Type-dependent prompt CycleQAG:
Cycle consistency for Multi-hop Question Generation

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Abstract

Multi-hop question generation (QG) is the process of generating answer related questions, which requires aggregating multiple pieces of information and reasoning from different parts of the texts. This is opposed to single-hop QG which generates questions from sentences containing an answer in a given paragraph. Single-hop QG requires no reasoning or complexity, while multi-hop QG often requires logical reasoning to derive an answer related question, making it a dual task. Not enough research has been made on the multi-hop QG due to its complexity. Also, a question should be created using the question type and words related to the correct answer as a prompt so that multi-hop questions can get more information. In this view, we propose a new type-dependent prompt cycleQAG (cyclic question-answer-generation), with a cycle consistency loss in which QG and Question Answering (QA) are learnt in a cyclic manner. The novelty is that the cycle consistency loss uses the negative cross entropy to generate syntactically diverse questions that enable selecting different word representations. Empirical evaluation on the multi-hop dataset with automatic and human evaluation metrics outperforms the baseline model by about 10.38% based on ROUGE score.

1 Introduction

Question Generation (QG) problem that automatically generates a question from a given document with a correct answer is a challenging and an interesting task in the field of natural language processing (Chan and Fan, 2019; Pan et al., 2021; Yu et al., 2020; Dong et al., 2019). With the advent of deep learning, the pre-trained language models (Devlin et al., 2019; Radford et al., 2018; Liu et al., 2019; Raffel et al., 2020; Clark et al., 2020; Peng et al., 2021) were proposed, after which the study of natural language processing began to develop rapidly.

These works not only use single-hop QA dataset such as SQuAD (Rajpurkar et al., 2016), which is a representative of research on Question Answering (QA), but also the multi-hop QA dataset such as HotpotQA (Yang et al., 2018). The QA dataset consists of (Context, Question, Answer) pairs along with a lot of QA data, that enables research on Automatic Question Generation (AQG). Most of the question generation methods evaluated questions using the single-hop QA datasets (Duan et al., 2017; Du et al., 2017; Sultan et al., 2020). However, in real-world situations, the questions can be very complex and sometimes require a complicated reasoning process (Gupta et al., 2020; Pan et al., 2021; Yu et al., 2020).

Multi-hop QG requires combining several pieces of information and reasoning over them to derive an answer related a question, making it a dual task. Multi-hop questions that can be encountered in the real world are largely divided into two types, bridges and comparisons. As shown in Fig. 1, the middle side is an example of a bridge-type question. When the question is “Who played Selby Wall in the film that Charlize Theron won an Academy Award for?”, the first thing we need to know is what film Theron won the Academy Award. Second, we should be able to obtain information about the actors who played Selby Wall among the actors in the movie. Here, Monster, the movie that connects the two, serves as a bridge. On the other hand, the comparison type shown on the right side of Fig. 1 is to create a question that can be answered by comparing two objects.

Some of the methods for multi-hop QG transform the input text into an intermediate representation such as a parsing tree (Ji et al., 2021), and then convert the resulting form into a question by some well-designed templates or general rules. In (Gupta et al., 2020), they use multi-task learning with an auxiliary loss for sentence-level supporting fact prediction. Graph-based methods (Su et al.,
Figure 1: Examples of Single-hop QAG and Multi-hop QAG pair in HotpotQA (Yang et al., 2018) dataset. Multi-hop QG for reasoning multi-hop by finding the contact points between the given Answer and supporting facts A and B. The left is a bridge type, and the right is an example of a comparison type multi-hop question. Both question types are multi-hop, but generate questions with different characteristics.

2 Related Works

Question Answering. Machine reading comprehension (MRC) is originally inspired by language proficiency tests, and the machine aims to answer a question by reading and understanding a given context (Zhu et al., 2021). (Seo et al., 2016) introduced the Bi-Directional Attention Flow (BIDAF) network, and proposed a model structure to represent contexts at various levels using a multi-level hierarchical structure. QANet (Yu et al., 2018) models an architecture that does not require a recurrent network and only consists of a convolution model and self-attention. Recently, research on new multi-hop QA datasets that require more complex and diverse information, such as HotpotQA (Yang et al., 2018), HybridQA (Chen et al., 2020), MultiModalQA (Talmor et al., 2021), is being actively conducted. For example, (Xiong et al., 2021) used a simple recursive framework to solve open domain multi-hop QA, and configured the model to use dense search for multi-hop setups. In this work, we propose a method to solve multi-hop QA reasoning by a top-down approach to find a specific answer in a whole context.
**Question Generation.** The ultimate goal of the QG task is to automatically generate questions from texts or knowledge data. With the advent of machine reading comprehension datasets such as SQuAD and pre-trained language models, QG research is conducting the multi-hop reasoning research that deals with more complex and inference-demanding thorny questions, to mimic humans (Pan et al., 2020; Yu et al., 2020; Pan et al., 2021). (Yu et al., 2020) proposed a whole generator evaluator network for generating questions by creating an entity graph to integrate various entities scattered in the texts. (Pan et al., 2021) proposed a multi-hop QG method that used predefined basic operators to search, generate, and aggregate information of each input according to the types of inputs. They also defined and used six inference types of reasoning graphs. In particular, an off-the-shelf template was used for generating a comparison type question that compares two subjects. Although such pre-defined templates or structured models can generate accurate questions for given data, they can be fatal in both quantitative and qualitative aspects when new complex data are given. To overcome some of these issues, we propose a new end-to-end approach to generate multi-hop questions.

