GENERATIVE SCENE GRAPH NETWORKS

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ABSTRACT

Human perception excels at building compositional hierarchies of parts and objects from unlabeled scenes that help systematic generalization. Yet most work on generative scene modeling either ignores the part-whole relationship or assumes access to predefined parts labels. In this paper, we propose Generative Scene Graph Networks (GSGNs), the first deep generative model that learns to discover the primitive parts and infer the part-whole relationship jointly from multi-object scenes without supervision and in an end-to-end trainable way. We formulate GSGN as a variational autoencoder in which the latent representation is a tree-structured probabilistic scene graph. The leaf nodes in the latent tree correspond to primitive parts, and the edges represent the symbolic pose variables required for recursively composing the parts into whole objects and then the full scene. This allows novel objects and scenes to be generated both by sampling from the prior and by manual configuration of the pose variables, as we do with graphics engines. We evaluate GSGN on datasets of scenes containing multiple compositional objects, including a challenging compositional CLEVR dataset that we have developed. We show that GSGN is able to infer the latent scene graph, generalize out of the training regime, and improve data efficiency in downstream tasks.

1 INTRODUCTION

Learning to discover and represent objects purely from observations is at the core of human cognition (Spelke & Kinzler, 2007). Recent advances in unsupervised object-centric representation learning have enabled decomposition of scenes into objects (Greff et al., 2019; Lin et al., 2020b), inference of 3D object models (Chen et al., 2020), and object tracking and future generation (Crawford & Pineau, 2019a; Jiang et al., 2020; Lin et al., 2020a). These neuro-symbolic approaches, where the discreteness of discovered objects provides the symbolic representation, facilitate various desired abilities such as out-of-distribution generalization, relational reasoning, and causal inference.

In this paper, we seek to further discover and represent the structure within objects without supervision. Our motivation is that natural scenes frequently contain compositional objects—objects that are composed of primitive parts. We humans can easily identify the primitive parts and recognize the part-whole relationship. Representing objects as explicit composition of parts is expected to be more efficient, since a vast number of complex objects can often be compositionally explained by a small set of simple primitives. It also allows us to imagine and create meaningful new objects.

A well-established representation for part-whole relationships in computer graphics is called the scene graph (Foley et al., 1996). It is a tree whose leaf nodes store models of primitive parts, and whose edges specify affine transformations that compose parts into objects.

While in computer graphics, the scene graph is manually constructed for rendering, in this paper, we are interested in inferring the scene graph from unlabeled images. To this end, we propose Generative Scene Graph Networks (GSGNs). We formulate this model as a variational autoencoder (Kingma & Welling, 2013) whose latent representation is a probabilistic scene graph. In the latent tree, each node is associated with an appearance variable that summarizes the composition up to the current level, and each edge with a pose variable that parameterizes the affine transformation from the current level to the upper level.

The design of the GSGN decoder follows the rendering process of graphics engines, but with differentiable operations helping the encoder to learn inverse graphics (Tieleman, 2014; Wu et al., 2017; Romaszko et al., 2017; Yao et al., 2018; Deng et al., 2019). As a result, the pose variables inferred

by GSGN are interpretable, and the probabilistic scene graph supports symbolic manipulation by configuring the pose variables.

One major challenge is to infer the structure of the scene graph. This involves identifying the parts and grouping them into objects. Notice that unlike objects, parts are often stitched together and thus can have severe occlusion, making it hard to separate them. Existing methods for learning hierarchical scene representations circumvent this challenge by working on single-object scenes (Kosiorek et al., 2019) and also providing predefined or pre-segmented parts (Li et al., 2017; Huang et al., 2020). In contrast, GSGN addresses this challenge directly, and learns to infer the scene graph structure from multi-object scenes without knowledge of individual parts.

Our key observation is that the scene graph has a recursive structure—inferring the structure of the tree should be similar to inferring the structure of its subtrees. Hence, we develop a top-down inference process that first decomposes the scene into objects and then further decomposes each object into its parts. This allows us to reuse existing scene decomposition methods such as SPACE (Lin et al., 2020b) as an inference module shared at each level of the scene graph. However, we find that SPACE has difficulty separating parts that have severe occlusion, possibly due to its complete reliance on bottom-up image features. Therefore, simply applying SPACE for decomposition at each level will lead to suboptimal scene graphs. To alleviate this, GSGN learns a prior over plausible scene graphs that captures typical compositions. During inference, this prior provides top-down information which is combined with bottom-up image features to help reduce ambiguity caused by occlusion.

For evaluation, we develop two datasets of scenes containing multiple compositional 2D and 3D objects respectively. The 3D objects are composed from shapes similar to those in the CLEVR dataset (Johnson et al., 2017), with variable sizes, colors, and materials. Hence, we name our 3D dataset the compositional CLEVR dataset.

The contributions of this paper are: (i) we propose the probabilistic scene graph representation that enables unsupervised and end-to-end scene graph inference and compositional scene generation, (ii) we develop and release the compositional CLEVR dataset to facilitate future research on object compositionality, and (iii) we demonstrate that our model is able to infer the latent scene graph, shows decent generation quality and generalization ability, and improves data efficiency in downstream tasks.

2 Related work

Object-centric representations. Our model builds upon a line of recent work on unsupervised object-centric representation learning, which can be categorized into scene-mixture models (Greff et al., 2017; 2019; Burgess et al., 2019; Engelcke et al., 2020; Locatello et al., 2020) and spatial-attention models (Eslami et al., 2016; Crawford & Pineau, 2019b; Lin et al., 2020b). They decompose the scene at the level of objects, while we go a step further by also decomposing objects into parts. We use spatial-attention models as the inference module at each level of the scene graph, because they explicitly provide object positions, unlike scene-mixture models. We combine the inference module with a learned prior to help improve robustness to occlusion. This also allows sampling novel scenes from the prior, which is not possible with spatial-attention models.

