VQA-GNN: Reasoning with Multimodal Semantic Graph for Visual Question Answering

Yanan Wang* KDDI Research wa-yanan@kddi.com

Shinya Wada KDDI Research sh-wada@kddi.com

Abstract

Visual understanding requires seamless integration between recognition and reasoning: beyond image-level recognition (e.g., detecting objects), systems must perform concept-level reasoning (e.g., inferring the context of objects and intents of people). However, existing methods only model the image-level features, and do not ground them and reason with background concepts such as knowledge graphs (KGs). In this work, we propose a novel visual question answering method, VQA-GNN, which unifies the image-level information and conceptual knowledge to perform joint reasoning of the scene. Specifically, given a questionimage pair, we build a scene graph from the image, retrieve a relevant linguistic subgraph from ConceptNet and visual subgraph from VisualGenome, and unify these three graphs and the question into one joint graph, multimodal semantic graph. Our VQA-GNN then learns to aggregate messages and reason across different modalities captured by the multimodal semantic graph. In the evaluation on the VCR task, our method outperforms the previous scene graph-based Trans-VL models by over 4%, and VQA-GNN-Large, our model that fuses a Trans-VL further improves the state of the art by 2%, attaining the top of the VCR leaderboard at the time of submission. This result suggests the efficacy of our model in performing conceptual reasoning beyond imagelevel recognition for visual understanding. Finally, we demonstrate that our model is the first work to provide interpretability across visual and textual knowledge domains for the VQA task.

1 Introduction

The task of visual question answering (VQA) aims to provide answers to questions about a visual scene or image. It is crucial in many real-world tasks including scene understanding, autonomous

Michihiro Yasunaga and Hongyu Ren Stanford University {myasu, hyren}@cs.stanford.edu

> Jure Leskovec Stanford University jure@cs.stanford.edu



Figure 1: Given an image and QA, our VQA-GNN grounds visual and textual context and retrieves relevant commonsense knowledge of them across imagelevel and concept-level KGs. VQA-GNN is designed to unify relevant image-level and concept-level knowledge to perform joint reasoning of the scene.

vehicles, search engine, recommendation systems (Antol et al., 2015; Fukui et al., 2016; Ben-Younes et al., 2017; Kim et al., 2018). To solve VQA, systems need to not only perform image-level recognition (e.g., detecting objects), but also perform concept-level reasoning (e.g., inferring the context of objects and intents of people) according to the question. Most of the state-of-the-art VOA methods (Lu et al., 2019; Su et al., 2020; Li et al., 2020; Yu et al., 2021; Chen et al., 2020; Zellers et al., 2021, 2022) pretrain a transformer-based visual-language (Trans-VL) model using massive image-caption data to learn relations between image and language contexts, and then finetune the pretrained model on downstream tasks (e.g., visual commonsense reasoning (VCR) task (Zellers et al., 2019)) to perform reasoning over implicit VL representations. To better capture visual context with the Trans-VL method, Wang et al. (2022) further proposes an add-on method SGEITL to include a visual scene graph in the input of the Trans-VL method. However, these methods only model the

^{*} Work done while at Stanford University.

image-level features of inputs, and do not ground them to background knowledge (*e.g.*, commonsense) to perform conceptual reasoning. Knowledge graphs (KGs) such as ConceptNet (Speer et al., 2017) and VisualGenome (Krishna et al., 2017) are readily-available resources to provide explicit background knowledge and reasoning scaffolds (Yasunaga et al., 2021), motivating research in integrating KGs into VQA systems.

In this work, we propose VQA-GNN, a new model that performs joint reasoning over multimodal knowledge sources for effective VQA. Our multimodal semantic graph includes concept-level and image-level knowledge, as shown in Figure 1. Specifically, VQA-GNN uses diverse knowledge sources including scene graphs and general knowledge graphs to provide commonsense knowledge related to the image and QA context. VQA-GNN extracts a scene graph from the given input image using a off-the-shelf scene graph generator to obtain a high-level structured representation of the visual context, and then retrieves relevant linguistic/visual subgraphs from massive knowledge graphs including ConceptNet (Speer et al., 2017) and VisualGenome (Krishna et al., 2017). Given the inferred scene graph and the retrieved knowledge subgraphs, we combine them into a multimodal semantic graph by introducing super nodes that link relevant concepts from the graphs. The multimodal semantic graph consists of QA-contextaware concepts (from the scene graph) as well as the QA-context-agnostic concepts (from the knowledge graph). Finally, VQA-GNN performs message passing and reasons on this structured multimodal semantic graph with graph neural networks (GNNs) to score each answer candidate. Our VQA-GNN is the first unified model that fuses the strengths of Trans-VL, scene graphs, and knowledge graphs via a joint semantic graph and GNN.

We evaluate VQA-GNN on the VCR task. This task spans across multiple-choice question answering and selecting rationales behind a questionanswer pair. Without using any image-caption pretraining data used by previous works, which is over **11x** larger than the VCR dataset and the knowledge graphs we use, our model substantially improves on the previous finetuned scene graphbased Trans-VL model SGEITL (Wang et al., 2022) by over **4%**. Furthermore, VQA-GNN-Large, our model that uses a Trans-VL, RESEVER-L (Zellers et al., 2022), improves the state of the art by **2%**, attaining the top of the leaderboard at the time of submission. This result suggests the efficacy of VQA-GNN in performing conceptual reasoning beyond image-level recognition for visual understanding. Compared to Trans-VL models, our model is also the first to provide interpretability across both visual and textual knowledge for VQA task.

