Knowledge-Routed Visual Question Reasoning: Challenges for Deep Representation Embedding

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Abstract—Though beneficial for encouraging the Visual Question Answering (VQA) models to discover the underlying knowledge by exploiting the input-output correlation beyond image and text contexts, the existing knowledge VQA datasets are mostly annotated in a crowdsource way, e.g., collecting questions and external reasons from different users via the internet. In addition to the challenge of knowledge reasoning, how to deal with the annotator bias also remains unsolved, which often leads to superficial over-fitted correlations between questions and answers. To address this issue, we propose a novel dataset named Knowledge-Routed Visual Question Reasoning for VQA model evaluation. Considering that a desirable VQA model should correctly perceive the image context, understand the question, and incorporate its learned knowledge, our proposed dataset aims to cutoff the shortcut learning exploited by the current deep embedding models and push the research boundary of the knowledge-based visual question reasoning. Specifically, we generate the question-answer pair based on both the Visual Genome scene graph and an external knowledge base with controlled programs to disentangle the knowledge from other biases. The programs can select one or two triplets from the scene graph or knowledge base to push multi-step reasoning, avoid answer ambiguity, and balanced the answer distribution. In contrast to the existing VQA datasets, we further imply the following two major constraints on the programs to incorporate knowledge reasoning: i) multiple knowledge triplets can be related to the question, but only one knowledge relates to the image object. This can enforce the VQA model to correctly perceive the image instead of guessing the knowledge based on the given question solely; ii) all questions are based on different knowledge, but the candidate answers are the same for both the training and test sets. We make the testing knowledge unused during training to evaluate whether a model can understand question words and handle unseen combinations. Extensive experiments with various baselines and state-of-the-art VQA models are conducted to demonstrate that there still exists a big gap between the model with and without groundtruth supporting triplets when given the embedded knowledge base. This reveals the weakness of the current deep embedding models on the knowledge reasoning problem.

Index Terms—Visual Question Answering, Knowledge Understanding.

I. INTRODUCTION

As a core task towards the complete AI, Visual Question Answering (VQA) demands the understanding of not only image and text but also the background knowledge that beyond

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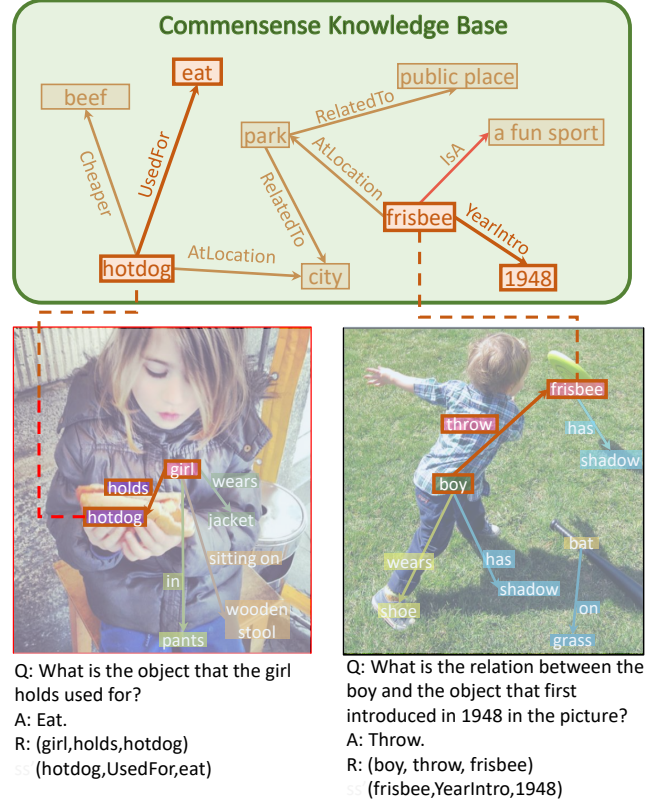
Fig. 1: Examples of our proposed KRVQR dataset. Each question is based on one or two triplets selected from the scene graph annotations or external commonsense knowledge base. To answer the question, a desirable VQA model must perform multi-step reasoning over both the image context and background knowledge.

observable inputs [1]. For example, to correctly answer the question "what is the object that the girl is holding used for", an agent should understand the reasoning process, perceive the "girl" and the object with relation "holding", and use the background knowledge "hotdog UsedFor eat" to generate the correct answer.

To push the VQA models to correctly understand the image and text, a balanced VQA benchmark plays a crucial role. However, the earlier VQA datasets often contain the annotator bias, which is exploited by VQA models to guess the answer instead of understanding the image and questions. To remove such superficial over-fitted relations, a lot of efforts have been made to balance the distribution of image/question and answer [2]–[4], and have lead to great success on the fused

image and text representation for answer prediction [5]–[8].

To enforce the VQA models to discover the knowledge by relations between questions and answers, current knowledge VQA datasets still crowdsourcingly annotate a large amount of the question-answer pairs to implicitly incorporate the knowledge. Actually, without applying no proper control, the statistics and annotator biases may be displayed throughout the dataset and result in the superficial relations between the questions and answers. Besides, the knowledge relation is inevitably tangled with other superficial relations due to the vast range of knowledge and relatively small annotated samples. These datasets contain the shortcut between the question and the answer. Instead of encouraging the existing VQA models to learn to perform knowledge reasoning, these datasets push them to increase the model's capacity and consume a large-scale of extra data to resource-consumingly fit all kinds of superficial correlation.

