

# Aligning LLM Agents by Learning Latent Preference from User Edits

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**Abstract** 18 14 7

We study interactive learning of language agents based on user edits made to the agent’s output. In a typical setting such as writing assistants, the user interacts with a language agent to generate a response given a context, and may optionally edit the agent response to personalize it based on their *latent* preference, in addition to improving the correctness. The edit feedback is *naturally generated*, making it a suitable candidate for improving the agent’s alignment with the user’s preference, and for reducing the cost of user edits over time. We propose a learning framework, **PRELUDE**, to conduct **PRE**ference **LE**arning from **U**ser’s **D**irect **E**dits by inferring a description of the user’s latent preference based on historic edit data and using it to define a prompt policy that drives future response generation. This avoids fine-tuning the agent, which is costly, challenging to scale with the number of users, and may even degrade its performance on other tasks. Furthermore, learning descriptive preference improves interpretability, allowing the user to view and modify the learned preference. However, user preference can be complex, subtle, and vary based on context, making it challenging to learn. To address this, we propose a simple yet effective algorithm named **CIPHER** (Consolidates Induced Preferences based on Historical Edits with Retrieval). CIPHER leverages a large language model (LLM) to infer the user preference for a given context based on user edits. In the future, CIPHER retrieves inferred preferences from the  $k$ -closest contexts in the history, and forms an aggregate preference for response generation. We introduce two interactive environments – summarization and email writing, for evaluation using a GPT-4 simulated user. We compare with algorithms that directly retrieve user edits but do not learn descriptive preference, and algorithms that learn context-agnostic preference. On both tasks, CIPHER outperforms baselines by achieving the lowest edit distance cost. Meanwhile, CIPHER has a lower computational expense, as using learned preference results in a shorter prompt than directly using user edits. Our further analysis reports that the user preference learned by CIPHER shows significant similarity to the ground truth latent preference.

## 1 Introduction

Language agents based on large language models (LLMs) have been developed for a variety of applications (Dohmke, 2022; Brynjolfsson et al., 2023), following recent breakthroughs in improving LLMs (Achiam et al., 2023; Ouyang et al., 2022b; Team et al., 2023). However, despite their impressive zero-shot performance, LLMs still need to adapt and personalize to a given user and task (Mysore et al., 2023; Li et al., 2023). In many applications, a natural feedback for LLM-based agents is user edits, where a user queries the agent and edits the agent’s response before their own final use. In

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<sup>†</sup>Our code and data are publicly available at <https://github.com/gao-g/prelude>.

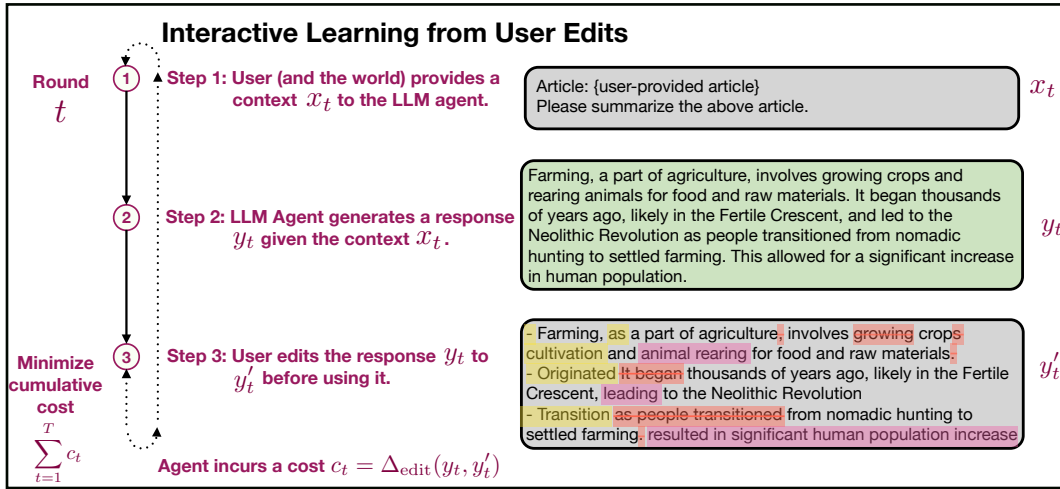


Figure 1: Illustration of interactive learning from user edits. Color coding in edits is for visualization only – our agent takes the plain revised text as feedback. 5

contrast, typical feedback used for fine-tuning, such as the comparison-based preference feedback in RLHF, is explicitly collected by providing annotators with model responses and asking them to rank (Ziegler et al., 2019; Stiennon et al., 2020; Nakano et al., 2021; Ouyang et al., 2022a, inter alia). making such feedback an expensive choice for improving alignment. Motivated by this observation, we focus on interactive learning of LLM-based language agents using user edits as feedback. 4

Consider the scenario in Figure 1 where a user interacts with an LLM-based writing assistant (agent) to complete their task. The interaction starts with the user (and the world) providing a context to the agent. This context may include a query prompt provided by the user, along with additional information provided by the world, such as the content on the screen, current time, and the user’s calendar information. The agent generates a textual response to the user given the context. 6

In the beginning, the agent’s response may not be optimal for the user, as it is not personalized to this user’s individual needs and preference. As most users are not familiar with prompt engineering, and LLMs are often able to generate an acceptable response for the task, therefore, users may find it the most convenient to simply edit the response when it is not ideal to suit their needs, rather than trying different prompts to get new responses. The example in Figure 1 illustrates that the user directly edits the summary generated by the agent to satisfy their preference on bullet point format. It takes time and efforts for the user to make edits. We can measure such cost using a variety of metrics, such as the edit distance between the agent-generated response and the user-revised text. Zero edit from the user is also a useful feedback, reflecting that the agent’s response satisfies this user’s needs. One important feature of our setting is that every natural use of the agent yields an edit feedback for learning. Since there is no distinction between training and testing in this setting, we care about minimizing the user’s efforts across all rounds of interaction with the agent. In summary, our goal is to learn from the implicit feedback in user edit history to minimize the cumulative cost of the user’s efforts. 7

We conjecture that user edits are driven by user’s hidden preference which can be described in natural language. These preference descriptions are different from the notion of comparison-based preference used in RLHF. In this paper, we use the word preference to mean preference descriptions. For instance, preference of the user in Figure 1 can be described as bullet points. In practice, user preference can be compound, such as preferring bullet point, informal, with emojis at the same time, and also context-dependent, e.g., informal tone when writing an email to a family member, and formal tone when writing to a colleague. In more complex settings, user preference can evolve with time (non-stationary), or depend on information unavailable in the context (partially observed). Such user preference may not be fully derivable from the context, and the user may not even be fully aware of all their preference. These considerations imply that user preference is latent to the language agent. If the agent could learn the latent preference correctly, it can significantly improve its performance by generating satisfactory responses accordingly. Furthermore, preference learned by the agent can be shown to the user to enhance interpretability, and can even be modified by the user to improve correctness. Motivated by this, we propose a learning framework, PRELUDE (PREference Learning from User’s Direct Edits), where we seek to learn a textual description of the user preference for a given context using the history of user edits. 8

In a typical real-world scenario such as writing assistants, one has to potentially update the LLM-based agent for every user. Efficient approaches, therefore, must scale with the number of users. This makes approaches that perform a full fine-tuning of the LLM used by the agent very hard to scale. Furthermore, LLMs typically undergo evaluation on a variety of metrics before being released, and thus fine-tuning them often results in breaking the generalization guarantees offered by these tests. For example, fine-tuning GPT-4 for millions of users can quickly turn very expensive. Approaches such as adding LORA and Adapter layers and only updating them, or using federated learning, can reduce the expense to some extent, while the loss of generalizable alignment remains as a concern. In this work, we focus on leveraging a frozen, black-box LLM, and instead learning a *prompt policy* that can infer textual description of user’s preference for a given context, and then use it to directly drive the response generation. 9

We introduce a simple yet effective algorithm **CIPHER** (Consolidates Induced Preferences based on Historical Edits with Retrieval) under the PRELUDE framework. For a given context, CIPHER first retrieves the  $k$ -closest contexts from history, and aggregates inferred preferences for these  $k$  contexts. It relies on this aggregate preference to generate a response for the given context. If the user performs no edits, then it saves this aggregate preference as the correct preference for the given context. Otherwise, it queries the LLM to infer a plausible preference that explains these user edits made to the agent response, and saves this inferred preference as the correct preference for the given context. A key advantage of CIPHER is that it typically leads to significantly shorter prompts compared to other retrieval methods that use the entire documents or context, as inferred preferences are much shorter than retrieved documents or contexts. This results in a significant reduction in the computational expense of querying the LLM. 10

We introduce two interactive environments for evaluation, inspired by writing assistant applications. In the first environment, we evaluate the agent’s ability to summarize a given document (articles from different sources). In the second environment, we evaluate the agent’s ability to compose an email using content from a given document (notes for various purpose). In both tasks, we simulate a GPT-4 user that can generate edits based on a pre-designed *latent* preference. We use documents from several existing domains as our user-provided context, and vary the GPT-4 user’s preference based on the domain, in order to capture the real-world context-dependent nature of human user’s preference. We evaluate CIPHER against several baselines, including approaches that learn context-agnostic user preferences, and retrieval-based approaches that do not learn preferences but directly use past user edits for generation. We show that for both tasks, CIPHER achieves the lowest user edit cost compared to baselines, and significantly reduces the cumulative cost compared to using the frozen base agent. Additionally, CIPHER results in a lower LLM query cost than other retrieval-based baselines. Finally, we qualitatively and quantitatively analyze preferences learned by our agents, and find that they show significant similarity to the ground truth latent preferences in our setup. 11

## 2 Interactive Learning from User Edits and the PRELUDE Framework 12

We first describe LLM agents and the general learning framework from user edits. We then describe our specialized PRELUDE framework for learning descriptive user preference, and discuss associated learning challenges. 13

**LLM and Language Agents.** We assume access to a language agent that internally relies on an LLM. We make no assumption about the language agent except that it can take input  $x_t$  as a piece of content and an additional prompt (which can be in-context learning examples or learned preferences) and generate a response  $y_t$ . The language agent may simply perform greedy decoding on the LLM, or may perform complex planning using the given LLM to generate a response. 15

### Protocol 1 Interactive Learning from User Edits. 16

- 1: **for**  $t = 1, 2, \dots, T$  **do**
- 2:   User and the world provide a context  $x_t$
- 3:   Agent generates a response  $y_t$  given the context  $x_t$
- 4:   User edits the response to  $y'_t$
- 5:   Agent receives a cost of  $c_t = \Delta_{\text{edit}}(y_t, y'_t)$
- 6: Evaluate the agent and learning algorithm on  $\sum_{t=1}^T c_t$  24

**Interactive Learning from User Edits.** In an application such as a writing assistant, a user interacts with the language agent over  $T$  rounds. [Protocol 1](#) shows such learning protocol. In the  $t^{\text{th}}$  round, the user and the world provide a context  $x_t \in \mathcal{X}$  where  $\mathcal{X}$  is the space of all possible contexts. This context will include the user prompt in text, along with additional information provided by the user or the world, and may include multimodal data as well such as images. Given the context  $x_t$ , the language agent generates a response  $y_t \in \mathcal{Y}$  in text, where  $\mathcal{Y}$  is the space of all texts. The user edits the response  $y_t$  to  $y'_t$ . If the user does not perform any edits, we treat this as setting  $y'_t = y_t$ . The agent receives a cost of  $c_t = \Delta_{\text{edit}}(y_t, y'_t)$  for this round, which measures the user's efforts on making edits. The goal of the agent is to minimize the sum of costs across all rounds  $\sum_{t=1}^T c_t$ .