**Dual task of QA and QG.** QA and QG are separate but closely related tasks. In (Tang et al., 2017), they jointly train the two tasks by exploiting the probabilistic correlation between QA and QG. In particular, the parameterized model was jointly trained to minimize the loss function according to the constraints. (Duan et al., 2017) used question generation as an auxiliary task to improve the text-based QA task. They calculated the relevance score between the input question and the answer candidates, and chose the highest relevance score as a correct answer. (Sun et al., 2020) generated additional training instances to further improve the QA model in (Tang et al., 2017), each consists of a question, an answer, and a label for a category. In addition, the question was created by clamping the answer part and providing the answer to the QG model. Many efforts have been made to improve each module by using QA and QG together. In this view, we not only propose a method of using cycle consistency to increase the robustness of QA and QG but also introduce the NCE that increases the diversity of questions.

### 3 Proposed model

The proposed model for question generation includes an intermediate task execution phase before the fine-tuning step. In the intermediate task, QA and QG are trained to have cycle consistency, where question paraphrasing and similarity are additionally used to increase the robustness of the question generation. We focus on using the multi-hop QG and QA together as a supplement to increase the performance of QG. We define QA as the top-down approach to find a right answer, and QG as the bottom-up approach to use abundant information from entities or sentences. The overall framework of our proposed model is explained in Fig. 2.

#### 3.1 Intermediate Task Training

The intermediate task is to fine-tune the pre-trained model for a task of interest before fine-tuning. We fine-tune the models used for the intermediate task based on the Google-T5 model (Raffel et al., 2020). In the intermediate task stage, QA and QG learn the "cycle consistency". This property was first introduced in the back-translation by Brislin (Brislin, 1970). This translates English to French, and translates the translated French back to English so that the original sentence can be reconstructed. Mathematically, this can be represented as a translator \( G : X \rightarrow Y, F : Y \rightarrow X \), where \( G \) and \( F \) are inverse of each other, and are connected like a bijection. Inspired by those properties, when generating questions and answers in the intermediate stage, the proposed QG and QA model uses a cycle-consistency loss that exchanges inputs and outputs in the reverse direction, respectively.

#### 3.1.1 Question Generation

We attempt to handle the multi-hop question generation using the answers and the context. First, we use Google-T5 (Raffel et al., 2020) as the baseline model to automatically generate the output question with a given input answer. While generating a question, as introduced in (Chan and Fan, 2019), there may be more than one instance of the same tokens as the correct answer in the context, then it may be confusing for the model to focus on question generation, we surround the annotated answer span tokens in the context with two tokens. Therefore, the format of the input can be represented as <sep>
Figure 2: The framework of our proposed model. The proposed model configures QA and QG to learn cycle consistency (a). In the intermediate task, it is possible to create richer questions and more accurate answers through QA and QG interaction. In (b) and (c), the process of QGA-consistency and QAG-consistency to which cycle consistency is applied is shown in detail.

$c_1, c_2, c_3 <\text{hl}>$, answer $<\text{hl}>$, $c_4, c_5, ..., c_m <\text{sep}>$, where $c_i$ is token of the context. The question generation module of the proposed model not only generates single-hop questions but also produces complex multi-hop questions that require multiple pieces of information. We train the model in such a way that the proposed QG module generates semantically similar and syntactically diverse questions. In particular, we introduce the NCE and the cross-entropy (CE) loss to train a QG model that generates more lexically diverse questions. It controls the probability of adopting information so that it can be semantically similar but syntactically diverse. When training QG, unlike in previous studies, we use the NCE. The probability of occurrence of a word can be lowered, but the essential meaning of a word does not change, thereby enriching the diversity of meaning.

Negative Cross Entropy loss (NCE loss). We use the NCE loss to generate questions more diverse. In general, most studies use the cross entropy (CE) to better train the model to maximize the probability of the correct class (Marek et al., 2021). However, as shown in Fig. 2 (a), in order to generate questions with a more diverse vocabulary for the bottom-up QG, we use the NCE to flatten the word occurrence probability distribution and increase the diversity of vocabulary. In this work, we use the NCE loss to reduce the distance between the predicted value and the actual value such that the generated question has similar meaning with increased lexical diversity.

Question Paraphrasing. In addition, to increase the robustness of the QG module, several questions are generated through a question paraphrasing process. This enables QG with the same meaning but different expressions. We use a paraphrasing model fine-tuned in advance using a Google-T5 model which was Quora Question Pair (QQP) * as the question paraphrasing dataset.

