Unsupervised Multi-hop Question Answering by Question Generation

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Abstract

Obtaining training data for Multi-hop Question Answering (QA) is extremely time-consuming and resource-intensive. To address this, we propose the problem of *unsupervised* multi-hop QA, assuming that no human-labeled multi-hop question-answer pairs are available. We propose MQA-QG, an unsupervised question answering framework that can generate human-like multi-hop training pairs from both homogeneous and heterogeneous data sources. Our model generates questions by first selecting or generating relevant information from each data source and then integrating the multiple information to form a multi-hop question. We find that we can train a competent multi-hop QA model with only generated data. The F1 gap between the unsupervised and fully-supervised models is less than 20 in both the HotpotQA and the HybridQA dataset. Further experiments reveal that an unsupervised pretraining with the QA data generated by our model would greatly reduce the demand for human-annotated training data for multi-hop QA.

1 Introduction

Extractive Question Answering (EQA) is the task of answering questions by selecting a span from the given context document, which can be divided into the single-hop (Rajpurkar et al., 2016, 2018; Kwiatkowski et al., 2019) and multi-hop cases (Yang et al., 2018; Welbl et al., 2018; Chen et al., 2020b). Unlike single-hop QA, which assumes the question can be answered with a single sentence or document, multi-hop QA requires combining disjoint pieces of evidence to answer a question. In this paper, we focus on multi-hop question answering and consider both the homogeneous case where relevant evidence is in the textual forms (Yang et al., 2018) and the heterogeneous case where evidence is manifest in both tabular and textual forms (Chen et al., 2020b).

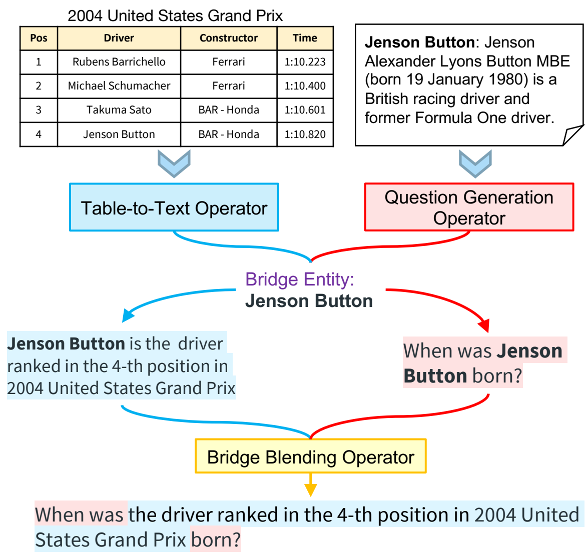


Figure 1: An overview of our approach for generating bridge-type multi-hop questions from table and text. The full set of supported input types and question types are described in Section 3.2.

Though different well-designed neural models (Qiu et al., 2019; Fang et al., 2020) have achieved near-human performance on the multi-hop QA datasets (Welbl et al., 2018; Yang et al., 2018), these approaches rely heavily on the availability of large-scale human annotation. Compared with single-hop QA datasets (Rajpurkar et al., 2016), annotating multi-hop QA datasets is significantly more costly and time-consuming because a human worker needs to read multiple data sources in order to propose a reasonable question.

To address the above problem, we pursue a more realistic setting, *i.e.*, *unsupervised* multi-hop QA, in which we assume no human-labeled training data is available, and we explore the possibility of *synthesizing* human-like multi-hop question-answer pairs to train the QA model. Though successful attempts have been made to synthesize single-hop question-answer pairs by style transfer (Lewis et al., 2019) or linguistic rules (Li et al., 2020), these methods are not directly applicable to the multi-hop setting for two reasons: 1) they cannot integrate information from multiple data sources, 2) they only consider the free-form text as input context, but do not apply to heterogeneous input contexts (Chen et al., 2020b).

We model the multi-hop QA with a latent inference process involving two steps: 1) selecting relevant information from each data source, 2) integrating the multiple information to form a question. We propose the Multi-Hop Question Generator (MQA-QG), a simple yet general framework to model this underlying process. The model first defines a set of basic *operators* (Section 3.1) to retrieve / generate relevant information from each input source or to aggregate different information. Afterwards, we define six *reasoning graphs* (Section 3.2). Each corresponds to one type of multi-hop question and is formulated as a computation graph built upon the operators. We generate multi-hop question-answer pairs by executing the reasoning graph. Figure 1 shows an example of generating a *table-to-text question*: a) Given the inputs of (table, text), the $FindBridge$ operator locates a bridge entity that connects the contents between table and text. b) We generate a simple, single-hop question for the bridge entity from the text ($QGwithEnt$ operator) and generate a sentence describing the bridge entity from the table ($DescribeEnt$ operator). c) The $BridgeBlend$ operator blends the two generated contents to obtain the multi-hop question.

We evaluate our method on two multi-hop QA datasets: HotpotQA (Yang et al., 2018) and HybridQA (Chen et al., 2020b). Questions in HotpotQA reason over multiple texts (homogeneous data), while questions in HybridQA reason over both table and text (heterogeneous data). The experiments show that MultihopGen can generate high-quality multi-hop questions for both datasets. The generated questions can be used to train a surprisingly well QA model. The F1 gap between the unsupervised and the fully-supervised setting is only 11.6 and 19.5 for HotpotQA and HybridQA, respectively. We also find that our method can be used in a few-shot learning setting, for example, obtaining 64.6 F1 with 50 labeled examples in HotpotQA, compared to 21.6 F1 without the warm-up training given by our method. Also, our ablations show that each component of our framework contributes to QA performance.

This paper makes the following contributions:

- To the best of our knowledge, this is the first work to investigate unsupervised multi-hop QA.
- We propose MQA-QG, a novel framework to generate high-quality multi-hop questions without the need of human annotation.
- We show that the generated training data can benefit the multi-hop QA system in both unsupervised and few-shot learning settings.

2 Related Work

Unsupervised Question Answering. To reduce the reliance on expensive data annotation, *Unsupervised / Zero-Shot QA* has been proposed to train question answering models without any human-labeled training data. Lewis et al. (2019) proposed the first unsupervised QA model which generates synthetic (context, question, answer) triples to train the QA model using unsupervised machine translation. However, the generated questions tend to have a lot of lexical overlaps with the context. Training with such synthetic data often results in a trivial QA model that learns to predict the answer simply by word matching. To address this, followup works utilized the Wikipedia cited documents (Li et al., 2020), predefined templates (Fabbri et al., 2020), or pretrained language model (Puri et al., 2020) to produce more natural questions resembling the human-annotated ones.

