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Abstract

Knowledge-grounded dialogue generation is proposed to solve the problem of general or meaningless responses in traditional end-to-end dialogue generation methods. It generally includes two sub-modules: knowledge selection and knowledge-aware generation. Most studies consider the topic information for knowledge-aware generation, while ignoring it in knowledge selection. It may cause the topic mismatch between the overall dialogue and the selected knowledge, leading to the inconsistency of the generated response and the context. Therefore, in this study, we propose a \textit{Topic-driven Knowledge Selection} method (TopicKS) to exploit topic information both in knowledge selection and knowledge-aware generation. Specifically, under the guidance of topic information, TopicKS selects more accurate candidate knowledge for the current turn of dialogue based on context information and historical knowledge information. Then the decoder uses the context information and selected knowledge to generate a higher-quality response under the guidance of topic information. Experiments on the notable benchmark corpus \textit{Wizard of Wikipedia} (WoW) show that our proposed method not only achieves a significant improvement in terms of selection accuracy rate on knowledge selection, but also outperforms the baseline model in terms of the quality of the generated responses.

\textbf{Index Terms:} dialogue systems, knowledge-grounded dialogue generation, knowledge selection

1. Introduction

Open-domain dialogue response generation systems have shown impressive potential to endow a machine with the ability to converse with a human using natural language [1]. However, the performance of response generation is still far from satisfaction in many real-world scenarios. For example, in dialogue systems, conditioning on only the input text, a text generation system often produces general or meaningless responses consist of frequent words or phrases in the corpus [2, 3], such as for a given input text “My skin is so dry,” it usually generates “Me too.” or “Oh my god!” These responses lack meaningful content compared to human responses with rich knowledge.

The general or meaningless responses are usually caused by the commonsense knowledge gap between machines and humans [4]. Commonsense knowledge provides information about the relationships between concepts in the context, thus potentially guiding humans to capture the implicit logic between the concepts. In this way, humans in real conversations often relate context to their commonsense knowledge to make informed responses [5]. To solve this problem, researchers have introduced some large-scale knowledge bases for enhancing dialogue generation [6, 7, 8]. The research topic is also greatly advanced by many knowledge corpora [9, 10]. The knowledge can be unstructured knowledge texts [11, 12], structured knowledge graphs [13, 14], or hybrid of them [15, 16]. We choose more informative unstructured knowledge texts as the external knowledge base for our study.

Knowledge-grounded dialogue generation aims at generating informative responses based on both discourse context and external knowledge [17]. It is mainly devoted to addressing two research problems [18]: (1) \textbf{knowledge selection}: selecting appropriate knowledge based on the dialog context and previously selected knowledge [19, 20]; and (2) \textbf{knowledge-aware-generation}: injecting the required knowledge to generate meaningful and informative responses [21, 22]. Since selecting the appropriate knowledge is a precursor to the success of knowledge-grounded dialog systems, we focus on the knowledge selection problem in this study.

Existing knowledge selection models are generally divided into two categories. The first category is \textbf{non-sequential selection}, which captures the relationship between only the current

![Figure 1: An illustrative example, the blue parts are topic information, candidate knowledge information, and user utterances. Yellow is the response of the system without the guidance of topic information, and red is the response of the system under the guidance of topic information.](image-url)
context and the background knowledge [23]. PostKS [24] estimates a posterior distribution over candidate knowledge sentences during the training procedure. It is calculated based on both the context and the golden response. Then the model only uses the context to estimate a prior distribution as an approximation of the posterior distribution during testing procedure. To further exploit the dialog history in both terms of context and knowledge, studies tend to use the second category sequential selection. In these studies, models not only rely on the current context, but also use previously selected knowledge to facilitate knowledge selection [25]. For example, DiffKS [26] not only tracks the hidden states of dialog history and previously selected knowledge sentences, but also calculates the difference of knowledge selected at different turns, which improves the accuracy of knowledge selection.

However, most of the previous studies ignored the guiding role of topic information in knowledge selection, and only used it for knowledge-aware generation [4]. It may cause the topic mismatch between the overall dialogue and the selected knowledge, leading to the inconsistency of the generated response and the context. Figure 1 illustrates an example, where the dialogue system selects different knowledge and generates corresponding responses with/without topic information. It can be seen that the dialogue system can select the knowledge matching the context better, and generate the more appropriate responses when guided by dialogue topic information. Therefore, it is necessary to consider topic information for knowledge selection.

