AI-native Memory 2.0: Second Me

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Abstract

Human interaction with the external world fundamentally involves the exchange of personal memory, whether with other individuals, websites, applications, or, in the future, AI agents. A significant portion of this interaction is redundant, requiring users to repeatedly provide the same information across different contexts. Existing solutions, such as browser-stored credentials, autofill mechanisms, and unified authentication systems, have aimed to mitigate this redundancy by serving as intermediaries that store and retrieve commonly used user data. The advent of large language models (LLMs) presents an opportunity to redefine memory management through an AI-native paradigm: **SECOND ME**. SECOND ME acts as an intelligent, persistent memory offload system that retains, organizes, and dynamically utilizes user-specific knowledge. By serving as an intermediary in user interactions, it can autonomously generate context-aware responses, prefill required information, and facilitate seamless communication with external systems, significantly reducing cognitive load and interaction friction. Unlike traditional memory storage solutions, SECOND ME extends beyond static data retention by leveraging LLM-based memory parameterization. This enables structured organization, contextual reasoning, and adaptive knowledge retrieval, facilitating a more systematic and intelligent approach to memory management. As AI-driven personal agents like SECOND ME become increasingly integrated into digital ecosystems, SECOND ME further represents a critical step toward augmenting human-world interaction with persistent, contextually aware, and self-optimizing memory systems.

1 Introduction

Jingbo: TODO: We will write the intro later

Jingbo: We will cite the previous AI-native memory paper Shang et al. (2024)

2 An Overview of SECOND ME

Last year, we introduced LPM(Shang et al. (2024)), a three-layer system centered around memory, designed to enhance efficiency through personalized memory management and cognitive capture. Second Me is the latest evolution, following a thorough re-evaluation of the AI ecosystem's development, our ecological positioning, and user needs.

In terms of positioning, we have clearly defined Second Me's core role as a Context Provider. It acts as a bridge between users, future AI agents, and the broader information world, facilitating seamless interaction.

From a technical perspective, we have further refined the Hybrid framework design and validated the iteration of personalized models, ensuring the system's efficiency and adaptability in addressing complex demands.

Second Me not only represents the cutting edge of our current technology but also embodies our product philosophy at this stage—reflecting our commitment to personalized and intelligent interactions.

2.1 Large Personal Model (LPM) 1.0: A Recap

In the report "Ai-native memory: A pathway from LLMs towards AGI," Shang et al. (2024) we delved into the critical elements required to achieve Artificial General Intelligence (AGI). At the core of our discussion is the idea that a truly effective AGI must account for each user's unique background and preferences. This means that an AGI system capable of delivering an exceptional user experience must incorporate memory functionality, rather than relying solely on a standalone model. Through experimentation, we discovered that even large language models (LLMs) with ultra long context capabilities fall short, both in terms of performance and cost, when it comes to meeting users' needs for searching, organizing, and reasoning within complex memory systems.

Building on this insight, we proposed a three-layered AI Native Memory system:

- **L0: Raw Data Layer.** This layer is akin to applying RALM/RAG directly to raw data, defining memory as the entirety of unstructured data.
- **L1: Natural language memory layer** This layer encompasses memories that can be summarized in natural language forms, such as a user's brief bio, a list of significant sentences or phrases, and preference tags.
- **L2: AI-Native Memory Layer.** This layer represents memories that do not necessarily require natural language descriptions. Instead, they are learned and organized through model parameters, with each LPM being a neural network.

For the L2 layer, we explored the challenges and potential solutions, focusing on issues such as training efficiency, serving efficiency, cold start, and catastrophic forgetting. We conducted initial experiments with L2, defining the tasks and evaluation metrics that AI Native Memory models must address. Collaborating with early adopters, we trained and tested the model, ultimately validating that its performance surpassed that of RAG and long-context models.

As the AI landscape continues to evolve rapidly, we can now articulate our vision with greater precision: in the era of AGI powered by general-purpose large models, the key to enabling humans to fully integrate into this system and reap its benefits lies in an AI system that stands on the user's side—one that considers each individual, possesses their memory, and has absorbed it meaningfully. This is the path to a truly user-centric AGI.

2.2 Overall Design of SECOND ME

SECOND ME represents an innovative system that transcends the limitations of traditional static data retention by leveraging memory parameterization based on large language models. This approach enables structured data organization, contextual reasoning, and adaptive knowledge retrieval, paving the way for a more systematic and intelligent framework for memory management.

With the growing prominence of reasoning models such as Deepseek R1(DeepSeek-AI et al. (2025)) and the continuous advancements in Agent capabilities within general-purpose large models, we have carefully considered the role that a context-aware SECOND ME should play in the evolving AI ecosystem. Our conclusion is that SECOND ME should primarily serve as a provider of context, aligned with the user's perspective, rather than functioning as a task executor on the supply side. Guided by this vision, we have defined the task scenarios for Second Me. A detailed discussion will be provided in Chapter 3.

