Language Modeling with Editable External Knowledge

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Abstract

When the world changes, so does the text that people write about it. How do we build language models that can be easily updated to reflect these changes? One popular approach is retrieval-augmented generation (RAG), in which new documents are inserted into a knowledge base and retrieved during prediction for downstream tasks. Most prior work on RAG has focused on improving model behavior during *prediction* through better retrieval or reasoning. This paper introduces ERASE, which instead improves model behavior *when new documents are acquired*, by incrementally deleting or rewriting other entries in the knowledge base each time a document is added. In two new datasets evaluating models' ability to answer questions about a stream of news articles or conversations, ERASE improves accuracy relative to conventional retrieval-augmented generation by 7–13% (Mixtral-8x7B) and 6–10% (Llama-3-8B) absolute. This improvement is complementary to improved retrieval or reasoning for RAG: we demonstrate an 11% improvement by applying ERASE on top of the advanced Self-RAG method.[1]

1 Introduction

The world—and the language we used to describe it—are constantly changing. Consider the example shown in Figure 1: after reading the article *After Queen Elizabeth II died, the Queen's oldest son Charles has now become King Charles III,* a knowledgeable reader might update an entire system of related beliefs, *e.g.,* that King Charles III is now also the new head of state for Scotland. How can we train language models to reflect these changes?

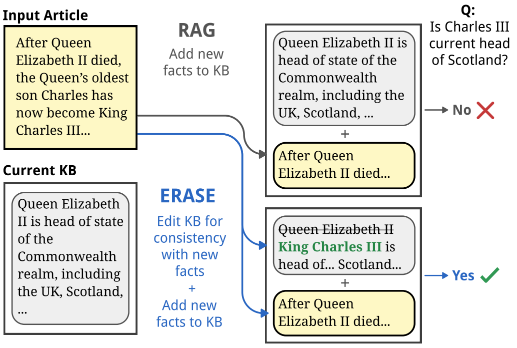
Input Article
After Queen Elizabeth II died, the Queen's oldest son Charles has now become King Charles III...
RAG
Add new facts to KB
Current KB
Queen Elizabeth II is head of state of the Commonwealth realm, including the UK, Scotland, ...
ERASE
Edit KB for consistency with new facts
+
Add new facts to KB
Queen Elizabeth II is head of state of the Commonwealth realm, including the UK, Scotland, ...
+
After Queen Elizabeth II died...
~~Queen Elizabeth II~~ King Charles III is head of... Scotland...
+
After Queen Elizabeth II died...
Q: Is Charles III current head of Scotland?
No ✗
Yes ✓

Figure 1: In standard retrieval augmented generation (RAG), new facts are simply added to an existing knowledge base $\mathcal{K}$. This can lead to stale facts in $\mathcal{K}$, which can in turn lead to incorrect predictions. In contrast, when ERASE reads a new input article, it not only adds new facts to $\mathcal{K}$, but also *updates* (edits or deletes) existing facts, thereby enabling correct predictions.

Continual learning methods tackle the problem of a changing world by incrementally *training* on new information (Mitchell et al., 2018; Wang et al., 2024). In language models (LMs), a simple but often extremely effective approach presents new information as input—using long-context models (Tay et al., 2022) or retrieval augmented generation (RAG; Lewis et al., 2020a), which appends new documents to a knowledge base, then retrieves and conditions on relevant documents during prediction (Guu et al., 2020; Lewis et al., 2020b).

A limitation of current RAG approaches is that they sometimes retrieve *stale* documents that have been invalidated by new information. In Fig. 1, the article *After Queen Elizabeth II died...* would be appended to the existing knowledge base, which includes a fact about Queen Elizabeth's reign when she was alive, *e.g., Queen Elizabeth II is head of state of...Scotland.* When answering questions about the Scottish head of state, this document might be retrieved, leading the LLM to produce incorrect answers. Past attempts to address this issue have focused on improved *retrieval* methods, but not on ensuring accuracy and consistency of the document collection itself.

This paper describes a method for retrieval-

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[1] Code and data are available at `https://anonymous.4open.science/r/ERASE-0FB8`

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augmented generation that attempts to ensure that the external knowledge base always represents the current state of the world. This method, which we call ERASE (**E**nhancing **R**etrieval **A**ugmentation with **S**elf-consistent **E**diting; §3), enables accurate language modeling by updating the knowledge base at *document insertion* time—*i.e.,* when new documents are read and added to the knowledge base—rather than at prediction time. Every time a new document is acquired, ERASE identifies related documents in the knowledge base and decides whether to keep, edit, or delete them. These operations allow new information to be propagated and prevent stale information from being used for inference. In Figure 1, ERASE not only adds the new article to the knowledge base, but also *edits* the existing fact *~~Queen Elizabeth II~~* → ***King Charles III*** *is head of...Scotland*, thereby enabling correct prediction when this document is retrieved.

We evaluate ERASE's performance on question-answering (QA) tasks about a set of continually changing facts described by a stream of text. To do so, we introduce a new benchmark dataset, CLARK (**C**ontinual **L**earning **A**nd **R**evising **K**nowledge; §4), which contains two domains: (1) CLARK-NEWS, a factual QA domain consisting of a set of timestamped news articles paired with questions and timestamped answers; (2) CLARK-CONVERSATIONS, a long-conversation domain where facts about conversation participants evolve over the course of the conversation. The conversation domain contains both single-hop and multi-hop edits, the latter of which requires multi-hop inferences at the memory updating stage.

Here ERASE outperforms standard RAG baselines and long-context models, giving 7–13% (Mixtral-8x7B) and 6–10% (Llama-3-8B) absolute improvements in accuracy compared to standard RAG on news and single-hop conversation questions. On the multi-hop subset, we find that ERASE performs comparably to baselines, suggesting there is room for future work to improve multi-hop memory editing. ERASE is not only applicable to standard RAG approaches—used in combination with the state-of-the-art SelfRAG method (Asai et al., 2024) it further improves accuracy by 11%.

2 Background and Related Work

ERASE belongs to a body of work aimed at developing LM-based systems that can be updated after training by modifying *inputs* rather than parameters—such methods are more flexible, and often more robust, than alternatives.

Long-context and retrieval-augmented generation: updating LMs via conditioning One simple and effective way to update LMs is to provide new information as input (e.g. prepending a question about current events with a sequence of news articles). But this approach begins to face challenges when text containing new information is extremely long (*e.g.,* thousands of articles). In these cases, it is necessary to use LMs specialized for very long input sequences, or to select a subset of inputs for each new query to the model (called retrieval-augmented generation, or RAG).

Long-context models (Wang et al., 2020; Kitaev et al., 2020; Press et al., 2021; Su et al., 2024) focus on modifying LM architectures to allow long sequences to be processed efficiently, or to extrapolate to long inputs. RAG methods, by contrast, dynamically construct relevant contexts tailored to individual queries (Guu et al., 2020; Lewis et al., 2020b). Previous work has explored auxiliary models that selectively choose when to perform retrieval (Mitchell et al., 2022b), or abstain from answering questions when retrieved sources present conflicting or outdated information (Chen et al., 2022; Zhang and Choi, 2023). Other work has examined augmenting LMs with *knowledge graphs* (Cai et al., 2023; Modarressi et al., 2024; Sanmartin, 2024), structured relational knowledge bases that may be timestamped and whose nodes and edges may be updated. However, such structure can be difficult to construct and risks throwing away essential information; these methods are generally less used than unstructured knowledge bases. A final class of methods uses search engine augmentation to retrieve articles for LMs (Yan et al., 2024). However, these methods can only be applied in domains where someone else has already done the work of keeping a search engine up to date, and cannot be applied to private information not on the web.

Continual learning: updating LMs via fine-tuning A broader class of methods, applicable to a much broader class of machine learning models, study the problem of robustly performing **continual learning** under a non-stationary data distribution (Mitchell et al., 2018; Wang et al., 2024) via training objectives that ensure that new information is retained but old information is not forgotten (Jang et al., 2022; Mehta et al., 2023; Jang et al., 2023). Previous work on LMs has explored the use

Benchmark	Timestamps?	Sources	Cross-source updating?	Attributed answers?	Changing answers?
SituatedQA (Zhang and Choi, 2021)	✓	Wikipedia	✓	✗	✓
TimeQA (Chen et al., 2021)	✓	Wikipedia	✗	✓	✓
TempLAMA (Dhingra et al., 2022)	✓	Wikipedia	✓	✗	✓
RealTimeQA (Kasai et al., 2023)	✓	News	✓	✓	✗
FreshQA (Vu et al., 2023)	✓	Wikipedia	✓	✗	Few ($<15\%$)
PAT-Questions (Meem et al., 2024)	✓	✗	-	✗	✓
CLARK (News)	✓	News	✓	✓	✓

Table 1: CLARK (News) contains real-world news articles as sources, ensures answers are changing across (rather than simply within) articles that are written over time, ensures that the version-attributed source texts containing the answer have been extracted, and ensures that answers for the same set of questions are being updated.

of continual pretraining (Jin et al., 2022), modified pretraining objectives (Xu et al., 2023), and synthetic data generation (Padmanabhan et al., 2023; Akyürek et al., 2024). Continual learning methods are computationally intensive and less widely used than RAG and related methods in language models.

Model editing: updating LMs with targeted interventions A final category of methods alter LM behavior by making targeted interventions to their parameters, either using specialized secondary "editing" models (Cao et al., 2021; Mitchell et al., 2022a) or performing closed-form updates (Meng et al., 2022, 2023). Current methods reliably update facts but not all their implications (Onoe et al., 2023; Hua et al., 2024), and are generally outperformed by retrieval- or fine-tuning-based methods.

