CLEVR3D: Compositional Language and Elementary Visual Reasoning for Question Answering in 3D Real-World Scenes

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Abstract

3D scene understanding is a relatively emerging research field. In this paper, we introduce the Visual Question Answering task in 3D real-world scenes (VQA-3D), which aims to answer all possible questions given a 3D scene. To tackle this problem, the first VQA-3D dataset, namely CLEVR3D, is proposed, which contains 60K questions in 1,129 real-world scenes. Specifically, we develop a question engine leveraging 3D scene graph structures to generate diverse reasoning questions, covering the questions of objects’ attributes (i.e., size, color, and material) and their spatial relationships. Built upon this dataset, we further design the first VQA-3D baseline model, TransVQA3D. The TransVQA3D model adopts well-designed Transformer architectures to achieve superior VQA-3D performance, compared with the pure language baseline and previous 3D reasoning methods directly applied to 3D scenarios. Experimental results verify that taking VQA-3D as an auxiliary task can boost the performance of 3D scene understanding, including scene graph analysis for the node-wise classification and whole-graph recognition.

1. Introduction

3D scene understanding is a critical task in computer vision, aiming to achieve the perception and interpretation of a scene from 3D data. This task demands not only the fundamental perception capability of recognizing and localiz-
ing objects in 3D scenes, but also the high-level reasoning capacities to capture objects’ context and relationships.

Traditional works on 3D scene understanding mainly concentrate on the perception tasks such as instance segmentation [17], semantic segmentation [4, 9] as well as 3D object detection and classification [29, 31]. These works pay more attention to each individual object but ignore the inter-object’s context and relationships, only utilizing them to improve the per-object recognition. Recently, applying natural language to cooperatively improve the scene understanding has become a hot research topic, where 3D visual grounding [1, 6], 3D dense captioning [8] and scene graph analysis [40, 42, 48] are increasingly studied. Compared with the reasoning from 2D images, reasoning in real-world 3D scenes can avoid the inherent spatial ambiguity in 2D data, and capture the real geometric information and inter-object relationships. Meanwhile, 3D scenes typically contain more instances and involve more complicated inter-object relationships. Despite significant efforts in exploring spatial representations to enhance scene comprehension, current works are still deficient in 3D perception (e.g., counting and verifying the existence) and referring the object attributes (e.g., size, material, and texture).

To address the above issues, this paper introduces the task of Visual Question Answering in 3D real-world scenes (VQA-3D). Different from previous 3D scene understanding tasks only focusing on specific aspects, VQA-3D expects the model to answer all possible questions, i.e., verifying object existence, counting, comparison, query object, and query attributes. Inspired by well-studied VQA on images [18], we first propose a CLEVR3D dataset based on the 3D semantic scene graphs [40]. Specifically, we develop a question engine, leveraging information about objects’ attributes and inter-object relationships provided in the semantic scene graph of each scene. Moreover, we enhance the question engine to conduct tight control over the answer distributions and mitigate question biases. Eventually, over 60K questions covering 13 categories are obtained, where several sample questions from different classes are displayed in Figure 1. Notably, the task of VQA-3D is different from traditional image-based VQA in the following aspects: 1) 3D data encodes real shape attributes and spatial relationships among objects, without the ambiguity in 2D images introduced by viewpoint changing, occlusion, and reprojection. 2) Unlike 2D images with regular grids and dense pixels, 3D data represented by point clouds are disordered and scattered in 3D space. Hence, even though the geometric shapes of the objects are easier to capture in 3D, their textures and materials are hard to identify. 3) A large 3D scene typically contains more instances, leading to more complicated inter-object relationships.

