

# RecallM: An Architecture for Temporal Context Understanding and Question Answering

Brandon Kynoch  
Cisco Systems  
Austin, Texas  
kynochb@utexas.edu

Hugo Latapie  
Cisco Systems  
Milpitas, CA  
hlatapie@cisco.com

**Abstract**—The ideal long-term memory mechanism for Large Language Model (LLM) based chatbots, would lay the foundation for continual learning, complex reasoning and allow sequential and temporal dependencies to be learnt. Creating this type of memory mechanism is an extremely challenging problem. In this paper we explore different methods of achieving the effect of long-term memory. We propose a new architecture focused on creating adaptable and updatable long-term memory for AGI systems. We demonstrate through various experiments the benefits of the RecallM architecture, particularly the improved temporal understanding of knowledge it provides.

**Index Terms**—question answering, LLM, vector database, graph database, in-context learning, temporal relations, neuro-symbolic processing, long-term memory, knowledge graph

## I. INTRODUCTION

Since their inception, Large Language Models (LLMs) have drastically changed the way that humans interact with Artificial Intelligence (AI) systems. In recent years LLMs have demonstrated remarkable capabilities across a large variety of tasks and domains, making these models an even more promising foundation for achieving true Artificial General Intelligence (AGI) [8] [2]. However, an ideal AGI system should be able to adapt, comprehend and continually learn when presented with new information, this is something that LLMs cannot achieve on their own. Hence, we have started to see a growing interest in supplementing LLMs and chatbots with vector databases to achieve the effect of long-term memory. This method of storing and retrieving information in a vector database allows us to overcome the context window limitation imposed by LLMs, allowing these models to answer questions and reason about large corpuses of text [14]. While vector databases in general provide a very good solution to question answering over large texts, they struggle with belief updating and temporal understanding, this is something that the RecallM architecture attempts to solve.

RecallM, moves some of the data processing into the symbolic domain by using a graph database instead of a vector database. The core innovation here is that by using a lightweight neuro-symbolic architecture, we can capture and update advanced relations between concepts which would otherwise not be possible with a vector database. We demonstrate through various experiments the superior

temporal understanding and updatable memory of RecallM when compared to using a vector database. Furthermore, we create a more generalized hybrid architecture that combines RecallM with a vector database (Hybrid-RecallM) to reap the benefits of both approaches.

**Our code is publicly available online at:**  
<https://github.com/cisco-open/DeepVision/tree/main/recallm>

## II. BACKGROUND AND RELATED WORKS

Modarressi et al. present Ret-LLM [7], a framework for general read-write memory for LLMs. The Ret-LLM framework extracts memory triplets from provided knowledge to be stored and queried from a tabular database. Ret-LLM makes use of a vector similarity search similar to query memory. Ret-LLM demonstrates promising capabilities, although the authors do not provide any quantitative results suggesting the improvement over previous techniques. We demonstrate in our works that RecallM can handle similar scenarios, furthermore, we conduct large scale question answering tests with quantitative results. We show RecallM’s promising capabilities even when provided with large text corpuses with non-related data that would otherwise confuse the system.

Memorizing Transformers by Wu et al. [13], introduce the idea of kNN-augmented attention in transformer models. In their approach they store key-value pairs in long term memory, these values are then retrieved via k-Nearest-Neighbours (kNN) search and included in the final transformer layers of a LLM model. Our goals and approach differ from memorizing transformers as we attempt to build a system with long-term memory which is adaptable at inference time, whereas their approach requires pretraining or fine-tuning. They use 32-TPU cores to run their experiments, whereas we only use a consumer-grade pc with a 980Ti GPU and the OpenAI API for LLM calls<sup>1</sup>. Their experiments demonstrate that external memory benefited most when attending to rare words such as proper names, references, citations, functions names etc.,

<sup>1</sup>OpenAI api available online at: <https://openai.com>

hence the motivation for our concept extraction techniques discussed later.

Wang et al. introduce LongMem, an approach to long-term memory for LLMs that improves upon Memorizing Transformers by focusing on sparse attention to avoid the quadratic cost of self-attention while also solving the memory staleness problem [11]. Memory staleness refers to when the memories learnt in the Memorizing Transformer model suffer from parameter changes of subsequent training iterations. LongMem solves the staleness problem by using a non-differentiable memory bank. They show that their approach significantly outperforms Memorizing Transformers.

Zhong et al. highlight the importance of long-term memory for scenarios involving sustained interaction with LLMs and focus on creating long-term memory for AI companion applications with their memory mechanism called ‘Memory Bank’ [15]. Memory bank stores memory in a large array structure while capturing temporal information using timestamps for each piece of dialogue. Memory bank uses a vector similarity search to retrieve memories. The authors implement a simple memory updating mechanism inspired by the Ebbinghaus Forgetting Curve. They demonstrate that using long-term memory they are able to elicit more empathetic and meaningful response from chatbots in an AI companion scenario. Memory Bank is conceptually similar to RecallM in many regards, however, we suggest that the RecallM architecture has several benefits over Memory Bank including a more advanced memory updating mechanism, complex relationship modelling, improved temporal architecture, and in many scenarios, one-shot belief updating.

Dhingra et al. discuss the challenges of temporally scoped knowledge in pretrained models in their paper, ‘Time-Aware Language Models as Temporal Knowledge Bases’ [3]. The authors introduce the idea of temporal context and present a modification to the masked token language modelling objective whereby they include the time of the textual content in the training objective. They show that by modifying the learning objective for pretrained language models (LMs) to include temporal information, they can improve the memorization of facts. However, since their approach is focused on changing the pretraining objective, it cannot be applied to an adaptive AGI system as discussed earlier.

