

# Ask Your Neurons: A Neural-based Approach to Answering Questions about Images

Mateusz Malinowski<sup>1</sup> Marcus Rohrbach<sup>2</sup> Mario Fritz<sup>1</sup>

<sup>1</sup>Max Planck Institute for Informatics, Saarbrücken, Germany

<sup>2</sup>UC Berkeley EECS and ICSI, Berkeley, CA, United States

## Abstract

We address a question answering task on real-world images that is set up as a Visual Turing Test. By combining latest advances in image representation and natural language processing, we propose *Neural-Image-QA*, an end-to-end formulation of this problem for which all parts are trained jointly. In contrast to previous efforts, we are facing a multi-modal problem where the language output (answer) is conditioned on visual and natural language input (question). Our result doubles the performance of the previous best result on this problem. We provide additional insights into the problem by analyzing how much information is contained only in the language part for which we provide a new human baseline. Further annotations were collected to study human consensus, which is related to the ambiguities inherent in this challenging task.

## 1. Introduction

With the advances of natural language processing and image understanding, more complex and demanding tasks have become within reach. Our aim is to take advantage of the most recent developments in order to push the state-of-the-art on answering natural language questions on real-world images. This task unites inference of question intent and visual scene understanding with a word sequence prediction task.

Most recently, architectures based on the idea of layered, end-to-end trainable artificial neural networks have improved the state of the art across a wide range of diverse tasks. Most prominently Convolutional Neural Networks have raised the bar on image classification tasks [12] and Long Short Term Memory Networks are dominating performance on a range of sequence prediction tasks as machine translation [20].

Very recently these two trends of employing neural architectures have been combined fruitfully with methods that can generate image [8] and video descriptions [3]. Both

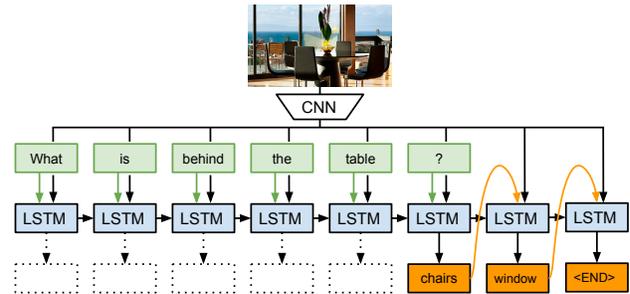


Figure 1. Our approach *Neural-Image-QA* to question answering with a Recurrent Neural Network using Long Short Term Memory (LSTM). To answer a question about an image, we feed in both, the image (CNN features) and the question (green boxes) into the LSTM. After the (variable length) question is encoded, we generate the answers (multiple words, orange boxes). During the answer generation phase the previously predicted answers are fed into the LSTM until the  $\langle \text{END} \rangle$  symbol is predicted.

are conditioning on the visual features that stem from deep learning architectures and employ recurrent neural network approaches to produce descriptions.

In order to further push the boundaries and explore the limits of deep learning architectures, we propose an architecture for answering questions about images. In contrast to prior work, this task needs conditioning on language as well visual input. Both modalities have to be interpreted and jointly represented as an answer depends on inferred meaning of the question and image content.

While there is a rich body of work on natural language understanding that has addressed textual question answering tasks based on semantic parsing, symbolic representation and deduction systems, which also has seen applications to question answering on images [15], there is initial evidence that deep architectures can indeed achieve a similar goal [25]. This motivates our work to seek an end-to-end architectures that learns to answer questions in a single holistic and monolithic model.

We propose *Neural-Image-QA*, an approach to question answering with a recurrent neural network. An overview

is given in Figure 1. The image is analyzed via a Convolutional Neural Network (CNN) and the question together with the visual representation is fed into a Long Short Term Memory (LSTM) network. The system is trained to produce the correct answer to the question on the image. CNN and LSTM are trained jointly and end-to-end starting from the word and pixel level.

**Contributions:** We propose a novel approach based on recurrent neural networks for the challenging task of answering of questions about images. It combines a CNN with a LSTM into an end-to-end architecture that predict answers conditioning on a question and an image. Our approach significantly outperforms prior work on this task – doubling the performance. We collect additional data to study human consensus on this task, propose two new metrics sensitive to these effects, and provide a new baseline, by asking humans to answer the questions without observing the image. We demonstrate a variant of our system that also answers question only based on the question, that beats the human baseline. Inspection of the answer produced by our “language only” system show that biases that can be interpreted as a form of common sense are captured by our system. Code and data will be made available at time of publication.

