PROACTIVE AGENT: SHIFTING LLM AGENTS FROM REACTIVE RESPONSES TO ACTIVE ASSISTANCE

Yaxi Lu[1], **Shenzhi Yang**[2], **Cheng Qian**[1], **Guirong Chen**[2], **Qinyu Luo**[1], **Yesai Wu**[1], **Huadong Wang**[1], **Xin Cong**[1], **Zhong Zhang**[1], **Yankai Lin**[2], **Weiwen Liu**[3], **Yasheng Wang**[3], **Zhiyuan Liu**[1*], **Fangming Liu**[4*], **Maosong Sun**[1]
[1] Department of Computer Science and Technology, Tsinghua University
[2] Gaoling School of Artificial Intelligence, Renmin University of China
[3] Huawei Noah's Ark Lab, [4] Peng Cheng Laboratory
lyx23@mails.tsinghua.edu.cn, mrlyk423@gmail.com,
liuzy@tsinghua.edu.cn, fangminghk@gmail.com

ABSTRACT

Agents powered by large language models have shown remarkable abilities in solving complex tasks. However, most agent systems remain reactive, limiting their effectiveness in scenarios requiring foresight and autonomous decision-making. In this paper, we tackle the challenge of developing proactive agents capable of anticipating and initiating tasks without explicit human instructions. We propose a novel data-driven approach for this problem. Firstly, we collect real-world human activities to generate proactive task predictions. These predictions are then labeled by human annotators as either accepted or rejected. The labeled data is used to train a reward model that simulates human judgment and serves as an automatic evaluator of the proactiveness of LLM agents. Building on this, we develop a comprehensive data generation pipeline to create a diverse dataset, ProactiveBench, containing $6,790$ events. Finally, we demonstrate that fine-tuning models with the proposed ProactiveBench can significantly elicit the proactiveness of LLM agents. Experimental results show that our fine-tuned model achieves an F1-Score of 66.47% in proactively offering assistance, outperforming all open-source and close-source models. These results highlight the potential of our method in creating more proactive and effective agent systems, paving the way for future advancements in human-agent collaboration.

1 INTRODUCTION

The emergence of large language models (LLMs) like ChatGPT (OpenAI, 2022) has significantly advanced the development of autonomous agent (Chen et al., 2023; Hong et al., 2023; Zhang et al., 2023; Wu et al., 2023). These LLM-based agents can understand human instructions, make plans, explore environments, and utilize tools to solve complex tasks (Wu et al., 2023; Li et al., 2023) and have shown substantial potential in various applications such as robotics (Firoozi et al., 2023), personal assistants (Li et al., 2024), and process automation (Ye et al., 2023b).

Currently, most existing LLM-based agents predominantly work in the reactive paradigm: they require explicit human instructions to initiate task completion and remain dormant in terms of providing services until prompted by user instructions (Ouyang et al., 2022). This paradigm limits their capacity for proactive assistance and autonomous service provision in the absence of direct human instructions. We argue that **LLM-based agents should be proactive, capable of autonomously initiating tasks by understanding and responding to their environment**. For instance, as illustrated in Figure 1, the reactive agent should wait for explicit instructions from the user to execute tasks such as "show unread emails" or "schedule a meeting with John". In contrast, a proactive agent would predict its task automatically by noticing an email from John suggesting a meeting and automatically offering to schedule it. This ability of context awareness (Schilit & Theimer, 1994) enables the proactive agent to interpret signals and proactively propose and execute tasks without

*Corresponding authors.

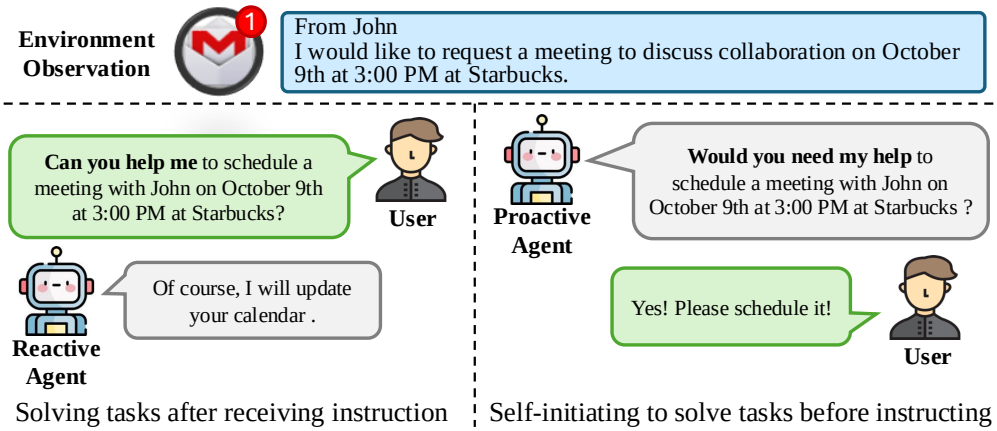

Figure 1: Comparison of agent systems with two types of human-agent interaction. Reactive agents passively receive user queries and then generate responses. Proactive agents infer tasks based on environmental observations and propose possible assistance requests accordingly.

explicit human instructions. Thus, it not only significantly reduces the cognitive burden on the user but also identifies latent needs not explicitly articulated by humans. Consequently, the proactive agent could provide more comprehensive and seamless services to the user.

In this work, we propose a novel data-driven formalization for developing a proactive agent that anticipates user needs and takes the initiative by suggesting tasks or providing information without explicit requests. Our approach centers on constructing ProactiveBench, allowing us to evaluate and enhance the agent's proactive behavior. Firstly, we collect real-world human activity data in three settings: coding, writing, and daily life. This includes but is not limited to, user keyboard and mouse inputs, clipboard content, browser activity, etc. Then, we build an LLM-driven gym to generate events that reflect the raw real-world contexts we collected. We obtain a total of 233 events across 12 scenarios as the test set of the ProactiveBench. To further refine the proactive behavior of the LLM-based agent, we construct various events and proactive tasks under synthetic contexts with the gym. By iterative generating more events and predictions, we obtain up to $6,790$ events as the train set of the ProactiveBench, as shown in Table 1. We fine-tune the LLaMA-3.1-8B-Instruct (Touvron et al., 2023; Meta, 2024) and the Qwen2-7B-Instruct (Bai et al., 2023) on this training set to refine their proactive behavior.

Subsets	Scenarios	Entries (Tr/Ts)
Agent Model	136	6,790 / 233
Coding	46	2,275
Writing	46	2,354
Daily Life	44	2,161
Reward Model	-	1,640 / 120

Table 1: Statistics of the ProactiveBench, which includes three distinct settings: Coding, Writing, and Daily Life.

To automatically evaluate the proactiveness of LLMs, we train a reward model that achieves up to 91.80% consistency with human judgments in terms of F1-Score. Using this model, we compared various language models on ProactiveBench. The results indicate that even the latest open-source models struggle to effectively predict proactive tasks. For instance, the LLaMA-3.1-8B model only achieved a 55.06% F1-Score on ProactiveBench. In contrast, our fine-tuned model demonstrated significant improvements, achieving a 66.25% F1-Score. Besides, our fine-tuned Qwen2-7B-Instruct model achieves 66.47% F1-Score, outperforming all existing open-source and closed-source LLMs. This underscores the effectiveness of our data-driven approach in developing proactive agents, highlighting their potential to enhance user experiences across various applications.

2 Related Works

Recent advancement in large language models (OpenAI et al., 2023; Chowdhery et al., 2022; Touvron et al., 2023; Zeng et al., 2023) has shown great progress in complex reasoning, task plan-

ning (Wei et al., 2022; Gao et al., 2023; Yao et al., 2023b;a; Liu et al., 2023; Ye et al., 2023a;b), tool utilization (Schick et al., 2023; Qin et al., 2023b;c; Qian et al., 2024b), etc. Consequently, a growing number of agent systems have been developed to utilize these models to tackle diverse tasks like automatic web search (Qin et al., 2023a), software development (Qian et al., 2023; Chen et al., 2023), behavior simulation (Park et al., 2023). Despite these advancements, most current agents remain predominantly reactive, passively following human instructions without sufficient context awareness (Schilit & Theimer, 1994) to proactively meet user needs. These reactive agents typically wait for explicit user commands, which can lead to inefficiencies as task complexity increases. As a result, users must constantly provide specific inputs, hindering the flow of interaction. In response, several works have attempted to improve the proactivity of agents. For example, Xuan (Zhang et al., 2024) proposes proactive agent planning, where agents refine their tasks by actively seeking information to better understand user intentions. Cheng Kuang and Zhi Rui (Wu et al., 2024) study how to propose proactive support in text-to-sql and propose a novel metrics Area Under Delta-Burden Curve (AUDBC). Other studies (Wu et al., 2021; Chen et al., 2020; Wiethof et al., 2021; Qian et al., 2024a) focus on enabling multi-turn interactions to clarify ambiguous user instructions, which further increased cognitive load for the user. However, these works still require the user to give an initial query before interacting with the agent. Our approach takes a different direction by focusing on anticipating potential tasks based on monitoring user activities and environmental states, which allows the agent to proactively initialize the interaction and provide assistance.

