

# PQ-NET: A Generative Part Seq2Seq Network for 3D Shapes

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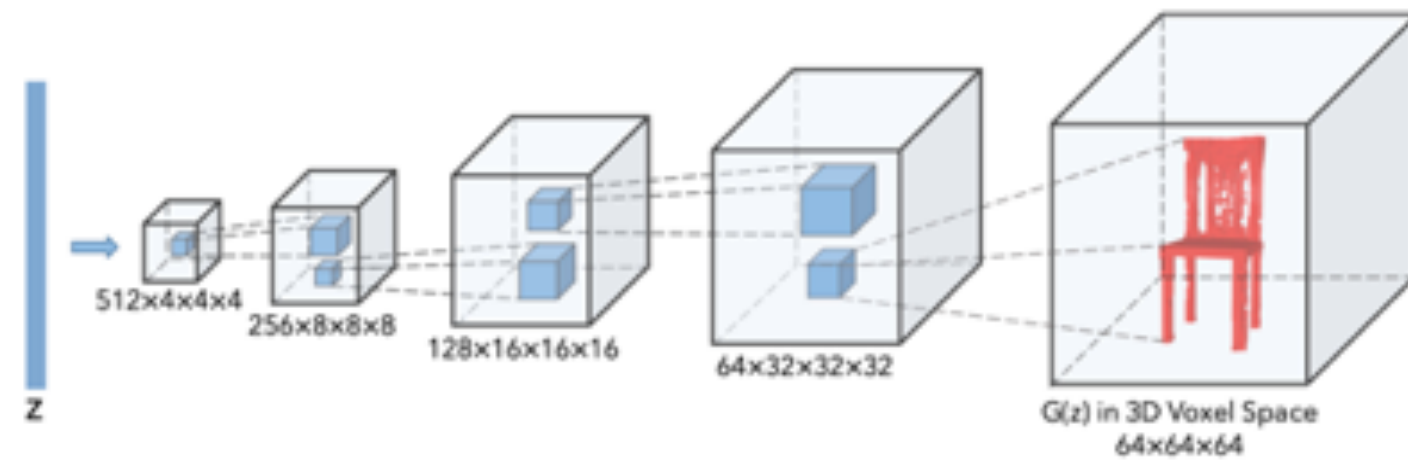
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# 3D shape generation

## Voxel grid

[3DGAN, NIPS 2016]



## Point cloud

[Pointflow, ICCV 2019]



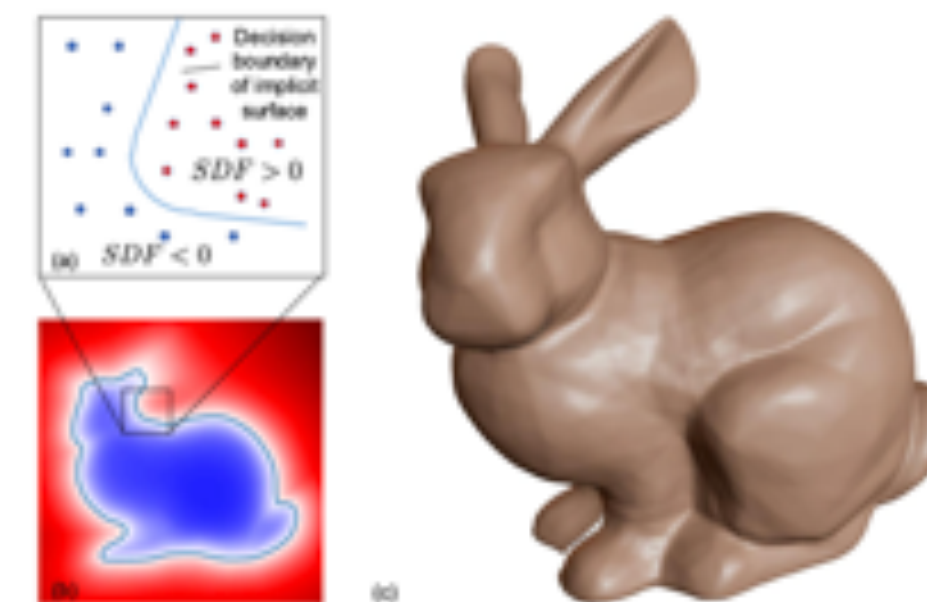
## Mesh

[AtlasNet, CVPR 2018]



## Implicit function

[DeepSDF, CVPR 2019]

