DVQA: Understanding Data Visualizations via Question Answering

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Abstract

Bar charts are an effective way for humans to convey information to each other, but today’s algorithms cannot parse them. Existing methods fail when faced with minor variations in appearance. Here, we present DVQA, a dataset that tests many aspects of bar chart understanding in a question answering framework. Unlike visual question answering (VQA), DVQA requires processing words and answers that are unique to a particular bar chart. State-of-the-art VQA algorithms perform poorly on DVQA, and we propose two strong baselines that perform considerably better. Our work will enable algorithms to automatically extract semantic information from vast quantities of literature in science, business, and other areas.

1. Introduction

Data visualizations, e.g., bar charts, pie charts, and plots, contain large amounts of information. These visualizations are specifically designed to communicate data to people, and they are not designed to be machine interpretable. Nevertheless, making algorithms capable to make inferences from data visualizations has enormous practical applications. Here, we study systems capable of answering open-ended questions about bar charts, which we refer to as data visualization question answering (DVQA). DVQA would enable vast repositories of charts within scientific documents, web-pages, and business reports to be queried automatically. In addition to practical benefits, DVQA serves as an important proxy task for generalized pattern matching and multi-step reasoning systems. Example DVQA images and questions are shown in Fig. 1.

DVQA is related to visual question answering (VQA) [24, 4], which deals with answering open-ended questions about images. VQA is usually treated as a classification problem, in which answers are categories that are inferred using features from image-question pairs. DVQA poses two major challenges that are overlooked by existing VQA datasets with natural images.

First, VQA systems typically assume two fixed vocabulary dictionaries: one for encoding words in questions and one for producing answers. In DVQA, assuming a fixed vocabulary makes it impossible to properly process many questions or to generate answers unique to a bar chart, which are often labeled with proper nouns, abbreviations, or concatenations (e.g., “Jan-Apr”). Our models demonstrate two ways for handling out-of-vocabulary words.

Second, natural images exhibit regularities that are not present in DVQA. For example, to infer the answer to “What is the weather like?” for the image in Fig. 2, an agent could use color tones and overall brightness to infer “sunny.” Changing the color of the fire hydrant will only change local information that impacts questions about the fire hydrant’s properties. However, in bar charts, information is conveyed in sparse structured elements. A small change, e.g., shuffling the colors of the legend in Fig. 2, will completely alter the chart’s information. This makes DVQA an especially challenging problem.

Figure 1: DVQA involves answering questions about diagrams. We present a dataset for DVQA with bar charts that exhibit enormous variety in appearance and style. We show that VQA systems cannot answer many DVQA questions and we describe more effective algorithms.
Figure 2: Natural images vs. bar charts. **Left:** Small changes in an image typically have little impact on a question in VQA. **Right:** Bar charts convey information using a sparse, but precise, set of visual elements. Even small changes can completely alter the information in the chart.

**This paper makes three major contributions:**
1. We describe the DVQA dataset, which contains over 3 million image-question pairs about bar charts. It tests three forms of diagram understanding: a) structure understanding; b) data retrieval; and c) reasoning. The DVQA dataset will be publicly released.
2. We demonstrate that both baseline and state-of-the-art VQA algorithms are not capable of answering many of the questions in DVQA.
3. We describe two DVQA systems capable of handling words that are unique to a particular image. One is an end-to-end neural network that can read answers from the bar chart. The second is a model that encodes a bar chart’s text using a dynamic local dictionary.

2. Related Work

2.1. Automatically Parsing Bar Charts

Extracting data from bar charts using computer vision has been extensively studied [1, 5, 15, 26, 28]. Some focus on extracting the visual elements from the bar charts [26], while others focus on extracting the data from each bar directly [28, 15]. Most of these approaches use fixed heuristics and make strong simplifying assumptions, e.g., [28] made several simplifying assumptions about bar chart appearance (bars are solidly shaded without textures or gradients, no stacked bars, etc.). Moreover, they only tested their data extraction procedure on 41 bar charts.

Our DVQA dataset has variations in bar chart appearance that go far beyond the capabilities of any of the aforementioned works. Moreover, DVQA requires more than just data extraction. Correctly answering DVQA questions requires language understanding and reasoning.

2.2. VQA with Natural Images

Over the past three years, multiple VQA datasets containing natural images have been publicly released [24, 4, 27, 22, 13]. The most popular dataset is The VQA Dataset [7, 4]. It is much larger and more varied than earlier VQA datasets, such as COCO-QA [27] and DAQUAR [24]. However, the first version of the dataset, VQA 1.0, suffered from extreme language bias, resulting in many questions not requiring the image to correctly answer them [7]. In the second version, VQA 2.0, this bias was greatly reduced; however, VQA 2.0 still suffers from heavily skewed distribution in the kinds of questions present in the dataset, with easy detection questions being more common than questions requiring reasoning.

Numerous VQA algorithms have been proposed, ranging from Bayesian approaches [12, 24], methods using spatial attention [32, 31, 23, 25], compositional approaches [2, 3], and bilinear pooling schemes [20, 6]. Almost all VQA algorithms pose it as a classification problem in which each class is synonymous with a particular answer. For more extensive reviews see [14] and [30].

While there are significant similarities between VQA and DVQA, one critical difference is that many DVQA questions require directly reading text from a chart to correctly answer them. This demands being able to handle words that are unique to a particular chart, which is a capability that is not needed by algorithms operating on existing VQA datasets with natural images.