Attempt to overcome the above-mentioned limitation of the existing datasets, we propose a novel challenging Knowledge-Routed Visual Question Reasoning (KRVQA) dataset to correctly evaluate the following abilities of a VQA model: i) correctly perceiving visual evidence in the image, ii) understanding the reasoning logic in the question, and iii) incorporating the supporting knowledge, by further disentangling the knowledge from other superficial relations. Similar to the previous unbiased VQA datasets [3], [4], we generate the question-answer pairs based on tight controlled programs operates on the Visual Genome scene graph [9] and an external knowledge base [10]. Each program consists of one or two triplets from the scene graph or knowledge base to ensure the questions can be and must be answered with the provided knowledge. Besides the same constraints on scene graph triplets, we further imply the following constraints on the knowledge triplets. Firstly, if an answer is from the knowledge base, then only one knowledge triplet is related to the image, such that this sample has a unique answer. Secondly, if an answer is from the image, then there should be multiple knowledge triplets related to the question, but only one knowledge relates to the objects in the image. We imply this constraint to prevent a model from memorizing the knowledge to predict an answer without perceiving the image context. Thirdly, all programs must rely on different knowledge triplets. Thus, a VQA model must learn to reason on the knowledge base. We enforce these constraints such that the model must correctly parse the question instead of memorizing the mapping from question to knowledge. Lastly, we balance the knowledge answer distribution to prevent the model from guessing the answer, but relax the image answer distribution to enforce the model to recognize small and rarely appeared objects. Given an image, we merge its scene graph with the knowledge base to form an image-specific knowledge graph, then we search the triplets that meet the above constraints and compose the program to generate the question-answer pairs. We illustrate the sample of the generated question-answer in Figure 1.

We conduct extensive experiments on various knowledge embedding baselines and state-of-the-art VQA models. We have shown that even with the state-of-the-art knowledge graph embedding method which obtains over 99% accuracy on

TABLE I: Comparison of KRVQR and previous datasets. Our KRVQR dataset is the first large-scale (more than 100,000 QA pairs) dataset that requires knowledge reasoning on natural images.

Dataset	Large Scale	Knowledge Reasoning	Supporting Knowledge Base	Diagnostic
CLEVR [3]	✓			✓
VQAv2 [2]	✓			
GQA [4]	✓			✓
FVQA [10]		✓	✓	✓
OKVQA [11]		✓		
VCR [12]	✓	✓		
Our KRVQR	✓	✓	✓	✓

knowledge triplets prediction, the current state-of-the-art VQA models still achieve low answering accuracy on our proposed KRVQR dataset. These experimental results demonstrate that our proposed dataset poses a new challenge towards current black-box VQA models and can push the boundary of visual knowledge reasoning.

II. RELATED WORKS

A. Visual question answering

The Visual Question Answering(VQA) task is to predict the answer given the image and question. It requires co-reasoning over multiple domains, including image and text and background knowledge. The pioneer works used the CNN-LSTM-based architecture and trained the neural networks in an end-to-end manner. Later, the attention mechanism [13]–[18] has been shown as a strong method in terms of the answering accuracy on various VQA benchmarks. Subsequently, a lot of efforts have been devoted to the joint embedding of image and question representation [5], [19]–[21], The combination of the attention mechanism and compact bilinear multimodal fusion has further improved performance [22], [23]. Most recently, BERT-like architecture [7], [8], [24] has been widely used and pretrained on various image-text tasks like image captioning and visual question answering to embed the text token and image object simultaneously. Moreover, some works [25], [26] have trained the BERT-like model on large scale corpus to encode the commonsense knowledge.

Besides the end-to-end neural networks, other works explore different ways of addressing compositional visual reasoning and interpretable answer prediction. The neural modular networks [27]–[29] have attracted substantial interest. Instead of inferencing on fixed architecture, these works exploited sub-modules to solve subtasks and assemble their results for final answer prediction. Most recently, graph convolution networks and symbolic inference have been widely studied. For instance, [30] applied a graph convolution network to obtain the question-specific graph representation and interactions in images. [31] transformed images to scene graphs and questions to functional layouts and then performed symbolic inference on the graph.

B. VQA based on external knowledge

As the VQA requires understanding the knowledge, other strands of research have attempted to leverage such information beyond image-question pairs. These works either retrieve

TABLE II: Templates for the question-answer pair generation.

Step	Qtype	Question Semantics	Answer	Reason
1	0	What is the relationship of $<$A$>$ and $<$B$>$?	$<$R$>$	
	1	what is $<$A$>$ $<$R$>$?	$<$B$>$	(A, R, B)
	2	what $<$R$>$ $<$B$>$?	$<$A$>$	
1	3	What is the relation $<$of$>$ the object that $<$A$>$ $<$R1$>$ and $<$C$>$?	$<$R2$>$	
	4	What is the relation of $<$A$>$ and the object that $<$R2$>$ $<$C$>$?	$<$R1$>$	(A, R1, B)
	5	what $<$A$>$ $<$R1$>$ $<$R2$>$?	$<$C$>$	(B, R2, C)
	6	what $<$R1$>$ $<$R2$>$ $<$C$>$?	$<$A$>$	

the external common knowledge and basic factual knowledge to answer the questions [10], [32], [33] or actively obtaining extra information and predicting the answer [34]–[36]. The proposed model in FVQA [10] answered the questions by learning query mappings and retrieve information in the knowledge base. [33] answers the questions by predicting the key triplet related to the question. These two methods require groundtruth triplets as the supervision signal and are only evaluated on one-hop reasoning questions.

[37] tried to learn the complementary relationship between questions and answers and introduced question generation as a dual-task to improve VQA performance. [38] dynamically selected example questions and answers during the training and encoded examples into a support set for answering the questions. [39] also utilized a graph convolution network but embedded the retrieved knowledge with image representation as a node, and they evaluated their method on the FVQA [10] knowledge-based VQA dataset.

C. VQA datasets

There are lots of VQA datasets that have been proposed in recent years and the VQA [1], [2] are the most popular VQA datasets. However, the annotation process does not involve hard controls and the dataset contains a severe bias, which is exploited by various black-box models to attain state-of-the-art performance [2], [40]. This concern has led to the proposal of unbiased datasets [3], [4], [36], [41], [42] that generate the question with programs to control the distribution of both questions and answers.

