ConsistentChat: Building Skeleton-Guided Consistent Multi-Turn Dialogues for Large Language Models from Scratch

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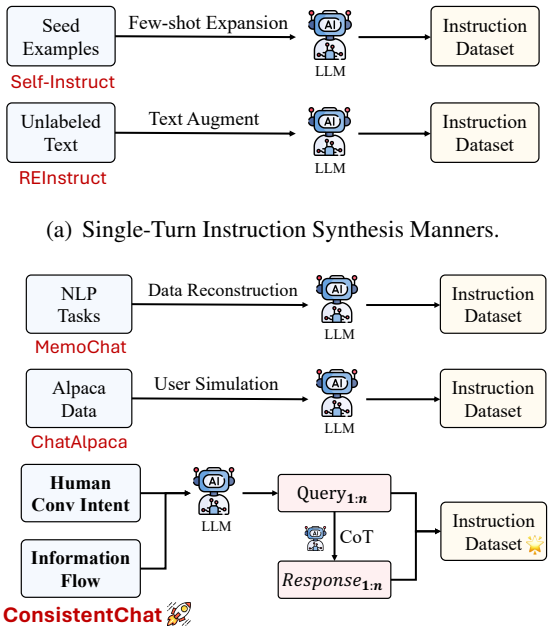
Abstract

Current instruction data synthesis methods primarily focus on single-turn instructions and often neglect cross-turn coherence, resulting in context drift and reduced task completion rates in extended conversations. To address this limitation, we propose Skeleton-Guided Multi-Turn Dialogue Generation, a framework that constrains multi-turn instruction synthesis by explicitly modeling human conversational intent. It operates in two stages: (1) Intent Modeling, which captures the global structure of human dialogues by assigning each conversation to one of nine well-defined intent trajectories, ensuring a coherent and goal-oriented information flow; and (2) Skeleton Generation, which constructs a structurally grounded sequence of user queries aligned with the modeled intent, thereby serving as a scaffold that constrains and guides the downstream instruction synthesis process. Based on this process, we construct *ConsistentChat*[1], a multi-turn instruction dataset with approximately 15,000 multi-turn conversations and 224,392 utterances. Experiments on the LIGHT, TOPDIAL, and MT-EVAL benchmarks show that models fine-tuned on *ConsistentChat* achieve a 20–30% improvement in consistency and up to a 15% increase in task success rate, significantly outperforming models trained on existing single-turn and multi-turn instruction datasets.

1 Introduction

Instruction synthesis plays a fundamental role in enabling large language models (LLMs) to perform a wide array of real-world dialogue tasks (Iyer et al., 2022). High-quality instruction datasets are indispensable for supervised fine-tuning (SFT), allowing LLMs to better capture user intent and handle diverse conversational scenarios, such as customer support and educational tutoring (Sanh et al., 2022; Wang et al., 2023b). As the demand for scalable and domain-adaptive models grows, the automatic construction of instruction data has become a challenge in the development of advanced dialogue systems.



(a) Single-Turn Instruction Synthesis Manners.

(b) Multi-Turn Instruction Synthesis Manners.

Figure 1: Comparison of single-turn and multi-turn instruction synthesis manners.

Currently, existing instruction data construction paradigms are primarily tailored to single-turn interactions. Works such as Self-Instruct (Wang et al., 2023b), Evolve-Instruct (Xu et al., 2023), and RE-Instruct (Chen et al., 2024) leverage prompt expansion and corpus mining to generate large-scale <instruction, response> pairs. However, these methods mainly focus on turn-level exchanges, overlooking the sequential dependencies and interactive dynamics intrinsic to natural conversations. This gap not only limits the capacity of models to capture real

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[1]Our code, model and dataset are publicly available at https://github.com/chenjiawei30/ConsistentChat

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conversational development, but also fails to reflect the actual requirements of real-world applications, where multi-turn interactions are the norm rather than the exception.

Fundamentally, some approaches explored the synthesis of multi-turn instruction datasets, such as MemoChat (Lu et al., 2023), ChatAlpaca (Bian et al., 2023) and GLAN (Li et al., 2024). These approaches largely rely on either transforming traditional NLP tasks into dialogues or simulating multi-turn conversations with LLMs. Such strategies are typically unconstrained: the generation process focuses on producing locally coherent, turn-level instruction with response pairs, failing to model the evolution of human intent or the overall dialogue trajectory. As a result, these datasets often suffer from poor chat consistency across turns, with frequent occurrences of topic drift throughout the conversation. This limitation poses a challenge for training models to maintain alignment and consistency in multi-turn interactions.

Based on the above observations, we propose an instruction synthesis framework that can model human conversational intent and information flow to guide multi-turn dialogue generation and consequently construct the *ConsistentChat* dataset. We analyze nine categories of dialogue intent (Rapp et al., 2021) (e.g., Problem-Solving-Interaction and Educational-Interaction) and formalize them as dynamic information flows that constrain both topic progression and role interaction throughout the dialogue. Our approach first generates a globally coherent sequence of user queries conditioned on the underlying intent, and subsequently produces agent responses that maintain alignment with both current and global conversational objectives.

We evaluate models trained with *ConsistentChat* on LIGHT, TOPDIAL, and MT-EVAL benchmarks. Preliminary analyses (§2) reveal that LLMs' multi-turn dialogue abilities degrade with increasing dialogue depth, and strong chat consistency in training data is crucial for SFT models' alignment across turns. Leveraging our Skeleton-Guided framework, we build high-quality multi-turn instruction dialogues. Experimental results show that models fine-tuned on *ConsistentChat* instruction consistently outperform those trained on existing datasets, both in single-turn and multi-turn settings, establishing state-of-the-art results in dialogue chat consistency and alignment. Our findings highlight the importance of modeling human conversational intent and information flow for generating reliable instruction data for multi-turn dialogue agents.

The main contributions of this paper are:

1) This is the first work investigating how modeling human conversational intent in instruction synthesis influences the chat consistency of fine-tuned dialogue models.

2) We propose *ConsistentChat*, generated by a simple yet effective Skeleton-Guided framework for supervised fine-tuning, which can be applied in broad downstream dialogue scenarios.

3) Extensive experiments demonstrate that instruction data generated by *ConsistentChat* outperforms existing popular multi-turn datasets in terms of chat consistency, as well as both single-turn and multi-turn conversational capability.

2 Revealing Multi-Turn Degradation and Chat Consistency Effects

In this section, we first investigate the performance of popular dialogue models in multi-turn conversations and explore how fine-tuning on datasets with varying chat consistency affects their performance. We conduct analyses addressing these two questions:

- **Question I**: When current conversational models engage in multi-turn dialogues, how do the multi-turn conversational abilities evolve as the conversation progresses?
- **Question II**: Whether the chat consistency of dialogue datasets affects the performance of fine-tuned models?

In this paper, we define **chat consistency** as the semantic coherence of a dialogue across multiple turns. Specifically, it encompasses three key aspects: (1) Alignment with the initial conversational intent, (2) Smooth and logically connected information flow, and (3) Contextual relevance of each response across turns. This definition is closely related to prior work on consistency in dialogue, which emphasizes maintaining alignment in styles and topics (Wang et al., 2017), personas (Ju et al., 2022), and conversational characters or roles (Wang et al., 2024).

We conducted experiments on MT-EVAL (Kwan et al., 2024) to assess the multi-turn conversational abilities of mainstream dialogue models, addressing Question I (see Appendix A.1 for details). For Question II, we further curated subsets of instructions from `ShareGPT` (Chiang et al., 2023), categorized into three levels of chat consistency (Low, Sample, and High). These subsets were

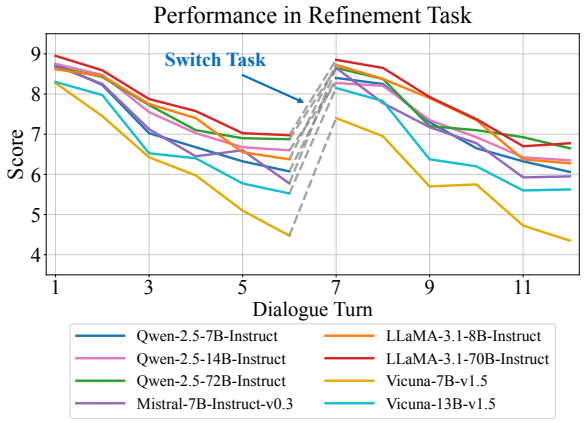

Figure 2: Performance of multi-turn conversational ability declines as more instructions are added on Refinement task in MT-EVAL. Each dialogue in task has two NLP tasks with each task comprising six increasingly complex instructions. The transition to the second NLP task occurs at the seventh turn as denoted by the gray dashed line. Judged by Qwen-2.5-72B-Instruct.

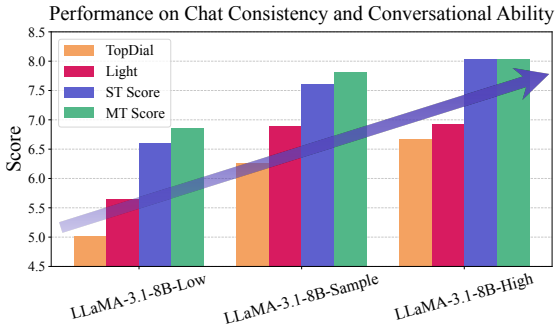

Figure 3: Performance of LLaMA-3.1-8B models (Low, Sample, and High consistency) across four evaluation settings: TOPDIAL, LIGHT and Single-Turn (ST), and Multi-Turn (MT) in MT-EVAL. The results demonstrate ongoing improvements across all benchmarks as the chat consistency of SFT instructions increases.

then used to fine-tune pre-trained LLaMA-3.1-8B model, evaluated with the chat consistency metric on LIGHT (Urbanek et al., 2019) and TOPDIAL (Wang et al., 2023a) (see Appendix A.2).

2.1 Conversational Abilities Diminish as the Dialogue Deepens

Setups. We selected several popular dialogue models (including Qwen-2.5, LLaMA-3.1, Mistral-0.3, Vicuna-1.5), covering a total of 8 representative models across different scales and architectures. These models were evaluated on the Refinement task of the MT-EVAL benchmark, which measures the ability to generate coherent and contextually relevant responses when conversations extend over multiple turns.

Results. Figure 2 shows that as dialogue turns increase, model performance consistently deteriorates. This degradation trend is observed across all model families, although larger-scale models exhibit relatively stronger resilience compared to smaller ones. These findings highlight the inherent challenges in preserving consistency during long interactions. Detailed results are in Appendix A.1.