Hierarchical scene representations. Modeling the part-whole relationship in scenes has attracted growing interest, and has been utilized for improving image classification (Sabour et al., 2017; Hinton et al., 2018; Kosiorek et al., 2019), parsing, and segmentation (Zhu et al., 2008). However, they have been applied to scenes with one dominant object only, and cannot perform scene generation. Recent work on assembly-based 3D shape modeling also learns the part-whole relationship (Tulsiani et al., 2017; Li et al., 2017; Zhu et al., 2018; Huang et al., 2020), but these methods require predefined or pre-segmented parts as input, and can only model single shapes with no background. By contrast, our model learns the part-whole relationship from multi-object scenes without knowledge of individual parts. Our approach infers compositional structures from static scenes, and is orthogonal to methods that use motion cues for decomposing dynamic scenes (Xu et al., 2019) and methods that infer physical interactions from dynamic scenes (Li et al., 2020; Stanić et al., 2020).

Hierarchical latent variable models. Our model can be regarded as a hierarchical latent variable model, and is inspired by several recent advances (Bachman, 2016; Sønderby et al., 2016; Zhao et al.,

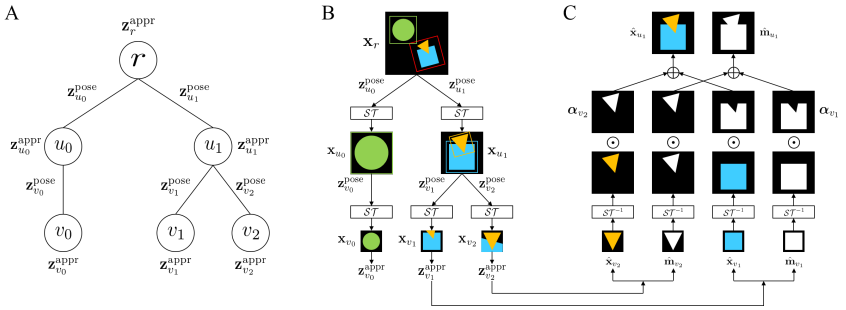

Figure 1: *(A)* Probabilistic scene graph representation. Each node represents an entity in the scene, and is associated with an appearance variable. Each edge is associated with a pose variable that specifies the coordinate transformation between the child node and the parent node. *(B)* Spatial attention during inference. We first decompose the scene into high-level objects, and then attend to to each object to figure out the constituent parts. *(C)* Recursive decoding process (a single recursive step shown). The image patch $\hat{\mathbf{x}}_{u_1}$ and mask $\hat{\mathbf{m}}_{u_1}$ of an internal node u_1 are decoded from the image patches and masks of all its children nodes.

2017; Maaløe et al., 2019) that have achieved impressive generation quality. While these methods focus on designing the hierarchical structure and training method that harness the full expressive power of generative models, our goal is to learn the hierarchical structure from unlabeled images that captures the compositional relationship among symbolic entities like objects and parts.

3 Generative Scene Graph Networks

3.1 Generative process

We assume that the image $\mathbf{x}$ is generated by a set of foreground variables collectively denoted $\mathbf{z}_{\text{fg}}$ and a background variable $\mathbf{z}_{\text{bg}}$ as follows:

$$p(\mathbf{x}) = \iint p(\mathbf{x} \,|\, \mathbf{z}_{\text{fg}}, \mathbf{z}_{\text{bg}})\, p(\mathbf{z}_{\text{bg}} \,|\, \mathbf{z}_{\text{fg}})\, p(\mathbf{z}_{\text{fg}})\; d\mathbf{z}_{\text{fg}}\, d\mathbf{z}_{\text{bg}} \;. \tag{1}$$

To represent the compositional structures within foreground objects, GSGN models $\mathbf{z}_{\text{fg}}$ as a tree-structured probabilistic scene graph, as shown in Figure 1A. Each leaf node represents a primitive entity that is not further decomposed. Each internal node represents an abstract entity that is composed from its children nodes. Similar to graphics engines, the composition is modeled as affine transformations, and is specified by the relative pose (including rotation, scaling, and translation) of each child node v with respect to its parent $pa(v)$. We use a pose variable $\mathbf{z}_v^{\text{pose}}$ to represent the relative pose, and associate it with the corresponding edge. We also associate an appearance variable $\mathbf{z}_v^{\text{appr}}$ with each node v. It is expected to represent the appearance of entity[1] v in its canonical pose, summarizing all lower-level composition in the subtree rooted at v. In particular, the appearance variable $\mathbf{z}_r^{\text{appr}}$ at the root node r summarizes the full scene. Due to this summarization assumption, given $\mathbf{z}_v^{\text{appr}}$, we can generate the pose and appearance variables for all children nodes of v in a conditionally independent way. Hence, for a given tree structure with V being the set of all nodes, the prior over foreground variables can be factorized according to the tree structure:

$$p(\mathbf{z}_{\text{fg}}) = p(\mathbf{z}_r^{\text{appr}}) \textstyle\prod_{v \in V \setminus \{r\}} p(\mathbf{z}_v^{\text{pose}} \,|\, \mathbf{z}_{pa(v)}^{\text{appr}})\, p(\mathbf{z}_v^{\text{appr}} \,|\, \mathbf{z}_{pa(v)}^{\text{appr}}) \;. \tag{2}$$

Here we further assume conditional independence between $\mathbf{z}_v^{\text{pose}}$ and $\mathbf{z}_v^{\text{appr}}$, since in graphics engines, one should be able to specify the pose and appearance separately.

