Visual Question Answering Using Semantic Information from Image Descriptions

Tasmia Tasrin, Md Sultan Al Nahian and Brent Harrison
University of Kentucky
{tasmia.tasrin, sa.nahian, brent.harrison}@uky.edu

Abstract

Visual question answering (VQA) is a task that requires AI systems to display multi-modal understanding. A system must be able to reason over the question being asked as well as the image itself to determine reasonable answers to the questions posed. In many cases, simply reasoning over the image itself and the question is not enough to achieve good performance. As an aid of the task, other than region based visual information and natural language questions, external textual knowledge extracted from images can also be used to generate correct answers for questions. Considering these, we propose a deep neural network model that uses an attention mechanism which utilizes image features, the natural language question asked and semantic knowledge extracted from the image to produce open-ended answers for the given questions. The combination of image features and contextual information about the image bolster a model to more accurately respond to questions and potentially do so with less required training data. We evaluate our proposed architecture on a VQA task against a strong baseline and show that our method achieves excellent results on this task.

1 Introduction

Visual Question Answering (VQA) is a task in which a system provides natural language answers to questions concerning an image. This is typically accomplished using deep learning systems that extract textual features from the question and image features from the image in question. Within last few years, VQA has gained the attention of researchers in the field because of its many applications to important problems. For example, VQA techniques could be used to aid the elderly or visually impaired interpret the world around them.

Approaches for VQA predominantly involve reasoning over image features, such as those extracted in other domains such as image captioning [Krause et al., 2017; Johnson et al., 2015; Karpathy and Li, 2014; You et al., 2016]. This information, however, may not be sufficient for VQA. While these features alone may be sufficient for image captioning, VQA requires more detailed information about the

| question | What sport is being played? |
|----------|-----------------------------|
| semantic info | `umpire catcher`, `blue helmet`, `player wearing blue helmet`, `baseball player uniform`, `white shirt black writing`, `catcher wearing red and black helmet`, `baseball players field`, `baseball field green grass`, `umpire wearing black shirt`, `catcher wearing white uniform` |
| ground truth answer | baseball |
| generated answer | baseball |

Table 1: An example image with one of its relative question available in VQA v2.0 dataset. The row semantic info represents the semantic information extracted from the image using Densecap. These three information are afterwards used to generate an answer which matches with the ground truth answer of the dataset.
VQA can be thought of as a more challenging as it requires both language understanding and image understanding simultaneously to do the task. To address this problem, the VQA challenge and dataset [Antol et al., 2015; Goyal et al., 2016] has opened up a path where by asking a question about an image, one trains a network that aims to both learn the features of an image and also perceive the text of the question. One difficulty that arises with this approach is that there is very little text signal that networks can use to derive semantic information in the image. This means that either 1) Large amounts of question and answer data must be gathered for ML techniques to learn effectively or 2) Approaches will struggle to draw a connection between image features and text semantics.

One solution that has been explored previously is the notion of neural attention. In previous work [Yang et al., 2015; Kazemi and Elqursh, 2017; Anderson et al., 2018; Teney et al., 2017; Das et al., 2016], authors have proposed different approaches for utilizing attention mechanisms that improve model performance on the VQA task. However, these networks are often unable to answer questions related to numbers or other contextual information about the images. This is because it is hard to ground visual information using natural language texts appropriately. In addition, it is unclear if these attention mechanisms address potential issues of scale that often occur with deep learning techniques. It is unclear how well these approaches will perform if small amounts of data are available.

To overcome these shortcomings, we propose to augment a deep learning architecture that utilizes attention with additional, external knowledge about the image. This approach has been used in the past [Kim and Bansal, 2019; Wu et al., 2019; Q. Wu and v. d. Hengel, 2016]; however, our work seeks to take advantage of a different form of knowledge. Our resulting network, which we call the Visual Question Answering-Contextual Information network (VQA-CoIn), improves upon past work by extending it to incorporate semantic information extracted from an image via image descriptions. We realise that if a deep neural network model is assisted with both visual features and contextual language information about an image, the architecture can learn more efficiently to produce answers for the related questions. The reason behind it could be, as the model has already learnt about the textual knowledge about an image, this fact can provide support to the system to express a visual feature with natural language words more effectively than has already been learnt by the model. This may also reduce the number of examples needed to build up these semantic connections in the neural network.

