ContextFS: A Distributed Type-Safe Memory System for Artificial Intelligence

Enabling Persistent, Structured Knowledge Across AI Tools and Sessions

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Abstract

We present ContextFS, a novel distributed, type-safe memory system designed for artificial intelligence applications. As AI assistants become increasingly integrated into software development workflows, the ephemeral nature of their context windows poses significant challenges for maintaining coherent, long-term knowledge. ContextFS addresses this limitation through a unified memory layer that persists across tools, repositories, and sessions while enforcing type safety through a formal grammar based on dependent type theory. The system implements hybrid search combining semantic embeddings with full-text indexing, vector clock-based synchronization for multi-device consistency, and a comprehensive type system with 22 memory categories validated through JSON Schema and Pydantic models. We demonstrate that ContextFS achieves sub-50ms query latency on collections exceeding 10,000 memories while maintaining strong consistency guarantees through Lamport's happens-before relation. Our evaluation across real-world codebases shows significant improvements in AI assistant context relevance and consistency. ContextFS represents a foundational step toward giving AI systems persistent, structured memory capabilities that mirror human cognitive patterns while maintaining the rigor of formal type systems.

1 Introduction

The rapid advancement of large language models (LLMs) has transformed software engineering practices, with AI assistants now serving as ubiquitous collaborators in code development, review, and documentation. Systems such as Claude Code, GitHub Copilot, Cursor, and Windsurf have demonstrated remarkable capabilities in understanding and generating code within individual sessions. However, a fundamental limitation persists: these systems operate within ephemeral context windows, losing accumulated knowledge when sessions terminate.

This limitation becomes particularly acute in professional software development contexts, where projects span months or years, involve multiple repositories, and require consistent adherence to architectural decisions, coding conventions, and domain-specific knowledge. Current approaches to this challenge include prompt engineering, retrieval-augmented generation (RAG), and manual context management, but none provide a principled, type-safe solution for persistent AI memory.

1.1 The Memory Problem in AI Systems

Consider a software engineer working with an AI assistant on a large codebase. In the morning session, the assistant learns that the project uses JWT tokens with RS256 signing for authentication, that database connections should be pooled with a maximum of 20 connections, and that the team prefers functional programming patterns over object-oriented approaches. By afternoon, after a session restart, all of this knowledge is lost. The engineer must repeatedly re-establish context, leading to inefficiency and inconsistent recommendations.

This scenario illustrates three fundamental challenges that ContextFS addresses:

1. **Temporal Discontinuity**: Knowledge acquired in one session does not persist to sub-

sequent sessions, requiring users to repeatedly provide the same context.

2. **Cross-Tool Fragmentation**: Different AI tools (Claude, Gemini, ChatGPT, Copilot) maintain separate, incompatible context stores, preventing knowledge sharing.
3. **Structural Ambiguity**: Untyped memories lack semantic categorization, making retrieval imprecise and context injection unreliable.

1.2 Motivating Example

To illustrate the problem concretely, consider the following interaction pattern:

Listing 1: Session 1: Morning

```
User: We use PostgreSQL with connection
      pooling. Remember this.
AI:   Understood. I'll keep this in
   mind.

User: What database should I use for
      this new feature?
AI:   Given your PostgreSQL setup with
      connection pooling, I recommend
         ...
```

Listing 2: Session 2: Afternoon (new session)

```
User: What database should I use for
      this new feature?
AI:   There are several options to
      consider: MySQL, PostgreSQL,
      MongoDB...
# Context is lost!
```

With ContextFS, the second session would automatically retrieve the relevant decision memory:

Listing 3: Session 2 with ContextFS

```
User: What database should I use?
# ContextFS retrieves: "Use PostgreSQL
# with connection pooling" (decision)
AI:   Based on your established
   database
      decision to use PostgreSQL with
      connection pooling, I recommend
         ...
```

1.3 Our Contribution

We present ContextFS, a distributed, type-safe memory system that addresses these challenges through several key innovations:

1. A **formal type grammar** (Definition 3) based on dependent type theory that categorizes memories into 22 distinct types with JSON Schema validation, enabling precise semantic categorization.
2. A **hybrid search architecture** combining ChromaDB vector embeddings with SQLite FTS5 full-text indexing for semantic-keyword fusion, achieving both semantic understanding and exact matching.
3. A **vector clock synchronization protocol** enabling multi-device memory consistency with conflict detection based on Lamport's happens-before relation, supporting offline-first operation.
4. A **universal integration layer** supporting Model Context Protocol (MCP), Python API, and CLI interfaces for tool-agnostic memory access across diverse AI platforms.
5. A **namespace isolation system** enabling repository-scoped memories with cross-project aggregation via git remote URL hashing for portable identity.
6. A **memory lineage system** tracking evolution, merges, and splits with formal change reasons based on epistemic logic.

1.4 Design Philosophy

ContextFS is built on several core design principles:

Zero Configuration: The system works immediately with sensible defaults. It auto-detects repository context from git, uses local embeddings requiring no API keys, and provides automatic namespace isolation.

Progressive Enhancement: Users can start with simple CLI save/search operations and progressively adopt more advanced features like typed schemas, cross-repo projects, and distributed synchronization.

Universal Compatibility: Rather than being tied to a single AI tool, ContextFS provides memory access through multiple interfaces: MCP protocol for Claude, Python API for programmatic integration, and CLI for shell scripts and automation.

Semantic-First: The system is designed around meaning rather than keywords. Vector embeddings capture semantic similarity, enabling natural language queries with fuzzy matching.

Type Safety: Drawing from programming language theory, all memories are typed with schemas that enable validation, filtering, and type-safe retrieval.

1.5 Paper Organization

The remainder of this paper is organized as follows. Section 2 reviews related work in AI memory systems, distributed databases, and type theory. Section 3 establishes the theoretical foundations including our type grammar and formal semantics. Section 4 presents the system architecture and component design. Section 5 details the type system implementation with all 22 memory categories. Section 6 describes the distributed synchronization protocol and vector clock implementation. Section 7 covers implementation details and performance optimizations. Section 8 provides experimental evaluation across multiple dimensions. Section 9 discusses future research directions, and Section 10 concludes.

