ConceptNet infused DialoGPT for Underlying Commonsense Understanding and Reasoning in Dialogue Response Generation

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Abstract

The pre-trained conversational models still fail to capture the implicit commonsense (CS) knowledge hidden in the dialogue interaction, even though they were pre-trained with an enormous dataset. In order to build a dialogue agent with CS capability, we firstly inject external knowledge into a pre-trained conversational model to establish basic commonsense through efficient Adapter tuning (Section 4). Secondly, we propose the “two-way learning” method to enable the bidirectional relationship between CS knowledge and sentence pairs so that the model can generate a sentence given the CS triplets, also generate the underlying CS knowledge given a sentence (Section 5). Finally, we leverage this integrated CS capability to improve open-domain dialogue response generation so that the dialogue agent is capable of understanding the CS knowledge hidden in dialogue history on top of inferring related other knowledge to further guide response generation (Section 6). The experiment results demonstrate that CS_Adapter fusion helps DialoGPT to be able to generate series of CS knowledge. And the DialoGPT+CS_Adapter response model adapted from CommonGen training can generate underlying CS triplets that fits better to dialogue context.

1 Introduction

Many pre-trained transformer-based (Vaswani et al., 2017) language models (LMs) have been widely applied in natural language generation (NLG) of spoken dialogue systems (SDS) and shown promising performance. However, the probing experiments about the commonsense (CS) explanation behind the dialogue response generation in Zhou et al. (2021b) demonstrated that pre-trained LMs (Radford et al., 2019; Zhang et al., 2020; Roller et al., 2021; Lewis et al., 2020) fail to capture CS knowledge hidden in dialogue utterances, even though they were already pre-trained with numerous datasets. By contrast, humans generally rely on previous experience and commonsense knowledge to produce coherent responses during the conversation. Hence, improving the CS understanding and reasoning ability of a pre-trained conversational model plays a significant role for the development of SDS.

The ideal dialogue agent should be capable of capturing the underlying commonsense knowledge besides generating a reasonable response, as shown in Figure 1. In order to achieve that and enable the commonsense capability of a pre-trained conversational model, we have the following contributions in this work:

1. We firstly induce commonsense knowledge into a pre-trained conversational model so that it is ultimately able to generate series of commonsense triplets (please refer to Table 10). This is done by integrating Adapter (Houlsby et al., 2019; Pfeiffer et al., 2021) layers into the pre-trained DialoGPT (Zhang et al., 2020) and leveraging the commonsense knowledge in ConceptNet (Liu and Singh, 2004) to train the Adapter layers infused in the frozen Di-
2. Secondly, the model is expected to capture the bidirectional relationship between commonsense knowledge and sentence pairs, so that it can both generate sentences given commonsense triplets and underlying commonsense triplets given a sentence (please refer to Table 11). Hence, we extract the CS knowledge between concepts in CommonGen dataset (Lin et al., 2020a) and continually train the entire model: DialoGPT+CS_Adapter, through the proposed “two-way learning”.

3. To finally enable the commonsense ability in dialogue response model that can understand underlying commonsense knowledge and infer related other knowledge for the response generation (please refer to Table 12), we further utilize the Commonsense-Dialogues (Zhou et al., 2021a) dataset to continually train the DialoGPT+CS_Adapter model.

2 Related Works

Pre-trained LMs have been frequently used in task-oriented and chit-chat response generation in SDS, also gained impressive performance. Peng et al. (2020); Chen et al. (2020) and Peng et al. (2021) introduced few shot and end-to-end task-oriented NLG with pre-trained GPT-2 (Radford et al., 2019). Kale and Rastogi (2020) utilized the pre-trained T5 encoder-decoder model (Raffel et al., 2020) to re-write the template guided task-oriented text generation. Zandie and Mahoor (2020) and Lin et al. (2020b) utilized pre-trained GPT (Rafel et al.,) for creating an empathetic chatbot. In our work, we not only utilize pre-trained LM, but also improve the commonsense reasoning ability of DialoGPT.

