From Two Graphs to N Questions: A VQA Dataset for Compositional Reasoning on Vision and Commonsense

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Abstract

Visual Question Answering (VQA) is a challenging task for evaluating the ability of comprehensive understanding of the world. Existing benchmarks usually focus on the reasoning abilities either only on the vision or mainly on the knowledge with relatively simple abilities on vision. However, the ability of answering a question that requires alternatively inferring on the image content and the commonsense knowledge is crucial for an advanced VQA system. In this paper, we introduce a VQA dataset that provides more challenging and general questions about Compositional Reasoning on vIsion and Commonsense, which is named as CRIC. To create this dataset, we develop a powerful method to automatically generate compositional questions and rich annotations from both the scene graph of a given image and some external knowledge graph. Moreover, this paper presents a new compositional model that is capable of implementing various types of reasoning functions on the image content and the knowledge graph. Further, we analyze several baselines, state-of-the-art and our model on CRIC dataset. The experimental results show that the proposed task is challenging, where state-of-the-art obtains 52.26% accuracy and our model obtains 58.38%.

1. Introduction

Artificial intelligence has made great progress in many specific tasks, such as image classification [12, 25, 17], object detection [34, 16], relationship detection [45, 26]. However, it is still a formidable challenge to answer a natural language question about an image (a.k.a. Visual Question Answering task, VQA), which requires a system to compositionally realize a wide range of abilities, such as, understanding the natural language, recognizing the content of an image and mastering the commonsense knowledge.

Recently, numerous works have made valuable contribu-

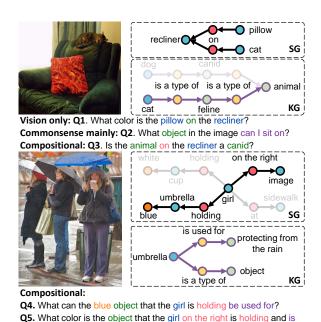


Figure 1. Examples of various forms of the questions in our CRIC dataset that require reasoning on the image content and the commonsense. To better visualize the reasoning procedure, we represent the image as a scene graph (SG, in black arrows) and the commonsense as a knowledge graph (KG, in purple arrows).

used for protecting from the rain?

tions on this topic and propose various datasets [6, 15, 20, 1] and sophisticated models [14, 3, 2, 28, 8]. Most of the existing datasets focus on one scope of abilities, e.g. the recognition of visual concepts (objects, scenes, attributes, relationships) [29, 33], spatial and logic reasoning on image [20, 19], visual related knowledge reasoning [39, 44]. However, to answer some common questions, it is inevitable for human to compositionally reason on the image and the knowledge. For example, to answer the very simple question **Q3** in Figure 1, we first find the things "on the recliner" by inferring on the image. Then, we filter the things that "is

a type of animal" by using some commonsense "cat is a type of animal, while pillow is not.". Finally, we check the statement "is cat a canid" by using commonsense "cat is a type of feline" and generate the answer.

To study this type of questions, we introduce a new VQA dataset, named CRIC (Compositional Reasoning on vIsion and Commonsense). The CRIC is constructed by a powerful question generator that can automatically generate a more general form of questions that require compositional reasoning on vision and commonsense from the scene graphs (from Visual Genome [24] in this paper) and the knowledge graph (using ConceptNet [27] in this paper). The question generator can also output the visiononly questions and commmonsense-mainly questions (like the question styles of other datasets) by controlling the percentage of the commonsense involved. Our dataset contains enormous questions with diverse forms and varying degrees of complexity, from simple and focused questions (e.g. Q1, 2 in Figure 1) to complex and compositional questions (e.g. Q4, 5).

Using such numerous samples with the annotation form (image, question, answer), it seems enough to evaluate the performance of a system as usually in existing datasets. But, are these annotations really enough to obtain a robust VQA model by training with them? Many works [13, 2] have observed that the deep networks inherently have large risks to converge to the solution using "trivial" shortcuts. Existing VQA systems that only utilize question answer (QA) pairs during training are likely to overuse the correlation between the questions and the answers to guess the answer [2, 32]. In contrast, it is natural for human to learn to solve a complex task by using other guidances and some proper inductive biases [7], rather than just watching numerous QA pairs. For example, to learn to answer a complex question like Q5 in Fig. 1, we learn how to decompose this complex task into some simpler sub-tasks (e.g. find the girl, recognize the color) and how to solve each sub-task. Then, for some subtasks, we learn to directly use some summarized knowledge (e.g. umbrella can protect from the rain) to achieve the goal, rather than try to summarize such rules all from samples.

Following this idea, our dataset provides three types of additional annotations about the information mentioned above to serve as human knowledge priors to help build robust VQA systems. *The first one* depicts what basic functions (sub-tasks) our dataset aims to evaluate, and how to execute these functions to answer questions (a.k.a. the functional programs of a question in [20], see Figure 2). We define the basic functions of reasoning on the image similar to [20] and further propose new basic functions of reasoning on the commonsense. *The second one* is the ground-truth output of every function in programs. These annotations not only can provide informative supervisions to train the building blocks, but also can help researchers precisely di-

agnose which part of the model goes wrong. *The third one* describes the knowledge triplets required for answering a commonsense question. This annotation can encourage the VQA system to explicitly reason on the precise and clear knowledge summarized by human.

In the following, we use CRIC to evaluate several representative VQA models on various forms of the questions. In addition, to evaluate the performance of one popular and potential type of model, the compositional model [4, 5, 18, 21, 43], we also present a new baseline model that builds upon the modular networks [18, 21] to fit the need of commonsense reasoning. The experiments show that the state-of-the-art obtains 52% accuracy, while our model achieves better accuracy 58%, which however indicates the task is still far from solved. Finally, we use our rich annotations to diagnose our model in detail and provide useful insights about the discovered weaknesses.

To summarize, the contributions of this paper are as follows: 1) We propose a new question type that require compositional reasoning on vision and commonsense and introduce new crucial challenges for VQA task: e.g. (i) the model not only needs to know *how*, but also *when* to use knowledge; (ii) how to explicitly conduct multi-hop reasoning on two graphs in two modals, etc. 2) We introducing rich annotations for each VQA sample (question-related graph, intermediate outputs) which can aid eliminating the disturbances of unrelated factors while diagnosing the VQA methods, and significantly ease the difficulty of demonstrating many potential methods. 3) We propose a new dataset construction method, which assembles basic template components to a whole template based on the image content, can quite efficiently save the cost on template collection.

