Abstract

Single-image 3D shape reconstruction is an important and long-standing problem in computer vision. A plethora of existing works is constantly pushing the state-of-the-art performance in the deep learning era. However, there remains a much difficult and largely under-explored issue on how to generalize the learned skills over novel unseen object categories that have very different shape geometry distribution. In this paper, we bring in the concept of compositional generalizability and propose a novel framework that factorizes the 3D shape reconstruction problem into proper sub-problems, each of which is tackled by a carefully designed neural sub-module with generalizability guarantee. The intuition behind our formulation is that object parts (e.g., slates and cylindrical parts), their relationships (e.g., adjacency, equal-length and parallelism) and shape substructures (e.g., T-junctions and a symmetric group of parts) are mostly shared across object categories, even though the object geometry may look very different (e.g., chairs and cabinets). Experiments on PartNet show that we achieve superior performance than baseline methods, which validates our problem factorization and network designs.

1. Introduction

Single-image 3D reconstruction is a critical and long-standing problem in computer vision. Existing works in the literature of 3D deep learning [4, 7, 50, 3, 28, 35] mostly focus on designing better network architectures for decoding 3D geometry from 2D image inputs, assuming that the training and test data come from the same or similar object categories.

We are interested in a much harder setting, where the training and test objects from different categories might follow very different whole-object level shape distribution, they often share similar distribution in terms of “substructures”. For example, among all man-made objects, slates and cylindrical parts are quite common. And
among all possible configurations of parts, parallel and T-junction relationships are more frequently observed. Taking the Bayesian’s view, the joint probability $Pr(p_1, p_2, \ldots, p_n)$ of all substructures could be very different across training and test sets. However, if we factorize the joint probability as products of low-order potentials $\phi(p_i)$ and $\phi(p_j)$, these potentials are often much better aligned. This motivates us to factorize the problem of shape reconstruction into subproblems of substructure prediction, which has the potential of being more generalizable cross categories.

We refer this factorization-enabled generalizability as *compositional generalizability* [33, 26]. In this framework, our goal boils down to factorizing the 3D shape reconstruction problem into proper sub-problems, which individually are likely to be transferable to the unknown test set, and together can be coupled to create the whole shape.

Toward this end, we leverage a structured parameterization of objects for 3D shape prediction. This parameterization provides a rich space of sub-problems, allowing us to identify good ones with strong cross-category transferrability. Specifically, we view 3D shapes as structured entities composed by a set of part primitives. We use oriented cuboids to represent the parts and we parameterize a 3D shape by connectivity, orientation, and scale of part cuboids. Notice that instead of focusing on fine geometry, this representation encodes abstract structure, which facilitates many applications that require structure-level reasoning [47, 30, 31].

To predict such structured shapes from an input image, we identify a series of sub-problems exhibiting strong transferrability across categories. We present modules to solve each of these sub-problems, which together form a modularized pipeline. In particular, our final design consists of five modules: (1) we first learn to predict part masks from the input image; (2) then, we learn to predict prominent relationships between parts, including parallelism, translational symmetry and part adjacency; (3) we group parallel parts and predict part cuboid edge direction for each group; (4) we group parts with translational symmetry and predict part cuboid edge length for each group, and (5) based on the predicted adjacency relationship, edge direction, and edge length, we predict relative positions between adjacent parts and assemble parts into a whole shape. Notice the modules have intrinsic dependencies, by which we generate the above ordering.

In this pipeline, Module (1) is essentially the standard instance segmentation problem, which has been studied vastly in the literature. For all the rest modules, we have carefully designed neural networks to achieve good cross-category transferrability. We heavily employ two principles behind all these designs: (a) *Isolation principle*: when making predictions for each part, we isolate information irrelevant to this part as much as possible, *e.g.*, by only keeping its own mask in the input and by mitigating unnecessary information interaction across parts in the network design. This isolation principle imposes inductive-bias so that the learned networks correspond to low-order potentials over substructures; (b) *Relativity principle*: we infer the geometry of parts based on their relative relationship as much as we can, *e.g.*, by predicting the relative position between parts instead of the absolusion position of each, and by grouping parts based on pairwise parallelism or translational symmetry for orientation and scale prediction. This is in contrast to common practices in literature, such as [60] that infers the absolute depth of each pixel, and [22] that infers the absolute translation of each part.

In summary, our contributions are three-fold. First, we are the first to explore compositional generalizability for single-view 3D structure prediction with a focus of generalizing to unseen object categories. Second, we identify proper sub-problems for single-view 3D structure prediction and we carefully design a modularized pipeline to solve each of these sub-problems in a transferrable manner. Third, we demonstrate significant improvement over prior arts and provide extensive analysis to justify our designs.

2. Related Work

We review previous works on reconstructing 3D shape from single images and part-based shape modeling, along with discussions and comparisons to our approach.

**Single-image 3D Shape Reconstruction.** Estimating 3D geometry from 2D single images is a long-standing problem in computer vision. Due to its ill-posed nature, learning-based methods [4, 45, 51, 39, 7, 24, 14, 50, 52, 11, 3, 28, 35, 40, 57] are proven effective recently since they can learn shape priors from training data. However, most of these works assume the alignment of the training and testing data distributions, *e.g.* either from the same object category or among multiple similar categories. Even though some works, such as [7], show that their methods, if trained in a category-agnostic manner over a large set of object categories, can reconstruct 3D shapes from novel categories, there are no explicit designs to guarantee such desired properties. Tatarchenko et al. [45] demonstrated that state-of-the-art single-image 3D shape reconstruction methods tend to memorize the training shapes and perform retrieval at the testing time. In our work, we design explicit network modules to discover part relationships and shape sub-structures that are shared across different object categories to gain better reconstruction generalization across category gaps.

It is an under-explored problem to extrapolate the reconstruction capabilities over out-of-the-distribution novel categories. GenRe [60] proposes to factorize the problem into a sequence of sub-tasks – depth estimation, depth spherical map inpainting, voxel-based 3D refinement, and observes better generalization capability to unseen testing object cate-
categories. GSIR [49] further extends the GenRe approach by bringing in the part structure information. Different from these two works that leverage depth as intermediate steps for generability, our approach learns to discover part relationships and shape sub-structures that are commonly shared among man-made object categories. Wallace et al. [48] and Michalkiewicz et al. [29] propose few-shot learning frameworks to quickly adapt the learned shape priors to novel categories. Our method uses a zero-shot setting that no data from the testing categories is needed at all.

