Multi-choice Dialogue-Based Reading Comprehension with Knowledge and Key Turns

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Abstract

Multi-choice machine reading comprehension (MRC) requires models to choose the correct answer from candidate options given a passage and a question. Our research focuses dialogue-based MRC, where the passages are multi-turn dialogues. It suffers from two challenges, the answer selection decision is made without support of latently helpful commonsense, and the multi-turn context may hide considerable irrelevant information. This work thus makes the first attempt to tackle those two challenges by extracting substantially important turns and utilizing external knowledge to enhance the representation of context. In this paper, the relevance of each turn to the question are calculated to choose key turns. Besides, terms related to the context and the question in a knowledge graph are extracted as external knowledge. The original context, question and external knowledge are encoded with the pre-trained language model, then the language representation and key turns are combined together with a will-designed mechanism to predict the answer. Experimental results on a DREAM dataset show that our proposed model achieves great improvements on baselines.

1 Introduction

Multi-choice Machine Reading Comprehension (MRC) has long been a heated topic, and various datasets and models have been proposed in recent years (Lai et al., 2017; Ostermann et al., 2018; Khashabi et al., 2018; Mostafazadeh et al., 2016; Richardson et al., 2013; Sun et al., 2019). However, most of them focus on MRC where passages are short articles. In contrast, specialized models for dialogue-based multi-choice MRC where passages are multi-turn dialogues are rarely seen, though it has no less significance than article-based multi-choice MRC in real life. The reason might be that understanding multi-turn dialogues are more complex than understanding short articles. Specifically, there are two key challenges. Multi-turn dialogues are multi-party, multi-topic and always have lots of turns in real word cases (e.g. chat history in social media). Besides, people rarely state obvious commonsense explicitly in their dialogues (Forbes and Choi, 2017), therefore only considering superficial contexts may ignore implicit meaning and misunderstand them.

To illustrate the challenges more clearly, we demonstrate two examples from DREAM dataset (Sun et al., 2019). Table 1 shows the topic shifts in different turns and only a few of them, called key turns, are related to the...
Dialogue 1

W: Well, I'm afraid my cooking isn't to your taste.
M: Actually, I like it very much.
W: I'm glad you enjoy it. Let me serve you some more fish.
M: No, thank you. I've had enough fish, but I'd like some soup.
W: Here it is. Help yourself!
M: Thanks. I didn't know you were so good at cooking.
W: Why not bring your wife next time?
M: OK, I will. She will be very glad to see you, too.

Question: What does the man think of the woman's cooking?

A. It's really terrible.
B. It's very good indeed. *
C. It's better than what he does.

Table 1: Turns in different format have different topics.

| Dialogue 2 |
|------------|
| M: Look at the girl on the bike! |
| F: Oh, yes she's really a smart girl. |

Question: Where are the two persons?

A. At home.
B. In their classroom. *
C. On the street.

Table 2: Commonsense is required in the question.

question. Treating all turns equally can seriously disturb the understanding of multi-turn dialogues as some works (Zhang et al., 2018; Yuan et al., 2019) have shown. Table 2 shows that external commonsense knowledge are required to answer the question (e.g. bikes are always on the streets), which emphasizes the importance of commonsense in understanding multi-turn dialogues.

Prior work in DREAM (Sun et al., 2019) first investigate the effects of incorporating dialogue structure and different kinds of general commonsense knowledge into both rule-based and machine learning-based reading comprehension models, acquiring great improvement compared to its baseline models. Recently, some works also achieve great performance on dialogue-based multi-choice MRC tasks, though they ignore special structures of dialogues and lack of commonsense (Zhu et al., 2020; Jin et al., 2019; Wang et al., 2019). Their structure can be divided into two parts: encoder and matching network. One important feature of these models is that they choose advanced pre-trained language models (LMs) such as BERT (Devlin et al., 2019) and GPT (Radford et al., 2018) as their encoders.

Inspired by previous works, we propose modeling with Knowledge and Key Turns (KKT) to get a better language representation of multi-turn dialogues. Our model choose a pre-trained LM as the encoder to get language representation, then utilize key turns and external knowledge to enhance the language representation and predict answers through a well-designed matching network. A pre-trained LM finetuned for natural language inference (NLI) is used to extract key turns from the context, since NLI-finetuned LMs prove to have a strong ability of generalization (Phang et al., 2018; Conneau et al., 2017; Subramanian et al., 2018) so it can figure out how large the relevance is between a turn and a specific question. Besides, needed commonsense is selected from a knowledge graph to enrich the context like K-BERT (Liu et al., 2019a) and ERNIE (Zhang et al., 2019b). Then the selected key turns and knowledge are used to refine the language representation. Finally, we use the refined language representaion of the context, question and candidate answers predict the correct answer through our matching network. The contributions of this paper are summarized as follows:

1. We adopt an explainable and efficient method to extract key turns from multi-turn dialogues.
2. We combine mature and systematic external knowledge from a knowledge graph to enrich its representation.
3. Experimental results on DREAM dataset achieve significant improvement, which shows the effectiveness of KKT.