2. Related Work

In the last few years, numerous works propose various VQA datasets. There are two main differences between the CRIC and other VQA datasets: 1) the CRIC proposes a more general form of the questions for reasoning on vision and commonsense and provides a wide range of compositional questions for real images. 2) Compared to existing real image VQA datasets, the CRIC provides much richer annotations and collects these annotations in an efficient way.

Visual Question Answering Task. At the early stage, many benchmarks [29, 33, 46, 22, 6] focus on evaluating a range of visual abilities, e.g. understanding various objects, attributes and complex relationships. More recently, CLEVR dataset [20] emphasizes the importance of a VQA system on compositional reasoning and provides compositional questions about synthetic images. Concurrent with our work, GQA dataset [19] introduces a real-image VQA dataset with compositional visual questions and more balanced answer distribution.

Dataset	Num. of Images	Num. of Questions	Task Focus	Scene Graph	Knowledge Graph	Functional Program
CRIC (Ours)	108K	1.3M	Commonsense (Compositional)	✓	✓	✓
VCR [44]	110K	290K	Commonsense	✓	X	X
KVQA [36]	24K	183K	Name Entities related Knowledge	X	✓	X
FVQA [39]	2.2K	5.8K	Commonsense	X	✓	X
KB-VQA [40]	0.7K	2.4K	Commonsense	X	X	X
GQA [19]	113K	22M	Vision (Compositional)	✓	X	✓
CLEVR [20]	100K	999K	Vision (Compositional)	✓	X	✓
VQA v2 [15]	204K	1.1M	Vision	X	X	X
VQA v1 [6]	204K	614K	Vision	X	X	X
VQA-abstract [6]	50K	150K	Vision (Scene Graph)	✓	X	X
COCO-QA [33]	69K	117K	Vision	X	X	X
DAQUAR [29]	1.4K	12K	Vision	×	X	X

Table 1. Main characteristics of major VQA datasets. Last three columns are about the additional annotations provided by the datasets. We note that CRIC is the first dataset containing compositional questions for commonsense reasoning, and providing rich annotations.

Another branch of works [44, 36, 39, 40, 23] expands the scope of the questions by requiring commonsense or the knowledge of a specific field. [39] introduces a new small dataset FVQA, where every question in dataset relates to one knowledge triplet in Knowledge Graph. [36] introduces KVQA dataset containing questions about name entities related knowledge extracted from Wikipedia, e.g. Who is to the left of Barack Obama. These two datasets require much deeper understanding of the knowledge, but involve relatively simple visual reasoning abilities (e.g. face recognition, visual concept recognition). The VCR dataset [44] focuses on challenging commonsense reasoning questions, e.g. inferring why something happened or the mental state of a person. While our CRIC relates to VCR in commonsense reasoning, they have clearly different focuses. CRIC focuses more on the background knowledge about the objects or events, while VCR focuses more on causal reasoning, and prediction of social interactions. In addition, our dataset hopes the model to answer a commonsense question by utilizing the knowledge graph, while VCR requires the model to answer the commonsense question mainly from the image content.

Our dataset proposes a more general form of the questions to unify the visual questions [29, 33, 15, 19] and the commonsense questions [39] in some datasets, and to provide more challenging compositional commonsense questions which are unique for existing datasets.

Dataset Annotations and Construction. Most of the real image VQA datasets [29, 33] only provide (image, question, answer) triplet for each sample. With the growth of the question's complexity, the supervision provided merely by the answer behaves more and more limited for training. In addition, it is a trend to design the models [42, 37, 28, 35] that can generate the intermediate results

of answering a question for enhancing the performance and transparency. This trend also urges the need of additional annotations that can be used to train the components and diagnose a complex model.

Existing works [20, 39] propose some types of additional annotations. FVQA [39] proposes to provide one type of additional annotations, that is, the knowledge triplet used to answer a question. CLEVR [20] provides useful annotations, such as scene graph and functional programs of the questions. To our knowledge, our dataset provides the richest annotations for a real image dataset. We collect both two types of the annotations involved in [20, 39], as well as the ground-truth output of every function in programs. More importantly, these annotations in CRIC are acquired automatically without extra labor cost. The main characteristics of major VQA datasets and CRIC are shown in Table 1.

For dataset construction, we are inspired by the CLEVR to automatically generate the compositional questions and additional annotations, rather than fully manually collect the question answer samples [6, 15]. However, CLEVR collects the templates of all possible questions. This method is less efficient and scalable for constructing a real image dataset that involves much larger concept vocabulary and commonsense knowledge. To address this problem, we dynamically assemble the question template from predefined basic template components given a specific scene graph and knowledge graph. In case of creating new templates to evaluate some new abilities, we just need to add some template components for these specific abilities, rather than rewrite or add numerous templates of the whole questions.

3. Dataset Collection

Overview. We introduce a new dataset CRIC with more general questions that require compositional reasoning on

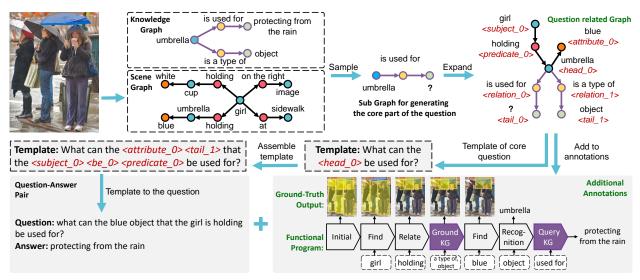


Figure 2. Overview of the QA sample generation process. The question and corresponding annotations are automatically generated from the Scene Graph of a given image and the Knowledge Graph. Our method first selects proper part of the Scene Graph and the Knowledge Graph that can generate a question, then assembles the question temple from predefined template components and finally generates the question-answer pair along with rich annotations.

the real image and the knowledge graph. The dataset contains 108K images, 1.3M balanced question-answer pairs and 3K selected knowledge triplets. In addition, to ease the difficulty of designing the compositional and interpretable systems, the dataset collects rich annotations about task decomposition, scene graph and knowledge graph that are related to every question, reasoning steps and their corresponding results for answering every question.