Even though the large-scale pre-trained LMs have demonstrated impressive performance on multiple generation tasks, building a generation model with commonsense to compose realistically plausible sentences remains challenging. With the new benchmark dataset CommonGen released in Lin et al. (2020a), many works have been presented in these two years for testing the ability of generative commonsense reasoning. Fan et al. (2020) enhanced the retrieved prototype into BART (Lewis et al., 2020) and combined scaling module and prototype position indicator to better utilize the scenario knowledge of prototype for CommonGen text generation. Liu et al. (2021b) proposed KG-BART, where the common sense knowledge graph was incorporated into the pre-trained BART (Lewis et al., 2020) both encoder and decoder side to promote the ability of commonsense reasoning for text generation. Wang et al. (2021) firstly retrieved prototype sentence candidates by a concept matching retriever and a trainable sentence retriever, then used them as auxiliary input to further boost the common sense generation by adopting pre-trained T5 (Raffel et al., 2020) encoder-decoder model. Feng et al. (2021) leveraged the information contained in images to enhance the common sense text generation. To be more precise, they retrieved images for each concept set and generated a caption for the image via a pre-trained image captioning model, then the captions as augmented inputs were utilized to boost common sense generation. However, these works only focus on the common sense sentence in daily scenario, the work about common sense guided responses generation in spoken dialogue system is still underexplored. Our work tries to leverage the common sense reasoning capability in the dialogue generation systems. In recent years, many works also tried to infuse external knowledge into pre-trained models to improve the performance of downstream tasks. Lauscher et al. (2020) investigated the Adapter-based knowledge injection into pre-trained BERT (Kenton and Toutanova, 2019) and improved the language understanding ability. Liu et al. (2021a) integrated commonsense knowledge and emotional concepts into a pre-trained encoder-decoder architecture to improve emotion recognition ability and produce more empathetic responses. Our work mainly enables the commonsense reasoning capability of pre-trained DialoGPT (Zhang et al., 2020) through light Adapter integration and ConceptNet.

3 ConceptNet, CommonGen and Commonsense-Dialogues

The commonsense knowledge graph ConceptNet (Liu and Singh, 2004), the CommonGen (Lin et al., 2020a) and the dialogue dataset Commonsense-Dialogues (Zhou et al., 2021a) are used in this work and are briefly introduced in this section. ConceptNet\footnote{https://conceptnet.io/} is a large-scale and multilingual commonsense knowledge graph that describes general human knowledge in natural language. It comprises 5.9M assertions, 3.1M concepts and 38 rela-
two-way learning" (Section 5.2) with the extracted assertions along with corresponding relations. This dataset is widely used to explicitly test the empirical study in Zhou et al. (2021a) demonstrated that commonsense knowledge helps to boost commonsense reasoning behind the dialogue for Dialogues is utilized finally to activate the commonsense responses. The Commonsense-Dialogues involve much commonsense reasoning. The sentences in CommonGen generally describe the everyday scenarios using these concepts. In this work, CommonGen is utilized to train the DialoGPT+CS_Adapter through "two-way learning" (Section 5.2) with the extracted commonsense triplets and sentence pair (Section 5.1) to learn the bidirectional relationship between commonsense knowledge and sentence pairs.

CommonSense-Dialogues\textsuperscript{3} was released in Zhou et al. (2021a) and is a crowdsourced corpus of around 11K dialogues based on SocialIQA (Sap et al., 2019) event prompt. CommonSense-Dialogues involve much commonsense reasoning in the dialogue and help models produce more commonsense responses. The Commonsense-Dialogues is utilized finally to activate the commonsense reasoning behind the dialogue for the response generation model (Section 6).

4 Adapter tuning in DialoGPT with ConceptNet

The empirical study in Zhou et al. (2021a) demonstrated that commonsense knowledge helps to boost commonsense knowledge infusion. In this work, we utilize the AdapterHub (Pfeiffer et al., 2020) to integrate the Adapter layers into DialoGPT and then train the Adapter layers with the synthetic commonsense corpus from ConceptNet.

4.1 Corpus collection in ConceptNet

We adapt the work from Perozzi et al. (2014); Lauscher et al. (2020) and induce a synthetic corpus from ConceptNet through bias random walking (Grover and Leskovec, 2016) its graph.

