TopKG: Target-oriented Dialog via Global Planning on Knowledge Graph

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Abstract

Target-oriented dialog aims to reach a global target through multi-turn conversation. The key to the task is the global planning towards the target, which flexibly guides the dialog concerning the context. However, existing target-oriented dialog works take a local and greedy strategy for response generation, where global planning is absent. In this work, we propose global planning for target-oriented dialog on a commonsense knowledge graph (KG). We design a global reinforcement learning with the planned paths to flexibly adjust the local response generation model towards the global target. We also propose a KG-based method to collect target-oriented samples automatically from the chit-chat corpus for model training. Experiments show that our method can reach the target with a higher success rate, fewer turns, and more coherent responses.

1 Introduction

Human-like dialog agents have three types of approaches: open-domain (Zhang et al., 2019a; Huang et al., 2020), task-oriented (Budzianowski et al., 2018; Rastogi et al., 2020; Yang et al., 2020), and target-oriented dialog (Tang et al., 2019; Qin et al., 2020; Zhong et al., 2021). The open-domain dialog only requires the dialog generation to be fluent and context coherent. In contrast, typical task-oriented dialog further completes a specific task by understanding users’ intention and collecting the required information of predefined sub-tasks of the intention. However, as a more challenging task, target-oriented dialog aims to achieve a global target that often can not be clearly defined as sub-tasks. The dialog agents are required to lead the conversation to the target flexibly, and the process is excepted to be coherent, effective, and successful. Due to its purpose and flexibility, target-oriented dialog agents have a broad-based demand, e.g., conversational recommendation (Li et al., 2018; Kang et al., 2019), psychotherapy (Sharma et al., 2020), and education (Clarizia et al., 2018). In these fields, a typical expectation of target-oriented dialog is to actively lead the conversation by smoothly changing the dialog topic to a designated one, e.g., a product, a stimulus of mind, and a knowledge point.

To reach a target topic effectively and coherently in dialog, existing approaches primarily represent the topic as keywords and adopt a two-stage architecture, i.e., predicting a next-turn keyword and keyword-augmented response retrieval (Tang et al., 2019). In this direction, Xu et al. (2020b) further introduces reinforcement learning with “target similarity” rewards to target-oriented dialog learning. However, the target-oriented dialog is a typical knowledge-rich task. Although dialog context can support the semantic concern of dialog generation, it is not quite effective to model the knowledge-driven process in the target-oriented dialog. To involve global knowledge, Qin et al. (2020) and Xu et al. (2020a) incorporate a dialog graph into the target-oriented dialog and Zhong et al. (2021) uses the external commonsense KG (ConceptNet (Speer et al., 2017)) to improve the performance.

Although existing target-oriented dialog works have demonstrated practical approaches in self-simulation test, there is still some open issues: (1) Lack of multi-turn target-oriented dialog corpus for training and benchmarks. Most existing target-oriented corpus are prepared for next-turn local target (e.g., OTTers (Sevegnani et al., 2021)), or adopt chit-chat corpora and randomly select a keyword in the next-turn utterance as the local target. (2) Lack of global planning of dialog process. Although the latest works use a global target to guide every turn of response generation, they adopt a short-sighted and greedy strategy instead of global planning to optimize the process towards the global target.

To this end, we propose Target-Oriented dialog with global Planning on Knowledge Graph (TopKG), which effectively supports the target-

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oriented process by global reasoning on KG concerning the dialog context. Specifically, to address the first data issue, we automatically select a new dataset named Target-Guided ConvAI (TGConv) from the chit-chat corpus ConvAI2 (Dinan et al., 2020). We select target-oriented samples from ConvAI2 by identifying the dialog utterances containing a go-through entity sequence that aligns with the KG path. Furthermore, we distinguish the selected dialog samples according to whether the global target is easy to reach or not to verify the performance of TopKG in dealing with hard global target-oriented cases. For instance, the sample in the left part of Figure 1 is target-oriented because the keywords in this dialog are connected (direct or low-order connected) in a commonsense KG, which embodies a smooth transition towards global target words. To address the second issue, we first improve the existing one-turn target-oriented response generation, trained in a supervised fashion to predict a next-turn keyword and generate a fluent and coherent response with the predicted keyword. Using the improved one-turn model as local-model, we further introduce a reinforcement learning based global-model to effectively guide the local-model towards a global target with global planning on KG. Specially, the global-model adjusts the next-turn keyword selection of the local-model to follow the global planning path on KG and reward the keyword-based response generation with success in reaching the global target.