However, all the existing studies are focused on the SQuAD (Rajpurkar et al., 2016) dataset to answer single-hop text-only questions. These methods can hardly be applied to general multi-hop QA because they lack integrating and reasoning over information from disjoint evidence sources. Furthermore, these proposed methods are restricted to text-based QA without considering structured knowledge and cannot be applied to KB/Table-QA (Berant et al., 2013). In contrast, we propose the first framework for unsupervised *multi-hop QA*, which can leverage disjoint structured or unstructured data sources to answer complex questions requiring reasoning.

Multi-hop Question Generation. Question Generation (QG) aims to automatically generate questions from textual inputs (Pan et al., 2019). Early QG works relied on syntax rules or templates to transform a piece of given text

Group	Operator	Inputs → Outputs	Description
Selection	$FindBridge$	(Table $\mathcal{T}$, Text $\mathcal{D}$) or Texts ($\mathcal{D}_1$, $\mathcal{D}_2$) → Bridge Entities $\mathcal{E}^B$	Select an entity $\mathcal{E}^B$ that links the two input texts $\mathcal{D}_1$ and $\mathcal{D}_2$ (or links the table $\mathcal{T}$ and the text $\mathcal{D}$)
	$FindComEnt$	Text $\mathcal{D}$ → Comparative Entities $\mathcal{E}^C$	Extract potential comparative entities from the input text (location, datetime, number, etc.).
Generation	$QGwithAns$	(Text $\mathcal{D}$, Answer $\mathcal{A}$) → Question $\mathcal{Q}$	Generate a single-hop question $\mathcal{Q}$ with answer $\mathcal{A}$ from the input text $\mathcal{D}$
	$QGwithEnt$	(Text $\mathcal{D}$, Entity $\mathcal{E}$) → Question $\mathcal{Q}$	Generate a single-hop question $\mathcal{Q}$ that contains the given entity $\mathcal{E}$ from the input text $\mathcal{D}$
	$DescribeEnt$	(Table $\mathcal{T}$, Entity $\mathcal{E}$) → Sentence $\mathcal{S}$	Generate a sentence $\mathcal{S}$ that describes the given entity $\mathcal{E}$ based on the information of the table $\mathcal{T}$
	$QuesToSent$	Question $\mathcal{Q}$ → Sentence $\mathcal{S}$	Convert a question $\mathcal{Q}$ into its declarative form $\mathcal{S}$
Fusion	$BridgeBlend$	(Question $\mathcal{Q}$, Sentence $\mathcal{S}$, Bridge $\mathcal{E}^B$) → Bridge-type multi-hop question $\mathcal{Q}^B$	Generate a bridge-type multi-hop question $\mathcal{Q}^B$ by fusing the single-hop question Q and the sentence S given the entity $\mathcal{E}^B$ as the bridge
	$CompBlend$	(Question $\mathcal{Q}_1$, Question $\mathcal{Q}_2$) → Comparative multi-hop question $\mathcal{Q}^C$	Convert a question $\mathcal{Q}$ into its declarative form $\mathcal{S}$

Table 1: The 8 basic operators for MQA-QG, categorized into 3 groups. **Selection**: retrieve relevant information from contexts. **Generation**: generate information from a single context. **Fusion**: fuse retrieved/generated information to construct multi-hop questions. Each operator is defined as a function mapping $f(X) \rightarrow Y$.

to questions (Heilman, 2011; Chali and Hasan, 2012). With the proliferation of deep learning, QG advanced to use supervised neural models, and most of them were trained to generate questions from *(passage, answer)* pairs in the SQuAD dataset (Du et al., 2017; Zhao et al., 2018; Kim et al., 2019).

However, over 90% of questions in SQuAD are simple, single-hop questions (Min et al., 2018) without requiring deeper comprehension and reasoning. To bridge this gap, a few recent works have started to generate questions that require *multi-hop reasoning*. Tuan et al. (2020) proposed a multi-state attention mechanism to mimic the multi-hop reasoning process. Pan et al. (2020) parsed the input passage as a semantic graph to facilitate the reasoning over different entities. However, these supervised methods require a large amount of human-written multi-hop questions as training data. As multi-hop questions are difficult to create in practice, we propose the first *unsupervised* QG system to generate multi-hop questions without access to any annotated data.

3 Methodology

The standard setup of multi-hop QA is as follows. Given a question q and a set of input contexts $\mathcal{C} = \{C_1, C_2, \cdots, C_n\}$, where each context C_i can be a passage, table, image, etc., the QA model $p_\theta(a|q, \mathcal{C})$ aims to predict the answer a for the question q, and answering the question q by chaining information from a set of input contexts.

Our proposed framework MQA-QG seeks to synthesize high quality training data to train the multi-hop QA model. In this paper, we mainly consider two-hop questions and denote the required contexts as C_i and C_j. Formally, each time our model takes as inputs $\langle C_i, C_j \rangle$ to generate a set of (q, a) pairs. In this work, we focus on two two modalities: heterogeneous case type(C_i, C_j) = (Table, Text) and homogeneous case type(C_i, C_j) = (Text, Text). However, our framework is flexible enough to generalize to multi-hop QA for other modalities.

The MQA-QG consists of three components: *operators*, *reasoning graphs*, and *data filtration*. Operators are atomic operations implemented by rules or off-the-shelf pretrained models to retrieve, generate, or fuse relevant information from input contexts (C_i, C_j). Different reasoning graphs define different types of reasoning chains for multi-hop QA with the operators as building blocks. Synthesized (q, a) pairs are generated by executing the reasoning graphs. Data filtration removes irrelevant and unnatural (q, a) pairs to give the training set $\mathcal{D}$ for multi-hop QA.

3.1 Operators

As shown in Table 1, we define eight basic operators and divide them into three types: 1) *selection*: retrieve relevant information from a single context, 2) *generation*: generate information from a single context, and 3) *fusion*: fuse multiple retrieved/generated information to construct multi-hop questions.

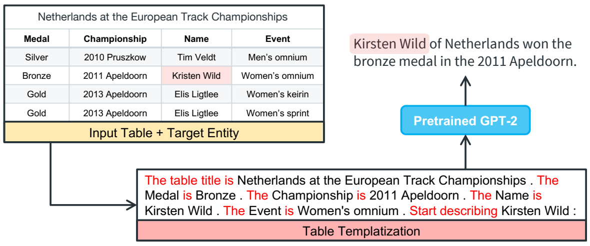


Figure 2: The implementation of *DescribeEnt* operator.

Figure 3: An example of the *BridgeBlend* operator.

