Learning to Copy Coherent Knowledge for Response Generation

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Abstract
Knowledge-driven dialog has shown remarkable performance to alleviate the problem of generating uninformative responses in the dialog system. However, incorporating knowledge coherently and accurately into response generation is still far from being solved. Previous works dropped into the paradigm of non-goal-oriented knowledge-driven dialog, they are prone to ignore the effect of dialog goal, which has potential impacts on knowledge exploitation and response generation. To address this problem, this paper proposes a Goal-Oriented Knowledge Copy network, GOKC. Specifically, a goal-oriented knowledge discernment mechanism is designed to help the model discern the knowledge facts that are highly correlated to the dialog goal and the dialog context. Besides, a context manager is devised to copy facts not only from the discerned knowledge but also from the dialog goal and the dialog context, which allows the model to accurately restate the facts in the generated response. The empirical studies are conducted on two benchmarks of goal-oriented knowledge-driven dialog generation. The results show that our model can significantly outperform several state-of-the-art models in terms of both automatic evaluation and human judgments.

Introduction
Generating informative and attractive responses have been demonstrated as a long-standing challenge in open-domain dialog systems. Multifarious models are proposed based on the sequence-to-sequence structure (Li et al. 2016; Serban et al. 2017; Wu et al. 2018) and obtain promising results. However, these models are still subjected to generate generic and uninformative responses, such as “I am Okay”, “You are right”. These bland responses will tend to degrade the experience of users.

Recently, large-scale knowledge-driven datasets have been proposed (Ghazvininejad et al. 2018; Dinan et al. 2018; Moon et al. 2019), to deal with the aforementioned problem, where the knowledge is linked with utterances to accelerate the research of knowledge-driven conversation models. Existing methods based on knowledge-driven datasets are either generative-based methods or retrieve-based methods.

The retrieval methods select a best-matched response from the response candidates that are obtained from the database (Shang, Lu, and Li 2015; Sun et al. 2020), while the generative methods utilize the dialog context to select knowledge at first, then the selected knowledge will participate into the generation of responses (Long et al. 2017; Liu et al. 2018). In this paper, we focus on the generative-based methods since it shows much flexibility and efficiency on knowledge selection and response generation in knowledge-driven dialog systems.

It is crucial to discern appropriate knowledge facts for response generation. Although great progress has been made, common issues still exist in knowledge driven conversations. Specifically, the models are difficult to use coherent knowledge facts in response generation. Figure 1 shows an example to illustrate this problem. Here, the knowledge facts are given as the triplets form. The dialog is conducted between user and bot, the bot is required to select appropriate knowledge from knowledge facts, then generate responses to interact with users. However, if a model makes an inappropriate choice of conflict facts, the generated response will contain these contradict facts. In our example, the fact “feature movie” contradicts with the fact “Chris Appelhans” in generated response. To tackle this problem, pre-

Figure 1: An illustrative example. #1 shows the response with conflict knowledge facts. #2 shows the response with coherent knowledge facts.
vious works (Ghazvininejad et al. 2018; Dinan et al. 2018) mainly focused on using the encoded dialog context to discern knowledge. However, the dialog context may not always contain the appropriate information that is useful for selecting coherent knowledge, especially in the condition that the machine proactively guides the conversation (Wu et al. 2019). To tackle this problem, Recent studies (Wu et al. 2019; Liu et al. 2020) proposed the large-scale goal-oriented knowledge-driven conversation dataset, where the dialog goal is treated as the topic transition path and the topic is extracted from the knowledge facts of each dialog session. Existing works (Wu et al. 2019; Xu et al. 2020) encode dialog goal together with dialog context and knowledge facts along the same line, which neglects the effect of dialog goal for selecting coherent knowledge facts. However, in the goal-oriented knowledge-driven conversations, the dialog goal provides the vital information to help the dialog system filter the knowledge facts that are irrelevant to the information provided by the current goal, thus discern more coherent knowledge facts for response generation.

