Abstract

Human communication relies on common ground (CG), the mutual knowledge and beliefs shared by participants, to produce coherent and interesting conversations. In this paper, we demonstrate that current response generation (RG) models produce generic and dull responses in dialogues because they act reflexively, failing to explicitly model CG, both due to the lack of CG in training data and the standard RG training procedure. We introduce Reflect, a dataset that annotates dialogues with explicit CG (materialized as inferences approximating shared knowledge and beliefs) and solicits 9k diverse human-generated responses each following one common ground. Using Reflect, we showcase the limitations of current dialogue data and RG models: less than half of the responses in current data is rated as high quality (sensible, specific, and interesting) and models trained using this data have even lower quality, while most Reflect responses are judged high quality. Next, we analyze whether CG can help models produce better quality responses by using Reflect CG to guide RG models. Surprisingly, we find that simply prompting GPT3 to “think” about CG generates 30% more quality responses, showing promising benefits to integrating CG into the RG process.

1 Introduction

Human communication is a collaborative effort (Grice, 1975; Allwood, 1976; Bohm et al., 2004) where participants strive to achieve common ground (CG), consisting of mutual beliefs and common knowledge (Stalnaker, 1978; Clark and Schaefer, 1989; Clark and Brennan, 1991). Conversational AI systems, while able to produce fluent texts, often generate generic and dull dialogue responses (Serban et al., 2017; Zhao et al., 2017), potentially because they do not explicitly model CG in communication (as illustrated in Figure 1). Specifically, existing models mostly follow a dialogue history → response training paradigm since such data can be easily obtained in the wild, skipping an important middle step that builds common ground, which naturally and universally exists in human communication, i.e., dialogue history → common ground → response. Moreover, the same history can yield numerous responses, predicated on the CG and intent of the responder. We conjecture that the omission of modeling CG explicitly is a crucial bottleneck in RG models because they are directly trained to produce responses without learning how and why those responses are uttered.

Modeling common ground between speakers, however, is challenging due to its implicit and subjective nature during conversations (Clark and Schaefer, 1989). Prior work on representing CG either mines noisy commonsense knowledge triples between dialogue history and existing re-
responses (Zhou et al., 2022) or collects human inferences after reading the whole dialogue as a bystander (Ghosal et al., 2022). Such approaches provide useful augmentation, but post-hoc analysis cannot mirror the generative process and intent of diverse human dialogue. Figure 2 illustrates three paradigms for RG. We argue that truly modeling this generative process requires (1) articulating CG prior to the response; (2) generating responses conditioned on CG; (3) differentiating response generation based on different types of CG.

To this end, we formalize common ground in dialogues as inferences made by one participant to approximate potential beliefs shared by other participants, as shown in Figure 1. In this work, we instantiate inferences as question-answer (QA) pairs in natural language (NL) such as “What might happen later?” “They might need to clean the floor” to elicit others’ beliefs, inspired by inquiry-based dialogic learning (Bruner, 1961; Habermas, 1985; Wells, 2000). Another critical aspect of CG is its multi-dimensional nature, i.e., given the same dialogue context, different plausible inferences can be made, which then lead to different responses. Following these principles, we create a novel dialogue resource with multiple explicitly human-annotated common ground, each of which is further substantiated as a next-turn response continuing the conversations (an example of expanded CG and responses for one context shown in Figure 3).

We design a two-stage data collection process by first asking crowdsourcing workers to answer different inference questions eliciting beliefs about CG (e.g., what is the speaker feeling right now?) Answers rely on common sense, and adopt the point of view of the conversational respondent. We use these QA pairs to approximate various (non-exhaustive) inference dimensions to extend the common ground (e.g., empathy and event causality). Our second step converts these CG into dialogue responses by asking different workers to write a coherent response based on the answer/inference collected in the first stage. Our collected data Reflect contains 9k diverse responses from 600 dialogue contexts, based on 5 inference dimensions for CG.

Using Reflect, we first test our hypothesis that explicitly modeling CG and using CG to construct responses creates more engaging conversations. We conduct human evaluation to compare the quality of responses between Reflect and “reflex” style datasets and models in terms of sensibility, specificity, and interestingness. We find that, compared to reflex-prone human-written and machine-generated dialogues, our two-stage data collection process results in more responses that are sensible, specific, and interesting as rated by humans. This highlights limitations of existing data collection procedures and models trained on the data.