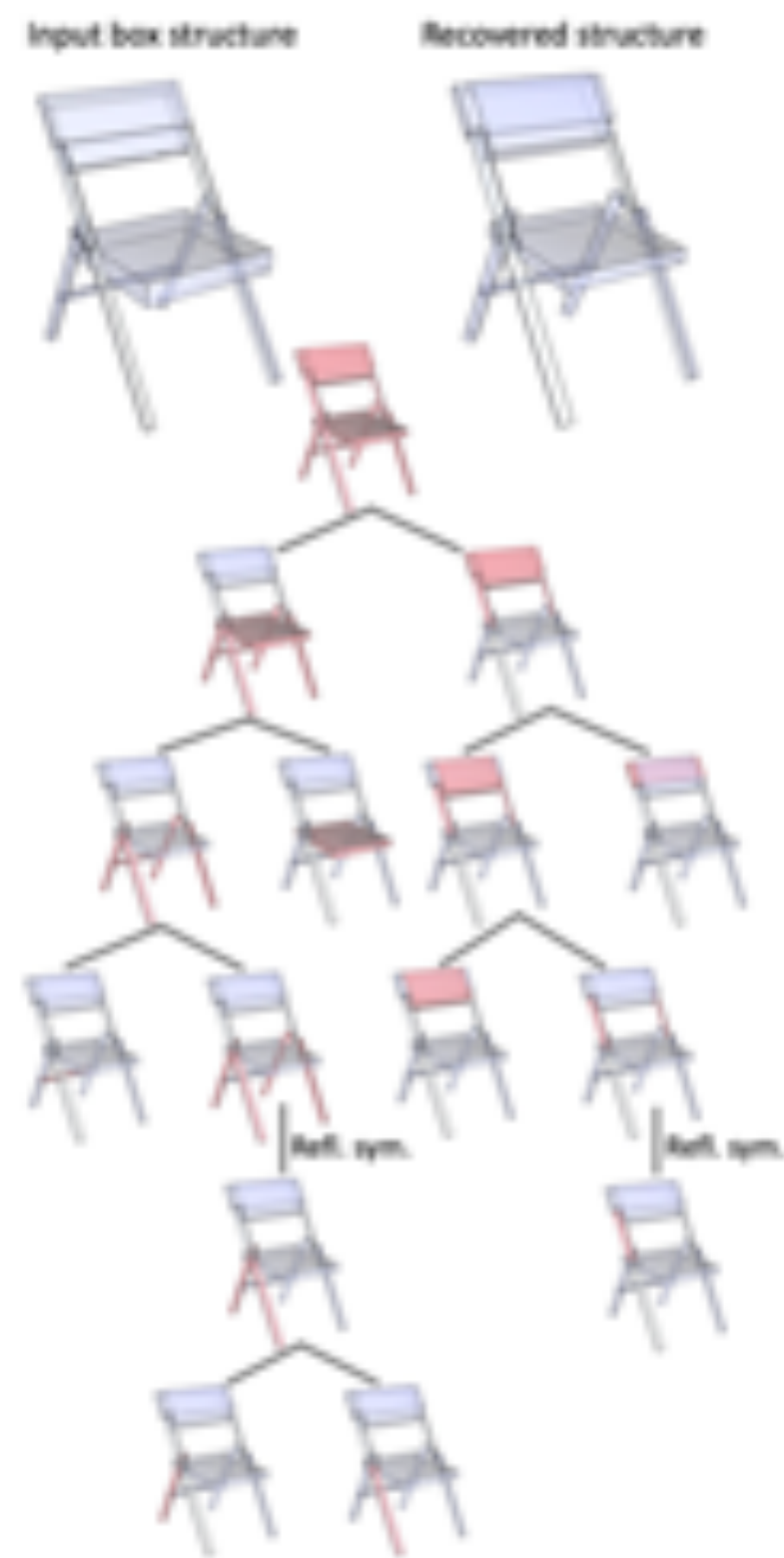


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3. T. Groueix, M. Fisher, V. G. Kim, B. C. Russell, and M. Aubry. A papier-mâché approach to learning 3d surface generation. In *Proc. CVPR*, pages 216–224, 2018.
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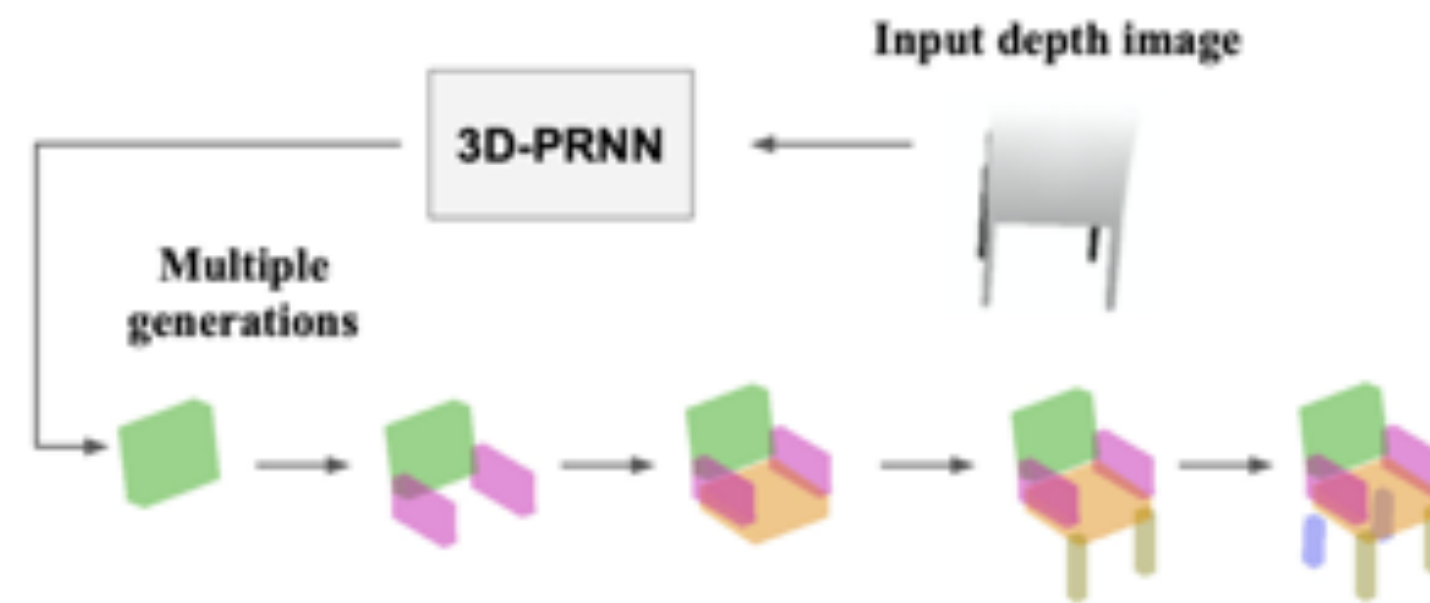


# Structural 3D shape generation

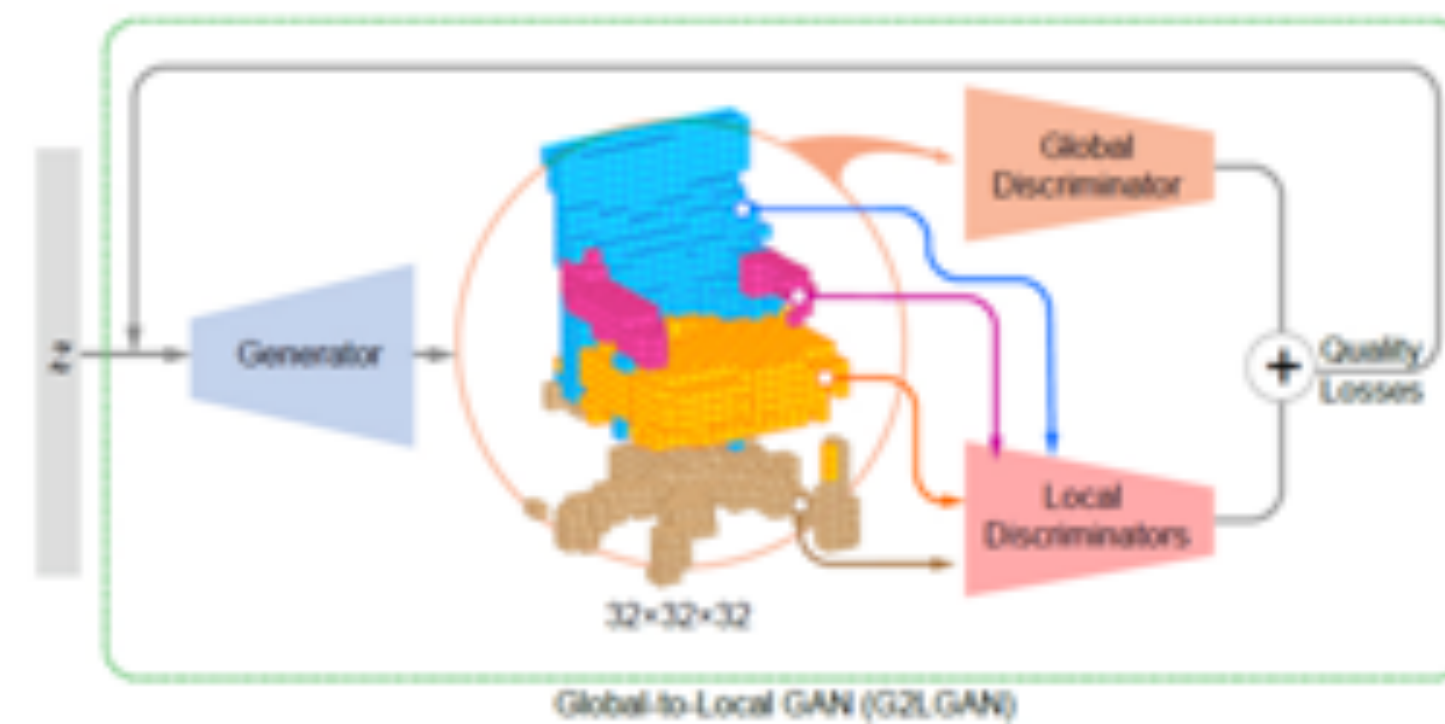
[GRASS<sup>1</sup>, SIG 2017]



