Think Before You Speak: Using Self-talk to Generate Implicit Commonsense Knowledge for Response Generation

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Abstract

Implicit knowledge, such as common sense, is key to fluid human conversations. Current neural response generation (RG) models are trained end-to-end, omitting unstated implicit knowledge. In this paper, we present a self-talk approach that first generates the implicit commonsense knowledge and then generates response by referencing the externalized knowledge, all using one generative model. We analyze different choices to collect knowledge-aligned dialogues, represent implicit knowledge, and elicit knowledge and responses. We introduce three evaluation aspects: knowledge quality, knowledge-response connection, and response quality and perform extensive human evaluations. Our experimental results show that compared with end-to-end RG models, self-talk models that externalize the knowledge grounding process by explicitly generating implicit knowledge also produce responses that are more informative, specific, and follow commonsense. We also find via human evaluation that self-talk models generate high-quality knowledge around 75% of the time. We hope that our findings encourage further work on different approaches to modeling implicit commonsense knowledge and training knowledgeable RG models.

1 Introduction

During communication, humans not just utter the right sentence but also contribute to the common ground, which consists of mutual beliefs and common knowledge (Stalnaker, 1978; Clark and Schaefer, 1989; Clark and Brennan, 1991). For example, in Figure 1, the participant needs to understand relevant implicit background knowledge such as “rose is a type of flower” and “rose is a symbol of love” — an implicit process often referred to as knowledge grounding (Barsalou et al., 2003). Recent state-of-the-art neural response generation (RG) models based on pre-trained language models (LM) mostly produce responses in an end-to-end way (Vaswani et al., 2017; Zhang et al., 2020b; Lewis et al., 2020; Roller et al., 2021), i.e., models are trained to take history and produce a response. Since implicit knowledge is not spoken out in the dialogue turns, RG models do not explicitly learn on the knowledge grounding step in between turns and thus may generate uninformative and hallucinated responses, as compared to human-like conversations.

To fill the gap between current model’s RG process and how humans use implicit knowledge in conversations, we decompose the RG process to externalize implicit knowledge grounding by self-talk.
ternalize the knowledge grounding step by training RG models to self-talk in a way that it can generate the relevant knowledge and reference them for responding. We argue that this decomposition brings two major benefits: 1) generated knowledge can augment and/or constrain the RG step to produce more informative and less generic responses; 2) since the RG process is based on the grounded knowledge, externalized implicit knowledge in natural language (NL) text helps shed light on the inner-workings of RG models by providing faithful explanations of what the RG systems use during generation. While recent work has explored ways to inject external knowledge to the RG models, they either perform knowledge retrieval upon a knowledge base (KB) (Zhou et al., 2018; Zhao et al., 2020) or cast knowledge as a latent factor in the generation (Tuan et al., 2020; Xu et al., 2021), posing limitation due to coverage in the KB or the lack of interpretability by not explicitly expressing knowledge in NL. Our approach reuses generative models without reliance on external knowledge bases (KB) during response generation as well as outputting knowledge explicitly.

In this study we focus on common sense as the implicit knowledge. We propose a Think-Before-Speak (TBS) RG framework that trains the RG model to talk with itself to elicit the implicit knowledge before making a response, inspired by inquiry-based discovery learning (Bruner, 1961) and the self-talk procedure (Shwartz et al., 2020a). This new RG paradigm poses two main challenges: how to identify implicit commonsense knowledge associated with dialogue turns, as they are unstated in dialogues, and how to represent such knowledge in the right form for generative models.

To collect knowledge associated with each dialogue instance, we propose weak supervision procedures to automatically align knowledge labels with each dialogue turn, rather than manually collecting human-annotations which is expensive and unscalable. Using ConceptNet (Speer et al., 2017) as our knowledge schema, we present a simple hard-matching approach using string matching, as well as a soft-matching approach where we use embedding similarity to align dialogue turns to ConceptNet triples. We explore several ways to format such aligned knowledge originally represented as structured triples into natural language so that RG models can adapt to the knowledge-response generation task easily. We experiment with structured triples, triples converted to natural language, and a more colloquial question answering format. Furthermore, we look into different prompt designs to signal knowledge and response in a pipeline training process — i.e., we first ask models to generate commonsense knowledge statement given the dialogue history and then generate responses given both knowledge and history.

