VQA-LOL: Visual Question Answering under the Lens of Logic

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Abstract

Logical connectives and their implications on the meaning of a natural language sentence are a fundamental aspect of understanding. In this paper, we investigate visual question answering (VQA) through the lens of logical transformation and posit that systems that seek to answer questions about images must be robust to these transformations of the question. If a VQA system is able to answer a question, it should also be able to answer the logical composition of questions. We analyze the performance of state-of-the-art models on the VQA task under these logical operations and show that they have difficulty in correctly answering such questions. We then construct an augmentation of the VQA dataset with questions containing logical operations and retrain the same models to establish a baseline. We further propose a novel methodology to train models to learn negation, conjunction, and disjunction and show improvement in learning logical composition and retaining performance on VQA. We suggest this work as a move towards embedding logical connectives in visual understanding, along with the benefits of robustness and generalizability. Our code and dataset is available online 1.

1. Introduction

Theories about logic in human understanding have a long history. In modern times, Piaget and Fodor [29] studied the development and representation of logical hypotheses in the human mind. Conjunction, disjunction, and negation were formalized into an “algebra of thought” by George Boole [5] as a way to improve, systemize, and mathematize Aristotle’s Logic [10]. Horn considers negation to be a fundamental feature and a defining characteristic of human communication [16], following the traditions of Sankara [30], Spinoza [36], and Hegel [15]. Recent studies in [9] have suggested that infants can formulate intuitive and stable logical structures to interpret dynamic scenes and to entertain and rationally modify hypotheses about the

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Visual question answering (VQA) \cite{vqa} lies at a crucial intersection of vision and language, and is an intuitive, yet challenging task in visual semantics. The task in VQA, given an input image and a question about it, is to provide a free-form or open-ended answer to the question. Consider the image in Figure 1 taken from the VQA dataset which shows a person in front of an open fridge. When asked the two questions $Q_1$ (Is there beer?) and $Q_2$ (Is the man wearing shoes?), independently, the state-of-the-art model LXMERT \cite{lxmlmert} answers both correctly. However when we ask a negation in $Q_2$ (Is the man not wearing shoes?) or when we ask a conjunction of two questions $\neg Q_2 \land Q_1$ ("Is the man not wearing shoes and is there beer?"), the system makes wrong predictions. Our motivation is to be able to reliably answer such logically composed questions. Consider the example, "Is every boy who is holding an apple or a banana, not wearing a hat?", humans are able to answer it to be true if and only if each boy who is holding at least one of an apple or a banana is not wearing a hat \cite{babylogic}. While we agree that natural language contains such complex logical compositions, we focus on the simplest – negation, conjunction, and disjunction. In this paper, we analyze VQA systems under this Lens of Logic and develop a visual question answering system that can answer such questions reflecting human logical inference. We offer our work as the first investigation into the logical structure of questions in visual question-answering and provide a solution that learns to interpret logical connectives in questions.

The first question is: can models pre-trained on the VQA dataset answer logically composed questions? Our results show remarkable failure to do so as illustrated in Figure 2 and Table 10. The question then arises: can the model answer such questions, if we explicitly train it with data that also contains logical compositions of questions? For this investigation, we construct two datasets, VQA-Compose and VQA-Supplement, by utilizing annotations from the VQA dataset and the object and caption annotations from the COCO dataset \cite{coco}. We train the state-of-the-art VQA model LXMERT \cite{lxmlmert} on these datasets and perform multiple experiments to test for robustness to logically composed questions. Our results show an improvement in performance on logical questions but a reduction on the VQA test set. We suspect that logical questions add another dimension to the diversity of the dataset, thereby making the overall task more challenging.

After this investigation, we develop a neural network architecture that jointly learns to answer the questions while understanding the type of question and which logical connective exists in the question. Figure 3 shows the model along with our modules to understand the question type and logical connectives. Our key finding is that our models are even better on logical questions, with a small deviation from state-of-the-art on VQA test set. Our models also exhibit better Compositional Generalization i.e. models trained on questions with single logical connective are able to answer those with multiple connectives.

Our contributions are summarized below:

- We conduct a detailed analysis of the performance of the state-of-the-art VQA model with respect to logically composed questions.
- We curate two large scale datasets VQA-Compose and VQA-Supplement that contain logically composed binary questions.
- We propose an end-to-end model with dedicated layers that answer questions by understanding the logical connectives in questions to answer questions.
- We show a capability of answering logically composed questions, while retaining performance on VQA data.

2. Related Work

Logic in Human Expression Is logical thinking a natural feature of human expression and thought? Evidence in psychological studies \cite{psychology1, psychology2} suggests that children and even infants are capable of logical reasoning by using intuitive theories, abduction, and by understanding objecthood and causes. More recently \cite{recent} have shown that children understand logical operations such as negation, disjunction, and conjunction in natural language and are able to compositionally compute meanings even in complex sentences containing multiple logical operators. Children are also able to use these meanings to assign truth values to complex experimental tasks. Given this, question-answering systems also need to answer compositional questions, and be robust to the manifestation of logical operators in natural language.

Logic in Natural Language Understanding In question-answering, the task of understanding compositionality in questions can also be interpreted as understanding logical connectives in text. While question compositionality is largely unstudied as far as we know, traditional approaches in natural language understanding seek to transform sentences into symbolic formats such as first-order logic \cite{logic}, relational tables \cite{table}, or a combination of semantic and symbolic logic \cite{logic2} for reasoning. While such methods benefit from interpretability they suffer from practical limitations like intractability, reliance on logical background knowledge, difficulty of scaling up inference, and failure to process noise and uncertainty. \cite{noise1, noise2, noise3} suggest that better generalization can be achieved by learning embeddings in order to reason about semantic relations, and to simulate the behavior of first-order logic \cite{first-order}.

It has been shown that recursive neural networks can learn logical semantics on synthetic English-like sentences \cite{recursive} to reason about conjunctions of relations non-atomically by using embeddings \cite{embeddings}. Models that learn
logical rules for reasoning in a differentiable manner have been introduced in [41, 12]. Detection of negation in text has been studied for information extraction and sentiment analysis [26]. Recently [19] have shown that BERT-based models are incapable of differentiating between negated and un-negated sentences. Since our work deals with both vision and language inputs, it comes with uncertainty and ambiguity, thus calling for question-answering system that is robust to logical constraints or transformations.

Visual Question Answering Question answering has been regarded as a strong demonstration of natural language understanding and text comprehension [21]. Visual Question Answering (VQA) [2] is the first effort at curating large-scale, human-annotated dataset for open-ended question-answering on images. Follow-up work [45, 14] balance the VQA dataset by collecting complementary images for each question-image pair such that every question is associated with a pair of similar images that result in two different answers. This also ensures that the number of questions in the VQA dataset with the answer “YES” is equal to those with the answer “NO”. The balanced version of the VQA dataset contains 204k images from the MS-COCO image dataset [23], 1.1M questions (belonging to either yes-no, numeric, or other type).