Recently, lots of works have focused on incorporating external knowledge for visual question answering. FVQA [10] constructs a knowledge base by collecting the knowledge triplets from WebChild [43], ConceptNet [44], and DBpedia [45]. Then it extracts the visual concepts and matched image with the knowledge to annotate the question-answer pairs. OKVQA [11] manually annotates the questions that require some outside knowledge. VCR [12] crowdsourcingly annotates not only the question-answer pair, but also annotates the rationale of the answer. The VCR casts both the answer and rationale prediction as a four-way multiple-choice problem. This work further applies adversarial matching to select the most confusing rationale from other samples as choice candidates. However, the manual annotation process inevitably includes the annotator bias. Also, annotating the rationale as a sentence introduces the extra difficulty in language understanding, making it hard to control the supporting knowledge range. To address the aforementioned issue, our proposed KRVQR leverages a knowledge base to limit the boundary

of candidate knowledge, and ensures the question-answer relations is based on a known knowledge triplet. Compared with previous knowledge VQA datasets, the proposed KRVQR advances in not only minimizing the dataset bias, but also providing groundtruth knowledge for further inspection.

III. KNOWLEDGE-ROUTED VISUAL QUESTION REASONING DATASET

The proposed Knowledge-Routed Visual Question Reasoning(KRVQA) dataset aims to evaluate the reasoning ability of external knowledge while prevent the models from exploiting superficial relations. It consists of $32,910$ images and $157,201$ question-answer pairs of different types for testing a variety of skills of the given VQA model. Compared with previous datasets, our proposed KRVQA has the following advantages: i) We use the tightly controlled program on explicit scene graph and knowledge base to minimize the bias on both image and knowledge; ii) We provide the groundtruth program to enable inspection on the reasoning behavior of a VQA model; and iii) each knowledge triplet only appears once for all questions to pose the new challenges for deep embedding networks to correctly embed the knowledge base and handle the unseen questions. Detailed comparisons on the properties of our KRVQA dataset with existing datasets can be found in Table I.

We construct the KRVQA dataset based on scene graph annotations from Visual Genome [9] dataset and the knowledge base from FVQA [10]. To generate the unbiased question-answer pairs, we first clean the object and relation name in the Visual Genome scene graph annotations. Then given an image, we combine its scene graph with the related knowledge triplets to form the image-specific knowledge graph. We further extract the facts from the graph and compose them into a reasoning program. Lastly, we generate the question-answer pairs based on the program layout and predefined question templates.

A. Image-specific Knowledge Graph

Given an image, we first clean its scene graph and integrate the scene graph with an external knowledge base to form an image-specific knowledge graph, which depicts the objects, relations, and knowledge related to this image.

Specifically, given the image and its corresponding scene graph, we only keep the objects and relations that have the "synset" annotations and use the "synset" as their class label to reduce the semantic ambiguity. For instance, all objects with the name "bike" or "bicycle" have the same synset "bicycle" as the label. To ensure the generated questions require reasoning

ability on external knowledge, we incorporate the large-scale knowledge base from FVQA [10]. The knowledge base has a total of $193,449$ facts from WebChild [43], ConceptNet [44], and DBpedia [45]. Each fact consists of three entries: head entity, relation, and tail entity. This knowledge base is merged the image scene graph by matching the knowledge entries with object synsets. The scene graph extended by the matched knowledge triplets is the image-specific knowledge graph, which is used to generate the question-answer pairs in our proposed KRVQA dataset.

B. Triplets sampling and entry query

The question with single-step inference, such as "What is on the desk?", can't evaluate the compositional reasoning ability and drive the VQA model to reason on image and knowledge base simultaneously. Thus, our KRVQA generates diverse multi-step reasoning questions via the compositional program based on a series of correlated triplets, such as the question "what is the object that the girl is holding used for".
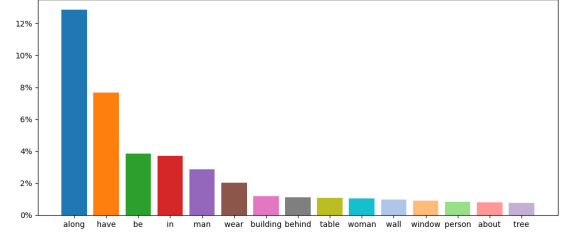
Specifically, given the image-specific knowledge graph, we perform traverse on the graph and randomly sample the traversed route with a maximum length of 2 to generate continuously linked triplets like "$(a, r_1, b) - (b, r_2, c)$".

We then sample one of the six elementary queries on each sample triplet to generate questions that require different types of inference. Given a triplet "(a, r, b)", where the "a", "r" and "b" represent *head entity*, *relation*, and *tail entity* respectively, each query type has the following semantics:
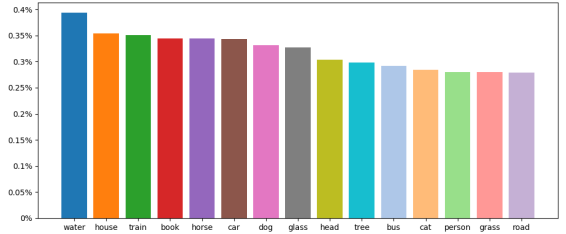
- Q_{ab_I}: Given a *head entity* and an *tail entity*, return the *relation* between the *head entity* and the *tail entity* exploited in the image.
- Q_{ar_I}: Given a *head entity* and an *relation*, return the *tail entity* exploited in the image.
- Q_{rb_I}: Given an *relation* and an *tail entity*, return the *head entity* exploited in the image.
- Q_{ab_K}: Given a *head entity* and an *tail entity*, return the *relation* between the *head entity* and the *tail entity* in the knowledge base.
- Q_{ar_K}: Given a *head entity* and an *relation*, return the *tail entity* in the knowledge base.
- Q_{rb_K}: Given an *relation* and an *tail entity*, return the *head entity* in the knowledge base.

C. Program Layout

With the sampled queries and triplets, we compose them into a program layout. For example, the sampled "(girl, holds, hotdog)" with query Q_{ar_I} is represented as (Q_{ar_I}, girl, holds), which requires inferring the "hotdog" given the "girl" and "holds" in the image scene graph. And the second sampled query is "(Q_{ar_K}, hotdog, UsedFor)" that requires inferring the "eat" given the head entity and relation in the knowledge base. we compose them into "(Q_{ar_K}, (Q_{ar_I}, girl, holds), UsedFor)" as the program for the question "what is the object that the girl is holding used for", which should be answered by first locating the "hotdog", then answer its functionality. The program layouts are used as the groundtruth inference process and can be used for deep inspection of VQA models.