To evaluate the TBS framework, we introduce new evaluation protocols to cover different aspects of the system, including knowledge quality, knowledge-response connection, and response quality. We conduct extensive human evaluation on different variants of our training procedure. Our experimental results show that models that generate implicit background knowledge before responding produce more informative, specific, and responses that make more common sense compared to end-to-end RG models. Further analysis shows that most knowledge generated makes sense and is relevant, soft-matching and using question answering as the knowledge format helps produce better responses, and our self-talk model can even outperform a knowledge-grounded RG model that takes in ground truth knowledge.

2 Problem Formulation

We provide definition of the task of response generation (RG) and our proposed think-before-speak (TBS) response generation process. Our TBS RG paradigm extends the traditional RG setting by incorporating an additional component of implicit knowledge in the generation process so that we externalize the knowledge grounding step in RG.

2.1 Response Generation

We follow the common dialogue response generation setup (Weizenbaum, 1966; Ritter et al., 2011; Sordoni et al., 2015): given a dialogue history $H$ (a sequence of dialogue utterances), generate an appropriate response $R$. Current state-of-the-art (SOTA) neural RG models often frame this task as a conditional language modeling problem. Specifically, given a history $(H)$ consisting of a sequence of $n$ dialogue turns: $X_1, X_2, ..., X_n$ (each turn refers to an utterance containing a sequence of $t_i$ tokens: $x_{1,1}, x_{1,2}, ..., x_{1,t_i}$) and a response $(R)$ sentence $Y$ comprised of a sequence of $m$ tokens $y_1, y_2, ..., y_m$, RG models aim to learn the conditional probability distribution by training on human
we examine if the generated knowledge that contains multiple natural language statements is \( I \) conditioned on the dialogue history \( H \). We use \( I \) to denote the implicit knowledge for brevity, which contains multiple natural language statements \( I = Z_1, Z_2, \ldots \) (each containing a sequence of tokens: \( z_{1,1}, z_{1,2}, \ldots \)) expressing commonsense knowledge. For example, in Figure 1, “rose is a type of flower” and “rose is a symbol of love” are two statements expressing the implicit commonsense knowledge in natural language text. To emulate realistic conversation scenario, we also fuse dialogue history \( H \) in traditional RG with implicit knowledge \( I \) for each turn and denote it with \( H' \), i.e. \( H' = X_1, I_1, X_2, I_2, \ldots, X_n, I_n \), where \( I_i \) indicates the implicit knowledge statements for the \( i \)-th turn in the dialogue history.

To externalize the knowledge grounding step, inspired by how humans communicate and inquiry-based learning (Bruner, 1961; Shwartz et al., 2020b), our TBS RG paradigm requires models to first generate implicit knowledge \( I \) conditioned on \( H' \) (we also use “self-talk” to refer this process) and then produce \( R \) given \( H' \) and \( I \), i.e. modeling the two conditional probabilities: \( P_\theta(I|H') \) and \( P_\theta(R|H', I) \) using the same RG model.

We introduce three evaluation criteria to measure the success of our TBS RG framework in its modeling of \( P_\theta(I|H') \) and \( P_\theta(R|H', I) \).

**Knowledge Quality (KQ)** We first examine the quality of the generated knowledge from self-talk, i.e., the quality of modeling \( P_\theta(I|H') \). Specifically, we examine if the generated knowledge \( I \) makes sense by itself and if the generated knowledge is relevant to the dialogue history \( H' \).

**Knowledge-Response Connection (KR)** After generating implicit background knowledge, the next task is to generate responses based on both the dialogue history and the generated knowledge. Thus, we evaluate whether the response generated is grounded to the knowledge produced by the self-talk.

**Response Quality (RQ)** Last but not least, the end goal is to generate an appropriate response, and thus we evaluate response quality that spans multiple dimensions including informative, coherent, engaging, makes more common sense, etc.

### 2.2 Think-Before-Speak Response Generation

Our goal is to decompose the end-to-end RG process above by making the implicit knowledge grounding step explicit. To do this, we introduce a new component to RG – implicit knowledge \( I \) that is conditioned on the dialogue history \( H \). We use \( \theta \) to denote the implicit knowledge for brevity, which contains multiple natural language statements \( I = Z_1, Z_2, \ldots \) (each containing a sequence of tokens: \( z_{1,1}, z_{1,2}, \ldots \)) expressing commonsense knowledge. For example, in Figure 1, “rose is a type of flower” and “rose is a symbol of love” are two statements expressing the implicit commonsense knowledge in natural language text. To emulate realistic conversation scenario, we also fuse dialogue history \( H \) in traditional RG with implicit knowledge \( I \) for each turn and denote it with \( H' \), i.e. \( H' = X_1, I_1, X_2, I_2, \ldots, X_n, I_n \), where \( I_i \) indicates the implicit knowledge statements for the \( i \)-th turn in the dialogue history.