Recent work seeks to incorporate reasoning in VQA, such as Visual Commonsense Reasoning [43] and spatial reasoning in [18]. There have been several efforts in visual reasoning [1] that integrate knowledge to understand images. While efforts such as these have an important role to play, we would like to take a step back and extensively analyze the simpler task of VQA and to evaluate it with respect to multiple aspects and hypotheses. We consider a rigorous investigation of a task, dataset, and models to be equally important as proposing harder challenges. In this paper we analyze existing state-of-the-art VQA models with respect to their robustness to logical transformations of questions.

3. The Lens of Logic

Lenses magnify the contents and workings of an object under investigation, by allowing us to zoom and focus on desired parts of an object. Our lens is logical transformation and composition of a question, and the object under investigation is visual question answering. The lens of logic explained in this section, allows us to magnify, identify and analyze the problems in the workings of VQA models.

Consider the examples in Figure 2. Each column shows an image, questions, and the answers provided by Pythia [34], the winner of the 2018 VQA Challenge [17]. In Figure 2(a), we transform the first question “Is the lady holding the baby?” by first replacing “lady” with an adversarial hyponym “man” and observe that the system provides a wrong answer with very high probability. Swapping “man” with “baby” results in a wrong answer as well. In (c) a conjunction of two questions containing the adversarial hyponym (girls vs boys) yields a wrong answer. We identify that the ability to answer composite questions created by negation, conjunction and disjunction of questions is crucial for visual question answering.

We use “closed questions” as defined in [4] to construct logically composed questions. Under this definition, if a closed question about an image has a negative (“NO”) answer then the negation of the closed question must have an affirmative (“YES”) answer. In the VQA dataset, one type of questions called “yes-no” questions satisfy this requirement. Recently [3] have identified that visual questions in the VQA dataset can have multiple correct answers. However, 20.91% of the questions (around 160k) in the VQA dataset are closed questions, i.e. questions with a single unambiguous yes-or-no answer This allows us to treat these questions as propositions and create a truth table for answers to composite logical questions as shown in Table 1.

3.1. Composite Questions

Let $\mathcal{D}$ denote the VQA dataset, and let $\mathcal{D}^I$ denote the set of images in the dataset. Let $Q_1$ and $Q_2$ be any two closed questions that can be asked about image $I$. We define the composite question $Q^*$ as:

$$Q^* = \widehat{Q}_1 \circ \widehat{Q}_2,$$

where $\widehat{Q}_1 \in \{Q_1, \neg Q_1\}$, $\widehat{Q}_2 \in \{Q_2, \neg Q_2\}$, and $\circ \in \{\lor, \land\}$.

3.2. Dataset Creation Process

Using the above definition we create two new datasets by utilizing multiple questions about the same im-
Table 1. Illustration of composition of closed questions (same example as Figure 1). QF: Question Formula, AF: Answer Formula.

| QF | Question | AF | Answer |
|----|----------|----|--------|
| $Q_1$ | Is there beer? | $A_1$ | Yes |
| $Q_2$ | Is the man wearing shoes? | $A_2$ | No |
| $\neg Q_1$ | Is there no beer? | $\neg A_1$ | No |
| $\neg Q_2$ | Is the man not wearing shoes? | $\neg A_2$ | Yes |
| $Q_1 \lor Q_2$ | Is there beer or is the man wearing shoes? | $A_1 \lor A_2$ | Yes |
| $Q_1 \land Q_2$ | Is there beer and is the man wearing shoes? | $A_1 \land A_2$ | Yes |
| $Q_1 \lor \neg Q_2$ | Is there beer or is the man not wearing shoes? | $A_1 \lor \neg A_2$ | Yes |
| $\neg Q_1 \lor \neg Q_2$ | Is there no beer or is the man not wearing shoes? | $\neg A_1 \lor \neg A_2$ | Yes |
| $\neg Q_1 \land \neg Q_2$ | Is there no beer and is the man not wearing shoes? | $\neg A_1 \land \neg A_2$ | Yes |
| $\neg Q_1 \lor \neg Q_2$ | Is there no beer or is the man not wearing shoes? | $\neg A_1 \lor \neg A_2$ | Yes |

3.3. Analytical Setup

In order to test the robustness of our models to logically composed questions, we devise four key experiments to analyze baseline models and our methods with our criteria and ablation studies. These experiments help us develop insights into the nuances of the VQA dataset, and allow us to develop strategies for incorporating robustness.

Effect of Data Augmentation: In this experiment, we compare the performance of models on VQA-Compose and VQA-Supplement with or without logically composed training data. This experiment allows us to test our hypotheses about the robustness of any VQA model to logically composed questions. We first use models trained on VQA data to answer questions in our new datasets and record performance. We then explicitly train the same models with our new datasets, and make a comparison of performance with the pretrained baseline.

Learning Curve: We train our models with an increasing number of logically composed questions and compare the ability of our models to answer them. Thus, this experiment serves as analysis about number of logical samples needed by the model to learn to understand logic in questions.

Training only with Closed Questions: In this ablative study, we restrict the training data of our model to only closed questions i.e. “Yes-No” VQA questions, VQA-Compose and VQA-Supplement. By doing so, we allow our model to focus solely on closed questions, and are able to verify performance on the datasets.

Compositional Generalization: Can training on closed questions containing single logical operation ($Q_1$, $\neg Q_1$, $Q_1 \lor Q_2$, $Q_1 \land Q_2$) generalize to multiple operations (such as $Q_1 \land \neg Q_2$, $\neg Q_1 \lor \neg Q_2$)? For instance, rows 1 through 6 in Table 1 are single operation questions, while rows 7 through 12 are multi-operation questions. Our aim is to have models that exhibit such compositional generalization.

VQA-Compose Consider the first two rows in Table 1. $Q_1$ and $Q_2$ are two questions about the image in Figure 1 taken from the VQA dataset. Additional questions are composed from $Q_1$ and $Q_2$ by using the formulas as shown in Table 1. Thus for each pair of closed questions in the VQA dataset, we get 10 additional logically composed questions. Using the same train-val-test split as the original VQA dataset, we get a total of 1.25 million samples in our VQA-Compose dataset. The dataset is balanced in terms of the number of questions with affirmative and negative answers.

VQA-Supplement The VQA dataset [2] was created by using images from the MS-COCO dataset [23] and follows the same train-val-test split as MS-COCO. Therefore, we are able to create additional closed binary questions, by using the objects present in the image, such as “Is there a bottle?” for the example in Figure 1. At the same time, we also create “adversarial” questions about objects, like “Is there a wine-glass?” by asking a question about an object that is not present in the image (wine-glass), but is semantically close to an object in the image (bottle). We use Glove vectors [28] to find the adversarial object with the closest embedding. Since we know what objects are present in the image, we know the ground-truth answers for all such object-based questions. Following a similar strategy, we also convert captions provided in COCO to closed binary questions, for example “Does this seem like a man bending over to look inside the fridge”. Since the captions describe a “true” scene, event or situation, we are able to obtain the ground-truth values for these.