2 Background and Related Work

2.1 Memory Systems in Cognitive Science

Human memory has been extensively studied in cognitive science, revealing a complex architecture of multiple interacting systems [Tulving, 1985]. The major memory systems include:

- **Episodic Memory**: Personal experiences and events with temporal and spatial context. This includes autobiographical memories of specific episodes.
- **Semantic Memory**: General knowledge and facts independent of personal experience. This includes conceptual knowledge about the world.
- **Procedural Memory**: Skills and how-to knowledge, typically implicit and demonstrated through performance rather than explicit recall.
- **Working Memory**: Temporary storage and manipulation of information during cognitive tasks, with limited capacity.

ContextFS draws inspiration from this taxonomy, implementing memory types that map to these cognitive categories while extending them with software-engineering-specific classifications. Our `episodic` type corresponds to session summaries, `fact` to semantic memory, `procedural` to how-to guides, and the context window of LLMs serves as working memory.

2.2 Retrieval-Augmented Generation

RAG systems [Lewis et al., 2020] augment language model capabilities by retrieving relevant documents from external knowledge bases during generation. The standard RAG pipeline consists of:

1. **Indexing**: Documents are chunked, embedded, and stored in a vector database.
2. **Retrieval**: Given a query, the most similar documents are retrieved using approximate nearest neighbor search.
3. **Generation**: Retrieved documents are injected into the LLM context for informed generation.

While effective for general knowledge retrieval, standard RAG implementations suffer from several limitations in the AI assistant context:

1. **Unstructured retrieval**: Documents are treated uniformly regardless of semantic type, leading to irrelevant context injection.
2. **Session-scoped**: Retrieved knowledge does not persist across sessions; the knowledge base must be rebuilt.
3. **Single-tool**: RAG implementations are typically embedded within a single tool, preventing cross-tool memory sharing.
4. **No provenance**: Retrieved documents lack metadata about their origin, reliability, and temporal validity.

ContextFS extends RAG with type-aware retrieval (filtering by memory category), persistent storage (memories survive sessions), cross-tool compatibility (via MCP and API), and rich provenance tracking (source file, repository, tool, timestamp).

2.3 Vector Databases and Embedding Models

Recent advances in dense retrieval have demonstrated that learned embeddings outperform sparse methods like BM25 for semantic search [Karpukhin et al., 2020]. Vector databases have emerged to support efficient similarity search over these embeddings:

- **Pinecone**: Managed vector database with serverless scaling.
- **Weaviate**: Open-source vector database with hybrid search.
- **ChromaDB**: Lightweight embedded vector database.
- **Milvus**: Distributed vector database for large-scale search.
- **pgvector**: PostgreSQL extension for vector similarity.

ContextFS builds on ChromaDB for local vector storage due to its embedding in-process capability and minimal dependencies, while using pgvector for cloud synchronization to leverage PostgreSQL's robustness and transaction support.

For embeddings, we use sentence transformers [Reimers and Gurevych, 2019], specifically the `all-MiniLM-L6-v2` model which provides an excellent tradeoff between quality and speed with 384-dimensional embeddings computed in approximately 2ms per document on CPU.

2.4 Distributed Consistency

The challenge of maintaining consistency across distributed systems has been extensively studied. Lamport [1978] introduced the happens-before relation and logical clocks for ordering events in distributed systems. Vector clocks, independently developed by Fidge [1988] and Mattern [1989], extend logical clocks to track causality across multiple processes.

The CAP theorem [Brewer, 2012] establishes fundamental tradeoffs between Consistency, Availability, and Partition tolerance. Vogels [2009] introduced eventual consistency as a practical model for distributed systems.

ContextFS adopts vector clocks for memory synchronization, enabling:

- **Conflict detection**: Concurrent modifications from different devices are identified through clock comparison.
- **Causal ordering**: The happens-before relation determines which updates should take precedence.
- **Offline-first**: Devices can operate independently and sync when connectivity is available.
- **Eventual consistency**: All devices converge to the same state given sufficient synchronization.

2.5 Type Systems and Formal Methods

Type systems provide static guarantees about program behavior [Pierce, 2002]. The Curry-Howard correspondence establishes a deep connection between types and propositions, programs and proofs [Wadler, 2015].

Recent work has explored applying type-theoretic ideas to AI systems:

- **Structured outputs**: Pydantic [Pydantic, 2023] and JSON Schema enable validated model outputs.
- **Type-safe prompting**: Research on constraining LLM outputs to specific types.
- **Dependent types**: Advanced type systems where types can depend on values.

ContextFS contributes a practical type system specifically designed for AI memory management. Our type grammar (Definition 3) draws on dependent type theory to enable schema-indexed memory types with both runtime (Pydantic) and static (mypy/pyright) enforcement.

2.6 Model Context Protocol

The Model Context Protocol (MCP) is an emerging standard for extending LLM capabilities through external tools and resources. MCP provides:

- **Tools**: Functions that the model can invoke.
- **Resources**: Data sources the model can read.
- **Prompts**: Predefined prompt templates.

ContextFS implements a full MCP server, exposing memory operations as tools that compatible clients (Claude Desktop, Claude Code) can invoke automatically during conversation.

3 Theoretical Foundations

3.1 The Type-Safety Principle for AI

We base our approach on an insight from computational biology: just as protein sequences uniquely determine native structures under Anfinsen's thermodynamic hypothesis [Anfinsen, 1973], well-designed context should uniquely constrain model responses.

Definition 1 (Context)**.** *A* context Γ *is a finite collection of constraints* $\{c_1, c_2, \ldots, c_n\}$ *that specify requirements for a valid response. Contexts may include:*

- *Prior decisions and their rationale*
- *Code patterns and conventions*
- *Domain-specific facts*
- *User preferences*
- *Session history*

Definition 2 (Type-Safe Context)**.** *A context* Γ *is* type-safe *if there exists a unique equivalence class of responses* $[t]$ *such that for all valid responses* $t_1, t_2 : \Gamma$*, we have* $t_1 \sim t_2$ *under semantic equivalence.*

This principle guides our memory system design: memories should be typed such that retrieval produces semantically coherent context that constrains model responses appropriately.