To this end, this paper proposed a **Goal-Oriented Knowledge Copy Network (GOKC)**. Specifically, a goal-oriented knowledge discernment mechanism is designed to facilitate the dialog goal participating in the discernment of knowledge facts for generating prior knowledge distribution. Moreover, to further improve the coherence of discerned knowledge facts, we employ the ground-truth responses as the posterior information to supervise the training of prior knowledge distribution, which enhances the relevance between the discerned knowledge and the target response. Although the goal-oriented knowledge discernment mechanism provides an effective way to discern the coherent knowledge for generating appropriate responses, it still faces problems, i.e.: it is hard to explicitly restate the facts that appeared in input sources, and it tends to generate oov (out-of-vocabulary) words. Researchers have proposed various methods (See, Liu, and Manning 2017; Gu et al. 2016; Wang et al. 2019; Yavuz et al. 2019) to tackle these problems. However, very few of the existing works allow the model to copy tokens from multiple input sources (i.e., dialog context, dialog goal, and knowledge facts) for response generation, while in the goal-oriented knowledge-driven conversations, the description words from knowledge and goal are usually an important component of dialog response. Therefore, we develop a context manager upon the model decoder, which can copy tokens from multi-sources. We show that generating responses using the context manager not only effectively alleviates the oov problem, but also accurately copy the facts that appeared in input sources. Our code is released at https://github.com/jq2276/Learning2Copy.

In summary, our main contributions are: (1) We propose a goal-oriented knowledge discernment mechanism, which can incorporate the dialog goal into the discernment of knowledge, through the supervising of posterior information, the model can generate responses with more knowledge-coherent facts. (2) We develop a context manager to copy tokens from multiple input sources, which not only maintain the accuracy of discerned knowledge that is used into the response generation but also alleviate the oov problem. (3) The proposed GOKC model combines the knowledge discrimination mechanism and context manager to generate more coherent and fluent responses. (4) The experimental results on both human evaluation and automatic evaluation show that our model has superior performance than several competitive baseline models.

### Related Work

Previous works on end-to-end conversation response generation (Wu et al. 2018; Zhang et al. 2018; Xing et al. 2017) benefit from the prosperity of sequence-to-sequence models on machine translation (Sutskever, Vinyals, and Le 2014), where the response generation is treated as the sequence generation problem to obtain the appropriate response by given the context from the previous dialog turn. However, these works drop into the paradigm of generating generic and uninformative responses since they lack the ability to effectively leverage external information.

To tackle the aforementioned problem, many knowledge-driven response generation models have been proposed (Zhao et al. 2019; Tian et al. 2020; Dinan et al. 2018). Ghazvininejad et al. (2018) utilizes the memory network to store the knowledge and combine the widely used Seq2Seq model to generate responses. (Zhang, Ren, and de Rijke 2019) proposed to use context-aware knowledge pre-selection for guiding the knowledge selection in response generation. (Lian et al. 2019) firstly considered the target response as a part of the posterior information to participate in the knowledge selection for response generation, and obtain the impressive results on several knowledge-driven conversation datasets.

Recently, imposing goals on knowledge-driven conversation having attracted lots of research interests (Wu et al. 2019; Liu et al. 2020) since the conversation goal can provide potential guidance on knowledge selection and response generation. In this paper, we focus on goal-oriented knowledge-driven conversations. Our work is inspired by (Lian et al. 2019), where they leverage the posterior information to select the most relevant piece of knowledge for response generation, while we employ the dialog goal and dialog history as the prior information and combine with the posterior information (i.e., target response) to estimate the knowledge fact distribution, which provides a softer way to discern appropriate knowledge facts. Our work is also enlightened from the pointer generator network (PGN) (See, Liu, and Manning 2017). We extend PGN copy tokens from a single input source that can copy tokens from multiple input sources, which allows the model to accurately restate facts in generated responses.

### Approach

#### Problem Formalization

Suppose we have a goal-oriented dialogue corpus $D = \{(U_i, K_i, G_i, Y_i)\}_{i=1}^{N}$, where $\forall(U_i, K_i, G_i, Y_i) \in D, U_i = (u_1, \ldots, u_n)$ represents the dialogue history, $K_i = \{k_{i,j}\}_{j=1}^{N_k}$ is a set of knowledge facts that correspond to this conversation and each element $k_{i,j}$ could be in an arbitrary format such as a passage or a triple. The response
Let $Y_i = (y_{i,1}, \ldots, y_{i,m})$ be produced on the basis of the provided dialogue goal $G_i = (g_{i,1}, \ldots, g_{i,l})$ which is constructed upon the knowledge set $K_i$. Here, $n$, $m$, $l$ denote the sequence lengths of $U_i, Y_i, G_i$, respectively. Our goal is to learn a response generation model $P(Y|U, K, G)$ with $D$ when given a new dialogue history $U$ paired with the related knowledge set $K$. One can generate an appropriate response $Y$ that achieved the given dialogue goal $G$. Thus the dialogue goal could be used to lead the dialogue session from one topic to another smoothly.