In our experiments, we use  $\Delta_{\text{edit}}$  as Levenshtein edit distance ([Levenshtein, 1965](#)) in the token space which computes the minimum number of total token addition, token deletion, and token substitution necessary to convert  $y_t$  to  $y'_t$ . In general, a higher edit distance implies that the user has made more edits and spent more efforts. We note that our framework is general enough to accommodate situations where the user tries different prompts with the same demand. We treat each call to the language agent as a different round with a different context (as the context includes the user prompt).

**PRELUDE Framework.** We describe our PRELUDE framework in [Protocol 2](#) which is a specialization of the general learning setup described above in [Protocol 1](#). In PRELUDE, in the  $t^{\text{th}}$  round, the agent infers the preference of the user as  $f_t$ , and uses it to generate a response. We assume that in this round and for the given context  $x_t$ , the user has a *latent* preference  $f_t^*$  that drives the user to perform all edits. Furthermore, we assume that if the agent was able to infer this *latent* preference ( $f_t = f_t^*$ ), then it will lead to minimal possible edits.<sup>2</sup> To remove the dependence on performance due to the choice of the base LLM agent, we compare with an oracle agent that has access to  $f_t^*$  at the start of each round. We assume that the LLM remains frozen across all methods in this work.

#### Protocol 2 PRELUDE: PREference Learning from User's Direct Edits

1: <b>for</b> $t = 1, 2, \dots, T$ <b>do</b>	
2:   User presents a text context $x_t$	
3:   Agent infers a preference $f_t$ using the history $\{(x_\ell, y_\ell, y'_\ell)\}_{\ell=1}^{t-1}$ and context $x_t$	
4:   Agent uses $f_t$ and $x_t$ to generate a response $y_t$	
5:   User edits the response to $y'_t$ using their <i>latent</i> preference $f_t^*$	
6:   Agent incurs a cost $c_t = \Delta(y_t, y'_t)$	
7: <b>Return</b> $\sum_{t=1}^T c_t$	46

**Challenges of Learning User Preference.** Learning user preference from edits is challenging. In practice, user preference are multifaceted and complex. Furthermore, user's preference can also significantly vary based on the context. The feedback in the form of user edits emerges naturally but is inherently implicit, lacking direct expressions of the actual preference and carrying subtleties that may lead to diverse interpretations. The combination of preference variability and the implicit nature of feedback poses considerable challenges for agents in accurately learning and integrating these preferences.

### 3 Learning User Preference through Retrieval and Aggregation

In this section, we present our method, CIPHER (Consolidates Induced Preferences based on Historical Edits with Retrieval), that learns user preference based on user edits.

[Algorithm 1](#) shows CIPHER which implements the PRELUDE framework. CIPHER maintains a preference history  $\mathcal{D}_t = \{(x_\ell, \tilde{f}_\ell)\}_{\ell=1}^{t-1}$  of past contexts  $x_\ell$  along with a preference  $\tilde{f}_\ell$  inferred by the agent. CIPHER assumes access to a *context representation function*  $\phi : \mathcal{X} \rightarrow \mathbb{R}^d$  that can map a context to a vector representation. For a given round  $t$  with context  $x_t$ , the agent first retrieves the  $k$ -closest contexts from the interaction history  $\mathcal{D}_t$ . We use cosine similarity for computing proximity, although other metrics such as Euclidean distance, or Hamming distance when  $\phi$  outputs a binary vector, can be used. Given the retrieved contexts and their inferred preferences  $\{(x_{z_i}, \tilde{f}_{z_i})\}_{i=1}^k$ , we

<sup>2</sup>The edit cost in practice may not always be 0, as the language agent could be incapable of adeptly using the correct preference, or the user may perform edits that are inconsistent with their preference.

query the underlying LLM to summarize the inferred preferences  $\{\tilde{f}_{z_i}\}_{i=1}^k$  into a single preference  $f_t$ . In the beginning, when  $t \leq k$ , we retrieve all the past  $t$  contexts. In particular, for  $t = 1$  we have  $f_1$  as an empty string as the agent has no prior knowledge of this user’s preference.<sup>3</sup>

The agent uses the inferred preference  $f_t$  to generate the response. This is done by concatenating the context  $x_t$  with an agent prompt such as “This user has a preference of  $\langle f_t \rangle$  which must be used when generating the response”, where  $\langle f_t \rangle$  indicates where we insert the inferred preference  $f_t$ . We list the actual template used in our experiments in Table 7 in Appendix A.

Given the user edits  $y'_t$ , if the user edits are minimal, i.e.,  $\Delta_{\text{edit}}(y_t, y'_t) \leq \delta$  for a hyperparameter  $\delta$ , then we set the inferred preference for this round as  $f_t = f_t$  as using  $f_t$  for generating a response resulted in minimal edits. However, if  $\Delta_{\text{edit}}(y_t, y'_t) > \delta$ , then we query the LLM a third time to generate the inferred preference  $\tilde{f}_t$  that explains why the user edited  $y_t$  to  $y'_t$ . We call this the *Latent Preference Induction* (LPI) step. In both cases, we append  $(x_t, f_t)$  to the preference history.

Note that we cannot query the LLM for the inferred preference in the first case where the user edit cost  $c_t$  is small, i.e.,  $c_t \leq \delta$ . In this case, querying the LLM to infer the preference to explain the edits in  $y'_t$  given  $y_t$ , will result in the LLM outputting that the agent has no preference. This is incorrect as it merely shows that the preference  $f_t$  used to generate  $y_t$  was sufficiently good to include most of the true user preference  $f_t^*$ .

**Computational Cost of CIPHER.** In a given round, CIPHER adds a maximum of 3 LLM calls on top of the cost of calling the underlying inference algorithm of the agent in line 6. CIPHER further reduces the memory storage by only storing the representation of contexts in the preference string instead of the input itself. Finally, CIPHER only adds a small prompt to the context  $x_t$ , before calling the agent’s inference algorithm. This only slightly increases the length of the prompt, thereby reducing the query cost associated with LLMs that scales with the number of input tokens.

