

Learning Deep Models with Primitive-based Representations

Despoina Paschalidou

Autonomous Vision Group, Max Planck Institute for Intelligent Systems
Tübingen
Computer Vision Lab, ETH Zürich



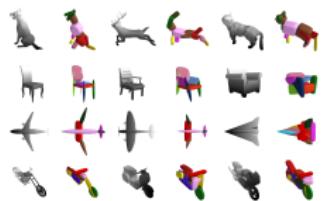
Max Planck Institute
for Intelligent Systems
Autonomous Vision Group



Slides are available at



<https://paschalidoud.github.io/talks/primitive-based-representations.pdf>

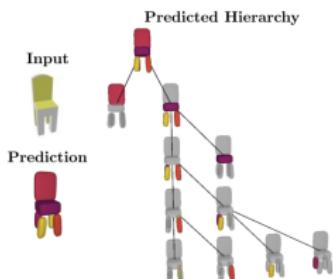


Superquadrics Revisited: Learning 3D Shape Parsing beyond Cuboids

Despoina Paschalidou, Ali Osman Ulusoy, Andreas Geiger

CVPR 2019

<https://superquadrics.com/learnable-superquadrics.html>



Learning Unsupervised Hierarchical Part Decomposition of 3D Objects from a Single RGB Image

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<https://superquadrics.com/hierarchical-primitives.html>











Neural networks for 2D computer vision tasks

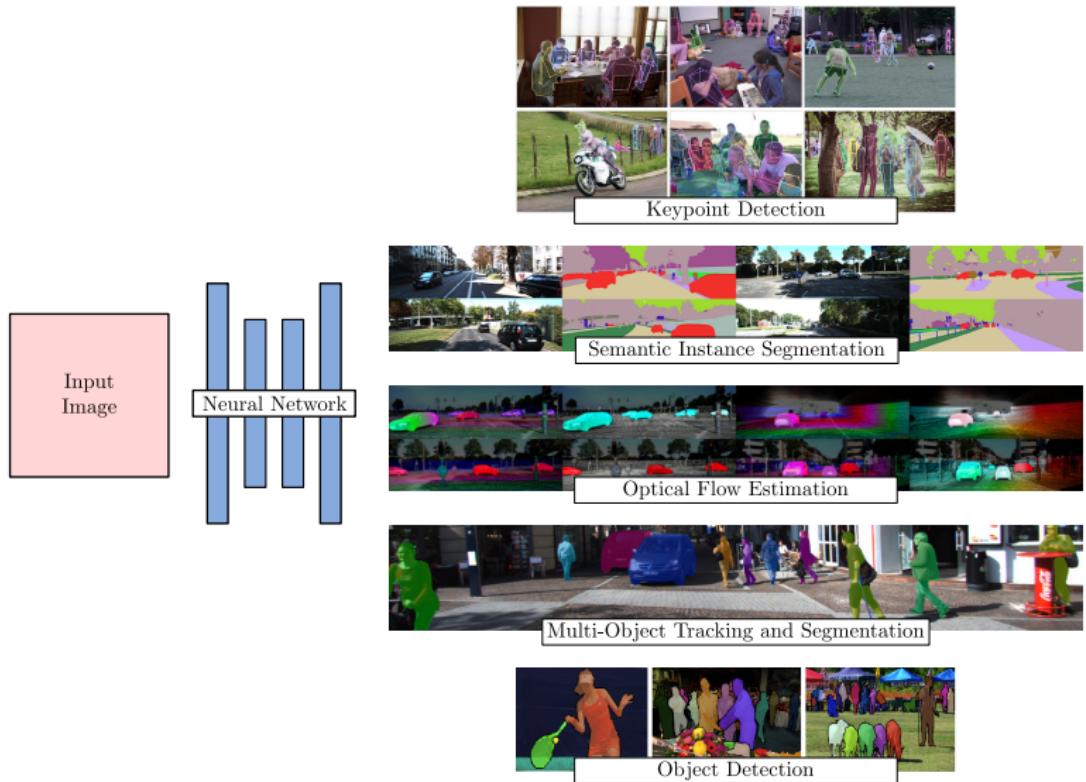
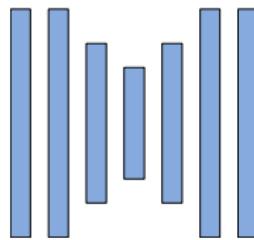


Image Source: KITTI Vision Benchmark and COCO Dataset

Can we learn to infer 3D from a 2D image?



Input Image

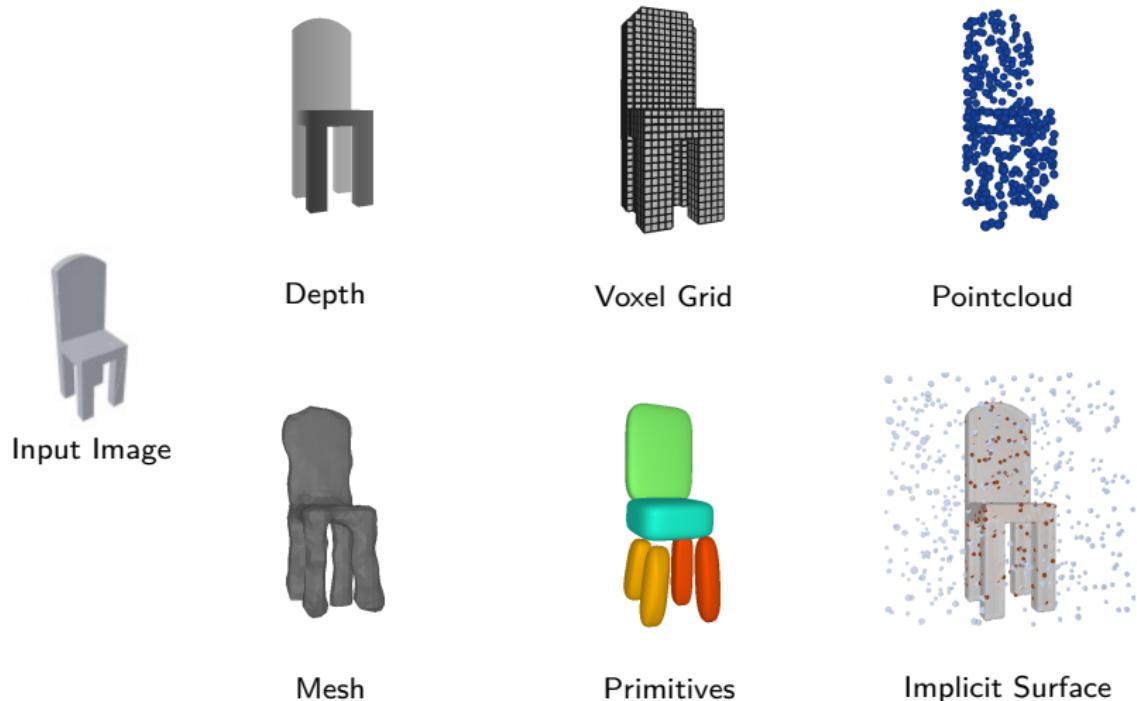


Neural Network

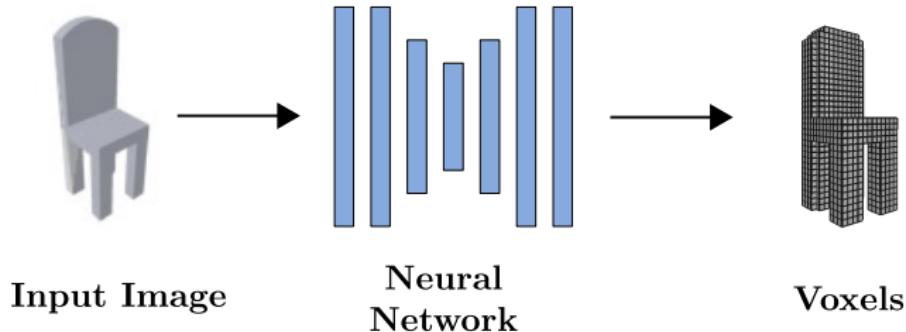


3D Reconstruction

What is the optimal 3D Representation?



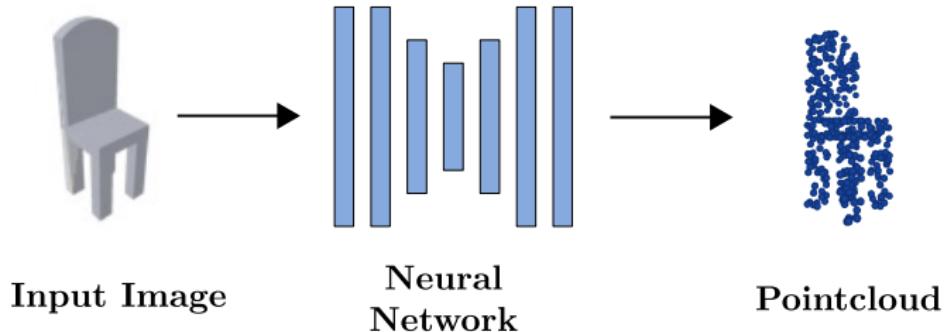
3D Representations



Discretization of 3D shape into grid:

- ✓ Accurately captures the **shape details**
- ✗ **Parametrization size** proportional to **reconstruction quality**
- ✗ Unable to yield **smooth reconstructions**
- ✗ Do not convey **semantic information**

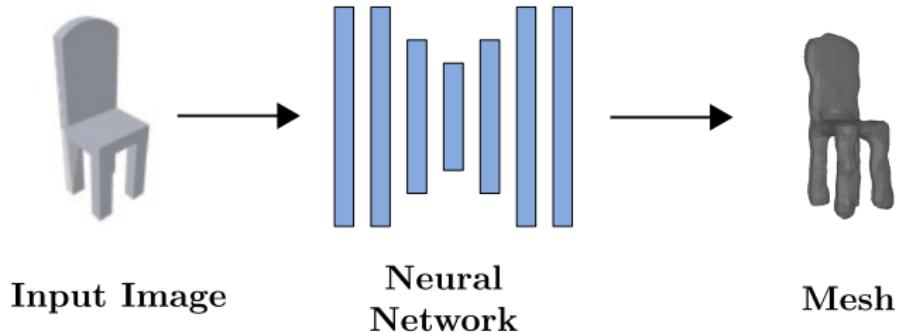
3D Representations



Discretization of surface with 3D points:

- ✓ Accurately captures the **shape details**
- ✗ Lacks surface connectivity
- ✗ Fixed number of points
- ✗ Parametrization size proportional to **reconstruction quality**
- ✗ Unable to yield **smooth reconstructions**
- ✗ Do not convey **semantic information**

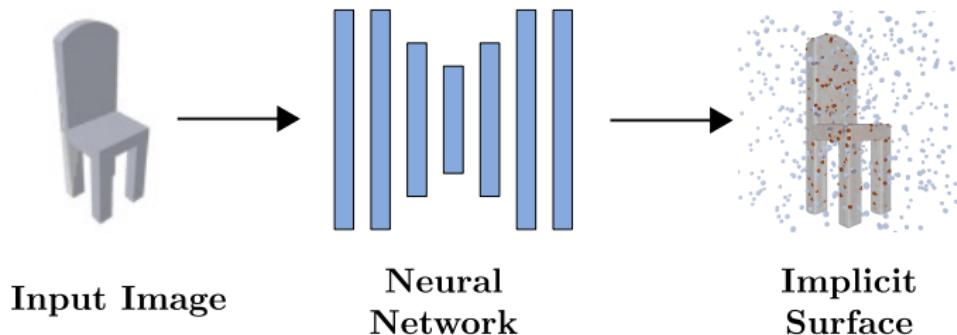
3D Representations



Discretization of surface into **vertices and faces**:

- ✓ Accurately captures the **shape details**
- ✓ Yields **smooth reconstructions**
- ✗ Requires class-specific template topology
- ✗ **Parametrization size**
- ✗ Do not convey **semantic information**

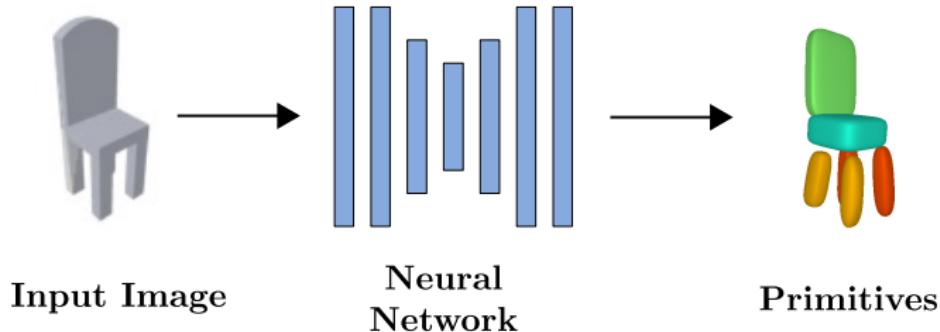
3D Representations



No discretization

- ✓ Accurately captures the **shape details**
- ✓ Low **parametrization size**
- ✓ Yields **smooth reconstructions**
- ✗ Requires post-processing
- ✗ Do not convey **semantic information**

