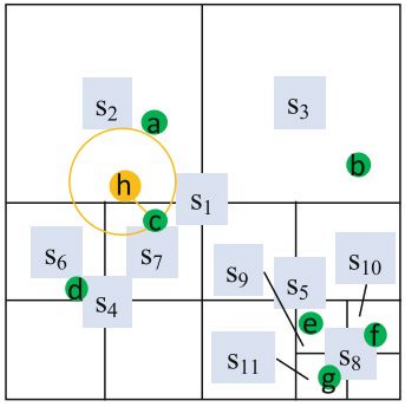


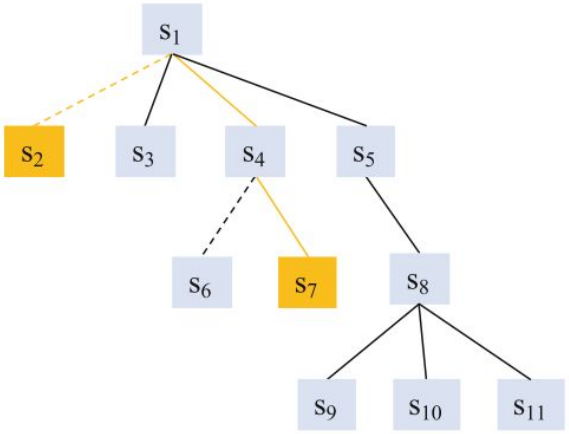
Octree search with K-NN

- Use Depth-First Search (DFS)
- Example :
  - Query **h**
  - k=2
  - Initialize distance **d = ∞**
  - Start from s1 find h in s2 among children > store **a**
  - Update d = ||h-a||
  - Ball circle(h, d) intersect with **s4**
  - Search children s4: s6,s7
  - Store **c** where d < |h-c|

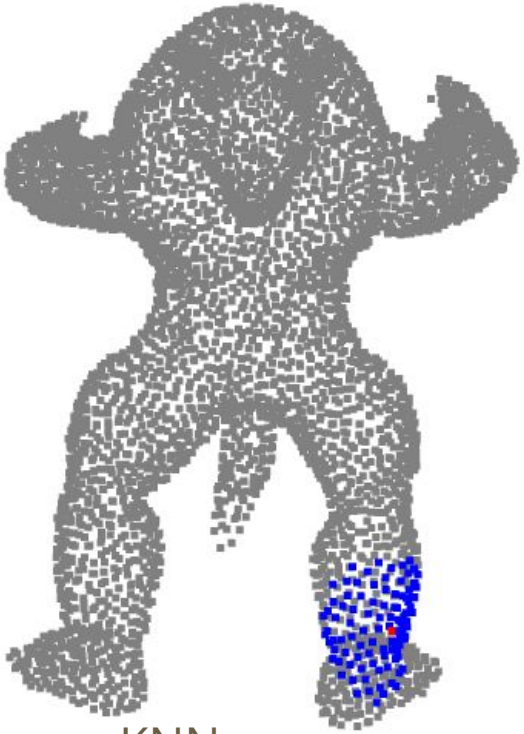




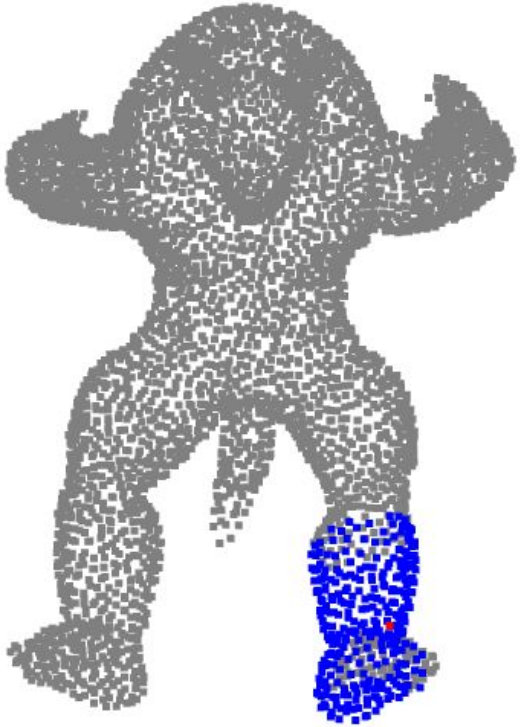




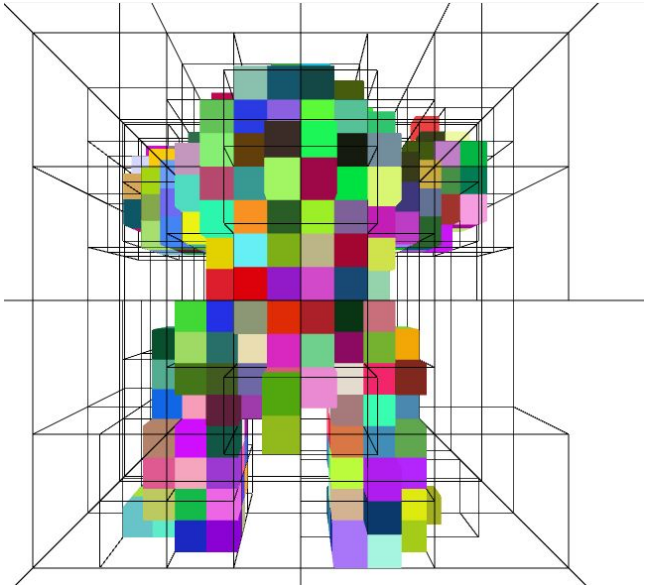
Example



KNN



Radius



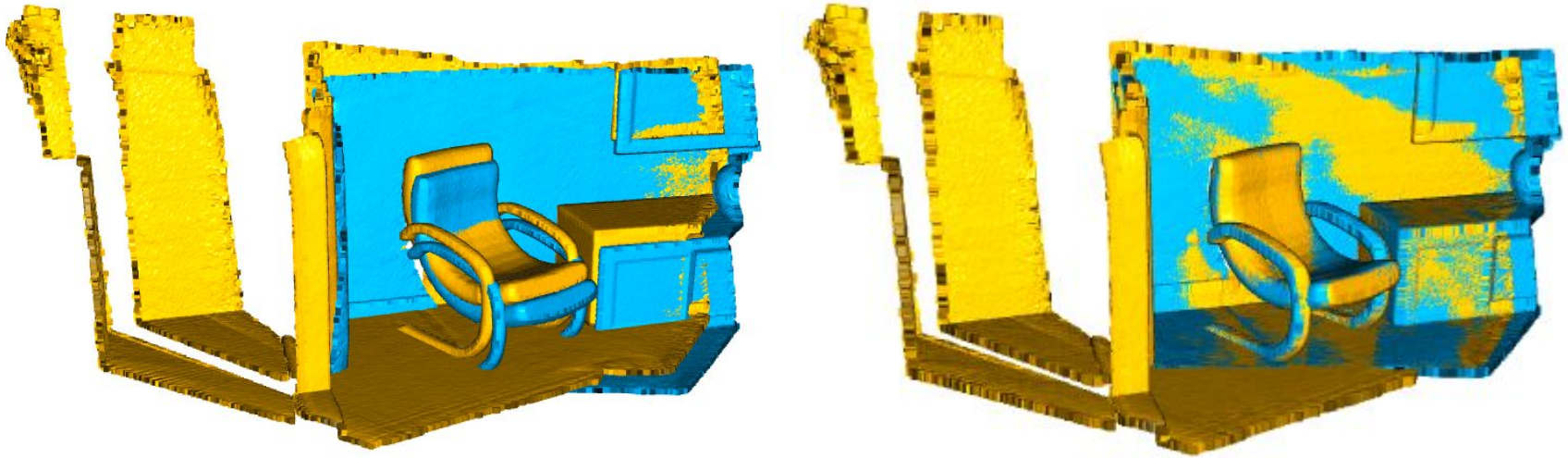
Octree

Registration

- Align two or more point clouds into **a common coordinate**
- Iterative Closest Point (ICP) is the most common method
  - Find the correspondence between two point sets
  - Find the transformation that minimizes the Euclidean distance between matching points
- Mathematic formation:
  - Let A = $\{a_i\}$, B = $\{b_j\}$ are two point sets
  - Let T is transformation
  - Point $\mathbf{m}_i$ in A which corresponding with $\mathbf{Tb}_j$
  - Find

