Goal-Oriented Dialogue Grounding over Structured Lists

Anonymous ACL submission

Abstract

Document-grounded goal-oriented dialogue systems are designed to respond to user queries by leveraging relevant external information. Previous studies have mainly focused on handling free-form documents, often overlooking structured data such as list items, which can represent a range of nuanced semantic relations. Motivated by the observation that even advanced language models like GPT-3.5 often miss semantic cues from lists, this paper aims to enhance dialogue systems for better interpretation and use of structured lists. To this end, we introduce the List2Dial dataset, a novel benchmark to evaluate the ability of dialogue systems to respond effectively using list information. This dataset is created from unlabeled customer service documents using language models and model-based filtering processes to enhance data quality, and can be used both to fine-tune and evaluate dialogue models. Apart from directly generating responses through fine-tuning models, we further investigate the explicit use of Intermediate Steps for List (ISL) information, including list types and alignment with user background, which better reflects how humans assess list items before formulating responses. Our experimental results demonstrate that models trained on List2Dial with our ISL approach outperform baselines across various metrics. Specifically, our fine-tuned Flan-T5-XL model shows increases of 3.1% in ROUGE-L, 4.6% in correctness, 4.5% in faithfulness, and 20.6% in completeness compared to models without applying filtering and the proposed ISL method. We make our source code and dataset publicly available.

1 Introduction

Document-grounded goal-oriented dialogue systems aim to assist users in interactively seeking information from external documents to address various real-world problems with more complex scenarios as seen in customer support. While previous work has primarily treated these external documents as unstructured text (Campos et al., 2020; Feng et al., 2020, 2021; Wu et al., 2021; Gao et al., 2022; Zhao et al., 2023), a significant portion of real-world content is presented in structured formats like lists. For instance, approximately 45% of passages in public policies in the UK [1] comprise lists to effectively present conditions to be verified, action-based steps, or general itemized information. Despite this prevalence, existing research has largely overlooked the nuanced challenges posed in understanding structured list data in relation to the complex background context of users accessing this information. Some studies have explored list information for condition verification purposes (Sun et al., 2021), but not in the realistic setup where retrieval is required to differentiate between conditional and non-conditional lists based on user backgrounds. Surprisingly, SOTA models such as GPT-3.5 (OpenAI, 2022) and Mixtral-8x7B (Jiang et al., 2024) show unsatisfactory performance on nuanced list information, as illustrated in Figure 1, despite their strong results on natural language inference (NLI) and reasoning tasks (Qin et al., 2023; Liu et al., 2023a; Guo et al., 2023).

Our work aims to address these limitations while testing LLM capabilities for more nuanced list-based content. Thus, we propose a novel benchmark called List2Dial, designed to evaluate dialogue systems on understanding list semantics with respect to user background. The dataset introduces diverse styles of list content for document grounding, such as specifying logical conditions for validation, describing actionable steps, or simply separating items without explicit logical relations. For dialogue turns, we construct scenarios where the user's background information may align with, contradict, or not address specific list items, which are oftentimes used to determine system responses.

Additionally, we explore pipeline approaches that focus on fine-tuning smaller, more efficient

[1] https://www.gov.uk

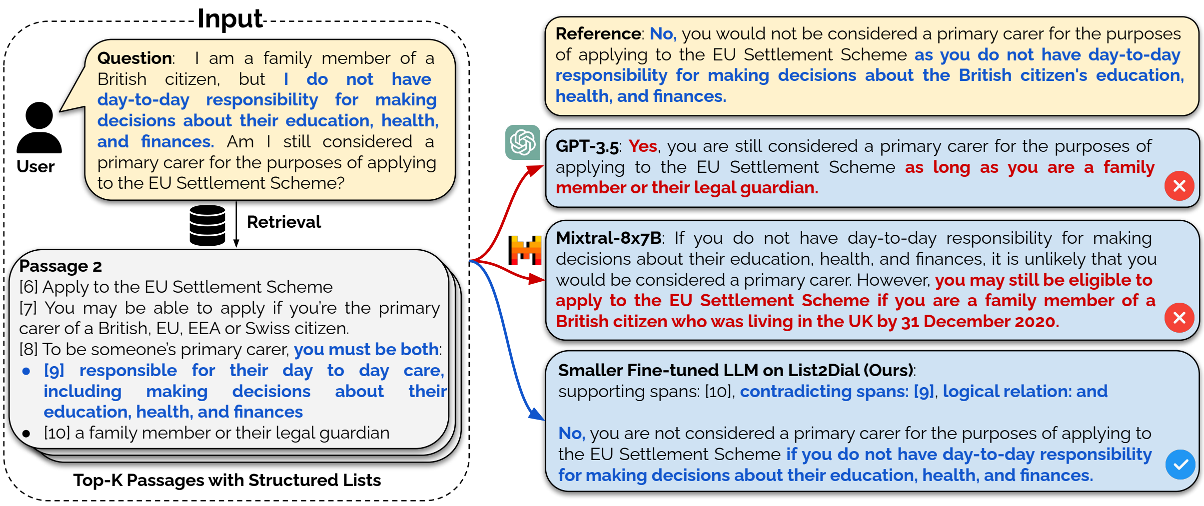


Figure 1: An example of a dialogue system response to the user question grounding over list-based contents. Blue texts indicate semantic cues for correct reasoning, while red texts indicate incorrect reasoning.

