Understanding Knowledge Gaps in Visual Question Answering: Implications for Gap Identification and Testing

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Abstract

Visual Question Answering (VQA) systems are tasked with answering natural language questions corresponding to a presented image. Current VQA datasets typically contain questions related to the spatial information of objects, object attributes, or general scene questions. Recently, researchers have recognized the need for improving the balance of such datasets to reduce the system’s dependency on memorized linguistic features and statistical biases and to allow for improved visual understanding. However, it is unclear as to whether there are any latent patterns that can be used to quantify and explain these failures. To better quantify our understanding of the performance of VQA models, we use a taxonomy of Knowledge Gaps (KGs) to identify/tag questions with one or more types of KGs. Each KG describes the reasoning abilities needed to arrive at a resolution, and failure to resolve gaps indicate an absence of the required reasoning ability. After identifying KGs for each question, we examine the skew in the distribution of the number of questions for each KG. In order to reduce the skew in the distribution of questions across KGs, we introduce a targeted question generation model. This model allows us to generate new types of questions for an image.

1. Introduction

When compared to artificially intelligent (AI) systems, human cognition demonstrates a reasonably flexible system when faced with gaps in knowledge required to execute a prescribed task (i.e., humans tend not to halt). Humans often demonstrate not only the identification of a gap in knowledge, but also an ability to resolve the identified gaps through different means (question asking, research, etc). The ability to identify and resolve knowledge gaps (KGs) provides mechanisms that promote increased flexibility and robustness when faced with imperfect or incomplete information. Knowledge gap (KG) refers to when an agent cannot comprehend or complete a given task due to limited or missing information.

Similar to humans, AI agents do not always have perfect knowledge of a specified task [17]. A framework for KG identification and resolution can facilitate flexibility for an AI agent during both training and execution. To understand how to build a framework for AI agents to detect, identify, and resolve the different types of KGs that can occur, we use visual question answering (VQA) tasks. VQA sits at an intersection of three components of artificial intelligence: language, vision, and reasoning, thus making it a challenging task. To the best of our knowledge, we are the first to systematically manipulate VQA questions to produce knowledge gaps within AI agents.

Many recent VQA papers have attempted to increase the diversity of questions to include some that rely on external knowledge or commonsense reasoning [18, 16, 15, 14]. One such dataset is GQA [5], which we use to formulate our problem of identifying possible KGs in a task given to an AI agent. We apply a previously derived KG taxonomy [23] to the GQA dataset and present a tailored set of KGs for the VQA setting. From the current set of KGs, we have manually identified eight different KGs that occur in GQA [5], namely: Direction, Location, Material, State, Sentiment, Reasoning, Size, and Attribute Gap. The KG taxonomy is also used to identify the dataset attributes, which can indicate the types of KGs that can occur for a given question. In Section 3, we define the different types of KGs that we have observed in the VQA setting. Section 4 contains the details of our KG tagging methodology used for each question. After identifying the relevant KGs for each question, we observe a skew in the distribution of the number of questions per KG category.
The GQA dataset [5] largely contains questions about spatial relations, object attributes, or the existence of objects. To overcome this skew and make questions more evenly distributed across KGs, we apply a neural framework to generate questions for specific KGs. Section 2.1 defines the neural question generation framework.

2. Related Work

In this section, we discuss the related work for two different settings. In Section 2.2, we explain current efforts in the VQA domain to improve the robustness of VQA agents. In Section 2.2, we discuss the question generation strategies that lead us to our current approach.

2.1. Commonsense Reasoning for VQA Agents

Recent VQA datasets are a result of the realization that VQA agents can be highly contingent upon statistical biases and tendencies of the answer distribution and linguistic features [3, 2, 20]. Researchers have pointed out that these biases often result in high accuracies of the models even if image features are ablated. These higher numbers incorrectly lead us to believe that current techniques are making significant progress towards visual understanding of images.

