MoCA: Incorporating Multi-stage Domain Pretraining and Multimodal Cross Attention for Textbook Question Answering

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Abstract

Textbook Question Answering (TQA) is a complex multimodal task to infer answers given large context descriptions and abundant diagrams. Compared with Visual Question Answering (VQA), TQA contains a large number of uncommon terminologies and various diagram inputs. It brings new challenges to the representation capability of language model for domain-specific spans. And it also pushes the multimodal fusion to a more complex level. To tackle the above issues, we propose a novel model named MoCA, which incorporates multi-stage domain pretraining and multimodal cross attention for the TQA task. Firstly, we introduce a multi-stage domain pretraining module to conduct unsupervised post-pretraining with the span mask strategy and supervised pre-finetune. Especially for domain post-pretraining, we propose a heuristic generation algorithm to employ the terminology corpus. Secondly, to fully consider the rich inputs of context and diagrams, we propose cross-guided multimodal attention to update the features of text, question diagram and instructional diagram based on a progressive strategy. Further, a dual gating mechanism is adopted to improve the model ensemble. The experimental results show the superiority of our model, which outperforms the state-of-the-art methods by 2.21\% and 2.43\% for validation and test split respectively.

1 Introduction

Recent years have witnessed the promising development of Visual Question Answering (VQA) task (Antol et al. 2015), which is required to infer the answers based on an image and its relevant question text. Promoted by the continued researches on multimodal inference, the previously proposed Textbook Question Answering (TQA) task (Kembhavi et al. 2017) leads a new trend. Similarly, the TQA task also requires the model to give the answers based on complex multimodal inputs. Figure 1 illustrates an example of TQA. Two questions are listed on the right part. Different from VQA in general domain, TQA dataset relates to the domain of textbook, containing a large number of span-level terminologies. The evidence spans like \textit{continental slope} in Q2 are crucial to TQA inference, but they are uncommon in the general domain. Meanwhile, the inference of questions relies on the joint consideration of abundant context and diagrams. Take Q1 as an instance, the model is required to focus on the span \textit{benthic zone} in the question and find the most related instructional diagram ID-2 in the context. After extracting the corresponding information of QD-1 and ID-2, the answer can be worked out. From these perspectives, TQA task raises new challenges to multimodal inference.

Firstly, general language model (LM) is insufficient for the specific domain knowledge. Pretraining-based Transformer structures (Vaswani et al. 2017), such as BERT (Devlin et al. 2019) and GPT (Brown et al. 2020), show excellent performance on the general domain. However, TQA context ranges from astrophysics to life science, containing a large number of terminologies in the field of textbook (e.g., \textit{benthic zone} and \textit{continental slope} in Figure 1). There exists an obvious gap between specific domain and general domain. Some previous works (Gururangan et al. 2020; Gu et al. 2020) have been aware of this situation and adapted LM to some domains (e.g., News, Economics, and Reviews). However, they focus on the token-level information for inference, which fails to concern about span-level terminologies and evidences. To the best of our knowledge, so far there is no attempt to enhance LM for TQA by adding external knowledge or attending to span-level information.

Secondly, it is difficult to fully utilize abundant multimodal inputs. Different from VQA with only single natural image, TQA contains various instructional diagrams and one question diagram as visual input. The two types of diagrams are similar in structure and all have complementary

Figure 1: An example of TQA. ID is short for instructional diagram while QD is short for question diagram.
information with text (e.g., QD-1 and ID-2 are closely connected under the guidance of text benthic zone in Figure 1). Although most popular VQA models (Anderson et al. 2018; Yu et al. 2019; Kim et al. 2018) are capable of fusing multimodal features, they lack the ability to update fine-grained features interactively between two diagrams. Several previous works in TQA (Gómez-Pérez and Ortega 2020; Ma et al. 2020; Li et al. 2018) have noticed the multiple types of diagrams, but they simply process two types in the same way, ignoring their independent effects.

In light of the above challenges, we propose a novel model MoCA, which incorporates multi-stage domain pretraining and cross-guided multimodal attention for the TQA task. We introduce multi-stage pretraining to conduct post-pretraining with the span mask strategy and pre-finetune sequentially between general pretraining-finetune paradigm. Especially for the employment of the terminology corpus, we propose a heuristic generation algorithm. Meanwhile, patch-level diagram representations are obtained through the Vision Transformer (Dosovitskiy et al. 2021). Then, we construct token-patch pair interaction and obtain attended features based on the multi-head guided attention. Inspired by the attention flow of human inference (Chen et al. 2020), the features of text, question diagram and instructional diagram are updated in a progressive and interactive way. After the final fusion of all the features, the answer is predicted with a dual gating mechanism. The main contributions are shown as follows:

- A unified model MoCA is proposed to address both the representation for terminologies and the feature fusion of abundant multimodal inputs. We are the first to simultaneously focus on the two challenges in TQA.