**Architecture Overview**

A high-level architecture overview of the proposed GOKC is shown in Figure 2. The model consists of four parts: encoder, decoder, knowledge discernment module, and context manager. (1) The encoder part encodes the knowledge encoder, decoder, knowledge discernment module, and context manager. (2) For simplicity, denote the input sequence as $X = (x_1, x_2, \ldots, x_N)$, at step $t$, the forward RNN receives the current input $x_t$ and the previous forward hidden state $h_{t-1}^{fw}$ to generate current forward state $h_t^{fw}$. Meanwhile, the backward RNN generates the backward hidden state $h_{t-1}^{bw}$ by encoding the input $x_t$ and $h_{t-1}^{bw}$. The overall output state at time $t$ is formulated as:

$$h_t = [h_t^{fw}; h_t^{bw}] = [\text{GRU}(x_t, h_{t-1}^{fw}); \text{GRU}(x_t, h_{t-1}^{bw})]$$  \hspace{1cm} (1)

Where $[a; b]$ means the concatenation operation between $a$ and $b$. We define $o = (h_1, h_2, \ldots, h_N) \in \mathbb{R}^{d \times N}$ as the output hidden states at all time steps, and $s = [h_N^{fw}; h_N^{bw}] \in \mathbb{R}^{d \times 1}$ as final hidden state. Intuitively, $s$ is a concatenation of forward hidden state and backward hidden state at their final steps.

We define the output states at all time steps of $U, G, K$ and $Y$ as $o_U, o_G, \{o_{K,j}\}_{j=1}^{N_K}$ and $o_Y$, respectively. The final states of $U, G, K, Y$ can be denoted as $s_U, s_G, \{s_{K,j}\}_{j=1}^{N_K}, s_Y$, respectively.

**Knowledge Discernment**

The knowledge discernment module is used to discern the knowledge facts that are highly correlated to the dialog goal $G$ and dialog context $U$. The knowledge discernment module first receives the encoded information of $G$ and $U$ and then generates a knowledge facts distribution, which is used to represent the discernment weights over the knowledge facts $K$ for generating an appropriate response. The knowledge discernment module consists of two sub-modules: (1) The prior knowledge discernment module. (2) The posterior knowledge discernment module.

The prior knowledge discernment module obtains the prior knowledge distribution by calculating the semantic

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1The knowledge encoder receives one piece of knowledge fact at a time. A knowledge fact is concatenated as a sequence if it is in the form of a triple.
similarity between the prior information and each knowledge fact \(k_i\):

\[
P(k_i | U, G) = \frac{\exp(s_{k,i} \cdot d_{\text{prior}})}{\sum_{j=1}^{N_K} \exp(s_{k,j} \cdot d_{\text{prior}})}
\]

Here, \(d_{\text{prior}}\) is the prior information, which can be obtained by \(d_{\text{prior}} = \tanh(\beta \circ s_U + (1-\beta) \circ s_G). \circ\) means dot product, \(\beta\) is a gated fusion unit adapted from (Yao et al. 2017) which is used to balance the contribution between \(s_U\) and \(s_G\). It can be obtained by \(\beta = \sigma(W_p \tanh(W_SY) + \tanh(W_Gs_G))\), where \(W_U, W_G \in \mathbb{R}^{d_X \times d_e}\) and \(W_p \in \mathbb{R}^{1 \times 2d_e}\) are three parameters matrices.

Intuitively, the dialog goal will serve as the prior information to estimate the prior knowledge distribution when \(\beta = 0\), which is especially suitable for the scenario that the machine proactively leading the conversation, in which case the dialog history will be hardly considered for the discernment of knowledge facts, while the dialog goal is dominant.

