# XTQA: Span-Level Explanations of the Textbook Question Answering

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# Abstract

Textbook Question Answering (TQA) is a task that one should answer a diagram/nondiagram question given a large multi-modal context consisting of abundant essays and diagrams. We argue that the explainability of this task should place students as a key aspect to be considered. To address this issue, we devise a novel architecture towards span-level eXplanations of the TQA (XTQA). It can provide not only the answers but also the span-level evidences to choose them for students based on our proposed coarse-to-fine grained algorithm. The algorithm first coarsely chooses top M paragraphs relevant to questions using the TF-IDF method, and then chooses top K evidence spans finely from all candidate spans within these paragraphs by computing the information gain of each span to questions. Experimental results show that our method significantly improves the state-of-the-art performance compared with baselines. The source code is available at https://github.com/keepsmile-001/opentga.

### 1 Introduction

Question Answering (QA) has attracted extensive interest in the fields of Computer Vision (CV) and Natural Language Processing, such as Visual Question Answering (VQA) (Yu et al., 2019; Khademi, 2020) in CV and Machine Reading Comprehension (MRC) (Nie et al., 2019; Saxena et al., 2020) in NLP. Recently, a new task named Textbook Question Answering (TQA) (Kembhavi et al., 2017) that aims to answer diagram/non-diagram questions given a large multi-modal context consisting of diagrams, text and few natural images was proposed. The task is developed from middle school science curricula and describes the real-life process of a student who learns new knowledge from books and assesses learning achievement. Compared with

MRC and VQA, TQA is more complex and more realistic

In real-life scenarios, the TQA robot should not only answer a question accurately, but also give *students* the reason to choose the answer. Although existing neural-symbolic works (Yi et al., 2018; Mao et al., 2019) on the CLEVR dataset make significant progress on the explainability, they are not applicable to the TQA dataset. Here are two reasons for this. First, the curriculum is diverse in the TQA dataset, which makes the design of the domain-specific language (DSL) difficult. Second, there is no any supervision information except the answer label.

An analysis (Kembhavi et al., 2017) of the information scope required to answer questions in the TQA dataset shows that about 80% of the questions require a single sentence or multiple sentences. Inspired by this, we may be able to provide the evidence spans<sup>1</sup> about questions for students, which would give them explainability to some extent. For example, when the TQA robot gives students the correct answer B to the question 1, it also provides an evidence span as the explanation in Figure 1. We make an assumption owing to the lack of supervision information of evidence spans in the TQA dataset. Assumption: if a question is answered accurately after fusing a generated span and other essential information, the span is a gold evidence to the question. For example, the span marked in green in the middle part of Figure 1 is a gold evidence to the question 1.

Based on the assumption, we devise a novel architecture towards span-level eXplanations of the Textbook Question Answering (XTQA) as illustrated in Figure 1. First, XTQA uses our proposed coarse-to-fine grained algorithm to generate evidence spans of questions. In the coarse grained

<sup>&</sup>lt;sup>1</sup>In this paper, spans are represented by the indexes of sentences instead of words.

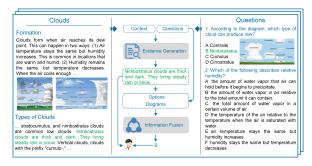


Figure 1: An example of the TQA task and a brief illustration of our work. The abundant essays and diagrams of a lesson are shown in the left part. The diagram/non-diagram questions of this lesson are shown in the right part.

phase, top M paragraphs relevant to questions are chosen from abundant essays by the TF-IDF score. In the fine grained phase, top K evidence spans are generated from all candidate spans within the top M paragraphs by computing the information gain of each span to questions. The larger information gain indicates the more uncertainty of questions reduced by spans. Second, XTQA fuses the information of generated evidence spans, questions, options and diagrams to provide answers. Finally, not only the answers but also the evidences to choose them are provided to students.

