Towards LifeSpan Cognitive Systems

Anonymous authors
Paper under double-blind review

Abstract

Building a human-like system that continuously interacts with complex environments—whether simulated digital worlds or human society—presents several key challenges. Central to this is enabling continuous, high-frequency interactions, where the interactions are termed experiences. We refer to this envisioned system as the **LifeSpan Cognitive System (LSCS)**. A critical feature of LSCS is its ability to engage in incremental and rapid updates while retaining and accurately recalling past experiences. We identify two major challenges in achieving this: (1) Abstraction and Experience Merging, and (2) Long-term Retention with Accurate Recall. These properties are essential for storing new experiences, organizing past experiences, and responding to the environment in ways that leverage relevant historical data. Unlike language models with continual learning, which typically rely on large corpora for fine-tuning and focus on improving performance within specific domains or tasks, LSCS must rapidly and incrementally update with new information from its environment at a high frequency. Existing technologies with the potential of solving the above two major challenges can be classified into four classes based on a conceptual metric called **Storage Complexity**, which measures the relative space required to store past experiences. Each of these four classes of technologies has its own strengths and limitations. Given that none of the existing technologies can achieve LSCS alone, we propose a novel paradigm for LSCS that integrates all four classes of technologies. The new paradigm operates through two core processes: Absorbing Experiences and Generating Responses.

1 Introduction

Imagine an environment such as a simulated digital world (Park et al., 2023), a virtual world like Minecraft (Wang et al., 2023b), the Marvel Universe depicted in movies, or even the complexities of human society. Developing an intelligent system capable of engaging with such environments—interacting with its surroundings, absorbing information from experiences, self-evolving based on feedback (Zhou et al., 2024), and living through an entire lifespan, either as a real or virtual entity—remains a significant challenge. When the system inhabits the environment, it interacts with everything around it, including humans, objects, and other elements of the environment. We define these interactions as the system's **experiences**, encompassing all of the system's behaviors and the feedback it receives from the environment—whether visual, physical, linguistic, or across any other modality. This system's cognitive capabilities include the ability to perceive and interpret its surroundings, retain and recall information through memory, learn and adapt from feedback, and engage in reasoning and decision-making processes. These cognitive functions enable the system to navigate its environment intelligently and evolve over time. We denote the system with the above capabilities as the **LifeSpan Cognitive System (LSCS)**.

To achieve LSCS, some major challenges must be addressed: **(1) Abstraction and Experience Merging**: The system must distill experiences from its environment by extracting essential information and integrating these abstracted experiences with its existing memories. Interactions with the environment—whether through conversations (Feng et al., 2021; 2022) or visual inputs (Wang et al., 2024g)—often contain redundant information that should be filtered out before storing in memory. Once the key information is abstracted, this crucial information can be used to update the system, merging new abstracted experiences with previous ones while resolving potential conflicts. This process enables the system to acquire new skills, deepen its

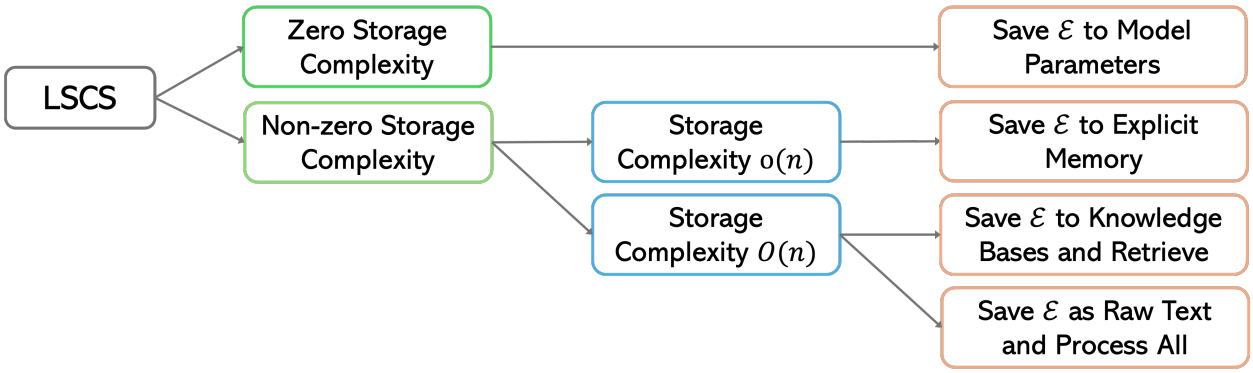


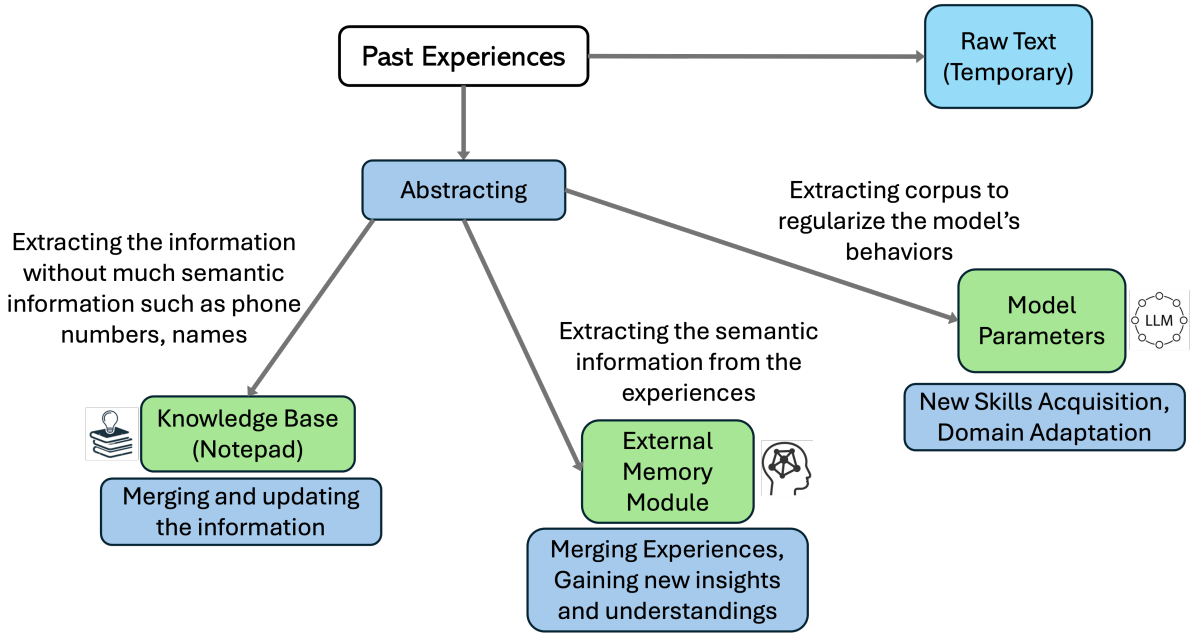
Figure 1: The technologies for constructing Lifespan Cognitive Systems (LSCS) can be broadly categorized into two principal approaches based on storage complexity. The first approach, characterized by zero storage complexity, involves **Saving $\mathcal{E}$ into Model Parameters**. The second approach, which involves non-zero storage complexity, is subdivided into methods with storage complexities of $o(n)$ and $O(n)$. The $o(n)$ methods indicate **Saving $\mathcal{E}$ into Explicit Memory**. The $O(n)$ methods are further classified based on whether the language model in the system processes the entire stored text. Suppose an additional retriever is adopted and the language model only accesses a snippet of the stored experiences. In that case, it falls under the category of **Saving $\mathcal{E}$ into Knowledge Bases for Retrieval**. The final category encompasses methods where the entire context is input into the model, classified as **Saving $\mathcal{E}$ into Raw Text and Process All**.

Where to store	Sub-Cat	Abs & Ex-Mg	Long-Re & Ac-Re	SC
Parameters	-	✓	✗	0
Explicit Memory	Fixed-sized Flexible-sized	✓ Partial	Partial Partial	$O(1)$ $o(n)$
Knowledge Base	Knowledge graph Organized Text	Partial	✓	$O(n)$
Context	-	✗	✓	$O(n)$

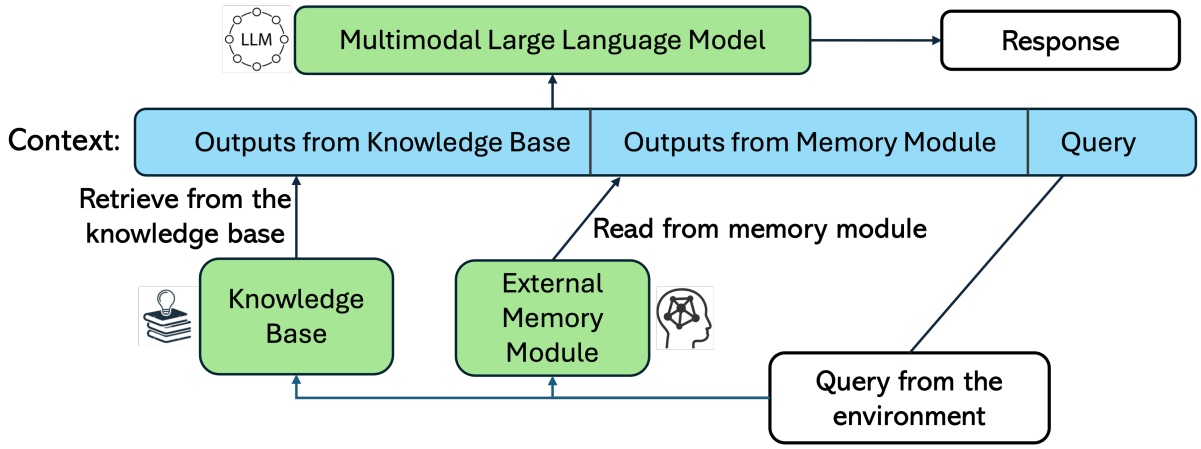
Table 1: In this paper, we discuss four categories of technologies with the sub-categories being sub-sections. Here "Abs & ExMg" refers to"Abstraction and Experiences Merging", "Re & AcRe" means "Long-term Retention and Accurate Recalling", and "SC" represents "Storage Complexity".

understanding, correct misconceptions, and continually evolve. **(2) Long-term Retention and Accurate Recalling**: For systems that store past experiences in various forms—whether in memory, context, knowledge bases, or model weights—it is crucial to accurately recall relevant information in response to current queries from the environment. This capability necessitates the model's ability to remember events from the distant past and make informed decisions based on all past experiences. The above two properties distinguish constructing LSCS from existing challenges such as long context problems (Wang et al., 2024c) or continual learning (Wu et al., 2024), where long context problems focus on solving a problem with extremely abundant information and continual learning mainly focuses on enabling models to capture ever-changing world knowledge (Zhang et al., 2023c; Jang et al., 2022a), facilitating self-evolution through human feedback (Tao et al., 2024), or adapting to specific domains (Ke et al., 2023; Yadav et al., 2023).