Evaluating updates Few resources are currently available for evaluating models' ability to generate text about *changing* features of the world while attributing these changes to known source of information. The Entity Cloze by Date (ECBD) dataset contains entities from Wikidata along with cloze-style sentences (Onoe et al., 2022), and the LoCoMo dataset contains long conversations to measure long-term memory in models (Maharana et al., 2024); unlike CLARK, these datasets do not isolate entities whose properties *change* over time. Many datasets (Zhang and Choi, 2021; Chen et al., 2021; Meem et al., 2024; Dhingra et al., 2022; Kasai et al., 2023; Vu et al., 2023) study temporally-situated question answering; however, contexts in these datasets consist only of dates and not source documents. Those that do have sources only contain a high-level, coarse-grained reference to Wikipedia, without attribution to versions or primary sources (Table 1). This makes it difficult to compare results across implementations: were improvements due to a better system, or simply due to a more complete set of documents in the knowledge base? In CLARK, we release both our questions and attributable source documents for those questions, enabling fair comparisons across methods.

3 ERASE Method

This paper introduces a system that generates text (e.g. for the question answering task depicted in Fig. 1) while updating its behavior in response to a continuous stream of documents describing a changing state of the world (e.g. the article about the death of Queen Elizabeth II, shown with a yellow background in Fig. 2) by populating and editing a knowledge base of natural-language facts extracted from documents (shown with gray backgrounds in Fig. 2). Importantly, the knowledge base records not just the content of each fact, but when it was first added, and (if relevant) when it ceased to be true. As new documents arrive, ERASE attempts to maintain the knowledge base in a *consistent* state—containing only facts that are currently true—by rewriting facts or marking them as false when contradictory facts are introduced by new documents (e.g. marking false facts about Elizabeth II's health and updating other references to the UK monarchy). During prediction, ERASE operates according to a normal RAG approach.

More formally, we begin with a **language model** encoding a conditional distribution over strings $p_{\text{LM}}(\text{prediction} \mid \text{context})$. When a new **document** d_i is received with some **timestamp** τ_i, we update a **knowledge base** $\mathcal{K}$—each entry in $\mathcal{K}$ consists of both a **fact** f_j and a **fact history** $H_j = [(\tau_{j0}, v_{j0}), (\tau_{j1}, v_{j1}), \ldots]$, where each τ_{jk} is a timestamp and v_{jk} is a **truth value** indicating whether f_j was known to be true or false at time τ_{jk}. We then parse the new document into a sequence of facts f_j using the LM.

Unlike standard RAG methods, it is not necessary for facts extracted from documents to correspond one-to-one with facts in the knowledge

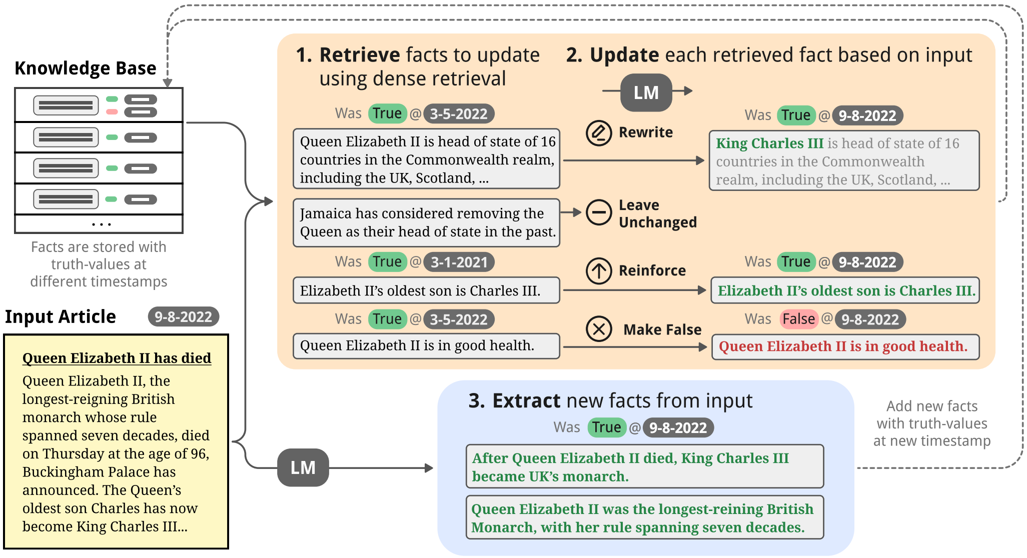
Knowledge Base
Facts are stored with truth-values at different timestamps
Input Article 9-8-2022
Queen Elizabeth II has died
Queen Elizabeth II, the longest-reigning British monarch whose rule spanned seven decades, died on Thursday at the age of 96, Buckingham Palace has announced. The Queen's oldest son Charles has now become King Charles III...
LM
1. Retrieve facts to update using dense retrieval
2. Update each retrieved fact based on input
LM
Was True @ 3-5-2022
Queen Elizabeth II is head of state of 16 countries in the Commonwealth realm, including the UK, Scotland, ...
Rewrite
Was True @ 9-8-2022
King Charles III is head of state of 16 countries in the Commonwealth realm, including the UK, Scotland, ...
Jamaica has considered removing the Queen as their head of state in the past.
Leave Unchanged
Was True @ 3-1-2021
Elizabeth II's oldest son is Charles III.
Reinforce
Was True @ 9-8-2022
Elizabeth II's oldest son is Charles III.
Was True @ 3-5-2022
Queen Elizabeth II is in good health.
Make False
Was False @ 9-8-2022
Queen Elizabeth II is in good health.
3. Extract new facts from input
Was True @ 9-8-2022
After Queen Elizabeth II died, King Charles III became UK's monarch.
Queen Elizabeth II was the longest-reining British Monarch, with her rule spanning seven decades.
Add new facts with truth-values at new timestamp

Figure 2: Overview of ERASE. We begin by retrieving existing facts relevant to input and prompting a LM to update them. We also extract facts from the input to add to our knowledge base.

base: knowledge base entries may also arise by editing old facts. To do this, ERASE incorporates new documents into the knowledge base in three steps: **retrieval**, **updating**, and **adding**.

Step 1: Retrieve facts to edit.

$$R \leftarrow \texttt{Retrieve}(\mathcal{K}, d) \qquad (1)$$

We retrieve a set of knowledge base entries $R = \{(f_{i_0}, H_{i_0}), \cdots (f_{i_m}, H_{i_m})\} \subset \mathcal{K}$. Here we assume that the facts most likely to require *editing* in response to d are those most similar to d.[2] Following most modern RAG approaches (Lewis et al., 2020a), ERASE performs **dense vector retrieval**, using a learned embedding model $\mathcal{E}$ to assign documents and facts vector representations, then retrieve a set of m to optimize:

$$\texttt{Retrieve}(\mathcal{K}, d) = \underset{(f_j, H_j) \in \mathcal{K}}{\arg\text{top-k}}\ \mathcal{E}(d)^{\top}\mathcal{E}(f_j)\ . \qquad (2)$$

Step 2: Update retrieved facts.

$$\forall (f_j, H_j) \in R,\ (f'_j, H'_j) \leftarrow \texttt{Update}(f_j, H_j, d, \tau)$$
$$\mathcal{K} \leftarrow \mathcal{K} \cup \{(f'_j, H'_j)\} \qquad (3)$$

We update the knowledge base by modifying each retrieved fact $f_i \in R$ in one of the following ways: **Reinforce fact**: If the fact f is supported by d, we add $(\texttt{true}, \tau)$ to H. *e.g.,*: f = *Mary works in a warehouse* and d = *Mary came back from her job at UPS where she sorted packages all day*.

Keep fact unchanged: If d does not affect the truth value of f, then we do nothing and let $f' = f$ and $H' = H$. *e.g.,* f = *Mary works in a warehouse* and d = *Mary took a jog in the park.*

Make fact false: If f is contradicted by d, we add $(\texttt{false}, \tau)$ to H'. *e.g.,* f = *Mary works in a warehouse* and d = *Mary got fired from her warehouse job.*

Rewriting: Alternatively, if f is contradicted by d, we may *rewrite* it into a new expression f' that is inferrable from d and the retrieved facts $\subset R$ that have been *reinforced* or *kept unchanged*. We then replace the old KB entry (f, H) with a new KB entry $(f', [(\texttt{true}, \tau)])$.

For all operations above, we prompt an LM (which may be the same LM used for prediction) to classify each retrieved fact into one of *reinforce, no change, make false*.[3] We then iterate through all facts classified as *make false*, and ask the LM if it can rewrite the fact into a true expression. In this second phase, the LM is allowed to condition on facts that it classified as *reinforce* or *no change*, allowing multi-hop edits. The full details of this procedure can be found in Appendix A.1.

Step 3: Add new facts.

$$\mathcal{K} \leftarrow \mathcal{K} \cup \texttt{Add\_facts}(T) \qquad (4)$$

We add all new facts by conditioning on d and

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[2] For efficiency, we retrieve facts relevant to the entire document in this step, rather than first parsing the document into facts, then retrieving facts relevant to each extracted fact.

[3] The task in the first pass is similar to probabilistic natural language inference. Inputs that make facts more likely (even if they do not exactly entail those facts) are classified as *support*, and inputs that make facts less likely (even if they do not exactly contradict those facts) are classified as *make false*.

prompting the LM to extract atomic facts f. The prompt we use can be found in Appendix A.2. Analogously, Chen et al. (2023) used a *propositionizer* to decompose articles into propositions.

Prediction: After updating, generation uses a standard RAG pipeline as described in step 1. An example prompt can be found in Appendix A.3.