$$T = \arg\min_{T} \left\{ \sum_{i} \| T \cdot b_i - m_i \|^2 \right\}$$

Example

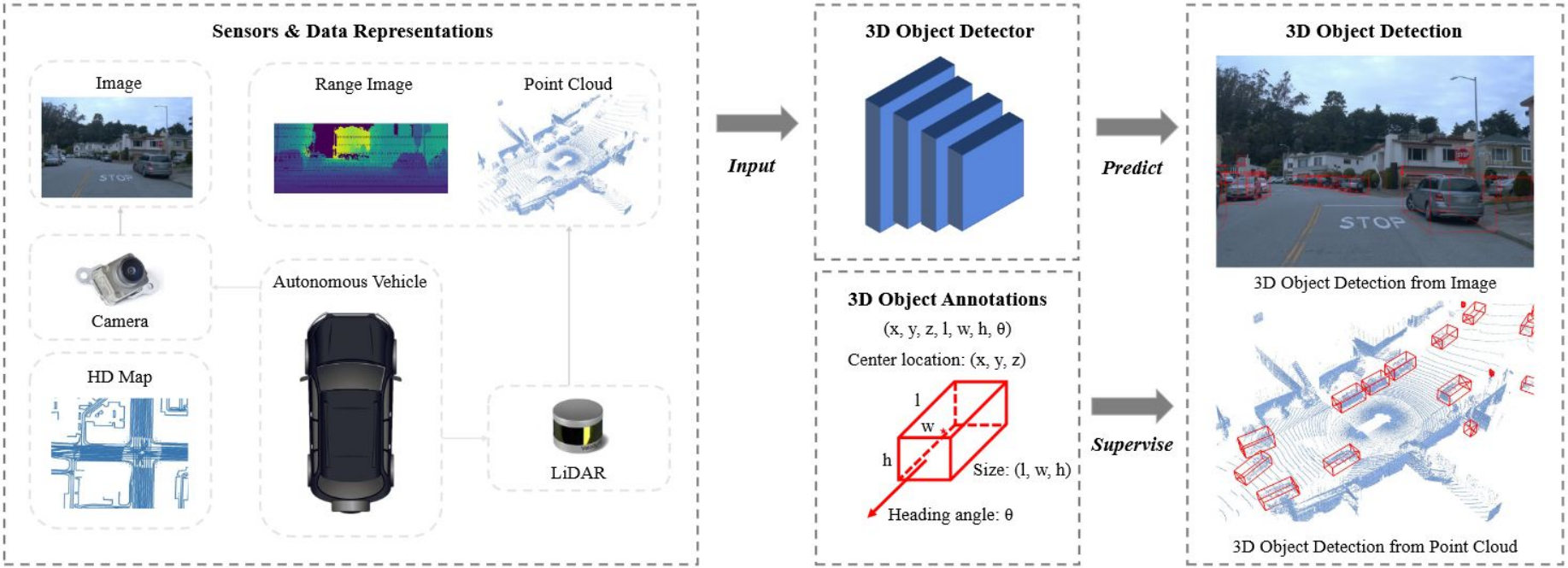


Coding Examples

- Introduction to **Open3D installation (v0.1)**
- Create folder to store all files below:
- Load a point cloud
  - Bin (KITTI): load_bin.py
  - Ply (Shapenet): load_ply.py
  - Txt (ModelNet): load_txt.py (convert from numpy PCL)
- Downsampling : **downsampling.py**
- Noise Removal : **noise_removal.py**
- Search neighbors: k-d-tree / octoc.tree (color search results)
- Registration: registration.py
- Reconstruct point cloud from RGB images and depth images:

Section 2
Deep Learning on Point Cloud

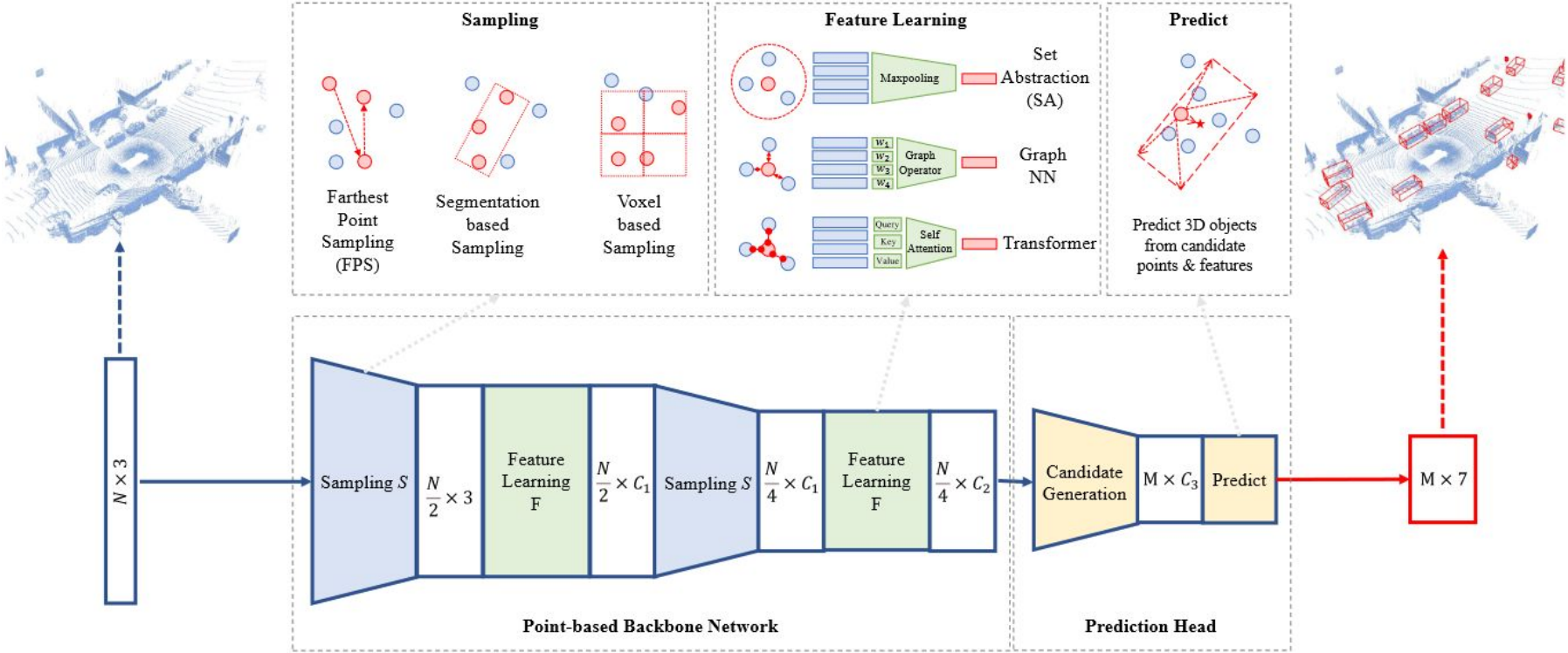
Overview


Sensors & Data Representations
Image
Range Image
Point Cloud
Camera
Autonomous Vehicle
HD Map
LiDAR
Input
3D Object Detector
3D Object Annotations
(x, y, z, l, w, h, θ)
Center location: (x, y, z)
l
w
h
Size: (l, w, h)
Heading angle: θ
Predict
Supervise
3D Object Detection
3D Object Detection from Image
3D Object Detection from Point Cloud

Datasets

Dataset	Year	Size (hr.)	Real-world	LiDAR scans	Images	3D annotations	Classes	night/rain	Locations	Other data
KITTI [80, 81]	2012	1.5	Yes	15k	15k	200k	8	No/No	Germany	-
KAIST [50]	2018	-	Yes	8.9k	8.9k	Yes	3	Yes/No	Korea	thermal images
ApolloScape [104, 166]	2019	100	Yes	20k	144k	475k	6	-/-	China	-
H3D [198]	2019	0.77	Yes	27k	83k	1.1M	8	No/No	USA	-
Lyft L5 [107]	2019	2.5	Yes	46k	323k	1.3M	9	No/No	USA	maps
Argoverse [29]	2019	0.6	Yes	44k	490k	993k	15	Yes/Yes	USA	maps
AIODrive [293]	2020	6.9	No	250k	250k	26M	-	Yes/Yes	-	long-range data
A*3D [202]	2020	55	Yes	39k	39k	230k	7	Yes/Yes	SG	-
A2D2 [82]	2020	-	Yes	12.5k	41.3k	-	14	-/-	Germany	-
Cityscapes 3D [77]	2020	-	Yes	0	5k	-	8	No/No	Germany	-
nuScenes [15]	2020	5.5	Yes	400k	1.4M	1.4M	23	Yes/Yes	SG, USA	maps, radar data
Waymo Open [250]	2020	6.4	Yes	230k	1M	12M	4	Yes/Yes	USA	maps
Cirrus [288]	2021	-	Yes	6.2k	6.2k	-	8	-/-	USA	long-range data
PandaSet [301]	2021	0.22	Yes	8.2k	49k	1.3M	28	Yes/Yes	USA	-
KITTI-360 [142]	2021	-	Yes	80k	300k	68k	37	-/-	Germany	-
Argoverse v2 [295]	2021	-	Yes	-	-	-	30	Yes/Yes	USA	maps
ONCE [172]	2021	144	Yes	1M	7M	417K	5	Yes/Yes	China	-