• ***FindBridge*** Most multi-hop questions rely on the entities that connect different input contexts, *i.e.*, *bridge entities*, to integrate multiple pieces of information (Xiong et al., 2019). The *FindBridge* operator takes two contexts (C_i, C_j) as inputs, and extracts the entities that appear in both C_i and C_j as bridge entities. For example, in Figure 1, we extract "Jenson Button" as the bridge entity between the table and the text.

• ***FindComEnt*** When generating comparative-type multi-hop questions, we need to decide what property to compare for the bridge entity. The *FindComEnt* operator extracts potential comparative properties from the input text. We extract entities with NER types $Nationality$, $Location$, $DateTime$, and $Number$ from the input text as comparative properties. An example can be found in the "Comparison" sub-figure in Figure 4.

• ***QGwithAns***, ***QGwithEnt*** These two operators generate simple, single-hop questions from a single context, which are subsequently used to compose multi-hop questions. We use the pre-trained Google T5 model (Raffel et al., 2019) fine-tuned on SQuAD to implement these two operators. Given the SQuAD training set of context-question-answer triples $\mathcal{D} = \{(c, q, a)\}$, we jointly fine-tune the model on two tasks. 1) answer-aware QG (*QGwithAns*) aims to generate a question q with a as the answer, given (c, a) as inputs. 2) entity-aware QG (*QGwithEnt*) aims to generate a question q that contains a specific entity e, given (c, e) as inputs. The evaluation of this T5-based model can be found in Appendix A.

• ***DescribeEnt*** Given a table T and a target entity e in the table, the *DescribeEnt* operator generates a sentence that describes the entity e based on the information in the table T. We implement this using the GPT-TabGen model (Chen et al., 2020a) shown in Figure 2. The model first uses template to flatten the table T into a document P_T and then feed P_T to the pre-trained GPT-2 model (Radford et al., 2019) to generate the output sentence Y. To avoid irrelevant information in P_T, we apply a template that only describes the row where the target entity locates. We then finetune the model on the ToTTo dataset (Parikh et al., 2020), a large-scale dataset of controlled table-to-text generation, by maximizing the likelihood of $p(Y|P_T;\beta)$, with β denoting the parameters of GPT-2 model. The implementation details and the model evaluation are in Appendix A.

• ***QuesToSent*** This operator convert a question q into its declarative form s by applying the linguistic rules defined in Demszky et al. (2018).

• ***BridgeBlend*** The operator composes a bridge-type multi-hop question based on: 1) a bridge entity e, 2) a single-hop question q that contains e, and 3) a sentence s that describes e. As exemplified in Figure 3, we implement this by applying a simple yet effective rule that replaces the bridge entity e in q with "the [MASK] that s" and employ the pretrained BERT-Large (Devlin et al., 2019) to fill in the [MASK] word.

• ***CompBlend*** This operator composes a comparison-type multi-hop question based on two single-hop questions q_1 and q_2. The two questions ask about the same comparative property p for two different entities e_1 and e_2. We form the multi-hop question by filling p, e_1, and e_2 into pre-defined templates (Further details in Appendix B).

3.2 Reasoning Graphs

Based on the basic operators, we define six types of *reasoning graphs* to generate questions with different types. Each reasoning graph is represented as a directed acyclic graph (DAG) $\mathcal{G}$, where each node in $\mathcal{G}$ corresponds to an operator. A node s_i is connected by an incoming edge $\langle s_j, s_i \rangle$ if the output of s_j is given as an input to s_i.

As shown in Figure 4, *Table-Only* and *Text-Only* represent single-hop questions from table and text, respectively. The remaining reasoning graphs de-

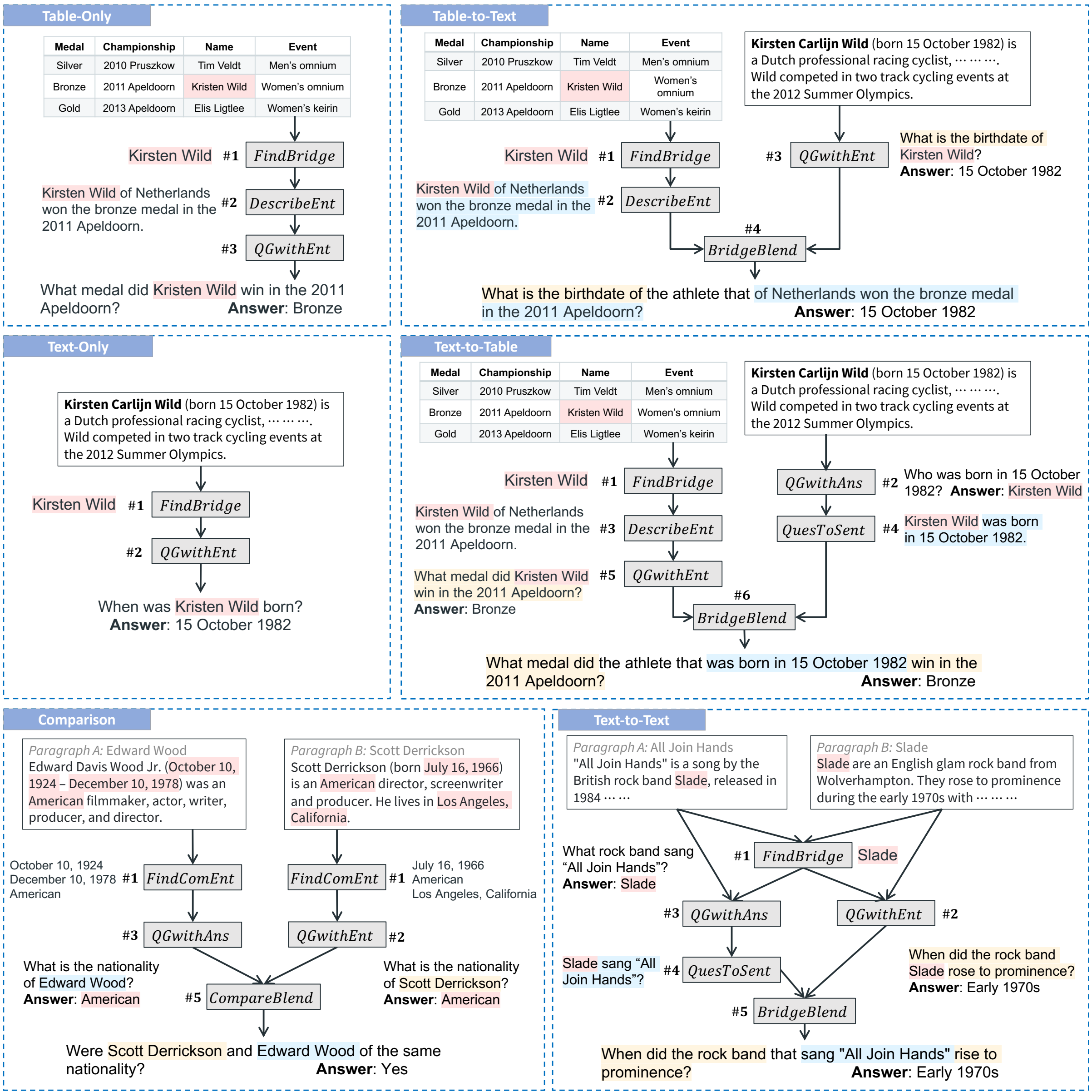


Figure 4: The 6 types of reasoning graphs for MQA-QG. Each graph is represented as a DAG of operators.