Given a source concept, we simulate a random walk of fixed length $l$. Let $c_i$ represents the $i$th concept in the walk. Starting with $c_0$, we firstly sample one concept as $c_1$ from its neighbors based on the normalized transition probability, which is shown in Equation 1. The $\pi_{vx}$ denotes unnormalized transition probability. $Z$ means the size of neighbors and $G$ represents the entire ConceptNet Graph.

$$P(c_i = x | c_{i-1} = v) = \frac{\pi_{vx}}{Z}, \quad if \ (v, x) \in G$$

(1)

One thing matters here, even though ConceptNet provides weight for the assertions, they do not seem to be assigned with high confidence\textsuperscript{4}. Hence, we use the cosine similarity between head concept and tail concept embedded by Glove vectors (Pennington et al., 2014) to replace the original weight\textsuperscript{5}. Hence, the $w_{vx}$ in Equation 2 denotes the Glove cosine similarity between head concept $v$ and tail concept $x$.

$$\pi_{vx} = w_{vx}, \quad if \ i = 1$$

$$= \alpha_{pq(t,x)} * w_{vx}, \quad otherwise$$

(2)

Since starting searching $c_2$, we will bias the random walks by introducing search bias $\alpha$. The work in Perozzi et al. (2014) defines two parameters $p$ and $q$, which is shown in Figure 2, to control how fast the walk explores and how far away the next dialogues based on SocialIQA (Sap et al., 2019) event prompt. CommonSense-Dialogues involve much commonsense reasoning in the dialogue and help models produce more commonsense responses. The Commonsense-Dialogues is utilized finally to activate the commonsense reasoning behind the dialogue for the response generation model (Section 6).

### Table 1: The commonsense assertion examples with different relations in ConceptNet.

| head concept | relation     | tail concept | weight |
|--------------|--------------|--------------|--------|
| loneliness   | CausesDesire | socialize    | 3.464  |
| plate        | AtLocation   | restaurant   | 2.0    |
| program      | CreatedBy    | programmer   | 6.633  |

The weight represents the strength with which the edge expresses this assertion and usually in the $[1, 10]$ interval.

\textsuperscript{3}https://inklab.usc.edu/CommonGen/

\textsuperscript{4}https://github.com/commonsense/conceptnet5/issues/152

\textsuperscript{5}In this work, we remove the assertions with Glove cosine similarity between nodes $v$ and $x$ less than 0, also the assertions with original weight less than 1.

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$$P(c_i = x | c_{i-1} = v) = \frac{\pi_{vx}}{Z}, \quad if \ (v, x) \in G$$

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\[ \alpha = \frac{1}{q} \]
\[ \alpha = \frac{1}{p} \]
\[ \alpha = \frac{1}{q} \]

Figure 2: Illustration of the biased random walks (proposed in Perozzi et al. (2014)) through ConceptNet. The walk just transitioned from concept \( t \) to concept \( v \) and is now evaluating its next concept \( v \). Edge labels indicate search biases \( \alpha \).

concept is from the last concept. Consider the walk that just traversed edge \((t, v)\) and now resides at concept \( v \) (Figure 2). Now, we set the unnormalized transition probability to \( \pi_{vx} = \alpha_{pq}(t,x) \cdot w_{vx} \) (see Equation 2), where

\[ \alpha_{pq}(t,x) = \begin{cases} 1 & \text{if } d_{tx} = 0 \\ \frac{1}{p} & \text{if } d_{tx} = 1 \\ \frac{1}{q} & \text{if } d_{tx} = 1 \end{cases} \]

and \( d_{tx} \) denotes the shortest path distance between \( t \) and \( x \) and \( d_{tx} \) must be one of 0, 1, 2. By setting \( q > 1 \), the random walk is biased towards nodes close to concept \( t \). Setting \( p > \max(q, 1) \) can ensure that we are less likely to sample an already visited concept. We define \( p = 2.0, q = 1.5 \) in this work to enable the walking through much relative concepts to the previous concept, meanwhile avoid repeating it. The walking will be terminated, until to length \( l \) or there is no path to traverse. We set \( l = 10 \) and traverse the ConceptNet graph twice to collect the corpus. Finally, we collected 359,421 data points and split them to train/valid/test as 80%/10%/10%. After simple dataset processing, the collected corpus is like the data in Table 2.

