

Analyzing the Behavior of Visual Question Answering Models

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Abstract

Recently, a number of deep-learning based models have been proposed for the task of Visual Question Answering (VQA). The performance of most models is clustered around 60-70%. In this paper we propose systematic methods to analyze the behavior of these models as a first step towards recognizing their strengths and weaknesses, and identifying the most fruitful directions for progress. We analyze the best performing models from two major classes of VQA models – with-attention and without-attention and show the similarities and differences in the behavior of these models.

Our behavior analysis reveals that despite recent progress, today’s VQA models are “myopic” (tend to fail on sufficiently novel instances), often “jump to conclusions” (converge on a predicted answer after ‘listening’ to just half the question), and are “stubborn” (do not change their answers across images).

1 Introduction

Visual Question Answering (VQA) is a recently-introduced (Antol et al., 2015; Geman et al., 2014; Malinowski and Fritz, 2014) problem where – given an image and a natural language question (e.g., “What kind of store is this?”, “How many people are waiting in the queue?”), the task is to automatically produce an accurate natural language answer (“bakery”, “5”). A flurry of recent deep-learning based models have been proposed for VQA (Antol et al., 2015; Chen et al., 2015; Yang et al., 2015; Xu

and Saenko, 2015; Jiang et al., 2015; Andreas et al., 2015; Wang et al., 2015; Kafle and Kanan, 2016; Lu et al., 2016; Andreas et al., 2016; Shih et al., 2015; Kim et al., 2016; Fukui et al., 2016; Noh and Han, 2016; Ilievski et al., 2016; Wu et al., 2015; Xiong et al., 2016; Zhou et al., 2015; Saito et al., 2016). Curiously, the performance of most methods is clustered around 60-70% (compared to human performance of 83% on open-ended task and 91% on multiple-choice task) with a mere 5% gap between the top-9 entries on the VQA challenge.¹ It seems clear that as a first step to understand these models, to meaningfully compare strengths and weaknesses of different models, to develop insights into their failure modes, and to identify the most fruitful directions for progress, it is crucial to develop techniques to understand the behavior of VQA models.

In this paper, we develop novel techniques for characterizing the behavior of VQA models. As concrete instantiations, we analyze two VQA models ((Lu et al., 2015),(Lu et al., 2016)), one from each of the two major classes of VQA models – with-attention and without-attention.

2 Related Work

Our work is inspired by previous works that diagnose the failure modes of models for different tasks. (Karpathy et al., 2015) constructed a series of oracles to measure the performance of a character level language model. (Hoiem et al., 2012) provided analysis tools to facilitate detailed and meaningful investigation of object detector performance. This paper

¹<http://www.visualqa.org/challenge.html>

aims to perform behavior analyses as a first step towards diagnosing errors for VQA.

(Yang et al., 2015) categorize the errors made by their VQA model into four categories – model focuses attention on incorrect regions, model focuses attention on appropriate regions but predicts incorrect answers, predicted answers are different from labels but might be acceptable, labels are wrong. While these are coarse but useful failure modes, we are interested in understanding the behavior of VQA models along specific dimensions – whether they generalize to novel instances, whether they listen to the entire question, whether they look at the image.

3 Behavior Analyses

We analyze the behavior of VQA models along the following three dimensions –

Generalization to novel instances: We investigate whether the test instances that are incorrectly answered are the ones that are “novel” i.e., not similar to training instances. The novelty of the test instances may be in two ways – 1) the test question-image (QI) pair is “novel”, i.e., too different from training QI pairs; and 2) the test QI pair is “familiar”, but the answer required at test time is “novel”, i.e., answers seen during training are different from what needs to be produced for the test QI pairs.

Complete question understanding: To investigate whether a VQA model is understanding the input question or not, we analyze whether the model ‘listens’ to only first few words of the question or the entire question, whether it ‘listens’ to only question (wh) words and nouns or all the words in the question.

Complete image understanding: The absence of a large gap in performance of language-alone and language + vision VQA models (Antol et al., 2015) provides evidence that current VQA models seem to be heavily reliant on the language model, perhaps not really understanding the image. In order to analyze this behavior, we investigate whether the predictions of the model change across images for a given question.

We present our behavioral analyses on the VQA dataset (Antol et al., 2015). VQA is a large-scale dataset containing $\sim 0.25M$ images, \sim

$0.76M$ questions, and $\sim 10M$ answers, with open-ended and multiple choice modalities for answering the visual questions. All the experimental results are reported on the VQA validation set using the following models trained on the VQA train set for the open-ended task –

CNN + LSTM based model without-attention (CNN+LSTM): We use the best performing model of (Antol et al., 2015) (code provided by (Lu et al., 2015)), which achieves an accuracy of 54.13% on the VQA validation set. It is a two channel model – one channel processes the image (using Convolutional Neural Network (CNN) to extract image features) and the other channel processes the question (using Long Short-Term Memory (LSTM) recurrent neural network to obtain question embedding). The image and question features obtained from the two channels are combined and passed through a fully connected (FC) layer to obtain a softmax distribution over the space of answers.

CNN + LSTM based model with-attention (ATT): We use the top-entry on the VQA challenge leaderboard (as of the time of this submission) (Lu et al., 2016), which achieves an accuracy of 57.02% on the VQA validation set.² This model jointly reasons about image and question attention, in a hierarchical fashion. The attended image and question features obtained from different levels of the hierarchy are combined and passed through a FC layer to obtain a softmax distribution over the space of answers.