fine four types of multi-hop questions. 1) *Table-to-Text*: bridge-type question between table and text, where the answer comes from the text. 2) *Text-to-Table*: bridge-type question between table and text, where the answer comes from the table. 3) *Text-to-Text*: bridge-type question between two texts. 4) *Comparison*: comparison-type question based on two passages. These four reasoning chains can cover a large portion of questions in existing multi-hop QA datasets, such as HotpotQA and HybridQA. Our framework easily extends to other modalities and reasoning chains by defining new operators and reasoning graphs.

3.3 Question Filtration

After obtaining the generated QA pairs by executing each reasoning graph, we add a pretrained GPT-2 model to filter out those questions that are in-fluent or unnatural. The top N samples with the lowest perplexity scores are selected as the generated dataset to train the multi-hop QA model.

4 Experiments

4.1 Datasets

We evaluate our framework on two multi-hop QA datasets: HotpotQA (Yang et al., 2018) and HybridQA (Chen et al., 2020b). HotpotQA focuses on multi-hop QA over homogeneous inputs, while

Split	Train	Dev	Test	Total
HotpotQA				
Bridge	72,991	5,918	–	78,909 (81 %)
Comparison	17,456	1,487	–	18,943 (19 %)
Total	90,447	7,405	–	97,852
HybridQA				
In-Passage	35,215	2,025	2,045	39,285 (56 %)
In-Table	26,803	1,349	1,346	29,498 (43 %)
Compute	664	92	72	828 (1.1 %)
Total	62,682	3,466	3,463	69,611

Table 2: Basic statistics of HotpotQA and HybridQA.

	Dataset	Size	Description
HotpotQA	$\mathcal{Q}_{bge}$	129,508	Bridge
	$\mathcal{Q}_{com}$	115,162	Comparison
	$\mathcal{Q}_{bge+com}$	244,220	$\mathcal{Q}_{bge} \cup \mathcal{Q}_{comp}$
	$\mathcal{Q}_{hotpot}$	100,000	$filter(\mathcal{Q}_{bge+com})$
HybridQA	$\mathcal{Q}_{tbl}$	56,448	Table-Only
	$\mathcal{Q}_{txt}$	47,332	Text-Only
	$\mathcal{Q}_{txt\rightarrow tbl}$	56,448	Text-to-Table
	$\mathcal{Q}_{tbl\rightarrow txt}$	70,661	Table-to-Text
	$\mathcal{Q}_{txt\leftrightarrow tbl}$	127,109	$\mathcal{Q}_{txt\rightarrow tbl} \cup \mathcal{Q}_{tbl\rightarrow txt}$
	$\mathcal{Q}_{hybrid}$	100,000	$filter(\mathcal{Q}_{txt\leftrightarrow tbl})$

Table 3: Basic statistics of all the generated datasets.

HybridQA deals with multi-hop QA over heterogeneous information. HotpotQA contains ∼100K crowd-sourced multi-hop questions, where each question requires reasoning over two supporting Wikipedia documents to infer the answer. HybridQA contains ∼70K human-labeled multi-hop questions, where each question is aligned with a structured Wikipedia table and multiple passages linked with the entities in the table. The questions are designed to aggregate both tabular information and text information, *i.e.*, lack of either form renders the question unanswerable.

Appendix C gives a data example for HotpotQA and HybridQA, respectively. Table 2 shows the statistics of these two datasets. There are two types of multi-hop questions in HotpotQA: bridge-type (81%) and comparison-type (19%). For HybridQA, questions can be categorized into "In-Table" (the answer comes from the table, 56%) and "In-Passage" (the answer comes from the passage, 44%). Most questions in HybridQA ($\sim$ 80%) require bridge-type reasoning.

4.2 Main Results

This section contains the results we obtain for unsupervised multi-hop question answering.

Question Generation In HybridQA, we extract its table-text corpus consisting of (T, D) input pairs, where T denotes the table and set of its linked passages D. We generate two multi-hop QA datasets $\mathcal{Q}_{tbl\rightarrow txt}$ and $\mathcal{Q}_{txt\rightarrow tbl}$ with MQA-QG by executing the "Table-to-Text" and "Text-to-Table" reasoning graphs for each (T, D), resulting in a total of 170K QA pairs. We then apply question filtration to obtain the high-quality training dataset $\mathcal{Q}_{hybrid}$ with 100K QA pairs. For the ablation study, we also generate two datasets with single-hop questions $\mathcal{Q}_{tbl}$ and $\mathcal{Q}_{txt}$ by executing the "Table-Only" and "Text-Only" reasoning graphs, respectively. Similarly, for HotpotQA, we first generate $\mathcal{Q}_{bge}$ and $\mathcal{Q}_{com}$, which contains only the bridge-type questions and only the comparison-type questions, respectively. Afterward, we merge them and filter the questions to obtain the final training set $\mathcal{Q}_{hotpot}$. Table 3 summarizes all the generated datasets.

Question Answering For HybridQA, we use the HYBRIDER (Chen et al., 2020b) as the QA model, which breaks the QA into linking and reasoning to cope with heterogeneous information, achieving the best result in HybridQA. For HotpotQA, we use the SpanBERT (Joshi et al., 2020) as the QA model since it achieved promising results on HotpotQA with reproducible codes[1]. We use the standard Exact Match (EM) and F_1 metrics to measure the performance.