**Algorithm 1** CIPHER( $\phi, k, \delta$ ). A context representation function  $\phi : \mathcal{X} \rightarrow \mathbb{R}^d$ , the retrieval hyperparameter  $k$ , and tolerance hyperparameter  $\delta \geq 0$ .

```

1:  $\mathcal{D} = \emptyset$ 
2: for  $t = 1, 2, \dots, T$  do
3:   User (and the world) presents a context  $x_t$ 
4:   Retrieve the top- $k$  examples  $\{\phi(x_{z_i}), \tilde{f}_{z_i}\}_{i=1}^k$  in  $\mathcal{D}$  with maximum cosine similarity to  $\phi(x_t)$ 
5:   If  $k > 1$ , then query the LLM to aggregate these preferences  $\{\tilde{f}_{z_i}\}_{i=1}^k$  into  $f_t$ , else  $f_t = \tilde{f}_{z_1}$ 
6:   Agent generates a text response  $y_t$  based on  $x_t$  and  $f_t$ 
7:   User edits the response to  $y'_t$  using their latent preference  $f_t^*$ 
8:   Agent incurs a cost  $c_t = \Delta_{\text{edit}}(y_t, y'_t)$ 
9:   if  $c_t \leq \delta$  then
10:     $\tilde{f}_t = f_t$ 
11:   else
12:     Query the LLM to generate a preference  $\tilde{f}_t$  that best explains user edits in  $(y_t, y'_t)$ 
13:     $\mathcal{D} \leftarrow \mathcal{D} \cup \{(\phi(x_t), \tilde{f}_t)\}$ 
14: Return  $\sum_{t=1}^T c_t$ 

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□

## 4 Experiment

In this section, we first introduce two interactive tasks for evaluating agents that learn from user edits. These tasks can be used more broadly even outside the PRELUDE framework, and can be of independent interest. We then describe our baselines and provide implementation details of CIPHER. Finally, we provide quantitative results in terms of user edit cost and qualitative analysis of the learned preferences.

<sup>3</sup>In practice, one can initialize with a publicly available preference history.



Table 1: Latent user preference design, specific to the document source. 39

Doc Source	Latent User Preference	Scenario	40
<b>Summarization</b>			
News article (See et al., 2017)	targeted to young children, storytelling, short sentences, playful language, interactive, positive	introduce a political news to kids	40
Reddit post (Stiennon et al., 2020)	second person narrative, brief, show emotions, invoke personal reflection, immersive	for character development in creative writing	40
Wikipedia page (Foundation, 2022)	bullet points, parallel structure, brief	take notes for key knowledge	40
Paper abstract (Clement et al., 2019)	tweet style, simple English, inquisitive, skillful foreshadowing, with emojis	promote a paper to invoke more attention and interests	40
Movie review (Maas et al., 2011)	question answering style, direct, concise	quickly get main opinions	40
<b>Email Writing</b>			
Personal problem (Stiennon et al., 2020)	informal, conversational, short, no closing	share life with friends	40
Paper review (Hua et al., 2019)	casual tone, positive, clear, call to action	peer review to colleague	40
Paper tweet (Bar, 2022)	engaging, personalized, professional tone, thankful closing	networking emails for researchers	40
Paper summary (Kershaw & Koeling, 2020)	structured, straight to the points, respectful, professional greeting and closing	milestone report to superiors	40

#### 4.1 Two Interactive Writing Assistant Environments for Learning from User Edits 36

**Task.** We introduce two tasks inspired by the use of LLMs as writing assistants (Mysore et al., 2023; Shen et al., 2023; Wang et al., 2023). In the first task, we evaluate the agent’s ability to summarize a given document. We use documents from 5 existing sources listed in Table 1.<sup>4</sup> These sources represent a diverse category of documents that a writing assistant would typically encounter, including news articles that are formal and concise, movie reviews that are informal, and paper abstracts that are technical. In the second task, we evaluate the agent’s ability to compose an email given notes. For this task, we use notes from four different sources including a variety of tasks such as writing emails to friends, describing reports to managers, and writing reviews for colleagues. In any given round, the user is provided a context that is a document from one of the document sources for the given task. Importantly, the agent is *unaware of the source of the given document* which as we discuss later, will determine the user preference. For both tasks, we run an experiment for  $T = 200$  rounds, with an equal number of randomly sampled documents from each document source. We mix documents from different sources and shuffle them to remove any temporal correlation in document source across rounds. 38

**Two-Stage GPT-4 Simulated User.** We simulate a user that can edit a given response. We define a set of *latent user preferences* for the user that vary based on the document source. Table 1 lists the preference and the corresponding document source. This captures the context-dependent nature of user preferences as the document source influences the type of context. For example, the *Personal problem* document source contains documents pertaining to discussions with a friend, and a user may have a different preference when writing an email to a friend compared to writing an email to a colleague. In real-world settings, the context dependence of the user preference can be more complex than just the document source. We assume that our user is aware of the document source  $d_t$  of a given context  $x_t$ . This implies, that we can express the true user preference for  $x_t$  as  $f_t^* = F(d_t)$  where  $F$  maps a given document source to the user preference. Recall that the *agent in our learning setup is never provided the document source of any context.* 42

We model our user using GPT-4 with a two-stage approach. Given an agent response  $y_t$  and the context  $x_t$ , we first query GPT-4 to check if the given response satisfies the preference in  $f_t^*$ . If the answer is yes, then the user performs no edits and returns  $y_t' = y_t$ . If the answer is no, then we use GPT-4 to generate the edited response  $y_t'$  given  $y_t$  and  $f_t^*$ . We use prompting to condition GPT-4 on these latent preferences. We provide examples of edits made by our GPT-4 user in Table 5 in Appendix A. 43

<sup>4</sup>Table 4 in Appendix provides links to each source dataset, used as user-provided context in our tasks. 38

We found that our two-stage GPT-4 user can generate high-quality edits, consistent with observations in prior work that LLM-written feedback is high-quality and useful to learn from (Bai et al., 2022; Saunders et al., 2022). We adopted a two-stage process since we found that using GPT-4 to directly edit the response  $y_t$  always resulted in edits even when the response satisfied the preference  $f_t^*$ . We evaluated several different prompts for modeling our two-stage GPT-4 user until we found a prompt such that an oracle GPT-4 agent with access to  $f_t^*$  achieves a minimal user cost.

**Evaluation Metric.** We propose three metrics for evaluating agents learning from user edits. Our main metric is the cumulative user edit cost  $\sum_{t=1}^T c_t$  over  $T$  rounds. In any given round, we compute the user edit cost  $c_t = \Delta_{\text{edit}}(y_t, y_t')$  using Levenshtein edit distance between agent response  $y_t$  and user edits  $y_t'$ . To compute the edit distance, we perform BPE tokenization using Tiktoken tokenizer, and compute the edit distance in the token space. In general, one can learn a metric that better captures the cognitive load associated with a user edit. However, Levenshtein edit distance provides a clean, transparent metric that is easy to interpret. Additionally, it doesn't have concerns shared by learned metrics such as erroneous evaluations when applying the metric to examples not covered by the metric's training distribution.

For CIPHER and any other method in the PRELUDE framework, we additionally evaluate the accuracy of the inferred user preference  $f_t$  used to generate the response  $y_t$ . Formally, given a context  $x_t$  containing a document from source  $d_t$ , we evaluate if the inferred preference  $f_t$  is closer to the true preference  $f_t^* = F(d_t)$  than preference  $F(d)$  of any other document source  $d \neq d_t$ . Let there be  $N$  document sources for a given task and we index  $d \in \{1, 2, \dots, N\}$ . Then we compute this metric as  $\frac{1}{N} \sum_{t=1}^T \mathbb{1}\{d_t = \arg \max_{d \in [N]} \text{BERTScore}(f_t, F(d))\}$ , where BERTScore (Zhang et al., 2020) is a popular text similarity metric.

Finally, we evaluate the token expense associated with querying the LLM across all methods. We compute the total number of tokens both generated by or provided as input to the LLM across all rounds. This is a typical metric used by popular LLM providers to charge their customers.

## 4.2 Details of CIPHER and Comparison Systems

We use GPT-4 as our base LLM for CIPHER and all baselines. We do not perform fine-tuning of the GPT-4 and do not add any additional parameters to the model. We use a prompt-based GPT-4 agent for all methods that uses a single prompt with greedy decoding to generate the response. Our main method CIPHER and the baselines, can be extended to more complex language agents that perform multiple steps of reasoning on top of the base LLM before generating a response.

**CIPHER Details.** We use a simple agent that uses GPT-4 with a prompt template to generate the response  $y_t$  given the context  $x_t$  and preference  $f_t$ . We list templates in Table 7 in Appendix A. We experiment with MPNET (Song et al., 2020) and BERT (Devlin et al., 2019) as our two context representation functions  $\phi$ , and use cosine similarity for retrieval. We experiment with two different values of the number of retrieved examples  $k \in \{1, 5\}$ .

**Baselines.** We evaluate CIPHER against baselines that either perform no learning, or learn context-agnostic preferences and against methods that do not learn preferences but directly use past user edits for generating a response.

1. *No learning*: The agent performs no learning based on interaction with the user. In each step, the agent generates a response  $y_t$  given the context  $x_t$ .
2. *Explore-then-exploit (E-then-e) LPI*: This baseline is based on the classic explore-then-exploit strategy in interactive learning (Garivier et al., 2016). The agent first generates responses for the first  $T_e$  rounds without performing any learning (exploration stage). It then infers a single user preference  $f_e$  using the user edits in the first  $T_e$  rounds using the LPI step similar to line 12 in CIPHER (Algorithm 1). It then uses the learned preference to generate the response for all remaining rounds (exploitation step).
