Diverse Visuo-Linguistic Question Answering (DVLQA) Challenge

Shailaja Sampat1, Yezhou Yang1, Chitta Baral1

1Arizona State University
{ssampa17, yz.yang, chitta}@asu.edu

Abstract

Existing question answering datasets mostly contain homogeneous contexts, based on either textual or visual information alone. On the other hand, digitalization has evolved the nature of reading [OECD, 2019], which often includes integrating information across multiple heterogeneous sources. To bridge the gap between two, we compile a Diverse Visuo-Linguistic Question Answering (DVLQA) challenge corpus, where the task is to derive joint inference about the given image-text modality in a question answering setting. Each dataset item consists of an image and a reading passage, where questions are designed to combine both visual and textual information, i.e. ignoring either of them would make the question unanswerable. We first explore the combination of best existing deep learning architectures for visual question answering and machine comprehension to solve DVLQA subsets and show that they are unable to reason well on the joint task. We then develop a modular method which demonstrates slightly better baseline performance and offers more transparency for interpretation of intermediate outputs. However, this is still far behind the human performance, therefore we believe DVLQA will be a challenging benchmark for question answering involving reasoning over visuo-linguistic context. The dataset, code and public leaderboard will be made available at https://github.com/shailaja183/DVLQA.

1 Introduction

Question answering (QA) is one crucial way to evaluate the ability of a system to understand both text and images. In recent years, a large body of natural language QA (NLQA) datasets and visual QA (VQA) datasets have been proposed and compiled to serve as benchmarking testbeds. For most VQA datasets, text is used merely as a question-answering mechanism rather than an actual modality that provides some contextual information. To our best knowledge, there are no benchmarking datasets that focus on reasoning over both images and text. In this paper, we formalize the task of deriving joint inference from the image-text modality in a question-answering setting, where one must utilize both visual and textual information to correctly answer the question as per Figure 1. To create a benchmark for this task, we develop and present a new dataset: DVLQA (Diverse Visuo-Linguistic Question Answering).

Our development of the DVLQA corpus- as a benchmark for multi-step reasoning over images and text, is inspired by one of the questions-patterns from PISA (Program for International Student Assessment) [OECD, 2019]. PISA is a psychometric test administered by OECD (Organisation for Economic Co-operation and Development) which assesses skills and knowledge of 15-year old school students (who are near to the end of compulsory education) in 79 countries. PISA assessments conducted post 2018 take into account “the evolv-
Figure 2: Examples from DVLQA. Each example contains an Image (I), corresponding Text Passage (P), Question (Q) and Answer Choices (A), with correct answer choice highlighted by the boldface.

Table 1: Examples from DVLQA. Each example contains an Image (I), corresponding Text Passage (P), Question (Q) and Answer Choices (A), with correct answer choice highlighted by the boldface.

2 Related Work

We identify Multi-modal Learning, Visual Question Answering and Multi-Hop Reasoning closest to our DVLQA. We provide detailed comparison of our DVLQA corpus with other existing vision-language datasets in Table 3).

2.1 Multi-modal Learning

Multi-modal learning aims to build models that can process and relate information from multiple modalities. Image-Text multi-modality has received growing interest from AI community in recent times.

TQA [Kembhavi et al., 2017] task uses long essays describing concepts in textbook-style learning. They evaluate the task through text QA and diagram QA. Also, a small portion of the A2D [Kembhavi et al., 2016] dataset has some additional text context beyond the visual question-answers to reason over. Diagram QA component of TQA share similarities with DVLQA in the sense that it has image-text content and question answering, but there are important distinctions. First, textual component for TQA is in form of lessons- multiple text passages (~50% sentences and 4-5 images on average), whereas text passage for DVLQA is relatively pretty short (3-5 sentences). The goal of TQA aligns more with careful selection of necessary facts from a pool of information whereas we focus on enhancing capability of AI models for joint reasoning over visuo-linguistic content with precise information.
Secondly, TQA does not impose that one has to use both provided modalities in order to answer the question. In fact, for TQA [Kembhavi et al., 2017], one can answer 40% of text questions just using a single sentence and 50% of the diagram questions using only provided image. In that case, significant portion of the dataset becomes analogous to a machine comprehension or VQA task, loosing out on the actual purpose of multi-modal learning. In DVLQA task, we design the questions in such a way that answering them requires joint reasoning over both image and text.

2.2 Multi-Hop Reasoning

In NLP domain, multi-hop reasoning task is proposed to encourage the development of models that can reason about two or more textual contexts. QAngaroo [Welbl et al., 2018] and ComplexWebQuestions [Talmor and Berant, 2018] datasets contain multi-hop reasoning questions which can be answered by linking multiple entities from a given knowledge base. HotpotQA [Yang et al., 2018] was then proposed as a multi-hop reasoning benchmark over pairs of text paragraphs collected from wikipedia, offering more diverse questions and answers by not being constrained with the fixed knowledge base schemas. QASC [Khot et al., 2019] dataset requires to retrieve necessary facts from a large corpus (knowledge ranking) and then compose them to answer a multi-hop question.