A Passage with a Step List
Title: Provide driving tests for your employees Qualifying as a delegated driving examiner Your employees must then: • complete an initial training course • reach an appropriate standard in the delegated driving examiner theory and practical tests
A Passage with an Option List
Title: Workplace pensions You can get free, impartial information about your workplace pension options from: • the Money Advice Service • the Pensions Advisory Service • Pension Wise if you're in a defined contribution pension scheme
A Passage with a Non-Action Info List
Title: Money and property when you divorce A mediator can help you and your ex-partner agree on how to split money and property. Mediation is not relationship counselling. It can help you agree on how you'll divide your assets, including: • pensions • property • savings

Table 1: Examples of passages with lists as steps, unordered options, and non-action itemized information.

LLMs, demonstrating their potential to outperform larger LLMs on our benchmark dataset. Inspired by recent successes in using large language models for automated data creation (He et al., 2024; Choi et al., 2024; Oh et al., 2024), we employ language models to simulate goal-oriented dialogues grounding over structured lists, and also investigate how to filter low-quality data to further improve performance.

Given that LLMs can often overlook logical relations among list items and their semantic alignment with user status (See Figure 1), we further investigate whether we can emphasize the semantic cues in lists and improve end-to-end performance. Thus, we introduce 'Intermediate Steps for List information (ISL)' in our approach, aligning better with how humans interpret list items before responding. By explicitly modeling structured list data and user contexts with ISL, our method outperforms baseline LLMs and fine-tuned models on the List2Dial dataset. Specifically, our ISL fine-tuned Flan-T5-XL model (Chung et al., 2024) shows increases of 3.1% in ROUGE-L, 4.6% in correctness, 4.5% in faithfulness, and 20.6% in completeness compared to baseline fine-tuning.

Our contributions are summarized as follows: (1) We introduce a novel benchmark called List2Dial that is designed to evaluate dialogue systems on question answering tasks involving nuanced list-based content. (2) We propose the Intermediate Steps for List information (ISL) method, which enhances alignment with human interpretation of list items before generating responses. (3) We demonstrate that fine-tuned models leveraging the ISL method significantly outperform larger LLMs on the List2Dial dataset, establishing a new state-of-the-art baseline for this task.

2 List2Dial

In this section, we first formulate the problem of generating system responses based on different types of lists and user scenarios. We then de-

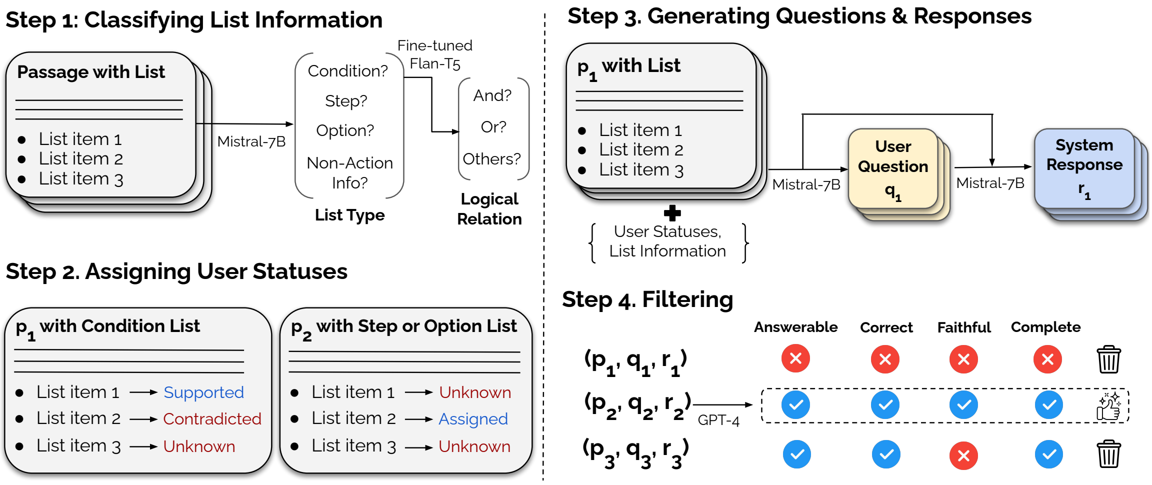


Figure 2: Overview of the List2Dial dataset creation pipeline: (Step 1) classifying list types and logical relations given passages with lists, (Step 2) assigning user statuses for each list item, (Step 3) generating user questions and system responses from the previous steps, and (Step 4) filtering out noisy samples based on four metrics.

tail the methodology used to create our List2Dial dataset, which involves an automated and pipeline-based simulation process utilizing language models. Lastly, we present more details about the dataset for training and validation.