Next, we look to study the potential of explicitly modeling CG in dialogue systems to help build models that can create more engaging conversations. As a case study, we use the inference dimensions from Reflect and test two simple ways to guide RG using CG. We surprisingly find that simple approaches such as appending an inference question to the dialogue context before the response in the few-shot (FS) in-context examples (from Reflect) help GPT3-175B (Brown et al., 2020) generate almost 30% more responses that are deemed sensible, specific, and interesting than vanilla FS learning GPT3 (no inference question). We demonstrate that, when prompted to “think” about an inference question (approximated CG), large models such as GPT-3 can create more engaging conversations. We also find that such effect is only shown in large models like GPT-3 as we find BlenderBot-440M (Roller et al., 2021) benefits from fine-tuning on Reflect, but appending inference questions does not further increase response quality.

In summary, our contributions are as follows: 1) we operationalize theories about common ground and formalize them for dialogue; 2) we collect the first large-scale (9k responses) dialogue dataset with diverse responses guided by CG and release this resource to facilitate training and evaluation; 3)
2 Inference-Based Common Ground

We formally introduce the notion of common ground in conversations as the implicit variable conditioned on dialogue history and provides conditions to the next-turn response.

2.1 Grounding in Communication

Successful collaborative communication activity relies on mutual understanding of shared knowledge and beliefs (Clark and Brennan, 1991; Bohm et al., 2004) called common ground. However, due to least collaborative effort (Grice, 1975; Clark and Schaerfer, 1989) where communication participants try to minimize the effort spent on contributing to the interaction, establishing CG relies on signals other than the surface communication information (i.e., actual utterances in a conversation). While humans in face-to-face communication receive some information from non-verbal signals such as gestures and facial expressions, virtual systems such as chatbots often do not have access to such signals. Thus, we argue that they have to rely heavily on another crucial way of getting signals for establishing CG: making inferences based on the surface communication utterances and common sense, in order to approximate two humans talking to create engaging conversations.

Furthermore, building CG by making relevant inferences also connects closely with the “dual process” theories of human reasoning (Stanovich and West, 2000; Evans, 2003; Kahneman, 2011). We argue that the “reflective” RG is mostly modeling “System 1” which is intuitive and associative, but a more deliberative and logical “System 2” is lacking.

2.2 Formulating CG in Dialogue

Consider three high-level components in communication efforts: context $C$ (often materialized as dialogue history consisting of a sequence of $n$ contributions $C = c_1, ..., c_n$), common ground $G$, and a new contribution continuing the context (often referred to as a “response” $c_{n+1}$). Specifically, for common ground $G$, we focus on signals gained from inferences and thus materialize $G$ as a list of $m$ potential inferences $G = I_1, ..., I_m$ conditioned on the context. We furthermore materialize each inference as a QA pair in NL $I_j = (Q_j, A_j)$ (examples included in Figure 3 between Stage 1 and 2). We use QA format to express inferences to mimic inquiry-based dialogic learning (Bruner, 1961; Habermas, 1985; Wells, 2000) and follow empirical evidence that neural models take in QA-format knowledge effectively (Shwartz et al., 2020; Zhou et al., 2022).

3 Collecting Reflect Data

Here we describe how we collect Reflect, a novel large-scale dialogue dataset with diverse human-annotated inference-based CG and grounded responses. An overview of the procedure with examples are shown in Figure 3. We first select base dialogues from a dataset that is constructed without considering CG and only has one plausible response for each context (3.1). Then we aim to expand and collect multiple responses based on different inference dimensions. We introduce a two-stage process to first crowdsource potential inferences people make in conversations (3.2) and then ask a second cohort of workers to generate diverse responses based on the inferences (3.3). We designed a two-stage data collection to 1) collect multiple, diverse responses based on each CG; 2) to allow response writers to validate CG as high quality, generic common sense inferences. Finally, we include discussions of data quality assurance (3.4).

3.1 Pre-Collection: Selecting Base Dialogue Turns for Expansion

Our first step is to select base dialogues and dialogue turns to expand on, in terms of both inference-
based CG and more potential responses following the CG. One important criterion for base turns is that they should not be “social glue” turns such as “You are welcome” in responding to “Thank you!” We aim at expanding turns that have semantically-rich dialogue context, enabling different plausible inferences to be made. After investigation of existing datasets, we use dialogues from Commonsense-Focused Dialogues (Zhou et al., 2021) that are converted to dialogues from SocialIQA (Sap et al., 2019b) contexts. We chose this dialogue data because SocialIQA (crowdsourced from ATOMIC (Sap et al., 2019a), an if-then inferential commonsense knowledge base) contains everyday situations where people can make various inferences on. Then, to select what turns to expand on, we use simple heuristics and select the turn that has the largest semantic overlap with the event in SocialIQA using SentenceBERT (Reimers and Gurevych, 2019).