Solving examples in DVLQA requires to link information from both- an image and a text passage. Therefore, DVLQA challenge can be considered as a novel kind of multi-hop task involving images and text, which we believe will be a driver for future research in vision-language domain.

2.3 Visual Question Answering

VQA [Antol et al., 2015] was one of the first large-scale task to propose image based question-answering. Followed by the success of VQA dataset, several variants of visual question answering have been proposed. The following variants are most relevant to our dataset;

Visual Lookup. Visual lookup refers to searching for the desired information from the visual in order to answer a query. Examples of visual lookup based datasets include VCR [Zellers et al., 2019], COCO-QA [Ren et al., 2015a], MSRVTT-QA [Xu et al., 2017], MemexQA [Jiang et al., 2017] etc. which contains an image and ask questions about that image. Visual lookup based datasets have demonstrated variety of question-answering styles such as multiple-choice, open-ended answers, fill-in-the-blank style and relational tuples.

VQA with Text embedded into Images VizWiz [Bigham et al., 2010] and TextVQA [Singh et al., 2019] datasets are developed to benchmark capability of VQA models to read text inside the images and reason about it in the context of the image to predict an answer. FigureQA [Kahou et al., 2017], DVQA [Kafle et al., 2018] are testbeds for question-answering on visual data representations (such as charts) also have text embedded in images.

A large portion of DVLQA dataset contains charts and diagrams containing embedded text, which will play an important role while reasoning. For 55% such images in DVLQA, we provide OCR (Optical Character Recognition) extracted text tokens as a part of dataset annotations to encourage novel approaches in addition to standard image-features based methods.

Reasoning-based VQA Reasoning based VQA datasets aim at measuring system’s capability to reason about set of objects, their attributes and relationships among them. CountQA [Chattopadhyay et al., 2017], HowManyQA [Trott et al., 2017] and TallyQA [Acharya et al., 2019] contain questions with complex object counting from images. CLEVR [Johnson et al., 2017] and NLVR [Suhr et al., 2017] target spatial reasoning capabilities over Synthetic images whereas SNLI-VE [Xie et al., 2019] and VCPA [Yeo et al., 2018] focus on causal reasoning.

DVLQA corpus contains variety of images (natural, synthetic and diagrams) and tests diverse reasoning capabilities through natural language question-answering. (For more details, refer to Section 3.2)

Knowledge-based VQA. There have been several works on developing vision-language tasks that require additional knowledge beyond provided image and text. F-VQA [Wang et al., 2018], KB-VQA [Wang et al., 2015] and KVQA [Shah et al., 2019] rely on retrieving commonsense or world knowledge from a given knowledge base (KB), whereas OK-VQA [Marino et al., 2019] is open-ended knowledge extraction from web. In DVLQA, 81% of samples require some commonsense or domain knowledge which is not explicitly stated in the image-text.

3 DVLQA Dataset

We will now formally define the multi-hop reasoning task over image-text context, explain our approaches to curate this dataset and necessary measures for quality assurance.

3.1 Task Overview

A datapoint in DVLQA task is a 4-tuple <I, P, Q, A>, which can be visualized from Figure 2.

Image(I). It is the provided imagery, which ranges from simple daily life scenes to diagrams representing complex information. In case of multiple images being present in a question, for the simplicity of processing and retrieval, we compose all necessary files as a single image. Each image within the composed image is bounded by a red box and referred by explicit detection tags ([I],[1],..) for the identification purposes, inspired from VCR [Zellers et al., 2019] object annotation style. This approach also provides a convenient way to refer images in passage, question or answer choices. We provide Faster R-CNN [Ren et al., 2015b] (with ResNet-101 [He et al., 2016] backbone) extracted features for all images to build models.

Passage(P). It is a textual passage that gives additional contextual information related to the image. Passages in DVLQA dataset consists of 1-5 sentences typically.

Question(Q). It is a question that requires reasoning over both I and P for getting the right answer. In addition to standard ‘Wh’ questions, sometimes question are in ‘do-as-directed’ forms.
Answer choices(A). DVLQA task is formed as a classification task over 2-way or 4-way plausible answer choices, with exactly one of the candidate answers being correct. Questions containing image detection tags ([0], [1], ..) as answer choices are identical to Image-selection vision-language task.

Task. Given DVLQA dataset as a collection of 4-tuple <I,P,Q,A> representations, the task is to build an AI model that can answer a given question using image-text multi-modal environment. It is important to note that only text or only image modality is not sufficient to answer the questions in DVLQA corpus. Correctness of the prediction is measured against the provided ground-truth answer. We also provide rich annotations (described in section 3.2) in addition to 4-tuple representation for the analysis purposes and to encourage methods which aim at tackling a subset of DVLQA problems.

