

ISAAQ - Mastering Textbook Questions with Pre-trained Transformers and Bottom-Up and Top-Down Attention

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Abstract

Textbook Question Answering is a complex task in the intersection of Machine Comprehension and Visual Question Answering that requires reasoning with multimodal information from text and diagrams. For the first time, this paper taps on the potential of transformer language models and bottom-up and top-down attention to tackle the language and visual understanding challenges this task entails. Rather than training a language-visual transformer from scratch we rely on pre-trained transformers, fine-tuning and ensembling. We add bottom-up and top-down attention to identify regions of interest corresponding to diagram constituents and their relationships, improving the selection of relevant visual information for each question and answer options. Our system ISAAQ reports unprecedented success in all TQA question types, with accuracies of 81.36%, 71.11% and 55.12% on true/false, text-only and diagram multiple choice questions. ISAAQ also demonstrates its broad applicability, obtaining state-of-the-art results in other demanding datasets.

1 Introduction

Within NLP, machine understanding of textbooks is one of the grand AI challenges. As originally put by (Reddy, 1988): "Reading a chapter in a college freshman text (say physics or accounting) and answering the questions at the end of the chapter is a hard (AI) problem that requires advances in vision, language, problem-solving, and learning theory.". Towards such goals, the Textbook Question Answering (TQA) dataset presented in (Kembhavi et al., 2017) offers an excellent testbed. Drawn from middle school science curricula, it describes fairly complex phenomena through a combination of text and diagrams. Answering questions may therefore involve text, diagrams or both, and require information from multiple sentences and/or diagrams in long textbook lessons.

Another characteristic of the TQA dataset that makes it rather unique and challenging is that questions often involve reasoning beyond methods based on co-occurrence analysis or simple look-up. TQA requires parsing information from different sentences, dealing with qualitative and quantitative information (*high frequency* vs. *20,000Hz*), and relating text or visual information with the question. Solving the TQA task also requires dealing with language about negation, conjunction, polarity or commonsense. On the visual side, TQA is rich with diagrams that describe potentially complex concepts, such as photosynthesis, the trophic chain, and the cycle of water, which are hard to represent as a single natural image. Quite on the contrary, diagrams contain simpler constituents and relationships between them, whose semantics needs to be captured in order to answer the questions.

Despite recent work, overall progress in the TQA dataset has been rather limited until now, suggesting that language and diagram understanding challenges like the ones above-mentioned are still far from solved. In this paper we address such limitations by building on the success of two recent developments in natural language processing and vision-and-language reasoning: large-scale, pre-trained language models and bottom-up and top-down (BUTD) attention. We demonstrate that, compared to previous approaches, transformer-based language models like BERT and RoBERTa can significantly contribute to increase the language understanding and reasoning capabilities required to answer TQA questions. We also show that BUTD attention, originally proposed for tasks like image captioning and visual question answering with natural images, can be effectively adapted to propose regions of interest in the diagram that are relevant for the question in hand, enabling the identification of diagram constituents and their relationships. The main contributions of this paper are the following:

- For the first time, we apply transformers to

language understanding in TQA, which involves fine-tuning of pre-trained transformers and ensembling.

- Based on BUTD attention we detect diagram constituents and their relationships, and link them to the question, its relevant background and answer options.
- We study the language and visual understanding capabilities of our approach, including several ablations, and demonstrate its robustness and broader applicability.
- We present ISAAQ (Intelligent System for Automatically Answering Textbook Questions), which implements our approach.

The remainder of the paper is structured as follows. Section 2 describes related work. Section 3 introduces the notation that will be used throughout the paper. We present our method in section 4, including an overview of the overall model, its main building blocks (background information retrievers, solvers, ensemble), and their interplay. We focus on each TQA question type, i.e. true/false and text and diagram multiple-choice (MC) questions, as sub-tasks of the main TQA task and propose specific solvers for each case, based on pre-trained transformers, fine-tuning and BUTD attention. In section 5, we present our experimental results, including an ablation study focused on understanding the specific contribution of each solver and their components. We also analyze the robustness of our model, its ability to generalize to other datasets, and its reasoning abilities. Finally, section 6 illustrates the impact of the different techniques used in ISAAQ to address diagram MC questions in TQA.

