Image Question Answering: A Visual Semantic Embedding Model and a New **Dataset**

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Abstract

This work aims to address the problem of imagebased question-answering (OA) with new models and datasets. In our work, we propose to use recurrent neural networks and visual semantic embeddings without intermediate stages such as object detection and image segmentation. Our model performs 1.8 times better than the recently published results on the same dataset. Another main contribution is an automatic question generation algorithm that converts the currently available image description dataset into QA form, resulting in a 10 times bigger dataset with more evenly distributed answers.

1. Introduction

Combining image understanding and natural language interaction is one of the grand dreams of artificial intelligence. We are interested in the problem of jointly learning image and text through a question-answering task. Recently, image caption generation (Vinyals et al., 2014; Kiros et al., 2014; Karpathy et al., 2014; Mao et al., 2014; Donahue et al., 2014; Chen & Zitnick, 2014; Fang et al., 2014; Xu et al., 2015; Lebret et al., 2015) has shown us feasible ways of jointly learning image and text to form higher level representations from models such as convolutional neural networks (CNNs) trained on object recognition and word embeddings trained on large scale text corpus. Image QA involves an extra layer of interation between human and computers. Here the inputs are combined image and text and the model needs to output an answer that is targeted to the question asked. The model needs to pay attention to details of the image instead of describing it in a vague sense. The problem also combines many com-

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puter vision subproblems such as image labelling and object detection. Unlike traditional computer vision tasks, it is not obvious what kind of task the model needs to perform unless it understands the question.

In this paper we present our contribution to the problem: a generic end-to-end QA model using visual semantic embeddings to connect a CNN and a recurrent neural net (RNN); an automatic question generation algorithm that converts description sentences into questions; and a new OA dataset (COCO-OA) which is generated using the algorithm. We will make the our COCO-QA dataset publicly available upon the release of the paper.



DQ212: What is the object close to the wall right and left of the cabinet? Ground truth: television VIS+LSTM-2: television (0.3950) LSTM: window (0.5004)



CQ318: How many young children are there standing behind stuffed bears? Ground truth: three VIS+LSTM-2: two (0.5197) VIS+BOW: two (0.6345) LSTM: two (0.6526)



CQ14732: What is the color of the Ground truth: three

LSTM: brown (0.1538)

VIS+LSTM-2: green (0.3015) VIS+BOW: white (0.2932)



CQ135: Where is the gray cat sitting? Ground truth: window VIS+LSTM-2: window (0.6956) VIS+BOW: window (0.5854) LSTM: sink (0.4757)

Figure 1. Sample questions and responses of a variety of models. Correct answers are in green and incorrect in red. Number in parentheses is the probability assigned to the top-ranked answer by the given model.

2. Problem Formulation

The inputs of the problem are an image and a question, and the output is an answer. In this work we assume that the answers consist of only a single word, which allows us to treat the problem as a classification problem. This also makes the evaluation of the models easier and more robust.

3. Related Work

Malinowski & Fritz (2014a) released a dataset with images and question-answer pairs, the DAtaset for QUestion Answering on Real-world images (DAQUAR). All images are from the NYU depth v2 dataset (Silberman et al., 2012), and are taken from indoor scenes. Human segmentations, image depth values, and object labellings are available in the dataset. The QA data has two sets of configurations, which differ by the number of object classes appearing in the questions (37-class and 894-class). There are mainly three types of questions in this dataset: object type, object color, and number of objects. Some questions are easy but many questions are very hard to answer even for humans. Figure 2 shows some examples of easy and hard questions. Since DAQUAR is the only publicly available image-based OA dataset, it is one of our benchmarks to evaluate our models.

Together with the release of the DAQUAR dataset, Malinowski & Fritz (2014b) presented an approach which combines semantic parsing and image segmentation. In the natural language part of their work, they used a semantic parser (Liang et al., 2013) to convert sentences into latent logical forms. They obtained multiple segmentations of the image by sampling the uncertainty of the segmentation algorithm. Their model is based on a Bayesian formulation that every logical form and image segmentation has certain probability. They also converted each image segmentation to a bag of predicates. To make their algorithm scalable, they chose to sample from the nearest neighbors in the training set according to the similarity of the predicates.