These insights have lead to the augmentation of traditional VQA datasets including VQA 2.0 [3], GQA [5], TextVQA [13], OK-VQA [9], KVQA [12], FVQA [16], and CRIC [4]. Each of these datasets has been designed to make VQA agents more robust. Authors of the VQA 2.0 dataset [3] augment the VQA 1.1 dataset with additional images to improve the entropy of answers by creating a uniform distribution of answer probabilities. In [11], training examples are represented in the form of \( (\text{Image} (I), \text{Question} (Q), \text{Answer} (A)) \) triples. The authors of [3] add similar images to each possible \( I \), such that the \( Q \) remains but the image and question pair result in a different \( A \). Hence, they maximize the number of \( (I, Q, A) \) triples in the dataset, where \( I \) are images similar to \( I \) and \( A \) are answers that are different from \( A \) to increase the model’s dependence on visual features. Singh et al. [13] augment the existing Open Images v3 dataset to increase question and image pairs that require reasoning over the text present in images. They aim to increase the dependency of VQA models on the text present in images. They filter for image and question pairs in which the answer requires the use of OCR text to answer the question. The authors of the GQA dataset [5] use the Visual Genome Scene Graphs [7] to create a new dataset. The goal of this work is to gain control over the answer distribution and mitigate the heavy dependence on linguistic features and priors in current VQA frameworks. The OK-VQA dataset [9] contains examples in which the image content is not sufficient to answer the questions. The authors are able to show that state-of-the-art models perform poorly with their new dataset.

Shah et al. [12] release a new dataset, KVQA, that requires compositional reasoning based on vision and commonsense. KVQA contains image and question pairs regarding named entities. The questions in their dataset also require multi-entity, multi-relation, and multi-hop reasoning over large knowledge graphs. Gao et al. [4], release a new dataset in which compositional questions are automatically generated using both the scene graph of a given image and an external knowledge graph. Their goal was to create a dataset. The FVQA dataset [16] primarily contains questions that require external information to answer them. This dataset not only contains image-question-answer triplets, but also contains the supporting-fact (from an external KB) that is used to answer the question.

These datasets aim to increase the robustness of VQA agents and improve their usability. Our work augments the GQA dataset and provides reasoning abilities needed to answer VQA questions. To the best of our knowledge, we are the first to tag questions with the reasoning skills required to answer them. Our approach provides a new way to analyze the performance of VQA agents using different KG categories.

2.2. Question Generation

Upon tagging questions with KGs, we observe a skew in the distribution of questions for each KG type. To overcome this skew, we generate new question templates that can be populated with image annotations. Our question generation work is inspired by [8] [10]. Serban et al. [10] generate question and answer pairs using a neural network architecture to transduce Knowledge Base (KB) facts into natural language questions. The authors use a sequence-to-sequence (seq2seq) framework to generate questions using \( \text{subject, predicate, object} \) triples from their KB. Similarly, Liu et al. [8] propose a neural network architecture that combines template-based question generation techniques and seq2seq learning approaches to generate new questions. The authors first generate question templates (from questions in the training data) by replace the subject of the question with a “SUB” placeholder token. They use these templates and KB triples to generate new question templates. Later, they populate the generated question templates with facts from KB triples. We closely follow the approach in [8] to generate question templates that complement the existing questions in the GQA dataset. However, we expand the question generation framework to use paths in an image’s scene graph. These newly generated question templates can be populated with information from the path that was used to generate the question template. Since our framework is not restricted to using triples (from a scene graph) to generate new question templates, we can generate questions templates for objects that connected to each other via other intermediate objects.
3. Definition of Knowledge Gaps

A Knowledge Gap (KG) can occur when information that is missing or incomplete hinders the ability of a human or an agent to answer a question in the VQA setting. KGs can occur at a global or local level. Global gaps are those in which the ground truth VQA response is both unknown to the machine and the oracle. One such example of a global KG occurs when the following question “What is the man drinking?” is asked for an image which shows a man drinking out of a cup with its contents hidden from view. Here, humans might be able to make an educated guess such as coffee or tea based on the cup’s shape. However, there is no correct answer based on just the image.

Local knowledge gaps occur when the correct response exists in some type of format and can be obtained. For example, humans are faced with this problem when given a novel lexical item. Similarly for machines, this gap can also occur when agents come across words that do not exist in their vocabulary. For the VQA setting, we propose to identify the types of local gaps that can occur when machines are presented with a question and image pair and present a refined taxonomy of local KGs (see Figure 1).

The taxonomy proposes five major types of knowledge gaps: Language Gaps, Spatial Gaps, Attribute Gaps, Reasoning Gaps, and Philosophical Gaps. Due to space limitations we define the five gaps and their relevant subtypes with respect to the VQA setting. Language gaps arise when unknown phrases or vocabulary words are introduced. Spatial gaps occur when there is an error in understanding the physical space of a given context. Attribute gaps can occur when an object’s (or person’s) characteristics are not well understood. Reasoning gaps indicate that an agent has difficulty in the cognitive process of understanding information. Philosophical gaps are similar to reasoning gaps, but require meta-cognitive processes. We refer the readers to [23] for a definition of all KGs presented in the taxonomy.