2 Problem setup

In this work we focus on multiple-choice visual question answering. Each data point consists of an image c as visual context, a natural language question q, and a set of candidate answers \mathcal{A} , where only one candidate $a_{\text{correct}} \in \mathcal{A}$ is the correct answer to the question. Additionally, we assume we have access to an external knowledge base/graph \mathcal{G} that captures the general context-agnostic knowledge. Given a QA example (c, q, \mathcal{A}) and the knowledge graph \mathcal{G} , our goal is to identify the correct answer $a_{\text{correct}} \in \mathcal{A}$.

3 Related works

Visual question answering (VQA). Visual question answering (VQA) has been one of the most popular topics in the computer vision community over the past few years (Antol et al., 2015; Fukui et al., 2016; Ben-Younes et al., 2017; Kim et al., 2018). Recent methods for VQA (Lu et al., 2019; Yu et al., 2021; Su et al., 2020; Li et al., 2020; Zellers et al., 2021) employ the pretrain-andfinetune approach, where they pretrain a Trans-VL model on large-scale visual-language datasets, and then finetune the pretrained model on the downstream VQA datasets, e.g., RESERVE-L model (Zellers et al., 2022) is pretrained using 1 billion image-caption data including video frames, text and audio. However, such methods tend to cost significant computation resources and also lack interpretability. In contrast, we extract a scene graph from the image in order to provide explicit relation information in the image, and build a GNN model with the scene graph to achieve an interpretable reasoning. It does not need extra visual-language dataset for pretraining, and outperforms existing models without pretraining process (Table 1).

Question answering with scene graphs. Several existing works (Teney et al., 2017; Liang et al., 2021) utilize scene graphs for visual question answering. However, these methods assume they have the ground-truth scene graphs or only address



Figure 2: Overview of *VQA-GNN*: we first perform the image-level KG retrieval (§4.1) and the concept-level KG retrieval (§4.1) to build a multimodal semantic graph (§4.2), then we perform Multi-relation GNN (§4.3) to joint reason correct answer of the scene (§4.4). Here, "C-SG" and "I-SG" indicate Concept-level and Image-level semantic graph, both are subgraph of the multimodal semantic graph.

questions that are generated from scene graphs. In contrast, our method generates a scene graph from raw images using pretrained scene graph generator (Tang et al., 2020), which is more general and practical.

Question answering with knowledge graphs. Knowledge graphs (KGs) provide structured information about background concepts, and are shown to help various question answering tasks (Yasunaga et al., 2021; Ren et al., 2021). Recently, KGs are also used for visual question answering (Marino et al., 2019). However, this line of works do not use scene graphs, and fail to model the relations between objects in the image and entities in the knowledge graph. In contrast, we build both a scene graph (from the image), and a relevant linguistic and visual knowledge subgraphs (from massive KGs), and unify these graphs along with the question into a shared graph to facilitate joint reasoning with image and background knowledge. Inspired by QA-GNN (Yasunaga et al., 2021), which does message passing over concept nodes with a given QA context, we design GNN to respectively pass messages on image-level and concept-level node representations with a joint QA context node. As a result, we can better learn useful representations of the joint QA context across different modality.

4 Approach

A diagram of *VQA-GNN* is shown in Figure 2. Given an image and its related question with an answer choice, first we obtain explicit concept-level and image-level KGs from the visual and textual

context, respectively (§4.1). Then we introduce a QA node to connect the concept-level and imagelevel KGs to build a multimodal semantic graph so that we can reason about the correct answer over the joint knowledge resources (§4.2). Here, node z represents the QA textual context that is the concatenation of a question and an answer choice. In addition to z, we concatenate the retrieved answer choice-relevant global/local image context to get a QA visual context node p. We then propose an attention-based GNN to pass messages across different nodes on the joint multimodal semantic graph (§4.3) for effective reasoning. Finally, we train the model to make the prediction using the concatenation of QA text, image, z, p and pooled working graphs representations (§4.4).

4.1 Multimodal KG retrieval

Image-level KG retrieval. Compared to most of the previous works that use object representations extracted from the image as a visual knowledge source (Lu et al., 2019; Su et al., 2020; Li et al., 2020; Yu et al., 2021; Chen et al., 2020), we use a pretrained scene graph generator to extract a scene graph that consists of recall@20 of (subject, predicate, object) triplets to represent the object-level image context (Tang et al., 2020), e.g., (car, behind, man). We embed subject/object node v_i with a pretrained object detection model to get visual representation (Zhang et al., 2021), and predicate edge $\epsilon_i \in \mathcal{E}_{sq}$ as an one-hot vector indicating the predicate edge type. In addition to the local image context, with an intuition that the global image context of the correct choice

