

MemAgent: A cache inspired framework for augmenting conversational Web Agents with task-specific information

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Abstract

Large Language Models (LLMs) have shown promise as web agents, but their current limitations hinder their widespread adoption for general users. A critical issue behind this is the misalignment between user expectations and the agent’s actions due to ineffective communication leading to a lack of crucial context required for successful task completion. To address this gap, we propose MemAgent, a novel pipeline for LLM-based web agents. Inspired by caching mechanisms, MemAgent incorporates a memory component to store task-specific information. This memory bank enables the LLM agent to proactively query for supplementary context relevant to the current task, thereby reducing user interaction overhead. Our evaluations demonstrate that MemAgent significantly enhances the agent’s performance and usability, bringing us a step closer to seamless LLM integration in web agent technologies.

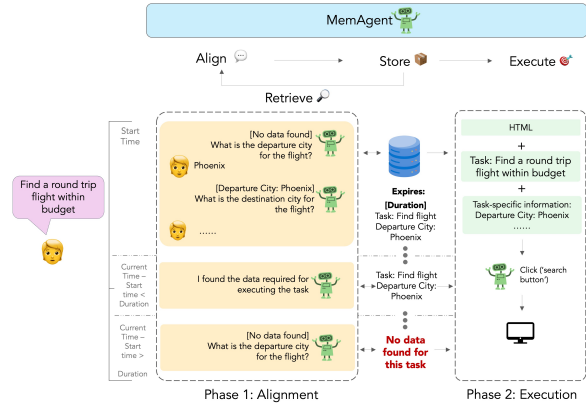


Figure 1: MemAgent Architecture. In *Alignment* phase, it engages in a multi-turn conversation with the users to extract and store task-specific information in a *memory cache bank (MCB)*. During *Execution* phase, MemAgent utilizes the MCB information to execute the task. Each MCB entry has a ‘expires’ field that determines how long it will stay valid.

1 Introduction

With the rise of the Large Language Model (LLM), we have seen an increase of automation in many aspects of our lives – given rise to the concept of *Web Agents* (Xi et al., 2023; Zhou et al., 2023; Deng et al., 2023; Wang et al., 2023; Yao et al., 2023a). Broadly, web agents are all systems that use LLMs as their engines and can perform actions on the websites based on observations. These agents can automate users’ web experience such as: booking a flight (Deng et al., 2023), shopping in amazon (Yao et al., 2023a) and so on.

Current state-of-the-art web agents typically require users to provide a well-crafted detailed task description to execute it. However, prior research shows that crafting effective prompts is a non-trivial task for users. Studies by (Zamfirescu-Pereira et al., 2023; Kim et al., 2022) highlight that users often provide abstract and incomplete

prompts, struggling to anticipate and convey all the necessary information. This issue is further exacerbated for recurring tasks as users need to repeatedly provide the same level of detail *every time*, leading to an inefficient and frustrating user experience.

To overcome these issues, recent works have explored augmenting agents with short-term, long-term and working memory (Packer et al., 2024). These agents typically store the information in their working/short-term memory and later bypass it into long-term memory. However, the transformation of these information is complex, and is not controllable. On the other hand, few works explored how to enable agents to ask follow-up questions when it is unsure (Lù et al., 2024) and there is missing information. Although these agents can engage with the users and ask follow-up questions *as it executes*, they still suffer from the memory limitation, i.e., users need to engage with agents every time they execute a task. This raises the question: *How can we bridge between these two paradigms with a*

062 *simple yet effective agent framework?*

063 To this end, we present MemAgent, a simple yet
064 effective agent that learns to store task information
065 in a cache by *conversing* with the users. MemA-
066 gent works in two phases: *Alignment* and *Execu-*
067 *tion*. In the *Alignment* phase, the agent is trained
068 to pose follow-up questions to users, capturing and
069 storing their responses in our dedicated *memory*
070 *cache bank (MCB)*. During the *Execution* phase, it
071 leverages this stored information to perform tasks,
072 thereby eliminating the need for users to repeatedly
073 engage in lengthy dialogues, as required by existing
074 models. Instead of using a short-term or long-term
075 memory mechanism (Sumers et al., 2023), we de-
076 sign a simpler, yet effective storage mechanism
077 similar to cache. MCB saves the task details, in-
078 cluding type and value information for each task
079 entity and includes an auto-expiration field, which
080 helps to refresh MemAgent’s storage periodically
081 and model user’s dynamic preference.