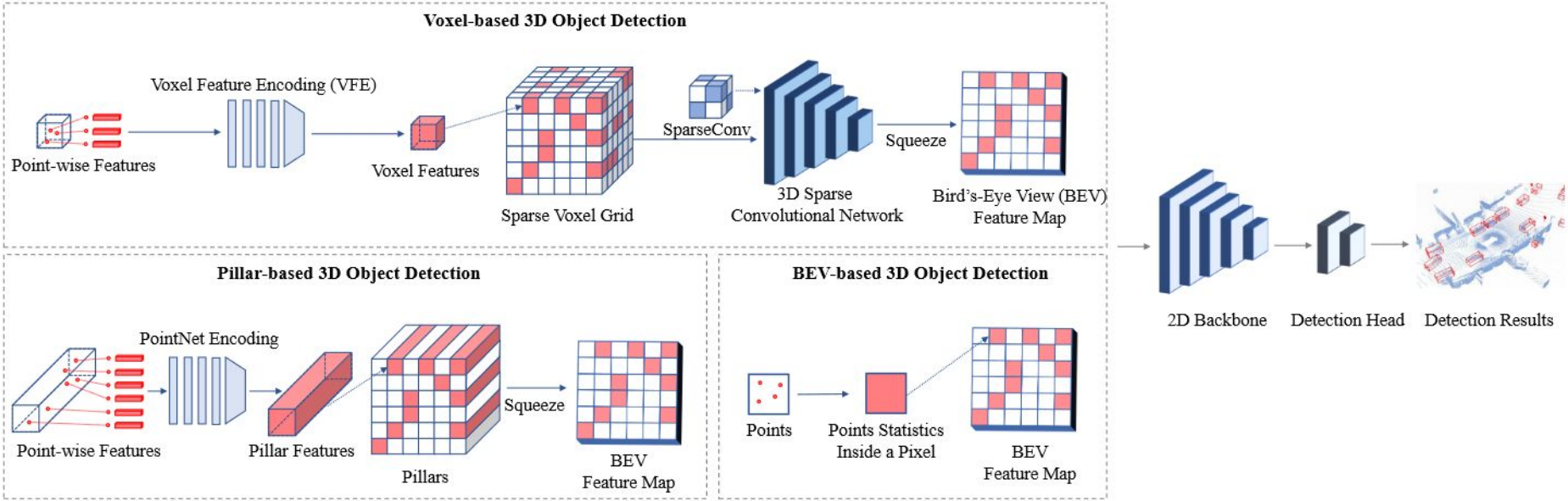
Point-based 3D methods



Examples

Method	Context Ω	Sampling S	Feature F
PointRCNN [234]	Ball Query	FPS	Set Abstraction
IPOD [318]	Ball Query	Seg.	Set Abstraction
STD [319]	Ball Query	FPS	Set Abstraction
3DSSD [321]	Ball Query	Fusion-FPS	Set Abstraction
Point-GNN [238]	Ball Query	Voxel	Graph
StarNet [189]	Ball Query	Targeted-FPS	Graph
Pointformer [193]	Ball Query	FPS + Refine	Transformer

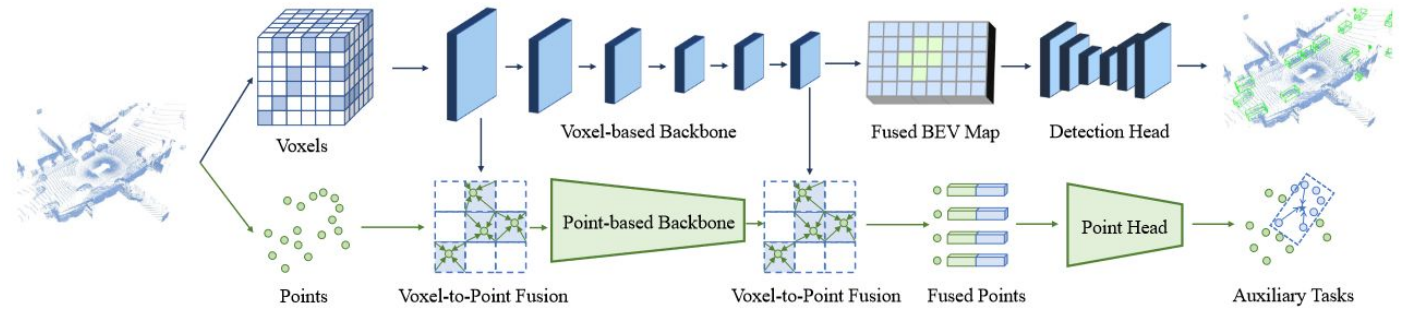
Voxel (3D grid)-based methods



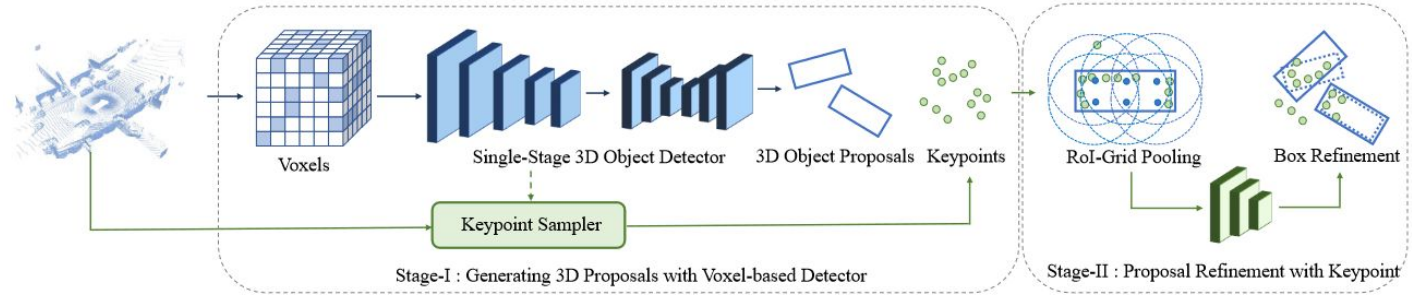
Example

Method	Representation	Feature Encoding	Backbone Model	Refinement Head
Vote3D [264]	voxel	voxelization	3D sparse CNN w/ voting	-
Vote3Deep [66]	voxel	voxelization	3D sparse CNN w/ voting	-
3D-FCN [118]	voxel	voxelization	3D FCN	-
VeloFCN [119]	BEV map	projection	2D FCN	-
BirdNet [10]	BEV map	projection	2D RPN	-
PIXOR [314]	BEV map	projection	2D CNN	-
HDNet [313]	BEV map, HD map	projection	2D CNN	-
VoxelNet [359]	voxel, BEV map	voxelization, VFE	3D sparse CNN, 2D RPN	-
SECOND [312]	voxel, BEV map	voxelization, VFE	3D sparse CNN, 2D RPN	-
MVF [360]	voxel, BEV+PV map	voxelization, VFE	2D CNN	-
PointPillars [117]	pillar, BEV map	PointNet encoding	2D CNN	-
Pillar-OD [283]	pillar, BEV+CYV map	PointNet encoding	2D CNN	-
Part-A^2 Net [236]	voxel, BEV map	voxelization, VFE	3D sparse CNN, 2D RPN	voxel head
Voxel R-CNN [57]	voxel, BEV map	voxelization, VFE	3D sparse CNN, 2D RPN	voxel head
CenterPoint [329]	voxel, BEV map	voxelization, VFE	3D sparse CNN, 2D RPN	-
Voxel Transformer [173]	voxel, BEV map	voxelization, VFE	3D Transformer, 2D RPN	-

Hybrid: Point-Voxel based methods



Single-Stage Point-Voxel Detection Framework



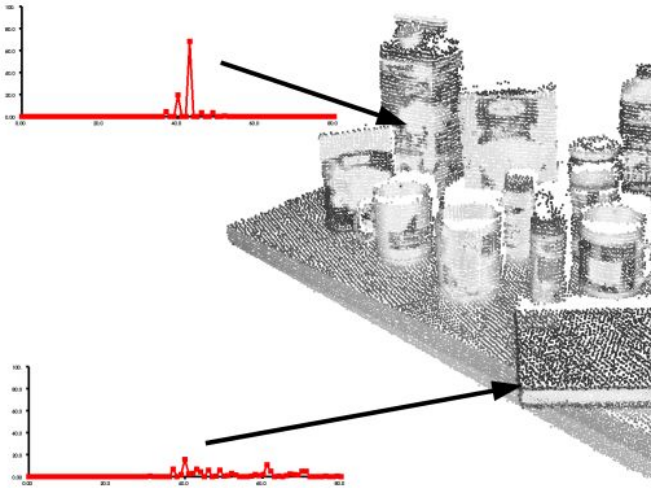
Two-Stage Point-Voxel Detection Framework

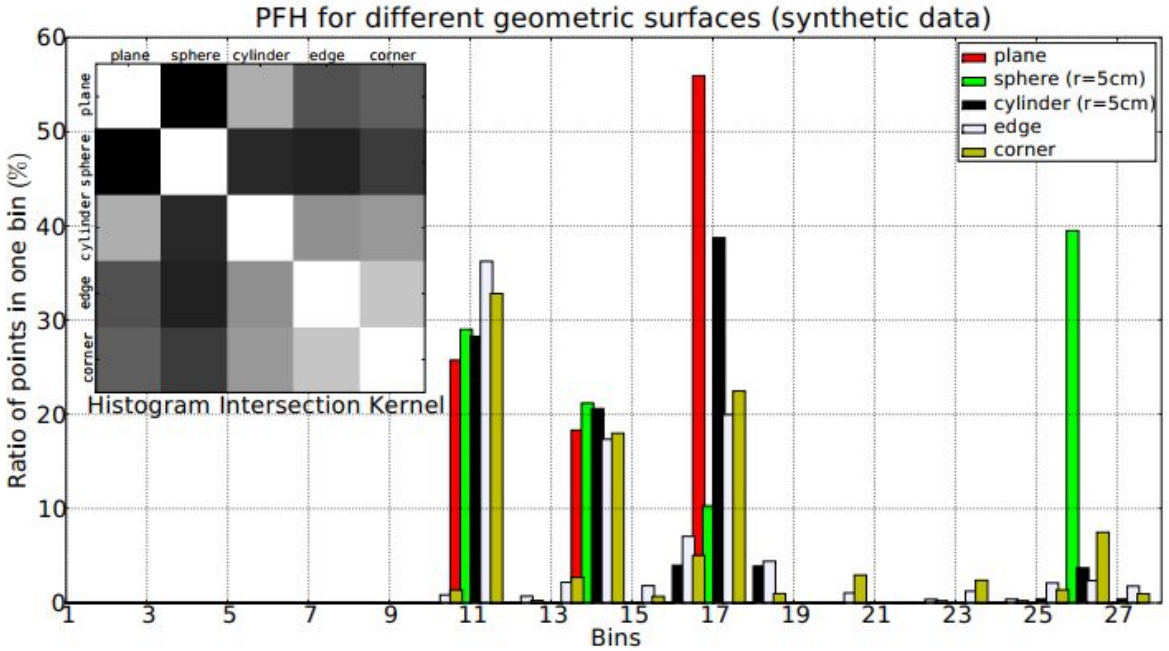
Examples

Method	Contribution
Single-Stage Detection Framework	
PVCNN [152]	Point-Voxel Convolution
SPVNAS [254]	Sparse Point-Voxel Convolution
SA-SSD [92]	Auxiliary Point Network
PVGNet [181]	Point-Voxel-Grid Fusion
Two-Stage Detection Framework	
Fast Point R-CNN [43]	RefinerNet
PV-RCNN [235]	RoI-grid Pooling
PV-RCNN++ [237]	VectorPool
Pyramid R-CNN [171]	RoI-grid Attention
LiDAR R-CNN [134]	Scale-aware Pooling
CT3D [233]	Channel-wise Transformer