Our dataset is constructed in six main steps: 1) we process the scene graph, 2) collect useful knowledge triplets, 3) define the basic functions that the question will involve, 4) automatically generate QA samples from the scene graphs and the knowledge graph, 5) obtain additional annotations and 6) balance the dataset, as shown in Figure 2.

Scene Graph Processing. The CRIC dataset utilizes the 108K images of Visual Genome and their corresponding Scene Graph annotations to generate QA samples. The scene graph is a structured representation of the image, where nodes are objects annotated with attributes and edges connect two related objects.

In this stage, we first clean up the scene graphs by filtering rare concepts and merging synonyms. Our processed scene contains 907 distinct objects, 225 attributes and 126 relationships. In addition, we observe that one object in the image might correspond to multiple object IDs and bounding boxes in scene graph. This will cause ambiguity in later question generation procedure. Thus, we merge bounding boxes which correspond to the same object name and have a high IoU (> 0.7).

Knowledge Graph Collection. The purpose of this stage is to collect commonsense knowledge that is useful

in daily life and related to the images in Visual Genome. In this paper, our knowledge graph is extracted from a large-scale commonsense Knowledge Graph ConceptNet [27]. The knowledge in ConceptNet is collected from a variety of resources, such as crowd-sourced resources (e.g. Open Mind Common Sense [38]) and expert-created resources (e.g. WordNet [30] and JMDict [10]), and is represented as a triplet <head, relation, tail>. head and tail represent two entities, where each entity describes a concrete or abstract concept (e.g. cat, boiling water). relation represents a specific relationship between them (e.g. UsedFor, RelatedTo). There are 37 distinct relationships in ConceptNet.

To collect satisfactory knowledge triplets, we first query the ConceptNet with all the concepts in the processed scene graph and obtain about 225K triplets. However, many of them are unnatural to appear in a visual related question, e.g. *<person*, *Desires*, own a house>. Thus, we select 10 types of relations that can make questions informative and interesting, e.g. IsA, UsedFor, HasA. In Figure 3, we present the selected 10 types of relations and show one example of each type. Then, we manually filter the triplets by checking if the triplet is suitable to make up a common visual question. It is worth mentioning that the IsA-type triplets in our dataset not only serve to provide commonsense knowledge (e.g. <cat, is a type of, feline>), but also represent the hierarchical relations between concepts (e.g. blue and red belong to color-type, leather and wood belong to material-type). These hierarchical relations are frequently used for human to answer a question and likely to be helpful in designing a model. Therefore, we hope to assign every concept to at least a category (what type). For

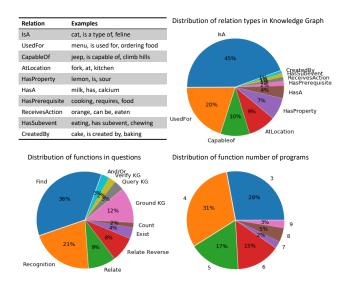


Figure 3. **Top left:** Relation types and their examples in our selected Knowledge Graph. **Top right:** The distribution of relation types in our selected knowledge graph. **Bottom:** The distributions of function in overall questions and function number of programs in overall questions.

the visual concepts not assigned to any category in ConceptNet, we refer their meanings in WordNet [30] to assign them into groups (if multiple concepts share the same hypernym, they will be assigned to one group). Moreover, we merge some entities that share the same meaning, but have different expressions, e.g. *calculate & making calculations*, to make the knowledge graph has denser connection. Finally, we obtain 3,019 carefully selected knowledge triplets and 113 categories. The distribution of relation types in selected Knowledge Graph is shown in Figure 3.

Function Definition. At this stage, we define the basic functions that the questions will involve. A VQA task ideally can evaluate any ability that can be queried by a natural language question, e.g. reading a clock, OCR, trafficsign recognition. However, it is challenging to build a dataset containing enough samples to fairly evaluate and sufficiently train all these abilities. In our dataset, we mainly evaluate the functions that are crucial or unique in VQA about compositional reasoning on vision and commonsense.

More specifically, there are 12 basic functions in our dataset. Four functions relate to basic logical operations: "And", "Or", "Exist", "Count". Four functions are about basic abilities of reasoning on the image: "Find", "Relate", "Relate Reverse", "Recognition". Note that "Relate" indicates the task that given *subject* and *predicate* in a scene graph relationship *subject*, *predicate*, *object*, the model needs to locate the region of *object*, while "Relate Reverse" indicates that given *predicate* and *object*, the model locates the region of *subject*. Moreover, we propose three new func-

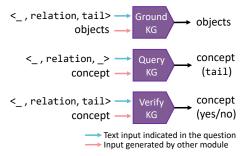


Figure 4. The basic functions related to commonsense reasoning. These functions take 1) some elements of a knowledge triplet <head, relation, tail> which are indicated in the question and 2) an object list or a concept index generated by some other module as inputs, and then generate the corresponding answer.

tions related to the commonsense reasoning: "Ground KG", "Query KG", "Verify KG", as shown in Figure 4. "Ground KG" requires the model to find image regions that satisfy a commonsense query, e.g. find the region contains the object that < _ , can be used for, drying wet hair> or < _ , is a type of, feline>. "Query KG" requires the model to generate a commonsense related answer, e.g. what can the <stove, be used for, _>. "Verify KG" requires the model to judge the correctness of the statement in the question, e.g. if the object $\langle -, can be, eaten \rangle$. It is worth mentioning that these three functions might need simple reasoning on multiple triplets, e.g. to find the food that is good for health, the model might need to use triplets <fruit, is, good for health>, <orange, is a type of, fruit>. Finally, we design a simple function "Initial" that is used to attend on all objects and is usually used at the start of the functional program. The full details of basic functions are in the appendix.