082 Our contributions can be summarized as follows:

- 083 1. A novel web agent pipeline, MemAgent that
084 can store task specific information in a mem-
085 ory cache bank (MCB). MemAgent learns to
086 create and retrieve information from MCB by
087 conversing with the users.
- 088 2. We evaluated MemAgent on a diverse set of
089 tasks to showcase its abilities and improve-
090 ment on top of existing web agents;

091 2 Related Work

092 2.1 Autonomous Web Agent

093 There has been a large body of works on au-
094 tonomous web agents, investigating how to effi-
095 ciently utilize large language models for automat-
096 ing usual web activities (Wang et al., 2023; Wen
097 et al., 2023; Zhang and Zhang, 2023; Zhou et al.,
098 2023; Deng et al., 2023; Yao et al., 2023a; Shi et al.,
099 2017; Kapoor et al., 2024). (Wen et al., 2023) per-
100 forms an offline exploration and creates a transition
101 graph, which is used to provide more contextual in-
102 formation to the LLM prompt. (Zhang and Zhang,
103 2023) introduces chain-of-action prompting that
104 leverages previous action history and future action
105 plans to decide the next action. Most of the early
106 works on Web UI are based on synthetic frame-
107 works, MiniWob (Shi et al., 2017) and WebShop
108 (Yao et al., 2023a). To capture the complexity of
109 real-world tasks, (Deng et al., 2023) and (Zhou
110 et al., 2023) introduce two realistic environments

and datasets encompassing real-world tasks. Per- 111
112 haps the closest to our work is WebLinx (Lù et al.,
113 2024), which is a multi-turn dialog dataset for web
114 activities. However, our approach is significantly
115 different from theirs. We separated the chat and
116 operation actions into two separate phases - Align-
117 ment and Execution. We primarily focus on im-
118 proving web agent’s performance for abstract task
119 descriptions and repetitive tasks. Our MCB is also
120 different from the approach used in WebLinx.

121 2.2 Memory augmentation for LLM Agent

122 There has been a growing interest on how to in-
123 corporate human cognitive principles into LLM
124 agents (Zhang et al., 2024). CoALA proposes
125 how a combination of procedural, semantic, and
126 episodic memory can be useful for improving the
127 reasoning capacity of agents (Sumers et al., 2023).
128 Ret-LLM proposes simple ‘read and write’ mem-
129 ory operations for language models (Modarressi
130 et al., 2023). MemGPT proposes a memory aug-
131 mentation for GPT models which can be accessed
132 with a simple function calling (Packer et al., 2024).
133 MemoryBank (Zhong et al., 2023) stores a sum-
134 mary of chat history and user portrait to help in
135 future conversations and recommendations. Un-
136 like their process, we do not store the summary,
137 but rather the user-specific detailed information of
138 each task individually, enabling more transparent
139 and accurate replication in the future. Moreover,
140 we use a caching memory update mechanism rather
141 than Ebbinghaus Forgetting Curve.

142 3 MemAgent

143 Given an abstract task description, \mathcal{T}_a , MemA-
144 gent’s task is to inquire about task details (*Align-*
145 *ment*, §3.1) and execute them (*Execution*, §3.3).
146 For Alignment, MemAgent asks a set of questions,
147 q , and parses user response to find the task-specific
148 information, $\mathcal{I}_q = \sum_{i=1}^{|q|} (type_i \mapsto value_i)$. Given
149 \mathcal{T}_a and \mathcal{I}_q , MemAgent executes the task during Ex-
150 ecution. $\mathcal{I}_q|\mathcal{T}_a$ is stored in a memory cache bank
151 (§3.2).

152 3.1 Phase 1: Alignment

153 Given \mathcal{T}_a , MemAgent engages in a multi-turn con-
154 versation with the users in *Alignment* phase to cu-
155 rate \mathcal{I}_q . In this phase, the agent has two key respon-
156 sibilities - 1) *Enquire*: Only ask questions that are
157 relevant to the current task; 2) *Extract*: Parse user
158 response to find out the information type and value.

3.2 Memory Cache Bank (MCB)

Central to MemAgent is the memory cache bank, MCB, which stores \mathcal{I}_q for each \mathcal{T}_a . Similar to cache, each \mathcal{I}_q has an ‘Expires’ field, which controls when it becomes stale. MCB provides several benefits to MemAgent: 1) *Reduced turn of conversation*: It stores the detailed information, \mathcal{I}_q for \mathcal{T}_a so that the user does not need to provide the detailed information every time they want to execute \mathcal{T}_a . 2) *Integration with Retrieval Augmented Pipeline*: MCB can be easily integrated with Vector Databases to support retrieval augmented execution for web agents (please see §B.1 for detailed experiments with Vector database).

3.3 Phase 2: Execution

Given \mathcal{T}_a and \mathcal{I}_q , MemAgent completes the task in the *Execution* phase. In this phase, we adopt a two-step workflow similar to the Mind2Act framework proposed by Mind2Web (Deng et al., 2023). Our approach differs in that we concatenate \mathcal{T}_a and \mathcal{I}_q instead of solely relying on the task description \mathcal{T}_a . This concatenation allows us to examine the efficacy of the additional context towards task completion, without altering execution strategy (§4.1). Similar to MindAct, our execution framework operates in two steps. – 1) candidate generation: a small LM ranks webpage elements based on \mathcal{T}_a ; ¹ 2) action prediction: a larger LM predicts the action and target element from top-k candidates ranked in the first step ($k = 10$).