Along with the dataset, we propose a framework TransVQA3D based on Transformer [38], which achieves 3D scene understanding by effectively bridging the perception and reasoning. After extracting objects from the 3D scene, the visual features of each object are obtained by a 3D feature extractor (i.e., PointNet++ [31]), and they are fed into several Transformer layers with given question embeddings. Furthermore, we construct scene graphs according to object spatial and feature space dependence. Then, a Scene Graph Aware Attention (SGAA) module is introduced to further enhance the feature representation via the well-designed twinning attention. Finally, under the simultaneous supervision by scene graph reasoning, TransVQA3D answers the given questions and achieves superior scene understanding performance. The experiments demonstrate that TransVQA3D achieves state-of-the-art results on the VQA-3D task against pure language models and previous 3D vision-language approaches directly applied to the VQA-3D scenario. Moreover, by utilizing VQA-3D, TransVQA3D can also improve the performance of scene graph analysis.

Our main contributions can be summarized as follows:

• We introduce a novel VQA-3D task, and contribute a CLEVR3D dataset containing 60K questions from 1,129 real-world 3D scenes.
• To tackle the challenging VQA-3D task, we propose a baseline TransVQA3D with well-designed architecture against traditional image-based VQA approaches.
• We show that TransVQA3D achieves state-of-the-art results on VQA-3D while boosting the performance of 3D scene graph analysis.

2. Related Work

Visual Question Answering on Images. VQA has gained significant attention recently. This task requires models to answer a text-based question according to the information contained in an image. Several datasets are proposed in this research field, spanning natural images [13, 15] and synthesis ones [18]. Among them, CLEVR [18] is a typical diagnostic dataset for image-based VQA. It uses 100,100 synthesis images to construct spatial and comparative relationships between different chromatic shapes. Inspired but different from CLEVR, our CLEVR3D applies 3D scene graphs to generate more diverse questions. In the image-based VQA tasks, early models [3, 20] obtain the joint embeddings of multi-modal features via the element-wise summation, multiplication, or concatenation. Since compact bilinear pooling [12] is effective in a wide range of visual tasks, several works [5, 11, 21] employ it to address VQA tasks with lower computing overheads and achieve more impressive performances. Motivated by the studies of Graph Convolutional Networks (GCN) [23], several works [16, 24, 37] encode visual and linguistic information on graph-based structures. Recently, Vision Trans-
Figure 2. Overview of the VQA-3D. Part (a) illustrates the data generation process of VQA-3D, where the whole process contains three steps: scene graph normalization, question engine design, and sampling. Part (b) shows the data statistics of question length and proportions. CLEVR3D contains more question types compared with the CLEVR dataset.

former [27, 35, 38, 45] has shown its superiority on image-based VQA, and some of these methods use pre-trained BERT [10] to boost the performance. However, considering the differences in representations and the complexity of 3D scenarios, previous image-based methods cannot be directly applied to 3D scene understanding.

Scene Graph Analysis. To manifest object relationships of images in an explicit and structured way, Scene Graph [19] is proposed, in which objects are modeled as the nodes and the edges linking them represent the relationships. Since the release of the large-scale 2D scene graph dataset, Visual Genome [22], a string of scene graph generation methods [25, 36, 37, 41, 43, 47] are substantially fostered, yet following a similar pipeline. In practice, a Region Proposal Network (PRN) is utilized to extract the object proposals along with their features. Then a fully connected graph refines the node and edge features to infer a scene graph. For instance, in the VCTree model [37], the visual features are obtained from Faster-RCNN [32], and a dynamic VCTree is established with a differentiable score matrix. Graph embeddings are refined using BiTreeLSTM [34]. The context features from graph embeddings are used for scene graph generation and VQA. In terms of the 3D scene graph analysis, Johanna et al. [40] is the pioneer. They propose the first 3D scene graph benchmark based on 3RScan dataset [39], and introduce a baseline model exploiting PointNet [30] to obtain object classes and inter-object relationships. Recently, Zhang et al. [48] adopts a graph-based model to enhance the graph analysis. Wu et al. [42] proposes a framework for incremental 3D scene graph generation from the RGB-D frames. However, these methods mainly focus on the object classes and relationships but ignore object existence and fine-grained object attributes.

