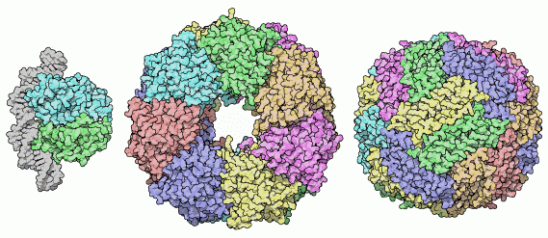
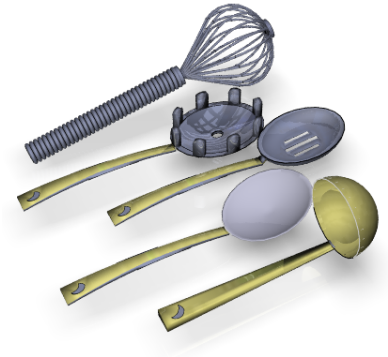
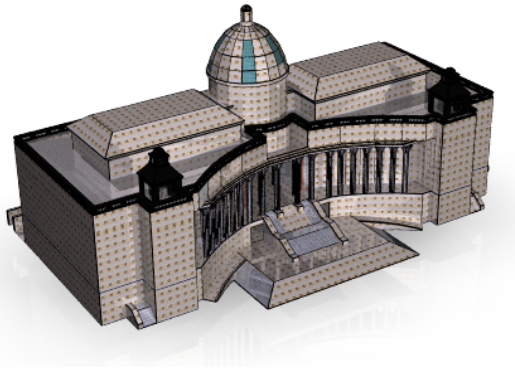
UC San Diego

Tutorial on 3D Deep Learning

Hao Su
Jiayuan Gu
Minghua Liu





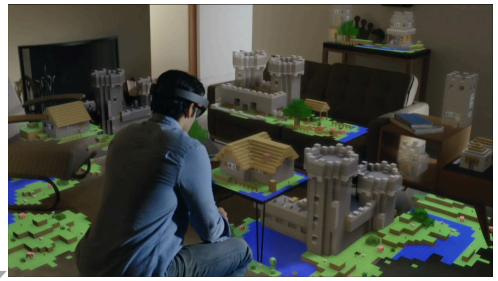


Broad Applications of 3D data

Robotics

Broad Applications of 3D data

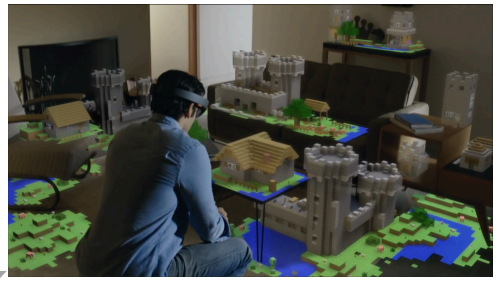
Robotics



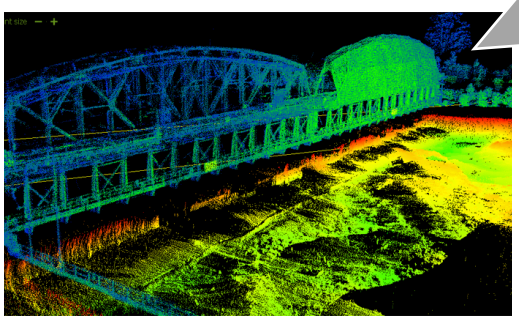
Augmented Reality

Broad Applications of 3D data

Robotics



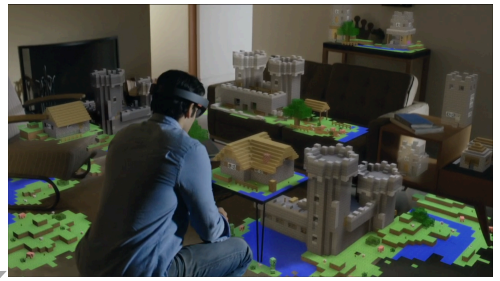
Augmented Reality



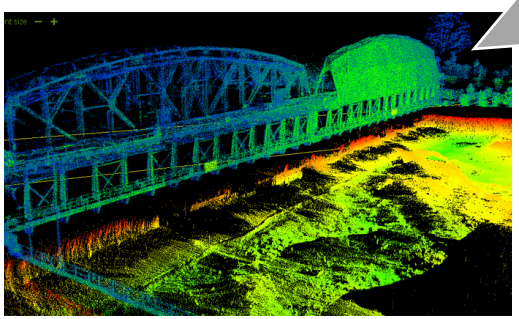
Autonomous driving

Broad Applications of 3D data

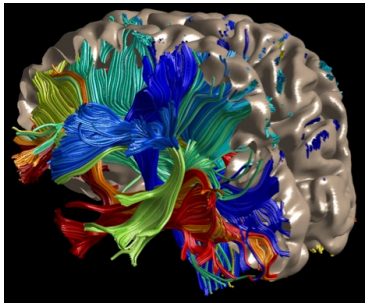
Robotics



Augmented Reality



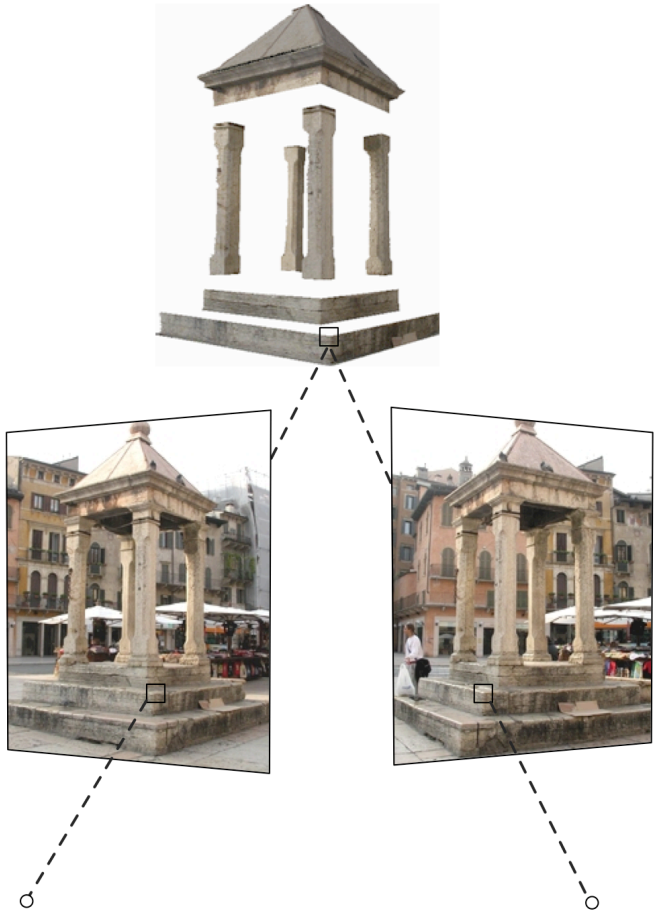
Autonomous driving



Medical Image Processing

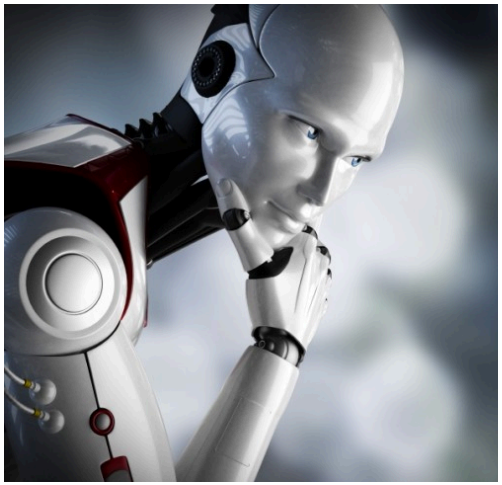
Traditional 3D Vision

Multi-view Geometry: Physics based



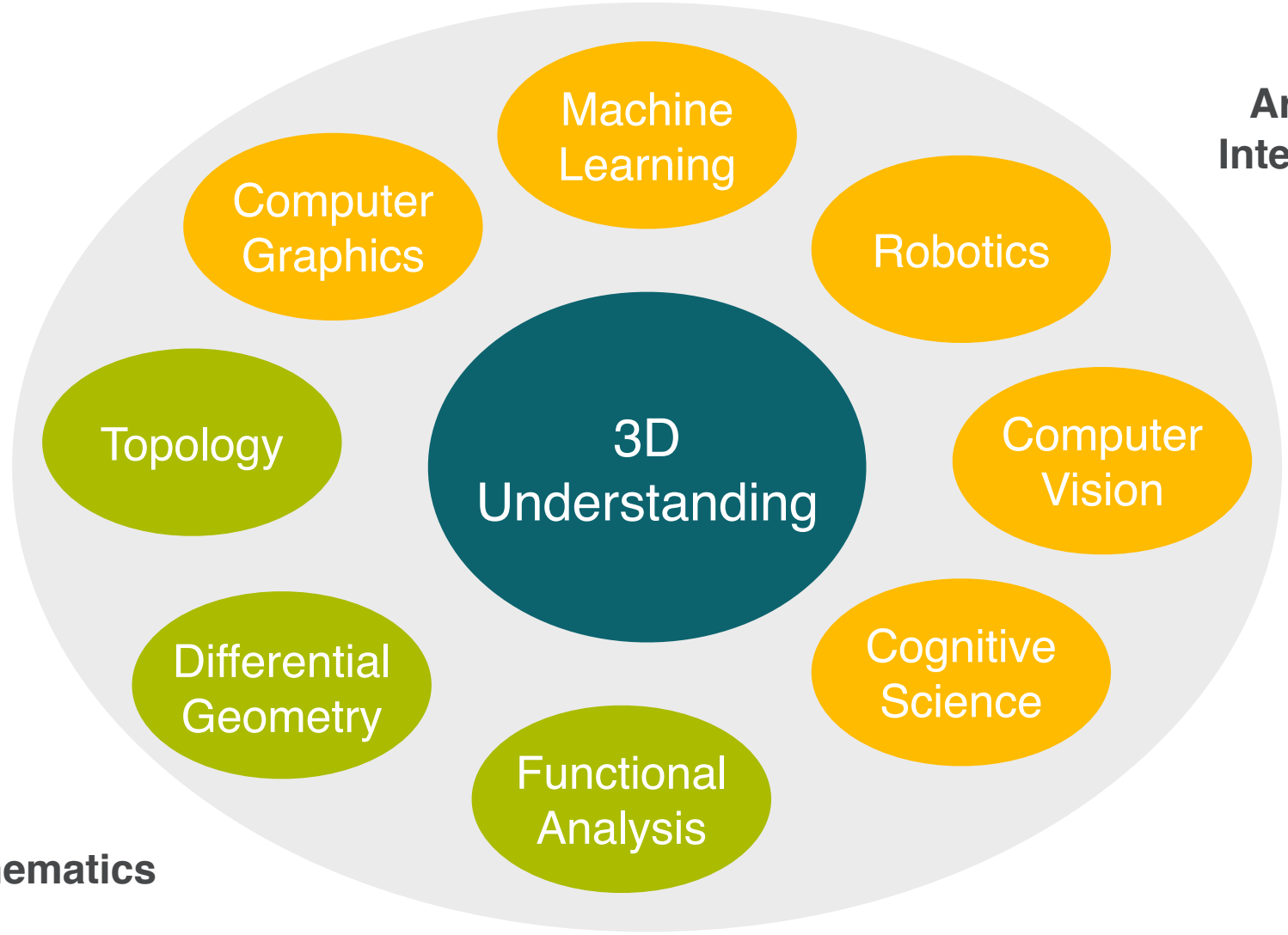
3D Learning: Knowledge Based

Acquire Knowledge of 3D World by Learning

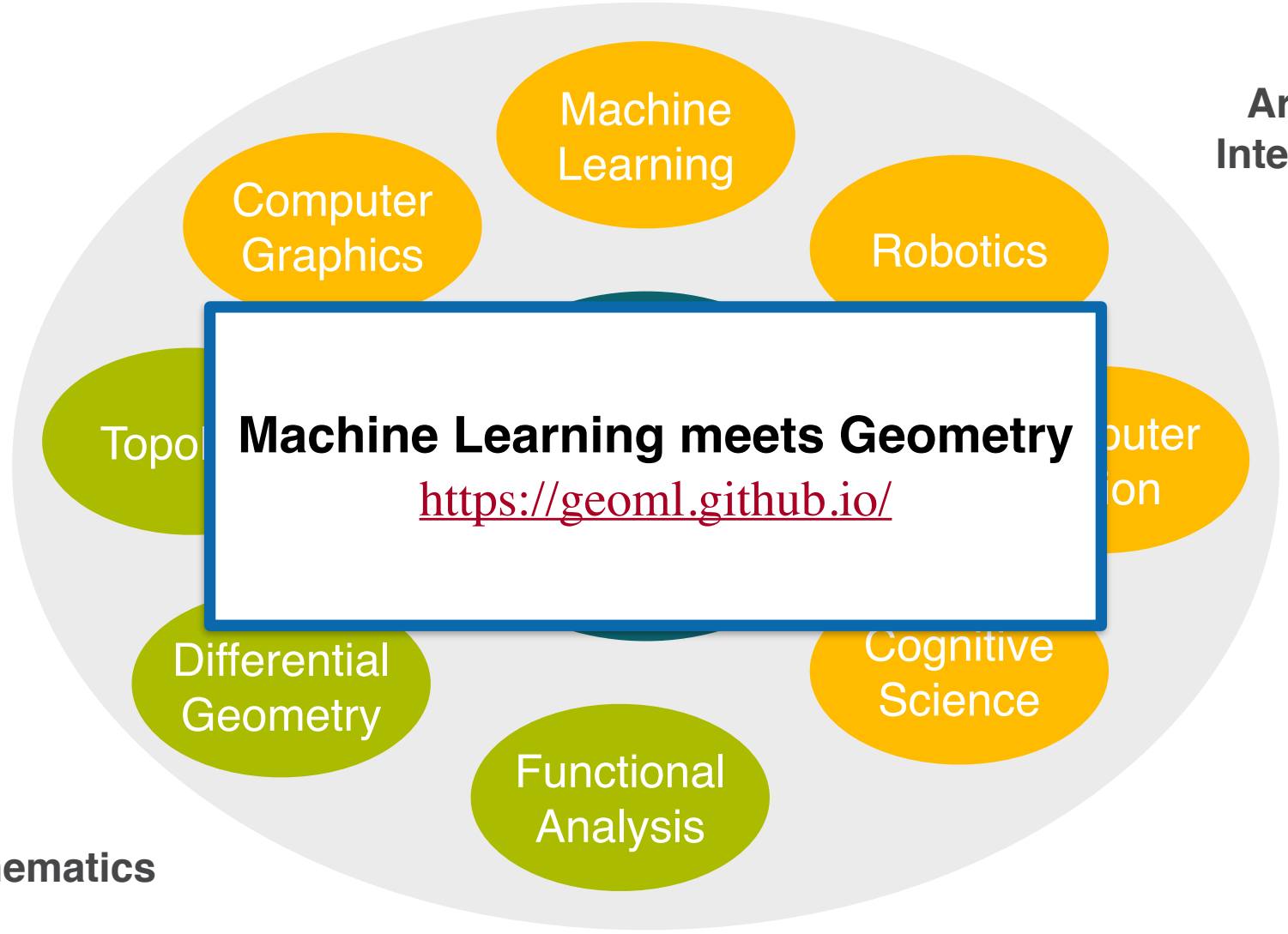


A priori knowledge of the 3D world

A New Rising Field



A New Rising Field



Instructor Team

Hao Su, Asst Professor

Jiayuan Gu, Ph.D. Student

Minghua Liu, Ph.D. Student

Schedule

- Time: 12:30PM-2:20PM
- Part I: 3D Data, by Hao Su
- Part II: Classification, by Hao Su
- Part II: Segmentation & Detection, by Jiayuan Gu
- Part III: 3D Data Synthesis, by Minghua Liu

Topics

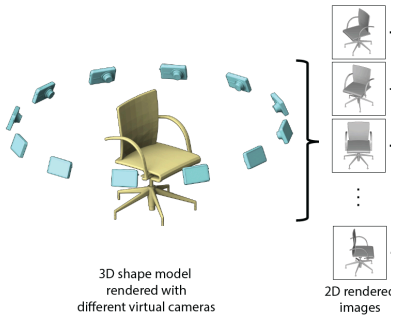
- **3D Data**
- **Classification**
- **Segmentation and Detection**
- **Reconstruction**

The Representation Challenge of 3D Deep Learning

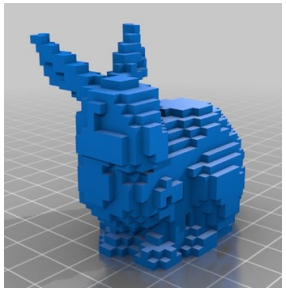
Rasterized form (regular grids)

Geometric form (irregular)

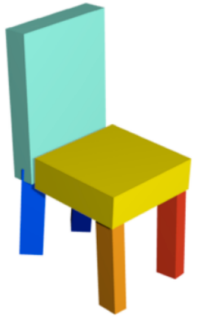
The Representation Challenge of 3D Deep Learning



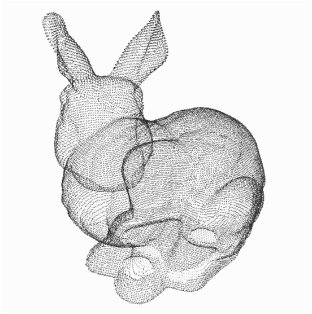
Multi-view



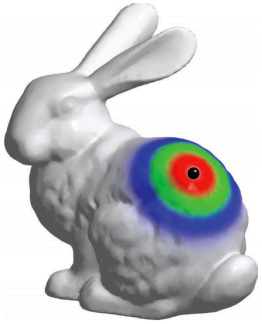
Volumetric



Part Assembly



Point Cloud



Mesh (Graph CNN)

$$F(x) = 0$$

Implicit Shape

Datasets for 3D Objects

Large-scale Synthetic Objects: ShapeNet

3DScan: Consumer-grade 3D scanning (click to open)

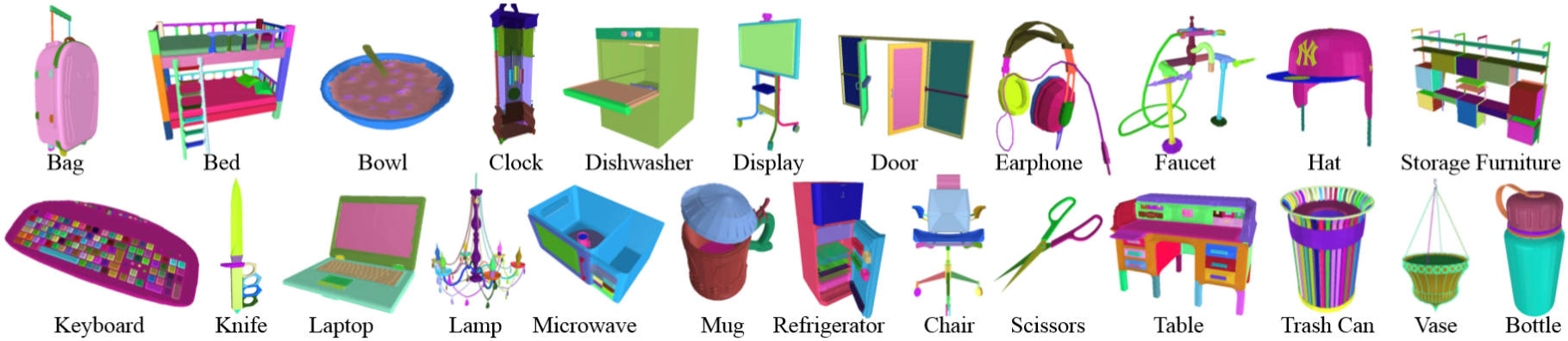
ModelNet: absorbed by ShapeNet

Chang et al., "**ShapeNet: An Information-Rich 3D Model Repository**" , *arXiv*
Wu et al., "**3D ShapeNets: A deep representation for volumetric shapes**", *CVPR 2015*
Choi et al., "**A Large Dataset of Object Scans**", *arXiv*

Datasets for 3D Object Parts

Fine-grained Part: PartNet (ShapeNetPart2019)

- Fine-grained (towards mobility)
- Instance-level
- Hierarchical



Mo et al., "**PartNet: A Large-Scale Benchmark for Fine-Grained and Hierarchical Part-Level 3D Object Understanding**", *CVPR 2019*

Datasets for Indoor 3D Scenes

Large-scale Synthetic Scenes: SceneNet

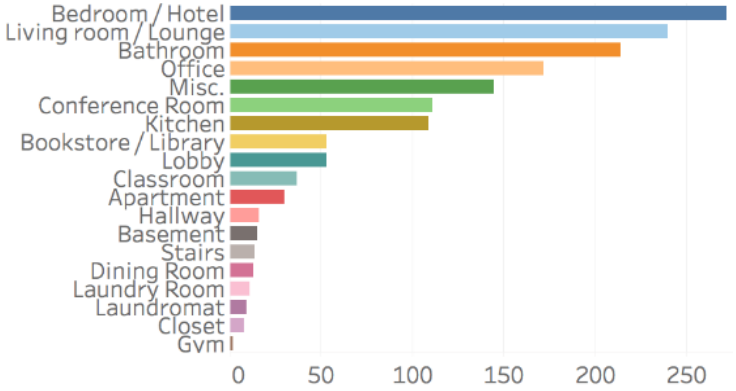
- 3D meshes
- 5M Photorealistic Images

Ankur et al., "**Understanding RealWorld Indoor Scenes with Synthetic Data**", *CVPR 2016*
McCormac et al., "**SceneNet RGB-D: Can 5M Synthetic Images Beat Generic ImageNet Pre-training on Indoor Segmentation?**", *ICCV 2017*

Datasets for Indoor 3D Scenes

Large-scale Scanned Real Scenes: ScanNet

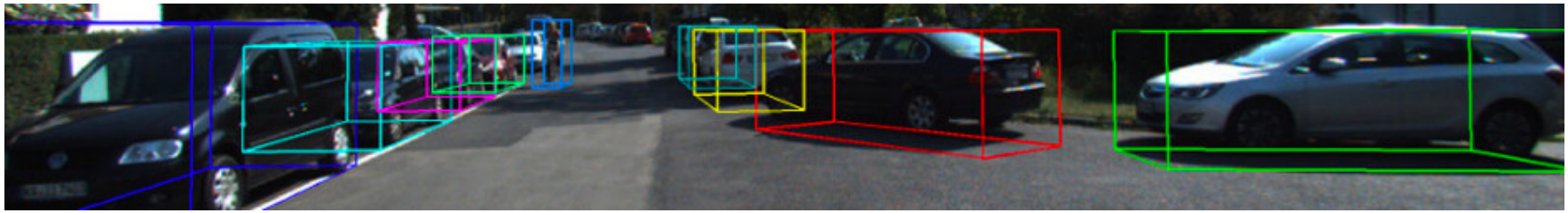
- 2.5 M Views in 1500 RGBD scans
- 3D camera poses
- surface reconstructions
- Instance-level semantic segmentations



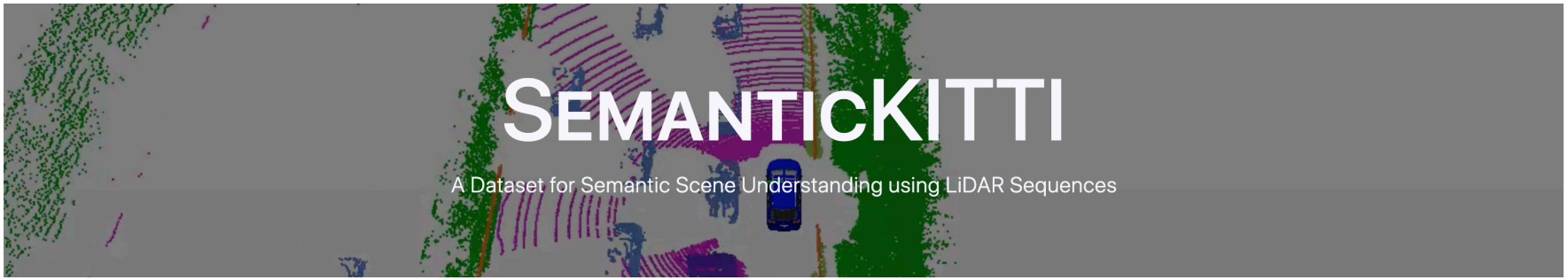
Dai et al., "**ScanNet: Richly-annotated 3D Reconstructions of Indoor Scenes**", *CVPR 2017*

Datasets for Outdoor 3D Scenes

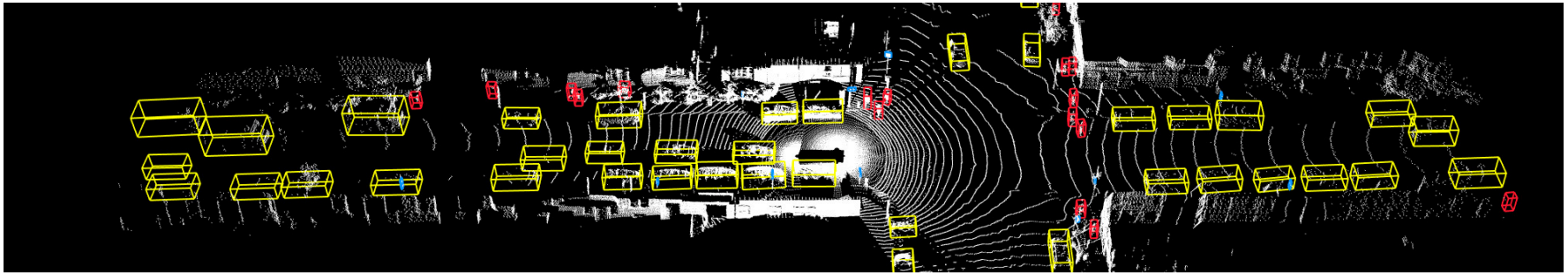
KITTI: LiDAR data, labeled by 3D b.boxes



Semantic KITTI: LiDAR data, labeled per point



Waymo Open Dataset: LiDAR data, labeled by 3D b.boxes



Topics

- 3D Data
- **Classification**
- Segmentation and Detection
- Reconstruction

Task: 3D Classification

This is a chair!

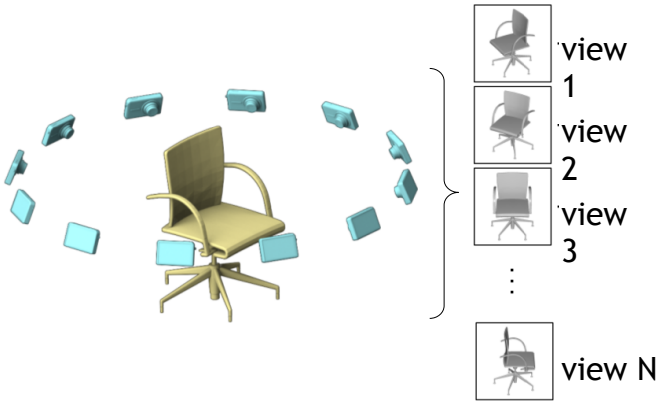
Covered methods: Volumetric CNN, OctNet, O-CNN, SparseConvNet, PointNet, PointNet++, RS CNN, DGCNN, Point ConvNet, KPConv, Monte Carlo Point Convolution, PConv, Multi-View CNN, Spectral CNN, Synchronized Spectral CNN, Spherical CNN

Multi-View CNN

Given an Input Shape

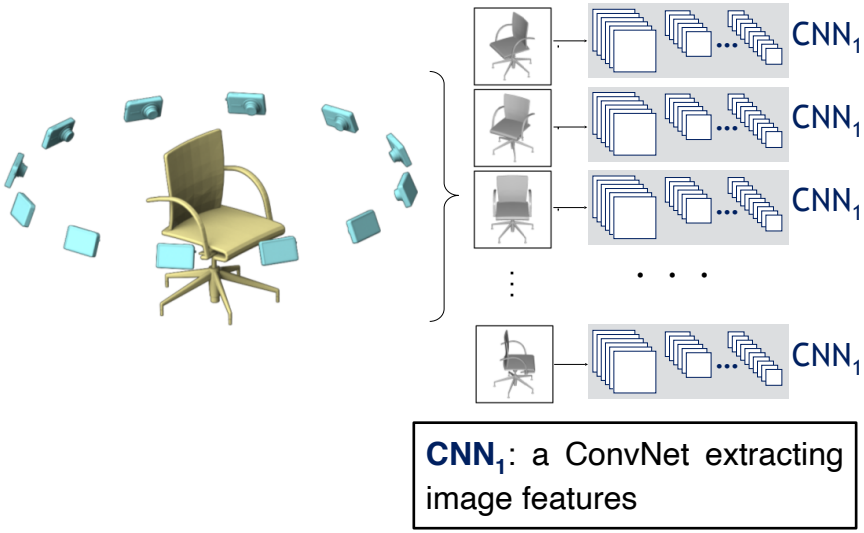
Su et al., "**Multi-view Convolutional Neural Networks for 3D Shape Recognition**", *ICCV 2015*

Render with Multiple Virtual Cameras



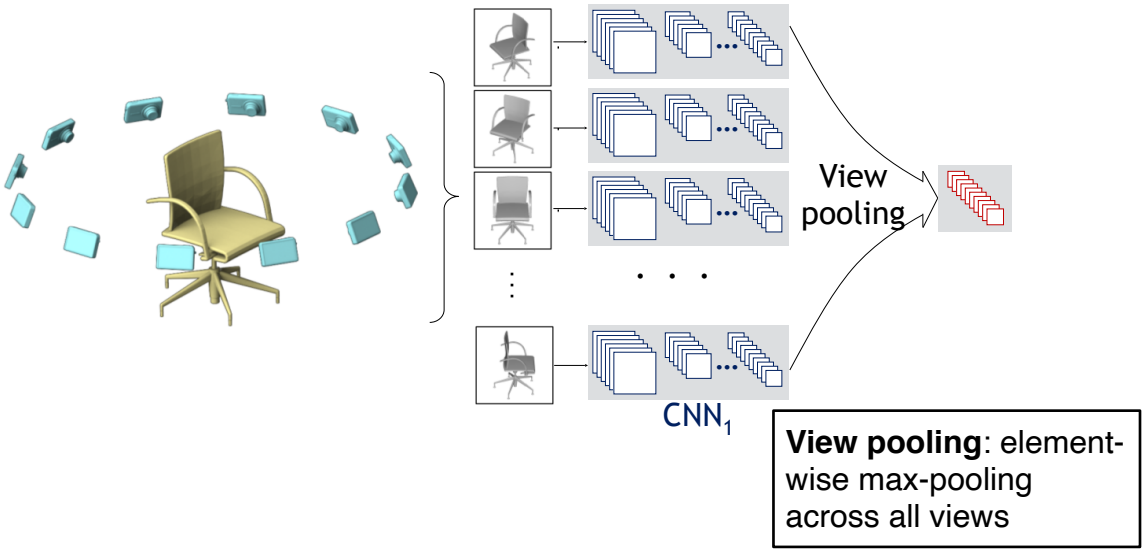
Su et al., "**Multi-view Convolutional Neural Networks for 3D Shape Recognition**", *ICCV 2015*

The Rendered Images are Passed through CNN_1 for Image Features



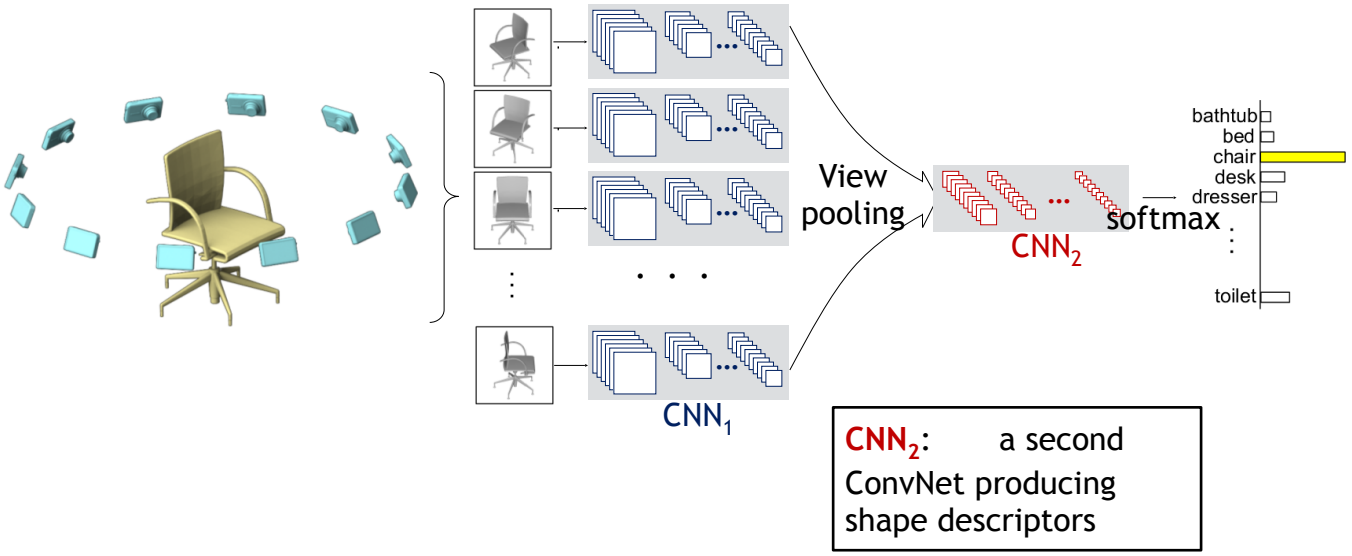
Su et al., "**Multi-view Convolutional Neural Networks for 3D Shape Recognition**", *ICCV 2015*

All Image Features are Combined by View Pooling



Su et al., "**Multi-view Convolutional Neural Networks for 3D Shape Recognition**", *ICCV 2015*

… and then Passed through CNN_2 and to Generate Final Predictions



Su et al., "**Multi-view Convolutional Neural Networks for 3D Shape Recognition**", *ICCV 2015*

Experiments – Classification & Retrieval

	Method	Classification (Accuracy)	Retrieval (mAP)
Non-deep	SPH [16]	68.2%	33.3%
	LFD [5]	75.5%	40.9%
	3D ShapeNets [37]	77.3%	49.2%
	FV, 12 views	84.8%	43.9%
	CNN, 12 views	88.6%	62.8%
	MVCNN, 12 views	**89.9%**	70.1%
	MVCNN+metric, 12 views	89.5%	**80.2%**
	MVCNN, 80 views	90.1%	70.4%
	MVCNN+metric, 80 views	**90.1%**	**79.5%**

On ModelNet40

[credit: Hang Su]

- Indeed gives good performance
- Can leverage vast literature of image classification
- Can use pertained features
- Need projection
- What if the input is noisy and/or incomplete? e.g., point cloud

Volumetric CNN

Can we use CNNs without 2D-3D projection?