In our proposed model, we have extend the work in [Kim et al., 2018] by incorporating semantic information of an image in addition to the image features and questions. Table 1 shows an example of three inputs for our model: image, question and semantic information produced for the image and a comparison of the ground truth answer from the data set and the generated answer by our model for the given question.

To evaluate the effectiveness that this additional information has, We have used the VQA v2.0 [Goyal et al., 2016] dataset to train and evaluate our architecture. For generating semantic information for each image of the dataset, we utilize DenseCap[Johnson et al., 2015] to extract salient image regions and produce image captions for them. We pre-process these captions to extract the important words out of them as we want to make sure that the information limits to a fixed length and the deep learning network used to encode these words focus on the meaningful texts. For evaluation of our network, we use accuracy as the evaluation metric like all prior works. To measure the test accuracy score, we use VQA challenge hosting site EvalAI where we submit the generated results and the site measures the scores for 3 categorical questions and overall test accuracy for the test split data. In addition, we also evaluate how well our techniques scales with data compared to other techniques by testing with different percentages of the training dataset. The contributions of our work can be summed up to the following:

- An end-to-end deep learning network using the contextual information of the images along with images and questions to generate more correct answers.
- Evaluation of the method using validation dataset, based on the training of different scales of training splits.

2 Related Works

Related to VQA, image captioning [Krause et al., 2017; Johnson et al., 2015; Karpathy and Li, 2014; You et al., 2016] has put a lot of effort into understanding images by identifying the objects of images and describing them using natural language. Prior research on image captioning focuses on generating image captions by encoding images, often using convolutional neural networks (CNNs) [Krause et al., 2017; Johnson et al., 2015; Karpathy and Li, 2014]. Later, attention mechanisms were introduced to detect important objects from an image and create more informative captions using the extracted information[Xu et al., 2015; You et al., 2016]. The authors of [Karpathy and Li, 2014] find the inter-modal correspondences between descriptions and images from datasets and then utilizing them to generate captions using CNNs and bidirectional RNNs. Densecap [Johnson et al., 2015], which we use in this work, describes an image at a finer level of detail using small sentences while [Krause et al., 2017] generates paragraphs focusing on various regions of an image. In [You et al., 2016], the model selectively attends semantic concept proposals and fuses them with the outputs of a RNN to produce better captions from images. While this is a related task, it is important to understand the fundamental differences between VQA and image captioning. In VQA, the network is attempting to determine the answer to a given question using the supplied image. Thus, while it needs to understand the content of the image, as in image captioning, it must also understand the nature of the question to be successful.

Given its similarity to image captioning, it is understandable that VQA researchers have followed a similar research trajectory to those in the image captioning community, first employing vanilla deep networks and then merging them with attention mechanisms. The introduction of the VQA v1.0 and VQA v2.0 datasets [Antol et al., 2015; Goyal et al., 2016] have drastically accelerated research in
this area. As a result, some interesting works like [Yang et al., 2015; Kazemi and Elqursh, 2017; Anderson et al., 2018; Teney et al., 2017; Das et al., 2016] have been proposed for the advancement in VQA. For instance, while the work in [Yang et al., 2015] focuses on putting stacked attention on images, [Anderson et al., 2018] has assigned bottom-up attention to figure out the regions and then used top-down mechanism to determine the important features. Both [Yang et al., 2015] and [Anderson et al., 2018] are the winners of the VQA challenge 2016 and 2017 respectively. The region based features introduced by [Anderson et al., 2018] have been utilized by several approaches [You et al., 2016; Kim et al., 2018; Jiang et al., 2018] including ours. In the 2018 VQA challenge, authors improved upon the 2017 winner by changing learning schedule, fine tuning the model, and using both grid level features and region features of images [Jiang et al., 2018]. But recently a research work has revisited grid based features of VQA and used them in end-to-end training [Huaizu Jiang, 2020], which has produced strong results.

There has been prior work that merges elements of image and text for the VQA task. For example, Kim and Bansal utilized both paragraph captions and object properties described using sentences as prior knowledge to aid in the VQA task on the visual genome dataset [Kim and Bansal, 2019]. Wu et al. proposed a free-form VQA model where internal textual representations of an image are merged with textual information sourced from a knowledge base [Q. Wu and v. d. Hengel, 2016]. They claim that by using this method, a VQA system can answer both complex and broad questions conditioned on images. In work by Wu, Hu, and Mooney [Wu et al., 2019], captions are generated from questions and are used as an input to the neural network. The model that we propose in this work focuses on using region-based descriptions as we believe this will better help our model bridge the gap between images and natural language questions.