3. *Continual LPI*: This method is similar to explore-then-exploit except that it never stops exploring. In any given round  $t$ , it uses the data of all past edits  $\{(y_i, y_i')\}_{i=1}^{t-1}$  to learn a

<sup>1</sup>We use the `microsoft/deberta-xlarge-mnli` to implement BERTScore.

preference  $f_t$  by performing the LPI step. It then generates a response using this preference. In contrast, to explore-then-exploit approach, Continual LPI can avoid overfitting to the first  $T_e$  rounds, but both approaches learn preferences that are independent of  $x_t$ .

4. *ICL-edit*: This is a standard retrieval-based in-context learning (ICL) baseline (Brown et al., 2020). In a given round  $t$ , the agent first retrieves the closest  $k$  examples  $\{(y_{z_\ell}, y'_{z_\ell})\}_{\ell=1}^k$  to the given context  $x_t$  using the representation function  $\phi$ . It then creates an ICL prompt containing these  $k$  examples where  $y_{z_\ell}$  is presented as the input, and  $y'_{z_\ell}$  is presented as the desired output. The agent then uses the context  $x_t$  and the ICL prompt to generate the response. This approach doesn't infer preferences but must instead use the user edit data directly to align to the given user preference. However, unlike explore-then-exploit LPI and Continual LPI, this approach can perform context-dependent learning as the generated response attends on both the given context  $x_t$  and the historical data.

**Baseline Hyperparameters.** For *explore-then-exploit LPI* and *continual LPI* baselines, we set the number of exploration  $T_e$  as 5. For *ICL-edit* baselines, we experiment with different  $k$  values for retrieval, and report our best results with  $k = 5$ .

**Oracle Method.** We additionally run an *oracle preference* method to provide an approximated upper bound on performance. In each round  $t$ , we let the GPT-4 agent generate a response by conditioning on the ground-truth latent preference  $f_t^*$  and the context  $x_t$ . This method can test whether our setup is well-defined, e.g., in a poorly designed setup, the user always edits the agent response no matter what the agent generates including providing user edits back to the user, and thus no method can effectively minimize the cost over time in this case. If the oracle method achieves a zero or a minimal user edit cost, then learning the optimal preference leads to success.

### 4.3 Main Result and Discussion.

**Main Results.** Table 2 reports the performance of baselines and our methods on summarization and email writing tasks on three metrics: *edit distance* which measures cumulative user edit cost, *accuracy* which measures mean preference classification accuracy, and *expense* measuring the total BPE token cost of querying LLM.<sup>6</sup> We report the mean and standard deviation across 3 different random seeds.<sup>7</sup>

Table 2: Performance of baselines and our methods in terms of cumulative edit distance cost and classification accuracy.  $\mu_\sigma$  denotes the mean  $\mu$  and standard deviation  $\sigma$  across 3 runs over different seeds. Expense column shows budget as the average number of input and output BPE tokens across 3 runs (unit is  $\cdot 10^5$ ). We use  $-k$  in method names to denote that we use  $k$  retrieved examples. Numbers in bold are the best performance in each column excluding *oracle preference* method, underline for the second best, and dotted underline for the third best.

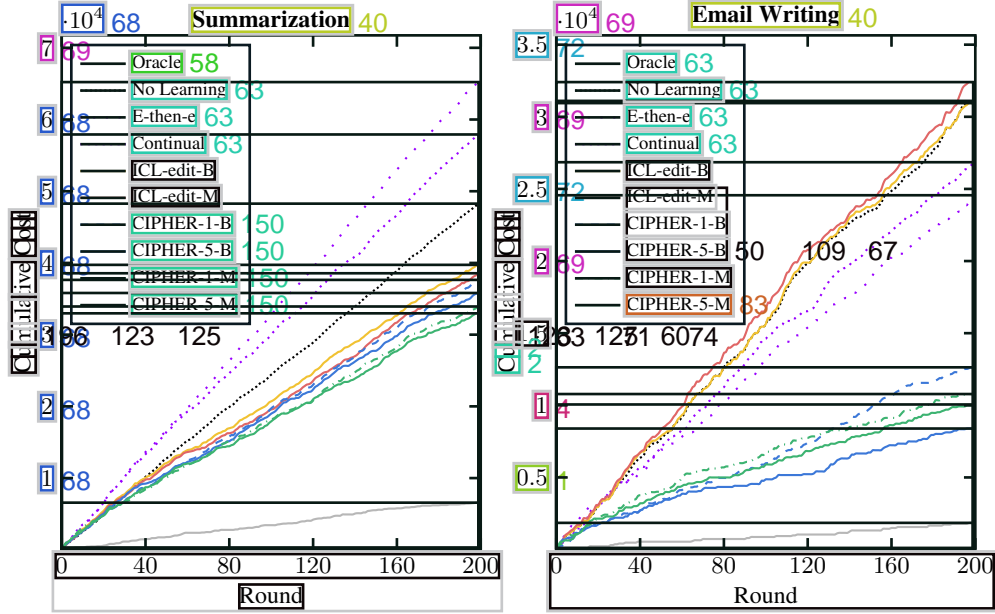
Method	Summarization			Email Writing		
	Edit Distance↓	Accuracy↑	Expense↓	Edit Distance↓	Accuracy↑	Expense↓
Oracle Preference	6,573 <sub>1,451</sub>	1.000	1.67	1,851 <sub>243</sub>	1.000	1.62
No Learning	48,269 <sub>957</sub>	-	1.50	31,103 <sub>900</sub>	-	1.65
E-then-e LPI	65,218 <sub>17,466</sub>	0.218 <sub>0.003</sub>	1.99	24,562 <sub>1,022</sub>	0.263 <sub>0.003</sub>	1.73
Continual LPI	57,915 <sub>2,210</sub>	0.233 <sub>0.010</sub>	8.89	26,852 <sub>1,464</sub>	0.243 <sub>0.019</sub>	8.63
ICL-edit-5-MPNET	38,560 <sub>1,044</sub>	-	8.00	32,405 <sub>1,307</sub>	-	12.12
ICL-edit-5-BERT	39,734 <sub>1,929</sub>	-	7.96	30,949 <sub>3,250</sub>	-	11.55
CIPHER-1-MPNET	33,926 <sub>4,000</sub>	0.520 <sub>0.022</sub>	2.74	10,781 <sub>1,711</sub>	0.435 <sub>0.084</sub>	1.94
CIPHER-5-MPNET	<b>32,974</b> <sub>195</sub>	0.478 <sub>0.010</sub>	3.00	10,058 <sub>1,709</sub>	0.467 <sub>0.081</sub>	2.09
CIPHER-1-BERT	37,637 <sub>3,025</sub>	<b>0.565</b> <sub>0.053</sub>	2.81	12,634 <sub>4,868</sub>	<b>0.487</b> <sub>0.125</sub>	1.99
CIPHER-5-BERT	35,811 <sub>3,384</sub>	0.478 <sub>0.028</sub>	3.03	<b>8,391</b> <sub>3,038</sub>	0.363 <sub>0.075</sub>	2.22

<sup>6</sup>Table 9 in Appendix shows the breakdown of expense in terms of input and output.

<sup>7</sup>We randomize the context sampling from source datasets, so experiments on different seeds contain different sets of input contexts. On the same seed, experiments across different methods are strictly comparable, as both the set of input contexts and the order of input context seen are the same in our implementation.



Figure 2: Learning curves of different methods based on cumulative cost over time (average across 3 seeds). In the legend,  $-k$  means with top  $k$  retrieved examples,  $-B$  for BERT, and  $-M$  for MPNET.



**Discussion of Main Result.** We observe that not performing learning results in a high edit cost, whereas using the Oracle preferences achieves a significantly smaller edit cost. This shows that our environments are sound and well-conditioned. E-then-e LPI and Continual LPI learn context-agnostic preferences which cannot capture the context-dependent preferences in the environments and end up doing poorly. For the summarization task, they end up with a higher edit distance than even performing no learning. One explanation is that using context-agnostic preferences can push the model to specialize to a given preference much more than the base model, resulting in more edits when that preference is incorrect. We see this in preference accuracy which is low for both of these baselines, and lower for the summarization task than the email writing task where they outperform no learning baselines. Further, Continual LPI has a higher expense cost due to constantly querying the LLM to infer the user preference.

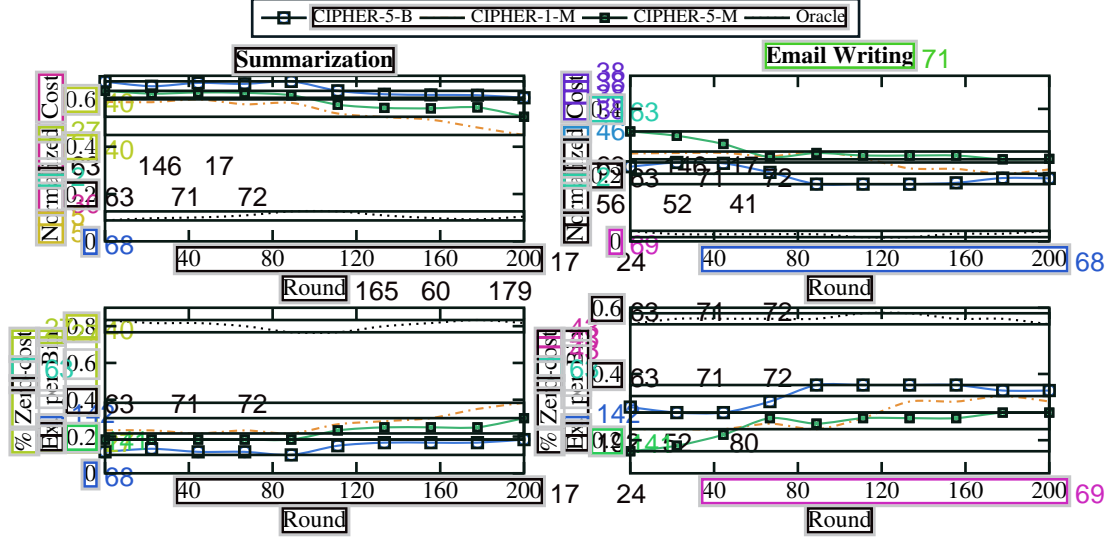
ICL-edit baselines perform significantly better on the summarization task. However, using a list of user edits in the prompt results in a higher token expense cost, as the responses and their edits can be significantly long in practice. Further, the ICL-edit baselines provide no interpretable explanation for their response or for explaining user behavior.

Finally, CIPHER achieves the smallest edit distance cost reducing edits by 31% in the summarization task and 73% in the email writing task. We observe that retrieving  $k = 5$  preferences and aggregating them achieves lower edit distance, however, the choice of ideal representation  $\phi$  seems task-dependent. Further, CIPHER achieves the highest preference accuracy showing that CIPHER can learn preferences that correlate more with the ground truth preference than preferences of other document sources. Note that the performance of a random preference classifier is only 20% for summarization and 25% for email writing. Further, CIPHER achieves a smaller cost than ICL-edit and Continual LPI baselines, as it doesn't use long user edits in the prompt for generating a response. Overall, CIPHER provides a cheap, more effective, and interpretable method than our baselines.

#### 4.4 More Analysis

**Learning Curves.** We plot mean cumulative user edit costs over rounds in Figure 2. The cumulative user edit costs in Figure 2 show that the angle of the learning curves decreases for CIPHER after an initial number of rounds, showing that learning helps decrease the rate at which user edits are accumulated. In contrast, the angle of the learning curve for the no-learning baseline remains unchanged.

Figure 3: Normalized cost and percentage of zero-cost examples of CIPHER over time, binned per 20 rounds to show the trend (average across 3 seeds). In the legend,  $-k$  means with top  $k$  retrieved examples,  $-B$  for BERT, and  $-M$  for MPNET.



**Evaluating Normalized Edit Cost.** The cumulative user edit cost measures the total effort of the user but is susceptible to outlier examples, as the edit distance for a given round is potentially unbounded. Therefore, we also compute a *normalized edit distance*  $\Delta_{\text{edit}}(y_t, y'_t)/|y_t|$  by dividing the edit distance by  $\max\{|y_t|, |y'_t|\}$ , i.e. the max length of the agent output or user revised text. As Levenshtein distance  $\Delta_{\text{edit}}(y_t, y'_t)$  is upper bounded by  $\max\{|y_t|, |y'_t|\}$ , therefore, the normalized cost is at most 1. Figure 3 reports normalized cost over rounds for the top 3 methods. We notice that for all variants of CIPHER for the summarization task, and for CIPHER-5-M for the email writing task, the normalized cost decreases notably as training progresses indicating learning. As the cost is normalized by the response length, even a small decrease can lead to a significant reduction in the number of tokens edited.

**Evaluating Fraction of Edited Response.** Recall that the first stage of our GPT-4 user checks if the agent response satisfies the latent user preference  $f^*$ . If it does, then the user performs no edits. Otherwise, in the second stage, the user edits the response. To measure how many times the agent response isn't edited, we also plot the percentage of examples with zero edit cost per 20 rounds bin in Figure 3. We notice a small increase in the number of examples with zero edit cost. This indicates that gains come from reducing edits across all examples, and not just by increasing the number of examples that avoid getting edited in stage 1 of our user.

**Qualitative Analysis of Learned Preferences.** We qualitatively analyze the learned preferences for CIPHER to understand the quality of learned preferences. We present our analysis on the summarization task, where our methods have a larger gap with the oracle performance compared to the email writing task. Table 3 lists 3 learned preferences per document source for CIPHER-5-MPNET which are randomly sampled at the beginning, middle, and end of the interaction history. We see that overall the agent can learn a reasonable description of the latent preference. For example, it can learn *bullet points* preference for Wikipedia articles, and *second person narrative* for Reddit posts, and *QA style* for Movie reviews. CIPHER can pick some preferences fairly early such as *bullet points* for Wikipedia and *emojis* for Paper abstract, whereas some are learned only later such as *Structured Q&A* for Movie reviews. This shows using CIPHER can quickly learn useful preferences, but further interaction continues to help.

**Failure Cases.** CIPHER notably reduces the edit cost and learns useful preference, however, significant gaps to the oracle method remain, especially in the summarization task. We manually analyze failure cases on summarization task with the best performing method CIPHER-5-MPNET. Table 10 in the Appendix reports the summary and example of our findings, categorized as preference

Table 3: Examples of learned preferences on summarization task with *CIPHER-5-MPNET*, grouped based on the document source and corresponding latent preference. We randomly sample 3 examples per type at the beginning, middle, and end of the interaction history.