Representing tree structures. The above factorization only works for a given tree structure. To deal with variable tree structures, we need to include them in the latent representation as well. We start by setting a maximum out-degree for each node so that the total number of possible structures is bounded. To determine the structure, it then suffices to specify the presence of each possible edge. Hence, for an arbitrary edge between node v and its parent, we introduce a Bernoulli variable $\mathrm{z}_v^{\text{pres}}$ to indicate its presence. If $\mathrm{z}_v^{\text{pres}} = 0$, meaning the edge is not present, then the pose variable associated

[1] We use v to refer to both node v in the probabilistic scene graph and the entity that node v represents.

with the edge along with all variables in the subtree rooted at v are excluded from the probabilistic scene graph. More precisely, let us define $\bar{\mathrm{z}}_v^{\mathrm{pres}}$ to be the product of all the presence variables along the path from root r to node v:

$$\bar{\mathrm{z}}_r^{\mathrm{pres}} = 1 \ , \quad \bar{\mathrm{z}}_v^{\mathrm{pres}} = \mathrm{z}_v^{\mathrm{pres}} \times \bar{\mathrm{z}}_{pa(v)}^{\mathrm{pres}} \ \text{ for } \ v \in V \setminus \{r\} \ . \tag{3}$$

The foreground variables now become $\mathbf{z}_{\mathrm{fg}} = \{\mathbf{z}_r^{\mathrm{appr}}\} \cup \{\mathrm{z}_v^{\mathrm{pres}}, \mathbf{z}_v^{\mathrm{pose}}, \mathbf{z}_v^{\mathrm{appr}}\}_{v \in V \setminus \{r\}}$, and the prior factorizes as follows:

$$p(\mathbf{z}_{\mathrm{fg}}) = p(\mathbf{z}_r^{\mathrm{appr}}) \prod_{v \in V \setminus \{r\}} \left[p(\mathrm{z}_v^{\mathrm{pres}} \,|\, \mathbf{z}_{pa(v)}^{\mathrm{appr}})\right]^{\bar{\mathrm{z}}_{pa(v)}^{\mathrm{pres}}} \left[p(\mathbf{z}_v^{\mathrm{pose}} \,|\, \mathbf{z}_{pa(v)}^{\mathrm{appr}}) \, p(\mathbf{z}_v^{\mathrm{appr}} \,|\, \mathbf{z}_{pa(v)}^{\mathrm{appr}})\right]^{\bar{\mathrm{z}}_v^{\mathrm{pres}}} \ . \tag{4}$$

We implement the pose and appearance variables as Gaussian variables, $p(\mathbf{z}_r^{\mathrm{appr}}) = \mathcal{N}(\mathbf{0}, \mathbf{1})$, and the parameters of each conditional distribution are output by an MLP.

Differentiable decoder. We design the decoder to closely follow the rendering process in graphics engines, helping the encoder to learn inverse graphics. First, for each leaf node v, we use a neural network $g(\cdot)$ to decode its appearance variable into a small image patch $\hat{\mathbf{x}}_v$ and a (close to) binary mask $\hat{\mathbf{m}}_v$: $(\hat{\mathbf{x}}_v, \hat{\mathbf{m}}_v) = g(\mathbf{z}_v^{\mathrm{appr}})$. Here, $g(\cdot)$ is implemented as a spatial broadcast decoder (Watters et al., 2019) optionally followed by sub-pixel convolutions (Shi et al., 2016).

We then recursively compose these primitive patches into whole objects and the full scene by applying affine transformations parameterized by the pose variables. Specifically, let u be an internal node, and $ch(u)$ be the set of its children. We compose the higher-level image patch $\hat{\mathbf{x}}_u$ and mask $\hat{\mathbf{m}}_u$ as follows:

$$\hat{\mathbf{x}}_u = \textstyle\sum_{v \in ch(u)} \mathrm{z}_v^{\mathrm{pres}} \cdot \boldsymbol{\alpha}_v \odot \mathcal{ST}^{-1}(\hat{\mathbf{x}}_v, \ \mathbf{z}_v^{\mathrm{pose}}) \ , \tag{5}$$

$$\hat{\mathbf{m}}_u = \textstyle\sum_{v \in ch(u)} \mathrm{z}_v^{\mathrm{pres}} \cdot \boldsymbol{\alpha}_v \odot \mathcal{ST}^{-1}(\hat{\mathbf{m}}_v, \ \mathbf{z}_v^{\mathrm{pose}}) \ . \tag{6}$$

Here, $\odot$ denotes pixel-wise multiplication, and $\mathcal{ST}^{-1}$ is an inverse spatial transformer (Jaderberg et al., 2015) that differentiably places $\hat{\mathbf{x}}_v$ and $\hat{\mathbf{m}}_v$ into the coordinate frame of the parent node u. To deal with occlusion, we include relative depth in $\mathbf{z}_v^{\mathrm{pose}}$, and compute a transparency map $\boldsymbol{\alpha}_v$ by the softmax over negative depth values. This ensures that entities with smaller depth will appear in front of entities with larger depth. See Figure 1C for an illustration.