While the VQA challenge dataset has been the primary one in use, there are others available [Mehrdad Alizadeh, 2020; Marino et al., 2019]. For instance, by observing the utilization of the attention mechanism in various later works, [Das et al., 2016] has proposed a new dataset which compares how a human and an AI usually attend to measure an important feature in any given image. Another dataset, imSituVQA[Mehrdad Alizadeh, 2020], has been introduced by augmenting images with the semantics available in verbs describing an image. The authors of the dataset also propose a model which classifies both answers and semantic frame elements. Moreover, VQA task has also attracted computer vision researchers from other fields such as medical and remote sensing domains. Like, [Binh D. Nguyen, 2019] has proposed a framework that can be efficiently trained using a small labeled training set using unsupervised Denoising Auto-Encoder (DAE) and supervised Meta-Learning and has already defeated the state-of-the-art medical VQA model. And a VQA task for remote sensing data has been introduced by [Sylvain Lobry, 2020] along with two datasets. The datasets are made of using low and high resolution remote sensing data and consist of image/question/answer triplets.

3 Method

Given an image and associated question, the aim of our proposed model is to produce an answer of the question utilizing the salient image features and semantic information of the image. We name our model as VQA-contextual information (VQA-CoIn) model and following this, in the rest of the paper, we will address the method by VQA-CoIn model. Through our network, we emphasize that adding contextual information of the image can help a VQA agent to learn more about the content of the target image to answer relative questions about the image.

In our proposed architecture, there are three different modules which make an end to end deep learning architecture for the Visual Question Answering task. The first module is the Input Encoder, where visual features are extracted using Faster r-CNN[Ren et al., 2015] method and textual features like natural language questions and semantic knowledge of the images are embedded using gated recurrent units (GRUs) [Cho and Bengio, 2014]. The next process in our model involves attending to images and semantic information of im-
ages works using a bilinear attention mechanism conditioned on question embedding vectors. The bilinear attention of our network is based on the attention mechanism used in Bilinear attention networks [Kim et al., 2018]. We also apply self attention on questions to learn the importance of the words residing in the given questions. The third component of the network is the classifier which predicts candidate answers using the concatenated vector produced from the sum pooling of the three output vectors of the previous two modules. Figure 1 shows an overview of our VQA-CoIn model. We will discuss each module of our architecture in greater detail below.

3.1 Input Encoder

The Input Encoder takes an image, associated question, and the semantic information of the image as inputs and produces three embedding vectors, one from each of the inputs. For the image features, we use the pre-trained bottom-up attention features which were generated in [Anderson et al., 2018]. They used Faster r-CNN algorithm [Ren et al., 2015] with ResNet-101 to train the model. We have considered adaptive number of features \( f_i \) per image to generate the vector representation \( f_i \times d_i \) for each image where \( d_i \) is the feature size of an image.

Our model uses semantic information (SI) extracted from the image as external knowledge to learn more about the image. To encode these semantic features, each word is embedded using pre-trained word embeddings. Then the embedded word vectors are propagated through GRU cell which gives us hidden vector for each corresponding word. The hidden vectors are used in the attention layer to create the encoding vector of the semantic features.

The final input for our task is the question related to the image which is embedded twice with two different hidden vector sizes in our model. We do this because we realize from our experiments that questions with large hidden vectors can contain more information from image while attending them. But in the case of prioritizing information from its own features and additional knowledge available for the question, hidden layers with smaller dimensions can perform this task more effectively. In Figure 1, questions with large vector sizes are represented using yellow color and questions with smaller dimensions are represented using the color blue. As with the SI embedding, to embed each word of a question, we use pre-trained word embedding for getting the vector representation of each word of the question. The obtained word embedding vector is then passed through two separate GRU cells [Chung et al., 2014] represented as GRU\(_1\) and GRU\(_s\) for larger and smaller hidden state respectively in Figure 1. The GRU\(_i\) cells have \( n_p \) numbers of hidden states \( h_{q_i} \) and \( h_{s_i} \). Here \( n_p \) is the number of words in the question, \( h_{q_i} \) denotes the hidden states from GRU\(_1\) and \( h_{s_i} \) denotes the hidden states from GRU\(_s\). Hidden states of both GRU cells are passed to the attention layer to generate the context vector of the questions.

3.2 Attention Layer

In the attention layer, we employ an attention mechanism to find out the importance of different parts of the input sequence based on a query vector. We use two different attention mechanisms on the input vectors: 1. Self-Attention, applied in the question embedding vector and 2. Bi-Linear Attention, applied in the image embedding, question embedding and semantic information embedding vectors.