Thus for every question, we obtain several questions about objects and questions created from captions. We use these to compose additional questions by following a process similar to the one for VQA-Compose. For each closed question in the VQA dataset, we get 20 additional logically composed questions by utilizing questions created from objects and captions, yielding a total of 2.55 million samples for the VQA-Supplement dataset.
4. Method

We introduce the current state-of-the-art VQA model LXMERT [38], and our novel module architectures and training mechanisms.

4.1. LXMERT

LXMERT [38] (Learning Cross-Modality Encoder Representations from Transformers) serves as one of the first cross-modal pre-trained frameworks for vision+language tasks, drawing inspiration from BERT [11]. It’s a large Transformer model [39] which combines a strong visual feature extractor [31] with a strong language model (BERT), pre-trained for Masked Cross Modality Language Modeling, Masked Object prediction, Cross-Modality matching, and Image Question Answering, on a large corpus of \( \sim 9M \) image-sentence pairs. This makes LXMERT a powerful cross-modal encoder for many vision+language abilities such as visual question answering and visual reasoning (NLVR2 [37]). LXMERT is the best single-model on VQA as compared to other baselines such as MCAN [42]. We choose it as a strong baseline for our experiments.

Let \( q \) denote the LXMERT network. For every question \( Q \) and corresponding image \( I \), we obtain the embedding \( z \) from LXMERT, \( z = q(Q, I) \).

4.2. Our Model

Our model design is driven by three key insights:

1. Logically composed questions are closed questions. In order to answer them correctly, the model must learn to predict type of questions, i.e. be able to identify closed questions.

2. The predicted answer to any question must be compatible with the predicted question type. For instance, a closed question can only have an answer that is either “Yes” or “No”.

3. The model must learn to identify the logical connectives in a question.

Given these insights, we develop two modules, the Type Module that learns the type of question (Yes-No, Number, or Other), and the Connective Module that predicts the connectives present in the question (AND, OR, NOT, no connective). The overall model architecture is shown in Figure 3.

**Type Module**: The VQA dataset contains questions of three types: 38% “Yes-No” questions, 12% “Number” i.e questions with a numeric answer, and 50% “Other” type of questions. We develop a feed-forward neural network \( f_{\text{type}} \) which takes question embeddings from LXMERT as input, and outputs \( P_{\text{type}} \) vector of length 3 representing the probabilities of each type of question, shown in Figure 3.

\[
P_{\text{type}} = \text{softmax}(f_{\text{type}}(z)).
\]  

We develop three parallel neural networks \( g_1, g_2, g_3 \) for each question type, to obtain three vectors \( z_1, z_2, z_3 \). These three vectors are then concate-
nated to produce a single vector $z^{type}$.
\[
z_i^{type} = P_i^{type} \cdot g_i(z), \text{ for } i \in \{1, 2, 3\}, \quad (3)
\]
\[
z^{type} = \left[ z_1^{type}, \ldots, \sum_{i=1}^{3} z_i^{type} \right]. \quad (4)
\]

**Connective Module:** We develop a feed-forward neural network $f_{conn}$ which takes the question embedding from LXMERT as input, and outputs $P_{conn}$ vector of length 4 which represents the probabilities of each type of connective (AND, OR, NOT or no connective). Note that since a question can have multiple connectives, we use a sigmoid ($\sigma$) instead of a softmax.
\[
P_{conn} = \sigma(f_{conn}(z)). \quad (5)
\]

Our Yes-No module ($g_3$) is additionally tasked with learning which of the connectives the question contains. In order to do so, we develop our Connective module with four parallel neural networks $h_1, h_2, h_3, h_4$ for each type of connective, to produce four vectors $z_1^{conn}, z_2^{conn}, z_3^{conn}, z_4^{conn}$, as shown in Figure 4.
\[
z_i^{conn} = P_i^{conn} \cdot h_i(z), \quad (6)
\]
\[
z^{conn} = [z_1^{conn}, \ldots, \sum_{i=1}^{4} z_i^{conn}, \prod_{i=1}^{4} z_i^{conn}]. \quad (7)
\]

**Training:** We train our models jointly with the loss function given by:
\[
\ell = (1 - \alpha_1 - \alpha_2) \cdot \ell_{ans} + \alpha_1 \cdot \ell_{type} + \alpha_2 \cdot \ell_{conn}. \quad (8)
\]

Here $\ell_{ans}$ represents the loss from the answering module. We multiply the final prediction vector with the mask $M_i$ (which is a binary vector with 1 for every answer-index of type-1 and 0 elsewhere) and the probability of the type-i. Thus our loss is conditioned on the type of question.
\[
\ell_{ans} = \ell_{BCE}(\sum_{i=1}^{3} \hat{y} \odot M_i \cdot P_i^{type}, y_{ans}). \quad (9)
\]

Our type-module is trained to minimize a softmax classification loss, and our connective module is trained to minimize a multi-label classification loss given by:
\[
\ell_{type} = \ell_{NLL}(softmax(z^{type}), y_{type}), \quad (10)
\]
\[
\ell_{conn} = \ell_{BCE}(\sigma(z^{conn}), y_{conn}), \quad (11)
\]

where $y_{ans}, y_{type}, y_{conn}$ are the ground-truth vectors for the answer, type and connective respectively. $\ell_{NLL}$ is the negative log-likelihood loss. $\ell_{BCE}$ represents the standard binary cross entropy function between predicted output $\hat{y}$ and ground-truth $y$ of length $n$ given by:
\[
\ell_{BCE}(\hat{y}, y) = \sum_{i=1}^{n} [y_i \cdot \log(\hat{y}_i) + (1 - y_i) \cdot \log(1 - \hat{y}_i)]. \quad (12)
\]

| Model          | Trained on | Validation Accuracy (%) ↑ |
|----------------|------------|---------------------------|
| LXMERT         | VQA        | 68.94 86.65 70.79 50.51  |
| VQA + Comp    | 67.85 85.32 85.03 80.85 |
| VQA + Comp + Supp | 68.01 84.83 70.28 87.97 |
| LXMERT + Type | VQA        | 69.08 85.32 48.99 50.54  |
| VQA + Comp    | 67.51 84.80 84.85 79.62 |
| VQA + Comp + Supp | 68.72 84.90 72.88 88.12 |
| LXMERT + Type + Conn | VQA + Comp | 68.94 85.15 85.79 80.74 |
| VQA + Comp + Supp | 68.81 84.80 74.43 88.51 |

Table 2. Comparison of LXMERT and our models when trained on VQA dataset and combinations with Compose, Supplement.

4.3. Implementation Details

We use three datasets for our experiment: the VQA dataset, a combination of VQA and our VQA-Compose dataset, and a combination of VQA, VQA-Compose and VQA-Supplement. The size of the training dataset is kept the same as the original VQA dataset (~443k) and the distribution of yes-no, number and other questions is retained, for fair comparison.