In this work, we focus on KGs that can be identified in the GQA dataset: Attribute, Direction, Location, Material, Reasoning, Sentiment, Size, and State Gaps. Questions that create other KGs (e.g. Explanatory, Context, and Inverse Gaps) can also be generated for the GQA dataset. We leave the generation of these KGs as future work and describe possible solutions in Section 6.1.

Questions in the VQA datasets typically inquire about components of visual concepts (e.g. objects, scenes, attributes, relationships, etc), along with spatial and logical reasoning on images. Recent datasets have aimed to include questions requiring external knowledge or commonsense [16, 15, 18]. However, it is not clear which reasoning abilities are required to answer such questions. Therefore, we aim to tag questions using the KG taxonomy, which can give us initial insights into the weaknesses of models used for VQA. The use of KGs can allow us to understand the types of cognitive skills are not well developed in AI agents yet. Given the types of questions asked in a VQA setting, we assign (one or more) of the following KGs: Direction Gap, Location Gap, Material Gap, Sentiment Gap, Reasoning Gap, Attribute Gap, Size Gap, and State Gap.

We now define these specific KGs and ground them for the VQA setting. Figure 2 contains sample images and questions from the GQA dataset [5]. Under each image in the figure, we present the KGs for each question that are identified using our KG tagging methodology. Figure 2 can help understand the different types of KGs that are defined below.

**Attribute Gap:** In the VQA setting, questions inquiring about the color or shape of an object in an image are marked with attribute gap.

**Context Gap:** A context gap can occur if the agent has no information about a concept but is aware that such a concept exists. In Section 6.1, we outline a method to generate these gaps.

**Direction Gap:** Direction gaps can arise when agents are not able to understand the differences in spatial relations, such as “left of”, “right of”, “near”, “beneath”. In a VQA setting, questions inquiring about relative positions of ob-
projects are tagged with direction gap.

Entity Resolution Gap: If an agent is unable to identify the correct entity mentioned in the related question or task, then it is encountering an entity resolution gap. These gaps can be simulated for the VQA setting. We describe this procedure in Section 6.1.

Inverse Gap: Inverse gaps can occur if an agent does not understand the inverse of a relationship or concept. These gaps can be simulated for the VQA setting. We describe this procedure in Section 6.1.

Location Gap: Location gaps can occur when there is a misunderstanding about the particular physical place or setting of a context. Questions in the VQA dataset inquiring about the location of the scene in the image are marked with this type of gap. For the GQA dataset, we separate location gaps from direction gaps to create a distinction between questions about an image’s scene and questions about the spatial relationships of objects in an image.

Material Gap: We define a material gap as a type of Attribute gap, as it is focused on understanding the composition of objects (i.e. wooden, metallic, fabric, and etc). Questions inquiring about the material or composition of objects in an image are marked with material gap.

Reasoning Gap: Questions inquiring that require external knowledge about the scene or the objects in an image are marked with reasoning gap.

Sentiment Gap: A sentiment gap can occur when an agent is not able to understand the emotion or attitude of another agent. Questions inquiring about the sentiment of an object (typically humans or animals) in an image are marked with sentiment gap.

Size Gap: Size gaps, a subtype of Attribute gap, can occur when an agent is trying to understand the physical space an object or a person occupies. Questions inquiring about the size, age, or height of an object in an image are marked with size gap.

State Gap: State gaps are a type of Attribute gaps. These gaps can occur when an agent is trying to understand the specific condition of an object or a person. Questions inquiring about the condition of an object in an image are marked with state gap.

We use these KG definitions to create a rule-based tagging system to automatically mark questions with their respective KGs. We allow for questions to have more than one KG, since many reasoning abilities could be needed to answer a specific question.

4. Knowledge Gap Identification

The GQA dataset consists of images, questions, object features, and spatial features. The dataset consists of 22M questions about various day-to-day images. For each image, there is a scene graph that contains the image’s objects, attributes and relations. Additionally, each question is
annotated with a structured representation of its semantics (in terms of a functional program) that describes the reasoning steps that have to be taken to answer it. We choose to work with the training dataset and direct the readers to the official GQA website for more information about the original dataset. This section explains the method used to identify the KGs for each question and the challenges we face.

4.1. Grounding KGs for the GQA Dataset

The GQA dataset provides a rich set of annotations for each question. We use the following annotations to automatically identify KGs for each question: detailed type, global group, and semantic filters. In Figure 3, we provide a sample question annotation (from the dataset) that corresponds to the first question of Figure 2a.