3D Representations



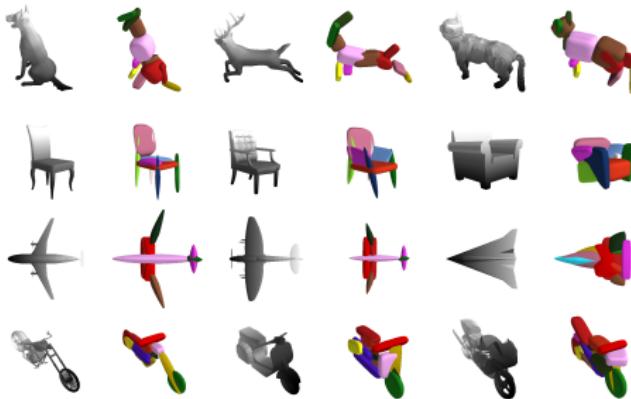
Discretization of 3D shape into parts:

- ✓ Low parametrization size
- ✓ Yields smooth reconstructions
- ✓ Yields semantic reconstructions
- ✓ Inter-object coherence
- ~ Accurately captures the **shape details**

Superquadrics Revisited: Learning 3D Shape Parsing beyond Cuboids

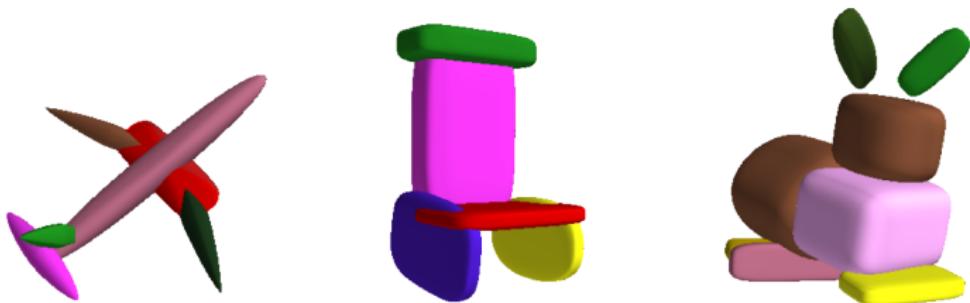
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CVPR 2019



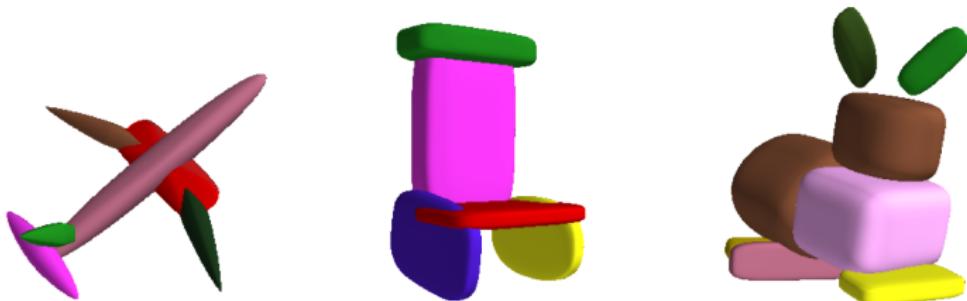
<https://superquadrics.com/learnable-superquadrics.html>

3D Geometric Primitives



Primitive-based 3D Representations:

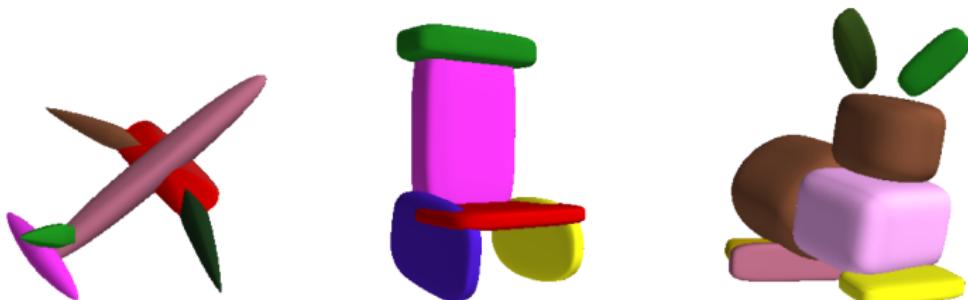
3D Geometric Primitives



Primitive-based 3D Representations:

- **Parsimonious Description:** Few primitives required to represent a 3D object

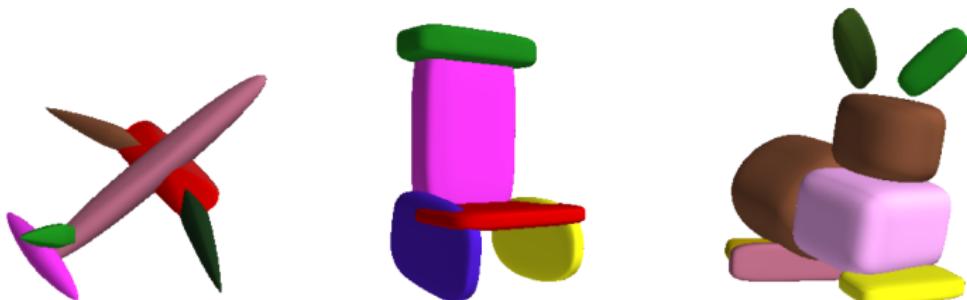
3D Geometric Primitives



Primitive-based 3D Representations:

- **Parsimonious Description:** Few primitives required to represent a 3D object
- Convey semantic information (parts, functionality, etc.)

3D Geometric Primitives



Primitive-based 3D Representations:

- **Parsimonious Description:** Few primitives required to represent a 3D object
- Convey semantic information (parts, functionality, etc.)
- **Main Challenge:** Variable number of primitives, few annotated datasets

3D Shape Abstraction

Goal of this work:



3D Shape Abstraction

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- Learn 3D shape abstraction from raw 3D point clouds or images



3D Shape Abstraction

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3D Shape Abstraction

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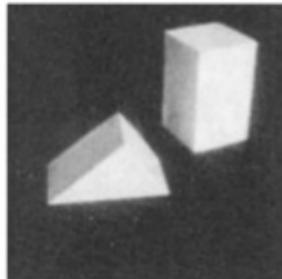
- Learn 3D shape abstraction from raw 3D point clouds or images
- Infer variable number of primitives
- No supervision at primitive level



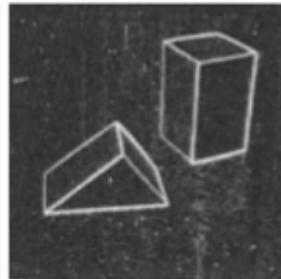
1963: 3D Solids



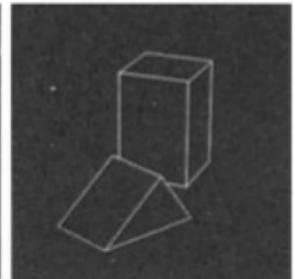
Larry Roberts
"Father of Computer Vision"



Input image

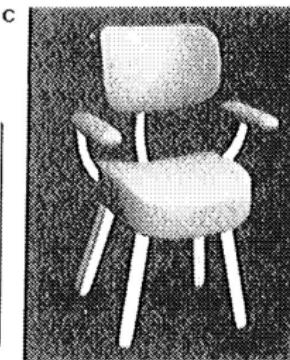
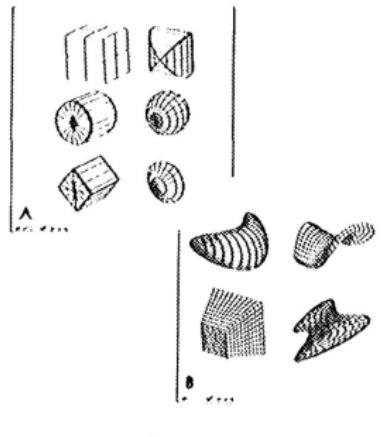
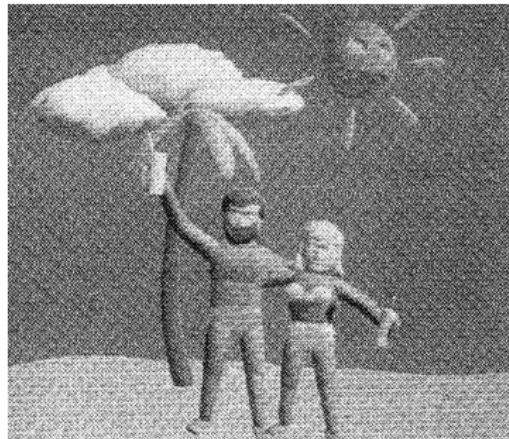


2x2 gradient operator



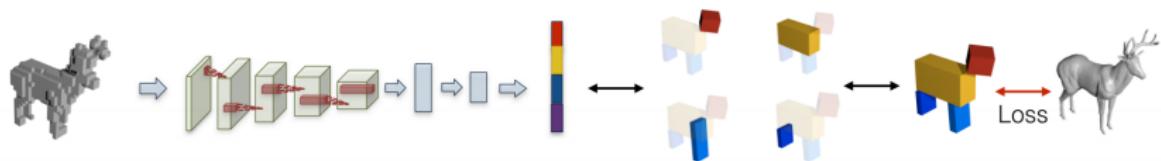
computed 3D model
rendered from new viewpoint

1986: Pentland's Superquadrics



- 1 superquadric can be represented with 11 parameters
- Scene on the left **constructed with 100 primitives** required less than 1000 bytes!
- Early fitting-based approaches did not work robustly

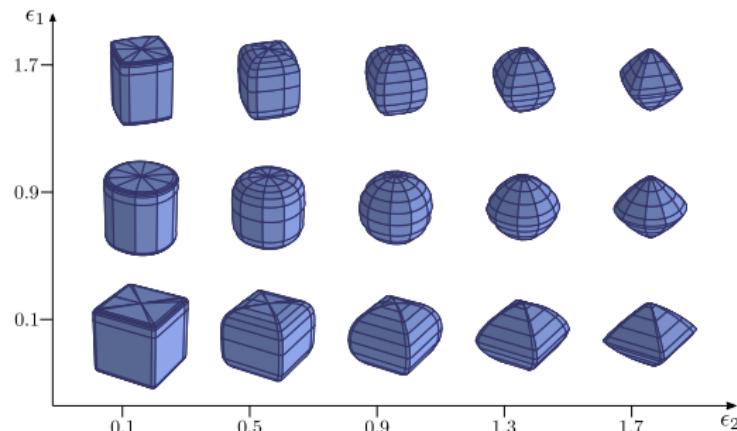
2017: 3D Reconstructions with Volumetric Primitives



- **Unsupervised** method for learning **cuboidal primitives**
- **Variable number of primitives**
- While **cuboids are sufficient for capturing the structure** of an object they **do not lead to expressive abstractions**.
- Computational expensive reinforcement learning for learning the existence probabilities

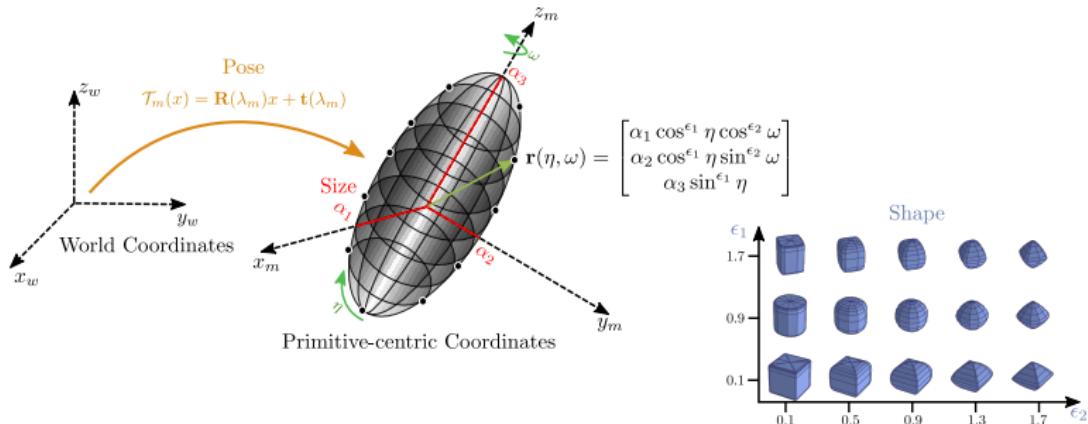
Can we train a network to output superquadrics?

*Everything in nature takes its form from the **sphere**, the **cone** and the **cylinder**.* - Paul Cezanne.



