

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

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Image	Question	Predicted Answer	Accuracy (%)
	Q_1 : Is there beer?	VQA YES (0.96)	SOTA 88.20
	Q_2 : Is the man wearing shoes?	VQA NO (0.90)	LOL 86.55
	$\neg Q_2$: Is the man <i>not</i> wearing shoes?	VQA-Compose NO (0.80)	50.69
	$\neg Q_2 \wedge Q_1$ Is the man <i>not</i> wearing shoes <i>and</i> is there beer?	VQA-Compose NO (0.62)	82.39
	$Q_1 \wedge C$ Is there beer and does this seem like a man bending over to look inside of a fridge?	VQA-Compose NO (1.00)	50.61
	$\neg Q_2 \vee B$ Is the man not wearing shoes or is there a clock?	VQA-Supplement NO (1.00)	87.80
	$Q_1 \wedge \text{ant}(B)$ Is there beer and is there a wine glass?	VQA-Supplement YES (0.84)	50.61

Fig. 1: State-of-the-art models answer questions from the VQA dataset (Q_1, Q_2) correctly, but struggle when asked a logical composition including negation, conjunction, disjunction, and antonyms. We develop a model that improves on this metric substantially, while retaining VQA performance.

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 whether visual question answering (VQA) systems trained to answer a question about an image, are able to answer the logical composition of multiple such questions. When put under this *Lens of Logic*, state-of-the-art VQA models have difficulty in correctly answering these logically composed questions. We construct an augmentation of the VQA dataset as a benchmark, with questions containing logical compositions and linguistic transformations (negation, disjunction, conjunction, and antonyms). We propose our Lens of Logic (LOL) model which uses question-attention and logic-attention to understand logical connectives in the question, and a novel Frchet-Compatibility Loss, which ensures that the answers of the component questions and the composed question are consistent with the inferred logical operation. Our model shows substantial improvement in learning logical compositions while retaining performance on VQA. We suggest this work as a move towards robustness by embedding logical connectives in visual understanding.

Keywords: Visual Question Answering, Logical Robustness

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1 Introduction

Theories about logic in human understanding have a long history. In modern times, Piaget and Fodor [35] studied the representation of logical hypotheses in the human mind. George Boole [7] formalized conjunction, disjunction, and negation into an “algebra of thought” as a way to improve, systemize, and mathematize Aristotle’s Logic [12]. Horn regarded negation to be a fundamental and defining characteristic of human communication [19], following the traditions of Sankara [36], Spinoza [43], and Hegel [18]. Recent studies [11] have suggested that infants can formulate intuitive and stable logical structures to interpret dynamic scenes and to entertain and rationally modify hypotheses about the scenes. As such we argue that understanding logical structures in questions, is a fundamental requirement for any question-answering system.

If a question can be put at all, then it can be answered. [45]

In the above proposition, Wittgenstein linked the process of asking a question with the existence of an answer. While we do not comment on the existence of an answer, we suggest the following softer proposition -

If questions $Q_1 \dots Q_n$ can be answered, then so should all composite questions created from $Q_1 \dots Q_n$

Visual question answering (VQA) [3] is an intuitive, yet challenging task that lies at a crucial intersection of vision and language. Given an image and a question about it, the goal of a VQA system is to provide a free-form or open-ended answer. Consider the image in Figure 1 which shows a person in front of an open fridge. When asked the questions Q_1 (*Is there beer?*) and Q_2 (*Is the man wearing shoes?*) independently, the state-of-the-art model LXMERT [44] answers both correctly. However when we insert a negation in Q_2 (*Is the man not wearing shoes?*) or for a conjunction of two questions $\neg Q_2 \wedge Q_1$ (*Is the man not wearing shoes and is there beer?*), the system makes wrong predictions. Our motivation is to reliably answer such logically composed questions. In this paper, we analyze VQA systems under this *Lens of Logic (LOL)* and develop a model 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? It turns out that these models are unable to do so, as illustrated in Figure 1 and Table 2. An obvious next experiment is to *split the question* into its component questions, predict the answer to each, and combine the answers logically. However language parsers (either oracle or trained parsers) are not accurate at understanding negation, and as such this approach does not yield correct answers for logically composed questions. The question then arises: can the model answer such questions, if we explicitly train it with data that also contains logically composed questions? For this investigation, we construct two datasets, **VQA-Compose** and **VQA-Supplement**, by utilizing annotations from the

VQA dataset, as well as object and caption annotations from COCO [25]. We use these datasets to train the state-of-the-art model LXMERT [44] and perform multiple experiments to test for robustness towards logically composed questions.

After this investigation, we develop our LOL model architecture that jointly learns to answer questions while understanding the type of question and which logical connective exists in the question, through our attention modules, as shown in Figure 3. We further train our model with a novel Frchet-Compatibility loss that ensures compatibility between the answers to the component questions and the answer of the logically composed question. One key finding is that our models are better than existing models trained 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 to answer questions with a single logical connective are able to answer those with multiple connectives.

Our contributions are summarized below:

1. We conduct a detailed analysis of the performance of the state-of-the-art VQA model with respect to logically composed questions,
2. We curate two large scale datasets VQA-Compose and VQA-Supplement that contain logically composed binary questions.
3. We propose *LOL* – our end-to-end model with dedicated attention modules that answer questions by understanding the logical connectives in questions.
4. We show a capability of answering logically composed questions, while retaining VQA performance.

2 Related Work

Logic in Human Expression: Is logical thinking a natural feature of human thought and expression? Evidence in psychological studies [10,16,11] suggests that infants are capable of logical reasoning, toddlers understand logical operations 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: The task of understanding compositionality in question-answering (QA) can also be interpreted as understanding logical connectives in text. While question compositionality is largely unstudied, approaches in natural language understanding seek to transform sentences into symbolic formats such as first-order logic (FOL) or relational tables [31,49,24]. While such methods benefit from interpretability, they suffer from practical limitations like intractability, reliance on background knowledge, and failure to process noise and uncertainty. [8,40,42] suggest that better generalization can be achieved by learning embeddings to reason about semantic relations, and to simulate FOL behavior [41]. Recursive neural networks have been shown to learn logical semantics on synthetic English-like sentences by using embeddings [9,33].



Fig. 2: Some questions in VQA-Supplement created with adversarial antonyms.

Detection of negation in text has been studied for information extraction and sentiment analysis [32]. [22] have shown that BERT-based models [13,26] are incapable of differentiating between sentences and their negations. Concurrent to our work, [4] show the efficacy of FOL-guided data augmentation for performance improvements on natural language QA tasks that require reasoning. Since our work deals with both vision and language modalities, it encounters a greater degree of ambiguity, thus calling for robust VQA systems that can deal with logical transformations.

Visual Question Answering (VQA) [3] is a large-scale, human-annotated dataset for open-ended question-answering on images. VQA-v2[17] reduces the language bias in the dataset by collecting complementary images for each question-image pair. This ensures that the number of questions in the VQA dataset with the answer “YES” is equal to those with the answer “NO”. This dataset contains 204k images from MS-COCO [25], and 1.1M questions.

