Textbook Question Answering with Knowledge Graph Understanding and Unsupervised Open-set Text Comprehension

Daesik Kim$^{1,2,*}$ Seonhoon Kim$^{1,3,*}$ Nojun Kwak$^{1}$
$^1$Seoul National University  $^2$V.DO Inc.  $^3$Naver Corporation
{daesik.kim|nojunk}@snu.ac.kr seonhoon.kim@navercorp.com

Abstract

In this work, we introduce a novel algorithm for solving the textbook question answering (TQA) task which describes more realistic QA problems compared to other recent tasks. We mainly focus on two related issues with analysis of TQA dataset. First, it requires to comprehend long lessons to extract knowledge. To tackle this issue of extracting knowledge features from long lessons, we establish knowledge graph from texts and incorporate graph convolutional network (GCN). Second, scientific terms are not spread over the chapters and data splits in TQA dataset. To overcome this so called ‘out-of-domain’ issue, we add novel unsupervised text learning process without any annotations before learning QA problems. The experimental results show that our model significantly outperforms prior state-of-the-art methods. Moreover, ablation studies validate that both methods of incorporating GCN for extracting knowledge from long lessons and our newly proposed unsupervised learning process are meaningful to solve this problem.

Introduction

What if artificial intelligence (AI) solves problems in the textbook for me? While AI studies complicated contexts in the textbook by itself and understands arbitrary questions, it seeks the right answer with logical reasoning. In this paper, we challenge a novel task, Textbook Question Answering (TQA) which aims to study large lessons and solve practice problems in the textbook like a middle school student (Kem-bhavi et al. 2017).

In a decade, question answering (QA) has been one of the most promising achievements in the field of natural language processing (NLP). Furthermore, it has shown great potential to be applied to real-world problems. However, most of datasets in QA have specified range of topic, vocabulary and contexts. In real textbook studying, it is trivial that we cannot specify the range of contexts and should learn new knowledge to solve new problems all the time. Therefore, it is worth solving more realistic QA problems like those in the TQA task.

The TQA task can describe real-life process of a student who learns new knowledge from books and practices to solve related problems (Figure 1). It also has several novel characteristics as a realistic dataset. Since the TQA contains visual contents as well as textual contents, it requires to solve multi-modal QA. Moreover, formats of questions are various which include both text-related questions and diagram-related questions. In this paper, we focus on the following two major characteristics of the TQA dataset (Kembhavi et al. 2017).

First, compared to other QA datasets, it requires to understand long lessons to obtain knowledge. Therefore, it is important not only to read sentences, but also to extract and understand exact knowledge from long texts. We establish knowledge graph and incorporate graph convolutional network (GCN) (Kipf and Welling 2016) to extract proper knowledge for solving questions.

Next, the various topics and subjects in the textbooks are spread over chapters and lessons, and most of the knowledge and terminology do not overlap between chapters and data splits. Therefore, it is very difficult to solve problems on subjects that have not been studied before. To resolve this problem, we encourage our model to learn novel con-
cepts and terms in an unsupervised manner before learning to solve specific questions.

In this paper, we make the following contributions:

- We propose a novel architecture which can solve TQA problems with texts and other modality.
- We incorporate GCN to extract knowledge feature from knowledge graph of long lessons in the textbook.
- We add novel unsupervised learning process into QA training to comprehend open-set texts to avoid an out-of-domain issues.

With the proposed model, we could obtain state-of-the-art performance on TQA dataset, which shows a large margin compared with the current state-of-the-art method.

**Related Work**

**Context question answering**

Context question answering, also known as machine reading comprehension, is a challenging task which requires a machine not only to comprehend natural language but also to reason how to answer the asked question correctly. Large amount of datasets such as MCTest (Richardson, Burges, and Renshaw 2013), SQuAD (Rajpurkar et al. 2016) or MS Marco (Nguyen et al. 2016) have contributed significantly to the textual reasoning via deep learning approaches. These datasets, however, are restricted to a small set of contents and contain only uni-modal problems requiring only textual information. In addition, these sets require relatively less complex parsing and reasoning compared to TQA dataset (Kembhavi et al. 2017). In this study, we perform TQA, the practical middle school science problems across multiple modalities, by transforming long essays into the custom-graphs for solving the questions on a textbook.

