Answer-driven Deep Question Generation based on Reinforcement Learning

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Abstract

Deep question generation (DQG) aims to generate complex questions through reasoning over multiple documents. The task is challenging and underexplored. Existing methods mainly focus on enhancing document representations, with little attention paid to the answer information, which may result in the generated question not matching the answer type and being answer-irrelevant. In this paper, we propose an Answer-driven Deep Question Generation (ADDQG) model based on the encoder-decoder framework. The model makes better use of the target answer as a guidance to facilitate question generation. First, we propose an answer-aware initialization module with a gated connection layer which introduces both document and answer information to the decoder, thus helping to guide the choice of answer-focused question words. Then a semantic-rich fusion attention mechanism is designed to support the decoding process, which integrates the answer with the document representations to promote the proper handling of answer information during generation. Moreover, reinforcement learning is applied to integrate both syntactic and semantic metrics as the reward to enhance the training of the ADDQG. Extensive experiments on the HotpotQA dataset show that ADDQG outperforms state-of-the-art models in both automatic and human evaluations.

1 Introduction

Neural question generation (QG) aims at generating specific answer related questions from a given document with a target answer based on deep neural networks. Its key applications include generating questions for reading comprehension (Du et al., 2017), enhancing question answering systems as a strategy of data augmentation (Tang et al., 2017; Zhang and Bansal, 2019) and helping digital assistants (e.g., Alexa, Cortana, Siri and Google Assistant) to start and continue a conversation.

Various methods have been proposed for general QG (Zhou et al., 2017; Zhao et al., 2018; Kim et al., 2019; Zhang and Bansal, 2019; Tuan et al., 2020). However, most existing methods focus on generating questions relevant to only one fact without deep comprehension and reasoning. For example, Min et al. (2018) find that more than 80% of the questions in the widely adopted SQuAD dataset (Rajpurkar et al., 2016) are shallow and only relevant to information confined to a single sentence. Generating deep question which requires higher cognitive skills is rarely studied (Pan et al., 2020). These skills include a thorough understanding of the input sources and the ability to reason over disjoint and relevant contexts.

This paper focuses on the task of deep question generation (DQG), which focuses on generating deep questions with multi-hop reasoning over document-level contexts. Previous work mainly focuses on the enhancement of document representations and obtains good performance. However, the answer information is also important since the generated questions should match the answer type and be answer-focused, and several common problems in QG are caused by the lack or improper use of the answer information: 1) The generated questions may be irrelevant to the answer. As shown in Figure 1, with a wrongly chosen question word, Inappropriate Question 1 is asking about time information but not place.

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2) Without proper guidance during generation, the generated questions may even give the answer away incautiously (Inappropriate Question 2 in Figure 1), especially when the copy mechanism (Gu et al., 2016) is applied.

In this paper, we propose an Answer-Driven Deep Question Generation (ADDQG) model, which makes better use of the target answer as a guidance to facilitate the generation of deep questions. The model is built on the encoder-decoder paradigm. First, in order to explicitly guide the choice of question words, a novel initialization module is designed to introduce both document and answer information to the decoder, with a gated connection layer to control the proportions of information. Second, we propose the semantic-rich fusion attention mechanism for information integration, thus promoting the proper handling of answer information during question generation. It is a collaborative attention mechanism which integrates the answer with the document representations, where the document representations are concatenations of node representations from Graph Attention Network (GAT) (Veličković et al., 2017) and contextual representations. Moreover, reinforcement learning is applied to provide feedback to fine-tune the question generator. In order to optimize the evaluation metrics, syntactic and semantic metrics are integrated as the reward to guide the training process, thus guaranteeing the meaningfulness of generated questions.

The contributions of this paper are listed as follows: 1) We propose an answer-driven end-to-end deep question generation model (ADDQG) based on reinforcement learning, which explores more semantic information from the answer to enhance deep question generation. 2) In order to incorporate answer information into the generation of questions, a novel answer-aware initialization module with a gated connection layer and a semantic-rich fusion attention mechanism are designed to promote the proper handling of answer information during the generation process. 3) ADDQG model achieves the state-of-the-art results on the HotpotQA dataset. Human evaluation further verifies the high quality of the generated questions.

