RECAP: REwriting Conversations for Intent Understanding in Agentic Planning

Anonymous ACL submission

Abstract

Understanding user intent is essential for effective planning in conversational assistants, particularly those powered by large language models (LLMs) coordinating multiple agents. However, real-world dialogues are often ambiguous, underspecified, or dynamic, making intent understanding a persistent challenge. Traditional classification-based approaches struggle to generalize in open-ended settings, leading to brittle interpretations and poor downstream planning. We propose RECAP (REwriting Conversations for Agent Planning), a new benchmark designed to evaluate and advance intent rewriting, reframing user-agent dialogues into concise representations of user goals. RECAP captures diverse challenges such as ambiguity, intent drift, vagueness, and mixed-goal conversations. Alongside the dataset, we introduce an LLM-based evaluator that compares planning utility given a user-agent dialogue. Using RECAP , we develop a prompt-based rewriting approach that outperforms baselines. We further demonstrate that fine-tuning two DPO-based rewriters yields additional utility gains. Our results highlight intent rewriting as a critical and tractable component for improving agent planning in open-domain dialogue systems.

1 Introduction

Understanding user intent is a foundational challenge in building effective conversational assistants, particularly in systems powered by large language models (LLMs) coordinating multiple agents to complete complex tasks (Xu et al., 2024b; Song et al., 2023a; Wang et al., 2024a). In such systems, accurate intent detection is crucial for effective planning, where the system must determine what action to take and how best to delegate or execute it across agents. Misinterpreting user intent can lead to planning errors, degraded user experience, and failure to complete tasks efficiently.

In real-world multi-turn conversations, user intent is rarely static or perfectly stated (Zhou et al., 2024). Users may revise goals mid-conversation, introduce ambiguous or incomplete commands, or digress into side topics. These natural phenomena of user-agent dialogue, such as vagueness, intent drift, and ellipsis, pose significant challenges for current planning modules that rely on a clear and up-to-date understanding of user goals. Traditional approaches to intent understanding, such as intent classification, often rely on a fixed schema of predefined intents and slots (Goo et al., 2018; Budzianowski et al., 2018). While effective in narrow domains, these approaches struggle with open-ended or evolving conversations common in LLM-powered assistants (Arora et al., 2024). Such methods are susceptible to intent drift within conversation, fail to generalize to unseen or out-of-domain queries, and often force user inputs into rigid categories that do not reflect their actual goals. These limitations make it difficult for downstream planning modules to act on user input with the necessary flexibility and accuracy. More adaptive strategies are, hence, needed to handle the fluid, underspecified, and dynamic nature of real human intent in open-domain systems.

One promising strategy is intent rewriting: introducing a module that rephrases the user-agent dialogue into a concise, clarified representation of the user's most recent intent (Galimzhanova et al., 2023). This rewritten intent distills the relevant context, removes distractions, resolves ambiguity, and refocuses the system on the core user goal. By providing a cleaner target for action, intent rewrites enable downstream planners to make better decisions with less reliance on the full dialogue history.

Despite the growing interest in task-oriented dialogue and agent planning (King and Flanigan, 2024; Xu et al., 2024a; Gan et al., 2025; Qiao et al., 2024), there remains a lack of benchmarks specifically designed to evaluate intent rewriting in this context. Existing datasets either focus narrowly on slot-filling and task completion (Budzianowski et al.,

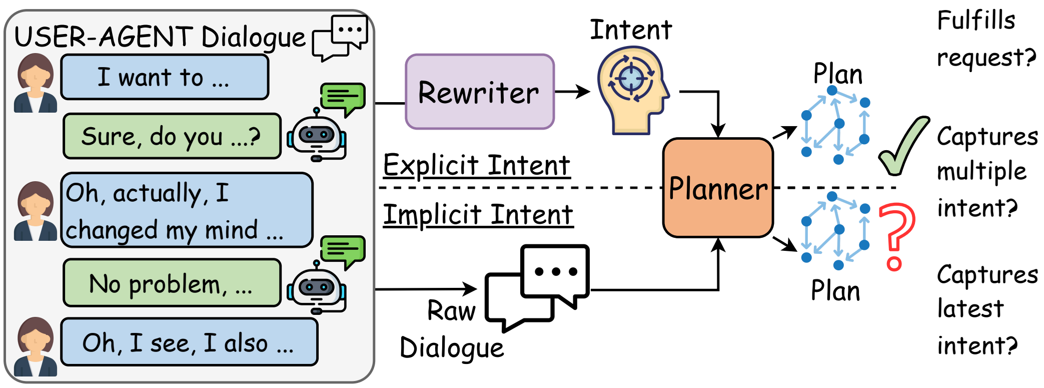


Figure 1: Comparing Agent Planning with explicit modeling of User Intent and Planning based on raw dialogue.

2018) or treat rewriting as a standalone summarization problem (Li et al., 2023), without grounding it in agent behavior or planning effectiveness. As a result, there is limited empirical understanding of what makes a rewrite effective for agent planning.

To bridge this gap, we introduce RECAP (REwriting Conversations for Agent Planning), a new benchmark that systematically captures diverse intent rewriting challenges across domains, including under-specified, drifted intent and multi-intent conversations. Alongside this dataset, we provide an effective LLM-based evaluator that judges the quality of agent plans given dialogue history and rewrites. Using RECAP , we develop a prompt-based intent rewriter that consistently outperforms baseline approaches. Building on this, we fine-tune two DPO-based rewriters starting from our best-performing zero-shot model, achieving further gains in planning utility.

2 Explicit Intent Modeling for Planning

Many task-oriented applications, such as virtual assistants, engage users through dialogue interfaces and increasingly rely on multi-agent collaboration behind the scenes to decompose and execute complex tasks. This architecture demands accurate and adaptable intent understanding, as well as effective agent planning. As illustrated in Figure 1, we assume the presence of a base chat agent that conducts multi-turn conversations with the user, maintaining a trajectory of USER–AGENT dialogue. Notably, the chat agent does not directly solve the task itself, but instead keeps the conversation flowing by presenting intermediate results generated by the underlying multi-agent system.

Complementing the chat agent is a planner that interprets user intent from the dialogue history up to the current point and generates a plan to coordinate action agents in order to complete the task (e.g., searching the web, drafting an email, creating a file). The planner produces a structured plan represented as a Directed Acyclic Graph (DAG), which captures the sequence and dependencies of sub-tasks required to achieve the user's goal. Each node in the DAG represents a sub-task, while edges define the logical flow between them. The planner is implemented using state-of-the-art LLMs, enabling flexible, context-aware plan generation.

While it may seem straightforward to feed the entire conversation history directly to the planner and rely on it to infer the implicit user intent, this approach can be problematic, particularly in real-world settings where User–Agent interactions are often noisy and include irrelevant or ambiguous turns. Specifically, we identify four common challenges in everyday User–Agent conversations that can lead to confusion or failure in planning: **underspecified intent**, where the user's goal lacks sufficient detail; **noisy input**, where irrelevant or off-topic dialogue turns obscure the main objective; **shifted intent**, where the user changes their goal mid-conversation; and **multi-intent**, where multiple distinct goals are presented simultaneously or sequentially without clear separation.

Table 1 presents qualitative examples of short dialogues with complex intents that confuse planners when processed in raw form. In the first dialogue, the user initially mentions an interest in Italian restaurants but later shifts to searching for a Mexican restaurant. The plan generated from the raw dialogue incorrectly interprets the chat agent's suggestions (e.g., pizza and pasta) as user requests

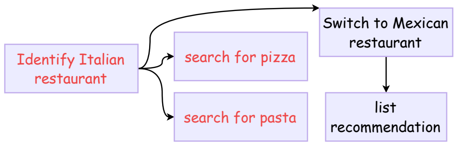
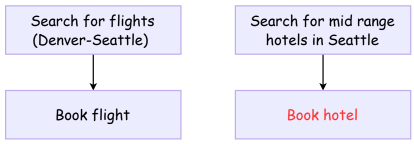
Example dialogue	Problematic plan from raw dialogue
Underspecified and Shifted Intent USER: I'm looking for a restaurant that serves Italian food, AGENT: Are you looking for pasta or pizza USER: Actually, I think I'd rather have Mexican food instead	
Multi-Intent USER: I want to book a flight from Denver to Seattle and also get information about hotels in Seattle', AGENT: Are you looking for a specific type of hotel, such as luxury or budget-friendly? USER: Yes, I'm looking for something mid-range	

Table 1: Qualitative examples of short dialogues with complex intents that confuse the planners when provided in raw form. Red nodes highlight issues in the generated plans.

and fails to recognize that the user's original intent is no longer relevant. In the second example, the user wants to book a flight but only seeks information about hotels. The planner, given the full dialogue without explicit intent modeling, mistakenly proceeds to book both the flight and a hotel. With explicit intent modeling, the correct interpretation would be: **"search for a Mexican restaurant"** and "book a flight from Denver to Seattle and gather information about mid-range hotels in Seattle." While these examples are brief due to space constraints, such confusion is far more frequent in longer, more complex dialogues.