When we reach the root node, we obtain an image $\hat{\mathbf{x}}_r$ and a mask $\hat{\mathbf{m}}_r$ of all foreground objects. We then use a spatial broadcast decoder (Watters et al., 2019) to decode $\mathbf{z}_{\mathrm{bg}}$ into a background image $\hat{\mathbf{x}}_{\mathrm{bg}}$. The full scene $\mathbf{x}$ can now be modeled as a pixel-wise mixture of foreground and background, where $\hat{\mathbf{m}}_r$ serves as the mixing weight:

$$p(\mathbf{x} \,|\, \mathbf{z}_{\mathrm{fg}}, \mathbf{z}_{\mathrm{bg}}) = \hat{\mathbf{m}}_r \odot \mathcal{N}(\mathbf{x} \,|\, \hat{\mathbf{x}}_r, \sigma_{\mathrm{fg}}^2 \mathbf{1}) + (\mathbf{1} - \hat{\mathbf{m}}_r) \odot \mathcal{N}(\mathbf{x} \,|\, \hat{\mathbf{x}}_{\mathrm{bg}}, \sigma_{\mathrm{bg}}^2 \mathbf{1}) \ . \tag{7}$$

Here, σ_{fg} and σ_{bg} are hyperparameters.

3.2 Inference and Learning

Since computing $p(\mathbf{x})$ in Equation 1 involves an intractable integral, we train GSGN with variational inference. The approximate posterior factorizes similarly as the generative process:

$$p(\mathbf{z}_{\mathrm{fg}}, \mathbf{z}_{\mathrm{bg}} \,|\, \mathbf{x}) \approx q(\mathbf{z}_{\mathrm{fg}}, \mathbf{z}_{\mathrm{bg}} \,|\, \mathbf{x}) = q(\mathbf{z}_{\mathrm{fg}} \,|\, \mathbf{x}) \, q(\mathbf{z}_{\mathrm{bg}} \,|\, \mathbf{z}_{\mathrm{fg}}, \mathbf{x}) \ . \tag{8}$$

To infer the foreground variables, we make the key observation that the probabilistic scene graph has a recursive structure. This suggests a recursive inference process, in which the children nodes of the root node are first inferred, and then inference is recursively performed within each subtree rooted at the children nodes. Hence, we design a top-down factorization:

$$\begin{aligned} q(\mathbf{z}_{\mathrm{fg}} \,|\, \mathbf{x}) = {} & q(\mathbf{z}_r^{\mathrm{appr}} \,|\, \mathbf{x}) \prod_{v \in V \setminus \{r\}} \left[q(\mathrm{z}_v^{\mathrm{pres}} \,|\, \mathbf{z}_{pa(v)}^{\mathrm{appr}}, \mathbf{x}_{pa(v)})\right]^{\bar{\mathrm{z}}_{pa(v)}^{\mathrm{pres}}} \left[q(\mathbf{z}_v^{\mathrm{pose}} \,|\, \mathbf{z}_{pa(v)}^{\mathrm{appr}}, \mathbf{x}_{pa(v)})\right]^{\bar{\mathrm{z}}_v^{\mathrm{pres}}} \\ & \times \prod_{v \in V \setminus \{r\}} \left[q(\mathbf{z}_v^{\mathrm{appr}} \,|\, \mathbf{z}_{pa(v)}^{\mathrm{appr}}, \mathbf{x}_v)\right]^{\bar{\mathrm{z}}_v^{\mathrm{pres}}} \ , \end{aligned} \tag{9}$$

where the inference of child node v is conditioned on the inferred appearance variable $\mathbf{z}_{pa(v)}^{\mathrm{appr}}$ of its parent. This crucially provides top-down information for separating lower-level entities, since $\mathbf{z}_{pa(v)}^{\mathrm{appr}}$ summarizes lower-level composition. We combine this top-down information with bottom-up image features. Specifically, we use spatial attention to crop a local image region $\mathbf{x}_v$ that is expected to

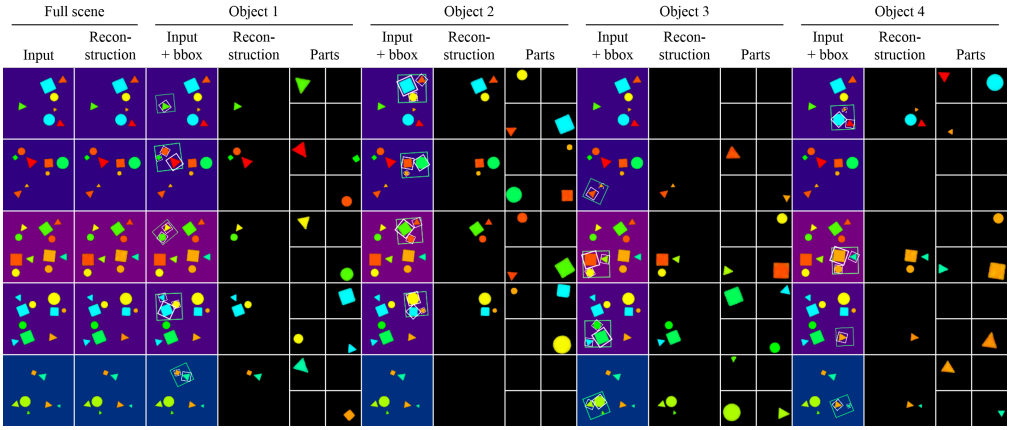

Figure 2: Visualization of inferred scene graphs on 2D Shapes dataset.

capture the entity v. This provides more relevant information for inferring the appearance and structure of entity v. The region $\mathbf{x}_v$ is specified by all the predicted pose variables along the path from root r to node v. More precisely, we define $\mathbf{x}_r = \mathbf{x}$, and recursively extract $\mathbf{x}_v = \mathcal{ST}(\mathbf{x}_{pa(v)}, \mathbf{z}_v^{\text{pose}})$ using a spatial transformer $\mathcal{ST}$ (Jaderberg et al., 2015), as shown in Figure 1B.