3.1 Generalization to novel instances

Do VQA models make mistakes because test instances are too different from training ones? To analyze the first type of novelty (the test QI pair is novel), we measure the correlation between test accuracy and distance of test QI pairs from training QI pairs. For each test QI pair we find its k nearest neighbors (k-NNs) and compute the average distance between the test QI pair and its k-NNs. The k-NNs are computed in the space of combined image + question embedding (just before passing through FC layer), using euclidean distance metric, for both the CNN+LSTM and ATT models.

²Code available at <https://github.com/jiasenlu/HieCoAttenVQA>

The correlation between accuracy and average distance is significant (-0.41 at $k = 50$ ³ for the CNN+LSTM model and -0.42 at $k = 15$ ⁴ for the ATT model). A high negative correlation value tells us that the model is less likely to predict correct answers for test QI pairs which are not very similar to training QI pairs, which suggests that the model is not very good at generalizing to novel test QI pairs.

We also found that 67.5% of mistakes made by VQA model *can be successfully predicted* by checking distance of test QI pair from its training nearest neighbors for the CNN+LSTM model (66.7% for the ATT model). Thus, this analysis not only exposes a reason for mistakes made by VQA models, but also allows us to build human-like models that can predict their own oncoming failures, and potentially refuse to answer questions that are ‘too different’ from ones seen in past.

To analyze the second type of novelty (the answer required at test time is not familiar), we compute the correlation between test accuracy and the average distance of the test ground truth (GT) answer with GT answers of its k-NN training QI pairs. The k-NNs are computed in the space of average Word2Vec (Mikolov et al., 2013) vectors of answers. This correlation turns out to be quite high, -0.62 for both CNN+LSTM and ATT models. A high negative value of correlation value tells us that the model tends to regurgitate answers seen during training.

These distance features are also good at predicting failures – 74.19% of failures can be predicted by checking distance of test GT answer with GT answers of its k-NN training QI pairs for CNN+LSTM model (75.41% for the ATT model). Note that unlike the previous analysis, this analysis only explains failures but cannot be used to predict failures (since it uses GT labels). See Fig. 1 for qualitative examples.

From Fig. 1 we can see that the test instance in row1 is semantically quite different from its neighbors, explaining the mistake. The second row shows an example where the model has seen the same question in the training set but, since it has not seen “green cone” in its nearest neighbor training set, it

³ $k = 50$ leads to highest correlation

⁴ $k = 15$ leads to highest correlation



Figure 1: Examples from test set where the CNN+LSTM model makes mistakes and their corresponding nearest neighbor training samples. See Appendix III for more examples.

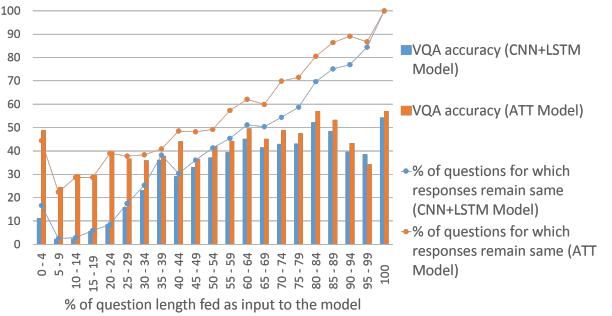


Figure 2: X-axis shows length of partial question (in %) fed as input. Y-axis shows percentage of questions for which responses of these partial questions are the same as full questions and VQA accuracy of partial questions.

is not able to answer the test sample correctly. This shows that current models lack compositionality – the ability to combine the concepts of “cone” and “green” (both of which have been seen in training set) to predict “green cone” as the answer to the test sample. This compositionality is desirable and central to intelligence.

3.2 Complete question understanding

We feed partial questions of increasing lengths (from 0-100% of question from left to right). We then compute what percentage of responses do not change when more and more words are fed.

Fig. 2 shows the test accuracy and percentage of questions for which responses remain same (compared to entire question) as a function of partial question length. We can see that for 40% of the questions, the CNN+LSTM model seems to have converged on a predicted answer after ‘listening’ to just half the question. This shows that the model is listening to first few words of the question more

than the words towards the end. Also, the model has 68% of the final accuracy (54%) when making predictions based on half the original question. The ATT model seems to have converged on a predicted answer after listening to just half the question more often (49% of the times), achieving 74% of the final accuracy (57%). See Fig. 3 for qualitative examples.

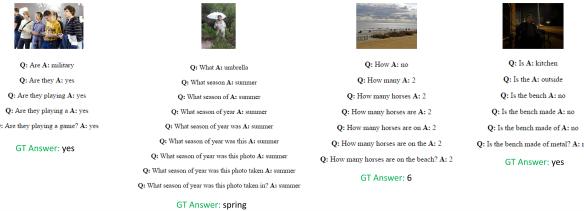


Figure 3: Examples where the CNN+LSTM model does not change its answer after first few question words. On doing so, it is correct for some cases (one example to left) and incorrect for other cases (the three examples to right). See Appendix V for more examples.