4 Dataset

To evaluate ERASE, we create a dataset that tests fact-updating abilities in naturally-occurring text, where the difficult task of integrating updates has not been already completed by humans, e.g., in Wikipedia articles. See Table 1 for a comparison of our news domain to prior datasets. Our datasets span two continual learning domains: one about the evolving state of the world, and one about the evolving state of agents in a conversation, the latter domain not being present in prior work. We acquire a set of natural-language texts L_t, a set of ground truth world states W_t and a series of questions $q_0 \cdots q_n$ associated with W_t. We focus on questions that *update* over time: the set of questions we ask at each timestep are the same, but each question is associated with a list of timestamped answers $(q_i, \{(a_{i0}, t_{i0}), (a_{i1}, t_{i1}), \cdots\})$. Samples from each dataset are in Figure 3. An overview of state transitions and questions is in Appendix C.

4.1 News Articles

World States In this domain, world states are expressed in the form `(subj, rel, obj)`: for instance, `(Elizabeth II, position held, monarch of the United Kingdom)`. We mine these triples from Wikidata.[4] As Wikidata is updated over time, each fact is also associated with a start and end date. To find changed facts, we extract `(subj, rel)` pairs for which there are at least two distinct fact relations at different timestamps between November 2021 and April 2024. Through this process, we obtain 1,174 triples for 10 unique relations, summarized in Table 12.

Documents For each world state `(subj, rel, obj, start_ts, end_ts)`, where the start and end timestamps are extracted from Wikidata, we obtain an English article confirming that fact between the start and end timestamps, validated by crowd workers. Through this process, annotators collected a total of **1149** articles.[5] See Appendix B.1 for details. These documents—rather than raw relation triples—are the input to ERASE.

Questions and Answers We automate the generation of questions and answers from W by writing templates for each relation and generating questions and answers from those templates. We generated a total of **1409** questions. The full list of templates can be found in Appendix B.1.

4.2 Synthetic Conversations

Following prior work (Maharana et al., 2024), we construct a conversation domain by placing two LLMs with different personas in conversation with each other. Conversations are engineered to reflect changing facts in the agents' simulated lives. A detailed overview of dataset construction can be found in Appendix B.2. To validate the LM generations, three authors manually examined 3 conversations (1008 questions) in total and got an average of 95% accuracy on these questions.

This synthetic domain allows us to rigorously control and evaluate forms of reasoning that may be hard to isolate in natural data like news articles.

World States We generate an independent world, modeled as a Markov chain, per conversation. In this world, states S are described by `(subj, rel, obj)` relations, and allowable transitions $T(S)$. States S are defined by entities including people, companies, jobs, hobbies, along with mutable and immutable relations between them. Transitions $t \in T(S)$ change one or more relations: *e.g.,*, *Bob left Microsoft for Google* changes the *employees* of Google, the *coworkers* of Bob, the *coworkers* of all Google employees, and the *coworkers* of all Microsoft employees. At each timestep, we sample a transition uniformly at random. The full list of entities, relations, and transitions and their downstream effects can be found in Appendix B.2.

Conversations We generate conversations by sampling two people p_1 and p_2 and prompting two LLMs with their corresponding personas and the initial world state S. We then generate twelve conversation "chunks"—separated by time—by sampling state transitions between *every other* chunk

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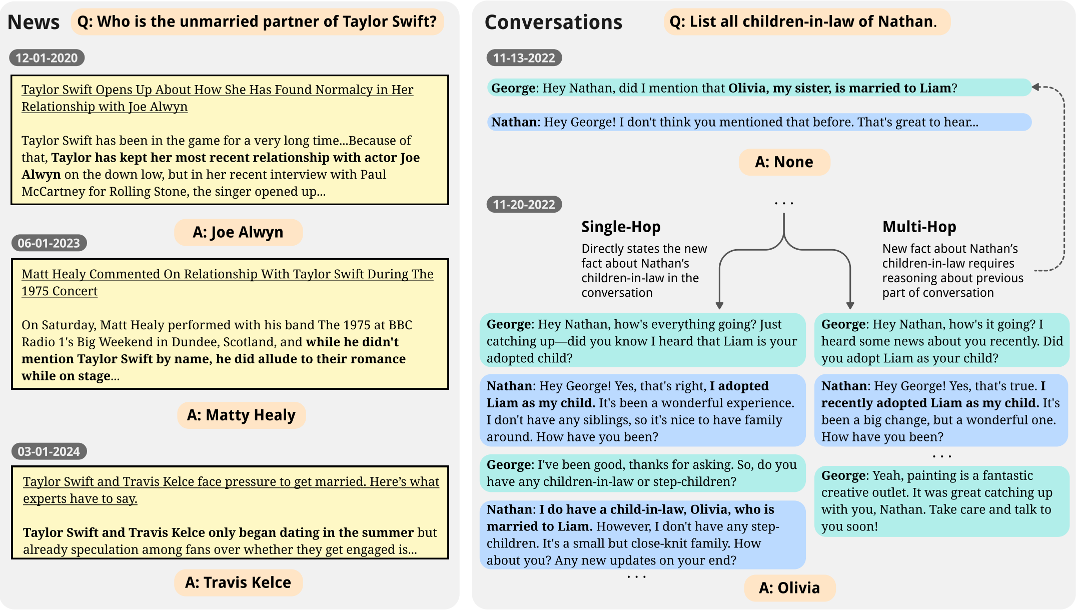
[4] `https://www.wikidata.org/`, which is public domain. Its license can be found at `https://www.wikidata.org/wiki/Wikidata:Licensing`.

[5] Note 1149 $<$ 1174, meaning at least a few articles were shared across relations – these represent difficult cases where a single article makes multiple relation changes.


News
Q: Who is the unmarried partner of Taylor Swift?
12-01-2020
A: Joe Alwyn
06-01-2023
A: Matty Healy
03-01-2024
A: Travis Kelce
Conversations
Q: List all children-in-law of Nathan.
11-13-2022
A: None
11-20-2022
Single-Hop
Directly states the new fact about Nathan's children-in-law in the conversation
Multi-Hop
New fact about Nathan's children-in-law requires reasoning about previous part of conversation
A: Olivia

Taylor Swift Opens Up About How She Has Found Normalcy in Her Relationship with Joe Alwyn

Taylor Swift has been in the game for a very long time...Because of that, **Taylor has kept her most recent relationship with actor Joe Alwyn** on the down low, but in her recent interview with Paul McCartney for Rolling Stone, the singer opened up...

Matt Healy Commented On Relationship With Taylor Swift During The 1975 Concert

On Saturday, Matt Healy performed with his band The 1975 at BBC Radio 1's Big Weekend in Dundee, Scotland, and **while he didn't mention Taylor Swift by name, he did allude to their romance while on stage**...

Taylor Swift and Travis Kelce face pressure to get married. Here's what experts have to say.

Taylor Swift and Travis Kelce only began dating in the summer but already speculation among fans over whether they get engaged is...

George: Hey Nathan, did I mention that **Olivia, my sister, is married to Liam**?

Nathan: Hey George! I don't think you mentioned that before. That's great to hear...

George: Hey Nathan, how's everything going? Just catching up—did you know I heard that Liam is your adopted child?

Nathan: Hey George! Yes, that's right, **I adopted Liam as my child.** It's been a wonderful experience. I don't have any siblings, so it's nice to have family around. How have you been?

George: I've been good, thanks for asking. So, do you have any children-in-law or step-children?

Nathan: **I do have a child-in-law, Olivia, who is married to Liam.** However, I don't have any step-children. It's a small but close-knit family. How about you? Any new updates on your end?

George: Hey Nathan, how's it going? I heard some news about you recently. Did you adopt Liam as your child?

Nathan: Hey George! Yes, that's true. **I recently adopted Liam as my child.** It's been a big change, but a wonderful one. How have you been?

George: Yeah, painting is a fantastic creative outlet. It was great catching up with you, Nathan. Take care and talk to you soon!

Figure 3: Sample data from our datasets. The News dataset consists of factual questions whose answers change over time, with the associated source inducing that change. The Conversations dataset consists of conversations between two personas with evolving life facts. The single-hop subset directly states all facts that are changed, while the multi-hop subset requires reasoning about previous chunks of conversation to infer all changes.

	Accuracy at final timestamp	Runtime (mins:sec)
Llama-2 + SelfRAG	36.8%	44:15
+ ERASE	47.9%	6:41

Table 2: Results with SelfRAG demonstrate that ERASE is complementary to retrieval- or inference-time improvements to RAG.

and having people converse about the facts that have changed after each transition.

We also construct a challenge set of *multi-hop* updates in this domain, which require reasoning about global coherence. For example, Bob may mention that he has changed jobs but may not mention that *Jane is no longer his coworker* or that *Mary (at Google) is now his coworker*. The LM must make multi-hop inferences to update the latter two facts.

We generate **100** conversations (50 single-hop, 50 multi-hop) in total. Conversations were on average **11045** tokens long in the single-hop subset and **11069** tokens long in the multi-hop subset. Detailed statistics may be found in Appendix Figure 7.

Questions and Answers Given a world state at time t, we query *all* facts about the world. Similar to the news setting, we automate generation of questions and answers through templates. We generate **140** questions per conversation.

5 Experiments

In our experiments, we present articles or conversational turns in chronological order, and periodically ask questions about the state of the world (as described by input documents) at that point in time.

5.1 Evaluation and Metrics

News articles We present the model with a stream of articles ordered by timestamp. As all answers are labeled with a start and end timestamp, we always know which answer is true for a given timestamp.[6] We ask questions at regular intervals corresponding to when 20%, 40%, 60%, 80%, and 100% of the total world state changes have been revealed to the model. Because it is too expensive to ask every question at every timestep, we ask *all questions whose answers have changed* Q, then sample a subset of *questions whose answers have not changed* Q', such that $|Q'| = |Q|$. Each question is multiple choice with challenging alternatives: the model must select between all answers that have been true for the question in the past, present, or future. We report exact-match accuracy.