Baselines We compare MQA-QG with both supervised and unsupervised baselines. For HybridQA, we first include the two supervised baselines *Table-Only* and *Passage-Only* in Chen et al. (2020b), which only rely on the tabular information or the textual information to find the answer. As we are the first to target unsupervised QA on HybridQA, there is no existing unsupervised baseline for direct comparison. Therefore, we construct a strong baseline *QDMR-to-Question* that generate questions from Question Decomposition Meaning Representation (QDMR) (Wolfson et al., 2020), a logical representation specially designed for multi-hop questions. We first generate QDMR expressions from the input (table, text) using pre-defined templates and then train a Seq2Seq model (Bahdanau et al., 2014) to translate QDMR into question. Further details on this baseline are in Appendix D. For HotpotQA, we introduce three unsupervised baselines. *SQuAD-Transfer* trains SpanBERT on SQuAD and then transfers it for

[1]https://github.com/facebookresearch/SpanBERT

Model		In-Table	In-Passage	Total
		EM / F_1	EM / F_1	EM / F_1
Supervised	S1. Table-Only (Chen et al., 2020b)	14.7 / 19.1	2.4 / 4.5	8.4 / 7.1
	S2. Passage-Only (Chen et al., 2020b)	9.2 / 13.5	26.1 / 32.4	19.5 / 25.1
	S3. HYBRIDER (Chen et al., 2020b)	**51.2 / 58.6**	**39.6 / 46.4**	**42.9 / 50.0**
Unsupervised	Z1. QDMR-to-Question	25.7 / 29.7	12.8 / 16.5	17.7 / 21.4
	Z2. MQA-QG *-w/o* Filtration	33.0 / 37.1	18.6 / 23.4	23.8 / 28.2
	Z3. MQA-QG	**36.2 / 40.6**	**19.8 / 25.0**	**25.7 / 30.5**

Table 4: Performance comparison between supervised models and unsupervised models on **HybridQA**.

Model		Bridge	Comparison	Total
		EM / F_1	EM / F_1	EM / F_1
Supervised	S4. SpanBERT (Joshi et al., 2020)	**68.2 / 83.5**	**74.2 / 80.3**	**69.4 / 82.8**
Unsupervised	Z4. Bridge-Only	55.4 / 71.4	12.4 / 19.1	46.7 / 60.9
	Z5. Comparison-Only	9.8 / 14.5	38.2 / 45.0	15.5 / 20.6
	Z6. SQuAD-Transfer	54.6 / 69.7	25.3 / 35.2	48.7 / 62.8
	Z7. MQA-QG *-w/o* Filtration	55.2 / 71.2	44.8 / 52.9	53.1 / 67.5
	Z8. MQA-QG	**56.5 / 72.2**	**48.8 / 54.4**	**54.9 / 68.6**

Table 5: Performance comparison between supervised models and unsupervised models on **HotpotQA**.

multi-hop QA. *Bridge-Only* / *Comparison-Only* use only the bridge-type / comparison-type questions by MQA-QG to train the QA model.

Performance Comparison Table 4 and Table 5 summarizes the QA performance on HybridQA and HotpotQA, respectively. For HybridQA in Table 4, we use the reported performance of HYBRIDER as the supervised benchmark (S3) and apply the same model setting of HYBRIDER to train the unsupervised version, *i.e.*, using our generated QA pairs $\mathcal{Q}_{txt \to tbl}$ (Z2) and $\mathcal{Q}_{hybrid}$ (Z3) as the training data. For HotpotQA, the original paper of SpanBERT only reported the results for the MRQA-2019 shared task (Fisch et al., 2019), which only includes the bridge-type questions in HotpotQA. Therefore, we retrain the SpanBERT on the full HotpotQA dataset to get the supervised benchmark (S4) and using the same model setting to train the unsupervised versions (Z7 and Z8).

Our unsupervised model MQA-QG attains 30.5 F_1 on the HybridQA test set and 68.6 F_1 on the HotpotQA dev set, outperforming all the unsupervised baselines (Z1, Z4, Z5, Z6) by large margins. Without using their annotated data, the $F1$ gap to the fully-supervised version is only 19.5 and 14.2 for HybridQA and HotpotQA, respectively. In particular, the results of Z2 and Z3 even outperform the two weak supervised baselines (S1 and S2) in HybridQA. This demonstrates the effectiveness of MQA-QG in generating good multi-hop questions for training the QA model.

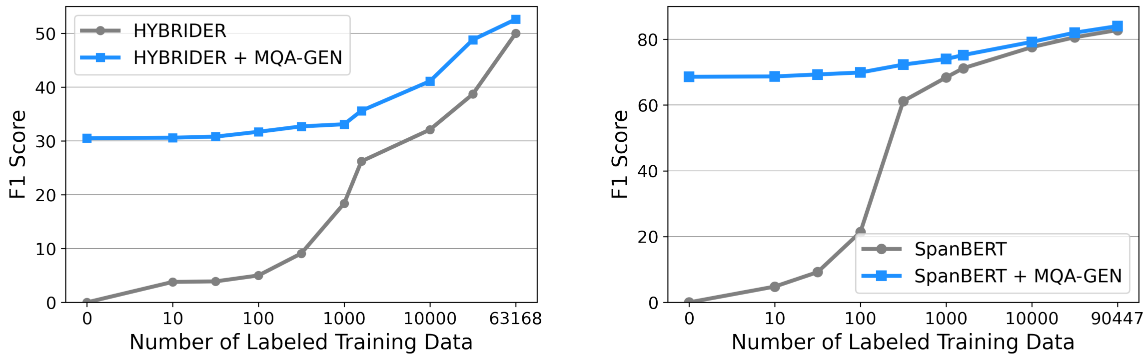
4.3 Ablation Study

To understand the impact of different components in MQA-QG, we perform an ablation study on the HybridQA development set. In Table 6, we compare our full model (A7) with six ablation settings by removing certain the model components (A1–A4) or by restricting the reasoning types (A5 and A6). We have three major observations.

Single-hop questions vs. multi-hop questions. A1 to A3 generates single-hop questions using the reasoning graph of *Text-Only* (A1), *Table-Only* (A2), or a union of them (A3). In other words, we use the dataset $\mathcal{Q}_{txt}$, $\mathcal{Q}_{tbl}$, and $\mathcal{Q}_{txt} \cup \mathcal{Q}_{tbl}$, respectively, to train the HYBRIDER model and test the multi-hop QA performance. In these cases, the model is trained to answer questions based on either table or text but lacking the ability to reason between table and text. As shown in Table 6, A1–A3 achieves a low performance of EM and F1, especially for In-Passage questions. This shows that single-hop questions alone are insufficient to train a good multi-hop QA system, revealing that learning to reason between different contexts is essential for multi-hop QA. This supports the ne-

Setting	Components				Reasoning Types		Performance		
	Text	Table	Fusion	Filtration	Table→Text	Text→Table	In-Table EM / F_1	In-Passage EM / F_1	Total EM / F_1
A1	✓						12.4 / 14.9	2.7 / 4.3	6.4 / 8.3
A2		✓					19.4 / 23.3	3.4 / 5.5	9.6 / 12.3
A3	✓	✓					14.8 / 19.2	5.6 / 7.8	9.1 / 12.1
A4	✓	✓	✓		✓		11.1 / 15.2	17.3 / 21.9	14.9 / 19.4
A5	✓	✓	✓			✓	41.5 / 47.9	0.2 / 1.9	16.2 / 19.8
A6	✓	✓	✓		✓	✓	33.0 / 37.1	18.6 / 23.4	23.8 / 28.2
A7	✓	✓	✓	✓	✓	✓	36.2 / 40.6	19.8 / 25.0	25.7 / 30.5

Table 6: Ablations on the HybridQA development set. **Text/Table**: whether we utilize the information in the text/table. **Fusion**: whether we fuse the information from table and text. **Filtration**: whether we perform question filtration. **Reasoning Types**: which types of multi-hop questions are generated.