We first consider a question’s given “detailed type” to tag a knowledge gap. The detailed type annotation describes the question’s structural (e.g. query (open), verify (yes/no)) and semantic type (e.g. attribute for questions about an object’s color). We manually define a mapping between the “detailed types” and KGs and present it in Table 2. If a question’s “detailed type” is in the list of “detailed types” for a particular KG, we assign that KG to the question. For example, if a question has placeVerify as its detailed type, we tag the question with Location Gap. Additionally, if a question has been assigned a KG in this step, we do not re-assign the same KG in any of the future steps. This ensures that a question cannot be tagged with the same KG more than once.

Next, we examine a question’s “global group” to assign a new KG. The global group is derived from the questions functional program that can be used to answer the question. The functional program for each question lists a series of steps needed to arrive at the answer. The global group is assigned based on the question’s answer type (e.g. color for “What color is the apple?”). The global groups that we have manually identified for each KG are also present in Table 2. Similar to the “detailed type” annotation, each global group is only assigned to one KG; therefore, only one KG can be assigned based on the question’s global group.

We then look at a question’s functional program and assign a KG based on the “filter” condition present in the semantic operations. The list of filters we use for each KG is also present in Table 2. In summary, during each step of the pipeline, we try to assign one KG (that has previously not been assigned) and do not reassign previously assigned KGs.

Table 1 presents the distribution of the number of questions for each KG. The first column (# of Total Questions) describes the number of questions per KG. The second column describes the number of unique question strings per KG. The same question can be asked across many images, but the answer may be different. Therefore, we provide the additional column to account for the number of truly unique questions. Moreover, we plot the distribution of questions in Figure 4 to show the skew in the distribution of the number of questions per KG. We can see that only a fraction of the questions are tagged with Reasoning, Size, and State Gaps, whereas, there are many questions in the dataset about object attributes, material compositions, location of image scenes, and spatial relations of objects. This apparent skew inspires us to use a question generation technique to balance dataset (in terms of KGs).

| KG      | # of Total Questions | # of Unique Questions |
|---------|----------------------|-----------------------|
| Attribute | 256961               | 179134                |
| Direction | 132712               | 70015                 |
| Location | 40493                | 7465                  |
| Material | 48744                | 33181                 |
| Reasoning | 4156                 | 968                   |
| Sentiment | 1601                 | 1243                  |
| Size     | 48744                | 38444                 |
| State    | 1306                 | 985                   |

Table 1: Number of total and unique questions per KG

We also keep track of the how each KG tag was assigned (i.e, “detailed”, “group”, or “semantic filter”). Table 3 describes the distribution of different sources of KGs. For example, we see that 114,083 questions are tagged with an
attribute gap using their “detailed type” annotation. Similarly, we can see that no sentiment gaps are assigned using the “detailed type” annotations. This is consistent with Table 2 as there are no “detailed type” annotations present in the dataset to identify sentiment gaps. Instead, we tag 50 questions using the “global group” label and 1,551 questions using the “semantic filters” annotations with sentiment gap.

Table 2: KG Tagging

| KG       | Detailed Types                                                                 | Global Group Label        | Semantic Filters |
|----------|-------------------------------------------------------------------------------|---------------------------|-----------------|
| Attribute| existAttr, existAttrOrC, existAttrNot, verifyAttrK, chooseAttr, verifyAttrs, verifyAttrC, verifyAttr, verifyAttrThis, existAttrC, existAttrOr, categoryAttr, verifyAttrsC, verifyAttrCThis, existAttrNotC, verifyAttrAnd, verifyAttrKC | color, shape              | color, shape    |
| Direction| dir, positionVerify, positionVerifyC, positionChoose, positionQuery           |                           | hposition, vposition |
| Location | place, placeVerify, placeVerifyC, placeChoose, locationVerifyC, locationVerify | place, room, nature environment, urban environment, road | location, place, room |
| Material | twoSameMaterial, sameMaterialRelate, materialChoose, verifyMaterialAnd, twoSameMaterialC, existMaterialNot, existMaterialNotC, existMaterialC, existMaterial, materialVerify, materialVerifyC, material | material, ingredient, texture, liquid, brightness, opaqueness, hardness, pattern | liquid, opaqueness, material, hardness, pattern, brightness |
| Reasoning| diffAnimals, diffAnimalsC, sameAnimals, sameAnimalsC, comparativeChoose       |                           | face expression  |
| Sentiment| face expression                                                               |                           | face expression  |
| Size     | age, height, thickness, depth, fatness, length, weight, width, size            | age, fatness, length, thickness, size, weight, depth, weight, width, height |                |
| State    | state                                                                        |                           | state           |