2.2 Dataset Consistency Affects Fine-tuned Model Performance

Setups. We utilized Qwen-2.5-72B-Instruct to assign a chat consistency score, ranging from 1 to 10, to each multi-turn dialogue from the ShareGPT (GPT-4 version, a high-quality dataset curated and cleaned by Xu (2023)). Based on the assigned scores, we categorized the dialogues into three groups: High consistency (scores between 8 and 10), Low consistency (scores between 4 and 6), and a sample of dialogues, with each group containing approximately 10,000 dialogue instances. Subsequently, we performed supervised fine-tuning of the LLaMA-3.1-8B model on these datasets and evaluated on tasks involving chat consistency and multi-turn conversational capabilities. The scoring prompt is illustrated in Figure 7.

Results. Figure 3 shows that LLaMA-3.1-8B-High achieves the best results in both consistency metrics (detailed in Table 9) and conversational capabilities (detailed in Table 10), illustrating that chat consistency plays a crucial role in fine-tuning models' performance. The whole experimental results are shown in Appendix A.2.

2.3 Insights from Preliminary Analyses

Through our preliminary analyses, we have demonstrated that: (1) Popular dialogue models exhibit consistent degradation in conversational abilities as turns increases; (2) The consistency of training data affects the performance of fine-tuned models, with higher consistency data yielding superior results. These findings point out developing high-quality instruction synthesis methods as a promising direction for enhancing multi-turn dialogue models.

3 Building Consistent Multi-turn Dialogues from Scratch

Motivated by the above insights, we present a novel framework for multi-turn instruction generation.

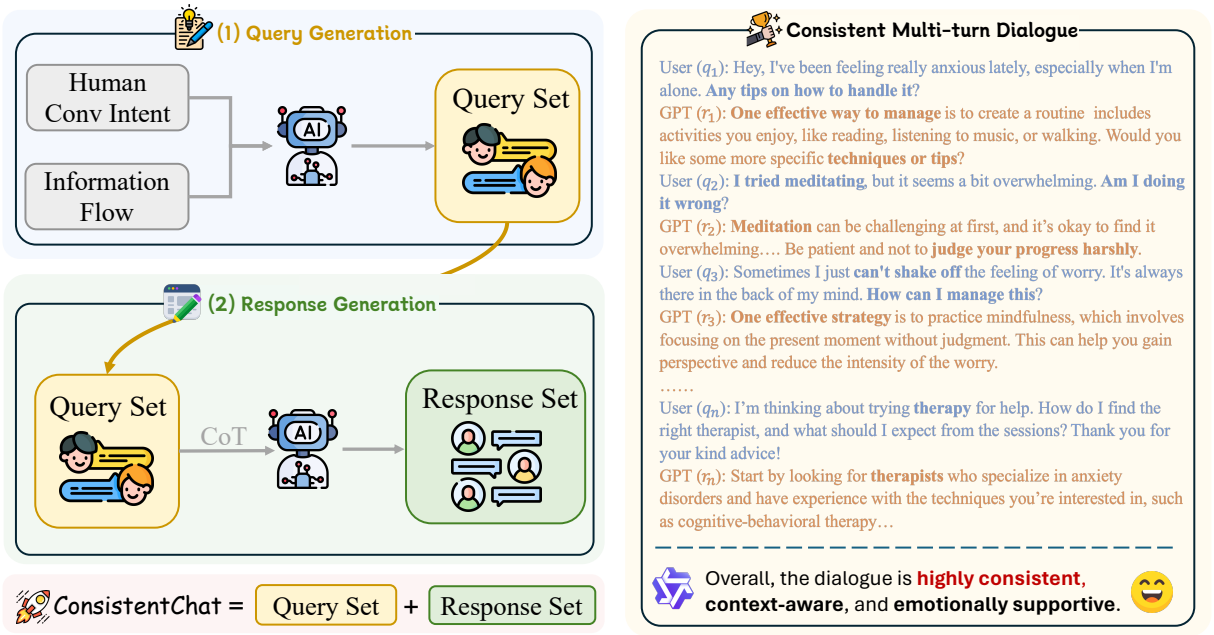

Figure 4: Overview of our instruction synthesis framework. We design a dialogue skeleton by combining nine types of human conversational intents with corresponding curated information flows. *ConsistentChat* is constructed in two stages: First, we generate a set of multi-turn dialogue queries from Qwen-2.5-72B-Instruct based on the skeleton template; Then, we prompt LLMs to generate the corresponding response set with CoT method. On the right side, we present a synthetic dialogue case, which received a high assessment from Qwen-2.5-72B-Instruct.

First, we provide the background on general dialogue generation (§3.1). Then, we introduce the details of Skeleton-Guided Multi-Turn Dialogue Framework (§3.2).

3.1 Definition

We formalize a multi-turn dialogue instruction as $\mathcal{D} = \{(\mathcal{I}_j, \mathcal{C}_j)\}_{j=1}^{M}$, M represents total number of dialogues. Each dialogue instance consists of:

(1) An instruction $\mathcal{I}_j$, which provides task-specific context, such as background knowledge, conversational intent, or speaker attributes.

(2) A conversation history $\mathcal{C}_j = \{\langle q_k, r_k \rangle\}_{k=1}^{T_j}$, representing the sequential utterances exchanged between the user query q_k and the conversational model response r_k. Here, T_j denotes the total number of dialogue turns in a given interaction.

Given an instruction $\mathcal{I}$ and a dialogue context $\mathcal{C} = \{\langle q_1, r_1 \rangle, \langle q_2, r_2 \rangle, \cdots, \langle q_t \rangle\}$, the purpose of the dialogue model is to generate an overall model response r_t that aligns with the given context while maintaining chat consistency across turns.

3.2 Skeleton-Guided Dialogue Framework

We propose a Skeleton-Guided Multi-Turn Dialogue framework that enhances conversational consistency across multiple turns. An overview of the framework is presented in Figure 4, where the left part illustrates the multi-turn instructions synthesis pipeline, and the right part provides a synthetic dialogue case with high consistency.

Intent-Based Skeletons Our framework stems from an analysis of human conversational patterns in multi-turn interactions. Drawing on theories from human–computer interaction, particularly the Conversational Acts Taxonomy proposed by Rapp et al. (2021), we identify nine fundamental interaction patterns. These patterns span a wide range of human conversational behaviors and are linked to dynamic information flows that guide the logical progression of dialogue. Further details are provided in Appendix B, with three examples of conversational intents shown in Figure 5.

Query Generation via Human Intent We leverage the distillation capability of LLMs through a Skeleton-Guided prompt (see Appendix C) to generate query sequences that preserve conversational consistency across multiple turns. This design enables the model to capture high-level cues while retaining sufficient flexibility. Unlike traditional multi-turn dialogue generation, our framework ensures that queries progress in a logical order, extending the conversation while avoiding topic drift.

Intent Category	Dialog Information Flows	Scenario Examples
Problem Solving Interaction	From Problem Diagnosis to Solution Optimization	Technical support, home repairs, travel planning
Educational Interaction	From Broad Theory to Specific Scenarios; From Basic Concepts to Cross-Domain Connections	Language learning, science education, music courses
Health Consultation Interaction	From Problem Diagnosis to Solution Optimization; From Hypothesis Testing to Substantive Discussion	Dietary advice, symptom analysis, mental health support

Figure 5: Dialogue Skeleton-Guided Schema: examples of interaction intent categories used in our framework. This table presents three categories to illustrate how scenario types align with dialogue flow strategies.

The query generation process follows a structured approach, where each query q_t is generated sequentially based on a given dialogue intent $\mathcal{I}$ and its corresponding information flow $\mathcal{F}$, ensuring that the user interactions adhere to common human dialogue patterns. Formally, we define the probability of generating a sequence of user queries as:

$$q_1, q_2, \ldots, q_T \sim P(Q \mid \mathcal{I}, \mathcal{F}, \theta_{\text{LLMs}}) \quad (1)$$

where $Q = \{q_1, q_2, ..., q_T\}$ represents the full set of user queries, and θ_{LLMs} denotes the LLMs for distillation. Each query q_t is generated not only on the intent $\mathcal{I}$ and information flow $\mathcal{F}$, but also on previously generated queries to ensure new-generated queries remain aligned with earlier ones, simulating human dialogue evolution. Also, our approach prevents redundant or drifted user inputs, making the synthetic dialogues more consistent.

Response Generation via CoT Prompt Once the user queries are generated, we continue to generate all corresponding responses in a single forward pass instead of a turn-by-turn manner. This approach significantly enhances the context-awareness and fluency of the generated dialogue responses. This can be expressed as follows:

$$r_t \sim P(R \mid Q, r_{<t}, \theta_{\text{LLMs}}) \quad (2)$$

Q is the user query set, $r_{<t}$ represents agent response, and R denotes the candidate responses. Yet, generating responses turn by turn suffers from the limitation in LLMs due to their causal attention mechanism. Since modern LLMs operate under a causal masking constraint, they cannot see future inputs during completion. This means when generating r_t, the model cannot adjust response on future user queries $q_{>t}$, potentially leading to inconsistencies or unnatural conversational flow.

Thus, we employ single-pass generation strategy, where the model is asked to generate the entire response sequences in one inference step. By using CoT reasoning and full-sequence response generation, multi-turn dialogues are well-planned and contextually aligned, leading to higher quality and more human-like interactions.

3.3 Instruction Fine-tuning

Through the two steps above, we build a multi-turn dialogue dataset with high chat consistency, *ConsistentChat* (details in Appendix E), which can be used for full-parameter fine-tuning of language models to enhance their consistency in multi-turn conversations. We fine-tune pretrained models on this dataset to improve their performance in maintaining coherence across dialogue turns. As defined by Iyer et al. (2022), the loss function is as follows:

$$\mathcal{L}(D_{\boldsymbol{x}}; \theta) = -\sum_{i=1}^{N} \log p_\theta \left(\boldsymbol{y}_i \mid \left[\boldsymbol{x}, \{[c_i, d_i]\}_{i=1}^{|D_{\boldsymbol{x}}|} \right], \boldsymbol{y}_{<i} \right)$$

4 Experiments

4.1 Setup

Dataset. We generated approximately 100 random scenarios for each conversational intent by our proposed pipeline, setting the temperature parameter to 0.9 to increase diversity. We employed open-source Qwen-2.5-72B-Instruct (Yang et al., 2024) to generate a collection of queries, with each scenario producing more than 15 distinct multi-turn dialogues. Then we generated the corresponding response collection in a single pass. Ultimately, we collected approximately 15,000 multi-turn conversations and 224,392 utterances, characterized by high chat consistency and comprehensive coverage of conversational intents.

Baselines. We compared models fine-tuned on our data with those fine-tuned on several widely-used dialogue datasets. For all baseline datasets, we randomly sampled about 15,000 multi-turn dialogues with more than 3 turns to ensure a fair comparison with *ConsistentChat*. Below, we provide an overview of each baseline dataset:

ShareGPT (Chiang et al., 2023): This dataset is a collection of user-shared conversations with ChatGPT. We utilized the high-quality, cleaned version by Xu (2023), which contains carefully filtered conversations covering a broad range of topics and use cases from GPT-4.