Quantitatively, we observe notable differences in preference, semantics, and structure between plans generated from raw conversation history and those generated from rewritten inputs. These discrepancies are consistent across multiple planning models, including the reasoning-capable `o3-mini`, highlighting the importance of clear and well-structured intent representations for effective agent planning. We present detailed results in Section 5.2.

3 RECAP Benchmark

Existing agent planning benchmarks either assume clearly defined tasks with well-specified requirements (e.g., TravelPlanner (Xie et al.)) or focus solely on vague or underspecified intent (e.g., IN3 (Qian et al.)). As demonstrated in Section 2, additional challenges such as intent shifts and nuanced details can lead to suboptimal downstream planning. To enable a deeper understanding of how to

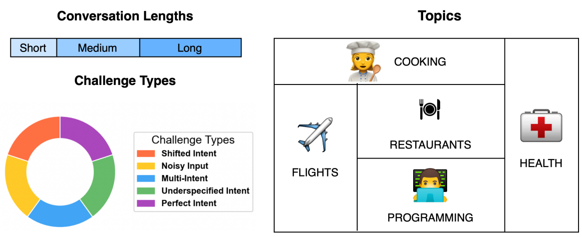


Figure 2: RECAP Dataset Characteristics

effectively represent complex user intent, we introduce RECAP , a benchmark designed to evaluate the ability of conversational rewriters to capture accurate, unambiguous, up-to-date, and comprehensive intent for downstream multi-agent planning.

3.1 Dataset Construction

Our goal is to construct a diverse and challenging dataset of user-agent conversations for intent understanding in planning tasks. We synthetically generate two-way dialogues that reflect realistic user-agent interactions. Specifically, we create conversations that span a variety of topics (*cooking, programming, health, flights, restaurants*), conversation lengths (short, medium, and long), and intent understanding categories (*shifted intent, noisy input, underspecified intent, multi-intent, perfect intent*), as illustrated in Figure 2. This design allows our dataset to capture a wide range of scenarios relevant to planning tasks based on understanding complex user intent.

We adopt a prompt-based generation approach (see Appendix A.2) using LLMs (`GPT-4o` OpenAI

(2024) and `LLaMA 3.3-70B` Meta (2024)) to simulate a back-and-forth conversation on a given topic between a user and a chat agent. Conversations are also designed to be challenging in at least one of the predefined categories.

The generated dialogues undergo careful human vetting to ensure they are coherent, adhere to the assigned topic and challenge type, and follow the specified conversation-length constraints. We also filter out any dialogues in which the chat agent hallucinates or attempts to solve the user's task. Additionally, since intent analysis is performed only on user utterances, we require each conversation to end with a user turn, and discard any that violate this constraint. In total, RECAP comprises 750 validated conversation instances (see Appendix F).

3.2 Evaluation Metrics

Having constructed a set of challenging user-agent conversations, we apply various rewriters to each conversation and feed the resulting rewritten intent into a planner to generate the final task plans. We evaluate the quality of these plans in a pair-wise method using three main categories of metrics.

Structural Metrics To capture structural differences between the plan DAGs, we compute the following metrics:
Node and Edge Count Differences: $\Delta_{\text{nodes}} = N_1 - N_2$, $\Delta_{\text{edges}} = E_1 - E_2$, where N_i and E_i denote the number of nodes and edges in plan P_i, respectively.
Graph Edit Distance (Sanfeliu and Fu, 1983) $\text{GED}(P_1, P_2)$, which measures the minimum cost of edit path to transform plan P_1 to P_2 such that they are isomorphic.
These metrics provide a quantitative view of how structurally similar or divergent two plans are.

Semantic Metrics We assess the semantic distance between generated plans using `BERTScore` (Zhang et al., 2019). Specifically, we compute `Semantic Distance` as: $1 - \text{BERTScore}(P_1, P_2)$, where P_1 and P_2 are the two plans being compared.

Preference Metric As the ultimate measure of utility, we assess whether the planner produces the most effective plan given a rewritten intent. In this work, we employ human annotators as well as utilize LLM-based evaluators, who are asked to judge plan preference on the following rubrics:

- **Latest Intent:** The plan should reflect the user's most recent goals or intent as expressed in the conversation.
- **Fabrication:** The plan should avoid unnecessary, repetitive, or fabricated steps.
- **Task Granularity:** The plan should offer specific and detailed actions.
- **Task Completeness:** The plan should include all necessary steps to fully accomplish the user's goal.
- **Logical Order:** Tasks should be arranged in a coherent, logical sequence. Parallelizable tasks should be grouped accordingly for efficiency.

We employ a pairwise comparison setup: two rewritten intents from the same source conversation are each fed into the planner, producing two separate plans. Human annotators, following the rubric above, are shown both plans (in randomized order) and asked to select the one that better aligns with the user's intended goal. If both are judged equally effective (or ineffective), a tie is recorded.

More on the implementation details of all metrics and human evaluation study is described in Appendix C.2.

3.3 LLM-as-Judge Evaluator

While human evaluation provides high-quality preference signals, it is both costly and time-consuming. To mitigate this, we explore the feasibility of training models to predict human preferences between pairs of plans. As a baseline, we prompt a frozen large language model (LLM) to select the preferred plan in a zero-shot setting, mirroring the structure of the human annotation task.

Beyond this, we fine-tune two preference models using the collected human labels on `RECAP-train` with the majority vote of the human preference labels obtained through the evaluation process described later in Section 5.3. These models take as input a source conversation along with two candidate plans and are trained to predict the preferred plan or indicate a tie. Further implementation and sampling details are mentioned in Appendix C.2.2.

4 RECAP Rewriters

4.1 Constructing Rewrites

We begin by introducing two baseline rewriters used to evaluate the impact of rewriting quality on downstream planning.

Dummy rewriter simply reproduces the original multi-turn USER-AGENT conversation verbatim, without any modification or abstraction. This baseline allows us to observe how the planner responds to raw, unprocessed dialogue input.

LLM-based Basic rewriter performs a direct summarization of the full conversation history using a generic summarization prompt (Appendix B). This approach does not receive any specific instructions regarding which parts of the conversation are important to preserve, such as intent shifts or irrelevant contents. As a result, the summary may omit critical information required for accurate planning, making it a useful reference point for assessing the added value of more targeted rewriting approaches.

To capture the nuanced aspects of query rewriting, we adopt a prompt-based generation approach (see Appendix B) using GPT-4o (OpenAI, 2024) with a temperature setting of 0. This setup is used to generate high-quality rewrites optimized for downstream planning, which we refer to as the Advanced rewriter.

The Advanced rewriter produces a refined and task-aware representation of the original multi-turn conversation. Unlike generic summarization, it is explicitly prompted to produce rewrites that are concise, unambiguous, and well-aligned with the user's most recent goals. It emphasizes fine-grained aspects of intent understanding, such as detecting the latest user intent(s), filtering out irrelevant or noisy input, and making reasonable assumptions in cases where the user's intent is underspecified. This guided approach allows the rewrite to serve as a more effective interface between the user's dialogue and the planner.

4.2 Training Rewriter

While the Advanced rewriter effectively captures many general principles of intent rewriting through carefully designed prompts, there remain important considerations that are difficult to encode explicitly via prompt rubrics. Furthermore, downstream planners may exhibit inherent biases or preferences for particular input formulations that cannot be easily anticipated or specified through prompting alone.