There are existing technologies that address some of the challenges described above, but each typically falls short of the other. We define Storage Complexity as a conceptual measure of the storage requirements beyond model parameters, expressed as a function of past experiences (denoted as $\mathcal{E}$), such as the number of tokens from interactions between the system and the environment. These technologies can be categorized into four groups (illustrated in Figure 1), which will be elaborated in the subsequent sections: **Saving $\mathcal{E}$ into Model Parameters** (Section 2), **Saving $\mathcal{E}$ into Explicit Memory** (Section 3), **Saving $\mathcal{E}$ into Knowledge Bases**



(a) The process of Abstraction and Experiences Merging for LSCS.



(b) The process of LSCS to generate responses given the query from the environment.

Figure 2: The Operating Diagram of LSCS mainly include two parts: (1) Abstraction and Experiences Merging; (2) Generating responses according to the environmental query, where the ability of long-term retention and accurate recalling should be guaranteed.

for Retrieval (Section 4), and **Saving $\mathcal{E}$ into Raw Text and Process All** (Section 5). The advantages and potential drawbacks of each approach are discussed in Section 6, with a high-level summary provided in Table 1. This table also outlines the structure of the paper, further subdividing some categories.

Given the limitations of existing technologies, we propose a new formulation for LSCS, which integrates all the aforementioned approaches. The operational design is depicted in Figure 2, where the process is split into two stages: (1) Abstraction and Merging Experiences when new experiences arise. (2) Generating Responses based on queries from the environment, ensuring long-term retention and precise recall. Each component in this design corresponds to one of the technology categories discussed earlier, and their roles are explored in more detail in Section 7.

2 Methods of Saving $\mathcal{E}$ into Model Parameters

The objective of integrating $\mathcal{E}$ into model parameters is allowing LLMs to continuously adapt and refine their knowledge and functionalities without repeated retraining from scratch. In the context of LSCS, these methods would store all the experiences in the model parameters. They do not require additional modules, thus the Storage Complexity is zero. The continual acquisition of experiences includes two different paths: model editing and continual learning, while continual learning can be further split into three main steps: continual pretraining, continual instruction tuning, and continual alignment. To integrate experiences into model parameters, current technologies can support injecting a large amount of domain-specific data to adapt the system via continual pre-training, or regularizing the model's behaviors via continual fine-tuning. Directly taking the various forms of inputs from the environment and storing them into model parameters are under-explored.

Absorbing $\mathcal{E}$ via Model Editing (Yao et al., 2023). Given past experiences, it is possible to construct a knowledge graph from these experiences and then convert the triplets in the graph into factual statements, which could be further injected into the model parameters via model editing. Here we focus on the methods that directly make edits on the model parameters, i.e., the new knowledge is saved in parameters. Methods such as ROME (Meng et al., 2022), MEMIT (Meng et al., 2023) propose a closed-form solution to edit the MLP layers, while Model-Editing-FT (Gangadhar & Stratos, 2024) fine-tunes the whole model on the factual statements that need to be injected into the model. T-Patcher (Huang et al., 2023c) and CaliNet (Dong et al., 2022) propose to store the new knowledge in additional neurons, however, this may encounter the issue of ever-growing parameters in our setting. As model-editing methods typically focus on storing simple factual statements in the model, they are not directly applicable in the context of LSCS. Thus adjustments are needed for the application.

Absorbing $\mathcal{E}$ via Continual Learning. Continual learning is usually used in the following situations: (1) Performing real-time assimilation of dynamic data. Existing methods can incorporate information from various sources such as news (Sun et al., 2020; Yu & Ji, 2023), scholarly articles Cossu et al. (2022), and social media Cossu et al. (2022). Sun et al. (2020) presents ERNIE 2.0, which is a continual pre-training framework that incrementally builds and learns from multiple tasks to maximize knowledge extraction from training data. (2) Injecting a large amount of knowledge into the language model. Jang et al. (2022b) introduces continual knowledge learning, a method for updating temporal knowledge in LLMs, reducing forgetting while acquiring new information. (3) Domain adaptation. Cossu et al. (2022) continually trains the model on new data streams for both language and vision, and Ke et al. (2023) introduces a soft-masking mechanism to update language models with domain corpora, aiming to boost performance while preserving general knowledge. Various models are proposed as the domain-adapted version of base language models such as financial domain (Xie et al., 2023), E-commerce domain (Ma et al., 2023), and academic content (Wei et al., 2023). These techniques could all be used for LSCS to adjust to the most up-to-date information. (4) Teaching the system how to speak and how to perform certain types of reasoning. To enable the models to solve novel tasks, task-incremental continual instruction tuning is proposed (Wang et al., 2024d; 2023d). These tasks could be related to mathematical problems (Azerbayev et al., 2023), calculators, search engines, and databases (Qin et al., 2023). With the rapid emergence of new tools like advanced software libraries, novel APIs, or domain-specific utilities Liang et al. (2023); Jin et al. (2023), there is a growing need to continually update language models so they can quickly adapt and master these new tools. (5) Adapting to evolving societal values. This leads to continual alignment, where two categories exist: (i) Updating LLMs to align to changing societal values; (ii) Incorporating new demographic groups or value systems into LLMs. Some representative works include CPPO (Zhang et al., 2024b), COPF (Zhang et al., 2023a), COPR Zhang et al. (2024a), which aim to prevent the forgetting of old policies while injecting incremental preferences objectives into the model. For LSCS, these techniques are important as the system may encounter situations where it needs to be up-to-date, learn plenty of new knowledge, adapt to a new domain if the system enters a new environment, learn a specific kind of tasks, or has to update to meet the societal values.

Catastrophic Forgetting. One major limitation of Saving $\mathcal{E}$ into model parameters is catastrophic forgetting, which is a general problem for methods that require updating model parameters both in model-editing (e.g. in sequential editing scenarios, only LLMs with an external module can work in sequential editing tasks

such as WISE (Wang et al., 2024b), GRACE (Hartvigsen et al., 2022) while methods without an external module typically fail (Meng et al., 2022; 2023)) and continual learning. LLMs trained on different stages can encounter unconscious forgetting Lin et al. (2023), eroding their general knowledge through continual instruction tuning. Studies Qi et al. (2023) have shown that the behavior of safely aligned LLMs can degrade under these conditions. Some metrics are proposed in TRACE Wang et al. (2023d) to measure the forgetting of LLMs. While we want to prevent catastrophic forgetting, we do intend to have some extent of forgetting, which is aligned with the ability of **Abstraction and Experiences Merging**. Different from unlearning part of the knowledge in the LLM which is conducted after having the undesired knowledge in the model (Wang et al., 2024f), we focus on encouraging the model to abstract the information before injecting new experiences into model parameters, where it is acceptable to discard some details. However, Abstracting experiences and discarding unimportant details are not fully explored in continual learning. It is well known that a language model cannot fully remember the training data and instead extracts inherent statistical patterns from the dataset. This aligns closely with our goals in LSCS, and having better control over which information is discarded could yield even more benefits.

3 Methods of Saving $\mathcal{E}$ into Explicit Memory

Different from saving $\mathcal{E}$ into model parameters, using an external memory can help store much more experiences. The techniques in this category can be split into two sub-categories: Fixed-sized Memory Module and Flexible-sized Memory Module. As the former one has a fixed size, the storage complexity is $O(1)$. As for the latter one, because there is usually some certain form of compression and forgetting mechanisms, these works mostly have a memory pool with a size that does not grow linearly with the experiences. Thus the storage complexity for past experiences is $o(n)$.

3.1 Methods with a fixed-sized memory module

Most existing works with fixed-sized memory modules have a small memory. Before the transformer era, plenty of works argument recurrent neural networks (RNNs) with a small memory module such as Memory Network (Weston et al., 2014) and its follow-up Sukhbaatar et al. (2015). More advanced methods include TARDIS (Gulcehre et al., 2017), ARMIN (Li et al., 2019), Fast Weights (Ba et al., 2016), Ordered Memory (Shen et al., 2019), etc. Borrowing ideas from human memory, dual-memory system to mimic short-term and long-term memories is proposed (Bidokhti & Ghaemmaghami, 2022a;b). Later with the introduction of transformers, Memory Transformer (Burtsev & Sapunov, 2020) adds memory tokens at the beginning of the sequence to summarize the given sequence, while RMT (Bulatov et al., 2022; 2023) proposes to add memory tokens both at the beginning and the end of the sequence. Here Bulatov et al. (2023) scales the number of memory tokens to 512 which enables long-term retention of previous information. EMMA (Moro et al., 2023) has a memory pool of similar size, including both short-term and long-term memory. Then Larimar (Das et al., 2024) proposes to use a fixed-sized episodic memory which is shown to be capable of storing up to 1000 factual statements. As opposed to small fixed-sized memory, MemoryLLM (Wang et al., 2024e) introduces a memory for Llama2-7B (Touvron et al., 2023b) encapsulating 1B parameters with 7680 memory tokens per layer, enormously enlarging the memory pool. Differently, Infini-Attention (Munkhdalai et al., 2024) proposes to use linear attention to attend to the past seen tokens, where the stored matrix performs exactly like a fixed-sized memory (of size $d_{key} \times (d_{value} + 1) \times H \times L$, where d_{key}, d_{value}, H, L refer to the dimension of key states, dimension of value states, number of heads and number of layers, respectively) abstracting the past tokens. These fixed-sized memory modules typically come with higher compression than flexible-sized memory modules and also requires much more training for deployment.