2 Related work

In (Kembhavi et al., 2016) several TQA baselines were proposed that were based on Machine Comprehension (MC) models like BiDAF (Seo et al., 2017) and MemoryNet (Weston et al., 2014), as well as Visual Question Answering (VQA) (Antol et al., 2015) and diagram parsing algorithms like DsDP-net (Kembhavi et al., 2016). Their results were rather modest (50.4, 32.9, and 31.3 in true/false, text and diagram MC questions), suggesting that existing MC/VQA methods would not suffice for the TQA dataset. Indeed, diagram questions entail greater complexity than dealing with natural images, as shown in (Gomez-Perez and Ortega, 2019), where we beat the TQA baselines using visual and language information extracted

from the correspondence between figures and captions in scientific literature enriched with lexico-semantic information from a knowledge graph (Deaux and Gomez-Perez, 2019). By contrast, (Li et al., 2018) focused on finding contradictions between the candidate answers and their corresponding context while (Kim et al., 2019) applied graph convolutional networks on text and diagrams to represent relevant question background information as a unified graph.

The field of NLP has advanced substantially with the advent of large-scale language models such as ELMo (Peters et al., 2018), ULMFit (Howard and Ruder, 2018), GPT (Radford et al., 2018), BERT (Devlin et al., 2018), and RoBERTa (Liu et al., 2019). Using large amounts of text, e.g. BERT was trained on Wikipedia plus the Google Book Corpus of 10,000 books (Zhu et al., 2015), they are trained to learn various language prediction tasks such as guessing a missing word or the next sentence. Language models and particularly transformers have been used in question answering, as illustrated by the success of the Aristo system (Clark et al., 2019) in standard science tests. Transformers have also proved their worth as soft reasoners (Clark et al., 2020), exhibiting capabilities for natural language inference. Furthermore, whilst learning linguistic information, transformers have shown to capture semantic knowledge and general understanding of the world from the training text (Petroni et al., 2019), including a notion of commonsense that can be useful in question answering. Our approach is the first to leverage the language understanding and reasoning capabilities of existing transformer language models for TQA.

Focused on natural images, some vision-and-language reasoning systems are also adopting transformer architectures at their backbone. VLBERT (Su et al., 2019) and LXMERT (Tan and Bansal, 2019) pre-train large-scale transformers that capture both visual concepts and language semantics, as well as cross-modal information. Pre-training is done via several tasks, like masked language modeling, masked object prediction, cross-modality matching, and image question answering, on large-scale text and visual datasets, like Conceptual Captions (Sharma et al., 2018), Google Book corpus, MS COCO (Lin et al., 2014) or Visual Genome (Krishna et al., 2017), requiring considerable compute. By contrast, our approach is much more frugal. We fine-tune pre-trained existing

transformers like BERT and RoBERTa and count on a much more limited variety of datasets focused on diagrams, like AI2D (Kembhavi et al., 2016). Like LXMERT, we extend region-of-interest (RoI) features with object positional embeddings. Finally, we apply bottom-up and top-down attention (Anderson et al., 2018) to focus on the most relevant diagram regions for each question.

3 Preliminaries and notation

3.1 The TQA dataset

The TQA dataset (Kembhavi et al., 2017) comprises 1,076 lessons from Life Science, Earth Science and Physical Science textbooks, with 78,338 sentences and 3,455 diagrams, distributed in 5,400 true/false questions, 8,293 text MC, and 12,567 diagram MC questions. The dataset is split in training, validation and test sets (table 3), which are disjoint at the lesson level. Thus, our model will often need to answer questions it was not trained for, which entails additional challenges to generalize beyond the training set (section 5). TQA questions are long compared to VQA, with a mode of 8 vs. 5 words per question. Almost 85% of the questions are *what*, *how* or *which* wh- questions. Another 10% is formulated assertively, bringing additional language understanding complexity. Most (80%) text MC questions can be answered with information from one or several sentences in a paragraph. The rest may require multiple paragraphs and lessons as well as external knowledge. Over 40% diagram MC questions require complex diagram parsing, only 2% can be answered with an OCR.

3.2 Notation

We divide the TQA task in three sub-tasks, one per question type. The solvers addressing each sub-task are denoted as TF_m (true/false questions), TMC_m (text MC) and DMC_m (diagram MC). Suffix m indicates the method used for background retrieval.

$\forall l \in L$, let ls_i be each sentence in lesson l , where L is the set of lessons in the dataset. We apply BERT-style transformers (Devlin et al., 2018) to MC questions, treating the task as multiple choice classification. Given a question $q \in l$ with answer options a_i and background knowledge K , we pass the following sequence s to the transformer:

$$seq(K, QA_i) = [CLS]K[SEP]QA_i[SEP] \quad (1)$$

with $QA_i = [q, a_i]$. Similarly, for true/false questions we explore the relation between a question

q and a sentence ls . Overloading the previous method, s is obtained as:

$$seq(q, ls) = [CLS]q[SEP]ls[SEP] \quad (2)$$

A transformer T will produce one vector for each token in s , including $[CLS]$, whose vector we denote as $T_{[CLS]}(s)$, which we use as a pooled representation of the whole sequence.