3.2 Constructing DVLQA

Data collection and Annotation

The main goal of our work is to collect a diverse question answering dataset that requires to derive joint inference from image-text modality. Our data collection process relied on three major sources: educational resources, web crawls and existing datasets. We collected variety of textual/visual information by crawling wikipedia pages, newspaper archives, info-graphics website, 'the world factbook' from CIA [Central Intelligence Agency, 2019] and various educational resources such as school textbooks, children encyclopedias, online practice worksheets and PISA tests. Further, we obtained a small subset of interesting samples from existing vision/NLP datasets such as RecipeQA [Yagcioglu et al., 2018], WikiHow [Koupaee and Wang, 2018], PhysicalQQA [Bisk et al., 2019], ART [Bhagavatula et al., 2019], VisualEntailment [Xie et al., 2019] and TQA [Kembhavi et al., 2017]. Since we impose the condition that a question can only be correctly answered through joint reasoning on both the modalities, we refactor textual/visual information collected from the above sources and mould it as per our task requirements. Figure 3 illustrates this process. Refactoring of these samples include manual or semi-automated post-processing such as replacing given textual/visual attributes with equivalent visual/textual counterpart respectively, adding/removing partial information to/from text or visuals, and creating hypothetical situations around images. Then we standardize all the information collected using the above methods as multiple choice question-answers in an image-text multi-modal environment.

Ensuring dataset integrity

Combined understanding of visual and textual inputs being the key objective in multimodal learning, we employ 2-level verification to ensure that both the modalities are necessary to answer the question. Firstly, we create 3 copies of the dataset and shuffle answer choices with the fixed seed. Then we create text-only baseline using Roberta [Liu et al., 2019] trained on RACE dataset [Lai et al., 2017] and image-only baseline using VL-BERT [Lu et al., 2019], where we completely ignore the other modality that is image and passage respectively and see if a model can still answer the question correctly. We run these models over all 3 dataset copies and filter out all the items that are predicted correctly, with a majority decision. Since DVLQA contains 2-way and 4-way multiple choice questions, there are 50% and 25% chances of randomly answering a question correctly. There is a high chance that some models may predict correct answers without proper reasoning. To discourage such models, we take all filtered out items for a further round of manual quality check. We instruct workers to follow a 2-step process, first trying to answer a
Measure Stats.

Multi-modal Context
- Total #Images 10209
- #Unique Text Passages 9156
- #Questions 9267

Dataset Split
- Train (80%) 7413
- Test (10%) 927
- Validation (10%) 927

Text-length Analysis
- Avg. Passage Length 34.1
- Avg. Question Length 15.0
- Avg. Answer Length 1.7
- Vocabulary Size 33259

Image-types Distribution
- Natural Images 4445
- Templated Figures 3920
- Free-form Figures 1854

Answer-types Distribution
- 4-way image MCQ 1172
- 4-way text MCQ 4647
- 4-way Sequencing 1088
- 2-way image MCQ 1088
- Binary Classification 1272
- (T/F or Yes/No) 3145

Knowledge/Reasoning-types Distribution
- No External Knowledge required 3145
- External Knowledge + Single-step Inference 2783
- External Knowledge + Multi-step Inference 2939

Hardness: Human Evaluated (100 samples)
- Easy 42
- Moderate 32
- Hard 26

Table 1: DVLQA Statistics and diversity based on answer choice types, image types and knowledge/reasoning types

- question just based on images and then trying to answer a question based on only the text passage. If a question can be answered with using a single modality, we suggest annotators to label as ‘Yes’, and otherwise ‘No’. For all the items that are labelled ‘Yes’ by the annotators, either we provide a fix or we replace it with another similar item.

Figure types and diversity
We categorize 10209 unique images in DVLQA into 3 major kinds: Natural Images, Template based Figures and Free-form Figures. Natural images incorporate day-to-day-life scenes around us that contain abundant objects and actions. Template based figures are sets of visuals that follow a common structure for information representation. Template based figures in DVLQA involve 22 sub-types including standard chart/plot types- bar, pie, scatter, line, area, bubble and timelines, hierarchies, maps, tables, cycles, and processes. The images which neither fit in any templates nor are Natural are put in a free-form category, for example, images of experimental setup used in explaining scientific concepts.

Language complexity and diversity
Each item in DVLQA dataset involves considerable amount of text in Passage, Question and Answer choices. We extract a lot of text in the dataset creation process through crawling, retrieval and manual efforts. As we create 9267 items for DVLQA, with average passage length of 34.1 tokens, the dataset offers diverse vocabulary of 33259 unique tokens.

External Knowledge and Inference types
Humans have powerful ability to make decision about where to look for the information in multi-modal environment based on what the question is about. But when it comes to machines, multi-modality has both pros and cons together. Presence of multiple modalities provide natural flexibility to develop more varied inference tasks, simultaneously making reasoning process more complex as information is now spanned across them and may require cross-inferencing before reaching the correct answer. We identify 15 different types of inferences such as counting, comparison, deductive reasoning, ordering, spatial reasoning, temporal reasoning, locating desired elements based on an attribute and many more commonsense tasks. We provide detailed annotation for each sample in the DVLQA corpus regarding which reasoning capability is being tested by a question. 61% of samples in DVLQA are observed to incorporate some commonsense or domain specific facts in addition to image-passage context, assuming that a person/an AI model not necessarily has a prior knowledge on subject or recollects from memory to solve these questions. This missing knowledge has to be retrieved through web in open-ended fashion similar to OK-VQA [Marino et al., 2019], whereas rest 39% of samples can be answered through a simple join of information from provided visuo-lingustic context.