- We introduce a heuristic generation algorithm for terminology corpus. Based on the external knowledge, we are the first to design a span mask strategy in the pretraining stage for the TQA task.

- To address the multimodal fusion challenges, a cross-guided attention mechanism is proposed to update the features of rich inputs. In a progressive manner, the interactive updates of the features are obtained.

- Extensive experiments show that our model significantly improves the state-of-the-art (SOTA) results in the TQA task. Furthermore, ablation and comparison experiments prove the effectiveness of each module in our model.

## 2 Related Work

**Visual Question Answering.** VQA has aroused wide concerns (Cao et al. 2021; Jain et al. 2021; Khademi 2020; Yu et al. 2020), as it is regarded as a typical multimodal task related to natural language processing and computer vision. Given an image as well as question text, the model is required to give the answer. Some early models attempted to jointly consider the multimodal inputs. Antol et al. (2015) encoded the image and text respectively and map them into a common space. Kim et al. (2016) proposed a residual structure to learn joint embeddings. These methods are limited to global and coarse information.

Therefore, more following works applied the attention mechanism to conduct fine-grained reasoning. Typically, Kim et al. (2018) proposed a bilinear attention network to reduce computational cost. Ben-younes et al. (2017) proposed a framework to efficiently parameterize bilinear multimodal interactions. Yu et al. (2019) included the self-attention and the question-guided attention within deep modular co-attention networks. Anderson et al. (2018) introduced the bottom-up and top-down attention to attend to object-level and salient information. However, these models are placed in an ideal scenario, which includes unitary input of an image and a short question. They lack the potential to process large context and abundant diagrams.

**Textbook Question Answering.** Much attention has been paid to the TQA task since it was proposed. For example, Li et al. (2018) aimed to find contradictions between answers and context, and further employ memory network for inference. Kim et al. (2019) built a multimodal context graph and introduced open-set learning based on self-supervised method. Ma et al. (2021) proposed fine-grained relation extraction to reason over the nodes of the constructed graphs. The above three methods focused more on inference process, but ignored the huge potential of multimodal encoding, causing relatively weak representation ability. Under this circumstance, Gómez-Pérez and Ortega (2020) utilized the pretrained transformers for text encoding and bottom-up and top-down attention for multimodal fusion, significantly improving the performance. However, it neglected the span-level knowledge during pretraining and simply treated the question and instructional diagrams in the same way. Ma et al. (2020) put the explainability at the first place and attempted to extract useful spans, but its text representation method is relatively weak for the textbook domain.

Considering the drawbacks of the above models, we apply external knowledge to enhance the span-level representation. Different from them, we treat two types of diagrams respectively to conduct fine-grained feature updates.

## 3 Methods

In this section, we will introduce our proposed model MoCA. The architecture of MoCA is shown in Figure 2. The left part is an input example of TQA. Then text and diagrams are encoded respectively, through Multi-stage Pretrain (MP) module and Patch-level Diagram Representation module (PDR). In PDR module, we employ Vision Transformer to obtain the patch-level representation of both types of the diagrams. Further, multimodal features are progressively updated based on Cross-Guided Multimodal Attention (CGMA). Finally, the answers are worked out by Gating Model Ensemble (GME). The details of three main modules MP, CGMA and GME will be covered as follows.

### 3.1 Task Formulation

Given the TQA dataset $D$ with $M$ questions, the inference of $i^{th}$ question ($i \in [0, M - 1]$) can be defined as follows:

$$\hat{a} = \arg \max_{a_i \in A_i} \left( a_{i,j} \mid c_i, q_i, A_i, d_i; \theta \right), \quad (1)$$
where $c_i$, $q_i$, $A_i$ represent the text-only context, question sentence and candidate set respectively. $d_i$ includes question and instructional diagrams. The option number in $A_i$ is $n$, $j \in [0, n-1]$ and $a_{i,j} \in A_i$ represents $j^{th}$ option. $\hat{a}$ is the predicted option. $\theta$ is the trainable parameter.

