Reasoning in Dialog:
Improving Response Generation by Context Reading Comprehension

Xiuying Chen\textsuperscript{1,2}, Zhi Cui\textsuperscript{3}, Jiayi Zhang\textsuperscript{3}, Chen Wei\textsuperscript{3},
Jianwei Cui\textsuperscript{1}, Bin Wang\textsuperscript{3}, Dongyan Zhao\textsuperscript{1,2}, and Rui Yan\textsuperscript{1,5,*}

\textsuperscript{1}Center for Data Science, AAIS, Peking University, Beijing, China
\textsuperscript{2}Wangxuan Institute of Computer Technology, Peking University, Beijing, China
\textsuperscript{3}Xiaomi AI Lab
\textsuperscript{4}Gaoling School of Artificial Intelligence, Renmin University of China
\textsuperscript{5}Beijing Academy of Artificial Intelligence
\textsuperscript{*}\text{Corresponding author (ruiyan@ruc.edu.cn).}

Abstract

In multi-turn dialog, utterances do not always take the full form of sentences (Carbonell 1983), which naturally makes understanding the dialog context more difficult. However, it is essential to fully grasp the dialog context to generate a reasonable response. Hence, in this paper, we propose to improve the response generation performance by examining the model’s ability to answer a reading comprehension question, where the question is focused on the omitted information in the dialog. Enlightened by the multi-task learning scheme, we propose a joint framework that unifies these two tasks, sharing the same encoder to extract the common and task-invariant features with different decoders to learn task-specific features. To better fusing information from the question and the dialog history in the encoding part, we propose to augment the Transformer architecture with a memory updater, which is designed to selectively store and update the history dialog information so as to support downstream tasks. For the experiment, we employ human annotators to write and examine a large-scale dialog reading comprehension dataset. Extensive experiments are conducted on this dataset, and the results show that the proposed model brings substantial improvements over several strong baselines on both tasks. In this way, we demonstrate that reasoning can indeed help better response generation and vice versa. We release our large-scale dataset for further research\textsuperscript{1}.

Introduction

In recent years, text generation has made impressive progress (Chen et al. 2019; Li et al. 2020; Yu et al. 2020; Liu et al. 2020; Zhang et al. 2021), and open-domain dialogue generation has become a research hotspot in Natural Language Processing due to its broad application prospect, in-cluding chatbots, virtual personal assistants (Qiu et al. 2019; Debnath, Sengupta, and Wabgaonkar 2018; Li et al. 2019), etc. However, studies (Carbonell 1983) show that users of dialogue systems tend to use succinct language which often omits entities or concepts made in previous utterances. To make appropriate responses, dialogue systems must be equipped with the ability to understand these incomplete utterances. This naturally leads to the reading comprehension task, where correctly answering questions about the context requires understanding of natural language of the dialog context (Rajpurkar et al. 2016).

Take Example 2 in Table 1 for example, contents in parentheses are information omitted in the utterance. Humans are capable of comprehending such missing utterances dependent based on previous utterances and commonsense. For instance, $A_3$ means sending an MV to B instead of a gift. However, though of high importance, it is difficult for models to capture the implicit dependency between utterances without specific design, and that is why the reading comprehension task is proposed (Rajpurkar et al. 2016; Reddy, Chen, and Manning 2019). In this case, by reasoning and correctly answering the question with keyword “MV”, the model learns that the dialog is focused on MV, which leads to a proper response that is also concentrated on music. Such cases that require dependency on the previous context to fully comprehend current utterance takes up about 60% according to a survey in Pan et al. (2019). This inspires us to come up with a multi-task framework that generates the response and answers reading comprehension question at the same time, which can boost the performance of each task.

Our Multi-task Response Generator (MRG) augments the previously proposed Transformer architecture (Vaswani et al. 2017) with the ability to encode multiple utterances in a question-aware fashion. The proposed model first uses a cross-attention mechanism (Vaswani et al. 2017) between the question and dialog words to identify representative words in dialog with the help of question. Concretely, we propose a memory updater, which updates its memory state using both the current inputs and previous memory state. The memory state can be interpreted as a container of the highly summarized dialog history information. During the cross-attention process, the current dialog representation is enhanced with the memory state from the previous step.