The remainder of the paper is organized as follows. Section 2 reviews related work. In Section 3 we describe details of KKT. Sections 4 and 5 show the experiments and analysis
respectively, and the conclusion of this study is in Section 6.

2 Related works

2.1 Pre-trained Language Model

Recently, pre-trained Language Models (LMs) have been shown to be effective in learning universal language representations, achieving state-of-the-art results in a series of flagship natural language processing tasks. Prominent examples are Embedding from Language Models (ELMo) (Peters et al., 2018), Generative Pre-trained Transformer (OpenAI GPT) (Radford et al., 2018), BERT (Devlin et al., 2019), Generalized Autoregressive Pre-training (XLNet) (Yang et al., 2019), Roberta (Liu et al., 2019b) and ALBERT (Lan et al., 2019). These models follow a pre-training and fine-tuning strategy: first pre-trained on large unlabeled corpus with some unsupervised tasks then fine-tuned on different downstream tasks.

2.2 Multi-choice Machine Reading Comprehension

Recently, lots of multi-choice Machine Reading Comprehension (MRC) datasets have been proposed (Richardson et al., 2013; Mostafazadeh et al., 2016; Khashabi et al., 2018; Ostermann et al., 2018; Lai et al., 2017; Sun et al., 2019). Most of questions in multi-choice MRC tasks are non-extractive, requiring multi-sentence reasoning and external commonsense knowledge. Zhang et al. (2019a); Zhu et al. (2020) choose pre-trained LMs as their text encoder to get the representation of passage, question and candidate options, and use a bidirectional matching network to predict the answer. Jin et al. (2019) also choose a pre-trained LM as encoder, and use a multi-step attention network as the classifier in top of encoder. Sun et al. (2019) are the first to design specific neural models for dialogue-based multi-choice MRC by adding a speaker embedding enhance representation of context on word-level.

2.3 Language Representation with Knowledge Graph

Recently, more attention are paid on modeling texts with Knowledge Graphs (KGs), since KGs obtain much systematic knowledge. Integrating knowledge in neural models was first proposed in the neural-checklist model by Kiddon et al. (2016) for text generation of recipes. (Liu et al., 2019a) combine knowledge triples in KGs with original texts before modeling them with BERT to get more hidden information. Lin et al. (2019) propose a knowledge-aware graph network based on GCN and LSTM with a path-based attention mechanism. Zhang et al. (2019b) fuse entity information with BERT to enhance language representation.

Inspired by the ideas of the above previous works, we decide to pick out related knowledge in knowledge graphs to enhance the representation of multi-turn dialogues. On the other hand, we focus on the topic shift in dialogues and extracting key turns to understand and model the dialogues better, which are ignored by most previous work on dialogue-based multi-choice MRC.

3 Methodology

The overall architecture of our model is shown in Figure 1.

3.1 Notations

The context $C$ is represented as $[T_1, T_2...T_{lc}]$, where $lc$ is the number of turns in the dialogue. For each turn $T_i$ in the context, we represent it as $[w_1, w_2...w_{ti}]$, where $ti$ is the number of tokens in $T_i$. The question $Q$ is represented as $[w_1, w_2...w_q]$ where $q$ is the number of tokens in $Q$. The candidate answers $A$ are represented as
Figure 1: Overall model architecture

\[ [A_1, A_2, ..., A_l_a] \] where \( l_a \) is the number of candidate answers and each one of them is represented as \([w_1, w_2, ..., w_{a_i}]\) where \( a_i \) is the number of tokens in \( j \)-th candidate answer \( A_j \). In this work, we treat the question and the candidate answers as an integral, so that we have \( QA_j = [Q : A_j] \). Therefore we need to find the most proper question-answer pair according to the context.