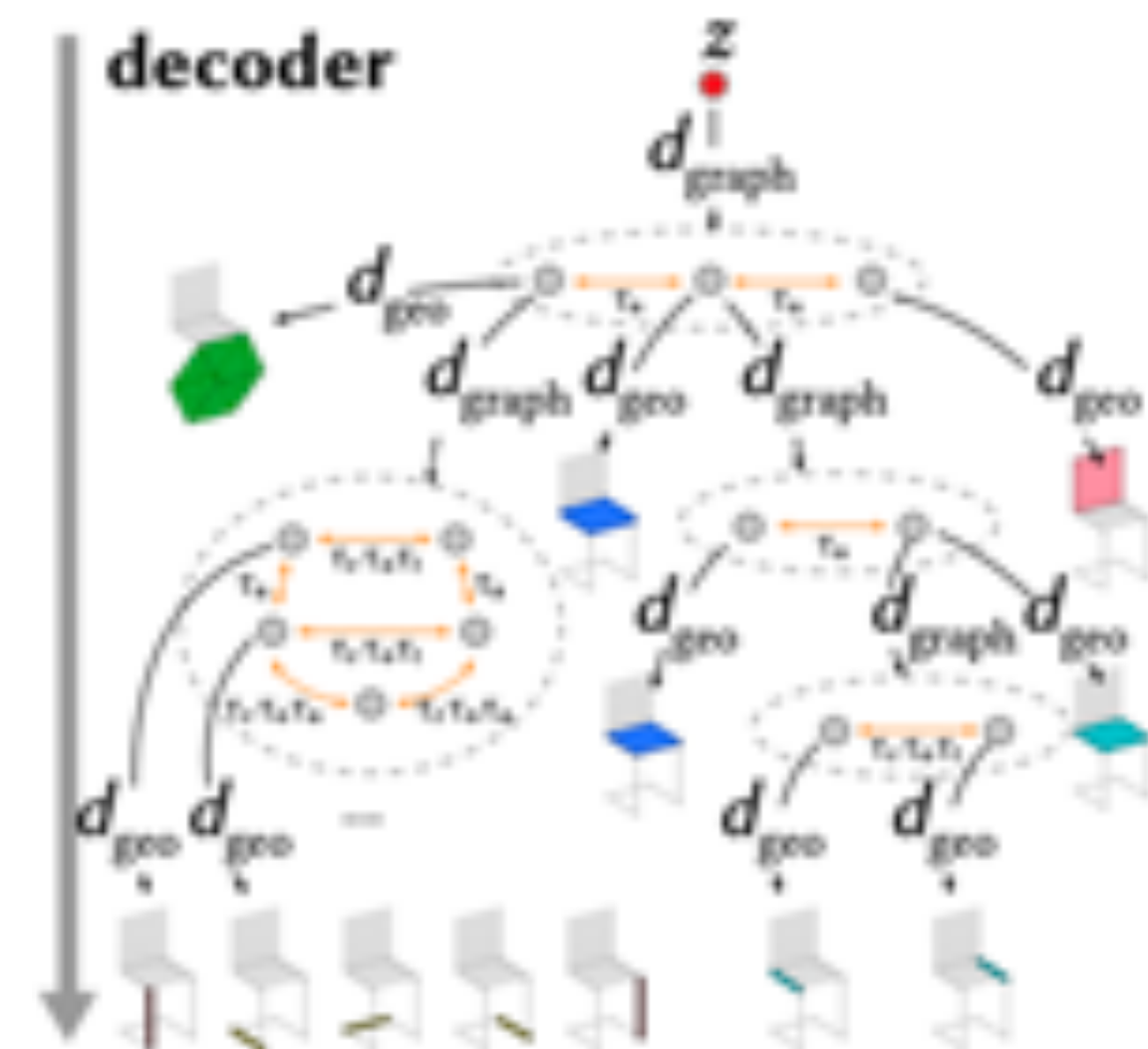
[3D-PRNN<sup>2</sup>, ICCV 2017]



[G2L<sup>3</sup>, SIGA 2018]



[StructureNet<sup>4</sup>, SIGA 2019]

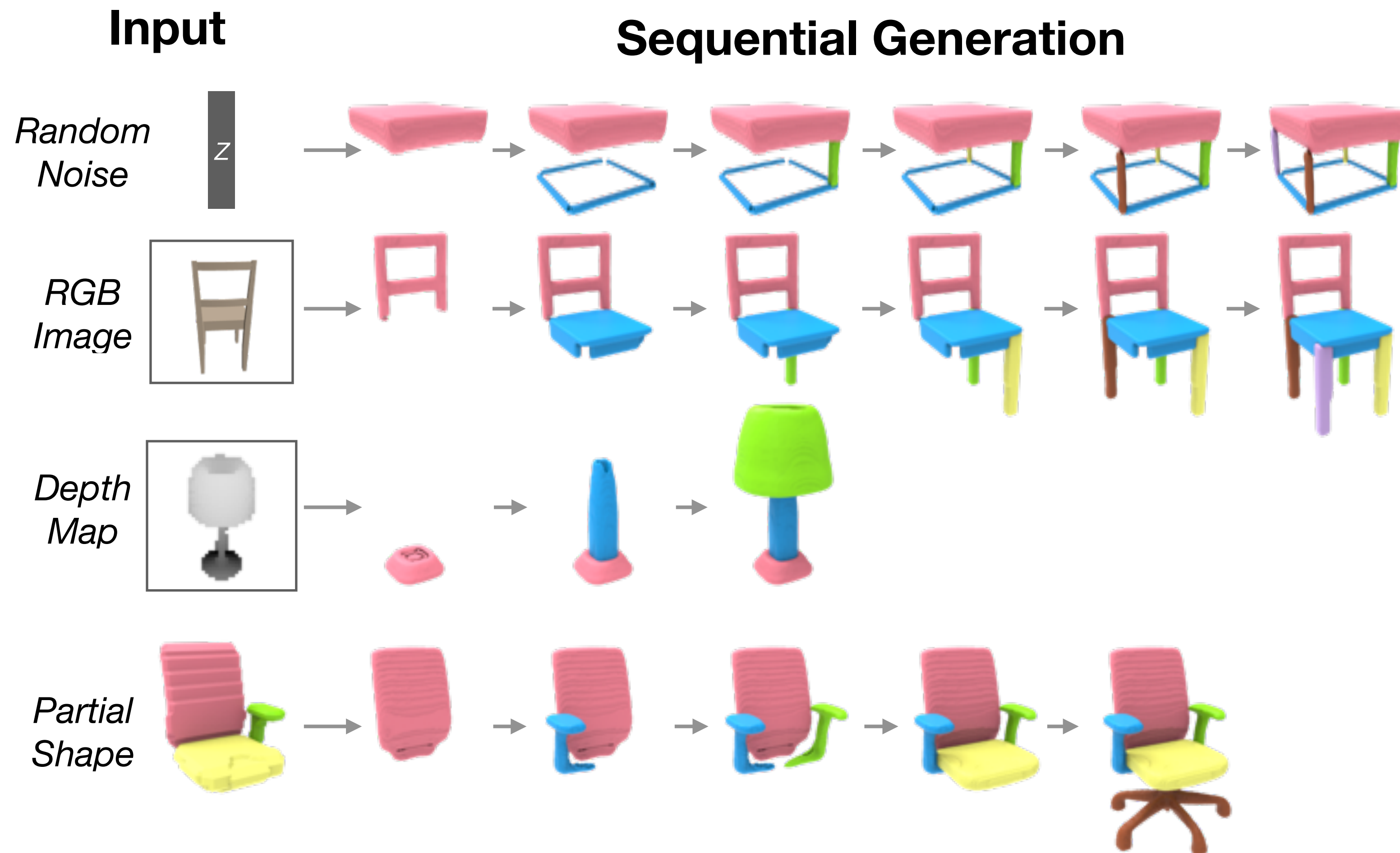


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2. C. Zou, E. Yumer, J. Yang, D. Ceylan, and D. Hoiem. 3D-PRNN: Generating shape primitives with recurrent neural networks. *2017 IEEE International Conference on Computer Vision (ICCV)*, Oct 2017.
3. H. Wang, N. Schor, R. Hu, H. Huang, D. Cohen-Or, and H. Huang. Global-to-local generative model for 3d shapes. *ACM Transactions on Graphics (Proc. SIGGRAPH ASIA)*, 37(6):214:1214:10, 2018.
4. K. Mo, P. Guerrero, L. Yi, H. Su, P. Wonka, N. Mitra, and L. J. Guibas. Structurenet: Hierarchical graph networks for 3d shape generation. *ACM Trans. on Graph. (SIGGRAPH Asia)*, 2019.