2.3. Reasoning, Synthetic Scenes, and Diagrams

While VQA is primarily studied using natural images, several datasets have been proposed that use synthetic scenes or diagrams to test reasoning and understanding [11, 18, 19]. The CLEVR [11] dataset has complex reasoning questions about synthetically created scenes, and systems that perform well on popular VQA datasets perform poorly on CLEVR. The TQA [19] and AI2D [18] datasets both involve answering science questions about text and images. Both datasets are relatively small, e.g., AI2D only contains 15,000 questions. These datasets require more than simple pattern matching and memorization. Similar to our work, their creators showed that state-of-the-art VQA systems for natural image datasets performed poorly on their datasets. However, there are key differences between these datasets and DVQA. First, none of these datasets contain questions specific to bar charts. Second, their datasets use multiple-choice schemes that reduce the problem to a ranking problem, rather than the challenges posed by having to generate open-ended answers. Studies have shown that multiple-choice schemes have biases that models will learn to exploit [10]. In contrast, we treat DVQA as an open-ended question answering task.

3. DVQA: The Dataset

DVQA is a challenging synthetic dataset that tests multiple aspects of bar chart understanding. DVQA’s images
exhibit enormous variation in appearance. Many questions contain novel words, and answers often are unique words. These challenges cause state-of-the-art methods for VQA to fail, which we demonstrate in experiments.

Synthetically generating DVQA gave us precise control over the positions and appearances of the visual elements. It also gave us access to meta-data about these components, which would not be available with real data. This meta-data contains all information within the chart, including the precise position of each drawing element, the underlying data used to create the chart and location of all text-elements. This data can be used as an additional source of supervision or to ensure that an algorithm is “attending” to relevant regions. As shown in Fig. 3, the DVQA dataset contains a large variety of typically available styles of bar chart. The questions in the dataset require the ability to reason about the information within a bar chart (see Fig. 1). DVQA contains 3,022,131 total question answer pairs for 300,000 images divided into three major question types. Tables 5 and 2 show statistics about the DVQA dataset. Additional statistics are given in the supplemental materials.

3.1. Appearance, Data, and Question Types

DVQA consists of bar charts with question-answer pairs that are generated by selecting a visual style for a chart, choosing data for a chart, and then generating questions for that chart. Here, we briefly explain how this was done. Additional details are given in supplemental materials.

3.1.1 Visual Style

As shown in Fig. 3, DVQA’s bar charts contain a large amount of variability in both appearance and style, which reflects the most common styles found in scientific documents and the Internet. These variations include:

1. Variability in the number of bars and/or groups of bars. Each bar chart has 2–9 bars and 1–5 groups.
2. Single-column vs. multi-column grouped charts.
3. Grouped bars vs. stacked bars. Stacked bars are divided into two types: 1) Additive stacking, where bars represent individual values, and 2) Fractional stacking, where each bar represents a fraction of the whole.
4. The presence/absence of grid-lines.
5. Hatching and other types of textures.
6. Variation in text label orientation.
7. Color randomization, including monochrome styles.
8. Legends placed in a variety of common positions, including legends that are separate from the chart.
9. Bar width and spacing.

To label individual bars and legend entries, we selected 500 random words from NLTK’s “words” corpus for the training and “easy” test sets that we call Test-Familiar. To measure a system’s ability to scale to unknown answers, we also created a more difficult test set, called Test-Novel, in which we use 200 new words that are not seen during training.

In the wild, some styles are more common than others. To reflect this, less common styles, e.g., hatched bars, are used only for a small subset of charts. However, every style-choice appears at least a 1000 times in the training set. The distribution of styles is discussed further in the supplemental materials.

3.1.2 Underlying Data

DVQA has three bar chart data value types:

- **Linear data.** Bar values are chosen from 0 – 10, in increments of 1. When the bars are not stacked, the axes are clipped at 10. When stacked, the maximum axis value is automatically set by the tallest stack. For a small number of plots, values are randomly negated.
- **Percentage data.** Bar values are randomly chosen from 0–100, in increments of 10. For a fraction of multi-column group bar charts with percentage data, we normalize the data in each group so that the values add up to 100, which is a common style.
- **Exponential data.** Bar values are randomly chosen in the range of 0 - 10^{10}. The axis is logarithmic.

3.1.3 Question Types

DVQA contains three types of questions: 1) structure understanding, 2) data retrieval, and 3) reasoning.
**Structure Understanding.** Structure understanding questions test a system’s ability to understand the overall structure of a bar chart. These questions include:

1. How many bars are compared?
2. How many groups of bars are compared?
3. How many bars are there per group?
4. Does the chart contain negative values?
5. Are the bars horizontal?
6. Are the bars stacked?
7. Are the bars hatched?

**Data Retrieval.** Data retrieval questions test a system’s ability to retrieve information from a bar chart by parsing the chart into its individual components. These questions often require paying attention to specific region of the chart. These questions include:

1. What type of scale is the chart using?
2. Which bar is the highest?
3. Which bar is the lowest?
4. What does the color represent?
5. What is the value of the third bar?
6. What is the label of the third bar?
7. What is the value of the fourth bar in the second group?
8. What is the label of second bar in every group?

**Reasoning.** Reasoning questions test a model’s ability to collect information from multiple components of a bar chart and perform operations on them. These include:

1. How many bars have values greater than \( N \)?
2. What is the value of the second and first bars summed?
3. Which group has the lowest/highest valued bar?
4. Which group has the lowest/highest summed value?
5. Is the value of the third bar greater than the second bar?
6. What is the sum of all the values in the third group?