Conversation We evaluate conversations independently, and report the mean and standard error

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[6] Note that this does not correspond to when these facts became true and false in the real world, but rather to when the article introducing the changed fact was written and read.

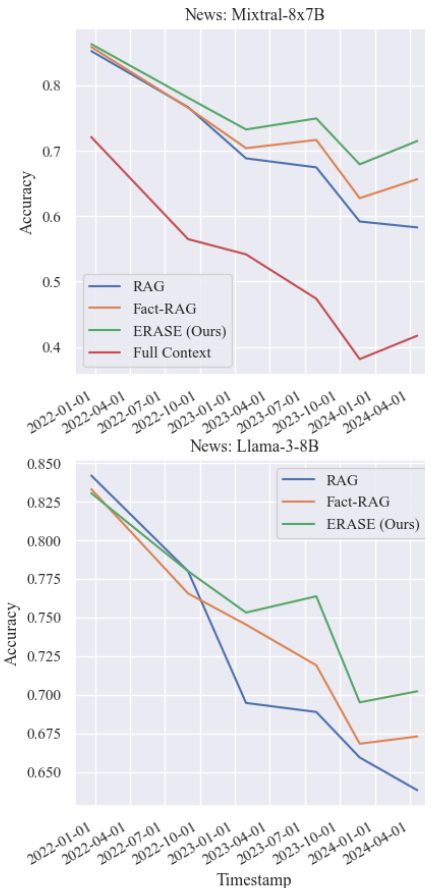

Figure 4: News results for Mixtral-8x7B (top) and Llama-3-8B (bottom). ERASE outperforms all baselines, especially in later timesteps.

of scores. We stream in *chunks* of conversations into the model, and ask questions after each conversation chunk. Similarly to the news domain, we subsample questions whose answers have not changed, such that at each timestep we are asking the same number of questions whose answers have changed as those whose answers haven't changed. For questions that have multiple true answers (e.g. `List all siblings of Liam`), we measure the set equality between the generated and true sets of answers. Otherwise, we use the same exact match accuracy as we use for the news articles domain.

5.2 Models

For our base models, we use a Mixtral 8x7b Instruct model (56B parameters; Jiang et al., 2024) , and Meta's Llama-3 8b Instruct model (8B parameters; AI@Meta, 2024).[7] At both inference and update-time, we sample from the LM with temperature 0. Details about infrastructure and compute can be found in Appendix F. For the encoder $\mathcal{E}$ used in dense retrieval, we use GTR (T5-large; 770M parameters; Ni et al., 2022), both in the inference stage and the retrieval step of updating. We use a fast inner-product search datastructure for efficient retrieval (Douze et al., 2024). During updating, we use the same LM as for inference. During retrieval for updating, we use a similarity threshold of $>$ 0.7 for retrieving facts to update. We restrict the context window to 4096 for the news domain and 2048 for the conversation domain.[8] At inference time, we allow all models to perform zero-shot chain-of-thought.

5.3 Baselines

RAG (Lewis et al., 2020a) stores and retrieves text at the granularity of *passages*. We save each article and conversation chunk as a separate passage in the knowledge base. For long articles and conversation chunks, we divide them into passages of length `context_window / 2`.

Fact-RAG To isolate the effects of *editing*, we benchmark against a version of RAG that stores and retrieves *facts* in the knowledge base, akin to Chen et al. (2023). We implement this baseline by prompting LMs to extract facts from passages, i.e. step 3 of ERASE, which outperformed the propositionizer from Chen et al. (2023).

Long context LMs Mixtral-8x7B has a context window of 32k. We run an in-context learning baseline by conditioning Mixtral on all timestamped news articles or conversation chunks, presented in chronological order. In the Conversations domain, this condition is a skyline since conversations fit completely into the context window.

Self-RAG Much recent work on RAG has focused on improving retrieval or inference. To evaluate how ERASE interacts with these techniques, we run an additional experiment in the news domain *combining* ERASE with Self-RAG (Asai et al., 2024), a state-of-the-art retrieval-based method that uses self-reflection to critique retrieval.

6 Results

Figure 4 and Table 2 show results for news, while Table 3 shows results for conversation.

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[7] Llama-3 8b's knowledge cutoff is March 2023. Mixtral's has not been published, but is likely late 2022 or early 2023.

[8] This is smaller than the original context windows for these models, both to run our experiments efficiently, and to simulate a (realistic) scenario where the total number of changes cannot fit into the context window of an LM.

		Single-hop			Multi-hop		
		0 updates	1 update	2+ updates	0 updates	1 update	2+ updates
Mixtral-8x7B	RAG (Lewis et al., 2020a)	**86.0**$_{\pm 0.7}$	56.7$_{\pm 1.8}$	50.9$_{\pm 3.2}$	**84.5**$_{\pm 0.8}$	**20.9**$_{\pm 1.4}$	20.0$_{\pm 2.3}$
	Fact-RAG (Chen et al., 2023)	82.7$_{\pm 0.8}$	51.5$_{\pm 1.8}$	52.7$_{\pm 3.1}$	81.8$_{\pm 0.8}$	18.0$_{\pm 1.3}$	**30.2**$_{\pm 2.7}$
	ERASE (Ours)	82.0$_{\pm 0.8}$	**59.1**$_{\pm 1.8}$	**57.9**$_{\pm 3.1}$	81.5$_{\pm 0.8}$	**20.1**$_{\pm 1.4}$	27.2$_{\pm 2.6}$
	Full Context	88.8$_{\pm 0.6}$	71.6$_{\pm 1.6}$	75.7$_{\pm 2.4}$	88.4$_{\pm 0.6}$	43.2$_{\pm 1.7}$	54.3$_{\pm 2.8}$
Llama-3-8B	RAG (Lewis et al., 2020a)	**84.4**$_{\pm 0.7}$	57.8$_{\pm 1.8}$	55.2$_{\pm 3.1}$	**83.6**$_{\pm 0.8}$	22.2$_{\pm 0.1}$	26.8$_{\pm 2.6}$
	Fact-RAG (Chen et al., 2023)	82.6$_{\pm 0.8}$	62.6$_{\pm 1.7}$	62.0$_{\pm 3.0}$	81.2$_{\pm 0.8}$	**26.4**$_{\pm 1.6}$	**32.1**$_{\pm 2.8}$
	ERASE (Ours)	82.0$_{\pm 0.8}$	**65.3**$_{\pm 1.7}$	**65.2**$_{\pm 2.9}$	81.0$_{\pm 0.8}$	**26.5**$_{\pm 0.2}$	**31.7**$_{\pm 2.7}$

Table 3: Results on the synthetic conversation domain. Full context serves as a skyline in this domain as the full conversation fits into the context window. We compare against other retrieval-based methods. In **bold** are results that are the **statistically significantly best** out of all other methods in the same setting (model, data subset, # updates). While ERASE significantly improves single-hop edits in both models, it still struggles with multi-hop edits. * We merge 2+ updates as generally there is a long tail of questions with more updates. Only 27 questions total have 3+ updates.

ERASE improves over standard RAG with passage retrieval. For Mixtral and Llama-3 in both domains, we see significant improvements using ERASE, particularly at later timestamps and/or with larger number of edits. Note in general that performance decays as the timestamp increases: the knowledge base becomes more noisy as it becomes contaminated with outdated knowledge. Conflicting, outdated knowledge may be retrieved for a particularly query. By deleting and rewriting old facts, ERASE is able to alleviate some of that noise.

For the conversation domain, we see that RAG with zero updates outperforms ERASE with zero updates: this can largely be explained by storing conversations as propositions (see RAG → Fact-RAG drop), rather than the ERASE method. The fact extraction step can introduce noise through imperfect paraphrase of facts; there is a trade-off between propositions being easy to edit (for knowledge updating), and being potentially noisy.

Editing existing facts improves beyond RAG with fact retrieval. For both Mixtral and Llama-3, ERASE improves over Fact-RAG as the number of edits increases, on both the news domain and the single-hop subset of the conversation domain. Improving knowledge base consistency helps *even combined with extra reasoning during prediction.*

Editing existing facts improves beyond RAG with self-reflection. In addition to offering improvements over standard retrieval methods, ERASE stacks on top of Self-RAG—providing an 11% improvement in accuracy while improving runtime by nearly an order of magnitude.

Editing existing facts reduces forgetting of old facts compared to RAG. Preventing decay of old facts is important for any continual learning system. In Table 4 we run an experiment where we ask RAG and ERASE Mixtral LMs to recover the answer to a question at the initial timestamp, given the state of the knowledge base, first at the *initial timestamp*, then at the *final timestamp*. We evaluate both on our news domain. While both RAG and ERASE demonstrate decay over time, ERASE systems decay less than RAG at reasoning about old information in the presence of new information.

	Initial answer accuracy at...	
	Init TS	Final TS
Mixtral-8x7B + RAG	85.1%	58.2%
Mixtral-8x7B + ERASE	85.9%	64.8%

Table 4: ERASE alleviates forgetting of old facts. We evaluate Mixtral-8x7B with RAG and ERASE on the news domain, and see how well we can recover answers about the initial timestamp (Init TS), given the state of the knowledge base at the final timestamp (Final TS).

In the news domain, ERASE improves over long-context modeling. In Figure 4, we plot Mixtral with its full context window on the news domain. Long-context models are unable to scale as more articles are added. However, we find that ERASE (and retrieval methods generally) are unable to compete against fitting full conversations in the context window Table 3. That said, the cost of conditioning on full conversations was much greater than the cost of conditioning on retrieved facts.

Multi-hop retrieval and editing is still challenging. Both LMs struggle with the multi-hop subset of the conversation dataset. A qualitative examination of failure cases (see Appendix D.1 for some examples) revealed that our retrieval model often failed to retrieve all downstream facts that need to be edited, and language models on the scale of Mixtral-8x7b and Llama-3-8b struggled with reasoning about multi-hop edits. A more powerful retrieval and editing model may be able to avoid these errors.