(a)

(b)

Fig. 2: The answer distribution of (a) KB-not-related questions and (b) KB-related questions respectively.

D. Template-based generation.

There are a total of 7 question composition types and corresponding templates that include different reasoning steps and various knowledge involvements, as depicted in Table II. Given the sampled triplets, query type, and composed program, we can determine its question type *Qtype* and use the corresponding templates to generate the question-answer pairs. For instance, given a triplet "(man, holds, umbrella)" and *Qtype 1*, we use the template "*Que*: what is <A> <R> *Ans*: <B>" to generate the question "what is the man holding" and the answer "umbrella". The reasoning step of a question can also be determined by the number of the selected triplets. For example, "(a, r, b)" corresponds to one-step question, and "$(a, r_1, b) - (b, r_2, c)$" is used to generate the two-step question. A question is considered as "KB-related" if one of its triplets is sampled from the knowledge base; otherwise, it is "KB-not-related". For example, the question above is a "KB-not-related" question because "(man, holds, umbrella)" can be detected in the image. However, "What is the usage of the object that the man is holding?", which is converted from "(man, holds, umbrella)-(umbrella, used for, keep out rain)", is "KB-related" because "(umbrella, used for, keep out rain)" only appears in the knowledge base.

We also add extra constraints to the randomly sampled process to avoid answer ambiguity and minimize the dataset biases. Specifically, we filter out invalid questions that have more than one answer or have no answer. We also restrict the answer frequency such that each answer cannot appear more than 100 times for each "KB-related" question types. To prevent the model from memorizing the question-knowledge pairs, a knowledge triplet cannot appear more than once for all questions of type: *qtype 2*, *qtype 3*, and *qtype 5*.

TABLE III: Number of questions of different types in KRVQA.

Step	qtype	Train	Val	Test	Total
	0	8,133	2,730	2,698	13,561
1	1	7,996	2,660	2,734	13,390
	2	25,171	7,982	8,344	41,497
	3	9,477	2,931	3,131	15,539
2	4	16,498	5,564	5,505	27,567
	5	10,482	3,291	3,518	17,291
	6	17,058	5,518	5,780	28,356

IV. DATASET STATISTICS

Our KRVQA dataset contains 32,910 images and 157,201 QA pairs. They are split into the train, validation, and test set at the ratio of 60%, 20%, and 20% respectively, as shown in Table III. According to the reasoning steps, questions can be divided into **one-step** and **two-step** types of questions, which consist of 68,448 and 88,753 samples respectively. Based on the knowledge involvement, a question is divided into **KB-related** and **KB-not-related**, with 87,193 and 70,008 samples respectively. The lengths of the questions range from 4 to 24 and are 11.7 on average. Longer questions correspond to samples that require more reasoning steps.

Answer distribution. For the KB-not-related questions, the answer vocabulary size is 2,378 and shows a long-tailed distribution, as shown in Figure 2a. For the KB-related questions, the answer vocabulary size is 6,536, which is significantly greater than that of KB-not-related questions because of the large scale words in the knowledge base. A total of 97% of the answers in the validation and test set can be found in the train split. As shown in Figure 2b, the distribution of the KB-related answers is balanced as we limit the maximal presence count for each answer.

Knowledge base. Following [10], the knowledge base contains 193,449 knowledge triplets, 2,339 types of relations and 102,343 distinct entities. We restrict each triplet to present only once for *Qtype 2*, *Qtype 3*, and *Qtype 5*, results in a total of 45,550 different knowledge triplets involve in the questions.

V. EXPERIMENTS

We first evaluate the performance of multiple state-of-the-art VQA models on our proposed KRVQA dataset. Then, we perform extensive experiments to inspect the properties of our proposed KRVQA dataset and evaluate a wide range of knowledge embedding methods, including knowledge graph embedding and question encoder pretraining.

A. Answering Accuracy of baseline and state-of-the-art VQA methods

We evaluate the following baseline and state-of-the-art methods on the KRVQA dataset.

Q-type. For each question, we use the most frequent training answer of its question type as the output answer. We use this baseline to inspect the question-answer bias.

LSTM. We first embed the question word into a 1024-dimensional vector, then use a bi-directional LSTM with 2048

hidden-size for each direction to encode the whole questions. The hidden vector of the last word is used as question embedding and is fed into a two-layer MLP that has 4096 hidden-size to predict the final answer.

Program Prediction. Given the question type and program that is used to generate the question-answer pair, one can retrieve the correct answer from the scene graph and knowledge base. We thus train a model to predict the program and question type with full supervision as a baseline that can access to all possible information. Similar to the "LSTM" baseline, this model embeds the word and question with a 1024-dimensional lookup table and a 2048-dimensional bi-directional GRU. The question embedding is used to predict the question type and fed into a 4096-dimensional GRU decoder to predict the sequential program. A sample is considered correct if both the predicted question type and program are correct.

Bottom-up attention. We evaluate the 1st-place method [48] of the 2017 VQA challenge. This method uses a GRU to encode the questions and extracts the image feature using a Fast-RCNN trained on the Visual Genome dataset. Then it performs multimodel bilinear pooling [5] and attention mechanism on the image object feature and question embedding. The attended feature is passed through an MLP to predict the answer. We use the top-36 object features that have the highest object scores as our image input.

MFH. The Multi-modal Factorized High-order pooling(MFH) [46] extracts the image object features similar to the bottom-up attention and encodes the question with an LSTM. It then performs attention and question and image separately. The attention features are fused using stacks of bilinear fusion blocks [46]. The answer is predicted by passing the fused feature through an MLP.

FiLM. The Feature-wise Linear Modulation(FiLM) [6] embeds the question with GRU and embeds the image with multiple convolutional blocks. In each block, the question embedding is transformed into two vectors, and is multiplied and added with the normalized feature maps respectively. It is a simple but efficient model that has achieved high accuracy on the CLEVR [3] dataset, which requires compositional reasoning ability.