Our main contributions are as follows:

1. We propose a simple yet effective way to automatically extract multi-turn global target-oriented dialog from the chit-chat corpus to develop global target-oriented dialog agent. We also distinguish the selected dialog into easy-to-reach target and hard-to-reach target.

2. We make the first step towards global planning in global target-oriented dialog. A two-stage learning framework is designed to guide a next-turn local model with a reinforcement learning based global model which is guided by global planning in commonsense KG.

3. With automatic and human metrics, we verify that TopKG exceeds baselines on reaching global target with more coherent semantics, fewer turns, and a higher success rate in reaching targets.

The dataset can be downloaded in data folders from https://github.com/yyyyyyzt/topkgchat

2 Related Work

**Target-oriented dialogue systems.** Current target-oriented dialog studies can generally be divided into local-target oriented and global-target oriented methods. Local-target oriented methods (Wang et al., 2021) pays attention to the next-turn target. For example, Xu et al. (2020b,a) proposes a hierarchical policy model to plan and generate responses of different levels where the high-level policy plans a topic. However, the low-level policy plans responses that are coherent to this topic instead of approaching it. Global-target oriented methods (Qin et al., 2020; Zhong et al., 2021) uses global target to guide every turn of response generation. These methods propose a keyword predictor to determine the next-turn keyword to talk about and produce a response relevant to the determined keyword. However, they adopt a short-sighted and greedy strategy instead of explicit planning to optimize the process towards the global target.

**KG-grounded dialogue systems.** Leveraging background information for dialogue system improvement is a well-researched topic, especially in target-oriented settings. Some work uses structured knowledge, DKRN (Qin et al., 2020) incorporates a dialog graph, and CKC (Zhong et al., 2021) uses the ConceptNet to improve the performance. For how to utilize KG, classical methods are divided into using full path (Ma et al., 2021) and using flexible path fragments (Zhou et al., 2021). These models enjoy rich knowledge augmentation since short KG paths relating to the context are encoded, but they lack the ability to plan on KG. Another set of works focuses on grounds in unstructured knowledge (Zhao et al., 2020; Wu et al., 2020), which can also be divided into independent sentences and documents. This unstructured knowledge is more challenging to use than KG.

3 Our Approach

**Task Definition** Formally, \( C = \{c_1, \ldots, c_i \} \) is the current dialog context involving latest \( i \) utterances. A knowledge graph \( G_{KG} = V_{KG} \times E_{KG} \) is composed of the commonsense entities \( V_{KG} \) and relations \( E_{KG} \). Given \( C, G_{KG} \) and a global target keyword \( K_{target} \), the global target-oriented dialog is firstly required to figure out a next-turn keyword \( z \) from the \( G_{KG} \), and generate a response \( r \) related to \( z \). Furthermore, with multi-turn response generation, the global target-oriented dialog need to successfully mentioned a global target keyword
Figure 1: The left part illustrates how to select target-oriented dialogs for model learning by matching the word sequence across utterances with reasoning paths in KG. The right part illustrates how the global-model uses reinforcement learning to guide a GPT-2 based local-model to follow the global planning in KG. Global Planning on KG is pre-performed before the learning of Local-Model and Global-Model, and planning paths are essential to guide the multi-turn responses generation.

$K_{target}$ with fewer turns and keep the response be coherent to the context in each turn.

### 3.1 Method Overview

Our approach consists of two main contributions: an automatic method for target-oriented conversation dataset collection and a two-stage learning model for global target-oriented dialog generation.

**Target-oriented Conversation dataset** As existing multi-turn dialog corpora are not specially created for target-oriented tasks, we firstly propose automatically selecting the target-oriented dialog session from the general dialog corpora. A dialog session was selected from the general chit-chat corpus by examining whether a KG-explainable entity path is running through a dialog. In addition, we indicate the entity path and specify the easy target and the hard target. The example shown in Table 1.

**Two-stage learning model** We divide the task into two progressive stages in Fig 1: local-model of next-turn strategy learning (stage 1) and global-model of multi-turn strategy learning (stage 2). Specifically, at stage 1, the local-model is supervised trained to predict next-turn keywords and generate a response related to the keywords. In stage 2, we design a reinforcement learning to adjust the local-model to explore all potential paths by global planning in a commonsense KG towards the global target word, where a bidirectional heuristic reasoning obtains the paths. We also reward the generated response in each turn by whether the dialog till this turn is target-oriented and whether the dialog finally reaches the global target word.