**Visual question answering**

As the intersection of computer vision, NLP and reasoning, visual question answering has drawn attention in the last few years. Most of pioneering works in this area (Xu and Saenko 2016, Yang et al. 2016, Lu et al. 2016) are to learn joint image-question embedding to classify correct answers where the context is proposed by images alone. Then, various attention algorithms have been mainly developed in this field and methods of fusing textual and visual information such as bilinear pooling (Fukui et al. 2016, Yu et al.) have also been widely studied. Thereafter, datasets focusing on slightly different purposes have been proposed. For instance, CLEVR (Johnson et al. 2017) encouraged to solve visual grounding problem and AI2D (Kembhavi et al. 2016) suggested new type of data for knowledge extraction from diagrams. In this paper, we incorporate UDPNet (Kim et al. 2017) to extract knowledge from diagrams in the textbook.

**Graph Convolutional Networks**

GCN (Kipf and Welling 2016) is attracting the most attention in an attempt to apply graphs to neural networks which aims to generalize CNN to graph structured data. In early stage, researchers proposed methods for problem-specific graph in some domains. More recent works generally adopt a spectral view on convolutions but computing exact convolutions over graph is computationally intensive. A recent research (Defferrard, Bresson, and Vandergheynst 2016) exploits Chebyshev polynomials to approximate smooth filters in the spectral domain. We adopt first-order approximation of the GCN in (Kipf and Welling 2016) to extract knowledge features in this work.

**Problem**

Formally, our problem can be defined as follows:

$$\hat{a} = \arg\max_{a \in \Omega} p(a|C, q; \theta)$$

where $C$ is given contexts which consist of textual and visual contents and $q$ is given question which can contain question diagrams for diagram problems. $\theta$ denotes the trainable parameters. With given $C$ and $q$, we are to predict the best answer $\hat{a}$ among a set of possible answers $\Omega_a$.

The TQA contexts contain almost all items in textbooks: topic essay, diagrams and natural images, lesson summaries, vocabularies, and instructional videos. Among them, we mainly use topic essay as textual contexts and diagrams as visual contexts. Questions in TQA are also distinctive compared to others. While the number of choices varies from 2 to 7, our model should have flexible structure to infer answers.

Among various issues, first problem we tackled is that the length of textual contexts in lessons is higher than other datasets such as SQuAD. Analysis of contexts in TQA dataset in comparison with SQuAD is shown in Figure 2. Figure 2(a) shows that the average length of contexts in the TQA is 668 words which is almost 5 times larger than that of the SQuAD which has 134 words on average. Due to this fact, we need to add an information retrieval step such as TF-IDF to narrow down scope of contexts from a lesson to a paragraph. Moreover, understanding scientific terms is important to solve practice problems in science textbooks.
Therefore, we incorporate knowledge graph to focus on scientific terms and exploit GCN to extract knowledge features.

Figure 2(b) shows how words in TQA and SQuAD datasets are spread over lessons and articles. We obtain normalized term frequency over contexts and 0.0188 word/context of the SQuAD is higher than 0.0175 word/context of the TQA. It means that terms in SQuAD dataset appear more frequently over contexts than those of TQA dataset. In Figure 2(c), we obtain the percentage of how much the terms in the validation set are appearing in the training set. The SQuAD shows 84% and the TQA results in 79%. Obviously ratio of the TQA is lower than that of the SQuAD which can leads out-of-vocabulary and domain problems more seriously in the TQA task. To avoid aforementioned issue, we apply a novel unsupervised learning process before learning to solve questions.