MCAN. The Modular Co-Attention Network(MCAN) [7] consists of 6 self-attention blocks to encode the question words and 6 guided-attention blocks to encode the image objects. The object features are fused with the question words at each guided-attention block and both the question and image outputs are used to predict the answer. The MCAN currently achieves the highest accuracy on the VQAv2 dataset without large amounts of pretraining data and has similar architecture blocks with other state-of-the-art works pretrained on various vision-language tasks.

The answering accuracy of each method on different question types is shown in Table IV. The two baselines "Q-type" and "GRU" predict the answer based on the question solely and achieve the accuracies of 8.12% and 8.81% respectively. These two Q-only baselines perform much worse than other methods, suggesting the image context is necessary to answer the questions in our proposed dataset. The state-of-the-art VQA models also have low accuracies compared to

TABLE IV: The answering accuracy (%) of different baseline and state-of-the-art VQA methods on the KRVQA dataset. Each column presents the accuracy of each question type.

Method	KB-not-related							KB-related					Overall
	one-step			two-step				one-step	two-step				
	0	1	2	3	4	5	6	2	3	4	5	6	
Q-type	36.19	2.78	8.21	33.18	35.97	3.66	8.06	0.09	0.00	0.18	0.06	0.33	8.12
LSTM	45.98	2.79	2.75	43.26	40.67	2.62	1.72	0.43	0.00	0.52	1.65	0.74	8.81
Program Predict	58.86	50.98	59.17	54.71	57.31	54.17	57.64	65.16	33.95	71.64	63.05	76.53	61.62
FiLM [6]	52.42	21.35	18.50	45.23	42.36	21.32	15.44	6.27	5.48	4.37	4.41	7.19	16.89
MFH [46]	43.74	28.28	27.49	38.71	36.48	20.77	21.01	12.97	5.10	6.05	5.02	14.38	19.55
UpDn [47]	56.42	29.89	28.63	49.69	43.87	24.71	21.28	11.07	8.16	7.09	5.37	13.97	21.85
MCAN [7]	49.60	27.67	25.76	39.69	37.92	21.22	18.63	12.28	9.35	9.22	5.23	13.34	20.52

TABLE V: The answering accuracy (%) of different methods of incorporating knowledge embedding on the KRVQA dataset.

Method	KB-not-related							KB-related					Overall
	one-step			two-step				one-step	two-step				
	0	1	2	3	4	5	6	2	3	4	5	6	
Baseline(MCAN)	49.60	27.67	25.76	39.69	37.92	21.22	18.63	12.28	9.35	9.22	5.23	13.34	20.52
+ GT knowledge triplet	50.55	27.18	24.90	41.46	37.29	23.05	20.83	90.90	75.83	12.67	63.66	16.51	42.08
+ GT knowledge entry	50.51	27.44	26.82	44.37	37.92	22.24	21.86	94.67	88.13	13.40	74.56	18.02	44.82
+ knowledge inference	52.38	26.92	24.26	46.28	41.56	22.10	20.37	22.75	54.18	10.75	17.84	13.56	26.34
+ knowledge retrieval	51.32	27.14	25.69	41.23	38.86	23.25	21.15	13.59	9.84	9.24	5.51	13.89	21.30
+ knowledge embedding extraction	50.33	27.56	25.20	41.38	37.54	22.51	20.31	12.48	9.23	9.32	4.74	12.96	20.69
w/ Masked-pretrain	54.58	26.88	25.01	46.82	42.06	23.66	20.95	15.11	10.46	9.52	5.12	13.84	22.23
w/ Triplet-pretrain	51.10	25.68	24.48	43.45	41.10	21.83	21.28	12.07	9.35	9.24	5.07	13.66	20.86

Question:	Can you name the object that belongs to the category of machine in such image?	What is the relationship between girl and skirt?	How is cabin related to the object that wearing jacket in such photo?	How is the object that woods under related to house?
Answer-gt:	toaster	wear	behind	part of
UpDn:	toothbrush	wear	behind	used for
Facts:	(toaster, BelongsTo, machine)	(girl, wear, skirt)	(cabin, behind, woman) (woman, wear, jacket)	(wood, under, chimney) (chimney, PartOf, house)
Program : qtype:	$(Q_{rb\_K}$, BelongsTo, machine) 2 KB-related	$(Q_{ab\_I}$, girl, skirt) 0 KB-not-related	$(Q_{ab\_I}$, cabin, $(Q_{rb\_I}$, wear, jacket)) 4 KB-not-related	$(Q_{ab\_K}$, $(Q_{ar\_I}$, wood, under), house) 3 KB-related

Fig. 3: Examples of the KRVQA and the results predicted by the bottom-up attention baseline method. The "Answer-gt" refers to the ground-truth answer and the "Fact" refers to the ground-truth supporting facts.

their performances on previous VQA datasets (e.g., VQAv2, CLEVR, etc.). The FiLM improves the accuracy by a large margin compared with the previous two baselines as it uses the image context. It is interesting that this bottom-up method performs better than other MFH and MCAN, suggesting that a complex method might be overfitting on our training set. All the methods perform worse on two-step questions than on one-step questions. These results show that multi-hop reasoning is extremely challenging, and also imply that the proposed dataset requires incorporating knowledge while reasoning.

B. Knowledge graph embedding

In this section, we evaluate several baseline methods that incorporate the embedding knowledge graph into the VQA model, i.e., MCAN. We use MCAN as baseline architecture

because it achieves state-of-the-art results on the VQAv2 dataset and shares the similar self-attention and guided-attention modules with other models that pretrained on large amounts of extra data. Specifically, we first train the RotatE [49] on the whole knowledge base to extract the entities and relation features. Then, we modify the guided-attention block to fuse the knowledge embedding vectors with the image object feature in a similar way as fusing the question words. We first give a simple description of the RotatE method and our modified MCAN, then present the accuracy results of different settings.