Latent User Preference	(Round) Learned Preference
<b>News article.</b> targeted to young children, storytelling, short sentences, playful language, interactive, positive	<p>{22} Fairy tale narrative style, informal and conversational tone, use of rhetorical questions, simplified language.</p> <p>{15} Simplified, childlike storytelling with playful language and imagery</p> <p>{192} Simplified and playful storytelling language</p>
<b>Reddit post:</b> second person narrative, brief, show emotions, invoke personal reflection, immersive	<p>{14} Concise and coherent storytelling</p> <p>{102} The user prefers a second-person narrative and a more direct, personal tone</p> <p>{194} Poetic and descriptive language, narrative perspective shift to second person</p>
<b>Wikipedia page.</b> bullet points, parallel structure, brief	<p>{19} Concise, Bullet-Pointed, Structured Summaries with a Narrative Q&amp;A Style</p> <p>{124} Concise and factual writing style, bullet-point formatting</p> <p>{197} Concise and streamlined formatting, with bullet points and clear subheadings for easy scanning</p>
<b>Paper abstract.</b> tweet style, simple English, inquisitive, skillful foreshadowing, with emojis	<p>{20} Concise, conversational summaries with bullet points and emojis.</p> <p>{111} Concise, conversational, whimsical bullet-point summaries with emojis.</p> <p>{193} Concise, conversational, and whimsical bullet-point summaries with emojis.</p>
<b>Movie review.</b> question answering style	<p>{12} The user prefers a straightforward, clear, and concise writing style with factual formatting.</p> <p>{123} The user prefers a clear and concise question and answer format with straightforward language.</p> <p>{199} Concise, Structured Q&amp;A with Whimsical Clarity</p>

inference from output-revision pair, consolidation of inferred preferences, and retrieval.<sup>8</sup> In brief, the most common type of failure is on the preference inference step given the agent output and user revision. For example, the agent often misses the exact keyword for *brief* or *short sentences*, and sometimes struggles with inferring the *second-person narrative* aspect.

## 5 Related Work

We describe related work in this area grouped by main themes in this work.

**Learning from Feedback.** Besides pair-wise comparison feedback from annotators used in Reinforcement Learning from Human Feedback (RLHF) research (Ziegler et al., 2019; Stiennon et al., 2020; Nakano et al., 2021; Ouyang et al., 2022a, inter alia), prior work has also studied free-form text feedback provided by annotators (Fernandes et al., 2023), such as on the task of dialog (Weston, 2016; Li et al., 2016; Hancock et al., 2019; Xu et al., 2022; Petrak et al., 2023), question answering (Li et al., 2022; Malaviya et al., 2023), summarization (Saunders et al., 2022), and general decision making (Cheng et al., 2023). This feedback, tailored to each example, is often utilized to rank candidate outputs, thereby improving task performance. Some work studies learning from text feedback to generate outputs directly (Scheurer et al., 2023; Bai et al., 2022; Shi et al., 2022), by generating multiple refinements of the original output based on the feedback and fine-tuning the original model to maximize the likelihood of the best refinement. In grounded settings such as instruction-based navigation, one line of work has also used hindsight feedback that explicitly provides a text instruction for the generated trajectory, to train policies (Nguyen et al., 2021; Misra et al., 2024). Moving beyond the conventional focus on text feedback that explicitly articulates human intent, we investigate feedback in the form of direct edits on the original model output. Such revisions by users occur naturally during model deployment in practice. Additionally, we examine the learning of user preferences through historical interactions, aiming to surpass the constraints of example-specific feedback.

<sup>8</sup>We provide additional analysis on the accuracy of retrieval in Table 11.

**Language Agents and Personalization.** LLMs have enabled the development of language agents for a variety of tasks from writing assistants (Lee et al., 2024), coding assistants (Dohmke, 2022), and customer service assistants (Brynjolfsson et al., 2023). Since these LLM-based assistants are often used by individuals, a natural question has arisen on how to personalize these agents for each user. Straightforward approaches for fine-tuning LLMs includes supervised learning, online DPO (Guo et al., 2024), learning-to-search (Chang et al., 2023), and reinforcement learning (Ouyang et al., 2022b). These approaches can be directly applied to our setting. For example, one can use  $(y_t, y'_t)$  in Protocol 1 as the preference data where  $y'_t$  is preferred over  $y_t$ , or use  $y'_t$  as the ground truth for supervised learning. However, fine-tuning is expensive and hard to scale with the number of users. Therefore, a line of work has explored improving the alignment of frozen LLMs by *prompt engineering*, such as learning a personalized retrieval model (Mysore et al., 2023), learning a prompt policy given a reward function (Deng et al., 2022), or more generally, learning to rewrite the entire prompt (Li et al., 2023). We focus on learning a prompt policy by learning from user edits, and specifically, using them to extract textual descriptions of user preference.

**Edits and Revisions.** Many prior work on editing model output focuses on error correction, such as fixing source code (Yin et al., 2018; Chen et al., 2018; Reid et al., 2023) and improving the factual consistency of model summaries (Cao et al., 2020; Liu et al., 2022; Balachandran et al., 2022). A line of work has explored understanding human edits based on edit history of Wikipedia (Botha et al., 2018; Faltings et al., 2020; Rajagopal et al., 2022; Reid & Neubig, 2022; Laban et al., 2023), or revisions of academic writings (Mita et al., 2022; Du et al., 2022; D’Arcy et al., 2023). Prior work explores predicting text revisions with edit intents (Brody et al., 2020; Kim et al., 2022; Chong et al., 2023), and modeling edits with various approaches, including latent vectors (Guu et al., 2017; Marrese-Taylor et al., 2020, 2023), structured trees (Yao et al., 2021), discrete diffusion process (Reid et al., 2023), or a series of singular edit operations (Stahlberg & Kumar, 2020; Mallinson et al., 2020; Agrawal & Carpuat, 2022; Zhang et al., 2022; Liu et al., 2023). However, these methodologies predominantly target generic improvements in model performance, overlooking the intricacies of individual user satisfaction and preference. Our research takes a distinct direction, focusing on understanding edits across a variety of examples to study user-level preferences, with a practical goal of aligning the agent to individual preferences.

## 6 Conclusion

We study aligning LLM-based agents using user edits that arise naturally in applications such as writing assistants. We conjecture that user edits are driven by a latent user preference that can be captured by textual descriptions. We introduce the PRELUDE framework that focuses on learning descriptions of user preferences from user edit data and then generating an agent response accordingly. We propose a simple yet effective retrieval-based algorithm CIPHER that infers user preference by querying the LLM, retrieves relevant examples in the history, and aggregates induced preferences in retrieved examples to generate a response for the given context. We introduce two interactive environments with a GPT-4 simulated user to study learning from edits, which can be of independent interest. In this work, we focus on aligning an LLM agent with a frozen LLM, in part, due to the challenge of scaling fine-tuning based approaches with the number of users. However, for settings where computational cost is not a barrier, applying fine-tuning approaches would be an interesting future work direction. Another promising future work direction is to learn user preference based on different levels of edits – words, sentences, paragraphs – to generate a satisfactory response.

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## References

Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

Sweta Agrawal and Marine Carpuat. An imitation learning curriculum for text editing with non-autoregressive models. <i>ArXiv</i> , abs/2203.09486, 2022.	152
Yuntao Bai, Saurav Kadavath, Sandipan Kundu, Amanda Askell, Jackson Kernion, Andy Jones, Anna Chen, Anna Goldie, Azalia Mirhoseini, Cameron McKinnon, Carol Chen, Catherine Olsson, Christopher Olah, Danny Hernandez, Dawn Drain, Deep Ganguli, Dustin Li, Eli Tran-Johnson, Ethan Perez, Jamie Kerr, Jared Mueller, Jeffrey Ladish, Joshua Landau, Kamal Ndousse, Kamile Lukosuite, Liane Lovitt, Michael Sellitto, Nelson Elhage, Nicholas Schiefer, Noemi Mercado, Nova DasSarma, Robert Lasenby, Robin Larson, Sam Ringer, Scott Johnston, Shauna Kravec, Sheer El Showk, Stanislav Fort, Tamera Lanham, Timothy Telleen-Lawton, Tom Conerly, Tom Henighan, Tristan Hume, Samuel R. Bowman, Zac Hatfield-Dodds, Ben Mann, Dario Amodei, Nicholas Joseph, Sam McCandlish, Tom Brown, and Jared Kaplan. Constitutional ai: Harmlessness from ai feedback, 2022.	153