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### 2.3 Challenges

To successfully model \( P_\theta(I|H') \) and \( P_\theta(R|H', I) \), we face two core challenges.

**Knowledge-Aligned Dialogue Data** To train RG models following the TBS paradigm, we need to provide dialogue data aligned with implicit knowledge. However, due to the implicit nature of commonsense knowledge and the cost and difficulty of obtaining high-quality human annotations, we need to come up with alternatives to obtain such knowledge labels.

**Knowledge Representation** Since we want RG models to generate implicit knowledge in the RG process, how to bridge the gap between natural language (NL) dialogue utterances and the knowledge statement needs to be investigated. Specifically, the same knowledge can be represented in different formats and we need to find a proper way to represent such knowledge to efficiently convey knowledge to model. Furthermore, it is crucial to create a natural transition between knowledge and the surface dialogue flow (from history to response) during generation for achieving a closely connected relation between knowledge and response.

### 3 Learning to Generate Implicit Knowledge by Self-Talk

This section introduces our proposed method to train a single model that can both talk with itself to explicitly generate background commonsense knowledge and generate response given only the dialogue history, i.e. \( P_\theta(I|H') \) and \( P_\theta(R|H', I) \).

#### 3.1 The Think-Before-Speak Framework

Here we provide formal definitions of inputs and outputs of our RG models following the TBS framework and overview of various model components described in later subsections. An illustration of our method is shown in Figure 2. Our model takes input of dialogue history with potential implicit knowledge after every utterance \( H' = X_1, I_1, X_2, I_2, \ldots, X_n, I_n \) and first outputs implicit knowledge \( I = Z_1, Z_2, \ldots \) containing knowledge statements relevant to the history. Then it
outputs response $R$ based on $H'$ and $I$ generated by itself. For training, we need to provide all three components to the self-talk RG model so that the model can learn to generate both implicit knowledge and response given only $H'$ at test time. To pair each dialogue with appropriate implicit knowledge, we first define a matching process and use a commonsense knowledge base such as ConceptNet (Speer et al., 2017) as the implicit knowledge source. Then, to construct training instances, we face two key method design choices: how to represent knowledge and how to connect the knowledge with the dialogue. Finally, we adopt a pipeline training procedure to train the same self-talk RG model to model $P_0(I|H')$ and $P_0(R|H', I)$ with the same parameters $\theta$.

3.2 Knowledge-Aligned Dialogues

Our goal is to collect a dataset $D$ for which each instance $d(H', R, I) \in D$ consists of three components: a dialogue history $H'$ fused with potential implicit knowledge, a response $R$ from humans that continues the dialogue from the history, and implicit knowledge statements $I$ that are based on the dialogue history $H'$ and relevant to the making of the response $R$. Figure 3 shows a complete example with three components. Collecting high-quality human annotations of implicit knowledge on massive dialogue data is costly and not scalable, so we focus on methods that create weakly-supervised knowledge labels for dialogues. Specifically, we deploy an automatic matching procedure to find potential relations between concepts mentioned in the dialogue utterances by referencing to a commonsense knowledge base (CSKB).

Hard-Matching Knowledge Triples to Dialogues First we consider a simple heuristic method based on lexical signals and use ConceptNet (Speer et al., 2017) as our CSKB. Consider the 2-turn dialogue in Figure 1, the hard-matching process first lemmatizes all the words in each utterance, e.g. "flowers" becomes "flower". Then we find candidate concepts $C$ in each turn by referencing ConceptNet to check if any of the lemmatized words are concepts in the CSKB. Next, for each utterance in the dialogue, we get a list of candidate triples (in ConceptNet, knowledge is represented as triples with two concepts linked by a relation, i.e., $(c_1, r, c_2)$ by retrieving all the triples in ConceptNet that contains any one of the candidate concepts appearing in this utterance. For example, "rose, TypeOf, flower" and "flower, IsA, plant" might be two candidate triples when we query the concept "flower" in ConceptNet. Finally, we search if any of the candidate concepts from the next turn also appears in one of the retrieved candidate knowledge. In this case, "roses" is in the triple "rose, TypeOf,
1999; Mintz et al., 2009).