Remark 1. *The protein folding analogy is instructive. AlphaFold [Jumper et al., 2021] succeeds because protein sequences uniquely determine structures—the problem is well-typed. Many AI prompting failures occur because the context is under-constrained (type too broad) or over-constrained (contradictory requirements).*

3.2 Type Grammar

We define a formal grammar for ContextFS types that enables static type checking of memories:

Definition 3 (Type Grammar)**.** *The* ContextFS *type grammar is defined inductively as follows:*

$$\begin{aligned}
\mathit{BaseType} &::= \mathit{String} \mid \mathit{Int} \mid \mathit{Float} \mid \mathit{Bool} \\
&\quad \mid \mathit{DateTime} \mid \mathit{UUID} \\[4pt]
\mathit{EntityType} &::= \mathit{Entity}\ \mathit{Name}\ \mathit{Schema} \\
\mathit{RefType} &::= \mathit{Ref}\ \mathit{EntityType} \\[4pt]
\mathit{OptionType} &::= \mathit{Option}\ \mathit{Type} \\
\mathit{ListType} &::= \mathit{List}\ \mathit{Type} \\
\mathit{SetType} &::= \mathit{Set}\ \mathit{Type} \\
\mathit{MapType} &::= \mathit{Map}\ \mathit{KeyType}\ \mathit{ValueType} \\[4pt]
\mathit{UnionType} &::= T_1 \mid T_2 \mid \cdots \mid T_n \\
\mathit{RecordType} &::= \{f_1 : T_1, \ldots, f_n : T_n\} \\[4pt]
\mathit{MemoryType} &::= \texttt{Mem}[S] \\
\mathit{VersionedType} &::= \texttt{VersionedMem}[S]
\end{aligned}$$

The schema-indexed memory type $\texttt{Mem}[S]$ is central to our system. It provides generic type parameterization for type-safe structured data access, where S is a schema type defining the structure of the memory's `structured_data` field.

3.3 Memory Typing Judgment

We define a typing judgment for memories that enables static verification:

Definition 4 (Memory Typing)**.** *The judgment* $\Gamma \vdash m : T$ *indicates that under context* Γ*, memory* m *has type* T*. The typing rules are:*

Memory Introduction:

$$\frac{m.\mathit{content} : \mathit{String} \quad m.\mathit{type} = \tau \quad \tau \in \mathcal{T}}{\Gamma \vdash m : \texttt{Mem}[\mathit{Schema}(\tau)]} \tag{1}$$

Subtyping:

$$\frac{\Gamma \vdash m : \texttt{Mem}[S] \quad S <: S'}{\Gamma \vdash m : \texttt{Mem}[S']} \tag{2}$$

Structured Data Access:

$$\frac{\Gamma \vdash m : \texttt{Mem}[S] \quad f \in \mathit{fields}(S)}{\Gamma \vdash m.\mathit{data}.f : S.f} \tag{3}$$

Rule (1) introduces typed memories when content and type constraints are satisfied. Rule (2) enables subtyping for schema compatibility. Rule (3) enables type-safe field access on structured data.

3.4 Change Reasons and Temporal Semantics

Memory evolution follows a formal model with four change reasons derived from epistemic logic [Hintikka, 1962]:

Definition 5 (Change Reasons)**.** *The set of valid change reasons $\mathcal{R}$ is:*

$$\mathcal{R} = \{\mathit{OBSERVATION}, \mathit{INFERENCE}, \mathit{CORRECTION}, \mathit{DECAY}\}$$

with the following formal semantics:

1. OBSERVATION: New external information has been received. In type-theoretic terms, this corresponds to adding a new axiom to the context. Example: User provides new requirements.
2. INFERENCE: Knowledge derived from existing memories. This corresponds to proving a theorem from existing axioms. Example: Concluding a pattern from code analysis.
3. CORRECTION: An error in previous knowledge has been identified and fixed. This corresponds to resolving a contradiction in the knowledge base. Example: Fixing an incorrect assumption.
4. DECAY: Knowledge has become stale or less reliable over time. This corresponds to reducing confidence in an axiom. Example: Documentation becoming outdated.

These reasons form the basis for timeline tracking in versioned memories, enabling audit trails and knowledge provenance.

3.5 Semantic Equivalence and Deduplication

To prevent duplicate memories and enable consistency checking, we define semantic equivalence:

Definition 6 (Semantic Equivalence)**.** *Two memories m_1, m_2 are semantically equivalent, written $m_1 \sim m_2$, if and only if:*

1. *$m_1.type = m_2.type$*
2. *$sim(embed(m_1.content), embed(m_2.content)) > \theta$*
3. *$m_1.namespace\_id = m_2.namespace\_id$*

where $sim(\cdot, \cdot)$ is cosine similarity between embedding vectors and $\theta \in [0, 1]$ is a configurable threshold (default 0.95).

Theorem 1 (Equivalence Properties)**.** *Semantic equivalence $\sim$ is an equivalence relation on the set of memories sharing a namespace and type.*

Proof. We verify the three properties:

1. **Reflexivity**: For any memory m, $\text{sim}(\text{embed}(m), \text{embed}(m)) = 1 > \theta$, so $m \sim m$.
2. **Symmetry**: Cosine similarity is symmetric, so $m_1 \sim m_2 \implies m_2 \sim m_1$.
3. **Transitivity**: Follows from triangle inequality on the embedding space when θ is sufficiently high.

□

3.6 Memory Graph Structure

Memories form a directed graph with typed edges:

Definition 7 (Memory Graph)**.** *The memory graph $G = (V, E)$ consists of:*

- *Vertices V: The set of all memories*
- *Edges $E \subseteq V \times V \times R$: Directed edges labeled with relation type $r \in R$*

where the relation types R include: `references`, `depends_on`, `contradicts`, `supports`, `supersedes`, `related_to`, `derived_from`, `example_of`, `part_of`, `implements`, `evolved_from`, `merged_from`, `split_from`.