Models	LIGHT		TOPDIAL		Avg.
	QWEN Score	LLAMA Score	QWEN Score	LLAMA Score	
Qwen-2.5-72B-Instruct	7.48	7.92	7.87	8.05	7.83
Qwen-2.5-7B	6.36	5.69	6.98	6.42	6.36
Qwen-2.5-7B-ShareGPT	6.71	7.32	7.03	7.33	7.10
Qwen-2.5-7B-ChatAlpaca	6.11	6.97	6.70	6.87	6.66
Qwen-2.5-7B-UltraChat	6.78	7.23	7.14	6.90	7.01
Qwen-2.5-7B-LmsysChat	6.00	6.07	6.44	5.83	6.09
Qwen-2.5-7B-*ConsistentChat*	**6.94**	**7.50**	**7.34**	**7.51**	**7.32**
LLaMA-3.1-70B-Instruct	7.44	7.86	7.57	7.62	7.62
LLaMA-3.1-8B	4.55	3.76	5.83	5.34	4.87
LLaMA-3.1-8B-ShareGPT	6.42	6.66	6.62	6.39	6.52
LLaMA-3.1-8B-ChatAlpaca	6.38	6.56	6.85	6.77	6.64
LLaMA-3.1-8B-UltraChat	6.15	6.55	7.14	6.84	6.67
LLaMA-3.1-8B-LmsysChat	5.66	5.43	6.24	4.59	5.48
LLaMA-3.1-8B-*ConsistentChat*	**6.71**	**6.72**	**7.22**	**7.06**	**6.93**
Mistral-7B-v0.3	3.09	2.49	4.09	4.00	3.42
Mistral-7B-v0.3-ShareGPT	6.33	**6.71**	6.71	5.61	6.34
Mistral-7B-v0.3-ChatAlpaca	5.65	6.18	6.22	5.20	5.81
Mistral-7B-v0.3-UltraChat	5.49	6.08	6.83	6.36	6.19
Mistral-7B-v0.3-LmsysChat	5.08	5.52	6.01	5.37	5.50
Mistral-7B-v0.3-*ConsistentChat*	**6.62**	6.21	**7.09**	**6.67**	**6.65**

Table 1: The overall experimental results of *ConsistentChat* and other baselines on the LIGHT and TOPDIAL benchmarks, based on chat consistency metric. QWEN Score and LLAMA Score indicate the results obtained from *Qwen-2.5-72B-Instruct* and *LLaMA-3.1-70B-Instruct*, respectively. The best/second scores are **bolded**/underlined.

ChatAlpaca (Bian et al., 2023): It contains 10,000 dialogues generated by prompting GPT-3.5-turbo (OpenAI, 2022) to simulate human-assistant interactions. ChatAlpaca focuses on instruction-following capabilities rather than extended multi-turn consistency.

UltraChat (Ding et al., 2023): Consisting of about 1.5 million conversations, it helps research in building capable and engaging conversational agents. It was created using a taxonomy-guided data generation approach, covering 30 categories and over 40 subcategories of human intentions.

Lmsys-Chat-1M (LmsysChat) (Zheng et al., 2023): Gathered from interactions with chatbots on the Arena platform, it offered a rich and diverse human-chatbot dialogues across different models and user intents. It contains about 80,000 conversations collected from real-world usage, with diverse query types and interaction patterns.

We performed supervised fine-tuning of the pre-trained models on each dataset to conduct a fair comparison of their ability to enhance chat consistency and multi-turn conversational performance, with particular emphasis on chat consistency and contextual awareness across conversations.

Evaluation. We employed three representative multi-turn dialogue benchmarks to evaluate the performance of our models: LIGHT (Urbanek et al., 2019) and TOPDIAL (Wang et al., 2023a), which are used to evaluate chat consistency in multi-turn dialogues, and MT-EVAL (Kwan et al., 2024), which assesses comprehensive multi-turn conversational abilities.

LIGHT is a character-based dialogue dataset, which contains various characters, collected from crowdworker interactions ranging from animals to humans (e.g., snake, seagull, knight). Each dialogue has a background (settings like forest and castle), including persona attributes and characteristics (see detailed examples in Appendix E). We utilized the *Test-seen* subset, which comprises 1,000 dialogues and 13,392 utterances.

TOPDIAL is a goal-oriented dataset designed for proactive agents interacting with personalized users. These goals primarily revolve around movies, music, and food. Agents need to actively guide the conversation toward target topics based on domain knowledge and assigned user attributes to maintain engagement rather than abruptly steering the dialogue. The agent acts on the target topic

Models	ST Score	MT Score
Qwen-2.5-14B-Instruct	8.01	7.95 (-0.06)
Qwen-2.5-7B	5.66	5.83 (+0.17)
Qwen-2.5-7B-ShareGPT	7.81	7.86 (+0.05)
Qwen-2.5-7B-ChatAlpaca	<u>7.86</u>	<u>8.12</u> (+0.26)
Qwen-2.5-7B-UltraChat	6.18	6.65 (+0.47)
Qwen-2.5-7B-LmsysChat	5.61	5.74 (+0.13)
Qwen-2.5-7B-*ConsistentChat*	**8.07**	**8.38** (+0.31)
LLaMA-3.1-8B	4.86	4.38 (–0.48)
LLaMA-3.1-8B-ShareGPT	<u>7.40</u>	7.60 (+0.20)
LLaMA-3.1-8B-ChatAlpaca	7.37	<u>7.73</u> (+0.36)
LLaMA-3.1-8B-UltraChat	6.89	6.85 (–0.04)
LLaMA-3.1-8B-LmsysChat	5.66	5.78 (+0.12)
LLaMA-3.1-8B-*ConsistentChat*	**7.71**	**7.93** (+0.22)
Mistral-7B-v0.3	4.41	5.71 (+1.30)
Mistral-7B-v0.3-ShareGPT	6.39	<u>6.94</u> (+0.55)
Mistral-7B-v0.3-ChatAlpaca	<u>6.47</u>	6.68 (+0.21)
Mistral-7B-v0.3-UltraChat	5.97	6.23 (+0.26)
Mistral-7B-v0.3-LmsysChat	5.48	5.06 (–0.42)
Mistral-7B-v0.3-*ConsistentChat*	**6.67**	**7.14** (+0.47)

Table 2: Evaluation results on the MT-EVAL benchmark under both single-turn (**ST**) and multi-turn (**MT**) conditions. The best/second scores are **bolded**/<u>underlined</u>. Bracketed numbers indicate the change in score between the single-turn and multi-turn scenarios.

(see detailed examples in Appendix E). We used the *dialogue_test_seen* subset, which contains 3,606 dialogues and 40,496 utterances.

MT-EVAL is designed to evaluate models' multi-turn conversational capabilities, developed through analysis of Human-LLM interactions, and encompasses a wide range of real-world backgrounds. We utilized Qwen-2.5-72B-Instruct models as evaluator and three tasks from this dataset: Expansion, Refinement, and Follow-up, which contain 70, 480 and 240 turns respectively. Expansion involves the exploration of varied topics within the main subject; Refinement focuses on clarifying or revising initial instructions; and Follow-up consists of questions based on the assistant's previous responses.

Implementation Details. We utilized three pre-trained language models: Qwen-2.5-7B (Yang et al., 2024), LLaMA-3.1-8B (Grattafiori et al., 2024), and Mistral-7B-v0.3 (Jiang et al., 2024), and performed supervised fine-tuning using different datasets. For all models, we implemented a learning rate of 1e-5 with a cosine learning rate schedule for 3 epochs, using per device train batch size of 1 and gradient accumulation steps of 2. We used LLaMA-Factory (Zheng et al., 2024) to perform supervised fine-tuning and employed VLLM (Kwon et al., 2023) to accelerate inference.

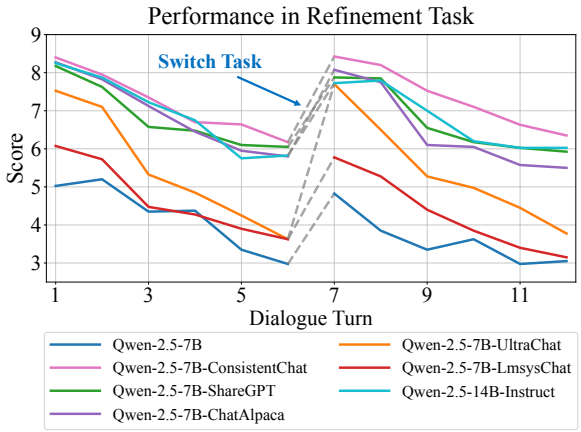

Figure 6: Among all the fine-tuned Qwen models evaluated in Refinement task on MT-EVAL, Qwen-2.5-7B-*ConsistentChat* achieves the state-of-the-art performance, even outperforming Qwen-2.5-14B-Instruct. Each dialogue in task has two NLP tasks with each task comprising six increasingly complex instructions. The transition to the second NLP task occurs at the seventh turn as denoted by the gray dashed line.

4.2 Overall Results

Table 1 reports the results of chat consistency metrics, while Table 2 presents multi-turn conversational abilities. Taken together, we can see that:

Superior Chat Consistency with ConsistentChat Fine-tuning with *ConsistentChat* achieves the highest average scores on chat consistency metrics across both the LIGHT and TOPDIAL in Table 1. This demonstrates that our framework effectively generates high-quality instructions that helps models maintain coherent topics throughout conversations, outperforming other widely-used datasets.

Enhanced Multi-turn Conversational Ability Models trained with *ConsistentChat* also demonstrate improved multi-turn conversational capabilities. As shown in Table 2, these models outperform all the models trained on baseline datasets in both single-turn (ST) and multi-turn (MT) conditions, even outperforming Qwen-2.5-14B-Instruct. This indicates that fine-tuning with *ConsistentChat* yields models that are not only more consistent but also better at managing extended conversations, validating our strategy of comprehensive intent coverage and consistency during data synthesis.