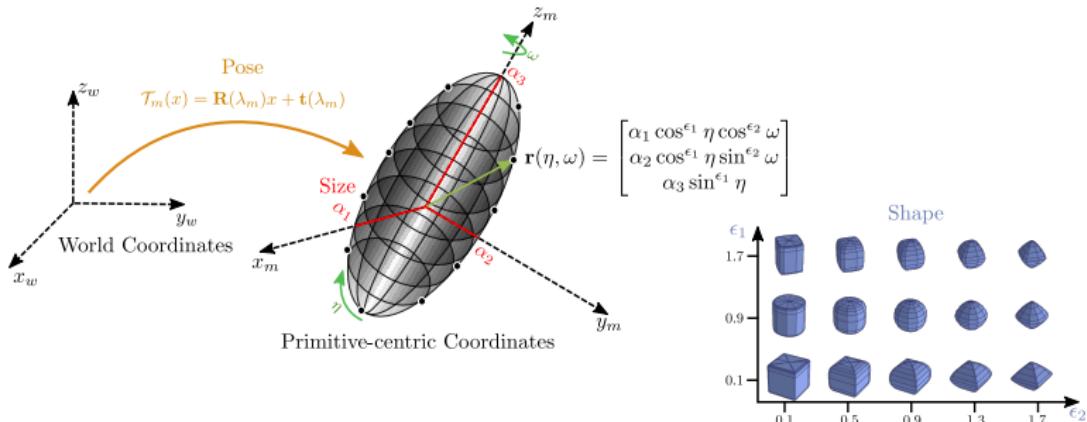
Superquadrics Space Shape

Superquadrics as geometric primitives



*Their chief advantage is that they **allow complex solids and surfaces to be constructed and altered easily from a few interactive parameters.** [Barr 1981]*

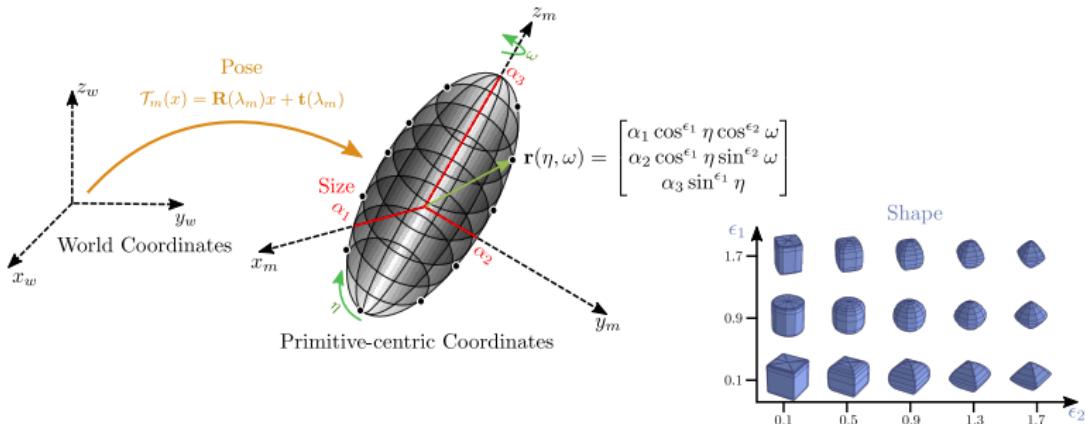
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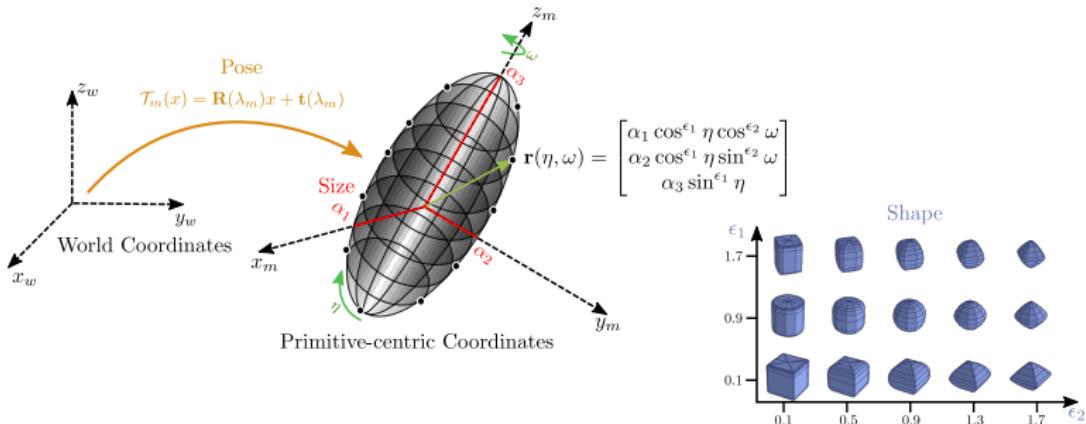
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- o Represent a diverse class of shapes such as cylinders, spheres, cuboids, ellipsoids in a **single continuous parameter space**

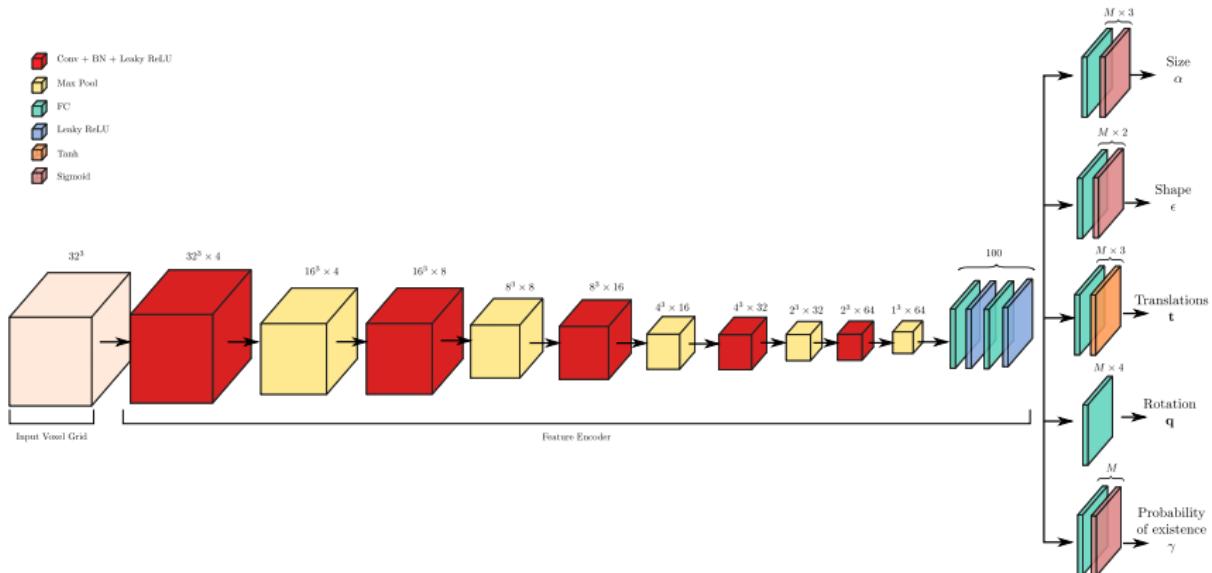
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- o Fully described with just 11 parameters
- o Represent a diverse class of shapes such as cylinders, spheres, cuboids, ellipsoids in a **single continuous parameter space**
- o Their large shape vocabulary allows for **faster** and **smoother fitting** than cuboids

Learning 3D Shape Parsing



Neural network encodes input image/shape and for each primitive predicts:

- o 11 parameters: 6 pose (\mathbf{R}, \mathbf{t}) + 3 scale (α) + 2 shape (ϵ)
- o Probability of existence: $\gamma \in [0, 1]$

Loss Function

Overall Loss:

$$\mathcal{L}(\mathbf{P}, \mathbf{X}) = \mathcal{L}_{P \rightarrow X}(\mathbf{P}, \mathbf{X}) + \mathcal{L}_{X \rightarrow P}(\mathbf{X}, \mathbf{P}) + \mathcal{L}_\gamma(\mathbf{P})$$

Composed of:

- $\mathcal{L}_{P \rightarrow X}(\mathbf{P}, \mathbf{X})$: Primitive-to-Pointcloud Loss
- $\mathcal{L}_{X \rightarrow P}(\mathbf{X}, \mathbf{P})$: Pointcloud-to-Primitive Loss
- $\mathcal{L}_\gamma(\mathbf{P})$: Existence and Parsimony Loss

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Target and Predicted Shape:

- **Target:** $\mathbf{X} = \{x_i\}_{i=1}^N$

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- **Predicted:** $\mathbf{P} = \{(\lambda_m, \gamma_m)\}_{m=1}^M$

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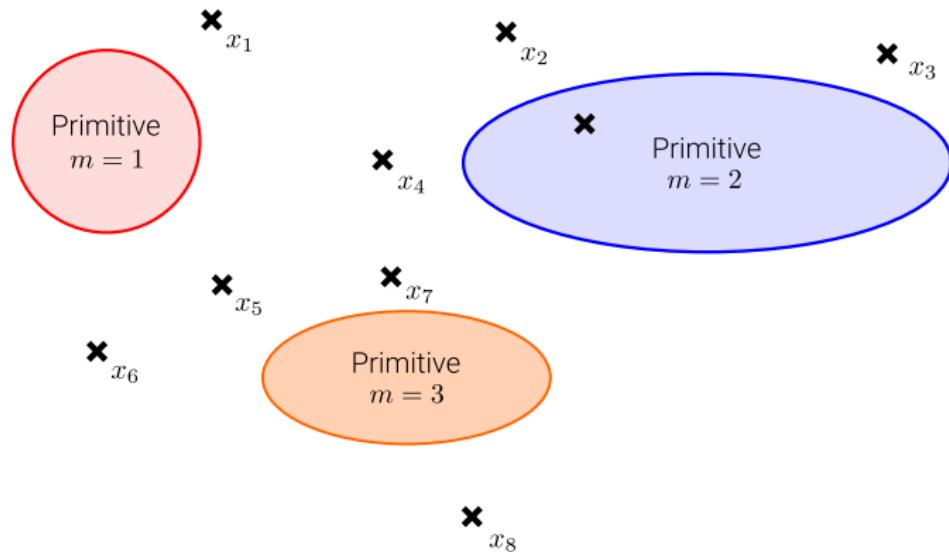
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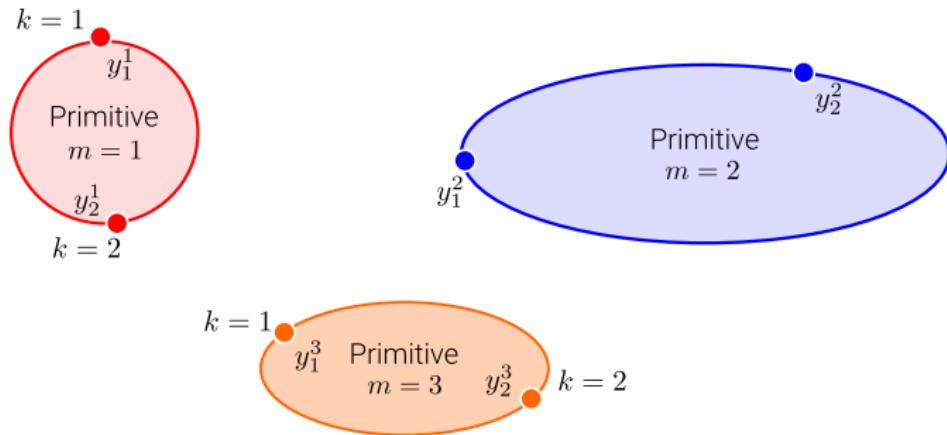
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- **Predicted:** $\mathbf{P} = \{(\lambda_m, \gamma_m)\}_{m=1}^M$
- **m-th primitive:** $\mathbf{Y}_m = \{y_k^m\}_{k=1}^K$

Loss Function



Target shape: $\mathbf{X} = \{x_i\}_{i=1}^N$

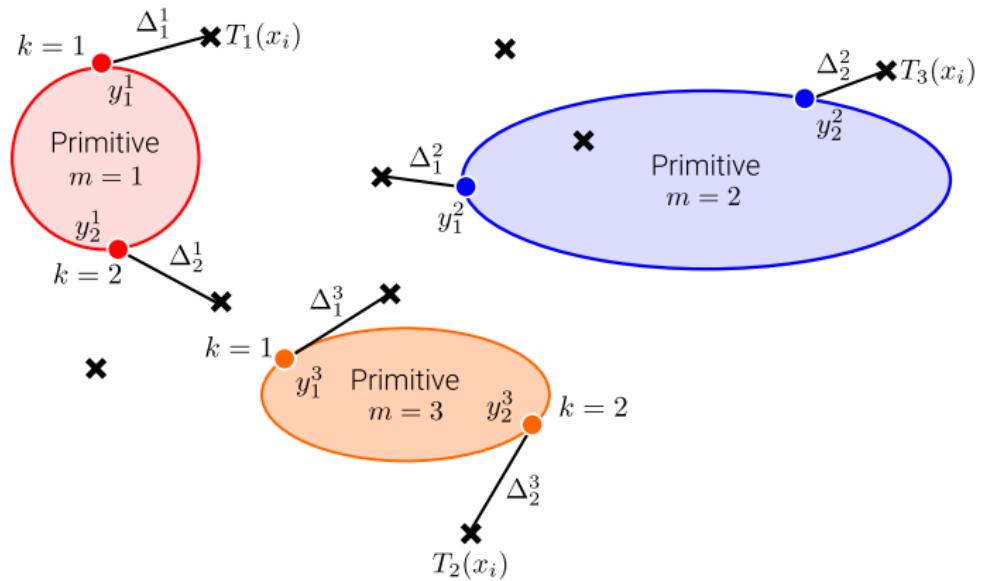
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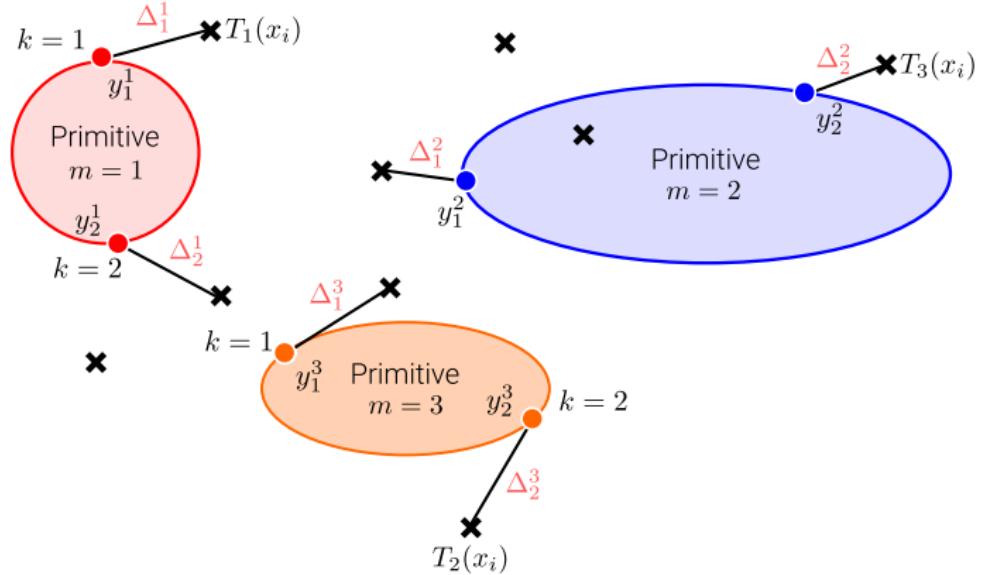
Primitive-to-Pointcloud Loss



$$\mathcal{L}_{P \rightarrow X}^m(\mathbf{P}, \mathbf{X}) = \frac{1}{K} \sum_{k=1}^K \Delta_k^m$$

$$\Delta_k^m = \min_{i=1,..,N} \|\mathcal{T}_m(\mathbf{x}_i) - \mathbf{y}_k^m\|_2$$