Dataset Splits
DVLQA contains 9267 datapoints in \(<I,P,Q,A>\) format which is split into train-test-dev partition in 80-10-10%, ensuring the uniform distribution of samples based on answer types, figure types, language aspects, reasoning skills and requirement of external knowledge.

4 Benchmarking
Random. DVLQA dataset contains 4-way and 2-way multiple choice questions. Based on the answer-type distribution provided in Table 1, the random baseline performance for ordinary and hard test set is 31.39% and 30.97% respectively. It is important to note that while splitting the dataset, we take answer-type into account to ensure equal distribution of 4-way and 2-way questions.

Human Performance We performed human evaluation on 100 carefully selected samples (covering all variety of images, text, reasoning and external knowledge requirements) from the test-set. First, we ask human-evaluator to take the test in isolation. In addition to answering the questions, we also asked evaluator to rate the questions according to difficulty levels (easy/medium/hard) and an optional choice to
mark question as ‘ambiguous’. The evaluator spent roughly 140 minutes in total for 100 examples. Then we evaluate his predictions against ground-truth answers which turned out to be 82%. We plan to further employ human study over complete dataset and provide explanations for the ground-truth answers for given visuo-linguistic context.

4.1 Best Existing Architectures

There are several models developed recently that aim to derive pre-trainable generic representations for visual-linguistic tasks. We pick top performing models from the visual commonsense reasoning (VCR) [Zellers et al., 2019] leaderboard as it best aligns with our data format, and evaluate their capabilities over the proposed DVLQA dataset. Following is a brief description about the architectures we experiment with.

**B2T2.** Bounding Boxes in Text Transformer (B2T2) [Alberti et al., 2019] was one of the earliest works in learning joint representation using pre-training, which significantly outperformed existing models on the VCR task. It leveraged concept of referential information binding that is mapping words to portions of the image through single cross-modal architecture pre-trained over Conceptual Captions [Sharma et al., 2018].

**VL-BERT.** Visual-Linguistic BERT [Su et al., 2019] is a single cross-modal transformer based architecture for generic representation of visual-linguistic tasks. It is pre-trained on Conceptual Captions [Sharma et al., 2018] as a visual-linguistic corpus with additional text-only corpus, which supported generalization on long and complex sentences.

**VisualBERT.** Identical to B2T2 and VL-BERT, VisualBERT [Li et al., 2019] is a single transformer based architecture supporting multimodal learning through self-attention based alignment of text and image regions. However, it is pre-trained on COCO Captions [Chen et al., 2015] and transfers capabilities to more downstream tasks compared to both of the above models.

**ViLBERT.** Vision-and-Language BERT (ViLBERT) [Lu et al., 2019] utilized two transformer based mechanisms pre-trained over Conceptual Captions [Sharma et al., 2018]. Firstly, it takes visual and textual inputs as separate streams which later interacts through co-attentional transformer layers to learn joint vision-language representations.

**DQA-Net.** [Kembhavi et al., 2016] introduced diagram parse graphs (DPG) to encode diagram constituents and their relationships in a graph.

**Proposed VLQA Model.** As we evaluate DVLQA data, we experiment with various existing vision-language models which are pretrained on large popular corpus and fine-tuned further on a dataset specific to the down-stream tasks. Specifically, we take pretrained VLBERT, ViLBERT, B2T2 and VisualBERT finetuned for visual commonsense reasoning (VCR) Q→A task as it aligns most with our data format and also supports more complex kind of reasoning than VQA. Since VCR task does not support additional text modality beyond a question, we combine Passage and Question and feed them jointly as Q in Q→A style and finetune this model on DVLQA.

From our primary results, we observe that finetuning on DVLQA does not lead to significant improvement in performance; this is possibly due to the relatively smaller data size of DVLQA. The bottleneck in massive scaling of DVLQA data is due to the requirement of questions that must support joint textual-visual understanding. Creation and validation of such data requires significant amount of manual effort. We
deliberately refrain from crowdsourcing for quality purposes and template-based approaches hinder diversity. As a solution to above problem, we propose a modular method based on existing architectures (see Figure ??) which offers more transparency as it produces interpretable outputs at intermediate stages. Inspired by human-like way of problem solving, we first utilize Image to Question (I2Q) Attention and Passage to Question (P2Q) Attention to determine which modality is more important as a starting point for solving a question. Based on this distinction, we term them ‘Image to Passage Hop’ (I2PH) and ‘Passage to Image Hop’ (P2IH). This is based on whether the starting point of information retrieval is the image or the passage. From experiments, we observe that pretrained vision-language architectures are Naturally trained to look for information from visual modality and generating a text response around it based on the task at hand. This behaviour is suitable for I2P hop but not for P2I hop since the first important piece of information to solve the question lies within the passage. Therefore, we formulate P2I hop task as a Machine Comprehension followed by a VQA task. First we try to answer the question (Q) from passage (P) in the style of SQuAD [Rajpurkar et al., 2016] using state-of-the-art ALBERT [Lan et al., 2019] architecture. It locates some information from the passage (referred as an intermediate answer A’) which is to be located in the visual modality in next step. We then formulate a new question Q’as ‘Where is A’ and feed it with the original candidate answer choices into the state-of-the-art VQA model LXMERT [Tan and Bansal, 2019]. Also, analysis of experimental results and intermediate interpretations demonstrated that the proposed hop based method was not adequate to perform higher order reasoning task of Ordering/Sequencing and deal with multiple images. Therefore, we propose a separate channel for the tasks that can be addressed using sequence of entailment tasks such as image selection, binary classification (true/false or yes/no questions) and ordering/sequencing of events. We provide a lightweight toolbox that supports all possible entailment combinations: image-text, text-image, image-image and text-text used off-the-shelf [Xie et al., 2019; Yeo et al., 2018; Khot et al., 2018] and tweaked a little.