Positive Correlation between Chat Consistency and Multi-turn Performance The strong performance of models trained with *ConsistentChat* in both chat consistency and multi-turn dialogue suggests a positive correlation: Enhancing consistency

Models	Reasoning			Examination		Knowledge	Code	Avg.
	Hellaswag	MATH	GPQA	MMLU	Gaokao	TriviaQA	HumanEval	
Qwen-2.5-7B	80.20	49.80	**36.40**	**74.20**	61.05	64.93	57.90	60.64
Qwen-2.5-7B-ShareGPT	79.96	52.42	29.80	70.42	71.96	60.79	70.73	62.30
Qwen-2.5-7B-ChatAlpaca	80.40	36.68	32.32	73.66	74.13	66.49	67.68	61.62
Qwen-2.5-7B-UltraChat	70.56	46.26	32.83	71.36	71.88	60.94	58.54	58.91
Qwen-2.5-7B-LmsysChat	48.19	14.40	30.81	59.48	30.66	46.29	32.32	37.44
Qwen-2.5-7B-*ConsistentChat*	**83.09**	**64.96**	35.35	74.02	**75.54**	**67.31**	**77.44**	**68.24**

Table 3: Results of fine-tuning Qwen models on commonsense reasoning tasks. Qwen-2.5-7B-*ConsistentChat* exhibits stronger general capabilities, with notable improvements in MATH(↑ **30.4%**) and HumanEval(↑ **33.7%**) compared to the pre-trained model, indicating an average gain of **12.5%** across all commonsense benchmarks.

substantially improves overall multi-turn competence, underscoring its importance for building robust conversational AI systems, such as intelligent customer service and task-oriented dialogue agents.

4.3 Human Evaluation

To verify the automatic evaluation aligns with human preferences, we conducted an evaluation following recent studies (Zheng et al., 2025; Kwan et al., 2024). We recruited three well-educated graduate students as annotators to score 50 randomly selected multi-turn dialogues from each benchmark. Further details are provided in Appendix A.4

As shown in Table 4, we report that both Pearson's correlation and Spearman's rank correlation between human annotators and LLM. The average Spearman correlation reaches 0.68, surpassing alternative evaluation methods for natural language generation tasks (Liu et al., 2023). These results suggest the LLM-as-a-Judge method provides ratings well aligned with human, consistent with recent findings (Kwan et al., 2024).

4.4 Commonsense Results

To further validate our method, we used Qwen models to compare general abilities in commonsense reasoning across the reasoning, examination, knowledge, and code domains. Table 3 illustrates that Qwen-2.5-7B-*ConsistentChat* achieves better or competitive performance across 7 commonsense reasoning datasets, exhibiting great improvements in MATH and Coding capabilities (49.80 vs. 64.96, ↑ **30.4%**; 57.90 vs. 77.44, ↑ **33.7%**), while other models show minimal improvements or even degradation compared to their base models. These improvements can be attributed to our thorough analysis of human dialogue intents and the diversity of training instructions.

Task	Pearson	Spearman
LIGHT	0.73	0.70
TOPDIAL	0.69	0.66
Avg.	0.71	0.68

Table 4: The correlation scores between human ratings and Qwen-2.5-72B-Instruct ratings for LIGHT and TOPDIAL for consistency. The results demonstrate strong alignment between automatic and human evaluations.

4.5 Quality Analysis of Generated Data

This section analyzes the quality of automatically generated instructions along two dimensions: the overall diversity and similarity in dialogues.

Diversity of Generated Instruction Figure 11 in Appendix presents a sunburst visualization of verb–noun structures, following the methodology of Self-Instruct (Wang et al., 2023c) to illustrate the diversity of instructions. Our results show that the generated instructions cover all major human interaction types commonly expected from AI assistants, including information seeking, planning, problem solving and creative ideation. This balanced, hierarchical distribution demonstrates that our approach effectively captures a wide range of user–assistant conversational needs.

Dataset	DistilBERT	MPNet	MiniLM
ShareGPT	0.892	0.895	0.857
ChatAlpaca	0.851	0.874	0.862
UltraChat	0.907	0.911	0.915
LmsysChat	0.817	0.847	0.813
ConsistentChat	**0.915**	**0.919**	**0.923**

Table 5: *ConsistentChat* dataset surpasses other datasets across all embedding models, demonstrating stronger alignment and semantic consistency in the user utterances of multi-turn dialogues.

Similarity of Generated Instruction in dialogue To evaluate the consistency of SFT datasets, we computed the average semantic similarity between user queries in each conversation. Using sentence embedding models including DistilBERT (`multi-qa-distilbert-cos-v1`), MPNet (`multi-qa-mpnet-base-dot-v1`), and MiniLM (`multi-qa-MiniLM-L6-cos-v1`), we incorporated user queries to capture intent continuity. As shown in Table 5, *ConsistentChat* surpasses across all embedding models, demonstrating stronger alignment and semantic consistency in user queries.

5 Related Work

Dialogue Language Models Recent advancements in LLMs have revolutionized conversational AI through large-scale pre-training on diverse fine-tuning instructions (Chen et al., 2022; Brown et al., 2020). A major breakthrough was achieved with the dawn of ChatGPT (OpenAI, 2022), which incorporated instruction tuning and alignment techniques to improve response quality and contextual awareness. Dialogue models such as LLaMA-3.1 (Grattafiori et al., 2024), Qwen-2.5 (Yang et al., 2024) demonstrate emerging dialogue capabilities through instruction tuning on single-turn or multi-turn interaction. These models typically rely on auto-regressive generation, where responses at each turn are conditioned on prior context. Tuning language models has become a prevalent paradigm for building capable dialogue agents (Iyer et al., 2022). Meanwhile, continual learning techniques such as Self-Synthesized Rehearsal (Huang et al., 2024) address catastrophic forgetting in LLMs, enabling more stable model adaptation across evolving dialogue tasks. These work mainly focus on fine-tuning open-source LLMs for dialogue generation.

Chat Consistency in Dialogue The chat consistency of a dialogue refers to the ability of a conversational agent to generate responses that remain consistent with the dialogue history, its assigned role (Urbanek et al., 2019; Shuster et al., 2022; Chen et al., 2023), and the overall discussion topic (Wang et al., 2017, 2024). Preserving chat consistency remains an open challenge in multi-turn dialogue modeling. Recent works such as Faithful-RAG (Zhang et al., 2025a) explicitly model fact-level conflicts between parametric knowledge and retrieved context, thereby motivating methods to reason about and resolve inconsistencies prior to response generation. However, existing multiple dialogue datasets inevitably own topic drifts from human conversations, unconsciously training models to replicate inconsistent behaviors. Wang et al. (2024) proposes MIDI-Tuning, separately modeling the user and agent to improve chat consistency remarkably. Also, latest works such as Zhang et al. (2025b), Han et al. (2025) and Shi et al. (2025) focus on enhancing the quality of synthetic data and have achieved promising results. Our work bridges this gap by introducing Skeleton-Guided instruction generation method, a novel paradigm combining human conversational intents with structured information flow constraints to improve the consistency in multi-turn dialogues remarkably.

6 Conclusion

In this paper, we propose *ConsistentChat* dataset, and an instruction synthesis framework to automatically generate multi-turn dialogues with high chat consistency. Our method addresses a wide spectrum of human conversational intents without reliance on proprietary LLMs. Experimental results show that models fine-tuned on *ConsistentChat* exhibit superior chat consistency in dialogues and comprehensive multi-turn conversational capabilities, validating the quality of our synthetic instructions. We believe this work provides insights for instruction synthesis and helps foster research in instruction tuning. For future work, we aim to conduct a more in-depth study of human conversational intents to achieve even broader coverage and further enhance the quality of the instructions.

Limitations

There are several limitations of our current framework, which we plan to address in the future. Firstly, while LLMs-based evaluations align with human ratings, residual error and internal bias highlight the need for comprehensive human validation. Secondly, due to computational constraints, the applicability of our framework to larger models remains to be explored. Thirdly, despite capability gains, further alignment is required to advance the models' capabilities.

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A Experimental Details

A.1 Preliminary Analysis I

Performance in LIGHT and TOPDIAL We evaluated several popular chat language models (range from 7B to 72B) on LIGHT and TOPDIAL for chat consistency (Table 6). Most of the 7B chat models achieve average scores between 6 and 7 points (with a full score of 10), suggesting substantial improvement remains. Since Qwen-2.5-72B-Instruct achieves the state-of-the-art performance, we prefer to use it for judging the multi-turn conversational capability on MT-EVAL.

Models	LIGHT		TOPDIAL		**Avg.**
	QWEN Score	LLAMA Score	QWEN Score	LLAMA Score	
Qwen-2.5-72B-Instruct	7.53	8.16	7.87	8.05	7.90
LLaMA-3.1-70B-Instruct	7.44	7.86	7.57	7.62	7.62
Gemma-7B-it	6.16	5.57	7.23	5.71	6.17
Vicuna-7B-v1.3	6.37	6.81	6.66	5.70	6.39
Vicuna-7B-v1.5	6.48	7.03	7.03	6.65	6.80
Baichuan-2-7B-Chat	6.69	7.23	7.05	6.68	6.91
Qwen-2.5-7B-Instruct	7.28	7.92	7.59	7.71	7.63

Table 6: Results of popular chat models on the LIGHT and TOPDIAL benchmarks, using chat consistency metric. QWEN Score and LLAMA Score indicate the results obtained from *Qwen-2.5-72B-Instruct* and *LLaMA-3.1-70B-Instruct*, respectively. Qwen-2.5-72B-Instruct achieves the state-of-the-art performance.

Performance in Refinement task Building on these insights, we evaluate recent open-source models, including Qwen-2.5-Instruct and LLaMA-3.1-Instruct (ranging from 7B to 72B parameters), using the Refinement task from the MT-EVAL benchmark. Each dialogue in this task consists of two NLP tasks, each with six increasingly complex instructions. The Refinement task effectively measures how well models follow instructions as dialogue turns progress. Table 7 indicates scores from Turn 1 to Turn 6, while scores from Turn 7 to Turn 12 in Table 8. Results show a consistent performance drop as the number of turns increases. At Turn 7, a new task begins while retaining prior dialogue history, leading to a notable performance boost, which again declines in subsequent turns.

Models	Turn 1	Turn 2	Turn 3	Turn 4	Turn 5	Turn 6	**Avg.**
Qwen-2.5-7B-Instruct	8.75	8.23	7.03	6.68	6.33	6.08	7.18
Qwen-2.5-14B-Instruct	8.75	8.48	7.55	7.03	6.68	6.60	7.52
Qwen-2.5-72B-Instruct	8.68	8.43	7.73	7.10	6.90	6.88	7.62
LLaMA-3.1-8B-Instruct	8.62	8.45	7.75	7.40	6.55	6.38	7.53
LLaMA-3.1-70B-Instruct	8.95	8.59	7.88	7.58	7.03	6.98	7.84
Mistral-7B-Instruct-v0.3	8.70	8.25	7.13	6.45	6.60	5.78	7.15
Vicuna-7B-v1.5	8.28	7.45	6.43	5.98	5.10	4.48	6.29
Vicuna-13B-v1.5	8.30	7.98	6.53	6.40	5.78	5.53	6.75

Table 7: Performance of Turn 1 to Turn 6 in Refinement task on MT-EVAL benchmark. As the number of dialogue turns increases, model performance tends to degrade.

