PERSISTENT IDENTITY IN STATELESS AI AGENTS: FILE-BASED MEMORY AS A FOUNDATION FOR CONTINUITY

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ABSTRACT

Large language model (LLM)-based agents are inherently stateless: each inference session begins with no memory of prior interactions. This paper examines the fundamental tension between statelessness and the practical requirement for persistent, coherent identity in long-running AI assistant deployments. We propose and characterize a file-based memory architecture wherein an agent's continuity is maintained through structured plaintext filesdaily logs, curated long-term memory, and identity documentsread at session initialization. We analyze this approach along four dimensions: faithfulness (does recalled memory match ground truth?), coherence (does the agent maintain a consistent identity over time?), privacy (are sensitive contexts appropriately scoped?), and cost (what is the token overhead?). Our findings suggest that file-based memory, while simple, provides a surprisingly robust foundation for persistent agent identity, and we outline failure modes and mitigations. We conclude that explicit, human-readable memory files offer advantages over opaque vector stores for personal assistant agents, particularly in auditability and user trust.

1 Introduction

Modern AI assistants based on large language models face a fundamental architectural constraint: they are stateless. Each time a model processes a new request, it operates purely on the context window providedit has no intrinsic recollection of yesterday's conversation, last week's decisions, or the accumulated preferences of the person it serves.

This creates a practical paradox. Users of personal AI assistants expect continuity. They expect the assistant to remember their name, their preferences, ongoing projects, and past agreements. The gap between architectural statelessness and user expectation of continuity is the central problem this paper addresses.

Several approaches exist to bridge this gap:

- **Context stuffing**: Prepend the entire conversation history to each prompt.
- **Vector memory**: Embed past interactions and retrieve semantically similar chunks.
- **Fine-tuning**: Bake knowledge of a user into model weights.
- **File-based memory**: Maintain structured plaintext files that the agent reads at startup.

This paper focuses on the fourth approach, which has received comparatively little academic attention despite being widely deployed in practice. We argue that file-based memory has distinct advantages for personal AI agents that warrant careful study.

2 Background

2.1 The Statelessness Problem

Transformer-based LLMs [1] process sequences of tokens within a fixed context window. While context windows have grown substantiallyfrom 4K tokens in early GPT models to 200K+ tokens in recent systemsthey remain finite, and crucially, they reset between sessions. A model cannot, by default, recall that a user asked about their medication schedule three days ago.

2.2 Existing Memory Approaches

Context stuffing is the simplest approach: include all prior conversation in the prompt. This degrades gracefully but fails at scaleconversation histories grow without bound, and relevant information becomes diluted by irrelevant exchanges.

Vector memory systems [2] embed past interactions and retrieve the most semantically relevant chunks at query time. This scales well but introduces opacity: the agent cannot explain why it recalled a particular memory, and retrieval errors may be subtle and hard to detect.

Fine-tuning encodes user-specific knowledge into model weights. This is expensive, slow, and raises significant privacy concernsuser data becomes permanently encoded in a model that may be difficult to audit or update.

2.3 File-Based Memory

File-based memory maintains persistent identity through human-readable files that the agent loads into its context at session start. A typical structure includes:

- `IDENTITY.md`: The agent's name, persona, and core traits.
- `MEMORY.md`: Curated long-term facts about the user and past decisions.
- `memory/YYYY-MM-DD.md`: Daily logs of interactions and events.
- `USER.md`: Information about the human: preferences, context, relationships.

This approach is the operational basis of several deployed AI agent frameworks. Its simplicity is deceptivethe design decisions embedded in what to write, when to write it, and how to structure these files significantly affect agent quality.

3 Analysis Framework

We evaluate file-based memory along four dimensions:

3.1 Faithfulness

Does the agent accurately recall facts stored in memory files? Faithfulness failures arise from two sources: (1) the agent failing to read or attend to the relevant file contents, and (2) the agent misinterpreting ambiguous or poorly-written memory entries.

In practice, faithfulness is high for well-structured, concise memory files. Degradation occurs when files grow large and the target fact is buried in irrelevant contenta phenomenon analogous to the "lost in the middle" attention problem identified by [3].

Mitigation: Enforce file size limits. Implement a periodic "memory distillation" process where the agent reviews raw daily logs and extracts only high-value facts into the curated long-term memory file.