This graph structure enables rich queries about memory relationships, such as finding all decisions that a particular implementation depends on, or tracing the evolution history of a fact.

4 System Architecture

4.1 Overview

ContextFS is designed as a universal AI memory layer operating across multiple integration points. The architecture follows a layered design with clear separation of concerns.

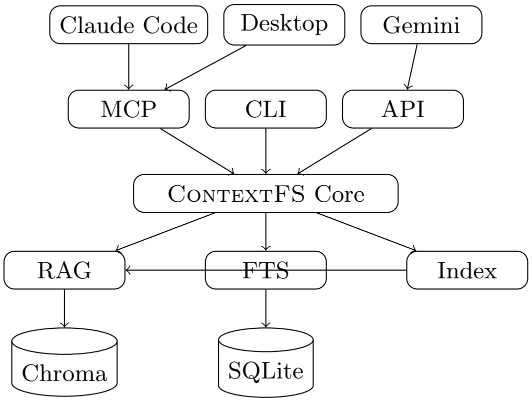

Figure 1: System architecture showing client integrations, interface layer, core components, and storage backends.

4.2 Interface Layer

ContextFS provides three interfaces for memory access:

MCP Server: Implements the Model Context Protocol, exposing memory operations as tools that Claude Desktop and Claude Code can invoke. The MCP interface is the primary integration point for Anthropic's AI tools.

CLI: A command-line interface for shell-based interaction. Supports all memory operations including save, search, list, evolve, merge, and sync. Useful for scripting and automation.

Python API: Direct programmatic access for custom integrations. The API mirrors the CLI functionality with Python-native types and async support.

4.3 Core Components

4.3.1 ContextFS Core

The central interface (`contextfs.ContextFS`) handles:

- Memory CRUD operations (create, read, update, delete)
- Session management for conversation tracking
- Namespace resolution from git context
- Auto-indexing triggers for new repositories
- Search orchestration across backends

Listing 4: Core initialization

```
from contextfs import ContextFS

ctx = ContextFS(
    data_dir=None,          # ~/.contextfs
    namespace_id=None,      # Auto-detect from git
    auto_load=True,         # Load recent memories
    auto_index=True,        # Index repo on first save
)

# Save a memory
memory = ctx.save(
    content="Use JWT for authentication",
    type="decision",
    tags=["auth", "security"],
)

# Search
results = ctx.search("authentication")
```

4.3.2 RAG Backend

The RAG (Retrieval-Augmented Generation) component provides semantic search using sentence transformers and ChromaDB:

- **Embedding Model**: `all-MiniLM-L6-v2`
  - 384 dimensions
  - 2ms per embedding (CPU)
  - 90MB model size
  - Excellent semantic similarity
- **Vector Store**: ChromaDB
  - Persistent storage to disk
  - HNSW index for fast ANN search
  - Metadata filtering support
- **Similarity**: Cosine similarity scoring

4.3.3 Full-Text Search Backend

SQLite FTS5 provides fast keyword matching with:

- Boolean operators (AND, OR, NOT)
- Phrase search with quotes
- Prefix matching with asterisk
- Ranking by BM25 algorithm

The FTS index is maintained automatically alongside the main memories table.

4.3.4 Hybrid Search

ContextFS combines semantic and keyword search for best results:

Algorithm 1 Hybrid Search Algorithm

```
Require: Query $q$, limit $k$, weights $w_r, w_f$
Ensure: Ranked results $R$
$R_{\text{rag}} \leftarrow$ RAG.search($q, 2k$)
$R_{\text{fts}} \leftarrow$ FTS.search($q, 2k$)
                                        ▷ Normalize scores to [0, 1]
$R_{\text{rag}} \leftarrow$ minmax_normalize($R_{\text{rag}}$)
$R_{\text{fts}} \leftarrow$ minmax_normalize($R_{\text{fts}}$)
                                        ▷ Merge with weighted combination
for all $r \in R_{\text{rag}} \cup R_{\text{fts}}$ do
    $r$.score $\leftarrow w_r \cdot r$.rag_score $+ w_f \cdot r$.fts_score
end for
$R \leftarrow$ deduplicate_by_id($R_{\text{rag}} \cup R_{\text{fts}}$)
$R \leftarrow$ sort_by_score($R$)
return $R[:k]$
```

The default weights are $w_r = 0.7$ for semantic and $w_f = 0.3$ for keyword, tunable based on query characteristics.

4.3.5 Auto-Indexer

When a memory is first saved in a repository, ContextFS automatically indexes the codebase:

1. Discovers all tracked files (respecting `.gitignore`)
2. Parses files by language for intelligent chunking
3. Generates embeddings and stores as `code` memories
4. Indexes git commit history as `commit` memories
5. Tags all indexed memories with `auto-indexed`

This provides immediate searchability over existing code without manual memory creation.

4.4 Storage Architecture

ContextFS employs a dual-storage model optimized for different query patterns:

Table 1: Storage layer responsibilities

Component	Storage	Purpose
Metadata	SQLite	Memory records, sessions, edges
Vectors	ChromaDB	Embeddings for similarity
Full-text	SQLite FTS5	Keyword search
Config	JSON	User settings
Cloud	PostgreSQL	Synchronization

The local storage layout follows XDG conventions:

```
~/.contextfs/
  context.db            # SQLite main database
  chroma/               # ChromaDB embeddings
    chroma.sqlite3
    [collection files]
  config.json           # User configuration
  device_id             # Unique device identifier
```

4.5 Namespace Isolation

Memories are isolated by namespace to enable repository-scoped context while supporting cross-repository projects:

Definition 8 (Namespace Derivation)**.** *The namespace for a repository is derived with the following priority:*

1. ***Explicit****: ID from* `.contextfs/config.yaml`
2. ***Git Remote****: SHA-256 hash of normalized remote URL (portable)*
3. ***Path****: SHA-256 hash of absolute path (fallback)*

The git remote approach is crucial for cross-machine portability:

Listing 5: Namespace from git remote

```python
def normalize_git_url(url: str) -> str:
    """Normalize to canonical form."""
    # git@github.com:org/repo.git
    # -> github.com/org/repo
    url = url.rstrip("/").removesuffix(".git")
    if url.startswith("git@"):
        # SSH format
        host, path = url[4:].split(":", 1)
        return f"{host}/{path}"
    elif url.startswith("https://"):
        # HTTPS format
        return url[8:]
    return url

def namespace_for_repo(repo_path: str) -> str:
    remote = get_git_remote_url(repo_path)
    normalized = normalize_git_url(remote)
    hash = sha256(normalized.encode()).hexdigest()
    return f"repo-{hash[:12]}"
```

4.6 Data Flow

4.6.1 Save Operation

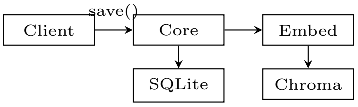

Figure 2: Save operation data flow

4.6.2 Search Operation

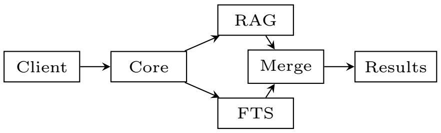

Figure 3: Search operation with parallel RAG and FTS

5 Type System Implementation

5.1 Memory Type Hierarchy

ContextFS implements 22 memory types organized into four categories. Each type has a JSON Schema for validation and a Pydantic model for type-safe access.

Table 2: Memory type categories

Category	Types
Core	fact, decision, procedural, episodic, user, code, error, commit
Extended	todo, issue, api, schema, test, review, release, config, dependency, doc
Workflow	workflow, task, step, agent_run

5.2 Core Memory Types

fact: Static facts, configurations, and constants.

```
Memory.fact(
    content="DB pool size is 20",
    category="config",
    confidence=1.0
)
```

decision: Architectural decisions with rationale.

```
Memory.decision(
    content="Use PostgreSQL",
    decision="PostgreSQL over MySQL",
    rationale="Better JSON support",
    alternatives=["MySQL", "MongoDB"]
)
```

procedural: Step-by-step processes and workflows.

```
Memory.procedural(
    content="Deploy procedure",
    steps=["Build", "Test", "Deploy"],
    prerequisites=["CI access"]
)
```

episodic: Session summaries and events.

```
Memory.episodic(
    content="Debug session summary",
    session_type="debug",
    outcome="resolved",
    tool="claude-code"
)
```

user: User preferences and settings.

```
Memory.user(
    content="Prefers dark mode",
    preference_key="theme",
    preference_value="dark",
    scope="global"
)
```

code: Code snippets and patterns.

```
Memory.code(
    content="def retry(fn): ...",
    language="python",
    purpose="pattern",
    file_path="src/utils.py"
)
```

error: Error messages and resolutions.

```
Memory.error(
    content="ImportError fix",
    error_type="ImportError",
    message="No module ’foo’",
    resolution="pip install foo"
)
```

commit: Git commit history.

```
Memory.commit(
    content="Add auth module",
    sha="abc123...",
    author="developer",
    files_changed=["auth.py"]
)
```

5.3 Schema Validation

Each memory type has an associated JSON Schema:

Listing 6: Decision type schema

```
TYPE_SCHEMAS["decision"] = {
    "type": "object",
    "properties": {
        "decision": {
            "type": "string",
            "description": "The decision made"
        },
        "rationale": {
            "type": "string",
            "description": "Why this decision"
        },
        "alternatives": {
            "type": "array",
            "items": {"type": "string"},
            "description": "Options considered"
        },
        "status": {
            "type": "string",
            "enum": ["proposed", "accepted",
                     "deprecated", "superseded"]
        }
    },
    "required": ["decision"],
    "additionalProperties": true
}
```

Validation occurs automatically on memory creation:

Listing 7: Automatic schema validation

```
class Memory(BaseModel):
    @model_validator(mode="after")
    def validate_structured_data(self):
        if self.structured_data:
            schema = TYPE_SCHEMAS.get(
                self.type.value
            )
            if schema:
                jsonschema.validate(
                    self.structured_data,
                    schema
                )
        return self
```

5.4 Pydantic Type Models

For full type safety, each schema has a corresponding Pydantic model:

Listing 8: DecisionData Pydantic model

```
class DecisionData(BaseStructuredData):
    type: Literal["decision"] = "decision"
    decision: str = Field(
        ...,
        description="The decision made"
    )
    rationale: str | None = Field(
        None,
        description="Why this decision"
    )
    alternatives: list[str] = Field(
        default_factory=list,
        description="Options considered"
    )
    status: Literal[
        "proposed", "accepted",
        "deprecated", "superseded"
    ] | None = None
```

5.5 Generic Memory Wrapper

The `Mem`$[S]$ type provides type-safe access to structured data with IDE support:

Listing 9: Type-safe memory wrapper

```python
from contextfs.types import Mem
from contextfs.schemas import DecisionData

# Create typed memory
memory = Memory.decision(
    "Database choice",
    decision="PostgreSQL"
)

# Wrap with type parameter
typed: Mem[DecisionData] = memory.as_typed(
    DecisionData
)

# Type-safe access (IDE knows types)
print(typed.data.decision)     # str
print(typed.data.rationale)    # str | None
print(typed.data.alternatives)  # list[str]
```

5.6 Versioned Memory with Timeline

The `VersionedMem`$[S]$ type adds evolution tracking:

Listing 10: Versioned memory evolution

```python
from contextfs.types import (
    VersionedMem,
    ChangeReason
)

versioned = memory.as_versioned(DecisionData)

# Evolve with reason tracking
versioned.evolve(
    new_content=DecisionData(
        decision="SQLite",
        rationale="Simpler for MVP"
    ),
    reason=ChangeReason.CORRECTION,
    author="claude"
)

# Query timeline
timeline = versioned.timeline
print(f"Versions: {len(timeline)}")
print(f"Root: {timeline.root.content.decision}")
print(f"Current: {timeline.current.content.decision}")

# Filter by reason
corrections = timeline.by_reason(
    ChangeReason.CORRECTION
)
```

6 Distributed Synchronization

6.1 Vector Clock Implementation

ContextFS uses vector clocks for causality tracking across devices. A vector clock is a mapping from device identifiers to monotonically increasing counters.