Cross-modal pre-trained models [44,27,50] have proved to be highly effective in vision-and-language tasks such as VQA, referring expression comprehension, and image retrieval. While neuro-symbolic approaches [29] have been proposed for VQA tasks which require reasoning on synthetic images, their performance on natural images is lacking. Recent work seeks to incorporate reasoning in VQA, such as visual commonsense reasoning [48,14], spatial reasoning [20,21], and by integrating knowledge for end-to-end reasoning [1].

We take a step back and extensively analyze the pivotal task of VQA with respect to various aspects of generalization. We consider a rigorous investigation of a task, dataset, and models to be equally important as proposing new challenges that are arguably harder. In this paper we analyse existing state-of-the-art VQA models with respect to their robustness to logical transformations of questions.

3 The Lens of Logic

A lens magnifies objects under investigation, by allowing us to zoom and focus on desired contents or processes. Our lens of logical composition of questions, allows us to magnify, identify, and analyze the problems in VQA models.

Consider Figure 2(a), where we transform the first question “*Is the lady holding the baby?*” by first replacing “*lady*” with an adversarial antonym “*man*” and observe that the system provides a wrong answer with very high probability.

Table 1: Illustration of question composition in **VQA-C**ompose, for the same example as in 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
$Q_1 \wedge Q_2$	Is there beer and is the man wearing shoes?	$A_1 \wedge A_2$	No
$Q_1 \vee Q_2$	Is there beer or is the man wearing shoes?	$A_1 \vee A_2$	Yes
$Q_1 \wedge \neg Q_2$	Is there beer and is the man not wearing shoes?	$A_1 \wedge \neg A_2$	Yes
$Q_1 \vee \neg Q_2$	Is there beer or is the man not wearing shoes?	$A_1 \vee \neg A_2$	Yes
$\neg Q_1 \wedge Q_2$	Is there no beer and is the man wearing shoes?	$\neg A_1 \wedge A_2$	No
$\neg Q_1 \vee Q_2$	Is there no beer or is the man wearing shoes?	$\neg A_1 \vee A_2$	No
$\neg Q_1 \wedge \neg Q_2$	Is there no beer and is the man not wearing shoes?	$\neg A_1 \wedge \neg A_2$	No
$\neg Q_1 \vee \neg Q_2$	Is there no beer or is the man not wearing shoes?	$\neg A_1 \vee \neg A_2$	Yes

Swapping “*man*” with “*baby*” results in a wrong answer as well. In 2(b) a conjunction of two questions containing antonyms (*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 VQA.

We use “closed questions” as defined in [6] to construct logically composed questions. Under this definition, if a closed question has a negative (“NO”) answer then its negation must have an affirmative (“YES”) answer. Of the three types of questions in the VQA dataset (yes/no, numeric, other), ‘yes-no’ questions satisfy this requirement. Although, visual questions in the VQA dataset can have multiple correct answers [5], 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, unanimously annotated by multiple human workers. This allows us to treat these questions as propositions and create a truth table for answers to compose logical questions as shown in Table 1.

3.1 Composite Questions

Let \mathcal{D} be the VQA dataset. For closed questions Q_1 and Q_2 about image $I \in \mathcal{D}$, we define the composite question Q^* composed using connective $\circ \in \{\vee, \wedge\}$, as:

$$Q^* = \widehat{Q_1} \circ \widehat{Q_2}, \quad \text{where } \widehat{Q_1} \in \{Q_1, \neg Q_1\}, \quad \widehat{Q_2} \in \{Q_2, \neg Q_2\}. \quad (1)$$

3.2 Dataset Creation Process

Using the above definition we create two new datasets by utilizing multiple questions about the same image (**VQA-C**ompose) and external object and caption annotations about the image from COCO to create more questions (**VQA-S**upplement).

The seed questions for creating these datasets are all closed binary questions from VQA-v2 [17]. These datasets serve as test-beds, and enable experiments that analyze performance of models when answering such questions.

VQA-COMPPOSE: 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 in Table 1. Thus for each pair of closed questions in the VQA dataset, we get 10 logically composed questions. Using the same train-val-test split as the VQA-v2 dataset [17], we get *1.25 million samples* for our VQA-COMPPOSE dataset. The dataset is balanced in terms of the number of questions with affirmative and negative answers.

VQA-SUPPLEMENT: Images in VQA-v2 follow identical train-val-test splits as their source MS-COCO [25]. Therefore, we use the object annotations from COCO to create additional closed binary questions, such as “*Is there a bottle*” for the example in Figure 1. We also create “adversarial” questions about objects, like “*Is there a wine-glass?*” by using 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 [34] to find the adversarial object with the closest embedding. 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 we know what objects are present in the image, and the captions describe a “true” scene, we are able to obtain the ground-truth answers for questions created from objects and captions. Similar methods for creation of question-answer pairs have previously been used in [38, 28].

Thus for every question, we obtain several questions from objects and captions, and use these to compose additional questions by following a process similar to the one for VQA-COMPPOSE. 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* as VQA-SUPPLEMENT.

3.3 Analytical Setup

In order to test the robustness of our models to logically composed questions, we devise five key experiments to analyse baseline models and our methods. These experiments help us gain insights into the nuances of the VQA dataset, and allow us to develop strategies for promoting robustness.

Effect of Data Augmentation: In this experiment, we compare the performance of models on VQA-COMPPOSE 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 pre-trained baseline.

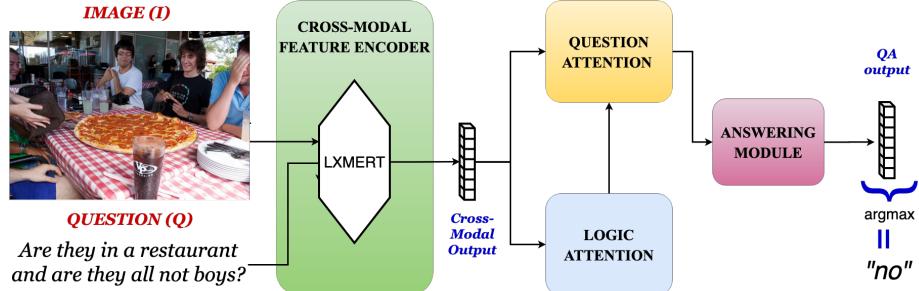


Fig. 3: LOL model architecture showing a cross-modal feature encoder followed by our Question-Attention (q_{ATT}) and Logic Attention (ℓ_{ATT}) modules. The concatenated output of is used by the Answering Module to predict the answer.

Learning Curve: We train our models with an increasing number of logically composed questions and compare performance. This serves as an analysis of the number of logical samples needed by the model to understand logic in questions.

Training only with Closed Questions: In this ablation study, we restrict the training data to only closed questions i.e. “Yes-No” VQA questions, VQA-Compose and VQA-Supplement, allowing our model to focus solely on closed questions.