The contributions of our work are as follows. (1) We devise a novel architecture that can give students evidences as well as answers for TQA. (2) We propose a coarse-to-fine grained algorithm to generate span-level evidences by computing the information gain of each span to questions. (3) We conduct extensive experiments and ablation studies on the TQA dataset (Kembhavi et al., 2017) to verify the effectiveness of the XTQA and our proposed assumption. Experimental results show that XTQA significantly improves the state-of-theart performance compared with baselines. (4) We also explore how to effectively integrate the selfsupervised learning method SimCLR (Chen et al., 2020) into the proposed architecture to further improve the accuracy of the TQA task.

# 2 Related Work

Since the TQA task is similar to MRC and VQA, we briefly review some of their research relevant to our work.

MRC requires a machine to answer questions accurately given a textual context (Lehnert, 1977). Wang et al. (2018) proposed a multi-granularity hi-

erarchical attention fusion network to answer questions for a given narrative paragraph. Lee et al. (2018) proposed a paragraph ranker to improve the answer recall with less noise. Ding et al. (2019) proposed CogQA that builds a cognitive graph by an implicit extraction module and an explicit reasoning module to address the multi-hop question answering. Although the above studies achieved success, they did not estimate the relationship and combined design of retrieval and comprehension. Nie et al. (2019) proposed a hierarchical pipeline model that reveals the importance of semantic retrieval to give general guidelines on the system design for MRC.

Unlike the MRC task, the TQA task not only involves the textual question but also the visual question. In this paper, we first apply the self-supervised learning method SimCLR (Chen et al., 2020) to learn the diagram representation in the TQA dataset to the best of our knowledge.

VQA requires a machine to answer questions accurately given an image (Antol et al., 2015). Yang et al. (2016) proposed stacked attention networks that perform multi-step reasoning to infer answers. Kim et al. (2017) proposed a low-rank bi-linear pooling method using Hadamard product to address the complex computation. However, the above methods consider little on the effectiveness of the explicit regions for answering. To address this issue, Anderson et al. (2018) proposed a combined bottom-up and top-down attention mechanism that computes attentions at the level of salient image regions and objects. Gao et al. (2019) proposed a multi-modality latent interaction module to model the summarization of language and visual information. However, these methods may not perform complex reasoning. To address this issue, Yi et al. (2018) proposed a neural-symbolic visual question answering architecture that disentangles question and image understanding from reasoning. Based on this paper, Mao et al. (2019) proposed a neurosymbolic reasoning module that executes generated programs on the latent scene representations to perform reasoning. These methods can execute complex logic reasoning based on the manually designed domain-specific language.

Unlike the VQA task, the TQA task contains multi-modal context except questions and diagrams. In this paper, we argue that the explainability of the TQA task should place *students* as a key aspect to be considered. We propose a coarse-to-fine

grained algorithm to provide the evidence spans of questions for students.

# 3 Task Formulation

The TQA dataset contains two types of questions: diagram questions and non-diagram questions. Therefore, the TQA task can be classified into two categories: diagram question answering and non-diagram question answering. Owing to the difference only at this point between them, here we give the task formulation of the diagram question answering.

Given a dataset  $\mathcal{S}$  consisting of n triplets  $(c_i,d_i,q_i,\mathcal{A}_i)$  with  $c_i\in\mathcal{C}$  representing multimodal context of a lesson,  $d_i\in\mathcal{D}$  representing a diagram,  $q_i\in\mathcal{Q}$  representing a question and  $\mathcal{A}_i\subsetneqq\mathcal{A}$  representing the candidate answers of  $q_i$ , one must optimize the parameters  $\theta$  of the function  $f:\mathcal{C}\times\mathcal{D}\times\mathcal{Q}\to\mathbb{R}^{|\mathcal{A}|}$  to produce accurate predictions.  $a_{i,j}\in\mathcal{A}_i$  denotes the j-th candidate answer of  $q_i$ .

A candidate evidence span  $e_{i,k} \in \mathcal{E}_i \subsetneq \mathcal{E}$  to  $q_i$  is represented by its start  $\mathrm{START}(k)$  and end  $\mathrm{END}(k)$  indexes respectively following (Ma et al., 2020), where  $\mathcal{E}_i$  represents the candidate evidence span set of  $q_i$ ,  $1 \leq k \leq N$ ,  $1 \leq \mathrm{START}(k) \leq \mathrm{END}(k) \leq t$  and  $N = \frac{t(t+1)}{2}$  is the number of candidate evidence spans supposing  $c_i$  containing t sentences. We rewrite the function  $f: \mathcal{E} \times \mathcal{D} \times \mathcal{Q} \to \mathbb{R}^{|\mathcal{A}|}$  since evidence spans and other essential information are fused to answer questions. To summarize, we optimize  $\theta$  to obtain not only the correct answer  $a_i$  but also the evidence span  $e_i$  to  $q_i$  based on the assumption in Section 1.