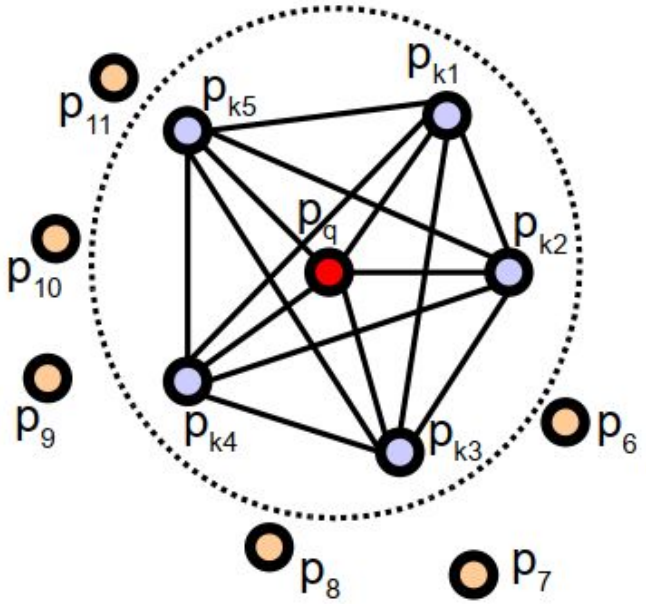
Intrinsic Geometry Features (Hand-crafted): Point Feature Histogram (PFH)

- Surface normal and curvature are too simple to represent point features





Algorithms

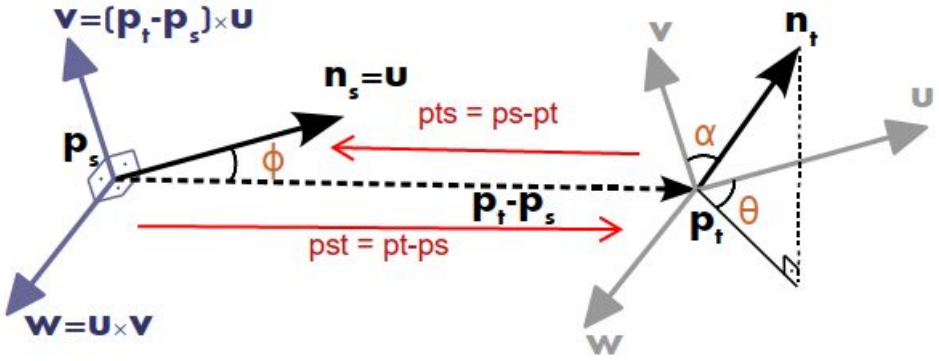


$$(\exists) r_1, r_2 \in \mathbb{R},\ r_1 < r_2,\ \text{such that} \begin{cases} r_1 \Rightarrow \mathcal{P}^{k_1} \\ r_2 \Rightarrow \mathcal{P}^{k_2} \end{cases}, \text{with } 0 < k_1 < k_2$$

Dual rings:

- First ring: estimate surface normal (see section 1)
- Second ring: estimate PFH

Darboux frame



$$\begin{cases} u = n_s \\ v = u \times \dfrac{(p_t - p_s)}{\|p_t - p_s\|_2} \\ w = u \times v \end{cases}$$

$$\alpha = v \cdot n_t$$

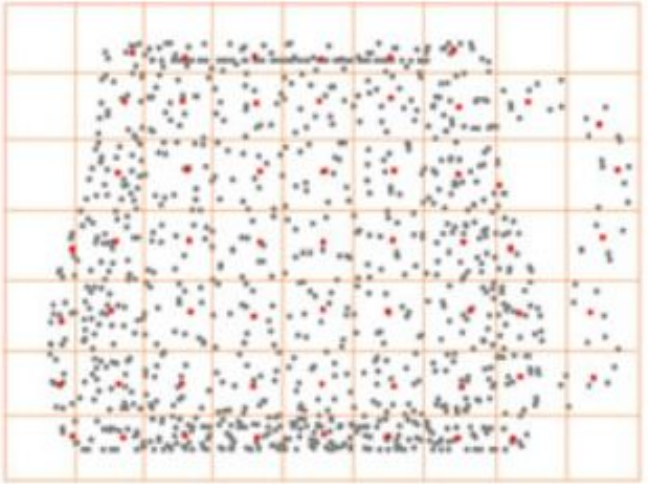
$$\phi = u \cdot \frac{(p_t - p_s)}{d}$$

$$\theta = \arctan(w \cdot n_t, u \cdot n_t)$$

- Binning quadruplets (α,ϕ,θ,d) and indexing to 1-dimension

Convolutional Operation on Point Cloud

- Cannot be applied directly as on images
  - Voxelize point cloud into grid coordinate
  - Define a fixed grid coordinate for all poincloud
  - 3D convolutional operation > memory & computing cost

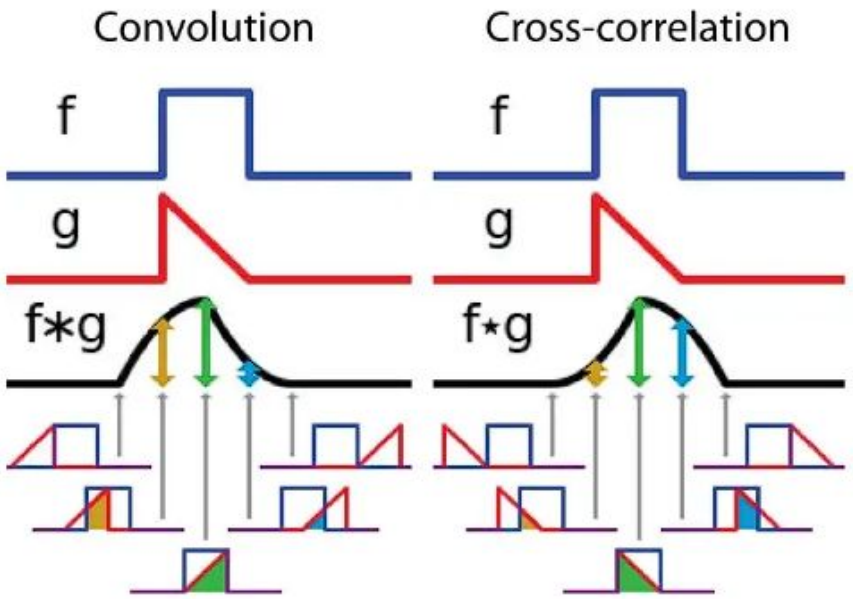


Reviews Convolution Operation

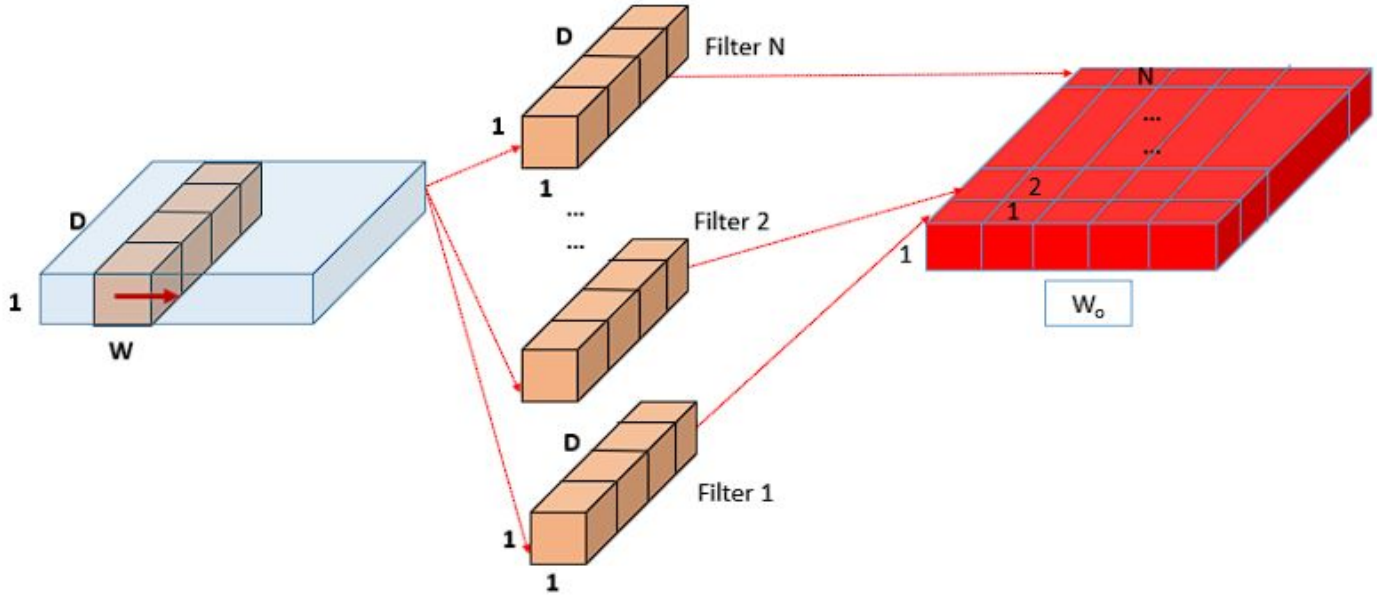
Continuous $(f * g)(t) = \int_{-\infty}^{\infty} f(\tau) \cdot g(t - \tau) d(\tau)$