We choose the top 3 triples from ConceptNet with UsedFor, romance. An important limitation of the above hard-matching approach to aligning knowledge with dialogues is that string matching only captures the surface form match and neglects many important semantic relations between words. For example, “rose, UsedFor, romance” cannot be matched using hard-matching since romance does not appear anywhere in the dialogue. However, it is closely related to the dialogue context as the person is buying flowers for their wife. We develop a soft-matching procedure that takes into account of semantic relatedness by using embedding similarity from SentenceBERT (Reimers and Gurevych, 2019) to measure semantic relations beyond lexical signals between dialogue turns and triples in ConceptNet. Specifically, we first extract concept candidates \( C_i \) following our hard-matching procedure for the i-th turn in a dialogue. Then we get a list of all the triples in ConceptNet that contain any of the concept candidates \( T_{C_i} \). Next, we form a query \( q_i \) by concatenating the i-th turn and the next-turn (i+1-th) response. Finally, we encode the query and all triple candidates using SentenceBERT and calculate cosine similarity between the query and candidate triples to get their semantic closeness. We choose the top 3 triples from ConceptNet with the highest similarity.

3.3 Knowledge Representation

Implicit commonsense knowledge \( I \) stored in ConceptNet is in the form of \((\text{subject } s, \text{ relation } r, \text{ object } o)\) triples, such as \((\text{rose, TypeOf, flower})\), however, this might not be the most natural way of presenting knowledge to RG models, which mostly take in natural language (NL) sentences. Limitations of representing \( I \) using structured triples include unfamiliarity to RG models and out-of-vocabulary relation tokens, which requires the model to learn a special embedding from scratch for each relation. Here we design two alternatives to represent the grounded knowledge in RG with self-talk and use the implicit knowledge in Figure 1 as a running example.

3.4 Think-Before-Speak (TBS) Training

After constructing knowledge-aligned dialogues, each of our data instance is a sequence of tokens with three components: a dialogue history \( H' \) fused with potential implicit knowledge after each turn, implicit knowledge (empty or non-empty) \( I \), and a response \( R \). Now we need to connect the three components to train RG models to generate both the implicit knowledge \( I \) and response \( R \) given history \( H' \).

How to elicit knowledge and response Traditional RG models generate responses directly from dialogue history. In our formulation, we must provide a signal to distinguish between the traditional inputs of history and response, and TBS implicit knowledge in the model input. This is to help our proposed self-talk RG models learn the TBS paradigm and generate outputs structured similarly: ground implicit knowledge first and then generate responses. At inference time, the model is only given dialogue history \( H' \) and needs to generate both implicit knowledge \( I \) and a response \( R \) in natural language. Meanwhile, to ensure the quality of the generated knowledge and response, the signal needs to provide natural and smooth transition. Here we consider two alternatives for creating such a signal.
Special symbols. Following the common practice of separating sequences in neural LMs (Radford et al., 2018; Devlin et al., 2019), we use a special symbol to serve as the separator. We enclose the implicit knowledge \( I \) with special symbols “<implicit>” and “<\implicit>” and add it between \( H' \) and \( R \), for example, “<speaker1> I need to buy some flowers for my wife. <implicit> rose is a type of flower <\implicit> <speaker2> Perhaps you’d be interested in red roses.” We train the models to generate everything after <\implicit> till the end, i.e., generate \( I \) and \( R \) conditioned on \( H' \).

Natural language prompts. More recent work has found that NL prompts help LMs to perform better on various downstream tasks, including natural language generation (NLG) (Brown et al., 2020; Liu et al., 2021). Specifically, (Zheng and Huang, 2021) found that using prompts helps with few-shot knowledge-grounded RG where knowledge is provided to the model. Here we consider a more challenging setting where we use the NL prompts to prompt RG models to generate implicit knowledge and responses. We use “The following background knowledge is helpful for generating the response:” to elicit knowledge and “Grounded on the background knowledge, what does the speaker probably say in the next response?” to elicit response.

Pipeline Training Since our TBS RG paradigm proposes to decompose RG and externalize the knowledge grounding step by explicitly generating implicit knowledge \( I \), we are modeling two conditional probabilities: \( P_\theta(I|H') \) and \( P_\theta(R|H', I) \) using the same set of parameters in the model. To help our models adapt to the two different distributions of input (history \( H' \) and implicit knowledge \( I \)) and outputs (implicit knowledge \( I \) and response \( R \)), we split each instance \( d(H', R, I) \in D \) to first train the model to generate just the knowledge \( I \) based on \( H' \) and then train it to generate \( R \) based on both \( I \) and \( H' \), i.e., \( P_\theta(I|H') \) and then \( P_\theta(R|H', I) \). For example, given the dialogue history: “<speaker1> I need to buy some flowers for my wife”, we will ask models to generate the implicit knowledge alone: “<implicit> rose is a type of flower <\implicit>.” Then we train the models to also generate the response “<speaker2> Perhaps you’d be interested in red roses” given both the history and the knowledge.