Editing existing facts is (in realistic use cases) more efficient than long-context and not significantly less efficient than RAG. Generally in the real world, the number of queries far outnumbers the number of documents generated about changes in the world. For example, Forbes reports that only 252,000 websites are created per day,[9] while Google receives about 8.5 billion searches daily.[10] This means that ERASE will not be much less efficient than RAG: with Mixtral in the conversations domain, we find that a typical query costs 1.7K tokens while a typical insertion (update and add) costs 42k tokens. Using the aforementioned number of searches vs. articles written, queries account for roughly 1.4×10^{13} tokens daily, whereas insertions use only 1.1×10^{10} tokens—a thousandfold difference, indicating that query handling dominates costs.

Additionally, conditioning Mixtral on full conversations in context would require 7.3K tokens per query. With the same search and article numbers, full-context conditioning would consume 6.2×10^{13} tokens daily, further underscoring the efficiency of targeted updates.

ERASE errors largely arise from failures to retrieve facts to overwrite and failures during inference We conduct a qualitative error analysis of 30 errors from ERASE with Llama-3-8B on the last timestep of the news domain. A breakdown of the errors can be found in Table 5. We find that the leading source of error comes from failure to retrieve all relevant facts to rewrite during the update stage, followed by failures during inference, followed by failures of the LM to infer over all retrieved facts, followed by not extracting all facts in new articles and failures to retrieve relevant facts during inference in a two-way tie. Notably, we find no cases of errors caused by LM hallucinations introducing factual errors during extraction or updating.

7 Conclusion

This paper introduced ERASE, an approach for *editing existing facts* in a knowledge base when new documents are being inserted. We also introduced two datasets for testing the ability of models to update their knowledge, accompanied by documents that induce those changes. Editing existing facts brings significant improvements to RAG-based models. Even if future models become better at reasoning about inconsistencies with scale, fact editing is useful for amortizing the cost of reasoning about consistency *at insertion time*, rather than having to re-evaluate consistency each time a fact is queried. Future work can focus on improving any part of the update pipeline, particularly focusing on retrieving downstream facts (step 1) that will be affected by an input (which is different from retrieving simply *relevant* facts), and improving LM ability to perform multi-hop updates (step 2).

Error Category	# Errors	% Errors
Retrieval during Updating	8	40%
LM Reasoning during Inference	7	35%
Extraction	6	30%
Retrieval during Inference	6	30%
Other	6	30%

Table 5: Qualitative analysis of thirty error cases in ERASE with Llama-3-8B on the last timestep of the news domain.

Limitations

As noted in Section 6, ERASE is still subpar for multi-hop updates, largely due to retrieval model's inability to retrieve all the necessary facts and the LMs' inability to reason about multi-hop edits. We believe that this limitation can be mitigated with better retrieval models and better LMs.

Second, because LMs have a tendency to hallucinate, allowing LMs to directly edit the knowledge base may introduce noise into the knowledge base. While our results found that the utility of propagation was greater than any hindrance due to such noise, this noise has the potential to snowball on long timescales as the number of new passages and edits grows beyond tens of thousands, hundreds of thousands, or millions. That said, we do not believe this limitation is inherent to knowledge-base editing: future work can explore more principled and rigorous approaches to editing with guarantees around what edits are made and to how many facts. Furthermore, we believe that for any approach to model editing, there is a natural tradeoff between noise and edit coverage.

Finally, having to process each document and update the knowledge base is less efficient than

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[9] `https://www.forbes.com/advisor/business/software/website-statistics/`

[10] `https://seo.ai/blog/how-many-people-use-google`

simply adding it to the retrieval store. We justify this cost by assuming that the number of insertions is far fewer than the number of queries. (For example, Forbes reports that 252,000 websites are created per day,[11] while Google receives about 8.5 billion searches daily.[12]) Thus, by shifting the cost of reasoning about consistency from query-time to insertion-time, ERASE is arguably *more efficient* in practice than RAG.

Ethical Considerations

Being able to interpretably edit models is useful for improving the safety and trustworthiness of models. If there is misinformation in the knowledge base, our method allows these facts to be corrected quickly and these corrections to propagate through the knowledge base. Our method magnifies the effect of each change, making it easy for system designers to keep knowledge up-to-date and remove any stale or incorrect knowledge. Conversely however, this could also empower malicious actors to insert false facts, which will also be propagated through the knowledge base. There will need to be safeguards in place to ensure that any inserted and propagated knowledge is from reliable sources, with potential vetting of each inserted article. One of the pros of ERASE is that we can see every LM operation occurring in real time: any update operation can be examined manually to ensure that the changes are desirable.

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[11] `https://www.forbes.com/advisor/business/software/website-statistics/`

[12] `https://seo.ai/blog/how-many-people-use-google`

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A Prompts for ERASE

In this section, we list all prompts that we use for each step of our method.

A.1 Fact Updating

In practice, we implement these operations by performing *two passes* over the retrieved facts. In the first pass, we prompt the LM with the input d and each fact $f \in R$ and prompt it to *classify* the fact into one of *reinforce, no change, make false*. From this first pass, we divide the retrieved facts into two sets: R_{true}, comprising facts that remain true (*reinforce, no change*), and R_{false}, comprised of facts that have become false (*make false*). In the second pass, we iterate through R_{false}, and prompt the LM to rewrite the fact into a true fact (if possible), conditioned on the new document d and R_{true}. This serves a few purposes:

1. If f is only made partially false by d, we may retain information expressed in f but not d. For example, if f is *Mary and Bob work at UPS*, and d is *Mary got fired from UPS*, we may rewrite f as *Bob works at UPS*, rather than negating the entire fact.
2. Conditioning on R_{true} allows the LM to make *multi-hop* edits. For example, if f is *Mary is coworkers with Bob*, and d is *Mary changed workplaces to Amazon*, if R_{true} contains *Quinn works at Amazon*, then we can rewrite f as *Mary is coworkers with Quinn*.

First round: classifying facts as becoming more or less likely to be true.

```
[Input] [Timestamp: {ts}] {context} [End Input]

The fact "{fact}" was previously true. In light of the input, is "{fact}" likely still true as of {ts}? Begin by summarizing the changes we learned from the input, then reasoning briefly about them to give your final answer with "Answer: Reinforce" (if the input makes the fact more likely) or "Answer: Make False" (if the input makes the fact less likely) or "Answer: No Change" (if the input doesn't affect the fact, e.g. if the input is irrelevant to the fact). Assume that the fact is still true (keep true) if nothing in the input contradicts it.
```

Second round: extracting rewrites

```
[Input] [Timestamp: {ts}] {context}
Other True Facts at {ts}: {", ".join(still_true_facts)}
[End Input]

The fact "{fact}" was previously true but no longer. Given the above input and true facts, can you rewrite it into one that is true as of {ts}? Output your answer in form "rewrite: rewritten fact" or "no rewrite possible".
```

A.2 Fact Extraction

```
Extract all facts from the input text, with each fact on a new line and without bullet points or numbered lists. Facts should be simple, independent, standalone, and decontextualized. Break up long facts into smaller facts. Resolve all references (e.g. pronouns, definite articles, etc.) by copying full reference object everywhere it is referenced. Only include facts referring to the current world state (what is true *now*), as opposed to facts true in the past. If there are no facts, please output "No new facts." Do not include any other text.
```

A.3 Inference

Given a question `question` at timestep `ts` (and choices `answer_choices`), We first retrieve facts $f_i, [(\tau_{i0}, v_{i0}), (\tau_{i1}, v_{i1}), \cdots]$ from the knowledge base with similarity threshold > 0.7 to `question`. We then prompt a LM with the following:

```
Read the statements/passages below then answer the question below

***BEGIN STATEMENTS***
{f_i} ({v_{i0}} at {tau_{i0}}, {v_{i1}} at {tau_{i1}}, ...)
```

```
{f_j} ({v_{j0}} at {tau_{j0}}, {v_{j1}} at {tau_{j1}}, ...)
...
***END STATEMENTS***

Given the above statements are true and any prior knowledge you have, answer the following question at timestep {ts}?:
{question}

Briefly reason then answer with one of: {answer_choices}.
```

For questions requiring list answers (e.g. list all the siblings of Rachel), we replace the last line with:

```
Briefly reason then answer with a JSON list, ["item1", "item2", ...], of zero or more of the following items: {answer_choices}. If you include any of the above items, make sure to copy their names exactly as is from the list. Your list may be empty, [], if none of the answers are true.
```

B Dataset Construction Details

B.1 News Articles

We construct this dataset in three stages:

Extracting World States W**.** We retrieve `(subj,rel)` pairs from Wikidata for which there are at least two distinct fact relations at different timestamps, e.g. `(subj,rel,obj1,start_ts1,end_ts1)` and `(subj,rel,obj2,start_ts2,end_ts2)`. These timestamped facts are used to "represent" W. We filter for subjects `subj` located in English-speaking countries to ensure we can find English-language sources. We use SPARQL[13] to obtain a set of `(subj,rel)` pairs.

Obtaining Documents L**.** We annotate each timestamped relation, `(subj,rel,obj,start_ts, end_ts)` with a source written between `start_ts` and `end_ts` (preferably close to the `start_ts`) stating that the `(subj,rel,obj)` relation is true. We crowdsource annotations from Prolific in two stages. In the first stage, Prolific annotators were presented with an interface which scraped candidate news articles off of Google[14], and were asked to select sources which stated that the fact `(subj,rel,obj,start_ts, end_ts)` is true, but **did not** state that any succeeding fact, `(subj,rel,obj2,start_ts2, end_ts2)` where `start_ts2` > `start_ts`, is true. In the second stage, we validated Prolific annotations from the first stage by presenting articles from the first round of annotations to annotators in the second round, and asking users whether those articles contained the fact in question. If second annotator does not affirm the fact is present in the article, we throw out the fact and the associated annotation. We do an additional third round of filtration with a language model, asking the language model to affirm that the text of an article contains `(subj,rel,obj,start_ts, end_ts)` but not any succeeding facts `(subj,rel,obj2,start_ts2, end_ts2)`. We only include articles and facts that pass all three rounds of annotation. We recruited English-speaking participants from the US for annotations for all annotations. The full set of instructions we give annotators can be found in Tables 6 and 7. Screenshots of the interface can be found in Figures 5 and 6.