(a) HybridQA

(b) HotpotQA

Figure 5: The few-shot learning experiment. The figure shows the F1 score on the HybridQA (a) / HotpotQA (b) development set for progressively larger training dataset sizes.

cessity of generating multi-hop questions. However, for HotpotQA, we observe that this effect is not as evident as in HybridQA: in Table 5, the SQuAD-Transfer (Z6) achieves a relatively good F1 of 62.8. A potential reason is that the examples of HotpotQA contain reasoning shortcuts through which models can directly locate the answer by word-matching, without the need of multi-hop reasoning, as observed by Jiang and Bansal (2019).

Effect of reasoning types. When we train the model with only the Text-to-Table questions (A5), the model achieves 47.9 F1 for In-Table questions and nearly zero performance for In-Passage questions. However, training with only the Table-to-Text questions (A4) also benefits the In-Table questions (15.2 F1). We believe the reason is that the information in the text can also answer some In-Table questions. Using both reasoning types (A6), the model improves on average by 8.6 F1 compared with the models using a single reasoning type (A4, A5). This shows that it is beneficial to train the multi-hop QA model with a generated dataset containing diverse reasoning chains.

Effect of question filtration. Question filtration also helps to train a better QA model, leading to a +2.3 F1 for HybridQA and +1.1 F1 for HotpotQA. We find that the GPT-2 based model prefers to filter out ungrammatical questions such as “Who publishes the the the that publishes Doctor Minerva comics?” rather than valid yet unnatural questions such as “Where was the event that is held in 2016 held?”.

4.4 Few-shot Multi-hop QA

We then explore MQA-QG’s effectiveness in the few-shot learning setting where only a few human-labeled (q, a) pairs are available. We first train the unsupervised QA model based on the training data generated by our best model. Then we fine-tune the model with limited human-labeled training examples. The blue line in Figure 5(a) and Figure 5(b) shows the F1 scores with different numbers of labeled training data for HybridQA and HotpotQA, respectively. We compare this with training the QA model directly on the human-labeled data without unsupervised QA pretraining

Type	#	Generated Question	Answer
Table	1	On what coast of India is the country that state tree is coconut located?	Kerala
↓	2	When did the one that won the Eurovision Song Contest in 1966 join Gals and Pals?	1963
Text	3	How many students attend the teams that played in the Dryden Township Conference?	1900
Text	4	What album did the Oak Ridge Boys release in 1989?	American Dreams
↓	5	What is the name of the sports stadium in the city that is the third - largest city in North Rhine - Westphalia?	Signal Iduna Park
Table	6	When was the name that is the name of the bridge that crosses Youngs Bay completed?	1921
Text	7	Two of the buildings in the area that is the name of Parbold are at what grade?	Grade II
↓	8	Which Canadian cinematographer is best known for his work on Fargo?	Craig Wrobleski
Text	9	What is illegal in the country that is Bashar Hafez al - Assad 's father?	Cannabis
Comp.	10	Which person is from American, Arthur Lubin or Ciro Ippolito?	Arthur Lubin
	11	Who was born first, Terry Southern or Neal Town Stephenson?	Terry Southern
	12	Are Beth Ditto and Mary Beth Patterson of the same nationality?	Yes

Table 7: Examples of multi-hop question-answers generated by MQA-QG, categorized by reasoning graphs.

(grey lines in Figure 5).

With progressively larger training dataset sizes, our model performs consistently better than the model without unsupervised pretraining for both two datasets. The performance improvement is especially prominent in very data-poor regimes; for example, our approach achieves 69.3 F1 with only 100 labeled examples in HotpotQA, compared with 21.4 F1 without unsupervised pretraining (47.9 absolute gain). The results show that MQA-QG greatly reduce the demand for human-annotated data. It can also be used to provide a "warm start" for online learning in which training data are quite limited at the beginning.

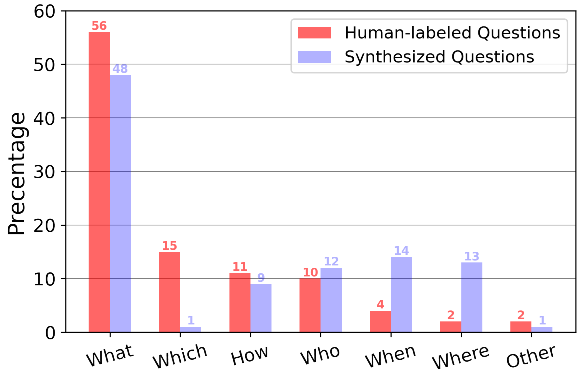


Figure 6: Question type distribution for our generated dataset and the human-labeled dataset for HybridQA.

4.5 Analysis of Generated Questions

The main goal of generated questions is to optimize for downstream QA performance. However, it is also instructive to examine the output question-answer pairs to better understand our system's advantages and limitations. In Figure 6, we plot the question type distribution[2] for both the human-labeled dataset and the generated data ($\mathcal{Q}_{hybrid}$) for HybridQA. We find that the two datasets have a similar question type distribution, where "What" questions constitute the major type. However, our model generates more "When" and "Where" questions but less "Which" questions. This is because the two reasoning graphs we apply for HybridQA are bridge-type questions while "Which" questions are mostly about comparing.

Table 7 shows representative examples generated by our model. Most questions are fluent and exhibit encouraging language variety, such as examples 1, 3, and 4. Our model also shows almost no sign of semantic drift, meaning most of the questions are valid despite sometimes unnatural. The two major drawbacks are *inaccurate reference* (in red) and *redundancy* (in blue), shown in examples 2, 6, 7, and 9. This can be addressed by incorporating minimal supervision to guide the fusion process, *i.e.*, including more flexible paraphrasing for fusion operators.