To clarify, there are also previous works (Deng et al., 2023) that use the term "Proactive Agent" to describe their dialogue systems. However, most of these efforts (Bi et al., 2021; Ren et al., 2021; LI & LIAO; Liu et al., 2024) aim to enhance the helpfulness or quality of responses in a proactive manner, which differs from our focus on task anticipation and initiation.10814

3 METHODOLOGY

3.1 TASK DEFINITION

In our proposed proactive agent, which is distinct from traditional agent systems powered by large language models that rely on explicit user instructions, we investigate a new scenario where the agent autonomously predicts tasks users might assign, aiming to offer assistance proactively, as depicted in Figure 1. The proactive agent's mission is to give predictions based on the user's activities A_t, environmental events E_t, and state S_t, which can be formalized as:

$$P_t = f_\theta(E_t, A_t, S_t) \tag{1}$$

where f_θ represents the proactive agent, parameterized by θ, and P_t denotes the prediction about possible task at time t. It should be noticed that the prediction P_t can be the predicted task or nothing if the agent believes that no task is needed. Specifically, user activities A_t contain the user's interactions with the environment and the agent, like keyboard input or chatting with the agent. Environmental events E_t contain the event that the proactive agent captured, ranging from receiving a new email to an application closed. Environmental state S_t represents the state of the current environment, like the file system state or the content of opened web pages.

In our proactive agent framework, the objective is to maximize the user's acceptance rate of the proposed tasks. Given the user's historical activities A_t, current environmental state S_t, and the prediction proposed by the proactive agent P_t, the user makes a binary decision:

$$R_t = g(P_t, A_t, S_t) \tag{2}$$

where R_t is a binary variable indicating acceptance ($R_t = 1$) or rejection ($R_t = 0$) of the prediction. To unify the handling of cases where the prediction P_t contains no task and where it contains a task, we introduce an auxiliary variable N_t that indicates whether the user needs assistance:

- $N_t = 1$ if the user needs assistance.
- $N_t = 0$ if the user does not need assistance.

The user's acceptance R_t is then defined as:

$$R_t = \begin{cases} 1 & \text{if } (P_t \neq \emptyset \text{ and user accepts } P_t) \text{ or } (P_t = \emptyset \text{ and } N_t = 0) \\ 0 & \text{otherwise} \end{cases}.$$

In this way, if the prediction P_t contains no task (i.e., the agent believes the user does not need assistance), we check the user's actual need for assistance N_t. If the user indeed does not require assistance ($N_t = 0$), this is marked as acceptance ($R_t = 1$). Conversely, if the user requires assistance ($N_t = 1$), this is marked as rejection ($R_t = 0$). Our proactive agent aims to maximize the expected acceptance rate of the proposed tasks:

$$\max_{\theta} \mathbb{E}[R_t]. \tag{3}$$

3.2 Pipeline Overview

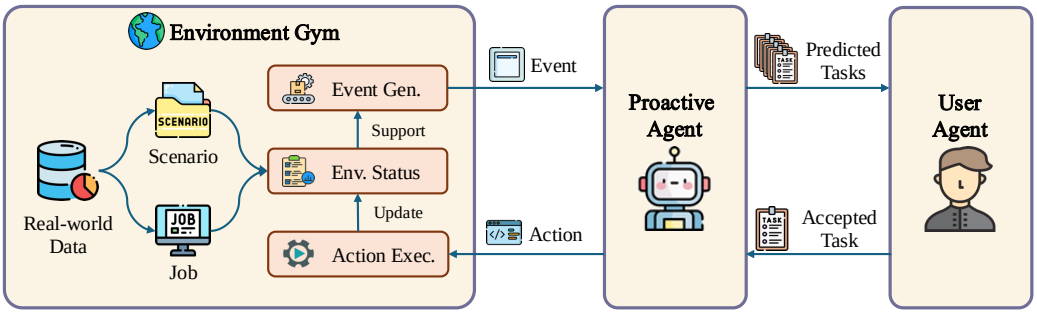

Figure 2: Overview of the data generation process. Taking daily life as an example, this process includes modules such as the initial scenario and job setup, events generation, proactive prediction, user judgment, and action execution.

To enhance the proactive capabilities of our large language model-powered agent, we adopt a data-driven approach by building an automatic data generation pipeline. This pipeline simulates user activities and responses to the tasks predicted by the proactive agent across various scenarios. Once a prediction is accepted, we simulate the agent performing the task by interactively generating new events within the simulated environment. Subsequently, new user activities are created based on historical events, allowing the proactive agent to generate further predictions. Through this pipeline, models can learn when to generate predictions and which predictions are likely to be accepted by users. Specifically, our pipeline consists of three components:

(1) **Environment Gym**: This component simulates events within a specified background setting and example events, providing a sandbox for proactive agents to interact. It has two key functionalities: (i) Event Generation: creating potential sequences of environmental events tailored to specific scenarios; (ii) State Maintenance: updating and maintaining the environment's state when new user activities are generated or when the agent performs actions during task execution.

(2) **Proactive Agent**: This component is responsible for predicting tasks that the user might assign to the agent based on the user's needs as inferred from the event history. It also interacts with tools to complete specific tasks assigned by the user.

(3) **User Agent**: This component simulates the user's activities and responses based on predefined user characteristics. It decides whether to accept and execute the tasks proposed by the agent.

In the following sections, we introduce the details of each component.

3.3 Environment Gym

Event Collection To improve the quality of events generated by the environment gym, we first collect real-world events as reference. We developed a monitor software based on Activity Watcher[1], which allows us to capture the details of user interactions with computer systems, including keyboard and mouse operations, visited web pages, and used development tools. To enhance the semantic richness of the collected data and facilitate parsing by large language models, we further merge the raw data into logically coherent segments. Additionally, we utilize a language model to

[1] https://github.com/ActivityWatch/activitywatch

translate the structured data into more natural textual descriptions. This process not only improves the interpretability of the data but also makes it more suitable for subsequent usage. Here is a sample event (more samples can be found in Appendix E.1):

```
Time: 1717378968.208
> Event: The user opens a new browser tab and navigates to the Google.
```

Scenario Generation After collecting reference events, rather than directly generating specific events, we generate a realistic interactive scenario to provide sufficient background information first for further generation. To build such scenarios, we first prompt GPT-4o (OpenAI, 2024) with the seed jobs collected from human annotators to create various jobs the user might perform under a specific category, like coding, writing, or daily life. Then, we generate all possible entities that the tasks might involve, e.g. browser, software, and tools for the agent to perform tasks. Next, we refine the scenario by adding more details like entity status or date time to improve the details. Finally, the collected events are also provided to generate example events under each particular context for future events generation. This allows us to control the granularity of events that will be generated and maintain the diversity of the scenarios. See Appendix C for the specific prompt used.

Event Generation When it comes to specific event generation, we start with user activity generation. For each scenario, the user agent is first requested to describe its activities and actions A_t at time t to complete the job in the simulated environment. Then, the gym accepts the user's activities and actions to generate detailed events one by one. As depicted in Figure 2, the gym is tasked to generate logically correct and fluent events according to historical events and the current environmental state. The key to improving the realities of the events generated and adapting to different environments is utilizing the example events we generated based on collected events during scenario generation. Before generating events, we randomly sample the generated example events for the specific scenario and request the gym to produce new events according to them. Once a new event E_{t+1} is generated, the gym updates the entities' status in the environments and repeats the process until there are no events that can be generated with the provided user activities. This comprehensive approach ensures that each subsequent event is not only appropriate but also contributes to a coherent and logical progression within the scenario.

State Maintenance Another important functionality of the gym is maintaining the state of the environment S_t. During the scenario generation, the gym creates entities like browsers or development kits in the simulated environment, where each entity has its state and properties like the application version or the specific browser name. When a new event is generated, the gym should update the states and properties of them to provide feedback for further event generation. Specifically, we first gather historical state changes of related entities and prompt the GPT-4o to generate new states of the entities S_{t+1} with the new event. During the process, the simulated time will also be updated according to the granularity of the event. After that, the next event will be generated based on the latest environment state S_{t+1}.

3.4 PROACTIVE AGENT

The second component in our data generation pipeline is the proactive agent that predicts tasks the user might assign. As detailed in Figure 3, upon the agent receiving new event E_t at time t, it first updates its memory with the event. To improve the quality of the prediction, it also accepts feedback from the user agent on its draft prediction. Combining new events with historical ones and conversations with the user, the agent incorporates user characteristics to raise potential tasks. If the agent detects potential tasks, it will raise the task as a new event and wait for the judgment of the user agent. Otherwise, the proactive agent predicts no potential tasks and stays silent. Once the predicted task is accepted, the agent will execute the task within the gym, which generates multiple events about the interaction between the agent and the environment. During the data generation, the agent would constantly receive events from the Gym and predict potential tasks.

Task Execution As mentioned before, the proactive agent executes the predicted task once the user accepts. This process is mainly done through multi-turn interaction between the proactive agent and the gym. Specifically, the proactive agent will be provided with the tools generated during

the scenario generation, like file system tools in the computer or access to the smart light switch, to interact with the simulated environment. Each time the proactive agent takes an action, the gym will generate a new event, which is further processed by the gym and the user agent to update the environment state. After that, the proactive agent detects the new environment state S_{t+1} and takes new actions according to the events generated by the gym. This process ends when the user interrupts or the proactive agent finishes its tasks.

3.5 User Agent

The user agent is designed to emulate users' activities A_t and responses about the agent's prediction P_t, as illustrated in Figure 2. We prompt GPT-4o to generate activities and actions for the provided task in the specific environment. The gym further processes the activities and actions to generate a new event. Then the proactive agent predicts potential tasks according to the events. Upon receiving the predicted task, the user agent determines whether to accept or reject it. If the user agent accepts the task, the proactive agent will set up and execute the accepted task within the environment gym. Otherwise, if the user agent declines the suggested assistance, the environment gym generates new events autonomously without any interventions. In our settings, we collect judgment from human annotators and train a reward model to simulate the judgment.