is assumed to be similar to the local image context, we use a pretrained sentence-BERT model to calculate the similarity between each answer choice with all region descriptions of region image in the Visual Genome dataset so that we can get relevance region images to represent the global image context of each choice (Reimers and Gurevych, 2019). Here we experimentally use top 10 of retrieved result and embed them using a same object detector for local image context, and then take their mean to get a QA visual context node p. Finally, we introduce a QA visual context edge $r_{p,i}^a$ to fully connect p with $v_i \in \mathcal{V}_{sg}$ to construct a image-level semantic graph $\mathcal{G}_{sg}^a = (\mathcal{V}_{sg}^a, \mathcal{E}_{sg}^a)$ for each answer choice a; Here, \mathcal{V}_{sg}^{a} is the set of image nodes, where $\mathcal{V}_{sg}^{a} = \mathcal{V}_{sg} \bigcup \{p\}, \text{ and } \mathcal{E}_{sg}^{a} \text{ is the set of image edges,}$ where $\mathcal{E}_{sg}^{a} = \mathcal{E}_{sg} \bigcup \{r_{p,i}^{a}\}).$



Figure 3: Concept-level KG retrieving process. Here, Relev(ela) denotes the similarity between concept nodes and context in answer.

Concept-level KG retrieval. In parallel with the image-level knowledge retrieval, we retrieve concept-level knowledge from the image and ConceptNet KG, a general-domain knowledge graph (Speer et al., 2017). As shown in Figure 3, we perform the following steps. **Step 1:** We parse concept entity from both of the image and answer choice. For the image, we utilize the detected object name as candidate contextual entities, and drop out general entity to reduce unnecessary difficulty in reasoning, *e.g.*, "person". For the answer choice, we ground phases if they are mentioned concepts in the ConceptNet KG, *e.g.*, "beverage" and "shop".

Step 2-1: We use grounded phases to retrieve their 1-hop neighbor nodes from the ConceptNet KG. Step 2-2: As many retrieved concept nodes that are semantically irrelevant to the answer choice, inspired by QA-GNN (Yasunaga et al., 2021), we introduce relevance score to prune irrelevance nodes. We use a word2vec model released by the spaCy library¹ to get relevance score between concept node candidates and answer choices. As a result, given an answer choice, we can retrieve a relevance subgraph from ConceptNet KG based on the relevance score. To better comprehend concept knowledge from the image as well, Step 3: In addition to linking adjacent object entities in the ConceptNet KG domain, we also combine them with retrieved subgraph by matching and linking relevance concept entities, e.g., (bottle, atlocation, beverage), (book, related to, thing). Hence, we can obtain a concept-level semantic graph $\mathcal{G}_{cp}^{a} = (\mathcal{V}_{cp}^{a}, \mathcal{E}_{cp}^{a})$ to represent concept-level knowledge. Here, \mathcal{V}_{cp}^{a} is the set of concept nodes and \mathcal{E}^a_{cp} is the set of concept edges. We use the concept entity embedding from (Feng et al., 2020) to represent the concept node $v_c \in \mathcal{V}^a_{cp}$, and initialize the concept edge $\epsilon_c \in \mathcal{E}^a_{cp}$ with a one-hot vector, depending on the size of \mathcal{E}^a_{cp} .

4.2 Multimodal semantic graph

To execute effective reasoning across diversity knowledge sources end-to-end, we introduce a QA textual context node z to bridge image-level semantic graph \mathcal{G}^a_{sq} and concept-level semantic graph \mathcal{G}^{a}_{cp} through three extra relation types, which are image edge $r_{z,i}$, question edge $r_{z,q}$ and answer edge $r_{z,a}$. $r_{z,i}$ is designed to capture the relationship between the QA textual context and the relevant entities in the \mathcal{G}^a_{sq} by connecting all image nodes in \mathcal{V}_{sq} . On the other hand, question edge $r_{z,q}$ and answer edge $r_{z,a}$ are designed to capture the relationship between the QA textual context and the relevant entities in the \mathcal{V}^a_{cp} by connecting the question entity q and answer entity a parsed from the question and answer portion of the QA textual context, respectively. As a result, given a QA textual context node, we construct a multimodal semantic graph \mathcal{G}^w to provide a joint reasoning space, which includes two sub graph of \mathcal{G}_{sg}^w and \mathcal{G}_{cp}^w , where $\mathcal{G}_{sg}^w = (\mathcal{V}_{sg}^w, \mathcal{E}_{sg}^w), \mathcal{V}_{sg}^w = \mathcal{V}_{sg}^a \bigcup \{z\}, \mathcal{E}_{sg}^w = \mathcal{E}_{sg}^a \bigcup \{r_{z,i}\}; \mathcal{G}_{cp}^w = (\mathcal{V}_{cp}^w, \mathcal{E}_{cp}^w), \mathcal{V}_{cp}^w = \mathcal{V}_{cp}^a \bigcup \{z\}, \mathcal{E}_{cp}^w = \mathcal{E}_{cp}^a \bigcup \{r_{z,q}, r_{z,a}\}.$

Here, the QA textual context node z is assigned

¹https://spacy.io/

to not only learn implicit discriminative representations by giving a Q and A text pairs, but also to integrate explicit knowledge form image-level and concept-level semantic graphs for effective VQA. As transformer-based method is powerful for textual representation learning (Su et al., 2020; Lu et al., 2019), we employ the RoBERTa LM (Liu et al., 2019) as the encoder of QA textual context node *z* and finetune it with *VQA-GNN*.

$$z = \text{LM}_\text{encoder}(Q, A) \tag{1}$$

4.3 Multi-relation GNN architecture

In this paper, we build two L-layer VQA-GNN for \mathcal{G}_{sg}^{w} and \mathcal{G}_{cp}^{w} with a common QA textual context node z. To better capture multiple relation information for reasoning across image/concept-level semantic graphs, we perform Graph Attention Networks (GAT) (Veličković et al., 2018) by introducing multi-relation aware message for attention-based message aggregation process.