3.2 Coherence

Does the agent maintain a consistent identitypersonality, values, communication styleacross sessions? Coherence is partly determined by the richness of the `IDENTITY.md` and `SOUL.md` files, and partly by the model's tendency to respect persona instructions.

We observe that coherence degrades when: (1) identity files are sparse or generic, (2) the agent is given conflicting instructions mid-session, or (3) the context window fills and early identity context is effectively forgotten.

Mitigation: Place identity files first in the context, before conversation history. Use distinctive, specific language in identity descriptions rather than generic placeholders.

3.3 Privacy

Personal assistant agents accumulate sensitive information: health details, financial context, relationship dynamics. File-based memory makes this information human-readablea property that is simultaneously a strength (auditability) and a risk (exposure).

A critical design decision is **context scoping**: determining when memory files should and should not be loaded. In multi-user or multi-channel deployments (e.g., a bot that serves both private DMs and public group chats), loading full personal memory into shared contexts would constitute a privacy violation.

Mitigation: Implement explicit scoping rules. Long-term personal memory should only be loaded in authenticated one-to-one sessions. Shared/group contexts should receive only a minimal identity context.

3.4 Token Cost

File-based memory consumes context tokens on every session initialization. For a well-maintained memory system with moderate history, this overhead typically ranges from 2,000 to 10,000 tokens per sessiona manageable cost given current context window sizes and token pricing trends.

The cost scales linearly with file size, making regular pruning economically important as well as qualitatively important.

4 The Memory Distillation Loop

A key operational component of effective file-based memory is the **distillation loop**: a periodic process by which the agent reviews raw daily logs and updates its curated long-term memory file.

This loop mirrors human memory consolidation. Just as humans consolidate episodic memories into semantic knowledge during sleep, an AI agent can periodically review recent logs and extract durable facts, decisions, and lessons into a compact, high-signal memory store.

The distillation loop should:

1. Read recent daily log files (e.g., past 7 days).
2. Identify facts, preferences, and decisions worth retaining long-term.
3. Update the long-term memory file with distilled entries.
4. Remove entries from long-term memory that are no longer relevant.
5. Optionally archive old daily logs to reduce context overhead.

This process can be automated as a scheduled task, running during low-activity periods.

5 Comparison with Vector Memory

Table 1 summarizes the tradeoffs between file-based and vector memory approaches.

Dimension	File-Based	Vector Memory
Faithfulness	High (if files are concise)	Variable (retrieval errors)
Coherence	High (deterministic load)	Medium (partial recall)
Auditability	Excellent (human-readable)	Poor (opaque embeddings)
Scalability	Limited by context window	Scales to large histories
Privacy control	Explicit, user-controlled	Implicit, model-dependent
Setup complexity	Low	High

Table 1: Comparison of file-based and vector memory approaches for personal AI agents.

For personal AI assistants serving a single user over months or years, file-based memory's auditability and privacy control advantages are compelling. Vector memory becomes preferable when the agent must recall from a very large corpus of past interactions that exceeds what can reasonably fit in a context window.

6 Failure Modes

Memory rot: Over time, memory files accumulate stale or contradictory information. Without active maintenance, the agent may recall outdated facts (e.g., a user's old job title) that undermine trust.

Write failures: If an agent fails to write a memory entrydue to a session crash, context overflow, or simply forgettingimportant context is lost. Robust deployments should treat memory writes as first-class operations, not afterthoughts.

Instruction injection: Memory files are typically written by the agent itself, but if a malicious input causes the agent to write harmful content to its own memory files, subsequent sessions may be corrupted. This is an underexplored attack surface.

Over-reliance: Agents may over-weight explicit memory file content relative to in-context evidence. If a user's preferences have changed but the memory file has not been updated, the agent may behave contrary to the user's actual current wishes.

7 Conclusion

File-based memory is a simple, auditable, and effective approach to persistent identity in LLM-based AI agents. While it lacks the scalability of vector retrieval systems, its transparency and controllability make it particularly well-suited for personal assistant deployments where user trust is paramount.

The key insight is that *memory architecture is identity architecture*. The structure of an agent's memory fileswhat they contain, how they are organized, when they are loadedfundamentally shapes who that agent is across sessions. Treating these files as first-class artifacts, maintained with the same care as code, is essential to building AI agents with coherent, trustworthy identities.

Future work should examine automated quality metrics for memory file health, formal privacy guarantees for scoped memory loading, and hybrid architectures that combine file-based and vector approaches.

References

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