Generating Question-Answers Pairs $(q, \{a\})$**.** We automate generation of questions and answers from W by writing templates for each relation and generating questions and answers from those templates. The full list of templates can be found in Table 8.

Prolific Details We recruited a total of 680 English-speaking prolific annotators from the United States, with each annotator spending an average of 16:50 minutes on the task (∼ 7 minutes to read and understand instructions). We paid annotators an average of $14.20 per hour. This task was deemed exempt from IRB review. No personally-identifiable information was collected or stored, and all prolific annotators were associated with an anonymous prolific ID.

B.2 Synthetic Conversations

We also construct this dataset in three stages:

---

[13] https://www.w3.org/TR/sparql11-query/

[14] In particular, we set the to-be-matched parameter of the search to "news", i.e. https://www.google.com/?tbm=nws

Please read these instructions carefully and only proceed once you have understood them. Once you start the task, you will have 10 minutes to get through as many questions as possible.
For each question, you will be presented a fact. Please find a news article that implies that the fact is true, according to the below requirements:

1. The article implies the fact, such that a reasonable person, without any prior knowledge, can infer that the fact is true from reading the article.

   Example: For fact Emad Mostaque is CEO of Stability AI (was True from 2020 to 2024-03-23)

   Good Sources: This startup is setting a DALL-E 2-like AI free, consequences be damned: Article says "...Stability AI CEO and founder Emad Mostaque wrote in a blog post"

   Bad Sources: Artists can now opt out of the next version of Stable Diffusion: Cannot conclude fact from text of article

2. The article is a news article or blog post.

   Example: For fact Taylor Aylmer is a member of the Racing Louisville FC sports tea

   Good Sources: Team News: Aylmer to make first regular season start

   Bad Sources: Taylor Aylmer - Racing Louisville FC Midfielder - ESPN, Taylor Aylmer - Instagram

3. The fact is stated in the main body of the article text, not in a table, list, image, image caption, embedded tweet, etc.

   Example: For fact Taylor Aylmer is a member of the Racing Louisville FC sports team

   Good Sources: Team News: Aylmer to make first regular season start, Recap: Racing rallies to beat Orlando, keep playoff hopes alive: Fact is in a list at the end, not the main text

   Bad Sources: Jaelin Howell, Racing Louisville bring community together to help people with Down syndrome: Fact is in an image caption but nowhere in the main text

4. The article is a web page, not a PDF or other file format.

   Example: For fact Ali Shojaie is a IMS Fellow

   Good Sources: Ali Shojaie elected fellow of the Institute of Mathematical Statistics

   Bad Sources: IMS Carver Award 2023: Source is a PDF file, not a web page

5. The article is written in English.

   Example: For fact Emad Mostaque is CEO of Stability AI (was True from 2020 to 2024-03-23)

   Good Sources: This startup is setting a DALL-E 2-like AI free, consequences be damned

   Bad Sources: [Bengali article]: Article is not in English

6. Avoid articles that state that the fact is or is about to become false. These are generally written near or past the end date of a fact being true.

   Example: For fact Emad Mostaque is CEO of Stability AI (was True from 2020 to 2024-03-23)

   Good Sources: This startup is setting a DALL-E 2-like AI free, consequences be damned

   Bad Sources: Stability AI founder Emad Mostaque plans to resign as CEO, sources say: Article is about the fact being about to be false

If no listed articles satisfy these requirements, you have the option to either find a news article that satisfies the requirements (a google search link is provided for reference, you may need to manually adjust the query or date parameters) or selecting "cannot find source" if you cannot find any source in a reasonable amount of time.
There may also be a second fact that you need to avoid. If you see this fact in the article, do not select it as a source.
Tip: You may use "ctrl-f" (find tool) to quickly validate whether or not a fact is in the article.

Table 6: Instructions for round 1 of annotation for news article.

Please read these instructions carefully and only proceed once you have understood them. Once you start the task, you will have 12 minutes to get through as many questions as possible.
For each question, you will be presented a fact and a news article. Please confirm that the news article implies that the fact is true, and conforms to the below requirements:

1. The article implies the fact, such that a reasonable person, without any prior knowledge, can infer that the fact is true from reading the article.

   Example: For fact Emad Mostaque is CEO of Stability AI (was True from 2020 to 2024-03-23)

   Good Sources: This startup is setting a DALL-E 2-like AI free, consequences be damned: Article says "...Stability AI CEO and founder Emad Mostaque wrote in a blog post"

   Bad Sources: Artists can now opt out of the next version of Stable Diffusion: Cannot conclude fact from text of article

2. The article is written in English.

   Example: For fact Emad Mostaque is CEO of Stability AI (was True from 2020 to 2024-03-23)

   Good Sources: This startup is setting a DALL-E 2-like AI free, consequences be damned

   Bad Sources: [Bengali article]: Article is not in English

3. Avoid articles that state that the fact is or is about to become false. These are generally written near or past the end date of a fact being true.

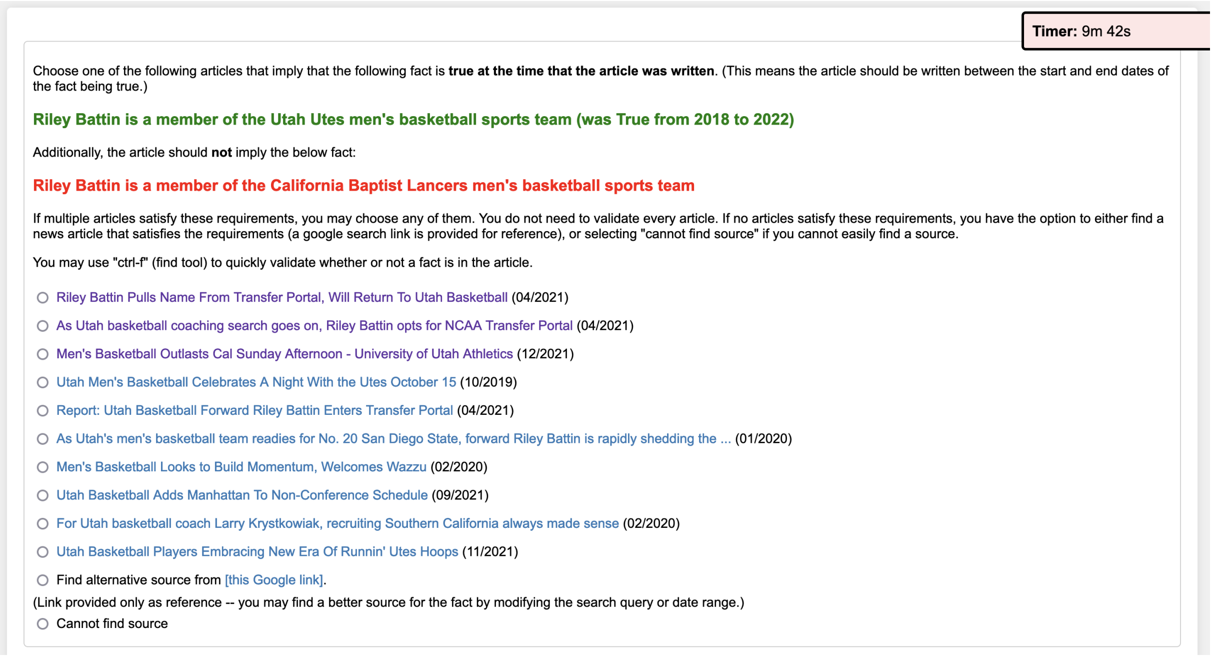
   Example: For fact Emad Mostaque is CEO of Stability AI (was True from 2020 to 2024-03-23)

   Good Sources: This startup is setting a DALL-E 2-like AI free, consequences be damned

   Bad Sources: Stability AI founder Emad Mostaque plans to resign as CEO, sources say: Article is about the fact being about to be false

If the provided article does not satisfy these requirements, you have the option to either find a news article that satisfies the requirements (a google search link is provided for reference, you may need to manually adjust the query or date parameters) or selecting "cannot find source" if you cannot find any source in a reasonable amount of time.
There may also be a second fact that you need to avoid. If you see this fact in the article, do not select it as a source.
Tip: You may use "ctrl-f" (find tool) to quickly validate whether or not a fact is in the article.

Table 7: Instructions for round 2 of annotation for news article.



Timer: 9m 42s

Choose one of the following articles that imply that the following fact is **true at the time that the article was written**. (This means the article should be written between the start and end dates of the fact being true.)