**Part-based Shape Structure Modeling.** Most 3D shapes are composed of sub-structures and parts. While most previous works mentioned above reconstruct 3D shape geometry as a whole entity, understanding shape structures and parts is a crucial perception task for robotic manipulation [18, 27, 56], shape generation [21, 6, 41, 53, 8, 30, 20, 16, 46] and editing [19, 58, 31, 44].

There are many recent works that learn to abstract shape parts using primitive shapes, such as cuboids [47, 62, 43], superquadrics [37, 36], mixtures of Gaussians [9, 10], convex hulls [5], etc. However, these works do not explicitly consider part relationships, such as the part adjacency and symmetry constraints. In this paper, we explicitly discover and model such part relationships not only for better reconstruction results, but also for generalizing to novel categories that share similar part structures.

Previous works studied various ways for modeling part relationships and constraints. Early works [2, 17, 15] studied pairwise part relationships using probabilistic graphical models. More recently, GRASS [21], Im2Struct [34] and StructureNet [30] organize parts in tree structures and also model part adjacency and symmetry constraints among sibling parts. SAGNet [55] and SDM-Net [8] also design explicit network modules to learn pairwise part relationships for shape generation. Recent papers [23, 13] learns part relationships for part assembly via graph neural networks. Though working well within a collection of shapes from the same object category or very similar categories, most of these works failed to generalize to novel categories, which is the central goal of our work.

### 3. Problem Statement

Given an Image $I$ of an object $O$, our goal is to predict the 3D structure of $O$, which is represented as an assembly of geometric primitives $\{p_i\}$. In our case, we adopt oriented bounding cuboids for each primitive following StructureNet [30], i.e., $p_i = [c_x, c_y, c_z, s_x, s_y, s_z, q]$, where $(c_x, c_y, c_z)$ denotes the center location, $(s_x, s_y, s_z)$ represents the length of each edge, and $q \in \mathbb{R}^4$ corresponds to the quaternion representation of the rotation.

Especially, we focus on the relative position between a pair of parts $(c_x^1 - c_x^2, c_y^1 - c_y^2, c_z^1 - c_z^2)$, in that the absolute position is more sensitive to the choice of the coordinate system, i.e., camera space or world space. In our case, an object-level shift of center location is allowed, as long as the relative positions between pairs keep. If not specified, the pose $(c_x, c_y, c_z, q)$ is defined in the world space.

The learning of all the modules in our work are supervised. During training, the groundtruth part instance segmentation masks and the ground-truth parameters of the oriented bounding cuboids are provided. In practice, the images are rendered from the CAD models in ShapeNet [1], and the ground-truth part decomposition and part parameters are generated according to 3D labels in PartNet [32]. The oriented bounding cuboid of a part are computed using Pinciple Component Analysis (PCA) according to its part geometry.

### 4. Method

Compared to previous methods, our proposed algorithm is trained only on the chair category and can generalize to unseen categories, such as bed, cabinet, and table. The key observation is that shapes across categories share similar parts and local part relationships, supporting compositional generalizability.

In our pipeline, we first learn to predict part masks using MaskRCNN [12], a well-established object instance segmentation approach (Sec 4.1). In Sec 4.2 and Sec 4.3, we introduce how to predict the direction and size of the oriented bounding cuboid for each part. Finally, in Sec 4.4, we introduce how to assemble the predicted cuboids into a complete shape.

#### 4.1. Part Instance Segmentation

The first step of our pipeline is to obtain the mask of each part in the input image. The goal of this step is exactly the same as the classical instance-level object segmentation problem. Due to the popularity of research into instance-level segmentation, we do not treat this step as the focus of our work. Instead, we borrow existing methods to obtain the part masks. Particularly, we choose the well-established MaskRCNN [12] and train it using the finest part masks rendered from PartNet. Please refer to Sec D.1 in the supplementary material for details.

It is reasonable to expect that learning-based approaches can transfer across categories for primitive-level part detection and segmentation. In our daily experience, though objects from different categories vary a lot in geometry, their part appearance usually share a lot similarity, especially for man-made objects. Such part-level similarity could be attributed to many factors, such as to fulfill affordance constraints (thin bars are suitable for grasping), manufacturing constraints (planes are easier to machining), and functionality constraints (wheels enable laborless movement). Besides, primitive parts tend to be made by the same material and
Figure 2: Our single-view 3D structure prediction pipeline. To extract the 3D structure from a single input image, we go through the following pipeline: (a) we apply MaskRCNN to extract the part instance masks; (b) we identify parallelism for part pairs, form parallel part groups, and predict the shared edge directions for each group; (c) we identify translational symmetry within part pairs, group parts with equal size, and predict the shared edge length; (d) we predict the connectivity for part pairs and extract a connectivity-based part tree; (e) we predict the relative position between adjacent parts and assemble the whole shape while traversing the part tree. We heavily use part masks as module inputs to induce a focus on local regions following the isolation principle. And we rely on pairwise relationships from (b)-(e) which reflects the relativity principle.

4.2. Part Cuboid Edge Direction Prediction

To represent the orientation of each part cuboid, we leverage the principal axes directions, which we refer to as edge directions. Provided with an image and a binary mask of each part, we design a neural network to estimate such edge directions. Specifically, we encode edge directions with a rotation matrix where each unit vector in a row corresponds to one edge and the network simply needs to regress the rotation, we evaluate its effect on a unit cube and define a proxy loss using the cube geometry. To be specific, the geometry of the unit cube is represented by its 8 vertices, denoted by $P_{cube} \in \mathbb{R}^{8 \times 3}$. The ground truth and predicted rotations are denoted by $R$ and $\hat{R}$. The objective is to minimize a geometric loss $L_1 = D(P_{cube} R^T, P_{cube}\hat{R}^T)$ between the rotated unit cube $P_{cube} R^T$ and the ground truth unit cube $P_{cube}\hat{R}^T$, where $D(\cdot, \cdot)$ is a distance measurement which could be either Chamfer Distance or Earth Mover’s Distance. We supervise a ResNet to predict $\hat{R}$.

