Introduction to Computer Vision

Lecture 8 - 3D Vision II

Prof. He Wang

Logistics

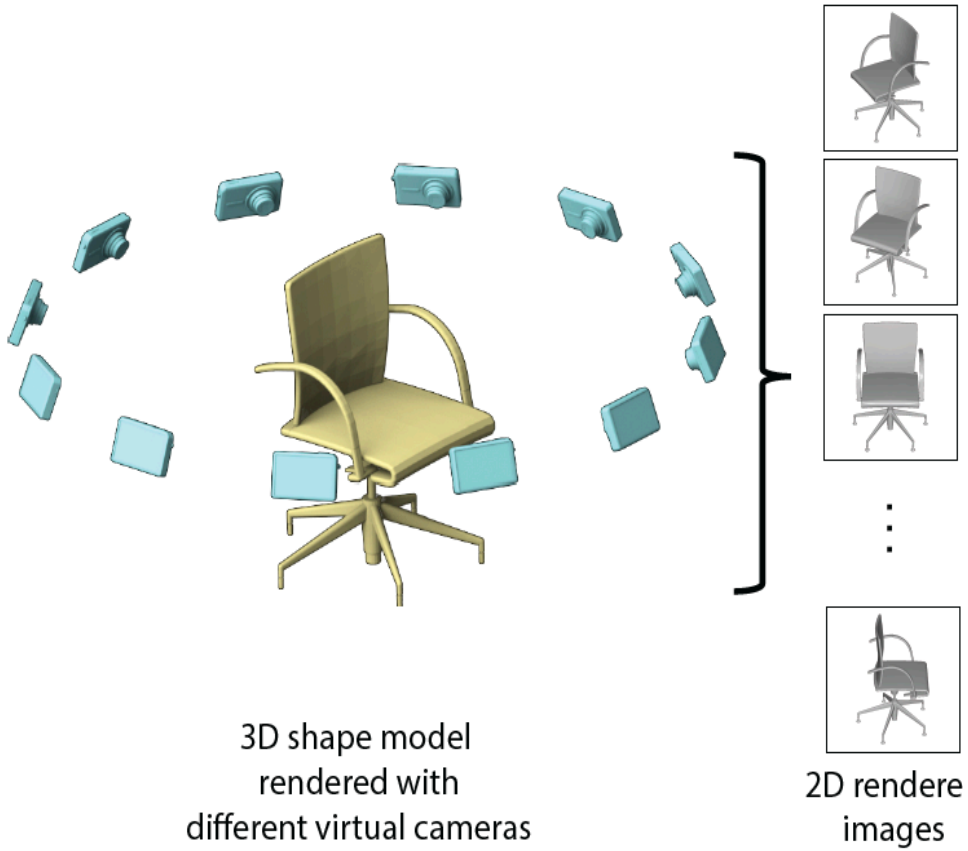
- Midterm: 4/26, in class
- One-page double-sided A4 cheatsheet
- Scope: from Lecture 1 - Lecture 8

3D Representations

2D Image Representations

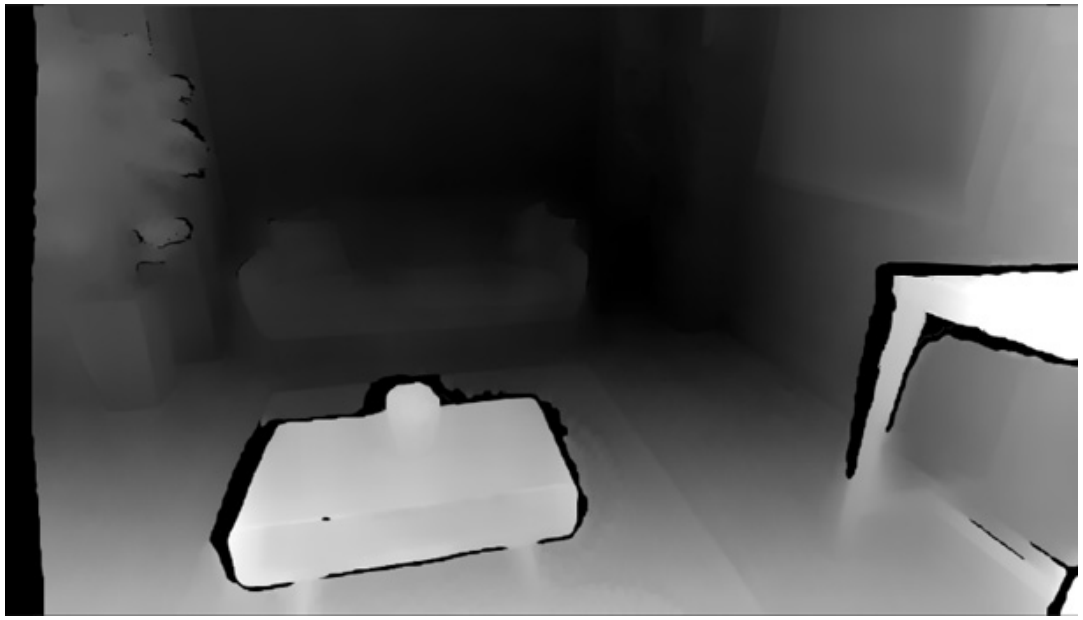
$$H \times W \times 3$$

Multi-View Images



- Multiple images from different viewpoints
- Contain 3D information
- Indirect, not a true 3D representation

Depth Image

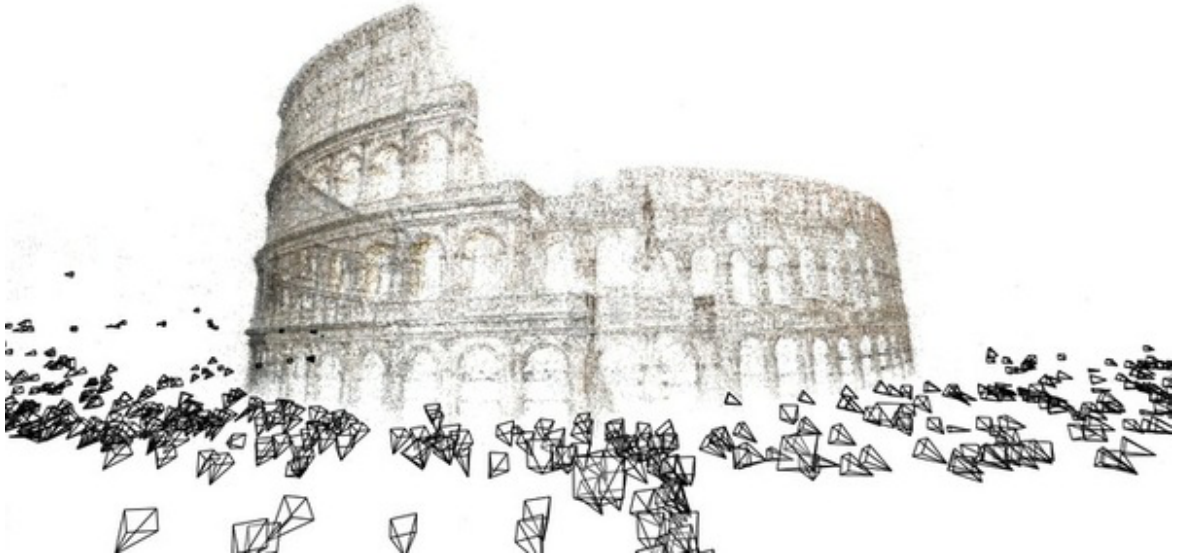


- A single-channel image filled by depth values
- A 2.5D representation

True 3D representation should enable distance measurement between two points.

We Live in a 3D World.

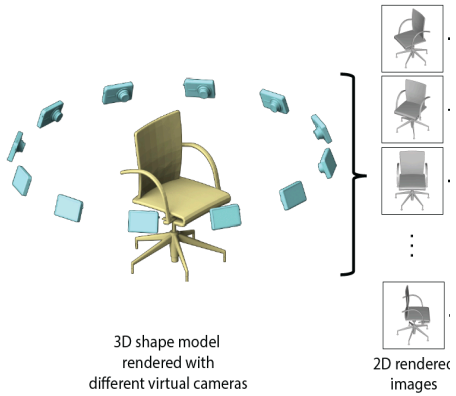
From partial observations to aggregate complete 3D scenes.



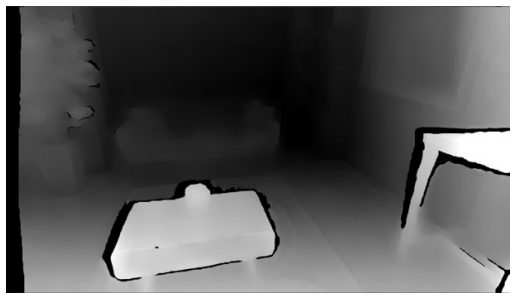
“Building Rome in a day.” Sameer Agarwal, Noah Snavely, Ian Simon, Steven M. Seitz and Richard Szeliski International Conference on Computer Vision, 2009, Kyoto, Japan.

Multiple 3D Representations

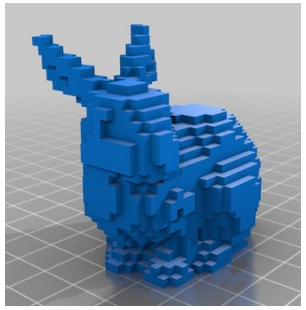
Regular form



Multi-view images

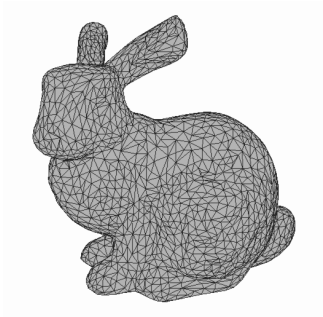


Depth

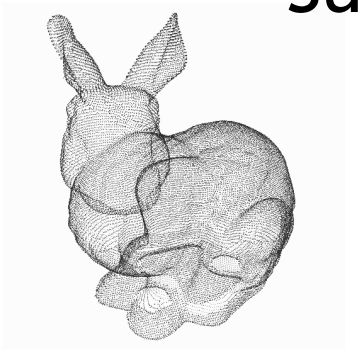


Volumetric

Irregular form



Surface Mesh

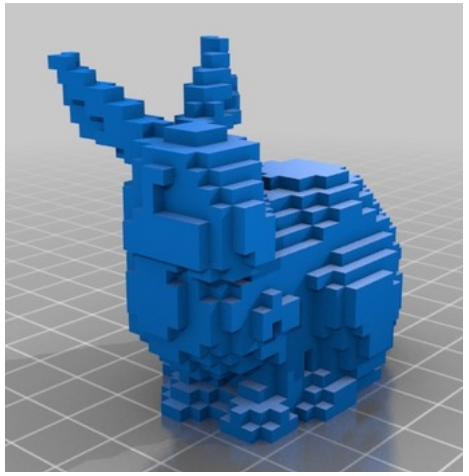


Point Cloud

$$F(x) = 0$$

Implicit representation

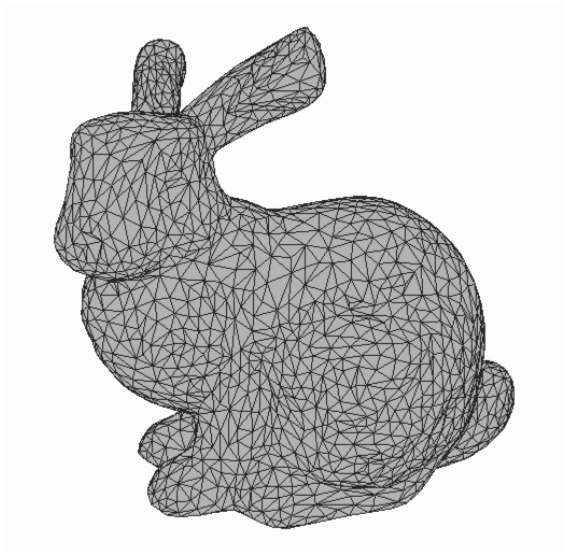
Voxels



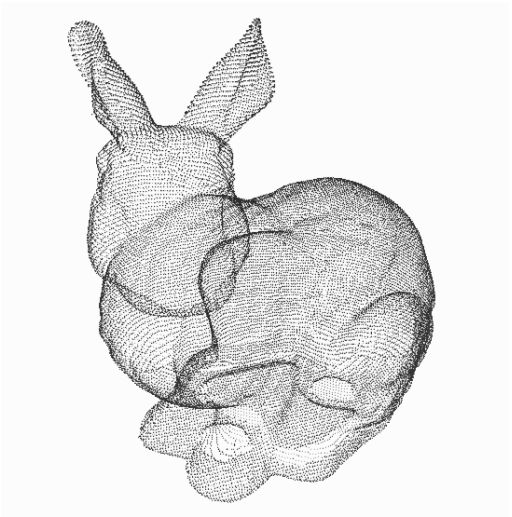
Voxels

- $H \times W \times D$
- Can be indexed
- An expensive geometry representation
- Not a surface representation
  - Where is the surface?
  - How to upsample?

Irregular 3D Representation



Mesh



Point Cloud

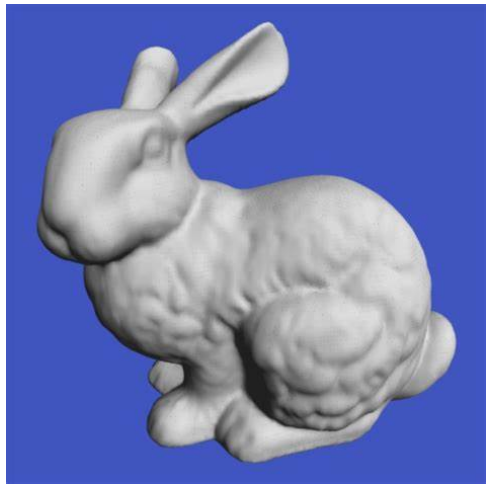
$$F(x) = 0$$

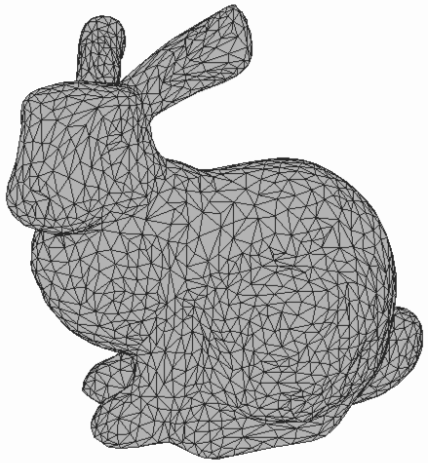
Implicit representation

- Irregular representation
- Model the 3D via capturing the surface or something on the surface

Mesh

Surface Mesh

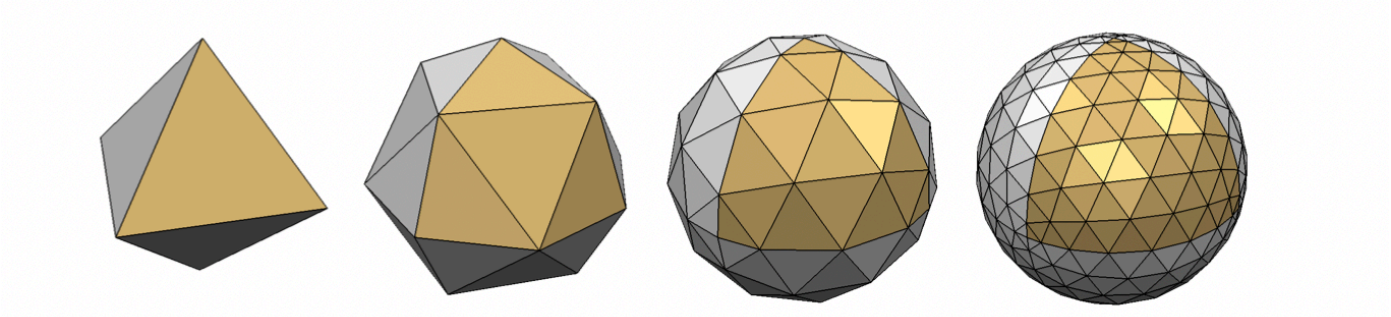




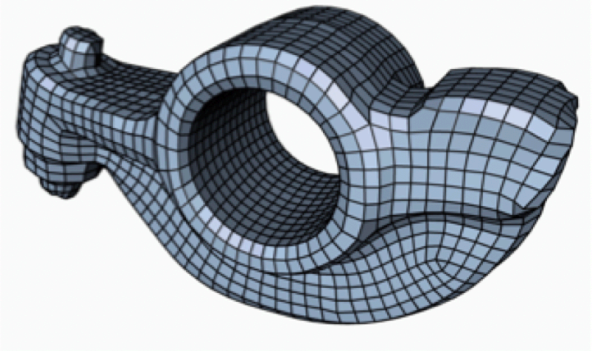
Mesh of
Stanford Bunny

- A piece-wise Linear Surface Representation
- Both a geometry and surface representation

Different Kinds of Mesh in Different Resolutions



Triangle mesh at different resolutions

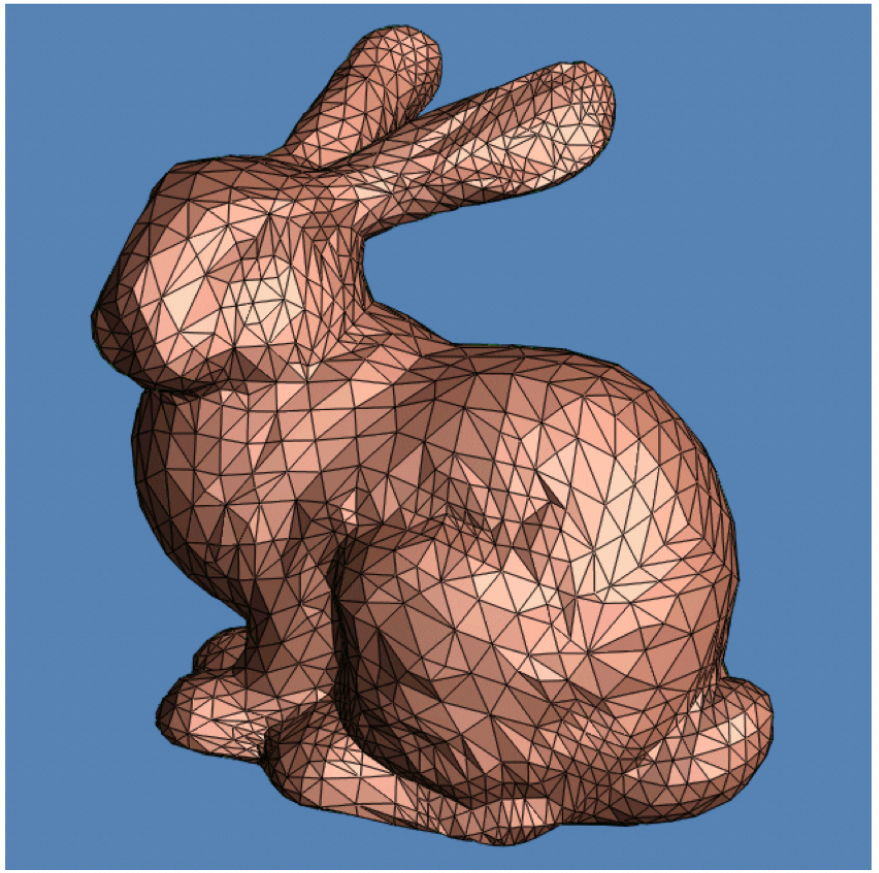


Quad mesh

Triangle Mesh

- Mesh essentially is a graph: {vertex, edge}
- Faces are triangles

$$V = \{v_1, v_2, \ldots, v_n\} \subset \mathbb{R}^3$$
$$E = \{e_1, e_2, \ldots, e_k\} \subseteq V \times V$$
$$F = \{f_1, f_2, \ldots, f_m\} \subseteq V \times V \times V$$



http://graphics.stanford.edu/data/3Dscanrep/stanford-bunny-cebal-ssh.jpg http://www.stat.washington.edu/wxs/images/BUNMID.gif

Data Structure for Mesh

- What information should be stored?
  - Geometry: 3D coordinates
  - Topology
  - Attributes
    - Normal, color, texture coordinates
    - Per vertex, face, edge

Simple Data Structure: Triangle List

- STL format (used in CAD)
- Stored information
  - Face: 3 positions
- No connectivity information

Triangles			
0	x0	y0	z0
1	x1	x1	z1
2	x2	y2	z2
3	x3	y3	z3
4	x4	y4	z4
5	x5	y5	z5
6	x6	y6	z6
...	...	...	...

Indexed Face Set

- Used in formats
  - OBJ, OFF, WRL
- Stored information
  - Vertex: position
  - Face: vertex indices
  - Convention is to save vertices in **counter-clockwise order (right hand rule)** for normal direction (pointing out)

Vertices			
v0	x0	y0	z0
v1	x1	x1	z1
v2	x2	y2	z2
v3	x3	y3	z3
v4	x4	y4	z4
v5	x5	y5	z5
v6	x6	y6	z6
…	…	…	…

Triangles			
t0	v0	v1	v2
t1	v0	v1	v3
t2	v2	v4	v3
t3	v5	v2	v6
…	…	…	…

Geodesic Distance

- Geodesic distance: the shortest distance from one point to the other point on the surface.

Compute Mesh Geodesic Distance

- A naive approximation: find the shortest path between two vertices of the mesh.

- A fast and more accurate approximation: Fast Marching method.http://www.mathworks.com/matlabcentral/fileexchange/6110-toolbox-fast-marching

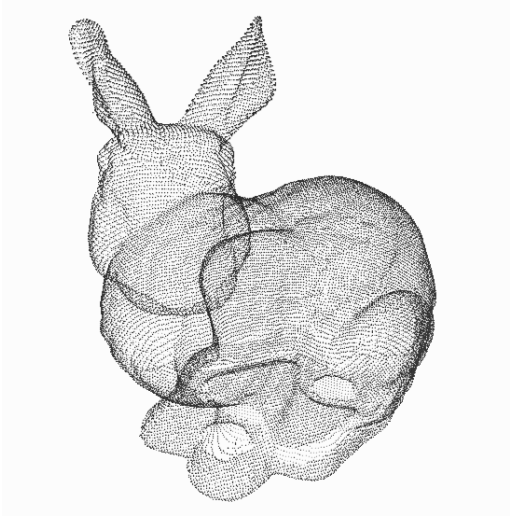
- Exact geodesic distance: MMP method proposed by Mitchell et al. (*The discrete geodesic problem. SIAM J. Comput. 16, 4 (August 1987), 647-668.*)

Summary of Polygonal Meshes

- Polygonal meshes are piece-wise linear approximation of smooth surfaces
- Vertices, edges, and faces are basic elements
- While real-data 3D are often point clouds, meshes are quite often used to visualize 3D and generate ground truth for machine learning algorithms

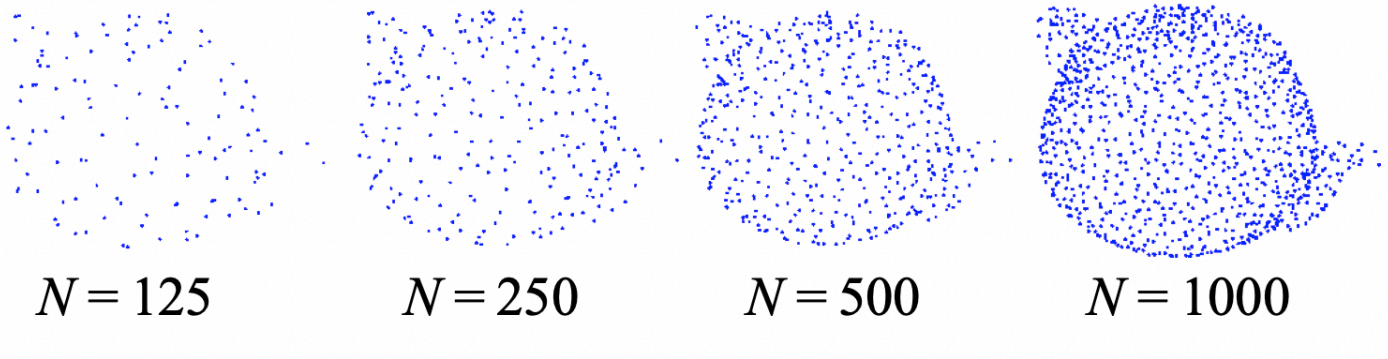
Point Cloud

Point Cloud

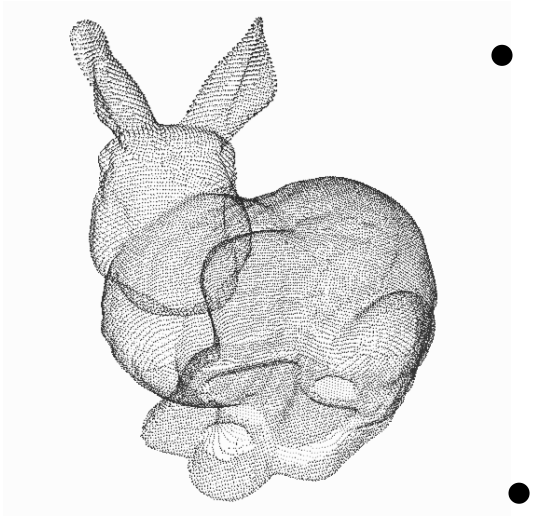


Point Cloud

- N*3
- Irregular and orderless data
- A light-weight geometric representation
  - Compact to store
  - Easy to understand and generally easy to build algorithms



Limitations of Point Cloud



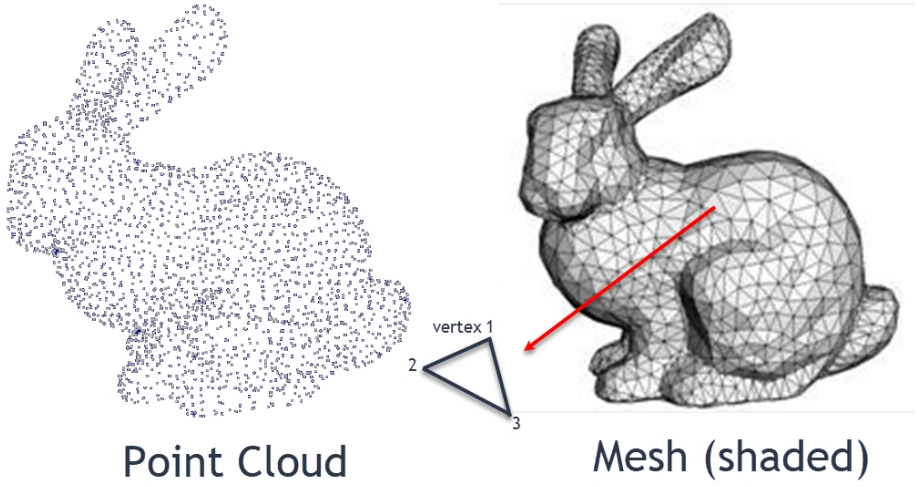
Point Cloud

- Point cloud is not a surface representation
  - where is the surface?