Riley Battin is a member of the Utah Utes men's basketball sports team (was True from 2018 to 2022)

Additionally, the article should **not** imply the below fact:

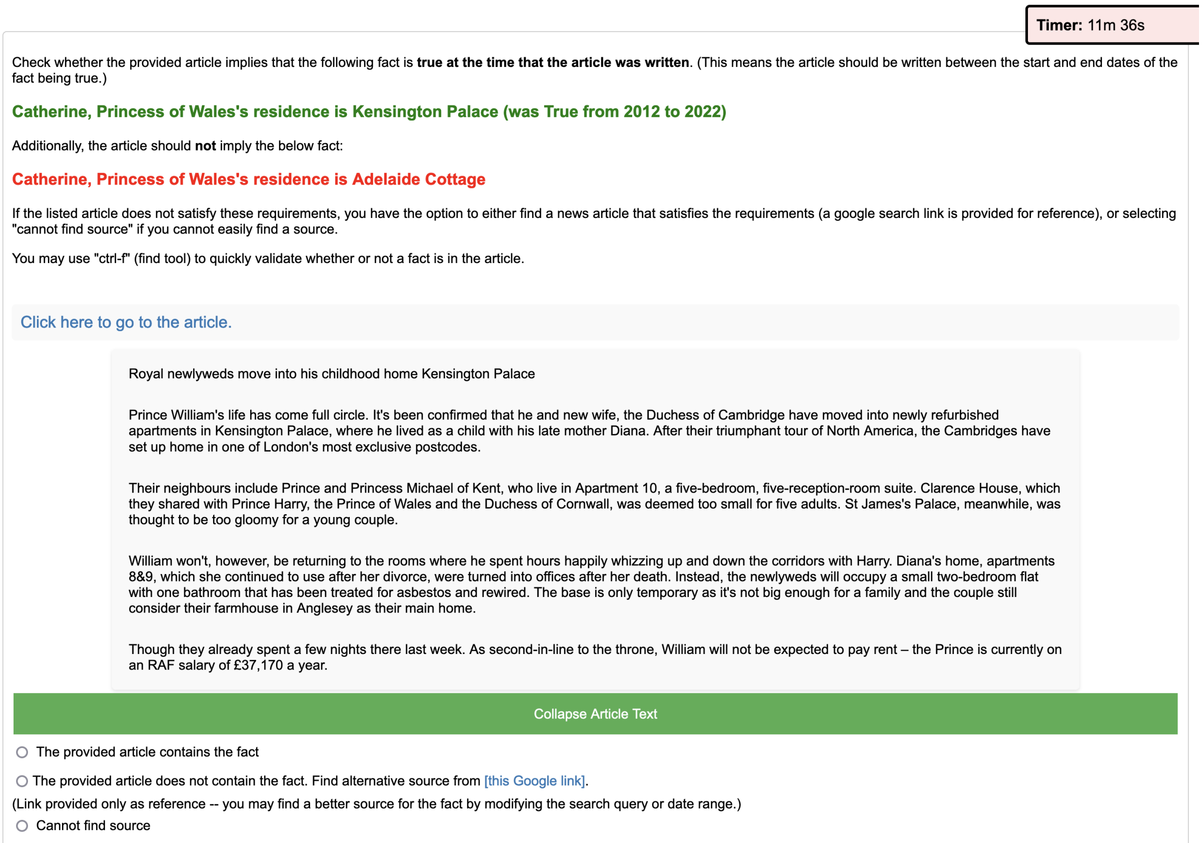
Riley Battin is a member of the California Baptist Lancers men's basketball sports team

If multiple articles satisfy these requirements, you may choose any of them. You do not need to validate every article. If no articles satisfy these requirements, you have the option to either find a news article that satisfies the requirements (a google search link is provided for reference), or selecting "cannot find source" if you cannot easily find a source.

You may use "ctrl-f" (find tool) to quickly validate whether or not a fact is in the article.

○ Riley Battin Pulls Name From Transfer Portal, Will Return To Utah Basketball (04/2021)
○ As Utah basketball coaching search goes on, Riley Battin opts for NCAA Transfer Portal (04/2021)
○ Men's Basketball Outlasts Cal Sunday Afternoon - University of Utah Athletics (12/2021)
○ Utah Men's Basketball Celebrates A Night With the Utes October 15 (10/2019)
○ Report: Utah Basketball Forward Riley Battin Enters Transfer Portal (04/2021)
○ As Utah's men's basketball team readies for No. 20 San Diego State, forward Riley Battin is rapidly shedding the ... (01/2020)
○ Men's Basketball Looks to Build Momentum, Welcomes Wazzu (02/2020)
○ Utah Basketball Adds Manhattan To Non-Conference Schedule (09/2021)
○ For Utah basketball coach Larry Krystkowiak, recruiting Southern California always made sense (02/2020)
○ Utah Basketball Players Embracing New Era Of Runnin' Utes Hoops (11/2021)
○ Find alternative source from [this Google link].
(Link provided only as reference -- you may find a better source for the fact by modifying the search query or date range.)
○ Cannot find source

Figure 5: Screenshot of round 1 of annotation for news article.



Timer: 11m 36s

Check whether the provided article implies that the following fact is **true at the time that the article was written**. (This means the article should be written between the start and end dates of the fact being true.)

Catherine, Princess of Wales's residence is Kensington Palace (was True from 2012 to 2022)

Additionally, the article should **not** imply the below fact:

Catherine, Princess of Wales's residence is Adelaide Cottage

If the listed article does not satisfy these requirements, you have the option to either find a news article that satisfies the requirements (a google search link is provided for reference), or selecting "cannot find source" if you cannot easily find a source.

You may use "ctrl-f" (find tool) to quickly validate whether or not a fact is in the article.

Click here to go to the article.

Royal newlyweds move into his childhood home Kensington Palace

Prince William's life has come full circle. It's been confirmed that he and new wife, the Duchess of Cambridge have moved into newly refurbished apartments in Kensington Palace, where he lived as a child with his late mother Diana. After their triumphant tour of North America, the Cambridges have set up home in one of London's most exclusive postcodes.

Their neighbours include Prince and Princess Michael of Kent, who live in Apartment 10, a five-bedroom, five-reception-room suite. Clarence House, which they shared with Prince Harry, the Prince of Wales and the Duchess of Cornwall, was deemed too small for five adults. St James's Palace, meanwhile, was thought to be too gloomy for a young couple.

William won't, however, be returning to the rooms where he spent hours happily whizzing up and down the corridors with Harry. Diana's home, apartments 8&9, which she continued to use after her divorce, were turned into offices after her death. Instead, the newlyweds will occupy a small two-bedroom flat with one bathroom that has been treated for asbestos and rewired. The base is only temporary as it's not big enough for a family and the couple still consider their farmhouse in Anglesey as their main home.

Though they already spent a few nights there last week. As second-in-line to the throne, William will not be expected to pay rent – the Prince is currently on an RAF salary of £37,170 a year.

○ The provided article contains the fact

○ The provided article does not contain the fact. Find alternative source from [this Google link].

(Link provided only as reference -- you may find a better source for the fact by modifying the search query or date range.)

○ Cannot find source

Figure 6: Screenshot of round 2 of annotation for news article.

`({subj}, employer, {obj})`	`Who is the employer of {subject}?`
	`Is {subject} an employee of {object}?`

`({subj}, chief executive officer, {obj})`	`Who is the CEO of {subject}?`
	`What company is {object} the CEO of?`
	`Is {object} the CEO of {subject}?`

`({subj}, chairperson, {obj})`	`Who is the chairperson of {subject}?`
	`What organization is {object} the chairperson of?`
	`Is {object} the chairperson of {subject}?`

`({subj}, head of state, {obj})`	`Who is the head of state of {subject}?`
	`Where is {object} the head of state of?`
	`Is {object} the head of state of {subject}?`

`({subj}, position held, {obj})`	`What government position does {subject} hold?`
	`Does {subject} hold government position {object}?`

`({subj}, member of sports team, {obj})`	`What sports team is {subject} a member of?`
	`Is {subject} a member of {object}?`

`({subj}, unmarried partner, {obj})`	`Who is the unmarried partner of {subject}?`
	`Who is the unmarried partner of {object}?`
	`Is {object} the unmarried partner of {subject}?`

`({subj}, residence, {obj})`	`Where does {subject} reside?`
	`Does {subject} reside in {object}?`

`({subj}, headquarters location, {obj})`	`Where is the headquarters location of {subject}?`
	`Is the headquarters location of {subject} in {object}?`

`({subj}, P463, {obj})`	`What organization is {subject} a member of?`
	`Is {subject} a member of {object}?`

`({subj}, member of political party, {obj})`	`What political party is {subject} a member of?`
	`Is {subject} a member of {object}?`

Table 8: Question-answer templates in the News domain

Generating World States W. We model the underlying world and its transformations as a Markov chain with states S and a set of allowable transitions $T(S)$ determined by S. At each timestep, we randomly sample a transition from $T(S)$ uniformly at random. States S are described by a set of relations `(subj, rel, obj)`. The full list of entities types and relations for each entity type can be found in Table 9. To construct each world, we subsample 10 people and 5 companies, and randomly initialize their kinship and employment relations. Transitions $t \in T(S)$ change one or more relation in the state. To be able to test the limits of our propagation, the set of transitions we define in this domain all change more than one relation: for example, "*Bob changed jobs to work at Google*" changes the *employees* of Google, the set of *coworkers* of Bob, the set of *coworkers* of all Google employees, and the set of *coworkers* of all employees of Bob's former company, etc. The full list of transitions and their downstream effects can be found in Table 10.

Generating Conversations L. We generate conversations by sampling two people in the world p_1 and p_2 and prompting two LLMs with their corresponding personas and initial facts. We then generate twelve conversation "chunks" as follows: We begin by sampling the next transition we want to make in the world. The transition corresponds to a natural language string that corresponds to only a single relation. However, we know that each transition is associated with multiple changing relations. To be able to infer the *downstream* changes of a single relation changing, we need to know auxiliary facts related to the *object* of the changed relation. In the multi-hop subset of this dataset, we mention auxiliary facts in the *prior* conversation chunks, while only mentioning the immediate transition (on a single relation) in the current chunk (*without* mentioning any downstream changes). Thus, to make the correct downstream inferences on this subset, the system must retrieve and reason across facts from prior conversation chunks.

For the singlehop subet, we mention *all downstream effects* in the same conversation chunk that a transition is made.