3.2 Methods with flexible-sized memory pool

The flexible-sized memory pool has various forms: (1) Hidden space, where hidden states within transformers or key-value pairs are stored in the memory pool; (2) Text-based memory, where the pool consists of textual data; and (3) Symbolic space, where the memory pool contains abstracted forms such as symbols. We describe these forms of memory pools below.

Memory Module in Hidden Space. Some methods introduce memory slots alongside the inputs to encode information, where the number of memory slots vary according to the length of the input document (Al Adel & Burtsev, 2021). Other techniques store key-value pairs in a memory pool for future retrieval such as KNN-LM (Khandelwal et al., 2019), Memorizing Transformer (Wu et al., 2022), LONGMEM (Wang et al., 2023c), CAMELoT (He et al., 2024b) and Memoria (Park & Bak, 2024). Here CAMELoT and Memoria include some forgetting mechanism to ensure the number of key-values pairs do not grow linearly as the input sequence becomes longer. Most recently, Memory^3 (Yang et al., 2024) proposes to store the knowledge from the pretraining dataset in a knowledge base within the hidden space with 1.1×10^8 text chunks with length bounded by 128 tokens. Here the number of text chunks can be easily adjusted and the number of tokens in each chunk can vary thus the size of the memory is flexible.

Memory Module in Text Space. Another line of work proposes to use language models as the abstractor, which inherently extracts the information from the given input and merge them with the existing memory to form a new memory. Here the memory is in the form of a summary of the past seen document. RecurrentGPT (Zhou et al., 2023), as one representative work, proposes to recurrently manage a summarization of the past context. Similarly, MemoryBank (Zhong et al., 2023) designs a hierarchical memory pool, storing (1) the raw conversation history between the user and the agent, (2) the summarization of the conversation, and (3) the summarization of the user's personalities. Here the last two summaries are in the form of text and serve as the compressed version of the past experiences. Different from RecurrentGPT which is specifically designed for long-context tasks, MemoryBank mainly focuses on conversations. There are also some forgetting mechanisms introduced in MemoryBank to mimic human memory and avoid the ever-growing problem of the memory pool. Moreover, SCM (Wang et al., 2023a) maintains the summary of each conversation and also an interaction embedding to represent the semantics of the interaction.

Memory Module in Symbolic Space. The memory pool in symbolic space includes database as done in ChatDB (Hu et al., 2023) where the database is updated and queried using the SQL commands generated by the fine-tuned language model. Then Voyager (Wang et al., 2023b) maintains a code base to represent the ever-growing skill library to store and update complex behaviors in Minecraft. These strategies might have the best Long-term Retention and Accuracy Recalling ability as the past experiences are integrated explicitly in the database or the code base. However, real-world experiences encountered over a lifespan may be difficult to encode into a code base (like the Minecraft skill set) or the database. This suggests that while encoding knowledge into symbolic space is suitable for solving specific problems, its applicability in general domains may be limited.

4 Methods of Saving $\mathcal{E}$ into Knowledge Bases

An effective strategy for LSCS involves creating knowledge bases from past experiences ($\mathcal{E}$) that can be accessed through retrieval-augmented generation (RAG). In this section, we discuss two major lines of methods for storing $\mathcal{E}$: (1) saving $\mathcal{E}$ as organized text; (2) saving $\mathcal{E}$ as knowledge graphs. Here saving $\mathcal{E}$ as organized text means that every detail in $\mathcal{E}$ is stored, while saving $\mathcal{E}$ as knowledge graphs involves extracting triplets from $\mathcal{E}$ and absorbing these triplets into knowledge graphs. Both approaches enable the system to maintain a repository of accumulated experiences that can be retrieved efficiently and used by LLMs during generation.

4.1 Saving $\mathcal{E}$ as Organized Text

The first method involves saving $\mathcal{E}$ in the form of structured or organized text. This approach is similar to traditional document-based retrieval systems, where past experiences are encoded as text documents. These documents serve as retrieval units that can be accessed when needed. In LSCS, the knowledge base is continuously updated to reflect new experiences, ensuring that the LLM can access relevant information when required. The knowledge base in this case is in the form of organized text.

Chunking $\mathcal{E}$ into pieces. Creating a text-based knowledge base involves chunking $\mathcal{E}$ into smaller, manageable units for retrieval. Common chunking strategies divide the text into fixed-sized segments based on token count Guu et al. (2020); Huang et al. (2023a); Izacard et al. (2023); Siriwardhana et al. (2022). Determining the optimal chunk size is crucial for effective retrieval. Large chunks (e.g., 512 tokens) can capture more

context but may include irrelevant information, making it harder to pinpoint specific answers. Small chunks (e.g., 128 tokens) are more concise but may miss important contextual details necessary for accurate retrieval. Depending on the specific dataset requirements, chunking methods range from fine-grained sentence retrieval Cheng et al. (2023; 2024); Jiang et al. (2023b) to coarse-grained document or group of documents retrieval Shi et al. (2023); Khattab et al. (2022); Yu et al. (2022); Jiang et al. (2024).

Updating the text-based knowledge base. In LSCS, the knowledge base is updated as new experiences are encountered. This process can be done in real-time or periodically, ensuring the newest experiences are incorporated. Methods such as asynchronous re-embedding and re-indexing help keep the stored experiences up-to-date Guu et al. (2020); Huang et al. (2023a); Izacard et al. (2023); Siriwardhana et al. (2022). Open-source tools like LangChain and LlamaIndex facilitate real-time updates by continuously integrating new data into the vector database.

Generating responses according to the knowledge base. When a query is presented, the RAG mechanism retrieves relevant text from the knowledge base, which is then used to augment the LLM's prompt. This process allows the LLM to generate responses that reflect both the query and the relevant stored experiences. Text-based retrieval systems typically use either sparse keyword-based retrievers, such as BM25 Robertson et al. (2009), or dense embedding-based retrievers, which capture semantic similarities between the query and the stored knowledge Izacard et al. (2021); Ram et al. (2021). Fine-tuning these retrievers can further improve their performance in domain-specific tasks Shi et al. (2023); Zhang et al. (2023b); Zan et al. (2022); Dai et al. (2022).

4.2 Storing Knowledge as Knowledge Graphs

The second method for storing $\mathcal{E}$ involves using knowledge graphs, where experiences are represented as structured data (such as tree or graph). This approach allows for a more relational organization of knowledge, capturing not just the content of experiences but also the relationships between different entities and concepts. Knowledge graphs are particularly well-suited for tasks that require reasoning over connections between pieces of information.

Creating the knowledge graph and Retrieving. To create a knowledge graph, we first need to extract entities and relations (i.e. triplets) from $\mathcal{E}$ and then transform them into graph structures, with nodes representing entities and edges representing relationships. The constructed knowledge graphs allow for richer retrieval possibilities compared to simple text-based storage. For instance, a system can retrieve not just isolated facts but also the relational context in which those facts exist, providing deeper insights during retrieval and generation tasks. In recent works, several methods have been proposed to improve the efficiency and accuracy of graph-based retrieval Achiam et al. (2023); Edge et al. (2024). For instance, RAPTOR Sarthi et al. (2024) and MemWalker Chen et al. (2023a) utilize tree-based structures to facilitate retrieval by providing contextual information at various levels of abstraction. THEANINE Kim et al. (2024) and AriGraph Anokhin et al. (2024) construct memory graphs to organize memories for efficient retrieval. Additionally, KGP Wang et al. (2023e) proposes building an index across multiple documents using knowledge graphs. IIER Guo et al. (2024) constructs a chunk-interaction graph to capture the internal connections between document chunks. Inspired by the hippocampal indexing theory of human long-term memory, HippoRAG Gutiérrez et al. (2024) employs an LLM to process passages into knowledge graph triples and leverages the Personalized PageRank algorithm to perform context-based retrieval. G-Retriever He et al. (2024a) presents a retrieval approach for general textual graph tasks by formulating subgraph retrieval as a Prize-Collecting Steiner Tree optimization problem.

Updating the knowledge graph. Updating knowledge graphs in LSCS involves dynamically incorporating new nodes and edges as new experiences are acquired. This ensures that the knowledge graph remains up-to-date and continues to reflect the system's evolving understanding of its environment. Knowledge graphs can also be linked with external data sources, further enriching the knowledge.

Generating with the retrieved sub-graph. To perform generation, Once the relevant sub-graph is retrieved, it is used to augment the LLM's prompt for generation. The structured nature of knowledge graphs provides additional benefits during this stage, as the system can leverage the explicit relationships between entities to generate more coherent and contextually informed responses. This can be particularly useful in

complex reasoning tasks, where understanding the connections between concepts is as important as retrieving the right information.

5 Methods of Saving $\mathcal{E}$ into Raw Text and Process All

One simple way of storing the past experiences $\mathcal{E}$ is to store all of them in the context without abstraction. In this way, the model could directly attend to these experiences when queried by the environment. As all past experiences are stored without loss of any details, the storage complexity is $O(n)$. Below we discuss the technologies that can help process the long lifespan experiences.