4 Experimental Setup

4.1 Dataset

While there are multiple datasets on web agents, there is no specific dataset in our desired format that includes multi-turn conversation and task information in slot filling style (Weld et al., 2022). Hence, we synthetically augment our dataset over Mind2Web (Deng et al., 2023) to create a conversational dialog between a user and an agent. Table 1 shows an example data from our augmented data. We use GPT-4.5-turbo to create this augmented data following Self-Refine framework (Madaan et al., 2024). Specifically, we tell the GPT model to generate the augmented data, followed by feedback in terms of conciseness (whether it includes repetitive conversation), usefulness (whether it includes useful questions), and verbosity (whether it asks

¹We use their off-the-shelf candidate generator since the data augmentation does not impact the ranking.

Abstract task, \mathcal{T}_a	Followup Questions for Alignment Phase	Memory Bank, \mathcal{I}_q
Calculate shipping cost for a package	What is the weight of the package?	Weight: 4 pounds
	Where is the package being shipped from ?	Shipped from: Texas
	What is the destination of the package?	Destination: New York
<i>Corresponding Task in Mind2Web</i>		
Calculate shipping cost for 4 pound package from Texas to New York		

Table 1: An example of augmented data in MemAgent.

the question with less verbosity) on a scale of 1 to 5. If score is below 5 on any metric, we ask the GPT to refine the augmented data further.

We picked Mind2Web over other datasets because it covers a wide range of websites and task difficulty levels. Although WebLinx is closely aligned with us, we did not consider the dataset since it is difficult to filter out the conversation from execution and it includes human-to-human dialogue whereas we wanted to target agent-to-human dialogue.

4.2 Models.

Finetuning. For alignment, we finetune Vicuna 7B and Mistral Instruct v2. We initialize the training in two ways: 1) empty MCB: agent has to ask all the questions relevant to the task; 2) pre-filled MCB: agent has to ask only the remaining questions relevant to the task. For execution, we finetune MindAct from Mind2Web in its three variants (Flan-T5 Base, Large, XL). Each training was completed either on a A100 or A6000 GPU. For hyperparameters, please see Appendix A.3.

In-context Learning (ICL). We also report the effectiveness of MemAgent with few-shot prompting for LLMs. We report our results both on GPT-4o and Gemini-1.5-pro with 2-shot prompting. For Alignment, we explore basic, CoT (Wei et al., 2022) and ReAcT (Yao et al., 2023b) prompting technique w/ or w/o MCB. For execution, we explore the 3-shot prompting similar to Mind2Web. Please see Figure 6 to 11 in appendix to find the corresponding prompt in each setting.

4.3 Evaluation Metrics

The overall evaluation scheme is outlined in Algorithm 1, §A.4.

Alignment. To measure whether the task information is curated successfully, we adopt the BERTScore (Zhang et al., 2019) and BLEUScore (Papineni et al., 2002) metrics to calculate the similarity between the ground truth and generated MCB. We also measure turn of conversation between the user and agent (lower is better), to compute how well the model can ask relevant question.

Execution. To measure if the task is executed successfully, we measure the metrics established in

Model Name	Cross-Task			Cross-Website			Cross-Domain			
	BleuScore (↑)	BertScore (↑)	Avg. # (↓)	BleuScore (↑)	BertScore (↑)	Avg. # (↓)	BleuScore (↑)	BertScore (↑)	Avg. # (↓)	
Vicuna _{7B} (w/ prefilled MCB)	43.17	0.92	2.52	45.53	0.94	2.94	45.04	0.93	2.64	
Vicuna _{7B}	40.85	0.93	3.56	38.92	0.93	3.24	39.91	0.93	3.66	
Finetuned model	Mistral _{7B} (w/ prefilled MCB)	45.02	0.92	3.70	46.38	0.94	3.07	46.00	0.93	2.69
2-Shot Prompting	GPT-4o	-	-	8.66	-	-	8.90	-	-	9.04
	GPT-4o + MCB	22.13	0.80	7.04	18.32	0.82	6.94	13.62	0.78	7.82
	GPT-4o + CoT + MCB	23.25	0.86	6.96	20.72	0.85	6.96	15.66	0.80	7.32
	GPT-4o + ReAct + MCB	19.48	0.81	7.28	18.54	0.83	7.26	20.14	0.74	7.26
	Gemini-Pro	-	-	5.44	-	-	5.20	-	-	5.00
	Gemini-Pro + MCB	17.78	0.76	6.52	22.90	0.87	5.64	14.25	0.83	5.34
3-shot	Gemini-Pro + CoT + MCB	27.78	0.83	4.60	27.05	0.83	3.96	29.35	0.79	3.88
	Gemini-Pro + ReAct + MCB	22.62	0.85	5.08	27.03	0.89	5.22	20.27	0.86	5.06

Table 2: MemAgent result for Alignment Phase. For ICL, CoT + MCB prompting performs best in most cases across the test splits. For fine-tuned model, the avg. turn of conversation is significantly less than the ICL version, denoting fine-tuning helps the model to learn to ask only contextualized questions.