5 Experiments

Evaluation Metrics. DVLQA contains a multiple-choice type questions with exactly one correct answer. We use accuracy as our evaluation metric.

Results on DVLQA. We evaluate and compare existing pre-trained vision-language architectures with proposed modular method in Table ?? . From experiments, we observe that pre-trained vision-language architectures are trained to look for information from visual modality and fails to solve variety of DVLQA items. Proposed modular method slightly outperforms pre-trained vision-language architectures which is more interpretable for analysis. We also report the performance of image-only and text-only baselines which we used for quality check. The poor performance of image-only and text-only baselines indicate that the DVLQA dataset requires models to jointly understand both image and text modalities.

| Method                  | Test(%) |
|-------------------------|---------|
| Human (100 samples)     | 82.0    |
| Random                  | 31.39   |
| Text-only               |         |
| Roberta (without I)     | 30.36   |
| Image-only              |         |
| VL-BERT (without P)     | 28.48   |
| Vision-Language         |         |
| VL-BERT                 | 36.92   |
| VisualBERT              | 33.17   |
| ViLBERT                 | 34.70   |
| B2T2                    | 32.47   |
| DQA-Net                 | 33.30   |
| Proposed Model          | 39.63   |

Table 2: Performance benchmarks over test-set of DVLQA task

These results suggest the pressing need of building generic AI models that can reason well over multi-modal information.

5.1 Discussion

Our proposed DVLQA dataset has several distinctions from existing VQA datasets. Firstly, it incorporates a text passage that contains additional contextual information. Secondly, it offers a variety of figure types including Natural images, templated images (semi-structured) and free-form images (unstructured), which is not so common for other VQA datasets. Thirdly, it tests diverse reasoning capabilities, including cross-inferencing between visual and textual modalities. As a result, DVLQA dataset turns out to be relatively harder, stimulating the need for more complex reasoning capabilities of AI models.

We performed human evaluation on 100 carefully selected samples from test-set for which reported accuracy was 82%. For 18 wrong answers provided by evaluator, we had a detailed discussion with to understand his thought-process and get a feedback. Based on our discussion with evaluator, we infer that in most cases either he misunderstood the provided information or lacked necessary knowledge to answer the question. Evaluator reported 3 items to have ambiguous textual content, which we agree upon and will incorporate them in revised dataset versions.