### 3.2 Stage 1. Inference Collection

Our first goal is to collect potential inferences people might make (e.g. “they might be feeling bad”) given conversation contexts C to approximate common ground. Each inference $I_j$ is further materialized as a QA pair $(Q_j, A_j)$ along multiple inference dimensions as formulated in Section 2.2.

**Inference Knowledge Schema** We adopt inference dimensions from ATOMIC2020 (Hwang et al., 2021) since it focuses on social commonsense inferences based on everyday scenarios. Specifically, we conduct a pilot study to choose 5 dimensions from the 14 dimensions, consolidating those that overlap (e.g., “what might happen later” and “what would others likely want to do after”) in the context of dialogues. Our final five dimensions for conversation-based inference dimensions are shown in Table 1.

**Crowdsourcing** Our Stage 1 crowdsourcing task is: given a dialogue context, imagine that you are participating as the responder and write answers to the 5 inference questions (more details in Appendix). We recruit a group of around 30 crowd-sourcing workers from Amazon’s Mechanical Turk platform (AMT) who are native English speakers and provide detailed feedback. Specifically, after carefully reading collected inferences from pilot studies, we provide feedback to Turkers by stressing on several principles to make the inferences collected more closely approximate CG, shown in Figure 4.

### 3.3 Stage 2. Response Collection

After the first stage, we have collected 5 inferences (approximating CG) in the form of QA pairs for each dialogue context. Our next step is to collect next-turn responses given both the dialogue context and the collected inference-based CG along different dimensions. To account for diversity in responses, for each dialogue context we ask three Turkers to write a next-turn response based on each of the given inferences, yielding 15 responses for each dialogue context. Similarly to Stage 1, we communicate our collection principles to workers to improve the collected data quality (Figure 4). Both Stage 1 and Stage 2 UI and positive/negatives examples for workers are included in Appendix.

### 3.4 Quality Control and Analysis

**Quality check for Inference Collection** In our second stage for response collection, we ask workers an additional question before writing a response: “do you think the shown inference answer is a valid...
reaction from the responder?” as a way to check the quality of the first collection stage results. We find that less than 7% (200/3000) of the inferences are deemed implausible by second stage workers and only keep the inferences where most workers agree that the inferences are plausible.

**Quality check for Response Collection** To check quality for our stage 2 response results, we randomly sampled around 5% of collected responses (500) and conduct a manual in-house check for two criteria: 1) is it a sensible continuation from the dialogue context? and 2) is the response based on the inference given? We find that around 93% of the responses are a sensible continuation and 89% are following the inferences given. Further human ratings of our collected grounded dialogue responses showing that our data improves the sensibility, specificity, and interestingness aspects compared to the base responses are included and discussed in Section 4.

**Comparison to prior work on representing CG**
We compare CG inferences from Reflect with TBS (Zhou et al., 2022) and CICERO (Ghosal et al., 2022), two prior work that aims to represent CG in dialogues using either ConceptNet (Speer et al., 2017) knowledge triples or post-hoc human annotations, respectively. Note we only compare inferences (CG) since neither collects new dialogue responses grounded in the inferences, and only consider a single response per context. Comparison results on sampled 100 inferences for each resource are shown in Table 2 where we find that inferences in Reflect are rated as make more sense and relevant to dialogue context than the prior dataset.

### 4 Limitations of Reflex-Prone Dialogue Data and Models
Most existing open-domain dialogue datasets are either crowdsourced by workers who do not have strong incentives to create engaging conversations (Rashkin et al., 2019; Zhou et al., 2021) or crawled from language learning websites and exams (Li et al., 2017; Cui et al., 2020). Both lack explicit CG. These collection processes can fail to capture engaging human-like conversations through under-specified response criteria. Accordingly, RG models trained on these data may mimic generic patterns. This section aims to demonstrate such limitations by comparing responses from Reflect with responses from both the original dialogue

| Dimensions       | Positive Examples                                                                 | Negative Examples                                                                 |
|------------------|-----------------------------------------------------------------------------------|-----------------------------------------------------------------------------------|
| Sensibleness     | Did you spill it in the kitchen? Let me help!                                    | Thank you                                                                         |
| Specificity      | It's actually blessing in disguise, wanna guess why?                             | Do you need help?                                                                 |
| Interestingness  | It's blessing in disguise, since I ordered extra from your favorite pasta place! | Let's eat something else.                                                         |
| Quality (SSI)    |                                                                                  | All above                                                                         |

Table 3: Evaluation dimensions for RG with examples (dialogue context from Figure 1).

