Robustness Analysis of Visual QA Models by Basic Questions

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Abstract

Visual Question Answering (VQA) models should have both high robustness and accuracy. Unfortunately, most of the current VQA research only focuses on accuracy because there is a lack of proper methods to measure the robustness of VQA models. There are two main modules in our algorithm. Given a natural language question about an image, the first module takes the question as input and then outputs the ranked basic questions, with similarity scores, of the main given question. The second module takes the main question, image and these basic questions as input and then outputs the text-based answer of the main question about the given image. We claim that a robust VQA model is one, whose performance is not changed much when related basic questions as also made available to it as input. We formulate the basic questions generation problem as a LASSO optimization, and also propose a large scale Basic Question Dataset (BQD) and $R_{score}$ (novel robustness measure), for analyzing the robustness of VQA models. We hope our BQD will be used as a benchmark for to evaluate the robustness of VQA models, so as to help the community build more robust and accurate VQA models.

1 Introduction

Visual Question Answering (VQA) is a challenging and young research field, which can help machines achieve one of the ultimate goals in computer vision, holistic scene understanding (Yao, Fidler, and Urtasun 2012). VQA is a computer vision task: a system is given an arbitrary text-based question about an image, and then tasked to output the text-based answer of the given question about the image. Currently, most of the state-of-the-art VQA models (Antol et al. 2015; Chen et al. 2016; Lu et al. 2016; Ben-younes et al. 2017; Fukui et al. 2016; Kim et al. 2017) only focus on how to improve accuracy. However, accuracy is not the only metric to score a given VQA model. Robustness is also a crucial property. For the image part, there is already a rapidly growing research on evaluating the robustness of deep learning models (Fawzi, Moosavi Dezfooli, and Frossard 2017; Carlini and Wagner 2017; Xu, Caramanis, and Mannor 2009). However, for the question part, we couldn’t find any acceptable method to measure the robustness of VQA algorithms after extensive literature review. To the best of our knowledge, this paper is the first work to analyze the robustness of VQA models.

When we directly add or replace some words or phrases by similar words or phrases to the given main question, the VQA model should output the same or a very similar answer. In some sense, we can consider the similar words or phrases as small perturbation or noise to the input. If the model can output the same answer as before in the presence of small noise, we can say that the model is robust. Moreover, if a human is presented with only the main question or the main question accompanied with some highly similar questions to the main question, (called basic questions of the main question), he/she tends to produce the same or a highly similar answer in both cases. Based on this observation, we consider the basic question of given main question as noise to the given main question. That is to say, a basic question with larger similarity score to the main question is considered smaller noise to the main question and a basic question with smaller similarity score is larger noise to the main question.
The above interesting concepts inspire us to propose a method, Visual Question Answering by Basic Questions (VQABQ) illustrated in Figure 1, to measure the robustness of VQA models. In the VQABQ model, there are two modules: the basic question generation module (Module 1) and the visual question answering module (Module 2). We take the query question, called the main question (MQ), encoded by Skip-Thought Vectors (Kiros et al. 2015), as the input of Module 1. In Module 1, we encode all of the questions, also by Skip-Thought Vectors, from the training and validation sets of VQA (Antol et al. 2015) dataset as a 4800 by 186027 dimension basic question (BQ) matrix, and then solve the LASSO optimization problem (Huang, Alfadly, and Ghanem 2017), with MQ, to find the top 3 similar BQ of MQ. These BQ are the output of Module 1. Moreover, we take the direct concatenation of MQ and BQ and the given image as the input of Module 2, the general VQA module, and then it will output the answer prediction of MQ. We claim that the BQ of given MQ can be considered as the small noise of MQ and it will affect the accuracy of VQA model. Then, we verify the above claim by the detailed experiments and use the VQABQ method to analyze the robustness of 6 available pretrained state-of-the-art VQA models, provided by papers’ authors, (Antol et al. 2015; Lu et al. 2016; Ben-younes et al. 2017; Fukui et al. 2016; Kim et al. 2017). Note that the available pretrained VQA models can be categorized into two main categories, attention-based and non-attention-based VQA models. According to the results of our experiments, we discover that attention-based models not only have the higher accuracy but also the better robustness compared with non-attention-based models. In this work, our main contributions are summarized below:

- We propose a new method to generate the basic questions of the given main question and utilize these basic questions to analyze the robustness of 6 available pretrained state-of-the-art VQA models.
- Also, we propose a novel large scale Basic Question Dataset (BQD) generated by our basic question generation algorithm and demonstrate how to use it with our $R_{score}$ (novel robustness measure) for the robustness analysis of VQA models.
- According to our experiments, we also discover that attention-based mechanism not only can help the accuracy but also the robustness of VQA models.

