Scene Text Visual Question Answering

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Abstract

Current visual question answering datasets do not consider the rich semantic information conveyed by text within an image. In this work, we present a new dataset, ST-VQA, that aims to highlight the importance of exploiting high-level semantic information present in images as textual cues in the VQA process. We use this dataset to define a series of tasks of increasing difficulty for which reading the scene text in the context provided by the visual information is necessary to reason and generate an appropriate answer. We propose a new evaluation metric for these tasks to account both for reasoning errors as well as shortcomings of the text recognition module. In addition we put forward a series of baseline methods, which provide further insight to the newly released dataset, and set the scene for further research.

1. INTRODUCTION

Textual content in human environments convey important high-level semantic information that is explicit and is not available in any other form in the scene. Interpreting written information in human environments is essential in order to perform most everyday tasks like making a purchase, using public transportation, finding a place in the city, getting an appointment, or checking whether a store is open or not, to mention just a few. Text is present in about 50% of the images in large-scale datasets such as MS Common Objects in Context [50] and the percentage goes up sharply in urban environments. It is thus fundamental to design models that take advantage of these explicit cues. Ensuring that scene text is properly accounted for is not a marginal research problem, but quite central for holistic scene interpretation models.

The research community on reading systems has made significant advances over the past decade [22, 10]. The current state of the art in scene text understanding allows dot-

Q: What is the price displayed in large letters on the sign?
A: 14.99

Q: What is written on the sign?
A: Stop

Q: Where is this train going?
A: To New York
A: New York

Q: What is the exit number on the street sign?
A: Exit 2

Figure 1. Recognising and interpreting textual content is essential for scene understanding. In Scene Text Visual Question Answering (ST-VQA) dataset leveraging textual information in the image is the only way to solve the QA task.

ting computer vision systems with basic reading capacity, although the community has not yet exploited this towards solving higher level problems.

At the same time, current visual question answering datasets and models present serious limitations as a result of ignoring scene text content, with disappointing results on questions that require scene text understanding. We therefore consider it is timely to bring together these two research lines in the VQA domain.

To move towards more human like reasoning, we contemplate that grounding question answering both on the vi-
ual and the textual information is necessary. Integrating the textual modality in existing VQA pipelines is not trivial. On one hand, spotting relevant textual information in the scene requires performing complex reasoning about positions, colors, objects and semantics, to localise, recognise and eventually interpret the recognised text in the context of the visual content, or any other contextual information available. On the other hand, current VQA models work mostly on the principle of classical [40] and operant (instrumental) conditioning [48]. Apart from leading to important dataset biases [19], failure in counting, comparison and attribute identification, etc, this makes the models unsuitable to directly integrate scene text information which is often orthogonal and uncorrelated to the visual statistics of the image.

To this end, in this work we propose a new dataset, called Scene Text Visual Question Answering (ST-VQA) where the questions and answers are attained in a way that questions can only be answered based on the text present in the image. Some sample images and questions from the collected dataset are shown in Figure 1. Additionally, we introduce three tasks of increasing difficulty that simulate different degrees of availability of contextual information. Finally, we define a new evaluation metric to better discern the models’ answering ability, that employs the Levenshtein distance [30] to account both for reasoning errors as well as shortcomings of the text recognition subsystem [10]. The dataset, as well as performance evaluation scripts and an online performance evaluation service are available through the ST-VQA Web portal.

The rest of the paper is organized as follows: in section 2, we overview the VQA literature and its relations to scene-text. In section 3, we explain how we collected the proposed dataset, its statistics and the evaluation metric we use. In the tasks section, we define 3 novel tasks and their implications. In the baselines section, we present our baseline results for each of the introduced tasks and finally we draw conclusions and future work.

2. RELATED WORK

The task of text detection and recognition in natural images sets the starting point of a generalized VQA system that can integrate textual cues for complete scene understanding. The most common approach in the text community consists of two steps, text detection and recognition. Several works have been proposed addressing text detection such as [32, 31, 55, 16] which are mostly comprised by a Fully Convolutional Neural Network. Text recognition methods such as the one presented in [18] propose recognizing text as a classification problem from a 90K English vocabulary. An attention based sequence-to-sequence model is used by [45] and a connectionist temporal classification (CTC) is proposed by [12]. Later works levitate towards end-to-end architectures such as the ones presented by [5, 34, 15], which mostly consist of an initial Convolutional Neural Network (CNN) that acts as an encoder and a Long Short Term Memory (LSTM) combined with attention that acts as the decoder.