Multi-head attention (Vaswani et al., 2017) is used in our paper to capture the relationshop among two sequences. Therefore we denote it as \( \text{MHA}() \) in brief, which is implemented as follows:

\[
\text{Att}(E'_Q, E'_K, E'_V) = \text{softmax}(\frac{E'_Q (E'_K)^T}{\sqrt{d_{\text{head}}}})E'_V
\]

\[
\text{head}_i = \text{Att}(E_Q W_i^Q, E_K W_i^K, E_V W_i^V)
\]

\[
\text{MHA}(E_Q, E_K, E_V) = \text{Concat}(\text{head}_i, ..., \text{head}_h)
\]

where \( W_i^Q \in \mathbb{R}^{d_{\text{model}} \times d_{\text{head}}}, W_i^K \in \mathbb{R}^{d_{\text{model}} \times d_{\text{head}}}, W_i^V \in \mathbb{R}^{d_{\text{model}} \times d_{\text{head}}}, E_Q \in \mathbb{R}^{d_q \times d_{\text{model}}}, E_K \in \mathbb{R}^{d_k \times d_{\text{model}}}, E_V \in \mathbb{R}^{d_v \times d_{\text{model}}}, d_q, d_k, d_v \) denote the dimension of Query vectors, Key vectors and Value vectors, \( d_{\text{head}} \) denotes the dimension in each head, \( h \) denotes the number of heads, and we always assume \( d_k = d_v \) and \( d_{\text{model}} = h \times d_{\text{head}} \).

3.2 Modeling knowledge

Items with weight less than a threshold or contain words not in the vocabulary of the chosen pre-trained LM are removed from KG. The items are triples with the form \{relation, head, tail\}, which are rewritten as facts (e.g. \{causes, virus, disease\} to \( \text{virus causes disease} \)). These facts are encoded with our pre-trained LM and the last hidden states \( H_k (H_k \in \mathbb{R}^{n \times d_{\text{model}}} \) where \( n \) denotes the number of tokens in the fact) are taken as the output so that the representation of knowledge and context are in the same vector space. A self-attention module is used to refine the representation of each fact. We use mean-pooling in the end to aggregate the representation of each token and get a final representation \( r_k (r_k \in \mathbb{R}^{d_{\text{model}}}) \) for each fact.

\[
\text{SelfAttention}(H_k) = \text{MHA}(H_k, H_k, H_k)
\]

\[
r_k = \text{mean}(\text{SelfAttention}(H_k))
\]
3.3 Retrieve relevant knowledge

Each turn $T_i$ is tagged part-of-speech (POS) tags. For tokens with POS tags like JJ (adjective), NN (noun) and VB (verb), we assume that they contain more implicit information than others, thus items related to them are retrieved in KG. In all the chosen items, top $p$ ($p$ is a hyperparameter) ones are selected to enhance to context representation. The selected knowledge items are denoted as $CK = [c_{t_1}, ..., c_{t_p}]$.

For a QA-pair $QA_j$, we follow the same steps in dealing with $T_i$ to get the relevant knowledge items $QAK_j = [r_{j_1}, r_{j_2}, ..., r_{j_k}]$, where $j_k$ is the number of chosen knowledge items for $QA_j$.

3.4 Extracting key turns

Key turns are extracted with a pre-trained LM finetuned for NLI. Each turn $T_i$ and each QA-pair $QA_j$ are concatenated and encoded with the NLI-finetuned LM. Pooled output are mapped into 3 dimensions, corresponding to contradiction, entailment, and neutral respectively. Dimension of entailment is chosen as the relevance score between $T_i$ and $QA_j$, and top $k$ turns $T_{i,j}^{key}$ are picked out as key turns for $QA_j$ according to the relevance scores ($k$ denotes the maximum number of key turns for each QA-pair).

3.5 Encoding and Representation Refinement

For each QA, it is concatenated with $C$ as input encoded with LM. The last hidden states $H_t \in \mathbb{R}^{l_{input} \times d_{model}}$ are then separated into context representation $H_c \in \mathbb{R}^{l_c \times d_{model}}$ and QA-pair representation $H_{QA} \in \mathbb{R}^{l_{QA} \times d_{model}}$.