\textsuperscript{1}https://github.com/yingttaomj/Reasoning-in-Dialog
MRG then uses a hierarchical inner attention, first over different words in each utterance, and then over all utterances in dialog history, to successively learn the utterance-level features. Finally, MRG utilizes the utterance-level and question features to select the answer to the question while generating the response words.

Since there lacks large-scale dialog reading comprehension datasets, we hire an annotation team to construct a dialog reading comprehension dataset (DRCD). Concretely, based on the Restoration-200K dataset proposed by Pan et al. (2019), where the omitted word span is annotated by humans, we ask the annotators to write a question where the answer is the missing phrase. We manually construct 10k cases, based on which we train a question generator and leverage the model to construct questions for the rest of the dataset. We benchmark several classic dialog generation and reading comprehension baselines on DRCD. We also conduct experiments to show that the proposed model brings substantial improvements over these baselines on both tasks. In this way, we demonstrate that reasoning can indeed help better response generation and vice versa.

Our contributions can be summarized as follows:

- We propose the multi-task learning framework, which jointly answers reading comprehension questions and generates a proper response in multi-turn dialog scenario.
- We augment the Transformer architecture with a memory updater, which helps selectively store and update history dialog information.
- We release a large scale dialog reading comprehension dataset. Experimental results on this dataset demonstrate the effectiveness of our proposed framework.

### Table 1: Examples from the dataset. Questions are concentrated on the omitted information of $A_3$ (which is shown in brackets), and reasoning type is the type of ability that is needed to answer the question.

| Example 1 | Example 2 | Example 3 |
|-----------|-----------|-----------|
| $A_1$ | $A_2$ | $A_3$ |
| 求帮忙取名字姓程，俩男孩 | 我喜欢的歌手是MJ | 那我们即使不死，也在天堂 |
| 请务必接受我的建议 | 我没听过呢。有这首歌的mv吗 | Then we are in heaven even |
| 咱俩一起生我就接受 | 我没听过呢。有这首歌的mv吗 | if we don’t die |
| (取名程和程) | 我没听过呢。有这首歌的mv吗 | 这话那抄的 |
| Yes (I have the MV), I’ll send it to you | 我没听过呢。有这首歌的mv吗 | Where did you copy that |
| 你好，我一直想看他的MV呢 | 我没听过呢。有这首歌的mv吗 | 三毛 |
| I’ll accept that (name as Cheng fan and Cheng cai) if they are our children | 我没听过呢。有这首歌的mv吗 | Sanmao |
| I’ll accept that (name as Cheng fan and Cheng cai) if they are our children | 我没听过呢。有这首歌的mv吗 | Remember that there was a handsome man named Dongmen |
| 我没听过呢。有这首歌的mv吗 | 我没听过呢。有这首歌的mv吗 | in Douban |
| I wanna see his MV | I wanna see his MV | Nanting is ID of what |
| 我的MV | I wanna see his MV | Douban is waiting for your ID |
| 豆瓣 | 豆瓣 | Douban |
| 很帅 | 豆瓣 | Douban |

### Related Work

#### Multi-turn Dialog

In recent years, text generation has made impressive progress (Li et al. 2018; Chan et al. 2019; Gao et al. 2020b; Xie et al. 2020), and multi-turn dialog model aims to take a message and utterances in previous turns as input and generates a response (Tao et al. 2019; Gao et al. 2020a). Several works (Zhang et al. 2019; Adiwardana et al. 2020; Chan et al. 2020) simplify the multi-turn dialog into single-turn problem by simply concatenating multiple sentences into one sentence, and utilized the basic Seq2seq based on RNN or Transformer to model long sequence. To make better use of multi-turn utterances, Xing et al. (2017) apply hierarchical attention on word-level and utterance-level information. There also various dialog datasets (Lowe et al. 2015; Zhang et al. 2018; Welleck et al. 2018; Reddy, Chen, and Manning 2019). However, these datasets do not contain reading comprehension question-answering pairs.