6 Conclusion

In this work, we introduced the Diverse Visuo-Linguistic Question Answering (DVLQA) challenge that we believe has the potential to open new research avenues in areas of joint vision & language. Our experiments show that a system equipped with state-of-the-art vision-language models does not perform well on the task that requires joint vision-language inference. Our future work would include extending this dataset to support more diverse visuo-linguistic tasks for future research on building generic AI models that can learn novel visual concepts through small set of examples.
| Dataset                  | Provided Modality | Visual-linguistic Content Type | Prediction Type | Task                              |
|-------------------------|-------------------|-------------------------------|----------------|-----------------------------------|
| **I**                  |                  | **T**                        |                |                                  |
| Clevr                   | ✓                 | Synthetic                     | Ques           | OE                               | VQA (Spatial Reasoning) |
| COCO                    | ✓                 | Natural                       | Caption        | OE                               | Text generation        |
| COCO-BISON              | ✓                 | Natural                       | Sent           | MC                               | Image Selection        |
| COCO-QA                 | ✓                 | Natural                       | Ques           | OE                               | VQA                   |
| COG                     | ✓                 | Synthetic                     | Ques / Sent    | MC                               | VQA / Instruction Following |
| ConceptualCaption       | ✓                 | Natural                       | Caption        | OE                               | Text generation        |
| CountQA                 | ✓                 | Natural                       | Ques           | OE                               | VQA                   |
| DAQUAR                  | ✓                 | Natural                       | Ques           | OE                               | VQA                   |
| DVQA                    | ✓                 | Synthetic                     | Ques           | OE                               | VQA (BarCharts)       |
| FigureQA                | ✓                 | Synthetic                     | Ques           | OE                               | VQA (Charts)          |
| FMIQA                   | ✓                 | Natural                       | Ques           | OE                               | VQA                   |
| GQA                     | ✓                 | Natural                       | Ques           | OE                               | VQA                   |
| HowManyQA               | ✓                 | Natural                       | Ques           | Numeral                          | VQA (Counting)        |
| LEAPQA                  | ✓                 | Synthetic                     | Ques           | OE                               | VQA (Charts)          |
| Memex-QA                | ✓                 | Natural                       | Ques           | MC                               | VQA                   |
| MSVRVTQ-QA              | ✓                 | Natural                       | Ques           | OE                               | VQA                   |
| NLVRv1                  | ✓                 | Synthetic                     | Sent           | True/False                       | Text classification   |
| NLVRv2                  | ✓                 | Natural                       | Sent           | True/False                       | Text classification   |
| OpenImagesV6            | ✓                 | Natural                       | Caption        | OE                               | VQA (Counting)        |
| RVQA                    | ✓                 | Natural                       | Ques           | OE                               | VQA                   |
| Shapes                  | ✓                 | Synthetic                     | Ques           | OE                               | VQA                   |
| ShapeWorld              | ✓                 | Synthetic                     | Sent           | Score [0,1]                      | Text classification   |
| SNLIV-VE                | ✓                 | Natural                       | Sent           | 3 classes                        | Visual Entailment     |
| TallyQA                 | ✓                 | Natural                       | Ques           | Numeric                          | VQA (Counting)        |
| TDIUC                   | ✓                 | Natural                       | Ques           | OE                               | VQA                   |
| TextVQA                 | ✓                 | Natural                       | Ques           | OE                               | VQA (Text in Images)  |
| VCR                     | ✓                 | Natural                       | Ques           | MC                               | VQA+Rationale         |
| Visual Genome            | ✓                 | Natural                       | Ques           | OE                               | VQA (Scene Graphs)    |
| Visual Madlibs           | ✓                 | Natural                       | Sent           | Blanks                           | VQA                   |
| Visual7W                | ✓                 | Natural                       | Ques           | MC                               | VQA                   |
| VisualDialogue          | ✓                 | Natural                       | Ques           | OE                               | VQA (Dialogue)        |
| VizWiz-Priv (v2)        | ✓                 | Natural                       | Question       | OE                               | VQA (Text in Images)  |
| VQA-CP v2/v1            | ✓                 | Natural                       | Ques           | OE / MC                          | VQA                   |
| VQAv1 Abstract          | ✓                 | Synthetic                     | Ques           | OE                               | VQA                   |
| VQAv1 Real              | ✓                 | Natural                       | Ques           | OE                               | VQA                   |
| VQAv2                   | ✓                 | Natural                       | Ques           | OE / MC                          | VQA                   |
| VAT2019                 | ✓                 | Natural                       | Caption        | OE                               | VQA                   |
| AI2 Geometry            | ✓                 | Diagrams                      | Ques           | MC                               | VQA (Geometry)        |
| AI2 Mercury             | ✓                 | Diagrams                      | Ques           | MC                               | VQA (Science)         |
| AI2 ScienceQ            | ✓                 | Diagrams                      | Ques           | MC                               | VQA (Science)         |
| AI2D                    | ✓                 | Diagrams                      | Ques           | MC                               | VQA (Science)         |
| FVQA                    | ✓                 | Natural                       | Ques           | OE                               | VQA (Commonsense)     |
| KBVQA                   | ✓                 | Natural                       | Ques           | OE                               | VQA (Commonsense)     |
| KVQA                    | ✓                 | Natural                       | Ques           | OE                               | VQA (World Knowledge) |
| OKVQA                   | ✓                 | Natural                       | Ques           | OE                               | VQA (World Knowledge) |
| VQA-Med                 | ✓                 | Medical                       | Ques           | OE / MC                          | VQA (Medical)         |
| VQA-RAD                 | ✓                 | Radiology                     | Ques           | OE / MC                          | VQA (Radiology)       |
| WKVQA                   | ✓                 | Natural                       | Ques           | OE                               | VQA (World Knowledge) |
| TQA                     | ✓                 | Science                       | Ques, Lesson   | MC                               | VQA (Diagrams)        |
| DVLQA (Our)             | ✓                 | Natural, Synthetic, Diagrams  | Ques, Para     | MC                               | VQA (Joint Reasoning over Image-Text) |

Table 3: **Appendices: Survey of existing vision-Language Datasets:**

**Provided Modality:** I (Images), T (Text), T+ (Additional Textual Context), K (Additional Knowledge).

**Visual Content Type:** Natural or Synthetic images are most common, with exceptions of Domain Specific Diagrams/Imagery.

**Textual Content Type:** Question (Ques), Sentence (Sent), Caption, Passage/Paragraph (Para) and Lesson (Multiple Paras)

**Prediction Type:** MC (Multiple Choice), OE (Open Ended), Caption are most common with few Numeric, N-class classification, Scoring

**AI Task:** Variants of Visual Question Answering (VQA), Caption generation and Text Classification are most common tasks for evaluation
Appendices: Additional Dataset Samples

**Image(s) (I)**

[Image of a rescue helicopter and a jar with different liquids.]

**Text Passage (P)**

Rescue Helicopters use the concept of Balanced forces to stabilize on water as shown in [0]. Forces in opposite directions can be Balanced out.

**Question (Q)**

Which of the following is a correct pair of balanced forces for a rescue helicopter?

**Answer Choices (A)**

a. lift and thrust
b. drag and gravity
c. lift and gravity
d. friction and gravity

[Image of a diagram showing electric vehicle sales share with Tesla leading.]  