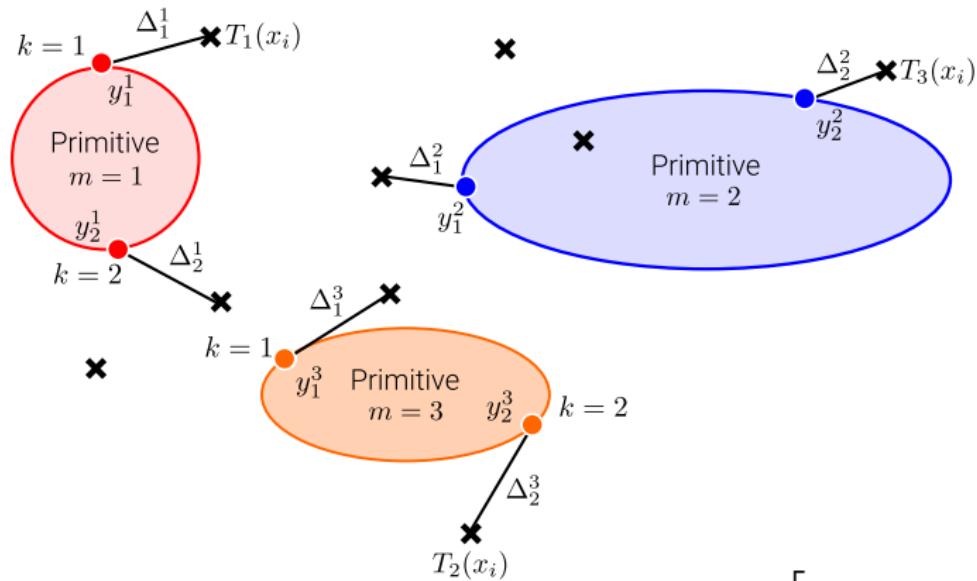
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Primitive-to-Pointcloud Loss



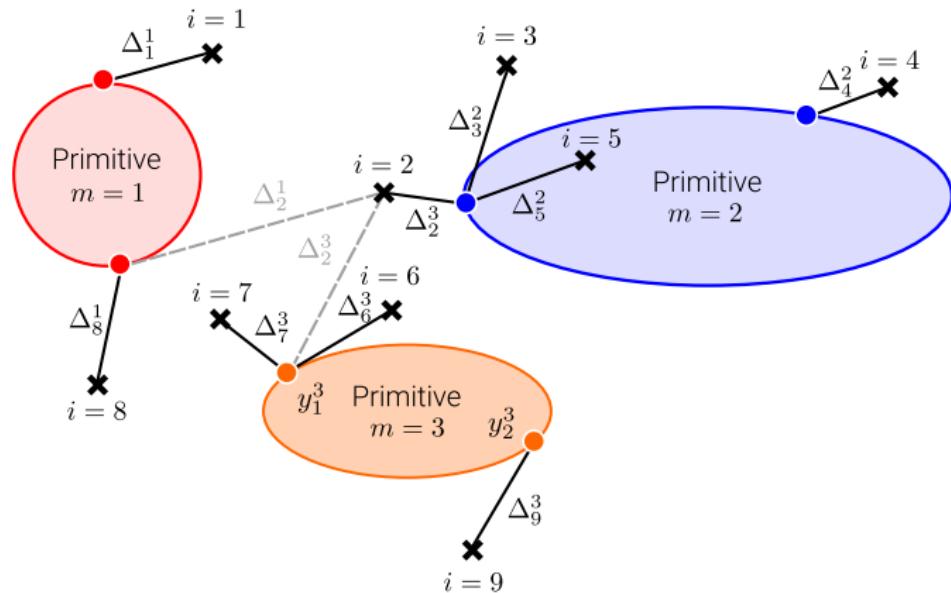
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$$\mathcal{L}_{P \rightarrow X}(\mathbf{P}, \mathbf{X}) = \mathbb{E}_{p(\mathbf{z})} \left[\sum_{m|z_m=1} \mathcal{L}_{P \rightarrow X}^m(\mathbf{P}, \mathbf{X}) \right]$$

$$= \sum_{m=1}^M \gamma_m \mathcal{L}_{P \rightarrow X}^m(\mathbf{P}, \mathbf{X})$$

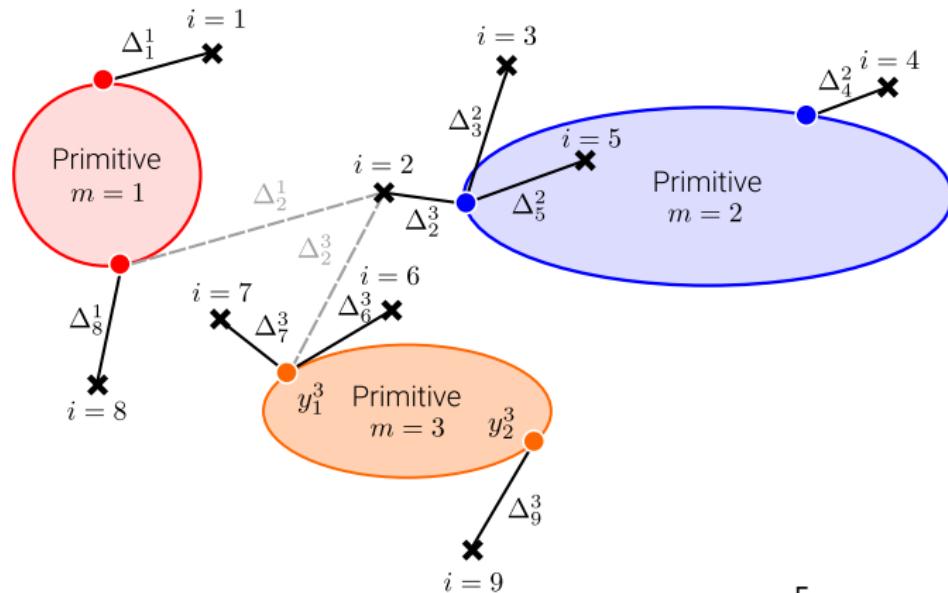
Pointcloud-to-Primitive Loss



$$\mathcal{L}_{X \rightarrow P}^i(\mathbf{X}, \mathbf{P}) = \min_{m | z_m=1} \Delta_i^m$$

$$\Delta_i^m = \min_{k=1, \dots, \kappa} \|\mathcal{T}_m(\mathbf{x}_i) - \mathbf{y}_k^m\|_2$$

Pointcloud-to-Primitive Loss

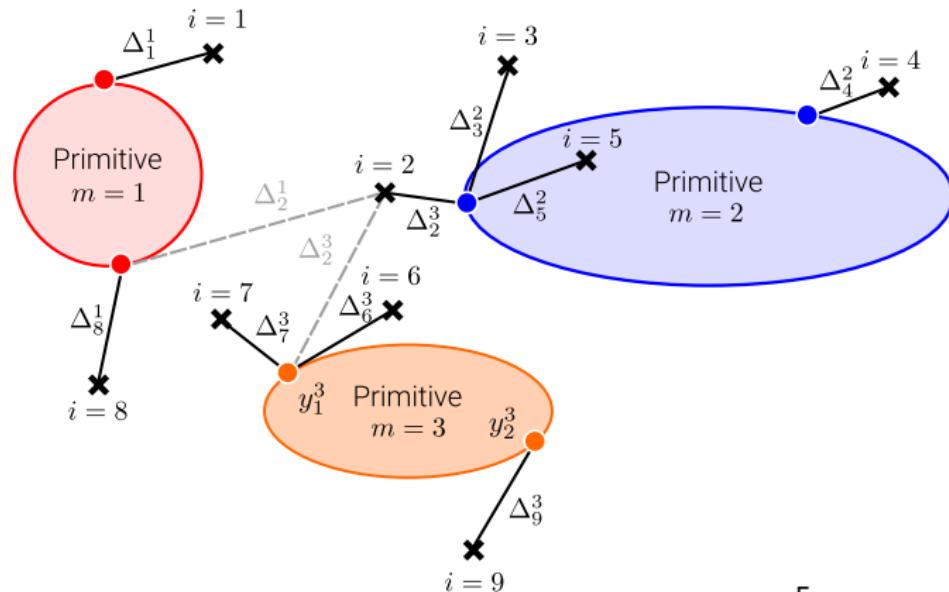


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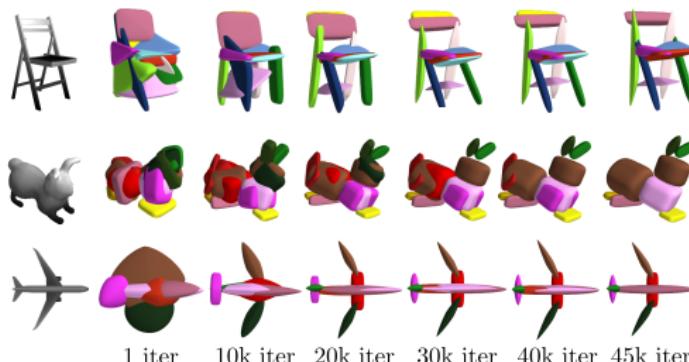
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$$= \sum_{\mathbf{x}_i \in \mathbf{X}} \sum_{m=1}^M \Delta_i^m \gamma_m \prod_{\bar{m}=1}^{m-1} (1 - \gamma_{\bar{m}})$$

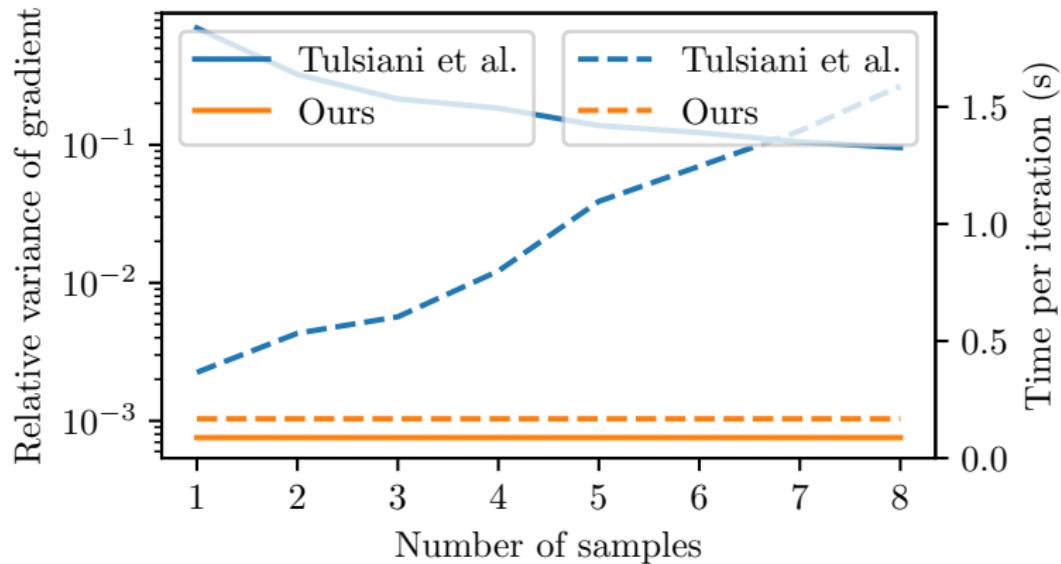
Existence and Parsimony Loss

$$\mathcal{L}_\gamma(\mathbf{P}) = \max \left(1 - \sum_{m=1}^M \gamma_m, 0 \right) + \beta \sqrt{\sum_{m=1}^M \gamma_m}$$

- **First term:** Enforces at least one primitive to exist
- **Second term:** Encourages parsimony
- Two-stage training