LXMERT model produces a vector $z$ of length 768 which is used by our type and connective modules, each having sub-networks $f_i, g_i$ with 2 feed-forward layers. We utilize the Adam optimizer [20] with a learning rate of 5e-5, batch size of 32 and train for 20 epochs. Our models are trained on 4 NVIDIA V100 GPUs, and take approximately 24 hours for training 20 epochs.

5. Experiments

We first conduct analytical experiments to test for logical robustness and transfer learning capability. We utilize a combination of VQA v2.0 [2], and our new datasets VQA-Compose and VQA-Supplement. Since VQA-Compose is generated using original questions from the VQA dataset which are human annotated, and VQA-Supplement using captions and objects from MS-COCO, we use the latter to analyze the ability of our models to generalize to a new source of data (MS-COCO) as well as questions containing adversarial objects.

After training, our type predictor and connective predictor networks $f^{type}$ and $f^{conn}$ achieve an accuracy of 99.9% on average, showing almost perfect performance when it comes to learning the type of question and the connectives present in the question.

5.1. Analysis

**Explicit Training With New Data:** Can models trained on the original VQA dataset answer VQA-compose and VQA-Supplement questions? The first section of Table

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2More training details in Supplementary Materials
Figure 5. Learning Curves: Red lines denote the LXMERT model, and Blue lines denote our type-only models. Models trained on VQA + Comp are shown in solid lines, and those trained on VQA + Comp + Supp are in dotted lines. Best viewed in color.

Table 3. Results for training with closed (yes-no) questions only.

| Training Dataset | Validation Accuracy (%) ↑ |
|------------------|---------------------------|
|                  | YN | Comp | Supp |
| LXMERT           | 84.13 | 84.44 | 79.39 |
| LXMERT + Conn    | 84.09 | 82.63 | 88.15 |
| LXMERT + Conn    | 85.26 | 84.37 | 89.00 |

Table 4. Compositional Generalization: The table shows results when training on a single operation and testing on multiple operations. Note that 50% is random performance.

| Trained on (single op) | Validation Accuracy (%) ↑ |
|------------------------|---------------------------|
|                       | YN | Com-Single | Com-Multi | Sup-Single | Sup-Multi |
| LXMERT                 | 84.16 | 84.71 | 65.60 | 80.63 | 66.55 |
| LXMERT + Conn          | 85.07 | 83.95 | 61.99 | 86.65 | 60.00 |
| LXMERT + Conn          | 85.13 | 85.85 | 66.87 | 81.66 | 79.10 |

Figure 6. Accuracy for each type of logically composed question. Table is available in supplementary materials.

10 shows the performance of VQA models trained on the original VQA data. LXMERT shows near random (~50%) on our logically composed datasets if only trained on questions from VQA, thus exhibiting no robustness to such questions. Can baseline model improve if trained explicitly with questions from these datasets? We train the models with data containing a combination of samples from VQA and VQA-Compose, as well as a combination of samples from VQA, VQA-Compose, and Supplement. When trained with logically composed questions, the accuracy on VQA-Compose and Supplement improves, but there is a drop in performance on closed questions from VQA. Our models, which use dedicated Type and Connective Modules are able to retain performance on VQA data while achieving improvements on all validation datasets. Since the VQA dataset does not contain logical questions, we do not use the Type + Conn architecture.

Training with Closed Questions only: In this experiment, we analyse the performance of models when trained only with closed questions from VQA, VQA + Comp and VQA + Comp + Supp and see that our model achieves the best accuracies on logically composed questions, as shown in Table 11. Since we train only closed questions, we do not use our type module for this experiment.

Effect of Logically Composed Questions: We increased the number of logical samples in the training data on a log scale from 10 to 100k. As can be seen from the learning curves in Figure 5(a), models trained on VQA + Comp + Supp are able to retain performance on VQA validation data, while those trained only on VQA + Comp data deteriorate. Figure 5(b) shows that our models improve on VQA Yes-No performance after being trained on more logically composed samples, exhibiting transfer learning capabilities. In (c) both of our models are comparable to the baseline, but our model shows improvements over the baseline when trained on VQA + Comp + Supp. In (d) we notice that for all levels of additional logical questions, our model trained on VQA + Comp + Supp is the best performing. From (c) and (d), we observe that a large number of logical questions are needed during training for the models to learn to answer them during inference. However, we know from [9] that humans, even children do develop the capability of logical composition with very few examples. We also see that our model yields the best performance on VQA-Supplement.

We conducted an additional experiment with the

4In all tables, best overall scores are bold, our best scores underlined.
LXMERT model pre-trained on VQA, and fine-tuned it on our VQA-Compose and VQA-Supplement datasets, and observed a steep drop in VQA performance.

**Compositional Generalization:** In this experiment, we train on questions with a maximum of one connective (single) and test on those with multiple connectives (multi). It can be seen from Table 13 that our models are better equipped than the baseline to generalize to multiple connectives and also to be able to generalize from VQA-Compose to Supplement.

**Accuracy per Category of Question Composition:**
In Figure 6 we show a plot of accuracies versus question type for each model. \( Q, Q_1, Q_2 \) are questions from VQA, \( B, C \) are object-based and caption-based questions from COCO respectively. From the results, we interpret that questions such as \( Q \land \text{antonym}(B), Q \land \neg B, Q \land \neg C \) are easy because the model is able to understand absence of objects, therefore can always answer these questions with a “NO”. Similarly, \( Q \lor B, Q \lor C \) are easily answered since presence of the object makes the answer always “YES”. By simply understanding object presence a lot of such questions can be answered in VQA-Supplementary.

### 5.2. Evaluation on VQA v2.0 Test Data

Finally, we evaluate our models on the VQA Test-Standard dataset. Table 5 shows that our models are able to retain overall performance on the VQA test dataset, while at the same time improving from random performance (~50%) on logically composed questions to 74.43% on VQA-Compose and 88.51% on VQA-Supplement. This shows that logical connectives in questions can be learned while not degrading the overall performance on the original VQA test set. We would also like to highlight that our best accuracy on the VQA test set (71.19%) is within ~1.5% of the state-of-the-art on all three types of questions.

### 6. Discussion

In this paper we have shown that existing VQA models are not robust to questions composed with logical connectives such as conjunction, disjunction, and negation. When humans are faced with such questions, we may refrain from giving binary (Yes/No) answers, and instead provide elaborate answers. For instance, logically, the question “Did you eat the pizza and did you like it?” has a negative answer if either of the two atomic questions has a negative answer. However, humans might answer the same question with the answer “Yes, but I did not like it”. We do not consider such elaborating in this work and focus only on a single binary answer. While we agree that the human question-answering is indeed descriptive, explainable, and clarifying, that is the scope of our future work.

We have shown how to learn the type and connectives in a question by enhancing LXMERT encoders with dedicated loss functions and feed-forward networks. We would like to stress that we do not explicitly use this information during inference, but instead train the network to be aware of it instead of predicting purely based on language model embeddings which fail to capture these nuances. Our work is an attempt to modularize logical components that can be learned through supervision and make the model understand how to combine type of question and type of connective to be able to answer the question. We believe this work can have potential implications on logically robust question answering and conversational agents (with or without images).