4 Proposed Method

Figure 1 shows our two-stage process to answer text and diagram MC questions. First, for each question we propose different retrievers to extract relevant language and visual background knowledge from the textbook. Note that we consider both approaches based on conventional information retrieval techniques and approaches that leverage transformers pre-trained on specific tasks.

During training, the retrieved background is provided along with the question and candidate answers to our solvers. Also during execution, providing the potential to “read” such knowledge and apply it to the question. We ensemble different solvers resulting from fine-tuning one or several transformers on a multiple choice classification task, which can be combined with others based e.g. on information retrieval.

For text and diagram MC questions, each transformer-based solver results from training the MCC task on the text passages produced by one of the text retrieval methods. Since each text retriever produces a different but complementary dataset of background text passages, the resulting solvers also complement each other, motivating their combination as an ensemble. In addition, for the visual part we apply BUTD attention as shown in figure 2. For true/false questions we follow an analogous two-stage process, in this case fine-tuning our transformers on a text entailment task.

4.1 Background knowledge retrieval

Information retrieval techniques to obtain background information from the text are usually keyword-based and potentially oblivious of the different artifacts of language, such as morphological variations, conjugations, terms that may be semantically related to the question, synonyms, hypernyms or multi-word expressions, which are particularly frequent in the domains of the TQA dataset. To address such shortcomings, we extend classic information retrieval approaches with pre-trained

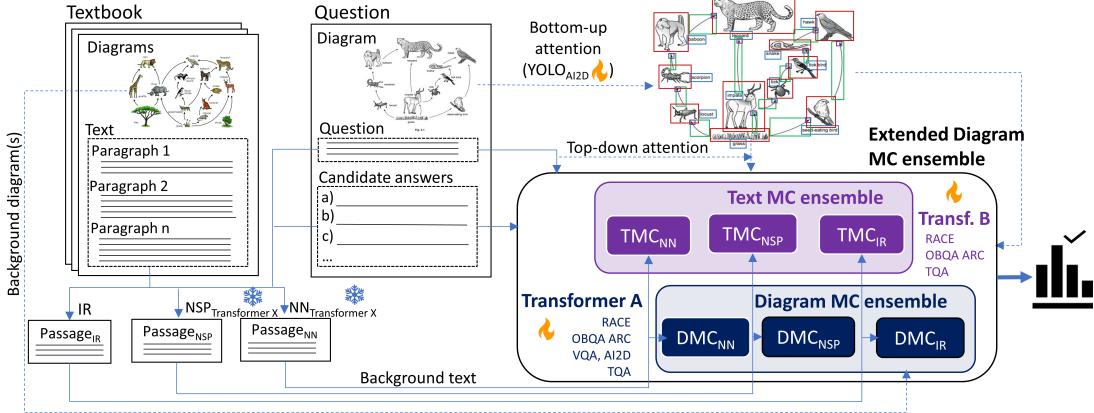


Figure 1: Overview of the proposed TQA model for text and diagram MC. Left: background retrieval stage. Right: Text and Diagram MC solvers are trained using transformers and BUTD. Flames indicate the underlying transformer is fine-tuned for the task at hand. Ice denotes the opposite. Dashed lines only apply for diagram MC.

models that leverage the language understanding capabilities of transformer language models. This results in three text background retrievers:

Information Retrieval (IR) The IR method searches the whole TQA dataset to see if question q along with an answer option is explicitly stated in the corpus. For each answer option a_i , we concatenate q and a_i and run the query against a search engine like ElasticSearch. Based on the search engine score, we take the top n sentences ($n = 10$) resulting from the query, where each sentence has at least one overlapping, non-stop word with a_i . This ensures that all sentences have some relevance to both q and a_i , while maximizing recall. Then, we concatenate the selected sentences following their ranking to compose a text passage with the desired background knowledge.

Next Sentence Prediction (NSP). We implement this retriever by treating the task as next sentence prediction using a transformer T with frozen weights. For each triple (q, a_i, ls_j) we produce a sequence $s_{ij} = seq([q, a_i], ls_j)$, where q is a question, a_i one of its possible answers, and ls_j a sentence in lesson l . We pass it to T and take the probability that ls_j can be semantically derived from the statement that a_i is the answer of q , with label `isNext`. Then, we rank the sentences based on such value, take the top n sentences, and return the passage resulting from their concatenation.

Nearest Neighbors (NN). For each question and candidate answer pair q, a_i and sentence ls_j in lesson l , we obtain their vector representations $C_i = T_{[CLS]}([q, a_i])$ and $C_j = T_{[CLS]}(ls_j)$. We calculate the cosine similarity between them, take the top n sentences based on their similarity score,

and concatenate them as a single paragraph.

Diagram retrieval. In addition to text, we also retrieve background diagrams. To this purpose, we pass the question and lesson diagrams through a ResNet-101 network pre-trained on ImageNet (Deng et al., 2009). We calculate the cosine similarity between the resulting features and select the lesson diagram closest to the question diagram.