Compositional Generalization: We address whether training on closed questions containing single logical operation ($\neg Q_1$, $Q_1 \vee Q_2$) can generalize to multiple operations ($Q_1 \wedge \neg Q_2$, $\neg Q_1 \vee Q_2$). 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.

Inductive Generalization: We investigate if training on compositions of two questions ($\neg Q_1 \vee Q_2$) can generalize to compositions of more than two questions ($Q_1 \wedge \neg Q_2 \wedge Q_3 \dots$). This studies whether our models develop an understanding of logical connectives, as opposed to simply learning patterns from large data.

4 Method

In this section, we describe LXMERT [44] (a state-of-the-art VQA model), our Lens of Logic (LOL) model, attention modules which learn the question-type and logical connectives in the question, and the Frchet-Compatibility (FC) Loss. This section refers to a composition of two questions, but applies to $n \geq 2$ questions.

4.1 Cross-Modal Feature Encoder

LXMERT (Learning Cross-Modality Encoder Representations from Transformers) [44] is one of the first cross-modal pre-trained frameworks for vision-and-language tasks, that combines a strong visual feature extractor [39] with a strong

language model (BERT)[13]. LXMERT is pre-trained for key vision-and-language tasks, on a large corpus of $\sim 9M$ image-sentence pairs, making it a powerful cross-modal encoder for vision+language tasks such as visual question answering, as compared to other models such as MCAN [47] and UpDn [2], and strong representative baseline for our experiments.

4.2 Our Model: Lens of Logic (LOL)

The design for our LOL model is driven by three key insights:

1. As logically composed questions are closed questions, understanding the type of question will guide the model to answer them correctly.
2. Predicted answers must be compatible with the predicted question type. For instance, a closed question can 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 the Question Attention module that encodes the type of question (*Yes-No*, *Number*, or *Other*), and the Logic Attention module that predicts the connectives (*AND*, *OR*, *NOT*, *no connective*) present in the question, and use these to learn representations. The overall model architecture is shown in Figure 3. For every question Q and corresponding image I , we obtain embeddings z_Q and z_I respectively, as well as a cross-modal embedding z_X .

Question Attention Module (q_{ATT}) takes cross-modal embedding z_x from LXMERT as input, and outputs vector $P_{type} = softmax(\mathbf{q}_{ATT}(z_x))$, representing the probabilities of each question-type. These probabilities are used to get a final representation \mathbf{z}^{type} which combines the features for each question-type.¹

Logic Attention Module (ℓ_{ATT}) takes the cross-modal embedding z_X from LXMERT as input, and outputs vector $P^{conn} = \sigma(\ell_{ATT}(z_X))$ which represents the probabilities of each type of connective. We use sigmoid (σ) instead of a softmax, since a question can have multiple connectives. These probabilities are used to combine the features for each type of connective into a final representation \mathbf{z}^{conn} which encodes information about the connectives in the question.

4.3 Loss Functions

We train our models jointly with the loss function given by:

$$\mathcal{L} = (1 - \alpha_1 - \alpha_2) \cdot \mathcal{L}_{ans} + \alpha_1 \cdot \mathcal{L}_{type} + \alpha_2 \cdot \mathcal{L}_{conn} + \beta \cdot \mathcal{L}_{FC}. \quad (2)$$

Answering Loss ℓ_{ans} is conditioned on the type of question. We multiply the final prediction vector with the probability and the mask M_i for question-type i . M_i is a binary vector with 1 for every answer-index of type-i and 0 elsewhere:

$$\mathcal{L}_{ans} = \mathcal{L}_{BCE}\left(\sum_{i=1}^3 \hat{y} \odot M_i \cdot P_i^{type}, y_{ans}\right). \quad (3)$$

Attention Losses: q_{ATT} is trained to minimize a Negative Log Likelihood (NLL) classification loss, ensuring a shrinkage of probabilities of the answer choices of

the wrong type. ℓ_{ATT} is trained to minimize a multi-label classification loss, using Binary Cross-Entropy (BCE) given by:

$$\mathcal{L}_{type} = \mathcal{L}_{NLL}(\text{softmax}(z^{type}), y_{type}), \quad (4)$$

$$\mathcal{L}_{conn} = \mathcal{L}_{BCE}(\sigma(z^{conn}), y_{conn}), \quad (5)$$

where y_{ans} , y_{type} , y_{conn} are labels for answer, question-type and connective.

Frchet-Compatibility Loss: We introduce a new loss function that ensures compatibility between the answers predicted by the model for the component questions Q_1 and Q_2 and the composed question Q . Let A, A_1, A_2 be the respective answers predicted by the model for Q, Q_1 , and Q_2 . Q_i can have negation. Then Frchet inequalities [7,15] provide us with bounds for the probabilities of the answers of the conjunction and disjunction of the two questions:

$$\max(0, p(A_1) + p(A_2) - 1) \leq p(A_1 \wedge A_2) \leq \min(p(A_1), p(A_2)). \quad (6)$$

$$\max(p(A_1), p(A_2)) \leq p(A_1 \vee A_2) \leq \min(1, p(A_1) + p(A_2)). \quad (7)$$

We define ‘‘Frchet bounds’’ b_L and b_R to be the left and right bounds for the triplet A, A_1, A_2 , and the ‘‘Frchet Mean’’ m_A to be the average of the Frchet bounds; $m_A = (b_L + b_R)/2$. Then, the Frchet-Compatibility Loss given by:

$$\mathcal{L}_{FC} = (p(A) - \mathbb{1}(m_A > 0.5))^2, \quad (8)$$

ensures that the predicted answer and that determined by m_A match.

4.4 Implementation Details

The LXMERT feature encoder produces a vector z of length 768 which is used by our attention modules, each having sub-networks $\mathbf{f}_i, \mathbf{g}_i$ with 2 feed-forward layers. We first train our models without FC loss. Then we select the best models with a checkpoint of 10 epochs and finetune these further for 3 epochs with FC loss, since the FC loss is designed to work for a model whose predictions are not random. Thus our improvements in accuracy are attributable to the FC Loss and not more training epochs. We utilize the Adam optimizer [23] 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.¹

5 Experiments

We first conduct analytical experiments to test for logical robustness and transfer learning capability. We use three datasets for our experiment: the VQA v2.0 [3] dataset, a combination of VQA and our **VQA-Compose** dataset, and a combination

¹ More training details in Supplementary Materials

² In all tables, best overall scores are bold, our best scores underlined.