## 2. Related Work

As our method touches upon different areas in machine learning, computer vision and natural language processing, we have organized related work in the following way:

### Convolutional Neural Networks for visual recognition

We are building on the recent success of Convolutional Neural Networks (CNN) for visual recognition [13, 17, 12], that are directly learnt from the raw image data and pre-trained on large image corpora. Due to the rapid progress in this area within the last two years, a rich set of models [19, 21] is at our disposal and following common practice we fine-tune such models for our task [7].

### Recurrent Neural Networks (RNN) for sequence modeling

Recurrent Neural Networks allow Neural Networks to handle sequences of flexible length. A particular variant called Long Short Term Memory (LSTM) [5] has shown recent success on natural language tasks such as machine translation [2, 20].

### Combining RNNs and CNNs for description of visual content

The task of describing visual content like still images as well as videos has been successfully addressed with a combination of the previous two ideas [28, 23, 3, 22, 8]. This is achieved by using the RNN-type model that first

gets to observe the visual content and is trained to afterwards predict a sequence of words that is a description of the visual content. Our work extends this idea to question answering, where we formulate a model trained to generate an answer based on visual as well as natural language input.

### Grounding of natural language and visual concepts

Dealing with natural language input does involve the association of words with meaning. This is often referred to as grounding problem - in particular if the “meaning” is associated with a sensory input. While such problems have been historically addressed by symbolic semantic parsing techniques [11, 16], there is a recent trend of machine learning-based approaches [9, 8, 10] to find the associations. Our approach follows the idea that we do not enforce or evaluate any particular representation of “meaning” on the language or image modality. We treat this as latent and leave this to the joint training approach to establish an appropriate internal representation for the question answering task.

**Question answering** Answering on purely textual questions has been studied in the NLP community [14, 1] and state of the art techniques typically employ semantic parsing to arrive at a logical form capturing the intended meaning and infer relevant answers. Only very recently, the success of the previously mentioned neural sequence models as RNNs has carried over to this task [6, 25].

### Visual Turing Test

Most recently question answering task based on images have been proposed that relates to the idea of a Visual Turing Test. [4] proposes such an approach where the task is limited to yes/no answers, and [24] proposes a set of different question answering benchmarks using synthetic data. Most related to our work, [15] presents a question answering system based on a semantic parser on a more varied set of human question-answer pairs that poses a sequence prediction problem based on language and vision. In contrast, our method is based on a neural architecture, that is trained end-to-end and therefore liberates the approach from any ontological commitment that would otherwise be introduced by a semantic parser.

## 3. Approach

Visual question is the problem of predicting an answer  $a$  given an image  $x$  and a question  $q$  according to a parametric probability measure:

$$\hat{a} = \arg \max_{a \in \mathcal{A}} p(a|x, q; \theta) \quad (1)$$

where  $\theta$  represent a vector of all parameters to learn and  $\mathcal{A}$  is a set of all answers. Later we describe how we represent  $x$ ,  $a$ ,  $q$ , and  $p(\cdot|x, q; \theta)$  in more details.

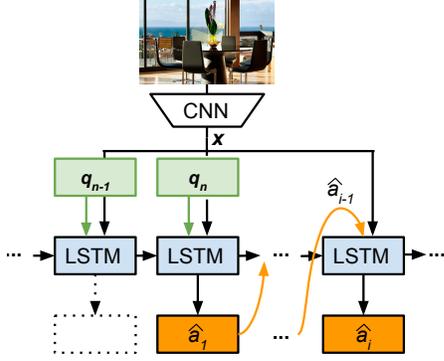


Figure 2. Our approach Neural-Image-QA, see Section 3 for details.