We also analyze the change in responses of the model’s predictions (see Fig. 4), when words of a particular part-of-the-speech (POS) tag are dropped from the question. The experimental results indicate that wh-words effect the model’s decisions the most (most of the responses get changed on dropping these words from the question), and that pronouns effect the model’s decisions the least.

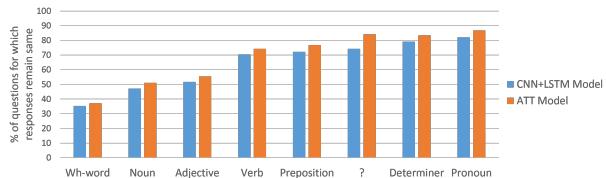


Figure 4: Percentage of questions for which responses remain same (compared to entire question) as a function of POS tags dropped from the question.

3.3 Complete image understanding

Does a VQA model really ‘look’ at the image? In order to analyze this, we compute the percentage of times (say X) the response does not change (i.e., answer for all images is “2”) across images for a given question (say “How many zebras?”) and plot histogram of X across questions (see Fig. 5). We do this analysis only for those questions in VQA validation set which have been asked for atleast 25 images, resulting in total 263 questions. The cumu-

lative plot indicates that for 56% of questions, the CNN+LSTM model outputs the same answer for at least half the images. This is fairly high, suggesting that the model is picking the same answer no matter what the image is. Promisingly, the ATT model (that does not work with a holistic entire-image representation and purportedly pays attention to specific spatial regions in an image) produces the same response for at least half of the images for fewer questions (42%).

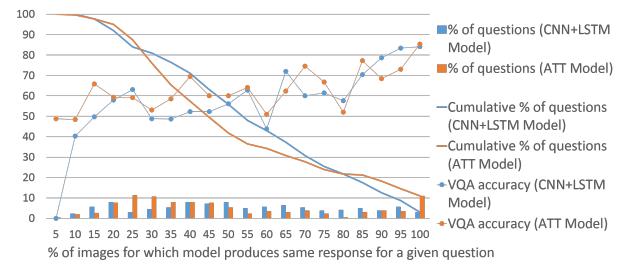


Figure 5: Histogram of percentage of images for which model produces same response for a given question and its comparison with test accuracy. The cumulative plot shows the % of questions for which model produces same answer for *atleast* x % of images.

Interestingly, the average accuracy (see the VQA accuracy plots in Fig. 5) for such questions (for which the models produce same response for at least half the images) is 56% for the CNN+LSTM model (60% for the ATT model) which is more than the respective average accuracy on the entire VQA validation set (54.13% for the CNN+LSTM model and 57.02% for the ATT model). Thus, producing the same response across images seems to be statistically favorable. Fig. 6 shows examples where the CNN+LSTM model predicts the same response across images for a given question. The first row shows examples where the model makes errors on several images by predicting the same answer across all images. The last row shows examples where the model is always correct even if it predicts the same answer across images. This is so because questions such as “*What covers the ground?*” are asked for an image in the VQA dataset only when ground is covered with snow (because subjects were looking at the image while asking questions about it).

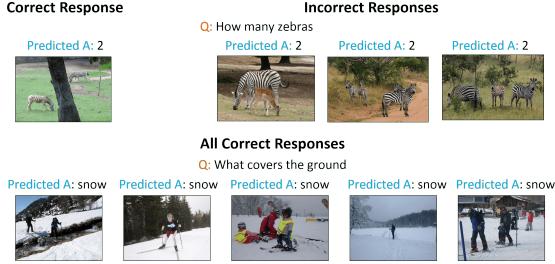


Figure 6: Examples where the predicted answers do not change across images for a given question. See [Appendix VI](#) for more examples.

4 Conclusion

We develop novel techniques for characterizing the behavior of VQA models, as a first step towards understanding these models, meaningfully comparing the strengths and weaknesses of different models, developing insights into their failure modes, and identifying the most fruitful directions for progress. Our behavior analysis reveals that despite recent progress, today’s VQA models often “jump to conclusions” (converge on a predicted answer after ‘listening’ to just half the question), are “stubborn” (do not change their answers across images) with attention based models being less “stubborn” than non-attention based models, and are “myopic” (tend to fail on sufficiently novel instances).

Appendix Overview

In the appendix, we provide:

- I - Behavioral analysis for question-only and image-only VQA models ([Appendix I](#)).
- II - Scatter plot of average distance of test instances from nearest neighbor training instances w.r.t. VQA accuracy ([Appendix II](#)).
- III - Additional qualitative examples for “generalization to novel test instances” ([Appendix III](#)).
- IV - The analyses on “complete question understanding” for different question types ([Appendix IV](#)).
- V - Additional qualitative examples for “complete question understanding” ([Appendix V](#)).
- VI - The analyses on “complete image understanding” for different question types ([Appendix VI](#)).
- VII - Additional qualitative examples for “complete image understanding” ([Appendix VII](#)).

Appendix I: Behavioral analysis for question-only and image-only VQA models

We evaluated the performance of both CNN+LSTM and ATT models by just feeding in the question (and mean image embedding) and by just feeding in the image (and mean question embedding). We computed the percentage of responses that change on feeding the question as well, compared to only feeding in the image and the percentage of responses that change on feeding the image as well, compared to only feeding in the question. We found that that the responses changed much more (about 40% more) on addition of the question than they did on addition of the image. So this suggests that the VQA models are heavily driven by question rather than the image.