For all structure understanding questions, no answers are chart labels. For data retrieval questions, 72% of questions have answers that are chart labels. For reasoning questions, 34% of answers are chart labels. These proportions are the same in the training and test splits.

In our main DVQA dataset, questions do not have chart-specific words in them. In Sec. 5.3, we analyze a version of the dataset in which questions do have chart-specific words.

### 3.2. Post-processing to Minimize Bias

Several studies in VQA have shown that bias in datasets can impair performance evaluation and give inflated scores to systems that simply exploit statistical patterns [10, 13]. In DVQA, we have taken several measures to combat such biases. To ensure that there is no correlation between styles, colors, and labels, we randomize the generation of charts.

| Total | Unique |
|-------|--------|
| 738,105 | 10 |
| 1,239,357 | 734 |
| 1,044,669 | 764 |
| **Grand Total** | **780** |

### Table 2: DVQA dataset statistics for different splits.

| Images | Questions | Unique Answers |
|-------|-----------|----------------|
| Train | 200,000 | 2,013,918 | 580 |
| Test-Familiar | 50,000 | 504,403 | 578 |
| Test-Novel | 50,000 | 503,810 | 279 |
| **Grand Total** | **300,000** | **3,022,131** | **780** |

Instead of using labels that could be exploited to find answer to questions, we use generic labels for titles and axes.

Some questions can have strong priors, e.g., the question “Are the bars hatched?” has a high probability of the correct answer being “no” because these hatched charts are uncommon. To compensate for this, we randomly remove these questions until yes/no answers are balanced for each question type where yes/no is an answer. A similar scheme was used to balance other types of questions, e.g., question answers about the type of the scale the chart are balanced among linear, percentage, and exponential.

### 4. DVQA Algorithms & Models

In this section, we describe two novel deep neural network algorithms along with five baselines. Our proposed algorithms are able to read text from bar charts, giving them the ability to answer questions with chart-specific answers or requiring chart-specific information.

All of the models that process images use the ImageNet pre-trained VGG-16 [29] CNN with 448 × 448 images. All models that process questions use a 512 unit single layer LSTM approach, in which each word is encoded using a one-hot vector for vocabulary size of 580, which is the total number of unique words found in the questions from the training set. Then, each of the one-hot vectors is encoded using a learned embedding layer that converts them into a 300 dimensional dense representation. Training details are given in Section 4.4.

### 4.1. Baseline Models

We evaluate five baseline models for DVQA:

1. **NO**: This model always outputs ‘no’, which is the most common answer in DVQA, by a small margin.
2. **IMG**: A question-blind model. Images are encoded using VGG-16 using the output of its final convolutional layer, and then the answer is predicted from them by an MLP with one hidden-layer that has 1,024 units and a softmax output layer.

3. **QUES**: An image-blind model. It uses the LSTM encoder to embed the question, and then the answer is predicted by an MLP with one hidden-layer that has 1,024 units and a softmax output layer.

4. **IMG+QUES**: This is a combination of the QUES and IMG models. It concatenates the LSTM and CNN embeddings, and then feeds them to an MLP with one 1024-unit hidden layer with a ReLU activation and a softmax output layer.

5. **SAN-VQA**: The Stacked Attention Network (SAN) [32] for VQA. In [17], it was shown that upgrading the original SAN’s image features produces state-of-the-art results on VQA 1.0 and 2.0. SAN operates on the last CNN convolutional feature maps, where it processes this map attentively using the question embedding from our LSTM-based scheme.

### 4.2. Multi-Output Model (MOM)

Our Multi-Output Model (MOM) for DVQA uses a dual-network architecture, where one of its sub-networks is able to generate chart-specific answers. MOM’s classification sub-network is responsible for generic answers. MOM’s optical character recognition (OCR) sub-network is responsible for chart-specific answers that must be read from the bar chart. The classification sub-network is identical to the SAN-VQA algorithm described earlier in Sec. 4.1. An overview is given in Fig. 4.

The OCR sub-network tries to predict the bounding box that contains the correct label and then applies a character-level decoder to this region. The bounding box predictor is trained as a regression task using a mean-squared-error (MSE) loss. This region has an image-patch extracted from it, and then a small 3-layer CNN is applied to this region. Since the orientation of the text in the box will vary, we employ an N-step spatial attention mechanism to encode the relevant features for each of the N possible characters in the image patch, where N is the largest possible character-sequence. For our dataset, we choose N = 10 based on the maximum expected word length. These N features are encoded using a bi-directional gated recurrent unit (GRU) to capture the character level correlations found in naturally occurring words. Finally, the GRU encoding is followed by a final classification layer that predicts the sequence of characters. This portion of the sub-network is trained using connectionist temporal classification (CTC) loss [8].

At test time, MOM must determine whether to use the classification sub-network or the OCR sub-network to answer a question. To determine this, we train a separate binary classifier that determines which of the outputs to trust. It takes the LSTM question features as input to predict whether the answer is generic or chart-specific. For our DVQA dataset this classifier is able to predict the correct branch with perfect accuracy on the test data.

### 4.3. SANDY: SAN with DYnamic Encoding Model

MOM handles chart-specific answers by having a sub-network capable of generating unique strings; however, it has no explicit ability to visually read text from a bar chart and its LSTM question encoding cannot handle chart-specific words. To explore overcoming these limitations, we modified SAN to create SANDY, SAN with DYnamic encoding model. SANDY uses a dynamic encoding model (DEM) that explicitly encodes chart-specific words in the question, and can directly generate chart-specific answers. The DEM is a dynamic local dictionary for chart-specific words. This dictionary is used for encoding words in a question as one-hot vectors and for generating answers.