Comparison to Tulsiani et. al. / REINFORCE

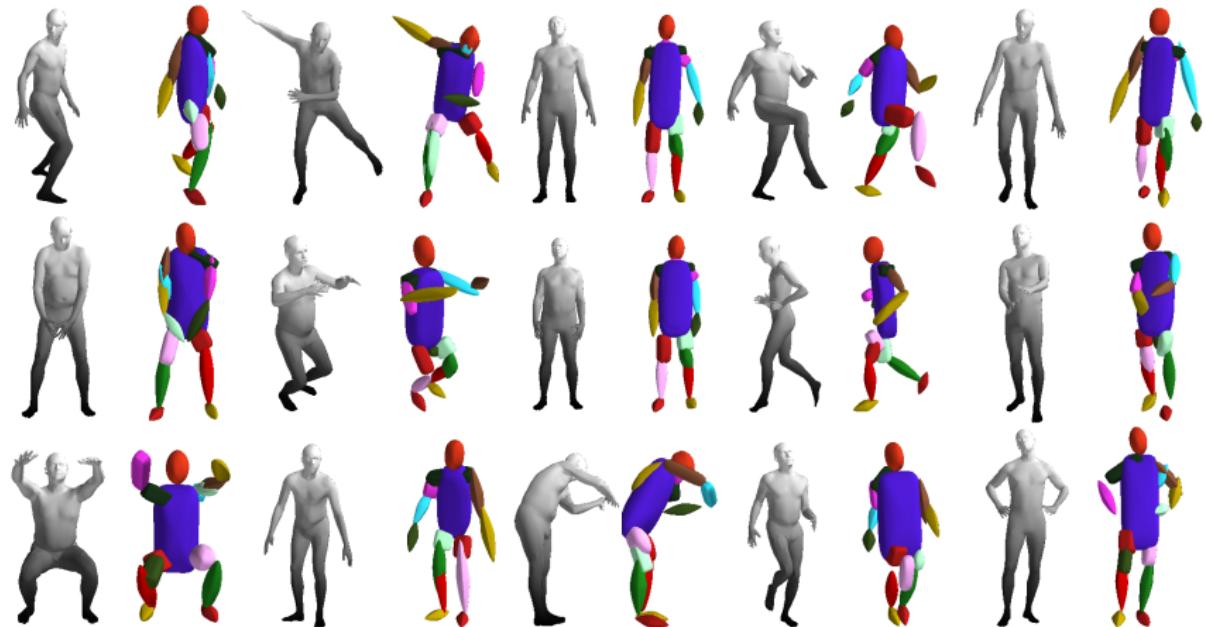


Single view 3D Reconstruction on ShapeNet



	Chamfer Distance			Volumetric IoU		
	Chairs	Aeroplanes	Animals	Chairs	Aeroplanes	Animals
Cuboids	0.0121	0.0153	0.0110	0.1288	0.0650	0.3339
Superquadrics	0.0006	0.0003	0.0003	0.1408	0.1808	0.7506

Single view 3D Reconstruction on SURREAL



3D Shape Abstractions with Superquadrics

Limitations:

3D Shape Abstractions with Superquadrics

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- Trade-off between number of primitives and representation accuracy

3D Shape Abstractions with Superquadrics

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3D Shape Abstractions with Superquadrics

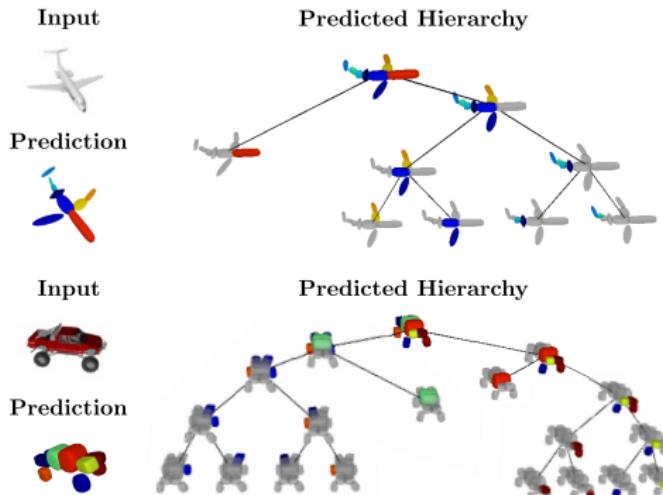
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- Superquadrics :-)

Learning Unsupervised Hierarchical Part Decomposition of 3D Objects from a Single RGB Image

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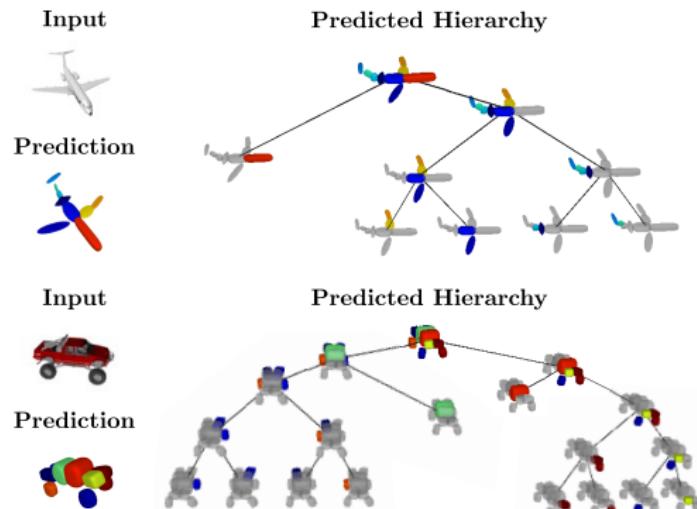
CVPR 2020



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Hierarchical Part Decomposition

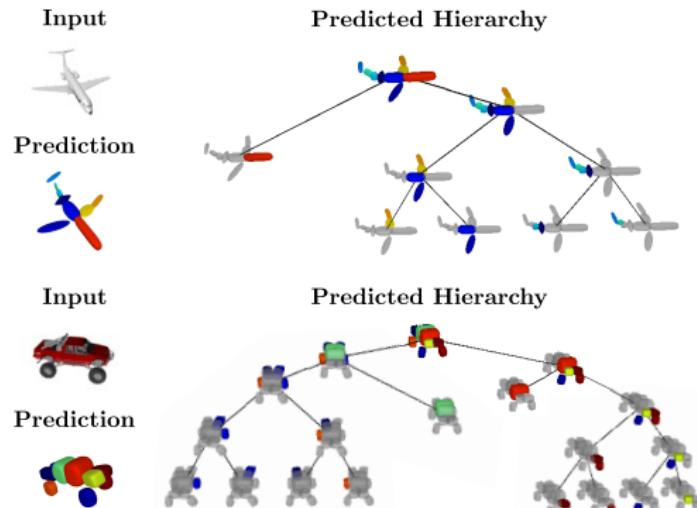
Goal of this work:



Hierarchical Part Decomposition

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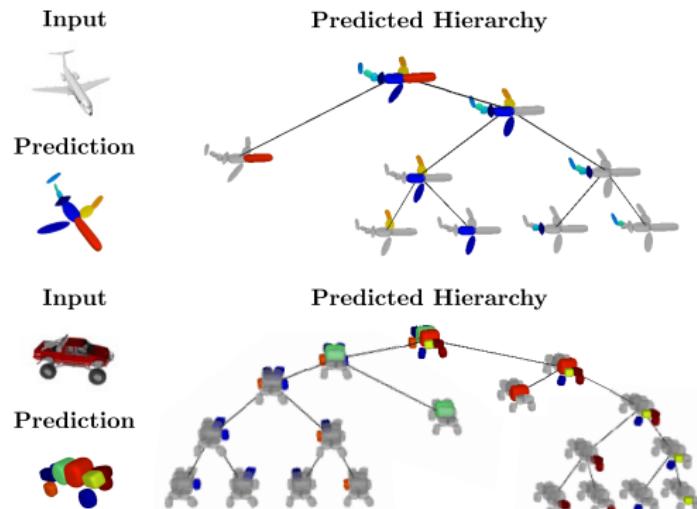
- Model relationships between parts



Hierarchical Part Decomposition

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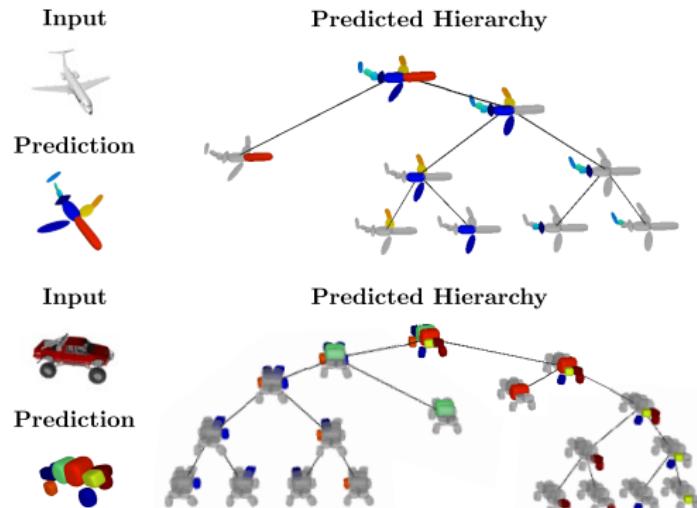
- Model relationships between parts
- Model objects with multiple levels of abstraction



Hierarchical Part Decomposition

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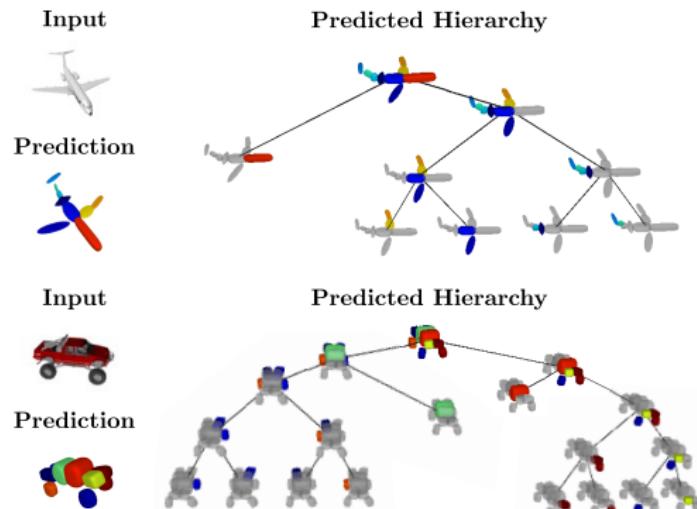
- Model relationships between parts
- Model objects with multiple levels of abstraction
- Infer variable number of primitives



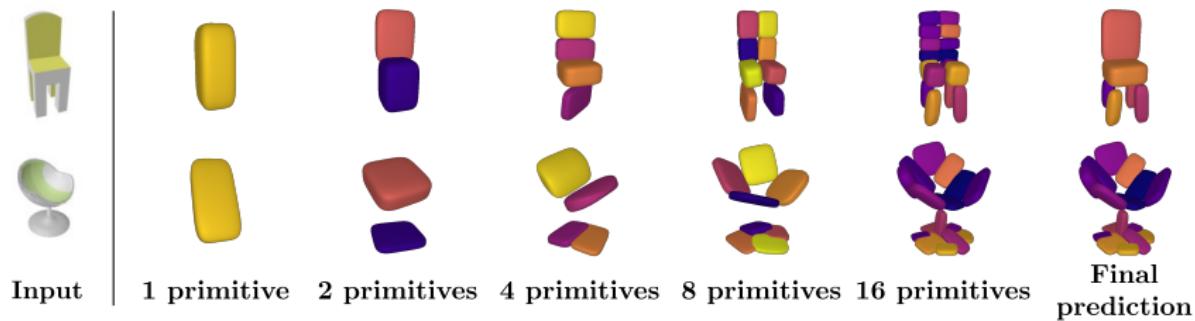
Hierarchical Part Decomposition

Goal of this work:

- Model relationships between parts
- Model objects with multiple levels of abstraction
- Infer variable number of primitives
- No supervision at primitive level and part relations

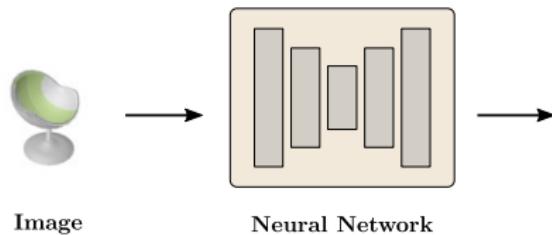


Representation with multiple levels of abstraction



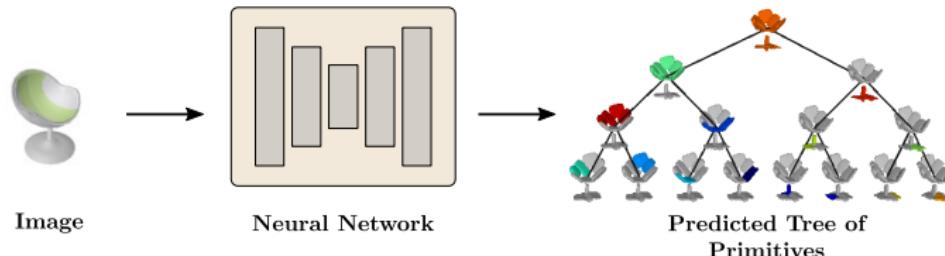
- Represent a 3D shape as a **binary tree of primitives**
- At each depth level, each node is **recursively** split into two until reaching the maximum depth
- Reconstructions from deeper depth levels are more detailed

Learning Hierarchical Part Decomposition of 3D Objects



Target and Predicted Shape:

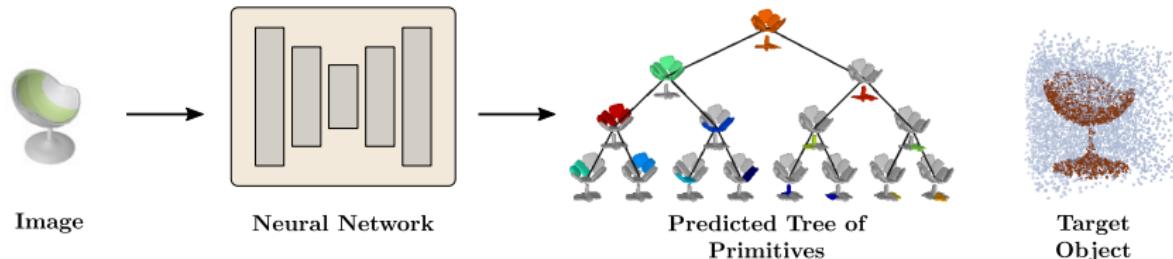
Learning Hierarchical Part Decomposition of 3D Objects



Target and Predicted Shape:

- **Binary Tree of Primitives:** $\mathcal{P} = \{\{p_k^d\}_{k=0}^{2^d-1} \mid d = \{0 \dots D\}\}$

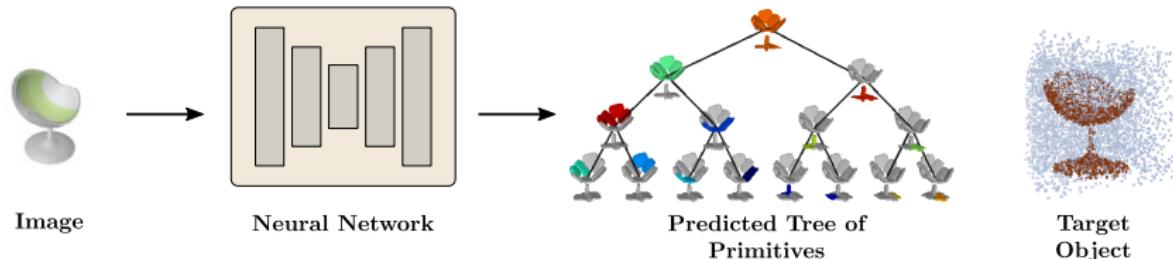
Learning Hierarchical Part Decomposition of 3D Objects



Target and Predicted Shape:

- **Binary Tree of Primitives:** $\mathcal{P} = \{\{p_k^d\}_{k=0}^{2^d-1} \mid d = \{0 \dots D\}\}$
- **Target:** Set of occupancy pairs $\mathcal{X} = \{(\mathbf{x}_i, o_i)\}_{i=1}^N$

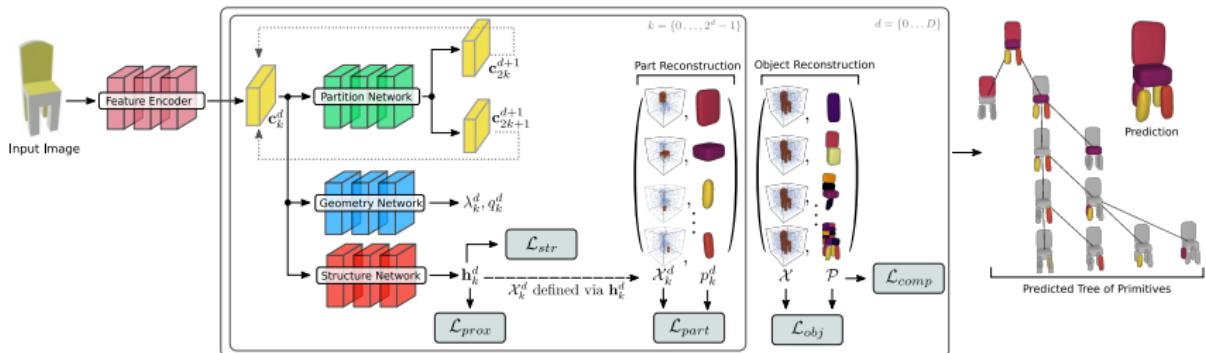
Learning Hierarchical Part Decomposition of 3D Objects



Target and Predicted Shape:

- **Binary Tree of Primitives:** $\mathcal{P} = \{\{p_k^d\}_{k=0}^{2^d-1} \mid d = \{0 \dots D\}\}$
- **Target:** Set of occupancy pairs $\mathcal{X} = \{(\mathbf{x}_i, o_i)\}_{i=1}^N$
- **Occupancy function of predicted shape at depth d:**
$$G^d(\mathbf{x}) = \max_{k \in 0 \dots 2^d-1} g_k^d(\mathbf{x}; \lambda_k^d)$$

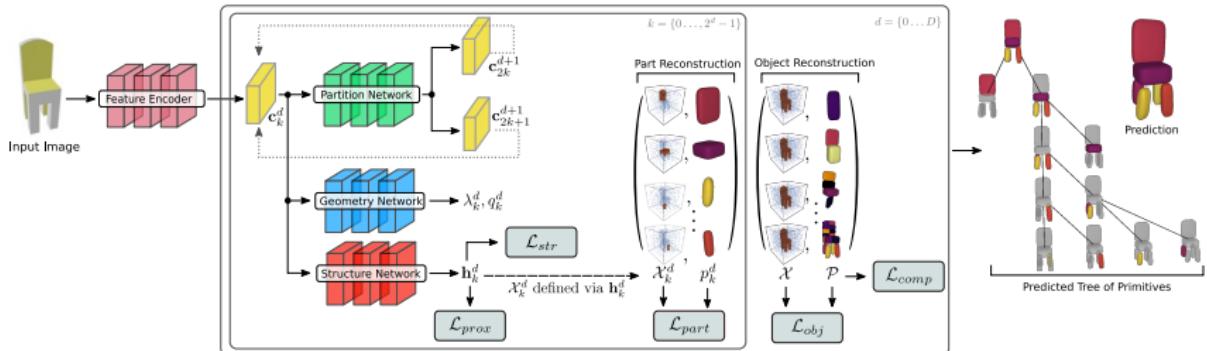
Learning Hierarchical Part Decomposition of 3D Objects



Neural network encodes input image/shape and for each primitive predicts:

- 11 parameters: 6 pose (\mathbf{R}, \mathbf{t}) + 3 scale (α) + 2 shape (ϵ)
- Reconstruction quality: $q_k^d \in [0, 1]$

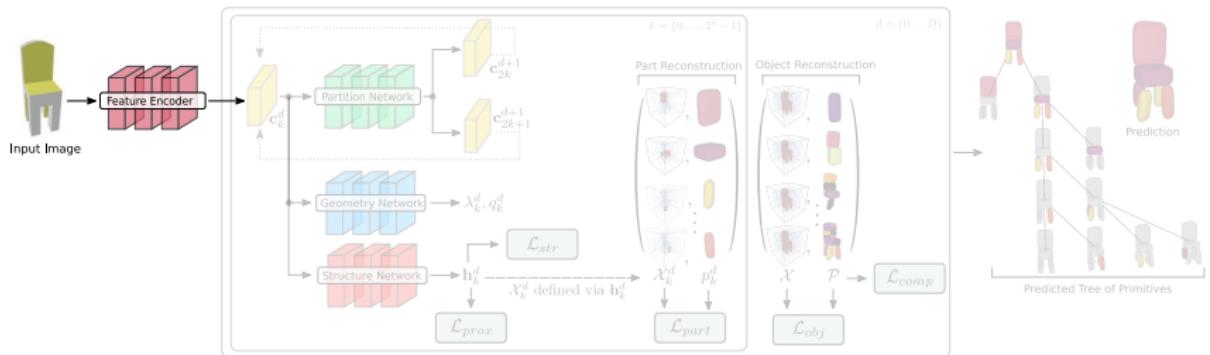
Learning Hierarchical Part Decomposition of 3D Objects



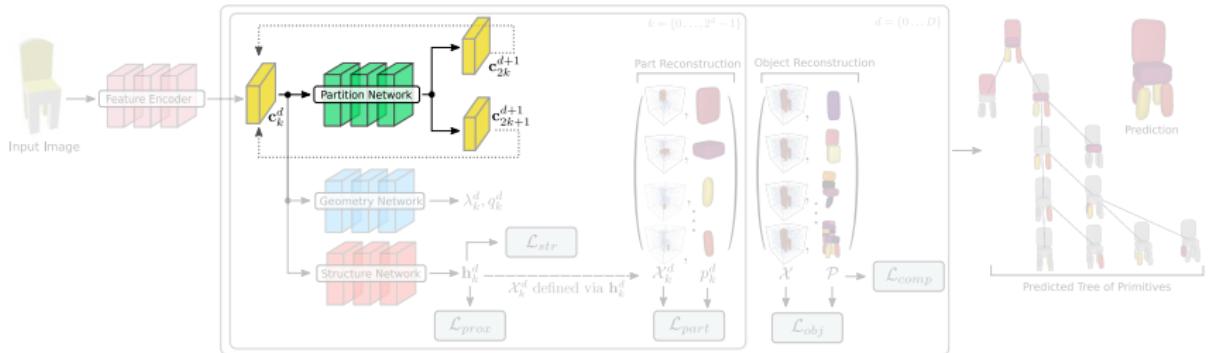
Components:

- Feature Encoder
- Partition Network
- Geometry Network
- Structure Network

Learning Hierarchical Part Decomposition of 3D Objects



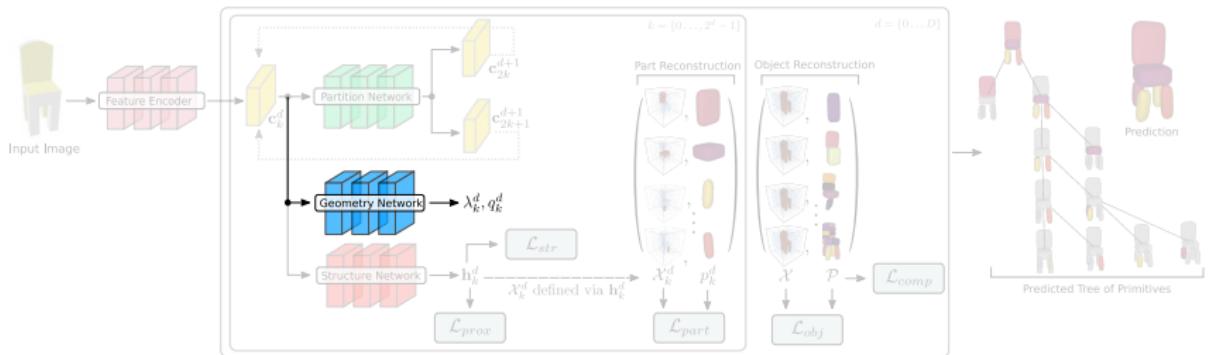
Learning Hierarchical Part Decomposition of 3D Objects



Partition Network: Recursively partition the **feature representation**

$$p_\theta(c_k^d) = \{c_{2k}^{d+1}, c_{2k+1}^{d+1}\}$$

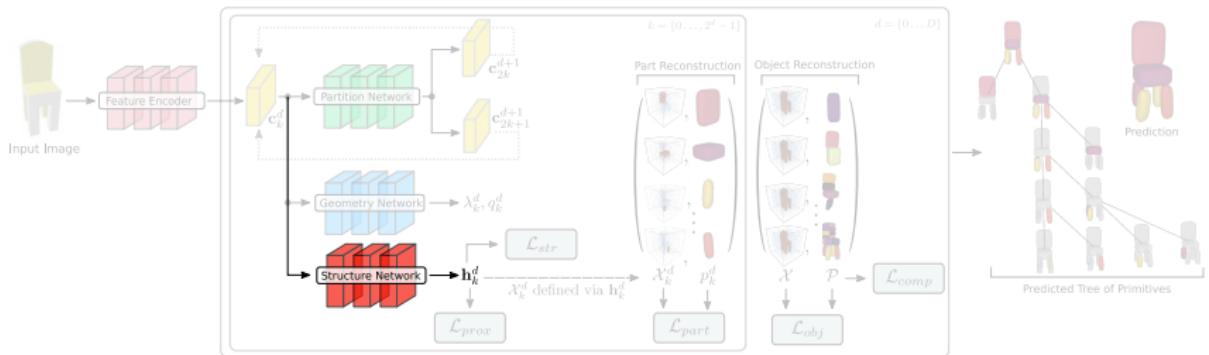
Learning Hierarchical Part Decomposition of 3D Objects



Geometry Network: Regress the primitive parameters

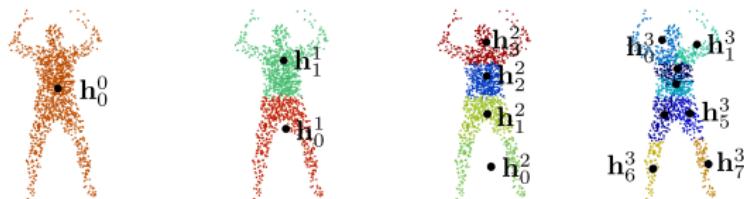
$$r_{\theta}(\mathbf{c}_k^d) = \{\lambda_k^d, q_k^d\}.$$