Similarity for generated paraphrasing question. Since it is important to ensure that the meaning of the generated question is the same even if a question with various expressions is generated, the similarity of the generated question should be measured. To find the similarity among paraphrased questions, Sentence-BERT (SBERT) is used, and the overall method is the same as that introduced in (Reimers and Gurevych, 2019), but uses T5 instead

*<https://www.kaggle.com/c/quora-question-pairs>
of BERT. We set the similarity value between 0 and 1. The similarity value obtained during the learning process is converted to $1 - \text{similarity}$ to train the model in such a way that the loss value decreases as the similarity increases.

Algorithm 1 Procedure of CycleQAG Framework

**Input:** Context = $(c_1, \ldots, c_n)$, Answer for QG

**Context = $(c_1, \ldots, c_n)$, Question for QA**

**Output:** Multi-hop Question

1. Initial QG ← Generate question by QG Input
2. Paraphrasing the generated question
3. Calculate the cosine-similarity between the generated questions and the original question
4. Initial QA ← Generate answer by QA Input
5. for $k ← 1$ to $N$ do
6. $C_k ← \text{cycle}(QA, QG)$
7. end for
8. return Multi-hop question, answer

3.1.2 Question Answering

To build a model that infers an answer using a given (question, passage) pair, the QA model is also trained using the Google-T5 model. In this paper, QA is used to improve the performance of QG, where the ultimate goal of the QA model is to approach the sentence related to the question in a given paragraph and access a correct answer.

3.1.3 Answer related words generation

Multi-hop QG requires more than two pieces of information when asking a question that can fit a correct answer. This requires gathering information in order to create a question. To this end, we use the title information of each supporting paragraph provided as in Fig. 1 to generate words related to a correct answer. Usually, the titles help by providing significant information in generating questions to arrive at a correct answer. We explain this in the appendix C with examples.

3.1.4 Cycle Consistency

We propose the cycle consistency which is widely used in the image field for QG and QA. By using this method, as shown in Fig. 2, QG and QA modules can help generate a robust model that can match the question and answer, respectively. There are not many, but existing multi-hop QG models use graphs or templates (Pan et al., 2021; Su et al., 2020; Kumar et al., 2019). However, we introduce the cycle consistency loss to train a text-based model that can learn by an end-to-end manner. We define the cycle consistency loss to reduce the difference between the predicted value and the actual value. The overall learning flow of the model with cycle consistency is given in Fig. 2 (a). Fig. 2 (b) refers to the QGA-consistency which predicts a question through QG using a given context and an answer, and then predicts an answer through the QA again. Conversely, Fig. 2 (c) refers to QAG-consistency for finding an answer with QA using a given context and a question and then predicting the question with QG. In here, the process flow shown in Fig. 2 (b) is to predict a correct answer, and it is necessary to predict question well through QG to predict correct answer through QA as shown in Fig. 2 (c). Our model uses the cycle consistency property so that answers and questions are learnt better. We describe the overall flow of the CycleQAG framework in Algorithm 1. In algorithm 1, N is the number of samples of the dataset and we use a common early stopping approach for cycle training.

3.2 Prompt-based fine-tuning

We use the multi-hop dataset for fine-tuning a target task after training an intermediate task. Unlike general fine-tuning, the prompt-based fine-tuning adds an element called a prompt. Prompt shows that GPT-3 (Brown et al., 2020) achieves remarkable performance in a few-shot setting, and has been used in many recent studies (Shin et al., 2020; Lester et al., 2021; Gao et al., 2021). In particular, prompt-based fine-tuning (PFT) aims to investigate the knowledge gained from pre-training by reducing the distribution gap between pre-training and fine-tuning stages. Considering these points, we use PFT instead of fine-tuning to make most of the information obtained from the intermediate task. The detailed process of the PFT process is described in Algorithm 2.

A multi-hop QG aims to generate a question using several pieces of information related to a correct answer. For this, we construct a prompt by extracting words related to a correct answer from an intermediate task. This not only uses the types of questions and the correct answers, but also words
Algorithm 2 Procedure of Type-dependent prompt fine-tuning for QG

**Input**: Prompt (P) ; Context with answer (X)

**Output**: Multi-hop Question (Y)

1: Configure required prompt token per context
2: Merge prompt token and context with answer
3: Maximize the likelihood of multi-hop question Y.
4: return $P_{R_{\theta}}(Y|[P; X])$, while keeping the model parameters, $\theta$, fixed.

related to the correct answers obtained from section 3.1.3 as a prompt. This enables providing more information when generating multi-hop questions. We show the results of questions obtained through PFT in appendix C.