Self-Attention

Self attention is an attention mechanism where relations among different parts of a sequence are computed using the same sequence as query. In our proposed architecture, we apply self-attention on a question to figure out the internal relations among the words of the question. For example, in a question like "what is the color of the bus?", invoking self-attention on itself would enable the model to identify that the words "color" and "bus" are interrelated and should be more emphasized to learn about the question.

Figure 2 shows the detailed architecture of the self-attention module. We implement the self-attention mechanism inspired by the idea of multi-headed attention which are featured in many transformer architectures [Vaswani et al., 2017]. In this process, we take into account all of the hidden states of the GRU\(_1\) instead of the final hidden state as RNNs have a tendency to forget the information encountered in the early steps of the sequence. All of the hidden states are passed through two fully connected layers and which generate two vectors, a query vector \( q \) and a value vector \( v \). In each fully connected layer, weight normalization and ReLU activation are performed on the input vectors. Then the resultant vectors \( q \) and \( v \) are multiplied together to create a new context vector. Here, the multiplication operation is the element-wise multiplication (Hadamard product) of the vectors. The new context vector is forwarded to another fully connected layer followed by a softmax layer to generate the attention weights of the input question embedding. Afterwards the attention weights are used to construct the final context vector \( c_{q_i} \) of a question by multiplying it with the initial question embedding. This final question context vector represents the prioritized words in the input question sequence.

\[
y = q \ast v
\]

\[
l_q = \text{Linear}(\text{ReLU}(y))
\]

\[
w = \text{softmax}(l_q)
\]

So, equation 1, 2 and 3 depict the self-attention mechanism.

As a next step, the self-attended context vector \( c_{q_i} \) is used to put bilinear attention [Kim et al., 2018] on the semantic concepts of the images.

Bilinear Attention

Bilinear attention is usually applied on two inputs with multiple channels so that the two input channels decrease their dimensionality concurrently. We adopt this attention mechanism from Bilinear attention networks [Kim et al., 2018]. In our case, we have two input groups to apply the attention: one group is the combined group of the image and question and the other is the combined group of the semantic information and question context vector. In the attention procedure, at
first an attention map is generated using image features conditioned on given questions embedded using GRU. Similar to [Kim et al., 2018], this attention map is then run through eight glimpses. In each glimpse, a vector representation from the image and question is produced using the bilinear attention map. Next, with this representation, for every glimpse, we keep integrating the resultant vectors of the residual learning network and counter module [Zhang et al., 2018]. As a result, at the last glimpse, we get a final output vector $b_{c,v}$.

For the input group of semantic information and the question context vector $c_{d,s}$, we similarly produce an attention map using the two input vectors. Unlike the image-question input group, we use one glimpse on the attention map of semantic information-question group to generate a vector. Also, we element-wise add the context vector $c_{d,s}$ of question with the resultant vector from the glimpse. This creates an output vector $b_{c,s}$.

### 3.3 Classifier Layer

$b_{c,v}$, $b_{c,s}$, and $c_{d,s}$ are the inputs of our classifier layer. The sum pooling of these three input vectors are concatenated as the next step of the classifier. And the concatenated vector is then redirected to two fully connected layers to gather the predicted answers for the questions. In the FC layers, we use ReLU as the activation function and the output dimension is set to the number of unique answers. We have selected these answers that appear at least 9 times for the distinct questions in the training dataset.

### 4 Experimental Setup

In this section, we are going to have a detailed discussion about the implementation procedure and experimental setup for VQA-CoIn model. First, we discuss the dataset we use for our task and then the preprocessing of our additional prior semantic knowledge. We will then outline the network parameters for our proposed model that we use in these experiments. To evaluate our method VQA-CoIn, we have used the available VQA challenge guidelines. We use BAN-8 [Kim et al., 2018] as our baseline. And we compare our validation and test scores with bottom-up attention model [Anderson et al., 2018] as well.

### 4.1 Dataset

We evaluate our proposed model on the VQA v2.0 dataset. We use the provided train/validation split of the dataset to train our network. In the training dataset, there are more than 400k questions and 82k images. 200k questions and 40k images are available in the validation split. Though we are utilizing full dataset, our model is trained to learn from the selective answers from the train split. Recall that these are chosen, because they appear as answers at least 9 times for the unique questions of the split. The number of these selective answers is 3,129. The test split of the dataset has around 82k images and 440k relevant questions on which we use for testing of our network. As VQA task is an open challenge, the ground truth answers for the questions in the test dataset are not available and cannot be compared with.