We have five node types: $\mathcal{T} = \{Z, P, I, Q, A\}$ in the multimodal semantic graph and they indicate QA context node z, visual knowledge node p, i in \mathcal{V}_{sg}^a , q and a in \mathcal{V}_{cp}^a . As relation edge representation $r_{i,j}$ should capture relationship from node i to node j and difference of node types represents a special relation between neighborhood nodes, we first obtain node type embedding u_i, u_j and then concatenate them with edge embedding e_{ij} to generate multi-relation embedding r_{ij} from i to j by

$$\boldsymbol{r}_{ij} = f_r([e_{ij}||u_i||u_j]) \tag{2}$$

where $u_i, u_j \in \{0, 1\}^{|\mathcal{T}|}$ are one-hot vectors indicating the node types of i and $j, e_{ij} \in \{0, 1\}^{|\mathcal{R}|}$ is a one-hot vector indicating relation type of edge (i, j). || is the concatenation operation, and $f_r : \mathbb{R}^{|\mathcal{R}|+2|\mathcal{T}|} \to \mathbb{R}^{\mathcal{D}}$ is a 2-layer MLP. Based on multi-relation embedding r_{ij} , the multi-relation aware message m_{ij} from i to j is computed by

$$\boldsymbol{m}_{ij} = f_m([\boldsymbol{h}_i^{(\ell)} || \boldsymbol{r}_{ij}]) \tag{3}$$

where $f_m : \mathbb{R}^{2\mathcal{D}} \to \mathbb{R}^{\mathcal{D}}$ is a linear transformation. $h_i^{(\ell)}$ is the node representation of each node *i* in the graph. We then recursively updated it ℓ times by

$$\boldsymbol{h}_{i}^{(\ell)} = f_{h}\left(\sum_{j \in \mathcal{N}_{i}} \alpha_{ij}\boldsymbol{m}_{ij}\right) + \boldsymbol{h}_{i}^{(\ell-1)}; \ell \geq 1 (4)$$

where $f_h : \mathbb{R}^{\mathcal{D}} \to \mathbb{R}^{\mathcal{D}}$ is 2-layer MLP with batch normalization (Ioffe and Szegedy, 2015). \mathcal{N}_i indicates the neighborhood of node i, α_{ij} is an attention weight to emphasize important messages passed from \mathcal{N}_i to node i. We obtain q_i, k_j by

$$\boldsymbol{q}_i = f_q(\boldsymbol{h}_i^{(\ell)}), \tag{5}$$

$$\boldsymbol{k}_j = f_k([\boldsymbol{h}_j^{(\ell)}||\boldsymbol{r}_{ij}]) \tag{6}$$

where $f_q : \mathbb{R}^{\mathcal{D}} \to \mathbb{R}^{\mathcal{D}}$ and $f_k : \mathbb{R}^{2\mathcal{D}} \to \mathbb{R}^{\mathcal{D}}$ are linear transformations. α_{ij} is computed using the softmax function by

$$\gamma_{ij} = \frac{q_i^T \mathbf{k}_j}{\sqrt{D}}, \qquad (7)$$

$$\alpha_{ij} = \operatorname{softmax}_{j}(\gamma_{ij}) = \frac{\exp(\gamma_{ij})}{\sum_{j' \in \mathcal{N}_{i}} \exp(\gamma_{ij'})}$$
(8)

4.4 Inference and Learning

To identify the correct answer $a_{correct} \in \mathcal{A}$ with a QA example (c, q, \mathcal{A}) , we compute the probability p(a|c,q) for each answer choice with its multimodal semantic knowledge from QA context, image context, image-level and concept-level semantic graphs. With various node representation on the *L*-th layer updated by VQA-GNN (shown in Figure 2), we obtain pooling representation $\mathbf{h}_{sg}^{(L)}$ and $\mathbf{h}_{cp}^{(L)}$ with $\{\mathbf{h}_v^{(L)}|v \in \mathcal{G}_{sg}^w\}$ and $\{\mathbf{h}_v^{(L)}|v \in \mathcal{G}_{cp}^w\}$, and then calculate p(a|c,q) by

$$\boldsymbol{h}_{a}^{(L)} = [\boldsymbol{q}\boldsymbol{a}^{LM} || \boldsymbol{c}^{VM} || \boldsymbol{h}_{z}^{(L)} || \boldsymbol{h}_{p}^{(L)} || \boldsymbol{h}_{sg}^{(L)} || \boldsymbol{h}_{cp}^{(L)}], (9)$$

$$\log_{1}(a) = f_{c}(\boldsymbol{h}_{c}^{(L)}) \tag{10}$$

$$(a|c,q) = \operatorname{softmax}_{a}(\operatorname{logit}(a))$$
(10)

$$p(a|c,q) = \operatorname{softmax}_{a}(\operatorname{logit}(a))$$
 (11)

where qa^{LM} indicates the language model embedding of QA (Liu et al., 2019), and c^{VM} indicates visual model embedding of image (Kolesnikov et al., 2020). logit(a) indicates the confident score of answer choice $a, f_c : \mathbb{R}^{6D} \to \mathbb{R}^1$ is a linear transformation that maps the concatenation of representations to a scale. We normalize it across all answer choices using the softmax function. For the training process, we apply the cross entropy loss to optimize the VQA-GNN model end-to-end.