Visual Question Answering (VQA) is to come up with an answer to a given natural language question about the image. Since its initial proposal, VQA has received a lot of attention from the Computer Vision community [3, 7, 43, 11, 19, 1] due to the access to large-scale datasets that allow the training of VQA models [3, 11, 29, 53, 49, 35]. Despite of VQA popularity, none of the existing datasets consider textual content, while in our work, exploiting textual information found in the images is the only way to solve the task at hand. The usage of text in other format exists as well as shortcuts of the text recognition subsystem [10]. The dataset, as well as performance evaluation scripts and online performance evaluation service are available through the ST-VQA Web portal.

Also related to the task proposed in this paper are recent works of Kafle et al. [20] and Kahou et al. [21] on question answering for bar charts and diagrams, and the work of Kembhavi et al. [25] on textbook question answering. The Textbook Question Answering (TQA) dataset [25] aims at answering multimodal questions given a context of text, diagrams and images, but textual information is provided in computer readable format. This is not the case for the diagrams and charts of the datasets proposed in [20, 21], meaning that models require some sort of text recognition to solve such QA tasks. However, the text found on these datasets is rendered in standard font types and with good quality, and thus represents a less challenging setup than the scene text used in our work. Similarly, Kise et al. [28] leverage OCR outputs to develop a QA system for machine printed document images.

TextVQA is a parallel work to the one presented in this paper, proposing an alternative dataset for VQA which, similarly to ST-VQA, requires reading and reasoning about scene text. Based on the limited information available on TextVQA at the time of writing [47], the two works are conceptually similar, although there are important differ-
ences in the implementation and design choices. The two datasets, namely ST-VQA and TextVQA, are based on images sourced differently. In the case of ST-VQA, a number of different datasets were used, including scene text understanding ones, while in the case of TextVQA all images come from the Open Images dataset. In addition, to select the images to annotate for the ST-VQA, we required a minimum amount of text (two instances) to be present, while in the TextVQA images were sampled on a category basis, emphasizing categories with more text. Despite the differences, it is important to note that the two datasets are highly complementary, as the images used do not intersect with each other, creating a valuable opportunity for transfer learning between them. In terms of annotations, we define questions that can be answered unambiguously using the text in the image, while in TextVQA any question related with the image text is allowed. The variability of the answers is therefore different; we define a single answer per question, verified by a second user, while in TextVQA various responses are collected per question. Combined with the evaluation metric we propose, ST-VQA is better suited for evaluating the joint efficiency of text extraction and reasoning.

3. ST-VQA DATASET

3.1. Collection

In this section we describe the process for collecting images, questions and answers for the ST-VQA dataset, and offer an in depth analysis of the collected data. Subsequently, we detail the proposed tasks and introduce the evaluation metric.

Images: The ST-VQA dataset comprises 23,038 images sourced from a combination of public datasets that include both scene text understanding datasets as well as generic computer vision ones. In total, we used six different datasets, namely: ICDAR 2013[23] and ICDAR2015[22], ImageNet [6], VizWiz[13], IIIT Scene Text Retrieval[37], Visual Genome [29] and COCO-Text [50]. A key benefit of combining images from various datasets is the reduction of dataset bias such as selection, capture and negative set bias which have been shown to exist in popular image datasets[26]. Consequently, the combination of datasets results in a greater variability of questions. To automatically select images to define questions and answers, we use an end-to-end single shot text retrieval architecture [8]. We automatically select all images that contain at least 2 text instances thus ensuring that the proposed questions contain at least 2 possible options as an answer. The final number of images and questions per dataset can be found in Table 1.

Question and Answers: The ST-VQA dataset comprises 31,791 questions. To gather the questions and answers of our dataset, we used the crowd-sourcing platform, Amazon Mechanical Turk (AMT). During the collection of questions and answers, we encouraged workers to come up with closed-ended questions that can be unambiguously answered with text found in the image, prohibiting them to ask yes/no questions or questions that can be answered only based on the visual information.

The process of collecting question and answer pairs consisted of two steps. First, the workers were given an image along with instructions asking them to come up with a question that can be answered using the text found in the image. The workers were asked to write up to three question and answer pairs. Then, as a verification step, we perform a second AMT task that consisted of providing different workers with the image and asking them to respond to the previously defined question. We filtered the questions for which we did not obtain the same answer in both steps, in order to remove ambiguous questions. The ambiguous questions were checked by the authors and corrected if necessary, before being added to the dataset. In some cases both answers were deemed correct and accepted, therefore ST-VQA questions have up to two different valid answers.

In total we ST-VQA comprises 23,038 images with 31,791 questions/answers pair separated into 19,027 images - 26,308 questions for training and 2,993 images - 4,163 questions for testing. We present examples of question and answers of our dataset in Figure 1.