Appendix II: Scatter plot of average distance of test instances from nearest neighbor training instances w.r.t. VQA accuracy

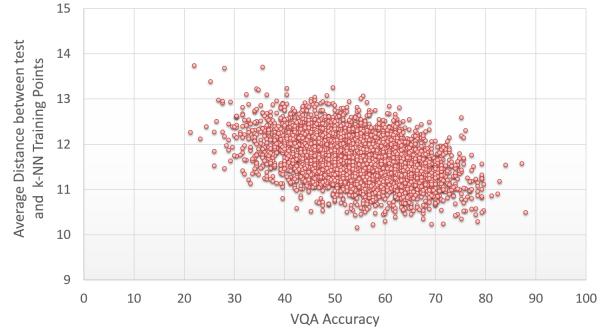


Figure 7: Test accuracy vs. average distance of the test points from k-NN training points for the CNN+LSTM model.

[Fig. 7](#) shows the variation of accuracy of test point w.r.t their average distance from k-NN training points for the CNN+LSTM model. Each point in the plot represents average statistics (accuracy and average distance) for a random subset of 25 test points. We can see that for the test points with low accuracy, the average distance is higher compared to test points with high accuracy. The correlation between accuracy and average distance is significant (-0.41 at best $k = 50$)

Appendix III: Additional qualitative examples for “generalization to novel test instances”

Fig. 8 shows test QI pairs for which the CNN+LSTM model produces the correct response and their nearest neighbor QI pairs from training set. It can be seen that the nearest neighbor QI pairs from the training set are similar to the test QI pair. In addition, the GT labels in the training set are similar to the test GT label.

Fig. 9 shows test QI pairs for which the CNN+LSTM model produces incorrect response and their nearest neighbor QI pairs from training set. Some of the mistakes are probably because the test QI pair does not have similar QI pairs in the training set (rows 2, 4 and 5) while other mistakes are probably because the GT labels in the training set are not similar to the GT test label (rows 1 and 3).

Appendix IV: Analyses on “complete question understanding” for different question types

We show the breakdown of our analyses from the main paper – (i) whether the model ‘listens’ to the entire question; and (ii) which POS tags matter the most – over the three major categories of questions – “yes/no”, “number” and “other” as categorized in (Antol et al., 2015). “yes/no” are questions whose answers are either “yes” or “no”, “number” are questions whose answers are numbers (e.g., “Q: How many zebras are there?”, “A: 2”), “other” are rest of the questions.

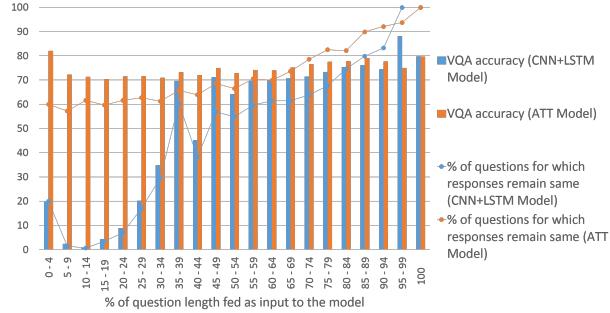


Figure 10: X-axis shows length of partial “yes/no” question (in %) fed as input. Y-axis shows percentage of “yes/no” questions for which responses of these partial “yes/no” questions are the same as full “yes/no” questions and VQA accuracy of partial “yes/no” questions.

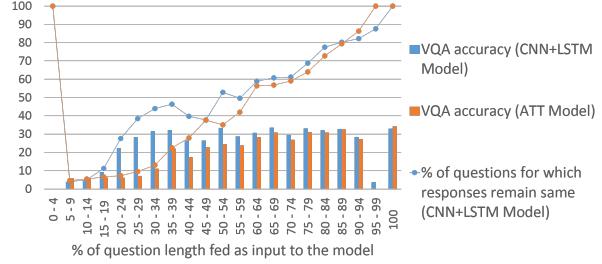


Figure 11: X-axis shows length of partial “number” question (in %) fed as input. Y-axis shows percentage of “number” questions for which responses of these partial “number” questions are the same as full “number” questions and VQA accuracy of partial “number” questions.

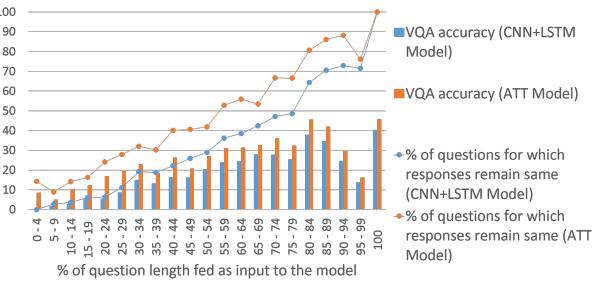


Figure 12: X-axis shows length of partial “other” question (in %) fed as input. Y-axis shows percentage of “other” questions for which responses of these partial “other” questions are the same as full “other” questions and VQA accuracy of partial “other” questions.

For “yes/no” questions, the ATT model seems particularly ‘jumpy’ – converging on a predicted answer listening to only the first few words of the question (see Fig. 10). Surprisingly, the accuracy is also as much as the final accuracy (after listening to entire question) when making predictions based on first few words of the question. On the contrast, the CNN+LSTM model converges on a predicted answer later, after listening to atleast 35% of the question, achieving as much as the final accuracy after convergence. For “number” and “other” questions, both ATT and CNN+LSTM model show similar trends (see Fig. 11 for “number” and Fig. 12 for “other”).