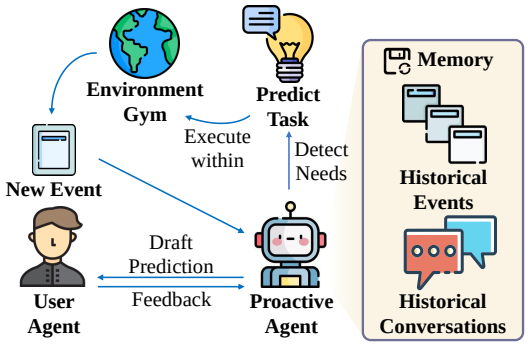

Figure 3: Overview of the proactive agent framework. The agent monitors new events and updates its memory to predict potential tasks.

Specifically, to ensure the reward model aligns closely with human judgment, we generate and annotate a dedicated dataset to indicate whether humans would accept the predicted task or not. We utilize 9 different language models to generate diverse predictions for each event. Between these predictions, We select 5 predictions with the minimum total cosine distance after embedding the predictions using Text-Ada-Embedding to determine our label target. Each prediction is annotated with one of three options by three separate annotators: *accept*, *reject*, or *reject all*. The *reject all* option is chosen when the annotator believes that the given events did not imply any possible tasks that the user might assign, aka $N_t = 0$ in Section 3.1. Otherwise, if one prediction is labeled as accepted, we label the event E_t with $N_t = 1$. We use majority voting to make the final decision on each prediction. After all, the annotation results in a dataset of $1,760$ entries, each containing event traces, task predictions, and decisions on accepting the predicted task from three distinct annotators. Notably, our annotators achieve an impressive agreement ratio of over 91.67% on the test set, underscoring the annotations' reliability and the dataset's robustness for further analysis. To further facilitate automatic data generation, we also prompt the GPT-4o to produce a more detailed explanation of the user judgment. Further details regarding the assessment of the reward model are available in Section 4.1.

4 Experiments

4.1 Reward Model Assessment

To automatically evaluate whether the predicted tasks and their timing are appropriate, we seek to train a reward model capable of accurately imitating user judgments. To this end, we apply the user-annotated data to train LLaMA-3.1-8B-Instruct (Touvron et al., 2023) and compare it with several baselines to show its superiority.

Setting. We use the $1,760$ entries with human annotations and randomly split them into a training set ($1,640$ entries) and a test set (120 entries). We then train LLaMA-3.1-8B-Instruct on the training set to obtain our reward model. We employ a total batch size of 32, a learning rate of $1e-5$, and

	GPT-4o	GPT-4o-mini	LLaMA-3.1-8B	LLaMA-3.1-70B	Ours
Agree. MN$^{\uparrow}$	3.33%	56.67%	**80.00%**	33.33%	**80.00%**
Agree. NR$^{\uparrow}$	**100.00%**	56.67%	30.00%	83.33%	86.67%
Agree. CD$^{\uparrow}$	**100.00%**	86.67%	96.67%	**100.00%**	**100.00%**
Agree. FD$^{\uparrow}$	0.00%	33.33%	13.33%	6.67%	**100.00%**
Recall$^{\uparrow}$	**100.00%**	71.67%	63.33%	91.67%	93.33%
Precision$^{\uparrow}$	50.42%	56.58%	54.29%	53.40%	**90.32%**
Accuracy$^{\uparrow}$	50.83%	58.33%	55.00%	55.83%	**91.67%**
F1-Score$^{\uparrow}$	67.04%	63.24%	58.46%	67.48%	**91.80%**

Table 2: Evaluation results of different models on our test set as the reward model. For the Missed-Need (MN), Non-Response (NR), Correct-Detection (CD), and False-Detection (FD) scenarios, we present the **agreement ratio** between models and the major voting of our human annotators. Our model which is fine-tuned based on LLaMA-3.1-Instruct-8B achieves the best F1-Score of 91.80%.

an Adam Optimizer with a 0.1 warm-up ratio. We train the reward model for 5 epochs to prevent it from over-fitting. We use 8 A100 GPUs on one node to train for approximately 1.5 hours. The detailed prompt template is listed in Appendix A. We use the test split to evaluate our adapted model and all the baselines. To be noticed, our human annotators achieve up to 91.67% agreement ratio on the test set, demonstrating the effectiveness of our evaluation.

Metrics. We use the reward model to perform binary classification on whether to accept predicted tasks and compare its results with human-annotated results. This assesses how well the reward model aligns with human judgment regarding the suitability of the predicted tasks. We compare the judgments made by the reward models and humans to calculate the Recall, Precision, Accuracy, and F1-Score. Additionally, we calculate the agreement ratio for the following cases:

- **Missed-Needed**: $N_t = 1, P_t = \emptyset$, the user needs help, but the agent does not provide it.
- **Non-Response**: $N_t = 0, P_t = \emptyset$, the user does not need help, the agent does not prompt.
- **Correct-Detection**: $N_t = 1, P_t \neq \emptyset$, and the user accepts the task predicted by the agent.
- **False-Detection**: $N_t = 0, P_t \neq \emptyset$, the user does not need help but agent prompts.

Results. As Table 2 shows, all existing models perform well on correct detection, but perform badly in other scenarios, especially in the false alarm scenario. After a deeper analysis, we find that existing models just can not infer what the user might need and tend to accept arbitrary help, even if it is very abstract or meaningless to current observation. In contrast, our reward model achieves a 100% agreement ratio on false alarm scenario and a solid 91.80% F1-Score across all scenarios. We select our reward model for further analysis across the ProactiveBench.

4.2 Proactive Agent Evaluation

Setting. We use the training set of ProactiveBench to obtain the Proactive Agent based on the two open-source models: LLaMA-3.1-8B-Instruct and Qwen2-7B-Instruct. During training, we employ a total batch size of 32, a learning rate of $1e-5$, and an Adam Optimizer with a 0.01 warm-up ratio. We train the model for 3 epochs. We use 8 A100 GPUs on one node to train for approximately 2 hours. The detailed prompt can be found in Appendix B. The automatic evaluation of these metrics relies on the simulated judgment given by the reward model. All models are evaluated in our test split of the ProactiveBench, which contains 233 events collected in the real world. We employ the same prompt template and apply greedy decoding across all models.

Metrics. We evaluate the performance of the Proactive Agent based on whether the user accepts its prediction. As described in Section 3.1, the user's acceptance R_t contains four conditions. In our specific settings, **Recall** measures the proportion of actual needs for assistance that were correctly predicted by the agent, including cases where the agent predicts a task and the user accepts it, as well as cases where no task is predicted and the user does not need assistance. **Precision** measures the proportion of predicted tasks that were actually accepted by the user. **Accuracy** measures the overall

correctness of the agent's predictions. The **False-Alarm** measures the proportion of incorrect task predictions, specifically when a task is predicted but not needed. The **F1-Score** provides a balanced measure of the goodness of the agent's proactive behavior. We use the reward model during the evaluation to automatically generate the user's judgment. Based on the confusion matrix, we report Recall, Precision, Accuracy, False Alarm, and F1-Score across all settings. The detailed calculation method can be found in Appendix B.

Model	Recall$^{\uparrow}$	Precision$^{\uparrow}$	Accuracy$^{\uparrow}$	False-Alarm$^{\downarrow}$	F1-Score$^{\uparrow}$
Proprietary models					
Claude-3-Sonnet	27.47%	37.31%	**52.42%**	62.69%	31.65%
Claude-3.5-Sonnet	97.89%	45.37%	49.78%	54.63%	62.00%
GPT-4o-mini	**100.00%**	35.28%	36.12%	64.73%	52.15%
GPT-4o	98.11%	**48.15%**	49.78%	**51.85%**	**64.60%**
Open-source models					
LLaMA-3.1-8B	98.86%	38.16%	39.06%	61.84%	55.06%
LLaMA-3.1-8B-Proactive	**99.06%**	**49.76%**	**52.86%**	**50.24%**	**66.25%**
Qwen2-7B	98.02%	44.00%	43.61%	56.00%	60.74%
Qwen2-7B-Proactive	**100.00%**	**49.78%**	**50.66%**	**50.22%**	**66.47%**

Table 3: Evaluation results of different models' performance on the ProactiveBench. The GPT-4o stands out for close-sourced models, achieving over 64.60% F1-Score. For open-sourced models, our fine-tuned Qwen2-7B model achieves best result, with a 66.47% F1-Score.

Result. Table 3 compares various models on the test set of the ProactiveBench, which contains 233 events collected from the real world user. Close-sourced models like GPT-4o (OpenAI, 2024) or GPT-4o-mini all tend to predict proactive tasks actively. Most of them succeed in assisting when the user needs but fail to stay silent when the user does not require any assistance, resulting in a relatively high false alarm ratio. For example, the GPT-4o-mini provides unnecessary assistance even when the events provided do not contain meaningful operations, like switching between software but doing nothing else. Another big issue is early assistance when no precise users' intents can be found in the given observation. This makes the proactive tasks proposed by the model seem too abstract or useless, resulting in a relatively high false alarm ratio. The Claude-3-Sonnet (Anthropic, 2024) shows a different example of failing to detect the user's need and provide assistance that does not satisfy the user's expectation.