- Point cloud = surface + sampling
  - How to sample point clouds from a mesh surface?

Sampling Strategy: Uniform Sampling

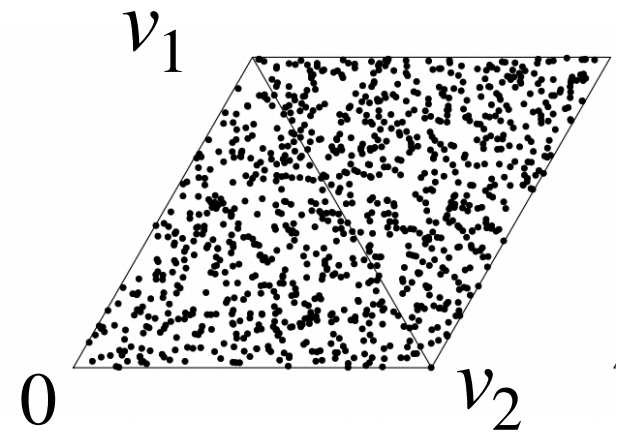
- 1. Compute the areas of each individual face
- 2. Compute the probability of each face and use it as weight
- 3. Independent identically distributed (i.i.d.) sample faces according to the weights
- 4. For each sampled face, uniformly sample from one triangle face



https://static.packt-cdn.com/products/9781788830409/graphics/9ddd542a-fa9b-4410-87c7-cae62c1e49a7.jpg

Uniform Sampling Points in a Triangle

- Special case: for a triangle with one vertex at the origin and the others at positions v_1 and v_2:
- To pick points uniformly distributed inside the triangle, we can do $x = a_1 v_1 + a_2 v_2$, where a_1 and a_2 are uniform variates in the interval $[0,1]$.
- This gives points uniformly distributed in a quadrilateral. The points not in the triangle interior can then be transformed into the corresponding point inside the triangle.

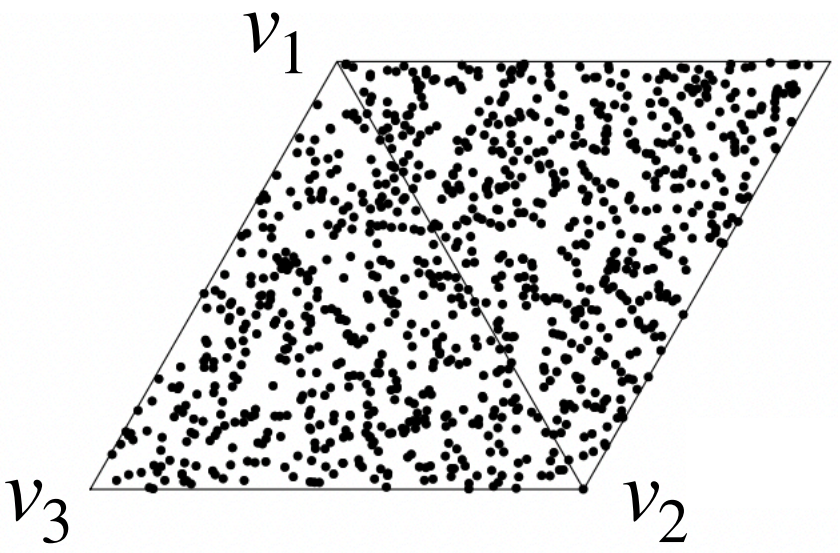


Uniform Sampling Points in a Triangle

- General case: for a triangle with vertices v_1, v_2, v_3:
- $x = v_3 + a_1(v_1 - v_3) + a_2(v_2 - v_3) = a_1 v_1 + a_2 v_2 + (1 - a_1 - a_2)v_3$, where a_1 and a_2 are uniform variates in the interval $[0,1]$

- If $a_1 + a_2 \leq 1$, then x will be inside the triangle (or on the edges);
- If $a_1 + a_2 > 1$, then x can be mapped back to the triangle interior via

$$x = (1 - a_1)v_1 + (1 - a_2)v_2 + (a_1 + a_2)v_3$$



Alternative Approach

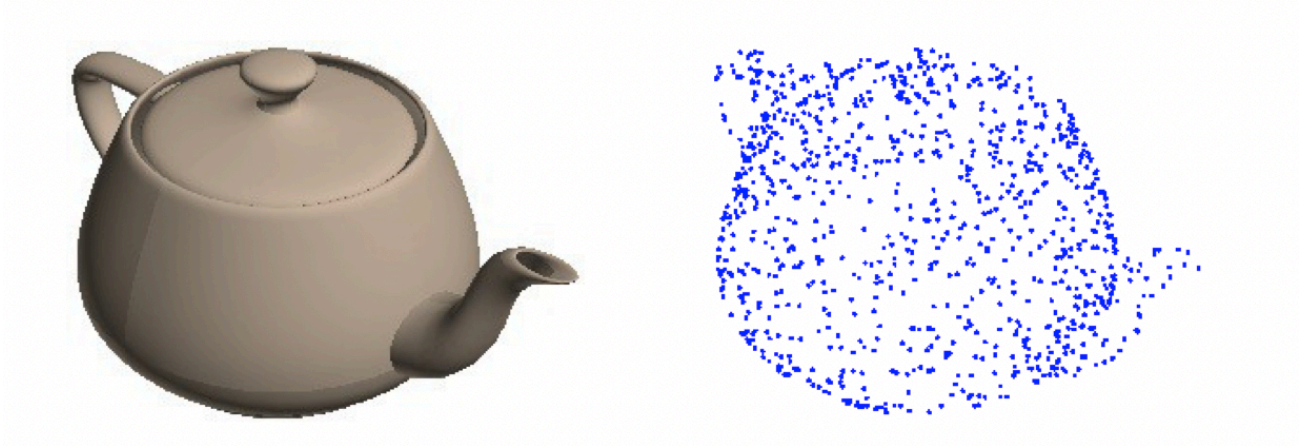
$$x = (1 - \sqrt{r_1})v_1 + \sqrt{r_1}(1 - r_2)v_2 + \sqrt{r_1}r_2v_3$$

- Here $r_1, r_2 \sim U(0,1)$.

- Proof:
  - If this is true for one triangle, it is true for all triangles, as we can find an affine transformation between them.
  - Use $v_1 = (0,0), v_2 = (1,0), v_3 = (0,1)$
  - Prove x is always inside the triangle.
  - Show that the probability to be within an area of $(0,x) \times (0,y)$ is always $2xy$.

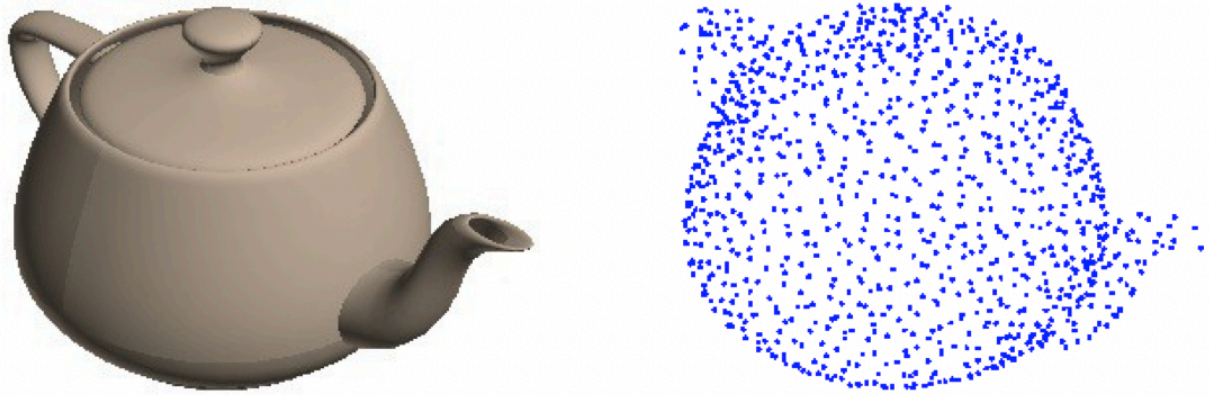
Sampling Strategy: Uniform Sampling

- Usually the easiest to implement
- Issue: Irregularly spaced sampling



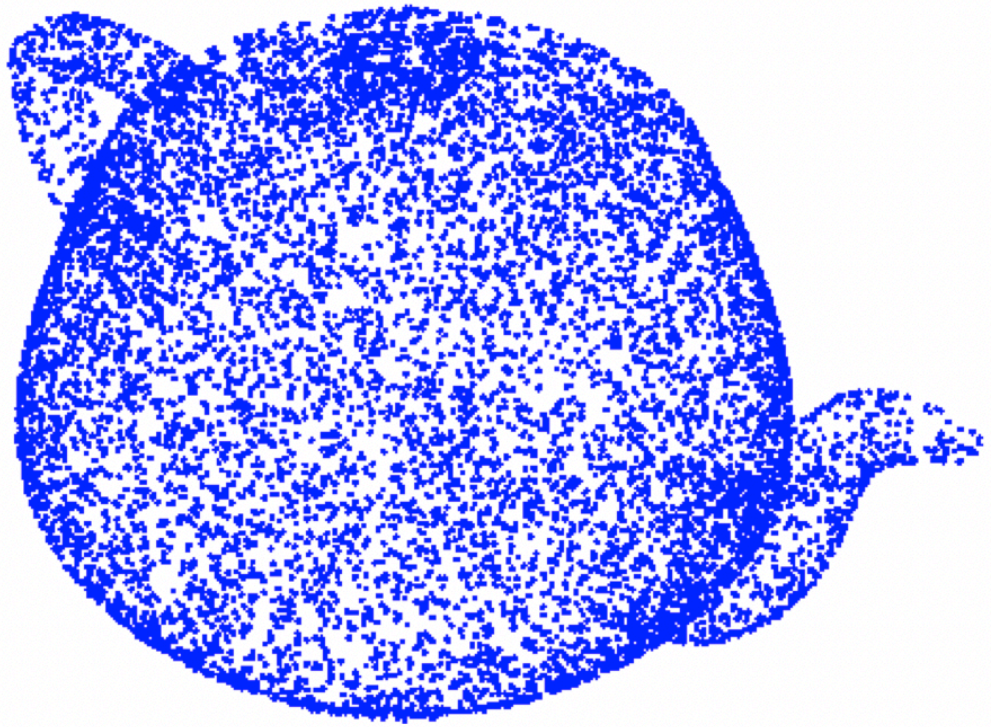
Farthest Point Sampling (FPS)

- Goal: Sampled points are far away from each other
- NP-hard problem
- What is a greedy approximation method?



Iterative Furthest Point Sampling

- Step 1: Over sample the shape by any fast method (e.g., uniformly sample N=10,000 i.i.d. samples)



Iterative Furthest Point Sampling

- Step 2: Iteratively select K points

U is the initial big set of points
$S = \{\}$

add a random point from U to S

for i=1 to K
    find a point $u \in U$ with the largest distance to S
    add u to S

Visualization: Uniform Sampling vs. FPS

- FPS
- Uniform sampling

With the same number of sampled points.

Wang et al. Rethinking Sampling in 3D Point Cloud Generative Adversarial Networks.

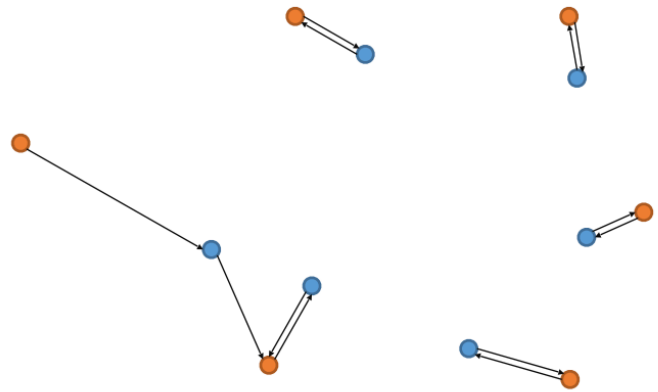
Distance Metrics for Point Cloud

- How to measure the distance between two point clouds?

Distance Metrics for Point Cloud

Chamfer distance We define the Chamfer distance between $S_1, S_2 \subseteq \mathbb{R}^3$ as:

$$d_{CD}(S_1, S_2) = \sum_{x \in S_1} \min_{y \in S_2} \|x - y\|_2 + \sum_{y \in S_2} \min_{x \in S_1} \|x - y\|_2$$



A Point Set Generation Network for 3D Object Reconstruction from a Single Image, CVPR 2016

Distance Metrics for Point Cloud

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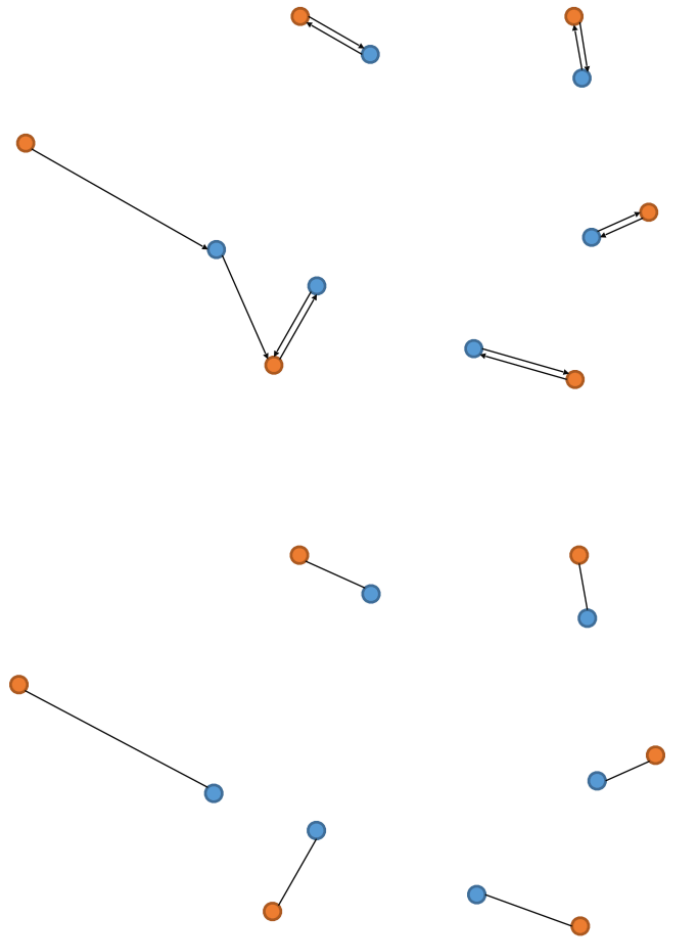
Earth Mover's distance Consider $S_1, S_2 \subseteq \mathbb{R}^3$ of equal size $s = |S_1| = |S_2|$. The EMD between A and B is defined as:

$$d_{EMD}(S_1, S_2) = \min_{\phi: S_1 \to S_2} \sum_{x \in S_1} \|x - \phi(x)\|_2$$

where $\phi : S_1 \to S_2$ is a bijection.



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Sum of the closest distances

Insensitive to sampling

Earth Mover's distance Consider $S_1, S_2 \subseteq \mathbb{R}^3$ of equal size $s = |S_1| = |S_2|$. The EMD between A and B is defined as:

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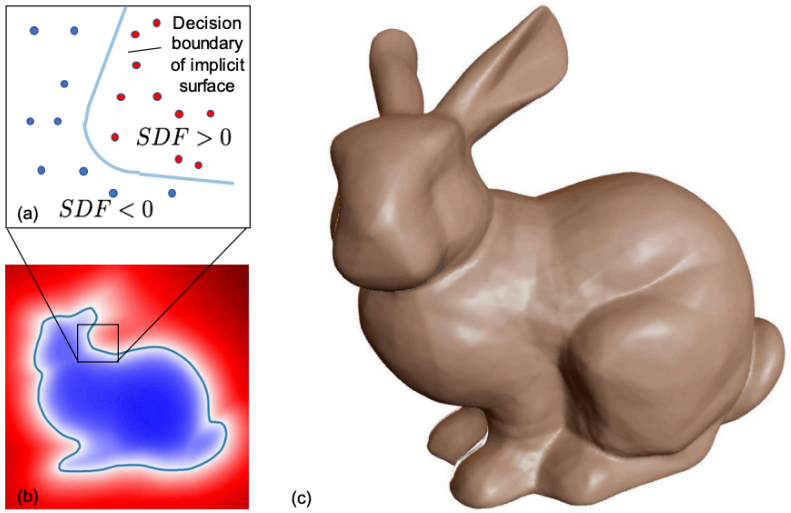
where $\phi : S_1 \to S_2$ is a bijection.

Sum of the matched closest distances

Sensitive to sampling

Implicit Field

Implicit Shape

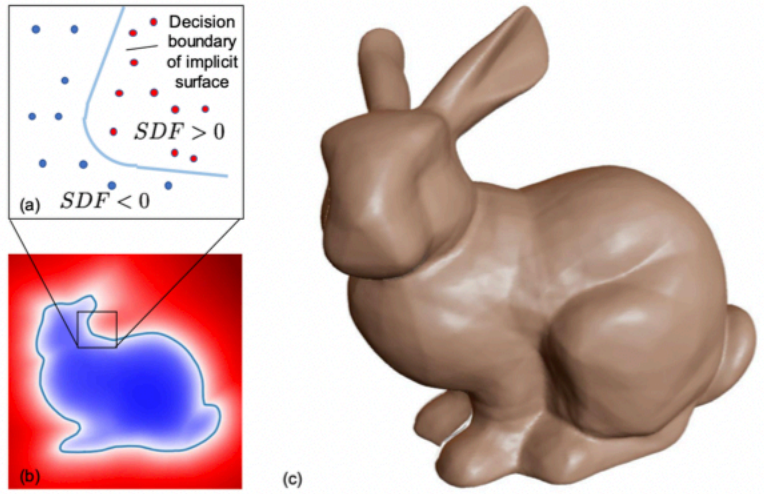


SDF

- Both an implicit geometry and surface representation
- Can convert into mesh
- Signed distance function, unsigned distance function, occupancy network

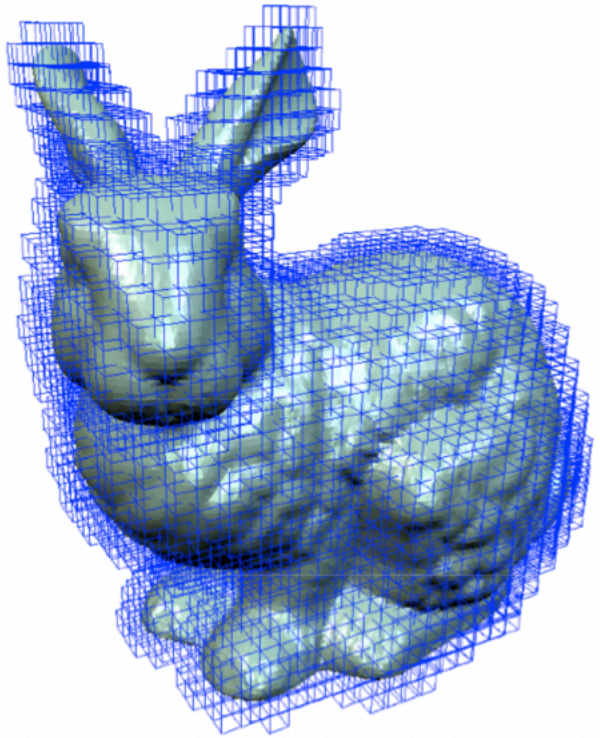
Signed Distance Function (SDF)

- Interior: $F(x, y, z) < 0$
- Exterior: $F(x, y, z) > 0$
- Surface: $F(x, y, z) = 0$ (zero set, zero iso-surface)
- Example implementation:
  - SDF: $F(x, y, z) =$ distance to the surface



How to Extract Zero Iso-Surface

Input: a signed distance field
(Implicitly assumed knowing the inside/outside of the shape, often needs to be estimated with **normal** information)