3.2 MP Module

Although the two-stage general pretraining and finetune models has achieved great success in many tasks, there exists an obvious gap between general domain and textbook domain. We attribute the problem to the lack of data about both specific domain and task. Under this circumstance, we propose MP module for the enhancement of text representation.

MP includes four stages in total, which is constructed with two unsupervised pretraining stages and two supervised finetune stages. Stage I and Stage IV inherit the traditional general paradigm, with pretraining on large general corpus and finetune on downstream task (TQA) respectively. We use RoBERTa [Liu et al., 2019] as the base model for Stage I, which utilizes the dynamic random mask strategy to focus on token-level performance.

For Stage II, to adapt the language model to the textbook domain, we introduce a coarse-to-fine strategy to heuristically generate external domain corpus. In the beginning, we crawl the textbook-related websites, forming the large coarse-level domain corpus. To evaluate the similarity of the external knowledge with TQA, we employ vocabulary overlap of the Top 1k most frequent words, which excludes nearly 900 stopwords. We define the overlap operator as $O(c_1|c_2)$. It stands for the overlap vocabulary list of input corpus or text $c_2$ with $c_1$, while $L(O(c_1|c_2))$ returns the number of overlap words. Based on the operator and coarse-level corpus, we design a heuristic method to generate fine-level domain corpus containing rich terminologies. For each line of the corpus, we retain the ones which contribute more to the vocabulary overlaps during every iteration (shown in Algorithm 1, more details are attached to Appendix). After obtaining fine-level corpus, we shuffle it with TQA text to prepare for the post-pretraining stage.

Considering that quite a lot of knowledge and question information consist of multiple words, we adopt span mask strategy to optimize domain-specific pretraining process. That is to say, given a sequence $S = \{t_1, t_2, ..., t_n\}$ consisting of $n$ tokens, each time we randomly mask one to ten tokens based on geometric distribution. Until the mask percentage reaches 15%, the process breaks automatically. Same as BERT, for 15% tokens selected in sequence $S$, 80% of them are replaced with `<mask>` flag, 10% of the tokens are substituted by random token and the others remain unchanged.

Algorithm 1: Heuristic Terminology Corpus Generation

| Input: | Coarse-level Corpus $C_{coarse}$, TQA Text $T$, threshold $\delta$ |
|---|---|
| Output: | Fine-level Corpus $C_{fine}$ |
| 1 | Calculate vocabulary overlap $O(T|C_{coarse})$ of coarse corpus with TQA text. |
| 2 | repeat |
| 3 | Take $C_{fine}$ as $C_{coarse}$ if not the first iteration |
| 4 | for Line $l_i \in C_{coarse}$ do |
| 5 | $W \leftarrow O(T|C_{coarse})$ |
| 6 | $Score(l_i) \leftarrow \frac{L(O(W|l_i)) - L(l_i)}{L(C_{coarse})}$ |
| 7 | if $Score(l_i) > \delta$ then |
| 8 | Include $l_i$ into fine-level corpus $C_{fine}$ |
| 9 | end |
| 10 | end |
| 11 | until $C_{fine}$ is reduced to a certain specification; |
| 12 | return Fine-level Corpus $C_{fine}$ |
Through PDR module, the original features of question diagram are the same space, we add a linear projection layer
Linear(P) as the input of CGMA module. Thus, three features with the same dimension can function to the computed attention, followed with layer normalization.

$$ f^*_Q = \text{LayerNorm}(f_{Q,D} + \text{Att}_M(Q_{Q,D}, K_T, V_T)). $$

Through the followed feedforward and layer normalization, the attended output feature of one multi-head guided attention layer is obtained. To further enhance the performance of the module, we concatenate $L$ paralleled layers and obtain the multi-layer updated feature $f^{**}_{Q,D}$.

$$ f^{**}_{Q,D} = \text{Layer}(1, ..., \text{Layer}_L) \cdot W^L, $$

where $W^L \in \mathbb{R}^{(L+d) \times d}$ is the projection matrix and $\text{Layer}_j$ represents the output feature $f^{**}_{Q,D} \in \mathbb{R}^{N \times d}$ of $i$-th layer.

Thus, the feature of question diagram is updated. The text feature can be updated with the similar process in Progress I. Considering that instructional diagram is similar to question diagram in structure and contains meaningful information related to text, we first integrate the multimodal features of text and question diagram and make it a guidance for the instructional diagram feature update in Progress II.