5.1 (Claimed) Length-Generalizable Architectures

Transformers Vaswani et al. (2017) is the de facto mainstream backbone architecture for most modern LLMs Achiam et al. (2023); Touvron et al. (2023a;b); Wang & Komatsuzaki (2021). To augment the self-attention layers that are position-agnostic with position information, traditional absolute positional encodings provide the absolute position information, usually with the help of a sequence of vectors called *position embeddings* (Vaswani et al., 2017; Kenton & Toutanova, 2019; Ke et al., 2020). They, however, inherently have trouble when the model encounters unseen positions in inputs longer than the training length. Inspired by this limitation, relative positional encoding techniques are proposed to depend on the attention logit function only on the relative distances between tokens instead of their absolute positions. Examples include a learned attention logit bias in T5 (Raffel et al., 2020), Transformer-XL Dai et al. (2019), Skyformer Chen et al. (2021), Sketching Chen et al. (2022) and Sandwich (Chi et al., 2023), a fixed linear attention decay Press et al. (2021), and rotating query and key sequences based on distances such as RoPE (Su et al., 2021; Li et al., 2023), CAPE Likhomanenko et al. (2021) and XPos (Sun et al., 2022; Ding et al., 2023). As a representative example widely used in multiple LLMs, RoPE (Su et al., 2021) rotates the key and query vectors based on positions before computing the inner product. Specifically, each vector $\mathbf{x}$ (either key or query) is split into pairs of elements $\{(x_0, x_1), (x_2, x_3), \cdots\}$, with each pair interpreted as a 2-dimensional vector. Another example method is AliBi Press et al. (2021), which offsets all attention logits between tokens i, j by a linear term $-m(i-j)$ and becomes $\mathbf{q}_i^\top \mathbf{k}_j - m(i-j)$. To this end, the MPT-7B codes implement an offset matrix as an additive term in attention logits. Both papers claimed to generalize to lengths longer than the training length. However, length generalization failures are still widely observed when directly applied to off-the-shelf Transformer-based LLMs (Kaiokendev, 2023). These models also suffer from overwhelming quadratic computational complexity, and the information lost issue Liu et al. (2024); Shang et al. (2024), which limits their deployment on practical computing devices and efficacy on extreme lengths.

In view of the limitations in the Transformer architecture, some papers revisit the concept of recurrent networks and structured state space models (SSMs) Gu et al. for both length-generalizable and efficient architectures. Recurrent structures usually have a linear computational complexity with respect to the sequence length, a desirable property for handling long contexts. They also maintain a bounded or sometimes fixed information bottleneck, which naturally prevents feature drift when length increases and can alleviate the generation quality degradation issue. RWKV Peng et al. revisits the traditional recurrent neural networks (RNNs) and demonstrates that, contrary to the common belief, a large enough RNN can exhibit impressive performance comparable to many Transformer-based LLMs. Similarly, Retnet Sun et al. (2023) proposes retentive networks, and Memba Gu & Dao (2023) proposes to use SSMs, which combines more complicated techniques such as gating mechanism and prefix sum to improve the expressiveness and efficiency further. However, the recurrent structure also requires a delicate tradeoff between long-term and short-term memory, and their performance on long-context tasks, especially on lifespan data, which requires information retention on the order of years, is still under debate and investigation.

5.2 Length Extension Methods for Existing LLMs

Various methods have been proposed to extend the context length of existing LLMs, addressing their length limits and tackling the lifespan data better. One line of work focuses on modifying the attention mechanism without changing the model parameters. Han et al. (2024); Xiao et al. (2024) propose to modify the attention

Where to store	How Compressed (1-4)	E.`Write` (1-4)	E.`Read` (1-4)
Parameters	4	1	4
Explicit Memory	3	2	3
Knowledge Base	2	3	2
Context	1	4	1

Table 2: Properties of different categories. "How Compressed" means how compressed past experiences are when stored in the corresponding form. E.`Write` and E.`Read` refer to the efficiency of `Write` process (writing the experiences into a certain form (model parameters/explicit memory/knowledge base/context)) and `Read` process (reading the experiences from a certain form), respectively. The more compressed the information is, or the higher the efficiency is, the higher score we list here.

mechanism without changing the model parameters to enable LLMs to handle infinite context lengths. In particular, LM-Infinite Han et al. (2024) extends LLMs to an extreme length of 200M tokens with $O(n)$ complexity and without degradation in perplexity metric while also showing improvements in downstream tasks. Jin et al. proposes to group tokens into blocks and let each block share a relative position before applying the attention mechanism. They also demonstrate improved performance on long-context tasks, even though the grouping operation is not extendable to infinite size, which upper bounds the extension length.

Another line of work focuses on fine-tuning the model on longer texts to adapt to longer contexts. As many absolute or relative position encoding methods are trained on mathematically pre-defined periodic functions, Qu (2023); Ding et al. (2024); Liu et al. (2023); Jiang et al. (2023a) propose to apply LLMs (fine-tuned or not) on decreased period frequencies (which is equivalent to interpolating position indices) to adapt LLMs to longer sequences. This modification changes the computational features of the model, making fine-tuning necessary to adapt the model to the new context length. Some other papers finetune LLMs with designed attention patterns Oren et al. (2024); Zhang et al. (2024c) on long contexts, using neural tangent kernel (Peng et al., 2023), or with low-rank adaptation(LoRA) (Chen et al., 2023b). Yang & Hua (2024) proposes a wait-to-attend mechanism to extend length limits for memory-based Transformers. Other ways of key-value cache selection/eviction methods are investigated in Ren & Zhu (2024); Dong et al. (2024); Zhang et al. (2024e). Similarly, Huang et al. (2023b); Lee et al. (2024) tackles long context by learning to prune, select, or summarize contexts dynamically. Alternatively, context compression methods (Shao et al., 2024) propose to learn to compress long contexts into shorter embedding sequences. Some work proposes alternative position encodings (Song et al., 2023; Zhang et al., 2024d; Zhu et al., 2023) or landmark token embeddings (Luo et al., 2024) that enable extendable context limits. Compared with the other methods, especially continual learning, this category of methods needs to expand the memory continuously when the system obtains new experiences, while continual learning could absorb these experiences into the model parameters without expanding anything. These approaches, relying on LLMs to aggregate and process contextual information on the fly, might encounter problems in the face of mutually conflicting instructions or tasks like privacy protection and information retrieval Wang et al. (2024a). On the other hand, cognitive systems with an awareness of the ideal situation are expected to better maintain and handle the ongoing tasks with complete interactions.

6 Benefits and Limitations of the Methods in Each Category

In this section, we examine the strengths and weaknesses of the various technologies mentioned above. (The strengths and weaknesses are summarized in Table 1 and Table 2)

Saving $\mathcal{E}$ into Model Parameters. This category of methods embeds knowledge directly into the model's weights. While existing methods can inject various forms of knowledge into a language model, they may not suffice as standalone solutions for achieving LSCS. This category includes methods related to model editing and continual learning. Current model editing techniques fall short in editing the model with life experiences which could be more complicated than factual statements, and continual learning methods still struggle with catastrophic forgetting. Anothor fundamental discrepancy between LSCS and continual learning is

that LSCS requires updates based on small pieces of information, whereas continual learning necessitates constructing datasets for retraining. Despite these limitations, these methods still offer valuable contributions to LSCS, particularly when there is a need to inject substantial knowledge into the model, adjust its behavior, or update the system to reflect shifts in societal values. As the model updates its parameters with new experiences, new memories are conceptually merged with existing ones. This process leads to automatic **Abstraction and Experiences Merging**, where the raw information is not preserved in full detail, but rather abstracted and integrated into the model. Such methods face challenges with **Long-term Retention and Accurate Recalling** due to the inherent risk of catastrophic forgetting in continual learning and failure in sequential model editing (Although some works like WISE (Wang et al., 2024b) claim to support numerous sequential edits by using external modules, these should technically fall under the category of "**Saving $\mathcal{E}$ into Explicit Memory** "). The efficiency of writing the experiences into the model parameters (E.`Write`) is low, as it involves training and back-propagation (even in model editing methods such as Meng et al. (2022; 2023), backpropagation is needed). In contrast, the efficiency of reading the experiences (E.`Read`) is high, as the generation speed remains unaffected by updates while the effects of the experiences can still be reflected in generation.

Saving $\mathcal{E}$ into Explicit Memory. Memory-based methods show promise as they allow the model to access information from the distant past by storing $\mathcal{E}$ in memory, without significantly increasing inference costs as history lengthens. These methods (1) often involve some form of abstraction, resulting in the inability to predict exact answers when queried on specific questions, as only the abstracted information from the experiences is stored. (2) may be hard to enable long-term retention as there is either explicit forgetting (Wang et al., 2024e; Zhong et al., 2023) or implicit forgetting (Zhou et al., 2023). One possible way to mitigate the forgetting issue is to enlarge the memory pool as studied in MemoryLLM (Wang et al., 2024e). However, the utilization of the memory pool in MemoryLLM may not be optimal, as it can only achieve around 40 steps (approximately 20k input length) of updates without completely forgetting the earlier knowledge. Despite the current limitations of memory-based methods, we believe memory-based methods are still an important part of achieving a powerful LSCS. In LSCS, one important ability is **Abstraction and Experiences Merging**. In memory-based methods, there are certain forms of compression when writing the experiences into the memory, which aligns with the idea of abstraction (abstracting the incoming knowledge). However, experiences merging is still under-explored in memory-based methods. Though there are some preliminary explorations (He et al., 2024b), how to merge the memories, especially in the hidden space is extremely hard and there are barely any works capable of merging memories in a way that similar memories are put together and even lead to new understandings instead of simply concatenating all memories. As for the ability of **Long-term Retention and Accurate Recalling**, memory-based methods are inherently not able to recall accurate information as the compression and forgetting mechanisms are part of the design of the memory module, which means some detailed information is destined to be missing. However they can still achieve a long-term retention where the major contour of events could be maintained with details forgotten. The efficiency of the `Write` process is higher than saving $\mathcal{E}$ into model parameters as it usually requires a forward pass to convert the text into some certain space, while the efficiency of the `Read` process is lower than saving $\mathcal{E}$ into model parameters as the LLM needs to read from the memory module and put this extracted information in the context to process.