#### 4.1 Human Evaluation Dimensions-SSI
We evaluate the quality of each response by head-to-head comparing across systems along several evaluation criteria. We follow the protocol used by LaMDA (Thoppilan et al., 2022) and measure SSI: sensibleness, specificity, and interestingness. Examples of positive and negative responses are shown in Table 3. Our assumption is that responses that contribute to more engaging conversations should satisfy all three dimensions and we refer to them as *quality* responses. We do not consider automatic metrics since they do not yet reliably replace human judgements on open-ended responses, especially for fine-grained evaluation dimensions.

#### 4.2 Comparing Original vs Reflect Responses
First, we compare the quality of responses in previous dialogue datasets with our Reflect responses to analyze the effects of explicitly incorporating CG in human RG. Here we present results by adopting the aforementioned evaluation protocol on human dialogues, both from the original base dialogues (Zhou et al., 2021) and from our Reflect dataset, derived from the same dialogues. We sampled 300 dialogue contexts and asked 3 crowdsourcing workers to rate the three SSI criteria, using majority voting to get final scores (Fleiss-kappa (Fleiss, 1971) agreement is around 0.67). We compare the original next-turn response from the contexts with a randomly sampled one from our Reflect responses.

*Reflect contains more specific and interesting responses than original dialogues* From human evaluation shown in Figure 5, we observe that our collected Reflect data, consists of dialogue responses that are on average more specific (20%) and interesting (13%) than the original data, while having slightly lower sensibility (4%) ratings. One possible contributor to the lower sensibility may be 2-stage collection where a new worker continues dialogues constrained by a specific inference generated by another person. Specifically, when
comparing the percentages of responses that satisfy all three criteria, i.e., quality responses, we find that there are substantially more (18%) such responses in Reflect than in original data. This observation raises an interesting question: “do existing dialogue training datasets capture high quality dialogues?” Without sensible, specific, and interesting responses to learn from, RG models will necessarily be limited in the quality of their output.

4.3 Comparing Reflex RG vs Reflect Data

We now compare Reflect with RG models trained on dialogue data that lacks explicit CG and to directly generate an utterance given a context.

Reflexive model baselines Specifically, we consider models from two categories: medium-sized RG models pre-trained on dialogue data such as BlenderBot (440M parameters) \(^2\) (Roller et al., 2021) and large-sized language models (LLM) pre-trained on general texts such as GPT3-DaVinci (175B parameters) \(^3\) (Brown et al., 2020). We directly use off-the-shelf Blender since it is pre-trained on dialogue data (Blender). For GPT3-175B, we apply few-shot in-context learning by providing 3 examples of dialogue context and response from existing data (GPT3-FS). We manually examine these responses to ensure their quality as demonstrating examples. Then we present a dialogue context from our test data and prompt GPT3 to generate a next-turn response. More details in Appendix A.

Models with no common ground struggle Unsurprisingly, as shown in Figure 6, we find a similar trend as comparing Reflect with original dialogue data: both BlenderBot-FT and GPT3-FS generate much fewer quality responses (53% and 38%, respectively) that satisfy all criteria and particularly on specificity. This further supports the hypothesis that RG models that learn from no-grounding dialogue responses struggle to capture what constituted meaningful conversations.

5 A Little CG Goes a Long Way

After showing that explicitly integrating inference-based CG helps humans produce more specific and interesting dialogue responses, we now test if this also holds for neural RG models. We take the non-exhaustive inference dimensions we used in Reflect as case studies to see how CG could improve the quality of existing RG systems’ responses, in terms of the SSI human evaluation (Thoppilan et al., 2022).

5.1 Experiment Setup

Inference-Guided reflect models We attempt to shift models from “reflexive” RG to “reflective” RG by taking into account of plausible inferences that humans use to build common ground during com-

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\(^2\)https://parl.ai/projects/recipes/  
\(^3\)https://beta.openai.com/docs/models/gpt-3
communication. Since both BlenderBot and GPT3 are trained to generate responses directly without integrating common ground, a non-trivial challenge is how to adapt them to use inference-based common ground before RG. Here we present our two intuitive and simple approaches.

For BlenderBot-440M, we follow the common practice of fine-tuning models to adapt to a new task format. We split our Reflect data into 60/10/30 for train/valid/test and first fine-tune BlenderBot-440M (Blender-FT) on only the collected responses to show potential benefits of training from inference-guided human responses. Then we fine-tune BlenderBot but modify the training task from outputting responses from contexts to inference-guided RG. Inspired by modular generation in dialogue RG (Adolphs et al., 2021; Zhou et al., 2022; Shuster et al., 2022), our training task is: given dialogue context and one of the five inference dimension questions, generate the answer as well as the response collected in Reflect (Blender-FT-InfQ), indicating that the model is given the Inference Question). More details in Appendix C.