To create a local word dictionary, DEM assumes it has access to an OCR system that gives it the positions and strings for all text-areas in a bar chart. Given this collection of boxes, DEM assigns each box a unique numeric index. It assigns an index of 0 to the box in the lower-left corner of the image. Then, it assigns the box with the position closest to the first box with an index of 1. The box closest to 0 that is not yet assigned an index is then assigned the index of 2, and so on until all boxes in the image are assigned an index. In our implementation, we assume that we have a perfect (oracle) OCR system for input, and we use the dataset’s annotations for this purpose. No chart in the training data had more than 20 text labels, so we set the local dictionary to have at most M = 20 elements.

The local dictionary augments the N element global dictionary. This enables DEM to create (M + N)-dimensional one-hot vectors that are used to encode each word in a question. If a word is found in the local dictionary, the appropriate index in the one-hot vector reserved for local words is assigned, otherwise an index is assigned by the global dictionary. The local dictionary is also used to augment the L element global answer dictionary. This is done by adding M extra classes to the classifier representing the dynamic words. If these classes are predicted, then the output string is assigned using the local dictionary’s appropriate index.

SANDY has an identical architecture to SAN-VQA, except the one-hot vectors for encoding the question had M extra entries and M extra output units were used.

### 4.4. Training the Models

All of the classification based systems, except MOM and SANDY, use a global answer dictionary containing 580 words, so they each have 580 output units. MOM’s classification branch contains 80 common answers, with answers
that require reading the chart being generated by its string generating sub-network. MOM’s classification branch was trained only for questions that did not require reading a chart’s labels, otherwise its string generating sub-network was trained. Similarly, SANDY’s output layer contains 100 units, where 80 units are for common answers and the remaining 20 are reserved for the local dictionary.

To allow for a fair comparison, we use the same training hyperparameters for all the models wherever possible. All the models are trained using early stopping, where training was stopped if the loss on the holdout set did not decrease for five epochs. All models were optimized using Adam [21] with an initial learning rate of 0.001.

5. Experiments

In this section, we describe the experimental results for models trained and tested on the DVQA dataset. DVQA’s extensive annotations are used to analyze the performance of each model on different question- and answer-types to reveal their respective strengths and weaknesses. In our experiments, we study the performance of algorithms on both familiar and novel chart labels, which are contained in two distinct test splits, Test-Familiar and Test-Novel. Every bar chart in Test-Familiar contains only labels seen during training. All of the models using the LSTM-encoder have entries in their word dictionaries for these familiar words, and all answers have been seen in the training set. The labels for the charts in Test-Novel are only seen in the test set, and no system has them in the dictionaries they use to encode words or to generate answers.

To measure performance, an algorithm gets a question correct only if it generates a string that is identical to the ground truth. To better assess MOM, we also measure its performance using edit distance, which is denoted MOM(+/-1). This model is allowed to get a question correct as long as the answer it generates is within one edit distance or less compared to the correct answer.

5.1. General Observations

Overall performance of each method broken down based on question-type are shown in Table 6. Across all question-types, NO, IMG, and QUES are the first, second, and third worst performing, respectively. Overall, SANDY performs best on both Test-Familiar and Test-Novel.

For structure questions, there is little difference across models for Test-Familiar and Test-Novel, which is expected because these questions ask about the general visual organization of a chart and do not require reading the labels. There is a large increase in performance for IMG+QUES compared to either IMG or QUES, indicating that it is necessary to combine image and question features to answer structure questions. MOM worked best for these, followed by SAN-VQA. MOM only uses its classification sub-network for these questions, which is based on SAN. MOM likely outperformed SAN-VQA because its classification sub-network is trained only using 80 common answers and does not include the additional 500 chart label answers needed by SAN-VQA.

For data retrieval and reasoning questions, SANDY and MOM both outperformed all baseline models. SANDY outperformed MOM, and this gap was greater for Test-Novel. The same pattern was true for structure questions, and they are significantly easier than the other two types.
Table 3: Overall results for models trained and tested on the DVQA dataset.

|                | Test-Familiar | Test-Novel |
|----------------|---------------|------------|
|                | Structure     | Data       | Reasoning  | Total     | Structure     | Data       | Reasoning  | Total     |
| NO             | 21.60         | 0.00       | 8.51       | 8.23      | 21.52         | 0.00       | 8.67       | 8.24      |
| IMG            | 39.74         | 0.30       | 10.79      | 13.59     | 39.40         | 0.30       | 10.84      | 13.49     |
| QUES           | 41.13         | 3.60       | 22.65      | 30.18     | 41.07         | 3.54       | 22.49      | 30.12     |
| IMG+QUES       | 83.14         | 6.24       | 27.09      | 32.28     | 83.07         | 6.41       | 27.29      | 32.33     |
| SAN-VQA        | 89.62         | 6.41       | 29.54      | 34.78     | 89.49         | 6.56       | 29.54      | 34.73     |
| MOM            | 91.74         | 13.38      | 31.69      | 36.11     | 91.79         | 8.22       | 31.24      | 36.57     |
| MOM(+/-1)      | 91.74         | 21.22      | 33.05      | 44.42     | 91.79         | 13.34      | 32.30      | 39.03     |
| SANDY          | 89.72         | 50.74      | 40.79      | 56.83     | 89.75         | 50.82      | 40.86      | 56.89     |