3.2. Analysis and Comparison

In Figure 2 we provide the length distribution for the gathered questions and answers of the ST-VQA datasets, in comparison to the recently presented TextVQA. It can be observed that the length statistics of the two datasets are extremely similar.

To further explore the statistics of our dataset, Figure 3 visualises how the ST-VQA questions are formed. As it can be appreciated, our questions start with “What, Where, Which, How and Who”. A considerable percentage starts with “What” questions, as expected given the nature of the task. A critical point to realize however, is that the questions are not explicitly asking for specific text that appears in the scene; rather they are formulated in a way that requires to
have certain prior world knowledge/experience. For example, some of the what questions enquire about the brand, website, name, bus number, etc., requiring knowledge about what a brand or website is.

There has been a lot of effort to deal with the language prior inside the datasets [11, 19, 54]. One of the reasons for having language priors in datasets is the uneven distribution of answers in the dataset. In VQA v1 [3], since the dataset is formed from the images of MSCOCO [33], the answers to the question of “what sport ...” are tennis and baseball over 50%. Another example is the question “is there ...”, having yes as an answer in over 70% of the cases. As can be seen from Figure 4, our dataset apart from the “sign” and “year” questions follows a uniform distribution for the answers, reducing the risk of language priors while having a big vocabulary for the answers.

3.3. Tasks

We define 3 novel tasks, suitable for the ST-VQA dataset, namely strongly contextualised, weakly contextualised and open vocabulary.

The proposed differentiation of tasks can be interpreted by how humans make use of prior knowledge to argue about their current situation. Such prior knowledge in the ST-VQA is provided as a dictionary, different for each task. Our formulation of the tasks is inspired by this corollary and the difficulty per task increases gradually. In the strongly contextualised task we capture this prior knowledge by creating a dictionary per image for the specific scenario depicted. In the weakly contextualised task we provide a single dictionary comprising all the words in the answers of the dataset. Finally, for the open dictionary task, we treat the problem as tabula rasa where no a priori and no external information is available to the model.

For the strongly contextualised task (1), following the standard practice used for end-to-end word spotting, we create a dictionary per image that contains the words that appear in the answers defined for questions on that image, along with a series of distractors. The distractors are generated in two ways. On one hand, they comprise instances of scene text as returned by a text recogniser applied on the image. On the other hand, they comprise words obtained by exploiting the semantic understanding of the scene, in the form of the output of a dynamic lexicon generation model [39, 9]. The dictionary for the strongly contextualised task is 100 words long and defined per image.

In the weakly contextualised task (2), we provide a unique dictionary of 30,000 words for all the datasets’ images which is formed by collecting all the 22k ground truth words plus 8k distractors generated in the same way as in the previous task. Finally for the open dictionary task (3), we provide no extra information thus we can consider it as an open-lexicon task.

By proposing the previously mentioned tasks the VQA problem is conceived in a novel manner that has certain advantages. First, it paves the way for research on automatically processing and generating such prior information, and its effect on the model design and performance. Second, it provides an interesting training ground for end-to-end reading systems, where the provided dictionaries can be used to prime text spotting methods.

3.4. Evaluation and Open Challenge

Since the answers of our dataset are contained within the text found in the image, which is dependent on the accuracy of the OCR being employed, the classical evaluation metric of VQA tasks is not suitable for our dataset. In all 3 tasks we use the normalized Levenshtein distance [30] as an evaluation metric. More formally, let ANLd be the average normalized Levenshtein distance function, N be total num-

![Figure 2: Percentage of questions (top) and answers (bottom) that contain a specific number of words.](image)

![Figure 3: Distribution of questions in the ST-VQA train set by their starting 4-grams (ordered from center to outwards). Words with a small contribution are not shown for better visualization.](image)
Figure 4. Distribution of answers for different types of questions in the ST-VQA train set. Each color represents a different unique answer.

In this section we define several baselines, which help researchers to evaluate their methods against a public validation/test dataset. Apart from baselines designed to exploit all the information available (visual information, scene text and the question), we have purposely included baselines that ignore one or more of the available pieces of information in order to establish lower bounds of performance. The following baselines are employed to evaluate the datasets:

Random: As a way of assessing aimless chance, we return a random word from the dictionary provided for each task: a per image dictionary of 100 words for task 1, a dictionary of 30k words derived from the full dataset for task 2 and the widely used English vocabulary of 90k words proposed by [18] for task 3.