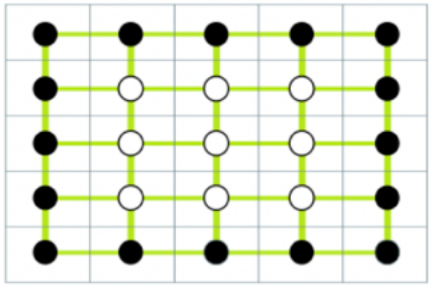
Classical Solution: 2D Marching Square

1	1	1	1	1
1	2	3	2	1
1	3	3	3	1
1	2	3	2	1
1	1	1	1	1

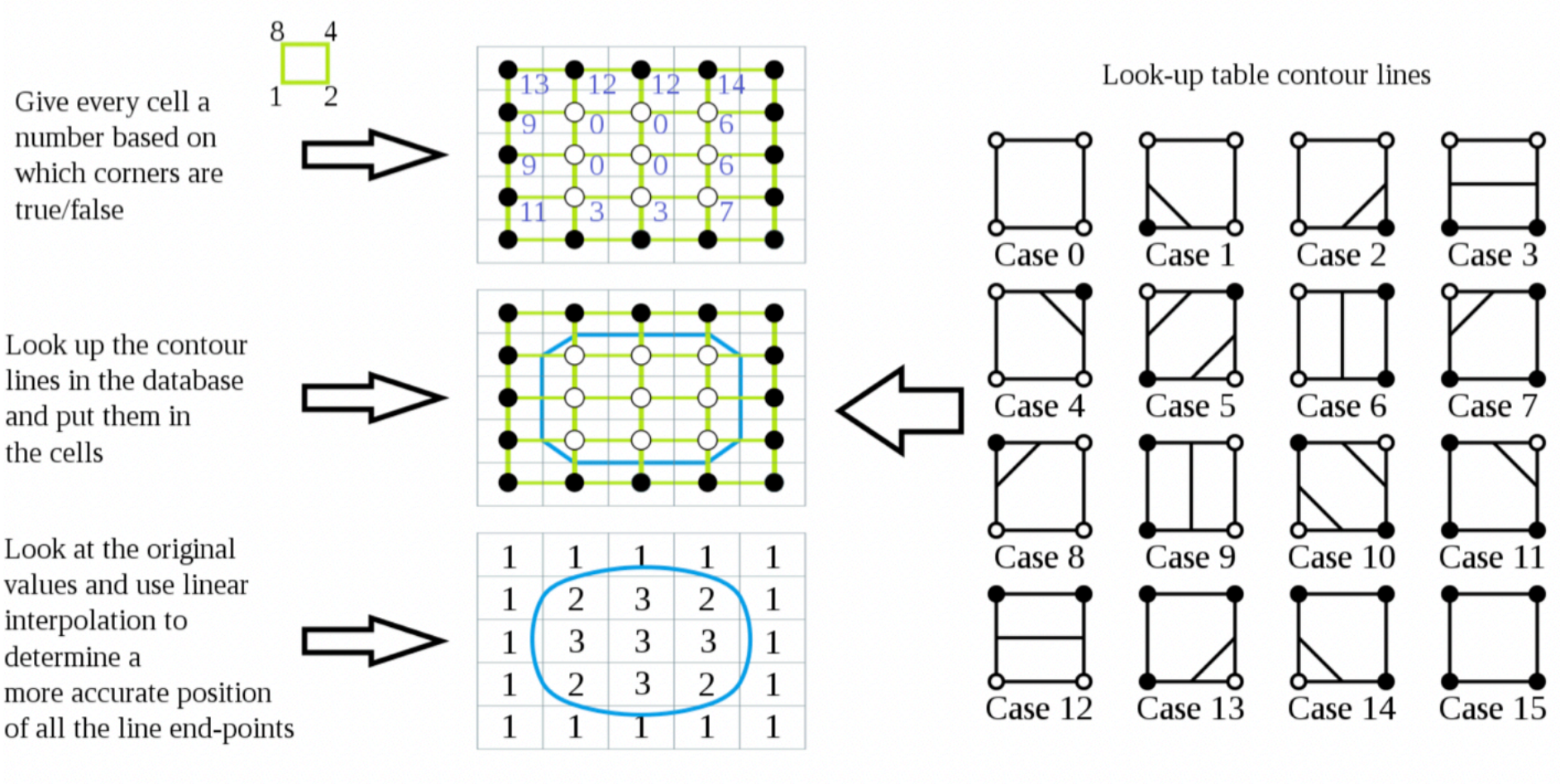
Threshold with iso-value

0	0	0	0	0
0	1	1	1	0
0	1	1	1	0
0	1	1	1	0
0	0	0	0	0

Binary image to cells

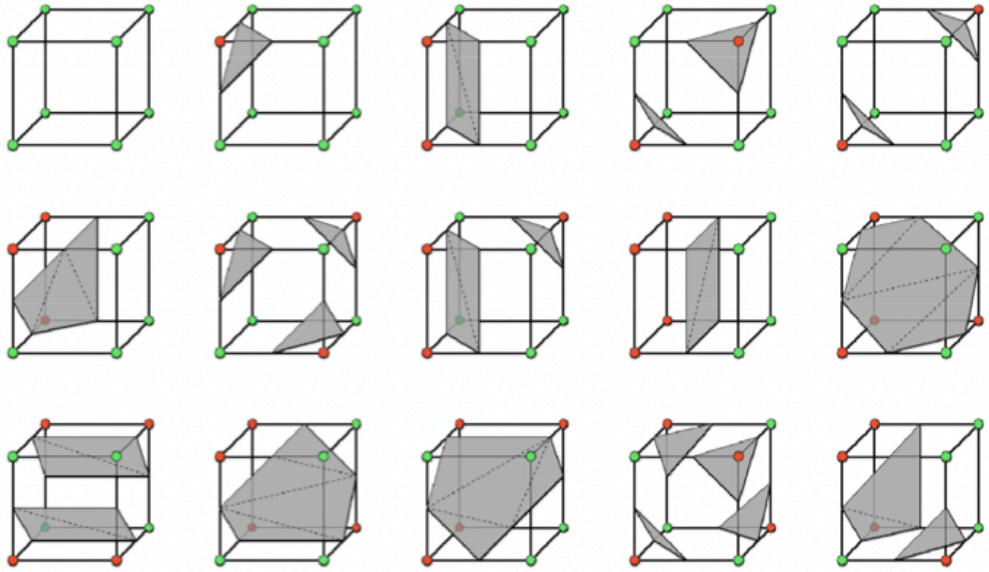


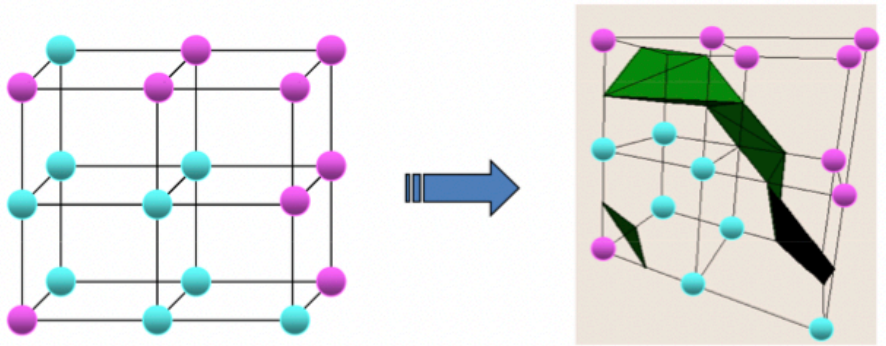
Classical Solution: 2D Marching Square



Classical Solution: 3D Marching Square

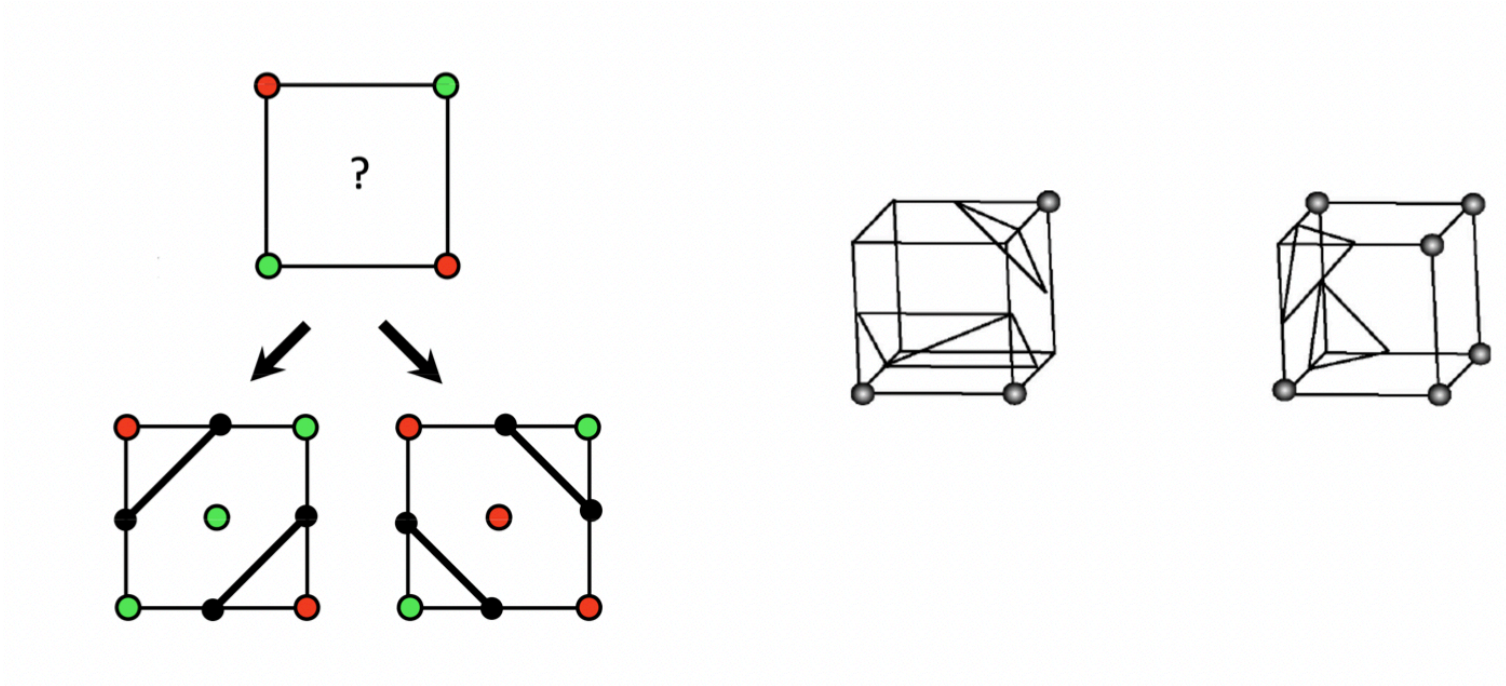
- $2^8 = 256$ cases
- The first published version exploits rotation and inversion, and only considers 15 unique cases:



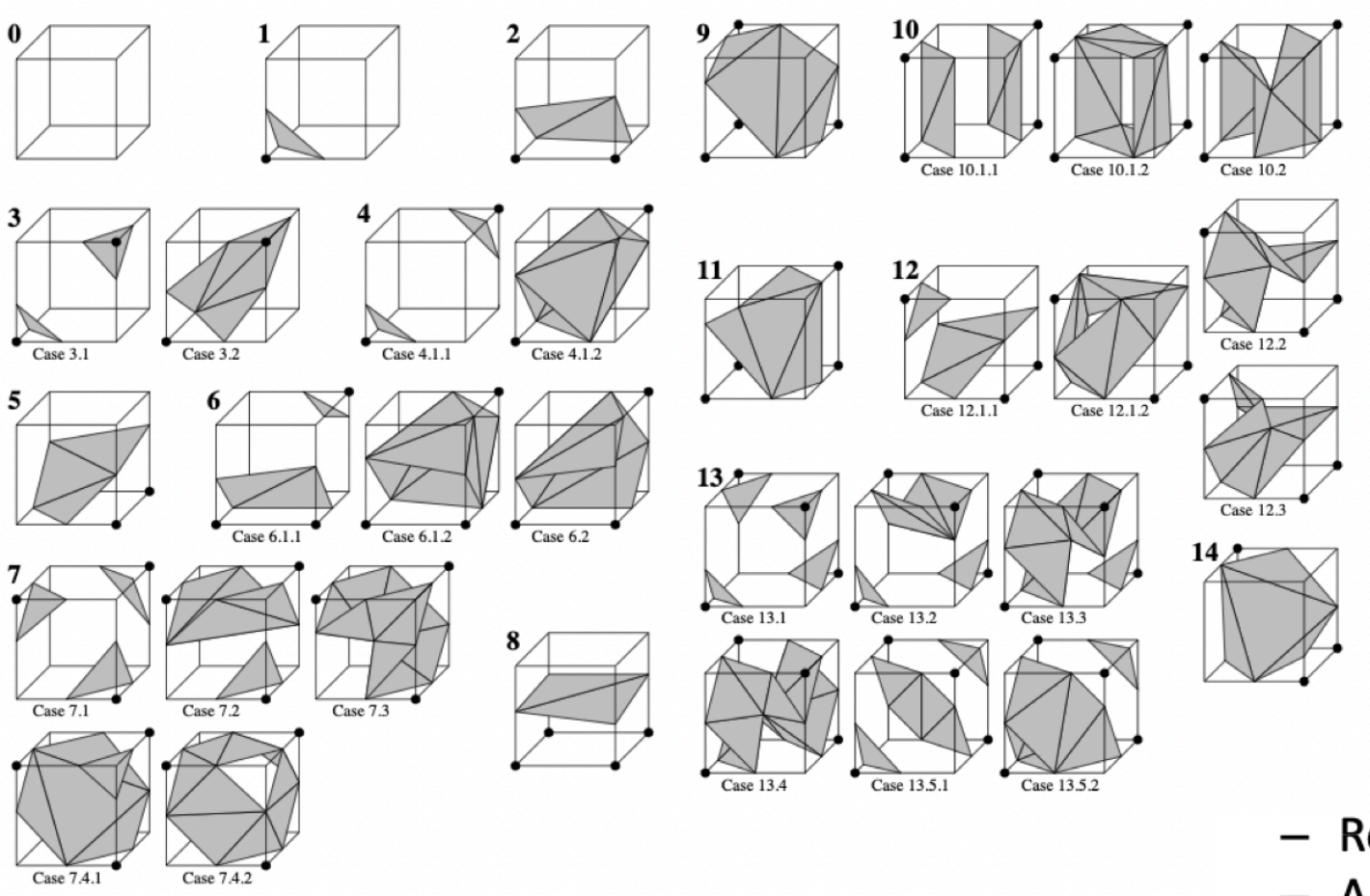


Ambiguity

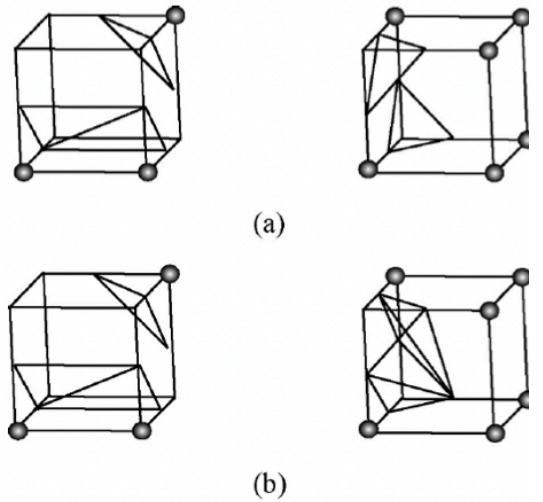
- Ambiguity leads to holes:



Solution to Ambiguity



a



- Rotation only
- Always separate same “color”
- → Ambiguous faces triangulated consistently

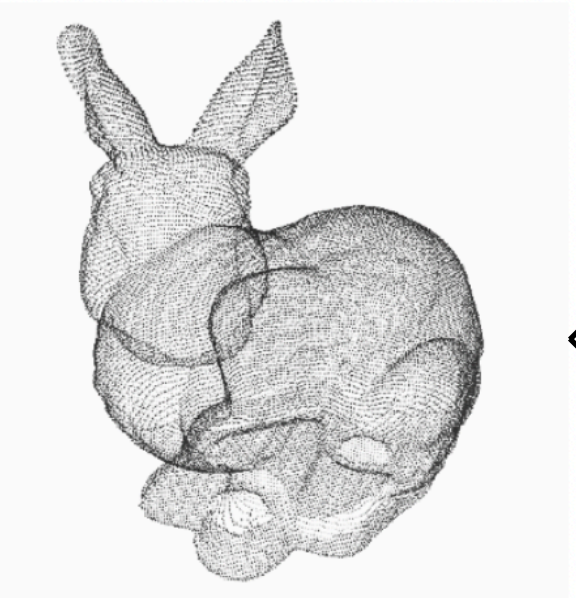
https://graphics.stanford.edu/courses/cs468-12-spring/LectureSlides/04_Surface_Reconstruction.pdf
Chernyaev et al., “Marching cube 33: Construction of topologically correct isosurfaces”, 1995

3D Deep Learning

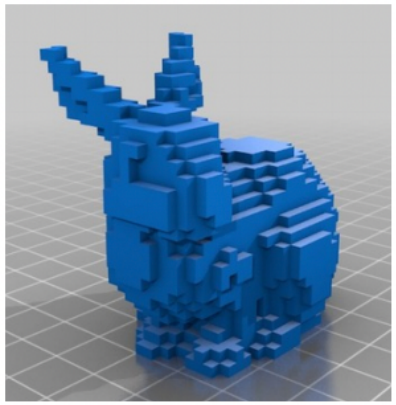
Outline

- Point Networks
  - PointNet
  - PointNet++
- Voxel Networks
- Networks for other representations
  - SDF
  - Mesh

Straightforward Ways of Processing Point Clouds

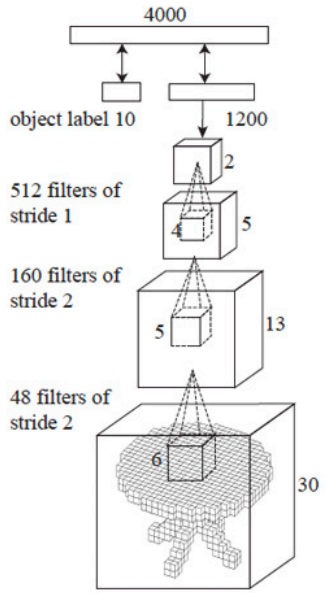


point cloud



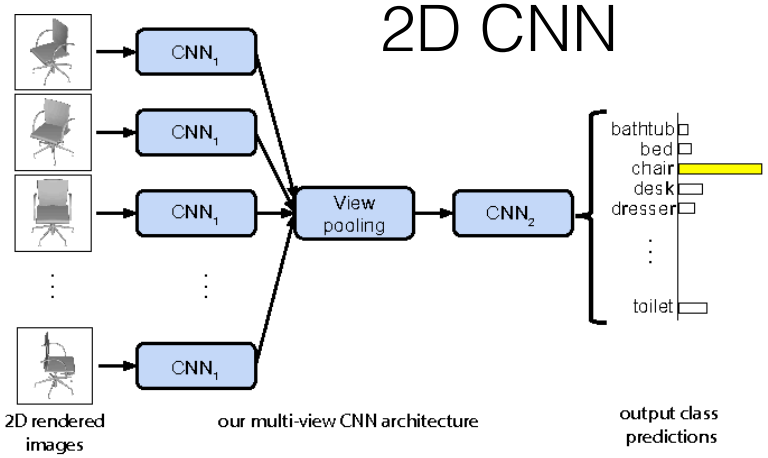
voxel grids

2D projection



3D CNN

3D shape model rendered with different virtual cameras



2D CNN

2D rendered images

our multi-view CNN architecture

output class predictions

Regular Image Grid vs. Irregular 3D Point Cloud

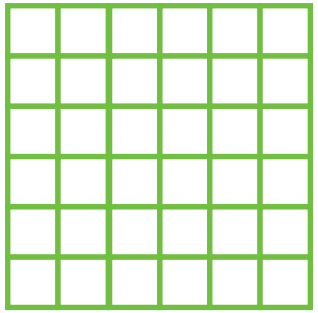
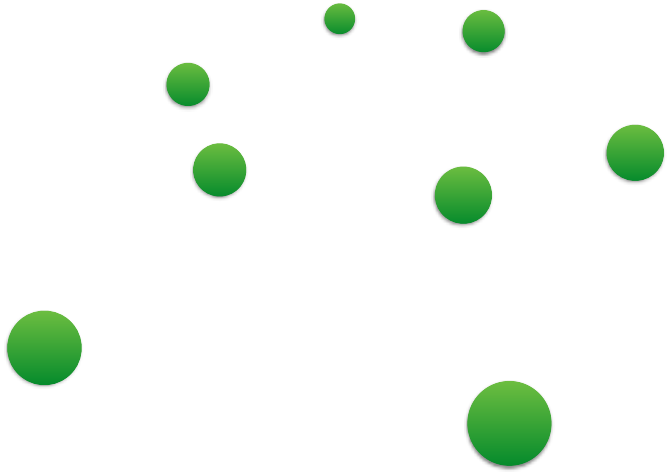


Image grid



Point cloud

Regular Image Grid vs. Irregular 3D Point Cloud

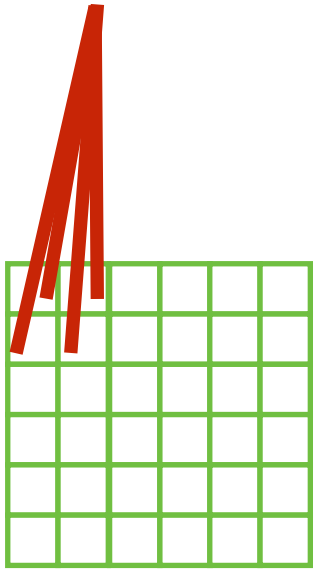
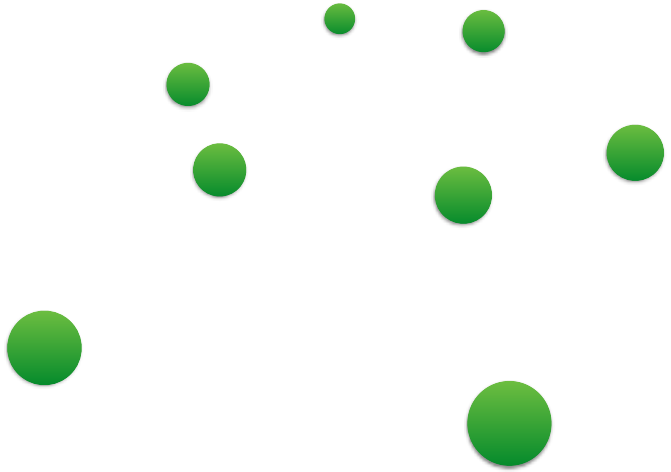


Image grid



Point cloud

Regular Image Grid vs. Irregular 3D Point Cloud

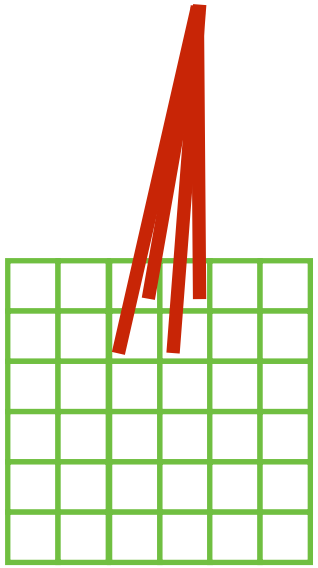
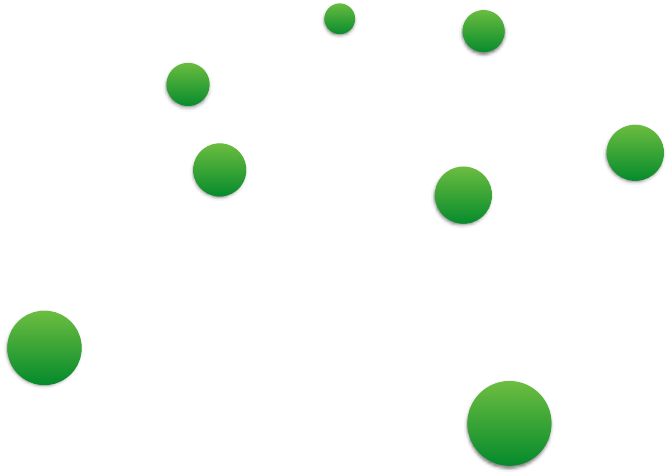


Image grid



Point cloud

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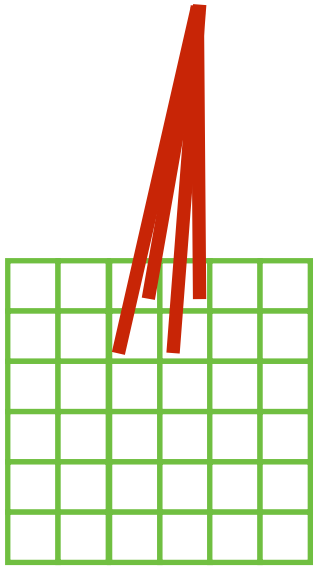
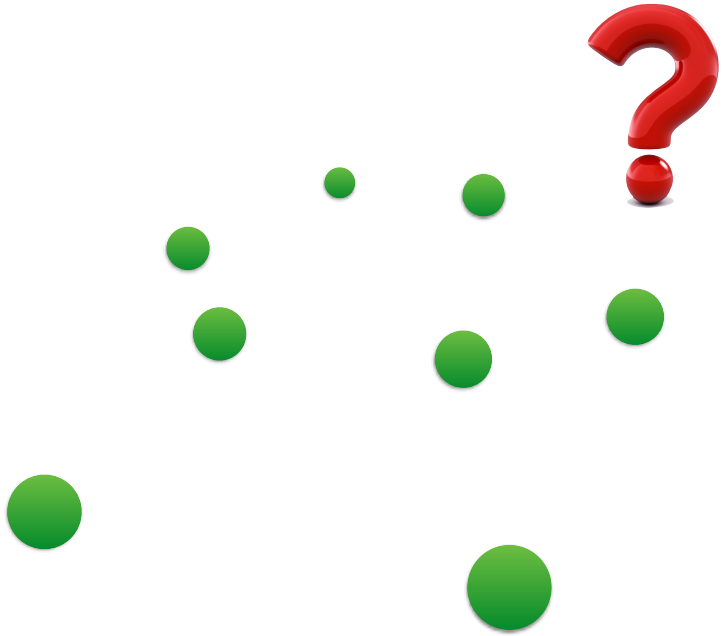