#### 4 Method

The architecture of the XTQA is shown in Figure 2. It consists of four modules: question/answer representation, evidence span generation, diagram representation and answer prediction.

**Question/Answer representation.** This module uses GRUs and learned attention mechanisms to obtain the word-level representations  $q_i'/a_{i,j}'$  and global representations  $q_i''/a_{i,j}''$  of the question/candidate answer  $q_i/a_{i,j}$  respectively.

**Evidence span generation.** This module uses our proposed coarse-to-fine grained algorithm to obtain the representations  $e_i^{'''}$  of the top K evidence spans to  $q_i$  and their indexes  $[\operatorname{START}(k), \operatorname{END}(k)]$  from all candidate spans within top M paragraphs  $p_i$ .

**Diagram representation.** This module uses CNNs to obtain the representation  $d'_i$  of the diagram  $d_i$ .

**Answer prediction.** This module gives students not only the predicted answer  $\hat{a}_i$  but also the evidence span  $e_i$  to choose it after multi-modal information fusing.

# 4.1 Question/Answer Representation

We use uni-directional GRUs to obtain the  $d_1$ -dimensional word-level representations  $q_i' \in \mathbb{R}^{X \times d_1}$  and  $a_{i,j}' \in \mathbb{R}^{Y \times d_1}$  of  $q_i$  and  $a_{i,j}$  respectively as follows:

$$q'_{i} = GRU_{s}(embeding(q_{i})),$$
  
 $a'_{i,j} = GRU_{s}(embedding(a_{i,j})),$ 

$$(1)$$

where  $q_i \in \mathbb{R}^{X \times 1}$  denotes the *i*-th question,  $a_{i,j} \in \mathbb{R}^{Y \times 1}$  denotes the *j*-th candidate answer of  $q_i$ , X and Y denotes the maximum length of  $q_i$  and  $a_{i,j}$  respectively, and  $embedding(\cdot)$  is used to get word embeddings.

We use learned attention mechanisms to obtain the  $d_1$ -dimensional global information  $q_i'' \in \mathbb{R}^{d_1 \times 1}$  and  $a_{i,j}'' \in \mathbb{R}^{d_1 \times 1}$  of  $q_i$  and  $a_{i,j}$  respectively as follows:

$$\alpha = \operatorname{softmax}(\operatorname{MLP}_{s}(q_{i}^{'})),$$

$$q_{i}^{"} = \sum_{u=1}^{X} \alpha_{u} \circ q_{i,u}^{'},$$
(2)

where  $\alpha \in \mathbb{R}^{X \times 1}$  is the learned attention weight matrix by MLPs,  $\circ$  denotes the element-wise product, and  $q_{i,u}'$  is the u-th word representations of  $q_i$ .  $a_{i,j}''$  is obtained by analogy.

### 4.2 Evidence Span Generation

Although the multi-modal context  $c_i$  contains abundant essays, only a single sentence or multiple sentences would be required to answer  $q_i$ . Inspired by this, we propose a coarse-to-fine grained algorithm to generate evidence spans of  $q_i$ .