This approach is notable as one of the first attempts at image QA, but it has a number of limitations. First, although they are handling a number of spatial relations, a human-defined possible set of predicates are very dataset-specific. To obtain the predicates, their algorithm also depends on a good image segmentation algorithm and image depth information. Second, before asking any of the questions, their model needs to compute all possible spatial relations in the training images, so even for a small dataset like 1500 images there could be 4 million predicates in the worst case (Malinowski & Fritz, 2014b). Even though the model searches from the nearest neighbors of the test images, it could still be an expensive operation in larger datasets. Lastly the accuracy of their model is not

very strong. We will show later that some simple baselines will perform better in terms of plain accuracy.

4. Proposed Methodology

The methodology presented here is two-fold. On the model side we applied recurrent neural networks and visual-semantic embeddings on this task, and on the dataset side we proposed new ways of synthesizing QA pairs from currently available image description dataset.

4.1. Models

In recent years, recurrent neural networks (RNNs) have enjoyed some successes in the field of natural language processing (NLP). Long short-term memory (LSTM) (Hochreiter & Schmidhuber, 1997) is a form of RNN which is easier to train than standard RNNs because of its linear error propagation and multiplicative gatings. There has been increasing interest in using LSTM as encoders and decoders on sentence level. Our model builds directly on top of the LSTM sentence model and is called the "VIS+LSTM" model. It treats the image as one word of the question. We borrowed this idea of treating the image as a word from caption generation work done by Vinyals et al. (2014). The difference with caption generation is that here we only output the answer at the last timestep.

- We used the last hidden layer of the Oxford Conv Net (Simonyan & Zisserman, 2014) trained on ImageNet (Russakovsky et al., 2014) as our visual embeddings. The conv-net (CNN) part of our model is kept frozen during training.
- We experimented with several different word embedding models: randomly initialized embedding, dataset-specific skip-gram embedding and general-purpose skip-gram embedding model (Mikolov et al., 2013). The word embeddings can either be frozen or dynamic.
- 3. We then treated the image as if it is the first word of the sentence. Similar to (Frome et al., 2013), we used a linear or affine transformation to map 4096 dimension image feature vectors to a 300 or 500 dimensional vector that matches the dimension of the word embeddings.
- 4. We can optionally treat the image as the last word of the question as well through a different weight matrix.
- We can optionally add a reverse LSTM, which gets the same content but operates in a backward sequential fashion.
- 6. The LSTM(s) outputs are fed into a softmax layer at the last timestep to generate answers.



DQ2355: What is the color of roll of tissue paper? Ground truth: white

Comment: This question is easy because toilet tissue paper is always white.



DQ1466: What is on the night stand? Ground truth: paper

Comment: This question is very hard because the object is too small to focus.



DQ2010: What is to the right of the table?

Ground truth: sink

Comment: There are too many cluttered objects.

Figure 2. Sample questions from DAQUAR, showing a variety of difficulty levels (last line contains our own editorial comments).

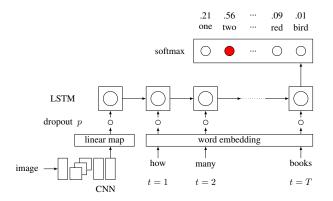


Figure 3. VIS+LSTM Model

4.2. Question-Answer Generation

The currently available DAQUAR dataset contains approximately 1500 images, with 7000 images on 37 common object classes, which might be not enough for training large complex models. Another problem with the current dataset is that simply guessing the mode can yield very good accuracy. We aim to create another dataset, to produce a much larger number of QA pairs and a more even distribution of answers. While collecting human generated QA pairs is one possible approach, and another is to generate questions based on image labellings, we instead propose to automatically convert descriptions into QA form.

As a starting point we used the Microsoft-COCO dataset (Lin et al., 2014), but the same method can be applied to any other image description dataset, such as Flickr (Hodosh et al., 2013), SBU (Ordonez et al., 2011), or even the internet. Another advantage of using image descriptions is that they are generated by humans in the first place. Hence most objects mentioned in the descriptions are easier to notice than the ones in DAQUAR's human generated questions,

and synthetic QAs from ground truth labellings. This allows the model to rely more on common sense and rough image understanding without any logic reasoning. Lastly the conversion process preserves the language variability in the original description and will result in more human-like questions than questions generated from image labellings.