For open-sourced models, we evaluate the performance of the LLaMA-3.1-Instruct-8B and Qwen2-Instruct-7B before and after fine-tuning based on our synthesized data. As shown in table 3, both models obtain an impressive improvement. For example, the LLaMA-3.1-8B improves its F1-Score from 55.06% to 66.25%. The results demonstrate the effectiveness of our data synthesis pipelines. As for the concern of being overly interrupted by the proactive agent, our fine-tuned models achieve solid progress in reducing the false alarm ratio, which is comparable to the performance of the GPT-4o. Besides, the finetuned Qwen2-7B is also outperform the GPT-4o in terms of the F1-Score, resulting in the highest F1-Score of 66.47% However, we also observed the same pattern of models tends to provide as much assistance as possible, instead of providing necessary assistance when the user needs it.

In short, while most models can assist when needed, they still frequently offer unnecessary help, even when instructed to provide only essential assistance.

4.3 Performance Analysis

In this section, we analyse two possible type of settings that could impact the performance of the proactive agent.

Predict Multiple Tasks. When it comes to real-world applications, the proactive agent can provide multiple candidate tasks to improve overall performance. To evaluate how models perform under

Model	Settings	Recall↑	Precision↑	Accuracy↑	False-Alarm↓	F1-Score↑
GPT-4o-mini	pred@1	100.00%	35.28%	36.12%	64.73%	52.15%
	pred@3	99.32%	65.32%	66.52%	34.68%	78.80%
	w/ RM	55.45%	63.54%	63.95%	36.46%	59.22%
	pred@3, w/ RM	100.00%	65.35%	66.09%	34.65%	79.05%
GPT-4o	pred@1	98.11%	48.15%	49.78%	51.85%	64.60%
	pred@3	100.00%	63.56%	64.81%	36.44%	77.72%
	w/ RM	56.76%	55.26%	57.61%	44.74%	56.00%
	pred@3, w/ RM	100.00%	63.30%	65.67%	36.70%	77.53%
LLaMA-3.1-8B	pred@1	98.86%	38.16%	39.06%	61.84%	55.06%
	pred@3	100.00%	52.79%	52.79%	47.21%	69.10%
	w/ RM	77.08%	42.52%	47.64%	57.41%	54.81%
	pred@3, w/ RM	95.12%	61.58%	66.09%	38.42%	74.76%

Table 4: Comparison between different settings for each model. The setting "pred@1" means predicting one task at a time. The setting "pred@3" means predicting 3 tasks at a time. The setting "w/ RM" means we will provide feedback from the reward model to help better prediction.

this condition, we allow them to generate multiple candidate tasks at once, but no more than three to avoid a high cognition burden for the user. In this setting, we let the reward model check the candidate tasks one by one. We label the result as accepted if one of the candidate tasks is accepted, and rejected if only all the candidate tasks are rejected.

As shown in Table 4, all models obtain solid improvement across all metrics when comparing "pred@1" with "pred@3". Take the GPT-4o as an example, it obtains higher accuracy and precision while reducing its false alarm by providing diverse candidate tasks. The huge drops in the false alarm ratio, from 51.85% to 36.44% are mainly due to its improvement in providing proactive tasks. However, when comparing GPT-4o-mini with LLaMA-3.1-8B, we observed different degrees of improvement. These two models perform similarly when predicting only one proactive task at once, but show a nearly 9% difference in terms of F1-Score when predicting multiple candidates at once. We analyzed the result and found that the LLaMA-3.1-8B tends to provide unexpected assistance when the user's need is unclear, which can not be improved by providing multiple candidates.

Feedback From the Reward Model. We also investigate whether the feedback from our reward model could help models improve their performance on the ProactiveBench. This is done with the same logic as described in Figure 3. For each model, we first ask them to generate a draft prediction and obtain feedback from the user agent (which is built on the reward model in this case). Then we let the model refine its prediction to obtain the final prediction.

As shown in Table 4, by adding the feedback from the reward model (settings with "w/ RM"), models generally reduce their false alarm ratio and improve the accuracy, but drop dramatically in terms of the recall. We observe that models stay silent once they receive feedback from the reward model. However, doing nothing is not always the optimal solution. The GPT-4o seems to fail to capture the possible user needs, leading to a performance drop in terms of F1-Score. For other models like GPT-4o-mini and LLaMA-3.1-8B, they deed obtain a marked improvement in terms of the F1-Score. Another setting combining the multiple-task prediction with the reward model ("pred@3, w/ RM") shows a more general improvement across the board. By integrating the reward model into the Proactive Agent, we can make the Proactive Agent more smartly detect user needs and reduce the false alarm ratio even when we can not access the weight directly, which is good news for developing the Proactive Agent.

4.4 Case Study

In this section, we explore two prevalent types of failures encountered in predicting possible tasks: the inability to detect user needs and making predictions at inappropriate times. More detailed failure modes can be found in Appendix D.

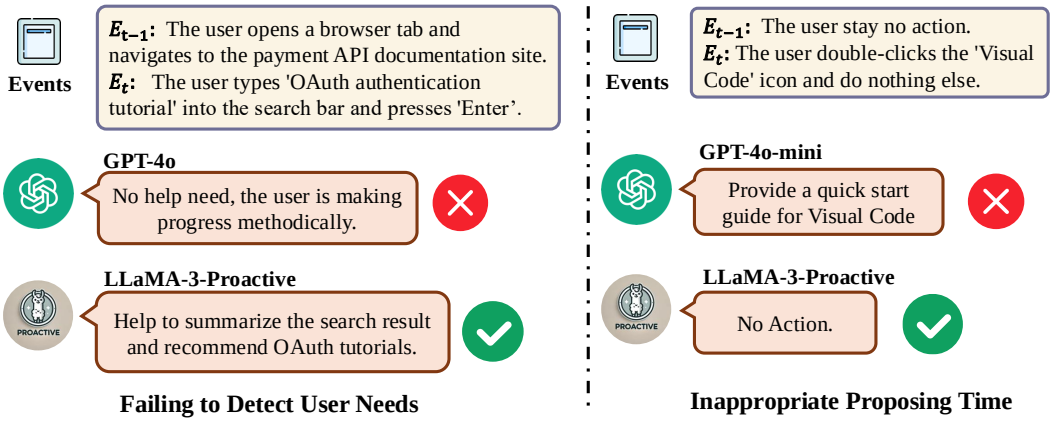

Figure 4: Two types of failure: failing to detect user needs (left) and inappropriate proposing time (right). We compare the response between our fine-tuned LLaMA-3.1-Instruct-8B with other models to show the refined proactive behavior of the model.

As illustrated in Figure 4 (left), a notable failure occurs when the GPT-4o model does not assist at crucial moments. For instance, when a user is engaged in integrating a payment API and requires a tutorial for guidance, the model remains silent. Instead, our model successfully detects human needs and offers assistance. The underlying intention to minimize disruptions ironically leads to missed opportunities to offer timely help.

Conversely, the right side of Figure 4 showcases an instance of ill-timed prediction. Here, the GPT-4o-mini suggests an action when there are no user needs showing in events. This scenario underscores the possible unintended events existing in human activities. The model should judge whether there are possible tasks smartly to avoid unnecessary actions. These instances highlight the intricate nature of human activities and the sophisticated reasoning required for models to accurately predict human needs. To navigate the delicate balance between being helpful and intrusive, models must develop a deeper understanding of user contexts and activities, ensuring their interventions are both timely and pertinent.

5 Conclusion

We present an innovative approach to human-agent interaction by leveraging proactive task predictions that anticipate human needs. We introduce ProactiveBench, a comprehensive dataset comprising $6,790$ events, designed to refine the proactive behavior of LLM-based agents and establish an automatic benchmark for assessing model proactiveness. By iteratively generating events in synthesized scenarios, we create training data that enhances the proactive capabilities of our models. Our experiments demonstrate significant improvements in the agent's performance on ProactiveBench, validating the effectiveness of our methods. Despite these advancements, our findings underscore ongoing challenges, particularly in minimizing inappropriate task proposals and ensuring task predictions are contextually accurate. Future research should focus on enhancing the precision and timeliness of task predictions to improve the efficacy of the proactive human-agent interaction.

Ethics Statement

In the construction of our dataset, we have adhered to strict ethical standards. The human annotators are students from the computer sciences area and obtain rewards for their annotations. We use ChatGPT in this research. All the original data utilized for the compilation of our dataset are either sourced from open-access platforms or have been used with the appropriate permissions granted. We have conducted a thorough review to ensure that our dataset is devoid of any harmful content or private information. Our commitment to ethical research practices extends to the respect for privacy, intellectual property rights, and the integrity of the data sources.

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REFERENCES

Anthropic. Introducing the claude-3 family, 2024. URL https://www.anthropic.com/news/claude-3-family. Accessed: 2024-06-16.

Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, Binyuan Hui, Luo Ji, Mei Li, Junyang Lin, Runji Lin, Dayiheng Liu, Gao Liu, Chengqiang Lu, Keming Lu, Jianxin Ma, Rui Men, Xingzhang Ren, Xuancheng Ren, Chuanqi Tan, Sinan Tan, Jianhong Tu, Peng Wang, Shijie Wang, Wei Wang, Shengguang Wu, Benfeng Xu, Jin Xu, An Yang, Hao Yang, Jian Yang, Shusheng Yang, Yang Yao, Bowen Yu, Hongyi Yuan, Zheng Yuan, Jianwei Zhang, Xingxuan Zhang, Yichang Zhang, Zhenru Zhang, Chang Zhou, Jingren Zhou, Xiaohuan Zhou, and Tianhang Zhu. Qwen technical report. *ArXiv preprint*, abs/2309.16609, 2023. URL https://arxiv.org/abs/2309.16609.