Template Collection & Question Generation. In this section, we introduce a scalable and low-cost question generator that can automatically create numerous questions by imitating the procedure of human creating a complex question. As shown in Figure 2, one question is generated from a dynamically composed question template based on a sub scene graph and a sub knowledge graph. To achieve this goal, we first need to build two types of template components. One type is the template of querying one object in the image or one element of object-attribute tuple or visual/ knowledge relationship triplet, e.g. the template of querying color "what color/which color/... is the <subject>?", where <subject> will be filled in based on the graph annotation. We write the template components for every group of concepts (defined in above). The other one is about how to use one object-attribute tuple or visual/ knowledge triplet to decorate one object, e.g. the <object> that <Relation> <Tail> (the <object> that is "is used for" "sitting on"). To increase the diversity of the question, one template component usually has multiple versions that



Vision only:

- 1. What is on the knife? sauce
- 2. Is the sauce on a napkin? no

Commonsense mainly:

- 3. What eating utensils can be used for moving food to the mouth? fork
- 4. What kitchenware can be used for turning food? spatula

Vision + Commonsense (Compositional):

5. Is the food on the plate a type of fast food? ves



Vision only:

1. Is the box that is next to the plastic bottle open or closed? open

Commonsense mainly:

2. What object can I use to hold drinks? plastic bottle

Vision + Commonsense (Compositional):

3. What place is the furniture that the woman is in likely to be found in? living room

4. Are the glasses that the woman is wearing used for correcting vision? no



Vision only:

- 1. Is there a helmet that is blue or green? no
- 2. What is red? car

Commonsense mainly:

3. Is there a vehicle that is a type of public transport? no

Vision + Commonsense (Compositional):

- 4. What can the hat that the batter is wearing be used for? protecting head
- 5. What color is the accessory that the man is wearing and is used for holding pants? brown

Figure 5. Some example questions from CRIC dataset. Our dataset contains vision only questions, commonsense related questions, as well as our unique compositional questions for reasoning on vision and commonsense knowledge.

will be randomly chosen to generate the question.

Then, the question is generated in following steps: 1) We select one relationship (or one object, object-attribute tuple) to generate the core part of the question. 2) We add proper relationships and attributes to decorate the core question, if the core question contains limited information to precisely locate image region, or we want to provide additional information to better locate the image region. 3) The template of the question will be automatically composed from basic template components. 4) The blanks in the template will be filled in based on the scene graph and the knowledge graph.

Obtaining Additional Annotations. For every QA sample in CRIC dataset, we provide the question and answer, along with additional annotations, including the sub scene graph and sub knowledge graph used in answering the question, the representation of the question in the form of a functional program and the ground truth output of every function in the program, as shown in Figure 2. The sub scene graph & sub knowledge graph and functional program can be automatically generated during the question generation. To collect the ground truth of each function, at every step of in program, we search on the scene graph and the knowledge graph to find objects satisfying the requirements of previous functions.

Balancing the Dataset & Dataset Statistic. Now, we obtain 6M automatically generated QA samples. However, these samples are highly unbalanced. To avoid the model overfitting on the bias of the dataset, we filter the QA samples and provide a more balanced dataset for training every function (unlike previous works that mainly balance the distribution of the answers). For the functions that output the concepts or boolean answer, e.g. Recognition, we down-

sample the questions based on the distribution of the answers in each concept group. For the functions that are used to locate the image region, e.g. Relate, Ground_KG, we downsample the questions based on the distribution of the text input. The distributions of the answers and the text inputs for some functions are shown in appendix.

Finally, we obtain the CRIC dataset which contains 108,077 images with 1,303,271 QA samples and 3,019 knowledge triplets. The question contains on average 7.62 words and involves on average 4.27 functions. In Figure 3, we show the distribution of the functions and the distribution of the function lengths. In Figure 5, we show some QA samples in our dataset.

The images of dataset are randomly split into train (60%), validation (20%) and test (20%). We evaluate the model by using the accuracy of the answers. To compare different methods in detail, we category questions by question type, defined as the name of the function that generates the final answer, e.g. Exist, Recognition. In addition, to better evaluate and diagnose the performance of the reasoning abilities, especially for grounding related functions, we provide the bottom-up features [3] with ground-truth bounding boxes as the image features. Moreover, the grounding related modules can be viewed as a multi-label classification problem that predicts the probability of each object if should be located. Thus, we use the accuracy accuracy = #correct predictions/#objects to evaluate these functions.

4. Approach

We introduce a new baseline model that builds upon one type of compositional models, neural module networks [18, 5, 21], for alternatively Reasoning on the Visual and Commonsense (RVC). RVC contains two main components: a set of neural modules, where each module is responsible for achieving one particular function, and a program prediction module that learns to dynamically assemble the neural modules to answer a given question. Compared to the previous methods, we add more neural modules and modify the program prediction module to fit the need of reasoning on commonsense.

4.1. Neural Modules

We design a set of neural modules to achieve different functions required by the questions. A neural module is a function $y=f(x_1,...,x_n,v,t)$ that takes n ($n\in\{0,1,2\}$ in our model) tensors $(x_1,....,x_n)$ generated from other neural modules, image features v and text input t extracted from the question as inputs, and outputs a tensor y which is either an attention map a over image regions or an discrete index c representing one concept. In this section, we mainly illustrate commonsense related modules, and the details of all modules are shown in appendix.

To utilize the commonsense knowledge graph in answering questions, we first learn the representations of the entities and the relations in triplets, and then use these representations that contain commonsense knowledge to achieve corresponding functions. To obtain representations of commonsense, we use one promising knowledge graph embedding method TransE [9]. For every triplet < h, r, t> in knowledge graph, TransE trains the embedding of elements \mathbf{h} , \mathbf{r} , \mathbf{t} to force them to satisfy the following equation: $\mathbf{h} + \mathbf{r} \approx \mathbf{t}$. Thus, given two elements in a triplet, we can infer the other one by using this equation.