# Generate as a sequence

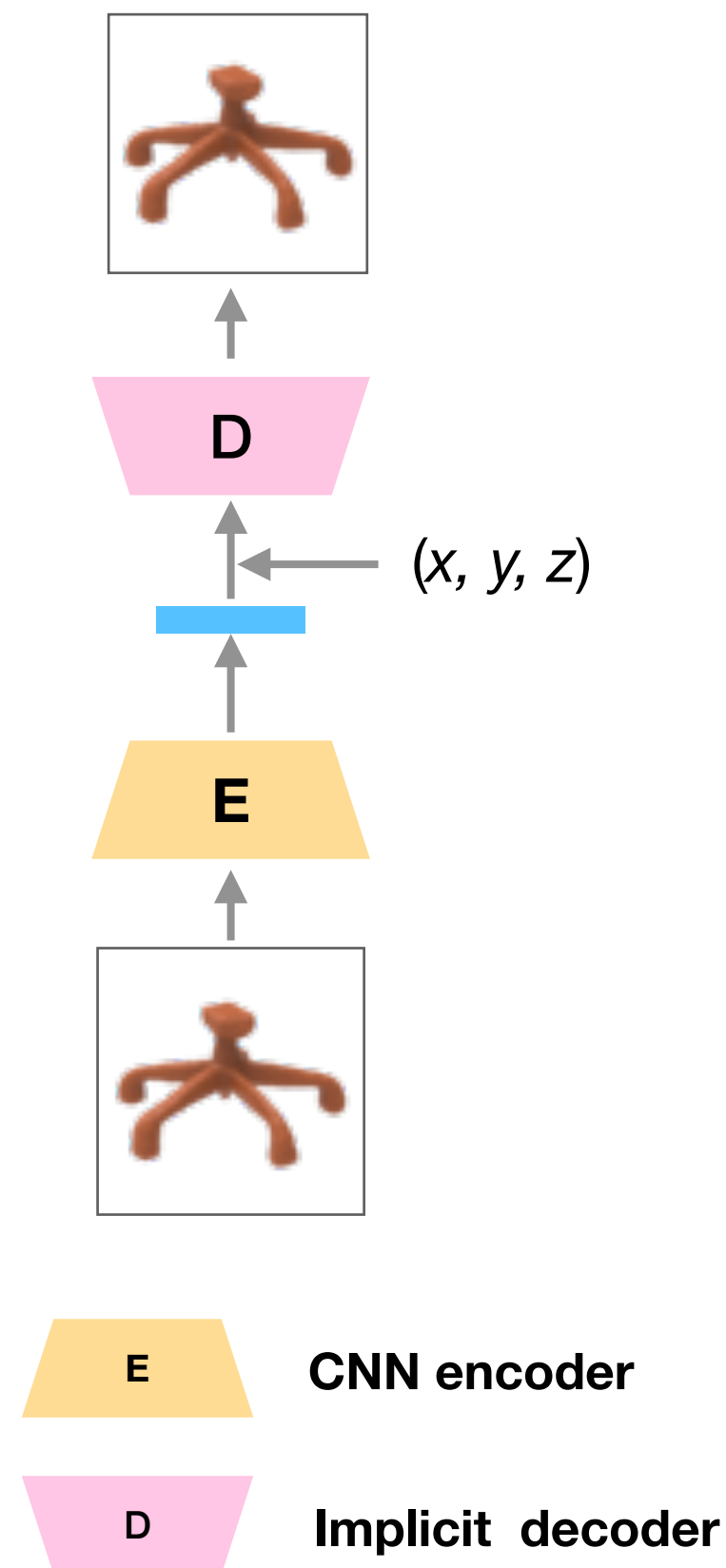
- Our network, PQ-NET, learns 3D shape representation via *sequential part assembly*



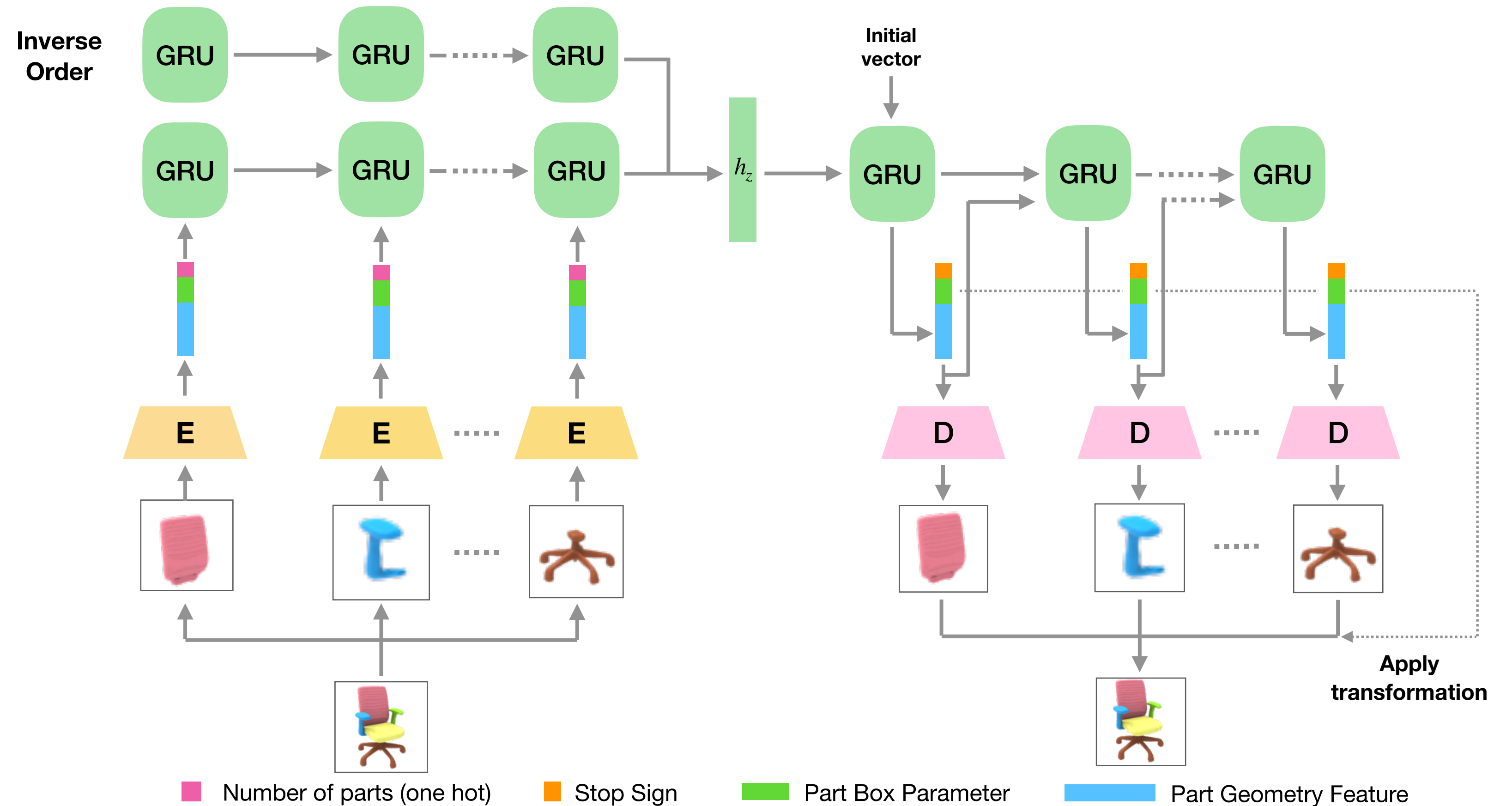
# Method

- Apply IM-NET to encode each scaled part's geometry
- Model sequential part assembly using a Sequence-to-Sequence Auto-encoder (Seq2Seq AE)