2.1 Problem Formulation

To formulate the problem, we first examine the various ways lists can be structured and how user scenarios interact with these lists. Our goal is to develop dialogue systems capable of providing responses specific to user scenarios based on relevant structured lists. We categorize lists commonly found in support documents (Feng et al., 2020; Sun et al., 2021) into the following types: conditions for eligibility ('condition'), step-by-step instructions ('step'), options for users to choose from ('option'), and the rest being mostly non-action information without explicit logical relation ('non-action info').

We define our task with an input consisting of a set of passages $\mathcal{P} \in p_1, \ldots, p_N$, a user question q_i, and the system response r_i as the model output. Each passage p_n contains list items. Each user question q_i includes user scenarios or statuses. We follow a retrieval-augmented generation (Lewis et al., 2020) pipeline where we employ a passage retriever to select the top-K most relevant passages for each user question. Based on retrieved passages and a user question, a language model generates system response by reasoning over the information described in the relevant text. Specially, we introduce 'Intermediate Steps for List information (ISL)', including: (1) identifying relevant passages among top-K passages, (2) classifying list types (i.e., conditions, steps, items, non-action info), (3) identifying logical relations between condition list items (i.e., and, or), and (4) determining entailment based on user statuses for condition list items (e.g., supported, contradicted, unknown) or selecting list items aligned with user statuses for step/option list items. The final system response, r_i, is generated as free-form text based on these intermediate steps.

2.2 Document Corpus

We consider two corpus sources ConditionalQA (Sun et al., 2021) and MultiDoc2Dial (Feng et al., 2021), both of which contains numerous diverse list items in their passages due to the nature of customer support documents. This allows us to develop our own dataset based on their document content. Instead of utilizing their annotations, which focus on plain text information, we use only the unlabeled documents and create all new instances as specified in Section 2.3.

ConditionalQA (Sun et al., 2021) is a dataset designed for conditional reading comprehension tasks. It uses documents related to public welfare in the UK (e.g., "Apply for Visitor Visa") and includes annotations for yes/no or extractive questions. We use document content from ConditionalQA for creating training, validation, and test sets.

MultiDoc2Dial (Feng et al., 2021) is based on public support documents such as 'ssa.gov' and 'va.gov'. We use the unlabeled documents from the MultiDoc2Dial corpus to increase the number of test samples in List2Dial. We can further evaluate models on domains that were not seen during training using data samples created from this source.

List Types	User Questions	System Responses
Condition	If there is no break clause mentioned in the tenancy agreement, **can I as a tenant end the tenancy early with your approval?**	Yes, you may be able to end the tenancy early with your landlord's approval, even if there is no break clause in the tenancy agreement.
Step	I'm setting up a business partnership. First, I need to decide on a name for the partnership. **What should I do next?**	Next, you need to choose a 'nominated partner' and register with HM Revenue and Customs (HMRC) to complete the setup of your business partnership.
Option	I need a private firm to conduct my drivers' medical exam for a lorry or bus license application. **Are there any other similar services that I can consider instead?**	You could also consider visiting your GP to complete the medical examination section on the D4 form for your lorry or bus driver license application.
Non-Action Info	I'm considering suspending or leaving my course. **Which types of student finance do I need to stop paying?**	You need to stop paying your student finance payments for Maintenance Loans, Tuition Fee Loans, and any grants or bursaries you may be receiving.

Table 2: Examples of generated questions and responses for each list type in the List2Dial dataset.

2.3 Dataset Creation Pipeline

Given the lack of existing datasets designed for building goal-oriented dialogue systems focused on structured lists, we propose a dataset creation pipeline specifically for addressing this challenge. First, we extract passages containing lists from unlabeled documents described in Section 2.2. [2] We aim to automate the process based on the advances of LLMs with the pipeline illustrated in Figure 2.

Step 1. Classifying list information To generate user queries with different contexts, we first identify the type of list information in each passage. Passages are categorized into one of four list types: 'condition', 'step', 'option' or 'non-action info'. For passages under the condition type, we also classify their logical relations: 'and' or 'or'. To this end, we fine-tuned Flan-T5-XL (Chung et al., 2024) using 72 manually annotated training samples. This approach significantly improved performance, achieving an F1 score of 78.0% on 30 manually annotated validation samples. See the details of the logical relation classifier in Appendix A.

Step 2. Assigning user statuses Next, we assign user statuses to one or more list items. For condition lists, we determine whether each item supports, contradicts, or is unknown in the user scenario. For step and option lists, we randomly select an item and assign it as the user status. For 'non-action info' lists, we create questions without specific user background. For condition lists, we aim to provide concluded answers ('yes', 'no', 'uncertain') that can be derived by considering both the logical relations and the user statuses of list items. As illustrated in Table 3, if a list has an 'And (Conjunctive)' relation where item 1 supports and item 2 contradicts the corresponding user statuses, the deduced answer is 'no'.