Table 2: Comparison of LXMERT and LOL trained on VQA data, combinations with **Compose**, **Supplement**, and our Frechet-Compatibility (FC) Loss ²

Model	Trained on	Validation Accuracy (%) ↑			
		VQA	YN	Comp	Supp
LXMERT	VQA	68.94	86.65	50.79	50.51
	VQA + Comp	67.85	85.32	85.03	80.85
	VQA + Comp + Supp	68.83	84.83	70.28	85.17
	VQA + Comp + Supp	67.84	84.92	75.31	85.25
LOL (qATT)	VQA	69.08	<u>85.32</u>	48.99	50.54
	VQA + Comp	67.51	84.82	84.85	79.62
	VQA + Comp + Supp	68.72	84.99	79.88	87.12
LOL (Full)	VQA + Comp	68.94	85.15	<u>85.13</u>	79.02
	VQA + Comp + Supp	68.86	84.87	81.07	87.54
	VQA + Comp + Supp	68.10	84.75	82.39	87.80
LXMERT	YN + Comp	-	84.13	84.44	79.39
	YN + Comp + Supp	-	84.09	82.63	88.15
LOL (ℓ ATT)	YN + Comp	-	85.22	85.31	79.87
	YN + Comp + Supp	-	85.26	84.37	89.00

Table 3: Validation accuracies (%) for Compositional Generalization and Commutative Property. Note that 50% is random performance.²

Model	VQA-Compose				VQA-Supplement				Model	VQA-Compose				VQA-Supplement			
	YN	Single	Multiple	Single	Multiple	$Q_1 \circ Q_2$	$Q_2 \circ Q_1$										
LXMERT	85.07	83.95	61.99	86.65	60.00	82.34	80.44	85.57	81.78	84.91	83.64	85.62	83.41	84.91	83.64	85.62	83.41
LOL	85.12	84.60	66.03	87.42	66.05												

of VQA, VQA-Compose and VQA-Supplement. The size of the training dataset and the distribution of yes-no, number and other questions is kept the same as the original VQA dataset ($\sim 443k$) for fair comparison. Since VQA-Supplement uses captions and objects from MS-COCO, we use it 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 attention modules (q_{ATT} and ℓ_{ATT}) achieve an accuracy of 99.9% on average, showing almost perfect performance when it comes to learning the type of question and the logical connectives present in the question.

5.1 Can’t We Just Parse the Question into Components?

Since our questions are a composition of multiple questions, an obvious approach is to split the question into its components, and to discern the logical formula

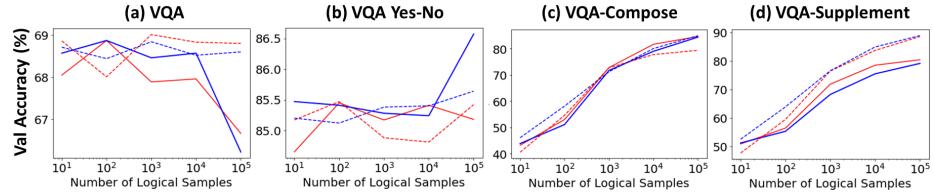


Fig. 4: Learning Curve comparison for models (Red: LXMERT, Blue: LOL) trained on our datasets (solid lines: VQA + Comp, dotted lines: VQA + Comp + Supp)

for composition. The answers to these component questions (predicted by VQA models) can be *re-combined* with the predicted logical formula to obtain the final answer. We use parsers to map components and logical operations to predefined slots in a logical function. The oracle parser uses the ground truth component questions and combines predicted answers using the true formula. However, at test time we do not have access to the true mapping and components. So we train a RoBERTa-Base [26] parser using B-I-O tagging [37] for a Named-Entity Recognition task with constituent questions as entities.¹

The performance of the oracle parser serves as the upper bound as we have a perfect mapping, with the QA system being the only source of error. The trained parser has an exact-match accuracy of 85%, but only a 72% accuracy in determining the number of operands. The parser has an accuracy of 89% for questions with 3 or less operands, but only 78% for longer compositions. End-to-end (E2E) models do not need to parse questions and hence overcome these hurdles, but do require an understanding of logical operations. Table 4 shows that both oracle and trained parsers when used with LOL outperform parsers with LXMERT, by 6.82% and 5.60% respectively. The LOL model without using any parsers is better than both LXMERT and LOL with the trained parser by 7.55% and 1.95% respectively.

5.2 Explicit Training with Logically Composed Questions

Can models trained on the VQA-v2 dataset answer logically composed questions? The first section of Table 2 shows that LXMERT, when trained only on questions from VQA-v2 has near random accuracy ($\sim 50\%$) on our logically composed datasets, thus exhibiting little robustness to such questions.

Can baseline model improve if trained explicitly with logically composed questions questions? We train the models with data containing a combination of samples from VQA-v2, VQA-Compose, and VQA-Supplement. The accuracy on VQA-Compose and VQA-Supplement improves, but there is a drop in performance on yes-no questions from VQA. Our models with our attention modules (q_{ATT} and ℓ_{ATT}) are able to retain performance on VQA-v2 while achieving improvements on all validation datasets.

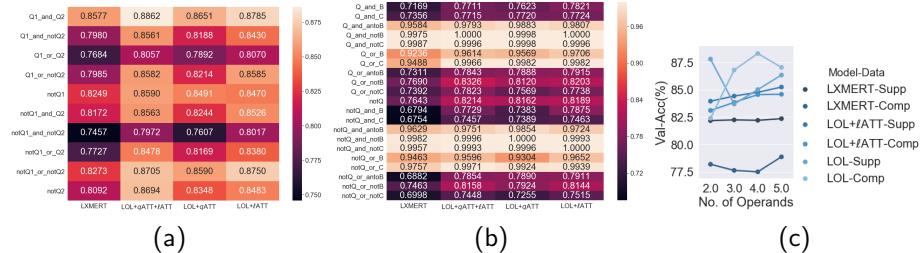


Fig. 5: Accuracy for each type of question in (a) VQA-Compose, (b) VQA-Supplement and for questions with number of operands greater than 2.

5.3 Analysis

Training with Closed Questions only: 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 accuracy on logically composed questions, as shown in sections 3 and 4 in Table 2. Since we train only closed questions, we do not use our question attention module for this experiment.

Effect of Logically Composed Questions: We increase 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 4(a), models trained on VQA + Comp + Supp are able to retain performance on VQA validation data, while those trained only on VQA + Comp deteriorate. Figure 4(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 our models are comparable to the baseline, but our model shows improvements over the baseline when trained on VQA + Comp + Supp. In (d) 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. We also see that our model yields the best performance on VQA-Supplement.

Compositional Generalization: To test for compositional generalization, we train models on questions with a maximum of one connective (single) and test on those with multiple connectives. It can be seen from Table 3 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.

Inductive Generalization: We test our models on questions composed with more than two components. Parser-based models have this property by default. As shown by Figure 5c our E2E models outperform the baseline LXMERT.