a) Part Geometry Encoding



b) Sequential Part Assembly and Generation





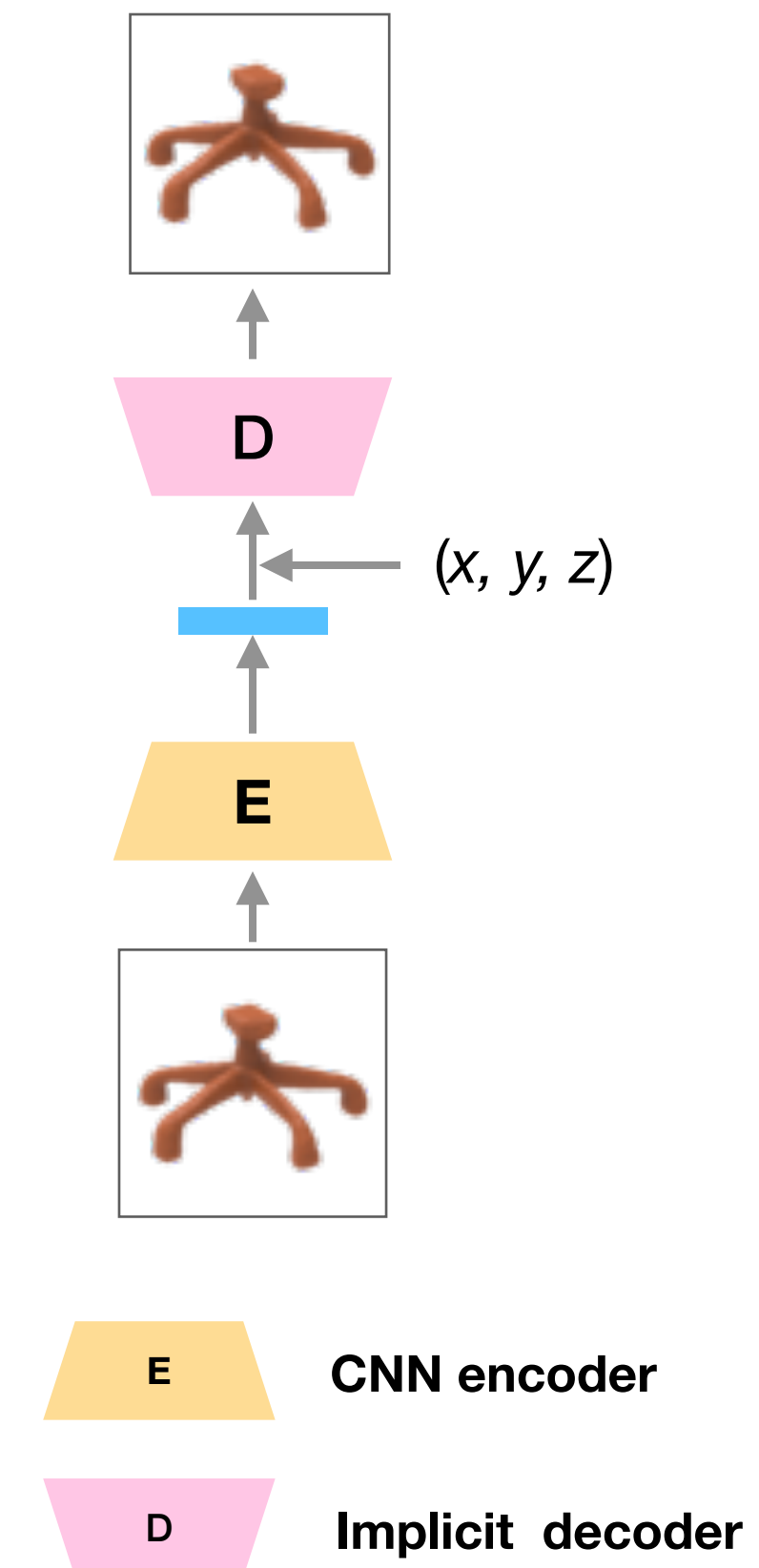
# Method - Part geometry encoding

Similar architecture as IM-NET<sup>1</sup>:

- a CNN encoder  $e$  maps  $64^3$  voxelized part  $P$  to 128D vector
- a MLP decoder  $d$  that predicts the occupancy of a given point  $p$

$$\mathcal{L}(P) = \mathbb{E}_{p \in T_P} |d(e(P), p) - \mathcal{F}(p)|^2$$

A set of sampled points from  $P$                       ground truth signed function

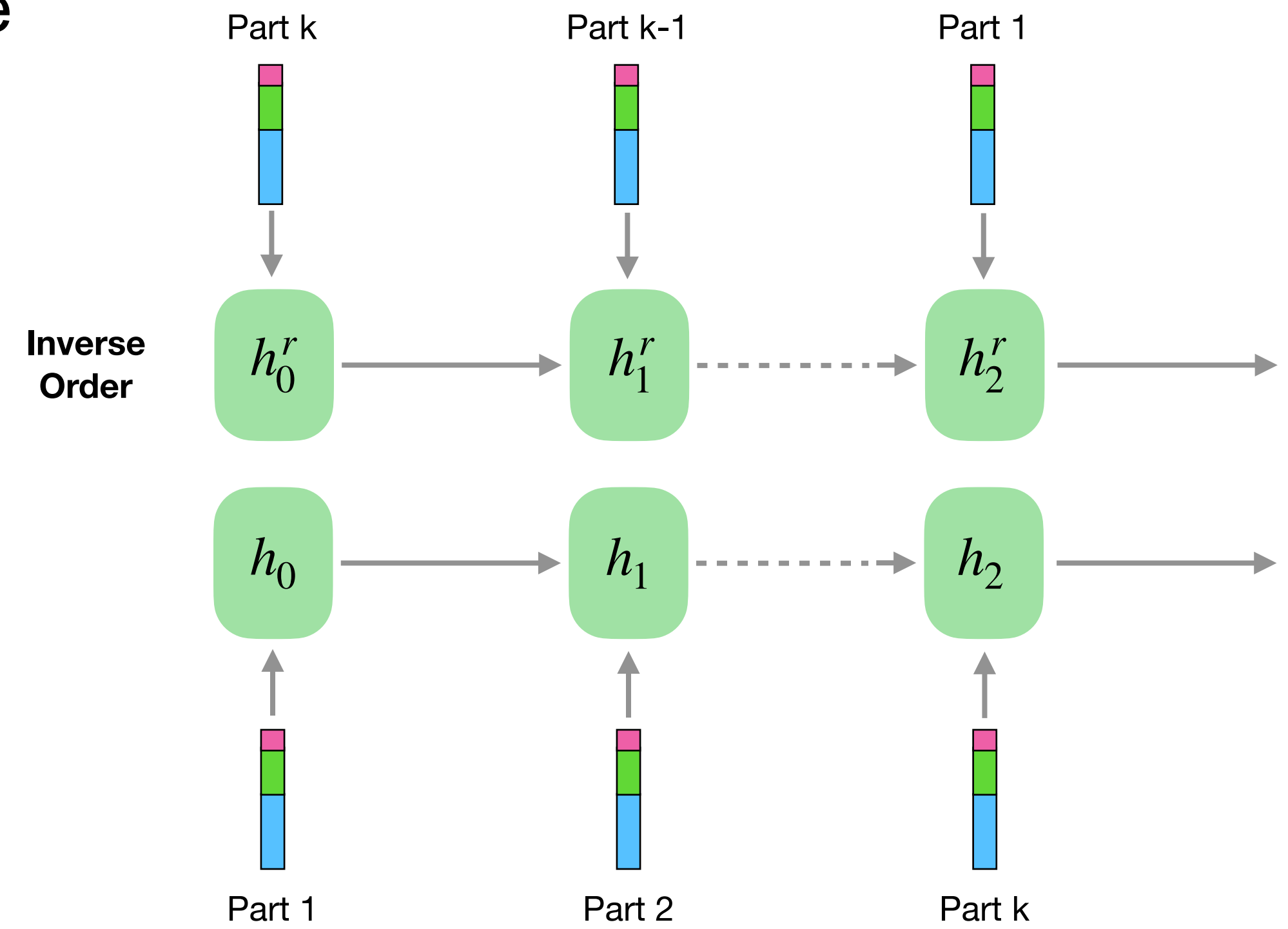
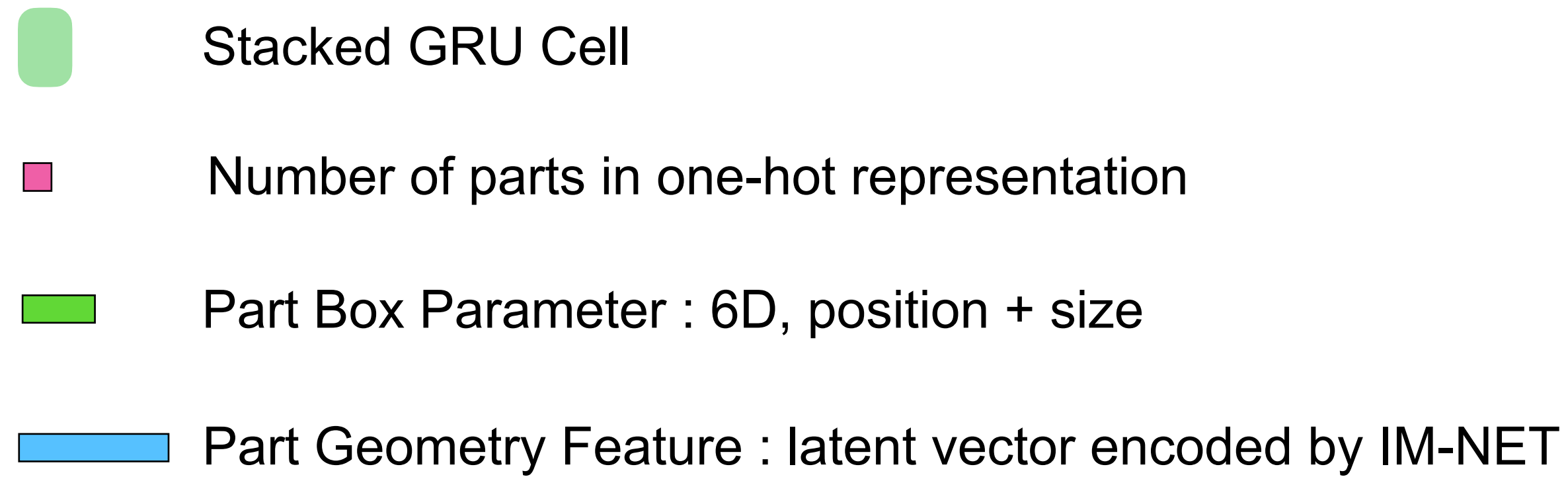


1. Z. Chen and H. Zhang. Learning implicit fields for generative shape modeling. *Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019.