#### Machine Reading Comprehension

Machine reading comprehension (MRC) focuses on modeling semantic matching between a question and a reference document, which read the full text to select relevant text spans and then infer answers. Choi et al. (2017) propose hierarchical coarse-to-fine methods in order to mimic the reading mode of human. Huang et al. (2017) come up with a fully-aware fusion attention mechanism and apply it on MRC tasks. Large-scale datasets for MRC have also been proposed in parallel. CommonsenseQA (Talmor et al. 2018) is a dataset for commonsense question answering extracted from CONCEPTNET (Speer, Chin, and Havasi 2016). DROP (Dua et al. 2019) and COSMOS (Huang et al. 2019) focus on factual understanding and commonsense comprehension, re-
Multi-task Learning. Multi-task learning (MTL) is a learning paradigm in machine learning and it aims to leverage useful information contained in multiple related tasks to help improve the generalization performance of all the tasks (Caruana 1997). There are a large quantity of natural language processing tasks based on multi-task learning, such as word segmentation, POS tagging, dependency parsing, and text classification (Bohnet and Nivre 2012; Hatori et al. 2012; Li et al. 2013; Liu, Qiu, and Huang 2016). Collobert and Weston (2008) describe a single convolutional network that jointly trained several NLP tasks, such as part-of-speech tags, chunks, named entity tags, semantic roles. Liu et al. (2015) develop a multi-task deep neural network combining tasks of multiple-domain classification and information retrieval to learn representations across multiple tasks. In this work, we apply multi-task learning on response generation and reading comprehension on dialog.

Problem Formulation

Before presenting our approach for the dialog reading comprehension multi-task, we first introduce our notations and key concepts.

We assume that a conversation is conducted between two users. Suppose there are already $N^u$ turns in a dialogue, so we have historical utterances as $X = (X_1, X_2, ..., X_{N^u})$, where each utterance $X_j$ is depicted as $X_j = (x_{1j}, x_{2j}, ..., x_{N_j}^j)$ and $x_{ij}^j$ denotes a word. Accordingly, MRG aims to predict the $(N^u+1)$-th utterance, i.e., the response, $Y = (y_1, y_2, ..., y_{N^V})$, according to the historical utterances $X$:

$$p(Y|X) = \prod_{i=1}^{N^V} p(y_i|X, y_1, ..., y_i-1)$$

Apart from the response generation, we also design a question-answering task for the model. That is, targeted at the $N^u$-th utterance, where some keywords are missing, there is a question $Q = (q_1, q_2, ..., q_{N^V})$ that asks about such missing information, and the answer is a score vector $A = (a_1, a_2, ..., a_{N^u})$ that extracts the missing keywords from previous utterances. $N^u = \sum_{i=1}^{N^u} N_i$. Each score $a_i \in \{0, 1\}$ denotes whether the $i$-th word is selected (1) or not (0). The objective is to maximize the likelihood of all word labels $A$ given the input:

$$p(A|X) = \prod_{i=1}^{N^u} p(a_i|X)$$

The Proposed MRG Model

Overview

In this section, we propose the Multi-task Response Generator, abbreviated as MRG. An overview of MRG is shown in Figure 1, which can be split into three main parts:

- Cross-hierarchical encoder first uses a memory-augmented cross-attention mechanism (Vaswani et al. 2017) between the question and dialog words to identify representative words in dialog with the help of question. It then uses a hierarchical inner attention, first over different words in an utterance, and then over all utterances in dialog history, to successively learn the utterance-level features.
- Answer selector takes the question representation and utterance-level dialog features as input to predict the answer.
- Response generator produces the response by attending to the utterance-level features.