We design three additional modules $Ground_KG$, $Query_KG$, $Verify_KG$ for achieving commonsense related functions. These modules take some elements in knowledge triplets < h, r, t> which are extracted from the question by program prediction module or the concept outputted by some other module, and then infer the other element and achieve corresponding functions, e.g. locate image regions ($Ground_KG$), verify the statement ($Verify_KG$). The formulations of three modules are as follow:

- ullet Ground_KG: $\mathbf{y}_a = \operatorname{sigmoid}(\operatorname{FC}(\mathbf{a}_1 \odot \mathbf{v}) \odot \operatorname{FC}(\mathbf{t}_t \mathbf{t}_r))$
- Query_KG: $y_c = \operatorname{argmax}(\operatorname{sigmoid}(\operatorname{FC}(\mathbf{c} + \mathbf{t}_r)))$
- Verify_KG: $y_c = \operatorname{argmax}(\operatorname{softmax}(\operatorname{FC}(\mathbf{c} + \mathbf{t}_r \mathbf{t}_t)))$

where \mathbf{t}_h , \mathbf{t}_r , \mathbf{t}_t are the TransE embeddings of inputs h, r, t, c is the TransE embedding of the input concept index, \mathbf{a}_1 is the input attention map, FC indicates a fully connected layer, \mathbf{y}_a indicates the output attention map, and y_c indicates the output concept index.

4.2. Program Prediction

The program prediction module predicts the function layout (a.k.a. a sequence of function names) and the text

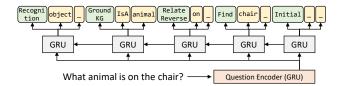


Figure 6. The program prediction module is an encoder-decoder network, where the encoder GRU extracts the question features and the decoder GRU predicts the function name and the text inputs at every time step. "-" indicates that the GRU will predict an index, but won't be used in other modules and the calculation of the loss.

inputs of each function for a given question, as shown in Figure 6. We design an encoder-decoder network [11] with attention mechanism to realize this function. For a question, the word sequence is first embedded into a list of word vectors and encoded by the encoder GRU. Then, the decoder GRU calculates a soft attention map over the encoded sequence and predicts the hidden state of every time step for the previous hidden state and current attended encoded sequence. Finally, three MLPs use the hidden state of every time step to predict three discrete indexes that indicate the function name and two text inputs of this function respectively. If a function needs less than two text inputs, the extra MLPs still predict text inputs, but the results have no use and make no contribution to the loss.

4.3. Training

The whole model is trained in two stages: training the program prediction module and training the neural modules. For training the program prediction model, we compute the cross-entropy losses of predicted function names and text inputs, and minimize the sum of the losses to train the module. For training the neural modules, we use the ground-truth function layouts to assemble the neural modules (the predicted program is used in testing), and minimize the sum of the cross-entropy losses for the predictions of all functions. Notably, the REINFORCE algorithm [41] is not used to jointly train the two components, because we want to utilize the annotations collected by our dataset to train the model with strong supervisions.

5. Results

5.1. Baselines

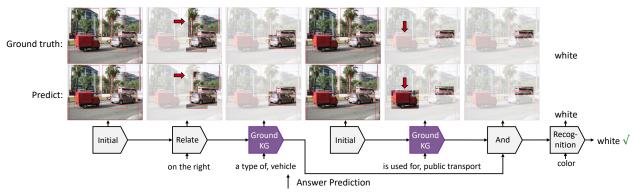
In this section, we evaluate the performance of following methods and some variations of our method on CRIC dataset:

Q-Type: Q-type uses the most common answer for each question-type in training split as the predicted answer.

Q-Only: Q-Only model only takes the LSTM question features as input.

Model	Recognition	Count	Exist	Query KG	Verify KG	Overall	Find	Relate	Ground KG
Q-Type	27.51	15.20	50.43	7.46	50.12	25.96	-	-	-
Q-Only	34.36	17.25	67.08	45.92	57.50	39.40	_	-	-
I-Only	9.47	10.34	43.61	13.17	41.33	14.18	_	-	-
Q+I	46.35	19.24	72.69	48.66	60.56	48.47	_	-	-
Bottom-Up [3]	50.28	22.80	77.15	51.57	63.25	52.26	-	-	-
RVC-l _{ans}	48.31	18.43	74.17	55.99	65.61	51.20	50.21	61.35	50.14
RVC-w/o-KG	53.71	20.50	77.59	52.93	62.59	54.68	90.30	85.91	80.36
RVC	55.89	20.46	78.64	65.03	71.25	58.38	90.34	85.59	84.27

Table 2. Results on test set of the CRIC dataset. The last three columns show the results of the functions related to the grounding. The scores of Relate and Relate Reverse are calculated together and shown in Relate column.



Predicted Program: Initial, Relate[on the right], Ground_KG[a type of, vehicle], Initial, Ground_KG[is used for, public transport], And, Recognition[color]

Program Prediction

Question: What color is the vehicle on the right that can be used for public transport?

Figure 7. Question answering example of RVC model on the CRIC dataset. Our method correctly predicts the functional program and the answer, while makes some mistakes on some specific functions, Relate and Ground KG.

I-Only: I-Only model only takes the image feature as input.

Q+I: Q+I concatenates the image features and the LSTM question feature, then uses an MLP to predict the answer distribution (No spatial attention).

Bottom-Up: Following [3], the Bottom-Up implements soft-attention on image regions. The attended image features and question features are combined to generate the final answer.

RVC- l_{ans} : A variation of RVC model that only uses the loss of the answer to train the neural modules.

RVC-w/o-KG: A variation of RVC model that don't use the Knowledge Graph to answer the question. It uses the trainable word vector to represent the text in commonsense related functions, rather than TransE embedding. More details of baselines are in appendix.

5.2. Analysis and Diagnosis

Comparison of different methods. The overall accuracy and the accuracies for each question type are shown in Table 2. We can see that question-only methods, Q-Type and Q-Only, both achieve relatively low accuracies which

indicate that the questions in dataset contain less language priors. Moreover, comparing CNN+LSTM with Bottom-Up, we find that the model can benefit from the attention mechanism. Comparing the Bottom-Up with RVC, we observe that the compositional method achieves better result on CRIC dataset. This could be because RVC decomposes the complex task into many simpler sub-tasks and can utilize rich annotations to sufficiently train each module. However, we observe that the performance gain of a compositional model in CRIC is not expected as large as in CLEVR. This might because: 1) The cascaded error impacts results, especially for our real-image QA. The sub-tasks in realimage QA are much more difficult than in synthetic-image. 2) Sequence information of a question as a prior sometimes is useful. Though we balance the dataset, question priors inevitably exist, because of the biases in the real world (e.g., most oranges are in orange). Bottom-Up explicitly uses such information in answering, while RVC only uses them in program prediction. Moreover, RVC-lans performs slightly worse than Bottom-Up, due to more serious cascaded errors caused by limited supervision and the lack of usage on questions.