The rest of this paper is organized as the following. We first review the related work in Section 2. In Section 3, we discuss the detailed methodology and shortly introduce the proposed basic question dataset. Finally, the experimental results are demonstrated in Section 4.

2 Related Work

Recently, there are many papers (Antol et al. 2015; Shih, Singh, and Hoiem 2016; Chen et al. 2016; Kafle and Kanan 2016; Ma, Lu, and Li 2016; Ren, Kiros, and Zemel 2015; Zhu et al. 2016; Wu et al. 2016; Lu et al. 2016; Ben-younes et al. 2017; Fukui et al. 2016; Kim et al. 2017) have proposed methods to solve the challenging VQA task. Our VQABQ method involves in different areas in Machine Learning, Natural Language Processing (NLP) and Computer Vision. The following, we discuss recent works related to our approach.

Sequence Modeling by Recurrent Neural Networks.

Recurrent Neural Networks (RNN) can handle the sequences of flexible length. Long Short Term Memory (LSTM) (Hochreiter and Schmidhuber 1997) is a particular variant of RNN and in natural language tasks, such as machine translation (Sutskever, Vinyals, and Le 2014; Cho et al. 2014), LSTM is a successful application. In (Ren, Kiros, and Zemel 2015), they exploit RNN and Convolutional Neural Network (CNN) to build a question generation algorithm, but the generated question sometimes has invalid grammar. The input in (Malinowski, Rohrbach, and Fritz 2015; 2017) is the concatenation of each word embedding with the same feature vector of the image. (Gao et al. 2015) encodes the input question sentence by LSTM and join the image feature to the final output. (Ma, Lu, and Li 2016) groups the neighboring word and image feature by doing convolution. In (Noh, Hongsuck, and Han 2016), the question is encoded by Gated Recurrent Unit (GRU) (Chung et al. 2014) similar to LSTM and they also introduce a dynamic parameter layer in CNN whose weights are adaptively predicted by the encoded question feature.

Sentence Encoding.

In order to analyze the relationship among words, phrases and sentences, several works, such as (Pennington, Socher, and Manning 2014; Kiros et al. 2015; Mikolov et al. 2013), proposed methods about how to map text into vector space. After we have the vector representation of text, we can exploit the vector analysis skill to analyze the relationship among text. (Pennington, Socher, and Manning 2014; Mikolov et al. 2013) try to map words to vector space, and if the words share common contexts in the corpus, their encoded vectors will close to each other in the vector space. In (Kiros et al. 2015), they proposed a framework of encoder-decoder models, called skip-thoughts. In this model, they exploit an RNN encoder with GRU activations (Chung et al. 2014) and an RNN decoder with a conditional GRU (Chung et al. 2014). Because skip-thoughts model emphasizes more on whole sentence encoding, in our work, we encode the whole question sentences into vector space by skip-thoughts model and use these skip-thought vectors to do further analysis of question sentences.

Image Captioning.

In some sense, VQA is related to image captioning (Xu et al. 2015; Karpathy and Fei-Fei 2015; Vinyals et al. 2015; Fang et al. 2015). (Fang et al. 2015) used a language model to combine a set of possible words detected in several regions of the image and generate image description. In (Vinyals et al. 2015), they used CNN to extract the high-level image features and considered them as the first input of the recurrent network to generate the caption of the image. (Xu et al. 2015) proposed an algorithm to generate one word at a time by paying attention to local image regions related to the currently predicted word. In (Karpathy and Fei-Fei 2015),
their deep neural network can learn to embed language and visual information into a common multimodal space. However, the current image captioning algorithms only can generate the rough description of an image and there is no so-called proper metric to evaluate the quality of image caption, even though BLEU (Papineni et al. 2002) can be used to evaluate the image caption.