**Text Passage (P)**

Figure [0] represents the electric vehicle sales share of different companies. A blog published on Tesla’s website confirm that Tesla has officially acquired VW.

**Question (Q)**

How much share of the electric vehicle market will be dominated by Tesla after this acquisition?

**Answer Choices (A)**

a. 40%
b. 55%
c. 45%
da. 50%

[Image of a table showing railway network with cities and distances.]

**Text Passage (P)**

[0] contains information about the railway network in various cities. Tokyo and Kyōto are Asian cities, London and Paris are in Europe. Los Angeles and Washington DC are popular American cities.

**Question (Q)**

Which continent has the smallest total railway route?

**Answer Choices (A)**

a. Asia  
b. Africa  
c. North America  
d. Europe

[Image of a diagram showing two magnets with one attracting and one repelling.]  

**Text Passage (P)**

Consider two cars carrying large magnets on top of them as per [0] and [1]. Red indicates north pole whereas blue indicates south pole. When you place the north pole of one magnet near the south pole of another magnet, they are attracted to one another. When you place like poles of two magnets near each other, they repel.

**Question (Q)**

Choose the correct statement about [0] and [1] based on the above information.

**Answer Choices (A)**

a. [0] will repel, [1] will attract  
b. [0] will attract, [1] will repel  
c. both [0] and [1] will attract  
d. both [0] and [1] will repel
One can see the candle through [0] but not through [1].

**Question (Q)**
Which scientific phenomena best supports the passage?

a. Cardboard box absorbs light rays before it reaches to candle.
b. Light always travels in straight line

c. Light rays can bend.
d. Cardboard box reflects light rays before it reaches to candle.

[0] demonstrates the flow of air in inhalation process when we breathe. Inhalation and Exhalation are complementary processes in breathing.

**Answer Choices (A)**
Which of the following is not correct about Exhalation?

a. Ribs move inside.
b. Diaphragm moves up.
c. Air is drawn out.
d. Ribs move outside.

Noel’s disk has 112 MB free space as of now. But he wants to store a photo album worth 350MB.

**Question (Q)**
Can he make the space for the photo album by deleting at most two music albums from information given in [0]?

a. Yes
b. No

---

**Text Passage (P)**
Figure [0] shows the changing levels of Lake Chad in Saharan North Africa. Today, its level is about the same as it was in AD 1000.

**Question (Q)**
What is the depth of Lake Chad today?

a. About 2m
b. About 15m
c. About 50m
d. It disappeared completely

**Answer Choices (A)**
Which subway station Julio, Maria and Don could meet based on the provided information in the passage?

a. Park
b. Unity
c. Market
d. Emerald

---

**Text Passage (P)**
Alice and Bob are playing a game where turn-by-turn a person removes a block from the table. Starting from configuration in [0], Bob takes the first turn and removes the Purple block.

**Question (Q)**
Choose the correct image [1] to [4] that describes configuration after the first move by Bob.

**Answer Choices (A)**
a. [1] b. [2] c. [4] d. [3]
References

[Acharya et al., 2019] Manoj Acharya, Kushal Kafle, and Christopher Kanan. Tallyqa: Answering complex counting questions. In AAAI, volume 33, 2019.

[Alberti et al., 2019] Chris Alberti, Jeffrey Ling, Michael Collins, and David Reitter. Fusion of detected objects in text for visual question answering. 2019.

[Antol et al., 2015] Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. Vqa: Visual question answering. In IEEE ICCV, pages 2425–2433, 2015.

[Bhagavatula et al., 2019] Chandra Bhagavatula, Ronan Le Bras, Chaithanya Malaviya, Keisuke Sakaguchi, Ari Holtzman, Hannah Rashkin, Doug Downey, Scott Wen tau Yi, and Yejin Choi. Abductive commonsense reasoning. In AAAI, pages 233–342. ACM, 2010.

[Bisk et al., 2019] Yonatan Bisk, Rowan Zellers, Ronan Le Bras, Jianfeng Gao, and Yejin Choi. Piqa: Reasoning about physical commonsense in natural language. arXiv preprint arXiv:1911.11641, 2019.

[Central Intelligence Agency, 2019] DC Central Intelligence Agency, Washington. The world factbook. 2019.

[Chattopadhyay et al., 2017] Prithvijit Chattopadhyay, Ramakrishna Vedantam, Ramprasaath R Selvaraju, Dhruv Batra, and Devi Parikh. Counting everyday objects in everyday scenes. In IEEE CVPR, 2017.

[Chen et al., 2015] Xinlei Chen, Hao Fang, Tsung-Yi Lin, Ramakrishna Vedantam, Saurabh Gupta, Piotr Dollár, and C Lawrence Zitnick. Ms coco captions: Data collection and evaluation server. arXiv preprint arXiv:1504.00325, 2015.

[He et al., 2016] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In IEEE CVPR, 2016.

[Jiang et al., 2017] Lu Jiang, Junwei Liang, Liangliang Cao, Yannis Kalantidis, Sachin Farfade, and Alexander Hauptmann. Memexqa: Visual memex question answering. arXiv preprint arXiv:1708.01336, 2017.