3D Vision and Language. Compared to image and language comprehension, 3D vision and language understanding is a relatively emerging research field. Existing works focus on using language to confine individual objects, e.g., detecting referred 3D objects [7] or distinguishing objects according to language phrases [2]. Recently, ScanRefer [6] and ReferIt3D [1] introduce a task of localizing objects within a 3D scene given the linguistic descriptions, namely 3D visual grounding. Following them, several works are proposed to improve the performance through instance segmentation [14, 46], or Transformer [33, 44, 49]. 3D dense captioning is proposed very lately in Scan2Cap [8]. It focuses on decomposing 3D scenes and describing the chromatic and spatial information of the objects. Inspired but different, in this paper, we introduce the task of VQA-3D for the first time, which allows the model to comprehensively understand the whole 3D scene.

3. CLEVR3D

In this paper, we propose the CLEVR3D dataset. In Section 3.1, we introduce the data generation process, including the normalization of scene graph, the design of question engine to generate diverse questions via templates, and the way to eliminate data bias. In Section 3.2, we provide the data statistics of CLEVR3D and make comparisons with the traditional VQA dataset - CLEVR [18].

3.1. Data Generation

Scene Graph Normalization. The foundation of our VQA-3D dataset is the 3D Semantic Scene Graph (3DSSG) annotations [40] on 3RScan dataset [39]. 3DSSG dataset has been initially probed for the 3D object instance re-localization task and then upgraded as a newly established benchmark for 3D scene graph analysis. Following 3DSSG, there are total 1,129 scenes that have scene graph annotations. A semantic scene graph $G$ in 3DSSG, is a set of tuples $(V, E)$ between nodes $V$ and relation edges $E$. Each node denotes an object in the 3D scene, e.g., table, chair and window, and it is linked to a bounding box indicating...
its position and size. Each object is associated with its attributes, i.e., color, shape, and material, and objects are connected by relation edges, representing spatial relations and comparatives. To alleviate the severe object class imbalance issues appearing within the original 3RScan dataset, we select RIO27 annotation (27 object classes) in our studies, rather than original annotations (534 object classes). For the inter-object relationship, we keep original 40 classes (e.g., standing on in Figure 2 (a)) in our data generation.

**Question Engine.** The question engine is responsible for generating diverse questions with various categories. We follow the process of traditional VQA dataset generation [18], exploiting question family to generate questions. Specifically, a question family includes a template for constructing questions, and one can change its parameters to express diverse questions. For instance, the question “How many white wooden table are there?” can be formed by the template “How many $<C>$ $<M>$ $<O>$ are there?” exploiting the parameters $<C>$, $<M>$ and $<O>$ (correspond to the values white, wooden and table) to indicate the attributes “color”, “material” and “object”. In practice, there are five parameters we used, namely $<C>$ (color), $<M>$ (material), $<S>$ (shape), $<R>$ (relationship) and $<O>$ (object). In total, there are 90 question families in CLEVR3D and each of them has an average of four parameters. As shown in Figure 2 (a), by applying different question families, diverse questions can be generated.

**Question Sampling and Balance.** During the question generation, we randomly sample combinations of values and reject those which lead to ill-posed or degenerated questions. For example, we eliminate questions of the form “What color is the $<O_1>$ to the $<R>$ of the $<O_2>$” with $<O_1>$ = “chair” and $<O_2>$ = “table” if the scenes do not contain “chair” or “table”. To further reduce the ambiguity, we do not consider the meaningless objects, e.g., “floor” and “other objects”, in the question, since the relationship with them is almost singular (every object “standing on” the floor). Besides, we use rejection sampling to produce an approximately uniform answer distribution for each question family, which helps minimize question-conditional bias in the dataset. Finally, we balance the answer distribution by eliminating answers that appear less than one hundred.