Scene Text Retrieval: This baseline leverages a single shot CNN architecture that predicts at the same time bounding boxes and a compact text representation (PHOC [2]) of the words in them [8]. It ignores the question and any other visual information of the image. We have defined two approaches: the first (“retrieval”) uses the specific task dictionaries as queries to a given image, and the top-1 retrieved word is returned as the answer; the second one (“bbox”), follows the intuition that humans tend to formulate questions about the largest text in the image. We take the text representation from the biggest bounding box found and then find the nearest neighbor word in the corresponding dictionaries.

Scene Image OCR: A state of the art text recognition model [15] is used to process the test set images. The detected text is ranked according to the confidence score and the closest match between the most confident text detection and the provided vocabularies for task 1 and task 2 is used as the answer. In task 3 the most confident text detection is adopted as the answer directly.

Standard VQA models: We evaluate two standard Visual Question Answering models. The first one named Show, Ask, Attend and Answer [24] (SAAA) consists of a CNN-LSTM architecture. On one hand, a ResNet-152 [14] is used to extract image features with dimension $14 \times 14 \times 2048$, while the question is tokenized and embedded by using a multi-layer LSTM. On top of the combination of im-
Table 2. Baseline results comparison on the three tasks of ST-VQA dataset. We provide Average Normalized Levenshtein distance (ANLd) and Accuracy for different methods that leverage OCR, Question (Q) and Visual (V) information.

| Method with | OCR | Q | V | Task 1 ANLd | Task 1 Acc. | Task 2 ANLd | Task 2 Acc. | Task 3 ANLd | Task 3 Acc. | Upper bound ANLd | Upper bound Acc. |
|-------------|-----|---|---|-------------|-------------|-------------|-------------|-------------|-------------|----------------|-----------------|
| Random      | X   | X | X | 0.015       | 0.96        | 0.001       | 0.00        | 0.00        | 0.00        | -              | -               |
| STR [8] (retrieval) |   |   |   | 0.171       | 13.78       | 0.073       | 5.55        | -           | -           | -              | -               |
| STR [8] (bbox) |   |   |   | 0.130       | 7.32        | 0.118       | 6.89        | 0.128       | 7.21        | 0.332          | -               |
| Scene Image OCR [15] |   |   |   | 0.145       | 8.89        | 0.132       | 8.69        | 0.140       | 8.60        | 0.287          | -               |
| SAAA [24] (1k cls) |   |   |   | 0.085       | 6.36        | 0.085       | 6.36        | 0.085       | 6.36        | 0.571          | 31.96           |
| SAAA+STR (1k cls) |   |   |   | 0.091       | 6.66        | 0.091       | 6.66        | 0.091       | 6.66        | 0.571          | 31.96           |
| SAAA [24] (5k cls) |   |   |   | 0.087       | 6.66        | 0.087       | 6.66        | 0.087       | 6.66        | 0.740          | 41.03           |
| SAAA+STR (5k cls) |   |   |   | 0.096       | 7.41        | 0.096       | 7.41        | 0.096       | 7.41        | 0.740          | 41.03           |
| SAAA [24] (19k cls) |   |   |   | 0.084       | 6.13        | 0.084       | 6.13        | 0.084       | 6.13        | 0.862          | 52.31           |
| SAAA+STR (19k cls) |   |   |   | 0.087       | 6.36        | 0.087       | 6.36        | 0.087       | 6.36        | 0.862          | 52.31           |
| QA+STR (19k cls) |   |   |   | 0.069       | 4.65        | 0.069       | 4.65        | 0.069       | 4.65        | 0.862          | 52.31           |
| SAN(LSTM) [52] (5k cls) | X |   |   | 0.102       | 7.78        | 0.102       | 7.78        | 0.102       | 7.78        | 0.740          | 41.03           |
| SAN(LSTM)+STR (5k cls) |   |   |   | 0.136       | 10.34       | 0.136       | 10.34       | 0.136       | 10.34       | 0.740          | 41.03           |
| SAN(CNN)+STR (5k cls) |   |   |   | 0.135       | 10.46       | 0.135       | 10.46       | 0.135       | 10.46       | 0.740          | 41.03           |

The second model named Stacked Attention Networks [52] (SAN) uses a pre-trained VGGNet [46] to obtain image features of shape $14 \times 14 \times 512$. Two question encoding methods are proposed, one that uses an LSTM and another that uses a CNN, both of them yielding similar results according to the evaluated dataset. The encoded question either by a CNN or LSTM is used along with the image features to compute two attention maps, which later are used with the image features to output a classification vector. We optimize the model with a batch size of 128 for 30 epochs. The starting learning rate is 0.001 which decays by half every 50K iterations.