In the coarse phase, the TF-IDF method is used to narrow down the scope of textual context from a lesson to top M paragraphs  $p_i$  relevant to  $q_i$ .  $p_i \in \mathbb{R}^{M \times L \times O}$  can be denoted as follows:

$$p_i = \text{TFIDF}(q_i, c_i), \tag{3}$$

where L is the maximum number of sentences in each paragraph, and O is the maximum length of each sentence. The shared  ${\rm GRU_s}$  in Equation 1 is

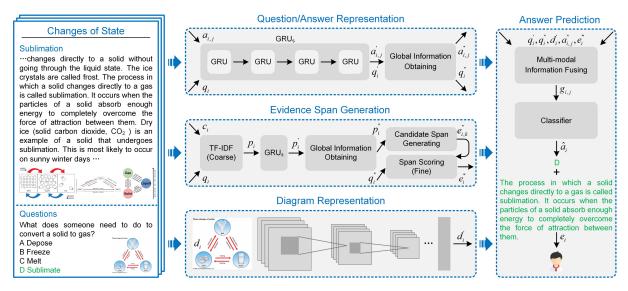


Figure 2: The architecture towards span-level eXplanations of the Textbook Question Answering (XTQA). The left part shows a lesson and a question in the TQA dataset. The index of the evidence span to a question is obtained by our proposed coarse-to-fine grained algorithm in the middle module of the middle part.

used to obtain the  $d_1$ -dimensional word-level representation  $p_i' \in \mathbb{R}^{M \times L \times O \times d_1}$  of  $p_i$ . We also use the shared learned attention mechanism in Equation 2 to obtain the  $d_1$ -dimensional global representations  $p_i'' \in \mathbb{R}^{M \times L \times d_1}$  of sentences within  $p_i$ .

# Algorithm 1: Evidence span generation

**Input:** question  $q_i$ , multi-modal context  $c_i$ . **Output:** representation  $e''_i$  of evidence span  $e_i$  and its index.

- 1 Choose top M paragraphs using Equation 3;
- 2 Obtain the whole candidate evidence span representations according to their indexes using Equation 4;
- 3 Compute the information gain of each span to  $q_i$  using Equation 6;
- 4 Choose top K evidence span.

In the fine-grained phase, top K evidence spans are generated from all candidate spans within top M paragraphs by computing the information gain of each span to questions. Concretely, the representation at the  $\operatorname{START}(k)$  and  $\operatorname{END}(k)$  index as described formally in Section 3 are concatenated to generate the candidate evidence span representation  $e_{i,k}^{'} \in \mathbb{R}^{M \times N \times 2d_1}$  as follows:

$$e_{i,k}^{'} = [p_{i,\text{START}(k)}^{"}; p_{i,\text{END}(k)}^{"}],$$
 (4)

where  $N=\frac{L(L+1)}{2}$  is the number of candidate evidence spans within each paragraph. To obtain the final candidate evidence span representation

 $e_{i,k}^{''} \in \mathbb{R}^{M \times N \times d_1}$ , we apply the average pooling AP with kernel size 2 on  $e_{i,k}^{'}$  as follows:

$$e_{i,k}^{"} = AP(e_{i,k}^{'}). \tag{5}$$

We compute the information gain  $g(q_i, e_{i,k})$  of each candidate evidence span  $e_{i,k}$  to the question  $q_i$  for obtaining the top K evidence span.  $g(q_i, e_{i,k})$  can be denoted as follows:

$$g(q_i, e_{i,k}) = H(q_i) - H(q_i|e_{i,k}),$$
 (6)

where  $H(q_i)$  is the entropy of  $q_i$ , i.e., the uncertainty of  $q_i$ , and  $H(q_i|e_{i,k})$  is the conditional entropy of  $q_i$  given  $e_{i,k}$ , i.e., the uncertainty of  $q_i$  given  $e_{i,k}$ . The larger information gain indicates the more uncertainty of  $q_i$  reduced by  $e_{i,k}$ .  $H(q_i)$  can be denoted as follows:

$$H(q_i) = \mathbb{E}[-\log(p(q_i))],$$
  

$$p(q_i) = \sigma(\text{MLP}_{\mathbf{h}}(q_i'')),$$
(7)

where  $\mathbb{E}$  is the expected value operator,  $p(q_i)$  denotes the probability of  $q_i$  being answered accurately, and  $\sigma$  is the sigmoid function.  $H(q_i|e_{i,k})$  can be denoted as follows:

$$H(q_{i}|e_{i,k}) = \mathbb{E}[-\log(p(q_{i}, e_{i,k}))],$$

$$p(q_{i}, e_{i,k}) = \sigma(\text{MLP}_{h}(\text{AP}([q_{i}'', e_{i,k}'']))),$$
(8)

where  $p(q_i, e_{i,k})$  is the probability of  $q_i$  being answered accurately given  $e_{i,k}$ , AP denotes the average pooling with kernel size 2. A formal description about this algorithm is shown in Algorithm 1.

