Bootstrapping a Conversational Guide for Colonoscopy Prep

Anonymous ACL submission

Abstract

Creating conversational systems for niche domains is a challenging task, further exacerbated by a lack of quality datasets. We explore the construction of safer conversational systems for guiding patients in preparing for colonoscopies. This has required a data generation pipeline to generate a minimum viable dataset to bootstrap a semantic parser, augmented by automatic paraphrasing. Our study suggests large language models (e.g., GPT-3.5 & GPT-4) are a viable alternative to crowd sourced paraphrasing, but conversational systems that rely upon language models' ability to do temporal reasoning struggle to provide accurate responses. A neural-symbolic system that performs temporal reasoning on an intermediate representation of user queries shows promising results compared to an end-to-end dialogue system, improving the number of correct responses while vastly reducing the number of incorrect or misleading ones.

1 Introduction

Colorectal cancer is the second leading cause of cancer-related deaths worldwide. Colonoscopy is a safe and effective strategy to screen asymptomatic individuals for precursors of colorectal cancer, but it requires a precisely timed multi-day, multi-step procedure to clear the colon. In today's standard practice, patients are given information sheets to help them prepare for the procedure. Unfortunately, these information sheets are frequently ineffective, resulting in rescheduled procedures with large economic, health-related and social costs.

In this paper, we report on our initial steps to develop a conversational assistant to improve the ease of following colonoscopy prep instructions. To avoid information overload, the assistant is designed to coach patients through the process, reminding patients when it is time to carry out each step in the instructions and allowing them to **ask questions at any time** about the procedure and the diet changes they need to make at different stages of the preparatory period.

Existing efforts to make it easier to follow colonoscopy prep instructions give strong evidence that our approach can greatly enhance patient success. Engaging patients with automatic text reminders greatly improved colonoscopy prep adherence (90% vs. 62%) when patients were invited to ask follow up questions with health-care providers (Mahmud et al., 2019), but a larger scale trial where patients were not invited to reply to the text messages (for lack of personnel) found no improvements over the control group (Mahmud et al., 2021). The **capacity to answer questions**—which we seek to automate—appears to have been the crucial difference (Clancy and Dominitz, 2021).

Embodied conversational agents (ECA) from the Northeastern Relational Agents Lab have been developed for a variety of health-care communication scenarios over many years. In particular, Ehrenfeld et al. (2010) develop an ECA for counseling patients on their options for anesthesia prior to surgery, but the system cannot answer specific questions patients ask in their own words.

With no existing data in this domain, we seek to take advantage of pretrained and large language models (PLMs/LLMs) to develop our system in a data-efficient way while **robustly avoiding unsafe behavior**. Recent years have witnessed enormous progress on a wide range of NLP tasks, including conversational AI ones, thanks to engineering advances in training large scale, transformer-based neural language models (Bowman and Dahl, 2021; Srivastava, 2022; Wei et al., 2022; OpenAI, 2023; Chen et al., 2020; Hosseini-Asl et al., 2020). However, their deployment for practical tasks has been hindered by concerns about safety, such as the propensity of these models to regurgitate toxic language or hallucinate fake news (Bender et al., 2021; Dinan et al., 2022). In health-care settings, these concerns are especially problematic, as with insuf-
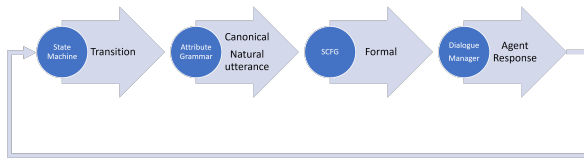
Figure 1: Generating a conversation cycles through four stages: transitioning in the state machine, which generates a unique attribute grammar production rule. The production rule translates to a canonical production, which is transformed into a JSON formal representation. The dialogue manage utilizes this representation to create an agent response, and the cycle begins again.

ficient controls PLMs could give harmful or even deadly advice (Bickmore et al., 2018).

To address these safety concerns, we have designed a neuro-symbolic system that uses PLMs for contextual natural language understanding (NLU) together with a rule-based dialogue manager and knowledge base. To bootstrap the system, we have used state machines to create simulated dialogues (Campagna et al., 2020) together with LLMs for paraphrasing, rather than crowdworkers as in the overnight method (Wang et al., 2015); further enhancement using Wizard-of-Oz (Kelley, 1984) methods is left to future work.

2 Methods

2.1 Conversational State Machine

A state machine can be used to model a multi-turn conversation for simulation purposes (Jurafsky et al., 1997; Campagna et al., 2020). Our implementation of conversational state machine models different conversational states as states in the state machine. The transitions in the state machine represent user and agent utterances that are possible for the given conversation state.