Model Name	Cross-Task				Cross-Website				Cross-Domain				
	Ele. Acc. (↑)	Op. F1 (↑)	Step SR (↑)	SR (↑)	Ele. Acc. (↑)	Op. F1 (↑)	Step SR (↑)	SR (↑)	Ele. Acc. (↑)	Op. F1 (↑)	Step SR (↑)	SR (↑)	
Fine-tuned	Flan-T5 _B	55.78	83.56	52.43	18.0	48.91	72.07	42.42	2.0	55.38	80.53	48.6	8.0
MindAct	Flan-T5 _L	62.04	82.51	57.13	14.0	53.9	71.63	47.14	2.0	62.61	82.57	56.82	10.0
Model	Flan-T5 _{XL}	67.73	82.11	62.33	16.0	56.75	72.83	48.71	6.0	59.83	76.76	51.92	12.0
3-shot	GPT-4o	60.34	79.44	54.62	6.0	56.03	73.05	47.44	6.0	63.1	84.75	58.88	16.0
	Gemini-Pro	50.87	69.58	45.26	4.0	48.04	70.17	36.91	2.0	54.43	78.97	48.27	4.0

Table 3: MemAgent result for Execution Phase. Finetuned models perform better on the cross Task split, whereas in ICL, the performance is consistent across the splits.

the literature (Deng et al., 2023) — Step success rate (if the step was successful), Element Accuracy (if the element matches ground truth), Operation F1 (if the operation matches ground truth) and overall success rate (SR) (if the whole task was successful).

5 Results

Similar to Mind2Web, due to budget constraints, we evaluate MemAgent on 150 test samples (50 from each split: Cross-Task, Cross-Website, Cross-Domain). §A.2 explains the selection process of these samples.

5.1 Alignment

Table 2 shows the results for MemAgent Alignment phase.

Finetuned model. All the finetuned models performed consistently across the test splits, whereas Vicuna w/ prefilled MCB being slightly better than the rest in terms of avg. turn of conversation.

In-context learning. Gemini-pro performed best when CoT + MCB strategy is applied. For baseline prompting, we only calculated the avg. turn of conversation since there is no MCB generated in this setting. We also notice that finetuned models perform better than few-shot prompting in general. Notably, with ICL, the models can sometimes ask repetitive questions often unnecessary for a given task. To circumvent this, we conclude the conversation when Avg. # reaches 10. See Figure 12 in appendix for an example.

5.2 Execution

Table 3 shows the results for MemAgent Execution phase. Flan-T5_{XL} and the GPT-4o model perform better than the rest. Flan-T5 models perform well in Cross-Task split due to the transferable knowledge between train and test samples.

However, the GPT-4o model generalizes better to the cross-domain split. The samples in our cross-domain split have fewer action steps(244) than the other two (312 and 263). This might have impacted the GPT-4o’s better performance in Cross-Domain.

6 Conclusion

In this paper, we presented MemAgent, a novel pipeline designed to address the limitations of LLM web agents, particularly the misalignment between user expectations and the agent’s actions. By incorporating MCB, MemAgent effectively stores task-specific information, allowing it to proactively query for supplementary context. This approach reduces user interaction overhead and enhances task completion success. Our evaluations demonstrate significant improvements in both performance and usability of the agent, indicating that MemAgent is a promising step towards seamless integration of LLMs in web agent technologies.

Limitation

MemAgent has been tested on Mind2Web, which is a static dataset. There might be additional chal-

309 lenges when MemAgent is deployed in an interac-
310 tive web environment, which is beyond the current
311 scope.

312 Currently, MemAgent supports the creation of
313 one MCB per task. In cases where users might
314 want to utilize multiple MCBs, it may not support
315 well. For example, a user wants to concurrently
316 book flights from New York - Florida and Chicago -
317 Pennsylvania. MemAgent may not be able to store
318 both of these at the same time.

319 Ethics Statement

320 The authors utilized third-party writing assistants
321 (ChatGPT, Gemini, Grammarly) to refine the
322 manuscript. This usage was limited to improving
323 the presentation and readability of the work and did
324 not involve these tools in any intellectual or creative
325 capacity (Nakazawa et al., 2022). The intellectual
326 contributions and research content remain solely
327 the product of the authors' efforts.

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A Appendix

A.1 Dataset Generation

Table 4 shows the train data distribution and Table 5 shows the test data distribution used in MemAgent.