For GPT-175B, we follow the few-shot in-context learning approach with one small addition in input: we append the dialogue context with an inference question and ask the model to generate a response. Our pilot studies show that GPT3 tends to generate directly an answer to the question, not a next-turn response to the dialogue context, thus we format the question into a prompt for GPT3 and stress that the end goal is RG. Specifically, we append the text “Think about this when responding: ” and then one of our inference questions after the dialogue context to prompt GPT3 to generate a response by reflecting on the questions (GPT3-FS-InfQ). Illustrative figures for prompting GPT3 are shown in Appendix A Figures 10.

To compare and analyze the effects of each inference dimension, we randomly sample one response for each of the five inference dimensions for GPT3-FS-InfQ and Blender-FT-InfQ and take their average. For GPT3-FS, Blender, and Blender-FT, we pick the top 5 responses generated using their default decoding strategy (beam search for GPT3 and nucleus sampling for Blender) and aggregate their evaluation results. In total, we evaluate 250 responses from each model following the procedure in Section 4.1.

5.2 Experimental Results

Prompting GPT3 to “think” about common ground improves response quality by 30% Figure 7 presents results when comparing models that has no access to inference-guided Reflect data with those that do. We test the hypothesis that whether guiding RG models with inference questions about common ground is helpful for generating more human-like responses. We find that with inferences, GPT3-FS-InfQ outperforms GPT3-FS on all evaluation dimensions. Specifically, inference-guided GPT3 produces almost 25% more specific and 30%
more quality responses. Moreover, 54% quality (sensible, specific, and interesting) responses already surpasses quality of human-written responses in original dialogues (49%), but still lags behind Reflect (58%) as shown in Figure 5.

Fine-tuning Blender on Reflect generates 26% more quality responses  For BlenderBot-400M, we find that fine-tuning on inference-guided human responses from Reflect helps generate almost 50% more specific and 26% more quality responses. In contrast to GPT3, BlenderBot with inference-guided fine-tuning does not seem to improve much. We speculate that model size might play a role in how much model is influenced by CG inferences, leaving future work for more inference-customized fine-tuning on moderate-sized models.

5.3 Analysis

Which inference dimension helps models the most (and which the least)?  Figure 8 shows the percentages of quality responses separated by the inference dimension we use to prompt humans and models. Interestingly, we find that on some dimensions, GPT3-FS-InfQ can produce significantly better responses than human responses from Reflect, especially event-based: “What might have happened before” and “what might happen after?”, and emotion-based CG about the other speaker “What is A (speaker1) feeling now?”. However, on “How would you describe A”, humans responses grounded on this question are much better. This dimension-specific analysis provides evidence that neural models’ capability to generate quality responses may depend on what types of CG we use to guide them.

Prompting GPT3-175B with complete human inferences  To show how well GPT3 can make use of complete human-annotated common ground, we further append the inference answer after the question from Reflect data and prompt GPT3 to generate a response given the fully materialized common ground. As expected, we observe further improvements in response quality especially in specificity (15% more) and general quality (16.7% more). This analysis shows promises to make reflect-style models produce better responses by providing quality inference answers for CG.

6 Related Work

We have presented discussion of previous work representing CG (Ghosal et al., 2022; Zhou et al., 2022) in Section 1 and relevant communication theory and psycholinguistic literature in Section 2. Here we provide additional discussions. Recent advances on neural RG models mainly focused on fine-tuning large pre-trained transformer models (Zhang et al., 2020; Roller et al., 2021; Thompson et al., 2022) on huge number of dialogue data. However, few of the data provides explicit common grounding. Modular RG (Adolphs et al., 2021; Shuster et al., 2022) aims to generate relevant knowledge first by retrieving from the web and the generate knowledge-grounded responses. Compared to these work, we focus on inferences based on common sense instead of external knowledge. Another closely related work by Cho and May (2020) examined incorporating dialogue data with techniques from improvisational theater to teach models to implicitly build common ground.

7 Conclusion

We introduce Reflect, a dataset with diverse inference-grounded responses inspired by CG and communication theories. We carefully design our two-stage collection process and apply quality control. Then we demonstrate limitations of existing dialogue data and models trained on it. Finally, we present promising signs that guiding models with CG results in more engaging conversations. We hope to encourage more work on improving RG quality by looking at how humans use CG and adapt the communication process to machine learning models. Future directions include providing a ranking of inference dimensions depending on dialogue context and train models to generate responses following the most suitable dimension. Reflect also enables potential automated metrics to evaluate response since more responses per dialogue might help gauge the plausible response space given a context.
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Ethics and Broader Impact

We collect a new dialogue dataset in English, which benefits English speakers more. We use Amazon Mechanical Turk to recruit crowdsourcing workers and we pay workers over $15/hour on average, well above the highest state minimum wage and engage in constructive discussions if they have concerns about the process. We also give each annotation instance enough time so that we do not pressure annotators. In our quality assurance process for this dataset, we also examine potential harmful biases and aggressive languages in responses and remove them in the final dataset. We also acknowledge that the generated responses from our experimented models might contain biases.