Vidhisha Balachandran, Hannaneh Hajishirzi, William Cohen, and Yulia Tsvetkov. Correcting diverse factual errors in abstractive summarization via post-editing and language model infilling. <i>ArXiv</i> , abs/2210.12378, 2022.	154
Nitsan Bar. Papertweet. <a href="https://github.com/bnitsan/PaperTweet/">https://github.com/bnitsan/PaperTweet/</a> , 2022.	155
Jan A. Botha, Manaal Faruqui, John Alex, Jason Baldridge, and Dipanjan Das. Learning to split and rephrase from wikipedia edit history. <i>ArXiv</i> , abs/1808.09468, 2018.	156
Shaked Brody, Uri Alon, and Eran Yahav. A structural model for contextual code changes. <i>Proceedings of the ACM on Programming Languages</i> , 4:1 – 28, 2020.	157
Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. <i>Advances in neural information processing systems</i> , 33:1877–1901, 2020.	158
Erik Brynjolfsson, Danielle Li, and Lindsey R Raymond. Generative ai at work. Technical report, National Bureau of Economic Research, 2023.	159
Mengyao Cao, Yue Dong, Jiapeng Wu, and Jackie Chi Kit Cheung. Factual error correction for abstractive summarization models. <i>ArXiv</i> , abs/2010.08712, 2020.	160
Jonathan D Chang, Kianté Brantley, Rajkumar Ramamurthy, Dipendra Misra, and Wen Sun. Learning to generate better than your llm. <i>arXiv preprint arXiv:2306.11816</i> , 2023.	161
Zimin Chen, Steve Kommrusch, Michele Tufano, Louis-Noël Pouchet, Denys Poshyvanyk, and Monperrus Martin. Sequencer: Sequence-to-sequence learning for end-to-end program repair. <i>IEEE Transactions on Software Engineering</i> , 47:1943–1959, 2018.	162
Ching-An Cheng, Andrey Kolobov, Dipendra Misra, Allen Nie, and Adith Swaminathan. Llf-bench: Benchmark for interactive learning from language feedback. <i>arXiv preprint arXiv:2312.06853</i> , 2023.	163
Ruining Chong, Cunliang Kong, Liu Wu, Zhenghao Liu, Ziyi Jin, Liner Yang, Yange Fan, Hanghang Fan, and Erhong Yang. Leveraging prefix transfer for multi-intent text revision. <i>Annual Meeting of the Association for Computational Linguistics</i> , 2023.	164
Colin B. Clement, Matthew Bierbaum, Kevin P. O’Keeffe, and Alexander A. Alemi. On the use of arxiv as a dataset, 2019.	165
Mike D’Arcy, Alexis Ross, Erin Bransom, Bailey Kuehl, Jonathan Bragg, Tom Hope, and Doug Downey. Aries: A corpus of scientific paper edits made in response to peer reviews. <i>ArXiv</i> , abs/2306.12587, 2023.	166
Mingkai Deng, Jianyu Wang, Cheng-Ping Hsieh, Yihan Wang, Han Guo, Tianmin Shu, Meng Song, Eric P Xing, and Zhiting Hu. Rlprompt: Optimizing discrete text prompts with reinforcement learning. <i>arXiv preprint arXiv:2205.12548</i> , 2022.	167
Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. <i>North American Chapter of the Association for Computational Linguistics</i> , 2019.	168



- Thomas Dohmke. Github copilot is generally available to all developers. <https://github.blog/2022-06-21-github-copilot-is-generally-available-to-all-developers/>, 2022. Accessed: April-20-2024. 169
- Wanyu Du, Vipul Raheja, Dhruv Kumar, Zae Myung Kim, Melissa Lopez, and Dongyeop Kang. Understanding iterative revision from human-written text. *ArXiv*, abs/2203.03802, 2022. 170
- Felix Faltings, Michel Galley, Gerold Hintz, Chris Brockett, Chris Quirk, Jianfeng Gao, and Bill Dolan. Text editing by command. *ArXiv*, abs/2010.12826, 2020. 171
- Patrick Fernandes, Aman Madaan, Emmy Liu, António Farinhas, Pedro Henrique Martins, Amanda Bertsch, José G. C. de Souza, Shuyan Zhou, Tongshuang Sherry Wu, Graham Neubig, and André F. T. Martins. Bridging the gap: A survey on integrating (human) feedback for natural language generation. *ArXiv*, abs/2305.00955, 2023. 172
- Wikimedia Foundation. Wikimedia downloads. <https://dumps.wikimedia.org>, 2022. 173
- Aurélien Garivier, Tor Lattimore, and Emilie Kaufmann. On explore-then-commit strategies. *Advances in Neural Information Processing Systems*, 29, 2016. 174
- Shangmin Guo, Biao Zhang, Tianlin Liu, Tianqi Liu, Misha Khalman, Felipe Llinares, Alexandre Rame, Thomas Mesnard, Yao Zhao, Bilal Piot, et al. Direct language model alignment from online ai feedback. *arXiv preprint arXiv:2402.04792*, 2024. 175
- Kelvin Guu, Tatsunori B. Hashimoto, Yonatan Oren, and Percy Liang. Generating sentences by editing prototypes. *Transactions of the Association for Computational Linguistics*, 6:437–450, 2017. 176
- Braden Hancock, Antoine Bordes, Pierre-Emmanuel Mazaré, and Jason Weston. Learning from dialogue after deployment: Feed yourself, chatbot! *Annual Meeting of the Association for Computational Linguistics*, 2019. 177
- Xinyu Hua, Mitko Nikolov, Nikhil Badugu, and Lu Wang. Argument mining for understanding peer reviews. *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, June 2019. 178
- Daniel James Kershaw and R. Koeling. Elsevier oa cc-by corpus. *ArXiv*, abs/2008.00774, 2020. doi: <https://doi.org/10.48550/arXiv.2008.00774>. URL <https://elsevier.digitalcommonsdata.com/datasets/zm33cdndxs>. 179
- Zae Myung Kim, Wanyu Du, Vipul Raheja, Dhruv Kumar, and Dongyeop Kang. Improving iterative text revision by learning where to edit from other revision tasks. *ArXiv*, abs/2212.01350, 2022. 180
- Philippe Laban, Jesse Vig, Wojciech Kryscinski, Shafiq R. Joty, Caiming Xiong, and Chien-Sheng Wu. Swipe: A dataset for document-level simplification of wikipedia pages. *Annual Meeting of the Association for Computational Linguistics*, 2023. 181
- Mina Lee, Katy Ilonka Gero, John Joon Young Chung, Simon Buckingham Shum, Vipul Raheja, Hua Shen, Subhashini Venugopalan, Thiemo Wambsganss, David Zhou, Emad A. Alghamdi, Tal August, Avinash Bhat, Madiha Zahrah Choksi, Senjuti Dutta, Jin L.C. Guo, Md. Naimul Hoque, Yewon Kim, Seyed Parsa Neshaei, Agnia Sergejuk, Antonette Shibani, Disha Shrivastava, Lila Shroff, Jessi Stark, S. Serman, Sitong Wang, Antoine Bosselut, Daniel Buschek, Joseph Chee Chang, Sherol Chen, Max Kreminski, Joonsuk Park, Roy Pea, Eugenia H. Rho, Shannon Zejiang Shen, and Pao Siangliulue. A design space for intelligent and interactive writing assistants. *Conference on Human Factors in Computing Systems*, abs/2403.14117, 2024. 182
- Vladimir I. Levenshtein. Binary codes capable of correcting deletions, insertions, and reversals. *Soviet physics. Doklady*, 10:707–710, 1965. 183
- Cheng Li, Mingyang Zhang, Qiaozhu Mei, Weize Kong, and Michael Bendersky. Automatic prompt rewriting for personalized text generation. *arXiv preprint arXiv:2310.00152*, 2023. 184

Jiwei Li, Alexander H. Miller, Sumit Chopra, Marc’Aurelio Ranzato, and Jason Weston. Dialogue learning with human-in-the-loop. <i>ArXiv</i> , abs/1611.09823, 2016.	185
Zichao Li, Prakhar Sharma, Xing Han Lu, Jackie Chi Kit Cheung, and Siva Reddy. Using interactive feedback to improve the accuracy and explainability of question answering systems post-deployment. <i>ArXiv</i> , abs/2204.03025, 2022.	186
Ruibo Liu, Chenyan Jia, Ge Zhang, Ziyu Zhuang, Tony X. Liu, and Soroush Vosoughi. Second thoughts are best: Learning to re-align with human values from text edits. <i>ArXiv</i> , abs/2301.00355, 2023.	187
Yixin Liu, Budhaditya Deb, Milagro Teruel, Aaron L Halfaker, Dragomir R. Radev, and Ahmed Hassan Awadallah. On improving summarization factual consistency from natural language feedback. <i>Annual Meeting of the Association for Computational Linguistics</i> , 2022.	188
Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. Learning word vectors for sentiment analysis. <i>Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies</i> , June 2011.	189
Chaitanya Malaviya, Subin Lee, Dan Roth, and Mark Yatskar. Pachinko: Patching interpretable qa models through natural language feedback. <i>ArXiv</i> , abs/2311.09558, 2023.	190
Jonathan Mallinson, Aliaksei Severyn, Eric Malmi, and Guillermo Garrido. Felix: Flexible text editing through tagging and insertion. <i>ArXiv</i> , abs/2003.10687, 2020.	191
Edison Marrese-Taylor, Machel Reid, and Yutaka Matsuo. Variational inference for learning representations of natural language edits. <i>ArXiv</i> , abs/2004.09143, 2020.	192
Edison Marrese-Taylor, Machel Reid, and Alfredo Solano. Edit aware representation learning via levenshtein prediction. <i>The Fourth Workshop on Insights from Negative Results in NLP</i> , 2023.	193
Dipendra Misra, Aldo Pacchiano, and Robert E Schapire. Provable interactive learning with hindsight instruction feedback. <i>arXiv preprint arXiv:2404.09123</i> , 2024.	194
Masato Mita, Keisuke Sakaguchi, Masato Hagiwara, Tomoya Mizumoto, Jun Suzuki, and Kentaro Inui. Towards automated document revision: Grammatical error correction, fluency edits, and beyond. <i>ArXiv</i> , abs/2205.11484, 2022.	195
Sheshera Mysore, Zhuoran Lu, Mengting Wan, Longqi Yang, Steve Menezes, Tina Baghaee, Emmanuel Barajas Gonzalez, Jennifer Neville, and Tara Safavi. Pearl: Personalizing large language model writing assistants with generation-calibrated retrievers. <i>arXiv preprint arXiv:2311.09180</i> , 2023.	196
Reiichiro Nakano, Jacob Hilton, S. Arun Balaji, Jeff Wu, Long Ouyang, Christina Kim, Christopher Hesse, Shantanu Jain, Vineet Kosaraju, William Saunders, Xu Jiang, Karl Cobbe, Tyna Eloundou, Gretchen Krueger, Kevin Button, Matthew Knight, Benjamin Chess, and John Schulman. Webgpt: Browser-assisted question-answering with human feedback. <i>ArXiv</i> , 2021.	197
Khanh X Nguyen, Dipendra Misra, Robert Schapire, Miroslav Dudík, and Patrick Shafto. Interactive learning from activity description. <i>International Conference on Machine Learning</i> , pp. 8096–8108, 2021.	198
Long Ouyang, Jeff 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 E. Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul Francis Christiano, Jan Leike, and Ryan J. Lowe. Training language models to follow instructions with human feedback. <i>ArXiv</i> , 2022a.	199
Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. <i>Advances in neural information processing systems</i> , 35:27730–27744, 2022b.	200

Dominic Petrak, Nafise Sadat Moosavi, Ye Tian, Nikolai Rozanov, and Iryna Gurevych. Learning from free-text human feedback - collect new datasets or extend existing ones? *ArXiv*, abs/2310.15758, 2023. 201

Dheeraj Rajagopal, Xuchao Zhang, Michael Gamon, Sujay Kumar Jauhar, Diyi Yang, and Eduard H. Hovy. One document, many revisions: A dataset for classification and description of edit intents. *International Conference on Language Resources and Evaluation*, 2022. 202