### 3.2 Target-oriented dialog corpus sampling

In this section, we construct a target-oriented dialog corpus (named **TGConv**) from chit-chat corpus ConvAI2 (Dinan et al., 2020).

#### 3.2.1 Identify target-oriented dialog

We suppose a dialog is a positive example of target-oriented dialog if there is a consistent reasoning path of words linking all the utterances in their order in the dialog. A dialog session was selected from the general chit-chat corpus by examining whether a KG-explainable entity path is running through a dialog. In addition, we indicate the entity path and specify the easy target and the hard target. The example shown in Table 1.

**Table 1**: A target-oriented example dialog in TGConv

| Dialog                                                                 | Entity Path                                      | Target | Art |
|-----------------------------------------------------------------------|-------------------------------------------------|-------|-----|
| A: I spend a lot of time outside.                                     | **Outside-Garden-Flower-Color-Art**              |       |     |
| B: I like the outdoors as well, especially gardening                  |                                                 |       |     |
| A: Wow! I used to have a garden too.                                  |                                                 |       |     |
| B: I love sipping coffee while enjoying flowers in my garden.        |                                                 |       |     |
| A: Flowers are always beautiful and colorful!                         |                                                 |       |     |
| B: I like anything with art, especially colorful things.              |                                                 |       |     |

To be logical, each neighbor word pair, i.e.,
We let the local-model learn next-turn target-ward search from goal/target entity toward source.

To link all the utterances in dialog, each utterance target entity and its neighbors on the ConceptNet text, and the target, respectively. Firstly, we get the \( z \) Fig 1. In order to predict the next turn keywords model architecture is shown in the right part of oriented policy in a supervised fashion. The local-oriented task scenarios, and the detailed process is shown in Algorithm 1.

3.4 Supervised Learning of Local-Model

We let the local-model learn next-turn target-oriented policy in a supervised fashion. The local-model architecture is shown in the right part of Fig 1. In order to predict the next turn keywords \( z \), we need to model the candidate words, the context, and the target, respectively. Firstly, we get the target entity and its neighbors on the ConceptNet to build a subgraph \( G_{\text{target}} \) and use the method in the previous section to get a global graph \( G_{\text{global}} \). Then we apply a multi-layer GCN encoder to model the graphs. Besides, we use a typical transformer encoder for context understanding. Finally, we predict a keyword and generate a coherent response by generator for approaching the target.

3.4.1 Graph-based Encoder

We use a graph-based encoder to model graph node representations for predicting keywords. Here we use two graphs \( G_{\text{global}} \) and \( G_{\text{target}} \). The \( G_{\text{global}} \) is a large graph that contains all potential paths from start context to target, and \( G_{\text{target}} \) only contains target entity and its neighbor nodes to enhance the target representation.

Therefore, to obtain the representation of concepts and relations, we apply multi-layer GCN (Kipf and Welling, 2016) encoders to encode the \( G_{\text{global}} \) and \( G_{\text{target}} \). Moreover, following the idea of the TransE model (Bordes et al., 2013), we update a concept embedding with the subtraction between each neighbor concept embedding and the corresponding relation embedding to obtain the relation representation. The concepts \( V \)

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Algorithm 1: Global Planning by Bidirectional Reasoning over ConceptNet
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| Input | ConceptNet, \( G_{\text{KG}} \); Target, \( K_{\text{target}} \); The set of concepts in start: \( V_{\text{start}} = \{v_1, v_2 \cdots v_m\} \); Output: A graph consists of all potential paths from source to target, \( G_{\text{global}} \)
|-------|---------------------------------------------------------------|
| Initialize graph \( G_{\text{global}} \); |
| foreach node \( v_i \) of the \( V_{\text{start}} \) do |
| Initialize a concept stack \( S \) contain \( v_i \); for \( h \) from 1 to maximum hops \( H \) do |
| while \( S \) is not empty do |
| Pop a head entity \( v_h \) from \( S \); \( N_i \); the neighbouring concepts of \( v_h \) in ConceptNet; |
| Select the top \( K \) concepts most similar to the head entity \( v_h \) from \( N_i \); |
| Select the top \( K \) concepts most similar to the target entity \( K_{\text{target}} \) from \( N_i \); |
| Add them to an empty temporal triple list \( T \); |
| foreach \( (v_h, r, v_t) \) in \( T \) do |
| Add \( v_h, v_t \) and \( r \) into \( G \); |
| if \( v_t \) not in \( G_{\text{global}} \) then |
| Push \( v_t \) in \( S \) |
| end |
| end |
| end |
| end |
| end |
| Repeat the above process from \( K_{\text{target}} \) to \( V_{\text{start}} \); |