In our scenario questions can have multiple word answers and we consequently decompose the problem to predicting a set of answer words  $\mathbf{a}_{q,x} = \{\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_{\mathcal{N}(q,x)}\}$ , where  $\mathbf{a}_t$  are words from a finite vocabulary  $\mathcal{V}$ , and  $\mathcal{N}(q, x)$  is the number of answer words for the given question and image. In our approach, named Neural-Image-QA, we propose to tackle the problem as follows. To predict multiple words we formulate the problem as predicting a sequence of words from the vocabulary  $\mathcal{V} := \mathcal{V}' \cup \{\$\}$  where the extra token  $\$$  indicates the end of the answer sequence, and points out that the question has been fully answered. We thus formulate the prediction procedure recursively:

$$\hat{\mathbf{a}}_t = \arg \max_{\mathbf{a} \in \mathcal{V}} p(\mathbf{a} | \mathbf{x}, \mathbf{q}, \hat{A}_{t-1}; \theta) \quad (2)$$

where  $\hat{A}_{t-1} = \{\hat{\mathbf{a}}_1, \dots, \hat{\mathbf{a}}_{t-1}\}$  is the set of previous words, with  $\hat{A}_0 = \{\}$  at the beginning, when our approach has not given any answer so far. The approach is terminated when  $\hat{\mathbf{a}}_t = \$$ . We evaluate the method solely based on the predicted answer words ignoring the extra token  $\$$ . To ensure uniqueness of the predicted answer words, which would make sense since we want to predict a set of the answer words, the prediction procedure can be trivially changed by maximizing over  $\mathcal{V} \setminus \hat{A}_{t-1}$ . However, in practice, our algorithm learns not to predict any previously predicted words.

As shown in Figure 1 and Figure 2, we feed Neural-Image-QA with a question as a sequence of words, i.e.  $\mathbf{q} = [\mathbf{q}_1, \dots, \mathbf{q}_{n-1}, [\text{?}]]$ , where each  $\mathbf{q}_t$  is the  $t$ -th word question and  $[\text{?}] := \mathbf{q}_n$  encodes the question mark - the end of the question. Since our problem is formulated as a variable-length input/output sequence, we model the parametric distribution  $p(\cdot | \mathbf{x}, \mathbf{q}; \theta)$  of Neural-Image-QA with a recurrent neural network and a softmax prediction layer. More precisely, Neural-Image-QA is a deep network built of CNN [13] and Long-Short Term Memory (LSTM) [5]. LSTM has been recently shown to be effective in learning a variable-length sequence-to-sequence mapping [3, 20].

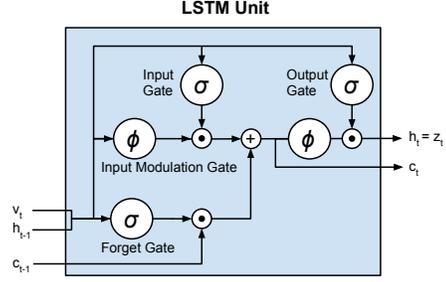


Figure 3. LSTM unit. See Section 3, Equations (3)-(8) for details.

Both question and answer words are represented with one-hot vector encoding (a binary vector with exactly one non-zero entry at the position indicating the index of the word in the vocabulary) and embedded in a lower dimensional space, using a jointly learnt latent linear embedding. In the training phase, we augment the question words sequence  $\mathbf{q}$  with the corresponding ground truth answer words sequence  $\mathbf{a}$ , i.e.  $\hat{\mathbf{q}} := [\mathbf{q}, \mathbf{a}]$ . During the test time, in the prediction phase, at time step  $t$ , we augment  $\mathbf{q}$  with previously predicted answer words  $\hat{\mathbf{a}}_{1..t} := [\hat{\mathbf{a}}_1, \dots, \hat{\mathbf{a}}_{t-1}]$ , i.e.  $\hat{\mathbf{q}}_t := [\mathbf{q}, \hat{\mathbf{a}}_{1..t}]$ . This means the question  $\mathbf{q}$  and the previous answers are encoded implicitly in the hidden states of the LSTM, while the latent hidden representation is learnt. We encode the image  $\mathbf{x}$  using a CNN and provide it at every time step as input to the LSTM. We set the input  $\mathbf{v}_t$  as a concatenation of  $[\mathbf{x}, \hat{\mathbf{q}}_t]$ .