Table 3: Number of total and unique questions per KG

| KG       | Detailed | Group | Semantic |
|----------|----------|-------|----------|
| Direction| 98809    | 0     | 33903    |
| Material | 17005    | 8385  | 23918    |
| Attribute| 114083   | 55718 | 87160    |
| Size     | 0        | 12654 | 36090    |
| Sentiment| 0        | 50    | 1551     |
| Location | 22920    | 14712 | 2861     |
| State    | 129      | 120   | 1057     |
| Reasoning| 4156     | 0     | 0        |

4.2. Challenges

The method described for automatically assigning KGs to questions is not free of errors. The current technique can both fail to assign relevant KGs or assign irrelevant KGs. The current method is highly dependent on the quality of the question annotations and the handcrafted question-annotations-to-KG mapping. Upon investigation, we have identified several sources of errors including but not limited to: garden path questions, multiple meaning words
Questions in the dataset can be lems in the KG tagging process.

Garden Path Questions: Questions in the dataset can be ambiguous due to the lack of punctuation. Therefore, there can be multiple correct answers to a question based on the question’s interpretation, e.g., “Are both the sofa and the bookcase to the left of the knife made of wood?”

Dataset Errors: Since there are over 22 million questions in the dataset and many of them are generated through templates, there are often errors in the question annotations. For example, for the following questions “Which is healthier, the orange or the muffins?” , “Which is healthier, the candies or the orange?” the “global group” label in the dataset is “color”. This is incorrect because the question is not about the color of an object, rather it is asking about the object, “orange”. Additionally, for some questions, there are parts of annotations that are missing, e.g., “Is the large pot to the right or to the left of the jar in the middle of the picture?”. There is no mention of “size” or “large” in the question annotation.

Multiple Meaning Word (MMW): The following questions: “Which is healthier, the orange or the muffins?”, “Which is healthier, the candies or the orange?” are tagged with attribute gaps by our system. Here, the word “orange” is a noun rather than an adjective. Our method fails to understand that the word “orange” is not an attribute.

5. Question Generation

Based on the skew in distribution of the number of questions per KG that we observed, we aim to generate new questions for images that lack certain KGs. Note, it may not be possible to generate questions to address all types of KGs for an image. For example, if an image does not contain a human, it does not make sense to generate a question for sentiment gap. By increasing the number of questions for certain KGs, we can make the dataset more balanced. For example, sentiment questions require commonsense reasoning and if VQA models perform poorly on these types of questions it may be because the dataset does not contain enough training examples. We do not currently focus on generating the correct answers for the newly generated question. We leave this as future work. Our neural question generation strategy is similar to that of [8]. We use a neural network architecture that combines template-based question generation methods and seq2seq learning to generate new question templates. We use the IBM Pytorch Seq2Seq framework [9]. Figure 5 depicts the model we use to generate new question templates.

We use the scene graphs provided for each image to generate new question templates. Figure 6 presents a visualized scene graph for Figure 7. The nodes in a scene graph are objects that have been identified in an image. The edges represent the relationships among the objects in the image. We aim to generate question templates from extracted paths in a scene graph. We have noticed that not all objects in a scene graph are connected (e.g. some nodes do not have an incoming or an outgoing edge). Currently, we do not use these isolated nodes in the scene graph. However, these nodes can be used to generate context gaps (see Section 6.1).

We can extract a simple path of length $L$ and use it to generate a question template which is concerned with the objects and the relationships along the path sequence. The question template generation method can be modeled in a probabilistic framework.

$$P(Q|P) = \prod_{i=1}^{N} P(w_i|w_{<i}, P)$$

$Q = (w_1, w_2, ..., w_N)$ represents the generated question template which consists of tokens $w_1, w_2, ..., w_N$. In most question templates, the last generated token $w_n$ should be “?”. $P$ represents the path sequence that is fed into the encoder of seq2seq model. Our template-based seq2seq model can be viewed as a translator that converts structured data (paths along a scene graph) into question templates. These templates can be populated in a downstream task with data from the path to generate a complete question.