5 Conclusion and Future Works

In this work, we propose unsupervised multi-hop QA to explore the possibility of training the QA system without using labeled QA data. To this end, we propose a novel framework MQA-QG to generate multi-hop questions via composing reasoning graphs built upon basic operators. The experiments on both HybridQA and HotpotQA show that our model can generate human-like questions that help to train a well-performing QA model in both the unsupervised and the few-shot learning

[2]Question type identification is based on the linguistic rules in Liu et al. (2020).

setting. However, while our results are encouraging, further work is required to include more flexible paraphrasing at the fusion stage. We can also design more reasoning graphs and operators to generate more complex questions and support more input modalities.

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Operator	Model	BLEU-4	METEOR	ROUGE-L
QGwithAns & QGwithEnt	NQG++ (Zhou et al., 2017)	13.51	18.18	41.60
	S2ga-mp-gsa (Zhao et al., 2018)	15.82	19.67	44.24
	CGC-QG (Liu et al., 2020)	17.55	21.24	44.53
	Google-T5 (Radford et al., 2019)	21.32	**27.09**	43.60
	UniLM (Dong et al., 2019)	**23.75**	25.61	**52.04**
DescribeEnt	Seq2Seq Attention (Bahdanau et al., 2014)	28.31	27.61	56.63
	GPT2-TabGen (Chen et al., 2020b)	33.92	32.46	55.61
	GPT2-Medium (Chen et al., 2020b)	**35.94**	**33.74**	**57.44**

Table 8: Performance evaluation of the *QGwithAns*, *QGwithEnt*, and *DescribeEnt* operator for different models. The best performance is in bold. We adopt the Google-T5 and the GPT2-Medium in our model MQA-QG.

A The *QGwithAns*, *QGwithEnt*, and *DescribeEnt* Operators

In this section, we describe the implementation of *QGwithAns*, *QGwithEnt*, and *DescribeEnt* operators in details and evaluate their performance. In summary, *QGwithAns*, *QGwithEnt* are T5-based question generation model trained on the SQuAD dataset, and *DescribeEnt* is a GPT-2 based model trained on the ToTTo dataset.

Implementation Details For the question generation model (the *QGwithAns* and *QGwithEnt* operators), we use the SQuAD data split from Zhou et al. (2017) to fine-tune the Google T5 model (Radford et al., 2019). We implement this based on the pretrained T5 model provided by `https://github.com/patil-suraj/question_generation`.

For the table-to-text generation model (the *DescribeEnt* operator), we adopt the GPT-TabGen model proposed in Chen et al. (2020b). The model first uses a template to flatten the input table T into a document P_T and then feed P_T to the pre-trained GPT-2 model to generate the output sentence Y. We fine-tune the model on the ToTTo dataset (Parikh et al., 2020), a large-scale dataset for controlled table-to-text generation. In ToTTo, given a Wikipedia table and a set of highlighted table cells, the objective is to produce a one-sentence description that best describes the highlighted cells. The original dataset contains 120,761 human-labeled training samples and 7,700 testing samples. To implement the *DescribeEnt* operator, we select the ToTTo samples that focuses on describing a given target entity e rather than the entire table, based on the following criteria: 1) the highlighted cells are in the same row and contains the target entity, 2) the description starts with the target entity. This gives us 15,135 training (T, e, s) triples and 1,194 testing triples, where T is the table, e is the target entity, and s is the target description.

We employ BLEU-4 (Papineni et al., 2002), METEOR (Lavie and Agarwal, 2007), and ROUGE-L (Lin, 2004) to evaluate the performance of our implementation. For question generation, we compare the T5-based model with several state-of-the-art QG models, using their reported performance on the Zhou split of SQuAD. For the table-to-text generation, we compare GPT-TabGen with the Seq2Seq baseline with attention.

Evaluation Results Table 8 shows the evaluation results comparing against all baseline methods. For question generation, the Google-T5 model achieves a BLEU-4 of 21.32, outperforming NQG++, S2ga-mp-gsa, and CGC-QG by large margins. This is as expected since these three baselines are based on Seq2Seq and do not apply language model pretraining. Compared with the current state-of-the-art model UniLM, the Google-T5 model achieves comparable results, with slightly lower BLEU-4 but higher METEOR. For the table-to-text generation model, we find that GPT2-TabGen outperforms Seq2Seq with attention by 5.61 in BLEU-4. When switching to GPT-2-Medium as the pretraining model, the BLEU-4 further improves by 2.04. In our final model MQA-QG, we use the Google-T5 and the GPT2-Medium in the operators.

B The *CompBlend* Operator

The inputs of the *CompBlend* operator are two single-hop questions Q_1 and Q_2 that ask about the same comparative property p; for example, Q_1 = "What is the nationality of Edward Wood?", Q_2

Comparative Property	#	Question Template	Answer
born, birthdate	1	Who was born first, $e1$ or $e2$?	$e1$ / $e2$
located, location	2	Are $e1$ and $e2$ located in the same place?	Yes / No
	3	Which one is located in $a1$, $e1$ or $e2$?	e_1
	4	Which one is located in a_2, $e1$ or $e2$?	e_2
	5	Are both $e1$ and $e2$ located in a_1?	Yes / No
nationality, nation, country	6	Are $e1$ and $e2$ of the same nationality?	Yes / No
	7	Which person is from $a1$, $e1$ or $e2$?	e_1
	8	Which person is from $a2$, $e1$ or $e2$?	e_2
live, live place, hometown	9	Are $e1$ and $e2$ living in the same place?	Yes / No
	10	Which person lives in $a1$, $e1$ or $e2$?	e_1
	11	Which person lives in $a2$, $e1$ or $e2$?	e_2

Table 9: The comparative properties and their corresponding question templates used in the *CompBlend* operator. $a1$ / $a2$ denotes the answer for the single-hop question Q_1 / Q_2.