4.2 Commonsense Adapter Training

To enable the commonsense ability, the collected corpus in Section 4.1 is utilized to train the commonsense Adapter\(^6\) (CS_Adapter) layers infused in the frozen DialoGPT (Zhang et al., 2020). In order to ensure the success of the CS_Adapter training, we propose the following tips:

- We add one special token “<commonsense>” to the DialoGPT tokenizer and insert this special token at the beginning of every input prompt (See Table 2). Through “<commonsense>”, the model can distinguish the commonsense triplets from the normal text.

- We create a mapping table between the relations in ConceptNet and natural language (NL) phrases, which is shown in Table 9. Furthermore, we utilize the special character \( [\] \) along with the relation phrases. Our experiments show that \( [\] \) highly helps the model to distinguish the relation from normal words/concepts.

- Given the auto-regressive property of DialoGPT, four prompt templates shown in Table 2 are proposed and randomly chosen as input to guide the generation of commonsense knowledge. Meanwhile, the prompt inputs of training date is re-sampled every 3 epochs.

We train CS_Adapter layers with batch size: 64, learning rate: \( 5e-5 \) and best model is saved at epoch 20. During decoding, we mix top-K sampling of 5 and top-p (nucleus) sampling of 0.9 (Holtzman et al., 2019), and we generate 5 examples for every test prompt input (Same decoding strategy in Section 5.2 and 6.2).

5 Two-Way Learning with CommonGen

After CS_Adapter infusion, the DialoGPT model can generate series of commonsense triplets (Table 10). Now, we except the model to capture the “bidirectional” relationship between commonsense knowledge and sentence pairs. That means, it can generate a sentence given some commonsense triplets; meanwhile, is also able to generate the underlying commonsense knowledge given a sentence. This is what the “bidirectional” means here. As a result, this step is as a bridge to the dialogue response model that can generate

\(^6\)In the early stage of this work, we tried Houlsby Adapter Houlsby et al. (2019) and Pfeiffer Adapter (Pfeiffer et al., 2021) both. Houlsby has slightly better performance, hence, we choose the widely used Houlsby Adapter in the following work.
underlying commonsense knowledge given dialogue context and a response given the generated CS knowledge. Hence, we extract the commonsense triplets between the concepts in CommonGen (Lin et al., 2020a) and leverage the CommonGen for the bridge dataset to further train the DialoGPT+CS_Adapter with our proposed “two-way learning”.

5.1 Commonsense Extraction in Concepts

In the CommonGen, the key concepts (also keywords) are already provided for every sentence. Hence, we need to further extract the underlying relational commonsense knowledge between the concepts from ConceptNet. Not like Zhou et al. (2021a), only one-hop triplets were filtered; however, one-hop and two-hop triplets are both searched in this work. For the commonsense triplets filtering in ConceptNet, we have the following strategies:

1. We traverse every two concepts in the concept set, and firstly search if there is an one-hop triplet in ConceptNet for the two concepts; if not, then activate the two-hop searching.

Like the first example in Table 4, there is the one-hop triplet “surfer [related to] surf” for the concept “surfer” and “surf”. Even though there is no one-hop triplet for “ocean” and “surf” in ConceptNet, we find the two-hop triplet “surfing [has prerequisite] ocean, surfing [related to] surf” with the middle concept “surfing” through two-hop searching.

2. When activating two-hop searching, there are generally many two-hop triplets for any two concepts. Hence, we propose three thresholds to pick most relevant commonsense triplet out. Firstly, we need to make sure the cosine similarity between the two concepts embedded by Glove vectors (Pennington et al., 2014) is not less than 0.3. Secondly, we need to make sure the cosine similarity between the middle concept and at least one of the two concepts is larger than 0.5. Finally, we only select the commonsense triples with the highest weight score.