Model	Non-diagram T/F	Non-diagram MC	Non-diagram All	Diagram	All
CMR (Zheng et al., 2020)	51.14	30.65	38.72	30.73	34.53
MUTAN (Ben-Younes et al., 2017)	51.72	31.18	39.27	30.29	34.56
MFB (Yu et al., 2017)	51.73	30.65	38.95	30.76	34.65
BAN (Kim et al., 2018)	51.70	31.11	39.22	30.65	34.73
MCAN (Yu et al., 2019)	51.72	32.55	40.10	30.58	35.10
XTQA	58.24	30.33	41.32	32.05	36.46

Table 1: Experimental results (% accuracy) of different-type questions on the validation split. We show the accuracy of True/False (Non-diagram T/F) questions, multiple-choice questions (Non-diagram MC), the whole non-diagram questions (Non-diagram All = Non-diagram T/F  $\cup$  Non-diagram MC), multiple-choice diagram questions (Diagram) and total questions (All = Non-diagram  $\cup$  Diagram). Note that all the baselines use the same BERT embeddings and the SimCLR model as XTQA for a fair comparison.

After generating the top K evidence spans and their representations  $e_i^{''} \in \mathbb{R}^{K \times d_1}$ , the learned attention mechanism in Equation 2 is used to obtain the final evidence span representation  $e_i^{'''} \in \mathbb{R}^{d_1 \times 1}$ .

# 4.3 Diagram Representation

We use CNNs to obtain the  $d_2$ -dimensional representation  $d_i' \in \mathbb{R}^{d_2 \times 1}$  of  $d_i$  as follows:

$$d_i' = \text{CNN}_{s}(d_i). \tag{9}$$

The CNNs could be ResNet (He et al., 2016), Sim-CLR (Chen et al., 2020) and so on.

### 4.4 Answer Prediction

After the above modules, we obtain the word-level/global representations  $q_i^{'}/q_i^{''}$  of  $q_i$ , the diagram representations  $d_i^{'}$  of  $d_i$ , the global representations  $a_{i,j}^{''}$  of  $a_{i,j}$ , the evidence span representations  $e_i^{'''}$  of  $e_i$  and the indexes  $[\operatorname{START}(k), \operatorname{END}(k)]$  of spans.

The mentioned representations are fused to obtain the global fusion feature  $g_{i,j} \in \mathbb{R}^{9d_1 \times 1}$  with j-th candidate answer as follows:

$$g_{i,j} = [q_i''; d_i'; a_{i,j}''; e_i'''; g_i^{\beta}; g_{i,j}^{\gamma}; g_i^{\mu}; g_{i,j}^{\eta};],$$

$$g_i^{\beta} = \text{BAN}(q_i', d_i'), \ g_{i,j}^{\gamma} = W q_i'' \circ W a_{i,j}'',$$

$$g_i^{\mu} = W q_i'' \circ W e_i''', \ g_{i,j}^{\eta} = W e_i''' \circ W a_{i,j}'',$$

$$g_{i,j}^{\psi} = W q_i'' \circ W a_{i,j}'' \circ g_i^{\beta},$$
(10)

where BAN is the bi-linear attention networks (Kim et al., 2018),  $W \in \mathbb{R}^{d_1 \times d_1}$  is the learned weight matrix,  $g_i^\beta, g_{i,j}^\gamma, g_i^\mu, g_{i,j}^\eta \in \mathbb{R}^{d_1 \times 1}$  denote the pairwise similarity, and  $g_{i,j}^\psi \in \mathbb{R}^{d_1 \times 1}$  is the triplewise similarity.

To obtain the estimation  $\hat{a}_i$  of the correct answer,  $g_{i,j}^{\rm T}$  is projected into a scalar score as follows:

$$\hat{a}_i = \underset{j \in |\mathcal{A}_i|}{\arg\max} \operatorname{softmax}(\operatorname{MLP_c}(g_{i,j}^{\mathrm{T}})).$$
 (11)

Eventually, not only the answer  $\hat{a}_i$  but also the evidence span is provided for students by optimizing the cross-entropy loss function.