Proposed Method

Figure 3 illustrates our overall framework which consists of three steps. In a preparation step, we use TF-IDF (term frequency–inverse document frequency) to select the paragraph most relevant to the given question or candidate answers and convert it into context graphs. Then we exploit GloVe (Pennington, Socher, and Manning 2014) to get general word representation of the question and one of answer candidates. In the embedding step, we obtain an overall embedding from three inputs (word representations for the question and an answer candidate plus a context graph) obtained in the first step. More specifically, we exploit an RNN denoted as RNN obtained in the first step. More specifically, we exploit an RNN (denoted as RNN in the figure) to embed textual inputs, a question and an answer candidate. Then we incorporate GCN to extract graph features from the context graph. After repeating previous steps for each answer candidates, we can stack each of concatenated features from the embedding step. Due to variation of the number of answer candidates from 2 to 7, we exploit another RNN (denoted as RNN in the figure) to solve variable inputs. Finally fully connected layer decides probabilities of answer candidates.

From now on, we denote the question, candidate answer, text context and diagram context as \(Q = \{q_1, q_2, \ldots, q_t\}\), \(A = \{a_1, a_2, \ldots, a_j\}\), \(C^t = \{c_1^t, c_2^t, \ldots, c^t_K\}\), and \(C^d = \{c_1^d, c_2^d, \ldots, c^d_L\}\), respectively where \(q_1/a_j/c_k^t/c_l^d\) is the \(i^{th}\) word of the question \(Q\), candidate answer \(A\), text context \(C^t\) and diagram context \(C^d\) (\(C\) is unified notation for the \(C^t\) and \(C^d\)). The corresponding representations are denoted as \(h_q, h_a, H^t\) and \(H^d\), respectively. Note that we use the diagram context \(C^d\) only in the diagram questions.

Knowledge Graph Understanding

Context graphs We build the context graphs using some parts of the lesson where the questions can focus on solving problems as follows. While each lesson consists of several paragraphs, a significant number of questions, especially in the text questions, can be answered correctly through multiple sentences within only one paragraph (Kembhavi et al. 2017). Each lesson can be divided into multiple paragraphs and we extract one paragraph which has the highest TF-IDF score using a concatenation of question and one of the candidate answers (Figure 3(a)).

Even in a paragraph, a lot of knowledge terms are written with logical relationships. And answers are likely to be located in a nearby question term in contexts. Therefore, we tried to extract more abstract relationship among terms as the graph structure. First, we build the dependency trees of the extracted paragraph utilizing the Stanford dependency parser (Manning et al. 2014), and designate the words which exist in the question and the candidate answer as anchor nodes. Then, the nodes which have more than two levels of depth difference with anchor nodes are removed and we build the context graphs using the remaining nodes and edges (See Process 1 for a detailed process of constructing the context graphs). When it comes to the diagram questions, we build additional diagram context graphs by converting the meaningful information in the images into texts using UDPnet (Kim et al. 2017). Except this, we do not use any additional visual features for our proposed architecture.

Graph Understanding Next, the GCN is used to understand the context which is already converted to context graphs. A graph matrix \(C\) containing node features and a normalized adjacency matrix are used as inputs of a GCN to comprehend the contexts where the \(C\) is composed of the word embeddings and the character representation. Based on the implementation of Kipf and Welling (2016), we incorporate one-layer GCN as

\[
H^t_c = f(C^t, A^t) = \sigma(\mathbf{A}^t C^t W^t) \\
H^d_c = f(C^d, A^d) = \sigma(\mathbf{A}^d C^d W^d) \tag{2}
\]

where \(W^t\) and \(W^d\) are learning parameters of linear layer for the text and diagram contexts and the element-wise operation \(\sigma\) is \(\tanh\) which acts as an activation function. As shown in (2), our method can give huge computational gain compared to the text embedding method that usually uses
RNN to convert sequences of word embeddings to sentence embedding. Due to lengthy context in this problem, it can be burden to train full texts. Since we compress whole text to nodes of graphs and exploit a first-order linear layer as an embedding layer, our method can be more efficient to embed contexts for long texts.