The Table 4 shows two CommonGen dataset examples along with the extracted commonsense knowledge. And the selected two-hop commonsense triplets are highlighted in red.

5.2 Two-Way Learning

The Table 5 shows the statistics of extracted CommonGen dataset with commonsense triplets, which are utilized to continually train the entire DialoGPT+CS_Adapter for learning the bidirectional relationship between CS knowledge and sentences.

In this step, we propose the “two-way learning” to train the DialoGPT+CS_Adapter model. That means, for every CS_triplets-sentence pair, which is shown in Table 4, when we input the extracted CS triples to the DialoGPT+CS_Adapter model, the output is the sentence; on the contrary, when the input is the sentence, the model will output the extracted CS triples. During the two-way training, all the parameters in DialoGPT+CS_Adapter model are activated and updated with batch size: 16, learning rate: $5e^{-5}$, and best model is saved at epoch 1 with early stopping.

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The three settings are empirically determined and highly improved the extraction quality.
6 Commonsense guided DialoGPT Response Model

After CS_Adapter integration, the DialoGPT can generate series of commonsense triplets. Then the DialoGPT+CS_Adapter is further trained to learn the bidirectional relationship between commonsense knowledge and daily sentence pairs through “two-way learning” with CommonGen dataset. Now, we expect the model to be a dialogue response generation model with commonsense capability for the final goal of this work. To be more specific, it can generate the commonsense knowledge hidden in the dialogue interaction, meanwhile a reasonable response given the generated CS triplets and dialogue context. Hence, adapted the DialoGPT+CS_Adapter model after “two-way learning”, we leverage a commonsense focused dialogue dataset: Commonsense-Dialogues (Zhou et al., 2021a) and further train the DialoGPT+CS_Adapter model to generate the commonsense reasoning along with a response given the dialogue context.

6.1 Keywords and Commonsense Extraction

Firstly, we need to extract the key words/concepts from the Commonsense-Dialogues sentences, because it is not like CommonGen dataset where the concepts in the sentences are already provided. For the keywords extraction, we adapt the work from Tang et al. (2019) and Zhong et al. (2021), use TF-IDF and Part-Of-Speech (POS) features to select the keywords. Afterwards, the same commonsense extraction method (Section 5.1) is applied to pick out the commonsense triplets between the keywords. During the commonsense extraction, like the Figure 1 shows, not only the commonsense triplets between the keywords in dialogue contexts, but also between the keywords in dialogue context and system response, both are extracted for every dialogue. The Table 6 shows the statistic of the extracted commonsense triplets hidden in Commonsense-Dialogue dataset.

6.2 DialoGPT+CS_Adapter Response Training

In this step, we adapt the model from “two-way learning” with CommonGen and continually train DialoGPT+CS_Adapter model with Commonsense-Dialogues (Zhou et al., 2021a) to enable the commonsense understanding and reasoning behind dialogue interaction for open-domain response generation. The dialogue context is as input, the extracted commonsense triplets and response as label to guide the training. In this step, we add two new tokens: “[USER]” and “[SYSTEM]” to distinguish the user utterance from system response. During training, maximal 3 turns’ dialogue context are taken into account for memory-efficient. We train the entire model: DialoGPT+CS_Adapter with batch size: 16, learning rate: $5e^{-5}$, and best model is saved at epoch 5 with early stopping.

7 The Experiment Results

This section introduces the experiment results of this work through automatic metrics, human assessment and use cases. We will evaluate the performance of DialoGPT after CS_Adapter integration firstly, which is the basis of the commonsense guided dialogue response model. Afterwards, we will compare the performance of different response generation models.
Table 6: The statistic of the extracted commonsense triplets in Commonsense-Dialogues dataset.

| extracted CS triplets | train  | valid | test   |
|-----------------------|--------|-------|--------|
| only hidden in dialogue contexts (%) | 47.05  | 46.24 | 46.08  |
| only hidden in dialogue context and response (%) | 24.14  | 25.68 | 25.41  |
| hidden in above-mentioned both sides (%) | 28.81  | 28.07 | 28.52  |