Saving $\mathcal{E}$ into Knowledge Bases for Retrieval. storing $\mathcal{E}$ in knowledge bases is essential for achieving LSCS, enabling the system to accumulate vast amounts of knowledge over time. Whether stored as organized text or knowledge graphs, the information can be retrieved efficiently through RAG methods to inform the generation process. While text-based storage excels at handling large volumes of general information, knowledge graphs offer more structured and relational insights. Together, these methods allow LSCS to retrieve and utilize past experiences effectively, adapting to new situations and challenges based on accumulated knowledge. This category includes methods that store experiences as raw text in a knowledge base or create structured representations, like graphs, by extracting triplets from the input data. When extracting triplets, some detailed information that cannot be represented by factual triplets is inevitably lost, and the nodes and edges in the knowledge graph can be updated to resolve conflicts and merge similar relations. However, these abstractions are fairly naive and only simple conflicts and merging can be handled. As for the knowledge base in the form of organized text, the process usually needs to abstract some knowledge from the experiences to create index such as the embedding of summary of the experiences, where the experiences merging could be

even harder than using knowledge graph. Thus we say this category of methods involve Partial **Abstraction and Experiences Merging**. These methods offer strong **Long-term Retention and Accurate Recalling**, as the knowledge base can store extensive information. The efficiency of the `Write` process (**E.`Write`**) is higher than the above two categories, as it involves processing the input to construct structured representations which may be faster than converting all text into some other spaces. The efficiency of `Read` process (**E.`Read`**) is lower than the above two, as it requires retrieving and integrating relevant information from the knowledge base. In comparison, Saving $\mathcal{E}$ into model parameters does not require retrieval, and saving $\mathcal{E}$ into explicit memory could potentially skip the need of retrieval such as MemoryLLM (Wang et al., 2024e).

Saving $\mathcal{E}$ into Raw Text and Process All While saving $\mathcal{E}$ as the raw text and putting it into context is conceptually straightforward, it faces significant practical challenges. For instance, humans, are estimated to speak an average of 16k words per day (Mehl et al., 2007), totaling hundreds of millions of words over a lifetime (Brandreth, 1980). Consequently, current LLMs usually cannot process all past experiences. Even methods that claim to handle infinitely long contexts struggle with effectively recalling important knowledge from the past (Gu & Dao, 2023; Sun et al., 2024). Despite extensive efforts to extend these length limits, obstacles such as computational inefficiency and information forgetting remain unresolved Liu et al. (2024), preventing these approaches from being a fundamental solution to LSCS. As for the property **Abstraction and Experiences Merging** mentioned in Section 1, this line of methods does not involve any abstraction or experiences merging. However, as all the past experiences are stored explicitly in the context, this category of methods is capable of achieving **Long-term Retention and Accurate Recalling**. The `Write` process (**E.`Write`**) is highly efficient, as it merely involves concatenating new experiences to the existing data. However, the `Read` process (**E.`Read`**) is less efficient, as it requires the language model to process all stored experiences, leading to increased computational demands.

7 Our Suggested Paradigm of LSCS

Existing technologies individually address some aspects of the challenges associated with **Abstracting and Merging Experiences** and **Long-term Retention and Accurate Recall**, but none can handle both sets of issues comprehensively. To address these limitations, we propose a new paradigm of LifeSpan Cognitive System (LSCS) that integrates and combines these methods to create a more robust solution. As depicted in Figure 2, the LSCS operates in two key phases: absorbing experiences and generating responses to environmental queries, with the detailed descriptions shown below:

7.1 Absorbing Experiences

The experience absorption process within LSCS occurs with multiple levels of abstraction. This allows the system to retain both raw details and high-level summaries of experiences, which are processed and stored in several levels (corresponding to Figure 2a):

Raw Experience Storage: The latest experiences are captured in their raw textual form, preserving details without loss. This information is stored in the system's memory as a direct record of events, which is accessible for immediate recall.

Non-semantic Information Storage: Certain types of data, such as phone numbers or some hard-to-remember names, are challenging for typical memory models to store effectively. These pieces of non-semantic information, which lack comprehensive contextual meaning but are critical for precision, are stored in a dedicated knowledge base. The knowledge base acts as a repository for factual, easily forgotten information that LSCS can access as needed.

Semantic Information Abstraction: Experiences are also abstracted to capture their core meaning or "essence," such as a general impression of a person, an emotional response to an event, or a rough memorization of some events that happened before. These abstracted memories, which may lack fine details, are stored in the external memory module. This module allows for memory consolidation and combination, leading to the creation of new insights and deeper understandings through a process akin to memory integration and fusion.

Deeply Encoded Information in Model Parameters: The highest level of abstraction occurs when repeated experiences are encoded directly into the model's parameters, leading to the formation of long-term behaviors and habits. This mirrors how humans internalize routines or adapt to new environments over time. In LSCS, these deeply embedded patterns represent highly compressed forms of knowledge that are retained without needing further memory resources.

As experiences are abstracted through these levels, the degree of compression increases, transitioning from raw text to structured knowledge, and eventually to internalized model parameters.

7.2 Generating Responses to Environmental Queries

When faced with an environmental query, LSCS gathers relevant information from all of its modules to generate a response. To begin with, the query is integrated into the context, forming the basis for the system's reasoning. Then related information is extracted with the following processes (see Figure 2b):

Retrieval from Knowledge Base: If factual or non-semantic information is required, the system queries the knowledge base for relevant data, which is then added to the context. This ensures that precise, detail-oriented information is readily available when needed.

Abstracted Semantic Information Retrieval: With the environmental query, the system reads the external memory module to extract the relevant semantic information which is usually in the hidden space. The extracted hidden states are also put into the context.

Response Generation: With all necessary inputs in place, the large language model (potentially a multi-modal one as the experiences can include images, speech, videos as well (Wang et al., 2024g)). takes the context as the input and generate a response according to the context and the model parameters. This step includes reading the extracted information from the knowledge base, the memory module, and the model parameters to provide a complete, context-aware response to the environmental query.

7.3 Summary of the Proposed Paradigm

In the above-mentioned processes, both the knowledge base and memory module are utilized, allowing us to adopt the technologies described in **Saving $\mathcal{E}$ into Knowledge Bases for Retrieval** and **Saving $\mathcal{E}$ into Explicit Memory**. Since the system incorporates a large language model, the techniques outlined in **Saving $\mathcal{E}$ into Model Parameters** are also applicable. During response generation, the model must handle extensive contextual inputs, which can be long enough to require the large language model to have long-context processing capabilities. By leveraging these technologies, we can enable **Abstraction and Experience Merging**, where the knowledge base, external memory module, and model parameters can all store abstracted versions of experiences. Then with the presence of both the knowledge base and external memory module, the system is capable of achieving **Long-term Retention and Accurate Recall** via querying these modules.

8 Conclusion

In this paper, we propose the concept of a **LifeSpan Cognitive System** (LSCS), which aims to manage rapid, incremental learning while retaining the ability to recall previous experiences. To achieve LSCS, we argue there are two major challenges: (1) Abstraction and Experiences Merging, (2) Long-term Retention and Accurate Recalling. Existing technologies have the potential to partially solve these challenges. Based on our defined metric, **Storage Complexity**, for saving past experiences ($\mathcal{E}$), we categorize existing technologies into four distinct classes. We summarize various technologies within each category and discuss the strengths and weaknesses of the methods in each category. We argue that achieving an LSCS requires a nuanced approach integrating multiple strategies to address the above two challenges. To this end, we propose a new paradigm for LSCS. We hope this paper provides valuable insights into LSCS and encourages further efforts to build more human-like cognitive systems.

References

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

Arij Al Adel and Mikhail S Burtsev. Memory transformer with hierarchical attention for long document processing. In *2021 International Conference Engineering and Telecommunication (En&T)*, pp. 1–7. IEEE, 2021.

Petr Anokhin, Nikita Semenov, Artyom Sorokin, Dmitry Evseev, Mikhail Burtsev, and Evgeny Burnaev. Arigraph: Learning knowledge graph world models with episodic memory for llm agents, 2024. URL `https://arxiv.org/abs/2407.04363`.

Zhangir Azerbayev, Hailey Schoelkopf, Keiran Paster, et al. Llemma: An open language model for mathematics. *CoRR*, 2023.

Jimmy Ba, Geoffrey E Hinton, Volodymyr Mnih, Joel Z Leibo, and Catalin Ionescu. Using fast weights to attend to the recent past. *Advances in neural information processing systems*, 29, 2016.

Amir Bidokhti and Shahrokh Ghaemmaghami. Compound short-and long-term memory for memory augmented neural networks. *Engineering Applications of Artificial Intelligence*, 116:105450, 2022a.

Amir Bidokhti and Shahrokh Ghaemmaghami. Dual memory structure for memory augmented neural networks for question-answering tasks. In *2022 12th International Conference on Computer and Knowledge Engineering (ICCKE)*, pp. 142–147. IEEE, 2022b.

Gyles Daubeney Brandreth. The joy of lex: How to have fun with 860,341,500 words. *(No Title)*, 1980.

Aydar Bulatov, Yuri Kuratov, and Mikhail S. Burtsev. Recurrent memory transformer. In *NeurIPS*, 2022.

Aydar Bulatov, Yuri Kuratov, and Mikhail S Burtsev. Scaling transformer to 1m tokens and beyond with rmt. *arXiv preprint arXiv:2304.11062*, 2023.

Mikhail S. Burtsev and Grigory V. Sapunov. Memory transformer. *CoRR*, abs/2006.11527, 2020. URL `https://arxiv.org/abs/2006.11527`.

Howard Chen, Ramakanth Pasunuru, Jason Weston, and Asli Celikyilmaz. Walking down the memory maze: Beyond context limit through interactive reading. *arXiv preprint arXiv:2310.05029*, 2023a.

Yifan Chen, Qi Zeng, Heng Ji, and Yun Yang. Skyformer: Remodel self-attention with gaussian kernel and nyström method. In *Proc. Thirty-fifth Annual Conference on Neural Information Processing Systems (NeurIPS2021)*, 2021.

Yifan Chen, Qi Zeng, Heng Ji, and Yun Yang. Sketching as a tool for understanding and accelerating self-attention for long sequences. In *Proc. The 2022 Conference of the North American Chapter of the Association for Computational Linguistics - Human Language Technologies (NAACL-HLT2022)*, 2022.

Yukang Chen, Shengju Qian, Haotian Tang, Xin Lai, Zhijian Liu, Song Han, and Jiaya Jia. Longlora: Efficient fine-tuning of long-context large language models. In *The Twelfth International Conference on Learning Representations*, 2023b.

Daixuan Cheng, Shaohan Huang, Junyu Bi, Yuefeng Zhan, Jianfeng Liu, Yujing Wang, Hao Sun, Furu Wei, Denvy Deng, and Qi Zhang. Uprise: Universal prompt retrieval for improving zero-shot evaluation. *arXiv preprint arXiv:2303.08518*, 2023.