**Multi-modal Problem Solving**

The GCNs and RNNs are used to embed the contexts and answer the questions as shown in Figure 3 (b). Two different RNNs are used in our architecture. One is the comprehending RNN (RNN\(_C\)) which can understand questions and candidate answers and the other is the solving RNN (RNN\(_S\)) which can answer the questions.

The input of the RNN\(_C\) is comprised of the word embedding, character representation and the occurrence flag for both questions and candidate answers. In word embedding, each word can be represented to \(e_{qi}/le_{ai}\) by using a pre-trained word embedding method such as word2vec or GloVe. The character representation \(c_{qi}/le_{ai}\) is calculated by feeding randomly initialized character embeddings into a CNN with the max-pooling operation. The occurrence flag \(f_{qi}/f_{ai}\) indicates whether the word occurs in the contexts or not. Our final input representation \(q_i^w\) for the question word \(q_i\) in RNN\(_C\) is composed of three components as follows:

\[
q_i^w = [e_{qi}; c_{qi}; f_{qi}].
\]  

The input representation for the candidate answers is also obtained in the same way as the one for the questions. Here, \(Emb\) is the trainable word embeddings and \(Char-CNN\) is the character-level convolutional network. \([; ; ;]\) is the concatenation operator. To extract proper representations for the questions and candidate answers, we apply the step-wise max-pooling operation over the RNN\(_C\) hidden features.

Given each of the question and the candidate answer representations, we use an attention mechanism to focus on the relevant parts of the contexts for solving the problem correctly. The attentive information \(Att_q\) of the question representation \(h_q\) against the context features \(H_c\) is calculated as follows:

\[
Att_q = \frac{\sum_{k=1}^{K} \alpha_k H_{ck}^T}{\sum_{i=1}^{K} \exp(g_i)},
\]

\[
g_k = h_q^T M H_{ck}.  
\]

Here, \(K\) is the number of words in the context \(C\) which equals the dimension of the square adjacency matrix \(A\). \(M\) is the attention matrix that converts the question into the context space. The attentive information of the candidate answers \(Att_a\) is calculated similar to the \(Att_q\).

RNN\(_S\) is one that can solve the problems and its input consists of the representations of question and candidate answer with their attentive information on the contexts as:

\[
I_{RNN_S}^q = [h_q; h_a; Att^q_a; Att^d_a],
\]

\[
I_{RNN_a}^d = [h_q; h_a; Att^q_a; Att^d_a].
\]

Unsupervised text comprehension

To comprehend out-of-domain contexts as well as in-domain ones, we apply the prior learning in an unsupervised manner as shown in Figure 3. This can enhance the performance of our model. While we exploit the same architecture described in the previous section, we have only changed the input and output of the model and the way to get an answer. To formulate the problem as an unsupervised one, we have reversed
Usual text comprehension step in our model. In this step, we pretrain our model with newly defined unsupervised manner. We set contexts as candidates we should predict and question and k-th answer as inputs. For each answer candidates, we obtain n context candidates from tf-idf methods and set top-1 candidate as correct answer. While we use same structure as in Figure 3, we can predict final distribution after all steps.

For each answer candidates, we obtain n context candidates for the pair of question-candidate answer, set but also the validation set. To be more specific, we select one candidate answer from question-candidate answers pairs in the first step. Next, we choose a number j, the number of candidate contexts for the pair of question-candidate answer, in the range 2 to 7 like the original dataset. If j is higher than the number of contexts in the lesson, we set j to be the number of contexts. Then, we extract top j paragraphs using the TF-IDF scores to set them as candidate contexts \( \Omega_c \). We build each context graph in the same way as the original method and get embeddings with the question-candidate answer pair we selected. Finally, we designate the final candidate which connects to the top 1 paragraph as a correct answer, and others as wrong answers.