### 3.4 GME Module

To reduce the computational cost, we first shorten the large context into a fixed number of sentences with the help of information retrieval method. In consideration of single retrieval has limitations and may bring unnecessary noise, we perform background retrieval three times in different ways. Following ISAAC (Gomez-Perez and Ortega 2020), we name them as IR, NSP and NN. Since three retrieval methods are independent and contribute differently to the inference, we design a weighted ensemble method to fully exploit the advantages of each retrieval. It means that the final feature $f^{\text{Ensemble}}_o$ for the prediction consists of three parts with different weights.

$$ f^{\text{Ensemble}}_o = \lambda_1 f^{IR}_o + \lambda_2 f^{NSP}_o + (1 - \lambda_1 - \lambda_2) f^{NN}_o, $$

where $f^{IR}_o, f^{NSP}_o, f^{NN}_o \in \mathbb{R}^{N \times d}$, and weight parameters $\lambda_1, \lambda_2, 1 - \lambda_1 - \lambda_2 \in [0, 1]$. 

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**Figure 3:** Progressive multimodal feature update in CGMA.
Further, for diagram multiple-choice questions, diagrams are considered an important part of the inference. However, in some cases, the help of diagram features can be negative, or the text-only feature can work out the correct answer. In order to reduce noise brought by diagram features, we integrate the text-only feature for inference in model ensemble. We set a gate parameter $\mu$ to model the importance of text-only features and multimodal features.

$$f_\text{o}^{\text{GME}} = (1 - \mu)f_\text{t}^{\text{Ensemble}} + \mu f_\text{mm}^{\text{Ensemble}},$$  \hspace{1cm} (9)

where $f_\text{t}^{\text{Ensemble}}$ and $f_\text{mm}^{\text{Ensemble}}$ represents the weighted text-only feature and multimodal feature respectively. For each option, we obtain different final features. Through the training of the classifier, the answers can be obtained.

## 4 Experiments

In this section, extensive experiments are conducted to compare our model with SOTA methods in TQA. Comparison study and parameter analysis are followed to improve the comprehensiveness of the proposed model.

### 4.1 Dataset and baselines

We conduct the experiments on TQA dataset. Covered in the textbook domain, TQA includes 1,076 subjects, namely Life Science, Earth Physics, etc. It consists of 26,260 questions in the form of True/False (T/F), Text Multiple Choice (T-MC) and Diagram Multiple Choice (D-MC). The number of candidate answers and dataset split are shown in Table 1. Column 2 to 5 represent the number of questions while the last column represents the number of candidate answers.

| Type    | Train Set | Val Set | Test Set | Candidate |
|---------|-----------|---------|----------|-----------|
| T/F     | 3,490     | 998     | 912      | 2         |
| T-MC    | 5,163     | 1,530   | 1,600    | 4-7       |
| D-MC    | 6,501     | 2,781   | 3,285    | 4         |

Table 1: Dataset split and candidate answer number

To prove the superiority of our model, we employ the following baselines, including the SOTA model.

- **Random**: Results based on random prediction.
- **MemN** (Kembhavi et al. 2017): It employs the concept of memory network and diagram parse graph to construct the context graph for the TQA task.
- **IGMN** (Li et al. 2018): It grasps the contradiction between candidate answers and context for reasoning.
- **FCC** (Gómez-Pérez and Ortega 2019): It considers diagrams and image captions.
- **f-GCN1** (Kim et al. 2019): A new f-GCN module based on graph convolution network is proposed to address multimodal fusion challenges.
- **XTQA** (Ma et al. 2020): It designs a coarse-to-fine algorithm to generate span-level evidences.
- **RAFR** (Ma et al. 2021): A fine-grained reasoning network is proposed to reason over the nodes of relation-based diagram graphs.

### 4.2 Implementation Details

All of the experiments are finished with a single GPU of Tesla V100. As for the encoder of text in MP module, we utilize the RoBERTa-large model for Stage I which has 1024-dimensional embeddings. For Stage II, we mix the external textbook corpus with TQA corpus and conduct the post-pretraining with 10 epochs based on the span mask strategy. For Stage III, we pre-finetune the model on RACE dataset with 4 epochs and select the best one based on the performance of test split. As for the background information retrieval, we follow the three methods introduced in ISAAQ (Gómez-Pérez and Ortega 2020) namely $IR$, $NSP$ and $NN$. Considering the length of retrieved context, we set the maximum input sequence length to 180, and the inputs shorter than 180 are padded to max. As for diagram representation, each diagram is cut into 14 patches with the dimension of 1024. As for CGMA module, we empirically set the multi-head number to 8 and the number of paralleled layers is searched for the best in $\{1,2,3,4\}$. To enhance the classifier for D-MC questions, we further finetune the model on VQA (Antol et al. 2015) and AI2D (Kembhavi et al. 2016). The detailed information of the corpus and dataset is shown in Table 2.