Attention-based VQA.

There are several VQA models that have the ability to focus on specific image regions related to the input question by integrating the image attention mechanism (Shih, Singh, and Hoiem 2016; Chen et al. 2016; Yang et al. 2016; Li and Jia 2016). In (Li and Jia 2016), in the pooling step, they exploited an image attention mechanism to help determine the relevance of original questions and updated ones. Before (Lu et al. 2016), no work applied language attention mechanism to VQA, but the researchers in NLP they had modeled language attention. In (Lu et al. 2016), they proposed a co-attention mechanism that jointly performs language attention and image attention. Because both question and image information are important in VQA, adding the co-attention mechanism in VQA models is very reasonable and intuitive. According to our experimental results, (Lu et al. 2016) is the state-of-the-art VQA model in robustness.

Multiple Modalities Fusion Strategies in VQA.

Because VQA task contains the image and text features, it is a kind of multimodal feature fusion tasks. Recently, there are some works (Kiros, Salakhutdinov, and Zemel 2014; Ben-younes et al. 2017; Fukui et al. 2016; Kim et al. 2017; Lin, RoyChowdhury, and Maji 2015) focus on modeling the interactions between two embedding spaces. (Kiros, Salakhutdinov, and Zemel 2014; Lin, RoyChowdhury, and Maji 2015) show that bilinear interactions can have great success in deep learning for multimodal language modeling and fine-grained classification. In (Fukui et al. 2016), Multimodal Compact Bilinear (MCB) pooling uses an outer product between textual and visual embeddings. (Kim et al. 2017), Multimodal Low-rank Bilinear (MLB) pooling, exploits a tensor to parametrize the full bilinear interactions between image and question spaces. The newest state-of-the-art VQA work, (Ben-younes et al. 2017), can efficiently parametrize bilinear interactions between visual and textual representations and the authors prove that MCB and MLB are the special cases of (Ben-younes et al. 2017).

3 Methodology

In Section 3, we mainly discuss how to encode questions and generate BQ and how do we exploit BQ to do robustness analysis on the 6 available state-of-the-art VQA models. The overall architecture of our VQA-BQ model can be referred to Figure 1. The model has two main parts, Module 1 and Module 2. Regarding Module 1, it will take the encoded MQ as the input and uses the encoded BQ matrix to output the BQ of query question. Then, Module 2 is a VQA model we want to analyze, and it will take the concatenation of the output of Module 1 and MQ, and the given image as input and then outputs the final answer of MQ. The detailed architecture of Module 1 also can be referred to Figure 1.

Question Data Preprocessing

We take the most popular VQA dataset (Antol et al. 2015) to develop our BQD. At the beginning, we take all of the training and validation questions from the VQA dataset (Antol et al. 2015) to be our basic question candidates. Then, we take all of the testing questions from the VQA dataset (Antol et al. 2015) to be our main question candidates. That is to say, our main question candidates and the number of main question candidates are exactly the same as the testing question set of VQA dataset (Antol et al. 2015). Because we model the basic question generation problem by LASSO, we remove the repeated basic question candidate and the basic question candidate exactly the same as any main question candidate. The above step guarantees that our LASSO can work well.

Question Encoding

There are many popular text encoders, such as Word2Vec (Mikolov et al. 2013), GloVe (Pennington, Socher, and Manning 2014) and Skip-Thoughts (Kiros et al. 2015). In these encoders, Skip-Thoughts not only can focus on the word-to-word meaning but also the whole sentence semantic meaning. So, we choose Skip-Thoughts to be our question encoding method. In Skip-Thoughts model, it uses an RNN encoder with GRU (Chung et al. 2014) activations, and then we use this encoder to map an English sentence into a vector. Regarding GRU, it has been shown to perform as well as LSTM (Hochreiter and Schmidhuber 1997) on the sequence modeling applications but being conceptually simpler because GRU units only have 2 gates and do not need the use of a cell.