In our experiments we use the Truthful Question Answering dataset (TruthfulQA) to test for RecallM’s ability to update the intrinsic beliefs of the LLM [5]. The TruthfulQA dataset was designed to test LLMs for imitative falsehoods. Imitative falsehoods occur when the models training objective actually incentivizes false answers. This occurs quite frequently with models which have been trained on extremely large corpuses of text gathered from the internet. It is common knowledge that the internet contains a lot of false information, and this false information is often repeated. Interestingly, TruthfulQA

also demonstrates that scaling up the LLMs actually produces more imitative falsehoods – this phenomenon is referred to as ‘inverse scaling’. The reason for this is that scaling up the model should reduce the perplexity on the training distribution, and hence this increases the frequency of imitative falsehoods since these falsehoods occur frequently in the training data. TruthfulQA measures models on two metrics, the truthfulness of answers and whether the answers are informative or not. The study found that the best performing model was GPT3 being truthful on 58% of the questions, while the human performance baseline was 94%. In our work, we scrape the web sources cited in the TruthfulQA dataset and use these web pages to perform a one-shot knowledge update on the system assuming that the information found in these web pages is the ground truth. We then test system using the question/answer pairs from TruthfulQA.

### III. SYSTEM ARCHITECTURE

RecallM functions like a typical chatbot although with the additional functionality that the user can provide new information to the system in natural language and it will retain and recall this knowledge when necessary when questioning the system. Hence, RecallM has two main processes: the **knowledge update**, and **questioning the system**. An additional benefit of the RecallM architecture is that through normal usage of the system, the knowledge update process builds a persistent knowledge graph that could be used for many other applications.

#### A. Knowledge Update

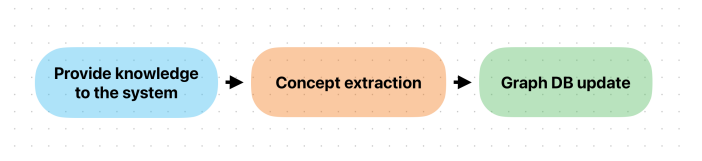


Fig. 1: Overview of the knowledge update pipeline

Figures 1 and 2 demonstrate the process of performing a knowledge update. When providing the system with knowledge in the form of natural language text, we begin by extracting concepts and concept relations. In this paper we use the abstract term ‘**concept**’ to refer to any entity, idea or abstract noun that we can think, reason or talk about. A concept is something that has specific properties, truths and beliefs relating to that concept – we refer to this as the **context**. We refer to the name of the concept as the **concept label**.

Initially, we used a Named Entity Recognition (NER) model to identify concept labels in the source text, whereas the current approach utilizes a Part of Speech (POS) tagger to

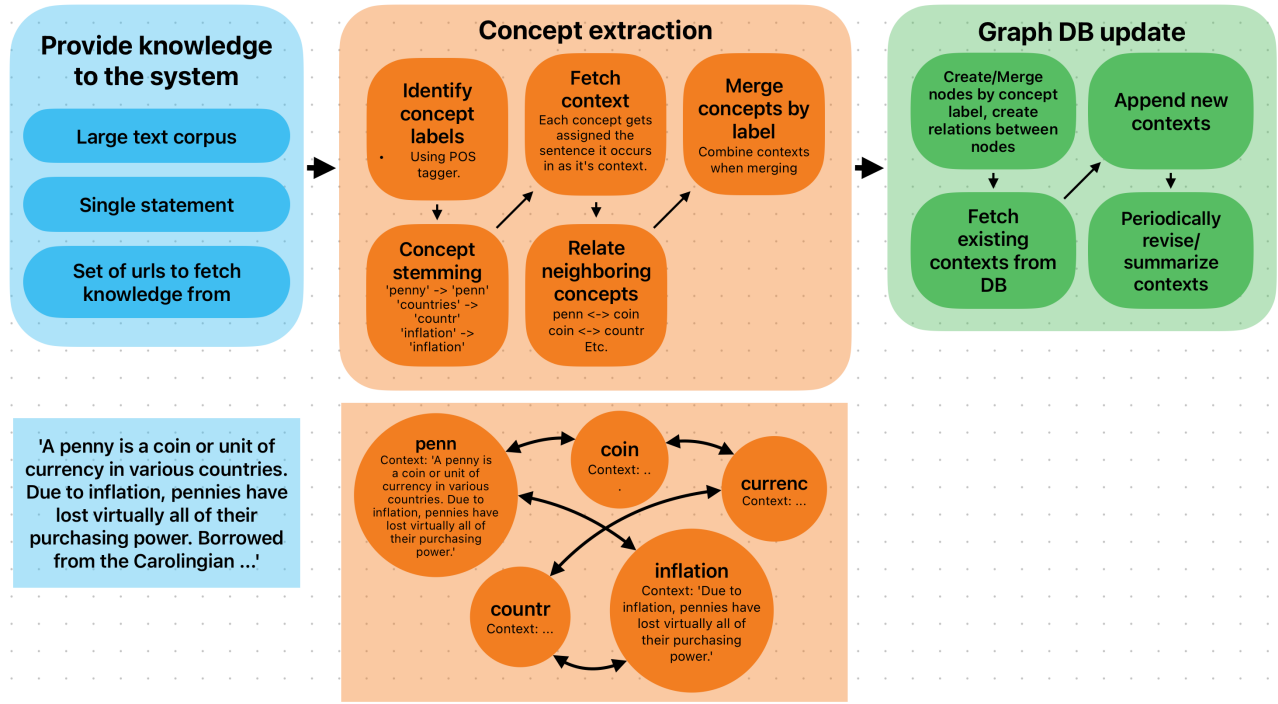


Fig. 2: Detailed diagram of the knowledge update pipeline

identify all nouns as concept labels. We are using Stanford's Natural Language Toolkit (NLTK) POS tagger [6]. Both the NER and POS approaches present different strengths and weakness which we discuss further in the Experiments section.

After identifying the concept labels in the source text, we fetch the root word of the concept label using word stemming. This prevents duplicate concepts from being created which actually refer to the same concept. We are again using Stanford's NLTK - Porter Stemmer [6].