Logical Relation	User Status 1	User Status 2	Short Answer
And (Conjunctive)	Supported	Supported	Yes
	Supported	Contradicted	No
	Supported	Unknown	Uncertain
Or (Disjunctive)	Supported	Contradicted	Yes
	Contradicted	Contradicted	No
	Contradicted	Unknown	Uncertain

Table 3: Concluded answers derived from the logical relations and the user statuses of list items.

Step 3. Generating user questions and system responses Based on list types and assigned user statuses, we sequentially generate user questions encompassing specific user scenarios and system responses. For this process, we employ Mistral-7B-Instruct, using three-shot in-context examples for each list type.

Step 4. Filtering created samples We aim to further improve the data quality by filtering out the instances with inaccurate information or hallucinations. To validate model-based automated approach, we first manually annotate 20 examples across four dimensions: question answerability, as well as response correctness, faithfulness, and completeness. We then obtain GPT-4-based (OpenAI, 2023) judgements for the same 20 examples and measured inter-annotation agreement (IAA) between human and model-based verifications. The Cohen's kappa scores are 100.0 for answerabil-

[2]The corpus we use is in HTML format, so we employ the <h> tag as a passage splitter and the <li> tag to indicate passages that contains list items.

Split	Condition	Step	Option	Non-Action Info	Total
Train	524	224	270	369	1,387
Dev	58	43	36	51	188
Test	346	161	215	201	923

Table 4: Data statistics of List2Dial.

ity, 63.0 for correctness, 65.5 for faithfulness, and 55.0 for completeness (see the prompt for verification in Appendix B). We retain samples only when questions are answerable and responses are correct, faithful, and complete, resulting in about 51.0% of the original samples after filtering. As a result, we generate 1.4K, 0.2K, and 0.9K samples for the training, development, and test sets, respectively. Examples of generated samples and the dataset statistics are detailed in Table 2 and Table 4.

3 Experiment

3.1 Experiment Setup

We consider models of various sizes to evaluate on List2Dial. For the larger models, we use GPT-3.5 [3] and Mixtral-8x7B-Instruct [4](Jiang et al., 2024) in the 0- and 4-shot setting, where 4-shot examples are randomly selected from samples with four different list types. For the smaller LLMs, we fine-tune Flan-T5-XL (Chung et al., 2024) and Mistral-7B-Instruct[5] (Jiang et al., 2023) on the List2Dial training set. We adopt QLoRA (Dettmers et al., 2024) with a learning rate of 5e-4 for Flan-T5-XL over 10 epochs and 2e-5 for Mistral-7B-Instruct over 2 epochs. For retrieval-augmented generation, we apply the LlamaIndex library (Liu, 2022), using 'all-mpnet-base-v2' (Reimers and Gurevych, 2019) as the passage retriever. We set the top-K to 3, achieving a recall@3 of 93.0% on our training set. For the questions without relevant passages retrieved, they are considered as 'unanswerable'. An example input and output with intermediate steps are shown in Table 5.

3.2 Evaluation Metric

To evaluate the responses generated by models on the List2Dial test set, we adopt both non-LLM-based and LLM-based evaluation. Among the non-LLM-based evaluation, we select ROUGE-L (Lin, 2004), which measures the lexical overlap between reference responses and generated responses. Additionally, recent work (Liu et al., 2023b; Kim et al., 2024) shows that advanced LLMs can effectively conduct fine-grained evaluations, such as detecting hallucinations or missing crucial information, aligning well with human judgments. Therefore, we adopt the LLM-based evaluation using GPT-4 (OpenAI, 2023) to measure whether models generate logically correct responses ('correctness'), whether the responses are solely based on the relevant passage ('faithfulness'), and whether the responses include all the necessary information ('completeness'). See Appendix C for the details.

[3] gpt-3.5-turbo-0125
[4] Mixtral-8x7B-Instruct-v0.1
[5] Mistral-7B-Instruct-v0.2

Input

Given the passages, generate the system response to the user's question, including intermediate steps:
Passage 1
[1] Master's Loan
[2] Healthcare and social work
[3] You can't get a Postgraduate Master's Loan if:
• [4] you are eligible for an NHS bursary
• [5] you get a Social Work Bursary
Passage 2
[6] Social work bursaries
[7] Eligibility
[8] Social work bursaries are available to eligible social work students who:
• [9] don't get funding from their employer
• [10] don't already have a higher education social work qualification
Passage 3
[11] Social work bursaries
[12] If you're training for social work you may get a bursary.
[13] Social work bursaries:
• [14] help with living costs and tuition fees
• [15] don't depend on your household income

User question: I already hold a higher education social work qualification. Am I still eligible for a social work bursary?