Question Encoder. Let \( w^i_1, \ldots, w^i_N \) be the words in question \( s_i \) and \( N \) is the total number of words in \( s_i \). Note that \( w^i_1 \) denotes the \( t \)-th word for \( s_i \) and \( x^i_t \) denotes its word embedding. The question encoder at each time step generates a hidden state \( h^i_t \). It can be considered as the representation of the sequence \( w^i_1, \ldots, w^i_T \). So, the hidden state \( h^i_T \) can represent the whole question. For convenience, here we drop the index \( i \) and iterate the following sequential equations to encode a question:

\[
\begin{align*}
    r^t &= \sigma(U_r h^{t-1} + W_r x^t) \\
    z^t &= \sigma(U_z h^{t-1} + W_z x^t) \\
    \tilde{h}^t &= \tanh(U(r^t \odot h^{t-1}) + W x^t) \\
    h^t &= z^t \odot \tilde{h}^t + (1 - z^t) \odot h^{t-1}
\end{align*}
\]

where \( U_r, U_z, W_r, W_z, U \) and \( W \) are the matrices of weight parameters. \( h^t \) is the state update at time step \( t \), \( r^t \) is the reset gate, \( \odot \) denotes an element-wise product and \( z^t \) is the update gate. These two update gates take the values between zero and one.

Problem Formulation

Our idea is the BQ generation for MQ and, at the same time, we only want the minimum number of BQ to represent the MQ, so modeling our problem as LASSO optimization problem is an appropriate way:

\[
\min_x \frac{1}{2} \|Ax - b\|_2^2 + \lambda \|x\|_1
\]
Table 1: LSTM Q+I model evaluation results on BQD and VQA dataset (Antol et al. 2015). "-" indicates the results are not available, "-std" means the accuracy of VQA model evaluated on the complete testing set of BQD and VQA dataset and "-dev" means the accuracy of VQA model evaluated on the partial testing set of BQD and VQA dataset. In addition, \( \text{diff} = \text{Original}_{\text{dev/All}} - X_{\text{dev/All}} \), where \( X \) is equal to "First", "Second", ..., "Seventh".

\[
\begin{array}{|c|c|c|c|c|c|}
\hline
\text{Task Type} & \text{Method} & \text{Test Set} & \text{dev} & \text{diff} \\
\hline
\text{Open-Ended} & \text{LSTM Q+I} & \text{First-dev} & 29.34 & 33.77 & 65.14 & 44.47 & 13.55 \\
\text{Open-Ended} & \text{LSTM Q+I} & \text{Second-dev} & 28.02 & 32.73 & 62.68 & 42.75 & 15.27 \\
\text{Open-Ended} & \text{LSTM Q+I} & \text{Third-dev} & 26.32 & 33.10 & 60.22 & 40.97 & 17.05 \\
\text{Open-Ended} & \text{LSTM Q+I} & \text{Fourth-dev} & 25.27 & 31.70 & 61.56 & 40.86 & 17.16 \\
\text{Open-Ended} & \text{LSTM Q+I} & \text{Fifth-dev} & 24.73 & 32.63 & 61.55 & 40.70 & 17.32 \\
\text{Open-Ended} & \text{LSTM Q+I} & \text{Sixth-dev} & 23.90 & 32.14 & 61.42 & 40.19 & 17.83 \\
\text{Open-Ended} & \text{LSTM Q+I} & \text{Seventh-dev} & 22.74 & 31.36 & 60.60 & 39.21 & 18.81 \\
\hline
\text{Original-dev} & \text{Original-std} & \text{First-dev} & 29.68 & 33.76 & 65.09 & 44.70 & 13.48 \\
\text{Original-dev} & \text{Original-std} & \text{Second-dev} & 43.40 & 36.46 & 80.87 & 58.02 & - \\
\text{Original-dev} & \text{Original-std} & \text{Third-dev} & 43.90 & 36.67 & 80.38 & 58.18 & - \\
\hline
\end{array}
\]

Table 2: HieCoAtt model evaluation results on BQD and VQA dataset (Antol et al. 2015). "-" indicates the results are not available, "-std" means the accuracy of VQA model evaluated on the complete testing set of BQD and VQA dataset and "-dev" means the accuracy of VQA model evaluated on the partial testing set of BQD and VQA dataset. In addition, \( \text{diff} = \text{Original}_{\text{dev/All}} - X_{\text{dev/All}} \), where \( X \) is equal to "First", "Second", ..., "Seventh".