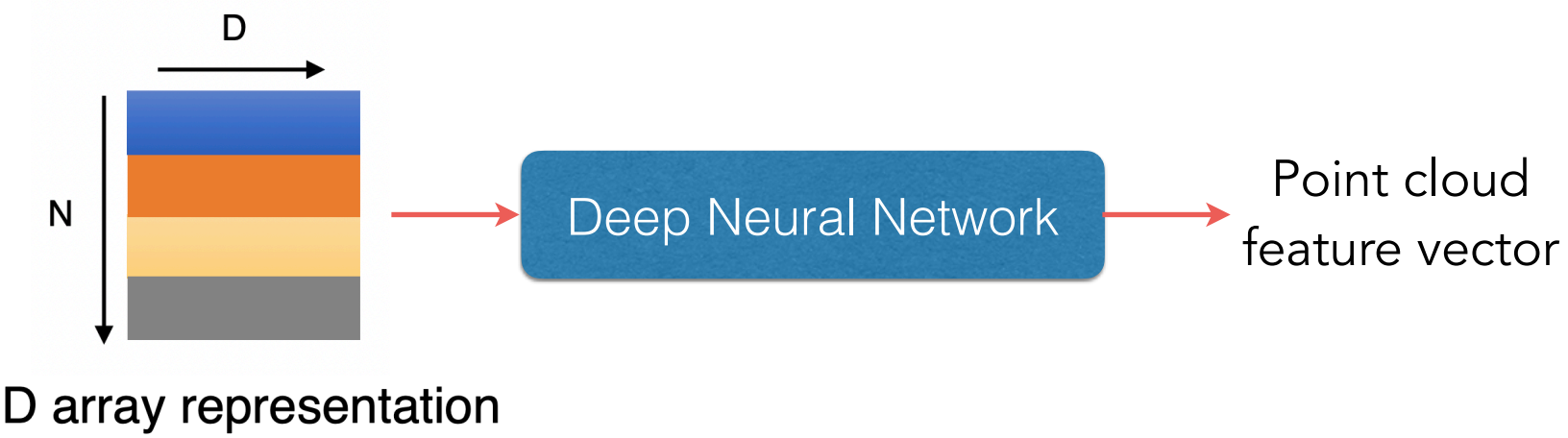
Image grid



Point cloud

Unordered Inputs

- Point cloud: N orderless points, each represented by a D dim coordinate



Unordered Inputs

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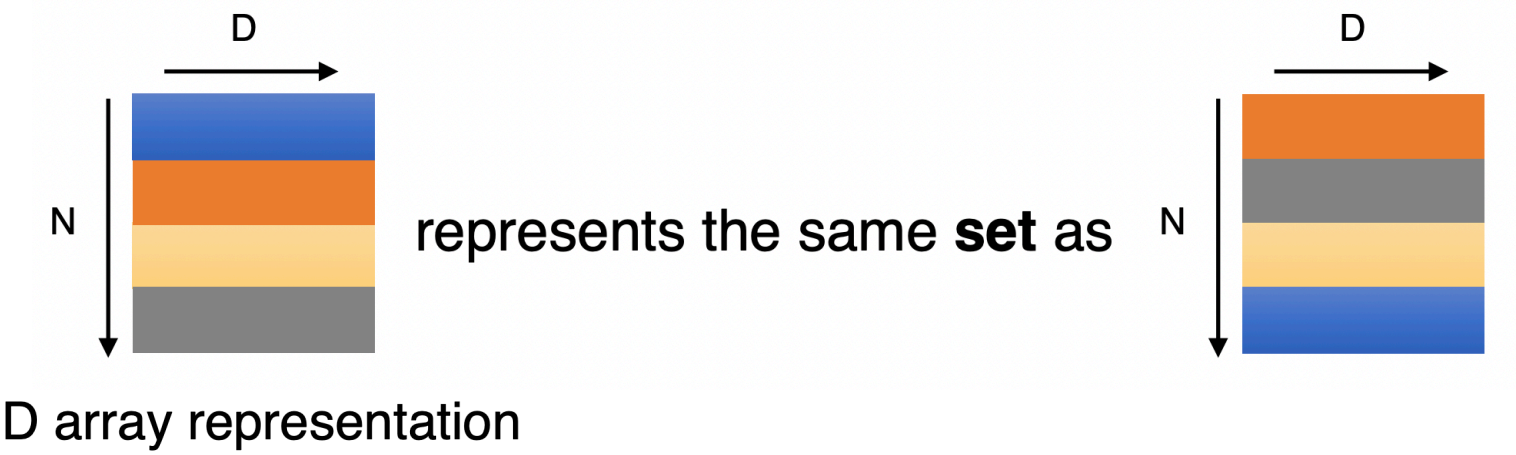
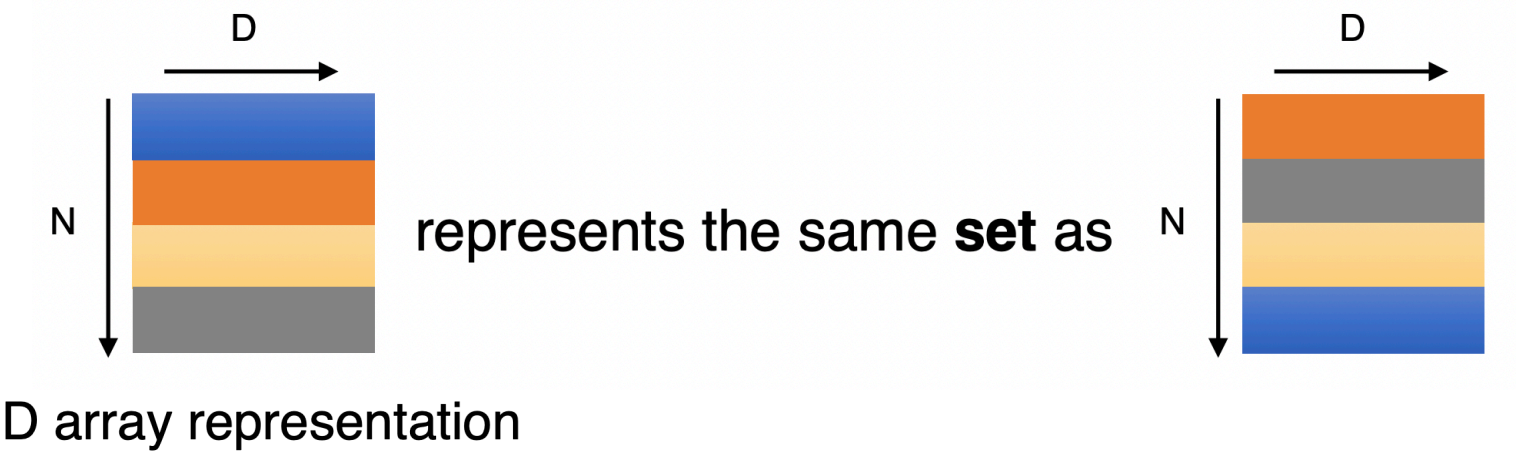


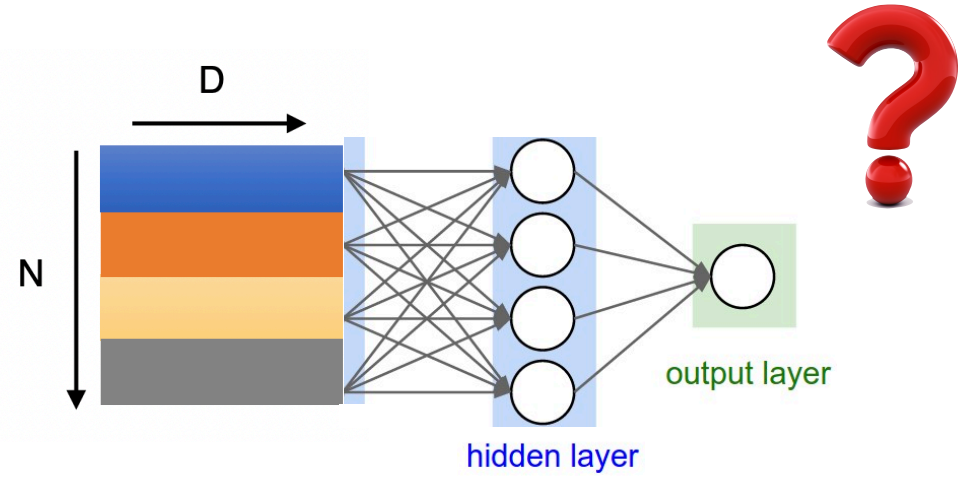
Desired Properties of a Point Cloud Network

- Point cloud: N orderless points, each represented by a D dim coordinate

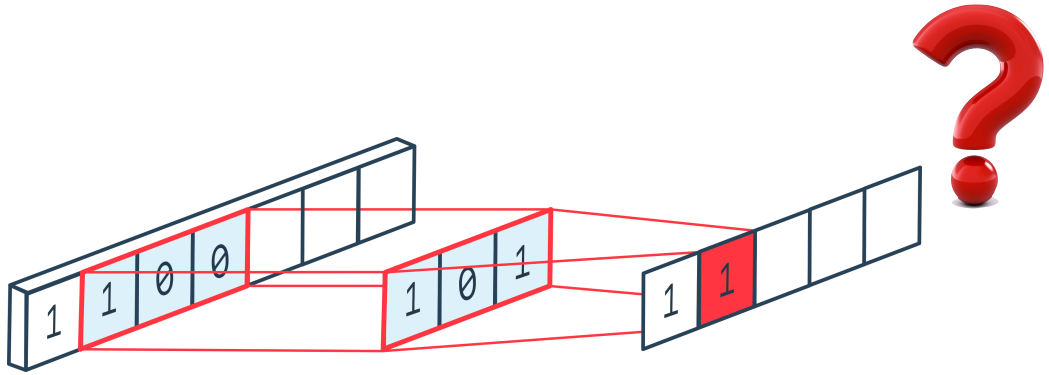


- Deep net needs to be invariant to N! permutations

Permutation Invariance



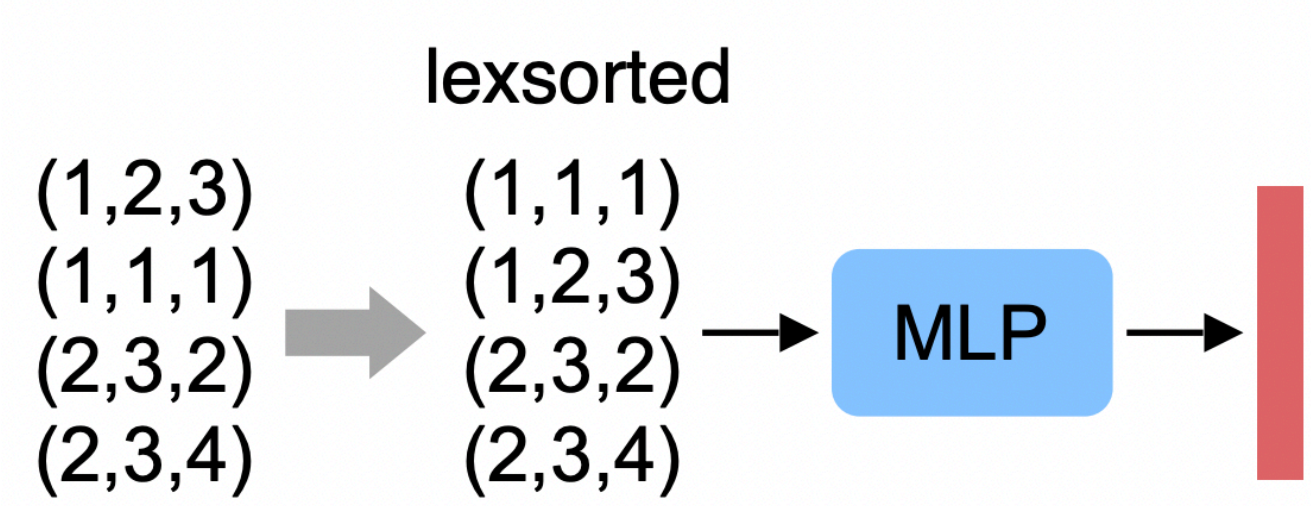
Fully connected network



1D convolutional network

Slide credit: Charles Qi

Permutation Invariance — Sorting?



Not a good idea! Adding one point will change the order dramatically!

Slide credit: Charles Qi

Permutation Invariance: Symmetric Function

$$f(x_1, x_2, \ldots, x_n) \equiv f(x_{\pi_1}, x_{\pi_2}, \ldots, x_{\pi_n}), \quad x_i \in \mathbb{R}^D$$

Slide credit: Charles Qi

Permutation Invariance: Symmetric Function

$$f(x_1, x_2, \ldots, x_n) \equiv f(x_{\pi_1}, x_{\pi_2}, \ldots, x_{\pi_n}), \quad x_i \in \mathbb{R}^D$$

Examples:

$$f(x_1, x_2, \ldots, x_n) = \max\{x_1, x_2, \ldots, x_n\}$$

$$f(x_1, x_2, \ldots, x_n) = x_1 + x_2 + \ldots + x_n$$

...

Slide credit: Charles Qi

Permutation Invariance: Symmetric Function

$$f(x_1, x_2, \ldots, x_n) \equiv f(x_{\pi_1}, x_{\pi_2}, \ldots, x_{\pi_n}), \quad x_i \in \mathbb{R}^D$$

Examples:

$$f(x_1, x_2, \ldots, x_n) = \max\{x_1, x_2, \ldots, x_n\}$$

$$f(x_1, x_2, \ldots, x_n) = x_1 + x_2 + \ldots + x_n$$

...

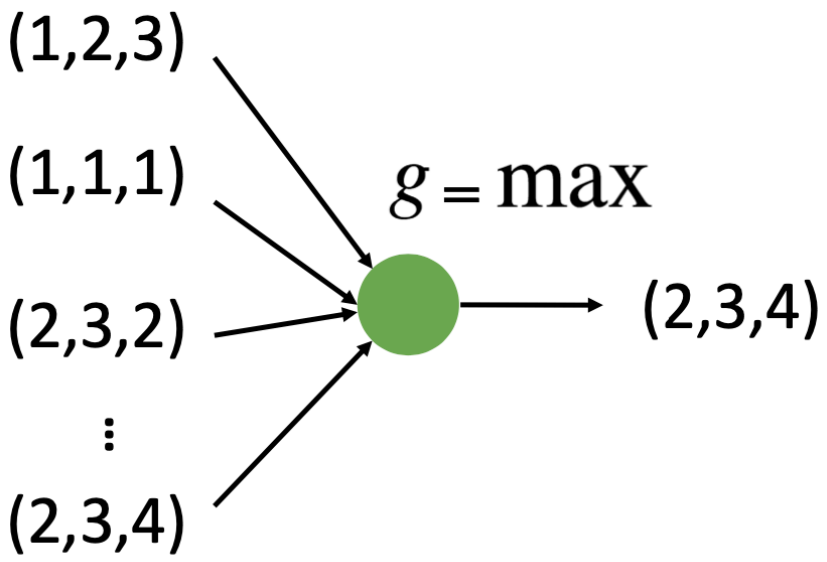
How can we construct a universal family of symmetric functions by neural networks?

Slide credit: Charles Qi

Construct Symmetric Functions by Neural Networks

Simplest form: directly aggregate all points with a symmetric operator g

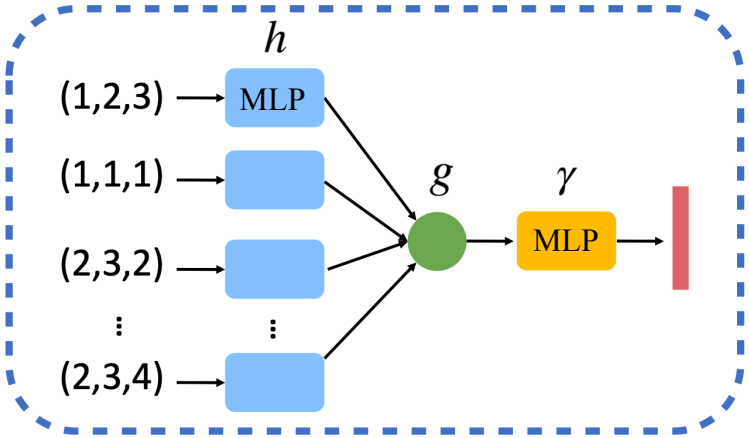
Just discovers simple extreme/aggregate properties of the geometry.



Slide credit: Charles Qi

Construct Symmetric Functions by Neural Networks

$f(x_1, x_2, \ldots, x_n) = \gamma \circ g(h(x_1), \ldots, h(x_n))$ is symmetric if g is symmetric

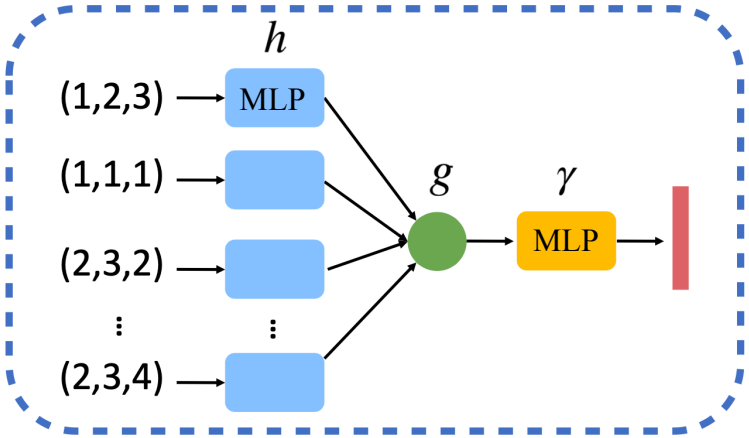


PointNet (vanilla)

Slide credit: Charles Qi

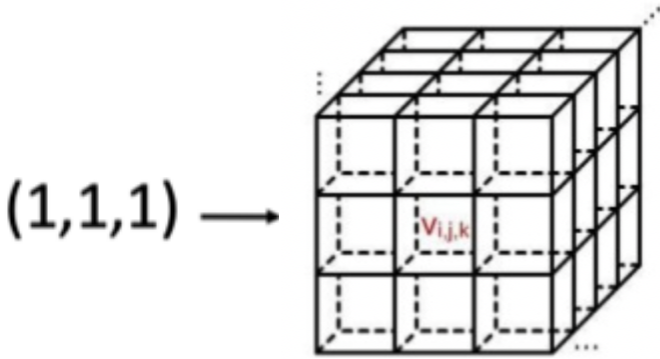
Construct Symmetric Functions by Neural Networks

$$f(x_1, x_2, \ldots, x_n) = \gamma \circ g(h(x_1), \ldots, h(x_n))$$ is symmetric if g is symmetric

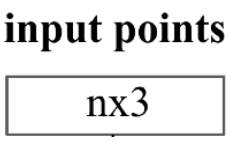


PointNet (vanilla)

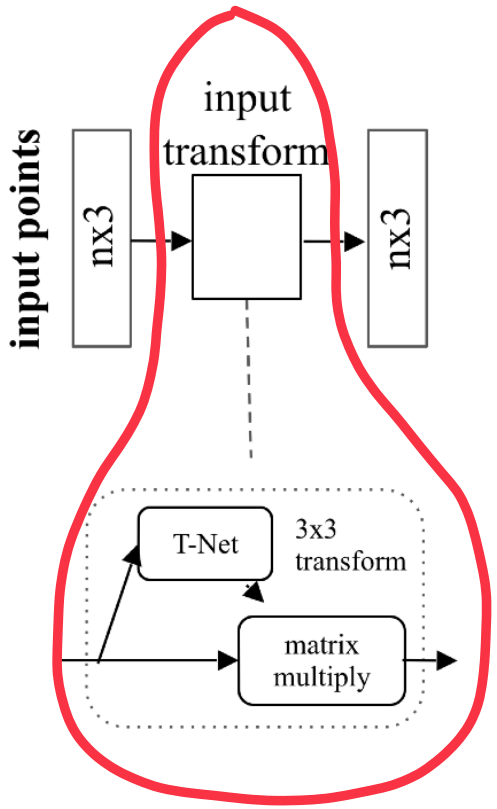
- Reflection: assuming g is a max operation, construct a function h where geometric details get kept after applying g.