It is interesting to note that VQA models are most sensitive to adjectives for “yes/no” questions (compared to wh-words for all questions) (see Fig. 13). This is probably because often the “yes/no” questions are about attributes of objects (e.g., “Is the cup empty?”). For “number” questions, the CNN+LSTM model is most sensitive to adjectives whereas the ATT model is most sensitive to wh-

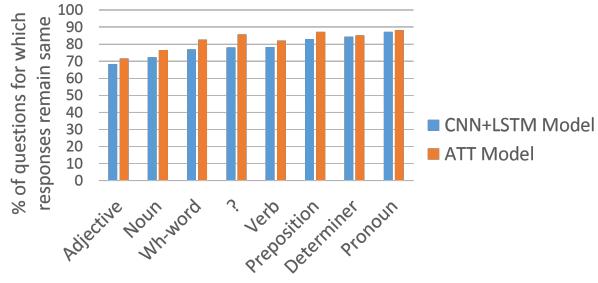


Figure 13: Percentage of “yes/no” questions for which responses remain same (compared to entire “yes/no” question) as a function of POS tags dropped from the “yes/no” question.

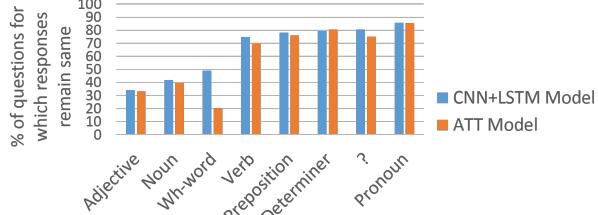


Figure 14: Percentage of “number” questions for which responses remain same (compared to entire “number” question) as a function of POS tags dropped from the “number” question.

words (see Fig. 14). For “other” questions, both the models are most sensitive to “nouns” (see Fig. 15).

Appendix V: Additional qualitative examples for “complete question understanding”

Fig. 16 shows examples where the CNN+LSTM model converges on a predicted answer without listening to the entire question. On doing so, the model gets the answer correct for some QI pairs (first three rows) and incorrect for others (last two rows).

Appendix VI: Analyses on “complete image understanding” for different question types

Fig. 17, Fig. 18 and Fig. 19 show the breakdown of percentage of questions for which the model produces same answer across images for “yes/no”, “number” and “other” respectively. The ATT model seems to be more “stubborn” (does not change its answers across images) for “yes/no” questions compared to the CNN+LSTM model, and less “stubborn” for “number” questions compared to the CNN+LSTM model.

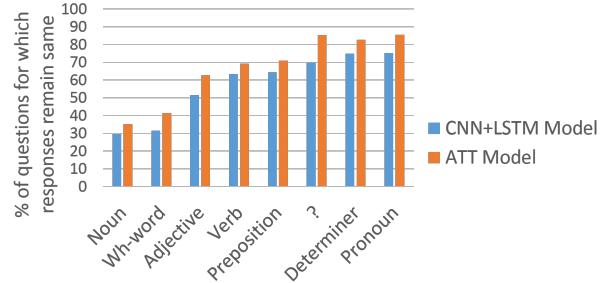


Figure 15: Percentage of “other” questions for which responses remain same (compared to entire “other” question) as a function of POS tags dropped from the “other” question.

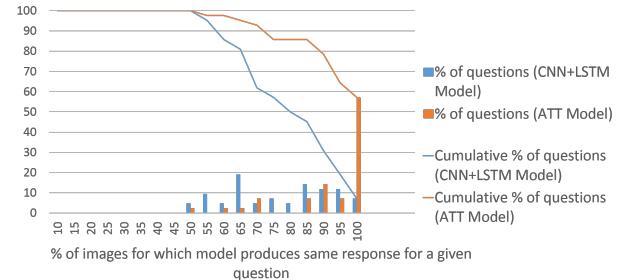


Figure 17: Histogram of percentage of images for which model produces same answer for a given “yes/no” question. The cumulative plot shows the % of “yes/no” questions for which model produces same answer for *atleast* x % of images.

Appendix VII: Additional qualitative examples for “complete image understanding”

Fig. 20 shows examples where the CNN+LSTM model produces the same answer for atleast half the images for a given question and the accuracy achieved by the model for such QI pairs.

References

- [Andreas et al.2015] Jacob Andreas, Marcus Rohrbach, Trevor Darrell, and Dan Klein. 2015. Deep compositional question answering with neural module networks. *CoRR*, abs/1511.02799. 1
- [Andreas et al.2016] Jacob Andreas, Marcus Rohrbach, Trevor Darrell, and Dan Klein. 2016. Learning to compose neural networks for question answering. *CoRR*, abs/1601.01705. 1
- [Antol et al.2015] Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C. Lawrence Zitnick, and Devi Parikh. 2015. Vqa: Visual question answering. In *International Conference on Computer Vision (ICCV)*. 1, 2, 6

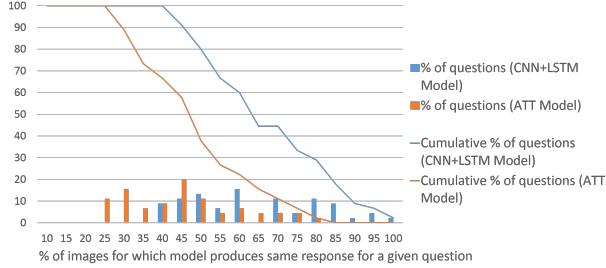


Figure 18: Histogram of percentage of images for which model produces same answer for a given “number” question. The cumulative plot shows the % of “number” questions for which model produces same answer for *at least* x % of images.