[Johnson et al., 2017] Justin Johnson, Bharath Hariharan, Laurens van der Maaten, Li Fei-Fei, C Lawrence Zitnick, and Ross Girshick. Clever: A diagnostic dataset for compositional language and elementary visual reasoning. In IEEE CVPR, 2017.

[Kafle et al., 2018] Kushal Kafle, Brian Price, Scott Cohen, and Christopher Kanan. Dvqa: Understanding data visualizations via question answering. In IEEE CVPR, pages 5648–5656, 2018.

[Kahou et al., 2017] Samira Ebrahimi Kahou, Vincent Michalski, Adam Atkinson, Ákos Kádár, Adam Trischler, and Yoshua Bengio. Figureqa: A figure dataset for visual reasoning. arXiv preprint arXiv:1710.07300, 2017.

[Kembhavi et al., 2016] Aniruddha Kembhavi, Mike Saltz, Eric Kolve, Minjoon Seo, Hannaneh Hajishirzi, and Ali Farhadi. A diagram is worth a dozen images. In ECCV, 2016.

[Kembhavi et al., 2017] Aniruddha Kembhavi, Minjoon Seo, Dustin Schwenn, Jonghyun Choi, Ali Farhadi, and Hannaneh Hajishirzi. Are you smarter than a sixth grader? textbook question answering for multimodal machine comprehension. In IEEE CVPR, pages 4999–5007, 2017.

[Khot et al., 2018] Tushar Khot, Ashish Sabharwal, and Peter Clark. SciTail: A textual entailment dataset from science question answering. In AAAI, 2018.

[Khot et al., 2019] Tushar Khot, Peter Clark, Michal Guerquin, Peter Jansen, and Ashish Sabharwal. Qasc: A dataset for question answering via sentence composition. arXiv preprint arXiv:1910.11473, 2019.

[Koupae and Wang, 2018] Mahnaz Koupae and William Yang Wang. Wikihow: A large scale text summarization dataset. arXiv preprint arXiv:1810.09305, 2018.

[Lai et al., 2017] Guokun Lai, Qizhe Xie, Hanxiao Liu, Yiming Yang, and Eduard Hovy. Race: Large-scale reading comprehension dataset from examinations. arXiv preprint arXiv:1704.04683, 2017.

[Lan et al., 2019] Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. Albert: A lite bert for self-supervised learning of language representations, 2019.

[Li et al., 2019] Liunian Harold Li, Mark Yatskar, Da Yin, Cho-Jui Hsieh, and Kai-Wei Chang. Visualbert: A simple and performant baseline for vision and language. arXiv preprint arXiv:1908.03557, 2019.

[Liu et al., 2019] Yinhua Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692, 2019.

[Lu et al., 2019] Jiasen Lu, Dhruv Batra, Devi Parikh, and Stefan Lee. Vilbert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks, 2019.

[Marino et al., 2019] Kenneth Marino, Mohammad Rastegari, Ali Farhadi, and Roozbeh Mottaghi. Ok-vqa: A visual question answering benchmark requiring external knowledge. In IEEE CVPR, 2019.

[OECD, 2019] OECD. Pisa: Programme for international student assessment. Recuperado el 2019.

[Rajpurkar et al., 2016] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. Squad: 100,000+ questions for machine comprehension of text. arXiv preprint arXiv:1606.05250, 2016.
[Ren et al., 2015a] Mengye Ren, Ryan Kiros, and Richard Zemel. Exploring models and data for image question answering. In *NIPS*, pages 2953–2961, 2015.

[Ren et al., 2015b] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. In *NIPS*, 2015.

[Shah et al., 2019] Sanket Shah, Anand Mishra, Naganand Yadati, and Partha Pratim Talukdar. Kvqa: Knowledge-aware visual question answering. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pages 8876–8884, 2019.

[Sharma et al., 2018] Piyush Sharma, Nan Ding, Sebastian Goodman, and Radu Soricut. Conceptual captions: A cleaned, hypernymed, image alt-text dataset for image captioning. In *56th ACL (Vol 1: Long Papers)*, 2018.

[Talmor and Berant, 2018] Alon Talmor and Jonathan Berant. The web as a knowledge-base for answering complex questions. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 641–651, New Orleans, Louisiana, June 2018. Association for Computational Linguistics.

[Wang et al., 2015] Peng Wang, Qi Wu, Chunhua Shen, Anton van den Hengel, and Anthony Dick. Explicit knowledge-based reasoning for visual question answering. *arXiv preprint arXiv:1511.02570*, 2015.

[Wang et al., 2018] Peng Wang, Qi Wu, Chunhua Shen, Anthony Dick, and Anton van den Hengel. Fvqa: Fact-based visual question answering. *IEEE PAMI*, 2018.

[Welbl et al., 2018] Johannes Welbl, Pontus Stenetorp, and Sebastian Riedel. Constructing datasets for multi-hop reading comprehension across documents. *Transactions of the Association for Computational Linguistics*, 6:287–302, 2018.

[Xie et al., 2019] Ning Xie, Farley Lai, Derek Doran, and Asim Kadav. Visual entailment: A novel task for fine-grained image understanding. *arXiv preprint arXiv:1901.06706*, 2019.