2 Related Work

Question Generation Question Generation is one of the typical natural language generation tasks (Reiter and Dale, 2000; Saggion and Poibeau, 2013; Balakrishnan et al., 2019). Generating questions from various kinds of sources, such as texts, search queries, knowledge bases and images, has attracted much attention recently. Our work is most related to previous work on generating questions from texts. Traditional methods are mostly rule-based, which rely on manual rules or templates and rank the generated questions by human-designed features (Heilman and Smith, 2010; Mazidi and Nielsen, 2014), which are costly and lack diversity. Neural QG models are usually variants of the encoder-decoder framework (Du et al., 2017; Zhou et al., 2017; Sun et al., 2018; Pan et al., 2019; Wang et al., 2019). Zhou et al. (2017) propose a feature-rich encoder for the Seq2Seq (Sutskever et al., 2014) model, and Zhao et al. (2018) process paragraph level inputs with maxout pointer and gated self-attention. To deal with the “exposure...
bias" problem, reinforcement learning models are applied (Zhang and Bansal, 2019; Chen et al., 2020). However, despite considering longer contexts, the above QG methods generate questions related to only one fact obtained from a single sentence or article without deep comprehension and reasoning. This work focuses on generating deep questions with multi-hop reasoning over document-level contexts.

**Deep Question Generation** Deep Question Generation (DQG) aims to generate complex questions that require reasoning over multiple pieces of information. This task is inspired by multi-hop question answering (Song et al., 2018; Chen and Durrett, 2019; Tu et al., 2020), which aggregate the scattered evidence fragments in multiple documents to predict the correct answer.

Pan et al. (2020) is the first to study the task of DQG. They propose a new framework which incorporates semantic graphs to enhance the document representations and jointly train the tasks of content selection and question decoding. However, they do not pay much attention to the answer information that is a key to question generation and simply introduce the answer to the decoder based on the encoding of word embedding. Our work makes better use of the target answer as a guidance to facilitate question generation with the help of the answer-aware initialization module and semantic-rich fusion attention mechanism. Reinforcement learning which integrates both syntactic and semantic metrics as the reward is also applied to enhance the training process.

3 Methodology

3.1 Overview

Deep question generation (DQG) requires the thorough understanding of the input sources and reasoning over disjoint and relevant contexts. In this section, we elaborate on ADDQG model for deep question generation. The key idea of the model is to use an answer-aware initialization module and a semantic-rich fusion attention mechanism to integrate the answer information with the document. Reinforcement learning is also applied to fine-tune the model to get better performance. Figure 2 shows the detailed architecture of the proposed model.

To be specific, given the document collection $X^d = (X^d_1, ..., X^d_n)$ and the corresponding answer $X^a = (x^a_1, ..., x^a_n)$, the DQG task is to find the best $\bar{Y} = (y_1, ..., y_n)$ to maximize the conditional

![Figure 2: Illustration of ADDQG at generation step $t$.](image)
likelihood given \(X^d\) and \(X^a\).

\[
\mathcal{Y} = \arg \max_{Y} P(Y|X^d, X^a).
\] (1)

Different from traditional QG, the generation of \(\mathcal{Y}\) involves reasoning over multiple evidence documents \(d_i\), where \(i \in [1, n]\) and \(d_i\) is in \(X^d\). \(X^a\) should not be included in \(X^d\) because reasoning is involved to obtain the answer.

### 3.2 Encoder

#### Word Encoder

The model adopts two encoders for the documents and the answer respectively, so target information can be more precisely located for subsequent operations. The input sources are represented as sequences of embedding vectors. In this work, we use pre-trained GloVE embeddings (Pennington et al., 2014), and get the word vector \((w_{i,1}, w_{i,2}, ..., w_{i,m})\) as the input for the documents \(X^d\) and the answer \(X^a\) respectively. We use bidirectional LSTM to obtain forward and backward context representations of each word:

\[
\overrightarrow{h}_{i,j} = LSTM \left( \overrightarrow{h}_{i,j-1}, w_{i,j} \right), \quad \overrightarrow{h}_{i,j} = LSTM \left( \overrightarrow{h}_{i,j+1}, w_{i,j} \right).
\] (2)

Then they are concatenated to get the final word representation \(h_{i,j} = [\overrightarrow{h}_{i,j}; \overrightarrow{h}_{i,j}]\). The answer and the document representations are \(H^A = \text{BiLSTM} (W_{emb}(X^a))\) and \(H^D = \text{BiLSTM} (W_{emb}(X^d))\) respectively.