In this study, to further exploit the topic information for both knowledge selection and response generation, we propose a Topic-driven Knowledge Selection method (TopicKS). The most obvious difference between our proposed method and previous sequential selection methods is that we explore the guidance of topic information on knowledge selection. Specifically, we minimize the distance of the prior and posterior distributions for knowledge selection in the training stage by using the Kullback-Leibler divergence loss (KL loss) under the guidance of topic information, so that the prior distribution can be used to select knowledge when there is no posterior distribution in the testing stage. Experiments are conducted on a notable benchmark corpus Wizard of Wikipedia (WOW), the automatic results show that TopicKS can use topic information to not only improve the accuracy of knowledge selection, but also generate a more promising response.

2. TopicKS

We propose a novel topic-driven knowledge selection method for knowledge-grounded dialogue generation named TopicKS, whose model is illustrated in Figure 2. We introduce task formulation in Section 2.1, context and knowledge encoders in Section 2.2, topic-driven knowledge Section method in Section 2.3, knowledge-aware generation decoder in Section 2.4, and loss function in Section 2.5.

2.1. Task Formulation

In multi-turn dialogue, given the context of each turn and a series of knowledge sentences, our goal is to select the appropriate knowledge from the candidate knowledge, and generate the response based on the context and selected knowledge.

Formally, We use \( f^t \) to represent the topic of the turn \( t \) of the dialogue. The post at turn \( t \) is a sequence of tokens \( x^t = (x^t_1,...,x^t_{|x^t|}) \), and the response to be generated is \( y^t = (y^t_1,...,y^t_{|y^t|}) \). The candidate knowledge \( k^t = (k^t_1,...,k^t_{|k^t|}) \) contains a sequence of knowledge sentences provided at the turn \( t \). For each \( i \), \( k^t_i = (k^t_i,1,...,k^t_i,|x^t_i|) \) is a sequence of tokens in the \( i \)-th sentence. The input of the model at turn \( t \) is \( f^t, x^t−1, y^t−1, x^t \) and \( k^t \). The output of the model is selected knowledge \( k^o \) and the response \( y^o \).

2.2. Context and Knowledge Encoders

We use BERT (base) [27] as our context encoder, which can take full advantage of pre-training with a large amount of data, and the multi-layer bidirectional attention mechanism in BERT can better realize the interaction between topic information and context information, leading to better representations. Specifically, as shown in the following equations.

\[
\begin{align*}
    h^c_x &= \text{avgpool} \left( \text{BERT} \left( [CLS] f^t [SEP] x^t [SEP] \right) \right) \\
    h^c_y &= \text{avgpool} \left( \text{BERT} \left( [CLS] f^t [SEP] y^t [SEP] \right) \right)
\end{align*}
\]

Our knowledge encoder adopts the same structure as the context encoder.

\[
\begin{align*}
    h^k_{k,i} &= \text{avgpool} \left( \text{BERT} \left( [CLS] f^t [SEP] k^t_i [SEP] \right) \right) \\
    h^k_f &= \text{avgpool} \left( \text{BERT} \left( [CLS] f^t [SEP] \right) \right)
\end{align*}
\]

2.3. Topic-driven Knowledge Selection

The main goal of the TopicKS module is to select the appropriate knowledge from candidate knowledge sentences according to the topic information and context information. In order to select more appropriate knowledge, our model also pays attention to the previously selected knowledge information, modeling it as latent variables, so as to conduct joint inference of multiple
rounds of knowledge selection and response generation. Specifically, given the encoded topic information \( f^t \) context information \( x^t \), knowledge \( k^t \), previously selected knowledge \( k^{t-1} \) and real response \( y^t \) (only in training stage), TopicKS module will make full use of this information to select an appropriate \( k^t \).

In training stage, the real responses \( y^t \) are used as pseudo-labels to assist the selection of knowledge, so the sampling of knowledge is based on the posterior distribution, denoted by \( p_{\text{post}} = p \left( k^t \mid f^t, x^{\leq t}, y^{\leq t}, k^{t-1} \right) \).

The main goal of the decoder is to generate \( t \)-turn response of next turn.