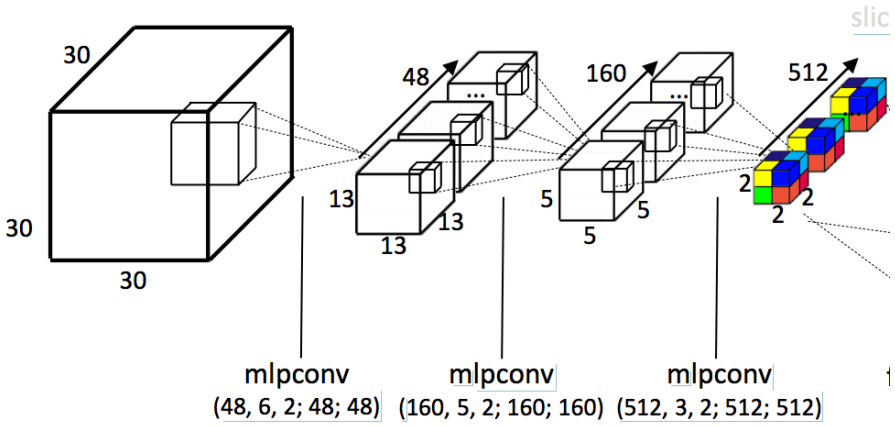
Straight-forward idea: 3D native convolution

Voxelization

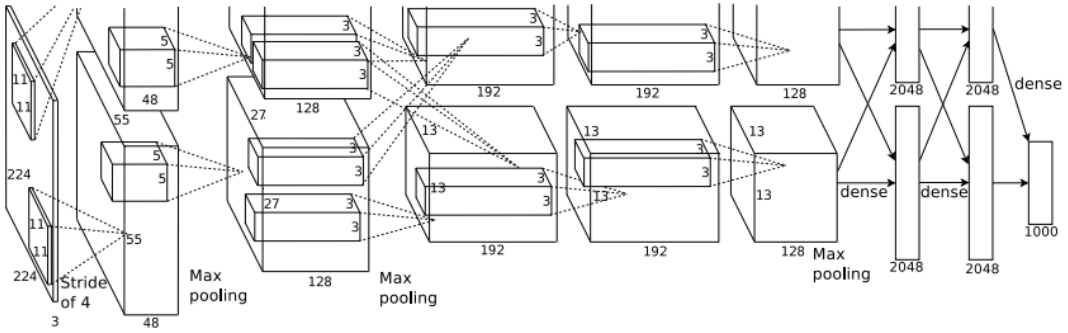
Represent the occupancy of regular 3D grids

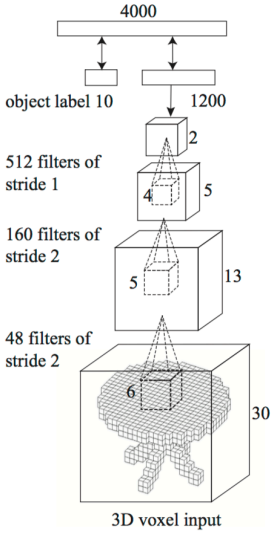
3D CNN on Volumetric Data

3D convolution uses 4D kernels



Complexity Issue





AlexNet, 2012

Input resolution: 224x224

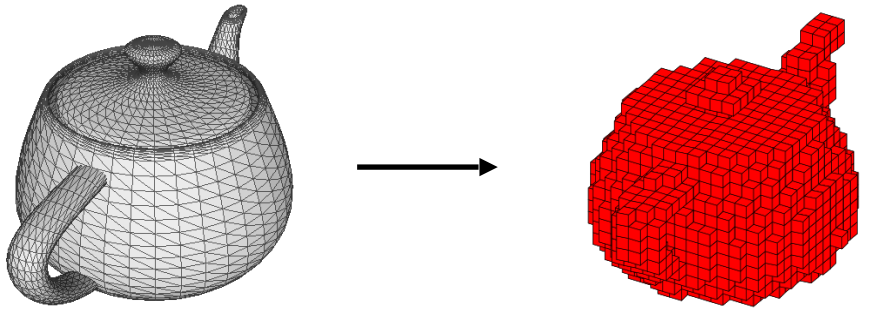
224x224=50176

3DShapeNets, 2015

Input resolution: 30x30x30

224x224=27000

Complexity Issue



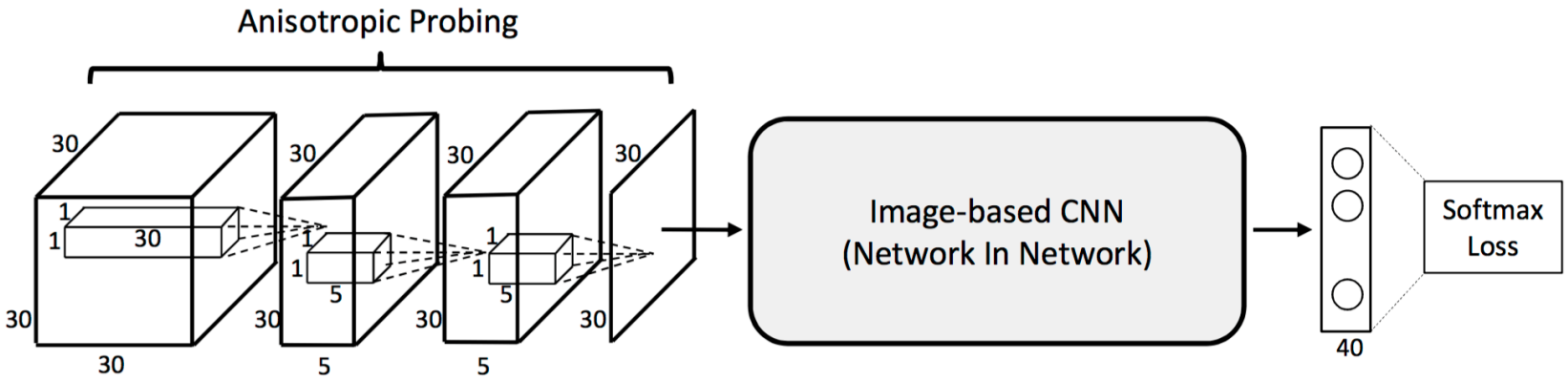
Polygon Mesh

Occupancy Grid
30×30×30

Information loss in voxelization

Idea 1: Learn to Project

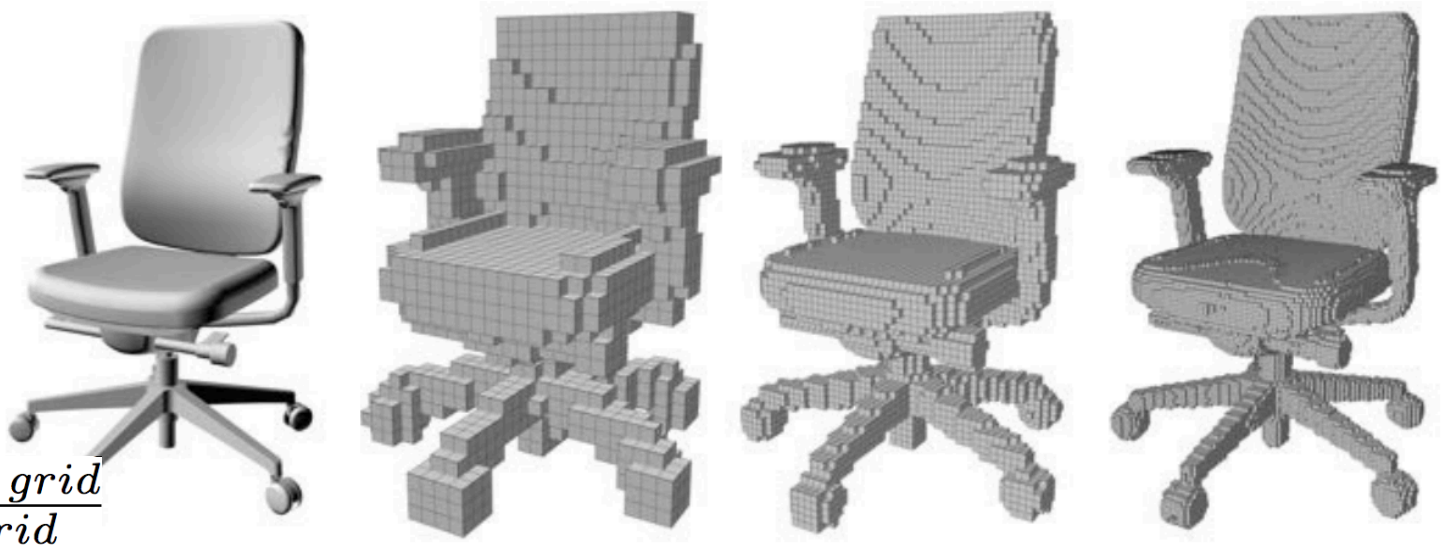
Idea: "X-ray" rendering + Image (2D) CNNs
very low #param, very low computation



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

Many other works in autonomous driving that uses bird's eye view for object detection

More Principled: Leverage Sparsity of 3D Surface Data

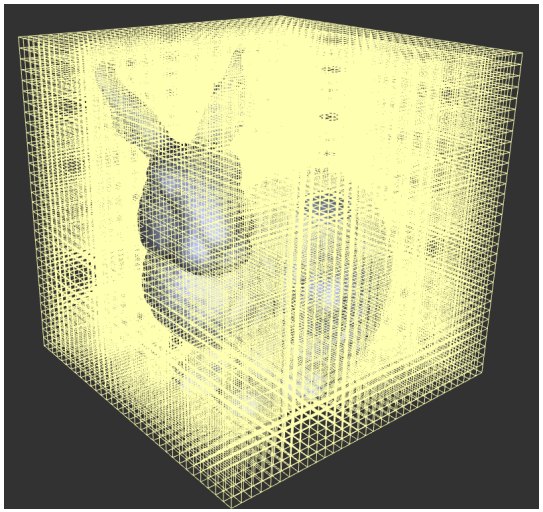


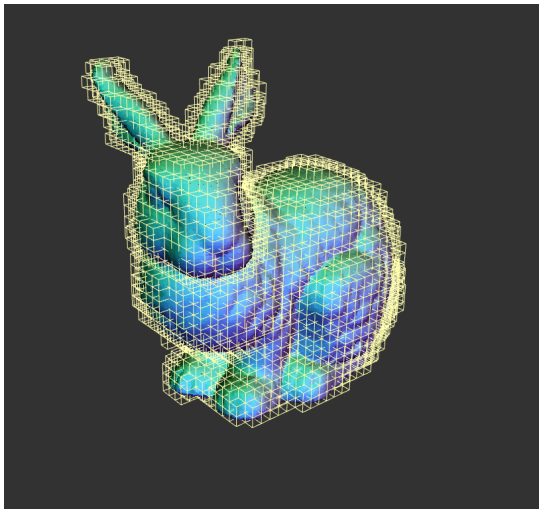
$$\frac{\#occupied\ grid}{\#total\ grid}$$

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

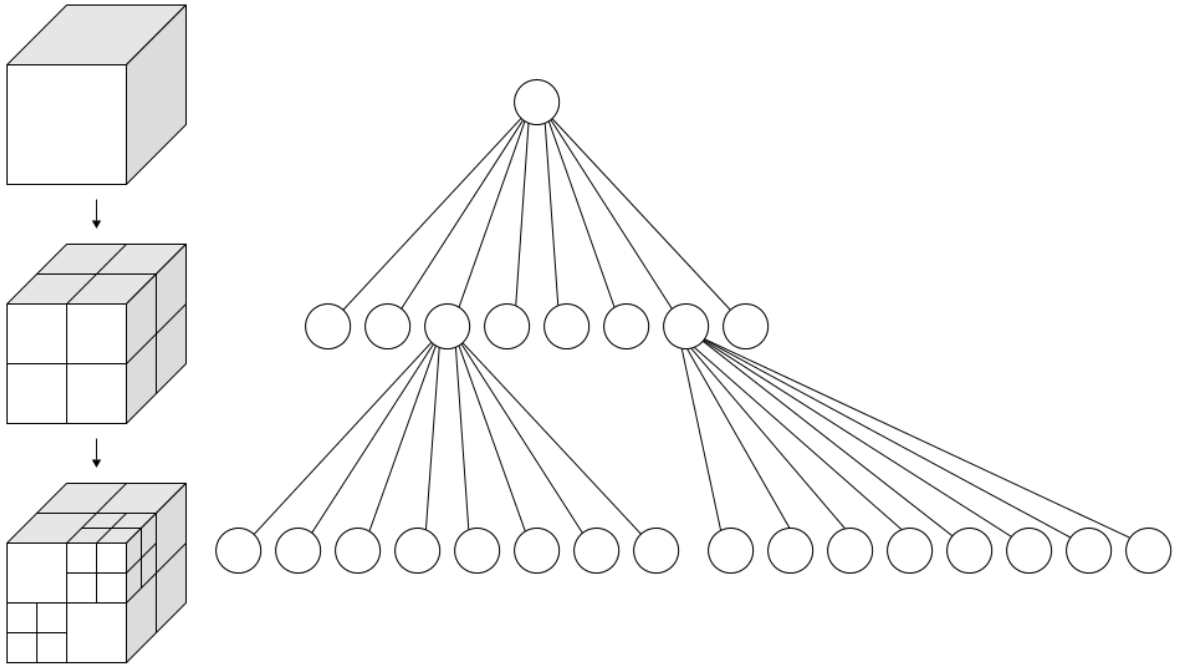




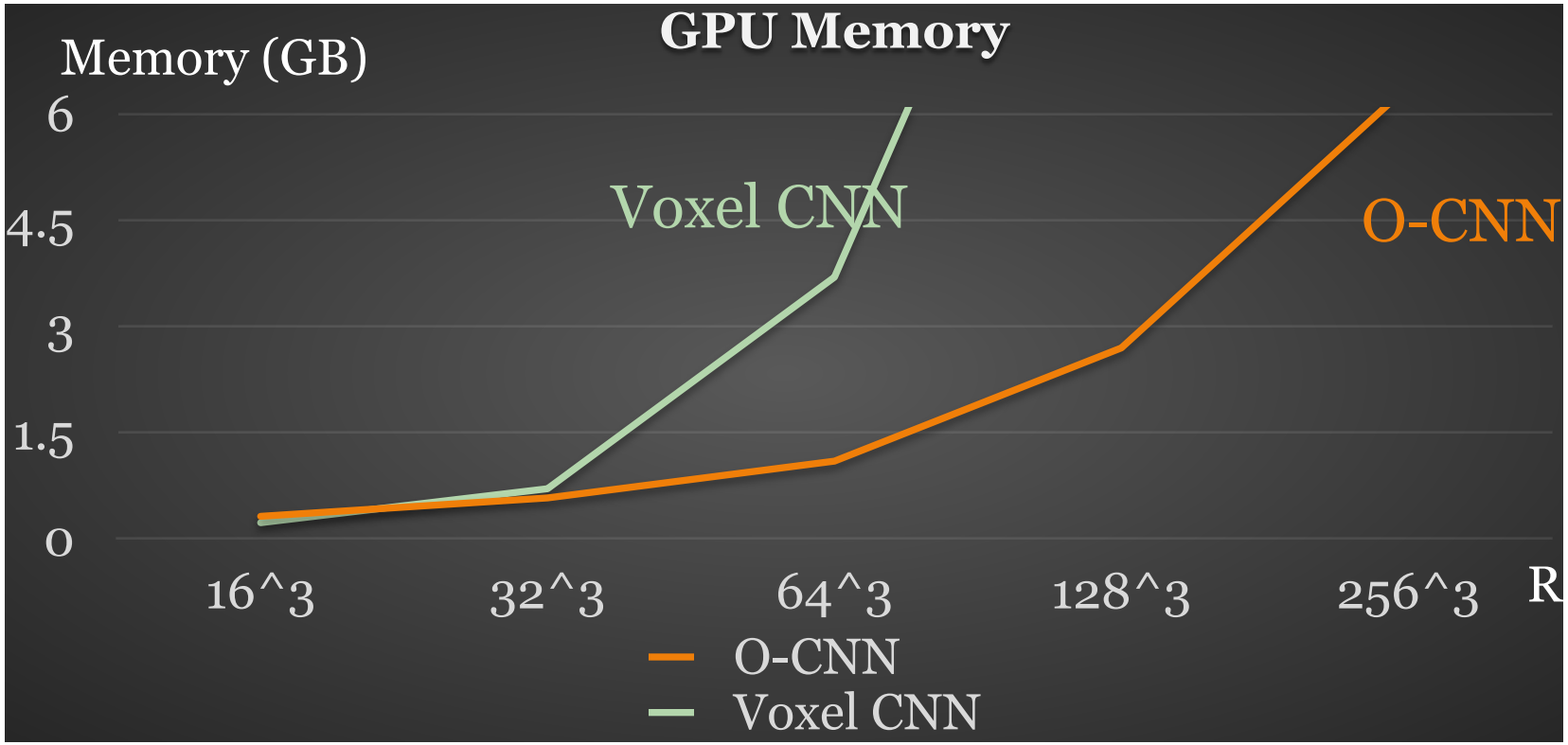
Octree: Recursively Partition the Space

Each internal node has exactly eight children

Neighborhood searching: Hash table



Memory Efficiency

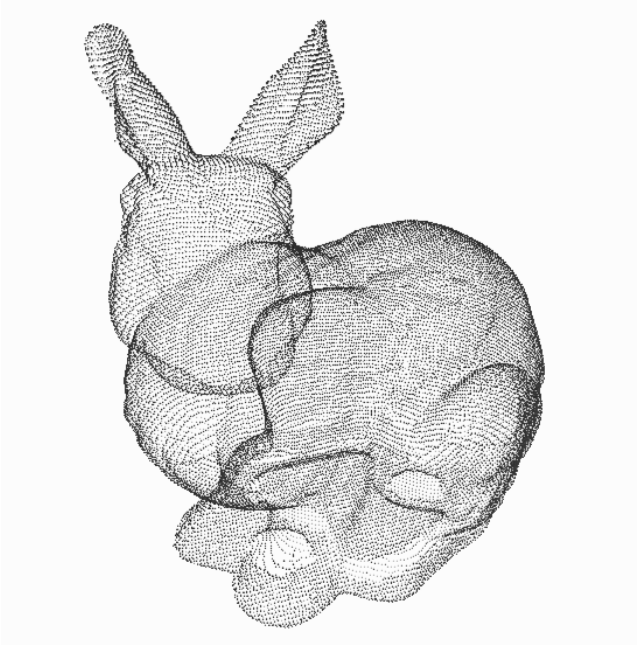


Implementation

- SparseConvNet
  - https://github.com/facebookresearch/SparseConvNet
  - Uses ResNet architecture
  - State-of-the-art for 3D analysis
  - Takes time to train

Graham et al., "**Submanifold Sparse Convolutional Networks**", *arxiv*

Point Networks



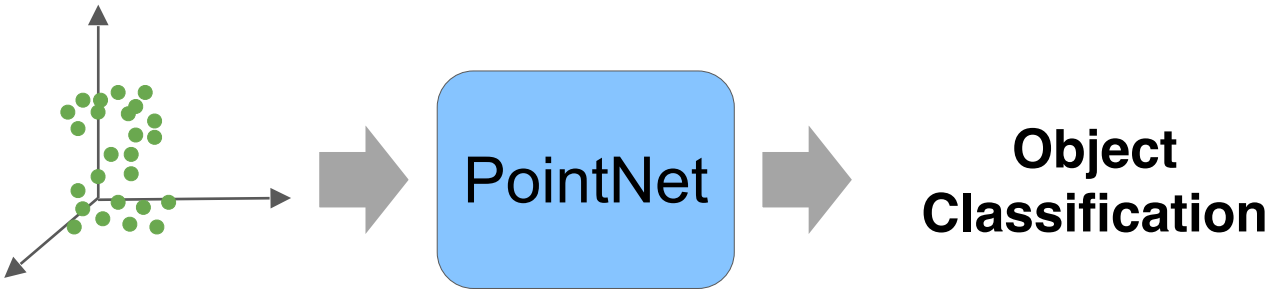
Point cloud

(The most common 3D sensor data)

Directly Process Point Cloud Data

End-to-end learning for **unstructured,**

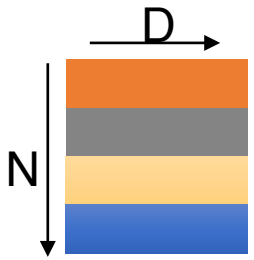
unordered point data



Qi, Charles R., et al. "**Pointnet: Deep learning on point sets for 3d classification and segmentation**", CVPR 2017
Zaheer, Manzil, et al. "**Deep sets**", NeurIPS 2017

Permutation invariance

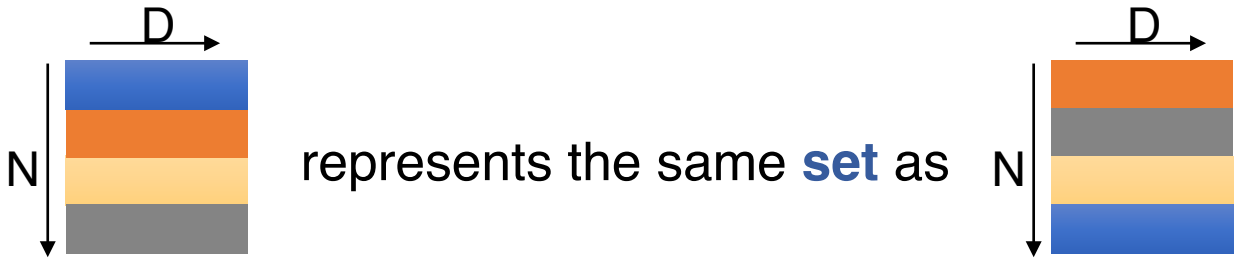
Point cloud: N **orderless** points, each represented by a D dim coordinate



2D array representation

Permutation invariance

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

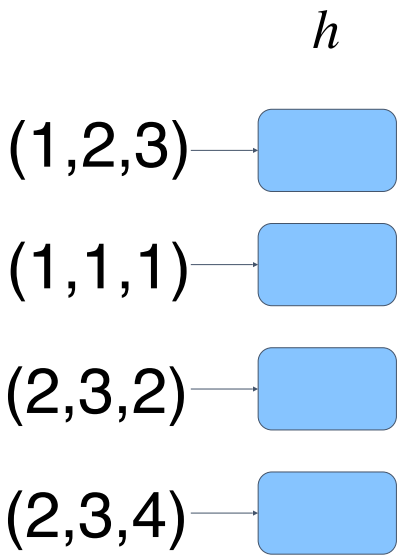


2D array representation

Construct a Symmetric Function

Observe:

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



Construct a Symmetric Function

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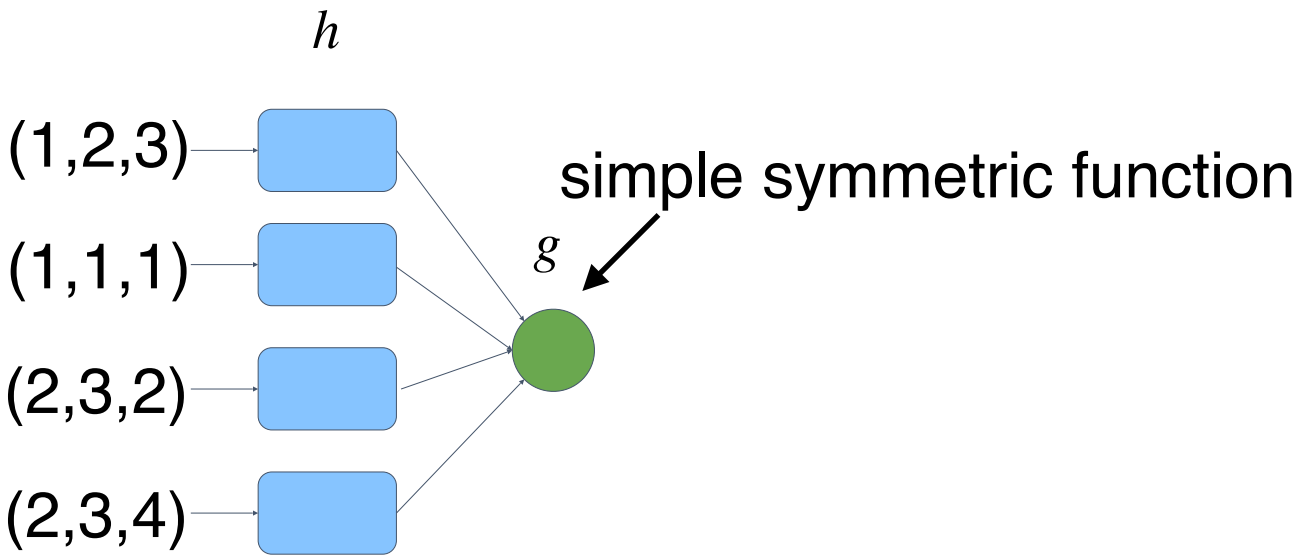

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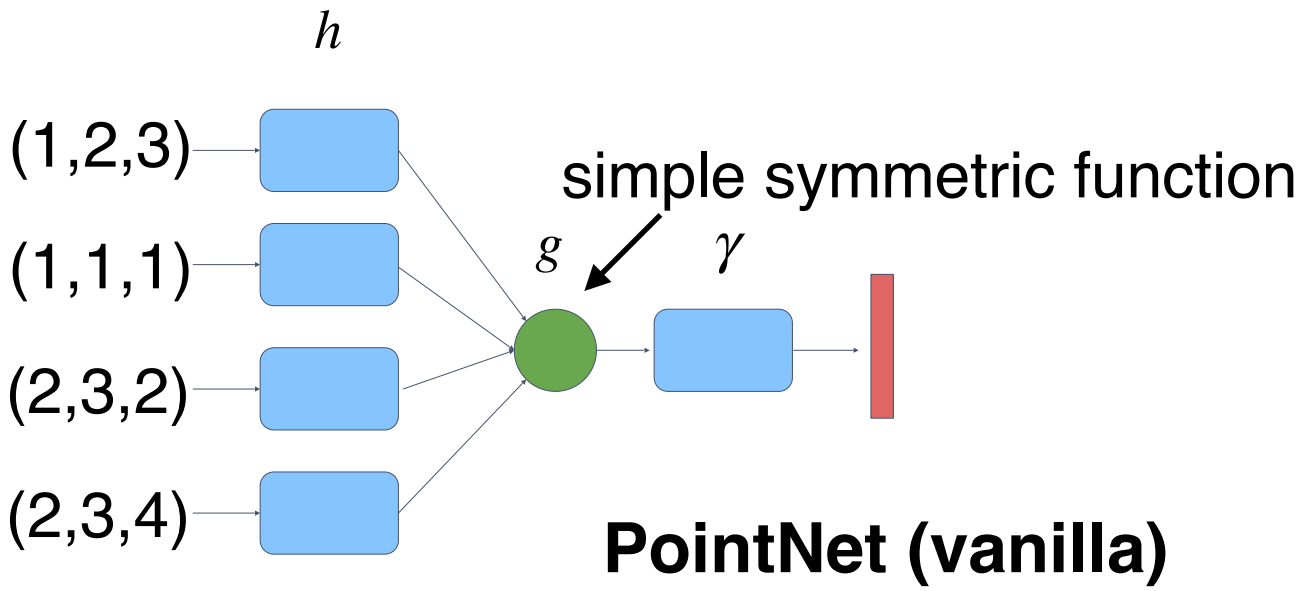
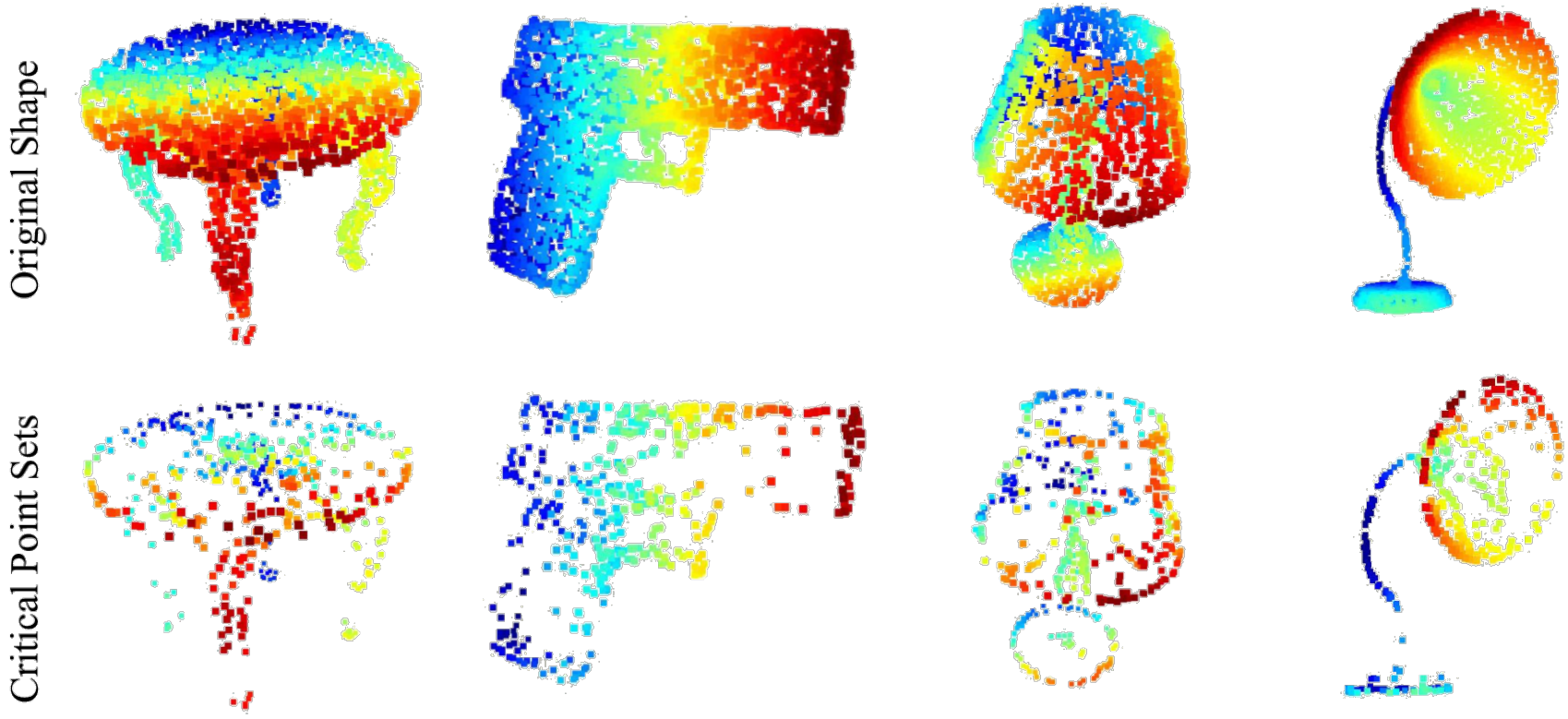
$f(x_1, x_2, \ldots, x_n) = \gamma \circ g(h(x_1), \ldots, h(x_n))$ is symmetric if g is symmetric



Visualize What is Learned by Reconstruction



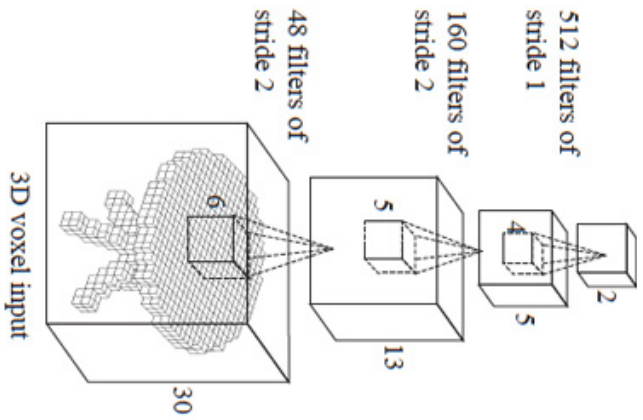
Salient points are discovered!