Question generation is still an open-ended topic. We are not trying to solve a linguistic problem but instead aim to create a usable image QA dataset. We adopt a conservative approach to generating questions: because we have the luxury of large publicly-available image description datasets, we can afford to reject many possible questions in an attempt to create high-quality questions.

4.2.1. COMMON STRATEGIES

1. Compound sentences to simple sentences
Here we only consider a simple case, where two sentences are joined together with a conjunctive words.
We split the original sentences into two independent sentences. For example, "There is a cat and the cat is running." will be split as "There is a cat." and "The cat is running."

2. Indefinite determiners to definite determiners. Asking questions on a specific instance of the subject requires changing the determiner into definite form "the". For example, "A boy is playing <u>baseball</u>." will have "the" instead of "a" in its question form: "What is **the** boy playing?".

3. Wh-movement constraints

In English, questions tend to start with interrogative words such as "what". The algorithm needs to move the verb as well as the "wh-" constituent to the front of the sentence. In this work we consider the following two simple constraints:

(a) A-over-A principle

The A-over-A principle restricts the movement of a wh-word inside an NP (Chomsky, 1973). For example, "I am talking to John and Bill" cannot be transformed into "*Who am I talking to John and" because "Bill" is an noun phrase (NP) that is under another NP "John and Bill".

(b) Clauses

Our algorithm does not move any wh-word that is contained in a clause constituent. This rule can be refined further in future work.

4.2.2. PRE-PROCESSING

We used the Stanford parser (Klein & Manning, 2003) to obtain the syntatic structure of the original image description.

4.2.3. Object QUESTIONS

First, we consider asking about an object using "what". This involves replacing the actual object with a "what" in the sentence, and then transforming the sentence structure so that the "what" appears in the front of the sentence. The entire algorithm has the following stages:

- 1. Split long sentences into simple sentences
- 2. Change indefinite determiners to definite determiners.
- 3. Traverse the sentence and identify potential answers and replace with "what". During the traversal of object-type question generation, we currently ignore all the prepositional phrase (PP) consituents.

4. Perform wh-movement

Figure 4 illustrates an example with tree diagrams. In order to identify a possible answer word, we used WordNet (Fellbaum, 1998) and NLTK software package (Bird, 2006) to get noun categories.

4.2.4. Number QUESTIONS

To generate "how many" type questions, we follow a similar procedure as the previous algorithm, except for a different way to identify potential answers. This time, we need to extract numbers from original sentences. Splitting compound sentences, changing determiners, and wh-movement parts remain the same.

4.2.5. Color Questions

Color questions are much easier to generate. This only requires locating the color adjective and the noun which the adjective attaches to. Then it simply forms a sentence "What is the color of the object" with the "object" replaced by the actual noun.

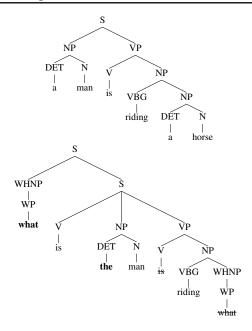


Figure 4. Example: "A man is riding a horse" => "What is the man riding?"

4.2.6. Location QUESTIONS

These are similar to generating object questions, except that now the answer traversal will only search within PP contituents that start with the preposition "in". We also added rules to filter out clothing so that the answers will mostly be locations, scenes, or large objects that contain smaller objects.

4.2.7. POST-PROCESSING

We will show in our experiment results that mode-guessing actually works unexpectedly well in the DAQUAR dataset. One of our design requirements of the new dataset is to avoid too common answers. To achieve this goal, we applied a heuristic to reject the answers that appear too rare or too often in our generated dataset. First, answers that appear less than a frequency threshold are discarded. In COCO-QA the threshold is around 20 in training set and 10 in test set. Then, all QA pairs are shuffled to mitigate the dependence between neighboring pairs. We formulate the rejection process as a Bernoulli random process. The probability of enrolling the next QA pair (q,a) is:

$$p(q, a) = \begin{cases} 1 & \text{if count}(a) \le K \\ \exp\left(-\frac{count(a) - K}{K_2}\right) & \text{otherwise} \end{cases}$$
 (1)

where count(a) denotes the current number of enrolled QA pairs that have a as the ground truth answer, and K, K_2 are some constants with $K \leq K_2$. In the COCO-QA generation we chose K=100 and $K_2=200$. After this

QA rejection process we obtain a more uniform distribution across the possible answers. Post-processing reduces the mode composition from 24.80% down to 6.65% in the test set of COCO-QA.