2.4. Knowledge-aware Generation Decoder

The main goal of the decoder is to generate \( t \)-turn response using the given topic information, context information, and knowledge information selected by the TopicKS module. The decoder is a GRU network. At each time, it can generate two types of words: vocabulary words and copied words. The decoder first updates the internal state:

\[
s_t = GRU_D \left( s_{t-1}, \mathbf{o} (y_{t-1}) ; h_k ; h_f \right)
\]

where \( W_D \) and \( b_D \) are trainable parameters, \( \mathbf{o} (y_{t-1}) \) denotes the embedding of the word generated in the last step, \( h_k \) denotes the embedding of \( k^t \) and \( h_f \) denotes the embedding of \( f^t \).

2.4.1. Vocabulary Words

The probability distribution \( p_c (y_t = w) \) over the vocabulary is given by:

\[
p_c (y_t = w) = \text{softmax} \left( W^T (W_V s_t + b_V) \right)
\]

where \( W_V \) and \( b_V \) are trainable parameters, and \( W \) is the one-hot vector of the word \( w \).

2.4.2. Copied Words

The decoder can use copy mechanism [29] to copy the word from the knowledge sentence \( k^t \). The probability distribution \( p_c (y_t = w) \) is calculated as:

\[
p_c (y_t = w) = \text{softmax} \left( \sum_{y_k \mid w} (s_k)^2 H (h_{k,s_k}) \right)
\]

where \( H \) is a fully connected layer activated with tanh.

2.4.3. Flexible Fusion

Previous two distribution can be fused as follows:

\[
p (y_t = w) = (1 - \alpha) p_c (y_t = w) + \alpha p_r (y_t = w)
\]

where \( \alpha \) is a hyper-parameter, we set \( \alpha = 0.5 \) in our experiments. Then we select the word from vocabulary with the highest probability \( y_t = \arg \max_{w \in V} p (y_t = w) \) where \( v \) is the vocabulary.

2.5. Loss

We use the NLL loss to narrow the difference between the real response and the response generated by our model. The negative log-likelihood loss is adopted:

\[
L_{\text{NLL}} (\theta) = - \sum_{t=1}^{T} \sum_{l=1}^{|y^t|} \log \mathcal{P} (y^t_l) ^{\theta}
\]

where \( y^t_l \) denotes the \( l \)-th word in the golden response at the \( t \)-th turn and \( T \) is the length of the whole dialogue.

At the same time, since the true responses are known in the training stage, we use the posterior distribution to select knowledge, but in the testing stage the true responses are unknown, so we can only use the prior distribution to select knowledge. To make the prior distribution approximate the posterior distribution, we use the KL Loss [30] during training. At \( t \)-th turn, according to the topic information \( f \), the context \( x \), and the real response \( y \), The KL Loss is defined as follows:

\[
L_{\text{KL}} (\theta) = \sum_{t=1}^{N} p (k = k_s \mid f, x, y) \log \frac{p (k = k_s \mid f, x, y)}{p (k = k_s \mid f, x)}
\]

(15)

In the process of minimizing the KL loss, the prior distribution keeps approximating the posterior distribution. After sufficient training, in the testing stage, our model can select appropriate knowledge even without the ground-truth responses as posterior information. The total loss is:

\[
L (\theta) = L_{\text{NLL}} (\theta) + \lambda L_{\text{KL}} (\theta)
\]

(16)

where \( \lambda \) is to balance the weight of NLL Loss and KL Loss, in our experiments, \( \lambda \) is set to 1.

3. Experiments

3.1. Datasets

The most popular external knowledge dataset Wizard of Wikipedia (WoW) [30] is used in our experiments. It consists of 18430 training dialogues, 1948 validation dialogues, and 1933 testing dialogues. The test set is divided into two subsets, Test Seen and Test Unseen. Test Seen contains 965 conversations whose topics appear in the training set or validation set, and Test Unseen contains 968 conversations whose topics never appeared in the training set and test set.
Table 1: Automatic evaluation results on Wizard of Wikipedia (WoW) Corpus. The “+Topic info” means the models are enhanced by the Topic information.