However, combining the geometric loss with a single-branch ResNet fails to solve the problem nicely in practice. This is mainly due to its vulnerability to local minimum caused by the network initialization. To ease the optimization, we introduce Mixture of Experts Network (MOE). Concretely, given the features extracted by the backbone, multiple branches (a.k.a. “experts”) are applied to predict multiple rotations $\{\hat{R}_j\}$ as well as probabilities $\{\hat{p}_j\}$ to select certain branches. The loss is then updated as $L_2 = \min_j D(P_{cube}\hat{R}_j^T, P_{cube}\hat{R}^T)$. Besides, we also maximize the log likelihood of the predictions under a mixture of Laplacian distributions, which is formulated as $L_3 = \log \sum_j \hat{p}_j \frac{1}{2\pi} e^{-\frac{D(P_{cube}\hat{R}_j^T, P_{cube}\hat{R}^T)}{\alpha}}$. The overall training loss is $L_2 + \lambda L_3$. During inference, we select the branch

painted with homogeneous textures, and their local geometrical patterns are usually simple (e.g., uniform curvature). Such uniformity would yield appearance patterns easily captured by Convolutional Neural Networks. According to our experiment in Sec 5.6, MaskRCNN trained on chairs only achieves high performance on novel categories such as bed, cabinet, and table.
with the maximum probability $\hat{q}_j$ to predict $\hat{R}_j$.

Instead of processing each part individually, we group parallel parts who share edge directions. In this case, we only need to predict the shared edge direction for each group. This allows us to leverage the complementary information among parallel parts and resolve ambiguities potentially caused by occlusion or perspective projection. To this end, we first train a ResNet that consumes the concatenation of an image and a pair of part masks to classify whether the pair of parts are parallel. For the details of part relationship prediction, please refer to Sec D.2 in the supplementary material. The groundtruth labels are generated by a heuristic algorithm, described in the supplementary. During inference, we cluster parts into groups so that pairs of parts in each group are all classified as parallel. To predict the shared edge directions for each group, we first employ a ResNet to extract the features of individual parts, and then aggregate them through max-pooling. The aggregated feature is finally passed through a regression head to output edge directions.

### 4.3. Part Cuboid Edge Length Prediction

The goal of this step is to predict the size of all the parts. This step takes three inputs: the image, a binary mask of each part, and a set of three unit vectors denoting the edge directions of the part cuboid. It should output the edge length along each edge direction for all the parts. We summarize our design here and include details in Sec D.4 of the supplementary material.

![Diagram of part cuboid edge length prediction](image)

**Figure 3:** Part cuboid edge length prediction. We use this network to predict shared edge length for each group of translational symmetric parts. We first stack the input reference image and the mask image of each part. We use a shared ResNet to extract per-part feature, which are then max-pooled to generate a group feature. We combine the group feature with predicted edge directions from Sec 4.2 to further estimate the edge length.

Similar to Sec 4.2, we believe that predicting part size in groups may help to improve prediction performance. Here, we form part groups by considering translational symmetry, yet our idea may be extended to leverage more symmetry types. Specifically, we group all parts into several clusters, so that parts in the same cluster can be translated to each other. The clustering scheme will allow us to predict a unified size for all the member parts in each cluster. Predicting part sizes in clusters brings at least three advantages: (1) Compared with predicting part sizes individually, we have more evidences from the input. Particularly, it significantly helps to reduce the ambiguity of object sizes under perspective projection; (2) Some parts may not be fully visible due to occlusions, and predicting their sizes individually is very difficult; (3) Having a unified size for translational symmetric parts is visually much more pleasing for humans.

At test time, we train a translational symmetry classifier to help form clusters. The classifier is a ResNet that consumes an image and a pair of part masks stacked together as the input. This ResNet is trained supervisely to tell whether the two parts highlighted by the input masks follow translational symmetry. Then, we build clusters of parts so that classification scores between any pair of parts in the same cluster are above a predefined threshold. We find that this classifier is transferable across categories by our experiments in Sec 5.6.

We are ready to predict the part size for each cluster of parts. Our architecture is illustrated in Fig. 3. We first use ResNet with shared weights to predict the features for each part in a cluster independently. Note that the input to each branch is the image and the mask of a single part. The mask induces the network to focus on the masked region, and since we only couple a single part mask with the image, it forms a low-order prediction task. We then use a max pooling layer to aggregate features of each individual part. No additional interaction across parts are allowed, which reduces the risk of making predictions by high-order potentials of parts. Finally, the aggregated feature is duplicated three times and coupled with each of the predicted edge directions from the edge direction prediction module (Sec 4.2). The purpose is to query the edge length along each direction. This edge length prediction network is learned supervisely by mean square loss.

### 4.4. Part Cuboid Assembly

Having computed the part mask, edge directions, and size of individual parts, this module learns to assemble them into a whole shape. Following the isolation principle, we restrict the reasoning process to be only based upon pairwise relationships. To this end, we first build a part tree, whose nodes are parts, and edges indicate the pairs of parts for assembly reasoning. Then, based on the relativity principle, we predict the relative position between each pair of parts in the tree. Finally, we create the whole shape starting from adding the root part with its predicted edge direction and
“canonical object space” is ill-posed. we use a contact point based approach, which incorporates However, absolute locations are sensitive to the shape scale as well as the translation along the optical axis, significantly hurting the performance even for the simpler within-category prediction setup. While shape-level canonicalization is often conducted to mitigate the issue in literature, for unknown object categories, any prediction involving the undefined “canonical object space” is ill-posed.

**Connectivity-based Part Tree.** We seek for strong pairwise relationships to assemble parts. In our implementation, we choose the connectivity-based relationship. Our general plan is to first identify spatially contacted pairs of parts, and then predict the relative position between them. We choose this relationship for three reasons: First, parts with contact points are spatially close and impose strong arrangement constraints to each other; Second, when occlusion is absent, assessing whether two parts are in touch is often not too hard from the image space and does not require category-level knowledge; Third, the relationship is quite common. The second and third reasons actually imply good transferability to novel category objects.