# Method - Seq2Seq AE

Encoder :

- a bidirectional stacked RNN to encode part sequence

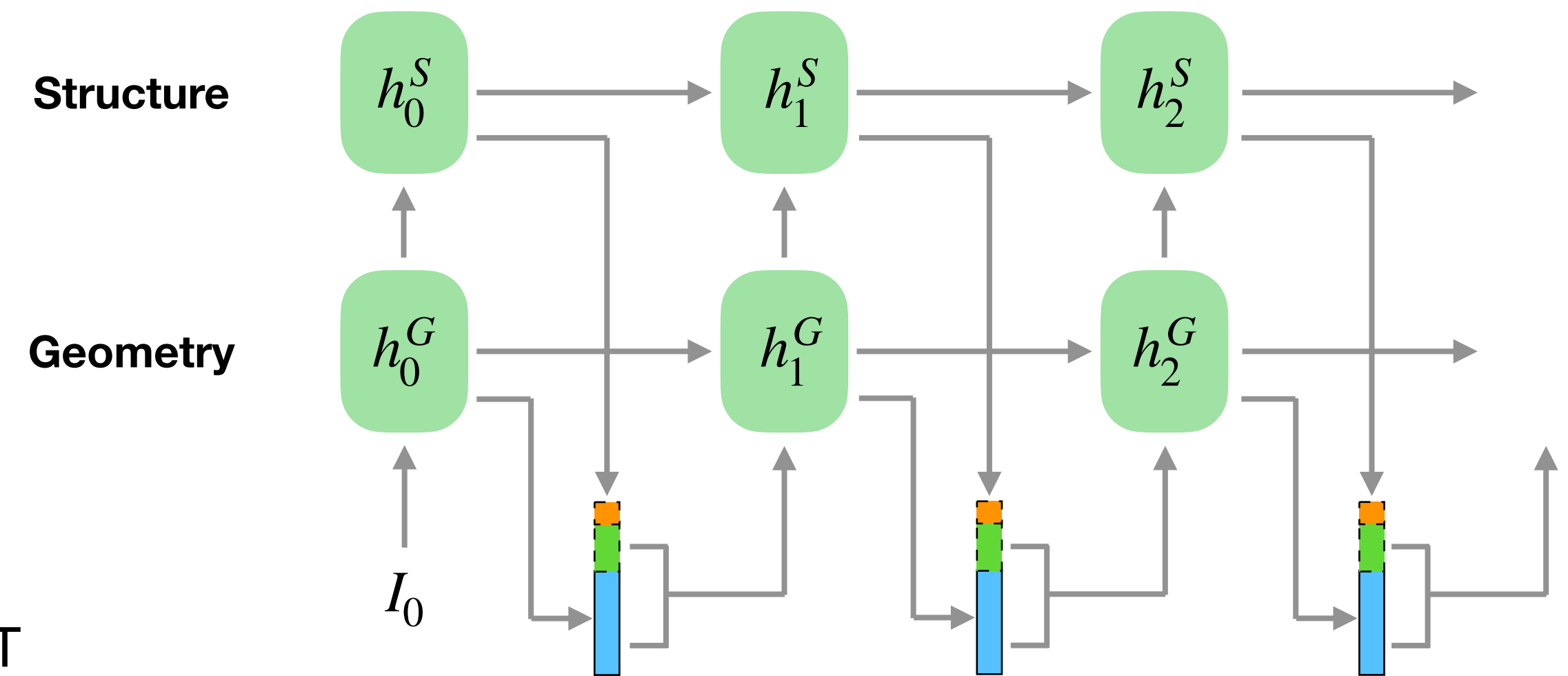
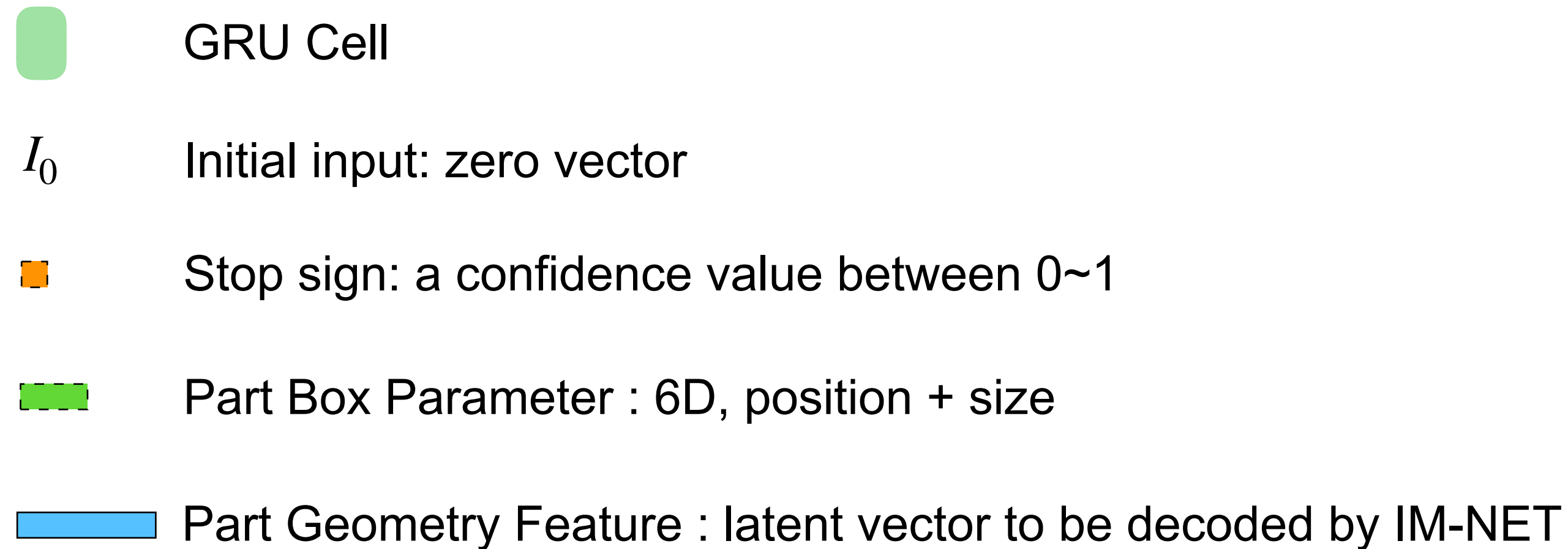




# Method - Seq2Seq AE

Decoder :