# 5 Experiments

#### 5.1 Datasets and Evaluations

We use the accuracy to evaluate XTQA on the TQA dataset (Kembhavi et al., 2017) that consists of 1,076 lessons with 78,338 sentences and 3,455 diagrams (including very few natural images). The lessons are obtained from the Physical Science, Life Science and Earth Science textbooks of the middle school on-line curricula. The TQA dataset is split into a training set with 666 lessons and 15, 154 questions, a validation dataset with 200 lessons and 5,309 questions, and a test set with 210 lessons and 5, 797 questions. Among of the total 26, 260 questions, 12, 567 of them have an accompanying diagram. There are four candidate answers for each diagram question. The non-diagram questions can be classified into two categories: True/False (T/F) with two candidate answers and Multiple Choice (MC) with two to seven candidate answers.

### **5.2** Implementation Details

In Question/Answer Representation, we use BERT (Devlin et al., 2019) to obtain 768-dimensional word embeddings and uni-directional one-layer GRUs with  $d_1=1024$  hidden units to encode questions and candidate answers. The shared MLPs (FC(1024)-Dropout(0.2)-FC(1)) are used to learn

Model	Non-diagram T/F	Non-diagram MC	Non-diagram All	Diagram	All
BAN (Kim et al., 2018)	48.080	32.96	38.44	27.28	32.11
MFB (Yu et al., 2017)	48.081	31.83	37.72	28.17	32.30
MCAN (Yu et al., 2019)	48.077	33.15	38.56	27.56	32.32
MUTAN (Ben-Younes et al., 2017)	48.075	32.90	38.40	28.29	32.67
CMR (Zheng et al., 2020)	52.022	33.15	39.99	29.54	34.06
Challenge	_	_	42.08	31.75	36.22
XTQA	56.218	33.40	41.67	33.34	36.95

Table 2: Experimental results (% accuracy) of different-type questions on the test split. We show the accuracy of True/False (Non-diagram T/F) questions, multiple-choice questions (Non-diagram MC), the whole non-diagram questions (Non-diagram All = Non-diagram T/F  $\cup$  Non-diagram MC), multiple-choice diagram questions (Diagrams) and total questions (All = Non-diagram  $\cup$  Diagram). Note that all the baselines use the same BERT embeddings and the SimCLR model as XTQA for a fair comparison.

attention coefficients. In Evidence Span Generation, the pylucene<sup>2</sup> is used to conduct paragraphs indexing and searching. The maximum number of paragraphs M, the maximum number of sentences within each paragraph L, the maximum length of each sentence O and the maximum number of evidence span K are set to 1/1, 5/15, 20/15 and 1/1for non-diagram/diagram question answering respectively. we set the maximum widths of candidate evidence spans to 2. In Diagram Representation, we resize the diagrams to 224 owing to the different sizes of them in the TQA dataset. To obtain  $d_2 = 2048$ -dimensional diagram representations, we first train the SimCLR<sup>3</sup> (Chen et al., 2020) on the diagrams within TQA dataset with default hyper-parameters, and then fine-tune the pre-trained model by the task-specific supervision (TQA). In Answer Prediction, the MLPc (FC(2048)-ReLU-Dropout(0.2)-FC(1)) is used to obtain the candidate answer scores.

XTQA is trained by the Adam optimizer with  $\beta_1=0.9, \beta_2=0.98$ . The base learning rate is  $\min(2.5\tau e^{-4}, 1e^{-4})$ , where  $\tau$  is the current epoch. The rate is decayed by 0.1 after 8 epochs. XTQA converges at the end of the 10-th epoch with the batch size 2.

### 5.3 Baselines

We compare XTQA with several methods that focus on multi-modality fusion as follows<sup>4</sup>:

**MFB** (Yu et al., 2017) is a multi-modal factorized bi-linear pooling approach. It aims at addressing

the high dimensionality of the output features and the huge number of parameters caused by the bilinear pooling based models (Tenenbaum and Freeman, 1997).