Formally, we follow standard way of modeling \( P_\theta \) in auto-regressive neural RG models and use Maximum Likelihood Estimation (MLE) to train our model to maximize \( P_\theta(I|H') \) by minimizing the conditional negative log-likelihood loss (NLL):

\[
\mathcal{L}_{\text{knowledge}} = - \sum_{i=1}^{m} \log P_\theta(Z_i|Z_{<i}, X_1, \ldots, X_n).
\]

And to model \( P_\theta(R|H', I) \) we minimize:

\[
\mathcal{L}_{\text{response}} = - \sum_{i=1}^{m} \log P_\theta(y_i|y_{<i}, X_1, I_1, \ldots, Z_1, \ldots).
\]

### 4 Experiment Setup

#### 4.1 Data Preparation

We use dialogue datasets from Zhou et al. (2021a) since they proposed “commonsense-focused dialogues” by filtering three existing dialogue datasets DailyDialog (Li et al., 2017), EmpatheticDialogues (Rashkin et al., 2019), MuTual (Cui et al., 2020) using ConceptNet triples, and also crowdsourced SocialIQA-prompted (Sap et al., 2020) dialogues. Their filtered datasets contain 31k dialogues and 159k turns. We then apply our hard- and soft-matching procedures on these dialogues. The total number of training instances from hard-matching is 57k and 71k from soft-matching. More details are shown in Table 1.

#### 4.2 Models and Baselines

We use GPT2-small (Radford et al., 2019) and DialoGPT-medium (Zhang et al., 2020b) as our base model and consider multiple baselines and different self-talk RG model variants. We first consider a vanilla RG model that follows the traditional RG set up, which we train on all of the 159K dialogues instances. Then we train a simple self-talk RG model (referred to as Self-Talk-Base) where we use hard-matching to construct knowledge-aligned dialogues, represent knowledge using triples with relations converted to NL, and use a special symbol <implicit> to separate knowledge and dialogues. Next, we train multiple model variants by considering alternatives in different components of our TBS models: use soft-matching
to construct knowledge labels (ST-soft), represent knowledge using information-seeking question-answer pairs (ST-QA), and elicit knowledge using NL prompts (ST-prompt).

Furthermore, we compare our self-talk RG models against several knowledge-grounded RG baselines that retrieve external knowledge instead of generating it. Specifically, following most existing knowledge-grounded RG work, we train RG models to model the conditional probability $P_\theta(R | H, I)$ where $I$ is the retrieved background knowledge. We consider different ways to provide the knowledge and compare their performance with our TBS model where knowledge is generated by the same RG model.

We use our base models from HuggingFace\(^1\) and implement our self-talk framework based on TransferTransfo (Wolf et al., 2019)\(^2\). We took 10% of all data to be our development set and used it to evaluate model performance during training and select hyper-parameters. We fine-tune the model for 3 epochs with batch size 4 and set the learning rate to be 6.25e-5. We perform gradient accumulation for 8 steps and gradient clipping with a max norm of 1.0 and optimize using the Adam optimizer. For decoding, we use top-k, top-p nucleus sampling (Holtzman et al., 2019) with temperature $T$ for decoding, where $k = 0$, $p = 0.9$ and $T = 0.7$ with a maximum decoding length of 300 tokens. Note that since we are also generating knowledge, this maximum length is larger than normal RG models.

### 4.3 Evaluation Protocol

Due to the one-to-many nature of the open-domain RG task and many reference-based metrics having low correlation with human judgements (Zhao et al., 2017; Liu et al., 2016), we focus on human evaluation and a reference-free metric GRADE (Huang et al., 2020) shown to have consistent correlation (Yeh et al., 2021) with human judgements to ensure the validity of experimental results. For human evaluation, we randomly sample 300 instances from unseen test dialogues. The test dialogues are from the original distributions from the 4 datasets considered by Zhou et al. (2021a) and only around one third of the instances have matched commonsense knowledge triples. This means that the testing samples should mimic dialogues in real everyday life instead of always consisting of concept connections from ConceptNet. For every human evaluation, we ask three turkers from Amazon Mechanical Turk (AMT) platform and use majority voting as the final result for each instance. As mentioned in Section 2.2, we evaluate three dimensions of the TBS RG model’s performance.

**Knowledge Quality (KQ)** We evaluate two aspects of knowledge quality using annotators from AMT. First, is the knowledge generated by the RG model valid in isolation, as a standalone fact? Then we show annotators the dialogue context which the model used to generate this knowledge and ask, is the knowledge relevant to the context?