Output

Intermediate Steps:
Relevant Passage: 2
List Type: Condition
Condition Status: [7]Unknown, [8]Contradicted
Logical Relation: And

Response: You are not eligible for a social work bursary because you already hold a higher education social work qualification.

Table 5: A sample for response generation with intermediate steps. Text in blue highlights rationale information for validation.

3.3 Experimental Results

We present evaluation results in Table 6. Notably, fine-tuned language models significantly outperform larger language models. For instance, the performance of Mixtral-8x7B-Instruct with 4-shot

Method	Model Size	Filtering	ROUGE-L	Correctness	Faithfulness	Completeness	Average
GPT-3.5 (0-shot)	Unknown	-	48.5	76.1	81.0	19.4	56.3
GPT-3.5 (4-shot)	Unknown	✓	54.2	86.9	85.6	63.3	72.5
Mixtral-8x7B-Instruct (0-shot)	47B	-	42.6	78.0	74.1	48.3	60.8
Mixtral-8x7B-Instruct (4-shot)	47B	✓	49.7	83.2	78.7	56.6	67.1
Flan-T5-XL (FT)	3B	✗	56.8	83.0	83.3	51.0	68.5
Flan-T5-XL (FT)	3B	✓	58.9 (+2.1)	85.3 (+2.3)	85.6 (+2.3)	64.4 (+13.4)	73.6 (+5.0)
+ ISL	3B	✓	**59.9 (+3.1)**	**87.6 (+4.6)**	**87.8 (+4.5)**	**71.6 (+20.6)**	**76.7 (+8.2)**
Mistral-7B-Instruct (FT)	7B	✗	51.4	89.7	82.2	78.4	75.4
Mistral-7B-Instruct (FT)	7B	✓	52.5 (+1.1)	**90.5 (+0.8)**	**85.4 (+3.2)**	81.2 (+2.8)	77.4 (+3.0)
+ ISL	7B	✓	**53.9 (+2.5)**	89.6 (-0.1)	85.3 (+3.1)	**82.2 (+3.8)**	**77.8 (+3.4)**

Table 6: Main experiment results for response generation on the List2Dial test set across four metrics. ISL refers to generating intermediate steps for lists before generating responses. 'FT' refers to fine-tuned models. Filtering indicates whether model-based filtering was applied to improve the quality of the training set.

examples lags behind fine-tuned Flan-T5-XL and Mistral-7B-Instruct by approximately 10.0% in average score. This underscores the importance of fine-tuning models to deepen the understanding of nuanced semantic relations in list information for generating dialogue responses. Our findings further confirm the ability of fine-tuned efficient language models to outperform larger ones on specific tasks, consistent with Li et al. (2024); Fu et al. (2024).

The results also demonstrate that model-based filtering of the training data consistently results in performance improvements across two models and four metrics, despite using almost half the number of training samples. Specifically, Flan-T5-XL trained on the filtered dataset outperforms the baseline by up to 5.0% on average. Notably, filtering particularly helps to reduce incomplete response generation, achieving a 13.4% improvement.

Additionally, our ISL method, which generates intermediate steps for list information, helps further improve performance. For instance, Flan-T5-XL with ISL achieves a 3.2% higher performance than without ISL across four metrics on average. However, there are exceptions where ISL degrades the correctness and faithfulness of the baselines, possibly due to incorrect information in the generated ISL that propagates errors to final responses. We plan to investigate this issue in future work.

Moreover, models based on Flan-T5-XL achieve higher ROUGE-L (59.9% vs. 53.9%) and faithfulness (87.8% vs. 85.3%) scores compared to those trained on Mistral-7B-Instruct. This could be partially because Mistral-7B-Instruct is more verbose than Flan-T5-XL, often producing unnecessary phrases. Conversely, this verbosity of Mistral-7B-Instruct models rather helps produce more correct (87.6% vs. 89.6%) and complete (71.6% vs. 82.2%) responses than Flan-T5-XL, highlighting a trade-off between base language model choices.