Limitations of PointNet

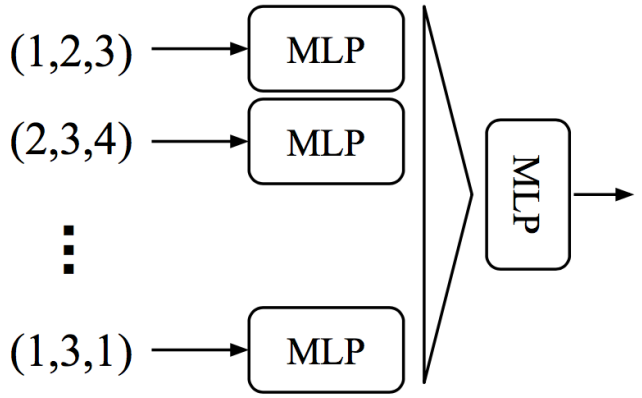
Hierarchical feature learning
Multiple levels of abstraction

v.s.

Global feature learning
Either one point or all points



3D CNN (Wu et al.)



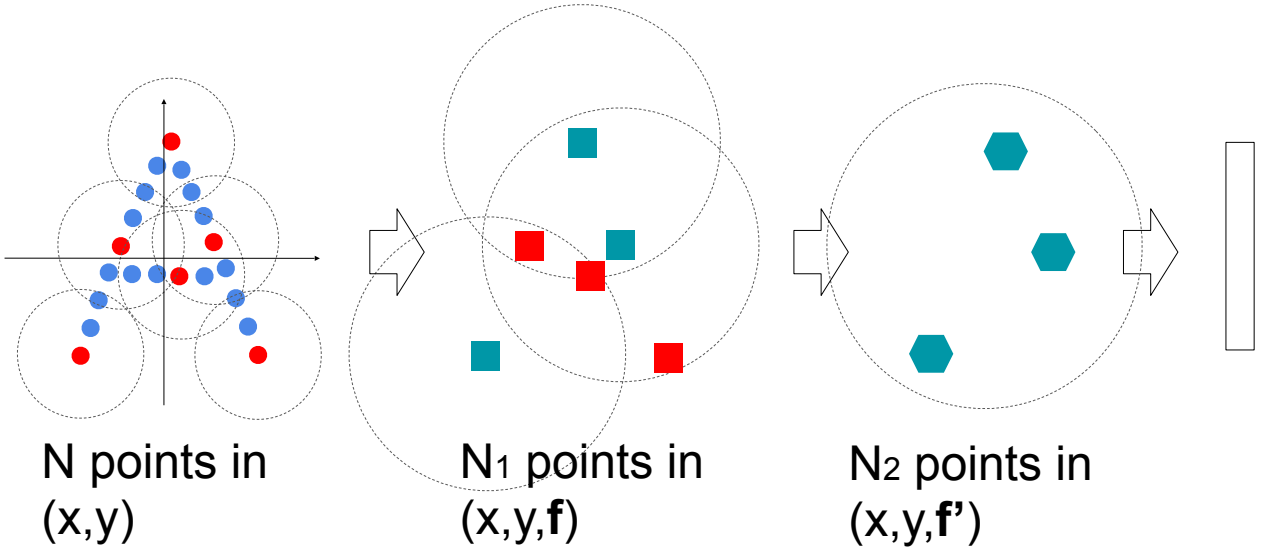
PointNet (vanilla) (Qi et al.)

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

Points in Metric Space

- Learn “kernels” in 3D space and conduct convolution
- Kernels have compact spatial support
- For convolution, we need to find neighboring points
- Possible strategies for range query
  - Ball query (results in more stable features)
  - k-NN query (faster)

PointNet v2.0: Multi-Scale PointNet

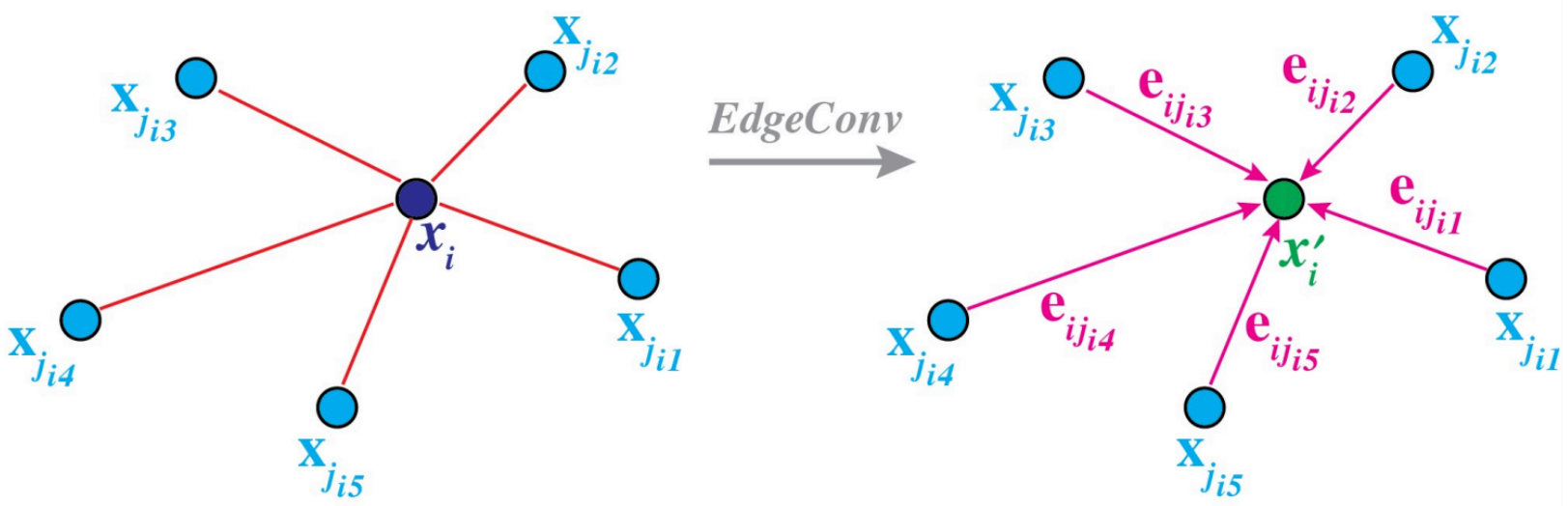


Repeat

- Sample anchor points
- Find neighborhood of anchor points
- Apply PointNet in each neighborhood to mimic convolution

Point Convolution As Graph Convolution

- Points -> Nodes
- Neighborhood -> Edges
- Graph CNN for point cloud processing



Wang et al., "**Dynamic Graph CNN for Learning on Point Clouds**", *Transactions on Graphics, 2019*

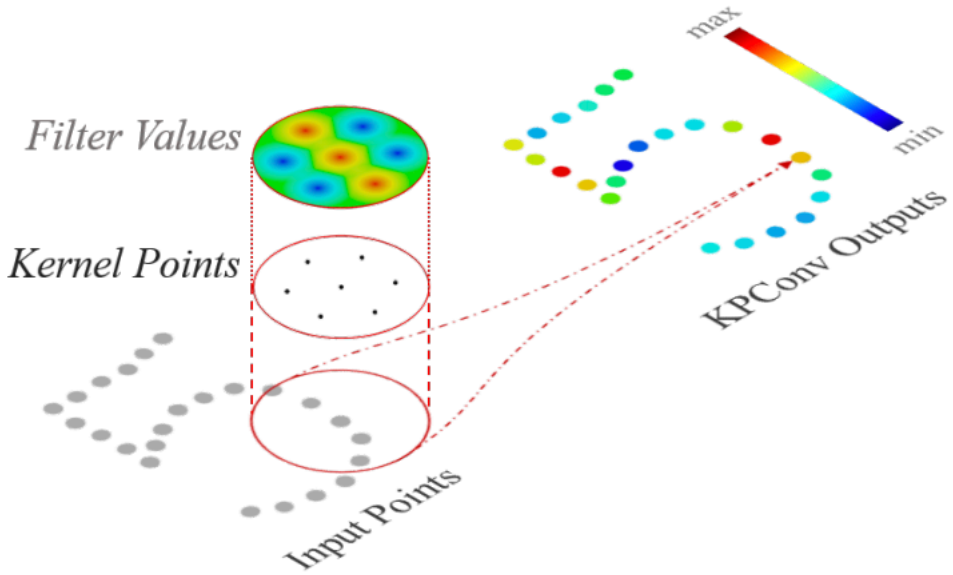
Liu et al., "**Relation-Shape Convolutional Neural Network for Point Cloud Analysis**", *CVPR 2019*

Standard GCNs are not Geometry-Aware

- Note that points are **sampled** from surfaces
- Ideally, features describe the geometry of underlying surface. Should be sample invariant
- But GCNs lack design to address sample invariance
- Remind us “density estimation” from a population
- Rescue: Estimate the continuous kernel and point density for continuous convolution

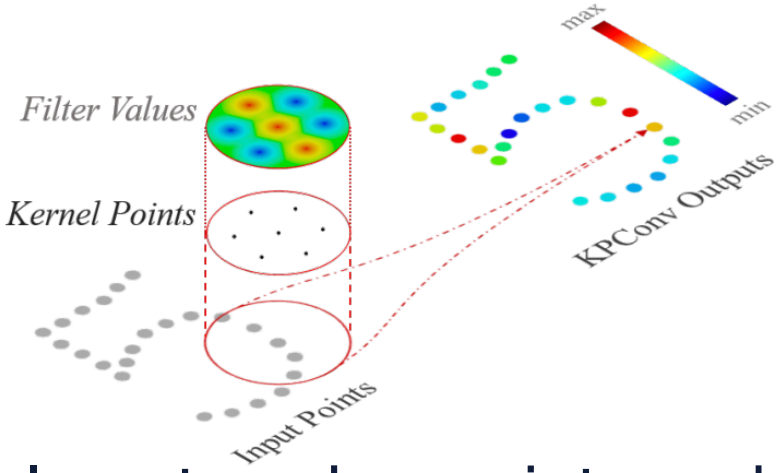
Mathematically Proper Conv. Discretization

- Continuous conv: $(\mathcal{F} * g)(x) = \int g(y - x) f(y) dy$
- Empirical conv: $(\mathcal{F} * g)(x) = \sum_{x_i \in \mathcal{N}_x} g(x_i - x) f_i$



Interpolated Kernel for Convolution

- Continuous conv: $(\mathcal{F} * g)(x) = \int g(y - x) f(y) dy$
- Empirical conv: $(\mathcal{F} * g)(x) = \sum_{x_i \in \mathcal{N}_x} g(x_i - x) f_i$



- Learn kernel value at anchor points and interpolate to build continuous kernel

$$\kappa_{jm}(z) = \sum_l k_{ljm} \Phi(|z - y_l|)$$

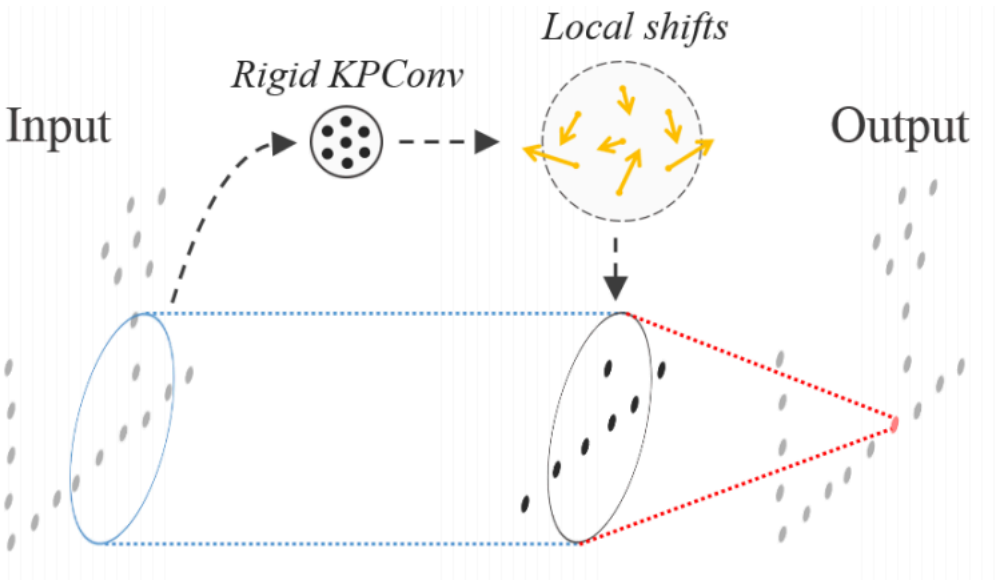
Φ: RBF kernel

Atzmon et al., "**Point Convolutional Neural Networks by Extension Operators**", *Trans. on Graphics, 2018*

Thomas et al., "**KPConv: Flexible and Deformable Convolution for Point Clouds**", *ICCV 2019*

Deformable Kernel for Deformable Objects

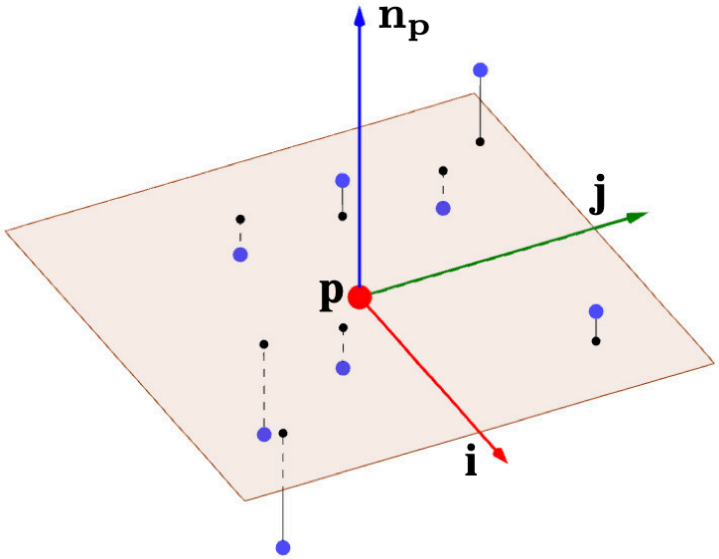
- Deformable point-based kernel
- The 3D version of 2D deformable convolution



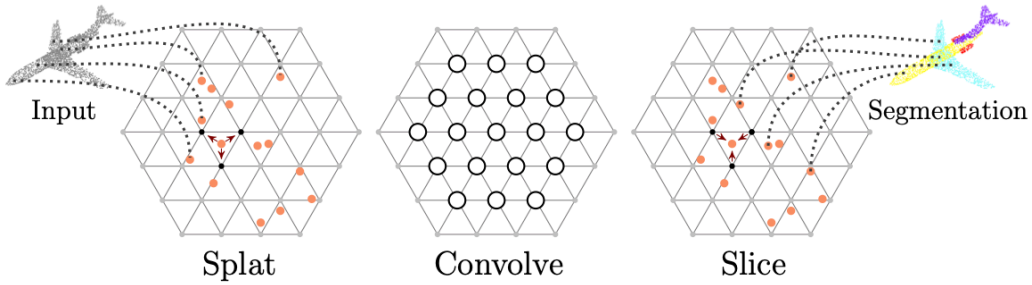
Thomas et al., "**KPConv: Flexible and Deformable Convolution for Point Clouds**", *ICCV 2019*

Other Ways to Address 3D Conv

- Tangent convolution:
  - Project & interpolate local points to the tangent plane (PCA for orientation)
- Lattice
  - high-dimensional space



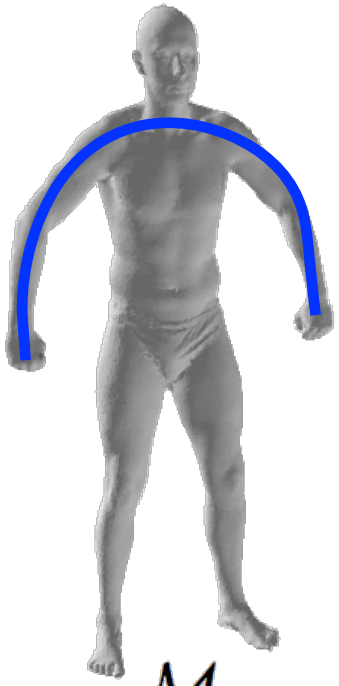
Tatarchenko, Maxim, et al. "**Tangent convolutions for dense prediction in 3d**", *CVPR* 2018.



Su, Hang, et al. "**Splatnet: Sparse lattice networks for point cloud processing**", CVPR 2018

Spectral Convolution

Recognition with Isometric Invariance?



$\mathcal{M}_1$

$\mathcal{M}_2$

geodesic = intrinsic

isometry = length-preserving transform

Spectral CNN

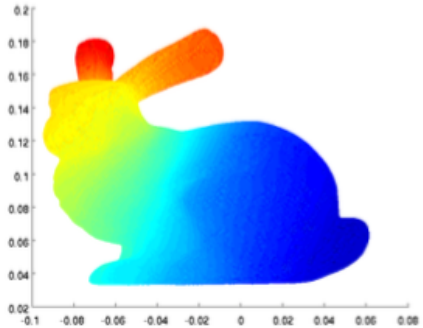
- Convolution done in the spectral domain
- Kernels are also built in spectral domain
- Activation done in the spatial domain

Masci et al., "**Geometric deep learning on graphs and manifolds using mixture model CNNs**", *CVPR 2017*

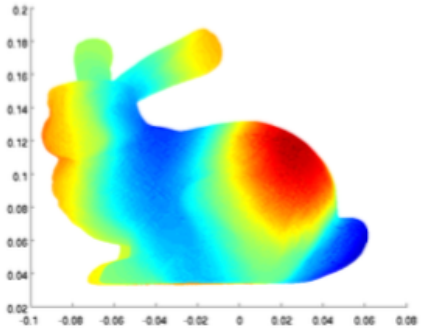
Challenge: Obtain Fourier Basis

- Derived by eigenfunctions of self-adjoint operators, e.g. Laplacian-Bertrami or Dirac operator

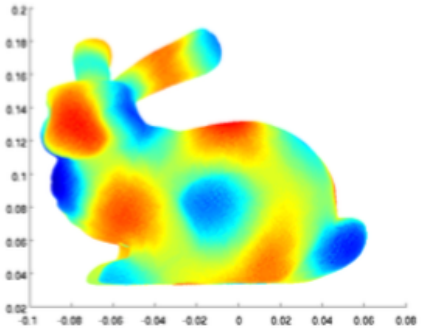
"Fourier basis" of the graph: V : Eigenvectors of Δ



v_2



v_{10}

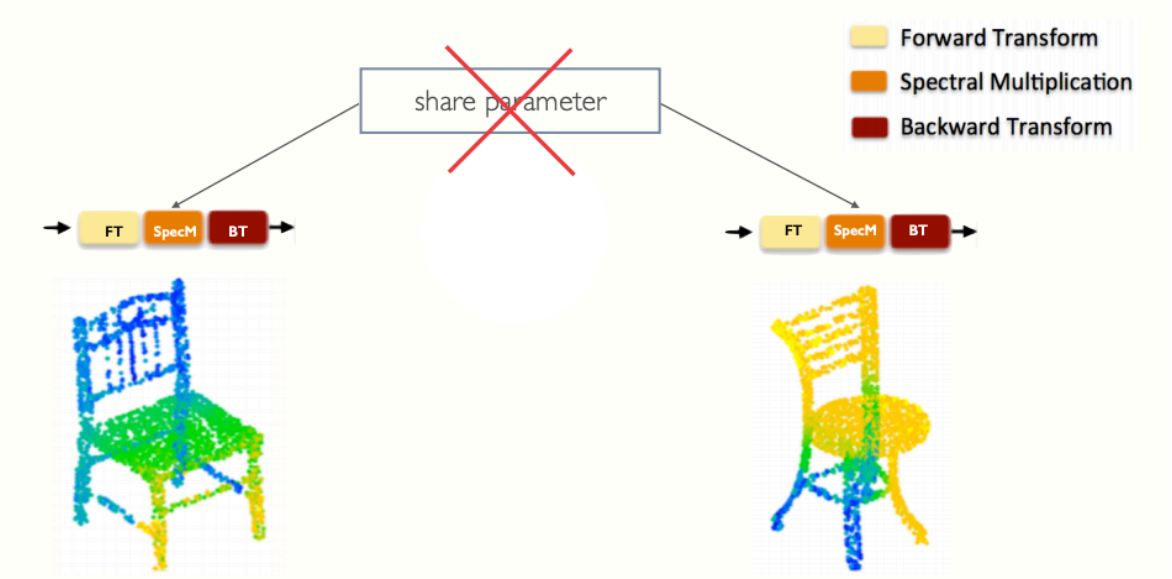


v_{30}

Masci et al., "**Geometric deep learning on graphs and manifolds using mixture model CNNs**", *CVPR 2017*

Fundamental Challenge of Spectral CNN

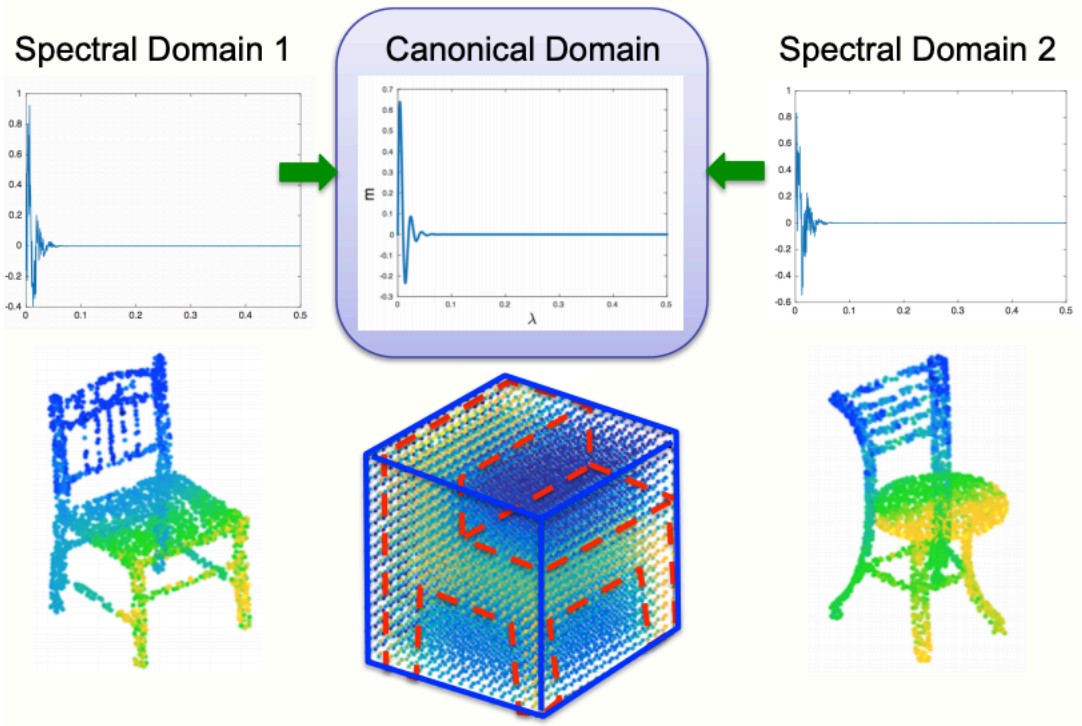
- If the shapes to compare are not isometric, their spectral domains are not aligned
- Function bases are derived by Laplacian operator, which is geometry dependent



Yi et al., "**SyncSpecCNN: Synchronized Spectral CNN for 3D Shape Segmentation**", *CVPR 2017*

Domain Synchronization

- Rescue: Synchronize spectral domains by functional maps

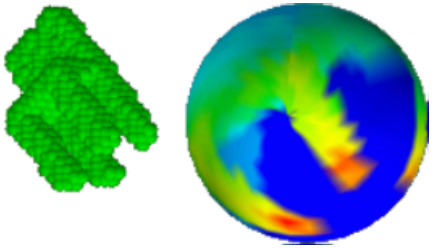


Yi et al., "**SyncSpecCNN: Synchronized Spectral CNN for 3D Shape Segmentation**", *CVPR 2017*

A Special Case: Spherical CNN

- If the surface is always a SPHERE, no worry about the functional space alignment anymore

- Generate a spherical representation

input  convert input to a function on sphere (spherical repr.)

- Do Spherical CNN
  - Has numerical tricks exploiting the symmetry of sphere

Cohen et al., "**Spherical CNN**", *ICLR 2018*

Esteves et al., "**Learning SO(3) Equivariant Representations with Spherical CNNs**", *ECCV 2018*

Learned Filters

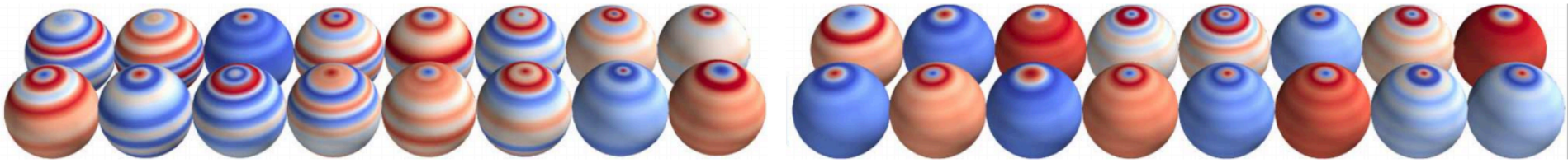


Fig. 4: Filters learned in the first layer. The filters are zonal. *Left:* 16 nonlocalized filters. *Right:* 16 localized filters. Nonlocalized filters are parameterized by all spectral coefficients (16, in the example). Even though locality is not enforced, some filters learn to respond locally. Localized filters are parameterized by a few points of the spectrum (4, in the example), the rest of the spectrum is obtained by interpolation.

A Special Case: Spherical CNN

- Rotation invariance guaranteed

Table 1: ModelNet40 classification accuracy per instance. Spherical CNNs are robust to arbitrary rotations, even when not seen during training, while also having one order of magnitude fewer parameters and faster training.

Method	z/z	SO3/SO3	z/SO3	params	inp. size
PointNet [7]	89.2	83.6	14.7	3.5M	2048 x 3
PointNet++ [38]	89.3	85.0	28.6	1.7M	1024 x 3
VoxNet [29]	83.0	73.0	-	0.9M	30^3
SubVolSup [8]	88.5	82.7	36.6	17M	30^3
SubVolSup MO [8]	89.5	85.0	45.5	17M	20×30^3
MVCNN 12x [9]	89.5	77.6	70.1	99M	12×224^2
MVCNN 80x [9]	**90.2**	86.0	- [2]	99M	80×224^2
RotationNet 20x [30]	**92.4**	80.0	20.2	58.9M	20×224^2
Ours	88.9	**86.9**	**78.6**	**0.5M**	$\mathbf{2 \times 64^2}$

- Can be used to improve the rot. invariance of MVCNN, as well

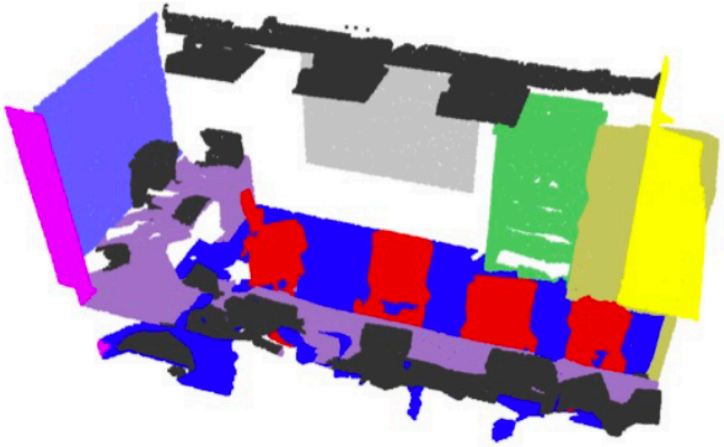
Esteves et al., "**Learning SO(3) Equivariant Representations with Spherical CNNs**", *ECCV 2018*

Esteves et al., "**Equivariant Multi-View Networks**", *ICCV 2019*

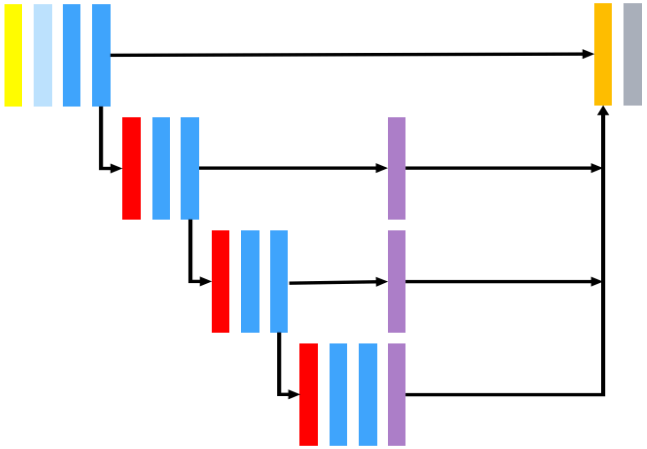
Topics

- 3D Data
- Classification
- **Segmentation and Detection**
- Reconstruction

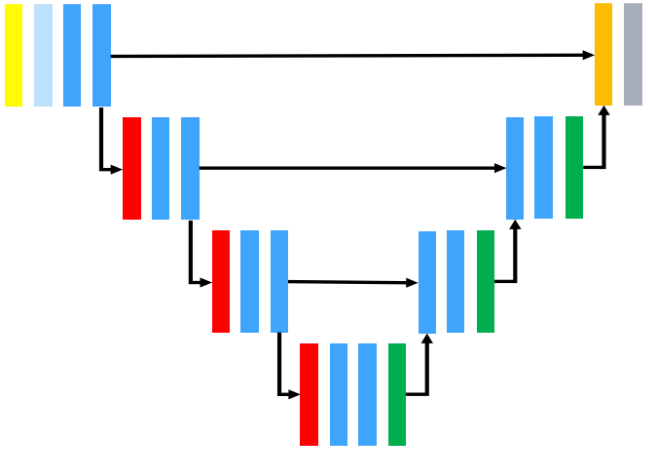
Task: 3D Semantic Segmentation



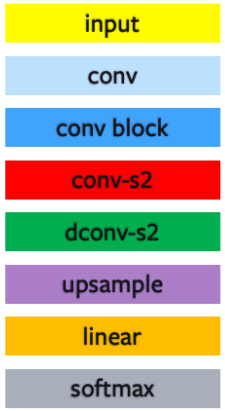
Encoder-Decoder



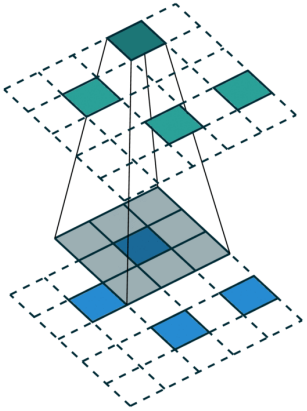
(a) Submanifold sparse FCN.



(b) Submanifold sparse U-Net.



Sparse Convolution

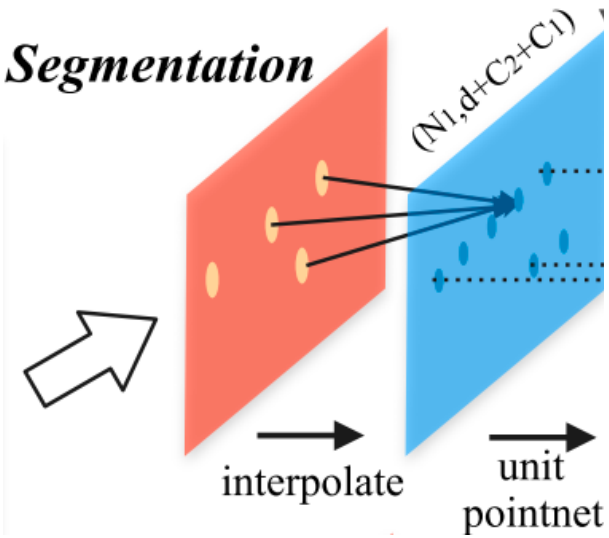


Sparse Deconvolution

Graham, Benjamin, Martin Engelcke, and Laurens van der Maaten. **"3d semantic segmentation with submanifold sparse convolutional networks."** CVPR 2018.

Choy, Christopher, et al. **"4D Spatio-Temporal Convnets: Minkowski Convolutional Neural Networks."** CVPR 2019

Encoder-Decoder



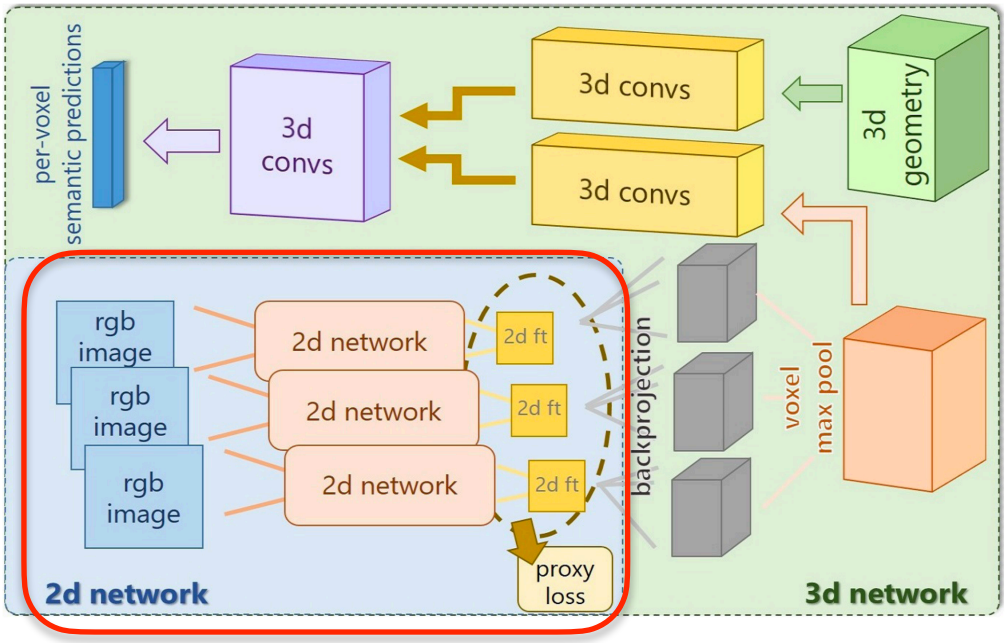
Lower resolution
Fewer points

Higher resolution
More points

Upsample point cloud features by interpolating from 3 nearest points in the point cloud of lower resolution.