Knowledge graph embedding and RotatE Given a knowledge graph consists of triplets (head entity, relation, and tail entity), the knowledge graph embedding method focuses on learning the representations of entities and relations for pre-
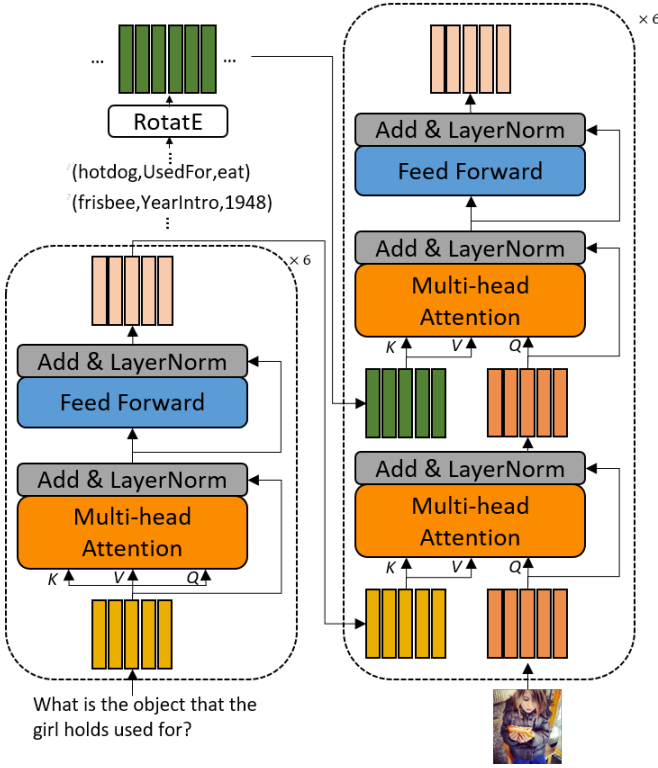
Fig. 4: The overview architecture of MCAN with the knowledge guided-attention block.

dicting the missing links. For example, TransE [50] is trained to encode a triplet as vectors (h, r, t) such that $h + r = t$. Thus, given two entry of a knowledge triplet, one can obtain the missing entry by performing corresponding operations on the embedding vector, such as $t = h + r$, $r = h - t$, etc.

The RotatE maps the embedding vectors to complex space and treats the relation as a rotation from head entity to tail entity. Thus, the entity has the from $h + ih_i$ and relation has $\cos r + i \sin r_i$. During training, it minimizes the distance between the rotated head entity and the tail entity, which is $|(h + ih_i)(\cos r + i \sin r_i) - (t + it_i)|^2$. Thus, we use the following equations to obtain the tail entity:

$$t = h * \cos r - h_i * \sin r_i$$
$$t_i = h * \sin r_i + h_i * \cos r \tag{1}$$

$$\cos r = (h * t + h_i * t_i)/(h^2 + h_i^2)$$
$$\sin r_i = h * t_i - h_i * t/(h^2 + h_i^2) \tag{2}$$

$$h = t * \cos r + t_i * \sin r_i$$
$$h_i = t_i * \cos r - t * \sin r_i \tag{3}$$

We train the RotatE on the provided knowledge graph and use 500-dimensional vectors to represent both the real part and the imaginary part. After 50 epochs, the RotatE can predict the tail entity with a mean rank 1.35 and top-1 accuracy 94.5%. We extract the entity and relation embedding and concatenate the real and imaginary parts to represent each entity and relation with a 1000-dimensional vector.

Knowledge guided-attention block We modify the guided-attention block of the original MCAN to incorporate the

extracted knowledge embedding. As shown in Figure 4, the guided-attention block first performs multi-head attention on image and question respectively. Then we add another multi-head attention whose key and value are based on knowledge embedding and the query is conditioned on the image. This layer can attend the candidate entity and relation embedding from the knowledge graph, and fuse them into the image representation. Other parts the MCAN remains the same for final answer prediction.

MCAN with groundtruth knowledge We first evaluate a baseline setting that the supporting knowledge is provided. As shown in Table V, the knowledge-guided MCAN achieves 42.08% and 44.82% if the supporting triplet or entry is provided and the model with supporting entry performs slightly better. This model achieves similar results with the MCAN on KB-not-related question and KB-related question type 4 and 6. The answers to these questions are from the image, thus the knowledge embedding can't provide much information. However, the models improve dramatically on question types 2, 3, and 5 by achieving the accuracy higher than 70%. These results demonstrate the effeteness of the knowledge embedding vector.

MCAN with knowledge inference We then evaluate the model with supporting entry obtained with Equation 1-3. Instead of providing the complete supporting triplet, we provide the model with two entries and then calculate the supporting entry with the above equations. The model achieves 26.34% overall accuracy. Its performance drops a lot on KB-related question type 2 and 5, but drops relatively small on question type 3. Since the answers to question type 2 and 5 are from the image, where the answers are also related to multiple knowledge triplets according to our dataset constraint. For example, the triplets "(car, faster, bicycle)" and "(plane, faster, bicycle)" are both valid for the query "(Q_{rb_K}, faster, bicycle)", but only the "car" is present in the image. Thus, a model can't simply obtain the knowledge embedding to predict the answer without image context, which leads to the large performance drop on question type 2 and 5 only. This demonstrates the importance of correctly perceiving the image context and associating them with knowledge.

MCAN with knowledge embedding extraction We also train a model to extract the knowledge embedding from the question and use the extracted and inferred embedding with Equation 1-3 as the guided-attention block input. Specifically, each knowledge triplet is associated with a surface text that describes this knowledge in natural language. We append the surface text with 3 tokens "[head]", "[r]" and "[tail]", and encode the extended surface text with an encoder. The encoder has the same architecture with the question encoder in MCAN, and is trained to minimize the L2 distance between the embedding of the three tokens and the RotatE knowledge embedding. It achieves a train loss of 0.6 and is used to extract the knowledge triplets embedding from questions. The extracted three entries and the three entries predicted with Equation 1-3 are attended and fused by the image via the guided-attention block. We also update its parameters with the rest of the MCAN during VQA training.