| Corpus | Domain | Size  | Source   |
| ------ | ------ | ----- | -------- |
| TQA   | Textbook | 5MB  | From TQA |
| External | Textbook | 350MB | Crawled  |

| Dataset | Domain | Size  | Type       |
|-------- | ------ | ----- | ---------- |
| TQA    | Textbook | 26,260 | Multimodality |
| RACE   | Exams  | 97,687 | Text-only  |
| VQA(Part) | General | 90,000 | Multimodality |
| AI2D   | Science | 8,730 | Diagram-only |

Table 2: The detailed information of corpus and dataset employed in the training process.

| Model   | T/F   | T-MC  | T-All | D-MC | All  |
|---------|-------|-------|-------|------|------|
| Random  | 50.10 | 22.88 | 33.62 | 24.96| 29.08|
| MemN    | 50.50 | 30.98 | 38.69 | 32.83| 35.62|
| IGMN    | 57.41 | 40.00 | 46.88 | 36.35| 41.36|
| FCC     | -     | 36.56 | -     | 35.30|-     |
| fGCN    | 62.73 | 49.54 | 54.75 | 37.61| 45.77|
| XTQA    | 58.24 | 30.33 | 41.32 | 32.05| 36.46|
| RAFR    | 53.63 | 36.67 | 43.35 | 32.85| 37.85|
| ISAAQ   | 81.36 | 71.11 | 75.16 | 55.12| 64.66|
| MoCA(Ours) | 81.56 | 76.14 | 78.28 | 56.49| 66.87|

Table 3: Experimental results on the validation split for TQA. The percentage signs (%) of accuracy values are omitted. The optimal and suboptimal results are marked in bold and underline respectively (same for the following tables).

- **ISAAQ** (Gómez-Pérez and Ortega 2020): It improves the SOTA baseline by introducing the pretrained LM and bottom-up and top-down attention mechanism.
has the further meaning that the answer includes the information of all options, which is hard to be reflected by LM. We divide them into two types: Positive and Negative. For the Positive type, like 'All of these', 'Both a and b', it means the final answer includes more than one option. We concatenate the options and replace the LSO with the spliced text. For the Negative one, like 'None of these', 'Neither a nor b', we set LSO to the empty string for simplicity. We also test the necessity of LSOs. The evaluation results are shown in Table 5. The consideration of LSOs brings 1.62% and 2.34% accuracy gain on validation and test split. From the results, the mapping of LSOs has equal contributions with MP. The former one improves the performance by manually designed rules while the latter one relies on the external knowledge.

Secondly, we select two popular mask strategies as comparison objects, that is random mask and whole word mask. Results on Table 6 show the superiority of the span mask strategy, especially on the retrieval of IR with 1.24% accuracy gain. Since pretraining on general domain (Stage I) utilizes the random mask strategy rather than span-level strategy, it still remains huge potentials for the improvement.

As MoCA includes three main modules, we conduct the ablation experiments for each module to explore the effectiveness. Meanwhile, comparison experiments on the mask strategy in MP module are also presented.

4.3 Main Results
MoCA model is evaluated on TQA dataset. The results on validation and test split are shown in Table 3 and Table 4 respectively. Since some previous baselines do not make the results of test split public, we only compare the validation split results for these models.

From the results, MoCA outperforms the SOTA results from all three types of questions. In general, we significantly improve the overall performance of SOTA by 2.21% and 2.43% on validation and test split respectively. It is worth mentioning that MoCA also shows better generalization capability. Especially for the text-only questions on the test split, MoCA outperforms the previous SOTA method by 3.62%. Also, results on previous models illustrate the different distributions between validation and test split for D-MC questions, while MoCA narrows this obvious gap.

4.4 Ablation and Comparison Experiments
As MoCA includes three main modules, we conduct the ablation experiments for each module to explore the effectiveness. Meanwhile, comparison experiments on the mask strategy in MP module are also presented.

MP module. We mainly experiment and analyze the effectiveness of multiple stages and the mask strategy in MP module. Firstly, we remove one or both of Stage II and Stage III. Without Stage II & III, the text-only accuracy drops by 1.5% and 2.42% on validation and test split respectively. Within the removed two stages, Stage II contributes most to the model performance. It proves that the unsupervised training on external knowledge makes a difference.