Qi, Charles R., et al. **"PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space."**, NeurIPS 2017

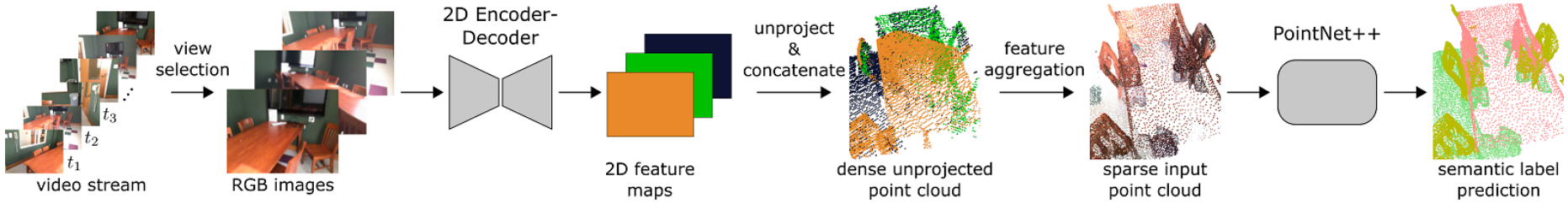
Multimodal



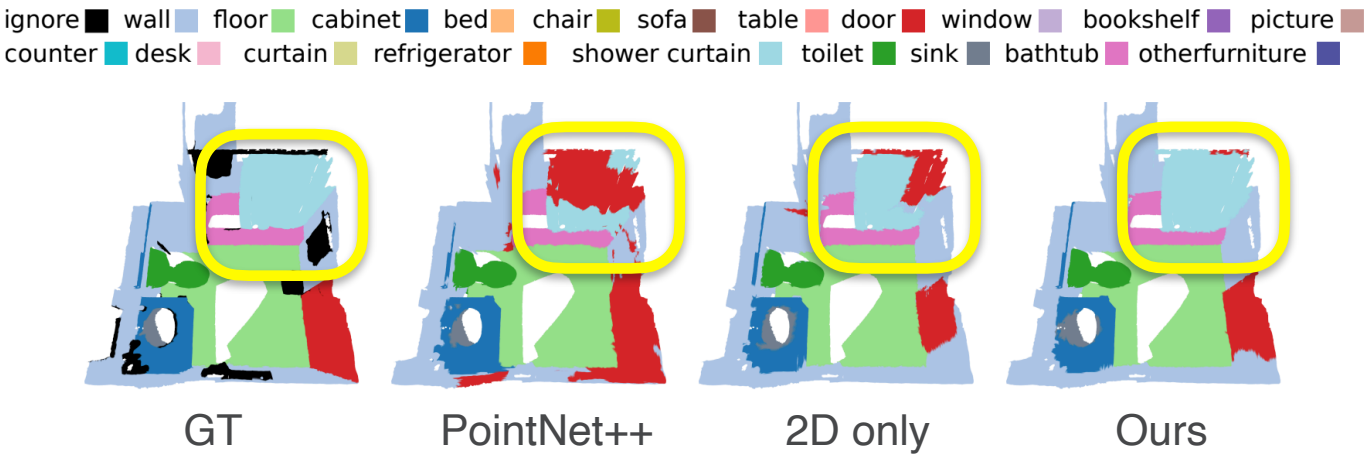
- Backproject 2D features to 3D voxels
- Apply voxel-wise max-pooling across multiple views
- Fuse 2D and 3D features at the intermediate level

Dai, Angela, and Matthias Nießner. **"3dmv: Joint 3d-multi-view prediction for 3d semantic scene segmentation."**, ECCV 2018

Multimodal



- Backproject 2D features to 3D points
- Apply PointNet to aggregate multi-view features
- Fuse 2D and 3D features as input to 3D network



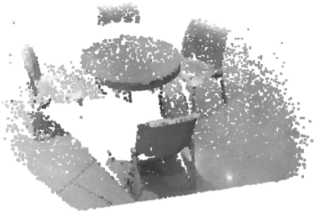
Jaritz, Maximilian, Jiayuan Gu, and Hao Su. "**Multi-view pointnet for 3D scene understanding.**", ICCV-W 2019.

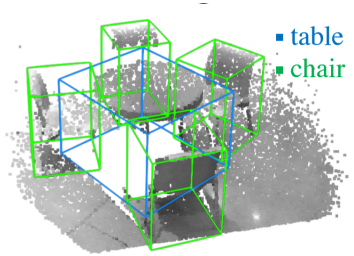
Task: Instance-level Understanding

Input

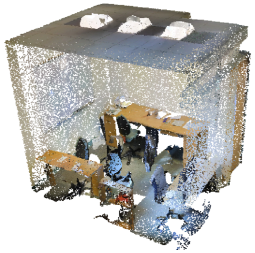
Output

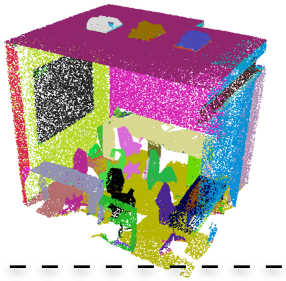
Object Detection





Object Segmentation



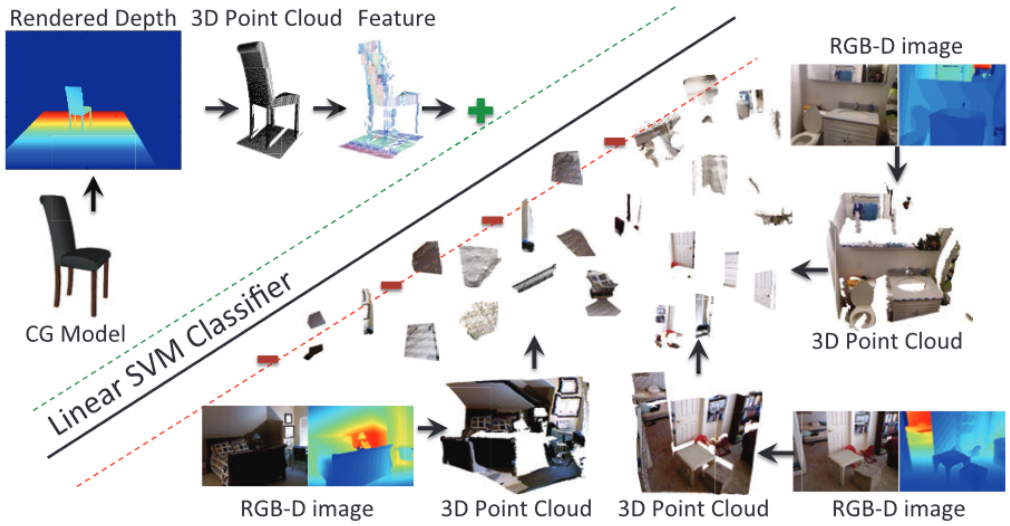


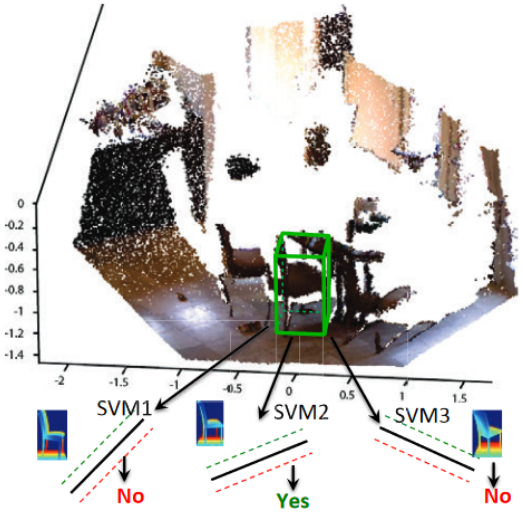
Part Segmentation

Top-down Methods

- Does this point cloud contain an object?
- How to select point clouds to classify objectness?

Sliding Shapes

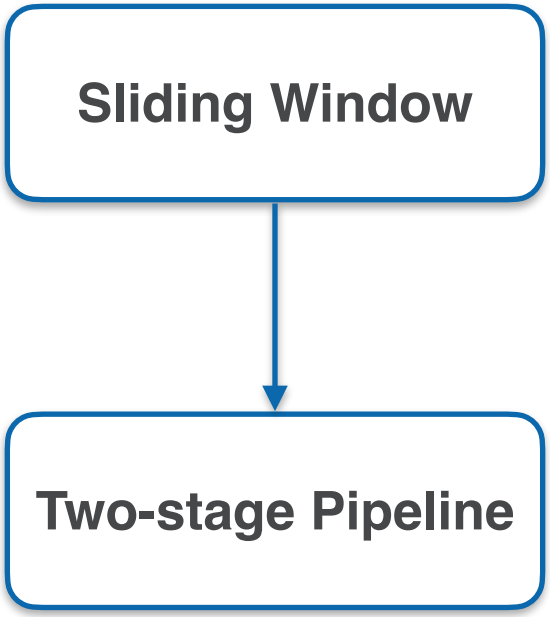




Sliding window to walk over the entire space

Expensive !

Song et al., "**Sliding Shapes for 3D Object Detection in Depth Images**", *ECCV 2014*

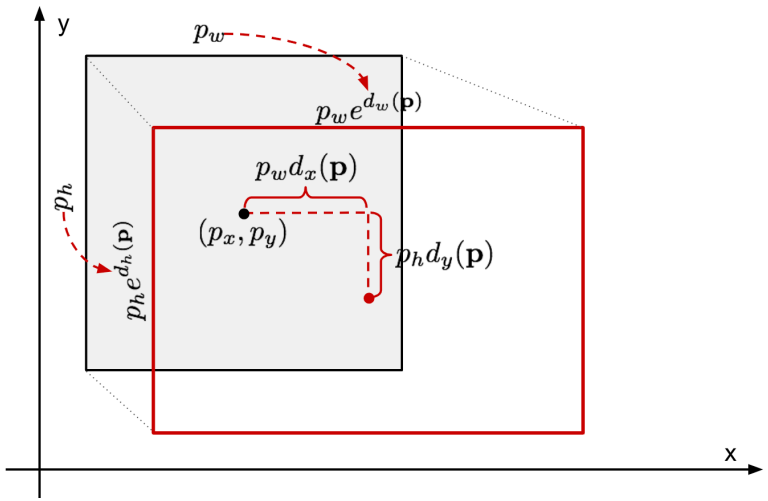


First stage: Proposal

Second stage: Refinement

Localization

- 3D bounding box regression
- Predefined bounding boxes (anchors) at each sliding window
- Re-parameterize as relative offsets



$$\Delta_x = \frac{\mu - \mu_{anchor}}{\phi_{anchor}}$$

Center shift

$$\Delta_w = \ln(\frac{\phi}{\phi_{anchor}})$$

Size scale

Figure from https://lilianweng.github.io/lil-log/2017/12/31/object-recognition-for-dummies-part-3.html

From Box to Instance Segmentation

- Box includes background points or other instances
- foreground/background segmentation

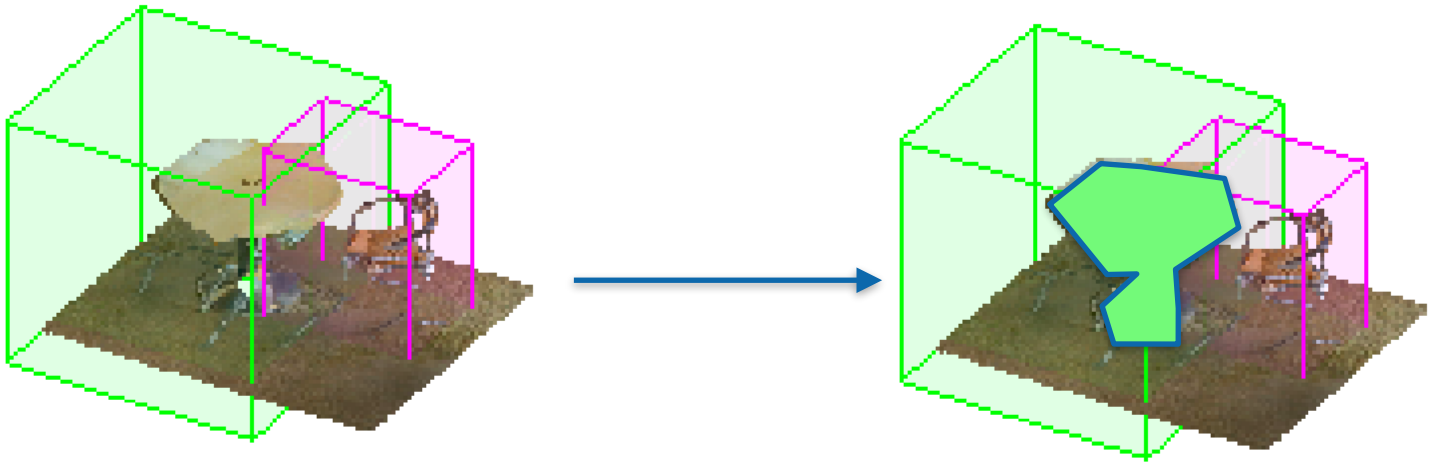
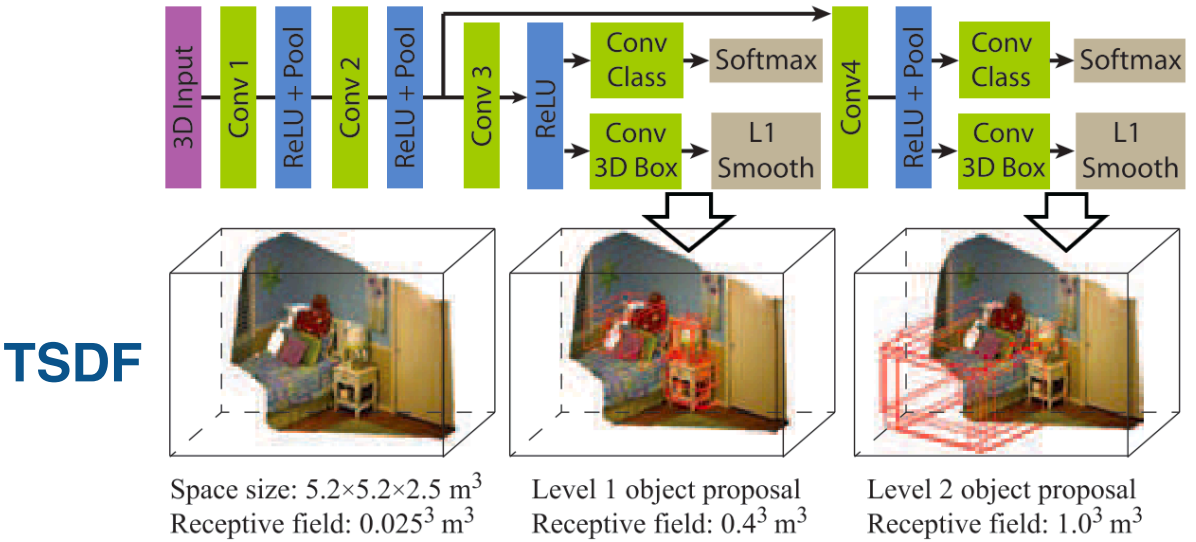


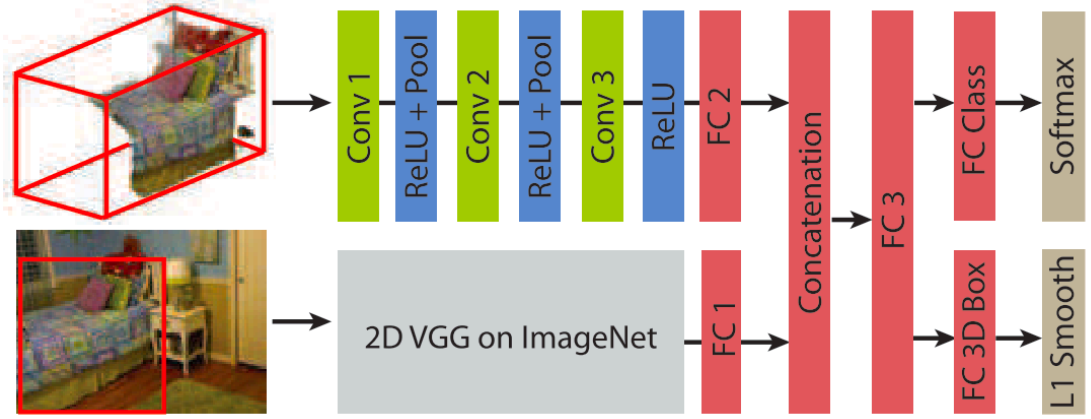
Figure from **"Learning Object Bounding Boxes for 3D Instance Segmentation on Point Clouds"**

Volumetric R-CNN

Stage1: 3D Region Proposal Network



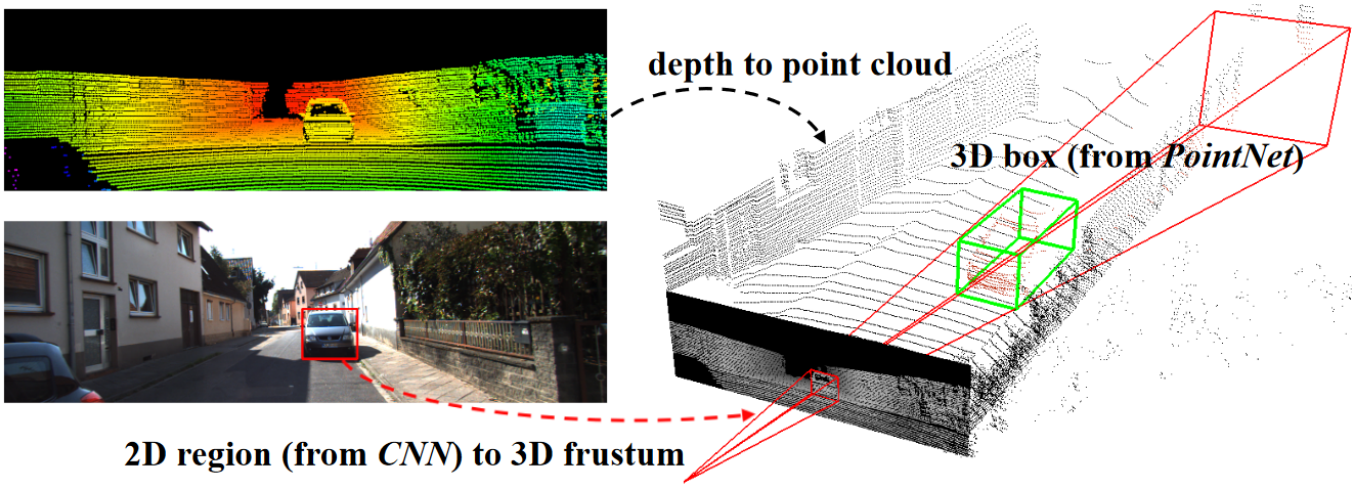
Stage2: Joint Object Recognition Network



Song et al., "**Deep Sliding Shapes for Amodal 3D Object Detection in RGB-D Images**", *CVPR 2016*

View-based Proposal

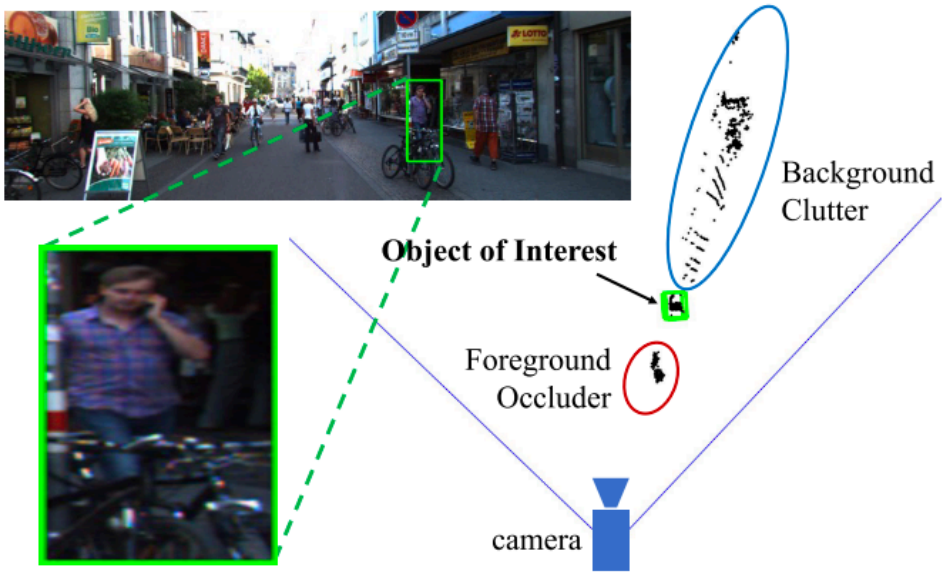
Generate object proposals from a view (e.g., using SSD)



Qi et al., "**Frustum PointNets for 3D Object Detection from RGB-D Data**", *CVPR 2018*

Stage 2: FG/BG Segmentation

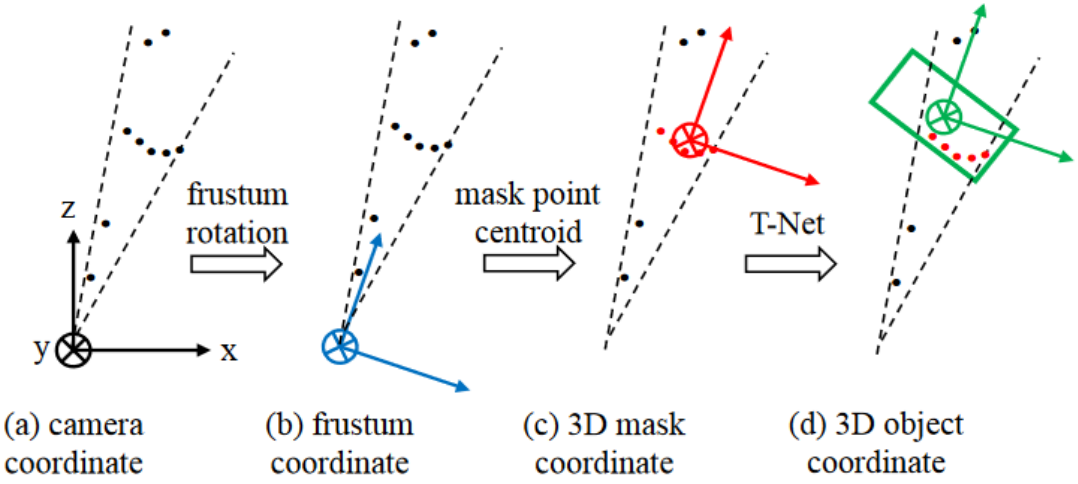
Instance segmentation to remove other foreground instances and background clutter



Qi et al., "**Frustum PointNets for 3D Object Detection from RGB-D Data**", *CVPR 2018*

Stage 2: Coordinate Normalization

Handle perspective variation in frustum point cloud by a series of coordinates normalization

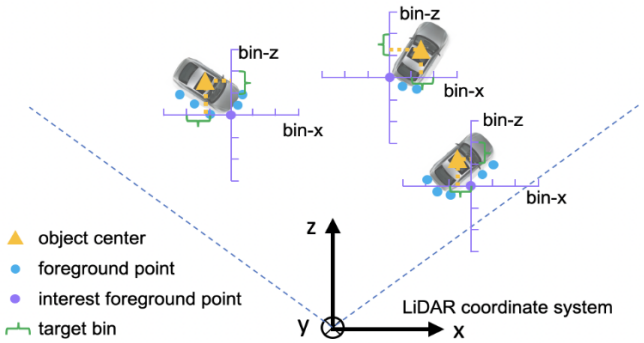


Qi et al., "**Frustum PointNets for 3D Object Detection from RGB-D Data**", *CVPR 2018*

Point-based Proposal

Stage-1: Foreground/Background segmentation and generate 3D proposals for each foreground point

Stage-2: Refine proposals in the canonical coordinates



Bin-based Box Representation

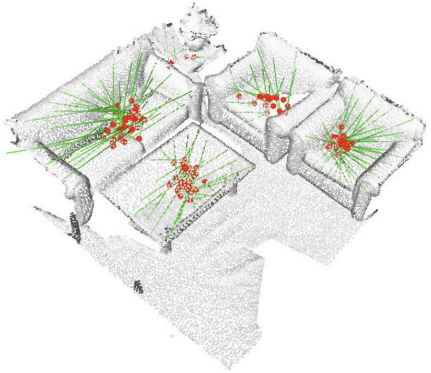
Shi et al., "**PointRCNN: 3D Object Proposal Generation and Detection from Point Cloud**", *CVPR 2019*

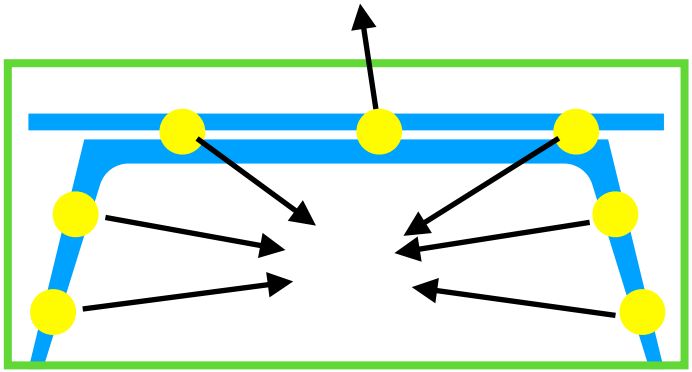
Proposal from Voting

Challenge: 3D object centroid can be far from any surface point, thus hard to regress accurately

- Sample a set of seed points and generate votes, targeting at object centers

Voting from input point cloud



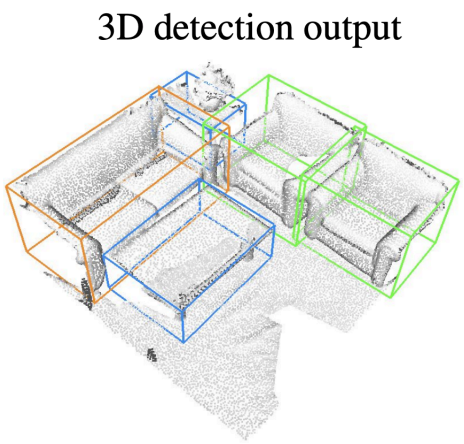


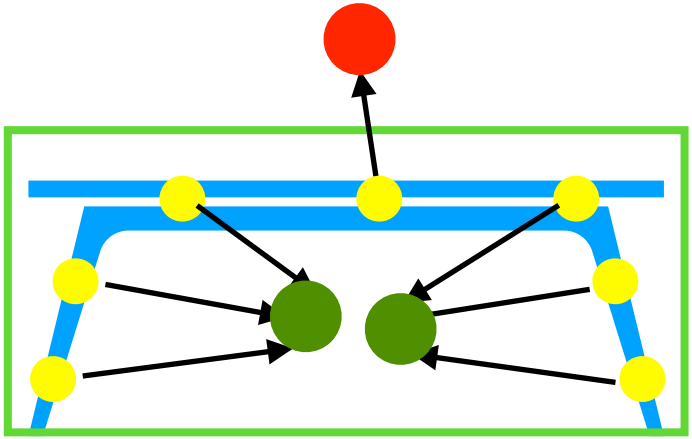
Qi et al., "**Deep Hough Voting for 3D Object Detection in Point Clouds**", *ICCV 2019*

Proposal from Voting

Challenge: 3D object centroid can be far from any surface point, thus hard to regress accurately

- Votes cluster near object centers
  (Farthest point sample votes to cluster)

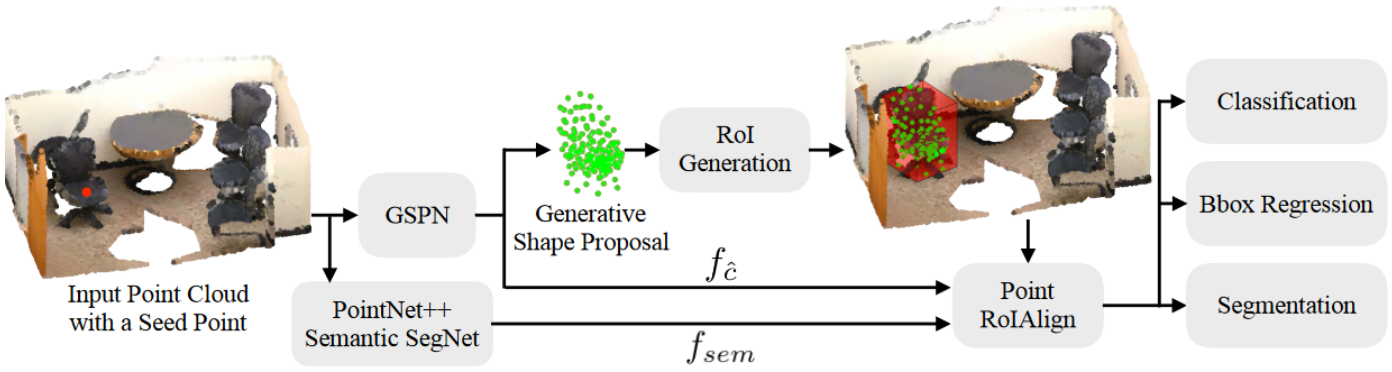




Qi et al., "**Deep Hough Voting for 3D Object Detection in Point Clouds**", *ICCV 2019*

Proposal from Generative Network

- Randomly sample seeds points
- Take point cloud and a seed point as input, use conditional VAE to generate a point cloud as proposal
- Convert the proposal to an ROI box
- R-PointNet (mask RCNN) to segment the object



Yi et al., "**GSPN: Generative Shape Proposal Network for 3D Instance Segmentation in Point Cloud**", *CVPR 2019*

Bottom-up Methods

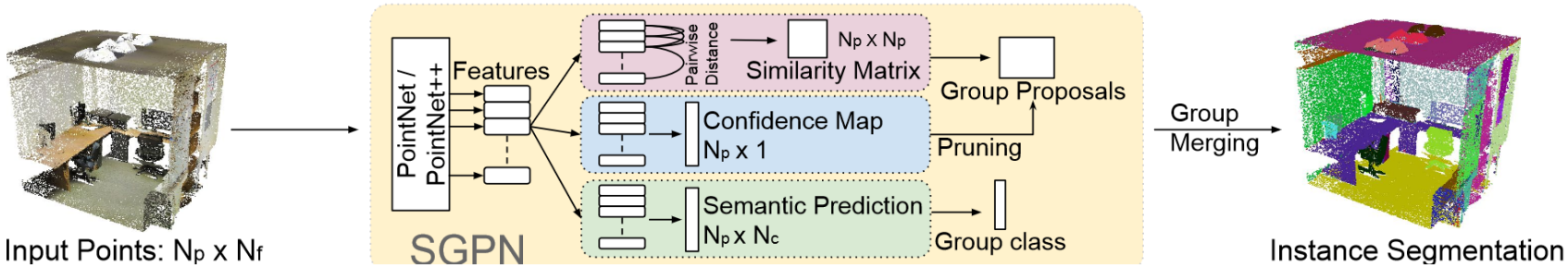
- Do these points belong to the same instance?
- How to measure the similarity between two points?