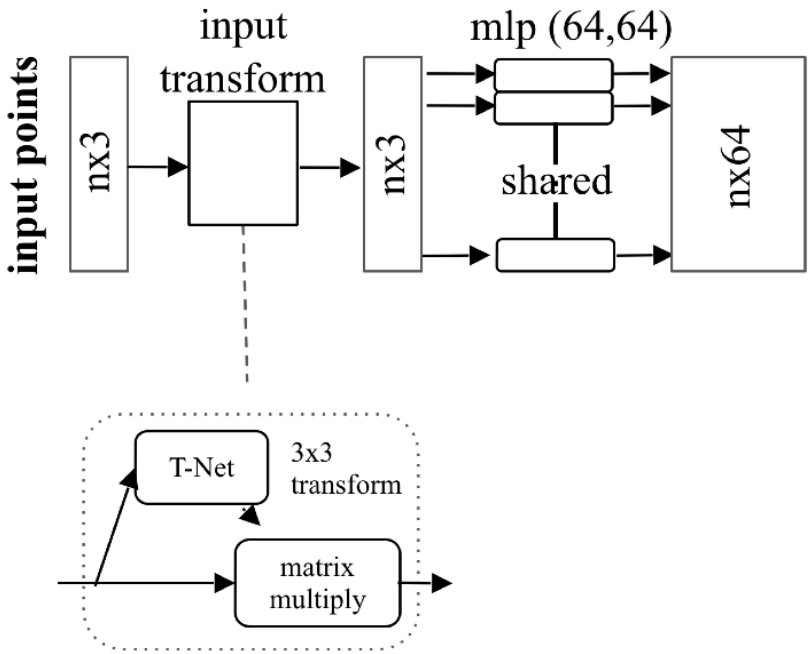
Spatial Hashing Function


input points
nx3

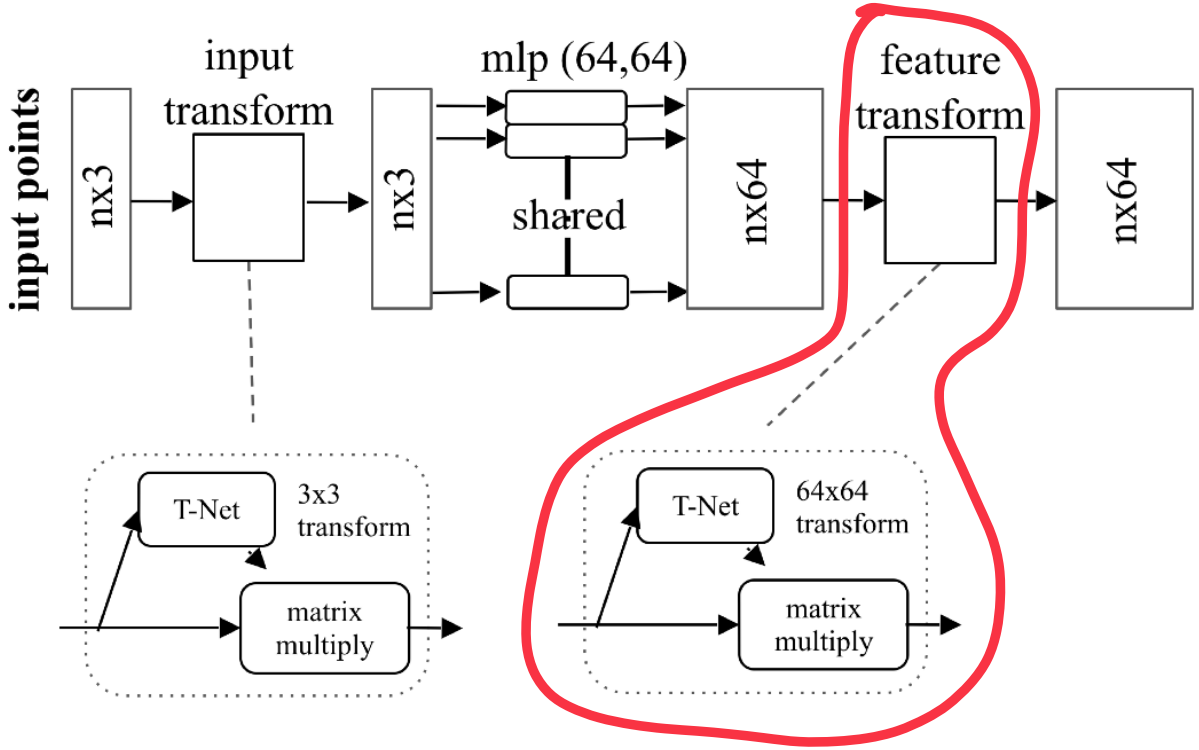
A Detailed Implementation of PointNet



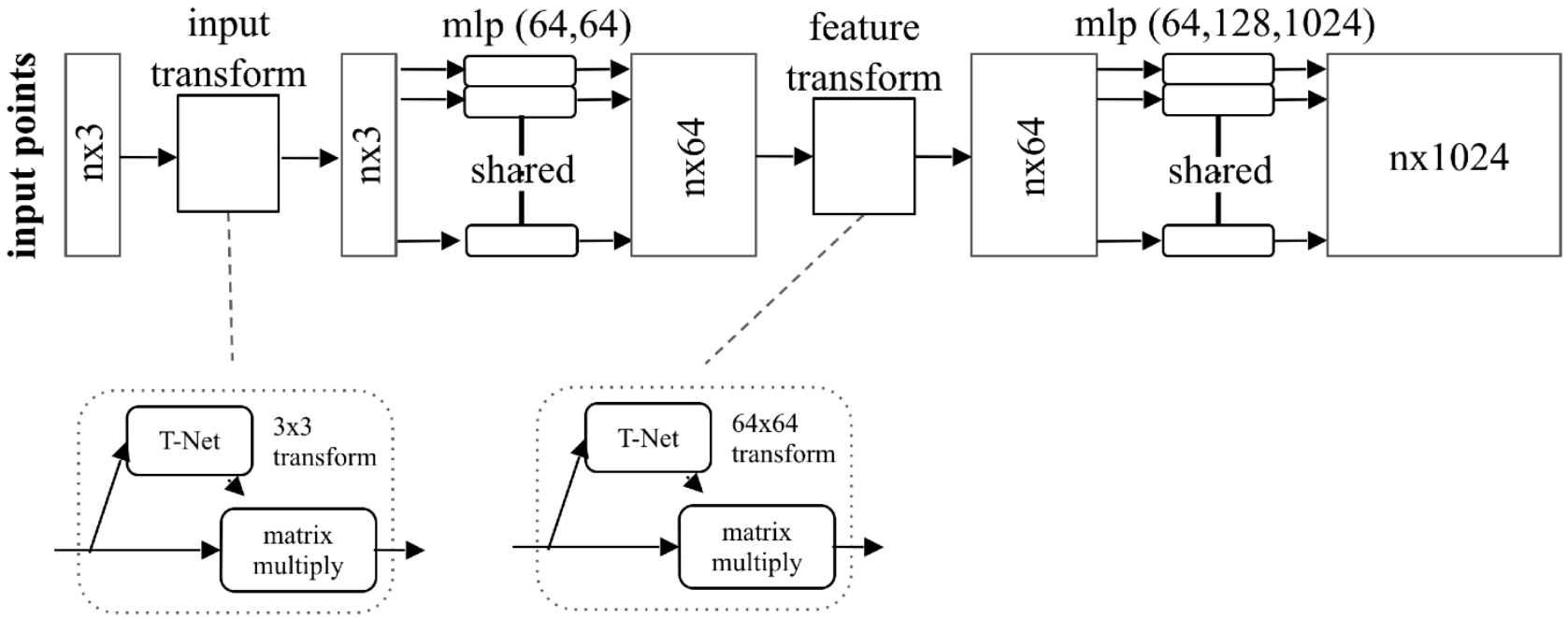
A Detailed Implementation of PointNet



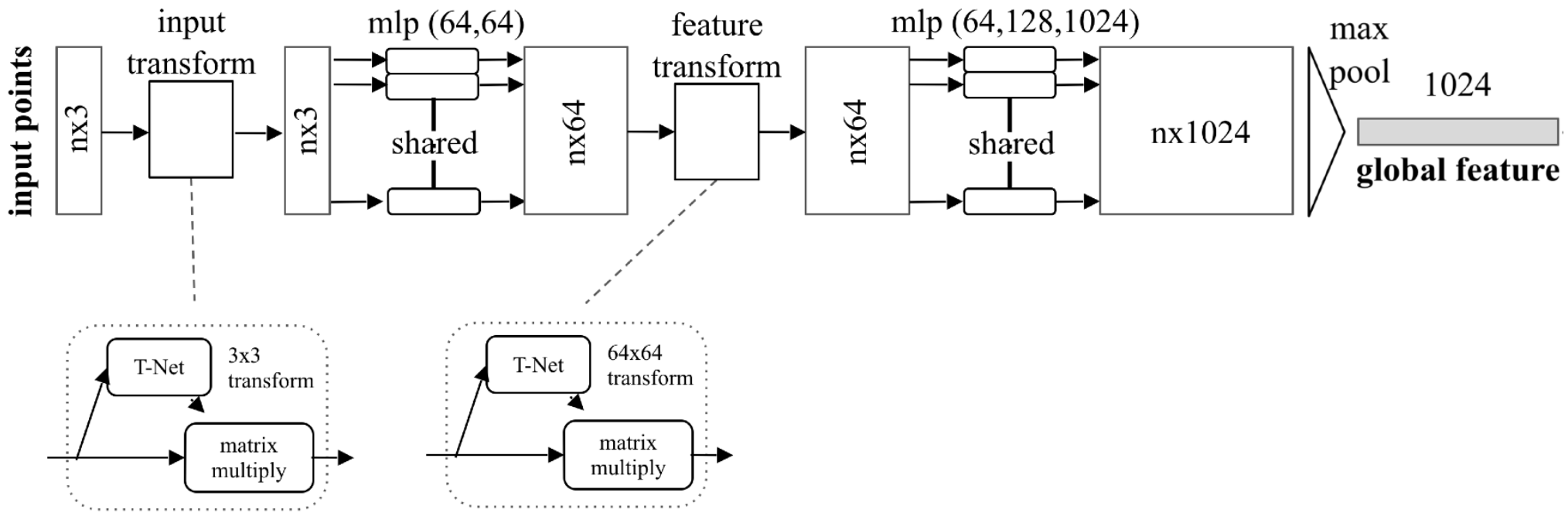
A Detailed Implementation of PointNet



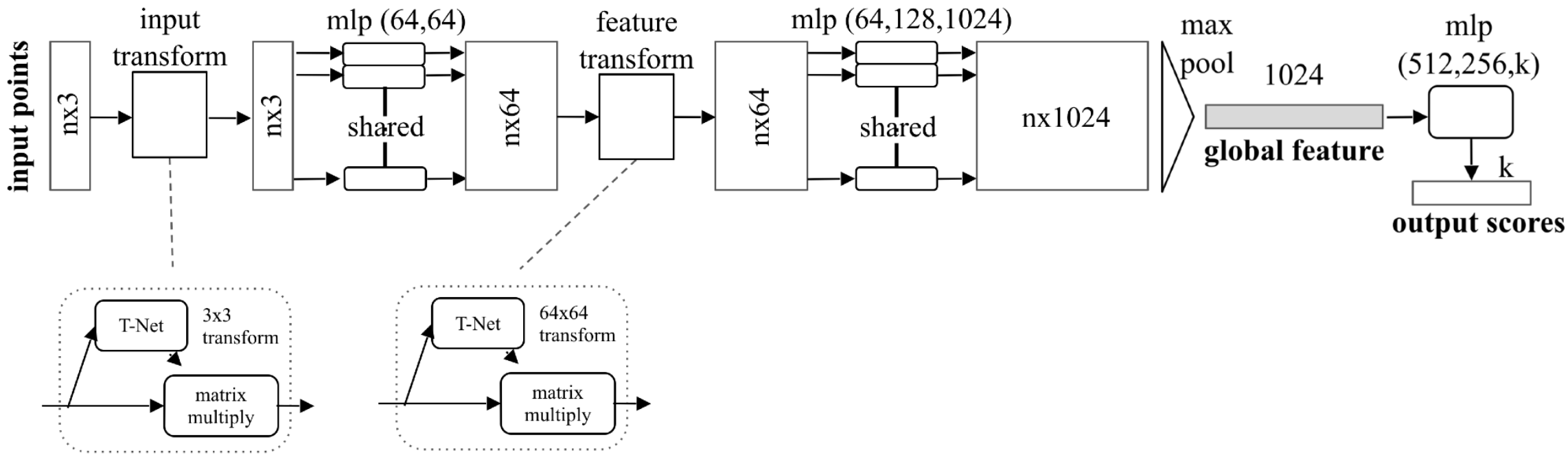
A Detailed Implementation of PointNet



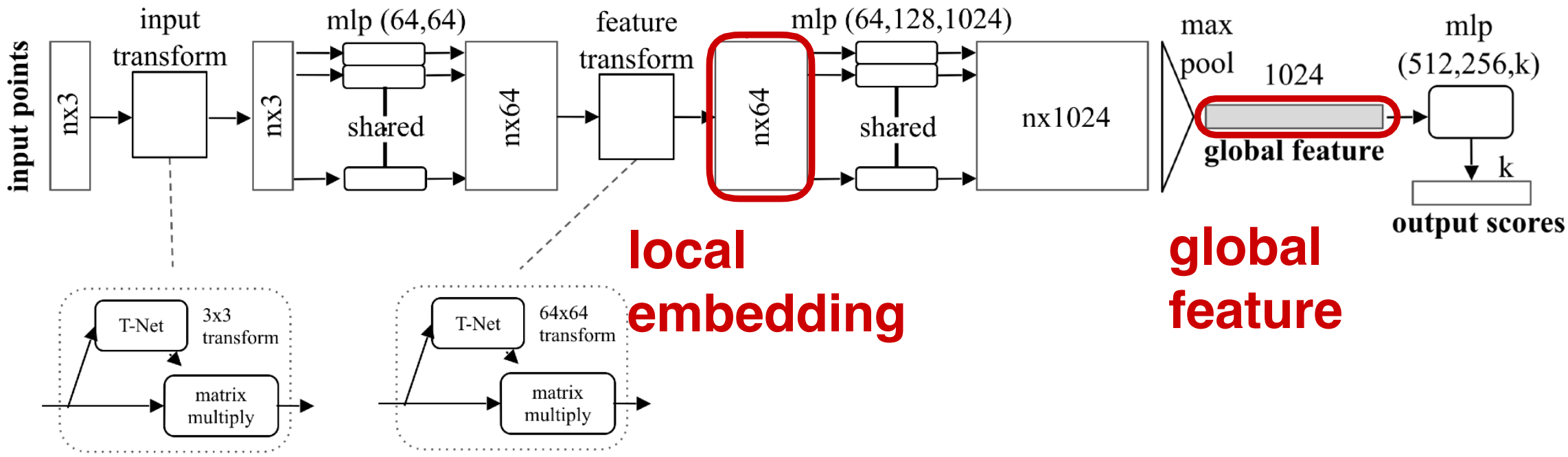
A Detailed Implementation of PointNet



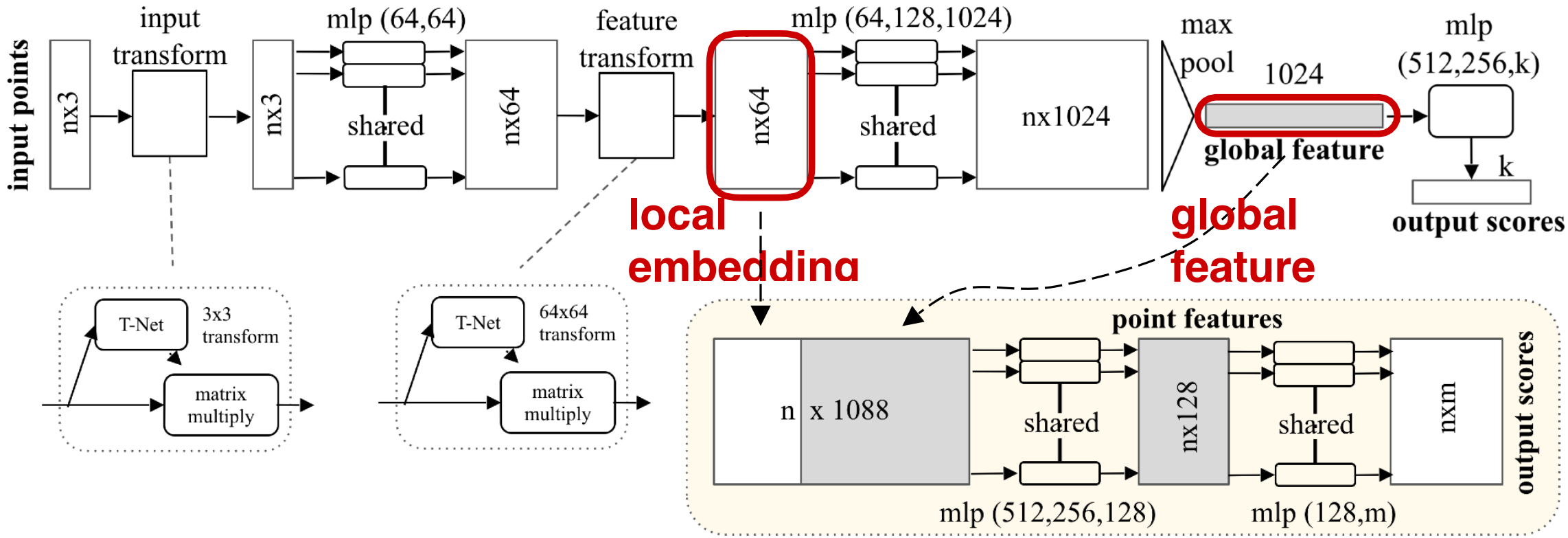
A Detailed Implementation of PointNet



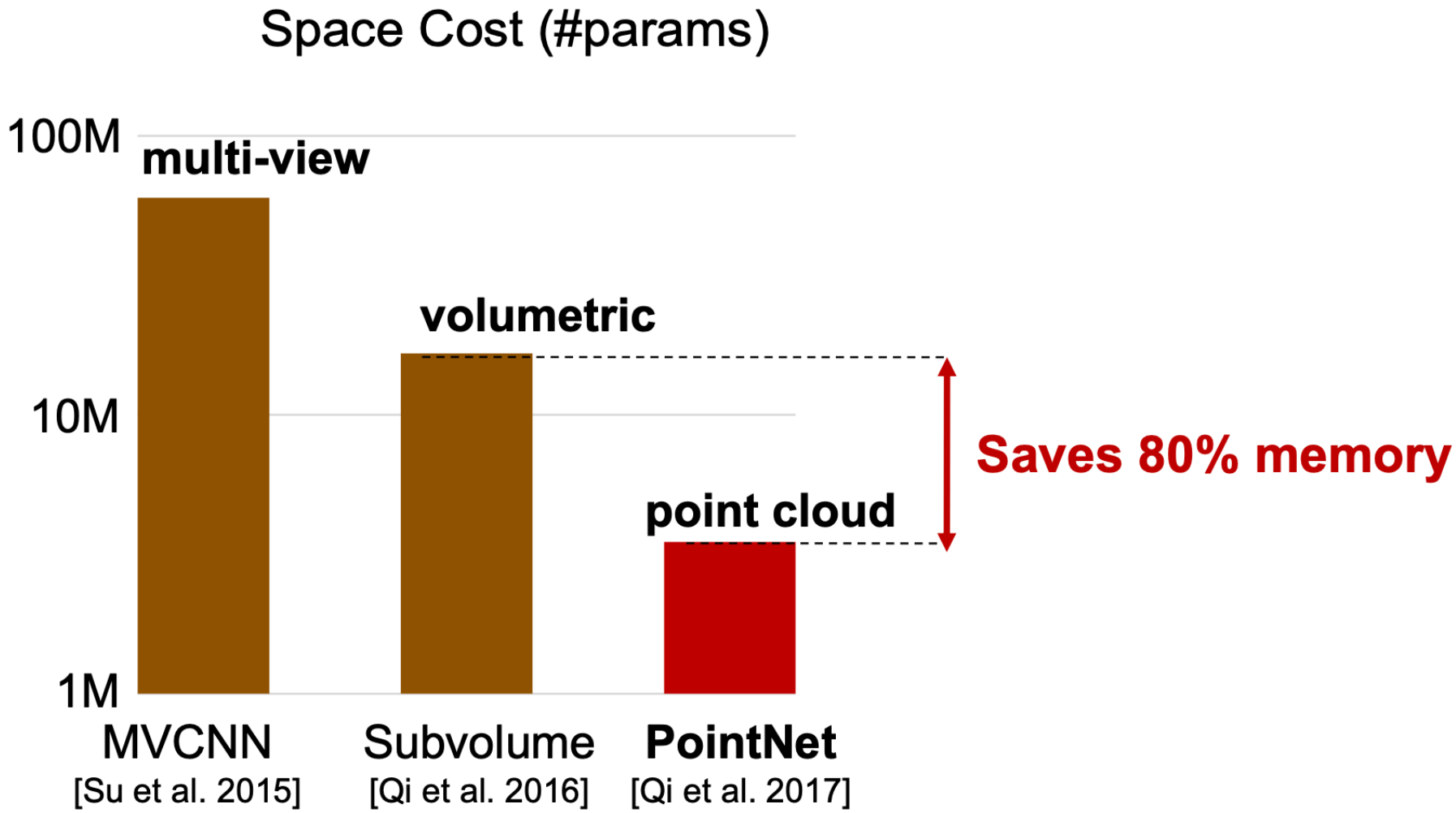
Extension to Segmentation



Extension to Segmentation

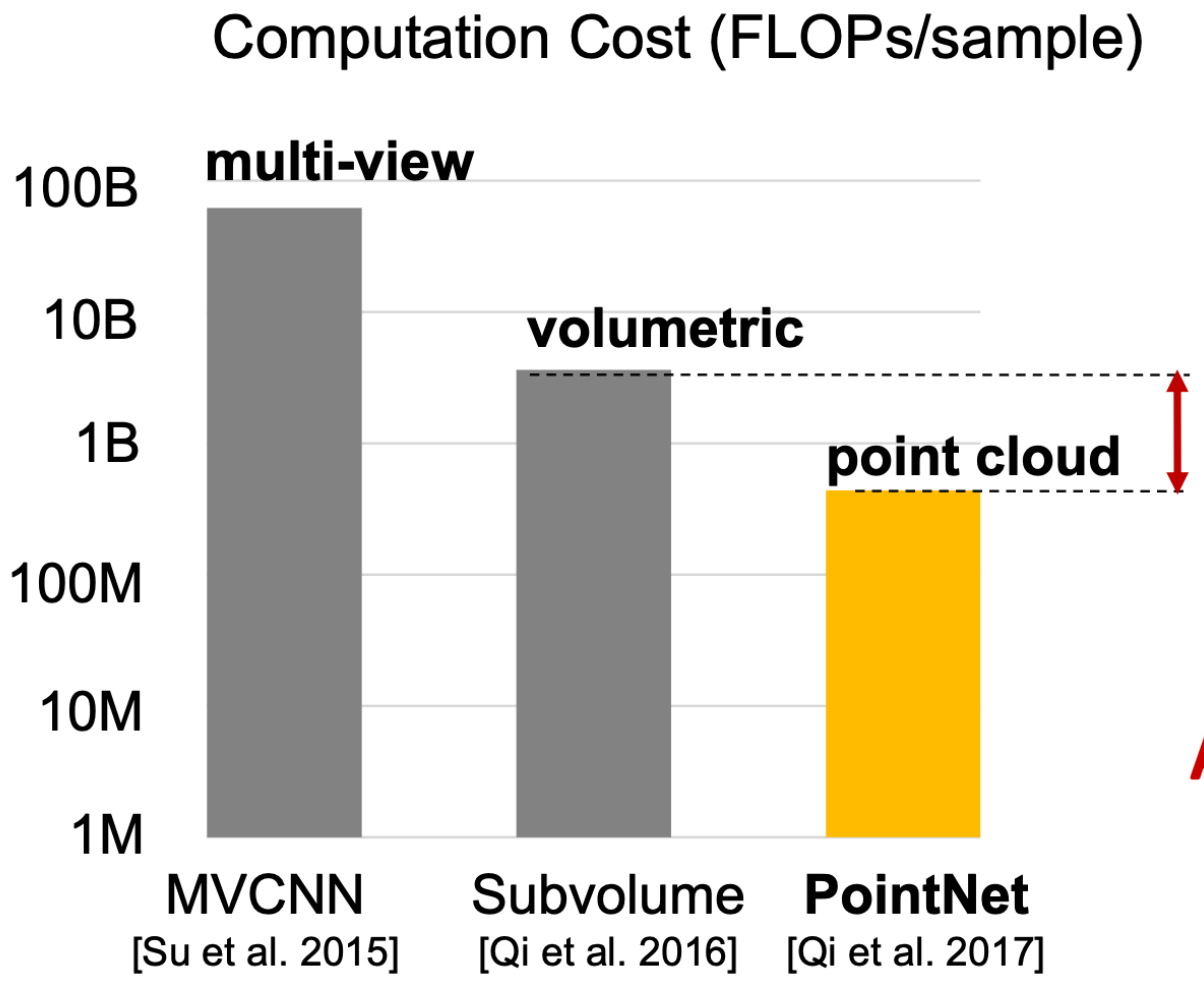


PointNet is Light-Weight and Fast



Slide credit: Charles Qi

PointNet is Light-Weight and Fast



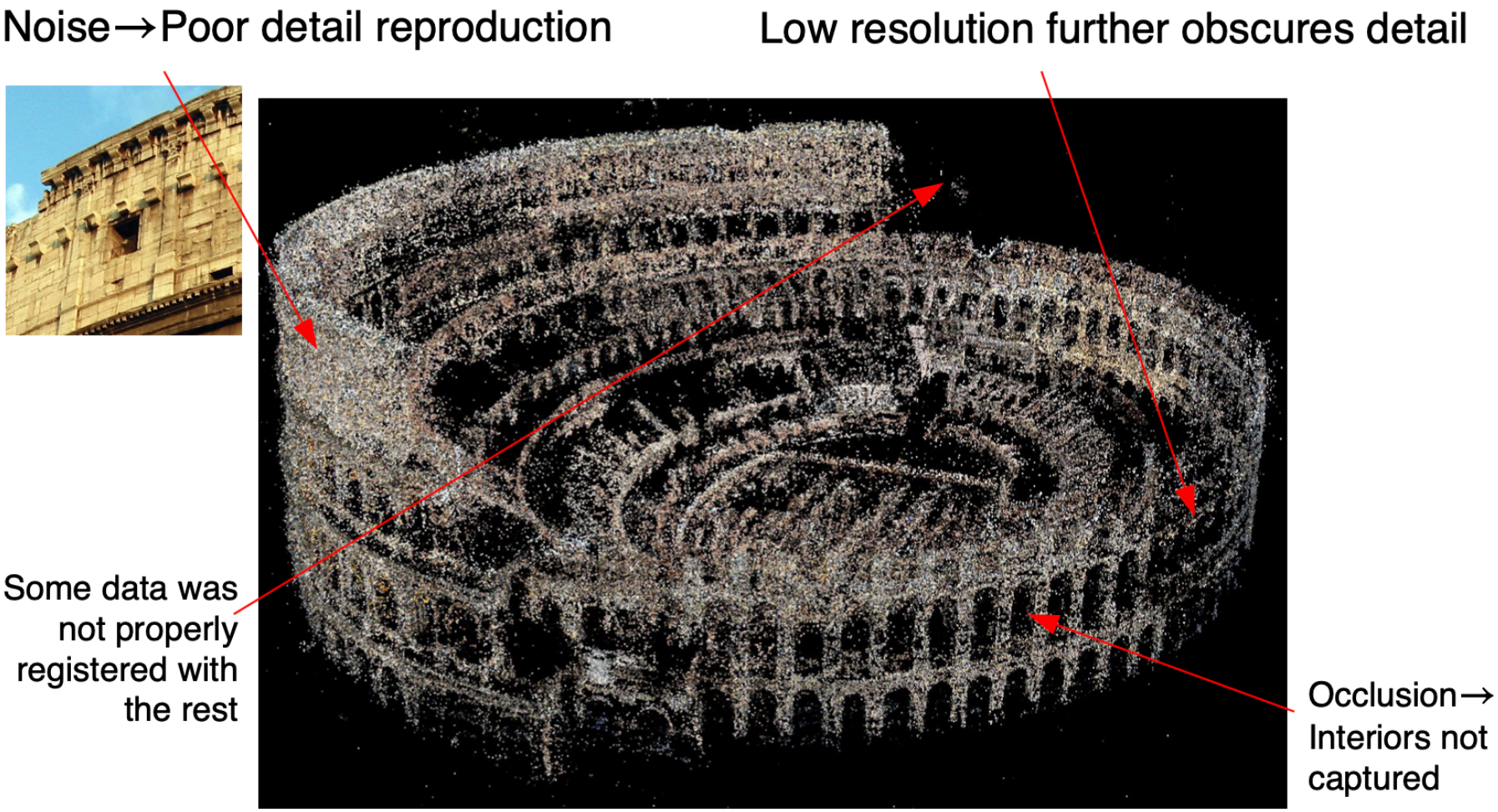
Saves 88% FLOPs

A promising architecture for portable devices!