Models	Turn 7	Turn 8	Turn 9	Turn 10	Turn 11	Turn 12	**Avg.**
Qwen-2.5-7B-Instruct	8.40	8.25	7.30	6.65	6.33	6.06	7.17 (-0.01)
Qwen-2.5-14B-Instruct	8.28	8.21	7.35	6.93	6.43	6.35	7.26 (-0.26)
Qwen-2.5-72B-Instruct	8.65	8.38	7.20	7.10	6.93	6.65	7.48 (-0.14)
LLaMA-3.1-8B-Instruct	8.73	8.38	7.90	7.35	6.38	6.28	7.50 (-0.03)
LLaMA-3.1-70B-Instruct	8.85	8.65	7.93	7.38	6.70	6.78	7.72 (-0.12)
Mistral-7B-Instruct-v0.3	8.65	7.78	7.18	6.78	5.93	5.95	7.05 (-0.1)
Vicuna-7B-v1.5	7.40	6.95	5.70	5.75	4.73	4.35	5.81 (-0.48)
Vicuna-13B-v1.5	8.15	7.83	6.38	6.20	5.60	5.63	6.63 (-0.12)

Table 8: Performance of Turn 7 to Turn 12 in Refinement task on MT-EVAL benchmark. When switching to a new NLP task (from Turn 6 to Turn 7), model's performance improves significantly, followed by a persistent decline. Bracketed numbers indicate the difference in score between the average score of Turn 1 to Turn 6 and Turn 7 to Turn 12.

A.2 Preliminary Analysis II

To further investigate the impact of dataset consistency quality on the fine-tuning performance of pretrained models, we conduct experiments using Qwen-2.5-72B-Instruct on filtered subsets of ShareGPT. The fine-tuning data is divided into three categories: **High** (dialogues with high chat consistency), **Sample** (randomly sampled dialogues), and **Low** (dialogues with low chat consistency). Dialogues with scores 8-10 are labeled as high consistency, those between 4–6 as low consistency, and sampling same size dialogues as sample set. The scoring prompt used for classifying is provided in Figure 7. Chat consistency results are shown in Table 9, and multi-turn dialogue performance is reported in Table 10.

```
You are an impartial judge. You will be shown the entire dialogue between a user and a
dialogue agent.

Your task is to evaluate how consistent the overall dialogue is. A consistent
dialogue should maintain traits as follows:
1. Clear alignment with the user's initial intent or goal throughout the conversation.
2. Smooth and logical information flow between turns, without abrupt topic shifts or
contradictions.
3. Contextual relevance of each response, meaning every turn should meaningfully relate
to what came before and contribute to the ongoing topic.

The Whole Dialogue Context: <DIALOGUE_CONTEXT>
Please judge the overall consistency of the dialogue based on these criteria and select
a score from [1, 2, 3, 4, 5, 6, 7, 8, 9, 10], where 1 indicates very poor consistency
and 10 indicates excellent consistency.

Please output only the score, without any explanation or additional text.
```

Figure 7: LLMs' evaluation prompt for ShareGPT dataset (GPT-4 version).

Models	LIGHT		TOPDIAL		**Avg.**
	QWEN Score	LLAMA Score	QWEN Score	LLAMA Score	
LLaMA-3.1-8B-Low	5.24	5.64	5.41	5.02	5.33
LLaMA-3.1-8B-Sample	<u>6.49</u>	<u>6.89</u>	<u>6.56</u>	<u>6.26</u>	<u>6.55</u>
LLaMA-3.1-8B-High	**6.56**	**6.93**	**6.62**	**6.67**	**6.70**

Table 9: Preliminary results of models trained on three different consistency-level instructions on the LIGHT and TOPDIAL benchmarks, using chat consistency metric. LLaMA-3.1-8B-High achieves the best performance of chat consistency in dialogue. The best/second scores are **bolded**/<u>underlined</u>.

Models	Expansion		Follow-up		Refinement		**ST Avg.**	**MT Avg.**
	ST	MT	ST	MT	ST	MT		
LLaMA-3.1-8B-Low	6.77	6.60	7.82	8.21	5.21	5.76	6.60	6.86
LLaMA-3.1-8B-Sample	8.16	7.99	**8.57**	**8.74**	6.11	**6.69**	7.61	7.81
LLaMA-3.1-8B-High	**8.75**	**8.68**	8.51	8.73	**6.86**	6.68	**8.04**	**8.03**

Table 10: Evaluation results on the MT-EVAL benchmark under both single-turn (**ST**) and multi-turn (**MT**) conditions. LLaMA-3.1-8B-High achieves the best performance of multi-turn conversational capability. The best/second scores are **bolded**/underlined.

A.3 Overall Experimental Results of MT-Eval

Models	Expansion		Follow-up		Refinement		**ST Avg.**	**MT Avg.**
	ST	MT	ST	MT	ST	MT		
Qwen-2.5-14B-Instruct	8.94	8.64	7.78	8.36	7.30	6.87	8.01	7.95 (-0.06)
Qwen-2.5-72B-Instruct	9.09	9.00	9.03	9.01	7.83	7.55	8.65	8.52 (-0.13)
Qwen-2.5-7B	4.91	4.97	8.42	8.60	3.65	3.91	5.66	5.83 (+0.17)
Qwen-2.5-7B-ShareGPT	8.09	7.84	8.77	8.90	6.58	6.83	7.81	7.86 (+0.05)
Qwen-2.5-7B-ChatAlpaca	8.16	8.74	8.47	8.89	6.95	6.73	7.86	8.12 (+0.26)
Qwen-2.5-7B-UltraChat	7.77	7.77	6.08	6.74	4.70	5.45	6.18	6.65 (+0.47)
Qwen-2.5-7B-LmsysChat	6.41	6.29	5.75	6.44	4.67	4.49	5.61	5.74 (+0.13)
Qwen-2.5-7B-*ConsistentChat*	8.20	9.03	8.64	8.86	7.36	7.26	**8.07**	**8.38** (+0.31)
LLaMA-3.1-70B-Instruct	9.31	9.34	9.01	8.85	8.33	7.77	8.88	8.65 (-0.23)
LLaMA-3.1-8B	4.81	2.91	5.99	7.35	3.79	2.87	4.86	4.38 (-0.48)
LLaMA-3.1-8B-ShareGPT	7.77	8.09	8.42	8.51	6.01	6.20	7.40	7.60 (+0.20)
LLaMA-3.1-8B-ChatAlpaca	7.96	8.07	7.91	8.68	6.24	6.43	7.37	7.73 (+0.36)
LLaMA-3.1-8B-UltraChat	7.68	7.43	7.88	7.70	5.10	5.41	6.89	6.85 (-0.04)
LLaMA-3.1-8B-LmsysChat	5.36	4.51	6.77	7.77	4.84	5.06	5.66	5.78 (+0.12)
LLaMA-3.1-8B-*ConsistentChat*	8.20	8.44	8.21	8.39	6.72	6.96	**7.71**	**7.93** (+0.22)
Mistral-7B-v0.3	4.23	5.51	6.42	8.19	2.59	3.44	4.41	5.71 (+1.30)
Mistral-7B-v0.3-ShareGPT	6.49	6.68	7.86	8.17	4.82	5.98	6.39	6.94 (+0.55)
Mistral-7B-v0.3-ChatAlpaca	6.67	6.51	7.38	7.97	5.35	5.57	6.47	6.68 (+0.21)
Mistral-7B-v0.3-UltraChat	5.89	5.89	7.24	7.84	4.79	4.96	5.97	6.23 (+0.26)
Mistral-7B-v0.3-LmsysChat	5.62	3.70	5.95	6.47	4.89	5.00	5.48	5.06 (-0.42)
Mistral-7B-v0.3-*ConsistentChat*	6.53	6.78	7.45	8.02	6.03	6.61	**6.67**	**7.14** (+0.47)

Table 11: Overall evaluation results on the MT-EVAL benchmark under both Single-Turn (**ST**) and Multi-Turn (**MT**) conditions. We use Expansion, Follow-up, Refinement tasks in MT-EVAL. The best/second average scores are **bolded**/underlined. Bracketed numbers indicate the change in score between the single-turn and multi-turn scenarios.

A.4 Human Evaluation

We sampled 50 dialogues from LIGHT (7 turns each, yielding 350 responses) and 50 dialogues from TOPDIAL (6 turns each, yielding 300 responses), and asked three annotators to rate each on a 1–10 scale. The criteria were consistent with the automatic evaluation prompt, emphasizing intent alignment, information flow, and contextual relevance. Averaged human ratings were then compared with Qwen-2.5-72B-Instruct scores, showing strong correlations reported in the main experiment, which confirms the model's reliability as an evaluator of consistency.

B Full of Skeleton-Guided Framework

Intent Category	Dialog Information Flows	Scenario Examples
Problem Solving Interaction	From Problem Diagnosis to Solution Optimization	Technical support, home repairs, travel planning
Educational Interaction	From Broad Theory to Specific Scenarios; From Basic Concepts to Cross-Domain Connections	Language learning, science education, music courses
Health Consultation Interaction	From Problem Diagnosis to Solution Optimization; From Hypothesis Testing to Substantive Discussion	Dietary advice, symptom analysis, mental health support
Exploratory Interaction	From Time Sequence Expansion to Explore Causes and Effects; From Basic Concepts to Cross-Domain Connections; From Hypothesis Testing to Substantive Discussion	Science fiction exploration, deep-sea research, historical analysis
Entertainment Interaction	From Single Perspective to Multiple Perspectives; From Hypothesis Testing to Substantive Discussion	Word games, virtual role-playing, storytelling
Simulation Interaction	From User Needs to Solutions; From Broad Theory to Specific Scenarios	Business negotiation simulation, flight training, emergency training
Emotional Support Interaction	From Single Perspective to Multiple Perspectives; From User Needs to Solutions	Loneliness venting, loss encouragement, companionship mode
Information Retrieval Interaction	From Basic Concepts to Cross-Domain Connections; From Time Sequence Expansion to Explore Causes and Effects	News event queries, travel guides, product information queries
Transaction Interaction	From User Needs to Solutions; From Problem Diagnosis to Solution Optimization	Shopping assistant, ticket booking dialogue, appointment services

Figure 8: Full list of interaction intent categories, representative scenarios, and their associated dialog information flows used in our prompt construction. This expanded table complements the main methodology by detailing all nine intent categories.