Description	Count
# of data samples w/o MCB	779
# of data samples w/ MCB	15136
# of action steps	6659
Split ratio	0.9
Train sample count	13785
Eval sample count	1532

Table 4: Train Data in MemAgent

Cross Task	
# of data samples w/o MCB	50
# of data samples w/ MCB	1752
# of action steps	312
Cross Website	
# of data samples w/o MCB	50
# of data samples w/ MCB	442
# of action steps	263
Cross Domain	
# of data samples w/o MCB	50
# of data samples w/ MCB	455
# of action steps	244

Table 5: Test Data in MemAgent

A.2 Evaluation Data Selection

As we use the Mind2Web’s off-the-shelf candidate generator, the failure of ranking ground-truth (*positive*) candidates could impact overall performance. To minimize this effect, we pick samples with the least missing candidates. Specifically, 50 samples in cross-domain have positive candidates for all task steps. For Cross-task and cross-website, the values are 43 and 29 respectively. To pick the remaining samples in these splits, we randomly select samples with missing candidates in only one step. This approach ensures a more reliable evaluation of MemAgent’s performance.

A.3 Experimental Setup Information

Framework: We use Fastchat and Axolotl framework for training the models in Alignment Phase. For Execution, we followed the official github repository by Mind2Web (Deng et al., 2023).

Hyperparameter setup: Execution Phase: We have fine-tuned all three Flan-T5 models with the learning rate $5e^{-5}$, which is the same as MindAct. Flan-T5_L and Flan-T5_{XL} were fine-tuned using LoRA. Table 6 shows the other hyperparameters: epoch, batch size, LoRA rank r, LoRA scaling factor α and the temperature parameters for ICL.

Fine-tuned MindAct Models			
	epoch	batch size	LoRA
Flan-T5 _B	5	32	
Flan-T5 _L	5	32	r=8 $\alpha=16$ dropout=0.05
Flan-T5 _{XL}	3	64	r=16 $\alpha=32$ dropout=0.05
3-shot prompting			
GPT-4o	temperature: 0		
Gemini-Pro	temperature: 0.5, top.p: 0.5		

Table 6: Hyperparameters of the Flan-T5 models

Algorithm 1: MemAgent Evaluation

Data: task, $[GT_{conv}]$, GT_{bank} , $[GT_{dom}]$
Result: s_{bert} , s_{bleu} , $turn$, $F1$, $step_SR$, $elem. acc$, SR
 $turn = 0$; $mem_bank, message = []$;
if task in bank: $message.append(GT_{bank}.task)$
if task in bank: $mem_bank.append(GT_{bank}.task)$
while true do
 $q, mem = alignment(message)$;
 $gt_q, gt_a = find_closest(q, GT_{conv})$;
 $s_{bert}, s_{bleu} = calculate(mem, GT_{bank}.task)$;
 $turn += 1$;
 $message.append(gt_a)$;
 $mem_bank.append(mem)$;
 if $(turn > 10 \parallel 'FINISH' \text{ in } q)$: break;
end
while true do
 $a = execution(mem_bank, task, GT_{dom})$;
 $F1, step_SR, elem. acc = calculate(a, GT_{dom}.a)$;
 if $('FINISH' \text{ in } a)$: break;
end
 $SR = (sum(step_SR) == len(GT_{dom}))$;

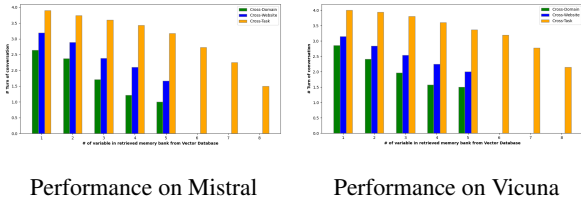


Figure 2: Statistics showing average count of conversation turn with respect to information present in the retrieved MCB. With more information present in the MCB, the conversation turn is significantly reduced without sacrificing the task completion accuracy.

A.4 Evaluation Algorithm

B Discussion

B.1 MemAgent for RAG

MemAgent’s modular components allow integration with the RAG framework (Lewis et al., 2020). MCB can be stored and queried from a vector database. Moreover, the alignment models, fine-tuned with a prefilled memory bank, ask questions only when information is missing. We perform an additional analysis with an open-sourced vector database, reporting the ratio of conversations to MCB entries (Figure 2). As anticipated, the alignment model asked fewer questions when the vector database contained more information.

B.2 MemAgent for dynamic preference modeling

Current agents struggle with handling user preferences effectively (Zhou et al., 2023). Although memory-augmented agents show promises in storing information (Packer et al., 2024), the transfor-

mation of memory remains complex. In contrast, our MCB is straightforward yet powerful, to store user preferences for a defined period before automatic removal. This enables MemAgent to *dynamically* model user preferences.

B.3 MemAgent for generalistic web modelling

MemAgent’s information is generalizable across websites. For example, to book a flight, we always need to know the time, departure and arrival location no matter which booking website we are using. Since our MCB only stores \mathcal{I}_q for each \mathcal{T}_a and is independent of the website, it can reuse the task information across websites with similar usecases.

B.4 Figures

This appendix includes some additional figures which provide visual insight into the discussed topics. Figure 5 shows the constructed task description. Figure 6-9 shows prompts used for 2-shot prompting in gpt-4o and gemini-pro evaluations. Figure 12 gives a insight about the repetitiveness of LLMs in generating follow-up questions. Figure 10 shows the prompt used for the gpt-4o execution. The prompt for the gemini-pro execution is the same. Additionally, the response format is added, as shown in Figure 11.