### 3.2. Data Statistics

CLEVR3D contains 60,105 questions from 1,129 scenes. The training and test sets include 49,650 and 10,455 questions from 996 and 133 scenes, respectively. We further categorize questions into different question types, defined by the outermost function in the question’s program. Figure 2 (b) illustrates question types (e.g., “query-color” and “count”), and shows the number of questions within each type, where we compare our CLEVR3D dataset with three classic VQA datasets, CLEVR [18], GQA [15], and VQA v2 [13] in the figure. Moreover, Table 1 demonstrates the comparison between CLEVR3D and the most typical one, i.e., CLEVR [18], which is most similar to our dataset since others are natural images containing human and relationships of behaviors. As shown in the table, since real-world 3D data are more challenging to collect compared with natural images, CLEVR3D contains fewer questions. However, the number of instances per scan is much larger than that of images (28 v.s. 6) and thus contains more questions (53 v.s. 9). Furthermore, CLEVR3D contains a wider range of categories for objects’ attributes, classes, and interrelationships. More question samples and question family templates can be found in the supplementary material.

### 4. Method

In this paper, we propose a strong baseline for the VQA-3D task built upon Transformer [38]. Figure 3 (a) illustrates the architecture of our proposed TransVQA3D, which contains three modules, i.e., object embedding, cross-modal transformer, and scene graph aware attention (SGAA) module. Section 4.1 introduces the input embedding, including feature embedding and positional encoding. The details of cross-modal transformer and SGAA is addressed in the Section 4.2 and Section 4.3.

#### 4.1. Input Embedding

The input to a VQA-3D model is a 3D scene $\mathcal{P} \in \mathbb{R}^{N \times D_{in}}$ (in the form of point clouds with $N$ points and a $D_{in}$-dimensional feature on each point) and a natural language question with $l$ words. To facilitate the setup, we only use the coordinate (XYZ) of each point and its color values (RGB) as a 6D input vector while ignoring additional hints such as normal vectors and projected 2D features [44].

**Language Embedding.** The input query description is first
tokenized into words and further mapped into a sequence of vectors $\mathcal{W} \in \mathbb{R}^{l \times 768}$ via a pre-trained BERT [10], where $l$ is the sequence length. To reduce the computational burden during training, a fully-connected layer maps the feature dimension to $d_{\text{enc}}$, following a dropout layer of ratio 0.1.

**Object Embedding.** Following previous studies [40], we assume that there are $m$ 3D object instances in the scene, and we use a class-agnostic point-to-instance indicator $\mathcal{M} \in \{1, ..., m\}^N$ to generate instance point clouds $\mathcal{P}^{\text{obj}} = \{\mathcal{P}^{\text{obj}}_i\}^m_i$ for each object $i$:

$$\mathcal{P}^{\text{obj}}_i = \{\mathcal{P}_n | \mathcal{M}_n = i; \ n = 1, ..., N\}. \quad (1)$$

After that, a share-weighted feature extractor [30] $\mathcal{F}^{\text{obj}}(\cdot)$ followed with a symmetric pooling function is performed on each instance point cloud to obtain instance feature, e.g., $\mathcal{X}^{\text{pos}}_i = \mathcal{F}(\mathcal{P}^{\text{obj}}_i) \in \mathbb{R}^{d_{\text{enc}}}$. Moreover, to encode spatial information, we further design object positional encoding $\mathcal{X}^{\text{pos}}$ as the following:

$$\mathcal{X}^{\text{pos}}_i = \mathcal{F}^{\text{pos}}([P^{\text{center}}_i; P^{\text{size}}_i; P^{\text{orient}}_i]) \in \mathbb{R}^{d_{\text{enc}}}, \quad (2)$$

where $\mathcal{F}^{\text{pos}}$ is a non-linear transformation function; $P^{\text{center}}_i \in \mathbb{R}^3$, $P^{\text{size}}_i \in \mathbb{R}^3$ and $P^{\text{orient}}_i \in \mathbb{R}^3$ are center, size (height, width, and length), and heading orientation of the object, respectively. $[; ;]$ denotes a concatenation operation.