Figure 1 illustrates the overall structure of our data generation pipeline. Each transition can yield multiple synthetic user utterances via random choices in an attribute grammar, along with a canonical, context-independent version of the user utterance. An SCFG translates the canonical string into a JSON string that represents the meaning in intent-and-slot style. The dialogue manager uses this formal representation to determine the system response, expressing it with simple templates.

By polling the state machine and recording the utterance emissions for each transition, we can generate diverse dataset of conversations that a patient

preparing for a colonoscopy might have with the patient prep system (Figure 2). The state machine also encodes the dialog context, which allows the system to reference previous utterances. This allows for insertion of coreferential anaphors ("it" or "that") as well as generating follow-up questions: "Agent: You can't eat strawberries so close to the procedure. User: How about bananas?" Similarly, we expect "why?" questions to be very elliptical and only interpretable in context (Figure 2).

2.2 System Design

Contextual NLU via semantic parsing converts the user utterance into a valid canonical string, taking the previous context into account (Shin et al., 2021). As detailed in the next section, we train neural models for this task, without using an explicit module for dialogue state tracking. If the semantic parser does not return a valid canonical string (e.g., for an out-of-scope user question), the SCFG translation will fail to return a formal representation, triggering a request for the user to rephrase.

Once the semantic parsing module correctly parses the user utterance to a formal representation, it is processed by the dialogue manager. The dialogue manager has 4 modules to respond to user questions, one for each of the categories Food, Procedure, Task, and General. Each module has predefined rule-based templates that ensure the information provided to the patients is accurate, safe, and not misleading (Table 3, Appendix A).

Questions in the food category are time sensitive and thus the most challenging to handle. The food module answers questions after first consulting a food knowledge graph to calculate when a patient must stop consuming the item relative to the procedure. For example, in permission questions like "Can I eat strawberries?" the answer is "no" if the procedure is less than 5 days away, but "Yes, but you must stop eating strawberries on [stop_date]" if it is 5 or more days away.

Our knowledge graph is used to store the stoppage time for different food (or more generally, ingestible) items. Each item, based on its entity type (solid, liquid, medicine, supplement), has attributes such as "has seeds" or "has leaves" which determine the stoppage time. The existing FoodOn (He et al., 2018) and FoodKG (Fernández et al., 2020) resources do not cover relations such as "has_skin" or "has_seeds", so we augmented our knowledge graph by asking ChatGPT to list the 200 common
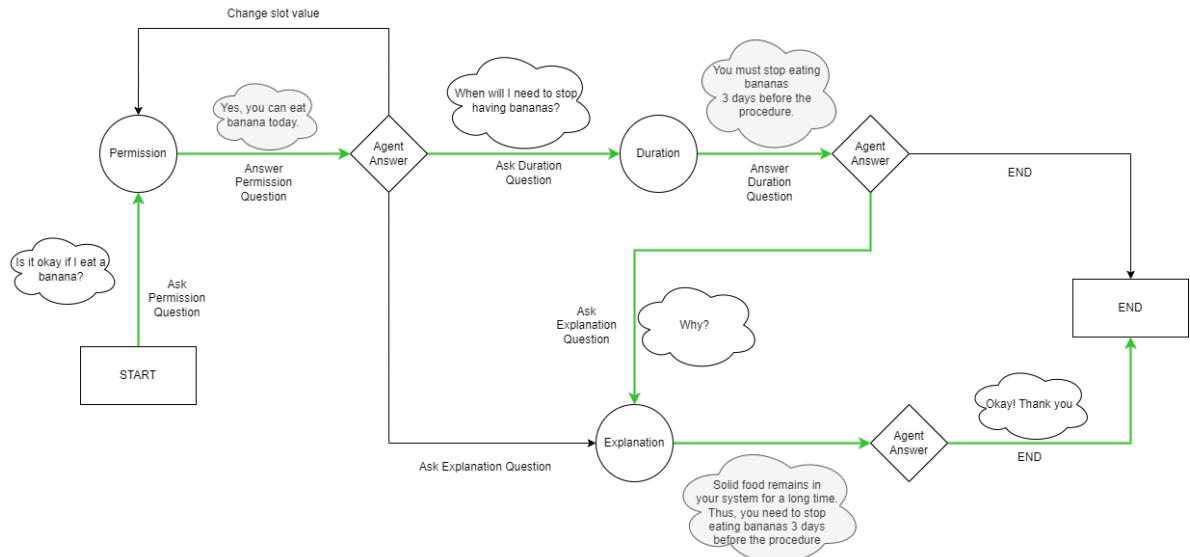
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Figure 2: An example conversation generation using the state machine, with utterances emitted on transitions. "Why?" is an incomplete query in isolation, requiring conversation context for full interpretation.

food items and beverages, along with 25 common over-the-counter medications and supplements including items that are mentioned in the information sheet provided to the patients. We then used ChatGPT to provide values for the essential food attributes by asking it yes/no questions (e.g., whether apples have seeds), followed by manual inspection to remove erroneous information.