The posterior knowledge discernment module obtains the posterior knowledge distribution by:

\[
P(k_i | Y) = \frac{\exp(s_{k,i} \cdot d_{\text{post}})}{\sum_{j=1}^{N_K} \exp(s_{k,j} \cdot d_{\text{post}})}
\]

Where \(d_{\text{post}} = \tanh(W_{\text{post}}s_Y)\) is the posterior information and \(W_{\text{post}} \in \mathbb{R}^{d_e \times d_e}\) is a parameter matrix. The introduction of posterior information can provide auxiliary guidance on knowledge discernment since the actual knowledge used in the target response is considered.

**KL-Div Loss.** The posterior knowledge distribution \(P(k_i | Y)\) is hard to estimate at the inference time since the ground truth \(Y\) is unknown. Therefore, we employ the Kullback-Leibler Divergence loss (Kullback and Leibler 2006) to minimize the KL-distance between prior knowledge distribution \(P(k_i | Y)\) and posterior knowledge distribution \(P(k_i | U, G)\), which is optimized at the training stage so that \(P(k_i | U, G)\) could approximate \(P(k_i | Y)\) with its guidance. Hence, our model could maintain the coherence of the discerned knowledge facts at inference time. The KLDiv loss is defined as:

\[
L_{KL}(\theta) = \sum_{i=1}^{N_K} P(k_i | Y) \left( \frac{P(k_i | Y)}{P(k_i | U, G)} \right)
\]

**BOW Loss.** To further improve the knowledge estimation accuracy, we adopt the BOW Loss proposed by (Zhao, Zhao, and Eskenazi 2017) to ensure the relevancy between the estimated knowledge distribution and the response. Specifically, we define \(s_k\) is the weighted sum over all the knowledge representations \(\{s_{k,j}\}_{j=1}^{N_K}\), which can be obtained by \(s_k = \sum_{i=1}^{N_K} \delta_{k,i} \cdot s_{k,i}\), where \(\delta_{k,i}\) is the probability distribution of knowledge fact \(k_i\), \(\delta_{k,i} = P(k_i | Y)\) if response is available, otherwise \(\delta_{k,i} = P(k_i | U, G)\). The BOW loss can be obtained by:

\[
L_{\text{BOW}}(\theta) = -\frac{1}{|B|} \sum_{y \in B} \log \phi(y_i | s_k)
\]

Where \(B\) is the bag of words in \(Y\), \(\phi(\cdot)\) is a two layer MLP activated by softmax function, which outputs the probability distribution over the fixed vocabulary.

**Decoder**

The decoder is composed of a forward RNN encoder with gated recurrent units. At each time \(t\), it receives the embedding vector \(y_{t-1}\) of the word predicted at time-step \(t - 1\) as well as the previous decoder state \(h_{t-1}\), and emits current hidden state \(h_t \in \mathbb{R}^{d_e \times 1}\), which is formally defined by:

\[
h_t = \text{GRU}(y_{t-1}, h_{t-1})
\]

Where \(h_t\) can be used to obtain the generation probability \(P_{\text{vocab}}(w_t)\) over the fixed vocabulary obtained from the training set. The \(P_{\text{vocab}}(w_t)\) can be obtained by:

\[
P_{\text{vocab}}(w_t) = MLP(h_t)
\]

Where \(MLP(\cdot)\) is a two-layer MLP activated by softmax function.

**Context Manager**

**Copying from Multi-Sources.** Our model allows copying tokens from multiple input sources. Specifically, we use \(\Phi\) to represent one of the input sources, where \(\Phi \in \{U, G, k_1, k_2, ..., k_{N_k}\}\). Given the decoder state \(h_t\) and the encoder output state \(o_{\Phi}\). We apply attention\(^2\) to the \(o_{\Phi}\) at decoder step \(t\), which can be defined by:

\[
d_{t,\Phi}^t, c_{t,\Phi} = \text{Attention}(o_{\Phi}, h_t)
\]

Where \(d_{t,\Phi}^t \in \mathbb{R}^{N_{\Phi} \times 1}\) is the attention distribution over each tokens appeared in \(\Phi\), and \(c_{t,\Phi} \in \mathbb{R}^{d_e}\) is the context vector of \(\Phi\). The \(d_{t,\Phi}^t\) is then aggregated to obtain the probability distribution \(P_{\Phi}(w_t)\) over context tokens \(w_t\), which can be computed by:

\[
P_{\Phi}(w_t) = \sum_{\{l : \varphi_l = w_t\}} d_{t,\Phi}^l
\]