w_i and \( w_{i+1} \), should match the names of the two nodes of an edge in the ConceptNet, respectively. To link all the utterances in dialog, each utterance in the dialog should provide at least one word to \( p \). To keep the order in dialogue, \( w_i \) should be in the same order in \( p \) as they appear in the dialog. Except for positive samples, other samples in the corpus are identified as negative examples.

3.2.2 Global target assignment

For each positive example dialog associated with a reasoning path \( p \), we select the last word \( w_m \) in \( p \) as the global target \( K_{\text{target}} \). Furthermore, to better evaluate the model’s ability to guide the dialogue to the target of different difficulties, we distinguish target words into “easy-to-reach” and "hard-to-reach". Specifically, target words with low frequency in the corpus are classified as "hard-to-reach" target words (less than 800) in local-model and global-model.

3.3 Global Planning

Global planning is the key to successfully accomplishing target-oriented task. We finally obtain a graph consisting of a set of potential paths through global planning, which embodies the keyword transition from the initial context to the global target word. Building a connected graph \( G_{\text{global}} \) from the starting to target allows us to learn a better graph representation and facilitate our model to explore better paths. Specifically, we identify the noun and verb concepts in the dialogue context and then use a bidirectional reasoning method to find KG paths over ConceptNet effectively. Bidirectional reasoning is a graph search algorithm that finds smallest path from the initial to the target entity. It runs two simultaneous search: 1) Forward search from source/initial entity toward goal entity and 2) Backward search from goal/target entity toward source entity. This algorithm is very suitable for target-oriented task scenarios, and the detailed process is shown in Algorithm 1.
We utilize a transformer encoder for conversation understanding. After we get the next-turn keyword $w$, we flatten conversation context in $\mathcal{C}$ as the input, and the following text $z$ as the reference. Specifically, the $z$ and $\mathcal{C}$ are first concatenated by a special separator token. The training objective follows a standard language model (LM) consisting at each turn of dialog, which is the discriminator score of the utterances sequence containing the global target through reinforcement learning. Therefore, we design a simulation-based environment to guide the local-model toward the global target through reinforcement learning.

To this end, we let the model talk to itself. At the start of the dialog, we explicitly search a set of planning paths (described in 3.3) in ConceptNet from the initial context to the global target word. Then we use searched planning paths to adjust the next-turn keyword prediction to obey the planning paths and generate a response with the keyword. Furthermore, the generated response is rewarded by its target-oriented coherence to the context and the success of the global target. Global-model consists of the following components.

### 3.5.1 State/Action
At each time step $t$, the state $S_t$ is a tuple of $[G_{\text{global}}; G_{\text{target}}; \mathcal{C}]$, where $G_{\text{global}}$ is a graph of planning paths obtained at the start of the dialog, and $G_{\text{target}}$ is the predefined global target word and its neighbors, and $\mathcal{C}$ is the current context. Given the current dialog state, an action is the next-turn keyword $z$, and the action space is the potential paths obtained by global planning.

### 3.5.2 Reward
We use Local Reward and Global Reward to encourage the dialogue to be contextual and coherent and explore global target-oriented strategy.

**Local Reward** encourages the contextual consistency at each turn of dialog, which is the discriminator score of the utterances sequence containing the current context and generated response, the details are as below.

**Global Reward** encourages the global target-oriented response by giving a positive reward of "1" if the global target word finally appears in the last turn or a negative reward of "-1" otherwise.