2.3 Simulated and Challenge Datasets

To create a dataset of simulated conversations, we ran the conversational state machine 25,000 times, yielding 11,388 unique conversations that were split 80/5/15 into training, validation, and test sets, respectively; there is 3.84% overlap at a turn level between our training and test set. For each conversation, the procedure date is set randomly 1 to 10 days in the future.

While the simulated conversations include a variety of synthetic user utterances, they lack linguistic diversity. To enrich these utterances, we used GPT-3.5 and GPT-4 (OpenAI, 2023) to paraphrase 200 conversations from the test set.[1] Since we found the paraphrases from GPT-3.5 to be as good or better than those of GPT-4, we then used GPT-3.5 to paraphrase the entire training set, for a total cost of approximately $10.

To aid in the analysis of our system, we also created a handcrafted dataset of 25 conversations that cover all possible use cases of our system,

which we refer to as the challenge set. This set was created by one of the authors without access to the attribute grammar or the automatic paraphrases in the simulated dataset. Of these 25 conversations, 15 are within the scope of the current system, though the conversations often diverge from the simulated ones, especially in their use of follow-up questions.

Sample paraphrased conversations appear in a supplement to the paper along with challenge ones.

3 Experiments

3.1 Models

The goal of the system is to reliably provide accurate and safe answers to user questions. Before training our own models, we first qualitatively tested ChatGPT in a zero-shot setting for our task by providing it relevant information (patient information sheet and procedure date) and asking it questions we envisioned patients asking our system. We found that it did not reliably provide accurate answers to questions requiring temporal reasoning, and that its guardrails against providing medical advice often prevented it from answering questions that the system should be able to answer. We thus moved on to training our own smaller, faster models, which also come with fewer privacy concerns. We used the Hugging Face implementation of pre-trained BART (Lewis et al., 2020), fine-tuning the base model (with 140M parameters) for 2 epochs with a learning rate of 1e-5. We compared a semantic parsing model trained on the synthetic user

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[1] We used gpt-4-0314 and gpt-3.5-turbo-0301 model checkpoints via OpenAI's API.

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NLU	Soft Match Acc.	BLEU
Explicit	88.4	0.918
Implicit	56.3	0.206

Table 1: Our system with explicit NLU dramatically outperforms the end-to-end, implicit NLU baseline on the PARA-GPT-3.5 test set.

	Explicit	Implicit
Correct	17	10
Nonresponsive	34	14
Misleading	4	8
Incorrect	4	27

Table 2: Our system with explicit NLU has many fewer incorrect responses on the in-scope challenge set.

utterances against one trained on the GPT-3.5 paraphrases, and found that the latter achieved 95.0% accuracy on the PARA-GPT-3.5 test set, a 6.5% absolute gain over the former. As a baseline for comparison, we also trained an end-to-end question answering model on the user inputs and system outputs; this model performs NLU implicitly, bypassing the dialogue manager and KB.

3.2 Explicit vs. Implicit NLU

To evaluate the accuracy of our paraphrase-trained model against the implicit NLU baseline, we employed a soft match for answer polarity, checking if "yes" or "no" is mentioned in the correct answer and also in the predicted answer. We qualitatively checked this soft match metric on a handful of conversations and found it to be generally effective at identifying correct/incorrect matches. Table 1 shows that the soft match accuracy for the explicit NLU model is dramatically higher (30% absolute) than the implicit NLU baseline, and has much higher BLEU scores as well.

Looking at the answers provided by the implicit NLU baseline, we find that it can reliably answer questions that can be memorized as static FAQs, but it does not reliably answer questions requiring temporal reasoning. For example, whether orange juice is allowed depends on how close one is to the procedure date, and thus the baseline model will sometimes respond to a question like "Can I have orange juice tomorrow?" with "Yes, you may drink orange juice tomorrow" when the correct answer is "No, you cannot have orange juice tomorrow." Such incorrect answers could easily lead to a user being inadequately prepared for a colonoscopy. By contrast, with the explicit NLU model, when the system does not respond correctly, the response is usually recognizable as a non-sequitur, with only a small number of requests to rephrase.