### 7. Conclusion

In this work, we investigate VQA in terms of logical robustness and introduce “Lens of Logic”: a method to analyze this capability. The key hypothesis is that the ability to answer questions about an image, must be extendable to a logical composition of two such questions. We show that state-of-the-art models trained on VQA dataset lack this. Our solution involves creation of VQA-Compose and VQA-Supplement, two datasets containing logically composed questions, and then a model architecture that learns to answer questions with negation, conjunction, and disjunction. Our models show improvements in terms of answering these questions, while at the same time retaining performance on the original VQA test-set.

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**Table 5. Test-set results. VQA results are reported on the test-standard splits. Note that our model performance is close to SOTA, but significantly better at logical robustness.**

| Model (Training Data) | Test-Standard Accuracy (%) ↑ | Validation Accuracy (%) ↑ |
|-----------------------|-------------------------------|---------------------------|
|                       | Yes-No | Number | Other | Overall | Comp | Supp |
| MCAN(VQA) [42]        | 80.82  | 53.20  | 60.72  | 70.90   | 52.42 |      |
| LXMERT (VQA) [38]     | 88.20  | 54.20  | 63.10  | 72.50   | 50.69 | 50.61 |
| LXMERT (VQA + Ours)   | 85.23  | 51.25  | 60.58  | 69.78   | 72.74 | 87.86 |
| LXMERT + Type (VQA)   | 87.33  | 54.03  | 62.40  | 72.03   | 48.99 | 50.54 |
| LXMERT + Type (VQA + Ours) | 86.79 | 52.66  | 61.85  | 71.19   | 72.88 | 88.32 |
| LXMERT + Type + Conn. (VQA + Ours) | 86.55 | 53.42  | 61.58  | 71.04   | 74.43 | 88.51 |

*MCAN code uses a fixed vocabulary for evaluation, it is unable to evaluate our VQA-Supplement questions which contain questions created from COCO captions. These are test-dev scores. # MCAN does not report their test-standard single model scores.*
Appendix

Abstract

In our paper, we investigated visual question answering (VQA) through the lens of logical transformation. We showed that state-of-the-art VQA models are unable to reliably predict answers for questions composed with logical operations, i.e., negation, conjunction, and disjunction. We introduced new datasets VQA-Compose and VQA-Supplement, created with logical composition and a novel methodology to train models to learn logical operators in questions. In this supplementary material, we provide additional details about:

• Our data creation process,
• Analysis of our datasets,
• Our training dataset for each experiment,
• Model training and hyper-parameters, and
• Further analysis and insights about our results.

Our code and datasets are available at [https://www.public.asu.edu/~tgokhale/vqa_lol.html](https://www.public.asu.edu/~tgokhale/vqa_lol.html).

A. Dataset Creation

The key idea behind our dataset creation process is to leverage existing annotations, i.e., questions from the VQA dataset [2], as well as object and caption annotations from MS-COCO [23] for each image in the VQA dataset. In order to create logically composed questions, we first filter out the “yes-no” questions (38% of the VQA data). We then further filter these by retaining only those yes-no questions with a single valid answer (20% of the VQA data). These closed questions are the atoms of our data creation process.

We use two closed questions corresponding to the same image to create logically composed questions using the Boolean operators: negation (¬), conjunction (∧), and disjunction (∨). Since they have a clear unambiguous answer that is either “yes” or “no”, we can treat them as Boolean variables, and obtain answers for all the new questions composed. For negating a question, we follow a template-based procedure that negates verbs in the question, as shown in Table 6. Note that our method chooses (randomly) to put a not or no either before a preposition, verb, or noun phrase. For instance, is this an area near the city? is transformed to either of {Is this not an area near the city?, Is this an area not near the city?}. Conjunction and disjunction are straightforward, we add the words “and” and “or” between two closed questions.

A.1. VQA-Compose

VQA-Compose is our dataset that is created solely from closed questions in the VQA dataset. As shown in Figure 8, we obtain 10 questions for each closed question in the VQA dataset. We obtain a total of 1.25M question-answer-image triplets as our VQA-Compose dataset.

A.2. VQA-Supplement

We create VQA-Supplement with composition of questions from VQA with questions created from object and caption annotations from MS-COCO. Figure ?? shows the captions available in the COCO dataset for our images. As shown in Figure 9, we use object and captions to create questions B and C respectively. We use these questions B to then logically compose questions using negation, conjunction, and disjunction.

In addition, we also generate questions about adversarial object antonyms. An adversarial object antonym is defined as an object that is not present in the image, but is closest semantically to an object in the image. Examples are shown in Table 7. We use Glove vectors [28] to obtain embeddings of all object class names in the COCO dataset. Then for each image, we find adversarial antonyms using these vectors by using a $\ell_2$ distance as a metric to sort and select adversarial antonyms. Since we know what objects are present in the image, and what aren’t we are able to determine the ground-truth answers for object-based questions.

Next, we utilize captions from COCO and convert them to questions using template-based methods. We use the same methodology to combine questions from VQA and caption-based questions with logical operators. For each

| Object       | Adversarial Antonym |
|--------------|---------------------|
| bottle       | wine glass          |
| cup          | bowl                |
| spoon        | fork                |
| surfboard    | skateboard           |
| skis         | snowboard           |
| motorcycle   | bicycle             |
| sink         | toilet              |
| suitcase     | backpack            |

Table 7. Examples of adversarial antonyms of objects present in an image. The antonym is chosen such that it is not in the image, but is semantically close to an object in the image.
Figure 7. Examples of captions from COCO for images in the VQA dataset. We convert these captions into questions and use them for our VQA-Supplement dataset.

- a surfer catching a wave on the ocean.
- a man surfing some waves on his white surfboard.
- a surfer catching a wave, while another man paddles over it.
- surfer at the top of a wave on top of a white board.
- a man in black wetsuit on a white surfboard.
- a street with buildings on one side and trees on the other side.
- view of an empty urban street from the sidewalk.
- city roadway with few cars and multiple storied buildings.
- a tall building towering over a red fire hydrant.
- a street view with cars, buildings, trees, light posts and a fire hydrant.
- a small boy is herding rams with a stick.
- a painting of a man herding sheep in the field.
- the 3d image shows a man herding a group of animals.
- herd of goats in grassy area with herder.
- a number of animals in a field with trees near by.
- a number of plates with food, spoon and glass.
- a picture of a couple plates of someone’s lunch sitting on a table.
- a number of plates with food and a glass on the table.
- a table topped with four plates filled with food.
- a variety of food on a dining room table.
- plates of food on a table at a restaurant.
- two giraffes standing near the grass, with their necks bent low.
- these giraffes are standing together on a dirt path.
- two giraffes are standing in a field with heads down.
- two giraffe standing on grass near a rocky wall.
- a couple of giraffe standing on top of a field near a rock mountain.

Question $Q$ we obtain 20 new object-based and caption-based questions. In total, our VQA-Supplement dataset contains 2.55M question-answer-image triplets.

B. Dataset Analysis

Here we analyze the VQA dataset as well as our new datasets with logically composed questions.