Decrete $(f * g)(t_k) = \sum_{i=0}^{m} f(\tau_i) \cdot g(t_k - \tau_i)$

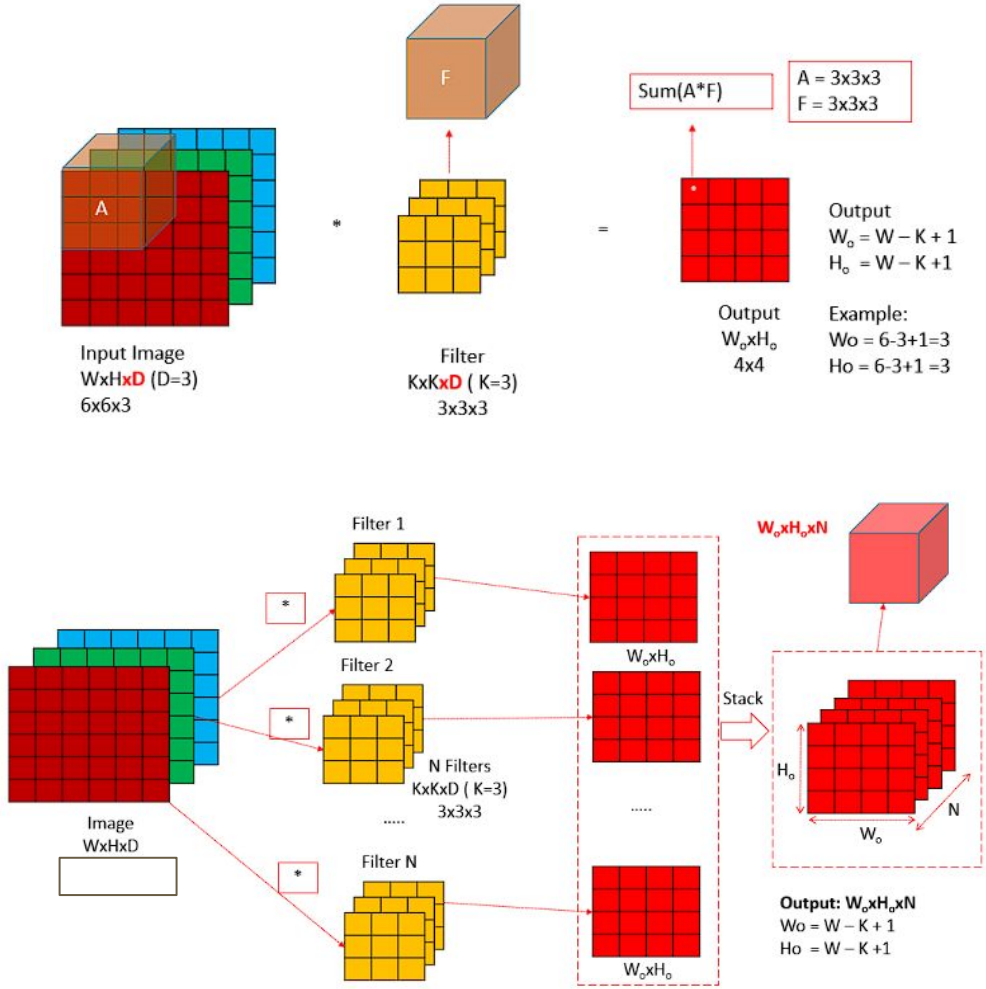
$$\begin{bmatrix} (f * g)(t_1) \\ (f * g)(t_2) \\ \dots \\ (f * g)(t_n) \end{bmatrix} = \begin{bmatrix} \sum_{i=0}^{m} f(\tau_i) \cdot g(t_1 - \tau_i) \\ \sum_{i=0}^{m} f(\tau_i) \cdot g(t_2 - \tau_i) \\ \dots \\ \sum_{i=0}^{m} f(\tau_i) \cdot g(t_n - \tau_i) \end{bmatrix}$$