Table 4: Results on DVQA for models based on their ability to predict generic and chart-specific answers.

|                | Test-Familiar | Test-Novel |
|----------------|---------------|------------|
|                | Generic       | Chart-specific | Total     | Generic       | Chart-specific | Total     |
| NO             | 14.04         | 0.00         | 8.23      | 14.05         | 0.00         | 8.24      |
| IMG            | 23.18         | 0.00         | 13.59     | 22.89         | 0.00         | 13.49     |
| QUES           | 32.92         | 0.19         | 19.38     | 32.79         | 0.00         | 19.24     |
| IMG+QUES       | 54.92         | 0.19         | 32.28     | 55.09         | 0.00         | 32.33     |
| SAN-VQA        | 59.18         | 0.21         | 34.78     | 59.19         | 0.00         | 34.73     |
| MOM            | 61.10         | 7.45         | 38.90     | 61.28         | 1.46         | 36.57     |
| MOM(+/-1)      | 61.10         | 16.33        | 42.57     | 61.28         | 7.43         | 39.03     |
| SANDY          | 59.57         | 52.95        | 56.83     | 59.57         | 50.82        | 56.89     |

5.2. Generic vs. Chart-specific Answers

Many DVQA questions have answers that are labels specific to the chart, e.g., “What is the label of the highest bar?” These chart-specific answers are in contrast to generic answers that are shared across many bar charts, e.g., “What is the value of the third bar?”

Table 7 shows accuracies for systems on questions with generic and chart-specific answers. All baseline systems perform abysmally on chart-specific answers. While this is expected for Test-Novel, they only perform slightly better on Test-Familiar, in which case these systems have seen the answers previously.

MOM and SANDY achieve respectable performance on chart-specific answers, with SANDY performing best. SANDY’s performance on chart-specific answers is similar in Test-Familiar and Test-Novel, whereas MOM’s performance is worse on Test-Novel. This may be because MOM’s string generation system is coping poorly with novel words. Supporting this, note that MOM often makes small string-generation errors, as shown by the improved performance of MOM(+/-1), which is evaluated using edit distance. MOM’s localization performance is explored in supplemental materials.

5.3. Handling Chart-Specific Words in Questions

In addition to SANDY’s ability to predict chart-specific answer tokens, it can also be used to properly tokenize the chart-specific words in questions. An LSTM based question encoder using a fixed vocabulary will not be able to encode the questions properly, especially when encoding questions with unknown words in Test-Novel. However, our main DVQA dataset does not contain questions with chart-specific words. To test SANDY’s ability to handle chart-specific words in questions, we created an alternative version of DVQA, denoted DVQA*. To make DVQA*, we converted the questions from DVQA that refer to the bar into question that use ‘chart-specific’ words. For example, the question “What is the value of the third bar?” in Fig. 1 (left) would become “What is the value of massai?”

We trained and evaluated both SANDY and SAN on DVQA*. For data retrieval questions, which contains majority of questions with chart-specific words, SAN achieves only an accuracy of 9% on Test-Familiar whereas SANDY achieves 28.5%. Furthermore, SANDY achieves 28.6% on Test-Novel compared to 6% for SAN. Additional details and results are given in supplementary materials.

6. Discussion

In this paper we presented the DVQA dataset and explored models for DVQA. Our experiments demonstrate that VQA algorithms are capable of answering structure questions only. They perform much more poorly on data retrieval and reasoning questions, whereas our approaches, SANDY and MOM, are able to better answer these ques-
Q: Are the bars stacked?
SAN: no  MOM: no  SANDY: no
Q: What is the value of first and second bar summed?
SAN: 9  MOM: 11  SANDY: 10
Q: How many groups of bars are there?
SAN: three  MOM: three  SANDY: three
Q: Which group has the smallest summed value?
SAN: updart  MOM: ch  SANDY: prich
Q: Are the bars horizontal?
SAN: no  MOM: no  SANDY: no
Q: Which group contains the lowest valued bar?
SAN: updart  MOM: obdus  SANDY: obelus

Figure 5: Example results for different models on DVQA. SAN does not generalize for chart-specific answers, whereas MOM often decodes only a part of the whole word (middle), or has an error of a few characters (right).

7. Conclusion

Here, we described DVQA, a dataset for understanding bar charts. We demonstrated that VQA algorithms are incapable of answering simple DVQA questions. We proposed two DVQA algorithms that can handle chart-specific answers, and we showed that they can accurately answer many kinds of questions. Solving DVQA will enable systems that can be utilized to intelligently query massive repositories of human-generated data, which would be an enormous aid to scientists and businesses. We hope that the DVQA dataset, which will be made publicly available, will promote the study of issues that are generally ignored with VQA with natural images, e.g., out-of-vocabulary words.
Appendices

A. Additional details about the dataset

A.1. Additional statistics

In this section, we present some additional statistics about the DVQA dataset. Table 5 extends upon the brief statistics presented in the Table 1 of the main paper to present several additional details about the distribution of different questions in the dataset.

A.2. Additional details about the data and visualization generation procedure

In this section, we discuss some additional details about the heuristics and the methods used for generating the question-answer pairs in the DVQA dataset.