8 Limitations

Our first limitation in modeling CG is that we are using inferences from one speaker to approximate CG during the communication process. To truly represent CG, we need to recollect dialogues and as participants continue the conversations, we should ask both of them the same inference questions and perform post-hoc analysis on the answers to the questions.

Our second limitation is the lack of explicitly modeling communicative intents. In future work, we plan to heuristically link each inference dimension to a general communication goal. For example, making inferences about “speaker emotion states” is helpful to build emotional connections with the other speaker.

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A Data Collection Details

We engage in active discussions with them in the TurkerNation\textsuperscript{4} Slack channel and provide detailed feedback after multiple rounds of pilot study to ensure the data quality.

A.1 Inference Collection

Here we present more detailed feedback for AMT workers on Stage 1. inference collection: First, we stress that the goal of these answers is to help with generating a response to continue the conversation instead of any inferences that might not be useful for directly generating engaging responses, such as “spaghetti is a type of food” for the example in Figure 1. Secondly, the answers should not be a direct copy-paste of some parts in the dialogue context as those would be trivial to collect, violate the least collaborative principle and the maxim of quantity (Grice, 1975), and and should not be worth making inferences over. Finally, we remind them that the inferences written should be considered as “common sense” so that the approximated CG is more likely to become shared knowledge and beliefs among the dialogue participants. Collection UI and provided examples for turkers are shown in Figures 12 and 13.

A.2 Response Collection

We specifically stress on several points to workers: 1) to collect more engaging and interesting responses, response should not directly paraphrase the inference such as “I think you are feeling relieved” from inference QA pair “What is speaker feeling now? Speaker is feeling relieved”; 2) the response should be both coherent to the dialogue context as what would be naturally uttered by the responder and based on the reactions to lead the conversation in an interesting direction; 3) Ultimately, we want responses that lead the conversations that are more enjoyable and engaging. Collection UI and provided examples for turkers are shown in Figures 14 and 15.

B Human Evaluation Details

Specifically, a sensible response is one that is reasonable in context. A specific response is one that relates closely to the given dialogue context, instead of a generic one that can be applied in dozens of different contexts. An interesting response can “catch someone’s attention or arouse their curiosity, or if it is unexpected, witty, or insightful.” (Thoppilan et al., 2022). For more detailed instructions, please refer to Thoppilan et al. (2022). Evaluation UI and provided examples for turkers are shown in Figures 16 and 17.

C Model Implementation Details

We use two base models in our paper: BlenderBot-440M and GPT3-175B. For BlenderBot, we use the ParlAI (Miller et al., 2017) package for pre-trained modeling and fine-tuning. The format for fine-tuning BlenderBot on inference questions is: input sequence is “<speaker1>... <speaker2>... <infq> What might have happened before?” and output sequence is “<infa>... <speaker2>...”, where we use “<infq>”, “<infa>” to indicate the start of an inference question and answer, respectively. We fine-tune BlenderBot-440M for 3 epochs with batch size 16 and set the learning rate to be 1e-06. 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-p nucleus sampling (Holtzman et al., 2019) with temperature T (p = 0.9 and T = 0.7), and a maximum decoding length of 300 tokens. BlenderBot-440M models are mostly trained on 4 Quadro RTX 8000 GPUs and take around 9 hours.

We use OpenAI-API\textsuperscript{5} to access GPT3-DaVinci (175B) and include prompting formats for GPT3-FS and GPT3-FS-InfQ in Figures 9 and 10, respectively.

D Additional Experimental Results

D.1 Inference-Separated Fine-Grained Evaluation Results

Inference dimension-separated full results are shown in Figure 11.
Figure 9: GPT3-Few Shot Prompting Format (no inference).