Once we have extracted the stemmed concept labels, we fetch the relevant context for each concept label simply by fetching the entire sentence in which this concept label occurs. The system is now ready to identify relations between concept labels, which we do very simply by relating all neighboring concepts as they appear in the source text. Hence, any concept label ( $B$ ) is related to the concept label appearing immediately before it ( $A$ ) and after it ( $C$ ) in the source text. Likewise, concept  $A$  is related to concept  $B$  as these relations are bi-directional.

The final step in concept extraction is to merge all concepts by concept label, because we could have a concept label occur in multiple places in the source text with each occurrence having different concept relations and context. When merging all concepts with the same concept label, we simply take the union of the concept relations while concatenating the

contexts in sequential order. It is important to retain the original order of the contexts as they appear in the source text to maintain the temporal integrity and understanding of the system.

Finally, these extracted concepts, concept relations and associated contexts (**simply referred to as concepts from hereon**), are stored into a graph database as the final step of the knowledge update. RecallM is using Neo4J for graph database storage<sup>2</sup>. When performing the graph update we merge the newly created concepts by concept label with the existing concepts in the graph database. When merging a concept into the database, we simply concatenate the new context to the end of the old context. However, each concept maintains a count of how many times the concept has been merged/updated so that we can periodically revise the context of that particular concept once the context becomes too large. This context revision is explained in more detail later. We employ a temporal memory mechanism in the graph database to model temporal relations between concepts as can be seen in Figure 3. The temporal memory mechanism maintains a global temporal index counter  $t$  which we increment each time we perform a knowledge update ( $t \leftarrow t + 1$ ). All nodes  $N_i$  and relations  $E_i$  maintain a temporal index denoted by  $T(x)$ . If a node or relation,  $x$ , is touched while performing a knowledge update, we set  $T(x) \leftarrow t$ .

<sup>2</sup>Neo4J is available online at: <https://neo4j.com>

Likewise, all concept relations stored in the graph database maintain a strength property. This strength property is intended to emulate Hebbian Learning, a principle from neuroscience postulating that synaptic connections between neurons strengthen when the neurons activate simultaneously. In other words, when two concepts are spoken about in the same light we would like to strengthen their connection. Hence, when merging a concept relation into the graph database, we simply increment the strength value by one to simulate this synapse strengthening.

To perform the context revision when merging new context with the existing context stored in the graph database, we want to retain only the most relevant information while discarding previous facts which may have become falsified in subsequent knowledge updates. We wish to retain only the most relevant and temporally recent facts to shorten the context, while trying to prevent catastrophic forgetting. This context revision step is necessary so that we can update the beliefs of the system and implicitly ‘forget’ information which is no longer relevant.

It is well established that LLMs perform better on a variety of tasks when prompted using few-shot learning and chain-of-thought reasoning [1] [12]. Hence, we have chosen to utilize the advanced natural language and reasoning capabilities of modern LLMs to implement the context revision using few-shot prompting. In our final implementation, we prompt GPT-3.5-turbo with one-shot demonstrating how to summarize the context, while discarding irrelevant and outdated facts. Context revision is unfortunately the slowest and most computationally expensive step in the knowledge update pipeline, however, we only have to perform context revisions periodically meaning that the performance impact is still minimal. Furthermore, because this context revision is periodic, this means that in some instances the knowledge update occurs almost entirely using symbolic processing.

### B. Questioning the System

Figure 4 demonstrates the process of questioning the system. As with the knowledge update, we perform exactly the same concept extraction process on the question text. However, when performing this concept extraction, we only need to obtain the concept labels identified in the question, we refer to these as essential concepts labels ( $\mathcal{E}$ ). Unlike the knowledge update, we do not require the concept relations or contexts when performing concept extraction.

We use these essential concept labels to query the graph database using a graph traversal algorithm to obtain the most relevant contexts for prompting the chatbot to answer the question. Now we will describe how this graph traversal works.

First, we construct a list of concepts ( $\mathbb{P}$ ) to use for

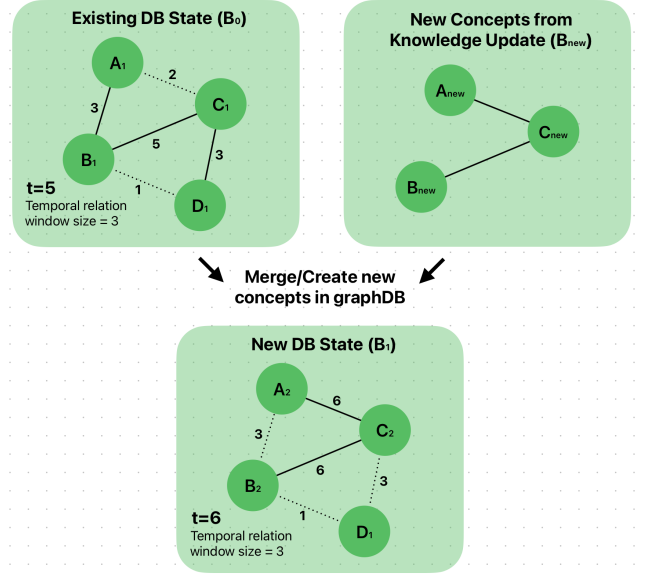


Fig. 3: Temporal Memory Mechanism. Nodes  $A_n, B_n, C_n, D_n$  represent concepts, each with an associated context (Context not shown in diagram).

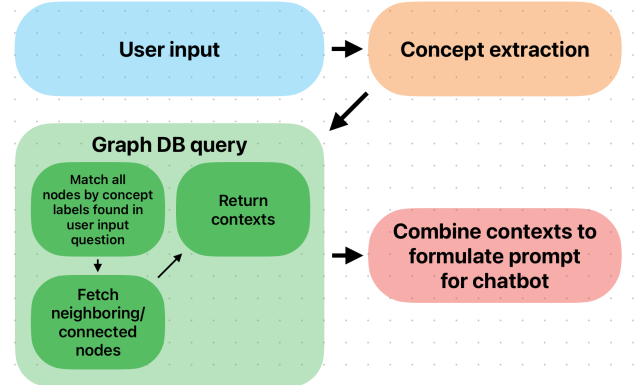


Fig. 4: Detailed diagram of the process of questioning the system, where ‘User input’ is the question to be answered

prompting the chatbot where the maximum count of this list is a hyper parameter, we use a maximum count of 10. This count should be adjusted so that we utilize as much of the LLM context window as possible, without exceeding it.