We train a connectivity classifier to assess whether a pair of parts touch each other in its original 3D shape. The training is supervised. Based upon the prediction of connectivity scores between all part pairs, we start to form a part tree. First, we build a graph of parts and connect pairs with scores above a threshold. Then, we use a greedy algorithm to build a spanning tree. Specifically, we choose the largest part (by predicted volume) as the root node. Next, we iteratively add more parts by selecting the largest remaining part in the 1-hop neighborhood of the current tree. Notice when the graph contains multiple connected components, we will simply generate a part tree for each component and form a part forest.

**Joint-based Relative Position.** We predict the relative position for selected part pairs in the part tree. The input includes the reference image and the information about each individual part in the pair. The output is the relative position between their part cuboid centers.

Instead of directly predicting relative center positions, we use a contact point based approach, which incorporates stronger relative position prior. The contact point between touching part pairs must lie within the cuboid of each part. Therefore, we obtain hard constraints over the relative position between part centers. In the following, we formulate how to infer the relative center position from contact point predictions (read Fig. 4 for better understanding):

![Figure 4: Relative position prediction. Left: Parameterize relative position between part centers (orange and blue spheres) by contact points (green sphere). Right: Network architecture illustration.](image)

- **Contact Point.** We use superscript to denote frame and subscript to denote part indices. Given two touching parts $p_1$ and $p_2$, we denote the contact point in a part frame sitting at the center of $p_1$ by $c^1$, and in a different part frame sitting at the center of $p_2$ by $c^2$.

  The relative center location $l_{1\rightarrow 2}^W$ can be inferred as:

  $$l_{1\rightarrow 2}^W = l_i^W - l_j^W = c^1 - c^2.$$  

  Next we discuss how to estimate the contact point $c^i$ in part frame.

- **Contact Point Estimation.** As the contact should be lying on the part cuboid surface or inside the cuboid, we denote the contact points $c^i$ as a linear interpolation of the cuboid vertices $v_{i,j}^c$: $c^i = \sum_{j=1}^{8} \omega_{i,j} \cdot v_{i,j}$, where $\sum_{j=1}^{8} \omega_{i,j} = 1$ and $\omega_{i,j} \geq 0$. We use a neural network to predict $\omega_{i,j}$’s. This network uses a softmax layer to satisfy the above two constraints. Our network consumes a stack containing the reference image and two part mask images and outputs a feature vector. We pair the feature vector with each vertex position $v_{i,j}$ of the two predicted part cuboids and use another network to predict $\omega_{i,j}$’s. To make the contact point estimation invariant to the ordering of cuboid vertices, the architecture of the second network is similar to the PointNet segmentation network [38]. Note that we share some network parameters with other modules. For more details, please refer to Sec D.5 in the supplementary materials.

5. Experiments

We conduct experiments on the PartNet dataset and compare our proposed method to two baseline methods. Our

\[\text{The orientation of the two frames can be arbitrarily chosen.}\]
method achieves superior performance over baselines on novel categories. We also present several ablation studies to validate the key module designs.

5.1. Dataset and Settings

We use the PartNet dataset as the main testbed. PartNet [32] provides fine-grained object part segmentation for 26,671 3D models covering 24 object categories in ShapeNet [1]. We pick four most commonly used object categories: chair, table, cabinet and bed. All the experiments, including the baseline methods and the ablation studies, are trained on chair shapes only and tested over the rest three categories.

To generate the input images for training, we render each shape with 12 random sampled flying views and randomly move the shape location. In our setting, we use a static camera and rotate the shape instead. The center location and orientation of each part oriented bounding cuboid is defined in the world space. Our proposed modules relies on the part mask to infer each part 3D information, so we generate each part mask along with the image. Besides, for training part joint positions, our model needs two adjacent parts. This adjacent relationship is calculated based on the adjacency information from the ground truth 3D part geometry. Our training set contains 2,576 chairs in total and 60,984 rendered chairs in total. For testing shapes, we rendered each shape with 6 random sampled flying views. The rendered image are of 256 × 256 resolution.

5.2. Training Details

Our proposed method mainly contains the following modules, the rotation module which estimates the rotation frames given images and part masks, the size module which infers each axis size given the part frame. At the training stage, we train each module separately. For example, to train the joint-based relative position, our module takes the rotation frame and axis size from ground truth labels. At testing stage, we directly combine these module together and empirically find it good enough to use without the need of further end-to-end joint finetuning.

5.3. Baseline Methods

We compare with two baseline methods on predicting 3D shape part structured cuboids: an naive encoder-decoder baseline and a Graph Convolutional Network (GCN) baseline. There are no previous works addressing the exactly same settings as ours. So, we try our best to adapt two previous works, namely StructureNet [30] and Li et al. [23], to create the two baselines.

The Naive Encoder-decoder Baseline. This baseline borrows the network design from StructureNet [30]. However, different from the StructureNet setting where they assume a shared canonical semantic part hierarchy for the same training and test object categories, in our settings, we do not assume to have such part hierarchies and we want to generalize across object categories. Thus, we remove the hierarchical part cuboid decoding stage in StructureNet and directly decode 50 part cuboids in one shot. For the image encoder, we follow StructureNet to use a ResNet-18 encoder to extract one global feature of dimension 256 for each input 2D image. We follow the exact same losses as our method to train for the box attributes, with an additional loss from StructureNet to train the part existence scores that finally select a subset of part cuboids from the 50 predictions.

The GCN Baseline. For this baseline, we use a similar network architecture as Li et al. [23], which builds part-graphs and uses GCN to propagate information among the adjacent part pairs. Concretely, for each part, we combine the RGB input image and one additional channel for the 2D part mask together to form a 4-channel input. Then, we feed it through a ResNet to extract one feature for this part. After obtaining one feature per part, we use the ground-truth part adjacency information to form a part-graph, with part features as nodes and adjacent part pairs as edges. We perform 3 iterations of graph message passing operations as used in Li et al. [23] to propagate features within the part graph and finally obtain per-part features for the part cuboid decoding. We use the same training losses for the part cuboid decoder as our method.