The model can be divided into a path encoder and a question template decoder. For each question, we leverage the respective image’s scene graph to extract paths up to length $L$ that contain the objects mentioned in the question. The input to our encoder is either a triple ($L = 1$) or a simple path of length $L$ that is extracted from an image’s scene graph based on the corresponding question. Triples are in the form of $P = (g(e_1), r_1, g(e_2))$. The simple paths are represented as $P = (g(e_1), IO, r_2, IO, ..., r_n, g(e_2))$. The entities $e_1$ and $e_2$ are objects mentioned in the training questions. The function $g(\cdot)$ describes entities as a concatenation of their attributes and their names in English. The $r_n$
along a path are the relations among entities. We chose to replace the intermediate entities along a path with a place holder “IO” (short for “INTERMEDIATE_OBJECT”), because we are only interested in entities $e_1$ and $e_2$ that are actually present in the training question. Additionally, using paths of $L > 1$ can allow us to generate questions about objects that are connected through intermediate nodes. For example, the scene graph for the image in Figure 7 does not have a direct edge between the annotated objects: “player” and “man”. However, if we search for a path between the objects “player” and “man” in the scene graph (Figure 6), we are able to find a relational path between them. Additionally, at this step we only select questions that have more than two object mentions. The path representations are fed into an encoder to learn a subset of the scene-graph’s representations.
To create training question templates, we replace the objects mentioned in the question with an “OBJ” placeholder and attributes mentioned in the question with the “ATTRIBUTE” placeholder. Table 4 presents sample questions and their templates that are used during training.

5.1. Experimental Setup

To generate new question templates, we train separate seq2seq models for each KG type. This allows us to control the types of templates that will be generated, as we try to remove the skew in distribution presented in Table 1. For each KG type, we train two seq2seq models: 1) using the triple representations \( L = 1 \), 2) using the path representations \( L \leq 5 \). We refer to the model that uses triples as the triple based model and the model uses that paths as the path based model. Table 5 describes the distribution of the triples dataset used for our first model that uses triples as input to the encoder. Table 6 describes the distribution of the paths dataset used for second model that uses paths as input to the decoder. We use 80% of our data for training, 10% for validation, and 10% for testing.

The IBM Pytorch Seq2Seq framework allows for both unidirectional and bidirectional LSTMs as a part of the encoder. We run our experiments with both unidirectional and bidirectional LSTMs and find that for some KGs a bidirectional LSTM results in better performance.

The decoder always uses a unidirectional LSTM to decode the encoder outputs. During decoding, we use teacher forcing to allow the decoder to learn how to generate question templates. The teacher-forcing ration is set to 0.25. Additionally, we use the built in attention mechanism along with TopKDecoder which performs a beam search of length \( K \). We add another constraint to limit the number of “ATTRIBUTE” placeholders in the generated template, while selecting the top template. This constraint was added because we noticed that the decoded sequences often contained many more “ATTRIBUTE” placeholders than the training question templates. We use the top \( K = 10 \) decoded sequences and select the template that contains the highest probability and has the same number of “ATTRIBUTE” placeholders in the generated template as the original training template. If none of the top \( K \) results meet this criteria, we simply use the template with the highest probability as our output.

| KG   | Split | # of Training Examples | # of Unique Training Templates | # of Unique Training Triples |
|------|-------|------------------------|-------------------------------|-------------------------------|
| Attribute | train   | 94936                  | 10921                         | 46520                         |
|        | val     | 12727                  | 1988                          | 9696                          |
|        | test    | 12795                  | 2003                          | 9701                          |
| Direction | train   | 34353                  | 4261                          | 17151                         |
|         | val     | 4370                   | 1096                          | 3452                          |
|         | test    | 4367                   | 1089                          | 3498                          |
| Location | train   | 1867                   | 471                           | 1486                          |
|          | val     | 236                    | 99                            | 218                           |
|          | test    | 236                    | 96                            | 225                           |
| Material | train   | 17328                  | 3886                          | 11270                         |
|          | val     | 2196                   | 549                           | 1873                          |
|          | test    | 2191                   | 563                           | 1951                          |
| Reasoning | train   | 659                    | 36                            | 392                           |
|          | val     | 130                    | 21                            | 92                            |
|          | test    | 129                    | 19                            | 101                           |
| Sentiment | train   | 1066                   | 309                           | 822                           |
|          | val     | 135                    | 53                            | 122                           |
|          | test    | 136                    | 59                            | 128                           |
| Size     | train   | 21925                  | 3336                          | 14165                         |
|          | val     | 2822                   | 737                           | 2458                          |
|          | test    | 2828                   | 762                           | 2445                          |
| State    | train   | 346                    | 101                           | 287                           |
|          | val     | 44                     | 23                            | 37                            |
|          | test    | 45                     | 20                            | 44                            |

Table 5: Triples Dataset Distribution

We perform a grid search for each KG model and select a best model based on our training loss and the validation loss.