4 Analysis

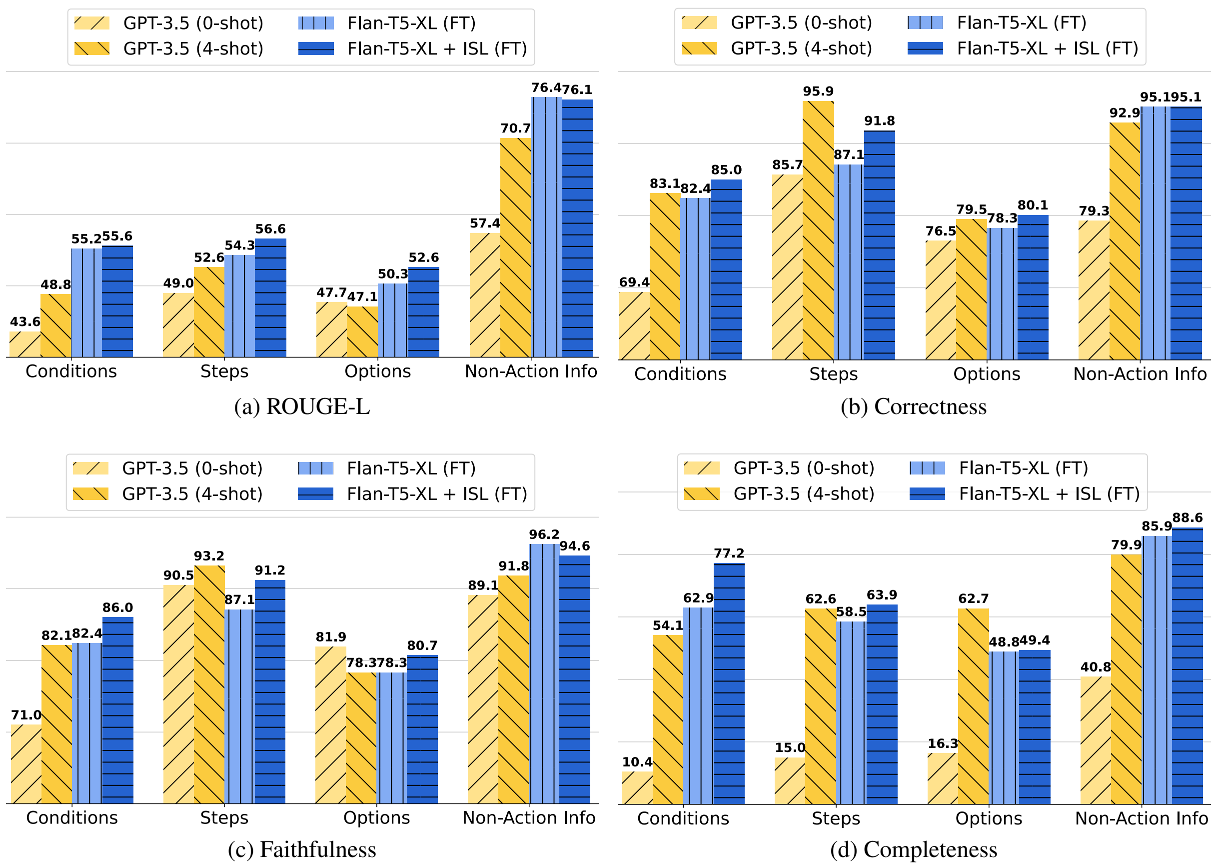
Identifying and understanding different types of lists and their associated semantic relations in structured passages remains a significant challenge for LLMs. Despite their impressive performance on various Question Answering (QA) benchmarks [6], our findings indicates LLMs struggle to generate accurate responses for specific list types.

4.1 Performance on Different List Types

Different list types necessitate distinct styles of user questions and corresponding intermediate steps. To understand the performance disparities, we analyzed four list types from the List2Dial test set: conditions, steps, options, and non-action information. Figure 3 illustrates that GPT-3.5 particularly struggles with responding over condition and non-action information lists compared to fine-tuned Flan-T5-XL by a large margin.

We observe that leveraging ISL consistently and significantly improves performance, with two exceptions in the non-action information list type regarding ROUGE-L and faithfulness. Specifically, Flan-T5-XL with ISL outperforms the baseline by up to 2.6% in correctness, 3.6% in faithfulness, and 14.3% in completeness on condition lists, highlighting the benefit of generating intermediate steps for more accurate responses. However, the exceptions observed in non-action information lists suggest that these lists do not typically require complex intermediate steps, such as tracking user status or logical relations. As a result, training the model on these lists might lead to the generation of unnecessary information in responses, thereby decreasing performance.

[6] https://mistral.ai/news/mixtral-of-experts



(a) ROUGE-L

(b) Correctness

(c) Faithfulness

(d) Completeness

Figure 3: Performance breakdown across the different list types.

Method	R-L	Correct	Faithful	Complete	Avg
		Seen Domain			
GPT-3.5 (0-shot)	50.4	76.5	82.2	20.5	57.4
Flan-T5-XL (FT)	60.8	87.4	87.6	68.6	76.1
+ ISL	**61.4**	**89.8**	**89.8**	**75.9**	**79.2**
Mistral-7B-Ins (FT)	52.6	90.1	83.1	83.8	77.4
+ ISL	**54.5**	**90.3**	**84.9**	**86.2**	**79.0**
		Unseen Domain			
GPT-3.5 (0-shot)	48.2	75.6	79.5	18.0	55.3
Flan-T5-XL (FT)	56.4	82.8	83.1	59.3	70.4
+ ISL	**58.0**	**84.8**	**85.3**	**66.5**	**73.6**
Mistral-7B-Ins (FT)	52.5	**91.1**	**88.4**	**78.1**	**77.5**
+ ISL	**53.2**	88.6	85.9	77.3	76.3

Table 7: Performance comparison on seen and unseen data.