5.4. Evaluation Metrics

To quantitatively evaluate the reconstruction results, we use the Earth-Mover Distance (EMD) [7]. The EMD loss is a widely-used metric for comparing shape quality in 3D space. To measure the shape distances, we need to first convert our part-cuboid representation to a shape point cloud. For this step, we first uniformly sample 1024 points from each estimate part cuboid and then re-sampled 1024 points using furthest point sampling as our shape points.

5.5. Results and Analysis

In this section, we provide both qualitative and quantitative comparison with baseline methods. Table 1 and Table 2 compare our results to the GCN baseline and the naive encoder-decoder baseline respectively. We observe that all three methods work well on the training categories – chairs, while our method achieves significantly better results when generalizing to the novel test categories – tables, cabinets and beds. We visualize some exemplar results in Fig. 5, where we clearly see that on the chair example, baseline methods achieve very competitive results to our method. However, the two baseline methods overfit to the training chair category, so that the performances on novel categories (tables, beds and cabinets) are pretty bad, while our method is still able to do high-fidelity structure prediction. The qualitative comparisons to GenRe shows that our method recovers the shape
Figure 5: We visualize our 2D part mask predictions and the 3D part cuboids predictions, compared with GenRe [60] and the two baseline methods. Notice that all models are trained on chairs only. The bottom three rows show shape reconstruction from novel unseen test categories: bed, cabinet, and table.

structure more faithfully. More qualitative comparisons with the GCN baseline, the naive encoder-decoder baseline and GenRe are provided in Sec. B of the supplementary material. Besides, quantitative and qualitative evaluation of individual modules are presented in Sec. C of the supplementary material.

| Loss       | Chair | Table | Cabinet | Bed |
|------------|-------|-------|---------|-----|
| Proxy-MOE  | 5.48  | 7.71  | 4.02    | 4.30|
| Proxy-Plain| 9.13  | 11.77 | 7.96    | 8.81|
| MSE        | 34.37 | 38.17 | 39.50   | 38.91|

Table 3: Comparison of different losses w.r.t the average geodesic error (angular difference in degrees) between the ground truth and predicted rotation matrices.

| Loss       | Chair | Table | Cabinet | Bed |
|------------|-------|-------|---------|-----|
| Proxy-MOE  | 0.005 | 0.018 | 0.028   | 0.018|
| Proxy-Plain| 0.012 | 0.043 | 0.053   | 0.030|

Table 1: Quantitative comparisons with the GCN baseline.

| Loss       | Chair | Table | Cabinet | Bed |
|------------|-------|-------|---------|-----|
| Proxy-MOE  | 0.013 | 0.064 | 0.064   | 0.032|
| Proxy-Plain| 0.012 | 0.043 | 0.053   | 0.030|

Table 2: Quantitative comparisons with the naive encoder-decoder baseline.

5.6. Ablation Studies

We conduct several ablation experiments to demonstrate the effectiveness of our key design components.

Part Cuboid Edge Direction Prediction. Table 3 compares different losses w.r.t the average geodesic error between the ground truth and predicted rotation matrices. The proxy loss with and without mixtures of experts, introduced in Sec 4.2, are denoted by Proxy-MOE and Proxy-Plain, respectively. MSE stands for the mean square error between between the ground truth and predicted rotation matrices, which does not take the rotation ambiguity into consideration. It performs much worse than other losses, which indicates that the rotation ambiguity hurts the learning process. Besides, Proxy-MOE outperforms Proxy-Plain on all the categories, which indicates that multiple predictions facilitate the network to escape poor local minima.

The Group Size. We demonstrate in this study that the group operation could effectively improve the visual quality of our reconstruction results. The group size infers the parallel and each size part information from images and the group size module is able to generalize to new categories such as cabinet. In Fig. 6, we show an example with and without the group size operation. This group size operation significantly keeps the strong clues from image and gives better visual quality.

6. Conclusion

In this paper, we first bring the concept of compositional generalizability to the task of estimating 3D shape structures from a single 2D image input and demonstrate much better reconstruction capabilities that generalize to the shapes from unseen object categories. At the core of our design, we factorize the whole problem into sub-problems that explicitly discover the commonly shared part relationships and shape substructure priors across different object categories.
We carefully design the network module for each of the sub-problem, which uses localized contexts for the generalizability guarantee. Experiments show that our method is effective on generalizing to novel categories.

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Supplementary Materials

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A. Overview

This document accompanies the main paper and provides additional qualitative results for the entire pipeline, extensive evaluations for each individual sub-module in our pipeline, detailed elaborations on the network architecture designs, an additional perceptual metric for evaluations, more ablation studies, and more details on parallelism label generation. We will release our code, data and pre-trained models upon paper acceptance.

Sec. B provides more qualitative results of our method and comparisons to the three baseline methods. In Sec. C, we provide more detailed evaluations of each individual network module. Sec. D presents more details about our network architecture designs and the implementation. In Sec. E, we evaluate the quality of 3D reconstruction by one more quantitative metric – perceptual metric [59]. Sec. F includes more ablation studies, besides the two shown in the main paper, to further analyze the effectiveness of our design choices in each module. Finally, details about parallelism label generation are given in Sec. G.

B. More Qualitative Results

We show more qualitative results comparing our methods against the two baseline methods: the naive encoder-decoder baseline and the graph-convolution-network baseline. Figures 12, 13, 14, and 15 show more chair, table, bed and cabinet results respectively. Notice that all methods are trained on chairs only. We see that our method achieves much better reconstruction generalizability than the baseline methods. We also present qualitative comparisons to GenRe [60] in Fig. 16, where we can clearly see that our method reconstructs the shape structure more faithfully.

C. Evaluations of Individual Modules

Our pipeline has many sub-network modules. Due to the page limit of the main paper, we cannot present detailed result visualization and discussion on each sub-network module. In this section, we provide qualitative and quantitative evaluations for several key network modules to illustrate the predicted results at each step in our pipeline.