Cross-hierarchical Encoder

To begin with, we use an embedding matrix $e$ to map a one-hot representation of each word in $X$, $Q$, into a high-dimensional vector space. We then employ a bi-directional recurrent neural network (Bi-RNN) to model the temporal interactions between words:

$$h_i^{x,j} = \text{Bi-RNN}_e (e(x_i^j), h_{i-1}^{x,j}),$$

$$h_i^q = \text{Bi-RNN}_e (e(q_i), h_{i-1}^q),$$

where $h_i^{x,j}$ and $h_i^q$ denote the hidden state of $i$-th step in Bi-RNN for $X_j$ and $Q$, respectively. Following (Zhao, Zhao, and Eskénazi 2017; Chen et al. 2018), we choose long short-term memory (LSTM) as the cell for Bi-RNN.

Memory-augmented Cross Attention. This module grounds the conversation context by the question and fuses the information of the question into the dialog representation. Concretely, it has a stack of $L$ identical layers. In each layer, we iteratively fuse the information from question words to the dialog words by Memory-augmented Cross Attention Module (MCAM). For convenience, we denote the output of $l$-th encoder layer as $m_i^{l,j}$ and the input for the first layer $m_i^{0,j}$ is initialized as $h_i^{x,j}$. Concretely, MCAM is based on the traditional Cross Attention Module (CAM) Transformer architecture (Vaswani et al. 2017). We first introduce the original CAM, and then introduce our modification.

The first input for CAM is for query $Q$ and the second input is for keys $K$ and values $V$ for attention, which we denote as $x_i$ and $h_i^q$ respectively:

$$m_i^{l,j} = \text{CAM}(m_i^{l-1,j}, h_i^q).$$

Each output element, $m_i^{l,j}$, is computed as weighted sum of a linearly transformed input values:

$$m_i^{l,j} = \sum_{k=1}^{N_j} \alpha_{i,k}^{l,j} (h_k^q W V).$$

Each weight coefficient, $\alpha_{i,k}^{l,j}$, is computed using a softmax function:

$$\alpha_{i,k}^{l,j} = \frac{\exp(\beta_{i,k}^{l,j})}{\sum_{k=1}^{N_j} \exp(\beta_{i,k}^{l,j})},$$

And $\beta_{i,k}^{l,j}$ is computed using a compatibility function that compares two input elements:

$$\beta_{i,k}^{l,j} = \left( m_i^{l-1,j} W Q \right) (h_k^q W K)^T, \quad \text{subject to} \quad \sum_{k=1}^{N_j} \beta_{i,k}^{l,j} = 1.$$
Self Attention

ing a residual connection and layer norm. We summarize
formation from both its intermediate hidden states

ation 4. Concretely, the memory updator aggregates the in-
ory updator, which will then be fed into CAM in Equa-

in a multi-slot way as illustrated in Figure 1. The input
helps to remember and update history dialog information
inability to fully utilize dialog history information. Thus,
method, it is less suitable for multi-turn dialog due to its

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d

where $d$ stands for hidden dimension. $W^Q, W^K, W^V \in \mathbb{R}^{N_j \times N_j}$ are parameter matrices.

While the aforementioned vanilla CAM is a powerful
method, it is less suitable for multi-turn dialog due to its
inability to fully utilize dialog history information. Thus,
we augment it with an external memory module, which helps to remember and update history dialog information
in a multi-slot way as illustrated in Figure 1. The input
for query, i.e., $m_i^{-1,j}$ is updated to $n_i^{-1,j}$ through a memory updator, which will then be fed into CAM in Equation 4. Concretely, the memory updator aggregates the information from both its intermediate hidden states $\tilde{m}_i^{-1,j}$ ($\tilde{m}_i^{-1} \in \mathbb{R}^{N_j \times d}$) and the utterance (memory) states $\hat{m}_i^{-1,j}$ from the last layer, using a multi-head attention. Specifically, the input for query $Q$ is $m_i^{-1,j}$, and input for key $K$ and value $V$ is $[\tilde{m}_i^{-1,j}, m_i^{-1,j}]$. The memory augmented hidden states are further encoded using a feed-forward layer and then merged with the intermediate hidden states $\tilde{m}_i^{-1,j}$ using a residual connection and layer norm. We summarize
the procedure below:

$$s_i^{-1,j} = \text{CAM}(m_i^{-1,j}, \tilde{m}_i^{-1}),$$
$$c_i^{-1,j} = \tanh(W_a^{-1}m_i^{-1,j} + W_b^{-1}s_i^{-1,j}),$$
$$z_i^{-1} = \text{sigmoid}(W_c^{-1,j}m_i^{-1,j} + W_d^{-1}s_i^{-1,j}),$$
$$n_i^{-1,j} = (1 - z_i^{-1,j}) \odot c_i^{-1,j} + z_i^{-1,j} \odot \hat{m}_i^{-1,j},$$

where $\odot$ denotes Hadamard product, $W_a^{-1}, W_b^{-1}, W_c^{-1},$ and $W_d^{-1}$ are trainable weights, $c_i^{-1,j}$ is the internal cell state, $s_i^{-1,j}$ is the update gate that controls which information to retain from the previous memory state.

History
Historical Utterance
Utterance 1 Utterance k
... Response Generator

Prediction Answer

Figure 1: Overview of MRG. We divide our model into three parts: (1) Cross-hierarchical Encoder (which consists of memory-augment cross attention and two hierarchical self attentions); (2) Answer Selecter; (3) Response Generator.

Hierarchical Self Attention. After utilizing question information to emphasize important keywords, $\hat{m}_i^{-1,j}$ (the output of last MCAM layer) is then processed by a hierarchical
attentive module to encode long-term dependency among words into the representations. The first level in our hierarchical attention encodes each utterance independently from other utterances at word-level, resulting in a fixed-dimensional representation of each utterance. Concretely, the word-level attentive module simplifies the Multi-head Attention Module (MAM) in Transformer, which is similar to CAM, but takes the same input for query, key and value:

$$h_{i}^{w,j} = \text{MAM}(m_i^{L,j}, m_i^{L,j}).$$

A mean-pooling operation is then used over word vectors in each utterance to obtain a fixed-length utterance-level representation:

$$h_{i}^{u,j} = \text{meanpool}\left\{h_{i}^{w,j}, \ldots, h_{i}^{w,j}\right\}.\tag{9}$$

Similar to word-level attention, an utterance-level MAM is applied on these representations to fuse information between different utterances:

$$h_{i}^{u,j} = \text{MAM}(h_{i}^{u,j}, h_{i}^{u,j}).\tag{10}$$

From the utterance representation, we can also obtain the overall dialog history representation, which will be used in the response decoder part:

$$h_{i}^{d} = \text{meanpool}\left\{h_{i}^{u,1}, \ldots, h_{i}^{u,N_u}\right\}.\tag{11}$$

Answer Selecter

After fusing information from question and dialog context, it is time to select words from context as the answer to the question. Since we have several utterance representations, and either taking the average or summing them together by specific weights is inappropriate and inelegant. Hence, we concatenate all utterance and question representations together and apply a multi-layer perceptron to them to generate the word extracting probabilities:
\[ h^q = \text{meanpool} \left( \{ h_1^q, \ldots, h_N^q \} \right) \]
\[ \hat{A} = W_f \tanh \left( W_c \left[ h^{u,1}; \ldots; h^{u,N_u}; h^q \right] + b^c \right) + b^f, \]
where \([: :]\) denotes concatenation operation.

**Response Generator**

To generate a consistent and informative response, we propose an RNN-based decoder that incorporates outputs of utterance representations as illustrated in Figure 1.