Associative Embedding

- Learn a per-point embedding, so that points from the same instance have similar embeddings

$$l(i,j) = \begin{cases} ||F_{SIM_i} - F_{SIM_j}||_2 & C_{ij} = 1 \\ \alpha \max(0, K_1 - ||F_{SIM_i} - F_{SIM_j}||_2) & C_{ij} = 2 \\ \max(0, K_2 - ||F_{SIM_i} - F_{SIM_j}||_2) & C_{ij} = 3 \end{cases}$$

- Clustering gives proposals

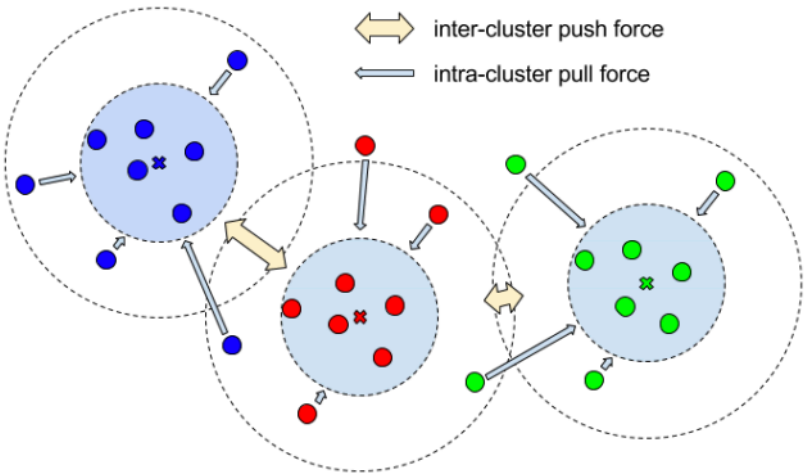


Wang et al., "**SGPN: Similarity Group Proposal Network for 3D Point Cloud Instance Segmentation**", *CVPR 2018*

JSIS3D

- A discriminative function to present the embedding loss

$$\mathcal{L}_{embedding} = \alpha \cdot \mathcal{L}_{pull} + \beta \cdot \mathcal{L}_{push} + \gamma \cdot \mathcal{L}_{reg}$$



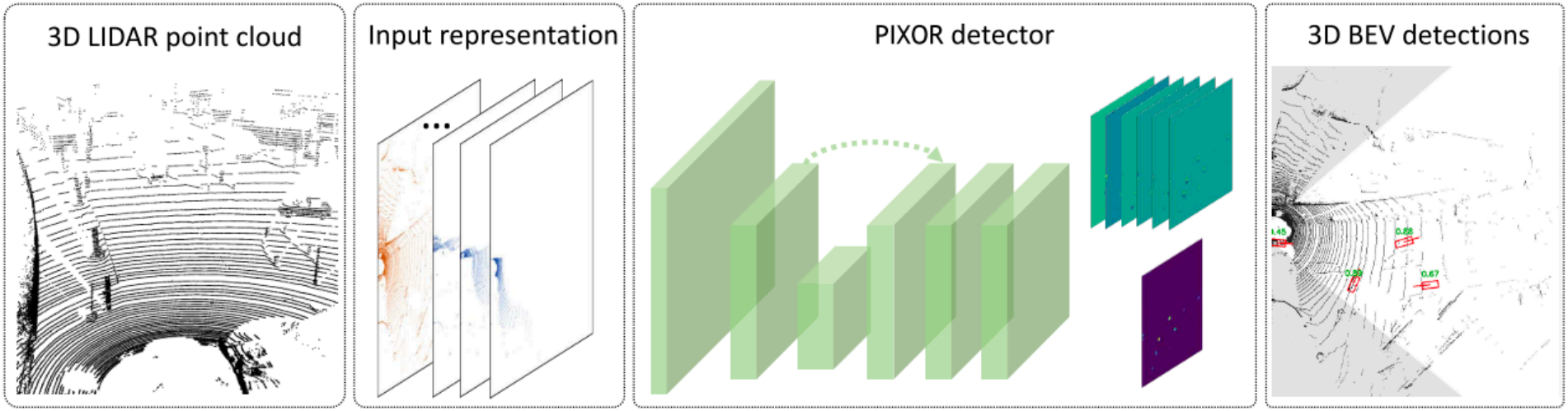
$$\mathcal{L}_{pull} = \frac{1}{K}\sum_{k=1}^{K}\frac{1}{N_k}\sum_{j=1}^{N_k}\left[\|\boldsymbol{\mu}_k - \mathbf{e}_j\|_2 - \delta_v\right]_+^2$$

$$\mathcal{L}_{push} = \frac{1}{K(K-1)}\sum_{k=1}^{K}\sum_{m=1,m\neq k}^{K}\left[2\delta_d - \|\boldsymbol{\mu}_k - \boldsymbol{\mu}_m\|_2\right]_+^2$$

$$\mathcal{L}_{reg} = \frac{1}{K}\sum_{k=1}^{K}\|\boldsymbol{\mu}_k\|_2$$

Pham, Quang Hieu, et al. **"JSIS3D: Joint Semantic-Instance Segmentation of 3D Point Clouds with Multi-Task Pointwise Networks and Multi-Value Conditional Random Fields."**, CVPR 2019

BEV (bird-eye view)



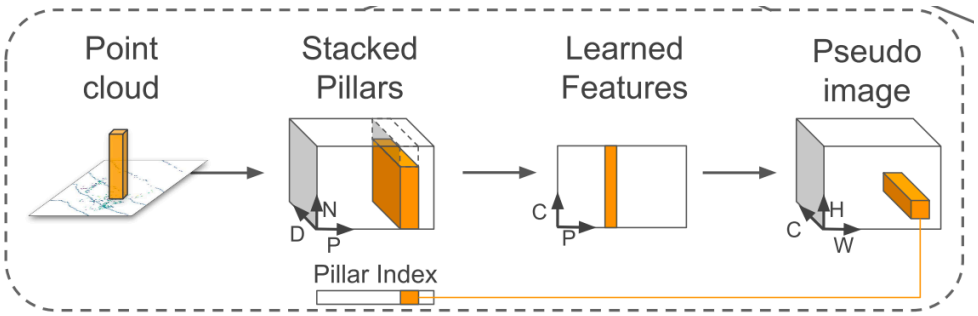
HxWxD voxels

HxW image
with D channels

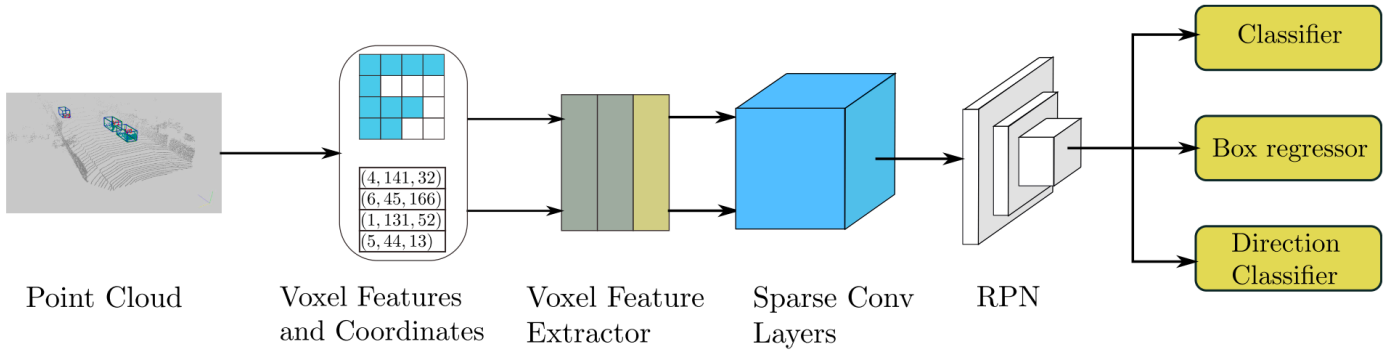
Yang, Bin, Wenjie Luo, and Raquel Urtasun. **"Pixor: Real-time 3d object detection from point clouds."** CVPR 2018

Feature Encoder

- Replace occupancy of each pixel with point cloud features of the pillar



- Sparse convolution to extract features



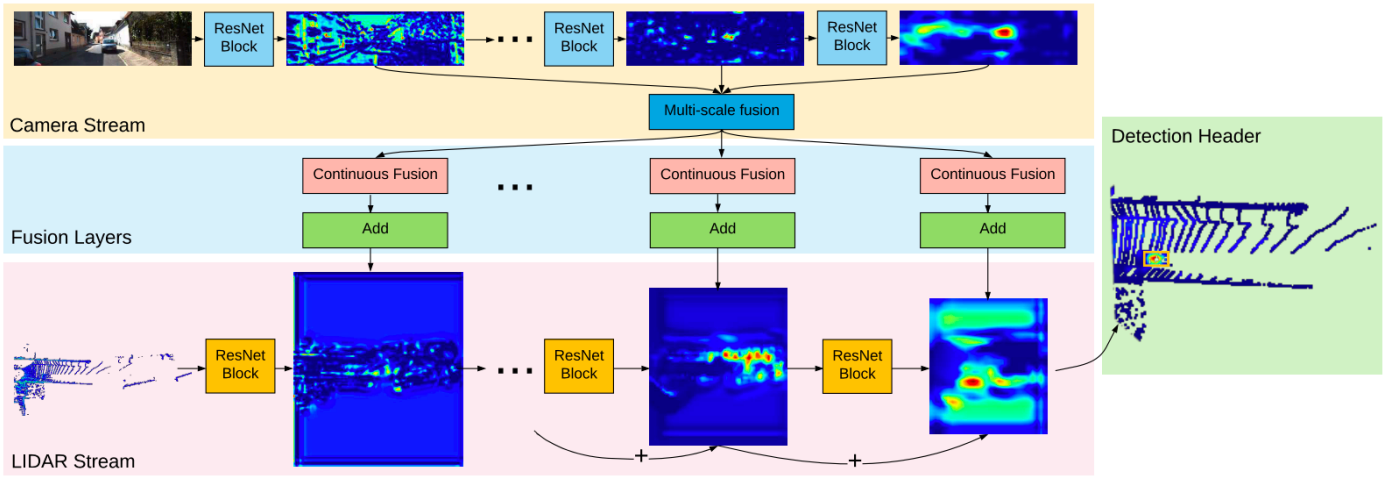
Yan, Yan, et al. **"Second: Sparsely Embedded Convolutional Detection."** Sensors 2018

Lang, Alex H., et al. **"Pointpillars: Fast Encoders for Object Detection from Point Clouds."** CVPR 2019

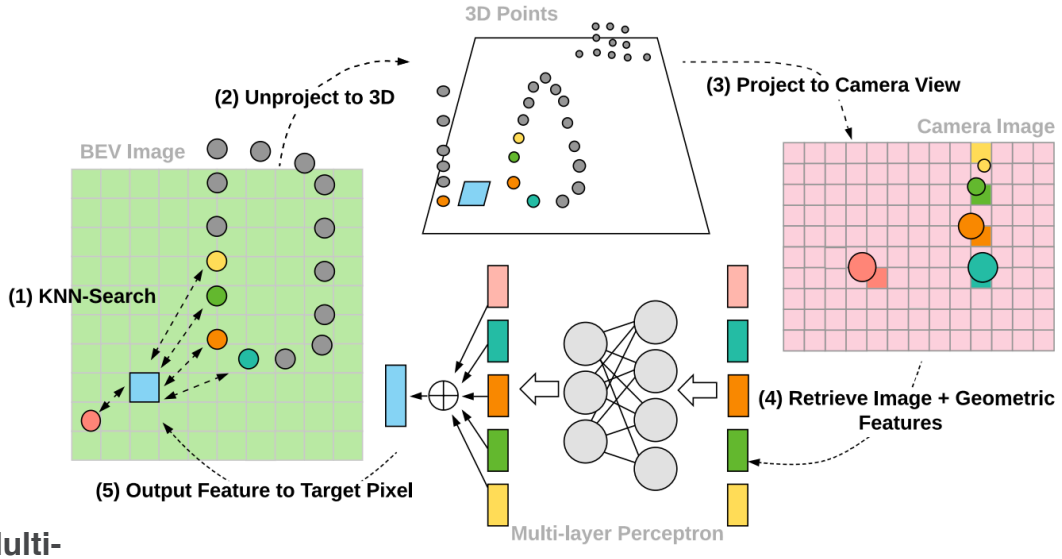
ContFuse

Image feature network: 2D image

BEV network: 3D voxel (HxWxC)



3D points as the intermediate media to transform from the camera to BEV



Liang, Ming, et al. **"Deep Continuous Fusion for Multi-Sensor 3D Object Detection."** ECCV 2018

Topics

- 3D Data
- Classification
- **Segmentation and Detection**
  - **Few-shot/Zero-shot Learning**
- Reconstruction

Why Few-shot/Zero-shot Learning by 3D?

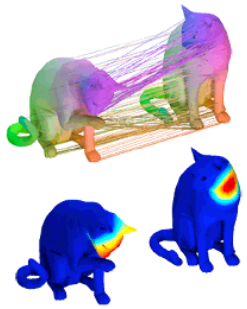
- Can be a better platform than images
- Shapes are **pure,** with no contamination by projection distortion, illumination, …

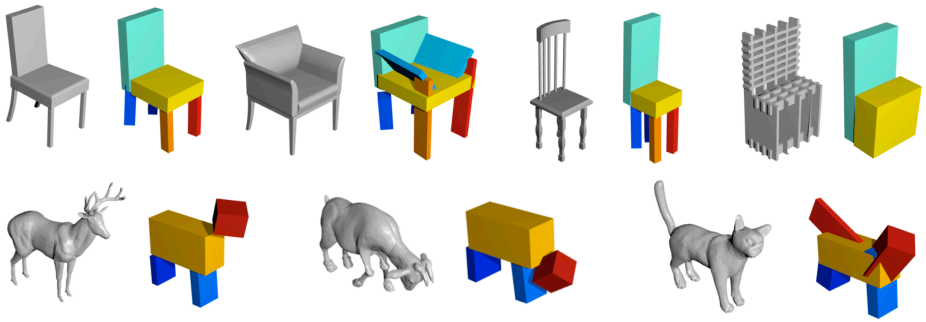
If one image is more than a thousand words, then one shape is more than one thousand pictures

Why Few-shot/Zero-shot Learning by 3D?

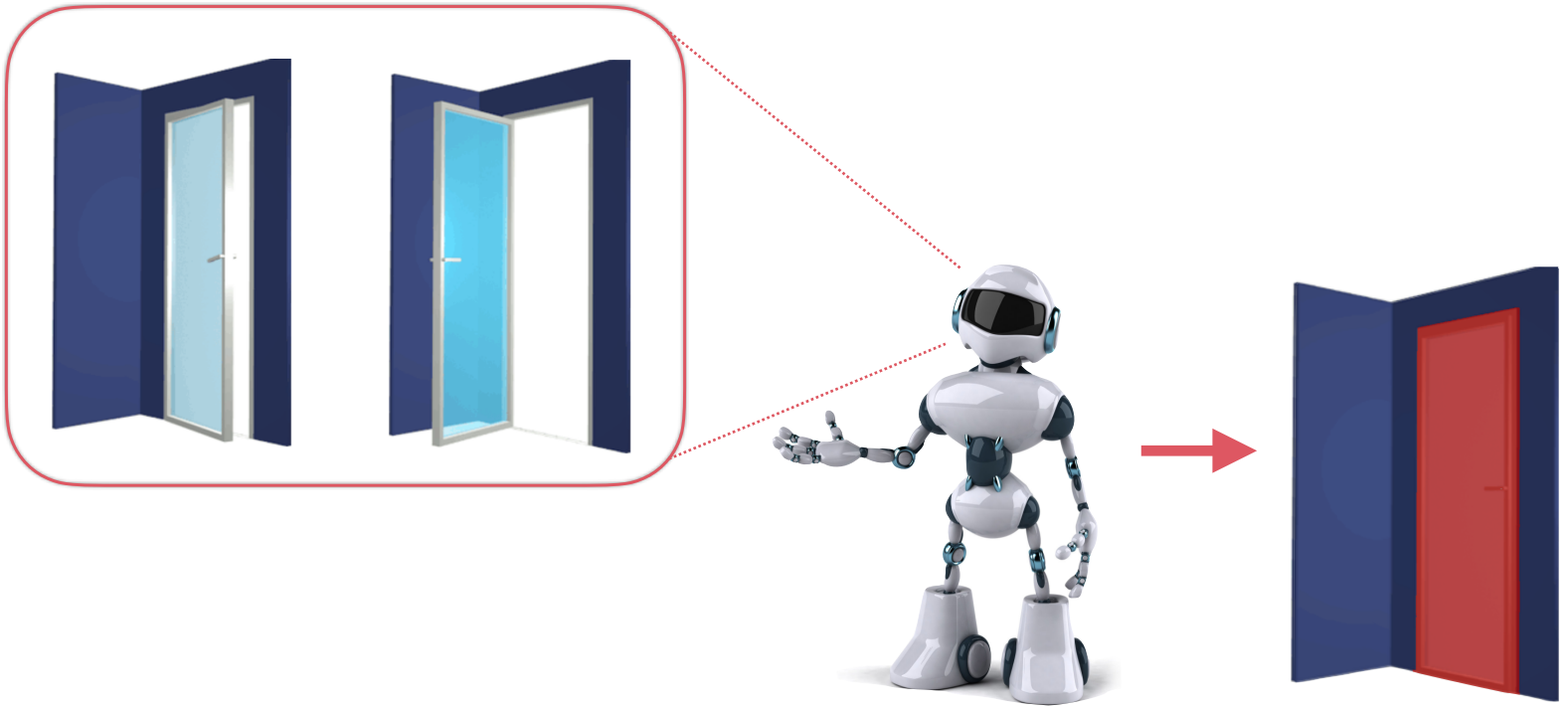
Algorithmically, 3D shapes are:

- easier to be **related (correspondence)**
- easier to be **compared**
- easier to **abstracted**

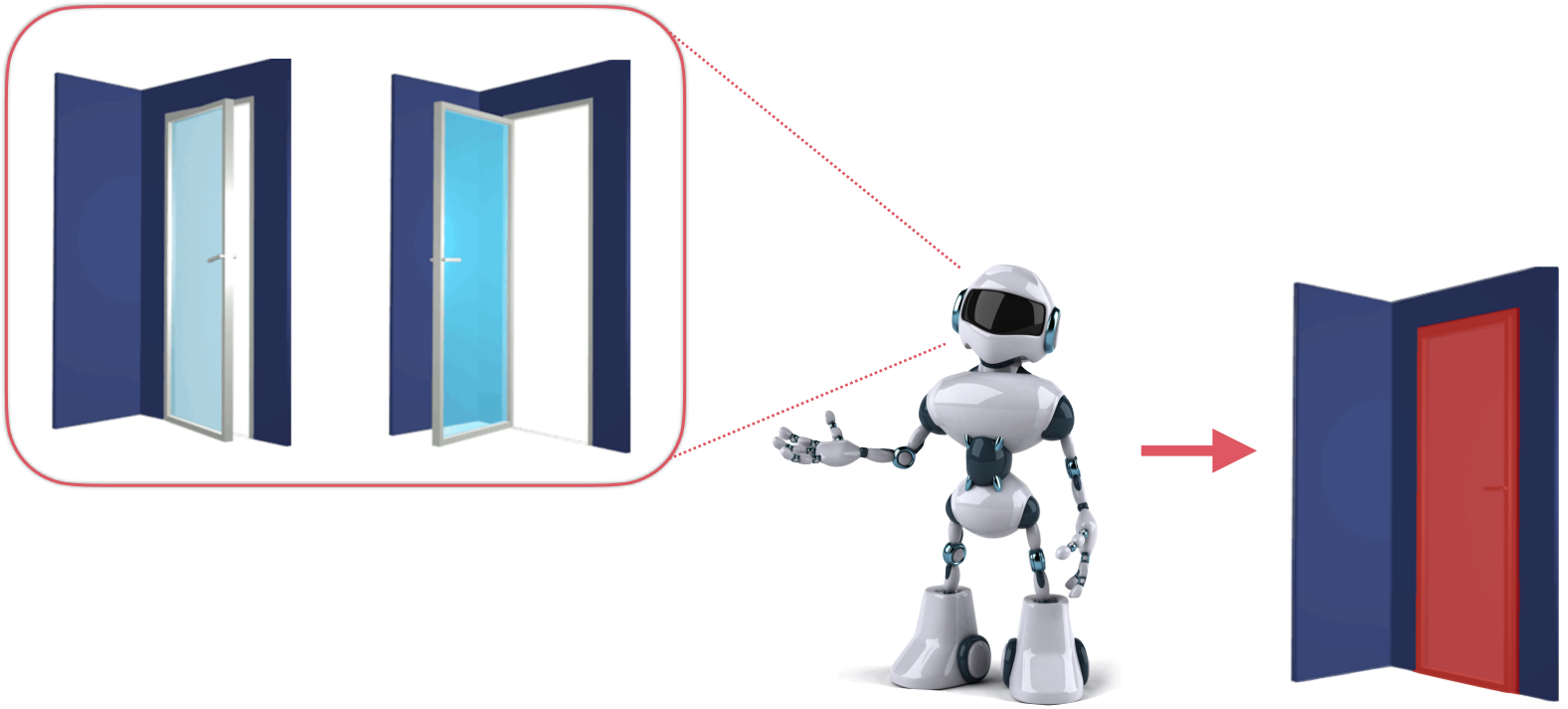




Task: Few-shot Structure Induction

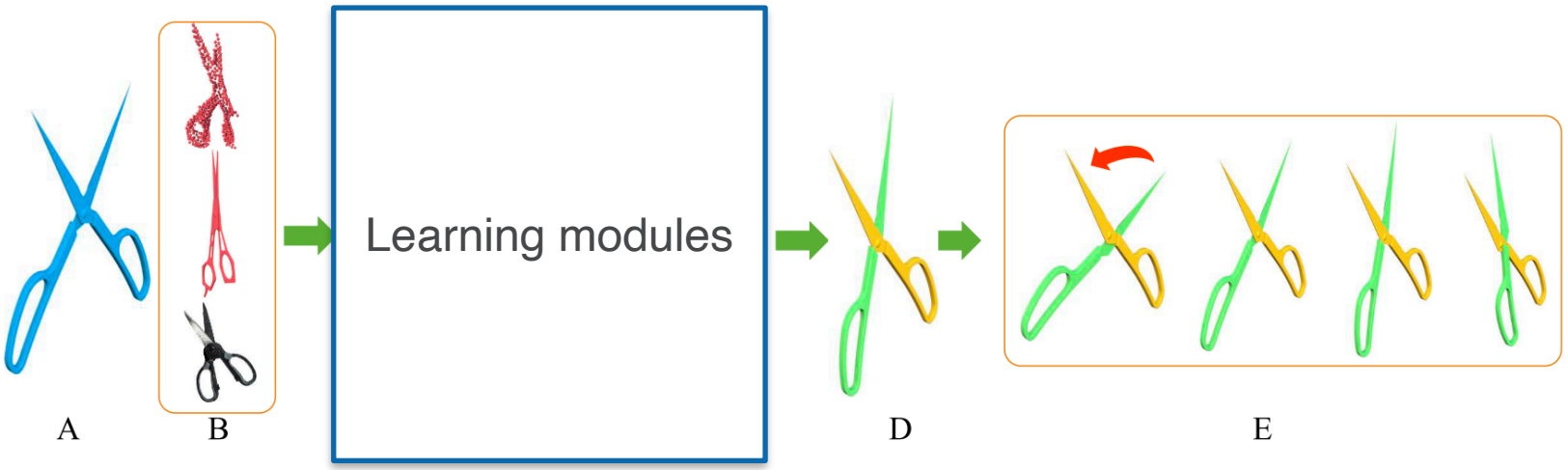


Emergence of Structure by Persistence



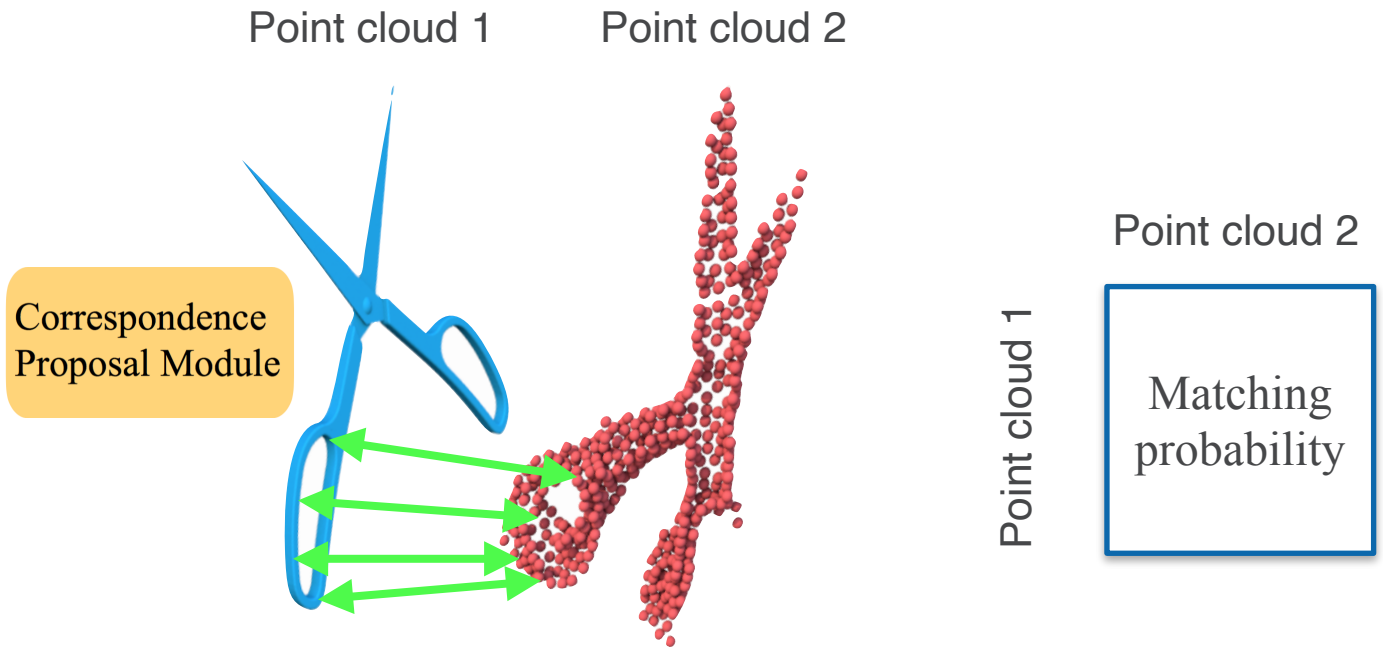
Capture re-occuring units!

Part Induction by Relating Shapes



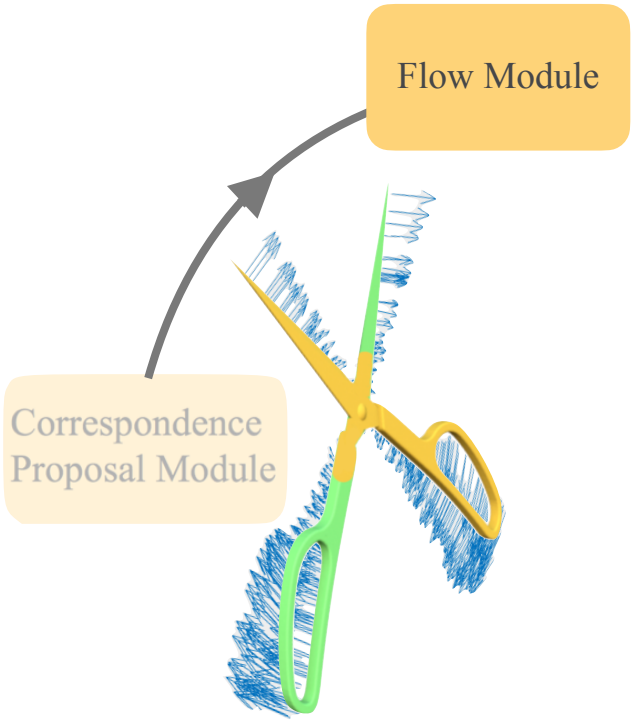
Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

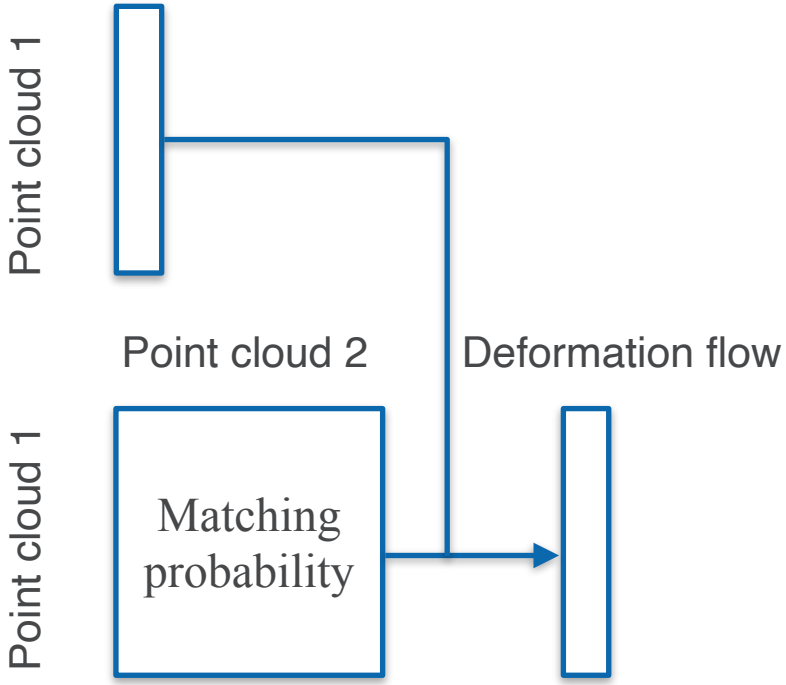
Part Induction by Relating Shapes



Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

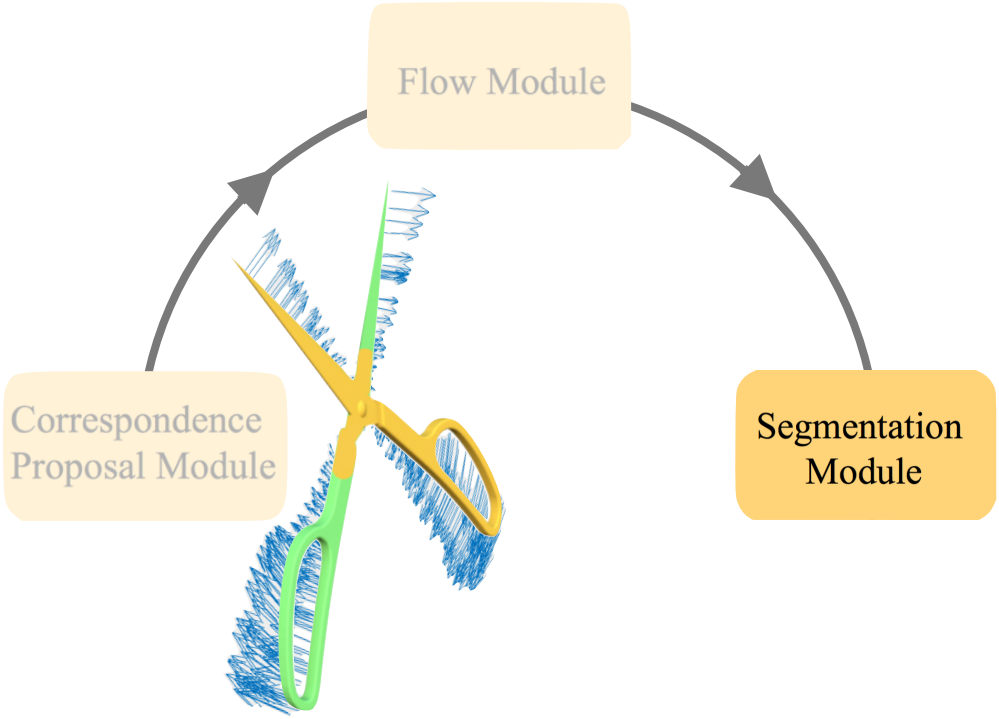
Part Induction by Relating Shapes





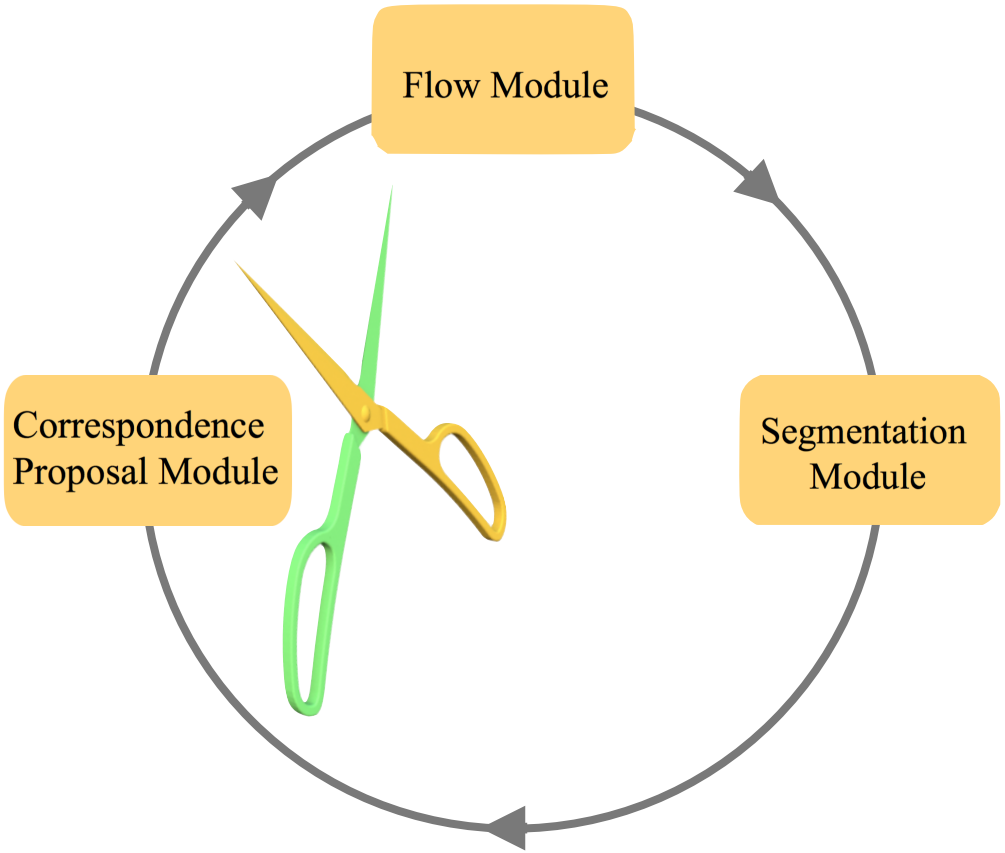
Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Part Induction by Relating Shapes