### 4.2 Preprocessing

As we have mentioned, our method exploits the semantic concepts of images available in the dataset as an input of our architecture. To generate this information, we use Densecap [Johnson et al., 2015], an image captioning model. For each image, Densecap generates a variable number of captions. We have found that after a certain number of generated captions, the generated information tend to be duplicates. For example, Densecap has generated both ‘man wearing a hat’ and ‘a man wearing a hat’ captions for an image. To avoid this duplicate words, we have removed a sentence which has at least 80% similarity with any previous selected sentence. After discarding the similar sentences, from the resultant list, first 10 sentences are taken and preprocessed. As preprocessing steps, we tag the words of each sentence with the NLTK part-of-speech tagger and then get rid of the stop words such as ‘the’, as well as any preposition and auxiliary verbs from the sentences. Afterwards, the remaining words are gathered in a list which we have used as the semantic information for the respective image.

### 4.3 Network Parameters

We consider our image feature size $d_i$ as 2048 and the number of features $f_i$ can be variant which is usually between 10 to 100 per image. For word embedding, pre-trained GLoVe vectors of size 300 have been used. As we mention in section 3.1, questions are embedded twice in our architecture. Question

![Diagram of VQA-CoIn architecture](image-url)
embeddings which are used for attending image features utilize GRU cells with a dimension of 1024 and the question representation utilized for self-attention and external knowledge prioritization consists of a 512 sized vector. The maximum word length $n_q$ for any embedded question in the proposed model is 14. To embed the semantic concept of an image, we fix the size of the GRU units to 512. The additional semantic knowledge about an image can consist of maximum 40 words. For training, we find that 18 epochs are enough to sufficiently train the network. For the first four epochs, the learning rate is gradually increased from 0.05e-3 to 0.2e-3 and for the next 6 epochs, the learning rate is fixed to 0.2e-3. Afterwards, a decay rate of the learning schedule for the upcoming eight epochs is applied and set to 0.25 which updates and decreases learning rate for each two consecutive epochs until epoch 14 and then each epoch until epoch 18. We have used the batch size of 180 for training and testing the dataset. The Adamax optimizer is used to optimize the classifier and dropout value of the classifier is set to 0.5 while fc layers have dropout of 0.2.

4.4 Baselines
BAN-8 [Kim et al., 2018] is our baseline architecture. To compare with the baseline model, we have re-trained the BAN model [Kim et al., 2018] from their github repository to reproduce the results. A note to mention, we deploy some changes to BAN model while reproducing it. First, we use batch size 180 to run their model as we deploy for our VQA-CoIn model. Second, we have omitted the effect of data augmentation of visual genome dataset from BAN model as we have not employ any data augmentation. The reason of making these changes is to appropriately compare our model with the baseline model.

4.5 Evaluation Criterion
For VQA tasks, question accuracy is the preferred evaluation metric. In this section, we are going to illustrate the evaluation process we have followed. Like previous VQA approaches, we have computed accuracy to decide how our architecture is performing to figure out the correct answers for a given question using both image features and contextual information about the image. According to the employed dataset, validation and test accuracy scores are calculated. Validation accuracy is measured by comparing against the ground truth answers available in the validation data split. And to obtain the testing score, we have generated the answers for the questions in the test split based on our model and submitted the results in the VQA challenge hosting site EvalAI. It provides scores for each category of questions which are already defined in the dataset.

| Scale% | VQA-CoIn | BAN |
|--------|----------|-----|
| 25     | 54.84    | 54.09 |
| 50     | 61.76    | 62.42 |
| 75     | 65.08    | 64.92 |

Table 2: Validation accuracy after training VQA-CoIn with different scales of train split.

| Method       | Validation Score |
|--------------|------------------|
| bottom-up    | 63.20            |
| BAN-8        | 66.28            |
| VQA-CoIn     | 66.33            |

Table 3: Validation scores computed on the full VQA v2.0 dataset for bottom-up model, BAN-8 and our architecture.

| Method       | yes/no | number | other | overall | test-dev |
|--------------|--------|--------|-------|---------|----------|
| bottom-up    | -      | -      | -     | 65.67   | 65.32    |
| BAN-8        | 83.61  | 50.45  | -     | 67.57   | 68.07    |
| VQA-CoIn     | 83.57  | 50.91  | 58.33 | 67.88   | 68.20    |

Table 4: Comparison of Test-standard scores among VQA-CoIn, BAN-8 and bottom-up model. VQA-CoIn are trained using VQA v2.0 train and validation splits and tested on test split. Note that all 3 models are single models.