As shown in Table V, this model achieves 20.69% overall

Fig. 5: The illustration of the two pretraining task settings. On the left, the knowledge surface text is appended with three extra tokens and the encoder is trained to predict the corresponding knowledge triplets. The question encoder on the right is trained to predict the masked token in the knowledge surface text.
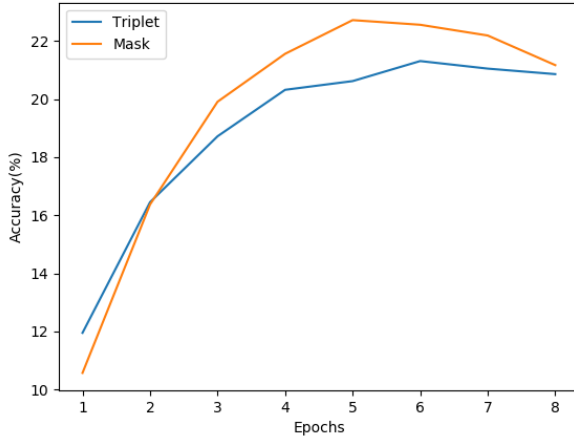

Fig. 6: The test answering accuracy (%) of the MCAN on KRVQA with respect to the training epochs. The blue line represents the MCAN accuracy with question encoder pretrained to predict knowledge triplets. And the orange line represents that the question encoder is pretrained on the masked token prediction task.

accuracy, which is almost the same with the baseline method and drops 5.65% compared with the "+ knowledge inference". This illustrates that the current black-box model can't discover the sparse knowledge through answer supervision only and validates that our proposed dataset can't be simply fit by deep models.

MCAN with related fact We retrieve the knowledge triplets from the knowledge base by matching the question tokens with the triplet entries. Specifically, we first extract the noun words from the question and sorts them according to their term frequency-inverse document frequency (TF-IDF). Then we match the words with the entities in the knowledge base and retrieve all triplets that are related to the matched entity. We fed the top-16 triplets to MCAN which performs attention on these 16 triplets. Table V shows that its result only improves 0.78%, compared with the baseline MCAN. This implies that only a small fraction of samples can retrieve the supporting knowledge, showing the difficulty of handling a large knowledge base.

C. Knowledge text pretraining

Most recent works [25], [26] have shown that the language model can encode the knowledge to a certain extend by training on a large corpus of text. Similar to these works, we pretrain the question encoder on knowledge text to encode the knowledge implicitly. Specifically, as each knowledge triplet has a corresponding surface text, we pretrain the self-attention question encoder of the MCAN to use the surface text as input, then either predict the corresponding triplets or predict the masked text tokens.

Triplet classification We first pretrain the question encoder to predict the knowledge triplet. As shown in Figure 5, we add three extra tokens to the end of the surface text, then fed the embedding of these three tokens to a fully-connected layer to predict the head entity, relation, and tail entity respectively. After training 30 epochs, the encoder predicts the head, relation, and tail with the accuracy of 99.64%, 99.90% and 98.82% respectively. We initialize the question encoder in MCAN with the pretrained parameters and it achieves 20.86%, as shown in Table V.

Masked token classification As shown in Figure 5, we randomly mask 1 or 2 tokens in the surface text then train the question decoder to predict the masked tokens. With 240 epochs training, the question encoder achieves token classification accuracy of 97.16%. And the MCAN initialized with the pretrained parameters has the answer accuracy of 22.23%, as shown in Table V.

We further investigate the test accuracy on different training epochs. As can be seen in Figure 6, the two pretrained models achieve their best results on epoch 5 and 6 respectively. Then, their test accuracies drop as the train loss decrease. This demonstrate that the pretrained question encoder has encoded useful information, but the deep embedding model overfits the training set later and can't handle the unused triplets very well.

VI. CONCLUSION

In this paper, we presented our Knowledge-Routed Visual Question Reasoning (KRVQA) dataset to evaluate a VQA method's ability on knowledge visual question reasoning and reveal the drawback of current deep embedding models. Specifically, we leverage the scene graph and knowledge base to retrieve the supporting facts and use the tightly controlled programs to generate the questions that require multi-step reasoning on external knowledge. The extensive

and comprehensive experiments have justified that the current VQA models can't achieve high performances by exploiting shortcuts, due to their difficulties in handling large scale of knowledge base and retrieving the supporting one for answer prediction. In future work, we will attempt to develop novel yet powerful VQA models and evaluate its performance on this proposed dataset.

ACKNOWLEDGMENT

APPENDIX

The supplementary material presents more randomly selected questions and its experimental results from HVQR. Each question is annotated with its answer, qtype, predicted supporting facts and the reasoning process of KM-net according to the predicted query layout.

Q:How is the girl dealing with the skirt?
A:wear
KM-net:wear
Facts-pred:(girl, wear, skirt)

Qtype:0
First-order
KB-not-related

Query:(Q_{ab_I} girl skirt)

Q:How does the fence relate to the bear?
A:behind
KM-net: behind
Facts-pred:(fence, behind, bear)

Qtype:0
First-order
KB-not-related

Query:(Q_{ab_I} fence bear)

Q:Tell me the object that the car is driving on?
A:road
KM-net:road
Facts-pred:(car, along, road)

Qtype:1
First-order
KB-not-related

Query:(Q_{ar_I} car along)

Q:In the picture, what is the girl wearing?
A:shirt
KM-net: shirt
Facts-pred:(girl, wear, shirt)

Qtype:1
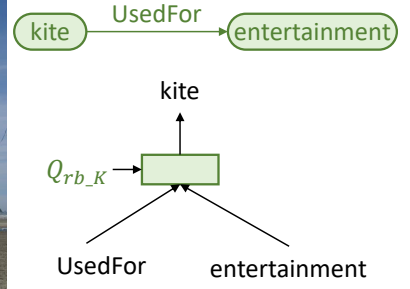**First-order**
KB-not-related

Query:(Q_{ar_I} girl wear)