<table>
<thead>
<tr>
<th>Models</th>
<th>Test (Seen)</th>
<th></th>
<th>Test (Unseen)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ACC</td>
<td>BLEU-2</td>
<td>BLEU-4</td>
<td>ROUGE-2</td>
</tr>
<tr>
<td>MemNet</td>
<td>13.3</td>
<td>6.6</td>
<td>1.8</td>
<td>3.2</td>
</tr>
<tr>
<td>+Topic info</td>
<td>19.1</td>
<td>7.5</td>
<td>2.3</td>
<td>3.5</td>
</tr>
<tr>
<td>PostKS</td>
<td>13.8</td>
<td>6.9</td>
<td>1.8</td>
<td>3.2</td>
</tr>
<tr>
<td>+Topic info</td>
<td>23.4</td>
<td>8.1</td>
<td>3.2</td>
<td>4.4</td>
</tr>
<tr>
<td>DiffKS</td>
<td>25.5</td>
<td>11.6</td>
<td>5.7</td>
<td>6.8</td>
</tr>
<tr>
<td>TopicKS</td>
<td>26.2</td>
<td>12.0</td>
<td>5.9</td>
<td>7.0</td>
</tr>
</tbody>
</table>

3.2. Experimental Settings

We use the following models as baselines. **Memnet** [11]: The method uses a memory network to store knowledge and select knowledge based on semantic similarity. We also evaluated a variant (MemNet+Topic info) where knowledge selection is guided by additional topic information. **PostKS** [24]: The method uses the posterior knowledge distribution as a pseudo-label for knowledge selection, but this method ignores the selected knowledge information of previous turns and the importance of topic information to the knowledge selection of the current turn. So we also evaluated a variant, that uses topic information to help knowledge selection(PostKS+Topic info). **DiffKS** [26]: The method exploits the differential information between selected knowledge in the multi-turn knowledge-grounded conversation for knowledge selection. It pays attention to the knowledge information of previous turns, but ignores the importance of topic information in knowledge selection.

3.3. Evaluation Metrics

In this work, we use the following metrics to automatically evaluate the accuracy of knowledge selection and the quality of generated responses:

1. **Accuracy(ACC)**: We use the accuracy metric to measure the accuracy of each knowledge selection on the test set.
2. **BLEU-2/4** [31]: We use precision-based BLEU-2/4 to evaluate the model’s ability to preserve information from knowledge and ground-truth responses.
3. **ROUGE-2** [32]: We use the recall-based Rouge-2 metric to examine the adequacy and fidelity between the generated responses and the truth responses.

3.4. Experimental Results and Analysis

As shown in Table 1, We compare the performance of different methods on the WoW dataset, and the experimental results of both Test Seen and Test Unseen show that our method has significant advantages, which indicates it can not only increase the accuracy of knowledge selection, but also improve the quality of response generation. Compared to baseline models, our model also demonstrates a stronger ability to generalization from in-domain (Test Seen) to out-of-domain data (Test Unseen).

Variants of MemNet and PostKS experimental results can further demonstrate the importance of topic information for knowledge selection, which is consistent with our hypothesis. Introducing topic information in knowledge selection can not only reduce the error in knowledge selection, but also improve the BLEU-2/4 and ROUGE-2 during response generation.

3.5. Ablation Tests

To verify the effectiveness of the topic-driven knowledge selection method proposed in our study, we conduct an ablation test. We remove the topic information from the model, train the model under this condition, and the experimental results are shown in Table 2. The results show that topic information plays a guiding role in knowledge selection. Under the global guidance of topic information, not only the accuracy rate of knowledge selection but also the quality of generated responses can be improved.

Table 2: Ablation tests on Wizard of Wikipedia (WoW) Corpus.

<table>
<thead>
<tr>
<th>Models</th>
<th>ACC</th>
<th>BLEU-2/4</th>
<th>ROUGE-2</th>
</tr>
</thead>
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<tr>
<td>Test Seen</td>
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<td>26.2</td>
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<td>5.9</td>
</tr>
<tr>
<td>-Topic info</td>
<td>24.9</td>
<td>11.6</td>
<td>5.1</td>
</tr>
<tr>
<td>Test Unseen</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TopicKS</td>
<td>20.2</td>
<td>10.2</td>
<td>4.8</td>
</tr>
<tr>
<td>-Topic info</td>
<td>18.3</td>
<td>9.8</td>
<td>3.8</td>
</tr>
</tbody>
</table>

4. Conclusions and Future Work

In this study, we propose a novel topic-driven knowledge selection method for knowledge-grounded dialogue generation. Under the global guidance of topic information, this method integrates historical knowledge selection information, and combines the prior distribution and posterior distribution of knowledge selection to better select suitable candidate knowledge for the current turn of dialogue. Experimental results show that our method not only selects knowledge more accurately but also generates a more informative responses. In future work, we will introduce more types of knowledge to increase the diversity of knowledge-grounded dialogue generation.

5. Acknowledgements

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6. References