We use GloVe embedding of size 300 (Pennington et al., 2014)

\[
\begin{align*}
\bar{h}_{l+1}^i &= \sigma \left(W_l^0 h_l^i + \sum_{j \in N_l^i} \frac{1}{|N_l^i|} W_l^0 (h_l^j - h_l^i) \right) \quad (1)
\end{align*}
\]

where $h_l^i$, $h_l^j$, and $h_r^l$ are the embeddings of node $v_i$, node $v_j$, and the relation between $v_i$ and $v_j$ at layer $(l - 1)^{th}$; $W_l^0$ and $W_l^1$ are the two trainable parameter matrices specific to the layer $(l - 1)^{th}$; and $\sigma$ is a non-linear active function. The relation embedding is also updated at the $(l + 1)^{th}$ layer via a linear active function: $h_r^{l+1} = W_l^0 h_r^l$. After $L$ layers, we are able to obtain a set of concept representations $\{h_{v_1}^{(L)}, \ldots, h_{v_{|V|}}^{(L)}\}$.

### 3.4.2 Conversation Context Encoder
We utilize a transformer encoder for conversation context understanding. Same as previous works, we flatten conversation context in $\mathcal{C}$, and then add a special token $[\text{CLS}]$ at the beginning of the input. $\mathcal{C} = [\text{CLS}; C]$ is fed into Transformer Encoder, then output representation of $[\text{CLS}]$ token denoting the global memory of the whole sequence.

### 3.4.3 Classification
Now we have the context representation, $G_{\text{global}}$ concepts representation, and $G_{\text{target}}$ concepts representation for predicting words. Finally, we concatenated these vectors and fed to a linear transformation layer, followed by a softmax layer. We limited the candidates to two-hop entities based on context. The entire model is optimized by minimizing the cross-entropy loss (Zhang et al., 2019b):

\[
\begin{align*}
p_{\Theta}(r | C, z) = \prod_{t=0}^{|r|} p(r_t | x, z, r_{0:t-1}) \quad (2)
\end{align*}
\]

where $r_t$ is the $t$-th token in $r$.

### 3.4.4 Keyword Augmented Generator
After we get the next-turn keywords word $z$, we employ a keyword-augmented GPT (Radford et al., 2019) to generate a response to approaching the target. The generator takes keywords $z$ and context $\mathcal{C}$ as the input, and the following text $r$ as the target reference. Specifically, the $z$ and $\mathcal{C}$ are first concatenated by a special separator token. The training objective follows a standard language model (LM)
3.5.3 Discriminator for local reward evaluation

To reward the dialog (context+response) which are more likely to be target-oriented, we train a discriminator to tell whether an utterance sequence is semantically target-oriented. To this end, the discriminator is trained to classify the positive and negative samples collected in section 3.2. Specially, the positive and negative samples with 1/0 label: $X = [CLS;c;SEP;r]$ or $X = [CLS;c;SEP;r]$ is fed into pre-trained language model (BERT) (Devlin et al., 2018), then output representation of [CLS] token is used for classification. The classification score is formulated as

$$f_{score}(X) = \sigma(w^T x_{CLS} + b)$$  \hspace{1cm} (3)

where $w$ and $b$ are trainable parameters. We use binary cross-entropy loss to optimize the models.

3.5.4 Training

We apply Proximal Policy Optimization (Schulman et al., 2017), a stable policy based RL algorithm using a constant clipping mechanism as the soft constraint, for dialog policy optimization:

$$J_t(\theta) = E_{s,a}\left[ \min \left\{ \beta_t \hat{A}_t, clip(\beta_t, 1 - \epsilon, 1 + \epsilon) \hat{A}_t \right\} \right]$$  \hspace{1cm} (4)

$$\hat{A}_t = R_t - \hat{V}_{\phi}(s_t)$$ is the estimated advantage, where $R_t = \sum_{\tau=t}^{T} \gamma^{\tau-t}$ is the local reward adding global reward, $\hat{V}_{\phi}$ is the estimated value function of state $S_t$ with parameters $\phi$, $\beta_t = \frac{\pi_0(a_t|s_t)}{\pi_{old}(a_t|s_t)}$ is the ratio of the probability under the new and old policies, $\delta$ is TD residual, $\lambda$ and $\epsilon$ are hyper-parameters.