4.2 Solvers

The ISAAQ solvers result from the combination of three main components: i) the specific models used to address each TQA question type as a particular sub-task within the overall model, ii) the underlying transformer language model, and iii) the background information associated to each question used to train the solver. Here we focus on the first of such components for the different types of questions in the TQA dataset: true/false, text, and diagram MC questions.

True/False Questions. We address true/false questions as an entailment task, where question q corresponds to the hypothesis and the premise is a sentence ls_i , with $q, ls_i \in$ lesson l . Such task is modeled as sequence classification, using a pre-trained transformer T . For each ls_i , sequence $s_i = seq(q, ls_i)$ is passed to the sequence classification model, obtaining a $2 - d$ logit vector. The answer, with possible labels `true` or `false`, is computed as the output of a binary classifier, trained by minimizing the negative log-likelihood of the correct answer produced by a softmax layer.

Text MC Questions. This solver aims to select the answer to question q amongst several answer options a_i , where the retrieved background knowl-

edge for q and a_i is a passage p . To this purpose we use a pre-trained transformer T to implement a multiple choice classification model. For each a_i , we pass the input sequence $s_i = \text{seq}(p, [q, a_i])$ and obtain an $N - d$ logit vector, with N the number of answer options. The answer to q is the output of a multi-class classifier, also trained by minimizing the negative log-likelihood of the correct answer.

Diagram MC Questions

Since diagram questions involve both text and diagrams, we need to address both branches in our model and merge them in order to answer the question based on both text and visual information (see figure 2). To encode the text part, we follow the same approach as with text MC questions. For the visual part, instead of using the feature map of the diagram produced by a convolutional neural network, we apply BUTD attention (Anderson et al., 2018) to take the features of the regions of interest (RoI) detected bottom-up in the diagram and then apply top-down attention on the question.

Each RoI $r_j \in \{r_1 \dots r_m\}$ is represented by two vectors: a visual feature vector f_j with dimensionality $d_f = 1000$ and a positional vector p_j with dimensionality d_p containing 4 bounding box coordinates. In contrast to directly using the feature vector f_j as in (Anderson et al., 2018) and in line with other work like (Tan and Bansal, 2019), we learn an embedding v_j of dimensionality $d_v = 1024$:

$$\begin{aligned}\hat{f}_j &= \text{LayerNorm}(W_F, f_j + b_f) \\ \hat{p}_j &= \text{LayerNorm}(W_P, p_j + b_P) \\ v_j &= (\hat{f}_j + \hat{p}_j) / 2\end{aligned}\quad (3)$$

To extract RoIs and their positional information we fine-tune YOLO (Redmon et al., 2015) on AI2D (Kembhavi et al., 2016), a dataset with TQA-style diagrams annotated with position and region type. The visual features v_j of each RoI detected bottom-up by YOLO are also made to attend top-down to the representation of question q , its background knowledge p and answer options a_i , produced by a transformer language model T (figure 2). $\forall a_i$ we provide T with input $s_i = \text{seq}(p, [q, a_i])$ and obtain $C_i = T_{[\text{CLS}]}(s) \in \mathbb{R}^H$, a pooled representation of s_i . We generate an unnormalized top-down attention weight a_{ij} for each m diagram RoI feature vector v_j as:

$$a_{ij} = w_a^T g_a([v_j, C_i]) \quad (4)$$

where $w_a \in \mathbb{R}^H$ is a learned vector. We implement the learned non-linear transformation g

as a gated hyperbolic tangent activation (Dauphin et al., 2017). The normalized attention weight and attended image feature \hat{v}_i for each option a_i are:

$$\begin{aligned}\alpha_{ij} &= \text{softmax}(a_{ij}) \\ \hat{v}_i &= \sum_{j=1}^m \alpha_{ij} v_j\end{aligned}\quad (5)$$

The distribution \hat{y} over the possible outputs is:

$$\hat{y} = \text{softmax}(UW_u) \quad (6)$$

where $U \in \mathbb{R}^{N \times H}$ is a matrix of u_i vectors, with N the number of answer options a_i , and $W_u \in \mathbb{R}^H$ a learned parameter vector. Each vector u_i is a joint representation of the question and the diagram for answer option a_i , where $u_i = C_i \circ \hat{v}_i$.

4.3 Ensemble

The choice of a specific background retriever may have a significant impact in the overall performance of each solver after training. Transformer-based background retrieval methods have deeper language understanding capabilities than those based on classic information retrieval approaches. However, they are also more computationally demanding. This has implications in terms of the textbook range that each retriever can reasonably cover. To address such trade-off we use information retrieval methods to extract background sentences from the whole textbook, knowing they may not be as accurate, while transformer-based methods focus on the lesson of the question to be answered, which potentially contains more relevant information.