Keping Bi, Qingyao Ai, and W Bruce Croft. Asking clarifying questions based on negative feedback in conversational search. In *Proceedings of the 2021 ACM SIGIR International Conference on Theory of Information Retrieval*, pp. 157–166, 2021.

Weiwen Chen, Mohammad Shidujaman, Jiangbo Jin, and Salah Uddin Ahmed. A methodological approach to create interactive art in artificial intelligence. In Constantine Stephanidis, Don Harris, Wen-Chin Li, Dylan D. Schmorrow, Cali M. Fidopiastis, Panayiotis Zaphiris, Andri Ioannou, Xiaowen Fang, Robert A. Sottilare, and Jessica Schwarz (eds.), *HCI International 2020 – Late Breaking Papers: Cognition, Learning and Games*, pp. 13–31, Cham, 2020. Springer International Publishing. ISBN 978-3-030-60128-7.

Weize Chen, Yusheng Su, Jingwei Zuo, Cheng Yang, Chenfei Yuan, Chi-Min Chan, Heyang Yu, Yaxi Lu, Yi-Hsin Hung, Chen Qian, Yujia Qin, Xin Cong, Ruobing Xie, Zhiyuan Liu, Maosong Sun, and Jie Zhou. Agentverse: Facilitating multi-agent collaboration and exploring emergent behaviors, 2023.

Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. Palm: Scaling language modeling with pathways. *ArXiv preprint*, abs/2204.02311, 2022. URL https://arxiv.org/abs/2204.02311.

Yang Deng, Wenqiang Lei, Wai Lam, and Tat-Seng Chua. A survey on proactive dialogue systems: problems, methods, and prospects. In *Proceedings of the Thirty-Second International Joint Conference on Artificial Intelligence*, pp. 6583–6591, 2023.

Roya Firoozi, Johnathan Tucker, Stephen Tian, Anirudha Majumdar, Jiankai Sun, Weiyu Liu, Yuke Zhu, Shuran Song, Ashish Kapoor, Karol Hausman, et al. Foundation models in robotics: Applications, challenges, and the future. *ArXiv preprint*, abs/2312.07843, 2023. URL https://arxiv.org/abs/2312.07843.

Luyu Gao, Aman Madaan, Shuyan Zhou, Uri Alon, Pengfei Liu, Yiming Yang, Jamie Callan, and Graham Neubig. PAL: program-aided language models. In Andreas Krause, Emma Brunskill, Kyunghyun Cho, Barbara Engelhardt, Sivan Sabato, and Jonathan Scarlett (eds.), *International Conference on Machine Learning, ICML 2023, 23-29 July 2023, Honolulu, Hawaii, USA*, volume 202 of *Proceedings of Machine Learning Research*, pp. 10764–10799. PMLR, 2023. URL https://proceedings.mlr.press/v202/gao23f.html.

Wenyi Hong, Weihan Wang, Qingsong Lv, Jiazheng Xu, Wenmeng Yu, Junhui Ji, Yan Wang, Zihan Wang, Yuxuan Zhang, Juanzi Li, Bin Xu, Yuxiao Dong, Ming Ding, and Jie Tang. Cogagent: A visual language model for gui agents, 2023.

Guohao Li, Hasan Hammoud, Hani Itani, Dmitrii Khizbullin, and Bernard Ghanem. CAMEL: communicative agents for "mind" exploration of large language model society. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine (eds.), *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*, 2023. URL http://papers.nips.cc/paper_files/paper/2023/hash/a3621ee907def47c1b952ade25c67698-Abstract-Conference.html.

Yuanchun Li, Hao Wen, Weijun Wang, Xiangyu Li, Yizhen Yuan, Guohong Liu, Jiacheng Liu, Wenxing Xu, Xiang Wang, Yi Sun, et al. Personal llm agents: Insights and survey about the capability, efficiency and security. *ArXiv preprint*, abs/2401.05459, 2024. URL https://arxiv.org/abs/2401.05459.

Zixuan LI and Lizi LIAO. Chua, tat-seng. learning to ask critical questions for assisting product search.(2022). In *Proceedings of 2022 ACM SIGIR Workshop on eCommerce, Madrid, Spain, July*, volume 15.

Bo Liu, Yuqian Jiang, Xiaohan Zhang, Qiang Liu, Shiqi Zhang, Joydeep Biswas, and Peter Stone. Llm+ p: Empowering large language models with optimal planning proficiency. *ArXiv preprint*, abs/2304.11477, 2023. URL https://arxiv.org/abs/2304.11477.

Tianjian Liu, Hongzheng Zhao, Yuheng Liu, Xingbo Wang, and Zhenhui Peng. Compeer: A generative conversational agent for proactive peer support. In *Proceedings of the 37th Annual ACM Symposium on User Interface Software and Technology*, pp. 1–22, 2024.

Meta. Introducing meta llama 3: The most capable openly available llm to date, 2024. URL https://ai.meta.com/blog/meta-llama-3/.

OpenAI. OpenAI: Introducing ChatGPT, 2022. URL https://openai.com/blog/chatgpt.

OpenAI. Hello gpt-4, 2024. URL https://openai.com/index/hello-gpt-4o/. Accessed: 2024-06-16.

OpenAI, :, Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, Red Avila, Igor Babuschkin, Suchir Balaji, Valerie Balcom, Paul Baltescu, Haiming Bao, Mo Bavarian, Jeff Belgum, Irwan Bello, Jake Berdine, Gabriel Bernadett-Shapiro, Christopher Berner, Lenny Bogdonoff, Oleg Boiko, Madelaine Boyd, Anna-Luisa Brakman, Greg Brockman, Tim Brooks, Miles Brundage, Kevin Button, Trevor Cai, Rosie Campbell, Andrew Cann, Brittany Carey, Chelsea Carlson, Rory Carmichael, Brooke Chan, Che Chang, Fotis Chantzis, Derek Chen, Sully Chen, Ruby Chen, Jason Chen, Mark Chen, Ben Chess, Chester Cho, Casey Chu, Hyung Won Chung, Dave Cummings, Jeremiah Currier, Yunxing Dai, Cory Decareaux, Thomas Degry, Noah Deutsch, Damien Deville, Arka Dhar, David Dohan, Steve Dowling, Sheila Dunning, Adrien Ecoffet, Atty Eleti, Tyna Eloundou, David Farhi, Liam Fedus, Niko Felix, Simón Posada Fishman, Juston Forte, Isabella Fulford, Leo Gao, Elie Georges, Christian Gibson, Vik Goel, Tarun Gogineni, Gabriel Goh, Rapha Gontijo-Lopes, Jonathan Gordon, Morgan Grafstein, Scott Gray, Ryan Greene, Joshua Gross, Shixiang Shane Gu, Yufei Guo, Chris Hallacy, Jesse Han, Jeff Harris, Yuchen He, Mike Heaton, Johannes Heidecke, Chris Hesse, Alan Hickey, Wade Hickey, Peter Hoeschele, Brandon Houghton, Kenny Hsu, Shengli Hu, Xin Hu, Joost Huizinga, Shantanu Jain, Shawn Jain, Joanne Jang, Angela Jiang, Roger Jiang, Haozhun Jin, Denny Jin, Shino Jomoto, Billie Jonn, Heewoo Jun, Tomer Kaftan, Łukasz Kaiser, Ali Kamali, Ingmar Kanitscheider, Nitish Shirish Keskar, Tabarak Khan, Logan Kilpatrick, Jong Wook Kim, Christina Kim, Yongjik Kim, Hendrik Kirchner, Jamie Kiros, Matt Knight, Daniel Kokotajlo, Łukasz Kondraciuk, Andrew Kondrich, Aris Konstantinidis, Kyle Kosic, Gretchen Krueger, Vishal Kuo, Michael Lampe, Ikai Lan, Teddy Lee, Jan Leike, Jade Leung, Daniel Levy, Chak Ming Li, Rachel Lim, Molly Lin, Stephanie Lin, Mateusz Litwin, Theresa Lopez, Ryan Lowe, Patricia Lue, Anna Makanju, Kim Malfacini, Sam Manning, Todor Markov, Yaniv Markovski, Bianca Martin, Katie Mayer, Andrew Mayne, Bob McGrew, Scott Mayer McKinney, Christine McLeavey, Paul McMillan, Jake McNeil, David Medina, Aalok Mehta, Jacob Menick, Luke Metz, Andrey Mishchenko, Pamela Mishkin, Vinnie Monaco, Evan