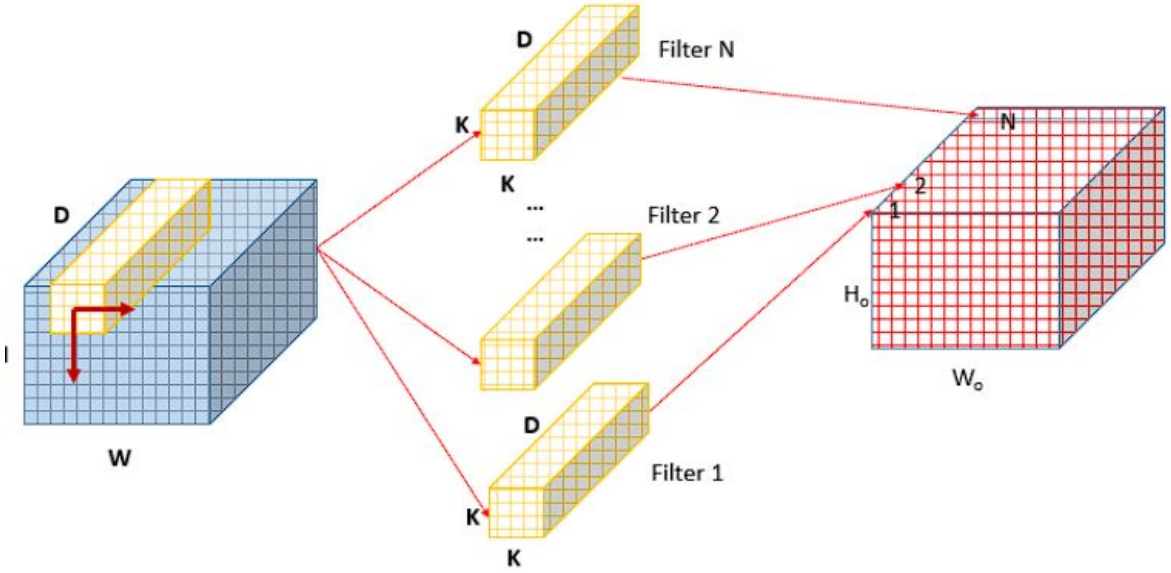
1D Convolutions



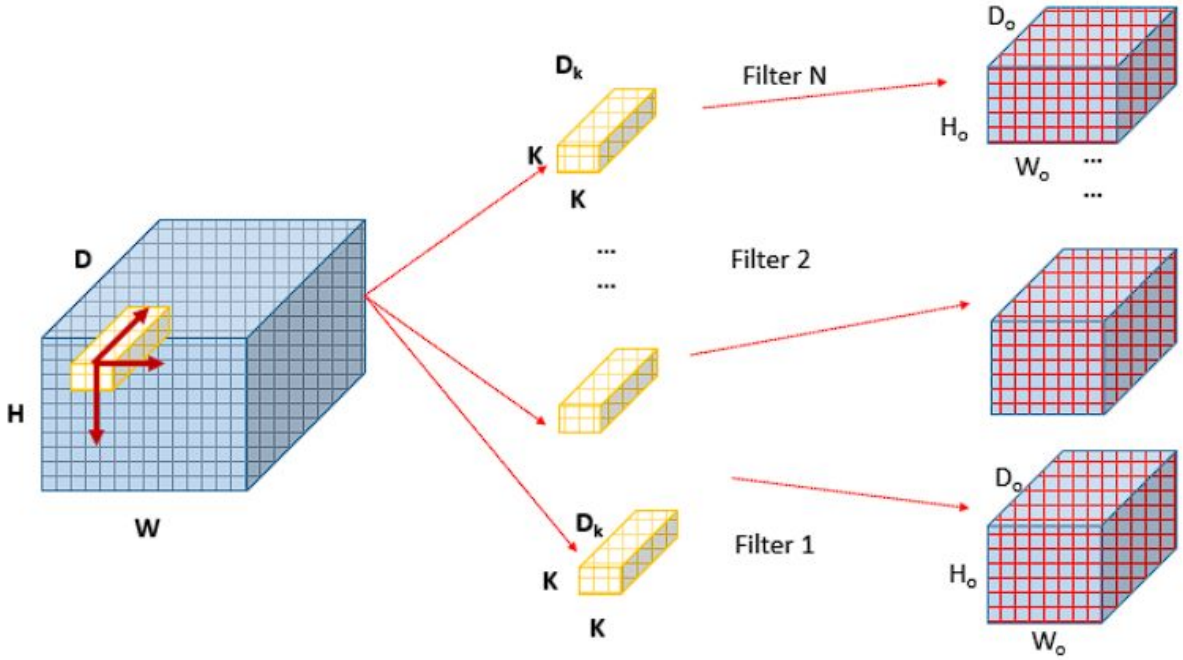
2D Convolution



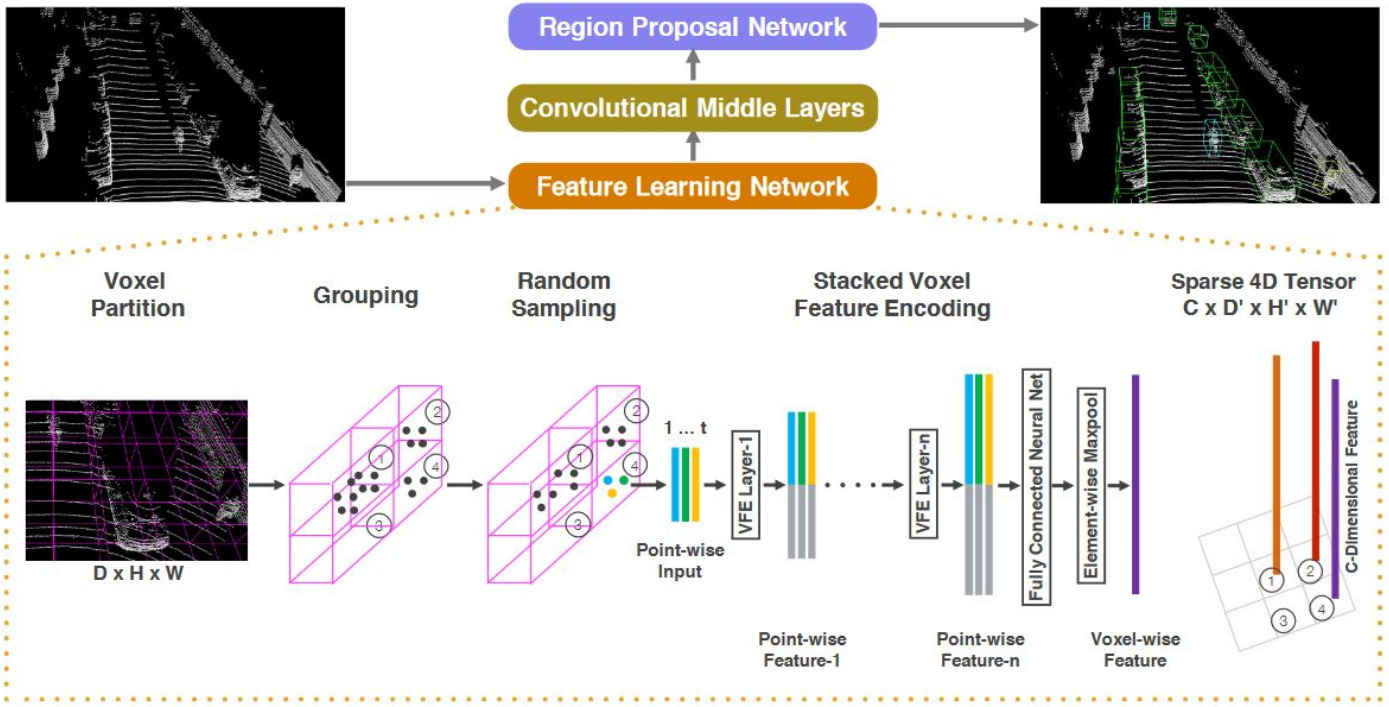
2D Convolution (cont')



3D Convolution

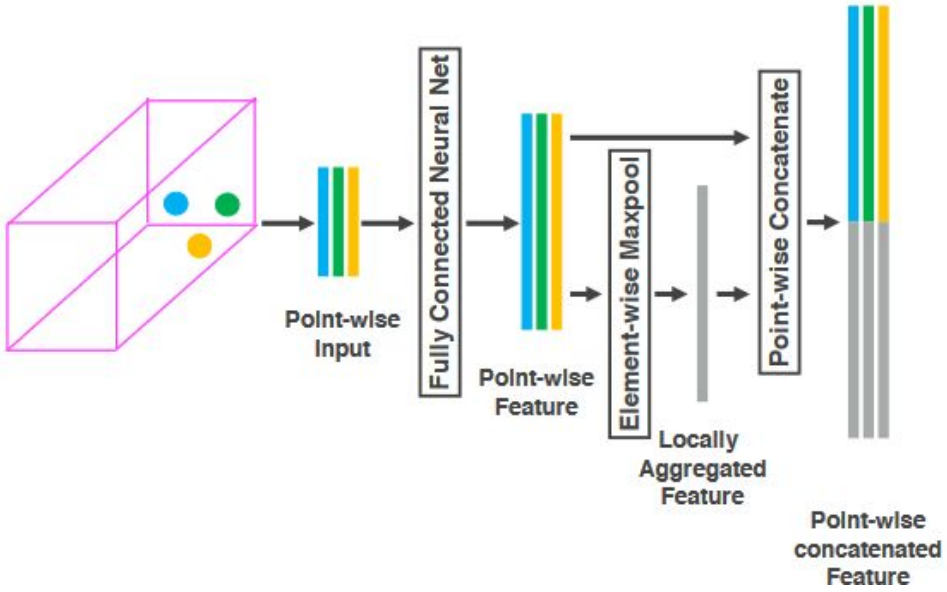


3D convolutional operator on 3D voxel grid



***VoxelNet**: End-to-End Learning for Point Cloud Based 3D Object Detection, (Yin Zhou et al)*

Voxel Feature Encoding (VFE)



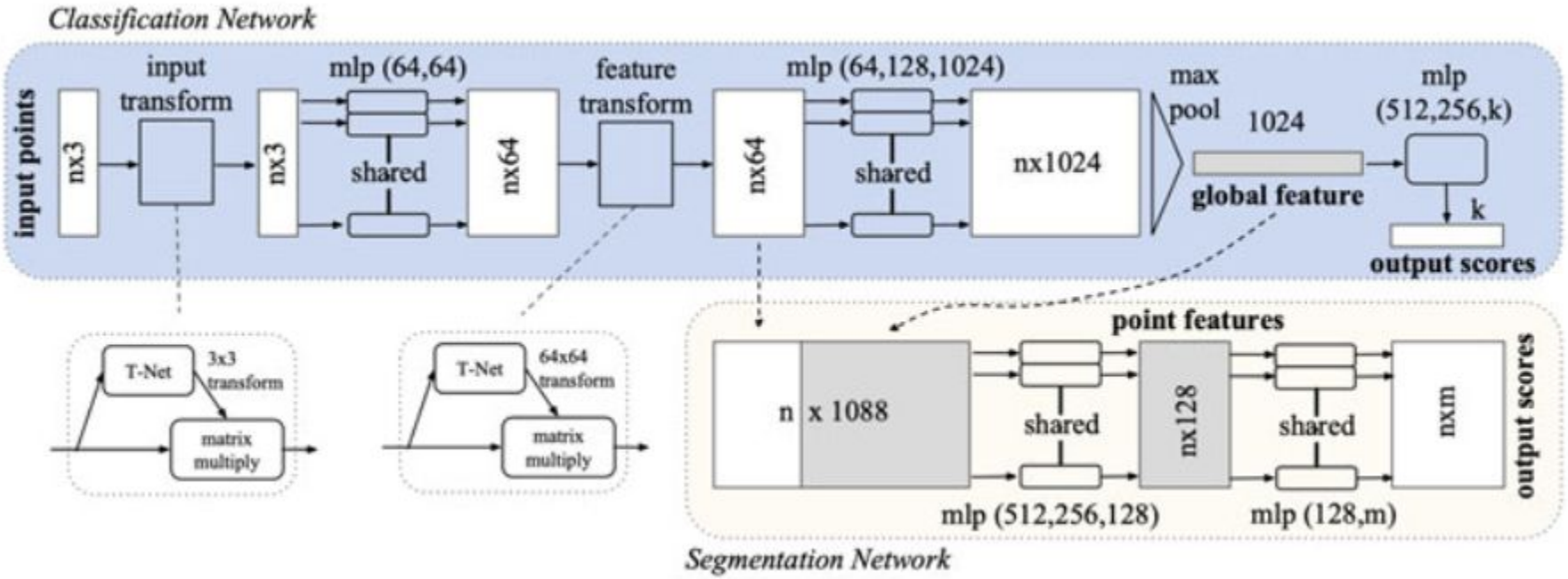
PointNet

- Consume direct point cloud with **n** points
- Use symmetric function like max-pooling

$$f(x_1, x_2, ..., x_n) = \gamma \left(\underset{i=1,...,n}{\text{MAX}} \{h(x_i)\} \right)$$