Learning Hierarchical Part Decomposition of 3D Objects



Structure Network: Assign object parts to primitives

$$\mathcal{H} = \{\{\mathbf{h}_k^d\}_{k=0}^{2^d-1} \mid d = \{0 \dots D\}\}$$



Loss Function

Overall Loss:

$$\mathcal{L}(\mathcal{P}, \mathcal{H}; \mathcal{X}) = \mathcal{L}_{str}(\mathcal{H}; \mathcal{X}) + \mathcal{L}_{rec}(\mathcal{P}; \mathcal{X}) + \mathcal{L}_{comp}(\mathcal{P}; \mathcal{X}) + \mathcal{L}_{prox}(\mathcal{P})$$

Composed of:

- $\mathcal{L}_{str}(\mathcal{H}, \mathcal{X})$: Structure Loss
- $\mathcal{L}_{rec}(\mathcal{P}, \mathcal{X})$: Reconstruction Loss
- $\mathcal{L}_{comp}(\mathcal{P}, \mathcal{X})$: Combatibility Loss
- $\mathcal{L}_{prox}(\mathcal{P})$: Proximity Loss

Loss Function

Overall Loss:

$$\mathcal{L}(\mathcal{P}, \mathcal{H}; \mathcal{X}) = \mathcal{L}_{str}(\mathcal{H}; \mathcal{X}) + \mathcal{L}_{rec}(\mathcal{P}; \mathcal{X}) + \mathcal{L}_{comp}(\mathcal{P}; \mathcal{X}) + \mathcal{L}_{prox}(\mathcal{P})$$

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- $\mathcal{L}_{comp}(\mathcal{P}, \mathcal{X})$: Combatibility Loss
- $\mathcal{L}_{prox}(\mathcal{P})$: Proximity Loss

Target and Predicted Shape:

- **Target:** $\mathcal{X} = \{(\mathbf{x}_i, o_i)\}_{i=1}^N$

Loss Function

Overall Loss:

$$\mathcal{L}(\mathcal{P}, \mathcal{H}; \mathcal{X}) = \mathcal{L}_{str}(\mathcal{H}; \mathcal{X}) + \mathcal{L}_{rec}(\mathcal{P}; \mathcal{X}) + \mathcal{L}_{comp}(\mathcal{P}; \mathcal{X}) + \mathcal{L}_{prox}(\mathcal{P})$$

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- $\mathcal{L}_{comp}(\mathcal{P}, \mathcal{X})$: Combatibility Loss
- $\mathcal{L}_{prox}(\mathcal{P})$: Proximity Loss

Target and Predicted Shape:

- **Target:** $\mathcal{X} = \{(\mathbf{x}_i, o_i)\}_{i=1}^N$
- **Binary Tree of Primitives:** $\mathcal{P} = \{\{p_k^d\}_{k=0}^{2^d-1} \mid d = \{0 \dots D\}\}$

Loss Function

Overall Loss:

$$\mathcal{L}(\mathcal{P}, \mathcal{H}; \mathcal{X}) = \mathcal{L}_{str}(\mathcal{H}; \mathcal{X}) + \mathcal{L}_{rec}(\mathcal{P}; \mathcal{X}) + \mathcal{L}_{comp}(\mathcal{P}; \mathcal{X}) + \mathcal{L}_{prox}(\mathcal{P})$$

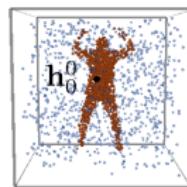
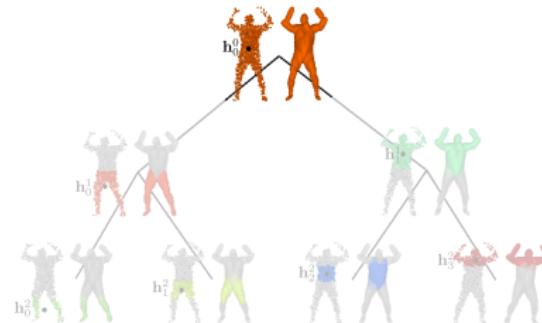
Composed of:

- $\mathcal{L}_{str}(\mathcal{H}, \mathcal{X})$: Structure Loss
- $\mathcal{L}_{rec}(\mathcal{P}, \mathcal{X})$: Reconstruction Loss
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Target and Predicted Shape:

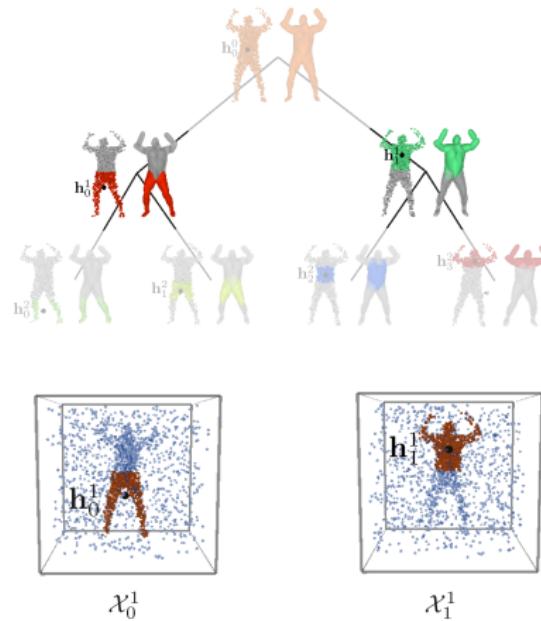
- **Target:** $\mathcal{X} = \{(\mathbf{x}_i, \mathbf{o}_i)\}_{i=1}^N$
- **Binary Tree of Primitives:** $\mathcal{P} = \{\{p_k^d\}_{k=0}^{2^d-1} \mid d = \{0 \dots D\}\}$
- **Geometric Centroids:** $\mathcal{H} = \{\{\mathbf{h}_k^d\}_{k=0}^{2^d-1} \mid d = \{0 \dots D\}\}$

Structure Loss

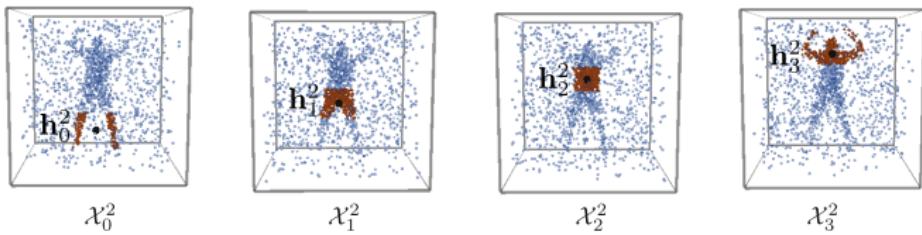
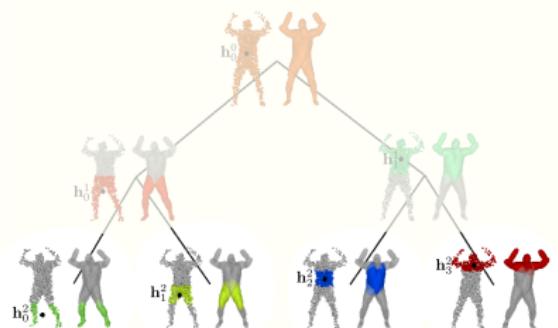


$$\mathcal{X}_0^0$$

Structure Loss



Structure Loss



Structure Loss



$$\mathcal{L}_{str}(\mathcal{H}; \mathcal{X}) = \sum_{h_k^d \in \mathcal{H}} \frac{1}{2^d - 1} \sum_{(\mathbf{x}, o) \in \mathcal{X}_k^d} o \|\mathbf{x} - \mathbf{h}_k^d\|_2$$

Reconstruction Loss

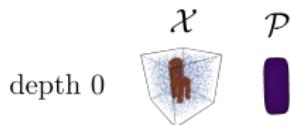
$$\mathcal{L}_{rec}(\mathcal{P}; \mathcal{X}) = \underbrace{\sum_{(\mathbf{x}, o) \in \mathcal{X}} \sum_{d=0}^D L\left(G^d(\mathbf{x}), o\right)}_{\text{Object Reconstruction}} + \underbrace{\sum_{d=0}^D \sum_{k=0}^{2^d-1} \sum_{(\mathbf{x}, o) \in \mathcal{X}_k^d} L\left(g_k^d\left(\mathbf{x}; \lambda_k^d\right), o\right)}_{\text{Part Reconstruction}}$$

Reconstruction Loss

$$\mathcal{L}_{rec}(\mathcal{P}; \mathcal{X}) = \underbrace{\sum_{(\mathbf{x}, o) \in \mathcal{X}} \sum_{d=0}^D \textcolor{red}{L} \left(G^d(\mathbf{x}), o \right)}_{\text{Object Reconstruction}} + \underbrace{\sum_{d=0}^D \sum_{k=0}^{2^d-1} \sum_{(\mathbf{x}, o) \in \mathcal{X}_k^d} \textcolor{red}{L} \left(g_k^d \left(\mathbf{x}; \lambda_k^d \right), o \right)}_{\text{Part Reconstruction}}$$

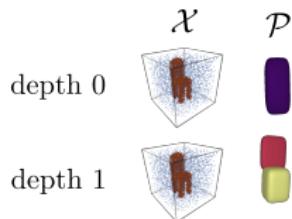
Reconstruction Loss

$$\mathcal{L}_{rec}(\mathcal{P}; \mathcal{X}) = \underbrace{\sum_{(\mathbf{x}, o) \in \mathcal{X}} \sum_{d=0}^D L\left(G^d(\mathbf{x}), o\right)}_{\text{Object Reconstruction}} + \underbrace{\sum_{d=0}^D \sum_{k=0}^{2^d-1} \sum_{(\mathbf{x}, o) \in \mathcal{X}_k^d} L\left(g_k^d\left(\mathbf{x}; \lambda_k^d\right), o\right)}_{\text{Part Reconstruction}}$$



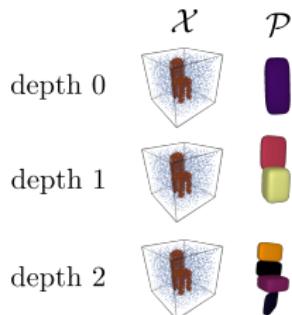
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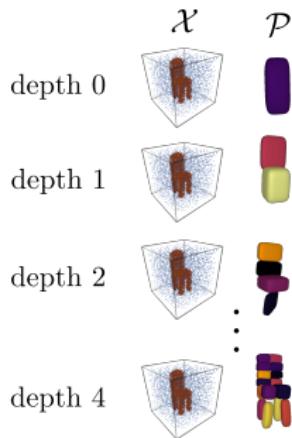
Reconstruction Loss

$$\mathcal{L}_{rec}(\mathcal{P}; \mathcal{X}) = \underbrace{\sum_{(\mathbf{x}, o) \in \mathcal{X}} \sum_{d=0}^D L\left(G^d(\mathbf{x}), o\right)}_{\text{Object Reconstruction}} + \underbrace{\sum_{d=0}^D \sum_{k=0}^{2^d-1} \sum_{(\mathbf{x}, o) \in \mathcal{X}_k^d} L\left(g_k^d\left(\mathbf{x}; \lambda_k^d\right), o\right)}_{\text{Part Reconstruction}}$$



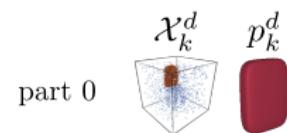
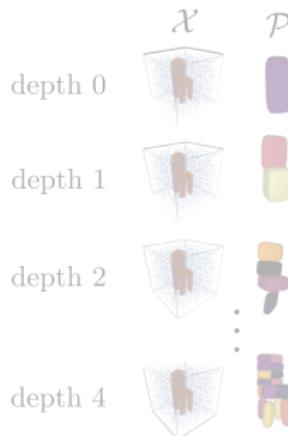
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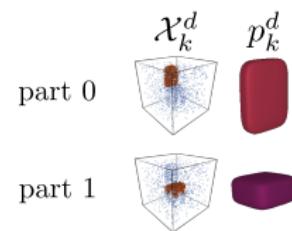
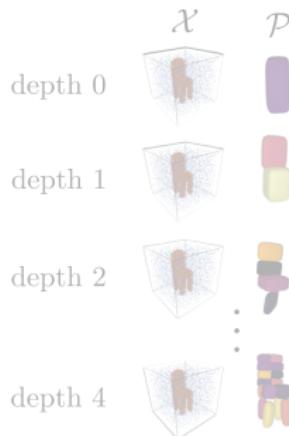
Reconstruction Loss

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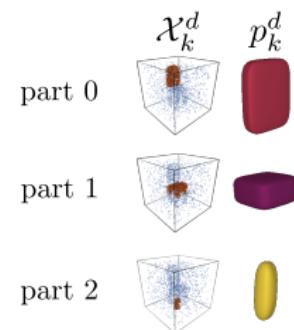
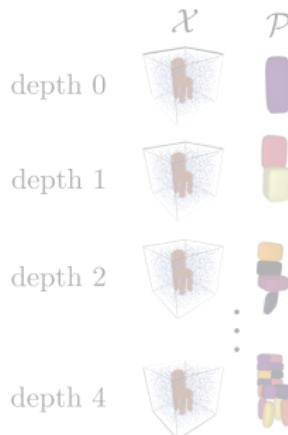
Reconstruction Loss