Concretely, we measure the quantitative accuracy of the part instance segmentation module and part adjacency relationship module. Then, we show qualitative results and analysis on the part cuboid edge direction prediction module, the cuboid group-based edge length prediction module, and the part relative position prediction module.

C.1. Part Instance Segmentation

In Table 4, we evaluate our 2D part mask instance segmentation sub-module using the standard 2D object detection metrics: bounding box average precision (AP) and mask AP.

|           | Chair | Table | Cabinet | Bed  |
|-----------|-------|-------|---------|------|
| box AP@0.5| 83.18 | 72.03 | 34.40   | 55.31|
| mask AP@0.5| 79.11 | 66.53 | 25.08   | 47.89|

Table 4: Results of our part instance segmentation. The metrics include bounding box AP (average precision) and mask AP with the IoU threshold 0.5.

We find that, though trained on chairs only, our part instance segmentation module generalizes well to novel categories in a zero-shot fashion. Figures 12, 13, 14, and 15 (left three columns) visualizes example predictions on the four object categories: chairs (training category), beds, tables, and cabinets (test categories). We can clearly see that the 2D part mask predictions are accurate enough to support the later 3D reasoning stages of our pipeline.

C.2. Part Cuboid Edge Direction Prediction

Fig. 17 shows qualitative results of our predicted part cuboid edge direction. To visualize each part cuboid, we take the estimated cuboid edge direction and use the ground truth cuboid edge length and position. While our model is only trained on chairs, we achieve superior results on table, bed, and cabinet categories.

C.3. Part Cuboid Edge Length Prediction

Fig. 18 presents qualitative example results of our estimated group-based edge length. To evaluate solely the performance of the group-based edge length module, we take the ground truth cuboid edge direction as input. We visualize each part with the estimated edge length and the ground truth edge direction and position. High quality results on table, bed and cabinet demonstrate that our part cuboid edge length module can generalize well to the unseen test categories.

C.4. Part Adjacency Relationship Prediction

Our shape assembly process depends on a part-graph structure to form a sequential part assembly tree. We leverage part adjacency relationships as the pairwise edges connecting the neighboring parts in the part-graph. We train a network that predicts whether two parts are adjacent or not to construct such part-graph structure. Table 5 shows the quantitative evaluation of our part adjacency relationship
predictions, where we see that the part adjacency relationships can be easily learned and generalized to unseen test categories.

C.5. Shape Assembly Process

Fig. 19 shows some example results for our joint-based part relative position estimation. The results here take the ground truth part cuboid edge direction and length as input. Each part is visualized with the estimated position and the
ground-truth edge direction and edge length. Though our model is trained on chairs only, our position estimation module can work well on very different shapes from the cabinet, bed, and table categories.

D. Network Architecture Details

In this section, we describe more network architecture and implementation details for our network modules.

D.1. Part Instance Segmentation

We use Mask-RCNN [12] implemented in Detectron2 [54] to do part instance segmentation, which is originally designed for COCO [25] object instance segmentation. Since the aspect ratios of PartNet [32] parts follow a different distribution from those of COCO objects, we add two additional aspect ratios (1:4 and 4:1) to each anchor (predefined sliding windows). The input image is resized to $800 \times 800$, and flipped randomly as data augmentation. The detector is a ResNet50-based FPN, pretrained on COCO. It is finetuned on the chair category for 80,000 iterations by SGD. The batch size is 4. The initial learning rate is 0.005, and is divided by 10 after 48,000 and 64,000 iterations. Other hyperparameters follow the default setting of Detectron2.

D.2. Part Relationship Prediction

In our method, we detect three types of part relationships including parallelism, translational symmetry and adjacency. The detection of relationship is modeled as a binary classification problem. The architecture of the relationship detection module is visualized in Fig. 7. The input to the network is the concatenation of an image and two part masks. A ResNet18 without pre-training followed by a convolution layer and an average-pooling layer is used to extract a global feature. The global feature is forwarded to two fully-connected layers but with 4 different branches. This illustrates the mixture-of-experts (MOE) method described in main paper Sec. 4.2 Paragraph 3 (Line 374–416), through which we hope to predict a distribution of rotations instead of a single output. The final outputs of each branch are the quaternion and the probability to select this branch.

Fig. 9 illustrates the network architecture of the extension to the group-based prediction. Given multiple parts that are considered parallel, we use the backbone of the basic module to extract their global features, and then apply a max-pooling layer to aggregate all the global features. Again, we adopt the same multi-branch structure as the single part cuboid edge direction module to better model the distribution of rotations and to allow a more effective training. During training, we leverage the ground truth parallelism relationship to generate the group. During inference, it is based on the prediction of the part relationship module.

The module is trained on the chair category for 20 epochs by the Adam optimizer. The batch size is 64. The initial learning rate is 0.001, and decays by 0.7 every 2 epochs.

D.3. Part Cuboid Edge Direction Prediction

We first show our network architecture for predicting part cuboid edge direction for a single part. Then, we describe our final version that performs group-based predictions considering a group of related parts.

Fig. 8 illustrates the network architecture of the basic module. The input to the network is the concatenation of an image and a part mask. A ResNet18 without pre-training followed by a convolution layer and an average-pooling layer is used to extract a global feature. The global feature is forwarded to two fully-connected layers but with 4 different branches. This illustrates the mixture-of-experts (MOE) method described in main paper Sec. 4.2 Paragraph 3 (Line 374–416), through which we hope to predict a distribution of rotations instead of a single output. The final outputs of each branch are the quaternion and the probability to select this branch.

Fig. 10 demonstrates the network architecture. Given all the parts that are considered of equal sizes, we use a shared backbone composed of a ResNet-18 without pre-training, a convolution layer and an average-pooling layer, to extract the image feature for each part. The input for each part is a stack of an input image and a part mask. Multiple part image features are aggregated by a max-pooling layer.

Inspired by PointNet [38], we consider each edge direction a ‘point’, and estimate its attribute (edge length) in a point-wise segmentation fashion. Such a design is permutation-equivariant to the order of edge directions. Concretely, we first concatenate the aggregated image feature and each edge direction as the input. Then, we apply a shared multilayer perceptron (MLP) to extract the feature of each edge direction. Following PointNet, a global feature is also extracted through the share MLP and concatenated with each local feature to enable the information communication between different edge directions. Finally, a scalar edge length is estimated from the feature of each edge direction. During training, we use ground truth edge directions as inputs and leverage ground truth edge lengths to generate groups. During inference, these ground truth information is replaced by predictions from the edge direction module and the part relationship module.