Question Length The average length of questions in VQA v2.0 [2] is 6.1 words. Our datasets have an average length of 12.25 words for VQA-Compose and 15.17 for VQA-Supplement.

Types of Answers The VQA dataset contains a fixed vocabulary of 3129 answers. We performed k-means clustering on the Glove [28] embeddings of the answers, and obtained 50 clusters. We show examples of some of these clusters in Table 9. Note that the cluster name is human labeled for clarity, and does not play a role in the clustering process. It is interesting to know that our cluster categories are similar to “knowledge categories” obtained in OK-VQA [24]. The categories in OK-VQA are annotated by human workers in Amazon Mechanical Turk.
Figure 8. Some examples from our VQA-Compose dataset. We show all 10 types of new questions created by original questions $Q_1$ and $Q_2$ and the corresponding answers. Q, A, QF, AF denote question, answer, question-formula, and answer-formula respectively. anto(B) represents the adversarial antonym of objects in present in the image.

### C. Training Data for Our Experiments

For each experimental setting, we train our models with a dataset containing questions from VQA, VQA-Compose, and VQA-Supplement. The ratio of these samples depends upon the specific experiment performed. For all our experiments we use the same train-validation-test split as in the VQA and COCO datasets. In this section, we explain our training datasets in detail.

#### C.1. Explicit Training with new data

In this experiment, we investigate if existing models trained on VQA data are able to answer questions in VQA-Compose and VQA-Supplement. We compare this with the LXMERT model [38] trained explicitly with our new data, and also with our models that use the Type and Connective modules. For this, we retain the original size of the VQA training dataset (443,754 samples) for fair comparison. We also use the same proportion of question-types as in VQA (38% yes-no, 12% number, and 50% other questions), as shown in Table 10. This allows us to improve the diversity of yes-no questions, by incorporating yes-no questions from VQA-Compose and VQA-Supplement.
Figure 9. Some examples from our VQA-Supplement dataset. We show all 20 types of new questions created by original questions $Q_1$ and $Q_2$ and the corresponding answers. $Q$, $A$, $QF$, $AF$ denote question, answer, question-formula, and answer-formula respectively. $\top$, $\bot$ are the standard Boolean symbols for top and bottom (true and false).

### C.2. Training with Closed Questions only

For this experiment, we evaluate the models when trained only on closed questions, under three settings:

1. Trained with yes-no questions from VQA
2. yes-no questions from VQA along with an equal number of questions from VQA-Compose,
3. yes-no questions from VQA along with an equal number of questions from VQA-Compose and VQA-Supplement

This allows us to compare the capability of models to answer different types of yes-no questions (original questions from VQA, logical compositions in VQA-Compose and logical compositions with object and caption-based questions in VQA-Supplement).

### C.3. Effect of Logically Composed Questions

In this experiment, we progressively add logically composed questions to the training data, and analyze the learning curve with respect to the number of logical samples. We add 10, 100, 1k, 10k, and 100k samples from VQA-Compose or both VQA-Compose and VQA-Supplement. The training set distribution is shown in Table 12.

### C.4. Compositional Generalization

In this experiment, our aim is to train on questions that contain a single logical connective (and, or, not) or no connective (original yes-no questions in VQA), and test performance on questions with more than one connective. To do
so, we restrict our training data to such single-connective questions as shown in Table 13.

## D. Model Training

We train our models as well as the baseline LXMERT model with the hyper-parameters mentioned in Table 8. We choose the best parameters from median of 5 different random seeds. LXMERT produces an embedding of size 768. We utilize this as input to our Type and Connective Modules. The size of hidden layers for the Type and Connective Module is 2*768. The answering module uses vectors output by these modules to predict a softmax vector of size 3129 which is the length of the VQA answer vocabulary.

## E. Analysis of Results

We provide accuracies of all four models as a heat-map in Figure 10, and also in Tables ?? and ?? . We have two key observations. In Figure 10a, we observe that for all models, the two hardest question categories are $Q_1 \lor Q_2$ and $\neg Q_1 \land \neg Q_2$. The two easiest categories are $Q_1 \land Q_2$ and $\neg Q_1 \lor \neg Q_2$. By DeMorgan’s laws, we see that the two hardest categories are:

$$Q_1 \lor Q_2, \neg(Q_1 \land Q_2),$$

while the two easiest categories are:

$$Q_1 \land Q_2, \neg(Q_1 \lor Q_2).$$

In Figure 10b we get more insights. Note that since questions $B$ and $C$ are composed from factually valid statements (about objects in the image, or from valid caption describing a scene), the answers to these questions are always “Yes”. Thus answers to any question that uses a disjunction (“or”) to combine $B, C$ with another question, is always “Yes”. Similarly answers to $\neg B, \neg C, anto(B)$ are always “No”. Thus answers to any question that uses a conjunction (“and”) to combine $\neg B, \neg C, anto(B)$ with another question, is always “No”. These question categories namely $Q \lor B, Q \lor C, \neg Q \lor B, \neg Q \lor C, and Q \land \neg B, Q \land \neg C, Q \land anto(B), \neg Q \land \neg B, \neg Q \land \neg C, \neg Q \land anto(B).$ It is interesting to note that questions about adversarial objects are relatively harder to answer for any category and any model, than the questions about objects present in the image. Thus we see that answering questions about objects in the image is much easier than other categories for each model.

Following a similar trend, we observe a difficulty in answering questions which use conjunction (“and”) to combine $B, C$ with another question, or which use disjunction (“or”) to combine $\neg B, \neg C, anto(B)$ with another question. This is because the answer to these questions changes according to the sample and depends on the answer to the question $Q$. 