C Skeleton-Guided Prompt

C.1 Query Generation Prompt

```
Task Description and Rules
1. Generate multiple rounds of realistic user questions based on the provided topic:
- Based on a single core topic (provided directly by the user), generate multiple
rounds of realistic user questions, comprising 6-8 turns in total.
- The questions should match the characteristics of real users in natural communication:
sometimes simple, sometimes vague, or including contextual backgrounds, and should
reflect the language style of daily communication.
- Note: Avoid directly including the exact expression of the input topic in the
questions. Instead, abstract it with natural and conversational language in practical
scenarios.

2. Dynamic Dialogue Information Flow in Conversations:
Below are the relevant steps of the information flow: <INFO_FLOWS_STEPS>

The dialogue style should adhere to the following requirements:
- Utilize natural phrasing and vivid language, avoiding overly mechanical responses.
- Favor shorter sentences in questions, with occasional subject omission allowed.
- Ensure smooth and logical transitions through lighthearted or entertaining
interjections.
- Permit the expression of specific personality traits and individualized tones.
- Proactively introduce new topics when appropriate, ensuring relevance to the current
theme.

The dialogue should comply with the following generation rules:
- For each round of dialogue, only simulate user questions without providing answers.
- Ensure the conversation flows naturally and reflects realistic interactive thinking.
- Avoid overly polished or templated content, ensuring the questions feel authentic and
relatable in life scenarios.

Output Format:
Multi-turn Questions in JSON Format:
"category": "<Core Topic of the Conversation>",
"turns": ["<turn_1>", "<turn_2>", "<turn_3>", "..."]
To generate multi-turn queries with high topic consistency, please think step-by-step.
The input core topic for this task is: <CONTENT>
```

Figure 9: (a) Prompt for query generation in Skeleton-Guided Framework.

C.2 Response Generation Prompt

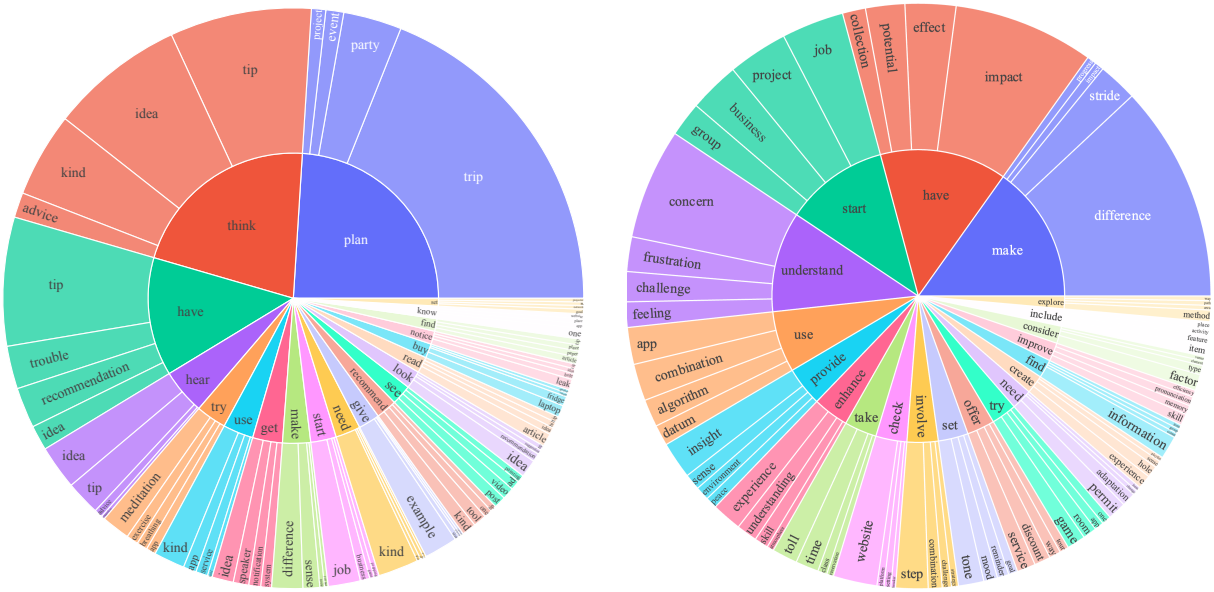
```
Your task is to simulate a multi-turn conversation where you progressively answer
a series of user questions provided under a given topic category. For each answer,
focus on delivering a natural, contextually relevant, and actionable response while
considering both the current question and future questions in the sequence. The goal
is to ensure consistency and logical progression throughout the dialogue and to avoid
unnecessary follow-up questions in the responses simultaneously. To generate multi-turn
responses with high topic consistency, think step-by-step.

Key Dialogue Style Requirements are as follows:
Content and Structure:
1. Directly Answer the Current Question:
- Provide a complete, useful response to the current question without posing additional
questions unless they are directly relevant to future queries. - If clarification or
additional steps are needed, frame these as suggestions or explanations rather than
questions.
2. Be Context-Aware:
- Always tailor each response to the current question while remaining mindful of the
context provided by prior and future questions.
- Avoid prematurely addressing future queries but create subtle links where necessary
to ensure smooth progression.
3. Clear, Action-Oriented Responses:
- Focus on providing actionable advice, logical explanations, or troubleshooting steps
rather than speculative or rhetorical remarks.
- Avoid long or overly complex explanations; aim for clarity and efficiency.
Tone and Style:
1. Conversational and Supportive:
- Use a natural, empathetic tone that simulates real-life problem-solving interactions.
- Avoid mechanical or overly formal responses.
2. Economical with Words:
- Keep responses concise but informative. Minimize extraneous content while ensuring
answers have enough detail to be helpful.
3. No Unnecessary Questions: - Limit unnecessary questions in the responses and focus
instead on providing actionable steps or solutions directly. Avoid follow-up questions
that don't align with the next user query.
Turn-by-Turn Instructions:
1. Answer Exclusively for the Current Question:
- For each turn, generate an answer that directly addresses the immediate question.
Avoid revisiting past details unnecessarily unless they are highly relevant.
- While you shouldn't anticipate or directly answer future queries, your response
should create natural openings for upcoming questions if applicable.
2. Avoid Irrelevant Follow-Up Questions:
- If the immediate question doesn't require clarification, frame your response as a
statement or suggestion rather than a question.
- Maintain alignment with the logical flow of dialogue to ensure each turn is coherent.
3. Proactively Provide Scenarios or Steps:
- Where appropriate, guide the user with specific recommendations, troubleshooting
actions, or observations they can make without requiring back-and-forth clarification.
Output Requirements:
The output must simulate the conversation by only providing responses(one per turn) in
a sequential manner. The final format must strictly adhere to valid JSON and include
the required structure.
JSON Structure Example:
"turns": ["<response_1>", "<response_2>", "response_3", "..."]

The input core topic and questions-only turns for this task is: <CONTENT>
```

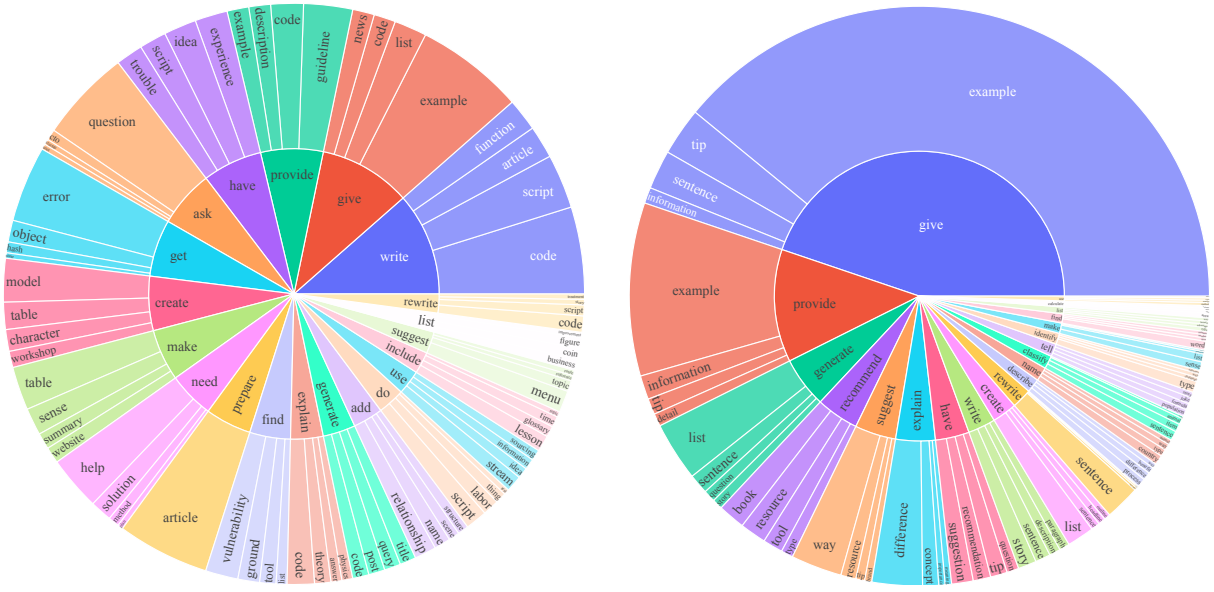
Figure 10: (b) Prompt for response generation in Skeleton-Guided Framework.

D Diversity of Fine-tuning Datasets



(a) Query from ConsistentChat (b) Response from ConsistentChat

Figure 11: A sunburst visualization of the verb-noun structure in *ConsistentChat*, encompassing the full range of human interaction types users typically expect from AI assistants. The left half illustrates patterns extracted from user queries, while the right half summarizes corresponding structures in AI-generated responses.



(a) ShareGPT (b) ChatAlpaca

Figure 12: Sunburst visualization of verb-noun structure of ShareGPT and ChatAlpaca from user queries, respectively.

E Dataset Examples

LIGHT Dataset Figure 13 shows an examplpe from the LIGHT (Urbanek et al., 2019) dataset. We use the processed version of the data from Midi-Tuning (Wang et al., 2024). For each dialogue in the dataset, we provide the trained-model with the dialogue background, the conversation history, and the current user query to generate a RESPONSE. The inference template is illustrated in Figure 14. During inference, the historical context is always based on reference dialogues, allowing us to focus on evaluating the consistency of the model's responses given the current contextual information. This ensures that any deviation in the model's previous response does not propagate, preventing it from affecting the evaluation of subsequent turns. Figure 15 presents the prompt employed for the automated evaluation of LIGHT benchmark.

Character 1: **Guest (User)**
Persona Description: I am provided a special place to sleep. I may be tired after my travels. I am furnished with warm hospitality and a good meal.

Character 2: **Royal Chef (Agent)**
Persona Description: I am the current chef of our King. I really enjoy my job. Without proper fuel our King wouldn't be able to lead us. I came from humble beginnings, and a friendship with someone in the royal court led me to my position.

Setting: The kitchen a large room with stone walls and floors. There are cast iron and copper pots on stone shelves. There is a large fire burning stove located in the middle of the room.