We train our solvers using variations of the background knowledge provided by the different retrieval methods. Then, for each question type, we combine the resulting solvers in a single ensemble. Our ensemble algorithm is based on the two-step approach proposed in (Clark et al., 2019) to produce a combined score in $[0, 1]$. In the first step, each solver s is calibrated by learning a logistic regression classifier from each answer option to a correct/incorrect label. Like (Clark et al., 2019), we also calibrate on the training set. The features for answer option a_i include the raw score s_i and its value across all question options, normalized with a softmax. This step returns a calibrated score per solver s and option a_i . The second step uses the calibrated scores as the input to another logistic regression classifier whose output is the ensemble score for each a_i .

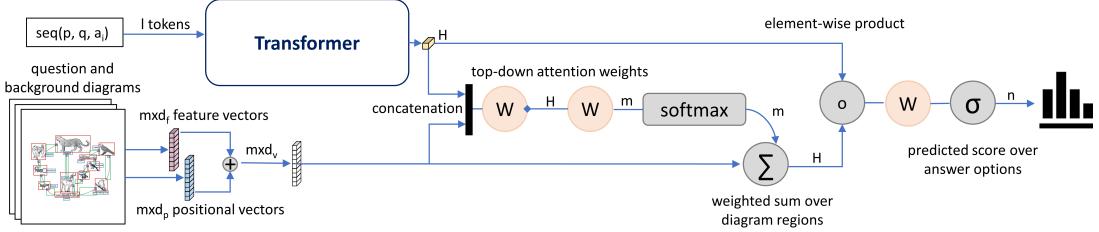


Figure 2: Overview of solver architecture for diagram questions, including BUTD attention.

5 Experiments and Results

5.1 Experimental settings

Our approach is rather frugal in terms of hardware. All training and evaluation has been done on a single server with 32GB of RAM, 1TB SSD and a single GPU GeForce RTX 2080 Ti. ISAAQ solvers have been implemented¹ using the Transformers library² and RoBERTa large. We apply Pareto to select maximum input sequences of 64 tokens for true/false questions and 180 for text and diagram MC. For text background retrieval we use a pre-trained BERT-base model. We train each TQA sub-task during 4 epochs and pick the epoch with the best accuracy. We take Adam (Kingma and Ba, 2014) with linearly-decayed learning-rate and warm-up as in (Devlin et al., 2018) and empirically select peak learning rates in the range $[1e^{-6}, 5e^{-5}]$, with $1e^{-5}$ for true/false and text MC questions and $1e^{-6}$ for diagram MC. Similarly, we choose a dropout value of 0.1 at the exit of the transformer. Training time per epoch is 1' for true/false questions, 30' for text MC, and 60' for diagram MC.

For diagram encoding, we pass each ROI to a pre-trained ResNet-101 (He et al., 2016) backbone. We have experimented with other visual models like VGG (Simonyan and Zisserman, 2015) with similar results. Unlike (Tan and Bansal, 2019) and (Anderson et al., 2018), who used Faster R-CNN (Ren et al., 2017) on natural images, we choose YOLO to extract ROIs from TQA diagrams. After fine-tuning on AI2D, YOLO outperformed Faster R-CNN with a test set accuracy of 81.2% vs 79.22%. Both results suggest around 20% margin for additional improvement in ROI selection. We apply Pareto to fix the maximum number of regions to 32 and fine-tune YOLO on AI2D with standard parameters³ for 242 epochs and initial learning rate $1e^{-4}$.

¹Models, source code, and examples are available at <https://github.com/expertailab/isaaq>

²<https://huggingface.co/transformers>

³<https://github.com/ultralytics/yolov3>

5.2 Language and visual pre-training

We pre-train our text MC question solvers on several datasets (table 3), including some not specific of science. The resulting fine-tuned transformer is also used to train the true/false solvers. We follow common practice in multi-step fine-tuning, with some variations in the usual order based on dataset size. First, we fine-tune on the training set of RACE (Sun et al., 2019), a challenging set of English comprehension MC exams given in Chinese middle and high schools. Then we continue with the training sets of a collection of scientific MC question datasets: ARC (Clark et al., 2018), both Easy and Challenge, and OpenBookQA (Mihaylov et al., 2018). Finally, we fine-tune the result of the previous step on the TQA training set for text and diagram MC. Peak learning rates are $1e^{-6}$ for the first fine-tuning step and $1e^{-5}$ for the second.