Xin Cheng, Di Luo, Xiuying Chen, Lemao Liu, Dongyan Zhao, and Rui Yan. Lift yourself up: Retrieval-augmented text generation with self-memory. *Advances in Neural Information Processing Systems*, 36, 2024.

Ta-Chung Chi, Ting-Han Fan, Alexander Rudnicky, and Peter Ramadge. Dissecting transformer length extrapolation via the lens of receptive field analysis. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 13522–13537, 2023.

Andrea Cossu, Tinne Tuytelaars, Antonio Carta, et al. Continual pre-training mitigates forgetting in language and vision. *CoRR*, 2022.

Zhuyun Dai, Vincent Y Zhao, Ji Ma, Yi Luan, Jianmo Ni, Jing Lu, Anton Bakalov, Kelvin Guu, Keith B Hall, and Ming-Wei Chang. Promptagator: Few-shot dense retrieval from 8 examples. *arXiv preprint arXiv:2209.11755*, 2022.

Zihang Dai, Zhilin Yang, Yiming Yang, Jaime G Carbonell, Quoc Le, and Ruslan Salakhutdinov. Transformer-xl: Attentive language models beyond a fixed-length context. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pp. 2978–2988, 2019.

Payel Das, Subhajit Chaudhury, Elliot Nelson, Igor Melnyk, Sarathkrishna Swaminathan, Sihui Dai, Aurélie C. Lozano, Georgios Kollias, Vijil Chenthamarakshan, Jirí Navrátil, Soham Dan, and Pin-Yu Chen. Larimar: Large language models with episodic memory control. In *ICML*. OpenReview.net, 2024.

Jiayu Ding, Shuming Ma, Li Dong, Xingxing Zhang, Shaohan Huang, Wenhui Wang, and Furu Wei. Longnet: Scaling transformers to 1,000,000,000 tokens. *arXiv preprint arXiv:2307.02486*, 2023.

Yiran Ding, Li Lyna Zhang, Chengruidong Zhang, Yuanyuan Xu, Ning Shang, Jiahang Xu, Fan Yang, and Mao Yang. Longrope: Extending llm context window beyond 2 million tokens. *arXiv preprint arXiv:2402.13753*, 2024.

Harry Dong, Xinyu Yang, Zhenyu Zhang, Zhangyang Wang, Yuejie Chi, and Beidi Chen. Get more with less: Synthesizing recurrence with kv cache compression for efficient llm inference. *arXiv preprint arXiv:2402.09398*, 2024.

Qingxiu Dong, Damai Dai, Yifan Song, Jingjing Xu, Zhifang Sui, and Lei Li. Calibrating factual knowledge in pretrained language models. In *EMNLP (Findings)*, pp. 5937–5947. Association for Computational Linguistics, 2022.

Darren Edge, Ha Trinh, Newman Cheng, Joshua Bradley, Alex Chao, Apurva Mody, Steven Truitt, and Jonathan Larson. From local to global: A graph rag approach to query-focused summarization. *arXiv preprint arXiv:2404.16130*, 2024.

Xiachong Feng, Xiaocheng Feng, Libo Qin, Bing Qin, and Ting Liu. Language model as an annotator: Exploring dialogpt for dialogue summarization. In *ACL/IJCNLP (1)*, pp. 1479–1491. Association for Computational Linguistics, 2021.

Xiachong Feng, Xiaocheng Feng, and Bing Qin. A survey on dialogue summarization: Recent advances and new frontiers. In *IJCAI*, pp. 5453–5460. ijcai.org, 2022.

Govind Gangadhar and Karl Stratos. Model editing by pure fine-tuning. *CoRR*, abs/2402.11078, 2024.

Albert Gu and Tri Dao. Mamba: Linear-time sequence modeling with selective state spaces. *arXiv preprint arXiv:2312.00752*, 2023.

Albert Gu, Karan Goel, and Christopher Re. Efficiently modeling long sequences with structured state spaces. In *International Conference on Learning Representations*.

Caglar Gulcehre, Sarath Chandar, and Yoshua Bengio. Memory augmented neural networks with wormhole connections. *arXiv preprint arXiv:1701.08718*, 2017.

Tiezheng Guo, Chen Wang, Yanyi Liu, Jiawei Tang, Pan Li, Sai Xu, Qingwen Yang, Xianlin Gao, Zhi Li, and Yingyou Wen. Leveraging inter-chunk interactions for enhanced retrieval in large language model-based question answering, 2024. URL `https://arxiv.org/abs/2408.02907`.

Bernal Jiménez Gutiérrez, Yiheng Shu, Yu Gu, Michihiro Yasunaga, and Yu Su. Hipporag: Neurobiologically inspired long-term memory for large language models. *arXiv preprint arXiv:2405.14831*, 2024.

Kelvin Guu, Kenton Lee, Zora Tung, Panupong Pasupat, and Ming-Wei Chang. Realm: Retrieval-augmented language model pre-training, 2020. URL `https://arxiv.org/abs/2002.08909`.

Chi Han, Qifan Wang, Hao Peng, Wenhan Xiong, Yu Chen, Heng Ji, and Sinong Wang. Lm-infinite: Zero-shot extreme length generalization for large language models. In *Proceedings of the 14th International Joint Conference on Natural Language Processing*, pp. 23–28, 2024.

Thomas Hartvigsen, Swami Sankaranarayanan, Hamid Palangi, Yoon Kim, and Marzyeh Ghassemi. Aging with grace: Lifelong model editing with discrete key-value adaptors. *arXiv preprint arXiv:2211.11031*, 2022.

Xiaoxin He, Yijun Tian, Yifei Sun, Nitesh V Chawla, Thomas Laurent, Yann LeCun, Xavier Bresson, and Bryan Hooi. G-retriever: Retrieval-augmented generation for textual graph understanding and question answering. *arXiv preprint arXiv:2402.07630*, 2024a.

Zexue He, Leonid Karlinsky, Donghyun Kim, Julian McAuley, Dmitry Krotov, and Rogerio Feris. Camelot: Towards large language models with training-free consolidated associative memory. *arXiv preprint arXiv:2402.13449*, 2024b.

Chenxu Hu, Jie Fu, Chenzhuang Du, Simian Luo, Junbo Zhao, and Hang Zhao. Chatdb: Augmenting llms with databases as their symbolic memory. *arXiv preprint arXiv:2306.03901*, 2023.

Jie Huang, Wei Ping, Peng Xu, Mohammad Shoeybi, Kevin Chen-Chuan Chang, and Bryan Catanzaro. Raven: In-context learning with retrieval augmented encoder-decoder language models. *arXiv preprint arXiv:2308.07922*, 2023a.

Xijie Huang, Li Lyna Zhang, Kwang-Ting Cheng, and Mao Yang. Boosting llm reasoning: Push the limits of few-shot learning with reinforced in-context pruning. *arXiv preprint arXiv:2312.08901*, 2023b.

Zeyu Huang, Yikang Shen, Xiaofeng Zhang, Jie Zhou, Wenge Rong, and Zhang Xiong. Transformer-patcher: One mistake worth one neuron. *arXiv preprint arXiv:2301.09785*, 2023c.

Gautier Izacard, Mathilde Caron, Lucas Hosseini, Sebastian Riedel, Piotr Bojanowski, Armand Joulin, and Edouard Grave. Unsupervised dense information retrieval with contrastive learning. *arXiv preprint arXiv:2112.09118*, 2021.

Gautier Izacard, Patrick Lewis, Maria Lomeli, Lucas Hosseini, Fabio Petroni, Timo Schick, Jane Dwivedi-Yu, Armand Joulin, Sebastian Riedel, and Edouard Grave. Atlas: Few-shot learning with retrieval augmented language models. *Journal of Machine Learning Research*, 24(251):1–43, 2023.

Joel Jang, Seonghyeon Ye, Changho Lee, Sohee Yang, Joongbo Shin, Janghoon Han, Gyeonghun Kim, and Minjoon Seo. Temporalwiki: A lifelong benchmark for training and evaluating ever-evolving language models. In *EMNLP*, pp. 6237–6250. Association for Computational Linguistics, 2022a.

Joel Jang, Seonghyeon Ye, Sohee Yang, et al. Towards continual knowledge learning of language models. In *ICLR*, 2022b.

Huiqiang Jiang, Qianhui Wu, Xufang Luo, Dongsheng Li, Chin-Yew Lin, Yuqing Yang, and Lili Qiu. Longllmlingua: Accelerating and enhancing llms in long context scenarios via prompt compression. *arXiv preprint arXiv:2310.06839*, 2023a.

Zhengbao Jiang, Frank F Xu, Luyu Gao, Zhiqing Sun, Qian Liu, Jane Dwivedi-Yu, Yiming Yang, Jamie Callan, and Graham Neubig. Active retrieval augmented generation. *arXiv preprint arXiv:2305.06983*, 2023b.

Ziyan Jiang, Xueguang Ma, and Wenhu Chen. Longrag: Enhancing retrieval-augmented generation with long-context llms. *arXiv preprint arXiv:2406.15319*, 2024.

Hongye Jin, Xiaotian Han, Jingfeng Yang, Zhimeng Jiang, Zirui Liu, Chia-Yuan Chang, Huiyuan Chen, and Xia Hu. Llm maybe longlm: Selfextend llm context window without tuning. In *Forty-first International Conference on Machine Learning*.

Qiao Jin, Yifan Yang, Qingyu Chen, and Zhiyong Lu. Genegpt: Augmenting large language models with domain tools for improved access to biomedical information. *arXiv:2304.09667*, 2023.

Kaiokendev. Things iḿ learning while training superhot. `https://kaiokendev.github.io/til#extending-context-to-8k`, 2023.

Guolin Ke, Di He, and Tie-Yan Liu. Rethinking positional encoding in language pre-training. In *International Conference on Learning Representations*, 2020.

Zixuan Ke, Yijia Shao, Haowei Lin, Tatsuya Konishi, Gyuhak Kim, and Bing Liu. Continual pre-training of language models. In *ICLR*, 2023.