3.3 Model Training

In this section, we describe in detail how the model trains an intermediate task. The total loss of the intermediate task consists of QA loss, QG loss, cycle consistency loss, and similarity loss. Therefore the loss is given by Eq. (1).

$$L_{\text{All}} = L_{QA} + L_{QG} + L_{\text{cycle}} + L_{\text{sim}}$$ (1)

Eq. (2) defines the cycle consistency loss which includes the loss for QA model and loss for QG. We learn QA and QG cyclically with the cycle consistency loss, allowing QA to narrow the range of correct answers, and QG to express more questions in an enriched expression. The similarity loss $L_{\text{sim}}$ determines whether the paraphrased questions are semantically close while learning the QG. $L_{QA}$ uses CE loss to find a right answer for a given question. $L_{QG}$ uses the CE loss and the NCE loss to generate a variety of questions that are similar to the original question.

$$L_{\text{cycle}} = \frac{1}{2} \left[ L_{CE}^{\text{QGA}} + \left\{ \lambda_1 L_{NCE} + (1 - \lambda_1) L_{CE}^{\text{QAG}} \right\} \right]$$ (2)

The first term of $L_{\text{cycle}}$ for learning the cycle-consistency is the loss obtained using the QGA-consistency, which is explained in section 3.1.4 and Fig. 2 (b). Here, the QGA learns to get closer to an original answer by generating a question using a answer and context and then generates a correct answer through the QA again. The remaining terms of the $L_{\text{cycle}}$ describe the process of learning the QAG-consistency in Fig. 2(c). While the previous methods use the CE alone, we propose to use the NCE to train the QAG consistency to improve diversity. The QAG learns to get closer to an original question by performing QG through QA. In this part, we adjust the NCE and the CE with $\lambda_1$ so that the semantic and the lexical are properly balanced.

For generating questions with a similar meaning, to increase the diversity of questions and reduce the occurrence of most probability words, we use the NCE as shown in Eq. (3). In other words, it is intended to flatten the probability of occurrence of words, so that words can appear in various ways.

$$L_{NCE} = \frac{1}{N} \sum_{i=1}^{N} y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)$$ (3)

However, if the model is trained only using Eq. (3), NCE may diverge (to $-\infty$), so we adjust the Eq. (4) and hyperparameter $\lambda_1$ values such that the probability of the word appearing in the question is lowered only to a certain level. We heuristically adjust $\lambda_1$ as 0.2.

$$L_{CE} = -\frac{1}{N} \sum_{i=1}^{N} y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)$$ (4)

4 Experiments

In the following experiments, we evaluate multi-hop QG based on semantic similarity and lexical diversity. We also evaluate whether the intermediate task has an affect on QG module performance. The baseline model is initialized with a Google-T5 model from HuggingFace Transformer (Wolf et al., 2020), fine-tuned with 3 epochs, with batch size 8. The GPU used in the experiment is 4 Quadro RTX 8000.

4.1 Dataset

We evaluate our model with a focus on multi-hop QA, HotpotQA (Yang et al., 2018). HotpotQA is a multi-hop dataset that is more complex and requires reasoning than existing single-hop QA datasets. As mentioned in RefNet (Nema et al., 2019), since the test set of HotpotQA is hidden, the validation set is used as the test set, and a part of the training set is used as a validation set. In the experiments, a dataset similar to the HotpotQA
Table 1: Performance comparison with baseline and the ablation study. The best performance is bold.

| MODEL                           | BLEU1 | BLEU2 | BLEU3 | BLEU4 | METEOR | ROUGE-L |
|---------------------------------|-------|-------|-------|-------|--------|---------|
| Baselines                       |       |       |       |       |        |         |
| B1. MQA-QG                      | 36.05 | 25.79 | 21.88 | 17.83 | 26.89  | 39.95   |
| B2. BART                        | 36.35 | 26.70 | 22.42 | 18.02 | 26.96  | 40.85   |
| B3. Google-T5                   | 36.89 | 26.89 | 22.14 | 18.27 | 27.26  | 41.02   |
| Proposed                        |       |       |       |       |        |         |
| P1. Type-dependent prompt CycleQAG | **38.28** | **29.77** | **24.32** | **20.51** | **29.01** | **44.10** |
| Ablation                        |       |       |       |       |        |         |
| A1. w/o type-dependent prompt   | 36.47 | 27.61 | 22.45 | 18.24 | 27.94  | 42.34   |
| A2. w/o Cycle (intermediate task) | 36.96  | 27.88 | 22.91 | 18.98 | 27.70  | 41.90   |
| A3. w/o similarity, paraphrase  | 37.20 | 28.18 | 23.11 | 19.33 | 28.57  | 43.44   |

Table 2: Performance of BERTSCORE. The best performance is bold.

| MODEL                              | BERTSCORE |
|------------------------------------|-----------|
| MQA-QG                             | 93.87     |
| BART-large                         | 91.03     |
| Google-T5                         | 91.27     |
| Type-dependent prompt CycleQAG (ours) | 91.94     |
| CycleQAG w/o type-dependent prompt |         |
| CycleQAG w/o Cycle                 | 91.94     |
| CycleQAG w/o similarity, paraphrase| 92.93     |

4.2 Baselines

Since the multi-hop QG has not yet been explored much, there are few comparison models that can be compared with ours. We use a text-based multi-hop QG model and a model with excellent performance in QG research as our baseline models.