\[
\begin{array}{|c|c|c|c|c|c|}
\hline
\text{Task Type} & \text{Method} & \text{Test Set} & \text{dev} & \text{diff} \\
\hline
\text{Open-Ended} & \text{HieCoAtt (Alt,VGG16)} & \text{First-dev} & 44.44 & 37.53 & 71.11 & 54.63 & 5.85 \\
\text{Open-Ended} & \text{HieCoAtt (Alt,VGG16)} & \text{Second-dev} & 42.62 & 36.68 & 68.67 & 52.67 & 7.81 \\
\text{Open-Ended} & \text{HieCoAtt (Alt,VGG16)} & \text{Third-dev} & 41.60 & 35.59 & 66.28 & 51.08 & 9.4 \\
\text{Open-Ended} & \text{HieCoAtt (Alt,VGG16)} & \text{Fourth-dev} & 41.09 & 35.71 & 67.49 & 51.34 & 9.14 \\
\text{Open-Ended} & \text{HieCoAtt (Alt,VGG16)} & \text{Fifth-dev} & 39.83 & 35.55 & 65.72 & 49.99 & 10.49 \\
\text{Open-Ended} & \text{HieCoAtt (Alt,VGG16)} & \text{Sixth-dev} & 39.60 & 35.99 & 66.56 & 50.27 & 10.21 \\
\text{Open-Ended} & \text{HieCoAtt (Alt,VGG16)} & \text{Seventh-dev} & 38.33 & 35.47 & 64.89 & 48.92 & 11.56 \\
\hline
\text{Original-dev} & \text{Original-std} & \text{First-dev} & 44.77 & 36.08 & 70.67 & 54.54 & 5.78 \\
\text{Original-dev} & \text{Original-std} & \text{Second-dev} & 49.14 & 38.35 & 79.63 & 60.48 & - \\
\text{Original-dev} & \text{Original-std} & \text{Third-dev} & 49.15 & 36.52 & 79.45 & 60.32 & - \\
\hline
\end{array}
\]

Basic Question Dataset

We propose a novel large scale dataset, called Basic Question Dataset (BQD), for robustness analysis of VQA models. BQD is the first basic question dataset generated by our basic question generation algorithm. Regarding the BQD, the dataset format is \{Image, MQ, 21 (BQ + corresponding similarity score)\}. All of our 81434 images are from the testing images of MS COCO dataset (Lin et al. 2014), all of our 244302 main questions (MQ) are exactly the same as the testing questions of VQA dataset (open-ended task) (Antol et al. 2015), the basic questions (BQ) are from the training and validation questions of VQA dataset (open-ended task) (Antol et al. 2015), and the corresponding similarity scores of BQ are generated by our basic question generation method, referring to Section 3. Note that we preprocess the training and validation question datasets from the VQA dataset (Antol et al. 2015), so the total number of basic question candidates is less than the total number of training and validation question datasets in VQA dataset (Antol et al. 2015). In BQD, we have 81434 images, 244302 MQ and 5130342 (BQ + corresponding similarity score). Furthermore, we exploit the BQD to do robustness analysis of the 6 available pretrained state-of-the-art VQA models (Antol et al. 2015; Lu et al. 2016; Ben-younes et al. 2017; Fukui et al. 2016; Kim et al. 2017) in the next subsection.

Robustness Analysis by Basic Questions

To measure the robustness of any model, we should evaluate it on clean and noisy input and compare the performance. The noise can be completely random, have a specific structure and/or be semantically relevant to the final task. For VQA the input is an image question pair and therefore the noise should be introduced to both. The noise to the question shouldn’t be random and it should have some contextual semantics for the measure to be informative. For the image part, there is already a rapidly growing research on evaluating the robustness of deep learning models (Fawzi, Moosavi Dezfooli, and Frossard 2017;
we report the robustness score $R_{score}$, i.e., the robustness score to be sensitive if the difference is small, but not before $t$. We append the top ranked $k$ BQs to each of the MQs in the dataset. In addition, $diff = |Acc_{dev|all} - X_{dev|all}|$, where $X$ is equal to "First", "Second", ..., "Seventh".