To further enhance the performance of the rewriter, we fine-tune the advanced summarizer using *Direct Preference Optimization (DPO)* (Rafailov et al., 2023) and name it DPO:human This method leverages human preference annotations on pairs of plans generated from the same source conversation. For each annotated plan pair, we trace back to the corresponding rewrites that produced them. The rewrite that led to the preferred plan is treated as a positive sample, while the other is treated as a negative sample. These preference pairs serve as training signals to fine-tune a GPT-4o model, encouraging it to generate rewrites that are more likely to result in plans preferred by humans. This setup enables indirect supervision of the rewriter, without requiring manually curated gold rewrites, by aligning the learning objective with the downstream metric of planning utility.

Because high-quality human preference labels are expensive and limited in quantity, we also train an additional version of the rewriter using pseudo-labels generated by our strongest automated plan preference evaluator. This model (DPO:LLM) follows the same DPO training paradigm, offering a scalable but weaker alternative to human-supervised fine-tuning. Training implementation details is further described in Appendix D.

5 Evaluation

5.1 Experimental setup

Planner To evaluate the impact of different input rewrites on downstream task planning, we adopt a controlled setup using a static LLM-based planner. In this setup, the planner agent does not interact with the user or the environment; instead, it receives a rewritten user intent as input and generates a task plan in the form of a directed acyclic graph (DAG). The raw output from the language model is parsed into a structured graph format (details provided in Appendix C.1, which allows us to verify the acyclicity of the plan and supports structured analysis. We use GPT-4o with temperature set to 0 to ensure deterministic generation, minimizing randomness across different runs. The detailed prompting setup used to guide the planner is described in Appendix C.1.

Data For our experiments in the following sections, we sample and utilize 150 conversation instances from RECAP due to cost constraints (eg. human annotations). We include studies on the entire dataset in Appendix F. We partition these 150 RECAP conversations into train, val, and test splits with a ratio of 60-10-30. By holding the planner fixed and systematically varying only the rewritten input, we isolate the effect of intent formulation on the resulting task decomposition.

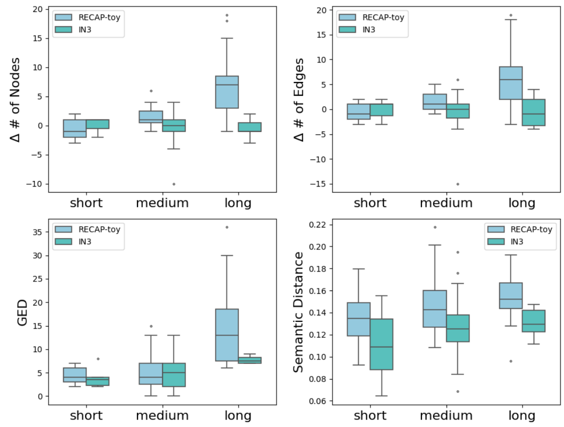


Figure 3: Structural and Semantic Differences between plans generated using `Dummy` and `Advanced` rewrites, on on `RECAP-toy` and `IN3`

This setup enables a controlled evaluation of how different rewriting strategies influence the structure and quality of generated plans.

5.2 Sensitivity

Length	RECAP-toy			IN3-70		
	`Dummy`	Tie	`Advanced`	`Dummy`	Tie	`Advanced`
Short	26.67	23.33	**50.00**	16.67	66.67	16.67
Medium	20.00	20.00	**60.00**	8.62	70.69	20.69
Long	16.67	20.00	**63.33**	33.33	66.67	0.00

Table 2: Plan Preference % between plans generated from `Dummy` and `Advanced` rewrites, on `RECAP-toy` and `IN3` datasets.

We begin by qualitatively comparing the quality and characteristics of plans generated from raw conversations versus rewritten user intent, to assess the sensitivity of LLM planners to input variation. This motivates the need for effective conversation rewriters. For each conversation, we generate two rewrites using `Dummy` and `Advanced` rewriters, simulating two extremes of rewriting. These are provided as input to a static LLM planner (`GPT-4o`, `temperature=0`) using a fixed prompt template (Appendix C.1). Evaluation is conducted on two benchmarks: a 70-instance subset of the `IN3` dataset (Qian et al.), and a synthetic `RECAP-toy` dataset of 70 USER-AGENT dialogues generated with `GPT-4o` (Appendix B), following the same procedure as the main RECAP data generation.

Table 2 shows that human annotators consistently prefer plans generated from `Advanced` rewrites on `RECAP-toy`, demonstrating that improved input formulations lead to better plan quality, even with identical planning models. Figure 3 further shows that these plans diverge structurally, in terms of node/edge counts and graph edit distance, especially as conversation length increases, highlighting amplified variability in complex dialogues. While plan pairs typically show limited semantic variability, potentially due to the inability of metrics like BERTScore to capture subtle distinctions, longer conversations tend to induce greater divergence.

In contrast to RECAP , `IN3` exhibits lower sensitivity across all metrics. Human preferences are more often tied, and structural and semantic differences are reduced regardless of conversation length. This indicates that `IN3` lacks the realism and complexity to surface input-sensitivity effects, reinforcing the need for more challenging datasets like RECAP .

To confirm these results are not planner-specific, we replicate the experiments on `RECAP-toy` using `LLaMA 3.3-70B` and `GPT-o3-mini` (Figures 9, 10). All models exhibit consistent sensitivity to rewrites under identical prompt and decoding settings.

5.3 Comparing Rewriters

Building on our findings from Section 5.2, we begin by evaluating the performance of the prompt-based rewriters introduced in Section 4.1 in generating rewrites that support effective plan generation. The analysis is conducted on conversations from `RECAP-train`.[1].

Structural and Semantic Comparisons: As shown in Table 3, plans derived from different rewrites exhibit noticeable structural divergence. Notably, GED is highest between plans generated from `Basic` and `Advanced` rewrites respectively, indicating that these input variants induce markedly different planning behaviors. Despite using identical prompts and models, such structural shifts reflect the planner's high sensitivity to surface form and implicit signals in the input.

Plan Preference Results in Table 4 highlight that plans derived from `Advanced` rewriter are consistently preferred across most intent-related challenges. This effect is particularly strong in conversations involving complex or evolving intents, eg. *Shifted Intent* and *Multi-Intent*. In contrast,

[1]The prompt-based rewriters are zero-shot and not trained for this task; we use the training partition to avoid contaminating the held-out test set used later for evaluating trained rewriters.

Plan Comparison	Δ_{nodes}	Δ_{edges}	GED	Semantic Distance
Dummy vs Basic	1.68	2.18	4.99	0.10
Dummy vs Advanced	1.70	2.36	5.56	0.11
Basic vs Advanced	1.87	2.49	6.44	0.11

Table 3: Average structural and semantic distances between plans generated with prompt-based rewriters.

Challenge	Rewriter	Win Rate	Tie Rate	Loss Rate
Shifted Intent	Dummy	21.43	59.52	19.05
	Basic	2.38	47.62	50.0
	Advanced	50.0	45.24	4.76
Noisy Input	Dummy	23.81	54.76	21.43
	Basic	11.90	54.76	33.33
	Advanced	30.95	57.14	11.90
Multi-Intent	Dummy	14.29	47.62	38.09
	Basic	19.05	52.38	28.57
	Advanced	40.48	52.38	7.14
Underspecified Intent	Dummy	12.5	55.0	32.5
	Basic	20.0	70.0	10.0
	Advanced	17.50	75.0	7.50
Perfect Intent	Dummy	11.36	63.64	25.0
	Basic	15.91	72.73	11.36
	Advanced	20.46	68.18	11.36
Total	Dummy	16.67	56.19	27.14
	Basic	13.81	59.52	26.67
	Advanced	**31.90**	59.52	8.57

Table 4: Win/Tie/Loss percentage for each rewriter grouped by challenge. Each rewriter competes against all other rewriters.

for *perfect intent* cases, where the user's request is explicit, even plans generated from Dummy or Basic rewrites yield competitive performance. Interestingly, in *Underspecified Intent* contexts, the Advanced rewriter underperforms slightly, suggesting that it may introduce unnecessary assumptions that misalign with annotator expectations.

These findings reinforce that input formulation plays a pivotal role in plan quality. While sophisticated rewriting can significantly enhance performance in complex scenarios, over-specification may be detrimental when user intent is vague.