**MUTAN** (Ben-Younes et al., 2017) is a multimodal tensor-based decomposition approach with a low-rank matrix constraint. It also aims at addressing huge dimensionality issues.

**BAN** (Kim et al., 2018) is a bi-linear attention network that aims at learning effective interactions between images and questions using the proposed bi-linear attention mechanism.

MCAN (Yu et al., 2019) is a deep modular coattention network. It aims at obtaining sufficient multi-modality interactions by modularly composing the self-attention of questions and images, as well as the question-guided-attention of images.

CMR (Zheng et al., 2020) is a cross-modality relevance module that can be used in an end-to-end framework. It learns the relevance representations between entities of input modalities and modeling the higher-order relevance between entity relations to perform language and vision reasoning.

**Challenge**<sup>5</sup> is a competition of the TQA task. We cite the best results on each type of questions of the test split. The results come from different teams.

# 5.4 Results

The experimental results on the validation/test split are shown in Table 1/Table 2 respectively.

In Table 1, we can see that XTQA outperforms the best baseline MCAN by 1.36% on the total questions of the validation split. For diagram questions, XTQA outperforms the best baseline MFB by 1.29%. For non-diagram questions, XTQA out-

<sup>&</sup>lt;sup>2</sup>https://lucene.apache.org/pylucene/

<sup>&</sup>lt;sup>3</sup>We open this code on https://github.com/keep-smile-001/SimCLR-TQA-master

<sup>&</sup>lt;sup>4</sup>All the baselines are implemented in our open source code *opentqa*.

<sup>&</sup>lt;sup>5</sup>https://competitions.codalab.org/competitions/16931#results

Models	Non-diagram All	Δ	Diagram	Δ	All	Δ
XTQA	41.32		32.05		36.46	
w/o fine-tuning the SimCLR model	41.32	0	30.36	-1.69	35.57	-0.89
w/o the BERT embeddings	41.20	-0.12	29.82	-2.23	35.24	-1.22
w/o fine-grained evidence spans	38.95	-2.37	30.36	-1.69	34.45	-2.01

Table 3: Ablation results (% accuracy) of the XTQA. Non-diagram All denotes the accuracy on the non-diagram questions. Diagram denotes the accuracy on the diagram questions. All denotes the accuracy on the total questions.  $\Delta$  denotes the accuracy reduction without the specific module.

performs the best baseline MCAN by 1.22%. For T/F-type questions, XTQA outperforms the best baseline MFB by 6.51%. XTQA performs worst on the MC-type questions, which may be caused by the different data distributions between T/F (two candidate answers) and MC (four to seven candidate answers) questions. Note that all the baselines perform information fusion between top 1 paragraph and questions for non-diagram questions considering the specificity of the TQA task.

In Table 2, we can see that XTQA outperforms the best baseline Challenge by 0.73% on the total questions of the test split. For diagram questions, XTQA outperforms the best baseline Challenge by 1.59%. For non-diagram questions, XTQA underperforms the best baseline Challenge by 0.41%. For TF-type questions, XTQA outperforms the best baseline CMR by 4.196%. All the methods perform poorly on this type of questions except XTQA and CMR, which may be caused by the different data distributions or the difficult questions. For MC-type questions, XTQA outperforms the best baseline MCAN and CMR by 0.25%. Note that XTQA achieves the best performance on the two splits, which shows the effectiveness of our method. In addition, the performance of baselines is different on the two splits, which may be caused by the following reasons. (1) The generation abilities of the baselines are different. (2) The data distribution is different between the validation split and test split. For example, the information of Lesson earth science and its branches is mutually exclusive in the two splits.

# 5.5 Ablation Studies

We perform ablation studies as shown in Table 3 to verify the effectiveness of each module.

The accuracy on the diagram questions drops by 1.69% without fine-tuning the SimCLR model, which shows that fine-tuning the pre-trained model

helps models to learn effective diagram representations to improve the TQA performance.

The accuracy on the non-diagram/diagram questions drop by 0.12% and 2.23% respectively without the BERT embeddings, which shows the significant performance difference of the BERT embeddings on the different task. This phenomenon may be caused by unstable optimizing on the diagram question answering.