5.2. Experimental Results

We use BLEU and METEOR scores to evaluate our question generation model. These score are commonly used for Natural Language Generation (NLG) task. BLEU scores are computed based on an average of unigram, bigram, trigram, and 4-gram precision. BLEU scores are relatively easier and faster to calculate when compared to human evaluation. METEOR scores are another metric used for evaluating machine translation models. These scores are claimed to have better correlation with human judgement when compared to BLEU scores. METEOR scores also take into account word order while evaluating generated text.

Table 7 presents the results of our model, where we feed scene graph triples \( L = 1 \) into our encoder. Table 8 presents the results of our model, where we feed simple paths from scene graph \( L \leq 5 \) into our encoder. Our reasoning, location, and material gaps models achieve the highest METEOR scores for our triple based input. Our reasoning, location, and direction gaps models achieve the highest METEOR scores for our path based input.

https://www.nltk.org/_modules/nltk/translate/bleu_score.html
https://www.nltk.org/_modules/nltk/translate/meteor_score.html
Table 4: Sample Question Templates

| KG      | Original Question                                           | Question Template                                           |
|---------|-------------------------------------------------------------|-------------------------------------------------------------|
| Attribute | What is the green object on the table made of?              | What is the ATTRIBUTE object on the OBJ made of?             |
| Direction | Where is the bird on the branch looking at?                  | Where is the OBJ on the OBJ looking at?                      |
| Location | Where are the people to the left of the umbrella sitting?   | Where are the OBJ to the left of the OBJ sitting?             |
| Material | Was plastic used to make the cookie on the counter?         | Was ATTRIBUTE used to make the OBJ on the OBJ?               |
| Reasoning | Which are healthier, the pizza or the peppers of the pizza? | Which are healthier, the OBJ or the OBJ of the OBJ?           |
| Sentiment | Is the man that is to the left of the other man both old and happy? | Is the OBJ that is to the left of the other OBJ both ATTRIBUTE and ATTRIBUTE? |
| Size | Is the truck to the left of the mirror white and small?     | Is the OBJ to the left of the OBJ ATTRIBUTE and ATTRIBUTE?    |
| State | Is the sheep that is to the right of the other sheep still or is it rough? | Is the OBJ that is to the right of the other OBJ ATTRIBUTE or is it ATTRIBUTE? |

Table 6: Paths Dataset Distribution

Table 7: Triple Based Model Results

Table 8: Path Based Model Results

highest METEOR scores for our path based input. Our models for state gap do not perform well. We suspect this is because of the low number of training examples (see Table 5 and Table 6).

Our path based model improves the METEOR score and BLEU score by 3% and 2% (respectively) for direction gap with respect to our triple based model. It does not improve
performance for other KGs. This result is acceptable, because questions regarding spatial relations can benefit from more information about how objects are related to each other in an image (via a scene graph). Similarly, question’s concerned with an object’s attribute are more dependent on the triples related to that object.

5.3. Case Study

In this section, we use a sample image to motivate our work. The image in Figure 7 is paired with the questions in Table 9 in the GQA dataset. Additionally, in the “KG(s)” column, we present the KGs assigned for each question by our KG tagging method. From Table 9 we can see that the questions related to sampled image are primarily about object attributes. This is consistent with the skew we observe in Figure 4. Additionally, there is one question about the location of the image scene and two questions about the spatial relations of the objects present in the image. Our KG tagging system identifies the following set of KGs for the questions: attribute, direction, and location gaps. However, there many more KGs that can be generated. Therefore, we use our models trained for sentiment gap, reasoning gap, material gap, and size gap to generate different types of question templates that can be populated to create new questions for the sampled image.

Using our trained KGs models, we can generate new question templates that can be populated to increase the variety of questions. We are able to generate questions for:

| Question                                                                 | KG(s)          |
|--------------------------------------------------------------------------|----------------|
| Where in this photo are the green chairs, in the top or in the bottom?   | Direction, Attribute |
| What place is this?                                                      | Location       |
| Is the hat of the players brown?                                         | Attribute       |
| Where are the chairs?                                                    | Location       |
| Which color is the lady’s hair?                                          | Attribute       |
| What kind of furniture is green?                                         | Attribute       |
| Which type of clothing is not orange?                                    | Attribute       |
| Which color does the shirt have?                                         | Attribute       |
| Are there any black hats or gloves?                                      | Attribute       |
| Is the man on the right or on the left side of the image?                | Direction       |
| Which kind of clothing is orange?                                        | Attribute       |
| What is the color of the shoes the player is wearing?                    | Attribute       |
| What color are the shorts?                                               | Attribute       |
| What color is the hat?                                                   | Attribute       |

Table 9: Questions in the Dataset for the Case Study Image

New template using our triple based material gap model:
INPUT: cap to the left of pants
OUTPUT TEMPLATE: “What is the OBJ near the OBJ made of?”
POPULATED TEMPLATE: “What is the cap near the pants made of?”