We have tried to design the DVQA dataset such that commonly found visual and data patterns are also more commonly encountered in the DVQA dataset. To do this, we downloaded a small sample of bar-charts from Google image search and loosely based the distribution in DVQA based on the distribution that we found in the wild. However, rarer types of choices, such as logarithmic axes, negative values, etc. are not easily found in the wild but are, nonetheless, encountered periodically. For these, we used our own judgment and chose to apply them only to a small portion of the whole dataset. As mentioned in section 3.1 in the main paper, we made sure that each of the choices were encountered at least a thousand times in the training set.

A.2.1 Distribution of different data-types

The majority (70%) of the data in the DVQA dataset is of the linear type (0–10). Among these, 10% of the charts are allowed to have negative values. Then, 25% of the data contain percentage scales (0–100), among which half are normalized so that the percentages within each group add up to a 100%. Remaining 5% of the data is exponential in nature ranging from $10^0$ to $10^{10}$.

A.2.2 Distribution of visual styles

First, 80% of all the charts are presented vertically and the rest are presented horizontally. Among multi-column bar-charts, 20% of the linear and normalized percentage bar-charts are presented in a stacked manner. The rest of the multi-column charts are displayed as groups. Similarly, 20% of multi-column charts have their legends presented outside the bounds of the main chart. We have used two styles commonly found in the wild: 1) using legend below the chart, and 2) using legend to the right of the chart.

A.2.3 Ensuring proper size and fit

Final chart images are drawn so that they have the same final width and height of $448 \times 448$ pixels. This was done for ease of processing and also to ensure that the images does not need to undergo stretching or aspect ratio change when being processed using an existing CNN architecture. Therefore, we need to ensure that all the elements in the chart fit in the fixed image size. We have taken several steps to ensure a proper fit. By default, the label texts are drawn without rotation i.e. horizontally. Then, if any of the texts overlap with each other, we rotate the text by either 45 or 90 degrees to ensure that they do not overlap. Another concern is when the labels take up too much space leaving too little are for the actual bar-charts, which often makes them illegible. This is usually a problem with styles that contain large texts and/or charts where legend is presented on the side. To mitigate this, we discard the image if the chart-area is less than half of the entire image. Similarly, we also discard a visualization if we cannot readjust the labels to fit without overlap despite rotating them. Fig. 6 shows some examples of discarded visualization due to poor fit.

A.2.4 Naming colors

We use python’s popular drawing tool, Matplotlib to generate our plots since it offers unparalleled programmatic control over each of the element drawn. We also make use of many of the pre-defined styles that are available with the package and further modify it with several new color schemes. Matplotlib allows us to access the RBG face-color of each drawn bar and legend entries so that we know the color of each of the element drawn in the image. However, to ask questions referring to the color of a bar or a legend entry, we need to be able to name it using natural language (e.g. ‘What does the red color represent?’). Moreover, simple names such as ‘blue’ or ‘green’ alone may not suffice to distinguish different colors in the chart. So, we employ the following heuristic to obtain a color name for a given
Table 5: Dataset statistics for different splits of dataset based on different question types

|                      | Total Questions | Unique Answers | Top-2 Answers | Chart-specific Answers |
|----------------------|-----------------|----------------|---------------|------------------------|
| **Structure**        |                 |                |               |                        |
| Train                | 491,678         | 10             | ('no', 105688), ('yes', 105688) | 0                      |
| Test-Familiar        | 123,432         | 10             | ('no', 26671), ('yes', 26671)   | 0                      |
| Test-Novel           | 122,995         | 10             | ('no', 26476), ('yes', 26476)   | 0                      |
| **Data**             |                 |                |               |                        |
| Train                | 826,124         | 534            | ('0', 19473), ('1', 14710)     | 596,349                |
| Test-Familiar        | 206,311         | 534            | ('0', 4761), ('1', 3591)       | 149,099                |
| Test-Novel           | 206,922         | 234            | ('0', 4739), ('1', 3757)       | 149,119                |
| **Reasoning**        |                 |                |               |                        |
| Train                | 696,116         | 564            | ('no', 59994), ('yes', 59704)  | 696,116                |
| Test-Familiar        | 174,660         | 561            | ('yes', 15040), ('no', 14870)  | 59,600                 |
| Test-Novel           | 173,893         | 262            | ('no', 15078), ('yes', 14879)  | 59,000                 |
| **Overall**          |                 |                |               |                        |
| Train                | 2,013,918       | 580            | ['no', 165682], ('yes', 165392) | 832,866                |
| Test-Familiar        | 504,403         | 578            | ('yes', 41711), ('no', 41541)  | 208,699                |
| Test-Novel           | 503,810         | 279            | ('no', 41554), ('yes', 41355)  | 208,119                |

RGB value.

1. Start with a dictionary of all 138 colors from the CSS3 X11 named colors. Each of the color is accompanied by its RGB value and its common name. The color names contain names such as darkgreen, sky-blue, navy, lavender, chocolate and other commonly used colors in addition to canonical color names such as ‘blue’, ‘green’, or ‘red’.

2. Convert all the colors to CIE standard L*a*b color space which is designed to approximate human perception of the color space.

3. Measure color distance between the L*a*b color of our chart-element and each of the color in the X11 color dictionary. For distance, we use CIE 2000 delta E color difference measure which is designed to measure human perceptual differences between colors.

4. Choose the color from the X11 colors which has the lowest delta E value from the color of our chart-element.

B. Additional experimental results

In this section, we present some additional results that were omitted from the main paper due to space concerns. Before presenting the results, we briefly remind the readers of the abbreviations used for the algorithms.