4.2. Cross-modal Transformer

Inspired by the great success achieved by Transformer [38] in both computer vision and natural language processing, we develop a cross-modal transformer for vision-language feature fusion. Specifically, we first concatenate the object embedding with language embedding in the length dimension, obtaining a $m + l$ length token set, where $m$ and $l$ respectively stands for instance number and language length. Then, we construct a Transformer by stacking three self-attention layers with four heads. After feeding object embedding $\mathcal{X}$ and language embedding $\mathcal{W}$ into the model, we gain their enhanced features $\mathcal{X}'$ and $\mathcal{W}'$ for performing scene graph aware attention.

4.3. Scene Graph Aware Attention

The inner structure of scene graph aware attention (SGAA) module is depicted in Figure 3 (b). The goal of the SGAA module is to simultaneously obtain the answer and create a scene graph $G = (\mathcal{V}, \mathcal{E})$, where nodes $\mathcal{V}$ and edges $\mathcal{E}$ depict the instances and their inner structural relationships, respectively. It contains two twinning attention and a cross-modal attention layers.

**Scene Graph Initialization.** To obtain a scene graph representation, the node feature is initialized as $\mathcal{X}_\mathcal{V} = \mathcal{X}' \in \mathbb{R}^{m \times d_{\text{enc}}}$, which is further propagated to obtain a $m^2$ one-to-one edges $\mathcal{X}_\mathcal{E}$. Each edge feature $\mathcal{X}_\mathcal{E} \in \mathbb{R}^{m \times m \times (2d_{\text{enc}} + 9)}$ contains the features of two nodes ($2d_{\text{enc}}$), and additional $\mathbb{R}^9$ features, i.e., two objects’ centers and their relative offsets.

**Twinning Attention.** To fully utilize the language and scene graph information to mutually enhance the performance of two tasks, we design a novel twinning attention. This mechanism takes nodes and edges of a scene graph as the inputs, and generates their enhanced representation.
Table 2. Accuracy per question type of the different VQA-3D methods on the CLEVR3D dataset.

| Method               | Existence Number | Counting | Compare Integer | Query Attr. | Query Object | Compare Attr. | Overall |
|----------------------|------------------|----------|-----------------|-------------|--------------|---------------|---------|
| L+LSTM               | 69.1             | 31.4     | 46.3            | 34.6        | 15.2         | 43.1          | 36.5    |
| L+Transformer        | 65.9             | 29.7     | 49.5            | 35.1        | 17.5         | 45.6          | 37.0    |
| ReferIt3D [1]        | 68.9             | 32.5     | 54.7            | 38.8        | 21.7         | 51.4          | 41.0    |
| L+V+Transformer      | 71.4             | 32.2     | 54.0            | 42.2        | 24.3         | 49.2          | 42.7    |
| TransVQA3D           | 70.5             | 37.2     | 56.5            | 42.5        | 24.5         | 56.2          | 44.6    |
| Human                | 82.6             | 65.2     | 69.6            | 88.4        | 73.9         | 73.9          | 76.3    |

Figure 4. Visualization of accurate predictions of TransVQA3D on CLEVR3D.

In specific, two steps are introduced for feature updating: edge-to-node and node-to-edge.

1) **edge-to-node**: It first updates node features through bidirectional edge attention. Given a node pair \((i, j)\), it considers both the relationship from node \(i\) to \(j\) and the inverse one from \(j\) to \(i\). In particular, for the \(i\)-th node feature \(\mathcal{X}_V^i\), it conducts feature aggregation within both row and column of the edges feature (i.e., \(\mathcal{X}_E^i\) and \(\mathcal{X}_E^j\)) by

\[
\mathcal{R}_i = \Sigma(W_3\{\mathcal{X}_E^i\}_j=1) \odot \Sigma(W_4\{\mathcal{X}_E^j\}_j=1) (4)
\]

where \(W_3\) and \(W_4\) are two linear projection from \(\mathbb{R}^{m \times d_{ae}}\). After independently merging row and column features into single vectors through a pooling function \(\Sigma(\cdot)\), it applies Hadamard product \(\odot\) to obtain the relation representation \(\mathcal{R} \in \mathbb{R}^{m \times d_{ae}}\). Then, the node feature is updated by

\[
\mathcal{X}_V^i = f(\mathcal{X}_V \odot \sigma(\mathcal{R})). (5)
\]

In Eqn. (5), a Sigmoid function \(\sigma(\cdot)\) is first conducted on edge relation and obtained edge-driven interactive scores. After applying the product between node and relation, a nonlinear activation function \(f\) is further adopted.