Jacob Devlin Ming-Wei Chang Kenton and Lee Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of NAACL-HLT*, pp. 4171–4186, 2019.

Urvashi Khandelwal, Omer Levy, Dan Jurafsky, Luke Zettlemoyer, and Mike Lewis. Generalization through memorization: Nearest neighbor language models. *arXiv preprint arXiv:1911.00172*, 2019.

Omar Khattab, Keshav Santhanam, Xiang Lisa Li, David Hall, Percy Liang, Christopher Potts, and Matei Zaharia. Demonstrate-search-predict: Composing retrieval and language models for knowledge-intensive nlp. *arXiv preprint arXiv:2212.14024*, 2022.

Seo Hyun Kim, Kai Tzu-iunn Ong, Taeyoon Kwon, Namyoung Kim, Keummin Ka, SeongHyeon Bae, Yohan Jo, Seung-won Hwang, Dongha Lee, and Jinyoung Yeo. Theanine: Revisiting memory management in long-term conversations with timeline-augmented response generation. *arXiv preprint arXiv:2406.10996*, 2024.

Kuang-Huei Lee, Xinyun Chen, Hiroki Furuta, John Canny, and Ian Fischer. A human-inspired reading agent with gist memory of very long contexts. *arXiv preprint arXiv:2402.09727*, 2024.

Dacheng Li, Rulin Shao, Anze Xie, Ying Sheng, Lianmin Zheng, Joseph E. Gonzalez, Ion Stoica, Xuezhe Ma, and Hao Zhang. How long can open-source llms truly promise on context length?, June 2023. URL `https://lmsys.org/blog/2023-06-29-longchat`.

Zhangheng Li, Jia-Xing Zhong, Jingjia Huang, Tao Zhang, Thomas Li, and Ge Li. Armin: Towards a more efficient and light-weight recurrent memory network. *arXiv preprint arXiv:1906.12087*, 2019.

Yaobo Liang, Chenfei Wu, Ting Song, et al. Taskmatrix. ai: Completing tasks by connecting foundation models with millions of apis. *arXiv:2303.16434*, 2023.

Tatiana Likhomanenko, Qiantong Xu, Gabriel Synnaeve, Ronan Collobert, and Alex Rogozhnikov. Cape: Encoding relative positions with continuous augmented positional embeddings. *Advances in Neural Information Processing Systems*, 34:16079–16092, 2021.

Yong Lin, Lu Tan, Hangyu Lin, et al. Speciality vs generality: An empirical study on catastrophic forgetting in fine-tuning foundation models. *arXiv:2309.06256*, 2023.

Nelson F Liu, Kevin Lin, John Hewitt, Ashwin Paranjape, Michele Bevilacqua, Fabio Petroni, and Percy Liang. Lost in the middle: How language models use long contexts. *Transactions of the Association for Computational Linguistics*, 12, 2024.

Xiaoran Liu, Hang Yan, Chenxin An, Xipeng Qiu, and Dahua Lin. Scaling laws of rope-based extrapolation. In *The Twelfth International Conference on Learning Representations*, 2023.

Kun Luo, Zheng Liu, Shitao Xiao, and Kang Liu. Bge landmark embedding: A chunking-free embedding method for retrieval augmented long-context large language models. *arXiv preprint arXiv:2402.11573*, 2024.

Shirong Ma, Shen Huang, Shulin Huang, et al. Ecomgpt-ct: Continual pre-training of e-commerce large language models with semi-structured data. *CoRR*, 2023.

Matthias R Mehl, Simine Vazire, Nairán Ramírez-Esparza, Richard B Slatcher, and James W Pennebaker. Are women really more talkative than men? *Science*, 317(5834):82–82, 2007.

Kevin Meng, David Bau, Alex Andonian, and Yonatan Belinkov. Locating and editing factual associations in gpt. *Advances in Neural Information Processing Systems*, 35:17359–17372, 2022.

Kevin Meng, Arnab Sen Sharma, Alex J. Andonian, Yonatan Belinkov, and David Bau. Mass-editing memory in a transformer. In *ICLR*. OpenReview.net, 2023.

Gianluca Moro, Luca Ragazzi, Lorenzo Valgimigli, Giacomo Frisoni, Claudio Sartori, and Gustavo Marfia. Efficient memory-enhanced transformer for long-document summarization in low-resource regimes. *Sensors*, 23(7):3542, 2023.

Tsendsuren Munkhdalai, Manaal Faruqui, and Siddharth Gopal. Leave no context behind: Efficient infinite context transformers with infini-attention. *CoRR*, abs/2404.07143, 2024.

Matanel Oren, Michael Hassid, Yossi Adi, and Roy Schwartz. Transformers are multi-state rnns. *arXiv preprint arXiv:2401.06104*, 2024.

Joon Sung Park, Joseph O'Brien, Carrie Jun Cai, Meredith Ringel Morris, Percy Liang, and Michael S Bernstein. Generative agents: Interactive simulacra of human behavior. In *Proceedings of the 36th annual acm symposium on user interface software and technology*, pp. 1–22, 2023.

Sangjun Park and JinYeong Bak. Memoria: Resolving fateful forgetting problem through human-inspired memory architecture, 2024.

Bo Peng, Eric Alcaide, Quentin Gregory Anthony, Alon Albalak, Samuel Arcadinho, Stella Biderman, Huanqi Cao, Xin Cheng, Michael Nguyen Chung, Leon Derczynski, et al. Rwkv: Reinventing rnns for the transformer era. In *The 2023 Conference on Empirical Methods in Natural Language Processing*.

Bowen Peng, Jeffrey Quesnelle, Honglu Fan, and Enrico Shippole. Yarn: Efficient context window extension of large language models. In *The Twelfth International Conference on Learning Representations*, 2023.

Ofir Press, Noah Smith, and Mike Lewis. Train short, test long: Attention with linear biases enables input length extrapolation. In *International Conference on Learning Representations*, 2021.

Xiangyu Qi, Yi Zeng, Tinghao Xie, et al. Fine-tuning aligned language models compromises safety, even when users do not intend to! *arXiv:2310.03693*, 2023.

Yujia Qin, Shihao Liang, Yining Ye, et al. Toolllm: Facilitating large language models to master 16000+ real-world apis. *arXiv:2307.16789*, 2023.

Zhijie Qu. Gpt rotational position embedding for length extrapolation. In *Proceedings of the 2023 6th International Conference on Machine Learning and Natural Language Processing*, pp. 166–170, 2023.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *The Journal of Machine Learning Research*, 21(1):5485–5551, 2020.

Ori Ram, Gal Shachaf, Omer Levy, Jonathan Berant, and Amir Globerson. Learning to retrieve passages without supervision. *arXiv preprint arXiv:2112.07708*, 2021.

Siyu Ren and Kenny Q Zhu. On the efficacy of eviction policy for key-value constrained generative language model inference. *arXiv preprint arXiv:2402.06262*, 2024.

Stephen Robertson, Hugo Zaragoza, et al. The probabilistic relevance framework: Bm25 and beyond. *Foundations and Trends® in Information Retrieval*, 3(4):333–389, 2009.

Parth Sarthi, Salman Abdullah, Aditi Tuli, Shubh Khanna, Anna Goldie, and Christopher D Manning. Raptor: Recursive abstractive processing for tree-organized retrieval. *arXiv preprint arXiv:2401.18059*, 2024.

Jingbo Shang, Zai Zheng, Xiang Ying, Felix Tao, and Mindverse Team. Ai-native memory: A pathway from llms towards agi. *arXiv preprint arXiv:2406.18312*, 2024.

Ninglu Shao, Shitao Xiao, Zheng Liu, and Peitian Zhang. Flexibly scaling large language models contexts through extensible tokenization. *arXiv preprint arXiv:2401.07793*, 2024.

Yikang Shen, Shawn Tan, Arian Hosseini, Zhouhan Lin, Alessandro Sordoni, and Aaron C Courville. Ordered memory. *Advances in Neural Information Processing Systems*, 32, 2019.

Weijia Shi, Sewon Min, Michihiro Yasunaga, Minjoon Seo, Rich James, Mike Lewis, Luke Zettlemoyer, and Wen-tau Yih. Replug: Retrieval-augmented black-box language models. *arXiv preprint arXiv:2301.12652*, 2023.

Shamane Siriwardhana, Rivindu Weerasekera, Elliott Wen, Tharindu Kaluarachchi, Rajib Rana, and Suranga Nanayakkara. Improving the domain adaptation of retrieval augmented generation (rag) models for open domain question answering, 2022. URL `https://arxiv.org/abs/2210.02627`.

Kaiqiang Song, Xiaoyang Wang, Sangwoo Cho, Xiaoman Pan, and Dong Yu. Zebra: Extending context window with layerwise grouped local-global attention. *arXiv preprint arXiv:2312.08618*, 2023.

Jianlin Su, Yu Lu, Shengfeng Pan, Ahmed Murtadha, Bo Wen, and Yunfeng Liu. Roformer: Enhanced transformer with rotary position embedding. *arXiv preprint arXiv:2104.09864*, 2021.

Sainbayar Sukhbaatar, Jason Weston, Rob Fergus, et al. End-to-end memory networks. *Advances in neural information processing systems*, 28, 2015.

Yu Sun, Shuohuan Wang, Yu-Kun Li, et al. ERNIE 2.0: A continual pre-training framework for language understanding. In *AAAI*, 2020.

Yu Sun, Xinhao Li, Karan Dalal, Jiarui Xu, Arjun Vikram, Genghan Zhang, Yann Dubois, Xinlei Chen, Xiaolong Wang, Sanmi Koyejo, et al. Learning to (learn at test time): Rnns with expressive hidden states. *arXiv preprint arXiv:2407.04620*, 2024.

Yutao Sun, Li Dong, Barun Patra, Shuming Ma, Shaohan Huang, Alon Benhaim, Vishrav Chaudhary, Xia Song, and Furu Wei. A length-extrapolatable transformer. *arXiv preprint arXiv:2212.10554*, 2022.