Diagnose the compositional method. One advantage of our dataset is providing the ground truth output for every function. These annotations are helpful in diagnosing a compositional model, e.g. RVC. Therefore, we not only evaluate the functions that can output the answer, but also evaluate the neural modules outputting the attention maps and program prediction. The accuracy of function name prediction is 99.95%, and the accuracy of text inputs prediction is 92.31%. This indicates that understanding the question is relatively easy. From the results in Table 2, we can identify that "Relate" and "Ground_KG" are relatively difficult.

Comparing the results of RVC and RVC- l_{ans} , we find that RVC strongly outperforms RVC-lans in attention related modules, but achieves relatively small improvement in overall accuracy. This is due to our evaluation metric of attention modules (that encourages finding all objects matching the text query - requires exact binary classification) is more strict than the common metric (that only finds the object most related to the focus of a question - requires rough ranking). The former metric evaluates the robustness and will amplify the performance gap, while the latter more relates to final accuracy. For RVC- l_{ans} , the distribution of attention outputs does not fit for the binary classification because of no such supervision, so the score in our metric is low; in contrast, the exploited answer supervision can guide to attend on the related object, so the final accuracy is not too bad.

In Figure 7, we show the intermediate steps of our model in answering a question. Our model predicts the correct program and correct answer, but the intermediate results have some mistakes. In this situation, our dataset can provide proper supervision to correct the behaviour of some modules, while other datasets that lack the annotations of ground-truth output of functions will give no punishment.

Effectiveness of additional annotations. Comparing RVC and RVC- l_{ans} in Table 2, we find that the ground-truth intermediate results are helpful for training a compositional model. The performance of the RVC- l_{ans} dramatically drops on grounding related modules compared to RVC, which indicates that it is difficult to obtain robust modules without the ground-truth intermediate results. Comparing the results of RVC and RVC-w/o-KG, we can see that the knowledge graph annotations can help model achieve better results on commonsense related functions, because learning the knowledge from QA samples is harder than directly using the commonsense that human summarized. More analyses of the models are shown in appendix.

Main Challenges of CRIC. We conduct two additional experiments: **experiment.1**: evaluate RVC accessing to "ground truth visual representation" (RVC model can using the ground-truth bounding boxes, object and attribute annotations). The accuracy improves from 58% to 87%. **experi-**

Modules w. GT	None	Program	Attention Related	Answer Output Related
Acc(%)	58.4	62.1	74.3	89.7

Table 3. Accuracies of the models that let some type of modules output ground truth (w. GT).

ment.2: evaluate the models that let some types of modules output ground truth results once their inputs are correct, and the accuracies are shown in Tab.1.

From **experiment.1**, we find that visual part is one crucial challenge and commonsense part also remains ample opportunity to explore. From **experiment.2**, we find answer output related tasks are main bottlenecks (the biggest performance increase). Note that the above exposed challenges are mainly for compositional models that reason on the image and commonsense separately. However, we hope *CRIC* can motivate more interesting ideas for other unique challenges: e.g. how to design a model to capture the structure and global information of the joint of two graphs; how to explicitly conduct multi-hop reasoning on these two graphs.

6. Conclusion

This paper introduces CRIC dataset that evaluates a more general form of the questions requiring compositional reasoning on the vision and commonsense. To build this dataset, we propose a powerful method to automatically generate numerous QA pairs and rich annotations. Our generation method has better scalability and requires lower cost, which can ease the difficulty of building a complex VQA dataset. In addition, we hope our proposed various annotations can help the study of more transparent and robust models, such as compositional model, graph based model.

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Appendix

In the appendix, we introduce more details of our CRIC dataset (on Sec. 7 and 8) and the experiments with several models on CRIC dataset (on Sec. 9 and 10).

7. Function Definition

In this section, we introduce 12 basic functions that our dataset aims to evaluate, as shown in Figure 8. These functions operate on some values that are indicated in a question or generated by some neural modules, and output an object list or a concept.

Inputs of functions. These basic functions have two types of inputs. The first one is the text input that is indicated in a question:

- object: An object name, e.g. dog, double decker.
- attribute: An attribute name, e.g. blue, open.
- predicate: A predicate name, e.g. on, holding.
- type: A category name that indicates recognizing one type of concepts (defined in Knowledge Collection procedure), e.g. color, object, animal.
- head, relation, tail: three types of concepts indicate the elements in a knowledge triplet <head, relation, tail>, e.g. head: wine, relation: has, tail: alcohol.

Another type of input is a value (or a vector) generated by some other modules:

- *objects*: a set of objects (could contain zero, one or multiple objects) in an image.
- *concept*: a concept generated by some modules, e.g. car, dog.

Outputs of functions. Our functions have two types of outputs:

- *objects*: a set of objects in a given image.
- *concept*: a concept that could be the name of a visual concept (object, attribute, scene, etc.), a non-visual concept in knowledge graph, a number, or a boolean value (indicates yes or no).

Basic Functions. In this part, we introduce 9 visual basic functions (the other 3 commonsense functions have been illustrated in our main paper in Sec. 3 "Function Definition" part and Fig.4).

• Find: Given a set of objects, filter the objects by the object name or the attribute name or both two, e.g. find "cat", find "black", find "black cat".

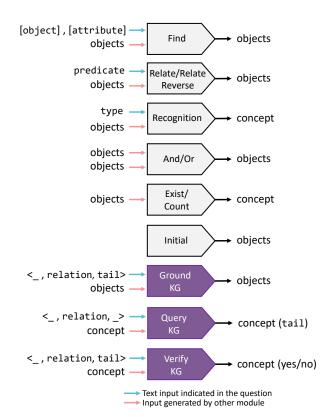


Figure 8. Catalog of basic functions evaluated in questions of CRIC dataset.