4 Experiments and Results

4.1 Datasets

We evaluate TopKG and baselines on two datasets. To verify the ability to guide the user to the target topic in multi-turn of dialogue, we use our proposed dataset TGConv, which is extracted from ConvAI2 (Dinan et al., 2020) and is distinguished into “easy-to-reach/hard-to-reach” targets with the method in section 3.2. ConvAI2 is a chit-chat dataset based on the PersonaChat for NIPS 2018 competition, which contains high-quality open-domain dialogues, including diverse topics. In addition, one-turn dialogue is a special case of multi-turn, therefore we also conduct our evaluation on a next-turn target-oriented dataset OTTers(ood)\(^2\) (Sevegnani et al., 2021). OTTers requires the agent pro-actively generate an “bridging” utterance to approach the target, which is consistent with the input and output of the task on TGConv. The statistics of the two datasets are presented in Table 2.

| Dataset    | Split | #Conv. | Avg. #Utter. | Avg. #Word. | Avg. #Entity. | Avg. #Coh. |
|------------|-------|--------|-------------|-------------|--------------|------------|
| OTTers     | Valid | 1152   | 3.0         | 9.56        | 2.95         | 0.45       |
|            | Test  | 1130   | 3.0         | 9.19        | 2.80         | 0.44       |
| TGConv     | Valid | 2681   | 7.96        | 12.29       | 2.85         | 0.31       |
|            | Test  | 1000   | 8.97        | 12.47       | 2.91         | 0.32       |

Table 2: Dataset statistics. Avg.#Utter., #Word., #Entity., #Coh. denotes the average number of utterances, words, entities, semantic similarity per dialogue, utterance, utterance, utterance.

\(^2\)OTTers have different train-dev-test (in-domain and out-of-domain) splits; we choose out-of-domain(ood) split. The ood split resembles a zero-shot scenario, where the model has to generate a shift between two topics it has never been fine-tuned on.

\(^3\)SacreBLEU (Post, 2018) provides hassle-free computation of shareable, comparable, and reproducible BLEU scores.

4.2 Baselines

We select four baselines in end-to-end (GPT-2, MultiGen) and pipeline style (DKRN, CKC), respectively. The first baseline is GPT-2 (Radford et al., 2019). Next, we test the recent Multi-Gen (Ji et al., 2020), extends GPT-2 with multi-hop reasoning on commonsense knowledge graphs. The third baseline is DKRN (Qin et al., 2020), which builds a dialog graph from the corpus for topic transition. The last baseline is CKC (Zhong et al., 2021), the state-of-the-art approach using ConceptNet for this task. In addition, DKRN and CKC are retrieval models. Here we replace the retriever with the generator in our paper.

4.3 Metrics

Local-Evaluation To evaluate models’ performance in generating next-turn response, we firstly perform automatic evaluation using commonly adopted text generation metrics, including CIDEr (Vedantam et al., 2015), ROUGE-L (Lin, 2004) and METEOR (Banerjee and Lavie, 2005). However, we report the full BLEU score\(^3\) (Papineni et al., 2002) that accounts for the overlap across 1-4 ngrams instead of only 4-grams (BLEU-4). In addition, we use hits@K ratio to measure the number of relevant entities correctly predicted by the
Table 3: Automatic evaluation of next-turn response generation on OTTers. Numbers marked with * indicate that the improvement is statistically significant compared with the best baseline (t-test with p-value < 0.05).

|        | BLEU1−4 | METEOR | ROUGE-L | CIDEr | hits@1 | hits@3 |
|--------|---------|--------|---------|-------|--------|--------|
| GPT2   | 11.58   | 10.26  | 17.67   | 13.75 | 4.39   | 15.79  |
| MultiGen | 13.57  | 12.51  | 26.27   | 15.48 | 6.58   | 20.51  |
| DKRN   | 12.86   | 11.90  | 21.52   | 14.33 | 4.91   | 17.72  |
| CKC    | 13.34   | 11.65  | 24.77   | 14.46 | 6.87   | 21.89  |
| TopKG  | 15.35∗  | 13.41∗ | 27.16   | 17.18∗ | 7.78   | 22.06∗ |
| w/o global plan | 14.89 | 12.89  | 26.99   | 16.22 | 7.45   | 21.14  |
| w/ small graph(K=5,H=3) | 13.24 | 10.65  | 25.53   | 15.62 | 6.77   | 21.22  |
| w/ large graph(K=20,H=6) | 15.24 | 11.65  | 27.53   | 16.62 | 7.79   | 21.63  |

Table 4: Automatic evaluation of global guiding on TGConv. Note that our task requirement is to reach the target smoothly and fast. "Coh." and "Turns" not the higher / lower the better.