Generating Question-Answers Pairs $(q, \{a\})$. Given a world state at time t, we query *all* facts about the world. Similar to the news setting, we automate generation of questions and answers through templates. Templates in this setting can be found in Table 11.

C Dataset Statistics

The breakdown of changes in each of our datasets can be found in Table 12 for news articles and Figure 7 for conversations. The breakdown of questions for conversations can be found in Table 13.

D Qualitative Analysis

D.1 Error Analysis: Conversations (Multihop)

Prototypical examples of multihop edit errors can be found below:

Retrieval Errors Sometimes, the full list of facts that need to be updated are not retrieved. For example:

Input conversation chunk:

> *2023-11-01*
>
> *Katie: Hey Olivia! How have you been? Guess what? I've changed my job to Library Assistant at Central Public Library! What's new with you?*
>
> *Olivia: Hey Katie! That's amazing news! Congrats on the new job as a Library Assistant at Central Public Library!*
>
> ...

Retrieved facts:

- *The role of General Practitioner at HealthFirst Medical Clinic is a full-time job.*
- *The role of Library Assistant at Central Public Library is a full-time job.*
- *Rachel has a full-time job as a Medical Assistant at HealthFirst Medical Clinic.*
- *Rachel works at HealthFirst Medical Clinic as a Medical Assistant.*
- *The work hours of a Library Assistant at Central Public Library are from 9 to 17.*
- *Katie works full-time at the Urban Development Project.*
- *Olivia works full-time at the airport.*
- *The salary for a Library Assistant at Central Public Library is $80,000.*
- *Peter works from 9 to 17 at the Central Public Library.*

Entity Type	Possible Relations
Person	spouse, parents, children, job, company, hobbies, coworkers, work location, boss, salary, industry, is-employed-full-time, work hours, workplace, siblings, parents-in-law, children-in-law, step-parents, step-children, equipment necessary for hobbies
Company	employees, jobs, head, location, industry, workplace type
Job	company, salary, is-full-time, work hours
Hobby	equipment necessary for hobby

Table 9: Full list of entities and relations defining each world state in the Conversation domain.

Transition type	Downstream effects
`person.job` changes from `job1` to `job2`	person.company, person.coworkers, person.work-location, person.boss, person.salary, person.industry, person.is-employed-full-time, person.work-hours, person.workplace, job1.company.employees, job2.company.employees
`person.spouse` changes from `person1` to `person2`	person.parents-in-law, person.parents.children-in-law, person.children.step-parents, person.step-children, person1.spouse, person1.parents-in-law, person1.parents.children-in-law, person2.spouse, person2.parents-in-law, person2.parents.children-in-law, person2.children.step-parents, person2.step-children
`person` adopts `child`	person.children, child.parents, child.siblings, child.spouse.parents-in-law, person.children-in-law, child.step-parents, person.spouse.step-children, person.children.siblings
`person` gets a new hobby `hobby`	person.equipment-necessary-for-hobbies
`job.salary` changes	for all people that have that job: person.salary
`job.work-hours` changes	for all people that have that job: person.work-hours

Table 10: Full list of possible state transitions in the Conversation domain. Note the set of available transitions may vary depending on the underlying state.

`({subj}, spouse, {obj})`	`Who is the spouse of {subj}?`
	`Who is the spouse of {obj}?`

`({subj}, job, {obj})`	`What is the job of {subj}?`
`({subj}, company, {obj})`	`Which company does {subj} work at?`
`({subj}, hobbies, {obj})`	`List all known hobbies of {subj}.`
`({subj}, coworkers, {obj})`	`List all known coworkers of {subj}.`
`({subj}, work location, {obj})`	`In which city does {subj} work?`
`({subj}, boss, {obj})`	`Who is the head of {subj}'s workplace?`
`({subj}, salary, {obj})`	`What is the salary of {subj}?`
`({subj}, industry, {obj})`	`What industry does {subj} work in?`
`({subj}, is-employed-full-time, {obj})`	`Does {subj} work full-time or part-time?`
`({subj}, work-hours, {obj})`	`What are the work hours of {subj}?`
`({subj}, workplace, {obj})`	`What type of workplace does {subj} work out of?`
`({subj}, parents, {obj})`	`List all parents of {subj}.`
`({subj}, children, {obj})`	`List all children of {subj}.`
`({subj}, siblings, {obj})`	`List all siblings of {subj}.`
`({subj}, parents-in-law, {obj})`	`List all parents-in-law of {subj}.`
`({subj}, children-in-law, {obj})`	`List all children-in-law of {subj}.`
`({subj}, step-parents, {obj})`	`List all step-parents of {subj}.`
`({subj}, step-children, {obj})`	`List all step-children of {subj}.`
`({subj}, necessary equipment for hobby, {obj})`	`List all equipment {subj} needs for their hobbies.`

Table 11: Question-answer templates in the Conversation domain

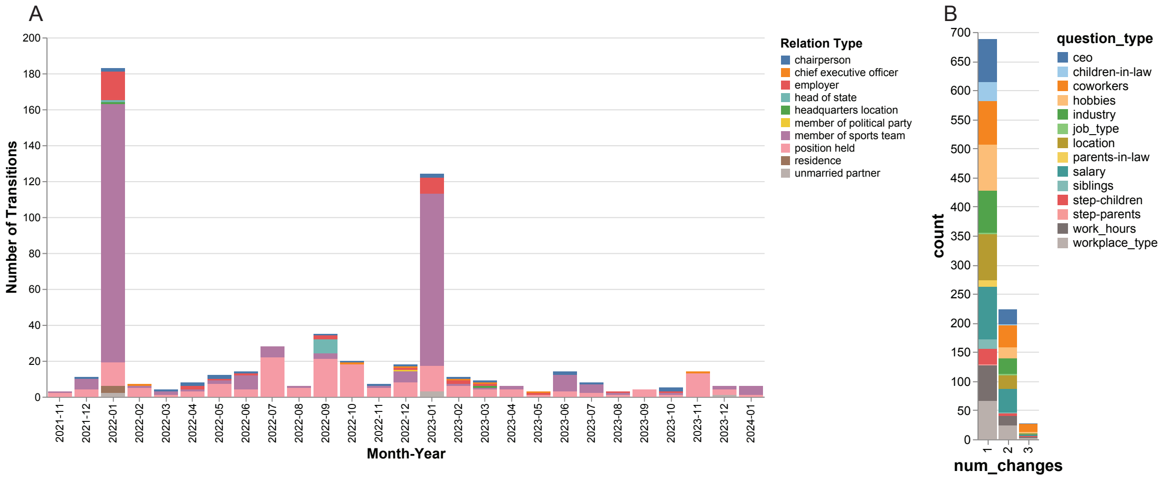


Figure 7: Distribution of changed relation types in the (A) News and (B) Conversation domains. (A) depicts the number of transitions per year of each month, while (B) depicts the number of relation types that underwent that number of changes across all conversations.

Relation type	`# (s, r)`	`# (s, r, o)`
Member of sports team	284	382
Position held	164	382
Employer	38	77
Chairperson	20	42
Head of state	9	18
CEO	6	13
Unmarried partner	5	12
Residence	4	8
Headquarters	2	4
Member of political party	1	2
Total	533	1174

Table 12: Breakdown of changed relation types in the News domain, categorized by number of unique `(subj, rel)` pairs and `(subj, rel, obj)` triples.

Question Topic	# Yes/No	# Multiple Choice	# MC Choices
Boss	140	74	26
Coworkers	481	-	-
Industry	-	74	26
Is employed full-time	82	-	-
Salary	158	80	11
Work hours	110	64	10
Work Location	274	72	20
Workplace	140	74	26
Total	1385	438	

Table 13: Distribution of generated questions in the Synthetic Conversation domain, categorized by question topic and type.

- *Diana and Liam both have full-time jobs at the Urban Development Project.*
- *The salary of an Archivist at Central Public Library is $130,000.*

The retriever at step 1 failed to retrieve the following facts to update. At inference time, these facts were retrieved and affected the LM's answer on questions:

- *Katie's working hours are from 10 to 15.*
- *Katie's salary is $100000.*
- *Diana and Liam work with Katie.*

Updating Errors Sometimes, facts that needed to be updated were retrieved, but were not updated by the LM. For example,

Input conversation chunk:

> *2023-11-26*
>
> *Katie: Hey Olivia! How have you been? I heard you changed your job to Safety Officer at Urban Development Project! How's the new role treating you?*
>
> *Olivia: Hey Katie! Yes, I did change my job to Safety Officer at Urban Development Project! The new role has been quite a change, but I'm really enjoying it so far. How have you been?*
>
> ...

Retrieved fact:

- *Olivia works from 9 to 17 at her job.*

Model-outputted update (and reasoning):

```
Summary of changes:


    Olivia changed her job to Safety Officer at Urban Development Project.

    No information is provided about Olivia's work schedule.


Reasoning:

The input does not provide any information that would suggest Olivia's work schedule has changed. The conversation is about Olivia's new job, Katie's hobbies, and their plans for social activities. There is no mention of Olivia's work schedule or any changes that would affect it. Therefore, the fact "Olivia works from 9 to 17 at her job" is likely still true as of 2023-11-01.

Answer: No Change
```

Note that this fact should've been flagged for potential updating and forwarded to the rewrite step (where the LM has an opportunity to retrieve more facts to confirm or deny this fact). However, the LM does not classify this fact as *make false* because it is not directly contradicted by the input.

E Use of AI Assistants

Code was written with Co-pilot turned on. GPT* models were also consulted for creating acronyms for the method and dataset names.

F Compute requirements

For Mixtral 8x7b Instruct, we queried using Together AI[15]. For Meta's Llama-3 8b Instruct model, we used a local copy run on one NVIDIA A100 GPU.

Inference and updating took a few hours to complete for both models and methods.

---

[15] https://www.together.ai/