Model	Train		Test	
	Acc%	F1	Acc%	F1
baseline:gpt-4o-mini	38.91	0.31	37.5	0.35
baseline:gpt-4o	36.36	0.31	43.75	0.39
baseline:gpt-4.1	38.55	0.38	45.0	0.46
ft:gpt-4o-mini	69.09	0.67	48.75	0.48
ft:gpt-4o	72.00	0.72	53.75	0.48
ft:gpt-4.1	74.91	0.73	65.01	0.65

Table 5: LLM-as-Judge plan preference evaluator, prompted and fine-tuned.

5.4 Learning to Predict Plan Preference

As discussed in Section 3.3, we explore the use of LLMs to predict human plan preferences, enabling scalable evaluation. We compare baseline and fine-tuned LLM evaluators on train and test splits sampled from `RECAP-train`, enriched with more challenging comparisons between plans from Advanced and DPO:human rewrites. Full details on setup and sampling methodology are provided in Appendix C.2.2.

Table 5 summarizes performance across of various LLM models. The fine-tuned `gpt-4.1` model achieves the highest accuracy and F1 scores on both train and test sets, substantially outperforming zero-shot baselines (`gpt-4o-mini`, `gpt-4o`, and `gpt-4.1`). These results highlight the promise of fine-tuned LLMs as reliable and cost-efficient evaluators in nuanced plan comparison tasks.

5.5 Evaluation of Trained Rewriters

Next, we evaluate how trained rewriters introduced in Section 4.2 compare to prompt-based rewriters. Specifically, we compare two DPO-based rewriters against our best-performing Advanced rewriter on the held-out `RECAP-test` set, using the static GPT-4o planner. The DPO:human model is trained using human preference labels from `RECAP-train`, while DPO:LLM is trained on the same plan pairs but uses preferences judged by an LLM-as-a-judge evaluator. We employ our best-performing LLM evaluator, a fine-tuned GPT-4.1.

As shown in Table 6, DPO:human achieves the highest win rate across nearly all intent challenge categories, outperforming the Advanced rewriter. Notably, it yields substantial gains in more difficult scenarios such as *Shifted Intent* and *Multi-Intent*, suggesting that aligning with human preferences helps capture finer nuances of user intent. In contrast, DPO:LLM performs competitively in categories like *Perfect Intent* and *Multi-Intent*, but does not consistently surpass Advanced across all intent-understanding categories. This indicates that while LLM-generated supervision offers scalability, it may still fall short of the effectiveness achieved through human preferences. Figures 7 and 8 further illustrate plan preferences across test cases.

These results highlight the value of human-aligned supervision for training robust rewriters and demonstrate DPO as a scalable path toward adaptive, human-aligned input reformulation in task-oriented dialogue systems.

Challenge	Rewriter	Win Rate	Tie Rate	Loss Rate
Shifted Intent	`DPO:human`	**55.56**	11.11	33.33
	`DPO:LLM`	22.22	33.33	44.44
Noisy Input	`DPO:human`	**44.44**	33.33	22.22
	`DPO:LLM`	44.44	0.0	55.56
Multi-Intent	`DPO:human`	**44.44**	33.33	22.22
	`DPO:LLM`	**33.33**	33.33	33.33
Underspecified Intent	`DPO:human`	30.0	50.0	20.0
	`DPO:LLM`	20.0	60.0	20.0
Perfect Intent	`DPO:human`	**75.0**	12.50	12.50
	`DPO:LLM`	**25.0**	62.50	12.50
Total	`DPO:human`	**48.88**	28.90	22.22
	`DPO:LLM`	28.88	33.33	37.78

Table 6: Win/Tie/Loss percentage for `DPO:human` vs `Advanced` and `DPO:LLM` vs `Advanced` rewriters

6 Related Work

Multi-Turn Intent Understanding Intent understanding is a core component of dialogue systems, particularly in multi-turn interactions where user intent can be vague, drift over time, or be obscured by noisy utterances. Traditional intent classification approaches and slot filling solutions in Dialogue State Tracking (DST) works (Budzianowski et al., 2018; Wu et al., 2019; Mrkšić et al., 2017; Rastogi et al., 2020) aim to map user utterances to one or more predefined intent categories, offering clear signals to inform the system's next action. However, these methods rely heavily on a well-defined intent taxonomy and often struggle to generalize across domains. To address these limitations, research on intent discovery and out-of-distribution (OOD) detection has emerged (Song et al., 2023b; Wang et al., 2024b). While these methods aim to identify novel or ambiguous intents, they face challenges such as low precision in distinguishing subtle intent variations and difficulty in adapting to evolving user goals. A more flexible approach is to directly rewrite user intent utterances, without relying on predefined intent classes.

Query Rewriting In information-seeking and Retrieval-augmented Generation(RAG) settings, query rewriting has been shown to enhance retrieval quality by incorporating conversational context. Wu et al. introduced CONQRR, a transformer-based model trained with reinforcement learning to optimize downstream retrieval rewards. Ye et al. explored prompting LLMs like GPT-3 to generate context-aware rewrites, showing that LLMs can infer implicit information from earlier turns. Mo et al. (2024) proposed CHIQ, a two-stage method where an LLM first enhances the dialogue history and then rewrites the final user query, achieving strong performance on conversational search tasks. While effective, these approaches are primarily designed for search scenarios and assume a task-agnostic, retrieval-focused environment. Intent rewriting in realistic multi-round conversations for planning and agent coordination remain underexplored.

LLM-Based Planning Recent work has explored LLMs for planning in ambiguous, multi-step dialogue settings. Chen et al. (2024) proposed ACT, a method that trains LLMs to proactively ask clarification questions using a contrastive self-training objective, promoting better discrimination between plausible next steps. Deng et al. (2024) introduced Self-MAP, a memory-augmented planner that uses reflection to adjust plans in response to evolving user goals, showing improved performance on complex instruction-following tasks. Although these approaches show promising signals in reasoning over ambiguity and intent drift, they typically require carefully designed planning solutions involving fine-tuning or the integration of additional components—such as dedicated reflection modules or memory-augmented agents. RECAP provides planner-agnostic benefits by operating independently of the underlying planner's architecture or capabilities and offers a more flexible and interpretable representation.

This gap of flexible intent understanding for agent planning is especially evident in the lack of robust benchmarks that reflect the complexities of real-world conversations. Qian et al. introduced IN3, a benchmark that captures vague user intents and focuses on generating clarification questions. However, it does not adequately address other challenging scenarios, such as intent shifts or multiple simultaneous intents.

7 Conclusion

We introduced RECAP , a new benchmark for evaluating intent rewriting in LLM-powered conversational systems, capturing key challenges like ambiguity, drift, and goal shifts. By reframing dialogue into concise intent representations, rewriting enables more accurate and flexible agent planning. Our experiments show that both prompt-based and DPO-trained rewriters significantly improve planning utility, even without explicit preference labels. These results highlight intent rewriting as a promising direction for building more effective and adaptive dialogue agents.

Limitations

While our study provides a systematic analysis of how input formulations affect plan generation in goal-oriented dialogue systems, few limitations still remain.

First, our experiments are restricted to text-only input representations. However, real-world task-oriented systems often involve multi-modal signals such as visual context, system state, or user behavior. Extending rewriting and planning approaches to such multi-modal input settings remains an important direction for future work.

Secondly, we evaluate plans using structural metrics and human preference judgments to give us strong signals on plan structure differences and downstream applications. However, these metrics may not fully capture cases where plans are structurally different but functionally equivalent in more actionable plan-execution settings. Our work can be extended to environments and datasets, where a more principled notion of plan equivalence or plan executability is present, which can also allow point-wise plan evaluation.

Lastly, while our approach learns to align rewrites with human preferences, we do not explicitly optimize for plan structure. Future work could explore structural supervision during rewrite training, incorporating signals from the plan itself into the rewriting loop. Furthermore, a deeper analysis into the characteristics of the rewrites and planner signals (from open LLMs) can be made to study the causality between the rewriter and plan output.

Ethics Statement

In this work, we propose a novel benchmark for intent rewriting and understanding for agentic planning. Our dataset was synthetically generated using LLMs which may introduce artifacts or biases inherent to the model used. However, we ensured to vet all generated samples to remove any unwanted instances, and also redact any use of real or fake names and contact information in the generated conversations.

In our evaluation methodology, we made sure that experiments involving human annotators were conducted in accordance with ethical research guidelines. Annotators provided informed consent for participation and the purpose of the task and the manner in which their annotations will be used was clearly communicated.