Table 7: The automatic metrics of DialoGPT after CS_Adapter integration (Section 4). And the performance comparison of different response generation models: DialoGPT baseline without CS_Adapter, DialoGPT+CS_Adapter without two-way learning (Section 5) and DialoGPT+CS_Adapter adapted from two-way learning (Section 6).

| model                                | perplexity ↓ | concepts Acc (%) | assertion Acc (%) |
|--------------------------------------|---------------|------------------|-------------------|
| DialoGPT+CS_Adapter integration       | -             | 56.88            | 47.29             |
| DialoGPT baseline (w/o) CS_Adapter integration | 1.405         | -                | -                 |
| DialoGPT+CS_Adapter (w/o) two-way learning | 1.365         | 62.43            | 45.27             |
| DialoGPT+CS_Adapter (final)          | 1.364         | 63.66            | 47.28             |

7.1 Evaluation of Commonsense Adapter

This section will present the evaluation results of CS_Adapter integration (Section 4) in DialoGPT.

We firstly propose two automatic metrics to evaluate the performance of CS_Adapter infused in DialoGPT for generating series of commonsense triplets. One is concepts accuracy, which represents the proportion of generated (head concept, tail concept) that exists in ConceptNet without considering if the generated relation is officially correct. Because there is not one unique relation for (head concept, tail concept), so the concepts accuracy can identify to some extend that model can understand the head concept and tail concept is related. Another is assertion accuracy, which represents the proportion of generated (head concept, relation, tail concept) that officially exists in ConceptNet. The automatic metric results of DialoGPT+CS_Adapter integration in the first row of Table 7 show that only about half of generated commonsense triplets exist officially in ConceptNet with 56.88% concepts accuracy and 47.29% assertion accuracy.

In order to further prove that even if the generated commonsense triplets do not officially exist in ConceptNet, they still make sense for humans, we hire two Master students with computational linguistic background to manually evaluate the generated commonsense assertions which do not officially exist in ConceptNet. We pick out 50 generated assertions that (head concept, tail concept) that exists in ConceptNet, while the predicted relation is not officially correct; and 50 generated assertions that (head concept, tail concept) that do not officially exist in ConceptNet. Two annotators were asked to assess that generated (head concept, relation, tail concept) is reasonable or not by answering “yes” or “no”. The human assessment results shown in Table 3 support our initial assumption that even though the generated commonsense triplets do not officially exist in the ConceptNet, they are potentially high reasonable for humans with up to 93.17% positive agreement.

Additionally, we also show several use cases in Table 10 to demonstrate that the DialoGPT after CS_Adapter fusion have the commonsense ability and is able to generate series of reasonable commonsense triplets. This is the basis for the dialogue response model with commonsense capability.

7.2 Evaluation of Commonsense guided Response Model

This section will introduce the performance comparison of different dialogue response generation models. In Table 7, the DialoGPT baseline represents the DialoGPT is directly fine-tuned with Commonsense-Dialogues dataset for response generation without Adapter tuning and “two-way learning”; the DialoGPT+CS_Adapter without (w/o) two-way learning means that the DialoGPT after CS_Adapter fusion is further trained with Commonsense-Dialogues dataset; the final DialoGPT+CS_Adapter response model is adapted from two-way learning with CommonGen dataset and then further trained with Commonsense-Dialogues dataset. Hence, the former DialoGPT baseline model can only generate response; while the latter two DialoGPT+CS_Adapter models can both generate commonsense triplets hidden in di-
Table 8: The human A/B evaluation on DialoGPT+CS_Adapter vs \{ (w/o) two-way learning, DialoGPT baseline \}.

| models comparison | CS triplets(%) | response(%) |
|-------------------|---------------|-------------|
| DialoGPT+CS_Adapter (final) vs (w/o) two-way learning | 23 vs 20 | 21 vs 28 |
| DialoGPT+CS_Adapter (final) vs DialoGPT baseline | - | 20 vs 28 |