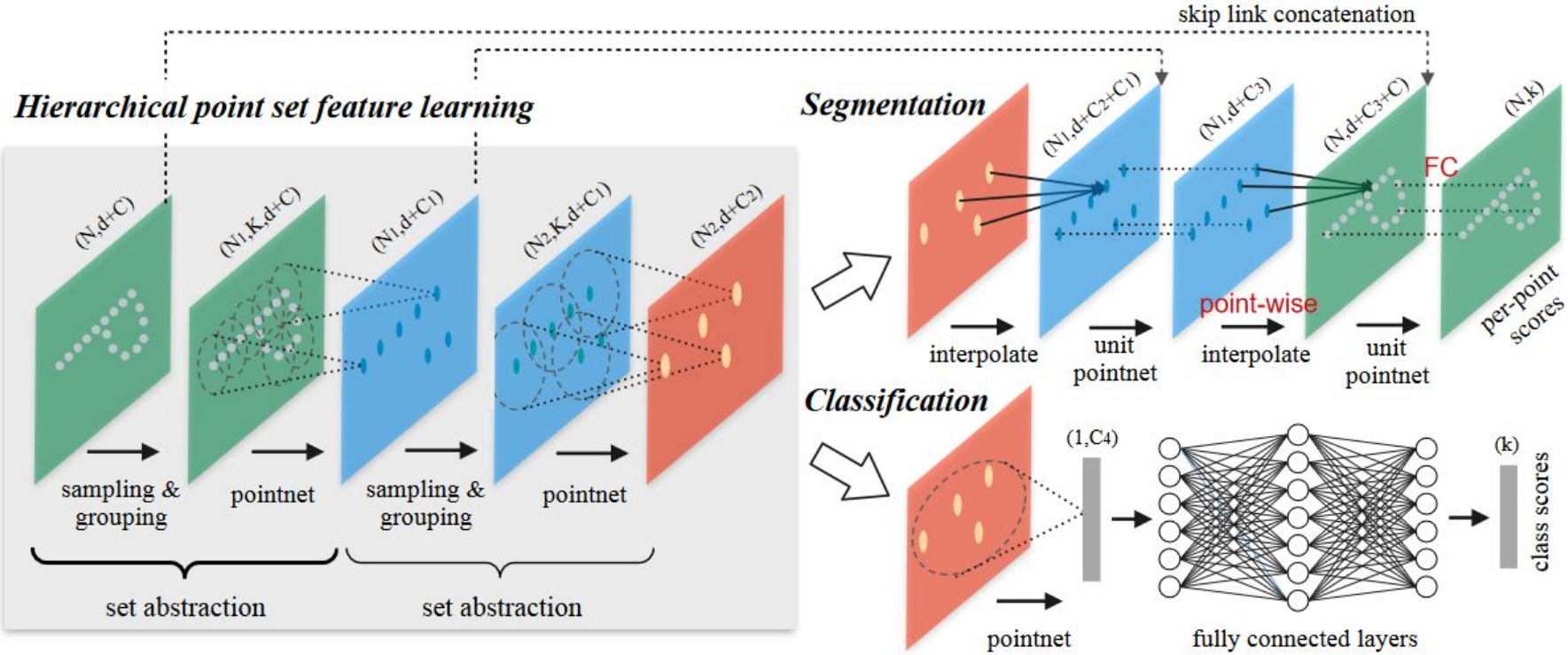
where γ and h are usually multi-layer perceptron (MLP) networks

Architecture

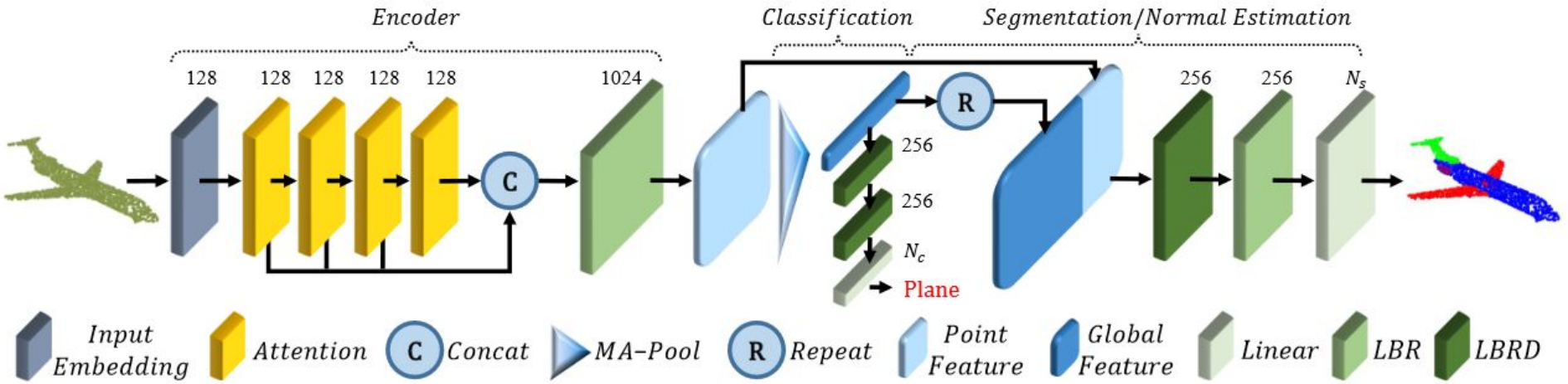


PointNet++

- Hierarchical Point Set Feature Learning
  - Multi-scale grouping (MSG)
  - Multi-resolution grouping (MRG)



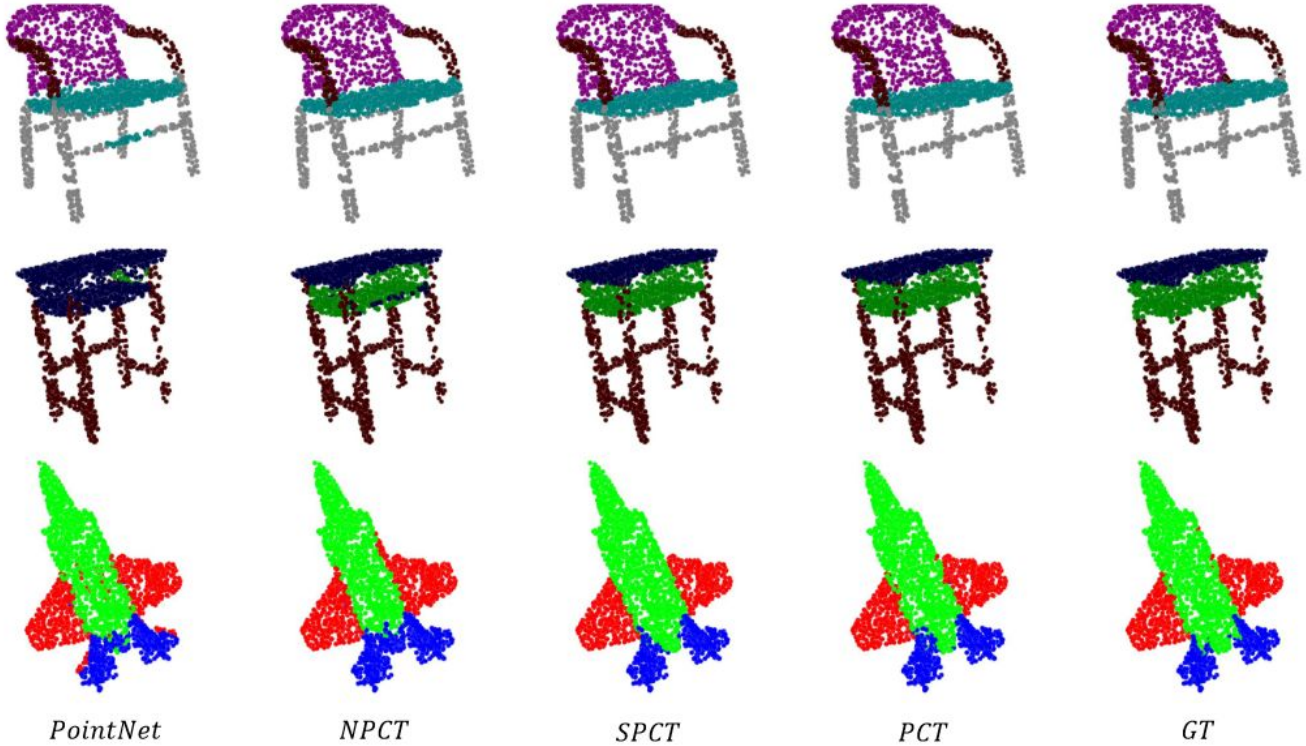
Point Transformer



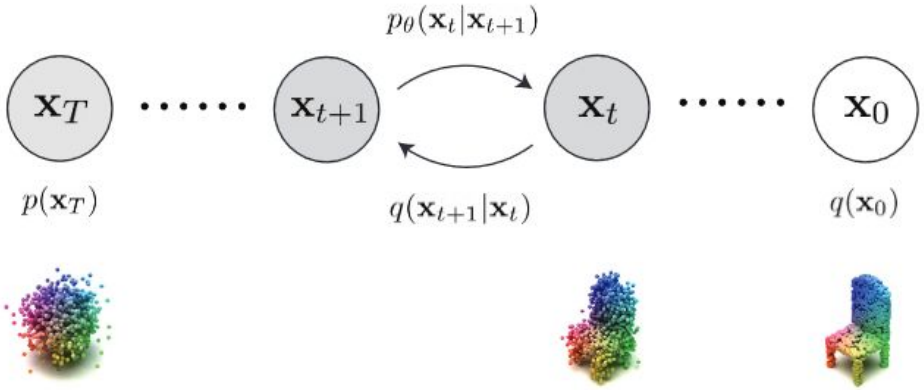
LBR: Linear, Batch, ReLu
LBRD: Linear, Batch, ReLu, DropOut

PCN: Point Cloud Transformer, Guo et al, 2021

Some results



Generative Point Cloud (Diffusion Approach)



$$q(\mathbf{x}_{0:T}) = q(\mathbf{x}_0)\prod_{t=1}^{T} q(\mathbf{x}_t|\mathbf{x}_{t-1}),$$ **forward**