Table 4: Performance on ‘test-standard’ set of VQA-v2 and validation set of our datasets. LOL performance is close to SOTA on VQA-v2, but significantly better at logical robustness. *MCAN uses a fixed vocabulary that prohibits evaluation on VQA-Supplement which has questions created from COCO captions. #Test-dev scores, since MCAN does not report test-std single-model scores²

Model	Parser	Training Data	Test-Std. Accuracy (%) ↑				Val. Accuracy (%) ↑		
			Yes-No	Number	Other	Overall	Compose	Supplement	Overall
MCAN	None	VQA [47]	86.82#	53.26#	60.72#	70.90	52.42	*	*
LXMERT	None	VQA [44]	88.20	54.20	63.10	72.50	50.79	50.51	50.65
LOL (qATT)	None	VQA	<u>87.33</u>	<u>54.03</u>	<u>62.40</u>	<u>72.03</u>	48.99	50.54	49.77
LXMERT	Oracle	VQA	88.20	54.20	63.10	72.50	86.38	74.29	80.33
LXMERT	Trained	VQA	88.20	54.20	63.10	72.50	86.35	68.75	77.55
LOL (full)	Oracle	VQA+Ours	86.55	53.42	61.58	71.04	85.79	88.51	87.15
LOL (full)	Trained	VQA+Ours	86.55	53.42	61.58	71.04	82.13	84.17	83.15
LXMERT	None	VQA+Ours	85.23	51.25	60.58	69.78	75.31	85.25	80.28
LOL (qATT)	None	VQA+Ours	86.79	52.66	61.85	71.19	79.88	87.12	83.50
LOL (full)	None	VQA+Ours	86.55	53.42	61.58	71.04	82.39	87.80	85.10

Commutative Property: Our models have identical answers when the question is composed either as $Q_1 \circ Q_2$ or $Q_2 \circ Q_1$, for logical operation \circ , as shown in Table 3. The parser-based models are agnostic to the order of components if the parsing is accurate, while our E2E models are robust to the order.

Accuracy per Category of Question Composition: In Figure 5 we show a plot of accuracy 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 $Q \wedge \text{antonym}(B), Q \wedge \neg B, Q \wedge \neg C$ are easy because the model is able to understand absence of objects, therefore can always answer these questions with a “NO”. Similarly, $Q \vee B, Q \vee C$ are easily answered since presence of the object makes the answer always “YES”. By simply understanding object presence many such questions can be answered. Figure 5 shows the model has the same accuracy for logically equivalent operations.

5.4 Evaluation on VQA v2.0 Test Data

Table 4 shows the performance the VQA Test-Standard datset. Our models maintain overall performance on the VQA test dataset, and at the same time substantially improve from random performance ($\sim 50\%$) on logically composed questions to 82.39% on VQA-Compose and 87.80% 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 (our models are within $\sim 1.5\%$ of the state-of-the-art on all three types of questions on the VQA test-set).

6 Discussion

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 [11]. Natural language contains such complex logical compositions, not to mention ambiguities and the influence of context. In this paper, we focus on the simplest – negation, conjunction, and disjunction. We have shown that existing VQA models are not robust to questions composed with these logical connectives, even when we train parsers to split the question into its components. When humans are faced with such questions, they may refrain from giving binary (Yes/No) 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 component questions has a negative answer. However, humans might answer the same question with the answer “*Yes, but I did not like it*”. While human question-answering is indeed elaborate, explanatory, and clarifying, that is the scope of our future work; here we focus only on predicting a single binary answer.

We have shown how connectives in a question can be identified by enhancing LXMERT encoders with dedicated attention modules and loss functions. We would like to stress on the fact that we do not use knowledge of the connectives during inference, but instead train the network to be aware of it based on cross-modal features, instead of predicting purely based on language model embeddings which fail to capture these nuances. Our work is an attempt to modularize the understanding of logical components to train the model to utilize the outputs of the attention modules. We believe this work has potential implications on logic-guided data augmentation, logically robust question answering, and for conversational agents (with or without images). Similar strategies and learning mechanisms may be used in the future to operate “logically” in the image-space at the level of object classes, attributes, or semantic segments.

7 Conclusion

In this work, we investigate VQA in terms of logical robustness. 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 the “Lens of Logic” model architecture that learns to answer questions with negation, conjunction, and disjunction. We provide **VQA-Compose** and **VQA-Supplement**, two datasets containing logically composed questions to serve as benchmarks. 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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Supplementary Material

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 elaborate upon the following topics:

- Data creation process,
- Dataset analysis,
- Training datasets used for each experiment,
- Additional details about model training and hyper-parameters,
- Additional details about parser models, and
- Further analysis and insights about our results.

1 Dataset Creation

The key idea behind our dataset creation process is to leverage existing annotations from the VQA-v2 dataset [3] and from MS-COCO [25] which is the source of images in VQA-v2. We use questions from VQA-v2, and object annotations and captions from MS-COCO for each image.

In order to create logically composed questions, we first filter out the “yes-no” questions which constitute 38% of the VQA dataset. We further filter these by retaining only those yes-no questions with a single valid answer. These questions which are 20% of the VQA data, have an unambiguous answer, chosen unanimously by all human annotators who created the VQA dataset. This satisfies the definition of “*closed questions*” [6] that we use, and are thus 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 (\neg), conjunction (\wedge), and disjunction (\vee). Since they have a clear unambiguous answer that is either “yes” or “no”, we can treat them as Boolean variables, and obtain answers for every new question composed. For negating a question, we follow a template-based procedure negates the question by adding a “no” or “not” before a verb, preposition or noun phrase, as shown in Table 1. Note that our data creation method chooses 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 *Is this not an area near the city?* or *Is this an area not near the city?* randomly. Conjunction and disjunction are straightforward, we add the words “and” and “or” between two closed questions.

Table 1: Examples of question negation. Q denotes the original question from the VQA dataset, $\neg Q$ denotes its negation.

Q	$\neg Q$
Is this an area near the city ?	Is an this area <i>not</i> near the city?
Are all the men wearing ties ?	Are all the men <i>not</i> wearing ties?
Is there a chair ?	Is there <i>no</i> chair?
Do you think it's gonna rain?	Do you think it's <i>not</i> gonna rain?

Table 2: Examples of adversarial antonyms for objects. The antonym is chosen such that it is not in the image, but is semantically close to an object in the image

Object	Adversarial Antonym
bottle	wine glass
cup	bowl
spoon	fork
surfboard	skateboard
motorcycle	bicycle
sink	toilet

1.1 VQA-Compose

VQA-Compose is our dataset that is created solely from closed questions in the VQA dataset, by using negation, conjunction and disjunction to compose questions. As shown in Figure 2, we obtain 10 questions for each closed question in the VQA dataset, resulting in a total of 1.25M question-answer-image triplets as our VQA-Compose dataset.

1.2 VQA-Supplement

Figure 1 shows examples of captions available in the MS-COCO dataset for images in the VQA-v2 dataset. As shown in Figure 3, we use object annotations and captions from MS-COCO to create questions B and C respectively, using template-based methods. We create VQA-Supplement by using logical operators (negation, conjunction, and disjunction) to combine B or C with original questions from VQA-v2.