3.3 Challenge Set

We also conducted an exploratory analysis of our system compared to the implicit NLU baseline on the in-scope subset of the challenge set. Three

authors judged the responses as correct, nonresponsive, misleading or incorrect; Table 2 shows the majority counts. Without defining these terms, chance-corrected agreement as measured by Krippendorff's α was only 0.48. Nevertheless, a highly significant difference was found between the two systems, χ^2 (3, N=59) = 28.5, $p < .001$. While both systems fared rather poorly overall, as the challenge set included a variety of unanticipated questions and made richer use of the context, the implicit NLU system clearly had many more incorrect responses. Although looking at the handful of incorrect responses our system made turned up some fixable bugs, we expect the misleading responses to be the more serious research challenge, as they depend on how patients might interpret responses in context (Tables 4–5, Appendix A).

4 Conclusions

Our initial development of a neuro-symbolic conversational guide for colonoscopy prep demonstrated that automatic paraphrasing of simulated conversations using GPT models can be successfully used to generate a diverse dataset for drawing meaningful insights into model behavior. We found that GPT and BART language models struggle with temporal reasoning; thus systems that rely upon explicit NLU and temporal reasoning are better suited for answering critical, time-sensitive questions. Further, we found few incorrect responses generated from our system under novel and out-of-scope situations, but misleading ones remain a challenging concern.

In future work, we plan to enhance and extend the system after collecting Wizard-of-Oz data with patients and re-evaluate the prevalence of misleading responses. We also plan to experiment with making the system more proactive by quizzing patients on their understanding of the instructions, in order to investigate whether improved understanding of diet restrictions and procedural steps leads to improved adherence to the prep protocol.

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6

A Appendix

Food Category

Permission U: Can I eat a strawberry tomorrow? S: No, you may not eat strawberries tomorrow.

Duration U: When can I eat a strawberry? S: You can have strawberries up to 5 days before the procedure. Your procedure is on 6th April 2023 at 5:00pm, you can have strawberries up to 5:00pm on 1st April 2023.

Explanation U: Why can I not eat a strawberry tomorrow? S: Your procedure is 3 days away and you need to stop having strawberries, as it can cause errors in the procedure and hence should not be consumed.

Task Category

Description U: What is in the instructions? S: The instructions guide you through the preparation for the procedure.

Duration U: By when should I read the instructions? S: You should read the instructions at least a week before your procedure.

Explanation U: Why should I read the instructions? S: The instructions help you prepare for the procedure. It is important that you understand the instructions and follow them to ensure that you are prepared for the procedure.

Procedure Category

Description U: What is a colonoscopy? S: A colonoscopy is an inspection of your colon and your large intestine.

Duration U: When is my procedure? S: Your procedure is on 6th April 2023 at 5:00pm.

Explanation U: How long is my procedure? S: The procedure should be 2 to 4 hours long.

Table 3: Sample responses for different categories and subtypes of user questions. Notice how food related questions are time sensitive in nature, while task questions can be answered without logical reasoning.

User:	Can I have ice cream today?
System:	Your procedure is four days away. Yes, you can still have ice cream.
User:	What if it has nuts in it? You told me to avoid nuts.
System:	You can have ice cream up to 2 days before the procedure. Your procedure is on Friday, 19 May at 09:30pm, you can have ice cream up to 09:30pm on Wednesday, 17 May.

Table 4: Example misleading system response from challenge set. After the system correctly says that the patient may have ice cream 4 days in advance of the procedure, the patient asks whether ice cream is still allowed if it contains nuts. Here, the system should say no, but instead says that the patient can have ice cream up to 2 days before the procedure. While this response is literally correct, it does not directly answer the patient's question; as such, it could easily mislead the patient into thinking an indirect positive answer had been given (via a Gricean quantity implicature).

User:	Do I have to stop taking my insulin before my colonoscopy?
System:	I am sorry, but I couldn't understand. Could you please rephrase?
User:	Can you contact my doctor?
System:	I am sorry, but I cannot provide information about insulin.
User:	Thank you. What should I do until I hear from them?
System:	The prescription contains Mirolax, Dulcolax and Gatorade.

Table 5: Example from out-of-scope portion of challenge set with incorrect responses that are not misleading. In this scenario, the user asks the system about adjusting their insulin dosage. Ideally our system should direct the user to seek approval from the doctor. However, for the first question, our system creates an illegal canonical string and replies that it does not understand the user query. For the next question, it creates a legal canonical string, and responds that it cannot provide information about insulin as it was not present in our knowledge graph. In the final turn, the system misunderstands the question as pertaining to the prep mix and responds with a non-sequitur.