Through exploratory data analysis, we also discover the characteristics of the options, which is the Latent Semantic Option (LSO). For example, the option 'All of the above' has the further meaning that the answer includes the information of all options, which is hard to be reflected by LM. We divide them into two types: Positive and Negative. For the Positive type, like 'All of these', 'Both a and b', it means the final answer includes more than one option. We concatenate the options and replace the LSO with the spliced text. For the Negative one, like 'None of these', 'Neither a nor b', we set LSO to the empty string for simplicity. We also test the necessity of LSOs. The evaluation results are shown in Table 5. The consideration of LSOs brings 1.62% and 2.34% accuracy gain on validation and test split. From the results, the mapping of LSOs has equal contributions with MP. The former one improves the performance by manually designed rules while the latter one relies on the external knowledge.

Secondly, we select two popular mask strategies as comparison objects, that is random mask and whole word mask. Results on Table 6 show the superiority of the span mask strategy, especially on the retrieval of IR with 1.24% accuracy gain. Since pretraining on general domain (Stage I) utilizes the random mask strategy rather than span-level strategy, it still remains huge potentials for the improvement.

CGMA module. We remove one or all of the cross-guided attention. Since previous SOTA models seldom take ID into consideration or just simply confuse it with QD, we also remove the input of ID to show its effectiveness. The experimental results in Table 7 show that all the attention employed brings 1.47% gain on the validation split. The consideration of ID improves the performance by 0.40% and 0.49% on the validation and test split respectively. Further, the update of text feature contributes most on the validation split and least on the test split. It shows the importance of text for D-MC in each split.

GME module. Our ensemble method has two gate parameters $\lambda$ ($\lambda_1, \lambda_2$) and $\mu$, which has different type of roles.
Therefore, we further compare three conditions. Firstly, utilize the multimodal features only for D-MC inference, which eliminates the effect of gate parameter $\mu$ ($\mu=0.5$). Secondly, simultaneously eliminate all the gate parameters, which means select the best single one as the final model ($\lambda$, $\mu$ not exist). Thirdly, keep both of the gate parameters while set all six models to equal contributions ($\lambda_1=\lambda_2=1/3, \mu=0.5$). Results are shown in Table 8. Generally, two gate parameters $\lambda$ and $\mu$ contribute 2.34% and 1.21% to the accuracy on the validation and test split respectively. On one hand, more models for ensemble bring better overall performance. On the other hand, single model of MoCA is still competitive to ensembled SOTA model.

We select several $\mu$ with an interval of 0.1 for visualization. The results on validation and test split are shown in Figure 4. The trend illustrates that MoCA reaches the best performance when the gate parameter $\mu$ is 0.6. With $\mu$ increasing, accuracy on the validation and test split witnesses an obvious drop. More specifically, the inference of TQA task relies on text-only evidences. It also proves the effectiveness and necessity of GME module.

### 4.5 Case Study

As text-only questions can be regarded as a special case of diagram questions, we conduct the case study on the diagram questions only. Figure 5 shows a successful case and a failure case. For the successful one, MoCA makes good use of multimodal information for inference. For the failure one, text information is limited and it is required to figure out the number of volcano type directly from QD. It reflects that MoCA is weak in counting and numerical reasoning.

We select the successful case to visualize the effects of three cross-guided attention in MoCA, shown in Figure 6. For better visualization, we mark some important patches with blue boxes in QD and ID, and present the order number above. Figure 6 also shows the results on validation and test split respectively. Generally, two gate parameters $\lambda$ and $\mu$ contribute 2.34% and 1.21% to the accuracy on the validation and test split respectively. On one hand, more models for ensemble bring better overall performance. On the other hand, single model of MoCA is still competitive to ensembled SOTA model.

### 5 Conclusion

We incorporate multi-stage domain pretraining and multimodal cross attention for the TQA task. Firstly, on the basis of general pretraining-finetune paradigm, we propose multi-stage domain pretraining module to bridge the gap between...
general domain and textbook domain. In the stage of domain post-pretraining, we propose a heuristic generation algorithm to employ terminology corpus. Span mask strategy is utilized to optimize the pretraining performance. Secondly, following the human inference pattern, we propose multimodal cross-guided attention to progressively update the features of text, question diagram and instructional diagram. Further, we adopt a dual gating mechanism to improve the ensemble model performance. Extensive experiments prove the superiority of our model and module effectiveness. In the future, we will pay more attention to the improvement of background text retrieval, as well as the employment of fine-grained diagram information.

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