5. Experimental Results

5.1. Datasets

Table 1 summarizes the difference between DAQUAR and COCO-QA. It should be noted that since we applied the QA pair rejection process, mode-guessing performs very poorly on COCO-QA; however, COCO-QA questions are actually easier to answer from a human point of view. This encourages the model to exploit salient object relations instead of exhaustively search all possible relations.

Table 1. General Statistics of DAQUAR and COCO-QA

DATASET	DAQUAR-37	COCO-QA
IMAGES	795+654	80K+40K
QUESTIONS	3825+3284	83K+39K
ANSWERS	63	410
GUESS	0.1885	0.0665

Table 2 gives a breakdown of all four types of questions present in the COCO-QA dataset, with train/test split information.

5.2. Model Details

We trained two versions of the architectures that we found to work the best. The first model is the CNN and LSTM with a weight matrix in the middle; we call this "VIS+LSTM" in our tables and figures. The second model has two image feature input at the start and the end of the sentence with different learned linear transformations, and also has LSTMs going in both the forward and backward direction. Both LSTMs output to the softmax layer at the last timestep. We call the second model "VIS+LSTM-2".

Table 2. COCO-QA Question Type Break-Down

CATEGORY	TRAIN	%	TEST	%
OBJECT NUMBER COLOR LOCATION	58352 6551 13337 5164	69.96% 7.85% 15.99% 6.19%	27497 2575 6047 2541	71.13% 6.66% 15.64% 6.57%
TOTAL	83404	100.00%	38660	100.00%

5.3. Baselines

To evaluate the effectiveness of our models, we designed a few baselines.

5.3.1. GUESS MODEL

One very simple baseline is to predict the mode based on question type. For example, if the question contains "how many" then the model will output "two." In DAQUAR, the modes are "table", "two", and "white" and in COCO-QA, the modes are "cat", "two", "white", and "room". This baseline actually works unexpectedly well in the DAQUAR dataset.

5.3.2. BOW MODEL

To avoid over-interpretation of the results, we designed "blind" models which are given only the questions without the images. One of the simplest blind models is to sum all the word vectors of the question into a bag-of-word (BOW) vector. We then use logistic regression to classify answers with an optional tanh hidden layer.

5.3.3. LSTM MODEL

Another blind model we experimented with simply inputs the question words into the LSTM alone.

5.3.4. VIS+BOW MODEL

This is the same as the blind BOW model but replaced the feature layer with bag-of-word sentence features concatenated with image features from the Oxford Net last hidden layer (4096 dimension) after a linear transformation (to 300 or 500 dimensions).

5.3.5. VIS MODEL

For each type of question, we train a separate CNN last hidden layer (with all lower layers frozen during training). Note that this model knows the type of question in order to make its performance somewhat comparable to the models that can take into account the words to narrow down the answer space. However, the model does not know anything about the question except the type.

5.4. Performance Metrics

To evaluate model performance, we used the plain answer accuracy as well as the Wu-Palmer similarity (WUPS) measure (Wu & Palmer, 1994; Malinowski & Fritz, 2014b). The WUPS calculates the similarity between two words based on their longest common subsequence in the taxonomy tree. The similarity function takes in a threshold parameter. If the similarity between two words is less than the threshold then a score of zero will be given to the candidate

answer. It reduces to plain accuracy when the threshold equals to 1.0. Following (Malinowski & Fritz, 2014b), we measure all the models in terms of accuracy, WUPS 0.9, and WUPS 0.0.

Table 3 summarizes the learning results on DAQUAR. Here we compare our results with (Malinowski & Fritz, 2014b). It should be noted that their result is for the entire dataset whereas our result is for the 98.3% of the original dataset with single-word answers.