- a stacked RNN to predict geometry and structure feature separately

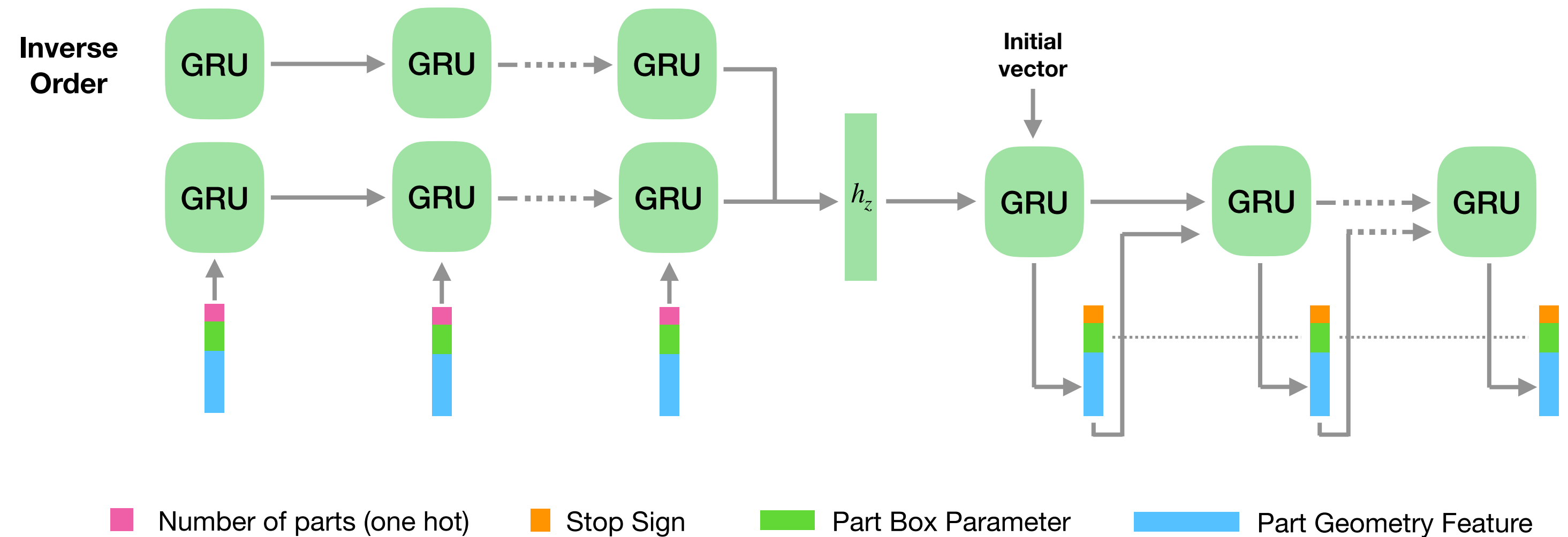


# Method - Seq2Seq AE

## Training losses

- *MSE* loss on the reconstruction of geometry feature  $g_i$  and structure feature  $b_i$
- *Binary Cross Entropy* loss on the stop sign  $s_i$  predicted by decoder

$$\mathcal{L}_r(S) = \frac{1}{k} \sum_{i=1}^k [\beta \|g'_i - g_i\|_2 + \|b'_i - b_i\|_2]$$
$$\mathcal{L}_{\text{stop}}(S) = \frac{1}{k} \sum_{i=1}^k [-s_i \log s'_i - (1 - s_i) \log(1 - s'_i)]$$



# Results : shape auto-encoding

a) Ground Truth



b) IM-NET-256



c) Ours-256



Metrics	Method	Chair	Table	Lamp
IoU	Ours-64	<b>67.29</b>	47.39	39.56
	IM-NET-64	62.93	<b>56.14</b>	<b>41.29</b>
CD	Ours-64	3.38	5.49	11.49
	Ours-256	2.86	5.69	10.32
	Ours-Cross-256	<b>2.46</b>	<b>4.50</b>	<b>4.87</b>
	IM-NET-64	3.64	6.75	12.43
	IM-NET-256	3.59	6.31	12.19
LFD	Ours-64	2734	2824	6254
	Ours-256	<b>2441</b>	2609	5941
	Ours-Cross-256	2501	<b>2415</b>	<b>4875</b>
	IM-NET-64	2830	3446	6262
	IM-NET-256	2794	3397	6622



# Results : shape generation

a) Ours



b) IM-NET



c) StructureNet



Category	Method	COV	MMD	JSD
Chair	Ours	<b>54.91</b>	8.34	<b>0.0083</b>
	IM-NET	52.35	<b>7.44</b>	0.0084
	StructureNet	29.51	9.67	0.0477
Table	Ours	56.51	7.56	0.0057
	IM-NET	<b>56.67</b>	<b>6.90</b>	<b>0.0047</b>
	StructureNet	16.04	14.98	0.0725
Lamp	Ours	<b>87.95</b>	<b>10.01</b>	<b>0.0215</b>
	IM-NET	81.25	10.45	0.0230
	StructureNet	35.27	17.29	0.1719



# Results : shape generation



# Results : latent space interpolation





# Results : single view reconstruction

a) Input image



b) IM-NET



c) Ours

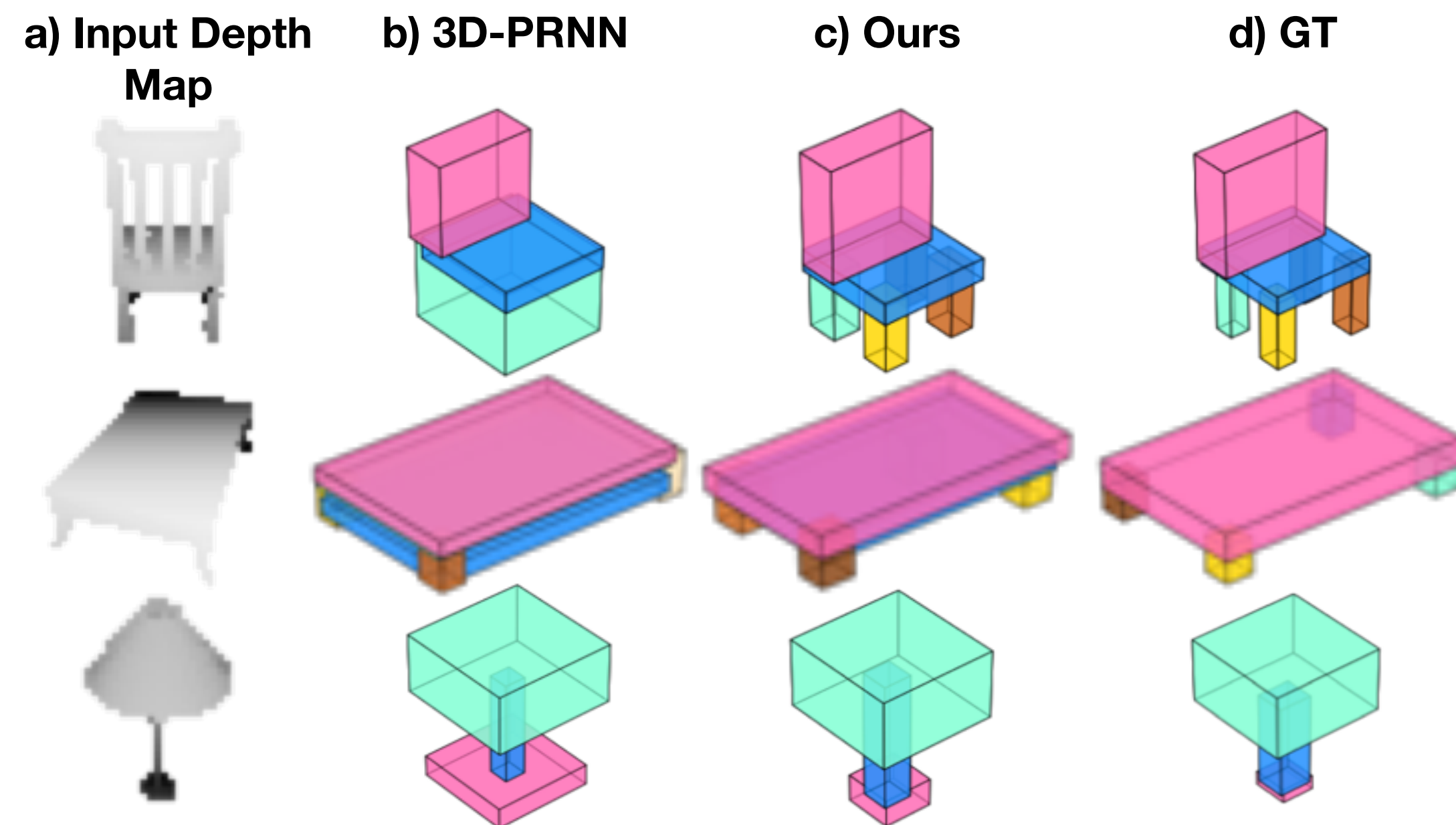


d) Ground Truth



# Results : comparison to 3D-PRNN

- Shape reconstruction from single depth image
- Compare on two orders: (A) PartNet default (B) enforced top-down