We first apply a linear transform layer on the input document vector representation \( h^d \) and use the output of this layer as the initial state of decoder LSTM, shown in Equation 12. In order to reduce the burden of compressing document information into the initial state \( s_0 \), we use the attention mechanism (Bahdanau, Cho, and Bengio 2015a) to summarize the utterance representations into context vector \( f_{t-1} \) dynamically and we will show the detail of these in this section later. Then we concatenate the context vector \( f_{t-1} \) with the embedding of previous step output \( e(y_{t-1}) \) and feed this into decoder LSTM, shown in Equation 13:

\[
s_0 = W_h h^d + b_g, \quad (12)
\]
\[
s_t = \text{LSTM} \left( s_{t-1}; [f_{t-1}; e(y_{t-1})] \right). \quad (13)
\]

Context vector \( f_{t-1} \) is the vector that stores the dialog context information at \( t \)-th step. Concretely, we use the decoder state \( s_{t-1} \) to attend to each utterance states \( h^{u,i} \) and results in the attention distribution \( \gamma_t \), shown in Equation 15. Then we use the attention distribution \( \gamma_t \) to weighted sum the document states as the context vector \( f_{t-1} \).

\[
\gamma'_{t-1,i} = W_n \tanh \left( W_s s_{t-1} + W_h h^{u,i} \right), \quad (14)
\]
\[
\gamma_{t-1,i} = \exp \left( \gamma'_{t-1,i} \right) / \sum_{j=1}^{N_u} \exp \left( \gamma'_{t-1,j} \right), \quad (15)
\]
\[
f_{t-1} = \sum_{i=1}^{N_u} \gamma_{t-1,i} h^{u,i}. \quad (16)
\]

Finally, an output projection layer is applied to get the final generating distribution \( P^w_t \) over vocabulary, as shown in Equation 17. We concatenate utterance context vector and the output of decoder LSTM \( s_t \) as the input of the output projection layer:

\[
P^w_t = \text{softmax} \left( W_v [s_t; f_t] + b_v \right), \quad (17)
\]

We use the negative log-likelihood as the loss function:

\[
L_g = -\sum_{t=1}^{N_y} \log P^w_t(y_t). \quad (18)
\]

**Experimental Setup**

**Dataset**

To our best knowledge, no existing works consider MRC in response generation task. Hence, we first propose a dialog reading comprehension dataset (DRCD). DRCD is based on the Restoration-200k dataset proposed by Pan et al. (2019), where the utterance with omitted information is manually annotated. Such omitted information leads to a difficulty in fully understanding the dialog context and requires reasoning ability to for a model. Hence, we hire an annotation team to write questions that are focused on the missing information.

Since it is time-consuming to write questions for the whole dataset, and based on the labeled answer it is rather easy to construct the question, we ask the team to write questions for 10k cases, and then automatically generate questions for the rest of the dataset. Concretely, we utilize PG (See, Liu, and Manning 2017) to generate questions due to its good performance in many tasks including summarization and dialog completion (Pan et al. 2019; Chen et al. 2019). We then conduct a human evaluation to examine the generation quality. Concretely, we randomly sample 200 cases and asked three annotators to state how well they agree with the following two statements, on a scale of one to five (strongly disagree, disagree, neutral, agree, or strongly agree): 1) The generated question asks about the omitted phrase. 2) The generated question is written in fluent Chinese. The result shows that generated questions that score over 3 takes up 76.5%, showing that most of the generated questions are of good quality. The kappa statistics indicate the moderate agreement between annotators.

We randomly split the dataset with question-answer pair to 113,116 training, 3,000 validation, and 3,000 test cases. The average character-level context length and utterance length of the dataset is and 43.4 and 9.05. Note that in the validation and test datasets the questions are all written by human, ensuring that the testing results are convincing.

**Comparison Methods**

To evaluate the performance of our proposed model, we compare it with the following response generation and MRC baselines:

**Response Generation baselines:**

- **Seq2Seq** (Bahdanau, Cho, and Bengio 2015b): the vanilla schema of the sequence to sequence model with attention mechanism.
- **HRED** (Serban et al. 2016): extends the hierarchical recurrent encoder-decoder neural network to the dialogue domain.
- **VAE** (Zhao, Zhao, and Eskénaži 2017): uses latent variables to learn a distribution over potential conversational intents and generates diverse responses.
- **Transformer** (Vaswani et al. 2017): is based solely on attention mechanisms.
- **PAC** (Pan et al. 2019): is a “pick-and-combine” model to restore the incomplete utterance from its context, and then use the restored utterance to generate the next response.