**Knowledge-Response Connection (KR)** To evaluate whether the response generated is grounded to the knowledge from self-talk, we show workers a dialogue history, the implicit knowledge from the model output, and the response from the output and ask them whether the response makes use of the knowledge.

**Response Quality (RQ)** We provide a dialogue history and two model responses and ask workers to select which one is better or not sure. We consider six dimensions following most previous RG evaluation: which response is more grammatical, coherent, engaging, informative, specific, and makes common sense. Specifically, informative refers to how much content a response carries and specific focuses on whether the response is not generic, i.e., one that cannot be made in many different scenarios.

### 5 Results

This section presents results on the three evaluation dimensions: knowledge quality (KQ), knowledge-
response connection (KR), and response quality (RQ).

5.1 Knowledge Quality

75% of knowledge generated makes sense and is relevant Table 2 shows human evaluation results on generated knowledge from different models. Given only the dialogue history $H$, we find that our RG models can generate mostly implicit commonsense knowledge $I$ that makes sense and is relevant to the context.

Model generates novel knowledge Out of the generated knowledge, we find that around 56% of them exactly matched one triple in ConceptNet (Speer et al., 2017), meaning that the model generates new knowledge that is not present in the knowledge base where we get training data from. We further find that the knowledge quality of the generated novel knowledge is similar to that of knowledge existing in ConceptNet. This shows a promising sign that self-talk RG model can potentially generate good-quality novel knowledge labels for unseen dialogues.

5.2 Knowledge-Response Connection

Most responses are grounded in the generated knowledge As shown in Table 2 “Used in Response” column, we also find at least 75% of generated knowledge is used in the generated response, i.e., the response is grounded in the knowledge from self-talk.

5.3 Response Quality

Does thinking before speaking help produce better responses? Table 3 presents comparison between a vanilla RG model trained on 159k dialogue instances and our simplest self-talk RG model trained with 57k hard-matching dialogue instances that represent knowledge using triples whose relations are converted to NL and use the “<implicit>” special symbol to separate dialogue and response. We find that humans prefer our self-talk model’s response to those from the vanilla RG model on all six criteria. Specifically, our model reaches statistically-significant ($p \leq 0.05$) improvement on informativeness, specificity, and the common sense aspects of generated responses. This might be due to that by generating implicit knowledge before responding, new concepts that have commonsense relation with concepts mentioned in dialogue history will be used in the response, making the response more contentful.

Input knowledge quality heavily influences response quality To better showcase the deep connection between knowledge and response, we examine how knowledge quality generated from self-talk can affect response quality. During inference, we randomly sample noisy knowledge from another dialogue, feed it to the model to generate a response conditioned on irrelevant knowledge, and compare the response quality with response generated from self-talk knowledge. Table 4 presents comparison of response quality on grammaticality, coherence, and engagingness. We find that there is a statistically significant ($p \leq 0.05$) drop in response quality in all three criteria. This indicates that the quality of knowledge input heavily influences response quality and that our trained self-talk RG models generated better responses due to decent knowledge quality.

Model variant analysis Table 5 shows evaluation results on three different model variants: soft vs. hard, prompt vs. symbol, and QA vs. NL-triple format. We compare these variants with the base RG model (the same in Table 3) on all six response quality criteria. We find that generally human evaluators prefer responses produced from these model variants (except for prompt variant for common sense criterion). Specifically, looking at the statistically significant improvements, we find that

| Criteria                      | Grammatical  | Coherent  | Engaging | Informative | Specific | Common Sense |
|-------------------------------|--------------|-----------|----------|-------------|----------|--------------|
| Prefers Self-Talk (57k)       | 141 (47.0%)  | 139 (46.3%) | 144 (48.0%) | **161 (53.7%)** | 165 (55%) | 158 (52.6%)  |
| Prefers Vanilla (159k)        | 135 (45.0%)  | 135 (45.0%) | 129 (43.0%) | 127 (42.3%) | 112 (37.3%) | 123 (41%)    |
| **p-value**                   | 0.76         | 0.85      | 0.27     | **0.05**    | 0.001    | **0.04**     |
| Not Sure                      | 24 (8.0%)    | 26 (8.7%)  | 27 (9.0%) | 12 (4%)     | 23 (7.7%) | 19 (6.3%)    |

Table 3: Human evaluation of 300 randomly sampled test data on six criteria by comparing self-talk models trained on 57k hard-matching knowledge-aligned dialogue data versus vanilla RG model (directly generates response from history) trained on 159k data instances. Bold numbers mean statistically significant ($p \leq 0.05$). We find that despite having less than half of the training data, self-talk models achieve statistically significant improvements on all informativeness, specificity, and common sense.