With this pre-training stage, we expect that our model can deal with almost all contexts in a lesson. Moreover, it becomes possible to learn contexts in the validation set or the test set with an unsupervised manner. This step is analogous to a student who reads and understands a textbook and problems in advance.

Experiments

Dataset

We perform experiments on the TQA dataset, which consists of 1,076 lessons from Life Science, Earth Science and Physical Science textbooks. While the dataset contains 78,338 sentences and 3,455 images including diagrams, it also has 26,260 questions with 12,567 of them having an accompanying diagram, split into training, validation and test at a lesson level. The training set consists of 666 lessons and 15,154 questions, the validation set consists of 200 lessons and 5,309 questions and the test set consists of 210 lessons and 5,797 questions. Since evaluation for test is hidden, we only use the validation set to evaluate our methods.

Implementation Details

We initialized word embedding with 300d GloVe vectors pre-trained from the 840B Common Crawl corpus (Pennington, Socher, and Manning 2014), while the word embeddings for the out-of-vocabulary words were initialized randomly. We also randomly initialized character embedding with a 16d vector and extracted 32d character representation with a convolutional network. We used 250 hidden units of Bi-LSTM for the RNN, whose weights are shared between the question and candidate answers. The maximum sequence length of them is equal to 30. Likewise, the number of hidden units of the RNN, is the same as the RNN, and the maximum sequence length is 7 which is the same as the number of the candidate answers. We employed 200d one layer GCN for both of textual and diagram contexts, and the number of maximum nodes is 75 and 35 for each of them. We use the tanh for the activation function of the GCN. The dropout was applied after all of the word embeddings with a keep rate of 0.5. The Adam optimizer with an initial learning rate of 0.001 was applied, and the learning rate was decreased by a factor of 0.9 after each epoch.

Baselines

We compare our method with several recent methods as followings:

- **MemN+VQA** This method is a baseline proposed in Kembhavi et al. (2017). It exploits Memory networks to embed texts in lessons and questions. It uses VQA methods for diagram questions which combine image features from diagram and text feature from LSTM.

- **MemN+DPG** This method is another baseline proposed in Kembhavi et al. (2017). It exploits Diagram Parse Graph (DPG) as knowledge graph on diagrams built by DsDP-net (Kembhavi et al. 2016). It infers graph structure from detected objects in diagrams and translate into sentences.
| Model                                      | Text T/F | Text MC | Text All | Diagram | All  |
|--------------------------------------------|----------|---------|----------|---------|------|
| Random                                    | 50.10    | 22.88   | 33.62    | 24.96   | 29.08|
| MemN+VQA (Kembhavi et al. 2017)           | 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 (Kembhavi et al. 2017)          | 50.40    | 30.46   | 38.33    | 32.72   | 35.39|
| Challenge                                 | -        | -       | -        | 45.57   | 35.85|
| IGMN (Li et al. 2018)                     | 57.41    | 40.00   | 46.88    | 36.35   | 41.36|

| Model                                      | Text T/F | Text MC | Text All | Diagram | All  |
|--------------------------------------------|----------|---------|----------|---------|------|
| Our full model w/o UTC (VAL)               | 60.82    | 49.08   | 53.72    | 36.53   | 44.72|
| w/o UTC (TR+VAL)                           | 60.72    | 46.34   | 52.02    | 36.57   | 43.93|
| w/o GCN & UTC (TR+VAL)                     | 58.62    | 44.77   | 50.24    | 35.2    | 42.36|

Table 1: Comparison of performance with previous methods and results of ablation studies. We demonstrate the accuracies of each type of questions, Text T/F (true-false in text only), Text MC (multiple-choices in text only), Text all (all in text only), Diagram and All (total questions). Results of previous methods are on the top of the table and results of ablation studies are in the bottom.

- **BiDAF+DPG**: This method is another baseline proposed in [Kembhavi et al. (2017)]. It incorporates BiDAF (Bi-directional Attention Flow Network) (Seo et al. 2016), a recent machine comprehension model which exploits a bidirectional attention mechanism to capture dependencies between question and corresponding context paragraph. It also uses DPG for diagram questions.