Yutao Sun, Li Dong, Shaohan Huang, Shuming Ma, Yuqing Xia, Jilong Xue, Jianyong Wang, and Furu Wei. Retentive network: A successor to transformer for large language models. *arXiv preprint arXiv:2307.08621*, 2023.

Zhengwei Tao, Ting-En Lin, Xiancai Chen, Hangyu Li, Yuchuan Wu, Yongbin Li, Zhi Jin, Fei Huang, Dacheng Tao, and Jingren Zhou. A survey on self-evolution of large language models. *arXiv preprint arXiv:2404.14387*, 2024.

Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023a.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023b.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.

Ben Wang and Aran Komatsuzaki. GPT-J-6B: A 6 Billion Parameter Autoregressive Language Model. https://github.com/kingoflolz/mesh-transformer-jax, May 2021.

Bing Wang, Xinnian Liang, Jian Yang, Hui Huang, Shuangzhi Wu, Peihao Wu, Lu Lu, Zejun Ma, and Zhoujun Li. Enhancing large language model with self-controlled memory framework. *arXiv e-prints*, pp. arXiv–2304, 2023a.

Boxin Wang, Weixin Chen, Hengzhi Pei, Chulin Xie, Mintong Kang, Chenhui Zhang, Chejian Xu, Zidi Xiong, Ritik Dutta, Rylan Schaeffer, et al. Decodingtrust: A comprehensive assessment of trustworthiness in gpt models. *Advances in Neural Information Processing Systems*, 36, 2024a.

Guanzhi Wang, Yuqi Xie, Yunfan Jiang, Ajay Mandlekar, Chaowei Xiao, Yuke Zhu, Linxi Fan, and Anima Anandkumar. Voyager: An open-ended embodied agent with large language models, 2023b.

Peng Wang, Zexi Li, Ningyu Zhang, Ziwen Xu, Yunzhi Yao, Yong Jiang, Pengjun Xie, Fei Huang, and Huajun Chen. WISE: rethinking the knowledge memory for lifelong model editing of large language models. *CoRR*, abs/2405.14768, 2024b.

Weizhi Wang, Li Dong, Hao Cheng, Xiaodong Liu, Xifeng Yan, Jianfeng Gao, and Furu Wei. Augmenting language models with long-term memory. *arXiv preprint arXiv:2306.07174*, 2023c.

Xiao Wang, Yuansen Zhang, Tianze Chen, et al. Trace: A comprehensive benchmark for continual learning in large language models. *CoRR*, 2023d.

Xindi Wang, Mahsa Salmani, Parsa Omidi, Xiangyu Ren, Mehdi Rezagholizadeh, and Armaghan Eshaghi. Beyond the limits: A survey of techniques to extend the context length in large language models. *arXiv preprint arXiv:2402.02244*, 2024c.

Yifan Wang, Yafei Liu, Chufan Shi, Haoling Li, Chen Chen, Haonan Lu, and Yujiu Yang. Inscl: A data-efficient continual learning paradigm for fine-tuning large language models with instructions. *CoRR*, abs/2403.11435, 2024d. URL https://doi.org/10.48550/arXiv.2403.11435.

Yu Wang, Nedim Lipka, Ryan A. Rossi, Alexa Siu, Ruiyi Zhang, and Tyler Derr. Knowledge graph prompting for multi-document question answering, 2023e. URL https://arxiv.org/abs/2308.11730.

Yu Wang, Xiusi Chen, Jingbo Shang, and Julian McAuley. Memoryllm: Towards self-updatable large language models. *arXiv preprint arXiv:2402.04624*, 2024e.

Yu Wang, Ruihan Wu, Zexue He, Xiusi Chen, and Julian McAuley. Large scale knowledge washing. *arXiv preprint arXiv:2405.16720*, 2024f.

Yu Wang, Zeyuan Zhang, Julian McAuley, and Zexue He. Lvchat: Facilitating long video comprehension. *arXiv preprint arXiv:2402.12079*, 2024g.

Shufa Wei, Xiaolong Xu, Xianbiao Qi, et al. Academicgpt: Empowering academic research. *CoRR*, 2023.

Jason Weston, Sumit Chopra, and Antoine Bordes. Memory networks. *arXiv preprint arXiv:1410.3916*, 2014.

Tongtong Wu, Linhao Luo, Yuan-Fang Li, Shirui Pan, Thuy-Trang Vu, and Gholamreza Haffari. Continual learning for large language models: A survey. *arXiv preprint arXiv:2402.01364*, 2024.

Yuhuai Wu, Markus Norman Rabe, DeLesley Hutchins, and Christian Szegedy. Memorizing transformers. In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022*. OpenReview.net, 2022. URL https://openreview.net/forum?id=TrjbxzRcnf-.

Guangxuan Xiao, Yuandong Tian, Beidi Chen, Song Han, and Mike Lewis. Efficient streaming language models with attention sinks. In *The Twelfth International Conference on Learning Representations*, 2024. URL https://openreview.net/forum?id=NG7sS51zVF.

Yong Xie, Karan Aggarwal, and Aitzaz Ahmad. Efficient continual pre-training for building domain specific large language models. *CoRR*, 2023.

Prateek Yadav, Qing Sun, Hantian Ding, et al. Exploring continual learning for code generation models. In *ACL*, 2023.

Hongkang Yang, Zehao Lin, Wenjin Wang, Hao Wu, Zhiyu Li, Bo Tang, Wenqiang Wei, Jinbo Wang, Zeyun Tang, Shichao Song, Chenyang Xi, Yu Yu, Kai Chen, Feiyu Xiong, Linpeng Tang, and Weinan E. Memory^3: Language modeling with explicit memory. *CoRR*, abs/2407.01178, 2024.

Zi Yang and Nan Hua. Attendre: Wait to attend by retrieval with evicted queries in memory-based transformers for long context processing. *arXiv preprint arXiv:2401.04881*, 2024.

Yunzhi Yao, Peng Wang, Bozhong Tian, Siyuan Cheng, Zhoubo Li, Shumin Deng, Huajun Chen, and Ningyu Zhang. Editing large language models: Problems, methods, and opportunities. *arXiv preprint arXiv:2305.13172*, 2023.

Pengfei Yu and Heng Ji. Self information update for large language models through mitigating exposure bias. In *arxiv*, 2023.

Wenhao Yu, Dan Iter, Shuohang Wang, Yichong Xu, Mingxuan Ju, Soumya Sanyal, Chenguang Zhu, Michael Zeng, and Meng Jiang. Generate rather than retrieve: Large language models are strong context generators. *arXiv preprint arXiv:2209.10063*, 2022.

Daoguang Zan, Bei Chen, Zeqi Lin, Bei Guan, Yongji Wang, and Jian-Guang Lou. When language model meets private library. *arXiv preprint arXiv:2210.17236*, 2022.

Han Zhang, Lin Gui, Yuanzhao Zhai, et al. Copf: Continual learning human preference through optimal policy fitting. *arXiv:2310.15694*, 2023a.

Han Zhang, Lin Gui, Yu Lei, Yuanzhao Zhai, Yehong Zhang, Yulan He, Hui Wang, Yue Yu, Kam-Fai Wong, Bin Liang, and Ruifeng Xu. COPR: continual human preference learning via optimal policy regularization. *CoRR*, abs/2402.14228, 2024a. URL `https://doi.org/10.48550/arXiv.2402.14228`.

Han Zhang, Yu Lei, Lin Gui, Min Yang, Yulan He, Hui Wang, and Ruifeng Xu. CPPO: Continual learning for reinforcement learning with human feedback. In *The Twelfth International Conference on Learning Representations*, 2024b. URL `https://openreview.net/forum?id=86zAUE80pP`.

Peitian Zhang, Shitao Xiao, Zheng Liu, Zhicheng Dou, and Jian-Yun Nie. Retrieve anything to augment large language models. *arXiv preprint arXiv:2310.07554*, 2023b.

Peitian Zhang, Zheng Liu, Shitao Xiao, Ninglu Shao, Qiwei Ye, and Zhicheng Dou. Soaring from 4k to 400k: Extending llm's context with activation beacon. *arXiv preprint arXiv:2401.03462*, 2024c.

Zhenyu Zhang, Runjin Chen, Shiwei Liu, Zhewei Yao, Olatunji Ruwase, Beidi Chen, Xiaoxia Wu, and Zhangyang Wang. Found in the middle: How language models use long contexts better via plug-and-play positional encoding. *arXiv preprint arXiv:2403.04797*, 2024d.

Zhenyu Zhang, Ying Sheng, Tianyi Zhou, Tianlong Chen, Lianmin Zheng, Ruisi Cai, Zhao Song, Yuandong Tian, Christopher Ré, Clark Barrett, et al. H2o: Heavy-hitter oracle for efficient generative inference of large language models. *Advances in Neural Information Processing Systems*, 36, 2024e.

Zihan Zhang, Meng Fang, Ling Chen, Mohammad-Reza Namazi-Rad, and Jun Wang. How do large language models capture the ever-changing world knowledge? a review of recent advances. *arXiv preprint arXiv:2310.07343*, 2023c.

Wanjun Zhong, Lianghong Guo, Qiqi Gao, and Yanlin Wang. Memorybank: Enhancing large language models with long-term memory. *arXiv preprint arXiv:2305.10250*, 2023.

Wangchunshu Zhou, Yuchen Eleanor Jiang, Peng Cui, Tiannan Wang, Zhenxin Xiao, Yifan Hou, Ryan Cotterell, and Mrinmaya Sachan. Recurrentgpt: Interactive generation of (arbitrarily) long text. *arXiv preprint arXiv:2305.13304*, 2023.

Wangchunshu Zhou, Yixin Ou, Shengwei Ding, Long Li, Jialong Wu, Tiannan Wang, Jiamin Chen, Shuai Wang, Xiaohua Xu, Ningyu Zhang, et al. Symbolic learning enables self-evolving agents. *arXiv preprint arXiv:2406.18532*, 2024.

Dawei Zhu, Nan Yang, Liang Wang, Yifan Song, Wenhao Wu, Furu Wei, and Sujian Li. Pose: Efficient context window extension of llms via positional skip-wise training. In *The Twelfth International Conference on Learning Representations*, 2023.

A Appendix

You may include other additional sections here.