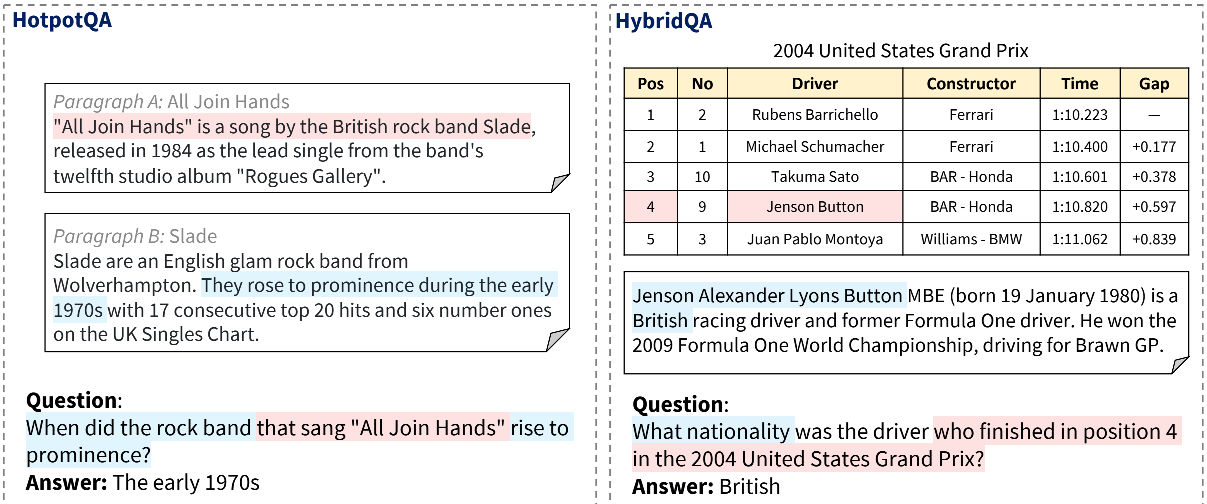

Figure 7: Data examples for the HotpotQA and the HybridQA dataset. Different colors (red and blue) highlight the evidences that are required to answer the multi-hop question from different sources.

= "What is the nationality of Scott Derrickson", and p = "Nationality". We then identify the entity appearing in Q_1 and Q_2, denoted as e_1 and e_2, respectively. To form the multi-hop question, we fill in the comparing entities $e1$ and $e2$ into the corresponding templates that we define for the comparative property p. One of the resulting comparison question for the above example is "Are Edward Wood and Scott Derrickson of the same nationality?". This paper considers four comparative properties and defined a total number of 11 templates for them, summarized in Table 9.

C HotpotQA and HybridQA Examples

Figure 7 gives data examples for the HotpotQA and the HybridQA dataset. The evidence used to compose the multi-hop question is highlighted, with different colors denoting information from different input contexts.

D Baseline: QDMR-to-Question

In this section, we introduce our proposed *QDMR-to-Question*, a strong unsupervised multi-hop QA baseline for HybridQA. We propose this baseline to investigate whether we can generate multi-hop questions from logical forms and compare them with our model MQA-QG.

The QDMR Representation The basic idea of QDMR-to-Question is first to generate a structured meaning representation from the source contexts and then convert it into the multi-hop

QDMR Template	Example	Question
Table-to-Text		
1) Return ⟨*column A*⟩ 2) Return #1 that ⟨*column B*⟩ is ⟨*row A*⟩ 3) Return #2 in ⟨*table title*⟩ 4) Return what is the ⟨*text attribute*⟩ of #3	1) Return Driver 2) Return #1 in Pos 4 3) Return #2 in 2004 United States Grand Prix 4) Return what is the birthdate of #3	What is the birthdate of the driver that pos is 4 in the 2004 United States Grand Prix?
Text-to-Table		
1) Return ⟨*column A*⟩ 2) Return #1 in ⟨*table title*⟩ 3) Return #2 that ⟨*predicate*⟩ ⟨*object*⟩ 4) Return what is the ⟨*column B*⟩ of #3	1) Return Driver 2) Return #1 in 2004 United States Grand Prix 3) Return #2 that born 19 January 1980 4) Return what is the Pos of #3	What is the pos of the driver in the 2004 United States that was born in 19 January, 1980?

Table 10: The QDMR templates used in the *QDMR-to-Question* model for HybridQA.

question. We use the Question Decomposition Meaning Representation (QDMR) (Wolfson et al., 2020), a logical representation specially designed for multi-hop questions as the intermediate question representation. QDMR expresses complex questions via atomic operations that can be executed in sequence to answer the original question. Each atomic operation either selects a set of entities, retrieves information about their attributes, or aggregates information over entities. For example, the QDMR for the question "How many states border Colorado?" is "1) Return Colorado; 2) Return border states of #1; 3) Return the number of #2". In contrast to semantic parsing, QDMR operations are expressed through natural language.

Based on the QDMR representation, Wolfson et al. (2020) crowdsourced BREAK, a large-scale question decomposition dataset consisting of 83,978 (QDMR, question) pairs over ten datasets.

Multi-hop Question Generation Given the table-text (T, D) as inputs, we first generate QDMR representations using two pre-defined templates that represent the *Table-to-Text* question and the *Text-to-Table* question, respectively. The templates with examples are given in Table 10. We generate QDMRs by randomly filling in the templates. Afterward, we translate the QDMR representation into a natural language question. To this end, we train a Seq2Seq model with attention (Bahdanau et al., 2014) on the BREAK dataset, where the input is a QDMR expression, and the target is the corresponding natural language form labeled by humans. We directly apply this Seq2Seq model trained on BREAK as the translator to transform our QDMR representations into multi-hop questions.

Evaluation and Discussions As shown in Table 4, QDMR-to-Question achieves 21.4 F1 on the HybridQA dataset, lower than our model MQA-QG by 9.1 F1. A typical example of generated question is shown in Figure 8. We believe that the main reason for the low performance of QDMR-to-Question is that it lacks a global understanding of the table semantics. Specifically, the model lacks an understanding of the table headers' semantic meaning and the semantic relationship between different headers because table columns and table rows are randomly selected to fill in the QDMR template. For example, in Figure 8, the model generates an unnatural expression "the name that medal is bronze" because it directly copies the table header "name" and "medal" without understanding them. Instead, as our MQA-QG applies the GPT2-based table-to-text model, which encodes the entire table as an embedding, it tends to produce more natural expressions that consider the general table semantics. For the same example, MQA-QG generates a better expression "the athlete that won the bronze medal".

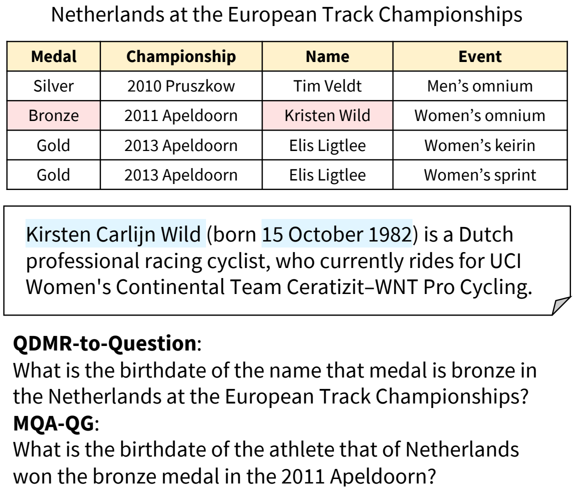

Figure 8: Examples of generated questions for the QDMR-to-Question model and the MQA-QG.