MQA-QG (Pan et al., 2021) generates a question according to a predefined reasoning graph according to the types of questions. In particular, they defined and used 11 templates for comparison type questions. We experiment with the same experiment settings as published in their paper. BART (Lewis et al., 2020) is a model that combines a Bidirectional Transformer and an Auto-Regressor Transformer, and is a pre-trained model using the denoising autoencoder method. In particular, it shows excellent performance in natural language generation. Google-T5 (Raffel et al., 2020) processes the NLP task using the text-to-text input and the output using C4 (Colossal Clean Crawled Corpus), a very large dataset and achieves the highest level in benchmarks such as SuperGLUE. We implement it using open code published by hug-

gingface‡ for BART and Google-T5.

4.3 Multi-hop QG Results and Analysis

Quantitative automatic evaluation and qualitative human evaluation are used to evaluate our proposed model. To this end, we describe in detail the automatic and human evaluation methods and discuss the results.

4.3.1 Automatic Evaluation Metrics

We perform automatic evaluation using n-gram and pre-trained language model based metrics.

N-gram based Metrics. BLEU (Papineni et al., 2002) score is a precision-based evaluation that computes the overlap of n-grams. METEOR (Lavie and Agarwal, 2007) is a relaxed F-measure-based evaluation method in which the unigrams of the hypothesis and the reference do not have an exact level of agreement, but they are synonymous. ROUGE-L (Lin, 2004) is a measure of the sequence of the longest common part between a pair of sentences (Sai et al., 2022). We use the nlg-eval § package released by (Sharma et al., 2017) to evaluate an n-gram-based metric.

Pre-trained Language Model based Metrics. BERTSCORE (Zhang* et al., 2020) is a method of evaluating NLG and computes a similarity score of each token of the candidate correct answer and the ground truth. Whereas existing evaluation methods evaluate based on exact match, BERTSCORE is

‡https://huggingface.co/
§https://github.com/Maluuba/nlg-eval
effective for paraphrase detection because it uses contextual embedding (Devlin et al., 2019). We download the package for bert-score from (Zhang* et al., 2020)\textsuperscript{4} and use it.

**Results and Analysis.** We compare the QG performance of the proposed type-dependent prompt CycleQAG model with baseline models and show the automatic metric results in Table 1. Our type-dependent prompt CycleQAG model outperforms all automatic evaluation metrics including ROUGE-L when compared to other models using the same data. Tables 2 indicates whether contextual meaning can be reflected, where BERTSCORE shows excellent performance. Also, it can be seen that they are semantically similar to the original question.

**Ablation study.** In order to understand the influence of the components of our proposed model, we conduct an ablation study with experimental data for type-dependent prompt CycleQAG. When we do not use the fine-tuning of the type-dependent prompt format that we suggest, it can be observed that the performance is lowered. It can also be observed that the presence or absence of additional information determines the performance improvement when performing a fine-tuning. The additional information referred to here is the types of questions and words related to the answer. We confirm through experiments that their role helps to improve overall performance. Also, fine-tuning the data without the cycle-consistency loss performed in the intermediate task stage, overall performance is degraded. This confirms that the intermediate task is helpful in the QG module when comparing the performance with B3 as shown in Table 1. When we train to generate questions in an intermediate task, we use paraphrase and similarity methods together to increase the lexical diversity of questions. If these methods are removed and tested, the overall performance is slightly degraded.

| MODEL | Fluency | Relevance | Answerability | Complexity | Diversity |
|-------|---------|-----------|---------------|------------|-----------|
| MQA-QG | 2.45    | 2.38      | 2.42          | 2.35       | 2.35      |
| BART  | 2.28    | 2.14      | 2.30          | 2.29       | 2.34      |
| Google-T5 | 2.39    | 2.42      | 2.45          | 2.40       | 2.47      |
| Type-dependent prompt CycleQAG (ours) | **2.56** | **2.62** | **2.59**     | **2.53**   | **2.66** |

Table 3: Human Evaluation Results.

### 4.3.2 Human Evaluation

In this section, we discuss the human evaluation metric. We employ fluency, relevance, answerability, complexity and diversity. Human evaluation is an additional support method for the reliability and robustness of automated evaluation. Here, we use fluency, relevance, and answerability to measure the quality of whether our proposed question is relevant to a given context and answer. Multi-hop QG has high complexity because it requires reasoning, and it is necessary to measure the complexity of the generated question. In addition, we use diversity to evaluate cases in which vocabulary expressions are expressed in various ways, although the meaning of the question is the same. We randomly select 50 question-and-answer pairs from the test set from 20 annotators to obtain evaluations of our model and other baseline models. In human evaluation, we perform the evaluations in a blind format. The range of scores used for evaluation is set to 1-3, and the higher the score, the better the evaluation. The results are shown in Table 3. Overall we consistently get better performance than the conventional models like the BART and Google-T5. We obtain significantly better results than other reference models, especially in terms of diversity and complexity.