Parameter sharing between prior and posterior. Inspired by Ladder VAEs (Sønderby et al., 2016), we find it beneficial to share parameters between the prior and the posterior. Specifically, we implement each factorized posterior as a product of the corresponding prior and a posterior obtained solely from image features. This also allows us to reuse existing scene decomposition methods such as SPACE (Lin et al., 2020b) as an inference module of GSGN. For example,

$$q(\mathbf{z}_v^{\text{appr}} \,|\, \mathbf{z}_{pa(v)}^{\text{appr}}, \mathbf{x}_v) \propto p(\mathbf{z}_v^{\text{appr}} \,|\, \mathbf{z}_{pa(v)}^{\text{appr}})\, q(\mathbf{z}_v^{\text{appr}} \,|\, \mathbf{x}_v) = p(\mathbf{z}_v^{\text{appr}} \,|\, \mathbf{z}_{pa(v)}^{\text{appr}})\, q_{\text{SPACE}}(\mathbf{z}_v^{\text{appr}} \,|\, \mathbf{x}_v)\,. \quad (10)$$

Training. We use reparameterization trick (Kingma & Welling, 2013) to sample the continuous pose and appearance variables, and Gumbel-Softmax trick (Jang et al., 2016; Maddison et al., 2016) to sample the discrete presence variables. The entire model can be trained end-to-end via backpropagation to maximize the evidence lower bound (ELBO):

$$\mathcal{L} = \mathbb{E}_q[p(\mathbf{x} \,|\, \mathbf{z}_{\text{fg}}, \mathbf{z}_{\text{bg}}) - D_{\text{KL}}[q(\mathbf{z}_{\text{fg}} \,|\, \mathbf{x}) \,\|\, p(\mathbf{z}_{\text{fg}})] - D_{\text{KL}}[q(\mathbf{z}_{\text{bg}} \,|\, \mathbf{z}_{\text{fg}}, \mathbf{x}) \,\|\, p(\mathbf{z}_{\text{bg}} \,|\, \mathbf{z}_{\text{fg}})]]\,. \quad (11)$$

Auxiliary KL loss. As pointed out by recent work (Chen et al., 2020), learnable priors have difficulty reflecting our prior knowledge. Hence, similar to (Chen et al., 2020), we introduce auxiliary KL terms between the posterior and some fixed prior that reflects our preference. In particular, we find it important to introduce a KL term between $q(\mathbf{z}_v^{\text{pres}} \,|\, \mathbf{z}_{pa(v)}^{\text{appr}}, \mathbf{x}_{pa(v)})$ and a Bernoulli prior distribution with low success probability to encourage sparse tree structures.

4 Experiments

Datasets. In order to evaluate GSGN's ability to learn the structure of compositional objects, we develop compositional versions of Multi-dSprites (Greff et al., 2019) and CLEVR (Johnson et al., 2017), two commonly used datasets for evaluating unsupervised object-centric representation learning models. We refer to our new datasets as 2D Shapes and Compositional CLEVR datasets, respectively. For each dataset, we define three types of primitive parts, and ten types of objects composed from these parts. Because the color and material of each part are randomly sampled, this setting covers a broad range of compositional structures. Three of the object types contain a single part, another three contain two parts, and the remaining four contain three parts. To construct a scene, we randomly sample the number of objects (between one and four) and their types, sizes, positions, and orientations. Each dataset consists of 128×128 color images, split into 64000 for training, 12800 for validation, and 12800 for testing.

GSGN implementation. While GSGN is a general framework for representing and inferring scene graphs of arbitrary depth, for our evaluation, we implement a three-level GSGN, containing part-, object-, and scene-level representations. We set the maximum out-degree to be 4 for each node.

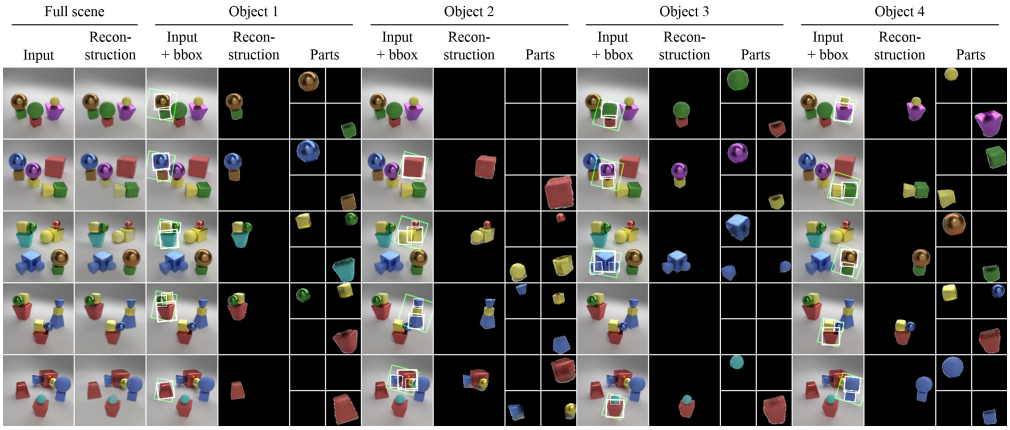

Figure 3: Visualization of inferred scene graphs on Compositional CLEVR dataset.

Baselines. Previous work on hierarchical scene representations assumes single-object scenes (Kosiorek et al., 2019) and requires predefined or pre-segmented parts (Li et al., 2017; Huang et al., 2020), and thus cannot work on our datasets. Hence, we compare with SPACE (Lin et al., 2020b), a state-of-the-art non-hierarchical scene decomposition model. Although SPACE cannot infer the scene graph, its hyperparameters can be tuned to decompose the scene into either objects (SPACE-O) or parts (SPACE-P). This allows us to compare the inference quality of individual nodes.