As visualized in detail in Figure 3, the LSTM unit takes an input vector  $\mathbf{v}_t$  at each time step  $t$  and predicts an output word  $z_t$  which is equal to its latent hidden state  $\mathbf{h}_t$ . As discussed above  $z_t$  is a linear embedding of the corresponding answer word  $\mathbf{a}_t$ . In contrast to a simple RNN unit the LSTM unit additionally maintains a memory cell  $\mathbf{c}$ . This allows to learn long-term dynamics more easily and significantly reduces the vanishing and exploding gradients problem [5]. More precisely, we use the LSTM unit as described in [27] and the *Caffe* implementation from [3]. With the *sigmoid* nonlinearity  $\sigma : \mathbb{R} \mapsto [0, 1]$ ,  $\sigma(v) = (1 + e^{-v})^{-1}$  and the *hyperbolic tangent* nonlinearity  $\phi : \mathbb{R} \mapsto [-1, 1]$ ,  $\phi(v) = \frac{e^v - e^{-v}}{e^v + e^{-v}} = 2\sigma(2v) - 1$ , the LSTM updates for time step  $t$  given inputs  $\mathbf{v}_t$ ,  $\mathbf{h}_{t-1}$ , and the memory cell  $\mathbf{c}_{t-1}$  as follows:

$$\mathbf{i}_t = \sigma(W_{vi}\mathbf{v}_t + W_{hi}\mathbf{h}_{t-1} + \mathbf{b}_i) \quad (3)$$

$$\mathbf{f}_t = \sigma(W_{vf}\mathbf{v}_t + W_{hf}\mathbf{h}_{t-1} + \mathbf{b}_f) \quad (4)$$

$$\mathbf{o}_t = \sigma(W_{vo}\mathbf{v}_t + W_{ho}\mathbf{h}_{t-1} + \mathbf{b}_o) \quad (5)$$

$$\mathbf{g}_t = \phi(W_{vg}\mathbf{v}_t + W_{hg}\mathbf{h}_{t-1} + \mathbf{b}_g) \quad (6)$$

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \mathbf{g}_t \quad (7)$$

$$\mathbf{h}_t = \mathbf{o}_t \odot \phi(\mathbf{c}_t) \quad (8)$$

where  $\odot$  denotes element-wise multiplication. All the weights  $W$  and biases  $b$  of the network are learnt jointly

with the cross-entropy loss. Conceptually, as shown in Figure 3, Equation 3 corresponds to the input gate, Equation 6 the input modulation gate, and Equation 4 the forget gate, which determines how much to keep from the previous memory  $c_{t-1}$  state. As Figures 1 and 2 suggest, all the output predictions that occur before the question mark are excluded from the loss computation, so that the model is penalized solely based on the predicted answer words.

**Implementation** We use default hyper-parameters of LSTM [3] and CNN [7]. All CNN models are first pre-trained on the ImageNet dataset [17], and next we fine-tune the last layer together with the full training of the LSTM network on the task. We find this step crucial in obtaining good results. We have explored the use of a 2 layered LSTM model, but have consistently obtained worse performance. In a pilot study, we have found that *GoogLeNet* architecture [7, 21] consistently outperforms the *AlexNet* architecture [7, 12] as a CNN model for our task and model.

## 4. Experiments

In this section we benchmark our method on a task of answering questions about images. We compare different versions of our proposed model to prior work. In addition, we analyze how well questions can be answered without using the image in order to gain an understanding of biases in form of prior knowledge and common sense. We provide a new human baseline for this task. We also realize ambiguities in the question answering tasks and analyze them further by introducing metrics that are sensitive to this phenomena and additional ground truth annotations to quantify the effects.

**Experimental protocol** We evaluate our approach on the DAQUAR dataset [15] which provides 12468 human question answer pairs on images of indoor scenes[18] and follow their evaluation protocol by providing results on accuracy and the WUPS score at  $\{0.9, 0.0\}$ . We run experiments for the full dataset as well as their proposed reduced set that restricts the output space to only 37 object categories and uses 25 test images.

### 4.1. Evaluation of Neural-Image-QA

We start with the evaluation of our Neural-Image-QA on the full DAQUAR dataset in order to study different variants and training conditions. Afterwards we evaluate on the reduced DAQUAR for additional points of comparison to prior work.