**MRC baselines:**

- **MemN2N** (Sukhbaatar et al. 2015): is an extension of RNNsearch to the case with multiple computational hops.
- **DMN** (Kumar et al. 2016): processes input sequences and questions, forms episodic memories, and generates relevant answers.
- **DMN+** (Xiong, Merity, and Socher 2016): proposes several improvements to memory and input modules of DMN.
- **QRN** (Seo et al. 2017): is a variant of RNN that effectively handles both short-term (local) and long-term (global) sequential dependencies to reason over multiple facts.
| Model   | BLEU1 | BLEU2 | BLEU3 | BLEU4 | Average | Extrema | Greedy |
|---------|-------|-------|-------|-------|---------|---------|--------|
| Seq2Seq | 0.2260| 0.1566| 0.0876| 0.0671| 0.4341  | 0.6695  | 0.7759 |
| HRED    | 0.2273| 0.1559| 0.0871| 0.0667| 0.4320  | 0.6601  | 0.7885 |
| VAE     | 0.2316| 0.1586| 0.0886| 0.0680| 0.4350  | 0.6396  | 0.7920 |
| Transformer | 0.2181| 0.1482| 0.0825| 0.0631| 0.4407  | 0.6500  | 0.7920 |
| PAC     | 0.2413| 0.1624| 0.0902| 0.0689| 0.4396  | 0.6447  | 0.7909 |
| MRG     | 0.2632| 0.1735| 0.0968| 0.0741| 0.4513  | 0.6769  | 0.8025 |
| MRG w/o MCAM | 0.2224| 0.1533| 0.0857| 0.0656| 0.4436  | 0.6630  | 0.7837 |
| MRG w/o MAM  | 0.2404| 0.1616| 0.0946| 0.0665| 0.4343  | 0.6740  | 0.7798 |
| MRG w/o MemUpd | 0.2498| 0.1585| 0.0894| 0.0747| 0.4419  | 0.6744  | 0.7798 |
| MRG w/o MT   | 0.2231| 0.1541| 0.0862| 0.0661| 0.4343  | 0.6734  | 0.7645 |

Table 2: Automatic evaluation results on response generation task. The best results are bold.

| Model   | Accuracy(%) |
|---------|-------------|
| MemN2N  | 37.85       |
| DMN     | 40.83       |
| QRN     | 40.80       |
| DMN+    | 43.97       |
| MRG     | **45.43**   |
| MRG w/o MT | 44.89   |

Table 3: Automatic evaluation results on MRC task. Best accuracy over 10 runs.

**Implementation Details**

We implement our experiments in TensorFlow (Abadi et al. 2016) on an NVIDIA GTX 1080 Ti GPU. We truncate input dialog to 100 words, with 20 words in each utterance. We chose 100 as our truncation size as we did not find significant improvement when increasing input length from 100 to 200 tokens. The minimum decoding step is 10, and the maximum step is 20. The word embedding dimension is set to 128 and the number of hidden units is 256. We initialize all of the parameters randomly using a Gaussian distribution. The batch size is set to 16, and we limit the vocabulary size to 50K. We use Adagrad optimizer (Duchi, Hazan, and Singer 2010) as our optimizing algorithm. We also apply gradient clipping (Pascanu, Mikolov, and Bengio 2013) with a range of $[-2, 2]$ during training. During the inference stage, the checkpoint with smallest validation loss is chosen and the beam-search size is set to 4 for all methods. Note that when evaluating the response generation performance, we use the generated questions as input instead of the ground truth human-written questions for the sake of fairness.

**Evaluation Metrics**

To evaluate the results of the generated responses, we adopt the following metrics widely used in existing research.