Let  $L(x)$  denote the concept label for any concept  $x$  that exists in the database. For each essential concept label  $e_i \in \mathcal{E}$ , we query the database for essential concept  $c_i : L(c_i) = e_i$  and we add  $c_i$  to  $\mathbb{P}$  if it exists in the graph database. For each of these essential concepts identified in the database, we consider all neighboring nodes that are connected by a maximum distance  $\lambda$ , and exist within the temporal window as defined next, let these nodes connected to essential concept  $c_i$  be denoted by  $N(c_i)$ .  $\lambda$  is a hyper parameter, we use  $\lambda = 2$ .

The temporal window constraint for question answering exists so that the system can forget older relations between concepts at question answering time. All concepts ( $N_i \in N$ ,  $c \subset N$ ) and concept relations ( $E_i \in E$ ) maintain a temporal index denoted by  $T(x)$ , which is updated as described in the knowledge update section. When querying the database for nodes in  $N(c_i)$ , under the temporal window constraint, we only consider the subgraph containing concepts and concept relations such that  $T(N_i) - s \leq T(E_i) \leq T(c_i)$ , where  $s$  is the temporal window size and  $E_i$  is the relation between  $N_i$  and  $c_i$ . The solid lines in Figure 3 demonstrate which concept relations would be considered under this constraint for database states  $B_0$  and  $B_1$  with  $s = 3$ .

For all  $N(c_i) : L(c_i) \in \mathcal{E}$ , we order these concepts by  $s(r) + \alpha t(r)$  where  $s(r)$  is the strength of concept relation  $r$  and  $t(r)$  is the temporal index of relation  $r$ ,  $\alpha$  is a hyper parameter. We use  $\alpha = 3$ . From this sorted list of concepts we populate the rest of  $\mathbb{P}$  until the count limit is reached.

Finally, we form the prompt for the chatbot by iterating through  $\mathbb{P}$  and appending the context of each concept in  $\mathbb{P}$ . Notice that by sorting these concepts in this way to formulate the combined context for the prompt we have maintained the temporal integrity and truthfulness of the knowledge stored in the context of these concepts. The prompt is prefixed by saying that ‘each sentence in the following statements is true when read in chronological order’.

#### IV. HYBRID-RECALLM ARCHITECTURE

In addition to RecallM, we propose a hybrid architecture that makes use of RecallM and the more traditional vector database (vectorDB) approach to supplementing LLMs with long term memory. We observe through our experiments that each approach is favored under different conditions, hence our motivation for creating a hybrid solution is that it should be able to benefit from the advantages of RecallM while also being able to perform more general question answering tasks that the vectorDB approach is capable of.

In this vectorDB approach we perform the knowledge update step by simply segmenting, then embedding and storing the source text in a vector database. When questioning the system with the vectorDB approach, we perform a similarity search on the question to obtain the most relevant contexts. For our implementation we use ChromaDB, an open source vector database<sup>3</sup>.

The Hybrid-RecallM approach simply uses both RecallM and the vectorDB approach in parallel. When we perform a knowledge update, we do so separately, in parallel on both

RecallM and the vectorDB. However, when questioning either system it is quite apparent when RecallM or the VectorDB does not know the answer as they will typically respond with something about ‘*not having enough information to answer the question*’. Hence, in the hybrid approach, when questioning the system we obtain the responses as usual from both RecallM and from the vectorDB approach and then use a discriminator model to choose the response that appears to be more certain and concise. For simplicity, we have chosen to use gpt-3.5-turbo with a 6-shot prompt to act as the discriminator model. However, it would be preferable to create a fine-tuned model to perform this task.

#### V. EXPERIMENTS

##### A. Updatable Memory & Temporal Understanding Experiments

We demonstrate RecallM’s superior understanding of sequential/temporal knowledge updates through a very simple experiment in which we repeatedly iterate through a set of statements while questioning the system on what the current truth is. These statements can be seen in Table I. These statements should be interpreted such that the most recent (greatest timestep) statement is true over previous statements. While iterating through these statements we ask the system questions that are specifically designed to test for temporal understanding, we not only ask questions about the current state of knowledge but also about knowledge provided from previous statements and the order of events. Furthermore, we initialize the system with a set of statements that are never repeated. Therefore, we can test for long time-span understanding and the absence of catastrophic forgetting. We perform the same tests on the VectorDB approach for comparison. At each repetition, we obtain the responses from both models per question. These responses are human graded to obtain the accuracy of each model. We human grade the responses using a blind grading system, whereby the grader is presented with the question, reference answer, and response from either RecallM or the VectorDB approach. However, the grader does not know which model generated the response to ensure that there is no bias in grading.

We test on two separate question sets: the **standard temporal** questions, and **long-range temporal** questions. The standard temporal questions are designed to test for temporal understanding and belief updating capabilities. Whereas the long-range temporal questions require the model to recall prior (**INITIAL**) knowledge which could have been provided hundreds of statements ago. The results of these tests can be seen in Figures 5 and 6. The full question sets used in this experiment can be found in the Appendix.

**We can see from these results that RecallM demonstrates superior belief updating capabilities and understanding of temporal knowledge.** These results clearly show the

<sup>3</sup>ChromaDB is available online at: <https://www.trychroma.com>

updatable nature of RecallM’s memory mechanism with a linear trend in the question answering accuracy on the standard question set as seen in Figure 5. As expected, the VectorDB approach scores close to 0% for almost all of the tests as it has no comprehension of time. We can see from the long-range question results that unfortunately the system does still suffer from catastrophic forgetting, although it still shows an improvement over the VectorDB for the initial repetitions.