#### Graph Encoder

As shown in Figure 1, the semantic relationship between entities is a powerful clue to determine the inquiry content and reasoning types included. In order to extract semantic information from documents, we use dependency relationship (Dozat and Manning, 2017) to construct a semantic graph based on parsing. First, we initialize each node \(v = \{w_j\}_{j=m}^{n}\) to calculate the attention distribution of \(H^D\) on all words in \(v\) as follows:

\[
\gamma_j^{v} = \text{softmax} \left( \text{ReLU} \left( W_0 \left[ H^D; w_j \right] \right) \right),
\] (3)

where \(w_j\) is the context representation of words in nodes, \(m/n\) is the starting/ending position of the text span, \(W_0\) is a trainable parameter. Finally, the node is initialized as \(h_i^0 = \sum_{j=m}^{n} \gamma_j^{v} w_j\). In order to represent multiple relationships of edges, we use Graph Attention Network (GAT) (Velickovic et al., 2017) to dynamically determine the weight of adjacent nodes in message delivery using attention mechanism.

\[
\eta_{ij} = W_t^{l-1} \left( \text{ReLU} \left( W_2^{l-1} \left[ h_i^{l-1}; h_j^{l-1} \right] \right) \right),
\]

\[
\alpha_{ij} = \frac{\exp (\eta_{ij})}{\sum_{k \in N_i} \exp (\eta_{ik})},
\]

\[
h_i^l = \sum_{j \in N_i} \alpha_{ij} W_t^{l-1} h_j^{l-1},
\] (4)

where \(N_{i,j}\) denotes the neighbors of node \(v_i\). \(\alpha_{ij}^{(k)}\) is the attention coefficients between two nodes. \(W_t^{l-1}\) and \(W_2^{l-1}\) are trainable parameters. Finally, a Gated Recurrent Unit (GRU) (Cho et al., 2014) is applied to merge the aggregated neighboring information and get the semantic graph representation \(H^K\).

### 3.3 Decoder

#### Answer-Aware Initialization Module

Most QG models use the last hidden state of the encoder to initialize the decoder. ADDQG applies an answer driven initialization method, so that it can explicitly guide the choice of question words and generate questions which are more answer-focused. We first design a fusion gate to control the information flow rate of the document and answer.

\[
g = \sigma (W_z[H^A; H^D; H^D \circ H^A; H^D - H^A] + b_z),
\] (5)
where $\sigma$ is the sigmoid function. $W_z$ and $b_z$ are trainable parameters.

Then the representations are combined through the gated connection layer:

$$Z = g \odot H^D + (1 - g) \odot H^A,$$

where $\odot$ is the component-wise multiplication. $Z$ is the final initialization of the decoder, which is the deep fusion of answer and document features.

**Semantic-Rich Fusion Attention** Semantic-rich fusion attention integrates answer with the document and semantic graph to better support the generation process. First, the semantic graph representation $H^K$ is combined with the document representation $H^D$ to get the semantic-rich document representation $H^{DK}$. To be specific, if node $v_i$ contains word $w_i$, the word representation $H^D$ and node representation $H^K$ are concatenated to get the fused representation $H^{DK}_i$ (padded with a special vector if there is no corresponding $v_i$):

$$H^{DK}_i = F([H^D_i; H^K_{v_i}]),$$

where $F(\cdot)$ is the standard nonlinear transformation function. To model the complex interactions between the input sources, we apply the collaborative attention mechanism (Lu et al., 2016) which focuses on both the answer $H^A$ and semantic-rich document representation $H^{DK}$. To be specific, we first calculate the correlation matrix $L = H^{DK} \odot H^A$, which contains the similarity scores of all pairs of document and answer words. The attention weights $A^{H^A}$ are across the answer for each word in the document, and the weights $A^{H^{DK}}$ are across the document for each word in the answer.