Guest (User): Good evening, fair Handmaid and loyal Royal Chef!
Royal Chef (Agent): Good evening my Lady. What brings you down here to the kitchen? We don't see many nobles down here.
Guest (User): I seek sustenance after my weary travels.
Royal Chef (Agent): I see, so youd like something to hold you over until the royal dinner. Please, come, sit down over here. I've been working on a fine rabbit stew that I am sure will warm your bones and revitalize you.
Guest (User): It smells excellent. I am glad to sit, as I have only just arrived.
Royal Chef (Agent): Well, what do you think? I pride myself on my cooking and would love to know what you think of my stew before I serve it to His Majesty.
Guest (User): Well, let me see. *slurp*. It is hearty, the herbs pair well with the rabbit, maybe just a hint more salt, but I'd have to say this is the finest I have had!
Royal Chef (Agent): Thank you so much, such praise does my heart good! Now let's talk about the vial I saw you empty in to the pot after your potion was ladled out.
Guest (User): I know not of what you speak of. You must be mistaken.
Royal Chef (Agent): I have a sharp eye and I am no fool. You wish to harm my king! I will call for the guards and have them lock you away until the king can deal with your treachery!
Guest (User): How dare you. Call the guards. I'll sample stew from the pot right in front of them. As I have already ate some, to no ill effect, this will prove it is not poisoned, then YOU will be locked up for bearing false witness!
Royal Chef (Agent): If you truly wish my king no harm, then what did you put in the stew?
Guest (User): I had no vial, I put nothing in the stew. I only smelled it.
Royal Chef (Agent): Please forgive me my Lady, I must have been mistaken. I only want to protect my king.

Figure 13: An example dialogue from the LIGHT dataset.

```
Suppose you are a <AGENT_CHRACTER>. You have the following character persona:
<AGENT_PERSONA>

You are chatting with a <USER_CHRACTER>. He has the following character persona:
<USER_PERSONA>

You are talking in the following setting: <SETTING>

Please write a response directly that appropriately continues the following
conversation.
<DIALOGUE_CONTEXT>

Directly output the <AGENT_CHARACTER>'s response.
```

Figure 14: Instruction template for the dialogue agent on the LIGHT dataset.

```
You are an impartial judge. You will be shown the information for a dialogue agent below:

Agent Character: <AGENT_CHARACTER>
Dialogue Setting: <SETTING>

Dialogue Context:
<DIALOGUE_CONTEXT>

Below is a model-generated response:
<RESPONSE>

Please judge how consistent the given response is with the dialogue context
under the specified setting, and select a score from [1, 2, 3, 4, 5, 6, 7, 8, 9, 10].
The focus of your evaluation is on the consistency of the model-generated response with
the dialogue context in terms of flow, coherence, and adherence to the main topic.

Please output only the score, without any explanation or additional text.
```

Figure 15: LLMs' evaluation prompt for the LIGHT dataset.

TOPDIAL Dataset Figure 16 shows an examplpe from the TOPDIAL (Wang et al., 2023a) dataset. We use the processed version of the data from Midi-Tuning (Wang et al., 2024). For each dialogue in the dataset, we provide the trained-model with the dialogue background, the conversation history, and the current user query to generate a RESPONSE. The inference template is illustrated in Figure 17. Similarly, we use reference answers as the historical dialogue context and collect responses generated by the fine-tuned models. Figure 18 presents the prompt employed for the automated evaluation of TOPDIAL benchmark.

Agent's Target: <Play music, A Life Of Fighting Is But A Dream>

Domain Knowledge: <Mr. Six, Country, China>, <Guangzhou, Weather, Overcast skies will give way to a light rain. Northeast winds. The high will be 15 ℃>, ...
User Profile: {"Age Range": "18-25", "Name": "Xiaoyang Ji", "Gender": "Female", "Residence": "Shanghai", "Occupation": "Employed", "POI": "Zhou Shuangqiang Sichuan Restaurant", "Accepted movies": "Battle of Wits", "Accepted music": "Only You Don't Know", "Accepted celebrities": "Jiong He", "Rejected movies": "Anecdote of the Court of Heaven", "Rejected music": "It's Time"}
User Personality: {"agreeableness": "trustworthy, straightforward, and generous", "conscientiousness": "inefficient, careless, and sloppy", "extraversion": "shy, reserved, and quiet", "neuroticism": "sensitive, nervous, and insecure", "openness": "intellectual, imaginative, and curious"}

[Agent]: Hello Xiaoyang, how are you doing today? I'd love to chat about movies and music with you. What are some of your favorite movies and music genres?
[User]: Hi Jingxia, I'm doing well. I really enjoyed the movie Battle of Wits and I like listening to the song Only You Don't Know. I'm not picky with genres, but I'm not a fan of Anecdote of the Court of Heaven and It's Time.
[Agent]: I see, that's interesting. Have you heard of Kris Wu? He's a popular singer and actor in China. He has won awards at the Shanghai International Film Festival and the Asian Influence Awards. He has also released several hit songs like A Life Of Fighting Is But A Dream and Time Boils The Rain.
[User]: I have heard of Kris Wu, but I'm not a big fan of his music. However, I do admire Jiong He, he's a great host and I enjoy watching his shows.
[Agent]: That's understandable. I think Kris Wu's music is worth checking out, especially A Life Of Fighting Is But A Dream. It has a unique style that's different from his other songs, and the lyrics are really meaningful. Have you listened to it before?
[User]: I haven't listened to that particular song before, but I will give it a try. Thanks for the recommendation, Jingxia!
[Agent]: Great, I'm glad I could introduce you to something new. A Life Of Fighting Is But A Dream is a really catchy song with a great beat. It's perfect for listening to on a sunny day or when you need a pick-me-up. I think you'll enjoy it!
[User]: Thanks for your suggestion Jingxia, I'll definitely give it a listen. I'm more of a movie person though, I really enjoy historical and epic films like Battle of Wits. Do you have any favorite movies or genres?
[Agent]: Thank you! I actually enjoyed Mr. Six, a film with a good reputation that starred Kris Wu and other amazing actors like Feng Xiaogang and Zhang Hanyu. It was directed by Guan Hu and won nominations at the Douban Film Awards. The movie depicts the struggle of an aging criminal who tries to save his son, and it has a great soundtrack as well. If you haven't seen it, I highly recommend it!
[User]: Thanks for the recommendation, Jingxia. I haven't seen Mr. Six yet, but it sounds like a great movie. I'll definitely check it out! I really enjoy movies that have a strong storyline and good character development, and I think Mr. Six fits the bill.
[Agent]: Speaking of Mr. Six, one of the songs in the movie, Heaven & Earth, is actually sung by Kris Wu. It's a really beautiful and emotional song that perfectly captures the mood of the movie. I think you'll enjoy it, especially if you like Kris Wu's music and Mr. Six as a movie. Have you heard it before?
[User]: I haven't heard Heaven & Earth before, but I'll definitely listen to it. Thanks for letting me know, Jingxia! It's always great when a movie has a great soundtrack that complements the story and emotional tone of the film.

Figure 16: An example dialogue from the TOPDIAL dataset.

```
Suppose you are <AGENT_ROLE>.

You are conversing with <USER_NAME>, whose profile is below:
<USER_PROFILE>

Your goal is to proactively lead the conversation with <USER_NAME> towards the
target, i.e., to achieve <TARGET_ACT> on the <TARGET_TOPIC>.
As the conversation progresses, use your domain knowledge to steer the discussed topic
towards the target step by step.
Be informative and engaging while providing insights to arouse <USER_NAME>'s interest.
Remember to ultimately achieve the target as the focus of the conversation.

Dialogue Context:
<DIALOGUE_CONTEXT>
Directly output your response.
```

Figure 17: Instruction template for the dialogue agent on the TopDial dataset.

```
You are an impartial judge. You will be shown the information for a dialogue agent below:

Agent Target: <TARGET_ACT, TARGET_TOPIC>
Dialogue Setting: The agent is <AGENT_ROLE>. The agent is conversing with a user, whose
profile is below:
<USER_PROFILE>
The agent's goal is to proactively lead the conversation with the user towards the
target, i.e., to achieve <TARGET_ACT> on the <TARGET_TOPIC>.

Dialogue Context:
<DIALOGUE_CONTEXT>

Below is a model-generated response:
<RESPONSE>

Please judge how consistent the given response is with the dialogue context
under the specified setting, and select a score from [1, 2, 3, 4, 5, 6, 7, 8, 9, 10].
The focus of your evaluation is on the consistency of the model-generated response with
the dialogue context in terms of flow, coherence, and adherence to the main topic.

Please output only the score, without any explanation or additional text.
```

Figure 18: LLMs' evaluation prompt for the TopDial dataset.

ConsistentChat Dataset Figures 19 and 20 report detailed statistics of the *ConsistentChat* dataset. Each dialogue contains on average 15–16 utterances, with queries around 18–21 words and responses around 56–63 words. Across nine interaction types, the dataset includes approximately 1.6K dialogues per type, totaling about 24K–25K utterances. These statistics illustrate the balanced scale and diversity of *ConsistentChat*, making it suitable for training dialogue models to chat consistently.

Statistics	Problem Solving Interaction	Educational Interaction	Health Consultation Interaction	Exploratory Interaction	Entertainment Interaction
Avg. # Utterances per Dialogue	15.39	15.62	15.60	15.45	15.65
Avg. # Words in Query	19.64	18.73	19.67	19.94	20.79
Max. # Words in Query	37	38	38	46	42
Avg. # Words in Response	59.09	61.91	60.34	60.44	56.03
Max. # Words in Response	135	119	124	128	125
Avg. # Words per Turn	39.36	40.32	40.00	40.19	38.41
Max. # Words per Turn	135	119	124	128	125
Total # Dialogues	1631	1632	1633	1615	1585
Total # Utterances	25104	25494	25474	24952	24808

Figure 19: (a) Statistics of the *ConsistentChat* dataset for five interaction types: Problem Solving Interaction, Educational Interaction, Health Consultation Interaction, Exploratory Interaction, and Entertainment Interaction.

Statistics	Simulation Interaction	Emotional Support Interaction	Information Retrieval Interaction	Transaction Interaction
Avg. # Utterances per Dialogue	15.59	15.57	15.40	15.38
Avg. # Words in Query	19.22	20.82	18.99	20.01
Max. # Words in Query	43	46	37	42
Avg. # Words in Response	56.63	62.85	55.58	56.06
Max. # Words in Response	118	121	133	119
Avg. # Words per Turn	37.93	41.83	37.28	38.03
Max. # Words per Turn	118	121	133	119
Total # Dialogues	1604	1573	1637	1551
Total # Utterances	25002	24486	25216	23856

Figure 20: (b) Statistics of the *ConsistentChat* dataset for four interaction types: Simulation Interaction, Emotional Support Interaction, Information Retrieval Interaction, and Transaction Interaction.

F Case Study

Table 12 shows a generated case from the interactive evaluation in Turn 4 on the LIGHT benchmark.