Table 3. DAQUAR Results

	Acc.	WUPS 0.9	WUPS 0.0
MULTI-WORLD	0.1273	0.1810	0.5147
GUESS	0.1824	0.2965	0.7759
BOW	0.3267	0.4319	0.8130
LSTM	0.3273	0.4350	0.8162
VIS+LSTM	0.3441	0.4605	0.8223
VIS+LSTM-2	0.3578	0.4683	0.8215
HUMAN	0.6027	0.6104	0.7896

Table 4. COCO-QA Results

Acc.	WUPS 0.9	WUPS 0.0
0.0665	0.1742	0.7344
0.3262	0.4396	0.7954
0.3516	0.4721	0.8065
0.4033	0.5681	0.8314
0.4490	0.5789	0.8360
0.5073	0.6243	0.8605
0.5161	0.6344	0.8628
	0.0665 0.3262 0.3516 0.4033 0.4490 0.5073	0.0665 0.1742 0.3262 0.4396 0.3516 0.4721 0.4033 0.5681 0.4490 0.5789 0.5073 0.6243

Table 5. COCO-QA Accuracy Per Category

	Овјест	Number	Color	LOCATION
GUESS	0.0211	0.3584	0.1387	0.0893
BOW	0.3201	0.3339	0.3434	0.3436
LSTM	0.3459	0.4383	0.3334	0.3680
VIS	0.4073	0.2769	0.4318	0.4207
VIS+BOW	0.4718	0.3773	0.4130	0.3609
VIS+LSTM	0.5321	0.4678	0.4439	0.4294
VIS+LSTM-2	0.5386	0.4534	0.4786	0.4258

6. Discussion

From the above results we show that our model outperforms the baselines and the existing approach in terms of answer accuracy and WUPS. It is interesting to see that the blind model is in fact very strong on the DAQUAR dataset, comparable to the VIS+LSTM model. We speculate that it is likely that the ImageNet images are very different from the indoor scene images which are mostly composed of furniture. Hence the VIS+LSTM cannot really make use of the image features unless the question is asking about the largest object, i.e., differentiating between sofas, beds, and tables. However, the VIS+LSTM model outperforms the blind model by a large margin on the COCO-QA dataset. There are three possible reasons behind. First, the objects in MS-COCO resemble the ones in ImageNet more; second, MS-COCO images have fewer objects whereas the indoor scenes have considerable clutter; and third, COCO-QA has more data to train complex models.

There are many interesting examples but due to space limitations we can only show a few in Figure 5, 6, 7. Full results are available to view at http://www.cs.toronto.edu/~mren/imageqa/results. For some of the examples, we specifically tested extra questions (the ones have an "a" in the question ID) to avoid over-interpretation of the questions that the VIS+LSTM accidentally got correct. The parentheses in the figures represent the confidence score given by the softmax layer of the models. "DQ" denotes questions from DAQUAR and "CQ" denotes questions from COCO-QA.

6.1. Model Selection

We did not find that using different word embedding has a significant impact on the final classification results. The best model for DAQUAR uses a randomly initialized embedding of 300 dimensions whereas the best model trained for COCO-QA uses a problem-specific skip-gram embedding to initialize. We observed that fine-tuning the word embedding and normalizing the CNN hidden image features help achieve better results. The bidirectional LSTM model can further boost the result by a little.

6.2. Object Questions

As the original CNN was trained for the ImageNet challenge, the VIS+LSTM benefited largely from its single object recognition ability. For some simple pictures in COCO-QA, the VIS+LSTM and VIS+BOW can easily get the correct answer just from the image features. However, the challenging part is to consider spatial relations between multiple objects and to focus on details of the image. Some qualitative results in Figure 5 show that the VIS+LSTM only does a moderately acceptable job on it. Sometimes it

fails to make a correct decision but outputs the most salient object, while sometimes the blind model can equally guess the most probable objects based on the question alone (e.g., chairs should be around the dining table).

6.3. Counting

In DAQUAR, we could not observe any advantage in the counting ability of the VIS+LSTM model compared to other blind baselines. In COCO-QA there is some observable counting ability in very clean images with single object type. The model can sometimes count up to five or six. However, as shown in Figure 6, the ability is fairly weak as it does not count correctly when different object types are present. As the VIS+LSTM model only beats the blind one by 3% on counting, there is a lot of room for improvement in the counting task, and in fact this could be a separate computer vision problem on its own.