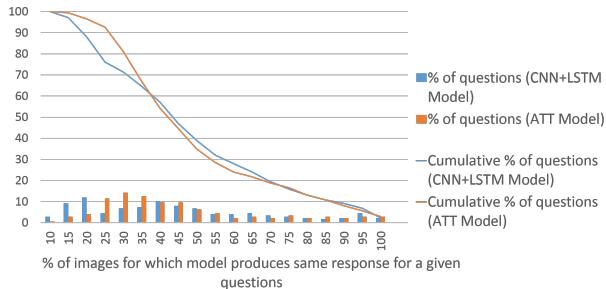


Figure 19: Histogram of percentage of images for which model produces same answer for a given “other” question. The cumulative plot shows the % of “other” questions for which model produces same answer for *at least* x % of images.

[Chen et al.2015] Kan Chen, Jiang Wang, Liang-Chieh Chen, Haoyuan Gao, Wei Xu, and Ram Nevatia. 2015. ABC-CNN: an attention based convolutional neural network for visual question answering. *CoRR*, abs/1511.05960. 1

[Fukui et al.2016] Akira Fukui, Dong Huk Park, Daylen Yang, Anna Rohrbach, Trevor Darrell, and Marcus Rohrbach. 2016. Multimodal compact bilinear pooling for visual question answering and visual grounding. *CoRR*, abs/1606.01847. 1

[Geman et al.2014] Donald Geman, Stuart Geman, Neil Hallonquist, and Laurent Younes. 2014. A Visual Turing Test for Computer Vision Systems. In *PNAS*. 1

[Hoiem et al.2012] Derek Hoiem, Yodsawalai Chodpathumwan, and Qieyun Dai. 2012. Diagnosing error in object detectors. In *Proceedings of the 12th European Conference on Computer Vision - Volume Part III*, ECCV’12. 1

[Ilievski et al.2016] Ilija Ilievski, Shuicheng Yan, and Jiashi Feng. 2016. A focused dynamic attention model for visual question answering. *CoRR*, abs/1604.01485. 1

[Jiang et al.2015] Aiwen Jiang, Fang Wang, Fatih Porikli, and Yi Li. 2015. Compositional memory for visual question answering. *CoRR*, abs/1511.05676. 1

[Kafle and Kanan2016] Kushal Kafle and Christopher Kanan. 2016. Answer-type prediction for visual question answering. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 1

[Karpathy et al.2015] Andrej Karpathy, Justin Johnson, and Fei-Fei Li. 2015. Visualizing and understanding recurrent networks. *CoRR*, abs/1506.02078. 1

[Kim et al.2016] Jin-Hwa Kim, Sang-Woo Lee, Dong-Hyun Kwak, Min-Oh Heo, Jeonghee Kim, Jung-Woo Ha, and Byoung-Tak Zhang. 2016. Multimodal residual learning for visual qa. *CoRR*, abs/1606.01455. 1

[Lu et al.2015] Jiasen Lu, Xiao Lin, Dhruv Batra, and Devi Parikh. 2015. Deeper lstm and normalized cnn visual question answering model. https://github.com/VT-vision-lab/VQA_LSTM_CNN. 1, 2

[Lu et al.2016] Jiasen Lu, Jianwei Yang, Dhruv Batra, and Devi Parikh. 2016. Hierarchical question-image co-attention. *CoRR*, abs/1606.00061v1. 1, 2

[Malinowski and Fritz2014] Mateusz Malinowski and Mario Fritz. 2014. A Multi-World Approach to Question Answering about Real-World Scenes based on Uncertain Input. In *NIPS*. 1

[Mikolov et al.2013] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. In *ICLR*. 3

[Noh and Han2016] Hyeonwoo Noh and Bohyung Han. 2016. Training recurrent answering units with joint loss minimization for vqa. *CoRR*, abs/1606.03647. 1

[Saito et al.2016] Kuniaki Saito, Andrew Shin, Yoshitaka Ushiku, and Tatsuya Harada. 2016. Dualnet: Domain-invariant network for visual question answering. *CoRR*, abs/1606.06108. 1

[Shih et al.2015] Kevin J. Shih, Saurabh Singh, and Derek Hoiem. 2015. Where to look: Focus regions for visual question answering. *CoRR*, abs/1511.07394. 1

[Wang et al.2015] Peng Wang, Qi Wu, Chunhua Shen, Anton van den Hengel, and Anthony R. Dick. 2015. Explicit knowledge-based reasoning for visual question answering. *CoRR*, abs/1511.02570. 1

[Wu et al.2015] Qi Wu, Peng Wang, Chunhua Shen, Anton van den Hengel, and Anthony R. Dick. 2015. Ask me anything: Free-form visual question answering based on knowledge from external sources. *CoRR*, abs/1511.06973. 1