Slide credit: Charles Qi

Robustness to Data Corruption

- Many challenges
  - Resolution
  - Occlusion
  - Noise
  - Registration



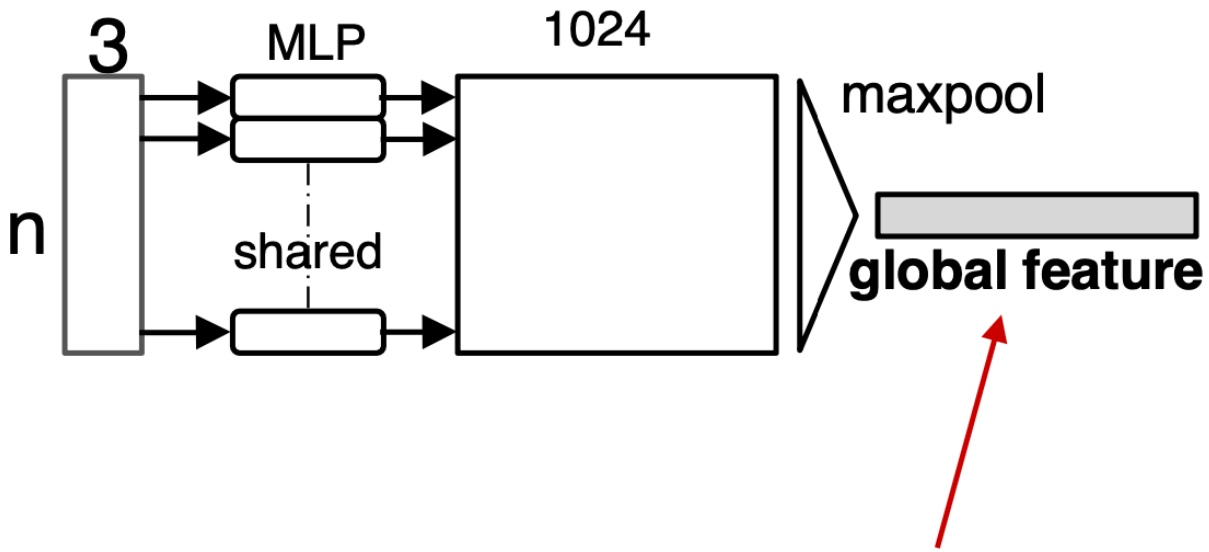
Robustness to Data Corruption

Less than 2% accuracy drop with 50% missing data

dataset: ModelNet40; metric: 40-class classification accuracy (%)

Slide credit: Charles Qi

Visualizing Global Point Cloud Features



Which input points are contributing to the global feature?
(critical points)

Slide credit: Charles Qi

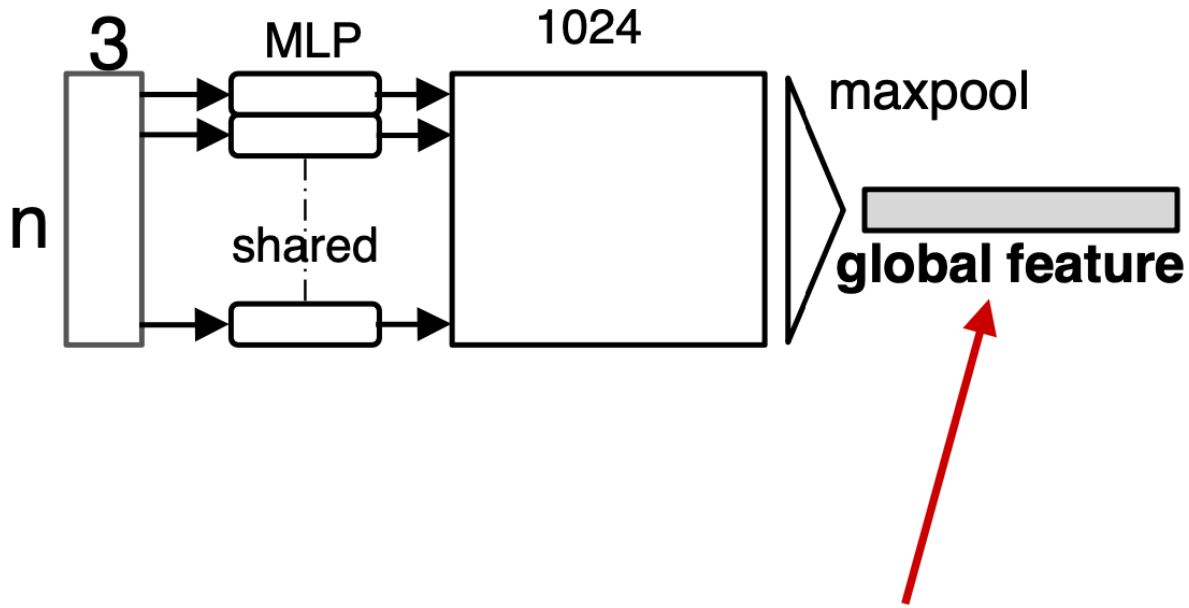
Visualizing Global Point Cloud Features

Original Shape:

Critical Point Set:

Slide credit: Charles Qi

Visualizing Global Point Cloud Features



Which points won't affect the global feature?

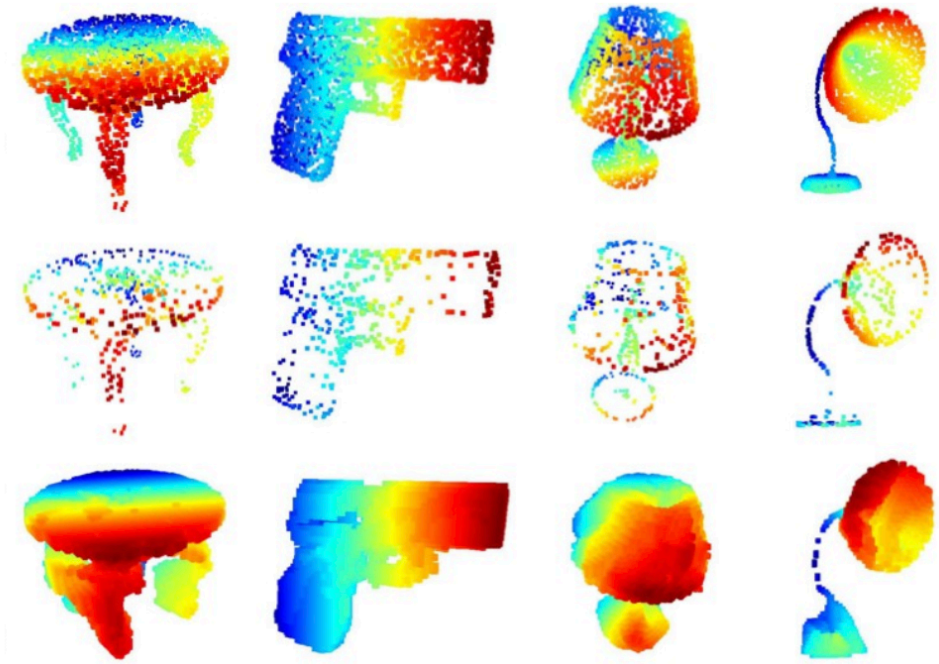
Slide credit: Charles Qi

Visualizing Global Point Cloud Features

Original Shape:

Critical Point Set:

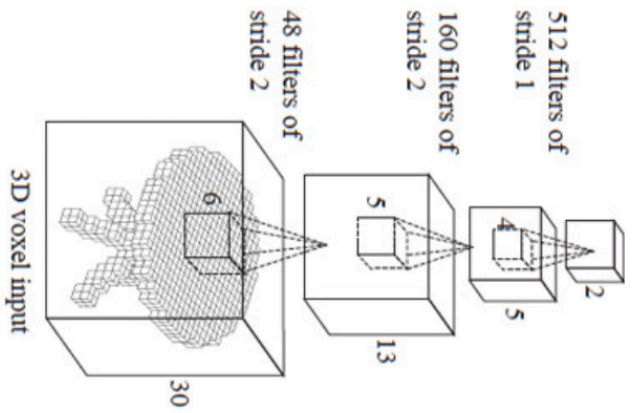
Upper bound set:



Slide credit: Charles Qi

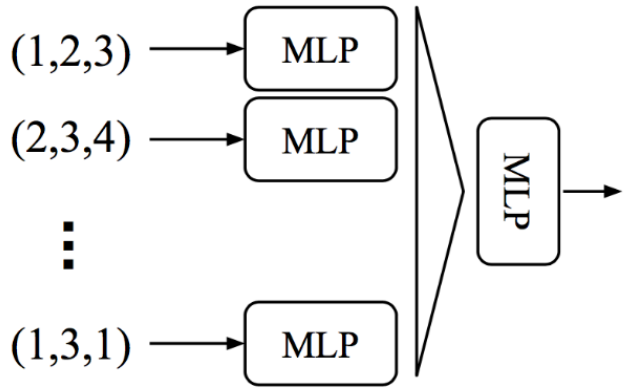
Limitation of PointNet

Hierarchical feature learning
Multiple levels of abstraction



3D CNN (Wu et al.)

Global feature learning
Either one point or all points



PointNet (vanilla) (Qi et al.)

- No local context for each point
- Global feature depends on absolute coordinate. Hard to generalize to unseen scene configurations!

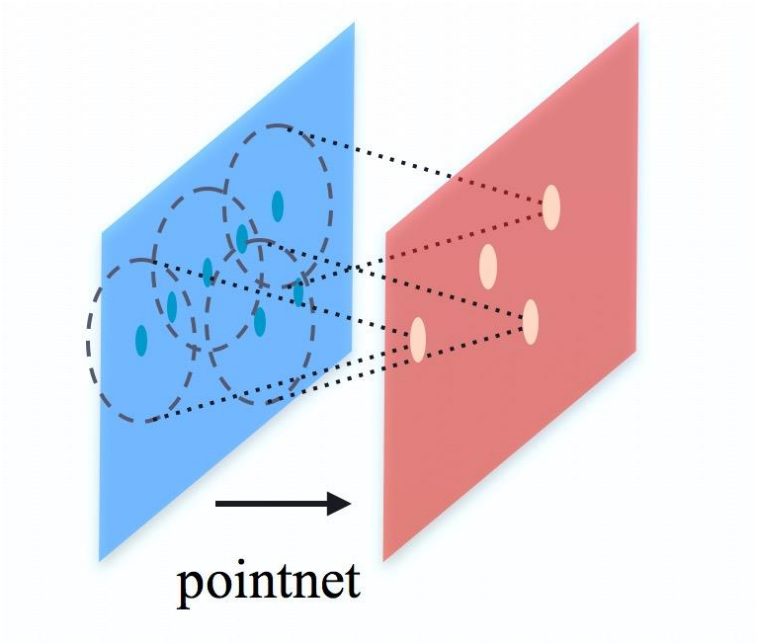
Outline

- Point Networks
  - PointNet
  - PointNet++
- Voxel Networks
- Networks for other representations
  - SDF
  - Mesh

PointNet++

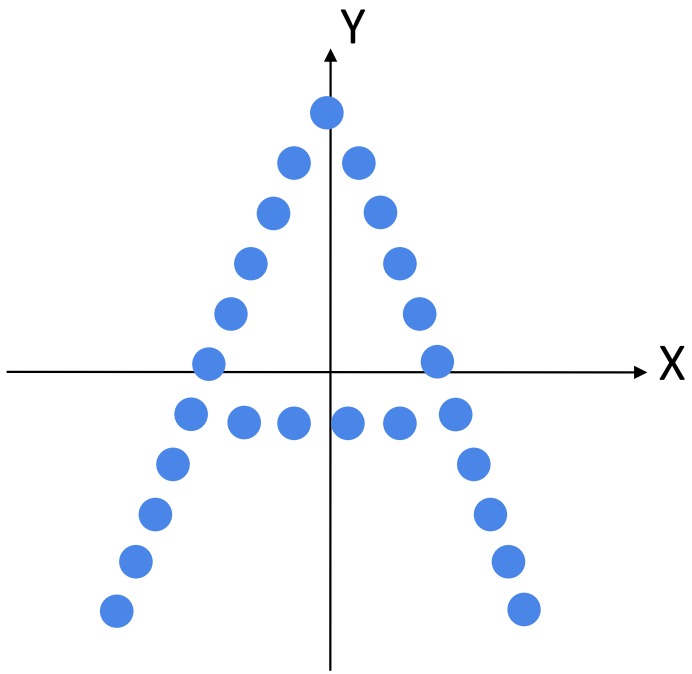
Basic idea: Recursively apply pointnet at local regions.

- ✓ Hierarchical feature learning
- ✓ Local translation invariance
- ✓ Permutation invariance



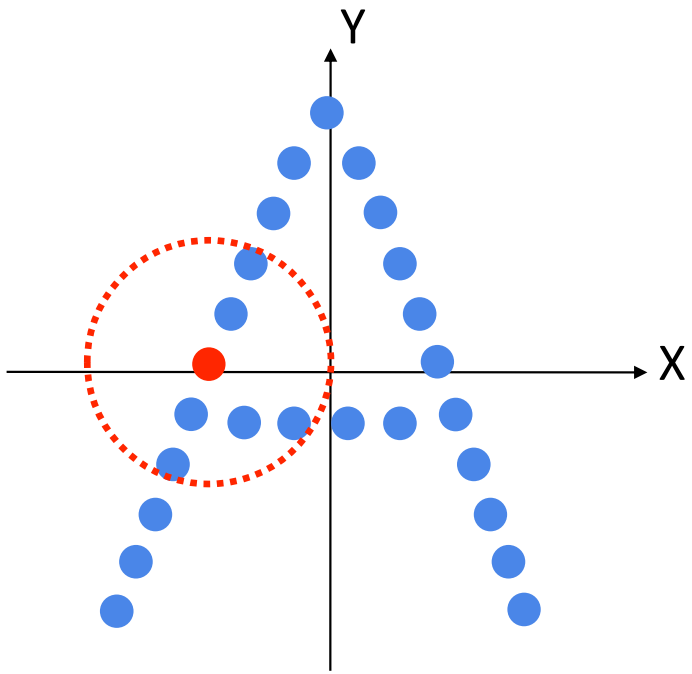
Charles R. Qi, Li Yi, Hao Su, Leonidas Guibas. PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space (NIPS'17)

Hierarchical Point Feature Learning

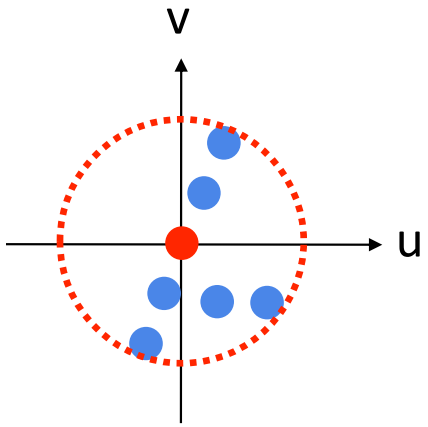


N points in (X,Y)

Hierarchical Point Feature Learning

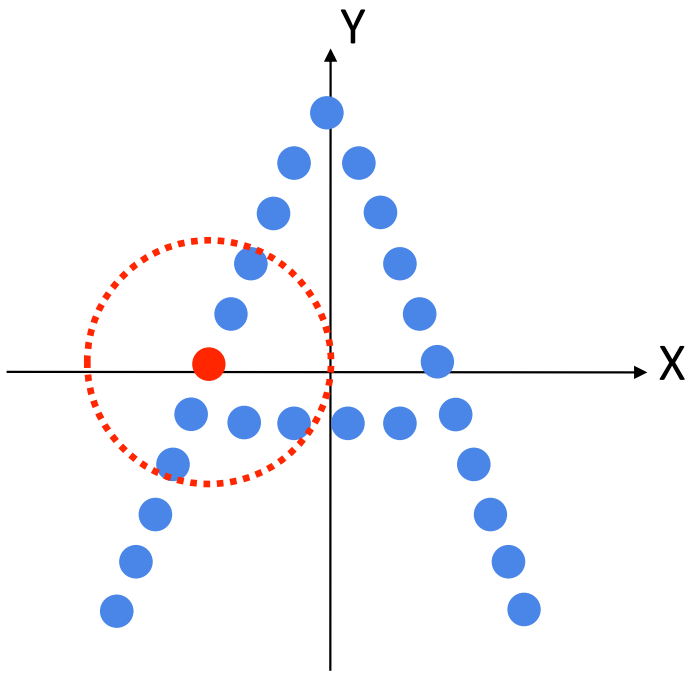


N points in (X,Y)



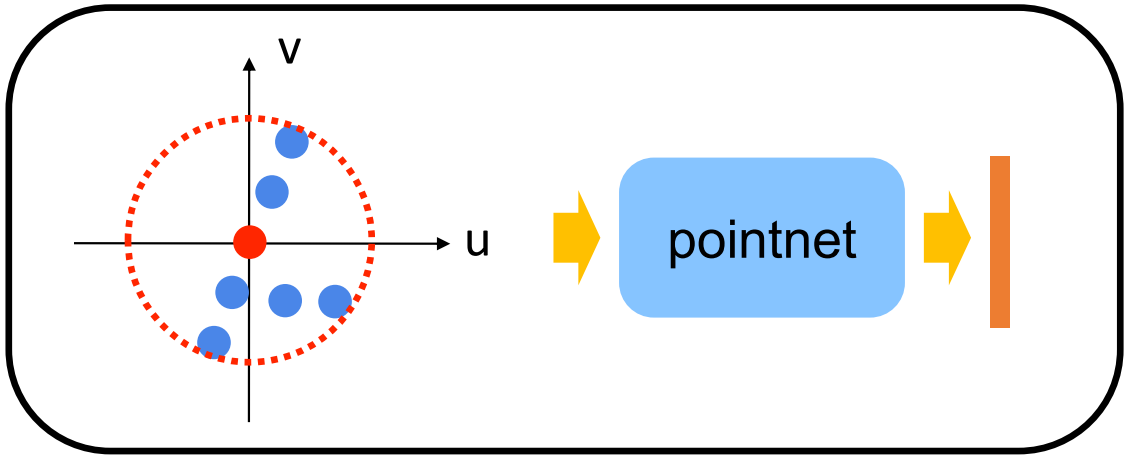
k points in local coordinates (u,v)

Hierarchical Point Feature Learning



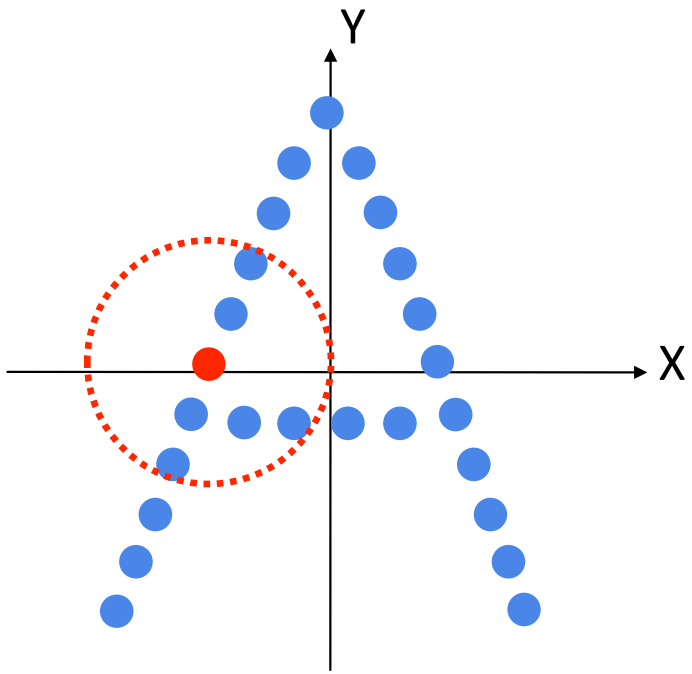
N points in (X,Y)

Apply pointnet at a local region

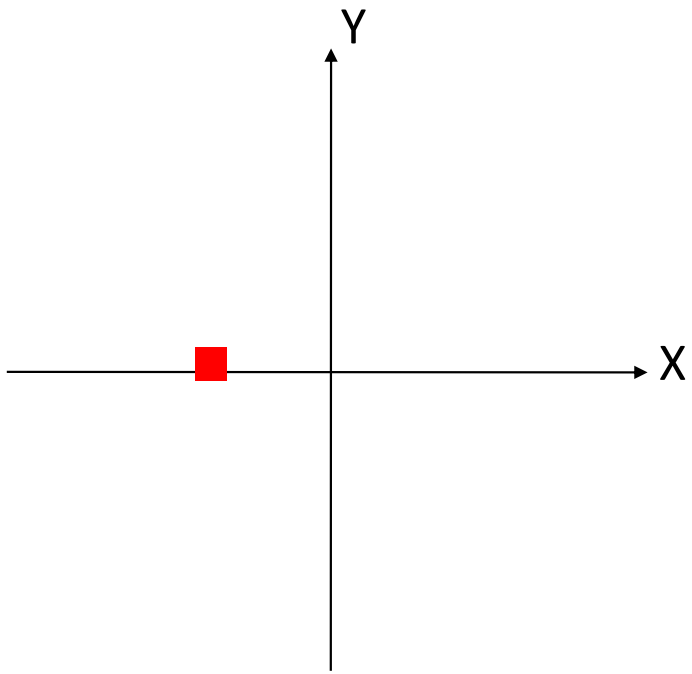


k points in local coordinates (u,v)

Hierarchical Point Feature Learning



N points in (X,Y)

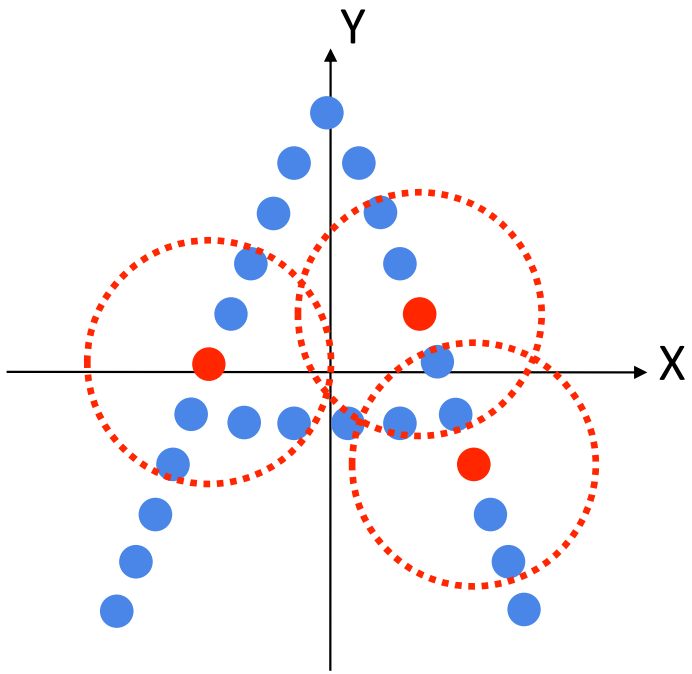


points in (X,Y, **F**)