The second model, named Fusing Modalities - Standard VQA Models + Scene Text Retrieval: Using the previously described VQA models, the purpose of this baseline is to combine textual features obtained from a scene text retrieval model with existing VQA pipelines. To achieve this, we use the model from [8] and we employ the output matrix before the non-maximal suppression step (NMS) is performed. The most confident PHOC above a threshold is selected relative to a single grid cell. The selected features form a tensor of size $14 \times 14 \times 609$, which is concatenated with the image features before the attention maps are calculated on both previously described VQA baselines. Afterwards the attended features are used to output a probability distribution over the classification vector. The models are optimized by using each respective strategy as it is described previously.

4.2. Results

The results according to the tasks defined are summarized in Table 2. As a way to compare the proposed Average Normalised Levenshtein distance (ANLd) metric, we also calculate the accuracy for each baseline. The accuracy is calculated by counting the exact matches between the model predictions and collected answers as is the standard practice in the literature. The last column, upper bound, shows the maximum possible score that can be achieved depending on the method. The upper bound for the Scene Text Retrieval [8] and Scene Image OCR [15] is calculated by obtaining the answer if it exists in either the PHOCs proposals or the OCR text proposals, respectively. If the method is a VQA model, the upper bound is calculated assuming the best possible classification score on the output vector constructed from the training set answers.

As it can be seen from Table 2, VQA models without any
textual information achieve similar scores, ranging between 6.6% to 7.75%. One crucial point is that although SAN [52] gets lower score than SAAA [24] in VQA v1 [3], in our dataset, the effect found is the opposite, due to the fact that our dataset is quite different compared to VQA v1.

Another important point is that the SAAA model increase the accuracy and ANLd points when using a bigger classification vector size from 1k to 5k classes; however, from 5k to 19k the results are worse, suggesting that learning a big vocabulary in a classification manner is not feasible.

Finally, VQA models without any textual information perform worse or comparable at best to the STR(retrieval) or Scene Image OCR models, despite the fact that these heuristic methods do not take into account the question. The obtained results confirm the necessity of leveraging textual information as a way to improve performance in VQA models. We demonstrate this effect by improving the results of VQA models with the usage of PHOC [8] features (details in baseline section), exhibited by achieving 0.3% – 0.8% accuracy improvement on SAAA while achieving around 3% accuracy boost on SAN.

For the analysis of the models’ outputs and the comparison between them, we provide two graphs. From Figure 5, in most of the question types, the STR model is better according to the ANLd metric rather than the ST-OCR. The effect of PHOC embedding is especially visible on the SAN model for correctly answering the question type such as “what year”, “what company” and “which”. Also, none of the models are capable of answering the questions regarding license plates, who and what number, making it imperative to create models that are generative in nature.

As it is stated in [8], the importance of using PHOC features lies in the ability of the embedding to capture the morphology of words rather than the semantics as in other embeddings such as Word2Vec [36] and others [41, 4]. An important point to consider is that several text instances and answers in the dataset do not contain any embedding representation in a pre-trained semantic model. The use of a morphological embedding like PHOC can provide a starting point for datasets that contain text and answers in several languages and out of dictionary words such as license plates, prices, directions, names, etc.

Lastly, we provide some qualitative results on Figure 6. The depicted models are “Stacked Attention Network + PHOC features”, “Show, Ask, Attend and Answer + PHOC features”, “Scene Image OCR”, and the “Scene Text Retrieval”.

5. Conclusions and Future Work

We presented a new dataset for Visual Question Answering, the Scene Text VQA, that aims to highlight the importance of properly exploiting the high-level semantic information present in images in the form of scene text to inform the VQA process. We thoroughly analysed the ST-VQA dataset through performing as series of experiments with baseline methods, which provided important insights, and established the lower performance bounds.

The dataset comprises questions and answers of high variability, and poses extremely difficult challenges for current VQA methods. The results obtained demonstrate that current VQA methodologies are not suitable for the proposed ST-VQA tasks. Existing VQA models usually address this problem as a classification task, but in the case of scene text based answers the number of possible classes is intractable. Dictionaries defined over single words are also limited. Instead, a generative pipeline such as the ones used in image captioning is required to capture multiple-word answers, and out of dictionary strings such as numbers, license plates or codes. The proposed metric, namely Average Normalised Levenshtein distance is better suited for generative models compared to evaluating classification performance, while at the same time, it has a smooth response to the text recognition performance.
As it is expected, a slight improvement is consistently achieved by the fusion of textual features in current VQA pipelines by employing the PHOC embedding. The main strength in using this embedding lies in the fact that the PHOC representation of a word uses its morphology rather than semantics and is capable of learning out of vocabulary words and different languages. Further research in other embedding methods can be undertaken as well as methods of combining visual and textual features contained within an image.

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