[Xiong et al.2016] Caiming Xiong, Stephen Merity, and Richard Socher. 2016. Dynamic memory networks for visual and textual question answering. *CoRR*, abs/1603.01417. 1

[Xu and Saenko2015] Huijuan Xu and Kate Saenko. 2015. Ask, attend and answer: Exploring question-guided spatial attention for visual question answering. *CoRR*, abs/1511.05234. 1

[Yang et al.2015] Zichao Yang, Xiaodong He, Jianfeng Gao, Li Deng, and Alexander J. Smola. 2015. Stacked attention networks for image question answering. *CoRR*, abs/1511.02274. [1](#), [2](#)

[Zhou et al.2015] Bolei Zhou, Yuandong Tian, Sainbayar Sukhbaatar, Arthur Szlam, and Rob Fergus. 2015. Simple baseline for visual question answering. *CoRR*, abs/1512.02167. [1](#)

Test Sample	Nearest Neighbor Training Samples					
<p>Q: Does someone have a birthday?</p>  <p>Predicted A: yes GT A: yes Accuracy: 100.0</p>	<p>Q: Could it be someone's birthday?</p>  <p>GT A: yes</p>	<p>Q: Might today be her birthday?</p>  <p>GT A: yes</p>	<p>Q: Does someone have a birthday?</p>  <p>GT A: yes</p>	<p>Q: Is there a basket on the bicycle?</p>  <p>GT A: yes</p>	<p>Q: Is there a balloon on the table?</p>  <p>GT A: yes</p>	
<p>Q: Which vehicle is towing a small trailer?</p>  <p>Predicted A: motorcycle GT A: motorcycle Accuracy: 100.0</p>	<p>Q: Which vehicle has a picture of a wooly mammoth?</p>  <p>GT A: motorcycle</p>	<p>Q: What is the police officer riding in the picture?</p>  <p>GT A: motorcycle</p>	<p>Q: What type of transportation?</p>  <p>GT A: motorcycle</p>	<p>Q: What is parked next to the motorbike?</p>  <p>GT A: bicycle</p>	<p>Q: What type of transportation is this?</p>  <p>GT A: motorcycle</p>	
<p>Q: What is the woman doing?</p>  <p>Predicted A: playing wii GT A: playing wii Accuracy: 100.0</p>	<p>Q: What is the woman doing?</p>  <p>GT A: talking on phone</p>	<p>Q: What is the woman doing?</p>  <p>GT A: playing wii</p>	<p>Q: What is the girl doing?</p>  <p>GT A: playing wii</p>	<p>Q: What is this lady doing?</p>  <p>GT A: waiting</p>	<p>Q: What is the woman doing?</p>  <p>GT A: playing wii</p>	
<p>Q: What color is the sky?</p>  <p>Predicted A: blue GT A: blue Accuracy: 100.0</p>	<p>Q: What color is the sky?</p>  <p>GT A: blue</p>	<p>Q: What color is the sky?</p>  <p>GT A: blue</p>	<p>Q: What color is the sky?</p>  <p>GT A: blue</p>	<p>Q: What color is the sky?</p>  <p>GT A: blue</p>	<p>Q: What color is the sky?</p>  <p>GT A: orange</p>	
<p>Q: How many tusks does the elephant have?</p>  <p>Predicted A: 2 GT A: 2 Accuracy: 100.0</p>	<p>Q: How many tusks does this animal have?</p>  <p>GT A: 2</p>	<p>Q: How many tusks does the elephant have?</p>  <p>GT A: 2</p>	<p>Q: How many tusks does this elephant have?</p>  <p>GT A: 1</p>	<p>Q: How many tusks does the animal have?</p>  <p>GT A: 2</p>	<p>Q: How many tusks does the elephant have?</p>  <p>GT A: 1</p>	

Figure 8: Test QI pairs for which the CNN+LSTM model produces the correct response and their nearest neighbor QI pairs from training set.

Test Sample	Nearest Neighbor Training Samples				
<p>Q: What kind of food is this?</p>  <p>Predicted A: dessert</p> <p>GT A: cereal with fruit</p> <p>Accuracy: 0.0</p>	<p>Q: What kind of food is this?</p>  <p>GT A: dessert</p>	<p>Q: What kind of food is this?</p>  <p>GT A: pizza</p>	<p>Q: What kind of food is this?</p>  <p>GT A: lunch</p>	<p>Q: What type of food is this?</p>  <p>GT A: pizza</p>	<p>Q: What kind of food is this?</p>  <p>GT A: salad</p>
<p>Q: What is red and driving down the road?</p>  <p>Predicted A: car</p> <p>GT A: bus</p> <p>Accuracy: 0.0</p>	<p>Q: What is the back of the motorbike?</p>  <p>GT A: box</p>	<p>Q: What is on the pole behind the bike?</p>  <p>GT A: sign</p>	<p>Q: What is around the corner to the right?</p>  <p>GT A: store</p>	<p>Q: What is the bike locked up to?</p>  <p>GT A: tree</p>	<p>Q: What is green and behind the people?</p>  <p>GT A: trees</p>
<p>Q: What breed of horse is this?</p>  <p>Predicted A: black and white</p> <p>GT A: clydesdale</p> <p>Accuracy: 0.0</p>	<p>Q: What breed of horse is this?</p>  <p>GT A: brown</p>	<p>Q: What kind of horse is this?</p>  <p>GT A: brown</p>	<p>Q: What kind of horse is this?</p>  <p>GT A: brown</p>	<p>Q: What type of horse is this?</p>  <p>GT A: brown</p>	<p>Q: Which kind of horse is this?</p>  <p>GT A: brown</p>
<p>Q: Is this Miley Cyrus?</p>  <p>Predicted A: yes</p> <p>GT A: no</p> <p>Accuracy: 0.0</p>	<p>Q: Is the train blue?</p>  <p>GT A: yes</p>	<p>Q: Does this look right?</p>  <p>GT A: no</p>	<p>Q: Is the skateboard flying?</p>  <p>GT A: yes</p>	<p>Q: Is the bus driver visible?</p>  <p>GT A: no</p>	<p>Q: Is the person female?</p>  <p>GT A: yes</p>
<p>Q: What is the name a state that grows these fruits?</p>  <p>Predicted A: new york</p> <p>GT A: florida</p> <p>Accuracy: 0.0</p>	<p>Q: What state is the can from?</p>  <p>GT A: new york</p>	<p>Q: What state is the mug from?</p>  <p>GT A: new york</p>	<p>Q: What face does the topmost fruit have?</p>  <p>GT A: happy</p>	<p>Q: What state is the bear representing?</p>  <p>GT A: new york</p>	<p>Q: What state is the truck from?</p>  <p>GT A: california</p>