Artifacts used in our work, including publicly available ones, have been clearly cited and utilized with intended use. We also used commercially available AI models (e.g., GPT) in a manner consistent with their terms of service. These data are intended for research purposes only and do not contain real user information.

Finally, while our findings point toward improved plan quality through rewrite optimization, we caution against over-reliance on such systems without human oversight, particularly in high-stakes or safety-critical domains.

References

Gaurav Arora, Shreya Jain, and Srujana Merugu. 2024. Intent detection in the age of llms. In *Conference on Empirical Methods in Natural Language Processing*.

Paweł Budzianowski, Tsung-Hsien Wen, Bo-Hsiang Tseng, Iñigo Casanueva, Stefan Ultes, Osman Ramadan, and Milica Gasic. 2018. Multiwoz - a large-scale multi-domain wizard-of-oz dataset for task-oriented dialogue modelling. In *Conference on Empirical Methods in Natural Language Processing*.

Maximillian Chen, Ruoxi Sun, Sercan Ö. Arik, and Tomas Pfister. 2024. Learning to clarify: Multi-turn conversations with action-based contrastive self-training. *ArXiv*, abs/2406.00222.

Yang Deng, Xuan Zhang, Wenxuan Zhang, Yifei Yuan, See-Kiong Ng, and Tat-Seng Chua. 2024. On the multi-turn instruction following for conversational web agents. In *Annual Meeting of the Association for Computational Linguistics*.

Elnara Galimzhanova, Cristina Ioana Muntean, Franco Maria Nardini, Raffaele Perego, and Guido Rocchietti. 2023. Rewriting conversational utterances with instructed large language models. *2023 IEEE International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)*, pages 56–63.

Bingzheng Gan, Yufan Zhao, Tianyi Zhang, Jing Huang, Yusu Li, Shu Xian Teo, Changwang Zhang, and Wei Shi. 2025. Master: A multi-agent system with llm specialized mcts. *ArXiv*, abs/2501.14304.

Chih-Wen Goo, Guang Gao, Yun-Kai Hsu, Chih-Li Huo, Tsung-Chieh Chen, Keng-Wei Hsu, and Yun-Nung Chen. 2018. Slot-gated modeling for joint slot filling and intent prediction. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers)*, pages 753–757, New Orleans, Louisiana. Association for Computational Linguistics.

Brendan King and Jeffrey Flanigan. 2024. Unsupervised end-to-end task-oriented dialogue with llms:

The power of the noisy channel. In *Conference on Empirical Methods in Natural Language Processing*.

Jieyu Li, Zhi Chen, Lu Chen, Zichen Zhu, Hanqi Li, Ruisheng Cao, and Kai Yu. 2023. Dir: A large-scale dialogue rewrite dataset for cross-domain conversational text-to-sql. *Applied Sciences*.

Meta. 2024. Llama-3.1.

Fengran Mo, Abbas Ghaddar, Kelong Mao, Mehdi Rezagholizadeh, Boxing Chen, Qun Liu, and Jian-Yun Nie. 2024. Chiq: Contextual history enhancement for improving query rewriting in conversational search. *ArXiv*, abs/2406.05013.

Nikola Mrkšić, Diarmuid Ó Séaghdha, Tsung-Hsien Wen, Blaise Thomson, and Steve Young. 2017. Neural belief tracker: Data-driven dialogue state tracking. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1777–1788, Vancouver, Canada. Association for Computational Linguistics.

OpenAI. 2024. Gpt-4o.

Cheng Qian, Bingxiang He, Zhong Zhuang, Jia Deng, Yujia Qin, Xin Cong, Zhong Zhang, Jie Zhou, Yankai Lin, Zhiyuan Liu, and Maosong Sun. Tell me more! towards implicit user intention understanding of language model driven agents.

Shuofei Qiao, Runnan Fang, Zhisong Qiu, Xiaobin Wang, Ningyu Zhang, Yong Jiang, Pengjun Xie, Fei Huang, and Huajun Chen. 2024. Benchmarking agentic workflow generation. *ArXiv*, abs/2410.07869.

Rafael Rafailov, Archit Sharma, Eric Mitchell, Stefano Ermon, Christopher D. Manning, and Chelsea Finn. 2023. Direct preference optimization: Your language model is secretly a reward model. *ArXiv*, abs/2305.18290.

Abhinav Rastogi, Xiaoxue Zang, Srinivas Sunkara, Raghav Gupta, and Pranav Khaitan. 2020. Towards scalable multi-domain conversational agents: The schema-guided dialogue dataset. In *Proceedings of EMNLP*.

Alberto Sanfeliu and King-Sun Fu. 1983. A distance measure between attributed relational graphs for pattern recognition. *IEEE Transactions on Systems, Man, and Cybernetics*, SMC-13(3):353–362.

Xiaoshuai Song, Keqing He, Pei Wang, Guanting Dong, Yutao Mou, Jingang Wang, Yunsen Xian, Xunliang Cai, and Weiran Xu. 2023a. Large language models meet open-world intent discovery and recognition: An evaluation of chatgpt. *ArXiv*, abs/2310.10176.

Xiaoshuai Song, Yutao Mou, Keqing He, Yueyan Qiu, Jinxu Zhao, Pei Wang, and Weiran Xu. 2023b. Continual generalized intent discovery: Marching towards dynamic and open-world intent recognition. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 4370–4382, Singapore. Association for Computational Linguistics.

Jiayin Wang, Fengran Mo, Weizhi Ma, Peijie Sun, Min Zhang, and Jian-Yun Nie. 2024a. A user-centric multi-intent benchmark for evaluating large language models. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 3588–3612, Miami, Florida, USA. Association for Computational Linguistics.

Pei Wang, Keqing He, Yejie Wang, Xiaoshuai Song, Yutao Mou, Jingang Wang, Yunsen Xian, Xunliang Cai, and Weiran Xu. 2024b. Beyond the known: Investigating LLMs performance on out-of-domain intent detection. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*, pages 2354–2364, Torino, Italia. ELRA and ICCL.

Chien-Sheng Wu, Andrea Madotto, Ehsan Hosseini-Asl, Caiming Xiong, Richard Socher, and Pascale Fung. 2019. Transferable multi-domain state generator for task-oriented dialogue systems. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 808–819, Florence, Italy. Association for Computational Linguistics.

Zeqiu Wu, Yi Luan, Hannah Rashkin, David Reitter, Hannaneh Hajishirzi, Mari Ostendorf, and Gaurav Singh Tomar. CONQRR: Conversational query rewriting for retrieval with reinforcement learning.

Jian Xie, Kai Zhang, Jiangjie Chen, Tinghui Zhu, Renze Lou, Yuandong Tian, Yanghua Xiao, and Yu Su. TravelPlanner: A benchmark for real-world planning with language agents.

Heng-Da Xu, Xian-Ling Mao, Puhai Yang, Fanshu Sun, and Heyan Huang. 2024a. Rethinking task-oriented dialogue systems: From complex modularity to zero-shot autonomous agent. In *Annual Meeting of the Association for Computational Linguistics*.

Weijie Xu, Zicheng Huang, Wenxiang Hu, Xi Fang, Rajesh Cherukuri, Naumaan Nayyar, Lorenzo Malandri, and Srinivasan Sengamedu. 2024b. HR-MultiWOZ: A task oriented dialogue (TOD) dataset for HR LLM agent. In *Proceedings of the First Workshop on Natural Language Processing for Human Resources (NLP4HR 2024)*, pages 59–72, St. Julian's, Malta. Association for Computational Linguistics.

Fanghua Ye, Meng Fang, Shenghui Li, and Emine Yilmaz. Enhancing conversational search: Large language model-aided informative query rewriting. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 5985–6006. Association for Computational Linguistics.

Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q. Weinberger, and Yoav Artzi. 2019. Bertscore: Evaluating text generation with bert. *ArXiv*, abs/1904.09675.

Wendi Zhou, Tianyi Li, Pavlos Vougiouklis, Mark Steedman, and Jeff Z. Pan. 2024. A usage-centric take on intent understanding in e-commerce. In *Conference on Empirical Methods in Natural Language Processing*.

A Constructing Conversations

In order to suit our study setting, we aim to obtain conversation instances between a USER and an AGENT focused on task-oriented dialogue with intent-related challenges. We utilize the existing IN3 dataset (Qian et al.), as well synthetically generate our own.