5.1 Knowledge Quality

75% of knowledge generated makes sense and is relevant Table 2 shows human evaluation results on generated knowledge from different models. Given only the dialogue history $H$, we find that our RG models can generate mostly implicit commonsense knowledge $I$ that makes sense and is relevant to the context.

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5.3 Response Quality

Does thinking before speaking help produce better responses? Table 3 presents comparison between a vanilla RG model trained on 159k dialogue instances and our simplest self-talk RG model trained with 57k hard-matching dialogue instances that represent knowledge using triples whose relations are converted to NL and use the “<implicit>” special symbol to separate dialogue and response. We find that humans prefer our self-talk model’s response to those from the vanilla RG model on all six criteria. Specifically, our model reaches statistically-significant ($p \leq 0.05$) improvement on informativeness, specificity, and the common sense aspects of generated responses. This might be due to that by generating implicit knowledge before responding, new concepts that have commonsense relation with concepts mentioned in dialogue history will be used in the response, making the response more contentful.

Input knowledge quality heavily influences response quality To better showcase the deep connection between knowledge and response, we examine how knowledge quality generated from self-talk can affect response quality. During inference, we randomly sample noisy knowledge from another dialogue, feed it to the model to generate a response conditioned on irrelevant knowledge, and compare the response quality with response generated from self-talk knowledge. Table 4 presents comparison of response quality on grammaticality, coherence, and engagingness. We find that there is a statistically significant ($p \leq 0.05$) drop in response quality in all three criteria. This indicates that the quality of knowledge input heavily influences response quality and that our trained self-talk RG models generated better responses due to decent knowledge quality.

Model variant analysis Table 5 shows evaluation results on three different model variants: soft vs. hard, prompt vs. symbol, and QA vs. NL-triple format. We compare these variants with the base RG model (the same in Table 3) on all six response quality criteria. We find that generally human evaluators prefer responses produced from these model variants (except for prompt variant for common sense criterion). Specifically, looking at the statistically significant improvements, we find that
using soft-matching to create knowledge-aligned dialogue dataset helps produce more grammatical responses and responses that make more common sense. Using QA, a knowledge format closer to the dialogue domain, to represent knowledge makes the responses more grammatical, coherent, as well as more common sensical.

**Comparison with RG model that takes ground truth as input**  We further consider a strong baseline where we train an RG model with knowledge provided (instead of generating knowledge as self-talk model), and during testing, we provide the ground-truth knowledge label from the test data. The ground-truth knowledge label contains word overlap with the reference response, so this approach is normally considered as the upper bound of RG performance. The results of comparing the RG that has access with ground-truth with our base self-talk model are shown in Table 6. We surprisingly find that even though our proposed self-talk model has no access to ground-truth knowledge labels and is trained on much less data, the self-talk RG model still achieves statistically significant improvement on the common sense aspect of responses while stays on par on other evaluation dimensions. This shows a promising sign that sometimes models can generate implicit knowledge with higher quality than the provided knowledge. It is worth noting that the ground-truth knowledge provided in this experiment is automatically identified using ConceptNet and is noisy.

**Automatic evaluation results**  To better benchmark the performances of different models and allow simpler evaluation for future models, we also present results from automatic metrics. Due to the one-to-many nature of the open-domain RG task and many reference-based metrics having low correlation with human judgements (Zhao et al., 2017; Liu et al., 2016), we use a state-of-the-art reference-free automatic metric GRADE (Huang et al., 2020), which is shown to produce consistent correlation with humans on open-domain RG in this recent comprehensive survey by Yeh et al. (2021). Results are shown in Table 7. We can see that, consistent with human evaluation shown before, all variants of self-talk RG models still outperform end-to-end RG despite training on much less data. The improvement by using soft-matching does not exist, in contrary to human evaluation. We also find that using information-seeking question-answer pairs boost the performance even more.