|        | Easy Target | Hard Target |
|--------|-------------|-------------|
|        | Succ.(%)    | Turns | Coh. | Succ.(%) | Turns | Coh. |
| GPT2   | 22.3        | 2.86  | 0.23 | 17.3     | 2.94  | 0.21 |
| MultiGen | 26.7        | 2.55  | 0.21 | 19.6     | 7.31  | 0.24 |
| DKRN   | 38.6        | 4.24  | 0.33 | 21.7     | 7.19  | 0.31 |
| CKC    | 41.9        | 4.08  | 0.35 | 24.8     | 6.88  | 0.33 |
| TopKG  | 48.9∗       | 3.95  | 0.31 | 27.3∗    | 4.96  | 0.33 |
| w/o global plan | 35.4 | 4.51  | 0.32 | 21.3     | 7.18  | 0.32 |

Table 5: Comparison of human evaluation metric Coherence and Effectiveness results on self-chat dialogues among our model and baselines. The agreement among the annotators is measured by the Fleiss’s kappa. The agreement ratio kappa in [0.41, 0.6] denotes the moderate agreement.

|        | Easy Target | Hard Target |
|--------|-------------|-------------|
|        | G-Coh. | Effect. | G-Coh. | Effect. |
| GPT2   | 1.13  | 1.20  | 1.13  | 0.86  |
| MultiGen | 1.24  | 1.29  | 1.17  | 1.13  |
| DKRN   | 1.26  | 1.23  | 1.19  | 1.18  |
| CKC    | 1.53  | 1.31  | 1.23  | 1.16  |
| TopKG  | 1.51∗ | 1.67  | 1.37  | 1.48  |
| w/o global plan | 1.42 | 1.34  | 1.24  | 1.13  |
| kappa  | 0.45  | 0.55  | 0.51  | 0.58  |

Local Evaluation To evaluate models’ performance in guiding the dialog to global target, as existing works (Qin et al., 2020; Zhong et al., 2021) do, we use a simulator to simulate multi-turn dialog. "Succ." automatically measures the success rate of generating the global target word within 8 turns. "Turns" indicates the average turns of all dialogs which successfully generate the global target word. "Coherence (Coh.)" automatically measures the contextual semantic similarity between the last utterance in the context and generated response.

As automatic metrics are widely criticized due to their lack of correlation with human judgments (Novikova et al., 2017; Reiter, 2018), we also employ two dialogue-level metrics by human evaluation: "Global-Coherence (G-Coh.)" manually examine whether the whole dialog is logical, fluent, and target-oriented. "Effectiveness (Effect.)" measures whether the target is efficiently reached. 100 dialogs are generated by simulation for each model. Three annotators score the generated dialogs rating in {0, 1, 2}, higher is better.

4.4 Results

Global Evaluation To evaluate models’ performance in guiding the dialog to global target, as existing works (Qin et al., 2020; Zhong et al., 2021) do, we use a simulator to simulate multi-turn dialog. "Succ." automatically measures the success rate of generating the global target word within 8 turns. "Turns" indicates the average turns of all dialogs which successfully generate the global target word. "Coherence (Coh.)" automatically measures the contextual semantic similarity between the last utterance in the context and generated response.

As automatic metrics are widely criticized due to their lack of correlation with human judgments (Novikova et al., 2017; Reiter, 2018), we also employ two dialogue-level metrics by human evaluation: "Global-Coherence (G-Coh.)" manually examine whether the whole dialog is logical, fluent, and target-oriented. "Effectiveness (Effect.)" measures whether the target is efficiently reached. 100 dialogs are generated by simulation for each model. Three annotators score the generated dialogs rating in {0, 1, 2}, higher is better.

4.4 Results

Local Evaluation Table 3 shows the next-turn results on OTTers. GPT2 performs poorly on the one-turn transition. The multi-hop reasoning component added by the MultiGen and our TopKG leads to substantial improvements. TopKG achieves substantially better performance than all baselines on OTTers. This advantage indicates that TopKG successfully improves the performance of the existing local-model, which aims at the next-turn target.

Global Evaluation As shown in Table 4, on cases with "easy-to-reach" targets, end-to-end models such as GPT and MultiGen have fewer turns.
We perform ablation studies for TopKG to better analyze the main components’ relative contributions. The results are shown in Tables 3, 4, 5.