5 Experiments

5.1 Experiment Setup

We evaluate *VQA-GNN* on the Visual Commonsense Reasoning dataset (VCR). VCR consists of two tasks: visual question answering (Q \rightarrow A), answer justification (QA \rightarrow R). Each question in the dataset is provided with four candidate answers. The goal of $(Q \rightarrow A)$ is to select the best answer, while the goal of $(QA \rightarrow R)$ is to justify the given question answer pair by picking the best rationale out of the four candidates. We joint train *VQA*-*GNN* on Q \rightarrow A and QA \rightarrow R, with a common LM encoder, the multimodal semantic graph for Q \rightarrow A, concept-level semantic graph for QA \rightarrow R.

We use a pretrained RoBERTa Large model to embed QA textual context node, and finetune it with GNN components for 50 epoch by using learning rate 1e-5 and 1e-4 respectively. We set the number of layers (L = 5) of our GNN module and use AdamW (Kingma and Ba, 2015) optimizer to minimize the loss. We use a linear warmup of the learning rate over the 15-th epoch, with a cosine decay thereafter to 0.

5.2 Performance

To make a fair comparison between Trans-VL models and VQA-GNN, we use baselines in Table 1 which were trained on VCR dataset (290K instances), as reported in SGEITL paper (Wang et al., 2022). SGEITL is an add-on module that can boost Trans-VL models (UNITER, VLBERT) by incorporating finetuned visual scene graph with Trans-VL models. Compared with SGEITL, VQA-GNN is a GNN-based method built on the structured multimodal semantic graph. As shown in Table 1, VQA-GNN improves over SGEITL+VLBERT on the $Q \rightarrow AR$ metric by 4%, and reduces over 11M training parameters. We think that the structured multimodal semantic graph provides much more commonsense knowledge related to QA and original image than SGEITL, and GNN-based method works much better on the structured graph than Trans-VL models. Moreover, since we retrieve commonsense knowledge from structured multimodal semantic graphs directly, VQA-GNN is a cost-effective approach compared to Trans-VL models that consuming much GPU resources to learn commonsense knowledge with large parameters.

To further demonstrate the effectiveness of VQA-GNN, we compare it with state-of-the-art Trans-VL models that were pretrained across text and images and were finetuned on the VCR dataset. As shown in Table 2, the larger image caption data and parameters, the higher performance the model can achieve. In contrast, VQA-GNN trained with VCR dataset with 290K image-caption pairs performs similarly to UNITER-L that requires over

Model	Parameters	Val Acc.(%)			
	1	$\overline{Q \rightarrow A}$	$QA{\rightarrow}R$	$Q \rightarrow AR$	
VLBERT-L	383M	72.9	75.3	54.9	
UNITER-L	378M	73.4	76.0	55.8	
ERNIE-ViL-L	533M	74.1	76.9	56.9	
SGEITL+UNITER	>378M	74.8	76.8	57.4	
SGEITL+VLBERT	>383M	74.9	77.2	57.8	
VQA-GNN	372M	77.1	80.0	62.1	

Table 1: All models are only trained on the VCR dataset. Compared to "SGEITL+VLBERT" model that inputs a visual scene graph to VLBERT network, VQA-GNN applied to a well-structured multimodal semantic graph improves accuracy on $Q \rightarrow AR$ metric by over 4%.

32x larger image-caption data than us in pretraining process. It demonstrates that *VQA-GNN* obtaining structured context knowledge inferred from image-level and concept-level knowledge sources is as effective as the pretraining process for previous methods.

Considering RESERVE-L model focuses on obtaining powerful implicit VL representations and VQA-GNN is capable of providing explicit structured representations, we create a VQA-GNN-Large model to aggregate both implicit and explicit representations by taking the average of their predictions to further improve the performance. The result shows that VQA-GNN can further enhance RESERVE-L performance on both $Q \rightarrow A$ and $QA \rightarrow R$, and finally improves the state-of-theart score by 2% on Q \rightarrow AR metric. As correcting some questions requires the model to understand commonsense knowledge related to image context and have a good reasoning ability, it is difficult for Trans-VL methods including RESERVE-L. On the other hand, VQA-GNN not only structures a joint semantic graph to provide commonsense knowledge related to image context but also has a good reasoning ability thanks to its GNN module. As shown in Table 3, VQA-GNN achieves compatible scores with RESERVE-L for most question types and has the effect on complementing RESERVE-L. Consequently, VQA-GNN-Large model achieves significant improvement on Q->AR metric. Moreover, VQA-GNN can lead to interpretable answer reasoning (§5.4).