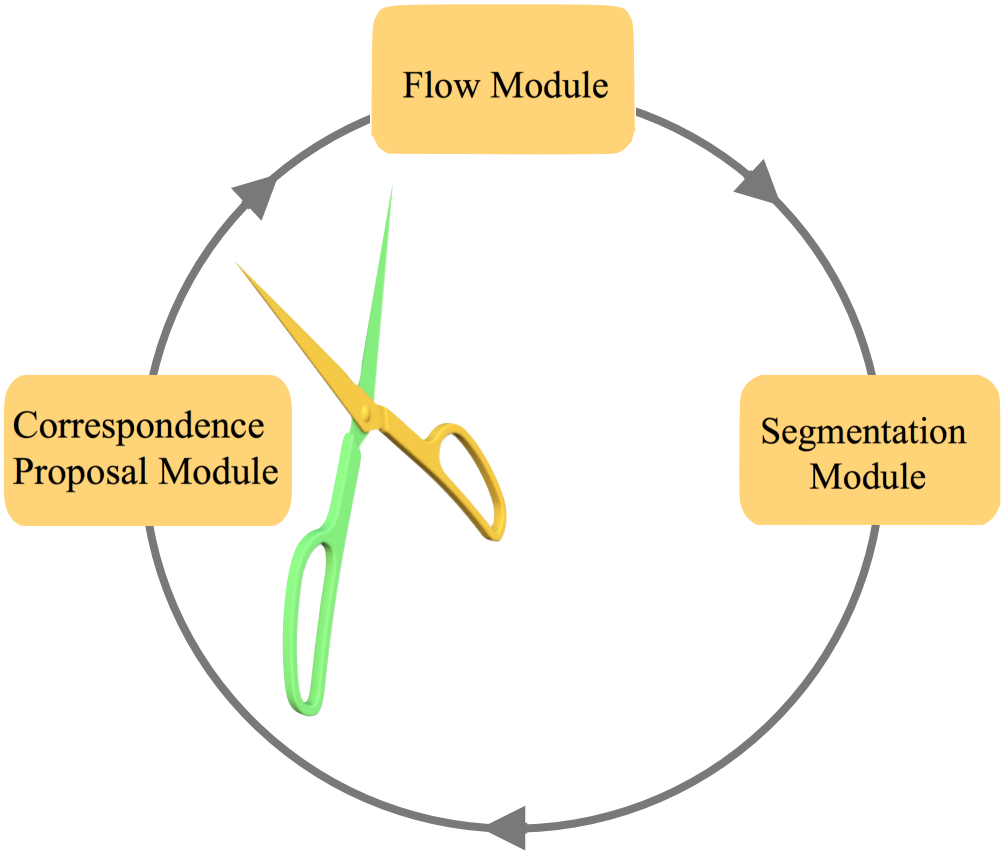
Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

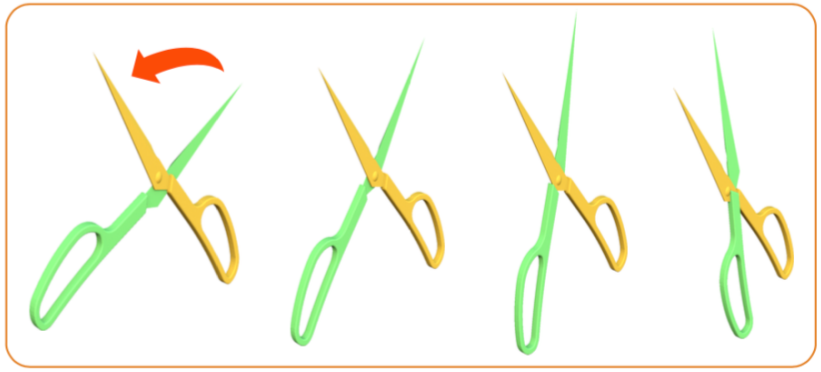
Part Induction by Relating Shapes



Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Mobility Induction



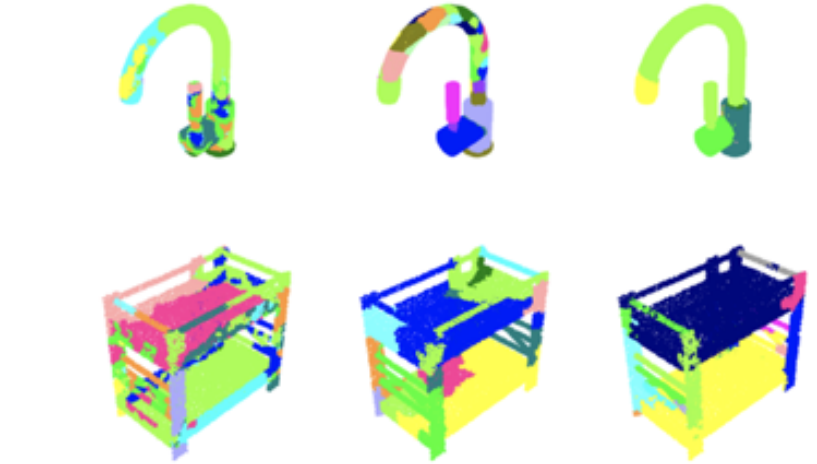


Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Task: Zero-shot Part Discovery

Train set

Test set



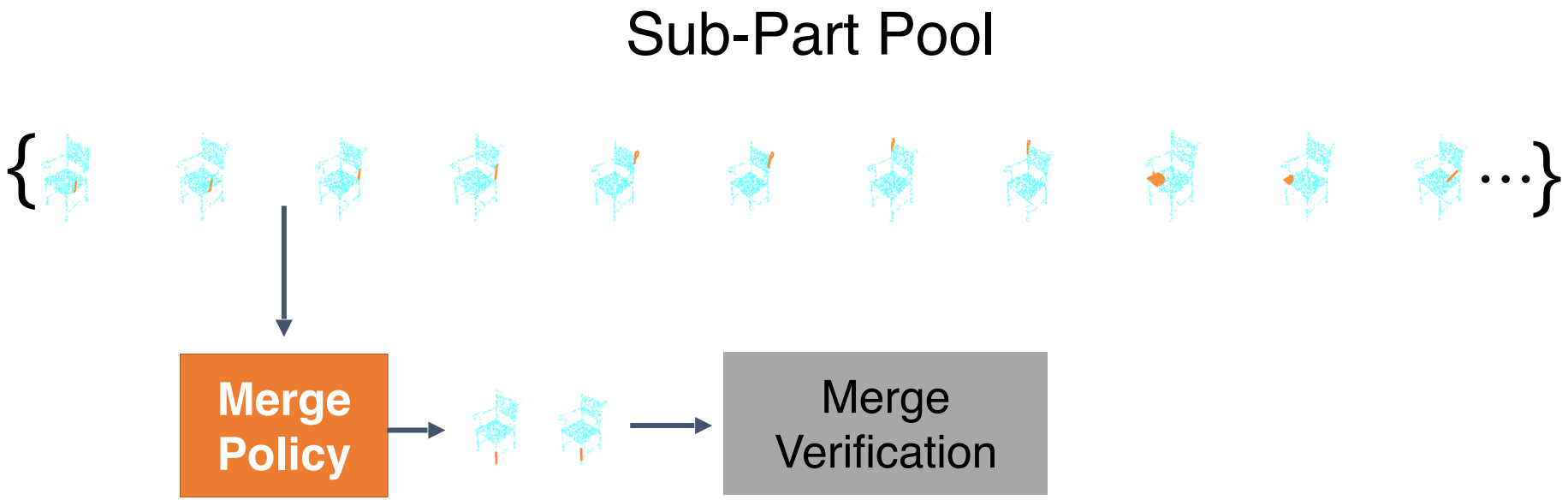
SOTA of Deep Learning (PartNet)

SOTA of Classics (WCSeg)

Ours

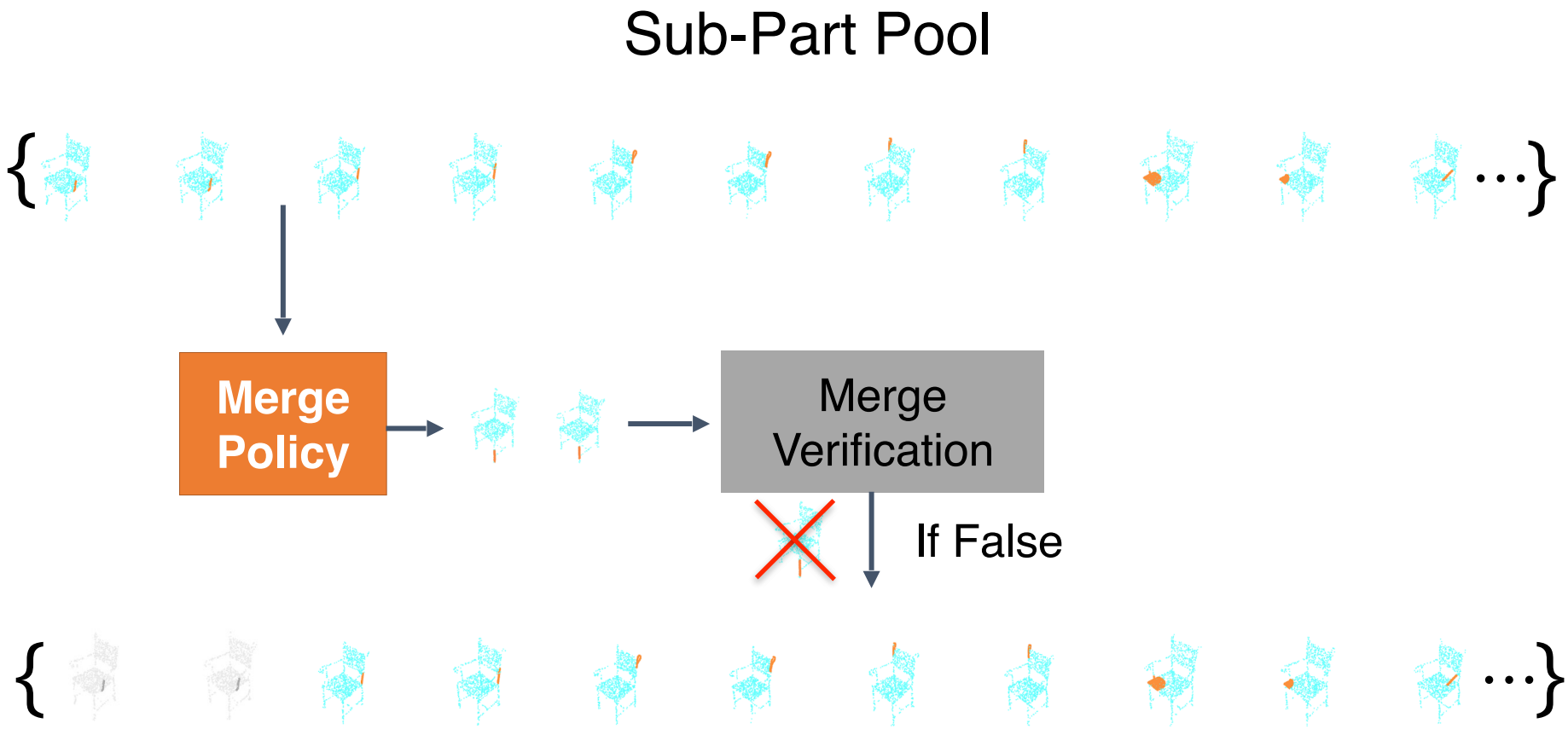
Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

Learning to Group



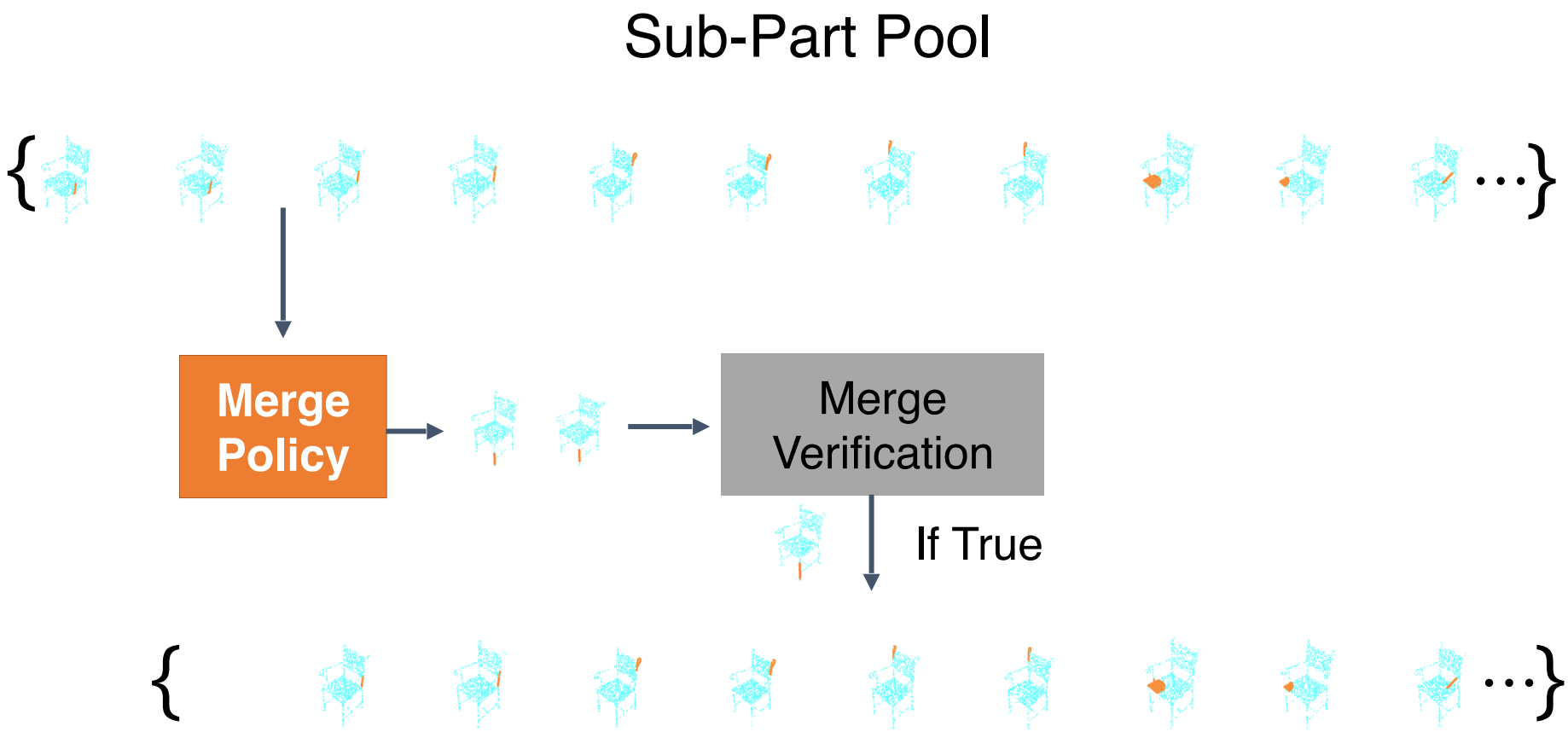
Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

Learning to Group



Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

Learning to Group



Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

Learning to Group

Sub-Part Pool

Merge Policy

Final

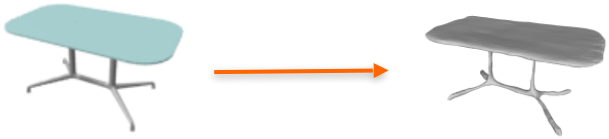
Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

Topics

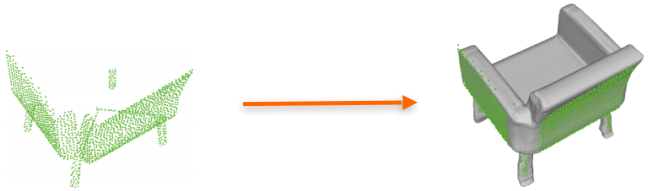
- 3D Data
- Classification
- Segmentation and Detection
- **Reconstruction**
  - **Generative Model**
  - Multi-View Stereo

Task

Conditional generation

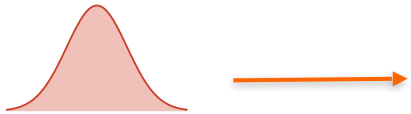


Single-image
3D reconstruction

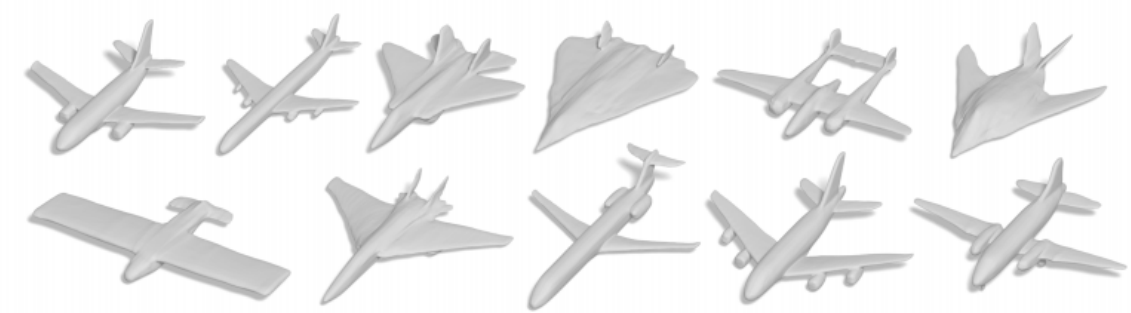


Shape Completion

Free generation



Gaussian Noise



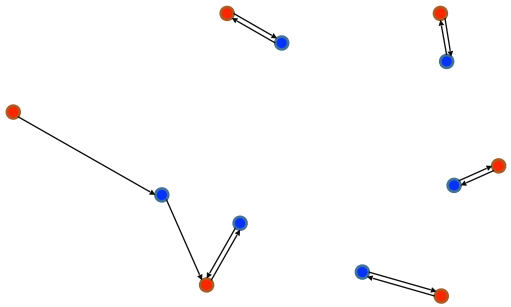
Metric

First of all,

how to evaluate the generated shapes?

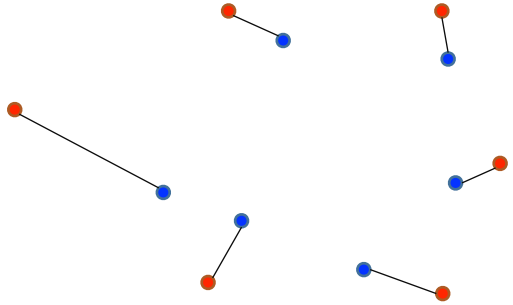
Metric for Point Clouds

Chamfer Distance



$$d_{CD}(S_1, S_2) = \sum_{x \in S_1} \min_{y \in S_2} \|x - y\|_2^2 + \sum_{y \in S_2} \min_{x \in S_1} \|x - y\|_2^2$$

Earth Mover's Distance



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

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

F-score

precision and recall are calculated by checking the percentage of points in one point cloud that can find a neighbor from the other point cloud within a threshold. F-score is then calculated as the harmonic mean.

Normal Consistency

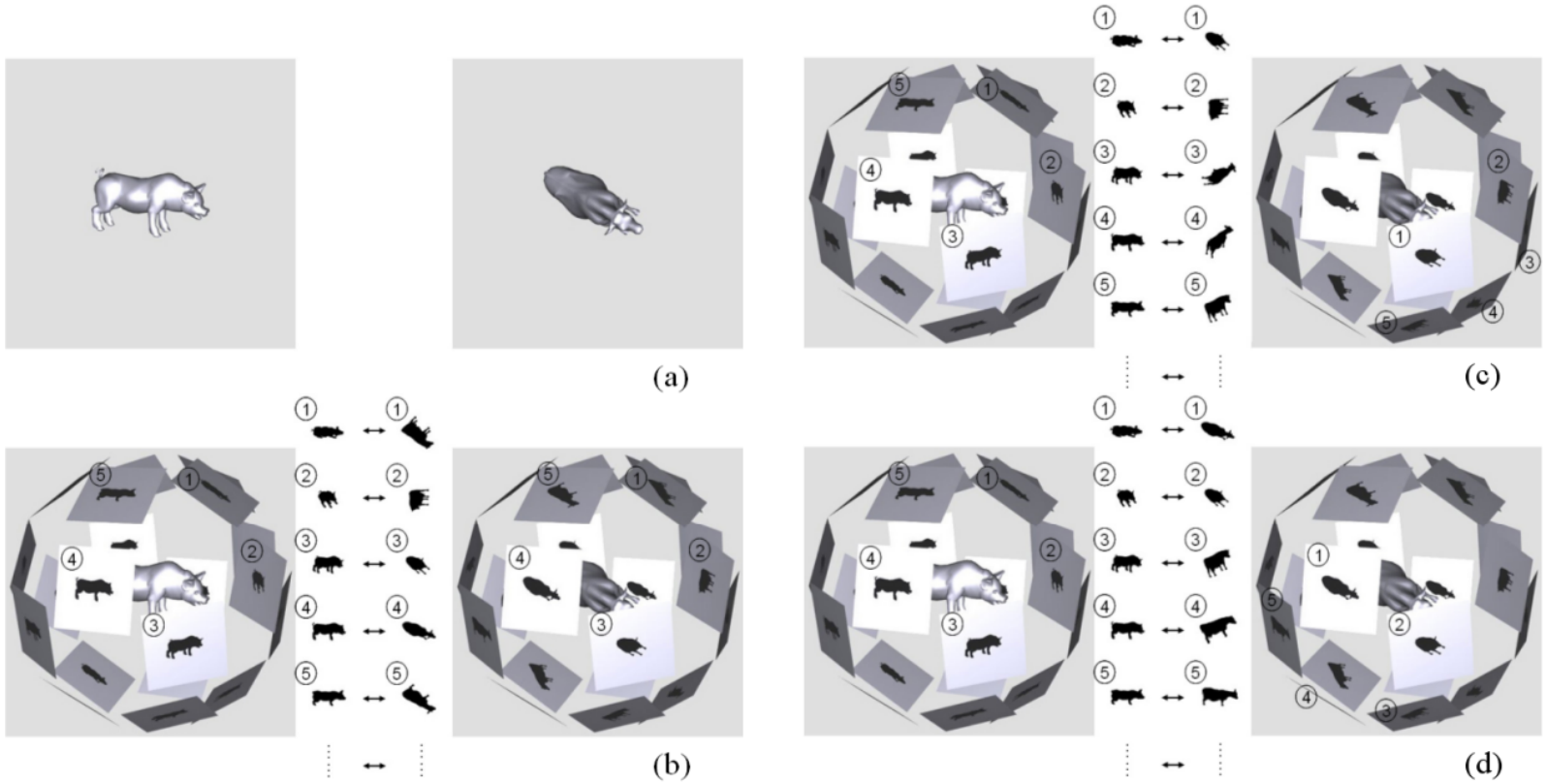
dot product of the normals of each point and its nearest neighbor

Fan et al., "**A Point Set Generation Network for 3D Object Reconstruction from a Single Image**", *CVPR 2017*
Wang et al., "**Pixel2mesh: Generating 3d mesh models from single rgb images**", *ECCV 2018*
Mescheder et al., "**Occupancy Networks: Learning 3D Reconstruction in Function Space**", *CVPR 2019*

Metric by Projection

Light Field Descriptor (LFD)

- Extract features from orthogonal projections



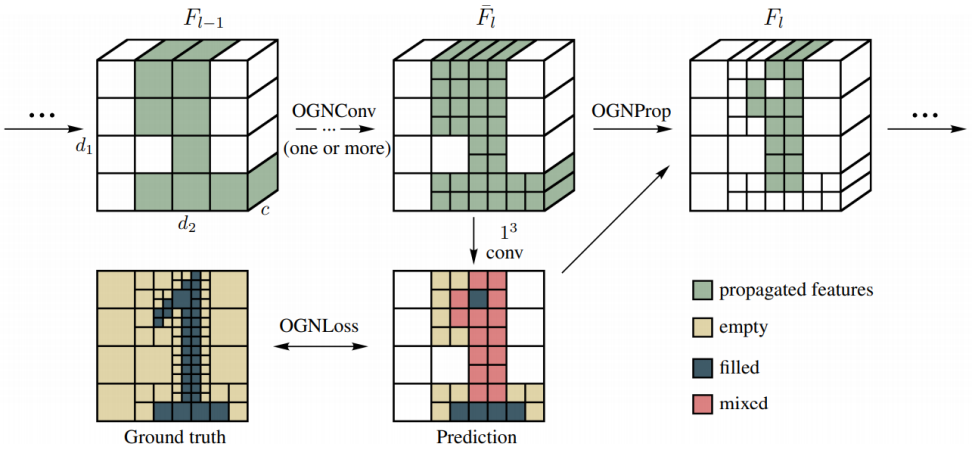
Chen et al., "**On Visual Similarity Based 3D Model Retrieval**", *Computer graphics forum*
Chen et al., "**Learning Implicit Fields for Generative Shape Modeling**", *CVPR 2019*

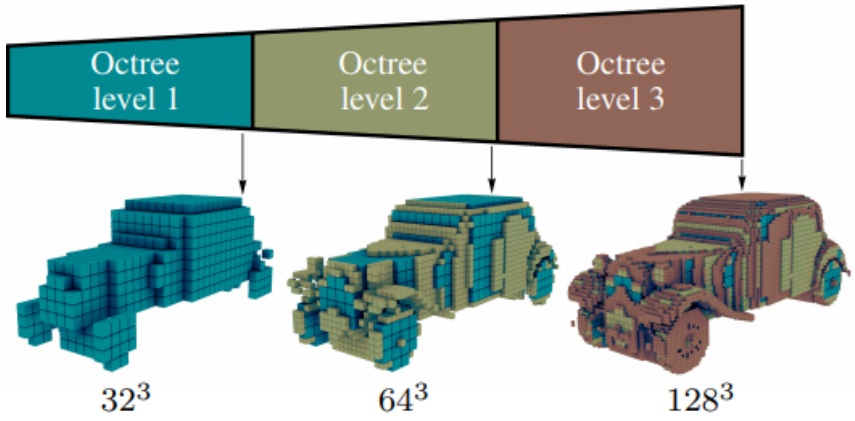
Algorithm for Conditional Generation

From Single Image to Volume

Avoid $\mathcal{O}(n^3)$ reconstruction

- Octree representation of shapes
- Generate the octree layer by layer

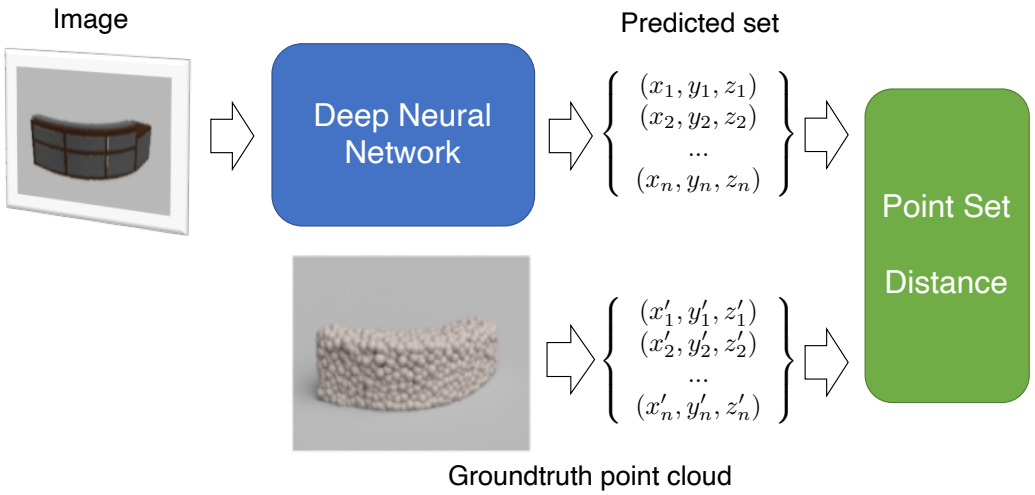




Tatarchenko et al., "**Octree Generating Networks: Efficient Convolutional Architectures for High-resolution 3D Outputs**", *ICCV 2017*

From Single Image to Point Cloud

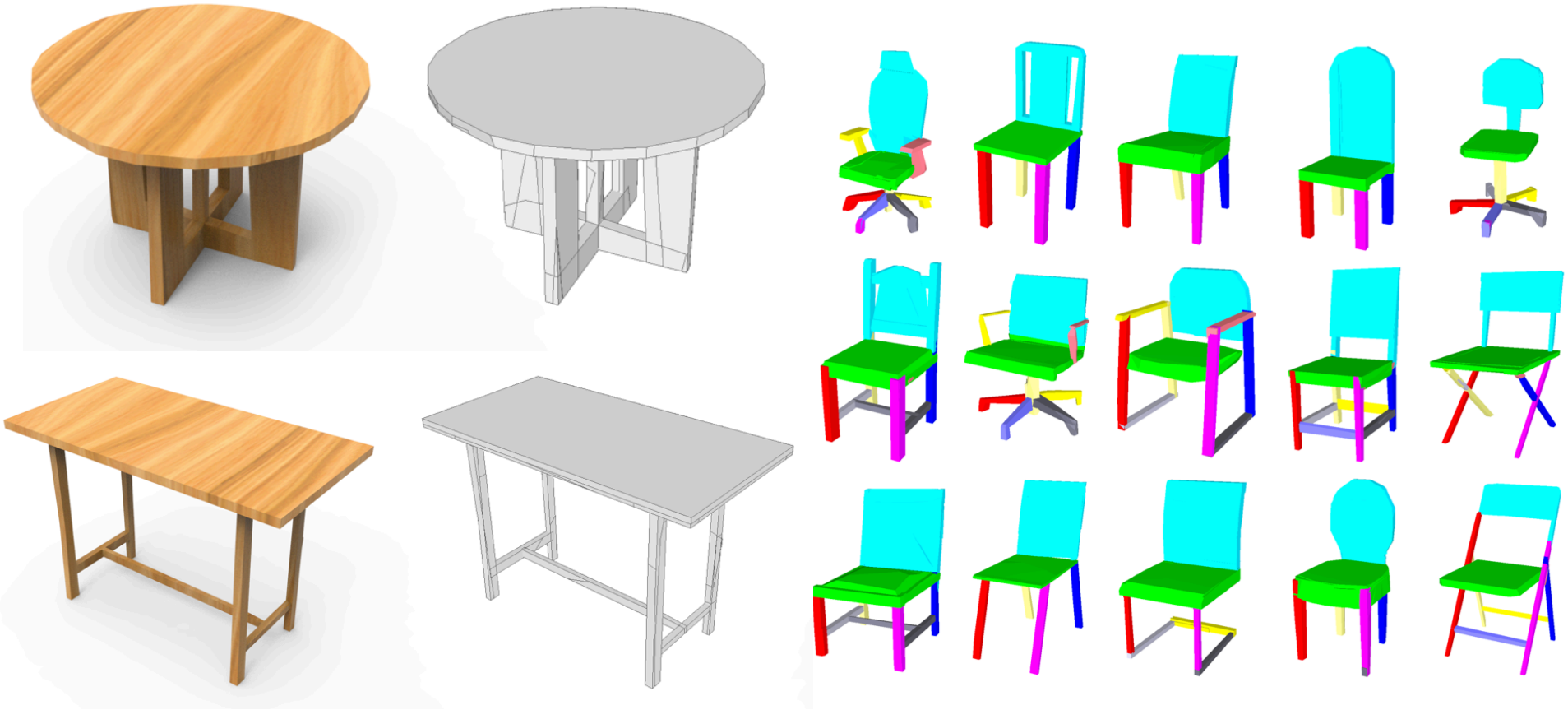
- It is possible to generate a **set** (permutation invariant)



Fan et al., "**A Point Set Generation Network for 3D Object Reconstruction from a Single Image**", *CVPR 2017*

From Image to Shape

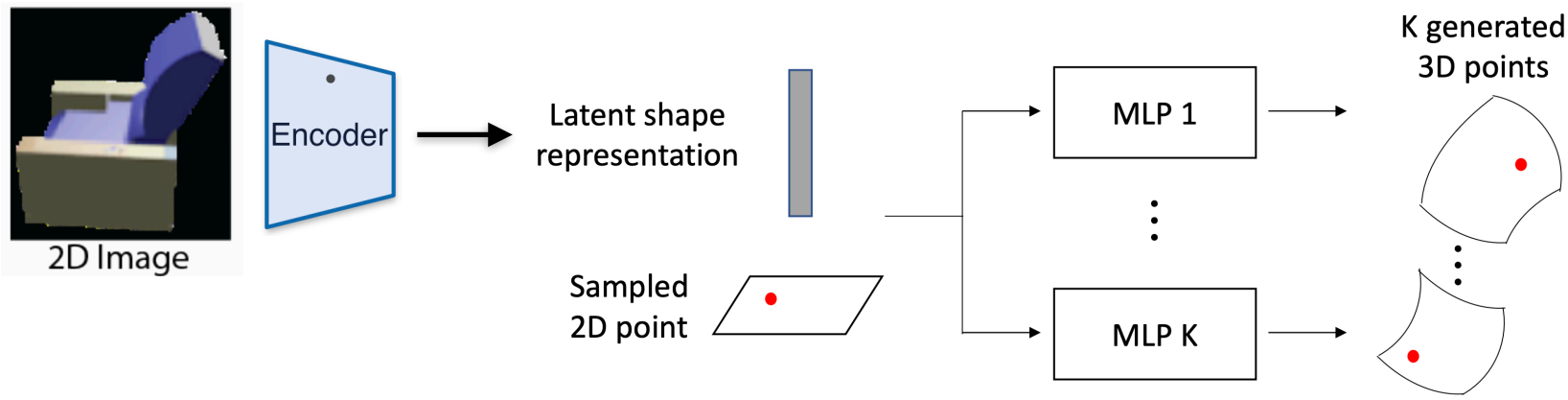
- Planes -> convex polytopes -> shape



Chen et al., "**BSP-Net: Generating Compact Meshes via Binary Space Partitioning**", *CVPR 2020*