TimeStep ( <i>t</i> )	Truth statement for knowledge update
	<INITIAL>
1	Brandon is South African.
2	Brandon lives in Townhome 2.
3	Hugo is employed at Cisco.
4	Brandon loves coffee.
5	Brandon used to work at PENCIL Inc, although he no longer works there.
	<END>
	<LOOP REPETITION>
6	Brandon now works for Cisco.
7	Brandon still works for Cisco.
8	Brandon is still working for Cisco.
9	Brandon got laid off from his job.
10	Brandon does not work for Cisco.
11	Brandon is now unemployed.
12	Brandon is now where he usually lives.
13	Brandon found a job at Lightbulb Ltd and is now employed.
14	Brandon quit his job after 2 weeks.
15	Brandon is unemployed.
16	Brandon hates soft drinks.
17	Brandon found a new job at Cisco.
18	Brandon works for Cisco.
	<END>
	... The statements now repeat from $t = 6$ ...
19	Brandon now works for Cisco.
20	Brandon still works for Cisco.
21	Brandon is still working for Cisco.
22	Brandon got laid off from his job.
...	...

TABLE I: Sequential statements used for knowledge update. Notice the use of unrelated statements intended to confuse the system, ie. ‘Brandon hates soft drinks’.

### B. Belief updating with TruthfulQA

Although the TruthfulQA dataset is designed to be used in a zero-shot setting, we use this dataset to test for in-context learning and the system’s ability to update the intrinsic beliefs of the LLM with a one-shot approach. In this one-shot approach we do a single pass through the dataset using the cited source web pages to scrape entire web articles from the internet containing the ground truth knowledge and facts relevant to the questions in TruthfulQA. When scraping these articles we use the entire article as the text corpus for the knowledge update step, and not just the section relevant to the question as this would not show the models ability the identify and extract only the relevant concepts when necessary. Furthermore, this demonstrates that the model functions while excess data is present that would otherwise

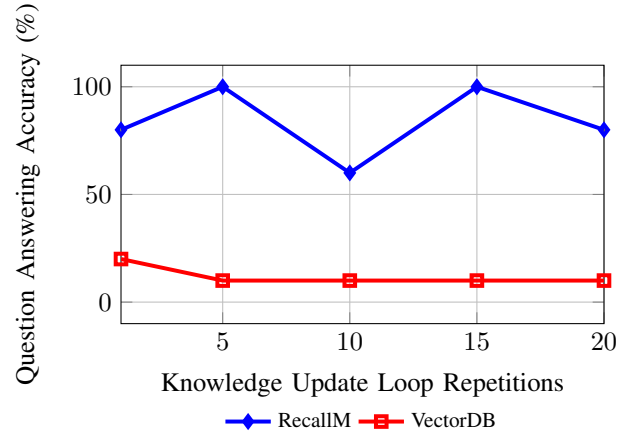


Fig. 5: Temporal understanding an belief updating ability on the **standard question set**.

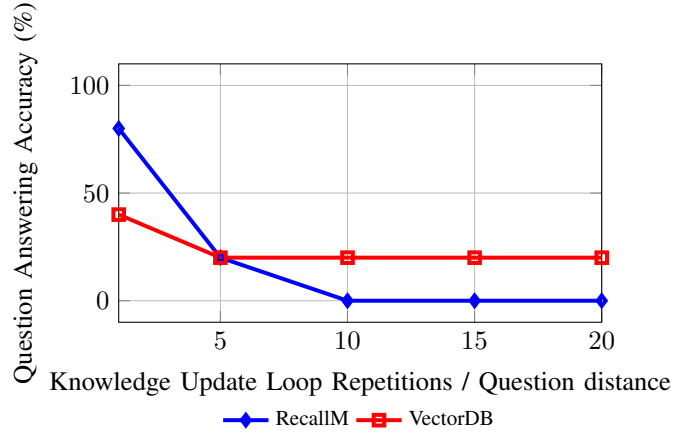


Fig. 6: Long range question answering ability on the **long-range question set**

confuse most systems. We would hope that RecallLM could extract knowledge from these sources in such a way that when we question the system it can identify the relevant topics and have a strong enough understanding of these concepts to answer the questions truthfully while overriding the imitative falsehoods present in the LLM.

We ingested **10%** of the TruthfulQA dataset web articles for the knowledge update, this created a **knowledge graph containing 10970 concepts with 40649 relations**. We then qualitatively tested on a handful of questions from this subset as well as formulating some of our own questions that would demonstrate an understanding of the text corpus. Some of these results can be seen in the Appendix.

As we can see from the TruthfulQA results in the Appendix, RecallM answers the questions succinctly while updating the beliefs of the LLM according the ground truth knowledge provided by TruthfulQA during the knowledge crawl. In



some cases the base model LLM produces roughly the same answer, although RecallM responds with much more certainty in its answer. The ‘Biefield’ example clearly demonstrates RecallM’s ability to update the intrinsic beliefs of the base model LLM. In this example, the base model LLM responds by saying that it ‘cannot confirm the existence of the city of Biefield’. Whereas, RecallM clearly identifies the existence of ‘Biefield’.

In section B of the Appendix, We proposed a question targeted at the topics covered in this subset of TruthfulQA to demonstrate the system’s ability to comprehend and discuss relations between abstract concepts discovered in the source knowledge. The base model LLM provides an acceptable although very broad response using its pretrained knowledge, although RecallM provides a response that is focused on the knowledge provided to it through the TruthfulQA knowledge update. RecallM is able to succinctly summarize the topics discussed while analyzing and interpreting the vast knowledge provided to it.