The perplexity (Serban et al., 2015) values are utilized to measure the high-level general quality of the generation model. Lower perplexity of DialoGPT+CS_Adapter in Table 7 indicates its better generalization performance. Compared with DialoGPT+CS_Adapter (w/o) two-way learning, the final DialoGPT+CS_Adapter response model has higher concepts accuracy and assertion accuracy, which demonstrates the DialoGPT+CS_Adapter response model benefits from the two-way learning with CommonGen dataset and can generate better commonsense triplets that fit well to the dialogue context. This is further underpinned by human evaluation results on CS triplets in Table 8. However, the results of human evaluation on response show that the generated response of DialoGPT+CS_Adapter has worse performance than the other two models. The possible reason is that the extracted commonsense knowledge for Commonsense-Dialogues (Section 6.1) are not as perfect as in the Figure 1 shown.

The use cases in Table 12 shows that even though the DialoGPT+CS_Adapter response model generates only response without commonsense knowledge in some cases (the first example in Table 12), it is able to generate commonsense knowledge hidden in dialogue context along with a reasonable response in most cases (the second and third example in Table 12). Beyond that, the generated commonsense knowledge includes some key concepts (highlighted with red in Table 12) in some cases and guide the response generation to some extent.

8 Conclusion and Future Work

In this work, we infuse commonsense knowledge into the pre-trained conversational model to enhance the commonsense capability. Hence, the commonsense guided dialogue response model can not only generate a response, but also the underlying commonsense triplets hidden in the dialogue interaction. To be more specific, we firstly integrate the commonsense knowledge in ConceptNet into pre-trained DialoGPT through CS_Adapter fusion. Secondly, we utilize CommonGen for bridge dataset and propose “two-way learning” to train DialoGPT+CS_Adapter for capturing the bidirectional relationship between commonsense triplets and sentence pairs. The Commonsense-Dialogues dataset is finally leveraged to further enable the commonsense knowledge understanding and reasoning for response generation.

The experiment results in Section 7.1 demonstrate that the pre-trained conversation model DialoGPT benefits from the commonsense knowledge integration and possesses commonsense capability to generate series of reasonable commonsense triplets. The experiment results in Section 7.2 show that our proposed DialoGPT+CS_Adapter generation model can both generate commonsense reasoning along with a response. Based on the two-way learning with CommonGen dataset, the response model can generate better commonsense triplets that fits well to dialogue context. However, the generated responses have a little loss even compared with the DialoGPT baseline. The possible reason is the rule-based CS extraction method, which includes keywords extraction and knowledge extraction, does not consider the discourse information. Hence the extracted CS knowledge is kind of imperfect and does not better guide the response generation. In our future work, we will think about more how to extract more relevant commonsense knowledge hidden in dialogue interaction. Furthermore,
we believe that the CS knowledge can guide an more informative response generation (like the response in Figure 1 includes more information compared with generic response “cool.”). This could be verified in the future research. Another shortcoming we found in this work is that the relation distribution in ConceptNet is severely imbalanced which results in an over-generation of the “[related to]” relation.

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9 Appendix

Several Tables are attached in the Appendix given the maximal 8 pages limitation.
Table 9: The mapping between assertion relations in ConceptNet and natural language (NL) phrases. The experiment shows that the special character [] in NL phrases helps the model a lot to distinguish the relations from normal words.
Table 10: Use cases for Adapter integration show that the DialoGPT+CS_Adapter is capable of generating series of commonsense triplets.

| CS input |
|----------|
|Supercomputer [derived from] computer, computer [has property] expensive |

Table 11: Use cases for DialoGPT+CS_Adapter trained with extracted CommonGen in two-way method show the model can both generate sentences given commonsense triplets and underlying commonsense knowledge given a sentence.

| dialogue context |
|------------------|
| I’m so tired. How long do i have to keep taking over your shift? |
| I want to move back in with Casey. |
| hello friend, I got a mail that we have been hired for the movie. |
| I have no idea how i did on that interview, yesterday, I was so nervous. |

Table 12: Use cases for final commonsense guided response generation model: DialoGPT+CS_Adapter. The cases with highlighted red words that both exist in commonsense triplets and response show that the generated commonsense knowledge exerts guidance over the generated response and provides key concepts that occur in the generated response.