To bring this concept to fruition, we have developed a novel Hybrid architecture. As depicted in Figure 1, this architecture preserves the L0, L1, and L2 layers from LPM 1.0(Shang et al. (2024)) while introducing an inner loop mechanism that facilitates seamless integration and collaboration among these layers. Furthermore, we have established an outer loop structure, enabling general large models and internet resources to operate under the guidance of SECOND ME. By incorporating the user's standpoint, perspective, and context, this design ensures that user needs are met with precision and relevance.

Let us now review the relationship between Second Me and LPM 1.0 along with their key upgrades.

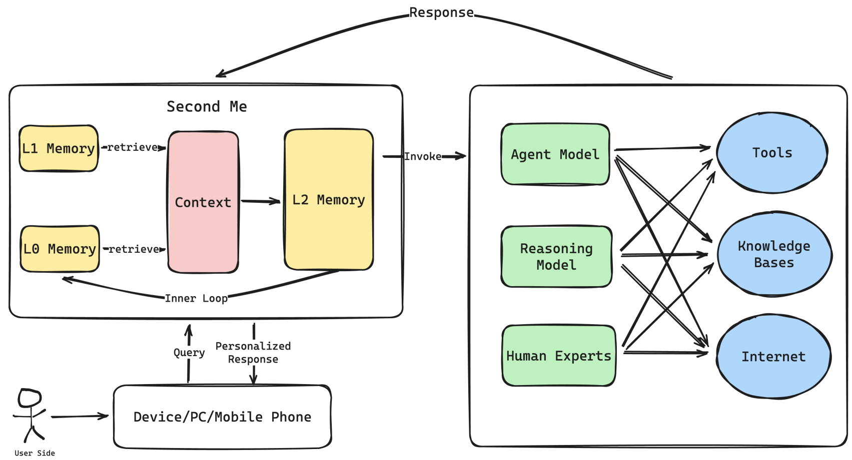

Figure 1: Hybrid Architecture of Second Me

Commonalities:

1) The three-layer architecture is maintained with consistent structural configurations across all layers.

Upgrades in Second Me:

1) **Enhanced Layer Integration**: While the three layers in LPM 1.0 operated relatively independently, Second Me redesigns L0 and L1 to serve as effective contextual supplements that provide detailed context to L2.

2) **Redefined L2 Role**: In LPM 1.0, L2 had ambiguous definitions and tended to directly complete tasks for users. In Second Me, L2 acts as an orchestrator that drives the entire system by leveraging external expert models to better fulfill usersćomplex requirements. This clarifies Second Meś positioning as an intelligent coordinator rather than a direct task executor.

3) **Automated Training Pipeline**: While LPM 1.0 only conducted preliminary experiments on L2 model training, Second Me establishes a fully automated pipeline encompassing data synthesis, data filtering, SFT (Supervised Fine-Tuning), DPO (Direct Preference Optimization), and evaluation. This enables Second Meś L2 layer to achieve state-of-the-art (SOTA) performance on relevant tasks under its new positioning.

3 SECOND ME: Practices and Results

Jingbo: Refer the previous paper's LPM as LPM 1.0

In previous workShang et al. (2024), we primarily highlighted that Large Language Models (LLMs) can serve as a medium for parameterizing and compressing various types of memories, which can be retrieved and utilized by users through conversation. In this section, we will introduce the improvements we have made to the model training, deployment, and evaluation processes. Specifically, we have further expanded the sources of training data for LLMs, added training tasks and new training phases, and designed a more comprehensive and automated evaluation system. These modifications represent our new vision for its relationship with users and provide a more detailed introduction to the reasons for these new changes, the specific implementation details, and our new vision for it.

3.1 Training

3.1.1 Training Objectives

We designed the benchmark data according to our expectation to the LPM model. These are what we consider to be the three most important types of tasks:

- **Memory QA** refers to the old tasks we design in our previous work , including knowledge retrieval, concept understanding, behavior prediction and item recommendation. This scenario can happen in the communication between the user and the trained LLM, but also, another person who is invited by the LLM owner can talk to this LLM.
- **Context Enhance** refers to the ability to enhance the user query when user ask an expert model to complete a difficult task. The trained LLM can include more details related to this query based on its understanding about user. It requires the trained LLM has deep understanding about user in all aspects, to realize what the user really need when looking at user query.
- **Response Judge** refers to the ability to judge if the response from an expert model satisfy user query when the expert model give feedback and answer to user. Similar to context enhance, the trained LLM should have deep understanding about the user as well as the query.