Ablations. We consider two ablated versions of GSGN. GSGN-No-Share does not share parameters between prior and posterior, namely it does not factorize the posterior as in Equation 10. GSGN-No-Aux directly optimizes the ELBO without auxiliary KL terms.

Scene graph inference. We visualize the inferred scene graphs in Figure 2 and Figure 3. Here, the bounding boxes visualize the inferred pose variables (including rotation, scaling, and translation), and the reconstructions are obtained by feeding the inferred appearance variables through the decoder. Empty slots indicate that the corresponding presence variables are zero. As can be seen, GSGN is able to correctly separate the parts and group them into objects, even when objects are close (Figure 2 Row 1-4, Figure 3 Row 1-2), parts have similar color (Figure 2 Row 4-5, Figure 3 Row 3), and there is occlusion between objects and parts (Figure 3 Row 4-5).

Table 1: Quantitative results on 2D Shapes dataset.

Metric	ELBO	Object Count Accuracy	Object F1 Score	Part Count Accuracy	Part F1 Score
SPACE-O	3.96	99.79%	99.95%	—	—
SPACE-P	3.95	—	—	98.75%	96.73%
GSGN	3.96	99.76%	99.85%	99.54%	99.91%
GSGN-No-Share	3.96	99.72%	99.90%	99.49%	99.89%
GSGN-No-Aux	3.96	25.00%	72.75%	95.79%	97.34%

Table 2: Quantitative results on Compositional CLEVR dataset.

Metric	ELBO	Object Count Accuracy	Object F1 Score	Part Count Accuracy	Part F1 Score
SPACE-O	3.50	98.02%	99.17%	—	—
SPACE-P	3.48	—	—	92.71%	99.03%
GSGN	3.49	98.66%	99.37%	98.63%	99.77%
GSGN-No-Share	3.50	96.21%	98.26%	97.09%	99.38%
GSGN-No-Aux	3.50	25.13%	72.87%	12.38%	79.09%

Table 3: Robustness to occlusion on Compositional CLEVR dataset.

Min Visible Pixels Per Part	<100		100∼200		>200	
Metric	Part Count Accuracy	Part Recall	Part Count Accuracy	Part Recall	Part Count Accuracy	Part Recall
SPACE-P	12.24%	86.03%	85.66%	97.95%	96.11%	99.48%
GSGN	95.92%	98.93%	98.33%	99.77%	98.76%	99.86%
GSGN-No-Share	85.71%	96.34%	96.13%	99.15%	97.56%	99.46%

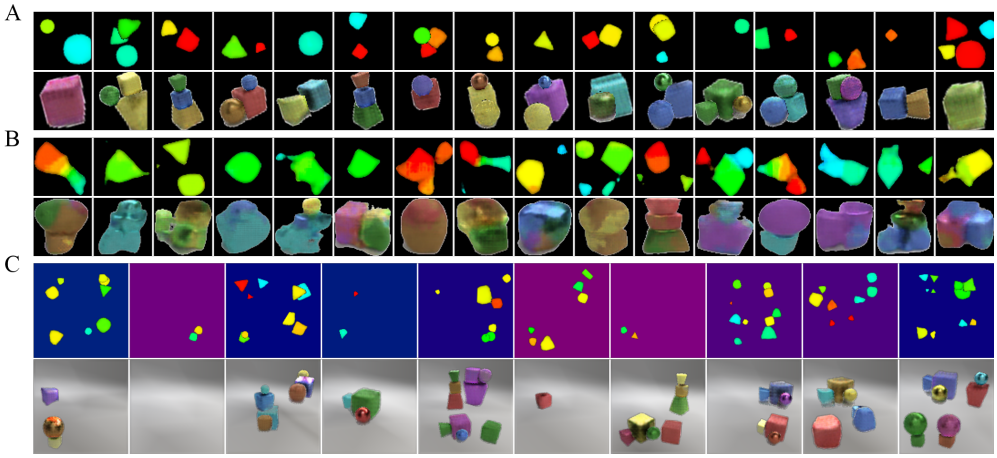

Figure 4: *(A)* Objects sampled from GSGN learned prior. *(B)* Objects sampled from SPACE-O prior. *(C)* Scenes sampled from GSGN learned prior.

We report quantitative results in Table 1 and Table 2. Here, counting accuracy measures the correctness of the number of nodes in the inferred scene graph. F1 score is the harmonic mean of precision and recall. We define a node to be true positive if it is sufficiently close to a groundtruth entity. Hence, F1 score reflects if the inferred nodes indeed capture entities. We measure closeness by the distance between center positions. The distance threshold for objects and parts are 10 and 5 pixels respectively. As can be seen, all models obtain similar reconstruction quality. GSGN-No-Aux fails to infer the scene graph structure. We find that it tends to set all presence variables to be one, resulting in redundant nodes. With auxiliary KL terms, GSGN and GSGN-No-Share are able to infer sparse structures, achieving comparable object-level decomposition performance with SPACE-O.

On the Compositional CLEVR dataset, GSGN achieves better part-level decomposition than SPACE-P. We observe that this is because SPACE-P has difficulty separating parts that have severe occlusion. We further investigate this by splitting the test set into three occlusion levels. Here we measure the amount of occlusion in an image by the minimum number of visible pixels per part. As shown in Table 3, when an image contains a part that has less than 100 visible pixels, SPACE-P performs significantly worse than GSGN. Its low recall suggests that SPACE-P tends to miss occluded parts. We also find GSGN-No-Share performs worse than GSGN in this scenario, indicating that parameter sharing helps better combine top-down information from the prior to reduce ambiguity caused by occlusion.