  For above 3 models, we use experimental results newly reported in [Li et al. (2018)].

- **Challenge**: This is the one that obtained the top results in TQA competition (Kembhavi et al. 2017). The results in the table are mixed with each of top score in text-question track and the diagram-question track.

- **IGMN**: This method is proposed in [Li et al. (2018)]. It uses the Instructor Guidance with Memory Networks (IGMN) based on Contradiction Entity-Relationship Graph (CERG). For diagram questions, it only recognizes texts in diagrams.

  Following methods are for our ablation study:

- **Our full model**: This method uses both of our novel methods, GCN and unsupervised text comprehension (UTC) on the training and the validation sets.

- **Our model w/o UTC (VAL)**: This method only uses training set to pretrain parameters in unsupervised text comprehension.

- **Our model w/o UTC (TR+VAL)**: This method eliminates UTC pre-train process before supervised training. It only uses GCN as Graph extractor and was trained only in a normal supervised learning manner.

- **Our model w/o GCN & UTC (TR+VAL)**: This method ablates both GCN module and UTC process. It replaces GCN as vanilla RNN, other conditions are the same.

**Quantitative Results**

**Comparison of Results** Overall results on TQA dataset are shown in Table 1. The results show that our model outperforms other recent models in all type of question. Our best single model shows about 4% higher than state-of-the-art model in overall accuracy. Especially, an accuracy in text question significantly outperforms other results with over 7% margin. We believe that our two novel proposals, context graph understanding and unsupervised text comprehension work well on this problem. However, a result on diagram question shows slight improvement compared to other baselines. We tried to extract knowledge sentences from diagrams but it could not deliver enough information to solve questions.

  Compared to MemN+VQA and MemN+DPG, our model outperforms with large margin. Those two baselines only use memory networks to extract knowledge from lessons. Ours also shows better results than BiDAF+DPG which uses one of the most popular MC models in these days. Compared to memory network and the BiDAF, our graph-based approach seems to work well on this problem. Besides, while those methods treat all features of words in text, it can be more efficient to exploit graph structure due to abstraction capability of the graph.

  Our model with GCN shows better result compared to IGMN with about 3% margin. IGMN also exploits a graph module of contraction, but our model outperforms especially in both text problems, T/F and MC with over 5% margin. We believe that the graph in our method can directly represents feature of context and the GCN also plays an important role in extracting the features of our graph.
Because the base of the outer core is solid, movement within Earth’s outer liquid outer core is liquid, while the inner core is solid. Convection currents form in the outer core. These convection currents occur in the inner core. Qa) True. 

Ground Truth: (a)

We perform ablation experiments to evaluate each method respectively in Table 1. First, we observe apparent decrease of our model when any part of modules is eliminated. It is surprising that unsupervised text comprehension method provides improvement on our model. Our full model shows about 1% higher performance than the model without UTC(TR+VAL). It is also interesting to compare our full model with our model without UTC(VAL). The results show that using additional validation set on UTC can improve overall accuracy compared to using only training set. It seems to have more advantage for learning unknown dataset in advance.

Our model without GCN & UTC(TR+VAL) eliminates our two novel modules and replace GCN with vanilla RNN. That model shows 1% of performance degradation compared with the model without UTC(TR+VAL) which means that it might not sufficient to deal with knowledge features with only RNN and attention module. Thus, context graph we create for each lesson could give proper representations with GCN module.

Table 2 shows results of ablation study about occurrence flag. All models in Table 2 do not use UTC method. In [3], we concatenate three components including occurrence flag to create question or answer representation. We found that the occurrence flag which explicitly indicates existence of a corresponding word in the contexts has a meaningful effect on the results. As shown in Table 2 results of all types degrade significantly as ablating occurrence flags. Especially, eliminating a-flag drops accuracy about 7% which is almost 4 times higher than the decrease due to eliminating f-flag. We believe that disentangled features of answer candidates can mainly determine the results while a question feature equally affects all features of candidates. Lastly, our model without both flags shows the lowest results due to loss of representation power.