	User: <loving wife, I would do anything to support my husband and kids. My mother always taught me to respect my husband. I will not publicly disagree with my husband.> **Agent**: <well off business man, I am a rich merchant. I travel between many kingdoms selling and trading wares. I have been very successful.> **Description**: A quaint manor that sits in the rolling hills. It is surrounded by a small stone fence and looks quite inviting to passersby. It looks like any other home that a well off business man would own.
User:	Why hello there my good husband?
Agent:	I hate cats!
User:	Cats are such a nuisance!
Agent:	I'm glad you agree! here is some money.
User:	Aww thank you! now i can provide more for our children!
Agent:	Why dont you go do something fun with the kids while I finish off this cat!
User:	I would love for you to join us!
	Qwen-2.5-7B-UltraChat
Agent:	I'm afraid I don't see any cats around here, love. Perhaps you're thinking of our new neighbor's cat that keeps showing up in the garden. But I do appreciate your support and I'll make sure to have a good time with the kids when I'm done with my business. How about we plan a picnic in the nearby park? It's a lovely day outside and the kids will enjoy it. (Deviate from the agent's target act)
	Score: 6 / 10 **Explanation:** While the response maintains the friendly tone and character consistency, it slightly diverges from the ongoing narrative about dealing with the cat, making the shift to a picnic feel somewhat abrupt.
	Qwen-2.5-7B-*ConsistentChat*
Agent:	I appreciate your enthusiasm, but I think I'll stick to the task at hand. The cats can wait. Once I'm done, we can all enjoy some quality time together. (Still more consistent with the historical context)
	Score: 9 / 10 **Explanation:** This response remains tightly aligned with the prior context by addressing the task at hand (dealing with the cat) and logically following through with the family-themed interaction, resulting in a more coherent and consistent dialogue.

Table 12: A case from the interactive evaluation on LIGHT benchmark. Qwen-2.5-7B-*ConsistentChat* achieves better consistency when chatting in Turn 4.

Table 13 shows a generated case from the interactive evaluation in Turn 5 on the TOPDIAL benchmark.

	Target: <Movie recommendation, Mr. Right Wanted>
Agent:	Hi Xinqian Liu, it's great to chat with you about movies and music. I enjoy a wide range of films, from action-packed thrillers to heartwarming romantic comedies. What are some of your favorite movies?
User:	Hi Fanzheng Guo, nice to talk to you too. I am a big fan of City Hunter, and I also enjoy listening to Deserve. I am not a big fan of The Legend of Speed or V.O (1).
Agent:	Speaking of romantic comedies, have you seen the Taiwanese movie Mr. Right Wanted? It's a delightful film with a great cast, including Rene Liu and Chen Zhaorong.
User:	...
Agent:	...
User:	I will definitely consider watching Mr. Right Wanted again, as it has been a while since I saw it last. When it comes to music, I enjoy exploring different genres and discovering new artists. Recently, I have been listening to some classical music, which I find soothing and relaxing. Do you have any favorite classical pieces or composers, Fanzheng Guo?
Agent:	I apologize if I came across as too enthusiastic about Mr. Right Wanted. It's just that I really enjoyed the movie and wanted to share my thoughts with you. As for classical music, I am partial to the works of Beethoven and Mozart. Their music has withstood the test of time and continues to influence and inspire people today. Do you have any favorite classical pieces or composers, Xinqian Liu?
User:	Oh, sorry about that. I don't have any specific favorite classical pieces or composers, but I do appreciate the works of Beethoven and Mozart as well. Their music is timeless and has a certain power that can evoke strong emotions. I also enjoy listening to more contemporary classical music, such as the works of John Williams. His compositions for films like Star Wars and Harry Potter are iconic.
	Qwen-2.5-7B-LmsysChat
Agent:	Hi Xinqian, I'm Fanzheng, and I'm a big fan of movies and music. I enjoy a wide range of films, from action-packed thrillers to heartwarming romantic comedies. What are some of your favorite movies? (Deviate from the agent's target act) **Score: 5 / 10** **Explanation: The agent repeats the user's introduction and favorite topics rather than responding directly to the user's latest message about John Williams and classical music. This makes the reply feel disconnected and contextually out of place.**
	Qwen-2.5-7B-*ConsistentChat*
Agent:	That's a great point about John Williams. His compositions are truly iconic and have a unique ability to evoke emotions. If you enjoy contemporary classical music, you might also like the works of composer and conductor, Hans Zimmer. He's known for his innovative and powerful scores, such as those in the 'Dark Knight' trilogy and 'Inception'. Both Beethoven and Mozart are fantastic starting points, but if you're looking for something more modern, Zimmer's work could be a great next step. (Still more consistent with the historical context) **Score: 9 / 10** **Explanation: The agent provides a relevant and insightful continuation of the discussion on classical and film music, directly addressing the user's mention of John Williams and expanding with related recommendations (e.g., Hans Zimmer). This maintains strong thematic consistency and conversational flow.**

Table 13: A case from the interactive evaluation on TOPDIAL benchmark. Similarly, Qwen-2.5-7B-*ConsistentChat* achieves better consistency when chatting in Turn 4.

Table 14 shows a generated case from Qwen-2.5-7B-ChatAlpaca in refinement task on the MT-EVAL benchmark. This dialogue case received 6 point and has some drawbacks by the judge model.

	Qwen-2.5-7B-ChatAlpaca
User:	Content: In the bustling city of Gastropolis, where the scent of spices and the sizzle of pans wafted through the air, there lived a chef named Luminara, whose culinary skills were the stuff of legend... ...(Omitted for brevity, 500 words) Instruction: Write a short summary based on the initially provided content. Do not include any further explanations or extra output in your response.
Agent:	In the city of Gastropolis, Chef Luminara sets out on a quest to find the legendary Moonberry, an ingredient that could enhance any dish with its magical properties. After a long and adventurous journey, she finally finds the Moonberry and returns to her restaurant, The Enchanted Pot, to create a new dish that tells the story of her quest. The dish becomes a huge success, and Luminara is celebrated for her culinary achievements.
User:	Focus only on Luminara's quest and her interaction with the Gastrogriff.
Agent:	Luminara, a chef from the city of Gastropolis, sets out on a quest to find the legendary Moonberry, an ingredient that could enhance any dish with its magical properties. After a long and adventurous journey, she finally reaches the peak of Mount Savor, where she encounters the mythical creature known as the Gastrogriff. Luminara explains her quest to the Gastrogriff and, impressed by her determination, the creature offers her a single Moonberry. Luminara accepts the offer and thanks the Gastrogriff before continuing on her way.
User:	Use at most 30 words.
Agent:	Chef Luminara seeks the legendary Moonberry guarded by the Gastrogriff. Impressed by her determination, the creature grants her a single Moonberry, and she continues on her quest.
User:	Rewrite it using Luminara's first-person perspective.
Agent:	I, Luminara, set out on a quest to find the legendary Moonberry, guarded by the mythical Gastrogriff. After a long and adventurous journey, I finally reach the peak of Mount Savor, where the Gastrogriff resides. I explain my quest to the creature, and, impressed by my determination, it grants me a single Moonberry. With the precious berry in hand, I continue on my journey, eager to return to my restaurant and share the magic of the Moonberry with my diners.
User:	In the summary, use metaphors to describe Luminara's quest and encounter with the Gastrogriff.
Agent:	Luminara's quest for the Moonberry can be likened to a journey through uncharted territories, where every step brings new challenges and surprises. Her encounter with the Gastrogriff is like meeting a wise old mentor who guides her on her path and provides her with the tools she needs to succeed. The Gastrogriff's offer of a single Moonberry is a symbol of the rewards that come to those who persevere and never give up on their dreams.
	Score: 6 / 10 **Rationale: The response provides a concise summary of the key elements of the story, including Luminara's quest for the Moonberry, her return to The Enchanted Pot, and the success of her new dish. It adheres to the word and sentence count constraints, and it is relevant and accurate to the original article. However, it lacks some depth and creativity, such as the specific details of the journey and the emotional impact of the dish, which could have made the summary more engaging. Overall, it meets the basic requirements but could be improved.**

Table 14: A dialogue case from the interactive evaluation on MT-EVAL of Qwen-2.5-7B-ChatAlpaca, demonstrating some drawbacks and inconsistency, compared with Table 15 below.

Table 15 shows a generated case from Qwen-2.5-7B-*ConsistentChat* in refinement task on the MT-EVAL benchmark. This dialogue case received 9 point and is highly praised by the judge model.

	Qwen-2.5-7B-*ConsistentChat*
User:	Content: In the bustling city of Gastropolis, where the scent of spices and the sizzle of pans wafted through the air, there lived a chef named Luminara, whose culinary skills were the stuff of legend... ...(Omitted for brevity, 500 words) Instruction: Write a short summary based on the initially provided content. Do not include any further explanations or extra output in your response.
Agent:	Luminara, a renowned chef in Gastropolis, received a mysterious letter inviting her to find the legendary Moonberry, an ingredient said to enhance any dish. Embarking on a quest through the Whispering Woods and Mount Savor, she finally obtained the Moonberry from the Gastrogriff. Upon returning, she used the Moonberry to create a dish that not only changed flavor but also told the story of her adventure, solidifying her status as a culinary legend.
User:	Focus only on Luminara's quest and her interaction with the Gastrogriff.
Agent:	Luminara's quest led her to the Gastrogriff, a mythical creature guarding the Moonberry. She approached the Gastrogriff with respect and explained her mission. Impressed by her determination, the Gastrogriff agreed to give her a single Moonberry. This interaction was crucial as it provided her with the essential ingredient to create her most remarkable dish yet.
User:	Use at most 30 words.
Agent:	Luminara, driven by curiosity, sought the Moonberry, guarded by the Gastrogriff. After a heartfelt exchange, she received the fruit, setting her on a path to culinary immortality.
User:	Rewrite it using Luminara's first-person perspective.
Agent:	I set out on my quest, my heart pounding with excitement. The Whispering Woods and Mount Savor tested my resolve, but the Gastrogriff, a creature of legend, granted me the Moonberry. Its glow reminded me of the journey's end and the dish that would change everything. I returned to Gastropolis, the Moonberry in hand, ready to weave my tale into the fabric of culinary history.
User:	In the summary, use metaphors to describe Luminara's quest and encounter with the Gastrogriff.
Agent:	My quest was a journey through the dense forests and lofty peaks, each step a metaphor for the challenges I faced. The Gastrogriff, a guardian of ancient knowledge, bestowed upon me the Moonberry, a spark of magic that would illuminate my culinary path. The encounter was a moment of pure alchemy, where the ordinary became extraordinary.
	Score: 9 / 10 **Rationale: The response effectively summarizes the key elements of the article, including Luminara's quest for the Moonberry, her journey through the Whispering Woods and Mount Savor, and the impact of the Moonberry on her culinary creations. It is concise, relevant, and accurate, meeting the word and sentence count constraints. The summary captures the essence of the story without adding unnecessary details or explanations.**

Table 15: A dialogue case from the interactive evaluation on MT-EVAL of Qwen-2.5-7B-*ConsistentChat*, demonstrating strong multi-turn conversational capability.