<speaker1>: I found a new friend in my neighborhood.
<speaker2>: you are new in that neighborhood, so how did you manage to have a new friend. <speaker1>: I went out running one morning and I met a lady.
<speaker2>: Of course you did Jan. You make new friends no matter where you go.
###
<speaker1>: Have I told you about the crazy daydreams I've had lately?
<speaker2>: Not that I remember. I hardly ever dream when I take a nap.
<speaker1>: Same here, but I just had one during my nap about chasing rainbows!
<speaker2>: Maybe you were looking for a pot of gold! I hope you sleep better tonight and that you catch a rainbow in your dreams.
###
<speaker1>: I can't wait until I have enough money to buy a new car.
<speaker2>: Why do you need a car?
<speaker1>: I was bumming rides to work with my neighbor but I just started at a new place downtown. Now I have to take the bus every day.
<speaker2>: I will ask around and see if there's any easy way to get money for your car.
###
<speaker1>: Where are my Commandments?
<speaker2>: Last I heard was that Remi had them.
<speaker1>: I need to find Remi so I can get them.
<speaker2>: 

Figure 10: GPT3-Few Shot-Inference Question Prompting Format.

<speaker1>: I found a new friend in my neighborhood.
<speaker2>: you are new in that neighborhood, so how did you manage to have a new friend.
<speaker1>: I went out running one morning and I met a lady.
<speaker2>: Of course you did Jan. You make new friends no matter where you go.
###
<speaker1>: Where are my Commandments?
<speaker2>: Last I heard was that Remi had them.
<speaker1>: I need to find Remi so I can get them.
Think about this when responding: How would you describe <speaker1>?
<speaker2>: 

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Figure 11: **Response evaluation separated by inference dimensions.** We find that GPT3-FS-InfQ generate better responses than humans on the potential consequences dimension while generates worse on attributes.

Figure 12: **Inference collection UI.**
### Good examples

| Dialogue: |
| --- |
| - Jordan: How’d you do on the exam? |
| - Friend: I failed it, so did everyone else I asked |
| - Jordan: Oh, I didn’t think it was that hard |
| - Friend: What did you get on it? |
| - Jordan: I got an A and I think if my friends studied harder they could have done the same |

### Bad examples

| Dialogue: |
| --- |
| - Jordan: How’d you do on the exam? |
| - Friend: I failed it, so did everyone else I asked |
| - Jordan: Oh, I didn’t think it was that hard |
| - Friend: What did you get on it? |
| - Jordan: I got an A and I think if my friends studied harder they could have done the same |

#### Friend Reaction 1:

**How would you describe Jordan?**

- A caring person.

**Explanation:** This is wrong because there is no place indicating that Jordan is caring from the context.

#### Friend Reaction 2:

**What might have happened BEFORE?** Your assumptions should be implied by the dialogue. Please do not state what’s obvious in the dialogue context. For examples, ${\text{[speaker]}}$ does ... BEFORE, ${\text{[speaker]}}$ thinks X is ..., etc.

- Jordan aced the exam.

**Explanation:** This is wrong because it is not an assumption implied but something explicitly stated as in “I got an A”.

#### Friend Reaction 3:

**What do you think might happen AFTER?**

- Jordan’s friends maybe mad at him and not want to speak to him for a while.

#### Friend Reaction 4:

**What do you think Jordan is feeling?** (e.g., nervous, annoyed, etc.)

- Proud

#### Friend Reaction 5:

**What do you think Friend (you) is feeling?** (E.g., happy, relieved, angry, ..)

- Sad

**Explanation:** No indication in dialogue

#### Friend Reaction 5:

**What do you think Friend (you) is feeling?** (E.g., happy, relieved, angry, ..)

- The person is happy.

**Explanation:** Not sure who “The person” is and no indication of feeling happy.

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**Figure 13:** Inference collection examples for turkers.
Welcome to our task! Please read our instructions very carefully. We’re excited to work with you on this and on the thousands of HITs we have coming. Your annotation quality will be evaluated.

Instructions
1. Here you will see an incomplete dialogue between ${speaker} and his/her Friend and it’s the Friend’s turn to respond.
2. You are also given several potential reactions from Friend upon hearing ${speaker}’s words.
3. Your task is to imagine that you are the Friend responding to this conversation BASED ON each of the reactions.
4. Please try NOT to directly copy/verbalize the reaction as a response such as "X is seen as kind" → "You are so kind!". Try to be creative in your response such as "X is seen as kind" → "Aren’t you the best roommate!".
5. Your first priority should be writing a response that is COHERENT to the dialogue context and try to include the reaction you are given.
The conversations will be checked for quality.