### Table 8. Hyper-Parameters for training LXMERT and our models on VQA/VQA+C/VQA+C+S

| Hyper-Parameters    | Model       |
|---------------------|-------------|
| Batch Size          | 32          |
| Learning Rate       | 5e-5        |
| Dropout             | 0.1         |
| Language Layers     | 9           |
| Cross-Modality Layer| 5           |
| Object Relation Layers | 5       |
| Optimizer           | BertAdam    |
| Warmup              | 0.1         |
| Max Gradient Norm   | 5.0         |
| Max Text Length     | 20          |
Figure 10. Accuracy for each type of logically composed question for each of our models.
| Cluster Name | Cluster Members                                                                 |
|--------------|---------------------------------------------------------------------------------|
| Food         | 'cooking', 'fast food', 'dishes', 'serving', 'grill', 'pizza hut', 'pizza box', 'lunch', 'restaurant', 'cafe', 'dinner', 'dairy', 'deli', 'menu', 'breakfast', 'cat food', 'burrito', 'food', 'dog food', 'eaten', 'burger', 'french fries', 'food processor', 'pizza cutter', 'grocery store', 'chef', 'pizza', 'vegetarian', 'eat', 'cook', 'food truck', 'chips', 'burgers', 'grocery', 'on pizza', 'eating', 'bar', 'sushi', 'sandwich', 'sandwiches', 'bars' |
| Geography, Language, Ethnicity | 'china', 'thailand', 'america', 'american', 'africa', 'mexican', 'indians', 'russian', 'arabic', 'cascadian', 'korean', 'american flag', 'german', 'russia', 'oriental', 'japan', 'hispanic', 'british', 'american airlines', 'asian', 'african american', 'italian', 'american', 'spanish', 'indian', 'india', 'thai', 'japanese', 'asia', 'brazil', 'french', 'african', 'persian', 'english' |
| Flowers, Plants | 'tulip', 'weeds', 'windowsill', 'tree branch', 'daffodils', 'carnations', 'leaves', 'elm', 'fern', 'grass', 'roses', 'garden', 'wreath', 'trees', 'pine', 'carnation', 'evergreen', 'sunflowers', 'tree', 'palm tree', 'ivy', 'palm', 'lily', 'iris', 'willow', 'christmas tree', 'vase', 'moss', 'bamboo', 'tulips', 'rose', 'bushes', 'plants', 'lilac', 'bush', 'dandelions', 'plant', 'orchid', 'flowers', 'lilies', 'vines', 'daisy', 'cactus', 'palm trees', 'flower', 'daisies', 'floral', 'branches', 'bark', 'maple leaf', 'leaf', 'daffodil' |
| Fruits | 'frits', 'mango', 'nuts', 'cereal', 'apples', 'juice', 'cherries', 'strawberries', 'ginger', 'watermelon', 'cane', 'cherry', 'sweet', 'peach', 'organic', 'cantaloupe', 'orange juice', 'banana split', 'ripe', 'bananas', 'seeds', 'lemonade', 'grape', 'fruit', 'sunflower', 'smoothie', 'coconut', 'strawberry', 'dr pepper', 'corn', 'lemon', 'green beans', 'banana peel', 'peaches', 'sesame seeds', 'fresh', 'fruit salad', 'banana bread', 'wheat', 'pear', 'maple', 'banana', 'berries', 'mint', 'lemons', 'pineapple', 'oranges', 'grapes', 'salt and pepper', 'grapefruit', 'almonds', 'blueberry', 'kiwi', 'apple and banana', 'blueberries', 'peanuts', 'raspberry', 'raspberries', 'honey', 'limes', 'rue', 'sweet potato', 'lime', 'spices', 'apple' |
| Birds | 'crows', 'pelicans', 'seagull', 'squirrel', 'finch', 'feathers', 'sparrow', 'stork', 'duck', 'parrots', 'rooster', 'eagle', 'bird feeder', 'peacock', 'bird', 'birds', 'goose', 'pigeon', 'crow', 'pigeons', 'owl', 'hummingbird', 'feeder', 'hawk', 'cranes', 'geese', 'flamingo', 'cardinal', 'nest', 'swan', 'ducks', 'parakeet', 'seagulls', 'parrot', 'woodpecker', 'swans', 'penguin' |
| Sports | 'tennis shoes', 'playing game', 'playing baseball', 'tennis', 'baseball bat', 'tennis court', 'football', 'soccer', 'playing video game', 'sports', 'tennis racket', 'baseball uniform', 'team', 'bowling', 'hockey', 'play', 'baseball glove', 'goalie', 'playing tennis', 'badminton', 'playing frisbee', 'tennis player', 'rugby', 'soccer field', 'play tennis', 'soccer ball', 'baseball game', 'athletics', 'baseball', 'stadium', 'volleyball', 'golf', 'baseball player', 'game', 'gym', 'playing', 'video game', 'boxing', 'playing soccer', 'coach', 'softball', 'tennis ball', 'tennis rackets', 'referee', 'player', 'baseball cap', 'playing wii', 'club', 'baseball field', 'tennis racquet', 'playing video games', 'players', 'baseball' |
| Dog Breeds | 'puppy', 'mutt', 'pomeranian', 'dogs', 'dachshund', 'bulldog', 'cocker spaniel', 'schnauzer', 'rottweiler', 'pit bull', 'corgi', 'golden retriever', 'german shepherd', 'clydesdale', 'greyhound', 'boxer', 'kitten', 'cat', 'chihuahua', 'dog', 'husky', 'lesh', 'terrier', 'dalmatian', 'throughbred', 'shepherd', 'sheepdog', 'collie', 'poodle', 'tabby', 'labrador', 'meow', 'beagle', 'calico', 'shih tzu', 'siamese' |
| Colors | 'yellow and red', 'white and blue', 'green and red', 'neon', 'red bull', 'silver and red', 'gray and black', 'blue and white', 'blue and gray', 'blue', 'opaque', 'pink and blue', 'orange and yellow', 'black and brown', 'gray and white', 'brown and white', 'blue and black', 'maroon', 'yellow', 'silver', 'gray and red', 'orange and black', 'white and brown', 'black and red', 'black and yellow', 'green', 'purple', 'red and yellow', 'white and orange', 'red and silver', 'colored', 'white and gray', 'black and gray', 'blue and pink', 'blue jay', 'orange and blue', 'white and yellow', 'yellow and white', 'blue and green', 'white' |
| Sports Teams | 'dodgers', 'mariners', 'mets', 'cardinals', 'braves', 'yankees', 'phillies', 'orioles' |
| Vegetables | 'cauliflower', 'sliced', 'lettuce', 'celery', 'parsley', 'basil', 'squash', 'peppers', 'beets', 'sesame', 'cucumber', 'onion', 'asparagus', 'carrots', 'mushrooms', 'mustard', 'beans', 'broccoli and carrots', 'carrot', 'ciliantro', 'cabbage', 'tomato', 'feta', 'veggies', 'avocado', 'peas', 'garlic', 'zucchini', 'pepper', 'vegetables', 'potatoes', 'tomatoes', 'radish', 'broccoli', 'olives', 'spinach', 'vegetable', 'cucumbers', 'onions' |
| Bathroom | 'toothbrushes', 'lotion', 'washing', 'toiletries', 'faucet', 'mouthwash', 'towel', 'urinal', 'above toilet', 'toothpaste', 'soap', 'pooping', 'bathtub', 'bathing', 'tub', 'drain', 'toilet brush', 'pee', 'shampoo', 'towels', 'on toilet', 'shower', 'bidet', 'toilet paper', 'peeing', 'laundry', 'toilets', 'shower head', '…' |
| Clothes | 'life jacket', 'hat', 'fabric', 'shirts', 'apron', 'bathing suit', 'adidas', 'belt', 'pocket', 'sweater', 't shirt', 'slacks', 'jeans', 'zipper', 'vests', 'bandana', 'costume', 'jackets', 'hoodie', 'strap', 'jacket', 'shoes', 'bow tie', 'pockets', 'yarn', 'denim', 'socks', 't shirt and jeans', 'khaki', 'tuxedo', 'shirt', 'robe', 'swimsuit', 'sleeve', 'overalls', 'uniform', 'cap', 'clothing', 'camouflage', 'fedora', 'suits', 'boots', '…' |