### 6 Related Work

**Dialogue Response Generation**  Recent work focused on fine-tuning large pre-trained transformer models (Radford et al., 2019; Zhang et al., 2020b) on dialogue data. Many dialogue datasets have been collected with different focuses such as incorporating knowledge (Gopalakrishnan et al., 2019; Dinan et al., 2019), empathy (Rashkin et al., 2019), personality (Zhang et al., 2018) and reasoning (Cui et al., 2020) within dialog systems. There has also been work on combining a variety of datasets to exhibit multiple attributes (Roller et al., 2021). Zhou et al. (2021b) treats common sense as a latent variable in the RG process and probes if state-of-the-art (SOTA) RG models understand the relationships between common sense and the response made. Zhou et al. (2021a) proposes

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**Table 4:** Human evaluation on response quality when comparing the same RG model that uses self-talk as knowledge with that takes noisy knowledge as input.

| Model Variants | Grammatical | Coherent | Engaging | Informative | Specific | Common Sense |
|----------------|-------------|----------|----------|-------------|---------|--------------|
| ST-hard-symbol-NL (57k) | N/A | 150 (50.0%) | 165 (55%) | 159 (53.0%) | 131 (43.7%) | 159 (53.0%) |
| ST-soft-symbol-NL (71k) | +48 (16.0%) | +4 (1.3%) | +20 (6.7%) | +12 (4.1%) | +28 (9.4%) | +33 (11%) |
| ST-hard-prompt-NL (57k) | +14 (4.6%) | +16 (5.3%) | +9 (3%) | +14 (4.8%) | +15 (5%) | -2 (0.7%) |
| ST-hard-symbol-QA (57k) | +38 (12.7%) | +39 (13%) | +22 (7.3%) | +19 (6.3%) | +23 (7.7%) | +35 (11.7%) |

**Table 5:** Human evaluation on response quality when comparing different model variants with the base model (hard-symbol-NL). We show how many more (or less) responses human prefer the variant compared against the base version and the percentage of the difference.
Table 6: Human evaluation on response quality when comparing the same RG model that uses self-talk as knowledge with that taking ground-truth knowledge as input.

| Models                        | Grammatical | Coherent | Engaging | Informative | Specific | Common Sense |
|-------------------------------|-------------|----------|----------|-------------|----------|--------------|
| Prefers Self-Talk (57k)       | 131 (43.6%) | 144 (48.0%) | 137 (45.6%) | 122 (40.7%) | 156 (52.0%) | 156 (52.0%) |
| Prefers Ground-Truth Knowledge (159k) | 151 (50.3%) | 137 (45.6%) | 141 (47.0%) | 129 (43.0%) | 126 (42.0%) | 123 (41.0%) |
| p-value                       | 0.3         | 0.7      | 0.8      | 0.7         | 0.08     | **0.05**     |
| Not Sure                      | 18 (6.0%)   | 19 (6.3%) | 22 (7.3%) | 49 (16.3%)  | 18 (6.0%) | 21 (7.0%)    |

Table 7: Automatic evaluation using GRADE on response quality from DialoGPT-based responses. We sampled 3000 instances from test data.

| Models                        | Average GRADE |
|-------------------------------|---------------|
| Vanilla RG (159k)             | 0.704         |
| ST-hard-symbol-NL (57k)       | 0.730         |
| ST-soft-symbol-NL (71k)       | 0.715         |
| ST-hard-prompt-NL (57k)       | 0.727         |
| ST-hard-symbol-QA (57k)       | **0.739**     |

Commonsense Reasoning The majority of recent CSR benchmarks (Zellers et al., 2018; Talmor et al., 2019; Bisk et al., 2020; Sap et al., 2019; Lin et al., 2021c,a, 2020) test a model’s ability to choose the correct option given a context and a question. Recent work also aims to probe models in these tasks to see if reasoning is actually achieved (Richardson and Sabharwal, 2020; Richardson et al., 2020; Zhou et al., 2020; Lin et al., 2021b). Arabshahi et al. (2020) focuses on if-then-because reasoning in conversations and design a theorem prover. In RG, several works have tried to incorporate commonsense (Zhou et al., 2018; Zhang et al., 2020a) using ConceptNet, a commonsense knowledge graph (Liu and Singh, 2004) to make responses more natural-sounding.

7 Conclusion

Inspired by how humans contribute to the common ground during communication, we aim to train RG models that first generate implicit background knowledge before generating responses. This brings us three main benefits compared with prior end-to-end RG models: 1) more informative and coherent responses by augmenting with knowledge; 2) generated knowledge provides faithful explanations of RG model’s inner-workings; 3) self-talk RG models do not rely on external knowledge bases in response generation time. To train such self-talk models, we first identify and align implicit knowledge for dialogue, then explore knowledge representation techniques for self-talk, and finally propose evaluation for our think-before-speak RG paradigm and conduct extensive evaluation on trained models. We find strong and promising results for our self-talk RG model compared with end-to-end RG. In particular, the self-talk RG model can produce good quality and novel knowledge, outperform end-to-end RG models despite training on less data, and even produce better responses than RG models that take ground-truth knowledge. We hope our findings encourage more future studies on making RG models better emulate human communication process and produce better-quality responses.

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