In addition, we 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 2. We use Glove vectors [34] 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 ℓ_2 distance as a metric to sort and select adversarial antonyms. Since the list of objects present in the image is available to us via

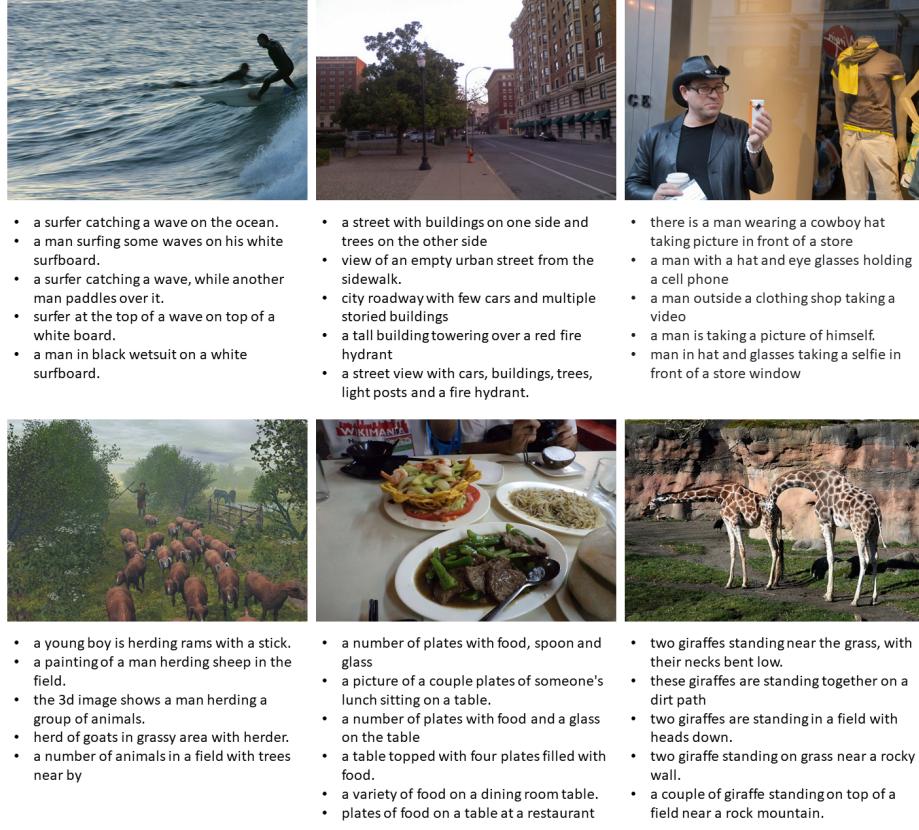


Fig. 1: Examples of captions from COCO for images in the VQA dataset. We convert these captions into questions and use them for our VQA-Supplement dataset

MS-COCO, we are able to determine the ground-truth answers for object-based questions.

For each 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.

2 Dataset Analysis

In this section, we analyze the VQA dataset as well as our new datasets that contain logically composed questions.

IMAGES from VQA Validation Set



Questions created in VQA-Compose

QF	AF	Q	A	Q	A	Q	A
Q_1	A_1	Is there a bird in this picture?	No	Do you see animals in picture?	No	Is the man wearing glasses?	Yes
Q_2	A_2	Is the person in the foreground drowning?	No	Is this a busy road?	Yes	Is he wearing a hat?	Yes
$\neg Q_1$	$\neg A_1$	Is there no bird in this picture?	Yes	Do you not see animals in picture?	Yes	Is the man not wearing glasses?	No
$\neg Q_2$	$\neg A_2$	Is the person in the foreground not drowning?	Yes	Is this a not busy road?	No	Is he not wearing a hat?	No
$Q_1 \wedge Q_2$	$A_1 \wedge A_2$	Is there a bird in this picture and Is the person in the foreground drowning?	No	Do you see animals in picture and Is this a busy road?	No	Is the man wearing glasses and Is he wearing a hat?	Yes
$Q_1 \vee Q_2$	$A_1 \vee A_2$	Is there a bird in this picture or Is the person in the foreground drowning?	No	Do you see animals in picture or Is this a busy road?	Yes	Is the man wearing glasses or Is he wearing a hat?	Yes
$\neg Q_1 \wedge Q_2$	$\neg A_1 \wedge A_2$	Is there a bird in this picture and Is the person in the foreground not drowning?	No	Do you not see animals in picture and Is this a busy road?	No	Is the man not wearing glasses and Is he wearing a hat?	No
$\neg Q_1 \vee Q_2$	$\neg A_1 \vee A_2$	Is there a bird in this picture or Is the person in the foreground not drowning?	Yes	Do you not see animals in picture or Is this a busy road?	No	Is the man not wearing glasses or Is he wearing a hat?	Yes
$Q_1 \wedge \neg Q_2$	$A_1 \wedge \neg A_2$	Is there a bird not in this picture and Is the person in the foreground drowning?	No	Do you see animals in picture and Is this a not busy road?	No	Is the man wearing glasses and Is he not wearing a hat?	No
$Q_1 \vee \neg Q_2$	$A_1 \vee \neg A_2$	Is there a bird not in this picture or Is the person in the foreground drowning?	Yes	Do you see animals in picture or Is this a not busy road?	No	Is the man wearing glasses or Is he not wearing a hat?	Yes
$\neg Q_1 \wedge \neg Q_2$	$\neg A_1 \wedge \neg A_2$	Is there a bird not in this picture and Is the person in the foreground not drowning?	Yes	Do you not see animals in picture and Is this a not busy road?	No	Is the man not wearing glasses and Is he not wearing a hat?	No
$\neg Q_1 \vee \neg Q_2$	$\neg A_1 \vee \neg A_2$	Is there a bird not in this picture or Is the person in the foreground not drowning?	Yes	Do you not see animals in picture or Is this a not busy road?	Yes	Is the man not wearing glasses or Is he not wearing a hat?	No

Fig. 2: 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.

2.1 Question Length

The average length of questions in VQA-v2 [3] is **6.1 words**. Our datasets have a average length of **12.25 words** for VQA-Compose and **15.17** for VQA-Supplement. This is longer than VQA-v2 since each of our logically composed questions is made up of multiple component questions.