**Results on full DAQUAR** Table 1 shows the results of our Neural-Image-QA method on the full set (“multiple words”). In addition, we evaluate a variant that is trained

to predict only a single word (“single word”) as well as a variant that does not use visual features (“Language only”). In comparison to the prior work [15] (shown in the first row in Table 1), we observe strong improvements of over 9% points in accuracy and over 11 in the WUPS scores [second row in Table 1 that corresponds to “multiple words”]. Note that, we achieve this improvement despite the fact that the number available for the comparison on the full set uses ground truth object annotations [15] – which puts our method at a disadvantage. Further improvements are observed when we train only on a single word answer, which almost triples the accuracy obtained in the prior work. We attribute this to a joint training of the language and visual representations and the dataset bias, where about 90% of the answers contain only a single word. We further analyze this effect in Figure 4, where we show performance of our approach (“multiple words”) in dependence on the number of words in the answer (truncated at 4 words due to the diminishing performance). The performance of the “single word” variants are shown as horizontal lines. Although accuracy drops rapidly for longer answers, our model is capable of producing a significant number of correct multiple word answers. The “single word” variants have an edge on the single answers and benefit from the dataset bias towards these type of answers. While we have made substantial progress compared to prior work, there is still a 30% points margin to human accuracy and 25 in WUPS score [“Human answers” in Table 1].

**Results on reduced DAQUAR** In order to provide performance numbers that are comparable to the proposed Multi-World approach in [15], we also run our method on the reduced set with 37 object classes and only 25 test images. Table 2 shows that Neural-Image-QA also improves on the reduced DAQUAR set, achieving 34.68% Accuracy and 40.76% WUPS at 0.9 substantially outperforming [15] by a 21.95% and 22.6 WUPS score difference. Similarly to previous experiments, we achieve the best performance using the “single word” variant.

### 4.2. Answering questions without looking at images

In order to study how much information is already contained in questions, we train a version of our model that ignores the visual input. The results are shown in Table 1 and Table 2 under “Language only (ours)”. The best “Language only” models with 17.15% and 32.32% compare very well in terms of accuracy to the best models that include vision. The latter achieve 19.43% and 34.68% on the full and reduced set respectively.

In order to further analyze this finding, we have collected a new human baseline “Human answer, no image”, where we have asked participants to answer on the DAQUAR questions without looking at the images. It turns out that hu-

	Accuracy	WUPS @0.9	WUPS @0.0
Malinowski et. al. [15]	7.86	11.86	38.79
Neural-Image-QA (ours)			
- multiple words	17.49	23.28	57.76
- single word	<b>19.43</b>	<b>25.28</b>	<b>62.00</b>
Human answers [15]	50.20	50.82	67.27
Language only (ours)			
- multiple words	17.06	22.30	56.53
- single word	17.15	22.80	58.42
Human answers, no images	11.99	16.82	33.57

Table 1. Results on DAQUAR with all classes, in %.

	Accuracy	WUPS @0.9	WUPS @0.0
Malinowski et. al. [15]	12.73	18.10	51.47
Neural-Image-QA (ours)			
- multiple words	29.27	36.50	79.47
- single word	<b>34.68</b>	<b>40.76</b>	79.54
Language only (ours)			
- multiple words	32.32	38.39	80.05
- single word	31.65	38.35	<b>80.08</b>

Table 2. Results on DAQUAR with a reduced set of 37 object classes and 25 test images, in %.

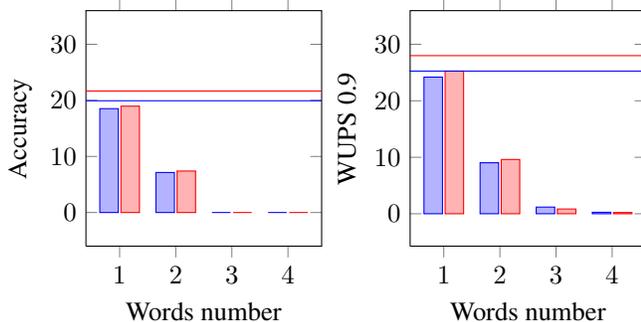


Figure 4. Comparison between the “Language only” (blue bar) and “Neural-Image-QA” (red bar) models. The blue and red horizontal bars represent a single word “Language only” and “Neural-Image-QA” models evaluated on the answers with exactly 1 words.

mans can guess the correct answer in 11.99% of the cases by exploiting prior knowledge and common sense. Interestingly, our best “language only” model outperforms the human baseline by over 5% for which we conclude that our model has captured some of the reoccurring patterns that can be viewed as a form of common sense knowledge.