We pre-train our diagram MC question solvers on the training sets of VQA abstract scenes and VQA, the latter being the largest visual resource available with support for MC questions and diagram-style images. The size of such datasets is still far from natural image datasets like Visual Genome or MS COCO. Also, note that AI2D is annotated for generic diagram constituents (blob, arrow, arrow head, text), i.e. it does not observe semantic visual categories like cloud, tree or mammal. Nor does AI2D annotate parts of diagram blobs, like the different layers of Earth or the organelles in a cell, which suggests further room for improvement. We train on VQA and AI2D with learning rate $1e^{-6}$ for 4 and 12 epochs, respectively.

5.3 Main results

Table 2 shows the results (% accuracies) obtained by ISAAQ in true/false, text and diagram MC. Figure 3 shows the ratio of correct vs. incorrectly answered questions per question type and subject matter. Results are very similar across all domains, with a slight preference for Physical sciences.

Since most previous approaches did not report

Dataset	Partition			
	Train	Dev	Test	Total
RACE	87,866	4,887	4,934	97,687
ARC-Easy	2,251	570	2,376	5,197
ARC-Challenge	1,119	299	1,172	2,590
OpenBookQA	4,957	500	500	5,957
VQA (abs. scenes)	60,000	30,000	60,000	150,000
AI2D	7,824	906	978	9,708
TQA	15,154	5,309	5,797	26,260

Table 1: Dataset partition sizes (#questions).

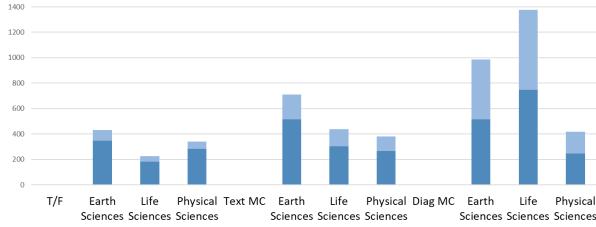


Figure 3: ISAAQ hits (darker) vs. misses (lighter).

on the test set, here we focus on validation. ISAAQ outperforms all other systems in all question types, establishing by a large margin a new SotA in TQA. We include a baseline using RoBERTa and a VQA model which, unlike ISAAQ, does not apply e.g. fine-tuning on related datasets or ensembling. This baseline outperforms all previous approaches, illustrating the benefits of applying transformers to this problem. However, ISAAQ clearly beats it in all question types, particularly in diagram MC, with a 14% improvement that demonstrates how ISAAQ successfully incorporates visual information into the transformer. On the other hand, our results also confirm the complexity of diagram MC compared to the other question types, suggesting future work in language-visual understanding. Finally, ISAAQ also obtains excellent results in all the datasets used for pre-training (table 3), confirming that our approach is robust and generalizes well.

To obtain a deeper understanding of ISAAQ’s reasoning ability we focus on ARC-Challenge, which only contains questions that neither retrieval nor co-occurrence methods can answer correctly. We run ISAAQ on a sample of 203 text MC questions manually annotated by (Boratko et al., 2018) against 7 knowledge and 9 reasoning types. Since these questions were extracted from the ARC-Challenge training set, for this experiment we previously removed them from the pre-training of our model. Figure 4 shows how the results we obtain for each reasoning type are in general in line with

our overall results in the ARC-Challenge test set (60.34%). We also notice an interesting spike in analogical reasoning, featured in (Kembhavi et al., 2017) as a key reasoning type in TQA, with 90% accuracy. This is consistent with the findings reported by (Clark et al., 2019, 2020) on the reasoning ability of transformer language models.

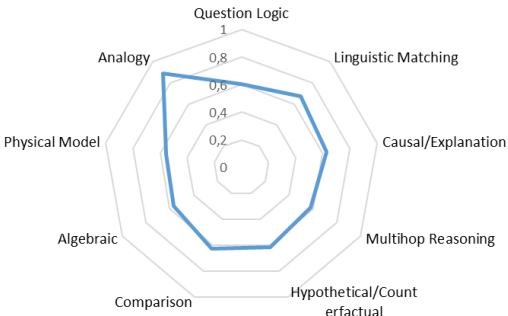


Figure 4: ISAAQ performance per reasoning type.

5.4 Ablation study

We drill down on the results reported in table 2 in order to understand the contribution of each solver to the ISAAQ ensemble, both in the validation and test sets. Tables 4, 5, and 6 show the individual results of such solvers for true/false, text, and diagram MC questions. For each sub-task, the differences between solvers result mainly from the background information used for training, which was produced by different retrievers (section 4.1).

In addition to RoBERTa large we experimented with BERT large, adding 3 more solvers to the true/false and MC ensembles. However, the added gain was extremely limited. Replacing BERT with RoBERTa large without pre-training on the datasets shown in table 3 had similar effect. Thus, we opted for the 3-way ensembles shown in the tables.