Table 9. Selected results of k-means clustering on the Glove embeddings of answers in VQA. k=50.
| Training Datasets          | VQA-Other | VQA-Number | VQA-YesNo | Comp | Supp | Training Samples |
|---------------------------|-----------|------------|-----------|------|------|-----------------|
| VQA                       | 50        | 12         | 38        | 0    | 0    | 443754          |
| VQA + Comp                | 50        | 12         | 19        | 19   | 0    | 443754          |
| VQA + Comp + Supp         | 50        | 12         | 12.66     | 12.66| 12.66| 443754          |

Table 10. Training dataset distribution and sizes, for explicit training with new data. Note that training dataset sizes are consistent with the VQA dataset.

| Training Datasets          | VQA-Other | VQA-Number | VQA-YesNo | Comp | Supp | Training Samples |
|---------------------------|-----------|------------|-----------|------|------|-----------------|
| YesNo                     | 0         | 0          | 100       | 0    | 0    | 168626          |
| YesNo + Comp              | 0         | 0          | 50        | 50   | 0    | 337253          |
| YesNo + Comp + Supp       | 0         | 0          | 50        | 25   | 25   | 505879          |

Table 11. Training dataset distribution and sizes, for training with closed questions only. Note that we retain only yes-no questions from VQA and remove all other questions.

| Training Datasets          | VQA-Other | VQA-Number | VQA-YesNo | Comp | Supp | Training Samples |
|---------------------------|-----------|------------|-----------|------|------|-----------------|
| VQA                       | 50        | 12         | 38        | 0    | 0    | 443754          |
| VQA + Comp (10)           | 49.999    | 11.999     | 37.999    | 0.00225 | 0    | 443764          |
| VQA + Comp (100)          | 49.989    | 11.997     | 37.991    | 0.0225  | 0    | 443854          |
| VQA + Comp (1k)           | 49.888    | 11.973     | 37.914    | 0.225  | 0    | 444754          |
| VQA + Comp (10k)          | 48.898    | 11.736     | 37.162    | 2.204  | 0    | 453754          |
| VQA + Comp (100k)         | 40.805    | 9.793      | 31.011    | 18.391 | 0    | 543754          |
| VQA + Comp (10) + Supp (10) | 49.998    | 11.999     | 37.998    | 0.00225 | 0.00225 | 443774          |
| VQA + Comp (100) + Supp (100) | 49.977    | 11.995     | 37.983    | 0.0225  | 0.0225 | 443954          |
| VQA + Comp (1k)+ Supp (1k) | 49.776    | 11.946     | 37.829    | 0.224  | 0.224 | 445754          |
| VQA + Comp (10k)+ Supp (10k) | 47.844    | 11.483     | 36.361    | 2.156  | 2.156 | 463754          |
| VQA + Comp (100k)+ Supp (100k) | 34.466    | 8.272      | 26.194    | 15.534 | 15.534 | 643754          |

Table 12. Training datasets distribution and sizes, for the experiment for understanding the effect of logically composed questions. We progressively add more logical samples, and get the learning curve as shown in the paper.

| Training Datasets          | VQA-Other | VQA-Number | VQA-YesNo | Comp-Single | Supp-Single | Training Samples |
|---------------------------|-----------|------------|-----------|-------------|-------------|-----------------|
| YesNo                     | 0         | 0          | 100       | 0            | 0            | 168626          |
| YesNo + Comp              | 0         | 0          | 50        | 50           | 0            | 337253          |
| YesNo + Comp + Supp       | 0         | 0          | 33.33     | 33.33        | 33.33        | 505879          |

Table 13. Training datasets distribution and sizes, for training with logical questions with a maximum of one connective. Sizes of these datasets are the same as those in Table 11.
| Question Formula | LXMERT | LXMERT+Conn | LXMERT+Type | LXMERT+Type+Conn |
|------------------|--------|-------------|-------------|-----------------|
| ¬Q₁               | 85.39  | 85.55       | 84.78       | 86.43           |
| ¬Q₂               | 84.38  | 85.45       | 84.94       | 86.08           |
| Q₁ ∧ Q₂           | 81.50  | 87.77       | 87.66       | 87.77           |
| Q₁ ∨ Q₂           | 85.26  | 81.58       | 80.54       | 80.97           |
| Q₁ ∧ ¬Q₂          | 87.12  | 86.22       | 85.98       | 85.53           |
| ¬Q₁ ∧ Q₂          | 85.10  | 85.34       | 84.83       | 85.53           |
| ¬Q₁ ∨ Q₂          | 80.76  | 78.92       | 83.79       | 84.75           |
| ¬Q₁ ∧ ¬Q₂         | 87.98  | 86.59       | 79.77       | 81.32           |
| ¬Q₁ ∨ ¬Q₂         | 87.12  | 85.42       | 87.42       | 87.74           |

Table 14. Accuracies on each type of question in VQA-Compose by each model

| Question Formula | LXMERT | LXMERT+Conn | LXMERT+Type | LXMERT+Type+Conn |
|------------------|--------|-------------|-------------|-----------------|
| Q                | 82.27  | 82.3        | 82.77       | 82.34           |
| Q ∧ B            | 78.03  | 77.92       | 78.16       | 78.36           |
| Q ∨ B            | 95.51  | 96.79       | 97.06       | 96.74           |
| Q ∧ anto(B)      | 95.64  | 97.55       | 98.07       | 96.72           |
| Q ∧ C            | 81.22  | 82.07       | 81.67       | 81.67           |
| Q ∨ C            | 99.84  | 99.89       | 99.84       | 99.89           |
| Q ∧ ¬B           | 99.96  | 99.93       | 99.98       | 99.89           |
| Q ∨ ¬B           | 82.39  | 82.54       | 82.09       | 81.69           |
| ¬Q ∧ B           | 95.08  | 96.52       | 96.52       | 95.51           |
| ¬Q ∨ ¬B          | 99.89  | 99.84       | 99.91       | 99.75           |
| ¬Q ∧ anto(B)     | 94.86  | 97.91       | 97.15       | 97.42           |
| Q ∧ ¬C           | 99.91  | 99.91       | 99.98       | 99.87           |
| Q ∨ ¬C           | 99.84  | 99.87       | 99.89       | 99.78           |
| ¬Q ∧ ¬C          | 99.84  | 99.87       | 99.89       | 99.78           |
| ¬Q                | 80.3   | 81.62       | 81.78       | 80.84           |
| Q ∨ anto(B)      | 77.92  | 77.83       | 79.13       | 78.43           |
| ¬Q ∧ B           | 76.27  | 76.9        | 78.88       | 77.31           |
| ¬Q ∨ ¬B          | 79.73  | 81.42       | 81.49       | 81.17           |
| ¬Q ∨ anto(B)     | 75.62  | 77.33       | 79.22       | 77.92           |
| ¬Q ∧ C           | 78.95  | 81.26       | 81.11       | 80.18           |
| ¬Q ∨ ¬C          | 79.87  | 80.77       | 81.51       | 80.61           |

Table 15. Accuracies on each type of question in VQA-Supplement by each model
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