A.1 Conversation Construction: IN3

Qian et al. provide an instruction understanding & execution benchmark, where a `task` eg. *"Find a recipe for homemade pizza."* is annotated with a label `vague`, denoting if the task-intent is vague or not. If the task is vague, the benchmark provides `missing details` with an `inquiry` i.e. a clarification question eg. *""Do you have any dietary restrictions or preferences?""* and possible answer `options` to this query eg. *"["Gluten-free", "Vegan", "No restrictions"]"*

We modify this dataset to build conversations prompting `gpt-4o` with `temperature=0` to convert the initial task and missing details as a USER-AGENT style conversation. The USER begins the conversation with the `task`, and the AGENT follows up with each `inquiry`. The USER answers the inquiry with one of the answer `options` provided, at random. The prompt used is shown in Prompt:A.1.

We perform this method on 70 instances of the IN3 data (to match the instances in RECAP-toy dataset) and filter only those tasks which have been labeled as vague.

Conversation Construction: IN3

```
You will be provided a task sentence and
some missing details as a list. Each missing
detail has an inquiry and corresponding
options. Your job will be to convert this to
a friendly User-Agent conversation. The User
begins conversation with the task. The Agent
responds with each missing detail inquiry
one at a time, and the User responds with
the option as response.

Task: task
Missing Details: missing_details

Output Format: Each conversation should a
list of strings starting with 'USER:' or
'AGENT:'.
```

A.2 Conversation Construction: RECAP

To generate a conversation dataset with tougher intent-understanding related challenges, we follow the methodology described in Section 3.1. The prompt used to generate such conversations is detailed in Prompt:A.2 which aims to generate conversations across different topics, conversation lengths and intent-understanding challenges. During simulation, we emphasize that the chat agent should not attempt to solve the user's task.

The topics included are *cooking, programming, health, flights, restaurants*, taking inspiration from existing intent classification works such as Budzianowski et al. (2018).

The conversation length categories are defined as:

short : where the total number of USER and AGENT utterances is up to 5

medium : where the total number of USER and AGENT utterances more than 5 but up to 10

long : where the total number of USER and AGENT utterances more than 10 but up to 20

Conversation Construction: RECAP

```
Generate a conversation between a USER and
an AGENT on the topic: {topic}.
The USER begins with a task-oriented query.
The AGENT only asks clarifying or follow-up
questions to understand the USER's intent
and constraints. It must not solve the task.

The conversation should be {conv_len}, stay
on-topic, and be coherent.

Each conversation must end with a USER
utterance and no utterance should include
unrelated or off-topic remarks.

The challenge types are:
{challenge_instructions}

Output a single JSON object with challenge
names as keys and conversations as values.
Each conversation is a list of strings
starting with 'USER:' or 'AGENT:'.
```

We utilize `gpt-4o` and `llama-v3p3-70b-instruct`(Fireworks) models with `temperature=1` to generate varied and diverse instances. We curate and pick 150 conversations generated using these different models separately, and modify if needed to ensure adherence to prompt instructions. Characteristics of the dataset are illustrated in Figure 2.

Examples of conversations across intent-understanding categories are included in Table 7.

A simplified version of this prompt (using only conversation length as criteria) is used to generate 70 instances for a toy dataset which we use for sensitivity analysis in Section 5.2.

B Rewrite Generation

Prompt used to Generate Rewrites

```
Basic Rewriter
Summarize the following USER-AGENT conversation

Conversation:
{conversation}
```

```
Advanced Rewriter
Summarize the following USER-AGENT conversation into a single, concise sentence describing the user's intended task.
The summary should reflect the user's goal or intent, in an instruction style.
Do not introduce new information. Only include what is stated or clearly implied.

Conversation:
{conversation}
```

Rewrites are generated using `gpt-4o` with `temperature` set to 0. Prompt:B outlines the prompt used to generate rewrites for the `Basic` and `Advanced` summarizers. The dummy rewriter simply outputs the input conversation as a string.

C Plan Generation and Evaluation

C.1 Generating Plans

We use the following prompt to generate plans given an input task i.e. output of a rewriter. For RECAP, we use a *static* `gpt-4o` planner with `temperature=0`, so as to obtain as deterministic outputs from the planner as possible.

Prompt used for Generating Plans

```
You are a planner responsible for creating high-level plans to solve any task. Understand the user intent from the input and plan accordingly. Consider breaking down complex tasks into subtasks.

Represent your plan as a graph where each node corresponds to a step, and each edge represents a dependency between two steps. If a node requires the output from a previous node as an input, ensure it is included in the edge list.

The output should be structured in the following JSON format:
'nodes': <list of JSON nodes with keys 'id': <node id as integer>, 'name': <sub-task node name> >,
'edges': <list of tuples [node_id, node_id]>

Input:
{input}
```

After obtaining the plan generated from the LLM, the plan is converted to DAG format using `networkx:MultiDiGraph` utilizng the corresponding nodes and edges.

C.2 Evaluating Plans

In Section 3.2, we defined the three categories of metrics we used to evaluate plans - structural, semantic and preference based.

C.2.1 Structural & Semantic Evaluation of Plans

Structural Metrics: $\Delta_{\text{nodes}} = N_1 - N_2$ and $\Delta_{\text{edges}} = E_1 - E_2$, are computed using in-built `networkx` functions, which corresponds to the difference in the number of nodes and edges, respectively, between two plans. We use the `optimize_graph_edit_distance` function within `networkx` to comput the graph edit distance between the two plans $\text{GED}(P_1, P_2)$. This measures the minimum cost of edit path (sequence of node and edge edit operations) transforming plan P_1 to P_2 such that they are isomorphic. While the generic `graph_edit_distance` function may be computationally expensive and slow, especially for larger graphs, the optimized version helps calculate the nearest approximation of GED for such cases.

Semantic Metrics: We combine the text from all task nodes from plan P_1 and P_2 respectively and report the F1 BertScore (Zhang et al., 2019) between them as
`Semantic Distance` = 1 - BertScore(P_1, P_2).

C.2.2 Plan Preference

For each conversation instance, given two plans generated correspondingly from two different rewriters (eg. `Dummy` vs `Basic`), we use human as well as LLM evaluators to measure the pair-wise performance between the two generated plans.

The evaluators are provided a conversation, two plans A and B (when presenting plans A & B to the user, the plans from the rewriters eg. *dummy* and *basic* are randomly shuffled to ensure no positional

Shifted Intent	Noisy Input	Underspecified Intent	Multi-Intent	Perfect Intent
USER: I want to bake a cake for my birthday. **AGENT**: What kind of cake are you thinking of? **USER**: Actually, I'd rather make some fresh chocolate chip cookies.	**USER**: Hi, how's it going? I need to cook dinner tonight. **AGENT**: Hello! Sure, I'll be happy to assist you today! I can help you with cooking. What type of dinner are you planning to make? **USER**: Thank you for assisting me! Umm, something with chicken.	**USER**: I need to cook something for a party. **AGENT**: How many people are you planning to serve? **USER**: Not sure, but I want it to be easy to eat.	**USER**: I want to make a meal that's both healthy and tasty. **AGENT**: Are you looking for a specific cuisine or dietary restriction? **USER**: I'm open to anything, but it should be quick to prepare and not too expensive.	**USER**: I want to make chicken parmesan with spaghetti for 4 people. Do you have a good recipe? **AGENT**: Would you like to use homemade or store-bought marinara sauce? **USER**: I'll use homemade sauce and serve it with a side salad.

Table 7: Example USER-AGENT dialogues with **short** conversation length in the **cooking** domain, illustrating different intent-related challenges.

You will be provided with a conversation between a user and a chat agent.

The user makes an initial query, and the chat agent asks some clarifying questions to better understand the user's intent.

Note:

1. In some cases, the user's intent may be fully clear through the conversation (e.g., "For dinner, I want to cook white sauce pasta with chicken").
2. While in other instances, few aspects of the user's intent remain vague (e.g., "I want to have pasta for dinner").
3. In some cases, the user may backtrack on their initial query and ask help regarding a different task (e.g., the user initially asks the agent to help find restaurants with Japanese cuisine, but later decides they want Italian cuisine instead).
4. In some cases, the user may provide multiple tasks to the agent (e.g., "Find me programming resources for Web Development and Mobile App Development").