6.4. Color

In COCO-QA there is a significant win for the VIS+LSTM model against the LSTM model on color-type questions. We further discovered that the model is not only able to recognize the dominant color of the image but sometimes associate different colors to different objects, as shown in Figure 7. However, the model is still not very robust and fails on a number of easy examples.

6.5. Limitations and Future Work

Image question answering is a fairly new research topic, and the approach we present here has a number of limitations. First the model is just an answer classifier. Ideally we would like to permit longer answers which will involve some sophisticated text generation model or structured output. Secondly, our question generation algorithm also assumes that all answers are single-word, and the implementation of the algorithm is heavily dependent on the question type. Furthermore, the algorithm is only applicable to the English language at this time. Lastly, it is hard to interpret why the model outputs a certain answer. By comparing the model to some baselines we can roughly infer whether the model understood the image but humans are prone to overinterpretation of the results. Visual attention is another future direction, which could both improve the results (based on recent successes in image captioning (Xu et al., 2015)) as well as help explain the model output by examining the attention output at every timestep.

7. Conclusion

In this paper, we consider the image QA problem and present our VIS+LSTM model, which combines CNN and LSTM(s) with visual-semantic embeddings. As the cur-

rently available dataset is not large enough, we designed an algorithm that helps us collect large scale image QA dataset from image descriptions. Our model shows a reasonable understanding of the question and some coarse image understanding, but it is still very naive in many situations. Our question generation algorithm is extensible to many image description datasets and can be automated without requiring extensive human effort. We hope that the release of the new dataset will encourage more data-driven approaches to this problem in the future.

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References

Bird, Steven. NLTK: the natural language toolkit. In ACL 2006, 21st International Conference on Computational Linguistics and 44th Annual Meeting of the Association for Computational Linguistics, Proceedings of the Conference, Sydney, Australia, 17-21 July 2006, 2006.

Chen, Xinlei and Zitnick, C. Lawrence. Learning a recurrent visual representation for image caption generation.

<u>CoRR</u>, abs/1411.5654, 2014. URL http://arxiv.
org/abs/1411.5654.

Chomsky, Noam. <u>Conditions on Transformations</u>. Academic Press, New York, 1973.

Donahue, Jeff, Hendricks, Lisa Anne, Guadarrama, Sergio, Rohrbach, Marcus, Venugopalan, Subhashini, Saenko, Kate, and Darrell, Trevor. Long-term recurrent convolutional networks for visual recognition and description.

<u>CoRR</u>, abs/1411.4389, 2014. URL http://arxiv.org/abs/1411.4389.

Fang, Hao, Gupta, Saurabh, Iandola, Forrest N., Srivastava, Rupesh, Deng, Li, Dollár, Piotr, Gao, Jianfeng, He, Xiaodong, Mitchell, Margaret, Platt, John C., Zitnick, C. Lawrence, and Zweig, Geoffrey. From captions to visual concepts and back. Corr., abs/1411.4952, 2014. URL VIRL http://arxiv.org/abs/1411.4952.

Fellbaum, Christiane (ed.). WordNet An Electronic Lexical

<u>Database</u>. The MIT Press, Cambridge, MA; London,
May 1998. ISBN 978-0-262-06197-1.

Frome, Andrea, Corrado, Gregory S., Shlens, Jonathon, Bengio, Samy, Dean, Jeffrey, Ranzato, Marc'Aurelio, and Mikolov, Tomas. Devise: A deep visual-semantic embedding model. In Advances in Neural