3.1.2 Training Architecture

There are two strategies for improving the ability of LLM in our work: Supervised Fine-tuning (SFT) and Direct Preference Optimization (DPO). Additionally, we make use of parameter-efficient fine-tuning (PEFT) to save time and reduce computational resources in training. While full parameter SFT can achieve stable and high performance ceiling, the costs in computational resources is significantly higher, which can make the on-device training impossible. Detailed analysis has shown that, the performance gap between full parameter SFT and PEFT is statistically not significant. **Jiale:** add a small table?

3.1.3 Training Data Construction

Data Sources Our training make use of the personal data under the following pipeline:

1. At stage 1, we categorized and summarize the uploaded multi-modal information, and make use of indexing and information extraction tools such as GraphRAG to find out useful entities, relations and communities.
2. At stage 2, we generate user biography and status description according to the extracted information in the first level. At the same time, the entities, relations and communities will be ranked according to their type and frequency, their descriptions and related text units will also be saved.
3. At stage 3, we generate trainable QA pairs given the data in stage 2 with corresponding context using data augmentation techniques, especially question generation and answering.

COT Data Trainable pairs generated in stage 3 above can be constructed in COT format, which can enhance model ability under inference, and also, give the LLM opportunity to behave like general expert model like GPT-4o. We use the following strategies to generate COT data:

- **Weak COT**: In the generation prompt, we let the expert model respond in COT pattern, without format checking and inference content constraint.
- **Multi-step COT**: In the first LLM inference node, we only generate the thinking content, then at the second LLM inference node, we generate answer given all the context, the query and the think content. In this strategy, we add constraint on the thinking length, prevent the thinking content from being too short to improve the overall answering quality.
- **Strong COT**: We let Deepseek-R1 as the expert model to generate long COT thinking and answer. Additional format constraint were applied in think and answer, and also the length limit, to make the response in proper length.

DPO Data

Data Filtering

3.2 Evaluation

3.2.1 Evaluation Tasks

Jingbo: mention that we have two users now? share some stats. **Jingbo**: also how did we do evaluation. why is the evaluation different than the previous paper?

3.2.2 Evaluation Data Construction

3.3 Results

4 Applications

Second Me provides multifaceted value to users in an era of information overload and complex social environments, helping them efficiently manage information and emotional issues while enhancing their professional influence and identity. As an auxiliary tool for individuals in today's society, Second Me demonstrates significant practical value.

From the demand-side solutions perspective, Second Me assists users in filtering and utilizing information, offering personalized knowledge and support to improve work efficiency and decision-making quality. Especially in the areas of career development and personal interests, it effectively manages information, reduces distractions, and boosts productivity.

On the internal application side, Second Me helps users organize their thoughts, reflect on decisions, and regulate emotions. It simulates cognitive and emotional needs, providing rational feedback and emotional support. Particularly when facing internal conflicts or complex emotions, Second Me aids users in making **more reasonable decisions**.

Externally, Second Me's applications extend beyond professional fields. One of the most promising aspects is its creation of a **human-AI network**. In this network, the **network effect grows exponentially**, and the reinforcement of Metcalfe's Law means the value of each node is influenced not only by human nodes but also by AI nodes and the interactions between humans and AI. As a result, the efficiency of the hybrid network's connections is enhanced by 3 to 5 orders of magnitude.

Additionally, Second Me drives the transformation of cognitive capital by constructing an NFT-based framework for personal cognitive assets and developing a quantifiable model for **knowledge flow efficiency**. This significantly improves the dissemination and application of knowledge. The emergence of socialized intelligence is also one of Second Me's key achievements. By building a distributed decision-making protocol, Second Me enhances collective cognitive abilities and enables more efficient group decision-making.

We have also open-sourced related project[1] on GitHub to allow users to complete the entire process locally on their computers, including data collection, learning, model training, and ultimately joining the network.

5 Conclusions, Limitations, and Outlooks

Currently, our technological applications are primarily focused on model training based on single-turn expansions. However, we hope to enhance model performance through deeper data synthesis strategies. In the field of reinforcement learning, we have explored the DPO algorithm. Given the vast potential of reinforcement learning, we plan to incorporate more advanced methods in the future to achieve better alignment. In our collaboration with users for model training and evaluation, although we have achieved some preliminary results, the feedback data remains limited due to resource constraints. We aim to validate the model on a larger user base in the future to further optimize its performance, which is one of the main reasons we are pursuing open-source projects. Moreover, we see the Second Me direction as a field with immense potential, one that is expected to profoundly transform the interaction and relationship between AI and humans. However, the challenge of comprehensively collecting and covering individual information and multimodal data remains ongoing, and it is a core issue faced by the industry.

References

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Appendix