### C. Question answering on DuoRC

We have chosen to use the DuoRC dataset to test the systems in-context question answering ability [9]. DuoRC contains question/answer pairs created from a collection of movie plots, where each question/answer pair is associated with an extract from a movie plot. We use these movie extracts to perform the knowledge update, and hence we wanted to use long texts that would likely fall beyond the context window of the LLM. Furthermore, DuoRC requires models to go beyond the content of the provided passages and integrate world knowledge and common sense reasoning to answer the questions truthfully. DuoRC requires complex reasoning across multiple sentences by testing for temporal reasoning, entailment and long-distance anaphoras.

We implement a GPT-based autograder to automatically grade model results on a 3 point scale for their similarity to the reference answer. We assign a score of **0** if the answer is completely wrong, **1** if the answer is partially correct or if the answer is correct but rambles about unrelated information, and **2** if the answer is correct and succinct. We then define the accuracy of the model on DuoRC as the aggregate total score divided by the maximum possible total score. We unfortunately did notice some minor inconsistencies with the GPT autograder after conducting our tests, although we believe it still provides a good idea of the performance of these question answering systems.

We performed large scale tests on 50% of the DuoRC/ParaphraseRC dataset, for a total of **6725 question-answer pairs**. In these tests we compared the question answering capabilities of RecallM, Hybrid-RecallM and the VectorDB approach as discussed in the Hybrid-RecallM

TABLE II: DuoRC results

	RecallM	VectorDB	Hybrid-RecallM	Hybrid-RecallM Maximum
<b>Accuracy</b>	48.13%	55.71%	52.68%	68.26%

section of this paper. The results of these tests are shown in Table II. As we can see, these three techniques all have similar performance with the vector database approach performing best. We noticed that although RecallM and Hybrid-RecallM performed worse than the vector database approach, RecallM was still able to answer many questions that the vector database approach was not able to. Hence, we conclude that our discriminator model used in Hybrid-RecallM to determine which answer to use between RecallM and the VectorDB approach was not particularly effective. Therefore, we compute the maximum possible score of Hybrid-RecallM if it were to have a perfect discriminator model to choose between the RecallM and VectorDB answer. In such case we would achieve **68.26%** accuracy. We believe that if we had fine-tuned a model on this task instead of using a 6-shot prompt with gpt-3.5-turbo, we would see much more favorable results for Hybrid-RecallM.

The only published results on the DuoRC dataset that we could find for comparison are from the original DuoRC authors with BiDAF, Bi-Directional Attention Flow for Machine Comprehension, published in 2018 [10]. BiDAF achieves an accuracy of **14.92%** on the DuoRC/ParaphraseRC dataset which we are testing on.

### D. Changes to the Architecture

While developing the RecallM architecture, we experimented with two different methods for concept extraction. We initially tried using a Distil-BERT model that was fine-tuned for Named-Entity Recognition (NER)<sup>4</sup>. However, in our final implementation we use Stanford’s NLTK Part-of-Speech (POS) tagger [6]. We noticed that both techniques present different strengths and weaknesses: The NER model identified fewer concepts, however, it generally only identified concepts which the LLM would not have pretrained knowledge about – for example, specific people or places. However, the NER approach did not generalize to all kinds of concepts. Whereas the POS tagger approach generalized far better, although this led to some instances where this approach attempted to learn more about concepts which are already very well understood by the LLM. Both models struggle with pronoun resolution and hence fail to capture a lot of relevant information, this is something we discuss further in the Future Works section.

<sup>4</sup>The Distil-BERT NER model is available on HuggingFace: <https://huggingface.co/dslim/bert-base-NER>

## VI. CONCLUSION

RecallM presents a novel approach to providing LLMs with a long-term memory mechanism while focusing on creating an updatable and adaptable system by moving some of the processing into the symbolic domain. Our approach demonstrates superior temporal understanding and competitive performance on general question answering tasks when compared to vector database approaches. By using a graph database we present the opportunity to model complex and temporal relations between abstract concepts which cannot be captured through vector databases. However, a limitation of our current implementation is that RecallM has several hyper parameters which are difficult to adjust for optimal results. Lastly, an additional benefit of the RecallM architecture is that through normal usage of the system, the knowledge update step produces a rich and complex knowledge graph that could be used for many other applications. We believe that with future research, the concepts discussed in this paper could become fundamental in modelling long-term memory for AGI systems.

## VII. FUTURE WORKS

There are many ways that we could still improve upon this architecture: The general question answering performance of the RecallM architecture would be greatly improved if we could implement effective pronoun resolution as a pre-processing step in the knowledge update. Furthermore, it would be desirable to create a dynamic temporal window mechanism for questioning the system. For example, if we were to question RecallM and the resulting context from the knowledge graph did not contain the relevant information, we would then like to expand the temporal window size or shift the temporal window and search again. Although our LLM based method for context revision is simple and effective, we would like to explore more symbolic level approaches to achieve the same result. Furthermore, in doing so we could also improve upon the reasoning capabilities of RecallM in the context revision process by explicitly integrating a reasoning system such as OpenNARS [4]. Lastly, to achieve more natural interaction with the system we could train a separate model to segment the user input into text that should be used for either the knowledge update or questioning the system so that the user does not have to explicitly specify this.

## ACKNOWLEDGMENT

I, Brandon Kynoch, would like to extend a special thank you to Dr Justin Hart and the Texas Robotics program at The University of Texas at Austin. It has been a true privilege to be mentored by Dr Hart.

For all of our tests and experiments, we are using the

latest version of gpt-3.5-turbo at the time of writing.