Q:The skateboard is being used by what?
A:person
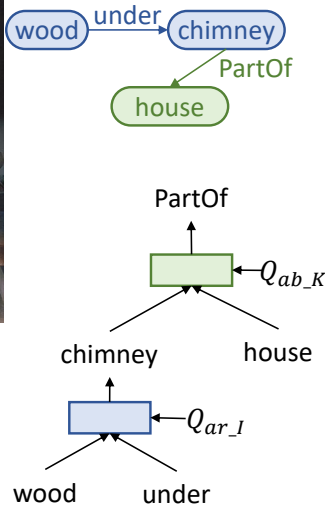**KM-net**:person
Facts-pred:(person, use, skateboard)

Qtype:2
First-order
KB-not-related

person

$Q_{rb\_I} \rightarrow$

use   skateboard

Query:(Q_{rb_I} use skateboard)

person → use → skateboard

Q:In the photo, what is for entertainment?
A:kite
KM-net: kite
Facts-pred:(kite, UsedFor, entertainment)
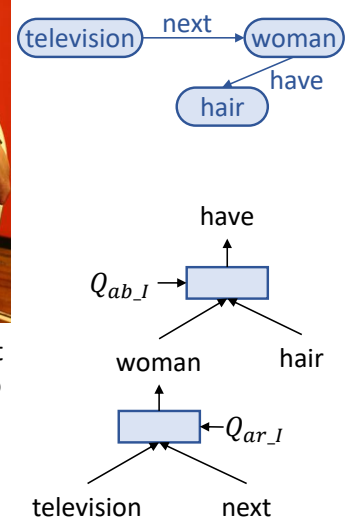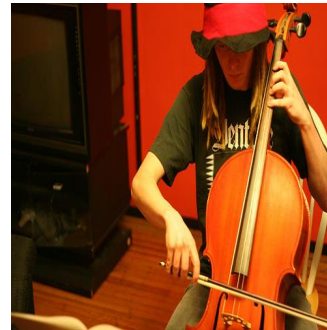
Qtype:2
First-order
KB-related

kite

$Q_{rb\_K} \rightarrow$

UsedFor   entertainment

Query:(Q_{rb_K} UsedFor entertainment)

kite → UsedFor → entertainment

Q:What is the object that woods under related to house?
A:PartOf
KM-net:PartOf
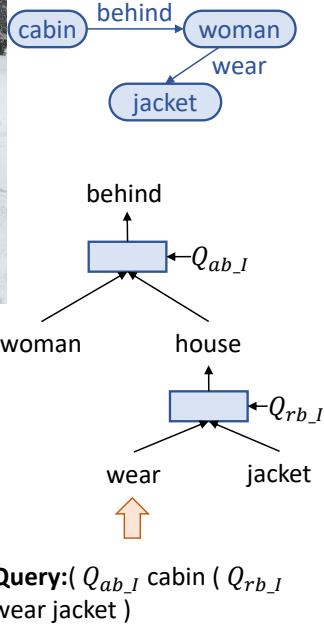**Facts-pred:**(wood, under, chimney)-(chimney, PartOf, house)

Qtype:3
Second-order
KB-related

PartOf

$\leftarrow Q_{ab\_K}$

chimney   house

$\leftarrow Q_{ar\_I}$

wood   under

wood → under → chimney → PartOf → house

Query:(Q_{ab_K} (Q_{ar_I} wood under) house)

Q:How does the object that television next to related to the hair?
A:have
KM-net: have
Facts-pred:(television, next, woman)-(woman, have, hair)

Qtype:3
Second-order
KB-not-related

have

$Q_{ab\_I} \rightarrow$

woman   hair

$\leftarrow Q_{ar\_I}$

television   next

television → next → woman → have → hair

Query:(Q_{ab_I} (Q_{ar_I} television next) hair)

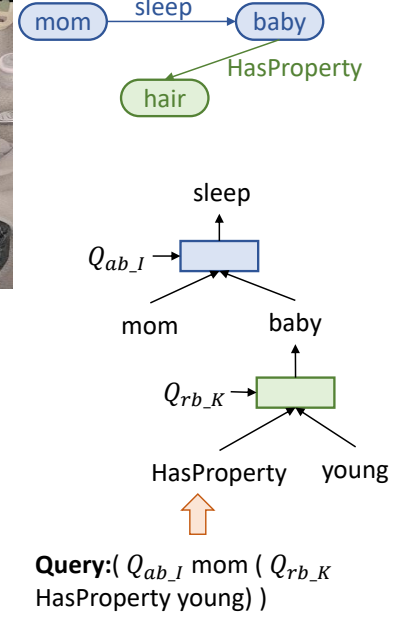**Q:**Something is wearing jacket;How is cabin related to something?
A:behind
KM-net:behind
Facts-pred:(cabin, behind, woman)-(woman, wear, jacket)

Qtype:4
Second-order
KB-not-related

Query:(Q_{ab_I} cabin (Q_{rb_I} wear jacket))

Q:How does the mom related to the object which is young?
A:sleep
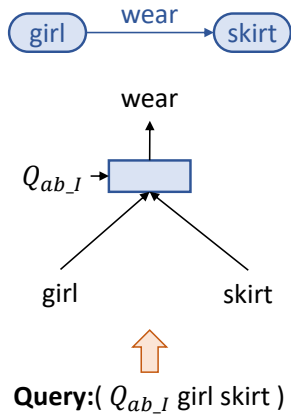**KM-net:** sleep
Facts-pred:(mom, sleep, baby)-(baby, HasProperty, young)

Qtype:4
Second-order
KB-related

Query:(Q_{ab_I} mom (Q_{rb_K} HasProperty young))

Q:How is the girl dealing with the skirt?
A:wear
KM-net:wear
Facts-pred:(girl, wear, skirt)

Qtype:0
First-order
KB-not-related

Query:(Q_{ab_I} girl skirt)

Q:How does the fence relate to the bear?
A:behind
KM-net: behind
Facts-pred:(fence, behind, bear)
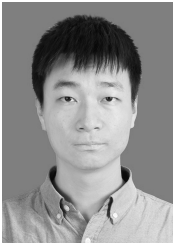
Qtype:0
First-order
KB-not-related

Query:(Q_{ab_I} fence bear)

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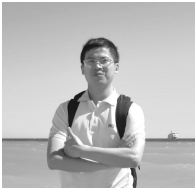
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