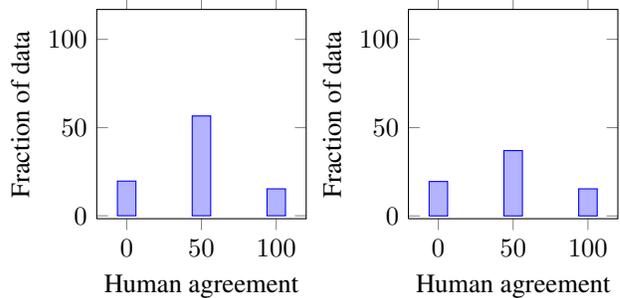


Figure 5. At  $x$ -axis: no consensus (0), at least half consensus (50), full consensus (100). Results in %. Left: consensus on the whole data, right: consensus on the test data.

### 4.3. Human Consensus

We observe that in many cases there is an inter human agreement in the answers for a given image and question and this is also reflected by the human baseline performance on the question answering task of 50.20% [“Human answers” in Table 1]. We study and analyze this effect further by supplying an extended set of human answers in Section 4.3.1, proposing new measure that handles disagreement in Section 4.3.2, as well as conducting additional experiments in Section 4.3.3.

#### 4.3.1 Extended annotation set

In order to study the effects of consensus in the question answering task, we have asked participants to answer the questions of the DAQUAR dataset given the respective images. We follow the same scheme as in the original data collection effort, where the answer is a set of words or numbers. We do not impose any further restrictions on the answers. This extends the original data to an average of 5 answers per image and question.

#### 4.3.2 Consensus Measures

While we have to acknowledge inherent ambiguities in our task, we seek a metric, that prefers an answer that is commonly seen as preferred. We make two proposals:

**Average Consensus:** We use our new annotation set that contains multiple answers per question in order to compute an expected score in the evaluation:

$$\frac{1}{NK} \sum_{i=1}^N \sum_{k=1}^K \min \left\{ \prod_{a \in A^i} \max_{t \in T_k^i} \mu(a, t), \prod_{t \in T_k^i} \max_{a \in A^i} \mu(a, t) \right\} \quad (9)$$

where for the  $i$ -th question  $A^i$  is the answer produced by the architecture and  $T_k^i$  is the  $k$ -th possible human answer corresponding to the  $k$ -th interpretation of the question. Both

answers  $A^i$  and  $T_k^i$  are sets of the words, and  $\mu$  is a membership measure, for instance WUP [26]. We call the metric in Equation 9 Average Consensus Metric (ACM) since, in the limits, as  $K$  approaches the total number of humans, we truly measure the inter human agreement of every question.

**Min Consensus:** The Average Consensus Metric puts more weights on more “mainstream” answers due to the summation over possible answers given by humans. In order to measure if the result was at least with one human in agreement, we propose a Min Consensus Metric (MCM) by replacing the averaging in Equation 9 with a max operator. We call such metric Min Consensus and suggest using both metrics in the benchmarks. We will make the implementation of both metrics publicly available.

$$\frac{1}{N} \sum_{i=1}^N \max_{k=1}^K \left( \min \left\{ \prod_{a \in A^i} \max_{t \in T_k^i} \mu(a, t), \prod_{t \in T_k^i} \max_{a \in A^i} \mu(a, t) \right\} \right) \quad (10)$$

Both Equation 10 and Equation 9 are multiplied by 100.0 to report the results in %. Intuitively, the max operator uses in evaluation a human answer that is the closest to the predicted one – which represents a minimal form of consensus.

### 4.3.3 Consensus results

Based on the additional answer we have collected on DAQUAR we can show a more detailed analysis of inter human agreement. Figure 5 shows the fraction of the data where the answers agree between all available questions (“100”), at least 50% of the available questions and do not agree at all (no agreement - “0”). We observe that for the majority of the data, there is partial agreement, but even full disagreement is possible. We split the dataset into three parts according to the above criteria “No agreement”, “ $\geq 50\%$  agreement” and “Full agreement” and evaluate our models on these splits (Table 3 summarizes the results). On subsets with stronger agreement, we achieve substantial gains up to 10% points in accuracy. These splits can be seen as curated versions of DAQUAR, which allows studies with factored out ambiguities - yet this approach comes with the problem of drastically reducing the test set size.