2) **node-to-edge**: It updates the edge feature through the nonlinear transformation \(f\) of the concatenation of newly generated node feature:

\[
\mathcal{X}_E \theta_j = f(W_5[\mathcal{X}_V^i; \mathcal{X}_E^j]). (6)
\]

**Cross-modal Attention**. To leverage the scene graph aware representation for the answer prediction, a cross-modal attention mechanism is applied in the SGAA module. Concretely, for each language feature \(\mathcal{W}_v^i\), it aggregates the node features through

\[
\hat{\mathcal{W}}_i = \Sigma(\{\sigma(\mathcal{W}_0[\mathcal{W}_v^i; \mathcal{X}_{E_j}^i]) \odot \mathcal{X}_V^j, \forall \mathcal{X}_{E_j}^i \in \mathcal{X}_E^i\}), (7)
\]

where the language feature \(\mathcal{W}_v^i\) is firstly concatenated with node feature \(\mathcal{X}_V^j\) and obtain normalized weights through Sigmoid function \(\sigma(\cdot)\). After that, it aggregates the node features through weighted average and pooling \(\Sigma(\cdot)\).

4.4 Prediction and Objectives

As shown in Figure 3 (a), TransVQA3D generates three kinds of outputs, including enhanced features for language, nodes, and edges. To facilitate the notation, we denote them as \(\mathcal{W}, \mathcal{X}_V\) and \(\mathcal{X}_E\), respectively. \(\mathcal{W}\) is used in the answer prediction by passing through several fully-connected layers, obtaining scores toward all candidate answers in the answer pool. \(\mathcal{X}_V\) and \(\mathcal{X}_E\) are independently fed into two classifiers, and the probabilities of object classes (nodes) and object-to-object relationships (edges) can be gained. The cross-entropy loss is used as the criterion for answer prediction and node classification (\(\mathcal{L}_{vqa}\) and \(\mathcal{L}_{node}\)). Since the edges of a scene graph generally have multiple labels, we
Table 3. Scene graph analysis on 3DSSG dataset. Top-K Recall is utilized as the evaluation metric. We compare different methods on node classification, predicate classification and relationship triplet prediction.

| Approach       | Object Class Prediction | Predicate Class Prediction | Relationships Triplet Prediction |
|----------------|-------------------------|----------------------------|----------------------------------|
|                | R@5 R@10                | R@3 R@5                    | R@50 R@10                        |
| SGPN [30]      | 66.2 77.5               | 72.5 98.8                  | 53.2 67.5                        |
| 3DSSG [40]     | 68.0 78.1               | 99.0 99.4                  | 64.9 75.8                        |
| TransVQA3D     | 71.8 80.6               | 99.8 99.9                  | 69.1 87.8                        |

use multi-label binary cross-entropy ($\mathcal{L}_{edge}$) on this branch. The final loss is a linear combination of these three losses.

5. Experiments

In the experiment, we benchmark the VQA-3D task and then compare the proposed TransVQA3D on the task of Scene Graph analysis. More experimental results are presented in the supplementary material.

5.1. Implementation Details

In the implementation, we employ the pre-trained BERT [10] to generate the initial language features. For the object features, we exploit PointNet++ [31] as the feature extractor. Each object contains 4,000 points through random sampling, and they are randomly rotated along the z-axis for augmentation. Cross-modal Transformer consists of three four-head attention layers, and the output of each layer preserves the identical 256 channels. The SGAA module includes two twinning attentions and cross-modal attention, where their hidden dimensions are the same as that of the cross-modal Transformer. We train the network for 20 epochs by using the Adam optimizer with a batch size of 32 (about 6 hours). The learning rate of the network is initialized as 0.0001 with a decay of 0.9 for every 10 epochs. According to the experiment results, the weights of three losses do not significantly affect the performance, and we eventually set them identical. All experiments are implemented on PyTorch with a single RTX2080 GPU.