1. SAN-VQA: The Stacked Attention Network model used for VQA.

2. MOM: Multi-Output Model. Our model that uses a bounding box predictor followed by OCR to answer questions with chart-specific answer and uses SAN-VQA for the rest of the questions.

3. SANDY: Our SAN model with dynamic encoding. For this model, we assume an oracle text-detector and use...
Table 6: Results for models trained and tested on the DVQA* dataset for different question-types.

| Question-type       | Test-Familiar | Test-Novel |       |       |       |       |       |
|---------------------|---------------|------------|-------|-------|-------|-------|-------|
|                     | Structure     | Data       | Reasoning | Total  | Structure | Data | Reasoning | Total  |
| SAN-VQA             | 87.99         | 9.99       | 29.40   | 39.95  | 88.12    | 6.93 | 27.22     | 38.08  |
| SANDY               | 86.61         | 28.58      | 38.11   | 48.91  | 86.97    | 28.60| 37.88     | 48.87  |

Table 7: Results on DVQA* for models based on their ability to predict generic and chart-specific answers.

| Question-type       | Test-Familiar | Test-Novel |       |       |
|---------------------|---------------|------------|-------|-------|
|                     | Generic       | Chart-specific | Total |       |
| SAN-VQA             | 58.54         | 0.28       | 39.95 | 55.87 |
| SANDY               | 56.43         | 32.86      | 48.91 | 56.59 |

Specifically, we present the results for SAN-VQA and SANDY when trained and evaluated on the version of the dataset that we named as the DVQA* dataset in the main paper. The DVQA* dataset contains questions with chart-specific labels in them. To achieve this, we replaced indirect positional references to bars in the question to chart-specific label for the corresponding bar. Fig. 7 shows some examples to demonstrate how we converted different types of questions to use chart-specific labels instead of referring to bars by their position. We apply similar conversion to all eligible questions in train, test-familiar and test-novel splits of the original DVQA dataset. Table 6 and 7 shows the results for SAN-VQA and SANDY when trained and tested in this dataset. We can clearly see that SANDY fares much better than SAN-VQA, especially on the test-novel splits. We see the most improvements for data retrieval questions, which contains the majority of questions with chart-specific words in them.

C. Analysis of MOM’s localization performance

In this section, we analyze the localization performance of the MOM model. In the main paper, we saw that many of the predictions made by MOM were close but not exactly correct, which was also corroborated by taking into account the edit-distance between the predicted and ground truth answer strings.

Here we study our hypothesis that this is caused due to poor localization of the predicted bounding boxes. First, let us observe some qualitative examples. Fig. 8 shows some predicted bounding boxes from MOM for test-familiar split of the dataset where the bounding are correctly predicted.

Table 8: Localization performance for MOM expressed in terms of IOU with the ground truth box.

| IOU with Ground Truth | Percentage of Boxes |
|-----------------------|----------------------|
| ≥ 0.2                 | 61.32                |
| ≥ 0.4                 | 44.53                |
| ≥ 0.5                 | 35.44                |
| ≥ 0.6                 | 25.78                |
| ≥ 0.7                 | 15.53                |
| ≥ 0.8                 | 5.97                 |
| ≥ 0.9                 | 0.69                 |
| ≥ 1.0                 | 0.03                 |

Table 9: Localization performance for MOM expressed in terms of distance from the ground truth box.

| Distance from Ground Truth | Percentage of Boxes |
|----------------------------|----------------------|
| ≤ 1 pixels                | 0.28                 |
| ≤ 8 pixels                | 13.19                |
| ≤ 16 pixels               | 30.52                |
| ≤ 32 pixels               | 51.61                |
| ≤ 64 pixels               | 72.65                |

This shows that the bounding box prediction network works with texts of different orientations and positions. However, Fig. 9 shows examples where boxes do not ‘snap’ neatly around the text area but are in the right vicinity. Since the OCR subnetwork in MOM operates only on the features extracted from the predicted bounding box, a poor bounding box would also translate to poor prediction. To quantify this behavior we conduct two separate studies.

First, we measure intersection over union (IOU) for predicted and ground truth bounding box. Then, we use different threshold value for IOU, above which the predicted box is deemed to be correct. Table 8 shows the results for this experiment.

Next, we measure what percentage of the predicted boxes are within a given distance from the ground truth...
Which bar is the highest? What does the steelblue color represent? What is the label of the second bar?

Figure 8: Some examples showing correctly predicted bounding boxes predicted by our MOM model.

Which group has the smallest summed value? Which bar is the lowest? What does the crimson color represent?

Figure 9: Examples showing the imperfectly predicted bounding boxes for our MOM model.

boxes. Table 9 shows the results for different threshold distance in pixels. The distance is measured as the Euclidean distance between the center x,y co-ordinates for predicted and ground-truth bounding boxes. It clearly shows that a majority of the boxes are within 32 pixels away from the ground truth boxes. We remind the readers that the dimensions of the images are $448 \times 448$ pixels.

The above experiments clearly show that while many of the bounding boxes are ‘near’ the correct boxes, they do not perfectly encircle the text. So, if the predicted bounding boxes are localized better, which could be achieved with additional fine-tuning of the predicted bounding boxes, we can expect a considerable increase in MOM’s accuracy on chart-specific answers.

D. Additional examples

In this section, we present additional examples to study the performance of different algorithms for different types of questions. Fig. 10 shows the example figures with some of the question-answer pairs for different algorithms and Fig. 11 studies some interesting failure cases.