- Information Processing Systems 26: 27th Annual Conference on Neural Information Processing Systems 2013. Proceedings of a meeting held December 5-8, 2013, Lake Tahoe, Nevada, United States., pp. 2121–2129, 2013.
- Hochreiter, Sepp and Schmidhuber, Jürgen. Long short-term memory. Neural Computation, 9(8):1735–1780, 1997.
- Hodosh, Micah, Young, Peter, and Hockenmaier, Julia. Framing image description as a ranking task: Data, models and evaluation metrics. <u>J. Artif. Intell. Res. (JAIR)</u>, 47:853–899, 2013.
- Karpathy, Andrej, Joulin, Armand, and Fei-Fei, Li. Deep fragment embeddings for bidirectional image sentence mapping. <u>CoRR</u>, abs/1406.5679, 2014. URL http://arxiv.org/abs/1406.5679.
- Kiros, Ryan, Salakhutdinov, Ruslan, and Zemel, Richard S. Unifying visual-semantic embeddings with multimodal neural language models. <u>CoRR</u>, abs/1411.2539, 2014. URL http://arxiv.org/abs/1411.2539.
- Klein, Dan and Manning, Christopher D. Accurate unlexicalized parsing. In <u>In Proceedings of the 41st Annual Meeting of the Association for Computational Linguistics</u>, pp. 423–430, 2003.
- Lebret, Rémi, Pinheiro, Pedro O., and Collobert, Ronan. Phrase-based image captioning. <u>CoRR</u>, abs/1502.03671, 2015. URL http://arxiv.org/abs/1502.03671.
- Liang, Percy, Jordan, Michael I., and Klein, Dan. Learning dependency-based compositional semantics. Computational Linguistics, 39(2):389–446, 2013.
- Lin, Tsung-Yi, Maire, Michael, Belongie, Serge, Hays, James, Perona, Pietro, Ramanan, Deva, Dollár, Piotr, and Zitnick, C. Lawrence. Microsoft COCO: common objects in context. In Computer Vision ECCV 2014 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part V, pp. 740–755, 2014.
- Malinowski, Mateusz and Fritz, Mario. Towards a visual turing challenge. <u>CoRR</u>, abs/1410.8027, 2014a. URL http://arxiv.org/abs/1410.8027.
- Malinowski, Mateusz and Fritz, Mario. A multiworld approach to question answering about real-world scenes based on uncertain input. In Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada, pp. 1682–1690, 2014b.

- Mao, Junhua, Xu, Wei, Yang, Yi, Wang, Jiang, and Yuille, Alan L. Explain images with multimodal recurrent neural networks. CoRR, abs/1410.1090, 2014. URL http://arxiv.org/abs/1410.1090.
- Mikolov, Tomas, Chen, Kai, Corrado, Greg, and Dean, Jeffrey. Efficient estimation of word representations in vector space. <u>CoRR</u>, abs/1301.3781, 2013. URL http://arxiv.org/abs/1301.3781.
- Ordonez, Vicente, Kulkarni, Girish, and Berg, Tamara L. Im2text: Describing images using 1 million captioned photographs. In Advances in Neural Information Processing Systems 24: 25th Annual Conference on Neural Information Processing Systems 2011. Proceedings of a meeting held 12-14 December 2011, Granada, Spain., pp. 1143–1151, 2011.
- Russakovsky, Olga, Deng, Jia, Su, Hao, Krause, Jonathan, Satheesh, Sanjeev, Ma, Sean, Huang, Zhiheng, Karpathy, Andrej, Khosla, Aditya, Bernstein, Michael S., Berg, Alexander C., and Fei-Fei, Li. Imagenet large scale visual recognition challenge. CoRR, abs/1409.0575, 2014. URL http://arxiv.org/abs/1409.0575.
- Silberman, Nathan, Hoiem, Derek, Kohli, Pushmeet, and Fergus, Rob. Indoor segmentation and support inference from RGBD images. In Computer Vision ECCV 2012 12th European Conference on Computer Vision, Florence, Italy, October 7-13, 2012, Proceedings, Part V, pp. 746–760, 2012.
- Simonyan, Karen and Zisserman, Andrew. Very deep convolutional networks for large-scale image recognition.

 <u>CoRR</u>, abs/1409.1556, 2014. URL http://arxiv.
 org/abs/1409.1556.
- Vinyals, Oriol, Toshev, Alexander, Bengio, Samy, and Erhan, Dumitru. Show and tell: A neural image caption generator. <u>CoRR</u>, abs/1411.4555, 2014. URL http://arxiv.org/abs/1411.4555.
- Wu, Zhibiao and Palmer, Martha. Verb semantics and lexical selection. In <u>In Proceedings of the 32nd Annual Meeting of the Association for Computational Linguistics</u>, pp. 133–138, 1994.
- Xu, Kelvin, Ba, Jimmy, Kiros, Ryan, Cho, Kyunghyun, Courville, Aaron C., Salakhutdinov, Ruslan, Zemel, Richard S., and Bengio, Yoshua. Show, attend and tell: Neural image caption generation with visual attention. CoRR, abs/1502.03044, 2015. URL http://arxiv.org/abs/1502.03044.