The representation of key turns $H_{kt}$ ($H_{kt} \in \mathbb{R}^{l_{kt} \times d_{model}}$) is extracted from $H_c$ based on the position of key turns in the context. We use $MHA(c)$ to calculate the key-turns-refined context representation and $H_{ckt}$ ($H_{ckt} \in \mathbb{R}^{l_c \times d_{model}}$). Similarly, we get the knowledge-refined representation of context and QA-pair.

$$H_{ckt} = MHA(H_c, H_{kt}, H_{kt})$$
$$H_{ck} = MHA(H_c, CK, CK)$$
$$H_{QA_k} = MHA(H_{QA}, QAK, QAK)$$

3.6 Representation fusion

Inspired by (Zhu et al., 2020), we use a Dual Multi-head Co-Attention (DUMA) module to fuse the representation of context and QA-pair.

$$MHA_1 = MHA(H_c, H_{QA}, H_{QA})$$
$$MHA_2 = MHA(H_{QA}, H_{QA}, H_c)$$
$$DUMA(H_c, H_{QA}) = \text{Concat}(\text{mean}(MHA_1), \text{mean}(MHA_2))$$

The fused representation is denoted as output. The original output $O_o$, key-turns-refined output $O_{kt}$ and knowledge-refined output $O_k$ are calculated with DUMA module based on different representation of context and QA-pair calculated above.

$$O_o = DUMA(H_c, H_{QA})$$
$$O_{kt} = DUMA(H_{ckt}, H_{QA})$$
$$O_k = DUMA(H_{ckt}, H_{QA_k})$$

Then these three kind of outputs are fused together as the final output. $O_k$ and $O_{kt}$ are concatenated together and mapped to dimension of $2d_{model}$ through a linear layer to get the knowledge-key-turns refined (KKT-refined) output $O_{kkt}$. Then we fuse the original output and the KKT-refined output to get the final output $O$. Concatenation is chosen as our fuse function for its simplicity.

3.7 Decoding

Our model decoder takes $O$ and computes the probability distribution over answer options. Let $A_i$ be the $i$-th candidate answer and $O_i$
is the corresponding output of \(< C, Q, A_i >\). The loss function is computed as follows:

\[
L(A_i|C, Q) = -\log\left(\frac{\exp(W^TO_i)}{\sum_{j=1}^{l_a} \exp(W^TO_j)}\right)
\]

where \(W\) is a learnable parameter and \(l_a\) is the number of candidate answers.

4 Experiments

4.1 Dataset

We evaluate our model on DREAM (Sun et al., 2019) dataset, which is the only dialogue-based multi-choice MRC dataset as of the date of writing. It is collected from English exams. Each dialogue as the given context has multiple questions and each question has three candidate answers. The most important feature of the dataset is that most of the questions (83.7%) are non-extractive. As a result, the dataset is small but still challenging.

4.2 Settings

Our model use an advanced pre-trained LM ALBERT\(_{xxlarge}\) (Lan et al., 2019) as our encoder. Our codes are written based on Transformers\(^1\). Results of ALBERT model as baseline are our rerunning unless otherwise specified. In this paper, NLTK (Loper and Bird, 2002) is chosen as our POS tagger and ConceptNet (Speer et al., 2017) is chosen as our KG. The NLI dataset used to finetune the LM for key turns extracting is SNLI (Bowman et al., 2015), and accuracy of this finetuned model on test set of SNLI is 90%.

The learning rate in our model is 1e-5, train batch size per gpu is 1 and warmup steps are 50. We train the model for 2 epochs on 8 nVidia V100 GPUs. In the following Section 5, for other model used for further analysis based on ALBERT\(_{base}\), our learning rate is 1e-5, no warmup steps and train batch size per gpu is 2. Those models used for ablation studies are trained on 8 GeForce GTX 1080 Ti GPUs. For all the above experiments, checkpoints are saved after each epoch, and the best result are chosen from all the checkpoints.

4.3 Main results

Table 3 gives out the main results of our experiments. To focus on the evaluation of syntactic advance and keep simplicity, we only compare with single models instead of ensemble and multi-tasking ones. Experimental results shows our model achieves the state-of-art performance for DREAM on both dev and test set.

| model                  | dev    | test   |
|------------------------|--------|--------|
| FTLM++                 | 58.1*  | 58.2*  |
| BERT\(_{large}\)       | 66.0*  | 66.8*  |
| XLNet                  | -      | 72.0*  |
| RoBERTa\(_{large}\)    | 85.4*  | 85.0*  |
| RoBERTa\(_{large}\)+MMM| 88.0*  | 88.9*  |
| ALBERT\(_{xxlarge}\)   | 89.2*  | 88.5*  |
| ALBERT\(_{xxlarge}\)+DUMA | 89.3\(\dagger\) | 90.4\(\dagger\) |
| ALBERT\(_{xxlarge}\)   | 89.1   | 88.2   |
| ALBERT\(_{xxlarge}\)+KKT | 90.2   | 89.8   |
| ALBERT\(_{base}\)      | 67.4   | 67.3   |
| ALBERT\(_{base}\)+KKT  | 69.3   | 68.7   |