The counting accuracy and F1 score evaluate the object- and part-level separately, without taking into account the overall tree structure. To directly measure the quality of the inferred tree structure, we perform a manual inspection on 100 test images from each dataset. GSGN achieves 100% and 99% structural accuracy on the 2D Shapes and Compositional CLEVR datasets respectively. We also consider a heuristic baseline, which starts from the parts predicted by SPACE-P, and groups the parts whose bounding boxes overlap. This baseline achieves 95% and 80% structural accuracy on the two datasets.

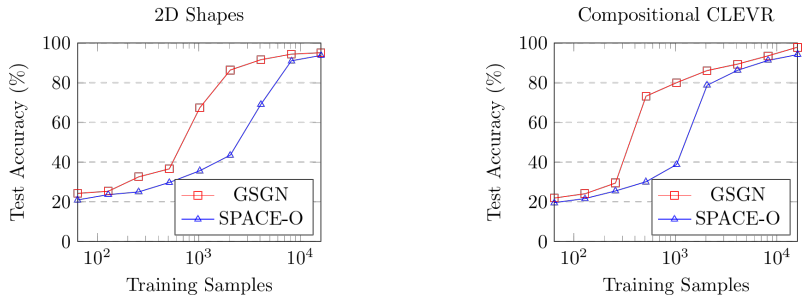

Figure 5: Comparison of data efficiency in a downstream task that requires reasoning of the part-whole relationship.

Object and scene generation. GSGN is able to generate objects and scenes by sampling the latent variables from the learned prior and feeding them through the decoder. We show generation results in Figure 4. We find that GSGN has captured many predefined object types in the dataset, and also managed to come up with novel compositions. The generated scenes are also reasonable, with moderate distance and occlusion between objects. The objects generated by SPACE-O are much less interpretable, since SPACE does not explicitly model the part-whole relationship. Also, SPACE cannot generate meaningful scenes, because the presence variables sampled from its prior will almost always be zero, leading to no object being put onto the scene.

Generalization performance. We evaluate GSGN's capacity to generalize to scenes with novel number of objects. We report the metrics in Table 4 and Table 5. As can be seen, GSGN demonstrates quite decent generalization performance.

Data efficiency in downstream tasks. The compositional structure learned by GSGN can be useful in downstream tasks that require reasoning of part-object relationships. Here we consider a classification task. The input images are generated from the same distribution but with different random seeds. The label for each image is obtained by first counting the number of distinct parts within each object, and then summing the count over all objects. We expect the representation learned by GSGN to bring better data efficiency compared to SPACE. Notice that SPACE-P cannot group the parts by itself and will fail in this task. Hence, we compare with SPACE-O, whose object-level representation implicitly encodes the constituent parts. We use pretrained GSGN and SPACE-O to obtain the latent representation for each image, and then train a classifier on top of the representation to predict the label. The classifier for SPACE-O first feeds the appearance variable of each object through an MLP, and then performs a learned weighted sum to aggregate them into a scene-level representation vector, which is fed to another MLP to output class probabilities. The classifier for GSGN first aggregates the appearance variables of parts into object-level representation vectors, and then performs the same operations as the classifier for SPACE-O. The tree structure learned by GSGN crucially allows us to use a graph net (Battaglia et al., 2018) within the subtree of each object for aggregation, providing more inductive bias for extracting interactions. We train the two classifiers using 64, 128, 256, 512, 1024, 2048, 4096, 8192, and 16000 training samples. We choose the best learning rate for both classifiers using a fixed validation set of size 12800. We report classification accuracy on a fixed test set also of size 12800. As shown in Figure 5, GSGN approximately doubles the data efficiency on this downstream task compared to SPACE.

5 Conclusion

We have proposed GSGN, the first deep generative model for unsupervised scene-graph discovery and compositional scene generation. GSGN learns the part-whole relationship from multi-object scenes without knowledge of individual parts. GSGN combines top-down prior and bottom-up image features to infer the probabilistic scene graph representation for a given scene. This utilizes the higher-level appearance information to guide lower-level decomposition. Through extensive experiments, we have demonstrated that GSGN is able to infer the latent scene graph from images containing multiple compositional objects with severe occlusion. An interesting future direction is to extend GSGN to the sequential setting.

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A GENERALIZATION PERFORMANCE

Table 4: Generalization performance on 2D Shapes dataset.

Training Set	1 & 3 Objects					
Test Set	2 Objects			4 Objects		
Model	SPACE-O	SPACE-P	GSGN	SPACE-O	SPACE-P	GSGN
ELBO	4.00	3.99	4.00	3.85	3.83	3.84
Object Count Accuracy	99.47%	—	99.51%	100.0%	—	100.0%
Object F1 Score	99.89%	—	99.73%	100.0%	—	99.47%
Part Count Accuracy	—	98.12%	99.21%	—	96.82%	99.39%
Part F1 Score	—	95.66%	99.86%	—	96.50%	99.95%

Table 5: Generalization performance on Compositional CLEVR dataset.