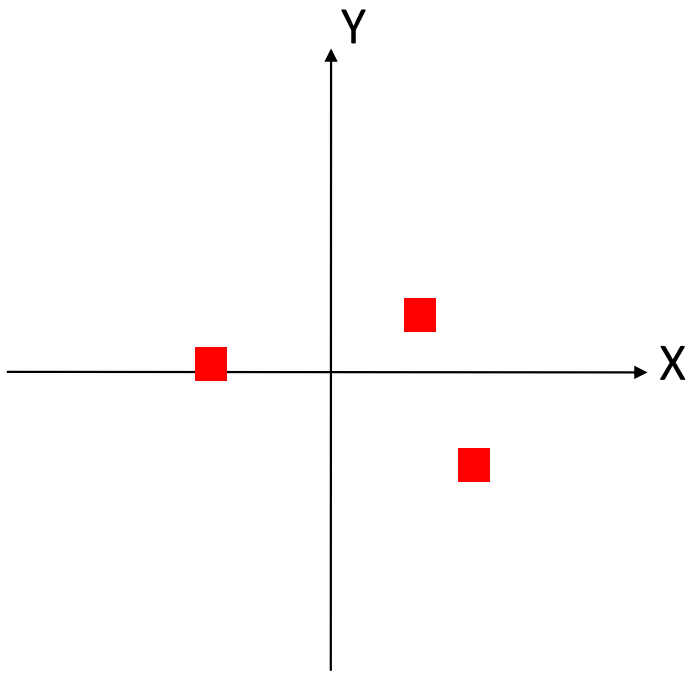
Euclidean space

high-dim feature space

Hierarchical Point Feature Learning

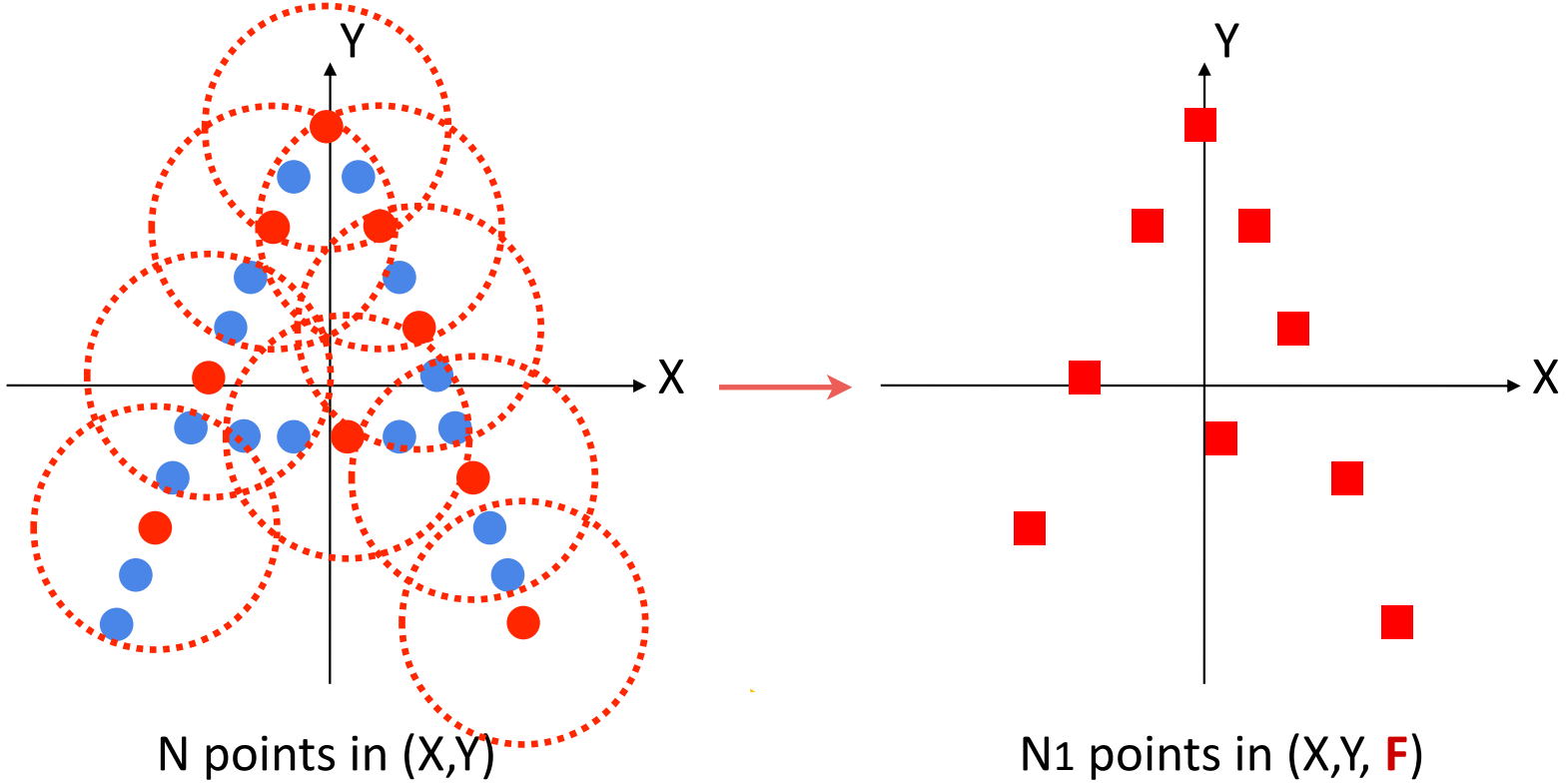


N points in (X,Y)



points in (X,Y, **F**)

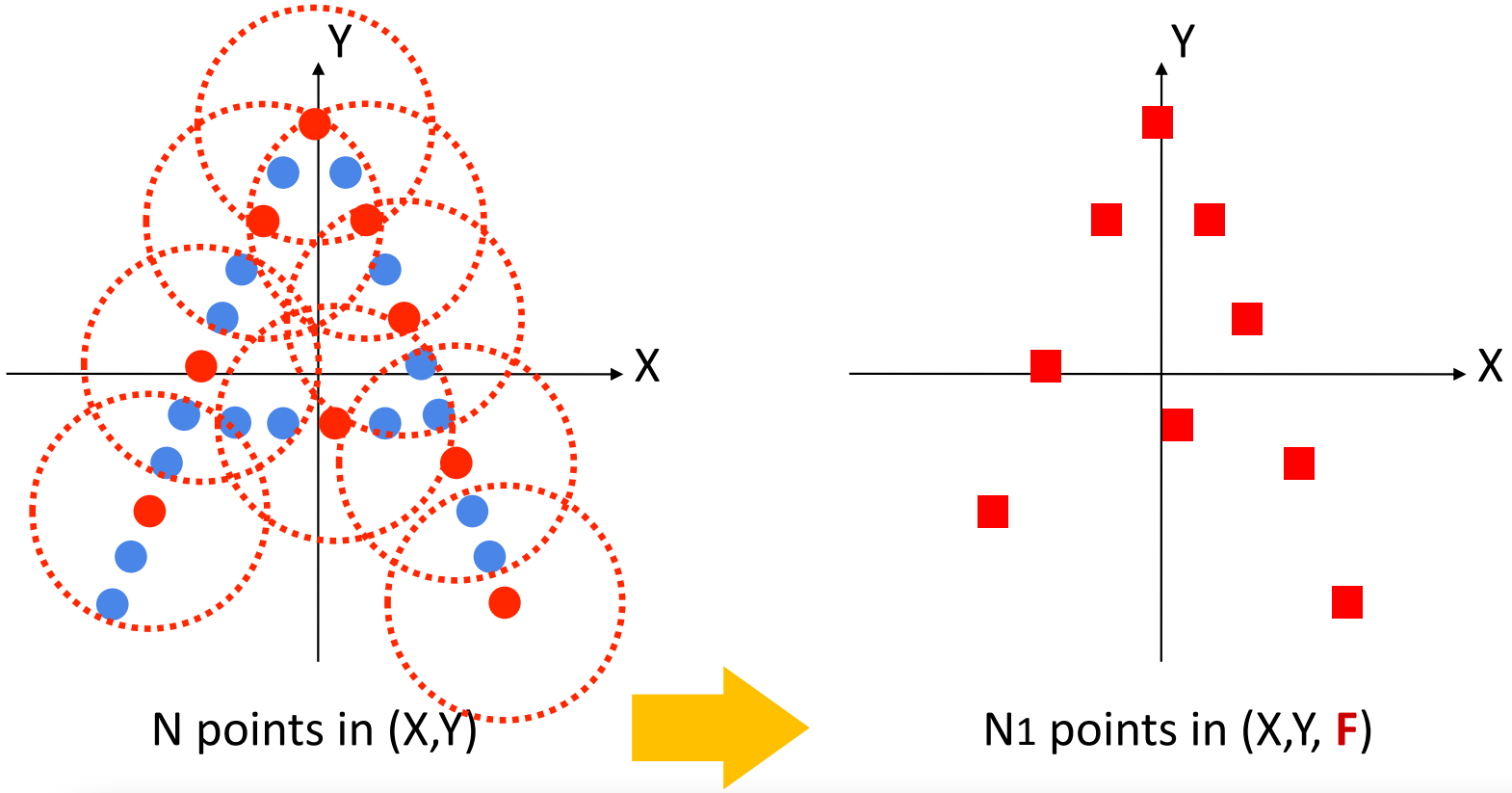
Hierarchical Point Feature Learning



N points in (X,Y)

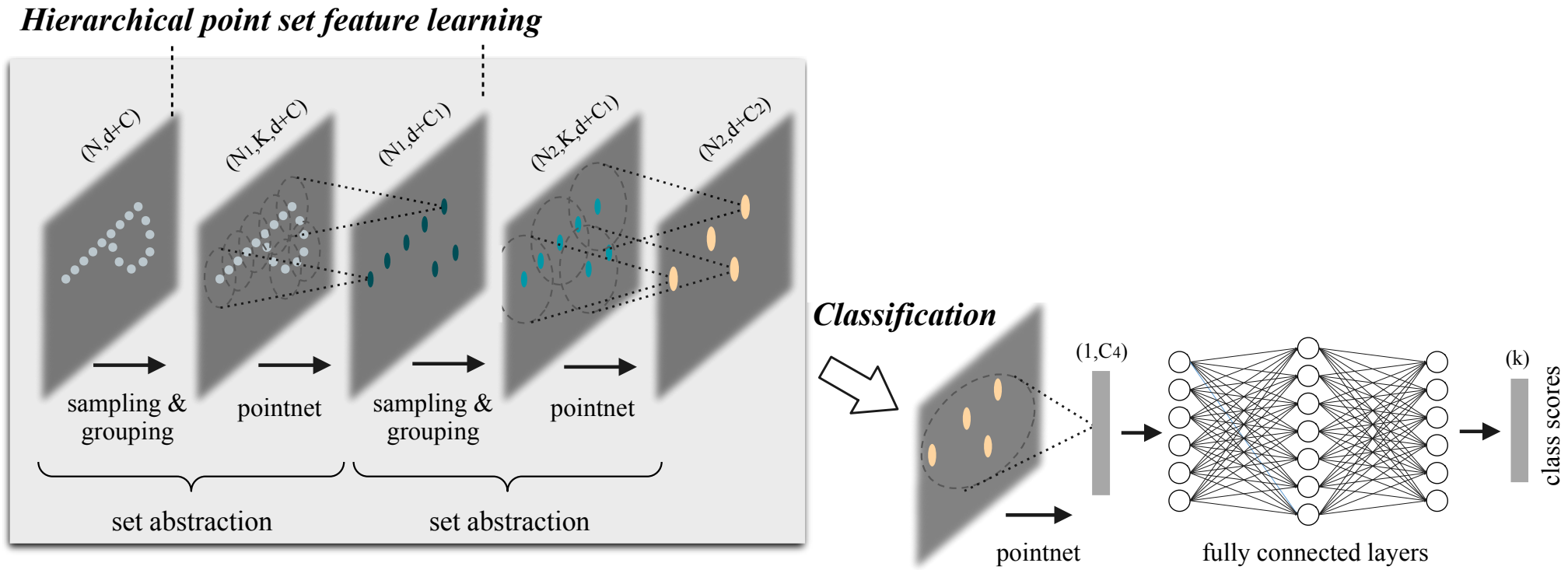
N1 points in (X,Y, **F**)

Hierarchical Point Feature Learning

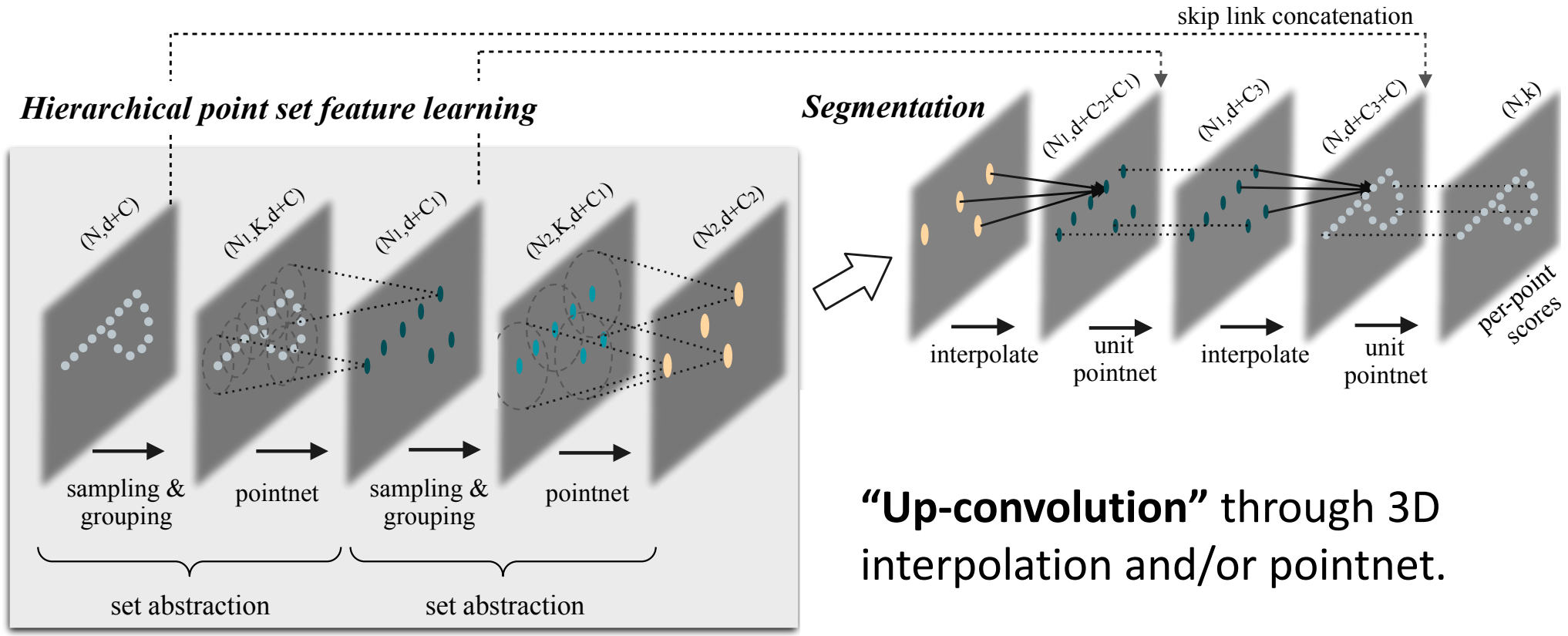


Set Abstraction: farthest point sampling + grouping + pointnet

PointNet++ for Classification



PointNet++ for Segmentation



"Up-convolution" through 3D interpolation and/or pointnet.

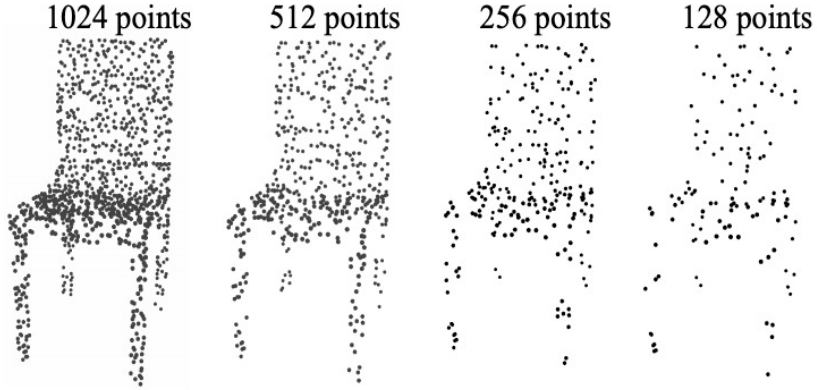
PointNet++: Classificiation

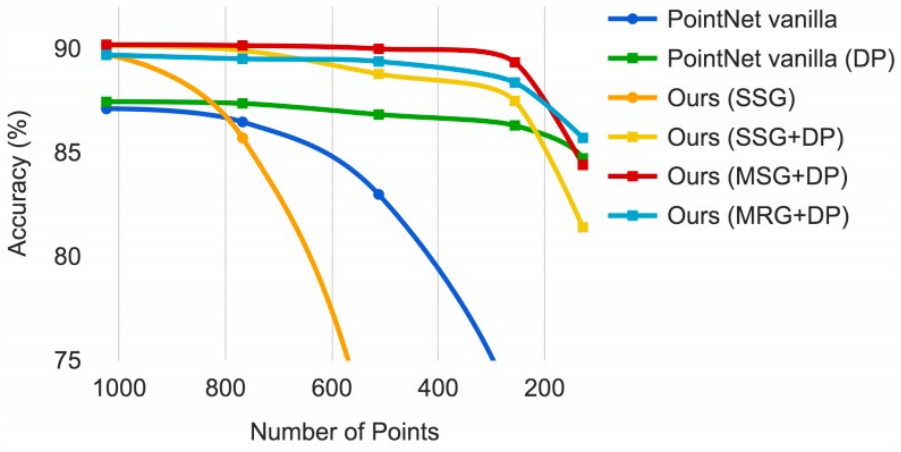
Method	Error rate (%)
Multi-layer perceptron [24]	1.60
LeNet5 [11]	0.80
Network in Network [13]	**0.47**
PointNet (vanilla) [20]	1.30
PointNet [20]	0.78
Ours	0.51

Table 1: MNIST digit classification.

Method	Input	Accuracy (%)
Subvolume [21]	vox	89.2
MVCNN [26]	img	90.1
PointNet (vanilla) [20]	pc	87.2
PointNet [20]	pc	89.2
Ours	pc	90.7
Ours (with normal)	pc	**91.9**

Table 2: ModelNet40 shape classification.





PointNet++: Segmentation

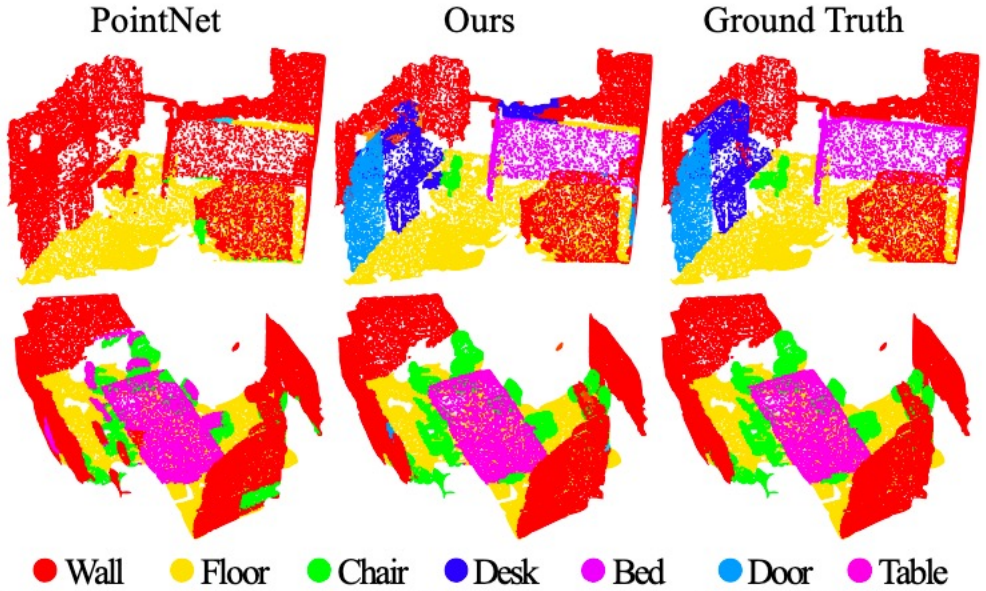


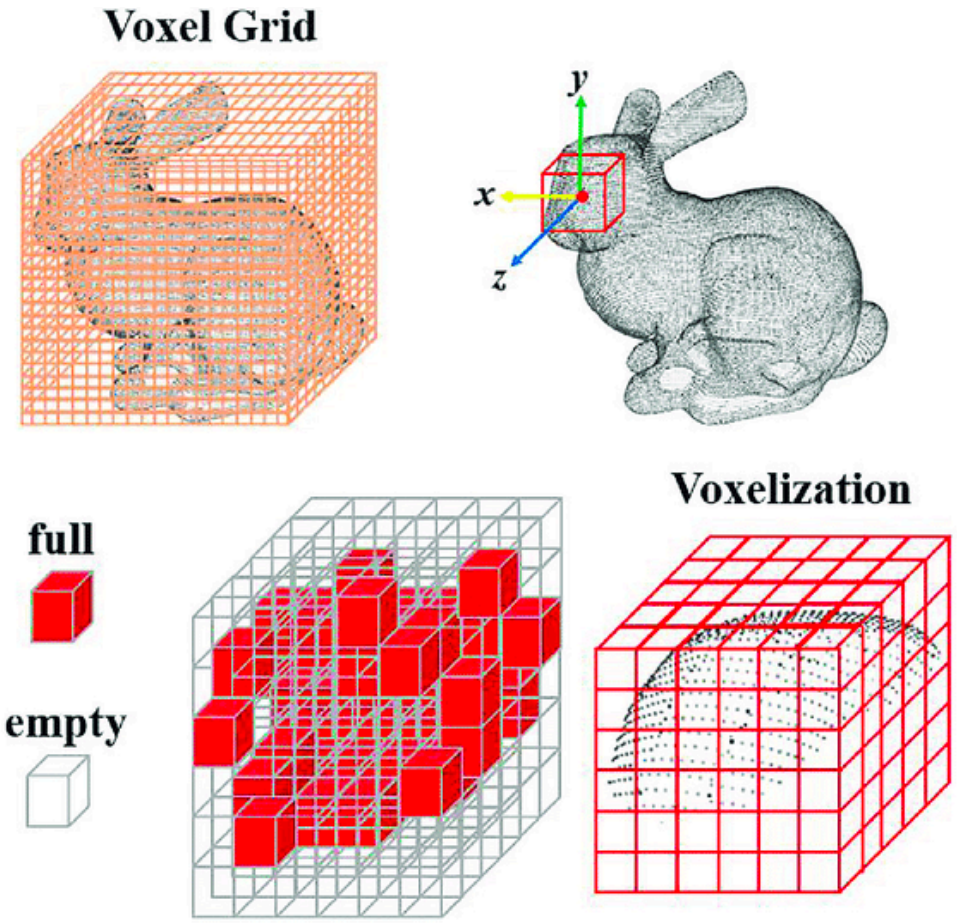
Figure 6: Scannet labeling results. [20] captures the overall layout of the room correctly but fails to discover the furniture. Our approach, in contrast, is much better at segmenting objects besides the room layout.