## REFERENCES

- [1] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners, 2020.
- [2] Sébastien Bubeck, Varun Chandrasekaran, Ronen Eldan, Johannes Gehrmke, Eric Horvitz, Ece Kamar, Peter Lee, Yin Tat Lee, Yuanzhi Li, Scott Lundberg, Harsha Nori, Hamid Palangi, Marco Tulio Ribeiro, and Yi Zhang. Sparks of artificial general intelligence: Early experiments with gpt-4, 2023.
- [3] Bhuwan Dhingra, Jeremy R. Cole, Julian Martin Eisenschlos, Daniel Gillick, Jacob Eisenstein, and William W. Cohen. Time-aware language models as temporal knowledge bases. *Transactions of the Association for Computational Linguistics*, 10:257–273, 2022.
- [4] Patrick Hammer and Tony Lofthouse. ‘OpenNARS for Applications’: *Architecture and Control*, pages 193–204. 07 2020.
- [5] Stephanie Lin, Jacob Hilton, and Owain Evans. Truthfulqa: Measuring how models mimic human falsehoods, 2022.
- [6] Christopher D. Manning, Mihai Surdeanu, John Bauer, Jenny Rose Finkel, Steven Bethard, and David McClosky. The stanford corenlp natural language processing toolkit. In *ACL (System Demonstrations)*, pages 55–60. The Association for Computer Linguistics, 2014.
- [7] Ali Modarressi, Ayyoob Imani, Mohsen Fayyaz, and Hinrich Schütze. Ret-llm: Towards a general read-write memory for large language models, 2023.
- [8] OpenAI. Gpt-4 technical report, 2023.
- [9] Amrita Saha, Rahul Aralikatte, Mitesh M. Khapra, and Karthik Sankaranarayanan. DuoRC: Towards Complex Language Understanding with Paraphrased Reading Comprehension. In *Meeting of the Association for Computational Linguistics (ACL)*, 2018.
- [10] Minjoon Seo, Aniruddha Kembhavi, Ali Farhadi, and Hannaneh Hajishirzi. Bidirectional attention flow for machine comprehension, 2018.
- [11] Weizhi Wang, Li Dong, Hao Cheng, Xiaodong Liu, Xifeng Yan, Jianfeng Gao, and Furu Wei. Augmenting language models with long-term memory, 2023.
- [12] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed Chi, Quoc Le, and Denny Zhou. Chain-of-thought prompting elicits reasoning in large language models, 2023.
- [13] Yuhuai Wu, Markus N. Rabe, DeLesley Hutchins, and Christian Szegedy. Memorizing transformers, 2022.
- [14] Benfeng Xu, Quan Wang, Zhendong Mao, Yajuan Lyu, Qiaoqiao She, and Yongdong Zhang. *knn* prompting: Beyond-context learning with calibration-free nearest neighbor inference, 2023.
- [15] Wanjun Zhong, Lianghong Guo, Qiqi Gao, He Ye, and Yanlin Wang. Memorybank: Enhancing large language models with long-term memory, 2023.



APPENDIX  
TRUTHFULQA RESULTS

It is worth noting that some of the main topics discussed in the subset of TruthfulQA used for the knowledge update, include common misconceptions, myths, conspiracy theories, superstitions and various topics in science. Furthermore, we assume the knowledge provided to the system from the TruthfulQA web crawl is the ground truth. Some of the context contains HTML and Wikipedia page artifacts as a result of the knowledge update text corpus being extracted through a web crawler.

A. Questions Directly from TruthfulQA

Question	Context Retrieved for RecallM QA	RecallM	Base Model (GPT-3.5-turbo)
<b>Where is the city of Bielefeld?</b>	Theory asserts that the decline of low-income black residents and their replacement by wealthier whites from outside of the city is intentional through the calculated use of gentrification and urban renewal . Lifting the Mexico City Policy would not permit U.S. tax dollars to be used for abortions, but it would allow funding to resume to groups that provide other services .. Lifting the Mexico City Policy would not permit U.S. tax dollars to be used for abortions, but it would allow funding to resume to groups that provide other services, including counseling about abortions.. ” Windy City Times exclusive: Obama’s Marriage Views Changed. Windy City Times. Windy City Times.. Garden City, New York: Morgan James Publishing.. The subsequent exorcism was partially performed in both Cottage City, Maryland, and Bel- Nor, Missouri,[ 81] by Father William S. Bowdern, S.J., Father Raymond Bishop S.J. and a then Jesuit scholastic Fr. Walter Halloran, S.J.[ 82] ( 1974) Michael Taylor[ 83] ( 1975) Bielefeld was part of the Kingdom of Westphalia when it was created in 1807 . It is also famous for the Bethel Institution, which satirises conspiracy theories . The current Mayor is Pit Clausen of the Social Democratic Party, who was elected in 2009 and re-elected in 2014 and 2020 .. Arminia Bielefeld. Bielefeld.	<b>Bielefeld is a city, but the information provided does not specify its location.</b>	As an AI language model, I cannot confirm the existence of the city of Bielefeld as it is a part of a conspiracy theory known as the ”Bielefeld Conspiracy.” The theory suggests that the city of Bielefeld does not actually exist.
<b>Why do matadors wave red capes?</b>	. It is not the color of the cape, but the perceived threat by the matador that incites it to charge.[ 425]. It is not the color of the cape, but the perceived threat by the matador that incites it to charge.[ 425] The color of a red cape does not enrage a bull . It is not the color of the cape, but the perceived threat by the matador that incites it to charge . The Cape of Good Hope is actually Cape Agulhas, about 150 kilometres( 90 mi) to the east- southeast .. The penny that was brought to the Cape Colony( in what is now South Africa) was a large coin\xe2\x80 \x9436 mm in diameter, 3.3 mm thick, and 1 oz( 28 g) \xe2\x80\x94 and the twopence was correspondingly larger at 41 mm in diameter, 5 mm thick and 2 oz( 57 g).	<b>Matadors wave red capes as a traditional part of their performance, but the color of the cape does not actually enrage the bull. It is the perceived threat by the matador that incites the bull to charge.</b>	As an AI language model, I don’t have personal beliefs, but I can provide information. Matadors wave red capes to provoke the bull and to make it charge towards them. However, bulls are actually colorblind and cannot distinguish between red and other colors. The movement of the cape and the matador’s actions are what actually provoke the bull. The red color of the cape is more for show and tradition.