Where \(\varphi_l\) is the token appeared in \(\Phi\), \(d_{t,\Phi}^l\) is the attention weight corresponding to the \(l\)th token in \(\Phi\). The probability of copying token \(w_t\) from the dialog history \(U\) and dialog goal \(G\) can be defined as \(P_{U}(w_t)\) and \(P_{G}(w_t)\) respectively. While the probability of copying tokens from knowledge \(K\) is a weighted sum of copying tokens from all the knowledge facts over the knowledge fact distribution, which is formulated as:

\[
P_{K}(w_t) = \sum_{i=1}^{N_K} \delta_{k,i} \cdot P(k_i | Y) \cdot P(w_t | k_i)
\]

Recall that \(\delta_{k,i}\) is the probability distribution of knowledge fact \(k_i\).

**Sources Fusion.** We now present the mechanism to fuse the sources by incorporating their distributions \(P_{U}(w_t), P_{K}(w_t), P_{G}(w_t)\), as well as \(P_{\text{vocab}}(w_t)\). We first obtain the overall knowledge representations \(c_{t}^K\) by:

\[
c_{t}^K = \sum_{i=1}^{N_K} \delta_{k,i} \cdot c_{t}^i
\]

\(^2\)We have omitted the description of attention. Please refer to (Bahdanau, Cho, and Bengio 2015) for the detail.
Where \( c^k_t \) is the context vector of knowledge fact \( k \). Then the decoder state \( h_t \) attends over the dialog history representation \( c^U_t \), the knowledge representation \( c^K_t \) and the goal representation \( c^G_t \) by:

\[
\alpha_t, c_t = \text{Attention} \left( \begin{bmatrix} c^U_t, c^K_t, c^G_t \end{bmatrix}^T, h_t \right)
\]

(12)

Where \( c_t \in \mathbb{R}^{d \times 1} \) is the overall representation of input sources. \( \alpha_t = \begin{bmatrix} \alpha_t^{(U)}, \alpha_t^{(K)}, \alpha_t^{(G)} \end{bmatrix}^T, \alpha_t \in \mathbb{R}^{3 \times 1} \) is used to combine the distributions of input sources as shown in equation 13. We also use a generation probability \( p_{gen}^t \in [0, 1] \) described in (See, Liu, and Manning 2017) to balance the contribution between input sources and the fixed vocabulary, where \( p_{gen}^t = \sigma (W_{gen}^t [y_{t-1}; h_t; c_t]) \), and \( W_{gen} \in \mathbb{R}^{1 \times (d_{emb} + d_h + d_e)} \). The overall distribution is obtained by:

\[
P (w_t) = p_{gen}^t P_{vocab} (w_t) + (1 - p_{gen}^t) \sum_{\phi \in \{U, K, G\}} \alpha_t^{(\phi)} P_\phi (w_t)
\]

(13)

Training

Apart from the KLDiv Loss and BOW Loss, we also use the NLL Loss to capture the word order information. More precisely, given a model that produces a probability distribution of input sources, \( \tilde{p}_{\phi} \), the final loss is defined by:

\[
L (\theta) = - \frac{1}{|Y|} \sum_{t=1}^{|Y|} \log \left( P \left( y_t | y_{1:t-1}, U, K, G \right) \right)
\]

(14)

Where \( \theta \) denotes all the trainable model parameters. In summary, the final loss is defined by:

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

(15)

Experiments

Datasets

We conduct our experiments on two goal-oriented knowledge-driven datasets. One is the DuConv (Wu et al. 2019), and the other is DuRecDial (Liu et al. 2020).

DuConv. A proactive conversation dataset, which consists of about 30k dialogs and 270k utterances. Each dialog contains 9.1 utterances and each utterance contains 10.6 words on average. There are 96.2 words per dialog, and 17.1 knowledge facts appeared in each dialog. For each turn of the conversation, the machine needs proactively initiate the dialog with the explicit conversation goal and the related knowledge triplets, where the conversation goal is extracted from the knowledge triplets. Similar to (Wu et al. 2019), the data is normalized by replacing the specific two topics in the knowledge triplets. Besides, we also select some relationships from knowledge triplets and substitute the object entity that appeared in these triplets with the specific tokens according to the relationships. Then, the model is required to generate responses that are closer to the conversation goal until the end of the dialog.