The module is trained on the chair category for 60 epochs by the Adam optimizer. The batch size is 64. The initial learning rate is 0.001, and decays by 0.9 every 2 epochs.
Figure 9: **Network Architecture of the Group-based Part Cuboid Edge Direction Prediction Module.** Given multiple parts that are considered parallel, we use the backbone of the single part edge direction module to extract their global features, and apply a max-pooling layer to aggregate all the global features. From the global feature, we then regress a mixture of quaternions, as with single part edge direction module.

Figure 10: **Network Architecture of the Group-based Part Cuboid Edge Length Prediction Module.** Similar to group-based edge direction module, the input to this module is a group of parts, which are considered to be translational symmetric. Single part image features are aggregated through max pooling, forming a grouped image feature. Then we predict edge lengths from this grouped image feature and part cuboid edge directions. Our edge length prediction module adopts a similar architecture to the PointNet segmentation network to maintain the property that edge lengths should be permutation equivariant to the order of edge directions. We consider each edge direction a 'point', and estimate its attribute (edge length) in a point-wise segmentation fashion. We first concatenate the aggregated image feature and each edge direction as the input. Then, we apply a shared MLP to extract the feature of each edge direction. Following PointNet, a global feature is also extracted through the share MLP and concatenated with each local feature to enable the information communication between different edge directions. Finally, a scalar edge length is estimated from the feature of each edge direction.
D.5. Part Relative Position Prediction

Fig. 11 shows the network architecture of our contact-point-based part relative position module. The network estimates the contact point of each part given the input image, part masks and the part cuboid shape, i.e. the cuboid edge direction and edge length. This contact point representation is then converted to a relative position, as explained in the main paper. As the process of estimating contact point is the same for both parts in a contacting pair, we illustrate the process for one of them as an example.

The 2D input is the concatenation of an image and masks of two adjacent parts. Note the masks are ordered where the first one corresponds to the part being considered and the second one corresponds to its contacting part. A ResNet18 without pre-training followed by a convolution layer and an average-pooling layer is used to extract an image feature.

Then, the image feature is concatenated with each cuboid vertex of the part. Similar to PointNet [38] for semantic segmentation, the concatenated feature is processed by a shared MLP to obtain a weight for each cuboid vertex. By summing all the vertex positions with their weights, we can induce the contact point of the part. During training, the ground truth orientation and scale are used to get the cuboid vertices. At testing stage, we take the predicted orientation and scaled by the predicted size from previous stages.

The module is trained on the chair category for 60 epochs by the Adam optimizer. The batch size is 64. The initial learning rate is 0.001, and decays by 0.9 every 2 epochs.

E. Evaluations using a Perceptual Metric

While Earth Mover Distance (EMD) measures the similarity between two 3D shapes in the 3D space, it is more direct to evaluate single-image 3D reconstruction performance by back-projecting the predicted 3D shapes back onto the 2D image plane and comparing to the 2D ground-truth. To this end, we adopt a perceptual metric [59] to evaluate how well the 3D reconstruction matches the input image. Concretely, given the 3D ground-truth and predicted part cuboids, we render 2D images with the same camera extrinsic and intrinsic matrices of the input images. Then, we employ a VGG16 [42] to extract 512-dimension image features of the 5th convolution layer. The cosine distance between two features is defined as our perceptual similarity. It indicates how similar the image rendered from the prediction looks to the ground-truth in the 2D space, which in fact focuses on the reconstruction quality of the visible portions of the geometry and the plausibility of part composition globally, rather than evaluating the absolute edge direction and length of each part in details.

Table 6 and 7 presents the perceptual similarity of our approach to the GCN baseline and the naive encoder-decoder baseline respectively. We record the percentage of images on which our method wins the comparison in the tables. It is clear to see that our approach outperforms the baselines across all object categories, especially on the unseen test object categories, which indicates that the perceptual quality of our approach is better, which explains the higher visual quality of our method, as shown in Figures 12, 13, 14, and 15.

F. Additional Ablation Studies

We provide additional ablation studies to validate the designs of some key network modules, complementing the two presented in the main paper.

F.1. Part Cuboid Edge Direction and Length: Joint or Sequential Predictions?

Our network design disentangles the predictions of part cuboid edge direction and length. Note that the order of the estimated edge directions is tightly coupled with the order of edge length predictions. As a result, in our final pipeline, we predict part cuboid edge direction and length in a sequential manner.

One alternative way is to estimate them jointly as proposed in [30]. The joint prediction is supervised by the Chamfer Distance between the ground-truth part cuboid and the cuboid scaled by the predicted size and transformed by the predicted rotation. Our experiments show that such joint prediction approach is more vulnerable to overfitting, since it allows more degrees of freedom in the output space and exploits less explicit constraints compared to our approach.
This module estimates the contact point of both parts given the image, part masks, and part cuboid shape, i.e., cuboid edge direction and edge length. After getting both parts contact point, we infer the part relative position to the other part, as described in the main paper Sec. 4.4 (Line 560-607). This contact-point module takes image and two adjacent part masks and part cuboid attributes, i.e., cuboid edge direction and edge length. The contact point is represented as a weighted sum of all vertex positions of the part cuboid. As the weight of each vertex is order-invariant to cuboid vertices, we take a similar architecture with PointNet. Each cuboid vertex is considered as a point. We first concatenate the aggregated image feature and each cuboid vertex as the input. Then, we apply a shared MLP to extract the feature of each edge direction. Following PointNet, a global feature is also extracted through the shared MLP and concatenated with each local feature. Finally, each vertex weight is estimated from the feature of each cuboid vertex.