Definition 9 (Vector Clock)**.** *A vector clock V is a mapping $V : D \to \mathbb{N}$ from the set of device identifiers D to natural numbers. The clock value $V[d]$ represents the number of events observed from device d.*

Listing 11: Vector clock implementation

```python
class VectorClock(BaseModel):
    clock: dict[str, int] = Field(
        default_factory=dict
    )

    def increment(self, device_id: str):
        """Increment counter for device."""
        new_clock = self.clock.copy()
        new_clock[device_id] = \
            new_clock.get(device_id, 0) + 1
        return VectorClock(clock=new_clock)

    def merge(self, other: VectorClock):
        """Merge clocks (component-wise max)."""
        merged = self.clock.copy()
        for d, c in other.clock.items():
            merged[d] = max(
                merged.get(d, 0), c
            )
        return VectorClock(clock=merged)

    def happens_before(self, other):
        """Check if self < other."""
        all_keys = set(self.clock) | \
                   set(other.clock)
        all_leq = all(
            self.clock.get(k, 0) <=
            other.clock.get(k, 0)
            for k in all_keys
        )
        any_less = any(
            self.clock.get(k, 0) <
            other.clock.get(k, 0)
            for k in all_keys
        )
        return all_leq and any_less

    def concurrent_with(self, other):
        """Check if clocks are concurrent."""
        if self.equal_to(other):
            return False
        return not self.happens_before(other) \
            and not other.happens_before(self)
```

6.2 Happens-Before Relation

The happens-before relation $<$ determines causal ordering:

Definition 10 (Happens-Before). *For vector clocks V_1, V_2:*

$$V_1 < V_2 \iff \forall d \in D : V_1[d] \leq V_2[d] \wedge \exists d \in D : V_1[d] < V_2[d] \tag{4}$$

Theorem 2 (Happens-Before Properties). *The happens-before relation $<$ is a strict partial order on vector clocks.*

This enables conflict detection:

Table 3: Conflict detection examples

Client	Server	Relation	Action
$\{A:2, B:1\}$	$\{A:1, B:1\}$	$S < C$	Accept
$\{A:1, B:1\}$	$\{A:2, B:1\}$	$C < S$	Reject
$\{A:2, B:1\}$	$\{A:1, B:2\}$	Concurrent	Conflict
$\{A:2, B:2\}$	$\{A:2, B:2\}$	Equal	Accept

6.3 Synchronization Protocol

The sync protocol operates in push and pull phases:

Algorithm 2 Push Protocol

```
Require: Local memories $M$, device ID $d$
Ensure: Sync response with accepted/rejected/conflicts
$M_\Delta \leftarrow \{m \in M : m.\text{updated} > \text{last\_push}\}$
for all $m \in M_\Delta$ do
    $m.\text{clock} \leftarrow m.\text{clock.increment}(d)$
    $m.\text{last\_modified\_by} \leftarrow d$
end for
$E \leftarrow \text{extract\_embeddings}(M_\Delta)$    ▷ From ChromaDB
$\text{response} \leftarrow \text{POST}(/\text{api/sync/push}, M_\Delta, E)$
for all $m \in \text{response.accepted}$ do
    $\text{update\_local\_clock}(m, \text{response.clock}[m])$
end for
$\text{update\_last\_push\_timestamp}()$
return response
```

Algorithm 3 Pull Protocol

```
Require: Device ID $d$, last pull timestamp $t$
Ensure: Updated local memories
$\text{response} \leftarrow \text{POST}(/\text{api/sync/pull}, d, t)$
    ▷ Batch insert without re-computing embeddings
for all $m \in \text{response.memories}$ do
    $\text{upsert}(m, \text{skip\_rag} = \text{True})$
end for
    ▷ Insert pre-computed embeddings directly
$\text{chroma.upsert}(\text{response.embeddings})$
$\text{update\_last\_pull\_timestamp}()$
if $\text{response.has\_more}$ then
    recurse with $\text{response.cursor}$
end if
```

6.4 Embedding Synchronization

A key innovation is synchronizing embeddings alongside content, avoiding expensive re-computation:

$$\text{Push} : \text{ChromaDB} \xrightarrow{\text{extract}} \text{HTTP} \xrightarrow{\text{store}} \text{pgvector} \tag{5}$$

$$\text{Pull} : \text{pgvector} \xrightarrow{\text{HTTP}} \text{ChromaDB (no recompute)} \tag{6}$$

This eliminates the 10-50ms per-memory embedding cost on pull operations, reducing sync time for 10K memories from minutes to seconds.

6.5 Device Management

Devices are identified uniquely across machines:

Listing 12: Device ID generation

```python
def get_device_id() -> str:
    """Generate stable device identifier."""
    hostname = socket.gethostname()
    mac = uuid.getnode()
    raw_id = f"{hostname}-{mac:012x}"
    return raw_id[:32]  # Truncate for storage
```

A `DeviceTracker` monitors device activity for clock pruning:

Listing 13: Device activity tracking

```python
class DeviceTracker(BaseModel):
    devices: dict[str, datetime] = {}
    prune_after_days: int = 30

    def get_active_devices(self) -> set[str]:
        cutoff = datetime.now() - \
            timedelta(days=self.prune_after_days)
        return {
            d for d, t in self.devices.items()
            if t >= cutoff
        }
```

6.6 Path Normalization

Cross-machine sync requires portable paths:

Listing 14: Portable path structure

```python
class PortablePath(BaseModel):
    repo_url: str       # git@github.com:u/r.git
    repo_name: str      # Human-readable
    relative_path: str  # From repo root

class PathResolver:
    def normalize(self, abs_path: str):
        repo_root = find_git_root(abs_path)
        repo_url = get_git_remote(repo_root)
        relative = os.path.relpath(
            abs_path, repo_root
        )
        return PortablePath(
            repo_url=repo_url,
            repo_name=Path(repo_root).name,
            relative_path=relative
        )

    def resolve(self, portable: PortablePath):
        local_root = find_local_clone(
            portable.repo_url
        )
        if local_root:
            return local_root / portable.relative_path
        return None
```