5 Results & Discussion
We have considered BAN-8 [Kim et al., 2018] model as our baseline and compared our results with it’s single model validation and test scores. Unlike other approaches, we also execute an experiment in which we check the validation accuracy while a model is trained with different scales of training data. Through this investigation, we want to figure out whether our model can learn and generate precise answers for the validation questions though it has been trained on different sets of train dataset.

5.1 Quantitative Results
Table 2 demonstrates the results for our data scaling experiment. We perform this experiment using on our VQA-CoIn model and our baseline model. We find that for one fourth and three fourth of the dataset, when we train our model, it is capable of functioning better than BAN-8 model. But while trained on 50% of our training split. BAN model perform better than VQA-CoIn. The reason behind this could be, as we are enforcing contextual information of the images generated by a pre-trained model in our method, some of these information may not carry knowledge related to the question to answer it correctly. This observation can lead our study to further investigation by producing and invoking semantic information using other pre-trained models in future. We still feel that this gives strong evidence that our approach can better utilize small amounts of data when compared to start-of-the-art approaches. Through Table 3, we estimate our validation score for the whole dataset with the state-of-the-art baseline and show that our method performs better in terms of accuracy.

In order to receive scores for the test set, we submitted the results produced by our model to the VQA competition using EvalAI. We also submit the reproduced answers of BAN in the same site to find out and compare the test-dev and test-standard scores with ours. According to the results returned,
displayed in Table 3. We can observe that VQA-CoIn has outperformed BAN and bottom-up [Anderson et al., 2018] in test-dev and test-standard challenges. If we consider each category of questions for BAN-8 and VQA-CoIn models, we can see that VQA-CoIn has surpassed the scores of BAN-8 for ‘number’ and ‘other’ categorical questions. For ‘yes/no’ category of questions, BAN has performed better than ours. We feel that these results are significant, especially our performance on the ‘other’ category. To answer any question from ‘other’ category, a model needs to understand more complex relation among the contents of an image from where it has to find an answer. Semantic information provides support behind this logic and helps our model to generate more accurate answers than our baseline models.

5.2 Qualitative Results

After the quantitative comparison of our and two state-of-the-art models, we do a qualitative contrast between VQA-CoIn and BAN-8 using the data of validation split. This is not meant to be a formal evaluation, but mainly meant to provide additional context to the results that our approach gives compared to our baselines. Table 5 represents the contrast. We have image, question and semantic information for each of three examples. The human annotated ground truth answers for the examples are also added so that the answers generated by both of the models can be compared with it. From the table, we can see that for image (a) and (b), our model generates correct answers. For the same images, BAN model generates answers that are very close to the answers from the dataset, but not accurate. Here, the reason of the success of our model is both image features and semantic information for images. The answers for the questions are already available in the semantic information. For ease of reading, we bold the texts on the row named as semantic info in the table. Now, if we match answers for image (c) of both models, answers are not exact to the ground truth answers. Our model is able to detect only two colors using both image features and semantic information (bold texts in semantic info row under image (c)) available for the input question. So, VQA-CoIn chooses these two colors as answer. It also means that, if better semantic information is used, our model can generate more correct answers.

We add a visualization of the attention map of an example question and semantic information from the test split in Figure 3. From the figure, it is visible that following the question ‘what sort of animal is this?', words ‘elephant’ are mostly attended from all texts of the semantic information. This further supports our claim that this additional semantic information can help bridge the gap between the natural language question and the image in question.

6 Conclusion

In this paper, we have proposed a novel VQA architecture, VQA-CoIn, which incorporates contextual information of an image to understand and represent a feature of an image with already available textual information about it. Our motivation for this is that incorporating semantic information in the form of natural language descriptions should better enable ML models to bridge the gap between the questions being asked and the image itself. We also hypothesize that this
should result in better data scaling, and enable these models to perform well with less data. We have compared our VQA-CoIn model with two state-of-the-art models and showed that our model performs better than those models both in terms of raw accuracy, and in terms of scaling performance. As our future work, we intend to train our model with contextual information generated by other pre-trained image captioning models to investigate how our model performs using those knowledge. We also have a plan to do human evaluation of the results we achieve.

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