Therefore, we also show in Table 3 the application of our new consensus measures: “Average Consensus Metric” and “Min Consensus Metric”. We observe that the “Min Consensus Metric” has the desired effect of providing an additional more optimistic evaluation, while still using the whole dataset. The “Average Consensus Metric” on the other hand takes alternative answers into account while encouraging prediction of the most agreeable one. We argue that these improved metrics on the extended annotation set should be further considered to facilitate more accurate

	Accuracy	WUPS @0.9	WUPS @0.0
<b>Subset: No agreement</b>			
Language only (ours)			
- multiple words	8.86	12.46	38.89
- single word	8.50	12.05	40.94
<hr/>			
Neural-Image-QA (ours)			
- multiple words	<b>10.31</b>	<b>13.39</b>	40.05
- single word	9.13	13.06	<b>43.48</b>
<hr/>			
<b>Subset: <math>\geq 50\%</math> agreement</b>			
Language only (ours)			
- multiple words	21.17	27.43	66.68
- single word	20.73	27.38	67.69
<hr/>			
Neural-Image-QA (ours)			
- multiple words	20.45	27.71	67.30
- single word	<b>24.10</b>	<b>30.94</b>	<b>71.95</b>
<hr/>			
<b>Subset: Full Agreement</b>			
Language only (ours)			
- multiple words	27.86	35.26	78.83
- single word	25.26	32.89	79.08
<hr/>			
Neural-Image-QA (ours)			
- multiple words	22.85	33.29	78.56
- single word	<b>29.62</b>	<b>37.71</b>	<b>82.31</b>
<hr/>			
<b>Average Consensus Metric</b>			
Language only (ours)			
- multiple words	11.60	18.24	52.68
- single word	11.57	18.97	54.39
<hr/>			
Neural-Image-QA (ours)			
- multiple words	11.31	18.62	53.21
- single word	<b>13.51</b>	<b>21.36</b>	<b>58.03</b>
<hr/>			
<b>Min Consensus Metric</b>			
Language only (ours)			
- multiple words	22.14	29.43	66.88
- single word	22.56	30.93	69.82
<hr/>			
Neural-Image-QA (ours)			
- multiple words	22.74	30.54	68.17
- single word	<b>26.53</b>	<b>34.87</b>	<b>74.51</b>

Table 3. Results on DAQUAR with all classes, Consensus in %.

measurements of progress on such question answering tasks that have a level of ambiguity inherent to the task.

## 4.4. Qualitative results

We show predicted answers of different variants of our architecture in Table 4, 5, and 6. We have chosen the examples to highlight differences between “Neural-Image-QA” and the “language only”. We call both versions of the former, either “multiple words” or “single word”, collectively “Vision+Language”. We use a “multiple words” approach

		
What is on the right side of the cabinet?	How many drawers are there?	What is the largest object?
<i>Vision+Language:</i> <b>bed</b>	3	<b>bed</b>
<i>Language only:</i> <b>bed</b>	6	<b>table</b>

Table 4. Examples of questions and answers. Correct predictions are colored in green, incorrect in red.

		
What is on the refrigerator?	What is the colour of the comforter?	What objects are found on the bed?
<i>Vision+Language:</i> <b>magnet, paper</b>	<b>blue, white</b>	<b>bed sheets, pillow</b>
<i>Language only:</i> <b>magnet, paper</b>	<b>blue,green, red, yellow</b>	<b>doll, pillow</b>

Table 5. Examples of questions and answers with multiple words. Correct predictions are colored in green, incorrect in red.

only in Table 5. Despite some failure cases, the latter model makes “reasonable guesses” like predicting that the largest object could be table or an object that could be found on the bed is either a pillow or doll. The last Table 6 shows remaining failure cases that include (in order) strong occlusion, a possible answer not captured by our ground truth answers, and unusual instances (red toaster).

## 5. Conclusions

We have presented a neural architecture for answering natural language questions on image that contrasts with prior efforts based on semantic parsing and outperforms prior work by doubling performance on this challenging task. A variant of our model that does not use the image to answer the question performs only slightly worse and even outperforms a new human baseline that we have collected under the same condition. We conclude that our model has learnt biases and patterns that can be seen as forms of common sense knowledge and prior knowledge

that humans use to accomplish this task. We contribute an extended collection of additional answers that complement the existing dataset and study inter human agreement and consensus on the question answer task. We propose two new metrics “Average Consensus” and “Min Consensus” that constitute a more realistic, which takes into account human disagreement, measure and a more optimistic one that ignores consensus but captures disagreement in human question answering.