Tables 5 and 6 show how the solvers based on transformers clearly outperform an information retrieval baseline (IR), which is itself already on par with the former TQA SotA (Kim et al., 2019) for text MC questions and clearly better for diagram MC. Each of the true/false, text MC, and diagram MC solvers perform similarly in their respective question type sub-tasks. They are also complementary: in average, 33.41% of the questions answered incorrectly by one of the solvers is correctly addressed by another. Such complementarity brings an extra performance boost by combining the different solvers in each sub-task as an ensemble.

While the results obtained for text MC questions

Model		Text T/F	Text MC	Text All	Diagram MC	All
Random	-	50.10	22.88	33.62	24.96	29.08
MemN+VQA		50.50	31.05	38.73	31.82	35.11
MemN+DPG	(Kembhavi et al., 2017)	50.50	30.98	38.69	32.83	35.62
BiDAF+DPG		50.40	30.46	38.33	32.72	35.39
FCC+Vecsigrafo	(Gomez-Perez and Ortega, 2019)	-	36.56	-	35.30	-
IGMN	(Li et al., 2018)	57.41	40.00	46.88	36.35	41.36
f-GCN1+SSOC	(Kim et al., 2019)	62.73	49.54	54.75	37.61	45.77
RoBERTa+VQA		76.85	62.81	68.38	41.14	54.09
ISAAQ		81.36	71.11	75.16	55.12	64.66

Table 2: ISAAQ performance and comparison (validation set) with previous SotA for the TQA dataset.

Dataset	ISAAQ	SotA	
RACE	71.63	90.90	(Shoeybi et al., 2019)
OBQA	83.60	86.00	
ARC-Easy	83.51	85.70	(Khashabi et al., 2020)
ARC-Cha.	60.34	75.60	
VQA abs.	64.75	74.37	(Teney et al., 2017)
AI2D	73.29	38.47	(Kembhavi et al., 2016)

Table 3: ISAAQ vs. SotA in pre-training datasets (test).

Dataset	TF _{IR}	TF _{NSP}	TF _{NN}	ISAAQ
validation	78.26	76.25	79.16	81.36
test	77.74	74.89	75.44	78.83

Table 4: Results of each of our solvers and the overall ISAAQ model for TQA true/false questions.

do not seem to depend on the specific split, for true/false and diagram MC questions we obtain clearly better results in the validation set compared to the test set. This emphasizes the heterogeneity of the TQA splits and how challenging it is to produce a model that generalizes well across them.

Looking at the incremental analysis of our diagram MC model in table 7, visual information only enters into play once pre-training on VQA and AI2D is added, outperforming the text baseline. Additional background diagrams adds a little in test. BUTD attention does improve considerably in both validation and test, but not much more than using just bottom-up (BU) attention. The final ISAAQ model is a 6-way ensemble that combines the transformer-based solvers for text MC (table 5)

Dataset	IR	TMC _{IR}	TMC _{NSP}	TMC _{NN}	ISAAQ
validation	47.91	67.52	68.63	64.64	71.11
test	48.31	68.94	67.19	65.31	72.06

Table 5: Individual text MC solvers and ISAAQ. Note the large delta vs. IR solver baseline (also in table 6). Pre-training on RACE, OBQA, ARC-Easy/Challenge.

Dataset	IR	DMC _{IR}	DMC _{NSP}	DMC _{NN}	ISAAQ
validation	39.12	53.83	52.14	51.28	55.12
test	32.57	50.50	50.84	51.08	51.81

Table 6: Individual diagram MC solvers and ISAAQ. Pre-training on VQA abstract scenes and AI2D.

and diagram MC (table 6) and uses VQA+AI2D pre-training and BUTD. These results indicate interesting challenges yet to be addressed.

Model	Val. acc.	Test acc.
text (w/o pre-training)	46.67	39.79
text	53.22	46.82
text+visual (w/o pre-training)	51.31	47.34
text+visual	53.54	51.32
text+visual+background diagram	53.47	51.84
text+visual+BU attention	53.93	51.60
text+visual+BUTD attention	54.26	52.15
ISAAQ	55.12	51.81

Table 7: ISAAQ ablations for diagram MC.

6 Qualitative study

Table 8 illustrates the impact of the different levels of attention on the question diagram, previously quantified in table 7. The first column shows question and answer options, while the second adds the question diagram. Third column illustrates the RoIs extracted through BU attention and the fourth adds attention heatmaps using BUTD. While BU assigns equal attention to all RoIs, BUTD also attends to the text of the question and each possible answer. For all the example questions, only the model with BUTD produces the correct answer.