CQ5429: What do two women hold with a picture on it? Ground truth: cake

VIS+LSTM-2: cake (0.5611) VIS+BOW: laptop (0.1443) LSTM: umbrellas (0.1567) BOW: phones (0.1447)



CQ24952: What is the black and white cat wearing? Ground truth: hat

VIS+LSTM-2: hat (0.6349) LSTM: tie (0.5821)



CQ25218: Where are the ripe bananas

sitting?

Ground truth: basket

VIS+LSTM-2: basket (0.4965)

LSTM: bowl (0.6415)

CQ25218a: What are in the basket?

Ground truth: bananas

VIS+LSTM-2: bananas (0.6443)

LSTM: bears (0.0956)



DQ585: What is the object on the chair? Ground truth: pillow

VIS+LSTM-2: pillow (0.6475) LSTM: clothes (0.3973)

DQ585a: Where is the pillow found? Ground truth: chair

VIS+LSTM-2: chair (0.1735) LSTM: cabinet (0.7913)



DQ2136: What is right of table?

Ground truth: shelves

VIS+LSTM-2: shelves (0.2780)

LSTM: shelves (0.2000)

DQ2136a: What is in front of table?

Ground truth: chair

VIS+LSTM-2: chair (0.3104)

LSTM: chair (0.3661)

Comment: Sometimes the blind model can infer indoor object relations without looking at the image.

CQ2007: What is next to the cup? Ground truth: banana VIS+LSTM-2: banana (0.3560)

LSTM: sandwich (0.0647)

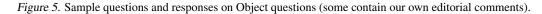
CQ2007a: What is sitting next to a banana?

Ground truth: cup

VIS+LSTM-2: banana (0.4539)

LSTM: cat (0.0538)

Comment: In this example the VIS+LSTM model fails to output different objects based on spatial relations.





CQ6805: How many uncooked doughnuts sit on the baking tray?

Ground truth: six VIS+LSTM-2: six (0.2779) VIS+BOW: twelve (0.2342)

LSTM: four (0.2345)



CQ32912: How many bottles of beer DQ1520: How many shelves are there?

are there?

Ground truth: three

VIS+LSTM-2: three (0.4153) VIS+BOW: two (0.4849)

CQ32912a: How many bananas are

there?

Ground truth: two

VIS+LSTM-2: three (0.1935) VIS+BOW: two (0.5307)



Ground truth: three

VIS+LSTM-2: two (0.4801) LSTM: two (0.2060)

DQ1520a: How many sofas are there?

Ground truth: two

VIS+LSTM-2: two (0.6173) LSTM: two (0.5378)

Comments: In the last two examples the model does not know how to count with

different object types.

Figure 6. Sample questions and responses on Number questions (some contain our own editorial comments).



DQ2989: What is the color of the sofa? Ground truth: red

VIS+LSTM-2: red (0.2152)

LSTM: brown (0.2061)

DQ2989a: What is the color of the ta-

ble?

Ground truth: white

VIS+LSTM-2: white (0.4057)

LSTM: white (0.2751)



CQ6200: What is the color of the cone?

Ground truth: yellow

VIS+LSTM-2: yellow (0.4250) VIS+BOW: white (0.5507)

LSTM: orange (0.4473)

CQ6200a: What is the color of the

bear?

Ground truth: white

VIS+LSTM-2: white (0.6000) VIS+BOW: white (0.5518)

LSTM: brown (0.5518)



CQ6058: What is the color of the coat?

Ground truth: yellow

VIS+LSTM-2: yellow (0.2942)

LSTM: black (0.2456)

CQ6058a: What is the color of the um-

brella?

Ground truth: red

VIS+LSTM-2: yellow (0.4755)

LSTM: purple (0.2243)

Figure 7. Sample questions and responses on Color questions (some contain our own editorial comments).