5.2. VQA-3D

Dataset. Our proposed CLEVR3D dataset is used to evaluate the performance of different methods for VQA-3D. The training and test sets include 49,650 and 10,455 questions in 996 and 133 scenes, respectively. We train all methods on the training set and evaluate their last checkpoints on the test set.

Baselines. To evaluate the VQA-3D task, we introduce several baselines, including pure language models (upper), vision-language cross-modal ones (middle), and humans (bottom). Table 2 demonstrates the comparison results among these methods.

\* L+LSTM: We directly exploit language embedding into a two-layer LSTM, whose feature of the last token is used for prediction.

\* L+Transformer: We only adopt the language-related components in TransVQA3D, including language embedding and Transformer layers. The outputs of language features directly generate answer predictions through two fully-connected layers.

\* ReferIt3D [1]: It is initially a model for the 3D visual grounding task. The network first extracts object features through PointNet++ [31]. Following that, it concatenates the global language feature with each object representation and exploits DGCNN [28] to obtain the score of each object. We discard its scoring step and apply max pooling to obtain a global feature to generate the answer prediction.

\* L+V+Transformer: We adopt the language and visual components of TransVQA3D while ignoring the scene graph aware attention (SGAA) module.

\* TransVQA3D: The full architecture as in Section 4.

\* Human: Besides these baseline models, we also report the responses of 4 human subjects for 1,000 randomly selected questions from the test set, selecting the answer with the majority of votes among 4 voters for each question.

Comparison. We adopt Accuracy as the evaluation metric, and present the results of different question types in Table 2. TransVQA3D achieves the best result almost in all question categories, significantly surpassing the pure language model. It should be noted that utilizing the feature fusion in ReferIt3D [1] cannot effectively improve the VQA-3D performance. Without the well-designed architecture and scene graph aware feature enhancement, the performance on 3D scene understanding will be degraded. Notably, there still exists a gap over the human responses, especially for “count” and “query object”. Some demos of TransVQA3D for VQA-3D are visualized in Figure 4.

5.3. Scene Graph Analysis

Dataset. To further validate the effectiveness of our proposed methods, we evaluate TransVQA3D on the task of scene graph analysis on 3DSSG dataset [40]. We follow the experimental settings of [40], including the train/test split and corresponding semantics. We further evaluate the model on 160 object classes and 7 relationship categories.

Comparison. Since there is no published training codes
Table 4. Ablation studies for multitask learning of VQA-3D and scene graph analysis. The upper, middle, and lower parts demonstrate the effectiveness of exploiting multitask, different designs for SGAA module and Cross-modal Transformer, respectively.

| Model | Task          | CMT | SGAA | VQA-3D |
|-------|--------------|-----|------|--------|
|       |              | NumLayer | PE  | TA | CMA | Node (R@1) | Edge (R@1) | Overall | ClassAvg |
| A     | VQA-3D       | 3   | ✓   | -  | -   | -           | -           | 39.7    | 40.1    |
| B     | VQA-3D+Node  | 3   | ✓   | -  | -   | 33.3        | -           | 42.7    | 45.6    |
| C     | Node+Edge    | 3   | ✓   | ✓  | ✓   | 29.9        | 91.7        | -       | -       |
| D     | VQA-3D+Node+Edge | 3  | ✓   | ✓  | ✓   | 35.1        | 94.8        | 44.6    | 47.9    |
| E     | VQA-3D+Node+Edge | 3  | ✓   | X  | ✓   | 32.5        | 15.7        | 42.5    | 44.3    |
| F     | VQA-3D+Node+Edge | 3  | ✓   | ✓  | X   | 34.9        | 94.1        | 43.7    | 47.5    |
| G     | VQA-3D+Node+Edge | 4  | ✓   | ✓  | ✓   | 34.7        | 93.6        | 44.5    | 47.4    |
| H     | VQA-3D+Node+Edge | 3  | ✓   | ✓  | ✓   | 34.9        | 93.2        | 43.2    | 45.1    |
| I     | VQA-3D+Node+Edge | 3  | ✓   | ✓  | ✓   | 31.0        | 92.5        | 42.1    | 44.9    |