Carlini and Wagner 2017; Xu, Caramanis, and Mannor 2009). However, for the question part, we couldn’t find any acceptable method to measure the robustness of visual question answering algorithms after extensive literature review. Here we propose a novel robustness measure for VQA by introducing semantically relevant noise to the questions where we can control the strength of noisiness.

First, we measure the accuracy of the model on the clean VQA dataset (Antol et al. 2015) and we call it $Acc_{vqa}$. Then, we append the top ranked $k$ BQs to each of the MQs in the clean dataset and recompute the accuracy of the model on this noisy input and we call it $Acc_{bqd}$. Finally, we compute the absolute difference $Acc_{diff} = |Acc_{vqa} - Acc_{bqd}|$ and we report the robustness score $R_{score}$.

$$R_{score} = \min \left( \max \left( \frac{1 - \sqrt{Acc_{diff} \cdot m}}{1 - \frac{t}{m}}, 0 \right), 1 \right)$$

(6)

where $0 < t < m < 100$. The parameters $t$ and $m$ are the tolerance and the maximum robustness limit, respectively, i.e., the robustness score $R_{score}$ decreases smoothly between 1 and 0 as $Acc_{diff}$ moves from $t$ to $m$ and remain constant out side this range. The rate of change of this transition is exponentially decreasing from exponential to sublinear in the range $[t, m]$. The reasoning behind this is that we want the score to be sensitive if the difference is small, but not before $t$, and less sensitive if it is large, but not after $m$.

### 4 Experiment

In Section 4, we describe the details of our implementation and experimental results of the proposed method.

#### Datasets

We conduct our experiments on BQD and VQA (Antol et al. 2015) dataset. VQA dataset is based on the MS COCO dataset (Lin et al. 2014) and it contains a large number of questions. There are questions, 248349 for training, 121512 for validation and 244302 for testing. In the VQA dataset, each question is associated with 10 answers annotated by different people from Amazon Mechanical Turk (AMT). About 98% of answers do not exceed 3 words and 90% of answers have single words. Note that we only develop our work on the open-ended case in VQA dataset because it is the most popular task and we also think the open-ended task is closer to the real situation than multiple-choice one.

#### Setup

In our LASSO model, we use $\lambda = 10^{-6}$ to be our parameter and in the later subsection, we will discuss how the $\lambda$ affects the quality of BQ. Furthermore, although we rank all of the basic question candidates for each MQ, we only collect top 21 BQ to put into our BQD. The most important reason is that the similarity scores are too small after twenty-first BQ. Regarding the limit of number of words of question input, for most of available pretrained state-of-the-art VQA models they are trained under the condition maximum number of words of input 26 words. Based on the above limitation, we divide each 21 ranked BQs into 7 partitions to do detailed analysis, referring Table 1 to Table 5, because the total number of words of each MQ with 3 BQs is less than or equal to 26 words.

#### Evaluation Metrics

VQA dataset provides multiple-choice and open-ended task for evaluation. Regarding open-ended task, the answer can be any phrase or word. However, in the multiple-choice task, an answer should be chosen from 18 candidate answers. For both cases, answers are evaluated by accuracy which can reflect human consensus. The accuracy is given by the following:

$$\text{Accuracy}_{VQA} = \frac{1}{N} \sum_{t=1}^{N} \min \left\{ \frac{\sum_{t \in T} \|a_t = t\}}{3}, 1 \right\}$$

(7)
Table 5: MLB with Attention model evaluation results on BQD and VQA dataset (Antol et al. 2015). "-" indicates the results are not available, "-std" means the accuracy of VQA model evaluated on the complete testing set of BQD and VQA dataset and "-dev" means the accuracy of VQA model evaluated on the partial testing set of BQD and VQA dataset. In addition, \( \text{diff} = \text{Original}_{\text{dev/All}} - \text{X}_{\text{dev/All}} \), where \( X \) is equal to "First", "Second", ..., "Seventh".