$$A^{H^A} = \text{softmax}(L), A^{H^{DK}} = \text{softmax}(L^\top).$$

Next, we calculate the co-dependent representation of the question and document $C^{H^{DK}}$ similar to (Cui et al., 2017):

$$C^{H^A} = H^{DK} A^{H^A}, C^{H^{DK}} = [H^A; C^{H^A}] A^{H^{DK}}.$$  \hfill (9)

Then the semantic-rich document information and answer information are integrated to get the fusion representation:

$$H^{DKA} = [H^{DK}; C^{H^{DK}}].$$  \hfill (10)

Finally, the semantic-rich representation $H^{DKA}$ is applied to obtain the context vector $c_t$:

$$e_t = v_d^T \tanh (W h^*_t + U H^{DKA}),$$

$$\alpha^*_t = \text{softmax} (e_t),$$

$$c_t = H^{DKA} \alpha^*_t,$$

where $W$, $v_d^T$, and $U$ are trainable parameters.

Taking $Z$ computed in Eq. 6 as the initialization, during decoding, the hidden state $h^*_t$ at step $t$ is:

$$h^*_t = \text{LSTM}_{Dec} \left([w_t; c_{t-1}] ; h^*_t \right),$$

where word $w_t$ is the input.

**Copy Mechanism and Maxout Pointer** In order to solve the out-of-vocabulary (OOV) problem, the decoder applies the copy mechanism (Gu et al., 2016) which allows the token to be copied from the input sources to the decoding step $t$. The mechanism utilizes the original attention scores $\alpha^*_t$ calculated in Eq. 11 to get the probability of copy $p_{\text{copy}}(y_t)$. We adopt the maxout pointer (Zhao et al., 2018) mechanism to limit the magnitude of scores of repeated words to their maximum value to solve the problem of repetition. The switch gate $k = \sigma (W^s h^*_t + U^s c_t + b^s)$ determines whether the generated word is sampled from the vocab or copied from the input sources.

$$p_{\text{final}} (y_t | y_{<t}; \theta) = kp_{\text{copy}}(y_t; \theta_1) + (1 - k)p_{\text{gen}}(y_t; \theta_2),$$

where $p_{\text{gen}}(y_t) = \text{softmax}(W^T [h^*_t; c_t])$ is the generative probability distribution.
3.4 Reinforcement Learning for Fine-Tuning

The loss function of question generation minimizes the negative log-likelihood of the output generative words as:

$$\text{Loss}_{\text{CE}} = - \sum_t \log P(y_t|y_{<t}, X^d, X^a, \theta).$$  \hspace{1cm} (14)

However, using the above cross-entropy loss in the sequence prediction model could make the process brittle, because models trained on a specific distribution of words are used for test data sets with potentially different distributions to predict the next word given the current predicted word (Kumar et al., 2018). This creates “exposure bias” during training (Ranzato et al., 2016), reinforcement learning is widely used to deal with the “exposure bias” in question generation and proved to be effective. We define $r$ as the reward, which is calculated by comparing the output sequence $Y$ with the corresponding ground-truth question $Y^*$ based on the metrics. Similar to (Chen et al., 2020), we use BLEU-4 as reward $r(Y, Y^*)_{\text{BLEU-4}}$ which is directly optimized towards the evaluation metrics, and word movers distance (WMD) as reward $r(Y, Y^*)_{\text{WMD}}$ which makes the model more effective and robust. However, instead of using weighted combination of $r(Y, Y^*)_{\text{BLEU-4}}$ and $r(Y, Y^*)_{\text{WMD}}$, we apply a multi-reward optimization strategy (Pasunuru and Bansal, 2018) to train the model with two mixed losses, because it is hard to find the complex scaling and weight balance among them.