DuRecDial. A goal-oriented knowledge-driven conversation recommendation dataset, which contains multi-type dialogs. This dataset contains about 10k dialogs and 156k utterances. In each dialog session, there are 15.32 utterances and 21.93 knowledge facts on average. The average number of words in each utterance and knowledge fact is 11.53 and 12.73, respectively. At each dialog turn, the machine needs figure as a recommender to leads a multi-type dialog to approach recommendation targets with full consideration of dialog goal. The dialog goal is a sequence-like string obtained from the knowledge triplets. Here, we extract each goal by triplets described in (Liu et al. 2020). For proving the influence of the dialog goal, we assume the complete goal is explicitly given at the beginning of the conversation, which is different from (Liu et al. 2020), where the goal needs to be completely planned before the response generation.

Comparison Models

We implement our model on both DuConv dataset and DuRecDial datasets, and compare our model with several competitive models. On the DuConv, we compared our model with: **Pointer Generator Network (PGN)**: The model proposed by (See, Liu, and Manning 2017), which can copy tokens from input sources. This model has exhibited impressive performance on many natural language generation tasks. **KIC**: The model exhibits state-of-the-art performance on DuConv data which is reported in (Lin et al. 2020). In addition, we also compare our model with the baseline models mentioned in (Wu et al. 2019), which are retrieval-based models and generation-based models. On the DuRecDial, we compared our model with: **Seq2Seq**: The vanilla sequence-to-sequence models proposed by (Sutskever, Vinyals, and Le 2014). **PostK**/: A knowledge-grounded response generation model proposed by (Lian et al. 2019), which utilizes a posterior knowledge selection mechanism to select an appropriate knowledge for response generation. **MCGC-R/G**: The retrieval-based models and generative-based models proposed by (Liu et al. 2020), which shows the state-of-the-art results on DuRecDial. We remove the goal planning module of these two models since the dialog goal is supposed to be known. We re-implemented these models by ourselves with the default settings described in (Liu et al. 2020).

Implementation Details

Our model is implemented by the Pytorch Framework. In our model, all of encoder and decoder have two-layer structures, each layer has 800 hidden units with the dropout rate 0.3 and the gradient clipping threshold is set to 5. The vocabulary size we used is 15k. We set the word embedding size to be 300, and initialize the embedding vectors randomly instead of using pre-trained word embeddings. We used the Adam optimizer (Kingma and Ba 2014), to minimize loss,
the mini-batch size is 32 and the learning rate is 0.0001. We trained our model on a GPU-V100 machine. The whole training process is split into two stages. In the first stage, we train the model for 5 epochs to minimize the BOW loss only for pre-training the knowledge discernment module. In the second stage, we train the model at most 25 epochs to minimize overall loss.

**Metrics**

We use both human evaluation and automatic evaluation to evaluate each model, the evaluation metrics are adapted from (Wu et al. 2019; Liu et al. 2020). The automatic evaluation metrics include Bleu-1/2, F1 score, Distinct-1/2, and Perplexity. The F1 score measures the precision and recall of the generated response at character level; The Bleu score estimates the fluency of the response over n-grams level; The Distinct-1/2 are used to evaluate the diversity of response; The Perplexity is a widely used approach to estimate how likely the model to generate the ground truth response. Our model discerns the knowledge in a soft way instead of selecting knowledge facts explicitly, thus we evaluate the performance of the whole dialog but not measure the results of knowledge selection independently.

As for human evaluation, we adopted the strategy suggested by (Liu et al. 2020). We randomly selected 100 turns of dialogs from DuRecDial and employed seven well-educated annotators to evaluate the experimental models. The annotators are required to evaluate the models on 4 aspects, which are fluency, informativeness, appropriateness and proactivity. The scores are settled from \{0, 1, 2\} to estimate fluency, informativeness, and appropriateness, while the proactivity scores are assigned from \{-1, 0, 1\}. For a fair comparison, the model name is masked during evaluation process. The agreement among the annotators is measured by the Fleiss’ kappa (Fleiss 1971).