2.2 Types of Answers

The VQA dataset contains a fixed vocabulary of answers. We obtained the Glove [34] embeddings of these answers, and performed k-means clustering on these embeddings to obtain 50 clusters. We show examples of some of these clusters in Table 3. It can be observed that similar answers, such as those

IMAGE
from VQA Validation Set



Objects (B)
person, cup, cell phone

Captions (C)

- *a man outside a clothing shop taking a video*
- *a man with a hat and eye glasses holding a cell phone*

Questions created in VQA-Supplement

QF	AF	Q	A
Q	A	Is he wearing a hat?	Yes
$\neg Q$	$\neg A$	Is he not wearing a hat?	No
$Q \wedge B$	A	Is he wearing a hat and is there a cell phone?	Yes
$Q \vee B$	T	Is he wearing a hat or is there a cell phone?	Yes
$Q \wedge \text{anto}(B)$	\perp	Is he wearing a hat and is there a bowl?	No
$Q \vee \text{anto}(B)$	A	Is he wearing a hat or is there a bowl?	Yes
$Q \wedge C$	A	Is he wearing a hat and is this a man outside a clothing shop taking a video?	Yes
$Q \vee C$	T	Is he wearing a hat or is this a man outside a clothing shop taking a video?	Yes
$Q \wedge \neg B$	\perp	Is he wearing a hat and is there no cell phone?	No
$Q \vee \neg B$	A	Is he wearing a hat or is there no cell phone?	Yes
$\neg Q \wedge B$	$\neg A$	Is he not wearing a hat and is there a cell phone?	No
$\neg Q \vee B$	T	Is he not wearing a hat or is there a cell phone?	Yes
$\neg Q \wedge \neg B$	\perp	Is he not wearing a hat and is there no cell phone?	No
$\neg Q \vee \neg B$	$\neg A$	Is he not wearing a hat or is there no cell phone?	No
$\neg Q \wedge \text{anto}(B)$	\perp	Is he not wearing a hat and is there a bowl?	No
$\neg Q \vee \text{anto}(B)$	$\neg A$	Is he not wearing a hat or is there a bowl?	No
$Q \wedge \neg C$	\perp	Is he wearing a hat and is it not a man with a hat and eye glasses holding a cell phone?	No
$Q \vee \neg C$	A	Is he wearing a hat or is it not a man with a hat and eye glasses holding a cell phone?	Yes
$\neg Q \wedge C$	$\neg A$	Is he not wearing a hat and is this a man outside a clothing shop taking a video?	No
$\neg Q \vee C$	T	Is he not wearing a hat or is this a man outside a clothing shop taking a video?	Yes
$\neg Q \wedge \neg C$	\perp	Is he not wearing a hat and is it not a man with a hat and eye glasses holding a cell phone?	No
$\neg Q \vee \neg C$	$\neg A$	Is he not wearing a hat or is it not a man with a hat and eye glasses holding a cell phone?	No

Fig. 3: 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, \perp are the standard Boolean symbols for top and bottom (true and false)

belonging a common category such as *food* or *sports* appear in the same cluster. This shows that Glove embeddings of these answers preserve a notion of similarity. Note that the cluster names in Table 3 are assigned by humans after clustering is complete, for the sake of clarity and illustration, 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 [30]. The categories in OK-VQA are annotated by human workers in Amazon Mechanical Turk.

Table 3: Selected results of k-means clustering on the Glove embeddings of answers in VQA. k=50.

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', 'caucasian', 'american flag', 'german', 'russia', 'oriental', 'japan', 'hispanic', 'british', 'american airlines', 'asian', 'african american', 'italian', 'virgin', 'chinese', 'spanish', 'india', 'thai', 'japanese', 'asia', 'brazil', 'french', 'african', 'persian', 'english'
Flowers, Plants	'tulip', 'weeds', 'windowsill', 'tree branch', 'daffodils', 'carnations', 'elm', 'fern', 'grass', 'roses', 'garden', 'wreath', 'trees', 'pine', 'carnation', 'evergreen', 'sunflowers', 'tree', 'palm tree', 'ivy', 'palm', 'lily', 'iris', 'willow', 'christmas tree', 'vase', 'bamboo', 'tulips', 'rose', 'bushes', 'lilac', 'dandelions', 'plant', 'orchid', 'flowers', 'lilies', 'vines', 'daisy', 'cactus', 'palm trees', 'flower', 'floral', 'branches', 'bark', 'maple leaf', 'leaf', 'daffodil'
Fruits	'mango', 'apples', 'juice', 'cherries', 'strawberries', 'ginger', 'watermelon', 'cane', 'cherry', 'sweet', 'peach', 'organic', 'cantaloupe', 'orange juice', 'banana split', 'ripe', 'lemonade', 'grape', 'fruit', 'sunflower', 'smoothie', 'coconut', 'strawberry', 'banana peel', 'peaches', 'sesame seeds', 'fresh', '...', 'mint', 'lemons', 'pineapple', 'oranges', 'grapes', 'salt and pepper', 'grapefruit', 'almonds', 'blueberry', 'kiwi'
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', 'pelican'
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', 'athletics', 'basketball', ...
Dog Breeds	'puppy', 'mutt', 'pomeranian', 'dogs', 'dachshund', 'bulldog', 'cocker spaniel', 'schnauzer', 'rottweiler', 'pitbull', 'pug', 'corgi', 'golden retriever', 'german shepherd', 'clydesdale', 'greyhound', 'boxer', 'kitten', 'cat', 'chihuahua', 'dog', 'husky', 'leash', 'terrier', 'dalmatian', 'thoroughbred', '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', '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 silver', 'colored', 'white and gray', 'black and gray'
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', 'cilantro', 'cabbage', 'tomato', 'feta', 'veggies', 'avocado', 'peas', 'garlic', 'zucchini', 'pepper', 'vegetables', 'potatoes', 'tomatoes', 'radish', ...
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 4: Training dataset distribution and sizes, for explicit training with new data. Note that training dataset sizes are consistent with the VQA dataset.

Training Datasets	Proportion of datasets (%)					Training Samples
	VQA	Other	VQA-Number	VQA-YesNo	Comp	Supp
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 5: 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	Proportion of samples (%)					Training Samples
	VQA	Other	VQA-Number	VQA-YesNo	Comp	Supp
VQA	50	12	38	0	0	443754
VQA + Comp (10)	49.999	11.999	37.999	0.002	0	443764
VQA + Comp (100)	49.989	11.997	37.991	0.022	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	0.002	0.002	443774
VQA + Comp (100) + Supp (100)	49.977	11.995	37.983	0.022	0.022	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

3 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 proportions of these samples in the training data depends upon the specific experiment performed. For each of our experiments we use the same train-validation-test splits as in the VQA-v2 and COCO datasets. In this section, we explain our training datasets in detail for each experiment, analysis, and ablation study.

3.1 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 [44] trained explicitly with our new data, and also with our models that use the attention modules for question-type and connective-type.

Table 6: Training datasets distribution and sizes, for training with logical questions with a maximum of one connective.

Training Datasets	Proportion of samples (%)					Training Samples
	VQA-Other	VQA-Number	VQA-YesNo	Comp-Single	Supp-Single	
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

For a fair comparison, we restrict the size of training dataset to the original size of the VQA training dataset (443,754 samples). 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 4. This allows us to improve the diversity of yes-no questions, by incorporating yes-no questions from VQA-Compose and VQA-Supplement.

3.2 Training with Closed Questions only

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

1. 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 such as the original questions from VQA, logical compositions in VQA-Compose, and logical compositions with object and caption-based questions in VQA-Supplement.

3.3 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 5. This allows us to understand how many additional logically composed questions are needed for our models to become robust.