Now, keeping in mind the **entire conversation** between the user and agent, two **plans** have been generated to **perform actions which shall help fulfil the task** described in the above conversation.

A plan breaks down the user's task(s) into various sub-tasks which are connected with arrows showing a logical flow from one sub-task to another.

Your task is to choose which plan is better to solve the task.

Please refer to the rubrics below when conducting the comparison:

- **latest_intent**: A good plan should fulfill the *user's updated goals/intent* from the conversation.
- **fabrication**: A good plan should be accurate and *not include unnecessary, repetitive or false tasks*.
- **task_granularity**: A good plan should provide *more specific and detailed steps*.
- **task_completeness**: A good plan should include *all necessary steps to achieve the user goal*.
- **logical_order**: A good plan should arrange tasks in a *coherent, logical* sequence. If tasks can be done in *parallel*, they should be done so for better efficiency.

Please select your preference: **PlanA**, **PlanB**, or **TIE** if you feel both plans are equally good and capable of solving the task.

Figure 4: Rubrics for Plan Evaluation

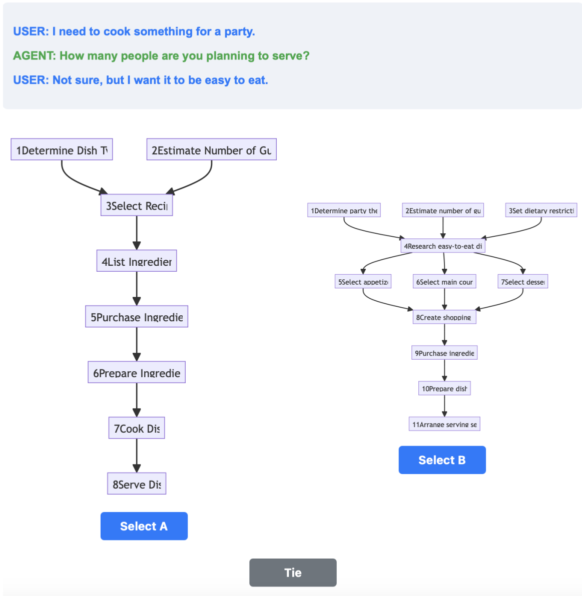


Figure 5: Interface for Human Preference Annotation

bias). The evaluators are further provided instructions with criteria to choose the best plan among the two – A, or B, or a tie if both plans are equally good.

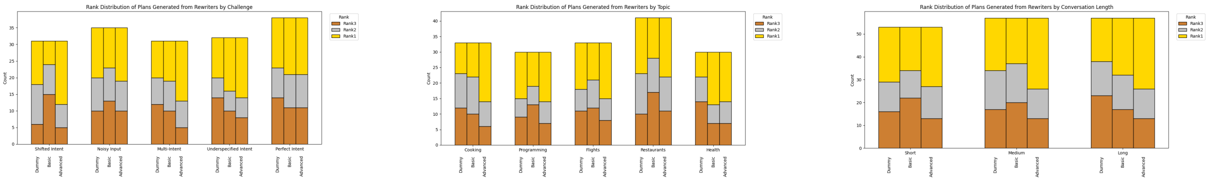
It is to be noted that (a) the evaluators are not provided any information about the rewriter (input to planner); and (b) that the plans are generated using a *static* planner (detailed in Section C.1) so as to indirectly measure the impact of the corresponding rewriter on the downstream plan performance/preference.

Human Annotators: We recruited 3 expert in-house annotators, who are proficient in English, and currently based in the United States of America, with at least a graduate-level degree. The annotators were clearly explained the objective of the task and how their annotations would be utilized. To measure agreement between the annotators we use average of the pair-wise accuracy scores between each of the annotators. We also note the subjectivity and difficulty of the task, which leads to *moderate* to *good* agreement scores across our human-evaluation studies.

The instructions provided to the human annotators were the same as provided to the LLM Evaluator which is detailed in Figure 4. An example of the interface used for human annotation is shown in Figure 5. Once the annotations are obtained, the majority label of the annotators is used as the preference label for the plan-pair.

To compare how plans from different rewriters were preferred by humans, we report the Win/Tie/Loss rates for each rewriter i.e. for all plan-pairs, how many times was the plan from the corresponding rewriter preferred (win), not preferred (loss), or a tie.

We also build a ranking mechanism to rank



(a) Human Preference of Plans by Intent Category

(b) Human Preference of Plans by Topic

(c) Human Preference of Plans by Conversation Length

Figure 6: Ranked Analysis: Human Preference of Plans across Rewriters (`Dummy`, `Basic` and `Advanced`) on `RECAP-test`: `Advanced` ranks 1st across all intent categories

the 3 plan-pairs per conversation instance. For the three rewrites and corresponding plans i.e. `Dummy`, `Basic` and `Advanced`, a +1 score is given to a rewriter if it is preferred over another, +0.5 given to both rewriters if there is a `TIE`, else 0 is given for losses. The total scores across plan-pairs for a conversation instance are used to rank the performance of these rewriters for that instance, using standard ranking mechanism eg. if `Basic` and `Advanced` both have +2.5 scores while `Dummy` has a score of 0, the ranks are:
`Advanced` rewriter: Rank 1
`Basic` rewriter: Rank 1
`Dummy` rewriter: Rank 3

The results from this ranked analysis is shown in Figures 6a, 6b, 6c, measuring the count that each rewriter was ranked r_i across the different intent-understanding challenges, topics, and conversation lengths in our dataset.The average pair-wise inter annotator accuracy is 75.4%.

LLM Evaluator: Human annotations are not scalable, hence we rely on LLMs as plan-preference evaluators on a large sclae. The LLM evaluator is also prompted with the same instructions as given to the users using Prompt:C.2.2.

Prompt used for Evaluating Plans

```
You will be given a task-oriented dialogue
between a USER and an AGENT as well
as two plans. Your task is to choose the
plan that better addresses the user's intent.

Please refer to the rubrics below when
conducting the comparison: RUBRICS

The plans are evaluated on their ability to
fulfill the above rubrics. Both plans are
considered equally good when they are equally
capable of fulfilling the above rubrics. In
that case, output TIE.

Conversation:conv
Plan A: planA
Plan B: planB

Which plan better fulfills the user's
request? Reply with 'A', 'B', or 'TIE'."
```

To further improve LLM evaluators, we fine tune them on the `RECAP-train` data with the majority vote of the human preference labels obtained earlier. We additionally add 40 samples comparing the `Advanced` vs `DPO:human` plans from Section 5.5 so as to include tougher instances of plan comparison while training our fine-tuned evaluator. These instances are also generated only from conversations included in `RECAP-train`, so as to not contaminate the `RECAP-test` dataset.

These samples (`RECAP-train` + tougher instances) are then split into `train-val-test` splits (60-10-30) for the sole purpose of fine-tuning LLM evaluators. We utilize the same Prompt:C.2.2 as previously to prepare the training, validation and test data. For our baseline, we use a zero-shot approach, prompting models `gpt-4o-mini`, `gpt-4o` and `gpt-4.1`. Furthermore, use OpenAI fine-tuning for each of these models using the human majority label, with hyperparameters: `batch_size`, `learning_rate_multiplier`, and `n_epochs` set to `auto`.

D Training Rewriters using DPO

In Section 4.2, we described adopting a preference-based learning strategy using Direct Preference Optimization (DPO), where given a pair of plans evaluated, we trace each plan back to its corresponding rewrite. The rewrite responsible for the preferred plan is treated as the `preferred_output`, and the other as the `non_preferred_output`. These preference pairs serve as supervisory signals to fine-tune a `gpt-4o` model, optimizing it to generate rewrites that are more likely to result in preferred plans. The prompt used to prepare the data is as follows in Prompt:D.

Prompt used for Training Rewriters using DPO

```
You will be given a task-oriented dialogue
between a USER and an AGENT. Your task is
to reinterpret or rewrite the conversation
in a format that clearly conveys the USER's
intent, optimized for a downstream planning
agent that will decompose the request into
actionable subtasks.
Based on your judgment, you may choose
to rewrite the conversation or retain the
original format.

Conversation: conversation
```

Once again, we train the DPO-rewriter on RECAP-train using either the human or LLM based preference labels which corresponds to the preferred_output or non_preferred_output. The resulting model is used to generate rewrites with Prompt:B, and subsequently plans using Prompt:C.1 – as previously to maintain consistency – on the RECAP-test set.