Table 8 shows the quantitative comparison, where we clearly see the advantage of our sequential approach over the joint one.

|       | Chair | Table | Cabinet | Bed  |
|-------|-------|-------|---------|------|
| Joint | 0.026 | 0.146 | 0.161   | 0.179|
| Sequential (ours) | **0.019** | **0.105** | **0.129** | **0.089** |

Table 8: Comparison of joint and sequential predictions of part cuboid edge direction and length. We report the average Chamfer Distance between the ground truth and predicted part cuboids.

F.2. Part Cuboid Edge Length: Unary or Group-based Predictions?

To verify the effect of our group-based part cuboid edge length prediction module, we compare it against the unary counterpart which predicts the edge length individually. The network architecture is the same except that we remove the max-pooling layer in Fig. 10 when predicting the edge length individually. Table 9 shows the quantitative comparison, where we use the L1 distance between the ground truth and predicted edge lengths as the metric. Note that the ground truth edge directions are provided here. We observe that the group-based edge length prediction module consistently outperforms the unary edge length prediction.

|       | Chair | Table | Cabinet | Bed  |
|-------|-------|-------|---------|------|
| Unary  | 0.054 | 0.134 | 0.183   | 0.136|
| Group  | **0.050** | **0.115** | **0.175** | **0.130** |

Table 9: Comparison of the unary and group-based size prediction. We report the average L1 distance between the ground-truth and prediction.

F.3. Part Relative Position Prediction: Center Offset or Contact Point?

One alternative to our contact-point-based part relative position prediction method, which regresses the contact point of two parts, is to directly regress an offset vector from the center of one part to that of the other. We conduct experiments to compare the performance of these two approaches. Table 10 shows the quantitative comparison w.r.t the L1 distance between the ground truth and predicted offset vectors. We argue that our contact-point-based part relative position prediction guarantees that two parts considered adjacent are contacted, which finally leads to superior performance.
Table 10: Comparison of Our Contact-point-based approach to an Center-offset-based Alternative. We report the average L1 distance between the ground truth and predicted offset vectors.

|                  | Chair | Table | Cabinet | Bed  |
|------------------|-------|-------|---------|------|
| Center Offset    | 0.027 | 0.042 | 0.051   | 0.046|
| Contact Point (ours) | **0.023** | **0.038** | **0.045** | **0.042** |

G. Parallelism Label Generation

In this section, we briefly describe our heuristic algorithm to generate labels for parallelism prediction. This parallelism prediction clusters parallel parts into a group and is the input of our group-based part cuboid edge direction module. We remind readers that the oriented bounding cuboid is the geometric primitive we use in the paper. We denote the three principle axes of a cuboid, which parameterizes the orientation (as well as the size), by $a, b, c \in \mathbb{R}^3$, where $|a| \geq |b| \geq |c|$. First, we categorize each part into 4 types according to its axial ratio: equant, prolate, oblate or bladed. Table 11 illustrates the rule of categorization, which is identical to the shape classes proposed by Zingg [61]. Then, for each shape, we iterate over all the possible pairs of parts, and assign parallelism labels to them according to the ground truth orientations and types of parts. In principle, we assign negative labels (i.e. not parallel) to parts of different types or parts sharing the same type but with very different principle axes directions. We refer readers to the codes for the exact algorithm.

| Type     | $|b|/|a|$ | $|c|/|b|$ | Example   |
|----------|---------|--------|-----------|
| equant   | $> 0.618$ | $> 0.618$ | cube     |
| prolate  | $< 0.618$ | $> 0.618$ | cylinder |
| oblate   | $> 0.618$ | $< 0.618$ | plane    |
| bladed   | $< 0.618$ | $< 0.618$ | general cuboid |

Table 11: The Rule to Categorize a Part Cuboid. $a, b, c$ are the principle axes of the cuboid, where $|a| \geq |b| \geq |c|$.
Figure 12: More Qualitative Results and Comparisons on Chairs (training category). From left to right, we present: input 2D image, GT 2D part mask, predicted 2D part mask, and 3D predictions of the GCN baseline, the naive encoder-decoder baseline, ours(GT mask), ours(predicted mask).
Figure 13: **More Qualitative Results and Comparisons on Tables (novel category).** From left to right, we present: input 2D image, GT 2D part mask, predicted 2D part mask, and 3D predictions of the GCN baseline, the naive encoder-decoder baseline, ours(GT mask), ours(predicted mask).
Figure 14: More Qualitative Results and Comparisons on Beds (novel category). From left to right, we present: input 2D image, GT 2D part mask, predicted 2D part mask, and 3D predictions of the GCN baseline, the naive encoder-decoder baseline, ours(GT mask), ours(predicted mask).
Figure 15: More Qualitative Results and Comparisons on Cabinets (novel category). From left to right, we present: input 2D image, GT 2D part mask, predicted 2D part mask, and 3D predictions of the GCN baseline, the naive encoder-decoder baseline, ours(GT mask), ours(predicted mask).
Figure 16: **Comparisons to GenRe [60].** We compare our results to GenRe and present each result from multiple views to clearly show the 3D reconstruction. For each object category, we present three rows of results for GenRe, ours(GT mask), ours(predicted mask) respectively, with the first column shows the input image. While the results from GenRe seems to be good from the input image views (the fifth column), the 3D reconstruction of GenRe is actually worse than ours if we compare from the other views. We also see that the GenRe model trained on chairs tends to overfit to the chair shapes, while our method can faithfully reconstruct shapes from unseen test categories.
Figure 17: Part Cuboid Edge Direction Predictions. For each part cuboid, we use the estimated edge direction prediction and the ground-truth part cuboid edge length and center position. For each object category, the first row shows the input images and the second row presents the 3D part cuboids reconstructions.
Figure 18: **Group-based Part Cuboid Edge Length Predictions.** To visualize each part cuboid, we use the estimated edge length and the ground truth part cuboid edge direction and part position. For each object category, the first row shows the input images and the second row presents the 3D part cuboids reconstructions. Note that results may show disconnected parts since the part cuboids use the ground truth center positions. Our follow-up shape assembly process will connect adjacent parts.
Figure 19: Joint-based Part Relative Position Predictions. To visualize each part cuboid, we use the estimated center position and the ground truth part cuboid edge direction and length. For each object category, the first row shows the input images and the second row presents the 3D part cuboids reconstructions.