Figure 14: Response collection UI.
| Good examples | Bad examples |
|---------------|--------------|
| **Dialogue:** | **Friend's Reaction 1:** |
| • ${speaker}: This place is awesome. | How would you describe ${speaker}? |
| • Friend: What place? | I would say ${speaker} is an excited and outgoing person. |
| • ${speaker}: The amusement park, it rocks | Response: "${speaker}, you are the coolest gal God has ever sent me. I love Amusement parks because of you..." |
| • Friend: Yeah, they are fun. | Explanation: It's NOT a coherent response to the dialogue context, i.e., it is disconnected from "I saw season ticket booth too." |
| • ${speaker}: I saw season ticket booth too. | **Friend's Reaction 2:** |
| **Friend's Reaction 1:** | What might have happened BEFORE the conversation? |
| How would you describe ${speaker}? | ${speaker} really enjoyed the rides in this amusement park. |
| I would say ${speaker} is excited and outgoing person. | Response: "You must really enjoy the rides in this park!" |
| Response: "Are you going to get season tickets? I'd love to visit here more often with someone who's always so energetic like you!" | Explanation: It's a direct copy-pasting of the reaction. |
| **Friend's Reaction 2:** | What do you think might happen AFTER this conversation? |
| What might have happened BEFORE the conversation? | ${speaker} may purchase season tickets. |
| ${speaker} really enjoyed the rides in this amusement park. | Response: "Oh where is it?" |
| Response: "Seems like you plan to frequent here. You must've had a blast with these rides." | Explanation: This response is NOT based on the reaction given. |
| **Friend's Reaction 3:** | **Friend's Reaction 4:** |
| What do you think might happen AFTER this conversation? | What do you think ${speaker} is feeling? |
| ${speaker} may purchase season tickets. | ${speaker} feels excited and satisfied with the amusement park. |
| Response: "Let me know if you purchase those season tickets and I'll go with you some time." | Response: "You must be happy and filled with anticipation." |
| **Friend's Reaction 4:** | Explanation: This response is NOT coherent to the dialogue context. |
| What do you think ${speaker} is feeling? | **Friend's Reaction 5:** |
| ${speaker} feels excited and satisfied with the amusement park. | What do you think Friend (you) is feeling? (E.g., happy, relieved, angry, etc.) |
| Response: "You enjoyed the rides so much that you plan to buy the season tickets now? Tell me all about it." | The other(s) are either bewildered or calm, more subdued than ${speaker}. |
| **Friend's Reaction 5:** | Response: "Heh, you guys need to match ${speaker}'s energy more, don't you all think? I'm kidding, I love you guys" |
| What do you think Friend (you) is feeling? (E.g., happy, relieved, angry, etc.) | Explanation: There is no indication of other people involved in the conversation and is not a coherent continuation from "I saw season ticket booth too." |
Figure 16: SSI evaluation UI.

Dialogue: 
$\langle$context$\rangle$

Response 1: 
$\langle$response_1$\rangle$

- Does this response make sense? 
  - Yes 
  - No
- Is the response specific? 
  - Yes 
  - No
- Is the response interesting? 
  - Yes 
  - No

Response 2: 
$\langle$response_2$\rangle$

- Does this response make sense? 
  - Yes 
  - No
- Is the response specific? 
  - Yes 
  - No
- Is the response interesting? 
  - Yes 
  - No

Response 3: 
$\langle$response_3$\rangle$

- Does this response make sense? 
  - Yes 
  - No

Thank you for your participation! Please provide feedback below on how we can improve the instructions, annotation interface, or anything else that you found confusing while completing the task.

Feedback
Welcome to our task! Please read our instructions very carefully.

Instructions
1. Here you will see an incomplete dialogue between two people.
2. You are given several responses from different systems.
3. Your task is to evaluate whether they are 1) sensible; 2) specific; and 3) interesting given the dialogue context.
4. Please read carefully of the "Instructions for each criterion" below to understand how to rate each response.
5. Treat each of the three criteria as separate measures, i.e. a response that is NOT sensible could possibly be specific or interesting and vice versa.

The evaluations will be checked for quality and we will give bonuses ;)

Instructions for each criterion:

Does the response make sense?
1. Use your common sense here. Is the response completely reasonable in context?
2. If anything seems off—confusing, illogical, out of context, or factually wrong—then rate it as Does not make sense.
3. If in doubt, choose Does not make sense.

Is the response specific?
1. For example:
2. – If A says "I love tennis" and B responds "That's nice", then mark it as Not specific. That reply could be used in dozens of different contexts.
3. – but if B responds "Me too, I can't get enough of Roger Federer!" then mark it as Specific, since it relates closely to what you're talking about.
4. If you're in doubt, or if the reply seems at all generic, rate it as Not specific.

Is the response interesting?
1. Choose Interesting if the response would likely catch someone's attention or arouse curiosity; also use that rating for anything insightful, unexpected, or witty.
2. If the response is monotonous and predictable, or if you're unsure, then pick Not Interesting.

Figure 17: SSI evaluation instructions.