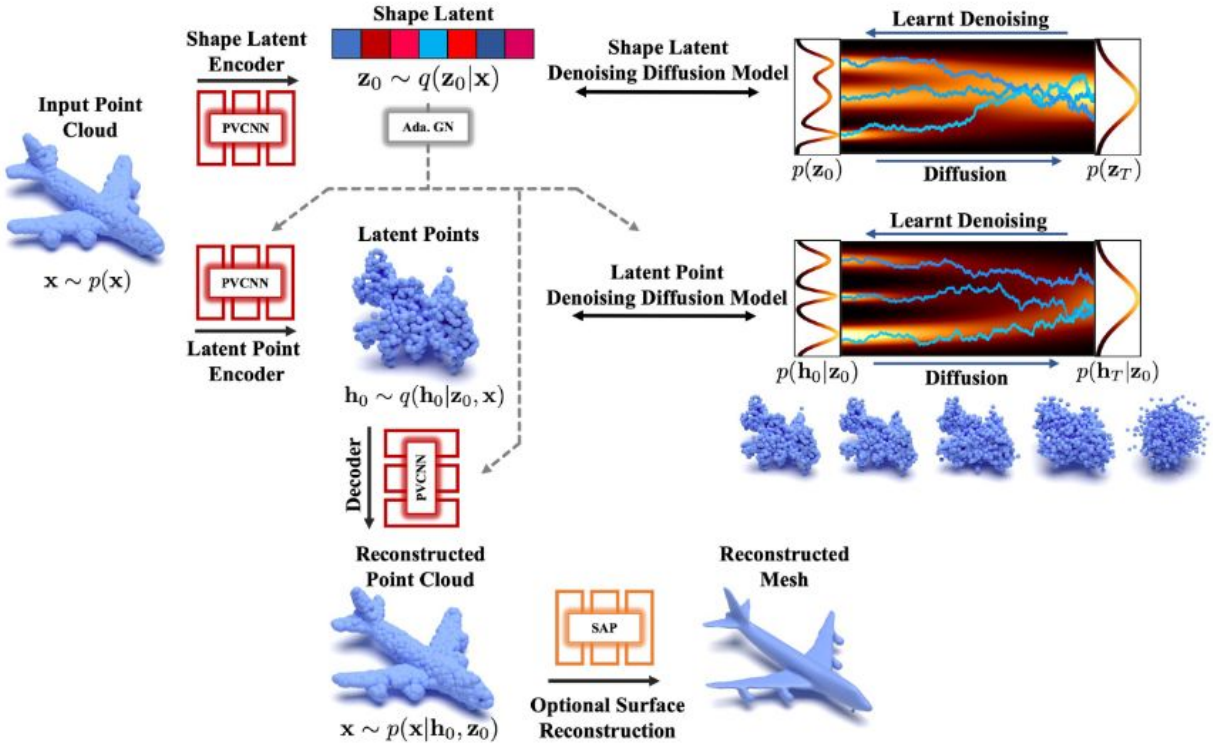
$$p_\theta(\mathbf{x}_{0:T}) = p(\mathbf{x}_T)\prod_{t=1}^{T} p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t),$$ **backward**

$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) := \mathcal{N}(\sqrt{1-\beta_t}\mathbf{x}_{t-1}, \beta_t\mathbf{I}),$$
$$p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) := \mathcal{N}(\mu_\theta(\mathbf{x}_t, t), \sigma_t^2\mathbf{I}).$$

$$\mathrm{E}_{q(\mathbf{x}_0)}[\log p_\theta(\mathbf{x}_0)] \geq \mathrm{E}_{q(\mathbf{x}_{0:T})}\left[\log \frac{p_\theta(\mathbf{x}_{0:T})}{q(\mathbf{x}_{1:T}|\mathbf{x}_0)}\right]$$

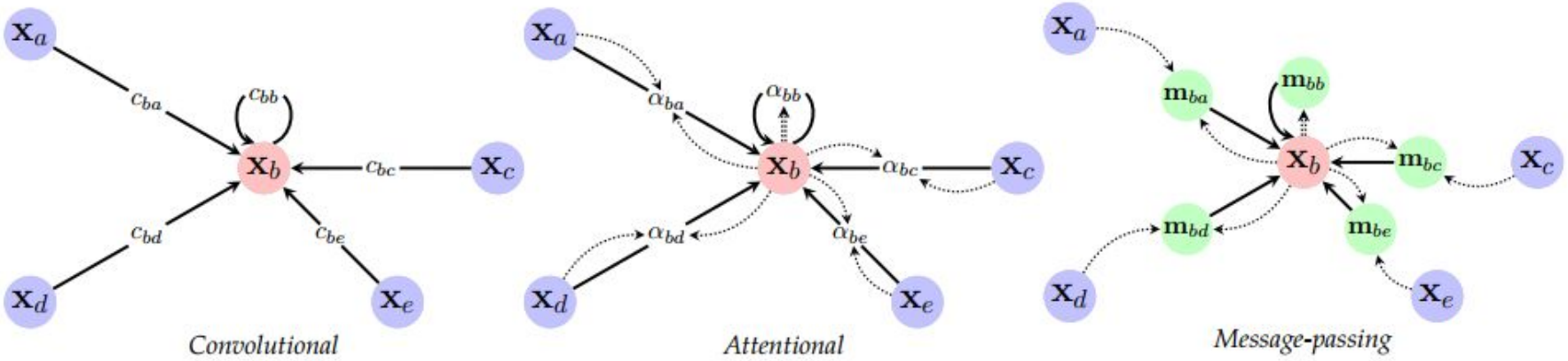
$$\max_\theta \mathrm{E}_{\mathbf{x}_0\sim q(\mathbf{x}_0), \mathbf{x}_{1:T}\sim q(\mathbf{x}_{1:T}|\mathbf{x}_0)}\left[\sum_{t=1}^{T}\log p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)\right]$$

Latent Point Diffusion



LION: Latent Point Diffusion Models for 3D Shape Generation, Zeng et al, 2022

Advanced: Graph Neural Network on Point Cloud



Formulation

Graph Convolutional

$$\mathbf{h}_u = \phi\left(\mathbf{x}_u, \bigoplus_{v \in \mathcal{N}_u} c_{uv}\psi(\mathbf{x}_v)\right)$$

Attention

$$\mathbf{h}_u = \phi\left(\mathbf{x}_u, \bigoplus_{v \in \mathcal{N}_u} a(\mathbf{x}_u, \mathbf{x}_v)\psi(\mathbf{x}_v)\right)$$

Message-passing

$$\mathbf{h}_u = \phi\left(\mathbf{x}_u, \bigoplus_{v \in \mathcal{N}_u} \psi(\mathbf{x}_u, \mathbf{x}_v)\right)$$

⊕: Aggregation, permutation-invariant function
Ψ: Point Feature Transform
ϕ : Point Feature Propagation (Diffusion)

$$\psi(\mathbf{x}) = \mathbf{W}\mathbf{x} + \mathbf{b};$$
$$\phi(\mathbf{x}, \mathbf{z}) = \sigma\left(\mathbf{W}\mathbf{x} + \mathbf{U}\mathbf{z} + \mathbf{b}\right),$$

Geometric Pytorch

latest

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Advanced Mini-Batching

Memory-Efficient Aggregations

Hierarchical Neighborhood Sampling

Compiled Graph Neural Networks

TorchScript Support

PyG Documentation

Note

This documentation is for an **unreleased development version**. Click here to access the documentation of the current stable release.

PyG Documentation

PyG *(PyTorch Geometric)* is a library built upon PyTorch to easily write and train Graph Neural Networks (GNNs) for a wide range of applications related to structured data.

It consists of various methods for deep learning on graphs and other irregular structures, also known as geometric deep learning, from a variety of published papers. In addition, it consists of easy-to-use mini-batch loaders for operating on many small and single giant graphs, multi GPU-support, torch.compile support, DataPipe support, a large number of common benchmark datasets (based on simple interfaces to create your own), the GraphGym experiment manager, and helpful transforms, both for learning on arbitrary graphs as well as on 3D meshes or point clouds.

Join our Slack community!

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- Installation

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Point Cloud Processing

This tutorial explains how to leverage Graph Neural Networks (GNNs) for operating and training on point cloud data. Although point clouds do not come with a graph structure by default, we can utilize PyG transformations to make them applicable for the full suite of GNNs available in PyG. The key idea is to create a synthetic graph from point clouds, from which we can learn meaningful local geometric structures via a GNN's message passing scheme. These point representations can then be used to, *e.g.*, perform point cloud classification or segmentation.

3D Point Cloud Datasets

PyG provides several point cloud datasets, such as the `PCPNetDataset`, `S3DIS` and `ShapeNet` datasets. To get started, we also provide the `GeometricShapes` dataset, which is a toy dataset that contains various geometric shapes such cubes, spheres or pyramids. Notably, the `GeometricShapes` dataset contains meshes instead of point clouds by default, represented via `pos` and `face` attributes, which hold the information of vertices and their triangular connectivity, respectively:

```
from torch_geometric.datasets import GeometricShapes

dataset = GeometricShapes(root='data/GeometricShapes')
print(dataset)
>>> GeometricShapes(40)

data = dataset[0]
print(data)
>>> Data(pos=[32, 3], face=[3, 30], y=[1])
```

Hand-on project

- PointNet
  - Classification
- Visualization:
  - Inference classification