## 5 Conclusion

In this work, we propose type-dependent prompt CycleQAG with cycle consistency. Since multi-hop QG needs to know more diverse information because it needs to gather more scattered pieces of information for generating a question, we introduce the NCE for the first time in the QG task. Also, we demonstrate that the intermediate task is effective in the QG task. Furthermore, we show a significant performance improvement by using prompt-style fine-tuning to make the most of the information obtained from the intermediate task. The experiments show that the proposed model outperforms in all automatic evaluations comparing with the existing text-based multi-hop model and several QG models. Although we use only multi-hop, single-hop-based
datasets, experiments can be performed without additional datasets later using the type-dependent prompt CycleQAG method. In other words, it is possible to learn QA and QG models using unsupervised learning. In the future, we would like to investigate a model that generates questions and answers by itself enough to imitate humans from knowledge through self-cyclic learning that is less influenced by data.

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Appendix

A Data statistics

| Dataset   | Data type   | Train set | Validation set | Test set |
|-----------|-------------|-----------|----------------|---------|
| HotpotQA  | All         | 90.4k     | 7.4k           | 7.4k    |
|           | Bridge type | 58.5k     | 5.9k           | (invisible) |
|           | Comparison type | 17.4k     | 1.5k           | (invisible) |
|           | Single-hop  | 14.5k     | -              | -       |
| SQuAD     | Single-hop  | 87.5k     | 10.5k          | -       |
| QQP       | Paraphrase  | 254k      | 10k            | 10k     |

Table A1: Statistics of Datasets. Number of data instances in the train, validation and test set of HotpotQA, SQuAD and Quora Question Pairs (QQP).

Table A1 is a statistic of the dataset used in the experiment. HotpotQA provides two dataset versions, a distractor setting and a full wiki setting. In this paper, we conduct all experiments on a distractor setting with 2 gold paragraphs and 8 distractor paragraphs. We use training and validation sets provided by HotpotQA to train and evaluate the model. The SQuAD dataset is similar to HotpotQA dataset, the answer to each question can be found in the form of a text span in the paragraph, and it consists of data that can answer diverse types of questions. The QQP dataset detects whether the intent of two given pairs of sentences is the same, and provides a label on whether the two sentences are semantically similar. The QQP dataset consists of more than 400,000 lines of potential question duplicate pairs, with a binary value indicating whether that row contains duplicate pairs. We obtain HotpotQA, SQuAD data through the datasets package provided by HuggingFace and use it for experiments, which can be downloaded from https://huggingface.co/datasets. QQP dataset can be downloaded from https://www.kaggle.com/c/quora-question-pairs.

B Error Analysis

We perform error analysis to analyze the experimental results. In Table A2, Case1 has the same meaning, but only the expression of the lexicon is different, which is a well-predicted case. However, in Case 2, an important entity is omitted, so the meaning of the question is completely changed, and the gist of the question cannot be grasped. In this question, an important "traditional sport considered a national sport" is predicted with the word "traditional", so it is an erroneously generated question because an entity related to the sport is omitted. This is not a well-formed question because we cannot conversely answer the question properly. Case 3 is the case of making a semantic error. The ground truth of Case 3 is to ask whether Mozart wrote Pomone or Idomeneo, but the meaning of the predicted question is a semantically different question because it asks which of Pomone or Idomeno premiered first. Case 4 is the case of generating a completely wrong question, where the intent of the question is completely changed by incorrectly predicting the meaning of "and" as "unlike".

| Types   | Example                                                                 |
|---------|-------------------------------------------------------------------------|
| Case1   | (GT.) Who was the director of the James Bond movie in which Anatole Taubman appeared as a henchman?  
(Pred.) Who directed the James Bond movie in which Anatole Taubman appeared as a henchman? |
| Case2   | (GT.) Which old, traditional sport is considered to be the national sport by some Swiss? 
(Pred.) What is an old tradition from the rural central cantons? |
| Case3   | (GT.) Of Pomone and Idomeneo which one was written by Amadeus Mozart?  
(Pred.) Which opera premiered first, Pomone or Idomeneo? |
| Case4   | (GT.) Unlike Xuzhou, where is Rugao under the administration of?  
(Pred.) Rugao and Xuzhou, Jiangsu are both county-level cities under the administration of who? |

Table A2: Error Analysis. GT is ground truth, and Pred is prediction example.
C Experimental result examples

In this section, an example of generating a multi-hop question using the type-dependent prompt CycleQAG method presented by us is shown in detail. In Table A3 and A4, we mark the correct answer we want to obtain in red text and the words related to the correct answer obtained through section 3.1.3 in blue text. If the correct answer and the word related to the correct answer overlap, it is indicated in cyan text. In particular, we can confirm that the meaning of the original question and the generated question did not change, but a vocabulary with a similar meaning was used, making the question richer. In addition, it can be seen through the example of the generated question that it has a considerable influence when generating a question by using the question type, answer, and answer-related words as a prompt. More specifically, in prompt based fine-tuning, we set the input as question type: type of question, answer-related words: combination of words related to the correct answer, context: context with answer and set the output to multi-hop question.