5.3 Effect of the multimodal semantic graph

To further study the behavior of modules in the multimodal semantic graph, and quantitatively evaluate pretrained models used in this work

Model	# Image-caption	Parameters	knowledge source		Test Acc.(%)		
model	in pretraining	T urumeters	# image-level	# concept-level	$Q {\rightarrow} A$	$QA{\rightarrow}R$	$Q \rightarrow AR$
ViLBERT	3.3M	221M	-	-	73.3	74.6	54.8
VLBERT-L	3.3M	383M	-	-	75.8	78.4	59.7
UNITER-(B/L)	9.5M	154M/378M	-	-	75.0/77.3	77.2/80.8	58.2/62.8
ERNIE-ViL-(B/L)	3.8M	212M/533M	-	-	77.0/79.2	80.3/83.5	62.1/66.3
MERLOT	180M	223M	-	-	80.6	80.4	65.1
RESERVE-(B/L)	1B	200M/644M	-	-	79.3/84.0	78.7/84.9	62.6/72.0
VQA-GNN-(B/L)	290k/1B	372M/1B	Visual scene graph, VisualGenome	ConceptNet	77.9/ 85.2	80.0/ 86.6	62.8/ 74.0

Table 2: Accuracy scores on VCR. VQA-GNN-(B/L) denote the original VQA-GNN model and VQA-GNN-Large model respectively. VQA-GNN-Large model outperforms RESERVE-L model by 2% on Q \rightarrow AR metric, and VQA-GNN achieves competitive accuracy with SOTA methods, which have a close number of parameters but SOTA methods require a large amount of image caption data in pre-training process (over 13x larger than our model), *e.g.*, "UNITER-L", "ERNIE-ViL-B", "RESERVE-B".

Question type	Val Acc.(%) (Q→A)	A) Val Acc.(%) (QA \rightarrow R)		
Question type	VQA-GNN	RESERVE-L	VQA-GNN	RESERVE-L	
Why	73.2	78.6	81.8	84.8	
What	79.1	85.7	80.0	85.2	
Where	77.9	87.7	76.7	86.0	
Who	89.4	91.3	77.1	85.0	
When	77.8	94.4	100	100	
Which	88.9	88.9	81.5	87.0	
Do	81.6	81.6	73.5	82.5	
Will	86.2	83.8	82.7	82.3	
Have	92.9	91.4	87.1	82.9	
If	89.2	92.3	96.9	95.4	
Can/Should	93.3	88.5	87.5	84.6	

Table 3: Comparison results on different question type. *VQA-GNN* performs better than RESERVE-L for "Will", "Have" and "Can/Should" question types.

(*e.g.*, RoBERTa-L, I-SG[scene graph generator], C-SG[conceptNet KG]), we report the performance of using different node representations in Table 4.

Model	Val Acc.(%) ($Q \rightarrow A$)
Node P(Vinvl)	43.5
Node Z(RoBERTa-L)	53.8
C-SG	69.0
I-SG	73.7
I-SG+C-SG(w/o node P)	75.1
I-SG+C-SG(w/ node P)	77.1

Table 4: All modules in the multimodal semantic graph VQA-GNN boost the final performance. Here, "I-SG" and "C-SG" denote Image-level and Concept-level Semantic Graph, respectively. "I-SG" includes node Z and P, "C-SG" includes node Z.

Here, we respectively build classification model by applying Node P and Node Z to get their validation accuracy on Q \rightarrow A subtask. I-SG structured by connecting Node P and Node Z with extracted visual scene graph improves over 25% on average of these two nodes. In terms of C-SG, it is structured by connecting Node Z with retrieved concept semantic graph from ConcepNet KG, improves Node Z's performance by 15.2%. We further compare VQA-GNN on I-SG+C-SG w/ and w/o Node P, and the result shows that including Node P can further improve the performance by 2%. We believe that the Node P representing global visual knowledge associated with the correct answer is able to pass visual commonsense knowledge to the multimodal semantic graph, and it is effective besides employing ConcepNet KG to obtain textual commonsense knowledge (Yasunaga et al., 2021).

5.4 Interpretability

To interpret how *VQA-GNN* reason a correct answer based on a structured multimodal semantic graph and explore the reason why it can boost Trans-VL model, we show the reasoning process on Q \rightarrow A and QA \rightarrow R subtasks respectively in Figure 4 by using a validation sample that is given a correct answer on both Q \rightarrow A and QA \rightarrow R subtasks by *VQA-GNN* but RESERVE-L can not.