Outline

- Point Networks
  - PointNet
  - PointNet++
- Voxel Networks
- Networks for other representations
  - SDF
  - Mesh

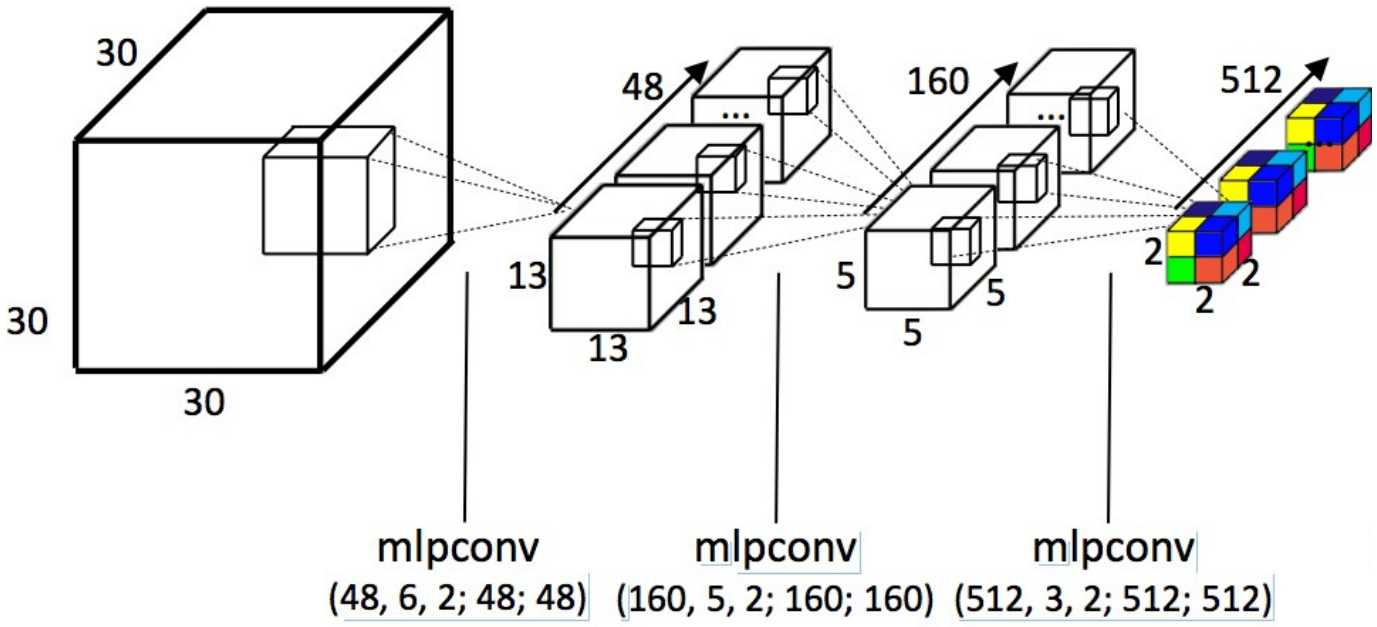
Voxelization

Represent the occupancy of regular 3D grids

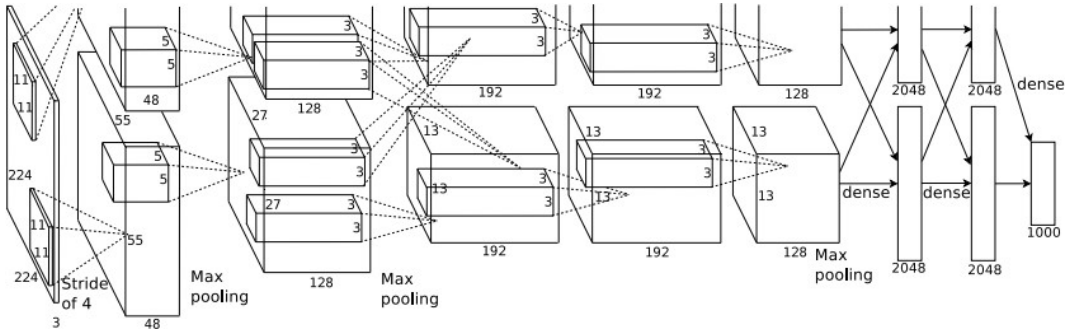


3D CNN on Volumetric Data

3D convolution uses 4D kernels



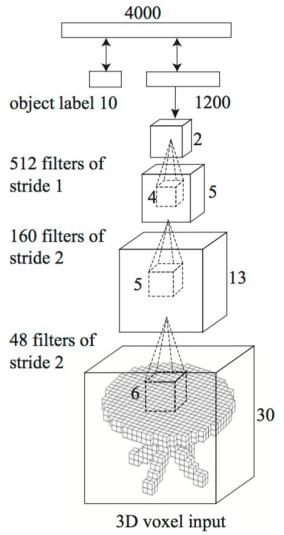
Complexity Issue



AlexNet, 2012

Input resolution: 224x224

224x224=50176

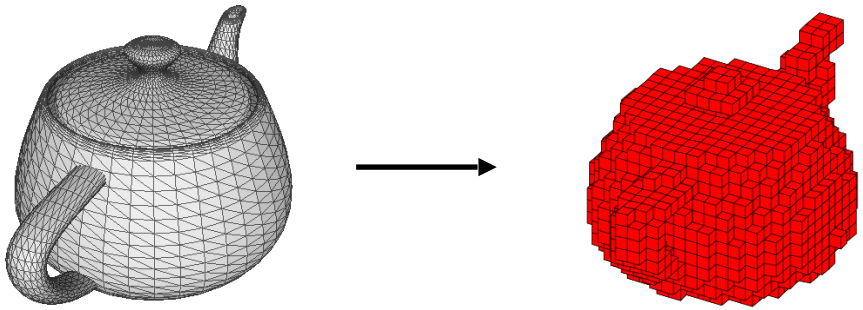


3DShapeNets, 2015

Input resolution: 30x30x30

224x224=27000

Complexity Issue



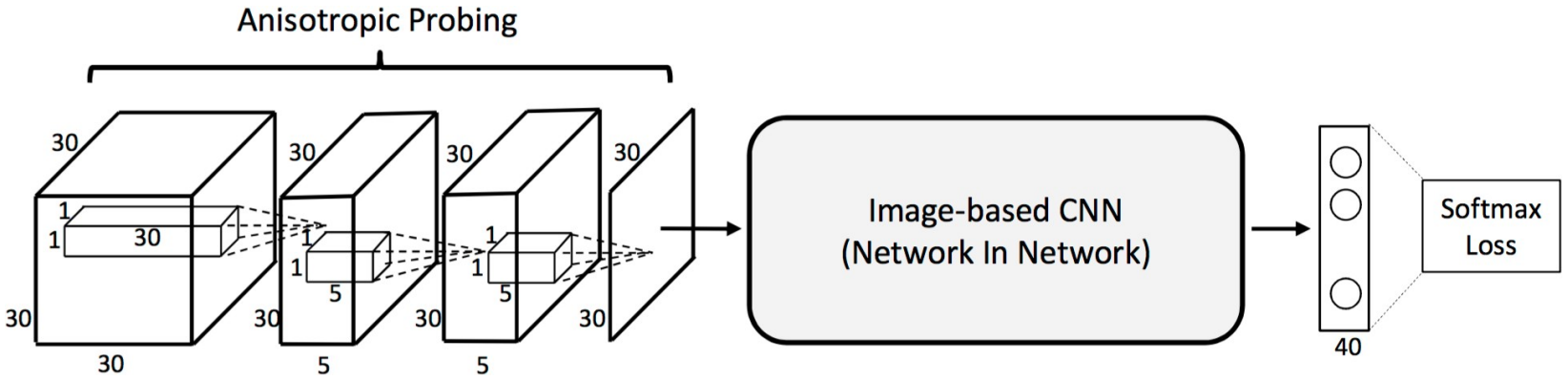
Polygon Mesh

Occupancy Grid
30x30x30

Information loss in voxelization

One Idea: Learn to Project

Idea: "X-ray" rendering + Image (2D) CNNs
very low #param, very low computation

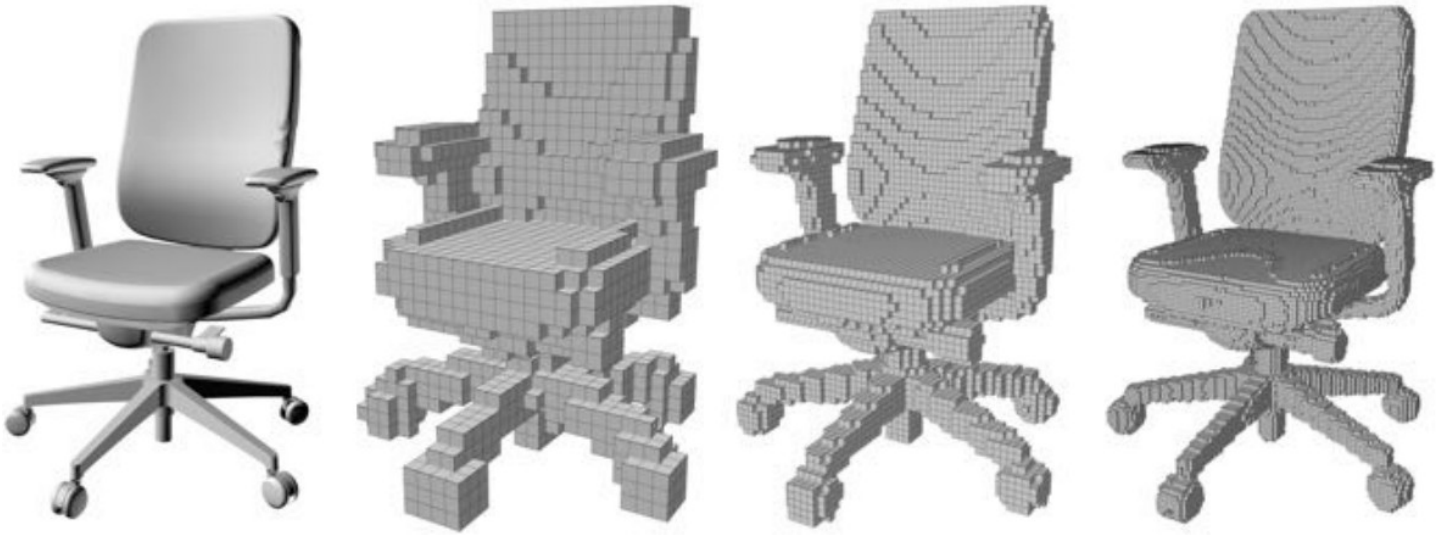


Su et al., "**Volumetric and Multi-View CNNs for Object Classification on 3D Data**", *CVPR 2016*

Many other works in autonomous driving use **bird's eye view** for object detection

Slide credit: Hao Su

More Principled: Sparsity of 3D Shapes

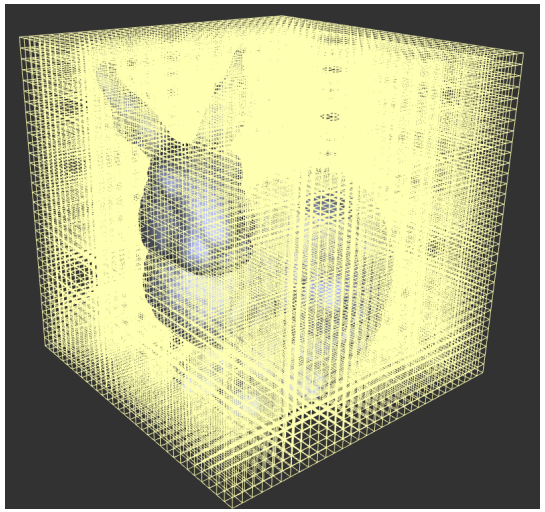


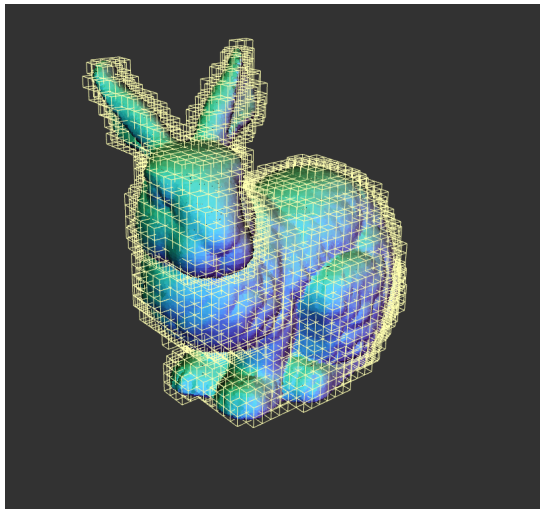
$\frac{\#occupied\ grid}{\#total\ grid}$

Occupancy:	10.41%	5.09%	2.41%
Resolution:	32	64	128

Store only the Occupied Grids

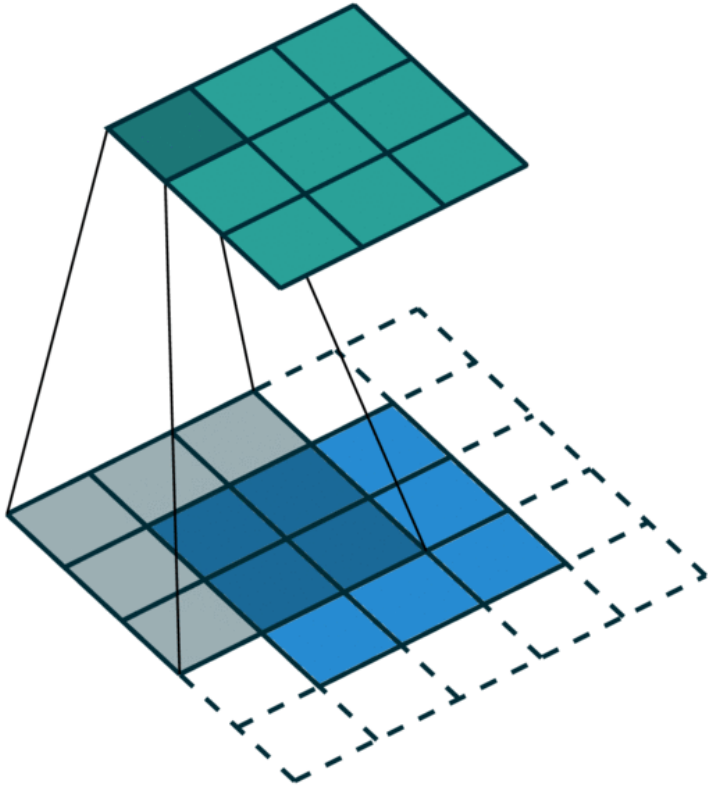
- Store the sparse surface signals
- Constrain the computation near the surface



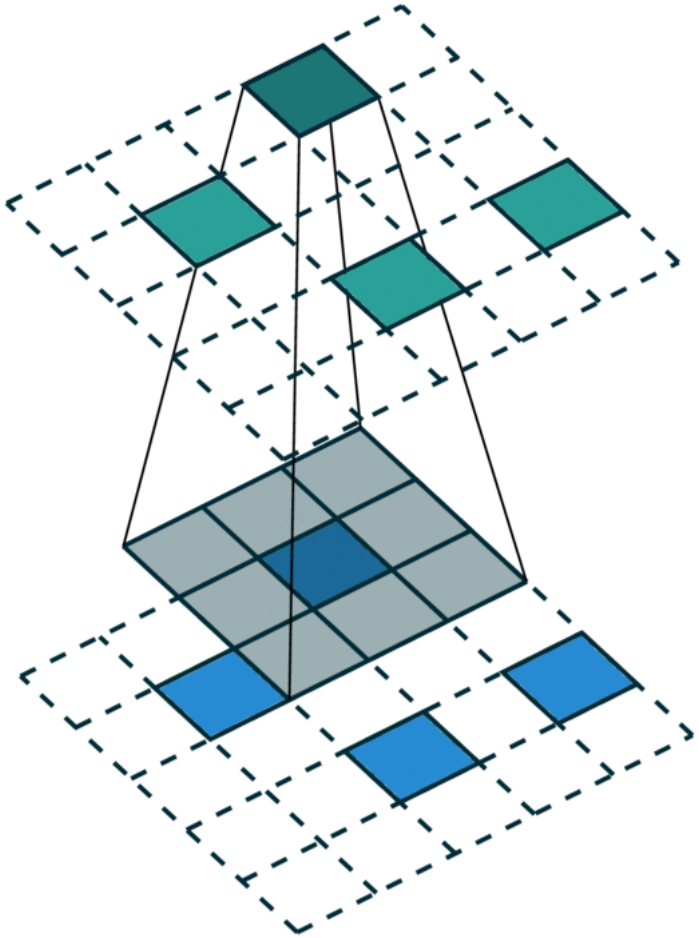


Slide credit: Hao Su

Sparse Convolution



Dense Conv



Sparse Conv

Image credit: Chris Choy

Sparse Convolution

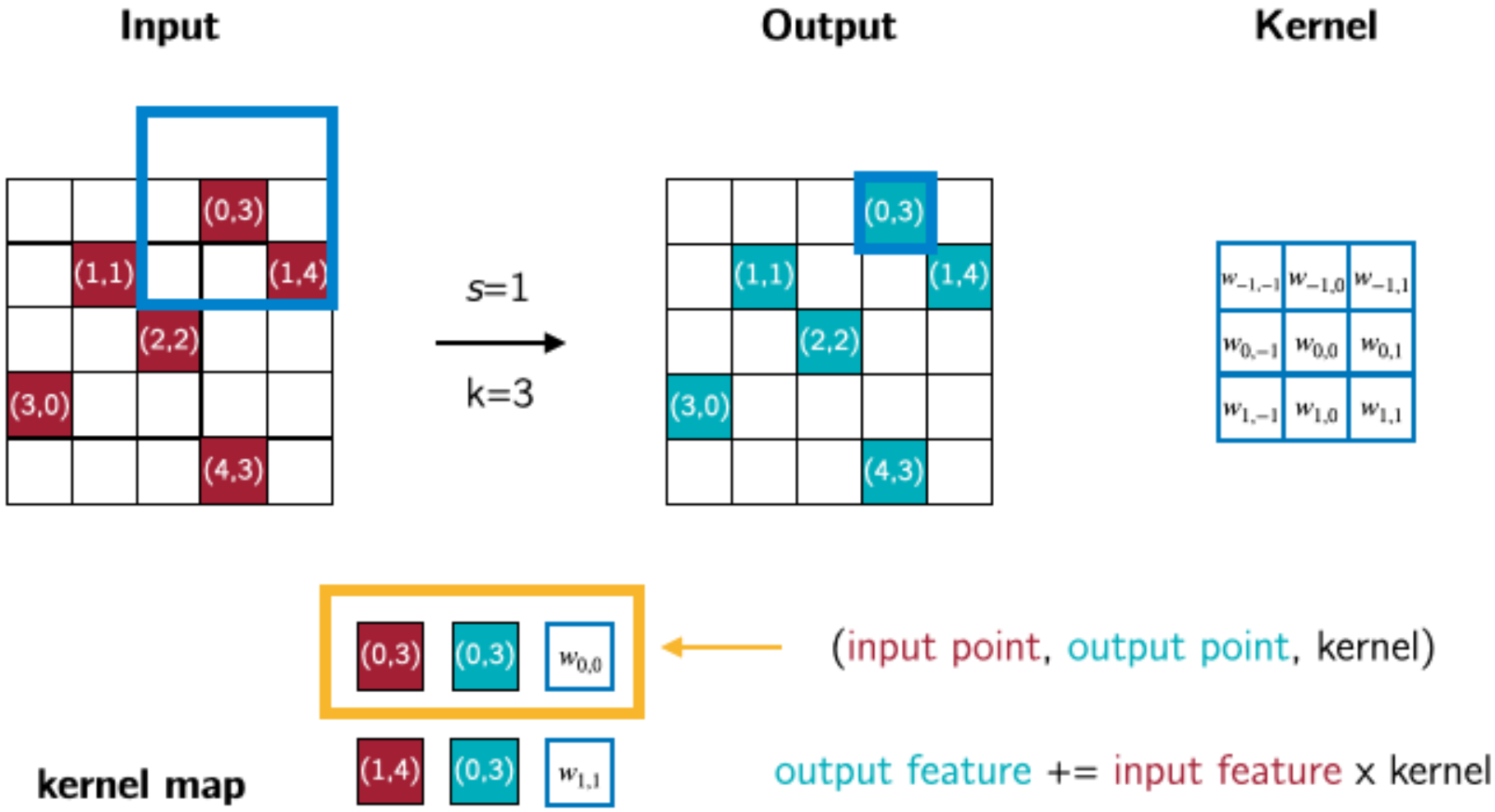


Image credit: torchsparse

Implementation

- SparseConvNet
  - https://github.com/facebookresearch/ SparseConvNet
  - Uses ResNet architecture
  - Takes time to train
- MinkowskiEngine
  - https://github.com/NVIDIA/MinkowskiEngine
- TorchSparse
  - https://github.com/mit-han-lab/torchsparse
- Tensorflow3D
  - https://github.com/google-research/google-research/tree/master/tf3d

Summary of Sparse Conv

- Pros:
  - A way higher efficiency than dense conv
  - Regular grid that supports indexing
  - Similarly expressive compared to 2D Conv
  - Translation equivariance similar to 2D Conv

- Cons:
  - Discretization error

Sparse Conv vs. Point Cloud Networks

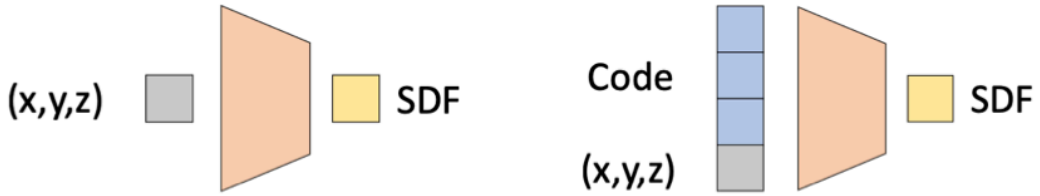
- Sparse Conv:
  - +: Kernels are spatial anisotropic
  - +: More efficient for indexing and neighbor query
  - +: suitable for large-scale scenes
  - -: limited resolutions

- Point cloud networks:
  - +: high resolution
  - +: easier to use and can be the first choice for a quick try
  - -: slightly lower performance
  - -: slower if performing FPS and ball query

Outline

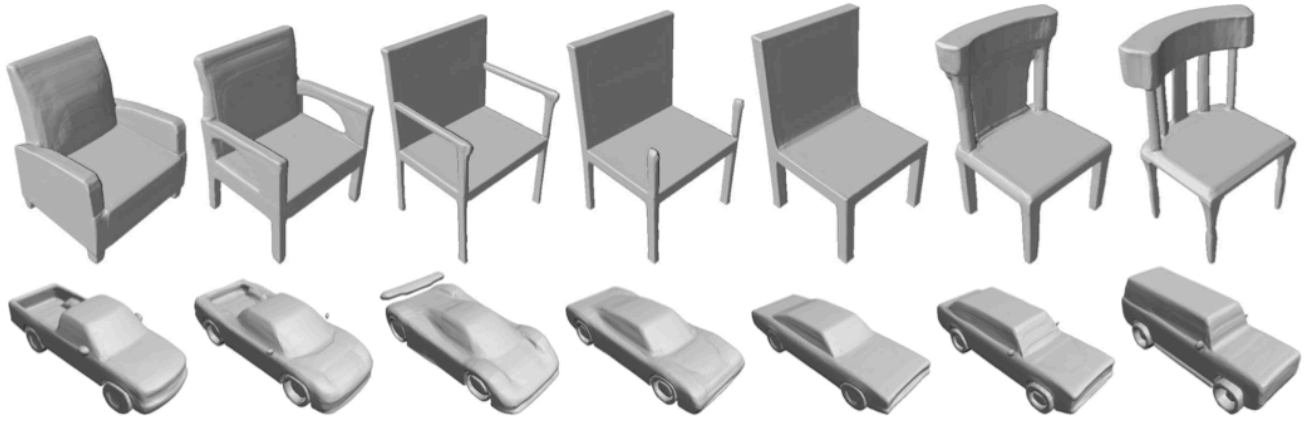
- Point Networks
  - PointNet
  - PointNet++
- Voxel Networks
- Networks for other representations
  - SDF
  - Mesh

Deep SDF



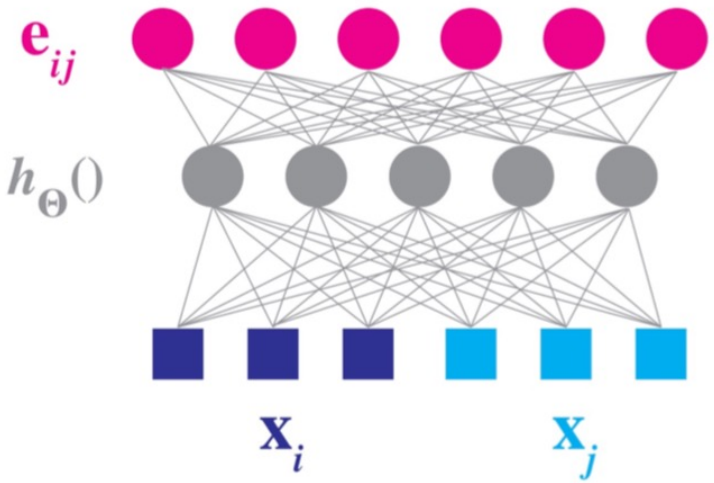
(a) Single Shape DeepSDF **(b)** Coded Shape DeepSDF

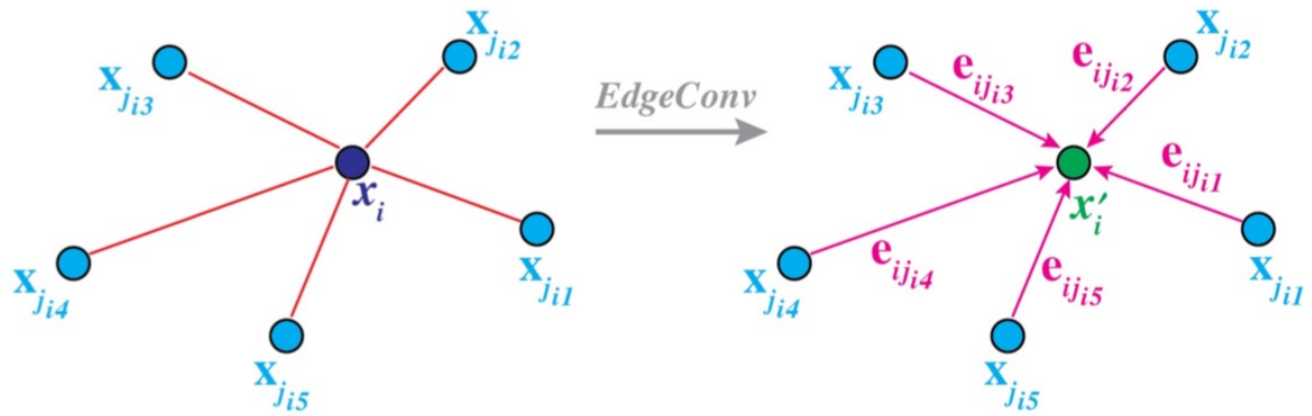
- (a) use the network to overfit a single shape
- (b) use a latent code to represent a shape, so that the network can be used for multiple shapes



Park et al., "DeepSDF: Learning continuous signed distance functions for shape representation.", CVPR 2019

Convolution on Mesh/Graph





Message passing: The output of EdgeConv at the i-th vertex is thus given by

$$\mathbf{x}'_i = \square_{j:(i,j)\in\mathcal{E}} h_\Theta(\mathbf{x}_i, \mathbf{x}_j). \quad (1)$$

Wang, et.al., Dynamic Graph CNN for Learning on Point Clouds, ToG 2019

Introduction to Computer Vision

Next Week: Lecture 9,
Temporal Data Analysis I