Training Set	1 & 3 Objects					
Test Set	2 Objects			4 Objects		
Model	SPACE-O	SPACE-P	GSGN	SPACE-O	SPACE-P	GSGN
ELBO	3.62	3.60	3.60	3.06	3.10	3.02
Object Count Accuracy	98.27%	—	98.93%	88.86%	—	87.78%
Object F1 Score	99.64%	—	99.72%	96.72%	—	96.41%
Part Count Accuracy	—	93.02%	98.69%	—	84.96%	87.20%
Part F1 Score	—	95.66%	99.71%	—	98.92%	97.99%

B LEARNING PRIMITIVE TEMPLATES

It is often reasonable to assume that the vast number of complex entities can be composed from only a modest number of primitive entities. Identifying such primitive entities through discrete latent variables would bring additional interpretability. Hence, we consider an extension to GSGN (denoted GSGN-Mem) where the leaf nodes become pointers to a jointly learned memory $\mathbf{M}$ of primitive templates. Each slot in $\mathbf{M}$ stores the low-dimensional shape embedding of a learned primitive part. These embeddings are considered model parameters, and are trained jointly via backpropagation. To link the probabilistic scene graph with the memory of primitives, we decompose the appearance variable $\mathbf{z}_v^{\text{appr}}$ for each leaf node v into $\mathbf{z}_v^{\text{appr}} = (\mathbf{z}_v^{\text{addr}}, \mathbf{z}_v^{\text{what}})$. Here, $\mathbf{z}_v^{\text{addr}}$ is a one-hot addressing variable that points to one of the slots in $\mathbf{M}$, and $\mathbf{z}_v^{\text{what}}$ is a continuous variable that explains the remaining variability in the appearance of primitives, such as color, material, and lighting effects. Similar to (Bornschein et al., 2017), we factorize the prior as:

$$p(\mathbf{z}_v^{\text{appr}} \,|\, \mathbf{z}_{pa(v)}^{\text{appr}}) = p(\mathbf{z}_v^{\text{addr}} \,|\, \mathbf{z}_{pa(v)}^{\text{appr}}, \mathbf{M})\, p(\mathbf{z}_v^{\text{what}} \,|\, \mathbf{M}[\mathbf{z}_v^{\text{addr}}])\ , \tag{12}$$

where $\mathbf{M}[\mathbf{z}_v^{\text{addr}}]$ is the retrieved memory content.

To decode from the templates, we first retrieve the embedding indexed by $\mathbf{z}_v^{\text{addr}}$, and decode it into a (close to) binary mask $\hat{\mathbf{m}}_v = g(\mathbf{M}[\mathbf{z}_v^{\text{addr}}])$ that captures the shape of v. We then add color, material, and lighting effects by applying multiplicative modification controlled by $\mathbf{z}_v^{\text{what}}$, and obtain $\hat{\mathbf{x}}_v = \hat{\mathbf{m}}_v \odot h(\mathbf{z}_v^{\text{what}})$. Here, $\odot$ denotes pixel-wise multiplication, $g(\cdot)$ is implemented as a spatial broadcast decoder (Watters et al., 2019), and $h(\cdot)$ a spatial broadcast decoder followed by sub-pixel convolutions (Shi et al., 2016).

We trained GSGN-Mem on the Compositional CLEVR dataset. We find it is able infer the scene graph, as we show qualitatively in Figure 6. The primitives have learned the appearance of all the parts in the dataset, while reserving some memory capacity for potential future use (See Figure 7).

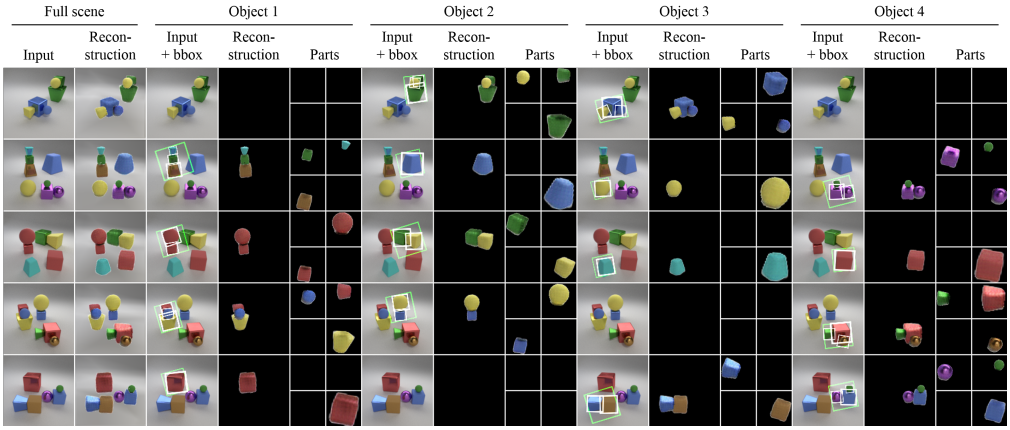

Figure 6: Visualization of inferred scene graphs on Compositional CLEVR dataset.

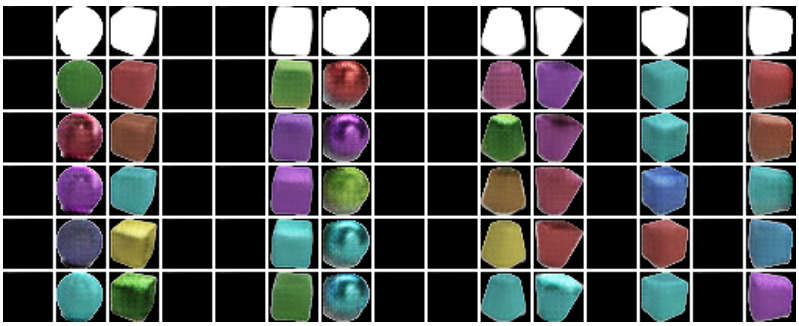

Figure 7: Learned memory of primitive parts. Each column corresponds to one slot. The first row shows the decoded mask that captures the shape of the parts. The remaining rows are samples from the learned prior that fill in plausible color, material, and lighting effects.