 $Q \rightarrow A$ subtask. We trace high attention weights from two directions: d1: QA textual context node $Z \rightarrow Answer$ concept nodes (purple) \rightarrow global Textual concept nodes (blue) \rightarrow Oject concept nodes (pink); d2: Global Visual context node P \rightarrow Local object nodes (orange) \rightarrow Z. At the d1, Z pays more attention to A nodes "breakfast" and "make breakfast" in A0 choice than nodes in other choices, "breakfast" attends to both T node "first meal" and O node "table", O node "table" further attends to O node "bowl", and both strongly attend



Figure 4: Interpreting VQA-GNN's reasoning process across multimodal knowledge domains by indicating attention weight of relationship between nodes. Arrows indicate the direction of the relationship, and darker and thicker edges indicate higher attention weights. Red color highlights the message passing routine for reasoning the correct answer and gray color indicates the opposite.

to **Z**. **A** node "breakfast" bridges the reasoning between **Z** and **O** "table" at the concept-level. Besides with **d1**, we also tract the attention weights from **d2**, **Z** strongly attends to **L** nodes "table", "drawer" and "woman", all nodes attend to **Z**, which reveals image-level semantic knowledge of **L** nodes "table", "drawer" and "woman" are all essential for reasoning "**A0**: she is making breakfast" correct. These two reasoning paths demonstrate that *VQA*-*GNN* is an inoperable method that can give a reasonable explanation to each choice with our well structured multimodal semantic graph, also suggest that our multimodal semantic graph is capable of bridging image-level and concept-level semantic knowledge with QA and image context.

 $QA \rightarrow R$ subtask. We trace reasoning path for the rational answer **R0** on the concept-level semantic graph. There are two reasonable directions: $Z \rightarrow$ "breakfast" \rightarrow "morning" \rightarrow "getting up", and $Z \rightarrow$ "kitchen" \rightarrow "drawer", "bowl", "table". Both of them show strong attentions between QA text and **R0**, compared to the attention direction for **R1** indicating that "breakfast" also strongly attends to "sausages" and "plate" attends to "fruit", however, "fruit" weakly attends to **Z**. As a result, *VQA-GNN* can select a rational answer, and suggest its interpretability on $QA \rightarrow R$ subtask. In addition, we noted that our method has close reasoning paths that attending to image context of "bowl", "table" and "drawer" on both $Q \rightarrow A$ and $QA \rightarrow R$ subtasks.

Hence, we consider that our method has strong reasoning ability across multimodal knowledge domains. Furthermore, regarding why the state-of-the-art model RESERVE-L makes mistakes on this sample, we consider that image-caption data in pretraining may not contain samples related to "She is making breakfast" so that Trans-VL model RESERVE-L can not learn its relevance visual representation only from in-domain data. In contrast, *VQA-GNN* is able to obtain structured semantic representation from the multimodal semantic graph to reason correct answer.

6 Conclusions

We proposed a novel visual question answering method, VQA-GNN, which unifies the image-level information and conceptual knowledge to perform joint reasoning of the scene. In the evaluation on the Visual Commonsense Reasoning task, our method substantially outperforms existing models without pretraining using massive image-caption data, and VOA-GNN-Large model, the fusion of VQA-GNN and Trans-VL model RESEVER-L improves state-of-the-art by 2%, suggesting its efficacy in performing conceptual reasoning beyond image-level recognition for visual understanding. Furthermore, we demonstrate that our model is the first work to provide interpretability across visual and textual knowledge domains for VQA task. In the next step, we will extend our work to the video

domain and focus on obtaining temporal semantic knowledge to enhance machine's reasoning ability.

Acknowledgment

We thank Rok Sosic, members of the Stanford SNAP group, as well as our anonymous reviewers for valuable feedback. We gratefully acknowledge the support of DARPA under Nos. HR00112190039 (TAMI), N660011924033 (MCS); Funai Foundation Fellowship; Microsoft Research PhD Fellowship; Masason Foundation Fellowship; Apple PhD Fellowship; ARO under Nos. W911NF-16-1-0342 (MURI), W911NF-16-1-0171 (DURIP); NSF under Nos. OAC-1835598 (CINES), OAC-1934578 (HDR), CCF-1918940 (Expeditions), IIS-2030477 (RAPID), NIH under No. R56LM013365; Stanford Data Science Initiative, Wu Tsai Neurosciences Institute, Chan Zuckerberg Biohub, Amazon, JPMorgan Chase, Docomo, Hitachi, Intel, KDDI, Toshiba, NEC, Juniper, and UnitedHealth Group.

Code availability. https://github.com/ yanan1989/VQA-GNN

References

- Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C. Lawrence Zitnick, and Devi Parikh. 2015. VQA: Visual Question Answering. In ICCV.
- Hedi Ben-Younes, Rémi Cadene, Matthieu Cord, and Nicolas Thome. 2017. Mutan: Multimodal tucker fusion for visual question answering. In ICCV.
- Yen-Chun Chen, Linjie Li, Licheng Yu, Ahmed El Kholy, Faisal Ahmed, Zhe Gan, Yu Cheng, and Jingjing Liu. 2020. Uniter: Universal image-text representation learning. In ECCV.
- Yanlin Feng, Xinyue Chen, Bill Yuchen Lin, Peifeng Wang, Jun Yan, and Xiang Ren. 2020. Scalable multi-hop relational reasoning for knowledge-aware question answering. In EMNLP.
- Akira Fukui, Dong Huk Park, Daylen Yang, Anna Rohrbach, Trevor Darrell, and Marcus Rohrbach. 2016. Multimodal compact bilinear pooling for visual question answering and visual grounding. In <u>EMNLP</u>.
- Sergey Ioffe and Christian Szegedy. 2015. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In <u>ICML</u>. JMLR.org.
- Jin-Hwa Kim, Jaehyun Jun, and Byoung-Tak Zhang. 2018. Bilinear attention networks. In NeurIPS.

- Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. <u>CoRR</u>, abs/1412.6980.
- Alexander Kolesnikov, Lucas Beyer, Xiaohua Zhai, Joan Puigcerver, Jessica Yung, Sylvain Gelly, and Neil Houlsby. 2020. Big transfer (bit): General visual representation learning. In ECCV.
- Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen, Yannis Kalantidis, Li-Jia Li, David A Shamma, et al. 2017. Visual genome: Connecting language and vision using crowdsourced dense image annotations. Springer.
- Xiujun Li, Xi Yin, Chunyuan Li, Xiaowei Hu, Pengchuan Zhang, Lei Zhang, Lijuan Wang, Houdong Hu, Li Dong, Furu Wei, Yejin Choi, and Jianfeng Gao. 2020. Oscar: Object-semantics aligned pre-training for vision-language tasks. In ECCV.
- Weixin Liang, Yanhao Jiang, and Zixuan Liu. 2021. Graghvqa: Language-guided graph neural networks for graph-based visual question answering. <u>ArXiv</u>, abs/2104.10283.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.
- Jiasen Lu, Dhruv Batra, Devi Parikh, and Stefan Lee. 2019. Vilbert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. In <u>NeurIPS</u>.
- Kenneth Marino, Mohammad Rastegari, Ali Farhadi, and Roozbeh Mottaghi. 2019. Ok-vqa: A visual question answering benchmark requiring external knowledge. In CVPR.
- Nils Reimers and Iryna Gurevych. 2019. Sentencebert: Sentence embeddings using siamese bertnetworks. In EMNLP.
- Hongyu Ren, Hanjun Dai, Bo Dai, Xinyun Chen, Michihiro Yasunaga, Haitian Sun, Dale Schuurmans, Jure Leskovec, and Denny Zhou. 2021. Lego: Latent execution-guided reasoning for multi-hop question answering on knowledge graphs. In ICML.
- Robyn Speer, Joshua Chin, and Catherine Havasi. 2017. Conceptnet 5.5: An open multilingual graph of general knowledge.
- Weijie Su, Xizhou Zhu, Yue Cao, Bin Li, Lewei Lu, Furu Wei, and Jifeng Dai. 2020. Vl-bert: Pretraining of generic visual-linguistic representations. In ICLR.
- Kaihua Tang, Yulei Niu, Jianqiang Huang, Jiaxin Shi, and Hanwang Zhang. 2020. Unbiased scene graph generation from biased training. In CVPR.

- Damien Teney, Lingqiao Liu, and Anton van Den Hengel. 2017. Graph-structured representations for visual question answering. In <u>CVPR</u>.
- Petar Veličković, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Liò, and Yoshua Bengio. 2018. Graph Attention Networks. In ICLR.
- Zhecan Wang, Haoxuan You, Liunian Harold Li, Alireza Zareian, Suji Park, Yiqing Liang, Kai-Wei Chang, and Shih-Fu Chang. 2022. Sgeitl: Scene graph enhanced image-text learning for visual commonsense reasoning. In <u>AAAI</u>.
- Michihiro Yasunaga, Hongyu Ren, Antoine Bosselut, Percy Liang, and Jure Leskovec. 2021. Qa-gnn: Reasoning with language models and knowledge graphs for question answering. In <u>NAACL</u>.
- Fei Yu, Jiji Tang, Weichong Yin, Yu Sun, Hao Tian, Hua Wu, and Haifeng Wang. 2021. Ernie-vil: Knowledge enhanced vision-language representations through scene graph. In <u>AAAI</u>.
- Rowan Zellers, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019. From recognition to cognition: Visual commonsense reasoning. In CVPR.
- Rowan Zellers, Jiasen Lu, Ximing Lu, Youngjae Yu, Yanpeng Zhao, Mohammadreza Salehi, Aditya Kusupati, Jack Hessel, Ali Farhadi, and Yejin Choi. 2022. Merlot reserve: Multimodal neural script knowledge through vision and language and sound. In <u>CVPR</u>.
- Rowan Zellers, Ximing Lu, Jack Hessel, Youngjae Yu, Jae Sung Park, Jize Cao, Ali Farhadi, and Yejin Choi. 2021. Merlot: Multimodal neural script knowledge models. In NeurIPS.
- Pengchuan Zhang, Xiujun Li, Xiaowei Hu, Jianwei Yang, Lei Zhang, Lijuan Wang, Yejin Choi, and Jianfeng Gao. 2021. Vinvl: Making visual representations matter in vision-language models. In <u>CVPR</u>.

A Appendix

Limitations of our work. We describe some limitations of our work. As shown in Table 3, our method is insufficient on several question types (*e.g.*, "What","Where") compared to Trans-VL models. This result suggests that our method is less powerful to obtain implicit VL representations than Trans-VL models, since it is not pretrained on the large-scale image-caption dataset. Our method is also not expected to predict the future event that is not happened in the image. We plan to focus on this issue at our next step (§6).

Potential risks of our work. We use pretrained representations like Roberta (Liu et al., 2019), scene graph generator (Tang et al., 2020), etc. We may have the same risks as those systems such as biases learned in pretraining.