$$r(Y, Y^*)_{\text{WMD}} = f_{\text{WMD}}(Y, Y^*), \hspace{1cm} r(Y, Y^*)_{\text{BLEU-4}} = f_{\text{BLEU-4}}(Y, Y^*).$$  \hspace{1cm} (15)

We follow the effective SCST strategy (Rennie et al., 2017) and take the reward of greedy search result DQG as the baseline $b$.

$$\text{Loss}_{\text{RL}} = (b - r(Y^*, Y^*)) \log P(y^*_t|y^*_{<t}, X^d, X^a, \theta),$$  \hspace{1cm} (16)

where $Y^*$ is the sampled output. We alternately train two mixed losses $\text{Loss}_{\text{WMD}}^{\text{mixed}}$ and $\text{Loss}_{\text{BLEU-4}}^{\text{mixed}}$ in a certain proportion.

$$\begin{align*}
\text{Loss}_{\text{WMD}}^{\text{mixed}} &= \alpha_{\text{WMD}} \text{Loss}_{\text{WMD}}^{\text{RL}} + (1 - \alpha_{\text{WMD}}) \text{Loss}_{\text{CE}}, \\
\text{Loss}_{\text{BLEU-4}}^{\text{mixed}} &= \alpha_{\text{BLEU-4}} \text{Loss}_{\text{BLEU-4}}^{\text{RL}} + (1 - \alpha_{\text{BLEU-4}}) \text{Loss}_{\text{CE}}.
\end{align*}$$  \hspace{1cm} (17)

where $\alpha$ is the scale factor to control the trade-off between cross-entropy loss $\text{Loss}_{\text{CE}}$ and reinforcement Learning loss $\text{Loss}_{\text{RL}}$.

4 Experiments

4.1 Experimental Setup

In DQG, question generation requires the thorough understanding of the input sources and reasoning over disjoint and relevant contexts. To evaluate DQG models, conventional QG datasets like SQuAD (Rajpurkar et al., 2016) dataset are insufficient because most of their questions are shallow and only relevant to information confined to a single sentence (Min et al., 2018).

We conduct experiments on HotpotQA (Yang et al., 2018), a challenging dataset in which the questions are generated by reasoning over multiple supporting documents to answer. HotpotQA contains around 113K Wikipedia-based questions. Each question is supported with two documents containing the evidence necessary for answer inferring. For fair comparison, we pre-process the original dataset to select relevant sentences and keep 90,440 / 6,072 examples for training and evaluation respectively.

In order to extract semantic information from documents, we use the dependency parsing method to construct semantics graph. The maximum length of the original document is 200 and the maximum length of target answer is 50. For word embedding, we use pre-trained GloVe word vectors with 300 dimensions and froze them during training. We set the LSTM hidden unit size to 512 and the number of layers to 2 in both the answer and document encoders and the decoder, we design a bidirectional GRU as the graph encoder with unit size 512. Optimization is performed by Adam (Kingma and Ba, 2015), with an initial learning rate of 0.0025.
4.2 Models for Comparison

As discussed earlier, DQG is still underexplored so far, and there are few existing baselines for our comparison. We compare the generation results with different neural network models, among which SGGDQ (Pan et al., 2020) is a DQG model, while the others are for conventional QG tasks. We choose the following QG models due to their high relevance with our task, and change their settings to fit our scenario.

**S2S-Att**
1 (Bahdanau et al., 2015): It is a Seq2Seq model with the attention mechanism. We connect the document with the answer as the input of the encoder.

**NQG**
2 (Zhou et al., 2017): It is a Seq2Seq model with a feature-rich encoder to encode answer position, POS and NER tag information.

**s2s-mcp-gsa**
3 (Zhao et al., 2018): It proposes a maxout pointer mechanism with a gated self-attention encoder to address the challenges of processing long text inputs for question generation.

**ASs2s-a**
4 (Kim et al., 2019): It proposes an answer-separated Seq2Seq model with a new module termed keyword-net, which better utilizes the information from both the passage and the target answer to generate an appropriate question.