| Test Set | Method | Partition | Other | Num | V/N | All | All |
|----------|--------|-----------|-------|-----|-----|-----|-----|
| Original-std | MLB with Attention | First-dev | 49.31 | 34.62 | 72.21 | 57.12 | 8.67 |
| | | Second-dev | 48.53 | 34.84 | 70.30 | 55.98 | 9.81 |
| | | Third-dev | 48.01 | 33.95 | 69.15 | 55.16 | 10.63 |
| | | Fourth-dev | 47.20 | 34.02 | 69.31 | 54.84 | 10.95 |
| | | Fifth-dev | 45.85 | 34.07 | 68.95 | 54.05 | 11.74 |
| | | Sixth-dev | 44.61 | 34.30 | 68.59 | 53.34 | 12.45 |
| | | Seventh-dev | 44.71 | 33.84 | 67.76 | 52.99 | 12.80 |
| Original-dev | MLB with Attention | First-std | 49.07 | 34.13 | 71.96 | 56.95 | 8.73 |
| | | Original-dev | 57.01 | 37.51 | 83.54 | 65.79 | - |
| | | Original-std | 56.60 | 36.63 | 83.68 | 65.68 | - |

Results and Analysis

We describe final results and analysis by the following:

i.) Are The Rankings of BQs Effective? The answer is yes. According to the Figure 2, we divide the top 21 ranked BQs into 7 partitions and each partition contains 3 ranked BQs and the accuracy is decreasing from the first partition to the seventh partition. Moreover, based on Figure 3, we can discover that the difference of accuracy of VQA models is increasing from the first partition to the seventh partition. These trends imply that the similarity of BQs to the given MQ is decreasing from the first partition to the seventh partition. That is to say, the noise strength is increasing from the first partition to the seventh partition because we assume that a BQ with lower similarity score to the given MQ means the BQ is a larger noise for the given MQ. That’s why we can say that the rankings of BQs are effective.

ii.) Who Can Affect The Quality of BQs? In our model, \( \lambda \) is one of the most important factors to affect the quality of BQ. Note that if a BQ can have highly enough similarity score and provide enough extra useful information to a given MQ, then we say that the BQ has the well enough quality. We discover that when \( \lambda \) is greater than \( 10^{-5} \) or less than \( 10^{-6} \), the quality of BQ is obviously not good based on the common sense knowledge. However, if we compare the quality of BQ of \( \lambda \) equal to \( 10^{-5} \) with \( \lambda \) equal to \( 10^{-6} \), we think the BQ quality of \( \lambda \) equal to \( 10^{-6} \) is slightly better than \( \lambda \) equal to \( 10^{-5} \) based on our common sense knowledge. We will put some randomly selected BQ examples from our BQD in the supplementary material for references. Note that

\[
\text{I}[\cdot] = \begin{cases} 
1 & \text{increasing from the first partition to the seventh partition} \\
0 & \text{else}
\end{cases}
\]

\( \text{diff} = \text{Original}_{\text{dev/All}} - \text{X}_{\text{dev/All}} \), where \( X \) is equal to "First", "Second", ..., "Seventh".

Figure 2: The accuracy of state-of-the-art VQA models evaluated on BQD and VQA dataset (Antol et al. 2015). Note that we divide the top 21 ranked BQs into 7 partitions and each partition contains 3 ranked BQs. Here, "First top 3" means the first partition, "Second top 3" means the second partition, ..., and "Seventh top 3" means the seventh partition.

Table 6: \( R_{\text{score}} \) of state-of-the-art VQA models. Note that LQI means \( \text{LSTM Q+I} \), HAV means \( \text{HieCoAtt-Alternating-VGG16} \), HAR means \( \text{HieCoAtt-Alternating-Res200} \), MU means \( \text{MUTAN without Attention} \), MUA means \( \text{MUTAN with Attention} \), and MLB means MLB with Attention.

| Model | LQI | HAV | HAR | MU | MUA | MLB |
|-------|-----|-----|-----|----|-----|-----|
| \( R_{\text{score}} \) | 0.19 | 0.48 | 0.45 | 0.30 | 0.34 | 0.36 |
Figure 3: The accuracy decrement of state-of-the-art VQA models evaluated on BQD and VQA dataset (Antol et al. 2015). Note that we divide the top 21 ranked BQs into 7 partitions and each partition contains 3 ranked BQs. Here, "First top 3" means the first partition, "Second top 3" means the second partition,...., and "Seventh top 3" means the seventh partition.