Given an input task description, you have to generate tuples of questions, answers and variables. Your response should mimic the way an agent will get detailed information from a user for the corresponding task.

Follow these guidelines:

1. Think step-by-step and include your thoughts in the response.
2. Include the simplified description in your response in <abs> tag. The simplified description should include the high-level description of the task.
3. Include the questions in <Questions> tag.
4. Mark the individual question, answer and variable with <Q>, <A>, <mem> tag.
5. Please do NOT ask lengthy questions. Try to write your questions with as less words as possible.
6. Do NOT include questions whose answers are not present in the task.
7. Do NOT hallucinate or guess the answers unless mentioned in the task.
7. Questions should be meaningful and ask for information that are crucial to execute the task.
8. The question should not sound robotic. Try to mimic how a casual conversation.

Here is an example:

Task: Subscribe to the 'Daily Fitness Tips' newsletter using the email john.fitnessfan@example.com under the name John Fitness, and indicate an interest in yoga and weight training.

Thought: The main task is to subscribe to a newsletter. The information needs to ask are: newsletter name, subscriber name and email address, interest.

Response:

```
<Abs> Subscribe to newsletter </Abs>
<Questions>
<Q> newsletter name to subscribe to? </Q>
<A> Daily Fitness Tips </A>
<mem> Newsletter Name: Daily Fitness Tips </mem>
<Q> What email address should be used? </Q>
<A> john.fitnessfan@example.com </A>
<mem> Email Address: john.fitnessfan@example.com </mem>
<Q> name for the subscription? </Q>
<A> John Fitness </A>
<mem> Subscriber's Name: John Fitness </mem>
<Q> areas of interest? </Q>
<A> Yoga and weight training </A>
<mem> Interest Areas: Yoga and weight training </mem> </Questions>
```

Task: {prompt}

Thought:

Figure 3: Prompt used during data generation

User wants to generate conversation data, (where <abs> includes the input task description and a consecutive list of question (Q), answer (A), and memory (mem) tuple) for input task description.

However, the conversation data collected is not always clean. Your task is to filter out repetitive tuples that are already present in <abs>.

Follow these guidelines:

1. If a question is already answered in the <abs>, discard it.
2. Rate the quality from 1-5 (1: bad, 5: good) for conciseness (whether it includes repetitive conversation), usefulness (whether it includes useful questions), and verbosity (whether it asks the question with less verbosity.)
3. Do NOT delete any information that was present in the original description but not in <abs>.
4. If the data looks good to you, you can just reply noop.

Here is an example:

Original Description: Find a latest post with more than 10k upvotes in r/announcements community and upvote it.

Input:

```
<Abs> Upvote latest post with high engagement </Abs>
<Questions>
<Q> Which community's latest post should be searched for? </Q>
<A> r/announcements </A>
<mem> Target Community: r/announcements </mem>
<Q> What is the minimum number of upvotes required for the post to be considered? </Q>
<A> More than 10,000 upvotes </A>
<mem> Minimum Upvotes Required: More than 10,000 </mem>
<Q> What action should be taken once a suitable post is found? </Q>
<A> Upvote it </A>
<mem> Action to Take: Upvote the post </mem>
</Questions>
```

Thought: The abstract description already mentioned that the task is to upvote a post which is repeated in the last question. So, I will discard the last question.

Rate:

conciseness: 3 (the last question is repetitive),
usefulness: 4 (count of upvotes is not a mandatory parameter, the rest are good),
verbosity: 2 (questions are too lengthy)

Output: <Abs> Upvote latest post with high engagement </Abs>

```
<Questions>
<Q> Which community's post? </Q>
<A> r/announcements </A>
<mem> Target Community: r/announcements </mem>
<Q> Minimum number of upvotes to be considered? </Q>
<A> More than 10,000 upvotes </A>
<mem> Minimum Upvotes Required: More than 10,000 </mem>
</Questions>
```

Now reply with your thought, rate, and output for the following.

Original Description: {tsk}

Input: {prompt}

Thought:

Figure 4: Self-Refine prompt used during data generation


```

<Abs> Book winery tour </Abs>
<Questions>
  <Q> What is the destination for the winery tour? </Q>
  <A> Napa Valley </A>
  <mem> Tour Destination: Napa Valley </mem>

  <Q> What type of cuisine should the winery serve? </Q>
  <A> Mediterranean cuisine </A>
  <mem> Cuisine Type: Mediterranean cuisine </mem>

  <Q> Does the tour include wine tasting? </Q>
  <A> Yes, it includes wine tasting. </A>
  <mem> Wine Tasting: Included </mem>

  <Q> How many guests will be attending the winery tour? </Q>
  <A> 4 guests </A>
  <mem> Number of Guests: 4 guests </mem>

  <Q> What is the date and time for the winery tour booking? </Q>
  <A> April 15, at 10 am. </A>
  <mem> Tour Date and Time: April 15, at 10 am. </mem>

  <Q> What type of setting is requested for the tour? </Q>
  <A> Outdoor setup. </A>
  <mem> Setup Preference: Outdoor setup. </mem>
</Questions>

```

Figure 5: Example of constructed task description

Given an initial task description, your task is to ask follow-up questions and parse the user's response. Only ask one question at a time. If you are done, reply with <Finish>. Please reply only with the question.