for [48], we compare TransVQA3D with 3DSSG [40] in Table 3. Its vanilla model (i.e., SGPN in the table) uses two PointNets [30] to extract the features of object and relationship, respectively. Upon this baseline, it further adopts the GCN to conduct feature aggregation between nodes (i.e., 3DSSG). Following [40], we separately evaluate the predicate (relationship) prediction in isolation from the object classes, where we adopt the Top-k Recall score [26] as the metric. Moreover, the performances of the object categories are reported. We further evaluate the most confident (subject, predicate, object) triplets against the ground-truth in a top-k Recall manner. As illustrated in Table 3, our model outperforms 3DSSG in all scene graph related metrics, especially for relationships triplet prediction. Without well-designed architecture and axillary VQA-3D, 3DSSG cannot achieve satisfactory 3D scene understanding.

5.4. Ablation Study

We conduct ablation studies on different designs of our architecture in Table 4. In the upper part (models A-D), we demonstrate the mutual enhancement between VQA-3D and scene graph reasoning. In the middle part (models E and F), we explore different designs of the SGAA module. In the lower part (models G-I), we present the results of using different Cross-modal Transformer (CMT) designs. Apart from the metric of Overall Accuracy (Overall) for VQA-3D, we also report the results of Class Average Accuracy (ClassAvg) to measure the abilities of models in cross-different question types.

Does scene graph analysis help VQA-3D? We provide the results of only exploiting VQA-3D task in model A, where we do not apply object (node) classification and edge (predicate) prediction. In Table 4, it is evident that model A gains a low overall accuracy of 39.7 for VQA-3D. When we apply additional supervision of object classification (model B) during the training, the Overall boosts from 39.7 to 42.7, which implies the significance of the object classification. Besides, scene graph prediction also help improve the VQA-3D results (model D). There is a noticeable improvement in the absolute accuracy by 2% when utilizing the SGAA module for edge prediction.

Does VQA-3D help scene graph analysis? We show the ablated results by model C, discarding the language features during the training. As shown in Table 4 (model C), only taking scene graph reasoning leads to an obvious degradation on both node and edge prediction (about 5% and 3%).

How to design the SGAA module? We independently validate two core components (i.e., twinning Attention (TA) and Cross-modal Attention (CMA) in the SGAA module) in models E and F. In model E, we ablate TA from the SGAA module, leading to a drop on both the VQA-3D and scene graph prediction. Inversely, the effectiveness of CMA is not prominent since it only affects the results of VQA-3D with about 1% and the results of scene graph analysis maintain. We ignore the analysis of the number of TA in the SGAA module in this section, since it does not significantly influence the performance within the range of [1, 3].

How to design Cross-modal Transformer? As displayed in the results of model I, positional encoding plays a significant role in the CMT. The number of layers (models G and H) in the CMT does not greatly affect the performances.

6. Conclusion

In this paper, we present CLEVR3D, the first benchmark dataset for enabling the Visual Question Answering task in 3D real-world scenes (VQA-3D). We introduce a question engine based on 3D scene graphs to generate diverse reasoning questions concerning object attributes and relationships. Besides, we provide the first baseline model for VQA-3D, namely TransVQA3D, achieving superior performance on this newly proposed dataset and showing that VQA-3D can greatly help the 3D scene understanding. We believe this benchmark can boost the development of 3D scene understanding, bringing sound reasoning, improved robustness, and solid multi-modal interactions. We strongly hope that CLEVR3D will motivate and support more re-
searchers in exploring 3D scene understanding and conducting advanced works on the VQA-3D.

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