**Overlap-based Metric.** Following Li et al. (2021); Xu et al. (2020), we utilize BLEU score (Papineni et al. 2002), an algorithm which has been widely used in machine translation and dialogue system, to measure n-grams overlaps between ground-truth and generated response. Specifically, we follow the conventional setting in previous work (Gu et al. 2019) to compute BLEU scores using smoothing techniques (smoothing 7).

**Embedding Metrics.** To capture the semantic matching degrees between generated responses and ground-truth, we perform evaluations on embedding space. In consistent with previous study (Gu et al. 2019), we compute the similarity between the bag-of-words (BOW) embeddings representations of generated results and reference. In particular, we calculate three metrics: 1) Greedy (BOW-Greedy), i.e., greedily matching words in two utterances based on the cosine similarities; 2) Average (BOW-Average), cosine similarity between the averaged word embeddings in the two utterances (Mitchell and Lapata 2008); 3) Extrema (BOW-Extrema), cosine similarity between the largest extreme values among the word embeddings in the two utterances (Forgues et al. 2014).

**Human Metrics.** We also employ human evaluation to assess the responses generated by our model and the baselines. Three well-educated annotators are hired to evaluate the quality of generated responses, where the evaluation is conducted in a double-blind fashion. Totally, 200 randomly sampled responses generated by each model are rated by each annotator with two different aspects, i.e., readability (Is the response grammatically formed and smooth?), informativeness (Does the response contains informative words?). Criteria are scored from 1 to 3, i.e., bad, normal, and good.

**Experimental Results**

**Overall Performance**

**Automatic evaluation.** We first examine whether our MRG outperforms generative baselines as listed in Table 2. Our model outperforms baselines on all automatic metrics. This demonstrates that our model generates more appropriate responses by reading comprehension, and understands the dialog context better by predicting response. Especially, our model improves approximately 16.46% over seq2seq on BLEU1, and outperforms PAC by 9.07%. We also list the results of ablation study in Table 2, aiming to assess the contribution of individual components. Our experiments confirmed that interacting between dialog and question by Memory-augmented Cross Attention Module is beneficial (see row w/o MCAM), as well as self-attention module (see row w/o MAM) memory updator (see row w/o MemUpd).
We next examine whether our MRG outperforms MRC baselines in Table 3. Generally, these baselines perform similar to the experiment on bAbI dataset (Bordes and Weston 2017). Specifically, DMN+ is the strongest baseline, which achieves 43.97% accuracy on average. QRN, however, does not perform as well as it does on bAbI dataset, obtaining 43.97% accuracy on average. Our model significantly outperforms most of the baselines in terms of all the metrics. Particularly, our model outperforms classic baselines. In the future we would like to apply our model to other multi-task scenarios.

Human evaluation. The results of human evaluation are listed in Table 5. Our model significantly outperforms most of the baselines in terms of all the metrics. Particularly, our model increases informativeness approximately 4.1% over PAC. This demonstrates that trying to answer reading comprehension question about dialog history if beneficial for improving and enriching the responses.

Analysis of Multi-task learning

Our model aims to generate response as well as answering MRC questions, which can be regarded as a multi-task. Hence, in this subsection, we examine whether these two tasks can complement each other. We list the performance on two single tasks by ‘MRG w/o MT’ in Table 2 and Table 3, which solely generates response and answers MRC question, respectively. It can be seen that by answering reading comprehension question, the performance of dialog generation increases by 12.1% in terms of BLEU4 score, and by generating responses at the same time, MRC accuracy increases by 1.2%.

**Table 4:** Responses generated by baselines and our model along with the QA pairs.

**Table 5:** Human evaluation on two aspects: Readability and informativeness.

In this paper we propose the multi-task framework to generate response and answer reading comprehension questions about multi-turn dialog. Concretely, the two tasks share the same encoder to extract the common and task-invariant features with different decoders to learn specific features. To better fusing information from the question and the dialog history in the encoding part, we propose to augment the Transformer architecture with a memory updater, which is designed to selectively store and update the history dialog information. Experimental results show that our proposed model outperforms classic baselines. In the future we would like to apply our model to other multi-task scenarios.
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