**Does the global planning work?** To prove the contribution of proposed global planning, we replace the global planning (w/o global plan) with a 2-hop neighbors graph (based on context entities), which results in the most significant performance drop in multi-turn evaluation. In contrast, the drop in the next-turn evaluation is not noticeable. The main reason is that the target often can be found in two-hop neighbors on the graph in a next-turn dialogue. This verifies the contribution of global KG planning to global target-oriented dialog.

**How much graph information we need?** We also explore the number of neighbors needed for initializing the $G_{global}$ graph’s nodes in two aspects (refer in Algorithm1): the maximum number of hops $H$, and the number of neighboring nodes in the $h_{th}$ hop (denoted as $K$). Contrary to our expectations, expanding the average size of the knowledge graphs from 1000 nodes to 2000 did not improve the hits@K ratio, as shown in the last row of Table 3. Therefore, the final version of TopKG adopts the global planning with $K = 10, H = 3$.

### 4.6 Case study

In the case study, we compare our TopKG with CKC, the most competitive baseline. In the left case of “Easy Target” in Table 6, TopKG and CKC followed different KG paths. In the first path followed by CKC, the novel indicates books, and the following two keywords are the topics of the books. In the second path followed by TopKG, the novel is an adjective, adventure is novel, and travel is one kind of adventure. In such easy cases, although the best existing method works well, TopKG can further explore diverse paths based on reinforcement learning. In the right case of “Hard Target” in Table 6, CKC gets trapped and fail to reach the goal. However, TopKG still successfully guides the dialog to the goal with effective global planning.

### 5 Conclusion and Future Work

We propose effectively guiding the target-oriented dialog towards a global target with global planning on KG. We first design a novel method to automatically select target-oriented samples from the chit-chat corpus by identifying KG reasoning paths.
throughout the dialog. We train a reinforcement learning model with a selected high-quality corpus that can guide a GPT-2 based response generation model to reach a global target word by global planning on ConceptNet. Automatic and human evaluations show that our method exceeds the baselines from both local and global views, and global planning provides a significant contribution. We will explore to balance the coherence and number of turns in global planning in future work.

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A Appendix

A.1 Discriminator

Discrimination measures the different between the positive/negative examples we extracted. In experiments, we verify the significant difference between the conversational behaviour of selected positive and negative examples by accurately classifying positive and negative examples by a discriminator.

|                      | Accuracy   |
|----------------------|------------|
| BERT-small           | 76.8%      |
| BERT-base            | 78.1%      |

Table 7: The accuracy of the discriminator classification

According to the result of the discriminator and data analysis, we found that some negative samples may contain positive segments (e.g., the first few utterances in a negative sample can generate a short reasoning path), so false negative may be a problem in training the discriminator.

A.2 Fail cases

Here are some cases of TopKG failures. It can be seen that the failure can be roughly divided into
two situations. One is that in the face of some uncommon words, even if there is a correct path, the generative model can only generate sentences with similar semantics. The other is that the path is very long and it is difficult to generate replies that contain relevant words.

### Table 8: Some failure cases

| Start: dye | Hard Target: volley |
|------------|---------------------|
| Context:   | A: hi i dye my hair 4 times a year. B: do you live in the sky ? i do . in the clouds. |
| TOPKG:     | A: i dye it dark brown B: do you also like the martant? it is my favorite. A: yes i like it because it is on the ground B: do you have a favorite field? ...can not reached |
| Path:      | dye-mordant-ground-volley |

| Start: mowing | Hard Target: ethicist |
|--------------|----------------------|
| Context:     | A: i also enjoy lawn mowing on sunny days . B: i enjoy green living and just put solar panels on roof |
| TOPKG:       | A: that’s awesome . solar roofs are awesome. B: yes they’re . are you good at math A: i am excellent at it . mornings mornings are like night. B: i like the night A: it is my favorite part B: what is your favorite part about it? ...can not mention related words and can not reached |
| Path:        | mowing-morning-forenoon-part-particular-ethicist |

### A.3 Implementation Details

The default parameter settings across all experiments are as follows. We select conceptnet-5.7.0 and glove.6B.300d for initialization. The discount factor $\gamma$ is 0.99 and the advantage discount factor is 0.95. Our policy reasoning model is trained for 200 epochs using Adam optimization with the learning rate of 5e-4 for actor network and 1e-3 for critic network with the batch size of 64. 256 action-state pairs to rollout for trajectory collection per epoch, 4 steps of gradient descent to perform on each batch, capacity of the replay buffer is 8.