New template using our triple based reasoning gap model:
INPUT: players to the right of man
OUTPUT TEMPLATE: “Which is younger, the OBJ or the OBJ?”
POPULATED TEMPLATE: “Which is younger, the players or the man?”

New template using our triple based sentiment gap model:
INPUT: spectator to the right of cap
OUTPUT TEMPLATE: “Is the ATTRIBUTE OBJ to the right of the OBJ?”
POPULATED TEMPLATE: “Is the happy spectator to the right of the cap?”

New template using our triple based size gap model:
INPUT: bat to the right of shoe
OUTPUT TEMPLATE: “How big is the OBJ near the OBJ?”
POPULATED TEMPLATE: “How big is the bat near the shoe?”

These new questions can be used along with the questions that exists in the GQA dataset. These new questions are not grammatically perfect. In our future work, we aim to borrow ideas from the NLG community to increase the quality of our generate questions.

6. Ongoing Work

6.1. KG Generation

The method described in Section 4.1 is designed to capture eight KGs (Direction, Location, Material, State, Sentiment, Reasoning, Attribute). As previously mentioned, the following KGs can be generated for the GQA dataset:
Context Gap, Entity Resolution Gap, Explanatory Gap, and Inverse Gap. A KG can be generated by asking a question that requires specific cognitive skills to answer it.

**Context Gap:** To simulate context gaps, we can use the scene graphs provided with images. We can identity isolated nodes in scene graphs and generate questions regarding those nodes. This is consistent with the definition of context gaps, since the agent knows there is an isolated object but is missing the information to connect the object with the rest of the image content.

**Entity Resolution Gap:** Questions about an object might be ambiguous if there is more than one object of the same type. For example, “On which side of the picture is the closed shelf?” cannot be answered correctly because there can multiple closed shelves in the image that is associated with the question. These gaps can be identified by counting the number of times the entity/object in the question occurs in the scene graph. This technique is highly dependent on the quality of scene graphs.

**Explanatory Gap:** Explanatory gap questions can be generated for the VQA dataset. Authors of [1] aim to generate questions that require external knowledge. They automatically generate compositional questions using an image’s scene graph and an external knowledge graph. Similarly, for each object in an image, ConceptNet [11] can be queried to search for the “UsedFor” edge. If such an edge exist, a question can be created in the format of “What is the object used for?” The answers to these questions can also be collected by using the nodes connecting the image objects with the “UsedFor” edge. This technique can result in some incorrect questions such as:

• What is the wine used for?
• What is the dog used for?
• What is the sit used for?
• What is the ocean used for?

**Inverse Gap:** Assigning an inverse gap tag requires identifying (or creating) an inverse question, Q′, that compliments the original question, Q. One technique to identify, an Q′ is to tokenize the original question Q and use WordNet [12, 14] to search for antonyms of the words in Q. To reduce noise, we can use NLTK [21] to identify the search space of the part-of-speech (POS) tag for each token. Then we can only search for antonyms of verbs, adjectives, determiners, and existentials. The WordNet query (through NLTK) can be refined using the token and its coarse-grain POS tag. For all synsets returned for a token, their lemmas’ can be used to find all antonyms. For each antonym, we can create a Q′ if the antonym is not in Q. We observe that this last check is necessary, because there are “comparative” questions in the dataset, e.g. “Is the table small or large?”. For these types of questions, it would not make sense to generate an inverse question Q′ that asks: “Is the table large or large?”.

The list of generated inverse questions can be further pruned by identifying all generated questions that exist in the dataset. This pruning technique removes questions like: “Is the ball to the wrong of the bat?” or “Is the table big or large?”. Finally, the remaining questions can then be assigned to the images and be tagged with an inverse gap.

6.2. Question Generation

Our question generation framework is able to generate question templates given a triple or a path from a scene graph. To make use of these templates, we can use an image’s annotation to replace the place holder text with the image’s data. We plan to improve the quality of our generated templates by using ideas from the NLG community. Additionally, we plan to try different models to generate questions and question answers that can be used during training.

7. Conclusion

In this work, we aim to understand the different types of reasoning skills needed for VQA tasks. We present a taxonomy of KGs that is used to design a framework to identity KGs for VQA questions. We have proposed a question generation technique to reduce the skew in the distribution of questions per KG type for the GQA dataset. Our work is an initial step towards understanding the cognitive skills need to advance AI agents.

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