- Relate: Return all objects in the image that have the specified relation predicate to the input objects, where input objects are the "subject", output objects are the "object". For example, find all objects that the man ("subject") is holding ("predicate").
- Relate Reverse: Return all objects in the image that have the specified relation predicate to the input objects, where input objects are the "object", output objects are the "subject". For example, find all objects that are on ("predicate") the table ("object").
- Recognition: Recognize the concept in the *objects*among one type of concepts, e.g. recognize the color
 in one image region. Note that, we only apply Recognition function when the *objects* contain only one object.
- And: Return the intersection of two sets of objects.
- Or: Return the union of two sets of objects.
- Exist: Given a set of objects, output *yes* if the set is non-empty and *no* if it is empty.
- Count: Output the size of the input set of objects.
- Initial: Output the set of all objects in the image.

8. Dataset Statistics & Examples

We present the distribution of answers and the distribution of text inputs for each basic function (among 12 functions, there are 7 functions that have text inputs.) in Figure 9. In addition, the word clouds of visual concept answers and commonsense related answers are shown in Figure 10. In Figure 11, we display more QA samples in CRIC dataset.

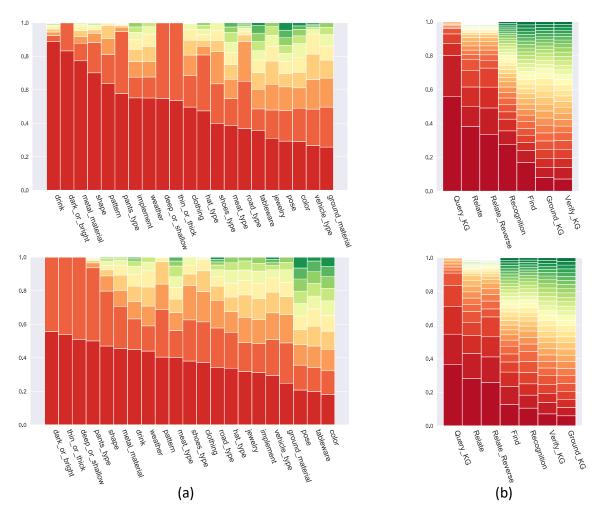


Figure 9. (a) **Top**: The distribution of answers for given categories (e.g. "dark & bright", "sunny, cloudy, snowy, etc.") before balancing the dataset. **Bottom**: The distribution of answers after balancing. (b) **Top**: The distribution of text inputs for each basic function (e.g. "on" and "standing" for Relate function) before balancing. **Bottom**: The distribution of text inputs after balancing.

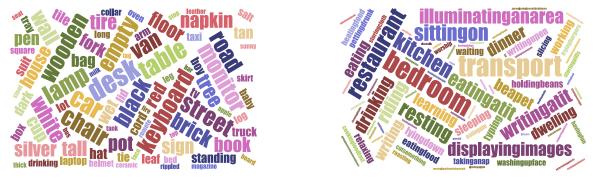


Figure 10. **Left:** Word cloud for frequent visual concept answers (object, attribute, etc.). **Right:** Word cloud for frequent commonsense related answers (some of them are phrases, e.g. "eating at it" is written as "eatingatit").



CRIC:

- 1. What is the girl holding? fork
- 2. What color is the plate? red
- 3. Is the plate in white or yellow? no
- 4. What object can I use to hold water? cup
- 5. Is there an object that can be used for holding water on the boy's hand? yes

VQA:

- 1. What color is the person on the right wearing?
- 2. What type of animal is printed on the napkin?
- 3. How many people are in this shot?



CRIC:

- 1. Which color is the dog? brown
- 2. Is the tv on the table on or off? off
- 3. What room is depicted in the image? living room
- **4.** What can the object that has the wheel be used for? move a box
- **5.** Is there an electronic device that I can use to make a call? yes

VOA:

- 1. What is the make of the laptop computer?
- 2. What color is the dog?
- 3. What is the man currently doing in this picture?



1. Is the player swinging a red bat? no

and is used for protecting head? blue

- 2. How many players are depicted in the image? 2

 3. What baseball position is the man who has blue
- **3.** What baseball position is the man who has blue hat playing? catcher
- What material is the catcher's glove? leather
 What color is the object that is on the catcher



CRIC:

- 1. How are the eggs cooked? scrambled
- 2. What material is the blue cup? ceramic
- 3. Does the beverage in the blue cup have alcohol?
- 4. What beverage can I use to stay awake? coffee
- 5. What object is the beverage that is good for babies in? glass

VQA:

- 1. Where is the meal being eaten?
- 2. What color are the curtains?
- 3. What kind of eggs are on the plates?



CRIC:

- 1. Is the sky cloudy? yes
- 2. What is the color of the bus? blue and white
- 3. What type of road is the car on? highway
- 4. Is there a vehicle that is capable of carrying cargo? yes
- 5. What color is the vehicle that can be used for hauling things? white and yellow

VOA:

- 1. How many trucks are there?
- 2. Was this picture taken on a cloudy day?
- 3. What color is the truck?
- 4. What is the cargo of the truck?



- 1. Is the street wet or dry? wet
- 2. What is the color of the jacket that the man is wearing? brown
- **3.** What material is the object that can be used for sitting on? wooden
- 4. Is the animal around the man a type of bird? yes
- 5. Which type of material is the object that is used for picking up the food? plastic



CRIC:

- 1. What color is the motorcycle? light blue
- 2. What type of shirt is the woman wearing? tank top
- 3. Is the street made of asphalt? no
- 4. What is the color of the object on the back of the motorcycle that is a type of identification document? white

VQA:

- 1. How many people are wearing red tank tops?
- 2. Is this motorcycle vintage?
- 3. What color is the motorcycle?



CRIC:

- 1. What color is the bear? red
- 2. What is the wall made of? wood
- **3.** What color is the object that can be used for making a call? black
- **4.** Is there a control device that can turn off the light? yes
- 5. What furniture do I need for a rest? bed

VQA:

- 1. What color is the bear?
- 2. Is the bed made?
- 3. Does the bear look comfortable?