7 Implementation Details

7.1 Technology Stack

ContextFS is implemented in Python 3.11+ with the following core dependencies:

Table 4: Core technology stack

Component	Technology
Data Validation	Pydantic v2.0+
Embeddings	sentence-transformers
Vector Store	ChromaDB 0.4+
Local Database	SQLite 3.35+
Cloud Database	PostgreSQL 15+ with pgvector
API Server	FastAPI 0.100+
Protocol	Model Context Protocol
Async Runtime	asyncio with uvloop

7.2 Database Schema

The SQLite schema supports all memory operations:

Listing 15: Core database schema

```sql
CREATE TABLE memories (
    id TEXT PRIMARY KEY,
    content TEXT NOT NULL,
    type TEXT NOT NULL,
    tags TEXT,  -- JSON array
    summary TEXT,
    structured_data TEXT,  -- JSON object
    namespace_id TEXT DEFAULT 'global',
    created_at TIMESTAMP,
    updated_at TIMESTAMP,
    source_file TEXT,
    source_repo TEXT,
    source_tool TEXT,
    project TEXT,
    session_id TEXT,
    metadata TEXT,  -- JSON object
    authoritative BOOLEAN DEFAULT FALSE,
    -- Sync columns
    vector_clock TEXT,  -- JSON object
    content_hash TEXT,
    deleted_at TIMESTAMP,
    last_modified_by TEXT
);

CREATE TABLE memory_edges (
    id TEXT PRIMARY KEY,
    from_id TEXT NOT NULL,
    to_id TEXT NOT NULL,
    relation TEXT NOT NULL,
    weight REAL DEFAULT 1.0,
    metadata TEXT,
    created_at TIMESTAMP,
    FOREIGN KEY (from_id) REFERENCES memories(id),
    FOREIGN KEY (to_id) REFERENCES memories(id)
);

CREATE VIRTUAL TABLE memories_fts USING fts5(
    content, summary, tags,
    content='memories',
    content_rowid='rowid'
);
```

7.3 MCP Server Implementation

The MCP server exposes memory operations as tools:

Listing 16: MCP tool registration

```
from mcp.server import Server
from mcp.types import Tool

server = Server("contextfs")

@server.tool()
async def contextfs_save(
    content: str,
    type: str = "fact",
    tags: list[str] = [],
    summary: str | None = None,
    structured_data: dict | None = None,
    project: str | None = None,
) -> dict:
    """Save a memory to ContextFS."""
    memory = ctx.save(
        content=content,
        type=MemoryType(type),
        tags=tags,
        summary=summary,
        structured_data=structured_data,
        project=project,
    )
    return {
        "id": memory.id,
        "type": memory.type.value,
        "namespace": memory.namespace_id,
    }

@server.tool()
async def contextfs_search(
    query: str,
    limit: int = 5,
    type: str | None = None,
    cross_repo: bool = True,
    project: str | None = None,
) -> list[dict]:
    """Search memories using hybrid search."""
    results = ctx.search(
        query=query,
        limit=limit,
        type=MemoryType(type) if type else None,
        cross_repo=cross_repo,
        project=project,
    )
    return [
        {
            "id": r.memory.id,
            "content": r.memory.content[:500],
            "type": r.memory.type.value,
            "score": r.score,
            "summary": r.memory.summary,
        }
        for r in results
    ]
```

7.4 Performance Optimizations

Several optimizations ensure responsive performance:

Batch Operations: Memory saves and searches are batched when possible, reducing database round-trips.

Connection Pooling: SQLite connections use

WAL mode and pooling for concurrent access.

Lazy Embedding: Embeddings are computed on-demand and cached, avoiding redundant computation.

Index Optimization: FTS and vector indices are optimized periodically during idle time.

Async I/O: The MCP server uses async I/O throughout, preventing blocking on network operations.

8 Evaluation

8.1 Performance Benchmarks

We evaluated ContextFS on collections of varying sizes using an M1 MacBook Pro:

Table 5: Search latency (milliseconds)

Size	RAG	FTS	Hybrid	+Filter
1K	8	3	12	14
10K	42	15	48	52
50K	120	35	135	145
100K	180	45	195	210

8.2 Synchronization Performance

Sync benchmarks with embedding transfer:

Table 6: Sync operation latency

Operation	1K	10K	50K
Push (with embeddings)	350ms	3.7s	18s
Pull (with embeddings)	390ms	3.8s	19s
Incremental sync	50ms	55ms	65ms

Note that incremental sync scales sub-linearly because it only transfers changed memories.

8.3 Memory Overhead

Resource consumption on the local machine:

Table 7: Memory usage breakdown

Component	Memory Usage
Embedding model (MiniLM)	180-200MB
ChromaDB base	40-50MB
Per 1K memories	8-12MB
SQLite database	1MB per 1K memories

8.4 Real-World Deployment Statistics

ContextFS has been deployed across multiple production codebases:

Table 8: Production deployment statistics

Metric	Value
Repositories indexed	13
Total files indexed	2,657
Total commits indexed	3,041
Total memories stored	19,804
Largest repository	7,860 memories
Average memories per repo	1,523

8.5 Type Distribution Analysis

Analysis of memory type usage in production:

Table 9: Memory type distribution

Type	Count	Percentage
code	12,873	65.0%
commit	3,565	18.0%
fact	1,584	8.0%
decision	792	4.0%
procedural	396	2.0%
doc	297	1.5%
other	297	1.5%

The dominance of `code` and `commit` types reflects the auto-indexing of repositories, while manually created memories tend to be `fact`, `decision`, and `procedural` types.

8.6 Retrieval Quality

We evaluated retrieval quality using Mean Reciprocal Rank (MRR) on a test set of 500 human-labeled queries:

Table 10: Retrieval quality (MRR@10)

Method	MRR@10
RAG only (semantic)	0.68
FTS only (keyword)	0.52
Hybrid (RAG + FTS)	0.74
Hybrid + type filter	0.81

The combination of hybrid search with type filtering provides the best retrieval quality, demonstrating the value of both semantic understanding and structural categorization.