The accuracy on the non-diagram/diagram questions drop by 2.37% and 1.69% respectively without fine-grained evidence spans, which shows the effectiveness of our proposed coarse-to-fine grained evidence span generation algorithm.

In short, each component makes its contributions to the performance of the XTQA and our proposed coarse-to-fine grained evidence span generation algorithm plays the biggest role.

#### 5.6 Case Studies

We conduct the case studies as shown in Figure 3 to present the strengths and weaknesses of our method intuitively.

**Strengths.** XTQA can provide the explicit evidence span for students by the coarse-to-fine grained algorithm. In addition, it can generate evidence spans of different lengths according to the specific question. For example, XTQA provides evidence span of length 1 of the diagram question, and provides evidence span of length 2 of the non-diagram question for students respectively as shown in the middle part of Figure 3.

Weaknesses. If the coarse-grained algorithm makes errors, it will cause the failure to find evidence spans in the fine-grained phase. For example, XTQA finds the wrong top 1 paragraph for the non-diagram question as shown in the middle part of Figure 3, which causes the failure to find the evidence span.

In short, XTQA gives students explainability to

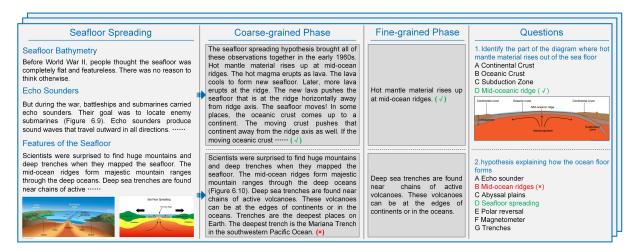


Figure 3: Case studies to show the strengths and weaknesses of the XTQA. The left part shows the multi-modal context of the Lesson *Seafloor Spreading*. The middle parts show the evidence generation processes by our proposed algorithm. The right part shows the questions of this lesson. These cases come from the validation split.

some extent, and optimizing the coarse-grained algorithm may be the further research direction.

### 5.7 Discussions

We make an assumption about the evidence generation in Section 1 owing to the lack of supervision. To verify the effectiveness of this assumption, we take some samples that are answered correctly from the test split and manually check whether the generated evidence spans can provide certain explainability for students. The results are show in Figure 4. The accuracy on the non-diagram questions, di-

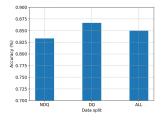


Figure 4: The accuracy of evidence spans on the non-diagram questions (NDQ), diagram questions (DQ), to-tal questions (ALL).

agram questions and total questions are 83.33%, 86.67% and 85% respectively. This shows the evidences for most of the questions answered correctly provide explainability for students and proves the validity of our assumption to some extent.

In addition, we find XTQA and other baselines have poor generalization abilities on the validation split and the test split, which may be caused by the following reasons. (1) Small datasets may easily lead to overfitting. (2) There may exist differ-

ent data distributions between splits. For example, the information of Lesson *earth science and its branches* is mutually exclusive in the data splits.

### **6 Conclusion and Future Work**

In this paper, we propose a novel architecture towards span-level eXplanations of the Textbook Question Answering (XTQA). It can provide not only the answers but also the evidences to choose them for students. To generate evidence spans, we propose a coarse-to-fine grained algorithm. In the coarse phase, the algorithm uses the TF-IDF method to find top M paragraphs relevant to questions within the multi-modal context. In the coarse-grained phase, it generates the top K evidence spans by computing the information gain of each candidate evidence span to questions. Experimental results show that XTQA achieves the state-of-the-art performance on the validation split and the test split of the TQA dataset.

In the future, the following directions will be explored: (1) Error reduction of the coarse-grained algorithm may improve the accuracy of evidence span generation. We will explore how to devise an end-to-end architecture to optimize the process of the coarse-grained evidence span generation. (2) External knowledge helps to improve the performance of other tasks such as named entity recognition and visual question answering. An analysis about the TQA dataset (Kembhavi et al., 2017) also shows that about 10% of the questions need external knowledge to answer. We will explore how to integrate the external knowledge into XTQA to improve its performance.

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