4.2 Performance on Seen and Unseen Domains

To evaluate the generalizability of our approach on unseen domains, we use samples from the ConditionalQA corpus for the seen domain and samples from the MultiDoc2Dial corpus for the unseen domain. As shown in Table 7, the fine-tuned models with ISL consistently outperform those without ISL on seen data, achieving up to a 3.1% higher average score. This trend extends to Flan-T5-XL with ISL on the unseen domain, showing a 3.2% increase, which demonstrates the robustness of fine-tuning Flan-T5-XL with ISL. However, Mistral-7B-Instruct with ISL struggles on the unseen domain, with a 0.8% decrease in predicting correct intermediate steps, highlighting the need for further improvements in generalizability.

4.3 Error Cases

Analyzing error cases provides valuable insights into the limitations of our models. In Table 8, fine-tuned Flan-T5-XL with ISL generates the phrase ‘within 30 days or you could face a financial penalty’, which is not present in the gold passage. Additionally, the model omits crucial information such as ‘check with the financial aid office ...’, which should have been included in the responses. Future work could explore more sophisticated approaches, such as preference optimization (Wu et al., 2024; Rafailov et al., 2024), to improve the generation of more faithful and complete responses in goal-oriented dialogue grounding over list information.

Gold Passages	Evaluation on Generated Responses
Title: Running a limited company Other changes you must report You must tell HMRC if: • your business' contact details change - for example, your name, gender, business name • you appoint an accountant or tax adviser	**Question:** I have recently changed the name of my business. Do I need to inform HMRC about this update? **Generated Response:** Yes, you need to inform HMRC about the name change of your business within 30 days or you could face a financial penalty. **Evaluation:** Correct, Unfaithful, Complete
Title: How to Correct or Update Your FAFSA Application How do I make changes to my FAFSA form? Submit your new information: • Write in the corrections or updates on your paper SAR, sign it , and mail it to the address provided on the SAR . • Check with the financial aid office at the school you plan to attend; the school might be able to make changes for you electronically.	**Question:** I need to make some corrections and updates to my FAFSA form. What should I do next with my paper SAR? **Generated Response:** Next, you should write in the corrections or updates on your paper SAR, sign it, and mail it to the address provided on the SAR. **Evaluation:** Correct, Faithful, Incomplete

Table 8: Sample errors, e.g., 'unfaithful' or 'incomplete', in generated responses by fine-tuned Flan-T5-XL with ISL. Text in red marks the information related to the errors.

5 Related Work

Document-Grounded Goal-Oriented Dialogue Our work is generally related to the document-grounded goal-oriented dialogue task (Feng et al., 2020, 2021; Wu et al., 2021; Gao et al., 2022; Zhao et al., 2023; Le et al., 2023). While previous research has largely concentrated on dialogue systems that respond to information-seeking user questions based on plain text knowledge, they often overlook user requests that involve verifying conditions found in support documents. Although some work, such as ShARC (Saeidi et al., 2018) and ConditionalQA (Sun et al., 2021), has begun to address this by focusing on conditional content presented as lists within documents, these tasks are still somewhat distant from real-world scenarios involving differentiating from other types of text and structured content. Our work bridges this gap by recognizing a broader range of list types and nuanced semantic relationships indicated by lists. We propose a novel approach that leverages large language models (LLMs) to better handle these complexities, thereby supporting further research in LLM-based dialogue systems.

Intermediate Steps Our approach involving Intermediate Steps for List information (ISL) for goal-oriented dialogue systems is generally related to generating intermediate reasoning for large language models (Wei et al., 2022; Kojima et al., 2022; Zhang et al., 2022; Zhou et al., 2022; Yao et al., 2023; Huang and Chang, 2023; Yu et al., 2023; Wang and Lu, 2023), which enhances the reasoning ability of large language models. While most previous works focus on using intermediate reasoning in for free-form text, structured approaches to intermediate reasoning have been proposed for mainly for specific tasks such as code generation (Li et al., 2023). Our work specifically focuses on understanding of the nuanced semantic relations for goal-oriented dialogue tasks. Additionally, our setup is within the context of data augmentation, featuring a development data simulation pipeline. We emphasize a pipelined approach that integrates data augmentation and efficient fine-tuning to enhance the performance of smaller LLMs, particularly in handling list semantics.

6 Conclusion

We present an novel pipeline-based approach to enhance document-grounded goal-oriented dialogue systems by addressing the nuanced challenges posed by list-based content. Our primary contributions include the introduction of the List2Dial dataset, a novel benchmark designed to assess dialogue systems' ability to effectively handle and respond to list information. Additionally, we develop the Intermediate Steps for List (ISL) method, which mirrors human interpretive processes for list items. Our experiments demonstrate that our approach, based on efficient fine-tuned models, consistently outperforms baseline approaches. By emphasizing the importance of dialogue systems' ability to handle list-based content with dynamic and nuanced semantics, our work paves ways for future research to further refine dialogue systems and expand their applicability across various domains.