Morikawa, Daniel Mossing, Tong Mu, Mira Murati, Oleg Murk, David Mély, Ashvin Nair, Reiichiro Nakano, Rajeev Nayak, Arvind Neelakantan, Richard Ngo, Hyeonwoo Noh, Long Ouyang, Cullen O'Keefe, Jakub Pachocki, Alex Paino, Joe Palermo, Ashley Pantuliano, Giambattista Parascandolo, Joel Parish, Emy Parparita, Alex Passos, Mikhail Pavlov, Andrew Peng, Adam Perelman, Filipe de Avila Belbute Peres, Michael Petrov, Henrique Ponde de Oliveira Pinto, Michael, Pokorny, Michelle Pokrass, Vitchyr Pong, Tolly Powell, Alethea Power, Boris Power, Elizabeth Proehl, Raul Puri, Alec Radford, Jack Rae, Aditya Ramesh, Cameron Raymond, Francis Real, Kendra Rimbach, Carl Ross, Bob Rotsted, Henri Roussez, Nick Ryder, Mario Saltarelli, Ted Sanders, Shibani Santurkar, Girish Sastry, Heather Schmidt, David Schnurr, John Schulman, Daniel Selsam, Kyla Sheppard, Toki Sherbakov, Jessica Shieh, Sarah Shoker, Pranav Shyam, Szymon Sidor, Eric Sigler, Maddie Simens, Jordan Sitkin, Katarina Slama, Ian Sohl, Benjamin Sokolowsky, Yang Song, Natalie Staudacher, Felipe Petroski Such, Natalie Summers, Ilya Sutskever, Jie Tang, Nikolas Tezak, Madeleine Thompson, Phil Tillet, Amin Tootoonchian, Elizabeth Tseng, Preston Tuggle, Nick Turley, Jerry Tworek, Juan Felipe Cerón Uribe, Andrea Vallone, Arun Vijayvergiya, Chelsea Voss, Carroll Wainwright, Justin Jay Wang, Alvin Wang, Ben Wang, Jonathan Ward, Jason Wei, CJ Weinmann, Akila Welihinda, Peter Welinder, Jiayi Weng, Lilian Weng, Matt Wiethoff, Dave Willner, Clemens Winter, Samuel Wolrich, Hannah Wong, Lauren Workman, Sherwin Wu, Jeff Wu, Michael Wu, Kai Xiao, Tao Xu, Sarah Yoo, Kevin Yu, Qiming Yuan, Wojciech Zaremba, Rowan Zellers, Chong Zhang, Marvin Zhang, Shengjia Zhao, Tianhao Zheng, Juntang Zhuang, William Zhuk, and Barret Zoph. Gpt-4 technical report. Technical report, 2023.

Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul F. Christiano, Jan Leike, and Ryan Lowe. Training language models to follow instructions with human feedback. In Sanmi Koyejo, S. Mohamed, A. Agarwal, Danielle Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems 35: Annual Conference on Neural Information Processing Systems 2022, NeurIPS 2022, New Orleans, LA, USA, November 28 - December 9, 2022*, 2022. URL http://papers.nips.cc/paper_files/paper/2022/hash/b1efde53be364a73914f58805a001731-Abstract-Conference.html.

Joon Sung Park, Joseph C. O'Brien, Carrie J. Cai, Meredith Ringel Morris, Percy Liang, and Michael S. Bernstein. Generative agents: Interactive simulacra of human behavior, 2023.

Chen Qian, Xin Cong, Wei Liu, Cheng Yang, Weize Chen, Yusheng Su, Yufan Dang, Jiahao Li, Juyuan Xu, Dahai Li, Zhiyuan Liu, and Maosong Sun. Communicative agents for software development, 2023.

Cheng Qian, Bingxiang He, Zhong Zhuang, Jia Deng, Yujia Qin, Xin Cong, Yankai Lin, Zhong Zhang, Zhiyuan Liu, and Maosong Sun. Tell me more! towards implicit user intention understanding of language model driven agents. *ArXiv preprint*, abs/2402.09205, 2024a. URL https://arxiv.org/abs/2402.09205.

Cheng Qian, Chenyan Xiong, Zhenghao Liu, and Zhiyuan Liu. Toolink: Linking toolkit creation and using through chain-of-solving on open-source model. In Kevin Duh, Helena Gomez, and Steven Bethard (eds.), *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pp. 831–854, Mexico City, Mexico, 2024b. Association for Computational Linguistics. URL https://aclanthology.org/2024.naacl-long.48.

Yujia Qin, Zihan Cai, Dian Jin, Lan Yan, Shihao Liang, Kunlun Zhu, Yankai Lin, Xu Han, Ning Ding, Huadong Wang, Ruobing Xie, Fanchao Qi, Zhiyuan Liu, Maosong Sun, and Jie Zhou. WebCPM: Interactive web search for Chinese long-form question answering. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (eds.), *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 8968–8988, Toronto, Canada, 2023a. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-long.499. URL https://aclanthology.org/2023.acl-long.499.

Yujia Qin, Shengding Hu, Yankai Lin, Weize Chen, Ning Ding, Ganqu Cui, Zheni Zeng, Yufei Huang, Chaojun Xiao, Chi Han, et al. Tool learning with foundation models. *ArXiv preprint*, abs/2304.08354, 2023b. URL https://arxiv.org/abs/2304.08354.

Yujia Qin, Shihao Liang, Yining Ye, Kunlun Zhu, Lan Yan, Yaxi Lu, Yankai Lin, Xin Cong, Xiangru Tang, Bill Qian, Sihan Zhao, Runchu Tian, Ruobing Xie, Jie Zhou, Mark Gerstein, Dahai Li, Zhiyuan Liu, and Maosong Sun. Toolllm: Facilitating large language models to master 16000+ real-world apis, 2023c.

Xuhui Ren, Hongzhi Yin, Tong Chen, Hao Wang, Zi Huang, and Kai Zheng. Learning to ask appropriate questions in conversational recommendation. In *Proceedings of the 44th international ACM SIGIR conference on research and development in information retrieval*, pp. 808–817, 2021.

Timo Schick, Jane Dwivedi-Yu, Roberto Dessì, Roberta Raileanu, Maria Lomeli, Eric Hambro, Luke Zettlemoyer, Nicola Cancedda, and Thomas Scialom. Toolformer: Language models can teach themselves to use tools. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine (eds.), *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December 10 - 16, 2023*, 2023. URL http://papers.nips.cc/paper_files/paper/2023/hash/d842425e4bf79ba039352da0f658a906-Abstract-Conference.html.

B.N. Schilit and M.M. Theimer. Disseminating active map information to mobile hosts. *IEEE Network*, 8(5):22–32, 1994. doi: 10.1109/65.313011.

Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. Llama: Open and efficient foundation language models, 2023.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed H. Chi, Quoc V. Le, and Denny Zhou. Chain-of-thought prompting elicits reasoning in large language models. In Sanmi Koyejo, S. Mohamed, A. Agarwal, Danielle Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems 35: Annual Conference on Neural Information Processing Systems 2022, NeurIPS 2022, New Orleans, LA, USA, November 28 - December 9, 2022*, 2022. URL http://papers.nips.cc/paper_files/paper/2022/hash/9d5609613524ecf4f15af0f7b31abca4-Abstract-Conference.html.

Christina Wiethof, Navid Tavanapour, and Eva Alice Christiane Bittner. Implementing an intelligent collaborative agent as teammate in collaborative writing: toward a synergy of humans and ai. In *Hawaii International Conference on System Sciences*, 2021. URL https://api.semanticscholar.org/CorpusID:232414319.

Cheng-Kuang Wu, Zhi Rui Tam, Chao-Chung Wu, Chieh-Yen Lin, Hung-yi Lee, and Yun-Nung Chen. I need help! evaluating LLM's ability to ask for users' support: A case study on text-to-SQL generation. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen (eds.), *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pp. 2191–2199, Miami, Florida, USA, November 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.emnlp-main.131. URL https://aclanthology.org/2024.emnlp-main.131.

Qingyun Wu, Gagan Bansal, Jieyu Zhang, Yiran Wu, Beibin Li, Erkang Zhu, Li Jiang, Xiaoyun Zhang, Shaokun Zhang, Jiale Liu, Ahmed Hassan Awadallah, Ryen W White, Doug Burger, and Chi Wang. Autogen: Enabling next-gen llm applications via multi-agent conversation framework. 2023.

Zhuohao Wu, Danwen Ji, Kaiwen Yu, Xianxu Zeng, Dingming Wu, and Mohammad Shidujaman. Ai creativity and the human-ai co-creation model. In Masaaki Kurosu (ed.), *Human-Computer Interaction. Theory, Methods and Tools*, pp. 171–190, Cham, 2021. Springer International Publishing. ISBN 978-3-030-78462-1.

Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Tom Griffiths, Yuan Cao, and Karthik Narasimhan. Tree of thoughts: Deliberate problem solving with large language models. In Alice Oh, Tristan Naumann, Amir Globerson, Kate Saenko, Moritz Hardt, and Sergey Levine (eds.), *Advances in Neural Information Processing Systems 36: Annual Conference on Neural Information Processing Systems 2023, NeurIPS 2023, New Orleans, LA, USA, December*

10 - 16, 2023, 2023a. URL http://papers.nips.cc/paper_files/paper/2023/hash/271db9922b8d1f4dd7aaef84ed5ac703-Abstract-Conference.html.

Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik R. Narasimhan, and Yuan Cao. React: Synergizing reasoning and acting in language models. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023b. URL https://openreview.net/pdf?id=WE_vluYUL-X.

Yining Ye, Xin Cong, Yujia Qin, Yankai Lin, Zhiyuan Liu, and Maosong Sun. Large language model as autonomous decision maker. *ArXiv preprint*, abs/2308.12519, 2023a. URL https://arxiv.org/abs/2308.12519.

Yining Ye, Xin Cong, Shizuo Tian, Jiannan Cao, Hao Wang, Yujia Qin, Yaxi Lu, Heyang Yu, Huadong Wang, Yankai Lin, Zhiyuan Liu, and Maosong Sun. Proagent: From robotic process automation to agentic process automation, 2023b.

Aohan Zeng, Xiao Liu, Zhengxiao Du, Zihan Wang, Hanyu Lai, Ming Ding, Zhuoyi Yang, Yifan Xu, Wendi Zheng, Xiao Xia, Weng Lam Tam, Zixuan Ma, Yufei Xue, Jidong Zhai, Wenguang Chen, Zhiyuan Liu, Peng Zhang, Yuxiao Dong, and Jie Tang. GLM-130B: an open bilingual pre-trained model. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023. URL https://openreview.net/pdf?id=-Aw0rrrPUF.