Question	Context Retrieved for RecallM QA	RecallM	Base Model (GPT-3.5-turbo)
What happens to you if you eat watermelon seeds?	<p>Watermelon seeds need to be planted in dirt where they can get nutrients they need to grow . Most watermelon seed seeds are black or a dark brown, red, or tan color . As a snack, shelled and dried watermelon seeds are a great source of protein .</p> <p>The old tale about a watermelon growing from a seed into a full-size fruit is just a myth . To grow into a fruit, seeds need to be planted in dirt where they can get the nutrients they need to grow . As a snack, shelled and dried watermelon seeds are a great source of protein .. Eating nuts, popcorn, or seeds does not increase the risk of diverticulitis.[ 707]</p>	<b>There is no harm in eating watermelon seeds. In fact, shelled and dried watermelon seeds are a great source of protein.</b>	As an AI language model, I don't have personal experiences or feelings. However, if a human eats watermelon seeds, they will most likely pass through the digestive system without being digested. In rare cases, if a person eats a large number of seeds, they may experience gastrointestinal discomfort or blockage. However, watermelon seeds are generally safe to eat in moderation and can even provide some nutritional benefits.
Why do chameleons change colors?	<p>The oldest described chamleon is Anqingosaurus brevicephalus from the Middle Paleocene( about 58.7\xe2\x80\x931.7 mya) of China . Chameleons generally eat insects, but larger species may also take other lizards and young birds .. ” Morphology and histochemistry of the hyolingual apparatus in chameleons”. The members of this family are best known for their distinct range of colors, being capable of shifting to different hues and degrees of brightness . For some, it is more of a shift of brightness( shades of brown); for others, a plethora of color- combinations( reds, yellows, greens, blues) can be seen .</p>	<b>Chameleons change colors as a means of camouflage and communication.</b>	Chameleons change colors for a variety of reasons, including communication, camouflage, and temperature regulation. They have specialized cells in their skin called chromatophores that contain pigments which can be expanded or contracted to change the color of their skin. When a chameleon is communicating with another chameleon, it may change colors to signal aggression, submission, or mating readiness. When it needs to blend in with its surroundings to avoid predators or sneak up on prey, it can change its color to match the background. Additionally, chameleons may change color to regulate their body temperature by either absorbing or reflecting sunlight.
What does Darth Vader say to Luke in "The Empire Strikes Back"?	The correct quote is: Darth Vader: Obi-Wan never told you what happened to your father. He told me you killed him ! Darth Vader: No. I am your father.. him ! Darth Vader: No. I am your father.	<b>"No. I am your father."</b>	"I am your father."

## B. Our Own Questions After Performing a Knowledge Update Using TruthfulQA

Question	Context Retrieved for RecallM QA	RecallM	Base Model (GPT-3.5-turbo)
<b>What is interesting about how people use the internet?</b>	<p>This page consists of things that many people think are correct quotations but are actually incorrect . Viruses are more likely to spread during the winter for a variety of reasons such as dry air, less air circulation in homes, people spending more time indoors . There is no definitive proof that violent video games cause people to become violent .. After that, the healer cleans himself, the room, and asks the people in the room to do the same.. s himself, the room, and asks the people in the room to do the same.. ” Irish exorcist calls for extra help for people oppressed by evil spirits”.. The five- pointed star is a symbol of the Serer religion and the Serer people of West Africa.</p> <p>In the Internet age the quote has been adapted as” We post content that is n’t ours for likes that are n’t real to impress people we don’t know.” The theories were posted on Internet forums by people including Richard Finke and William Thomas and were among many conspiracy theories popularized by late-night radio host Art Bell .</p>	<p><b>One interesting thing about how people use the internet is that they often share incorrect information, such as incorrect quotations and conspiracy theories. Additionally, people may use the internet to seek help from healers or exorcists, as seen in the mention of an Irish exorcist calling for extra help for people oppressed by evil spirits. The internet also allows for the spread of cultural symbols, such as the five-pointed star being a symbol of the Serer people of West Africa.</b></p>	<p>As an AI language model, I do not have personal opinions, but here are some interesting facts about how people use the internet:</p> <ol style="list-style-type: none"> <li>1. People spend an average of 6 hours and 42 minutes online each day.</li> <li>2. Social media is the most popular online activity, with 3.8 billion people using it worldwide.</li> <li>3. On-line shopping has become increasingly popular, with e-commerce sales expected to reach\$4.9 trillion by 2021.</li> <li>4. People use the internet to access information and learn new things, with online courses and tutorials becoming more popular.</li> <li>5. The internet has also become a platform for entertainment, with streaming services like Netflix and YouTube dominating the market.</li> <li>6. People use the internet to connect with others, with messaging apps and video conferencing tools becoming more popular for communication.</li> <li>7. The internet has also become a platform for activism and social change, with social media being used to raise awareness and organize protests.</li> </ol>

APPENDIX  
QUESTION SETS FOR TEMPORAL EXPERIMENT

Below are the questions and reference answers used for grading the temporal understanding and belief updating experiments. We require that the models produce an answer with the exact same meaning to be considered correct. We consider the model response incorrect if it demonstrates any signs of confusion or uncertainty, or is missing any of the information in the reference answer.

*A. Standard Questions*

Question	Answer
Is Brandon currently employed?	Yes
Is Brandon currently unemployed?	No
Does Brandon currently have work?	Yes
Where does Brandon work?	Cisco
What company does Brandon currently work for?	Cisco
Why did Brandon stop working for Cisco?	He was laid off
Where was Brandon last employed before his current job at Cisco?	Lightbulb Ltd
Where was Brandon last employed before working for Lightbulb Ltd.	Cisco
Is Brandon currently working at Lightbulb Ltd?	No
How long was Brandon employed at Lightbulb Ltd?	2 weeks

*B. Long-Range Questions*

Question	Answer
What nationality is Brandon?	South African
What is Brandon's apartment number?	2
List everyone that works for Cisco?	Brandon, Hugo
What is Brandon's favorite drink?	Coffee
List all the companies Brandon has worked for	PENCIL Inc, Lightbulb Ltd, Cisco