| Data Fields                  | Example                                                                 |
|-----------------------------|-------------------------------------------------------------------------|
| **Answer**                  | Jacksonville station                                                    |
| **Generated answer related words** | Silver Meteor, Jacksonville station                                     |
| **Context**                 | The Silver Meteor is a passenger train operated by Amtrak between New York City and Miami, Florida. The first diesel-powered streamliner between New York and Florida, since being introduced by the Seaboard Air Line Railroad (SAL) in 1939, it remains in operation now. The train is part of Amtrak’s “Silver Service” along with the “Silver Star”, another former SAL streamliner. Jacksonville station is an Amtrak train station in Jacksonville, Florida, United States. It serves the “Silver Meteor” and “Silver Star” trains as well as the Thruway Motorcoach to Lakeland. The station lies next door to a freight facility with its own platform and is also just east of Norfolk Southern’s Simpson Yard. |
| **Original question**       | Where does the train that runs from NYC and Miami station at Florida?   |
| **Generated question**      | Which Amtrak station serves the passenger train operated by Amtrak between New York City and Miami, Florida? |
| **Answer**                  | Julianne Moore                                                          |
| **Generated answer related words** | Emanuelle Goes to Dinosaur Land, Julianne Moore                        |
| **Context**                 | "Emanuelle Goes to Dinosaur Land" is the of the fourth season of the American television comedy series “30 Rock”, and the 79th overall episode of the series. It was written by supervising producer Matt Hubbard and directed by Beth McCarthy-Miller. The episode originally aired on the National Broadcasting Company (NBC) network in the United States on May 13, 2010. Guest stars in this episode include John Anderson, Elizabeth Banks, Jon Hamm, Kristin McGee, Julianne Moore, Michael Sheen, Jason Sudeikis, and Dean Winters. Julianne Moore (born Julie Anne Smith; December 3, 1960) is an American actress, prolific in films since the early 1990s. She is particularly known for her portrayals of emotionally troubled women in both independent and Hollywood films, and has received many accolades, including the 2014 Academy Award for Best Actress. |
| **Original question**       | What 2014 Academy Award winner guest starred in "Emanuelle Goes to Dinosaur Land"? |
| **Generated question**      | Which guest star in "Emanuelle Goes to Dinosaur Land" won the 2014 Academy Award for Best Actress? |
| **Answer**                  | Lantern Waste                                                           |
| **Generated answer related words** | Lantern Waste, Tumnus                                                   |
| **Context**                 | Lantern Waste is a fictional place in "The Chronicles of Narnia" series by C. S. Lewis. It is a wood and is notable as the place where Lucy Pevensie and Mr. Tumnus meet, which is the first scene of Narnia described in the books. The lamppost in the wood is an iconic image of Narnia, and the question of its origin is what convinced Lewis to write more than one book on Narnia. One of King Edmund’s titles is "Duke of Lantern Waste". Tumnus is a fictional character in C. S. Lewis’ series “The Chronicles of Narnia”. He is featured prominently in "The Lion, the Witch and the Wardrobe" and also appears in "The Horse and His Boy" and "The Last Battle". He is close friends with Lucy Pevensie and is the first creature she meets in Narnia, as well as the first Narnian to be introduced in the series. Lewis said that the first Narnia story, "The Lion, the Witch and the Wardrobe", all came to him from a single picture he had in his head of a faun carrying an umbrella and parcels through a snowy wood. In that way, Tumnus was the initial inspiration for the entire Narnia series. |
| **Original question**       | What is the name of the place in The Chronicles of Narnia where Lucy Pevensie and Mr. Tumnus meet? |
| **Generated question**      | What is the name of the fictional place where Lucy Pevensie and Mr. Tumnus meet? |

Table A3: Example of generated bridge type multi-hop question.
Emory University is a private research university in metropolitan Atlanta, located in the Druid Hills section of DeKalb County, Georgia, United States. The university was founded as Emory College in 1836 in Oxford, Georgia by the Methodist Episcopal Church and was named in honor of Methodist bishop John Emory. In 1915, the college relocated to metropolitan Atlanta and was rechartered as Emory University. The university is the second-oldest private institution of higher education in Georgia and among the fifty oldest private universities in the United States. Emory is frequently cited as one of the world’s leading research universities and one of the top institutions in the United States. Vanderbilt University (also known informally as Vandy) is a private research university located in Nashville, Tennessee. Founded in 1873, it was named in honor of shipping and rail magnate Cornelius Vanderbilt, who provided the school its initial $1 million endowment despite having never been to the South. Vanderbilt hoped that his gift and the greater work of the university would help to heal the sectional wounds inflicted by the Civil War.