Qualitative Results

Figure 5 shows three qualitative results of text-type questions. We illustrate contexts, questions and answer candidates as well as related subgraphs of full context graphs. In subgraphs, gray circles represent words in questions and blue circles represent words related to answers. Green rectangles represent relation types of the dependency graph.

**Ablation Study**

We perform ablation experiments to evaluate each method respectively in Table 1. First, we observe apparent decrease of our model when any part of modules is eliminated. It is surprising that unsupervised text comprehension method provides improvement on our model. Our full model shows about 1% higher performance than the model without UTC(TR+VAL). It is also interesting to compare our full model with our model without UTC(VAL). The results show that using additional validation set on UTC can improve overall accuracy compared to using only training set. It seems to have more advantage for learning unknown dataset in advance.

Our model without GCN & UTC(TR+VAL) eliminates our two novel modules and replace GCN with vanilla RNN. That model shows 1% of performance degradation compared with the model without UTC(TR+VAL) which means that it might not sufficient to deal with knowledge features with only RNN and attention module. Thus, context graph we create for each lesson could give proper representations with GCN module.

Table 2 shows results of ablation study about occurrence flag. All models in Table 2 do not use UTC method. In [3], we concatenate three components including occurrence flag to create question or answer representation. We found that the occurrence flag which explicitly indicates existence of a corresponding word in the contexts has a meaningful effect on the results. As shown in Table 2 results of all types degrade significantly as ablating occurrence flags. Especially, eliminating a-flag drops accuracy about 7% which is almost 4 times higher than the decrease due to eliminating f-flag. We believe that disentangled features of answer candidates can mainly determine the results while a question feature equally affects all features of candidates. Lastly, our model without both flags shows the lowest results due to loss of representation power.

Qualitative Results

Figure 5 shows three qualitative results of text-type questions. We illustrate contexts, questions and answer candidates as well as related subgraphs of full context graphs. In subgraphs, gray circles represent words in questions and blue circles mean words related to answers. Green rectangles represent relation types of the dependency graph.

The first example describes a pipeline on a T/F question. Three words, “currents”, “core” and “convection” are set as anchor nodes as shown in the left of Figure 5. Within two levels of depth, we can find “outer” node which is the opposite to “inner” in the question sentence. As a result, our model predicts the true and false probabilities of this question as 0.332 and 0.668, respectively, and correctly solves this problem as a false statement.

The last example shows a more complicated multiple choice problem. In the context graph, we set “organelle”, “recycles”, “molecules” and “unneeded” as anchor nodes with each word in answer candidates. Then we can easily find an important term, “lysosome” in choice (a). Therefore, choice (a) has a probability close to one among 7 candidates. These examples demonstrate abstraction ability and relationship expressiveness which can be huge advantages of graphs. Moreover, those results could support that our model can explicitly interpret the process of solving QA problems.

**Conclusion**

In this paper, we proposed two novel methods to solve TQA problems which are more realistic than other QA datasets. We tackle two main issues to improve model capacity based on the analysis of the TQA dataset. To comprehend scientific contexts well in long lessons, we extract knowledge feature by building knowledge graphs and exploiting GCN as a feature extractor. Next, we add a novel unsupervised text learning process before learning specific QA problems to overcome the out-of-domain issue.

Our method demonstrates state-of-the-art results compared to previous results. And we also present qualitative results to show our process explicitly. We believe that our
work can be a meaningful step in realistic QA applications and solving the out-of-domain issue in the field of NLP.

References

[Defferrard, Bresson, and Vandergheynst 2016] Defferrard, M.; Bresson, X.; and Vandergheynst, P. 2016. Convolutional neural networks on graphs with fast localized spectral filtering. In Advances in Neural Information Processing Systems, 3844–3852.