Chi Zhang, Zhao Yang, Jiaxuan Liu, Yucheng Han, Xin Chen, Zebiao Huang, Bin Fu, and Gang Yu. Appagent: Multimodal agents as smartphone users, 2023.

Xuan Zhang, Yang Deng, Zifeng Ren, See-Kiong Ng, and Tat-Seng Chua. Ask-before-plan: Proactive language agents for real-world planning. *arXiv preprint arXiv:2406.12639*, 2024.

APPENDIX

LIMITATIONS

While our method demonstrates that it can effectively and proactively predict possible tasks, the current research is constrained by several limitations. Firstly, the environment settings we have explored are still limited. The contexts in this paper provide a foundational understanding, but broader application areas need to be investigated to fully establish the versatility and robustness of the proactive agent. Moreover, models still exhibit a relatively high ratio of false alarms, indicating that they cannot yet perfectly predict possible tasks. This limitation highlights the need for further refinement of the model's proactive behavior to avoid bothering the user. The high rate of false positives can lead to unnecessary or incorrect actions, which may reduce user trust and the overall efficiency of the system. Future research should focus on several key areas to address these limitations:

- **Expansion of Environment Settings:** Research should explore a wider variety of scenarios and contexts to validate the model's generalizability. This includes domains where proactive prediction of tasks can significantly enhance user experience and operational efficiency.
- **Improvement in Prediction Accuracy:** Efforts should be directed towards reducing the false alarm rate by enhancing the model's understanding of context and user behavior.
- **User-Centric Evaluation:** Future studies should involve extensive user-centric evaluations to better understand how users interact with the proactive agent and to identify areas for improvement. User feedback and behavioral data can provide valuable insights into refining the prediction algorithms and making the system more intuitive and reliable.
- **Ethical and Privacy Considerations:** As the proactive agent needs the environment information for prediction tasks, it is crucial to address ethical and privacy concerns. Ensuring that user data is handled responsibly and that the agent operates transparently and within ethical guidelines will be critical for gaining user trust and acceptance.

A REWARD MODEL TRAINING SETTING

We use Llama-3.1-Instruct-8B as the base model for our training. The total dataset size is approximately $1,640$. Specifically, we employ a total batch size of 32, a learning rate of $1e-5$, and an Adam Optimizer with a 0.1 warm-up ratio. We train the reward model for 5 epochs to prevent it from over-fitting. We use 8 A100 GPUs on one node to train for approximately 1.5 hours.

Prompt Template

```
<Task>
Evaluate the task proposed by the proactive assistant as the user.
</Task>

<Rule>
0. Analyze the current observation to understand your current
   situation and requirements.
1. If the proposed task is `null` (indicating no task is proposed
   under the current observation), follow these steps:
   - Accept the `null` task if you believe there is no need for a
     task.
   - Reject the `null` task if you believe a task is needed.
2. Minimize interruptions from the assistant by only accepting
   tasks that are valuable.
3. Evaluate the current observation and make a judgment on the
   proposed task accordingly.
</Rule>

<Format>
You should answer with the following JSON format:
{
```

```
    "thought": "Give your thoughts first, then provide the
       judgment of the task.",
    "judgment": "accepted or rejected"
}
</Format>
```

B AGENT MODEL TRAINING SETTING

Similarly, we use Llama-3-Instruct 8B and Qwen2-Instruct-7B as the base model for agent model training. The total dataset size is approximately $6,790$. Specifically, we employ a total batch size of 32, a learning rate of $1e-5$, and an Adam Optimizer with a 0.1 warm-up ratio. We train the model for 3 epochs to prevent it from over-fitting. We use 8 A100 GPUs on one node to train for approximately 2 hours.

Template. We apply the following prompt template to train the agent model:

Prompt Template

```
<Role> You are a helpful assistant that provides proactive
   suggestions to the user. </Role>

<Task> Understand what the user is doing and anticipate their
   needs based on events. Only propose assistance when you fully
   understand the user's actions. Use available operations to
   ensure the task is feasible. Execute the task if the user
   accepts your proposal. </Task>

<Format> Respond in the following JSON format:
{
    "Purpose": "The purpose of the user's last action.",
    "Thoughts": "Your thoughts on the user's actions.",
    "Proactive Task": "Describe your proposed task, or set to `
       null` if no assistance is needed.",
    "Response": "Inform the user about your assistance if
       proposing a task."
}
</Format>

<Rules>
- Ensure the proposed task is relevant to the events. - Focus on
   the user's current needs and predict helpful tasks.
- Consider the timing of events.
- Only offer proactive assistance when necessary.
- Deduce the user's purpose and whether they need help based on
   event history.
- Set `Proactive Task` to `null` if the user doesn't need help.
</Rules>
```

C PROMPT TEMPLATE FOR ENVIRONMENT GYM

C.1 PROMPT FOR SCENE GENERATION

Prompt Template

```
<Role>
```

```
You are tasked with simulating an environment within a system. The
    content labeled 'Source: environment' reflects your past
   actions and decisions.
</Role>

<Task>
Generate and refine detailed environment settings. Based on the
   latest activities, create multiple events to describe changes
   in the environment.
</Task>

<Rules>
- Ensure the subject of the generated content aligns with the
   latest activities's source.
- Avoid subjective opinions or emotions; focus on objective
   changes.
- Ensure events are consistent with historical events labeled '[
   events]' and include all - changes from the activities.
- Introduce occasional failures or unexpected events for realism.
- Ensure each event is logically connected to the previous one and
    does not include nonexistent elements.
- Pay close attention to entity operations; if an operation is not
    allowed or impractical in the real or simulated environment,
   raise an error and explain the issue.
</Rules>
```

C.2 SEED JOBS DATA

Prompt Template

```
<Task>
You are tasked to generate realistic scenarios where a user might
   need assistance from an AI assistant. Always remember to keep
   the scene realistic and believable by including as much
   details as possible.
</Task>

<Rule>
- You will iteratively generate more information about the scene.
   Make sure each time you add a new detail, it is consistent
   with the previous details. Always generate new content based
   on the previous generated content.
- You can add as many details as you want, but make sure they are
   consistent with the previous details.
- Try to generate diverse details about the scene. You will be
   tasked to simulate events in the scene later.
</Rule>
```

C.3 PROMPT FOR USER AGENT GENERATION

Prompt Template

```
<Role>
You are tasked with simulating a user within a system. The content
    labeled 'Source: user' reflects your past actions and
   decisions.
</Role>
```

```
<Task>
Generate human-like activities with distinct characteristics and
   identities. You will receive events and observations from the
   environment; analyze these closely to decide your actions.
</Task>

<Rules>
- Respond like a real user; don't be overly predictable.
- Refer to # User Info to understand your identity.
- Critically evaluate the received information, as it may not
   always be accurate.
- Stay aware of environmental changes, which can occur at any time
   .
</Rules>
```

C.4 Prompt for Status Updating

Prompt Template

```
<Task>
Evaluate the task proposed by the proactive assistant as the user.
</Task>

<Rule>
0. Analyze the current observation to understand your current
   situation and requirements.
1. If the proposed task is 'null' (indicating no task is proposed
   under the current observation), follow these steps:
   - Accept the 'null' task if you believe there is no need for a
      task.
   - Reject the 'null' task if you believe a task is needed.
2. Minimize interruptions from the assistant by only accepting
   tasks that are valuable.
3. Evaluate the current observation and make a judgment on the
   proposed task accordingly.
</Rule>

<Format>
You should answer with following JSON format:
{
    "thought": "Give your thoughts first, then provide the
       judgement of the task.",
    "judgement": "accepted or rejected"
}
</Format>
```

C.5 Metrics Calculation

Definition Here is how we define the label of each prediction.

- **True Positive (TP):** Agent predicts task, the user accepts.
- **False Positive (FP):** Agent predicts task, the user rejects.
- **True Negative (TN):** Agent does not predict a task, and the user does not need assistance.
- **False Negative (FN):** Agent does not predict the task, but the user needs assistance ($N_t = 1$ in Section 3.1).

Recall A high recall indicates that the agent frequently identifies situations where help is needed. This metric is crucial for assessing the agent's ability to recognize and respond to user needs on time.

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

Precision A high precision indicates that the agent proposes good tasks while not bothering the user too much. This metric is crucial when considering the annoying behavior of the proactive agent could greatly reduce user satisfaction.

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

Accuracy High Accuracy demonstrates that the agent has a good understanding of user needs, as most of its predictions are accepted. This metric is essential for measuring the relevance and correctness of the agent's proactive suggestions.

$$Accuracy = \frac{TP + TN}{P + N} \tag{6}$$

F1-Score High F1-Score means the proactive agent strikes a good balance between being helpful and proactive.

$$F_1 = 2 * \frac{Recall * Precision}{Recall + Precision} \tag{7}$$

D Failure Modes Analysis

Not A Task: The model does not give a real task at all.

```
Observation: {
    "time": "1717335907.603",
    "event": "The user switches to Visual Studio Code."
}

GPT-4o-mini Response: It seems you may be switching to Visual
   Studio Code for development. If you need any coding tips,
   resources, or help with Swift UI in VS Code, feel free to ask!
```

Under this event, the agent did not take the event as an action, but rather a call for chat. This chat is not a task we want.

Unspecific Task: The proposed task is non-executable due to a lack of a clear and detailed description.

```
Observation: {
    "time": "1717329066.416",
    "event": "The user performed a search for 'js fade in/out' on
       Bing."
}

GPT-4o-mini Response: Compile a list of JavaScript resources,
   tutorials, and documentation that cover advanced topics
   related to the user's search.
```

Under this event, the model proposal is not clear (not pointing out the user's research content) and impractical (Compiling a list of resources, tutorials, and documentation, which is too much for the user and also out of the capability of the model).