**SemQG**
5 (Zhang and Bansal, 2019): It proposes two semantics-enhanced rewards obtained from downstream question paraphrasing and question answering tasks to regularize the QG model to generate semantically valid questions.

**SGGDQ**
6: It constructs a semantic-level graph for the input document, then use the document-level and graph level representations to perform joint training of content selection and question decoding.

4.3 Evaluation Metrics

**Automatic Evaluation** In previous work, BLEU (Papineni et al., 2002), ROUGE (Lavie and Agarwal, 2007) and METEOR (Lin, 2004) have been widely used to evaluate the overall performance of question generation. Therefore, in order to make a fair comparison with the existing methods, we use the same automatic evaluation metrics. Initially, BLEU and METEOR are used to evaluate machine translation systems (Papineni et al., 2002; Lin, 2004), and ROUGE-L is used to evaluate text summarization systems (Lavie and Agarwal, 2007). We use them to evaluate the similarity between the generated questions and references.

**Human Evaluation** In order to evaluate the effect of our model more intuitively, we also conducted a manual evaluation to check the quality of the question generated by the model. We have designed three evaluation criteria: 1) **Naturalness**, a metric which indicates the grammaticality and fluency of the generated question. 2) **Complexity**, a metric which measures difficulty of answering the generated question. 3) **Relevance**, a metric which is a measure of how relevant the generated question is to the answer. Five well-educated annotators were asked to rate the generation on a scale of one to five according to the three criteria, with five indicating the best results.

4.4 Results and Analysis

4.4.1 Comparisons with Baseline Models

Table 1 shows the overall experimental automatic evaluation results of our model and baselines on the HotpotQA dataset. We also have some observations as follows:

- ADDQG has achieved significant improvements of 2.01, 0.41, 1.15 points in terms of BLEU-4, METEOR and ROUGE-L respectively compared to the best baseline SGGDQ. It has made great progress in BLEU-4, which may be the contribution of reinforcement learning (regarded as a reward). The BASE model (similar to SGGDQ, but without the support of answer information)
Table 1: The ROUGE, BLEU and METEOR scores of different methods on the HotpotQA dataset.

| Dataset       | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | METEOR | ROUGE-L |
|---------------|--------|--------|--------|--------|--------|---------|
| S2S-Att (Bahdanau et al., 2015) | 32.23  | 20.36  | 14.68  | 11.40  | 16.88  | 32.30   |
| NQG (Zhou et al., 2017)          | 35.51  | 22.32  | 15.94  | 11.73  | 16.79  | 32.12   |
| s2s-mcp-gsa (Zhao et al., 2018)  | 38.54  | 25.09  | 17.49  | 13.48  | 18.73  | 33.45   |
| ASs2s-a (Pan et al., 2019)       | 37.67  | 23.79  | 17.21  | 12.59  | 17.45  | 33.21   |
| SemQG (Zhang and Bansal, 2019)   | 39.92  | 26.73  | 18.73  | 14.71  | 19.29  | 35.63   |
| SGGDQ (DP) (Pan et al., 2020)    | 40.55  | 27.21  | 20.13  | 15.53  | 20.15  | 36.94   |
| **Our Model**                |        |        |        |        |        |         |
| BASE                      | 41.17  | 27.64  | 20.47  | 15.81  | 19.07  | 37.24   |
| w/AAI (Answer-Aware Initialization Module) | 41.99  | 28.13  | 20.81  | 16.11  | 19.85  | 37.17   |
| w/SRF (Semantic-Rich Fusion Attention) | 43.12  | 29.84  | 21.62  | 17.07  | 20.24  | 37.52   |
| w/RL (Reinforcement Learning for Fine-Tuning) | 42.03  | 28.26  | 20.95  | 16.21  | 19.86  | 37.26   |
| **ADDQG**                  | **44.34** | **31.32** | **22.68** | **17.54** | **20.56** | **38.09** |

Table 2: Human evaluation results of ADDQG compared with baseline models, where 1 is the worst and 5 is the best.