Some observations follow. ROI detection (column three) fails to detect inner shapes in nested diagrams, e.g. state of matter, question four. The intensity of BUTD attention (column four) is rather low, with maximum values between 0.08 and 0.2 in

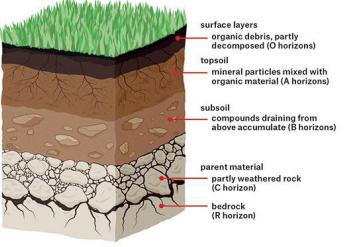
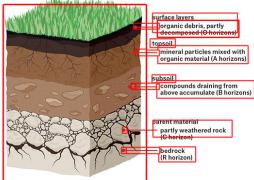
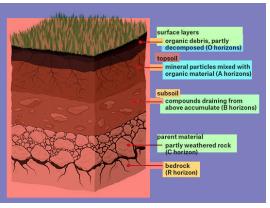
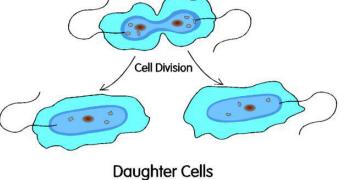
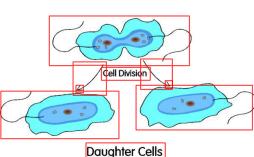
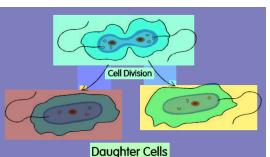
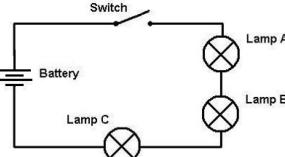
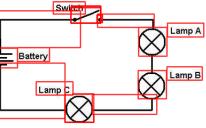
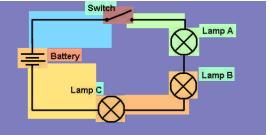
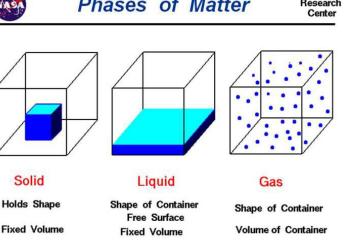
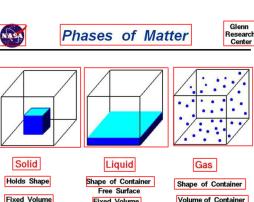
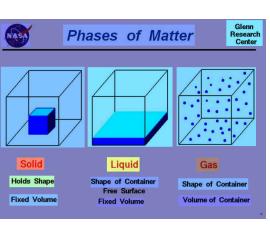
Question	Diagram	Diagram MC+BU	Diagram MC+BUTD
Which of the following layers comprises mineral particles? a) bedrock b) subsoil c) surface layers d) topsoil ✓			
Which phase is shown in the picture below? a) mitosis ✓ b) prophase c) interphase d) mitotic			
Which lamps would turn on if switch is connected? a) b ✓ b) a c) a, b, c d) c			
In which state does the substance hold shape? a) solid ✓ b) liquid c) gas d) none			

Table 8: Study of the attention on question diagrams (red stands for higher attention). Samples from validation set.

a 0 to 1 scale, suggesting an opportunity to improve the cross-modal aspects of our model. When the text of the correct answer (*topsoil*, *solid*) appears explicitly in the diagram, its ROI is generally more attended than the rest. Other times, the ROI labeled by such text (*switch*) is the warmest. ISAAQ seems to attend to aspects of the diagrams that are key to answer correctly, suggesting both language and visual understanding: the two cells resulting from the original one through mitosis, the circuit segment where a lamp flashes upon switch actuation or the properties of the state in which a substance holds shape. Other examples seem to indicate some ability to deal with counting and spatial reasoning. All will deserve further investigation in future work.

7 Conclusion

This paper reports on ISAAQ, the first system to achieve accuracies above 80%, 70% and 55% on TQA true/false, text and diagram MC questions. ISAAQ demonstrates that it is possible to master

the grand AI challenge of machine textbook understanding based on modern methods for language and visual understanding, with modest infrastructure requirements. Key to this success are transformers, BUTD attention, pre-training on related datasets, and the selection of complementary background information to train and ensemble different solvers. Our approach allowed overcoming critical challenges like the complexity and relatively small size of the TQA dataset or the scarcity of large diagram datasets. Still, further research is necessary to keep pushing the boundaries of textbook understanding, e.g. by charting and expanding the reasoning skills of transformers, making model outcomes more interpretable by humans, and further exploiting diagrams. Additional effort will also be needed in activities like the development of large diagram datasets, including the semantic annotation of diagram constituents and connectors, and annotating diagram questions with the reasoning and knowledge types required to answer them.

Acknowledgements

This research was funded by the EU Horizon 2020 grant European Language Grid (ELG-825627). Special thanks to Peter Clark, Oyvind Tafjord and the Allen Institute for sharing data and insights on the ARC-Easy and ARC-Challenge datasets.

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