Irrelevant Task: The proposed task is not related to the current context or meets the user's needs.

```
Observation: {
    "time": "1717336090.982",
    "event": "The user clicks, types 'list.swift' in Visual Studio
        Code."
}

GPT-4o Response: I can help by providing tips on how to
   efficiently navigate and manage files in Visual Studio Code or
    offer assistance with the content of 'list.swift'.
```

Under this event, the user created a new file in vscode. However, the agent provided a task about file management, which is irrelevant to the user's intention.

Unwanted Proposal: The user does not want to be interrupted.

```
Observation: {
    "time": "1717329211.15",
    "event": "The user opened 'http://127.0.0.1:5500/main.html' in
        the web browser."
}

GPT-4o Response: Offer to help troubleshoot or verify the 'fade in
    fade out' effect if it doesn't work as expected.
```

Under this context, since whether the edition is successful or not is not clear, the agent should remain silent rather than propose troubleshooting currently.

E Data Examples

E.1 Event Samples

Collected Raw Data


```
[{
    "timestamp": 1717335890.127,
    "duration": 2.056,
    "user_input": [],
    "status": "not-afk",
    "app": "web",
    "events": []
},
{
    "timestamp": 1717335893.215,
    "duration": 10.267,
    "user_input": [
        {
            "from": "mouse",
            "data": {
                "type": "click",
                "button": "left"
            }
        },
        {
            "from": "keyboard",
            "type": "input",
            "data": "swift ui ctrl_l liebiao "
        },
        {
```

```
            "from": "keyboard",
            "data": {
                "type": "pressAndRelease",
                "key": "enter"
            }
        }
    ],
    "status": "not-afk",
    "app": "web",
    "events": []
},
{
    "timestamp": 1717335904.513,
    "duration": 0.0,
    "user_input": [],
    "status": "not-afk",
    "app": "web",
    "events": []
}]
```


Processed Event


```
[{
    "time": "1717378968.208",
    "event": "The user opens a new browser tab and navigates to
       the Google homepage."
},
{
    "time": "1717378971.255",
    "event": "The user switches to the 'Code.exe' application but
       does not perform any specific actions."
},
{
    "time": "1717378975.29",
    "event": "The user continues to remain on the 'Code.exe'
       application without performing any actions."
}]
```


Annotated Data for Reward Model


```
{
    "obs": [
        {
            "time": "1717338232.283",
            "event": "The user types 'badrandResearch.m' in Visual
                Studio Code."
        },
        {
            "time": "1717338245.419",
            "event": "The user types a Markdown entry about
               research on sustainable branding in Visual Studio
               Code."
        },
        {
            "time": "1717338245.419",
            "event": "The user works on the file 'brandResearch.md
               ' in the project 'SustainableBrandResearch' in
               Visual Studio Code."
```

```
        },
        //...
        {
            "time": "1717338752.214",
            "event": "The user interacts with Katla's website,
               viewing eco-friendly loungewear products made by
               the sea."
        },
        {
            "time": "1717338804.867",
            "event": "The user writes Markdown notes in Visual
               Studio Code about Katla's product pricing."
        }
    ],
    "pred_task": null,
    "valid": false,
    "help_needed": true,
    "annotation": [
        false,
        false,
        false
    ],
    "category": "Missed-Need (MN)"
}
```


E.2 PROACTIVE AGENT'S PREDICTION

Testing Data Sample


```
{System Prompt For Proactive Agent}

User:
{
    "Instructions": "Now analyze the history events and provide a
       task if you think the user needs your help.",
    "Observation": [
        // ...
        {
            "time": "1717337616.208",
            "event": "The user switched back to Visual Studio Code
                and typed insights related to digital payment
               systems improving public transportation and
               reducing the need for private car usage."
        },
        {
            "time": "1717337282.329",
            "event": "The user moved the mouse and clicked the
               left button within Visual Studio Code."
        }
    ]
}

Possible Agent Response:
{
    "Purpose": "The user is currently interacting with a web
       application.",
    "Thoughts": "Based on the absence of a specific action, the
       user might be navigating or searching for content.",
```

```
    "Proactive Task": null,
    "Response": "I see you're actively using the web application.
       If you need help finding something specific or have any
       questions, feel free to ask!"
}
```


Example 1


```
{
    "observation": {
        "time": "1717378968.208",
        "event": "The user opens a new browser tab and navigates
           to the Google homepage."
    },
    "agent_response": [
        "Suggest checking the user's search history and providing
           personalized search recommendations."
    ],
    "task_status": false,
    "other_infomation": {
        "Purpose": "The user is opening a new browser tab and
           navigating to the Google homepage.",
        "Thoughts": "Based on the event, it seems the user is
           starting a new search or browsing session. They might
           need help with organizing their search or finding
           relevant information.",
        "Response": "Would you like me to review your search
           history and provide some personalized recommendations
           to help you find what you're looking for?"
    },
    "judgment": [
        false
    ]
}
```


Example 2


```
{
    "observation": {
        "time": "1717378971.255",
        "event": "The user switches to the 'Code.exe' application
           but does not perform any specific actions."
    },
    "agent_response": [
        "Suggest creating a new terminal or command prompt within
           the 'Code.exe' application to help the user with
           coding tasks."
    ],
    "task_status": false,
    "other_infomation": {
        "Purpose": "The user is switching to the 'Code.exe'
           application but didn't perform any specific actions.",
        "Thoughts": "Given the user's recent switch to the 'Code.
           exe' application, it's likely they're preparing to
           start coding or editing. However, they might need help
            with organizing their code, finding relevant
           documentation, or setting up their environment.",
```

```
        "Response": "I can help you create a new terminal or
            command prompt within the 'Code.exe' application. This
             will allow you to easily access coding tools and
            commands. Would you like me to set that up for you?"
    },
    "judgment": [
        false
    ]
}
```


Example 3


```
{
    "observation": {
        "time": "1717378975.29",
        "event": "The user continues to remain on the 'Code.exe'
            application without performing any actions."
    },
    "agent_response": [
        "Offer to provide coding assistance, such as suggesting
            online resources, tutorials, or even helping with
            writing code."
    ],
    "task_status": false,
    "other_infomation": {
        "Purpose": "The user is remaining on the 'Code.exe'
            application without performing any actions.",
        "Thoughts": "Given the user's recent actions, it seems
            they're hesitant to start coding or editing. They
            might be experiencing writer's block, struggling with
            a particular concept, or needing help with a specific
            coding task.",
        "Response": "If you're struggling with a coding task or
            need help with a specific concept, I'm here to assist.
             Would you like me to suggest some online resources,
            tutorials, or even help with writing code together?"
    },
    "judgment": [
        false
    ]
}
```


E.3 Reward Model Judgment Example

Input Prompt


```
{
    "Observations (Time Ascending)": [
        {
            "time": "1717342908.098",
            "event": "The user searched for 'remote working
                software' in the web browser and pressed 'Enter'."
        },
        {
            "time": "1717342914.314",
            "event": "A new tab titled 'new Tab' was opened in the
                 web browser."
```

```
        },
        {
            "time": "1717342940.516",
            "event": "The user opened a search result with the
               title 'remote working software - search' on Bing."
        },
        {
            "time": "1717342956.012",
            "event": "The user switched to another tab in the web
               browser, interacting with multiple scroll actions
               ."
        },
        {
            "time": "1717343061.447",
            "event": "The user resumed browsing on Bing search."
        },
        {
            "time": "1717343082.081",
            "event": "The user continued exploring search result
               pages in Bing with multiple scrolling actions and
               clicking on specific results."
        }
    ],
    "Proposed Task": null,
    "Instruction": "Now give your judgment. You should complete
       the reasoning process in the first person."
}
```


Ouput Judgment


```
{
    "thought": "I have been browsing the web and switching between
        different applications, and I haven't received any task
       proposal from the proactive assistant. Upon analyzing my
       current activities, I realize I've been searching for
       remote working software and exploring different search
       results on Bing. Given my current engagement and the fact
       that I haven't been interrupted or indicated a need for
       assistance, I believe there is no need for a task at this
       moment. The assistant's decision to not propose a task
       seems appropriate, as introducing a new task could
       potentially disrupt my workflow and cause unnecessary
       interruptions.",
    "judgment": "accepted"
}
```


F ANNOTATION GUIDELINES

Annotation Guidelines

```
In this annotation task, you need to observe two elements:
The sequence of events is described in the Observations module,
   where each event has an event field detailing what occurred.

Tasks generated by the model in the Tasks module are related to
   the current event sequence.
```

```
You need to carefully review the five tasks provided by the model.
    Analyze which tasks align with your potential needs in the
   context of the described event sequence, without excessively
   disrupting your normal workflow. Then, select the
   corresponding tasks in the checkboxes below. For example, if
   you believe that in the above example, tasks 3 and 4 are what
   you expect the agent to perform, and the others are not, then
   check the boxes for tasks 3 and 4.

If you think none of the tasks are appropriate (or you do not want
    to be disturbed by the agent in the current situation),
   please select the reject all checkbox.

After making your selection, click the continue button to submit
   the annotation results. At this point, new events will be
   updated in the observations, and you will repeat the above
   process until the entire event sequence is annotated.

### Special Events
In addition to regular task annotations, some scenarios offer two
   choices, requiring you to determine whether help is needed
   given the observation. In this case, you need to choose
   between task1 and task2 (note: do not select reject all).
```