|                      | NQG  | s2s-mcp-gsa | ASs2s-a | SemQG | SGGDQ | ADDQG |
|----------------------|------|-------------|---------|-------|-------|-------|
| Naturalness          | 2.65 | 3.34        | 2.89    | 3.75  | 3.83  | 4.28  |
| Complexity           | 2.46 | 3.56        | 2.43    | 4.01  | 3.96  | 4.47  |
| Relevance            | 1.94 | 2.97        | 2.13    | 2.94  | 3.25  | 4.29  |
| Average score        | 2.35 | 3.29        | 2.48    | 3.57  | 3.68  | 4.35  |

4.4.2 Ablation Study

The ablation experimental results on the HotpotQA dataset are listed in Table 1. We analyze the detailed impact of each module as follows:

**w/AAI** The answer-aware initialization (AAI) module helps the BASE model to increase by 0.30 in BLEU-4, 0.78 in METEOR. This module introduces both document and answer information to the decoder for initialization, which helps the model guide the choice of question words.

**w/SRF** The semantic-rich fusion attention (SRF) module has brought an average improvements of 1.26 in BLEU-4, 1.17 in METEOR and 0.28 in ROUGE-L, which contributes the most to the good performance of ADDQG compared to the other modules. This module incorporates the answer information...
The 1974 Texas Tech Red Raiders football team represented Texas Tech University in the Southwest Conference during the 1974 NCAA Division I football season.

Texas Tech University, often referred to as Texas Tech, Tech, or TTU, is a public research university in Lubbock, Texas.

Answer: Texas Tech University

Reference Question: The 1974 Texas Tech Raiders football team represented what public research university in Lubbock, Texas?

SGGDQ: Texas tech red raiders football team represented where university in lubbock?

w/AAI: What university in lubbock, texas, 11 tech red raiders football team represent?

w/SRF: The 1974 Texas Tech Red Raiders football team represented what university?

w/RL: Texas Tech Raiders football team represented what public university in Lubbock?

ADDQG: The 1974 Texas Tech Raiders football team represented what public research university in Lubbock?

Figure 3: Example of questions generated by ADDQG. We also reproduce the SGGDQ model for comparative analysis.

with the document information into the generation of questions, which promotes the proper handling of answer information during question generation.

w/RL With the help of reinforcement learning, the model has made an improvements of 0.4 in BLEU-4, 0.79 in METEOR and 0.02 in ROUGE-L. Reinforcement learning integrates both syntactic and semantic metrics to enhance the training process.

Table 1 also indicates that our proposed three methods help to bring improvements to the performance of the BASE model obviously, and the combination of them further helps the hybrid model (ADDQG) to achieve state-of-the-art performance.

4.4.3 Case Study

In this section, we present examples generated by our model and SGGDQ model for comparison in Figure 3. As can be seen from the figure, SGGDQ model misses part of semantic information (like “The 1974”) and selects the wrong question word (“where” should be replaced with “what”). w/AAI, w/SRF and w/RL all have selected the right question word “what” that is consistent with the reference question, which show our models make better use of the target answer as a guidance to facilitate question generation. The question generated by ADDQG is the most close to the reference question, which further demonstrates the effectiveness of the designs.

5 Conclusion and Future Work

Deep question generation aims to generate complex questions that require reasoning over multiple pieces of information. In this paper, we propose an answer-driven end-to-end deep question generation model (ADDQG) based on reinforcement learning. An answer-aware initialization module with a gated connection layer and a semantic-rich fusion attention mechanism are designed to incorporate document and answer information into the generation process. Reinforcement learning is further applied to integrate both syntactic and semantic metrics as the reward to enhance the training of ADDQG. Experiments show that ADDQG outperforms the state-of-the-art systems on the challenging DQG dataset. Ablation studies have demonstrated the effectiveness of our designs, and human evaluations show that our model can produce more coherent and answer-focused questions.

Future research can be carried out in several directions. First, we will try deep graph convolutional encoders (Diego Marcheggiani, 2018; Guo et al., 2019) to get deeper semantic information and explore more elaborate mechanisms for the integration of document and answer information. Second, we will apply a pre-trained multi-hop question answering model to generate the reward to optimize ADDQG, thus further enhancing the reasoning ability of this DQG model.
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