For the examples shown in Fig. 10, we can see that SAN-VQA, MOM and SANDY all perform comparably for structure understanding questions, i.e. with high accuracy across different styles. This is unsurprising since all the models use the SAN architecture for answering these questions. However, SAN is incapable for answering questions with chart-specific answers, and always repeats the same answer regardless of the question being asked. Furthermore, it should be noted that these examples are drawn from the test-familiar split of the dataset. So, the SAN-VQA model has already seen the answer-words in the training set. In comparison, MOM shows some success in decoding the chart-specific answers. Since the MOM’s chart-specific answers depend on the accuracy of the bounding box prediction, we found that its predictions were close but not exact for a lot of questions, which shows poor localization of the bounding boxes. As discussed in section C, we saw that the majority of the predicted bounding boxes are in the right area of the image but have poor localization. We believe
with additional fine-tuning, e.g. regressing for a more exact bounding box based on the features surrounding the initial prediction, could improve the model’s performance significantly. Finally, SANDY shows a remarkable success in predicting the chart-specific answers. SANDY’s dynamic dictionary essentially converts the task of predicting the answer to predicting the position of the text in the image, making it easier to answer. Unlike MOM, once the position is predicted, there are no additional potential sources of error for SANDY and therefore, the prediction is precise.

In Fig. 11, we study some failure cases to better understand the nature of the errors made by the current algorithms. Error in predicting exact value of the data is one of the most commonly encountered errors for the algorithms that we tested. Often, predicting these values involve extracting exact measurement and also performing arithmetic operations across different values. The models clearly show some ability to perform the measurement and the models predict values that are close to the correct answer, e.g. predicting smaller values when the correct answer is small (Fig. 11a, 11e and 11f) and predicting larger values when the correct answer is large (Fig. 11b and 11d). In addition, the predictions are also in the right kind of scale e.g. For Fig. 11d, the prediction for the value is in percentage scale (0–100) and for Fig. 11f, the prediction is in linear scale (0–10). However, the models often fail to predict the precise answer which, understandably, is a very hard task. For some cases the models also seem to gravitate towards the value accompanied by a tick label e.g. for Fig. 11f, the correct answer, 5, is between the tick labels of 4 and 6, and the models fail to interpolate between the two and simply predict the nearest tick label. Similarly, some of the errors could be caused by algorithms inability to consider that some bars may have zero/missing value, e.g. for Fig. 11d, two out of three models predict 90, which is the value of the third bar instead of the second.

Next class of the commonly encountered errors is the prediction of chart-specific answers. We have already established that the SAN-VQA model completely fails to answer questions with chart-specific answers, which is clearly seen in all the examples in Fig. 10 and 11. Our MOM model also makes errors for several of the examples in 11. The errors range from single letter errors (Fig. 11f) to more catastrophic errors (Fig. 11a). For some cases, the OCR works perfectly, but is reading the wrong bounding box (Fig. 11b). While our SANDY model shows vastly increased accuracy for these answers, it also can make occasional errors for these questions (Fig. 11b).

Finally, structure understanding type questions are answered with very high accuracy by all models. Fig. 11c shows one of the rare errors in structure understanding questions where SAN models makes an error in counting the number of bars being compared. This could potentially be due to one of the bars having a missing/zero value.
Example question-answer pairs for different models

(a) Q: What is the sum of all the values in the fifth group? A: 13
SAN: 13 MOM: 13 SANDY: 12
Q: What is the label of first bar in every group? A: anopla
SAN: updart MOM: anopla SANDY: anopla

(b) Q: Is the value of the third bar greater than the second bar? A: yes
SAN: yes MOM: yes SANDY: yes
Q: What type of scale is the graph using? A: log
SAN: log MOM: log SANDY: log

(c) Q: Are the bars hatched? A: no
SAN: no MOM: no SANDY: no
Q: How many groups contain bars that are greater than 3? A: 2
SAN: 2 MOM: 2 SANDY: 2

(d) Q: What is the value of the third bar? A: 80
SAN: 80 MOM: 60 SANDY: 80
Q: What is the label of the fourth bar? A: tottle
SAN: updart MOM: tottle SANDY: tottle

(e) Q: Does the chart contain negative values? A: yes
SAN: yes MOM: yes SANDY: yes
Q: How many groups contain bars that are greater than 3? A: 2
SAN: 2 MOM: 2 SANDY: 2

(f) Q: What does the green color represent? A: begari
SAN: updart MOM: begari SANDY: begari
Q: How many groups of bars are compared? A: three
SAN: three MOM: three SANDY: three

Figure 10: Some example question-answer pair for different algorithms on the Test-Familiar split of the dataset. The algorithms show success in variety of questions and visualizations. However, the SAN model is utterly incapable of predicting chart-specific answers.
Q: What is the sum of all the values in the second group? A: 8
SAN: 9  MOM: 7  SANDY: 9
Q: What does the darkorange color represent? A: svelte
SAN: updart  MOM: epltte  SANDY: svelte
Q: What does the mediumseagreen color represent? A: smurr
SAN: updart  MOM: alaeck  SANDY: golf
Q: What is the sum of all values in the second group? A: 18
SAN: 18  MOM: 24  SANDY: 21
Q: How many bars are compared? A: seven
SAN: six  MOM: seven  SANDY: seven
Q: Is the value of second bar greater than third bar? A: yes
SAN: no  MOM: yes  SANDY: yes

Figure 11: Some failure cases for different algorithms on the Test-Familiar split of the dataset.