From Image to Surface

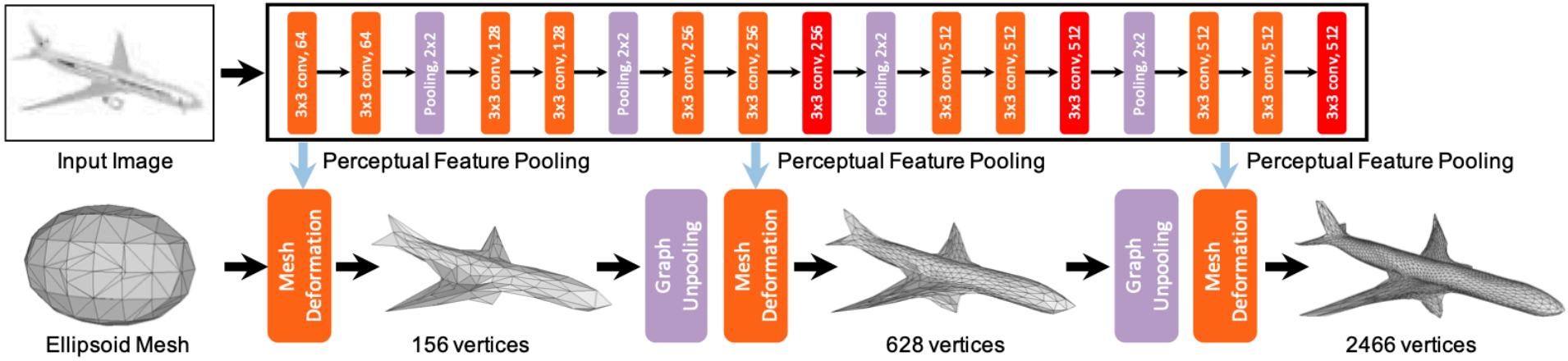
- Learn to warp a plane to surface



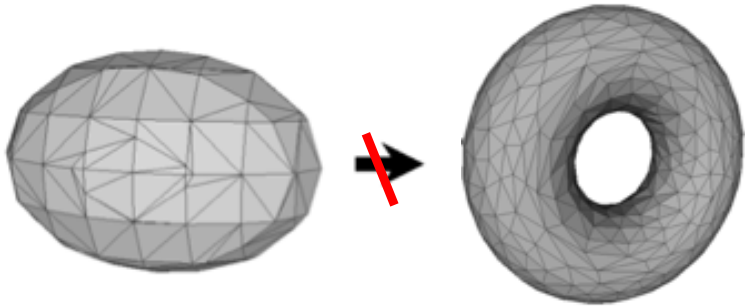
Groueix et al., "**AtlasNet: A Papier-Mâché Approach to Learning 3D Surface Generation**", *CVPR 2018*
Yang et al., "**Foldingnet: Point cloud auto-encoder via deep grid deformation**", *CVPR 2018*

From Image to Surface

- Polygon meshes are irregular
- Learn to deform a template mesh

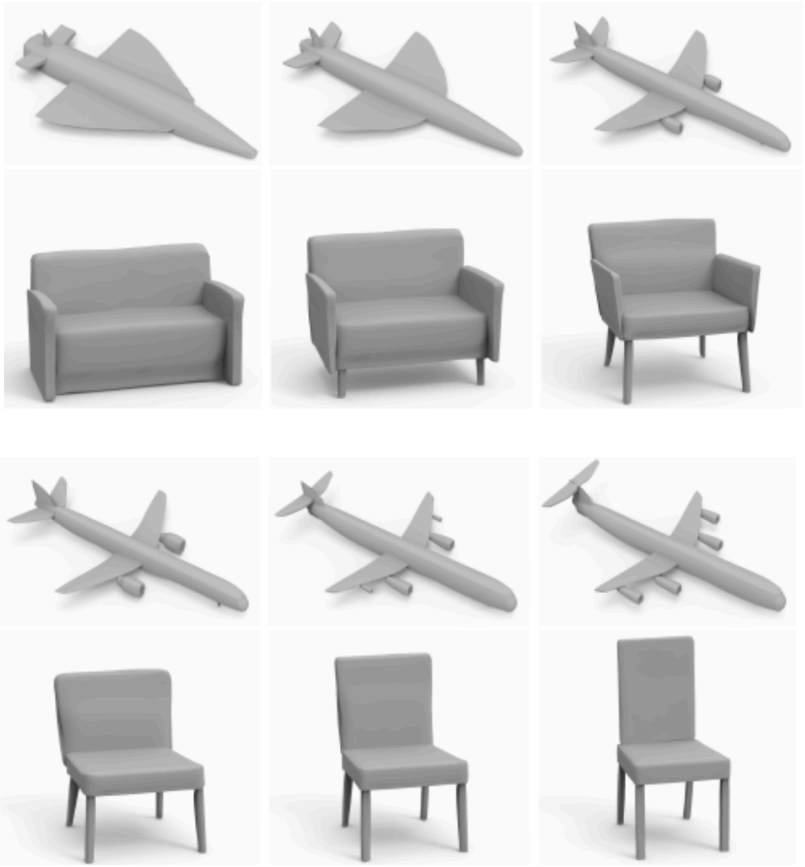


cannot change the topology of the template mesh



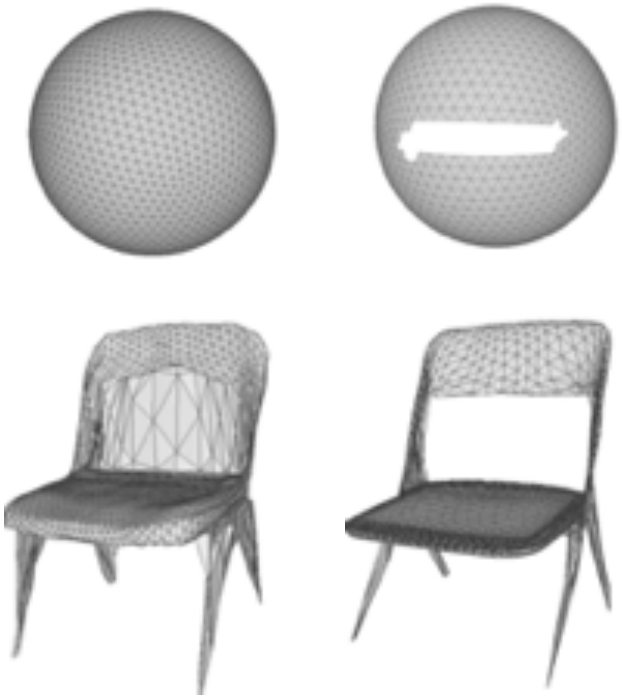
From Image to Surface

part-level deformation



Gao et al., "**SDM-NET: Deep generative network for structured deformable mesh.**", *Siggraph Asia 2019*

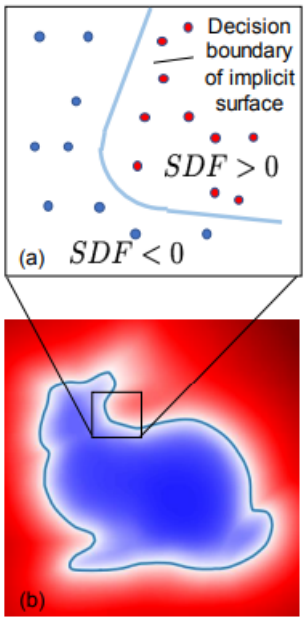
modify the topology of the template mesh

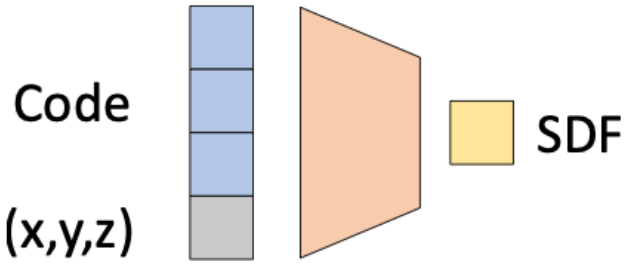


Pan et al., "**Deep Mesh Reconstruction from Single RGB Images via Topology Modification Networks.**", *ICCV 2019*

Implicit Surface Reconstruction

- Implicit field function $F(x)$ (e.g., signed distance)
- Extract the iso-surface $F(x) = 0$



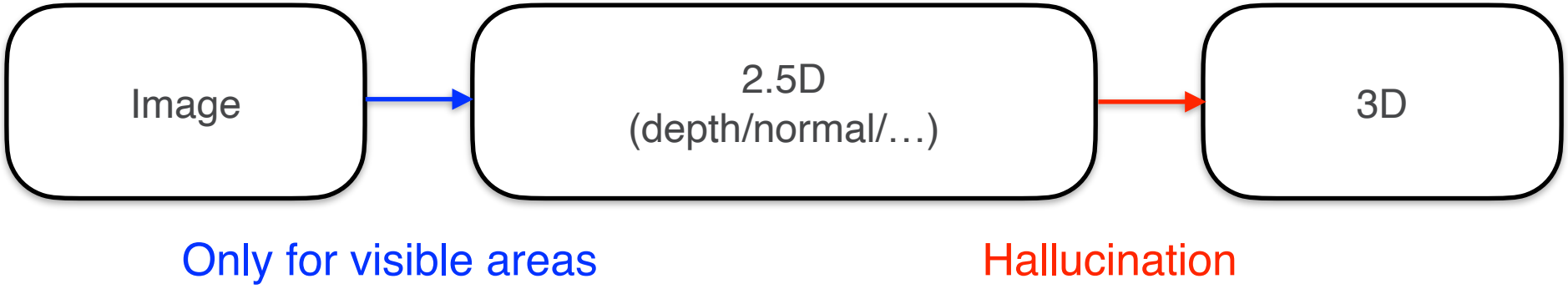


Park et al., "**DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation**", *CVPR 2019*
Other two similar paper on implicit representation:
Mescheder et al., "**Occupancy Networks: Learning 3D Reconstruction in Function Space**", *CVPR 2019*
Chen et al., "**Learning Implicit Fields for Generative Shape Modeling**", *CVPR 2019*

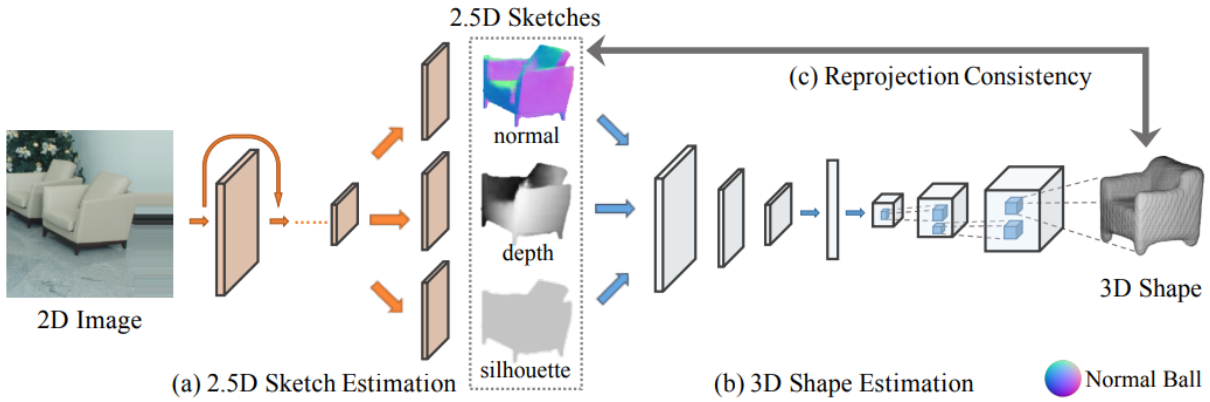
- In general,
  - First map the input to a shape embedding
  - Then reconstruct by decoding

- Limitation
  - Output is not explicitly grounded on the input
  - Structures of 3D objects are not explicitly leveraged
  - Cannot generalize to unseen objects

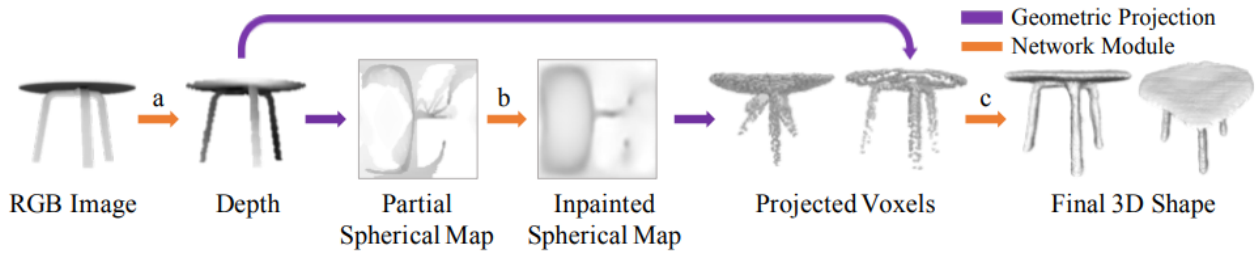
Visually Grounded Prediction: 2.5D to Bridge



Visually Grounded Prediction: 2.5D to Bridge



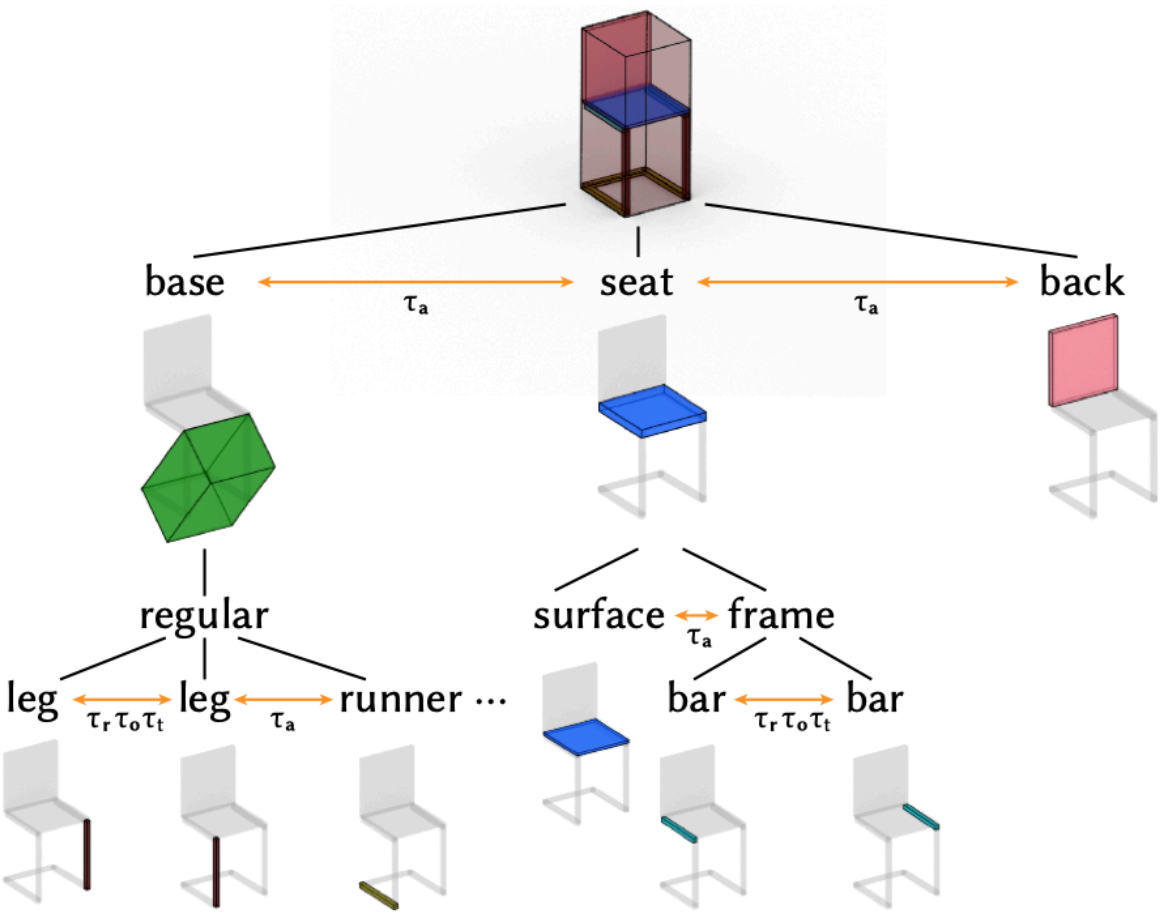
Wu et al., "**MarrNet: 3D Shape Reconstruction via 2.5D Sketches**", *NeurIPS 2017*



Zhang et al., "**Learning to Reconstruct Shapes from Unseen Classes**", *NeurIPS 2018*

Structured Prediction: Part-based

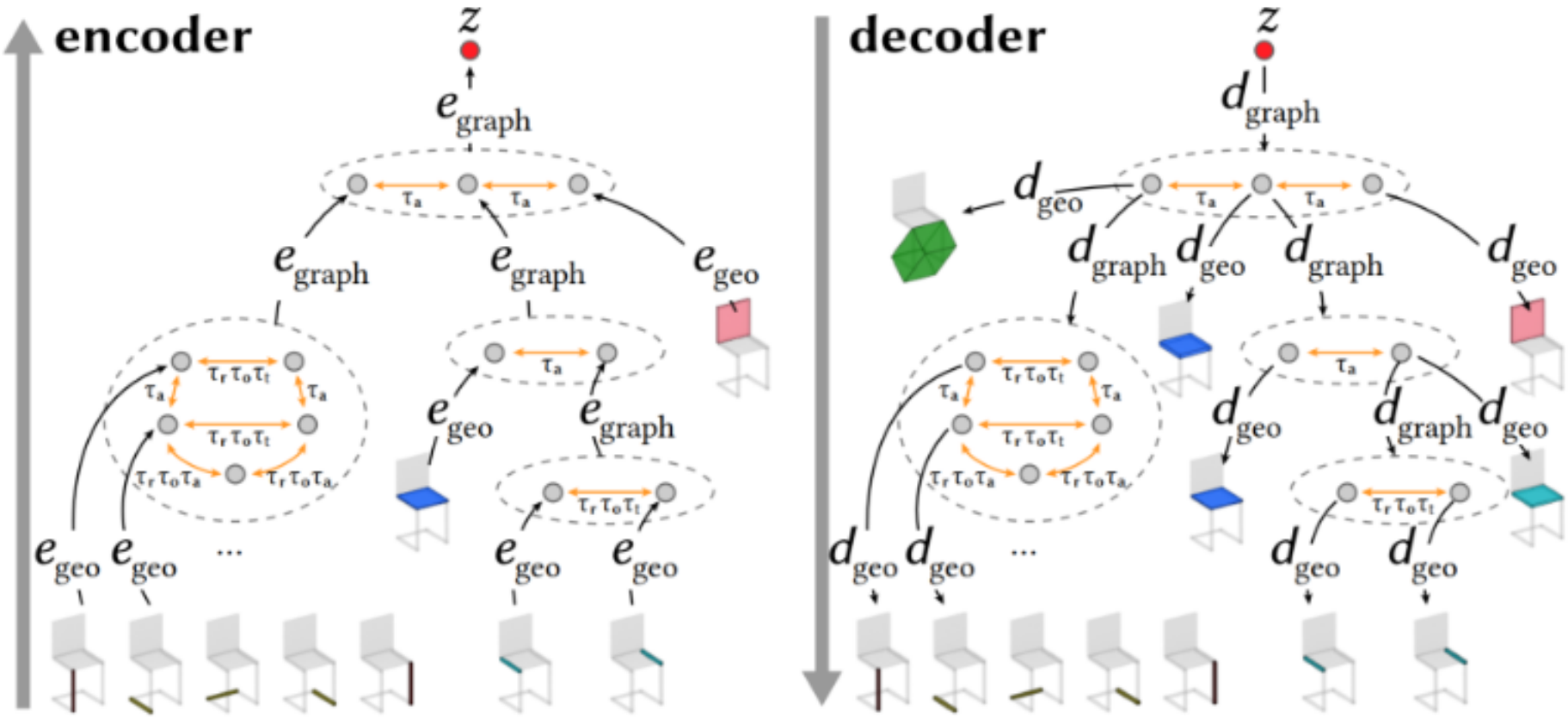
Hierarchical Graph



Mo et al., "**StructureNet, a hierarchical graph network for learning PartNet shape generation**", *Siggraph Asia 2019*

Structured Prediction: Part-based

Recursive Network for Hierarchical Graph AE



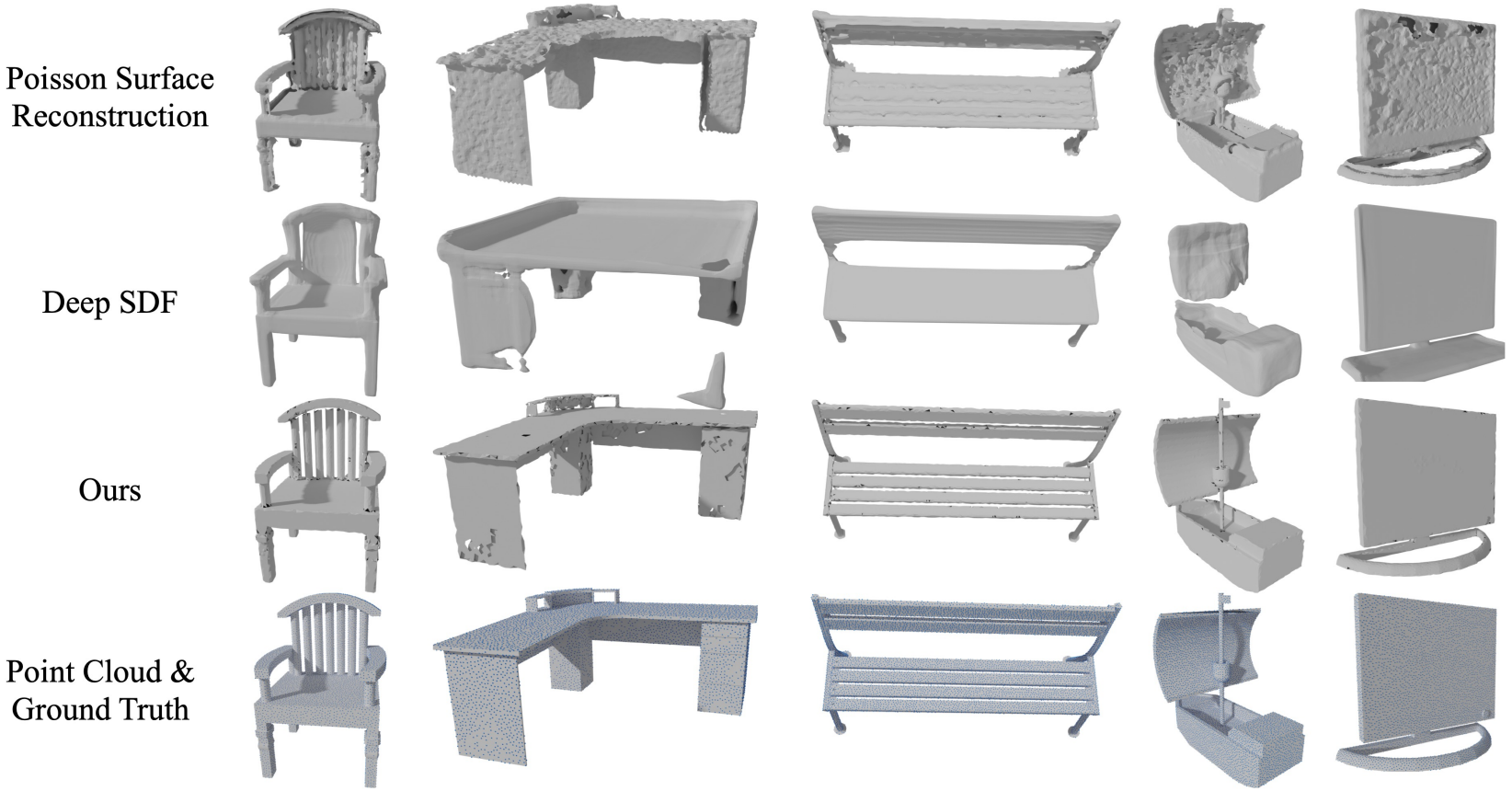
Mo et al., "**StructureNet, a hierarchical graph network for learning PartNet shape generation**", *Siggraph Asia 2019*

Structured Prediction: Part-based

Mo et al., "**StructureNet, a hierarchical graph network for learning PartNet shape generation**", *Siggraph Asia 2019*

From Point Cloud to Mesh

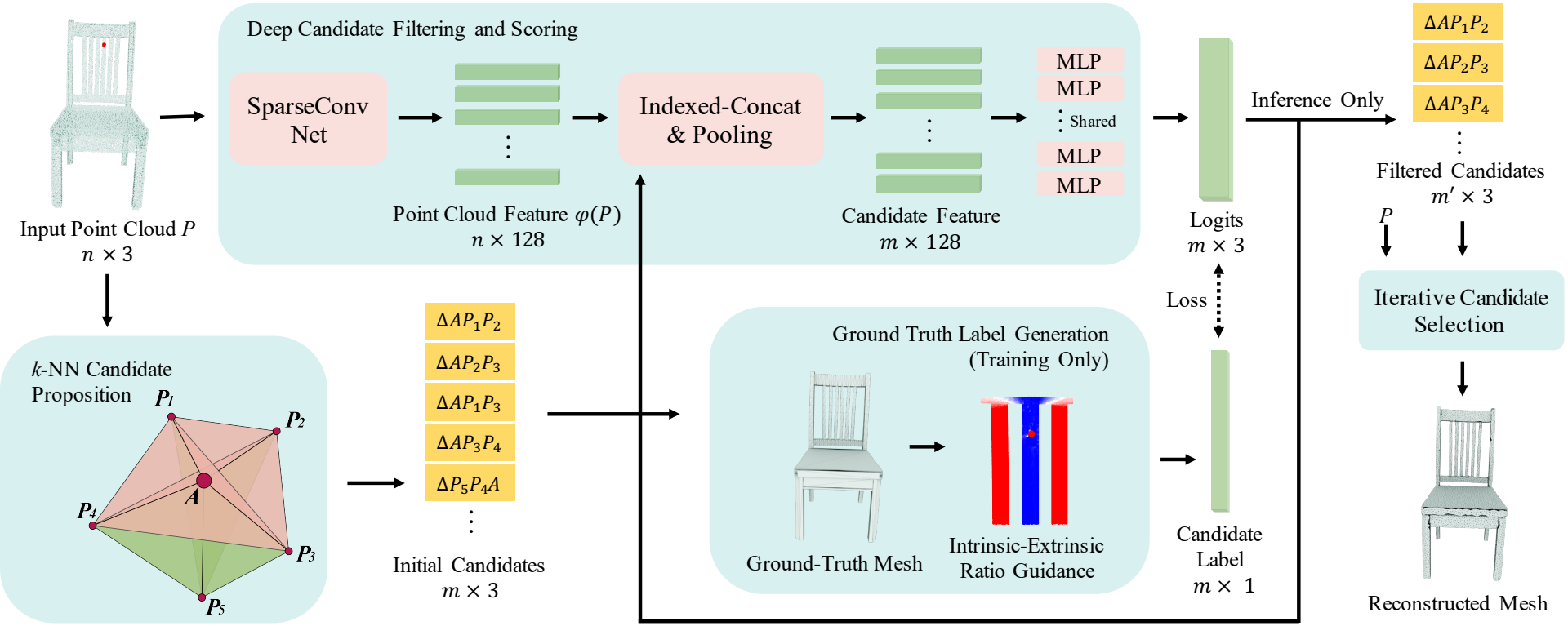
- Traditional methods: cannot handle ambiguous structures (e.g., thin structures) when the resolution of point clouds is limited
- Existing learning-based methods: cannot generate fine-grained details or generalize to unseen objects



From Point Cloud to Mesh

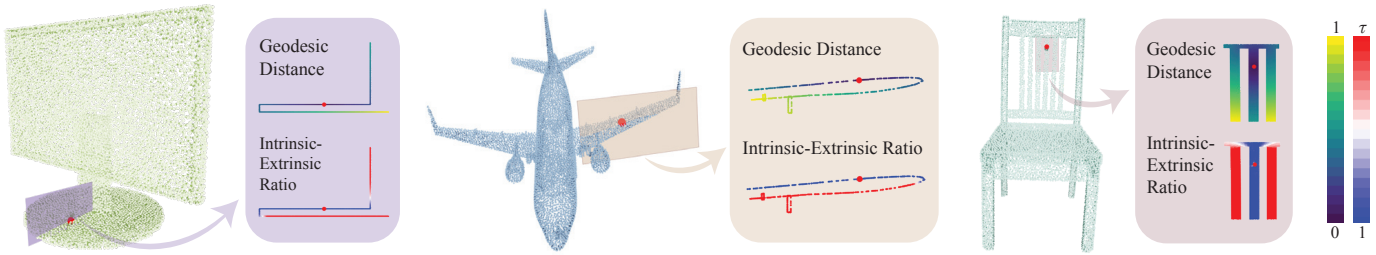
Fully utilize grounded input point clouds

1. Propose candidate triangles
2. Classify the candidates (filter out the incorrect triangles)
3. Merge the remaining candidates in a greedy way

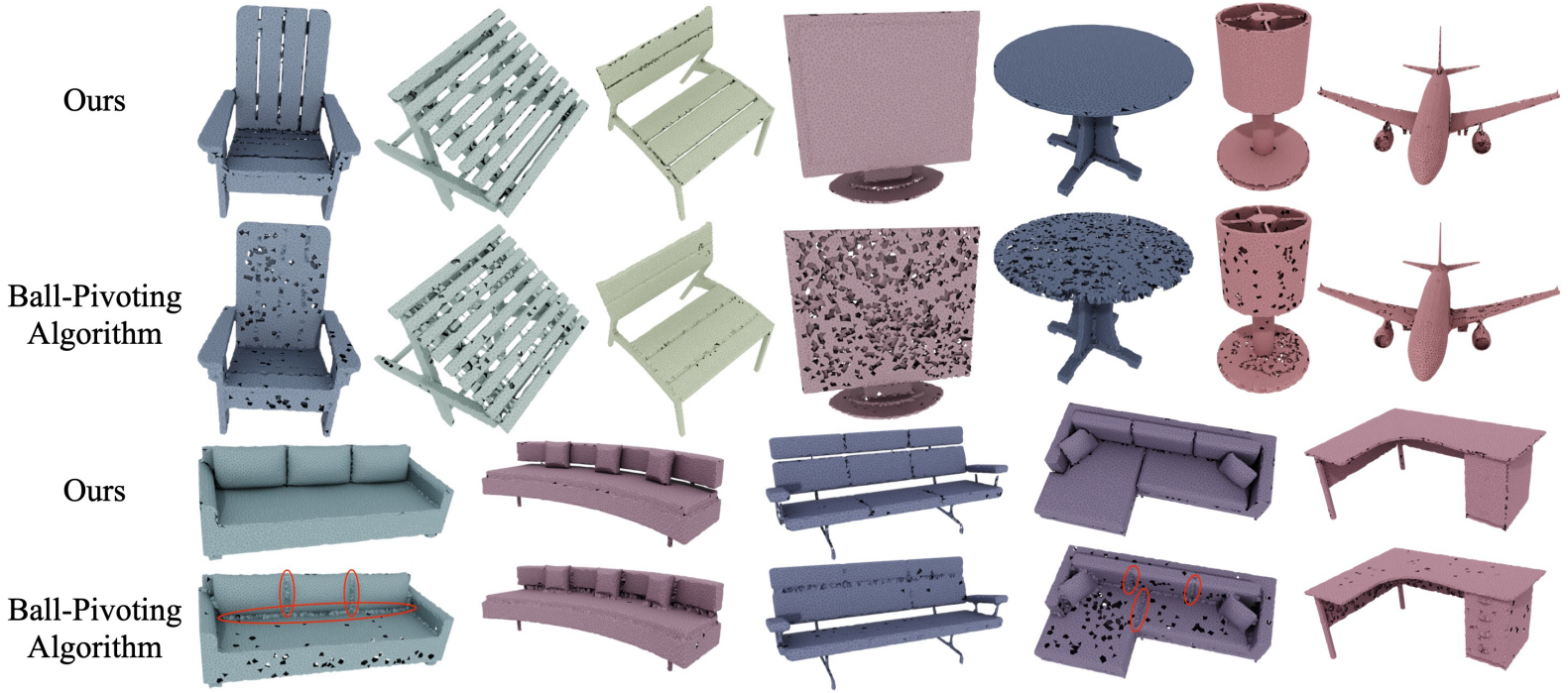


From Point Cloud to Mesh

Utilize “Intrinsic-Extrinsic Ratio” to label the candidate triangles



Leverage local priors and thus possess strong generalizability



anonymous submission

Algorithm for Free Generation (GAN)

Challenges

Similar challenges as GAN for images:

- Good by human eye v.s. Good by objective metric

Metrics

Comparison between two sets of points clouds A and B:

- A: generated point clouds
- B: a held-out test set

Geometry Quality of Generated Shape

- e.g., minimum matching (B -> A) distance for CD/EMD

Coverage

- The fraction of the shapes in B that were matched to shapes in A

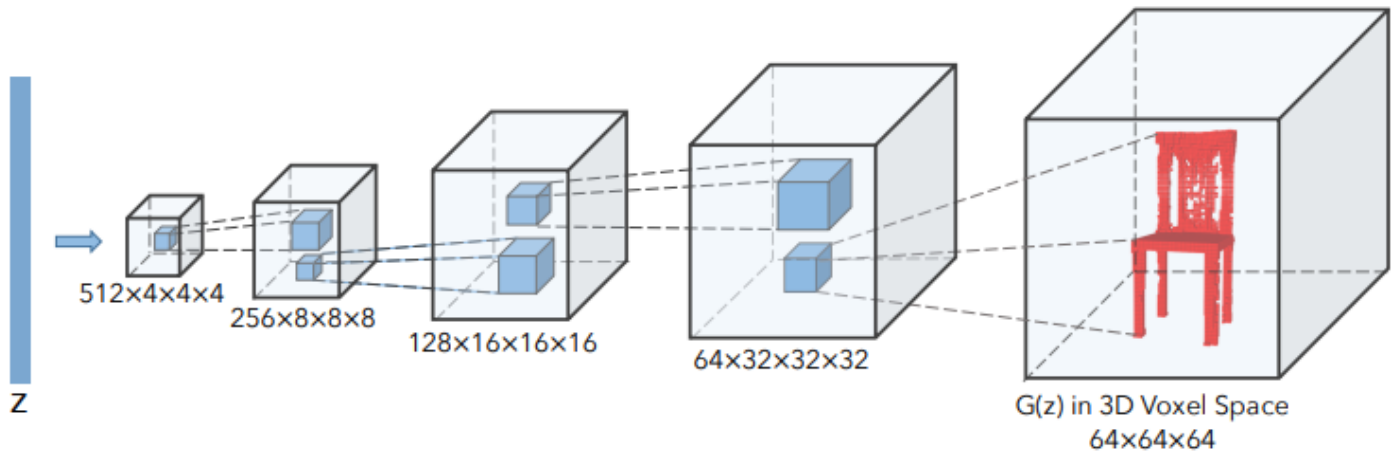
Perceptually Correct

- Feature distribution distance (e.g. Frechet Point Cloud Distance)

$$\mathrm{FPD}(\mathbb{P},\mathbb{Q}) = \|\mathbf{m}_{\mathbb{P}} - \mathbf{m}_{\mathbb{Q}}\|_2^2 + \mathrm{Tr}(\Sigma_{\mathbb{P}} + \Sigma_{\mathbb{Q}} - 2(\Sigma_{\mathbb{P}}\Sigma_{\mathbb{Q}})^{\frac{1}{2}})$$

Achlioptas et al., "**Learning Representations and Generative Models for 3D Point Clouds**", *ICML 2018*
Shu et al., "**3D Point Cloud Generative Adversarial Network Based on Tree Structured Graph Convolutions**", *ICCV 2019*

Volumetric Generation

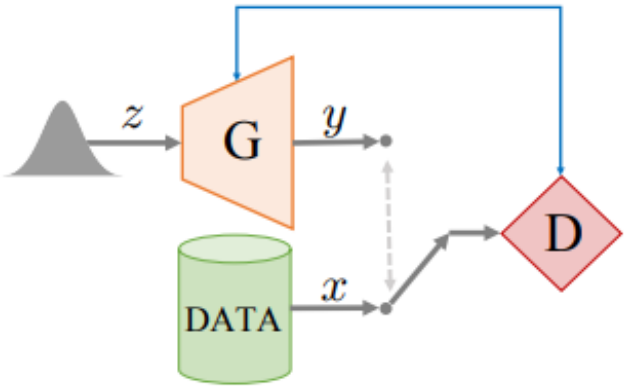


$$logD(x) + log(1 - D(G(z)))$$

Wu et al., "**Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling**", *NeurIPS 2016*

Point Cloud Generation

- FC layer as generator
- PointNet as discriminator
- WGAN



Achlioptas et al., "**Learning Representations and Generative Models for 3D Point Clouds**", *ICML 2018*

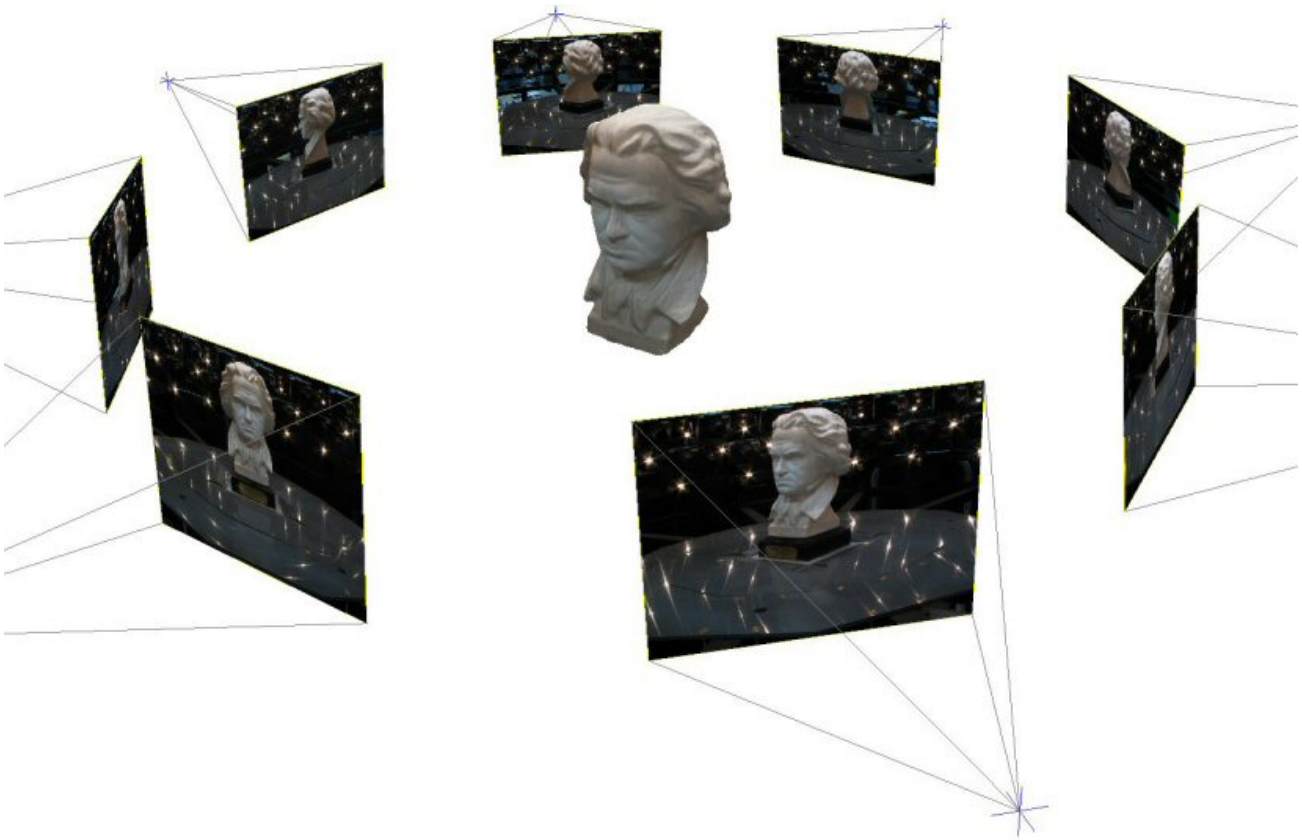
Many Issues

- Still cannot generate high quality local details
- Still hard to generate complex structures
- For point clouds, using strong classifiers (than PointNet) as discriminator is highly tricky

Topics

- 3D Data
- Classification
- Segmentation and Detection
- **Reconstruction**
  - Generative Model
  - **Multi-View Stereo**

Task: Reconstruction

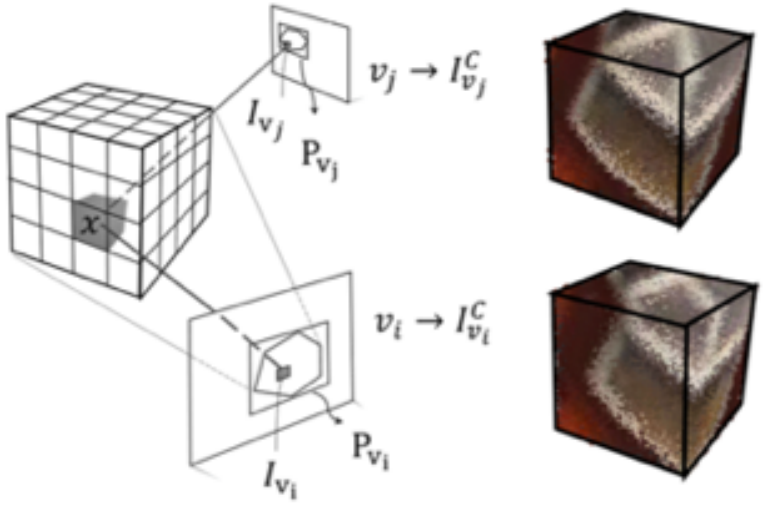


[image: oswald]

Covered methods: SurfaceNet, LSM, GC-Net, MVSNet, R-MVSNet, PointMVSNet, BA-Net

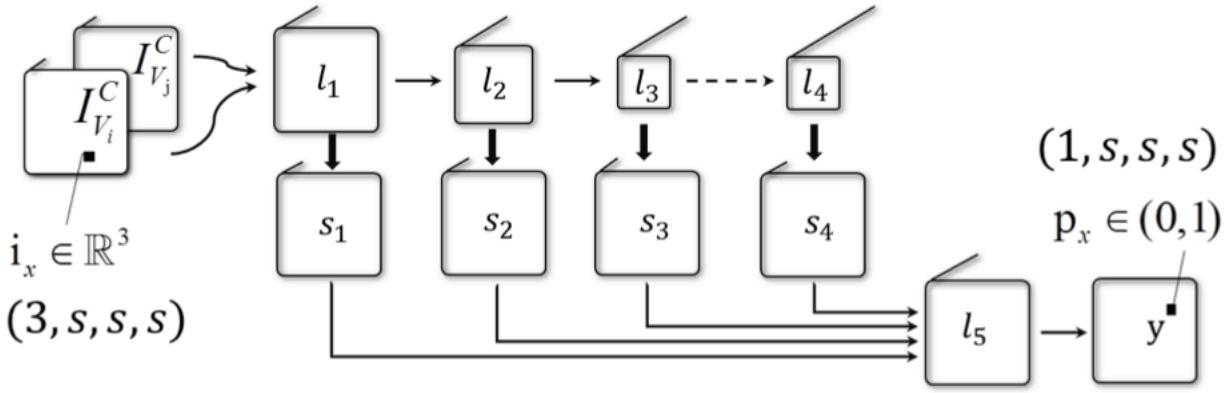
Surface Reconstruction as Voxel Occupancy Prediction

project along viewing rays to build colored voxel cubes.



Ji et al., "**SurfaceNet: An End-to-End 3D Neural Network for Multiview Stereopsis**", *ICCV 2017*

Predict the surface confidence for each voxel:



$$L(I^C_{v_i}, I^C_{v_j}, \hat{S}^C) =$$
$$-\sum_{x \in C} \{\alpha \hat{s}_x \log p_x + (1-\alpha)(1-\hat{s}_x)\log(1-p_x)\}$$

binarization as post-processing

Ji et al., "**SurfaceNet: An End-to-End 3D Neural Network for Multiview Stereopsis**", *ICCV 2017*

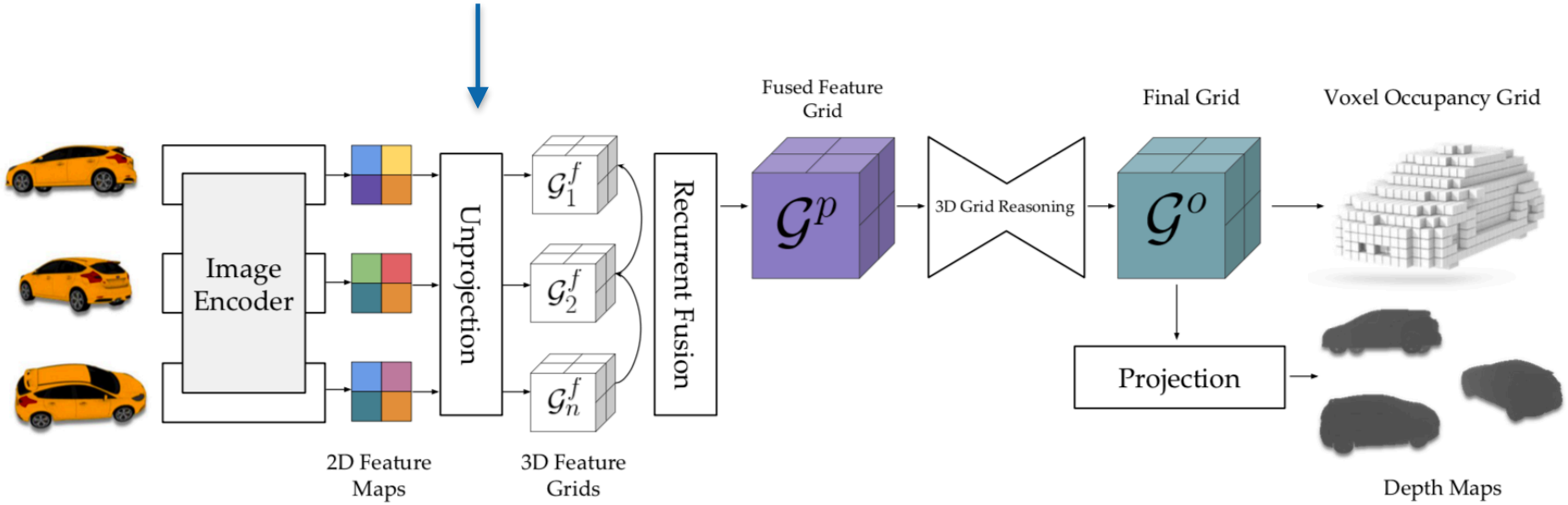
Limitations:

- Pre-computed voxel cubes can only take RGB colors at coarse resolution
- Voxel binarization introduces quantization errors.

Learning-Based Stereopsis

End-to-end learning of deep features for each image pixel

Unproject image features into 3D grids

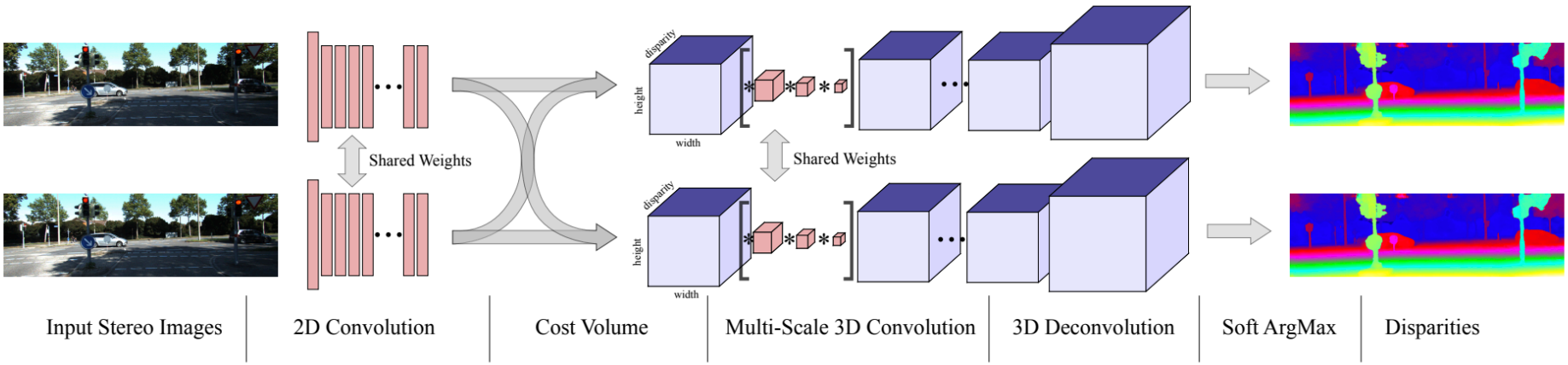


Kar et al., "**Learning a Multi-View Stereo Machine**", *NeurIPS 2017*

Still very coarse resolution (32x32x32) due to volumetric representation.

Kar et al., "**Learning a Multi-View Stereo Machine**", *NeurIPS 2017*

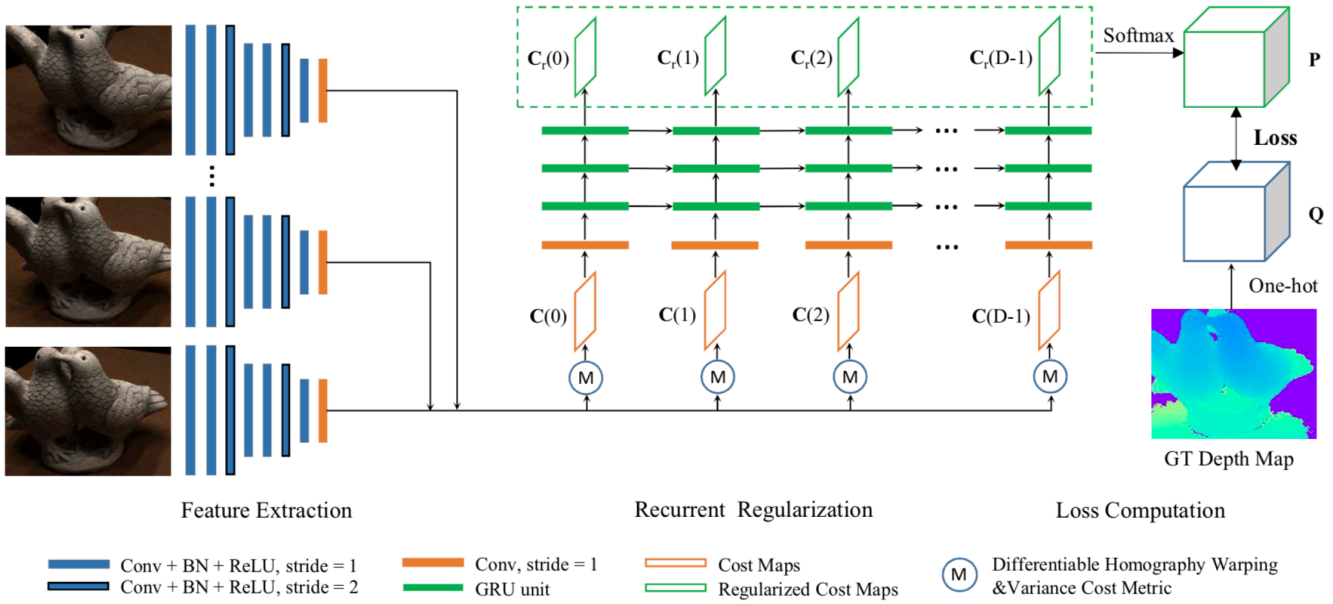
- View-aligned cost-volume construction
- Differentiable soft-argmin to achieve sub-pixel accuracy



$$soft\ argmin := \sum_{d=0}^{D_{max}} d \times \sigma(-c_d)$$

Kendall et al., "**End-to-End Learning of Geometry and Context for Deep Stereo Regression**", *ICCV 2017*

Idea 1: Slide-by-Slide Processing of Cost Volume by Recurrent Neural Network

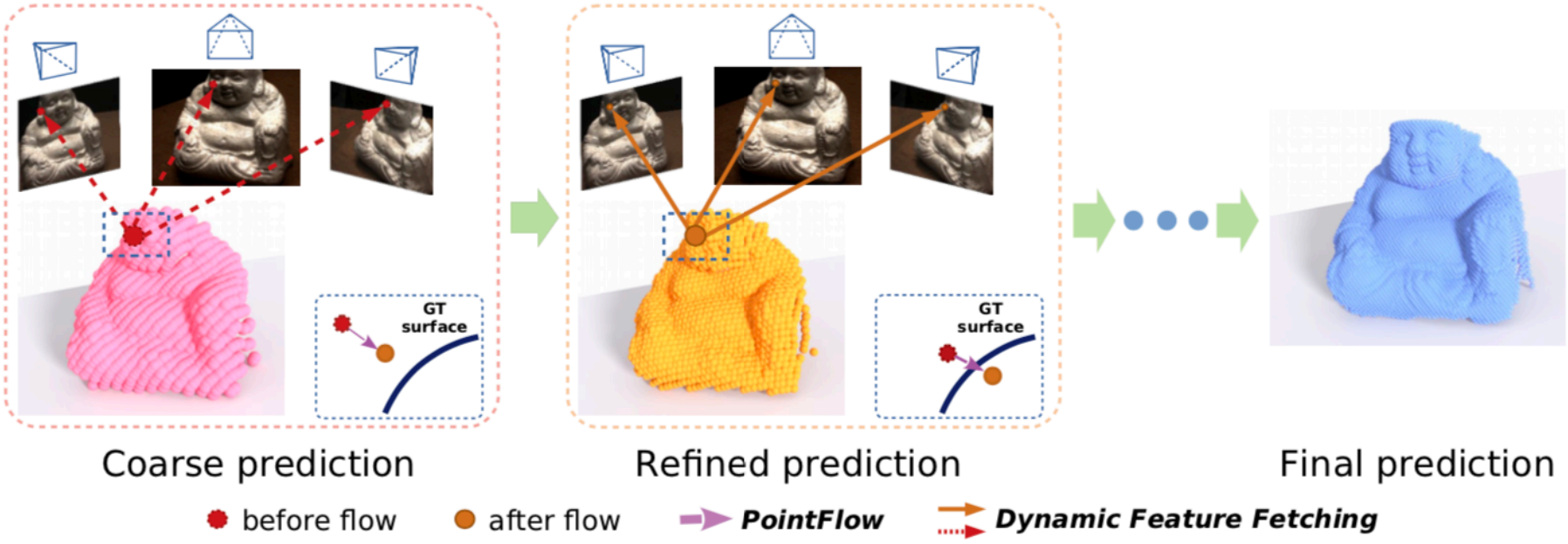


The cost volume is sequentially regularized along the depth direction.

Yao et al., "**MVSNet: Depth Inference for Unstructured Multi-view Stereo**", *ECCV 2018*
Yao et al., "**Recurrent MVSNet for High-resolution Multi-view Stereo Depth Inference**", *CVPR 2019*

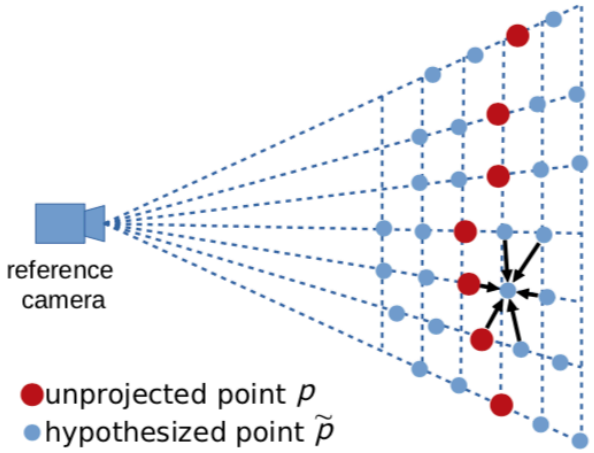
Idea 2: Point-based MVS

- Point-based representation for computational efficiency.
- Iteratively update the location of points and spawn more points.
- More flexible and accurate.

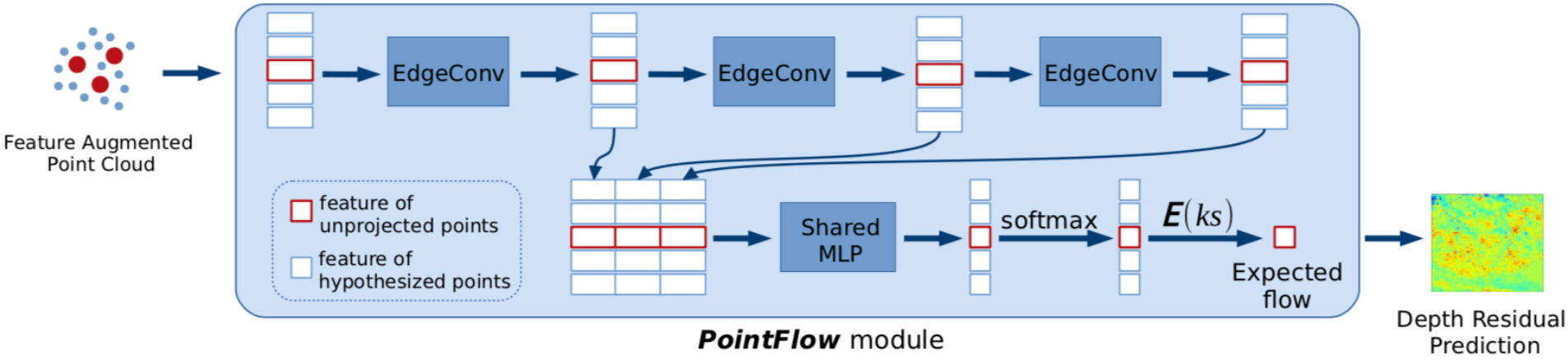


Chen et al., "**Point-Based Multi-View Stereo Network**", *ICCV 2019*

hypothesized point generation along camera direction:

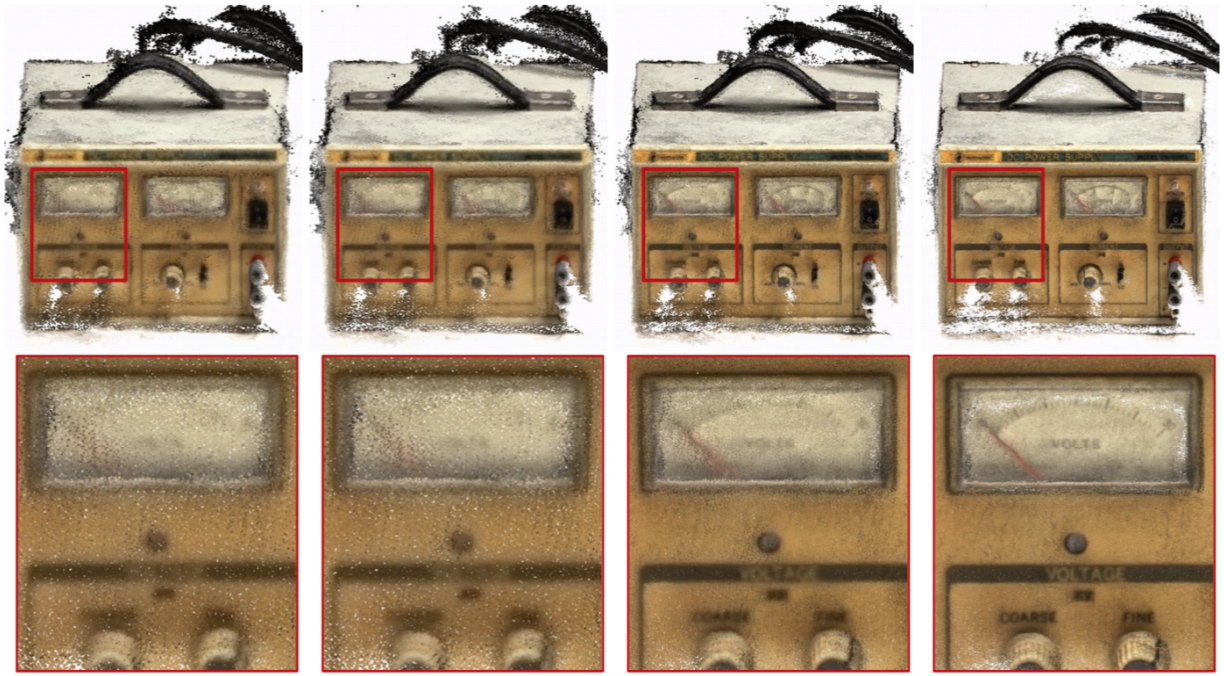


- PointFlow: iteratively pull all the points to the right position.



Chen et al., "**Point-Based Multi-View Stereo Network**", *ICCV 2019*

Iterative refinement:



Initial Iter1 Iter2 Iter3

Results on DTU benchmark

Iter.	Acc. (mm)	Comp. (mm)	Overall (mm)	0.5mm *f-score*	Depth Map Res.	Depth Interval (mm)	GPU Mem. (MB)	Runtime (s)
-	0.693	0.758	0.726	47.95	160×120	5.30	**7219**	**0.34**
1	0.674	0.750	0.712	48.63	160×120	5.30	7221	0.61
2	0.448	0.487	0.468	76.08	320×240	4.00	7235	1.14
3	**0.361**	**0.421**	**0.391**	**84.27**	**640×480**	**0.80**	8731	3.35
MVSNet[29]	0.456	0.646	0.551	71.60	288×216	2.65	10805	1.05

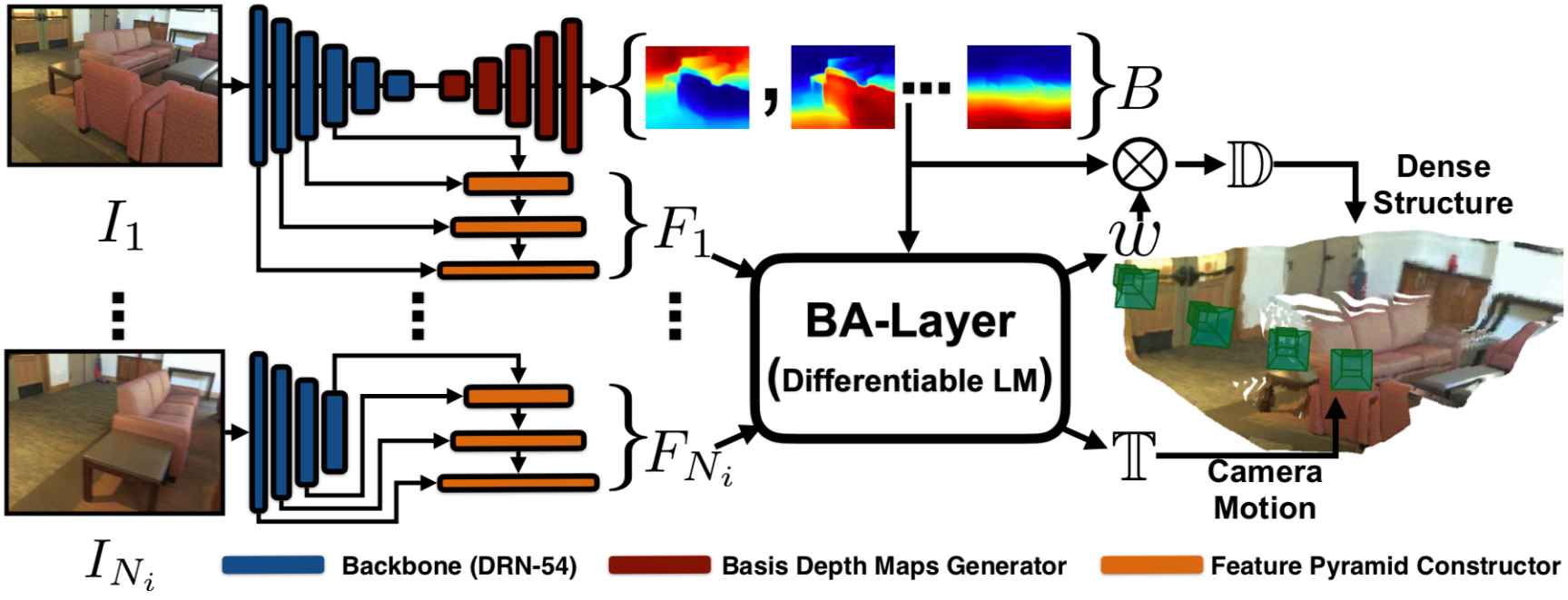
Chen et al., "**Point-Based Multi-View Stereo Network**", *ICCV 2019*

Learning for SfM

- Above learning-based MVS methods all **assume camera poses are available**
- What if not?
  - Classic 3D: Bundle Adjustment
- Learning-based bundle adjustment

BA-Net

End-to-end pipeline for SfM with differentiable bundle adjustment.

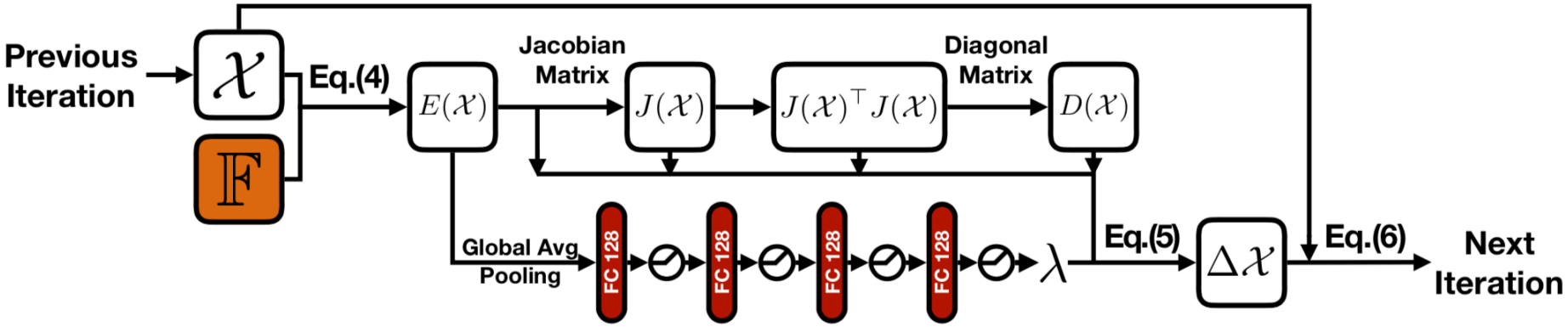


Tang et al., "**BA-Net: Dense Bundle Adjustment Network**", *ICLR 2019*

Differentiable LM algorithm:

- Iterative update as rollout of network layers
- Use network to predict the damping factor lambda.

BA-layer:



$$\Delta\mathcal{X} = (J(\mathcal{X})^\top J(\mathcal{X}) + \lambda D(\mathcal{X}))^{-1} J(\mathcal{X})^\top E(\mathcal{X}).$$

Tang et al., "**BA-Net: Dense Bundle Adjustment Network**", *ICLR 2019*

Slides posted on
http://ai.ucsd.edu/~haosu/

(Homepage of Prof. Hao Su)