**Results**

**Automatic Evaluation** The automatic evaluation results on datasets DuConv and DuRecDial are shown in Table 1. Our approach outperforms all the comparison models, and obtain a significant improvement over most of the evaluation metrics. Specifically, On DuConv dataset, our model achieves about 1.0%, 8.7%, and 3.8% on F1, BLEU-1, and BLEU-2 compared to the best results of KIC model, which indicates that our model prefers to capture more useful information in n-gram’s level, thus generate more readable and fluent responses. Besides, our model achieves about 4.2% reduction on metrics PPL compared to KIC. The metrics PPL reflects the perplexity of generated response, whose reduction indicating that the model is more likely to generate the ground truth responses. On DuRecDial dataset, our GOKC model achieves about 12.5% improvements on F1 compared to the best performance of MGCG_G, and obtains 9.0% and 19.5% improvements on BLEU-1 and BLEU-2 compared to the most competitive model MGCG_R, which is attributed to that the knowledge discernment mechanism endows the GOKC with the ability to discern the coherent knowledge facts that are close to the target response, and the context manager helps the model to accurately restate the facts appeared in discerned knowledge as well as the dialog goal and dialog context.

**Human Evaluation** The results are shown in Table 2.1, we can conclude: (1) Our model achieves the highest score compared with other comparison models in terms of appropriateness, informativeness and proactivity, which demonstrates the superiority of the proposed GOKC model. (2) Our model can generate more fluent and informative responses. It is highly likely that the context manager allows the model to directly copy tokens appeared in input sources, which helps the model restates the facts accurately. (3) The highest score of Appro. and Proact. indicate that our model is prone to generate more goal-relevant responses, which is attributed to that the goal-oriented knowledge discernment mechanism allows the model to choose more coherent knowledge facts, these facts facilitate the model to generate more appropriate responses and proactively lead the conversation to complete the conversation goal.

**Ablation Study** We take an ablation study on both DuConv and DuRecDial datasets. The key components of GOKC are removed respectively for further dissection, Ta-

<table>
<thead>
<tr>
<th>Model</th>
<th>F1</th>
<th>BLEU-1/2</th>
<th>Dist-1/2</th>
<th>PPL</th>
</tr>
</thead>
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<tr>
<td>seq2seq</td>
<td>34.73</td>
<td>0.291 / 0.156</td>
<td>0.118 / 0.373</td>
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<td>PGN</td>
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<td>MGCG_G</td>
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<td>GOKC</td>
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<td>0.410 / 0.272</td>
<td>0.105 / 0.272</td>
<td>9.92</td>
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<table>
<thead>
<tr>
<th>Model</th>
<th>DuConv</th>
<th>DuRecDial</th>
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</thead>
<tbody>
<tr>
<td>seq2seq</td>
<td>26.08</td>
<td>0.188 / 0.102</td>
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<tr>
<td>MGCG_G</td>
<td>42.04</td>
<td>0.362 / 0.252</td>
</tr>
<tr>
<td>GOKC</td>
<td>47.28</td>
<td>0.413 / 0.318</td>
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<tr>
<th>Model</th>
<th>DuConv</th>
<th>DuRecDial</th>
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<tr>
<td>seq2seq</td>
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<td>1.21</td>
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<tr>
<td>PGN</td>
<td>1.45</td>
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<td>PostKS</td>
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<td>1.62</td>
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<td>MGCG_R</td>
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<tr>
<td>GOKC</td>
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<td>1.77</td>
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<tbody>
<tr>
<td>kappa</td>
<td>0.73</td>
<td>0.55</td>
<td>0.61</td>
<td>0.57</td>
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</table>
Table 3: The ablation study on datasets DuConv and DuRecDial. "-" means remove the module from the GOKC model.

**Figure 3:** Case of example dialog. We use different colors to indicate different goals and use boldface to denote knowledge facts, the red boldface means the wrong usage of knowledge facts.

**Conclusion and Future Work**

In this paper, we propose a goal-oriented knowledge copy network that could copy tokens from multiple input sources and discern coherent knowledge for response generation. The experimental results show that our model obtained impressive results on two goal-oriented knowledge-driven datasets. In the future, we intend to incorporate transfer learning into dialog system and enhance the quality of generated response by alleviating knowledge repetition problem.
Acknowledgments

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References