Table 7: "avg" denotes average and "std" denotes standard deviation.

| score1 | score2/score1 | score3/score2 |
|--------|---------------|---------------|
| avg    | 0.33          | 0.61          | 0.73          |
| std    | 0.20          | 0.27          | 0.21          |

Table 8: Note that appending BQ means doing the concatenation with MQ.

|                  | 0 BQ (%) | 1 BQ (%) | 2 BQ (%) | 3 BQ (%) |
|------------------|----------|----------|----------|----------|
| # Q              | 236570   | 7512     | 211      | 9        |

Table 9: The number of BQs are appended. Here, "X BQ" means X BQs are appended by MQ, where X = 0, 1, 2, 3, and "# Q" denoted the number of questions.

BQs are well enough, then even we use the naive concatenation, i.e. direct concatenation, method to concatenate MQ and BQs, it still can directly help the accuracy of VQA models. For justifying our claim, we propose a thresholding criterion, referring to Table 8, to select the BQ with good quality.

v.) Basic Question Concatenation. In this subsection, we propose a thresholding criterion to select the BQ with good quality. In BQD, each MQ has 21 corresponding BQ with scores. We can have the following format, \( \{MQ, (BQ1, score1), ..., (BQ21, score21)\} \), and these scores are all between 0 and 1 with the following order:

\[
score1 \geq score2 \geq ... \geq score21
\]

and we define 3 thresholds, \( s_1, s_2 \) and \( s_3 \). Note that, for convenience, we only take the top 3 BQs to do selection because our BQs are ranked. Moreover, we compute the following 3 averages (\( avg \)) and 3 standard deviations (\( std \)) to \( score1, score2/score1 \) and \( score3/score2 \), respectively, and then use \( avg \pm std \), referring to Table 7, to be the initial estimation of proper thresholds. The BQ utilization process can be explained as the Table 8.

Does BQ can directly help accuracy? The answer probably is yes. In our experiment, we use the \( avg \pm std \), referring to Table 7, to be the initial guess of proper thresholds of \( s_1, s_2 \) and \( s_3 \). We discover that when \( s_1 = 0.60, s_2 = 0.58 \) and \( s_3 = 0.41 \), we can get the BQs, referring to Table 9, who can directly help accuracy with the naive concatenation method. Accordingly to the Table 9, 96.84% of testing questions from VQA dataset cannot find the proper basic questions to help the accuracy by naive concatenation method. Although we only have 3.16% of testing questions can benefit from the basic questions, our method still can improve the state-of-the-art accuracy (Lu et al. 2016) from 60.32% to 60.34%, referring to supplementary material. Then, we have 244302 testing questions, so that means the number of correctly answering questions of our method is more than state-of-the-art method 49 questions. In other words, if we have well enough basic question dataset, we can increase accuracy more, especially in the counting-type question, referring to supplementary material. We conjecture that because the Co-Attention Mechanism is good at localizing, the counting-type question is improved more than others. Accordingly, based on our experiment, we believe that basic questions with well enough quality can directly help accuracy by only using the naive concatenation method.

5 Conclusion and Future Work

In this paper, we propose a novel VQABQ method and Basic Question Dataset (BQD) for robustness analysis of VQA models. The VQABQ method has two main modules, Basic Question Generation Module and VQA Module. The former one can generate the basic questions for the query question, and the latter one can take an image, basic and query questions as the input and then output the text-based answer of the query question about the given image. Furthermore, we can use the proposed BQD, \( R_{score} \) and VQA dataset (Antol et al. 2015) to measure the robustness of VQA models.

According to previous state-of-the-art VQA methods, most of them get the highest accuracy in the Yes/No-type question. Accordingly, how to effectively only exploit the Yes/No-type basic questions to do VQA will be an interesting work. Furthermore, how to build a VQA model with high robustness and accuracy at the same time will be also an in-

Algorithm 1 Basic Question Concatenation

Note that \( s_1, s_2, s_3 \) are thresholds we can choose.

1: \( \text{if} \ score1 > s_1 \)
2: Append BQ1 with the largest score
3: \( \text{if} \ score2/score1 > s_2 \)
4: Append BQ2 with the second large score
5: \( \text{if} \ score3/score2 > s_3 \)
6: Append BQ3 with the third large score
teresting research direction. The above future works will be our next research focus.

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