We train the gpt-4o-2024-08-06 model using OpenAI DPO fine-tuning, with hyperparameters beta=0.1, n_epochs=3, batch_size=auto and learning_rate_multiplier=auto.

D.1 DPO:human Downstream Performance

After training the DPO model on the train data with human preference labels, we obtain the corresponding rewrite and plan (DPO:human) on RECAP-test. To restrict cost due to a cross product of comparison between rewriters, we only compare DPO:human plans with the best performing Advanced summarizer (from Table 4).

The results of this comparison using ranked analysis is shown in Figures 7a, 7b, 7c corresponding to intent-understanding challenge, topic, and conversation length respectively. The average pair-wise inter annotator accuracy is 64.3%.

D.2 DPO:LLM Downstream Performance

We repeat the same analysis, this time using which is the rewriter model trained using LLM (gpt-4.1 as it was the best performing model from Table 5) on RECAP-test. The results of the comparison between plans generated from DPO:LLM and Advanced rewriters is shown in Figures 8a, 8b, and 8c. The average pair-wise inter annotator accuracy is 61.48%.

E Sensitivity Analysis

E.1 Toy Datset Construction

To construct the toy dataset utilized for sensitivity analysis we generate USER-AGENT style conversations using gpt-4o, temperature=0 using a prompt similar to A.2 without specifying explicit challenge instructions. The conversation length i.e. conv_len categories are defined as:

short : where the total number of USER and AGENT utterances is up to 5

medium : where the total number of USER and AGENT utterances more than 5 but up to 10

long : where the total number of USER and AGENT utterances more than 10 but up to 20

E.2 Sensitivity Analysis Across Planners

Although we use a *static* planner through our experiments, we extend our initial sensitivity analysis (Section 5.2) to various state-of-the-art LLM-based planners. This is done to perform a preliminary validation experiment that the results we see across our work is not a sole result of the planner quality we use i.e. GPT-4o.

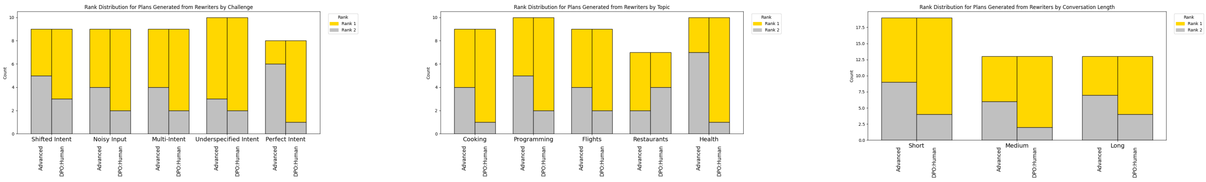
We utilize the prompt defined in Appendix C.1 and employ LLaMA 3.3-70B with a temperature setting of 0 and GPT-o3-mini to generate plans using Dummy and Advanced rewriters on RECAP-toy data, as consistent with Section 5.2.

We use the same metrics defined in 3.2 to observe plan variation to input. Figures 9 10 also show similar trends to GPT-4o (3) indicating that plan outputs are sensitive to the input characteristics – output of the rewriter.

F RECAP Benchmark

We release 750 conversations as the RECAP benchmark. In our experiments, due to cost and effort constraints because of human annotation, we only utilized 150 of these conversation instances.

Stats The RECAP dataset is uniformly distributed across five distinct topics — *cooking*, *programming*, *flights*, *restaurants*, and *health* — with 150 instances each. Similarly, the intent_category dimension covers the different intent-understanding related categories: *shifted_intent*, *noisy_input*, *underspecified_intent*, *multi_intent*, and *perfect_intent*, also with 150 instances each. Conversation lengths (conv_len) are

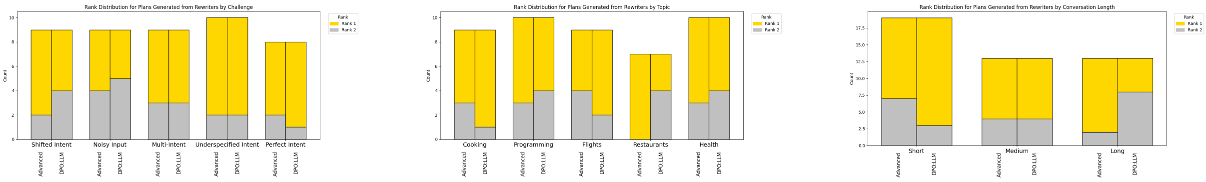


(a) Human Preference of Plans on RECAP-test by Intent Category

(b) Human Preference of Plans on RECAP-test by Topic

(c) Human Preference of Plans on RECAP-test by Conversation Length

Figure 7: Ranked Analysis: Human Preference of Plans generated between Advanced and DPO:human on RECAP-test: DPO:human ranks 1st across all intent categories, conversation lengths and most topics



(a) Human Preference of Plans on RECAP-test by Intent Category

(b) Human Preference of Plans on RECAP-test by Topic

(c) Human Preference of Plans on RECAP-test by Conversation Length

Figure 8: Ranked Analysis: Human Preference of Plans generated between Advanced and DPO:LLM on RECAP-test: DPO:LLM ranks better for short conversation lengths and performs comparatively well across intent categories

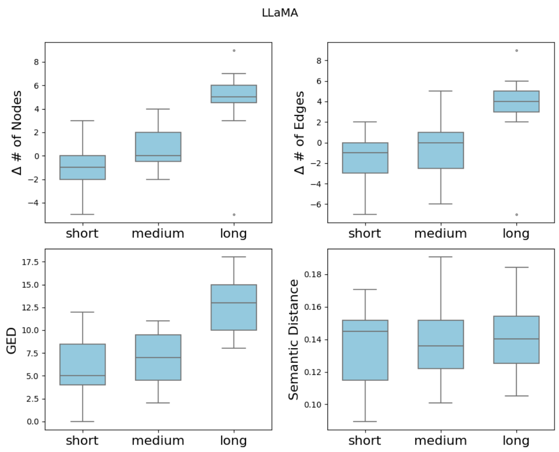


Figure 9: Sensitivity analysis for LLAMA

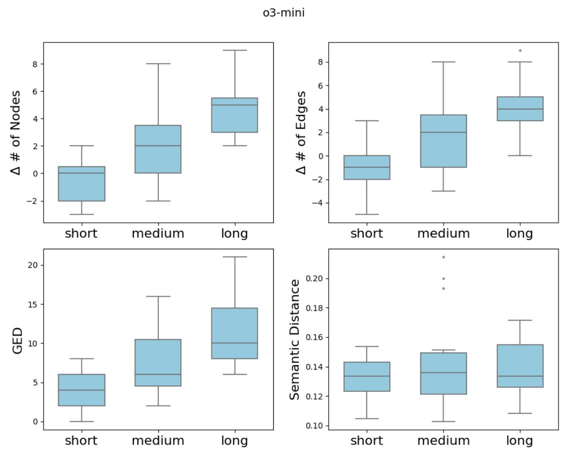


Figure 10: Sensitivity analysis for o3-mini

evenly distributed across three buckets: *short* (250), *medium* (250), and *long* (250), ensuring balance across all dimensions.

Vetting The synthetically generated conversations are vetted for adherence to instructions, overall coherency, and to ensure no bias or malicious content is present. Personal information such as names, contact details (even if generated by the LLMs, serving as placeholders) were redacted.

Evaluation Using the best-performing fine-tuned evaluator (Table 5), we evaluate the plans generated on the entire RECAP dataset. The plans are generated using DPO:human and Advanced rewriters, utilizing the planner described in Appendix C.1.

Intent Category	Win Rate	Tie Rate	Loss Rate
Shifted Intent	35.33	40.00	24.67
Noisy Input	26.67	47.33	26.00
Multi-Intent	24.00	46.00	30.00
Underspecified Intent	22.00	54.00	24.00
Perfect Intent	26.00	35.33	38.67
Total	26.80	44.53	28.67

Table 8: Win/Tie/Loss percentage for plans generated from DPO:human vs Advanced across intent categories

The results are shown in Table 8, where Win Rate denotes the plan from DPO:human was preferred to Advanced rewriter, and Loss Rate denotes vice versa. We observe there is largely neutral preference across intent categories.