- 1. How many cones are in the image? 4
- 2. How is the weather? cloudy
- 3. Is the door of the airplane open or closed? open
- 4. What is the blue object that the man is pulling? suitcase
- **5.** What color is the object that is usually used for transport? blue

Figure 11. Top two rows display the COCO images in Visual Genome and the corresponding questions from CRIC and VQA [15]. The bottom row displays the Flicker images in Visual Genome and the corresponding questions from CRIC. CRIC contains various types of compositional questions: vision only questions (in red numbers) and commonsense related questions (in purple numbers), while VQA mainly focuses on visual questions, and the questions are less compositional.

Module	text inputs	inputs	output	Implementation details
Find	t_o, t_a	a	att	$\mathbf{y}_a = \operatorname{sigmoid}(\operatorname{FC}(\operatorname{FC}(\mathbf{a} \odot \mathbf{v}) \odot \operatorname{FC}([\mathbf{t}_o, \mathbf{t}_a]))$
Relate/Relate_Reverse	t_p	a	att	$\mathbf{y}_a = \operatorname{sigmoid}(\operatorname{FC}(\operatorname{FC}(\mathbf{v}) \odot \operatorname{FC}(\operatorname{sum}(\mathbf{a} \odot \mathbf{v})) \odot \operatorname{FC}(\mathbf{t}_p)))$
Recognition	t_{type}	a	concept	$y_c = \operatorname{argmax}(\operatorname{sigmoid}(\operatorname{FC}(\operatorname{FC}(\operatorname{sum}(\mathbf{a} \odot \mathbf{v})) \odot \operatorname{FC}(\mathbf{t}_{type}))))$
And/Or	(none)	$\mathbf{a}_1, \mathbf{a}_2$	att	$\mathbf{y}_a = \operatorname{sigmoid}(\operatorname{FC}(\operatorname{FC}(\mathbf{a}_1) \odot \operatorname{FC}(\mathbf{a}_2)))$
Exist/Count	(none)	a	concept	$y_c = \operatorname{argmax}(\operatorname{softmax}(FC(\mathbf{a})))$
Initial	(none)	(none)	att	$\mathbf{y}_a = \mathbf{e}_N$
Ground_KG	t_r, t_t	\mathbf{a}	att	$\mathbf{y}_a = \operatorname{sigmoid}(\operatorname{FC}(\operatorname{FC}(\mathbf{a} \odot \mathbf{v}) \odot \operatorname{FC}(\mathbf{t}_t - \mathbf{t}_r)))$
Query_KG	t_r	c	concept	$y_c = \operatorname{argmax}(\operatorname{sigmoid}(\operatorname{FC}(\mathbf{c} + \mathbf{t}_r)))$
Verify_KG	t_r, t_t	c	concept	$y_c = \operatorname{argmax}(\operatorname{softmax}(\operatorname{FC}(\mathbf{c} + \mathbf{t}_r - \mathbf{t}_t)))$

Table 4. The details of neural modules in RVC. Each function takes some text inputs indicated in the question and some inputs generated by some other module as inputs, then achieves corresponding founction and outputs an attention map (shorted as "att") or a concept index. Note that, for visual functions, the text inputs t_o, t_a, t_p, t_{type} are embedded into GLoVe word vector, $\mathbf{t}_o, \mathbf{t}_a, \mathbf{t}_p, \mathbf{t}_{type}$ respectively. For commonsense related functions, the text inputs t_h, t_r, t_t and c are embedded into TransE embedding $\mathbf{t}_h, \mathbf{t}_r, \mathbf{t}_t, \mathbf{c}$ respectively. The operator \odot is element-wise multiplication, sum is summing the results over spatial dimensions, \mathbf{e}_N is an N dimensional (the number of objects in the image) vector where all elements are 1, and [,] indicates concatenation of two vectors.

9. Details of Models

Details of RVC. Our proposed model RVC has two main components: neural modules and program prediction module, as introduced in our main paper. In Table 4, we present the formulation of each neural module. We omit the word embedding procedure in implementation details in Table 4 for simplicity. For commonsense related modules, that is, "Ground_KG", "Query_KG" and "Verify_KG", the concept and text inputs are embedded into TransE [9] embeddings. For other modules, the text inputs are embedded into GLoVe [31] word vector.

Details of other models. We evaluate several representative models on CRIC dataset. For all the models that use questions features, we use GLoVe word embeddings with 300 dimensions to encode the words in a question, then use GRU with 512 hidden units to obtain the questions features. For all the VQA models without attention mechanism, we use pre-trained spatial features of ResNet [17] to extract the image features. For Bottom-Up [3] and RVC series models, we use the object-level image features generated by faster R-CNN model [34] trained on our training split of Visual Genome dataset. In addition, all the models are implemented by using the PyTorch.

10. Results Analysis

In Table 5, we show the results of several models on vision-only and vision+commonsense questions. The results show that the commonsense related questions are relatively harder than visual questions. In addition, we find that our model performs much better on commonsense questions. Comparing the results of RVC-w/o-KG and RVC, we observe that additional knowledge graph annotations are useful for answering commonsense questions.

In Figure 12, we show the accuracy of several models for

Model	Vision	Vision + Commonsense
Q-Only	41.13	38.33
I-Only	16.97	13.59
Q+I	50.96	46.72
Bottom-Up	55.01	50.16
RVC-w/o-KG	57.85	51.32
RVC	58.02	59.47

Table 5. The results on Vision-only questions and Vision + Commonsense questions in CRIC dataset.

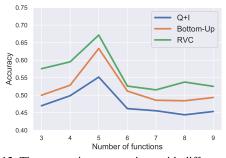


Figure 12. The accuracies on questions with different numbers of functions.

questions that involve different numbers of functions. We find that all models obtain relatively lower accuracy on short questions, perform better on middle length questions, and obtain lower accuracy on complex questions. This might be because many short questions in CRIC involve commonsense reasoning and provides limited information to help ground the correct image region, e.g. "what kitchenware is green?". This question requires the model to correctly recognize the name of all objects, recognize their colors, and understand all their categories. In addition, counting ques-

tions which are hard for most current models are also usually short. In contrast, the middle length questions are easy to be parsed, and contain proper information to locate the image region, e.g. "what object is on the table?". Finally, the results show that our model achieves better accuracy on all type of questions, especially on the short and long question. This is because our model is better on commonsense reasoning and parsing complex questions.