Limitations

There are certain limitations in current scope of this work: (1) Although we currently handle only two types of logical relations in conditional lists, namely ‘and’ and ‘or’, there are more diverse logical relation types, such as ‘nor’ or nested relations, in passages containing lists. We plan to investigate these in future work. (2) While we focus only on single-turn dialogue tasks in this paper, multi-turn dialogues grounding over structured lists, where systems need to respond considering dialogue history, can be more practical. We leave this exploration of multi-turn goal-oriented dialogues grounding over structured lists for future work. (3) Evaluating models’ generation across ‘correctness’, ‘faithfulness’, and ‘completeness’ using GPT-4 is costly (Tang et al., 2024), which hinders more extensive evaluations, and is somewhat less accurate compared to human evaluation. In the future, we aim to develop an automatic evaluation method for document-grounded goal-oriented dialogue systems that is less expensive and more accurate.

Ethical Considerations

The dataset and models presented in this work have some ethical considerations: (1) The data simulation process should ensure diversity and avoid representation biases by incorporating input from humans with diverse backgrounds; (2) The goal-oriented dialogue system should provide transparent explanations for its responses to build appropriate trust with users; (3) Further testing is needed to proactively evaluate fairness and safety issues before deployment to real users, in order to prevent harm.

References

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A Details of Logical Relation Classifier

We found that classifying logical relations between list items is surprisingly difficult for large language models using in-context learning. Table 9 shows that Mistral-7B-Instruct, and even the larger Mixtral-8x7B-Instruct, with 8-shot in-context examples, struggle with the seemingly simple task of classifying 'And' or 'Or,' achieving F1 scores lower than 30 on the validation samples. To address this issue, we fine-tuned Flan-T5-XL using 72 manually annotated training samples and achieved an F1 score of 78.0 on 32 manually curated validation samples.

Model	**And F1**	**Or F1**	**Avg F1**
Flan-T5-XL (72-shot FT)	**77.6**	**78.4**	**78.0**
Mistral-7B-Instruct (8-shot IC)	34.9	22.7	28.8
Mixtral-8x7B-Instruct (8-shot IC)	49.4	4.1	26.8

Table 9: Comparison of models for classifying logical relations on 32 manually curated validation samples. 'FT' refers to fine-tuning, and 'IC' refers to in-context learning.

B Prompt for Model-based Data Filtering

Table 10 describes the prompt used for filtering out noisy samples in which user questions are considered unanswerable or the system responses are found to be incorrect, unfaithful, or incomplete on the given context.

C Prompt for Response Evaluation

Table 11 describes the prompt evaluating whether generated responses are correct, faithful, or complete based on the given context and the user question.

You will be evaluating a system's response to a user question, given some context. Here is the context:

<context>
{{CONTEXT}}
</context>

Here is the user's question:

<question>
{{QUESTION}}
</question>

And here is the system's response:

<response>
{{RESPONSE}}
</response>

First, determine if the question can be answered based solely on the information provided in the context. Output your reasoning inside <answerability_reasoning>. Then output "answerable" or "unanswerable" inside <answerable> tags.

Next, if the question is answerable, evaluate the system's response across three dimensions:
- Correctness: Is the response factually correct based on the context?
- Faithfulness: Does the response avoid claiming anything not directly supported by the context?
- Completeness: Does the response include all relevant information from the context to fully answer the question?

If the question is unanswerable, output "NA" for each of the three dimensions. For each dimension, first output your reasoning inside <correctness_reasoning>, <faithfulness_reasoning> and <completeness_reasoning> tags. Then output your assessment (correct/incorrect/NA, faithful/unfaithful/NA, complete/incomplete/NA) inside <correctness>, <faithfulness> and <completeness> tags.

Table 10: Prompt for Model-based Data Filtering

You will be evaluating a system's response to a user question, given some context. Here is the context:

<context>
{{CONTEXT}}
</context>

Here is the user's question:

<question>
{{QUESTION}}
</question>

And here is the system's response:

<response>
{{RESPONSE}}
</response>

Evaluate the system's response across three dimensions:
- Correctness: Is the response factually correct based on the context?
- Faithfulness: Does the response avoid claiming anything not directly supported by the context?
- Completeness: Does the response include all relevant information from the context to fully answer the question?
If the question is unanswerable, output "NA" for each of the three dimensions. For each dimension, first output your reasoning inside <correctness_reasoning>, <faithfulness_reasoning> and <completeness_reasoning> tags. Then output your assessment (correct/incorrect/NA, faithful/unfaithful/NA, complete/incomplete/NA) inside <correctness>, <faithfulness> and <completeness> tags.

Table 11: Prompt for Response Evaluation