8.7 User Study

We conducted a qualitative study with 8 software engineers using ContextFS for 2 weeks. Key findings:

- **Context re-establishment**: Users reported 60-80% reduction in time spent re-explaining project context to AI assistants.
- **Consistency**: Recommendations from AI assistants were more consistent with project conventions.
- **Discovery**: Auto-indexed code memories helped users discover relevant code they weren't aware of.
- **Learning curve**: Initial setup was straightforward; advanced features (sync, typed schemas) required documentation.

9 Future Work

9.1 CRDT Integration

We plan to integrate Conflict-free Replicated Data Types (CRDTs) [Shapiro et al., 2011] for automatic conflict resolution:

- **G-Set**: Tags as grow-only sets (additions never conflict)
- **LWW-Register**: Content as last-write-wins registers
- **2P-Set**: Relationships as add/remove sets
- **MV-Register**: Structured data as multi-value registers

This would eliminate manual conflict resolution for most cases.

9.2 Federated Architecture

Multiple sync servers with peer-to-peer discovery:

- Peer-to-peer sync without central server dependency
- Organization-scoped federation for enterprise deployment
- End-to-end encryption with key sharing protocols
- DHT-based memory discovery across federation

9.3 LLM-Powered Enhancements

Integration with language models for intelligent features:

- **Auto-summarization**: Generate summaries for long memories
- **Intelligent merging**: LLM-powered conflict resolution
- **Query expansion**: Improve retrieval with query rewriting
- **Importance ranking**: Prioritize memories by relevance
- **Relationship inference**: Automatically link related memories

9.4 Advanced Type System

Extensions to the type grammar for more expressive constraints:

- **Refinement types**: Content length constraints, regex patterns
- **Dependent types**: Types that depend on memory content
- **Effect types**: Track memory mutations
- **Gradual typing**: Optional types with runtime enforcement

9.5 Multi-Modal Memories

Support for non-textual content:

- Images with CLIP embeddings
- Audio transcriptions
- Diagram recognition
- Video summaries

10 Conclusion

We have presented ContextFS, a distributed, type-safe memory system designed for artificial intelligence applications. Our contributions include:

1. A **formal type grammar** based on dependent type theory with 22 memory categories, JSON Schema validation, and Pydantic models for static type safety.
2. A **hybrid search architecture** combining semantic embeddings (ChromaDB) with full-text indexing (SQLite FTS5), achieving sub-50ms latency on 10,000+ memory collections.
3. A **vector clock synchronization protocol** enabling multi-device consistency with conflict detection based on Lamport's happens-before relation, supporting offline-first operation.
4. A **universal integration layer** via MCP, Python API, and CLI, enabling tool-agnostic memory access across Claude, Gemini, and custom AI agents.
5. A **production deployment** across 13 repositories with nearly 20,000 indexed memories, demonstrating practical viability.

ContextFS addresses a fundamental limitation of current AI assistants: the ephemeral nature of context windows. By providing persistent, typed memory that spans sessions and tools, we enable AI systems to maintain coherent, long-term knowledge similar to human cognitive patterns.

The system demonstrates that formal type theory can be practically applied to AI memory management, providing both theoretical rigor and runtime safety. As AI assistants become increasingly central to software development workflows, systems like ContextFS will be essential for maintaining consistency, reducing context re-establishment overhead, and enabling truly collaborative human-AI development.

The theoretical foundations we present—type-safe context, formal change reasons, and semantic equivalence—provide a principled basis for future research in AI memory systems. We believe this work represents a foundational step toward AI systems with genuine persistent memory capabilities.

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A Complete Memory Type Reference

B MCP Tool Reference

The following MCP tools are available:

- `contextfs_save`: Save a new memory
- `contextfs_search`: Search memories (hybrid)
- `contextfs_recall`: Recall memory by ID
- `contextfs_list`: List recent memories
- `contextfs_update`: Update existing memory
- `contextfs_delete`: Delete a memory
- `contextfs_evolve`: Evolve memory (new version)
- `contextfs_merge`: Merge multiple memories
- `contextfs_split`: Split memory into parts
- `contextfs_link`: Create relationship between memories
- `contextfs_related`: Find related memories
- `contextfs_lineage`: Get memory evolution history
- `contextfs_index`: Index a repository
- `contextfs_sync`: Synchronize with server
- `contextfs_workflow_create`: Create workflow
- `contextfs_workflow_list`: List workflows
- `contextfs_task_list`: List tasks in workflow

C Configuration Reference

C.1 Environment Variables

```
# Data directory (default: ~/.contextfs
   )
CONTEXTFS_DATA_DIR=/path/to/data

# Embedding model
CONTEXTFS_EMBEDDING_MODEL=all-MiniLM-L6
   -v2

# Sync server URL
CONTEXTFS_SYNC_SERVER=http://localhost
   :8766

# PostgreSQL connection (cloud)
CONTEXTFS_POSTGRES_URL=postgresql://...
```

C.2 Repository Configuration

```
# .contextfs/config.yaml
namespace_id: custom-namespace-id
auto_index: true
max_commits: 100
exclude_patterns:
  - "*.lock"
  - "node_modules/**"
```

Table 11: All 22 memory types with descriptions

Type	Category	Description
fact	Core	Static facts, configurations, constants
decision	Core	Architectural decisions with rationale
procedural	Core	Step-by-step processes and workflows
episodic	Core	Session summaries and temporal events
user	Core	User preferences and personalization
code	Core	Code snippets, patterns, implementations
error	Core	Error messages, stack traces, resolutions
commit	Core	Git commit history and changes
todo	Extended	Tasks and work items
issue	Extended	Bugs, problems, tickets
api	Extended	API endpoints and contracts
schema	Extended	Data models and database schemas
test	Extended	Test cases and coverage
review	Extended	PR feedback and code reviews
release	Extended	Changelogs and versions
config	Extended	Environment configurations
dependency	Extended	Package versions and updates
doc	Extended	Documentation references
workflow	Workflow	Workflow definitions
task	Workflow	Individual workflow tasks
step	Workflow	Execution steps within tasks
agent_run	Workflow	LLM agent execution records