Machel Reid and Graham Neubig. Learning to model editing processes. *Conference on Empirical Methods in Natural Language Processing*, 2022. 203

Machel Reid, Vincent J. Hellendoorn, and Graham Neubig. Diffuser: Diffusion via edit-based reconstruction. *International Conference on Learning Representations*, 2023. 204

William Saunders, Catherine Yeh, Jeff Wu, Steven Bills, Ouyang Long, Jonathan Ward, and Jan Leike. Self-critiquing models for assisting human evaluators. *ArXiv*, abs/2206.05802, 2022. 205

J’er’emy Scheurer, Jon Ander Campos, Tomasz Korbak, Jun Shern Chan, Angelica Chen, Kyunghyun Cho, and Ethan Perez. Training language models with language feedback at scale. *ArXiv*, abs/2303.16755, 2023. 206

Abigail See, Peter J. Liu, and Christopher D. Manning. Get to the point: Summarization with pointer-generator networks. *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, July 2017. 207

Zejiang Shen, Tal August, Pao Siangliulue, Kyle Lo, Jonathan Bragg, Jeff Hammerbacher, Doug Downey, Joseph Chee Chang, and David Sontag. Beyond summarization: Designing ai support for real-world expository writing tasks. *arXiv preprint arXiv:2304.02623*, 2023. 208

Weiyang Shi, Emily Dinan, Kurt Shuster, Jason Weston, and Jing Xu. When life gives you lemons, make cherryade: Converting feedback from bad responses into good labels. *ArXiv*, abs/2210.15893, 2022. 209

Kaitao Song, Xu Tan, Tao Qin, Jianfeng Lu, and Tie-Yan Liu. Mpnet: Masked and permuted pre-training for language understanding. *ArXiv*, abs/2004.09297, 2020. 210

Felix Stahlberg and Shankar Kumar. Seq2edits: Sequence transduction using span-level edit operations. *Conference on Empirical Methods in Natural Language Processing*, 2020. 211

Nisan Stiennon, Long Ouyang, Jeff Wu, Daniel M. Ziegler, Ryan J. Lowe, Chelsea Voss, Alec Radford, Dario Amodei, and Paul Christiano. Learning to summarize from human feedback. *ArXiv*, abs/2009.01325, 2020. 212

Gemini Team, Rohan Anil, Sebastian Borgeaud, Yonghui Wu, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, et al. Gemini: a family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805*, 2023. 213

Sitong Wang, Lydia B Chilton, and Jeffrey V Nickerson. Writing with generative ai: Multi-modal and multi-dimensional tools for journalists. *The Second Workshop on Intelligent and Interactive Writing Assistants at ACM CHI*, 2023. 214

Jason Weston. Dialog-based language learning. *ArXiv*, abs/1604.06045, 2016. 215

Jing Xu, Megan Ung, Mojtaba Komeili, Kushal Arora, Y-Lan Boureau, and Jason Weston. Learning new skills after deployment: Improving open-domain internet-driven dialogue with human feedback. *Annual Meeting of the Association for Computational Linguistics*, 2022. 216

Ziyu Yao, Frank F. Xu, Pengcheng Yin, Huan Sun, and Graham Neubig. Learning structural edits via incremental tree transformations. *ArXiv*, abs/2101.12087, 2021. 217

Pengcheng Yin, Graham Neubig, Miltiadis Allamanis, Marc Brockschmidt, and Alexander L. Gaunt. Learning to represent edits. *ArXiv*, abs/1810.13337, 2018. 218

Jiyang Zhang, Sheena Panthaplackel, Pengyu Nie, Junyi Jessy Li, and Miloš Gligorić. Coditt5: Pretraining for source code and natural language editing. <i>Proceedings of the 37th IEEE/ACM International Conference on Automated Software Engineering</i> , 2022.	219 219 219
Tianyi Zhang*, Varsha Kishore*, Felix Wu*, Kilian Q. Weinberger, and Yoav Artzi. Bertscore: Evaluating text generation with bert. <i>International Conference on Learning Representations</i> , 2020.	220 220
Daniel M. Ziegler, Nisan Stiennon, Jeff Wu, Tom B. Brown, Alec Radford, Dario Amodei, Paul Christiano, and Geoffrey Irving. Fine-tuning language models from human preferences. <i>ArXiv</i> , 2019.	221 221 221

## Appendix

### A Additional Details 102

**Dataset Examples.** We list links to dataset sources for our user-provided context in Table 4.

**GPT-4 User’s Edits** We list examples of OUR GPT-4 user’s edits with different latent preference on summarization in Table 5. 114 85 89 17 61 116

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**ICL-edit Templates.** Prompt templates used by *ICL-edit* baseline are provided in Table 8.

### B Additional Analysis 112

**Detailed Expense Analysis.** We list a detailed computational expense of different methods in Table 9.

**Failure Cases.** We summarize our failure case analysis of CIPHER on summarization in Table 10. 106

**Retrieval Accuracy.** We calculate retrieval accuracy for CIPHER as the fraction of all retrieved contexts that are of the same document type as the currently given context across all seeds and time steps. We report the results in Table 11. We find that the retrieval accuracy is higher on the summarization task than on email writing, and using MPNET typically performs better than using Bert to encode context. 118 118 118 118 118

Table 4: Link to each source dataset, from which we randomly sample examples as the user-provided context in our tasks. 119

Data Source	Link and Example	120
CNN Daily Mail (See et al., 2017)	<a href="https://huggingface.co/datasets/cnn_dailymail">https://huggingface.co/datasets/cnn_dailymail</a>	120
SLF5K (Stiennon et al., 2020)	<a href="https://huggingface.co/datasets/JeremyAlain/SLF5K">https://huggingface.co/datasets/JeremyAlain/SLF5K</a>	120
Wikidump (Foundation, 2022)	<a href="https://huggingface.co/datasets/wikipedia">https://huggingface.co/datasets/wikipedia</a>	120
Arxiv (Clement et al., 2019)	<a href="https://huggingface.co/datasets/CShorten/ML-ArXiv-Papers">https://huggingface.co/datasets/CShorten/ML-ArXiv-Papers</a>	120
IMDb (Maas et al., 2011)	<a href="https://huggingface.co/datasets/imdb">https://huggingface.co/datasets/imdb</a>	120
PaperTweet (Bar, 2022)	<a href="https://huggingface.co/datasets/nitsanb/paper_tweet">https://huggingface.co/datasets/nitsanb/paper_tweet</a>	120
Elsevier OA CC-BY (Kershaw & Koeling, 2020)	<a href="https://huggingface.co/datasets/orieg/elsevier-oa-cc-by">https://huggingface.co/datasets/orieg/elsevier-oa-cc-by</a>	120



Table 5: Examples of user edits with different latent preference on summarization. The agent output column shows the agent generation without conditioning on any preference. The latent preference for the user edits is in bold and parenthesis. We truncate some examples due to limited space.

Agent Output	User Edits
<p>Leon Fenner, the suspected gunman in a \$2 million diamond heist at Watch Standard Jewelry in New York City, was arrested in Maryland. The robbery occurred on November 11 and resulted in the injury of the store owner's elderly father. Fenner's accomplice, Rondu Frisby, was a friend of the store owner and was apprehended a week after the heist. The robbery took place during the city's Veteran's Day Parade, leading to a block shutdown. Fenner and Frisby stole numerous jewels and 20 luxury watches, but were caught on surveillance cameras. Fenner is set to appear before a federal court in Maryland.</p>	<p><b>(targeted to young children, storytelling, short sentences, playful language, interactive, positive)</b></p> <p>Once upon a time in the big, bustling city of New York, during a parade filled with music and marching on Veteran's Day, something sneaky happened at a place called Watch Standard Jewelry. This wasn't just any store; it was a treasure chest full of sparkling diamonds and shiny watches that could make your eyes twinkle like stars.</p> <p>Now, two not-so-nice men, Leon Fenner and his buddy Rondu Frisby, thought they could be sneaky and take these treasures without asking. On November 11, while everyone was watching the parade, they tiptoed into the store. But oh no! They accidentally hurt the store owner's dear old dad, which wasn't very kind at all. [TRUNCATED]</p>
<p>The article describes a situation where a neighbor's cat, one of seven rescued by a "cat lady," has started frequenting the author's front yard after leaving its original home due to the presence of other cats. Over the past few months, the cat has become more consistent in its visits, meowing at the author and their family members for attention. The cat allows itself to be petted and shows affectionate behavior, such as rubbing against legs and headbutting hands, until it is fed. After eating, the cat typically leaves but returns in the evening. The author is seeking advice on how to handle the situation, expressing concern about feeding the cat because it is not legally theirs and there could be potential ownership and legal issues.</p>	<p><b>(second person narrative, brief, show emotions, invoke personal reflection, immersive)</b></p> <p>Imagine yourself in a quaint neighborhood, where the gentle purrs of a feline friend have become a familiar part of your daily routine. This isn't just any cat—it's one of seven, a charming escapee from the home of a local "cat lady," seeking solace in the tranquility of your front yard. Over recent months, this whiskered wanderer has turned your doorstep into its personal stage, meowing for attention with a persistence that tugs at your heartstrings.</p> <p>Each encounter with this affectionate creature is a dance of mutual admiration. You find yourself captivated by its soft fur and the way it eagerly rubs against your legs, headbutting your hands in a silent plea for affection. [TRUNCATED]</p>
<p>The Puerto Plata Province is a northern province in the Dominican Republic, known for its beautiful beaches and as a popular tourist destination since the late 1990s. Its capital is San Felipe de Puerto Plata, named after the silver clouds Columbus saw on a mountain nearby in 1493. The city of Puerto Plata was founded in 1502.</p> <p>Historically, the first European town in the Americas, La Isabela, was established by Columbus near Puerto Plata in 1493. In 1605, the governor Antonio de Osorio destroyed Puerto Plata and other towns to curb illegal trade, leading to the formation of new settlements.</p> <p>Puerto Plata became a Maritime District in 1865 and was later recognized as a province in the 1907 constitution. Over time, it expanded to include more municipalities and municipal districts, with the latest additions in 2007. [TRUNCATED]</p>	<p><b>(bullet points, parallel structure, brief)</b></p> <ul style="list-style-type: none"> <li>Location: Northern Dominican Republic</li> <li>Capital: San Felipe de Puerto Plata</li> <li>Founding: 1502 by Europeans</li> <li>Historical site: La Isabela (1493, first European town in the Americas)</li> <li>1605: Destruction by Governor Antonio de Osorio to stop illegal trade</li> <li>Status: Became Maritime District in 1865, recognized as province in 1907</li> <li>Expansion: Added more municipalities, latest in 2007</li> <li>Borders: Atlantic Ocean, Espaillat, Santiago, Valverde, Monte Cristi provinces</li> </ul> <p>[TRUNCATED]</p>