Figure 9: Test QI pairs for which the CNN+LSTM model produces incorrect response and their nearest neighbor QI pairs from training set.

 <p>GT A: no Accuracy of predicted answer for full question: 100.0</p>		<p>Q: Is there a tram to the west of where the people are? A: yes Q: Is A: outside Q: Is there A: beach Q: Is there a A: yes Q: Is there a tram A: yes Q: Is there a tram to A: yes Q: Is there a tram to the A: yes Q: Is there a tram to the west A: yes Q: Is there a tram to the west of A: yes Q: Is there a tram to the west of where A: yes Q: Is there a tram to the west of where the people are? A: yes Q: Is there a tram to the west of where the people are? A: yes Q: Is there a tram to the west of where the people are? A: yes</p>
 <p>GT A: 3 Accuracy of predicted answer for full question: 90.0</p>		<p>Q: How many different directions are the benches facing? A: 2 Q: How A: yes Q: How many A: 2 Q: How many different A: 2 Q: How many different directions A: 2 Q: How many different directions are A: 2 Q: How many different directions are the A: 2 Q: How many different directions are the benches A: 2 Q: How many different directions are the benches facing? A: 2 Q: How many different directions are the benches facing? A: 2</p>
 <p>GT A: grass Accuracy of predicted answer for full question: 100.0</p>		<p>Q: What type of surface is the man standing on? A: grass Q: What A: umbrellas Q: What type A: shadow Q: What type of A: kite Q: What type of surface A: grass Q: What type of surface is A: grass Q: What type of surface is the A: grass Q: What type of surface is the man A: grass Q: What type of surface is the man standing A: grass Q: What type of surface is the man standing on? A: grass Q: What type of surface is the man standing on? A: grass</p>
 <p>GT A: bathroom Accuracy of predicted answer for full question: 0.0</p>		<p>Q: Where is the light fixture in the photo? A: window Q: Where A: bathroom Q: Where is A: outside Q: Where is the A: bathroom Q: Where is the light fixture A: counter Q: Where is the light fixture A: on left Q: Where is the light fixture in A: window Q: Where is the light fixture in the A: window Q: Where is the light fixture in the photo? A: window Q: Where is the light fixture in the photo? A: window</p>
 <p>GT A: continental airlines Accuracy of predicted answer for full question: 0.0</p>		<p>Q: What company is a sponsor of this match? A: polo Q: What A: shadow Q: What company A: nike Q: What company is A: polo Q: What company is a A: polo Q: What company is a sponsor A: polo Q: What company is a sponsor of A: polo Q: What company is a sponsor of this A: polo Q: What company is a sponsor of this match? A: polo Q: What company is a sponsor of this match? A: polo</p>

Figure 16: Examples where the CNN+LSTM model converges on a predicted answer without listening to the entire question.

<p>Q: What time is on the clock?</p> <p>A: noon</p> <p>Average Accuracy: 0.0</p> <p>Number of Images: 56</p>					
<p>Q: Where is the bus going?</p> <p>A: nowhere</p> <p>Average Accuracy: 3.87</p> <p>Number of Images: 31</p>					
<p>Q: What color is the court?</p> <p>A: blue</p> <p>Average Accuracy: 60.29</p> <p>Number of Images: 68</p>					
<p>Q: Is the window open?</p> <p>A: yes</p> <p>Average Accuracy: 64.0</p> <p>Number of Images: 35</p>					
<p>Q: Is it day or night?</p> <p>A: day</p> <p>Average Accuracy: 96.15</p> <p>Number of Images: 26</p>					

Figure 20: Examples where the CNN+LSTM model produces the same answer for atleast half the images for each of the questions shown above. “Q” denotes the question for which model produces same response for atleast half the images, “A” denotes the answer predicted by the model (which is same for atleast half the images), “Number of Images” denotes the number of images for which the question is repeated in the VQA validation set and “Average Accuracy” is the VQA accuracy for these QI pairs (with same question but different images).