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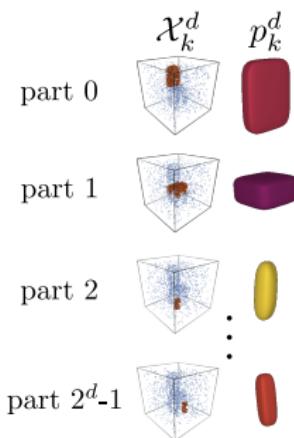
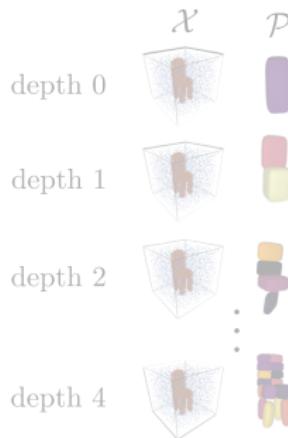
Reconstruction Loss

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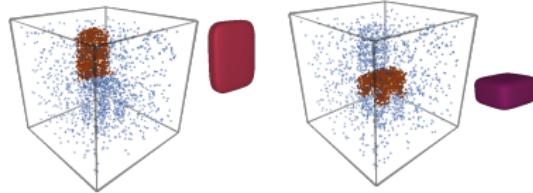


Reconstruction Loss

$$\mathcal{L}_{rec}(\mathcal{P}; \mathcal{X}) = \underbrace{\sum_{(\mathbf{x}, o) \in \mathcal{X}} \sum_{d=0}^D L\left(G^d(\mathbf{x}), o\right)}_{\text{Object Reconstruction}} + \underbrace{\sum_{d=0}^D \sum_{k=0}^{2^d-1} \sum_{(\mathbf{x}, o) \in \mathcal{X}_k^d} L\left(g_k^d\left(\mathbf{x}; \lambda_k^d\right), o\right)}_{\text{Part Reconstruction}}$$



Compatibility Loss



$$\mathcal{L}_{comp}(\mathcal{P}) = \sum_{d=0}^{\mathcal{D}} \sum_{k=0}^{2^d-1} \left(q_k^d - \text{IoU}(p_k^d, \mathcal{X}_k^d) \right)^2$$

Proximity Loss



(a) **Input**



(b) **without**



(c) **Ours**

$$\mathcal{L}_{prox}(\mathcal{P}) = \sum_{d=0}^D \sum_{k=0}^{2^d-1} \|\mathbf{t}(\lambda_k^d) - \mathbf{h}_k^d\|_2$$

Loss Function

Overall Loss:

$$\mathcal{L}(\mathcal{P}, \mathcal{H}; \mathcal{X}) = \mathcal{L}_{str}(\mathcal{H}; \mathcal{X}) + \mathcal{L}_{rec}(\mathcal{P}; \mathcal{X}) + \mathcal{L}_{comp}(\mathcal{P}; \mathcal{X}) + \mathcal{L}_{prox}(\mathcal{P})$$

Composed of:

Loss Function

Overall Loss:

$$\mathcal{L}(\mathcal{P}, \mathcal{H}; \mathcal{X}) = \mathcal{L}_{str}(\mathcal{H}; \mathcal{X}) + \mathcal{L}_{rec}(\mathcal{P}; \mathcal{X}) + \mathcal{L}_{comp}(\mathcal{P}; \mathcal{X}) + \mathcal{L}_{prox}(\mathcal{P})$$

Composed of:

- $\mathcal{L}_{str}(\mathcal{H}, \mathcal{X})$: Decomposes shape into parts

Loss Function

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Composed of:

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- $\mathcal{L}_{rec}(\mathcal{P}, \mathcal{X})$: Predicted primitives match the shape

Loss Function

Overall Loss:

$$\mathcal{L}(\mathcal{P}, \mathcal{H}; \mathcal{X}) = \mathcal{L}_{str}(\mathcal{H}; \mathcal{X}) + \mathcal{L}_{rec}(\mathcal{P}; \mathcal{X}) + \mathcal{L}_{comp}(\mathcal{P}; \mathcal{X}) + \mathcal{L}_{prox}(\mathcal{P})$$

Composed of:

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- $\mathcal{L}_{comp}(\mathcal{P}, \mathcal{X})$: Allows for variable number of primitives

Loss Function

Overall Loss:

$$\mathcal{L}(\mathcal{P}, \mathcal{H}; \mathcal{X}) = \mathcal{L}_{str}(\mathcal{H}; \mathcal{X}) + \mathcal{L}_{rec}(\mathcal{P}; \mathcal{X}) + \mathcal{L}_{comp}(\mathcal{P}; \mathcal{X}) + \mathcal{L}_{prox}(\mathcal{P})$$

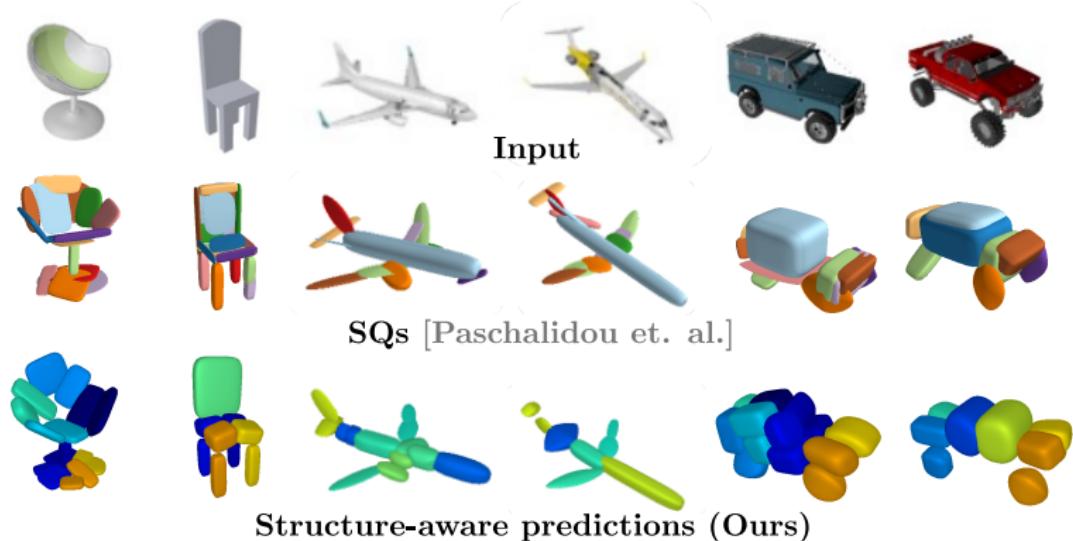
Composed of:

- $\mathcal{L}_{str}(\mathcal{H}, \mathcal{X})$: Decomposes shape into parts
- $\mathcal{L}_{rec}(\mathcal{P}, \mathcal{X})$: Predicted primitives match the shape
- $\mathcal{L}_{comp}(\mathcal{P}, \mathcal{X})$: Allows for variable number of primitives
- $\mathcal{L}_{prox}(\mathcal{P})$: Prevents vanishing gradients

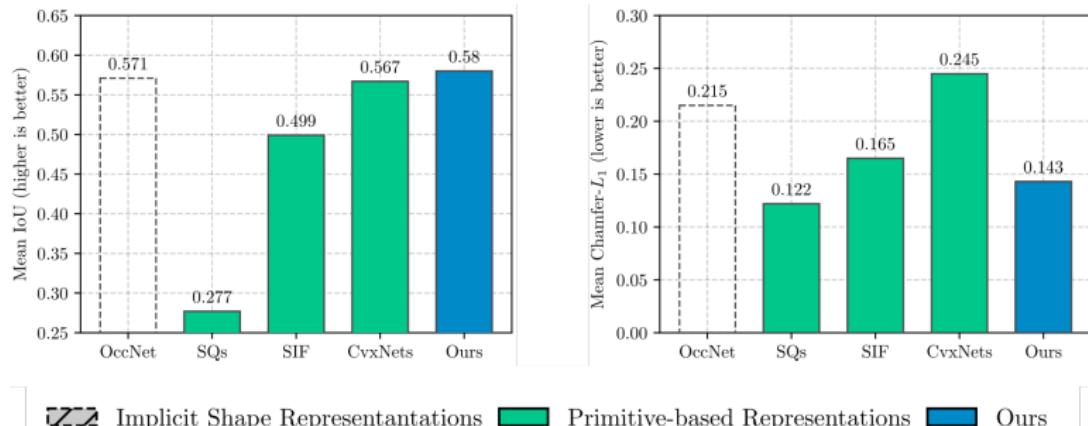
Expressive Shape Abstractions



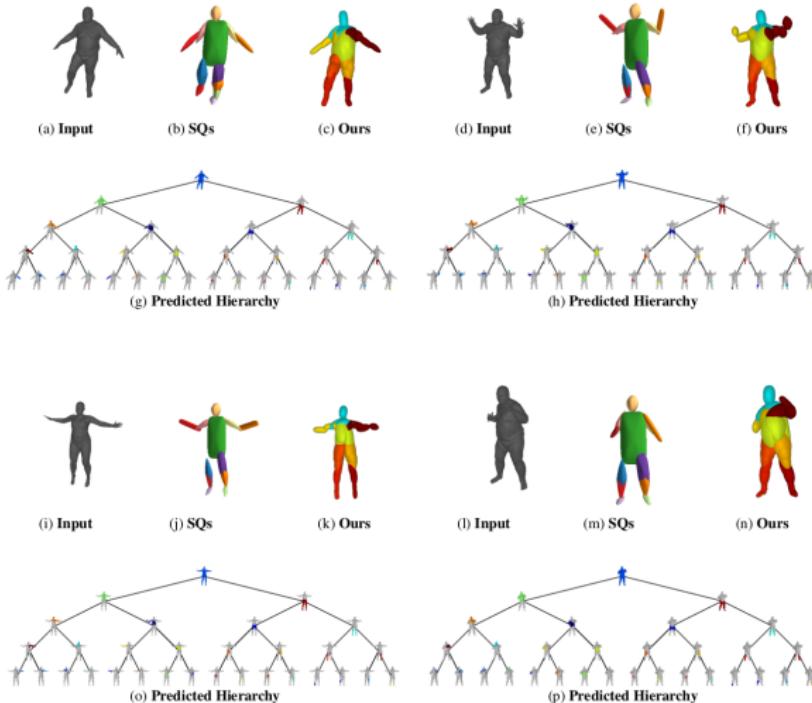
Single-view 3D Reconstruction on ShapeNet



Single-view 3D Reconstruction on ShapeNet



Single-view 3D Reconstruction on Dynamic FAUST



Semantic Interpretation of Learned Hierarchy



Learning Hierarchical Part Decomposition of 3D Objects

Limitations:

Learning Hierarchical Part Decomposition of 3D Objects

Limitations:

- Part decomposition does not guarantee semantic parts

Learning Hierarchical Part Decomposition of 3D Objects

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- Part decomposition does not guarantee semantic parts
- Fixed maximum tree depth

Learning Hierarchical Part Decomposition of 3D Objects

Limitations:

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- Occupancy loss (IoU) focuses less on fine details

Learning Hierarchical Part Decomposition of 3D Objects

Limitations:

- Part decomposition does not guarantee semantic parts
- Fixed maximum tree depth
- Occupancy loss (IoU) focuses less on fine details
- Superquadrics :-)

What comes next?

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- o Learning semantic parts
 - ▶ semanticness should not be enforced through geometry
 - ▶ consistency across pose and instances



Image Source: Shapira 2008

What comes next?

- Learning semantic parts
 - ▶ semanticness should not be enforced through geometry
 - ▶ consistency across pose and instances
- Recovering higher level semantics
 - ▶ predict object dynamics, skeletons, joints, etc.
 - ▶ single RGB image is not sufficient

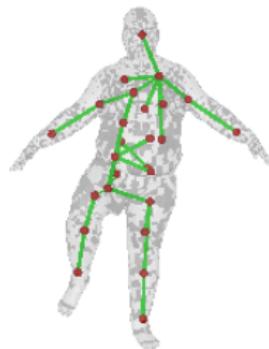


Image Source: Shapira 2008

What comes next?

- Learning semantic parts
 - ▶ semanticness should not be enforced through geometry
 - ▶ consistency across pose and instances
- Recovering higher level semantics
 - ▶ predict object dynamics, skeletons, joints, etc.
 - ▶ single RGB image is not sufficient
- More expressive primitives
 - ▶ trade-off between parsimony and geometrically accurate reconstruction

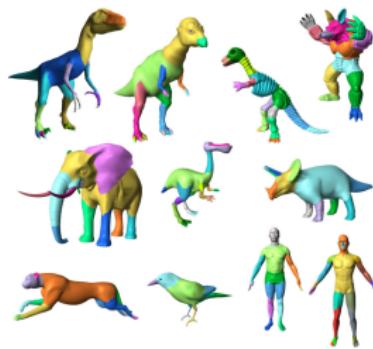


Image Source: Shapira 2008

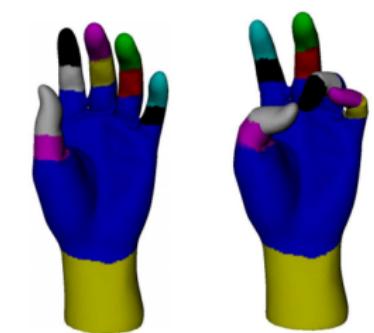
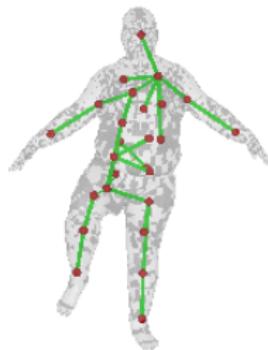


Image Source: Tierny 2007

Thank you for your attention!

<https://superquadrics.com/>