Table 3: Results on DREAM dataset. Results denoted by * are from (Jin et al., 2019), † are from (Zhu et al., 2020). Corresponding papers are following: BERT(Devlin et al., 2019), XLNet(Yang et al., 2019), RoBERTa(Liu et al., 2019b), RoBERTa+MMM(Jin et al., 2019), ALBERT(Lan et al., 2019), ALBERT+DUMA(Zhu et al., 2020)
Table 4: Comparison between our model (knowledge refined only) and baseline.

| model         | dev    | test   |
|---------------|--------|--------|
| ALBERT$_{base}$ | 67.40  | 67.31  |
| our model     | 67.94  | 67.66  |

5 Analysis

5.1 Effects of External Knowledge

Appending

Multi-turn dialogues always contain lots of implicit commonsense between lines, therefore understanding them require external knowledge. To overcome the difficulty, a knowledge graph is used to enhance our modeling by adding related knowledge items. In the example in Table 2 (in section 1), we need to know where a bike is likely to appear to answer the question. Correspondingly, a knowledge item $\{\text{atlocation, bike, street}\}$ can be found in our KG which means Bikes are always found on the street. It has a weight of 2, indicating it is more important than others with a lower weight. Appended such a fact, our model can answer the question correctly.

To state the effects more clearly, we remove the key-turns refined output from our model and evaluate it. The maximum number of knowledge items is 30. The results are shown in Table 4.

5.2 Effects of Key Turns Extraction

As has mentioned in the previous section, a challenge in understanding and modeling multi-turn dialogues is the shift of topic in different turns, which means only a few of them are related to the question. By using an NLI-finetuned LM, we can get the relevance score for each turn-QA pair. A higher relevance score indicates that we are more likely to conclude the QA given the corresponding turn. The example shown in Table 5 proves our hypothesis. Turns with top 2 entailment scores can directly conclude the answer, while other turns have nothing to do with the answer. So it is reasonable to choose them as the key turns, and use them to refine the context to get a better representation.

To state the effects more clearly, we remove the knowledge refined output from our model and evaluate it on dev set. The results are shown in Figure 2. We can clearly see the improvement from the graph.
5.3 Effects of Number of Key Turns
To find out the relationship between the performance of our model and the number of key turns, we evaluate our model on different number of selected turns on dev set. The results on dev set are shown in Figure 2. No matter how many key turns are chosen, obvious improvement can be observed on all cases. The best performance occurs when number of key turns is 2 - 6, which means when the key turns are less but more accurate. On that case, key turns can help filter the noise in other turns to a great extent. When more key turns are chosen, the effects of filtering noise are weaker, but the computational cost rises, so we tend to use a small number of key turns in our model to refine context.

![Figure 3: Different numbers of knowledge key turns](image)

![Figure 4: Only encoding key turns](image)

5.4 Effects of Number of External Knowledge Items
The number of external knowledge items can affect performance as well. So we evaluate our model on different number of external knowledge items on dev set. The results are shown in Figure 3. Contrary to our expectation, the results show little difference on various number of external knowledge items. We suppose that the attention mechanism employed to refine context with external knowledge is the reason, because knowledge items with small weight tend to have small weight in the attention mechanism as well since they are less relevant to the context. As a result, the knowledge-refined context are similar for different number of knowledge items, leading to a similar final performance.

5.5 Only Encode Key Turns
It’s natural to think about only encoding the selected key turns, since it will reduce the computational cost a lot if fewer tokens are encoded. So we only choose key turns as our input and evaluate our model on dev set. The results are shown in Figure 4. The performance is much worse than baseline when the number of key turns is too small. But when it goes beyond 10, the performance approaches and even surpass the baseline, which is astonishing. It indicates that by designing methods properly, we can use only some key turns of the dialogue to represent it better.

Besides, we also try using external knowledge to enhance context representation when only encoding key turns. The number of knowledge items we choose is 30. The results are also in Figure 4. However, the performance becomes worse after appending external knowledge. Possible reason might be that for small amount of input tokens, the external knowledge becomes noise and hurt the encoding. We will do further studies to find out the reason in the future.

6 Conclusion
In this paper, we propose modeling multi-turn dialogue with knowledge and key turns for dialogue-based multi-choice MRC. We first pick out turns related to the question as key turns using an NLI-finetuned LM. Besides, relevant knowledge items are also picked out and encoded with LM. Question and context are refined with key turns and external knowledge items for better language representation. Experiments on DREAM dataset show the method achieve new state-of-the-art results on single task learning.
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