The Battle of Manila (February 3, 1945 – March 3, 1945) was a major battle of the Philippine campaign of 1944-45, during the Second World War. It was fought by American and Filipino forces against Japanese troops in Manila, the capital city of the Philippines. The month-long battle, which resulted in the death of over 100,000 civilians and the complete devastation of the city, was the scene of the worst urban fighting in the Pacific theater. Japanese forces committed mass murder against Filipino civilians during the battle. Along with massive loss of life, the battle also destroyed architectural and cultural heritage dating back to the city's foundation. The battle ended the almost three years of Japanese military occupation in the Philippines (1942–1945). The city’s capture was marked as General Douglas MacArthur’s key to victory in the campaign of reconquest. The Second Battle of Guam (21 July – 10 August 1944) was the American recapture of the Japanese-held island of Guam, a U.S. territory in the Mariana Islands captured by the Japanese from the U.S. in the 1941 First Battle of Guam during the Pacific campaign of World War II.

The orchid genus Dracula, abbreviated as Drac in horticultural trade, consists of 118 species native to Mexico, Central America, Colombia, Ecuador and Peru. The name "Dracula" literally means "little dragon", an allusion to the mythical Count Dracula, a lead character in numerous vampire novels and films. The name was applied to the orchid because of the blood-red color of several of the species, the strange aspect of the long spurs of the sepals. Pistacia is a genus of flowering plants in the cashew family, Anacardiaceae. It contains 10 to 20 species that are native to Africa and Eurasia from the Canary Islands, all of Africa, and southern Europe, warm and semidesert areas across Asia, and North America from Mexico to warm and semidesert United States, such as Texas or California.

| Data fields       | Example                                                                 |
|-------------------|-------------------------------------------------------------------------|
| Answer            | Emory University                                                        |
| Generated answer related words | Emory University, Vanderbilt University                              |
| Context           | Emory University is a private research university in metropolitan Atlanta, located in the Druid Hills section of DeKalb County, Georgia, United States. The university was founded as Emory College in 1836 in Oxford, Georgia by the Methodist Episcopal Church and was named in honor of Methodist bishop John Emory. In 1915, the college relocated to metropolitan Atlanta and was rechartered as Emory University. The university is the second-oldest private institution of higher education in Georgia and among the fifty oldest private universities in the United States. Emory is frequently cited as one of the world’s leading research universities and one of the top institutions in the United States. Vanderbilt University (also known informally as Vandy) is a private research university located in Nashville, Tennessee. Founded in 1873, it was named in honor of shipping and rail magnate Cornelius Vanderbilt, who provided the school its initial $1 million endowment despite having never been to the South. Vanderbilt hoped that his gift and the greater work of the university would help to heal the sectional wounds inflicted by the Civil War. |
| Original question | Was Vanderbilt University or Emory University founded first?             |
| Generated question| Which university is older, Vanderbilt University or Emory University?   |
| Answer            | Battle of Guam                                                          |
| Generated answer related words | Battle of Manila , Battle of Guam                                      |
| Context           | The Battle of Manila (February 3, 1945 – March 3, 1945) was a major battle of the Philippine campaign of 1944-45, during the Second World War. It was fought by American and Filipino forces against Japanese troops in Manila, the capital city of the Philippines. The month-long battle, which resulted in the death of over 100,000 civilians and the complete devastation of the city, was the scene of the worst urban fighting in the Pacific theater. Japanese forces committed mass murder against Filipino civilians during the battle. Along with massive loss of life, the battle also destroyed architectural and cultural heritage dating back to the city's foundation. The battle ended the almost three years of Japanese military occupation in the Philippines (1942–1945). The city’s capture was marked as General Douglas MacArthur’s key to victory in the campaign of reconquest. The Second Battle of Guam (21 July – 10 August 1944) was the American recapture of the Japanese-held island of Guam, a U.S. territory in the Mariana Islands captured by the Japanese from the U.S. in the 1941 First Battle of Guam during the Pacific campaign of World War II. |
| Original question | Which battle occurred first, the Battle of Manila or the Battle of Guam? |
| Generated question| Which battle took place first, Battle of Guam or Battle of Manila?       |
| Answer            | Dracula                                                                 |
| Generated answer related words | Dracula, Pistacia                                                        |
| Context           | The orchid genus Dracula, abbreviated as Drac in horticultural trade, consists of 118 species native to Mexico, Central America, Colombia, Ecuador and Peru. The name "Dracula" literally means "little dragon", an allusion to the mythical Count Dracula, a lead character in numerous vampire novels and films. The name was applied to the orchid because of the blood-red color of several of the species, the strange aspect of the long spurs of the sepals. Pistacia is a genus of flowering plants in the cashew family, Anacardiaceae. It contains 10 to 20 species that are native to Africa and Eurasia from the Canary Islands, all of Africa, and southern Europe, warm and semidesert areas across Asia, and North America from Mexico to warm and semidesert United States, such as Texas or California. |
| Original question | Which genus has more species, Dracula or Pistacia?                     |
| Generated question| Which genus contains more species, Pistacia or Dracula?                 |

Table A4: Example of generated comparison type multi-hop question.