First Example:

User: Book me a flight
Agent: Where are you going?

Second Example:

User: Subscribe to newsletter
Agent: newsletter name to subscribe to?
User: Daily Fitness Tips
Agent: What email address should be used?
User: john.fitnessfan@example.com
Agent: <Finish>

Now complete the following task:

Figure 6: Baseline LLM prompt (Alignment)

Given an initial task description, your task is to ask follow-up questions and parse the user's response for answer type and value to be stored into <mem>type: value</mem>. Only ask one question at a time. If you are done, reply with <Finish>. Please reply only with the question and <mem> if any.

First Example:

User: Book me a flight
Agent: Where are you going?

Second Example:

User: Subscribe to newsletter
Agent: newsletter name to subscribe to?
User: Daily Fitness Tips
Agent: <mem> Newsletter Name: Daily Fitness Tips </mem> What email address should be used?
User: john.fitnessfan@example.com
Agent: <mem> Email Address: john.fitnessfan@example.com </mem><Finish>

Now complete the following task:

Figure 7: LLM + MCB prompt (alignment)

Given an initial task description, your task is to ask follow-up questions and parse the user's response for answer type and value to be stored into `<mem>type: value</mem>`. Only ask one question at a time. If you are done, reply with `<Finish>`. Please include your question in `<Q>` tag and parsed answer in `<mem>` tag.

First Example:

User: Book me a flight.

Agent: Let's think step by step. To book a flight, we need to know the departure, arrival location, and time. I will first ask about the departure location. `<Q>Where are you going? </Q>`

Second Example:

User: Subscribe to newsletter.

Agent: Let's think step by step. To subscribe, I need to know the newsletter name first. `<Q>What is the newsletter name to subscribe to?</Q>`

User: Daily Fitness Tips.

Agent: Let's think step by step. I will put the user response into the mem bank as a newsletter name. I also need to ask about their email address. `<mem> Newsletter Name: Daily Fitness Tips </mem> <Q>What email address should be used?</Q>`

User: john.fitnessfan@example.com.

Agent: Let's think step by step. Since all the information is already asked, I will finish now and store the email address from the last reply. `<mem>Email Address: john.fitnessfan@example.com </mem><Finish>`

Now complete the following task:

Figure 8: LLM + CoT+ MCB prompt (Alignment)

Given an initial task description, your task is to ask follow-up questions and parse the user's response for answer type and value to be stored into `<mem>type: value</mem>`. Only ask one question at a time and include your thought and action. If you are done, reply with `<Finish>`. Please include your question in `<Q>` tag and parsed answer in `<mem>` tag.

First Example:

User: Book me a flight

Agent: Thought: To book a flight, we need to know the departure, arrival location, and time. I will first ask about the departure location. Action: `<Q> Where are you going? </Q>`

Second Example:

User: Subscribe to newsletter

Agent: Thought: To subscribe, I need to know the newsletter name first. Action: `<Q> Newsletter name to subscribe to? </Q>`

User: Daily Fitness Tips

Agent: Thought: I will put the user response into the mem bank as a newsletter name. I also need to ask about their email address. Action: `<mem> Newsletter Name: Daily Fitness Tips </mem> <Q> What email address should be used? </Q>`

User: john.fitnessfan@example.com

Agent: Thought: Since all the information is already asked, I will finish now and store the email address from the last reply. Action: `<mem> Email Address: john.fitnessfan@example.com </mem><Finish>`

Now complete the following task:

Figure 9: LLM + ReACT + MCB prompt (alignment)

```

Role: System
Content: You are a helpful assistant that is great at website design, navigation, and executing tasks for the user.

Role: User
Content:
'''
<html> <div> <div> <a tock home page /> ... <span> Explore now </span> </div> </div> </div> </html>
'''

Based on the HTML webpage above, try to complete the following task:
Task: Check restaurant availability for pickup. City: Boston, NY, Date and Time: March 18, 5pm, Number of Guests: 1
Previous actions:
None
What should be the next action? Please select from the following choices (If the correct action is not in the page above, please
select A. 'None of the above'):

A. None of the above
B. <button id=0 book a reservation. toggle open> <span> Book a
C. <select id=1 type> <option reservations true> Dine in </option> <option
D. <div id=2> <p> Celebrating and supporting leading women shaking up

Role: Assistant
Content:
Answer: C.
Action: SELECT
Value: Pickup

Role: User
Content:
'''
<html> <div> <main main> <section tabpanel> ... </a> </ul> </div> </footer> </div> ... </html>
'''

Based on the HTML webpage above, try to complete the following task:
Task: Compare fare types for booking a train ticket. Departure Location: Springfield, IL, Arrival Location: Austin, TX,
Travel Date: April 29th, 2023, Number of Adults: 1
Previous actions:
[combobox] Enter your departing city, airport name, or airpor... -> TYPE: SPRINGFIELD
[button] Springfield, IL, US (SPI) -> CLICK
[combobox] Enter your destination city, airport name, or airp... -> TYPE: AUSTIN
[button] Austin, TX, US (AUS) -> CLICK
What should be the next action? Please select from the following choices (If the correct action is not in the page above, please
select A. 'None of the above'):

A. None of the above
B. <li id=0 tab heading level 3 search and> <span> Hotel
C. <div id=1> <div> <span> Dates* </span> <button button clear dates
D. <ul id=2> <a mobile tools> </a> <a open united's tiktok

Role: Assistant
Content:
Answer: A.

Role: User
Content:
'''
<html> <div> <nav main menu> <ul> <li> <div button> Car Sales </div> ... </html>
'''

Based on the HTML webpage above, try to complete the following task:
Task: Find a rental vehicle. Vehicle Type: Mini van, Rental Location: Brooklyn City, Rental Start Date: April 5th,
Rental End Date: April 8th, Renter's Age: 22 years old
Previous actions:
[searchbox] Pick-up & Return Location (ZIP, City or Airport) (... -> TYPE: Brooklyn
[option] Brooklyn, NY, US Select -> CLICK
What should be the next action? Please select from the following choices (If the correct action is not in the page above, please
select A. 'None of the above'):

A. None of the above
B. <div id=0> <div> <div> <div> Buy A Car </div> <div>
C. <div id=1> Enterprise Fleet Management </div>
D. <button id=2 selected pick-up date 03/19/2023> <span> <span> 19 </span>

Role: Assistant
Content:
Answer: D.
Action: CLICK

```

Figure 10: Prompt GPT-4o (Execution). The HTML part of the prompt is shortened here

```

Same as GPT-4o prompt with the following added for format specification:
"Give your answer in the format:
Answer: <option>A|B|C|D|E|F</option>
Action: <action>CLICK|SELECT|TYPE</action>
Value: <value>if Action is SELECT|TYPE</value>"

```

Figure 11: Prompt Gemini-Pro (Execution)

```

Task: Open the most helpful 5 star reviews of Alpine Ridge
Q: Which product or service are the reviews for?
A: Alpine Ridge

Q: Would you like to see the most recent reviews or the top-rated ones?
A: Not specified

Q: Which platform would you like to open the reviews on? (e.g., Amazon, Yelp, Google Reviews)
A: Not specified

Q: Could you please provide more details or specify the context in which these 5-star reviews should be opened?
A: Not specified

Q: Are you looking to open the 5-star reviews for a particular purpose, such as market research, customer feedback, or for promotional use?
A: Not specified

Q: Can you specify whether you have a particular browser or tool that you would like to use to open the reviews?
A: Not specified

Q: Could you please clarify whether you need assistance finding these reviews, or do you already have a source and just need them opened?
A: Not specified

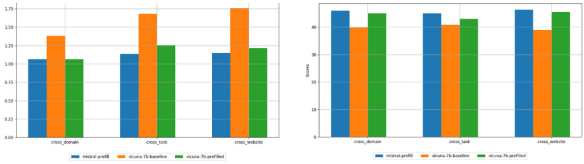
Q: Do you have any specific requirements or preferences regarding the format in which the reviews should be opened, such as a document, spreadsheet, or web page?
A: Not specified

Q: Are you looking for reviews in a specific language or region?
A: Not specified

Q: Is there a specific date range for the reviews you are interested in?
A: Not specified

```

Figure 12: Example of repetitive questions in Gemini-Pro baseline prompting.



False Negative Analysis BLEU Score Analysis

Figure 13: Statistics showing Mistral model minimizes false-negative quantity and achieves the maximum BLEU score in all the categories

```
deepspeed fastchat/train/train_lora.py
--model_name_or_path lmsys/vicuna-13b-v1.5
--lora_r 32
--lora_alpha 64
--lora_dropout 0.05
--num_train_epochs 4
--learning_rate 2e-4
--lr_scheduler_type "cosine"
--q_lora True
```

(a) Parameters for fine-tuning lmsys/vicuna-7b-v1.5

```
axolotl version: `0.4.0`
---yaml
base_model: mistralai/Mistral-7B-Instruct-v0.2
model_type: MistralForCausalLM
load_in_8bit: true
adapter: lora
sequence_len: 2048
lora_r: 32
lora_alpha: 16
lora_dropout: 0.05
lora_target_linear: true
lora_target_modules:
  - gate_proj
  - down_proj
  - up_proj
  - q_proj
  - v_proj
  - k_proj
  - o_proj
lr_scheduler: cosine
learning_rate: 2e-5
---
```

(b) Parameters for fine-tuning mistralai/Mistral-7B-Instruct-v0.2

Figure 14: Parameters for fine-tuning models