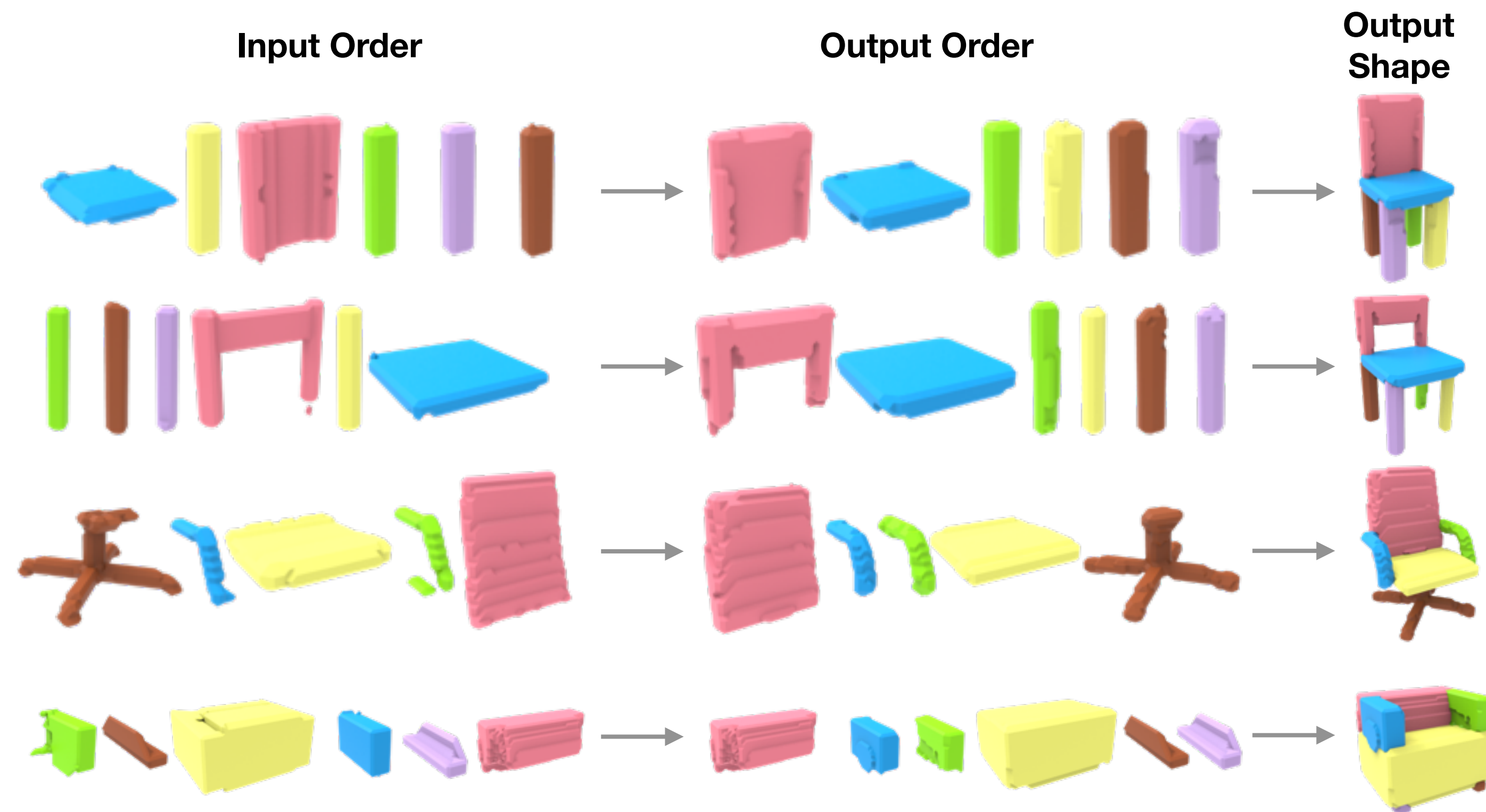


Method	Order	Chair	Table	Lamp	Average
Ours	A	<b>61.47</b>	<b>53.67</b>	<b>52.94</b>	<b>56.03</b>
	B	58.68	48.58	52.17	53.14
3D-PRNN	A	37.26	51.30	47.26	45.27
	B	36.46	51.93	43.83	44.07



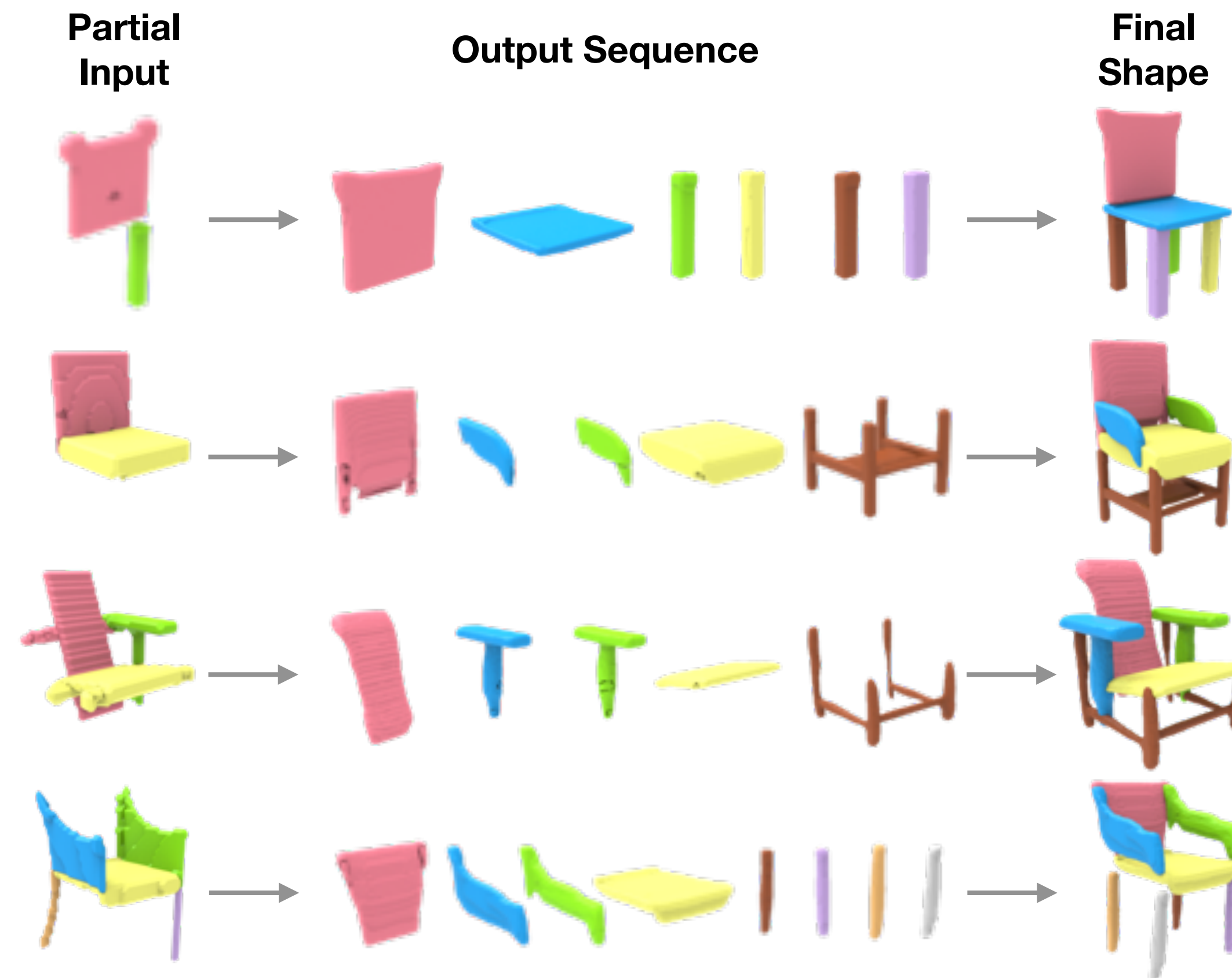
# Results : applications

- Order denoising and part correspondence
  - Re-train the model the correct the input order



# Results : applications

- Partial shape completion
  - Re-train the model to reconstruct from partial shape input



# Limitation

- PQ-NET do not produce part relations
  - Comparing to prior works that seek to hierarchical representation
- The order of parts could affect the performance
  - A consistent part order over the dataset is required

# Thanks!

Code and data: <https://github.com/ChrisWu1997/PQ-NET>