[Fukui et al. 2016] Fukui, A.; Park, D. H.; Yang, D.; Rohrbach, A.; Darrell, T.; and Rohrbach, M. 2016. Multimodal compact bilinear pooling for visual question answering and visual grounding. arXiv preprint arXiv:1606.01847.

[Johnson et al. 2017] Johnson, J.; Hariharan, B.; van der Maaten, L.; Fei-Fei, L.; Zitnick, C. L.; and Girshick, R. 2017. Clevr: A diagnostic dataset for compositional language and elementary visual reasoning. In Computer Vision and Pattern Recognition (CVPR), 2017 IEEE Conference on, 1988–1997. IEEE.

[Kembhavi et al. 2016] Kembhavi, A.; Salvato, M.; Kolve, E.; Seo, M.; Hajishirzi, H.; and Farhadi, A. 2016. A diagram is worth a dozen images. In European Conference on Computer Vision, 235–251. Springer.

[Kembhavi et al. 2017] Kembhavi, A.; Seo, M.; Schwenk, D.; Choi, J.; Farhadi, A.; and Hajishirzi, H. 2017. Are you smarter than a sixth grader? textbook question answering for multimodal machine comprehension. In 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 5376–5384. IEEE.

[Kim et al. 2017] Kim, D.; Yoo, Y.; Kim, J.; Lee, S.; and Kwak, N. 2017. Dynamic graph generation network: Generating relational knowledge from diagrams. arXiv preprint arXiv:1711.09528.

[Kipf and Welling 2016] Kipf, T. N., and Welling, M. 2016. Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907.

[Li et al. 2018] Li, J.; Su, H.; Zhu, J.; Wang, S.; and Zhang, B. 2018. Textbook question answering under instructor guidance with memory networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 3655–3663.

[Lu et al. 2016] Lu, J.; Yang, J.; Batra, D.; and Parikh, D. 2016. Hierarchical question-image co-attention for visual question answering. In Advances In Neural Information Processing Systems, 289–297.

[Manning et al. 2014] Manning, C.; Surdeanu, M.; Bauer, J.; Finkel, J.; Bethard, S.; and McClosky, D. 2014. The stanford corenlp natural language processing toolkit. In Proceedings of 52nd annual meeting of the association for computational linguistics: system demonstrations, 55–60.

[Nguyen et al. 2016] Nguyen, T.; Rosenberg, M.; Song, X.; Gao, J.; Tiwary, S.; Majumder, R.; and Deng, L. 2016. Ms marco: A human generated machine reading comprehension dataset. arXiv preprint arXiv:1611.09268.

[Pennington, Socher, and Manning 2014] Pennington, J.; Socher, R.; and Manning, C. 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), 1532–1543.

[Rajpurkar et al. 2016] Rajpurkar, P.; Zhang, J.; Lopyrev, K.; and Liang, P. 2016. Squad: 100,000+ questions for machine comprehension of text. arXiv preprint arXiv:1606.05250.

[Richardson, Burges, and Renshaw 2013] Richardson, M.; Burges, C. J.; and Renshaw, E. 2013. Mctest: A challenge dataset for the open-domain machine comprehension of text. In Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing, 193–203.

[Seo et al. 2016] Seo, M.; Kembhavi, A.; Farhadi, A.; and Hajishirzi, H. 2016. Bidirectional attention flow for machine comprehension. arXiv preprint arXiv:1611.01603.

[Xu and Saenko 2016] Xu, H., and Saenko, K. 2016. Ask, attend and answer: Exploring question-guided spatial attention for visual question answering. In European Conference on Computer Vision, 451–466. Springer.

[Yang et al. 2016] Yang, Z.; He, X.; Gao, J.; Deng, L.; and Smola, A. 2016. Stacked attention networks for image question answering. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 21–29.

[Yu et al.] Yu, Z.; Yu, J.; Fan, J.; and Tao, D. Multi-modal factorized bilinear pooling with co-attention learning for visual question answering.