3.4 Compositional Generalization

In this experiment, our aim is to train models on questions that contain a single logical connective (*and*, *or*, *not*) or no connective at all (original yes-no questions in VQA), and to test their 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 6

Table 7: Hyper-Parameters for training LXMERT and our models

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

Table 8: Precision-Recall and F1-Scores for the RoBERTa-based NER parser

Operands	Precision	Recall	F1-Score
2	84.98	86.69	85.83
3	81.55	83.62	82.57
4	81.63	83.72	82.66
5	76.29	79.45	77.84

4 Model Architectures and Training Settings

We train our models and baseline LXMERT [44] model with the hyper-parameters in Table 7, chosen from the median of 5 random seeds. The length of cross-modal embeddings produced by LXMERT for each question-image pair is 768. We utilize this as input to our attention modules \mathbf{q}_{ATT} and ℓ_{ATT} . The hidden layers of these attention modules have a size of 2×768 . The answering module uses the outputs of these modules to predict softmax answer probabilities.

5 Parser Training and Results

One of our baselines involves using a parser to split a question into its components, answer them separately, and combine the answers logically to get the final answer. We use the RoBERTa-Base language model [26] and train it for the Named-Entity Recognition (NER) task. We modify the RoBERTa-NER model from the Huggingface Transformers [46] framework. We create our parser dataset using the constituent questions as target entities and the original question as the input text. The sequence is classified using B-I-O (*Beginning-Inside-Outside*) [26] tagging scheme, where all constituent tokens are predicted to be tagged as B-Const, I-Const and the connectives are tagged as O.¹ There is only one entity class.

¹ “Const” refers to constituent.

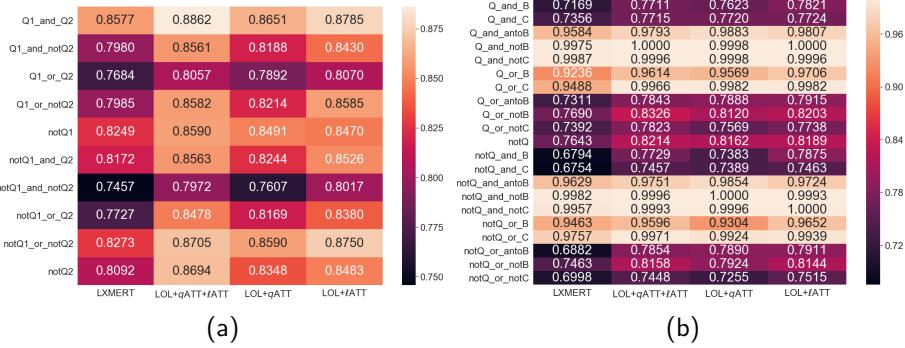


Fig. 4: Accuracy for each type of question in (a) VQA-Compose, (b) VQA-Supplement and for questions with number of operands greater than 2.

We train the model for 20 epochs, with a batch size of 32, and learning rate of 1e-5. The results of our parser are shown in Table 8. It can be observed that the performance of the parser deteriorates as the number of operands in the question increases. This is a major drawback of parser-based methods.

6 Analysis of Results

We provide accuracies of all four models as a heat-map in Figure 4, and also in Tables 9 and 10. We have two key observations.

In Figure 4a, we observe that for all models, the two hardest question categories are $Q_1 \vee Q_2$ and $\neg Q_1 \wedge \neg Q_2$, while the two easiest categories are $Q_1 \wedge Q_2$ and $\neg Q_1 \vee \neg Q_2$. Using DeMorgan’s laws to rewrite these logical formulas, we see that the two hardest categories are:

$$Q_1 \vee Q_2 , \quad \neg(Q_1 \vee Q_2),$$

while the two easiest categories are:

$$Q_1 \wedge Q_2 , \quad \neg(Q_1 \wedge Q_2).$$

Figure 4b provides similar 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 are $Q \vee B, Q \vee C, \neg Q \vee B, \neg Q \vee C$, and $Q \wedge \neg B, Q \wedge \neg C, Q \wedge anto(B), \neg Q \wedge \neg B, \neg Q \wedge \neg C$, and $\neg Q \wedge anto(B)$.

Table 9: Accuracies on each type of question in VQA-Compose by each model. QF is Question Formula

QF	LXMERT	LXMERT+ ℓ_{ATT}	LXMERT+ q_{ATT}	LXMERT+ $q_{ATT}+\ell_{ATT}$
$\neg Q_1$	85.39	85.55	84.78	86.43
$\neg Q_2$	84.38	85.45	84.94	86.08
$Q_1 \wedge Q_2$	81.50	87.77	87.66	87.77
$Q_1 \vee Q_2$	85.26	81.58	80.54	80.97
$Q_1 \wedge \neg Q_2$	85.71	85.77	84.45	85.02
$Q_1 \vee \neg Q_2$	87.12	86.22	85.98	85.53
$\neg Q_1 \wedge Q_2$	85.10	85.34	84.83	85.53
$\neg Q_1 \vee Q_2$	80.76	78.92	83.79	84.75
$\neg Q_1 \wedge \neg Q_2$	87.98	86.59	79.77	81.32
$\neg Q_1 \vee \neg Q_2$	87.12	85.42	87.42	87.74

Table 10: Accuracies on each type of question in VQA-Supplement by each model

QF	LXMERT	LXMERT+ ℓ_{ATT}	LXMERT+ q_{ATT}	LXMERT+ $q_{ATT}+\ell_{ATT}$
Q	82.27	82.3	82.77	82.34
$Q \wedge B$	78.03	77.92	78.16	78.36
$Q \vee B$	95.51	96.79	97.06	96.74
$Q \wedge anto(B)$	95.64	97.55	98.07	96.72
$Q \wedge C$	81.22	82.07	81.67	81.67
$Q \vee C$	99.84	99.89	99.84	99.89
$Q \wedge \neg B$	99.96	99.93	99.98	99.89
$Q \vee \neg B$	82.39	82.54	82.09	81.69
$\neg Q \vee B$	95.08	96.52	96.52	95.51
$\neg Q \wedge \neg B$	99.89	99.84	99.91	99.75
$\neg Q \wedge anto(B)$	94.86	97.91	97.15	97.42
$Q \wedge \neg C$	99.91	99.91	99.98	99.87
$Q \vee \neg C$	82.45	82.21	82.3	81.46
$\neg Q \vee C$	99.80	99.91	99.75	99.82
$\neg Q \wedge \neg C$	99.84	99.87	99.89	99.78
$\neg Q$	80.30	81.62	81.78	80.84
$Q \vee anto(B)$	77.92	77.83	79.13	78.43
$\neg Q \wedge B$	76.27	76.90	78.88	77.31
$\neg Q \vee \neg B$	79.73	81.42	81.49	81.17
$\neg Q \vee anto(B)$	75.62	77.33	79.22	77.92
$\neg Q \wedge C$	78.95	81.26	81.11	80.18
$\neg Q \vee \neg C$	79.87	80.77	81.51	80.61

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 (“and”) to combine $\neg B, \neg C, \text{anto}(B)$ 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 , and cannot be simply “explained away”.

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