The article discusses the challenge of detecting and classifying stuttered speech, which affects many people but has been subject to limited research. The authors present a new model that differs from most existing methods, which typically use language models for stutter identification. Instead, their model is based on acoustic features, which allows it to identify various kinds of stuttering disfluencies without relying on speech recognition technology. The proposed model combines a deep residual network with bidirectional long short-term memory (LSTM) layers to classify different stutter types. It has been shown to significantly outperform current leading methods, reducing the average miss rate to 10.03%, which is a 27% improvement over the state-of-the-art.	(tweet style, simple English, inquisitive, skillful foreshadowing, with emojis) 131 Ever struggled with stuttering or know someone who does? 🗣️ Research on detecting stutters hasn't been huge, but guess what? A new study is changing the game! 🎮 Instead of just looking at words, this smart model listens to how things are said. 🗣️ It's like a detective for sounds, using cool tech called deep learning and memory networks to spot different stutter types. 🕵️ And it's crushing it, beating old methods by 27%! Missed stutters? Down to just 10%! 📉 This could be a big deal for speech therapy! 🗣️ #Stuttering #SpeechTech #Innovation 131	131
The article discusses a movie that begins promisingly but later becomes confusing due to a poorly depicted portrayal of ancient black magic rituals. The male lead delivers a strong performance despite his character's unfavorable outcome in the climax. The movie is compared to a mix of "Boomerang" and "Extremities."	(question answering style, direct, concise) 132 What is the general sentiment of the article about the movie? 132 The article suggests that the movie starts off well but eventually becomes muddled. The depiction of ancient black magic rituals is criticized for being confusing. 133 How does the article describe the male lead's performance? 133 The male lead's performance is described as strong, even though his character does not have a favorable outcome in the climax. 135 What films is the movie compared to in the article? 136 The movie is compared to "'Boomerang'" and "'Extremities'" in the article. 137	132 133 133 133 134 135 135 136 137

Table 6: Prompt templates for the AI user. The first step is to prompt the user for yes/no answer regarding satisfaction. If the answer is no, the second step is to ask the user edit the agent output according to the latent preference. If the answer is yes, the agent output receives 0 edits. 138

Summarization		Email Writing 139
Step 1	Article: {user-provided article} 139 Summary: {agent-generated summary} 139 Is the above summary of the above article good for person who would love to use the following style: {latent user preference}? Please answer yes or no. 139	Notes: {user-provided notes} 139 Email: {agent-generated email} 139 Is the above email based on the above notes good for a user who wants the following style: {latent user preference}? Please answer yes or no. 139
Step 2	Summary: {agent-generated summary} 139 Please revise the above summary of an article to meet your style: {latent user preference}. 139	Email: {agent-generated email} 139 Assume that you prefer {latent user preference}. Please revise the above email to meet your style. 139

Table 7: Prompt templates for CIPHER. 140

	Summarization	Email Writing 141
Task prompt conditioned on inferred preference (line 6 in Algorithm 1)	Article: {user-provided article} 141 Assume that you need to summarize the above article for a user, who prefers the following style: {inferred user preference}. Please write a summary of the above article to address those specified preferences. 141	Notes: {user-provided notes} 141 These notes are written by a user who prefers the following style of emails: {inferred user preference}. Please write a short email based on the above notes to address those specified preferences. 141
Prompt to infer user preference based on revision (line 12 in Algorithm 1)	Original summary of an article: {agent-generated summary} 142 Revised summary by a user: {user revision} 142 Based on the edits and revision by this user on the original summary in the above examples, what do you find about this user’s generic preference in terms of writing style and formatting? Please answer in a short phrase and only recommend those preferences that are widely used. 142	Original email: {agent-generated email} 142 Revised email: {user revision} 142 Based on the edits and revision by this user on the original email in the above examples, what do you find about this user’s generic preference in terms of writing style and formatting? Please answer in a short phrase and only recommend those preferences that are widely used. 142
Prompt to consolidate inferred preferences from history (line 5 in Algorithm 1)	List of user preferences successfully being used to generate summaries of similar documents: {inferred preference in a retrieved example} 142 {inferred preference in a retrieved example} 142 ... 142 Based on the the above examples, please come up with short phrase with the most represented summarization preferences of the user. 142	List of user preferences successfully being used to generate emails of a similar kind: {inferred preference in a retrieved example} 142 {inferred preference in a retrieved example} 142 ... 144 Based on the the above examples, please come up with short phrase with the most represented writing preferences of this user. 142

Table 8: Prompt templates for the ICL-edit baseline. 143

	Summarization	Email Writing 144
Prompt with retrieved user edit examples 144	Original summary of an article: {agent-generated summary in a retrieved example} 142 Revised summary by a user: {user revision in a retrieved example} 142 Original summary of an article: {agent-generated summary in a retrieved example} 142 Revised summary by a user: {user revision in a retrieved example} 142 ... 142 Article: {user-provided article} 142 Based on the edits and revision by this user on the original summary in the above examples, Please summarize the above article: 142	Original summary of an article: {agent-generated summary in a retrieved example} 144 Revised summary by a user: {user revision in a retrieved example} 144 Original summary of an article: {agent-generated summary in a retrieved example} 144 Revised summary by a user: {user revision in a retrieved example} 144 ... 144 Notes: {user-provided notes} 144 Based on the edits and revision by this user on the original email in the above examples, Please write an email based on the above notes for this user: 144

Table 9: Expense of different methods: number of BPE tokens in terms of input, output and total. Each number is the average across 3 runs (unit is  $\cdot 10^5$ ). 145

Method 146	Summarization			Email Writing 146		
	Input	Output	Total	Input	Output	Total
Oracle Preference	1.14	0.53	1.67	0.91	0.71	1.62
No Learning	1.06	0.44	1.50	0.85	0.80	1.65
E-then-e LPI	1.16	0.83	1.99	0.94	0.79	1.73
Continual LPI	8.14	0.75	8.89	7.89	0.73	8.63
ICL-edit-5-MPNET	7.35	0.65	8.00	11.05	1.06	12.12
ICL-edit-5-BERT	7.32	0.64	7.96	10.51	1.03	11.55
CIPHER-1-MPNET	2.02	0.72	2.74	1.21	0.73	1.94
CIPHER-5-MPNET	2.27	0.73	3.00	1.44	0.64	2.09
CIPHER-1-BERT	2.10	0.71	2.81	1.27	0.73	1.99
CIPHER-5-BERT	2.32	0.71	3.03	1.48	0.73	2.22

Table 10: Summary of failure cases on summarization task with CIPHER-5-MPNET. 147

Type of Failures	Summary	Examples
Preference inference based on an output-revision pair ( $f_t$ ) (the most common failure type)	<p>1) Not totally wrong but insufficient, i.e. the inferred preference only captures a few aspects of user’s latent preference. This is most common for news articles and Reddit posts, for which the user shows nuanced preference for several aspects.</p> <p>2) Sometimes fail to infer some important aspects, even though the user edits clearly show such preference.</p>	<p>The dominant missing aspect is <i>brief</i> or <i>short sentences</i> across different context, although the agent can infer keywords such as <i>concise</i>. For news article context, the agent tends to infer the preference keyword <i>whimsical</i>. The agent has difficulty to infer subtle aspects, including <i>invoke personal reflection, immersive, positive, parallel structure, inquisitive</i>, and <i>skillful foreshadowing</i>.</p> <p>The agent often could not infer <i>second-person narrative</i>. For <i>question answering style</i>, the agent occasionally only learns <i>consistent format</i>.</p>
Consolidation of induced preferences from retrieved interactions ( $f_t$ )	Overall, this step can capture the majority preference relatively well, although it tends to result in a more general preference compared to the retrieved ones.	When both specific phrase <i>second-person narrative</i> and general phrase <i>narrative</i> or <i>narration</i> occur in retrieved examples, the agent often chooses to give a final preference not including the second-person perspective aspect.
Retrieval of historical examples relevant to the given context	The retrieval part in general works reasonably well, with more than half of the retrieved example being truly relevant to the given context. Note that one incorrect retrieved example typically does not affect the performance, as we instruct the agent to only use the most represented preference keywords among all five retrieved examples.	The agent sometimes retrieves wrong examples for Wikipedia context when its topic very relates to other context, e.g. wrongly retrieving past examples on news articles and movie reviews when the topic in the given Wikipedia context relates to these domains.

Table 11: We report retrieval accuracy as the percentage of total retrieved document representations across all time steps and seeds that are of the same document source type as the context document for which they were retrieved. We use 3 seeds. We retrieve 600 examples for  $k = 1$  and 2970 examples for  $k = 5$ . 149

Method	Summarization	Email Writing
CIPHER-1-B	72.00	25.83
CIPHER-1-M	<b>82.00</b>	<b>26.33</b>
CIPHER-5-B	65.79	<b>26.57</b>
CIPHER-5-M	<b>76.33</b>	25.45