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## References

- [1] J. Berant and P. Liang. Semantic parsing via paraphrasing. In *ACL*, 2014.
- [2] K. Cho, B. van Merriënboer, C. Gulcehre, F. Bougares, H. Schwenk, D. Bahdanau, and Y. Bengio. Learning phrase



How many chairs are there?



What is the object fixed on the window?



Which item is red in colour?

<i>Vision+Language:</i>	1	curtain	remote control
<i>Language only:</i>	4	curtain	clock
<i>Ground truth answers:</i>	2	handle	toaster

Table 6. Examples of questions and answers - failure cases.

- representations using rnn encoder-decoder for statistical machine translation. In *EMNLP*, 2014.
- [3] J. Donahue, L. A. Hendricks, S. Guadarrama, M. Rohrbach, S. Venugopalan, K. Saenko, and T. Darrell. Long-term recurrent convolutional networks for visual recognition and description. In *CVPR*, 2015.
- [4] D. Geman, S. Geman, N. Hallonquist, and L. Younes. Visual Turing test for computer vision systems. *Proceedings of the National Academy of Sciences*, 2015.
- [5] S. Hochreiter and J. Schmidhuber. Long short-term memory. *Neural Computation*, 1997.
- [6] M. Iyyer, J. Boyd-Graber, L. Claudino, R. Socher, and H. D. III. A neural network for factoid question answering over paragraphs. In *EMNLP*, 2014.
- [7] Y. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell. Caffe: Convolutional architecture for fast feature embedding. *arXiv:1408.5093*, 2014.
- [8] A. Karpathy and L. Fei-Fei. Deep visual-semantic alignments for generating image descriptions. In *CVPR*, 2015.
- [9] A. Karpathy, A. Joulin, and L. Fei-Fei. Deep fragment embeddings for bidirectional image sentence mapping. In *NIPS*, 2014.
- [10] C. Kong, D. Lin, M. Bansal, R. Urtasun, and S. Fidler. What are you talking about? text-to-image coreference. In *CVPR*, 2014.
- [11] J. Krishnamurthy and T. Kollar. Jointly learning to parse and perceive: Connecting natural language to the physical world. *TACL*, 2013.
- [12] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In *NIPS*, 2012.
- [13] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 1998.
- [14] P. Liang, M. I. Jordan, and D. Klein. Learning dependency-based compositional semantics. *Computational Linguistics*, 2013.
- [15] M. Malinowski and M. Fritz. A multi-world approach to question answering about real-world scenes based on uncertain input. In *NIPS*, 2014.
- [16] C. Matuszek, N. Fitzgerald, L. Zettlemoyer, L. Bo, and D. Fox. A joint model of language and perception for grounded attribute learning. In *ICML*, 2012.
- [17] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. Fei-Fei. Imagenet large scale visual recognition challenge. *arXiv:1409.0575*, 2014.
- [18] N. Silberman, D. Hoiem, P. Kohli, and R. Fergus. Indoor segmentation and support inference from rgb-d images. In *ECCV*, 2012.
- [19] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv:1409.1556*, 2014.
- [20] I. Sutskever, O. Vinyals, and Q. V. V. Le. Sequence to sequence learning with neural networks. In *NIPS*. 2014.
- [21] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. *arXiv:1409.4842*, 2014.
- [22] S. Venugopalan, H. Xu, J. Donahue, M. Rohrbach, R. Mooney, and K. Saenko. Translating videos to natural language using deep recurrent neural networks. In *NAACL*, 2015.
- [23] O. Vinyals, A. Toshev, S. Bengio, and D. Erhan. Show and tell: A neural image caption generator. *arXiv:1411.4555*, 2014.
- [24] J. Weston, A. Bordes, S. Chopra, and T. Mikolov. Towards ai-complete question answering: A set of prerequisite toy tasks. *arXiv:1502.05698*, 2015.
- [25] J. Weston, S. Chopra, and A. Bordes. Memory networks. *arXiv:1410.3916*, 2014.

- [26] Z. Wu and M. Palmer. Verbs semantics and lexical selection. In *ACL*, 1994.
- [27] W. Zaremba and I. Sutskever. Learning to execute. *arXiv preprint arXiv:1410.4615*, 2014.
- [28] C. L. Zitnick, D. Parikh, and L. Vanderwende. Learning the visual interpretation of sentences. In *ICCV*, 2013.